

UNIVERSITY OF THE AEGEAN



DOCTORAL THESIS

**Analysis & Design of an Opinion Mining
System for Policy Making in
E-Participation**

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Samos, November 2019

Declaration of Authorship

I, Lefkothea Spiliotopoulou, declare that this thesis entitled, “ Analysis & Design of an Opinion Mining System for Policy Making in E-Participation” and the work presented in it are my own. I confirm that:

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“The true meaning of policy making is to be seen as a viable system.”

Lefkothea Spiliotopoulou

Abstract

The rapidly emerging Web 2.0 and social media platforms have been initially exploited by private sector firms, in order to support mainly their marketing and customer relations functions. Considerable research has already been conducted for developing frameworks and practices focused on the effective utilization of these new communication media in the private sector. However, much less has been achieved towards the embodiment of similar technologies in the public sector despite the considerable relevant knowledge developed in this area for the private sector. Governments started exploiting the high capabilities and popularity of the social media platforms only the last few years, so there has been much less research concerning their effective utilization by government agencies. Currently, both governments and organizations are making considerable efforts, trying to enhance citizens' participation in the process of decision making and policy formulation.

A contemporaneous phenomenon observed nowadays is that governments worldwide are constantly facing the challenge of citizens' involvement in the decision making process. Traditional direct policy making mechanisms, such as the referendum calls, cannot be utilized in a daily basis due to the high required citizens' commitment and the increased cost of such a democratic act. What is more, the large volumes of user-generated content in multiple social media platforms, create the need to utilize and develop advanced techniques (topic modeling, opinion mining, sentiment classification, stance classification, etc.) and practices in order to process citizens' interactions and offer substantial support to governments make more efficient political decisions by taking into consideration peoples' feedback and expectations.

Computational approaches to opinion mining have mostly lie their interest on sentiment polarity detection by classifying the given text as positive, negative or neutral. While, there is less research in the direction of socio-political opinion mining, particularly in the field of stance classification, determining favorability as for, against or neutral towards given targets or topics of interest, specifically for online content like news comments and tweets. The target may be a person, an organization, a government policy, a movement, a product, etc. Current approaches for stance classification often treat each target independently, ignoring the potential dependency that could exist among targets.

Considering all the above, this thesis contributes to filling the mentioned research gaps, and aims to present an integrated opinion mining mechanism by developing and evaluating a framework for advanced and highly automated exploitation of multiple social media by government agencies. The above framework offers useful insights on the societal impact of strong political issues through the exploitation and combination of topic modeling, sentiment analysis and stance classification techniques, unraveling public's

stance and empowering citizens' participation in the decision making process, with the policy's life cycle as a baseline. This thesis has main scope to enable government agencies to communicate with wider and more heterogeneous audiences, increase public participation in their policy making processes, collect useful knowledge, ideas and opinions from citizens, and finally design better, more socially rooted, balanced and realistic policies.

Keywords: Social Media, e-Participation, e-Governance, Public Policy Formulation, Policy Making, Participatory Decision-Making, Government, Web 2.0, Crowdsourcing, Democracy, Opinion Mining, Sentiment Analysis, Topic Modeling, Stance Classification

Περίληψη

Οι ταχέως αναπτυσσόμενες τεχνολογίες διαδικτυακού ιστού 2.0 και τα κοινωνικά μέσα δικτύωσης αρχικά χρησιμοποιήθηκαν σε σημαντικό βαθμό από επιχειρήσεις του ιδιωτικού τομέα, προκειμένου να υποστηρίξουν κυρίως τις λειτουργίες μάρκετινγκ και δημοσίων σχέσεων με τους πελάτες. Έχουν ήδη πραγματοποιηθεί σημαντικές έρευνες για την ανάπτυξη πλαισίων και πρακτικών επικεντρωμένων στην αποτελεσματική αξιοποίηση αυτών των νέων μέσων επικοινωνίας στον ιδιωτικό τομέα. Ωστόσο, έχει επιτευχθεί λιγότερη πρόοδος όσον αφορά την ενσωμάτωση παρόμοιων τεχνολογιών στον δημόσιο τομέα, παρά τις σημαντικές σχετικές γνώσεις που έχουν αποκτηθεί στον ιδιωτικό τομέα. Οι κυβερνήσεις άρχισαν να εκμεταλλεύονται τις υψηλές δυνατότητες και τη δημοτικότητα των κοινωνικών μέσων μόνο τα τελευταία χρόνια, οπότε υπήρξε πολύ λιγότερη έρευνα σχετικά με την αποτελεσματική αξιοποίησή τους από τα κυβερνητικά στελέχη. Επί του παρόντος, τόσο οι κυβερνήσεις όσο και οι επιχειρήσεις καταβάλλουν σημαντικές προσπάθειες, προσπαθώντας να ενισχύσουν τη συμμετοχή των πολιτών στη διαδικασία λήψης αποφάσεων και στη διαμόρφωση πολιτικής.

Ένα σύγχρονο φαινόμενο που παρατηρείται στις μέρες μας είναι ότι οι κυβερνήσεις σε όλο τον κόσμο αντιμετωπίζουν συνεχώς την πρόκληση της συμμετοχής των πολιτών στη διαδικασία λήψης αποφάσεων. Οι παραδοσιακοί μηχανισμοί άμεσης χάραξης πολιτικής, όπως το δημοψήφισμα, δεν μπορούν να χρησιμοποιηθούν σε καθημερινή βάση, λόγω της μεγάλης απαιτούμενης δέσμευσης των πολιτών και του αυξημένου κόστους μιας τέτοιας δημοκρατικής πράξης. Επιπλέον, οι μεγάλοι όγκοι περιεχομένου που παράγεται από χρήστες σε πολλαπλές πλατφόρμες κοινωνικών μέσων δημιουργούν την ανάγκη χρήσης και ανάπτυξης προηγμένων τεχνικών (μοντελοποίηση θέματος, εξόρυξη γνώμης, ανίχνευση συναισθήματος, κατηγοριοποίηση προσωπικών στάσεων κλπ.) και πρακτικών για την επεξεργασία αλληλεπιδράσεων προερχόμενων από τους πολίτες και για να προσφέρουν ουσιαστική υποστήριξη στις κυβερνήσεις να λαμβάνουν πιο αποτελεσματικές πολιτικές αποφάσεις, έχοντας υπόψη τις ανάγκες και τις προσδοκίες των πολιτών.

Οι υπολογιστικές προσεγγίσεις στο πεδίο της εξόρυξης γνώμης έχουν ως επί το πλείστον το ενδιαφέρον τους στην ανίχνευση των συναισθημάτων, ταξινομώντας το δεδομένο κείμενο ως θετικό, αρνητικό ή ουδέτερο. Ενώ υπάρχει λιγότερη έρευνα προς την κατεύθυνση της κοινωνικο-πολιτικής εξόρυξης γνώσεων, ιδιαίτερα στον τομέα της ταξινόμησης της προσωπικής στάσης, προσδιορίζοντας την ευνοϊκότητα ως υπέρ, εναντίον ή ουδέτερη προς συγκεκριμένους στόχους ή θέματα ενδιαφέροντος, ειδικά για περιεχόμενο στο διαδίκτυο όπως τα σχόλια ειδήσεων και τα τweet. Ο στόχος μπορεί να είναι ένα άτομο, ένας οργανισμός, μια κυβερνητική πολιτική, ένα κίνημα, ένα προϊόν κλπ. Οι τρέχουσες προσεγγίσεις για την ταξινόμηση των προσωπικών στάσεων συχνά αντιμετωπίζουν κάθε στόχο ανεξάρτητα, αγνοώντας την πιθανή εξάρτηση που μπορεί να υπάρχει μεταξύ των στόχων.

Λαμβάνοντας υπόψη όλα τα παραπάνω, η διατριβή αυτή συμβάλλει στην κάλυψη των προαναφερθέντων ερευνητικών κενών και αποσκοπεί στην παρουσίαση ενός ολοκληρωμένου μηχανισμού εξόρυξης γνώμης αναπτύσσοντας και αξιολογώντας ένα πλαίσιο για προηγμένη και αυτοματοποιημένη χρήση πολλαπλών κοινωνικών μέσων από κυβερνητικά στελέχη. Το παραπάνω πλαίσιο προσφέρει χρήσιμες γνώσεις σχετικά με τον κοινωνικό αντίκτυπο ισχυρών πολιτικών ζητημάτων μέσω της χρήσης του συνδυασμού της μοντελοποίησης θεμάτων, της ανίχνευσης συναισθημάτων και της κατηγοριοποίησης προσωπικών στάσεων, καθορίζοντας τη στάση της κοινής γνώμης και της ενδυνάμωσης της συμμετοχής των πολιτών στη διαδικασία λήψης αποφάσεων, έχοντας ως γραμμή βάσης τον κύκλο ζωής μιας πολιτικής. Η διατριβή αυτή έχει ως κύριο στόχο να επιτρέψει στις κυβερνητικές υπηρεσίες να επικοινωνούν με ευρύτερα και πιο ετερογενή ακροατήρια, να αυξήσουν τη συμμετοχή του κοινού στη διαδικασία λήψης πολιτικών, να συλλέξουν χρήσιμες γνώσεις, ιδέες και απόψεις από τους πολίτες και να σχεδιάσουν τελικά καλύτερες, πιο κοινωνικά ριζωμένες, ισορροπημένες και ρεαλιστικές πολιτικές.

Λέξεις-κλειδιά: Κοινωνικά Μέσα, Ηλεκτρονική Συμμετοχή, Ηλεκτρονική Διακυβέρνηση, Διαμόρφωση Δημόσιας Πολιτικής, Συμμετοχική Λήψη Αποφάσεων, Διακυβέρνηση, Πληθοπορισμός, Συμμετοχική Λήψη Αποφάσεων, Εξόρυξη Γνώμης, Ανίχνευση Συναισθήματος, Μοντελοποίηση Θεμάτων, Κατηγοριοποίηση Στάσεων

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Abbreviations

ICT	Information and Communication Technologies
API	Application Programming Interface
CMS	Content Management Systems
DOI	Diffusion of Innovation Theory
DSR	Design Science Research
DSS	Decision Support System
ECB	European Central Bank
IDS	Iterative Design Science
IID	Iterative and Incremental Development
IMF	International Monetary Fund
IS	Information Systems
LDA	Latent Dirichlet Allocation
LIWC	Linguistic Inquiry and Word Count
MEP	Greek Members of the European Parliament
MPQA	Multi-Perspective Question Answering
NLP	Natural Language Processing
NLTK	Natural Language ToolKit
NMF	Non-negative Matrix Factorization
PADGET	Policy Gadget
PMI	Point-wise Mutual Information
POS	Part-of-Speech
SA	Sentiment Analysis
SQL	Structured Query Language
SO	Semantic Orientation
TAM	Technology Acceptance Model

Chapter 1

Introduction

1.1 Challenges in eGovernment & eParticipation Era

Governments worldwide are constantly facing the challenge of citizens' involvement in the decision making process. In order to succeed an efficient policy making, public sector shifts its interest from the 'elitist model' of public policy development, with experts being the source of policies, towards a more 'democratic model', with citizens having an actual active role in policies' formulation. This has as a result the adoption of more participative democratic ideas, growing the engagement of stakeholder groups in the formulation of public policies [Alexiadou \(2018\)](#), [Barber \(1984\)](#), [Macpherson, Rowe and Frewer \(2000\)](#) and the need to develop mechanisms that listen citizens' sentiment on key political issues. Public participation is considered 'the practice of consulting and involving members of the public in the agenda-setting, decision-making and policy forming activities of organizations or institutions responsible for policy formulation [Rowe and Frewer \(2004\)](#).

In the last few years, there has been effort towards the exploitation of Information and Communication Technologies (ICT) for the development of new governance models enabling a more open, citizen-centric and participatory policy making process. This has led to a rapid growth of research and practice in the area of e-participation¹ and in

¹Commission of the European Communities. (2006). i2010 eGovernment Action Plan: Accelerating eGovernment in Europe for the Benefit of All. SEC(2006) 511. Available at: <http://data.consilium.europa.eu/doc/document/ST-12080-2016-INIT/en/pdf>

general e-governance² in the last 15 years Loukis and Charalabidis (2012), Rowe and Frewer (2000), Rowe and Frewer (2004), Sæbø et al. (2008), Watson and Mundy (2001), Reese (2007), Timmers (2007). One of the most promising ICT for these purposes is the advent of Web 2.0 and social media platforms diffusion.

Social media penetration has increased dramatically reshaping both structure and public discourse in society, reforming communities on a whole new level and resetting agendas in various topics ranging from social, religious to political issues Freeman and Quirke (2013). These online interaction platforms, functioning as e-participation channels, experienced a rapid shift from pure web-based sites to large and ubiquitous interactive communication platforms. Social media platforms crucially increased the possibilities for users to express their opinions (i.e. positive/negative/neutral) concerning any topic of discussion and offering their personal position towards the topic or else their stance (i.e. positive/negative) Somasundaran and Wiebe (2009). These new communication channels have been initially exploited by private sector firms, in order to support mainly their marketing and customer relations functions; so there has been considerable research in this area, which has already developed useful knowledge on methods and practices for the effective utilization of social media in the private sector, and their critical success factors Constantinides (2009), Constantinides (2010), Dwivedi et al. (2011), Evans (2010), Heath et al. (2013).

As for the public sector, less research has been conducted oriented to the exploitation of the social media Punie et al. (2010). Governments started exploiting the high capabilities and popularity of the social media for enhancing public participation much later, so there has been less research and knowledge concerning their effective utilization by government agencies³. Their aim is to make a shift from e-government to we-government, through the exploitation of social media platforms Linders (2012) creating a new era of democratic involvement, transparency and accountability through political openness Freeman and Quirke (2013). Therefore it is necessary to develop new knowledge in this recently emerged area, concerning methods and practices for the effective utilization of social media in government, their impact and value, and also the challenges

²Commission of the European Communities (2010). A digital Agenda for Europe. SEC(2010) 245. Available at: https://europa.eu/european-union/file/1497/download_en?token=KzfsSz-CR

³United Nations (2008). United Nations e-Government Survey 2008. From e-Government to Connected Governance. Department of Economic and Social Affairs Division for Public Administration and Development Management. Available at: <https://publicadministration.un.org/egovkb/portals/egovkb/documents/un/2008-survey/unpan028607.pdf>

they pose and their limitations, which will enable a mature and effective exploitation of social media by government agencies [Chun and Reyes \(2012\)](#), [Criado et al. \(2013\)](#).

These online interaction platforms are already used extensively by citizens for political discussions and for organizing and coordinating political activity [Agarwal et al. \(2011\)](#), [Larsson and Moe \(2011\)](#), so governments realize that can not be absent from them. Thus, public sector focuses on accelerating public sector regulations to reach society cost—effectively, avoiding any bureaucratic obstacles with stakeholders (i.e. citizens, public/private bodies), creating channels of offline participation and facilitating collaborative governance [Stylios et al. \(2012\)](#).

At the beginning, the tools that have been used were traditional channels. The first generation of e-participation contained many ‘official’ e-participation spaces operated by government agencies offering information about decisions, policies and plans taken by the government and the ability to citizens to write their opinions or enter a discussion on various topics. The need for increasing the quality led to more structured e-spaces and required more focused and disciplined discussions⁴. As a result, the groups of people that could take part in such discussions needed to be educated and have a great variety of knowledge. Governments, actually, considered that citizens would visit these websites and actively participate in public debates about policy issues and get familiar with the structure, language and rules of the official websites. However, this action had not as much impact as it was expected [Chadwick \(2009\)](#), [Ferro and Molinari \(2010\)](#).

Most of these e-government spaces were unknown for the majority of online users because the promotion cost a large amount of money and there was a slow pace of dissemination. What is more, many of the topics were initiated by government and did not affect at all citizens who seemed having other problems in relation to which were open for discussion. Additionally, many of these online spaces were not user-friendly and as a consequence their use was not easy for all. These problems along with the heterogeneity of online users with respect to political - cultural interests and technological – educational skills as well as the simultaneous evolution of Web 2.0 and social media led the government agencies to exploit the virtual spaces used and adopted by the online users widening the role of e-participation.

⁴Organization for Economic Co-operation & Development. (2004b). *Promise and Problems of e-Democracy: Challenges of Online Citizen Engagement*. Paris/France, OECD Publication Service. Available at: <http://www.oecd.org/gov/digital-government/35176328.pdf>

Furthermore, the not user-friendly online environments offered by these ICT tools led citizens to visit other social media platforms creating online discussions on their own and moving towards a second generation of e-participation. Some of the topics that are discussed have a political content [Agarwal et al. \(2011\)](#), [Honeycutt and Herring \(2009\)](#), [Larsson and Moe \(2011\)](#), [Mergel et al. \(2009\)](#), [Osimo \(2008\)](#), [Punie et al. \(2010\)](#). While government agencies were trying to bring closely citizens, they moved their interest towards the platforms where citizens have online discussions and create content exchanging ideas, perspectives, views, opinions. In these electronic places, governments cannot be absent but only present expressing their decisions, policies, actions and listening to citizens. In this way, agencies make an effort of gaining a better understanding of public's needs and expectations and create a communication channel with them. To succeed this, the government agencies need to overcome many challenges and learn to utilize social media platforms in an efficient way promoting public participation and policy making.

Considering the above milestones, [Loukis and Charalabidis \(2012\)](#) proposed a categorization of digital mechanisms for public participation delineated by the advent of Web 2.0. Table 1.1 depicts a comparison among four paradigms of online participation. The first one is focused on the utilization of electronic forums, i.e. traditional e-participation channels, enabling electronic consultations on multiple policy related topics [Sæbø et al. \(2008\)](#). The second paradigm lies on their transformation into structured electronic forums, offering to citizens the ability to enter only semantically annotated postings according to a predefined discussion ontology [Loukis and Wimmer \(2012\)](#), [Xenakis and Loukis \(2010\)](#). The third paradigm is linked with the beginning of the systematic exploitation of popular social media with citizens choosing the platforms to discuss and generate online content [Charalabidis et al. \(2015\)](#). It is specifically based on the use of Web 2.0 architectures allowing governmental bodies to post content (e.g. short or longer text, images, video) related to policies under formulation in multiple social media, collect citizens' interactions with it and finally analyse it as feedback (e.g. views, comments, likes/dislikes etc.).

Nevertheless, the rapid growth of the volumes of data generated in Web 2.0 sources (e.g. social media sites, blogs and microblogs, news sharing sites, online forums, etc.) by citizens freely have led to the creation of another mechanism based on content monitoring associated with public policies and decisions under formulation by government

TABLE 1.1: Comparison of four digital mechanisms for public participation [Loukis and Charalabidis \(2012\)](#)

Mechanism	Basis	Participation Quantity	Participation Quality	Government Control - Moderation	Type of Crowdsourcing
Electronic Forum	Web 1.0	low	high	high	active - wide
Structured Electronic Forum	Web 1.0	very low	medium	very high	active - experts
Centralized exploitation of multiple social media	Web 2.0	high	medium	low	active – very wide
Web 2.0 content collection and analysis	Web 2.0	very high	medium	none	passive – very wide

agencies. The main difference among the four digital mechanisms is the level of moderation exercised by governments. In the first two mechanisms governmental bodies determine the rules and topics of discussion, in the third one participation is initiated and stimulated by government agencies following the rules of the particular social media channel used. Last but not least, the fourth is more innovative with no moderation or limitation through government postings. This explains the divergence among the four digital mechanisms into active (first three mechanisms) and passive crowdsourcing (fourth mechanism) respectively.

In parallel, significant advancements in evolving ICT fields, such as Artificial Intelligence, Machine Learning, Big Data Analysis and Opinion Mining have offered new ways in dealing with the weaknesses and limitations observed since the original e-participation methods, by empowering more structured interaction between citizens, stakeholder groups and governmental bodies. Multiple advanced techniques and tools stemming from the above ICT fields, move forward the birth of new innovative digital mechanisms that will empower the decision making process along with the quality of public participation. The exploitation of such tools and methods for collecting, extracting, analyzing, processing, mining and modelling online user-generated content based on public’s opinions and sentiments on policies and policy issues under discussion will provide useful insights to policy makers for more informed decision support.

Summarizing the above, we are in front of research challenges characterising a new era in Policy Making with the adoption of new tools for advanced social media exploitation aiming to empower citizens’ involvement in the decision making arena [Ferro and Molinari \(2010\)](#). [Chun and Reyes \(2012\)](#) move forward this goal by proposing three directions of additional research: i) employment of advanced forms of social media usage

in government, and suitable methodologies for evaluating them; ii) development of mining techniques for online text processing based on citizens' interactions with government extracted from social media platforms, in order to determine opinions and sentiments; iii) exploring the effects of social media exploitation by government on citizens' participation and collaborative governance. **The current dissertation aims to accomplish all the above goals by addressing the upcoming challenges and providing a mechanism for efficient policy making.**

Therefore, in order to unravel the full potential of citizens' empowerment in policy formulation, it is necessary to design and implement an effective 'socio-technical architecture' based on social media exploitation and advanced mining to enhance public participation in governmental decision making. The **application of real-case scenarios** of the proposed architecture can offer us useful insights on citizens' sentiments concerning critical events during each case-studies' timeline. **The ultimate goal of this dissertation is to provide a holistic approach on how an opinion mining system can be utilized in digital government for direct democracy empowerment.**

1.2 Research Problem & Research Hypothesis

Over the years, societies worldwide have become more and more divergent and contrasting in terms of culture and complexity in various issues that emerge along with the upcoming needs and public's concern. Over the last 20 years, public administrations have shifted their interest in increasing the accountability of governments through the use of efficient public policy-making. In order to design and assess government programmes, laws and regulations, it is crucial to take account of their interactions and synergies with other government programmes and ensure that are performing well achieving their objectives. Additionally, to fortify that policies are effective and efficient, performance assessments of the regulatory framework are required so that corrective measures and methodical mechanisms can be taken rapidly. Thus, in this context, **it is essential to consider whether the current policy-making process can be improved** [Charalabidis et al. \(2015\)](#).

This causes as an effect the **prerequisite for new methodologies, techniques and approaches to deal with them**. This social heterogeneity is implicit to the formulation of public policies that aim to address the constantly emerging social problems. Innovation in information technology developments and the proliferation of social media platforms that thrive at a very fast pace, offer a real possibility to governments to facilitate collaborative governance with citizens and empower their participation in the decision making process [Spiliotopoulou et al. \(2017\)](#). Thus, in order for governments to achieve their goal, they **need to gain useful insights of public's needs, concerns and sentiments towards political issues and policies under formulation**. To do so, the collection and process of vast amounts of external information on different political issues and governmental policies is required. Knowledge on what the public thinks over policies impacts the policy itself by triggering new insights and creating awareness of new opportunities.

To cope with these critical factors, government agencies responsible for public policy formulation have recognized the significance of taking into account all different perspectives and **leveraging the knowledge of citizens when designing and implementing a policy decision**. In the e-participation approaches, individuals are considered carriers of tacit knowledge in order to better understand social needs, identify expectations, concerns and assess the effectiveness of policies.

Social media and online collaboration platforms can play a crucial role in decoding this implicit knowledge, allowing citizens to directly propose new solutions to societal challenges. Furthermore, previous research on creativity field has pinpointed the importance of heterogeneous social networks, since generation of creative ideas is often the result of innovative combinations of multiple perspectives that individuals are exposed to via social interaction, offering access to a wide formation of views, skills, and information [Perry-Smith and Shalley \(2003\)](#), [Wu and Chang \(2013\)](#).

Therefore, assuming that the design of a public policy for addressing a social problem usually needs the design of innovative actions in order to supervise all the different dimensions of the problem, we expect that **social media exploitation by both the public sector and citizens will allow the acquisition of knowledge on the design of highly innovative public policies**. Another presumption is that if the **systematic exploitation** is based on the latest ICT developments, it can **empower**

government agencies to collect online user-generated content provided by citizens on political issues and topics that have to be addressed through public policies.

The advantage in utilizing social media platforms is that they serve as e-participation channels where users express freely their opinions and actually offer their personal position or else their stance towards the specific topic of discussion. A large part of these discussions refers to political figures along with the parties they represent, governmental issues, and political decisions that are taken by the public sector. This has a consequence the continuous growth of online data that leads to vast amounts of information becoming available to explore and understand. A large part of these discussions refers to ideological dual-sided topics, considering political issues in which users' stance can take only two polarizing sides, specifically for or against [Anand et al. \(2011\)](#). Such topics, used for expressing and forming opinions, often stem heated discussions and attract large audience of people [Mukherjee and Liu \(2013\)](#), [Walker et al. \(2012\)](#).

Thus, in order to be able to properly collect, analyze and process large amounts of such types of data, **there is a need to utilize advanced data mining techniques in order to efficiently process the data**. Over the years, multiple mining methods have been developed, such as topic modeling, sentiment analysis [Liu \(2012\)](#) and stance classification [Anand et al. \(2011\)](#). Although it is important to determine whether a user's opinion is positive or negative, it is even more essential to determine the user's personal position towards a specific topic as for or against. **The challenge that arises lies on the fact that extracting and classifying users' personal stance on governmental actions can help us not only understand how certain communities react on specific events, but also predict significantly their sentiments to future events and decisions, invigorating an efficient policy making process** [Spiliotopoulou et al. \(2017\)](#).

Another problem that governments have to face is that when taking fundamental decisions, **traditional direct policy making mechanisms**, such as the referendum calls, gallops and online polls **cannot be utilized in a daily basis** due to the high required citizens' commitment and the increased cost of such a democratic act. **Thus, in order modern societies to make more efficient political decisions, they need**

to adapt a modern mechanism that explores public's voice and opinions on essential political topics and utilizes them as input in the governmental decision making processes, giving that way birth to the true scope of electronic democracy in the digital era we live in.

1.3 Research Objectives & Questions

To address the above challenges and validate the research hypothesis, the following objectives have been formulated within this thesis:

- **Obj1.** Design and implement a novel architecture for effective utilization of social media by government agencies to promote participative governance
- **Obj2.** Review existing techniques in the opinion mining field to develop advanced methods
- **Obj3.** Determine public's feeling towards critical political decisions taken in a timeline of events in policy formulation process
- **Obj4.** Explore how text mining techniques can be combined to produce knowledge for the decision makers
- **Obj5.** Identify if mining techniques can be utilized in real political events to evaluate and extract knowledge
- **Obj6.** Evaluate system's outcomes throughout the entire policy formulation under the prism of the policy life cycle
- **Obj7.** Examine if a new era of democratic involvement through political openness, social media and intelligent services can contribute in providing decision support to policy makers and enable a more socially-rooted citizen-centric policy making

The above objectives have been framed under the following six research questions:

1. **RQ1.** What are the research challenges in the areas of e-participation and social media in public policy formulation?

2. **RQ2.** What is the present state of play in the exploitation of Social Media in Government?
3. **RQ3.** What is the current state of the art on the already existing techniques developed in the fields of Topic Modeling, Sentiment Analysis and Stance Classification?
4. **RQ4.** How should an architecture be designed in order to support social media exploitation?
5. **RQ5.** How should multiple mining techniques be utilised in order to extract online public sentiment towards governmental decisions??
6. **RQ6.** How policy making formulation can benefit from e-Part & Social Media through the usage of an Opinion Mining system?

1.4 Contribution

The current research contributes to the enrichment of our knowledge on the utilization of Social Media in Government, by designing, applying and evaluating three mechanisms of advanced social media exploitation in the public policy formulation. In order to successfully solve the research problems, accomplish the aforementioned objectives and fill existing gaps in the research fields, the mechanisms that are developed follow different approaches of crowdsourcing. The first mechanism presents a Generic framework which introduces the concept of Policy Gadget (Padget), presenting a micro web application or content that combines a message on a certain policy with underlying group knowledge in social media platforms and interacts with end users in order to forward their feedback to policy makers. It is used by government policy makers in order to publish the above-mentioned policy-related content and deploy these micro web applications to multiple social media, and then collect users' interactions with them in an automated manner using their application programming interfaces (API). The second mechanism presents an Advanced Framework in which citizens post their comments on various social media platforms towards critical political issues without any intervention from government agencies. The third mechanism presents a Multi-layer framework with the online content collection lying in both from the public and the public sector. These mechanisms

or else approaches integrate various concepts related with e-participation and employ a combination of processing and mining techniques in order to enhance public policy formulation. The thesis opens up new directions on the use of Social Media by the public sector. More specifically:

- **C1.** Promote the concept of a central platform that enables social media utilization to empower citizens' involvement in the decision-making process
- **C2.** Introduce opinion mining solutions for social media exploitation in policy making process
- **C3.** Design, employ and evaluate 3 architectures that support the proposed mining solutions
- **C4.** Determine public's stance in a timeline of critical events, having policy life cycle as baseline
- **C5.** Predict the political decisions outcomes and compare them to the real results using text mining techniques
- **C6.** Determine how political figures can feel citizens' sentiment during the policy making process
- **C7.** Provide a holistic approach on how an opinion mining system can be utilized in digital government in a way to strengthen participatory democracy

Figure 1.1 depicts a joint combination of text mining techniques, specifically topic modeling, sentiment analysis and stance classification for policy making.

For all the above, the thesis contributes in building knowledge of how a general framework that combines various advanced mining techniques can be actually utilized for collaborative decision making across the policy life cycle. Figure 1.2 depicts how the research problems, the research objectives, the overall contribution and the three mechanisms for policy making connect.

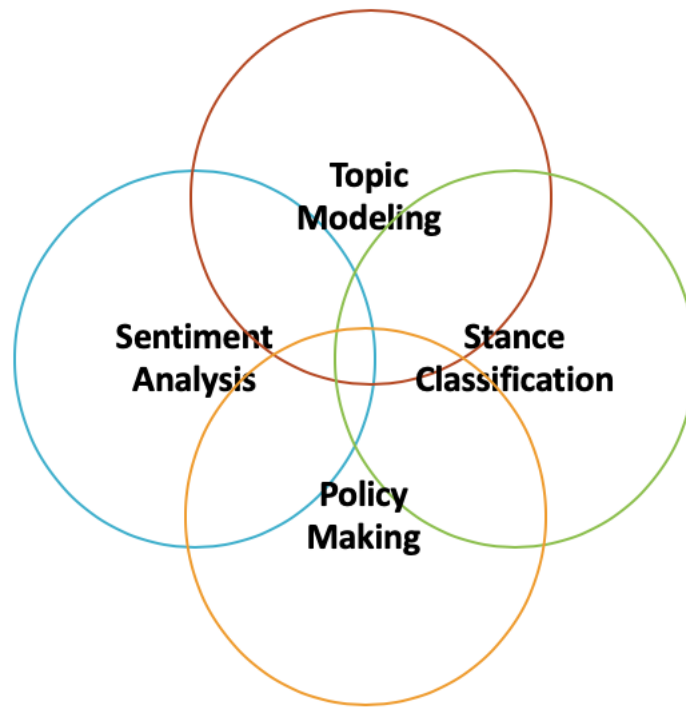


FIGURE 1.1: Combination of Text Mining Techniques for Policy Making

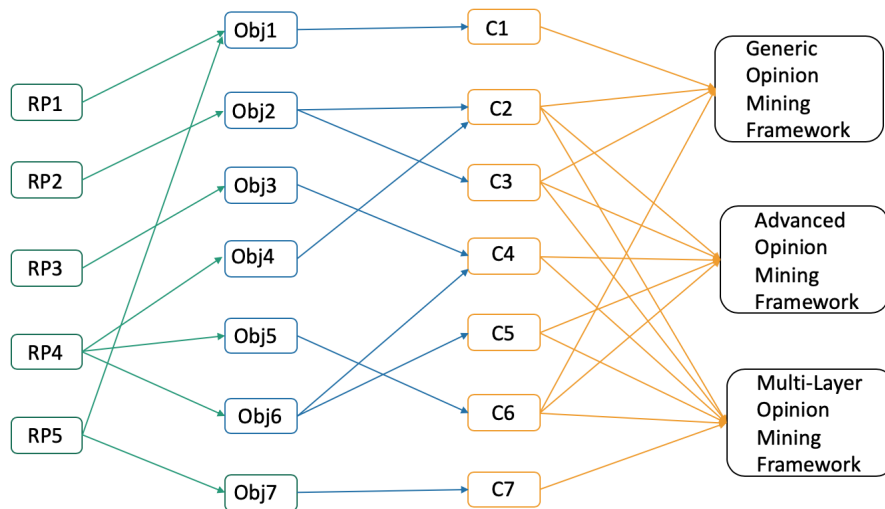


FIGURE 1.2: Thesis Contribution

1.5 Thesis Structure

The dissertation is structured in seven chapters. The current Chapter 1, which is an introduction, presents the scope of the research study, indicating the problem that constitutes the focus of the Thesis and profiling the current challenges in the scientific

domain we are lying our interest. Then, it specifies in thorough detail the objectives of the current dissertation and forms the research questions that it intends to address. Last but not least, this chapter closes with the contribution that the Thesis aims to accomplish.

Chapter 2 describes the overall methodology that has been adopted for conducting the research, including the description of the design process and data collection methods and tools. Furthermore, it provides the theoretical foundations on how social media platforms exploitation and various processing and mining techniques can be linked with the application of crowdsourcing from the public sector in an effort to promote citizens' involvement in the decision-making process.

Chapter 3 provides the theoretical background of the overall research and a review of the relevant literature with the definition of the key concepts.

The second part of the thesis is composed by chapters 4, 5 and 7 which provide in a thorough detail the three approaches and their underlying opinion mining mechanisms designed and implemented for public participation, emerged from the current research.

Chapter 4 presents the Generic Opinion Mining framework relying on centralised exploitation of various social media sources, its practical application and the results from its evaluation.

Chapter 5 presents the Advanced Opinion Mining Framework that identifies public's opinion and stance towards governmental decisions, concerning policy formulation and promoting in that way the decision making process. Additionally, its practical application and the results from its evaluation are also presented in details.

Finally, Chapter 7 presents the Multi-layer Opinion Mining Framework, that combines multiple processing and mining techniques for social media exploitation along with its application and evaluation. This last integrated framework offers a holistic approach on how to support governments in the policy making process empowering bringing citizens to the forefront.

Chapter 2

Research Approach

2.1 Introduction

The aim of this chapter is to present the overall research design and strategy used for the implementation of this PhD dissertation, which guided the research work and lead to the accomplishment of the research objectives and the realisation of the anticipated contributions (mentioned in the previous chapter). More specifically, in the following subsections, a set of well-established methodologies in the domain of ICT and other application domains are introduced. Also it is explained how these methodologies were adapted to formulate our research methodology. As such, the iterative design process was used to form the overall orientation of the research while traditional software engineering methodologies, i.e. waterfall model, scrum, have been applied in the individual iterations. Since in the iterative process, design is guided by the feedback and evaluation, the framework developed for the evaluation of the research artifacts, forms a core aspect of the research methodology. Therefore, in the second half of the of the chapter the methodology adopted for the evaluation stage inside the different cycles, providing some information on the theoretical foundations for their design and presenting relevant approaches. In addition, the set of methods of data collection and analysis are listed. As an instance of case-based research, cross-case analysis has been applied at the final stage of the methodology to aggregate the overall findings and generate the conclusions, structuring the accumulated knowledge in the ‘Social Media in Government’ field.

In this chapter, we present our theoretical background and a literature review with similar studies specifying the points in which our approach is more efficient than the rest. Our research work lies in the areas of Web 2.0 penetration, participative policy making, social media exploitation, application of crowdsourcing ideas in the public sector, and text mining techniques utilization such as topic modeling, sentiment analysis and stance classification. Consequently, we offer an in-depth analysis of the related works in all the aforementioned domains.

2.2 Research Methodology

2.2.1 Design Science Research

The premises of the adopted research methodology lie on the design science paradigm, which confines analytical techniques for performing Information Systems Research [March and Storey \(2008\)](#). As [Hevner et al. \(2004\)](#) mentioned Design Science paradigm aims to generate innovations that determine the ideas, practices, technical capabilities, and products through which the analysis, design, implementation, and use of Information Systems can be both effectively and efficiently accomplished [Hevner et al. \(2004\)](#). During the last decades, design is appraised to be indispensable to information systems discipline [Glass \(1999\)](#), [Winograd \(1996\)](#). The focus of design science research reclines on the investment on IT artifacts as a means to solve significant real-life problems and achieve organisational goals [Alter \(2003\)](#), [Simon \(1996\)](#). The design science paradigm lies on the formation, modelling and evaluation of new innovative artifacts that contribute in strengthening human and organisational capabilities [Hevner et al. \(2004\)](#). According to them, evaluation artifacts may be constructs (concepts), models, methods, or instantiations. Our research goals are oriented in building new conceptual methods, models and mechanisms that provide significant benefit to the improvement of public sector's capabilities and the adaptation to the desired situation of more encompassing policy making for addressing complex societal problems.

The Design Science paradigm has been extensively endorsed in the Information Systems development as a way to address what are considered to be wicked problems [Rittel and Webber \(1973\)](#), i.e. problems that are characterized by unreliable requirements, complex interactions among various issues of the same problem, implicit flexibility to

alter design processes and products, a critical dependence lying on human cognitive abilities to produce efficient solutions, and a critical dependence on human social abilities (e.g. teamwork) to produce successful solutions.

2.2.2 Iterative Design Process

In order to develop the artifacts serving to our research purpose, we utilize and endorse the iterative design process as a design methodology. An iterative design, according to Wikipedia, is considered a design methodology for developing a new product, system or method for a unique situation through a “cyclic process of prototyping, testing, evaluating the results, and refining a product or process”. The key concept lies on the fact that the design should not be done at once, but rather elaborated in repeated cycles. In iterative design, the interaction along with the designed system is exploited as a form of research for informing and evolving a project, as successive and refined versions, or iterations of a design are implemented. Each new cycle draws on the feedback and results of the last complete the one. The results of testing from the most recent iteration of a design are integrated in the design of the next cycle and determine the changes. One of the major advantages of this approach is its ability to eliminate unexpected problems, usability flaws, mistakes and misunderstandings, saving both effort and time (Karat, 1990) and at the end improve the quality and functionality of a design. Iterative development helps ameliorating the research artifact by adjusting specific requirements to the changing world. Iterative design is often confused with incremental development. Cockburn (2008) differentiates these two terms with incremental design dealing with adding into the development process, while iterate lying in re-doing things. In his research, presents cases and provides suggestions on how these two types of development can be combined together, while Larman and Basili (2003) offer a historical review of the IID practices in software engineering projects dating from the 1960’s.

Iterative design has multiple applications in many domains. More precisely, in the industrial design, it is applied in architecture and in various subfields of the IS discipline, such as web design, human computer interfaces, software or information systems design Bailey (1993), Ishii et al. (1994), Kelley (1984), Nielsen (1995), Wachter et al. (2003). Offering an example application from the public sector, an iterative user-centered process has been implemented in the evaluation and improvement of the US governmental

portal giving information and services to citizens Bailey (1993). In terms of software development, the spiral model has basis on the iterative design principles Boehm (1988).

Following the iterative design approach stages, our research has been developed in three design cycles as shown in Figure 2.1, structured into phases that are repeated periodically over the three iteration models, constructing a casual chain between them. The selected research approach, allowed us to design, implement and evaluate three different paradigms on crowdsourcing and policy making formulation and obtain results on their applicability building our base around the critical research questions. Each iteration follows the methodology for conducting DSR in IS, which contains six steps: problem identification and motivation, definition of the objectives for a solution, design and development, demonstration, evaluation, and communication Peffers et al. (2007). The designed IT artifacts offered insights on the understanding of each one of the proposed methodologies and frameworks proposing their implementation in the public sector. These implementations allow the evaluation of the feasibility of each crowdsourcing approach, their effectiveness and added value. The users of the designed framework and the evaluators were the online users. Based on their feedback, we re-worked and redesigned the approaches adjusting them to the new research challenges. In the end of each cycle we examined if the approach was correct through the evaluation phase.

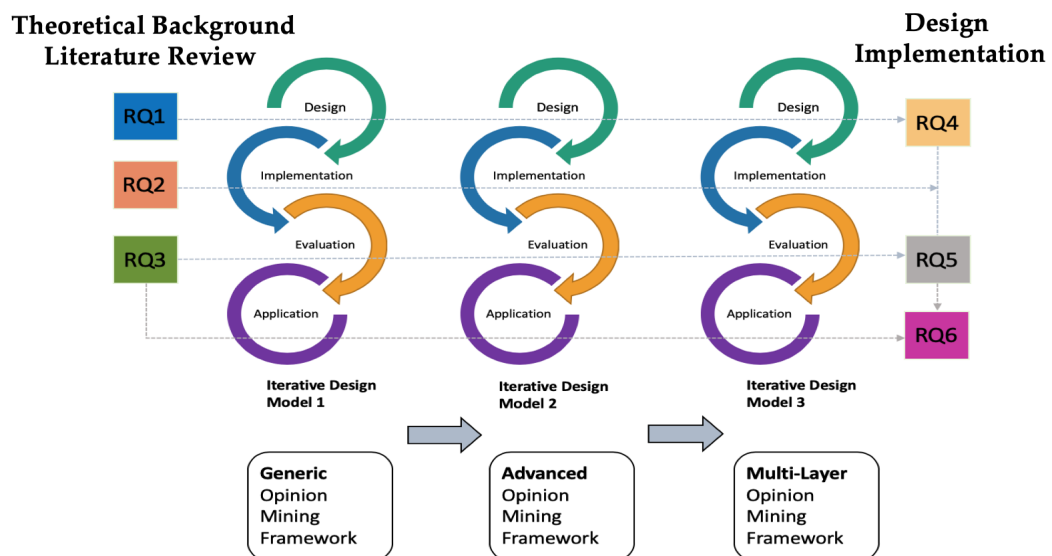


FIGURE 2.1: Research Models

2.2.3 System Modeling, Iterative Cycles & Sequence of Phases

In order to model our system, a combination of a traditional software development process with an agile approach has been adopted. Implementing an evolving system, our methodology employs the Waterfall model [Bell and Thayer \(1976\)](#) with a balance of agility and flexibility. Therefore, the design process of each iterative cycle has as a sequence of phases that follow the waterfall model. In a waterfall model, each phase or stage must be completed before the next phase can begin and there is no overlapping in the phases. The following phases of each design iteration are:

1. Requirements: understanding and definition of what are the needs to design and what is the system's purpose based on the system's specifications
2. System Design: studying of the requirement specifications and preparation of system's design. In this phase the overall system's architecture is determined
3. Implementation: with inputs from system design, system development initially in small programs referred as modules, integrated into the next stage. Each module is then developed and tested for its functionality
4. Integration: integration of all the modules developed in the implementation phase into a system (framework) after testing each module separately
5. Evaluation: assessment of our system with an initial cross-evaluation performed through a preliminary study and then overall evaluation of our proposed system's performance in terms of accuracy and f-measure
6. Application: after the evaluation of the proposed architecture, the framework is applied through a number of pilots in real life conditions, so that its added value in the policy making process can be assessed and potential improvements can be explored

2.3 Social Media Crowdsourcing in Policy Making Formulation

2.3.1 Web 2.0 & Wicked Problems

Web 2.0 is considered being a set of technologies, applications and values [O'Reilly \(2007\)](#), [Osimo \(2008\)](#). The new technologies being introduced, such as XML, Open API, Flash, Ajax focus on increasing usability, integration and re-use of web applications. Based on the aforementioned technologies, applications have already been developed providing the ability to create content, publish content, share information and collaborate. Blogs, Wikis, RSS Feeds, Social Networking Sites, Virtual Spaces are some examples of applications. Applications, on the one hand, build on the user's knowledge and skills and on the other hand, enable user to build both content and services. At the beginning, Web 2.0 was used as a mean for social communication while later it was used by the private sector mostly for advertising and marketing [Constantinides \(2009\)](#), [Constantinides \(2010\)](#). Recently, there is a shift towards the use of Web 2.0 applications from the public sector not only for public relations but also for more complicated and significant issues such as knowledge management, law enforcement, and public participation.

Social problems, that are most typically assigned to policy makers, are issues (poverty, equality, health, wellness, etc.) difficult to be solved because they are fuzzy, incomplete, partially contradictory, and with changing requirements. Due to the fact that our societies have become more heterogeneous and pluralistic in terms of culture, values, concerns, and lifestyles, the nature of social problems and the methodology of addressing them has changed as well. Therefore, public policies that focus on addressing contemporary problems inherit this increasing complexity. [Rittel and Webber \(1973\)](#) theorize that social problems are usually "wicked," because they are lacking clear and widely agreed definition and objectives.

Previous research has revealed that the solution of the modern complex and "wicked" policy problems can be greatly supported by Information Systems that allow stakeholders to enter and exchange relevant perceived "topics" and "questions", and also "ideas" and "arguments" (positive and negative ones), which are called "Issue-Based Information Systems" and can stimulate and promote a controlled and productive way of discussion among competent government agencies and different stakeholder groups, and

also facilitate mutual understanding and convergences among them [Kunz et al. \(1970\)](#), [Conklin and Begeman \(1988\)](#). In general, ICT can enable and facilitate extensive exchange of information, knowledge, perceptions and opinions among government agencies and policy stakeholders, which can be highly beneficial for the development of better, more balanced and acceptable public.

2.3.2 e-Participation & Social Media Collaboration

The emerging Information and Communication Technologies along with the need to address the wicked problems, has led to a rapid development of e-participation research and practice¹. Especially the emerged Web 2.0 social media and their high penetration in modern societies created big opportunities for a wider low-cost application of these approaches, involving more and diverse citizens groups in policy consultations². There is already considerable literature that analyses the great potential of social media use in government [Osimo \(2008\)](#), [Bertot et al. \(2012a\)](#), [Bertot et al. \(2012b\)](#), [Bonson et al. \(2012\)](#), [Linders \(2012\)](#), [Magro \(2012\)](#), [Criado et al. \(2013\)](#).

It has been concluded over many researches that social media platforms provide government agencies extensive capabilities to:

- Increase citizens' participation and engagement, providing to more groups of modern societies a voice in debates on public policies development and implementation
- Promote transparency and accountability, and reduce corruption, enabling governments to open up large quantities of activity and spending related data, and at the same time enabling citizens to collectively take part in monitoring the activities of their governments
- Proceed to public services co-production with citizens, enabling government agencies and the public to develop and design jointly government services
- Exploit citizens' knowledge and talent in order to develop innovative solutions to the increasingly serious and complex societal problems

¹Commission of the European Communities (2009). European eParticipation Summary Report. Available at: <https://ec.europa.eu/digital-single-market/en/news/european-e-participation-summary-report>

²Tapscott, D., Williams, A.D. and Herman, D. (2008), *Government 2.0: Transforming Government and Governance for the Twenty-First Century*, nGenera Corporation, Sunnyvale, CA.

2.3.3 Crowdsourcing Spreading in Public Sector with Social Media

Furthermore, social media platforms enable the application of crowdsourcing ideas [Howe \(2008\)](#), [Brabham, Brabham \(2013\)](#) in the public sector, which can be quite beneficial for the design of better, more socially rooted, balanced and realistic policies. Management literature has been discussing for long time the capability of a large network of people connected through ICT, termed as “crowd”, to perform successfully difficult design and problem-solving activities [Levy \(1997\)](#). This collective intelligence has recently started being exploited systematically, mainly by private sector firms. This practice is referred to as “crowd-sourcing”, defined as: [...] the act of a company or institution taking a function once performed by employees and outsourcing it to an undefined (and generally large) network of people in the form of an open call.

There is already considerable literature on crowdsourcing in the private sector, which initially focused on the analysis of success stories, and later on the identification of patterns and trends in this area. A typical example of the later is the work of [Hetmank](#), who, based on a review of crowdsourcing literature, identified a basic process model of it, which includes ten activities: define task, set time period, state reward, recruit participants, assign tasks, accept crowd contributions, combine submissions, evaluate submissions, select solution and finally grant rewards. Also, he identified a basic pattern in the structure of crowdsourcing IS, which includes four main components performing:

1. User management (providing capabilities for user registration, user evaluation, user group formation and coordination)
2. Task management (providing capabilities for task design and assignment)
3. Contribution management (providing capabilities for contributions evaluation and selection) and
4. Workflow management (providing capabilities for defining and managing workflows), respectively.

However, there is much less literature concerning the application of crowdsourcing ideas in the public sector. [Linders \(2012\)](#) proposed a typology of social media-based government “citizens co-production” initiatives, aiming to support the future systematic analysis of them. It includes three main categories of such initiatives:

1. “Citizen sourcing” (having a citizens-to-government (C2G) orientation: citizens assist government to become more responsive and effective)
2. “Government as a platform” (having a government-to-citizens (G2C) orientation: government provides to citizens extensive information and knowledge to assist them to improve their well-being and productivity)
3. “Do it yourself government” (having a citizen to citizen orientation: government provides to citizens support to “self-organize” and provide some simple kinds of public services themselves to other citizens)

[Mergel and Desouza \(2013\)](#) analyze the experience gained from the Challenge.gov, a crowdsourcing -- open innovation initiative of the US government, which adopts a crowdsourcing approach similar to the above mentioned private sector one. In particular, it includes the organization of contests, aiming to engage individual citizens, or teams of citizens, in solving particular problems of government agencies; independent judges' committees evaluate the submitted solutions, and the best is awarded a predefined prize.

Last but not least, it should be noted that government agencies initially adopted simpler practices of social media use, which included operating manually accounts in some social media, posting relevant content to them (e.g. concerning current and future policies and activities) manually and then reading citizens' interactions with it to draw conclusions from them. Gradually, there is some research on and experimentation with more advanced and sophisticated forms of social media use in government, which exploit the extensive capabilities provided by the APIs of social media platforms; most of them aim at the automated retrieval and analysis of content from various “external” Web 2.0 sources to identify citizen's needs, problems and opinions [Kokkinakos et al. \(2012\)](#).

2.3.4 Public Participation & Policy Making in Government

E-Governance has become a very popular research topic over the years. Many are those that believe that e-Governance and e-Democracy are two concepts very similar to each other regarding consultation and its mechanisms [Marche and McNiven \(2003\)](#). A different point of view focuses on the application of Information and Communication Technologies in delivering Government services, exchanging information and integrating systems [Fakeeh \(2016\)](#). Governance is actually what Government does in the fields of

power, policy and management. The concept of E-Governance includes E-Government and in fact contains three fields: e-Administration, e-Government and e-Democracy [Molinari and Ferro \(2009\)](#).

Participation, as we have already mentioned earlier, plays an important role in the relation between citizens and government because increasing citizens' involvement, good Governance is improving quality of engagement³ and decision making⁴. According to [Kunz et al. \(1970\)](#), designing public policy is a "wicked" problem, as mentioned earlier. This means that over the years the nature of the design problems of public policy is changing due to the different and heterogeneous views of the problems that exist, making urgent the need of newer and more sophisticated methods for addressing them. These problems demand a combination of public participation on the one hand and technocratic analysis on the other [Rittel and Webber \(1973\)](#), [Conklin and Begeman \(1988\)](#), [Conklin \(2003\)](#).

In many countries governments promote public participation by supporting different types of interactions during the policy-making life cycle [Charalabidis et al. \(2010\)](#), [Loukis and Charalabidis \(2012\)](#). These types are distinguished in:

- Information Provision: governments produces and delivers the information to citizens ('one-way' relation)
- Consultation: citizens provide governments with opinions on issues that have been raised (asymmetric 'two-way' relation)
- Active participation: citizens propose new policy issues and discussion topics along with those presented by governments helping them formulate the policy agenda (symmetric 'two-way' relation)

More precisely, public participation means consultation of different stakeholders during negotiations in order to formulate a common definition of the problem and the objectives. Having this as base, in the next phase, we can move on the technocratic analysis

³Organization for Economic Co-operation & Development. (2004a). Evaluating Public Participation in Policy Making. Paris/France OECD Publication Service, Paris/France, OECD Publication Service. Available at: <http://www.eiaportal-at-sk.eu/attachments/article/29/OECD%202005%20evalu%20pp.pdf>

⁴Organization for Economic Co-operation & Development. (2003). Engaging Citizens Online for Better Policy-making, Policy Brief, Paris/France, OECD Publication Service. Available at: <http://www.sigmaxweb.org/publicationsdocuments/35063274.pdf>

by experts using mathematical optimization algorithms for the definition of the problem. Additional research on this approach has brought to light that the solution of policy problems can be supported by information systems allowing stakeholders to enter ‘topics’, ‘questions’, ‘ideas’ and ‘arguments’. These systems are called ‘Issue Based Information Systems’ and are able to stimulate a controlled way of reasoning which reveals the arguments [Rittel and Webber \(1973\)](#). The rapid penetration of Web 2.0 and social media creates more opportunities for a wider application of these approaches involving more citizens and social groups on a public policy problem that government is facing. Social media allow government agencies to collect content and knowledge based on a public policy discussion in an efficient way and at a low cost.

In many decision making situations, the complexity in all kinds of organizations, public, private or non-governmental exists. The complexity is proportional to the difficulty of a situation and can be addressed through decision support tools that increase the quality of the decision process [Beers et al. \(2006\)](#), [Courtney \(2001\)](#), [Sterman \(1994\)](#). [Anthony \(1965\)](#) in his research described management activities as decisions based on strategic planning, management control and operational control. What is more, [Conklin \(2003\)](#) described decision problems as existing on a continuum from repetitive and well-structured to new, novel and difficult to be solved. [Gorry and Scott-Morton \(1971\)](#) in their research combined the two previous ones and described decision problems as structured, semi-structured and unstructured.

[Conklin \(2003\)](#) also described the decision-making process as a set of three phases: intelligence, design and choice. Intelligence means searching the environment for problems which is the fundamental need to make a decision. Design includes all the alternative ways used for solving the problem, and choice consists of the alternatives’ analysis and the choice those for implementation. Once the problem is recognized, it is defined with the creation of mathematical models. Alternative solutions are created, and the models are developed in order to analyze the multiple alternatives. The choice is finally made and the appropriate alternatives are implemented. If the solutions presented for the specific problem do not work out, then a new process cycle continues. Even though these systems are used in a great extent in the private sector, they started gaining popularity in the public sector as well, providing either ‘vertical’ or ‘horizontal’ solutions.

Collective intelligence is considered being a key ingredient of a “distributed problem-solving” system due to the fact that its output is able to enrich the decision support process. Specifically, politics moves towards cooperation in decision making processes [Shim et al. \(2002\)](#), [Brabham \(2008\)](#). However, DSSs for decision making are still in narrow circles. Still, the implementation of a DSS in public sector has not become reality yet. In order to enhance the quality of the decision based on knowledge and simulation scenarios, DSS depend on the availability of relevant, timely and accurate information. As a result, the traditional DSS need to be combined with e-participation in order to bring the needed functionality to the decision maker [Sherif \(1998\)](#). After all, e-Governance programs can be successful admitting the existence of DSSs helping decision makers face problems through interaction with data and analytical models.

2.3.5 Opinion Mining & Policy Formulation

Opinion mining is considered being an area in which much research has been conducted. It is defined as the advanced processing of sentiments, feelings, opinions and emotions found or expressed in a text [Maragoudakis et al. \(2011\)](#). Living in the era of “social web”, users through the exploitation of Web 2.0 social media create various types of content most of which are expressed in the form of text and especially in the form of opinions. Users have shown an interest towards this type of content and focusing on opinion expressions, most Internet specialists are able to indicate people’s positive, neutral or negative sentiments or feelings on various topics.

It first started to appear in the private sector when firms wanted to analyse comments and reviews about their products made from online users in various websites. Analysing their comments, firms could draw conclusions as to if users like the specific products or not (through sentiment analysis), conclusions about the products’ certain features that users have commented (through features extraction) and the comments’ orientations (positive, negative or neutral). These sentiment analysis techniques can be applied in the public sector as well, since content created in the Web is a valuable source of information useful for government decision and policy making.

The content created in the Web is a valuable source of all kind of information (e.g. commercial, political, etc). In order to analyse the textual feedback of a proposed public policy provided by social media users and make conclusions on the general feelings on the

specific policy we need to determine public's sentiment polarity as positive, negative or neutral. To succeed this, we utilize Opinion Mining techniques such as topic modeling, sentiment analysis and stance classification.

2.4 Summarization

Summarizing, the nature of government decision and policy making problems, that increasingly become "wicked problems", necessitate stakeholders' participation and consultation. Web 2.0 along with social media platforms can play an important role in this direction enabling the application of crowdsourcing ideas in the public sector. However, the collection of large amounts of extracted online citizens-generated content towards a particular decision or a policy making problem, necessitates the utilization of opinion mining techniques. Exploiting advanced mining techniques such as topic modeling, sentiment analysis and stance classification and jointly combining them together to analyze, process and extract sentiment polarity is one of the main pillars in our PhD thesis.

These systems allow stakeholders to enter the following four types of elements, which are regarded as the basic "ontology" of a consultation (i.e., the main types of entities that a consultation includes): "topics" (defined as broad discussion areas), "questions/ issues" (defined as particular problems to be addressed within a discussion topic), "ideas" (defined as possible alternative solutions/activities for addressing the above questions/ issues), and "arguments" (defined as positive or negative evidence or viewpoints that respectively support or object to ideas). Therefore, the evaluation of the potential of a particular method and "socio-technical architecture" of social media (and ICT in general) to enhance and support policy formulation should focus on assessing to what extent the former is useful for addressing the above mentioned inherent complexities of the social problems targeted by the latter: i) by enabling more stakeholders to participate in relevant consultations at a lower cost and in shorter time, ii) by collecting knowledge revealing topics, questions/issues, solutions/ideas for addressing them and relevant positive/negative arguments, which are perceived by various stakeholder groups, iii) and also by facilitating synthesis and convergence (at least to some extent) between the stakeholders on the definition of the problem, the main questions/issues, the required solutions/activities, and also their advantages and disadvantages.

Chapter 3

Theoretical & Research

Background

3.1 The concept of Topic Modeling

3.1.1 What is Topic Modeling

One of the initial applications of natural language processing is to automatically extract the topics people are discussing from large volumes of unlabeled text. Topics provide us the ability to represent the large volume of these unstructured texts. Topic reveals the correlations of words. For example, when words like hobby, leisure time, family, friends appears with high frequency, we know the topic “hobbies” is talking about. Those correlations of words are captured by defining topic as a probability distribution over words [Deerwester et al. \(1990\)](#), [Hofmann \(1999\)](#), [Blei et al. \(2003\)](#). Some examples of text can be feeds from social media, customer reviews, user feedback, news stories, customer complaints etc.

Gaining knowledge of what people are talking about and unveiling their problems, needs and opinions is highly valuable to businesses, organizations, public administrations and political campaigns. It is extremely difficult to manually read through such large volumes of text and compile the topics. Thus an automated algorithm is required to read through the collection of documents and automatically output the topics discussed.

A topic model is a type of statistical analysis that scrutinizes a set of documents (known in NLP field as a corpus), unravels the from the hidden structures, examines how words and phrases co-occur in them, and automatically “learns” clusters of words that characterize those documents. These sets of words often appear to represent a coherent theme or topic by using a process of similarity.

As a consequence, topic modeling is considered as a form of text mining, employing unsupervised and supervised statistical machine learning techniques in a way to identify patterns in a corpus or large amount of unstructured text. It actually is a technique to extract the hidden topics of text and provides us with tools and methods to organize, understand and summarize large collections of textual information. It helps in:

- Discovering hidden topical patterns that presented across collection of documents
- Annotating the collections according to these specific topics
- Using the annotations to organize and summarize texts

There are a variety of commonly used topic modeling techniques including Non-negative Matrix Factorization, Latent Dirichlet Allocation (LDA), and Structural Topic Models utilized to capture the topic models. Latent Dirichlet Allocation(LDA) is the most popular algorithm for topic modeling. The challenge lies on how to extract good quality of topics that are clear, segregated and meaningful. This depends on the quality of text pre-processing and the ability to find the optimal number of topics in the collection of documents.

A topic can be modeled in two-ways: supervised or unsupervised. In the supervised context, topics are explicit and have human labeled names. Taking the previous example, “abortion” is the human labeled name for that topic. Supervised methods, like Native Bayes Classifier (NBC), Support Vector Machine (SVM) [Burges \(1998\)](#), can be utilized to identify correlations between human labeled topics and the words. In the unsupervised context, topics are latent and no human labeled names. Although there is no human labeled name, topics are self explainable. Based on the previous example again, topic is a proportional distribution over words, where words like hobbies, family, friends have the highest probability. We can easily guess this latent topic expresses the topic about “hobbies”. Unsupervised methods, like Latent Semantic Indexing (LSI) [Deerwester](#)

[et al. \(1990\)](#), Probabilistic Latent Semantic Indexing (PLSI) [Hofmann \(1999\)](#) and Latent Dirichlet Allocation (LDA) [Blei et al. \(2003\)](#) can be used for discovering correlations between latent topics and words.

3.1.2 How Topic Models work

Topic models provide an easily understandable way to analyze large volumes of unlabeled text. A "topic" consists of a cluster of words that frequently occur together. Using contextual clues, topic models relate words with similar meanings and distinguish those with multiple meanings.

Both ways, every topic modeling algorithm initiates with the assumption that the documents consist of a specific number of topics. The model assesses the underlying structure of the words within the collections of data and tries successfully to find the groups of words that best "fit" the corpus based on that constraint. At the end of modeling, the output provides two tables: the term-topic matrix, which breaks the topics down in terms of their word components, and the document-topic matrix, which describes documents in terms of their topics. Depending on the algorithm that is utilized in the modeling part, a word may be assigned to multiple topics in varying proportions, or assigned to a single topic exclusively.

Figure 3.1 depicts an example of a term-topic matrix, based on topics from our topic modeling research. The first column contains an arbitrary identifier for each topic in order to refer to each topic by a name, followed by a column for every possible word that each topic may contain (known as "vocabulary"). The values in the cells depict how much each word "belongs" to each topic proportionally. Their exact meaning depends on the algorithm used, but usually the most common value in this table can be zero (or close to zero), since only a fraction of the vocabulary can be exclusively relevant to any particular topic. The topic modeling tables are too large to be depicted, thus, we provide in this part only a small part of topic modeling results showing three topics and a few of their top words.

Since this output can be difficult to be read and interpreted, researchers often sort through the words for each topic and distinguish the top words based on some measure of importance. For models that assign words to topics proportionally, we look up for

	hobby	pursue	ability	giving	...
Topic 4	0.5	0.3	0.0	0.0	
Topic 5	0.0	0.0	0.0	0.8	
...					
Topic 88	0.0	0.2	0.5	0.0	
...					

FIGURE 3.1: Term Topic Matrix Example

words having the highest weights for each topic, those that make up the greatest share of the topic and have the highest frequency of appearance across all modeled topics. There are also other metrics to be utilized, like mutual information, which compares the words in each topic against all of the other topics, and collects the words that are most distinctive. Deploying one of these methods, we select the five or ten most meaningful words for each topic, making it easier to view and interpret them. As illustrated in Figure 3.2 Topic 4 shows that some of our documents have to deal with the pursuit of hobbies and passions for fun. Topic 5 seems to have something to do with charity and society, and Topic 88 gives a more spherical view of spending time and contributing to more serious things, like family, travel and work.

Topic 4: hobby, rewarding, pursue, pursue hobby, leisure time, leisure, passion, family hobby, time hobby, friend, social
Topic 5: giving, woman, grateful, charitable, giving community, nonprofit, philosophy
Topic 88: ability, contribute, ability travel, time, ability work, pursue, time pursue, family, community, contribute community, contribute society

FIGURE 3.2: Example of Top words across Topics

What is more, we can use this topic model for a distinct categorization of individual documents, which can be useful to make comparisons between documents and analyze how different topics are distributed. To do so, we need to examine the other topic modeling result's output, the document–topic matrix.

Most topic models fragment documents according to topic proportions. In topic modeling that allocates topics to documents as proportions, we can analyze the topics as either continuous variables, or as discrete classifications by setting a cutoff threshold

Document	Topic 4	Topic 5	...	Topic 88	...
I have a number of great hobbies and plenty of time to pursue them	0.7	0.3		0.0	
Life is most rewarding when I'm giving back to the community	0.5	0.2		0.8	
I have a great job that gives me the ability to pursue meaningful goals at work	0.3	0.7		0.0	
...					

FIGURE 3.3: Example of Document-Topic Matrix

to decide whether a document contains a topic or not. Figure 3.3 shows an example of what the corresponding weights for the three example documents look like, for the specific three topic modeling topics below. Thus, topic modeling gives us the opportunity to automatically identify and measure the main themes or topics in a collection of documents exploiting our model as a measurement tool.

3.2 The concept of Sentiment Analysis

In the early age of the Web, its content was usually published by websites associated with traditional information sources such as news media and organizations, among other companies. Additionally, the online content was mainly focused on “facts” which are objective statements on particular entities or topics. In the 2000s, with the rise of Web 2.0 platforms [O'Reilly \(2005\)](#), e.g., blogs, online social networks and microblogging services, this situation altered by allowing users to generate and share textual content in a much easier way. This status caused a tremendous growth of subjective information (i.e., personal opinions) available on the Web, which provided new opportunities for information system developers. As the factual information has been traditionally processed using mining techniques such as information retrieval and topic classification, different types of methods are required in order to process the “subjective” user-generated content.

The word ‘sentiment’ is defined as ‘an attitude, thought or judgment prompted by feeling’ in Merriam-Webster dictionary¹. It is additionally considered as ‘a specific view or notion: opinion’ and ‘emotion’. The word ‘opinion’ is usually referred to as ‘a view, judgment or appraisal formed in the mind about a particular matter (ibid)’. As Liu Liu (2012) states it ‘opinions are usually subjective expressions that describe people’s sentiments, appraisals or feelings toward entities, events and their properties.’ Although the field of sentiment analysis and opinion mining has gained a lot of attention from both groups of researchers and marketers, there has been a steady undercurrent of interest in analyzing opinions extensively. Much of the early research on textual information processing has been centered on mining and retrieval of factual information, such as information retrieval, text classification or text clustering Gawron et al. (2012). Nevertheless, there has been little opinionated text available before the era of World Wide Web. As Liu (2012) declared, a person usually asked his/her friends or family for opinions before making a final decision and an organization normally conducted opinion polls, surveys and focus groups to find out the sentiments of the general public about its products or services. After the Internet started to be widely used due to the development of information and communication technologies, people started expressing their opinions and emotions by posting reviews of products or services online and as Liu concluded: ‘This online word-of-mouth behaviour represents new and measurable sources of information with many practical applications.’ Furthermore, Pang and Lee (2008) also illustrated additionally three factors which led to a huge outbreak of research of sentiment analysis field: ‘1) the rise of machine learning methods in natural language processing and information retrieval; 2) the availability of datasets for machine learning algorithms to be trained on, and the development of review aggregation websites; and last but not least the 3) realization of the intellectual challenges along with the commercial and intelligence applications that the area offers.’

With the explosion of Web 2.0 platforms, such as blogs, social media like Twitter, Facebook and other types of online communication platforms, an individual has unprecedented channels to express and share his/her opinions and brand experience regarding any product or service. Furthermore, the companies can modify their marketing strategies through social media monitoring and analysis. However, it can still be a challenging task to find opinion sources and monitoring them, due to the large number of diverse

¹<https://www.merriam-webster.com/dictionary/opinion>

sources such as online forums, discussion groups, and blogs. Also, each source is filled with have a large volume of user-generated content indicating feelings, emotions, views and opinions generally. At the same time, another problem that [Zabin and Jefferies \(2008\)](#) described in their research report is the need to define a uniform terminology in the field of analysing consumers' online conversations [Pang and Lee \(2008\)](#). As a matter of fact, the identification of the relevant sources, the extraction of information from texts with opinions and their summarization is confirmed as a formidable task. Thus, a system is required to automatically unravel and analyze the online opinionated texts (texts with opinions or sentiments) with sentiment analysis growing out of this need [Liu \(2012\)](#). [Pang and Lee \(2008\)](#) claimed that sentiment analysis deals with the computational treatment of opinion, sentiment and subjectivity in text. Such work has come to be known as opinion mining. In natural language processing (NLP), sentiment analysis contains diverse aspects concerning how information about emotions, attitudes, perspectives and social identities is conveyed in language (ibid). [Ma et al. \(2016\)](#) concluded that the purpose of sentiment analysis is to extract consumers' attitudes and opinions through automatic analysis of texts of commodity reviews. [Dave et al. \(2003\)](#) were the first that used the term 'opinion mining' arguing that an ideal opinion-mining tool would 'process a set of search results for a given item, generating a list of product attributes (quality, features, etc.) and aggregating opinions about each of them (poor, mixed, good)'. [Pang and Lee \(2008\)](#) stated that 'the history of the phrase sentiment analysis parallels that of opinion mining in certain respects' as many researchers utilized the term 'sentiment' and 'opinion' interchangeably in their scholar papers in regard to the automatic analysis of evaluative texts [Turney \(2002\)](#). Thus, it seems "sentiment analysis" and "opinion mining" designate the same research area. Besides the specific ones, there are also other names and slightly different tasks used for the same purpose, such as opinion extraction, sentiment mining, subjectivity analysis, affect analysis, emotion analysis, review mining etc [Liu \(2012\)](#). The term 'sentiment analysis' is more commonly used in the industry, while both terms 'sentiment analysis' and 'opinion mining' are frequently implemented in academia (ibid). Thus in this thesis, the terms sentiment analysis and opinion mining will be exchangeable. Sentiment analysis in general is related to not only to opinions but also to emotions, feelings, views and attitudes.

3.2.1 Sentiment Polarity Definition

Let d be an opinionated document (e.g., a product review) consisted of a list of sentences s_1, \dots, s_n . As stated in [Liu \(2009\)](#), the basic components of an opinion expressed in d are:

- **Entity:** a product, individual, event or topic on which an opinion is expressed (opinion target). It is comprised of a hierarchy of components and sub-components where each component has a set of attributes. For example, a cell phone is composed of a screen, a battery among others, the attributes of which can be the size and the weight. For simplicity reasons, components and attributes are both referred to as aspects
- **Opinion Holder:** the person or company that holds a specific opinion on a particular entity. While in reviews or blogs, the holders are usually the authors of the documents or posts, in news articles the holders are commonly indicated explicitly [Bethard et al. \(2004\)](#)
- **Opinion:** a view, attitude, or appraisal of an object from an opinion holder. An opinion can have a positive, negative or neutral sentiment polarity or orientation, where the neutral orientation is commonly interpreted as no opinion. The polarity is also named as semantic orientation [Turney \(2002\)](#)

An opinion is a quadruple (E, S, H, T) [Liu \(2012\)](#), where

- **E** is the sentiment target
- **S** is the sentiment about the target
- **H** is the opinion holder
- **T** is the time when the opinion was expressed

Sentiment analysis can be done on different levels of granularity.

1. **Document level** is usually used on various reviews, where the task is to determine or classify the overall sentiment towards the target (e.g. product or movie)

2. **Sentence level** analyses the overall sentiment towards the sentence
3. **Aspect-based sentiment analysis** is based on the exact features (aspects) of the sentiment target. Both document and sentence level of sentiment analysis fail to provide insights exactly on which aspect of the target is branded by the opinion holder with the given sentiment
4. **Word level** of sentiment analysis identifies the polarity of each word in the sentence of a document

3.2.2 Levels of sentiment analysis

Based on the levels of granularity, sentiment analysis has been mainly explored at four different levels: document level, sentence level, aspect level and word level [Pang and Lee \(2008\)](#), [Liu \(2012\)](#). We analyze in details each level separately.

3.2.2.1 Document level

The task of document-level sentiment analysis is to categorize the sentiment expressed of an opinionated document that comments on an object as positive or negative opinion. For example, a sentiment analysis system determines the overall polarity of a customer review about a specific product or brand. This level of sentiment classification assumes that one document expresses opinions on a single object, such as customer reviews of products and services, because usually the result of sentiment analysis only has two (positive and negative) or three sentiment orientations (positive, negative and neutral). However, it is common that there might be a few different opinions in one document, thus it is not applicable to documents in which opinions are expressed on multiple products. A great number of researchers have performed document-level sentiment analysis [Turney \(2002\)](#), [Pang and Lee \(2008\)](#). Their mainly interest focused on how to separate the positive texts from negative texts automatically and have presented various methods to improve performance in terms of accuracy. Due to the output of sentiment classification, the major limitation of document-level sentiment analysis is the lack of in-depth analysis [Liu \(2012\)](#).

3.2.2.2 Sentence level

The sentence level of sentiment analysis involves classifying each sentence expressed as positive, negative or neutral [Aue and Gamon \(2005\)](#). There is no fundamental difference between document-level and sentence-level sentiment analysis, due to the fact that sentences are considered short documents [Liu \(2012\)](#). It usually contains two sub-tasks:

1. Determining whether the sentence is subjective or objective (with opinion or no opinion at all)
2. If the sentence is subjective, determining whether it expresses a positive or negative opinion

This level is related to subjectivity classification [Hatzivassiloglou and Wiebe \(2000\)](#), which focuses on distinguishing the subjective sentences that express sentiments or views from objective sentences that express only factual information. The subjectivity classification task is very important and challenging, because it excludes sentences that contain no opinions. The sentence level of sentiment classification assumes that one sentence expresses a single opinion from a single opinion holder. However, [Kouloumpis et al. \(2011\)](#) pointed out that a single sentence may contain multiple opinions, both subjective and factual clauses. Thus, it is important to indicate the factual clauses and discover the strength of sentiments. The value of neutral usually pinpoints the objective sentences or sentences absent of opinions. It is also of great value to notify that subjectivity is not equivalent to sentiment, as [Liu \(2012\)](#) states, because objective sentences may also imply sentiments, for example: “ I bought this phone one week ago and now the battery only lasts three hours”. Those objective sentences that indicate opinion also belong to another subset of opinionated sentences. As for compound sentences, they might be comparative or have grouped opinions about different aspects of an object, thus sentence-level classification is not suitable for them and there begins a need to investigate the opinions expressed in aspect level.

3.2.2.3 Aspect level

Classifying opinions at document level or sentence level is useful in many cases, but they are insufficient because they do not identify sentiment targets or assign opinions

to these targets [Liu \(2012\)](#). At the document level, a positive document on an object does not actually mean that the author has a positive opinion towards all aspects of this topic. What is more, sentence-level classification is often an intermediate step since it is more useful to gain knowledge on which of the features or entities of the object the opinions are on specifically. Thus, aspect level that performs finer-grained analysis is needed. Aspect level is also called entity level or feature level in some researches [Hu and Liu \(2004\)](#) , [Pang and Lee \(2008\)](#).

The aspect level of sentiment analysis focuses on opinions itself instead of looking at the constructs of documents, such as paragraphs, sentences and phrases. It is not enough to identify the polarity of the opinions; identifying the opinion targets is also crucial in this part. The aspect-level sentiment analysis can be decomposed into two sub-tasks [Liu \(2012\)](#):

1. aspect extraction
2. aspect sentiment classification

The task of aspect extraction is also named as information extraction and aims to discover the aspects that the opinions are on. For example, in the sentence, “the screen of this Samsung S6 is amazing but its battery life is too short”, the words “Screen” and “battery life” are the aspects of the entity “Samsung S6”. The basic approach in order to extract the aspects is to pinpoint frequent nouns or noun phrases, which are defined as aspects. Then the text containing aspects is classified as positive, negative or neutral [Blair-Goldensohn et al. \(2008\)](#).

However, an issue that still rises in aspect-level sentiment analysis is the fact that most studies are based on the assumptions of the pre-specified aspects by keywords [Wang and Rosé \(2010\)](#). [Liu \(2012\)](#) pointed that the accuracy at aspect level sentiment is still in low percentages because the already existing algorithms cannot deal with complex sentences well enough. Thus, the aspect level sentiment analysis is a far more difficult task than both document-level and sentence-level classifications. [Wang et al. \(2017\)](#) proposed a framework to rank the aspects but again the aspects are predefined before the classification task lacking in accuracy results and evaluations.

3.2.2.4 Word level

Recognizing the semantic orientation of subjective terms (words or phrases) is a fundamental task for sentiment lexicon generation. These sentiment or else opinion lexicons are compiled in automatically with an optional final human check. The task of discovering semantic word orientation is also called words polarity detection. There are publicly available resources including sentiment polarity of words e.g. General Inquirer, Dictionary of Affect of Language, WordNet-Affect or SentiWordNet [Baccianella et al. \(2010\)](#). These resources are mainly used for computing the sentence or document sentiment by dictionary methods or as features for machine learning techniques. Another use is the generation of a domain specific lexicon.

[Turney \(2002\)](#) estimated semantic orientation of words by the computation of the Pointwise Mutual Information (PMI) between the given word and paradigm words (e.g. good, bad, nice, nasty). Another approach [Kamps et al. \(2004\)](#) measured the synonym relation of words based on WordNet. A popular way of using WordNet is by obtaining a list of sentiment words by an iterative process of expanding the initial set with synonyms and antonyms like the one proposed by [Kim and Hovy \(2004\)](#). [Kim and Hovy \(2004\)](#) specifically categorized the sentiment polarity of unknown words according to the relative count of their positive and negative synonyms.

[Hatzivassiloglou and Wiebe \(2000\)](#) and [Kouloumpis et al. \(2011\)](#) created the Multi-Perspective Question Answering (MPQA) corpus which includes 535 news articles from a wide variety of news sources and described the overall annotation scheme. They also compiled a subjectivity lexicon with tagged prior polarity values of words. [Rao and Ravichandran \(2009\)](#) utilized sentiment polarity detection as a semi-supervised label propagation problem in a graph, where the nodes represented the words and the edges the relations between the words. WordNet and OpenOffice thesaurus were utilized as positive and negative seed sets. As demonstrated by [Fahrni and Klenner \(2008\)](#) words polarity is considered domain specific and lexicon-based approaches have difficulty with some domains. Machine learning algorithms naturally adapt to the corpus domain by training. Statistical approaches to lexicon generation adapt the lexicon to the target domain. [Fahrni and Klenner \(2008\)](#) proposed a way to derive posterior polarities exploiting the co-occurrence of adjectives in order to create a corpus-specific dictionary.

Saif et al. (2016a) employed Information Retrieval methods to build a dictionary by extracting frequent terms from the dataset. The sentiment polarity of each document is computed as a relevance score to a query composed of the top terms from this dictionary. Finally, the opinion relevance score was combined with the topic relevance score, providing a ranking of documents on that topic. Wang and Cardie (2016) indicated the polarity of terms using a structural inference motivated by compositional semantics. Their experiments illustrated that lexicon-based classification with compositional semantics can perform better than supervised learning methods that do not incorporate compositional semantics (accuracy of 89.7% vs. 89.1%), but a method that integrated compositional semantics into the learning process performed better than the previous approaches (90.7%). The results were achieved on the MPQA dataset. Later they studied the adaptability of lexicons to other domains using an integer linear programming approach Wang and Cardie (2016). Mei et al. (2007) developed another approach based on Sentiment Hyperspace Analogue to Language (S-HAL) in which the semantic orientation of words was characterized by a specific vector space. This feature vectors were used to train a classifier in a way to identify the sentiment polarity of terms. Saif et al. (2016b) adapted social media sentiment lexicon from Paltoglou and Thelwall (2010) by extracting contextual semantics of words to update prior sentiment strength in lexicon and applied it to three Twitter datasets achieving an average improvement of 2.46% and 4.51% in terms of accuracy and F-measure respectively.

3.2.3 Approaches of sentiment analysis

Sentiment analysis (or as we have already mentioned opinion mining) has been the focus of growing attention in academia and business industry due to its tremendous value and potential for practical applications, especially in the era of Web 2.0 Pang and Lee (2008). Traditionally, sentiment analysis can be considered a binary classification of opinion. Baccianella et al. (2010) indicated that sentiment classification can be divided into three specific subtasks, which are:

1. Determining subjectivity, meaning deciding whether a given text has factual information or subjective information
2. Determining the orientation or polarity of the text, meaning deciding whether a given subjective text expresses a positive or negative opinion respectively

3. Determining the strength of that sentiment orientation

Due to the large volume of subjective data on the Web, automated sentiment analysis is required to tack that problem [Liu \(2009\)](#). Research on sentiment analysis has been dominated by two main approaches: semantic orientation approach and machine learning approach [Medhat et al. \(2014\)](#). The semantic orientation approach is also referred to as lexicon-based approach and is based on words and phrases used as indicators of semantic orientation with the overall text polarity being an averaged sum of indicators' polarities [Hatzivassiloglou and Wiebe \(2000\)](#), [Pang and Lee \(2008\)](#). The machine learning approach focuses on selecting the appropriate machine-learning algorithm and the right features of texts to classify the polarities of the text. Researchers also refer to these two approaches as unsupervised learning and supervised learning [Liu \(2012\)](#), [Asghar et al. \(2017\)](#). Moreover, by combing both approaches, hybrid classification systems of sentiment analysis are also proposed [Paltoglou and Thelwall \(2010\)](#). Figure 3.4 depicts the categorization of sentiment analysis approaches.

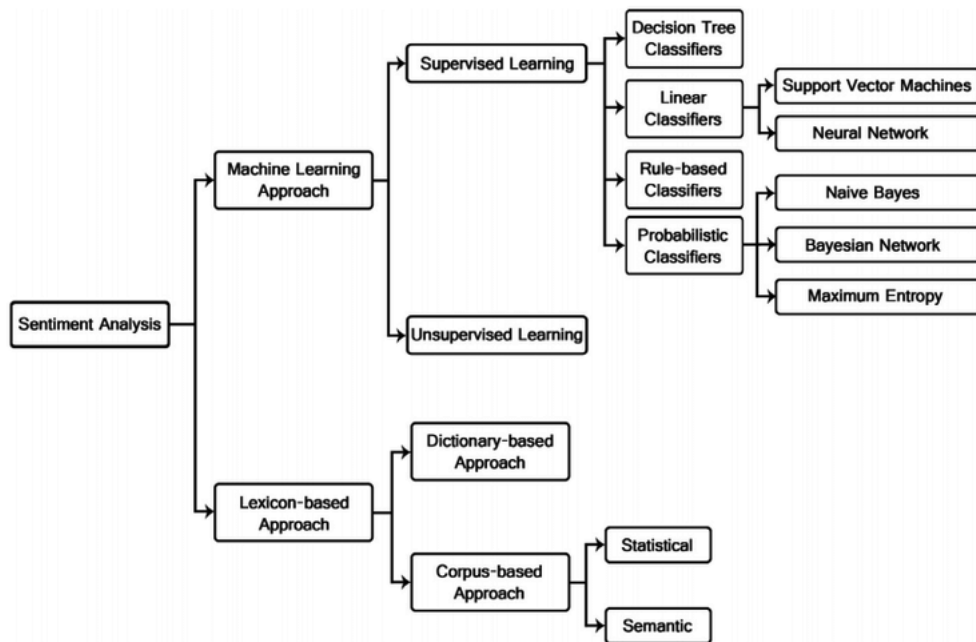


FIGURE 3.4: Sentiment analysis approaches [Medhat et al. \(2014\)](#)

3.2.3.1 Semantic Orientation Approach

The semantic orientation or polarity of a word is the feature that indicates the direction of deviation from the norm of its semantic group or lexical field [Lehrer \(1974\)](#), which is considered as an evaluative factor [Witkowski \(1991\)](#). It is also known as valence, which is employed to discuss emotions in the linguistics literature [Frijda \(1986\)](#). Semantic orientation has multiple directions (positive, negative or neutral) and intensity (mild to strong) [Turney \(2002\)](#). Positive semantic orientation of a word denotes a desirable state (e.g., beautiful, wonderful), while negative semantic orientation of a word represents undesirable states (e.g. hate, disgusting) [Hatzivassiloglou and Wiebe \(2000\)](#). The studies depict that words with polarities, especially adjectives, are used as good indicators of subjectivity [Hatzivassiloglou and Wiebe \(2000\)](#), [Turney \(2002\)](#). Thus, the semantic orientation approach is based on words and phrases as the bearers of polarities, and the overall semantic orientation of the whole text is determined by the sum of indicators with polarities. It is also referred to as lexicon-based approach [Liu \(2012\)](#), [Medhat et al. \(2014\)](#).

The representative of semantic orientation approach for sentiment analysis is the lexicon-based approach. It utilizes a dictionary of sentiment words with their associated polarities and strength to detect the sentiments in the corpus [Taboada et al. \(2011\)](#). The sentiment words are also called opinion words, which are commonly used to express positive or negative sentiments. For example, words such as good, beautiful, amazing, extraordinary are positive sentiment words while other words such as horrible, disgusting, bad, awful are negative sentiment words. Many researchers call the dictionary of sentiment words as sentiment lexicon or opinion lexicon [Liu \(2012\)](#). There are three different methods to generate dictionaries for the lexicon-based approach:

1. The dictionary of sentiment words can be created manually, with great accuracy but time consuming
2. The dictionary can be generated relying on syntactic or co-occurrence patterns in a large corpus, which is named as corpus-based method
3. The bootstrapping method using a set of seed opinion words and an online dictionary like WordNet for sentiment analysis, which is called also dictionary-based method

3.2.3.2 Corpus-based Approach

In an effort to generate a sentiment dictionary, corpus-based method mainly focuses on the syntactic patterns and a list of seed words to expand opinion words into a large corpus [Luo et al. \(2015\)](#), [Liu \(2012\)](#). Seed words are a small set of opinionated words with strong positive or negative orientation, which are usually defined and collected manually. The key idea was proposed initially by [Hatzivassiloglou and Wiebe \(2000\)](#). They presented a method to predict the semantic orientation of words in an automatic way from conjunctions between adjectives in a large corpus of 21 million words. This happened due to constraints the conjunctions impose on semantic orientation of words. [Hatzivassiloglou and Wiebe \(2000\)](#) demonstrated that conjunctions between adjectives provide indirect information about their sentiment polarity. They built a training set of seed words containing 1336 adjectives from a corpus of 21 million words, and then they manually labeled each word as positive or negative (657 positive and 679 negative). To validate their labels, they asked from four different individuals to independently label some sample of the words, which showed an agreement of 89%. After labeling the training set of words, [Hatzivassiloglou and Wiebe \(2000\)](#) followed a four-step process to infer the semantic orientation of adjectives from constraints on conjunctions:

1. All conjunctions of adjectives were extracted from the given text
2. Each pair of conjoined adjectives was labeled if they were of same or different orientation by a supervised learning algorithm combining evidence from different conjunctions
3. The linked adjectives with graph structure were divided into two subsets of adjectives with different orientation using a clustering algorithm
4. The subset with the higher average frequency was classified with positive orientation due to the fact that positive adjectives tend to be used more frequently than the ones with negative orientation

The work of [Turney \(2002\)](#) is a well-known example of sentiment analysis via the corpus-based approach and the combination of mutual information and co-occurrence in the text with seed words has been employed by a number of researchers [Pang and Lee \(2008\)](#). Instead of applying a unigram (single word) approach, [Turney \(2002\)](#) employed

bigram techniques to extract two consecutive words from text in order to get more information of context; then from the two seed words ('excellent' and 'poor') began to exploit the semantic orientation of other words. At the beginning, phrases containing adjectives or adverbs are extracted because adjectives are good indicators of subjectivity [Hatzivassiloglou and Wiebe \(2000\)](#). However, [Turney \(2002\)](#) assumed that an isolated adjective or adverb may pinpoint subjective feelings or emotions but it may not be able to provide sufficient context to classify its semantic orientation. After a part-of-speech (POS) tagger has been applied to the given text, two consecutive words were extracted from the text if POS taggers conform to any of the patterns in [Figure 3.5](#). The JJ tags denote adjectives, the NN tags indicate nouns, and the RB tags denote adverbs. The first pattern, for example, indicates that the two consecutive words are extracted, if the first word is an adjective and the second word is a noun. Additionally, the third word behind it could be any word but won't be extracted.

	First word	Second word	Third word (Not Extracted)
1.	JJ	NN or NNS	anything
2.	RB, RBR, or RBS	JJ	not NN nor NNS
3.	JJ	JJ	not NN nor NNS
4.	NN or NNS	JJ	not NN nor NNS
5.	RB, RBR, or RBS	VB, VBD, VBN, or VBG	anything

FIGURE 3.5: POS Tags Patterns for extracting two-word phrases [Turney \(2002\)](#)

Furthermore, the polarity of extracted phrases can be estimated by using the Pointwise Mutual Information (PMI) algorithm. The mutual information is a measure of the strength of semantic association between two words according to [Church and Hanks \(1990\)](#), who compare the probability of observing word1 and word2 together with the probabilities of observing word1 and word2 independently. The Pointwise Mutual Information (PMI) between two words is defined as follows:

$$PMI(word_1, word_2) = \log_2 \frac{p(word_1 \& word_2)}{p(word_1)p(word_2)} \quad (3.1)$$

To classify the polarity of the extracted phrases, [Turney \(2002\)](#) utilizes the PMI algorithm building the associations between the phrases and the two seeds of words: 'excellent' and 'poor'. The two seed words of opposing sentiment polarity ('excellent' and 'poor') were chosen because in a five star review system, the word 'excellent' is used to

describe five star review while the word “poor” is used in one star review (ibid). The semantic orientation (SO) of an extracted phrase is calculated as follows:

$$SO(\text{phrase}) = PMI(\text{phrase}, 'excellent') - PMI(\text{phrase}, 'poor') \quad (3.2)$$

According to the formula [Turney \(2002\)](#), if the phrase tends to be more strongly associated with the word ‘excellent’ than ‘poor’, the SO would be positive; otherwise the semantic orientation of the phrase would be negative. After calculating the SO values of all extracted phrases in the given text, the sentiment polarity of the overall text is the average of SO values of all phrases. The text is classified as positive, if the average SO is positive, otherwise negative.

The corpus-based method has as a major advantage the domain and context specific opinion words along with their polarities, but it requires a large corpus to cover all English words, which is very difficult to be prepared. Thus it is not as effective as dictionary-based methods for sentiment analysis [Liu \(2009\)](#), [Luo et al. \(2015\)](#).

3.2.3.3 Dictionary-based Approach

The dictionary-based method relies on a dictionary to compile opinion words, which is also named as lexicon-based method in some studies [Pang and Lee \(2008\)](#). [Liu \(2009\)](#) describes it as an effective approach to generate the sentiment lexicon. The meaning of dictionary-based method lies on collecting a small set of seed words with different polarities manually, and then a dictionary (e.g. WordNet) is used to grow this initial set of opinion words via their synonyms and antonyms. The newly generated words from the dictionary are added to the set of seed words. This process is repeated until no other new opinion words can be found from the dictionary. In the end, manual inspection is needed for correction before using the generated sentiment lexicon for sentiment analysis [Hu and Liu \(2004\)](#).

Many researchers use widely the online dictionary, such as WordNet [Miller \(1982\)](#) for sentiment analysis [Kamps et al. \(2004\)](#), [Kim and Hovy \(2004\)](#). WordNet is an online lexical reference system and a large lexical database of English resulting in combining effectively lexicographic information and high-speed computation [Miller \(1982\)](#). In

WordNet, nouns, verbs, adjectives and adverbs are grouped into different sets of synonyms (synsets). The synonyms indicate the same concept and can be exchangeable in some contexts. Each synset has a specific concept and is related to another synset by means of conceptual-semantic and lexical relations [Miller \(1982\)](#). Moreover, the synsets are connected frequently via a super-subordinate relation, which is also referred as hyperonymy and hyponymy relation.

[Hu and Liu \(2004\)](#) utilized WordNet to determine the sentiment polarity of customer reviews. Unfortunately, dictionaries like WordNet do not have any information on semantic orientation for each word. Thus this method relies on the idea that adjectives share the same orientation as their synonyms and opposite orientations as their antonyms. They created a set of seed adjectives with known semantic orientation manually and then using WordNet they generated new words from synonyms and antonyms of seed words. Their sentiment polarities were finally predicted in the light of the orientation of the seed words.

The work of [Baccianella et al. \(2010\)](#) has led to the foundation of SentiWordNet which is an extension of WordNet with each synset to be annotated with sentiment orientation information. Based on this work, SentiWordNet is built in a two-step stage using a semi-supervised method: initially, a set of seed words with already known semantic orientation (positive or negative) is collected manually and then the term relationships in WordNet such as synonym, antonym and hyponymy are discovered to generate more words. After a number of iterations, two subsets of terms of WordNet are obtained with positive and negative labels. Then, the glosses of these terms are used to train the classifier applying different algorithms and different sets sizes. As an automatically generated lexical resource, SentiWordNet assigns to each synset of WordNet a triple of sentiment-related values: Pos(s), Neg(s) and Obj(s), describing how positive, negative and objective the words in the synset are.

[Addawood et al. \(2017\)](#) proposed a hybrid method to categorize sentiment orientations of movie reviews by making use of SentiWordNet. They built a sentiment dictionary named as SentiMi based upon the mutual information and applied a supervised learning method for sentiment polarity detection. In this experimental phase, only the scores of adjective terms in the document were accumulated.

3.2.3.4 Machine Learning

The rise of machine learning techniques in natural language processing has led to increased ubiquity of research in sentiment analysis field. In the approach of machine learning, a textual feature representation has been employed grouped with several algorithms such as Naïve Bayes, Support Vector Machines (SVM), Maximum Entropy, which are commonly used to build the classifiers for sentiment analysis. These classifiers are based on algorithms that learn the rules or use decision criteria to conduct sentiment analysis in an automatic way [Singh et al. \(2013\)](#), [Ghiassi et al. \(2013\)](#). This clearly pinpoints that the machine learning approach for sentiment analysis is a kind of supervised learning paradigm, with a large number of labeled training data required to train the classifier before being used for categorizing the new data [Singh et al. \(2013\)](#), [Pang and Lee \(2008\)](#). The logic behind the machine learning approach is based on the framework of supervised classification (shown in Figure 2.5) and consisted of two stages:

1. Learning the model from a corpus of labeled training data via classification algorithms
2. Classifying the new data based on the trained model

Generally, the overall process of the classification task involves several sub-tasks, such as data pre-processing, feature selection, representation, classification and post processing. Figure 3.6 shows the framework of a supervised classification [Bird et al. \(2009\)](#).

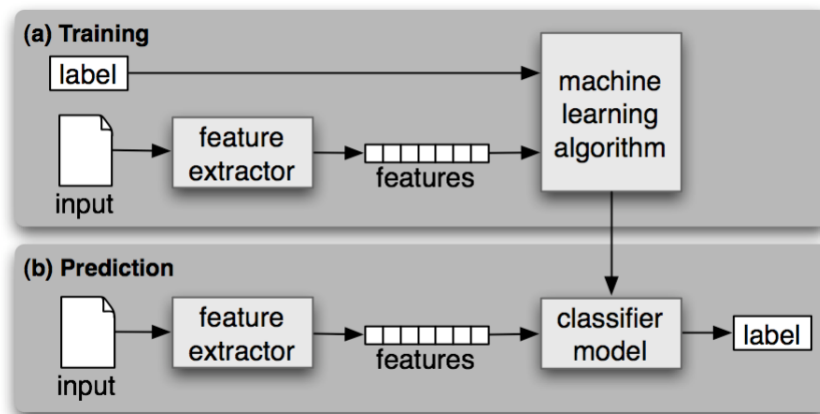


FIGURE 3.6: Framework of supervised classification [Bird et al. \(2009\)](#)

TABLE 3.1: Confusion matrix

		Predicted Class		
		YES	NO	
Actual Class	YES	True Positive (TP)	False Negative (FN)	YES
	NO	False Positive (FP)	True Negative (TN)	NO

3.3 Metrics used in Biometrics and Evaluation

The performance of methods used for sentiment analysis is evaluated by calculating various metrics like accuracy, precision, recall and F-measure (also known F-score).

We define these measures on a binary classification of positive and negative labels, but any number of labels can be actually used. Taking all possible and actual incidents into account during classification, we predict and categorize an event making four assertions. Table 3.1 summarizes these terms and depicts the results in the form of a confusion matrix Bergadano and Raedt (1994).

The terms Accuracy (ACC), Precision (p), TP Rate (TPR), FP Rate (TPR), TN Rate (TNR), FN Rate (FNR), F-measure and EER are widely used in research articles to measure the efficiency and performance of a classification system Bergadano and Raedt (1994):

- *Accuracy (ACC)* Accuracy is a proportion of all correctly predicted labels compared to all sentences. The more efficient the accuracy values, the higher the rate of correctly detected incidents.

$$ACC = \frac{TP + TN}{TP + FP + FN + TN} \quad (3.3)$$

- *Precision or Confidence (p)* is a measure of trust that the objects marked as positive are really positive.

$$p = \frac{TP}{TP + FP} \quad (3.4)$$

- *True Positive Rate (TPR)* or *Sensitivity* or *Recall (r)* is a measure of trust, that all the positive objects are marked as positive. Better detection is achieved if this value is high.

$$TPR = r = \frac{TP}{TP + FN} \quad (3.5)$$

- *False Positive Rate (FPR)* or *False Acceptance Rate (FAR)* measures the proportion of actual positive objects incorrectly identified as negative.

$$FPR = FAR = \frac{FP}{FP + TN} \quad (3.6)$$

- *True Negative Rate (TNR)* or *Specificity* measures the proportion of actual negatives that are correctly identified as such.

$$TNR = \frac{TN}{TN + FP} \quad (3.7)$$

- *False Negative Rate (FNR)* or *False Rejection Rate (FRR)* measures the proportion of negative objects incorrectly identified as positive.

$$FNR = FRR = \frac{FN}{TP + FN} = 1 - TPR \quad (3.8)$$

- *F-measure* or else balanced *F-score* is a harmonic mean between precision and recall and it is considered to be an overall perspective.

$$F - measure = 2 * \frac{precision * recall}{precision + recall} \quad (3.9)$$

- *Equal Error Rate (EER)* is also employed in literature to assess the potentials of a classification system. Specifically, EER is a kind of percentage rate, which both accepts and rejects errors as equals. That is, the lower the error rate value, the higher the accuracy of the system.

$$EER = FAR + FRR/2 \quad (3.10)$$

To acquire the EER for a classification mechanism, a number of participants need to be invited to test it and their individual EERs need to be recorded. The average EER from all the participants is then calculated signifying the EER for the system. As a result, the performance of a classification system is heavily reliant on the number of participants, the uniqueness of each participant and the sophistication of the employed classification method. Figure 3.7, illustrates an example of Receiver Operating Characteristics (ROC) curve [Bergadano and Raedt \(1994\)](#).

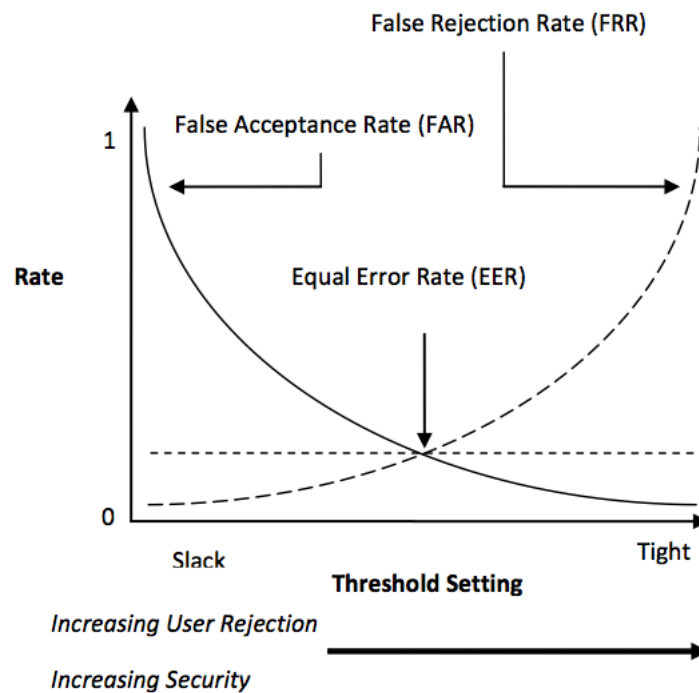


FIGURE 3.7: ROC curve [Bergadano and Raedt \(1994\)](#)

3.4 The concept of Stance Classification

Over the past decade, there has been active research in modeling the overall users' personal positions in user-generated contexts. However, the majority of research works lies on congressional debates [Hofmann \(2001\)](#) or debates in online forums [Somasundaran and Wiebe \(2009\)](#), [Anand et al. \(2011\)](#) [Walker et al. \(2012\)](#) [Hasan and Ng \(2013\)](#), [Sridhar et al. \(2015\)](#). The advantage of using such domains is that gold labels are given by the authors. However, stance detection in other forms of user-generated contents like Twitter data and online news comments are mostly unexplored.

Stance detection is defined as the problem of classifying the attitude taken by an author in a short piece of text. Typical stances include showing support, denying, commenting on or querying an existing claim or fact. Gaining knowledge on the stance that authors hold in response to claims, e.g. in online commentary, gives useful insights. It reveals rumours and fake news claims as the discourse around them is monitored [Procter et al. \(2013\)](#). Stance reflects how specific authors are of a claim's veracity, enabling the effective detection of potential false rumours [Lukasik et al. \(2016\)](#). Stance additionally reveals how online populations react to business and political news.

Stance classification, or else the automated classification of the author's positive (=for) or negative (=against) stance towards a given proposition, is the most recent addition to the group of sub-tasks associated with Sentiment Analysis. The most fundamental work dealing with the automated classification of argument stance is that of [Somasundaran and Wiebe \(2009\)](#), [Somasundaran and Wiebe \(2010\)](#), [Anand et al. \(2011\)](#), [Walker et al. \(2012\)](#), [Hassan et al. \(2010\)](#), [Hasan and Ng \(2013\)](#), [Saif et al. \(2016a\)](#). These researchers have introduced several supervised approaches to this type of classification task using a corpus of online debates. Although there are abundant annotated data for traditional opinion mining, there are no comparable resources for stance classification work.

Supervised learning has been used in almost all of the current approaches for stance classification, in which a large set of data has been collected and annotated in order to be used as training data for classifiers. The system of [Somasundaran and Wiebe \(2009\)](#) proposed a supervised approach to the classification of stance in these online debate data. A significant feature set aspect developed in this work is the use of a stance lexicon comparable to the opinion lexicons traditionally used in sentiment analysis tasks. This lexicon was constructed using annotations from the Multi-Perspective Question Answering Project (MPQA) [Somasundaran and Wiebe \(2010\)](#). Moreover, all debate text was pre-processed in a way that information considering the target of a given expression of argument stance (in the death penalty should be abolished, the target is death penalty and the expression of stance polarity is should) is directly attached to all stance-taking expressions in the text. With stance-target features, the system includes features recording information regarding the targets of opinion. Ablation experiments were performed using combinations of stance-target and opinion-target features represented as a frequency-valued bag-of-words vector.

In [Anand et al. \(2011\)](#), various linguistic features were employed in a rule-based classifier, such as unigrams, bigrams, punctuation marks, syntactic dependencies and the dialogic structure of the posts. The authors showed that there is no significant difference in performance between systems that use only word unigrams and systems that also use other features such as Linguistics Inquiry Word Counts (LIWC) and POS generalized dependencies. The dialogic relations of agreement and disagreements between posts were also utilized by [Walker et al. \(2012\)](#). The online debate exchanges collected typically take one of two forms, main topic response, in which a poster writes in direct response to the debate topic, or quote-and-response, in which posters quote all or part of the main topic response of a previous poster and attempt to rebut it. The aim of such systems is to categorize debate posts as argument or rebuttal rather than as positive (=for) or negative (=against) stance. The feature set exploited in this system contained unigram and bigram counts, grammatical category features derived from the Linguistic Inquiry and Word Count toolkit [Pennebaker Conglomerates Inc.](#), syntactic dependencies capturing stance-target relationships inspired by similar work in [Kouloumpis et al. \(2011\)](#), and generalized dependencies [Joshi and Penstein-Rosé \(2009\)](#).

[Faulkner \(2014\)](#) explored the problem of detecting document-level stance in student essays by making use of two sets of features that represent stance-taking language. These features are divided into six main groups: n-grams, length-based, syntactic, sentiment, argumentative, and non-linguistic constraints. Different machine learning algorithms are employed for automatic classification of overall position from unstructured text. While SVM and logistic regression were widely used in multiple studies [Walker et al. \(2012\)](#), [Somasundaran and Wiebe \(2010\)](#), Conditional Random Fields (CRF) and Linear Integer Programming were exploited in [Wang and Cardie \(2016\)](#) and [Hasan and Ng \(2013\)](#) to additionally unravel agreement and disagreement in user interactions. The assumption in [Hasan and Ng \(2013\)](#) is that consecutive posts are not independent of each other and constraints on adjacent posts define the problem as a sequence labeling task.

In [Ahmed et al. \(2011\)](#), an extension to the Latent Dirichlet Allocation (LDA) algorithm is explored to model each word as the interaction of ideological and topical dimensions. In one of a few works in stance detection in Twitter, [Rajadesingan and Liu \(2014\)](#) classified stance at user-level focusing on the assumption that if several users retweet one pair of tweets about a controversial topic, it is more likely to support the same side of a debate. In another work for Twitter stance detection, bi-directional Long Short

Term Memory was used to encode the target and the tweet [Zubiaga et al. \(2017\)](#). In that work, the representation of the tweet and the target depend on one another and the experiments proved that improvement is needed over encoding the tweet and the target independently.

3.4.1 Features Identification

Choosing the most appropriate feature set for sentiment analysis has the highest importance as it has a strong impact on the evaluation results. Features are often pre-processed by multiple techniques reducing the feature space. The importance of this pre-processing phase depends on the language.

Feature identification and selection is integrated as the most important part of treating the corpus training data in the machine learning approach [Kummer and Savoy \(2012\)](#). With other words, it aims to convert a piece of text into a feature vector or any other representation for computational processing ?. Initially, the training data are labeled as positive, negative or neutral. Then a set of features is extracted from the labeled training data. The collection of features is encoded using value types, such as Booleans, numbers and strings. Since the training data usually is comprised of two group data (positive and negative), each word in each group can be seen as a feature vector. Some of words such as Stop Words (e.g. “a”, “is”, “the”) and alphabet might not provide any sentiment information thus are usually filtered out. The method that adds individual words to the feature vector is usually named as unigrams approach [Thomas et al. \(2006\)](#). There is an extensive research work dealing with the feature selection in machine learning approach and we offer an in-depth analysis in features categorization. Figure 3.8 depicts a categorization of stance classification features according to [Sobhani et al. \(2015\)](#).

3.4.1.1 Words and Stems

A classic technique in information retrieval is to stem the words to their morphological roots. Stemmed feature vectors are smaller in size, aggregating across occurrences of variants of a given word. Stemming is used in both information retrieval and text mining.

Features Type	Features	Reference
<i>n</i> -grams	Words unigrams and bigrams	Somasundaran and Wiebe (2010); Anand et al. (2011)
Length-based	Number of sentences, words, and characters	Sridhar et al. (2014)
Syntactic	Dependencies and generalized dependencies with respect to POS tags	Joshi and Penstein-Rosé (2009); Somasundaran and Wiebe (2009b); Anand et al. (2011)
Sentiment	Linguistics Inquiry Word Counts (LIWC), MPQA to select the subset of generalized dependency features and replaced opinion words with their sentiment	Lin et al. (2006); Anand et al. (2011); Somasundaran and Wiebe (2010)
Argumentative	Repeated punctuation, Initial unigram, bigram and trigram, Arguing Lexicon, Modal verbs	Anand et al. (2011); Somasundaran and Wiebe (2010)
Non-Linguistic constraints	Author constraints, User-interaction constraints, Ideology constraints	Lu et al. (2012); Walker et al. (2012b); Hasan and Ng (2013)

FIGURE 3.8: List of Stance Classification Features [Sobhani et al. \(2015\)](#)

3.4.1.2 Binary versus Term Frequency Weights

A standard approach in information retrieval is to use term frequency (TF) weights to determine the relative importance of features in document representations. Nevertheless, research has shown that binary weighting (0 if the word appears in the document, 1 otherwise) is more beneficial for sentiment polarity classification [Pang and Lee \(2008\)](#). In a study of the standard information retrieval weighting schemes in SA, [Paltoglou and Thelwall \(2010\)](#) discovered that using binary features performs better than raw term frequency.

3.4.1.3 Negation

Negations such as not and never are often included in stop-word lists, and are removed from the text analysis. Combined with other words, negations reverse the polarity of words. Due to the fact that polarity classification can be affected by negations, Sentiment Analysis researchers have tried to incorporate them into the feature vector. We utilize the approach of [Yan and Candan \(2006\)](#) who use a heuristic to point the negated words and we create a new feature by appending NOT- to the words (for example, a phrase “don’t like” results in feature NOT-like).

3.4.1.4 N-gram Features

N-grams and their frequency is often used as a valid baseline. In some cases word positions and TF-IDF weighting scheme can be considered effective features. N-gram features do not have to use only words. For example, POS patterns are simply POS n-grams [Guthrie et al. \(2006\)](#). There are:

1. N-gram: Word n-grams are used to capture frequent word sequences. The presence of unigrams, bigrams and trigrams is often utilized as binary features.
2. Character N-gram: Similarly to the word n-gram, character ngram features can be used. Character trigrams are often used to capture frequent emoticons.
3. Skip Bi-gram: Instead of using sequences of adjacent words (n-grams) skipgrams, can be used to skip over arbitrary gaps. Basic approach uses skip-bigrams with 2 or 3 word skips and removes skipgrams with a frequency less than or equal to 20 ($i=20$)
4. Bag-of-words: Set of words without any information on the word order is referred as bag of words

3.4.1.5 POS-related features

Direct usage of part-of-speech n-grams that unravel sentiment patterns has not shown any specific improvement in the related work. Still, POS tags provide certain characteristics of a text. Such features have been used in related works e.g., number of nouns, verbs, and adjectives, the ratio of nouns to adjectives and verbs to adverbs, and the number of negative verbs obtained from POS tags [Kouloumpis et al. \(2011\)](#).

3.4.1.6 Lexical features

Lexical resources such as sentiment lexicons or SentiWordNet can be used as features. These resources use additional external knowledge to improve the results of sentiment analysis [Baccianella et al. \(2010\)](#).

3.4.1.7 Lexico-syntactic features

Significant part of research deals with lexico-syntactic features of stance-taking language focusing on features that can be collectively described as “evidential.” Evidential features allow speakers to express certainty or doubt concerning the truth of a proposition. These markers contain the classes of lexical verbs (conclude, demonstrate, indicate), modal adverbs (assuredly, indeed, allegedly, supposedly), hedges (perhaps, maybe), boosters (certainly, clearly), predictive modals (will, would), possibility modals (might, could), and necessity (or, deontic) modals (ought to, should). For some researchers [Chafe and Nichols \(1986\)](#), the correlation of stance-taking language and evidentiality is very close and the two terms can be used exchangeably. [Halliday and Matthiessen \(2004\)](#) claim that evidentiality “enacts the speaker’s opinion—an enactment of his or her degree of commitment to the proposition”.

3.4.1.8 Semantic features

Distributional semantics represent a significant part in sentiment analysis due to their ability to be regarded as the meaning of texts by using a statistical analysis. The direct application of a joint sentiment and topic model proved to be useful [Lin and He \(2009\)](#). Semantic models can be further utilized as new sources of information for classification (e.g. n-gram features or as bag of clusters instead of bag of words). The key distinction between attitudinal and stance-taking language turns on the semantic class of the target of the attitude taking entities and stance taking propositions as targets. This part of research starts with the syntactic observation [Hunston and Thompson \(2000\)](#) that the quintessential markers of stance in English, such as verbs of epistemic judgment (think, believe), necessity (or, deontic) modals (ought, should), and modal adverbs (possibly, certainly), all are grouped in grammatical classes that typically select for clauses rather than noun phrases.

The attitude=entity/stance=proposition distinction has important consequences. Opinion (attitude) classification tasks deal with review corpus which use entities such as movies, books as their targets [Sobhani et al. \(2015\)](#) while stance classification tasks focus on debate corpora which take full propositions as their targets. The online debates used as corpora in [Somasundaran and Wiebe \(2010\)](#), [Walker et al. \(2012\)](#), [Hassan et al.](#)

(2010), [Hasan and Ng \(2013\)](#) are headed by topic posts such as God exists, Abortion should be banned, and Creationism is false. These topic posts are seen as the target propositions of stance markers in debate posts arguing for or against the statement in the topic post, as shown in these examples: Example 1:

1. God exists
2. God absolutely does not exist and that is why there are so many wrongs in the world

Example 2:

1. Should abortion be legal?
2. Abortions have to be legal or all hell will break loose.

Example 3:

1. Should marriage for same-sex couples be legal?
2. I cannot agree with gay marriage because I believe in right and wrong and that homosexuality is wrong

3.4.1.9 Other Features

Syntactic features try to unravel word dependencies and sentence structure by employing syntactic information generated from parse trees

Orthographic features focus specifically on the appearance of the word, e.g. the first letter is a capital letter, all letters are capital or the words consists of digits. Emoticons Lists of positive and negative emoticons identify the number of occurrences of each class of emoticons within the text.

Punctuation-based features comprised of special characters, number of words, exclamation marks, question marks, quotation marks. However, such features usually do not significantly improve classification results [Martínez-Cámara et al. \(2014\)](#).

3.4.1.10 Features Selection

The main reason for using feature selection methods for supervised sentiment analysis is twofold: first, feature set reduces the computing demands for the classifier, and, second, removing irrelevant features leads to better classification performance in terms of accuracy. Furthermore, noise in the feature space increases the likelihood of overfitting [Abbasi et al. \(2011\)](#).

A study by [Sharma and Dey \(2012\)](#) compares five methods for feature selection, specifically Information Gain, Chi Square, Gain Ratio, Relief-F, and Document Frequency, with seven different classifiers. Evaluation results are based on the movie review database from [Pang and Lee \(2008\)](#). The best performance was achieved by using the SVM classifier and the Gain Ratio selector with the number of features ranging from 2,000 to 8,000 and exploiting only unigrams as features sorted by their frequency.

[Abbasi et al. \(2008\)](#) presented an entropy-weighted genetic algorithm combining Information Gain with a genetic algorithm for selecting features in a bootstrapping manner. They performed document-level binary sentiment of English and Arabic using SVM as the main classifier with results superior to other approaches. In another work, [Abbasi et al. \(2011\)](#) proposed another method called Feature Relation Network in which they manually constructed a network of feature dependencies (e.g., subsumption1 or parallel relations of various n-grams) relying on SentiWordNet in order to assign the final feature weights.

[Forman \(2003\)](#) discovered a metric called Bi-Normal Separation comparing it with other twelve existing feature selection methods. Using SVM as classifier, the proposed method performed better. Other examples of feature selection methods for sentiment analysis or text classification can be found in [Du et al. \(2012\)](#), [Mukherjee and Liu \(2013\)](#), [Chen and Liu \(2014\)](#) works.

3.5 The concept of Policy Making

Every policy problem has deep-rooted value dimensions. It is on the basis of values that a state is perceived as unpleasant, and thus acknowledged as a problem. This situation makes the process of defining the meaning of a problem an essentially political

process. Bureaucracy and expertise have a strong influence regarding the formation of policy problems. A knowledge view prevails within the public managerial area, which complicates the political dimension of problem formulation, while policy problems tend to be approached as a matter of efficiency.

3.5.1 Identifying Wicked Problems

Problems vary according to their complexity. Some problems are just simple, or “tame”. Solving such problems, is a straightforward process and the same solution works every time. Other problems, which are considered complicated and require more expertise to be solved, can be managed within the traditional scientific paradigm. Solutions may be found that are feasible and verifiable. However, in complex problems, expertise and experience can be useful, but there is no guarantee of a successful solution, as every complex problem is unique [Glouberman and Zimmerman \(2002\)](#). These problems are described as “wicked” [Kunz et al. \(1970\)](#). The discourse in wicked problems arised in the 1970s as a result of criticism of the rational technical approaches of solving complex social policy problems [Head and Alford \(2015\)](#). Most people agree that wicked problems have no single cause and therefore no simple solution. These problems typically involve multiple sectors in various organizational levels, and many actors. Wicked problems have the following characteristics [Kunz et al. \(1970\)](#).

1. The wicked problem cannot be understood until its solution is developed. Thus, both their definition and solution develop independently
2. The wicked problem lacks a definite conclusion
3. A solution is either better or worse Without specific objective criteria for the evaluation
4. Every wicked problem is unique. Thus, solutions must be adapted to the problem’s particular social context
5. Every solution to a wicked problem is a “one-shot operation”

Three main strategies for solving wicked problems have been suggested over time: collaborative, authoritative, and competitive strategies. Collaborative strategies, are most

commonly used and require that stakeholders create a shared understanding of the problem and develop possible solutions [Kalkan et al. \(2014\)](#), [Roberts \(2001\)](#). Authoritative strategies require that a group of people will be assigned a problem-solving responsibility. Competitive strategies, require that stakeholders acquire the ability to define the problem and influence its possible solution ([Roberts 2000](#)). Although it is sometimes stated that collaborative strategies are the best way to solve those wicked problems, in some cases it may be more essential to combine the authoritative strategy or the competitive strategy with the collaborative strategy².

3.5.2 Defining Public Policy

Public policy describes governments' actions and values related to the common good. Nevertheless, public policy reflects the actions and values that governments promote ([Dye 1995](#)). More specifically, public policy reflects the intent of governments to grant resources to certain issues in order to achieve particular purposes in a specific timeframe. The view in this thesis is that public policy contains both tools and goals ([Sabatier & Weible 2014](#)).

Governments utilize comprehensive policies to address wicked problems ([Yin & Davis 2007](#)). Alternative governance forms may be more useful in managing wicked problems than laws and regulations. They reflect the engagement and the collaboration among multiple groups of stakeholders and the development of systemic capability ([Ferlie et al. 2013](#)).

3.5.3 Policy problems as Constructs

It is well theorized a how a specific policy problem reaches the political agenda [Quirk \(1986\)](#), [Lodge et al. \(2016\)](#). Many researchers examine how a policy problem is addressed, why and with what results (e.g., evaluation research, or research on decision making). Policy researchers with a theoretical background in discursive theory have upheld the configurative aspect of policy formation. The representation of a social problem should not be seen as a direct reflection of reality, 'but as the practices through which things take on meaning and value; to the extent that a representation is regarded as

²<https://www.finance.gov.au/files/2013/01/APS_{ICT}strategy.pdf>

realistic'. Policy has a constructive power. It forms categorizations and interpretations of people and their acts, and by doing that it imposes identities and behaviours [Bacchi \(2016\)](#).

To understand the formation of policy problems, a framework is needed that captures the constructive process.

3.5.4 Constructing Frameworks as Solution to Policy Problems

When we try to understand a situation, within research as well as in everyday life, what we use is a frame(work). A frame is comprised of belief and perception that structure the information and direct the interpretations of a situation. A frame is often organized around concepts. The understanding of a policy problem, which gives it legitimacy as a policy issue, is not neutral nor is the preferred state, which implies 'the problem'; hence, policy issues are not foremost about accuracy. Even within a particular frame, accuracy would be difficult to achieve. Due to an increasing information flow, of research and practical examples people need filtering mechanisms [Rein and Schön \(1996\)](#).

3.5.5 Governing Wicked Problems

It is possible to identify some general trends in the institutional arrangements of policy fields that govern wicked problems. To get a perspective on the characteristics of institutional arrangements it is useful to mention three generations of policy fields. First-generation policy fields are the initial institutions of national democracy (e.g. defence and taxation), while second-generation policy fields are the sectoral institutions [Kallberg et al. \(2019\)](#), [Painter \(2009\)](#). Policy fields that have become institutionalized over the last decades are governed by characteristics other than those of the traditional ones, and these are the ones defined as third-generation policy fields. Policy fields cannot simply be attributed to one or the other of these generations on the basis of when they were institutionalized. A policy field bears characteristics of more than one. However, the contribution of the conceptualization of policy generations is that it illustrates changing conditions in policy fields over time giving perspective on contemporary institutional/organizational trends [Painter \(2009\)](#).

Third-generation policy fields are emerging around ideas about the problems or challenges of contemporary society, problems defined as complex, multidimensional or wicked problems [Kunz et al. \(1970\)](#). Governance through networks is often considered to be the most suitable organizational model for finding effective solutions to complex problems [O'Toole Jr. \(2015\)](#). These changing forms of policy institutions alter the conditions for power to operate. They put the relationship between power and knowledge in the forefront. The primary goal of these policy institutions is to provide insights and to shape the understanding of a particular problem and how it should be addressed. These institutional assignments can be identified as a politicization of the public authorities. The authorities have to a larger extent taken over both the problem-defining assignment and the expert and opinion-making role [Painter \(2009\)](#).

3.5.6 Research Implementation on Policies

Policy implementation research concerns how governments put policies into practice. Interest in policy implementation research emerged in the 1970s as a result of the increasing concern about the effectiveness of public policies. Early policy implementation research was characterized by a top-down, "success-or-failure" perspective, and a rational-linear view of change. In the 1980s, new theories emerged trying to take a view of the various factors that influence the policy process [Nilsen et al. \(2013\)](#).

Following this theoretical development, a debate arose between the top-down and the bottom-up view of policy implementation. The bottom-up view emphasizes on the role of the frontline staff as the actual implementer of policies. Current developments in policy implementation research support an approach that synthesizes the top-down and bottom-up perspectives and that enhances the methodological precision of the research [Lipsky \(2010\)](#).

Contemporary policy implementation research, which is often related to the concept of governance, acknowledges the need for collaboration among the multiple actors at the multiple levels of government [Hill and Hupe \(2003\)](#), [Hupe and Hill \(2016\)](#). Network approaches, that examine the complex networks of actors who work with the policy process, in particular regarding the policy processes that address wicked problems, are favoured [Head and Alford \(2015\)](#), [Klijn and Koppenjan \(2000\)](#).

3.6 Literature Review on Text Mining & Policy Making

3.6.1 Topic Modeling Analysis

This part of our literature research lies on modeling online discussions to find and extract the topics of discussion. Topic modeling focuses on analyzing a great amount of unlabeled text to create cluster of words that frequently occur together characterized by their distributional probability. LDA [Blei et al. \(2003\)](#), [Graells-Garrido et al. \(2015\)](#), a three-level hierarchical Bayesian model, pLSA [Hofmann \(1999\)](#), a latent variable model for co-occurrence data and unsupervised pLSA [Hofmann \(2001\)](#) that uses a generative latent class model to perform a probabilistic mixture decomposition, are utilized for probabilistic latent semantic indexing. They are viewed as the most methodical choices for mining topics from large volumes of online data. Nevertheless, there have been proposed other various extensions of LDA, with [Blei and Lafferty \(2006\)](#) developing sequential topic models for discrete data using Gaussian time series, [Titov and McDonald \(2008\)](#) extracting the ratable aspects of objects from online user reviews through multi-grain topics and [Mcauliffe and Blei \(2008\)](#) focused on a supervised LDA (sLDA) deriving a maximum-likelihood procedure for parameter estimation.

Furthermore, [Ramage et al. \(2009\)](#) proposed the Labeled LDA (L-LDA) directly learning word-tag correspondences and [Lacoste-Julien \(2009\)](#) presented a Discriminatively trained LDA (DiscLDA) model, in which a class-dependent linear transformation is introduced on the topic mixture proportions and is estimated by maximizing the conditional likelihood. Moreover, [Wang and Rosé \(2010\)](#) identified initiation-response pairs in asynchronous, multi-threaded, multi-party conversations as a pairwise ranking problem and proposed a new variant of Latent Semantic Analysis (LSA) to overcome limitations of standard LSA models and [Du et al. \(2012\)](#) proposed a Sequential LDA (SeqLDA), explicitly considering the document structure in the hierarchical modelling.

Additionally, [Mukherjee and Liu \(2013\)](#) developed JTE-P model, to jointly model AD-expressions, pair interactions, and discussion topics into a single framework. [Chen and Liu \(2014\)](#) developed a knowledge-based topic model that dynamically balances the use of learned knowledge and the information in the actual document collection during Gibbs sampling. [Yuan et al. \(2015\)](#) developed a LightLDA, enabling web-scale corpora to be

processed on a small computer cluster. [Luo et al. \(2015\)](#) proposed to cluster frame-by-frame detections and treat objects as topics, allowing the application of the Dirichlet Process Mixture Model (DPMM).

[Greene and Cross \(2016\)](#) extracted latent thematic patterns in political speeches, by developing a dynamic topic model based on two layers of Non-negative Matrix Factorization (NMF), to investigate how the plenary agenda of the EP has changed over three parliamentary terms. [Chen et al. \(2016\)](#) adapted the approach of a sentence-layered LDA and introduced the notion of sentence topics by adding a set of latent variables which serve as additional sub-document constructs in between the document and the words. [Lim et al. \(2016\)](#) proposed a Twitter-Network (TN) topic model to jointly model text and social network in a full Bayesian nonparametric way, employing the hierarchical Poisson-Dirichlet processes (PDP) for text modeling and a Gaussian process random function model for social network modeling. [Ma et al. \(2016\)](#) adapted a method for public opinion analysis on social media website utilizing the LDA model, the deep learning model named word2vec and time series analysis to analyse the public emotion intensity for a given social event. [Li et al. \(2016\)](#) proposed a topic model for short texts based on the Dirichlet Multinomial Mixture (DMM) model and exploiting auxiliary word embeddings.

3.6.2 Sentiment Analysis

Sentiment analysis determines the opinions expressed on large volumes of data according to their sentiment polarity as positive, negative or neutral.

Sentiment analysis indicates and classifies the sentiment orientation of opinions expressed on documents as positive, negative or neutral [Liu \(2012\)](#) [Pang and Lee \(2008\)](#). Main tasks incorporate aspect extraction [Popescu and Etzioni \(2005\)](#) [Mukherjee and Liu \(2012\)](#), opinion polarity identification [Hassan et al. \(2010\)](#) and subjectivity analysis [Hatzivassiloglou and Wiebe \(2000\)](#). Sentiment Analysis is often employed in researches that focus on the use of ICTs and social media platforms by government agencies for participative policy formulation. [Stylios et al. \(2012\)](#) explored various features in user-generated content discussing governmental decisions in an effort to automatically extract

citizens' opinions derived from online posts based on public sector regulations. [Sobkowicz et al. \(2012\)](#) designed an opinion formation framework drawing attention on both content analysis of social media and sociophysical system modeling.

[Charalabidis et al. \(2015\)](#) proposed sentiment analysis exploitation aiming to leverage the extensive policy community of the European Union. [Cambria et al. \(2015\)](#) proposed a concept-level sentiment analysis (CLSA) model, taking into account all the natural-language-processing tasks necessary for extracting opinionated information from text such as microtext analysis, semantic parsing, subjectivity detection, anaphora resolution, sarcasm detection, topic spotting, aspect extraction, and polarity detection. [Giatsoglou et al. \(2017\)](#) proposed a methodology for sentiment detection out of textual snippets which express people's opinions in different languages, adopting a machine learning approach with which textual documents are represented by vectors and are used for training a polarity classification model. [Pannala et al. \(2016\)](#) explored aspect-based sentiment analysis to provide positive, negative and neutral reviews for different products in the marketing world, identifying the aspects of entities and the sentiment expressed for each aspect. [Etter et al. \(0\)](#) utilized social media data and sentiment analysis to study the affect-based responses to organizational actions by citizens, comparing the proposed method with existing quantitative ones for legitimacy measurement.

[Saif et al. \(2016b\)](#) presented SentiCircles, a lexicon-based approach for sentiment analysis on Twitter, offering a fixed and static prior sentiment polarities of words regardless of their context and allowing for the detection of sentiment at both entity-level and tweet-level. [Asghar et al. \(2017\)](#) exploited the wealth of user reviews, available through the online forums, to analyze the semantic orientation of words by categorizing them into positive and negative classes and classifying emoticons, modifiers, general-purpose and domain-specific words expressed in the public's feedback about the products. [Keshavarz and Abadeh \(2017\)](#) improved polarity classification of sentiments in microblogs by building adaptive sentiment lexicons and proposed a genetic algorithm with novel penalty and reward mechanisms to solve the optimization problem. [Märkle-Huß et al. \(2017\)](#) advanced sentiment analysis by the use of rhetoric structure theory (RST), providing a hierarchical representation of texts at document level.

3.6.3 Stance Classification

A relatively novel and challenging mining task for an in-depth inquisition is stance classification: given a post written online referring to a topic of discussion, we aim to determine whether the author's personal position towards this topic is either for or against. There are numerous studies of related work that focus on classifying a stance covering three different debate settings. We are only interested in classifying stances stemmed from online websites and public forums.

[Somasundaran and Wiebe \(2009\)](#) designed an unsupervised model for debate-side classification implementing Integer Linear Programming. [Somasundaran and Wiebe \(2010\)](#) moved one step further modeling opinions along with their targets using relational sentiment analysis techniques. [Anand et al. \(2011\)](#) employed meta-post features, contextual features, dependency features and word-based features to identify agreement and disagreement between posts in online debate sites. [Lu et al. \(2012\)](#) modeled unsupervised discovery of supporting and opposing groups of users for topics in online military forums, formulating a linear program (LP), combining multiple textual and reply-link signals and suggesting the benefits of jointly modeling textual and reply-link features.

[Walker et al. \(2012\)](#) classified posts using MaxCut over rebuttal links between the posts to separate them into opposite clusters. [Ranade et al. \(2013\)](#) determined user's stance as pro or con investigating users' intentions and debates structure. [Hasan and Ng \(2013\)](#) used conditional random fields (CRFs) locating opposite stances between sequences of posts. [Sridhar et al. \(2015\)](#) utilized hinge-loss Markov random fields (HL-MRFs) to provide consistency between labels indicating stance in a post level and observe post-level textual agreements and disagreements. [Boltužić and Šnajder \(2014\)](#) and [Ghosh et al. \(2014\)](#) exploited numerous linguistic features to model stance and agreement interactions respectively. [Sobhani et al. \(2015\)](#) proposed a one-to-one mapping between pre-defined argument sets and extracted topics using supervised modeling.

[Ebrahimi et al. \(2016\)](#) performed collective classification of stances on Twitter, using Hinge-Loss Markov Random Fields (HL-MRFs) and Statistical Relational Learning (SRL) to train any linear text classifier when the network structure is not available or is costly. [Ferreira and Vlachos \(2016\)](#) presented Emergent, a real-world data source for a variety of natural language processing tasks, and addressed the task of determining the article headline stance using a logistic regression classifier. [Wang and Cardie \(2016\)](#)

proposed an isotonic Conditional Random Fields (isotonic CRF) based sequential model to make predictions on sentence- or segment-level. [Mohammad et al. \(2016\)](#) proposed a stance detection system using a linear-kernel SVM classifier that relied on sentiment features from lexicons and word-embedding features from additional unlabeled data. [Mandya et al. \(2016\)](#) described and evaluated a set of scrutable features for stance classification of argumentative texts using a Distributional Lexical Model (DLM) that captures the writer's attitude towards the topic term. [Lukasik et al. \(2016\)](#) developed an automated, supervised classifier based on Gaussian Processes that uses multi-task learning to classify the stance expressed in each individual tweet in a rumourous conversation as either supporting, denying or questioning the rumour.

[Bar-Haim et al. \(2017\)](#) introduced the complementary task of claim stance classification and proposed a semantic model for contrast detection. [Zubiaga et al. \(2017\)](#) focused on how individual posts in social media observably orientate to the postings of others determining the veracity of the underlying rumour. [Addawood et al. \(2017\)](#) proposed a machine learning approach to classify stance in debate, and a topic classification that used lexical, syntactic, Twitter-specific, and argumentative features as a predictor for classifications. [Simaki et al. \(2018\)](#) presented a study for the identification of stance-related features in non-annotated data from Twitter and Facebook. [Küçük and Can \(2018\)](#) targeted at stance detection on sports-related tweets and presented the performance results of SVM-based stance classifiers on such tweets utilizing as features unigrams, bigrams, hashtags, external links, emoticons, and named entities. [Zhang et al. \(2018\)](#) tackled the stance detection problem as a ranking problem and proposed a ranking-based method to improve detection performance.

3.6.4 Policy Making

There is common consent that a comprehensive policy life cycle consists of at least the following broad stages:

- **Agenda-Setting:** Identifying the problem that demands government attention, defining the nature of the problem, setting the objectives, choosing the best solution, select policy instruments and generally articulate the rationale of a policy

- Decision-Making: developing policy options for addressing the problem, determining various approaches for achieving the policy objectives, ensuring that the chosen policy instruments have the appropriate support
- Policy Implementation: Implementing and monitoring the policy, validating that the policy decisions are carried out as planned
- Policy Evaluation: Assessing the impact and efficiency of the policy with either maintaining or terminating the policy, and utilizing the feedback to either improve the existing policy or inform the development of a new one

Governments, organizations and researchers are interested in modeling user's stance as pro or con in discussion topics of social media debates. There are works that predict user's stance on a specific issue supporting the identification of social and political groups (Abu-Jbara et al. (2012), Anand et al. (2011), Gawron et al. (2012), Qiu et al. (2013), Sridhar et al. (2015)). Additionally, there are works that aim on the use of ICTs and social media platforms exploitation by government agencies, researchers and organizations for participative policy formulation utilizing advanced textual analysis of online users' comments (Thomas et al. (2006), Maragoudakis et al. (2011), Spiliotopoulou et al. (2014)).

Miller (1982) analysed the use of referendum in Denmark and its restrictive role in Danish policy-making. Mazey (1986) examined the policy performance of the French Socialist administration from the perspective of rationalist and incremental models of policy-making. Koppen (1992) modeled judiciary in the Netherlands and presents how significant policy-making is performed in Dutch politics. Pagoulatos (1996) attempted to draw insights on the problem of governance by examining policy making in the Greek banking sector and highlights a set of conceptual tools to describe and explain the transforming environment of a policy network.

Papadopoulos (2001) underlined referendum mechanisms that result from pressure "from below", which differentiate Switzerland and Italy at the national level with referendum institutions. Kassim and Galès (2010) demonstrated how new policy instruments might improve the implementation of public policy, open new perspectives on EU policy-making and make the EU more transparent and more participatory. Tresch et al. (2013) analysed the level of media coverage and the distribution and correspondence of issue

attention between media and political agendas across the four phases of the decision-making process in Switzerland. [Ingold and Gschwend \(2014\)](#) presented the Advocacy Coalition Framework investigating the role that science plays in policy processes.

[Henökl \(2015\)](#) composed a behavioural analysis of the European External Action Service decision-making. [Wonka \(2017\)](#) studied the relations between members of the German parliament and interest groups on issues related to EU policy-making and discovered that the model of information provision for the US context also holds for European policy-making in the German Parliament. [Talving \(2017\)](#) demonstrated the overall voter reactions to alternative policy approaches and considered the possibility that higher levels of international intervention in national policy actions weaken the electoral punishment of incumbents for unpopular austerity measures.

Chapter 4

A Generic Opinion Mining Mechanism for Policy Making

This chapter introduces the first approach for crowdsourcing that aims to promote and support policy formulation. This generic opinion mining mechanism lies on the combined exploitation of multiple social media platforms. More specifically, it is based on a central ICT platform, which publishes as content various types of discussions concerning a social problem or a public policy under formulation to a series of social media simultaneously, and also collect from them citizens' interactions, using the API of the social media. At last, this interaction content is being analyzed through the exploitation of various types of processing (e.g. opinion mining, sentiment classification, etc.) in order to draw useful conclusions for public policy issues from them. The proposed approach has been evaluated through three pilot applications organised in cooperation with members of the European Parliament. The results of these applications are underlined along with the results of the evaluation of the approach from political perspective, based on the specification of a research methodology. A comprehensive description of this particular mechanism is provided in (Spiliotopoulou et al. 2014, Loukis et al. 2013, Spiliotopoulou and Charalabidis 2013).¹

¹The research presented in this chapter has been conducted as part of the research project PADGETS ("Policy Gadgets Mashing Underlying Group Knowledge in Web 2.0 Media"), which has been partially funded by the "ICT for Governance and Policy Modeling" research initiative of the European Commission. More information at <http://www.padgets.eu>

4.1 Requirements & Methodology of the Generic Opinion Mining Mechanism

In order to build an ICT architecture based on social media (and ICT in general) exploitation to collect effectively knowledge, ideas and opinions from citizens, we designed and developed an active crowdsourcing mechanism consisted of five stages. Its development was performed through cooperation with public-sector employees experienced in public policy-making, using both qualitative and quantitative techniques: semi-structured focus group discussions, scenarios development and questionnaire surveys.

In particular, the methodology we adopted for the development of the generic opinion mining framework is the following:

- Initially, three semi-structured focus group discussions were conducted as user partners (Center for eGovernance Development (Slovenia), ICT Observatory (Greece), Piedmont Regional Government (Italy)) in the three government agencies involved in the PADGETS project to gain an understanding of their policy making processes, the degree and form of public participation in them. They were all based on the questionnaire shown in Appendix [A.1](#)
- The same questionnaire was filled in and returned to us through e-mail by another four government agencies [City of Regensburg (Germany), World Heritage Coordination (Germany), North Lincolnshire Council (UK), IT Inkubator Ostbayern GmbH (Germany)]. This helped us to obtain the above data covering multiple levels of government (national, regional and local)
- The main idea of the active crowdsourcing approach was formulated on the basis of the information gathered in the above two phases: combined use of multiple social media to consult with citizens on a social issue or public policy, and sophisticated processing of relevant content generated by citizens
- In collaboration with PADGETS' partners, three scenarios with "real life" pilot applications were developed concerning the combined use of several social media in a highly automated and efficient manner for consultation with citizens on the following public policy subjects aiming at "crowdsourcing":

- “Legal and illegal immigration and integration of third-country nationals” (in cooperation with the Center for eGovernance Development — Slovenia);
 - “Introduction of citizen electronic identity card” (in cooperation with ICT Observatory – Greece);
 - “Large-scale implementation of tele-medicine in Piedmont region” (in cooperation with Piedmont Regional Government — Italy); and
 - each of these scenarios described which social media should be used and how, what content should be posted to them, and also how various types of citizens’ interactions with it (e.g. views, likes, comments, retweets, etc.) should be monitored and exploited, and what analytics would be useful to be computed from them
- Finally, a survey was conducted, using a shorter online questionnaire concerning the required functionality from an ICT tool supporting the use of social media for public policy-related consultations over social media, which is shown in Appendix [A.2](#). It was distributed by personnel to colleagues from the same or other government agencies, who have working experience in public policy-making, and, finally, filled in by 60 persons

Based on the responses of the participants in Stages I and II, the scenarios from Stage IV, and the responses in the survey of Stage V, initially our GENERIC framework for exploitation of multiple social media in government was formulated, then a supporting ICT infrastructure and an application process model for it were developed, as shown in the next Sections of this chapter.

For the evaluation of the proposed framework, ten pilot applications of it were conducted. They concerned social media consultations on the following subjects:

1. “Media freedom”
2. “Corruption”
3. “Cooperative institutes’ contribution to poverty reduction, employment generation and social integration”
4. “Tax evasion and fraud”

5. “European year of citizens and citizenship”
6. “Employment, entrepreneurship and freedom of speech for European youth”. [the above six pilot applications were organized and conducted by the Center for eGovernance Development, Slovenia, in cooperation with Slovenian Members of the European Parliament (MEP)]:
7. “Under-representation of women executives in the higher management of enterprises”;
8. “Financial crisis in the Southern European countries”
9. “Exploitation of wind energy”. (these three pilot consultations were organized and conducted by the University of the Aegean, as the Greek ICT Observatory had been abolished at that time as part of the Greek government austerity program, in cooperation with a Greek MEP),
10. “Large-scale implementation of tele-medicine in Piedmont region” (this pilot consultation was organized and conducted by Torino Polytechnico in cooperation with Piedmont Regional Government).

After the end of these pilot applications, semi-structured focus group discussions were conducted for evaluating them, in which participated the involved personnel of users partners and MEP assistants. They were based on the evaluation questionnaire shown in Appendix A.3, which is based on previous research on “wicked” policy problems and “issue-based information systems” [Kunz et al. \(1970\)](#), [Conklin and Begeman \(1988\)](#). It aims to assess to what extent the proposed framework is useful for conducting policy-related social media consultations in a short time and at a low cost, and for reaching wide audiences; also, to what extent it is useful to identify for a particular domain of government activity or public policy what are the particular problems/issues, possible solutions to them and relevant advantages — positive arguments and disadvantages — negative arguments; and finally, to what extent it allows identifying stakeholders groups with different views and concerns and facilitates convergence (at least to some extent) among them. All focus group discussions were tape-recorded, transcribed and then coded manually, using an open-coding approach [Maylor and Blackmon \(2005\)](#).

The main concept around which the strategy model was developed, is to build online public policy initiatives that are being debated through multiple social media platforms.

This ICT active crowdsourcing infrastructure is introduced as a systematic way of producing analytics on policy messages (policy-related comments in social media) in one single dashboard for the whole policy life cycle. Through tracking the reactions and interactions of people to relevant posts and combining modeling and simulation methods, the outcome of policy implementation could be predicted. A Sentiment Analysis module is developed to unravel public sentiment towards a specific policy, leading to decisions that are better informed and culturally ingrained. In summary, by evaluating the overall impact of such a political initiative, it offers a groundbreaking framework of policy making.

This approach involves two types of stakeholders: the policy maker launching a policy initiative and publishing messages, and the user engaging in the underlying social media with these messages through their social media profile. Through social media platforms, users are met, ensuring a policy message will be posted in the underlying social media and the end user communicates with them, e.g. on Facebook or through feedback on a blog post.

Our research methodology for the generic opinion mining mechanism is illustrated in Figure 4.1.

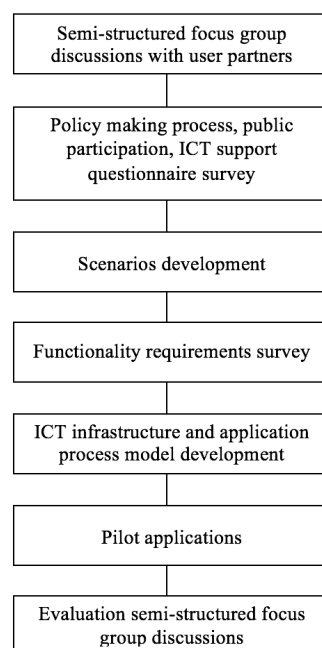


FIGURE 4.1: Research Methodology

4.2 Designing the Generic Opinion Mining Mechanism

In order to design our generic opinion mining mechanism, our main objectives were to:

- Design and implement an environment for creating and deploying policy campaigns across social media
- Provide architectural design and specification of the platform
- Implement the various components (for context, decision and interface), integrate them together and deploy a platform to be used as a service over the internet
- Support pilot scenarios

4.2.1 Communicating with citizens via Policy Gadgets

In particular, a Padget (Policy Gadget) is composed of four elements as shown below in Figure 4.2.



FIGURE 4.2: Basic Elements of a Padget

A Padget is composed of:

- A policy message, which can be a public policy at any stage, e.g. a law at its final stage, a legal document under formulation
- An interface, which will allow users to interact with the policy gadget (setup, deploy, keep track of)
- Relevant group knowledge, in the form of relevant content and users' activities that have been produced in external social media (social context)

- A set of decision support services using as input the above data from the interaction of a Padget with the public

In order to design a typical application of our generic framework, based on our research methodology in a policy making process, a policy maker needs to initiate the process making the decision about the future of a policy or for possible modifications based on the citizens input. The process that needs to be followed, consists of four steps shown in Figure 4.3.

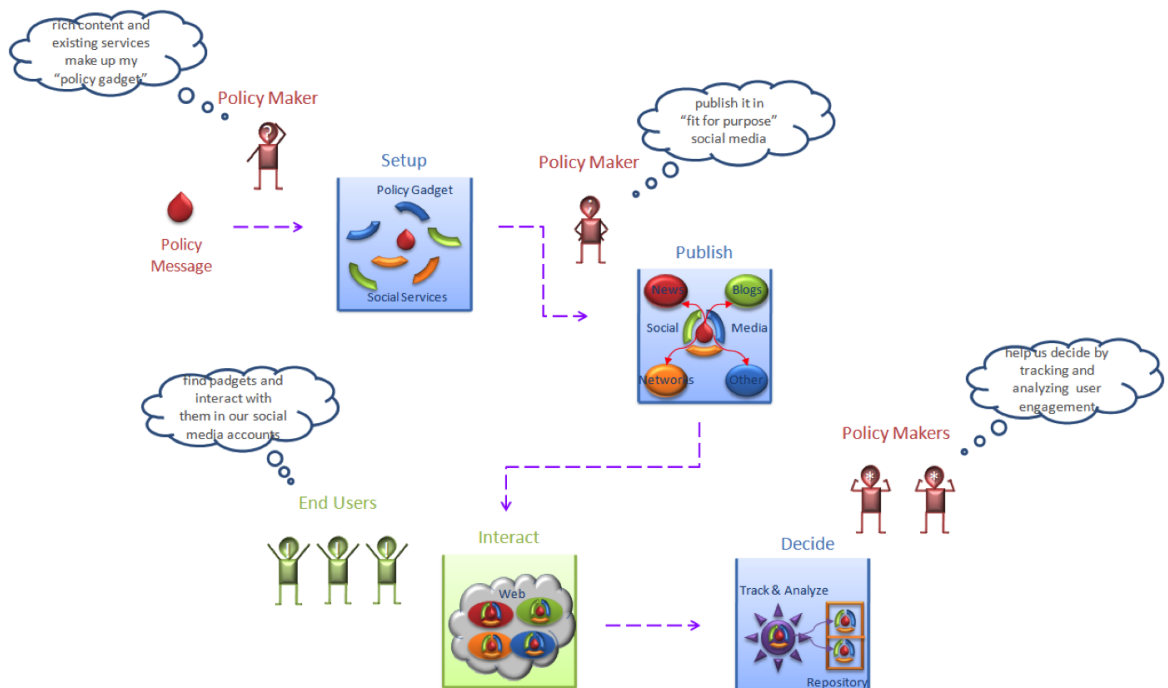


FIGURE 4.3: Typical application approach of the Generic Framework's Methodology

- Through a graphical user interface, the policy maker designs a campaign using application capabilities. She can add content to the campaign and publish it in various social media. The policy maker can develop and deploy a Padget application that includes content and different features (e.g. voting, e-survey) in selected social media
- The launch of a campaign is made by publishing the above content and deploying the Padget according to its intent in the selected social media
- In the specific social networks, user interactions take place in different ways with the published content and the Padget. In general, users can gain access to them, display the policy message, vote in a positive or negative way, rate it and comment

- iv. The interactions of the above users were extracted from all the social media used and analyzed using sophisticated methods and techniques to help policy makers decide by measuring and evaluating user engagement. This could be the end of a campaign

4.2.2 Analysing Citizens' Response

After collecting the data obtained from various Web 2.0 social media platforms that include the engagement of users with the policy messages posted on the platforms, as a next step in our methodology, we need to analyze them first and provide the policy maker with knowledge that will help him / her in making a decision. This series of analysis and processing take place in the decision support area of the central platform. The inputs of the Decision Support Area come from three different sources:

- Social Media Platforms
- Gadgets
- Policy Maker

The data coming from the social media platforms and our generic platform can be unstructured (e.g. open text content) or structured (e.g. users' actions and selections). Data from the three different sources will help policy makers understand the level of interest and concern shown by citizens about a specific policy discussed in multiple social media, the orientation of citizens' opinions indicating whether they are positive or negative towards the policy and the interpretation of the policy elements through comments, likes or dislikes provided by the same citizens.

4.3 Generic Opinion Mining Framework Description

The proposed generic opinion mining system for government agencies to leverage Web 2.0 social media and promote participatory democracy is based on the aforementioned background and links two developed domains: the domain of creation of mashup-based web applications (gadgets) (which is a design paradigm characterizing Web 2.0) and the domain of simulation modelling for the analysis of complex systems behaviour.

The main characteristics of the proposed framework for social media exploitation by government agencies are:

- Simultaneous use of multiple social networks, targeting various groups of citizens to meet and engage broad and diverse audiences;
- in a centrally controlled and highly automated manner, based on a central ICT platform, and exploiting the application programming interfaces (APIs) of the utilized social media to have high levels of efficiency and effectiveness;
- Publishing public policy-related content in multiple government agency accounts on these social media and actively tracking citizens' interactions with such content, so that effective new initiatives can be made in time (i.e. by publishing new relevant content on some of the social media outlets listed above) where necessary; and
- Having the above-mentioned interactions highly sophisticated in order to maximize the inference of conclusions, the extraction of information from them and crowdsourcing in particular and, eventually, policy-makers' involvement

The basic approach adopted by our proposed Generic Opinion Mining Framework is illustrated in Figure 4.4.

We can see that it is focused on a centralized automated content publishing in multiple government agencies – or policy-makers' accounts in various Web 2.0 social media (e.g. Facebook, Twitter, YouTube, Picasa, Blogger) and then capturing and tracking different types of citizens' interactions with this content (e.g. views, likes, ratings, reviews, and retweets) through a central ICT utilizing available APIs. In general, a government policymaker initiates a campaign on a specific topic or policy in multiple social networks through a web-based portal or a mobile phone application. He / she generates appropriate multimedia content for this purpose (e.g. short or longer topic description, photographs, video, etc.), which is then automatically posted in the related social media (e.g. short topic description in Twitter, longer one in Blogger, video in YouTube, photos in Picasa, etc.). Citizens can view and communicate with this content (in all the ways that each social media platform allows), either through such social media, or through a mobile app. Then, through the above Web-based dashboard or mobile phone request, these interactions will be automatically retrieved and continuously shown to

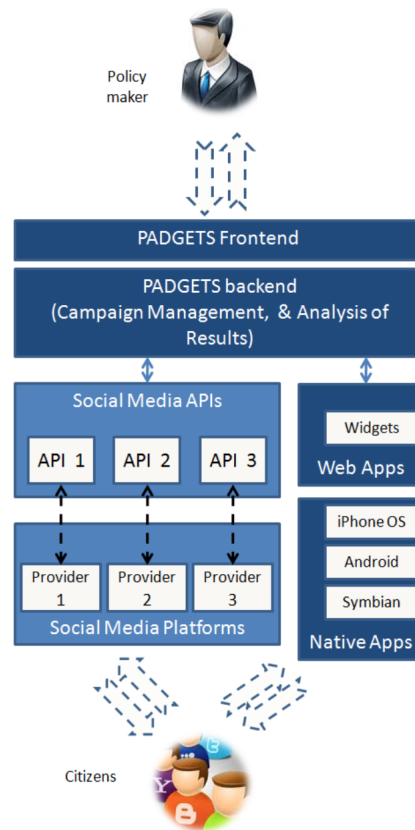


FIGURE 4.4: The basic approach of the proposed Generic Opinion Mining Framework

the policy maker. Eventually, sophisticated analysis of all citizens' experiences with the above-mentioned content will be carried out in this central ICT system after the end of the campaign, using a variety of techniques to provide useful insights and information extraction to support government decision-making and policy-making.

In particular, the categories of social media that are targeted for exploitation are the following:

- Platforms for Communications, e.g. Blogs, Forums, Social Networking Sites, Social Network Aggregation Sites, Event Sites
- Platforms for Collaboration, e.g. Social Bookmarking Sites, Social News, Opinion Sites, Wikis
- Platforms for Multimedia and Entertainment, e.g. Photo Sharing, Video Sharing, Live Casting, Virtual World Sites

- Platforms for News and Information, e.g. Google News, Institutional sites with high number of visitors (Human Rights, WWF)
- Platforms for Policy Making and Public Participation, e.g. governmental organizations' forums, blogs, petitions

An initial approach is to categorize social media platforms based on their core activities (e.g. cooperation, networking, thoughts, etc.) and work intention (business, leisure, political involvement). In addition, the number of their registered users and their key features, the languages available, the type of content, accessibility, user engagement and political representation are examined. A list of the most popular social media sites is created as a next step based on their number of unique users, content quality, top popularity, multilingual support and political representation (type of political discussion or political content). Based on the above analysis, a list with the most social media platforms is created. From that list, it is important to isolate and pick those channels that provide the best coverage for European users based on demographic categories (e.g. income, education, sex, age) and going a little further, select those that are most popular by category (content type and key activity), with the greatest multilingual support and provide the correct API frameworks to access users' profiles.

Each one of these selected social media platforms opens Application Programming Interfaces (API) in the form of Web Services for communicating with it. For examining the feasibility of the already mentioned platforms, the APIs of the most highly popular social are analyzed. The most popular social media platforms were Facebook, Twitter, YouTube, LinkedIn, Blogger, Delicious, Flickr, Picasa, Digg and Ustream. For each one of them we examined the following characteristics:

- Available APIs and types of provided capabilities
- Capabilities for pushing content through their API (e.g. posts, photos, videos, rating, voting, etc.)
- Capabilities for retrieving content through their API (e.g. comments on posts, photos, videos, approved requests, etc.)
- Capabilities for deploying applications (gadgets) and interacting through them with social media users

Analyzing the social media platforms, as a conclusion is derived that these social media have a specific strategy of becoming more open and accessible and follow API standards attracting third parties to develop applications [Charalabidis et al. \(2010\)](#). Via their APIs, they provide rich functionality to post and retrieve content revealing methods that provide an increasing array of capabilities for third-party developers. It includes, generally, data push functionality and functionality that supports direct retrieval of various types of content created by the user. Therefore, this content is generated, removed, updated and uploaded by many APIs. Just a few social media, however, allow the deployment of micro-applications such as Facebook and Twitter in their community.

The practical application of the above-mentioned model would result in a series of large amounts of content generated by people in different Web 2.0 social media relevant to the particular topic or policy under discussion, so it will be crucial to establish highly sophisticated methods of processing it in order to support conclusions, information extraction and crowdsourcing in general. This requires the design of suitable decision support systems (DSS) that can improve the quality of the process of government policy making [Shim et al. \(2002\)](#), [Schwaninger et al. \(2008\)](#). Because a large part of this citizen-generated content to be collected from social media is described as the advanced processing of text, to extract thoughts, feelings, opinions and emotions [Maragoudakis et al. \(2011\)](#) will be a critical technology for our DSS. The development and use of opinion mining first started in the private sector, as firms wanted to analyze comments and reviews about their products, which had been entered by their customers in various Web sites to draw conclusions as to whether customers like the specific products or not (through sentiment analysis), the particular features of the products that have been commented (through issues extraction) and the orientations (positive, negative or neutral) of these comments (through sentiment analysis). These ideas can be applied in the public sector as well, as citizens created content in the Web is a valuable source of information that can be quite useful for government decision- and policy-making; it is important to identify the main issues posed by citizens (through issues extraction) on a particular topic or policy-making we are dealing with, and also the corresponding sentiments or feelings (positive, neutral or negative — through sentiment analysis).

4.4 Generic Opinion Mining Platform Architecture

A platform for our generic opinion mining mechanism has been developed for supporting the practical application of the above framework, providing all required functionalities to the two main types of users of it: government policy-makers and citizens. In particular, a “policy makers’ dashboard” [accessible through a Web-based or a mobile interface (Android mobile application)] enables policy-makers:

- i. to create a multiple social media campaign by defining its topic, the starting and ending date/time, the social media accounts of the policy-maker to be used and the relevant messages and multimedia content to be posted to them;
- ii. to monitor continuously citizens’ comments on the messages; in Figure 4.5, we can see this part of the Web-based policy-makers’ interface, which is structured in three columns:
 - in the first column, the active campaigns are presented, by selecting one of them;
 - in the second column the corresponding messages posted by the policy-maker are shown (the initial, and the subsequent ones) and, last, by selecting one of these messages; and
 - in the third column citizens’ comments on it are depicted (textual feedback stream)
- iii. after the end of the campaign, to view (in graphics and visualizations form) a set of analytics and opinion mining results, which are produced by the decision support component of the platform (described later in this section) for the whole campaign.

Citizens can view the content of each campaign, as well as the interactions of other citizens with it (e.g. textual comments), either through the interfaces of the relevant social media or a dashboard that allows citizens to monitor active campaigns and choose one of them to view or add a new post to all policy makers and citizens’ comments.

The technical architecture of the generic mechanism that supports the implementation of the above-mentioned framework was built on the basis of the specific functional requirements of the PADGETS project user partners (Greek ICT Observatory, supervised by



FIGURE 4.5: Policy makers' interface for viewing active campaigns, messages and citizens' feedback

the Ministry of Finance, Piedmont Region, Italy and Center for eGovernance Growth, Slovenia), as we have already mentioned at the introductory section and is shown in Figure 4.6.

We can see that it consists of two main areas:

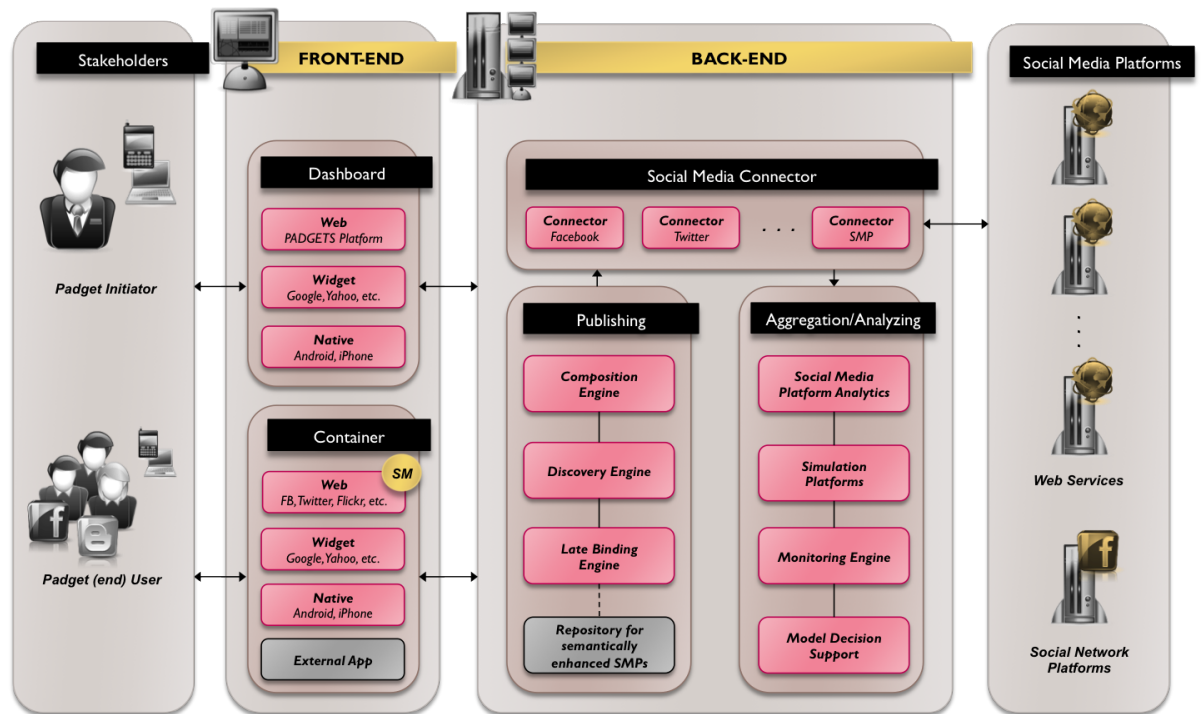


FIGURE 4.6: Generic Platform Technological Architecture

- i. The Front-end area. It includes three sub-areas. The first provides the policy maker with a web-based interface (enabling login / register, getting input to set up a social media campaign, offering feedback from citizens on government-related content posting, presenting results graphically, etc.). In addition, the sub-areas Mobile Native Application and Widget establish complementary network control interfaces to policy makers and citizens alike.
- ii. The Back-end area. It includes three sub-areas. The first is the Publishing, Tracking and Storing Content Area, which is accountable for posting content in multiple social channels and in specific types of content, tracking citizens' input on textual content and storing all relevant information (published content, user interactions, social media analytics). The second is the System Discovery, Composition and Binding sub-area, capable of providing the necessary infrastructure for system interaction internally between application components and externally between these components with external systems (widgets, social media platforms). Finally, the third is the Decision Support sub-area, which is responsible for monitoring citizen-generated content from the social media engaged (= different types of citizen interactions with the policy messages that we published in social media, such as

opinions, likes, retweets, textual comments) using various advanced techniques (analytics analyses, opinion mining, simulation modeling) offering decision support to the policy maker.

Particularly important is the above-mentioned decision support sub-area, so it is worth reviewing it in more detail. It is composed of three layers. The first layer gathers and analyses the 'raw data' generated by the analytics engines of social media. From our analysis of the most popular social media sites and the functionality offered, we decided that they can provide a very wide range of raw analytics that our decision support modules can use to support. The second layer incorporates more advanced analytics, called 'Padgets Analytics', which relies on the textual inputs of people (e.g. blog posts, reviews, opinions, etc.) in the social media chosen, analyzing them using opinion mining techniques that extract the general feelings (positive, negative or neutral) of these comments and opinions regarding our policy messages, as well as the key issues raised by these comments and opinions [Maragoudakis et al. \(2011\)](#). Finally, the third layer performs simulation modeling with two main goals: to predict the results of various citizens' initiatives on the public policies under examination, and also to predict future levels of citizen engagement and awareness of these policies [Loukis and Charalabidis \(2012\)](#).

The second opinion mining layer will perform the following three types of tasks [Maragoudakis et al. \(2011\)](#):

- Classification of an opinionated text as expressing as a whole a positive, negative or neutral opinion (this is referred to as document-level sentiment analysis)
- Classification of each sentence in a text, first as subjective or objective (i.e. determination of whether it expresses an opinion or not), and for each subjective sentence (i.e. expressing an opinion) classification as positive, negative or neutral (this known as sentence-level sentiment analysis)
- Extraction of specific features or subtopics commented by the author of the text, and for each feature identify the opinion orientation as positive, negative or neutral (this is referred to as feature-level sentiment analysis)

A process model for the above opinion mining tasks has been formulated, which consists of five stages:

- i. Categorization of each post as positive, negative or neutral on the basis of document-level sentiment analysis and measurement of relative frequencies of positive, negative and neutral posts
- ii. Identification and classification of the subjective sentences included in each of the posts as positive, negative or neutral, using sentence-level analysis
- iii. Comparison and synthesis of findings from the above levels, as well as findings from the study of non-textual input from people; this will deliver a more comprehensive picture of the overall feelings of citizens regarding government policies, whether they are positive or negative
- iv. Identification of the main issues addressed, using feature extraction methods, by further review of all comments on a specific policy
- v. For each of these topic we perform classification of each sentence of it as positive, negative or neutral, through sentence-level sentiment analysis, and calculation of the relative frequencies of positive, negative or neutral subjective sentences. This will help in recognizing not only the main issues posed by people, but also their general feelings about them (e.g. positive / negative implications or consequences of a policy being debated or introduced, recommendations for change, etc.)

With respect to the simulation modelling, based on a literature review, we identified two main approaches that can be adopted [Loukis and Charalabidis \(2012\)](#):

- i. System Dynamics, which enables high / macro level modeling and continuous computation of complex systems, so it can be useful to determine impacts or policy proposals [Schwaninger et al. \(2008\)](#). Complex systems are described as comprising of a variety of 'stocks' (employed / unemployed people, groups of citizens of different levels of income-education, etc.), including 'flows' that are affected by system structure and regulations (such as those established by public policy). This particular approach is therefore ideal for modeling and simulating different policy alternatives. It has also been used with considerable success in the past to model and simulate various issues regarding public policy, so it has achieved a strong maturity level in this field.

- ii. Agent-based Modelling and Simulation, which is an approach used for modelling and simulation at both the meso and the macro level Epstein (1999), Ferro et al. (2010). To estimate its behaviour, it does not require any description of the basic structure of the system, but it needs us to specify the actions and interaction rules of single units (e.g. companies, staff, etc.). Given that it is easier to determine the former than the latter in most socio-economic systems, it appears that System dynamics can be more effective than agent-based modeling and simulation..

However, for cases where it is easier to define the behavior of individual units, the preferred approach would be the agent-based modeling and simulation.

Considering all the elements above that synthesize the overall architecture of our proposed general opinion mining process, we depict in Figure 4.7 an overview of the graphical representation of the aforementioned platform.



FIGURE 4.7: Platform for the Generic Framework

4.5 Application Model

Furthermore, an application process model has been created for the current generic framework; it provides a description of the system to be followed for practical application

by government agencies, and includes a sequence of various activities to be carried out. Typically, the implementation of this system is initiated by a government policy-maker (or his/her assistants) who has to decide on a new policy or a modification of a current one and would like to have consultation with people to gather actual knowledge, ideas and opinions (i.e. conduct crowdsourcing) from them. The process that needs to be followed consists of the following eight activities, which are also shown in Figure 4.8:

- i. the policy maker initially creates a policy campaign using the capabilities of the central generic framework mentioned in the previous section via a graphical user interface;
- ii. He / she also produces textual content for this initiative (both brief and longer policy statements and incorporates different types of multimedia content (e.g. policy images, video, etc.);
- iii. and finally defines the multiple social media accounts to be used in this campaign;
- iv. as well as views a preview of the campaign in each of them;
- v. the campaign starts by publishing the above content (the correct portion of the above content will be automatically published in each of these multiple social networks, e.g. a brief policy statement will be published on Facebook, a longer one on Blogger, a video on YouTube, photos on Picasa, etc.);
- vi. citizens engage in different ways with the published content in these social media (in ways that each allows): access and display this content, rate it and comment on it, retransmit it to their networks, etc.;
- vii. The above-mentioned interactions of people are automatically extracted from all the social media used on the central ICT platform and processed there using various sophisticated methods (as defined in the ?? section) to quantify useful analytics to assist and support policy-makers; and
- viii. the results are sent immediately to the policy-maker, by e-mail or SMS message.

This may be the start of the campaign or it may lead to a second round of content publishing in these social media, so it will replicate those actions from 1 to 8, etc.

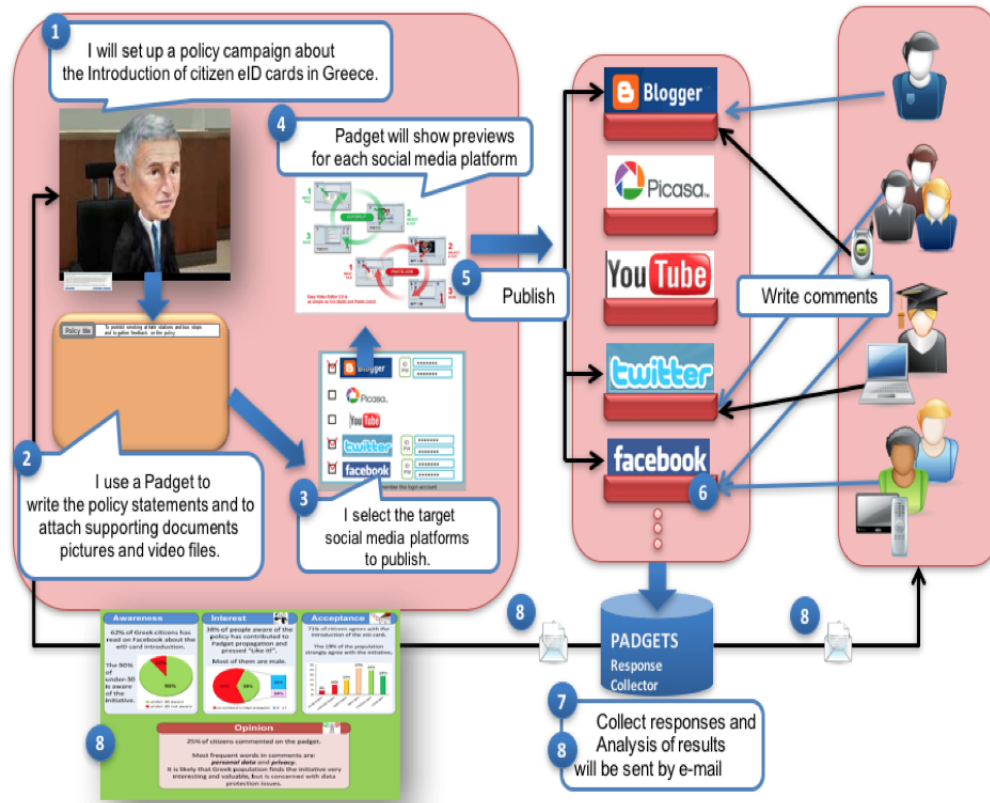


FIGURE 4.8: A process model for the application of the proposed Generic Framework

The above process model we developed for implementing the proposed framework has similarities with the traditional crowdsourcing process model, but also significant differences. Our application process model covers six out of ten activities of this standard crowdsourcing process model (defining task, setting time, assigning tasks, accepting crowd contributions, merging submissions and reviewing submissions) in general; however, most of them in a quite different form. On the contrary, the former does not include the remaining four activities of the latter (state reward, recruit participants, select solution and, finally, grant rewards) due to implicit discrepancies of the proposed framework from the typical crowdsourcing (e.g. lack of reward, participants management through our accounts in the utilized social media).

The above application process model has been further elaborated, leading to the development of a more detailed one, which is shown in Figure 4.9.

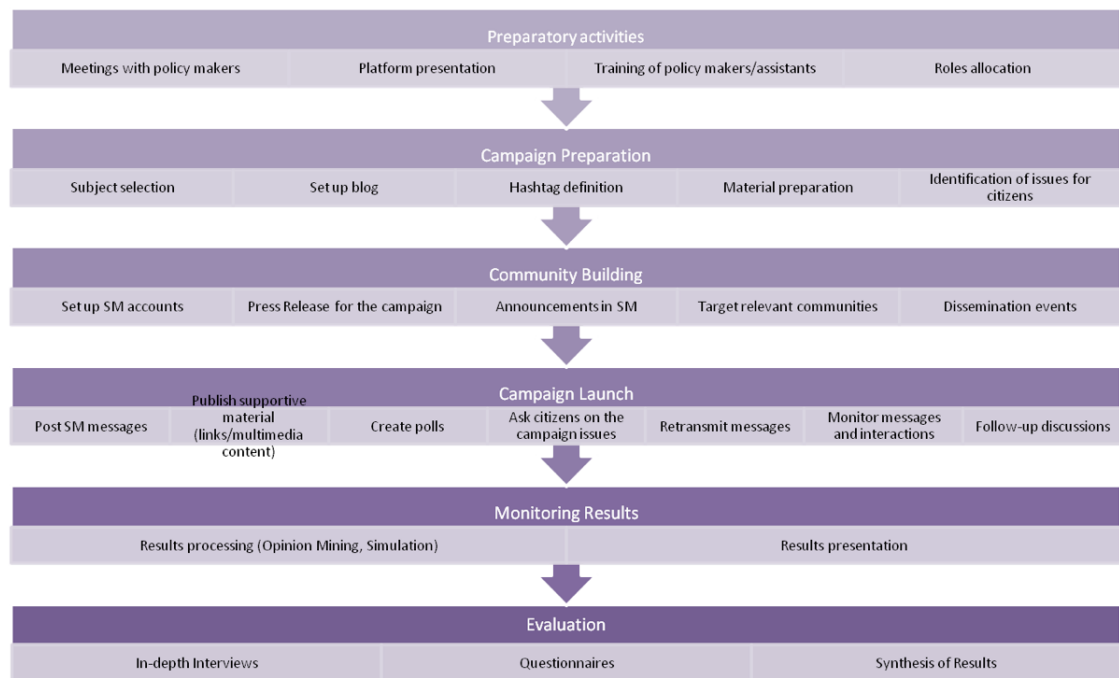


FIGURE 4.9: A more detailed process model for the application of the proposed Generic Framework

4.6 Evaluation Model

An evaluation model for the proposed Generic Framework, as it is implemented using the central platform described in section 4.4, has been developed, based on one hand subjective perceptions of the two main stakeholder groups, government policy makers (= campaign initiators) and citizens (= campaign participants), assessed through both quantitative and qualitative techniques, and also on the other hand on objective actual usage metrics. Its basic structure is shown below in Figure 4.10.

Its main theoretical foundations are the Technology Acceptance Model (TAM) and Rogers' Diffusion of Innovation (DOI) theory. According to the TAM [Davis \(1989\)](#), [Venkatesh and Davis \(2000\)](#), [Venkatesh et al. \(2003\)](#), The attitude towards the use of an IS, which ultimately determines its intention to use it and its actual use, is determined primarily by two features: its perceived 'facility of use' (= the degree to which potential users believe that using it will require minimal effort) and its perceived 'usefulness' (= the level to which potential users believe that using it would enhance their job performance). The DOI theory [Rogers \(2003\)](#) proposes five critical characteristics of an innovation that determine the degree of its adoption: relative advantage (= the degree

	Policy Initiators	Actions	Citizens		Actions
quantitative	Structured questionnaires	Send emails	Structured questionnaires		Links on Android
qualitative	In depth interviews	Skype or in person interview	Short interviews		In person with special groups of citizens (e.g. workshops, students)
Actual Usage	Relative Platform metrics	Platform statistics	App metrics	SM metrics	App stats

FIGURE 4.10: Basic Structure of the Evaluation Model

to which an innovation is perceived as better than the idea, work practice or object it supersedes), compatibility (= the degree to which an innovation is perceived as being consistent with the existing values, past experiences, and needs of potential adopters), complexity (= the degree to which an innovation is perceived as difficult to understand, implement and use), trialability (= the degree to which an innovation may be experimented with on a limited scale basis). Based on the above theoretical foundations, each of the components of our evaluation model shown in Figure 4.10 has been further elaborated. For instance, in Figure 4.11 we can see the elaboration of the quantitative evaluation (through structured questionnaires) by the policy makers (initiators), whose main dimensions are ease of use, usefulness, attitude toward using and behavioural intentions to use (taken from TAM), and also relative advantage, observability, compatibility, trialability and complexity-simplicity (taken from DOI).

The above evaluation should be based on real-life applications of the proposed framework. For this purpose pilot applications are already in progress, in cooperation with four Greek Members of the European Parliament (MEP). MEPs tend to be the most appropriate individuals in these pilot applications to play the role of policy makers. They will be responsible for identifying the campaign's main topics, formulating their main policy proposals and developing the appropriate multi-media content, tracking the campaign's progress and eventually evaluating the outcomes. The main topics of these pilot applications/campaigns will be: renewable energy sources, immigration issues, renegotiation of Greek Memorandum terms and growth prospects within the financial crisis. The main social media that will be used for these pilot applications / campaigns are the

four MEPs' Facebook and Twitter pages, while connections to them will be posted on their official websites. In addition, their Twitter accounts will be linked to the Twitter accounts of other experts in order to create a network. In addition, YouTube will be used in these campaigns as well as an alternative platform to promote the delivery of multimedia content.



FIGURE 4.11: Elaboration of quantitative evaluation by policy makers

4.6.1 Evaluation Results

In all the discussion of the evaluation focus group, there was broad agreement among the participants that the suggested framework is a time- and cost-effective method for organizing wide-ranging policy consultations that reach wide audiences, communicate policy-related multimedia messages to them and facilitate and empower them to think about the public policies being formulated and to express their emotional responses. Compared to traditional methods already used by government agencies for this purpose (such as physical events and meetings with representatives of the most important stakeholders), it allows a much wider reach and participation of more citizens (representatives of affected citizens' groups and individuals) with lower effort and cost. It can be particularly useful for involving younger target groups in policy debates, which currently, with traditional consultation methods, seems difficult to achieve.

Participants in these focus group discussions described our framework and endorsing the generic platform as valuable tools to recognize the main issues identified by people with regard to a particular social problem or field of government activity, and to collect interesting ideas from citizens on potential solutions and directions of government activity to

resolve them. Indeed, for the design of better, more socially rooted, more balanced and realistic policies, these are quite important. As one of the participating MEP assistants pointed out, "the result of the campaign provided an overview of the problems to be taken into account in the creation and design of approaches as feedback from society".

Some participants, however, stated that their consultations provided only "high-level information" (i.e., key issues and specific directions for solutions), but not the more comprehensive and in-depth information they would need about ongoing issues, alternatives, advantages and disadvantages. Therefore, it was proposed that a series of such consultations might have to follow in order to reach this higher level of depth and detail, perhaps more oriented ones on specific sub-topics and/or groups of participants. Specifically, it was suggested that a good practice be to process the information gathered from such a consultation and then use it to coordinate subsequent more oriented discussions on specific sub-topics mentioned in the first consultation, as well as on social actors with keen interest and extensive knowledge about the particular issue / policy and experts.

Another disadvantage listed was that we did not have balanced debates in many of these multiple social media discussions, with specific and varied views and perspectives being shared, so we did not have the ability to recognize stakeholder groups with different views, viewpoints and concerns, and to have interaction between them and, ultimately, convergences that are very important for the formulation of accepted public policies. On the contrary, in some other consultations (e.g. in the consultation on the development of wind power organized in collaboration with an MEP), we had more inclusive and pluralistic debates, with greater diversity of views and opinions expressed, in which various clusters of opinions could be clearly identified, eventually offering more assistance and support for the formulation of public policy. This was attributed by the participants in the subsequent discussion of the focus group to the fact that in the latter meetings particular emphasis was put on and great effort was made to create a wide and diverse community by inviting a large number of civil society organizations and individuals with keen interest and extensive knowledge on the subject topic / policy and also diverse perspectives.

In addition, several participants noted that traditional consultations carried out by their government agencies as part of their policy-making processes usually involve a variety of different stakeholders with different perspectives, orientations and opinions. This

does not necessarily happen with this multiple approach to social media consultation, which could lead to conversations among like-minded individuals who belong to the initiator government policy-maker networks, resulting in a decreased diversity of views and perspectives. Hence, it was recommended that it is critical that such consultations should not be based only on social media accounts and networks of one government policy-maker and that it would be useful to:

- Invite additional interested individuals and civil society organizations with extensive knowledge of the related topic / policy, as well as diverse perspectives and orientations;
- Take advantage of other politicians' social media accounts and networks, ideally from different political parties and orientations, as well as from other social actors; and
- Access to a wide range of communities with interest in the topic/policy under discussion and knowledge. It was also widely agreed that the results of these various social media appointments should be merged and integrated with the results of other types of consultations usually carried out by government agencies that use traditional methods and expert studies' recommendations.

4.7 Use-Case Scenarios for the Generic Opinion Mining Framework

Pilot scenarios were created in order to test our proposed generic system in real-life conditions and evaluate the value derived from the policy gadgets as well as the decision support models in the policy making process. The scenarios reflect policy making needs. The necessary policy gadgets are created and run in different Web 2.0 platforms for each specific scenario, offering online users the ability to interact and significantly contribute to the policy making process. The three pilots are delivered by the Aegean University (AEGEAN), the South East Europe Development Center for E-Governance (CEGD) and the Piedmont Region (PIED). In this section, we will analyze the case of the Greek pilot.

Pilots focus on high-priority EU issues, aiming to develop a blended policy modeling and prediction model with innovative applications for citizen engagement in social networking. It is anticipated that the use of Policy Gadgets will enable better interaction between government and society and a better policy decision making process, providing a clear vision of the views, concerns and expectations of the different stakeholders.

It was suggested to search for topics with wider acceptance in order to attract a wider portion of citizens. However, more policy makers have been engaged as end-users of the use scenarios, and as a result they are accountable for first formulating decisions, second implementing policies, and third using added value to determine their policy messages. Immigration, Climate and Finance were the subjects chosen to be used.

In addition, as far as the Greek pilot is concerned, the Policy Makers team is comprised of four Greek Members of the European Parliament and their advisors involved in meetings and presenting their ideas within the European Parliament. The four members of the European Parliament tend to be the most appropriate persons in the pilot scenarios to play the role of policy makers. The European Parliament and Greek political parties are other bodies that are directly interested in the Greek pilot. The EU legislation that the European Union has entered into requires the approval of the European Parliament and the countries concerned. That's why participating in the specific pilot is so important to the above-mentioned groups of people (both policy makers and organizations). It is the duty of the four MEPs to launch the proposals, plan the policy messages and track the outcomes to use them in the process of policy making as feedback. The Aegean University team provides crucial support in the preparation of the pilot.

The pilot will be targeted to Greek citizens between the age of 15 -- 75 and the pilot campaigns will be bilingual so that both Greek and European citizens can offer their input. It is expected that all kinds of citizens contribute to the piloting but there are five citizens group that can be distinguished, with the more possibilities to offer feedback during the piloting:

- Academics and Research bodies
- Public sector representatives
- Non — Governmental Organisations (NGOs)

- Private institutions that manage projects
- Journalists and media representatives

The pilot campaigns and online discussions between MEPs and citizens are expected to improve the outcome of the procedures of the European Parliament and provide projections of what people think about a specific policy. A set of metrics can indicate pilot campaigns value proposition for policy makers:

- Level of citizens' willingness to participate in policy formulation
- General public engagement in targeted issues
- Amount of ideas from the general public
- Level of citizens' interest and awareness on various topics
- Rating among European policies under discussion
- Level of acceptance of the proposed actions by citizens
- Amount of opinions shared and feedback to refine initial formulation
- Level of networking and collaboration in cross -- border debate
- Valuable insights stemming from a comparative analysis between member states

Ultimately, the pilot results will help politicians achieve a more clear point of view on topics for discussion in both Greece and European countries with the general public. However, assessments will help politicians recognize the policies preferred and what people see as challenges in policy actions.

The Greek pilot is based on subjects that attract Greek interest at a specific period of time as well as European emerging issues. The subjects used in pilot campaigns are:

- Renewable energy sources: A project named "HELIOS" will be implemented and requires the installation of photovoltaic systems for solar energy production on land that is a Greek State property. Its primary objective is the Greek State to export the produced "green" energy to Europe and use this income to decrease the public debt but it has triggered a lot of reactions due to its environmental consequences

- Immigration Issues: European Union develops a common approach when dealing with issues such as the EU Asylum and integration of migrants. The specific EU directive focuses on attracting high qualified migrants and sanctioning employers of irregular migrants. Now is in the stage of draft bill in Greece. In order to acquire a better understanding on Europe's view on this issue, this subject will be common for Greek and Slovenian pilots
- Renegotiation of Memorandum terms: The consequences of the Memorandum enforcement monopolize Greek citizens and European attention. During the recent elections candidates of political parties were dealing with the renegotiation of Memorandum terms in order Greece to escape from the financial crisis
- Growth prospects within the financial crisis: this is based on the growth prospects that can emerge under conditions of financial crisis. This pilot is planned to be a collaborative effort between Greek MEPs with European partners in order to overcome the financial troubles

The pilot campaign's key content is a text that describes the pilot topic and is used as the campaign's core reference. The document contains the discussion subject definition and issues related to the effects of the specific topic, the steps to be taken and the solutions suggested. Continuing, policy makers and their consultants are working together to create short policy messages related to the topic and attractive enough to gain the attention of citizens for discussion. In addition, Facebook and Twitter are the social media platforms that will be used for the Greek pilot campaigns. In general, for the MEPs participating in the campaigns, Facebook and twitter pages will be built. Links will be placed on their official personal websites to the Facebook pages. In addition, their twitter accounts will be linked to the twitter accounts of other experts so that an original network can be built and last but not least, YouTube will be used as an alternative means to support digital presentation of content.

Chapter 5

An Advanced Opinion Mining Mechanism for Policy Making

This section presents an advanced opinion mining mechanism for crowdsourcing, that aims to endorse the concept of policy formulation process by combining multiple mining techniques towards a joint learning of sentiment and stance from social media exploitation. In particular it is based on an advanced framework, which can collect in Web 2.0 sources like news sites and social media platforms, for content over political topics of discussion or a public policy under formulation, which has been created by citizens freely, without any initiation, stimulation or moderation through government postings. Utilising a subset of tools, technologies and techniques presented in Chapter 3, this content is collected and analyzed through advanced processing in order to extract external knowledge and draw conclusions concerning the needs, issues, opinions and proposals coming from citizens or else the public. The chapter contains an analysis towards a critical political issue that affected not only the country in which it took place but also Europe as a whole and the advanced opinion mining framework designed and implemented in this chapter, is evaluated through the conduction of empirical studies also analyzed thoroughly. The chapter concludes with valuable insights on the effective use of social media exploitation and the applicability of the integration of multiple mining techniques in public policy formulation. A comprehensive description of the method is provided in (Spiliotopoulou et al. 2017).

5.1 Political Occurrences Impact In Decision Making & Policy Formulation

Over the past few years, social media penetration has dramatically increased the reshaping of society's culture and public discourse, transforming societies on a whole new level, and resetting agendas on multiple topics varying from cultural, religious and political issues [Freeman and Quirke \(2013\)](#). Users express their views on any topic of discussion that gives their personal position to the topic or their stance (i.e. positive / negative) [Somasundaran and Wiebe \(2009\)](#) with a major part of these discussions being related to ideological dual-sided topics considering political issues [Anand et al. \(2011\)](#). Such topics, used for expressing and forming opinions, often lead to heated discussions and attract large audience of people [Mukherjee and Liu \(2013\)](#), [Walker et al. \(2012\)](#).

An occurrence of major importance which drew the attention of a high percentage of online users on social media platforms is the European debt crisis, which emerged when Eurozone nations, including Greece, were unable to fund their government debt or bailouts without the assistance of other Eurozone countries or the European Central Bank (ECB) or the International Monetary Fund (IMF). European debt crisis has become a widespread problem creating fears that other European countries will have the same result leading to a potential Eurozone break-up.

On 27 June 2015, under a "Grexit" threat, Greece's Prime Minister declared the Greek Bailout Referendum as a direct democratic act which occurred on 5 July 2015, responding to whether Greece would accept the bailout terms provided by the European Commission, the IMF and the ECB. Greek citizens would vote, either stating "Not approved/No" or "Approved/Yes" on two previous documents, entitled "Reforms for the Completion of the Current Program and Beyond" and "Preliminary Debt Sustainability Analysis". The result of the referendum demonstrated that bailout conditions were denied by the approval of a majority of over 61% to 39%. While the outcome was disappointing, the Greek government demanded a three-year loan from the rescue fund of Eurozone, ensuring that the necessary measures and changes would be enforced. A "crisis summit" was planned for European finance leaders to evaluate the Greek request and a few days later the package with the completed proposal was sent to the Eurogroup.

This severe and unexpected change in the political decision of the Greek government not to accept the overall result of Referendum indicates that its sentiment was affected by a series of numerous events, altering the final political decision. Thus, our goal through the implementation of the Advanced Opinion Mining Mechanism focuses on understanding the stance of online posts over a sequence of critical political events that occurred in the EU due to the debt crisis in Greece. The period we are considering (26 June to 16 July) is marked as unique in terms of the amount of significant political decisions taken between European countries and influencing the feelings and the opinions of two online audience groups in Europe and Greece, respectively. From the day the referendum was declared until the day the third memorandum was signed, it can be viewed as a policy life cycle that resulted in a massive collection of everyday sequential events. Each decision taken on a daily basis by one of the two groups, Europe and Greece, resulted in the next day in the generation of a new event producing a timeline of events from which the most critical political conventions were identified.

5.2 Requirements & Methodology of an Advanced Opinion Mining Framework

In order to eliminate the weaknesses identified in our Generic Opinion Mining Framework and more specifically, to interact with wider and more heterogeneous audiences in a short time and at a low cost, increase public engagement in policy making processes, collect significant citizens' insights, ideas and opinions (i.e., apply "citizen — sourcing") and, finally, formulate better and more socially rooted public policies, we design and develop an Advanced Opinion Mining Framework. The advanced one can provide considerable opportunities for broader interaction with society. Its development lies on social media exploitation with a more integrated view towards mining online emotional opinions over democratic actions that follow a policy life cycle. Our interest specifically focuses on the Greek Bailout Referendum due to Greek Financial Crisis covering a whole policy making process.

In particular, the methodology we adopted for the development of the Advanced Opinion Mining Framework is the following:

- Initially, we select the top EU–Greek financial crisis topics discussed on social media platforms and news sites to determine through stance classification the citizens’ stance polarity (for–stance or against–stance) towards these topics
- Knowing that the Greek financial crisis is indissolubly linked with the economic policies of the EU partners, we separate online audiences and study both Greek’s and EU citizens’ stance on the political actions taken by the governments during the specific period.
- The main idea of this crowdsourcing approach was formulated on the basis of developing a bilingual stance classification architecture with integrated mining techniques for social media employment and focusing specifically on online content generated only from the public
- To evaluate our proposed system, multiple machine learning classifiers were cross–evaluated through 10– fold validation in order to select the one with the greater percentage of Accuracy. From this preliminary study, we selected our classification engine
- Taking into consideration the performance results derived from the evaluation phase, our proposed Advanced Opinion Mining System is utilized in real case scenarios. To achieve this and aiming at “crowdsourcing”, we conduct 3 empirical studies focusing on how to employ a stance classification system in reality

The Greek financial crisis, which resulted in the incident of the Referendum, triggered a sequence of upcoming simultaneous incidents concerning not only Greece’s economy, but also the EU as a whole. Consequently, this crisis created the need to hear the pulse of opinion from audiences inside and outside the borders of Greece towards this political occurrence. That’s why we gathered online posts with both English and Greek content.

As we have already mentioned, We performed 3 empirical studies based on real case scenarios, aiming to fully understand:

- i. Topic Stance Classification: determine citizens’ stance polarity in a timeline of critical political events, among European citizens, by indicating the diversity in the opinions

- ii. Predicting the Greek Referendum Result: predict the outcome derived from citizens' political decisions, such as a referendum call and evaluate these predictions compared to the real results
- iii. Policy Making: examine whether citizens' sentiments converge or diverge with governmental decisions made in each stage of a policy life cycle

The key principle around which the strategy model was built, was to obtain a deeper understanding of whether the views of people can be reconciled with those of political figures, defining the personal position of the public against governmental decisions, concerning policy formulation and thus facilitating the decision-making process. In summary, through the Advanced Opinion Mining Framework, we explore whether a new era of democratic engagement can stimulate citizens' participation in the decision-making process through public transparency, social media employment and intelligent services.

5.3 Advanced Opinion Mining Platform Architecture

This section describes the overall architecture of our proposed advanced mechanism, providing implementation details about the most important modules. Figure 5.1 depicts the overall system's overview of the 9 modules implemented to automatically collect, process and determine stance polarity.

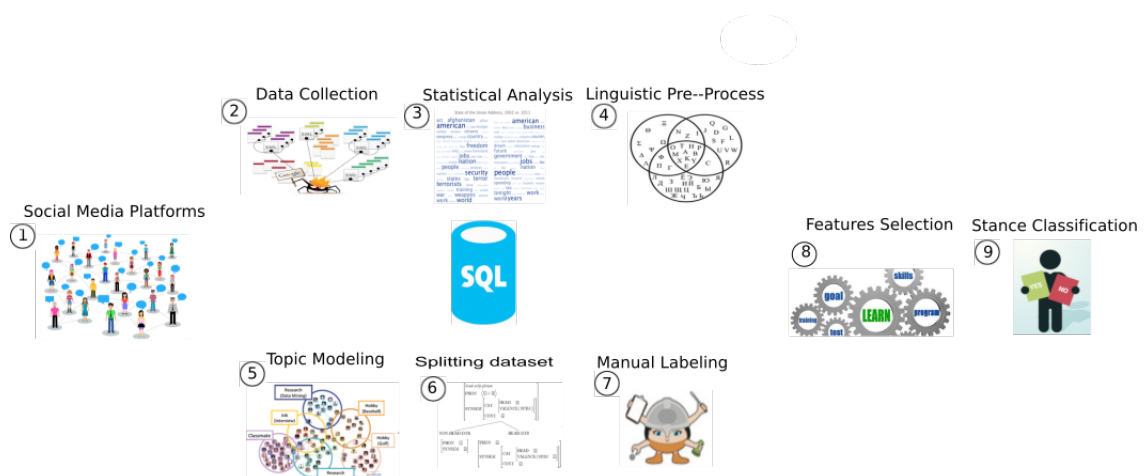


FIGURE 5.1: An Advanced Opinion Mining Architecture

5.3.1 Social Media Platforms Selection

For our study, we rely on online newspapers and weblogs to gather our information for research, given the rapid growth and popularity of social media platforms such as Facebook and Twitter. Greek financial crisis resulting from the Referendum incident triggered a series of daily events and political decisions that only online newspapers and weblogs reported the news in an organized (*Title, Post, Comments of Discussion*), transparent (built with CMS structure) and secured way, by freedom of communication and speech.

On a daily basis, all newspapers publish articles related to the political and financial events that occurred the same day or the day before, enabling online users to share their personal opinions at the end of the articles via discussion boards. Using *Social Media Platforms module*, we picked a total of 20 online platforms based on their high popularity and broad user base measured by top news sites from Alexa.

5.3.2 Data Collection

The data collection process began on the day of the call for a referendum, June 26, 2015, and continued until the day that the Greek government signed a third memorandum, July 16, 2015. We choose this period of time because it represents a complete cycle of policy making by the Greek government and the EU, allowing us to track EU citizens' feelings, as well as monitor all actions taken by the EU to address the Greek crisis.

In a two-month summer period in 2015, a dataset of 1734250 posts from 1129 topics was compiled using the *Data Collection module*. We created two smaller datasets during a preliminary study; the first to train the model of stance classification, and the second to test our proposed system through three empirical studies.

To collect the data, it was important to monitor new topics and collect comments for both new and old topics for the whole period of time. Online platforms are based on content management systems (CMFs) which enable the use of interchangeable components or personalized web content management software. A customizable set of parsers developed in the Python programming language perform data collection and are modified accordingly for each online news website and weblog. The module is able to collect the

event title, the article, and the participants' posts, username, and the timestamp (date and time) of each post written either in the Greek or the English language. To store the data, we utilize the Structured Query Language [SQLite \(2015\)](#) database engine.

5.3.3 Statistical Analysis

Aim of the *Statistical Analysis module* is to distinguish the days when the number of posts and comments cumulatively in a high rate. We assume that a high number of post & comments indicate the occurrence of a dominant event that results in users to discuss it online and express their opinion. To automatically process the data a python script was build.

5.3.4 Linguistic Pre-Process

Next, a series of linguistic processes, follows with both grammatical and semantic analysis, creating n-grams, in our case both uni-grams and bi-grams. N-gram [Tripathy et al. \(2016\)](#) is a contiguous sequence of n items (letters, words or base pairs), from a given sequence of text or speech. Here the goal is twofold; i) use the n-grams and via Topic modeling to identify the topics in each post, and ii) use them as features for stance classification. We are interested in building uni-grams and bi-grams by utilizing words that are nouns, adjectives and verbs. These words are considered opinionated words and can be used later as additional features.

Developing the *Linguistic Pre-process module*, we start with tokenization, splitting each posts' sentence into words. We continue with stemming, finding the root of each word and with part-of-speech (POS) tagging [Tripathy et al. \(2016\)](#), marking up each word in the corpus as corresponding to a particular part of speech, based on both its definition and context. Last but not least, we end with n-grams generation, specifically uni-grams and bi-grams. For tokenization, sentence splitting, (POS) tagging and n-gram generation, we installed components of Natural Language Toolkit [NLTK Project \(2015\)](#). For stemming, we utilized and imported in our program Porter Stemming Algorithm [Porter \(2006\)](#). The algorithms, implemented for textual analysis, are language dependent. This means that we had to create two different tools, that follow the same methodological approach, one for the Greek and one for the English language.

5.3.5 Topic Modeling

As described in the Social Media Platforms Selection subsection, we collect the comments from articles published in online newspapers and weblogs. Although each article focuses on a specific event on that day, users tend to discuss in their comments related topics too (e.g., in an article related to the financial crisis, users may discuss also about topics like the education or health). Thus, the utilization of *Topic Modeling module*, is a crucial part in our research aiming to identify all the topics of each sentence in each post, and keep only those related to the topic we are analyzing each time.

Due to the bilingual comments, we decided to use two different approaches for topic modeling, one for English and a different one for the Greek language. Both methodologies are well evaluated in the recently literature providing the best results.

To analyze the English content and reveal the hidden thematic structures inside the post, we utilize Mallet [McCallum \(2015\)](#), a tool for modeling our datasets and extracting the topics of discussion. Mallet used a generative statistical model called Latent Dirichlet Allocation (LDA) [Blei and Lafferty \(2006\)](#). LDA allows sets of observations to be explained by unobserved groups that explain why some parts of the data are similar. We trained the model under a set of commands preserving the document as a sequence of word features, converting all words to lowercase and removing stop-words. As an output of this modeling process, we obtain the most probable topics and the most probable words, called top-words, that appear with the highest frequency across posts.

In order to extract the topics being discussed using the Greek language, we developed a python script that relies on the [Gliozzo et al. \(2004\)](#) study and the uni-grams of each post's sentence, specifically to those that contain adjectives and nouns. The study of [Gliozzo et al. \(2004\)](#) point that posts containing adjectives have high probability of indicating implicit user opinions as opposed to posts that contain no adjectives at all, and topics are most likely to appear in a post in the form of a noun. Having the uni-grams and bi-grams from the previous stage, we employed a syntactic dependency parser to identify which adjectives refer to which nouns across the posts, making adjective-noun pairs that serve as bi-grams and then we counted their frequency. Finally, we selected all those n-grams with the highest appearance and we considered these as our topics and top-words.

5.3.6 Features Selection

Aiming to build an automated tool with advanced opinion mining that utilizes machine learning classifiers to determine the stance of a sentence, as for or against, it is important to evaluate and select correctly a set of linguistic features. As our baselines, we use unigrams and a set of three lexico-syntactic features proposed by [Anand et al. \(2011\)](#).

Following [Anand et al. \(2011\)](#) methodology, *Features Selection module*, retrieving data from online posts, is based on the composition of lexico-syntactic features: basic, sentiment and argument. As basic features, we utilize the number of words and sentences in a post; posts' length; cue words representing posts' initial uni-gram and bigram sequence and repeated punctuation (e.g. !! or ??) normalized by the number of uni-grams in a post. As sentiment features, we employ pronominal forms, positive and negative emotion words extracted in the English comments via the Linguistics Inquiry Word Count (LIWC) tool [Pennebaker Conglomerates Inc.](#) and in the Greek comments utilizing Greek Sentiment Lexicon by [Tsakalidis et al. \(2014\)](#). As argument features, for the English comments, we exploit repeated punctuation (e.g. !! or ??) normalized by the number of uni-grams in the post, POS generalized dependencies and opinion dependencies using MPQA Dictionary [MPQA Dictionary \(2019\)](#) of emotion words, and syntactic dependencies using the Stanford Parser [Stanford NLP Group](#). For the Greek comments, we extract the exact same features utilizing our own syntactic dependency parser.

5.3.7 Splitting Dataset

Although selecting the proper features is considered the key element in designing a modern machine learning system, the utilization of the right data to build the classification model is the proper way to achieve high Accuracy and predict correctly the stance. During a preliminary study, through the *Splitting Dataset module*, we test various combinations and percentages in splitting the dataset, before concluding that the best way to create the training dataset is by learning from the 20% of the daily topics that contain the top words. In this way, the classification model contains instances that appear in most topics.

5.3.8 Manual Labeling

We rely on manually annotation to label the training dataset. Hence, with *Manual Labeling module*, we label each post's stance towards a topic as a for—stance or against—stance, removing sentences that are objective, which contain no sentiment towards any topic. Furthermore, having in our possession the top—words that appear across all posts, we label them determining their sentiment polarity as positive or negative, and we create an additional feature.

Creating training instances by employing the two feature sets as well as its manually annotated stance as its class label, we train the stance classifiers determining the post's stance.

5.3.9 Stance Classification

The classification engine is considered the most important part of stance classification system. To choose the right classifier as our stance classification engine, we conducted multiple experiments and cross—evaluated various algorithms. At the end, we selected the classifier with the highest performance. To build our *Stance Classification module*, we utilize the Weka library [Weka The University of Waikato \(2014\)](#) that includes a collection of machine learning algorithms for data and opinion mining tasks such as classification, and the Random Forest classifier as our engine. We choose Random Forest, please refer to System Evaluation Section 5, due to its high Accuracy in automatically classifying the stance in online comments.

5.4 Evaluating the Advanced Opinion Mining Mechanism

This section provides results derived from the evaluation of the proposed advanced opinion mining system. Figure 5.1 illustrates a high—level overview of the proposed architecture composed of 9 main components that follow our proposed methodology.

During a small scale preliminary study, various machine learning classifiers were used for the needs of this paper. In general, we are cross-evaluating four supervised machine learning algorithms, i.e. Bayesian Networks, Radial Basis (RBF), K – Nearest Neighbor

TABLE 5.1: Comparison of Proposed Approach with previous work in terms of Accuracy and F-measure.

Model	Baseline%		Approach%	
	Accuracy	F1 Score	Accuracy	F1 Score
Somasudaran & Wiebe Somasundaran and Wiebe (2009)	53.2	56.4	66.1	66.1
Somasudaran & Wiebe Somasundaran and Wiebe (2010)	66.6	-	70.5	-
Anand et al. Anand et al. (2011)	56.4	-	67.9	-
Walker et al. Walker et al. (2012)	71	46	88	80
Hasan & NG Hasan and Ng (2013)	66.9	56.6	75.4	61.1
Ranade et al. Ranade et al. (2013)	64.2	-	74.3	-
Boltuzic & Snajder Boltužić and Šnajder (2014)	-	77.9	-	81.6
Ghosh et al. Ghosh et al. (2014)	-	59.9	-	66.9
Sobhani et al. Sobhani et al. (2015)	-	41	-	77
Proposed Model	62.4	51.6	82.7	79.3

(KNN) and Random Forest. The data analysis was carried out using Weka [Weka The University of Waikato \(2014\)](#). In addition, a 10-fold cross validation method was used to determine how the tests were generalized into an individual dataset. We selected 5 random yet sequential days as a data set for the preliminary study. Data analysis was conducted on a 2.53 GHz Intel Core 2 Duo T7200 CPU and 8 GB RAM laptop computer. The OS of this machine is OS X El Capitan.

We evaluate the performance of our stance classification system in terms of two metrics: i) the Accuracy, and ii) the F-measure. Accuracy denotes the correct instances that are classified [F-measure \(2015\)](#). F-measure [F-measure \(2015\)](#) is the harmonic mean of two other metrics, precision and recall, whereas precision [F-measure \(2015\)](#) indicates how well a classifier categorizes instances correctly and recall [F-measure \(2015\)](#) measures the fraction of relevant instances correctly retrieved from all possible instances.

Table 5.1 portrays the performance of our proposed stance classification system (see red annotation numbers) as compared to the performance of the other research works referred to in the related work Section, related to stance classification. The comparison is based on the same measurement criteria, specifically accuracy and F-measure, and these quality results are also described in the table, derived from the cross-evaluation of each method, both ours and the recent literature review. We note that Random Forest is the most promising method showing optimal results of 82.7% Accuracy and 79.3% F-measure. All studies pose highly accurate findings as a general observation, thereby providing strong evidence that developing a bilingual stance classification system can be a very accurate way to analyze large amounts of data. We exemplify that the performance of our system significantly exceeds the approach of both the baseline and similar researches with promising results.

5.5 Use-Case Scenarios for Advanced Opinion Mining Framework

Having achieved high performance results, our proposed advanced opinion mining mechanism can be used in real case scenarios. We conducted 3 empirical studies on how to utilize a stance classification system in real life.

In the first scenario, our goal is to determine whether citizens' sentiment polarity in Europe and Greece may converge or diverge in a series of events occurred under the umbrella of a single political topic.

In the second scenario, we aim to explore whether a stance classification system can replace traditional mechanisms of extracting citizen's opinion towards a political event, such as gallups and online polls.

Taking policy's life cycle as a baseline, in our third scenario, we examine how public's sentiment polarity changes in all stages of a policy according to the political decision taken in each stage.

The following list presents the events utilized in the 3 real empirical studies. The starting day of the timeline corresponds to when the Greek bailout referendum was announced, while the last event to when Greek Government signed the Third Memorandum. We selected these days because they are considered as the starting and ending point of a full policy life cycle.

- 26/6/2015** Greek Referendum Call
- 27/6/2015** Eurogroup declares that the crisis has commenced
- 28/6/2015** Pause of emergency support to Greek banks by European Central Bank
- 29/6/2015** Capital controls begin
- 30/6/2015** Greek Prime Minister asks from Greeks to vote “NO” in Bailout Referendum
- 1/7/2015** Europe prepares for a Grexit
- 2/7/2015** Cash decrease in Greek banks
- 3/7/2015** Capital controls leave Greece with shortages in multiple sectors
- 4/7/2015** Europe claims Greek Government is worsening the crisis
- 5/7/2015** Greece voted “NO” in Bailout Referendum
- 6/7/2015** European Central Bank keeps Greek banks’ Emergency Liquidity Assistance frozen
- 7/7/2015** European Commission considers bridge program for Greece
- 8/7/2015** Greek Bailout solution with a Third Memorandum proposed in EuroSummit or Grexit
- 9/7/2015** Greek Government suggests Bailout proposals
- 10/7/2015** Greek Prime Minister implores Syriza party to accept proposed reforms
- 11/7/2015** Issue of trust between European creditors and Greek Government
- 12/7/2015** German plan demands €50bn of state assets to be transferred to external fund
- 13/7/2015** Greece gets Bailout deal in EU Summit
- 14/7/2015** German financial minister discusses with European ministers for parallel currency in Greece
- 15/7/2015** Greek Parliament votes for the Third Memorandum
- 16/7/2015** Greek Parliament voted “YES” and Greek Government signs the Third Memorandum

5.5.1 Stance classification

In this empirical study, we seek to establish whether European citizens' opinion polarity remains the same or varies in the sequence of these political rallies on each event. Because each group, Greek and Europe (EU governments, European Commission, IMF and ECB), corresponds to specific policy-making decisions, each group's sentiment polarity can be affected differently.

We carry out topic stance classification, marking each post as for or against the topic being discussed in the particular post. Having all stance classification results, we determine the final stance over each topic, in the timeline of events, formulating the sentiment polarity for both Europe and Greek online audience.

Hence, in Figure 5.2, we depict stance polarity with for-stances colored in green and against-stances colored in red, GR for Greece and EU for Europe. It is evident that in some events sentiment polarity for both groups remains the same when in others it changes orientation. Specifically, both groups have a positive feeling towards this political call, starting with the day when the referendum was announced. This is likely because both groups believe in the existence of democracy and feel that it is the people who need to make the final decision in such important political decisions affecting the future of a state. As days approach the voting day, we observe, that on 1st July, maybe Europe considers Grexit as an option on the table of negotiations and sentiment orientation changes. Europe continues being positive, unlike Greece's sentiment that turns into negative, most likely because capital controls and cash shortage in Greek banks start affecting their decision towards the referendum vote.

We note a fluctuation of views again, but on the side of Europe. Such alternation of polarity is perhaps based on the belief that if Greece could not yet pay IMF loans, it would not be able to pay additional loans, remaining in a perpetual financial debt. Therefore, a potential Grexit might not have been a wrong decision. Nevertheless, a change in the orientation of opinion is being formulated, turning sentiment in both groups into positive on 5 July, with Greeks voting 'NO' to an agreement plan on the one hand and Europeans being positive about what Greeks would decide on the other. As shown in our estimate, this specific day is considered a crucial event due to the tremendous number of comments posted online, reaching around 20000 in our study.

Another fluctuation in opinion took place from July 7th to 10th, when both groups were allocated with opposite polarity. While Greeks voted negatively in this timeframe, the Greek government, under the pressure of Grexit, is initiating a series of negotiations with the EU Summit proposing rescue proposals. Most probably, this political action had a negative effect on Europeans who thought that the Greek government had not taken into account the vote of people, generating a hostile attitude towards the Greek government. Until the last day of our timeline, we notice that sentiment orientation remains positive on the Greek side, with the Greek government eventually signing the third memorandum, even with more austerity measures than those proposed at the start of the timeline, signaling its urge to stay in the European Union and a potential Grexit to be prevented. Europeans on the other hand, while their feeling was negative because of the Greek government's credibility issues, it finally turned into positive in the end due to the reassurance that all the steps signed in the Greek government's third memorandum will be fulfilled.

At the end of this study we are able to classify the stance on each topic of discussion for both social groups. It is very important to acknowledge that their sentiment polarity has been influenced by every political decision made at both European and national level and that the days when crucial events took place were very clear. Nevertheless, we should not ignore that all events in the timeline are related to a single central political topic of interest, the EU financial crisis, which is our research interest and topic.

5.5.2 Predicting the Greek Referendum Result

The Greek bailout referendum, considered to be the most important act of democracy, is a key issue that affects not only Greece but Europe as a whole, making it unlikely to forecast the final result. Gallups and online polls are two common tools that have been adopted in recent decades at the dawn of a crucial political event like elections, referendums, etc. [The Washington Post \(2015\)](#). These methods use analytics in order to extract citizens' opinion.

In this empirical study, we intend to figure out if these traditional methods still provide accurate predictions or new ways such as sentiment classification can be used as possible techniques. The results of the referendum, suggesting that 61.31% of Greeks voted "No," are illustrated with the black dotted line in Figure 5.3. Online poll results are shown

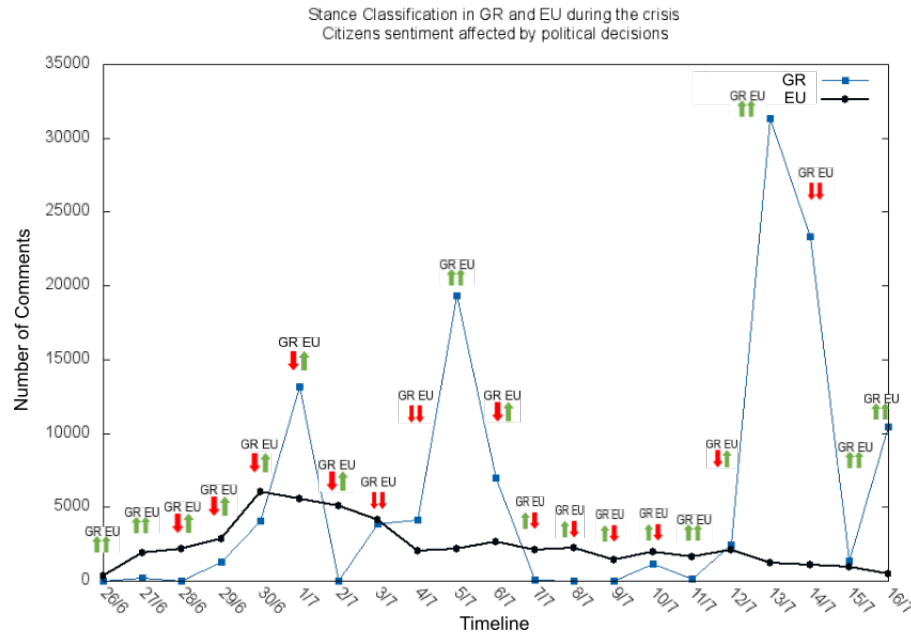


FIGURE 5.2: Stance Classification

with the green line and those from gallups are shown with the black line. On June 30th, after Greek Prime Minister invited citizens to vote "NO" in the bailout referendum, the online polls were initiated and ended with Greeks voting "NO" in the referendum on July 5. From our analysis, we can note that the percentage of "NO" votes moved in the same range from the first to the last day, reaching a remarkable level of about 80%. Comparing the results of online polls to the actual result of the referendum, it is highly shocking that such a significant difference occurs. The same goes for the predictions of the gallup, but in reverse. More precisely, while online polls correctly predicted the "NO" vote would be the referendum's real outcome, the percentage of "NO" was actually 20% higher than the actual one. We have the opposite trend with the gallups. Although gallups also correctly predicted the "NO" vote would prevail, this means that the percentage of "NO" was about 20% lower than the actual result of the referendum, but still won the "YES" vote.

It is clear that the predictions made from both traditional methods gave the right result, but the aberration in the percentage rate was too high and this is an incredibly rare phenomenon.

Focusing on the results of our model, illustrated for Greece with blue line and Europe

with red line, we find that the rate of the predicted stance result is very close to accurate, providing a percentage of 57% for Greece and 65% for Europe on the day of the referendum, respectively. The blue and red line cross the black dotted line at some points, as shown in the figure, having a total match of our prediction with the actual result.

This occurrence offers us the ability to believe that a stance classification system can perform greater than traditional mechanisms in predicting political events and potentially replace them. Hence, maybe stance classification can be viewed as an e-government tool promoting decision making and empowering citizens in the policy making formulation.

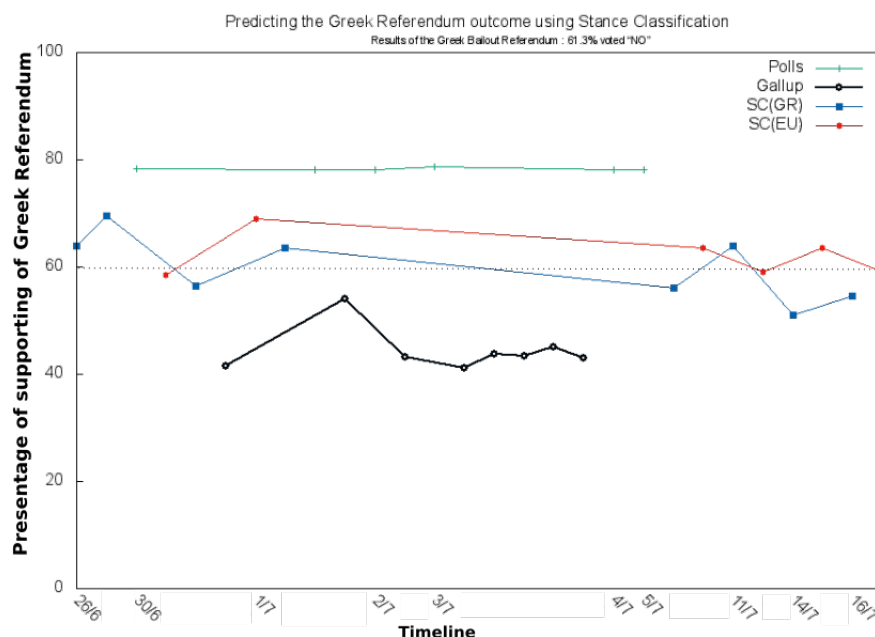


FIGURE 5.3: Predicting the Greek Referendum Result

5.5.3 Policy Making via Stance Classification

Policy, as a product of a political process, can be viewed as a sealed black box. In politics, policy refers to the basic principles by which a government is guided.

A policy model can be treated as a cycle of different discrete stages, each comprised as a coherent chain of events with a given context according to their ? chronological occurrence. These events can be related to one another rationally and predictions can be made based on their sequential appearance. Taking policy's life cycle as a baseline, we make the following consideration. We consider the sequence of events that took place

in our timeline as a policy from the day the Greek referendum was declared to the day the Greek government signed the third memorandum. The goal is to explain how the polarity of public sentiment shifts during the various stages of the political life cycle when a different political decision is made at each point.

In Figure 5.4, we present how opinion shifts with regard to the two groups of people in Europe and Greece at each political stage in the sequence of significant political events. We demonstrate in which critical events the sentiment polarity of both groups remains the same or varies, having already conducted stance classification. When opinion has the same polarity in both groups then the critical event is shown in green color, otherwise in red.

Thus, reflecting the fluctuation of opinions, the first phase of agenda-setting begins with the announcement of the Greek bailout referendum on 26 June. It is colored in green for both Europeans and Greeks to acquire a for-stance. The policy formulation process involves a sequence of crucial sequential events that take place at the onset of the next stage from June 27th to July 15th. At this time, a series of negotiations with the European Commission, IMF and ECB were launched by the Greek government, proposing rescue plans even though Greek citizens voted in the call for a referendum. As we can observe from our figure, each critical event, in this timeline, is determined by a specific sentiment polarity colored either in green with both groups of people sharing the same sentiment or in red in which the sentiment differs. Finally, arriving at the decision-making level, with the Greek government requesting the parliament to vote in favor of signing the third memorandum, sentiment polarity is positive in both groups. Finally, measures are enforced with the Greek government signing the third memorandum and ensuring that EU creditors will obey the proposed measures and reforms.

From this empirical study, we have been able to indicate that at the initiation of a policy the feeling may have a certain polarity, but until the last phase of a policy the political decision is constantly evolving, dynamically affecting the original feeling, causing a possible shift in its orientation. We therefore believe that a dynamic system should be developed based on the synergy between citizens and politicians that bridges the gap between the two groups and empowers citizens in the decision-making process.

This online platform utilizing stance classification and policy making methods would offer to politicians the ability to acquire feedback from citizens' opinions and make

a decision based on these opinions. If politicians were willing to use this mechanism effectively, then a policy would need less time to be formulated and the final decisions would be closer to citizens' will.

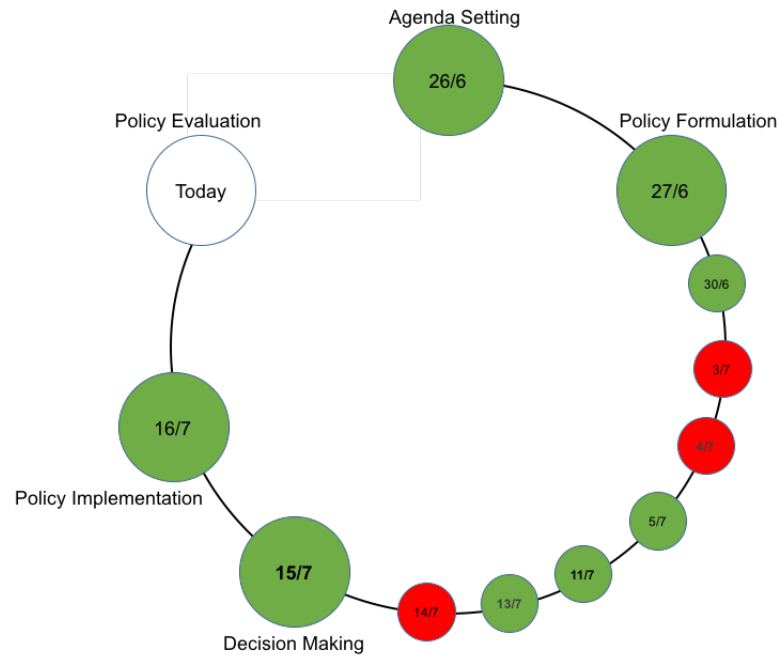


FIGURE 5.4: Policy Making Life Cycle via Stance Classification

Chapter 6

A Multi-Layer Opinion Mining Mechanism for Policy Making

This chapter outlines a multi-layer opinion mining mechanism that supports crowdsourcing and public policy formulation originating from the need of government agencies to utilise knowledge when addressing critical societal problems. This multi-layer platform exploits policy-related content published in various social media platforms, third party services and web sites, without any direct stimulation or direction by government by combining opinion mining techniques (topic modeling, sentiment analysis and stance classification) to determine both sentiment and stance towards a specific policy. Although it is important to indicate separately whether an opinion is positive or negative, or a personal position towards a specific topic as for or against, it is more crucial and intriguing to classify an overall emotional state. Extracting and classifying users' sentiment and stance on governmental actions and critical political decisions, can help us not only understand how certain communities react on specific events, but also predict significantly their emotional states to future events and decisions, invigorating an efficient policy making process [Spiliotopoulou et al. \(2017\)](#).

Traditional direct policy making mechanisms, such as the referendum calls, gallops, online polls [Spiliotopoulou et al. \(2017\)](#), [Charalabidis et al. \(2015\)](#), [Spiliotopoulou et al. \(2014\)](#), [Maragoudakis et al. \(2011\)](#) cannot be utilized in a daily basis due to the high required citizens' commitment and the increased cost of such a democratic act. Thus, a multi-layer opinion mining mechanism capable of extracting citizens' sentiment and

stance would be a possible solution for allowing governments to proceed into a more effective policy making process. The ideal method to test such a proposition is to analyze fundamental key political issues and direct acts of democracy occurred in the past such as referendum calls, presidential elections or even a whole presidential term and cross-evaluate their already known final result with the one we propose. A comprehensive description of this mechanism is provided in (submitted in Elsevier, Special Issue on "Information Fusion for Effective Computing and Sentiment Analysis").

6.1 Requirements & Methodology of the Multi-Layer Opinion Mining Mechanism

In order to determine the feeling arising from the public towards critical governmental decisions, taken in a timeline of events that are based on policy formulation, empowering citizens' participation in the decision making process, we design and develop a Multi-Layer Opinion Mining Framework. In the specific mechanism, we proceed a step further from the advanced one, by combining sophisticated mining techniques, and more precisely topic modeling, sentiment analysis and stance classification in order to categorize the stance polarity of our classification system. Last but not least, through the development of this multi-layer architecture and having the policy life cycle as baseline, we aim to explore if a new era of democratic involvement, through social media exploitation, can strengthen participatory democracy, bringing citizens' engagement to the forefront.

In particular, the methodology we adopted for the development of the Multi-Layer Opinion Mining Framework is the following:

- Initially, we provide a holistic approach on how a multi-layer opinion mining mechanism can be utilized in digital government for direct democracy empowerment
- We design and implement a novel stance classification architecture offering a fusion of topic modeling, sentiment analysis and stance classification
- We select the social media platforms and news sites to explore, exploit and extract the online data used to determine public's stance polarity (for-stance or against-stance) towards a policy

- The main idea of this crowdsourcing approach was formulated on the basis of developing a stance classification architecture with integrated mining techniques for social media exploitation and determining the stance for both citizens and political figures
- We investigate whether citizens' stance converges or diverges with governmental decisions made in each stage of a policy life cycle
- We evaluate our proposed mechanism's performance and we compare our prototype with similar models from recent literature review in terms of accuracy
- Taking into consideration the performance results derived from the evaluation phase, our proposed Multi-Layer Opinion Mining System is utilized in real case scenarios. To achieve this and aiming at "crowdsourcing", we conduct 6 empirical studies with pilot applications

Our use-case scenarios or else our pilot applications utilized in this part of our research constitute direct acts of democracy, specifically we deal with empirical studies that refer to the 4 Referendums that took place in the EU and the 2016 U.S.Presidential Elections.

Our first study lies on 4 political occurrences, the European Union Referendums, that are considered acts of direct democracy, offering people the authority to determine their country's future on proposals or measures that go directly on the ballot. These decisions taken from the people affect not only the future of each country directly, but also the future of the European Union indirectly as a whole. In order for EU to function properly, efficient decision-making needs to be taken at both levels. It is therefore necessary to formulate a digital policy-making mechanism on how to make such effective decisions in an effort to help society shape an integrated policy-making model for a more direct democracy.

Our second case study focuses on the 2016 U.S.Presidential Elections timeline, aiming to indicate the citizens' stance as for or against towards political occurrences that took place during the elections. This will allow us to determine how each political candidate can affect people's decision on the elections' outcome.

Last but not least, as our third case study, we track the U.S. President's personal position on various societal issues (e.g. abortion, guns control) and how his views and

opinions expressed through social media exploitation can affect even the trade market stock fluctuation.

More precisely, we perform 3 empirical studies based on real case scenarios aiming to fully understand:

- Study 4 EU Referendums to investigate whether citizens' stance shifts in polarity based on the political decisions made during each referendums' policy life cycle, and if this loop-back mechanism can be used to improve the decision making process in modern e-participation
- Examine political candidates' news or personal opinions, during the 2016 U.S. Presidential Elections, towards popular topics, and how these affect peoples' sentiment
- Explore U.S. President' personal position towards societal issues and how it can affect even trade market fluctuation

6.2 A Multi-layer Opinion Mining Architecture

This section describes the overall architecture of our proposed multi-layer opinion mining mechanism, offering implementation details on the modules. Our proposed architecture consists of 3 main modules, the Web-Interface module, the Back-End Module and the Policy-Making module. Each one of them includes other sub-modules responsible for performing separate tasks.

The core of the service is built on a Flask instance, a micro web framework written in Python, providing support through its API for the front-end and back-end application code.

Figure 6.1 depicts system's overview of the modules employed to automatically collect, process and determine sentiment polarity.

6.2.1 Back-End Module

It includes three sub-areas: the Social Media Platforms selection, the Third Party services and the Data Collection. We analyze each one of them in a detailed way.

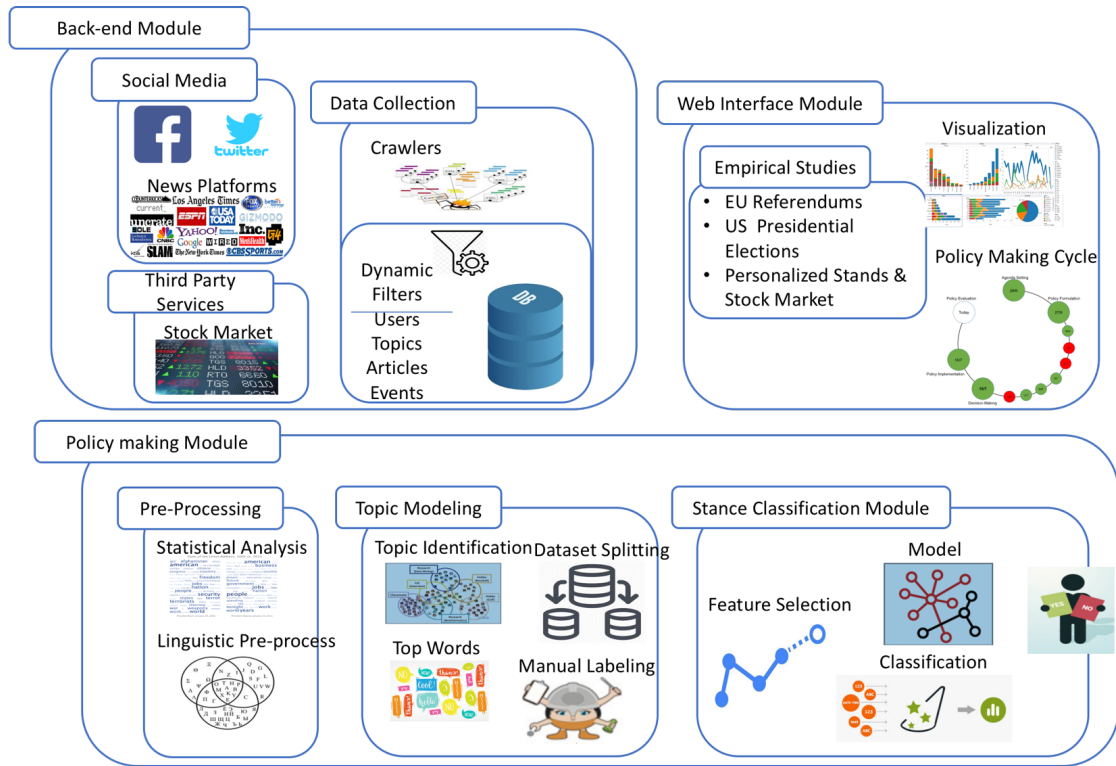


FIGURE 6.1: A Multi-layer Opinion Mining Architecture

6.2.1.1 Social Media Selection & Third Party Services

Online newspapers, Facebook and Twitter are the social media platforms utilized to collect our data. Most of the very big newspapers, have a digital representation, which allow journalists to publish their articles, and users to comment. We chose online newspapers that provide access to the Title, article, and posts, and are built with a CMS platform. This kind of structure, allowed us to build scripts in python, to crawl and create our datasets. In addition, Facebook and Twitter, provide API Frameworks making the collection of the data a much easier task.

We created Python scripts for 30 online newspapers. The selection of the online newspapers is based on their high popularity and broad user base measured by Alexa top news sites. In addition to the social media, our back-end is capable of supporting extensions, with the proper scripts, to other services like government services, financial institutes, or third-party in order to share or correlate the data.

In Figure 6.2, we illustrate a data collected from third party services, in this case the stock market.

```

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{"Low": "136.110001", "Volume": "20836900", "Symbol": "AAPL", "High": "137.119995", "Open": "136.429993", "Date": "2017-02-22", "Close": "137.110001", "Adj_Close": "137.110001"},
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{"Low": "134.619995", "Volume": "35623100", "Symbol": "AAPL", "High": "136.270004", "Open": "135.520004", "Date": "2017-02-15", "Close": "135.509995", "Adj_Close": "135.509995"}]

```

FIGURE 6.2: Stock Market Script Interface

6.2.1.2 Data Collection

All newspapers daily published articles that occurred either the previous or the same day, allowing users to post online their personal positions and express their opinions over the topics of discussion in the specific articles. This gives us also to chance to collect comments from past articles, or update our database, with newly comments.

Usually, online social media platforms base their structure on Content Management Systems (CMSs) facilitating the utilization of reusable components or customized software for web content management. Data collection is performed by a customizable set of parsers, presented in Appendix C, developed in Python programming language and modified for each news site accordingly. The module gathers the event title, the content of the article and users' posts, users' username and timestamp (date and time) of each post. As for the social networking sites, they provide their APIs which we used in order to collect the data from both Facebook and Twitter. To store the data, we utilized Structured Query Language (SQL) Lite database. The data collection process was initiated for each case study separately.

In Figure 6.3, we present a segment of our script for the data collection process. This one is implemented to crawl twitter comments from U.S.President Donald Trump.

```

def test_get_tweet(self):
    self.assertEqual(run_app.get_tweet(None, 0, 0), [])
    self.assertEqual(run_app.get_tweet("Donald Trump", None, 0), [])
    # Valid parameters
    twitter_data = run_app.get_tweet("@realDonaldTrump", 1490227200, 1490227200)
    self.assertEqual(len(twitter_data), 5)
    self.assertEqual(twitter_data[0].get('id', ''), '845037368386207746')
    self.assertEqual(twitter_data[0].get('time', 0), 1490227200)
    self.assertEqual(twitter_data[0].get('sentiment', 0), 0.7125)

```

FIGURE 6.3: Twitter Script for Data Collection

6.2.2 Web Interface Module

The front end is a combination of CSS, PHP, Javascript, and Dash application layouts, to have a logic for graphs, interfaces with the database, and activates all the crawling from the social media.

6.2.2.1 Visualization

This module allows users to view in the form of statistical graphics, diagrams and other tools, the sentiment analysis and stance classification results, which are produced by the policy-making module. It is built on top of Plotly.js, React, and Flask and ties modern UI elements like dropdowns and graphs directly to python code.

Figure 6.4 depicts the graphical representation of the sentiment interface that we utilized to graphically present the classification results.

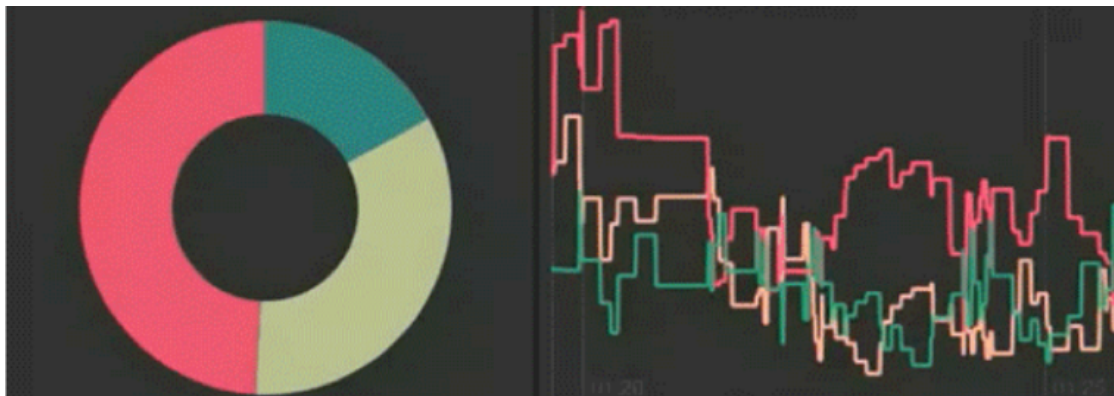


FIGURE 6.4: Sentiment Interface

6.2.2.2 Use-Case Scenarios

The users have the ability to run 6 different experiments through the web interface. This module is responsible for: i) crawling recent comments and update the database, ii) selecting all the required data from the local database, ii) determining the stance polarity based on the selected empirical study or use-case scenario, and finally iv) presenting the results, aiming to explore whether citizens' sentiment converge or diverge with governmental decisions taken in each stage of a policy life cycle.

More precisely, this module provides access to the 4 EU Referendums; i) Greek Bailout Referendum, ii) Dutch Ukraine-EU Association Agreement Referendum, iii) Brexit and UK EU Membership Referendum, and last but not least iv) Hungarian Migrant Quota Referendum. In addition, it offers a holistic study focused in the 2016 U.S. Presidential Elections between the two most popular candidates Donald Trump and Hilary Clinton. Finally, it explores, in a personalized shape, the 2016 U.S. Presidential sentiment orientation towards societal issues and how it affects even the stock market fluctuation.

6.2.3 Policy-Making Module

This particular sub-area consists of all the modules responsible for processing, modeling, analyzing the collected datasets of the 6 case-studies and determines the stance as for or against towards each topic of discussion. It includes the Pre-Processing, the Topic Modeling and the Stance Classification modules.

A pseudocode is presented in Appendix B with the steps that we followed in order to employ all the multiple modules in our proposed multi-layer opinion mining architecture.

6.2.3.1 Pre-Processing

It consists of the *Statistical Analysis* and the *Linguistic Pre-Process*. Aim of the Statistical Analysis is to distinguish in each empirical study the days with the highest cumulatively number of posts and number of comments in the online articles. We presume that the occurrence of a critical event is determined by the excessive number of posts-comments. That actually indicates that an increased number of users discuss the specific issue expressing their opinion. To automatically process the data, a script was built in python programming language.

Next, a series of linguistic process tasks follows, with the grammatical and semantic analysis which lies on the n-gram generation, specifically uni-grams and bi-grams. N-gram generation is the creation of adjacent sequence of n items from a given text. We focus on building uni-grams and bi-grams by utilizing words that are adjectives, nouns and verbs, as they are considered as opinionated words and will be utilized as features in the stance classification module. As uni-grams we will use verbs and as bi-grams the pairs adjective and noun.

Initiating the Linguistic Pre-process, we start with tokenization, splitting each post into sentences and each posts' sentence into words. We continue with *Part-of-Speech (POS)* tagging [Mitkov \(2003\)](#), marking up each word in the datasets as corresponding to a particular part of speech, based on its definition and context. We identify the conjunctions inside each sentence and we separate the sentences into sub-sentences if a conjunction exists in a sentence. Additionally, from all POS-tags, we keep only adjectives, nouns and verbs. We utilize *Stanford Parser* [Stanford NLP Group](#) to calculate the shortest distance between the words of the same sentence in order to create the correct pairs of bi-grams – adjectives and nouns – and uni-grams – verbs. We then implement *Porter Stemming Algorithm* [Porter \(2006\)](#) to find the root of each word and we finish with n-grams generation creating uni-grams and bi-grams. For tokenization, sentence splitting, POS-tagging and n-gram generation, the *Natural Language Toolkit* [NLTK Project \(2015\)](#) was utilized.

Figure 6.5 represents a paradigm of NLTK utilization and implementation in Twitter in order to acquire the sentiment and its score for each POS-tag.

```
def test_nlp(self):
    self.assertEqual(nltk_twitter.get_sentiment(TextBlob("Good")), ['Good', 0.7, []])
    self.assertEqual(nltk_twitter.get_sentiment(TextBlob("Bad")), ['Bad', -0.6999999999999998, []])
    self.assertEqual(nltk_twitter.get_sentiment(TextBlob("Neutral"))[0:2], ['Neutral', 0.0])
```

FIGURE 6.5: Twitter NLTK Paradigm

6.2.3.2 Topic Modeling

Although each article we analyze focuses on a specific event occurred in a certain day, online users tend to refer in their posts to related topics too (e.g. the article may refer to Greek Bailout Referendum question, but users may also discuss about Greek deficit and capital controls). Thus, we aim to identify all the different topics that are discussed in each post and each posts' sentence. To succeed this, we utilize Mallet, a tool for modeling the datasets, revealing the hidden thematic structures in order to extract the topics being discussed along with the top-words that appear with the highest frequency across all posts. Mallet uses a generative statistical model called *Latent Dirichlet Allocation (LDA)* to produce the topic modeling results. The model for each empirical study was trained under a set of commands preserving the dataset as a sequence of word features, removing the stop-words and converting all the lowercase.

Having the topic modeling results, we utilize the *sentenceLDA* [Balikas et al. \(2016\)](#), giving as input each posts' sentence and obtaining as output the topics discussed in the sentence along with the top-words. Sentence-LDA is an extension of LDA whose goal is to overcome the limitation of lost information in sentences during the modeling process by incorporating the structure of the text in the generative and inference processes. We follow the same procedure for all posts' sentences of all empirical studies. We then employ the online tool *diffchecker* [Redserg \(2013\)](#) in order to compare and identify whether the topics of discussion and the top-words of each posts' sentence is the same with the ones of the topic modeling results respectively. If so, then the sentence is relative and refers to the specific topic with its top-words. We then follow the same procedure for all datasets of all empirical studies.

In order to design an efficient multi-layer opinion mining system and achieve high accuracy results in predicting correctly the stance towards each topic, we need to utilize the correct data to build the classification model. Thus, during our preliminary study, we test various combinations and percentages in splitting the datasets, before concluding that the best way to create the training set is by learning from the 20% of the daily topics of each empirical study. In this way, the classification model consists of instances that appear in most topics.

In our research, we depend on manual annotation to label the training datasets, one for each case study. Two human annotators, via the Mechanical Turk engine, were trained through discussions to label each post's sentence stance towards the topics of discussion as for or against or neutral, keeping the sentences that contain no topic stance. We do so, in order to train our model effectively from every topic chosen to be discussed in the critical events and learn from the sentences. To start the annotation process of the 20% of data, we instructed the two annotators to first annotate each sentence based on the topic to which it was most related (topic classification), and to then annotate the post's overall position towards the topic (**stance classification**).

In Figure 6.6, we picture the results derived from this modeling phase.


```

{
  "tweet": "Congratulations to Justice Neil Gorsuch on his elevation to the United States Supreme Court. A great day for America! #SCOTUS",
  "id": "851555178910064640",
  "time": 1491782400,
  "sentiment": 1,
  "noun_phrases": [
    "congratulations",
    "neil gorsuch",
    "supreme court",
    "great day",
    "america",
    "scotus"
  ],
  "sentence_breakdown": [
    [
      "Congratulations to Justice Neil Gorsuch on his elevation to the United States Supreme Court.",
      0,
      [
        "congratulations",
        "neil gorsuch",
        "supreme court"
      ]
    ],
    [
      "A great day for America!",
      1,
      [
        "great day",
        "america"
      ]
    ],
    [
      "#SCOTUS",
      0,
      [
        "scotus"
      ]
    ]
  ]
}

```

FIGURE 6.6: Modeling Results

6.2.3.3 Stance Classification

It includes *Features Selection, Modeling and Classification*. Aiming to build an efficient stance classification system that uses machine learning classifiers to determine the stance as for or against towards the topic of discussion, it is essential to select and evaluate correctly a set of linguistic features. Having already created the uni-grams and bi-grams from our dataset for each empirical study, we check whether the top-words derived from topic modeling results are the same with the words that are identified as *uni-grams* or *bi-grams* in a sentence. If yes, then we calculate the top-word score using the *tf-idf* metric Manning et al. (2008) and we assign the score at the specific POS-tag as a weight during the classification phase. We then use the MPQA subjectivity lexicon [MPQA Dictionary \(2019\)](#) to assign to the POS-tags of our datasets the sentiment polarities respectively. Thus, each uni-gram and bi-gram is characterized by its weight and its sentiment polarity (positive, negative, neutral) and will be employed as features in the classification task.

The classification engine is the most important part of the stance classification system. We conduct multiple experiments and cross-evaluate many algorithms to find the most accurate classifier used as the classification engine. At the end of this procedure, we selected Random Forest, due to its highest performance aka highest accuracy in classifying the stance in online posts/comments. To build our system, we used *Weka* library ?,

which contains a collection of machine learning algorithms for data and opinion mining tasks such as classification, and the Random Forest algorithm as our engine. As classification features, we utilized the uni-grams and bi-grams with their sentiment polarity and corresponding weight. The predicted class was the Topic Stance with values for or against. Also, via the *senLDA* algorithm [Balikas et al. \(2016\)](#), we have in mind that we already know the topics and top-words of each sentence in each post. Thus, during the classification phase, we categorize the topics' stance of each sentence in each datasets as for or against. Knowing each sentence stance, we identify the overall topic stance of each post of the datasets by summing up the for-stances and the against-stances respectively. We utilize summarization as the same procedure to determine the overall stance across all posts of each empirical study.

Due to the fact that our multi-layer mechanism should be able to process text written in Greek, Hungarian and Dutch along with the English language, we conducted small modifications to the system, so it can be adapted to our proposed research model.

More specifically, for the Greek language we develop a python script that is contingent to [Gliozzo et al. \(2004\)](#) study which pinpoints that posts containing adjectives have a high probability of indicating implicit user opinions opposed to posts that contain no adjectives and topics are more likely to appear in the form of a noun. A syntactic dependency parser is also employed for adjectives identification creating pairs of bi-grams and uni-grams counting their frequency. The POS-tags with the highest appearance across posts were selected as top-words. Last but not least, we utilized Greek Sentiment Lexicon by [Tsakalidis et al. \(2014\)](#) to assign sentiment polarities in the selected POS-tags.

Concerning the Hungarian language, a tokenizer with sentence splitting was used along with a sequential tagger for *NLP* using Maximum Entropy Learning and Hidden Markov Models for the POS-tagging. For the linguistic processing a Hungarian toolkit was implemented [oroszgy \(2018\)](#).

Considering the Dutch language, an integration of memory-based natural language processing (NLP) modules was developed performing POS-tagging, lemmatisation, morphological analysis, named entity recognition, shallow parsing, and dependency parsing [proycon \(2018\)](#).

6.3 Evaluating the Multi-Layer Opinion Mining Mechanism

To evaluate our multi-layer opinion mining architecture, a preliminary study was conducted stressing the performance of our proposal in terms of accuracy. The performance of our automated stance classification system is evaluated in terms of accuracy which denotes the correct classified instances.

Data were analyzed and processed via the Weka library and a 10-fold cross validation technique was utilized to evaluate how data generalize to an independent dataset. Data analysis has been performed on the antsle one pro server with a 2.40GHz Intel 8 Core, 32GB ECC DDR3, 12TB internal storage.

We utilize various machine-learning classifiers and more specifically, we cross-evaluated four supervised machine-learning algorithms, i.e., Bayesian Networks, Radial Basis Function (RBF), K-Nearest Neighbor (KNN), and Random Forest [Damopoulos et al. \(2014\)](#).

The preliminary study includes the following steps:

- Select and collect 10 political events with at least 1000 comments
- Use two human annotators via the Mechanical Turk engine to label each post's sentence stance towards the topics of discussion as for or against or neutral
- Evaluate the accuracy of 4 different classifiers (Bayesian Networks, RBF, KNN, Random Forest) in through a 10 fold cross-validation
- Conduct the evaluation process for the English, Greek, Hungarian, and Dutch language
- Select the best combination of features, classifiers that gave us the higher accuracy, across all the preliminary experiments

Table 6.1 represents the performance of our proposed multi-layer opinion mining mechanism (*see the numbers in red annotation*) in comparison to the performance of other similar research works mentioned in the Related Work section 6.1. This comparison is based on the same evaluation metric, accuracy, and the results obtained from the system's cross evaluation, both ours and from literature review works, are all demonstrated

TABLE 6.1: Related Research Works & Proposed Models Comparison

	Model	Classification Accuracy (%)
Related Research Works	Somasundaran and Wiebe (2010)	63.93
	Anand et al. (2011)	69
	Walker et al. (2012)	88
	Hasan & NG (2013)	75.4
	Ranade et al. (2013)	74.3
	Ferreira and Vlachos (2016)	73
	Mohammad et al. (2016)	69
	Addawood et al. (2017)	83.8
Proposed Model based on the Empirical Studies	Greek	82
	Dutch Model	68
	English Model	93
	Hungarian Model	73

in the specific table. We indicate that Random Forest is the most promising classifier showing optimal results of accuracy for all the empirical studies that we conducted in our research. More precisely, as shown in Table 6.1, for the 4 EU Referendums, our proposed model obtained 75% accuracy on the Hungarian Migrant Quota Referendum, 75% accuracy on the Dutch-Ukraine Association Agreement Referendum, 82% accuracy on the Greek Referendum and 93% on the UK EU Referendum respectively. Last but not least, for the 2016 U.S. Presidential Elections case-study, our proposed model gained 93% accuracy.

Through our research, we show that our multi-layer system's performance exceeds significantly similar research approaches with promising results. As a general feeling, we note that all experiments present high accurate results, thus providing strong evidence that designing and implementing a multi-layer stance classification system – across 4 different languages – can become a very precise way of analyzing a big volume of data.

6.4 Use-Case Scenarios

The core of this work is to provide a holistic approach on how a stance classification system can be utilized in digital government and e-participation empowering direct democracy. Employing our proposed architecture on 3 case-studies allows us explore how sentiment diverges in a policy making life cycle affected by political decisions. Also, it offers the ability to explore how a personal stance of a president of a country expressed on

social media towards a sensitive social issue can influence not only the public sentiment but even the trade stock market fluctuation.

6.4.1 The portrait of EU Referendums

Direct democracy has become more popular in the last few years through the announcement of referendum calls and initiatives. Many European countries, including ours, aim to effectively utilize direct democracy in the political culture, with citizens being directly and widely included in the decision-making process. Direct democracy is actually an umbrella used to describe the forms of democracy that involve people directly making law as opposed to having laws made by elected representatives. Since 1970s, the use of referendums has increased in a great extent and an emerging number of voices describe direct democracy as an elixir for increasing disappointment with politicians and political parties.

A referendum is defined as a direct vote in which an electorate is invited to vote on a particular proposal that may result in the adoption of a new law. In some countries, it is synonymous with a plebiscite or a vote on a ballot question. If a referendum is going to take place, legislation will be passed containing the question that needs to be answered and the rules on how the referendum is to be run.

The upcoming use of direct democratic procedures such as the referendum calls in each country separately but also cross-nationally increases the interest of the research on theoretical and empirical level. Consequently, it is vital to examine the influence of direct democratic elements of the political system such as the referendum calls that have occurred in the last few years in the European Union and how these affect not only each country but also the EU as a whole.

This is not the first time that referendums are the centre of research. According to our previous research [Spiliotopoulou et al. \(2017\)](#), we studied the Greek Bailout Referendum and successfully compared our stance classification system to traditional mechanisms such as gallops and online polls towards the Referendum results. The results showed that the traditional methods provided the correct outcome but the deviation in the percentage rate was too large. Surprisingly, our system performed greater in predicting the political event, offering the ability to believe that such a sentiment classification

system can be used as a new potential tool promoting decision making and empowering citizens in the policy making formulation.

In this empirical study, We examine 4 Referendums; i) the Greek Bailout Referendum, ii) the Dutch Ukraine-EU Association Agreement Referendum, iii) the UK EU Membership Referendum, aka Brexit, and last but not least iv) the Hungarian Migrant Quota Referendum. These referendums focus on the European Union and took place in the last three years.

Specifically, in 2015, Greece, facing a multi-year debt crisis, announced the Greek Bailout Referendum. In April 2016, the Dutch Ukraine - European Union Association Agreement Referendum was announced for the approval of a treaty between the European Union, its 28 Member States and Ukraine. In June 2016, UK, dealing with migrant crisis, published the UK EU Referendum, considering whether remaining a member of, or leaving, the European Union. Last but not least, in February 2016, Hungarian government held a referendum on whether to accept the European Union's proposed mandatory quotas for relocating migrants.

More specifically, our study is focused on extracting online users' comments from social media platforms and online newspapers for the aforementioned referendums aiming, in this analysis to achieve four main goals:

- Track sentiment for each referendum's policy cycle
- Gain knowledge on how users comment on multiple events and feel towards political decisions that take place in each referendum accordingly stating their position as for or against
- Examine whether there is a trend and a connection between the users' feeling extracted online with the final outcome of each referendum discovering similarities or divergence
- Cross-evaluate different political EU referendums in an effort to strengthen our initial hypothesis, made in our previous research, that not only a prediction can be made but also significantly accurate results can be derived from our proposed methodology compared to traditional online polls

6.4.1.1 EU Referendums Methodology

In the last few years, various governments in the EU have conducted referendums asking citizens' opinion on critical political topics. These referendums can be utilized as a key pillar, not only to evaluate our proposed multi-layer opinion mining system performance, but also to derive a deeper understanding on how governments can exploit both social media platforms and people's opinion towards improving, in an efficient, accurate, and organized way, their decision making process in real-time underlying citizens' sentiment orientation.

The four aforementioned EU Referendums caused a sequence of daily events reported online in a great extent with a huge volume of articles and comments in newspapers and social media platforms. In this part of our study, we exploited online newspapers with data reported in a structured (title, article, users comments), clear (CMS systems structure) and protected way and Facebook platform with its API for data collection.

More precisely, data collection for the Dutch Ukraine-EU Association Agreement Referendum, data were accumulated from 18 February 2008 when Formal negotiations between the Ukrainian government and the EU Trade Commissioner to sign the Association Agreement were launched till 6 April 2016 with Ukraine-EU Association Agreement Referendum being signed. Moreover, regarding the UK EU Referendum started 11 June 2015 with UK planning an in/out referendum on its EU membership and lasted till 29 March 2017 when EU Council President Donald Tusk received a formal notice that UK will withdraw from the EU within the next two years. As for the Hungarian Migrant Quota Referendum, the data process lies between 23 June 2015 with Hungary suspending the key EU asylum rule and 2 October 2016 when Hungary Prime Minister claimed EU migrant quota referendum victory, despite the low turnout that rendered it invalid. Last but not least, concerning the Greek Bailout Referendum, data were collected from 26 June 2015 when the referendum was announced till 16 July 2015 with the third memorandum being signed by the Greek government. Table 6.2 represents the timeline of research for these 4 EU Referendums.

The following sessions provide an insight about the period of each referendum we are analyzing, followed by the dates and topics that we considered critical for the decision making process. During the selected dates, a critical mass of users' comments indicate that a positive or a negative critical event occurred, compared to the rest of the days,

TABLE 6.2: EU Referendums Research Timeline

EU REFERENDUMS	PERIOD OF RESEARCH (month/day/year)
Dutch Ukraine-EU Association Agreement Referendum	02/18/2008 - 04/06/2016
UK EU Referendum	07/11/2015 - 03/29/2017
Hungarian Migrant Quota Referendum	07/23/2015 - 10/2/2016
Greek Bailout Referendum	07/26/2015 - 08/16/2015

worth to be explored. For each referendum, a policy making cycle was created to visually depict the stance polarity of an event. If politicians were able in real time to utilize our proposed multi-layer system, they would be able not only to have a direct and accurate feedback from citizens, but also gain knowledge on the feeling of an upcoming decision and possible re-evaluate their own political strategy.

6.4.1.2 Greek Bailout Referendum

European debt crisis, also known as Eurozone crisis, is a multi-year debt crisis that has been taking place in European Union since the end of 2009. This occurrence happened due to the inability of Eurozone members, including Greece, Portugal, Ireland, Spain and Cyprus, to pay their governmental debt or bail-out over-indebted banks under national supervision without the assistance of other Eurozone countries, or of the European Central Bank (ECB), or of the International Monetary Fund (IMF). To fight the crisis, some governments focused on raising taxes and lowering expenditures, but that contributed to social unrest emerging a crisis of confidence with the widening of bond yield spreads between these countries and other European member states.

Although European debt has risen significantly in only a few Eurozone countries, affecting mostly Greece, Ireland and Portugal, it has become a widely identified problem rising the speculation that other European countries will have the same outcome leading to a possible break-up of the Eurozone. In 2010, Greek government announced a series of austerity measures securing a three-year €110bn loan. Although the austerity measures helped bringing down Greek primary deficit, they also contributed to worsening Greek recession. As a result, the country was guided in the crossroads of choosing whether to remain in Eurozone or withdraw, reintroducing its national currency the drachma. Troika, a committee of European Commission, IMF and ECB, offered Greece a second bailout loan in 2012 and another €10bn in 2013 and 2014 leading on the implementation of further austerity measures and a debt restructure agreement.

In 2015, Greece facing the threat of a potential exit from Eurozone again, also called as “Grexit”, attempted to settle an agreement with Troika to activate the transfer of the frozen bailout funds in its current program. Eurogroup granted a six-month technical extension of Greece’s current bailout program asking Greece to finalize negotiations and implement the proposed measures in order to unlock the remaining bailout transfers.

In the early morning of 27 June 2015, Greece’s Prime Minister, Alexis Tsipras announced the Greek Bailout Referendum. The Greek Referendum, that took place on 5 July 2015, was to decide whether Greece would accept the bailout conditions in its government-debt crisis proposed jointly by the EC, IMF and ECB, on 25 June 2015. The Greek government asked to vote on two previous documents, entitled “Reforms for the Completion of the Current Program and Beyond” and “Preliminary Debt Sustainability Analysis”. The possible answers were stated as “Not approved/No” and “Approved/Yes”. The Referendum result proved that bailout conditions were rejected by a majority of over 61% to 39% approving. Although Greek people voted “No”, Greek government surprisingly requested for a three-year bailout from Eurozone’s rescue fund, reassuring to implement the needed measures and reforms.

This was considered as an extreme change of political direction from Greek’s part. European finance leaders scheduled a “crisis summit” considering and evaluating the Greek request. A few days later, Greek Prime Minister’s request for a three-year bailout was approved by the Greek Parliament and the package with the completed proposal was forwarded to the Eurogroup. The extreme and unpredictable change in Greek government’s political decision not to follow Referendum’s result indicates that a series of multiple events affected its sentiment, altering the final political decision. Hence, we aim to investigate the reason why the change in the opinion orientation changed defining the events that caused simultaneous alternations in the opinion polarity.

In Figure 6.7, we present how sentiment shifts at each stage of the policy making cycle in a timeline of critical political events. When a cycle is coloured in green, it means that the stance polarity is positive towards the specific occurrence, otherwise it is red with a negative stance.

Mirroring the divergence of opinions throughout the cycle, it is evident that the agenda-setting initiates with a positive feeling, a for-stance, towards the announcement of the Greek bailout referendum. The stance is positive due to the fact that a referendum

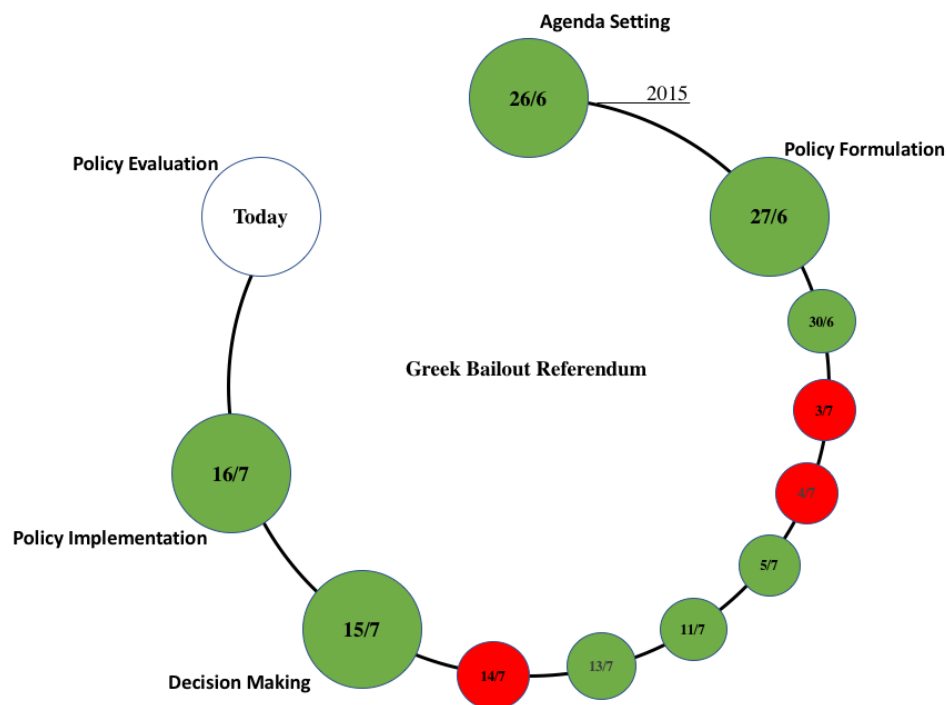


FIGURE 6.7: Greek Bailout Referendum Policy Cycle

call is considered a direct act of democracy and is a fundamental political decision that affects a country's future. During the phase of policy formulation, specifically from 27 June 2015 till 15 July 2015, under a Grexit threat, Greek government deals with a series of negotiations with the EU Summit suggesting bailout proposals even though citizens have voted negatively in the the bailout referendum on 5 July 2015.

For this period of time, we need to mention that although there is generally a positive stance towards the governmental actions, there are events with negative stances in which Europe's feeling is against Greek Government. This happens due to its decision not to take into consideration citizens' vote on the referendum result and remain in a financial debt worsening the Greek crisis. Then, in the decision-making stage, with Greek government asking from the parliament to vote positively towards the signing of a third memorandum proposed by the EU Commission in an effort to avoid Grexit and remain in the EU, sentiment polarity shifts in green pointing a for-stance. Finally, policy is implemented with the signing of the third memorandum and the Greek government assuring the EU creditors that will follow the proposed measures and reforms. In this final stage, the stance remains positive.

6.4.1.3 Dutch Ukraine-EU Association Agreement Referendum

The Dutch Ukraine – European Union Association Agreement is a treaty between the European Union (EU), their 28 Member States and Ukraine establishing a political and economic association between the parties. The agreement has not entered yet into force, but parts are applied provisionally. The parties are committed to co-operate and converge economic policy, legislation, and regulation across a broad range of areas, including equal rights for workers, steps towards visa-free movement of people, exchange of information, modernization of Ukraine’s energy infrastructure, and access to the European Investment Bank. The parties are also bound to regular summit meetings, and meetings among ministers, officials and experts. Additionally, the agreement establishes a Deep and Comprehensive Free Trade Area between the involved parties.

The agreement commits Ukraine to economic, judicial, and financial reforms to converge its policies and legislation to those of the European Union. Ukraine is pledged to gradually conform to EU technical and consumer standards. The EU agreed to provide Ukraine with political and financial support, access to research and knowledge, and preferential access to EU markets. Such agreement obligates both parties to promote a gradual convergence toward the EU’s Common Security and Defence Policy and European Defence Agency policies. The Ukraine–European Union Association Agreement Approval Act was voted upon in the House of Representatives and Senate in 2015. The Act received royal assent on 8 July 2015. The Minister of Foreign Affairs published a decision at which point the law became eligible for a referendum.

The Dutch Ukraine–European Union Association Agreement referendum was based on the approval of the Association Agreement between the European Union and Ukraine, held in the Netherlands on 6 April 2016. The referendum question was stated as “Are you for or against the Approval Act of the Association Agreement between the European Union and Ukraine?” With a turnout of 32.28%, the threshold for a valid referendum was met. 61% of votes were against the Approval Act, but only 19.5% of all the eligible voters. As the Act was rejected, the States General had to enact a follow-up law to either repeal the Act or put it into effect at last. The referendum was the first since the enactment of the Advisory Referendum Act that took place on 1 July 2015.

The decision to hold a referendum was made after more than 427,000 valid requests were received within six weeks, more than the required number of 300,000 requests. The referendum was suspensory and non-binding, and following the rejection, the Government had to propose as soon as possible a new act to either gain parliamentary approval for either retraction of the approval act or for its entry into force. The government secured an additional agreement between the 28 Member States of the European Union addressing the concerns of the no-vote. Following the approval of the additional agreement, a new law was passed approving the Association Agreement in May 2017 enabling the Netherlands to approve its ratification on 15 June 2017. The association agreement entered into force on 1 September 2017.

- 18/2/08** Formal negotiations between the Ukrainian government and the EU Trade Commissioner to sign a Free Trade Agreement were launched
- 31/3/2012** The EU Association Agreement was initiated
- 19/7/12** The finalized Association Agreement was initiated
- 21/11/13** A Ukrainian government decree suspended preparations for signing the Association agreement that was scheduled to be signed in an EU Summit in Vilnius
- 1/11/14** Specific parts of the Agreement have been applied provisionally
- 22/5/15** EU and its partners declared that the 'provisional application' of the DCFTA will start on 1 January 2016
- 8/7/15** The Ukraine – European Union Association Agreement Approval Act was finally voted and entered into force between the EU, Georgia, Moldova and Ukraine respectively
- 14/10/15** The Council of State in Ukraine allowed the holding of the referendum
- 29/10/15** The Council of State in Ukraine announced the date of the Association Agreement Referendum
- 1/1/16** Establishment of Deep and Comprehensive Free Trade Areas (DCFTA)
- 9/1/2016** The European Commission President, Jean-Claude Juncker, warns that a No vote could lead to a "continental crisis"
- 6/4/16** Dutch Ukraine – EU Association Agreement Referendum call
- 31/5/2017** Approval of Additional Agreement between the EU with the European Atomic Energy Community and its Member States and Ukraine
- 15/7/17** Association Agreement Ratification Approval in Netherlands
- 1/9/2017** Association Agreement Becomes Operational

Figure 6.8 illustrates how stance alters at each stage of the policy making cycle in a timeline of pivotal legislative events. On July 2008, it was announced that a Stabilisation and Association Agreement would be signed between Ukraine and the European Union and that the Association Agreement had to be ratified by all member states of the EU in order for the document to take effect. Thus, our cycle begins with a for-stance for a prior critical decision being implemented and then evaluated in order to arrive to the agenda-setting stage with the day when the Referendum was announced and the core policy cycle to get initiated. We observe that the next occurrences during the first cycle

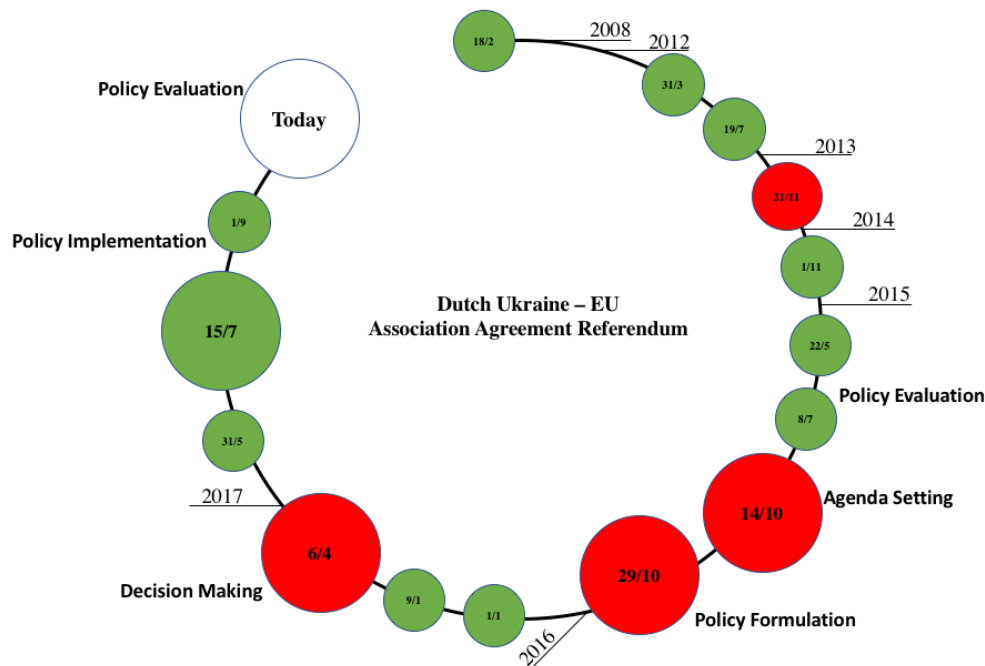


FIGURE 6.8: Dutch Ukraine - EU Association Agreement Referendum Policy Cycle

of policy implementation have a positive stance towards the signing of an Association Agreement between the EU and Ukraine reaching the day when a Ukrainian government decree suspended preparations for signing that was scheduled in an EU summit in 21 November 2013 shifting the stance into negative.

However, a resolution was approved by Ukrainian parliamentary members ensuring that the EU Foreign Affairs Council recommendations will be implemented switching the stance into positive towards this Association Agreement. Till the stage of the first cycle of policy evaluation when at an EU Summit, the new Ukrainian Prime Minister and European Union leaders along with the 28 national political leaders or heads of state on the European Council, signed in Brussels the political provisions of the Association Agreement the stance remains positive. The second policy cycle begins in October 2015, when a group of citizens using a new Dutch law forced the Dutch government to hold a non-binding referendum about a recently passed bill concerning the treaty with Ukraine shifting the stance into negative. Although the referendum was non-binding, the Dutch government decided to take the referendum outcome into account. The stage of decision-making corresponds to the Dutch Ukraine–EU Referendum held on the approval of the

Association Agreement on April 2016. The Ukraine treaty was rejected by 61.1% but accounted for only 19.5% of eligible voters – with a low turnout of 32.2 percent leaving a negative stance. As the Act was rejected, the Dutch States General enacted a follow-up law to either repeal the Act or put it into effect after all.

During the decision-making stage, with Jean-Claude Juncker having already mentioned the possibility of a continental crisis, the Centre-right Liberal Prime Minister Rutte not wanting to flat-out ignore the results, or push ratification through set, out to find a third option convincing his 27 counterparts to support a text that explained what the treaty with Ukraine was about changing the stance towards the Association Agreement into positive. The declaration mentioned that the treaty would not guarantee EU membership to Ukraine, and that the Netherlands was not obliged to provide Ukraine military assistance. On 15 July 2017 the Association Agreement was approved and ratified in Netherlands by all signatories leaving a positive stance, continuing with the same positive feeling in the implementation cycle with the Association Agreement coming into force and becoming operational in 1 September 2017.

6.4.1.4 UK EU Membership Referendum

Membership of the EU and its predecessors has long been a topic of debate in the United Kingdom. The country had joined, in 1973, what was then the European Economic Community. A referendum on continued membership of the European Communities was held in 1975, and it was approved by 67% of voters. In 2012, UK Prime Minister David Cameron rejected calls for a referendum on the UK's EU membership, but suggested the possibility of a future referendum to gauge public support. David Cameron, under pressure from many of his MPs and from the rise of UKIP party, in January 2013, announced that if elected in 2015, a Conservative government would hold an in-out referendum on EU membership before the end of 2017, on a renegotiated package with more favourable arrangements for continuing British membership of the EU.

Unexpectedly, the Conservative Party won the 2015 general election with a majority and soon afterwards the European Union Referendum Act 2015 was introduced into Parliament to enable the referendum. Cameron favoured remaining in a reformed European Union and sought to renegotiate on four key points: protection of the single market for

non-Eurozone countries, reduction of “red tape”, exempting Britain from “ever-closer union”, and restricting EU immigration.

The outcome of the re-negotiations was announced in February 2016. Some limits to in-work benefits for EU immigrants were agreed, but these would apply on a sliding scale for four years and would be for new immigrants only; before they could be applied, a country would have to get permission from the European Council. Thus, in a speech to the House of Commons on 22 February 2016, Cameron announced a referendum date of 23 June 2016 and commented on the renegotiation settlement. Cameron spoke of an intention to trigger the Article 50 process immediately following a leave vote and of the “two-year time period” to negotiate the arrangements for exit.

The EU had offered David Cameron an “emergency brake”, which would have allowed the UK to withhold social benefits to new immigrants for the first four years after they arrived; this brake could have been applied for a period of seven years. That offer was still on the table at the time of the Brexit referendum, but would expire when the vote would determine that the UK would leave the EU.

On 23 June 2016, the United Kingdom European Union membership referendum, also known as the UK EU referendum and the Brexit referendum, took place in the United Kingdom (UK) and Gibraltar to gauge support for the country either remaining a member of, or leaving, the European Union (EU). The referendum resulted in 51.9% of voters voting in favour of leaving the EU. The UK government initiated the official EU withdrawal process on 29 March 2017 putting the country on course to complete the withdrawal process by 30 March 2019.

After the result was declared, Cameron announced that he would resign by October. He stood down on 13 July 2016, with Theresa May becoming Prime Minister after a leadership contest. Withdrawal from the European Union is governed by Article 50 of the Treaty on European Union. Under the Article 50 invocation procedure a member notifies the European Council and there is a negotiation period of up to two years, after which the treaties cease to apply – although a leaving agreement may be agreed.

Although the 2016 referendum act did not expressly require Article 50 to be invoked, the UK government stated that they would expect a leave vote to be followed by withdrawal, despite government refusal to make contingency plans. Following the referendum result

Cameron resigned and said that it would be for the incoming Prime Minister to invoke Article 50. In October 2016, Theresa May promised a “Great Repeal Bill”, which would repeal the European Communities Act 1972 and restate in UK law all enactments previously in force under EU law.

The period for negotiation began on 29 March 2017 when the letter notifying withdrawal, signed by the United Kingdom’s prime minister, was handed to the president of the European Council in Brussels. Following the United Kingdom’s notification under Article 50, draft guidelines for the negotiations were sent to EU delegations. The draft was prepared by the President of the European Council. It stated that the guidelines define the framework for negotiations under Article 50 and set out the overall positions and principles that the Union would pursue throughout the negotiation. It stated that in the negotiations the Union’s overall objective would be to preserve its interests, those of its Member States, its citizens and its businesses, and that, in the best interest of both sides, the Union would be constructive throughout and strive to find an agreement.

As part of the withdrawal negotiation there could be a proposal by EU27 member states for the UK to pay a “divorce bill”, reportedly of up to £52bn, although a report of the European Union Committee of the House of Lords published on 4 March 2017 stated that if there is no post-Brexit deal at the end of the two-year negotiating period, the UK could withdraw without payment. Theresa May, has announced 12 negotiating objectives for UK withdrawal, confirming that the UK government would not seek permanent single market membership.

In Figure 6.9, we present how sentiment polarity reshapes at each stage of the policy making cycle in a timeline of critical political events. Following the oscillation of opinions, the cycle initiates in the agenda setting stage with a for-stance towards the political decision of Prime Minister David Cameron to renegotiate Britain’s membership terms in the EU through a UK EU Referendum. In the policy formulation stage, the stance remains positive as the EU Commission itself provides recommendations on how the Referendum question needs to be set for the voters.

- 11/5/15** UK plans an in/out referendum on its EU membership in 2016
- 1/9/15** UK EU Referendum Question set
- 10/11/15** UK outlines demands on EU membership
- 18/12/15** UK Prime Minister David Cameron returns from EU summit with a 52-word memo
- 02/02/16** EU deal: The President of the European Council issues EU compromise plan between UK and Brussels
- 19/2/16** EU Commission reveals there is no guarantee of UK's future in EU
- 17/6/16** Bank of England reveals 'capital flight' due to the UK EU Referendum
- 23/6/16** EU Referendum Result - UK voted for Brexit with Leave vote winning
- 24/6/16** UK Prime Minister announces his resignation after vote for Brexit
- 13/7/16** Home Secretary Theresa May becomes UK Prime Minister
- 02/10/16** PM Theresa May, at her first Tory conference speech, promises to trigger Brexit by next March
- 24/1/17** British Supreme Court rules for parliamentary approval before Article 50 can be triggered by government
- 13/3/17** UK Parliament gives government power to begin EU exit and passes Brexit authorization Bill
- 28/3/17** UK Prime Minister signs the letter that will trigger Brexit
- 29/3/17** EU Council President Donald Tusk receives a formal notice that UK will withdraw from the EU within the next two years

Additionally, from his part, David Cameron signalled that the UK will stage its referendum on membership of the European Union in July 2016 but made clear that UK's continued membership is vital not just to economic security but also to the fight against international terrorism, withholding the overall opinion polarity to positive. The sentiment remains positive as negotiations in Brussels continue until the UK Prime Minister David Cameron returns from EU summit with a 52-word memo and the President of the European Council issues an EU deal - compromise plan between UK and Brussels. The stance starts to change by the time that Donald Tusk reveals that the EU deal with the proposed measures towards immigration and other multiple issues is 'legally binding and irreversible'. Thus if it is accepted and signed, UK needs to follow the proposed

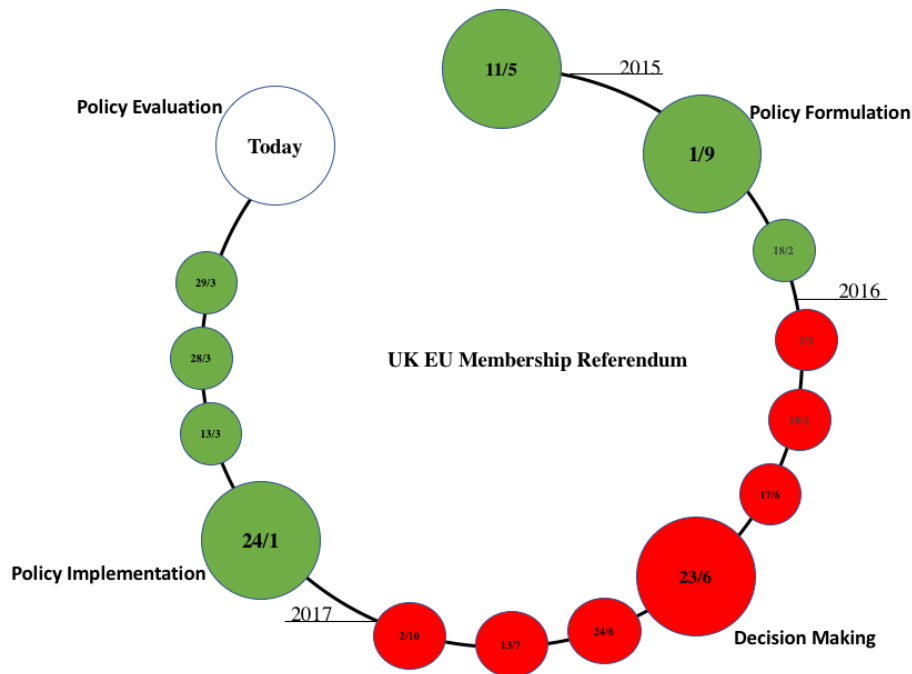


FIGURE 6.9: UK EU Membership Referendum Policy Cycle

guidelines. Under the uncertainty of UK's tomorrow fear and the possibility of a Brexit, the Bank of England reveals a capital flight' due to the UK EU Referendum, altering the overall stance into negative.

What is more, the negativity increases with IMF claiming that if Britain leaves the EU, there will be a short-term impact on stability and long-term costs to its economy. On 23 June 2016, specifically on the decision-making stage of the policy making cycle, UK votes for Brexit with Leave vote winning 52% to Remain vote acquiring 48% in the UK EU Membership Referendum acquiring an for-stance towards the result. Due to the negative outcome result, David Cameron, announces his resignation after vote for Brexit and Brussels claim that UK must leave the EU immediately, as it was chosen, shifting the stance into negative. The overall feeling remains as Theresa May is appointed as the new Prime Minister by the Queen on 13 July 2016 and commits, at her first Tory conference speech, that she will follow the result as it happened triggering Brexit by next March. At the same time, under the negative essence, EU Commission confirms UK will lose unrestricted access to the single market without freedom of movement and

the EU Chief negotiator hands to Theresa May a £50billion divorce bill to be paid for Brexit as soon as Article 50 is actually triggered.

On 24 January 2017, we arrive in the policy implementation stage, with the British Supreme Court ruling for parliamentary approval before Article 50 can be triggered by government and as a result on 13 March 2017 UK Parliament gives government power to begin EU exit and passes Brexit authorization Bill, altering the overall stance into positive. Till the last critical occurrence of this cycle, the stance remains positive, with UK Prime Minister signing the letter that will trigger Article 50 of the Lisbon Treaty indicating Brexit and EU Council President Donald Tusk receiving a formal notice that UK will withdraw from the EU within the next two years.

6.4.1.5 Hungarian Migrant Quota Referendum

The European migrant crisis, or else the European refugee crisis, began in 2015 when rising numbers of people arrived illegally in the European Union, travelling across the Mediterranean Sea or overland through Southeast Europe. These people included not only asylees seeking to apply for refugee status and the right of asylum, but also encompassed various others, such as economic migrants. During this crisis, four states (Germany, Hungary, Sweden, and Austria) received around two-thirds of the EU's asylum applications in 2015, with Hungary being one of the top recipients of asylum applications per capita. As a result, on 17 June 2015, Viktor Orbán's Fidesz government in Hungary announced the construction of a 175-kilometre-long fence along its southern border with Serbia.

On 22 September 2015, the European Union's interior ministers meeting in the Justice and Home Affairs Council approved a plan to relocate 120,000 asylum seekers over two years from the frontline states Italy, Greece and Hungary to all other EU countries, while Hungary should have to accept 1,294 refugees from other member states. However Hungary voted against the relocation plan, as a result its 54,000 asylum seekers were not taken into consideration, that number relocated to Italy and Greece instead. Following the decision, Hungary and Slovakia took legal action over EU's mandatory migrant quotas at the European Court of Justice in Luxembourg.

On 24 February 2016, Hungarian Prime Minister Viktor Orbán announced that his government would hold a referendum on whether to accept the European Union's proposed mandatory quotas for relocating migrants. On 5 May, after examining the legal challenges, the Supreme Court allowed the holding of the referred quota referendum. The National Assembly officially approved the referendum initiated by the government on 10 May. The initiative was approved with 136 votes cast in favour by the pro-government Fidesz. On 21 June, the Constitutional Court rejected all four appeals against plans to hold the quota referendum. Finally, President János Áder set 2 October 2016 as the date for the referendum.

While an overwhelming majority of voters rejected the EU's migrant quotas, ballot result was invalid due to low voter turnout. Specifically, 98.3% of Hungarian voters rejected mandatory EU asylum seeker quotas in the referendum question and only 1.7% of the voters answered "Yes" to the referendum question. The turnout of 43.8%, or 3.6 million voters, was above the threshold, meaning that the referendum was declared invalid with 200,000 ballots to have been spoiled. The Hungarian government failed to achieve a referendum result rejecting EU-imposed quotas on migrant numbers, after an insufficient number of people turned out to vote.

- 23/6/2015** Hungary suspends key EU asylum rule
- 12/9/2015** Record of 4,000 migrants move from Serbia to Hungary
- 14/9/15** Hungary enacts new migrant laws preventing the inflow of illegals
- 17/9/15** UN Secretary General "shocked" with Hungarian police forcing migrants back from its borders
- 22/9/15** EU' interior ministers approved a relocation plan of asylum seekers over two years to all other EU countries
- 18/10/15** Thousands of migrants enter Slovenia after Hungary closes borders
- 24/2/16** Hungarian Prime Minister Viktor Orbán announced a Referendum call on whether to accept the EU's proposed mandatory quotas for relocating migrants
- 5/5/16** The Supreme Court allowed the holding of the referendum, after examining the legal challenges
- 21/6/16** The Constitutional Court rejected all four appeals against plans to hold the referendum
- 5/7/16** Hungarian President János Áder set 2 October 2016 as the date for the referendum
- 2/10/16** Hungary votes for Migrant Quota Referendum
- 3/10/16** Hungary Prime Minister claims victory in a Referendum on mandatory EU migrant quotas, despite a low turnout that rendered it invalid
- 4/10/16** Hungary will bargain its position in EU deliberations on migrant policy in next week negotiations
- 10/10/2016** EU Commission tries to "appease" Hungary, increasing European Investment Fund support for small Hungarian rural firms by €160m

In Figure 6.10, we depict how stance polarity changes at each stage of the policy making cycle in a timeline of decisive political occurrences. Hungary being overburdened by illegal immigration, decided to suspend a key EU rule taking back asylum seekers who first enter Hungary but travel on to other countries. Thus, the first cycle of policy making begins from the point of key asylum suspension in order to reach the stage in which the Hungarian Referendum is announced. The stance of the first cycle from policy implementation in 23 June 2015 till the policy evaluation stage is negative.

During that period of time, Europe as a whole was struggling to deal with an enormous

influx of people, mostly from Syria but also from Afghanistan, Eritrea and other countries. Hungary was the the main entry point for those entering the borders in search of a better life and dealt with a record of 4,000 migrants reaching the limit. Hungary was considered at that time one of the countries worst-hit by the influx. As a consequence, Hungary declared a state of emergency claiming the need of tough new laws in order to stop migrants entering illegally from Serbia and other adjacent countries.

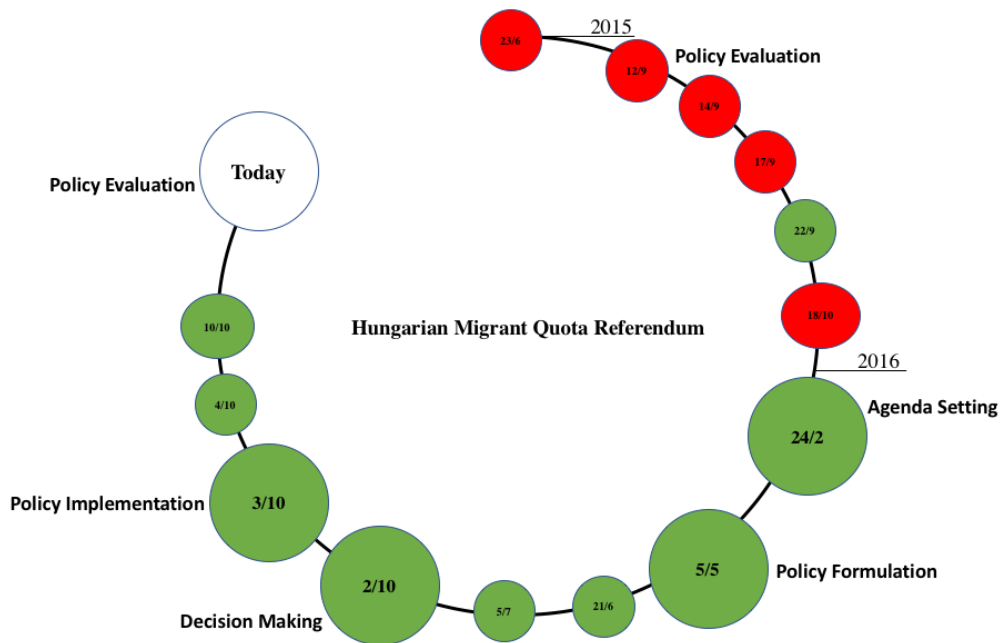


FIGURE 6.10: Hungarian Migrant Quota Referendum Policy Cycle

At the same time, Croatia not being able to accommodate the immigrants inside the country, was pushing Hungary to accept migrants by continuing sending them to the borders. Although on 22 September 2015, EU' interior ministers approved the need of a relocation plan of asylum seekers to other EU countries altering the overall stance into positive, the EU leaders at last failed to agree to a plan backed by Hungary to send a force to prevent migrants altering again the stance polarity into negative. As a result, Hungary reaching its own limits for not being able to respond to the country's needs, closed its border with Croatia in an effort to stem the flow of migrants through the country en route to western Europe. On 24 February 2016, Hungarian Prime Minister Viktor Orbán announced to hold a referendum on whether to accept the EU's proposed

mandatory quotas for relocating 160,000 refugees from Hungary, Italy and Greece to elsewhere in the European Union, initiating the second cycle of policy making.

The referendum referred to EU plans to establish a permanent way of relocating refugees from countries who received a disproportionate number of migrants. From the first stage of agenda setting with the referendum announcement till the stage of decision-making, the overall stance towards the call is positive. On 2 October 2016, the Referendum, initiated by the Hungarian government and related to the European Union's migrant relocation plans was held. Nearly 98% of those who took part in the Referendum supported the government's call to reject the EU plan. But with only 40.4% cast valid ballots the turnout was too low to make the poll valid. However, the Hungarian government claimed that the outcome was binding "politically and legally".

It is observed, that closing the policy cycle with the policy implementation till the final stage of evaluation, the stance remains positive due to the upcoming occurrences in the political scene. Specifically, Mr Orban insisted that parliament should pass legislation to advance the referendum's goal even if turnout did not have the support needed. In the days that followed, Hungary decided to bargain its position in EU deliberations on migrant policy in a series of negotiations with EU Commission in Brussels meetings. Simultaneously, EU Commission tried at last to "appease" Hungary, increasing European Investment Fund support for small Hungarian rural firms by €160m.

6.4.1.6 Discussion

From this empirical study and the policy cycles, we are able to indicate that the stance may start with a certain polarity at the initiation stage, but till the last phase of the policy making cycle, the specific polarity differentiates. This happens due to the fact that with political decisions constantly evolving, the original stance is affected dynamically and can change causing an alternation in its orientation.

Both groups of politicians and policy analysts, based on the aforementioned studies, can benefit from i) change of sentiment polarity, ii) possibility of predicting policy making outcomes, iii) acquisition of a visualization tool to easily understand and evaluate the daily citizens' concerns and expectations.

Thus, a dynamically automated stance classification system needs to be adopted based on the synergistic model of both citizens and governmental bodies in order to empower users' participation in the modern era of Digital Direct Democracy.

6.4.2 Electing U.S. President

The election of the President of the United States is an indirect election in which citizens of the United States who are registered to vote in one of the 50 U.S. states or Washington, D.C. cast ballots for members of the U.S. Electoral College, known as electors. These electors then in turn cast direct votes, known as electoral votes, for President. The candidate who receives an absolute majority of electoral votes is then elected to that office. If no candidate receives an absolute majority for President, the House of Representatives chooses the President.

An election for President of the United States occurs every four years on Election Day, held the first Tuesday after the first Monday in November. The election process initiates with the primary elections and meetings and moves to nominating conventions, during which each political party selects a nominee to unite behind. The nominee also announces a Vice Presidential running collaborator. Then the candidates campaign across the country to express their views and plans to voters and participate in debates with candidates from other political parties.

During the general election, Americans go to their polling place to cast their vote for President. But the tally of those vote does not determine the winner. Instead, Presidential elections use the Electoral College. To win the election, a candidate must receive a majority of electoral votes. In the event, no candidate receives the majority, the House of Representatives chooses the President and the Senate chooses the Vice President. [USA.gov \(2018\)](#)

The U.S Presidential election process:

- Spring of the year before an election: Candidates announce their intentions to run
- Summer of the year before an election through spring of the election year: Primary and debates take place
- January to June of election year: States and political parties hold primaries and meetings
- July to early September: Political parties hold nominating conventions to choose their candidates
- September and October: Candidates participate in Presidential debates
- Early November: Election Day
- December: Electors cast their votes in the Electoral College
- Early January of the next calendar year: Congress counts the electoral votes
- January 20: Inauguration Day

6.4.2.1 2016 U.S. Presidential Candidates

In the USA, Twitter is the mostly used social media by politicians to express their personal positions. Elections is a fundamental event of democracy allowing citizens to re-shape directly the political future of their country. In the US, the elections policy cycle lasts for a year. Consequently, studying such an occurrence will offer us the ability not only to stress our proposed system but also explore whether it can be possibly utilized as a digital direct democratic mechanism.

From the political parties that were involved in the 2016 U.S. Presidential elections, in our research, we mainly focused on the Democratic and the Republican parties along with their candidates Hillary Clinton and Donald Trump respectively. These two candidates were the ones that received the greatest percentage of votes and their political campaigns acquired a great number of online comments.

Hillary Clinton was the 67th United States Secretary of State and previously a United States Senator from New York. Clinton's main competitor in the 2016 Democratic primary election was Vermont Senator Bernie Sanders. She focused her campaign on

several issues, including expanding racial, LGBT, women's rights and improving health-care. Clinton was declared the presumptive nominee of the Democratic Party after she reached the required number of delegates.

Donald John Trump before entering politics was a businessman and television personality. Trump defeated sixteen opponents in the primaries and became the Republican leader for the 2016 presidential race. As a Republican, his political views on social issues were in totally contrast to those expressed from Clinton as the leader of the Democratic party. During his campaign, many of his public statements were considered controversial or false. Although polls, leading up to election day, had predicted a Clinton victory, in a surprise Trump was elected president winning the electoral vote while losing the popular vote.

6.4.2.2 U.S. Presidential Election Methodology

Policy, as an outcome of a political process, signifies the basic principles by which a government is guided. Thus, a policy model can be viewed as a cycle of stages, that each one represents a chain of consistent events based on their chronological occurrence. These instances, due to their sequential prevalence, are rationally connected to each other and consequently predictions upon them can be made in an effective way. Taking into account the policy life cycle as a baseline, we regard the timeline of U.S Presidential Elections as a policy. According to the chronological occurrence of critical political events that represent a major political decision taken at that specific time, we aim to present how public's sentiment polarity diverts at each policy stage.

Last but not least, considering the 2016 U.S. Presidential Elections, the time period of data collection initiated from 12 April 2015 when Former Secretary of State Hilary Clinton formally announced her candidacy for the presidential nomination of the Democratic Party till 20 January 2016 with the inauguration of the 45th President Donald Trump and the 48th Vice President Mike Pence.

6.4.2.3 The Timeline of 2016 U.S. Presidential Elections

The United States presidential election of 2016 was the 58th quadrennial American presidential election, held on Tuesday, November 8, 2016. The Republican party with

the businessman Donald J. Trump defeated the Democratic party represented by the former Secretary of State Hillary Clinton winning the Electoral College with 304 votes compared to 227 votes for Hillary Clinton. The U.S. Congress certified the electoral result on January 6, 2017, and the new President and Vice President were inaugurated on January 20, 2017 with Donald Trump taking office as the 45th President of the U.S.

The following is a timeline of major events leading up to, during, and after the United States presidential election of 2016.

- April 12, 2015: Former Secretary of State Hilary Clinton formally announces her candidacy for the presidential nomination of the Democratic Party
- April 30, 2015: U.S. Senator Bernie Sanders formally announces his candidacy for the presidential nomination of the Democratic Party
- June 15, 2015: Former Governor of Florida Jeb Bush formally announces his candidacy for the presidential nomination of the Republican Party
- June 16, 2015: American businessman Donald Trump, of New York, officially declares his candidacy for the presidential nomination of the Republican Party and launches his campaign by calling Mexicans rapists
- August 6, 2015: First Republican debate
- October 13, 2015: First Democratic debate
- October 22, 2015: Hilary Clinton testifies towards the Benghazi Committee
- December 7, 2015: Donald Trump campaign calls for a Muslim ban
- December 19, 2015: Third Democratic debate - Bernie Sanders' apology to Hilary Clinton
- January 14, 2016: Sixth Republican debate - battle over birthright
- February 1, 2016: Iowa caucuses - Democratic caucus is won by Hilary Clinton and the Republican by Ted Cruz
- February 9, 2016: New Hampshire primary - the Republican primary is won by Donald Trump and the Democratic by Bernie Sanders
- February 18, 2016: Donald Trump feuds with Pope Francis
- February 20, 2016: Jeb Bush formally withdraws his candidacy for the Republican presidential nomination
- March 30, 2016: Donald Trump states there has to be some form of punishment for women who have abortions
- April 19, 2016: Hilary Clinton won New York primary
- May 3, 2016: Ted Cruz formally withdraws his candidacy for the Republican presidential nomination
- May 26, 2016: Donald Trump crosses the minimum amount of delegates required to secure the Republican presidential nomination
- June 9, 2016: President Barack Obama officially endorses Hilary Clinton
- July 5, 2016: FBI director recommends no charges for Hilary Clinton based on her handling of classified information while acting as Secretary of State
- July 21, 2016: Donald Trump formally accepts the Republican nomination

- July 28, 2016: Hillary Clinton accepts the nomination from the Democratic Party, becoming the first female presidential nominee of a major party in U.S. history
- September 2, 2016: FBI releases documents on Clinton emails
- September 26, 2016: First presidential general election debate
- October 9, 2016: Second presidential debate
- October 19, 2016: Third and final presidential debate
- October 28, 2016: FBI reviews new emails related to Clinton server
- November 7, 2016: FBI says there is no evidence of wrongdoing in Clinton emails
- November 8, 2016: US Election Day
- December 19, 2016: Electoral College electors meet to cast their ballots. Trump receives 304 electoral votes, Clinton receives 227
- January 6, 2017: President of the Senate Joe Biden formally announces the electoral result
- January 20, 2017: Inauguration of the 45th President Donald Trump and the 48th Vice President Mike Pence

As shown in Figure 6.11, we illustrate how stance polarity diverges in the 2016 U.S. Presidential Elections timeline. The circles depict the events that took place during the specific elections timeline. With the colour red we indicate that the stance of the specific critical event is negative, with the green that is positive and with the yellow that is neutral respectively. The arrows determine the stance polarity over the two popular candidates Hilary Clinton (C) and Donald Trump (T) respectively, Thus, with the colour red we specify that the stance for the specific candidate is negative and with the green that is positive accordingly. The timeline initiates on 12 April 2015 with Hilary Clinton announcing her candidacy for the Democratic Party and concludes on 20 January with the Inauguration Day.

Observing the histogram of Figure 6.11, it is evident that the number of comments remains relatively low for both candidates till both political parties nominate their candidates and officially initiate their political campaigns. This is considered, for our study, the first day of the agenda setting cycle on 21 July 2016 with Donald Trump formally accepting the Republican nomination. At that specific event, both stances towards Clinton

and Trump are positive as political parties supporters are confident for their candidates for the presidential nomination.

Overall, during the policy formulation stage, the stance towards Hilary Clinton remains negative. This stance is compelled by the negative criticism coming from not only the Republic candidates but also from the rest Democratic Party candidates. The stance shifts only on 28 July when she accepted the nomination from the Democratic Party, becoming the first female presidential nominee of a major party in U.S. history.

Till the last day of the policy making cycle and during all debates, the stance polarity for Hilary Clinton remains negative, maybe affected by the fact that FBI released documents on Clinton emails although there were claims for no evidence of wrongdoing. With FBI director recommending no charges for Hilary Clinton based on her handling of classified information while acting as Secretary of State, the overall stance is not diverged and continues being negative towards her name.

As for Donald Trump, it is evident that in the initial stages of policy making cycle, the stance is positive but shifts into negative on the last two stages (Decision-making and Policy implementation phases) due to his references in the presidential debates for his personal negative stance in social issues such as punishment for women who have abortions, Muslim bans, Mexican barriers, etc.

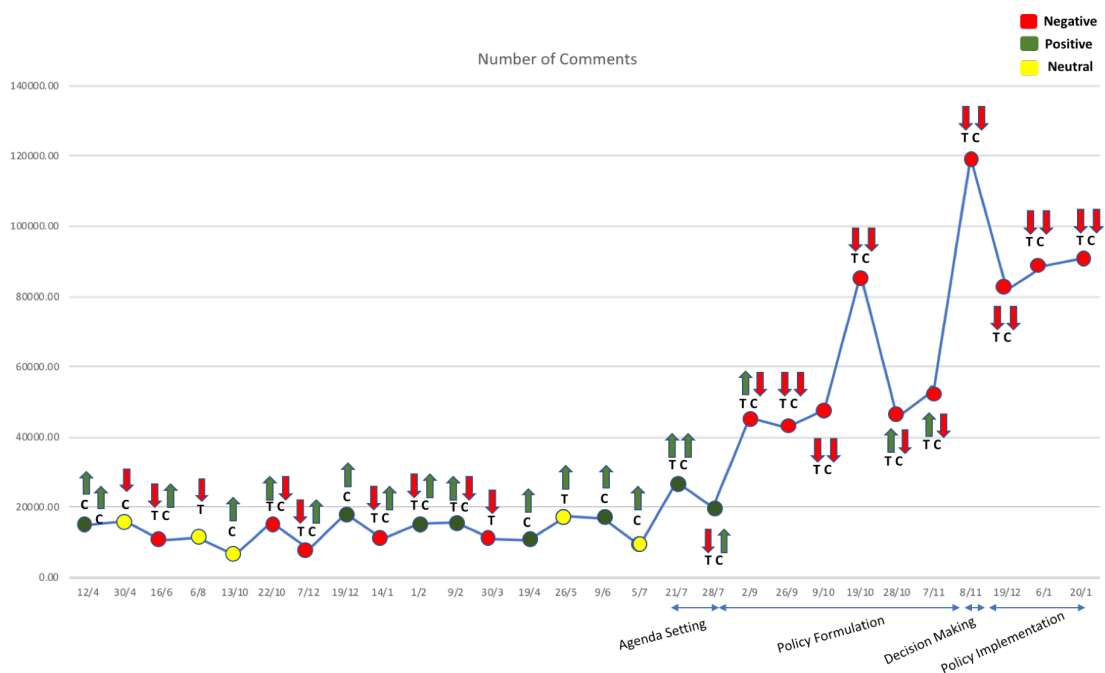


FIGURE 6.11: 2016 U.S. Presidential Elections Feeling

Processing the data collected online for both Donald Trump and Hilary Clinton, we were able to successfully classify the overall stance towards these two political figures in Twitter and categorize it as positive, negative and neutral. Figure 6.12 illustrates the stance classification results in the form of percentages in a pie, picturing with green the positive outcome, with red the negative and with yellow the neutral one, respectively. Observing the scheme, we notify that for Donald Trump the sentiment tweets have an overall negative feeling reaching a 45%, leaving the other half of the pie in the middle for positive and negative ones, with 28% positive and 27% neutral sentiment tweets respectively. Donald Trump remains historically unpopular and our research results from the proposed stance classification system comes in line with a research from Gallup according to which Trump ended the 2016 campaign with the worst favorability ratings in history [Saad, Lydia \(2018\)](#).

In contrast to Trump tweets, we observe that for Hilary Clinton, the positive and the neutral sentiment tweets have the same percentage of 38%, leaving a smaller part for the negative ones reaching only the 24% of the pie. The general feeling is that people's opinion about Hilary Clinton in Twitter remains till the last day of the presidential elections in an almost neutral position in contrast to Trump which is negative. During Hilary Clinton's campaign there was a time frame when allegations were made that Russia was behind the election-year hacks of Hillary Clinton's campaign and the Democratic National Committee affecting dramatically Clinton's figure and potential as a U.S.President. This specific critical event with Russia was also pinpointed in other researches during the elections [Pew Research \(2018a\)](#).

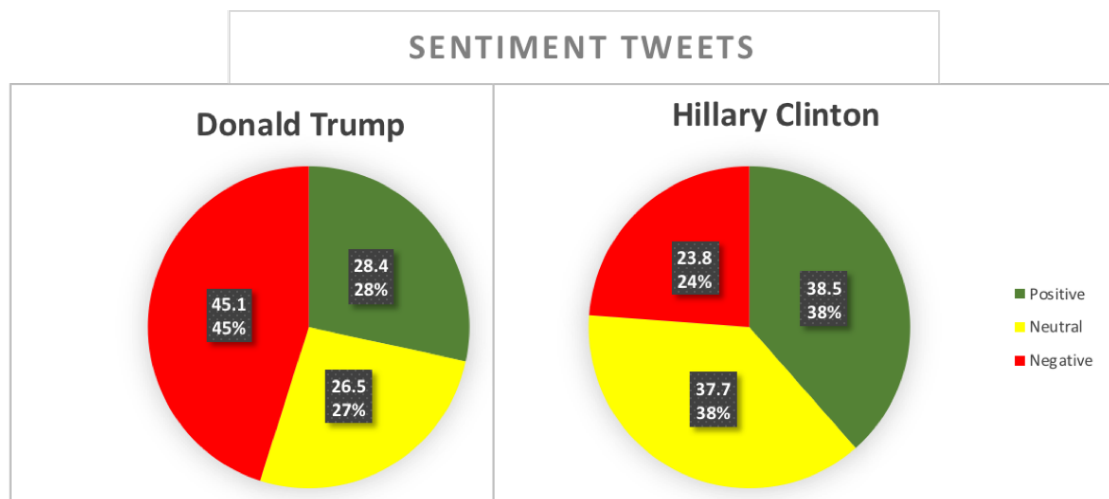


FIGURE 6.12: Trump & Clinton Twitter Stance

An additional point that needs to be underlined, refers to the number of followers and their fluctuation over time for both presidential candidates, as shown in Figure 6.13. Although the number of Twitter followers for both candidates is rising in a great pace, especially during the presidential debates, we notice that when Hilary Clinton announced her candidacy the number of followers started growing rapidly, leaving lower the followers of Donald Trump who remained less even when Trump announced his own candidacy for the Republican Party. What needs to be noticed, is that during the debates both candidates have to state both their personal political positions on social issues that affect U.S. as a country and also the directions and the policies that they will follow if they become U.S. President. In that way, the public feeling and the public stance towards both candidates changes and alters its polarity into positive or negative respectively according to what the public think and feels to what the candidates state. Nevertheless, there is a change in October 2015, with Donald Trump followers overpassing Hilary Clinton's and remained more increasing rapidly till the last day of the elections. During October, a critical event took place. Hilary Clinton testified towards the Benghazi Committee and this occurrence possibly was a major event that affected the number of people following her political activities from that day on till the last one.

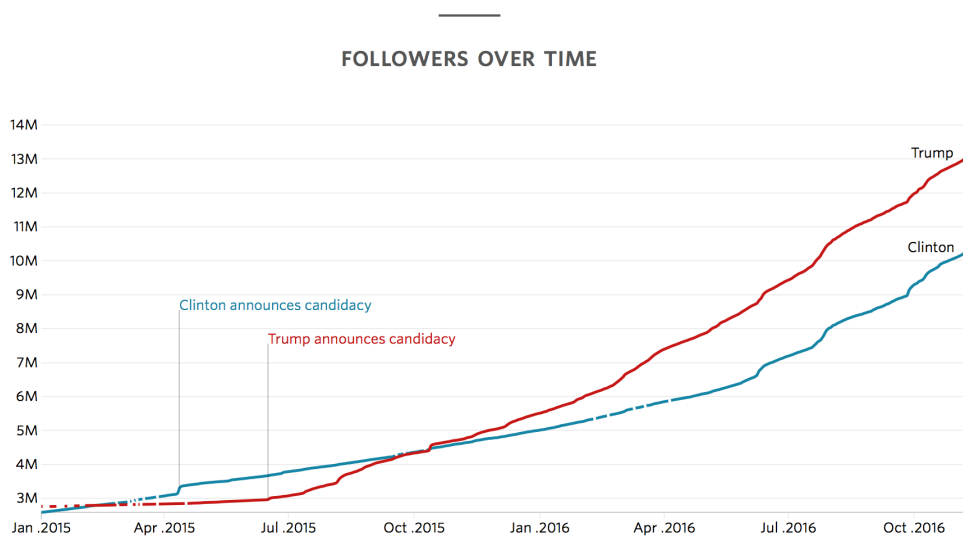


FIGURE 6.13: Trump & Clinton Followers Fluctuation

As we have already mentioned, during the 2016 U.S. presidential elections, both candidates formulated their personal stances especially over various social issues that concerned the U.S. community. We selected the topics with the highest popularity such as

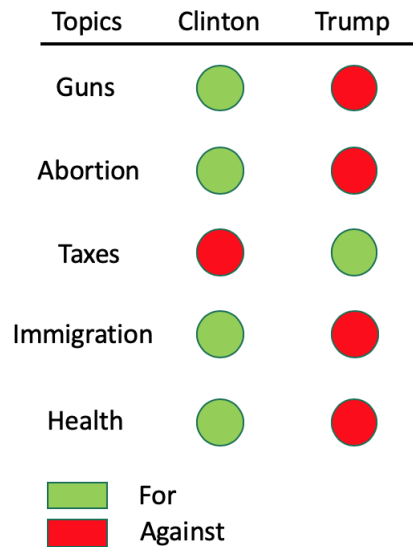


FIGURE 6.14: Trump & Clinton Topics Stance Polarity

abortion, guns control, taxes, immigration, health system. In Figure 6.14, we present the overall stance of Donald Trump and Hilary Clinton concerning all the aforementioned topics. The positive stance is illustrated in green, the negative in red and the neutral in yellow, respectively. Each candidate representing its political party follows a specific set of guidelines, views and directions on these social issues with a political position either for or against it. Observing the scheme, it is remarkable that neither of the two candidates has the same stance over the same topic. It is considered actually logical due to the fact that candidates represent their political parties and the Republican and the Democratic have opposite policies and directions towards the social issues. Both political candidates express a point of view with the exact opposite stance over each topic of discussion. More precisely, Hilary Clinton representing the Democratic Party has a positive stance towards guns control, positive towards abortion and construction of clinics for women who proceed to abortions, positive in opening the barriers for immigrants, and positive in improvements in the health system. On the other side, Donald Trump representing the Republican Party has a positive stance only in taxes and negative to all the rest social issues respectively.

From our stance classification system, we extracted the POS-tags with the highest frequency referred in the speeches, in the comments and in the tweets of Donald Trump and Hilary Clinton respectively. From all the words, we chose to present in Table 6.3 the adjectives along with the number of times used from each political candidate separately.

TABLE 6.3: Mostly Used Adjectives for Trump - Clinton

Trump		Clinton	
Word	#	Word	#
great	342	new	84
new	193	better	34
big	132	great	30
amazing	59	prod	29
bad	54	wrong	29
good	43	equal	26
nice	42	good	26
crooked	40	safe	25
dishonest	38	progressive	23
special	36	dangerous	23
wonderful	34	strong	20
sad	31	systemic	19
failing	31	important	19
negative	29	presidential	19
better	27	productive	19
lyin	27	happy	16
weak	26	comprehensive	15
illegal	26	qualified	15
strong	24	hard	12
little	23	fair	10
tough	20	serious	10
hard	20	smart	10
worst	19	strong	9
biased	18	rekless	9
crazy	17	hardworking	8
dumb	17	wealthy	8

6.4.2.4 Lessons Learned

Social media platforms but especially Twitter is a widely powerful tool. It is utilized by the the political candidates not only to express their political positions and influence their audience, but also to attack their opponents in the online political arena. For both key candidates, Donald Trump and Hilary Clinton, the citizens stance remained negative through the most policy making stages and a prediction of the final winner was not possible even by the gallops and the online polls conducted during the presidential elections period.

Certainly, employing our proposed stance classification system in real time could offer critical insights to the political campaign analysts making possible not only to monitor

the topics that negatively affect the candidate, but also help them shift the sentiment polarity during the policy formulation stage.

6.4.3 U.S. President's Feeling

Politics is considered the vehicle by which progress and change for the people occurs. The purpose of each government is to meet the needs of the people and the greatest challenge that faces is to re-engage the public in the political process.

Each political leader follows a specific guideline towards various societal issues (religious, social, etc.) expressing the specific positions of the political party he/she represents. For example, the Republican party follows the conservatism ideology in which abortions should be illegal. The Republican party stated on March 2015 that abortions should be illegal and its leader Donald Trump supported "some form of punishment" for women who had them. However, during his campaign as US President, quickly backed down from that statement asserting that the candidate believed the legality of the procedure should be left up to individual states, with any criminal penalties being reserved for abortion providers.

Consequently, the ideologies and political stances of each party as for or against social topics, affect directly the decisions made for an entire population, causing a great impact on their daily lives. Society changes according to politics, but also political stances and governmental commitments can be altered according to what society demands and expects.

What is more, nowadays both political parties and its leaders utilize in a great extent social media platforms rather than the traditional press to demonstrate their actions and decisions [Spiliotopoulou et al. \(2017\)](#). It was observed, that three days after winning the presidency in 2008, President-elect Barack Obama held a press conference, taking questions from reporters, in contrast to President-elect Donald Trump who turned to Twitter three days after winning the presidency in 2016. Since Election Day, Trump tweeted a list of countries with the leaders he has spoken before his team sent out a press release. An unusual feature of Donald Trump's successful campaign for president was his personal use of Twitter and it has continued as Trump meets with advisers and potential members of his cabinet.

During this part of our study, we aim to explore how presidential comments shared through a social media platform form the political environment, citizens' stance and the country's prosperity. Thus, we aim to answer certain research questions that emerge; Can we see if there is a swift from his prior announcements of specific topics? Can we see a change in his/her personal views on sensitive topics? Can political comments affect on a larger scale the economy of a country, of start a riot?

In this analysis, we aim, on the one hand, to track the U.S. President's feeling towards specific societal issues and predict with significantly high accuracy how the U.S. President will respond to a such an upcoming critical event determining its sentiment polarity. On the other hand, our goal is not only to understand how the public will react to the US President's decisions, but also how the economy of the U.S. will be positively or negatively affected. The stock market value is a measurement that will allow us to correlate political presidential statements with stock market fluctuation.

We will succeed this, by examining whether people's feeling converges or diverges with the presidential sentiment and discover how the public can affect and alter his final decisions not only by producing comments on social media platforms but also by moving towards actual actions.

A paradigm that we will utilize in our research to provide results is to find whether there is a relationship between Trump's tweets manifesting his governmental actions and how this can affect the stock market. In Figure 6.15, we depict a stock market graph representing the online trading that occurred for one year, after the 2016 U.S. Presidential Elections, specifically from June 2017 to May 2018. We notify that although the market initiated with a positive percentage in the trading, there was a fall in January 2018 that kept a negative sentiment till May 2018, when the sentiment towards the market share becomes positive.

6.4.3.1 Extracting U.S. President's Feeling Methodology

At this part of our research, we use Twitter as the selected social media platform for data collection and we accumulate Donald Trump tweets from the time when he became the 2016 U.S. President and through our mining techniques, we label them as positive - for, negative - against, or neutral. Thus, we aim to acquire knowledge on Trump's



FIGURE 6.15: Stock Market Trading

personalized position and sentiment towards social issues in order to predict, through our multi-layer classification system, his stance as for or against on upcoming critical events and political decisions.

Figure 6.16, illustrates Donald Trump's Tweets over time with red indicating negative stance, with green a positive stance and with yellow a neutral stance accordingly. In this Figure, we observe 2016 U.S. President Donald Trump's tweets stance towards policies under formulation (e.g. immigration law). According to Pew Research Center research on 2019 Public Policy Priorities in Donald Trump's agenda, the top of the list included Economy, Health Care, Education and Security [Pew Research \(2018e\)](#).

Utilizing as policy the Security and specifically the immigration law as a paradigm, we measure stock market value exploring the correlation of 2016 U.S. presidential statements with stock market capitalization. When Donald Trump became U.S. President formed a policy to increase the barriers for immigrants both inside and outside the U.S. However, many tech companies in the U.S. base their Human Resources on employees that have origin outside the U.S. (Asians, Indians, Europeans, etc) meaning that these companies would be greatly affected by the policy formulation on the specific immigration law.

Thus, as shown in Figure 6.16, when Donald Trump tweets include a negative stance towards the immigration law, it is observed that the stock market cap is greatly affected. When the tweets become positive then the market is quietly affected and last when the tweets do not contain any negativity (neutral) towards the immigration barriers then the market is not strongly affected.

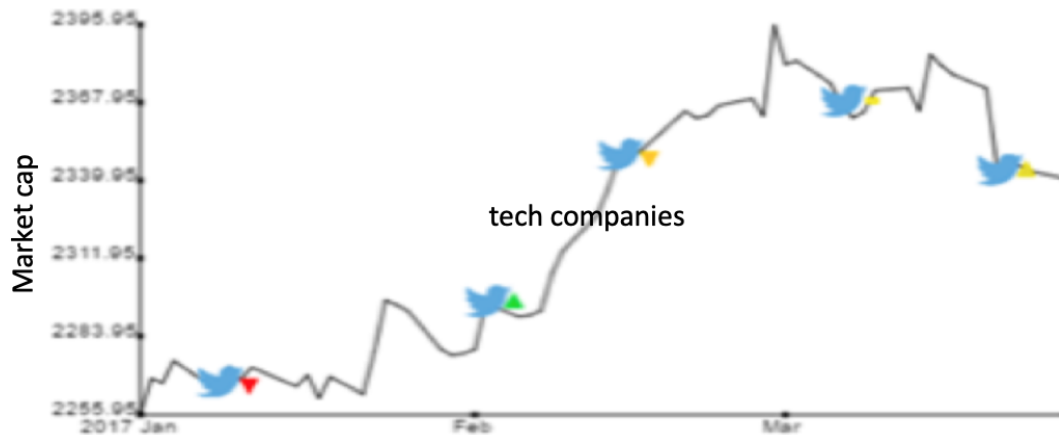


FIGURE 6.16: Donald Trump Personalized Tweets

From stance classification in Trump’s personalized tweets, we extracted the topics being mentioned along with the stance towards each one of them. As it is shown in Figure 6.17, almost all social issues referred to his tweets are coloured in red, with Donald Trump having an against stance, a personalized negative personal position towards them.

At the same time, we also categorized public sentiment towards the exact same topics as positive - for, negative - against or neutral and as it is depicted in the specific Figure, the public’ feeling diverges from Trump’s opinion in almost all topics, offering an opposite stance. In the Figure, we also indicate how the stock market is affected from the fluctuation between the opinion of the public and the one from the 2016 U.S. President. Specifically, in the stock market sector all topics including Finance, Healthcare, Technology and Retail have a negative fall creating an instability in the stock market trade.

6.4.3.2 Discussion

During this last part of our research, our proposed architecture is utilized twofold: i) as a personalized stance classification mechanism capable of tracking changes in U.S. Presidents’ stance towards various societal issues, and ii) as a tool to determine citizens’ sentiment polarity towards U.S. Presidents’ personal positions.

In general and considering the above, from the exploitation of these two different approaches, a leader can benefit if utilizing the proposed mechanism by early identifying

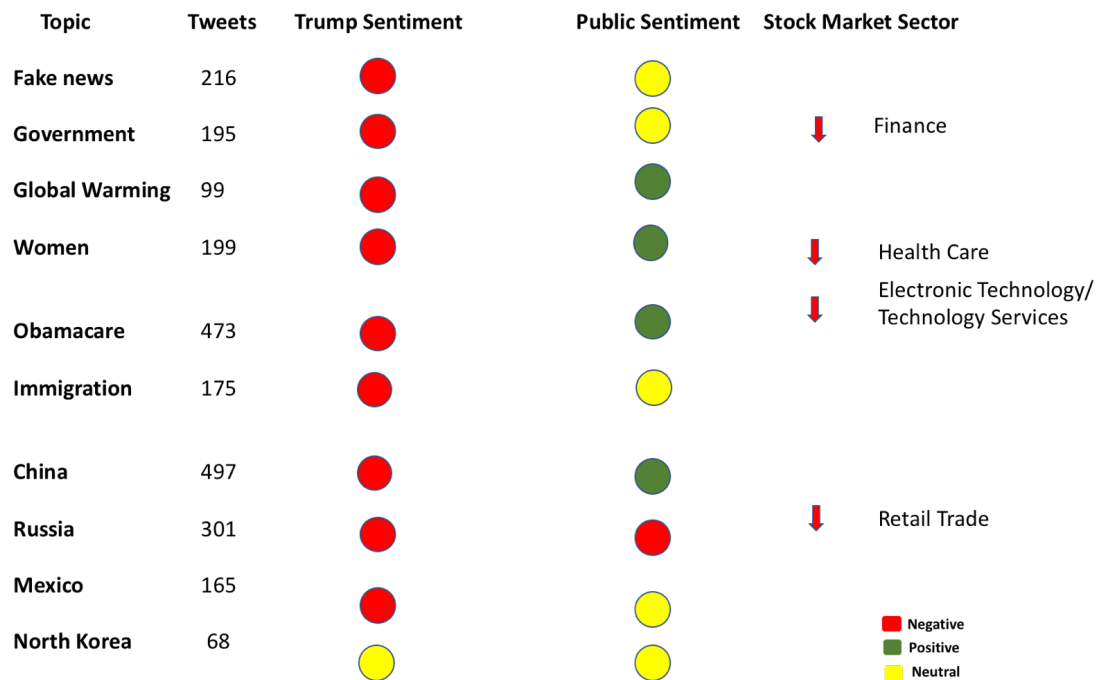


FIGURE 6.17: Donald Trump Personalized Tweets

personal stances or decisions that negatively affect a country or a company, and shift their leadership style.

6.4.3.3 Stance Classification Machine in Numbers

Since 1935, gallups are considered being a traditional way of delivering relevant, timely and visionary research on what the public worldwide thinks and feels on various critical events such as elections, referendums, etc. [The Washington Post \(2015\)](#). Companies in each country use data collected over the phone and increasingly online to conduct public opinion surveys and online polls asking public's views and sentiments over a topic of discussion in the form of question and answer. Analyzing and monitoring the collected data, companies identify and capture the human need to share opinions shaping public's reactions towards critical events in the form of visualized results predicting the event's outcome. In order for such a company to function, a great cost is required [Gallup, Inc \(2018\)](#).

Although gallups exist as long-established mechanisms to provide accurate predictions, there were many times in the last decades when the gallups missed their mark offering

results with a great percentage of error. [Spiliotopoulou et al. \(2017\)](#). More specifically, during the Greek Bailout Referendum gallups predicted correctly that “NO” vote would win but the percentage of “NO” was approximately 20% lower than the referendum’s real result giving a surprisingly unexpected large deviation from the real outcome [Spiliotopoulou et al. \(2017\)](#). Also, another paradigm deals with the 2016 U.S. Presidential Elections with results coming as a surprise to nearly everyone who had been following the national and state election polling, which consistently projected Hillary Clinton as defeating Donald Trump. Relying greatly on opinion polls, forecasters put Clinton winning at anywhere from 70% to as high as 99%, and appraised her as the favorite to win states such as Pennsylvania and Wisconsin which in the end were taken by Trump. The question that aroused was why online polls were that wrong with the elections results and the reason appeared to be that the polls underestimated Trump’s level of support [Pew Research \(2018f\)](#).

Regarding such paradigms, it is somehow evident that the forecasts made from traditional methods offer in a great percentage accurate results, but the aberration in the percentage rate can be too large and this is an astonishingly uncommon phenomenon. Such examples offer us the ability to believe that an automated mechanism, more precisely, a stance classification system, with a fusion of text mining techniques, can perform greater than traditional mechanisms in predicting political events with also a smaller cost and potentially replace them. Hence, maybe stance classification can be viewed as an e-government tool endorsing decision making and empowering citizens in the policy formulation process.

In this part of our research, we present our stance classification machine in the form of numbers in comparison to the gallups that conduct also predictions through public opinion polls indicating the times that our system outperforms the traditional mechanism. Table 6.4 offer insights towards this comparison. More precisely, taking as baseline the 2016 U.S. Presidential elections along with the surveys that have been conducted concerning the gallups and the online polls towards these elections [Pew Research \(2018d\)](#), [Pew Research \(2018c\)](#), [Pew Research \(2018b\)](#), [American Association of Public Opinion Research \(2018\)](#) we have in our capacity 1 stance classification system for predicting the elections result in comparison to a total of 100 U.S. interstate gallups. The total amount of people engaged in the gallup surveys were calculated to 500,000 in contrast to our system that collected 50,000,000 online profiles. Additionally, the forecasters were able

TABLE 6.4: Stance Classification Machine in Numbers

	Gallups & Online Polls	Stance Classification	Time better	
Total Polls/ Gallups inter-State	100	1		
Total people (engaged)	500,000	50,000,000	100	times better
Total words processed	100,000	85,000,000	850	times better
Total opinion processed	500,000	50,000,000	1	
Total			85,000	85,000
Cost	10,000,000	10,000	1,000	times more cost
Total cost / effectiveness ratio			85,000,000	times better

to process a total amount of 100,000 words cumulatively when our classification system simultaneously processed 85,000,000 words making the proposed system 850 times better than the traditional one. As for the total amount of the opinions extracted, gallups explored 500,000 opinions compared to 50,000,000 opinions of our system. Measuring and calculating the aforementioned results, the stance classification system outperforms the gallups over 85,000 times. Considering also the cost of such an act, our system had an actual cost of 1,000 u.s.dollars when the gallups that lasted for a year during the presidential elections had a cost of 10,000,000. As a consequence, calculating the effectiveness ratio between the two mechanisms, it is evident that the proposed classification system is 85,000,000 times better than the traditional gallups in terms of cost.

6.5 Political Value & Novelty

Acquiring a spherical view from the above analysis, a number of parallel dimensions emerges. It provides a broader, more comprehensive and deeper involvement of people in the formation of public policies by systematically exploiting the new Web 2.0 social media and involving various groups, that typically do not visit official government e-participation websites. Instead they are open to share their political views by posting their comments on social media platforms. More specifically, it ambitions to bring government a step closer to citizens, using online platforms in which both citizens and government generate online content. In this way, the distance between policy making and society is minimized in comparison to the first generation of e-participation approaches in terms of time and tools needed.

It offers low cost and adaptability by developing a framework for citizens and political figures with various opinions and multiple priorities in order to improve the efficiency of a political decision making process. Giving the ability to government agencies to hear directly from citizens their thoughts, feelings and concerns in online spaces where

they feel free to express their opinions and make suggestions for improvements, enables the agencies to collect, evaluate and decide about society's future using citizens input through an innovative way. Considering that policy design problems are 'wicked', our general approach provides a stronger interaction between makers of a policy under formulation and government both in an efficient way and at a low cost. Thus, the problems acquire a better definition and the main objectives become more targeted leading to a more socially-rooted policy.

Moreover, the ability to collect citizens' feedback from different online sources in a single platform' and acquire knowledge on their sentiments and stance over policies and societal issues that affect even a country, infusing mining techniques jointly, offers a synthesis of data for achieving successfully citizens' involvement in the decision-making process.

Chapter 7

Conclusions & Further Steps

7.1 Overview of the Three Opinion Mining Mechanisms

Web 2.0 and social media were initially exploited by private sector firms, primarily in their processes of marketing and customer relations. It was much later that government agencies began to exploit them in their public policy-making processes for interacting with citizens. Through this dissertation, our aim was to focus our research attention on the development of knowledge on how (i.e. through which frameworks methods and practices) social media can be effectively and efficiently utilized in government.

Following that direction, three different mechanisms of social media exploitation for empowering e-participation and enhancing public policy formulation have been proposed. All of them have been designed, implemented, tested and evaluated with real use-case scenarios. The first one, named as Generic Opinion Mining Mechanism, performs ‘active crowdsourcing’ through centralized platform publishing and collection of policy related content focused on automated and centrally managed combined use of various social media for establishing bi-directional communication with multiple citizens’ groups. The second one, named as Advanced Opinion Mining mechanism, performs ‘passive crowdsourcing’, in which government has a passive role, allowing the collection of online content on a specific topic or public policy that has been freely generated by citizens without any stimulation by government. It focused specifically on classifying the stance of online posts by determining the stance polarity of a popular and critical political event. The

third mechanism, named as Multi-Layer Opinion Mining mechanism, endorses crowdsourcing and public policy formulation based on the need of government agencies to utilise knowledge when addressing critical societal problems. It offers a novel approach on how a stance classification system can be utilized in e-government empowering direct democracy. It also introduces a stance classification architecture that employs novel linguistic features to train the stance classification model combining mining techniques such as topic modeling, sentiment analysis and stance classification and determining public's stance as for or against towards critical governmental decisions in a timeline of political events. Although it is important to determine separately whether a user's opinion is positive or negative, or his/her personal position towards a specific topic as for or against, it is more crucial and intriguing to classify an overall emotional state.

The findings from the research designing and implementing each one of the above three opinion mining mechanisms indicate that the above approaches can definitely contribute to increase public participation and empower citizens in the decision-making process. In general, we can remark that these new digital mechanisms enable a more extensive and less costly application of the e-participation paradigm. Their main differentiations lie on:

- i. type of crowdsourcing they perform (active or passive)
- ii. targeted audience (citizens, governments, political representatives)
- iii. level of participation (first mechanism lies on e-Engaging whereas the other lie two on e-Empowering)
- iv. processing methods (first mechanism focuses on sentiment analysis, second one on topic modeling and stance classification and the third one on the combination of all 3 mining techniques)

All approaches, exploit multiple Web 2.0 social media sources simultaneously, in a centrally managed manner based on a central platform. Data acquisition is automated using either their APIs when provided or rely on the development of specialised crawlers. All three methods make sophisticated processing of the collected content, in order to extract the most significant points from it, in order to reduce the 'information overload' and provide meaningful insights for the policy formulation process. For instance, they all

employ opinion mining techniques such as topic modeling, sentiment analysis and stance classification in order to extract the opinion and stance from the social media input.

The major advantages of ‘passive’ crowdsourcing approaches over the ‘active’ one is that: (i) it enables government agencies to access, retrieve and exploit a larger volume of more diverse policy relevant content from a wider variety of social media sources of different political orientations; and (ii) this content already exists online, so government agencies do not have the need to find ways to attract citizens to participate in and generate new content. It should be emphasized that content accumulated freely generated is much more extensive and politically diverse than the content generated in government websites and online platforms under government direction or stimulation.

This is rational since the ‘active crowdsourcing’ approach uses the accounts of the particular government agency in several social media, while the passive one utilizes other accounts, blogs, websites, etc. not belonging to the government. That is also the reason for characterising the level of participation as ‘e-engaging’ in the first mechanism, in comparison to ‘e-empowering’ in the other two. E-engagement deals with top-down consultation of citizens by government, while e-empowerment follows the bottom-up perspective, where citizens are considered producers rather than just consumers of policy.

It has been generally concluded that these three opinion mining mechanisms for social media exploitation by government agencies can significantly enhance and support public policy formulation (development of new public policies for addressing complex and ‘wicked’ social problems), as they can provide to government agencies extensive knowledge of high importance for this purpose. In particular, the mechanisms extract from various social media platforms and online news sites large amounts of data concerning the level of interest in the society for a particular topic of discussion or an existing or under development policy, and the sentiment/stance of citizens.

Additionally, acquiring insights through the extraction and mining process of the collected data on issues that trigger citizens’ discussions like a referendum call, these proposed mechanisms offer to policy makers the knowledge for solving relevant problems or improving policies and relevant arguments (positive or negative), which can considerably facilitate, promote and empower policy innovation, policy formulation and decision making. Last but not least, it is intriguing to mention that all three mechanisms are capable of ‘sensing’ the emotional changes in the sentiment polarity towards policies under

formulation, empowering government agencies to 'sense' more efficiently these changes coming from the public.

Closing this research, it is fundamental to mention that the Research Questions outlined in the beginning of this dissertation have all been answered through the detailed analysis presented in the above chapters and through the design and implementation of the three proposed opinion mining mechanisms. Figure 7.1 depicts the answered Research Questions.

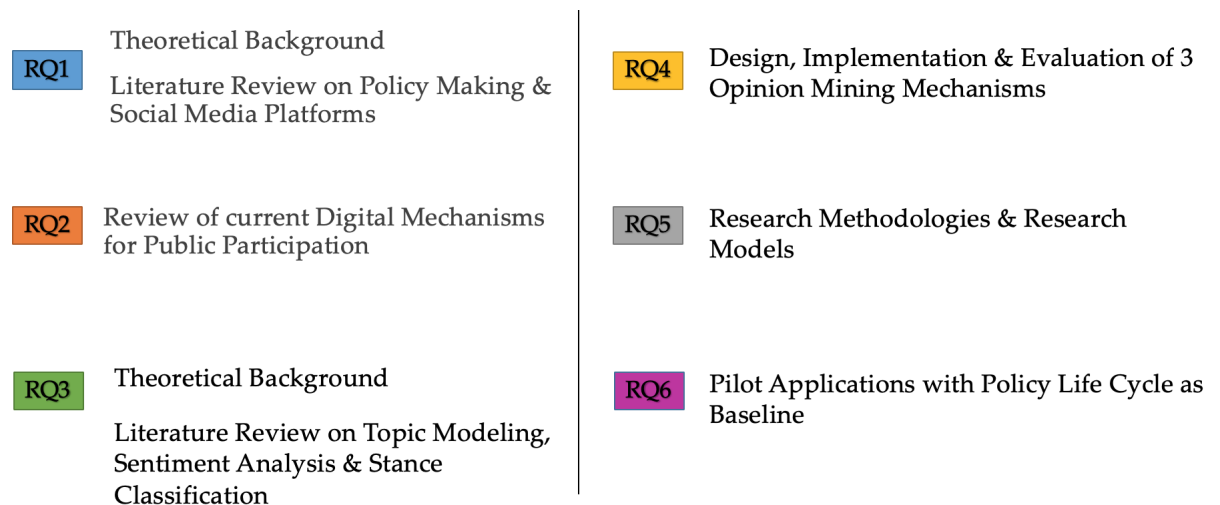


FIGURE 7.1: Research Questions Answered

7.2 Implications

Useful insights on the capabilities, strengths and weaknesses of the three proposed systems were developed from this evaluation. In general, it was concluded that these three processes are a time- and cost-effective way to organize wide-ranging policy consultations that reach large audiences, convey policy-related multimedia messages to them, and inspire and empower them to think about public policies under development and to share their specific ideas, expertise and opinions. The three mechanisms can also be a valuable tool for identifying the main issues perceived by people with regard to a particular social problem or field of government activity and for gathering from them useful ideas on potential solutions and directions of government activity (i.e. for implementing crowdsourcing ideas in the public sector).

Our research has interesting implications as it opens up new academic opportunities on advanced mechanisms, approaches and strategies for successful social media exploitation by governments, as well as the design of advanced information systems for this purpose, and relevant application process models. It also provides different methodologies from a public policy perspective for their theoretically sound evaluation. With regard to government practice and management, it provides government agencies with effective methods and ICT resources to interact with wider and more heterogeneous audiences in a short time and at a low cost, increase public engagement in their policy making processes, gather valuable citizens' insights, ideas and opinions and, ultimately, better more socially rooted public policies. It can provide considerable opportunities for broader interaction with society.

7.3 Limitations & Future Steps

At the same time, there are some limitations in our research study, which should be dealt in the future research.

The proposed Generic Opinion Mining mechanism offers a "soft" model for implementing crowdsourcing ideas in government. It has been examined in a small number of pilot applications, so it requires further evaluation, in different types of government agencies and for various types of policy consultations. Furthermore, it focuses on the utilization of social media by government agencies as a means of more intensive "external communication" with their external environment (e.g. with society – civil society organizations and individual citizens), so that further research on the exploitation of social media as a means of more intensive "internal communication" between different governments is required concerning the design and implementation of public policies.

What is more, some risks have been identified, during the development of the proposed Advanced Opinion Mining Mechanism. One issue raised is linked with the degree of representativeness of the citizens' groups who produce the content collected from the selected social media platforms, along with its reliability (i.e. whether it is non-biased, non-manipulated and of good quality). Nevertheless, despite the possible limitations, the results from the second proposed classification mechanism are very promising and highly useful for the development or improvement of public policies. The selection of

the Web 2.0 sources to be monitored is also of significant importance in this matter. Moreover, from its evaluation and validation through the use-case scenarios, it has been concluded that the advanced opinion mining mechanism possesses to a good extent all the required characteristics for a wide adoption by government agencies.

When designing and developing the Multi-Layer Opinion Mining Mechanism, there were some limitations that our research needed to deal with. Specifically, more and more online news sites nowadays require users' subscription with a specific amount of fee to be paid in order for a user to sign in and collect user's comments. What is more, the APIs from Twitter or third party services frequently change or upgrade so the APIs used in our research needed to be constantly checked. Last but not least, the requirement to regularly update such a platform with so many multiple modules is a very challenging task.

It has become a great challenge also to identify unwanted or malicious content through social media exploitation. Traditional examples include social network spam as well as the spread of false news online that are identified being major new concerns, that emerge critical solutions to ensure integrity and authenticity of the user's input.

Last but not least, the collaboration with political parties to run real time policy making campaigns employing our proposed architectures with a set of tools for descriptive and predictive analysis of time series, is considered fundamental to empower users' participation in the modern era of Digital Direct Democracy.

As a future work, in order to acquire greater knowledge, it is necessary to conduct additional research for the development and evaluation of other types of crowdsourcing methods relying on the exploitation of social media, both 'active' and 'passive' ones. Further research is required in order to develop a wide range of ICT-based methods and practices in government. What is more, it would be interesting to explore emotions containing tolerance or irony employed as additional features in our stance classification system.

Moreover, additional models could be reviewed in order to increase the performance of our stance classification system. Furthermore, we could examine more sophisticated classifiers such as the utilization of Deep Learning to discover hidden features that are able to not only improve the performance but also to lead into new metrics. Another

stream of future research is related with the challenges with regard to users' privacy protection due the continuous exposure of their personal sensitive data in the social media platforms.

Through our entire research in this dissertation, we concluded that there does not exist a simple approach to create a modern and efficient policy making cycle that involves real time citizens' participation and utilizes only one single model. It is evident that a multi-layer policy making process is required to successfully manage to track public's stance over governmental critical decisions in all stages of policy making life cycle and engage citizens in the decision-making process.

Appendix A

Appendix A: Questionnaires

A.1 Appendix 1

Policy-making process, public participation and ICT support questionnaire

- i. Which are the main public policies (at a local or central level) you are responsible for?
- ii. Which are the main stakeholder groups affected by these public policies?
- iii. To what extent do you have discussions– consultations with representatives of the above stakeholder groups on these policies?
- iv. In which stages of the policy-making lifecycle? – And how?
- v. Which are the main obstacles for this?
- vi. How important do you think it is to have discussions-consultations with representatives of the above stakeholder groups on these policies?
- vii. What is the final outcome you would expect to get from these discussions– consultations with representatives of the above stakeholder groups that would assist you in designing-implementing better policies?
- viii. To what extent do you have wider discussions–consultations with the wider public affected by these policies?

- ix. In which stages of the policy-making lifecycle? – And how?
- x. Which are the main obstacles for this?
- xi. To what extent would be useful a software tool that would publish a political message or public policy under formulation to several appropriate Web 2.0 social media, and then collect and process users' ratings, comments and other interactions?
- xii. What social indicators would you like to know for the involved citizens during policy planning or implementation?
- xiii. What other means (ICT-based or not) you think would contribute to successful policy planning and implementation for your organization?

A.2 Appendix 2

Functionality requirements questionnaire

- i. What functionality should future tools for policy-making over social media provide?
- ii. What are useful indicators for a policy-making campaign over social media?
- iii. Where is the value in having policy-making consultation over social media?
- iv. What kind of content would you prefer to publish in policy messages reaching wide?
- v. How important do you think it is to have age, sex and instruction level of people reached in policy-making?

A.3 Appendix 3

Evaluation questionnaire To what extent this approach is useful for:

- conducting policy-related social media consultations that reach and involve wide audiences in a short time and at a low cost;

- identifying the particular problems/issues in a particular domain of government activity or public policy;
- identifying possible solutions to them;
- as well as relevant advantages – positive arguments and disadvantages – negative arguments;
- identifying stakeholders' groups with different views and concerns; and
- finally, facilitating convergence (at least to some extent) among them.

Appendix B

Appendix B: System - Source Code

Appendix Chapter, System - Source Code, contains the python scripts, HTML, PHP, CSS, and SQL databases, used to build the core systems. It utilizes the various text mining scripts described in Appendix Chapter C: Data Analysis - Source Code, in order to process the text and display the data. The source codes are grouped in thematic categories. A list of the source files is followed by a short description.

- Social Media
 - Twitter Module
 - NY Times Module
 - NY Time Api
 - Guardian Module
 - Article Module
 - Hashtag Module
 - Stocks Module
 - Stock Data Collection

- Backend:
 - SQLite Module

- Json to MongoDB
- Database MondoDB
- Backend
- Backend Client
- Website:
 - Front End - Home
 - Front End - Search
 - Front End - Setting
 - Website - Menu CSS
 - Website - Search
 - Website - Settings
 - Website - Home
 - Website - Base

B.1 Twitter Module

```
import twitter
import datetime
import os
import requests

api = twitter.Api(consumer_key='gZ5obhA8sp11Wt09g6XLi8Abr',
                  consumer_secret='J8fjMSu6vdoEH1dJhxred3xheitCxs6hyMFmPW1ETZ0xHIix1C',
                  access_token_key='1100502152026439687-MRZGuGeKI01lvCgemznQcTn9aVZMa4',
                  access_token_secret='VF4C5xsbZPhpnX1PhJMo7kjN76g81wfvuYSPZWih6UTUk')

def get_tweets(company, start_date, end_date):
    """
    Returns an array of 50 tweets in string form. \n

    Arguments:\n
    company - a string that is the name of a company you wish to search tweets for \n
    start_date - a string that is the date to start from. Can only look 1 week into past due to
    api limitations. YYYY-MM-DD \n
    end_date - a string that is the date to end at. Cannot be past today. YYYY-MM-DD
    """
    if not isinstance(company, str):
```

```
        raise Exception("Company must be a string")
    search = api.GetSearch(company, count=50, since=start_date, until=end_date)
    array = []
    for tweet in search:
        array.append(tweet.text)
    return array

def print_tweets(tweets):
    """
    Writes the tweets to a text file.
    """
    f = open("tweets.txt", "w")
    for tweet in tweets:
        f.write(tweet)
        f.write("\n")
    f.close()

def delete_tweet_file():
    """
    Deletes the tweet text file.
    """
    os.remove("tweets.txt")

# def main():
#     print_tweets(get_tweets("facebook", "2019-03-24", "2019-03-26"))

# if __name__ == "__main__":
#     main()
```

B.2 Twitter Stream

```
import oauth2 as oauth
import urllib2 as urllib

access_token_key = "29904935-AHA0f5xnBEg7Mry6KGw4dbGBWwIuBKQqaWWDzdgQ"
access_token_secret = "EVZ9PMsZHxAh2Daz0VjZbLjce3aTVimisa6CIOKj4"

consumer_key = ""
consumer_secret = ""

_debug = 0

oauth_token = oauth.Token(key=access_token_key, secret=access_token_secret)
oauth_consumer = oauth.Consumer(key=consumer_key, secret=consumer_secret)

signature_method_hmac_sha1 = oauth.SignatureMethod_HMAC_SHA1()
```



```
http_method = "GET"

http_handler = urllib.HTTPHandler(debuglevel=_debug)
https_handler = urllib.HTTPSHandler(debuglevel=_debug)

'''
Construct, sign, and open a twitter request
using the hard-coded credentials above.
'''

def twitterreq(url, method, parameters):
    req = oauth.Request.from_consumer_and_token(oauth_consumer,
                                               token=oauth_token,
                                               http_method=http_method,
                                               http_url=url,
                                               parameters=parameters)

    req.sign_request(signature_method_hmac_sha1, oauth_consumer, oauth_token)

    headers = req.to_header()

    if http_method == "POST":
        encoded_post_data = req.to_postdata()
    else:
        encoded_post_data = None
        url = req.to_url()

    opener = urllib.OpenerDirector()
    opener.add_handler(http_handler)
    opener.add_handler(https_handler)

    response = opener.open(url, encoded_post_data)

    return response

def fetchsamples():
    url = "https://stream.twitter.com/1/statuses/sample.json"
    parameters = []
    response = twitterreq(url, "GET", parameters)
    for line in response:
        print line.strip()

if __name__ == '__main__':
    fetchsamples()
```

B.3 NY Times Module

```

import json
from time import sleep
import requests

def nytimes_comments(article):
    article=article.replace(':', '%253A') #convert the : to an HTML entity
    article=article.replace('/', '%252F') #convert the / to an HTML entity
    offset=0 #Start off at the very beginning
    total_comments=1 #set a fake minimum number of contents
    comment_list=[] #Set up a place to store the results
    while total_comments>offset:
        url='http://www.nytimes.com/svc/community/V3/requestHandler?callback=NYTD.commentsInstance
        .drawComments&method=get&cmd=GetCommentsAll&url='+article+'&offset='+str(offset)+'&sort=
        newest' #store the secret URL
        sleep(.2) #They don't like you to visit the page too quickly so take a one second break
        before downloading
        file = requests.get(url).text
        file=file.replace('*/ NYTD.commentsInstance.drawComments(', '') #remove some clutter
        file=file[:-2] #remove some clutter
        results=json.loads(file) #load the file as json
        comment_list=comment_list+results['results']['comments']
        if offset==0: #print out the number of comments, but only the first time through the loop
            total_comments=results['results']['totalCommentsFound'] # store the total number of
            comments
            print('Found '+str(total_comments)+' comments')

        offset=offset+25 #increment the counter

    return comment_list #return the list back

def comment_body(comment_list):
    comments = []
    for comment in comment_list: #loop through the list
        comments.append(comment['commentBody'])
    return comments

'''
A sample of what it does.
You probably want to run it over a loop of articles.
You might also store the fields you want in a CSV file for later use or export.
'''

# article_url='https://www.nytimes.com/2019/04/20/business/boeing-dreamliner-production-problems.
    html'# URL of the article you want to get
# comments=nytimes_comments(article_url)

```

```
# comment_texts = comment_body(comments)

# for comment in comment_texts: #loop through the list
#     print(comment) #print out the comment text

'''
Fields:
commentID
status
commentSequence
userID
userDisplayName
userLocation
userTitle
userURL
picURL
commentTitle
commentBody
createDate
updateDate
approveDate
recommendations
replyCount
replies
editorsSelection
parentID
parentUserDisplayName
depth
commentType
trusted
recommendedFlag
permID
isAnonymous
'''
```

B.4 NY Time Api

```
import requests

API_ROOT = 'http://api.nytimes.com/svc/search/v2/articlesearch.'

API_SIGNUP_PAGE = 'http://developer.nytimes.com/docs/reference/keys'

class NoAPIKeyException(Exception):
    def __init__(self, value):
```

```
        self.value = value
def __str__(self):
    return repr(self.value)

class articleAPI(object):
def __init__(self, key = None):
    """
    Initializes the articleAPI class with a developer key. Raises an exception if a key is not
    given.
    Request a key at http://developer.nytimes.com/docs/reference/keys
    :param key: New York Times Developer Key
    """
    self.key = key
    self.response_format = 'json'

    if self.key is None:
        raise NoAPIKeyException('Warning: Missing API Key. Please visit ' + API_SIGNUP_PAGE +
        ' to register for a key.')
```

```
def _bool_encode(self, d):
    """
    Converts boolean values to lowercase strings
    """
    for k, v in d.items():
        if isinstance(v, bool):
            d[k] = str(v).lower()

    return d

def _options(self, **kwargs):
    """
    Formats search parameters/values for use with API
    :param |\*kwargs: search parameters/values
    """
    def _format_fq(d):
        for k,v in d.items():
            if isinstance(v, list):
                d[k] = ' '.join(map(lambda x: '"' + x + '"', v))
            else:
                d[k] = '"' + v + '"'
        values = []
        for k,v in d.items():
            value = '%s(%s)' % (k,v)
            values.append(value)
        values = ' AND '.join(values)
        return values

    kwargs = self._bool_encode(kwargs)
```

```
values = ''

for k, v in kwargs.items():
    if k is 'fq' and isinstance(v, dict):
        v = _format_fq(v)
    elif isinstance(v, list):
        v = ', '.join(v)
    values += '%s=%s&' % (k, v)

return values

def search(self,
           response_format = None,
           key = None,
           **kwargs):
    """
    Calls the API and returns a dictionary of the search results
    :param response_format: the format that the API uses for its response,
                           includes JSON (.json) and JSONP (.jsonp).
                           Defaults to '.json'.
    :param key: a developer key. Defaults to key given when the articleAPI class was
    initialized.
    """
    if response_format is None:
        response_format = self.response_format
    if key is None:
        key = self.key

    url = '%s%s?%sapi-key=%s' % (
        API_ROOT, response_format, self._options(**kwargs), key
    )

    self.req = requests.get(url)
    return self.req.json()

def web_url_tuple_list(self, data):
    newlst = []
    data = data["response"]["docs"]
    for elem in data:
        newlst.append((elem["web_url"], elem["snippet"]))
    return newlst

def web_url_list(self, data):
    newlst = []
    data = data["response"]["docs"]
    for elem in data:
```

```
newlst.append(elem["web_url"])
return newlst
```

B.5 Guardian Module

```
from bs4 import BeautifulSoup
import urllib

#Returns the page HTML
def getHTML(url):
    html = urllib.urlopen(url).read()
    return BeautifulSoup(html)

#Function to collect and scrape comments
def scrapeComments(url):
    articleSoup = getHTML(url)
    articleTitle = articleSoup.find('h1', class_="content__headline").getText().strip().encode('utf-8')
    commentUrl = articleSoup.find(class_='discussion__heading').find('a')['href']
    print 'Finding comments for [{0}]({1})\n'.format(articleTitle, url)
    commentSoup = getHTML(commentUrl)
    paginationBtns = commentSoup.find_all('a', class_='pagination__action')
    LastPaginationBtn = commentSoup.find('a', class_='pagination__action--last')
    if LastPaginationBtn is not None:
        totalPages = int(LastPaginationBtn['data-page'])
    elif paginationBtns:
        totalPages = int(paginationBtns[-1]['data-page'])
    else:
        totalPages = 1

#Function to return the comments in string form
def getComments(url):
    soup = getHTML(url)
    print 'Fetching {0}'.format(url)
    commentArray = []
    for comment in soup.select('li.d-comment'):
        commentObj = {}
        commentObj['id'] = comment['data-comment-id']
        commentObj['timestamp'] = comment['data-comment-timestamp']
        commentObj['author'] = comment['data-comment-author'].encode('utf-8')
        commentObj['author-id'] = comment['data-comment-author-id']

        body = comment.find(class_='d-comment__body')
        if body.blockquote is not None:
            body.blockquote.clear()
```

```

        commentObj['text'] = body.getText().strip().encode('utf-8')
        replyTo = comment.find(class_='d-comment__reply-to-author')
        if replyTo is not None:
            link = replyTo.parent['href'].replace('#comment-', '')
            commentObj['reply-to'] = link
        else:
            commentObj['reply-to'] = ''
        commentArray.append(commentObj)
    commentArray = commentArray[::-1]
    return commentArray
allComments = []
for i in range(totalPages, 0, -1):
    params = urllib.urlencode({'page': i})
    url = '{0}?={1}'.format(commentUrl, params)
    pageComments = getComments(url)
    allComments = allComments + pageComments

return allComments

```

B.6 Article Module

```

import requests
from pprint import pprint

def get_links(company, keyword, low, high):
    CK = company + " " + keyword
    url = ('https://newsapi.org/v2/everything?'
          'q='+ CK +'&'
          'to='+ low +'&'
          'from='+ high +'&'
          'sortBy=popularity&'
          'apiKey=86c6d36203f040c59a0bc227fbad3eb3')

    response = requests.get(url)
    articles = []
    descriptions = []
    res = []

    i=0
    while i < len(response.json()['articles']):
        articles.append(response.json()['articles'][i]['url'])
        descriptions.append(response.json()['articles'][i]['description'])
        i += 1

    pprint(articles)

```

```

    pprint(descriptions)
    res.append(articles)
    res.append(descriptions)
    return res

if __name__ == '__main__':
    get_links("Microsoft", "xbox", "2019-04-20", "2019-04-25")

#start date and end date
#company and keyword -> append with a space and use that as q

```

B.7 Stock Data Collection

```

from alpha_vantage.timeseries import TimeSeries
from pprint import pprint
import json
from datetime import datetime

API_KEY = "GXJEL4HVS9C84WT4"
ts = TimeSeries(key='API_KEY', output_format='json')

#takes in the symbol for a company and returns market data stored in a python dictionary
def get_stock_market_data(company_symbol):
    data = ts.get_daily_adjusted(symbol=company_symbol, outputsize = 'compact')
    # for d in data:
    #     print(d)
    return data[0]

def get_average_adjusted(company_symbol, start_date, end_date=datetime.today().strftime("%Y-%m-%d")):
    data = get_stock_market_data(company_symbol);
    array = []
    temp = datetime.strptime(start_date, '%Y-%m-%d')
    upper = datetime.strptime(end_date, '%Y-%m-%d')
    while(temp <= upper):
        array.append((temp.strftime("%Y-%m-%d"), data[temp.strftime("%Y-%m-%d")]["5.
adjusted close"]))
        print(data[temp])
        temp = temp + timedelta(days = 1)
    return array

# def get_stock_market_data_specific_dates(to_date, from_date=datetime.today())
#write a function that takes a date and returns data from that date to today. Function will also
have a default value

```



```

#turn dictionary to array
#turn array into a file
def main():
    # return get_stock_market_data("MSFT")
    return get_average_adjusted("MSFT", "2019-04-02", "2019-04-01")

if __name__ == '__main__':
    main()

```

B.8 Stocks Module

```

from alpha_vantage.timeseries import TimeSeries
from datetime import datetime, timedelta
import os

def get_json(code):
    """
    Initializes the API and grabs the data for the specified company code.
    Returns a dictionary.
    """
    ts = TimeSeries(key='GXJEL4HVS9C84WT4', output_format='json')
    y = ts.get_daily_adjusted(symbol=code, outputsize="compact")
    return y[0]

def get_stocks(code, start_date, end_date=datetime.today().strftime("%Y-%m-%d")):
    """
    Returns an array of tuples where each tuple has the date as its first element and the stock
    price as its second element. \n
    Arguments: \n
    code - company code in a string \n
    start_date - starting date \n
    end_date - ending date (defaults to today)
    """
    json_data = get_json(code)
    array = []
    temp = datetime.strptime(start_date, '%Y-%m-%d')
    upper_bound = datetime.strptime(end_date, '%Y-%m-%d') + timedelta(days = 1)
    while(temp < upper_bound):
        try:
            array.append((temp.strftime("%Y-%m-%d"), json_data[temp.strftime("%Y-%m-%d")]
                ["5. adjusted close"]))

```

```
        temp = temp + timedelta(days=1)
    except KeyError:
        temp = temp + timedelta(days=1)
    return array

def print_stocks(stocks):
    """
    Writes the stocks to a text file. \n
    Format: [date] | [stock price]
    """
    f = open("stocks.txt", "w")
    for stock in stocks:
        f.write(stock[0] + " | " + stock[1])
        f.write("\n")
    f.close()

def delete_stock_file():
    """
    Deletes the stocks text file.
    """
    os.remove("stocks.txt")

def stock_analysis(stocks):
    """
    Returns the analysis of the given stocks
    """
    first = float(stocks[0][1])
    last = float(stocks[len(stocks)-1][1])
    result = last - first
    percent = (result / first)
    string = "Over the supplied date range, the stock price "
    if percent < -.15:
        string = string + "dropped substantially, with a " + "{0:.0%}".format(percent*-1) + " drop
        ."
    elif percent < 0:
        string = string + "dropped somewhat, with a " + "{0:.0%}".format(percent*-1) + " drop."
    elif percent > .15:
        string = string + "increased substantially, with a " + "{0:.0%}".format(percent) + "
        increase."
    elif percent > 0:
        string = string + "increased somewhat, with a " + "{0:.0%}".format(percent) + " increase."
    return string

# stock = get_stocks("MSFT", "2019-02-27", "2019-03-07")
# print(stock)
# print(stock_analysis(stock))
# print_stocks(get_stocks("MSFT", "2019-03-27"))
```

B.9 Hashtag

```
import tweepy
import csv
import json

# Twitter API credentials

with open('twitter_credentials.json') as cred_data:
    info = json.load(cred_data)
    consumer_key = info['CONSUMER_KEY']
    consumer_secret = info['CONSUMER_SECRET']
    access_key = info['ACCESS_KEY']
    access_secret = info['ACCESS_SECRET']

# Create the api endpoint

auth = tweepy.OAuthHandler(consumer_key, consumer_secret)
api = tweepy.API(auth)

# Mention the maximum number of tweets that you want to be extracted.

maximum_number_of_tweets_to_be_extracted = \
int(input('Enter the number of tweets that you want to extract- '))

# Mention the hashtag that you want to look out for

hashtag = input('Enter the hashtag you want to scrape- ')

for tweet in tweepy.Cursor(api.search, q='#' + hashtag,
rpp=100).items(maximum_number_of_tweets_to_be_extracted):
    with open('tweets_with_hashtag_' + hashtag + '.txt', 'a') as \
the_file:
        the_file.write(str(tweet.text.encode('utf-8')) + '\n')

print ('Extracted ' + str(maximum_number_of_tweets_to_be_extracted) \
+ ' tweets with hashtag #' + hashtag)
```

B.10 SQLite Module

```
import sqlite3 as lite

con = None

def connect():
    global con
    con = lite.connect('pypolDB.db')

def create():
    global con
    with con:
        cur = con.cursor()
        cur.execute(
            "CREATE TABLE IF NOT EXISTS Tweets(id INT, text TEXT, clean_text TEXT, category TEXT,"
            "date TEXT, class INT, PRIMARY KEY (id, category), UNIQUE(text) ON CONFLICT IGNORE)")
        cur.execute(
            "CREATE TABLE IF NOT EXISTS Stats(category TEXT, positive TEXT, negative TEXT, date
            TEXT,"
            "PRIMARY KEY(category, date) ON CONFLICT IGNORE)")

# tweets is a dict
def insert(tweets):
    global con
    with con:
        cur = con.cursor()
        tweets_arr = []
        for i in range(len(tweets['id'])):
            if tweets['clean_text'][i].strip() == "":
                continue # no greek text -> throw away
            tweets_arr.append([tweets['id'][i], tweets['text'][i], tweets['clean_text'][i], tweets
            ['category'][i],
                                tweets['date'][i], tweets['class'][i]])
        cur.executemany("INSERT OR IGNORE INTO Tweets VALUES(?, ?, ?, ?, ?, ?)", tweets_arr)

def insert_stats(stats):
    global con
    with con:
        cur = con.cursor()
        cur.executemany("INSERT OR IGNORE INTO Stats VALUES(?, ?, ?, ?)", stats)

def select(query):
```

```
global con
with con:
    cur = con.cursor()
    cur.execute(query)
    return cur.fetchall()
```

B.11 Json to MongoDB

```
'use strict';

const mongodb = require('mongodb');
const client = mongodb.MongoClient;

module.exports = bot;

function bot(config) {
  /* Bot that helps to import your data into db
   * @param {object} config
   * {
   *   fields: [],           // {array} data to import
   *   db: 'name',         // {string} name of db
   *   collection: 'collection' // {string|function} name of collection, or return a name
   *   host: 'localhost:27017', // {string} [optional] by default is 27017
   *   username: 'sofish',   // {string} [optional]
   *   password: '***'      // {string} [optional]
   *   callback: (err, db) => {} // {function} [optional]
   * }
   */

  if(!config.host) config.host = '127.0.0.1:27027';
  if(!config.callback) config.callback = () => {};

  var callback = config.callback;
  var auth = config.username ? `${config.username}:${config.password}@` : '';
  client.connect(`mongodb://${auth}${config.host}/${config.db}`, (err, db) => {
    if(err) return callback(err);

    if(!config.fields || !config.fields.length) {
      callback(null);
      return db.close();
    }

    // remove empty fields;
    let fields = config.fields.filter(item => !!item);
```

```
    if(!fields.length) return db.close(); // fields can be empty

    var c = config.collection;
    var collections = {};

    // map collection
    if(typeof c === 'function') {
        fields.forEach(item => {
            var name = c(item);
            if(collections[name]) return collections[name].push(item);
            collections[name] = [item];
        })
    } else if(typeof c === 'string') {
        collections[c] = fields;
    } else {
        callback({message: 'not matched, no 'collection' is specific'});
    }

    var i = 0, l = Object.keys(collections).length - 1;
    for(let c in collections) {
        db.collection(c).insertMany(collections[c], (err, ret) => {
            if(i++ === l) db.close();
            if(err) return callback(err);
            callback(null, ret);
        });
    }
};
```

B.12 Database MondoDB

```
from json import loads
from os.path import basename
from re import match
from sys import exit

import warnings
import click
from pandas import read_csv
from pymongo import MongoClient
from pymongo.errors import ServerSelectionTimeoutError

__VERSION__ = "0.0.2"
```

```
warnings.filterwarnings("ignore", category=DeprecationWarning)

@click.command()
@click.help_option("-h", "--help")
@click.version_option(__VERSION__, "-v", "--version", message="Version %(version)s")
@click.option(
    "-d",
    "--database",
    metavar="name",
    default="test",
    help="Database name.",
    show_default=True,
)
@click.option(
    "-c",
    "--collection",
    metavar="name",
    default="test",
    help="Collection name.",
    show_default=True,
)
@click.option(
    "-H",
    "--host",
    metavar="host",
    default="0.0.0.0",
    help="Host name.",
    show_default=True,
)
@click.option(
    "-p",
    "--port",
    metavar="port",
    default=27017,
    help="Port number.",
    show_default=True,
)
@click.option(
    "-t",
    "--timeout",
    metavar="sec",
    default=5,
    help="Connection timeout (seconds).",
    show_default=True,
)
@click.option(
```

```

    "-f", "--force", default=False, is_flag=True, help="Overwrite collection if exists."
)
@click.option(
    "-y", "--yes", default=False, is_flag=True, help="Automatic yes to prompts."
)
@click.argument("file")
def cli(database, collection, host, port, timeout, force, yes, file):
    """Import a csv FILE to MongoDB"""

    # Connect to MongoDB client
    click.echo(".....")
    click.echo(f"Connecting to {host}:{port}")
    click.echo(".....")
    print()
    mongo_client = MongoClient(host, port, serverSelectionTimeoutMS=timeout)
    check_connection(mongo_client, host, port)

    # Get database, collection, and format csv to json
    db = mongo_client[database]
    coll = db[collection]
    data_csv = read_csv(file)
    data_json = loads(data_csv.to_json(orient="records"))

    # Ask for user confirmation on "database" and "collection"
    if not yes:
        # TODO: use "click.prompt"
        prompt = f"Import {basename(file)} to database={database} collection={collection} [y/N]? "
        if not match(r"[yY]", input(prompt)):
            cancel_upload()

    # Check if collection already exists
    if not force:
        if collection in db.collection_names():
            # TODO: use "click.prompt"
            prompt = f"Collection={collection} already exists. Overwrite [y/N]? "
            is_overwrite = match(r"[yY]", input(prompt))
            coll.remove() if is_overwrite else cancel_upload()

    # Insert collection into database
    coll.insert(data_json)

    click.echo(click.style("Import complete!", fg="green"))

def check_connection(mongo_client, host, port):
    try:
        mongo_client.server_info()
    except ServerSelectionTimeoutError as e:

```



```
        click.echo(f"Connection error while attempting to connect to {host}:{port}")
        exit(1)

def cancel_upload():
    print()
    click.echo(click.style("Import cancelled!", fg="red"))
    exit(1)

if __name__ == "__main__":
    cli()
```

B.13 Backend

```
//Import Libraries for IPC
#include <sys/types.h>
#include <sys/socket.h>
#include <netdb.h>
#include <string.h>
#include <stdio.h>
#include <stdlib.h>
#include <unistd.h>
#include <sys/wait.h>

//
//FUNCTIONALITY: CONNECTIVITY TEST
//

#define MAXLINE 1024

int confirm(int connfd);
int open_listenfd(char* port);

//Arguments: [1] Port to listen at
int main(int argc, char** argv){
    int listenfd, connfd;
    socklen_t clientlen;
    struct sockaddr_storage clientaddr;
    char client_hostname[MAXLINE], client_port[MAXLINE];

    //Open listening socket and listen until terminated externally
```

```

listenfd = open_listenfd(argv[1]);
while(1){
    clientlen = sizeof(struct sockaddr_storage);

    //Program waits until connection is made
    connfd = accept(listenfd, (struct sockaddr* __restrict__) &clientaddr, &clientlen);

    getnameinfo((const struct sockaddr*) &clientaddr, clientlen, client_hostname, MAXLINE,
        client_port, MAXLINE, 0);

    printf("Connected to (%s, %s)\n", client_hostname, client_port);
    if(confirm(connfd) < 1) printf("Error reporting result");
    close(connfd);
    printf("Connection to (%s, %s) Closed\n",client_hostname, client_port);
}

exit(0);
}

//Arguments: [1] Open Connection's fd
int confirm(int connfd){
    size_t n;
    char buf[MAXLINE];
    char* clean;
    char* comp_name;
    char* stock;
    char* keyword;
    char* s_date;
    char* e_date;
    //char respond[MAXLINE];

    //Recieve data
    if((n = read(connfd, buf, MAXLINE)) > 0){
        //sprintf(respond, "%i", (int) n);

        //Create Output File
        FILE* out = fopen("./output.txt", "w");
        if(out == NULL){
            printf("Error creating output file");
        }

        //Parse string for tokens, Assume format is correct
        clean = strtok(buf, "\n");
        comp_name = strtok(clean, " ");
        stock = strtok(NULL, " ");
        keyword = strtok(NULL, " ");
        s_date = strtok(NULL, " ");
        e_date = strtok(NULL, " ");
    }
}

```

```

//Write output to file
fprintf(out, "%s\n%s\n%s\n%s\n%s", comp_name, stock, keyword, s_date, e_date);
fclose(out);

//Call Python Script
system("python3 input.py");

//Send response to app

FILE* result = fopen("./result.txt", "r");
if(result == NULL){
    printf("Error opening result file\n");
    return -1;
}
char buffer[MAXLINE];
fgets(buffer, MAXLINE, result);

write(connfd, buffer, MAXLINE);
}
else{
    printf("An error ocured reading from the client\n");
}
return 0;
}

//Open and bind socket with error checking
int open_listenfd(char* port){
    struct addrinfo hints, *listp, *p;
    int listenfd, optval=1;
    /* Get a list of potential server addresses */
    memset(&hints, 0, sizeof(struct addrinfo));
    hints.ai_socktype= SOCK_STREAM;          /* Accept connect. */
    hints.ai_flags= AI_PASSIVE | AI_ADDRCONFIG; /* ...on any IP addr*/
    hints.ai_flags|= AI_NUMERICSERV;        /* ...using port no. */
    getaddrinfo(NULL, port, &hints, &listp);

    /* Walk the list for one that we can bind to */
    for(p = listp; p; p = p->ai_next) {

        /* Create a socket descriptor*/
        if((listenfd= socket(p->ai_family, p->ai_socktype, p->ai_protocol)) < 0)
            continue; /* Socketfailed, trythe next*/

        /* Eliminates "Address already in use" error from bind */
        setsockopt(listenfd, SOL_SOCKET, SO_REUSEADDR, (const void*)&optval, sizeof(int));
    }
}

```

```
    /* Bind the descriptor to the address */
    if(bind(listenfd, p->ai_addr, p->ai_addrlen) == 0)
        break; /* Success */
    close(listenfd); /* Bind failed, try the next */
}

/* Clean up */
freeaddrinfo(listp);
if(!p) /* No address worked */
    return -1;

/* Make it a listening socket ready to accept conn. requests */
if(listen(listenfd, 1) < 0) {
    close(listenfd);
    return -1;}

return listenfd;
}

//
// END CONNECTIVITY TEST
//
```

B.14 Backend Client

```
#include <sys/types.h>
#include <sys/socket.h>
#include <netdb.h>
#include <string.h>
#include <stdio.h>
#include <stdlib.h>
#include <unistd.h>

#define MAXLINE 500

int open_clientfd(char* hostname, char* port); /*Opens the client

int main(int argc, char**argv){
    int clientfd;
    char *host, *port, buf[MAXLINE];
    int temp = 0;

    host = argv[1];
    port = argv[2];
```

```
if((clientfd = open_clientfd(host, port)) < 0){
    printf("No connection available at that host\n");
}

while(fgets(buf, MAXLINE, stdin) != NULL){ //takes in the text
    write(clientfd, buf, strlen(buf));
    memset(buf, 0, MAXLINE);
    read(clientfd, buf, MAXLINE);
    temp = atoi(buf);
    printf("The server recieved %i bytes\n", temp);
    memset(buf, 0, MAXLINE);
}

close(clientfd);
exit(0);
}

int open_clientfd(char* hostname, char* port) {
    int clientfd;
    struct addrinfo hints, *listp, *p;

    /* Get a list of potential server addresses */
    memset(&hints, 0, sizeof(struct addrinfo));
    hints.ai_socktype = SOCK_STREAM; /* Open a connection */
    hints.ai_flags = AI_NUMERICSERV; /* ...using numeric port arg. */
    hints.ai_flags |= AI_ADDRCONFIG; /* Recommended for connections */
    getaddrinfo(hostname, port, &hints, &listp);

    /* Walk the list for one that we can successfully connect to */
    for(p = listp; p; p = p->ai_next) {
        /* Createa socketdescriptor*/
        if((clientfd= socket(p->ai_family, p->ai_socktype, p->ai_protocol)) < 0)
            continue; /* Socketfailed, trythe next*/

        /* Connect to the server */
        if(connect(clientfd, p->ai_addr, p->ai_addrlen) != -1)
            break; /* Success */
        close(clientfd); /* Connect failed, try another */
    }

    /* Clean up */
    freeaddrinfo(listp);
    if(!p) /* All connects failed */
        return -1;
    else /* The last connect succeeded */
        return clientfd;
}
```

B.15 Front End - Home

```
import React from 'react';
import { StyleSheet, Text, View, AppRegistry, Button } from 'react-native';
import { createStackNavigator, createAppContainer } from 'react-navigation';
import { Image } from 'react-native';

import Settings from './Settings';
import Search from './Search';
import AboutUs from './AboutUs';

class Home extends React.Component {
  render() {
    return (
      <View style={{ flex: 1, alignItems: "center", justifyContent: "center",
        backgroundColor: '#000000' }}>
        <Image
          style = {{width:150, height:150}}
          source = {require('./Symbol.png')}
        />
        <Text style={{color: 'white', padding:20, fontSize:28}}>Welcome to OvalOffice!</Text
      >
      <View style = {{padding:20}}>
        <Button title="Search" onPress={() => this.props.navigation.navigate('Search')}>
      </View>
      <Button title="Go to Settings" onPress={() => this.props.navigation.navigate('
Settings')}>
      </View>
    );
  }
}

const AppNavigator = createStackNavigator(
  {
    Home: Home,
    Settings: Settings,
    Search: Search,
    AboutUs: AboutUs,
  },
  {
    initialRouteName: "Home",
    headerMode: 'none'
  }
);

export default createAppContainer(AppNavigator);
```

B.16 Front End - Search

```
// Search page
import React from 'react';
import { StyleSheet, Text, View, AppRegistry, Button, TextInput } from 'react-native';
import { createStackNavigator, createAppContainer } from 'react-navigation';

import Home from './Home';

export default class Search extends React.Component {
  constructor(props) {
    super(props);
    this.state = {
      address: 'Server Address',
      company: 'Company Name',
      ticker: 'Stock Ticker',
      keyword: 'Keyword',
      start: 'Start Date',
      end: 'End Date',
      result: ''
    };
  }
  static navigationOptions = {
    title: 'Search',
  };
  render() {
    const {navigate} = this.props.navigation;
    return (
      <View style={{flex: 1, color: 'white', backgroundColor: '#000000'}}>
        <View style={{ width: "85%", justifyContent: "center", padding: 20 }}>
          <TextInput
            style={{height: 40, color: 'white', borderColor: 'gray', borderWidth: 1}}
            onChangeText={(text) => this.setState({address: text})}
            value={this.state.address}
          />
        </View>
        <View style={{ width: "85%", justifyContent: "center", padding:20 }}>
          <TextInput
            style={{height: 40, color: 'white', borderColor: 'gray', borderWidth: 1}}
            onChangeText={(text) => this.setState({company: text})}
            value={this.state.company}
          />
        </View>
        <View style={{ width: "85%", justifyContent: "center", padding:20 }}>
          <TextInput
            style={{height: 40, color: 'white', borderColor: 'gray', borderWidth: 1}}
            onChangeText={(text) => this.setState({ticker: text})}
            value={this.state.ticker}
          />
        </View>
      </View>
    );
  }
}
```

```

    />
  </View>
  <View style={{ width: "85%", justifyContent: "center", padding:20 }}>
    <TextInput
      style={{height: 40, color: 'white', borderColor: 'gray', borderWidth: 1}}
      onChangeText={(text) => this.setState({keyword: text})}
      value={this.state.keyword}
    />
  </View>
  <View style={{ width: "85%", justifyContent: "center", padding:20 }}>
    <TextInput
      style={{height: 40, color: 'white', borderColor: 'gray', borderWidth: 1}}
      onChangeText={(text) => this.setState({start: text})}
      value={this.state.start}
    />
  </View>
  <View style={{ width: "85%", justifyContent: "center", padding:20 }}>
    <TextInput
      style={{height: 40, color: 'white', borderColor: 'gray', borderWidth: 1}}
      onChangeText={(text) => this.setState({end: text})}
      value={this.state.end}
    />
  </View>
  <Text>
    {this.state.result}
  </Text>
  <View style={{ width: "85%", justifyContent: "center", padding:20 }}>
    <Button
      color = "#32CD32"
      title="Go home"
      onPress={() => navigate('Home')}>
    </Button>
  </View>
  <View style={{ width: "85%", padding:20 }}>
    <Button
      color = "#32CD32"
      title="Results"
      onPress={() => {
        var uri = 'ws://' + this.state.address + ':2000/';
        var ws = new WebSocket(uri);
        ws.onopen = () => {
          // connection opened
          ws.send(this.state.company + ',' + this.state.ticker + ',' + this.state.
keyword + ',' + this.state.start + ',' + this.state.end);
        };
        ws.onmessage = (e) => {
          this.setState({result: e.data});
        };
      }
    </Button>
  </View>

```



```
        >>
      </Button>
    </View>
  </View>
);
}
}
```

B.17 Front End - Setting

```
import React from 'react';
import { StyleSheet, Text, View, AppRegistry, Button } from 'react-native';
import { createStackNavigator, createAppContainer } from 'react-navigation';

import Home from './Home';
import Search from './Search';
import AboutUs from './AboutUs';

export default class Settings extends React.Component {
  static navigationOptions = {
    title: 'Settings',
  };
  render() {
    const {navigate} = this.props.navigation;
    return (
      <View style={{flex: 1, backgroundColor: '#000000'}}>
        <View style={{width: "85%", justifyContent: "center", padding:20, alignSelf:'center' }}>
          <Button
            color = "#32CD32"
            title="Search"
            onPress={() => navigate('Search')}>
          </Button>
        </View>
        <Text style={{color: 'white', padding:20, fontSize:20, justifyContent: "center", alignSelf: 'center'}}>Learn more about OvalOffice below!</Text>
        <View style={{width: "50%", justifyContent: "center", padding:20, alignSelf:'center' }}>
          <Button
            color = "#32CD32"
```

```
        title="About Us"
        onPress={() => navigate('AboutUs')}>
      </Button>
    </View>

    <View style={{ width: "85%", justifyContent: "center", padding:20, alignSelf:'
center' }}>
      <Button
        color = "#32CD32"
        title="Go home"
        onPress={() => navigate('Home')}>
      </Button>
    </View>
  </View>
);
}
}
```

B.18 Website - Menu CSS

```
body {
  margin: 0;
  font-family: "Poppins", sans-serif;
}

.menu {
  background-color: black;
}

.menu h1 {
  position: absolute;
  top: 50%;
  left: 50%;
  transform: translate(-50%, 50%)
}

body {
  margin: 0;
  font-family: "Poppins", sans-serif;
}

.menu {
  overflow: hidden;
  background-color: #000000;
}
```

```
.menu a {
  float: left;
  display: block;
  color: #f2f2f2;
  background-color: black;
  text-align: center;
  padding: 14px 16px;
  text-decoration: none;
  font-size: 17px;
}

.menu a:hover {
  background-color: #ddd;
  color: black;
}

.active {
  background-color: #6a0311;
  color: white;
}

.menu .icon {
  display: none;
}

.menu a:hover {
  background-color: black;
  color: #ddd;
}

.active {
  background-color: #6a0311;
  color: white;
}

.menu .icon {
  display: none;
}

@media screen and (max-width: 600px) {
  .menu a:not(:first-child) {display: none;}
  .menu a.icon {
    float: right;
    display: block;
  }
}

@media screen and (max-width: 600px) {
```

```
.menu.responsive {position: relative;}
.menu.responsive .icon {
  position: absolute;
  right: 0;
  top: 0;
}
.menu.responsive a {
  float: none;
  display: block;
  text-align: left;
}
}

#upload-text-form {
  display: flex;;
  flex-direction: column;
  float: left;
}
}
```

B.19 Website - Search

```
import React from 'react';
import { StyleSheet, Text, View, AppRegistry, Button, TextInput } from 'react-native';
import { createStackNavigator, createAppContainer } from 'react-navigation';

import Home from './Home';

export default class Search extends React.Component {
  constructor(props) {
    super(props);
    this.state = {
      address: 'Server Address',
      company: 'Company Name',
      ticker: 'Stock Ticker',
      keyword: 'Keyword',
      start: 'Start Date',
      end: 'End Date',
      result: ''
    };
  }
  static navigationOptions = {
    title: 'Search',
  }
}
```

```
};
render() {
  const {navigate} = this.props.navigation;
  return (
    <View style={{flex: 1, color: 'white', backgroundColor: '#000000'}}>
      <View style={{width: "85%", justifyContent: "center", padding: 20 }}>
        <TextInput
          style={{height: 40, color: 'white', borderColor: 'gray', borderWidth: 1}}
          onChangeText={(text) => this.setState({address: text})}
          value={this.state.address}
        />
      </View>
      <View style={{width: "85%", justifyContent: "center", padding: 20 }}>
        <TextInput
          style={{height: 40, color: 'white', borderColor: 'gray', borderWidth: 1}}
          onChangeText={(text) => this.setState({company: text})}
          value={this.state.company}
        />
      </View>
      <View style={{width: "85%", justifyContent: "center", padding: 20 }}>
        <TextInput
          style={{height: 40, color: 'white', borderColor: 'gray', borderWidth: 1}}
          onChangeText={(text) => this.setState({ticker: text})}
          value={this.state.ticker}
        />
      </View>
      <View style={{width: "85%", justifyContent: "center", padding: 20 }}>
        <TextInput
          style={{height: 40, color: 'white', borderColor: 'gray', borderWidth: 1}}
          onChangeText={(text) => this.setState({keyword: text})}
          value={this.state.keyword}
        />
      </View>
      <View style={{width: "85%", justifyContent: "center", padding: 20 }}>
        <TextInput
          style={{height: 40, color: 'white', borderColor: 'gray', borderWidth: 1}}
          onChangeText={(text) => this.setState({start: text})}
          value={this.state.start}
        />
      </View>
      <View style={{width: "85%", justifyContent: "center", padding: 20 }}>
        <TextInput
          style={{height: 40, color: 'white', borderColor: 'gray', borderWidth: 1}}
          onChangeText={(text) => this.setState({end: text})}
          value={this.state.end}
        />
      </View>
    <Text>
```

```

    {this.state.result}
  </Text>
  <View style={{ width: "85%", justifyContent: "center", padding:20 }}>
    <Button
      color = "#32CD32"
      title="Go home"
      onPress={() => navigate('Home')}>
    </Button>
  </View>
  <View style={{ width: "85%", padding:20 }}>
    <Button
      color = "#32CD32"
      title="Results"
      onPress={() => {
        var uri = 'ws://' + this.state.address + ':2000/';
        var ws = new WebSocket(uri);
        ws.onopen = () => {
          // connection opened
          ws.send(this.state.company + ',' + this.state.ticker + ',' + this.state.
keyword + ',' + this.state.start + ',' + this.state.end);
        };
        ws.onmessage = (e) => {
          this.setState({result: e.data});
        };
      }}>
    </Button>
  </View>
</View>
);
}
}

```

B.20 Website - Settings

```

import React from 'react';
import { StyleSheet, Text, View, AppRegistry, Button } from 'react-native';
import { createStackNavigator, createAppContainer } from 'react-navigation';

import Home from './Home';
import Search from './Search';

```

```
import AboutUs from './AboutUs';

export default class Settings extends React.Component {
  static navigationOptions = {
    title: 'Settings',
  };
  render() {
    const {navigate} = this.props.navigation;
    return (

      <View style={{flex: 1,backgroundColor: '#000000'}}>
        <View style={{width: "85%", justifyContent: "center", padding:20, alignSelf:'
center' }}>
          <Button
            color = "#32CD32"
            title="Search"
            onPress={() => navigate('Search')}>
          </Button>
        </View>

        <Text style={{color: 'white', padding:20, fontSize:20, justifyContent: "center",
alignSelf: 'center'}}>Learn more about OvalOffice below!</Text>

        <View style={{width: "50%", justifyContent: "center", padding:20, alignSelf:'center'
}}>
          <Button
            color = "#32CD32"
            title="About Us"
            onPress={() => navigate('AboutUs')}>
          </Button>
        </View>

        <View style={{width: "85%", justifyContent: "center", padding:20, alignSelf:'
center' }}>
          <Button
            color = "#32CD32"
            title="Go home"
            onPress={() => navigate('Home')}>
          </Button>
        </View>
      </View>
    );
  }
}
```

B.21 Website - Home

```
import React from 'react';
import { StyleSheet, Text, View, AppRegistry, Button } from 'react-native';
import { createStackNavigator, createAppContainer } from 'react-navigation';
import { Image } from 'react-native';

import Settings from './Settings';
import Search from './Search';
import AboutUs from './AboutUs';

class Home extends React.Component {
  render() {
    return (
      <View style={{ flex: 1, alignItems: "center", justifyContent: "center",
        backgroundColor: '#000000' }}>
        <Image
          style = {{width:150, height:150}}
          source = {require('./Symbol.png')}
        />
        <Text style={{color: 'white', padding:20, fontSize:28}}>Welcome to OvalOffice!</Text
      >
      <View style = {{padding:20}}>
        <Button title="Search" onPress={() => this.props.navigation.navigate('Search')}/>
      </View>
      <Button title="Go to Settings" onPress={() => this.props.navigation.navigate('
Settings')}/>
      </View>
    );
  }
}

const AppNavigator = createStackNavigator(
  {
    Home: Home,
    Settings: Settings,
    Search: Search,
    AboutUs: AboutUs,
  },
  {
    initialRouteName: "Home",
    headerMode: 'none'
  }
);

export default createAppContainer(AppNavigator);
```


B.22 Website - Base

```
<!DOCTYPE html>
{% load static %}
<html>
  <head>
    <meta name="viewport" content="width=device-width, initial-scale=1">
    <link rel = "stylesheet" href = "https://fonts.googleapis.com/css?family=Poppins">
    <link rel="stylesheet" href={% static 'website/menu.css' %}>
    {% block head %}{% endblock %}
  </head>
  <body>

    <div class="menu" id="mymenu">
      <a href="{% url 'home' %}" class="active">Home</a>
      <a href="{% url 'news:index' %}">Articles</a>
      <a href="{% url 'stocks:index' %}">Stock Correlation</a>
      <a href="#trends">Sentiment Trends</a>
      <a href="{% url 'text_upload:index' %}">Text Upload</a>
      <a href="{% url 'about' %}">About</a>
      <a href="javascript:void(0);" class="icon" onclick="myFunction()">
        <i class="fa fa-bars"></i>
      </a>
    </div>

    <div class="container">
      {% block content %}{% endblock %}
    </div>

    <script>
      function myFunction() {
        var x = document.getElementById("mymenu");
        if (x.className === "menu") {
          x.className += " responsive";
        } else {
          x.className = "menu";
        }
      }
    </script>
```

```
    </body>  
</html>
```

Appendix C

Appendix C: Data Analysis - Source Code

Appendix Chapter, Data Analysis-Source Code, includes python scripts designed to modify process and analyze the data collected. It also provides scripts to conduct various text mining techniques, such as: Opinion Mining, Sentiment Analysis and Classification. The source codes are grouped in thematic categories. A list of the source files is followed by a short description.

- Pre-Process: Allows us to conduct the first pre-process of the collected data
 - Stemmer
 - GreekAnalyzer
 - Stopwords
 - Check Language
- Processing: The next scripts build a dictionary of terms and their scores
 - Term Classifier
 - Term Sentiment
- Text Mining: Scripts that allowed us to utilize text mining techniques to further process our data
 - Tokenize
 - Remove symbols
 - Stopwords
 - Lemmatization
 - Sentiment analysis
- Sentence Analysis: a module to test our sentiment analysis with individual sentences, and a script to perform sentiment analysis in twitter messages

- Sentiment Analysis Test Module
- Sentiment Analysis Twitter
- Classifier : allows us to build models, and make prediction
 - Train Model
 - Predict Model
 - Save Model
 - Read Model
- Utilities: scripts to allow us perform various important operations while we are processing the text
 - Greek lexicon
 - Greek Text Analyze Module
 - Analyze text
 - Topwords
 - Sentences splitting
 - Lemmatized sentences splitting
 - Parts of Speech
 - Predict Category
 - Model Mapping
 - Visualize text

C.1 Language Check

```
from __future__ import unicode_literals

import unittest
import warnings
from collections import namedtuple

import language_check

class TestLanguageTool(unittest.TestCase):

    CheckTest = namedtuple('CheckTest', ('text', 'matches'))
    Match = namedtuple('Match', ('fromy', 'fromx', 'ruleId'))

    check_tests = {
        'en': [
            CheckTest(
                ('Paste your own text here... or check this text too see '
                 'a few of the problems that that LanguageTool can detect. '
```

```

        'Did you notice that their is no spelcheckin included?'),
    [
        Match(0, 47, 'TOO_TO'),
        Match(0, 132, 'THEIR_IS'),
    ]
    ),
],
'fr': [
    CheckTest(
        ('Se texte est un exemple pour pour vous montrer '
         'le fonctionnement de LanguageTool. '
         'notez que LanguageTool ne comporte pas '
         'de correcteur orthographique.'),
        [
            Match(0, 0, 'SE_CE'),
            Match(0, 3, 'TE_NV'),
            Match(0, 24, 'FRENCH_WORD_REPEAT_RULE'),
            Match(0, 82, 'UPPERCASE_SENTENCE_START'),
        ]
    ),
    CheckTest(
        'je me rappelle de tout sans aucun soucis!',
        [
            Match(0, 0, 'UPPERCASE_SENTENCE_START'),
            Match(0, 6, 'RAPPELER_DE'),
            Match(0, 28, 'ACCORD_NOMBRE'),
            Match(0, 34, 'FRENCH_WHITESPACE'),
        ]
    ),
],
}

correct_tests = {
    'en-US': {
        'that would of been to impressive.':
        'That would have been too impressive.',
    },
    'fr': {
        'il monte en haut si il veut.':
        'Il monte s[U+FFFD]il veut.',
    },
}

def test_check(self):
    lang_check = language_check.LanguageTool()
    for language, tests in self.check_tests.items():
        try:
            lang_check.language = language

```

```
    except ValueError:
        version = language_check.get_version()
        warnings.warn(
            'LanguageTool {} doesn[U+FFFD]t support language {}'.format(
                version, language
            )
        )
    for text, expected_matches in tests:
        matches = lang_check.check(text)
        for expected_match in expected_matches:
            for match in matches:
                if (
                    (match.fromy, match.fromx, match.ruleId) ==
                    (expected_match.fromy, expected_match.fromx,
                     expected_match.ruleId)
                ):
                    break
            else:
                raise IndexError(
                    'can[U+FFFD]t find {}'.format(expected_match))

def test_correct(self):
    lang_check = language_check.LanguageTool()
    for language, tests in self.correct_tests.items():
        try:
            lang_check.language = language
        except ValueError:
            version = language_check.get_version()
            warnings.warn(
                'LanguageTool {} doesn[U+FFFD]t support language {}'.format(
                    version, language
                )
            )
        for text, result in tests.items():
            self.assertEqual(lang_check.correct(text), result)

def test_languages(self):
    self.assertIn('en', language_check.get_languages())

def test_version(self):
    self.assertTrue(language_check.get_version())

def test_get_build_date(self):
    self.assertTrue(language_check.get_build_date())

def test_get_directory(self):
    path = language_check.get_directory()
    language_check.set_directory(path)
    self.assertEqual(path, language_check.get_directory())
```

```
def test_disable_spellcheck(self):
    sentence_with_misspelling = 'This is baad.'

    lang_check = language_check.LanguageTool()
    self.assertTrue(lang_check.check(sentence_with_misspelling))

    lang_check.disable_spellchecking()
    self.assertFalse(lang_check.check(sentence_with_misspelling))

    lang_check.enable_spellchecking()
    self.assertTrue(lang_check.check(sentence_with_misspelling))

def test_README_with_unicode(self):
    tool = language_check.LanguageTool('en-US')
    text = ('A sentence with a error in the '
           'Hitchhiker[U+FFFD]s Guide tot he Galaxy')
    matches = tool.check(text)
    self.assertEqual(len(matches), 2)
    self.assertEqual((matches[0].fromy, matches[0].fromx),
                     (0, 16))
    self.assertEqual((matches[0].ruleId, matches[0].replacements),
                     ('EN_A_VS_AN', ['an']))
    self.assertEqual((matches[1].fromy, matches[1].fromx),
                     (0, 50))
    self.assertEqual((matches[1].ruleId, matches[1].replacements),
                     ('TOT_HE', ['to the']))
    corrected = language_check.correct(text, matches)
    self.assertEqual(corrected, 'A sentence with an error in the '
                       'Hitchhiker[U+FFFD]s Guide to the Galaxy')

if __name__ == '__main__':
    unittest.main()
```

C.2 Pre-Process

```
import re
import unicodedata

# #### Stemmer
class GreekAnalyzer:
```

```

one_suff = ('[U+FFFD]', '[U+FFFD]', '[U+FFFD]', '[U+FFFD]', '[U+FFFD]', '[U+FFFD]', '[U+FFFD]'
)
three_suff = ('[U+FFFD][U+FFFD][U+FFFD]', '[U+FFFD][U+FFFD][U+FFFD]', '[
[U+FFFD][U+FFFD][U+FFFD]', '[U+FFFD][U+FFFD][U+FFFD]')
two_suff = ('[U+FFFD][U+FFFD]', '[U+FFFD][U+FFFD]', '[U+FFFD][U+FFFD]', '[U+FFFD][U+FFFD]', '[
[U+FFFD][U+FFFD]', '[U+FFFD][U+FFFD]', '[U+FFFD][U+FFFD]', '[U+FFFD][U+FFFD]', '[
[U+FFFD][U+FFFD]', '[U+FFFD][U+FFFD]', '[U+FFFD][U+FFFD]', '[U+FFFD][U+FFFD]', '[
[U+FFFD][U+FFFD]')

class Sentence:
    # This class represents a string which will be cleaned as part of a pre-processing
    procedure
    def __init__(self, sentence):
        self.sentence = str(sentence).upper()

    def __repr__(self):
        return str(self.sentence)

    # Default argument values are evaluated at function define-time,
    # but self is an argument only available at function call time.
    # Thus arguments in the argument list cannot refer each other.

    def strip_accents(self, sentence=None):
        if sentence is None:
            sentence = self.sentence
        return GreekAnalyzer.Sentence(''.join(c for c in unicodedata.normalize('NFD', sentence
)
                                     if unicodedata.category(c) != 'Mn'))

    def strip_specialcharacters_numbers(self, sentence=None):
        if sentence is None:
            sentence = self.sentence
        return GreekAnalyzer.Sentence(re.sub(r'^[^U+FFFD]-[U+FFFD][U+FFFD]-[U+FFFD] ]', '',
sentence, flags=re.MULTILINE))

    def strip_links(self, sentence=None):
        if sentence is None:
            sentence = self.sentence
        return GreekAnalyzer.Sentence(re.sub(r'^https?:\\/..*[\\r\\n]*', '', sentence, flags=re.
MULTILINE))

    def strip_tags(self, sentence=None):
        if sentence is None:
            sentence = self.sentence
        return GreekAnalyzer.Sentence(re.sub(r'#\w*|@\w*', '', sentence, flags=re.MULTILINE))

    def stem(self, sentence=None):
        if sentence is None:

```



```

        sentence = self.sentence
    stemmed = ""
    for term in sentence.split():
        # Check if term is numeric
        pattern = re.compile("[+-]?(\d+(\.\d*)?|\.\d+)([eE][+-]?\d+)?")
        if pattern.match(term):
            return ''
        # Remove first level suffixes only if the term is 4 letters or more
        if len(term) >= 4:
            # Remove the 3 letter suffixes
            if term.endswith(GreekAnalyzer.three_suff):
                term = term[:-3]
            # Remove the 2 letter suffixes
            elif term.endswith(GreekAnalyzer.two_suff):
                term = term[:-2]
            # Remove the 1 letter suffixes
            elif term.endswith(GreekAnalyzer.one_suff):
                term = term[:-1]
        stemmed += term + ' '
    # return GreekAnalyzer.Sentence(stemmed[:-1])
    return GreekAnalyzer.Sentence(stemmed[:-1])

def strip_stopwords(self, sentence=None, stop_words=None):
    if sentence is None:
        sentence = self.sentence
    if stop_words is None:
        return GreekAnalyzer.Sentence(sentence)
    for w in stop_words:
        sentence = re.sub(r'\b'+w+r'\b', '', sentence)
    return GreekAnalyzer.Sentence(sentence)

def __init__(self, sentence):
    if isinstance(sentence, GreekAnalyzer.Sentence):
        self.sentence = sentence
    else:
        self.sentence = GreekAnalyzer.Sentence(sentence)

def clean(self, sentence=None, stop_words=None):
    if sentence is None:
        sentence = self.sentence
    if isinstance(sentence, GreekAnalyzer.Sentence):
        return str(sentence
            .strip_accents()
            .strip_links()
            .strip_tags()
            .strip_specialcharacters_numbers()
            .strip_stopwords(stop_words=stop_words).stem()
        )

```

```
        else:
            return GreekAnalyzer(GreekAnalyzer.Sentence(sentence)).clean(stop_words)

# ### Loading stopwords
fstopwords = open('resources\greekstopwords.txt', 'rt', encoding="utf8")

stopwords = [w.strip() for w in fstopwords.readlines() if w.strip() != '']
del (stopwords[0]) # for some reason it's a garbage word

fstopwords.close()

def clean_tweets(tweets: dict):
    proc = []
    for text in tweets['text']:
        analyzer = GreekAnalyzer(text)
        proc.append(analyzer.clean(stop_words=stopwords))
    tweets['clean_text'] = proc
    return tweets

def format_time(time):
    strtime = str(time)
    digits = len(strtime)
    if digits == 1:
        return "0"+strtime
    else:
        return strtime
```

C.3 Processing

```
import numpy as np
import pandas as pd
import csv
import random
from sklearn.metrics.pairwise import cosine_similarity
from sklearn.metrics.pairwise import euclidean_distances
from sklearn.feature_extraction.text import CountVectorizer
import os

import warnings
warnings.filterwarnings("ignore")
```

```
fposlex = open('resources\PosLex.csv', 'rt', encoding="utf8")
fneglex = open('resources\\NegLex.csv', 'rt', encoding="utf8")

def populate_lex(file):
    lex = []
    reader = csv.reader(file)
    next(reader, None) # skip first line
    for row in reader:
        if row[2] not in lex: # using a set would be a solution, but it requires conversion to
            list
            lex.append(row[2])
    return lex

poslex = populate_lex(fposlex)
neglex = populate_lex(fneglex)
fposlex.close()
fneglex.close()

def classify(tweets, categories):
    tdf = pd.DataFrame(tweets)
    texts = tdf['clean_text']
    cv_pos = CountVectorizer(input='content', vocabulary=poslex, decode_error='ignore', lowercase=
        False)
    X_pos = cv_pos.fit_transform(texts).toarray()
    cv_neg = CountVectorizer(input='content', vocabulary=neglex, decode_error='ignore', lowercase=
        False)
    X_neg = cv_neg.fit_transform(texts).toarray()
    sentiment = []
    for irow in range(X_pos.shape[0]):
        prow = X_pos[irow, :]
        nrow = X_neg[irow, :]
        tsentiment = np.sum(prow) - np.sum(nrow)
        if tsentiment > 0:
            sentiment.append("Positive")
        elif tsentiment < 0:
            sentiment.append("Negative")
        else:
            sentiment.append(random.choice(['Positive', 'Negative']))
    tweets['class'] = sentiment
    return tweets

class TermClassifier:

    def __init__(self, X, rank):
```

```
self.cv = CountVectorizer(input='content', decode_error='ignore', lowercase=False, min_df
=2)
self.U_terms = self.get_terms_svd(self.cv.fit_transform(X).toarray().T, rank)

def normalize_terms(self, U):
    normalized = []
    for row in U:
        norm = np.linalg.norm(row)
        if norm == 0:
            normalized.append([0 for _ in row])
        else:
            normalized.append([cell/norm for cell in row])
    return normalized

def distance(self, a, b):
    return cosine_similarity(a, b)

def get_terms_svd(self, X, rank=300):
    U, S, V = np.linalg.svd(np.array(X), full_matrices=False)
    return self.normalize_terms(U[:, :rank])

def get_closest_neighbors(self, term, index, n_neighbors):
    distances = []
    for i in range(len(self.U_terms)):
        x = self.U_terms[i]
        if index == i:
            distances.append(-99999)
            continue # it's it self
        distances.append(cosine_similarity(x, term))
    return np.argsort(distances)[-n_neighbors:][-n_neighbors:]

def classify_terms(self, n_neighbors):
    dir = str(n_neighbors) + '_neighbors\\'
    ext_pos = {}
    ext_neg = {}
    pos_sum = 0
    neg_sum = 0
    new_pos = set()
    new_neg = set()

    terms = self.cv.get_feature_names()
    t = 0
    for u_term in self.U_terms:
        term = terms[t]
        sentiment = 0
        if term in poslex:
            sentiment = 1
        elif term in neglex:
```

```
        sentiment = -1
    else:
        t += 1
        continue

    idx = self.get_closest_neighbors(u_term, t, n_neighbors)
    neighs = [terms[i] for i in idx]

    if sentiment == 1:
        ext_pos[term] = neighs
        filename = dir + 'ExtPos(' + term + ').txt'
        os.makedirs(os.path.dirname(filename), exist_ok=True)
        with open(filename, "w", encoding='utf-8') as f:
            for tn in neighs:
                f.write(tn+"\n")
    else:
        ext_neg[term] = neighs
        filename = dir + 'ExtNeg(' + term + ').txt'
        os.makedirs(os.path.dirname(filename), exist_ok=True)
        with open(filename, "w", encoding='utf-8') as f:
            for tn in neighs:
                f.write(tn+"\n")

    t += 1
# end for loop
for term, neighbors in ext_pos.items():
    for n in neighbors:
        if n in poslex:
            pos_sum += 1
        else:
            new_pos.add(n)
for term, neighbors in ext_neg.items():
    for n in neighbors:
        if n in neglex:
            neg_sum += 1
        else:
            new_neg.add(n)
pos_all = len(ext_pos)
neg_all = len(ext_neg)
pos_mean = pos_sum / pos_all
neg_mean = neg_sum / neg_all
print("\n\n--- Based on nearest %d neighbors classification ---" % n_neighbors)
print("Mean value of already known positive terms: ", pos_mean)
print("Mean value of already known negative terms: ", neg_mean)
print("\n~~~~~Newly found positive terms:")
for pterm in new_pos:
    print(pterm, end=" ")
print("\n\n~~~~~Newly found negative terms:")
for nterm in new_neg:
```

```
print(nterm, end=" ")
```

C.4 Sentence Analysis

```
'''  
Sentiment Analysis  
'''  
import emoji  
  
def sent_analysis(str1):  
    '''Analyzes sentiment of a single word'''  
    str = "word1=" + str1 + " "  
    matchedLine = ''  
    weight = 0  
  
    with open('lexicon.txt', 'r') as file:  
        for line in file:  
            if str in line:  
                matchedLine = line  
                break  
        if matchedLine == '':  
            return -9  
  
        if "type=strongsubj" in matchedLine:  
            if "priorpolarity=negative" in matchedLine:  
                weight -= 1.0  
            elif "priorpolarity=positive" in matchedLine:  
                weight += 1.0  
            elif "priorpolarity=neutral" in matchedLine:  
                return 9  
  
        elif "type=weaksubj" in matchedLine:  
            if "priorpolarity=neutral" not in matchedLine:  
                if "priorpolarity=negative" in matchedLine:  
                    weight -= .5  
                elif "priorpolarity=positive" in matchedLine:  
                    weight += .5  
  
    return weight  
  
def map_sent(arr):  
    '''maps each word in an array to a sentiment classifier
```

```

and returns the total sentiment'''
sentiment = 0.0
count = 0
for word in arr:
    if word in emoji.UNICODE_EMOJI:
        word = 'U+{:X}'.format(ord(word))
    sa = sent_analysis(word)
    if sa != -9:
        '''a sentiment of -9 is used when the word does not exist in the lexicon'''
    if sa == 9:
        '''a sentiment of 9 is used when the word has strong subjectivity and a neutral
polarity. Increases
count without changing the sentiment, therefore adding more weight to a neutral
sentiment.'''
        count += 2
    else:
        sentiment += sa
        count += 1
if count == 0:
    return 0
return sentiment / count

```

C.5 Sentiment Analysis Test Module

```

import sys
import json
import re

# Read the sentiment_file, and build a dictionary of terms and their scores.
def dictFromSentimentFile(sf):
    scores = {}
    for line in sf:
        term, score = line.split('\t')
        scores[term] = int(score)
    #print scores.items()
    return scores

def filterTweet(t):
    et = t.encode('utf-8') # <type: str>
    # Remove punctuations and non-alphanumeric chars from each tweet string
    pattern = re.compile('[^A-Za-z0-9]+')
    et = pattern.sub(' ', et)

```

```
#print encoded_tweet

words = et.split()

# Filter unnecessary words
for w in words:
    if w.startswith("RT") or w.startswith("www") or w.startswith("http"):
        words.remove(w)

return words

# Derive each tweet's sentiment
def computeTweetSentiment(td, sc):
    sentiment = 0.0
    words = filterTweet(td)

    # Derive sentiment from each tweet by summing up sentiments of individual words.
    for w in words:
        if w in sc:
            sentiment = sentiment + sc[w]

    #print sentiment
    return sentiment

def main():
    sent_file = open(sys.argv[1])
    tweet_file = open(sys.argv[2])

    scores = dictFromSentimentFile(sent_file)

    count = {}
    state_sents = []
    max = 0.0
    happiest = ""

    for line in tweet_file:
        sent = 0.0
        response = json.loads(line)

        print response.get('entities')
        #print response['entities']['hashtags']

        if (response.get('place') != None):
            if (response['place']['country_code'] == 'US'):
                #print response['place']['full_name'].split(',')[1]
                state = (response['place']['full_name'].split(',')[1]).encode('utf
-8').strip()

                #print state
```



```
        if "text" in response.keys():
            sent = computeTweetSentiment(response["text"], scores)
            if state in count:
                #print "another " + state, sent
                count[state] = count[state] + sent
            else:
                count[state] = sent
            #print count

    for s in count.keys():
        if count[s] > max:
            max = count[s]
            happiest = s

    print happiest

if __name__ == '__main__':
    main()
```

C.6 Sentiment Analysis Twitter

```
import sys
import json
import re

def hw():
    print 'Hello, world!'

def lines(fp):
    print str(len(fp.readlines())) # File is closed right after fp.readlines().

def main():
    sent_file = open(sys.argv[1])
    tweet_file = open(sys.argv[2])
    #hw()
    #lines(sent_file)
    #lines(tweet_file)

    # Read the sentiment file and build dictionary
    scores = {} # initialize an empty dictionary
    for line in sent_file:
        term, score = line.split("\t") # The file is tab delimited.
```

```
scores[term] = int(score)

#print scores.items() # Print every (term, score) pair in the dictionary. As a list.

# Read the tweet file: "output.txt"
tweet_data = []
for line in tweet_file:
    response = json.loads(line)
    '''if "lang" in response.keys():
        print response["lang"]'''
    if "text" in response.keys():
        tweet_data.append(response["text"])
        #print response["text"]
    #print response.keys()

#print len(tweet_data)

# For each tweet
for t in tweet_data:
    total = 0
    # Convert from <type 'unicode'> to <type 'str'>
    encoded_t = t.encode('utf-8')

    words = encoded_t.split()
    # print (str(words))

    for w in words:
        if w.startswith("RT") or w.startswith("www") or w.startswith("http"):
            words.remove(w)

    # Filtered out non alpha-numeric characters, including @, punctuations.
    pattern = re.compile('[^A-Za-z0-9]+')
    words = [pattern.sub("", w) for w in words] # Sans lambda
    #print words

    # Sum up the sentiment of words in a tweet.
    for w in words:
        if w in scores:
            total = total + scores[w]

    print '%0.2f' % total

if __name__ == '__main__':
    main()
```

C.7 Term Sentiment

```
import sys
import json
import re

# Read the sentiment_file, and build a dictionary of terms and their scores.
def dictFromSentimentFile(sf):
    scores = {}
    for line in sf:
        term, score = line.split('\t')
        scores[term] = int(score)

    #print scores.items()
    return scores

# Read the tweet_file. Extract each tweet per line. Append to the tweet_data list.
def readTweetFile(tf):
    tt = []
    for line in tf:
        response = json.loads(line)
        if "text" in response.keys():
            tt.append(response["text"])
    return tt

def filterTweet(et):
    # Remove punctuations and non-alphanumeric chars from each tweet string
    pattern = re.compile('[^A-Za-z0-9]+')
    et = pattern.sub(' ', et)
    #print encoded_tweet

    words = et.split()

    # Filter unnecessary words
    for w in words:
        if w.startswith("RT") or w.startswith("www") or w.startswith("http"):
            words.remove(w)

    return words

def computeTweetSentiment(td, sc):
    sentiments = []

    for t in td:
        sentiment = 0.0
        encoded_tweet = t.encode('utf-8') # <type: str>
        words = filterTweet(encoded_tweet)
```

```
        # Derive sentiment from each tweet by summing up sentiments of individual words.
        for w in words:
            if w in sc:
                sentiment = sentiment + sc[w]

        #print sentiment
        sentiments.append(sentiment)

    return sentiments

def computeTermSentiment(td, sc, ts):
    idx = 0
    occur = {}

    for t in td:
        words = filterTweet(t.encode('utf-8'))
        #occur = {w: 0 for w in words}
        for w in words:
            occur[w] = 0
        #print occur

    for t in td:
        words = filterTweet(t.encode('utf-8'))
        for w in words:
            occur[w] = occur[w] + 1
            if w not in sc:
                sc[w] = ts[idx]
            else:
                sc[w] = (sc[w] + ts[idx]) / occur[w] # take the average

        #print(w + " occur: ", occur[w])
        print w + " ", sc[w]

        #print "====tweet " + str(idx)
        idx = idx + 1

    return sc

def main():
    sent_file = open(sys.argv[1])
    tweet_file = open(sys.argv[2])

    scores = dictFromSentimentFile(sent_file)
    #print scores.items()

    tweet_data = readTweetFile(tweet_file)
```

```

    tweet_sentiments = computeTweetSentiment(tweet_data, scores)
    '''for s in tweet_sentiments:
        print s'''

    '''for i in range(len(tweet_sentiments)):
        print tweet_sentiments[i]'''

    computeTermSentiment(tweet_data, scores, tweet_sentiments)

if __name__ == '__main__':
    main()

```

C.8 Text Mining

```

'''
'''
import nltk
import emoji
from sent import map_sent

pre_data = ["I really like this show. It's fun and entertaining and the cast is amazing!
            [U+FFFD] [U+FFFD]"]

#=====
# Tokenize: Break down sentence into words
#=====

def tokenize(data):
    from nltk.tokenize.casual import TweetTokenizer
    tknzs = TweetTokenizer(preserve_case=False, strip_handles=True, reduce_len=True)
    post_token = []
    for x in data:
        token = tknzs.tokenize(x)
        post_token.append(token)
        #=====
        # for w in token:
        #     post_token.append(w)
        #=====
    #for t in post_token:
    #    print(t)
    return post_token

#=====

```



```
for x in data:
    word = lem.lemmatize(x, get_post(x))
    if x=="hating" or x=="hated":
        word = "hate"
    lemmatized.append(word)
#for x in lemmatized:
    #print(x)
return lemmatized

=====
# Overall function to process the data before actually performing sentiment analysis
=====

def process(data):
    t = tokenize(data)
    r = rem_stopwords(t)
    l = lemma(r)
    p = removesymbols(l)
    return p

=====
# Function to interpret the numerical sentiment value
=====

def interpret(sentiment):
    if sentiment < 0:
        if sentiment <= -0.65:
            return "very negative"
        elif sentiment <= -0.35:
            return "negative"
        elif sentiment <= -0.1:
            return "somewhat negative"
        else:
            return "neutral"
    else:
        if sentiment < 0.1:
            return "neutral"
        elif sentiment < 0.35:
            return "somewhat positive"
        elif sentiment < 0.65:
            return "positive"
        else:
            return "very positive"

=====
# Main function
=====

def main(data):
    text_processed = process(data)
    sentiment = map_sent(text_processed)
    return "The sentiment is " + interpret(sentiment) + "."

if __name__ == '__main__':
```

```
#print("\U0001f600")
sentiment = main(pre_data)
#print(sentiment)
#print(j);
#print("The sentiment value is " + str(sentiment) + " which is " + interpret(sentiment) + ".")
```

C.9 Classifier

```
import os
import sys
import argparse
import pandas as pd
import re
import string
import _pickle as cPickle
import numpy as np

from sklearn.model_selection import train_test_split
from bs4 import BeautifulSoup
from nltk.corpus import stopwords as sw
from nltk.corpus import wordnet as wn
from nltk import WordNetLemmatizer
from nltk import wordpunct_tokenize
from nltk import pos_tag
from sklearn.feature_extraction.text import CountVectorizer
from sklearn.feature_extraction.text import TfidfTransformer
from sklearn.naive_bayes import MultinomialNB
from sklearn.ensemble import RandomForestClassifier
from sklearn.linear_model import SGDClassifier
from sklearn.pipeline import Pipeline
from sklearn.naive_bayes import BernoulliNB
from sklearn.feature_selection import SelectKBest, chi2
from sklearn.model_selection import GridSearchCV
from sklearn.metrics import classification_report

stopwords = set(sw.words('english'))
punctuation = set(string.punctuation)
lemmatizer = WordNetLemmatizer()
minlength = 3
maxlength = 25

def parseArguments():
    ap = argparse.ArgumentParser()
```



```

    ap.add_argument("-t", "--training_datafile",required=False, help="path to training data
file.")
    ap.add_argument("-m", "--modelpath",required=False, help="path to learned model file for
testing.")
    ap.add_argument("-i", "--test_datafile",required=False, help="path to test data file.")
    ap.add_argument("-r", "--resultfile",required=False, help="result file name.")

    args = vars(ap.parse_args())
    for keys, values in args.items():
        print("Parsing arguments: {} : {}".format(keys,values))

    if args["training_datafile"] is None and args["modelpath"] is None:
        ap.error('-- either of one ( training_datafile/modelpath) is required')
    if args["modelpath"] is not None and args["test_datafile"] is None:
        ap.error('-- both modelpath and test_datafile are required for testing')
    return args

def getWornetPOS(tag):
    tagMap = {
        'N' : wn.NOUN,
        'V' : wn.VERB,
        'R' : wn.ADV,
        'J' : wn.ADJ
    }

    if tag[0] in tagMap.keys():
        return tagMap[tag[0]]
    else:
        return ''

def messageToWords(message):
    message_text = BeautifulSoup(message,"html.parser").get_text()
    clean_message = re.sub("[^a-zA-Z]", " ", message_text)
    words = []

    for word, tag in pos_tag(wordpunct_tokenize(clean_message)):
        word = word.lower()
        word = word.strip()
        word = word.strip('_')
        word = word.strip('*')

        if word in stopwords:
            continue

        if all(char in punctuation for char in word):
            continue

        tag = getWornetPOS(tag)
        if tag=='':
            continue

```

```
        else:
            word = lemmatizer.lemmatize(word, tag)
            words.append(word)

    words = [w for w in words if minlength < len(w) < maxlength]
    return ( " ".join( words ) )

def getDataFrame(datafile):
    print ("reading data file...")

    data_df = pd.read_csv(datafile, header=0, delimiter="\t", quoting=3)
    print ("data shape: ", data_df.shape)
    print ("data colums: ", data_df.columns.values)
    return data_df

def cleanDataFrame(dataframe):
    print ("pre-processing data...")

    for index, row in dataframe.iterrows():
        row['message'] = messageToWords(row['message'])

    return dataframe

def trainModel(training_set, pipeline):
    print ("learning model...")
    model = pipeline.fit(training_set["message"], training_set["domain"])
    return model

def predictModel(test_set, model):
    predicted = model.predict(test_set["message"])
    return predicted

def saveModel(model, filename="model.pkl"):
    with open(filename, 'wb') as fid:
        cPickle.dump(model, fid)

def readModel(filename="model.pkl"):
    model = None
    if os.path.isfile(filename):
        with open(filename, 'rb') as fid:
            model = cPickle.load(fid)
    return model

if __name__ == '__main__':
    args = parseArguments()

    if args["training_datafile"] is not None:
        print ("-----Training-----")
```

```
original_training_df = getDataFrame(args["training_datafile"])
clean_training_df = cleanDataFrame(original_training_df.copy())

print ("splitting data into training and validation set")
training_set, validation_set = train_test_split(clean_training_df, test_size=0.3)
print (training_set.shape)
print (validation_set.shape)

pipeline = Pipeline([
    ('vect', CountVectorizer(ngram_range=(1, 4), token_pattern=r'\b\w+\b',
analyzer = "word", tokenizer = None, preprocessor = None, stop_words = None, min_df=1)),
    ('tfidf', TfidfTransformer()),
    ('clf', SGDClassifier(loss='hinge', penalty='l2', alpha=1e-3, n_iter=5,
random_state=42))]
    model = trainModel(training_set, pipeline)

print ("----Validation and Classification Report----")
predicted = predictModel(validation_set, model)
target_domains = list(set(validation_set["domain"]))
print(classification_report(validation_set["domain"], predicted, target_names=
target_domains))

print ("----Saving Model----")
if args["modelpath"] is not None:
    saveModel(model, args["modelpath"])
else:
    saveModel(model)
if args["modelpath"] is not None and args["test_datafile"] is not None:
    print ("----Testing----")
    model = readModel(args["modelpath"])
    original_test_df = getDataFrame(args["test_datafile"])
    clean_test_df = cleanDataFrame(original_test_df.copy())

    predicted = predictModel(clean_test_df, model)

    print (original_test_df["message"][0])
    print (clean_test_df["message"][0])

    print ("----Saving Results----")
    output = pd.DataFrame( data={"message":original_test_df['message'], "predicted":
predicted} )
    if args["resultfile"] is not None:
        resultfile = args["resultfile"]
    else:
        resultfile = "result.tsv"
    output.to_csv(resultfile, index=False, sep='\t', quoting=3 )
```

```

# pipeline = Pipeline([('vect', CountVectorizer(analyzer = "word", tokenizer = None, preprocessor =
    None, stop_words = None)),
#                       ('tfidf', TfidfTransformer()),
#                       ('clf', SGDClassifier(loss='hinge', penalty='l2', alpha=1e-3, n_iter
    =5, random_state=42))])
#
#
# pipeline = Pipeline([
# ('count_vectorizer', CountVectorizer(ngram_range=(1, 2))),
# ('tfidf', TfidfTransformer()),
# ('classifier', BernoulliNB(binarize=0.0)) ])
#
#
# pipeline = Pipeline([
# ('count_vectorizer', CountVectorizer(ngram_range=(1, 2))),
# ('tfidf', TfidfTransformer()),
# ('classifier', RandomForestClassifier(n_estimators = 100))]

```

C.10 Greek Text Analyze Module

```

import requests
import json2table
import json2table

url = 'https://nlpbuddy.io/api/analyze'

text = input("Please enter something: ")
print("You entered: " + text)

res = requests.post(url, json={'text': text})

from json2table import convert

build_direction = "LEFT_TO_RIGHT"
table_attributes = {"style" : "width:100%"}
json_object =res.json()
html = convert(json_object, build_direction=build_direction, table_attributes=table_attributes)

print(html)

```

```
import webbrowser

f = open('Results.html', 'w')

message = """
<html>
<meta charset="UTF-8">
<meta name="viewport" content="width=device-width, initial-scale=1">
<link rel="stylesheet" href="https://www.w3schools.com/w3css/3/w3.css">

<body>

    <p> """+ html + """</p>

</body>
</html>"""

f.write(message)
f.close()

import webbrowser

import sys, os

#print('sys.argv[0] =', sys.argv[0])
pathname = os.path.dirname(sys.argv[0])

#print('path =', pathname)
#print('full path =', os.path.abspath(pathname))
scriptaki=os.path.abspath(pathname)
dasi="/"
arxeio="Results.html"
path_name_file=scriptaki +dasi+arxeio
url_path="file://"
url_path_file=url_path+path_name_file
print(url_path_file)
url = url_path_file
webbrowser.open(url,new=2)
```

C.11 Utilities for Sentiment Analysis

```
import os
import tempfile
from subprocess import check_output
```

```
from collections import defaultdict

from django.conf import settings
from spacy import displacy
from gensim.summarization import summarize
import pandas as pd
import operator
import re

fasttext_path = '/opt/demo-app/fastText/fasttext'

# uncomment for debugging purposes
import logging
fmt = getattr(settings, 'LOG_FORMAT', None)
lvl = getattr(settings, 'LOG_LEVEL', logging.DEBUG)
logging.basicConfig(format=fmt, level=lvl)

MODEL_MAPPING = {
    'el': '/opt/demo-app/demo/el_classifier.bin'
}

ENTITIES_MAPPING = {
    'PERSON': 'person',
    'LOC': 'location',
    'GPE': 'location',
    'ORG': 'organization',
}

POS_MAPPING = {
    'NOUN': 'nouns',
    'VERB': 'verbs',
    'ADJ': 'adjectives',
}

def load_greek_lexicon():
    indexes = {}
    df = pd.read_csv(
        'datasets/sentiment_analysis/greek_sentiment_lexicon.tsv', sep='\t')
    df = df.fillna('N/A')
    for index, row in df.iterrows():
        df.at[index, "Term"] = row["Term"].split(' ')[0]
        indexes[df.at[index, "Term"]] = index
    subj_scores = {
        'OBJ': 0,
```

```

        'SUBJ-': 0.5,
        'SUBJ+': 1,
    }

    emotion_scores = {
        'N/A': 0,
        '1.0': 0.2,
        '2.0': 0.4,
        '3.0': 0.6,
        '4.0': 0.8,
        '5.0': 1,
    }

    polarity_scores = {
        'N/A': 0,
        'BOTH': 0,
        'NEG': -1,
        'POS': 1
    }

    return df, subj_scores, emotion_scores, polarity_scores, indexes

df, subj_scores, emotion_scores, polarity_scores, indexes = load_greek_lexicon()

def analyze_text(text):
    ret = {}
    # language identification
    language = settings.LANG_ID.classify(text)[0]
    lang = settings.LANGUAGE_MODELS[language]
    ret = {}
    doc = lang(text)
    ret['language'] = settings.LANGUAGE_MAPPING[language]
    # analyzed text containing lemmas, pos and dep. Entities are coloured
    analyzed_text = ''
    for token in doc:
        if token.ent_type_:
            analyzed_text += '<span class="tooltip" data-content="POS: {0}<br> LEMMA: {1}<br> DEP:
{2}" style="color: red;" >{3} </span>'.format(
                token.pos_, token.lemma_, token.dep_, token.text)
        else:
            analyzed_text += '<span class="tooltip" data-content="POS: {0}<br> LEMMA: {1}<br> DEP:
{2}" >{3} </span>'.format(
                token.pos_, token.lemma_, token.dep_, token.text)

    ret['text'] = analyzed_text

    # Text category. Only valid for Greek text for now

```

```

if language == 'el':
    ret.update(sentiment_analysis(doc))
    try:
        ret['category'] = predict_category(text, language)
    except Exception:
        pass

try:
    ret['summary'] = summarize(text)
except ValueError: # why does it break in short sentences?
    ret['summary'] = ''

# top 10 most frequent keywords, based on tokens lemmatization
frequency = defaultdict(int)
lexical_attrs = {
    'urls': [],
    'emails': [],
    'nums': [],
}
for token in doc:
    if (token.like_url):
        lexical_attrs['urls'].append(token.text)
    if (token.like_email):
        lexical_attrs['emails'].append(token.text)
    if (token.like_num or token.is_digit):
        lexical_attrs['nums'].append(token.text)
    if not token.is_stop and token.pos_ in ['VERB', 'ADJ', 'NOUN', 'ADV', 'AUX', 'PROPN']:
        frequency[token.lemma_] += 1
keywords = [keyword for keyword, frequency in sorted(
    frequency.items(), key=lambda k_v: k_v[1], reverse=True)][:10]
ret['keywords'] = ', '.join(keywords)

# Named Entities
entities = {label: [] for key, label in ENTITIES_MAPPING.items()}
for ent in doc.ents:
    # noticed that these are found some times
    if ent.text.strip() not in ['n', '', ' ', '.', ',', '-', '[U+FFFD]', '_']:
        mapped_entity = ENTITIES_MAPPING.get(ent.label_)
        if mapped_entity and ent.text not in entities[mapped_entity]:
            entities[mapped_entity].append(ent.text)
ret['named_entities'] = entities

# Sentences splitting
ret['sentences'] = [sentence.text for sentence in doc.sents]

# Lemmatized sentences splitting
ret['lemmatized_sentences'] = [sentence.lemma_ for sentence in doc.sents]

```



```

# Text tokenization
ret['text_tokenized'] = [token.text for token in doc]

# Parts of Speech
part_of_speech = {label: [] for key, label in POS_MAPPING.items()}

for token in doc:
    mapped_token = POS_MAPPING.get(token.pos_)
    if mapped_token and token.text not in part_of_speech[mapped_token]:
        part_of_speech[mapped_token].append(token.text)
ret['part_of_speech'] = part_of_speech
ret['lexical_attrs'] = lexical_attrs
ret['noun_chunks'] = [re.sub(r'^\w\s', '', x.text) for x in doc.noun_chunks]
return ret

def predict_category(text, language):
    "Loads FastText models and predicts category"
    text = text.lower().replace('\n', ' ')
    # fastText expects a file here
    fp = tempfile.NamedTemporaryFile(delete=False)
    fp.write(str.encode(text))
    fp.close()

    model = MODEL_MAPPING[language]
    cmd = [fasttext_path, 'predict', model, fp.name]
    result = check_output(cmd).decode("utf-8")
    category = result.split('__label__')[1]

    # remove file
    try:
        os.remove(fp.name)
    except Exception:
        pass

    return category

def visualize_text(text):
    language = settings.LANG_ID.classify(text)[0]
    lang = settings.LANGUAGE_MODELS[language]
    doc = lang(text)
    return displacy.parse_deps(doc)

def sentiment_analysis(doc):

    subjectivity_score = 0

```

```

anger_score = 0
disgust_score = 0
fear_score = 0
happiness_score = 0
sadness_score = 0
surprise_score = 0
matched_tokens = 0
for token in doc:
    lemmatized_token = token.lemma_
    if (lemmatized_token in indexes):
        indx = indexes[lemmatized_token]
        pos_flag = False
        for col in ["POS1", "POS2", "POS3", "POS4"]:
            if (token.pos_ == df.at[indx, col]):
                pos_flag = True
                break
        if (pos_flag):
            match_col_index = [int(s) for s in col if s.isdigit()][0]
            subjectivity_score += subj_scores[df.at[indx,
                                                    'Subjectivity' + str(match_col_index)]]

            anger_score += emotion_scores[str(
                df.at[indx, 'Anger' + str(match_col_index)])]
            disgust_score += emotion_scores[str(
                df.at[indx, 'Disgust' + str(match_col_index)])]
            fear_score += emotion_scores[str(
                df.at[indx, 'Fear' + str(match_col_index)])]
            happiness_score += emotion_scores[str(
                df.at[indx, 'Happiness' + str(match_col_index)])]
            sadness_score += emotion_scores[str(
                df.at[indx, 'Sadness' + str(match_col_index)])]
            surprise_score += emotion_scores[str(
                df.at[indx, 'Surprise' + str(match_col_index)])]
            matched_tokens += 1
    try:
        subjectivity_score = subjectivity_score / matched_tokens * 100
        emotions = {'anger': anger_score, 'disgust': disgust_score, 'fear': fear_score,
                   'happiness': happiness_score, 'sadness': sadness_score, 'surprise':
                   surprise_score}
        emotion_name = max(emotions.items(), key=operator.itemgetter(1))[0]
        emotion_score = emotions[emotion_name] * 100 / matched_tokens
        ret = {'subjectivity': round(subjectivity_score, 2),
              'emotion_name': emotion_name, 'emotion_score': round(emotion_score, 2)}
        # logging.debug(subjectivity_score)
        return ret
    except ZeroDivisionError:
        return {}
    except Exception:
        return {}

```


Appendix D

List of Own Publications

D.1 Journal Papers

A Framework for Advanced Social Media Exploitation in Government. **L. Spiliotopoulou**, Y. Charalabidis, E. Loukis, V. Diamantopoulou. Transforming Government: People, Process and Policy (TGPPP). Emerald, Year 2014, Vol8, Issue 4, pp. 545-568

A Fusion of Topic Modeling, Sentiment Analysis and Stance Classification towards a Decision-Making Process through Social Media Exploitation. **L. Spiliotopoulou**, Y. Charalabidis, E. Loukis, S. Gritzalis, D. Damopoulos. Information Fusion. Elsevier. (Approval Pending)

D.2 Conference Papers

Europe in the shadow of financial crisis: Policy Making via Stance Classification. **L. Spiliotopoulou**, D. Damopoulos, Y. Charalabidis, M. Maragoudakis, S. Gritzalis. Proceedings of the 50th Hawaii International Conference on System Sciences (HICSS 2017), January 4-7, 2017, Hawaii, US

A Framework for Utilizing Web 2.0 Social Media for Participative Governance. Y. Charalabidis, E. Loukis, **L. Spiliotopoulou**, V. Diamantopoulou. European, Mediterranean Middle Eastern Conference on Information Systems 2013 (EMCIS 2013), October 17-18, 2013, Windsor, United Kingdom

Open Data Movement in Greece: A Case Study within the Financial Crisis. C. Alexopoulos, **L. Spiliotopoulou**, Y. Charalabidis. Proceedings of the 17th Pnhellenic Conference on Informatics (PCI 2013), September 19-21, 2013, Thessaloniki, Greece

D.3 Book Chapter

Web 2.0 in Governance: A Framework for Utilizing Social Media and Opinion Mining Methods and Tools in Policy Deliberation. **L. Spiliotopoulou**, Y. Charalabidis. In K.J. Bwalya, Technology Development and Platform Enhancements for Successful Global E-Government Design. IGI Global

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