DETECTION OF TOPIC-BASED OPINION LEADERS IN MICROBLOGGING ENVIRONMENTS

by

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ABSTRACT

DETECTION OF TOPIC-BASED OPINION LEADERS IN MICROBLOGGING ENVIRONMENTS

Recently, the world has become a huge virtual and social environment where people spend a great deal of time expressing their thoughts, feelings and opinions. This virtual socialization seems to bring us to a new era where valuable virtual information is being accumulated. Social networking applications, especially microblogging sites, are the leading actors of this data accumulation. Their free format characteristics lead different kinds of opinions to emerge, interact and broadcast rapidly. In this perspective, detecting opinion leaders, that is people whose opinions are followed, accepted, or taken into consideration, has become crucial in various domains such as marketing, advertisement, and politics. In this research, we focused on identifying topic-specific opinion leaders in *Twitter*. We extracted four different relationship types, namely *retweet, mention, reply*, and *follow*, between Twitter users who were interested in specific topics. Then we formed weighted and directed topic-based social graphs by combining these relationships to compute the edge weights. In order to detect opinion leaders, we applied social network analysis methods including PageRank, betweenness and closeness centrality metrics. We used sentiment analysis methods to evaluate the detected opinion leader candidates. The overall topic-based sentiment and opinion change of the community guided us whether the candidates are the real influencers in a predefined topic or not.

ÖZET

MİKROBLOG ÇEVRELERİNDE KONU TABANLI FİKİR ÖNCÜLERİNİN TESPİT EDİLMESİ

Son yıllarda dünya, insanların vakitlerinin büyük bir bölümünü duygularını, düşüncelerini, ve fikirlerini ifade ederek geçirdikleri sanal ve sosyal bir çevre haline geldi. Bu sanal sosyalleşme, bizleri değerli sanal bilgilerin toplandığı bir çağa taşıyor gibi gözüküyor. Sosyal ağ uygulamaları, özellikle mikroblog siteleri, bu bilgi birikiminde başrol oynuyorlar. Bu sitelerin özgür formatta bilgi paylaşımına olanak sağlayan karakteristik özellikleri, çok çeşitli fikirlerin hızlıca ortaya çıkmasını, etkileşmesini, ve yayılmasını sağlıyor. Bu bağlamda, fikirleri takip edilen, kabul edilen ve dikkate alınan fikir öncülerinin tespit edilmesi, pazarlama, reklam, politika gibi çok çeşitli alanlarda kritik bir öneme sahip olmaya başladı. Bu çalışmamızda, Twitter sosyal ağındaki konu tabanlı fikir öncülerinin belirlenmesine odaklandık. Daha önceden belirlenmiş konular üzerinde ilgisi olan Twitter kullanıcıları arasındaki dört farklı ilişki tipini çıkararak, düğümleri bu Twitter kullanıcıları olan sosyal ağlar oluşturduk. Bu sosyal ağlardaki her bir kenarın ağırlığını, bu ilişki tiplerini belirli kurallar ile birleştirerek hesapladık. Sonrasında ise, oluşturduğumuz bu sosyal ağlara, PageRank gibi çeşitli merkezilik metriklerini içeren sosyal ağ analizi yöntemlerini uygulayarak fikir öncülerini tespit etmeye çalıştık. Son olarak, tespit ettiğimiz fikir öncüsü adaylarını değerlendirebilmek için ise duygu analizi yöntemlerini kullandık. Topluluğun konu tabanlı genel duygu durumu ve o konulardaki fikir değişimi, bulunan fikir öncüsü adaylarının belirlenmiş konuda gerçekten öncü olup olmadığını tespit etmemizde bize yol gösterdi.

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

LIST OF SYMBOLS

F_{ij}	Following rate (node i follows node j)
M_{ij}	Mention rate (node i mentions node j)
Re_{ij}	Reply rate (node i replies to node j)
Rt_{ij}	Retweet rate (node i retweets node j)
W_{ij}	Total weight of the edge from node i to node j

LIST OF ACRONYMS/ABBREVIATIONS

API	Application Programming Interface
JSON	Java Script Object Notation
NLP	Natural Language Processing
REST	Representational State Transfer
SNA	Social Network Analysis

1. INTRODUCTION

In the past few years, we have been living in a digital age where our daily habits are changing form and our real environments that we live in are turning into virtual environments. The main reason of this reality-to-virtuality transition and the relatively more content accumulation in virtual spaces is the rapid emergence of social media sites and social networking applications. Social networking applications differentiate in terms of their purpose of usage. For example, while people prefer to use Facebook[1] for sharing their personal interests, photos, or videos, they prefer LinkedIn[2] for commanding their professional lives, seeking jobs or connecting with coworkers. Similarly, people write long blogs about technical, political, or social topics by using Tumblr[3] while they prefer to express their opinions much more concisely by means of Twitter[4] .

Due to the increase in popularity of social media and social networking applications, several research studies in these fields have been conducted in the recent years as well [1–6]. These studies are generally related with link prediction, trend and opinion leader detection, sentiment analysis, knowledge extraction, and information diffusion. The main motivation behind this popularity is the valuable content that Internet users have contributed. According to the research of Kaplan and Haenlein [1], social media can be defined as "a group of Internet based applications that are built on the ideological and technological foundations of Web 2.0, which allows the creation and exchange of user-generated content." In the past, the content on the internet consisted of the contributions of the web site admins and these admins only facilitated entry for these web sites. Owners of the websites could provide content, but non-owners had no chance to contribute content. However, Web 2.0 introduced a new approach in which the web users had a chance to change the content of the web. What's more, web sites consisting only of the contents generated by the contributions of web users were created. Since then, people have begun to initiate, express and spread their ideas

[1]http://www.facebook.com
[2]http://www.linkedin.com
[3]http://www.tumblr.com
[4]http://www.twitter.com

by means of social networking sites, especially with the blogging and microblogging services. Why people prefer to share their opinions in these kinds of platforms instead of outside world is an important question that should be taken into consideration and analyzed. One possible reason might be the free and comfortable ambiance of these relatively less rule-based and less limited platforms that make people feel more comfortable and share their opinions. Thus, valuable information begins to accumulate on the web. Another reason might be the flexibility of these platforms where people can easily form groups and communities, and take actions by just sitting on their chairs, which may even result in change of the world. The mobile social applications, which let people express themselves easily anywhere and anytime, also played roles in the widespread use of the social media platforms.

Twitter is a popular social networking and microblogging service that allows you to answer the question, "What are you thinking about?" by posting short text messages, 140 characters in length, called tweets, and your followers get notifications of your tweets via feeds. Twitter has gained popularity worldwide and is estimated to have 200 million active users creating over 400 million Tweets each day.[5] It is a free-style sharing platform in which a new idea may emerge and different ideas may spread very quickly through millions of users. Although people share their opinions using a limited number of characters, tweets may tell a lot indeed. A 140 character-long tweet may sometimes initiate new formations in the community about technological or political events, while it may sometimes refer to a web url which includes lots of information about a specific subject. In the last few years, several civil uprising events such as "Arab Spring"[6] in the late 2010s and "Occupy Wall Street"[7] in 2011 emerged where the collaboration and coordination in the Twitter platform played important roles. A recent example of the influence of Twitter on opinion evolution and spread is the "Gezi Parkı Events"[8] in Turkey where Twitter has played an important role since the beginning of the protests that started in Taksim, Istanbul. Another use of Twitter is as a review platform where users share their comments about emerging products

[5]https://blog.twitter.com/2013/celebrating-twitter7
[6]https://en.wikipedia.org/wiki/Arab_Spring
[7]https://en.wikipedia.org/wiki/Occupy_Wall_Street
[8]https://en.wikipedia.org/wiki/2013_protests_in_Turkey

and spread their ideas to the rest of the community. These comments are significant for product owners or companies because they find a chance to be informed about the general tendency of the community about their products. All these usages of Twitter indicate that there are many tweets holding valuable information about lots of topics ranging from technological events to worldwide protests. On the other hand, there are also many tweets that are spam, deliberately misleading or not very informative. Additionally, the volume of the tweets and their small sizes make information extraction from them a very challenging problem. Therefore, tweets should be evaluated and analyzed by regarding these abuses and inefficiencies. Despite of these challenges, extracting the valuable information from these tiny tweets is an important and critical task which has become a popular research area in the recent years.

The opinion leadership concept has been first mentioned by Katz and Lazarsfeld in 1955 [7] who defined opinion leaders as "the individuals who are likely to influence other persons in their immediate environment". This definition can be extended by defining opinion leaders as influencers in the community who are accepted as leaders in a specific topic and thus, can change the opinions of several people and direct them towards their own opinions. Opinion leader detection is significant in many cases especially in the marketing area. Bodendorf and Kaiser [2] say that, "the orientation function of opinion leaders with positive opinions can be used to deliberately spread specific information." Thus, opinion leaders are the target customers for companies in order to introduce their new products or spread the usage of their products easily.

Several approaches for detecting opinion leaders in various domains such as blogs, Facebook, and Twitter have been proposed. These approaches commonly try to consider different kinds of relationships between the nodes such as following, co-occurrence in the same blog and topic similarity. Most of these approaches use web and text mining methods, and then apply social network analysis to the content they extract. In blogging environments, opinion leaders usually refer to the bloggers who influence the others by being heavily referenced in other bloggers' posts. According to the indegree and outdegree interactions between the blog posts, opinion leadership scores are calculated. It is assumed that the more a blog post is mentioned in other blogs and the more a blog post attracts attention by getting comments, the greater its influence is. In other domains like Facebook, Twitter, or Foursquare[9] , generally the friendship and following relationships are taken into consideration. The friendship relation in Facebook and Foursquare is bidirectional while the following relationship in Twitter is unidirectional. People who have more friends or followers are assumed to be key players and are likely to influence the others in word-of-mouth environments.

Twitter is a platform where the opinion leadership concept has recently drawn the attention of several researchers. The conducted studies generally consider different relationships between Twitter users, form relationship graphs and then analyze them according to various social network analysis methods. However in most cases the relationships are examined separately rather than in combination. Separately examined relationships are sometimes compared with each other in order to identify which relationship is more likely to be used for indicating the influence of the users in the community. Additionally, the proposed approaches usually try to identify general opinion leaders, not topic-based ones.

In our study, we take the previously mentioned approach one step further and try to look from a different perspective. We extract four different relationship types namely retweeting, replying, mentioning and following from Twitter. These extracted relationships are combined and utilized at the same time not separately as in the former methods. Our motivating assumption is that each relationship between any two Twitter users has an impact on the overall opinion leadership. We argue that while the retweeting, replying, mentioning and following relations all strengthen the ties between users, they have different impacts. Unlike most of the previous studies, our study is based on analyzing topic-specific tweets, which in turn results in topic-specific opinion leadership. One of the main contributions of our work is the method that we use while evaluating the opinion leader candidates that we found. We propose that the sentiment change of tweets in time reveals the general tendency of the opinions and opinion leaders play important roles in this sentiment change in a topic-specific community. Briefly, in our study, a methodology is proposed in order to detect opinion

[9]https://foursquare.com/

leaders in Twitter. This methodology includes extracting different relationship types from topic-specific tweets and forming weighted and directed social graphs by taking each relation into account. After the formation, centrality metrics are measured in order to analyze the social network. The identified opinion leader candidates are evaluated according the sentiment change of the community.

2. BACKGROUND

In this study, we aimed to detect topic-specific opinion leaders in Twitter and then evaluate the identified candidates according to sentiment analysis methods. In this chapter, we will give a brief background on the relevant terms and areas such as Twitter, natural language processing, text mining, sentiment analysis, social network analysis, and JSON.

2.1. Twitter

Twitter is an online social networking and microblogging service that enables its users to send and read text-based messages whose sizes are no more than 140 characters. These short text-based messages are known as "tweets". A Twitter user can write any tweet about any subject and followers get notifications of those tweets via feeds. As mentioned in Chapter 1, there are 200 million active Twitter users according to March, 2013 statistics and also there are unregistered users who are not able to write any tweets but are able to read publicly written tweets. Although by default the tweets are publicly available and can be read by other registered or unregistered user, a user has the right to restrict the delivery of his tweets only to his followers.

A user in Twitter can subscribe to receive particular users' tweets through the following relation. The following relation is not bidirectional and when a user follows any other user, the latter one does not have to follow back the former one. In addition to being free format text-based messages, tweets may include hashtags *"#"*, urls, *"@"* signs and *RT* patterns within it. Hashtags are usually related with specific topics and are used to emphasize those topics in a tweet. A Twitter user can reply to or mention any other Twitter user by using the "@" character. In addition, he may retweet any other user's tweet by retweeting or by using the *RT* pattern.

According to the research done by a market-research firm Pear Analytics in 2009 by examining a tweet dataset of 2,000 tweets, they identified six tweet categories.[10] Their categories and the frequency percentages can be listed as follows:

- Pointless babble - 40%
- Conversational – 38%
- Pass-along value – 9%
- Self-promotion – 6%
- Spam – 4%
- News – 4%

2.2. Natural Language Processing

Natural Language Processing (NLP) is an area of research and application that deals with how computers can be used to understand and analyze natural language text or speech. NLP considers knowledge on how human beings understand and use language so that appropriate tools and techniques can be developed to make computer systems understand and manipulate natural languages to perform the desired tasks [8]. NLP researches include various disciplines such as computer science, artificial intelligence, computational logic, psychology, linguistics, and mathematics. There are several tasks researched in NLP, most of which are performed by using modern NLP algorithms that are based on statistical machine learning. Machine translation, summarization, information retrieval, relationship extraction, and sentiment analysis are examples to such tasks.

2.3. Text Mining and Sentiment Analysis

Text mining refers to the extraction of unknown and not-yet-discovered information from unstructured text [6]. It refers to parsing input texts by regarding linguistic properties of the texts and then extracting meaningful data patterns for creating more structured data. Text mining differs from data mining. Data mining works with structured data from databases while text mining works with unstructured data sets such as

[10] http://www.pearanalytics.com/wp-content/uploads/2012/12/Twitter-Study-August-2009.pdf

emails, documents, HTML files [9]. Sub-domains included in text mining area are information extraction, topic tracking, summarization, categorization, clustering, concept linkage, information visualization and question answering. These kinds of technologies are used in variable cases. There are lots of application types mentioned in [9]. They are categorized into different sectors such as publishing and media, telecommunications, information technology, banks, insurance, and etc. Also web mining is an emerging area in text mining domain. It is the activity of identifying patterns in large web document collections and same text mining techniques are applied to web documents in order to discover unknown patterns. Actually, most of the studies related with opinion leader detection have been dealing with web mining methods in order to identify the opinion leaders on the web.

Sentiment analysis is one of the NLP applications combined with text mining and machine learning methods. The main goal of sentiment analysis is determining the sentiment of a text, which refers to the attitude or emotional feeling of the text writer. Sentiment means "feeling" in combination with attitude, emotion and also opinion. Basically, in order to perform sentiment analysis for a given text, the text is categorized into different aspect levels such as positive, negative, and neutral. More advanced sentiment analysis methods may include deeper aspect levels such as specific emotions of the text writer like happy, angry, sad, and etc. The polarity classification of the texts can be performed by using supervised and unsupervised machine learning methods.

2.4. Social Network Analysis

Social Network Analysis (SNA) is the analysis of the various relations among a set of nodes in a social graph. A social graph is composed of social actors and social ties which refer to interactions between actors. Interactions between actors can be defined using the relationships such as friendship, kinship, co-occurrence, and etc. Several techniques are used to analyze social networks from different perspectives. Some of the techniques are used to identify strong and weak ties in a social network, while some of them deal with detecting central nodes in a network. Social graphs can be weighted or unweighted, as well as directed or undirected depending on the relationship type between nodes.

2.5. JSON

JSON refers to “Java Script Object Notation” and is syntax for storing and exchanging text information. It is a language independent, lightweight text-data interchange format.[11] Since it is language independent, web services usually use this format in their requests and responses, and server-client communications are commonly held by interchanging data by JSON. Responses of the Twitter API methods used in this study are JSON formatted data. This makes it easier to parse and process the upcoming tweets. An example JSON response is shown in Figure 2.1:

```
{"references": {
        "title": "on",
        "book": {
                "title": "Sample Book Title",
                "author": "Sample Book Author",
                "year": "2007",
                "publisher":  "Sample Book Publisher"},
        "article": {
                "title": "Sample Article Title",
                "author": "Sample Article Author",
                "journal": "Sample Article Journal",
                "year": "2012",
                "pages": "10--20" }
        }
}
```

Figure 2.1. Example JSON Response.

[11] http://www.w3schools.com/json/

3. RELATED WORK

Detection of opinion leaders in virtual communities has been one of the hottest subjects nowadays. There are several studies completed and also still being conducted in this area. Some of these studies propose techniques that include combination of text mining techniques and social network analysis methods [2,4,10,11]. Some of them recommend mathematical formulas in order to compute the opinion leadership scores [5,12–14]. However they differentiate in the details of the techniques used, the relation selections when building a social network graph and also the virtual environment that they have made the experiments on.

Joshi, Finin, Java, Kale, and Kolari [15] proposed a system for the analysis of social media systems in order to recognize spam blogs, to find opinions on specific topics and interests, and to detect opinion leaders by using trust relationships. Like most of the previous work, Blogosphere analysis is performed in this research because of the richer network structure of it. Richer network structure of Blogosphere comes from various relationship types existing between blogs and also between the bloggers. These relationships can be exemplified as indegree, outdegree, co-occurrence, and reference relations. Influence in Blogosphere is modeled by concerning the fact that the influence on web is often a function of topic. Also it is mentioned that the influence is measured effectively by considering the sentiment and opinions. However, spam blogs, spam comments, non-content blog-rolls, link-rolls, and advertisements are the obstacles that reduce the accuracy of identification of influential users. To handle these obstacles the authors propose techniques using local and relational features of blogs. After detections of the spams, they use the idea of polarization of opinions. Link polarity depends on the sentiment of the text that surrounds the link between the blogs. For this study, the authors used a dataset of 1,490 blogs with a label of democrat and republican for each blog. At the end, their experiments showed that using polar links for classification yields better results than plain link structure.

Bodendorf and Kaiser [2] detect opinion leaders and trends in online communities by using text mining and social network analysis. The approach consists of four steps. The first one is the recognition of the opinions by applying text mining techniques. These techniques include the extraction of features from texts and then applying learning algorithms to identify the polarity of the texts. The authors use supervised learning for classifying the texts into three classes, which are positive, negative and neutral. The second step is the identification of the relationships. In order to handle this, co-reference resolution and relationship extraction techniques are used. Co-reference resolution refers to recognizing whether two words in one text refer to the same object or not. After these two steps, social network analysis is applied and the "centrality" concept is taken into account for detecting the opinion leaders. Degree, closeness and betweenness centralities are considered as centrality metrics throughout the process. After the opinion leaders are detected, there comes the detection of the trends. In order to analyze the opinion leaders, the network properties including density, closeness centrality, and Randic connectivity, which is the level of branching within the network, are considered. The higher the density and the lower the Randic connectivity, the more forum users are connected with each other and communicate directly. Besides, centralization shows whether a trend arises from an opinion leader or not. For the experiments, threads extracted from slashfm.de and pcfreunde.de forums are used.

In order to detect the influencers in virtual communities, the most common approach in the literature is using and analyzing blogs. There is a study conducted by Agarwal, Liu, Tang, and Yu [16] and they propose a model for identifying the influential bloggers in a community. One of the main contributions of the article is the definition of influential bloggers. Although active bloggers and influential bloggers are in general defined in the same way, active bloggers are not necessarily influential and influential bloggers may be inactive. A blogger is called influential if more than one of his blog posts are influential. In this context, four different properties are measured which are related to the blog post influence. One of them is recognition, which means that an influential blog post is recognized by many bloggers. So it has so many in-links from other blog posts. Another property is the activity generation, which is highly related with the number of comments and discussions that appear on the blog post. The third property is novelty that is based on the number of out-links to the other blog posts. The final property is eloquence, which deals with the length of the blog post.

According to these properties and their characteristics, an influence graph is proposed. For the proposed model, The Unofficial Apple Weblog (TUAW) is crawled. The results of the model are compared with the results of the active blogger list of TUAW itself. The results reveal that an active blogger is not always an influential one and vice versa. Also for the evaluation, the results of Digg[12] are examined in which the blog posts are given more points if they are liked more. According to the evaluations, it is concluded that influential blog posts are longer in length and have more comments and in-links. However, the number of out-links are low. Also the weights of the properties used in the proposed model are the key points, since when they are changed, the results change accordingly. It is thought that the comment rate and the pairwise correlation of the properties should be taken into account in the future.

Another influence detection method in blogs is applied in the study by Hui and Gregory [3]. They tried to quantify sentiment and influence in blogspaces by using a combination of Natural Language Processing (NLP) and sentiment analysis methods. Similar to our study, they investigate blogs in terms of topics. In order to classify the blogs into topics, they use NLP techniques. Then the comment parts of these topic-specific blogs are examined according to their sentiment range which is measured through sentiment analysis methods. After these classifications, they compute influence with respect to individual topics by using four criteria: number of followers, relevancy, comments and followers. The final criteria captures the notion that if a blogger, who is assumed to be influential with respect to some topic and follows a second author whose posts are generally on the same topic as well, then the followed author should be considered as influential too. Consequently, they propose an algorithm by using these criteria whose principals are similar to Google's PageRank in order to detect influencers in blogspaces.

[12]http://digg.com/

Social network analysis is one of the most common approaches used in opinion leader detection as mentioned in the previous articles. In another example to these kinds of papers is the research conducted by Van Der Merwe and Van Heerden [4]. In this work, the authors try to find opinion leaders by linking opinion leadership to social network theory. It is proposed that individuals who are at the center of a network are the leaders and also domain-specific leadership is strongly related with the general leadership. In addition to these, it is mentioned that a high correlation exists between self-reported opinion leadership and opinion leadership reported by others. For the research, the data was collected from survey questionnaires that were distributed to five different groups of college students. Self-reported opinion leadership was measured by summing the personal answers provided by each respondent to calculate a total measure of self reported opinion leadership. On the other hand, a measure for opinion leadership as reported by others was calculated by weighting the nominations each person received from their classmates. A limitation in the study is that the domain-specific concept was based on specifically only one domain. Therefore, as future work the authors suggest studying the link between domain-specific and non-domain-specific opinion leadership.

Another study about leaders in opinion networks was performed by Zhou, Zeng, and Zhang in 2009 [17]. They deal with the sentiment information instead of classical centrality characteristics of the social graphs in opinion networks. A PageRank like algorithm, which the authors name as "OpinionRank", is proposed in order to find the opinion leaders. First, they extracted sentiments' orientation and strength by using machine learning techniques. Then they defined opinion networks as the networks based on the implicit opinion orientations in which the nodes participate in dialogues and other social activities, and they gradually form their opinions on each other. In the proposed method, sentiment information is utilized by incorporating opinion scores and adapting the PageRank algorithm according to these scores. At the end, all the nodes in opinion network are ranked according to their influences. They use the content from Epinions.com web site as a dataset in their experiments.

There are two types of influence diffusion theories according to the study made by Kardara, Papadakis, Papaoikonomou, Tserpes, and Varvarigou [5]. One is the theory of the minority, which states that highly popular but unrelated people influence all others; and the other one is that the individuals are influenced by all their peers and so all of them are influential. They have chosen Twitter for their research since there are strict rules for social interaction; there is dynamicity of topic communities and it is easy to access to data. The main focus is on studying the dynamics of influence in the context of specific topics in Twitter. They measure four types of influences which are indegree, mention, retweet and tweet influences. Indegree influence represents the number of community members following a particular person. Mention influence shows the number of mentions that a particular person gets from the others. Retweet influence reveals how often the tweets of a person are retweeted. And tweet influence represents the number of tweets a person post on a specific topic. By using these different metrics, different groups are formed. In the rest of the paper, the authors present different influence patterns which are used to evaluate the opinion leader candidates found in the four different influence metrics. One of the patterns is Cross Criterion Overlap Pattern. They try to find whether different metrics consider the same users as the most influential ones in terms of specific topics. In order to combine and find the overlaps of these groups, Jaccard similarity metric is used. The second type of pattern that they use for evaluation is the Sentiment Pattern. They propose that real influencers are expected to determine the overall sentiment of the community. In order to handle this, they use the polarity ratio and the Pearson correlation coefficient concepts. Other two pattern types used are Content Volume Patterns in which it is investigated what part of a community's overall activity stems from its core group and Structure Patterns in which it is investigated the extent to which core users share a common background with respect to their opinions. The final influence patterns examined throughout the paper are Intra-Core Reference Patterns and Cross-Community Influence Patterns. The former one deals with whether core users know each other and socialize extensively regardless of their connections on the graph. On the other hand, the latter one deals with whether there is an overlap between the core groups of two different topic communities with respect to the same influence criterion.

Another research conducted on Twitter is about analyzing sentiment influence in social networks, especially on Twitter [12]. The authors first collect tweets of users and for each tweet, they apply a sentiment analysis technique. As a sentiment analysis technique, they use an unsupervised lexicon based method in which they decide the polarity of a tweets by counting the positive and negative words in it. After that, they define an influence probability model according to the mention, retweet and reply characteristics and combine this model with sentiment results found in the previous step. To detect sentiment influence, they compute positive "user to user" influence probability by using only positive mentions, replies and retweets over the total positive tweets published by users, and do the same for the negative ones too. This is similar to our proposed model in terms of the relations used but there are still differences. In this model there is no topic-specific relationship between users and also in our study we use sentiment analysis in the evaluation phase, not in the opinion leader detection phase.

Weng, Lim, Jiang, and He [10] propose using an extension of the PageRank algorithm in order to find topical similarity and link structure in Twitter. They propose that there exists homophily in Twitter, which means a Twitter user (Twitterer) follows a friend because she is interested in the topics the friend publishes in her tweets and the friend follows back because she finds they share similar topic interest. To handle this, 1,000 Singapore-based twitterers were examined, the followers and friends of these twitterers were crawled and also all the tweets of each were gathered. Topic extraction methods were applied for the tweets for each twitterer, and then topical differences between each two twitterers were found. They form a social graph which contains "following" relationships and in the extended version of PageRank, random surfer visits each twitterer with certain probability, that is topic-specific random walk, by following the appropriate edge.

As complementary to the research of Weng *et al.* [10], Welch, Schonfeld, He and Cho [11] argue that retweet links are better suited for inferring a user's topical relevance than follow links and they propose a rich graphical model for Twitter with multiple semantic edges, and demonstrate the key principle that "not all edges are created equal." Their methodology is based on both follow and retweet links and given a seed set of users relevant to a topic, they compute "topic sensitive" PageRank (of Weng *et al.* [10]) on two sub-graphs of the Twitter graph, one based only on follow links and another based on retweet links. Then evaluate the topical relevance of the resulting high-ranked users. According to their results, the high ranking users based on retweets are more likely to remain topically relevant than the high ranking users based on follow links.

Another influence detection related article is a publication written by Leavitt, Burchard, Fisher, and Gilbert [13] in which all the relationship patterns of Twitter are taken into consideration. They compute follower-to-followee ratio and also the conversation and content related responses. They define conversation-related responses as the percentage of replies and mentions and content-related reponses as retweets. By computing the average number of responses for each follower of the Twitter users, they try to find the influential users in Twitter.

A study similar to ours is conducted in [14], where the authors take care of all the relationship types in Twitter and define three types of influences namely indegree, retweet, and mention influences. They compare all types of influences and finally examine how these types of influential users performed in spreading popular news topics. They come up with some general conclusions:

- Users who get mentioned often also get retweeted often, and vice versa.
- Indegree, however, was not related to the other measures.
- A popular user who is good at spawning mentions from others can do so over a wide range of topics, more easily than when she is retweeted over diverse topics.

Our work is different from this study in terms of the usage of the relationship types of Twitter. We do not consider the relationships separately as in this study; instead we combine all the relationships when identifying opinion leaders.

Retweet relationship in Twitter can be classified into two types. One of them is the retweeting the original tweet and the other one is editing the original tweet before retweeting. In our study, we propose that these edited retweets can be used in order to decide whether the user who retweets actually agrees with the retweeted user. There is a study conducted in this area by Mustafaraj and Metaxas [18] which is based on the tweets related with political opinions of the users and their decision criteria is based on the following assumptions:

- If a user follows the original sender and has retweeted his tweet verbatim, then he agrees with the retweeted user.
- If a user shares the same political orientation with another user, as observed by their use of hashtags, then they agree and vice-versa.
- If two users don't share the same political orientation and they don't follow each-other on Twitter, then they potentially disagree on political issues.
- There are two opposing political positions, conservatives and liberals.

When deciding the agreement or disagreement in examining edited retweets, another study is taken into consideration [19] which is not related with the Twitter retweets but related with the online debates. In this study, they make an agreement and disagreement classification according to the sentimental, emotional and durational features. They first build a local classifier to determine whether a pair of posts agree with each other or not, and then, aggregate over posts for each pair of participants in one discussion to determine whether they agree with each other.

Opinion leaders are important nodes in online communities, since there are many areas where detection of these leaders is useful. For example, one of the most common ways of usage of detecting opinion leaders is in the marketing area. A company can offer new campaigns, or new products to these opinion leaders before offering them to the public and make them spread their positive opinions to the public. Another area of usage is analyzing sociological attitudes of the community when a political event occurs or a technological improvement comes true, or any other national/international activity happens. All these studies deal with opinion leader concepts in online communities but there are still some uncertainties and open ended questions when defining opinion leaders and detecting them. In our study, we propose a more comprehensive method including all kinds of relationship types appearing in the Twitter platform. As distinct from others, our study aims to detect opinion leaders of a topic-specific dataset. That means tweets related with a specific topic are collected and thus the candidates are opinion leaders about a predefined topic not general opinion leaders. This brings more accurate results to opinion leader concept since topic-specific opinion leaders seem to be more reliable than general ones. There are studies dealing with tweets but most of them use only Twitter's retweeting and following relationship types, and in most cases consider them separately. We believe that other relationship types like mention or reply are worth to be considered too because they include interactions between users and all kinds of interactions should be considered as key factors when detecting opinion leaders. Therefore, in this research, all the relationship types are taken into consideration. The main idea is building a weighted and directed social graph and then analyzing it according to social network analysis algorithms. Validating the detected opinion leaders is a challenging task. We propose using a sentiment analysis approach to evaluate the candidate opinion leaders.

4. METHODOLOGY

Our study is based on the analysis of topic-specific tweets, which are related with US Elections held in November 2012 and were collected between October 2, 2012 and November 16, 2012. We divided the dataset into chunks in terms of debates occurring during the election period and made separate analysis for each chunk. For each debate period, we extracted relationships between Twitter users in terms of retweet, mention, reply and follow characteristics of Twitter and generated weighted and directed social graphs. Each graph was analyzed according to centrality measurements in order to find the opinion leader candidates during that debate period. Finally, we evaluated these candidates by using sentiment analysis methods. The whole methodology is summarized in Figure 4.1.

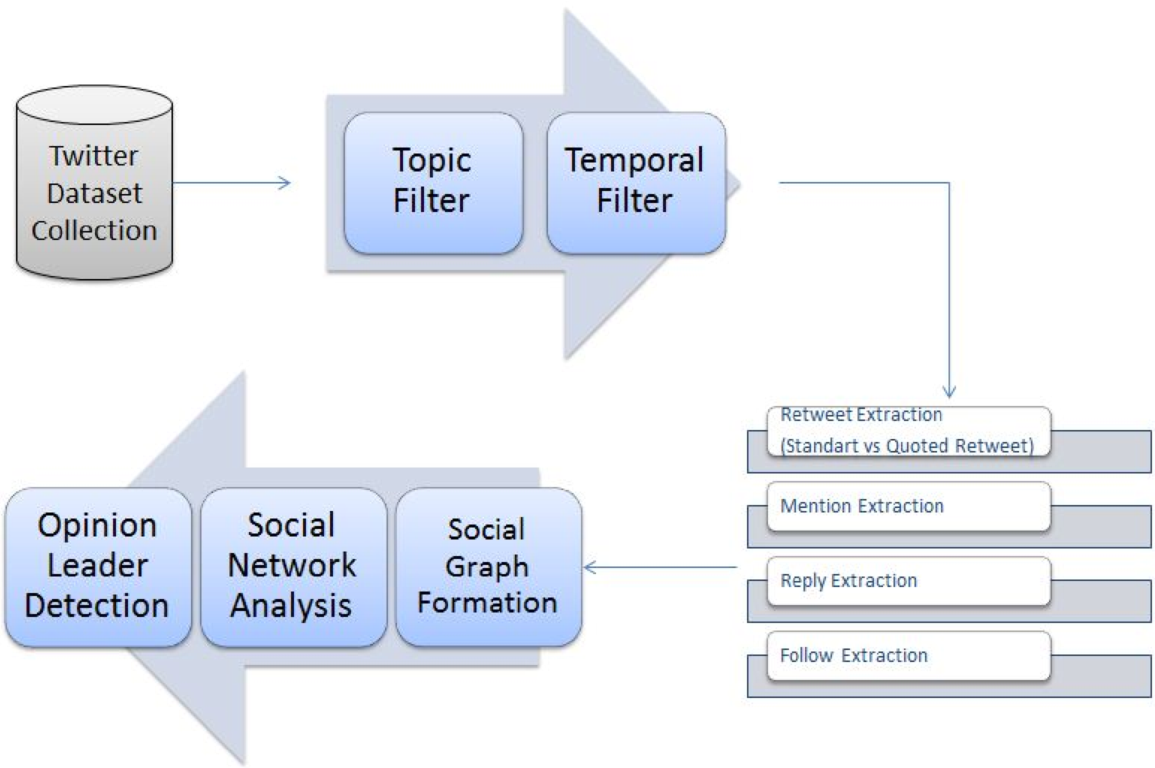

Figure 4.1. Opinion Leader Detection Methodology.

4.1. Data Set

Tweets related with US elections held in the late 2012 were collected during a time period starting from October 2, 2012 and ending at November 16, 2012 using Twitter Streaming API (at Soslab[13] , which is one of the laboratories in the Computer Engineering Department of Bogazici University). The API gives low latency access to Twitter's global stream of Tweet data and makes tweet filtering possible by letting custom query setup. The query keywords which we used when querying and collecting the US Election related tweets were *BarackObama, MittRomney, Barack, Obama, Mitt, Romney, democrat, republican, election2012.* According to these query keywords, tweets containing at least one of these keywords were accumulated. In the late 2012, presidential elections of US were one of the hottest topics worldwide. Therefore, there was a dynamically growing potential of writing tweets specifically about the US elections topic in this time period. Also during this election period, eight debates each of which has its own topic were held. People tended to write and express their opinions a lot in order to be informed or to inform the others about the progress during these debate periods.

The data that we collected consist of all the tweets related with the keywords given in the previous paragraph. It is hard to extract meaningful information from these tweets. Therefore, we decided to filter the existing tweets one more time according to the significant topics which were discussed a lot during the election period. These topics can be exemplified like bailout, abortion, immigration, and job opportunity. Filtering the twitter dataset according to these topics makes the data more topic-specific, as well as easier to process and analyze. Additionally, since during the debate periods different topics were discussed, we separated the tweet dataset into time intervals one more time and evaluated each interval separately.

We considered four different debates. The times of these debates and the corresponding time intervals used to select the tweets related with these debates are given below.

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[13]www.cmpe.boun.edu.tr/soslab

- Debate#1: The debate was held on 3 October. The time interval is [2 October – 7 October]
- Debate#2: The debate was held on 16 October. The time interval is [14 October – 20 October]
- Debate#3: The debate was held on 22 October. The time interval is [20 October – 26 October]
- Debate#4: The debate was held on 4 November. The time interval is [2 November – 8 November]

These four time intervals include the days before and after the exact debate times so the tweets show the influence of debate-specific topics, the speeches made by politicians during the debate and also the effects of these speeches over the people.

For our experiments, we used the bailout and abortion topics. The tweets selected based on these topics were further classified according to the president candidates, Obama and Romney, who were the strongest two names of the elections and the debates were mainly held between these two president candidates. So, the tweets were classified according to three criteria sequentially: time, topic, and president candidate. After this filtering, 112,978 tweets were extracted and analyzed.

4.2. Approach

The proposed approach consists of five steps. The first one is relationship extraction from tweets which refer to the determination of interactions between users. The second step is social graph formation in which weighted and directed graphs are generated for each debate period. The weights of the edges in the graphs are calculated according to the specific rules that will be described in Section 4.2.2. The third step comes with the social network analysis part in which centrality metrics are applied to the social graphs. The fourth step is opinion leader detection and the final one is the evaluation part in which the opinion leader candidates found in the previous steps are evaluated according to sentiment analysis methods.

4.2.1. Relationship Extraction

Tweets are text-based messages up to 140 characters. Although this length is not long enough to tell too much, it is enough to express the main point about a specific subject. For example, a tweet with just a url information in it or just a one-sentence comment written as a tweet about an ongoing event may be enough for emphasizing the intention. Tweets are kind of summaries of the opinions and ideas, therefore they are worth to be extracted and analyzed.

A tweet may be an individual tweet about any topic that the user desires, a retweet of another tweet, a reply to some other tweet, or may refer to some other Twitter users by mentioning them. All these kinds of relations are worth to consider because each of them indicates an interaction between Twitter users. Since the social graph consists of users as nodes, the relationships between nodes should represent the interactions between these users. Another relationship between Twitter users is the “following” relationship. A user may subscribe to another user’s tweets by following him. Since this is not a bidirectional relation like a friendship concept of other social networking sites, one does not have to follow back a user who follows him. The relationships extracted for the social graph formation are listed below.

<u>4.2.1.1. Retweet.</u> Retweeting is re-posting another user’s tweet in Twitter. By retweeting, the user indicates that he gives importance to the opinion of the retweeted user regardless of the agreement or disagreement, and also he is influenced by the point of view of the retweeted user. There are two types of retweeting, namely standard retweet and quoted retweet. These retweet types differ in terms of their agreement and disagreement paradigms and this difference causes each retweet to gain different weight when forming a social graph.

- *Standard Retweet:* Retweeting in which the retweeted content is directly re-posted without any modification on it. According to the example below, since SantaCsruz4OBAMA does not make any modifications to the original tweet, SantaCsruz4OBAMA is assumed to agree with NBCPolitics.

Example: (filtered keyword: bailout) User *SantaCruz4OBAMA* retweets *NBCPolitics.*

Original: NBCPolitics: Obama reminds Ohio voters: Romney opposed bailout http://t.co/oA7xEf1D

Retweet: RT @NBCPolitics: Obama reminds Ohio voters: Romney opposed bailout http://t.co/oA7xEf1D

- *Quoted Retweet:* Retweeting in which the user modifies the tweet content before re-posting it with additional comments before or after the original tweet. These comments often indicate whether he agrees or disagrees with the retweeted user. Table 4.1 shows a quoted retweet where *BentleyturboR* does not directly retweets the original tweet, but changes the original tweet by adding "You really need to read this!". His comment indicates that he agrees with the original writer. On the other hand, in the second example shown in Table 4.2 *kathismoak* does not agree with the tweet of *TwitchyTeam.* Disagreement can be inferred from the comment that he wrote after the original tweet.

Table 4.1. Agreement in a quoted retweet.

Keyword	bailout
User	Bentleyturbo
Retweeted User	TruthTeam2012
Original Tweet	"Mitt Romney's bailout bonanza" : http://t.co/UXxmuZUN
Retweet	"@TruthTeam2012: "Mitt Romney's bailout bonanza": http://t.co/UXxmuZUN". *You really need to read this!*

Standard retweets are easy to detect since the JSON response that Twitter API provides includes information about retweeting. However, it is not that trivial to detect quoted retweets since Twitter API does not provide any information about these kinds

Table 4.2. Disagreement in quoted retweet.

Keyword	abortion
User	kathismoak
Retweeted User	TwitchyTeam
Original Tweet	Obama in 2004: Unborn baby is ‘potential life’ http://t.co/0mchH6cf
Retweet	“@TwitchyTeam: Obama in 2004: Unborn baby is ‘potential life’ http://t.co/0mchH6cf” *But he won’t cover expenses if they survive abortion.*

of retweets. In order to handle this, regular expression matching technique is used. Pattern matching is applied to the tweets and if a match exists, tweet is divided into three parts namely original tweet, comment before the original tweet and comment after the original tweet. While standard retweeting is a strong signal that the user agrees with the retweeted user, quoted retweeting does not guarantee agreement. The comments that are written before or after the original tweet show the real opinion of the user about the subject which the original tweet is about. Agreement/disagreement detection is not a trivial task and is still an open research problem. In this study, we use a text mining algorithm which is “exact matching” in order to decide whether a text refers to an agreement or a disagreement.

Exact Matching: Text mining refers to the extraction of unknown and not-yet-discovered information from unstructured text [6]. Since tweets are short texts which are suitable for knowledge extraction, text mining methods can be applied in order to make decision about agreement / disagreement classification. Exact matching is one of the techniques used in text mining. To perform this algorithm, two lists (Table 4.3 and Table 4.4) containing agreement and disagreement words and phrases are prepared. These lists are prepared according to the occurences of words and phrases containing agreement-related and disagreement-related meanings in the dataset. The contents of the lists can be expanded as the dataset enlarges. In order to determine whether a retweet conveys agreement or disagreement with the original poster of the tweet, the comment part of the quoted retweet is matched against the words and the phrases occurring in both lists. At the end, the total number of agreement matches and disagreement matches are calculated.

- If # of agreement matches > # of disagreement matches, then the text is assumed to be an agreement.
- If # of agreement matches < # of disagreement matches, then the text is assumed to be a disagreement.
- The text is assumed to be neutral otherwise.

Table 4.3. Agreement List.

yes	true	right
correct	exactly	certainly
totally	absolutely	definitely
clearly	surely	win
won	awesome	good
here we go	agree	agreement
smile	hahah	heheh
congrats	congratulations	love
like	want	success
thank you	thanks	yeah
sure	truth	nice
must read	must-read	wow!
worth watching	worth reading	must watch
:)	:-)	;)

4.2.1.2. Mention. When a Twitter user wants to emphasize another user in his tweet, he adds @ character to the corresponding user's username like `@username`. By doing

Table 4.4. Disagreement List.

disagree	disagreement	false
not true	wrong	not right
incorrect	not correct	dislike
don’t like	don’t agree	don’t want
don’t love	dont like	dont agree
dont want	dont love	exactly disagree
certainly disagree	totally disagree	absolutely disagree
definitely disagree	clearly disagree	surely disagree
hate	bad	fail
no	not	don’t
dont	sane	fucking
lie	didn’t like	disturbing
creep	really?	shocking
disgusting	sickening	omg
jerk	bullshit	epic

so, he can respond to a tweet that the user has written, can just mention the user's username in his own tweet for attracting attention, or can write personal messages directly to that user. This form of communication includes interaction between users. In order to detect mention tweets, each tweet response that is extracted via the Twitter API is parsed. Each tweet object includes *user_mentions* tag and there may be more than one mentioned usernames in a single tweet.

4.2.1.3. Reply. When a Twitter user just wants to respond to another user's tweet, he replies back through that tweet. This is a mention relationship at the same time because in order to reply to someone, one needs to mention that user by the mention `@username` method. A reply relation is assumed to have higher priority over the mention relation, because every *reply* is a *mention* while not all *mentions* are *replies*.

Both *mention* and *reply* relationships indicate that a user takes the opinion of the corresponding user into account, since he mentions his username in his own tweet or replies to his tweet.

4.2.1.4. Follow. Following is the most standard relationship type in social networks. This form of relation refers to unidirectional interaction between any two users due to its nature of being "x follows y" situation. There are different reasons for subscribing to one's tweets in Twitter. One of them is just a friendship relation. Because two users are friends in real life like in Facebook, they follow each other in Twitter too. However, there are still some other reasons that a user wants to follow one's tweets. One of the main motivations is sharing of similar world-views. One may want to be informed about the tweets of a person who thinks the same way with him. This kind of following shows that he usually trusts and appreciates the opinions of the followed person. Another motivation for following is related with being fan of a famous user such as a celebrity or a politician. This does not mean that the user always is in an agreement with the followed person but means that he wants to track the actions, ideas, and opinions of the followed person. He shows his opinion and side by retweeting, mentioning or replying to the followed person.

Twitter API provides follow information methods called *GET friends/ids* and *GET followers/ids*. For each user extracted in the specified time period according to the keywords mentioned, friends (the users that he follows) are gathered and then checked whether there is a following relationship between any other user in the set, or not.

4.2.2. Social Graph Formation

By using the *retweet, mention, reply* characteristics and the *following* relationship in Twitter, we created a relationship graph whose nodes are Twitter users. While forming a graph about a specific topic, a user is a node in the social graph if he posts a tweet about that topic and has an interaction with any other node in the graph. The tweet may be a standard tweet, or a retweet, a reply or a mention about that topic. There is an edge between two nodes, i and j, in the social graph if:

(i) i retweets a tweet of j which is about that topic
(ii) i replies to j and reply tweet of i is related with that topic
(iii) i mentions j in a tweet which is related with that topic
(iv) i follows j

Relationships are formed between two nodes if there is at least one *Retweet, Mention, Reply,* and *Follow* relation between them.

This social network graph formed between Twitter users is directional and also weighted. The *direction* is determined as follows.

- If i retweets j : i $\rightarrow$ j
- If i mentions j : i $\rightarrow$ j
- If i replies to j : i $\rightarrow$ j
- If i follows j : i $\rightarrow$ j

The *weight* of a relation is calculated according to a mathematical formula whose parameters are based on:

- Retweet rate
- Mention rate
- Reply rate
- Following rate

The sum of retweet, mention, reply and follow rates of an edge is assumed to be the total edge weight and the total weight function for a relation can be calculated as in Equation 4.1.

$$W_{ij} = Rt_{ij} + M_{ij} + Re_{ij} + F_{ij} \tag{4.1}$$

where:

W_{ij} = Total weight of the edge from node i to node j

Rt_{ij} = Retweet rate (node i retweets node j)

M_{ij} = Mention rate (node i mentions node j)

Re_{ij} = Reply rate (node i replies to node j)

F_{ij} = Following rate (node i follows node j)

Each rate is a function (e.g. $f\_retweet(i, j)$) multiplied with a coefficient factor (e.g. a). The coefficient factor is based on the weight given to corresponding type of relation between users.

$$\mathbf{Rt}_{ij} = \mathbf{a} \times \mathbf{f\_retweet}(i, j) \tag{4.2}$$

$$\mathbf{M}_{ij} = \mathbf{b} \times \mathbf{f\_mention}(i, j) \tag{4.3}$$

$$\mathbf{Re}_{ij} = \mathbf{c} \times \mathbf{f\_reply}(i, j) \tag{4.4}$$

$$\mathbf{F}_{ij} = \mathbf{d} \times \mathbf{f\_follow}(i, j) \tag{4.5}$$

One of the main motivations of this study is to determine the order of these coefficient factors that indicates which relationship type has more precedence over another for detecting opinion leaders. Determining the exact values of these coefficient factors is left as a future work. In order to investigate the order of the coefficient factors, the function $f\_x(i, j)$ is chosen as a frequency function which denotes the number of times the corresponding relationship type x occurred between the users i and j in the dataset used.

$f\_retweet(i, j)$ = Number of times user i retweeted user j.

$f\_mention(i, j)$ = Number of times user i mentioned user j.

$f\_reply(i, j)$ = Number of times user i replied to user j.

$f\_follow(i, j)$ = Number of times user i followed user j.

4.2.3. Social Network Analysis

When the social graph is formed, there comes the analysis part in order to determine the opinion leaders in this community. There are different social network analysis techniques in the literature. In this research, centrality measurements, which denote the importance of a node in a graph, are used to analyze the formed social graph. In particular PageRank, closeness and betweenness centralities are used.

PageRank is a link analysis method which is proposed by Larry Page *et al.* in 1998 [20] and still being used by the Google search engine. The main logic behind PageRank is assigning numerical weights to each web site on World Wide Web by considering the relative importance within all the sites [20]. The reason why we choose PageRank for social network analysis part of our study is that opinion leaders are the nodes who have higher importance in a community and thus influence the other nodes. The social graphs that we formed consist of directed links and PageRank applies a link-based ranking to the nodes in these graphs. The importance of a node in a graph is proportional to the importance of the nodes which are close to that node. This approach is in parallel with our opinion leader definition.

Closeness centrality describes the closeness of a node to all other nodes in the graph. It is defined as the inverse sum of all path distances from the measured node to all the other nodes. On the other hand, *betweenness* centrality indicates how often a specific node is found on the shortest path between all pairs of nodes in the graph. It is measured as the fraction of the number of the shortest paths that pass through the observed node and the number of all shortest paths [21]. The weights in both centrality metrics are considered for determining the shortest paths. However, in our study the weight factor of the relations indicates positive values and the more weight the link has, the more importance the corresponding node has. Therefore, the weight values are inversed ($\frac{1}{W_{ij}}$) and then these metrics are calculated according to the inversed values. So, the edge weight function that is used for calculating the betweenness and closeness centralities is defined as in Equation 4.6:

$$W'_{ij} = \frac{1}{W_{ij}} \tag{4.6}$$

4.2.4. Opinion Leader Detection

We applied the PageRank, betweenness, and closeness centrality metrics to analyze the social graphs and detect the opinion leaders. After applying the three types of centrality measurements to the different social graphs formed for different debate periods, the resulting sets are compared. The intersection nodes of each method are extracted and then examined because each method has its own characteristics and importance, and the combination of them may result in better and more accurate inferences. Since betweenness and PageRank algorithms differentiate in their measurement styles and their working concepts, we believe that, the nodes in the intersection set are more influential and worth further investigation. In addition to the comparison of PageRank and betweenness centralities, PageRank and closeness centralities are compared too. Since closeness means the closeness of a node to all other nodes in the graph, it is likely that the PageRank scores of the nodes who are closer than others are higher too. Therefore, the intersection set of the opinion leaders identified by PageRank and the ones identified by closeness centrality is expected to be large.

4.2.5. Evaluation

Detection of opinion leaders is not sufficient for determining whether the identified candidates are real opinion leaders. The evaluation part is as important as the whole opinion leader detection process. However, evaluating whether the candidates detected in this study are opinion leaders indeed is not a trivial operation. Examining the candidates one by one may contribute to this evaluation, but there is still lack of accuracy when deciding the real opinion leaders in the community.

In order to evaluate the candidate opinion leaders, we applied a method based on analyzing the sentiment of the communities. We believe that the general opinion of a community is affected by the sentiment of the opinion leaders in that community. For example, if the frequency of users with negative sentiment in a community is higher than the ones with positive and neutral sentiment, we expect that the majority of the opinion leaders of that community to hold negative sentiments too. Additionally, the percentage of the sentiments and the change in these percentages during specific time periods are the other deciding factors for determining opinion leaders. In this context, the evaluation method is based on that if the percentage of a sentiment is increasing day by day, then the same sentiment should apply to those opinion leader candidates too. In order to handle these evaluations, tweets are categorized according to their sentiments for each debate period. Then sentiment frequency vs time graphs and sentiment percentage vs time graphs are created. Sentiment frequency vs time graphs show the change in the number of positive, negative and neutral tweets during the defined time period. Similarly, sentiment percentage vs time graphs indicate what percentage of tweets each sentiment utilize during the defined time period. By examining these graphs, how sentiment frequencies change over time can be seen easily. This helps us to confirm that the candidates that are found in the analysis part are more likely to be real opinion leaders.

In addition to the general opinion change, local changes occurring around the opinion leader candidates are taken into consideration as well. We analyzed the sentiments of the nodes that are connected to the identified opinion leader candidates. The main idea behind this evaluation is observing whether the sentiment change of the connected nodes are in parallel with the opinion leader node that they are connected to. Also it is likely that the number of connected nodes of a candidate increases during debate period because of his influence on them. In order to observe this, different social graphs for the same opinion leader candidate in successive dates are formed and it is seen that size of the graphs increases as time passes by.

Tweets are classified to their sentiment by checking whether they contain negative or positive words in their contents. After each checking operation, each tweet has a resulting score that shows its sentiment. Sentiment of standard retweets are the same as the original parts of them while sentiment of quoted retweets may change to the comment parts of the tweets. Mentions and replies show the general sentiment of the user to the mentioned or replied user and also the topic that is used in filtering. In order to handle sentiment analysis, we used a sentiment analysis tool, SentiStrength[14] .

[14]http://sentistrength.wlv.ac.uk/

SentiStrength estimates the strength of positive and negative sentiment in short texts. It reports two sentiment strengths and gives scores to the short texts in a 1-to-5 scala. In the score calculation, -1 indicates being *not negative* while -5 indicates being *extremely negative*. Similar scoring is used for positive sentiments, that is 1 indicates being *not positive* while 5 indicates being *extremely positive*. The word lists that SentiStrength uses are so huge and classified that it is possible to give different sentiment scores to the words appearing in a tweet. Because not every word or phrase has the same sentiment strength, the possibility of the sentiment accuracy of a tweet is high. In order to measure the overall score of a tweet, SentiStrength uses different lists containing words and phrases holding different weights such as idiom, emotion, emoticon, negating, question words etc. Two of the ten word lists used in SentiStrength are in Table 4.5 and 4.6.

Table 4.5. Booster Word List.

word	score	word	score
absolutely	1	complete	1
completely	1	could	-1
definitely	1	did	-1
especially	1	extremely	2
fuckin	2	fucking	2
hugely	2	incredibly	2
just	-1	may	-1
might	-1	ought	-1
overwhelmingly	2	really	1
should	-1	slightly	-1
so	0	some	-1
sometimes	-1	sum	-1
total	1	totally	1
very	1	would	-1

Table 4.6. Idiom Lookup Table.

word	score
how are you	2
it hanging	2
shock horror	-2
wat up	2
what's good	2
what's up	2
whats good	2
whats up	2
wuts good	2

According to SentiStrength, each tweet is analyzed by using various lists and an example tweet and its analysis can be seen below. Tweet is a retweet indeed and, the positive and negative scores of the tweet are 1 and 5 respectively.

Tweet: RT @mboyle1: Docs posted on ways & means website are damning. Proves auto bailout was not a success for all. Only for who Obama want ...

Score: Positive = 1 Negative = -3

RT[0] @mboyle1[0] Docs[0] posted[0] on[0] ways[0] *&[0] means[0] website[0] are[0] damning[0] [[Sentence=-1,1=word max, 1-5]] Proves[0] auto[0] bailout[0] was[0] not[0] a[0] success[2][NegatedDueToPreviousWord] for[0] all[0] [[Sentence=-3,1=word max, 1-5]] Only[0] for[0] who[0] Obama[0] want[0] [[Sentence=-1,1=word max, 1-5]][[[1,-3 max of sentences]]]

According to the analysis, each word has a separate score value shown in square brackets next to each word. The words except from *success* get zero points since they do not match with any word in the word and phrase lists that SentiStrength uses.

However, the word *success* gets 2 points. Due to the negation word *not* occurring before *success*, its score is negated (-2). Since the minimum negative score in SentiStrength is -1 and it is assumed to be *not negative*, the overall negative score of the tweet which is -2 is mapped to -3. There is no word holding positive score, so the positive score of the tweet is 1 which is the minimum positive score in SentiStrength and is assumed to be *not positive*. In total, the overall score of the tweet is calculated as $1 + (-3) = -2$ and thus the sentiment of the tweet is negative.

5. EXPERIMENTS AND RESULTS

We have divided the tweets about US elections into four different debate periods mentioned in Section 4.1. Although tweets were collected from Twitter Streaming API according to specific keywords like US elections, Obama, Romney, republican, democrats, and etc, we filtered them one more time according to the primary topics such as bailout, abortion, immigration, and job opportunity, which were discussed during the debates. In our experiments, we used the topic "bailout" and the results related with this topic will be shared.

After filtering the tweets in the dataset according to their topics, we filtered these topic-based tweets one more time. The second filter diffraction is the most powerful president candidates during the 2012 elections, Barack Obama and Mitt Romney. The reason behind this second filtering is that people wrote their opinions not only about that topic but also about Obama and Romney. That means, a tweet includes the opinion about the topic and the president candidates at the same time. Therefore, two different graphs emerged for each debate period respectively "bailout + Obama" and "bailout + Romney".

The relations which can be extracted from the tweets in the dataset were *retweet, mention,* and *reply.* The *following* relation cannot be gathered from the dataset since it is not a content-based relation and the dataset includes contents related with specific keywords. The following information between any two Twitter users is gathered via separate requests and we called *GET friends/ids* method in Twitter API to reach this information.

For all four debate periods, there are 24,959 tweets in total for the topic "bailout + Obama" while 38,047 tweets exist for the topic "bailout + Romney".

Without considering the following relationship, the total relation count statistics for the topic "bailout_obama" are shown in Table 5.1.

Table 5.1. Relationship statistics for keyword “bailout_obama”.

Debates	# of Tweets	# of Relation	# of Relation(weight = 0)
1st Debate	844	778	238
2nd Debate	7,586	7,086	1,721
3rd Debate	8,643	8,217	1,678
4th Debate	1,619	1,597	439

Without considering the following relationship, the total relation count statistics for the topic “bailout_romney” are shown in Table 5.2.

Table 5.2. Relationship statistics for keyword “bailout_romney”.

Debates	# of Tweets	# of Relation	# of Relation(weight = 0)
1st Debate	498	488	164
2nd Debate	10,967	10,410	2,025
3rd Debate	14,180	13,596	2,539
4th Debate	3,664	3,624	844

Zero weight means there is a self-relation (from himself to himself) only, indicating that the user tweets about the specified topic and there is no interaction between him and any other user. These relations were not taken into consideration while forming the social graph because those users have no connection to any other user and they are disjoint nodes in the graph. Therefore, they have no impact on any edge that leads to the constitution of the opinion leadership.

There are different graph visualization tools in the literature. We preferred to use “Gephi Graph Visualization and Manipulation Tool”[15] , because of its well-documented tutorial, its capabilities of visualizing graphs with thousand nodes and its convenience of applying algorithms like PageRank to the graphs. Besides, graphs can easily be

[15]https://gephi.org/

visualized according to the PageRank scores of the nodes and the layouts such as Force Atlas, Fruchterman Reingold, and Yifan Hu.

Three of the Twitter relations, namely retweet, mention and reply are associated with date/time information. However, the Twitter API does not provide information about the date and time when a user started to follow another user. Therefore, the following relationship differs from the other relations in terms of its time-independent characteristic. Although there is a conceptual difference between them and the initiation time of following is not clear, it is still necessary to consider the following relation when merging all the relations to create one single relation. The main reason is that although there is no interaction between two users like retweeting, mentioning or replying, they still affect and influence each other. If one of them has an interaction with any other third node, that third node has an influence on the other one too who has no interaction. There are still drawbacks about the inclusion of the following relationship in the same set of other relationships because of its time-independent characteristic. However, the tolerance is not so high that it is concluded during the experiments that, the coefficient factor of following relation is extra smaller than the other relations' coefficient factors.

Apart from the collection of tweets related with US elections, we used Twitter API one more time for collecting the friend lists of the users who take place in the graph. Before getting friend list of each user, *GET users/lookup* method is called for the username-id mapping for each user. Then, *GET friends/ids* method is called via REST requests for each user, and all the data is stored in MongoDB[16] which is a NoSQL database containing documents as records in JSON formats. There are two reasons for using MongoDB in this phase. The first one is that Twitter returns a lookup table and friends lists of the users in JSON format and MongoDB keeps its documents in this format too. Therefore, it is reasonable to store this information directly in such kinds of databases. Another reason for preferring MongoDB is that the number of distinct users for each debate period is very large and the processing times of the requests of information for each user are time-consuming. Since MongoDB performs

[16]http://www.mongodb.org/

I/O operations efficiently, it enables us to increase the performance of the retrieval process.

5.1. Social Graphs of Debate Periods

We have defined four debate periods, which were mentioned in the previous sections. We generated separate social graphs for each debate period after extracting the relationships. Each relationship has its own weight, which is calculated according to their own coefficient factors. As in mentioned in the approach section, relationship rates are the multiplication of relationship coefficients and the relationship functions. The function $f\_x(i, j)$ is chosen as a frequency function which stands for the number of relationship type occurrences in the dataset used between the users i and j.

For the experiments, we gave different weights to each relation and then for each order we generated individual graphs. The retweet relationship includes standard and quoted retweets. We give different weights to each different type of retweet. We propose that standard retweets imply agreement with the owner of the original tweets, while not all quoted retweets imply agreement. We assigned positive weights to disagreement retweets as to the other retweet types. This is because although a user does not agree with another user, he may retweet and add his own comment to the original tweet. This does not mean he does not appreciate or takes any notice of the retweeted user. Despite of a disagreement, he is still influenced by the retweeted user and this detail is taken into consideration in our study. Therefore, the coefficient factors that we used for the retweet relations are as follows.

$$StandartRetweet = AgreementRetweet = NeutralRetweet > DisagreementRetweet$$

Although there are four different relationship types in Twitter, the reply and mention interactions are similar in terms of their contexts. A “reply is indeed a “mention” and their impacts on leadership are assumed to be similar. Therefore, we proposed that their coefficient factors are approximately the same. In the lights of these intuitive assumptions, there are six different relationship coefficient orders that are given below.

- $Order_1 = RETWEET > MENTION \approxeq REPLY >> FOLLOW$
- $Order_2 = RETWEET > FOLLOW > MENTION \approxeq REPLY$
- $Order_3 = FOLLOW > RETWEET > MENTION \approxeq REPLY$
- $Order_4 = FOLLOW > MENTION \approxeq REPLY > RETWEET$
- $Order_5 = MENTION \approxeq REPLY > RETWEET >> FOLLOW$
- $Order_6 = MENTION \approxeq REPLY > FOLLOW > RETWEET$

For each order, different social network graphs are formed and they are analyzed. The evaluation of which order generates more accurate results are explained in Section 5.3. Within all these experiments, the order $Order_1 = RETWEET > MENTION \approxeq REPLY >> FOLLOW$ was the most effective one. The weight of *follow* is seriously small when compared to other relations because users with no interactions but with so many followers should not be recorded as opinion leader candidates just because they have lots of followers. The following relation should not exceed the other interactive relations in this perspective. After the formation of each debate graph, we applied the PageRank algorithm to each of them. The bigger the nodes are, the higher PageRank scores the nodes have. Also the thicknesses of the edges are related with the weights on them. For each debate period, the social graphs are shown in Figures 5.1, 5.2, 5.3 and 5.4.

(i) 1st Debate:
  Keyword: bailout_obama
  # of Nodes: 808
  # of Edges: 13,329
  The social graph is shown in Figure 5.1. According to the graph, *BarackObama* seems to have the highest PageRank score, but this is because of the topical keyword selection used in the dataset. Other Twitter users having high PageRank scores apart from BarackObama should be inferred and taken into account.

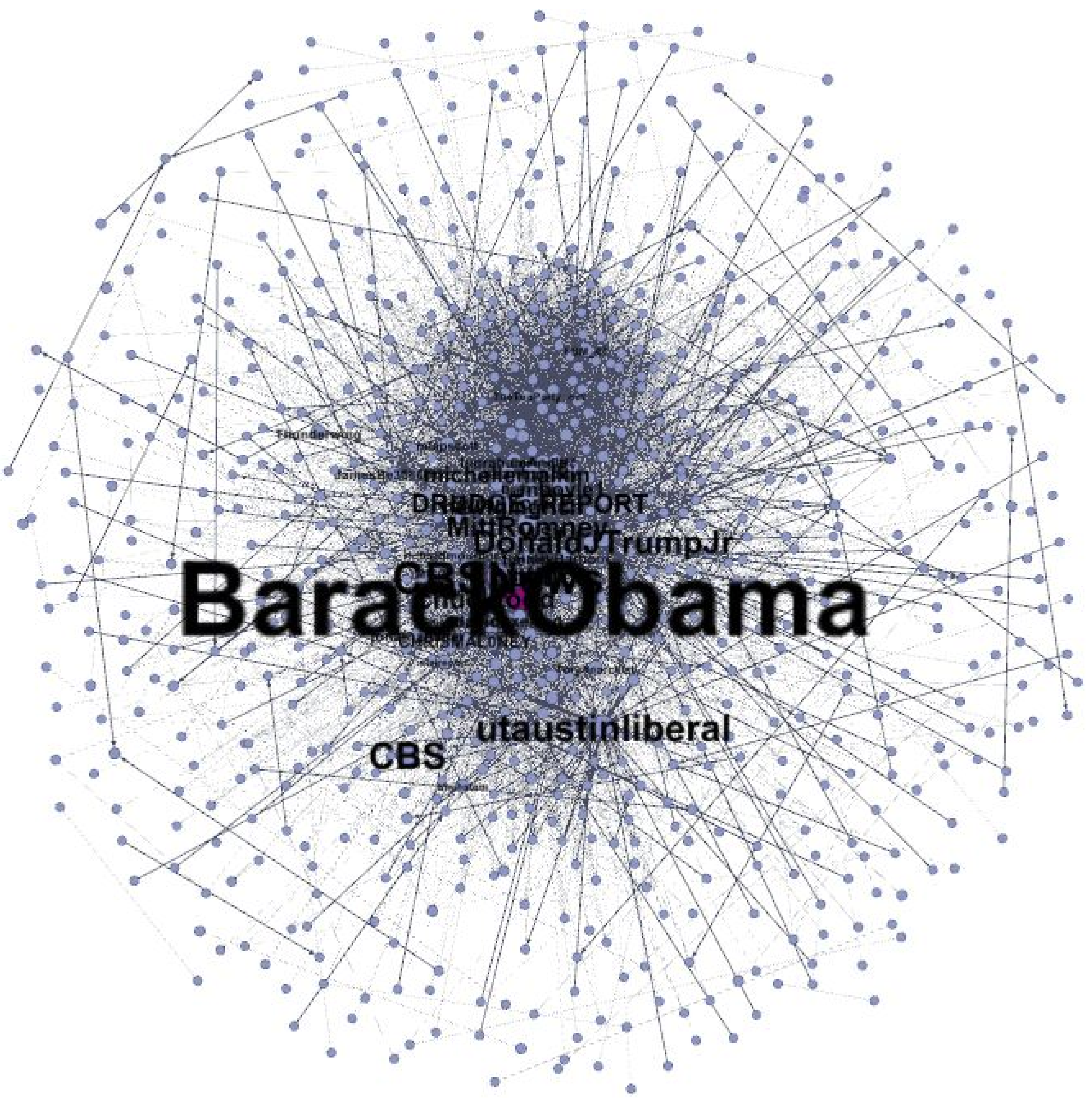

Figure 5.1. 1st Debate Social Graph.

(ii) 2nd Debate:

Keyword: bailout_obama

# of Nodes: 5,930

# of Edges: 746,442

The social graph is shown in Figure 5.2. Because of the high percentage of the following relationship, the number of edges in this social graph is high and it is hard to see the individual edges between the nodes. The bigger the nodes and the labels are, the higher the PageRank scores of the nodes are. Therefore, bigger nodes are likely to be opinion leaders.

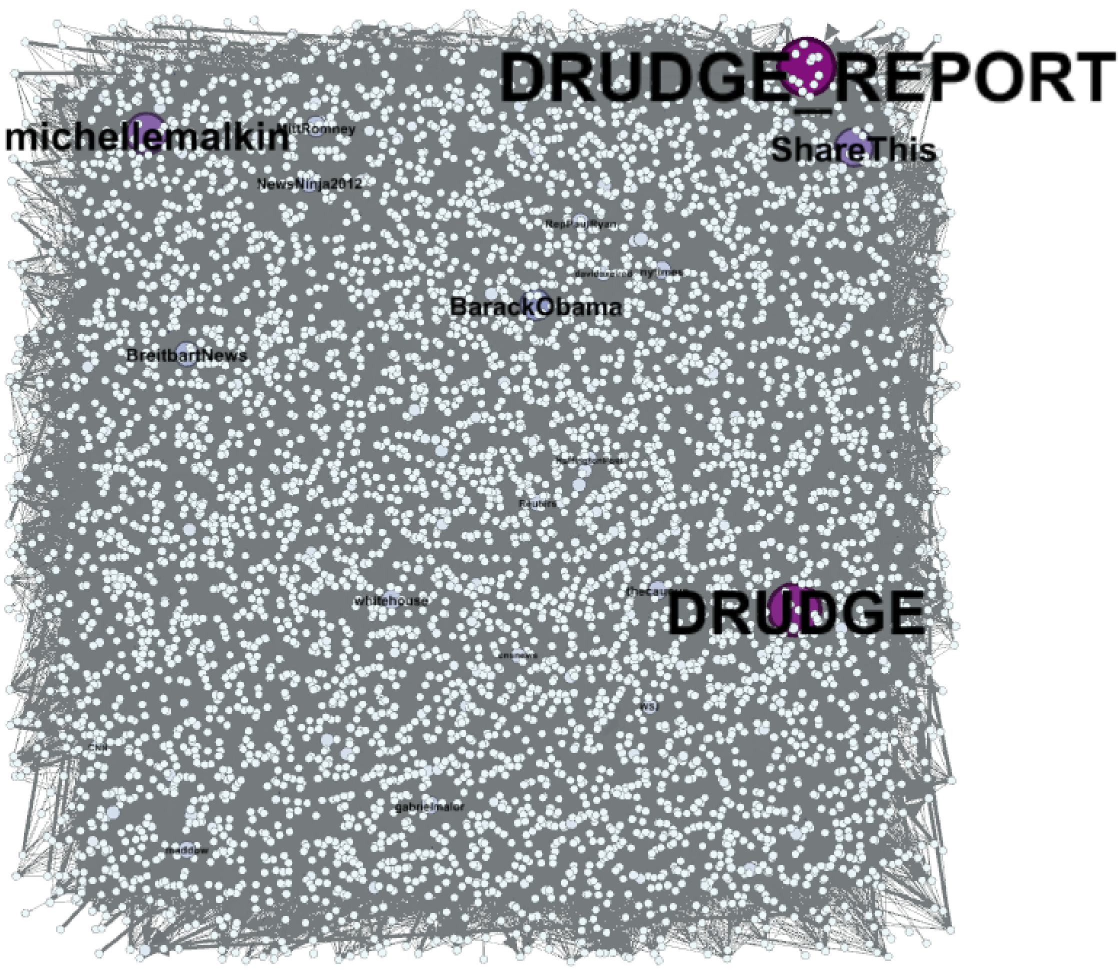

Figure 5.2. 2nd Debate Social Graph.

(iii) 3rd Debate:

Keyword: bailout_obama

# of Nodes: 6,888

# of Edges: 631,595

The social graph is shown in Figure 5.3. Similarly to social graph of the 2nd Debate, the total edge count is high due to the high number of following relationships. Twitter users apart from BarackObama should be considered as opinion leader candidates.

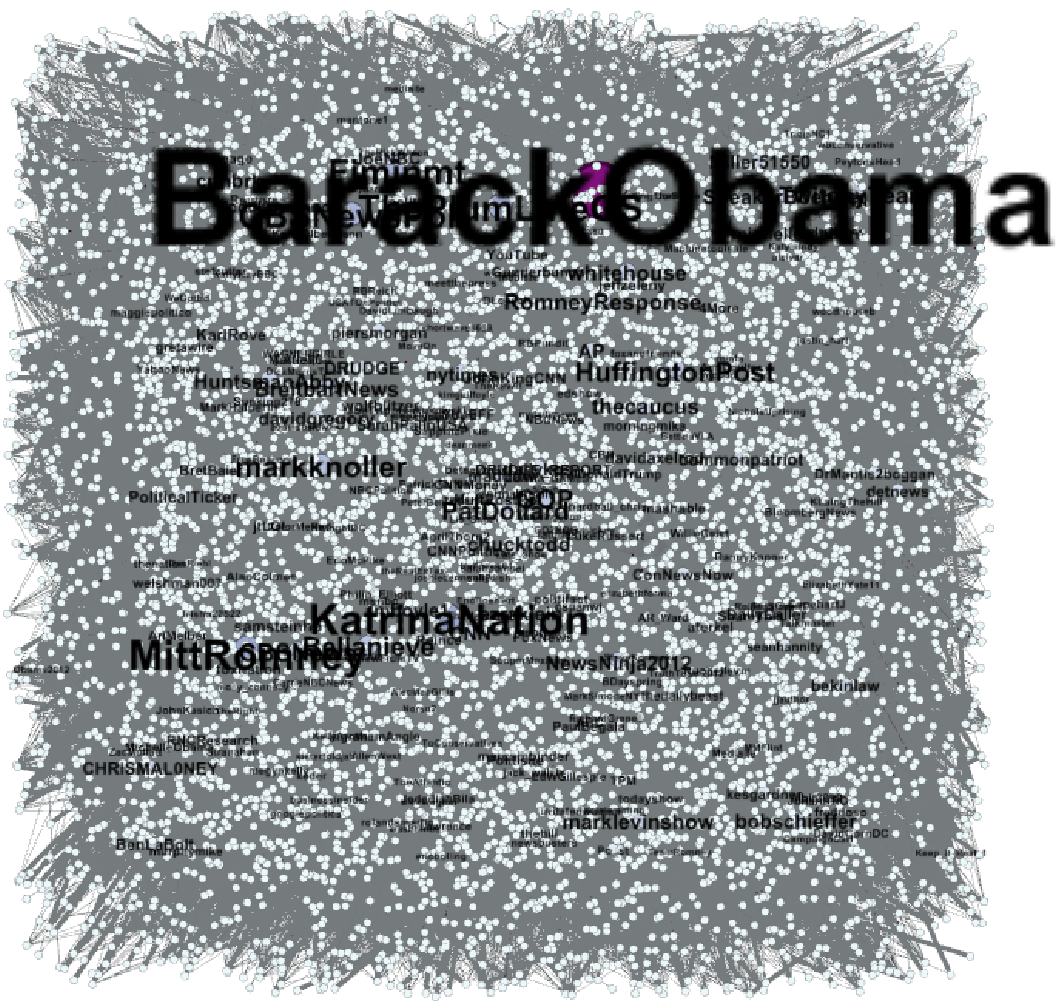

Figure 5.3. 3rd Debate Social Graph.

(iv) 4th Debate:

Keyword: bailout_obama

# of Nodes: 1,711

# of Edges: 59,458

Social graph is in Figure 5.4.

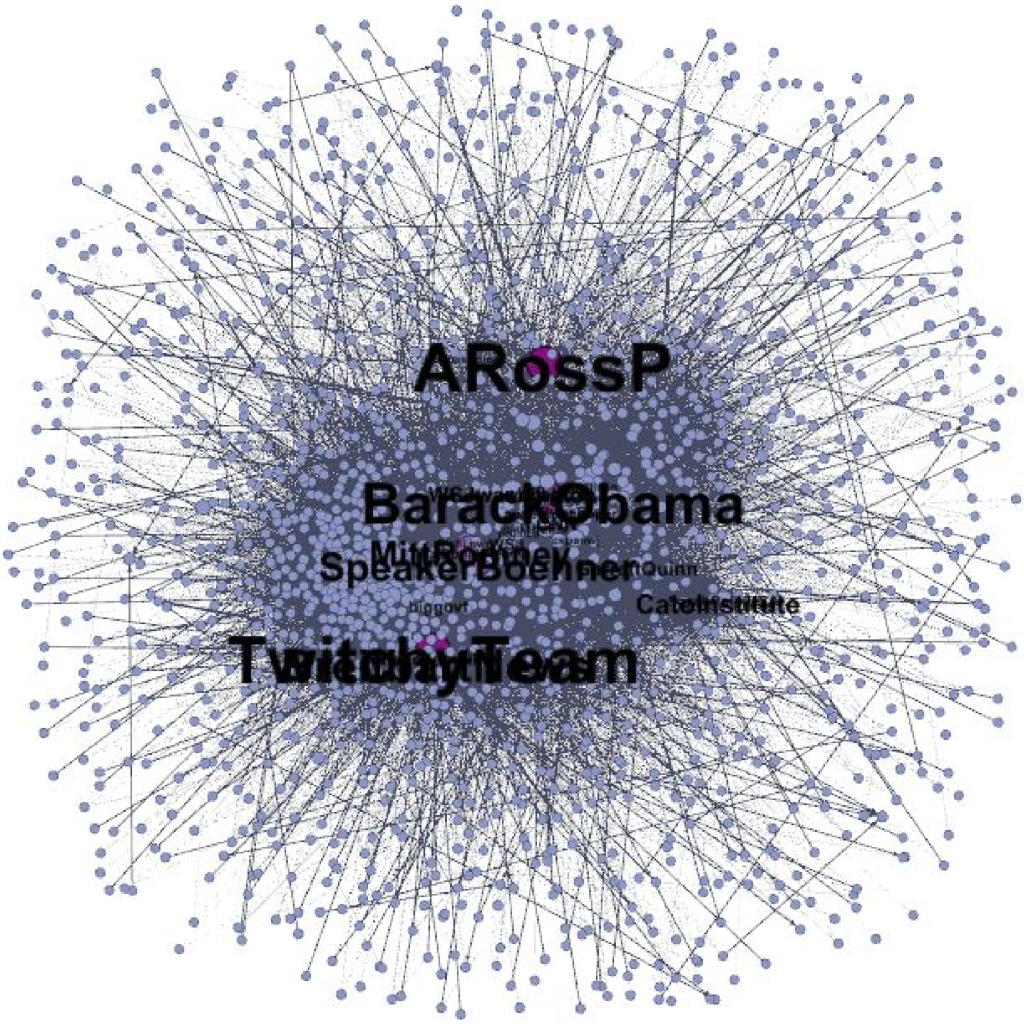

Figure 5.4. 4th Debate Social Graph.

5.2. Comparison of Centrality Measurements

In addition to the PageRank algorithm, other centrality metrics are taken into consideration too in order to compare the results of different centrality measurements. In order to calculate betweenness and closeness centrality scores of the nodes, the weight values are inversed ($\frac{1}{W_{ij}}$) and then these metrics are calculated according to the inversed values. The weight function that is used in betweenness and closeness measurements is as follows:

$$W'_{ij} = \frac{1}{W_{ij}}$$

Betweenness vs PageRank: The definitions and measurements of these two metrics are different from each other. Nevertheless, there are several intersection nodes that have higher scores in both. That means users with easy-accessible and critical positions in the graph are also close to important users and have direct access from them. Therefore, these intersection nodes are worth to consider and more likely to be opinion leaders in the community.

Closeness vs PageRank: These two metrics are similar in concept. Therefore the intersection set consists of many nodes.

Table 5.3 shows the percentages of these two comparisons for the 4th debate period with keyword “bailout_obama”. 35% of opinion leader candidates detected by betweenness centrality metric intersect with opinion leaders detected by PageRank. Besides, 81% of those in closeness centrality intersect with opinion leaders in PageRank. We assume that these intersected nodes are more likely to be more influential and we left examining these nodes more carefully as a future work.

5.3. Evaluation

In order to evaluate the opinion leader candidates, we applied sentiment analysis techniques. We used the SentiStrength tool, which uses different word and phrase lists

Table 5.3. Intersection Set of Opinion Leaders.

Compared methods	intersection set percentage
PageRank vs Betweenness	35%
PageRank vs Closeness	81%

containing variable word scores to be applied to the short texts given. For each debate period, we extracted all the tweets and applied sentiment analysis to them. At the end, each tweet has its own sentiment namely positive, negative or neutral. For each debate period, we formed time-sentiment graphs in order to indicate how the general opinion of the community during a debate period changes. We used this sentiment change for deciding whether the opinion leader candidates share the same or similar sentiments with the majority of the community.

5.3.1. Sentiment Change in Community

(i) 1st Debate:

Keyword: bailout_obama

1st Debate Period includes the tweets written between 2 October and 7 October 2012. The presidential debate was held on 3 October 2012. Therefore, the selected period is around the exact debate time. Figure 5.5 refers to the graph of the sentiment change of the community between October 2 and October 7. The x-axis in the graph shows the number of positive, negative and neutral tweets written about the keyword *bailout_obama*, while the y-axis indicates the time period. Each sentiment is shown in its own graph and in green, red, and blue bars respectively. In Figure 5.6, percentages of positive, negative and neutral tweets in terms of their frequencies are visualized. For each time slot, what percentage of positive, negative and neutral tweets occur in the community is calculated. The y-axis indicates the time period and x-axis shows the percentage (%) value for each sentiment.

Tweets of the identified opinion leader candidates are examined and most of them seem to write positive or neutral tweets about the keyword *bailout_obama*. As it can be seen from both Figure 5.5 and Figure 5.6 that the number of positive and neutral tweets seem to be larger than negative tweets between October 2 and October 7. Also, the percentages of positive and neutral tweets are increasing in time when compared to negative tweets. Opinion leader candidates seem to influence the community in terms of changing their sentiment over time. The opinions of the community are likely to converge to the opinions of the candidates and this evaluation may indicate that identified opinion leaders candidates are likely to be real opinion leaders.

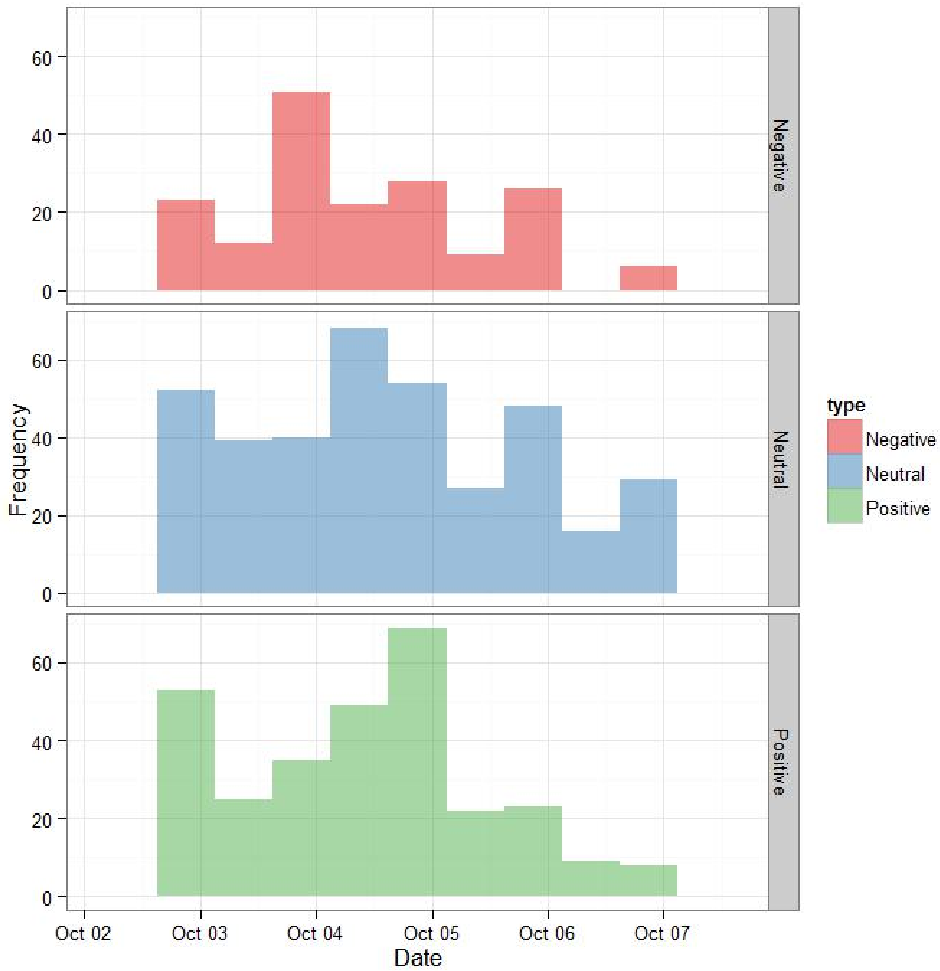

Figure 5.5. 1st Debate : Sentiment Frequency vs Date.

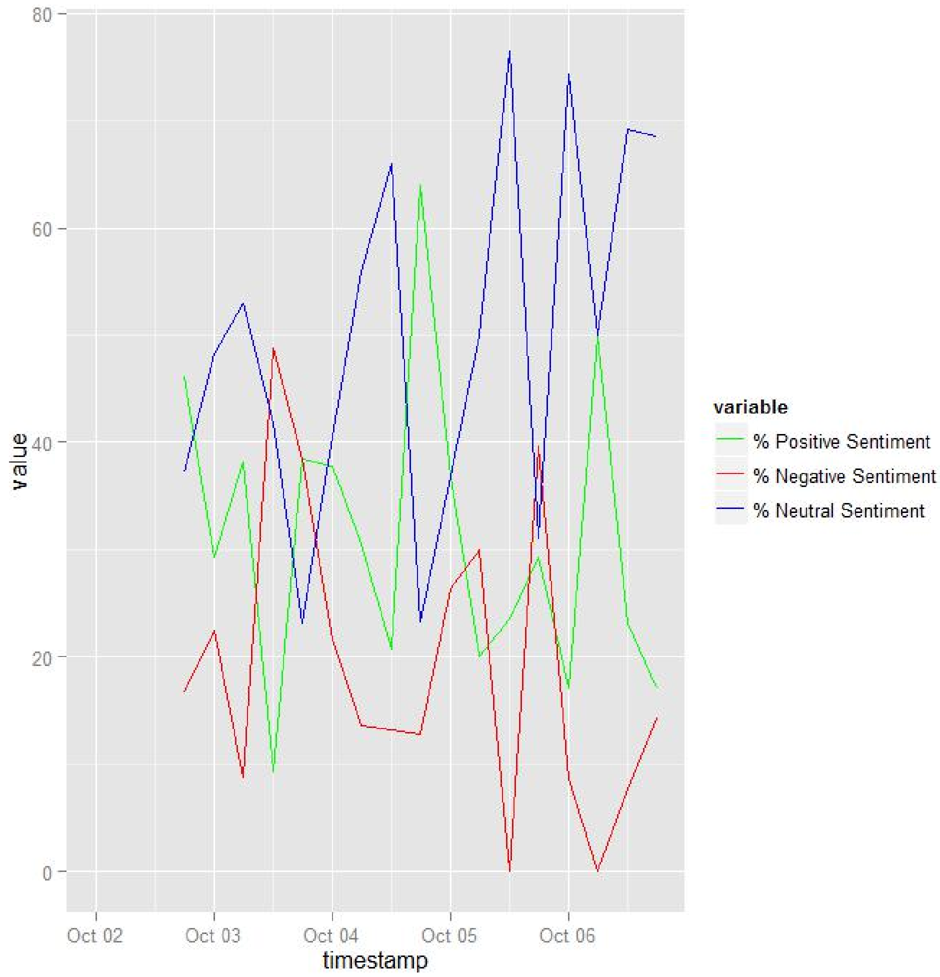

Figure 5.6. 1st Debate : Sentiment Percentage vs Date.

(ii) 2nd Debate:

Keyword: bailout_obama

2nd Debate Period includes the tweets written between 14 October and 20 October 2012. The presidential debate was held on 16 October 2012. Similar to the 1st Debate, Figure 5.7 is a graph of positive, negative and neutral tweet frequency in the defined time period. x-axis in Figure 5.8 refers to what percentages of total tweets are positive, negative and neutral and how these percentages change between October 14 and October 20.

Tweets of the identified opinion leader candidates are examined and most of them seem to write negative tweets about the keyword *bailout_obama*. As it can be seen from both Figure 5.7 and Figure 5.8 that the number of negative tweets seem to be larger than positive and neutral tweets between October 14 and October 20. Also, the percentages of negative tweets are increasing in time when compared to others. The dramatic change in negative sentiment can easily be seen by examining both frequency and percentage graphs. Especially, when the debate event started, the number of tweets written was increased. In this perspective, opinion leader candidates seem to influence the community in terms of changing their sentiment over time. The opinions of the community are likely to converge to the opinions of the candidates and this evaluation may indicate that identified opinion leaders candidates are likely to be real opinion leaders.

(iii) 3rd Debate:

Keyword: bailout_obama

3rd Debate Period includes the tweets written between 20 October and 26 October 2012. The presidential debate was held on 22 October. Details of the characteristics of the graphs in Figure 5.9 and Figure 5.10 are explained in the 1st and 2nd Debate results. Opinion leader candidates found according to our proposed method, seem to write negative tweets and hold negative feelings about the keywords during 3rd debate period. By examining both graphs, we observe that both the number of negative tweets and the percentage of the negative

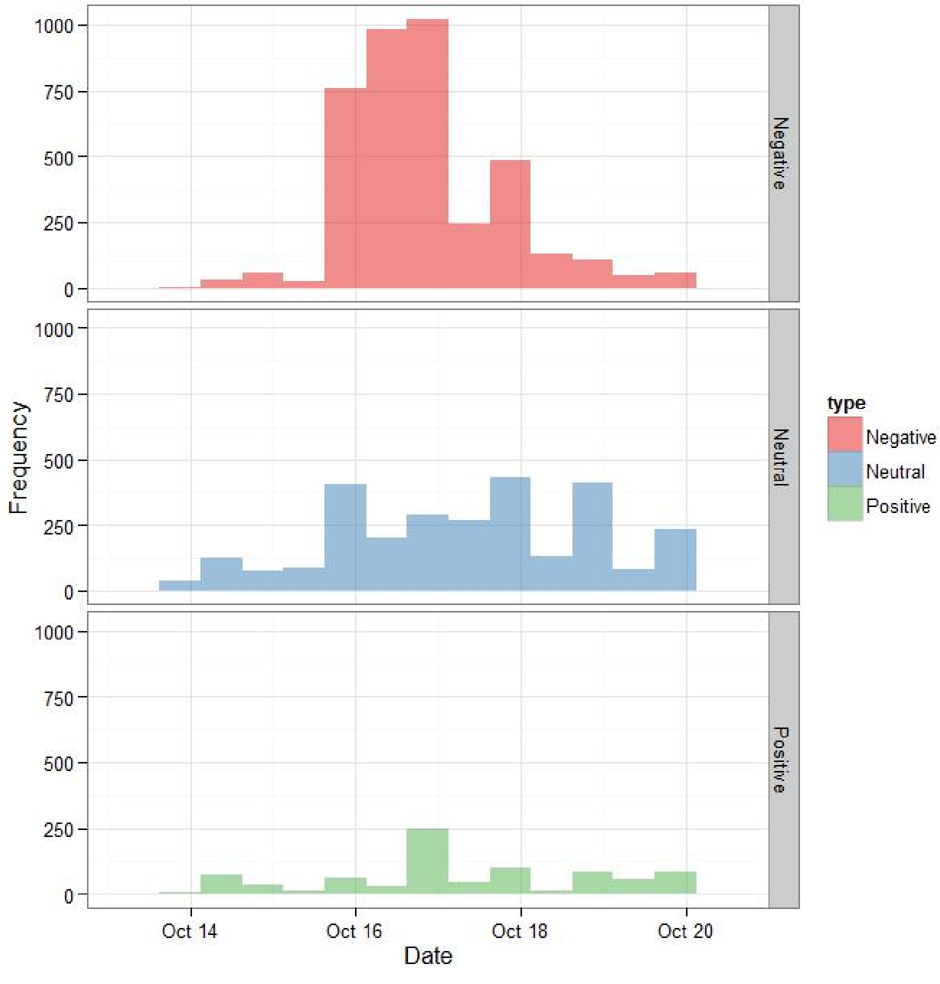

Figure 5.7. 2nd Debate : Sentiment Frequency vs Date.

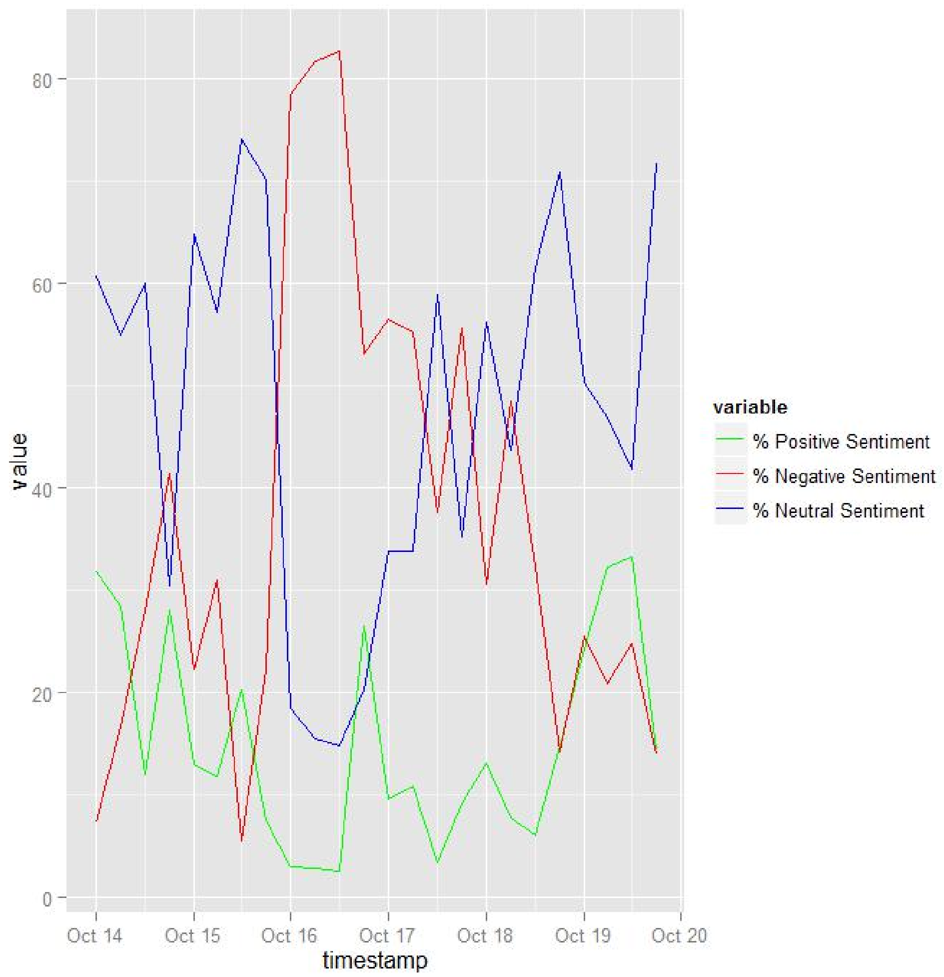

Figure 5.8. 2nd Debate : Sentiment Percentage vs Date.

tweets in the community are larger than other tweets. Negative tendency for the keyword *bailout_obama* over time can be derived from both graphs and positive tweet proportion is decreasing at the same time. This evaluation may indicate that identified opinion leaders candidates are likely to be real opinion leaders.

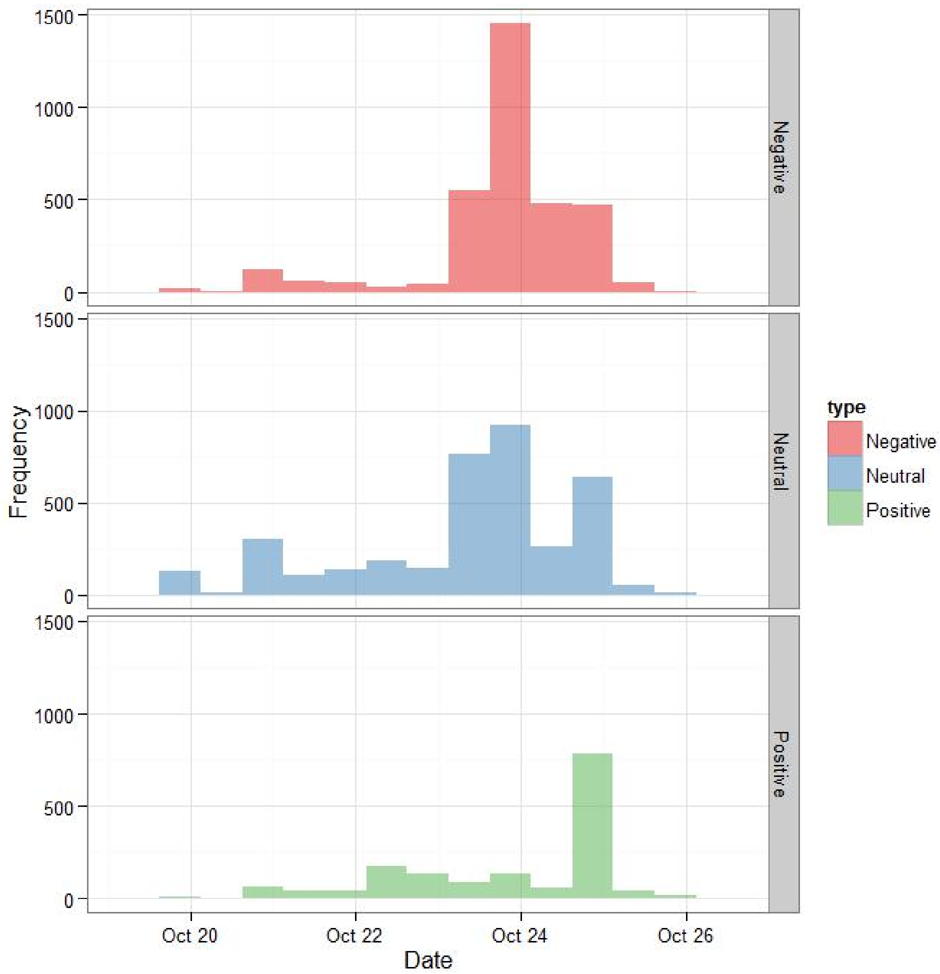

Figure 5.9. 3rd Debate : Sentiment Frequency vs Date.

(iv) 4th Debate:

Keyword: bailout_obama

4th Debate Period includes the tweets written between 02 November and 08 November 2012. The presidential debate was held on 04 November. Details of the characteristics of the graphs in Figure 5.11 and Figure 5.12 are explained in the 1st and 2nd Debate results. Opinion leader candidates, which are identified according to our proposed method, seem to write negative tweets and hold negative feelings

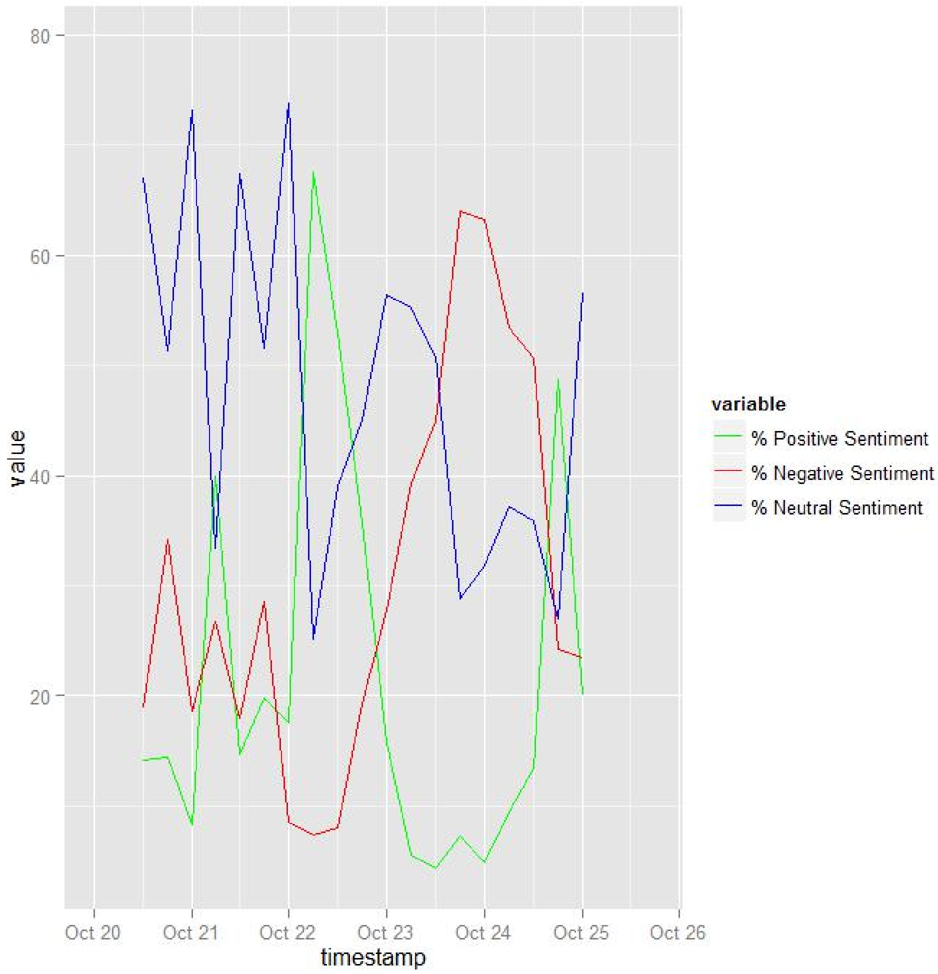

Figure 5.10. 3rd Debate : Sentiment Percentage vs Date.

about the keywords during 4th debate period. By examining both graphs, we can reach that both the number of negative tweets and the percentage of the negative tweets in the community are larger than other tweets. Negative tendency for the keyword *bailout_obama* over time can be derived from both graphs and positive tweet proportion is decreasing at the same time. Also since the election was held on 06 November 2012, the number of tweets began to decrease after election day. This evaluation may indicate that identified opinion leaders candidates are likely to be real opinion leaders.

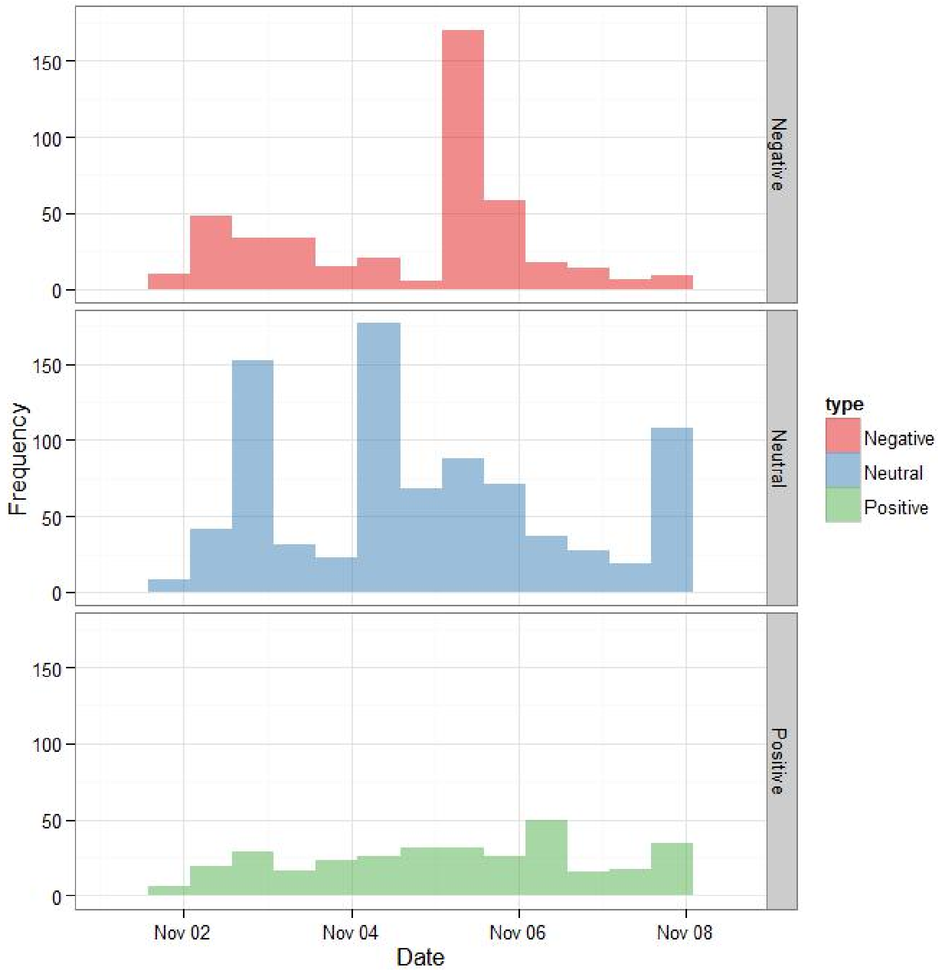

Figure 5.11. 4th Debate : Sentiment Frequency vs Date.

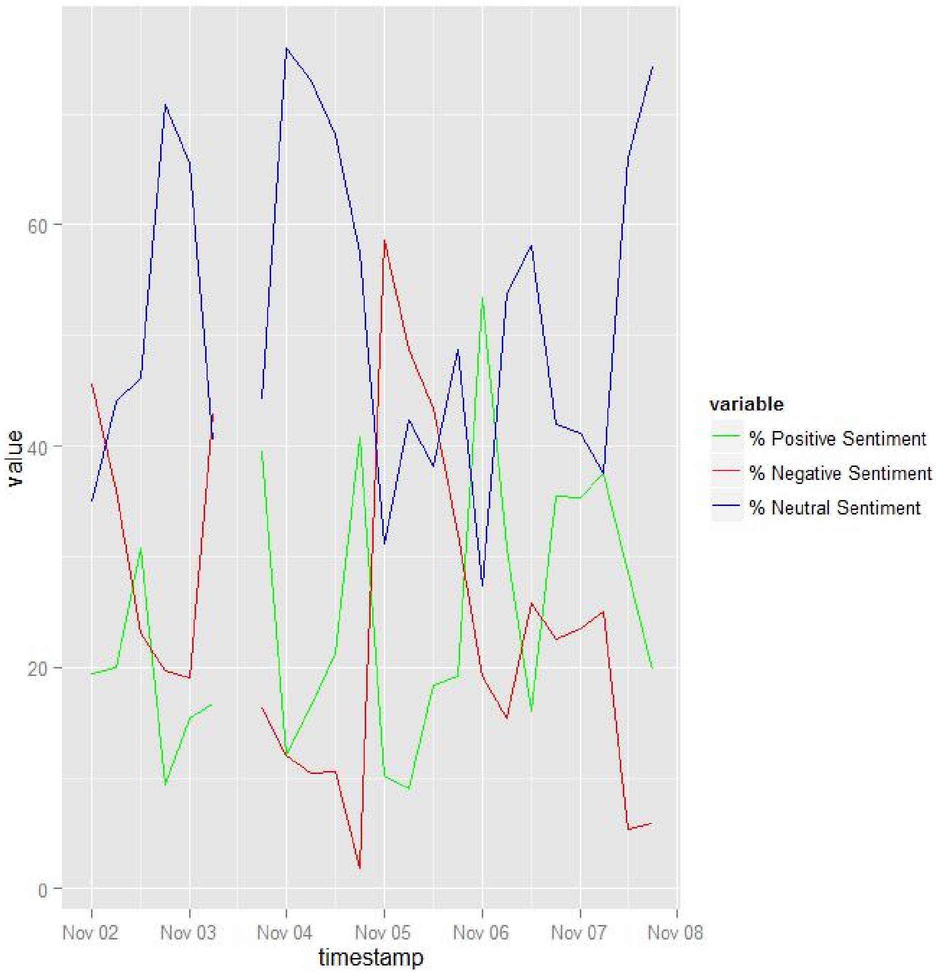

Figure 5.12. 4th Debate : Sentiment Percentage vs Date.

5.3.2. Evaluation of Relationship Coefficients

Main motivation of this study is combining all the relationships and interactions in order to create weighted and directed social networks and then analyzing them for determining opinion leaders. Combination of the relationships and interactions were held according to a mathematical formula in which each relationship type gained separate weights. The weight function of each relationship was calculated according to the frequency of each relationship in the dataset and coefficient factors which were specific to it. Determining exact values of coefficients is not a trivial task. Therefore, in this study we aimed to propose the most reasonable order for these constants. In the previous section, we have mentioned six different relationship orders which can be listed as below:

- $Order_1 = RETWEET > MENTION \approxeq REPLY >> FOLLOW$
- $Order_2 = RETWEET > FOLLOW > MENTION \approxeq REPLY$
- $Order_3 = FOLLOW > RETWEET > MENTION \approxeq REPLY$
- $Order_4 = FOLLOW > MENTION \approxeq REPLY > RETWEET$
- $Order_5 = MENTION \approxeq REPLY > RETWEET >> FOLLOW$
- $Order_6 = MENTION \approxeq REPLY > FOLLOW > RETWEET$

For each order, we created separate social network graphs for different debate periods. During the experiments and decision of coefficients, we have taken the two main principles into consideration. The first one is that in case of smaller value of FOLLOW relation, its weight is seriously small when compared to other relations because users with no interactions but with so many followers should not be recorded as opinion leader candidates just because they have lots of followers. In order to prevent this ambiguity, smaller FOLLOW values are assumed to be excessively smaller. The second one is that not all the RETWEET relations have the same weight. Agreement retweet relations and neutral retweet relations have higher weights than disagreement relations. ($Agreement = Neutral > Disagreement$) This is because although a user does not agree with another user, he may retweet and add his own comment to the original tweet. This does not mean that he doesn't appreciate or takes any notice of the retweeted user. Despite of a disagreement, he is still influenced by the retweeted user and this detail is taken into consideration in our study. In the lights of these assumptions, the experimental coefficient values of each relation are listed in Table 5.4. RETWEET (+) means agreement in retweet which includes standard retweets, agree and neutral quoted retweets while RETWEET (-) means disagreement in retweets which includes disagree quoted retweets.

Table 5.4. Experimental Relationship Coefficients.

Order #	RETWEET (+)	RETWEET (-)	MENTION=REPLY	FOLLOW
$Order_1$	10,000	6,000	1,000	1
$Order_2$	10,000	6,000	10	100
$Order_3$	100	60	1	1,000
$Order_4$	1	1	100	1,000
$Order_5$	1,000	600	10,000	1
$Order_6$	10	6	10,000	100

For different debate periods, we generated six different social graphs and applied the PageRank algorithm to each of them. Opinion leader candidates which were on the top lists of the PageRank results were evaluated according to their sentiment change. This sentiment evaluation helped us to investigate whether the top list of each debate period included candidates who were likely to be opinion leaders. After this investigation, we found the number of probable opinion leaders exist in the top list and thus calculated the percentages of probable opinion leaders. According to these information, we concluded that $Order_1$ which is $Order_1 = RETWEET > MENTION \sim REPLY >> FOLLOW$ was the most effective order.

2nd Debate:

Keyword: bailout_obama

# of nodes : 5,930

# of edges: 746,442

PageRank Threshold: 0.004

According to second debate sentiment results, both frequency and percentage of negative sentiments are more than other sentiments. Therefore, the opinion leader candidates are expected to have negative sentiments too. The percentage of opinion leader candidates who have negative sentiments are shown in Table 5.5.

Table 5.5. 2nd Debate: Percentage of candidates having negative sentiments.

Order description	Percentage
$RETWEET > MENTION \simeq REPLY >> FOLLOW$	70%
$RETWEET > FOLLOW > MENTION \simeq REPLY$	50%
$FOLLOW > RETWEET > MENTION \simeq REPLY$	39%
$FOLLOW > MENTION \simeq REPLY > RETWEET$	41%
$MENTION \simeq REPLY > RETWEET >> FOLLOW$	43%
$MENTION \simeq REPLY > FOLLOW > RETWEET$	44%

3rd Debate:

Keyword: bailout_obama

# of nodes : 6,888

# of edges: 631,595

PageRank Threshold: 0.004

According to third debate sentiment results, both the frequency and percentage of negative sentiments are more than the other sentiments' frequencies and percentages. Therefore, the opinion leader candidates are expected to have negative sentiments too. The percentage of opinion leader candidates who have negative sentiments are shown in Table 5.6.

5.3.3. Evaluation of Opinion Leader Candidates

In a social graph, opinion leader candidates are assumed to influence the others directly or indirectly. The nodes directly connected to these candidates are likely to change their opinions in the direction of these candidates. We evaluate the opinion

Table 5.6. 3rd Debate: Percentage of candidates having negative sentiments.

Order description	Percentage
$RETWEET > MENTION \simeq REPLY >> FOLLOW$	51%
$RETWEET > FOLLOW > MENTION \simeq REPLY$	42%
$FOLLOW > RETWEET > MENTION \simeq REPLY$	37%
$FOLLOW > MENTION \simeq REPLY > RETWEET$	36%
$MENTION \simeq REPLY > RETWEET >> FOLLOW$	40%
$MENTION \simeq REPLY > FOLLOW > RETWEET$	38%

leader candidates based on the assumption that the number of nodes connected to a real opinion leader tend to increase in time and the sentiments of these connected nodes towards the topic of interest tend to converge to his sentiment. Twitter users that we have found as opinion leaders seem to influence their directly connected neighbours and change their overall sentiment towards the given topic over time. The analysis of two example opinion leader candidates are provided below.

(i) @michellemalkin: This Twitter user is one of the opinion leader candidates during the second debate period according to the method we proposed. It can be inferred from her tweets and political perspective that she holds negative sentiment about the keywords, bailout and Obama. In order to evaluate whether she is one of the real opinion leaders or not, Twitter users who are connected to michellemalkin are supposed to have negative sentiments at the end of the debate period. In order to have a connection between michellemalkin and the other users, one of them should retweet, mention, reply or follow the other one. The sentiments of the connected nodes are determined by analyzing the tweets and retweets of them. The graph of sentiment change in percentage of the connected nodes to @michellemalkin is shown in Figure 5.13. Also, Figure 5.14 shows that the number of negative sentiments of the community around her is increasing in time. That means the sentiments of the people who are connected to michellemalkin are changing in the direction of her sentiment and she influences the community by imposing her own opinion.

Similarly, the number of connected nodes to michellemalkin seems to increase in time. In three different date snapshots, three social graphs which have michellemalkin as central node are generated. Without considering the following relationship (it is ignored for visualization because of its excessive edge count addition to the graph), it can be seen from these graphs generated on 14th, 17th and 20th October that during the second debate her tweets were taken into consideration and followed, and thus she influenced her neighbours directly. The graphs get more intense as time passes by. All these three graphs are shown in Figures 5.15, Figure 5.16 and Figure 5.17.

(ii) @BrietbartNews: This Twitter user is one of the opinion leader candidates during the second and third debate periods according to the method we proposed. It can be inferred from his tweets and political perspective that he holds negative sentiment about bailout and Obama. In order to evaluate whether he is one of the real opinion leaders or not, Twitter users who are connected to BrietbartNews are supposed to have negative sentiments at the end of the debate period. In order to have a connection between BrietbartNews and the other users, one of them should retweet, mention, reply or follow the other one. The graph of sentiment change in percentage of the connected nodes to @BrietbartNews is shown in Figure 5.18. Also, Figure 5.19 shows that the number of negative sentiments of the community around him is increasing in time. That means the sentiments of the people who are connected to BrietbartNews are changing in the direction of him and he influences the community by imposing his own opinion.

Similarly, the number of connected nodes to BrietbartNews seems to increase in time. In three different date snapshots, three social graphs which have BrietbartNews as central node are generated. Without considering the following relationship (because of its excessive edge count addition the graph), it can be seen from these graphs generated on 10th, 17th and 25th October that during the

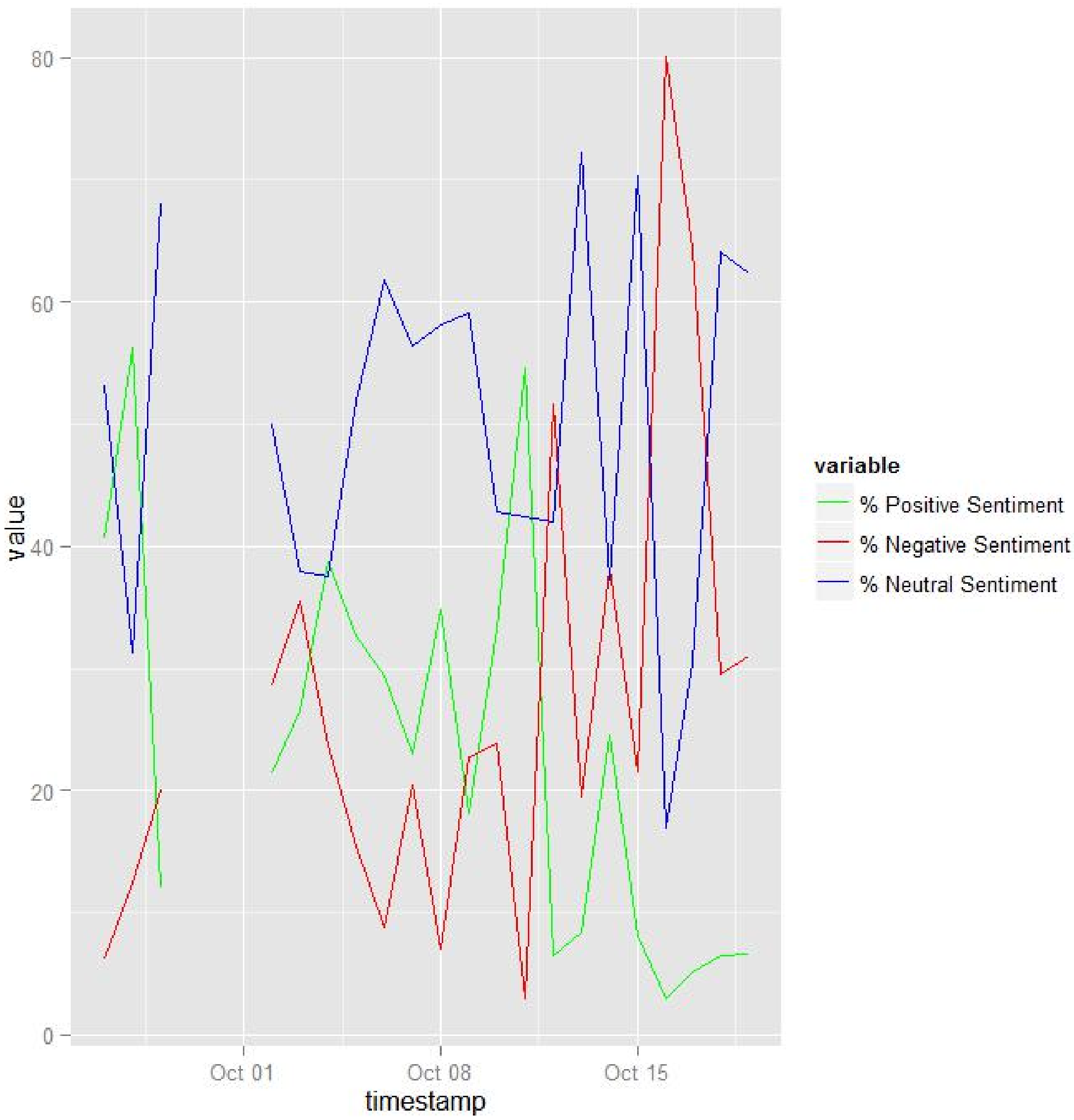

Figure 5.13. Sentiment Percentage Change of the Nodes Connected to @michellemalkin.

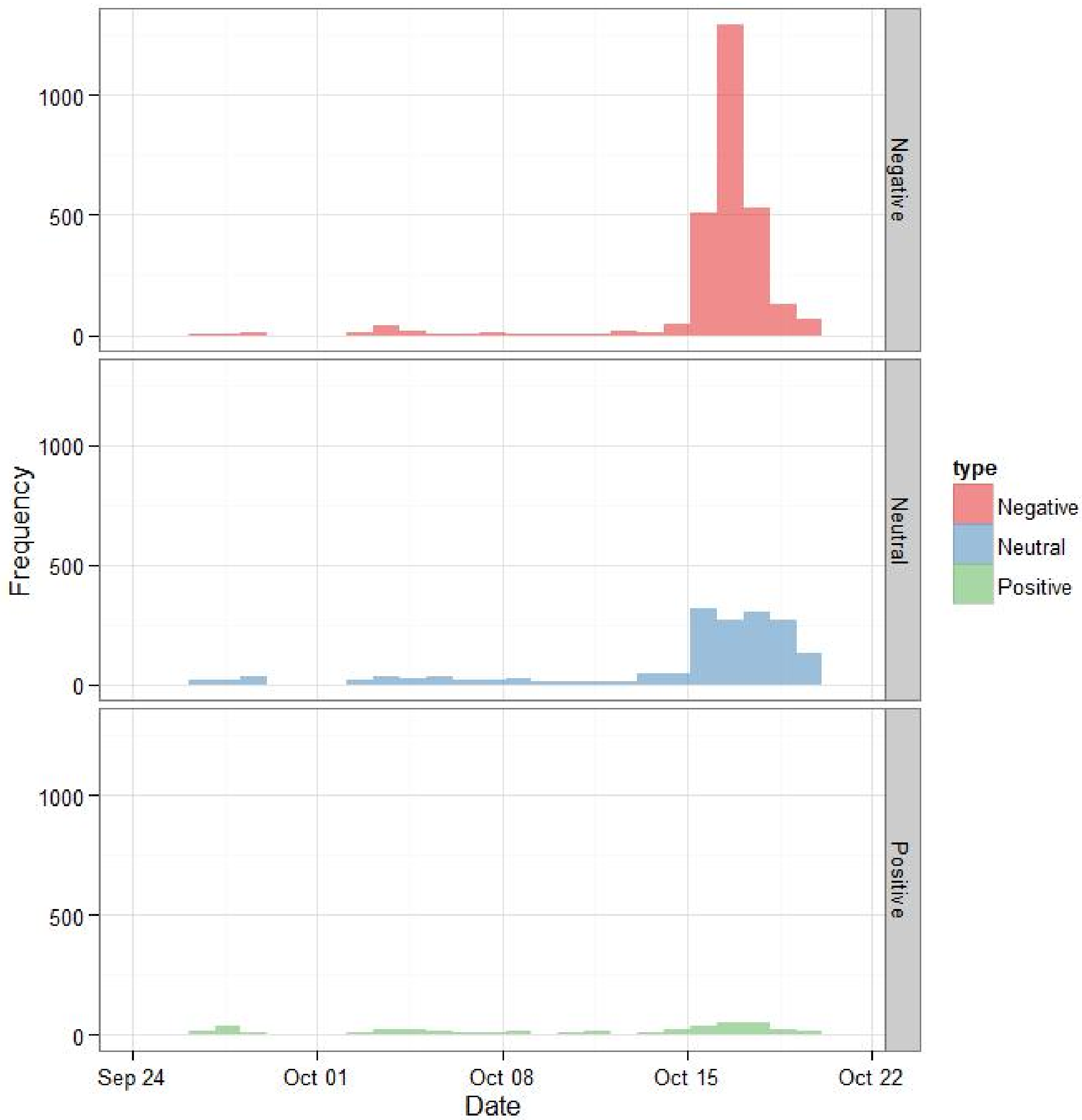

Figure 5.14. Sentiment Frequency Change of the Nodes Connected to @michellemalkin.

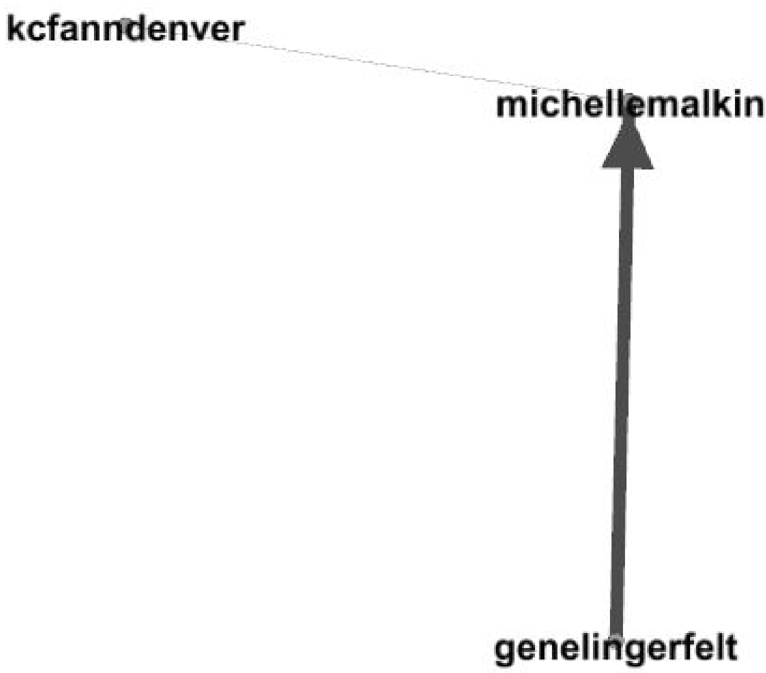

Figure 5.15. Social Graph of @michellemalkin before 14 October 2012.

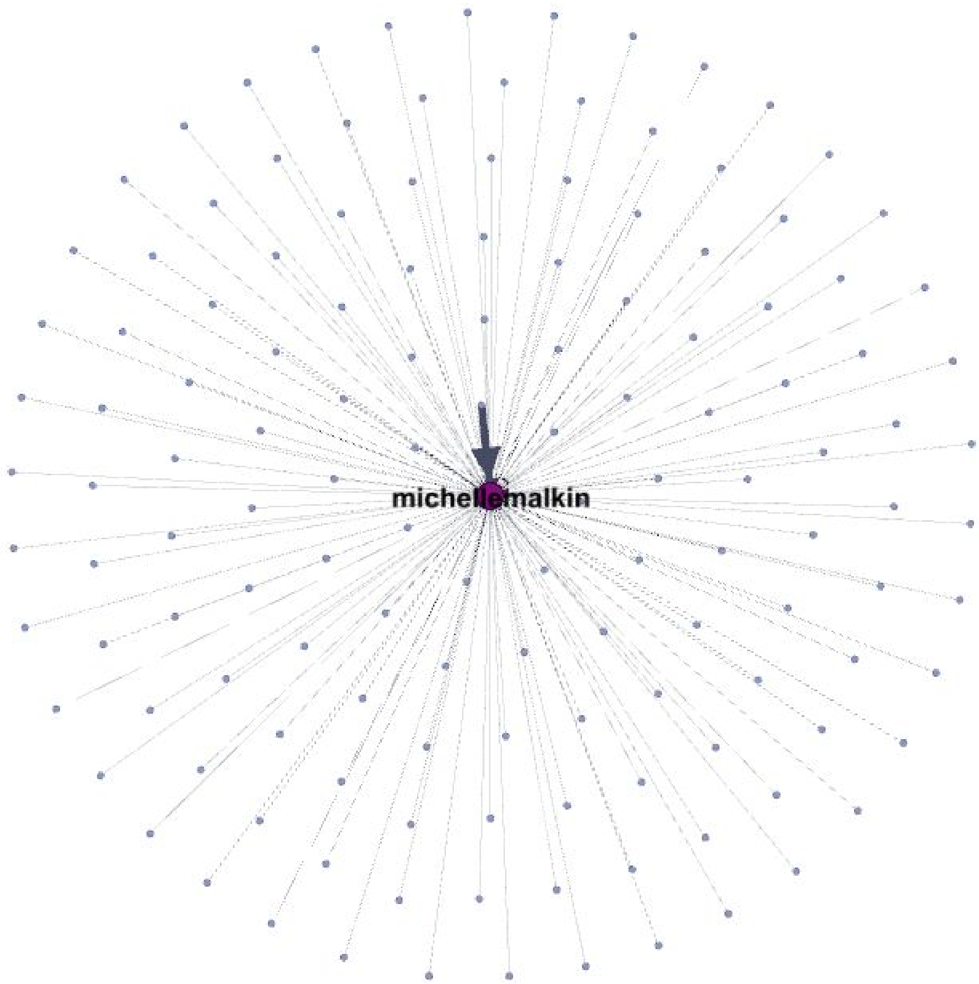

Figure 5.16. Social Graph of @michellemalkin before 17 October 2012.

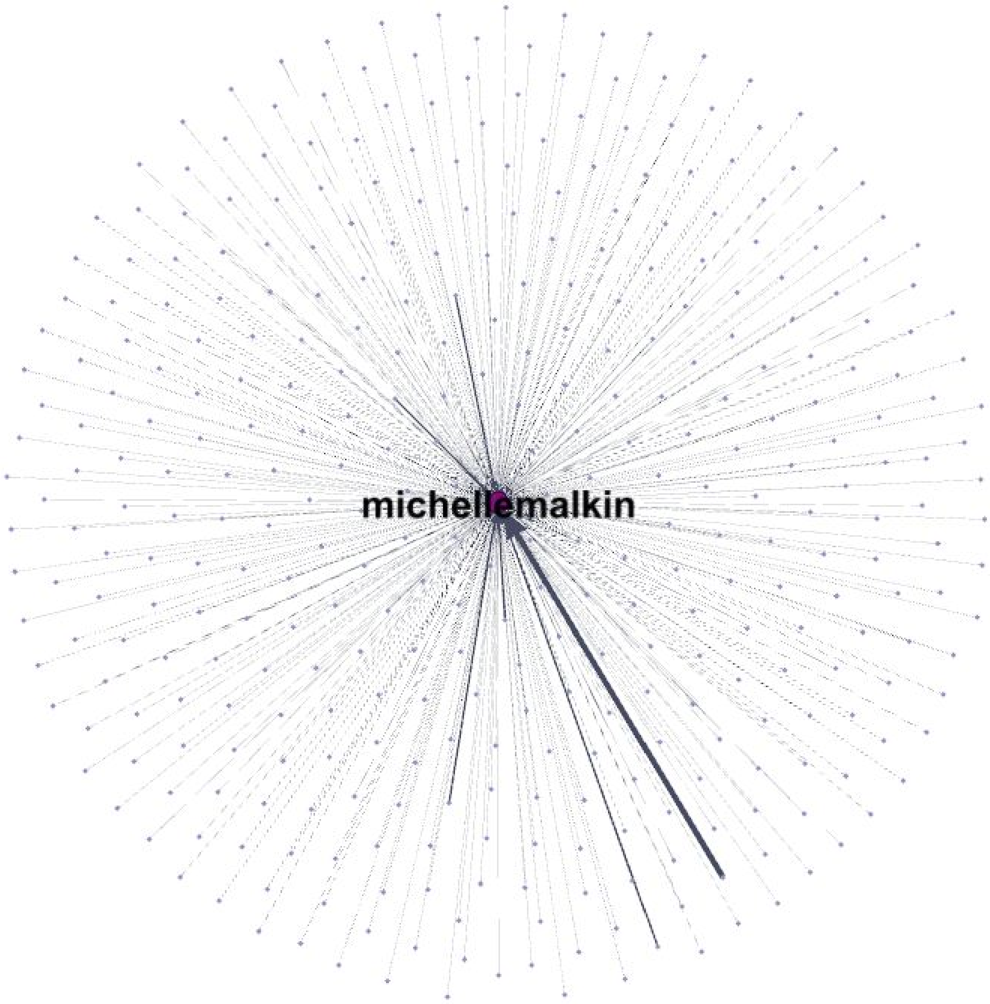

Figure 5.17. Social Graph of @michellemalkin before 20 October 2012.

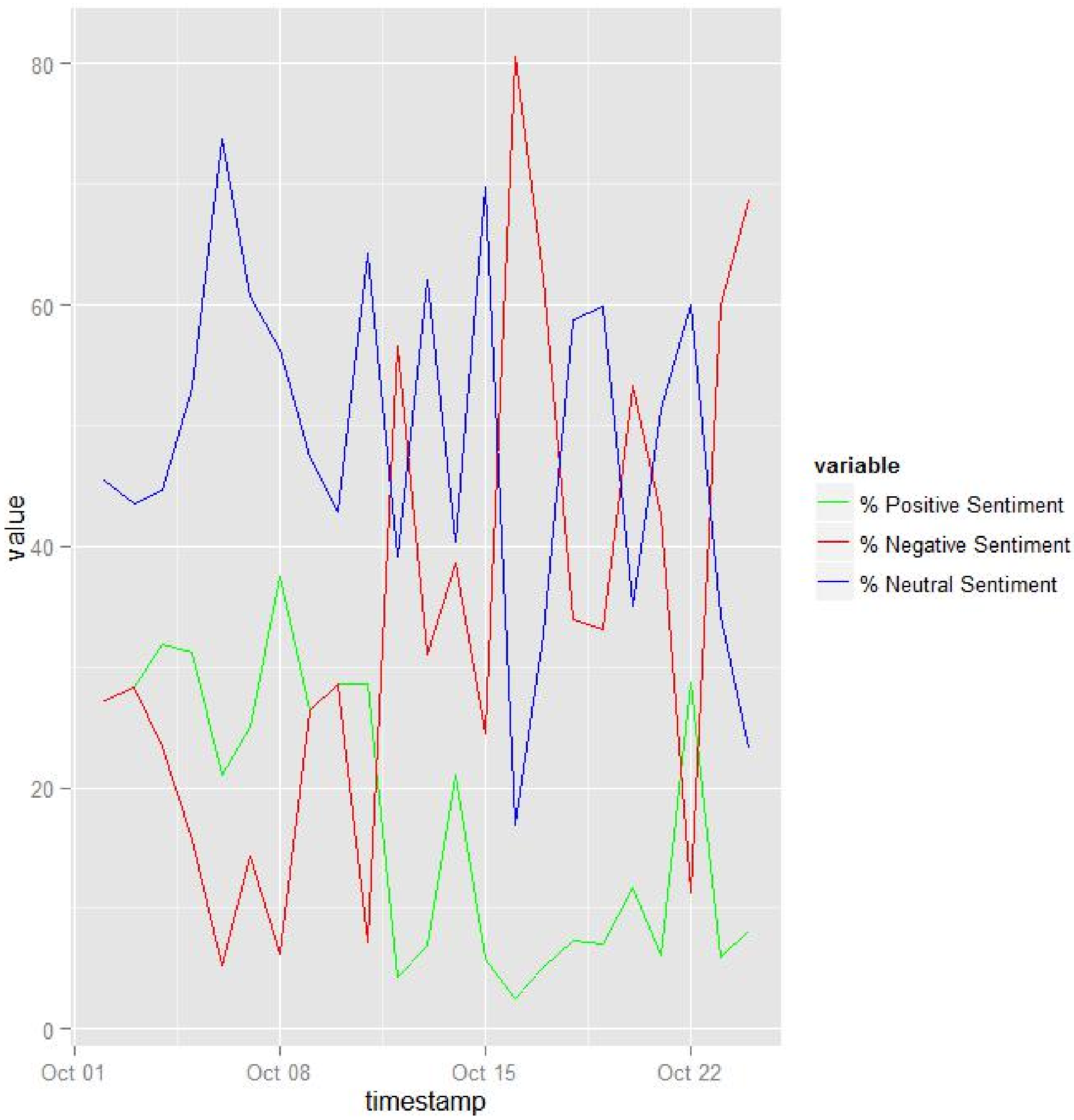

Figure 5.18. Sentiment Percentage Change of the Nodes Connected to @BrietbartNews.

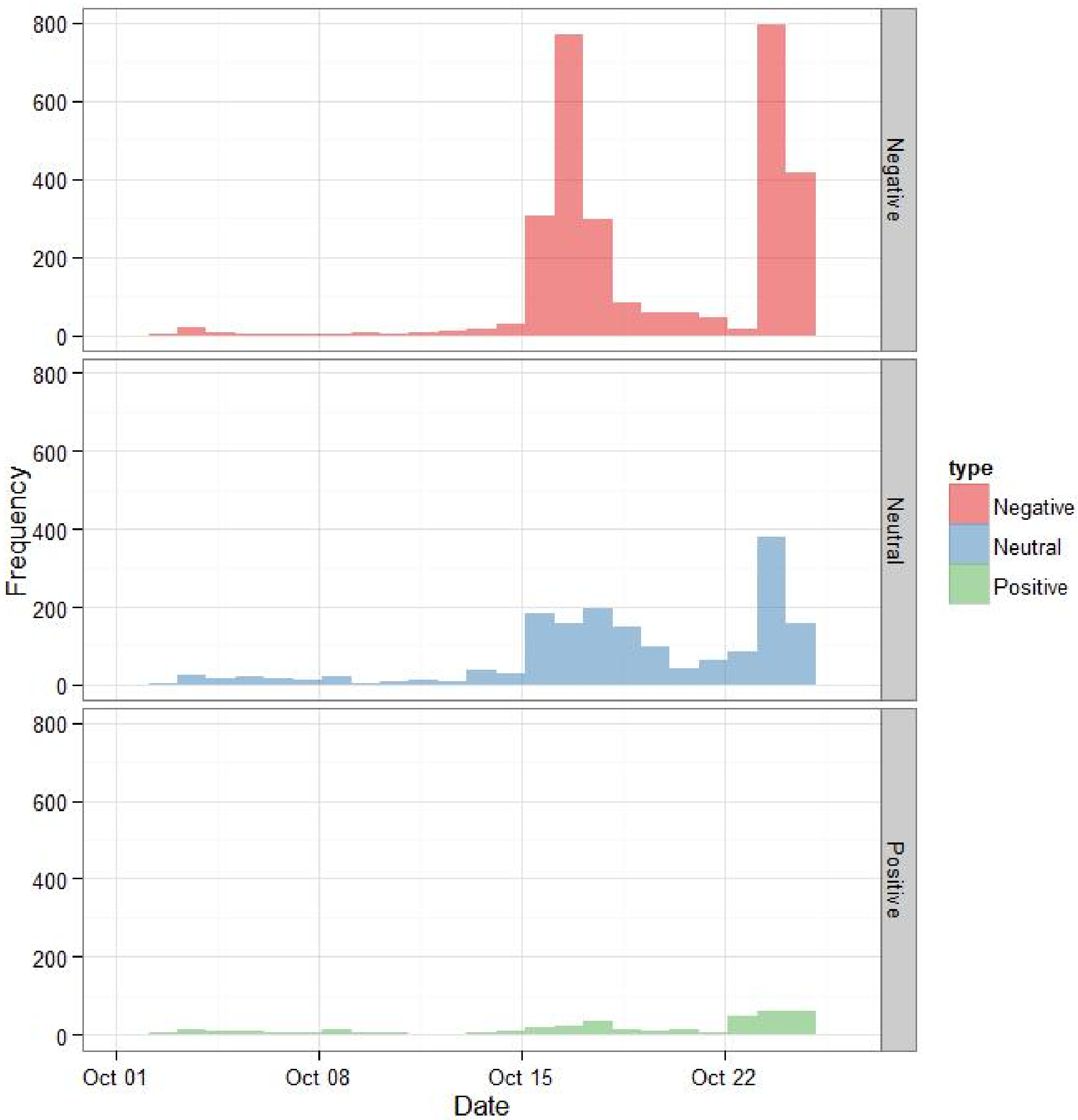

Figure 5.19. Sentiment Frequency Change of the Nodes Connected to @BrietbartNews.

second debate his tweets were taken into consideration and followed, and thus he influenced her neighbours directly. All these three graphs are shown in Figures 5.20, 5.21 and 5.22.

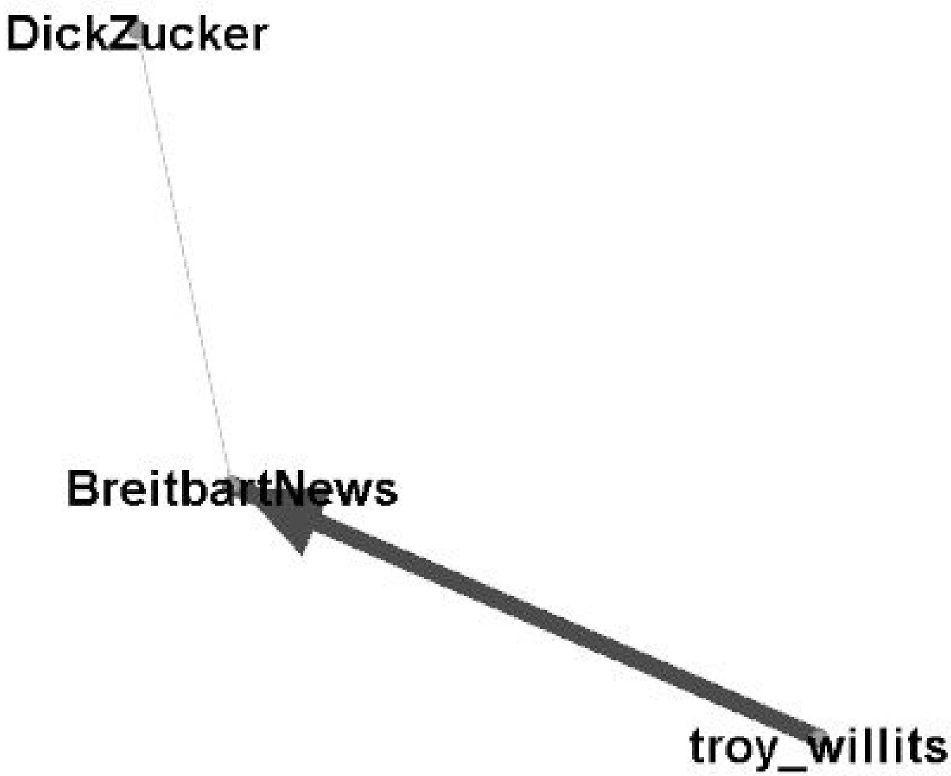

Figure 5.20. Social Graph of @BrietbartNews before 10 October 2012.

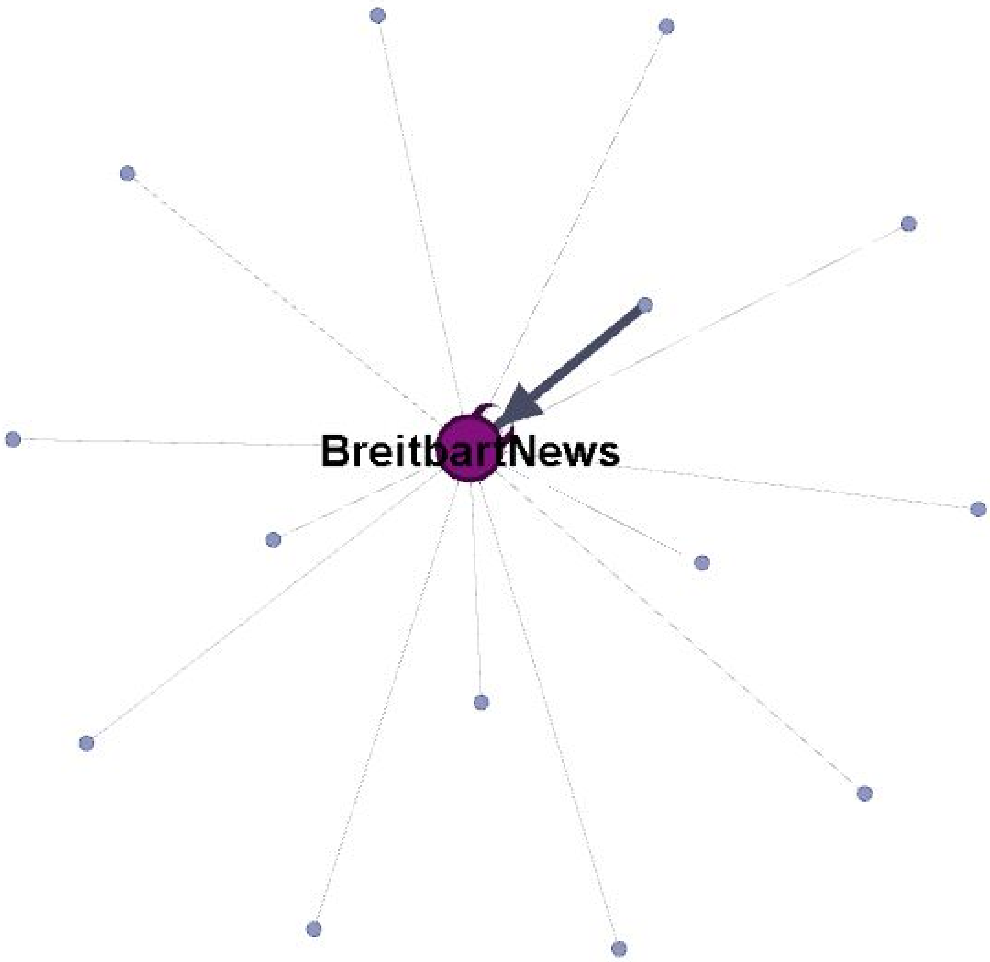

Figure 5.21. Social Graph of @BrietbartNews before 17 October 2012.

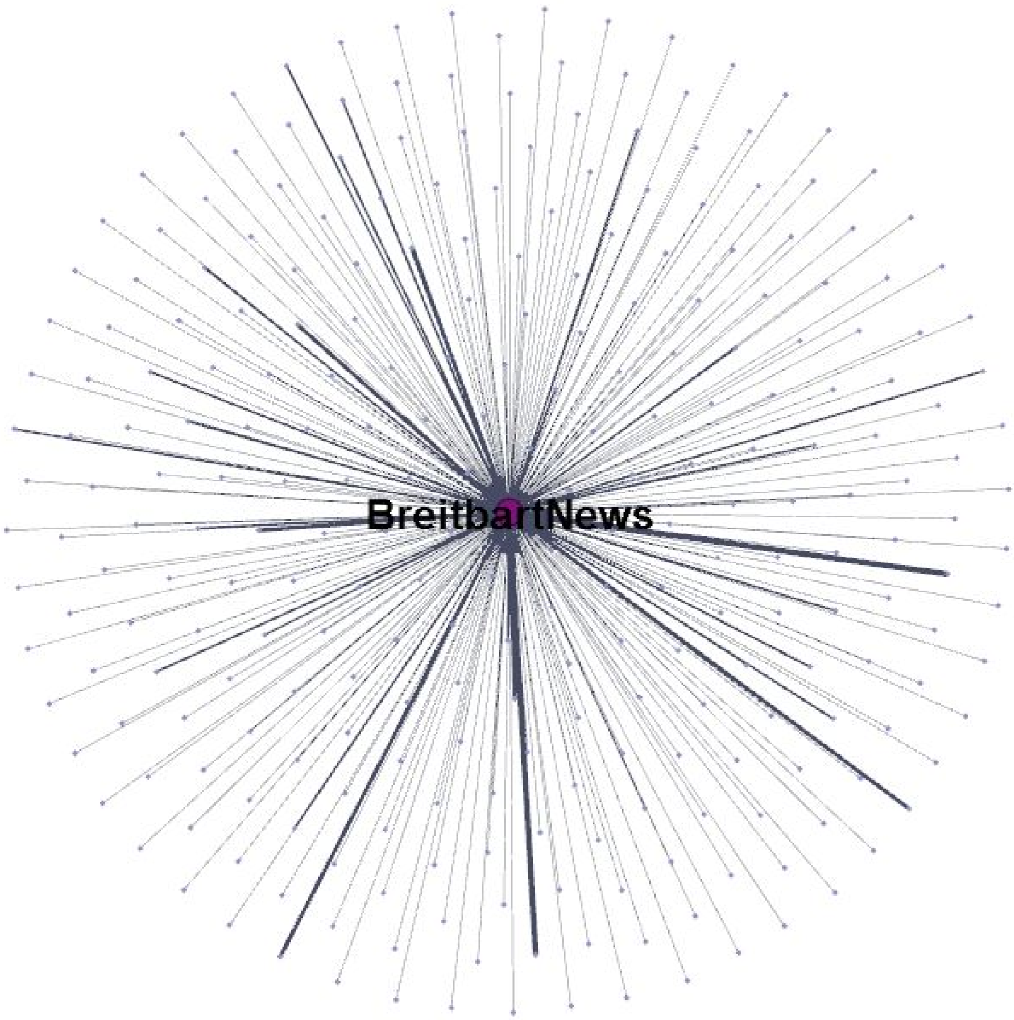

Figure 5.22. Social Graph of @BrietbartNews before 25 October 2012.

6. CONCLUSION

In this study, we proposed a method to detect opinion leaders related with predefined topics in microblogging environments. As a microblogging environment, we used Twitter because of its free format environment for writing short texts and its convenience for analyzing human behaviors by extracting meaningful data from tweets. One of the main contributions of our study is that instead of detecting general opinion leaders, we tried to detect opinion leaders who specialize on specific topics. We argued that in order to detect topic-specific opinion leaders, all the interactions between users should be considered and each interaction should have individual impact on this detection process. Four interaction types, namely retweeting, mentioning, replying and following are used to form relationship graphs and these graphs are analyzed according to centrality metrics. According to the experiments we conducted, it is concluded that retweet impact is greater than the impacts of mention and reply relationships, and also follow impact is the smallest one. In order to distinguish the users with thousands of followers from the real opinion leaders, the weight of the follow relation is assumed to be extremely small when compared to the other relationship weights. Additionally, mention and reply relations have similar impacts on the ties between users because each reply relation is a mention indeed and requires mentioning any other user in a tweet. So, their usage of concept in tweets is similar.

We analyzed the detected opinion leaders using a sentiment analysis based approach. The results show that the sentiments of most of the found opinion leaders are in parallel with the general sentiment of each debate community. This means that, an opinion leader has a significant influence on the community in terms of affecting the emotions, feelings and opinions of the other people in community. Additionally, users connected to opinion leaders are likely to share similar opinions as time passes by and the number of connected nodes to opinion leaders seems to increase in time. This sentiment and frequency change may show that opinion leaders directly affect the neighbour nodes and have direct impact on their opinions on specific topics. Some of the candidate opinion leaders who are in the top rankings of different debate period graphs intersect. This intersection may reveal that some of the users are consistent in terms of being opinion leaders and they should be recognized in the crowd periodically.

Users may “reply to” or “mention” opinion leaders although they do not agree with their opinions. In other words, there are people who influence the society although they are not agreed with and their tweets draw negative reactions. People tend to reply to them or protest them. But this is not an obstacle for them to be influential, on the contrary it shows that they reach many people and impress them in some sort of way. If the “mention” and “reply” relationship types were not taken into consideration like most of the recent studies, it would not have been possible to detect these kinds of opinion leaders. This shows that considering all the relationship types and calculating a weight function for each of them is a reasonable approach in this study.

In more general, we observed from our experiments that twitter users prefer to share negative opinions rather than positive opinions. This may indicate a behavioral pattern of people in Twitter that people tend to criticize or decry the others about a particular subject instead of appreciating them. We also observed that mainstream media, blogs, political writers or bloggers are in the foreground in Twitter because of their huge number of followers and also the huge number of retweet counts. Additionally, the newspapers are kind of opinion leaders too because the daily news that they publish are retweeted by many people.

7. FUTURE WORK

The methodology that we proposed for opinion leader detection contains several steps. These steps can be improved as a future work in order to reach more accurate results. One improvement may be related with the coefficient selection of each weight factor in social graphs. In this study, we aimed to find out the order of these coefficients but the calculation of the actual values of them was left as a future work. Similarly, when calculating each relationship rate, the related coefficient factor is multiplied with a function, which is assumed to be frequency in our study. An improved function such as combination of frequency with date/time characteristics of the tweets can be chosen in this case in order to reach more accurate results.

During the evaluation steps, we used a sentiment analysis method in order to guess the sentiment of each tweet in our dataset. We used the SentiStrength tool, which uses predefined words and phrases when calculating sentiment scores for small texts. There have been lots of studies conducted in the sentiment analysis area in the recent years and these methods can be taken into consideration in order to reach more precise sentiment results.

Another improvement may be in the text mining method used for classifying retweet comments in terms of agreement and disagreement. We used a keyword-based pattern matching approach. Determining agreement/disagreement is an open research area. More enhanced approaches using linguistic and machine learning methods can be developed for identifying whether retweet comments indicate agreement or disagreement with the poster, which in turn can improve the accuracy of the opinion leader detection method.

In addition to the suggestions described in the previous paragraphs, some of the tweets can be eliminated according to the contents of them. In other words, a filtering step may be beneficial for getting rid of unnecessary tweets and thus the performance of opinion leader detection can be improved. Similarly, some of the tweets include urls in their contents. When analyzing the sentiments of the tweets, this urls have no meanings and thus they cause misleading results. During the analysis, these urls can be visited and the whole texts can be crawled in order to decide whether these tweets hold positive or negative sentiments.

REFERENCES

1. Kaplan, A. M. and M. Haenlein, "Users of the World, Unite! The Challenges and Opportunities of Social Media", *Business Horizons*, Vol. 53, No. 1, pp. 59–68, 2010.

2. Bodendorf, F. and C. Kaiser, "Detecting Opinion Leaders and Trends in Online Communities", *Digital Society, 2010. ICDS '10. Fourth International Conference on*, pp. 124–129, 2010.

3. Hui, P. and M. Gregory, "Quantifying Sentiment and Influence in Blogspaces", *Proceedings of the First Workshop on Social Media Analytics*, SOMA '10, pp. 53–61, ACM, New York, NY, USA, 2010.

4. Merwe, R. V. D. and G. V. Heerden, "Finding and Utilizing Opinion Leaders : Social Networks and the Power of Relationships", *South African Journal of Business Management*, Vol. 40, No. 3, pp. 65–77, 2009.

5. Kardara, M., G. Papadakis, T. Papaoikonomou, K. Tserpes and T. Varvarigou, "Influence Patterns in Topic Communities of Social Media", *Proceedings of the 2nd International Conference on Web Intelligence, Mining and Semantics*, WIMS '12, pp. 10:1–10:12, ACM, New York, NY, USA, 2012.

6. Bartal, A., E. Sasson and G. Ravid, "Predicting Links in Social Networks Using Text Mining and SNA", *2009 International Conference on Advances in Social Network Analysis and Mining*, Vol. 0, No. 1, pp. 131–136, 2009.

7. Katz, E. and P. F. Lazarsfeld, *Personal Influence: The Part Played by People in the Flow of Mass Communications*, Free Press, Glencoe, IL, 1955.

8. Chowdhury, G. G., "Natural Language Processing", *Annual Review of Information Science and Technology*, Vol. 37, No. 1, pp. 51–89, 2003.

9. Gupta, V. and G. S. Lehal, "A Survey of Text Mining Techniques and Applications", *Journal of Emerging Technologies in Web Intelligence*, Vol. 1, No. 1, pp. 60–76, 2009.

10. Weng, J., E.-P. Lim, J. Jiang and Q. He, "TwitterRank: Finding Topic-sensitive Influential Twitterers", *Proceedings of the Third ACM International Conference on Web Search and Data Mining*, WSDM '10, pp. 261–270, ACM, New York, NY, USA, 2010.

11. Welch, M. J., U. Schonfeld, D. He and J. Cho, "Topical Semantics of Twitter Links", *Time*, Vol. 30, No. 2, pp. 327–336, 2011.

12. Wu, Y. and F. Ren, "Learning Sentimental Influence in Twitter", *2011 International Conference on Future Computer Sciences and Application*, pp. 119–122, 2011.

13. Leavitt, A., E. Burchard, D. Fisher and S. Gilbert, "The Influentials : New Approaches for Analyzing Influence on Twitter", *Web Ecology*, Vol. 04, No. September, p. 18, 2009.

14. Cha, M. and K. P. Gummadi, "Measuring User Influence in Twitter : The Million Follower Fallacy", *Artificial Intelligence*, Vol. 146, No. 1, pp. 10–17, 2010.

15. Joshi, A., T. Finin, A. Java, A. Kale and P. Kolari, "Web 2.0 Mining: Analyzing Social Media", *Proceedings of the NSF Symposium on Next Generation of Data Mining and Cyber-Enabled Discovery for Innovation*, October 2007.

16. Agarwal, N., H. Liu, L. Tang and P. S. Yu, "Identifying the Influential Bloggers in a Community", *Proceedings of the International Conference on Web Search and Web Data Mining WSDM 08*, p. 207, 2008.

17. Zhou, H. Z. H., D. Z. D. Zeng and C. Z. C. Zhang, "Finding Leaders from Opinion Networks", *2009 IEEE International Conference on Intelligence and Security*

Informatics, pp. 266–268, 2009.

18. Mustafaraj, E. and P. Metaxas, “What Edited Retweets Reveal About Online Political Discourse”, *AAAI Workshops*, 2011.

19. Yin, J., P. Thomas, N. Narang and C. Paris, “Unifying Local and Global Agreement and Disagreement Classification in Online Debates”, *Proceedings of the 3rd Workshop in Computational Approaches to Subjectivity and Sentiment Analysis*, WASSA ’12, pp. 61–69, Association for Computational Linguistics, Stroudsburg, PA, USA, 2012.

20. Page, L., S. Brin, R. Motwani and T. Winograd, *The PageRank Citation Ranking: Bringing Order to the Web*, Technical Report 1999-66, Stanford InfoLab, November 1999, previous number = SIDL-WP-1999-0120.

21. Wasserman, S. and K. Faust, *Social Network Analysis: Methods and Applications*, Vol. 8, Cambridge University Press, 1994.