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Identification and monitoring polarization from social network perspective

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ABSTRACT

Polarization is a new phenomenon that threatens the cohesion and social development of our society. The raise of social media is known to have contributed significantly to the emergence of this phenomenon as it can be noticed from the multiplication of far right and racist online communities as well as the ill-structured political discourse. This can be noticed from scrutinizing recent US or EU elections. Automatic identification of polarization from social media plays a key role in devising appropriate defence strategy to tackle the issue and avoid escalation.

This thesis implements several methods to identify polarization from Twitter data issued from Trump-Clinton US election campaign using metrics like Belief Polarization Index (BPI) and Sentiment Analysis. Furtherly, semantic role labelling and argument mining were applied to derive structure of arguments of polarized discourse. Especially, we constructed thirteen topics of interests that were used as potential candidates for polarized discourse. For each topic, the cosine distance of the frequency of the topic overtime between the two candidates was used to indicate the polarization (called as Belief Polarization Index). The statistics inference of sentiment scores was implemented to convey either a positive or negative polarity, which are then further examined using argument structure. All the proposed approaches provide attempts to measure the polarization between two individuals from different perspectives, which may give some hints or references for future research.

Keywords: polarization, social media, sentiment analysis, semantic role labelling, argument mining

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TIIVISTELMÄ

Polarisaatio on uusi ilmiö, joka uhkaa yhteiskuntamme yhteenkuuluvuutta ja sosiaalista kehitystä. Sosiaalisen median nousun tiedetään vaikuttaneen merkittävästi tämän ilmiön syntymiseen, koska se voidaan havaita äärioikeistolaisten ja rasististen verkkoyhteisöjen lisääntymisestä sekä huonosti jäsennellystä poliittisesta keskustelusta. Tämä voidaan havaita tarkastelemalla äskettäisiä Yhdysvaltojen tai EU: n vaaleja. Polarisaation automaattisella tunnistamisella sosiaalisesta mediasta on keskeinen rooli sopivan puolustusstrategian suunnittelussa ongelman ratkaisemiseksi ja eskalaation välttämiseksi.

Tässä opinnäytetyössä toteutetaan useita menetelmiä polarisaation tunnistamiseksi Yhdysvaltain Trump-Clintonin vaalikampanjan Twitter-tiedoista käyttämällä mittareita, kuten vakaumuspolarisaatio indeksi (BPI) ja mielipiteiden analyysi. Lisäksi semanttisen roolin merkintöjä ja argumenttien louhintaa sovellettiin polarisoidun diskurssin argumenttien rakenteen johtamiseen. Erityisesti rakensimme kolmetoista aihepiiriä, joita käytettiin potentiaalisina ehdokkaina polarisoituneeseen keskusteluun. Kunkin aiheen kohdalla kahden ehdokkaan aiheiden ylityötiheyden kosinietäisyyttä käytettiin osoittamaan polarisaatiota (kutsutaan nimellä Belief Polarization Index). Tunnelmapisteiden tilastollinen päättely toteutettiin joko positiivisen tai negatiivisen napaisuuden välittämiseksi, joita sitten tutkitaan edelleen argumenttirakennetta käyttäen. Kaikki ehdotetut lähestymistavat tarjoavat yrityksiä mitata kahden ihmisen välistä polarisaatiota eri näkökulmista, mikä saattaa antaa vihjeitä tai viitteitä tulevaa tutkimusta varten.

Avainsanat: polarisaatio, sosiaalinen media, mielipiteiden analyysi, semanttisten roolien merkitseminen, argumenttien louhinta

FOREWORD

I would like to express my sincere appreciation to my Supervisor, Prof. Mourad Oussalah who gives me a chance to work on my master's thesis in the Center for Machine Vision and Signal Analysis at University of Oulu, Finland. Prof. Mourad Oussalah spent a lot of time supporting my thesis work in structure design, methodology guidance, and the documentation. Additionally, I would like to extend my thanks to my second supervisor, Dr. Juha Partala for providing advice in improving the thesis. Besides, I would like to thank Mr. Yazid Bounab for giving suggestions and support when I met with some difficulties.

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Xiaowen Wang

ABBREVIATIONS

NLP	Natural Language Processing
NER	Named Entity Recognition
SA	Sentiment Analysis
BPI	Belief Polarization Index
SRL	Semantic Role Labelling
AM	Argument Mining
θ	angle of vectors
μ	statistics symbols
$\iint$	double integral
dx	differential of the variable x
dy	differential of the variable y
$f(x)$	function of the variable x
$f(y)$	function of the variable y
$\lvert x - y\rvert$	distance between the variable x and the variable y
Σ	summation
$\in$	belongs to
$P\,(H \mid E)$	probability of event H given event E occurred
$\boldsymbol{A_i}$	vector element
$\boldsymbol{B_i}$	vector element
$\lVert\mathbf{A}\rVert$	norm of vector **A**
$\lVert\mathbf{B}\rVert$	norm of vector **B**

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1. INTRODUCTION

Polarization research has been getting more and more attention from researchers of various disciplines, which testifies of its paramount importance at different aspects of our society. In social science, the concept of polarization originates from economics studies where "income polarization" has been seen as an unfair process of wealth distribution among citizens where the middle-class proportion narrows down, creating a lower marginal propensity to consume. In political science, polarization appears as a divergence of political attitudes to ideological extremes, leading to potential conflict among opposing views. This has several manifestations. For instance, partisans of a given political party are increasingly rejecting their opponents and their social norms yielding an increase of what is referred to in some literature as *affective polarization*, which corresponds to the degree to which political partisans dislike, distrust, and avoid the other side [1]. Similarly, rising animosity, a phenomenon known as *negative partisanship* yields improper behaviour and sometimes, violence when dealing with tackling opponent's views [2], which has further promoted the political polarization phenomenon. Likewise, when distinguishing the topics of a given political program, polarization arises when each party follows a rigid position with no or little constructive debate that may narrow the gap with the opponent's doctrine. This is referred to as *ideological polarization* [3]. In the context of intense debates among political opponents, research has also highlighted the growing misconceptions about the opponent, which led to what is referred to as *false or perceive polarization* [4]. Besides the link among these polarization types is quite intuitive and straightforward. For instance, false polarization can lead to affective polarization, which, in turn, can lead to ideological polarization. Furthermore, the impact of media and social media [5] as an important channel that fuels false polarization and ideological polarization. See Figure 1 highlights a conceptual framework of these polarization types [5]. Nowadays, more and more people share their opinions through online social media as inherited from [4]. This thesis primarily focuses on the intertwine between the social media sphere and ideological polarization, where the ideology is interpreted in terms of specific of topical debates that took part in Clinton and Trump's political discourse as constructed from the Twitter dataset.

Strictly speaking, Twitter, Facebook, and other social media have already become an important part of people's daily life. It is also quite popular for politicians to use social media to seek support for their causes and win more votes. Evidence shows that the popularity of social media amplified the political polarization to a large extent, which can result in negative consequences for the evolution of democratic system as a whole in the long run.

There is a large amount of literature researching polarization identification from social media [6][7][8][9][10][11][12][13][14][15][16][17][18][19][20]. While this literature has been mostly focused on the polarization in terms of group characteristics, for instance, Left and Right in politics. In social media, there is one phenomenon called echo chamber which stipulates that many like-minded people repeat the information from some purveyors until most of the people believe the story is true even if it is a bit twisted or completely imaginary. This kind of clusters can lead to polarization in opinions, public debate, etc. It is no surprise that elites or experts play an important role in the process of creating an "echo chamber" effect because they are more convincible and well known. Polarization research regarding the leaders in politics is a key factor to know if polarization already exists before triggering the effect of the “echo chamber”. Two people who represent two different parties with opposing prior beliefs both strengthen their beliefs after observing some events. They may continue to show opinions about the same events or themes to make followers agree with or even accept what they say for getting more votes through social media. Opinion mining from social media provides a good approach for policymakers to know the opinions of their citizens for the benefit of making better decisions. Sentiment analysis is a common way to get positive, negative, or neutral feedback from users through text mining. A positive or negative polarity can be identified by statistical inferences [21].

In the second Chapter of this thesis, we review the concept of polarization and its measurement metrics. Then we revisit social media concepts to discover the impacts of social media on polarization in the third Chapter. In Chapter 4, we extend the technologies of text mining in the field of Natural Language Processing (NLP) including text processing, named entity recognition, sentiment analysis, semantic role labelling and argument mining. In Chapter 5, we explore how polarization between two candidates can be manifested through their Twitter discourse using several metrics including Belief Polarization Index (BPI) and sentiment analysis. Semantic role labelling and argument mining were applied furtherly to check if there is any difference regarding the selected polarized topics between two candidates that can explain the polarization landscape. A special focus on topics associated to “Obama”, “job”, and “terrorism” because of early indications about polarization occurrence. Chapters 6 and 7 detail the methodology of our approach and the results / discussions, respectively.

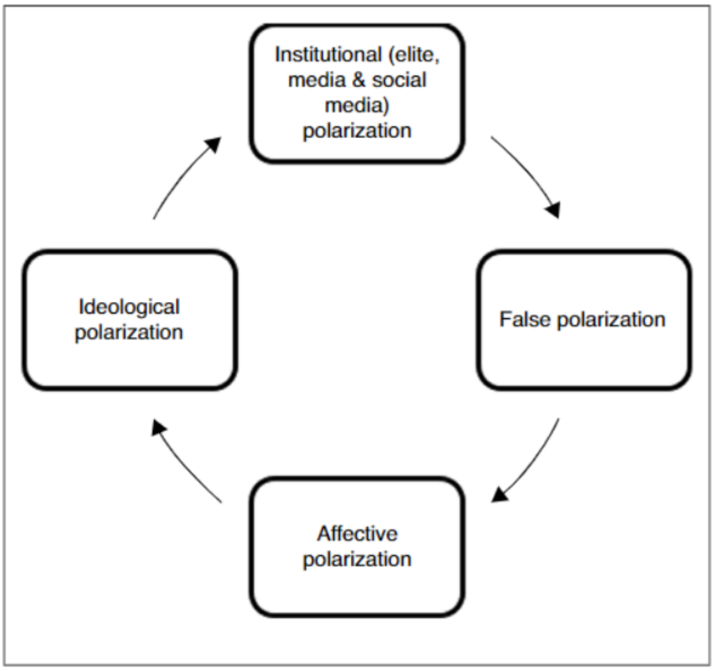

Figure 1. Political polarization in the United States.

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2. POLARIZATION

2.1. What does polarization involve?

Polarization appears in multidisciplinary fields. Polarized distribution can be pictured as two large groups opposed to each other without intersection, which can induce tension and incompatibilities within the whole group. In recent years, polarization has been studied broadly in social science due to the consequences that the polarization is closely related to the existence of social tension or conflict phenomena [6]. Economists, political scientists, and sociologists are all interested in different dimensions of polarization [22].

The concept of polarization initiated by Esteban and Ray (1994) focuses on income polarization from the perspective of economics [23]. In their research, social polarization was defined as [23]:

"*Suppose that a population of individuals may be grouped according to some vector of characteristics into "clusters," such that each cluster is very "similar" in terms of the attributes of its members, but different clusters have members with very "dissimilar" attributes. In that case we say that the society is polarized.*"

They proposed a strongly influenced Identification-alienation framework, which namely demonstrates polarization is related to two factors: alienation and identification. Alienation that individuals feel from a given group can be defined by religion, race, income, education, etc. Identification that unites members of any given group. An axiomatic characterization of a class of polarization indices based on distances between income was developed. Wolfson (1994) also attempted to provide rigorous definitions of polarization (also noted as "disappearing middle class"). The polarization is concerned more with the dispersion of the distribution of income from the median towards the extreme points [24][25]. Ezcurra found that the level of income polarization is negatively associated with regional growth [26].

Polarization also appeared more frequently in politics research [7][27][28][29][30][31][32][33]. As Bartels studied, party identification (ID) has become a better predictor of vote decisions since the mid-1970s [29], and voters today are less likely to split their tickets [34]. Regarding political polarization, there is little literature to define political polarization. Although the previous work in economics provides the foundation of polarization, the theories are specified to income polarization within-group and cannot be entirely transferred to opinion polarization between-group in politics [8]. DiMaggio et al. [9] claim that polarization can be either a state which refers to a distribution of opinions with multiple local maxima or a process which refers to the increase in such opposition over time. In the world, the United States faces polarization more deeply than in other countries. Pew Research 2014 shows that the gap between the Republican and Democratic Parties have been growing since 1994 (Figure 2). The Democratic Party has moved more to the "left," while the Republican Party has moved more to the "right." Considering the foundations of democracy, a lot of research shows how populist and illiberal leaders are putting democracy in danger worldwide [35]. Political polarization has negative effects on governance and public trust which may weaken democracy.

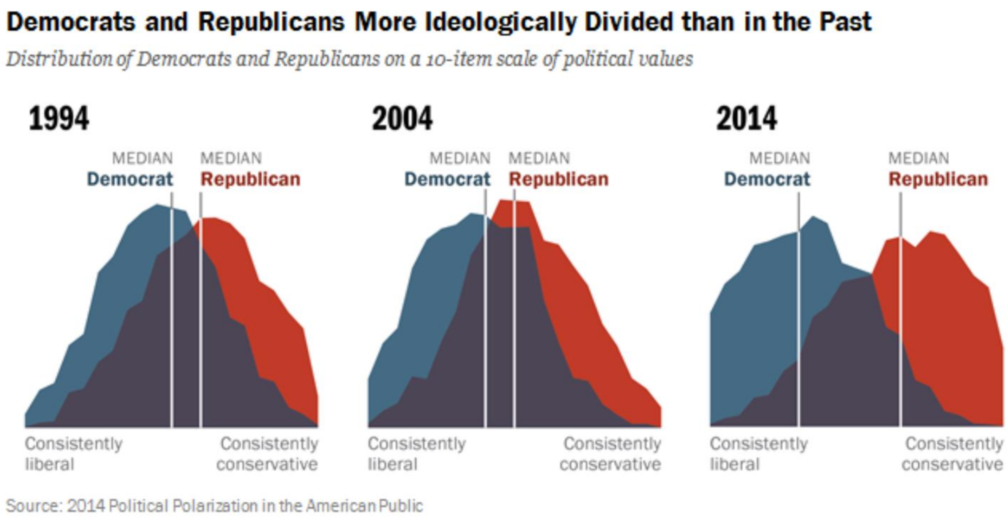


Figure 2. Political polarization in the United States.

Besides, there is another group of polarization called social polarization. The concept of social polarization was defined by ESCWA [36] as below:

"*Social polarization is associated with the segregation within a society that may emerge from income inequality, real-estate fluctuations, economic displacements etc. and result in such differentiation that would consist of various social groups, from high-income to low-income.*"

Wikipedia summarized three types of social polarization including attitude polarization (also known as belief polarization), group polarization, and racial polarization [37]. For example, by social polarization, the societies can be divided into different groups like poor and rich, black, and white, etc. Social polarization may destroy the balance of society or communities and brings in more problems like discrimination, conflicts, etc. People in worldwide have been interested in the topic of social polarization since 2004 (Figure 3).

Figure 3 shows google trends of search items of economic polarization, political polarization, and social polarization over time from 2004 to 2020 (https://trends.google.com/trends/?geo=US). Among these three main types of polarization, it is easily noticed that political polarization and social polarization get more and more attention in recent years, which may be caused by the popularity of digital technology.

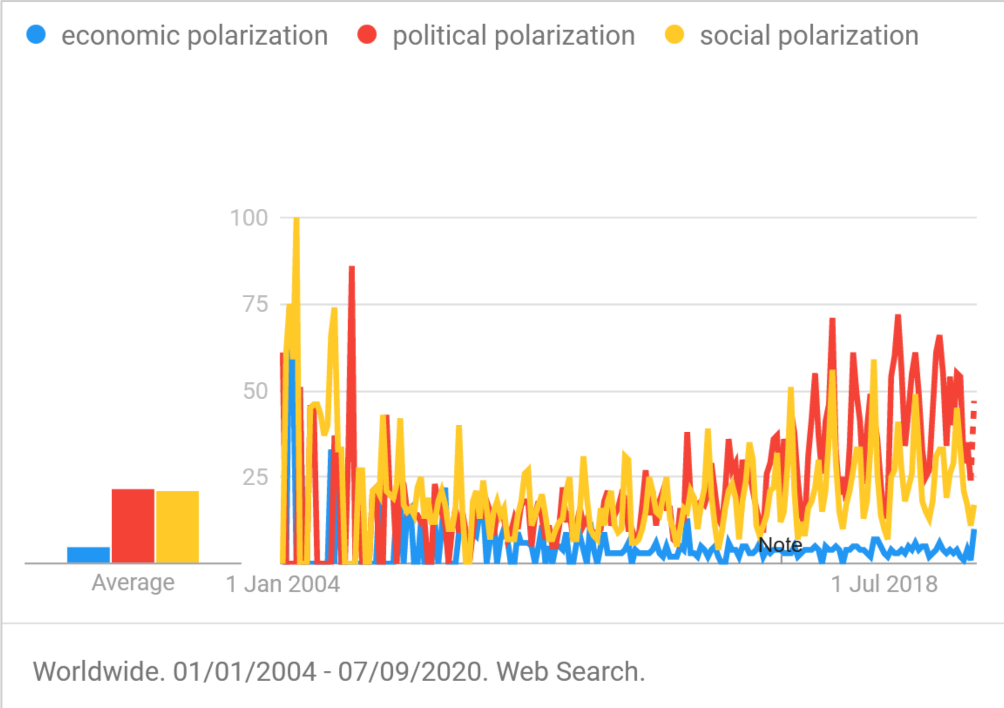


Figure 3. Google trends of search term: economic, political, and social polarization.

2.2. Measurement of polarization

As discussed above, polarization appears in the literature as more than one concept [8]. Correspondingly, polarization has varieties of measurements as well. Generally, it is agreed that polarization is designed to capture separation or distance across clustered groups in distribution [40]. In economics, different polarization measurements were compared by Esteban, J., & Ray, D. (2012), and the polarization measurement was grouped into two families: measures of polarization which are designed to capture the formation of any arbitrary number of poles and measures of bipolarization which treat polarization as a process [40]. The earliest and most influenced measurement of polarization is the ER model from Esteban and Ray (ER 1994) which was applied in economics. More formally, suppose F to be a distribution with the density f, polarization in this model can be expressed as [23]:

$$Polarize(F) = \iint T(f(x), |x-y|) f(x) f(y) dx dy \qquad (1)$$

where:

- T refers to the effective antagonisms increasing in its second argument and with $T(0, a) = T(i, 0) = 0$
- x refers to an individual with income x
- y refers to an individual with income y

The overall polarization corresponds to the sum of all T functions. Here the function fulfills $T(i, a) = T(f(x), |x-y|)$ which demonstrates that the identity i depends on the group size $f(x)$ and the inter-personal alienation a depends on income distance $|x - y|$.

Duclos, Esteban and Ray (2004) [41] refined the equation (1) by adding the further restriction that the income density functions (*f*) whose integrals of these functions corresponding to various population sizes. Compared with Gini index, their measure overcomes various biases in measures of inequality and polarization by an axiomatic approach.

Based on the measurement of polarization in economics, Reynal-Querol adjusted ER index of income polarization to the case of ethnicity and suggested an index of ethnic or religious polarization in social science. RQ index was used to be a predictor for estimating the occurrence of civil wars which displays maximum polarization where the entire population is split equally between two ethnic groups only and each of the remaining groups has zero population size [42]. Social polarization was measured fundamentally as a two-group phenomenon with median income as the divide [24][25][43].

Political polarization can be measured by the ideological distance between candidates, parties, or voters [40]. The distribution of ideological position shifts when the ideological distance grows. Weighted variance calculations are often used to devise indices of political party system polarization [45][46][47]. Party dispersion also can be measured on the conflict dimension of party system [48].

In the measurements of network or social polarization, many models or methods were tried to measure the divergence of opinions of individuals in the network, for instance, DeGroot's model of opinion formation [49], Friedkin and Johnsen model [50], measurement based on community boundaries [40], etc.

More formally, in a social graph $G = (V, E)$ with n nodes and m edges, Matakos A., et al. [5] demonstrated the popular model of Friedkin and Johnsen as:

$$z_i = \frac{w_{ii}s_i + \sum_{j \in N(i)} w_{ij} z_j}{w_{ii} + \sum_{j \in N(i)} w_{ij}} \qquad (2)$$

where:
- i refers to person i
- j refers to person j
- w_{ii} refers to the importance that node i places on their own opinion
- w_{ij} refers to the strength of the connection between i and j
- s_i refers to a persistent internal opinion that person i has in the network
- z_i refers to an expressed opinion which depends on both on their internal opinion s_i and the expressed opinions of their neighbors

The interval of opinions was set as [-1, 1] with a value of -1 implying a negative opinion, with a value of 1 meaning a positive opinion, and with a value of 0 meaning a neutral position. Usually, the polarization of the network was quantified by measuring the distance to the state of complete neutrality.

Due to the varieties of polarization measurement, polarization was summarized by Bramson [8] as nine senses in terms of individual's and group's characteristics as shown in Figure 4. Polarization can be often measured in terms of groups, for instance, the properties of within/between groups. From the perspective of individuals, four types of polarization measurement can be explained as below and visualized in Figure 5-8 [8]:

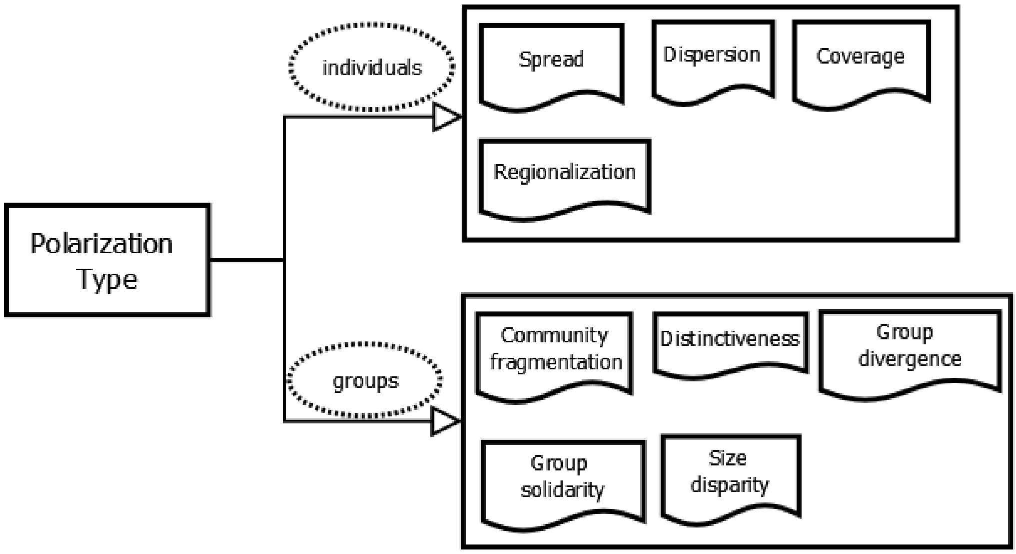


Figure 4. Types of polarization.

- Spread – polarization equals to the difference between the value of the agent with the highest belief value (Max) and the value of the agent with the lowest belief value (Min), which considers only the extremes of the population. For instance, belief distribution *b* is more polarized than distribution *a* (Figure 5).
- Dispersion – polarization is measured by the method of statistical dispersion, for instance, mean, standard deviation, coefficient of variation, etc. It considers the overall shape of the distribution. In the sense of dispersion, Figure 6 shows that distribution *c* is more polarized than distribution *b*, which is more polarized than distribution *a*.
- Coverage – firstly divide the spectrum of possible beliefs into small bins. The polarization is represented by the proportion of empty bins. This approach is suitable for the society or community with little diversity of opinion. As shown in Figure 7, distribution *a* has less coverage than distribution *b* on the spectrum of possible beliefs, which indicates distribution *a* is more polarized than *b*.
- Regionalization – polarization was measured by counting the completely distinct clusters in the distribution. Figure 8 gives two distributions with the same coverage and spread. However, distribution *b* shows more empty spaces between occupied areas than distribution *a*. In this case, distribution *b* is more polarized than distribution *a*.

On the basis of the earlier work, we can see that most of the studies pay more attention to the distribution research in terms of individual's charactstics.

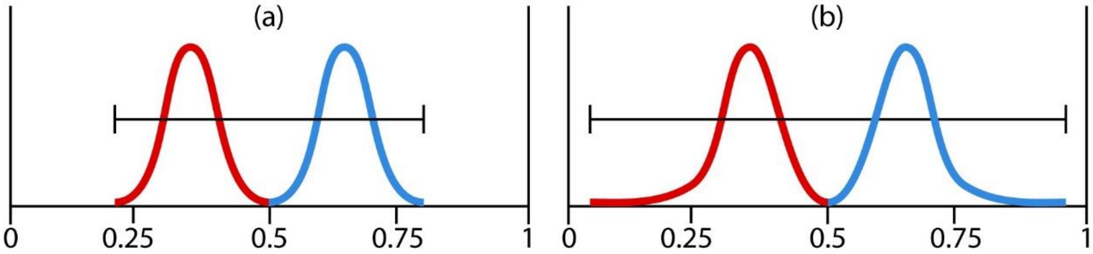


Figure 5. Polarization type: spread.

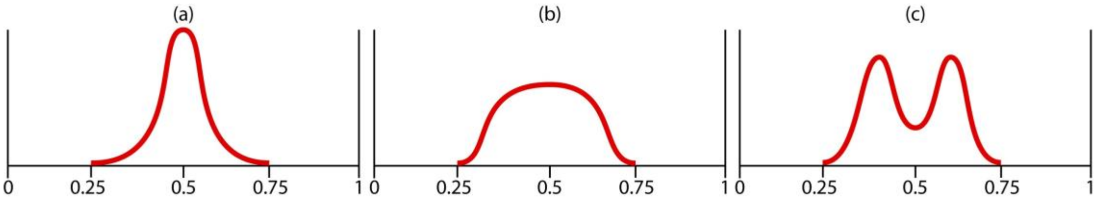


Figure 6. Polarization type: dispersion.

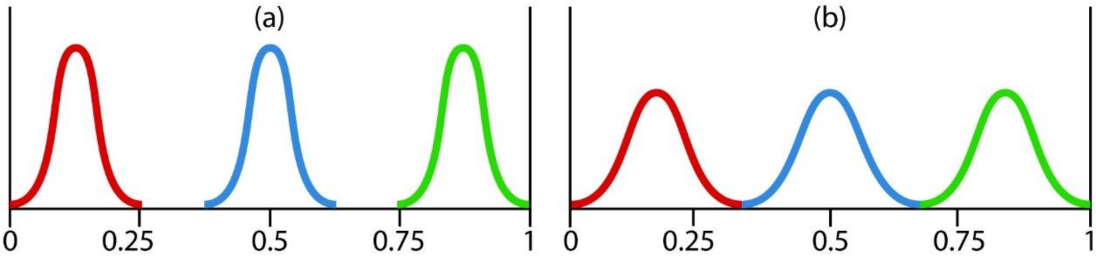


Figure 7. Polarization type: coverage.

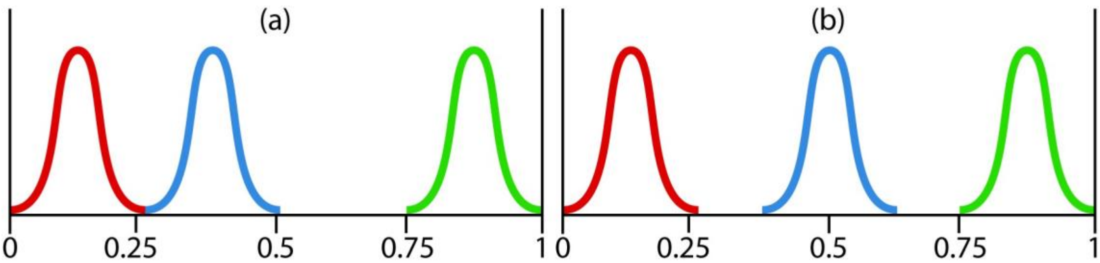


Figure 8. Polarization type: regionalization.

3. POLARIZATION ON SOCIAL MEDIA

In the 21st century, social media develops dramatically with plenty of platforms created and nowadays becomes one of the most popular online activities. From 2004 to 2018, the number of active users using social media platforms increases incredibly reported by Esteban Ortiz-Ospina [38]. Facebook, YouTube, and WhatsApp already have more than one billion users each (Figure 9). According to the report from statista.com, it is estimated that worldwide 3.6 billion people will use social media in 2020 and a number projected will be increased to almost 4.41 billion in 2025 [39]. With its popularity, social media are broadly applied in government, business, education, politics, and individuals. As we know, nothing interesting is ever completely one-sided. Social media brings in lots of benefits but also results in some impacts like disparity, political polarization, stereotyping, physical and mental health, sleep disturbances, etc.

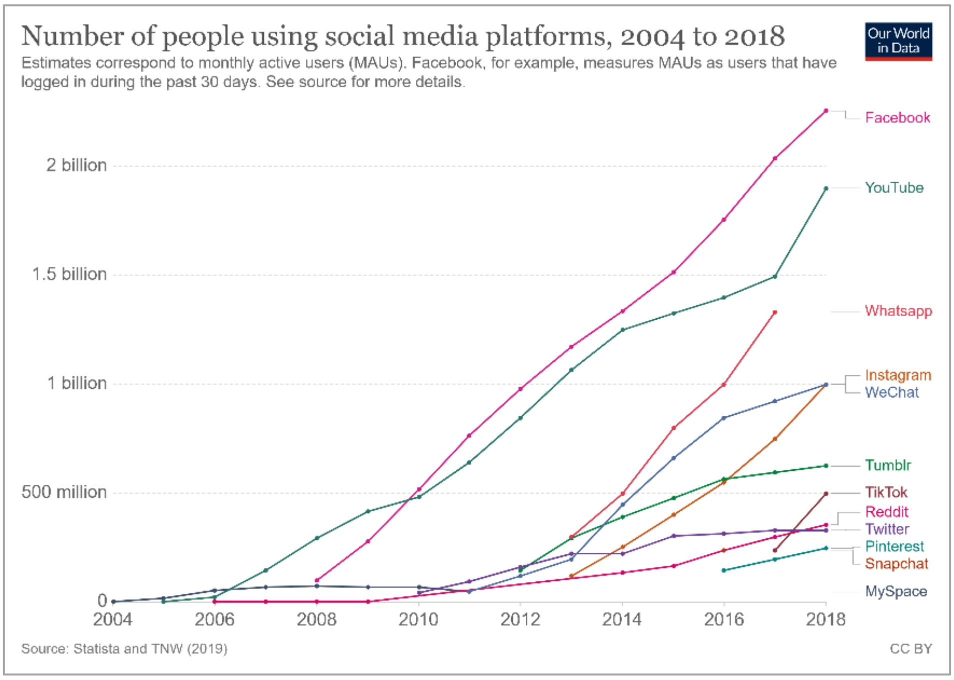


Figure 9. The number of people using the social media platform from 2004 to 2018.

Owing to the importance of social media, in academic research many researchers stepped into the research field of social media [51][52]. In the United States and even around the world, social media play an important role in shaping political discourse [11][12][53][54][55][56]. Figure 10 shows that the quality of democracy can be affected by social media, misinformation, political polarization, and political engagement [12]. Political polarization can be increased because of politicians' polarization [12][57][58]. In the European Union, social media has amplified political messages [13]. As an online social network and microblogging service, Twitter allows users to post and read real-time messages (called tweets) [59]. Tweets are short messages restricted to 140-characters in length, which can be used to share information about their daily activities, discuss with others, and follow others to stay connected with others [60].

Social Media footprints of candidates have grown during the last decade. Richardson et al., noted that most candidates in the United States have a Twitter account [61]. According to the Pew Research Center survey in 2019 [62], Twitter had 68 million monthly active users in the United States in the first quarter of 2019. Around 22% of U.S. adults use Twitter and about 42% of U.S. adults on Twitter use its site to discuss politics at least some of the time. During the 2016 US Presidential Election, Twitter was unprecedented used by the candidates and the public has also increased their reliance on social media sites for political information [63].

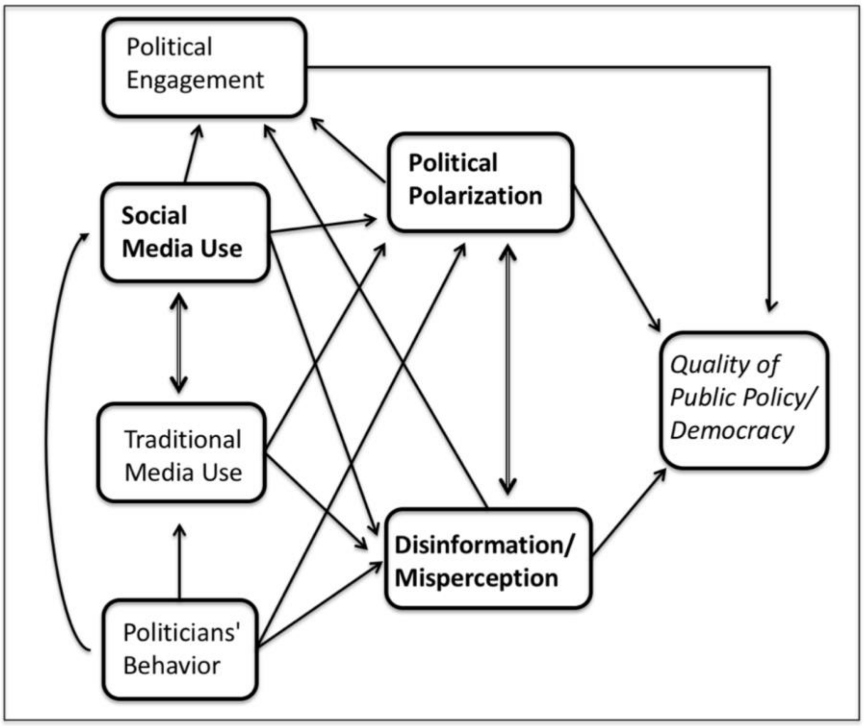


Figure 10. The impacts of social media on politics.

In academic research, polarization on Twitter got wide interest from many researchers. Generally, polarization on Twitter can be investigated from three aspects including network analysis with machine learning, changes of polarization, and sentiment analysis.

Based on the content shared on Twitter, political orientation can be analyzed, for example, users can be classified as Democrats or Republicans by using a combination of machine learning and social work analysis [64][65]. Conover, M.D., et al. [14] investigate how Twitter shapes the public and facilitate communication between communications with Left and Right by examining retweet and mention networks using network clustering algorithms and annotated data. Moreover, the political alignment of Twitter users was studied by applying a support vector machine (SVM) to hashtag metadata and latent semantic analysis to the content of users' tweets [15]. Political polarization in Twitter can be detected by social network analysis to find the clustering effect [16]. There are some papers that focused on study of how political polarization changes with different variables like locations, time, etc. From 2009 to 2016, political polarization in the US on Twitter has increased around 10%-20% [17]. The intensity of polarization on Twitter varies greatly from one country to another. The polarization is the highest in the two-party systems with plurality electoral rules and the lowest in multi-party systems with proportional voting [18]. An analysis of the tweets' political sentiment can be used to indicate that the content of Twitter messages plausibly reflects the offline political sentiment [66]. Public opinion was measured from polls with sentiment measured from the text [67].

4. THE POLARIZATION INDEX

In this section, we proposed some metrics for identifying the polarization on social media (e.g. Twitter) by text mining. In the beginning, we implemented a belief polarization index using a combination of the concept of belief polarization from Batson [68] and cosine similarity to measure how polarized the topics are between two individuals. Belief polarization (also called attitude polarization) describes a phenomenon in which two people with opposing prior beliefs both strengthen their beliefs after observing the same data or event [69]. Belief polarization was studied broadly in many topics, for instance, the death penalty [70], nuclear breakdown [71], climate change [72][73], worldview backfire effect [74] and weapon of mass destruction [75], etc.

Before measuring the cosine distance, belief divergence needs to be investigated. Consider a situation in which two people (noted as *A* and *B*) observe event *E* that bear on some hypothesis *H*. After observing *E*, opposite updating occurs whenever one person's belief in *H* increases and the other person's belief in *H* decreases (Figure 11) [68], or equivalently, when

$$[P_A(H|E) - P_A(H)][P_B(H|E) - P_B(H)] < 0 \qquad (3)$$

where:
- $P_A(\cdot)$ refers to the probability distributions that capture person *A*'s beliefs
- $P_B(\cdot)$ refers to the probability distributions that capture person *B*'s beliefs

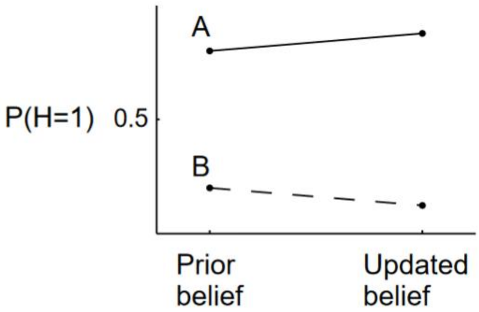


Figure 11. Belief divergence.

For a given event, belief divergence can be used as a trigger for the occurrence of polarization. The gap between the two lines implies the level of polarization. In this work, we use modified cosine similarity to measure the distance within two sets of belief divergence regarding some topics between two people. Given two non-zero vectors of belief divergence, Belief Polarization Index (BPI) is defined as:

$$\mathrm{BPI} = 1 - \cos\theta = 1 - \frac{\boldsymbol{A}\cdot\boldsymbol{B}}{||\boldsymbol{A}||||\boldsymbol{B}||} = 1 - \frac{\sum_{i=1}^{n} \boldsymbol{A}_i \boldsymbol{B}_i}{\sqrt{\sum_{i=1}^{n} \boldsymbol{A}_i^2}\sqrt{\sum_{i=1}^{n} \boldsymbol{B}_i^2}} \qquad (4)$$

where $\boldsymbol{A}_i$ and $\boldsymbol{B}_i$ are components of vector $\boldsymbol{A}$ and $\boldsymbol{B}$, respectively.

The score of BPI is between 0 and 1, specifically, with a score of different opinions and with a score of 0 meaning the same opinions between two users towards the topic.

5. NATURAL LANGUAGE PROCESSING (NLP)

As a branch of artificial intelligence, **Natural Language Processing** (also shorten as NLP) is to design and develop a computer system that can analyze, understand, and synthesis natural human languages [76]. For NLP, there are also other names available like text analytics, computational linguistics, and data mining. Over the years there are many applications available in NLP, for example:

- Speech recognition
- Language translation
- Information retrieval/extraction
- Text summarization
- Text classification
- Sentiment analysis
- Question answering
- Social media monitoring
- Etc.

Apart from speech analysis, the main task in the NLP field is to understand the text through analyzing the language patterns. With the rapid development of social media in recent years, social media analysis through NLP techniques has been getting more and more attention such as Twitter, Facebook, etc. By semantic analysis, NLP not only helps to understand strategic, operational, and tactical intelligence uses of social media but also supports in developing automated tools and algorithms for monitoring, capturing, and analyzing big data collected from social media for behaviour prediction. Sentiment analysis is often used by companies to target happy/unhappy customers and popular products which can be implemented in marketing, advertising, or sales.

5.1. Text processing for social media texts

In the era of social media, social media mining is quite important for checking the performance of social media strategy and tracking how users engaged with the content or channels like LinkedIn, Facebook, and Twitter. Text is one of the most important part in social media data which are obtained from user-generated content on social media. Through text mining, researchers can extract patterns and form conclusions about users. For commercial users, they can act upon the information analyzed to improve business.

The first step in text mining is to do text processing. The properties of text from social media have some features like real-time, non-structured text in many formats, written in many languages/styles, containing emotions or other special characters, etc. Thus, there is quite a lot of noise in the text, which is difficult to do analysis without cleaning the text. Here are two examples of texts from Twitter:

"*Hillary Clinton wanted to discuss ditching #Taiwan: WikiLeaks | Taiwan News http://www. taiwannews.com.tw/en/news/3069884*"

"*Every 👈 time 👈 @realDonaldTrump 👈 makes 👈 you 👈 mad 👈 chip 👈 in 👈 $1. https://t.co/dMjk7sxuSh https://t.co/yoDchxFpPZ*"

Twitter texts are kind of quick and short messages which may contain emotions and other non-letter characters like hashtags#, @, |, 👈, etc. All this unnecessary information should be cleaned beforehand. After that tokenization, stopwords removal, and stemming can be implemented to do text processing for better performance.

- Tokenization

Tokenization is the act of breaking up a sequence of strings into pieces such as words, terms, keywords, phrases, symbols, and other elements called tokens. The purpose of tokenization is to extract those tokens from original text data. In the process of tokenization, some characters like punctuation marks might be discarded.

- Stopwords removal

Stop word removal is commonly used as a part of the tokenization process if analyses or measurements are carried for raw words and/or terms or normalized term frequencies. Stop words are natural language words that are extremely common in all sorts of texts and most likely have no or very little meaning or useful information. Common words collected in sets of English stop word libraries are such as "and", "the", "a", "an", is", "has", and similar words. Depending on the used NLP methods or techniques the removal of stop words may or may not increase the performance of tested models or algorithms.

- Stemming

Word stemming is a technique of the tokenization process whereas words are transformed into their root forms. Generally stemming process or algorithm defines related words of the same stem. The Porter stemming algorithm is the oldest and simplest stemming algorithm originally developed by M. F. Porter [77]. Even though also other popular stemming algorithms are easily available, those are usually more aggressive than Porter stemmer in a stemming process [78].

5.2. Named entity recognition

As a subfield of artificial intelligence, named entity recognition is one of the key information extraction tasks in the NLP field [79]. One of the first research papers aiming at automatically identifying named entities (company names) in texts was proposed by Rau [80]. In text mining, it is essential to recognize information units like person, organization and location names, or numeric expressions including time, date, money, and percent expressions [81]. Wikipedia defined named-entity recognition (NER) (also known as entity identification, entity chunking and entity extraction) as [82]:

"*A subtask of information extraction that seeks to locate and classify named entities mentioned in unstructured text into pre-defined categories such as person* *names, organizations, locations, medical codes, time expressions, quantities, monetary values, percentages, etc.* ”

Figure 12 shows one example of how NER works [83]:

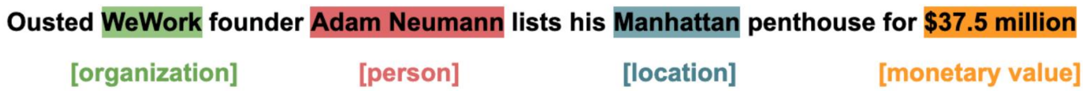


Figure 12. Named entity recognition example.

Through named entity recognition tools, names (organization, person, and location) and monetary values were detected (Figure 12). Named entity recognition has many different applications such as question answering, text summarization, or machine translation. In real life, named entity recognition can be used for categorizing tickets in customer support, customer feedback and analyzing resumes, etc.

To recognize the entities from a large amount of data, necessary technology and tools are needed. The well-known NER software as open source is StanfordNLP, Natural Language Toolkit (NLTK), Open NLP, SpaCy and Gate, etc. Among NER software, StandfordNLP usually performs the best [84]. Compared with StanfordNLP, as a Python framework, SpaCy is very easy and fast to use. SpaCy uses a deep learning formula for implementing NLP models, summarized as “embed, encode, attend, predict” [85].

Spacy is an open-source software library for advanced natural language processing, written in the programming languages Python and Cython. The library is published under the MIT license and its main developers are Matthew Honnibal and Ines Montani, the founders of the software company Explosion. SpaCy features convolutional neural network models for part-of-speech tagging, dependency parsing, text categorization, and named entity recognition (NER). It supports for more than 59 languages. Models support the following 18 entity types [86] in Table 1. “PERSON” and “ORG” belongs to the entities we need in this research.

Table 1. Entities types in spaCy

Types	Descriptions
PERSON	people
NORP	Nationalities, religious or political group
FAC	Buildings, airports, highways, bridges, etc.
ORG	Companies, agencies, institutions, etc.
GPE	Countries, cities, states.
LOC	Non-GPE locations, mountain ranges, bodies of water.
PRODUCT	Objects, vehicles, food, etc. (Not services.)
EVENT	Named hurricanes, battles, wars, sports events, etc.
WORK_OF_ART	Title of books, songs, etc.
LAW	Named documents made into laws.
LANGUAGE	Any named languages.
DATE	Dates or periods.
TIME	Times smaller than a day.
PERCENT	Percentage, including "%".
MONEY	Monetary values including unit.
QUANTITY	Measurements, weight or distance
ORDINAL	First, second, etc.
CARDINAL	Numerals that do not fall under another type.

5.3. Sentiment analysis (SA)

As one of the most important fields of NLP, sentiment analysis (SA) (also known as Opinion mining) is using a machine learning technique to detect people's opinions, attitudes, and emotions (e.g. *positive*, *negative, or neutral*) within the text. Sentiment analysis is very useful for business unities to understand their customers, which is widely applied in many aspects, for instance, product reviews [87], stock markets [88, 89], news articles [90], and political debates [91], etc.

Many tools have been developed in recent years to do sentiment analysis in short informal social media texts include uClassify, ChatterBox, Sentiment140 [92], Textalytics, SentimentAnalyzer, TextProcessing, Semantria, SentiStrength [93], etc. SentiStrength is one of the tools with the best overall performance and achieves with average accuracies above 66% [94]. Developed because of published academic research, SentiStrength [93] is a popular stand-alone sentiment analysis tool that is widely used in academic research. The Windows version can be downloaded free from the website http://sentistrength.wlv.ac.uk/ free for researchers and educational users. Commercially, SentiStrength is used by a range of online information management companies worldwide such as Yahoo! [95].

Generally, SentiStrength uses a sentiment lexicon approach to assign scores to negative and positive phrases in the text. The overall sentiment score is calculated by summing negative and positive scores. Take one text "*I love dogs quite a lot but cats I really hate*." as an example. Figure 13 shows the result from SentiStrength that the positive value equals to 3.000 and the negative value equals to -5.000. Then the overall sentiment score is the sum of the positive value and the negative value, which equals to -2.000.

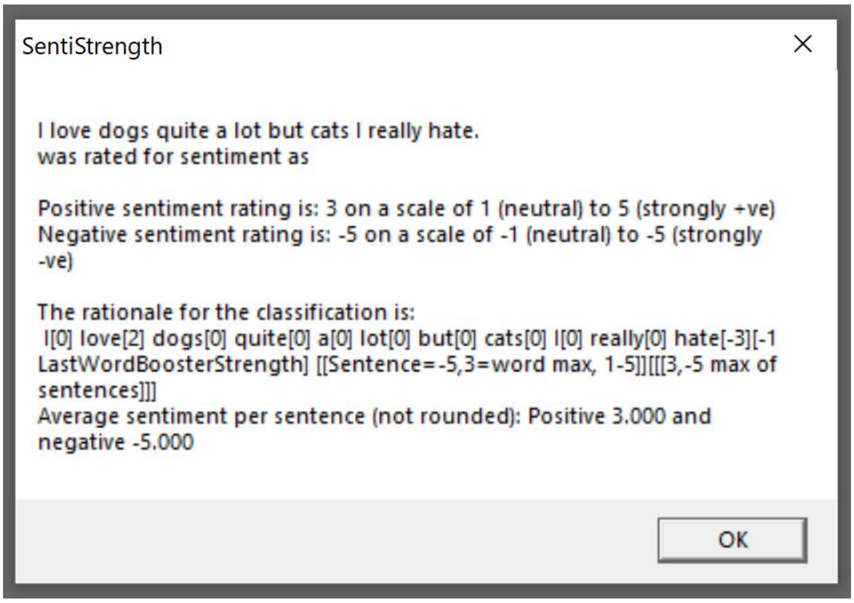


Figure 13. SentiStrength example.

5.4. Semantic role labelling (SRL)

Semantic role labeling (shorten as SRL, also called shallow semantic parsing) is to give a semantic role to the syntactic constituent of a sentence [96]. In NLP tasks, SRL is a key task for answering "*Who*", "*When*", "*What*", "*Where*", "*Why*", etc. questions in Information Extraction, Question Answering, and Summarization. Typical semantic arguments include Agent, Patient, Instrument, and adjunctive arguments, etc. For example, the following sentence might be tagged *"[John]*$_{ARG0}$ *[ate]*$_{REL}$ *[the apple]* $_{ARG1}$", where "*ate*" is the predicate or verb. The precise arguments depend on a verb's frame and more verbs in a sentence some words might have more tags. A similar key for semantic roles was shown in Figure 14 [97].

Currently, the approaches to semantic role labeling are based on supervised machine learning, often using the FrameNet [98] and PropBank [99] resources to define the set of roles used in the task and provide the training and testing sets. As a fast semantic role labelling tool, SENNA is a software distributed under a non-commercial license (https://ronan.collobert.com/senna/), which outputs part-of-speech (POS) tags, chunking (CHK), name entity recognition (NER), semantic role labeling (SRL), and syntactic parsing (PSG) [100][101]. For semantic role labelling in SENNA, it assigns roles ARG0-5 to words that are arguments of a verb (or a predicate) in the sentence following the rules in PropBank. The software can be downloaded from https://ronan.collobert.com/senna/download.html and installed in different systems like Windows, Linux, and Mac OS.

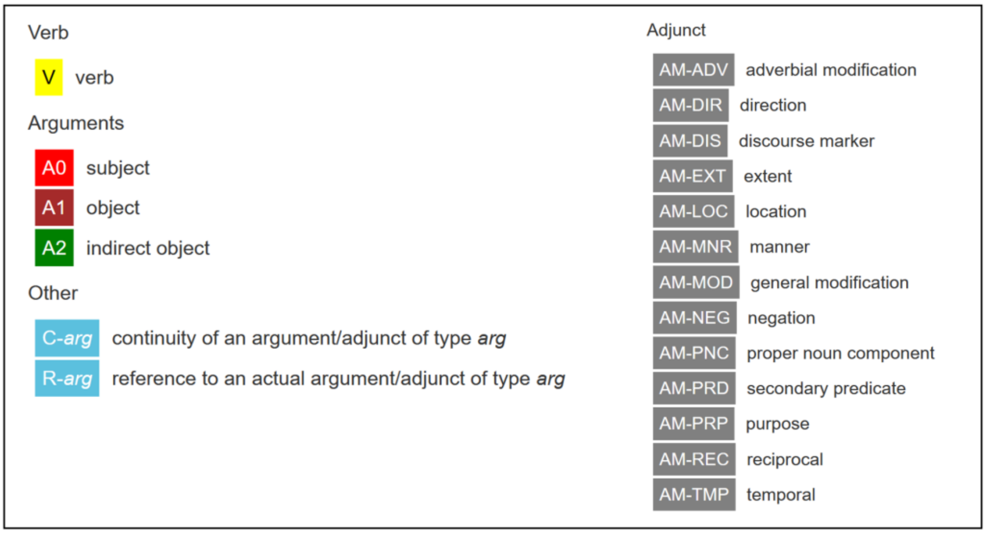


Figure 14. Key for semantic roles.

5.5. Argument mining (AM)

As one of the research fields within NLP, argument mining (shorten as AM) is to automatically extract structured arguments from unstructured textual documents, which has come to a hot topic in processing information from Web and especially from social media [102]. Argumentation is one of the central parts in human communication, which is the process of conveying attitudes, opinions, and trying to make others accept them or even adopt them [103]. In Artificial Intelligence, argumentation has been increased as a central study [104] due to its ability to connect the needs with related cognitive models and computational models for automated reasoning [105]. Argument mining has been applied in many different genres including the qualitative assessment of social media content (e.g. Twitter, Facebook), where it provides a powerful tool for policymakers and researchers in social and political sciences [102].

According to the definition from Merriam-Webster, the argument is a coherent series of reasons, statements, or facts intended to support or establish a point of view [106]. A typical structure of an argument includes one or more premises that provide reason or support for the claims and only one claim (also called conclusions) which is a statement indicating what the arguer is trying to convince the partner. In the argument mining system, currently, the main approaches focus on three tasks involving argumentative sentence detection, argument component boundary detection, and the structure prediction (Figure 15) [102].

For common users, nowadays there are four publicly available systems of argument mining, for instance, ArgumenText [107], args.me [108], MARGOT [105], TARGER [109]. Among these tools, TARGER provides a neural argument mining framework that not only can tag arguments from free input texts but also retrieve arguments from an argument-tagged web-scale corpus. Moreover, TARGER offers different pre-trained state-of-art models, which can be switched easily. The modular architecture of TARGER was shown in Figure 16. TARGER is a PyTorch implementation of BiLSTM-CNN-CRF neural tagging method based on works of

Lample, et. al., 2016 [110] and Ma et. al., 2016 [111] for identifying argumentative units and then classifying them as claims or premises. Users can access TARGER web-application and web-service online through the link http://ltdemos.informatik.uni-hamburg.de/targer/.

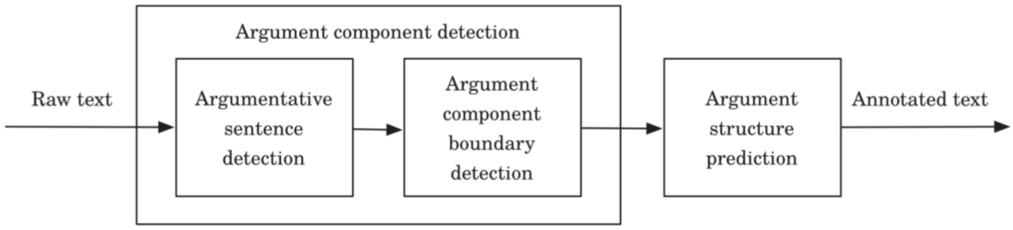


Figure 15. Pipeline architecture of an argument mining system.

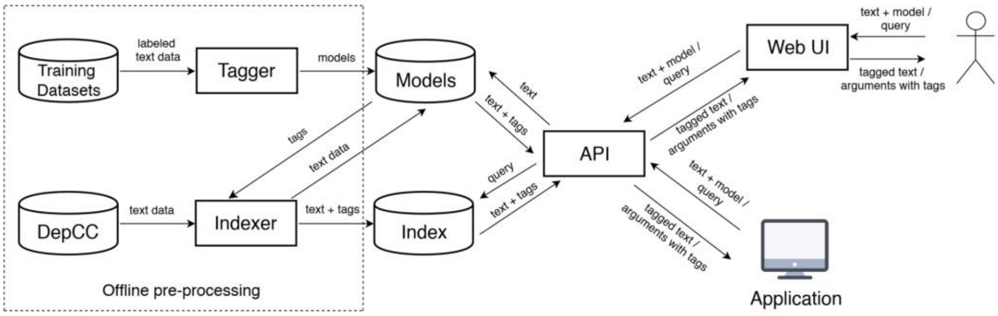


Figure 16. The modular architecture of TARGER.

6. METHODOLOGY

Tweets from two candidates (Hillary Clinton and Donald Trump) were analyzed according to the framework of methodology shown in Figure 17. Firstly, tweet texts were filtered and processed by cleaning methods. Then topics we have interest in were summarized and named entities were recognized by available software. The last part is to detect the polarization between two candidates. Two metrics were proposed to measure the polarization involving Belief Polarization Index (BPI) and sentiment analysis (SA). Besides, we attempted to investigate more about the tweets from the perspective of arguments. Semantic role labelling (SRL) and argument Mining (AM) was implemented in this research.

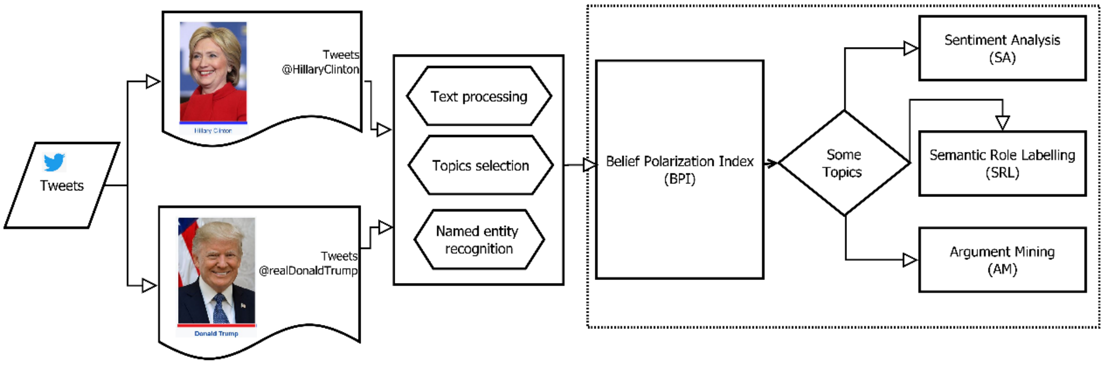


Figure 17. The framework of tweet text analysis.

6.1. Text processing

As mentioned before, text from Twitter contains a lot of noise, for instance, punctuation marks, special characters, and other non-letter characters, etc. In NLP processes, the first step is to clean the text before any computation. **Algorithm 1** gives the basic method to clean the text.

6.2. Visualization

Data visualization was conducted by histogram and Word Clouds. Histograms of words or topics frequency were plotted by python library Matplotlib (*v3.3.1*). Word Clouds were used to display how important words are in a collection of texts. The more frequent the word is, the greater space it occupies in the image.

6.3. Named entity recognition (NER)

General-purpose pre-trained model from spaCy (*v2.3*) was chosen as NER tool to predict named entities including person and organizations.

Algorithm 1 Text processing (*Text_clean*)

```
Input: text
Output: Text_clean(text): tokens
S ← remove_url (text)
S ← remove_whitespace (S)
S ← compound_split (S)
S ← remove_punctuations (S)
S ← remove_nonalphabet (S)
wordlist ← tokenizer (S)
wordstop ← []
for word in wordlist do
        if word not in English_Stop_Words then
                wordstop.append (word)
        end if
end for
wordstem ← stemmer (wordstop)
return: Text_clean(text)→wordstem
```

6.4. Polarization measurement

6.4.1. Belief Polarization Index (BPI)

After completing the topics of interest, the probability of each topic that appeared overtime between two candidates was computed and plotted. Then Belief Polarization Index (BPI) was calculated based on the Equation (4). The values of BPI indicate how polarized between two candidates regarding some topics.

6.4.2. Sentiment analysis (SA)

To investigate if sentiment polarity exists between two candidates regarding some topics, SentiStrength (*v2.3*) was implemented to analyze sentiment for each tweet. The overall sentiment score for each tweet was computed by summarizing the positive score and negative score. The statistic inferences were also introduced to check if the results are significant in sentiment polarity regarding the given topics between the candidates.

6.4.3. Semantic role labelling (SRL)

As addressed in Chapter 5, SENNA (*v3.0*) was implemented to do semantic role labelling for each tweet after removing some invalid characters. The proportion of each argument (A0, A1, A2…) for tweets from two candidates were computed corresponding to some topics.

6.4.4. Argument Mining (AM)

To review is there any evidence to support the conclusions posted on Twitter regarding some topics from both candidates, firstly TARGER was used to tag the arguments in the tweets. After then, the proportion of premises and claims were computed for each candidate.

7. DATA COLLECTION AND ANALYSIS

7.1. Dataset

The present dataset was downloaded from Kaggle [112] including the tweets from the major party candidates (Hillary Clinton and Donald Trump) for the 2016 US Presidential Election. Another possible solution is to extract tweets through Twitter API.

7.2. Results and analysis

In this section, we will do tweet text mining through data visualization, cleaning, named entities recognition, and the analysis of polarization metrics consisting of Belief Polarization Index (BPI) and sentiment analysis (SA). Accordingly, semantic role labelling (SRL) and argument mining (AM) were tried to furtherly check if there is any difference regarding the selected polarized topics between two candidates.

7.2.1. Dataset visualization

The dataset contains 6444 values of text and 28 columns including id, handle, time, text, place id, place name, place type, author, etc. In this research, we have interesting mainly in tweets text mining for each candidate overtime. After removing duplicated and none values from texts, unique tweets were obtained for each candidate in Table 2. In this study, the time range was set as starting from 2016-04-17 to 2016-09-25. In the set periods, we investigate the number of tweets published for each candidate every 7 days. As shown in Figure 18, the results draw us an image that Hillary Clinton is bit more active than Donald trump in posting tweets. In particular, the number of tweets posted by Hillary Clinton reached a peak from July 14 to July 22. During that week, Donald Trump and Mike Pence were formally nominated for President and Vice President, respectively, by the party's state delegations.

Table 2. Dataset

Candidates	**Total tweets**	**Unique tweets**	**Time range for unique tweets**
@HillaryClinton	3226	3224	2016-04-17 to 2016-09-28
@realDonaldTrump	3218	3210	2016-01-05 to 2016-09-27
Total	6444	6434	

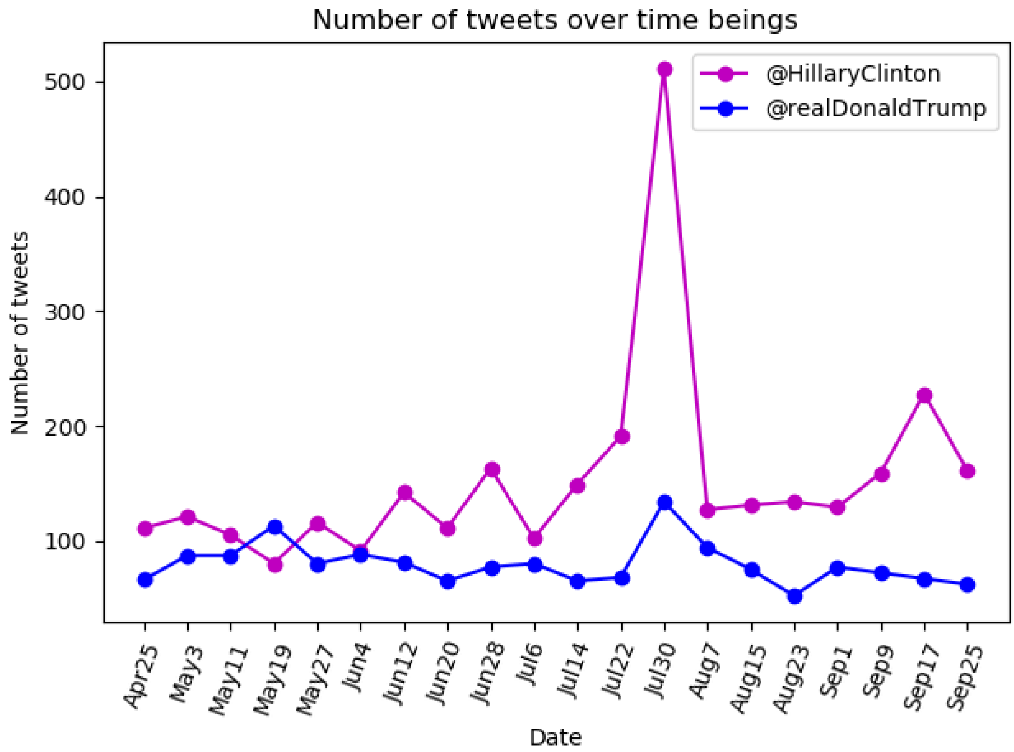
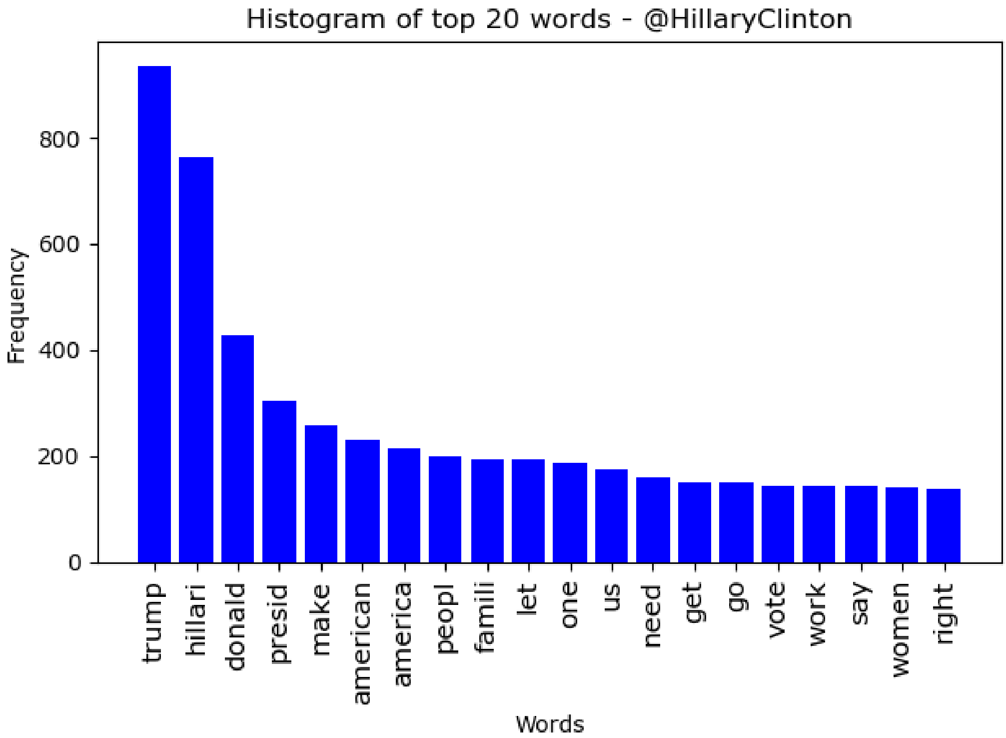
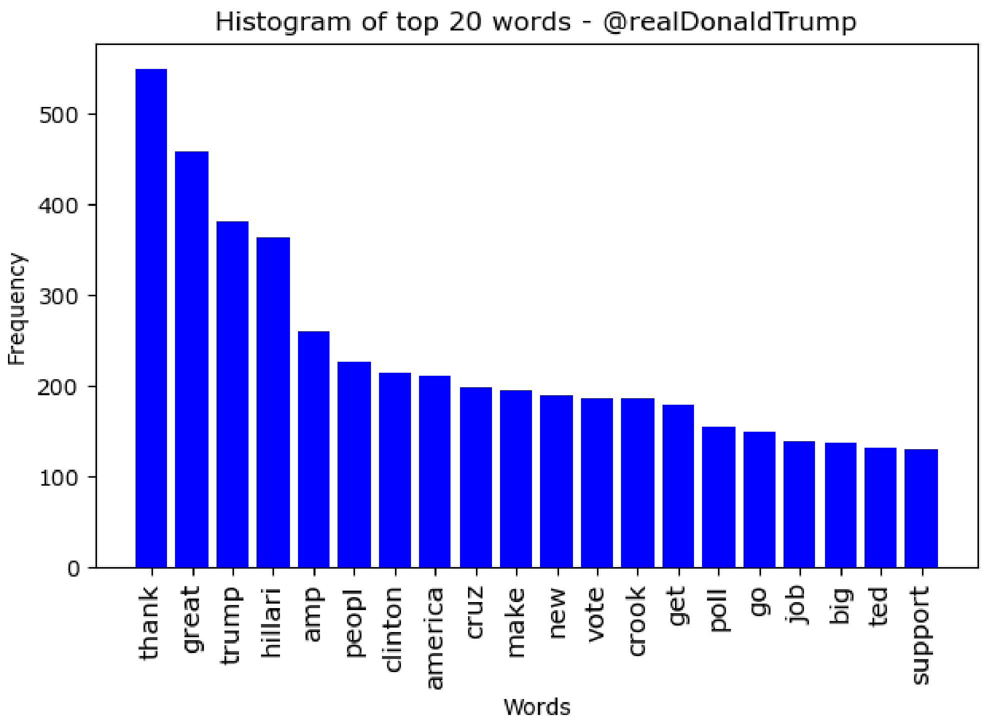


Figure 18. Number of tweets from two candidates overtime.

After text processing using **Algorithm 1**, the histogram of the top 20 frequency words from each candidate was visualized in Figure 19. From the histogram, the common words of both candidates used cover "*trump*", "*hillari*", "*make*", "*america*", "*peopl*", "*get*", "*go*" and "*vote*". Seemingly, Hillary Clinton used words like "*familii*" and "*women*" more. Donald Trump liked to use "*great*" and "*big*" more instead. However, these results cannot give us clear direction in which we should dive into in terms of detecting the polarization. In this case, ten topics we have interest in were selected to do more analysis. The topics include *climate*, *women*, *family*, *healthcare*, *trade*, *business*, *job*, *tax*, *violence*, and *terrorism*. The dictionaries of keywords for each topic were constructed in Table 3.



(a)



(b)

Figure 19. Histogram of top 20 frequency words appeared in the tweets for each candidate: (a) @HillaryClinton; (b) @realDonaldTrump.

Table 3. Dictionaries of keywords for each topic

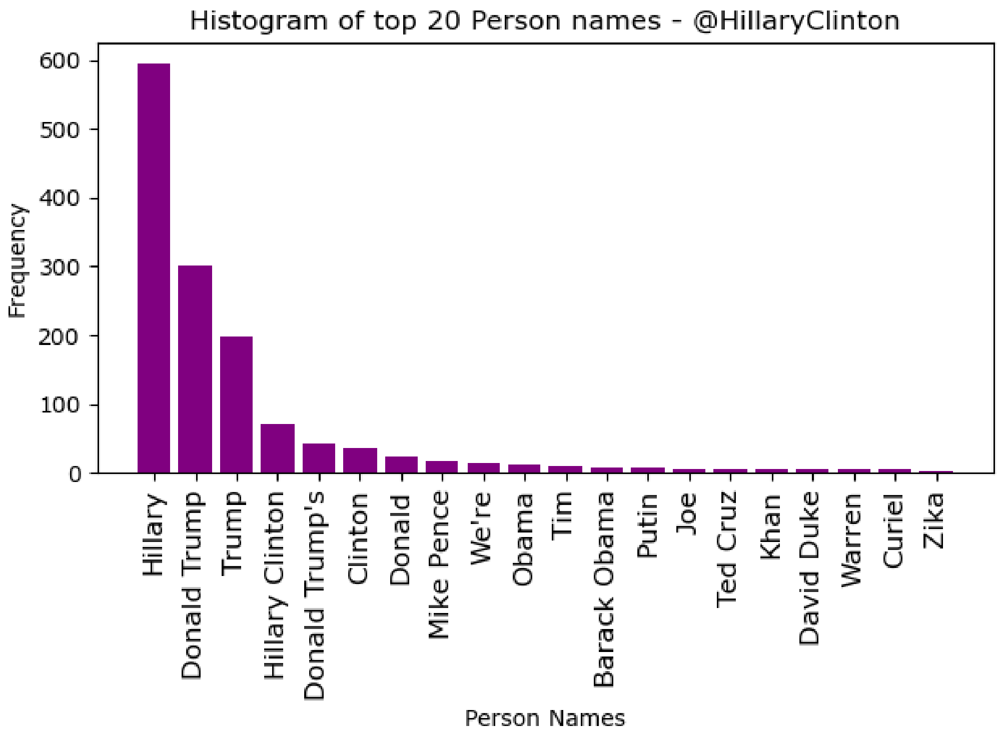
Topic	Dictionaries of keywords
climate	"climate"
women	"women|woman|wife|female"
family	"family|families"
healthcare	"healthcare|health"
trade	"trade"
business	"business|company|companies|firms|firm|entrepreneurship|entrepreneur|entrepreneurs"
job	"job|jobs|employment|employ|employs|employing|employed"
tax	"tax|taxes"
violence	"violence|gun|weapon"
terrorism	"terrorism|terrorist"

7.2.2. Named entity recognition

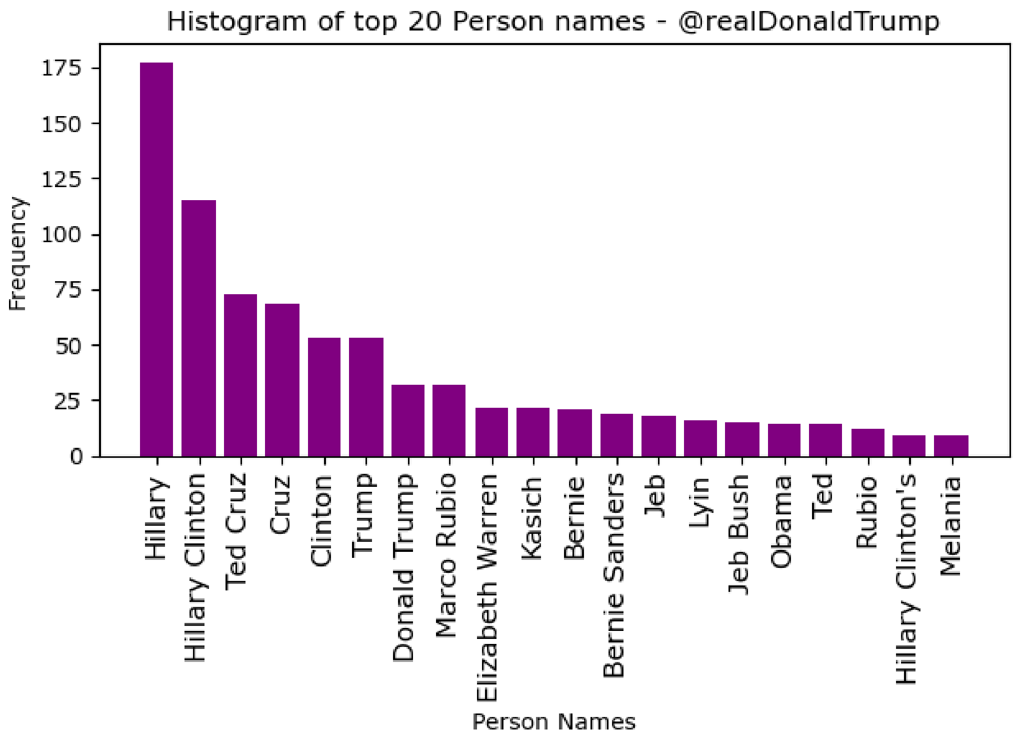
Furthermore, we also have an interest in named entities (person, organization) mentioned in both tweets' texts. With the aid of the spaCy tool, the top 20 person names and organization names were detected from the tweets of both candidates (Figure 20 and Figure 21). Figure 20 gives the results of the top 20 person names detected by software: (a) for Hillary Clinton; (b) for Donald Trump. The results show that "*Hillary*, *Hillary Clinton*, *Trump*, *Donald trump*, *Obama*, *Ted Cruze*" are the common person names mentioned by both candidates. Regarding organizations, the common names only contain "*trump*, *GOP*, *DNC*." As shown in Figure 21, Hillary Clinton mentioned "*LGBT*" more often and Donald trump mentioned "*GOP*" more often. To furtherly analyze the polarization, three entities (*obama*, *LGBT* and *GOP*) were added into the topics list above. The dictionaries of keywords were created in Table 4.

Table 4. Dictionaries of keywords for each topic

Topic	Dictionaries of keywords
lgbt	"lgbt"
gop	"gop"
obama	"obama|barack obama"

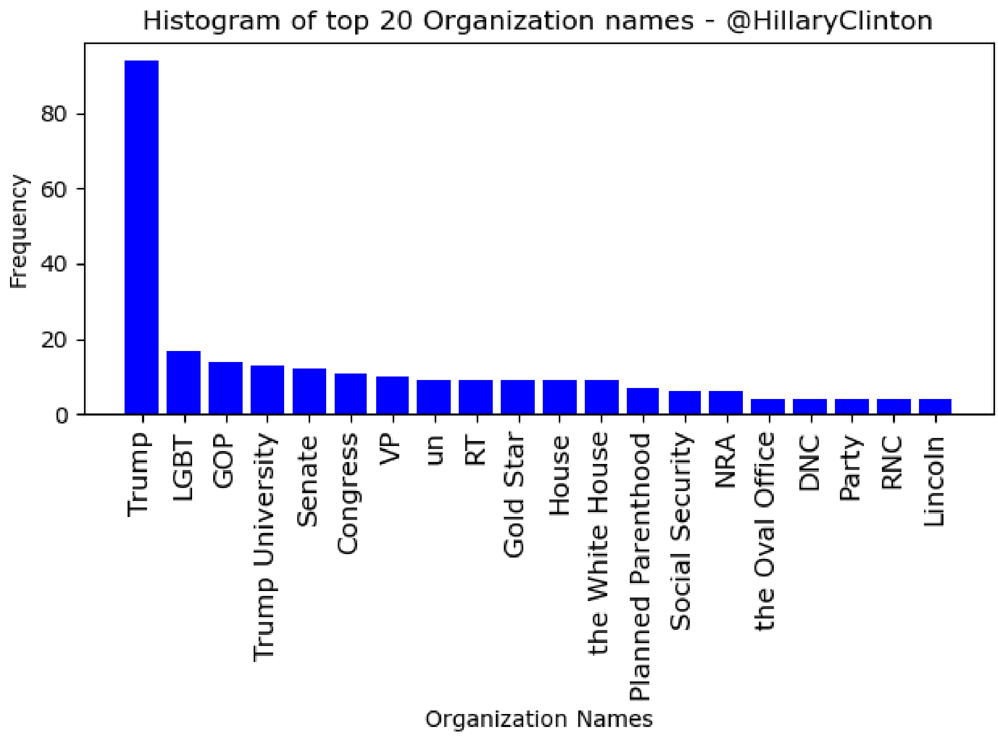


(a)

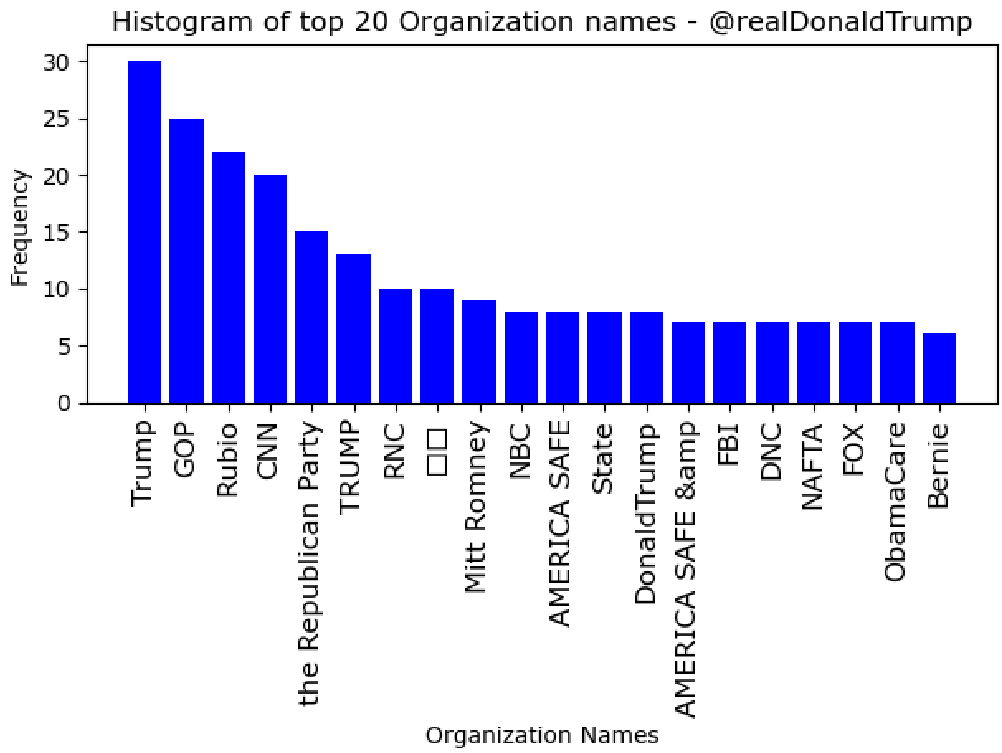


(b)

Figure 20. Top 20 person names appeared in the tweets for each candidate: (a) @HillaryClinton; (b) @realDonaldTrump.



(a)



(b)

Figure 21. Top 20 organizations appeared in the tweets for each candidate: (a) @HillaryClinton; (b) @realDonaldTrump.

7.2.3. Topics and named entities analysis

In this part, we will conduct topics and named entities analysis. Firstly, we investigate how frequently the topics and named entities are mentioned in the tweets from both candidates. The results in Figure 22 display that there are different focuses for both candidates. Hillary Clinton talked more about *climate*, *women*, *family*, *healthcare*, *business*, *tax*, *violence*, and *lgbt*. Compared with Hillary Clinton, Donald Trump had relatively fewer posts. Donald Trump did not mention anything about *climate* and only had a few posts about *healthcare*, *tax*, *lgbt*, and *violence*. The topics with a smaller gap of frequency were found in *job*, *terrorism*, and *obama*. The changes of the number of tweets posted related to topics overtime for each candidate were plotted in Figure 23. During each week, both candidates post the different numbers of tweets related to topics.

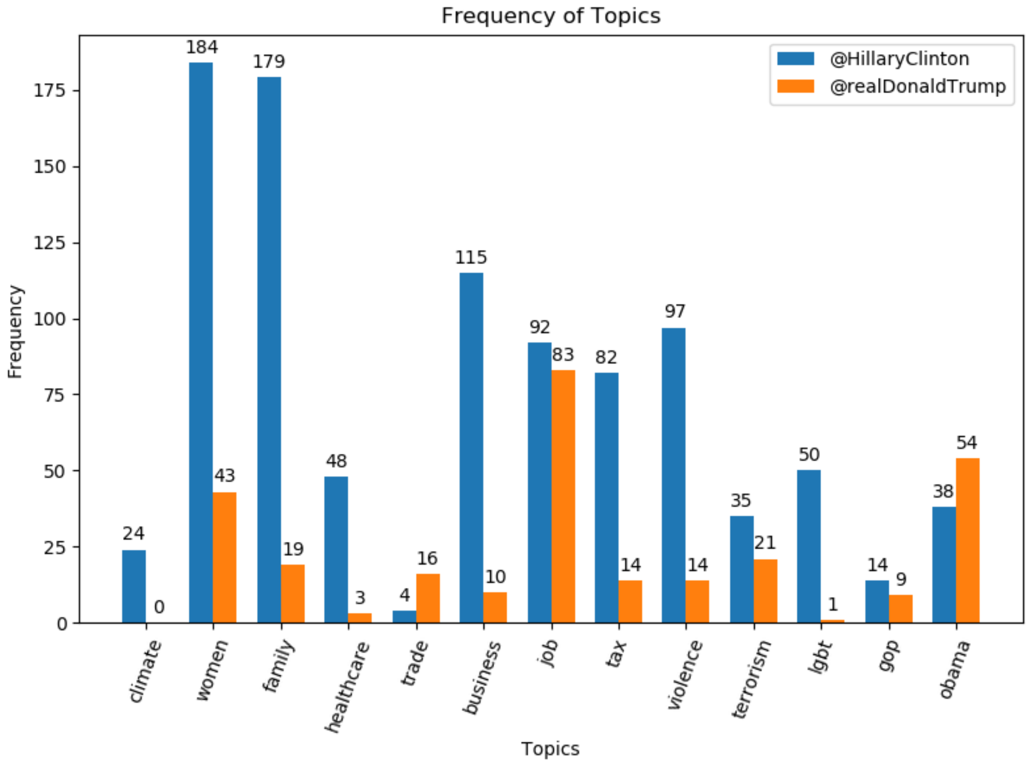
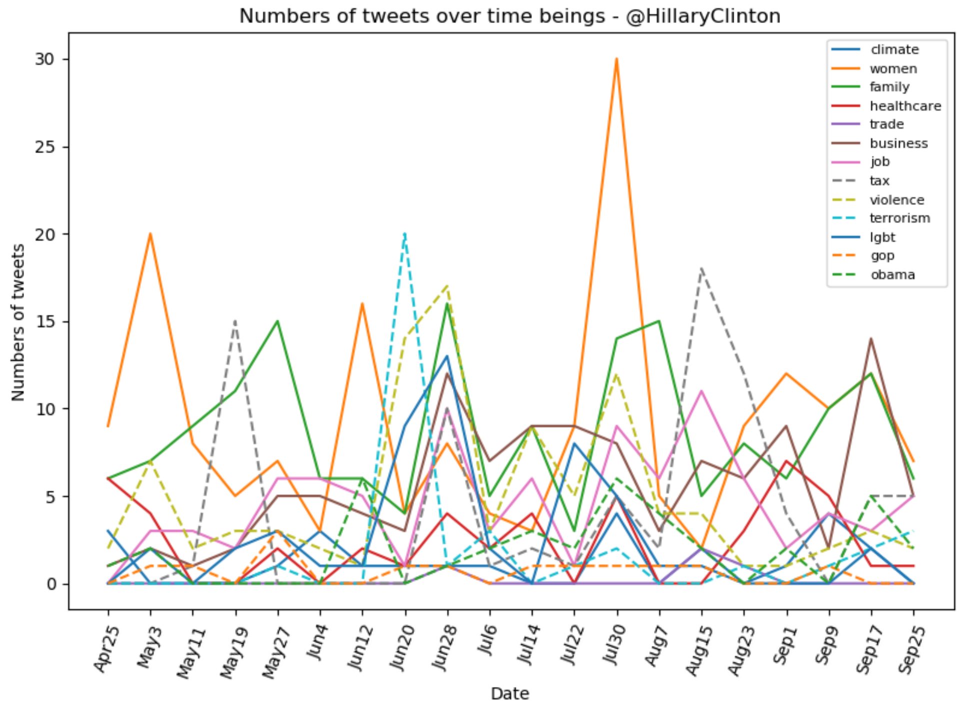
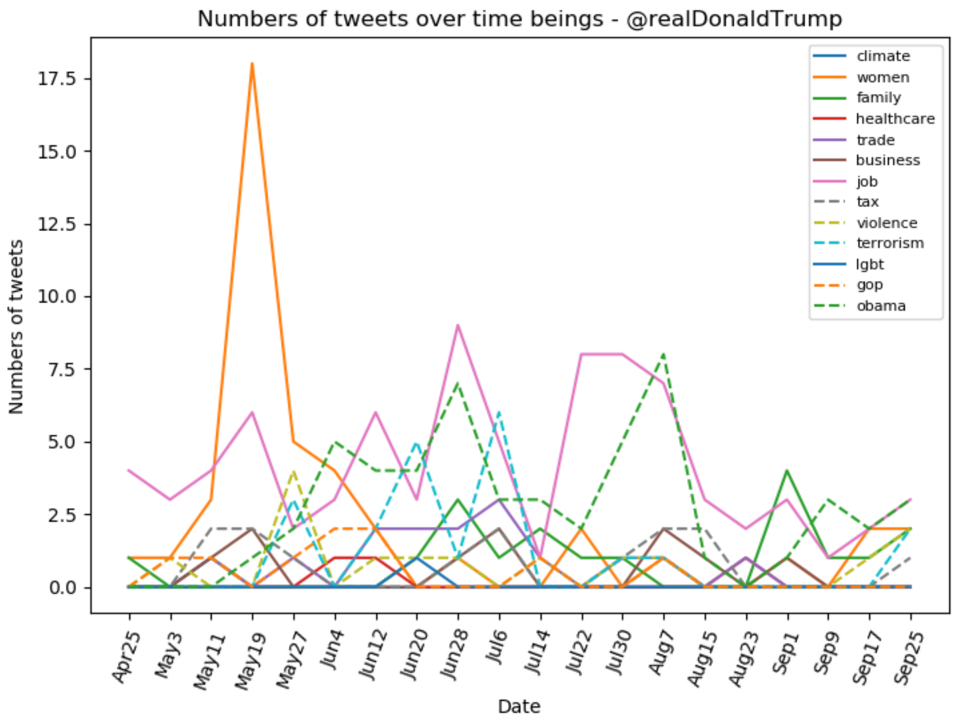


Figure 22. Histogram of frequency of topics from both candidates.



(a)



(b)

Figure 23. Number of tweets posted related with topics overtime for each candidate: (a) @HillaryClinton; (b) @realDonaldTrump.

7.2.4. Polarization measurement

Divergence of topics between candidates was displayed in Figure 24 – 36, which gives the trend of probability changes with time beings. Figure 24 gives information that there is no post related to the topic of "*climate*" from Donald Trump. Overall, it is noticed that both candidates nearly have the opposite trend towards some topics, for instance, *job*, *terrorism*, and *obama*. In Figure 33, there is one sharp peak for "terrorism" topic from Hillary Clinton from June 4 to June 12. Correspondingly, Donald Trump also has an increasing interest in this topic. The reality is that the Orlando nightclub shooting happened on 12 June 2016. This founding match with the hypothesis of "*The issues mentioned in Hillary Clinton's tweets will predict the issues mentioned in Donald Trump's tweets*" [113]. Based on the divergence of topics, the distance (or BPI) between candidates for each topic was calculated by the Equation (4). The results were listed in Table 5. BPI for climate topic has no value because no post is from Donald Trump. The topics with top 3 BPI were found in the topics of *job*, *terrorism*, and *obama*. The values of BPI indicate the polarization level between candidates. The bigger BPI value implies more polarized.

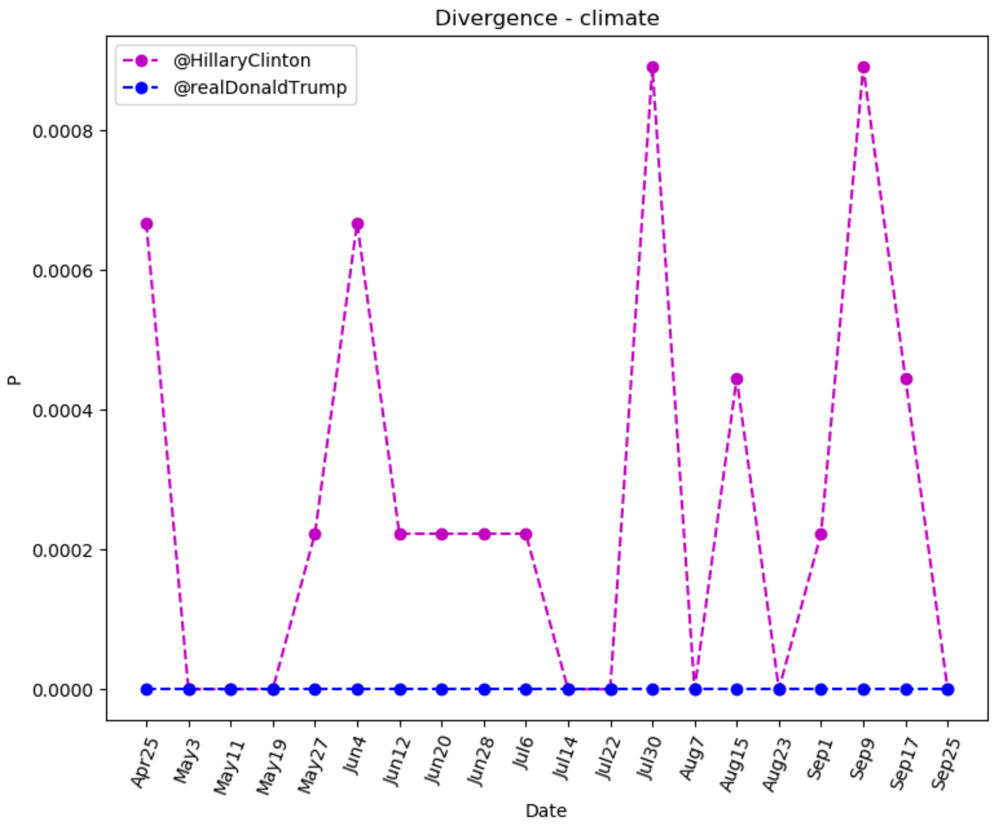


Figure 24. Divergence - climate

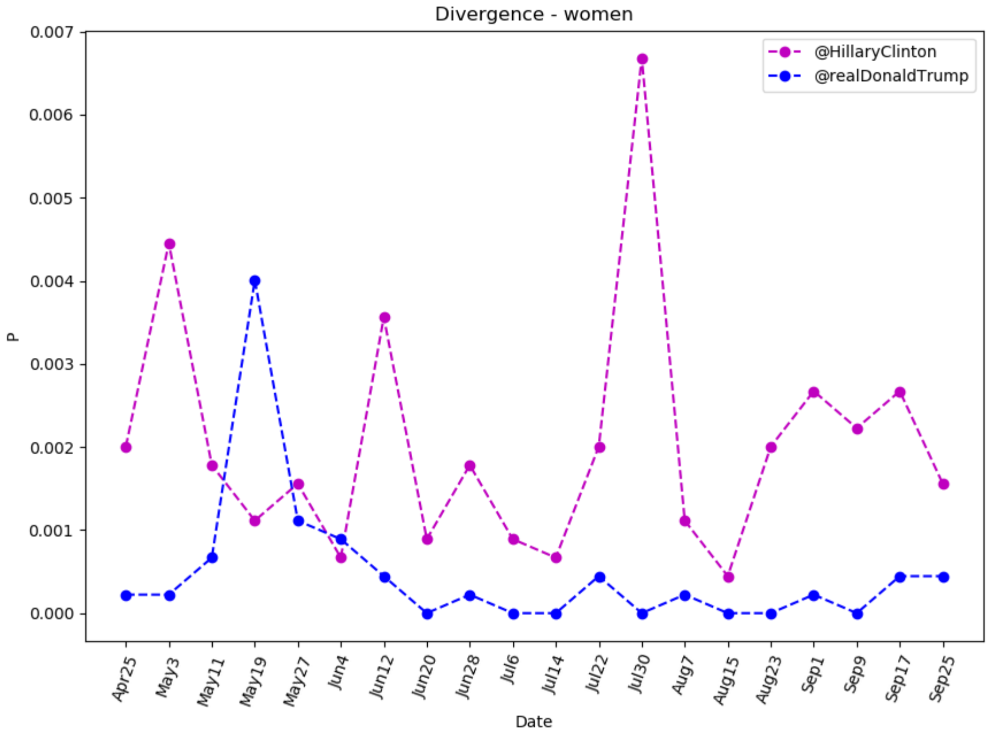


Figure 25. Divergence - women

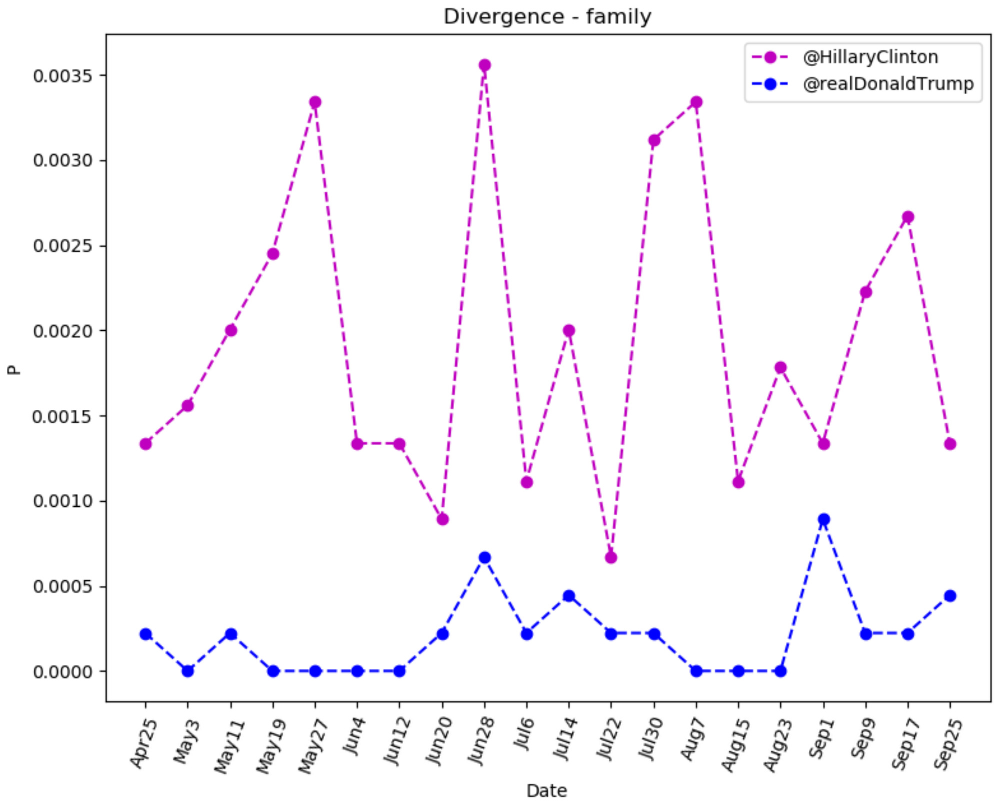


Figure 26. Divergence - family

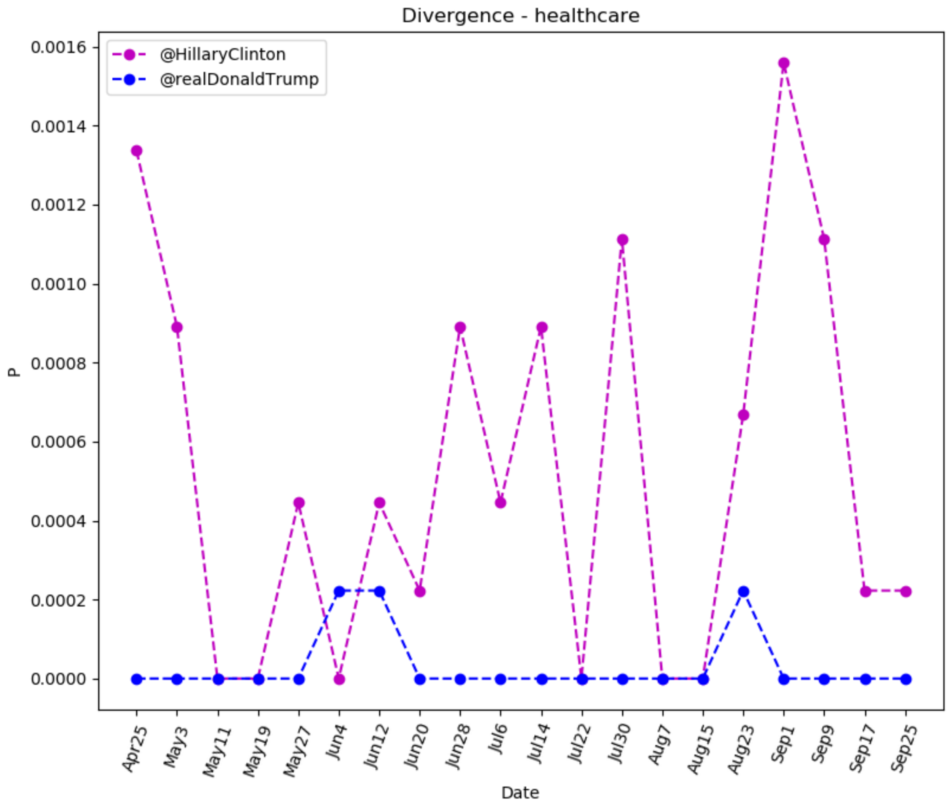


Figure 27. Divergence - healthcare

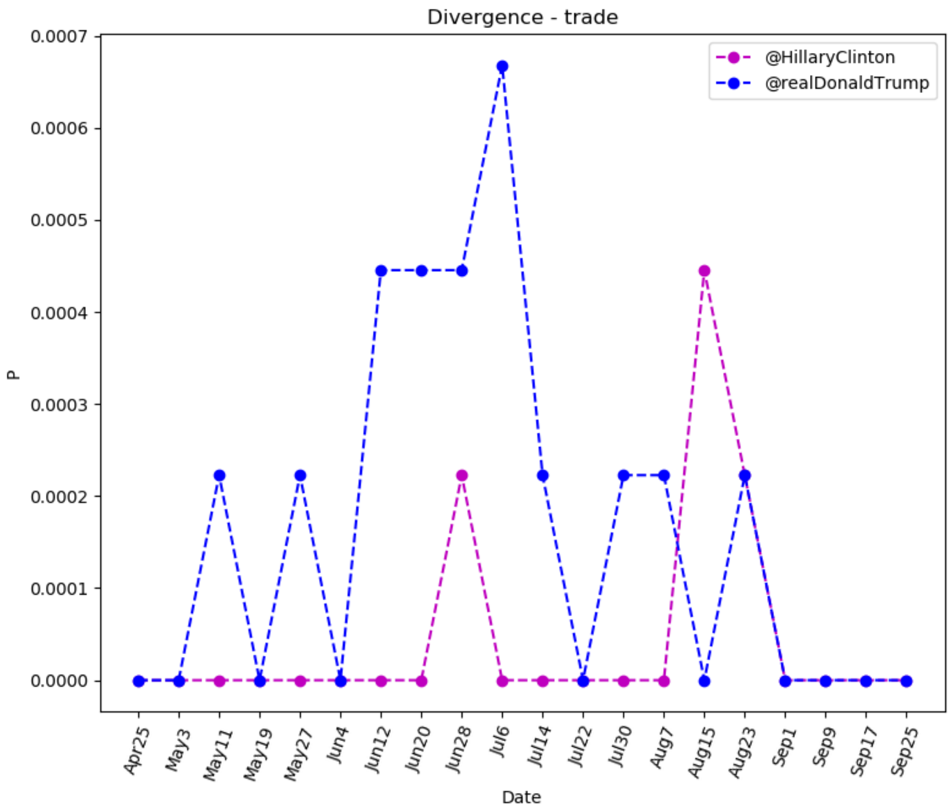


Figure 28. Divergence - trade

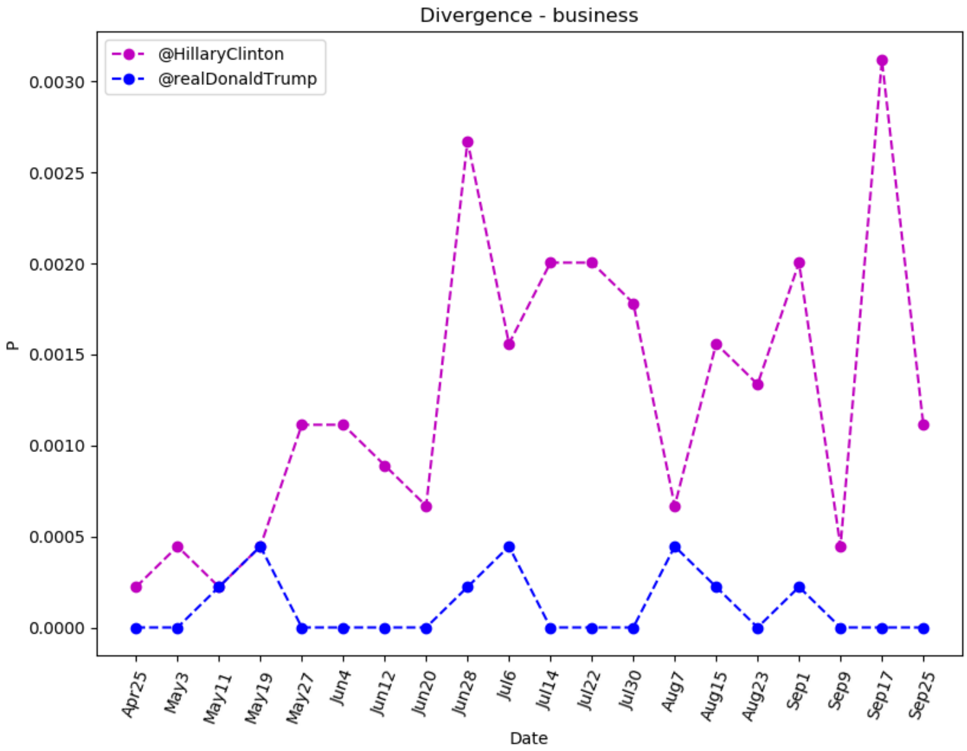


Figure 29. Divergence - business

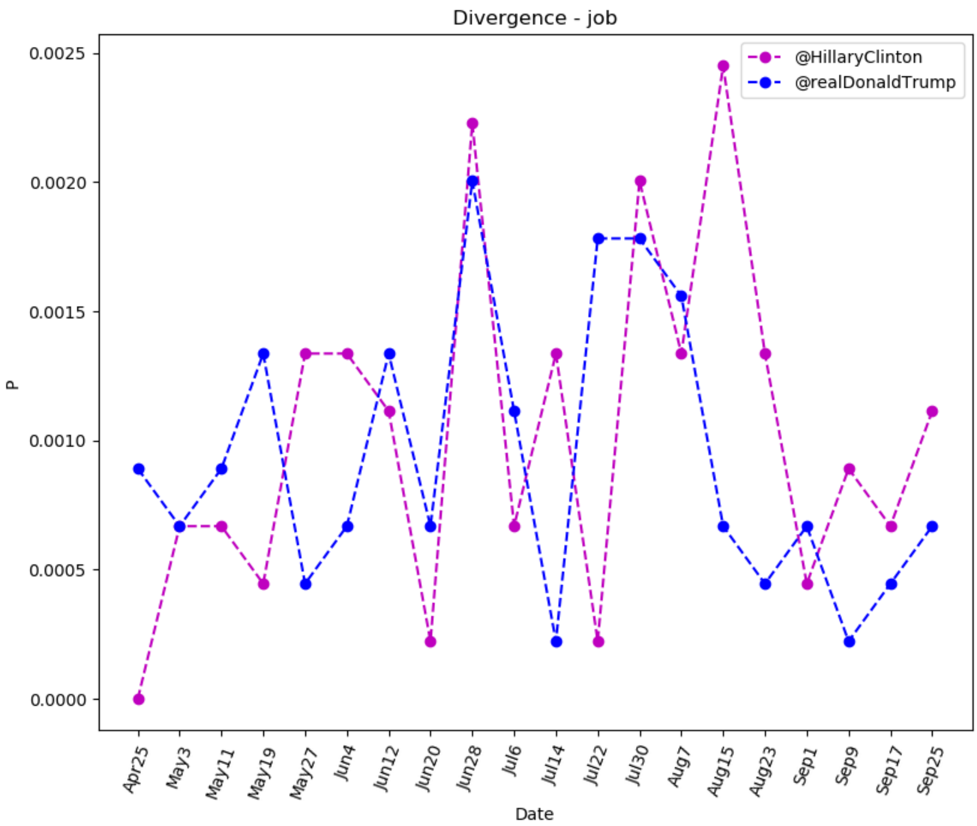


Figure 30. Divergence – job.

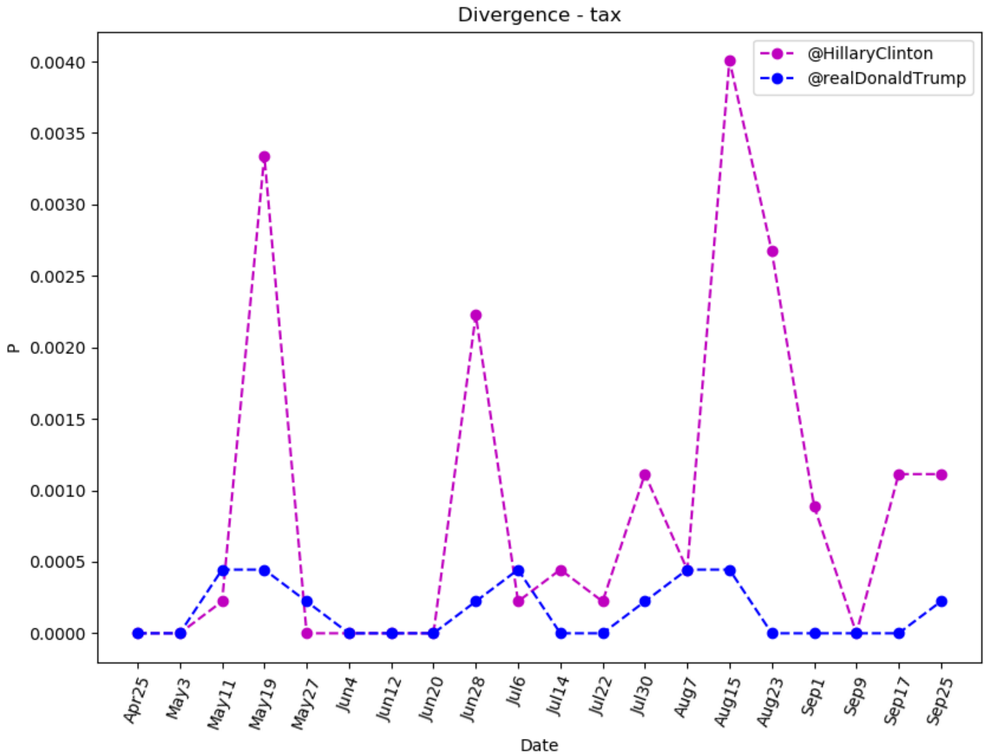


Figure 31. Divergence – tax.

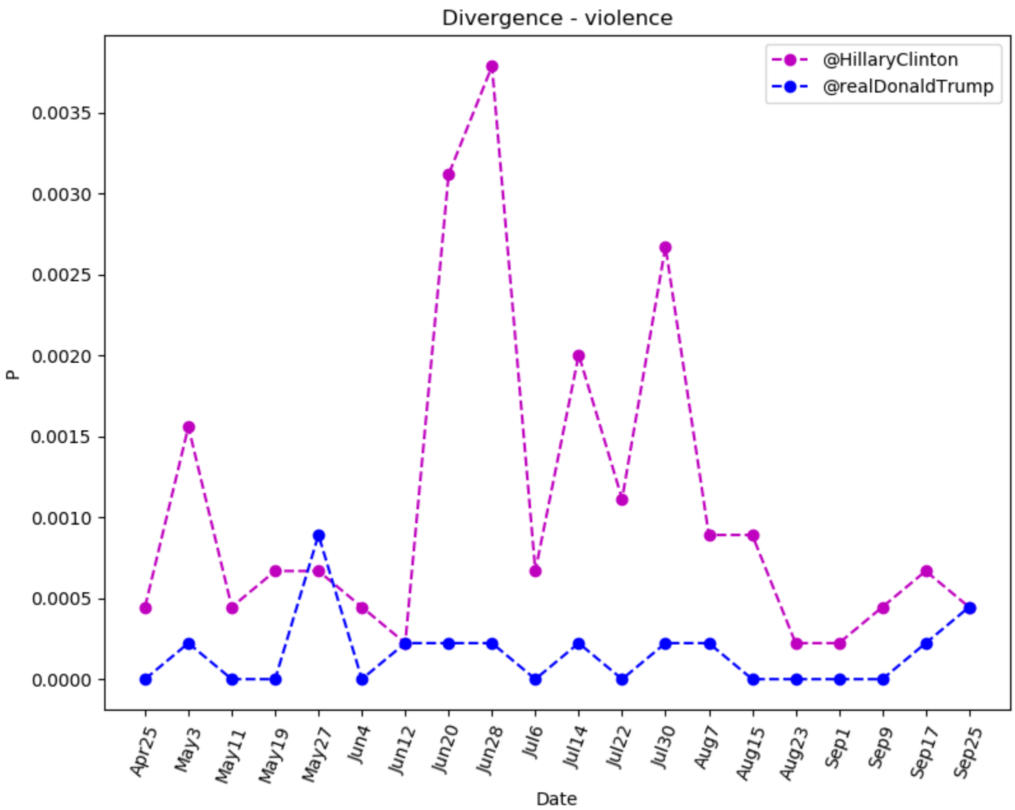


Figure 32. Divergence – violence.

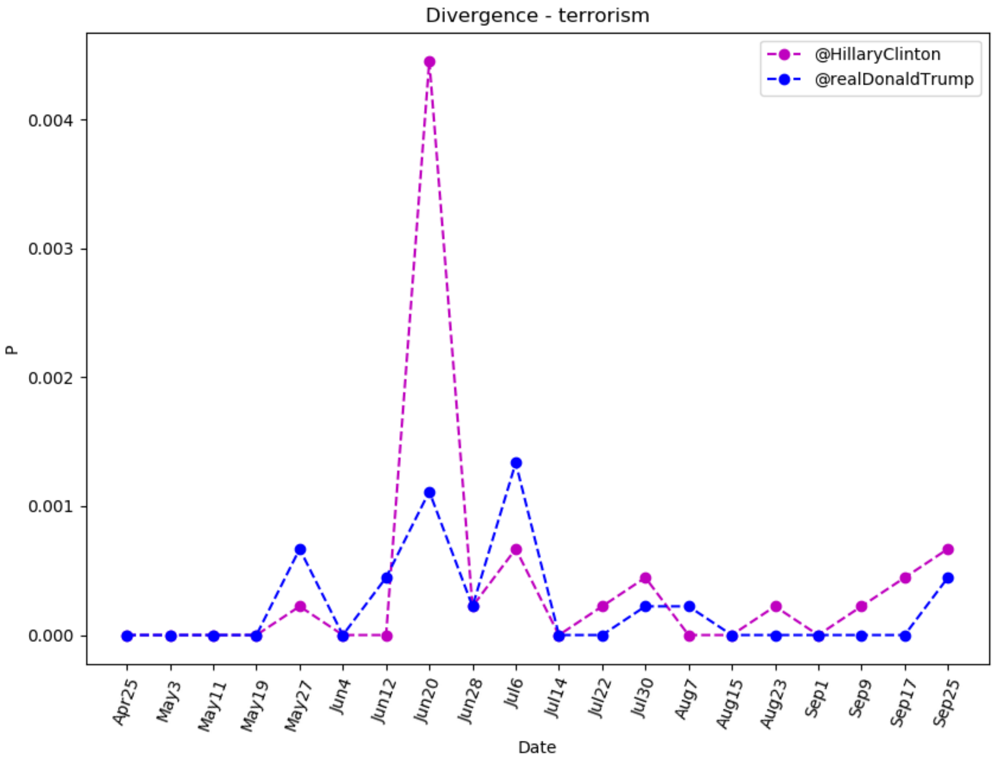


Figure 33. Divergence – terrorism.

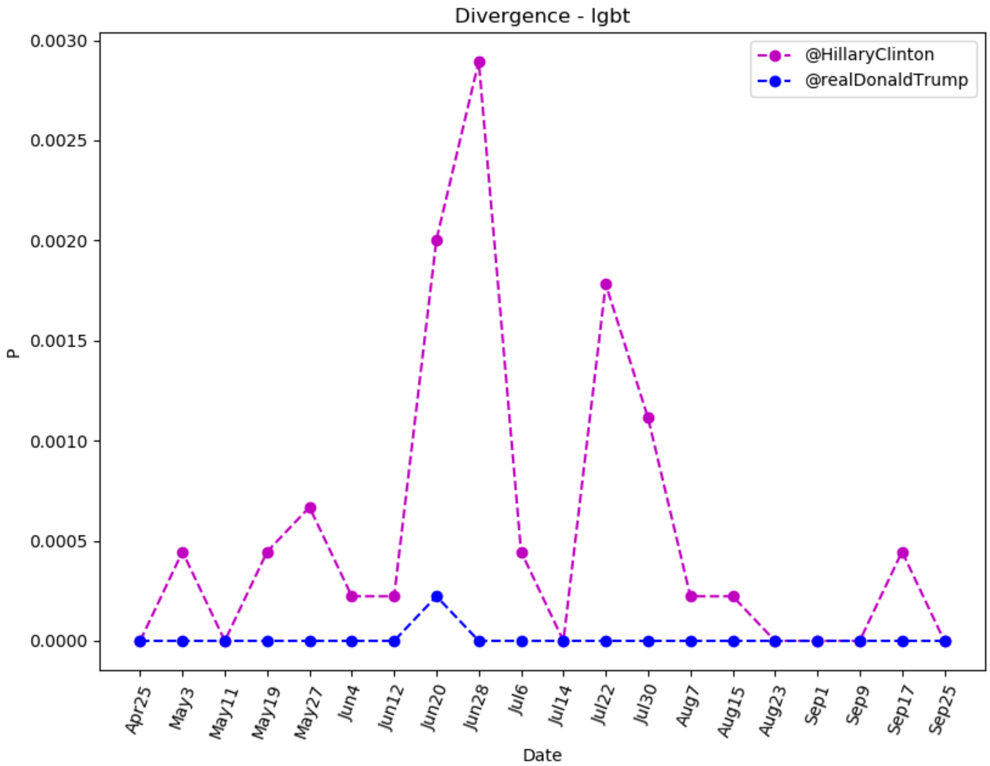


Figure 34. Divergence – lgbt.

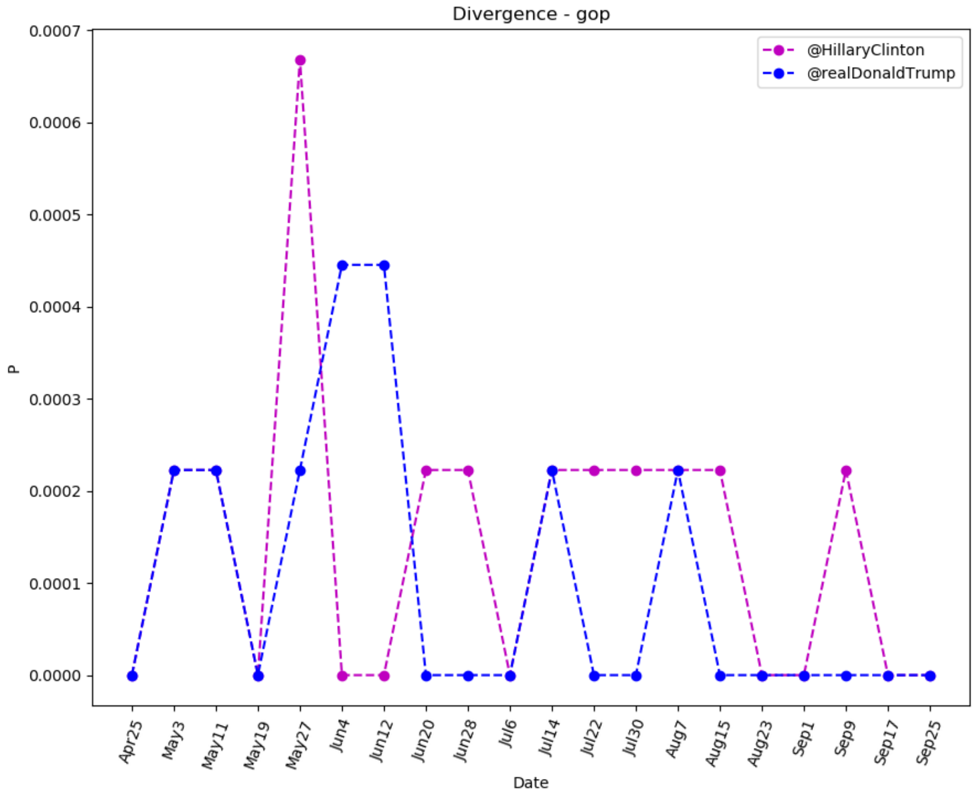


Figure 35. Divergence – gop.

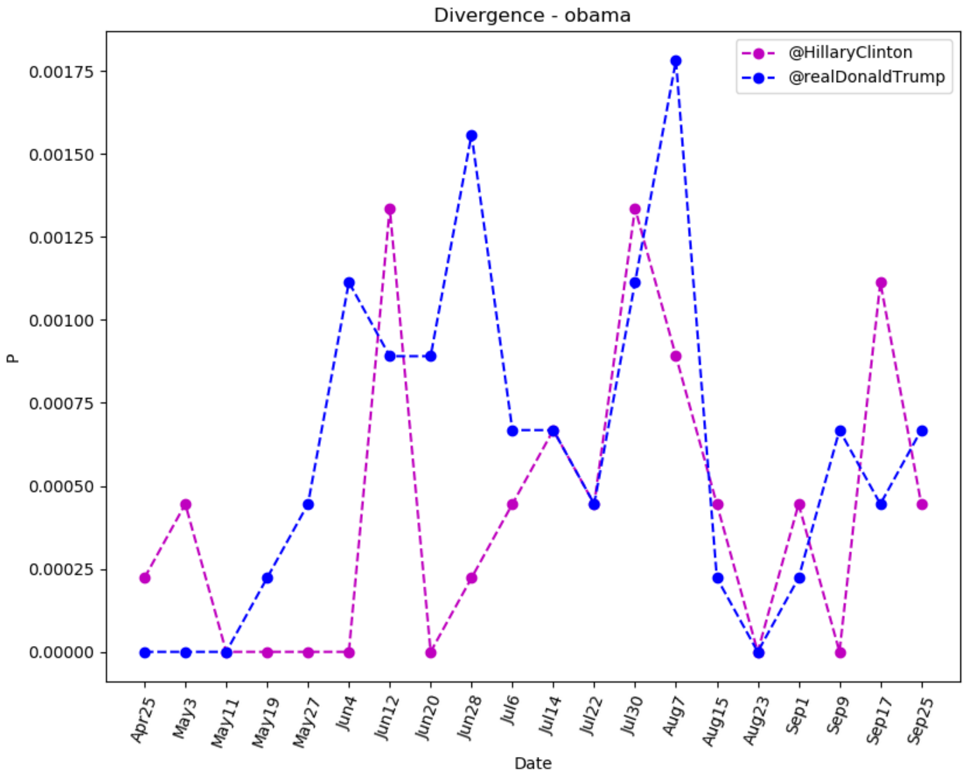


Figure 36. Divergence – obama.

Table 5. Belief Polarization Index (BPI)

Category		Belief polarization Index (BPI)
Topics	climate	-
	women	0.304
	family	0.608
	healthcare	0.201
	trade	0.236
	business	0.441
	job	0.779
	tax	0.641
	violence	0.530
	terrorism	0.696
Named entities	lgbt	0.469
	gop	0.445
	obama	0.692

Sentiment analysis was conducted on three topics (*job*, *terrorism*, and *obama*) for each candidate by SentiStrength. The example result of the topic "*obama*" was shown in Figure 37 and Figure 38. Donald Trump is less positive than Hillary Clinton. The Word Cloud shows that Donald Trump used more negative words like "*wrong*, *bad*, *worst*, and *never*" (Figure 39), while Hillary Clinton would like to use the verbs like "*thank*, *hope* and *endorse*" with relatively more positive meanings (Figure 40).

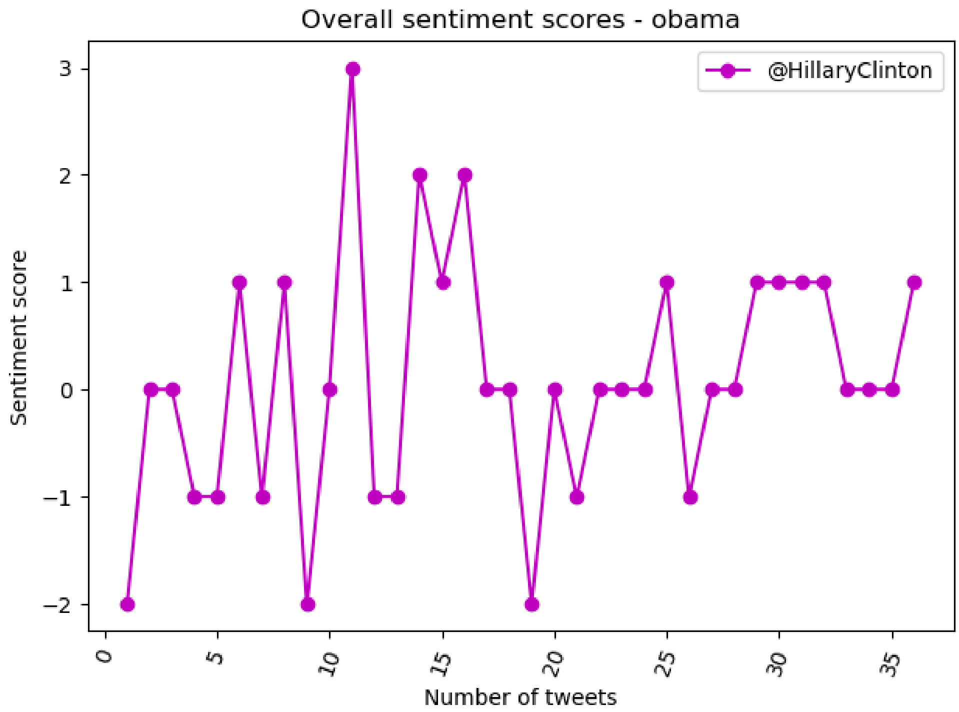


Figure 37. Sentiment analysis on "obama" from Hillary Clinton.

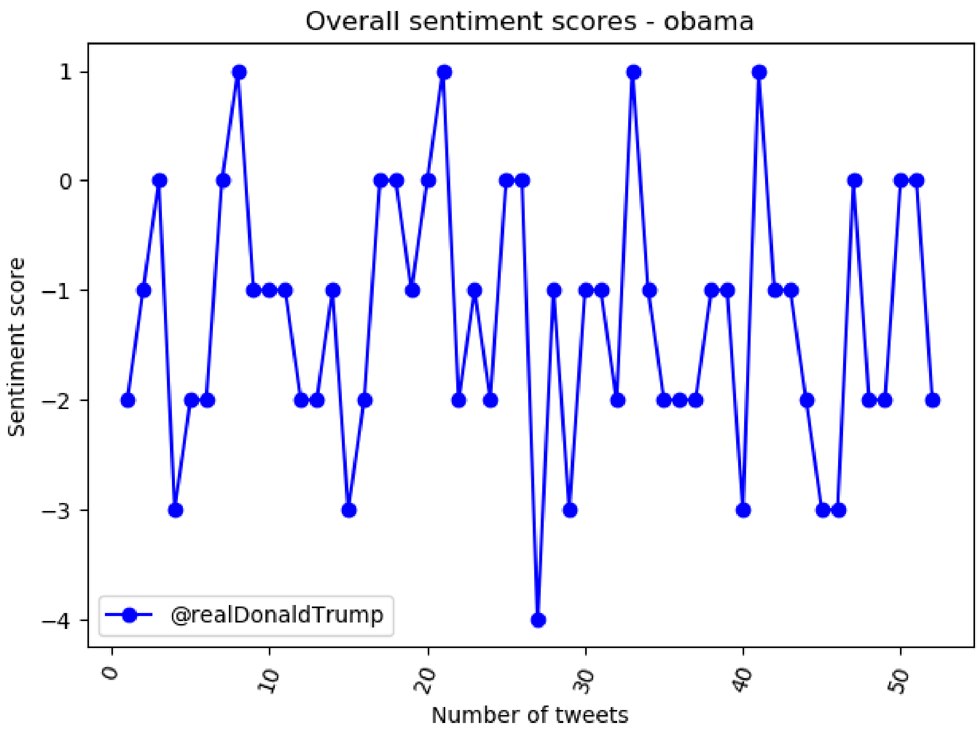


Figure 38. Sentiment analysis on “obama” from Donald Trump.

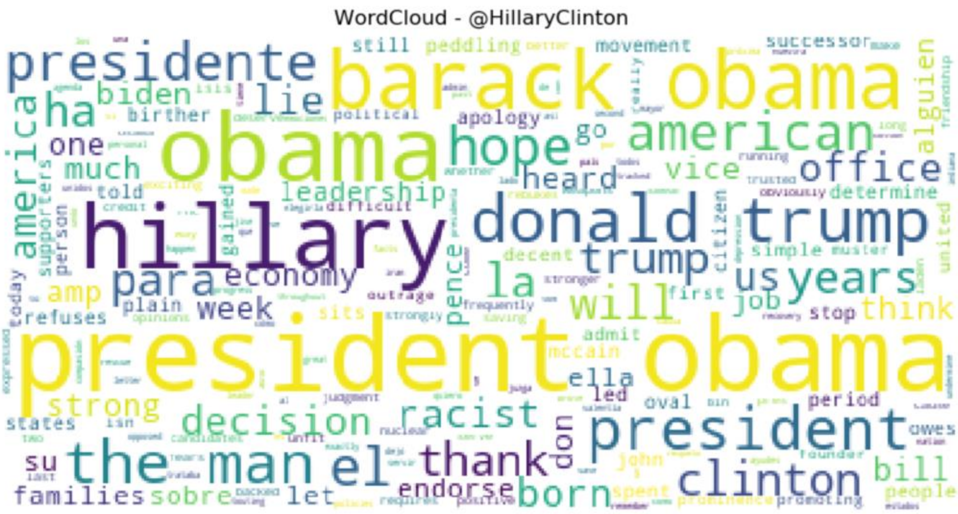


Figure 39. Word Cloud on “obama” from Hillary Clinton.

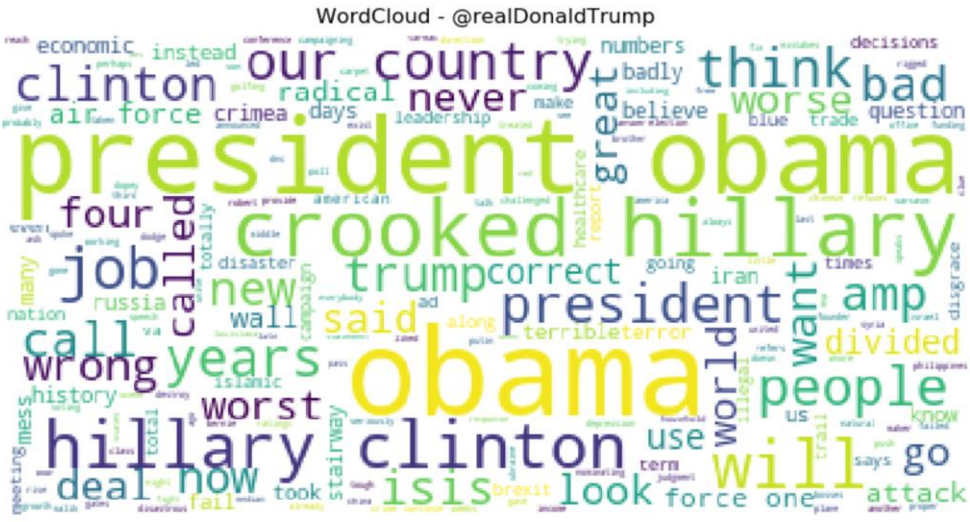


Figure 40. Word Cloud on “obama” from Donald Trump.

Inspired by the statistical inferences for polarity identification from Pröllochs, N., et al. [21], we utilize this method to evaluate if there is significantly positive or negative polarity for these three topics between two candidates.

HYPOTHESIS: *Hillary Clinton shows more positive at these three topics (job, terrorism, and obama) than Donald Trump*.

To test the hypothesis, we compute the overall sentiment scores for each topic from each candidate (μ_c, μ_t refers to Hillary Clinton and Donald Trump respectively). The summary statistics of μ_c, μ_t are shown in Table 6. Then we test the null hypothesis:

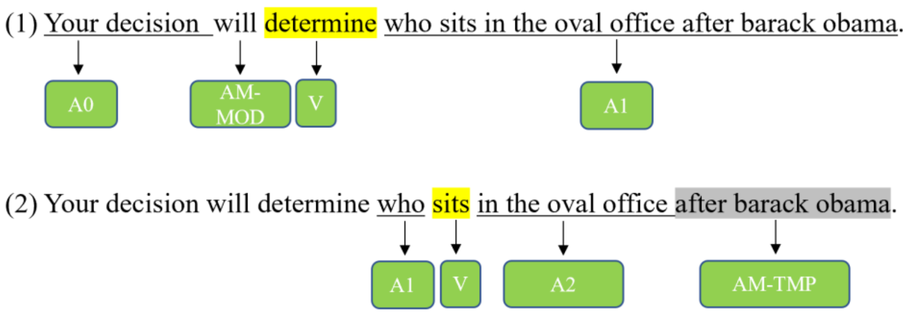
H_0: $\mu_c > \mu_t$ (*Hillary Clinton is more positive than Donald Trump*)
H_1: $\mu_c < \mu_t$ (*Hillary Clinton is less positive than Donald Trump*)

According to our results, Hillary Clinton shows more positive at the topics of “*terrorism*” and “*obama*” than Donald Trump excluding the topic of “*job*”. The mean sentiment regarding the topic “*job*” from Hillary Clinton amounts to $\mu_c = 0.0435$, whereas for Donald Trump it is $\mu_t = 0.2289$. To examine the difference $\mu_c - \mu_t$ between two sentiment values, a two-sided *t*-test was performed. The *t*-test result indicates that there is no statistically significant at the 0.1% significance level. For the topic “*terrorism*”, Hillary Clinton has a negative sentiment of $\mu_c = -1.7714$ on average, while Donald Trump has a more negative sentiment of $\mu_t = -2.095$. Similarly, we found that the difference between these two sentiment values is not significant at the 0.1% significant level. For the topic “*obama*”, Hillary Clinton has a positive sentiment of $\mu_c = 0.0513$ on average, while Donald Trump has a negative sentiment of $\mu_t = -1.2407$. The difference between these two values is statistically significant at the 0.1% significant level. Thus, we accept our hypothesis that Hillary Clinton shows more positive at the topic of “*obama*”. However, we have to reject the hypothesis for the other two topics (“*job*” and “*terrorism*”).

Table 6. Summary statistics for hypothesis testing with topics of job, terrorism and obama

	Overall sentiment scores					
	job		terrorism		obama	
	μ_c	μ_t	μ_c	μ_t	μ_c	μ_t
Mean	0.0435	0.2289	-1.7714	-2.095	0.0513	-1.2407
Min.	-4.0	-3.0	-4.0	-3.0	-2.0	-4.0
25% Quantile	-1.0	-1.0	-2.0	-3.0	-1.0	-2.0
Median	0.0	1.0	-2.0	-2.0	0.0	-1.0
75% Quantile	1.0	2.0	-1.0	-2.0	1.0	0.0
Max.	2.0	3.0	1.0	-1.0	3.0	1.0
Std. Dev.	1.102	1.645	0.9587	0.7499	1.13	1.170
Skewness	-0.524	-0.304	0.5032	0.1572	0.112	0.0591
Kurtosis	0.634	-1.1499	0.9778	-1.2102	0.00622	-0.545

We attempted to investigate the semantic roles of tweets from both candidates to see if there is a difference between them. SENNA was implemented to give semantic role labelling for the words or phrases in a tweet. With the aid of SENNA, the output results of an example of the sentence "*Your decision will determine who sits in the oval office after barack obama.*" were summarized as below:



Similarly, we applied it to the tweets covering three topics of *job*, *terrorism*, and *obama* from both candidates. The percentage of labels was listed in Table 7. The data was visualized in Figures 41, 42 and 43. The results give us an expression that there is no big difference between the two candidates about these three topics. Compared with Donald Trump, the higher percentages of labels existing in *job*, *terrorism*, and *obama* for Hillary Clinton are (A0, A2), (A2), and (A0, A1, A4) respectively. A2 is the label with the max difference of percentage for all these topics.

Table 7. The percentage of semantic role labels for both candidates

Candidates	Topics	Semantic role labelling				
		A0	A1	A2	A3	A4
@HillaryClinton	job	39.52%	40.48%	18.10%	1.43%	0.47%
	terrorism	40.54%	37.84%	20.27%	1.35%	0
	obama	41.03%	41.03%	15.38%	1.28%	1.28%
@realDonaldTrump	job	38.55%	42.77%	13.25%	3.61%	1.82%
	terrorism	39.02%	41.46%	17.07%	2.45%	0
	obama	38.21%	38.21%	19.51%	3.25%	0.82%

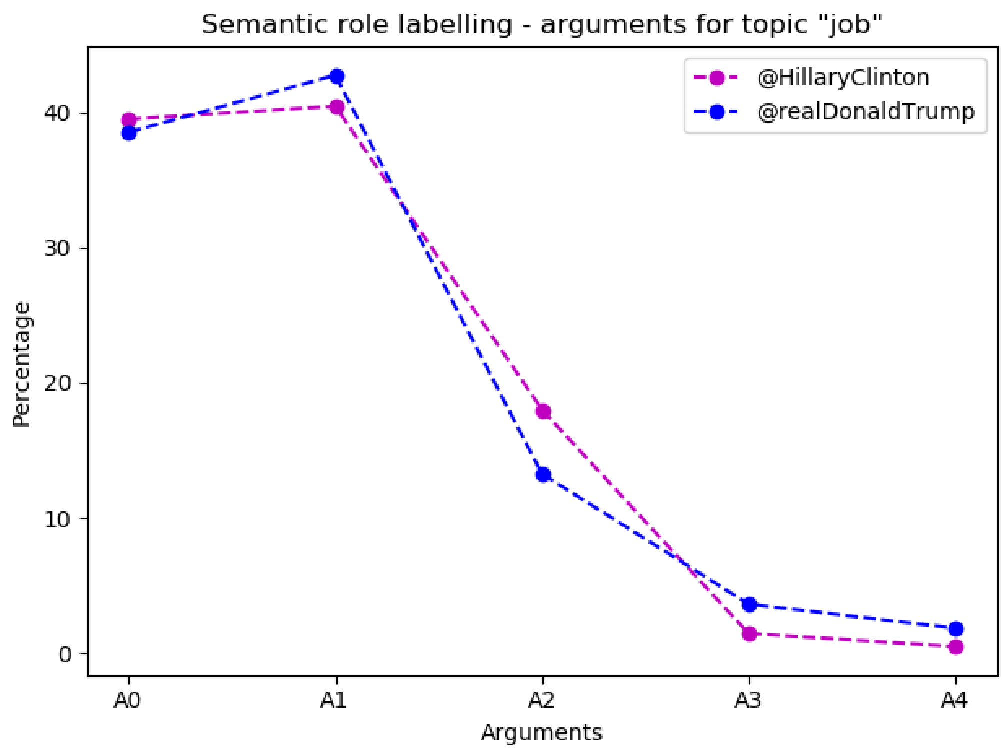


Figure 41. Divergence on arguments for the topic “job”.

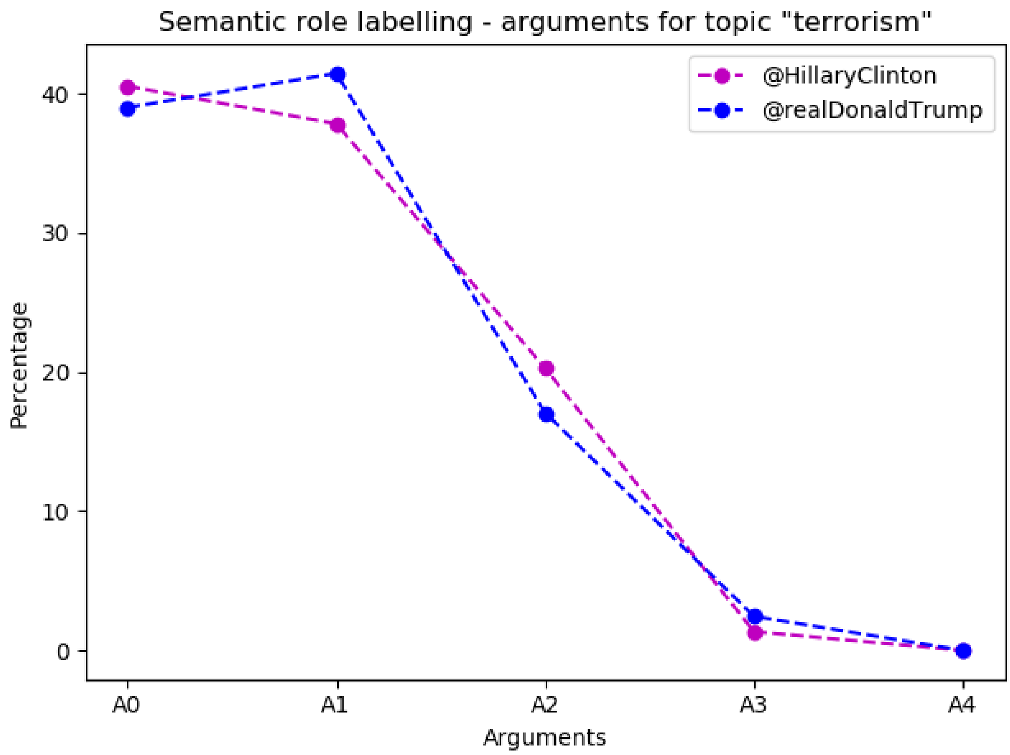


Figure 42. Divergence on arguments for the topic “terrorism”.

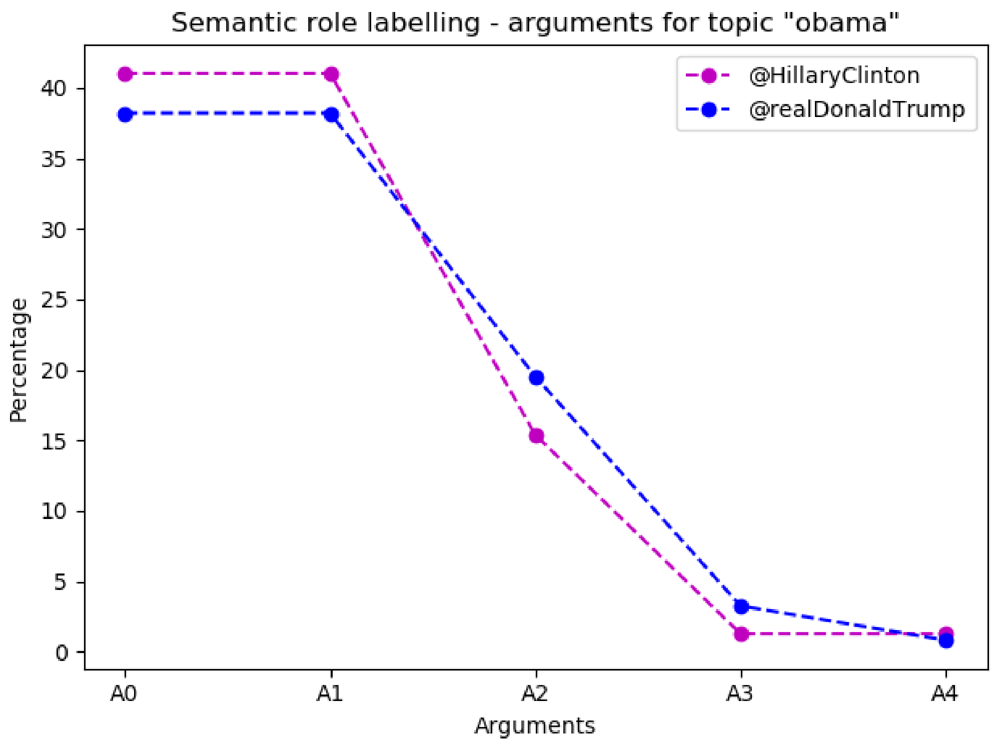


Figure 43. Divergence on arguments for the topic “obama”.

In the following, we also tried argument mining to check is there any difference between the two candidates. TARGER tool was implemented to tag the argument. One example of outputting results of a given tweet was shown in Figure 44. In TARGER, seven models are available to give labels for the input text. In our case, IBM (fastText) model was applied to tag the argument with premises or claims. The tweets related to the topics (*job*, *terrorism*, and *obama*) from two candidates were input to TARGER system. According to the results in Table 8, we can see that claims were only found in the tweets related to *terrorism* from both candidates. In Twitter, people often post tweets to show their opinions about some topic, which may be a lack of evidence to support their viewpoints due to its limitation of text size [114].

Table 8. Argument Mining (AM) for topics of job, terrorism and obama

Candidates	Topics	Argument Tagger	
		premises	claims
@HillaryClinton	job	100%	0%
	terrorism	100%	0%
	obama	100%	0%
@realDonaldTrump	job	100%	0%
	terrorism	98%	2%
	obama	100%	0%

Figure 44. Example of argument tagging on TARGER.

8. DISCUSSION

A few methods were proposed to identify and monitor the polarization from the perspective of the social networks in this research work. The polarization on Twitter between two candidates was measured by text mining in terms of modified cosine distance of topics that appeared in tweets between two candidates and sentiment analysis. Moreover, semantic role labelling and argument mining were tried to furtherly check if there is any difference regarding the selected polarized topics between two candidates. In this research, polarization was measured based on the topics of interest, which may be limited by the keywords we selected, and the numbers of tweets posted by the candidates. The computation of the polarization index may be affected when there is a big difference in the numbers of tweets posted between the two candidates.

As Liu, B., et al. [115] said, there is no easy problems in natural language processing task. During the research, we also face other challenges and uncertainties, which were summarized as below:

a) Text processing: tweets text collected from Twitter were parsed through the process called text-clean which includes removing the whitespace, removing the punctuation, removing non-alphabet, tokenization, removal of stop words, stemming and removal of special character for the later usage. During text processing, we noticed that only using "*word_tokenize()*" is not adequate to clean the text. For example, some tweets may contain compound words. Therefore, compound words splitting was added in the text processing. However, the output of stemming still has some issues left, for example, "*people*" is stemmed as "*peopl*", "*president*" is stemmed as "*presid*", etc. Furthermore, owing to short messages required on Twitter, people may use slang, misspellings, profanity, or neologisms. All those expressions may fool the program. Currently, text processing is not designed for non-English posts. For non-English posts have to be translated into an English version.

b) For named entity recognition, spaCy software was chosen as an entity detection tool. As addresses before, spaCy does not have better performance than Standford NLP although it is a fast solution. Optimizing the detection tools may be good practice for getting more accurate results in the future.

c) For sentiment analysis, as designed to process the text from social media SentiStrength has near-human accuracy on social media texts. But SentiStrength has a weakness that does not attempt to use grammatical parsing (e.g., part of speech tagging) to disambiguate between different word senses [116]. Regrading some grammatical information, sometimes SentiStrength cannot give the correct sentiment. Take sentences of "*I like a cat*." (positive) and "*I look like an idiot*." (negative) as an example. The word "like" will be given as a neutral score according to SentiStrength's rules. In political discussion, SentiStrength has less accuracy especially when the texts often contain sarcasm [116]. Moreover, the system's result maybe also wrong because of a text-by-text basis. For instance, the tweet "*You are killing it*!" may mean either positive or negative. It is bit difficult for the automated sentiment analysis tool currently exists to handle this kind of difference.

d) Analyzing arguments from social media is quite a challenging task because of its informal structure of contents. Argument mining was tried to check if there is any difference between two candidates. The example of results for three topics (job, terrorism, and obama) shows that there are almost only premises in the tweets. The measurement may be limited by the standard argument mining approaches due to the short text on Twitter [117][118]. This part of the work still needs to be explored more in the future.

e) Collecting data from Twitter is a time-consuming job due to the limitation of free Twitter API. In this research, we adopted the dataset available from Kaggle. As we thought, more datasets still need to be tried and tested.

Certainly, there are plenty of methods to measure the polarization on social media. In this research, the solutions are still limited due to the limitations of our understanding or knowledge regarding the given problem. However, some progress was made, and it presents some ways to measure the polarization on social media from a new perspective.

9. CONCLUSION

Considerring the foundation of the democratic system, there is a lot of progress in the research of political polarization, e.g. ideologic polarization. With the rapid development and popularity of social networks/media, polarization on social media also gets much attention. Still, there is much space to dig more about polarization on social networks due to the limitation of our knowledge.

The main objective of this thesis is to find solutions to identify the polarization in the perspective of social networks. Overall, this objective has been achieved successfully during the process of this thesis. The dataset we analyzed is the tweets of Hillary Clinton and Donald Trump during the 2016 President Election from Twitter. We proposed and implemented the methods of identifying the polarization (e.g. Belief Polarization Index (BPI), Sentiment Analysis) between two individuals who represent their own ideologies. Furthermore, we applied semantic role labelling and argument mining to check if there is any difference regarding the selected polarized topics between two candidates that can explain the polarization landscape.

In this research, the first contribution we make is to carry out a thorough review of state-of-the-art literature regarding polarization and the impacts of social media. Firstly, we have reviewed the concepts of polarization in the aspects of economics, politics, and sociology. Accordingly, we also reviewed the measurements of polarization regarding these three aspects. Political polarization got a wide interest in academic research and the measurement of polarization mainly focuses on the distribution of belief in terms of individuals. Secondly, we have gone through the impacts of social media on political polarization. It is manifested that political polarization can be amplified by social media. That is one reason why there is a necessity to research the polarization in the perspective of social networks/media.

Additionally, we have reviewed the related NLP technologies which will be applied in this thesis. The NLP technologies mentioned include text processing, named entity recognition, sentiment analysis, semantic role labelling, and argument mining. In this section, we generally introduced its concept, applications, and tools for each technology. In recent years, much progress has been achieved in the field of NLP. However, it is always a bit challenging to do text mining through language by computers due to the complexity of human language, especially from social media.

The work present in this research includes topic selection, polarization measurement, and the exploration of the polarization landscape by text mining. Firstly, we attempt to find the most frequent words from the tweets by text processing and histogram visualization of word frequency. Our findings show that it is a bit difficult to choose the suitable words to analyze the polarization. That is why we decide to construct some topics of interest by building the keywords dictionary. The keywords we selected may be limited in this research. Then the frequency of topics that appeared in the tweets overtime is investigated between the two candidates before computing the distance of polarity. In the measurement of polarization, we propose two methods of measurement including Belief Polarization Index (BPI) and Sentiment Analysis. BPI is to measure the distance of similarity regarding the topics between the two candidates, which can be used as an indicator of the level of polarity. As an alternative, it is possible to set some threshold as a benchmark to give the output as "polarized" or "non-polarized". In this research, the bigger BPI values for some topic is supposed to imply that two candidates are more polarized at this topic. The results show that the top 3 BPI values exist in the topics of "*job*", "*terrorism*" and "*obama*". After that, we investigated if there is sentiment polarity in these three topics between two candidates by the method of statistics inference of sentiment scores. According to the results of statistical analysis, we accept the hypothesis of "*Hillary Clinton is more positive at the topic of "obama"*." There is no significant difference in sentiment between the two candidates regarding the topics of "*job*" and "*terrorism*".

As a further analysis, to explain the polarization landscape, we study if there is any difference regarding the selected polarized topics ("*job*", "*terrorism*" and "*obama*") between the two candidates by the methods of semantic role labelling and argument mining. Semantic role labelling is used to give semantic labels to the syntactic constituent of a text, which depends on a verb's frame. Our results indicate that A2 is the label with the max difference of percentage for all these three topics between the two candidates. Argument mining is another approach to explore if there is some evidence provided in the text to support the viewpoint. We perform the argument mining for the tweets regarding the same three topics between the two candidates to detect premises and claims. We find that claims were only found in the tweets related to "*terrorism*" from both candidates. This may be caused by the limitation of the text size on Twitter, in which people often post their opinions without adequate evidence.

In this thesis, our approaches provide a solution to identify the ideological polarization of the two politicians in the perspective of social networks/media, which may give some inspiration for the research of polarization on social media. In the era of social media, there is a real and huge need to reveal its veil to know the behaviors of people to find some depolarization solutions. During the research, there are also many limitations or challenges we faced as described in the previous chapter. In the future, it still needs more work to improve the accuracy of measurement, software development, testing, etc.

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