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Prediction and Analysis of Pakistan Election 2013 based on Sentiment Analysis

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***Abstract*—The significance of social media has already been proven in provoking transformation of public opinion for developed countries in improving democratic process of elections. On the contrary, developing countries lacking basic necessities of life possess monopolistic electoral system in which candidates are elected based on tribes, family backgrounds, or landlord influences. They extort voters to cast votes against their promises for the provision of basic needs. Similarly voters also poll votes for personal interests being unaware of party manifesto or national interest. These issues can be addressed by social media, resulting as ongoing process of improvement for presently adopted electoral procedures. People of Pakistan utilized social media to garner support and campaign for political parties in General Elections 2013. Political leaders, parties, and people of Pakistan disseminated party's agenda and advocacy of party's ideology on Twitter without much campaigning cost. To study effectiveness of social media inferred from individual's political behavior, large scale analysis, sentiment detection & tweet classification was done in order to classify, predict and forecast election results. The experimental results depicts that social media content can be used as an effective indicator for capturing political behaviors of different parties Positive, negative and neutral behavior of the party followers as well as party's campaign impact can be predicted from the analysis. The analytical findings proved to be having considerable correspondence with actual results as published by Election Commission of Pakistan..**

Keywords*—*Twitter Forecasting Sentiment Analysis Prediction

I. Introduction

The dramatic increase of social media application was seen in recent years. Social media comprises of many internet-based applications crafted for the creation and exchange of user based contents [23]. Individuals, organizations and different communities are benefited from social media applications. By the passage of time, computer based social media applications were remodeled as *micro-blogs* for hand-held devices like mobiles. These micro-blogs are responsible for exchanging text, image and media links among users. People need to keep themselves in touch with others to be better informed. This explosive growth is very much seen generally for Facebook, LinkedIn, FriendFeed, MySpace etc., and especially Twitter.

II. Related Work

The political developments and events are reflected in tweets and even resulted in top trends maintained by twitter. German Federal Elections were held in 2009, Tumasjan revealed tweets obtained for related political parties, leader asserted resemblances with originally compiled results and concluded twitter can act as a mirror to offline political landscape [3]. They investigated ideological ties between parties and political coalitions by studying tweets. Besides this they also compared share of tweets with actual votes for 6 main parties with calculation of MAE as 1.65% [3]. According to Tumasjan they considered all tweets as one document for sentiment detection, which was a drawback in their research by ignoring once again individual tweet's sentiment.

The importance of twitter and other social media applications was also unveiled during Singapore General Elections 2011 which found twitter to be integral part of election campaign and mobilization of citizens to cast vote [1]. They focused on seven political parties and calculated MAE of prediction as 5.23% whereas on constituency level they were unable to find convincing correlation between percentage of the votes for opposition and tweets received by them [1].

Jessica Chung performed sentiment analysis of tweets collected from MAsen10 campaign [12]. They used OpinionFinder a technique to find sentiment analysis, and achieved overall accuracy of 41% which is not reliable. In order to improve accuracy they further used SentiWordNet a lexical resource with 207, 000 pair of words [12] and overall accuracy increased to 47.19%. They introduced sentiment analysis to tweets but failed to increase the accuracy with methods they adapted.

Daniel Gayo-Avello used the data-set belonging to MAsen10 and USsen10 in studying predictive power of social media against several Senate races by conducting several sentiment analysis experiments [14]. According to them election results cannot be predicted using simple tweet share, sentiment analysis has to be performed for achieving better results. Daniel did not rely on studies conducted by Tumasjan and Brendan [3] [13] but also studied claims that social media cannot be used for predicting elections. On the basis of both streams, Daniel followed [13] techniques and concluded pre-election volume of tweets for MAsen10 seemed to be good for prediction of elections. They calculated MAE 17.1% following Tumasjan method and sentiment analysis MAE as 7.6%.

The conventional Irish General Elections 2011 results were related by social analysts and researchers with combined approach involving volume based and sentiment based results obtained from twitter by Adam Bermingham and companions [2]. They collected around 32K tweets related to five main Irish parties based upon party names and abbreviations. To predict sentiment based on trained data they used Weka tool for classification and applied Adaboost MNB classifier which resulted in 65.09% classification accuracy [2].

Another detailed study for US Midterm Elections 2010 was carried out by Livne who also found cohesion in the outcomes of US midterm elections 2010 and tweets [22]. In their study, they analyzed around 460K tweets over three years for 687 candidates contesting for National House, State Governor or Senate seats. Model built by them based on graph structure, content and election results was able to predict winner or loser candidate with accuracy of around 88.0%.

The Comparison of 2012, French and US Presidential elections was made by Farhad [4] who adopted the approach of performing time series sentiment analysis by restricting their findings to only two candidates, Barack Obama and Mitt Romney in case for US. They performed time series sentiment analysis for US candidates [4] and for French candidates by computing scores, based on three difference scoring functions, *polarity*, *sentiment,* and *affinity*. They claimed twitter to be the best medium for judging the candidates and responding their voters and vice versa

III. Methodology

A. Twitter Corpus Collection

To study qualitative behavior of twitter by using twitter API we have collected 612,802 tweets, these tweets were based on switches / keywords which comprised of full names and acronyms of different political parties and political celebrities. These names were taken from election commission of Pakistan's website. This resulted in downloading huge amount of relevant and irrelevant tweets from other geographical region, and in different languages. The regions were verified from the locations provided by the twitter users in their profile.

B. Pre-processing Tasks

The tweets data downloaded were in JavaScript Object Notation (JSON) format. We identified relevant fields for extraction which could be useful during classification and further analysis of tweets. For Classification purpose we required only Text part of JSON format whereas rest of information was kept in repository for further analysis.

C. Tweets Annotations

In order to overcome sentiment inconsistency with emoticons we preferred manual labeling of tweets based on technique following technique mentioned by Theresa et al. [11]. Tweets projecting either appreciation or showing satisfaction with for some party were labeled as positive tweet. In contrary to this the tweets containing negative words, emoticons, for certain party were labeled as negative tweet. Similarly tweets which did not show any tilt towards any party but it was related to general elections campaign were termed as neutral tweets. In this way we got politically positive, negative and neutral

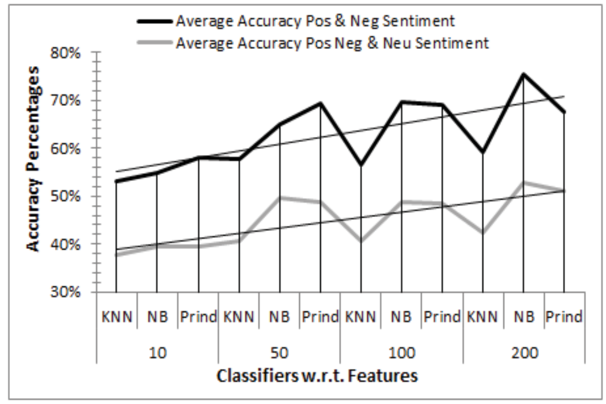

Fig. 1. Effect of Feature Size for Rainbow

sentiments tweets for several parties in our data. We started with labeling of approx. 3600 tweets with 1200 tweets (approx. 33.33%) for each positive, negative and neutral class. These tweets were labeled by three different persons and finally their results were combined to set a basis for training data. The labeled data in a text file with each line representing individual tweet, was then pre-processed with the removal of duplicate tweets, URLs, Extra whitespaces, Repeated words, words starting with number, Small words (threshold set 3), and Punctuations. Mentions words and Hashtag words were kept separately for further analysis. Finally whole tweet text data was converted to lower case.

Data pre-processing step reduced the size of text considerably. Now we have three folders based on our three preset classes positive, negative and neutral. The cleaned labeled dataset is bifurcated with each tweet to be stored in separate text document using python. These tweets are placed in their respective folders according to their label/class. Each of These three folders sentiment positive, negative and neutral contained around 1200 tweets text documents which were later used by *Rainbow* program and *Weka* tool for classification as a training purpose.

D. Algorithms & Approaches Used

Using Rainbow we used classifications methods NB, KNN, and Prind. We took set of words (uni-gram) with highest mutual information as features vectors ranging from 10 to 200. In order to smooth word probabilities we used *Laplace* method which helped in avoiding zero values. Stemming was performed with *Porter Stemmer*. The accuracies were obtained for positive versus negative sentiments, positive, negative and neutral sentiments separately with 40% data placed in test set and remaining for training set. As in Fig. 1, we can see that an average accuracy of 70% calculated and above was obtained for two classes positive and negative. With the inclusion of neutral class our accuracies dropped because we have tweets which are neither positive nor negative.

Same data set was tested with some more algorithms like RF, SVM, NB and NBMN for supervised machine learning classification. We applied TF-IDF transformations for finding the words that were strongly related to relevant documents. The reduced feature vectors after stemming with set of attributes ranging from 10 to 200 were given to classifiers for prediction

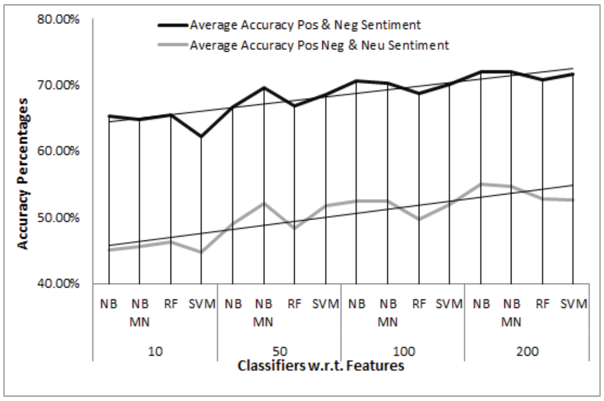

Fig. 2. Effect of Feature Size for Weka

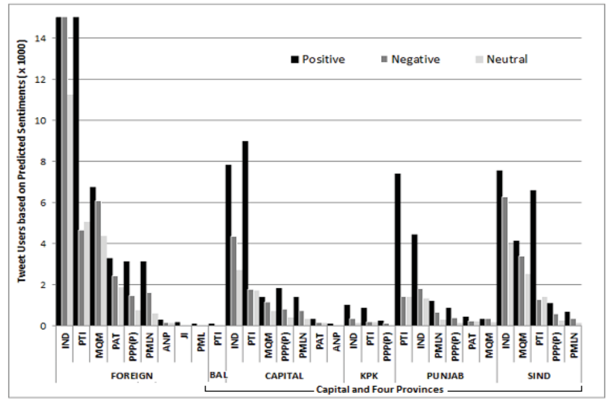

Fig. 3. Province wise Sentiment prediction for Parties.

purpose. We used 5-fold cross validation in case of Weka. Fig. 2 shows increase in accuracy with increase in number of attributes. NB performed best with few more percent on average accuracy for both sets of sentiments from rest of classifiers. RF & SVM were almost together with accuracies. We used RF a decision tree learner, different tree (10 trees in our case) were built with each tree predicting a number using random samples and random features.

E. Study of Quantitative Behavior

Study of quantitative behavior for twitter corpus involved in predicting sentiment for whole relevant tweets with extensive data cleaning, labeling for other relevant fields for better analysis purpose. This relevant tagging of tweets was based on English language, region, country, as we were more concerned with tweets related to Pakistan's General Elections. We chose NB Classifier as it showed better average accuracies both for Rainbow and Weka to classify our tweets based on already trained labeled data. After sentiment prediction using NB classifier and thorough annotations we were left with 226,510 politically positive, negative and neutral tweets (out of total tweets collected through API).

User participation can be easily identified by number of political tweets, as it contained mentions. These mentions contained political parties name, political celebrities and people involved in political campaign. The cleaned data contained about 42,270 tweets started with mention, related to Pakistan's political scenario. This showed direct involvement of people who not only share their views but also involved others in this campaign. About 18,225 tweets contained mention in the tweet text. This showed that tweets sent to different individuals which lead towards group discussion regarding any political development. There are tweets which users sent as it is, to their followers called re-tweets. This could be text, a URL linking other website, media or image. In our relevant tweet data about 50, 354 tweets were found re-tweets. There were 37, 564 re-tweets with simple text, 12,790 tweets containing URLs.

IV. Results

In subsequent subsections province wise sentiment classified for different parties are discussed. Also how twitter users participated for provincial capitals was discussed with the help of graphs.

A. Province wise Sentiment prediction for Parties

By keeping identity of each tweet in contact we related user information, political party information with predicted sentiment. As we already annotated our data province wise, and city wise, so this helped us in drilling down from National Level to Province Level, from political party to individual twitter user belonging to them. We came to know there are majorly two streams of users, one of them with locations not from Pakistan, they were termed as *Foreign Pakistanis*. They could only participate in discussions on social media. The other stream belongs to *local users* within domain of Pakistan. In the Fig. 3, we can find positive participation of foreign users sentiment wise for each political party. The Fig. 3 also shows sentiment detection for local users belonging to Federal Capital and other provinces. All parties campaigned positively on twitter by setting accounts for party and party leadership. We noticed less number of twitter participants for province Baluchistan and KPK, the reason behind could be low population and literacy rate.

B. Twitter User Participation for Capital and Provisional Capitals

We have found as mentioned in Fig. 4, that twitter users actively participated over its platform for election campaign from all part of Pakistan. We can see the party-wise trends for Federal Capital and Provisional Capitals.

C. Top 5 Parties with Sentiment Tweets and actual Polled votes

Election Commission of Pakistan (ECP) after successful holding the Elections for Pakistan in May 2013, published complete results [24]. ECP published Top political parties securing votes from all over Pakistan, the percentages are shown in Table I. This shows sentiment-wise participation percentages along with percentages of actual polled votes. We can relate positive sentiment with actual votes gained by the political party with some differences against PTI and Independent twitter users and voters. This shows PTI had more twitter users over social media campaigning positively.

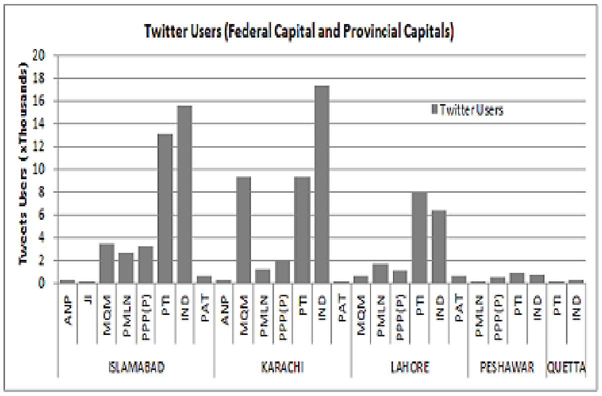

Fig. 4. Twitter User Participation Capital and Provisional Capitals.

TABLE I. TOP 5 PARTIES WITH SENTIMENT TWEETS AND ACTUAL POLLED VOTES.

Party	Pos	Neg	Neu	Actual Polled Votes
PTI	72.29%	13.57%	14.14%	20.32%
PPP(P)	59.38%	27.80%	12.82%	18.28%
PMLN	57.50%	30.03%	12.47%	39.35%
IND	49.72%	30.44%	19.83%	15.56%
MQM	40.28%	34.97%	24.75%	6.50%

V. CONCLUSION AND FUTURE WORK

Using Sentiment detection, we tried to find out the predictive power of Twitter. With the use of different classifiers we achieved average 70% classification accuracy for predicting positive and negative sentiments, whereas by adding neutral sentiment the average classification accuracy achieved was 50%. This work of forecasting elections for developing countries especially for *Pakistan* is of unique attempt. We also deduced that there are certain political parties and leaders who have low electability but high popularity from Elections results in actual and our predictions. We have seen independent twitter users acted as drivers for change. We also ignored on ground realities of not considering major part of population living in rural areas with tribal loyalties. These people with low literacy rate plays vital role in setting political party's fortune as it could be seen in the case of PMLN and PPP(P) traditional rivals. We have seen, with the inclusion of PTI the left right alignment of these parties have been controlled to some extent. In addition to above, the political parties may use twitter as a parameter for refining their campaign, and redefining their goals. We also found that no mechanism was adopted by ECP for stopping social media campaign over internet, twitter in our case, as it continued till and by voting date.

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