

Twitter Sentiment Analysis for Real-time Customer Experience Feedback in Indian Telecommunication Sector



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ABSTRACT: Corporations have always desired prompt customer experience feedback about their products for amending current pricing and policies to stay ahead of their competitors. A positive customer experience can be created by analyzing customer sentiments and acting on them promptly. Social networks like Twitter represent collective intelligence and opinion of the general public and hence can be harnessed for real-time feedback. They have evolved as a resource for extracting sentiments for applications in various fields. Sentiment analysis can be used to obtain the overall customer experience of a large customer base on real-time. In this research, a total of 108814 distinct tweets for Twitter handles of three popular telecom brands in India: Vodafone India, Reliance Jio and Bharti Airtel were extracted for three months. The results indicate positive customer sentiments about the brand which they prefer, reflected by the number of new subscribers added with that brand in the study period. The sentiment analysis results can be used by managements to take timely actions for improving the future customer experience.

Keywords: Social Network, Text Mining, Customer Experience, Sentiment Analysis, Opinion Mining

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1. Introduction

The world is getting more and more interconnected both economically and socially thanks to the recent advancements in the Internet and networking technologies[20]. There has been a remarkable rise in the last few years in the number of Internet users. Around 3.7 billion people have access to the Internet representing about half of the global population and this number has been growing at an enormous rate since the year 2000, primarily due to the smartphone revolution in the telecom sector [33]. People create their own content, share videos, images or repost other user's content [2]. This content is related to the user's social activities and personal experiences about different services, products and events. Today, most of the businesses have their pages on social network websites [11]. It helps them advertise their upcoming services and products at much lower cost compared to traditional marketing models and maintain a close relation with customers. Upcoming festivals, music albums, movies, sporting events and new product releases create a buzz among the general public much ahead of the release and this can be gauged

through social network responses related to them [25]. Thus, social networks are finding their way in business models as they are helpful in recognizing new opportunities and threats. Users have long friend lists, and they participate in discussions of mutual interest. This way a lively, complex and enormous network of relationships evolves on a social network where influences are created depending upon the number and nature of ties among entities. For each and every popular event or opinion shared by the users there can be a large number of connected responses by other users. This leads to an accumulation of a huge collection of text data posted on social networks, which represents the collective wisdom of the general public.

Managements of corporations spend a huge amount of money and time on brand monitoring and collection of real-time customer experience feedback to keep a watch on their sales and revenues. Most of the traditional methods of monitoring and feedback have a huge cost involved with them and have latency issues. The feedback results are summarized and presented to competent authorities of higher management after a delay of a few days to a couple of weeks from the actual start of the feedback gaining process. Within this span, market scenarios and equations get changed. The delayed planning can lead to drop in market position and further corrective actions occur after a further lag of time. Sales figures for Fast Moving Consumer Goods (FMCG), telecom service providers, box office collections, etc., which are dependent on a large consumer population spread on a vast geographic area are difficult to be monitored day in and day out.

1.1. Social Networks

The diffusion of information on social media is at an enormous scale and real-time analysis techniques focus on it to provide predictive inferences [27]. People prefer the social network endorsement of brand over other types of endorsements [6,21]. Social networks provide electronic word of mouth option to the public, which influences them more and its measurement is also feasible [23,24]. Researches discuss how people seek opinions from others be it everyday chores or national elections emphasizing the need for opinion mining. Respondents may not be comfortable with the traditional feedback methods or in some cases don't have time for feedback surveys. Respondents may not report their true opinions while filling written questionnaires, but they let out their feelings on social networks when they like or dislike certain brands and companies. In the research carried out, social network sentiment analysis has been used to provide a solution to this problem. Social network data can be fetched real-time and requires less time and effort to summarize and lead to conclusions.

Twitter is one of the most popular social network websites. It is a microblogging service that lets registered users Tweet (post) their views on any topic [10,32]. It has become a popular mode of sharing one's views about current trends and events. The 'following and being followed' relationship on Twitter does not require reciprocation as is the case with many other social networking websites. Twitter was selected for mining user opinions as it has millions of registered users who everyday post close to 500 million Tweets and also that the tweets are made available to the general public using APIs within specified rate limits [34]. Twitter uses Open Authentication (OAuth) for APIs requesting information from it [9]. The crawled data includes pairs of userids, tweet, the relation between userids, relationship date, hashtags in Tweet etc.

1.2. Indian Telecomm Sector

India has the second largest telecommunication network in the world by the number of mobile users with 730 million subscribers [22,35]. India also has one of the cheapest call tariffs in the world. The low call tariffs have led to a cut throat competition amongst the various service providers who keep on thriving to increase their subscriber base and sustain their market position. In the research presented, Bharti Airtel and Vodafone India, the largest telecom players and Reliance Jio, the youngest telecom player in the Indian market were chosen for their social network sentiment analysis score to be compared with their market performance in terms of growth of the number of subscribers over the base subscriber number.

Bharti Airtel has been a market leader in India with over 278 million subscribers in India and strong presence in 20 Asian and African Countries [36]. In India, Bharti Airtel has been operating in all telecom circles for more than two decades and always occupied the number 1 spot. Vodafone India has over 210 million subscribers and has been operating in India since 1994 as a subsidiary of the Vodafone Group [37]. Reliance Jio is a subsidiary of Reliance Industries Limited ranking 215th in the Fortune Global 500 list [38]. It launched its commercial services in September 2016 and grew to 112 million subscriber base in just 9 months.

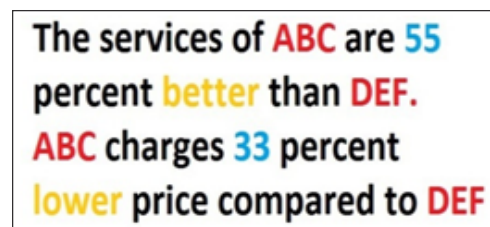
1.3. Sentiment Analysis

Sentiment analysis is the process of analysing opinions and views of authors about a particular entity [2,12]. The main objective of the sentiment analysis process is to identify opinions, identify their sentiments and classify the polarity [15,31]. It is one of the fastest evolving research areas in computer science. The decision making of individuals is affected by the opinions formed

by collective reviews from others. This decision making has shifted from a few personal references to a huge number of social media user opinions from across the globe. With the growth of social media websites, the size of the opinion dataset has grown enormously that it can no longer be manually parsed to generate an inference leading to the evolution of sentiment analysis processes using specialized software.

Sentiment analysis software or sentiment analysis systems use natural language processing (NLP) for processing text articles to identify the underlying relationships [7]. Sentiment analysis focuses on how sentiments are expressed in a text and also if the sentiment points to a positive (favorable) opinion or a negative (unfavorable) opinion on the subject in question [18]. Therefore the analysis focuses on capturing expressions with sentiments, their polarity and relationship with the subject. Consider an expression “A is taller than B”. Here the sentiment “taller” signifies a positive sentiment for A but a negative sentiment for B. Social media sentiment analysis consists of three processes: fetching data, analyzing the data and finally presenting meaningful interpretations of the data [3]. The work presents an overview of more than 50 articles on Twitter sentiment analysis and discussed popular methods for opinion retrieval, irony detection and tracking sentiment over time [5]. Open issues in sentiment analysis like multilingual content, data sparsity, use of deep learning, lack of benchmarks and multidisciplinary research were discussed.

Figure 1 describes the lexical analysis of a phrase of the given text. The tokens representing an entity or a concept are identified and are given due weightage in determining positive or negative opinion. Here the tokens “ABC” and “DEF” represent entities, “better” and “lower” help in comparing the identified entities ABC and DEF; and “33” and “55” are used in assigning numerical values to weights.



The services of ABC are 55 percent better than DEF.
ABC charges 33 percent lower price compared to DEF

Figure 1. Text lexical analysis

Sentiment analysis process comprises of identifying the polarity of user-defined concepts and entities by letting users define their own dictionary, imparting flexibility to be applied to any scenario. Additionally, it determines if the given text being processed is subjective or objective. It is also checked if the text contains some distinctive text keywords at a global level, giving additional information about the reliability of the polarity.

2. Related Work

Social media has emerged as a platform for brand managers to generate and work on brand specific content [13]. Sentiment analysis can be applied to automate categorization of Tweets as neutral, positive or negative. In recent years, the trend of sharing health related issues on social networks has increased analyzing user posted content has come up as a challenge in semantic analysis [14]. Adverse Drug Reactions (ADRs) which are a leading cause of deaths in patients admitted in hospitals. Patients on their own reported on social media about ADRs on social media. Twitter and other forums focusing on Spanish respondents were explored by the TrendMiner project to monitor the content related to drugs and related reactions. Social networks are vast repositories of public created data that contain information representing a general mood about brands and events [5]. In the airline industry, collecting feedback from customers is an important task for which the conventional methods are inefficient and incorrect [30]. The study created a dataset of 107,866 for the major airlines in North America. Tweets were labeled as positive, negative and neutral for the segregation process.

Performance of various sentiment classification approaches was compared to develop an ensemble approach. As per the study, in the airline industry, sentiment-analysis and classification is accurate enough to be used for customer satisfaction investigation [17]. The researchers used social media opinion mining to Poland’s 2010 political crisis discussion dataset containing a high conflict level and deep polarization [26]. The study also analyzed the relation between online sentiment and its impact on Java Governing Board’s open sourcing decision of Java.

The researchers studied the application of sentiment analysis process in economic and financial modeling and concluded that Tweet sentiment analysis is one of the best methods to automate the sentiment analysis process [8]. They proposed to develop an ontology based method for segmenting individual Tweet rather than treating each Tweet as a single expression being assigned a sentiment score. The research suggested that a brand's social network is an effective way of attracting consumers and attaching them emotionally to the brand [19]. Also, existing consumer's bonding with the brand is reflected in the brand's social network on different social network websites. Sentiment analysis helps organizations to scrutinize social media content on a real-time basis and act accordingly [4]. Sentiment analysis of social media can help in picking promising stocks for better returns.

3. Research Method

Social networks have become a valuable source of knowledge in the form of sentiments for a number of sectors such as public opinion management, brand building customer relationship management [16]. Social networks allow APIs to query them for a particular keyword generally superseded by # (hashtag). As most of the social networks have users of the order of millions, any current news item, trend, product, organization or service is flooded with numerous user opinions on them. This information is of great use for governments and corporate managements to assess general public's opinion and capture experience feedback.

3.1. Dataset Creation

In the research, tweets for #reliancejio, #vodafonein and #airtelindia the Twitter handles for Reliance Jio, Vodafone India and Bharti Airtel respectively, were extracted on a daily basis from 1st April 2017 to 30th June 2017. This period is selected for research as Reliance Jio had announced to start charging its customers for all its services from 1st April, 2017 (though actual charging of services started on 15th April). This could be a real test for Reliance Jio to analyze if the general public is inclined towards its services or not amidst the presence of operators like Bharti Airtel and Vodafone India which were operating for many years in the past. The combined sentiment of the general public needed to be compared to check if the general public is showing interest towards the new entrant Reliance Jio or existing market leaders like Bharti Airtel and Vodafone India, when all of them were now offering mobile services at similar competitive tariffs.

The number of tweets extracted on a particular instance is restricted by the Twitter rate limiting. During the said period, 204,715 tweets for #airtelindia, 1,45,262 tweets for #vodafonein and 197,642 tweets for #reliancejio were extracted. Then, the filter was applied to this dataset on the Tweet column containing Tweet content to remove duplicate tweets generated from retweets. As a result, distinct tweets for #airtelindia were 42,985, for #vodafonein were 26967 and for #reliancejio were 38,862. The tweets in an individual dataset of #airtelindia, #vodafonein and #reliancejio have each other's mention in some cases where the user wants to compare them in terms of different parameters like network usage charges, coverage, call drops, Internet speed etc.

3.2. Dataset Processing

Semantic analysis was performed on each of the hashtag's datasets to classify the Tweets into five levels of polarity N+, N, NEU, NONE, P and P+. N+ and N represent a negative polarity generated for a negative opinion in the text, whereas P and P+ represent positive polarity. NEU polarity is generated for neutral opinion or when the polarity cannot be calculated.

Polarity	N+	N	NEU	P	P+
Weight	-2	-1	0	1	2

Table 1. Polarity and weights

Table 1 shows weights assigned to the standard polarities. NEU category of polarities Tweets contains neutral opinion about the concept or entity and hence they have been given zero weight. Negative opinion Tweets (N and N+) have been given -1 and -2 weight depending upon the magnitude of negative opinion. Similarly positive opinion Tweets (P and P+) have +1 and +2 weights. A sentiment dictionary is a critical part of sentiment analysis to recognize the sentiment tokens in any document [28]. This dictionary contains words, phrases, related concepts and sentiment polarity and valuable information used to identify certain significant phrases from the source and establish agreements and weight for them. Table 2 shows the custom dictionary created for performing sentiment analysis of the Tweet datasets. Some of the most influential keywords for describing opinion about likes and dislikes for a telecom brand have been included in this dictionary to capture the essence of user comments.

The sentiment analysis was separately performed on datasets of distinct tweets of #airtelindia, #vodafonein and #reliancejio. The

sentiment score of a particular Tweet is calculated by multiplying its identified polarity with the weight assigned to that polarity. The total sentiment score of a hashtag is obtained by summing up the score of all tweets and the following results were obtained. Figure 2 shows a snapshot of sentiment analysis for #reliancejio dataset.

Table 3 data and figure 2 shows the polarity distribution for Tweets of #airtelindia, #vodafonein and #reliancejio. It is evident that there are a large number of Tweets with polarity value 0. These are the neutral sentiment Tweets for which positive or negative sentiment could not be determined. The frequency of neutral sentiment does not contribute to the overall sentiment score.

Keyword	App	Call drop	Cost	Kbps	Mbps	Network coverage	Port to	Signal	Support
Type	Entity	Concept	Concept	Concept	Concept	Concept	Concept	Entity	Concept

Table 2. Sentiment analysis dictionary

Hashtag N+	N	NEU	P	P+	Total	tweets
#airtelindia	2800	9541	18169	10521	1954	42985
#reliancejio	2621	4121	13458	5365	1402	26967
#vodafonein	2354	7546	16876	9814	2271	38862

Table 3. Polarity distribution for hashtags

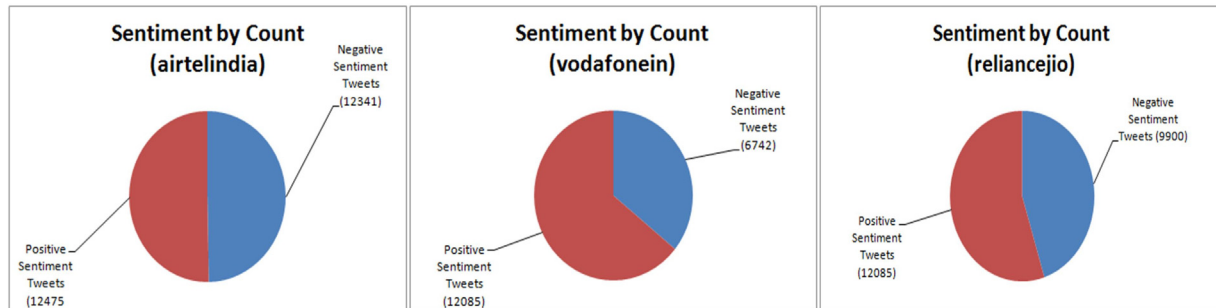


Figure 2. Sentiment count for positive and negative tweets of #airtelindia (left), #vodafonein (middle) and #reliancejio (right)

Figure 2 shows the positive and negative sentiment Tweets of #airtelindia, #vodafonein and #reliancejio. For #airtelindia and #vodafonein, the number of negative sentiment is greater than the positive sentiment and hence the overall score of #airtelindia and #vodafonein is negative. The overall sentiment score of #reliancejio is positive as the positive sentiment count is greater than the negative sentiment count. Sentiment count without weightage or polarity does not carry the essence of the dataset. Sentiment score is calculated by multiplying number of tweets having a particular polarity with the weight of that polarity. In Figure 4, #airtelindia has got a nearly equal number of Tweets having positive and negative sentiments, but the overall sentiment score is negative.

Table 4 data shows that the combined sentiment score of #reliancejio is +2101, #vodafonein is -1194 and that of #airtelindia is -712. The score indicates that the general public has a positive opinion about Reliance Jio and a negative opinion about Bharti Airtel and Vodafone India. It is a reflection of respondent’s individual experience about the brand in terms of different parameters based on different issues related to mobile network service and pricing. This affects their bonding with the brand they are using or the decision making for the brand to which they want to switch over to.

Polarity→	N+	N	NEU	P	P+	Total
Weight (W) →	-2	-1	0	1	2	
No of tweets for #airtelindia (A) →(W*A) →	2800	9541	18169	10521	1954	42985
	-5600	-9541	0	10521	3908	-712
No of tweets for #vodafonein(V) →(W*V) →	2621	4121	13458	5365	1402	26967
	-5242	-4121	0	5365	2804	-1194
No of tweets for #reliancejio (R) →(W*R)→	2354	7546	16876	9814	2271	38862
	-4708	-7546	0	9814	4542	2102

Table 4. Final sentiment score

The data for the number of subscribers for Bharti Airtel, Vodafone India and Reliance Jio was downloaded from the website of the Cellular Operators Association of India [39]. This website provides month-wise subscriber data for all the telecom operators in India, including Bharti Airtel, Vodafone India and Reliance Jio mentioned in Table 5.

Company	March subscriber number	April subscriber additions	May subscriber additions	Total subscriber addition	% Increase On March
Bharti Airtel	273648383	2853044	2098006	4951050	1.81
Vodafone India	209062866	756637	1131435	1888072	0.90
Reliance Jio	72157644	36523128	3469493	39992621	55.42

Table 5. Bharti Airtel, Vodafone India and Reliance Jio subscriber data

Table 5 data show that there is a huge difference in net subscriber addition to the March subscriber base between Reliance Jio and Bharti Airtel. While Reliance Jio added a total of 39,992,621 new subscribers, Bharti Airtel added 4,951,050 and Vodafone India could add only 1888072 new subscribers. Reliance Jio's performance in terms of adding new subscribers is 8 times that of Bharti Airtel and 21 times that of Vodafone India. Compared to their March subscriber base benchmark, the increase for Reliance Jio is 55.42% compared to a mere 1.81% for Bharti Airtel and 0.90% for Vodafone India.

The addition of a large number of new subscribers to Reliance Jio's subscriber base could be seen as customer churn of subscribers shifting away from other telecom operators as they failed to monitor customer sentiment and act in time to prevent it. Data mining techniques can be used by managements to take timely actions to predict and prevent such customer churn [1, 29]

4. Conclusion

During the test period, there is a huge difference in the percentage growth of subscribers of Vodafone India (0.90%), Bharti Airtel (1.81%) and Reliance Jio (55.42%) over their March month subscriber data base value which is clearly reflected in their social network sentiment scores. Sentiment score represents customer experience feedback. A positive sentiment score of a company is an indicator of brand preference of the public and a negative sentiment score indicates customer dissatisfaction or inclination towards any other company which is better suited to their needs. Social networks like Twitter which are being used by a large section of society contain vast repositories of user responses about different events and entities.

With greater penetration and 24*7 availability of Internet services, one can fetch almost real-time feedback from the masses using social network based sentiment analysis. Twitter mining and sentiment analysis of the obtained dataset can be of great use for corporations and brands looking for real-time customer experience feedback for planning and maintaining their business models for competitive success and survival.

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