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TrendNet Algorithm: Towards Personalization of Twitter Trends

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***Abstract:** Twitter displays a list of currently popular keywords and hashtags on the user homepage which are referred as trends. Trends play an important role in discovering the hottest emerging topics of discussion and also help in categorizing the tweets through which the user can easily find similar tweets in that group. Twitter provides its user with a list of top ten trending topics but these trends are general topics which are popular based on the user location and are not context sensitive. These suggestions are not personalized. This paper examines an application for finding personalized trending topics on Twitter. We propose a novel real time trend recommendation system referred as TrendNet that helps its users to find what is currently popular in their network of friends by considering both the tweet content and the social structure. Comprehensive experiments on real Twitter users having different interests were conducted in order to evaluate the effectiveness of the algorithm. The results demonstrate that our scheme provides more accurate and personalized recommendations of trends as compared to the existing scheme.*

***Index Terms:** Collaborative Filtering, Content Based Recommendation, Favorite, Hashtags, , Retweet, Trending Topic*

I. INTRODUCTION

Millions of users are active on Twitter and they consume and disseminate messages resulting in collection of massive information. Every second, on average, around 6,000 tweets are tweeted on Twitter, which corresponds to over 350,000 tweets sent per minute, 500 million tweets per day and around 200 billion tweets per year. The active users use this platform to share useful information and get updated about the latest news and keep track of their friends. In order to provide user with personalized information service, the recommendation system is considered as an effective method that can alleviate the information overload problem. The different aspects that can be recommended in Twitter includes similar users, interest related tweets, and other twitter elements like hashtags and URL. The majority of the user connections in Twitter is unidirectional that clearly indicates that most of the users use Twitter as a source of information and have connected to seek information rather than disseminate their content. Such users are interested in finding out currently popular information on the network. Due to large number of active users in a network it is very difficult and time consuming to find relevant and reliable information. To deal with such massive scale of information, recommendation schemes are used to select the information of interest. Collaborative filtering schemes use the similarities or the preferences of the different users in the network. Another kind of recommendation scheme leverages the user content by generating the user profile from the posted tweets.

The main contribution of this paper is to develop a novel hybrid technique to recommend trends by considering both the information sources of social structure and content relevance. Based on these factors a linear weighted hashtag ranking method is proposed that personalizes this trend list which is important when the user wants to see what is trending in his network of users rather than the location specific topics as recommended by Twitter. Nowadays this trend list also contains promoted trends purchased by advertisers who want to reach a wider group of users which has nothing to do with the user interests.

The rest of the paper is structured as follows. In Section 2, we discuss the related work and cover the different issues in hashtag recommendation. Section 3 presents the proposed TrendNet algorithm. In Section 4, the performance of the proposed scheme is evaluated and the results are compared to the existing scheme. Section 5 concludes this work with the possible future work.

II. RELATED WORK

The majority of Twitter trend list contains the popular hashtags along with other popular keywords. As the use of hashtags has gained popularity, so has the research in the development of hashtag recommendation system. Hashtags is a keyword that is used to describe a topic which in many researches has been used to categorize tweets so that it is easy for other users to find and follow similar tweets. Hashtags have the potential to become trending topics. Trending Topics are hashtags that are being widely discussed and are very popular. Hashtags are used in very limited tweets which reduces its usefulness so the major shift of existing research is to predict hashtags that could be recommended to users before they post their message. Most of the work in hashtag recommendation is to recommend a hashtag to the newly generated tweet based on the tweet content so as to promote the usage of hashtags in the Twitter network.

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Zangerle et al [21] introduces the hashtag recommendation approach by analyzing the existing tweets of other users from the data set and finding the most similar messages and extracting the hashtags used in them and ranking and recommending the list of hashtags appropriate for a given user who has just written a new tweet. The other direction of research is towards classification of hashtags into predefined categories [3][5][6]. Twitter updates its trend list momentarily but has not disclosed its method by which they determine these trending topics; but claims to be tailored based on user location and people followed or can be changed to view trends in a particular geographical area. If different users view this list of trending topics it is clearly visible that the trends are more based on the user locality and very few trends reflects the user interest. These topics are almost similar for the majority of users in the same location as these trends do not take into consideration the interest of the user. If the user wants to know what is currently popular among his friend circle he has no direct way to know the same and has to drill down hundreds to thousands of tweets depending on the number of social connections in his network. Filtering out the popular content becomes a trivial task and in such situations trends can be useful. So other than recommending hashtag to a new tweet or categorizing them into predefined groups; another important research issue which is still unexplored is to personalize the recommended trend list. Towards this, our algorithm combines the user network connections and the tweet contents posted in the network to provide tailored trends to the user. Trend recommendation should be personalized and it should also consider the user preferences.

III. THE TRENDNET ALGORITHM: TREND RECOMMENDATION TECHNIQUE

The structure of Twitter network is referred as Follower-Followee network where if user X follows user Y, we refer X as Y's follower and Y as X's followee. The social structure information is an important resource in our recommendation model as it is used to define the User Network Model that reflects the user interest. The Algorithm takes as input the user name of the Twitter user to whom trends are to be recommended. The user is represented by their own tweets and another by the tweets of their followers/friends. From the collected content the possible hashtag entities are extracted. For each user, the frequency of different hashtags occurring in different tweets is computed. A hashtag limit is imposed on each hashtag in order to avoid any user from promoting their keywords as trend. The frequency of each occurred hashtag is computed for all the users resulting in the computation of hashtag weight. Popularity count of each hashtag is computed using two popular Twitter indicators of Favorite and Retweet. Interest Rate for each hashtag is computed by multiplying the hashtag weight and popularity count. Then this list of hashtags in arranged in the descending order of their Interest Rate Count. The detailed description of algorithm and its components is described in the following subsections.

USER NETWORK MODEL

Twitter promotes two-way communication with its following and followers features, but like other social networks like Facebook it does not force the connection between them. The Twitter users you follow are the people whose updates you subscribe to. Twitter users who subscribe to the updates you publish follow you. People who follow you are called your followers. Followers are users following the specific user and Friends are every user the specific user is following. The objective of this work is to personalize the user trends by taking into consideration the network of the user rather than the entire Twittersphere. The user network is represented by the user and the set of other users being followed by him referred as his friends. The mathematical representation of Network of User U_T is represented as union of IDs of Target User and all his friend connections and is shown as follows:

Here, U_T is used to denote the Target User to whom trends are to be recommended and U_{T_ID} is used to denote the Userid of Target User

For the input user U_T; find its corresponding U_{T_ID}

Let $\{U_{F_i} \mid i = 1,2, \ldots .. n\}$ be all the friend connections of U_T

For i=1, 2…n: U_{F_i} find U_{F_ID}

$$U_{TF\_ID} = \left\{ \bigcup_i U_{F\_ID} \middle| i = 1,2, \ldots ., n \right\}$$

Network of User U_T is represented as U_{TN} which is union of userid of U_T and his friends U_F:

$$U_{TN} = U_{TF\_ID} \bigcup U_{T\_ID}$$

The users who follow the target user are not considered as the part of this network because they do not reflect the user interest.

USER CONTENT GENERATION

The interest of the user can be seen from his published tweets and the tweets of the users been followed by him. As a trend refers to what is currently popular so in order to generate what is trending in the user network; the latest tweets of each user from the network U_{TN} is retrieved. The mathematical representation of Tweet Corpus T_{TN} to be considered for recommendation can be described as follows:

Let T_{rj} be all Tweets for all users j ∈ U_{TN}

$$\left\{ \bigcup_j \bigcup_r T_{rj} \middle| j \in U_{TN}, r = 1,2, \ldots .., m \right\}$$

As the trends reflects the currently popular information. So from the total 'm' generated tweets the 'n' latest tweets are retrieved to form the tweet corpus.

$$T_{TN} = \left\{ \bigcup_j \bigcup_r T_{rj} \middle| j \in U_{TN}, \quad \begin{matrix} r = 1,2, \ldots .., n \\ n \leq m \end{matrix} \right\}$$

In our work, the top ten tweets are retrieved for each user. The collected tweets are then stored in the database that is used to contain information related to tweet which is referred as Status. It is used to store the StatusText, StatusID, UserID, Username, FavoriteCount, RetweetCount, and Time of creation of tweet.

The database stores the latest tweets of the target user and their friend connection. As each user is identified by the username or its userid, similarly the tweet is identified by its StatusID and the status text. The Favorite Count and Retweet Count are stored in the database as an indicator of the tweet popularity.

TWEET PROCESSING

The collected tweet corpus represents the tweets of target user and his friends. Tokens are extracted from the tweets are the corresponding hashtag entities are retrieved from it. The mathematical representation of the process of fetching the tokens from the tweets of user j is described as follows:

$$T_{rj} = \sum_{s=1}^{l} t_{sj} \text{ where } r = 1,2, \ldots p \text{ and } l \text{ is tweet length}$$

The token representation of tweets of all users belonging to user network

$$t_{TN} = \sum_{j} T_{rj} ; j = 1,2 \ldots . . n+1$$

From the generated tokens, the probable hashtag entities are extracted. Fetching hashtag entities from tokens t_{TN} can be represented as follows:

$$H_{TN} = \{h_{sj}\}$$

Where, $h_{sj} = \left\{ h_{tj} \middle| \begin{matrix} s = 1,2 \ldots , z \\ j = 1,2, \ldots . n+1 \end{matrix} \right\}$

The possible extracted hashtags are saved in the database as shown in Figure 1 below.

Rid	StatusId	Tag

Figure 1: Hashtag Database

The database contains the StatusID and Tag. StatusID is used to identify the tweet in which the corresponding tag is appearing.

HASHTAG PROCESSING

All the possible keywords that can be used to represent the tweets are extracted and stored in the hashtag database. In hashtag processing phase, first the frequency count of each hashtag for a specific user is computed and compared against the hashtag limit. If the hashtag count is greater than the set limit then its count is set to the hashtag limit. A Hashtag Limit is imposed in the scheme, in order to prevent a specific user from repeating the keyword in order to promote his tweet. In our work, we have set the hashtag limit to 2.

Computing Hashtag Count and Hashtag Limit

For each user j:

For each user hashtag h_s :

h_{s_cnt} = get_count (h_s)

if$(h_{s_cnt} > H_{limit})$ $then\ set$ $(h_{s\_cnt} = H_{limit})$

$$hc_s = h_{s\_cnt}$$

Now, the collection of hashtags over the User Network U_{TN} is represented as:

$$H_{TN} = \bigcup_{j=1}^{n+1} \left\{ hc_{s_j} \middle| s = 1,2 \ldots . z \right\}$$

After setting the limit on each hashtag for a given user; the next step computes the Hashtag Weight. In this process the hashtag count for each hashtag over the set of all users is computed. This means that frequency count of each hashtag is calculated over the set of all the users.

Computing Hashtag Weight

Till now, from the users latest tweets the frequency count of each hashtag is computed. Next it is seen that for the set of the other users in the user network how many times that hashtag is appearing. The hashtag weight is computed for the hashtag over the set of the users in the user network.

For each hashtag h_s:

$$HW_s = \sum_{j=1}^{n+1} (hc_{sj})$$

After obtaining the occurrence frequency count of each hashtag over the set of all considered users. For each hashtag, its corresponding tweets are obtained and the relative favorite and retweet count of each tweet is retrieved which determines the popularity of the hashtag in the twitter network amongst the considered users.

Computing Hashtag Popularity

Every user in social media is unique and it is important for the social media to identify the particular user interests. In this step the computation of popularity count of hashtag is performed using two popular Twitter indicators of Favorite and Retweet. From the large array of topics ranging from sports, fashion, music, politics, television and technology Favorite helps in tracking the important topics of interest of the user. A favorite is represented by small star icon next to a Tweet and is used as an indicator that a tweet is liked or is popular among the users. A Retweet is a repost of another Twitter user's tweet. User indicates a retweet by typing RT at the beginning of the tweet to indicate that they are re-posting someone else content. Retweeting can be considered as something that one finds is important to share or recommend reading in his circle. From the tweet and the hashtag databases the popularity of the hashtag is computed as follows:

For each hashtag h_s:

For each tweet t_y related to hashtag h_s:

$$HP_s = \sum_{s=1}^{z} TR_{sy} + TFC_{sy}$$

where, TR_{sy} is Retweet Count and TFC_{sy} is Favorite Count of the tweet in which that hashtag appears

Computing Hashtag Interest Rate

Hashtag Weight and Hashtag Popularity measures computed above are used to represent the Interest Rate of the hashtag. For each hashtag both these measures are multiplied as follows:

$$HIR_s = \sum_{s=1}^{z} \left(\prod_{s} HP_s \ \ HW_s \right)$$

The hashtags are ranked in the decreasing order of the hashtag interest rate. This list is then recommended to the target user as possible trend list.

IV. EXPERIMENTAL EVALUATION

In this section the effectiveness of the TrendNet Algorithm is evaluated through experiments on real twitter users. Firstly the description of the dataset is provided which is followed by the different evaluation metrics used in order to compare the results. The purpose of comparison of Twitter TrendList with that of TrendNet Recommendation List is not to claim that the list of trends generated by twitter is wrong while that of TrendNet is correct. The motivation behind the proposed work is towards the personalization of this trend list.

Dataset Description

As the trend list is visible on the user homepage and there is no other way of fetching the same. So it is not possible to fetch the trend list of a specific user. In order to validate our results purposefully five different Twitter users are created that belong to different interest areas ranging from Big Data, Indian Movies and Entertainment, Indian Government and Politics, Cricket and Science and Engineering. The interest of the user can also be inferred from other users been followed. So the list of other users been followed by them also belong to their interest area. Trends are real time and are changed momentarily by the Twitter based on what is currently popular. The current list of top ten trends is generated by running both the algorithms (Twitter Trend Algorithm and the proposed TrendNet Algorithm) in parallel for each stated user. The trend list generated by the Twitter is clearly not personalised and majorily reflects the trends currently popular in the given location. As all the above users belong to same location; it yields to a similar generated trend list even though their interests are disjoint. The twitter trend list contain promoted trends which are same irrespective of the user which highlights the specific interest area. Also from the ten trends which are recommended by the Twitter, there are many common hashtags in the trend list of all the users even though their interest areas are different. Apart from the overall available news, the twitter user is more interested in finding out what has been popular in his social network the entire day. But due to large user base the timeline is flooded with information. It is trivial to find out the relevant information. One way is to read through his timeline but due to large number of twitter messages it is very tedious to read every post and find useful content. Another approach is to use the trend list but as it is momentarily refreshed still there is scope that some important updates are lost.TrendNet algorithm can be helpful in this scenario where the user aims to search for useful content that is of his interest and provides an insight to the user about the different topics that has been in discussion the entire day.

Evaluation Metrics

Trend Validation means whether the trends in the recommendation list is valid or not for the given user. Three different metrics i.e Precision, Recall and F-Measure are used to validate the trend list. Precision metric aims to find how useful the results are while Recall metric determines how complete the results are. For any recommendation system it is trivial to achieve recall of 100% (returning all relevant trends). The main objective of the work is to recommend as useful hashtag trends as possible based on the interest of the user than focusing on the completeness of the recommendation results.

Precision is the number of trends correctly labeled as belonging to the relevant class divided by the total number of retrieved trends.

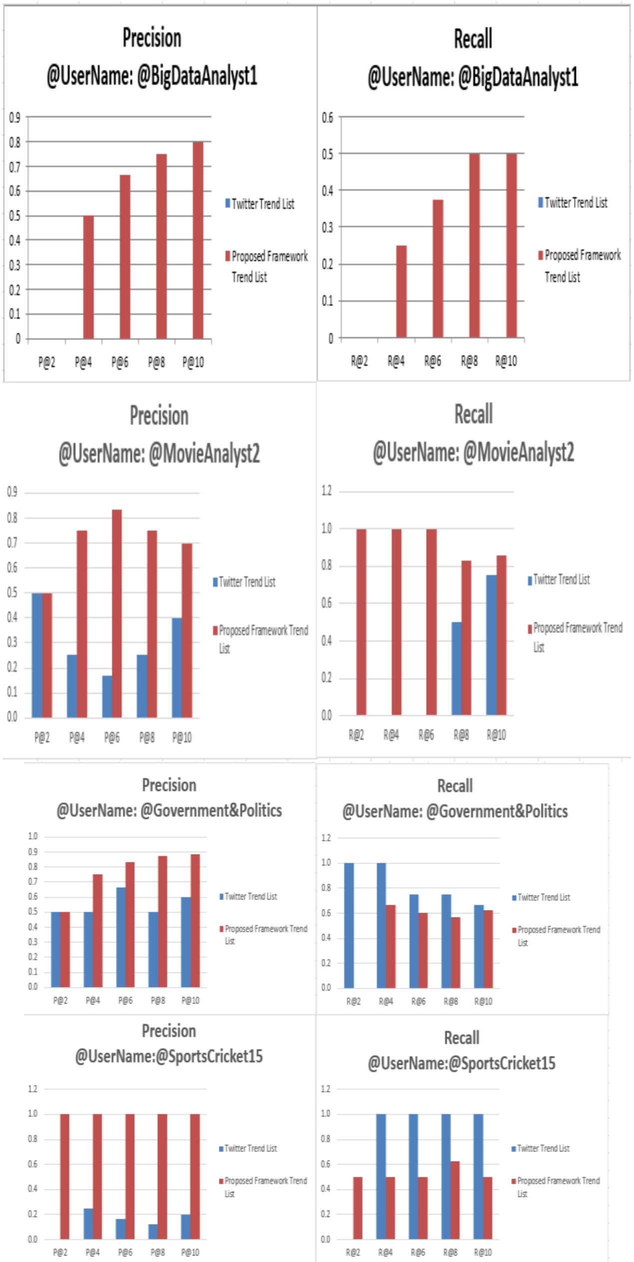
$$\text{Precision} = \frac{\text{Relevant Trends from the Retrieved Trend List}}{\text{Retrieved Trend List}}$$

Recall is defined as the actual number of trends considered relevant from the retrieved trend list divided by the total number of claimed relevant trends.

$$\text{Recall} = \frac{\textit{Relevant Trends from the Retrieved Trend List}}{\textit{Relevant Trends}}$$

F-score/ F-Measure is the measure that combines precision and recall and is defined as the harmonic mean of precision and recall.

$$\textbf{F-score} = 2 * \frac{Precison * Recall}{Precison + Recall}$$



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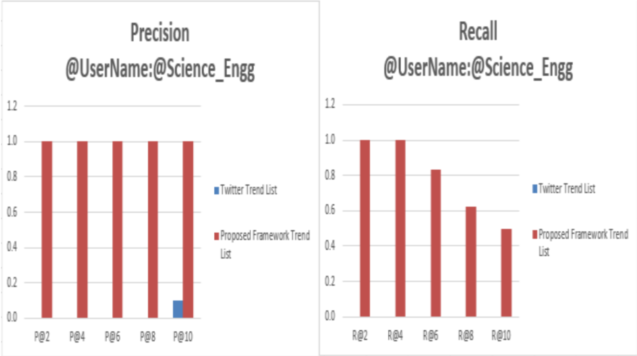

Figure 2: Graphs comparing the Precision and Recall Metrics for Twitter Trend List and Proposed Framework Trend List for different Twitter Users

For the top-n recommendations where n=10; the Table 1 below compares the F-measure values over the different Twitter users considered.

Table I: F-Measure Computation for For Top 10 Recommendations

UserName	Twitter Trend List F-Measure	TrendNet Trend List F-Measure
@BigDataAnalyst1	0	**0.614**
@MovieAnalyst2	0.533	**0.787**
@govt_politic	0.646	**0.72**
@SportsCricket15	0.333	**0.666**
@Science_Engg	0	**0.666**

For all the different interest based users, the results shows clearly that using the proposed framework the results are more useful and user can relate those hashtags with their interest as these hashtags are retrieved from the tweets of the user and the other users followed by him. The user interested in the news on Big data and Science and Engineering cannot relate the general trend list presented to him by Twitter as it contain no element belonging to his choice and are just the genric trends momentarily popular in the location of the user. When compared with the TrendNet recommendation list 61% of trends recommended to Big Data user were found useful while 66% of trends recommended to Science and Engineering interest oriented user were found useful.

V. CONCLUSION AND FUTURE WORK

Majority of the users on Twitter are categorized as Information Seekers who rarely disseminate information but regularly follow other users. So for such category of users who do not write any tweets; hashtag can be very beneficial and that too personalized may add an advantage. The objective of the paper was to implement an effective and personalized hashtag recommendation system that provides real time suggestions of hashtags for the Twitter users based on their interest. While our research has shown promising results but still the scope of the research can be extended in several other directions in the future. The resulted trends may include trend descriptions. User sentiments can be used to enhance the interest of the user and can be used to make better hashtag recommendations.

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