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Automatic Extraction of Social Interface System using Big-Data Analysis with Emergency Alert

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ABSTRACT

In the world scenario, there is no proper fast generating alert system was implemented to report about the natural disasters. There is less possible to take immediate rescue process to save the people. The proposed model generates an automatic alert text as SMS or E-mail by extracting keywords from the tweets shared by the twitter users. The Support vector machine a machine learning algorithm used to analyze on tweets for separating positive and negative class. The system interfaces Maximum Peak of the particular keyword like Earthquake along with a particular time and at a particular location. The time and location is extracted using Stemming algorithm. Immediately an automatic alert is send as SMS and E-mail to the registered tweet users as well as to the Nearest Rescue Team.
Keywords: tweets, Earthquake, Stemming.

I. INTRODUCTION

In the current world scenario Social media twitter has got much attention recently by millions of users that connects people from one area to other with their friends, neighbors, relatives colleagues which makes it necessary to exploit highly accurate recommender systems to assist them to find out target results. Traditional collaborative filtering techniques do not consider social relations, making them difficult to provide accurate recommendations. It is significant and challenging to discover social contextual factors from the contextual information and integrate them into a unified recommendation framework. Users typically examine items' content and information on senders. For example, in Twitter, when a user receives a tweet that is posted by one of his friends (the sender), he usually reads its content to see whether the item is interesting. This information is gained from item content and user-item interaction information. In this case, the user cares about who the sender is and whether the sender is a close friend or authoritative. If more than one friend sends him the same tweet, he may read it more attentively.

This knowledge can be learnt from social relation and user-user interaction information. Both of these aspects are important for the user to decide whether to adopt (e.g., share, retweet) the item. The above can be summarized as two contextual factors as 1.Individual preference 2.Interpersonal influence. By viewing it in Psychological and sociological studies have proved that individual preference and interpersonal influence affect users' decisions on information adoption.

In Bond's work [4], it is indicated that individuals are to some extent influenced by others' behaviors, rather than making decisions in- dependently (i.e. purely preference driven). In [5], web-based experiments are designed for music adoption pre- diction. This work demonstrates that the introduction of interpersonal influence into the preference-driven decision process (as is the case in real social networks) makes user behaviors more complicated and thus increases the unpredictability of the item adoption. Therefore, only when individual preference and interpersonal influence are properly incorporated into recommendation, can the uncertainty be reduced and quality improved.

This framework is based on a probabilistic matrix factorization method to incorporate individual preference and interpersonal influence to improve the accuracy of social recommendation. More specifically, we factorize the user-item interaction matrix into two intermediated latent matrices including user-item influence matrix and user-item preference matrix, which are generated from three objective latent matrices: user latent feature matrix, item latent feature matrix, and user item influence matrix. Moreover, as we can partially observe individual preference and interpersonal influence based on previous user-item and user-user interaction data, we further utilize the observed social contextual factors to compute the three objective latent matrices.

II. METHODS AND MATERIAL

A. Existing System

In the Existing System, there is no proper automatic alert System was implemented to report about the Emergency. There is no way to take immediate rescue process to save the People. So that it is very time Consuming process. Loss rate will be increased in the both the Streams namely

1. Economically
2. Emotionally.

Disadvantages of Existing System

- Very Time Consuming Process.
- Loss Rate will be increased.

B. Proposed System

In the proposed system, we are implementing particle mechanism which used to extracts the keywords from the tweet using Stemming Algorithm along with location and time of the Tweets. By using these information, the system can analyze if the maximum peaks of the keywords like "Earth Quake, Tsunami" etc. at a particular time and location. We are generating the automatic alter as an SMS and Emails to registered tweet users as well to the nearest Rescue Process Team. So that rescue team can take immediate action to protect the people from disasters. Twitter—a microblogging service that enables users to share information with outside world through post messages ("tweets") of up to 140 characters. It supports a variety of communicative practices participants use Twitter to communicate with individuals, groups, and the public at large, so when conversations emerge, they are often experienced by either individual or a group of audiences.

C. Advantages of Proposed System

- Less Time Consuming Process, because the automatic alert is immediately send to the nearest users' location.
- We may able to reduce the Loss rate, due to the immediate action taken by the rescue to save the people from disaster.

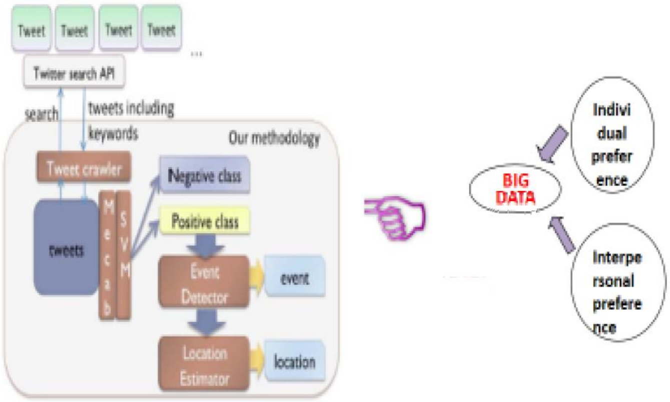

Figure 1: Architecture Diagram

D. System Modules

1. Creation of twitter application.
2. Classification of tweets.
3. Extraction of keyword.
4. Mapping and reducing.
5. Generation of automatic alert.

1. Creation of twitter application.

An application is created using JSP and Servlets to share information through tweets with our friends. The design fields like First name, Last name, gender, Username, Password, Phone, address and other information are assigned for registration details. The user is allowed to login. Also the server will store the data and allow the user to enter in to the chat application.

2. Classification of tweets.

Server verifies the user information and allows the User to tweet with their friends. The machine learning algorithm Support vector machine (SVM) will analyze application by processing each tweets posted by the user and the tweets are classified as positive and negative class.

3. Extraction of target keyword.

The Particle filter along with the stemming algorithm will extract the Keywords from the tweets selected in the positive training set was compared with the target keyword i.e. Earthquake. If particular keyword is achieved the maximum peak then it becomes the target event that we are going to alert.

4. Mapping and reducing.

The Server will be retrieving the user information like Access time and location which is used to find the User's location i.e. the event location. The location estimation is made by map reducer which first maps the tweeted user locations and then finalizes the target location by reducer.

5. Generation of automatic alert system.

To generate an SMS alert will include the Java Archive file called "JSMS " and will get the Rescue team's information in via Coding. So that we'll generate the SMS. For Email Alert we will generate the email using Email Coding and it will be send to the Rescue Team via Internet. For sending an SMS will connect the Nokia PC suite configured mobile via Data cable with Server. This Nokia PC suite configured mobile will transmit the SMS to the rescue team. Thus achieving the target to save people by giving awareness before the occurrence of natural disasters.

E. Related Works

In this section we survey several papers for social recommendation methods, algorithms and filtering mechanisms. Context preferences can be explained as individual preference and interpersonal influence which are the two major aspects analyzed on social media users. Individual preference tells about the each individual user preference on the data and the data item that they like. Interpersonal influence tells that whether the user has close relationships with the sender of the information. In the paper [11] Stefanidis and Pitoura, proposed enhanced preferences with context related information. Preferences tell on user interest on a detailed n number of information stored in relational database. Being variety of context models Stefanidis followed a data centric methodology by representing context as a set of parameters that take values from multi-level domains. These parameters capture information that is not part of the database, such as the user location or the current weather.

Retweeting a concept that inviting the users to tweet and discuss with them without directly pointing at them. In this paper, they had been argued that, as of link-based blogging [12], retweeting can be understood both as a form of information diffusion and as a means of participating in a diffuse conversation. Passing of information through tweets is not simply to get messages out to new users of the target location, but also to alert and engage public and rescue teams with one another. In paper [7] was to describe and map out the various conventions of retweeting, and to provide a framework for examining retweeting practices. This serves multiple purposes. First, as Twitter and other technologies begin providing features to support practices like retweeting, it took detailed study on tweet background, tweet conventions, and took samples of tweets in real time.

Several approaches towards social recommendation [14] matrix factorization methods have been proposed. The matrix factorization models focus on representing the user item rating matrix with low-dimensional latent vectors. Recognizing that influence is a subtle force that governs the dynamics of social networks, influence based recommendation involves interpersonal influence into social recommendation cases. Trust-based approaches exploit the trust network among users and make recommendation based on the ratings of users who are directly or indirectly trusted. SoRec [2] is proposed as a probabilistic factor analysis framework which fuses the users' tastes and their trusted friends' favors together.

Aiming at improving recommender systems by incorporating users' social network information into both friend network and trust network, Ma et al. [3] proposes a matrix factorization model with social regularization which has Good scalability, Accurate prediction, Flexibility.

The basic matrix factorization model shows that we would model directly the observed ratings only, while avoiding over fitting through a regularized model. That is: to learn the factor vectors, the system minimizes the regularized squared error on the set of known ratings:

In this content filtering and collaborative filtering are describes that content filtering is based on the profile and the problem is external information is needed While collaborative filtering based on the interactions and problem is cold start. Collaborative filtering is domain free that can address data aspects that are often elusive and difficult to profile and generally more accurate than content-based techniques. There are two areas of collaborative filtering: Latent factor models and Neighborhood methods.

III. CONCLUSION

As described in this paper, we investigated the real-time nature of Twitter, devoting particular attention to event detection. Semantic analyses were applied to tweets to classify them into a positive and a negative class. We regard each Twitter user as a sensor, and set the problem as detection of an event based on sensory observations. Location estimation methods such as particle filtering are used to estimate the locations of events. As an application, we developed an earthquake reporting system, which is a novel approach to notify people promptly of an earthquake event.

IV. Acknowledgment

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