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A Survey on Various Travel Recommender Systems

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ABSTRACT: Recommender systems are software agents that can predict preference or interest of individual customers and recommend items accordingly. Online recommender systems have been improving systematically in the last decade. With the booming of location sharing services, location and travel recommendation systems are also improving. In Location Based Social networks (LBSN) users share their geo-spatial locations and location related contents. The enlarging geo-spatial dataset in Location Based Social Networks, inspired development of novel techniques and features in recommender systems. Travel Recommender systems (TRS) are emulation of offline travel agents. TRS provide users travel suggestions which helps in their decision making. In this paper a review of travel recommender systems is provided. An extensive survey is conducted on each work and is presented. The merits and demerits of selected works are summarised and is presented.

KEYWORDS: Recommender systems, LBSN, Travel recommender system.

I. INTRODUCTION

Recommender systems [1] suggests items like news, music, places, movies etc. to users in the social network. Using user preference such as user profiles and item ratings, recommender system predict items the user is likely to be interested in. The information overload can be reduced by recommender systems by filtering the information based on its relevance. Recommender systems use appropriate algorithms to map user's needs into some specific set of alternatives from which the user can choose. Social networks are advancing very fast and a lot of location based social networks (LBSN) are also being used. In location based social networks the spatial aspects of users are added. LBSN can be defined as a social network in which geographic services and capabilities are incorporated to enable social dynamics. The improvements in LBSN brought new opportunities for the recommender systems. Location recommendation and itinerary recommendation are integrated with LBSN. The large amount of data collected from LBSN can be analysed and used to guide the location recommendation systems. In order to provide the recommendation, various algorithms and dataset are being used by the systems. In this research a study of different travel location recommender systems is performed.

This survey paper is organized as follows. In section II, related work done in the previous years is discussed. Section III consists of detailed review of each work. Section IV consists of the merits and demerits of selected works presented in a table, followed by conclusion in section V.

II. RELATED WORK

A tourism recommender system is designed by Liangliang [2] based on geotagged web photos. In this recommendation system, users can enter an image of the desired scenery or a keyword describing the place of interest and the system suggests destinations which match the user interest or visual characteristics.

Yu Zheng and Xing Xie proposed an algorithm [3] for location recommendation using the correlation of locations from a large number of user-generated GPS trajectories. The algorithm considers the user's travel experience and the

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sequentiality of locations. The location correlation is integrated into a collaborative filtering algorithm for personalized location recommendation.

Kai Jiang, Peng Wang, and Nenghai Yu proposed a method called Context Rank [4]. In this context information of geotagged photos is used to enhance personalized recommendation. Using photos GPS location landmarks are detected and then popularity of each landmark is estimated. The representative tags and images are extracted from each landmark. Context Rank also make use of users travel history to calculate user similarity. The user preferences of a landmark is predicted using geotagged photos and tags. For the final recommendation a learning to rank algorithm is used.

A hybrid context aware system for tourist guidance [5] is proposed by G. Fenza et al. The system suggests Points of Interests (POI) to tourists according to their profile and context. In order to predict and suggest POIs both content based and collaborative filtering methods are used. Soft computing and data mining techniques are also used. The general frame work consists of user profiles, social network history and POI data.

Anastasios Noulas, Salvatore Scellato, et al. proposed a model for new venue recommendation [6]. A new model is proposed where personalized random walk is performed over a user-place graph which combines social network and venue visit frequency data. The paper examines the problem of recommending unvisited venues from behavioural, social and spatial data. For new venue recommendation, the model make use of the variety of user preference signals that location based services collect about their users.

Takafumi Hasegawa and Takahiro Hayashi proposed a spot recommendation system [7] continuously available in user's home areas and away areas. The system can recommend spots to a user which are highly rated by other nearby users whose preference is similar to that of the user. Collaborative filtering method is used for spot recommendation. The system can recommend spots which are nearby or far away from the home location of the user.

A HITS-based POI recommendation algorithm [8] had been proposed by Xuelian Long and James Joshi. In this paper the POI recommendation issue is examined. The popularity of POI depends on both number of users checked in as well as their check in behaviour. HITS model for POI recommendation considers the user activities, user relations etc. This approach can be used for personalized recommendation. It can support weight functions.

Lury Nunesand and Leandro Marinho proposed a personalized geographic based diffusion model [9] for location recommendation. In this paper collaborative filtering and geographic information are integrated into one single diffusion based recommendation model. In this model the locations visited by users, distance between places visited and not visited and regions of user interest are considered. A personalized ranking of locations for a target user is performed for recommendation.

Pavlos Kosmides et al. [10] presented a method for predicting user location using machine learning techniques. The prediction results are used to make suggestions for venues or points of interests to users, based on their interests and social connections.

A user based tourist attraction recommender system [11] is developed by Zhiyang Jia, et al. It is capable of generating a personalized list of preference attractions for the tourist. Collaborative filtering is used for the recommendation process. The recommendation is divided into three steps, representation of user information generation of neighbour users and the generation of attraction recommendations. The user similarity is calculated using the Cosine method. Using the visiting history of user's neighbours the recommendations are generated.

Shuhui Jiang et al. proposed Author topic model POI recommendation [12]. In this approach, the author topic model is used to extract user preference topics from textual descriptions. In this model, POIs are mined using a coarse to fine based approach. The rich textual description and user information are analysed to get topic categories and these topics can be applied to personalized travel recommendation.

Sentimental POI mining and recommendation [13] is proposed by Peiliang Lou, et al. In this paper sentimental analysis is used for POI mining in Travel recommender system. Sentiment based algorithms are proposed for POI mining and recommendation. User information and location features are common factors used in POI recommendation but sentimental features are not considered. The method introduced in this paper recommends locations with desired sentimental features required by the target user.

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A novel POI recommendation system [14] is proposed by Mayy Habayeb et al. The proposed model combines user interests, obtained from the web interactions together with Location information, obtained from Open Street Map. This information is combined with the user's real time trajectory information and a list of POIs is created.

III. DETAILED REVIEW

A tourism recommender system [2] is designed by Liangliang based on geotagged web photos [15]. In this recommendation system, users can enter an image of the desired scenery or a keyword describing the place of interest and the system suggests destinations which match the user interest or visual characteristics. The tourism recommender system by Liangliang used a two-step method. In the offline step geotagged database is organized and representative samples are extracted. An efficient clustering algorithm divides earth area into regions which is based on geographical coordinates and distribution of geotagged images. For each cluster, representative images and tags are looked which are called r-images or R-tags. In the offline step, the user enter queries and search for the representative images. The corresponding geotagged regions are obtained as the recommended destinations. The characteristics of the system includes a clustering algorithm for geographical images, representative images for tourism recommendation which describe the location characteristics and flexible interface for users. In the system, mean shift algorithm is used for the GPS coordinates to cluster geotagged photos. The input is the GPS coordinates of a point and output is the neighbouring clusters. To find the representative samples i.e. R-tags and R-images different methods are used. Occurrence of each tag in each cluster is computed and tags with occurrence larger than a threshold is accepted. To find R-images, affinity propagation which uses similarity measurement is employed.

In the location recommender system by Yu Zheng [3], the location correlation is integrated into a more effective and accurate collaborative filtering model, which can predict the user's interest in a location. In this system, the user trajectories are obtained from the GPS device from which the stay points are detected. Stay points are some geographic regions where the user stayed over a certain time interval. The extracted stay points are clustered into geographic regions using clustering algorithm. Using these locations and user trips, user's interest level or rating is inferred. The locations with relatively high rating are retrieved as the recommendation.

Kai Jiang, Peng Wang, and Nenghai Yu proposed a method called Context Rank [4]. In this context information of geotagged photos is used to enhance personalized recommendation. Using photos, GPS location landmarks are detected and then popularity of each landmark is estimated. The representative tags and images are extracted from each landmark. In Context Rank method landmarks are detected from geo-coordinates of large number of photos sharing websites. Depending on the visual features, representative photos are extracted. Representative tags are extracted by ranking textual tags. Using travel history of user, landmark popularity can be estimated. These are content context information. From user's travel histories social context information can also be exploited. Using landmark popularity score, visual similarity score, textual similarity score and collaborative score the user's preference in a landmark can be predicted. Finally a ranking model is applied to combine the scores, which is the personalized ranking score so that final recommendation can be given to the users. For personalized recommendation collaborative filtering is used. The basic principle is that similar people will take similar decisions. Therefore user similarity is used here. A user preference can be estimated as sum of top N users preference weighted by their user similarities. Advantages of this method is it is efficient and is relieved from cold start problem.

The hybrid context aware recommendation system [5] for tourist guidance is mainly based on the soft computing and data mining techniques. The framework of the proposed system consists of two work flows, knowledge discovery and recommendation. Knowledge discovery process make use of fuzzy clustering and classifiers to integrate user clusters and POIs [16] with historical data. The recommendation process consists of user classification and rule matching to provide appropriate POI recommendation.

Anastasios Noulas, et al. proposed a model for new venue recommendation [6]. A new model is proposed where personalized random walk is performed over a user-place graph which combines social network and venue visit frequency data. The paper examines the problem of recommending unvisited venues [17] from behavioural, social and spatial data. The work proposed a method to combine the variety of user preference signals collected by the location based services for new venue recommendation. In the random walk approach a network is defined which connects

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places and users and a random walk is performed on it for personalized recommendation. This approach combines the collaborative filtering for venue similarity, social filtering for user similarity and spatial filtering for geographic distance. The data is represented in the form of a directed graph with user and places as nodes which are linked. A random walk is performed on the graph and steady state probabilities are computed. Each place is ranked in the decreasing order of steady state. These places will be new venues which are connected to the user through friends, visited places or through any combination factors.

The spot recommendation system [7] uses the visiting history of users, for recommendation process. The histories are collected via a user-interface. The user interface has voting buttons and the spot list. The users can vote any spot as the favourite spot and it will be registered. This information will be used for the recommendation step. For the recommendation process two data are considered, user's home area and user preferences. Both the data can be estimated from the genres of spots visited by the user. From the preference matching in spot genre selection the correlation between users can be evaluated.

A HITS-based POI recommendation algorithm [8] had been proposed by Xuelian Long and James Joshi. In this paper the POI recommendation issue is examined. The popularity of POI depends on both number of users checked in as well as their check in behaviour. HITS model for POI recommendation considers the user activities, user relations etc. This approach can be used for personalized recommendation. It can support weight functions. HITS is the abbreviation of Hyper Text Induced Topic Search. HITS is also known as hubs and authorities. It is aimed to extract information from the link structures. HITS assigns two values to a page. First one is the authority score which is the sum of the hub values of the pages pointed to it. Second is the hub score which is the sum of the authority values of the pages it point to. A mutually reinforcing relationship is exhibited by hubs and authorities. A good hub page points many good authority pages and a good authority page is pointed to many good hubs. This is the basic HITS model. The proposed HITS model based POI recommendation algorithm considers the social relation between users and their check-ins. It uses a social graph and a check in graph. From the analysis hub score of each user and authority score of POIs can be determined. The POIs with higher authority scores are recommended to the user. The algorithm performs well in both precision and recall.

Lury Nunesand and Leandro Marinho proposed a personalized geographic based diffusion model [9] for location recommendation. In this paper collaborative filtering and geographic information are integrated into one single diffusion based recommendation model. In this model the locations visited by users, distance between places visited and not visited and regions of user interest are considered. A personalized ranking of locations for a target user is performed for recommendation. In this work a new model is proposed for representing check in data, distance between locations and user preferences for POIs. The relation between the three kinds of data is exploited through a random walk algorithm on a diffusion model. In this model if the user has at least one check-in in the place of interest the relevant places nearby will be recommended to the user. The recommender model is known as Diffusion Geographic Model (DGM). The diffusion model captures user preferences, geographical distance, and regions of interest in a single model. For recommendation random walk is performed on the unified model and the locations are sorted in the decreasing order of probability and top locations are recommended. There is no need to use two or more specialized recommenders. The diffusion based collaborative algorithm is proved to obtain high accuracy.

In the system proposed by Pavlos Kosmides [10] et al., the user's data are collected from mobile terminals and are sent to the cloud. In order to produce recommendations, machine learning mechanisms are applied. The proposed system consists of two basic components, one related to the mobile device and other related to the cloud platform. The mobile device is responsible for collecting user information regarding check-ins and ratings. For the cloud platform Machine Learning Engine (MLE) training system, MLE training scheduler and MLE training execution are there. The recommendations are estimated by the location suggestion system, based on the user preferences or their friend's preferences.

The tourist attraction recommendation system developed by Zhiyang Jia et al. [11] is based on collaborative filtering. The recommendation process is divided into three steps. Initial step is the representation of user information. Second step is the generation of neighbour users. Using the visiting history data and the collaborative filtering algorithm, the similarity of users can be calculated. The user similarity is calculated using cosine similarity method. In this method, tourist rating are viewed as vectors and similarity is computed by the angle between vectors.

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Recommendations of attractions are computed by the number of times visit of neighbours. The viewing times are considered as the feedback of tourists. Finally the top N attractions will be recommended to the user. According to the steps in the recommendation process, using the user information and past travel history, the neighbour list can be calculated and recorded in the user database. When the user log in to the system, the tourist attraction recommendations are presented to the user based on the travel history of neighbours.

Author topic model POI recommendation [12] is proposed by Shuhui Jiang, et al. In this approach the author topic model is used to extract user preference topics from textual descriptions. In this POIs are mined using a coarse to fine based approach. The rich textual description and user information are analysed to get topic categories and these topics can be applied to personalized travel recommendation. In the ATM model the author is the set of users who uploads document which is the tag set of an image. Coarse to fine POI and user history mining are the main steps in ATM model. In Coarse to fine POI mining, coarse POI clustering is performed first. For clustering, mean shift algorithm is used. Then city level POI refinement is performed based on visual feature matching. Next is merging of clusters, after the visual similarity based merging POIs are obtained. The user history mining also consists of two steps. Initially User images are mapped to clusters and then the travel history mapping are refined to POIs. In ATCF, instead of user-POI matrix author topic model of users are used for similarity measurement. ATCF POI recommendation consists of user similarity detection and ranking of POIs. The top ranked POIs are recommended to the user. The algorithm works efficiently without GPS records.

Sentimental POI mining and recommendation [13] is proposed by Peiliang Lou, et al. Sentiment based algorithms are proposed for POI mining and recommendation. The method introduced in this paper recommends locations with desired sentimental features [18] required by the target user. In this system, microblogs are analysed and sentimental attributes of POIs are detected. The POIs which suits the user's sentimental preferences are recommended. Two algorithms are proposed in the paper. Sentimental POI mining and sentimental POI recommendation. The geographic attributes and sentimental attributes are incorporated. SPM method has two steps. The first step is the sentimental analysis of microblogs. Lexicon method is used for the analysis. The second step is clustering of POIs. Traditional mean shift algorithm is used in SPM method considering the sentimental attributes. For recommendation SPR algorithm is proposed. It is based on latent factor model. Latent factor model is realized by probabilistic matrix factorization. Sentiment similarity is the factor used to find the user preference of POI. Using matrix factorization [19] number of check-ins of user POI pairs can be predicted. Item based collaborative filtering is used to find the similarity. The geographical distance between user and POI and the sentimental similarity between user and POI are analysed and nearby POIs with suited sentimental features are recommended to the target user.

In the novel POI recommendation system [14], the sparsity problem [20] is solved. The Open Street Map (OSM) is the main source of the Points of Interest Recommendation. It is a free editable map of the world. User trajectory information is obtained from the signal transmission. User interests are gathered by looking into several details such as browsing history, most frequently visited websites, and social graph etc. The model consists of two modules. The offline module filter the relevant POIs from OSM, tag the filtered POIs and find the user to user similarity. The online module receives user trajectories and retrieves nearest POIs.

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IV. EXPERIMENTAL RESULTS

In the previous sections various travel recommender systems are explained. The merits and demerits of some selected works are presented below.

Sl .No	Title	Merits	Demerits
1	A novel point of interest (POI) location based recommender system utilizing user location and web interactions	Sparsity problem is solved	Accuracy problem exists
2	Schedule a Rich Sentimental Travel via Sentimental POI Mining and Recommendation	Sentimental analysis is used for POI mining	The sparsity problem is not examined
3	Author Topic Model-Based Collaborative Filtering for Personalized POI Recommendations	Sparsity problem is solved.	Only Textual information is used
4	User-based Collaborative Filtering for Tourist Attraction Recommendations	Efficient in tourist attraction recommendation	Number of visits is considered as the implicit feed back
5	A personalized geographic-based diffusion model for location recommendations in LBSN	Nearby POI Can be recommended using a single model	Time of check-in and categories of location are not considered.
6	A HITS-based POI Recommendation Algorithm for Location-Based Social Networks	Performs well in precision and recall	Geographical distance is not considered
7	A Random Walk Around the City: New Venue Recommendation in Location-Based Social Networks	Predicts previously unvisited places	Not efficient for abundant data
8	A hybrid context aware system for tourist guidance based on collaborative filtering	POI recommendation using user context and profile information	Accuracy changes
9	Context Rank: Personalized Tourism recommendation by Exploiting Context Information of Geotagged Web Photos	Context information is used. Performs well in cold start.	Users last visited land mark is considered as user preference
10	A worldwide tourism recommendation system based on geotagged web photos	Effective to cluster geographic images	Recommendation is limited and not intelligent

From the table it can be seen that dataset used by the TRS enhances with time. As more attributes are added to the dataset, the algorithms can be combined together and the problems like sparsity and cold start can be effectively reduced as well as efficiency can be increased

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V. CONCLUSION

From the survey it can be observed that different methods are introduced in travel recommender systems to increase its efficiency. Travel recommendation systems use historical data and models based on historical data for recommendation. The historical data used consists of images, textual descriptions, and user check-in data, user ratings, influence of other users etc. Collaborative filtering is the most commonly used algorithm in travel recommender systems. The most important factor considered in all algorithms is the geometrical attributes. The use of sentimental attributes along with geometrical attributes for POI mining can improve the travel recommendation performance. However, the challenges like cold start need to be solved effectively. The combination of web interaction attributes of users with other attributes can reduce the problems. As the dataset of LBSN increase with more attributes novel technologies will be emerged in the field of travel recommendation.

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