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Demonetization and its aftermath: an analysis based on twitter sentiments

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Abstract. Sentiment analysis has become a very useful tool in recent times for studying people's opinions, sentiments and subjective evaluation of any event of social and economic relevance, and in particular, policy decisions. The present paper proposes a framework for sentiment analysis using twitter data for the 'demonetization' effort of the Government of India. The paper employs twitter data using Twitter API. The methodology of the paper involves collection of data from twitter from different cities of India using geolocation and preprocessing followed by a lexicon-based approach to analyse users' sentiments over a period of five weeks preceding the policy announcement. In addition to this, the paper also attempts to analyse the sentiments of specific groups of people representing diverse interest groups.

Keywords. Demonetization; data analysis; data preprocessing; opinion extraction; sentiment classification; machine learning.

1. Introduction

The recent 'demonetization' effort of the Government of India raised so much of hue and cry in terms of the attention it received from the media, academia and common people that no other policy had ever received in the post-independent India. The Prime Minister of India announced on 8th November, 2016 evening via media broadcast that 500 and 1000 denomination notes [1, 2] would cease to exist as legal tender with effect from the very next day [3, 4] (actually from 12 am). The Gazette Notification of the Ministry of Finance dated 8th November came after the announcement of the Prime Minister. The Finance Ministry notification stated that the policy measure was announced on the recommendation of the Central Board of Directors of the Reserve Bank of India (RBI), the country's central bank. However, from the very beginning, it was considered to be a favoured policy of the central government, in particular the Prime Minister. The crux of the policy announcement was centred around fake currency and unaccounted wealth (black money in common parlance)[1]. The concern for the fake currency in circulation on the part of the government has been receiving greater attention in recent times[2]. Subsequently the RBI also endorsed the policy decision, and in its order dated 9th November it issued guidelines to banks for implementation of the policy of demonetization. The policy of demonetization led to the reduction of 86% of cash in circulation in value terms, which adversely impacted on the transaction capability of the public starting from the inability to pay for daily needs, such as food or emergency services, medical attention and business, thereby affecting economic growth in the medium and long run. There is no history of successful

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[1]The Gazette of India Extraordinary, part II-Section 3-Sub-section (ii), Ministry of Finance (New Delhi: Controller of Publications, Government of India, and November 8, 2016).

[2]A joint study conducted by National Investigation Agency and Indian Statistical Institute estimates the value of fake currency notes to the tune of at least Rs. 4000 million between 2010–11 and 2014–15 (Rahul Tripathi, The Economic Times, November 15, 2016). Also see the replies to Lok Sabha Starred Question Number 41 on 18/11/2016, which puts the value of actual seizure of counterfeit notes between 2013 and September 2016 at Rs. 1550 million. Another Rajya Sabha Unstarred Question Number 3777 on 13th August 2014, Ministry of Home Affairs, reports that between 2011 and 30th June 2014 the total amount of seized currency notes is Rs. 838 million. The National Investigation Agency puts the value of fake currency notes at Rs. 160,000 million (The Indian Express, June 11, 2012).

implementation of demonetization in any other country. As a matter of fact Venezuela also announced a policy demonetization around a month after the Indian policy announcement, but was forced to withdraw within a few days after food riots and other violence rocked the country. In the past, Nigeria was also not successful in the implementation of similar demonetization exercise. As for the unaccounted wealth in high denomination notes is concerned, it was pointed out that they are also part of the income generation process in the economy – The Informal Economy. The informal economy is very large in India like other developing economies both in terms of its share of national income as well as a source of employment. The informal economy is not registered (though there are different layers of informality) and hence is not subject to regulations and is not in the tax net (direct or indirect). However, these informal activities cannot be grouped into the same category as drug, smuggling or human trafficking. In this backdrop the policy announcement of demonetization assumes its importance to all segments of the society. From the very first day after the announcement, electronic media [5, 6] and social networking sites were flooded with debates and discussions on the issue. In academia, several critiques were published immediately after the policy announcement. For example, Rajakumar and Shetty [7], Lahiri [8], Nag [9], Reddy [10] and several articles in The Economist and other news magazines. Generally the articles disputed the efficacy of the policy and concluded that apart from the short-term problems faced by the public, GDP would be adversely affected in the medium and long run. However, some of the supporters of demonetization came up with the argument that the dip in income and growth would be temporary, but the policy shock would lead to expansion of banking practices by the public that would generate efficiency in the economic sphere in the country and extension of the tax net. Regarding the unexpected policy shock, it was argued that in order to make the policy effective the Government or RBI did not have the option to implement the policy in a phased manner, because anticipated policy has limited effectiveness. Dasgupta [11], in a theoretical analysis, shows that the medium to long run [12, 13] effects do not look 'rosy'. It is further pointed out, based on Lucas (1997), that an unanticipated monetary contraction may lead to depression. Apart from academia or the policy makers, electronic media and social networking sites were rocked with the discussion with policy decision from the very first day. In recent years, big on-line social media data have found many applications in the intersection of social science, statistics and computer science. Text categorization was started long time ago (Salton and McGill, 1983); however [14, 15], categorization based on sentiment was introduced more recently in Das and Chen (2001), Morinaga *et al* (2002), Pang *et al* (2002), Tong (2001), Turney (2002) and Wiebe (2000), and it has spread from computer science to management sciences (Archak, Ghose and Ipeirotis 2007; Chen and Xie 2008; Das and Chen 2007; Dellarocas, Zhang and Awad 2007 Ghose, Ipeirotis and Sundararajan 2007; Hu, Pavlou and Zhang 2006; Park, Lee and Han 2007). In 2012, Federico Neri Carlo *et al* had developed an idea of sentimental analysis using 1000 Facebook posts [16, 17] about new casts, comparing the [18, 19] sentiments for the Italian public broadcasting service – towards the emerging and most dynamic private companies. In 2015, Xing Fang *et al* presented an idea of sentiment analysis using product review data [8, 20]. His main aim was to tackle the problem [21, 22] of sentiment polarity categorization of sentiments analysis [23, 24]. Despite the fact that social media data cover only a limited segment of the population of a country, especially in India with very little access of the common people to Internet and smart phone, it captures the mood of the population in some way. There are 292 million users of social network sites in India; the corresponding figure for US is 207 million, and 564 million in China (Source: Statista, 2017)[3]. In per capita terms, Indian social media penetration is way behind China or USA (half and one third, respectively); nonetheless, the absolute number itself is very large. The present paper aims to analyse the impact of the demonetization effort on the common people as well as the opinions of different groups of people or organization, such as economists, politicians, industry and banking sector, etc. Our analysis is based on tweets, which is very popular in the on-line social media platform. A large number of tweets were collected from the twitter by Twitter API [25, 26] using different keywords related to demonetization in different major cities of India within a particular time period, date and geographical location. The tweets were categorized into positive, negative or neutral opinion [27] to estimate the overall sentiment of people on the current situation. With this introduction the paper is organized as follows. Section 2 provides the methodology, section 3 presents the empirical findings and analysis of the sentiments and the last section concludes.

2. Sentiment analysis methodology: background

There are several approaches for sentiment analysis, of which lexical approach and supervised approach or machine learning approach has been used here.

2.1 *Score evaluation method using SentiWordnet*

Extraction of sentiment for a particular tweet is executed as ternary sentiments – positive, negative or neutral. This is obtained by the following scoring method. Here, SentiWordnet is used for polarity detection. SentiWordnet is the result of the automatic annotation of all the synsets of

[3]https://www.statista.com/statistics/278341/number-of-social-network-users-in-selected-countries (as on 10.07.2017).

WORDNET according to the notions of positive negative and neutral to three numerical scores Pos(s), Neg(s) and Obj(s) associated with each synset [3, 28]. After pre-processing of tweets, each tweets token has been parsed with the help of POS tagger. POS tagger assigns a tag [29] to each token and then the word is passed in SentiWordnet to check the score as well as polarity of that particular word. SentiWordnet will return the sentiment-type of the seven possible categories strong-positive, positive, weak-positive, neutral, weak-negative, negative and strong-negative words [30, 31]. Now the number of positive (pos_count) and number of negative (neg_count) adjectives in each sentence have been counted. If the neg_count is an ODD number then the sentence is considered "Negative" and if If the neg_count is an EVEN number then the sentence is considered "Positive". If a word in the tweet is found to be unknown then it is matched with the dictionary containing acronym words and replaced with the proper words, and the same scoring method is performed as before.

Let Score St be the Number of Positive Words Match−Number of Negative Words Match. Let C be the set of cities from where tweets are collected for the event, and T be the set of tweets collected from a city $c \in C$ for the event on a particular date. Also define each tweet $t \in T$ to carry a score St $(0 > \ = St > 0)$, such that if $St > 0$ then the tweet shows full support of the event demonetization. If $St < 0$ then the tweet shows no support of the event demonetization. Then, for city c, its approval score (positive, negative or neutral) can be defined as follows:

$$\sum_{t \in T} \frac{St}{|T|}. \tag{1}$$

We represent the scoring of all the cities with the date in figures 1 and 2. Averaging over all cities in C, the average tweet leaning for event demonetization is

$$X = \frac{1}{|C|} \sum_{c \in C} \sum_{t \in T} \frac{St}{|T|}. \tag{2}$$

2.2 *Sentiment analysis by machine learning method*

Machine learning is one of the most prominent techniques, gaining the interest of researchers [16, 20] due to its adaptability and accuracy [32]. This method also involves three stages, viz. data collection, preprocessing and training data classification and plotting of results [11, 33].

A common algorithm employed in the machine learning approach is the Naïve-Bayes classifier [34, 35], which is a simple classification of words based on the Bayes theorem. It is a Bag of words approach for subjective analysis of content. Naïve Bayes assigns a document dj to a class ci. By the Naïve-Bayes theorem

$$\frac{P(dj/ci)P(ci)}{P(dj)} \tag{3}$$

where $P(dj)$ is the probability that a randomly picked document d contains vector dj. $P(ci)$ is the probability that a randomly picked document belongs to class ci.

Support Vector Machine (SVM) classifier is also used here for classification. Classification is done by constructing hyperplanes in a multidimensional space [36, 37] that separates cases of different class labels. SVM supports both regression and classification tasks and can handle multiple continuous and categorical variables.

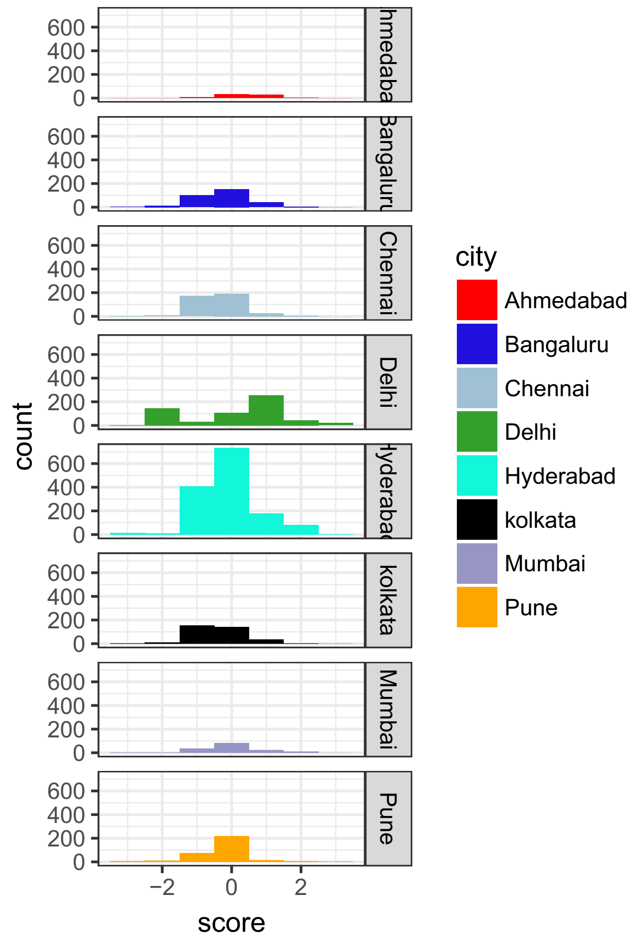

Figure 1. Comparative scores of eight cities at first phase (08.11.16).

2.3 *Parts of speech (Pos) tagging*

Pos tagging is a form of annotating text where part of speech is assigned to each word. The part of speech tagger marks tokens with their corresponding word type based on the token itself and the context of the token.

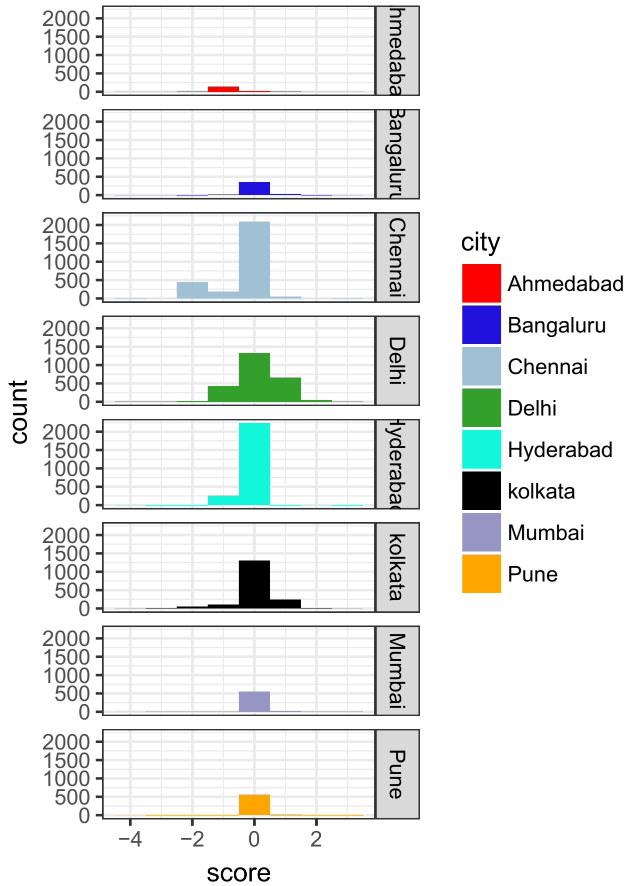

Figure 2. Comparative scores of eight cities at second phase (14.12.16).

Part-of-speech tags are assigned to character strings. Part-of-speech or word categorization is the grammatical nature or category of a lexical item. For example, every term has been associated with a relevant tag indicating its role in the sentence, such as VBZ (verb), NN (noun), JJ (adjective), etc.

3. Material and methods

3.1 *Data collection*

Table 1 contains a brief description of total number of tweets and re-tweets with proper keywords. In our choice the most important keyword is demonetization. To capture the same context, some additional keywords, viz. black money, cash clean-up [33, 38], etc. are included. Using these keywords, totally 57536 tweets are downloaded separately from eight major Indian cities between 08/11/2016 and 14/12/2016 using Twitter API [7, 39].

3.2 *Data preprocessing method*

After collecting data, they are preprocessed [40]. The preprocessing step is used to handle the following issues: (i) removing punctuations, (ii) cleaning text – removal of non-alphanumeric characters from the text, (iii) removing URLs and un-necessary white spaces and tabs, etc., (iv) stop-word removal – i.e., words that do connecting function in the sentence, such as prepositions, articles, etc. and (V) convert to lower case.

3.3 *Score analysis*

After data preprocessing is completed, the Stanford POS tagger is used to tag the dataset with its parts of speech and the tagged documents are fed as input to SentiWordNet for scoring positive, negative and neutral terms.

3.3a *City-wise sentiment score analysis*:
First the frequency of sentiment scores has been calculated from the tweets set of eight major cities immediately after the policy decision was announced on November 8, 2016 and after about five weeks, on December 14, 2016, when the impact of initial shock is expected to die down and general population adjusts to the new policy regime (figures 1 and 2).

Table 1. Daily tweet collection from date 08/11/16 to 14/12/16 using proper keywords.

Date	HashTag	Cities	Total tweets collected
08/11/16–14/12/16	#Demonetization,#demonetised, #demonetizing,#demonetise, #demonetizationsaveslife, #DemonetizationDisaster, #DemonetizationResponse, #SupportDemonetization, #blackMoneycleanup, #DeMonetizationMess, #demonetizationaffected, #demonetizationmythsbusted, #Demonetization,#CashCleanUp	Ahmedabad	3467
		Bengaluru	5886
		Chennai	6336
		Delhi	16494
		Hyderabad	8283
		Kolkata	7232
		Mumbai	5792
		Pune	4046
		Total	57536

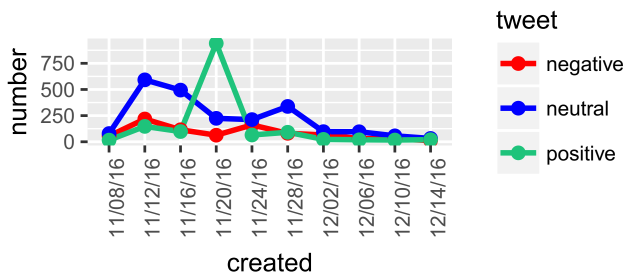

Figure 3. Sentiment analysis day-wise of some major cities: Bengaluru (08/11/2016–14/12/2016).

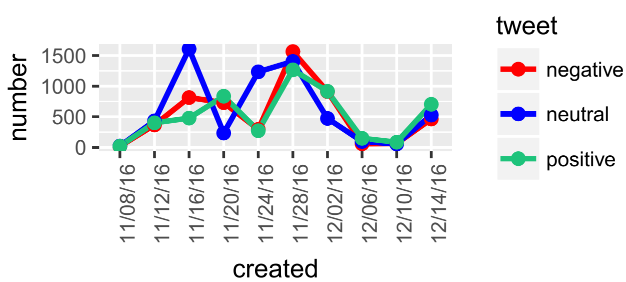

Figure 4. Sentiment analysis day-wise of some major cities: Delhi (08th Nov.–14th Dec. 2016).

3.3b *Sentiment analysis across date*:
Next the sentiment scores for each of the eight cities over the period of time have been analysed and the aggregate counts plotted for the three types of sentiment scores – positive, negative and neutral on each day between 08/11/2016 and 14/12/2016 (figures 3–5).

3.3c *Sentiment analysis for different groups*:
For the Group of Economists and Politicians, tweets have been collected separately from the supporting and opposing groups, resulting into two panels for these groups. The supporting group of the economists is known to be close to the current government at the centre and part of the policy making body and the opposing group is known for their allegiance to the previous government led by Congress Party (oppose demonetization).

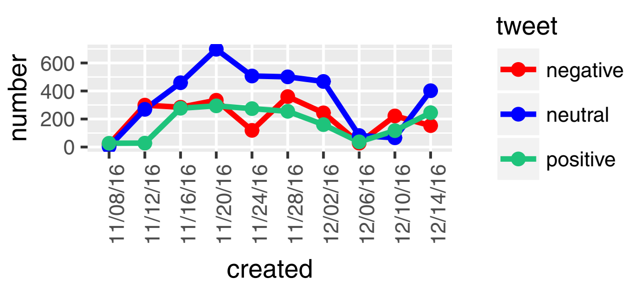

Figure 5. Sentiment analysis day-wise of some major cities: Kolkata (08th Nov.–14th Dec. 2016).

Table 2. Typical example of acronym and their expansion.

Acronym	English expression
gr8,gr8t	Great
lol	Laughing out loud
rotf	Rolling on the floor
bff	Best friend forever

3.3d *Computation of sentiments with machine learning method*:
Here the Naïve-Bayes Classifier has been used to classify sentiment of people of different cities, trained on Carlo Strapparava and Alessandro Valituttis emotions lexicon. In this method the unigrams which are found in the lexicon [41, 42] are assigned a polarity score. Tweets are analysed and compared to the following categories of emotion: anger, anticipation, disgust, fear, joy, sadness and surprise. Among the emotions, as classified by the Naïve-Bayes method the most important sentiment is reported to be 'disgust' followed by 'anger'. Together with the occurrence of other emotions it readily follows that on the whole, public emotions did not favour the policy announcement.

3.3e *Package used*:
Packages and other details that are used in this analysis are as follows.

a) R software has been used as the computational environment and some of the packages that have been used are TwitteR, ggplot2, NLP, Tm, etc.
b) SentiWordNet: The SentiWordNet is a lexical resource associated with two numerical scores ranging from 0 to 1 that indicate Pos(s) and Neg(s), describing how positive or negative terms are contained in the synsets. Here SentiWordNet is used for document level sentiment classification using the polarity dataset of different cities and groups.
c) To train the model we use the Naïve-Bayes function [43] from the e1071 package.
d) Here we use Natural Language Processing (NLP) libraries such as the Stanford CoreNLP [17, 44] for POS tagging.
e) The following Acronym Dictionary (table 2) is used.

4. Result and analysis

The methodology for the analysis of sentiments described in the previous section has been used to analyse sentiments in a number of ways – sentiment analysis for initial impact and after some time, across cities, for the whole period across cities, for specific groups, etc. Tweets have been collected in two phases: first phase after the policy decision was announced on November 8, 2016 and the second phase

Table 3. Net sentiment score of Indian cities.

	Net score (first phase)			Net score (second phase)		
City name	Positive (%)	Negative (%)	Neutral (%)	Positive (%)	Negative (%)	Neutral (%)
Ahmedabad	15.5	25.3	59.1	5.5	80.4	15
Bengaluru	25.3	25	48.4	35.6	25.4	39
Chennai	9.5	34.5	54.4	5	70	25
Delhi	50	10	39.6	65.4	14	20.6
Hyderabad	10	32.3	56.7	20.5	29.5	50
Kolkata	26	27	45	24.4	21	54.6
Mumbai	19.3	20	59.5	20	10	70
Pune	15.4	64.6	20	20.5	14.5	65

after five weeks, on December 14, 2016, and the scores of all the eight cities are compared (table 3). Next the sentiment scores for each of the eight cities over the period of the day from 08 / 11 / 2016 to 14 / 12 / 2016 have been calculated (figures 3–5).

There are huge differences in sentiment scores across cities over this period. From the analysis, fluctuation of opinion per day has been observed. During the immediate post-demonetization days, typically the first two weeks, there were large variations across the three types of sentiments. In general, frequency of tweets decreased from the second week until around 06/12/2016; then we can find a sudden spurt in tweets sentiments. Only in the case of Bengaluru, frequency of tweets shows a steady decline where the neutral score is marginally higher. Delhi shows large fluctuations to begin with, a reversal in the intermediate days and finally closes with a positive mark. Kolkata shows dominance of neutral sentiments in the initial days until 06/12/2016 when all the three types show a tendency of convergence, but closes with a higher neutral sentiment.

Now sentiments of different groups, viz., Group of Economists, Industries Group, Political Group and Bank Group are analysed within the time period of 08/11/2016–14/12/2016 (figures 6–10). Economists and politicians are divided into two groups: one supporting demonetization and other opposing it.

Reactions of different banks related to this policy are also analysed. It has been observed that for bank group, there is a mixed reaction of positive, negative and neutral sentiments and industries group has neutral sentiment.

4.1 *Visualization and quantification of frequency of words of relevance*

In order to get an idea of the people's perception about the impact of the specific event of demonetization on the economy and society, top 5 frequencies of specific words of relevance for each group (table 4) are analysed here and visualized with the word cloud of different cities (figures 6–10). Collected tweets contain natural language text [35, 45] and frequent words. Specific mappings have been applied

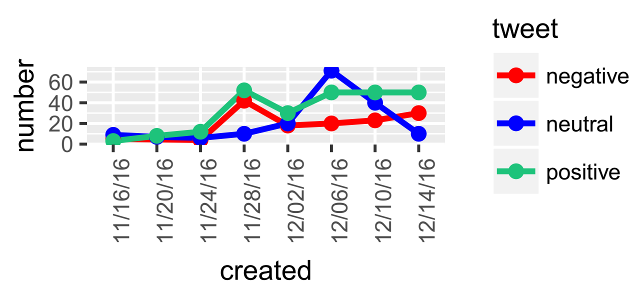

Figure 6. Economist Group who support demonetization.

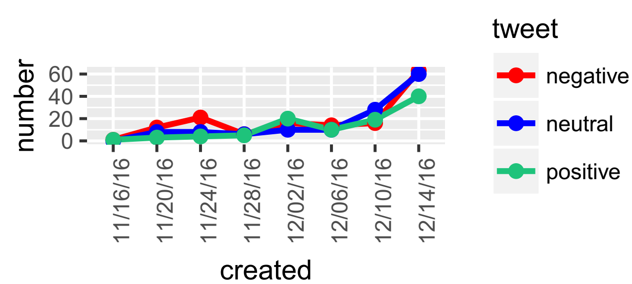

Figure 7. Economist Group who oppose demonetization.

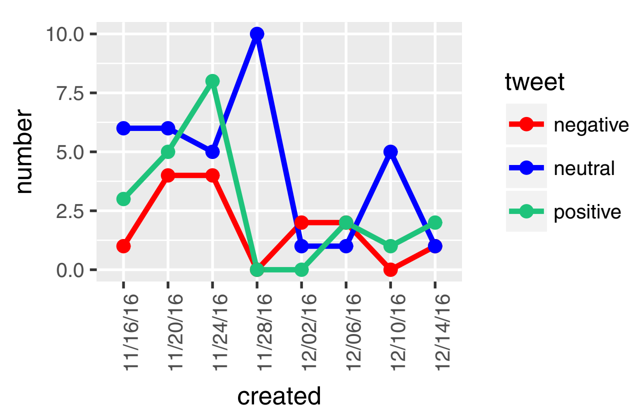

Figure 8. Sentiments of different banks (ICICI).

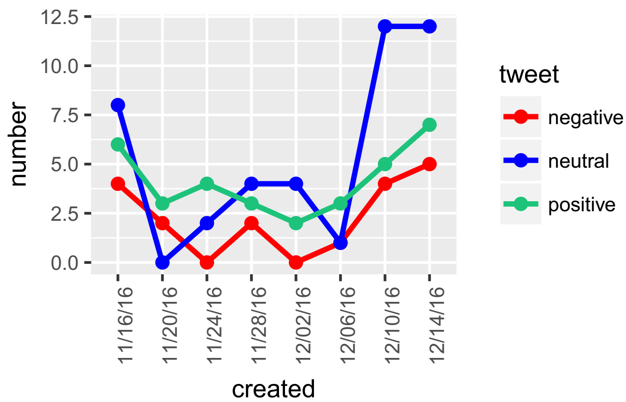

Figure 9. Sentiments of different banks (SBI).

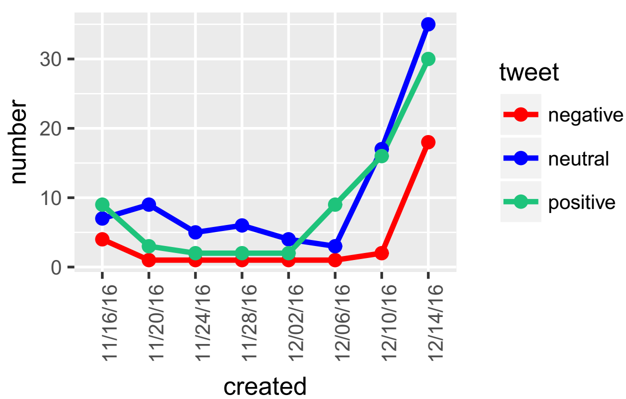

Figure 10. Sentiments of different banks (Axis).

Table 4. Top 5 word frequency for the four groups.

Economist Group	Industry Group	Politician Group	Bank Group
Black money	Cashless	UPI	e-commerce
Farmer	Informal business	Poor	Paytm
Fake currency	Recession	Farmer	Black money
Paytm	Fake currency	Agriculture	Cashless
Mobile wallet	mPay	Suffer	mPay

Note: Paytm, mpay, e-wallet and digital wallet are variants of mobile payment system; UPI is also another mobile payment system launched by the Government of India.

to the documents containing tweets corresponding to the most frequent words, and the most frequent words used by different people in different cities are visualized through word cloud (figure 11) via term-document matrix (table 5), a matrix of numbers that keeps track of documents in a corpus use of terms. Here, the term-document matrix of four groups, i.e. Group of Economists, Group of Industries,

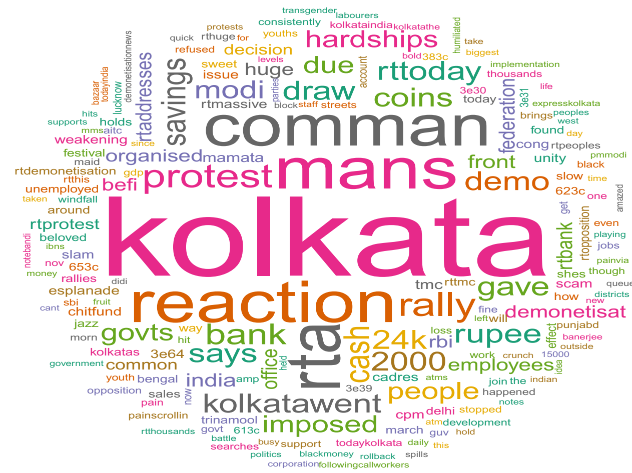

Figure 11. Word cloud with some popular terms of the city Kolkata (08/11/2016–14/12/2016).

Table 5. Document matrix of the groups.

Terms	*Doc 1*	*Doc 2*	*Doc 3*	*Doc 4*
Agriculture	1	0	50	0
Black money	2	0	0	7
Fake currency	7	59	0	0
Farmer	97	0	7	0
Cashless	8	104	0	7
Mobile wallet	0	0	0	0
mPay	8	7	0	63
Paytm	0	0	0	7
e-commerce	7	0	0	8
Recession	0	7	0	0
Informal business	0	8	0	0
UPI	0	0	8	0
Poor	0	1	7	0
Suffer	0	0	6	0

Group of Politicians and Group of Banks (Group 1, 2, 3 and 4, respectively) has been constructed.

4.2 *Significant test of four groups*

Performing an ANOVA is a standard statistical test to determine whether there is a significant difference between multiple sets of data (number of positive and negative tweets). Here, testing has been done on number positive and number of negative tweets of four groups over the span of two months (08/11/2016–14/12/2016). One-way ANOVA is used for the group analysis and the results are presented in tables 6 and 7.

Here, in table 6, sum square and mean square are used to calculate the F value; from the F chart, the F ratio (3, 36) (3 across, 36 down) has been obtained. These numbers come from the Df (degrees of freedom) column. From the chart it

Table 6. Analysis of variance table for positive tweets.

	Values (positive tweets)				
Response	Df	Sum sq.	Mean sq.	F value	Pr(>F)
Ind	3	6777.9	2259.29	7.5446	.000486
Residuals	36	10780.5	299.46		

Signif. codes: 0 ∗ ∗ ∗ 0.001 ∗ ∗0.01 ∗ 0.05.0.11

Table 7. Analysis of variance table for negative tweets.

	Values (negative tweets)				
Response	Df	Sum sq.	Mean sq.	F value	Pr(>F)
Ind	3	7841.7	3280.57	8.7179	.000177
Residuals	36	9417.4	261.59		

Signif. codes: 0 ∗ ∗ ∗ 0.001 ∗ ∗0.01 ∗ 0.05.0.11

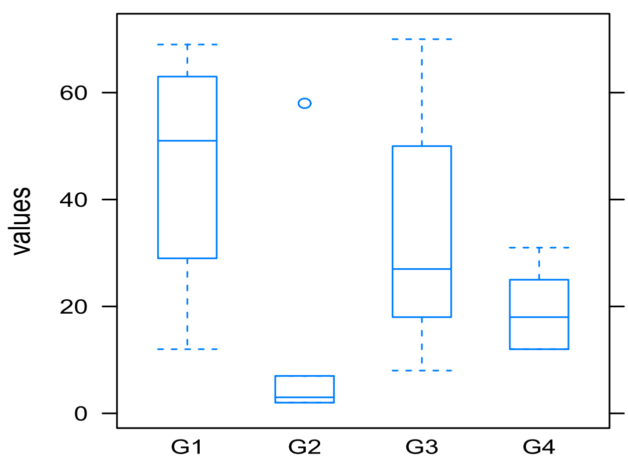

Figure 12. Visualization comparison of different groups with respect to positive score of four groups G1–G4 using Box plots.

has been observed that F value is 2.87. Our F value is 7.5446 for positive score and 8.7179 for negative score of four groups, which is more than 2.87. This means our ANOVA test proves significance. Most standard significance tests use 0.1 or 0.05 as a value to shoot for. Our p-value is 0.0004856 for positive score and 0.0001766 for negative score of four groups. Hence, our p-values come under this value. Hence, we definitely found proof of variance. Now, comparison of different groups can be visualized using Box plots (figures 12 and 13).

To confirm our one-way Anova, we have done one more test, i.e., homogeneity of variance (Brown Forsyth) test. The p-value here is 0.13 and 0.24 for positive and negative score of four groups, respectively, which is above normal significance levels of 0.10 and 0.05 (tables 8 and 9). Hence, this means there is no reason to disclaim our F-test.

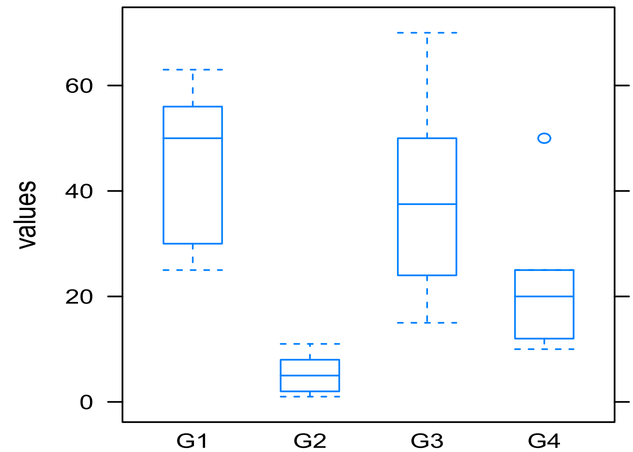

Figure 13. Visualization comparison of different groups with respect to negative score of four groups G1–G4 using Box plots.

Table 8. Homogeneity of variance test using Brown Forsyth test for positive score.

data:	values		
$F = 2.0004$	df:ind = 3	$df: Residuals = 36$	p-value = 0.1313

Alternative hypothesis: variances are not identical.

Table 9. Homogeneity of variance test using Brown Forsyth test for negative score.

Data:	Values		
$F = 3.5118$	df:ind = 3	$df: Residuals = 36$	p-value = 0.2481

Alternative hypothesis: variances are not identical.

Table 10. Accuracy testing of our method.

	Naïve Bayes	SVM
Specificity	0.3578947	0.4031
Pos. pred. value	0.7002457	0.353
Neg. pred. value	0.7391304	0.2514
Precision	0.7002457	0.7684
Recall	0.9223301	0.98647
$F1$	0.7960894	0.813
Balanced accuracy	0.6401124	0.70654
Prediction accuracy	0.7074148	0.78756

4.3 *Evaluation of sentiment detection method*

Here sentiment classification effectiveness has been measured in two ways.

4.3a *Calculating precision and recall score*:
Now the sentiment of people of eight cities has been analysed over the span of two months using lexicon and machine learning approaches. Naïve-Bayes and SVM

Table 11. Correlation matrix of city score of tweets from 08/11/2016 to 14/12/2016.

Ahmedabad	Bengaluru	Chennai	Delhi	Hyderabad	Kolkata	Mumbai	Pune
Ahmedabad	1						
Bengaluru	–0.208	1					
Chennai	–0.0016	0.7589	1				
Delhi	0.0986	0.1746	0.129	1			
Hyderabad	–0.27	0.1473	0.3771	–0.3176	1		
Kolkata	–0.2322	0.1862	0.3168	0.0556	0.4892	1	
Mumbai	–0.1797	0.6378	0.4878	–0.1393	0.4309	0.1585	1
Pune	0.0673	–0.7585	–0.8662	–0.0127	–0.6136	–0.3617	–0.5577

classifiers are used on the data and accuracy of the method is tested. The classification performance is evaluated in terms of three measures: precision (P), recall (R) and F-measure based on the numbers of true positives (TPs), false positives (FPs) and false negatives (FNs). Precision can be defined as TP/(TP + FP), recall = TP/(TP + FN) and F-measure or balanced F-score = 2(precision × recall)/(precision + recall). Results are shown in table 10. The prediction accuracy of a classification model is 70% for Naïve Bayes and 79% for SVM.

4.3b *Calculating citywide correlation matrix*:
After calculating city-wise total score per day from 08/11/2016 to 14/12/2016, a co-relation coefficient matrix among the scores of eight cities has been calculated (table 11), which indicates how accurate the sentiment classification is, and it shows to what degree the fluctuation patterns of a sentiment are predicted by the model.

5. Conclusion

In this paper, we have tried to implement a dictionary-based methodology of sentiment analysis and analysed large amount of data to estimate the tweet sentiment of the public in the aftermath of the recent 'demonetization' drive of the central government. We employed document level analysis based on our own approach, which helped infer opinion and sentiment of people of different cities over a five-week period. It is readily observed that while the sentiments vary across cities over time or across interest groups, the impact dies down during the latter part of the period under consideration. While the academia and print media reported concern about the adverse impact on GDP and growth rate, bias against the poor, informal sector and agriculture, the tweets of the different groups do not conform to this view, and the relevant words are seldom shown up in the tweets. The concern of the ruling political group also does not conform to the primary agenda as described in the Gazette Notification. This method is applicable to other areas also, e.g., socio-political events, customer review for public utility services, such as airlines or railways, etc., which immediately raise public sentiments.

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