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EXPLOITING CREDIBILITY FOR SENTIMENTS: IT WORKS!

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Abstract

Sentiment analysis has been one of the hot topics for researchers for previous two decades. Researchers from domains like natural language processing (NLP), statistic, computational linguistics and information retrieval (IR) have been targeting different types of problems related to sentiment analysis. While the number of research problems related to sentiment analysis has been varying according to the global user requirements, major task of sentiment analysis has always been focus of the core sentiment analysis research i.e. to classify the given text into positive or negative categories (and sometimes a neutral category is also added). Researchers have been using several kinds of approaches for this core tasks while exploiting several types of features. Most of the time, researchers tend to use textual features for sentiment analysis task. While several have tried to exploit richness of non-textual features, focus has been revolving around the non-textual features like exploiting document structure, text position within the text, using social network evidences etc depending upon the nature of data collection being used. In this paper, we propose a novel approach of using credibility of sentiment analysis. Two twitter data sets are used for experimentation purposes collected over two different durations from Twitter using Twitter APIs. Both data collections consist of geotagged tweets from six different cities of Pakistan. The standard method of pooling is used for creating the gold standard. We exploit the credibility of information as strong evidence for sentiment analysis and the proposed approach has shown effectiveness in its results. A unique approach ("trust the trusted") has been proposed to exploit the credibility of information for sentiment analysis purpose.

1 Introduction

Twitter is an online service with millions of online users [1]. It only allows 140 character long status updates along with multimedia content. Twitter is mostly used through mobiles with almost more than 50 percent of its users [2] using it on mobility. Therefore, Twitter supports real time dissemination of breaking news and events and other such messages in mass public. Some users post their own observations or news on it while some others will attach some kind of external link to cite their news. Obviously, a tweet coming from official and reputable sources is considered more trusted and is propagated more rapidly. Users can re-tweet a certain tweet and this laid the foundation for diffusion of information across the whole online social media. While such network is good at information diffusion in a quicker way but it may not be able to separate true information from false rumors. For example in 2010, there was a earthquake in Chile and when there was no effective communication by the officials then several rumors were spread on Twitter contributed to increase the sense of chaos and insecurity in the local population.

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In this work, we propose a sentiment-analysis [3, 4, 5] approach based on factors representing credibility of information. The proposed approach is unique in the sense that it exploits information credibility evidences in a unique way to perform sentiment analysis. Based on our hypothesis of trusting evidences beyond the given text, we believe that external sources (i.e. beyond the given text) if exploited intelligently, can lead to improvement of results for the task of sentiment analysis. The proposed approach uses information credibility evidences and trusts the most credible tweet representing a handsome collection of tweets. The proposed approach is also interesting in the sense that it also used topical information retrieval to create a pool of similar tweets i.e. tweets referring to same topic.

This paper is organized as follows: section 2 discusses some related work while in section 3, we describe the data collection used in the in the experiments. The section 4 describes the proposed approach in detail. In section 5, experiments have been described in detail along with the results. The section 6 concludes the work.

2 Literature Review

In this section, we discuss few works that have been working with credibility of data whether they have used credibility of information for some other task or they have worked on computing credibility of information itself.

Author [6] proposed an improved framework for identifying tweets with false news content using strategies that include Twitter user account statistics analysis, distorted image search, conflicting verification of false media sources, and data mining. The results of the experiment in the database of large mixed events show the effectiveness of our proposed method in identifying fake tweets.

Author [7] used a user-related content and features, and author use emotion analysis to generate new features for the discovery of Arabic fiction. Emotional analysis has led to improved accuracy of the prediction process. Among the number of machine learning algorithms used to train division models, four selected algorithms, namely Random Forest, Decision Tree, AdaBoost, and Logistic Regression. Experimental tests show that our system can filter out false stories with 76% accuracy.

Author [8] has modified some of the existing literature and concluded that many previous methods have investigated the reliability of information on Twitter and the limited number of Facebook by proposing a new method for measuring the reliability of posts. Author used proposed model used to measure the reliability of a Facebook post using a formula compiled from page profile level and post-analysis school. The model was tested and achieved an accuracy of 87.45%.

Author [9] proposes a machine learning approach to determine reliability. Author combines content-based features and source-based features. The results show that the proposed approach achieves significant improvement over other methods.

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Author [10] discusses the problem of finding trusted information sources among Twitter users to identify spread of fake information. Existing research activities related to source reliability are graph. This article proposes a new approach in this that includes analyzing the user's reputation. It is reported that that the accuracy of the proposed method satisfies the stated purpose of identifying trusted Twitter users.

3 Data Collection

This work depicts the process of data collection to generate two datasets from Twitter. We use Twitter Search APIs for downloading both data collections. Twitter Search API also provides the facility to extract geotagged tweets using different keywords and geo-locations (in the form of Latitude and Longitude values).

3.1 Search Keyword Selection

For our data collection, we need tweets about the selected set of political parties. For this purpose, we need a set of keywords for searching tweets about each party. To select this set of keywords for each party,we consult Twitter Search Trends and look for the alternate keywords used to search the selected political parties. All the unique keywords directly related to the political parties are carefully chosen to download the data collection. The details of all parties and selected keywords are given in Table 1.

Table 1: Parties and Keywords Searched

Political Parties	Chosen Keywords
PTI (Pakistan Tehreek-e-Insaaf)	Pakistan Tehreek-e-Insaaf, Imran khan, tehreek-e-insaaf, PTI
PMLN (Pakistan Muslim League Nawaz)	Pakistan Muslim League Nawaz, Nawaz Sharif, PML-N
PPP (Pakistan Peoples Party)	Pakistan Peoples Party, Asif Zardari,Belawal Bhutto, PPP
MQM (MutahedaQaumi Movement)	Altaf Bhai, MQM, Altaf Hussain, MutahedaQaumi Movement
JUI-F (JamiatUlma Islam- FazlurRehman Group)	JUI, JUI-F, Jamiat, FazlurRehman, MaulanaFazlurRehman
ANP (Awami National Party)	ANP, Asfandyaar, Asfandyar, Afsandyar(Asfanyaar) Wali Khan

3.2 Selected Geo-Locations

Major cities are chosen as Geo-locations for extracting data from downloaded tweets. A total of six cities are chosen for this purpose. The idea behind the selection of these cities is that a greater number of Internet users tends to come from major cities. Another reason for the selection of these cities is that the population of major cities is more affected by Govt. policies and hence, people living in major cities are more interested in online political debates. Figure 1 provides a graphical representation of the number of tweets from each selected city in both periods i.e., NOW (2018) and THEN (2014) while Table 2 gives details of geo-locations of selected cities using bounding box geo-coordinates fromhttps://www.openstreetmap.org. Figure 2 and Figure 3 are depicting the distribution on THEN and NOW periods respectively. Due to the data rate limits of Twitter Search API, we made a utility that consistently saves the data in the MySQL database with a predefined schema so that we could analyze and process it later in an efficient way.

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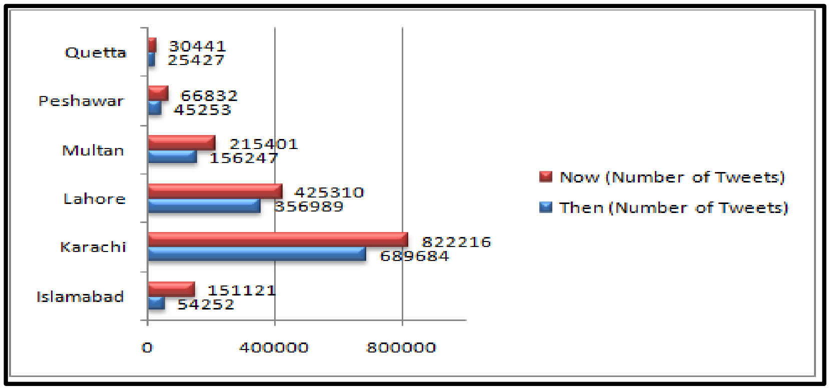

Figure 1: Graph with number of votes' city wise in both data collections i.e., NOW (2018)

Table 2: Bounding boxes of selected cities

No.	Latitude	Longitude	Geo-Location
1	24:9823; 24:7562	67:2954; 66:8882	Karachi city
2	31:6656; 31:3237	74:1426; 74:5236	Lahore city
3	30:3118; 30:0673	71:3198; 71:6858	Multan city
4	30:2904; 30:0691	66:7495; 67:2280	Quetta city
5	34:1094; 33:8966	71:3438; 71:7880	Peshawar city
6	33:8567; 33:5311	72:7164; 73:4141	Islamabad city

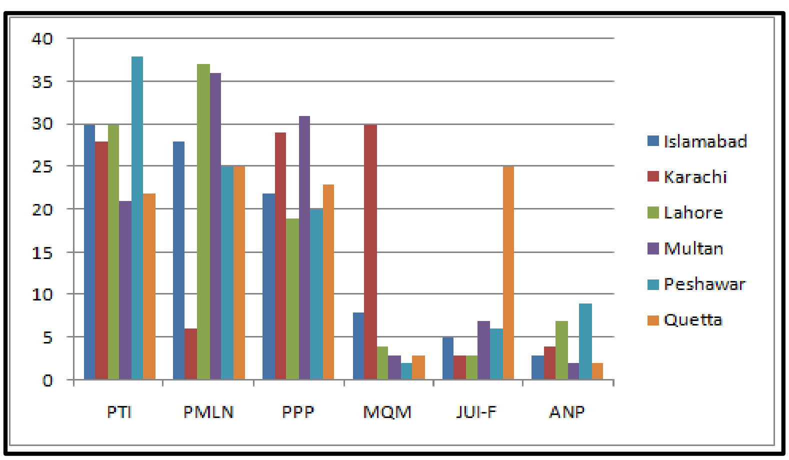

Figure 2: Graph showing the city-wise percentage of tweets in different cities in 2014 data collection

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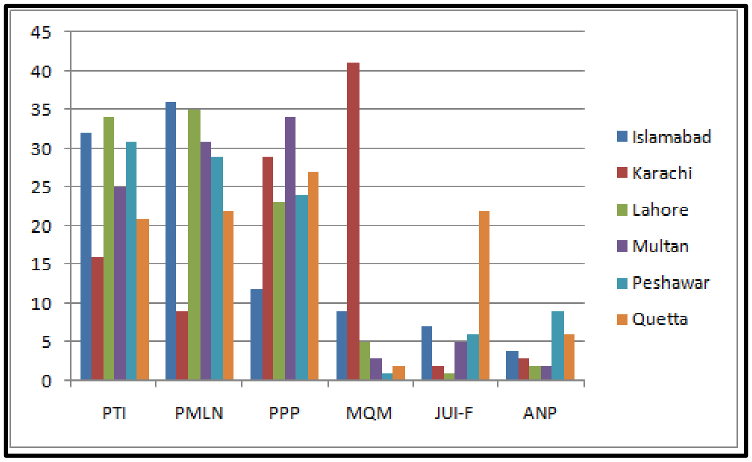

Figure 3: Graph showing the city-wise percentage of tweets in different cities in 2018 data collection

Labeling huge collections of data is one of the big challenges in information retrieval (IR) but it is mandatory for the fair evaluation of IR systems. For annotating the collected data, we plan to follow the standard pooling procedure which is also considered one of the authentic ways of data labeling and is often used in evaluation campaigns like Text Retrieval Conference (TREC) [11]. We use the following sentiment analysis APIs to create a pool of positive and negative tweets for all selected parties:

- Aylian Sentiment Analysis SDK1
- Sentiment140 APIs2

A collection of tweets for a particular party are provided to the programs using these APIs as input. The objective of this process is to get 1200 unique labeled tweets for each party with a ratio of 600 positive tweets and600 negative tweets. We have the choice of using two approaches to complete this task:

- **Approach 1:** To provide the same list of tweets to both APIs and remove the duplicate labeled tweets. If the number of tweets in the resulting set is less than 1200 then repeat this step and keep repeating until we get a labeled pool of 1200 tweets for each party.
- **Approach 2:** To provide a separate list of tweets to each API and combine the results later.

We choose Approach 2 for this purpose because it is a straightforward approach. Hence, tweets for a party are divided into two equal subsets and provided to both APIs to get labeled sets of tweets labeled as ‘Positive’ and ‘Negative’. Both SDKs are supposed to provide a total of 600 unique labeled tweets for each party with a ratio of 300 positive and 300 negative tweets which makes a total of 7200 unique labeled tweets in total individually for both data collections i.e., THEN and NOW. Hence, the top 300 positive and top 300 negative tweets are chosen from each SDK for each party for making a pool. The results

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of pooling are further verified manually by hiring two experts. These experts verify the labels assigned by the chosen SDKs. All 7200 labeled tweets are verified by both experts for both data collections and we get an average annotation agreement (kappa measure) of 0:89. It is to be noted that while the geographic locations of tweets are ignored in this process, we provide a detailed analysis of geotagged tweets in a separate sub-section.

4 The Proposed Approach

The block diagram of the proposed approach is shown below in figure 4.

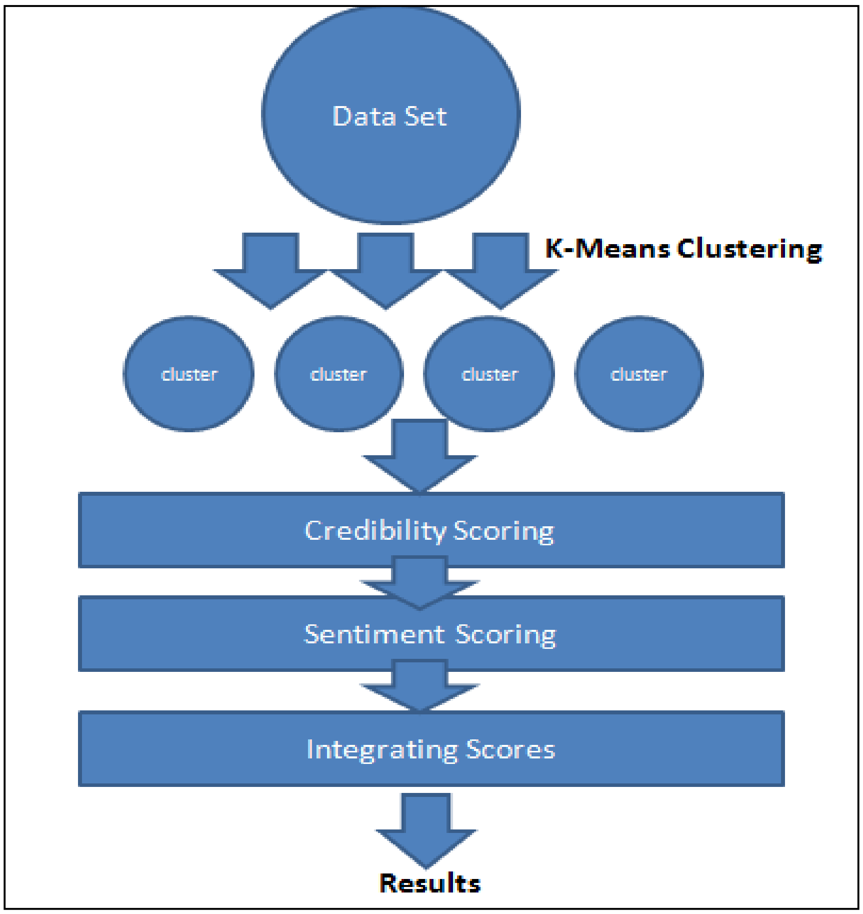

Figure 4: Block Diagram of the Proposed System

Below we explain each component shown in the diagram above.

4.1 Topical Clusters

In first step of our proposed approach, we create different clusters of similar tweets for tweets of each party. For this purpose, we use the classic K-means clustering approach.

K-means algorithm is one of the simplest tools used for clustering when using machine learning for a particular task. Generally clustering techniques does not need labeled data collection as is the case in supervised machine learning. The idea of k-means clustering

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is to identify similar items and group them together in same cluster and try to find underlying hidden patterns. Below we summarize the way K-means clustering works:

- First of all, there is a need to fix number of clusters i.e. k. A cluster is a group of similar objects.
- Each cluster is then represented by a centroid. A centroid is the imaginary or real location representing the center of the cluster.
- A data point is matched with the centroid of the cluster and is allocated to the cluster which is the most similar. This similarity is computed depending on the the approach adopted.
- The learning starts with selection of centroids. The process of learning stops when either the centroids have stopped changing — there is no change in their values because the clustering has been successful.

4.2 Credibility Score

Each tweet in a cluster is assigned a credibility score [2] based on following credibility evidences we listed out for our approach.

- Presence of external link
- Number of re-tweets,
- Number of followers of the person tweeting
- Types of emotion generated

While our approach for credibility calculation is impressed from [12] but we adopt a different method for classifying tweets as credible. Our approach assigns a credibility score to tweets between 0 to 1 signifying that the highest the score, the more credible the tweet. It is to be noted that researchers have been using credibility or trustworthiness of information for different purposes [13, 14]

4.3 Sentiment Score

Each tweet is assigned a score based on presence of several sentimental evidences in the tweet. This score scales between 0 and 1 and represents positivity of the tweet. For example if a tweet is assigned a score of 0.5, it means its positivity score is 0.5 while negative score is 0.5 hence it can be considered neutral. If a tweet is assigned score of 0.6, it will be considered more positive with ration of 60:40.

4.3.1 Combining Scores

We devise a very unique approach for combining sentimental and credibility scores.

- **Trust the Trusted (TTT):** In this approach, we take half population of each cluster (i.e. half the tweets) in descending order of their credibility score. We check the sentimental scores of filtered credible tweets. Each tweet is labeled positive, negative or neutral according to its sentimental score. If tweets of a specific label are 60 percent

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or more than 60 percent of the filtered tweets then we label the full cluster with the same label (excluding those which have been labeled with label with less population). Let say we had a cluster of 500 tweets and we take 250 tweets with top credibility scores. Tweets are then labeled according to their sentimental scores and lets imagine 200 tweets are labeled as Positive while 50 are labeled as Negative i.e. major population among the most credible tweets are positive tweets. Hence, we label other half of the less credible tweets (i.e. other 250 tweets) with Positive label and therefore total 450 tweets (200 + 250) are labeled as positive while 50 are considered Negative.

For a fair evaluation of the TTT approach, we propose another rather simpler approach for combining both scores.

- **Equal-Equal:** In this approach both scores are simply multiplied and a threshold of 0.6 is fixed to label a tweet positive if its resultant score is equal or more than 0.6 otherwise it's labeled as negative.

5 Experiments

In previous section, we explained the proposed approach in detail. In this section we describe experimental settings and results of the experiments. Experiments have been performed under two major settings.

5.1 Without Credibility Scoring

In this phase of experiments, we perform experiments without using credibility scoring i.e. tweets are simply scored on behalf of the sentiment computation approach.

5.2 With Credibility Scoring

In this phase of experiments, tweets are assigned credibility scores and then sentiment scores are assigned to tweets (as shown in block diagram of the proposed approach).

5.3 Results

We report only precision results for our experiments because we are not reporting separate results for negative and positive tweets hence pool remains same so in such case precision and recall will result in same values.

Table 3: Results

No.	Experiment	PRECISION
1	Without Credibility (Baseline)	0.69
2	With Credibility (Equal-Equal)	0.78
3	With Credibility (TTT)	0.88

From the table 3, we have shown results for three different settings. Setting 1 serves as baseline for our experiments because no credibility information is used in this particular set of experiments. Experiments at 2 and 3 represent the results obtained using credibility information under two different settings. As shown in results, we achieved the maximum

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performance improvement in TTT setting using credibility information which proves the effectiveness of the proposed approach.

6 Conclusions

In this chapter, we proposed our second approach on exploiting resources beyond the given text for the task of sentiment analysis. We combine NOW and THEN data collections for this purpose. We have proposed a unique approach for sentiment analysis by devising a unique TTT method to label the tweets with sentiment orientations. Results have shown the effectiveness of the proposed approach.

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