SENTIMENT ANALYSIS OF DEMONETIZATION OF BANKNOTES BY INDIAN GOVERNMENT (1944 WORDS)

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1. Introduction

The Bharatiya Janata Party (BJP) focused heavily on rampant corruption in the government machinery during its campaign for the 2014 Indian General Elections, promising the Indian public that if the party was elected, it would solve the problem of black money, which is at the root of many of India's problems. Since the BJP's resounding victory, they were chastised by both opposition parties and the public for doing nothing to combat black money. On November 8, 2016, at 8:15 p.m. Indian Standard Time, Prime Minister of India Narendra Modi made a historic speech on television, announcing that larger denominations (i.e., 500- and 1000-rupee notes) of currency would be demonetized to combat the problem of black money. It was a significant step in realizing the dream of a digitalization and making India a cashless economy, in addition to curbing black money. The purpose of [1] was to use the notion of sentiment analysis to examine the impact of the Indian government's demonetization policy. Their findings suggest that a sizable portion of the Indian population approves of the policy. During the early days, public opinion was more negative, as the common man had to endure several hardships. Eventually, as the new banknotes were accessible, people's attitudes changed for the better. The data in [2] reveals that most people are in favor of the move, however there are others who are against it. The LDA (Latent Dirichlet Allocation) model discovered the most relevant subjects automatically in [3]. Further clustering is carried out to portray a clear picture of citizens' and notably public leaders' reactions to this decision.

2. Research Question

How did citizens of India feel about the demonetization of 500 and 1000 rupee note by the Indian government? Which topics are prominent in these discussion threads?

3. Method

a) Data:

To address the above-mentioned research questions data was collected from Twitter. It was gathered using the snscrape package available in python. The search keywords used were hashtags like demonetization and black money.

A total of 2000 tweets were collected in two phases. Phase 1 included initial 4 weeks after demonetization i.e., from November 9, 2016, to December 9, 2016. Phase 2 included dates from December 10, 2016, to January 10, 2017. 1000 tweets under phase 1 and 1000 tweets under phase 2 were collected. The reason for this 2-phase separation is to understand the feelings during initial change and feelings after substantial time. The following things were collected: date, content, and user.

Tweets were collected from 8 different metro cities in India namely New Delhi, Mumbai, Kolkata, Chennai, Hyderabad, Ahmedabad, Pune, and Lucknow. For each city a perimeter of 15 kms is fixed from where the tweets are extracted using geo tags. Also, for each city 50 tweets are collected for the keyword ‘Demonetization’ and 50 tweets are collected for the keyword ‘Black Money’. In this way for each city there are 100 tweets and thus for each phase there are 1000 tweets. Tweets with language 'en' i.e., English are extracted.

Duplicate tweets and retweets are removed from each phase. After deletion of duplicates, 961tweets were left in Phase 1 and 921 tweets were left in Phase 2. To perform seamless analysis, tweets are cleaned by removing punctuations, any links, usernames tagged, hashtags without the words that follow the hashtags.

b) Analysis:

First step involved in analysis is the sentiment analysis of the cleaned tweets. It is important to perform sentiment analysis on the cleaned data since unnecessary noise will give a wrong indication of the sentiment score. To avoid that, tweets are cleaned by removing username, hashtags and links as discussed above in the data section. The Python module Valence Aware Dictionary and Sentiment Reasoner (VADER) is utilized to calculate the sentiment score. VADER returns 4 values: positive sentiment percentage, negative sentiment percentage, neutral sentiment percentage and a compound score which is a normalized value of those sentiment percentages. Further, the final sentiment label is decided based on the compound score. If the compound score is greater than 0.05 then the tweet is labelled as positive, if the compound score is less than -0.05 then the tweet is labelled as negative, otherwise the tweet is labelled as neutral if it is between 0.05 and -0.05. The goal of sentiment analysis in this use case is to understand what people feel about the decision made by the government. Additionally, sentiments are also checked for 10 top metro cities in India using the geo location tag of the tweet. Given its diversity, India should ideally not be evaluated as a single entity; this is where geolocation becomes important. It was observed that VADER is not perfect in classifying the tweets into their sentiments as there are a lot of things that needs to be considered while doing sentiment analysis. Mainly, the domain of the concerned topic, local language used by paraphrasing it as English, confusing words, misspelled words, etc. lead to an incorrect classification. Below, Table 2 shows few examples of false classification done by VADER.

Positive Sentiment	**Negative Sentiment**	**Neutral Sentiment**
High success of rally in Luckno w will definitely shut the mouth of demonetization opponents.	What did we achieve by Demo netization 150 Deaths Huge In convenience to common peopl e Economic Slowdown Lakhs of people lost their Job?	After Demonetization how much of your transactions are cashless.
Demonetization drive is like a purification campaign PM Modi .	Nothing like telling it as it is from ground zero demonetizati on to politics no holds barred.	Go to Assam tea garden and ask labors that before Demonetization when was the last time, they got full salary on time.

Table 1. Examples of positive, negative and neutral tweets from the dataset collected

False-Positive Sentiment	False-Negative Sentiment	False-Neutral Sentiment
Why there is no raid or discover y of black money after Dec 31st Pl Share progress with citizens Demonetization was against bla ck money. (Should be negative)	The demonetization though caus ed considerable public inconveni ence has yet marked impact on t he future of the country (Should be positive)	Not a word over 100 deaths due to demonetization. (Should be negative)
Modi ji is trigger happy just now as the common man is reeling under the demonetizatio n it's not good on the part of co untry's PM. (Should be negative)	Govt sources: Demonetization cr ippling blow to Terror FCN racket insurgents Black money h oarding. (Should be positive)	Petrol pumps won't accept plast ic demonetization has become a joke. (Should be negative)

Table 2. Examples of false positive, false negative and false neutral tweets from the dataset collected

Second step involves topic modelling using Latent Dirichlet Allocation (LDA). In this work, Topic Modeling (LDA) is done with Gensim python module. The problem is determining how to extract high-quality topics that are distinct, and significant. This is very dependent on the text preparation quality and the approach for determining the ideal number of topics. Since LDA is an unsupervised technique, we need to come up with an ideal number of topics to fit our data. Steps performed to achieve topic modeling using LDA:

1) **Preprocessing**: While doing the text preprocessing, the first step is to remove stop words because they don't contribute towards topic modelling. The next step is to tokenize the sentences into an array of words. While doing so punctuations and unnecessary characters are removed. Further, Bigram and Trigram models are built to get more information from the frequently occurring words together. Lemmatization is also performed to get the root of the individual words in the sentences.
2) **Modeling**: The dictionary(id2word) and the corpus are the two basic inputs to the LDA topic model. Dictionary consists of all the unique words in the documents and corpus gives the frequency of each word in the document. The number of topics will be a random guess at the start or an intuition from the data available. Initially, the above LDA model is made up of 10 separate topics, each of which is made up of several keywords, each of which gives a specific amount of weight to the subject. Once the model is implemented on the data, we get keywords for each topic and weightage of each keyword.
3) **Optimization:** Finding the optimal number of topics in this study entails creating several LDA models with varying numbers of topics (k) and selecting the one with the highest coherence value. Choosing a 'k' that denotes the end of a rapid increase in topic coherence frequently yields themes that are meaningful and comprehensible. The LDA model is run on a loop with the initial topic number as 2, step size of 3 and an upper limit of 40 topics. In figure 1 and figure 2 you can see the coherence scores for the different topic numbers in Phase1 and Phase 2 respectively. For Phase 1, the optimal coherence score comes around topic number 11 as you can see, similarly for Phase 2, the optimal coherence score comes around topic number 11.

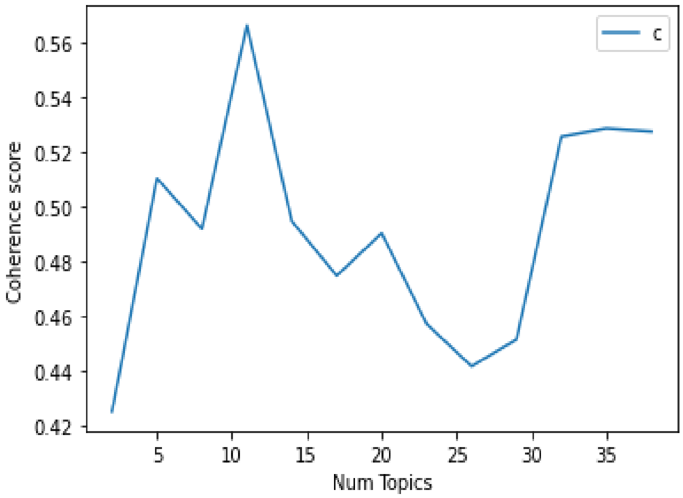

Fig 1. Coherence Scores for Topics in Phase 1

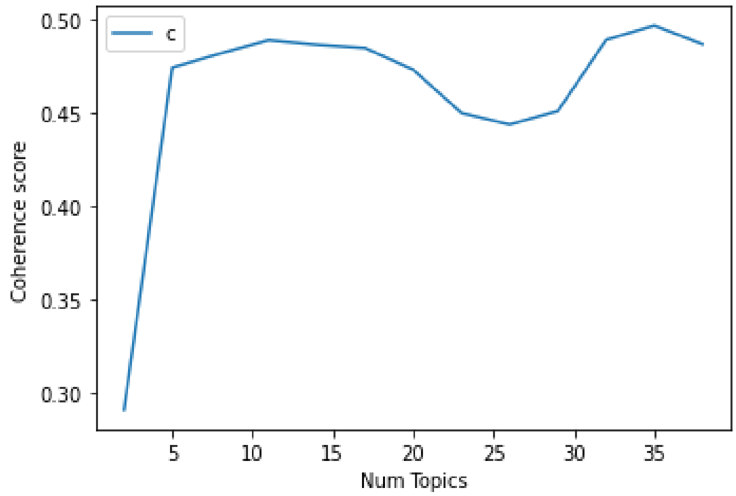

Fig 2. Coherence Scores for Topics in Phase 2

4. Result

Coming to the results, let's focus first on the sentiment analysis scores from both the phases. In the first phase out of the 961tweets, 358 tweets were positive, 352 tweets were negative, and 251 tweets were Neutral. The distribution can be seen in the figure 3 below. In the second phase out of the 926 tweets, 332 tweets were positive, 325 tweets were negative, and 269 tweets were Neutral. The distribution can be seen in the figure 4 below. From the above results we can say that in both the phases the number of positive and negative tweets were relatively similar to each other. In the both the phases positive tweets slightly edged more in number but the difference between positive and negative tweets is not that significant. In both the phases, neutral tweets count to a significant amount of the total tweets but relatively in comparison with the positive and negative tweets they are lesser in number.

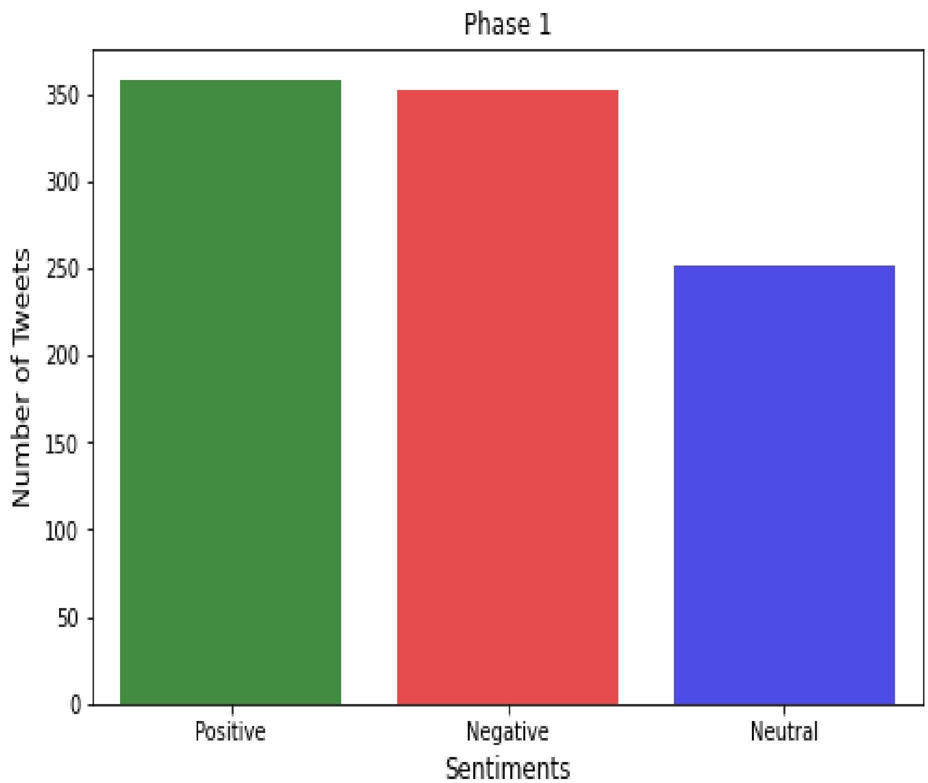

Fig 3. Sentiment Distribution for Phase 1

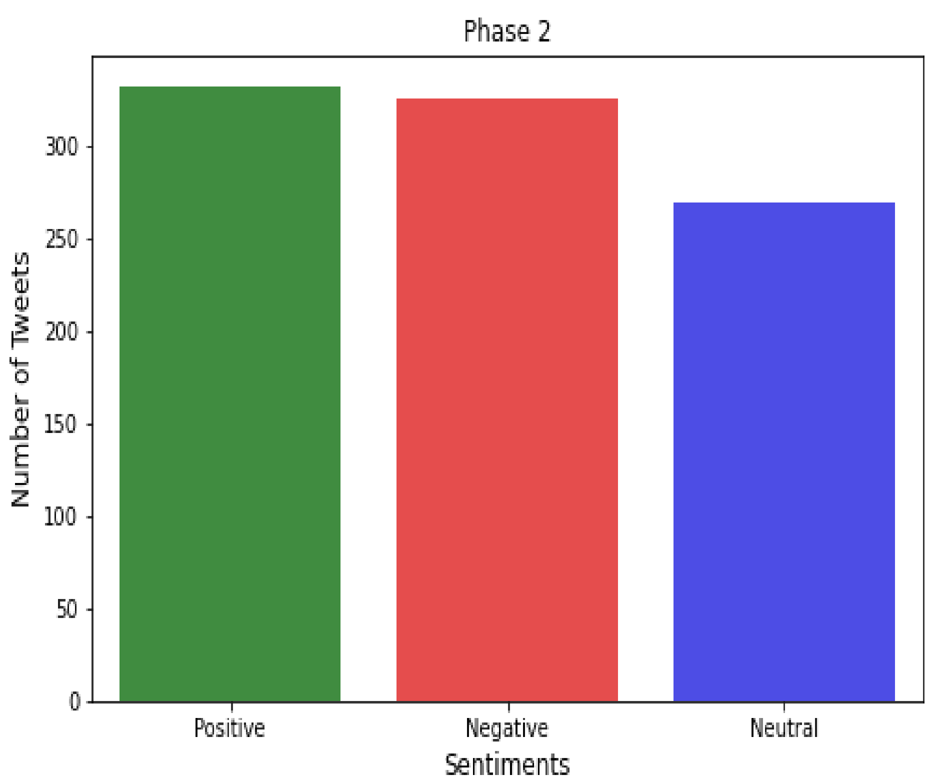

Fig 4. Sentiment Distribution for Phase 2

Further, sentiment analysis is looked at a granular level by considering the top 10 metro cities in India (Table 3). From the Table 3 following assumptions can be made: 1) During Phase 1 and Phase 2, Jaipur had the highest percentage of positive sentiments and Lucknow had the highest percentage of negative sentiments. 2) Lucknow had more percentage of negative sentiments in both the phases but during the phase 2 there was a slight increase in the positive sentiments. 3) In Pune and Hyderabad, from phase 1 to phase 2 there was an increase in the negative sentiments and decrease in the positive sentiments. 4) In Mumbai, Ahmedabad, and Chennai, from phase 1 to phase 2 there was an increase in the neutral sentiments and decrease in the positive sentiments. 5) In New Delhi and Bangalore, from phase 1 to phase 2 there was an increase in the positive sentiments and decrease in the negative sentiments.

Cities	**Positive Sentiment %**	**Negative Sentiment %**	**Neutral Sentiment %**
Ahmedabad			
Phase 1	39.6	38.5	21.9
Phase 2	37.2	38.3	24.5
Chennai			
Phase 1	39.1	34.8	26.1
Phase 2	30.5	35.8	33.7
Hyderabad			
Phase 1	38.3	24.5	37.2
Phase 2	32.0	32.0	36.0
Kolkata			
Phase 1	36.0	39.0	25.0
Phase 2	37.8	33.7	28.6
Lucknow			
Phase 1	30.0	45.6	24.4
Phase 2	38.8	42.9	33.0
Mumbai			
Phase 1	42.0	34.0	24.0
Phase 2	33.0	34.0	33.0
New Delhi			
Phase 1	36.0	42.0	22.0
Phase 2	40.8	29.6	29.6
Pune			
Phase 1	42.7	34.4	22.9
Phase 2	31.2	42.7	26.0
Bangalore			
Phase 1	24.0	40.6	35.4
Phase 2	35.7	34.7	29.6
Jaipur			
Phase 1	45.3	32.6	37.2
Phase 2	46.8	21.3	31.9

Table 3. Sentiment Distribution across top 10 metro cities in India in the two phases

Topic modeling gave some interesting results in both the phases. In both the phases 11 topics each were extracted by the LDA algorithm but some of them were overlapping so thus for simplification top 3 topics are displayed in the Table 4 and 5 respectively below. The top three topics are selected based on their occurrence in the tweets. The top 3 topics in Phase 1 focus on the move of demonetization, PM's speech, it's effect on the black money, the hardships Indian citizens had to go through to exchange notes and questions on the decision. The maximum number of tweets in Phase 1 were focused on the PM's speech and opinions about the advantage/disadvantage of the move. The top 3 topics in Phase 2 focus on the fight against black money, supporting the decision, hardships faced by the poor, government opposition, achieving the goal of demonetization by getting rid of black money.

Topic no.	Keywords	Repeated in no. of tweets	Inferring the topic from keywords
1	money, black, demonetization, blackmoney, demonetisation, people, india, pm, bank	602	Topic 1 is related to Prime Minister Modi's New Year's address, which included a real agenda of demonetization in India. How much black money was found, and what did the country gain as a result of the demonetization?
2	know, demonetization, would, move, time, loss, real, daily, fact, false	49	Topic 2 tries to address how demonetization in India effected people since they had to stand in long lines outside banks to get their money exchanged.
3	govt, note, opposition, see, suffer, well, demo netization, never, great, create	49	Topic 3 hints that PM Modi diverted from the genuine aim of black money and demonetization. The government faced opposition.

Table 4. Top 3 topics from phase 1 according to the LDA algorithm

Topic no.	Keywords	Repeated in no. of tweets	Inferring the topic from keywords
1	black, money, blackmoney, pm, corruption, g ovt, demonetisation, tax, fight, political	179	Topic 1 talks about fight against black money and corruption and indicates that the decision made by the PM was widely supported later in phase 2.
2	demonetization, go, people, cash, india, poor, would, digital, stop, oppose, government	150	Topic 2 tries to talk about how the decision affected the poor and draws government opposition.
3	get, money, black, note, way, day, demonetiza tion, see, rid	108	Topic 3 hints about getting rid of the black money and working towards the real goal of demonetization.

Table 5. Top 3 topics from phase 2 according to the LDA algorithm

5. Conclusion and Limitation

From the above analysis and results there are 3 takeaways for the given experimental dataset. The difference between positive and negative sentiments is negligible in both the phases. There are interesting insights for the sentiments at the city level, certain cities see a dip in the positive and increase in the negative sentiments from phase 1 to phase 2 whereas some cities see an increase in the positive and decrease in the negative sentiments. Topic modeling gives some interesting insights in both the phases. Phase 1 topics were more centered towards criticizing the decision as people had to go through hardships to adjust. Phase 2 topics talk more about the fight against corruption and support the decision.

Although this research gives us insight into the kind of characteristics that may give user feelings on social media for demonetization, there are a few limitations that suggest areas for further research. One of the most significant of these limits is the scale. This research examines 2000 tweets from. As a result, more study is needed in which the scope is broadened and possibilities to study more tweets exists. The future work could extend on analyzing more tweets from different geo locations so that the conclusions drawn can be backed by a good amount of data. Also, more work can be done to improve the sentiment analysis model, since the current model gives some false positives and false negatives.

This research comes up with a customized scheme for determining the topics across tweets. Hyperparameters in the LDA topic model can be changed to obtain better results. More work can be done to understand the various tags/topic across the tweets and derive meaningful insights.

6. References

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