# INTEREST RECOMMENDED STRATEGIES IN LOCATION BASED SOCIAL NETWORKS

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## Abstract

**we address the problem of recommendation in location-based social networks and seek novel methods to improve limitations of existing techniques. We first propose a spatial topic model for top-k POI recommendation problem, and the proposed model discovers users' topic and geographical distributions from user check-ins with posts and location coordinates. Then we focus on mining spatio-temporal patterns of user check-ins and propose a spatio-temporal topic model to identify temporal activity patterns of different topics and POIs. In our next work, we argue that all existing social network-based POI recommendation models cannot capture the nature of location-based social network. Hence, we propose a social topic model to effectively exploit a location-based social network. Finally, we address the problem of determining the optimal location for a new store by considering it as a recommendation problem, i.e., recommending locations to a new store. Latent factor models are proposed and proved to perform better than existing state-of-the-art methods.**

## Introduction

Millions of people now use social networking websites to enjoy online interaction with friends and meeting new people. Social networking sites, such as Twitter1 , Facebook2 , and LinkedIn3 etc, are attracting an increasing number of users, many of whom have integrated these sites into their daily practices. Thanks to the widespread adoption of various smart mobile devices, people can easily post their routine status from anywhere at anytime. Consequently, we can see the unprecedented access to the news, events, and activities, with tons of user-generated data in highly dynamics. Since users tend to have personalized results but are not willing to spend a lot of time to specify their personal information needs, it becomes necessary to have tools to select relevant part of information automatically. Recommender systems have emerged to bridge the gaps between users and social media providing recommendations on all kinds of products, e.g., movies, books, and music etc. Since the early papers [55, 23] published in mid-1990s on collaborative filtering, recommender systems is increasingly attracting the attention of academic and industry researchers developing new approaches over the last decades [1]. On the one hand, [12, 59, 50, 43, 22] are the research representatives published in early 2000s at different research areas, e.g., information retrieval, web mining, and human factor analysis. Recommender systems grows and becomes an independent research area since the ACM Recommender System conference (RecSys) is founded in 2007. More and more.

Definition 1 : Recommender System. A recommender system is a particular form of information filtering, that exploits past behaviors and user similarities to generate a list of information items that is personally tailored to a user's preferences.

Demands for Recommendation The Web has become the primary source of information, and search engines are the primary tools that people

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use to find information. Different from the keyword search on the Web, recommender systems applies personalization techniques for users in finding and selecting products, services, or information. Although the efficiency of recommendation can be worse than keyword search, it enables online web services to provide personalized and accurate recommendations for users. We note that there are non-personalized recommendations that are useful in certain applications, but they are not normally addressed in the area of recommender systems. Ricci et al.present some facts that prove the interest in recommender systems has grown in recent years which is shown as follows:

Proposed system

Recommender systems play an important role in the following highly rated websites as Amazon, YouTube, Netflix, Yahoo, Tripadvisor, Last.fm, and IMDb. Many social media companies are developing and deploying recommender systems as part of their services. • Related conferences and workshops are booming in recent years, such as, ACM Recommender System conference (RecSys), ACM SIGIR Special Interest Group on Information Retrieval (SIGIR), User Modeling, Adaptation and Personalization (UMAP), and ACM’s Special Interest Group on Management Of Data (SIGMOD).

Context-free Recommendation

As we mentioned, many traditional recommendation approaches are designed for contextfree recommendations, in which there are only two entities: users and items. Formally, we assume that there are a set of users U = {u1, u2, ...,u|U|} and a set of items I = {i1, i2, ..., i|I|}, where |U| and |I| represent the number of users and items, respectively. Each user performs actions on a set of items. The actions performed by users on items are given in a matrix A = [au,i]|U|×|I| , where au,i denotes the action of user u on item i. We should note that normally more than 90% entries in the matrix A are missing or unknown. For the remaining known entries, au,i can be any real number, and convey various meanings according to varying types of recommendations. For example, in movie recommender systems, au,i can be integers normally in the range of [1, 5] to represent user ratings on items. 6 Furthermore, au,i can be binary numbers to represent whether users browse or purchase the item in product recommendations.

(Top-k Item Recommendation) Given a user u ∈ U and a set of items I, the recommender system returns a top-k ranked list of unseen items in which the given user u will be interested by using the incomplete action matrix

A = [au,i]|U|×|I| .

We have proposed models implementing learning to rank for top-k item recommendation. We should note that the results of rating prediction of a user can be served for top-k item recommendation, that is predicted top-k rated items are returned for the given user. For top-k item recommendation, the measurement of the RMSE or MAE is replaced by a ranking function as the metric function. NDCG@k is by far the most commonly used metrics to measure the performance of recommender systems [22, 67, 18] for top-k item recommendation.

Normalized Discounted Cumulative Gain@k (NDCG@k):

The NDCG@k for a user is computed by comparing the predicted ranked list of items and the ground truth of ranked list of items. To compute DCG@k of the recommended list of items for a user u, we use the following equation:

whereln represents the recommended item index that is ranked at n th position, and rel(ln) represents the relevance of the item. We use its relative position in the ground truth ranked list as used in  Note that the relevance value is 1 when the item is ranked first and decreases to 0 when the ranking goes down. The DCG@k is normalized by the iDCG@k (ideal DCG@k) as follows:

where the iDCG@k is the DCG@k score of the ranked list of ground truth. According to the recommendation methodologies, we group context-free recommendation approaches into content-based and collaborative filtering-based categories. We discuss them in the following subsections.

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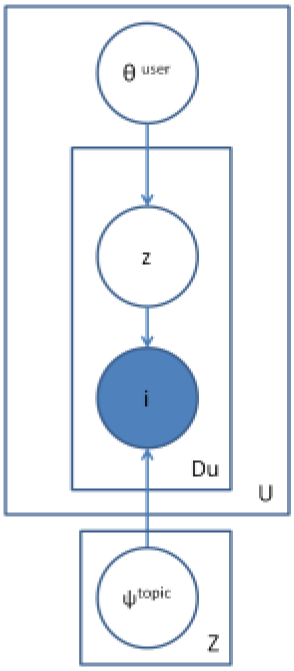


Context-aware Recommendation

In this section, we summarize the existing works in the area of context-aware recommendations. The majority of existing recommendation approaches focus on recommending most relevant items to users without considering any contextual information. However, in many applications, like recommending a restaurant, it may not be sufficient to consider only users and items. It is important to include contextual information, such as location, time, and social connections, into the recommendation process. Many companies started incorporating some contextual information into their recommendation engines. For example, when recommending a news article for the user, the LinkedIn's news recommender system takes into the consideration the colors of photos or pictures (the context) that the given user liked. 13 In this section, we discuss two areas of context-aware recommendation: social-based recommendation, i.e., recommending items using social networks, and location-based recommendation, i.e., recommending Point-of-Interest (POI) using spatio-temporal (coordinates of POIs and time) contexts. We would like to demonstrate that depending on the application and the availability of the data, certain contextual information can be helpful for better recommendations. We also believe that there are many other context-aware recommendation problems.


Figure : the structure of user POI data

Social-based Recommendation

With the rapidly growing of social networking websites such as Facebook and LinkedIn on the WWW, it is hard to ignore the power of social networks to help existing recommender systems for better recommendations. The most common problem in social-based recommendation is rating prediction. Formally, along with the user-item action matrix, there are social networks available. The problem is to predict unknown ratings of users for items. A social network is usually represented as a directed/undirected graph, where nodes denote users and edges denote social relationships. For example, in Epinions users provide ratings on products, and users establish a trust network, and Flixster serves as a platform for users to rating movies and has a social network from Facebook. Some representative works [49, 47, 32, 33, 48, 68, 62] in social-based recommendation utilize the social network to help the recommender system make the decision. Intuitively, friends in the social network tend to have similar rating patterns than non-friends. Social recommendation methods have been proved successfully on rating prediction, especially on "cold start" users. In memory-based social recommendation approaches for a user they propose to find top-k similar users as the same in the memory-based recommendation approaches of context-free recommendation introduced in the previous sections. They also propose to find top-k similar friends of the given user. Additionally, proposes to explore not only the 1st degree friends but also the


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friends of nth degree, and the importance of each friend in the social network is weighted by the random walk probability starting from the given user, i.e., the importance of each friend is penalized by the length between the friend and the given user. The predicted unknown rating score of a user on an item is a weighted average of the ratings of top-k similar users and top-k similar friends.

2.3 Social Network-based Approaches

Most of the early works in POI recommendation are social network-based approaches. In the problem 3 of POI recommendation, given a user-POI matrix, coordinates of POIs, and a social network among users, they build a POI recommender system that recommends POIs for users. A social network is represented as an undirected graph G = 19 (U, E), where U denotes the set of users, and an undirected edge (u, v) ∈ E, u ∈ U, v ∈ U from user u to user v represents the fact that u and v are friends. In general, given a target user, these approaches [71, 20] search his/her friends in the social network, and recommend POIs visited by his/her friends for the given user. Their theoretical foundation is based on the prominent phenomenons of homophily and social influence in social networks, i.e., the homophily phenomenon suggests that similar users are more likely to connect to each other, and the social influence phenomenon indicates that friends tend to influence each other’s preferences and actions. Basically, the latent factors of users and POIs are learned from the user-POI matrix using collaborative filtering approaches, and the users’ latent factors are influenced by their friends. Moreover, based on coordinates of POIs, they compute the social influence weight between two friends by the distance of their historical POIs, and short distances indicate large social network weights. Experimental results in [71, 20] show that social network-based approaches outperform those approaches without social networks, but the top-k POI recommendation accuracy improvement is not as substantial (∼5%) as in the top-k movie recommendation (∼30%) in [69]. We argue the reason is that check-in actions require users’ physical commitment to POIs, which are more serious than actions of rating a movie online. In this case, the co-occurrences of friends at POIs are less than the movies that friends co-like. How to accurately profile users for POI recommendation becomes the major challenge for social network-based approaches.

POI Recommendation

The ST model can be employed for POI recommendation as follows. Given a document with a user, our task is to recommend top-k “new ” POIs, i.e., the POIs that the user has

Conclusion

In this chapter’s work, we address the problem of spatial topic modeling in online social media, such as Twitter and Yelp, for user-generated content with POI. Previous work has explored topic models and recommendation algorithms that model either user and POI, or user and post, but they do not consider all of them together. We propose the first spatial model to capture spatial and textual aspects of posts, as well as user profiles in a single topic model, called Spatial Topic (ST) model. ST exploits the interdependencies between user movements, and between user interests and user movements. More specifically, ST is based on the intuition that 1) users’ movements correlate with each other; 2) users’ interests affect the movements of users. We argue that taking the correlation of users’ movements, and the correlation of user movement and user interest into account enables a more accurate discovery of relevant regions and topics. We present the graphical model of ST and a corresponding method of parameter learning. We perform an experimental evaluation on Twitter and Yelp data sets from New York City and Phoenix. We compare ST against a state-ofthe-art geographical topic model and a state-of-the-art recommendation method in terms of POI recommendation. Our experiments demonstrate drastically improved performance in POI recommendation.

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