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# SERVICE RATING PREDICTION BY USING GEOGRAPHICAL LOCATIONS OF SOCIAL MOBILE USERS

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ARTICLE INFO	A B S T R A C T
Article History:	Currently, advances in shrewd mobile tool and positioning strategies have fundamentally improved social networks, which allows users to share their reports, opinions, scores,
Received in revised form 5 <sup>th</sup>	pictures, take a look at-ins, and many others. The geographical data positioned by way of
December, 2017	clever cellphone bridges the gap among bodily and virtual worlds. Region records
Accepted 3 <sup>rd</sup> January, 2018	functions as the connection between consumer's physical behaviors and virtual social
Published online 28th February, 2018	networks established by using the clever smartphone or internet services. We confer with these social networks regarding geographical information as region-based social networks (LBSNs). On this paper, we make full use of the mobile users' place sensitive traits to carry out score predication. We mine: 1) the relevance among person's ratings and person-object geographical region distances, called as user-item geographical connection, 2) the relevance among users' score variations and user-consumer geographical location distances, known as user-person geographical connection. It's miles observed that people' rating behaviors are stricken by geographical place considerably.
Key words:	
Physical behaviors geographical data, mobile users, social networks.	

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# **INTRODUCTION**

Recently, with the fast development of cell devices and ubiquitous net get entry to, social community offerings, along with facebook, Twitter, Yelp, Foursquare, Epinions, emerge as regular. Consistent with information, clever smartphone customers have produced records quantity ten times of a popular cellular phone. In 2015, there had been 1.nine billion clever phone customers within the international, and 1/2 of them had accessed to social community services. The mobile device or on-line place based totally social networks (LBSNs), we can proportion our geographical role data or test-ins. This provider has attracted tens of millions of customers. It additionally lets in users to share their reviews, which includes opinions, ratings, pics, take a look at-ins and moods in LBSNs with their pals. Such data brings opportunities and challenges for recommender systems.

#### LITERATURE SURVEY

G. Adomavicius, and A. Tuzhilin: An overview of the field of recommender systems and describes the current generation of recommendation methods that are usually classified into the following three main categories: content-based, collaborative, and hybrid recommendation approaches.

\**Corresponding author:* Sai Kishore T Department of Computer science, Sree Vidyanikethan Engineering College Tirupati, India This paper also describes various limitations of current recommendation methods and discusses possible extensions that can improve recommendation capabilities and make recommender systems applicable to an even broader range of applications. These extensions include, among others, an improvement of understanding of users and items, incorporation of the contextual information into the recommendation process, support for multi criteria ratings, and a provision of more flexible and less intrusive types of recommendations.

Recommender systems have become an important research area since the appearance of the first papers on collaborative filtering in the mid-1990s [45], [86], [97]. There has been much work done both in the industry and academia on developing new approaches to recommender systems over the last decade. The interest in this area still remains high because it constitutes a problem-rich research area and because of the abundance of practical applications that help users to deal with information overload and provide personalized recommendations, content, and services to them. However, despite all of these advances, the current generation of recommender systems still requires further improvements to make recommendation methods more effective and applicable to an even broader range of real-life applications, including recommending vacations, certain types of financial services to investors, and products to purchase in a store made by a "smart" shopping cart.

These improvements include better methods for representing user behavior and the information about the items to be recommended, more advanced recommendation modeling methods, incorporation of various contextual information into the recommendation process, utilization of multi criteria ratings, development of less intrusive and more flexible recommendation methods that also rely on the measures that more effectively determine performance of recommender systems. Although the roots of recommender systems can be traced back to the extensive work in cognitive science [87], approximation theory [81], information retrieval [89], forecasting theories [6], and also have links to management science.

#### Y. Koren

Recommender systems provide users with personalized suggestions for products or services. These systems often rely on Collaborating Filtering (CF), where past transactions are analyzed in order to establish connections between users and products. The two more successful approaches to CF are latent factor models, which directly profile both users and products, and neighborhood models, which analyze similarities between products or users. In this work we introduce some innovations to both approaches. The factor and neighborhood models can now be smoothly merged, thereby building a more accurate combined model. Further accuracy improvements are achieved by extending the models to exploit both explicit and implicit feedback by the users. The methods are tested on the Netflix data. Results are better than those previously published on that dataset.

Modern consumers are inundated with choices. Electronic retailers and content providers offer a huge selection of products, with unprecedented opportunities to meet a variety of special needs and tastes. Matching consumers with most appropriate products is not trivial, yet it is a key in enhancing user satisfaction and loyalty. This emphasizes the prominence of recommender systems, which provide personalized recommendations for products that suit a user's taste [1]. Internet leaders like Amazon, Google, Netflix, TiVo and Yahoo are increasingly adopting such recommenders. Notably, CF techniques require no domain knowledge and avoid the need for extensive data collection. In addition, relying directly on user behavior allows uncovering complex and unexpected patterns that would be difficult or impossible to profile using known data attributes. As a consequence, CF attracted much of attention in the past decade, resulting in significant progress and being adopted by some successful commercial systems, including Amazon [15], TiVo and Netflix.

Neighborhood models are most effective at detecting very localized relationships. They rely on a few significant neighborhood relations, often ignoring the vast majority of ratings by a user. Consequently, these methods are unable to capture the totality of weak signals encompassed in all of a user's ratings. Latent factor models are generally effective at estimating overall structure that relates simultaneously to most or all items. However, these models are poor at detecting strong associations among a small set of closely related items, precisely where neighborhood models do best.

#### N. N. Liu, M. Zhao, and Q. Yang

A central goal of collaborative filtering (CF) is to rank items by their utilities with respect to individual users in order to make personalized recommendations. Traditionally, this is often formulated as a rating prediction problem. However, it is more desirable for CF algorithms to address the ranking problem directly without going through an extra rating prediction step. In this paper, we propose the probabilistic latent preference analysis (pLPA) model for ranking predictions by directly modeling user preferences with respect to a set of items rather than the rating scores on individual items. From a user's observed ratings, we extract his preferences in the form of pairwise comparisons of items which are modeled by a mixture distribution based on BradleyTerry model. An EM algorithm for fitting the corresponding latent class model as well as a method for predicting the optimal ranking are described. Experimental results on real world data sets demonstrated the superiority of the proposed method over several existing CF algorithms based on rating predictions in terms of ranking performance measure NDCG.

Recommender system is a promising technology that aims to automatically generate item recommendations from a huge collection of items based on users' past feedback. Broadly speaking, existing technologies underlying recommender systems fall into either of the following two categories: content-based filtering versus collaborative filtering. Contentbased filtering approach analyzes the content information associated with the items and users such as product descriptions, user profiles etc., in order to represent users and items using a set of features. To recommend new items to a user, content-based filters match their representations to those items the user has expressed interests on. In contrast, the collaborative filtering (CF) approach does not require any content information about the items, it works by collecting ratings on the items by a large number of users and make recommendations to a user based on the preference patterns of other users. The CF approach is based on the assumption that a user is often interested in those items that have been selected by some users with similar tastes.

A very important function of most recommender systems is the generation of the Top-N item list for each user in order to make personalized recommendations, which essentially involves solving a ranking problem. To rank items, most collaborative filtering algorithms formulate this as a rating prediction problem in which a user's potential ratings on the items are first predicted and then used to order the items. However, there are several drawbacks with such rating prediction based framework.

#### M. Jamali, and M. Ester

Recommender systems are becoming tools of choice to select the online information relevant to a given user. Collaborative filtering is the most popular approach to building recommender systems and has been successfully employed in many applications. With the advent of online social networks, the social network based approach to recommendation has emerged. This approach assumes a social network among users and makes recommendations for a user based on the ratings of the users that have direct or indirect social relations with the given user. As one of their major benefits, social network based approaches have been shown to reduce the problems with cold start users. In this paper, we explore a model-based approach for recommendation in social networks, employing matrix factorization techniques. Advancing previous work, we incorporate the mechanism of trust propagation into the model. Trust propagation has been shown to be a crucial phenomenon in the social sciences, in social network analysis and in trustbased recommendation. We have conducted experiments on two real life data sets, the public domain Epinions.com dataset and a much larger dataset that we have recently crawled from Flixster.com. Our experiments demonstrate that modeling trust propagation leads to a substantial increase in recommendation accuracy, in particular for cold start users.

For instance, while we seek a restaurant thinking about comfort, we will by no means pick out a far flung one. Furthermore, if the geographical vicinity information and social networks can be mixed, it isn't always tough to find that our mobility can be influenced by way of our social relationships as customers may also favor to go to the places or eat the gadgets their friends visited or consumed before. In our opinion, while customers take a long journey, they will preserve an excellent emotion and attempt their fine to have a pleasant journey. Maximum of the services they devour are the local featured things.

#### J. Zhang, C. Chow, and Y. Li

Geographical influence has been intensively exploited for location recommendations in location-based social networks (LBSNs) due to the fact that geographical proximity significantly affects users' check-in behaviors. However, current studies only model the geographical influence on all users' check-in behaviors as a universal way. We argue that the geographical influence on users' check-in behaviors should be personalized. In this paper, we propose a personalized and efficient geographical location recommendation framework called iGeoRec to take full advantage of the geographical influence on location recommendations.

In iGeoRec, there are mainly two challenges: (1) personalizing the geographical influence to accurately predict the probability of a user visiting a new location, and (2) efficiently computing the probability of each user to all new locations. To address these two challenges, (1) we propose a probabilistic approach to personalize the geographical influence as a personal distribution for each user and predict the probability of a user visiting any new location using her personal distribution. Furthermore, (2) we develop an efficient approximation method to compute the probability of any user to all new locations; the proposed method reduces the computational complexity of the exact computation method from O(ILIn3) to O(ILIn) (where ILI is the total number of locations in an LBSN and n is the number of check-in locations of a user).

Finally, we conduct extensive experiments to evaluate the recommendation accuracy and efficiency of iGeoRec using two large-scale real data sets collected from the two of the most popular LBSNs: Foursquare and Gowalla. Experimental results show that iGeoRec provides significantly superior performance compared to other state-of-the-art geographical recommendation techniques.

#### J. Zhang and C. Chow

# CONCLUSION

Recommending users with their preferred points-of-interest (POIs), e.g., museums and restaurants, has become an important feature for location-based social networks (LBSNs), which benefits people to explore new places and businesses to discover potential customers. However, because users only check in a few POIs in an LBSN, the user-POI check-in interaction is highly sparse, which renders a big challenge for POI recommendations. To tackle this challenge, in this study we propose a new POI recommendation approach called GeoSoCa through exploiting geographical correlations, social correlations and categorical correlations among users and POIs.

The geographical, social and categorical correlations can be learned from the historical check-in data of users on POIs and utilized to predict the relevance score of a user to an unvisited POI so as to make recommendations for users. First, in GeoSoCa we propose a kernel estimation method with an adaptive bandwidth to determine a personalized check-in distribution of POIs for each user that naturally models the geographical correlations between POIs. Then, GeoSoCa aggregates the check-in frequency or rating of a user's friends on a POI and models the social check-in frequency or rating as a power-law distribution to employ the social correlations between users.

Further, GeoSoCa applies the bias of a user on a POI category to weigh the popularity of a POI in the corresponding category and models the weighed popularity as a power-law distribution to leverage the categorical correlations between POIs. Finally, we conduct a comprehensive performance evaluation for GeoSoCa using two large-scale real-world check-in data sets collected from Foursquare and Yelp. Experimental results show that GeoSoCa achieves significantly superior recommendation quality compared to other state-of-the-art POI recommendation techniques.

# CONCLUSION

We mine: 1) the relevance among customers' scores and consumer-item geographical place distances, 2) the relevance among customers' score differences and consumer-consumer geographical region distances. it's far discovered that people' score behaviors are tormented by geographical vicinity extensively. a personalized location based totally rating Prediction (LBRP) version is proposed through combining 3 factors: user-object geographical connection, person-user geographical connection, and interpersonal hobby similarity. Specifically, the geographical place denotes consumer's realtime mobility, especially while customers journey to new cities, and those elements are fused collectively to improve the accuracy and applicability of recommender systems. In our destiny paintings, test-in behaviors of users can be deeply explored by thinking about the thing of their multi-activity facilities and the characteristic of POIs.

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