

# Analyzing Sentiments about Political Parties in Punjab Election 2017 using Twitter Data

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*Abstract*— Nowadays, most of the people generally used to give their opinions or their views on social sites like facebook, twitter, etc. Out of these, Twitter is mostly used social site which is practical for analyzing the sentiments about any query term. In this research work, the query is about *Punjab elections 2017* regarding which we have taken a corpus of tweets about the query mentioned. Corpus are used by two or three annotators for the annotation process to determine its polarity about the three major parties in *Punjab elections, 2017* i.e. Aam Aadmi Party (AAP), Congress party and SAD-BJP party. The positive or negative sentiments of tweets show that people either are in favor of the party or against it, if neither it is positive nor negative then it is considered as a neutral. After annotation, there are four classifiers we used i.e Lexicon approach, Naïve Bayes, Naïve Bayes with Binary features and Extension of Naïve Bayes using lexicon which define the positive, negative and neutral sentiments. After this, standard measure of evaluation (precision, recall, and f score) are used to find the accuracy of every approach.

*Index Terms*—Twitter, Sentiment Classification, Lexicon approach, Naïve Bayes approach .

## I. INTRODUCTION

Sentiment analysis is also known as opinion mining. It is a process which determines that the piece of text is positive, negative or neutral. It is an important type of text analysis which can be handled as a Natural Language Processing task[1]. Basically, semantic analysis is a particular study which helps to observe individuals experience on various things like either it can be on some products, services and events also. Sentiments and opinions are the most important part of all human activities because these are the key influencers of their behavior. Generally, it totally depends upon the view of the customer like what a speaker thinks about the product and the way he or she gives their opinion is came under sentiment analysis.

### *Sentiment Classification*

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The catalogue of sentiment is part of NLP which defines the process of changing subjective text into positive or negative thought[2].

To classify a sentiment, there are many different levels:

**1. Word / phrase level:** This is the most common level in the sentiment classification which express the polarity of the word or phrase.

**2. Sentence level:** At this level, each and every sentence is taken as a separate sentence and can be explained by their polarity. This analysis of sentence level is related to subjectivity classification. Subjectivity classification is classified into objective sentences and subjective sentences.

**3. Document level:** In the document level, analysis classification is done on the bases of the whole document. At this point, the sentiment of the opinion holder is taken as overall sentiment analysis. The main task is to find the whole sentiment orientation of the document which depends on classes and it can be positive or negative or neutral.

**4. Entity level:** It is also called feature level. Its main task is to produce a feature-based opinion summary of multiple reviews.

### *Twitter sentiment classification*

With the rapid development of the Internet, a famous micro blog service i.e, Twitter is used all over the world. Tweets are divided in positive, negative or neutral with respect to a particular domain. A person go through from tweets before buying any product for his or her satisfaction. Twitter helps them to find the various sentiment of the product. Twitter The difference between tweets and reviews are simply defined as that reviews could be the summary of any product and on the flip side tweets are categorised or encapsulate into criteria of short and simple and its of 140 character

Merits of a tweet in twitter:

**1. Length:** The length of tweet is like a newspaper headline and the maximum length of tweet is 140 character.

**2. Availability of data:** For training purpose, with the help of Twitter API it is much more easier to collect the data

**3. Domain:** Tweets in a twitter can be about a variety of topics.

Initially, tweets are very noisy. Noisy in the sense, it contains URLs, emotions, retweet tags (RT @user), hastags

(#), numeric words etc. Another step after extracting the tweets is to normalize the tweets by removing the stop words, twitter source handler, URLs, hashtags, punctuation marks, numeric words etc. After the normalization process, tweets are known as normalized tweets

The focus of present research is to determine the polarity of the views (opinions) given by different users about the Punjab election 2017 on different aspects such as, liking or disliking for three major political parties of Punjab. Punjab election 2017 this time is going to be hard fought elections with expectedly three cornered fight. As the micro blogging platforms such as, Twitter are being increasingly used by various people to express their views about these elections, it would be interesting to observe the sentiments of people about the political parties and elections in general during different period of time during the process.

From the Twitter API tweet messages will be collected for training and then with respect to a query term these tweets are categorised as positive, negative or neutral lexicons. For the classification machine learning methods will be used and all approaches will be evaluated using standard measures of evaluation (Precision, Recall & F-measure). The comparative analysis of the lexicon and learning approaches will be carried out to determine their utility for this kind of classification.

## II. TRAINING DATA SET

For our task, the data is collected from the twitter. The data set include the tweeter messages about a query term which is Punjab Election 2017 here.. For the training, it can be collected from the Tweeter API by using different keywords related to the punjab elctions. Tweets have been extracted from 1<sup>st</sup> july 2016 to 11<sup>th</sup> march 2017. There are 1500 tweets which have been used in this dataset. According to our domain which is Punjab election, we observe the tweets and try to find the opinions of positive and negative sentiments of three major political parties

After the extraction of tweets, another task is to remove the noisy words. Some of the noisy words are:

**1. Username:** Users on twitter can tweet by using their unique username and for this there are some requirements like @ symbol is used before the username to refer another user (e.g.@divyajaju).

**2. Emoticons:** There are various emoticons or punctuations like ?, (, ), ;, : etc. are used to express the feeling in a sentence.

**3. Hashtags:** The # symbol is used to index the topic or keywords. E.g., #demonetization, #elections, etc.

**4. Links:** Sometimes user give the links in their tweets to provide whole information about something

Example of original tweet:

"MubsKhan1: RT @KapilFans: @KapilSharmaK9 has something to say on Punjab Election\n\nPlease, choose your leader wisely :) <https://t.co/dIDAAByzYp>"

Example of normalized tweet:

*Choose your leader wisely*

### Annotated data classification

After removing the noisy words, tweets are classify according to their category by the annotators. Human annotators may two or more who worked on 1500 sentences. The sentences are annotated in four categories for sentiment classification such aspositive and negative sentiment of three major political parties (AAP, CONGRESS, BJP) and NEUTRAL. There are some guidelines used by the annotators to get the consistent annotation.

#### Guidelines of Annotation Process

**1. Dealing with suggestion:** Sometimes sentences are comes under the suggestion which can be either positive or negative. In this case we consider these as neutral because they are not expressing the opinion holder's sentiment. For example,

"Choose your leader wisely" (this is a suggestion, but not a direct sentiment of person)

"Please friends go and vote this time" (this is a suggestion, but not a direct sentiment of person)

**2. Dealing with Expectations:** Sometimes sentences are comes under the suggestion or hope which can be either positive or negative. In this case we consider these as neutral because they are not expressing the opinion holder's sentiment. For example,

"I hope AAP will win this time" (this is a expectation or hope, but not a direct sentiment of person)

**3. Reporting of facts/actions/Information:** Sometimes sentences are comes under the information/action/fact which can be either positive or negative. In this case we consider these as neutral because they are not expressing the opinion holder's sentiment. For example,

"Date of election in Punjab is 4 feb" (this is information, but not a direct sentiment of person)

"Election Parties has announced their manifesto" (this is an action which is takes by parties, but not a direct sentiment of person)

In this research work, there are two annotators who worked for annotation. Following table shows the inter annotator agreement between two annotators A and B. Initially, the annotation of two annotators is 86.2% which was without discussion. The final agreement is grow up to 94% after the discussion.

Table I. The agreement between two annotators

| Comparison               | Total number of Tweets | Total agreement between |             |             |
|--------------------------|------------------------|-------------------------|-------------|-------------|
|                          |                        | A and B                 | Final and A | Final and B |
|                          |                        | 1293                    | 1422        | 1428        |
| Sentiment classification | 1500                   | 86.2%                   | 94.8%       | 95.2%       |

### Sentiment classifier tools

Java language is used to implement the sentiment classifiers. I have implemented four different approaches in this project that are :

#### 1. Sentiment Lexicon Baseline

Positive and negative tokens in a test data are describe by sentiment lexicon approach, and then the class with most token is given as an output [3]. When the number of positive tokens and negative tokens are same, then the neutral class is selected as an output. This approach always ignore the training data.

#### 2. Naive Bayes

It is also known as Multinomial Naïve Bayes Classifier. This probabilistic model is based on Bayes rule having a strong independence assumption. This assumption underscore that the words are conditionally independent of each other, given a class. It makes classification algorithm really fast without affecting much the accuracy in classification [4].

#### 3. Naive Bayes with Binary Features

Another approach we applied is Multinomial Naive Bayes with binary features. In this model, the frequency of a given word in a given document is either 0 (if the word does not occur in the document) or 1 (if the word occurs 1 or more times in the document). Repeation of a words are neglected in this approach.

#### 4. Extension of Naive Bayes with Usage of Lexicons

We can create two types of Lexicons using sentiment analysis, i.e. Negative Lexicon list and other one is Positive Lexicon list. Negative Lexicon list contains list of words with negative meaning and Positive Lexicon list contains list of words with positive meaning. The way of using lexicons in classifier is to use the occurrences of positive and negative words in lexicon. It will lead to more generalized results.

### III. EVALUATION AND RESULTS

**Precision:** To explore the purity or accuracy of a classifier Precision measures are used. When less false positives are available then it means Higher Precision, on the flip side when more false positives are available then it means Lower Precision. The formula for calculating the precision is

$$P = tp/(tp+fp)$$

Where P denotes Precision, tp denotes true positive and fp denotes false positive.

**Recall:** To explore the completeness or sensitivity of a classifier Precision measures are used. When less false negatives are available then it means Higher Recall, on the flip side when more false negatives are available then it means Lower Recall. The formula for calculating the recall is

$$R = tp/(tp+fn)$$

Where P denotes Precision, tp denotes true positive and fp denotes false negative.

**F-score:** F-score is also famous with the another name which is f-measure, which is the weighted harmonic mean of precision and recall. The formula for calculating the f-score is

$$F\text{-measure} = 2*(precision*recall)/(precision+recall)$$

### IV. EXPERIMENTATION AND RESULTS

In this research work, we calculated the precision, recall and f score of every approach.

#### A. Lexicon approach

By looking at the results in the table II, it is observed that accuracy of lexicon baseline approach is 55% and also the classification based on this model gives a Precision of every party for “Positive, Negative and Neutral” class. Moreover, table III shows Recall of every party for “Positive, Negative and Neutral” class and table IV shows the F-score as well.

#### B. Naïve Bayes approach

The another approach we implemented is Naïve Bayes approach which gives the better results than the Lexicon approach. Table V shows the accuracy of Naïve Bayes approach which is 84.1% and also the classification based on this model gives a Precision of every party for “Positive, Negative and Neutral” class. Moreover, table VI shows Recall of every party for “Positive, Negative and Neutral” class and table VII shows the F-score as well.

#### C. Naïve Bayes with binary features approach

For more improvements we implemented another approach which is Multinomial Naive Bayes with binary features approach.

Table VIII shows the accuracy of Naïve Bayes approach which is 84.4% and also the classification based on this model gives a Precision of every party for “Positive, Negative and Neutral” class. Moreover, table IX shows Recall of every party for “Positive, Negative and Neutral” class and table X shows the F-score as well. The results of this approach are almost same as the Naïve Bayes.

#### D. Extension of Naïve Bayes using lexicons

Table XI shows the accuracy of Naïve Bayes approach which is 64% and also the classification based on this model gives a Precision of every party for “Positive, Negative and Neutral” class. Moreover, table XI shows Recall of every party for “Positive, Negative and Neutral” class and table XII shows the F-score as well.

From all above mentioned approaches , Naïve Byaes with Binary Feature approach is best because it gives a better results than all other.

Table II. Precision of lexicon approach

| MODEL                      | ACCURACY | Precision |          |          |          |          |          |         |
|----------------------------|----------|-----------|----------|----------|----------|----------|----------|---------|
|                            |          | AAP       |          | SAD-BJP  |          | CONGRESS |          | NEUTRAL |
|                            |          | Positive  | Negative | Positive | Negative | Positive | Negative |         |
| Sentiment Baseline Lexicon | 55%      | 1.0       | 1.0      | 1.0      | 1.0      | 1.0      | 1.0      | 0.31    |

Table III. Recall of lexicon approach

| MODEL                      | ACCURACY | RECALL   |          |          |          |          |          |         |
|----------------------------|----------|----------|----------|----------|----------|----------|----------|---------|
|                            |          | AAP      |          | SAD-BJP  |          | CONGRESS |          | NEUTRAL |
|                            |          | Positive | Negative | Positive | Negative | Positive | Negative |         |
| Sentiment Baseline Lexicon | 55%      | 0.81     | 0.40     | 0.11     | 0.69     | 0.16     | 0.13     | 1.0     |

Table IV. F score of lexicon approach

| MODEL                      | ACCURACY | F-SCORE  |          |          |          |          |          |         |
|----------------------------|----------|----------|----------|----------|----------|----------|----------|---------|
|                            |          | AAP      |          | SAD-BJP  |          | CONGRESS |          | NEUTRAL |
|                            |          | Positive | Negative | Positive | Negative | Positive | Negative |         |
| Sentiment Baseline Lexicon | 55%      | 0.89     | 0.57     | 0.20     | 0.12     | 0.28     | 0.23     | 0.47    |

Table V. Precision of Naïve Bayes approach

| MODEL       | ACCURACY | Precision |          |          |          |          |          |         |
|-------------|----------|-----------|----------|----------|----------|----------|----------|---------|
|             |          | AAP       |          | SAD-BJP  |          | CONGRESS |          | NEUTRAL |
|             |          | Positive  | Negative | Positive | Negative | Positive | Negative |         |
| Naïve Bayes | 84.1%    | 0.71      | 1.0      | 1.0      | 1.0      | 1.0      | 1.0      | 1.0     |

Table VI. Recall of Naïve Bayes approach

| MODEL       | ACCURACY | RECALL   |          |          |          |          |          |         |
|-------------|----------|----------|----------|----------|----------|----------|----------|---------|
|             |          | AAP      |          | SAD-BJP  |          | CONGRESS |          | NEUTRAL |
|             |          | Positive | Negative | Positive | Negative | Positive | Negative |         |
| Naïve Bayes | 84.1%    | 1.0      | 0.894    | 0.925    | 0.524    | 0.875    | 0.066    | 0.872   |

Table VII. F score of Naïve Bayes approach

| MODEL       | ACCURACY | F-SCORE  |          |          |          |          |          |         |
|-------------|----------|----------|----------|----------|----------|----------|----------|---------|
|             |          | AAP      |          | SAD-BJP  |          | CONGRESS |          | NEUTRAL |
|             |          | Positive | Negative | Positive | Negative | Positive | Negative |         |
| Naïve Bayes | 84.1%    | 0.835    | 0.944    | 0.961    | 0.668    | 0.933    | 0.125    | 0.931   |

Table VIII. Precision of Naïve Bayes with Binary Features

| MODEL | ACCURACY | Precision |          |          |          |          |          |         |
|-------|----------|-----------|----------|----------|----------|----------|----------|---------|
|       |          | AAP       |          | SAD-BJP  |          | CONGRESS |          | NEUTRAL |
|       |          | Positive  | Negative | Positive | Negative | Positive | Negative |         |
| Naïve |          |           |          |          |          |          |          |         |

|                   |       |       |     |     |     |     |     |     |
|-------------------|-------|-------|-----|-----|-----|-----|-----|-----|
| Bayes with Binary | 84.4% | 0.722 | 1.0 | 1.0 | 1.0 | 1.0 | 1.0 | 1.0 |
|-------------------|-------|-------|-----|-----|-----|-----|-----|-----|

Table IX. Recall of Naïve Bayes with Binary Features

| MODEL                   | ACCURACY | RECALL   |          |          |          |          |          |         |
|-------------------------|----------|----------|----------|----------|----------|----------|----------|---------|
|                         |          | AAP      |          | Bjp      |          | CONGRESS |          | NEUTRAL |
|                         |          | Positive | Negative | Positive | Negative | Positive | Negative |         |
| Naïve Bayes with Binary | 84.4%    | 1.0      | 0.894    | 0.919    | 0.524    | 0.889    | 0.033    | 0.885   |

Table X. F score of Naïve Bayes with Binary Features

| MODEL                   | ACCURACY | F-SCORE  |          |          |          |          |          |         |
|-------------------------|----------|----------|----------|----------|----------|----------|----------|---------|
|                         |          | AAP      |          | Bjp      |          | CONGRESS |          | NEUTRAL |
|                         |          | Positive | Negative | Positive | Negative | Positive | Negative |         |
| Naïve Bayes with Binary | 84.1%    | 0.839    | 0.944    | 0.958    | 0.688    | 0.941    | 0.064    | 0.939   |

Table XI. Precision of Extension of Naïve Bayes with Binary usage of Lexicons

| MODEL   | ACCURACY | Precision |          |          |          |          |          |         |
|---|----------|-----------|----------|----------|----------|----------|----------|---------|
|   |          | AAP       |          | SAD-BJP  |          | CONGRESS |          | NEUTRAL |
|   |          | Positive  | Negative | Positive | Negative | Positive | Negative |         |
| Extension of Naïve Bayes with Usage of Lexicons | 64.1%    | 0.584     | 1.0      | 1.0      | 1.0      | 1.0      | 1.0      | 0.585   |

Table XII. Recall of Extension of Naïve Bayes with Binary usage of Lexicons

| MODEL   | ACCURACY | RECALL   |          |          |          |          |          |         |
|---|----------|----------|----------|----------|----------|----------|----------|---------|
|   |          | AAP      |          | SAD-BJP  |          | CONGRESS |          | NEUTRAL |
|   |          | Positive | Negative | Positive | Negative | Positive | Negative |         |
| Extension of Naïve Bayes with Usage of Lexicons | 64.1%    | 1.0      | 0.456    | 0.229    | 0.079    | 0.245    | 0.033    | 0.1     |

Table XIII. F score of Extension of Naïve Bayes with Binary usage of Lexicons

| MODEL   | ACCURACY | F-SCORE  |          |          |          |          |          |         |
|---|----------|----------|----------|----------|----------|----------|----------|---------|
|   |          | AAP      |          | SAD-BJP  |          | CONGRESS |          | NEUTRAL |
|   |          | Positive | Negative | Positive | Negative | Positive | Negative |         |
| Extension of Naïve Bayes with Usage of Lexicons | 64.1%    | 0.737    | 0.626    | 0.373    | 0.146    | 0.393    | 0.235    | 0.738   |

## V. FUTURE SCOPE

There are plethora of advantages of using sentiment analysis like people share their different views on different domains or different projects. By sentiment analysis one can easily find the property of the sentence like in this project this domain is based on recent Punjab election 2017 and in this project we took different tweets on election and with the help of sentiment analysis and by using further different approaches we are able to find the property of the tweet like that tweet is either positive or negative or neutral.

In future also one can easily sort out their problem on any domain.

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