A Social Media Based Profiling Approach for Potential Churning Customers: An Example for Telecom Industry

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Abstract

Customer churn prevention has been one of the most pressing concerns for telcos to tackle in the rapidly changing telecom business over the past decade, as the industry has faced increased market saturation and intense competition. Social media electronic word-of-mouth (e-WoM) offers telcos with insights into the consumer experience. Capturing preferences and views about products/services via text messaging might increase the recovery mechanism for clients who may churn. This study collects postings from social media forums concerning Taiwan's top five telecom firms in order to perform an opinion analysis that is thought to be strongly linked with prospective churning consumers. To collect topic-sentiment information, we employ the doc-based Heuristics-N-Phrase-Rules technique. In this study, the sentiment score of negative terms is determined, and correspondence analysis is used to highlight the features and profiles of probable churn consumers. To validate its efficacy, we propose comparing the derived profile information to the telecom company's lost consumers.

Keywords: Electronic Word-of-Mouth (e-WoM), Social media, Sentiment analysis, Correspondence analysis

1 Introduction

Public opinion on social networks is continually being updated and modified in the Internet age. Negative information that appears on social media, news portals, forums, news reviews, etc. will surely have an impact on businesses' sales volume and brand reputation. As a result, responding to and dealing with public opinion quickly has become a significant challenge for enterprise management. Since the services offered by different operators are comparable for telcos, pricing wars are frequently employed to attract new consumers or keep hold of existing ones when the market is close to saturation. However, this method frequently leads to more competition. At the same time, when telcos make more active attempts to increase the number of new customers, customer churn analytics has always had a significant influence on business choices that should not be underestimated [1].

According to study, when purchasing a product, the typical individual will first refer to the experience of other consumers, and the purchasing decision will be substantially influenced on the opinion orientation of word of mouth. Products with favorable word of mouth are far more likely to be purchased by customers than those with bad word of mouth [2]. Furthermore, Sheshasaayee and Jayanthi suggest that customer satisfaction will alter as a result of factors such as consumer expectations, loyalty, and product complaints [3]. Merchants frequently utilize word-of-mouth marketing to boost the number of new consumers, and they will also be more active in taking essential actions in reaction to poor public opinion analysis results. When dealing with client replies, complaints, pain points, and so on, for example, it should be adjusted promptly to limit the risk of customer turnover [4]. The data frequently utilized to forecast customer turnover is nothing more than usage/consumption, purchasing behavior, socioeconomic, and demographic information. Alternatively, the usage of variables containing information about customers' most recent purchase time, frequency of purchase, and spending may also help in churn prediction [5]. Olle and Cai claimed that in the past, data mining was used to evaluate fundamental call-related indicators such as customer use time and call charges to anticipate if consumers would churn [6]. However, social media mining has increasingly supplanted the conventional survey approach and has transformed the industry. Customers will eventually be lost if companies fail to recognize or misunderstand what consumers care about most in the midst of a vast volume of public opinion data. After all, these attitudes represent support for acquired goods or services over the Internet, as well as projected purchasing behavior [7-8]. Text sentiment analysis has numerous sorts of study or significant uses in practice, such as employing unstructured public opinion analysis to forecast the degree of client attrition [9]. Customer turnover exhibits a variety of behavioral patterns, and existing models are more complicated and less testable [10]. As a result, there is still space for improvement in precisely identifying the major causes of client turnover.

Previously, research have found that the emotions conveyed by users' social media posts are related to product sales [11]. As a result, we gathered online word-of-mouth information related to Taiwan's top five telcos via social media. This study uses the doc-based Heuristics-N-Phrase-Rules approach [12] to assess public opinion and explain sentiment score calculation, focusing on sentiment terms that customers care about or are unsatisfied with. Finally, negative keywords and CA (Correspondence Analysis)-generated Position Maps are utilized to illustrate and compare them graphically [13].

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The CA approach utilized in this study is a visual analysis tool that is frequently used to investigate the link between brands and qualities [14]. This study aims to compare the phrases of negative sentiment and position map among the negative posts of all the topics chosen by each telco. The experimental results reveal that the accurate topic-sentiment prediction accuracy reaches 80%. As a result, we use the position map generated by the CA to highlight the characteristics and profiles of potentially lost clients, giving telcos the option to further validate the research viability.

2 The Literature Review

Nowadays, word-of-mouth communication is different than in the past, and there are numerous outlets. Internet communication is the most extensively used, and forums have long been an important medium for online word-of-mouth transmission. The average user on the most popular social networks browses up to hundreds of pages of documents per day [15]. And, after purchasing a product, consumers usually can share their experiences and views on the forum at any time and from any location. These experiences or product remarks typically have a large amount of effect and fermentation, so that potential clients who are interested in the products may rely heavily on these reviews as a deciding factor.

A good brand reputation has a significant influence on customer loyalty in the telco business [16], and favorable word of mouth is even thought to successfully cut telco marketing costs. There is a 48% rise in consumers wanting to buy their favorite products on the website via social media [15]. Other, many consumers believe that the product usage experience attached to the advertisement is a general marketing tool and does not have the tendency to influence consumers to purchase the product [17]. Furthermore, little research has been conducted on how to leverage online customer product reviews to differentiate from significant competitors in order to boost competitiveness. In the past, most of these studies only used limited information from online reviews (for example, extracting a single summary opinion from the evaluations), which cannot provide management with more appropriate reactions [18].

As a result, this study focuses on consumers' word-of-mouth comments on various services linked with Taiwan's top five telcos in order to identify the important issues and keywords that most consumers care about. Based on the foregoing information, an analysis of the advantages and disadvantages of one particular telco in comparison to other competitors will be presented.

Today's companies generate vast volumes of data at a fast rate, and improvements in NLP analytics technology have accelerated in recent years. In this context, the telecommunications business is no exception, since it has grown more difficult to maintain existing clients due to vigorous rivalry among competitors. When clients are dissatisfied with a firm's service or are enticed by better incentives from another company, this results in customer churn. However, while retaining existing customers is simpler and cheaper than recruiting new ones, sustaining customer satisfaction becomes difficult, especially when social media comments are more demanding [19]. Jeong, Yoon, and Lee presented a social media text mining approach that assesses each issue's relevance and satisfaction and recommends potential development options [20].

When the number of customers falls below a specific threshold, a churn warning signal is generated, and machine learning technology is utilized to determine the causes of customer churn [1, 10]. Bi et al. used machine learning techniques such as the RF random forest algorithm and analyses such as K-means clustering to predict client attrition [21]. It is also suggested to extract important information from online social media, particularly to explore the link between each issue and rivals, and the findings of the analysis are also very beneficial for management. According to the literature review, a consumer's voice is essentially a succession of text, and the structure of the content is mostly formed of semi-structured or unstructured data types containing important information. In this study, similar technologies are utilized to pre-process the text, create a thesaurus, assess the sentiment of the reviews by in an automatic way to accurately analyzing online public opinion.

There are several approaches for constructing perceptual maps, which are typically used to represent brand positioning. User ratings of telecom services can be further subdivided into specific aspects that can be visually represented on coordinate axes. CA is a low-dimensional map representation approach for categorical data. It is one of the most widely used visualization techniques for creating perceptual maps, and it has been effectively employed in a variety of sectors. CA may be used to uncover a brand's competitive strengths and recommendations for improving a brand's competitive position [14]. CA is also enhanced and utilized in perceptual maps to generate confidence regions around brands and attributes [22]. CA is used on a two-dimensional perceptual map in this study to graphically illustrate the links between telecom companies and consumers' judgments about various features, where the distances on the map signify correspondence.

CA's first two primary axes account for a considerable amount of overall variation for visualization and ease of interpretation. The distance on the map denotes closeness; so, closer proximity indicates higher perceived resemblance [23].

3 The Proposed Method

Figure 1 depicts the research structure for this research, which includes two primary stages: preprocessing and execution. The Preprocessing Stage is followed by Post Tagging and Text Segmentation. Post tagging is done manually, which results in a topic label and sentiment score for each post, and thus a topic terms thesaurus is built. Text Segmentation finds and filters hidden and stop words, as well as treating the retrieved sentiment words with a sentiment degree thesaurus. We used the online word segmentation system CKIP (Chinese Knowledge and Information Processing) created by the Central Academy of Sciences' thesaurus team.

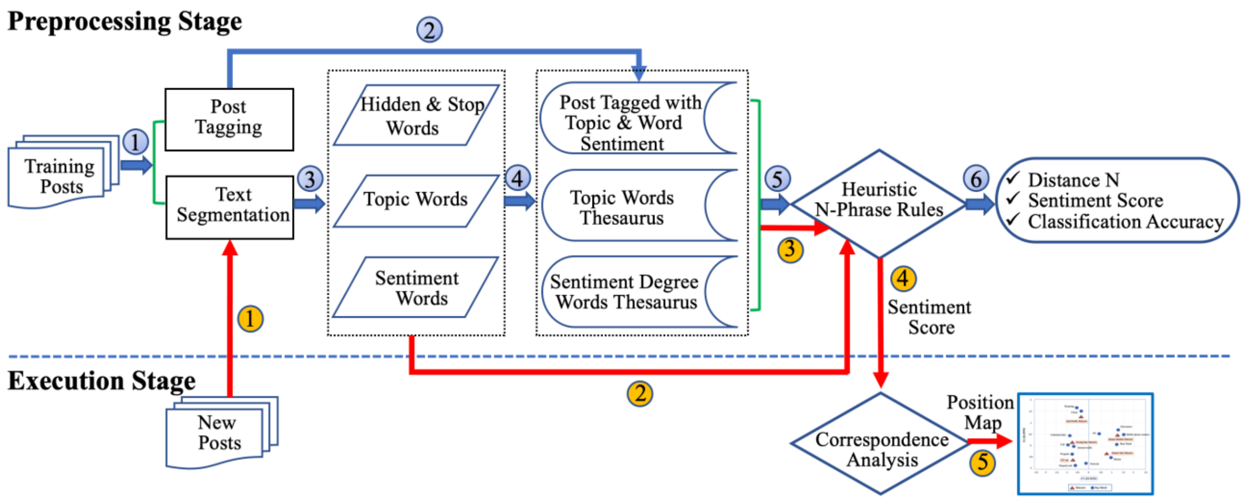

Figure 1. The research framework

The sentiment score of an opinion or topic term is calculated using HowNet [24] and the National Taiwan University Sentiment Dictionary [25].

Heuristics-N-Phrase-Rules is used to extract topic-sentiment pairs that comprise subject and sentiment terms that are often found near one other.

In Chinese posts, the topic or subject is usually placed before the sentiment word rather than after it. To determine the sentiment of an attribute in postings, the Heuristics-N-Phrase-Rules technique is presented. A continuous slice comprising n words or phrases from a lengthier sentence is referred to as an n-phrase. Size 2 is referred to as a bi-phrase; size 3 is referred to as a tri-phrase; size 4 is referred to as a four-phrase, and so on. Using the Heuristics-N-Phrase-Rules with the training posts, we can determine the best distance N, from which we may gain a more accurate classification of the sentiment orientation of the posts on the given topic.

3.1 Heuristics-N-Phrase-Rules

This work enhances the sentence-based Heuristics-N-Phrase-Rules [12] and employs it to discover the best mix of topic and sentiment for the whole post by referencing a thesaurus built from a full-text search. However, if there is no relevant topic word or inferred term in the message, Heuristics-N-Phrase-Rules considers it to be irrelevant. Figure 2 depicts the Heuristics-N-Phrase-Rules process flow. The following are the stages for Heuristics-N-Phrase-Rules:

Step 1: Determine if the characteristic in a processed phrase is in the established topic word list.
Step 2: Look for hidden words.
Step 3: Examine sentiment terms inside N-grams to see whether sentiment information exists.
Step 4: Examine sentiment words that are within 4 grams.
Step 5: Using weights, check negators for sentiment words within 10 grams to precisely identify sentiment orientation.
Step 6: Look for sentiment terms inside 10 grams to see if there is any sentiment information.

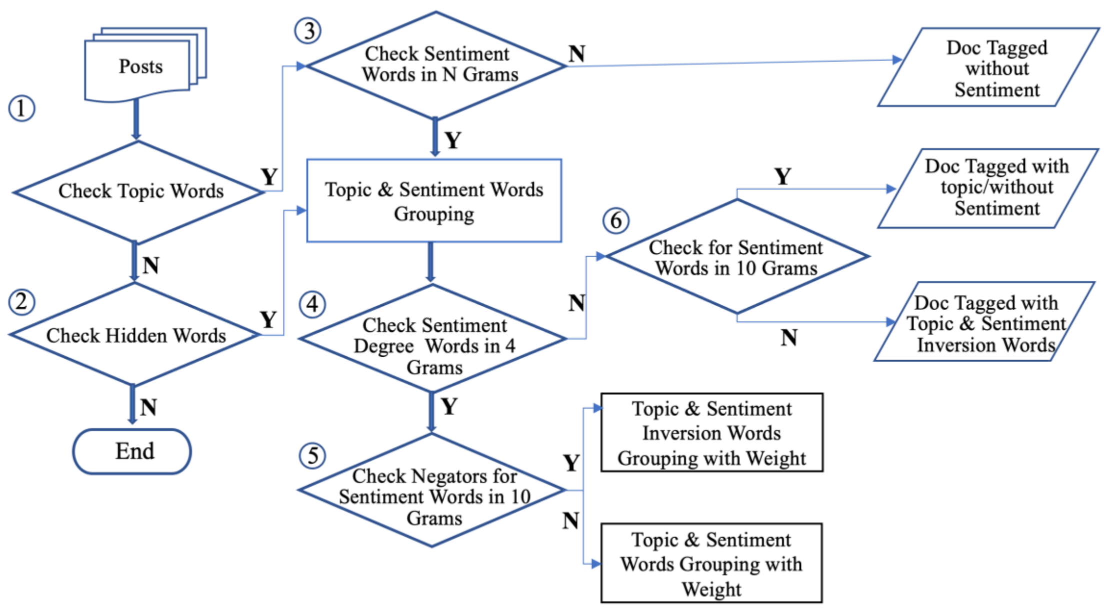

Figure 2. Process flow of Heuristics-N-Phrase-Rules

3.2 The Post Sentiment Scoring with Topic

The sentiment is computed based on the matched opinion words, degree words, and negations. Let *G* denote a set of web posts. To extract and evaluate the opinion for the posts, the scoring function is defined as follows:

Where

OS_i: sentiment score of the *i*-th post in *G*

n: the total number of post

w_k: *k*-th topic word

m: the number of identified topic words in the post

$$\mathrm{OS}_i = \sum_{j=1}^{n}\left(\omega \times \sum_{k=1}^{m} \mathrm{SO}\left(w_k\right)\right). \quad (1)$$

SO(w_k): the polarity (+1 or -1) of a topic word

ω: the degree weights assigned to six categories of degree words: (1) insufficiently: 0.83; (2) acceptable: 1.67; (3) more: 2.50; (4) very: 3.33, (5) most: 4.17; (6) over: 5.00.

4 The Experiments Results and Discussions

In this study, we obtained web posts about five major telecommunications companies (anonymously called Com-A, Com-B, ... Comp-E) from Taiwan's two largest online forums, PTT Industrial Square and Mobile01. We looked at three aspects: total post quantity for each topic, post content analytics, and position map for each telco.

In addition to a Strengths-Weaknesses-Opportunity-Threat (SWOT) analysis, the visual chart presentation makes an effort to explain the traits of each telecom firm based on several themes. The experiment data came from PTT and Mobile01, which had a total of 20,587 and 19,949 posts, respectively. The data gathering period is from 2015/01/01 to 2016/01/02. We randomly selected around 2,000 posts from each of these two datasets. These 4000 datasets were utilized in the Preprocessing Stage, while the remaining datasets were used in the Execution Stage to create the position map as a result of correspondence analysis. Based on the distance N of 5, the Heuristics-N-Phrase-Rules obtain a classification accuracy of 81% for the topic-sentiment pair, according to Formula (1). Product Information (PI), Tariff Plan (TP), Retail Store Services (RSS), Online Customer Services (OCS), and Call and Connection Quality (CCQ) are among the topics revealed during the Preprocessing Stage.

This research focuses on postings with negative sentiment to identify a telco's weaknesses in comparison to other rivals. Our primary argument is based on the notion that existing consumers of a given telco would no longer be satisfied with service shortages or weak areas that are not noticeable or worse in other telcos. As a result, it would imply that these dissatisfied consumers will become high-potential churners sooner or later.

The total number of occurrences of each topic term in all posts is used as the topic volume in this study.

In comparison to other telcos, Com-E has the highest post volume in terms of product information and tariff plans due to its good and negative voices, as well as total voices. This research presents an in-depth analysis for this firm as an illustrative case for explaining the trial findings.

This study uses the total number of occurrences of each topic word in all posts as the topic volume of the topic. Compared with other telecommunications companies, Com-E is found as the company with the largest post volume in terms of product information and tariff plans due to its positive and negative voices and overall voices. For discussing the experiment results, this study proposes an in-depth analytic for this company as an illustration example.

4.1 The Derived Position Maps

The relevant terms occurring in each telco's unfavorable messages are utilized as the word analysis foundation of the Position Map in this study, as shown in Figure 3, and the words with greater word frequency are chosen to prevent too many words appearing in the Position Map. The most popular terms used by each telco in each topic in unfavorable messages may be shown on Position Map. The larger the proportion of the term in the posts, the closer the word is to the firm.

We may see the most often mentioned terms inside a certain topic that are close to a specific telco by examining the Position Map. Based on this revealed information, we may determine which service or product attributes are most concerned by customers. Furthermore, those opinion or sentiment words linked with a certain topic may highlight the causes leading to possible customer turnover, allowing the telco to remedy the cause in order to prevent further customer churn.

Table 1 summarizes the explanatory powers for the postion maps shown in Figure 3, Figure 4, and Figure 5 respectively.

Table 1. Summrized expanatory powers of position maps

	F1 Axis	F2 Axis	F1+F2
Figure 3	34.65%	26.89%	61.54%
Figure 4	55.91%	27.45%	83.36%
Figure 5	35.72%	27.7%	63.42%

The position map in Figure 3 has a total explanatory power of 61.54% (> 50%), suggesting that the explanatory power is significant, and F1 has a larger explanatory power than F2. From the perspective of the F1 axis, the most frequent phrases for Com-E in negative posts are Unlimited Data, Call, & Traffic Flow; Usage Plan & Pre-paid Card for Com-B; Minute & Base Station for Com-D; Disconnected, Contract, & Base Station for Com-C; and Roaming & User for Com-A.

The position map in Figure 4 has a total explanatory power of 83.36% (> 50%), suggesting that the explanatory power is significant, and F1 has a larger explanatory power than F2. According to the F1 axis, the most frequently mentioned words for Com-A Telecom in negative postings about Product Information topic are Traffic & Academic; Tablet & Short Message for Com-D; Number, Program, & Traffic Data for COM-C; Big Savings & Easy Card for Com-E; and Program, Pre-Paid, Card, & Number for Com-B.

The position map in Figure 5 has a total explanatory power of 63.42% (> 50%), suggesting that the explanatory power is significant, and F1 has a larger explanatory power than F2. According to the F1 axis, the most frequently mentioned words for Com-B Telecom in negative postings about

Communication Quality topic are Contract Disconnected & Weak Signal; Receiving Signal, Speed, & Disconnected for Com-A; Poor Network Traffic & Slow Network Traffic Com-D; Traffic Jam, Slow Network Traffic, & Traffic Flow Com-E; Bandwidth for Com-C.

4.2 The Merits of Heuristics-N-Phrase-Rules

The doc-based Heuristics-N-Phrase-Rules can help tackel sentence-based issues of broken sentences and the subject categorization that needs taking into account multi- topic for the entire article.

This approach not only can classify articles across many categories, but it can also filter out irrelevant content and calculate sentiment scores for full postings. When compared to general traditional machine learning, most calculations cannot be conducted for both sentiment and multi-topic classification at the same time, and usually cannot combine the sentiment calculation method with the classification algorithm. As a result, this study proposes that employing doc-based Heuristics-N-Phrase-Rules to sentiment calculation and article classification is a viable technique that yields good accuracy rates.

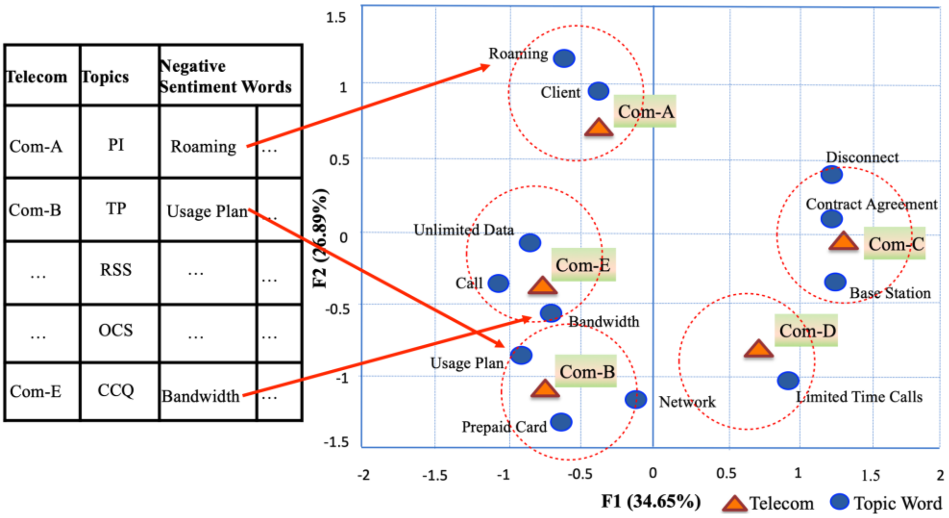

Figure 3. Major negative words associated with each telco in the global position map

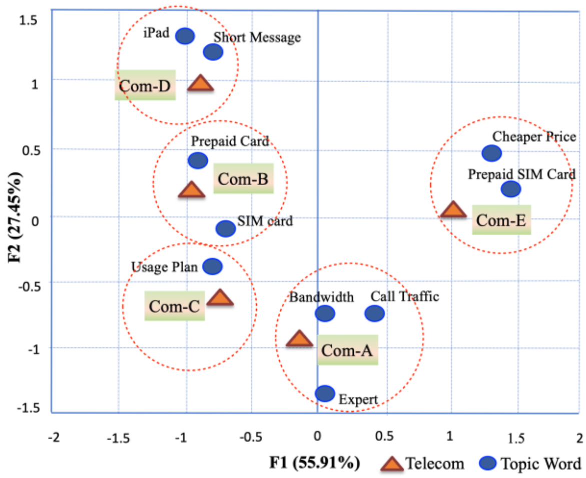

Figure 4. Position map for product information among all telcos

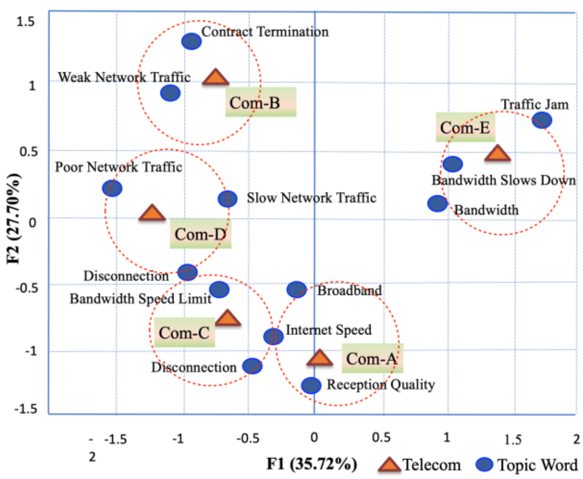

Figure 5. Position map for communication quality among all telcos

4.3 SWOT Analysis

We conducted a SWOT analysis for COM-E as an illustration based on the post analytics in the preceding data.

The resulting SWOT analysis evaluates COM-E's competitive position among Taiwan's five telcos as well as its strategic plans. The position maps of five separate topics are used to infer these contents. The SWOT analysis for COM-E is shown in Table 2.

Table 2. SWOT for Com-E

S	W
*As Com-E's customer scale is one of the top 3 telcos, it has a large users base, and the brand is highly discussed. *The present renewal plan is quite favorable and well acknowledged by consumers.	*The price of unlimited data package plan is higher than other telco(s). *Internet traffic is under limitation.
O	T
*Most of the consortia bidding for 4G telecom are well-funded by the government and the new market offers numerous business prospects. *The overall number of new clients has consistently reached a record high in recent years, and there are enormous economic potential.	*Competition is strong as other consortia strive to aggressively penetrate new areas. *Health awareness of the possible danger from base station radiation is developing, making it difficult in building more base stations and improving communication quality.

5. The Conclusion and Future Works

This work provides Heuristic-N-Phrase-Rules, a text processing method that can effectively extract the topic and emotional content of postings and calculate the sentiment score. We have utilized the position map to further portray the perceptual position of items or services among numerous competitors based on the obtained findings of post analytics. Based on this map, it is simple to identify the relative lack or disadvantage of each telco's products or services in comparison to the entire market competition, and even lead to customer loss as a result of these relatively shortcomings or a combination of these weakness to become a profile of potential churn customers. As a result, understanding online public opinion is an important aspect of enterprise management, which is related to the enterprise's steady development and even influences the enterprise's success and fall. Negative web posts from existing customers, in particular, should be handled effectively, including the improvement of the quality of existing items or services, as well as substantial recompense or emotional reassurance for them. According to this study, while judging the combination of subject and sentiment, Heuristics-N-Phrase-Rules should be modeled separately depending on different data sources or post length, and it may have varying distance N for different sorts of websites or post nature.

The difference in post length may also have an effect, and N can be adjusted accordingly. In the future, when the size of the online posts grows, it may be essential to alter or amend topic words again, or to run the Preprocessing Stage on a frequent basis.

Furthermore, this work shows that topic modeling algorithms such as LDA (Latent Dirichlet Allocation) can be utilized in the future to aid Heuristics-N-Phrase-Rules in finding the combination of sentiments with numerous topics. Finally, given the prevalence of false posts, determining ways to better distinguish them from normal posts while preserving the reference value of significant posts is an important research area in the future.

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