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Text Analytics of Customers on Twitter: Brand Sentiments in Customer Support

Iman Raeesi Vanani

Assistant Professor, Department of Industrial Management, Faculty of Management and Accounting, Allameh Tabataba'i University, Tehran, Iran. ORCID: 0000-0001-8324-9896.
E-mail: imanraeesi@atu.ac.ir

Abstract

Brand community interactions and online customer support have become major platforms of brand sentiment strengthening and loyalty creation. Rapid brand responses to each customer request though inbound tweets in twitter and taking proper actions to cover the needs of customers are the key elements of positive brand sentiment creation and product or service initiative management in the realm of intense competition. In this research, there has been an attempt to collect near three million tweets of inbound customer requests and outbound brand responses of international enterprises for the purpose of brand sentiment analysis. The steps of CRISP-DM have been chosen as the reference guide for business and data understanding, data preparation, text mining, validation of results as well as the final discussion and contribution. A rich phase of text pre-processing has been conducted and various algorithms of sentiment analysis were applied for the purpose of achieving the most significant analytical conclusions over the sentiment trends. The findings have shown that the sentiment of customers toward a brand is significantly correlated with the proper response of brands to the brand community over social media as well as providing the customers with a deep feeling of reciprocal understanding of their needs in a mid-to-long range planning.

Keywords: Brand community; Sentiment analysis; Text mining; Twitter; Customer support.

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Introduction

From two decades ago, there have been many attempts to create effective social media platforms. Social media connects people and businesses in an inter-related network of active players. It can create an ever-increasing value-added for all of the social media users as well as the social media owners. Media such as Twitter and Facebook, will increasingly create an encompassing role in enabling continuous direct, indirect, and real-time communication (Chandler, Salvador, & Kim, 2018; Greco & Polli, 2019).

A permanent and effective increase in the content generation of the social media users, will be the output of the effective communication (He, Zha, & Li, 2013). The generated content is mostly centered about the activities, attitudes, behaviors, preferences, policies, likes and dislikes, and also the values that are freely expressed and shared. A big data is the output of the massive generation of multi-format information over the social media. Analysis of such platforms with the rapid and relatively cheap generation of huge volumes of data will require efficient and robust analytical methods. Utilization of data science and machine learning methods opens up new opportunities for research and industrial development of solutions for marketing, sales, and after-sales services of international enterprises as well as small and medium businesses.

Analysis of brand sentiment through the online customer feedbacks does not have a long history. The main purpose of branding still remains to attract new customers and their loyalty to the business (Weber, 2009). The spread of social media has changed the brand management initiatives, but the purpose is still to measure and improve the sentiments to the brand of company. Customers often use the social media to express their interests and feelings toward products and services. This will consequently create a good basis for analyzing their attitudes towards brands (Fan, Che, & Chen, 2017; Fronzetti Colladon, 2018).

In this paper, a huge number of tweets were gathered from the twitter social media platform for many of the IT-enabled enterprises that have an international level of activities and impact. Afterwards, through a text pre-processing phase, the tweets were cleansed and transformed into meaningful structures for appropriate machine learning algorithms. After applying and validating various algorithms over the final textual dataset, the outputs were analyzed and the brand sentiment that is impacted by the inbound customer tweets and outbound services of enterprises through response tweets are discussed in detail. In the next section, a brief review of the related literature is provided.

Literature Review

Social Media and Brand Communities

The presence of enterprises in social media is by now mandatory which must be effectively covered. Most of the branding efforts of international firms take place in the virtual environment in recent years. That is the reason behind the creation of brand communities in which customers and prospects come together to discuss the quality and usefulness of products and services of a specific brand.

Marketing managers have also focused on using brand communities to build international brands (Lin et al., 2019). A brand community can be defined as a "…group of customers with a shared enthusiasm for the brand and a well-developed social identity, whose members engage jointly in group actions to accomplish collective goals and/or express mutual sentiments and commitments" (Bagozzi & Dholakia, 2006). Many internationally well-known brands are using sophisticated marketing and sales algorithms and initiatives to research the interests and to predict the future requests of their customers (like Apple, Microsoft, SAP, various airways, hotel and tourism industry and so on) in order to address their future needs.

A brand community can provide customers with a variety of services as well as invaluable information, such as user experiences sharing, solutions to the problems, connections with other related brands and trademarks, marketing initiatives, discounts, and also competition information between companies. It can also be surely considered for further analysis to enhance the brand loyalty and commitment (Lin et al., 2019).

Prior research has identified the impact of brand communities on product marketing and brand equity (Laroche et al., 2012; Zaglia, 2013), however, few managers have achieved considerable international results from traditional marketing and customer support (Fournier & Lee, 2009). There is a broad range of opportunities to explore about the influence of brand communities on consumer behavior and branding.

Customers surely value the brand and their relationship with other members in the community (Carlson et al., 2008; Jang et al., 2008), thus, it will be beneficial to provide support services to the customers through social media channels dedicated to brand communities. Geographical concentration of brand community in a country or continent might be of importance and value for better physical service provision but the online virtual presence of support teams can surely help in receiving new ideas, problems, issues, and possible solutions (Dholakia et al., 2004; Scott & Rajiv, 2008).

Social Media Analysis

The scraping of social media comments over a meaningful period of time allows for the data gathering of huge amounts of textual data, typically unstructured and non-numerical, in a short amount of time. Therefore, there is a need to utilize effective methodologies to process unstructured data in order to extract the hidden patterns and trends.

As provided in the literature, the online communication is majorly analyzed through text mining algorithms for different purposes, such as product planning (Jeong, Yoon, & Lee, 2017), marketing (AlAlwan, Rana, Dwivedi, & Algharabat, 2017; Kapoor et al., 2018), voting behavior forecasting (e.g., Greco, Maschietti, & Polli, 2017; Grover et al., 2018), disaster management (Singh et al., 2017), campaign surveys (Afful-Dadzie & Afful-Dadzie, 2017), and in the assessment of web sites, customer review effectiveness and customer perceptions of digital marketing (Antonacci et al., 2017; Aswani et al., 2018; Gloor et al., 2017; Rekik et al., 2018; Singh et al., 2017; Sohrabi et al., 2012; Sohrabi et al., 2011; Sohrabi & Raeesi Vanani, 2011). Text Analytics has proven to be a valuable and effective tool in business intelligence as well as social media marketing and branding (Dwivedi et al., 2015; Lin, Li, & Wang, 2017; Xu, Wang, Li, & Haghighi, 2017). There have also been many attempts to apply data mining and text mining algorithms to various datasets to reach a robust decision making initiative and proper recommendations for enterprises (Raeesi Vanani, 2017; Raeesi Vanani & Jalali, 2017; Raeesi Vanani & Jalali, 2018; Sohrabi et al., 2017; Sohrabi et al., 2018; Sohrabi et al., 2019).

Within the realm of text analytics, the sentiment analysis has emerged as one of the most interesting and useful sets of algorithms that are used to describe the sentiments of customers toward a brand through a series of communications and comments analysis over a social media. In the next section, sentiment analysis is described in more detail.

Sentiment Analysis

The growing ease and enthusiasm with which researchers and practitioners can access a variety of information sources over the web on the international markets is a strategic resource for brand management (Shirdastian, Laroche, & Richard, 2017). It also plays a critical role in improving the perceived value of a product, service or brand over time. The use of a sentiment analysis approach to classify the sentiment of a text has been broadly explored and discussed in the literature (e.g., Balbi, Misuraca, & Scepi, 2018; Fronzetti Colladon, 2018; Gloor, 2017; Jeong et al., 2017).

Sentiment analysis (Agarwal et al., 2015) uses the natural language processing (NLP), text mining algorithms and computational intelligence to extract and categorize the people’s sentiments from reviews or other textual comments. The main goal of analyzing sentiments is to analyze the reviews and examine their scores. Sentiment analysis has been broadly used across many scientific fields such as Customer Relation Management, marketing, sales, book reviews, customer reviews, websites, social media texts, and so on. Sentiment analysis has become a hot area in decision-making (Matthew et al., 2015, Mohamed Hussein, 2018; Tawunrat and Jeremy, 2015; Zhang, Zeng, Li, Wang, & Zuo, 2009).

In April 2013, it was revealed that 90 percent of customer’s decisions rely on online reviews (Ling et al., 2014). A customer opinion may be regarded as a statement in which the customer makes a specific claim about a brand or product through a comment with a specific sentiment (Mostafa, 2013).

Sentiment analysis basically uses natural language processing (NLP) that makes use of computational linguistics and text mining to extract the text sentiment, typically as positive, neutral or negative or as a finite or infinite range of positive to negative numerical scale. The mentioned technique is also known in the literature as opinion mining, emotional polarity analysis (EPA), appraisal extraction, or review mining (Zagal, Tomuro, & Shepitsen, 2012). Therefore, the Sentiment Analysis can be seen as a knowledge discovery technique that focuses at finding hidden patterns in a very large number of reviews, like posts in a blog or tweets in the Twitter.

Sentiment Analysis in text mining, implicitly or explicitly, refers to a sociological or a psychological theoretical approach which explains the sentiments behind the social interactions that take place in the business-related or even daily communications. As stated by Liu (2012), it is not sufficient to classify the sentiment lexicon in order to perform a sentiment analysis since a positive or negative sentiment word, may have an opposite meaning depending on the context. In fact, the meaning of a word is subject to the way it combines with other words, that is the association with other sentiments.

Text Pre-Processing and Sentiment Score

Scraping of Twitter or any other social media can lead to the collection of hundreds of thousands of texts. Therefore, it is important to apply appropriate pre-processing algorithms to cleanse and transform the data into the formats that are suitable for further analysis (Greco and Polli, 2019). Most of the online text-based communications on social media ignore the rules of spelling and grammar. As a matter of fact, noisy texts pose considerable problems at the lexical and the syntactic levels (Mostafa, 2013).

Jargon, contractions of existing words/abbreviations, the use of emoticons and the creation of new words are the norms at the lexical level and at the syntactic level, has resulted in very few real sentences. This form of writing is most evident in social networks (e.g., Derks, Fischer, & Bos, 2008). Therefore, it is crucial to make use of sophisticated algorithms that focus on extracting the most meaningful features from the noisy texts, known as text pre-processing algorithms. The details of utilized algorithms are discussed in the following sections.

After the finalization of text pre-processing, the steps of Sentiment Analysis will initiate. There are three types of sentiments in the texts (Mohamed Hussein, 2018):

- **Structured Sentiments** are usually found in formal sentiment reviews; however, this type targets the formal issues as books or research. Because the authors or writers are professional in writing sentiments about the scientific or fact issues.
- **Semi-Structured Sentiments** lie on the spectrum between the formal structured sentiments and unstructured sentiments. This type is listed separately by the writer and the contents of comments over the issues are usually short phrases.

- **Unstructured Sentiments** are an informal and free text format and the author or the writer does not follow any constraints (Arjun et al., 2013). The content may also consist of several sentences and comments.

For the purpose of sentiment score calculation, the sentiment obtained from the text should be compared to a lexicon or a dictionary to determine the strength of the sentiment using a semi-supervised method to assign each word with positive, negative, and neutral scores. There are also methods that use a range of varying numbers to assign a more accurate score to the sentiment, as conducted in the current research (Mostafa, 2013). Several studies have recently investigated various textual datasets through Sentiment Analysis (e.g., Leong, Lee, & Mak, 2012), however few studies have concentrated on investigating customers' sentiments towards major international brands such as Apple, Amazon, and Uber.

The analysis of the summations or the distribution of scores and comparison of the results to the service provision of international brands can provide many clues for quality improvements and future trends prediction and scenario planning. In the following sections, the research method, data gathering and pre-processing, sentiment analysis, and results discussion are provided.

Materials and Methods

As a well-established research method for data mining, CRISP-DM has proven to work well with data science projects. It stands for Cross-Industry Standard Platform for Data Mining. The six steps that are driven from various industrial projects, help practitioners and researchers to develop and test their models and reach proper conclusions, based on the data mining algorithm's implementations and results analysis.

CRISP-DM proposes the following steps of research and development (Chapman et al., 2000; Koh & Tan, 2011):

- **Business understanding**: international brands and their positioning in the global economy are to be studied and analyzed in this step. Since there has been many brands in the textual dataset, the most internationally well-known brands have been chosen for further analysis.
- **Data understanding**: features of data like the fields and records and types of data under each field will be studied in this step. The result will be a dataset that is ready for pre-processing.
- **Data preparation**: This is the step in which the noisy texts and comments will be cleansed and transformed. The output will be a clean textual data that is ready for the modeling phase in which various algorithms of sentiment analysis are applied.

- **Modeling**: text mining algorithms will be configured and applied on the cleansed textual data so as to calculate the sentiment scores and to draw conclusions upon the best results of algorithms outputs.
- **Evaluation**: the validation phase concentrates on the accuracy of scores and the value of algorithms outputs for further analysis. If the results seem to be satisfactory, a proper discussion will be provided on the findings of brands sentiments based on the customer tweets.
- **Communication of findings**: The last phase of the research belongs to the deployment of results to the business which in our case is the communication of findings with the scholars and practitioners in the field through the current research paper.

For the purpose of data gathering and modeling, the Python language is used. Various libraries like NumPy, Pandas, NLTK, Spacy, Matplotlib, String, and other packages are also applied for the purpose of data preparation, sentiment analysis, and visualization. In the next step, the details of the dataset, pre-processing steps, analytical algorithms and findings are discussed.

Data Gathering and Pre-Processing

In the data understanding phase, two million eight hundred eleven thousand and seven hundred seventy four (2,811,774) records of inbound and outbound tweets from various international brands were obtained. Inbound tweets refer to the tweets that customers send to the companies for indicating a problem with the product or services or opinions that might lead to their improvements. Outbound tweets are the responses provided by the international brands to their customers regarding the requested posted in twitter.

The data field titles are record_id, tweet_id, author_id, inbound/outbound, creation_time, main_text, response_to_tweet, in_response_to_tweet.

In the pre-processing phase, the following approaches to cleansing and transformation were applied. The final result of the text pre-processing is illustrated in Figure 1:

- **Lower casing**: the approach of lower-case analysis is to convert the input text into a casing format so that a word like 'text', 'Text' and 'TEXT' are treated the same way. Lower casing can be done using vectorizers and tokenizers like sklearn TF-IDF Vectorizer and Keras Tokenizer features that in our case, the sklearn vectorizer is used.
- **Removal of emoticons**, **URLs, and HTML tags:** by removing the mentioned items, the text will be cleared from non-textual formats and images that cannot be processed by text mining algorithms or may not be analyzed with the text analytics outputs for the same purpose of the research.
- **Removal of Punctuations**: another common text preprocessing technique is to remove the punctuations from the text data (characters like: !"#$%&\'()*+). This is a text standardization process that will help to treat ‘text’ and ‘text!’ in the same way. The String

Punctuation module in python contains a full list of symbols and is used for the removal of punctuations.

- **Removal of stop words:** Stop words are commonly occurring words in a language, like ‘a’, ‘the’, and so on. They can be removed from the text most of the times, as they don't provide valuable information for further analysis. Stop word lists are already compiled for different languages as the stop words list for English language are prepared in the NLTK package and used in this research.
- **Removal of frequent words:** In the previous preprocessing step, stop words were removed based on language information. If we have a domain specific corpus, there might be many very frequent words (like ‘please’, ‘yes’, ‘bye’) that are just used frequently without specific sentiment intentions. In this step, the frequent words are processed and removed.
- **Removal of rare words:** This is very similar to previous preprocessing step but the rare words are considered for removal from the text. It is important to notice that the removal of stop words, frequent words, and rare words can be combined and conducted in a single step.
- **Spelling correction:** If there are spelling and grammatical errors, there might be a need to correct them, but since the volume of records is very high, it will have a marginal and little impact on the analysis of findings (as test during the implementation of algorithms).
- **Stemming of words:** the process of reducing words to their word stem or root forms is called stemming. For example, if there are two words in the corpus like introduce and introducing, then stemming will stem the suffix to make them the same as ‘introduc’ or ‘introduce’. There are several types of stemming algorithms. One of the famous algorithms is the porter stemmer which is widely used. In this research, the porter stemmer is used for stemming through an import from the NLTK package.

	text	text_lower	text_no_punct	text_no_stopwords	text_no_frequents	text_no_rares	text_stemmed
0	@115712 I understand. I would like to assist y...	@115712 i understand. i would like to assist y...	115712 i understand i would like to assist you...	115712 understand would like assist would need...	115712 understand would assist would need priv...	115712 understand would assist would need priv...	115712 understand would assist would need priv...
1	@sprintcare and how do you propose we do that	@sprintcare and how do you propose we do that	sprintcare and how do you propose we do that	sprintcare propose	sprintcare propose	sprintcare propose	sprintcar propos
2	@sprintcare I have sent several private messag...	@sprintcare i have sent several private messag...	sprintcare i have sent several private message...	sprintcare sent several private messages one r...	sprintcare sent several private messages one r...	sprintcare sent several private messages one r...	sprintcar sent sever privat messag one respond...

Figure 1. Text Pre-Processing Results

Discussion

After the preparation of textual data, the sentiment intensity analyzer from the NLTK package was used for calculating the sentiment scores of tweets. The final scores will show the level of happiness or churn from the brand in a specific period of time. The mentioned algorithm provides a very accurate score for the overall sentence sentiment. For example, the scores of the following sentences are calculated using sentiment intensity analyzer:

- 'I love your brand!' : **Sentiment score**: 0.6696
- 'I do hate your trademark!' : **Sentiment score**: -0.6114
- 'I do hate and love your product!': **Sentiment score:** 0.2003

A similar approach has been conducted for all of the inbound tweets of customer for each international brand. The trend of brand outbound tweets to the customer tweets is also considered in the dataset. The result of prompt replies to the customer needs has been responded by happier inbound tweets of customers at a later time.

After the completion of sentiment score calculations, a distribution of scores was retrieved as shown in Figure 2.

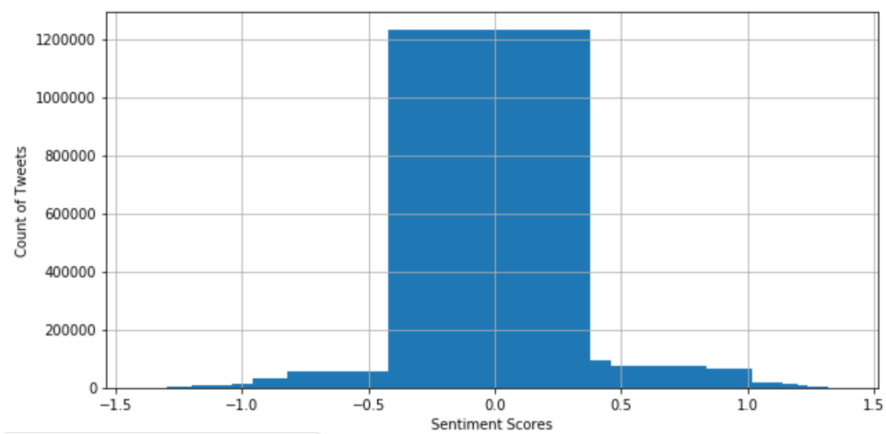

Figure 2. Distribution of Sentiment Scores

The distribution indicates the overall scores given to the customer tweets follow a normal distribution and most of the comments and tweets are centered around general purpose sentences that are majorly targeted for or against a specific brand, however, the rest of the scores on the two tails of the distribution are indicating the streams that can be focused on for future improvements of products and services as well as the customer loyalty.

For understanding the number of tweets per brand, it is also useful to illustrate the frequencies as shown in Figure 3.

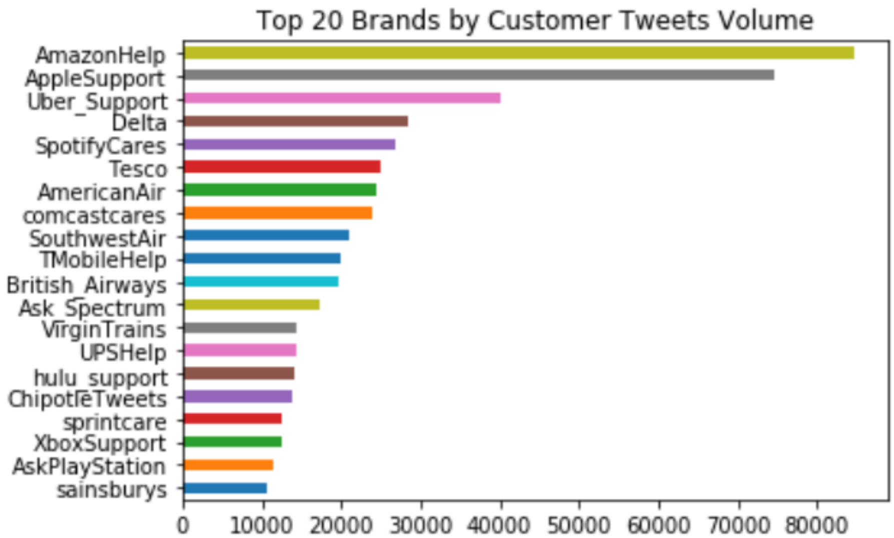

Figure 3. Customer Tweet Volumes for the top 20 brands

It can be concluded that the Amazon, Apple, and Uber companies are doing well in responding to the customers in twitter. For each of the top 20 brands, the sum of sentiments is also calculated based on the mean scores given to each brand. This also provides an amazing output for further analysis as shown in Figure 4.

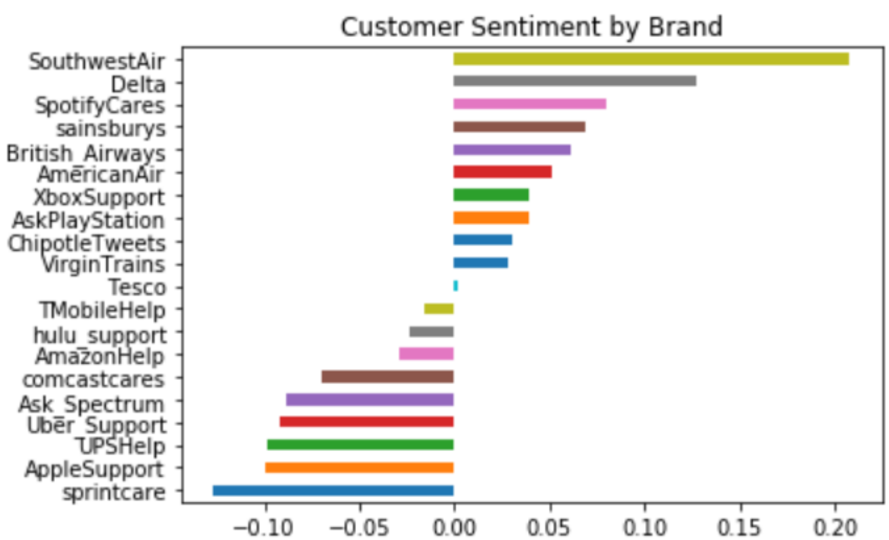

Figure 4. Customers Sentiments toward top 20 brands

As shown in Figure 4, the sentiments toward airway companies are mostly positive while the sentiments toward giant companies with IT products and services are mostly negative. This is a major fact that provides clues on why there are so many tweets towards these companies and how their international brand reputations are rapidly fluctuating and sometimes deteriorating by introducing a new but immature product or service to the market. The quality and intervals of new product introduction and marketing as well as new service provisions are key factors in developing a strong international brand. Through a more detailed view of the sentiment analysis, it is well perceived that the sentiments for a brand fluctuate rapidly with the quality of reactions and responses that each brand provides to its brand community. Figure 5 provides a one-month analysis of inbound tweets count to six of the major companies and also the sentiments of customers towards the same brand.

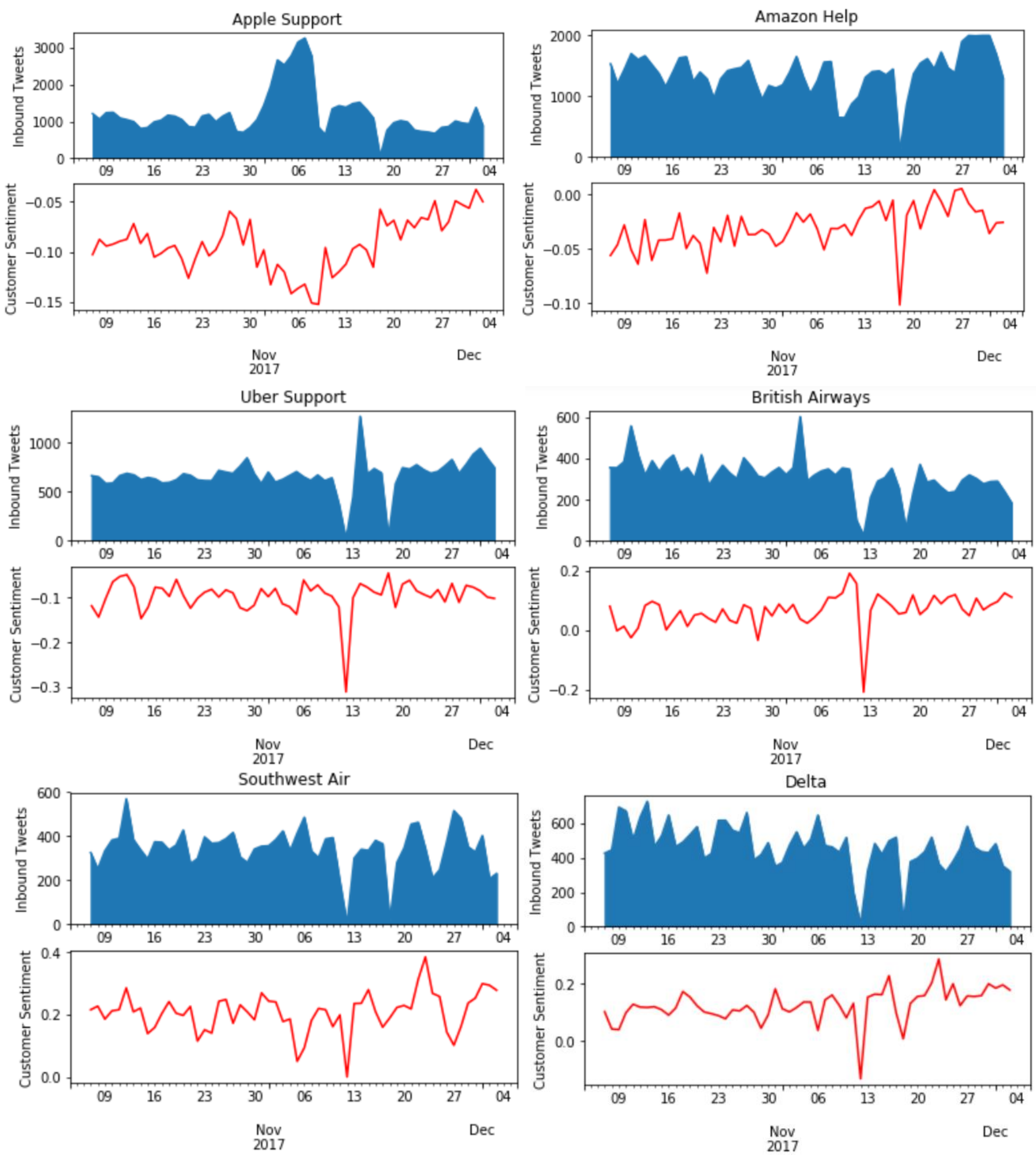

Figure 5. Tweet Counts and Customers Sentiments

The quality of customer support clearly shows the results of sentiments within the next days of each tweet count fall. It can be seen that the rapid responses by the brands has led to the improvement of customer sentiments upon receiving favorable customer supports. It is also interesting to know that for the Apple brand, a tweet count rise can be seen, while at the same time, the sentiments of customer fall rapidly. This is not the case for the Amazon company. Whenever the count of tweets falls for this company, the sentiments towards the company reduces as well which might be a possible key factor towards a future reputation loss since customers do not inform the company of the problem when there is actually a problem to solve. The same approach of analysis can be conducted for other companies.

According to the flow theory (Csikszentmihalyi, 1997) in positive psychology, an individual may experience a feeling of full engagement, and enjoyment when performing an activity like informing a problem with product and services to the community of the brand. Such consumer experiences lead to positive effects and satisfaction among all of the community members. Flow is not just about positive experiences. It requires individuals' active participations in the community and can motivate people both individually and in the community. That is why a quick and efficient response to the needs of customers over the social media is a key factor in creating a deep satisfaction and loyalty for the customers (Lin et al., 2019).

Conclusion

Brand communities are great opportunities around which customers exchange their ideas, experiences, and viewpoints regarding the products and services of major international companies. In this study, a broad range of tweets were collected and pre-processed for the purpose of analyzing the brand sentiments of customers while they are connected to the customer support and after-sales services through social networks. The results show that there is a meaningful correlation between the trends of inbound tweets from customers toward international brands and their positive or negative sentiments. The proper service provision of brands after receiving various converging tweets will show the future of company reputation as well as the future churn or loyalty of customers in a broader perspective.

It is suggested to analyze the announcements of new products and services or the R&D results and feedbacks through the collection of tweets. This will also show the polarity of thoughts and ideas towards or against the business product or service so as to improve the future decision-making process. The utilization of deep learning algorithms combined with text analytics will also reveal new horizons for more sophisticated analysis of customers sentiment in order to realize the steps of decision making when they are thinking about buying a product or service or when they are deciding to gradually become loyal to a brand or have a churn.

Nevertheless, this case study was limited to Twitter. So, its results may not be generalized to other platforms, as also indicated in similar research outputs (Kapoor et al., 2018). However, the approach of analysis and the resultant outcomes can be considered as an efficient and effective approach in developing new and automated decision making and marketing initiatives for brand community. A comparative study of research findings to other similar researches will also shed light in the new opportunities for marketing and sales initiatives.

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