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Detection of the Spiral of Silence Effect in Social Media

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Abstract: Opinion mining has been a crucial research topic among recent studies, particularly concerning data from social media. However, a widely discussed communication concern called "the spiral of silence effect" has not been examined in opinion mining studies. In this paper, we propose an approach for detecting the spiral of silence effect in social media. We believe that the accuracy of opinion mining can be improved by considering the effect of the spiral of silence. The details and steps of the detection approach are discussed. We also collected data from two popular social networking websites, namely Facebook and Twitter, for performance measurement. Analysis findings show that the average accuracy of the proposed approach was higher than 0.85, indicating that the approach is highly effective.

Key Words: Spiral of silence, social network analysis, social network, social media
Categories: I.2.7, J.4, H.2.4

1 Introduction

Social networking websites such as Facebook, Google+, and Twitter have become popular platforms for users to share ideas as well as various aspects of their daily lives. In the area of communication, these types of websites are referred to as social media. Social networking websites are a form of worldwide social media in which information spreads rapidly. Furthermore, users can immediately receive responses and feedback from other users. Therefore, people commonly use social media as a main channel for expressing their opinion. For example, numerous government departments treat social media as an essential platform for promoting policies or political agendas [Version and Auvinen 2013].

For the aforementioned reasons, data from social networking websites are considered valuable. Effectively analyzing and applying these data can facilitate gaining a clearer understanding of the opinions and behaviors of social media users [Ting, Chang, and Wang 2012]. Numerous experts in the area of information technology have investigated techniques to efficiently and accurately determine user opinions. Such techniques include web mining, text mining, social network analysis (SNA), sentiment analysis, and opinion mining [Agrawal, Rajagopalan, Srikant, and Xu 2003], [Somprasertsri 2010].

Among related studies, a highly crucial theory in the area of communication studies has been ignored; this theory is known as "the spiral of silence" (SOS), and it refers users' tendency to hide their opinions when they understand that their opinions are nonmainstream [Matthes, Morrison, and Schemer 2010]. Researchers have suggested that the effect of SOS also occurs on social networking websites, which may affect accuracy in detecting user opinions [McCurdy 2010]. Therefore, devising a methodology that can be applied to automatically detect the SOS effect in social networking website data would be useful. Related studies on the SOS are discussed in section 2 of this paper.

According with the background and motivation of this study, we propose an approach that is based on SNA, sentiment analysis, opinion mining, and the classification technique of data mining. In this approach, we defined a "turning point" to detect the SOS. To determine the accuracy of the proposed approach, we collected data from 2000 Facebook fan page posts, classifying them into two groups with 1000 posts each, namely the "SOS" and "nonSOS" groups. Subsequently, we performed SNA to determine relevant measurements, comprising degree, closeness, diameter, betweenness, and a clustering coefficient. Furthermore, keywords from the posts were extracted as an additional parameter. These parameters were subsequently employed in assigning the post classification to determine the parameters that were useful in detecting the SOS effect.

In the remainder of this paper, further background and literature review concerning the theory of the SOS, SOS, sentiment analysis, and opinion mining is provided. In section 3, we propose the research design and the framework of the proposed approach for detection of the SOS effect. An experimental and data analysis is presented in section 4; we provide the discussion and conclusion in section 5.

2 Background and Literature Review

In this section, we first introduce background information regarding the SOS effect, which is the theory applied in this paper. Furthermore, related essential techniques from previous studies concerning SOS detection are reviewed, including SNA, sentiment analysis, and opinion mining.

2.1 Spiral of Silence

The SOS (i.e., "the SOS effect") is a well-known theory in the area of communication studies. The theory was proposed by Noelle-Neumann in 1973; Figure 1 shows the conceptual presentation of the SOS effect as defined by Noelle-Neumann [Noelle-Neumann 1993].

In Figure 1, the left hand side represents the distribution of strength viewpoint, whereas the right hand side represents public support for people with a minority viewpoint. When the distribution of strength viewpoint becomes more prevalent, and the public support for people with a minority viewpoint becomes less prevalent, people with a minority viewpoint start to hide their true opinions. Eventually, they remain silent and even show support for the distribution of strength viewpoint. The effect represents a spiral, and therefore has been called "the SOS effect."

In the theory, humans are gregarious animals, and therefore require support from one another. Humans fear loneliness; thus, people frequently review their viewpoint to determine whether it is a unique or minority viewpoint. If people notice that they hold a minority viewpoint, they tend to hide it to avoid loneliness and remain silent. However, some studies have suggested that silence may not be the only reaction when people fear loneliness, but there is no evidence to prove this [Salmon and Kline 1985]

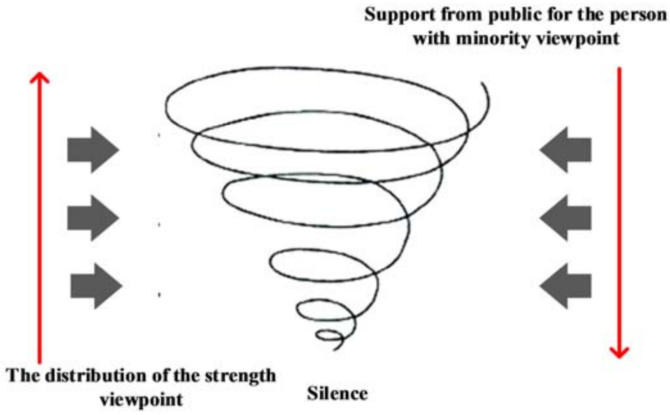

Figure 1: Concept of the SOS effect [Noelle-Neumann 1993]

Some researchers have claimed that because of the prevalence of anonymity in the era of the Internet and social networking, users can easily hide their true identities, and that the SOS effect is disappearing [Web 2013]. However, many researchers have indicated that the SOS effect remains and occurs frequently [Gearhart and Zhang 2013]. The SOS effect may be more obvious in certain situations than in others [Chen 2011], [C. Wang 2011], [Fu and Sim 2011], [Stratta 2004]. The bandwagon effect is another theory that is an extension of the SOS effect. The bandwagon effect refers to a situation whereby people who have expressed public opinions can claim that their opinions are supported by a large proportion of people in order to attract other people to agree with their opinions. For example, candidates in an election tend to claim that they have the support of most people and may even produce false poll results to validate this claim [Stratta 2004], [Fu and Sim 2011].

2.2 Social Network Analysis

SNA is a research methodology in the area of sociology for observing and analyzing the interactions among social activists to determine social network structures [Wasserman and Faust 1994]. Because of the long history of SNA, numerous terms and definitions have been widely applied in various research areas such as sociology, management, business, biology, and information technology [Wilson 1989], [June, Kim, Kim, and Choi 2006], [Chang, Ting, and Wang 2011], [Wang, Ting, and Li 2011], [Lee, Ting, and Liou 2012], [Wang, Ting, and Wu 2013].

The basic concept and methodologies of SNA have been thoroughly explained in two well-known books, namely *Social Network Analysis: A Hand Book* and *Social Network Analysis: Methods and Applications* [Wasserman and Faust 1994], [Scott 2000]. These works have included the definitions of social network roles and measurements of social relationships (e.g., centrality, closeness, betweenness, cluster coefficient, network diameter, and structure hole) [Wellman and Berkowitz 1988], [Burt 1992]. The following measurements were applied in this study:

(1) **Network Diameter:** Network diameter is the average distance of the shortest path for each pair of nodes.
(2) **Density:** Density = D/L; L is the maximum possible lines (i.e., edges) in a graph; D is the total lines (i.e., edges) in a graph.
(3) **Centrality:** Two different types of centrality exist, namely local centrality and global centrality.
Local Centrality (absolute) = Degree…………………………….……...Equation (1)
Local Centrality (relative) = Degree/Degree (total) -1……………….Equation (2)
Global Centrality = $\sum$ Distance to each nodes …………...…....Equation (3)

		A	*B*	*C*
Local Centrality	absolute	3	4	3
	relative	0.43(3/7)	0.57(4/7)	0.43(3/7)
Global Centrality		15	12	15

Table 1: Example of different centrality analyses

The following three measurements are extensions of the centrality measurement:
(4) **Degree Centrality:** Degree centrality can be employed to measure the most active node in a network, which is the node having the highest number of relationships with other nodes in the network. Assuming that the highest degree of a node is |V|-1, the degree centrality of the node is D(V)/(|V|-1) after normalization.
(5) **Closeness Centrality:** In a social network, a higher closeness centrality indicates a shorter average distance between nodes.
(6) **Betweenness Centrality:** The node that interacts with the highest number of other nodes in a social network has the highest betweenness centrality in that network. In this situation, most nodes must pass through this node to contact other nodes. Assume that for each node ***i***, there exist two nodes, ***j*** and ***k***, that must communicate. $g_{jk}(n_i)$ denotes the number of shortest paths that pass through ***i*** to connect ***j*** and ***k***. Equations (4) and (5) measure the normalized betweenness centrality.

$$C_B(n_i) = \sum_{j<k} \left(\frac{g_{jk}(n_i)}{g_{jk}} \right)$$ ………………………………….....Equation (4)

$$C'_B(n_i) = \frac{C_B(n_i)}{(g-1)(g-2)/2}$$ ……………………………….............Equation (5)

2.3 Opinion Mining

In recent years, a high quantity of data has been aggregated with the rapid growth of social networking websites. Researchers from various fields have regarded such data as valuable. However, the high quantity of data renders executing efficient analysis difficult, and this is a critical concern in information technology. Opinion mining was developed as a solution to this problem, referring to the automatized extraction of Internet user opinions [Cho et al. 2011]. Opinion mining, also called sentiment analysis, has become a critical application in data mining, text mining, and nature language processing [Hu and Liu 2004].

Distinct from traditional detection methods, opinion mining does not focus on explicit topics and keywords, but on sentimental expressions. Therefore, the major tasks in opinion mining are to extract sentimental messages and transform unstructured documents into structured ones. Positive and negative sentimental expressions can then be distinguished and classified by sentiment analysis [Pang, Lee and Vaithyanathan 2002], [Turney 2002], [Pang and Lee 2005]. Some researchers have also treated sentiment as a continuous interval to determine the level of sentiment in data [Thelwall, Buckley, Paltoglou, Cai, and Kappas 2010].

In opinion mining, sentimental messages can be extracted from documents through two methods, namely corpus-based and thesaurus-based opinion mining [Pang and Lee 2005]. In recent studies, the corpus-based method has provided more data than has the thesaurus-based method concerning sentimental keywords; therefore, it is regarded as the mainstream method of sentiment analysis. Generally, opining mining comprises four steps: feature extraction, opinion keyword extraction, opinion classification, and opinion summarization (i.e., determining the connection between opinion keywords and keyword features) [Jakob and Gurevych 2010], [Ting and Yen 2012], [Ting 2015].

Opinion mining currently has numerous applications. Pang and Lee proposed an approach to classify positive and negative comments of movies based on opinion mining [Jakob and Gurevych 2010]. Opinion mining is also used for the detection of spam or false opinions, which is useful for users to detect true opinions on social networks [Mukherjee et al. 2013], [Qian and Liu 2013]. Notably, opinion mining can also be applied in the prediction of public support for political parties or public concerns. This type of prediction is highly similar to election polls, but focuses on data from social media platforms such as Twitter or Facebook [Younus et al. 2011].

In most current applications for opinion mining, the SOS effect is seldom discussed and accounted for. This is because it is a theory in the area of communication. However, as mentioned, the SOS effect has been proven to remain in social networking platforms [McCurdy 2010]. Therefore, developing a method of detecting the SOS effect among these platforms is valuable, and such a method can facilitate improving the performance and accuracy of opinion mining. Furthermore, the technique of opinion mining is useful in modeling the SOS effect as well as in identifying the pattern of an SOS (e.g., the frequency of positive and negative opinions; turning point).

3 Research Design and Framework

On the basis of the background and motivation discussed in the previous sections, we developed an approach for detecting the SOS effect in social media. In this study, we focused solely on data from Twitter and Facebook. Figure 2 illustrates the research design and framework; the corresponding 10 steps are discussed in this section as follow.

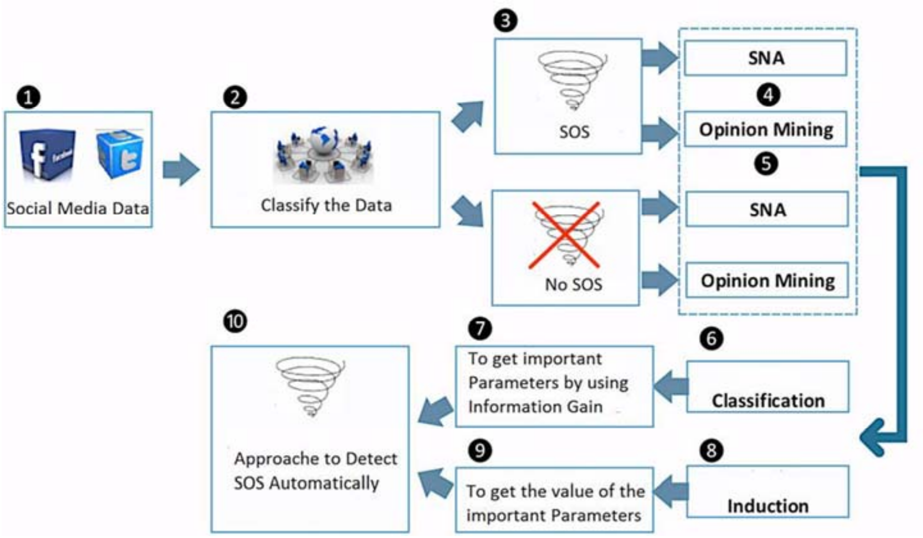

Figure 2: Research design and framework

(1) Social Media Data:
In this study, Twitter and Facebook were selected as social media platforms. Regarding Facebook, we collected data from fan pages related to social policy or politics by using the Facebook application program interface (API). A sample of Facebook fan page data is shown in the left panel of Figure 3. We collected data from a fan page posts for all interactions, comprising likes, shares, and comments.

Figure 3: Sample Facebook fan page data (left) and Twitter data (right)

Concerning data from Twitter, we used the Twitter API to extract data during the period from January 2012 to March 2012; approximately 100 million data items were collected. A sample Twitter data item is shown in the right panel of Figure 3. As with Facebook data, we also collected data from Twitter posts for all interactions, comprising retweets, responses, and likes.

(2) Data Classification:
After step 1, we invited 10 experts on SOS to determine whether an SOS effect was evident in the discussions.

(3) Classified Data; SOS and NonSOS:
After step 2, the experts spent approximately 2 months classifying the data as either data with SOS or data without SOS (nonSOS). Ultimately, we retained 2000 data items from Facebook in Chinese (1000 SOS and 1000 nonSOS) and 2000 data items from Twitter in English (1000 SOS and 1000 nonSOS). These data were employed in this study for training and experimentation.

(4) Social Network Analysis:
All the data collected in the previous steps were applied to a relationship matrix to represent the interactions among the users in a post, with factors including likes, comments, subcomments, and shares. Figure 4 shows an example matrix transformation; the relationships were identified and the frequencies of interaction were tallied. For example, if user A likes user B's comment, a value of 1 is applied to the matrix; no weighting was performed for different interactions. The final matrix was then used for SNA measurements.

	A	B	C	D	E	F	G
A	x	2	2	2	2	2	2
B	2	x	1	1	1	1	1
C	2	1	x	1	1	1	1
D	2	1	1	x	1	1	1
E	2	1	1	1	x	1	1
F	2	1	1	1	1	X	1
G	2	1	1	1	1	1	X

Figure 4: Example relationship matrix transformation

In this study, the following SNA measurements were employed: network diameter (*ND*), average degree (*AD*), closeness(*C*), betweenness (*B*), cluster coefficient (*CC*) and density (*DE*). These measurements were determined for each post collected. Equation 6 represents the vector of SNA.

$$DMSNA_i = (ND_i, AD_i, C_i, B_i, CC_i, DE_i) \quad \text{............................Equation (6)}$$

(5) Opinion Mining:

Opinion mining was the main step in this study, after which the sentimental value of the keyword in a post was analyzed. The process of opinion mining is shown in Figure 3.

In the process of opinion mining, discussion posts were first subjected to sentence segmentation. Through the use of a thesaurus, features (i.e., keywords) in a sentence could be selected. The features were subsequently analyzed to measure the degree of sentimental value by using a sentiment dictionary and WordNet. Sentimental value was the essential measurement in this study to detect the effect of the SOS, which was analyzed in the final step of the experiment.

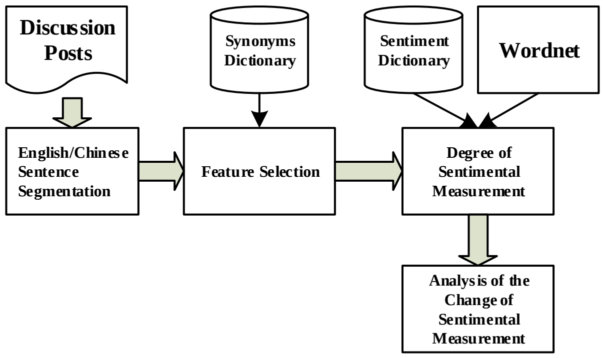

Figure 3: Process of opinion mining

After the measurement of sentimental value, for each discussion data item, we employed a vector, as shown in Equation (7). In Equation (7), $\boldsymbol{a_i}$ is the sentimental vector of discussion $\boldsymbol{i}$. $\boldsymbol{O_n}$ denotes the opinion degree of the $\boldsymbol{n}^{th}$ response in discussion $\boldsymbol{i}$.

$$DMOMa_i = (O_0, O_1 ......, O_n) \quad \text{..Equation (7)}$$

For each discussion $\boldsymbol{i}$, there is another vector $\boldsymbol{DMOMb_i}$, or turning point vector, as shown in Equation (8). This vector comprises $\boldsymbol{AO_i}$ and $\boldsymbol{TP_i}$, where $\boldsymbol{AO_i}$ denotes the average opinion degree of discussion $\boldsymbol{i}$ and $\boldsymbol{TP_i}$ denotes the turning point of discussion $\boldsymbol{i}$.

$$DMOMb_i = (AO_i, TP_i) \quad \text{..Equation (8)}$$

$$TP = \frac{m_n}{M} \quad \text{Equation (9)}$$

Equation (9) represents the turning point measurement. In this equation, $\boldsymbol{M}$ is the total responses in a discussion, and $\boldsymbol{m_n}$ denotes the $\boldsymbol{n^{th}}$ response. Therefore, the value of $\boldsymbol{TP}$ is greater than 0 and less than 1. The turning point $\boldsymbol{m_n}$ is the point when a positive sentimental measurement decreases and remains below zero, or when a negative sentimental measurement increases and remains above zero.

(6) Vector Classification:
Three generated vectors, namely $\boldsymbol{DMSNA_i}$, $\boldsymbol{DMOMa_i}$, and $\boldsymbol{DMOMb_i}$, were classified and used for training to understand the crucial parameters. We used the Waikato Environment for Knowledge Analysis (Weka) and C4.5 for the classification.

(7) Parameter Determination through Information Gain:
After the processing in the previous step, we used the Weka to determine the importance of the parameters of the three vectors by applying information gain. Through this analysis, we could determine which parameters were significant for classifying post data into the SOS effect or nonSOS effect groups.

(8) Induction:
Induction is another method of manually determining parameter importance; in this study, this method was employed as a supplement to the previous step.

(9) Crucial Parameter Value Determination:
After steps 7, 8, and 9, we expected to possess the values of crucial parameters that could be applied in distinguishing SOS from nonSOS data. For example, ***TP*** in Equation (9) represents the turning point; by this step, we obtained the optimal value of ***TP*** for detecting the SOS effect.

(10) Approach for Automatic SOS Detection:
Finally, we developed an approach to automatically detect the SOS effect on the basis of the results acquired in the previous steps. We generated a set of rules and values for the detection, including crucial parameters and values.

4 Experiment and Evaluation

We organized a series of experiments according to the approach developed in the previous steps, employing the crucial parameters and values acquired, to test the performance of our method in detecting the SOS effect.

We collected data from Facebook and Twitter, as mentioned in steps 1 and 2, by employing the research design and framework introduced in section 3. After classifying the data, we retained a total of 4000 data items, consisting of 2000 data items from Facebook and another 2000 from Twitter. The data from Facebook mainly employed traditional Chinese (a common written language in Taiwan and Hong

Kong). Among the 2000 data items from Facebook, 1000 were SOS items, whereas the other 1000 were nonSOS items. Concerning the data from Twitter, the language employed was English. As with the data from Facebook, we obtained 1000 SOS data items and 1000 nonSOS items. A summary of the collected data is shown in Table 2.

	Facebook (Traditional Chinese)	Twitter (English)	Total
With SOS	1000	1000	2000
Without SOS	1000	1000	2000
Total	2000	2000	4000

Table 2: Summary of the collected data

To determine the accuracy of our proposed approach in detecting the SOS effect, we analyzed all the data items and calculated the related measurements [see Tab. 3]. Weka was again employed; the evaluation method applied a 10-fold validation. The accuracy, precision, and recall were measured for data from both Facebook and Twitter.

The analysis results generally indicated that our approach achieved a high accuracy in detecting the SOS in the data from Twitter (English), and a low accuracy for data from Facebook (traditional Chinese). However, the accuracy for both data was adequate: the accuracy was 0.843 or higher for each platform, with an average accuracy between both platforms of 0.878; indicating that more than 80% of the total data with SOS could be detected accurately.

We investigated the reason for the relatively high detection accuracy for English SOS data, compared with that for traditional Chinese. On observing the data, we found that most of the errors occurred when users employed ambiguous words. Notably, this occurred mostly for users employing traditional Chinese. One reason this may have occurred is because there is a higher number of ambiguous terms in traditional Chinese than in English. Therefore, the employed dictionary may need to be expanded to more adequately distinguish the terms. Another reason may have been the different cultures of Chinese- and English-speaking users; this is a notable topic concerning cultural differences that may be employed as a research focus in the future.

	Accuracy	Precision	Recall
English SOS (Twitter)	0.912	0.901	0.923
Traditional Chinese SOS (Facebook)	0.843	0.874	0.796
Average	0.878	0.888	0.856

Table 3: Analysis results (10-fold validation)

In addition to the average accuracy for both data sources, we tested the method accuracy for different numbers of posts in a thread (every 100 posts from 100–2000 posts). The test results are shown in Figure 4 and Figure 5; in both figures, the x axis represents the number of posts and the y axis denotes the accuracy of SOS detection.

As shown in Figure 4, the accuracy for most cases of Facebook data was between 0.85 and 0.95, which is considered highly stable. This implies that there was no significant difference in accuracy when the number of Facebook posts varied.

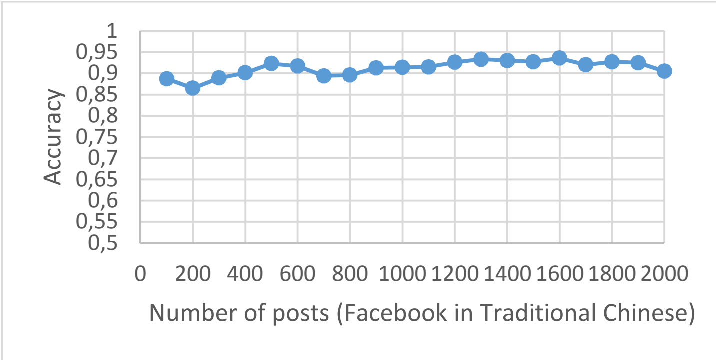

Figure 4: Accuracy for Facebook data with different numbers of posts

As shown in Figure 5, the accuracy for most cases of Twitter data was between 0.8 and 0.85. The accuracy was slightly higher only when the number of posts was 1600. As evidenced in Figure 5, the performance was highly stable, indicating that there was no significant difference in accuracy when number of Twitter posts varied.

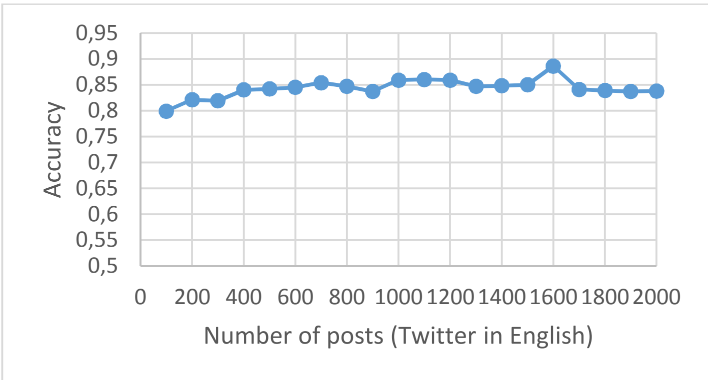

Figure 5: Accuracy for Twitter data with different numbers of posts

5 Conclusions and Future Studies

Opinion mining is a highly popular and crucial research method, particularly in the era of social networking: Opinion mining can be applied to determine the opinions of social media users. Recently, several studies have focused on opinion mining; however, the critical topic of the SOS effect has rarely been applied in such studies because it may cause bias when analyzing social media data.

In this study, we developed an approach to detect the SOS effect. The approach combines the techniques of opinion mining (i.e., sentiment analysis) and SNA; we believe that the pattern of the SOS may be modeled on the sentimental value of the interactions among social media users. After employing the approach proposed herein, we determined crucial parameters by observing the mean accuracy of the information obtained from the classification technique and induction. These parameters can be used for the detection of SOS.

We collected 2000 data items each from Facebook and Twitter for training the parameters and for use in a series of experiments to measure the performance of the proposed SOS detection approach. The analysis findings show that the data accuracy values for Facebook and Twitter were 0.912 and 0.843, respectively, with an average data accuracy of 0.878 between the platforms. Therefore, the accuracy of the proposed approach is higher than expected.

This is our first paper concerning the application of SNA and opinion mining techniques to detect the SOS effect. On the basis of our findings, several future research topics can be investigated. For example, we would like to use this approach to verify election results in Taiwan and the United States, as well as to compare the differences among election polls. We would also like to compare differences among cultures and countries, as well as to expand our research to other social media platforms.

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