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Su Mon KYWE
Singapore Management University, monkywe.su.2011@smu.edu.sg

Ee Peng LIM
Singapore Management University, eplim@smu.edu.sg

Feida ZHU
Singapore Management University, fdzhu@smu.edu.sg

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A Survey of Recommender Systems in Twitter

Su Mon Kywe, Ee-Peng Lim and Feida Zhu

Singapore Management University, Singapore
{monkywe.su.2011,eplim,fdzhu}@smu.edu.sg

Abstract. Twitter is a social information network where short messages or tweets are shared among a large number of users through a very simple messaging mechanism. With a population of more than 100M users generating more than 300M tweets each day, Twitter users can be easily overwhelmed by the massive amount of information available and the huge number of people they can interact with. To overcome the above information overload problem, recommender systems can be introduced to help users make the appropriate selection. Researchers have began to study recommendation problems in Twitter but their works usually address individual recommendation tasks. There is so far no comprehensive survey for the realm of recommendation in Twitter to categorize the existing works as well as to identify areas that need to be further studied. The paper therefore aims to fill this gap by introducing a taxonomy of recommendation tasks in Twitter, and to use the taxonomy to describe the relevant works in recent years. The paper further presents the datasets and techniques used in these works. Finally, it proposes a few research directions for recommendation tasks in Twitter.

Keywords: Twitter, recommender systems, personalization

1 Introduction

1.1 Motivation

Twitter is an online social information network launched in July 2006. By 2012, the number of Twitter users has grown to over 140 million [1]. Unlike many other online social networks, the user-user relationships in Twitter network can be social or informational, or both. This is because users not only follow other users for maintaining social links, but also for gaining access to interesting information generated by others[13, 15]. For example, Twitter has been often used to share information and sentiments about live events including the 2011 Egypt's revolution[5].

As Twitter users generate more than 300M tweets each day, these users are also overwhelmed by the massive amount of information available and the huge number of people they can interact with. To overcome the above information overload problem, recommender systems can be introduced to help users make

[1] http://en.wikipedia.org/wiki/Twitter

the appropriate selection. While some of these are already deployed so far, most of them are still being studied as research projects in universities and industry labs. These research projects usually address individual recommendation tasks. There is currently no comprehensive survey for the realm of recommendation in Twitter to categorize the existing works as well as to identify areas that need to be further studied. The paper therefore aims to fill this gap by introducing a taxonomy of recommendation tasks in Twitter, and to use the taxonomy to describe the relevant works in recent years.

Our taxonomy is designed considering the unique functions users can perform in Twitter. Before we show the taxonomy, we first review these functions as follows.

– **Tweet** - This refers to posting a message of up to 140 characters, known as tweets. The content of tweets may vary from users' daily activities to news[13]. Some messages may also include URLs to web pages or hashtags to relate tweets of similar topics together. Each hashtag is a keyword prefixed by a # symbol. For example, #Egypt and #Jan25 have been used to group tweets related to Egypt's revolution in January 2011.
– **Retweet** - This refers to forwarding a tweet from another user to the followers. Such re-sharing of tweets is a prevailing mechanism in Twitter to diffuse information.
– **Follow** - This refers to linking to another user and receiving the linked user's tweets after that. The user creating such a link is called the *follower* and the linked user is known as the *followee*.
– **Mention** - One may mention one or more users in a tweet by including in the tweet the mentioned user name(s) prefixed by the @ sign. The mentioned user(s) will subsequently receive the tweet. This is a means for users to gain attention from the other users so as to start new conversations.

1.2 A Taxonomy of Recommendation Tasks for Twitter

Our taxonomy represents the information required for the above user functions. We represent the information involved in different functions by different tuples as shown in the Table 1. For example, a tweet action performed can be represented by $tweet_i = \langle u_i, t_i, Url_i, Tag_i \rangle$ where u_i, $text_i$, Url_i, Tag_i denote the user who tweets, tweet's text, the set of URLs and set of hashtags that appear in the tweet respectively.

For each of the above functions, one can define one or more recommendation tasks to aid users in deciding the missing field(s) in the corresponding tuples. For example, a user u_0 trying to perform a tweet function may have written a piece of text, e.g., "SocInfo2012 has announced the keynote speakers" but does not know what hashtag(s) to use. In this case, we have a tuple $\langle u_0,$ "SocInfo2012 has announced the keynote speakers"$, \{\}, Tag? \rangle$ with the hashtag information to be suggested as represented by the $Tag?$ variable. This tuple with a variable therefore corresponds to a recommendation task that suggests hashtags for a given piece of text written by a given user.

Function	Tuple	Function	Tuple
$tweet_i$	$\langle u_i, text_i, Url_i, Tag_i \rangle$ u_i: user who tweets $text_i$: tweet's text Url_i: set of URLs in the tweet Tag_i: set of tags in the tweet	$mention_i$	$\langle u_i, U_i, text_i, Url_i, Tag_i \rangle$ u_i: user who mentions others U_i: users who are mentioned $text_i$: the tweet's text Url_i: set of URLs in the tweet Tag_i: set of tags in the tweet
$retweet_i$	$\langle u_i, u_j, t_j \rangle$ u_i: user who retweets u_j: user whose tweet is retweeted t_j: the tweet that is retweeted (URLs and tags may already exist in t_j)	$follow_i$	$\langle u_i, u_j \rangle$ u_i: user who follows u_j: user who is followed

Table 1. Tuple Representations

One can work out a variety of recommendation tasks by assuming that some field(s) in some tuples are not known. In Figure 1, we show our proposed taxonomy of recommendation tasks in Twitter and each task is accompanied by its corresponding tuple representation and recommendation statement. In the remaining parts of this paper, we will survey some of the recommendation tasks which have been studied or are being studied.

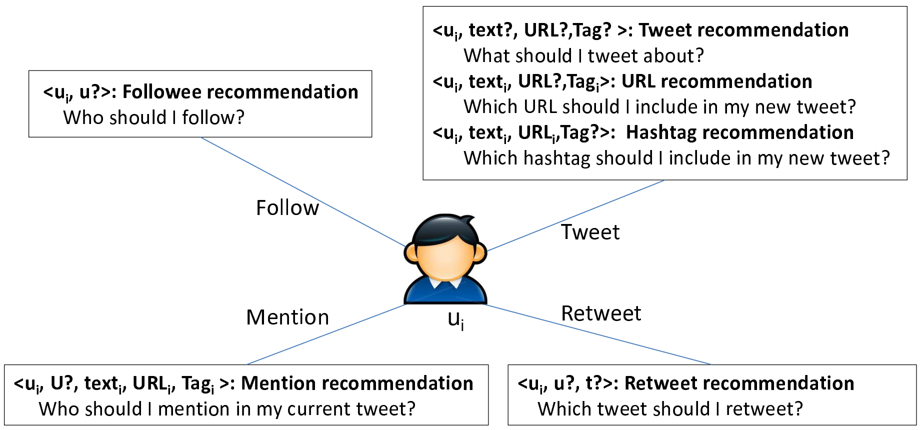

Fig. 1. Taxonomy of Recommendation Tasks in Twitter

1.3 Paper Outline

The remainder of the paper is structured as follows. Section 2 provides a summary of the traditional recommendation methods. Followees, followers, hashtags, tweets, retweets and news recommendation tasks and their methods are summarized in Section 3, 4, 5, 6, 7, and 8 respectively. We finally conclude the paper in Section 9.

2 Traditional Recommender systems

Recommender systems perform information filtering by suggesting to a user some new items (e.g., songs, books, or movies) to purchase or some new users for building friendships [21]. There are two types of recommender systems – *personalized* and *non-personalized*. The personalized recommender systems consider the preferences of users to be recommended. The non-personalized recommender systems however do not make use of user preferences. An example of non-personalized recommendation method is to return top ten songs of the current month. Most recommendation methods to be surveyed in this paper are personalized. Personalized recommender systems utilize characteristics of items, profiles of users and the interactions or transactions between users and items to predict the users' future item adoptions. Collaborative filtering and content-based approaches are often used in personalized recommendation.

2.1 Collaborative filtering and Content-based recommendation

The underlying assumption of the *user-to-user based collaborative filtering approach* is that if a person X has the same opinion as a person Y on an issue A, X is more likely to adopt Y's opinion on a different issue B than a randomly chosen person. The recommender system finds people with similar tastes or preferences, according to their past ratings or implicit interactions. Then, the system predicts the preference of a user on an unrated item using the preferences of similar users [23].

Another personalized recommendation approach is *item-to-item collaborative filtering* which is used by Amazon.com's recommender system. Items A and B are highly similar if a relatively large portion of the users who purchase item A also buy item B. Then, the preference of a user over an unrated item B is predicted based on the user's rated item A.

Content-based recommender system finds similar items by comparing their features and characteristics. Then, the recommendation of an item is made to the user who likes or purchases similar items before. In other words, various candidate items are compared with items previously rated by the user and the best-matching items are recommended.

2.2 Other Approaches in Social Media

Social recommender systems recommend items based on the preferences of a user's friends or other social media information, such as tags and comments. The recommended items might not necessarily be components of social networks. For example, in the case of Twitter, one can recommend news articles making use of the attention the articles received from Twitter users. Hence, such recommendation may be targeted for users outside of Twitter.

Technique wise, the existing recommendation methods used in social media have to adapt to the unique features in Twitter. For example, the friendship recommendation methods that work well at social networking sites such as Facebook may not work well in Twitter's follow link recommendation as the latter is asymmetric (i.e. users do not necessarily follow back those who follow them).

3 Followee Recommendation

In Twitter, users are interested in finding not only their close friends but also new relevant contacts not yet known to them. A user may follow other users whom he or she does not know offline but who share interesting trending topics. These users can be treated as information sources for the user. Depending on the target user needs, different followee recommendation algorithms can be used. For instance, one may use number of common friends to recommend known friends, or use user profile similarity measures to recommend users with similar interests, or popularity scores to find good information sources.

Twitter has a "Who to follow" feature at Twitter home page, the user profile pages, and Connect and Discover pages [2]. It recommends followees who are similar to the existing followees of the target user, and followees of those followees. When the target user visits another user's profile page, users who are similar to the visited user profile will be recommended. The exact recommendation algorithm behind this feature is however unknown. The recommendation algorithm also includes advertiser accounts which are labeled as "promoted" accounts.

3.1 Topology-Based Methods

Armentano et al. proposed three very similar topology-based approaches for followee recommendation [3, 2, 1]. They [3] use both collaborative filtering and content-based recommendation.

Collaborative filtering approach is considered a topology-based method since similar users are found based on follow graph. The authors assume that the target user is similar with the followers of his or her followees. Hence, candidate followees are ranked according to the number of common followees with the target user, page rank and the number of mentions. The top ranked candidates are then recommended as potential followees. The number of common followees represents the similarity between the two users' preferences. Both page rank and number of mentions determines the popular and reliable information source.

In the content-based approach proposed by the same research group, user interest is represented by the tweet content of his or her followees. The users whose followees' tweets are similar to the followees' tweets of the target user will therefore be recommended. The implicit assumption is that a target user

[2] `https://support.twitter.com/`

is likely to follow those who are similar. This is consistent with the homophily effect where individuals have tendency to bond with similar people [18].

The above two approaches are somewhat different from typical collaborative filtering which recommends followees of similar users, instead of similar users. For instance, a user X follows those who tweet about A, while a user Y follows those who tweet about A and those who tweet about B. In a typical collaborative filtering approach, if user X and user Y are similar, user X should be recommended with those who tweet about B as potential followees. Nonetheless, user Y is recommended as a potential followee in the above approaches.

3.2 Weighted Content-Based Methods

The paper proposed by Garcia [7] identifies features that might be useful for recommending followees. Although five features, namely popularity, activity, location, friends in common and content of the tweets, are predicted to be relevant for recommendation, only popularity and activity have been evaluated. The intuition of the paper is that if a target user has many popular and active followees, other popular and active followees should be recommended to the user. If the target user has only popular followees, only popular followees should be recommended. A similar approach can be applied for target users with active followees.

Popularity is measured by the follower and followee count ratio, while activity is defined by the number of tweets a user has posted since he registered on Twitter. A user is regarded as popular or active when the score is greater than certain threshold. Then, the preference score of a user towards popularity is defined by the fraction of followees who are popular. The preference score of a user towards activity is defined by the fraction of followees who are active. When the preference score of the target user towards popularity or activity is greater than certain threshold, popular or active followees will be recommended.

Moreover, the paper observes that the two features together perform better in prediction than alone. It gives an insight that if more features are considered, the recommendation accuracy can be further improved.

3.3 Structural Methods

A structural approach to contact recommendations in Twitter is introduced by Golder et al. [8]. This work introduces 'reciprocity', 'shared interests', 'shared audience' and 'filtered people' methods for recommending followees. The reciprocity method assumes that a user will follow back his or her followers, just to return the attention.

Shared interests and shared audience methods are based on the assumption of homophily, which states that people form ties with like-minded or similar others. A set of users is considered similar or shares the same interest if they are following the same people. Similarly, users who share the same audience or followers are considered similar. A user is then recommended to follow his similar users.

Filtered people of a user are the users whose tweets are retweeted by the followees of this user. The paper states that a user may be interested to follow those filtered people who are the followees of the user's followees because they may also share the same interest.

3.4 Twittomender

In [9–11], Hannon el al. presents a Twittomender system that recommends followees using both content-based and collaborative-based approaches.

In their content-based approach, users are represented by: (i) their own tweets, (ii) their followees' tweets, (iii) their followers' tweets, or (iv) combination of all of them. In case (i) where a user is represented by his own tweets, users with similar tweets are recommended to the targeted user. In case (ii), a target user is recommended with a list of users whose followees' tweets are similar to those of this user's followees. Cases (iii) and (iv) are treated similarly. In all these cases, each user is represented by TF-IDF weighting scheme [22].

In the collaborative-based approach, the users are represented by IDs of their followees, IDs of their followers or combination of them. IDs are treated as keywords and each user is represented by a set of his follower/followee IDs. Then, TF-IDF weighting scheme is used to find users with similar follower/followee IDs. For example, in the first case where the users are represented by IDs of their followees, a followee is more likely to represent the user's interest if it is not followed by a lot of other people (IDF score). When two users have such common followee, they are more likely to be similar than if they share a common followee who is followed by many users.

Experiments have shown that the above collaborative methods is more precise than the content-based methods. The three most precise methods are, the combination of all the individual methods, followed by the method where users are represented by their followees' IDs, and the method where users are represented by both of their followees' IDs and followers' IDs.

3.5 Recommendation Based on Followers and Lists

In the paper of Krutkam et al. [14], followee recommendations are made based on the number of followers that the user has, the number of lists or groups that the user is listed in and the number of news related group the user is in. The methods are not personalized. In other words, they suggest the most popular users based on the above methods, without considering the individual user's preferences. According to the surveyed results, recommendation based on the number of followers significantly outperforms recommendation based on the number of lists the user is in.

4 Follower Recommendation

While the needs of the general users are targeted by the followee recommender systems, marketers and politicians are interested in finding out new followers who can spread their tweets by retweeting. The following paper emphasizes on identifying followers who can efficiently share information, recommendations and news (such as conference announcements and events) with like-minded users in a community.

4.1 Tadvise

Nasirifard et al. introduced Tadvise to recommend new followers based on their hashtags. The purpose of Tadvise is to help users know their followers better[19]. A set of hashtags is associated with each user's profile as the hashtags appear in the user's tweets. The weight of each hashtag in the user's profile is defined by the total PageRank of the users who mention the profile's owner with the corresponding hashtag. The intuition behind this is that a hashtag is highly relevant to a user if it is frequently used in the user's incoming tweets by highly authoritative users.

Tadvise then recommends well-connected topic-sensitive users as followers. These users may serve as hubs for broadcasting a tweet to a larger relevant audience. The candidate followers are ranked by their hub scores which represent the number of interested users who could potentially receive tweets from the former.

Given a user and a tweet with at least one hashtag, Tadvise determines whether the tweet will likely diffuse from the user. Firstly, Tadvise identifies if the hashtag(s) used in the tweet are relevant to the followers and followers-of-followers. If there are a large number of relevant followers and followers-of-followers who have high weight profiles for the given hashtag, the tweet is expected to attract much attention. Otherwise, the followers and followers-of-followers may choose to ignore the tweet.

5 Hashtag Recommendation

There are multiple purposes of using hashtags. Some people use them to categorize their tweets. Some use them as mass broadcast media for disasters or special events like elections. Hashtags are also used for brand promotion or micro-meme discussions [12]. Since hashtags are neither registered nor controlled by any user or group, it may be hard for some users to find appropriate hashtags for their tweets. Therefore, recommender systems for suggesting appropriate hashtags to the users are proposed.

5.1 Recommending Hashtags in Twitter with TF-IDF Scheme

The paper by Zangerle et al. [25] assumes that the primary purpose of the hashtags is to categorize the tweets and facilitate the search. The paper recommends suitable hashtags to the user, depending on the content that the user enters without considering user's preference for specific hashtags.

When a user writes a tweet, the recommender system retrieves a set of tweets similar to the given tweet. Similarity score is calculated by TF-IDF scheme. Then, the hashtags are extracted from the retrieved similar tweets and are ranked using their number of occurrences in the whole dataset (OverallPopularityRank score), their number of occurrences in the retrieved dataset (Recommendation-PopularityRank score) or similarity scores of the tweets (SimilarityRank score). The precision and recall measures of these three ranking scores show that SimilarityRank score is the best among them and the performance of the recommender system is the best when only five hashtags are recommended.

5.2 Suggesting Hashtags on Twitter using Bayes Model

Another paper which recommends hashtags on Twitter is proposed by Mazzia et al. [17]. Similar to the previous paper, this paper recommends hashtags by observing the content that the user generates. Unlike the previous paper, this paper proposes to use Bayes model which calculates the probabilities of using hashtags.

Before processing the data, the paper cleans the data by removing micro-memes and spams. Micro-memes are detected by identifying tweets which use the same hashtags but are very dissimilar. Spams are filtered by limiting the number of tweets with a particular hashtag from a user. The Bayes model used in this paper is represented by the following formula.

$$p(C_i|x_1, ..., x_n) = p(C_i)p(x_1|C_i)...p(C_i)p(x_n|C_i)/p(x_1...x_n)$$

where C_i represents the i^{th} hashtag and $x_1, ..., x_n$ represents the words. $p(C_i|x_1, ..., x_n)$ is the probability of using hashtag C_i given the words that the user provides and the hashtags with the highest probabilities are recommended to the user. $p(C_i)$ is the ratio of the number of times hashtag C_i is used to the total number of tweets with hashtags. $p(x_1|C_i)...p(x_n|C_i)$ is calculated from the existing data of tweets.

The paper also suggests another model which makes use of Inverse Document Frequency (IDF) to calculate the probability.

$$p(x_1, ..., x_n|C_i) = p(x_1|C_i)^{(1-t_1)}...p(x_n|C_i)^{(1-t_n)}$$

where t_j is the IDF weight of the word x_j.

5.3 High Dimensional Euclidean Space Model

The paper proposed by Li et al. [16] also recommends hashtags based on the information provided by the previous similar tweets. It constructs high dimensional Euclidean space with the words of tweets. Hashtags of the tweets which have the minimal distances are recommended. Distance of tweets in this approach is measured as 1) Euclidean Distance, 2) Ontology Based Distance (OBD), or 3) Centralized Ontology Based Distance (COBD). The comparison of error rates for these three methods shows that OBD method performs the best.

6 Tweet Recommendation

All tweets from the followees of a user are displayed in the user's home page. When the user is following many active users, there are chances that the user might miss out reading some interesting tweets. With the careful information filtering, important tweets can be chosen and emphasized according to the user's preference.

6.1 User Oriented Tweet Ranking: A Filtering Approach to Microblogs

A personalized tweet filtering approach is proposed [24], which introduces two methods – ranking incoming tweets and ranking targeted users. In the first method, for each user, tweets are ranked according to their probabilities of being retweeted by the user. In the second method, for each tweet, users are ranked according to their probabilities of retweeting the tweet. The underlying assumption is that a tweet is considered relevant and recommended to a user if the user is likely to retweet the tweet.

This paper treats the ranking as a classification problem. First, the classifier is trained with four features, namely author-based, tweet-based, content-based and user-based features.

- Author-based features are features that can be inferred from the user profile, such as number of followers, tweet rate, age of the account, etc.
- Tweet-based features are the syntactic features of the tweet, such as hashtags, URLs, etc.
- Content based features are the ones related to the information contained in the tweet, such as minimum cosine distance to other tweets.
- User-based features are related to the user whose tweet is being ranked, such as "Is the author following me?", "Is the author my conversation friend? (i.e. did we mention each other before?)".

The trained classifier will predicts whether a given tweet is likely to be retweeted by a given user, depending on the above features. Tweets with high probabilities of being retweeted by the target user will be recommended.

7 Retweet Recommendation

Currently, there is no paper about personalized retweet recommendation. However, the work [24] introduced in Section 6.1 can be considered as a retweet recommender system because they are suggesting tweets according to the probabilities of being retweeted by the user. Tadvise [19] identifies whether the hashtags used in the tweets are relevant to the followers of the targeted user. It can also be used to recommend tweets which the user should retweet for his followers.

8 News Recommendation

Since the tweets are actively written or retweeted by the user, they can be assumed to strongly reflect the user's interest. The following two papers recommend news articles to the user based on the tweets generated by that user.

8.1 Recommending URL from Information Streams

The paper by Chen et al. [4] takes URL as a unit of news information in Twitter. They design and implement a URL recommender system called Zerozero88 which recommends URLs that a particular user might find interesting. This paper uses a *choose-and-rank* approach, where a candidate set of URLs is chosen first and then ranked according to two methods summarized as follows.

The candidate set of URLs are chosen by *followees of followees* and *popularity* methods. The first method is based on the intuition of the locality – neighborhood of a user is considered similar and relevant to the user, such that the URLs posted by a user's neighborhood are likely to produce high quality recommendations. Therefore, this approach selects only the URLs posted by the followees and followers of followees of a user. In the second method, popularity score of URLs are utilized to select the candidate set.

After choosing the candidate URL set, two methods are used to rank the candidate URL set. The first method uses topic relevance and the second uses social process. In the topic-relevance method, two factors are considered, which are the similarity between the tweets containing candidate URLs and the tweets of this user, and the similarity between the tweets containing candidate URLs and the tweets of this user's followees. In the social process method, candidate URLs are ranked according to the vote powers of the users who tweet the URL. The vote power of a user is proportional to his follower count, and inversely proportional to the frequency of tweeting.

After testing different combinations of choosing and ranking methods, the paper concludes that using the *followees of followees* approach in choosing candidate set gives the highest probability of recommending the most interesting URLs. For the ranking methods, the method which performs best is the one that combines 1) the similarity between the tweets containing candidate URLs and the tweets of this user, and 2) the vote powers of the users who tweet the URLs.

8.2 Personalized News Recommendation by analyzing Tweet Contents

The personalized news recommender system by Morales [6] uses tweets to build user profiles and recommend interesting Yahoo news articles to users based on the supervised learning method. The recommendation ranking algorithm is given by the following formula.

$$R_T(u,n) = \alpha . \textstyle\sum_T(u,n) + \beta . \mathit{\Gamma}_T(u,n) + \gamma . \prod_T(n)$$

where
$R_T(u, n)$ = Ranking of news n for user u;
$\sum_T(u, n)$ = Content-based relatedness between user u and news n at time T;
$\Gamma_T(u, n)$ = Social-based relatedness between user u and news n at time T;
$\prod_T(n)$ = Popularity of news n at time T;
α, β, γ = Coefficients that specifies the relative weights of the components.

The paper uses spectrum entity extraction system [20] and applies the concept of entity to find the relatedness between tweets and news articles. Content-based relatedness ($\sum_T(u, n)$) captures the intuition that if the news articles and the user's tweets are under common entities, then the news is relevant to the user. Social-based relatedness $\Gamma_T(u, n)$ computes the relevant scores by taking into account of the tweets authored by the neighboring users. Other features, such as age, hotness and click count of news articles are also applied in the learning algorithm. For the purpose of testing and evaluation, Twitter user IDs and Yahoo toolbar cookie IDs are linked by the simple heuristic that a user visits his own account more often.

9 Conclusions

Several recommender systems have been proposed to help Twitter users perform information sharing and social interactions more easily. Our paper outlines a taxonomy to classify all the recommendation tasks into a few categories defined around the types of user functions in Twitter. Using the taxonomy, we have surveyed several recommendation methods specially developed for Twitter. To the best of our knowledge, this is the first time a taxonomy is used to classify recommendation tasks in Twitter. Our survey shows that while some recommendation tasks have been well studied, there are some tasks that could be included in future social media mining research. For instance, the current hashtag recommendation systems only consider the content of tweets but not user preferences or effectiveness of hashtags in spreading information. There are also very few works on mention or retweet recommendation. When solutions to these recommendation tasks are developed and evaluated with high accuracies, one can envisage a more comprehensive range of recommendations personalizing the use of Twitter.

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