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New Credibility Inspection Operation For Evaluate Data On Twitter Using Latent Dirichlet Allocation Model

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Abstract: *Now a day's social media plays an important role in information propagation among the people. In the crisis, twitter is the commonly used social media that brings millions of users together. We analyzed the credibility of information in tweets corresponding to fourteen high impact news events of 2011 around the globe. From the data we analyzed, on average 30% of total tweets posted about an event contained situational information about the event while 14% was spam. Only 17% of the total tweets posted about the event contained situational awareness information that was credible. We developed the system for credibility on Facebook. First, we have developed FB credibility evaluator for measuring credibility of each post by manual human's labeling. We then collected the training data for creating a model using Support Vector Machine (SVM). Secondly, we developed a chrome extension of FB credibility for Facebook users to evaluate the credibility of each post. We discuss a third model which combines facets from both models in a hybrid method, using both averaging and filtering hybrid strategies. We identify structural patterns of temporarily representative conversation sub graphs and represent their topics using Latent Dirichlet Allocation (LDA) modeling. We analyze how the information had propagated, and the actions were taken based on the source. The feature retweet was considered as a measure of analysis to enhance the reliability of the spread information. The performance of our ranking algorithm significantly enhanced when we applied re-ranking strategy.*

Index Terms: *Credibility, Support vector machine, Hybrid method, Retweet, Crisis, Tweets, Facebook, Reliability, and social media.*

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I. Introduction

Using social networking platforms for information seeking and sharing is an increasingly common practice the use of social media for information access, the underlying paradigm still relies on individual search. In this setting, the information access is generally enriched by cues stemming from a seeker's social relationships [1]. The primary focus and contribution of this paper is on an evaluation and comparison of three novel approaches for predicting credible information for specific topics on Twitter is important challenge given the abundance of useless information in the forum [2]. We first model social credibility, then focus on content-based credibility, and lastly on a hybrid of features from both approaches [3]. This content will be news, events, or some opinion. Social media has many types such as Facebook Twitter, LinkedIn, Google+, and Instagram. Facebook is the most popular social networking site in Thailand and in the world [4]. Face book users can update status that can be a personal message or webpage link [5]. The top-left tweet provides correct and credible information about the event. The top-right tweet, is related, but contains no information about the event it expresses personal opinion of the user [6]. Even though the bottom tweet contains related words, it includes a URL to an advertisement to sell a product, so it is a spam tweet with respect to the event [7]. The user can follow another user to get updated info about the particular topic spread information. Twitter is used for constructing collective wisdom which can prompt accurate and precise information which shall be utilized in the crisis management [8]. The hash tags are created for a group or an individual for the emergency situations. It can update the other members of the group about the conditions, feedbacks, and crowd sourced information of disaster [9].

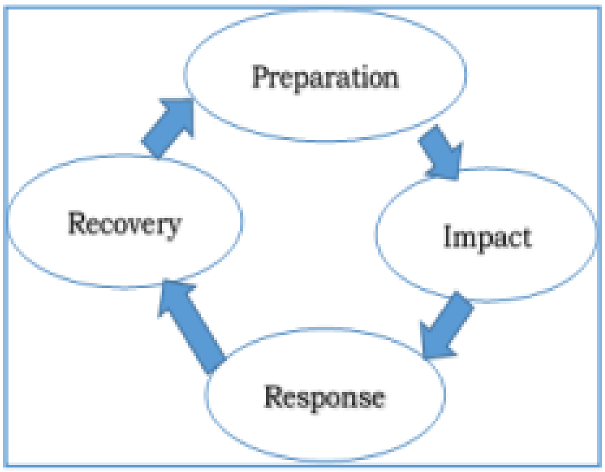

Figure: 1. Life cycle of disaster management

II. Related Works

Although generally perceived as a solitary process, information seeking and retrieval increasingly imply collaboration with others either within small-sized work teams open social web spaces [11]. The first research initiative dealing with the use of social media and favoring large-scale collaboration has been raised by the DARPA challenge aiming at identifying ten red balloons across the USA [12]. Collaboration could be defined according to various dimensions: namely, intent, depth, concurrency, and location, leading to fundamentally distinct processes and research challenges [13]. Twitter has been studied extensively from a media perspective as a news distribution mechanism both for regular news and for emergency situations such as natural disasters for example [14]. Castillo describe a very recent study of information credibility, with a particular focus on news content, which they define as a statistically mined topic based on word co-occurrence from crawled is define a complex set of features over messages, topics, propagation and users, which trained a classifier that predicted at the 70-80% level for precision against manually labeled credibility data [15]. On the other hand, web-page dependent approaches use features of each social media for computing credibility such as like, comment and re-tweet [16]. The advantage of this approach is that it attempts to understand the media the main drawback of web-page-dependent is that this algorithm is dependent on social media types [17]. They showed an increase in the use of URLs in tweets and a decrease mentions during emergency situations. An automated framework to enhance situational awareness during emergency situations was developed by viewer. They extracted geo-location and location-referencing information from users' tweets; which helped in increasing situation awareness during emergency events [18].

III. System Model

The system overview is consists of two subsystems, which are FB credibility evaluator and FB credibility. Those systems call at Python server via https by using JSON. Based on the usage of FB credibility evaluator by users, the system creates a model by using LIBSVM [19]. In FB credibility, we retrieved Facebook data to compute the credibility score. FB credibility evaluation was developed to evaluate the credibility of each post. An evaluator will select the range of credibility from 1 to 10 and then click the submit button to send this credibility value selection to the Python server. An important distinction between these techniques and the approaches presented here is that personalization is only performed at the topic level in our algorithms is personalized preferences for a single target user are not considered, only those for a target group who are interested in a specific topic [20].

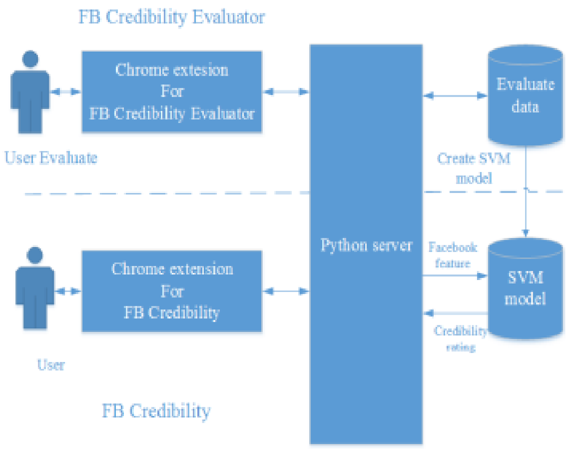

Fig. 2 System overview

IV. Proposed System

We collected data from Twitter using the Streaming API is enables researchers to extract tweets in real time based on certain query parameters like words in the tweet time of posting of tweet. We queried Trends API after every hour for the current trending topics, and collected tweets corresponding to these topics as query search words for the streaming API [21]. Some researchers are using classifiers like naïve Bayes decision tree and SVM to identify spam phishing and unreliable data on twitter information. Ranking algorithms with trust related queries are applied to obtain reliable data is shared to automated classification technique is used to detect the news topics from conversational topics and assessed their credibility many features of twitter. [22].

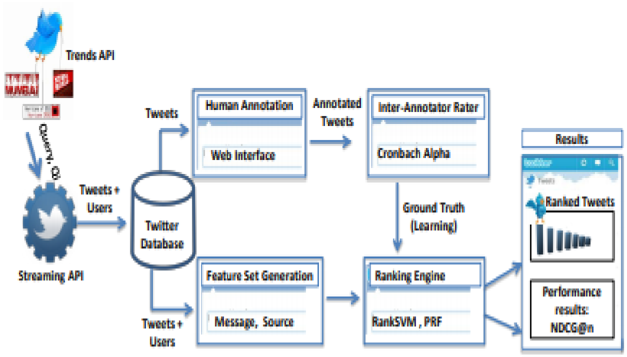

Figure 3: Describes the methodology and analysis performed

V. Pseudo Relevance Feedback

Pseudo Relevance Feedback (PRF) also known as Blind Relevance Feedback is a prominent re-ranking technique used in data retrieval tasks to improve the performance of ranking results [23]. The basic idea of PRF is to extract K ranked documents and then re-rank those documents according to a defined score. In our algorithm the improvement achieved by re-ranking using PRF is highly dependent on the quality of top K results given by the ranking algorithm. The algorithm describes all the steps of extracting top k ranked tweets. Function Extract Features (T) computes message is based features for each tweet from the set of tweets T. The Rank SVM (F, T) function, takes the feature set matrix F and the column vector A containing the ground truth annotation value for each of the n tweets. F reqLUnigrams (TK) extracts the frequent L word unigrams from the top K tweets. BM25 method computes the similarity score between the top L unigrams and each tweet ti in T [24].

Algorithm Ranking (T [1...n], A [1...n])

```
for i <- 0 to n − 1 do
Fi <- Extract Features (T[i])
end for
Feature Rank <- RankSV M (F, A)
T0 <- SortAsc (Feature Rank)
for i <- 0 to k − 1 do
```

TK[i] <- T0 [i]
end for
WL = F reqLUnigrams(TK)
PRFRank <- BM25 (TK, WL)
Tweet Rank <- SortDsc (PRFRank)
return TweetRank[1..k]

VI. Modeling Credibility

Traditional recommendation strategies such as content-based [14] filtering [9] [21] typically compute a personalized set of recommendations for a target user based on some derivation from that user's profile of item preferences. An important distinction between these techniques and the approaches presented here is that personalization is only performed at the topic level in our algorithms. We propose the following three models for identifying credible information, borrowing from the content and collaborative synergies identified by the recommender system community.

1. **Social Model:** A weighted combination of positive credibility indicators from the underlying social network.
2. **Content Model**: A probabilistic language based model identifying patterns of terms and other tweet properties that tend to lead to positive feedback such as re-tweeting and credible user ratings.
3. **Hybrid Model:** A combination of the above, firstly by simple weighting, and secondly through cascading / filtering of output.

We describe the data collection process and provide an overview of each topic-specific collection. Next a brief statistical analysis of the data is presented to highlight core trends across each set with specific focus on our larger data set on the topic.

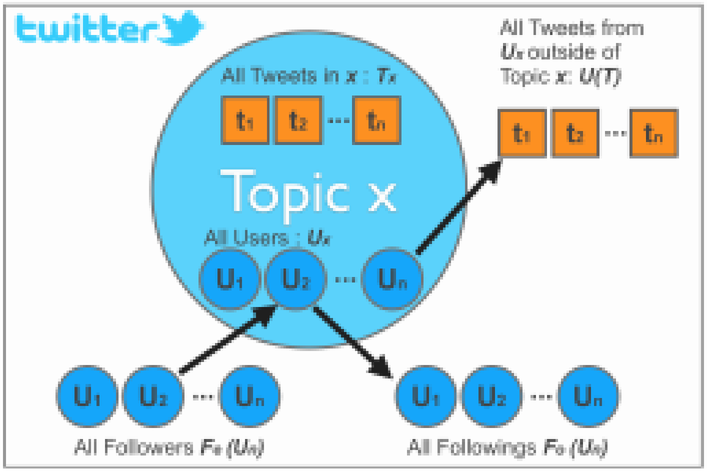

Figure 4. The crawled data current topics.

IMPLICATIONS FOR SOCIAL MEDIA COLLABORATION RESEARCH

We believe that our findings have important implications relevant for the research in social web collaboration, including:

• **Recommendation of collaborators:** Our findings indicate the social graph of collaborative groups of users engaged in similar or shared search and sharing tasks is a set of weakly connected small-sized sub-graphs [25]. People are likely to be connected with a small audience while, being involved in an open social web space, they believe that they are connected to the crowd.

• **Enhancement of social awareness:** The analysis of collaborative group's connectivity demonstrated that active users are involved in many conversations with distinct topics either sub-topics of the root search task topic or even other tasks dealing with other topics. Thus another interesting implication for future research would be to design algorithms that enhance the information seeking process by detecting complex information needs and tasks [26].

VII. Experiments And Result

We have published FB credibility evaluator to FB credibility on Google Chrome web store. Users can install one app per time. There have been 1,348 post feedbacks, and 1,103 records agree with proposed credibility score. This means 81.82% of evaluations agree with the proposed credibility score to details of the percentage of disagree the proportion of the number of posts at each score point out of the total number of posts.

We were also interested in analyzing the effects of Twitter context on perceived credibility performed a within subjects study, varying source context with the goal of examining the effect on perceived credibility rating 145 participants took the online study, which lasted about 10 minutes. We must assess and compare performance of each model. Given our available resources, substantial credibility assessment data could only be collected on the Libya data set, so we focus on that set for most of the following evaluation, namely, where comparisons against user provided assessments are performed.

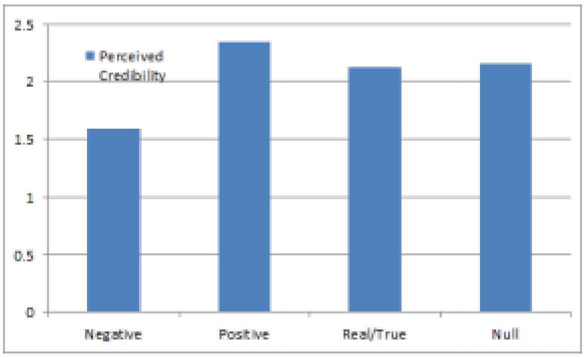

Figure 5. Plot showing perceived credibility in each Twitter contexts

VIII. Conclusion And Future Work

Identifying misinformation is imperative in online social media platforms, because information is circulated easily across the online community by unverified sources. To be able to automatically detect key participants, who contribute to the spread of misinformation, can be useful in analyzing activist movements. User accounts that include many URLs, @username mentions and hash tags in their tweets, which are posted in set intervals of time, could be potentially identified as spam or phishing accounts. These accounts also tend to follow many people compared to the number of followers they have, and have more shallow retweet propagation trees. Through sentiment analysis, tweets with negative opinions appear to be related to information that is credible. It has also been revealed that users themselves are not very good judges of credibility, especially when analyzing the content of a tweet alone. Cultural influences also play a role in credibility perception, therefore it is not recommended to completely rely on these approaches to validate results.

This paper presented three computational models for assessing such credibility, using social, content-based and hybrid strategies. In particular credibility data during high impact events can be important. Researchers shown that role of Twitter during mass convergence and emergency events differs considerably is regular Twitter activity. In the crisis, re-tweets plays a vital role in connecting the affected with the respondent. Re-tweet's source and geo-location is identified and the request outside the crisis area can be eliminated. In future the dyadic pairs would be identified and the contents would be compared for #hash tag and relevant @reply to identify the victims who were rescued and avoid out dated tweets and help responded tweets.

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