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Discovering Optimal Services with Multi Criteria based Analysis on Social Network Reviews

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Abstract

The social networks are build to share the user reviews, photos, videos and opinions on products and locations. The geographical location information are collected with smart phone based applications. The check in and user posting details are maintained under the Location Based Social Networks (LBSN). The huge volume of data values are processed with the big data environment. The big data values are processed with the support of the cloud resources.

The user spatial parameters and review information are utilized in the service rating prediction operations. The Location Based Rating Prediction (LBRP) algorithm is applied for the service rating prediction process. The LBRP uses the three measurements for the prediction process. The user-item geographical connections, user-user geographical connections and interpersonal interest similarity measures are estimated for the rating prediction process. The user – item geographical connection indicates the distance between the user ratings and the user – item geographical locations. The user – user geographical connection indicates the user rating differences and the user – user geographical location distances.

The optimal service discovery operations are carried out with user behavior discovery and service score index methods. The user behavior estimation process is carried out with multi activity centers. The service score estimation and index operations are performed with the attributes of the Point of Interests (POI). The user recommendation task is integrated with the system to suggest better services with reference to the user behavior and ratings. The user category, region and seasonal aspects are employed in the multi criteria based recommendation process.

Index Terms: Location Based Social Networks (LBSN), Service Rating Prediction, User Behavior Analysis, Social Network Reviews and Recommender Systems

1. Introduction

In location-based social networks (LBSNs), users share information about their locations, the places they visit and their movement alongside with other social information. Visits are reported explicitly or implicitly by allowing smartphone applications to report visited locations to the LBSN. This information is then shared with other users who are socially related. The same information can be exploited by the LBSN operator to propose new points of interest to users. Recommending new locations is an important issue; it allows efficiently advertising companies with a physical presence and creating revenue for the LBSN operator.

Recommender systems are widely used and they have been studied in research quite extensively. The most popular approach in recommender systems is that of collaborative filtering, where recommendations are created based on whether a user has purchased a product in the past and on whether she liked it or not [10]. Using the past behavior of a user, new recommendations are created based on the similarity of users or the similarity of products. While these algorithms can be adjusted to the problem of recommending new locations to users, by taking into account previous user checkins, significant information like the distance of the proposed location to the user neighborhood or the social interaction between the user and those users that have visited this location are ignored.

The social links of a user and the distance of a location to her previous visits are important factors in predicting whether she will visit a new location or not. We show more than 80% of the new places visited by a user are in the 10km vicinity of previous check-ins and more than 30% of the new places visited by a user have been visited by a friend or a friendof- a friend in the past. These facts imply that geographical and social information significantly affect the choices of a user when deciding which new place to visit.

Geographical and social information are exploited for creating recommendations. The most closely related work to ours is the work, a recommendation algorithm that takes into account the rich knowledge of the LBSNs. It is shown that the additional information allows for more accurate recommendations than those created by traditional algorithms. Our proposal delves deeper in the properties of LBSNs, people often visit new locations that are geographically close to their past visited locations, and such new visits are usually influenced by their social relationships. Based on such properties, we propose recommendation algorithms that outperform the methods a wide margin.

2. Related Work

Recently with the rapid growth of LBSNs, like Foursquare, Gowalla, Facebook places, etc., recommending locations for users becomes prevalent [6]. In general, there are four main categories for existing location recommendation approaches: collaborative filtering, social influence, geographical influence, and temporal influence.

Collaborative filtering techniques. Although there are a few works that recommend POIs through the content based techniques, most studies provide POI recommendations by using the conventional collaborative filtering techniques based on users' check-in data, travel tour data, GPS trajectory data or text data. In particular, some techniques [1] employ users' residence to derive their similarity weights as an input of the conventional collaborative filtering techniques. The performance of all these techniques is considerably limited due to no consideration for the social influence, geographical influence, or temporal influence.

Social influence. Since friends are more likely to share common interests, social link information has been widely utilized to improve the quality of recommender systems in the conventional social networks like Twitter [4] and the LBSNs by deriving the similarity between users based on their social friendships and integrating it into the collaborative filtering techniques.

Geographical influence. The geographical proximity between POIs significantly affects the check-in behaviors of users on the POIs. To exploit geographical influence for improving the quality of location recommendations, the studies [7] view locations as ordinary nonspatial items and consider the geographical influence of locations by predefining a range; locations only within this range will be possibly recommended to users. The literature [11] presents a geo-topic model by assuming that if a location is closer to the locations visited by a user or the current location of a user, it is more likely to be visited by the same user [3]. More sophistically, model the distance between two locations visited by the same user as a common distribution for all users, e.g., a power-law distribution or a multi-center Gaussian model. In particular, our previous papers [5] personalize the geographical influence by modeling the distance between locations visited by the same user as a personalized distribution for each user.

Temporal influence. The time-dependent recommendation techniques can be divided into five main categories. (1) Absolute time factor. The time factor has been widely used for the conventional recommendations by considering the time gap between the occurring time of a previous rating and the recommendation time as a decaying factor to weigh the rating [10], which is different from the periodic time factor for location recommendations. (2) Sequential time factor. The time sequence has also been utilized to recommend next POI for users, which is distinct from the time slots in a day. Accordingly, the method cannot generate time-aware recommendations for users. (3) Using time information for location predictions. The literature [9] study the relationship between visited locations and temporal information for location predictions that refer to predicting an existing location. It is not straightforward to apply these techniques in location recommendations that refer to recommending a new location. (4) Periodic time pattern discovering. The works only show the temporally periodic patterns of users visiting locations without using the patterns to make location recommendations.(5) Periodic time pattern deducing. To the best of our knowledge, there only exist three literatures utilize the temporal influence in location recommendation. Specifically, they split a day into time slots, e.g., 24 hours, divide the user-location check-in data according to the check-in time and the time slots, and apply matrix factorization, user-based collaborative filtering, or graph-based method [2] to infer users' preferences on locations at each time slot.

3. Service Rating Prediction with Social Network Data

Recently, with the rapid development of mobile devices and ubiquitous Internet access, social network services, such as Facebook, Twitter, Yelp, Foursquare, Epinions, become prevalent. According to statistics, smart phone users have produced data volume ten times of a standard cellphone. In 2015, there were 1.9 billion smart phone users in the world and half of them had accessed to social network services. Through mobile device or online location based social networks (LBSNs), we can share our geographical position information or check-ins. This service has attracted millions of users. It also allows users to share their experiences, such as reviews, ratings, photos, check-ins and moods in LBSNs with their friends. Such information brings opportunities and challenges for recommender systems. Especially, the geographical location information bridges the gap between the real world and online social network services. For example, when we search a restaurant considering convenience, we will never choose a faraway one. Moreover, if the geographical location information and social networks can be combined, it is not difficult to find that our mobility may be influenced by our social relationships as users may prefer to visit the places or consume the items their friends visited or consumed before.

In our opinion, when users take a long journey, they may keep a good emotion and try their best to have a nice trip. Most of the services they consume are the local featured things. They will give high ratings more easily than the local. This can help us to constrain rating prediction. In addition, users take a long distance travelling a far away new city as strangers. They may depend more on their local friends. Therefore, users' and their local friends' ratings may be similar. It helps us to constrain rating prediction [16]. Furthermore, if the geographical location factor is ignored, we search the Internet for a travel, recommender systems may recommend a new scenic spot without considering whether there are local friends to help us to plan the trip or not. But if recommender systems consider geographical location factor, the recommendations may be more humanized and thoughtful. These are the motivations why we utilize geographical location information to make rating prediction.

With the above motivations, the goals of this paper are: 1) to mine the relevance between user's ratings and useritem geographical location distances, called as user-item geographical connection, 2) to mine the relevance between users' rating differences and user-user geographical location distances, called as user-user geographical connection and 3) to find the people whose interest is similar to users. In this paper, three factors are taken into consideration for rating prediction: user-item geographical connection, user-user geographical connection and interpersonal interest similarity. These factors are fused into a location based rating prediction model. The novelties of this paper are user-item and user-user geographical connections, i.e. we explore users' rating behaviors through their geographical location distances.

4. Issues on Service Rating Prediction Schemes

The social network maintains the user review details to estimate the service rating values. The service rating prediction operations are carried out with the user location and review details. The Location Based Rating Prediction (LBRP) algorithm is applied for the service rating prediction process. The LBRP uses the three measurements for the prediction process. They are user-item geographical connections, user-user geographical connections and interpersonal interest similarity measures. The user – item geographical connection indicates the distance between the user ratings and the user – item geographical locations. The user – user geographical connection indicates the user rating differences and the user – user geographical location distances. The category distribution vector is constructed with inter personal interest similarity measures. The following issues are identified from the current service rating prediction schemes. User behavior estimation is not performed. Service score indexing process is not supported. Point of Interest (POI) attributes are not used in the rating process. Recommendation process is not optimized.

5. Discovering Optimal Services with Multi Criteria based Analysis

The service rating prediction process is constructed with user behavior discovery and service score index methods. The user behavior estimation process is carried out with multi activity centers. The service score estimation and index operations are performed with the attributes of the Point of Interests (POI). The user recommendation task is integrated with the system to suggest better services with reference to the user category, region and seasonal aspects.

Service rating prediction and recommendation operations are carried out under the Location Based Social Networks (LBSN). User behavior and service scores are used in the prediction and recommendation process. The recommendation process is improved with regional and seasonal factors. The system is partitioned into five major modules. They are Social network data management, Service rating prediction process, User behavior discovery, Service score indexing process and Service recommendation process.

The user, location and review details are maintained under the social network data management. The service rating prediction process is carried out with Location Based Rating Prediction (LBRP) algorithm. User reviews and their relationships are analyzed to estimate the user behavior values. The service scores are calculated and arranged in the service score indexing process. The recommendation process suggests best services with user behavior and service score values.

User profile, check in details and product review are collected from social networks. Foursquare, Twitter and Yelp social network data values are used in the system. User check-in venue and time details are maintained in location data values. User submitted messages are maintained under customer review data collection. The Location Based Rating Prediction (LBRP) algorithm is applied for the service rating prediction process. User reviews and location details are analyzed to estimate the service rating values. User-Item geographical connections and user-user geographical connections are evaluated in the rating prediction process. Inter personal interest similarity is used to build category distribution vector for rating prediction process.

The user behaviors are discovered with the support of the multi activity centers. User reviews, location and rating details are used in the user behavior estimation process. User and item relationship with location details are analyzed in the user behavior estimation process. User behaviors are represented as user community categorie. Service score values are estimated with service rating information. Service scores are indexed with service priority levels. Point of interest attributes are used in the score estimation and indexing process. The service score index is passed to the service recommendation process. Service recommendation process is build to suggest better services based on the user reviews. User behavior and service score index are used in the service recommendation process. Single and multiple attribute based recommendation process is supported in the system. User category, region and seasonal factors are used in the multi attribute based recommendation process.

6. Performance Analysis

The service rating prediction and recommendation tasks are carried out on the social network review details. The Location Based Rating Prediction (LBRP) scheme is used to estimate the service rating levels. The User Behavior Discovery with Service Score Index (UBD-SSI) scheme is build to estimate service score and recommendation tasks.

The service scores and their ratings are estimated with the user reviews that are published in the Location Based Social Networks (LBSN). The precision analysis is estimated to evaluate the rating prediction accuracy levels. The Service Rating Precision analysis between the Location Based Rating Prediction (LBRP) and User Behavior Discovery with Service Score Index (UBD-SSI) is shown in figure 6.1. and table 6.1.. The User Behavior Discovery with Service Score Index (UBD-SSI) technique increases the Service Rating Precision 20% than the Location Based Rating Prediction (LBRP) technique.

Table No: 6.1. Service Rating Precision Analysis between LBRP and UBD-SSI techniques

Reviews	LBRP	UBD-SSI
500	0.6573	0.9874
1000	0.6217	0.9716
1500	0.6076	0.9572
2000	0.5891	0.9346
2500	0.5587	0.9181

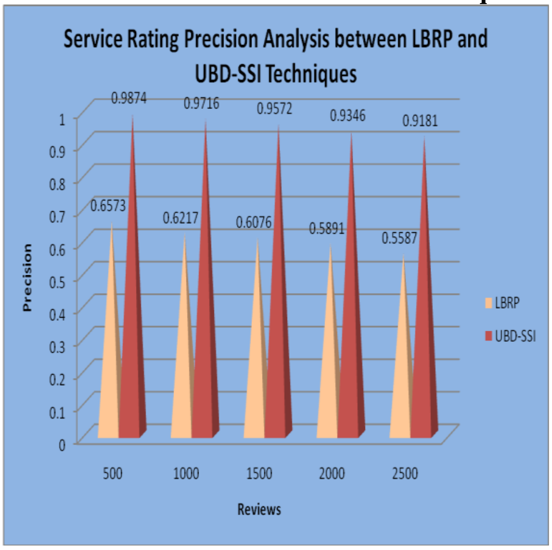

Figure No: 6.1. Service Rating Precision Analysis between LBRP and UBD-SSI techniques

7. Conclusion and Future Work

Location based Social Networks (LBSNs) manages the users with their access location details. The Location Based Rating Prediction (LBRP) algorithm is used to recommend services. User behavior estimation and service score index models are combined for the rating prediction and recommendation process. The recommendation process is improved with user category, region and seasonal aspects. The Location Based Social Network (LBSN) data values are analyzed for service rating prediction process. User behaviors are estimated with user, item and location relationships. The rating prediction process is improved with service score estimation and index operations. Spatial regions and temporal intervals are used in the recommendation process. The system can be improved with privacy preserved mining features.

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