The Knowledge Engineering Review, Vol. 32, e7, 1–30.
doi:10.1017/S0269888916000308

A comparative study of location-based recommendation systems

FAISAL REHMAN, OSMAN KHALID and SAJJAD AHMAD MADANI

Department of Computer Science, COMSATS Institute of Information Technology, Abbottabad 22060, Pakistan; e-mail: frehman@ciit.net.pk, osman@ciit.net.pk, madani@ciit.net.pk

Abstract

Recent advancements in location-based recommendation system (LBRS) and the availability of online applications, such as Twitter, Instagram, Foursquare, Path, and Facebook have introduced new research challenges in the area of LBRS. Use of content, such as geo-tagged media, point location-based, and trajectory-based information help in connecting the gap between the online social networking services and the physical world. In this article, we present a systematic review of the scientific literature of LBRS and summarize the efforts and contributions proposed in the literature. We have performed a qualitative comparison of the existing techniques used in the area of LBRS. We present the basic filtration techniques used in LBRS followed by a discussion on the services and the location features the LBRS utilizes to perform the recommendations. The classification of criteria for recommendations and evaluation metrics are also presented. We have critically investigated the techniques proposed in the literature for LBRS and extracted the challenges and promising research topics for future work.

1 Introduction

Recent innovations in communication infrastructure with easy access to mobile social networks and e-commerce applications, such as Twitter, Facebook, Amazon, Instagram, Path, and Foursquare have shifted the focus of the research community from information extraction, to the filtering of relevant information (Bobadilla *et al*., 2013). In such advancements, users can effortlessly share a variety of life experiences in the physical world via smart phones and other mobile devices. Moreover, recent advancements in position localization techniques have primarily improved the social networking services that result in sharing users location-related information (Bao *et al*., 2015). The exponential increase in the quantity and diversity of already massive volumes of data with interacting Web services and networked devices results in an increased complexity for service providers and end users to search, discover, and access significant personalized information (Bobadilla *et al*., 2013).

Recommendation systems (RSs) were introduced in the early 1990s to deal with the challenges of personalized and automatic data retrieval from diverse sources of information (Bobadilla *et al*., 2013). Various knowledge discovery-based techniques are applied to users contextual and historical data to extract information, services, and products that place paramount importance on a users preference. RS use a variety of data sources to provide prediction and recommendation of items that match users preferences. Such systems attempt to balance various factors such as stability, accuracy, disparity, and novelty in the recommendations (Bobadilla *et al*., 2013).

Innovative mobile social networks, such as Foursquare, Facebook, and Instagram have initiated a new wave of research in the area of location-based recommendation system (LBRS). Such services collect huge volumes of data such as comments, check-ins, and locations on a daily basis. The existence of the huge volumes of data has shifted the focus of researchers from the problem of information retrieval to data refinement such that the information extracted must be more specific and related to the users query. The existing approaches used in various LBRS mostly rely on collaborative filtering (CF) (Lü *et al.*, 2012; Bao *et al.*, 2015; Bobadilla *et al.*, 2013). However, most of the existing approaches commonly face the issues such as (a) *data sparseness*: when limited number of users visits to places results in sparse user-to-location matrix (Lü *et al.*, 2012); (b) *cold start*: occurs when the system generates recommendation for a user who is new to the system, and not sufficient data are already present for the users past activities (Doytsher *et al.*, 2011; Lü *et al.*, 2012); and (c) *scalability*: refers to the ability of a RS to maintain the performance under an increased load, especially when performing real-time parsing of massive volumes of data (Chang *et al.*, 2011; Doytsher *et al.*, 2011; Noulas *et al.*, 2012). For the past few years, there has been significant research in the area of RS (Jannach *et al.*, 2010; Bobadilla *et al.*, 2011; Burke *et al.*, 2011; Cacheda *et al.*, 2011; Cantador *et al.*, 2011; Bostandjiev *et al.*, 2012; Konstan & Riedl, 2012; Lü *et al.*, 2012; Park *et al.*, 2012; Felfernig *et al.*, 2013; Guy, 2015; Pirasteh *et al.*, 2015). In the literature, the authors used different approaches to deal with the challenges of personalized data retrieval from diverse sources of information. The majority of existing work utilized various approaches, such as content-based filtering and CF with an intention to balance various factors such as accuracy, diversity, novelty, familiarity, and so on. Moreover, the existing work also attempted to deal with challenges, such as scalability, cold start, and data sparseness that are frequently encountered in RS.

In recent years, various literature surveys have been presented summarizing commonly used techniques and challenges in the field of RS (Desrosiers & Karypis, 2011; Chen & Pu, 2012; Pu *et al.*, 2012; Verbert *et al.*, 2012; Zuva *et al.*, 2012; Bobadilla *et al.*, 2013; Sharma & Gera, 2013; Shi *et al.*, 2014). Bobadilla *et al.* (2013) provided a general overview of recommender systems and discussed various CF algorithms. The authors also provided classification in terms of similarity, neighborhood, predictions, and recommendations. Moreover, the aforementioned survey provided a discussion on various K-nearest neighbors (KNN) schemes for RS and the cold start issues, along with evaluations. However, the authors did not specifically discuss location-based recommendations. In the article presented in Sharma and Gera (2013) and Shi *et al.* (2014), the focus is on the research challenges of RS. The authors provided an overview of the major techniques like CF, content-based filtering, and hybrid recommendations along with the various challenges faced by such techniques. The authors in Pu *et al.* (2012) and Zuva *et al.* (2012) attempted to summarize the evaluation metrics and techniques used in RS. In the latest survey on RS, the main focus is on neighborhood-based recommendation methods used for item recommendation (Desrosiers & Karypis, 2011).

Most of the above-mentioned surveys provided a general overview and research challenges of commonly deployed techniques in RS. To the best of our knowledge, there has not been any extensive survey conducted on LBRSs as we have presented here. A related survey was presented in Bao *et al.* (2015). However, the aforementioned survey was conducted on the topic of location-based social networks, whereas we have focused specifically on LBRS. In Bao *et al.* (2015), the authors restricted their analysis to the data sources used (e.g. user profiles, history of user visited location, and history of online user activities on LBSNs), methodology employed for recommendation (e.g. content based, collaborative based, and link analysis based), and the objectives of the recommendations (e.g. users, locations, social media, and activities). In contrast, our survey presents a qualitative comparison of various techniques proposed in LBRS not only for individuals but also for group-based location recommendations. Moreover, we have additionally discussed numerous significant services offered by LBRS. Such services are categorized as (a) geo-tagged media based which are the services that allow users to add location with users media contents, such as text, videos, and photos that were created in the physical world; (b) point location-based services that allow users to add and share users locations, such as restaurants, shopping malls, or cinemas; and (c) trajectory-based services that allow users to add both destination point locations and the routes to that destination. Furthermore, we have also presented the distinguishing features of the locations which are utilized by LBRS for recommendations. The location features are categorized as (a) location hierarchy, (b) distance of locations and users, and (c) sequential ordering. We have also discussed criteria to build a users trust and confidence on a RS. The criteria includes (a) accuracy, (b) familiarity, (c) novelty, (d) diversity, (e) context compatibility, (f) justification of recommendations, and (g) sufficiency of information. The survey also presents basic similarity calculations and evaluation metrics, such as (a) cosine-based similarity (Zheng *et al*., 2011), (b) correlation-based similarity (Cechinel *et al*., 2013), and (c) adjusted cosine similarity (Ye *et al*., 2010; Arora *et al*., 2014). In the end, a comparative study and a tabular summary of the existing schemes is presented.

The rest of the survey is organized as follows. In Section 2, an overview of the recommendation methods is given. A brief overview of services offered by LBRS and distinguishing features of LBRS is provided in Section 3. In Section 4, we have illustrated the criteria for recommendations. Basic similarity measures followed by evaluation of recommendation are discussed in Sections 5 and 6, respectively. In Section 7, a detailed study of models and techniques proposed in the literature for LBRS are discussed. Section 8 presents various challenges in developing scalable LBRS. Section 9 presents brief discussion on the opportunities in LBRS. Finally, future directions and conclusions are discussed in Sections 10 and 11, respectively.

2 Overview of the recommendation methods

The emphasis of the research community on the problems of recommendation, such as cold start, data sparseness, and scalability emerged in the mid of 1990s and RSs began to emerge as an independent research area. RSs have a profound association with cognitive science (Bobrow, 2014) and information retrieval (Lewis, 2014). Different methods have been used for the recommendation problem and the methods are normally categorized as content-based and CF methods. Figure 1 shows the hierarchy of the recommendation techniques, whereas Figure 2 depicts the types of recommendations, recommendation algorithms, and data sets used by RS.

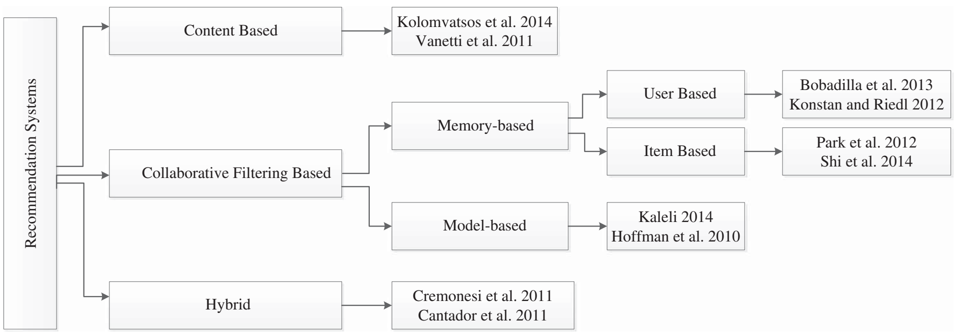

Figure 1 Hierarchy of the recommendation techniques

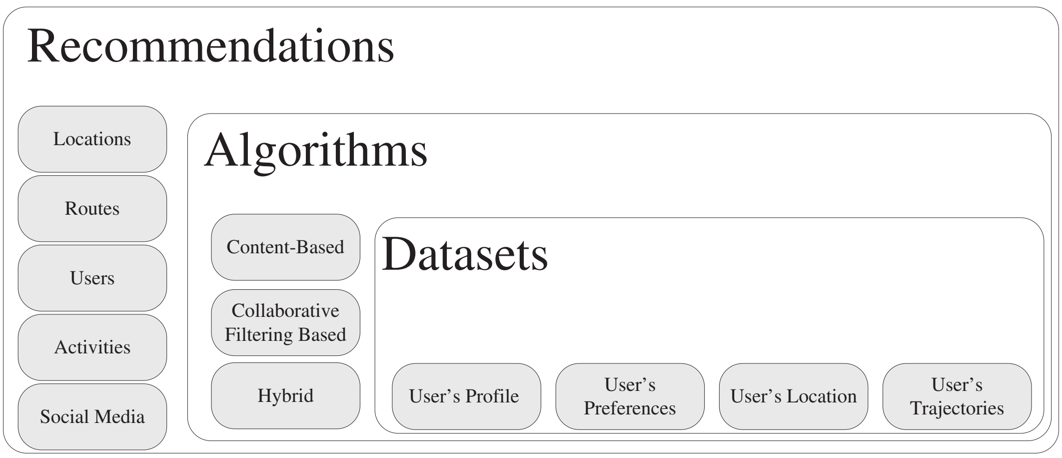

Figure 2 Component of recommendation systems

2.1 Content-based methods

The main idea of content-based (or cognitive) methods (such as Jannach *et al.*, 2010; Vanetti *et al.*, 2010; Lops *et al.*, 2011; Kolomvatsos *et al.*, 2014) is to recognize the common characteristics of a particular item that has already been evaluated and rated by a user. The system then finds and recommends a new item that shares the identical characteristics to the users preferences. In content-based RSs, complete information of the item is implicitly available in the form of a feature vector. For other items such as text documents (Vanetti *et al.*, 2010; Lops *et al.*, 2011),and Web documents (Jannach *et al.*, 2010; Kolomvatsos *et al.*, 2014), the feature vector usually comprises the term frequency–inverse document frequency (TF–IDF) weights of the most revealing keywords (Lewis, 2014). The TF–IDF approach was also used for prediction of the ratings of a user for any new item (Vanetti *et al.*, 2010). Similarly for rating predictions, Bayesian approaches were also used (Jannach *et al.*, 2010; Vanetti *et al.*, 2010; Guo *et al.*, 2013).

Content-based RSs suffer from two main problems: (a) inadequate analysis of contents and (b) over specialization (Shi *et al.*, 2014). Inadequate analysis of contents stems from the circumstance where the RS have limited or incomplete information about the contents of the item or about the users. There are numerous reasons behind such lack of information. For example, privacy is a major concern for many users that might restrict a user from providing sufficient personal information. Similarly, information about items such as music or images is costly or difficult to acquire. And finally, in some cases the information about the item is inadequate to evaluate the quality of the item. For instance, it is quite difficult to differentiate between a well-written article and a badly written article when both of the articles use the same terms. Alternatively, over specialization is the problem that is a side effect of the methodology in which RSs recommend new items. The rating predictions of a user is high for an item if the characteristics of the item are similar to the ones already rated high by the same user. For example, a recommendation application for a movie may recommend a movie of the same category to the user, if the user has rated movies of the same category previously. Similarly, a system may recommend a movie to the user which has the same actors to that of the previously rated movie. Because of the nature of the content-based recommendation technique, the system does not consider any other movie that is different yet might be fascinating to the user. For the aforementioned issue, solutions were proposed that introduce diversity in recommendations by adding some randomness in the recommendations (Shi *et al.*, 2014) or filtration of too similar items (Vanetti *et al.*, 2010; Hurley & Zhang, 2011).

2.2 Collaborative filtering method

Unlike content-based methods, in which the main idea is to recognize the common characteristics of a particular item that has already been evaluated and rated by a user, CF-based methods depend on the ratings of a user along with other users ratings in the system (Wei *et al.*, 2012; Shi *et al.*, 2014). CF is the most commonly used technique for the recommendation problem (Ye *et al.*, 2010; Lü *et al.*, 2012; Bao *et al.*, 2015; Bobadilla *et al.*, 2013). Although CF-based methods are frequently used with other filtering techniques such as knowledge-based or content-based, the main objective of using CF-based RS is to locate the subset of similar users who have similar profiles and preferences. Rating by a user u_1 for an item i is expected to be the same as rated by another user u_2, if and only if u_1 and u_2 had followed a similar pattern in rating other items. Similarly, u_1 is likely to rate two items i and j in a same manner, if similar rating has been given to both items by other users. The CF-based RS function by matching a particular users items record in matrix with other stored users record. The matrix must contain users visited locations and the number of visits for each location. The CF-based methods present valuable recommendations to a given user by extracting the ratings shared by similar users on the items.

CF-based methods eliminate certain existing problems of content-based RSs. For instance, when the rating information about an item is needed, and it is not available or difficult to acquire, CF-based models can still generate recommendations to the users through the feedback and ratings of other users. Moreover, in CF-based methods, users mostly rate an item keeping in consideration the quality of the item. This is not the case in content-based methods that mostly rely on content matching, which may lead to poor quality of recommendation. The two generic classes of CF approaches are memory based and model based.

Table 1 Description of combinations used in Hybrid Technique

Hybrid methods	Description
Weighted (Chen & Pu, 2012)	The weights (votes, scores, ratings) of different techniques are combined together
Mixed (Bostandjiev *et al*., 2012)	Different recommendations by different recommendations are presented simultaneously
Switching (Parra *et al*., 2014)	Switching between different techniques is done by the system according to the situation
Cascade (Lampropoulos *et al*., 2012)	Refinement done by one technique on recommendations offered by other
Feature combination (Zarrinkalam & Kahani, 2012)	Combination of features of different recommendation data sources
Feature augmentation (Cremonesi *et al*., 2011)	Input of technique is the output of other technique
Meta-level (Khribi *et al*., 2015)	Input of the technique is the complete model of other technique

In memory-based CF-based method, often referred to as neighborhood based (Shi *et al*., 2014) or heuristic based (Felfernig *et al*., 2013), user-item rating matrix stored in the system is directly accessed and used for the prediction of ratings for new items. Memory-based models are further categorized as item based and user based, as reflected in Figure 2. In item-based methods (Park *et al*., 2012; Shi *et al*., 2014), the prediction of rating for a user is based on already stored ratings for the similar items of that user. The system considers two items similar if and only if most of the users rated that item in the same way. Alternatively, user-based approaches (Konstan & Riedl, 2012) consider a users interest toward an item using the previously stored ratings of other users for the same item. The similarities are calculated among all the pairs of users based on the users ratings. The similarity computations, such as cosine similarity or Pearson's correlation are used for calculating the similarity among the users (Ye *et al*., 2011). The resultant correlated users are known as neighbors that are used for the rating prediction of the other users. In model-based approaches, data mining and machine learning algorithms are applied to train the probabilistic models for various patterns. Compared with memory-based approaches, model-based approaches are better in a sense that these approaches help in reducing the size of the user-item rating matrix that decreases the online processing time (Bao *et al*., 2015; Bobadilla *et al*., 2013). Also model-based methods surpass at characterization of users preferences that may include some hidden factors. For instance, without actually defining any notion such as suspense or horror, a movie RS recommends a movie that is both suspense and horror (Desrosiers & Karypis, 2011). In such a situation, model-based approaches determine a users preferences about a movie, without the user explicitly stating the preferences (Desrosiers & Karypis, 2011). Alternatively, memory-based methods extract associations in the users-items rating matrix. As a result, the RS may recommend a movie to a user that is totally against their taste or a movie that is not very popular, just because one of the users nearest neighbors highly rated that movie. Techniques commonly used in model-based RSs include Bayesian Clustering (Shi *et al*., 2014), latent semantic analysis (Evangelopoulos *et al*., 2012), latent Dirichlet location (Hoffman *et al*., 2010), maximum entropy (Kaleli, 2014), and support vector machines (Desrosiers & Karypis, 2011).

2.3 Hybrid

Combination of two or more techniques forms a hybrid RS. Usually, for achieving the best performance, techniques are combined in a way that the techniques with few drawbacks are chosen (Cremonesi *et al*., 2011). CF is the most commonly used technique for combination with any other technique. Some of the combination methods used for the creation of hybrid RS is shown in Table 1.

3 Location-based recommender systems

A social network is a network in which people of same or different cultures, age groups, locations, professions, and societies connect with each other to form different types of relations such as friendships, collaborative knowledge, and mutual interest (Marin & Wellman, 2011). The individuals in a social network use various social networking services that are the digital depiction of real-world social networks. The use of social networking services not only enrich such networks but also empower the growth of the network by providing the users to share events, ideas, interests, locations, and activities to strengthen the relationship with each other. The advent of sharing locations with each other in social networking services helps strengthening the association between real-world social networks and online social networking services (Zheng, 2012). LBRS is the system in which people share the location embedded information with each other (Symeonidis *et al.*, 2014). Moreover, users in LBRS share location-tagged media contents such as text, videos, and photos (Zheng *et al.*, 2012). Furthermore, the physical location comprises the immediate location of the user with a timestamp as well as the location history of the given user for a certain period. When same location is shared by two or more users, the information also includes the complete knowledge of the users common behavior, interests, and activities extracted from the users location history and location-tagged information (Bao *et al.*, 2015).

3.1 Services offered by location-based recommendation system

Existing LBRS services can be categorized as geo-tagged media based, point location based, and trajectory based.

3.1.1 Geo-tagged media based

Geo-tagged media-based services allow users to add location with users media contents such as text, videos, and photos that were created in the physical world (Majid *et al.*, 2013). Passive tagging occurs when a user explicitly creates and adds the contents along with the location (Majid *et al.*, 2013). Geo-tagged media-based services allow a user to view other users content in a geographical context by using digital maps on smart phones (Chon & Cha, 2011). Popular applications that provide LBRS services include Geo Twitter[1], Flickr[2], and Panoramio[3]. It has been shown in Ye *et al.* (2010) that addition of only location dimensions (such as longitude, latitude) does not necessarily attract users, as users are more interested by actual media content. Therefore, the addition of location information only acts as an add-on to enrich and unify the media contents. The authors in Ye *et al.* (2010) further indicated that addition of the location feature does not have much impact on the connections and relationships among the users; rather it is the media content that is responsible for such connections and relationships between users.

3.1.2 Point location based

Point location-based services allow users to add and share users locations such as restaurants, shopping malls, or cinemas (Gao *et al.*, 2015). The most common applications to offer such services are Foursquare, Instagram, and Facebook that encourage users to share their existing location. Users of such applications are provided with options to perform a check-in at different locations that are visited by the users in their daily routine to share experiences and knowledge by giving a tip or feedback (Ye *et al.*, 2010; Sarwat *et al.*, 2013). For example, a user can share their views about a dinner to their community on an online social site while using their smart phone. Moreover, such services also keep track of the users geospatial check-in data (such as time and longitude/latitude) (Ye *et al.*, 2010). In Foursquare, after checking in at different locations, the application awarded badges and points to the user. The user that has the most number of visits at a particular location has been capped as Mayor. One of the main advantages of such services that allow real-time location tracking of users is that users can discover friends around their physical locations that help in boosting a users social activities in the physical world. For instance, after discovering a friends physical location from his/her social network, one can offer the friend to have a lunch or shopping activity. The use of tip or feedback in location-based services allows users to share comments and suggestions that can be either positive or negative. Such tips or feedbacks are pivotal in aggregating recommendations.

[1] `http://geo-twitter.appspot.com/`
[2] `https://www.flickr.com/`
[3] `http://www.panoramio.com/`

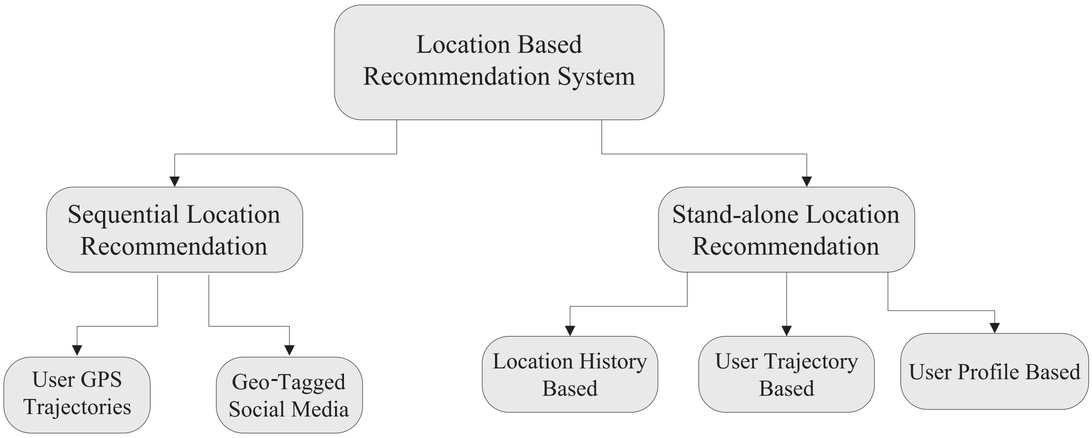

Figure 3 Categories of location-based recommendation system

Unlike geo-tagged media, a point location (venue) is the main component for the users that determine the connection between the users and the media content such as feedbacks, badges, and tips are associated with the point location (Zheng, 2012).

3.1.3 Trajectory based

Trajectory-based services allow users to add both point locations and the routes to that point location. The most common applications that offer such services are Bikely[4], Microsoft GeoLife[5], and SportsDo[6]. Trajectory-based approaches compute information by extracting data about a users visit patterns at different locations, duration of stays, and the paths selected. Such services allow users to add information such as speed, distance, duration, and route about a specific trajectory, as well as the users media contents such as tips, tags, and photos along with the given trajectory (Ye *et al*., 2010; Ying *et al*., 2010). Other users of the same community can take guidance from the experiences of their friends by following the trajectory using digital maps or smart phones. In summary, such services offer both how and what along with where and when. Figure 3 shows the categorization of LBRSs.

3.2 Distinguishing features of locations

In LBRS, the focus of the recommendations remains on the locations beside the media contents. Therefore, it is important for the RS to recognize and consider the unique features of the locations to make recommend actions to a user that meets the criteria of both accuracy and quality of recommendation. Following are the distinguishing features of the location.

3.2.1 Location hierarchy

There are multiple scales at which location can be considered. A location can be a small shop or restaurant or it can be a big town or city. Such locations, smaller or bigger form a hierarchy where locations at the bottom are refer to smaller geographical areas (Xiao *et al*., 2014). For instance, a location (restaurant, cinema, shopping mall) may belong to a community, a community belongs to a town, and a town belongs to a country, and so on. The different levels of hierarchical formulation of locations lead to diverse user-location and location-location graphs. Bao *et al*. (2015) suggested that even if a user has identical location histories, different user-location and location-location graphs will be formulated. The importance of the hierarchical relationships and their consideration is essential for the RS because these relationships have a very significant role in establishing the connections between the users (Wang *et al*., 2013). For example, users who share locations such as restaurant or shopping malls that are considered as lower level

[4] `http://www.bikely.com/`
[5] `http://research.microsoft.com/en-us/projects/geolife/`
[6] `www.sportsdo.com.br/`

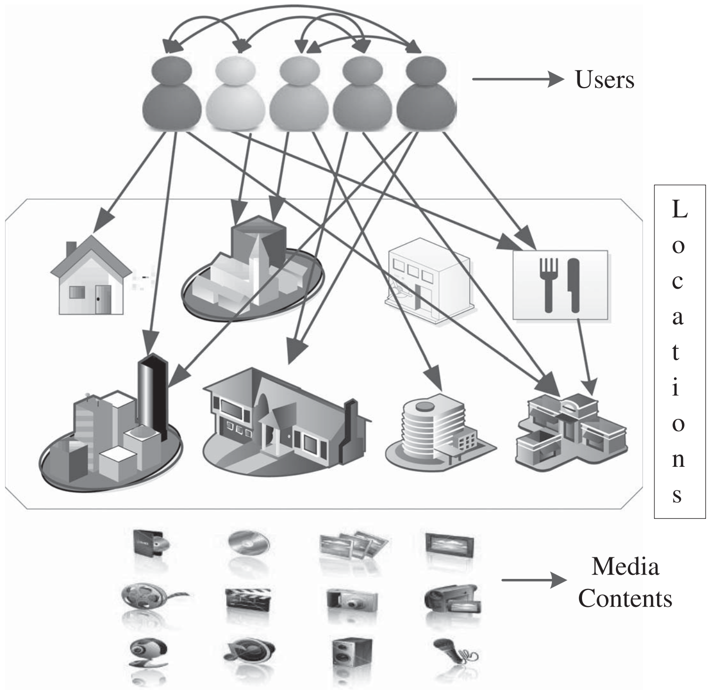

Figure 4 Visit patterns of user in location-based recommendation system

items in the hierarchy possibly have strong connections than users who share locations such as towns or countries that are considered as higher level hierarchy. As a consequence, the hierarchical property in LBRS is unique and needs to be considered.

3.2.2 Distance of locations and users

The second distinguishing property of locations in LBRS is distance. To find the strength of relationship and connections between the users, distance must be considered. The shorter the distance the stronger will be the relationship. There are three geospatial distance relations defined to compute the relationship and connections among the users using distance (Wang *et al*., 2013). The three geospatial distance relations are the distance between the users, the distance between a location and a user, and the distance between two locations. Distance in all three aforementioned cases can affect the RSs in three possible ways. In the first case, the distance between two users shows the similarity between users. For instance, users who have similar history of visiting same location have high priority to have similar preferences and interest (Xiao *et al*., 2010; Arora *et al*., 2014) and the users who have similar residential area are possibly friends (DeScioli *et al*., 2011). In the second case, the distance between users and locations shows the probability of a users attraction to the specific location. For example, users frequently visit nearby places than other places that are far away from users homes (Levandoski *et al*., 2012). In the last case, the distance between two locations shows the association between different locations. For instance, restaurants and shopping malls are mostly situated near to each other (Ye *et al*., 2011).

3.2.3 Sequential ordering

Most users visit favorite places at regular intervals. Such regular intervals create a relationship between users in a sequential order. For example, two users of the same company regularly dine at two different restaurants and meet again in the cinema, an ordering of visits can be created that may show some common preferences among them (Bao *et al*., 2015) or that may possibly show traffic conditions (Tang *et al*., 2010). Figure 4 shows the visit patterns users can have in a LBRS. A user can visit different locations and add such locations with media contents like tips, tags, and feedbacks.

4 Criteria for recommendations

In a RS, a users main concern is the quality of the recommendations generated for an item. Users review the resultant recommendations offered by the system and justify them as appropriate or inappropriate depending on their personalized preferences. In addition, it is important for the RS to present such recommendations in a manner that is acceptable for the users. Therefore, presentation of the recommendations must be handled carefully to influence the users to accept the recommendations (Pu *et al.*, 2012). For example, would the recommendations include only top ranked items or locations, and similar ones? Or would the recommendations include the popular locations or items, and also well-proportioned highly ranked one? Similarly, another key aspect of RS is trust (Shani & Gunawardana, 2011). The user has more trust on the system if the recommendations generated by the system best match the users preferences. Therefore, a users expectation is directly dependent on trust in the system (Bedi & Sharma, 2012; Liu, 2014). The RSs also affect a users confidence in the system that whether the generated recommendations are satisfying a user or not. The users are more likely to accept the recommendations if their confidence in the system is high (Avazpour *et al.*, 2014). In the following subsections, we will discuss some of the criteria for the RS that must be considered to build trust and confidence of the users.

4.1 Accuracy

To evaluate a RS, one of the most dominant and important criteria is accuracy (Rana & Jain, 2015). Numerous works have been carried out in the past decade to achieve the goal of enhancing the accuracy of recommendations (Pu *et al.*, 2011). The most common measure used by most of the researchers in the rating-based RSs is Mean Absolute Error (MAE) (Bobadilla *et al.*, 2011). MAE measures the difference between the ratings predicted by the algorithm and the actual ratings of the users (Pu *et al.*, 2012). Similarly, for content-based RSs, switching task is used to measure the accuracy (Bostandjiev *et al.*, 2012). Switching task measures the change (switching) of user preferences before and after the recommendation (Bostandjiev *et al.*, 2012). If some user changes his/her preferences after the recommended list, the accuracy of the system will be decreased (Pu *et al.*, 2011). In recent years, the focus of the research is shifted toward users perceived accuracy. Users perceived accuracy measure is the degree of users satisfaction level (Cremonesi *et al.*, 2011). If the recommendations generated by the system best matches a users interest and preferences, the degree of the users perceived accuracy will be high. Perceived accuracy has more direct impact on users trust level as compared with objective algorithm accuracy (Chen & Pu, 2012). However, it was also shown by some researchers that both perceived accuracy and objective accuracy do not have a direct correlation with each other (Pu *et al.*, 2011). Moreover, it was shown that users like to have other factors incorporated, such as diversity and novelty in the recommendations (Vargas & Castells, 2011). Studies such as Shani and Gunawardana (2011) showed that accuracy alone is not sufficient for the selection of related algorithm. For example, user may have intent to incorporate novelty in the recommendations. Therefore, considering accuracy alone as the criteria for recommendation is not sufficient (Pu *et al.*, 2012). We concluded from different studies that for LBRS the user-based CF (based on KNN) has been verified to achieve high accuracy (Ye *et al.*, 2011).

4.2 Familiarity

Another criterion for the RSs is familiarity. The most familiar stuff is most likely to be recommended (Pu *et al.*, 2012). As compared with unfamiliar recommendations, users liking for familiar recommendation is high. The study conducted in Pu *et al.* (2012) showed that when the items that are highly liked by a user are included in the recommendations, the items increase the users trust in the system. The study also showed that the users are more likely to be interested in the familiar items rather than unfamiliar ones. In the study conducted in Chang *et al.* (2011), familiar road segments were recognized and then familiar road networks were constructed using historic trajectories to generate personalized routes. While the preference of a user is always toward the familiar recommendations but the user also needs new recommendations to which the user was previously unfamiliar. For example, if LBRS recommends a similar restaurant to a user, the user might feel that the system is not capable of recommending new restaurants that might change their taste (Liu, 2014).

4.3 Novelty

The limitation shown in the previous criteria of the RS can be handled by introducing novelty in the recommendations. Novelty is another important criterion that needs to be considered by the RSs. The main idea of introducing novelty is to provide users with unexpected recommendations. Novelty is also sometimes referred to as serendipity (Rana & Jain, 2015). However, the difference between novelty and serendipity was elaborated in Pu *et al.* (2011), where novelty means new and serendipity means new and surprising. Therefore, it can be concluded that novelty is the extent to which recommendations are newer for a user (Liu, 2014). In a study conducted in Adomavicius and Kwon (2012), the researchers discovered that users give high ratings to the music recommended by Pandora. Pandora is considered as a novel music RS because it frequently provides listeners with latest music tracks. The study also showed that the music RSs that offer new choices are most well known as users prefer to use such systems rather than the RSs that focus only on users preferences.

4.4 Diversity

Another key criterion for RSs is diversity (Pu *et al.*, 2012). Diversity and novelty are different notions though both are closely related. Novelty of the recommendation can be referred to as how the recommendation is different with respect to previously seen recommendations. Whereas, diversity indicates how distinctly dissimilar the recommendations are when compared with each other (Vargas & Castells, 2011). In item-to-item CF algorithm, a user is trapped in a similarity junction that provides the user with similar recommendations according to his/her or friends preferences (Rana & Jain, 2015). Therefore, the focus of the researchers is shifted toward diversity in recent years. At the same time, the focus should also be on maintaining the balance between diversity and similarity (Adomavicius & Kwon, 2012; Liu, 2014; Javari & Jalili, 2015). Moreover, highly diverse recommendations also affect the similarity and accuracy criteria for the user. Therefore, the diversity of the recommendations should be provided with a balance in aforementioned tradeoffs (Adomavicius & Kwon, 2012). The study showed that users like diverse recommendations as compared with more accurate recommendations (Vargas & Castells, 2011). Decision confidence of a user may be affected when the user receives low diversity recommendations (Pu *et al.*, 2012). It was also showed in another study that the satisfaction level of users drive beyond accuracy and that the users are more likely to accept more diverse recommendations (Javari & Jalili, 2015).

4.5 Context compatibility

Context compatibility is a criteria for RSs in which the current context should be considered before the final recommendation. Contextual occasions are the key to the users satisfaction. A good RS is the one that provides recommendations taking into account the users current contextual information (Pu *et al.*, 2012). For example, if a user wants to dine in a restaurant, the current context includes current location, food choice, who is accompanying the user, and weather conditions. Similarly, if a user wants to watch a movie, the current context should be considered because the users preferences of watching a movie with their friends may differ compared with watching a movie with their family (Verbert *et al.*, 2012). One of the advantages of adding contextual considerations in the RSs is that it helps new users to get recommendations instantly without adding robust profiles (Pu *et al.*, 2012).

4.6 Justification of recommendations

For user satisfaction, it is not enough to give recommendations according to the users preferences and ratings. In addition, the user must understand the criteria of selection of items for recommendations. Studies showed that a users satisfaction and trust level is enhanced in those RSs that also provide good justifications with the recommendation list (Desrosiers & Karypis, 2011). Some of the primary goals of including the justifications to recommendations are transparency, effectiveness, and smoothness (Desrosiers & Karypis, 2011). After realizing the importance of justifications of recommendations,

Table 2 Criteria for recommendations in different research

Criteria for recommendations	References
Accuracy	Pu *et al*. (2011), Shani and Gunawardana (2011), Ye *et al*. (2011), Chen and Pu (2012), Pu *et al*. (2012), Rana and Jain (2015)
Familiarity	Chang *et al*. (2011), Liu (2014)
Novelty	Pu *et al*. (2011), Vargas and Castells (2011), Adomavicius and Kwon (2012), Liu (2014), Rana and Jain (2015)
Diversity	Vargas and Castells (2011), Adomavicius and Kwon (2012), Pu *et al*. (2012), Liu (2014), Javari and Jalili (2015), Rana and Jain (2015)
Context compatibility	Pu *et al*. (2012), Verbert *et al*. (2012)
Justification of recommendations	Desrosiers and Karypis (2011), Pu *et al*. (2012)
Sufficiency of information	Pu *et al*. (2011)

commercial websites like Netflix, Pandora, and Amazon have also added features, such as why this was recommended on the Web pages (Pu *et al*., 2012).

4.7 Sufficiency of information

The last criteria for RSs is to provide sufficient information with the recommendation list to facilitate the user and help enhancing the decision-making process of the user. For example, when Amazon recommends a book to a user, the information needed by the user is sufficient. The title of the book, author name, edition, binding (hardcover or paperback), current ratings, and price of the book, all the necessary information, is displayed with recommended book. Studies showed that the availability of the descriptive information about the individual item positively correlated with perceived effectiveness and ease of access of the RS (Pu *et al*., 2011). For example, if LBRS recommend a shopping mall to a user, then the user would like to have more detailed information about the shopping mall, such as its distance from the user, the shortest path to the shopping mall, driving routes, and the description of different shops in the shopping mall. Therefore, the RS must consider the criteria of adding sufficient information with the recommendations. Table 2 is the summary of criteria for recommendations applied in various research works.

5 Similarity calculations in location-based recommendation system

One of the most critical steps in recommendations in LBRS is to compute the similarity between users and locations. The process of computing similarity starts by computing the similarity between users and locations, and then the RS selects the most similar locations for recommendations. The basic idea in computing the similarity between two locations l_1 and l_2 is to identify the users who have rated both the locations and then apply similarity computation methods to find the similarity $S_{l_1 l_2}$. For example, in Table 3, user u_1 and u_2 have both rated locations l_1 and l_3. Similarly, the similarity between two users u_1 and u_2 can be calculated using the existing similarity computation techniques. A variety of different techniques exists to compute the similarity between users and locations (Ye *et al*., 2010; Zheng *et al*., 2011; Cechinel *et al*., 2013; Arora *et al*., 2014). The most common among such techniques include cosine-based similarity, correlation-based similarity, and adjusted cosine similarity.

5.1 Cosine-based similarity

In cosine-based similarity, two different locations are the two vectors in the user-location matrix. The cosine similarity between two locations is calculated by computing the cosine of the angles between the locations (Zheng *et al*., 2011). Suppose we have $m \times n$ user-to-location matrix as shown in Table 3, then similarity between two locations l_1 and l_2 can be calculated using the following formula (Wei *et al*., 2012):

$$\text{sim}(l_1, l_2) = \cos\left(\vec{l}_1, \vec{l}_2\right) = \frac{\vec{l}_1 . \vec{l}_2}{\left|\left|\vec{l}_1\right|\right| \times \left|\left|\vec{l}_2\right|\right|} \quad (1)$$

Table 3 User-location matrix

	Ratings of users on locations					
User-location	l_1	l_2	l_3	.	.	l_n
u_1	4	3	5	.	.	–
u_2	3	–	4	.	.	–
u_3	3	5	.	.	.	–
.	.	.	.	.	.	–
.	.	.	.	.	.	–
u_n	–	–	–	–	–	–

where . represents the dot product of two vectors. Cosine-based similarity is considered to be computationally tractable (Lyakhov *et al.*, 2010). Cosine similarity ranges between 0 and 1. One of the basic drawback of cosine similarity is that it does not show the negative values of similarity that happens in cases when users have rated the different set of locations. This deficiency of cosine similarity is taken into account in the Pearson's correlation coefficient. If the attribute vectors $\vec{l}_1$ and $\vec{l}_2$ are normalized by subtracting the vector means, the measure is called centered cosine similarity and is equivalent to the Pearson's correlation coefficient. Pearson's correlation is discussed in the next subsection.

5.2 *Correlation-based similarity*

In correlation-based approach, the similarity between two locations l_1 and l_2 is calculated using Pearson's r correlation $corr_{l_1 l_2}$ (Cechinel *et al.*, 2013). The calculation of Pearson's r correlation starts with the isolation of different locations that are already rated by the user u. For example, in Table 3, the locations l_1 and l_2, both are rated by user u_1. If we have a set of users (u_1, u_2, u_3, …, u_n) denoted by U, then the Pearson's r correlation similarity is given by (Pirasteh *et al.*, 2015):

$$\mathrm{sim}(l_1, l_2) = \frac{\sum_{u_1 \in U} \left(R_{u_1,l_1} - \overline{R}_{l_1}\right)\left(R_{u_1,l_2} - \overline{R}_{l_2}\right)}{\sqrt{\sum_{u_1 \in U} \left(R_{u_1,l_1} - \overline{R}_{l_1}\right)^2} - \sqrt{\sum_{u_1 \in U} \left(R_{u_1,l_2} - \overline{R}_{l_2}\right)^2}} \tag{2}$$

In the above equation, $R_{(u_1,l_1)}$ represents the rating of user u_1 for location l_1 and R_{l_1} the average rating of the lth location. Compared with cosine similarity, Pearson's correlation evaluates to more accurate similarity computations as it incorporates the negative similarity values as well. The negative similarity depicts how far the two users are in their preferences. However, it is important to note that Pearson's correlation has two issues which must be taken into account while computing similarity between users, items, or locations. The first issue occurs when one user has rated an item or location but the other user has not rated the same item or location. In such a case, Pearson's correlation will only look for common set of items rated by both users for similarity computation. As a result, a large set of items could be ignored that are not commonly rated by both users, though, still those items could have some impact on similarity computations. The other issue with Pearson's correlation is that users with only a few commonly rated items or locations could have high similarities, despite the smaller item count. This could induce bias in the similarity values, and the issue can be resolved by using significance weighting (Chen *et al.*, 2013).

5.3 *Adjusted cosine similarity*

One of the main differences between the similarity computations of users and locations is that the similarity of users is computed along the rows of the matrix and similarity of locations are computed along the columns of the user-to-location matrix (Ye *et al.*, 2010; Arora *et al.*, 2014). Basic cosine similarity has one limitation that it does not calculate the difference in rating scales of the users. In adjusted cosine similarity, the drawback of basic cosine similarity is eliminated by subtracting the corresponding users rating average from each co-rated pair of locations. The similarity between locations using adjusted cosine similarity is calculated as (Xia *et al*., 2015)

$$\mathrm{sim}(l_1, l_2) = \frac{\sum_{u_1 \in U} \left(R_{u_1,l_1} - \overline{R}_{u_1}\right)\left(R_{u_1,l_2} - \overline{R}_{u_1}\right)}{\sqrt{\sum_{u_1 \in U} \left(R_{u_1,l_1} - \overline{R}_{u_1}\right)^2} - \sqrt{\sum_{u_1 \in U} \left(R_{u_1,l_2} - \overline{R}_{u_1}\right)^2}} \tag{3}$$

where, $\overline{R}_{u_1}$ is the average rating of the *u*th users rating. The above-mentioned similarity calculations are a primary step to find out similar users or locations. After computing the similarity, the RS selects the most similar locations and generates the recommendation lists accordingly. A variety of performance metrics are used to evaluate the resulting recommendation lists. In the next section, we will discuss in detail the most commonly used evaluation metrics in the field of LBRS.

6 Evaluation of recommendations using evaluation metrics

To analyze quality of recommendations, it is important to evaluate the recommendations using evaluation metrics. The use of evaluation metrics helps in the comparison of various solutions proposed by the researchers and as a result, recommendations have been improved gradually (Cacheda *et al*., 2011). The existing evaluation metrics have a standard formulization that is used for the testing and evaluations of the recommendations (Bobadilla *et al*., 2013). A variety of evaluation metrics (Bobadilla *et al*., 2013) are used, but the most common ones are classified as prediction metrics, set recommendation metrics, rank recommendation metrics, and diversity metrics. Prediction metrics are used to find the accuracy of recommendations using MAE (Bobadilla *et al*., 2011), normalized mean average error (NMAE) (Dakhel & Mahdavi, 2011), and root of mean square error (RMSE) (Golbandi *et al*., 2011). Predictions methods are also used to find the coverage. Set recommendation metrics include recall (Esparza *et al*., 2012), precision (Esparza *et al*., 2012), and receiver operating characteristics (Hsu *et al*., 2012). Rank recommendation metrics include half-life (Cacheda *et al*., 2011) and discounted cumulative gain (Balakrishnan & Chopra, 2012). Diversity metrics include novelty and diversity of the recommendations (Vargas & Castells, 2011). Moreover, the validation process is completed using the most commonly used cross-validation technique known as k-fold cross-validation (Bobadilla *et al*., 2013) and random sub-sampling validations (Gan & Jiang, 2013). The next subsection provides the elaboration of each of the evaluation metrics in detail.

6.1 Prediction metrics

To find accuracy of recommendations, researchers usually employ the calculations of the most commonly used prediction error metrics like MAE and its associated metrics, such as NMAE, mean squared error (MSE), and RMSE (Shani & Gunawardana, 2011). Suppose a set of users $(u_1, u_2, u_3, \ldots, u_n)$ denoted by U, a set of items $(i_1, i_2, i_3, \ldots, i_n)$ denoted by I, $r_{u,i}$ is the rating of user u on item i, α the lack of ratings (i.e. $r_{u,i} = \alpha$ means user u has not rated item i), and $p_{u,i}$ the prediction of item I on user U. Let X_u be the set of items rated by user u having prediction values, where $X_{u,i} = i \in I | \rho_{u,i} \neq \alpha \wedge r_{u,i} \neq \alpha$. The systems MAE and RMSE are the average of the users MAE. The prediction error is the absolute difference between real values and the prediction, denoted as $p_{u,i} - r_{u,i}$. RME (Zuva *et al*., 2012) and RMSE (Golbandi *et al*., 2011) are given by the following two formulas, respectively:

$$\mathrm{RME} = \frac{1}{|U|} \sum_{u \in U} \left(\frac{1}{|X_u|} \sum_{i \in O_u} \left| \rho_{u,i} - r_{u,i} \right| \right) \tag{4}$$

$$\mathrm{RMSE} = \frac{1}{|U|} \sum_{u \in U} \sqrt{\frac{1}{|X_u|} \sum_{i \in O_u} \left(\rho_{u,i} - r_{u,i} \right)^2} \tag{5}$$

The metric coverage measures the percentage of situations in which there are chances of at least 1 k-neighbor of each active user that can rate the unrated item of that active user (Shani & Gunawardana, 2011).

Let $K_{u,i}$ be the set of neighbors of a user u that has rated an item i. The coverage of the system is the average of the users total coverage. Let

$$C_u = \{i \in I \mid r_{u,i} = \alpha \wedge K_{u,i} \neq \phi\}$$
$$\text{and } D_u = \{i \in I \mid r_{u,i} = \alpha\}$$

then the coverage can be calculated using the following equation (Shani & Gunawardana, 2011):

$$\text{coverage} = \frac{1}{|U|}\sum_{u \in U}\left(100 \times \frac{|C_u|}{|D_u|}\right) \tag{6}$$

6.2 *Quality of the set of recommendations*

A users satisfaction not only depends on accuracy, but it also depends on being provided with a concise as well as diverse set of recommendations. The combination of accuracy, diversity, and concise items list compose the quality of recommendations (Kim *et al.*, 2010). The most common recommendation metrics used for quality measurement are precision, recall, and $F1$ (Jäschke *et al.*, 2012). Precision is the number of relevant recommendations out of the total recommendations. Recall is the number of relevant recommendations from the number of relevant locations. $F1$ is the combination of recall and precision. $F1$ is generally used because of the advantage that it considers both the values of precision and recall and returns the value of only positive results (Jäschke *et al.*, 2012). Suppose r_u is the set of recommendations to user u, N_u the set of n recommendations to u. The relevancy threshold is θ, the evaluation recall, precision, and $F1$ measures for obtained recommendations by taking n test recommendations to user u, assuming all the users take n test recommendations, then precision, recall, and $F1$ can be calculated by (7), (8), and (9), respectively (Jäschke *et al.*, 2012).

$$\text{precision} = \frac{1}{|U|}\sum_{u \in U}\frac{\left|\{i \in N_u \mid r_{u,i} \geqslant \theta\}\right|}{n} \tag{7}$$

$$\text{recall} = \frac{1}{|U|}\sum_{u \in U}\frac{\left|\{i \in N_u \mid r_{u,i} \geqslant \theta\}\right|}{\left|\{i \in N_u \mid r_{u,i} \geqslant \theta\}\right| + \left|\{i \in N_u^c \mid r_{u,i} \geqslant \theta\}\right|} \tag{8}$$

$$F1 = \frac{2 \times \text{precision} \times \text{recall}}{\text{precision} + \text{recall}} \tag{9}$$

6.3 *Quality of the list of recommendations*

A common issue faced by users of RS is when users select only the first item from a large list of recommendations. Ignoring the rest of the list of recommendations may affect the selection of recommendations as there may be some quality recommendations down the list. To address the aforementioned issue, ranking metrics are often used by researchers. Such ranking metrics include half-life and discounted cumulative gain. In half-life (Bobadilla *et al.*, 2013), when users move away from the recommendations at the top, it assumes an exponential decrease in the interest of users. Half-life assumes that the selection probability of relevant recommendation decreases exponentially down the list. Half-life is calculated using (10). In discounted cumulative gain (Baltrunas *et al.*, 2010), it is assumed that the selection probability of relevant recommendation decreases logarithmically down the list and can be calculated using (11).

$$\text{Half-life} = \frac{1}{|U|}\sum_{u \in U}\sum_{i=1}^{N}\frac{\max\left(r_{u,q_i} - d,\ 0\right)}{2^{\frac{i-1}{\alpha-1}}} \tag{10}$$

$$\text{Discounted cumulative gain}(\text{DCG})^f = \frac{1}{|U|}\sum_{u \in U}\left(r_{u,q_i} + \sum_{i=2}^{f}\frac{r_{u,q_i}}{\log_2(i)}\right) \tag{11}$$

In (10) and (11), the set of recommendation list is represented by $q_1, q_2, q_3, \ldots, q_n$, $r_{(u,q_i)}$ is the true rating of the user u for the item q_i, f is the rank of the evaluated item, α is the position of the item in the list such that there is 50% chance that the user will rate that item, and d is the default rating.

6.4 Novelty and diversity

Novelty can be measured to an extent where recommendations are new and interesting for the users. Novelty metrics calculate the difference between the actual recommendations recommended to the user with those already known by a user that are significant. Alternatively, diversity metric calculates the internal difference of the recommendations. At present, no standard metric was defined for novelty and diversity. Therefore, different metrics are proposed by researchers (Vargas & Castells, 2011). Most of the authors used the following mathematical calculations to find the novelty and diversity in recommendations (Hurley & Zhang, 2011).

$$\text{diversity}_{R_u} = \frac{1}{|R_u|(|R_u|-1)} \sum_{1 \in R_u} \sum_{j \in R_{uj \neq 1}} [1 - \text{sim}(i, j)] \tag{12}$$

$$\text{novelty}_i = \frac{1}{|R_u|-1} \sum_{j \in R_u} [1 - \text{sim}(i, j)],\ i \in R_u \tag{13}$$

In (13), set of n recommendations is represented by R_u, and item-item memory-based similarity measure is represented by sim(i, j).

6.5 Stability

A user has a more trust in a RS when the recommendations generated by the system best match the users preferences. A RS is known as stable when the recommendations generated do not deviate over a short period (Adomavicius & Zhang, 2012). The metric defined for the evaluation of the stability of RS is mean absolute shift (MAS) (Verbert *et al.*, 2012). The MAS metric consists of a set of known ratings R_1 known by the user and a set of unknown ratings Q_1. After a period of time, the user rated some of the unknown ratings and the new recommendations Q_2 are generated by the system. Now, MAS can be calculated in the following equation (Verbert *et al.*, 2012)

$$\text{stability} = \text{MAS} = \frac{1}{|Q_2|} \sum_{(u,i) \in Q_2} |Q_2(u, 1) - Q_1(u, 1)| \tag{14}$$

6.6 Reliability

When a user gets a recommendation, it is important to know whether the recommendation is valuable for the user or not. A valuable recommendation is considered reliable for the user. The most commonly used metrics to find reliability of the recommendations are Pearson's correlation, the mean squared difference (MSD), Pearson's correlation constrained, Spearman's rank-order correlation, and the Jaccard plus MSD (Hernando *et al.*, 2013). The reliability measures are proposed according to the notion that more reliable a prediction, the less liable to be wrong (Bobadilla *et al.*, 2013). However, the reliability metric is just used to evaluate the RSs based on the KNN algorithm. It is based on the numeric factors $S_{u,i}$ as shown in (15) and $V_{u,i}$ as shown in (16), where $S_{u,i}$ the similarity of the neighbors used for giving recommendations $p_{u,i}$ and $V_{u,i}$ is the dissimilarity among the ratings of the neighbors. Now, the reliability will be calculated using (17) (Shani & Gunawardana, 2011):

$$f_s(S_{u,i}) = 1 - \frac{\overline{S}}{\overline{S} - S_{u,i}},\ \text{where } S_{u,i} = \sum_{v \in K_{u,i}} \text{sim}(u, v) \tag{15}$$

$$f_v(V_{u,i}) = \left(\frac{\max - \min - V_{u,i}}{\max - \min}\right)^{\frac{\ln 0.5}{\ln \frac{(\max - \min - \overline{v})}{\max - \min}}} \tag{16}$$

Table 4 Summary of evaluation metrics

Criteria	Metrics	References
Accuracy	MAE, NMAE, MSE, and RMSE	Cacheda *et al.* (2011), Shani and Gunawardana (2011)
Quality of set of recommendations	Precision, recall, and *F*1	Kim *et al.* (2010), Jäschke *et al.* (2012)
Quality of the list of recommendations	Half-life, DCG	Baltrunas *et al.* (2010), Bobadilla *et al.* (2013)
Novelty and diversity	No standard metric defined	Hurley and Zhang (2011), Vargas and Castells (2011)
Stability	MAS	Verbert *et al.* (2012)
Reliability	COR, MSD, CORC, SR, and JMSD	Bobadilla *et al.* (2013), Hernando *et al.* (2013)

MAE = Mean Absolute Error; NMAE = normalized mean average error; MSE = mean squared error; RMSE = root of mean square error; DCG = discounted cumulative gain; MAS = mean absolute shift; COR = Pearson's correlation; MSD = mean squared difference; CORC = COR constrained; SR = Spearman's rank-order correlation; JMSD = Jaccard plus MSD.

$$\text{reliability} = \frac{\sum_{v \in K_{u,i}} \text{sim}(u, v)\left(r_{v,i} - \overline{r}_v - \rho_{u,i} + \overline{r}_u\right)^2}{\sum_{v \in K_{u,i}} \text{sim}(u, v)} \tag{17}$$

In (15), (16), and (17), $\overline{s}$ and $\overline{v}$ are the medians of $S_{(u,\ i)}$ and $V_{(u,\ i)}$, respectively. $K_{(u,\ i)}$ is the set of neighbors of user u that have rated the item I, and (min, … , max) is the discrete rating values. Table 4 summarizes the evaluation metrics used in various research works.

7 Techniques used in location-based recommender systems

In recent years, numerous social networking applications for location-acquisition and wireless communications were developed for smart phones and mobile devices. The most popular among them is Facebook, Foursquare, and Instagram. In a users context, location can be considered as one of the most important entities. By using the location history of a user, one can easily extract extensive knowledge about the preferences and behavior of that particular user (Ying *et al.*, 2010). Use of location contents of the users help in bridging the gap between the online social networking services and the physical world (Bao *et al.*, 2015). Another advantage of using location content is the generation of new relations among users, among locations, and among users and locations. More recently, the availability of huge volumes of users geospatial data has motivated the research community to focus efforts on the design of various location-based RSs that are based on extracted information and data by mobile social networking applications (Ye *et al.*, 2010; Lü *et al.*, 2012; Bobadilla *et al.*, 2013; Sarwat *et al.*, 2013). Such systems perform recommendations of different locations to users that are directly related to the users preferences. LBRS can be divided into two main categories: (a) generic location recommendation and b) personalized location recommendation. In generic location recommendations, public opinions are extracted and the system recommends the most popular locations according to the extracted public opinions (Cao *et al.*, 2010). The limitation of such type of systems is the identical recommendations from the system due to the lack of users preferences. Alternatively, personalized location recommendations have been proposed to overcome the limitation of generic location recommendations. Such systems provide users with the most relevant locations according to the preferences given by the user (Rikitianskii *et al.*, 2014). Varieties of location recommendation approaches are available such as matrix factorization, explicit rating, implicit rating, route recommendations, location recommendations, and location-based group recommendations. In the following subsections, we will discuss in details some of the techniques used in LBRS. We have categorized this section based on the different techniques used in LBRS.

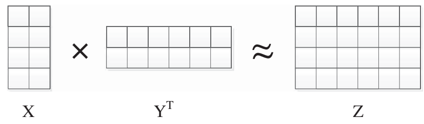

Figure 5 Concept of matrix factorization

7.1 Matrix factorization techniques

In matrix factorization, we try to find out two more small matrices by factorizing a larger matrix, such that when we multiply the smaller matrices, we will approximately get the large matrix[7]. Matrix factorization discovers the latent features underlying the interactions between two different kinds of entities that help in predicting ratings in CF. Formally, let U represent a set of users and a set L of locations. Let Z be the matrix of size $|U||L|$ that contains all the ratings of the users assigned to locations. Also, assume that we would like to find N latent features. Therefore, we have to find two matrices X (with dimensions $|U|N$) and Y (with dimensions $|L|N$), such that, when we multiply matrices X and Y, the result approximates to matrix Z (as indicated in Figure 5 and the following equation). The equation for matrix factorization can be given as

$$Z \approx X \times Y^T = \hat{Z} \tag{18}$$

In this way, each row of matrix X and Y would represent the strength of the association between user and features, as well as, location and features, respectively. For a user u_i, prediction of rating for a location l_j can be calculated by the dot product of the two vectors corresponding to u_i and l_j as

$$\hat{r}_{ij} = x_i^T y_j = \sum_{n=1}^{n} x_{in} y_{jn} \tag{19}$$

The most common recommendation approach used in various literatures is matrix factorization (Yang *et al*., 2013). Matrix factorization was first used in LBRS in Zheng *et al*. (2010). Using an experimental Global Positioning System (GPS) data set, interesting activities and locations are revealed for recommendations. Among different matrix factorization models, the most popular model used for recommendations in LBRS is the 0/1 scheme model (Ye *et al*., 2010; Ye *et al*., 2011). The value 0 is used for non-visited locations and 1 is used for visited locations. By using the 0/1 model, authors (Ye *et al*., 2010; Ye *et al*., 2011) studied the social and geographical influence in point-of-interest (POI) recommendation based on CF techniques. Moreover, another model was proposed by Berjani & Strufe (2011) based on the frequencies of check-ins in order to compute the preferences of users for venues. With the help of this scheme, the author developed a LBRS using matrix factorization method. Furthermore, in Cheng *et al*. (2012), the authors proposed a multi-center Gaussian model in combination with matrix factorization. The multi-center Gaussian model was used to capture the geographical influence and matrix factorization was combined with social regularization to develop a LBRS.

7.2 Explicit rating techniques

Recently, many online social services have evolved that permit users to explicitly rate the locations visited by the users. In rating-based RSs, existing ratings data are utilized to generate user preferred recommendations. Ying *et al*. (2010) and Wei *et al*. (2012) have presented similar models based on users existing ratings to compute personalized CF-based location recommendations. A similar approach was proposed in Lü *et al*. (2012) that applies an item-based CF-based method with all the ratings of locations in users surroundings. The aforementioned techniques may strictly capture users preferences, but are less effective in terms of scalability. Similarly, very few entries in a user rating matrix results in the data sparseness

[7] `http://www.quuxlabs.com/blog/2010/09/matrix-factorization-a-simple-tutorial-and-implementation-in-python/`

Table 5 Example of explicit rating

	Ratings of users on locations					
User-location	l_1	l_2	l_3	l_4	l_5	l_6
u_1	4	1	3	3	.	2
u_2	2	–	4	4	5	1
u_3	5	3	4	3	.	5
u_4	2	.	.	.	.	2

problem in the above-mentioned approaches. In addition to model/memory-based categorization, LBRS (such as Bao *et al.*, 2015; Bobadilla *et al.*, 2013; Oh *et al.*, 2013; Sarwat *et al.*, 2013; Chiang & Huang, 2015), are also classified as being trajectory based, check-in based, and explicit rating based. The trajectory-based graphical model was proposed in Doytsher *et al.* (2011) in which tracks are recorded for most frequent routes travelled by users and in return, the system recommends the best available route to a new user. Similarly, an approach to compute personalized route recommendations is proposed in Chang *et al.* (2011). Extracting the most popular location by mining of GPS trajectories is presented in Bao *et al.* (2015). The process of extraction is based on users travel history. All the above-mentioned techniques recommend locations based on users visited routes/trajectories, but such systems cannot properly perform the differentiation between the locations in terms of the categories that will be the main task in our proposed framework. Moreover, most of the aforementioned techniques relied on memory-based CF-based models that allow such techniques to represent a users expectations based on the users previous activities. However, such techniques are not capable of providing sufficient scalability by simultaneously processing massive amount of real-time data. Table 5 shows an example of explicit rating in which each user has rated some locations.

7.3 Implicit rating techniques

There are some techniques proposed in which the models are based on implicit ratings (Ye *et al.*, 2010; Ying *et al.*, 2010). In implicit ratings, the numbers of check-ins performed by a user at multiple locations are recorded. In Noulas *et al.* (2012), the authors applied a random-walk-with-restart approach on a user-location check-in matrix to compute personalized recommendations for a specific user. A similar kind of recommendation approach is proposed in Sarwat *et al.* (2013) that compute region-wise popular locations and users from check-in data. Figure 6 shows the basic concept of implicit ratings based on number of check-ins performed by the users.

7.4 Route recommendation techniques

Liu (2014) focused on the problem of traffic jams and long queues while traveling to tourist hotspots. Tourists suffer from congestion on the road, time wastage due to the long queues or they often miss their favorite spot because of the traffic conditions. The aforementioned problem of self-driving tourists may affect their interest and satisfaction level toward their favorite locations and hot spots (Denstadli & Jacobsen, 2011). The main idea is to eliminate the traffic jam problem by utilizing personalization techniques and real-time traffic information. The techniques used to overcome such problem include, vehicle-to-vehicle communication system (V2VCS), fuzzy set theory, and genetic algorithms (GA). V2VCS (Cheng *et al.*, 2013) is used to share the real-time traffic information among self-drive tourists. Fuzzy set theory (Ren *et al.*, 2011) along with Technique for Order Preference by Similarity to Ideal Solution (Lemke, 2014) is used to automatically score all the candidate routes instead of asking the user to rate huge number of candidate routes. Such candidate routes are scored according to the given preferences of the user and real-time value of five routes attributes (such as POI, road condition, distance, fee, and traffic).

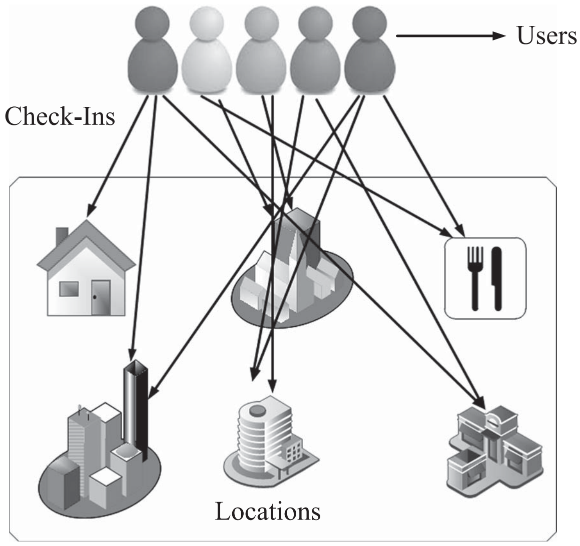

Figure 6 Basic concept of implicit rating using check-ins

A GA (Whitley, 2014) is used to find the most appropriate and relevant route from the entire candidate routes according to the preferences given by the tourist. A GA is also used to explore the route scores and real-time traffic information. The assumptions made in the research are that information about personalization and real-time context can be collected by the system instantaneously. For the evaluation of the system, a Web prototype was designed for the simulation of self-drive tourists. The main contributions of the research are to introduce a novel technique to score all the candidate routes, propose a route generation technique, and designing of the personalized RS to offer the service of real-time recommendations of routes. However, the authors did not consider attributes like travel time, route complexity, time of day, and the location type. Also, flexibility in the route recommendations was not considered that allow the tourists to customize their own route preferences. And finally, V2VCS is not applicable to some countries because of the lack of infrastructure. Moreover, in many developing and under developed countries, the vehicles embedded with V2VCS sensors are of latest models and are not affordable by majority of population. Therefore, other platforms like smart phones need to be considered for the route recommendation services. Similarly, a route recommendation technique is proposed in Su *et al.* (2014). The authors addressed the problem that a users preferences on the selection of routes are influenced by many dynamic and latent factors that are difficult to model by using existing techniques. For solving the aforementioned problem, the CrowdPlanner (Su *et al.*, 2014) technique is used. This is a crowd-based route recommendation technique that uses a crowds knowledge. A large-scale real trajectory data set and hundreds of volunteers were involved for the experiments and evaluation of the technique. The main achievement of the work is the selection of the best route that was verified by comparing the results of the technique with the previous techniques, mining algorithms, and Web services. The authors of CrowdPlanner did not consider the quality controls of popular route mining algorithms and mining latent factors that may affect the driving route.

7.5 Locations recommendation techniques

Location recommendations on the basis of the preferences of users are also proposed in Bao *et al.* (2012). In addition to users preferences, social opinions from the local experts are also considered for the final recommendations to the users. The main focus of the work is to overcome the problem of data sparsity. The user-location matrix is sparse due to the limited visits to locations. Therefore data sparsity occurs and it will become more challenging when users travel outside their native city. A weighted category hierarchy is used to model each users preference and a preference-aware candidate selection algorithm is used to select candidate local experts for taking the social opinions. A real data set collected from Foursquare was

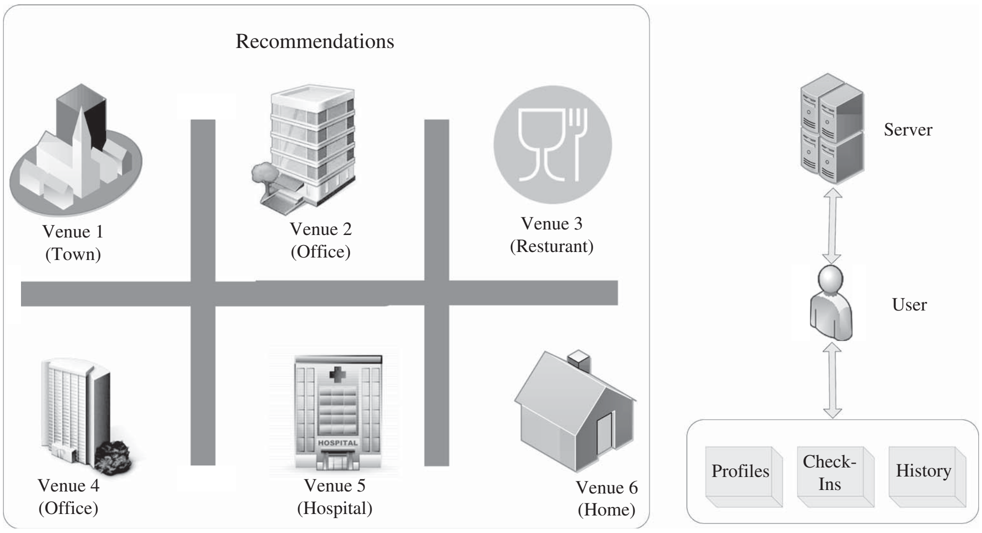

Figure 7 Overview of location recommendations

used for evaluation. The authors claim that their system is more efficient than the major LBRSs like most-preferred-category based (Bao *et al*., 2015), location-based collaborative filtering (Ye *et al*., 2010), and preference-based collaborative filtering (Bellogín *et al*., 2013). However, the authors have not considered real-world factors such as weather conditions and temporal features to achieve the quality of recommendations. In Levandoski *et al*. (2012), the authors proposed location-aware RS. The authors have proposed a technique that used spatial properties for location recommendation that were not considered in the previous techniques. The primary recommendation technique used in the work is CF. The secondary technique used is user partitioning. It is a technique that is used to retain an adaptive pyramid structure. The data set used for the evaluation of the techniques is taken from MovieLens[8] and Foursquare[9]. For improving the proposed technique, location attributes of real-time world factors should be considered. Preoţiuc-Pietro and Cohn (2013) considered patterns of human mobility that is one of the important aspects of recommendation, especially in LBRS. More than 10 000 frequent users of LBRS were investigated for monitoring their frequent mobility patterns. The system investigates the metadata related with the location of the users, considering the type of location and their evolution over time. The clustering of users is then performed based on users movement behavior and then the system predicts the users next movements. The users of the system perform a check-in for sharing their current location with the system. GPS-enabled devices are used for performing the check-ins. Foursquare data are used for the evaluation of the system. The authors claimed that the proposed system efficiently predicts the human mobility when compared with traditional systems. The system also predicts better mobility patterns, even when provided with the limited history of the user. Besides the achievements, the authors did not consider the location predictions using temporal pattern models. Noulas *et al*. (2011) proposed an approach for modeling human activities and geographical areas by categorizing the locations. A spectral clustering algorithm is used on users similarities and locations of two cities using a data set from Foursquare. The approach used in the work allows urban neighborhood comparison within and across cities and identification of communities based on identical visits to the same category of locations. The key achievement of the work includes profiling and dividing users into communities and relating users of mobile phones with their particular category and locations. The authors of the work did not consider temporal variations for further characterization in order to characterize users and areas at certain periods of a day. User tips and comments are also not considered for including semantic information. Figure 7 shows the overview of location recommendations.

[8] MovieLens: `https://movielens.org`
[9] Foursquare: `http://foursquare.com`

Table 6 Strength and weaknesses of the selected techniques

Reference	Description	Weaknesses
Liu (2014)	Scoring of all the candidate routes, introducing route generation technique, and real-time recommendation of routes	Some key routes attributes were ignored like travel time, route complexity, time of day, and the location. Customization options for users to plan their routes were missing. Platforms like smart phones need to be considered
Bao *et al*. (2012)	Location-based CF, and preference-based CF. Achieved better performance than most-preferred-category based	Real-world factors like weather conditions and temporal features were ignored
Levandoski *et al*. (2012)	Spatial properties of the users are introduced using CF-based and user portioning techniques that are previously ignored by traditional RSs	Location attributes of real-time world factors were not considered
Su *et al*. (2014)	Use of mining algorithms and Web services to find optimal route.	Quality control of popular route mining algorithms and mining latent factors were not considered.
Preoţiuc-Pietro and Cohn (2013)	Better prediction of human mobility patterns. Well-handled data sparsity problem	Location predictions using temporal pattern models were not considered. Trajectory-based information also not considered
Noulas *et al*. (2011)	Profiling and dividing users in communities. Relating users of mobile phones with their particular category and locations	Temporal variations for further characterization and including semantic information need to be considered

CF = collaborative filtering; RS = recommendation system.

7.6 Location-based group recommendations

With the continuous evolution of social networking services, the significance of recommendation models considering group preference has also increased. However, most of the existing traditional recommendation schemes do not take into account group of friends scenarios (Noulas *et al*., 2011; Preoţiuc-Pietro & Cohn, 2013; Su *et al*., 2014). In group scenarios, the RS not only models the preferences of a group member but the location of each member must also be taken into account to satisfy all the members in the group. The individuals preferences and their preferred locations are then aggregated as the recommendation for the whole group (Christensen & Schiaffino, 2014). There has been some limited work carried out in the recent past on group recommendations, such as Masthoff (2011), Christensen and Schiaffino (2014), Hao *et al*. (2015). Most of the existing techniques proposed in the literature do not specifically focus on the effects of real-time physical factors, such as distance from location, traffic, and weather conditions on group recommendations. To achieve the objective of group recommendation, the following factors must be taken into account: (a) users preferences, (b) current context (such as time and location), (c) past check-ins, (d) geospatial characteristics, and (e) collaborative social opinion. However, the complexity and cost of processing the large-scale data sets negatively affect the performance and efficiency of RS. In the context of LBRS, there has been limited work performed on group-based location recommendations. In Hao *et al*. (2015), the authors proposed a location-sensitive recommendations. The recommendations are used in *ad hoc* social network environments. The paper proposed an approach known as spatial social union which computes recommendations not only for a single user but also for group of users. The approach computes the similarity between two users and generates multiple matrices derived from user-user, user-item, and user-location graphs. The online data set of MovieLens is used for evaluation. In Zhang *et al*. (2013), the authors proposed personalized event-based group recommendations. The main contribution of the work is group recommendations to the users living in the same city. The localization property of users and groups was extracted and further integration of latent factor model with explicit features of location was done in order to provide group recommendations. The data set used is Meetup, which is an online social media site. Table 6 summarizes the description and weaknesses of the selected techniques and Table 7 provides a summary of some of the selected techniques.

Table 7 Summary of some of the selected techniques in location-based recommendation system

Author	Problems	Techniques	Data set used	Recommendations
Liu (2014)	Traffic jams, long queue	V2VCS, fuzzy set theory, genetic algorithm	Questionnaires, V2VCS data	Routes
Bao *et al*. (2012)	Data sparsity cold start	Hyperlinked-induced topic search	Foursquare	Location
Chang *et al*. (2011)	Uncertain trajectories	User explicit ratings	Real data set	Location
Chow *et al*. (2010)	Personalized routes	User explicit ratings	Questionnaire	Location
Levandoski *et al*. (2012)	Quality of recommendations	K-nearest neighbor	MovieLens, Foursquare	Location
Doytsher *et al*. (2011)	Optimal routes	Implicit ratings	Open street map project, spatial data set	Routes
Noulas *et al*. (2012)	Un-visited locations	Random walk with restart	Gowalla, Foursquare	Locations
Zheng *et al*. (2010)	Un-visited locations and activities	Matrix factorization	Real data set using GPS trajectories	Locations
Berjani and Strufe (2011)	Spot identification	Matrix factorization	Austin in Texas (ATX) and New York City (NYC) data sets	Locations
Cheng *et al*. (2012)	Un-visited locations	Multi-centered Gaussian model and matrix factorization	Gowalla	Locations
Christensen and Schiaffino (2014)	Implicit similarities	Hybrid recommendations	Yahoo! Movie Yahoo! Music	Group recommendations
Hao *et al*. (2015)	Location sensitive	Spatial social union	MovieLens	Group-based location recommendations

V2VCS = vehicle-to-vehicle communication system; GPS = Global Positioning System.

8 Challenges in location-based recommendation system

Some of the unsolved problems of the previous research works discussed above are still affecting the performance of current LBRS. These problems include.

8.1 Data sparseness

Users visiting limited numbers of locations results in sparse user-to-location check-in matrix. The negative effect of data sparseness is the non-optimal computations of the nearest neighbor set of similar users with the particular user that also affect the accuracy of recommendations. Moreover, performances of the existing LBRS are also affected by the sparseness of user-to-user relationship matrix when directly manipulated with CF-based models (Lü *et al*., 2012).

8.2 Cold start

Cold start is the problem when the system generates recommendation for a user who is new to the system. Such problem occurs in many existing CF-based RSs (Doytsher *et al*., 2011; Lü *et al*., 2012). When the system does not have enough records available from the new user, it is almost impossible to compute similarity measures. Inadequate entries causes 0 values of similarity calculations that poorly affect the performance and quality of recommendations.

8.3 Scalability

In memory-based CF RSs, user rating data are utilized to apply simple methods to perform similarity computations between items or users (Chang *et al*., 2011; Doytsher *et al*., 2011; Noulas *et al*., 2012). Neighborhood-based CF (e.g. KNN) is one of such kinds of memory-based CF approaches. However, scalability is the main issue in such systems as a major requirement is the real-time parsing of massive volumes of data that result in poor efficiency and performance. As a result, such systems are not able to handle big data. To overcome the scalability problems, model-based CF is applied in some of the existing techniques (Ye *et al*., 2010; Ying *et al*., 2010; Khalid *et al*., 2014). Compared with memory-based approaches, model-based approaches are better in the sense that such approaches help in reducing the size of the user-item rating matrix that decreases the online processing time (Bao *et al*. 2015; Bobadilla *et al*., 2013). However, a tradeoff between recommendation quality and reduced data set is still a hurdle. Quality of recommendations may be affected if the data set is significantly reduced to improve efficiency of online real-time processing.

8.4 Over specialization problem

Over specialization problem occurs when RS restrict users to get only those recommendations that match a users preferences or that are already rated by the user (Sharma & Gera, 2013). The problem prevents users to discover new items or locations. However, many RSs also focus on diversity as an important feature of the recommendations. Diversity indicates how distinct the recommendations are when compared with each other (Vargas & Castells, 2011). At the same time, the focus should also be on maintaining the balance between diversity and similarity (Adomavicius & Kwon, 2012; Liu, 2014; Javari & Jalili, 2015). Therefore, a tradeoff between diversity and matching user preferences is still a challenging problem for the RS.

8.5 Recommendation of popular objects

In some cases the focus of the RS is to recommend only those items that are popular among others and are likely to be highly rated by the users. In this case, the items or locations that are less popular may be overlooked (Yin *et al*., 2012). Popular items or locations are easy to discover by users, as compared with unpopular items. Therefore, a recommendation list must also include the less popular items or locations that are unlikely to be discovered by the users.

8.6 Attacks on recommendations

One of main challenges faced by RS is security issues. RS are widely used in e-commerce applications and are likely to be targeted by malicious attacks. The attackers may try to hinder or promote some locations or items unjustly (Gong, 2013). Therefore, keeping in view the threat of attacks, a good RS should be equipped with wide scale of tools in order to prevent different kind of attacks. In Burke *et al.* (2011), the authors exposed eight different strategies of attackers which must be considered by the RS in their prevention tools.

8.7 Selection of evaluation metrics

There are many distinct evaluations metric as discussed in Section 6. It is very important to carefully select an evaluation metric (see Section 6) as each of the evaluation metric has some tradeoffs. Therefore, RS must select the appropriate evaluation metric so that the performance should remain consistent on real deployment of RS.

9 Opportunities in location-based recommendation system

The LBRS have vast applications in the areas, such as healthcare, transportation, tourism, and education. In the following subsections, we briefly discuss some of the opportunities in adopting the services of LBRS.

9.1 Healthcare

Healthcare is one of the main areas where LBRS can significantly enhance the efficiency, reliability, and effectiveness of the system (Hoens *et al.*, 2013; Middleton *et al.*, 2013; Wiesner & Pfeifer, 2014). People from various domains often require multiple healthcare services, such as disease specific specialist, hospitals, and health insurance plans (Abbas *et al.*, 2015) that closely match a users preferences. LBRS can play an important role in the healthcare industry in order to connect and provide localized recommendations for patients, healthcare providers, and insurance companies.

9.2 Transportation

Another interesting area for the adoption of LBRS is transportation. LBRS can be helpful in route recommendations, for example, for individuals driving their personal vehicles, cab drivers, and public transporters (Liu *et al.*, 2014; Su *et al.*, 2014). Heavy traffic in peak hours is one of the significant problems all over the world. In such situations, people can use the services of LBRS for different routes to their destinations. Similarly, carpooling is also among one of the services provided by LBRS[10] (Zhang *et al.*, 2014). Effective LBRS adoption in transportation can significantly reduce the cost of fuel and enhance the reliability of users in the services provided by LBRS.

9.3 Tourism

An important area where LBRS are actively deployed is the tourism industry where people want to plan in advance their preferred locations to visit. Sometimes it is difficult to choose the appropriate place when you have to make a decision from multiple available choices. LBRS has been used to provide the effectiveness in tourism by recommending the appropriate trip plans, as well as the other well known nearby POIs like hotels, restaurants, shopping malls (Chen *et al.*, 2013; Le & Pishva, 2016). The adoption of LBRS in tourism can significantly save the time of tourists to reach their destination in a suitable time.

[10] `www.uber.com`

9.4 Education

Another key area where the services of LBRS can significantly play an important role is education. Students need better institutions such as colleges and universities for their higher education. LBRS can be used to discover the best institutes according to the preferences of the student[11,12].

10 Future directions

To improve the efficiency of recommendations offered by LBRS, some important factors need to be considered. Such factors include:

a. When the system is offering routes along with locations, then the key location and routes attributes like location type, distance of the location, travel time, route complexity, time of day, and real-time world factors with temporal features need to be considered.
b. For better results and customization point of view, users customization to plan their visits using platforms like smart phones need to be considered.
c. Most of the existing LBRS use only a single type of data source for recommendations. Using diverse data sources will enable the LBRS to provide effective recommendations. Diverse data sources may include distance from location, traffic conditions, weather conditions, multiple routes to location, and time of the day (morning, evening, or night).
d. For achieving the best efficiency of recommendations, hybrid techniques need to be considered that will overcome the limitations of the existing techniques.
e. Real-time factors and group features are also ignored in most of the existing literature. The main motivation behind consideration of real-world parameters is to include the current context of each of the group member in the location recommendation process. By doing so, the selected location will be based on mutual consensus of group members, and will be the one that satisfies all the members in a group. It is noteworthy to mention that providing real-time recommendations is highly compute-intensive task as the workload consists of huge volumes of users data accumulated in the system over time.

11 Conclusions

In this article, we presented a systematic review of the scientific literature and summarized the efforts and contributions of researchers in the area of LBRS. First, we discussed the basic filtration techniques like content based and CF based and also the hierarchy of the said techniques used in RSs. Second, the basic overview of LBRS is presented followed by the services offered by LBRS and the distinguishing features of locations that are of major importance in offering the recommendations in LBRS. Third, the classification of criteria for recommendations that include accuracy, familiarity, novelty, diversity, content compatibility, justification of recommendations, and sufficiency of information is discussed in detail. The evaluation metrics used in LBRS are also presented in detail. Finally, we have critically investigated the techniques proposed for LBRS. We summarize the following observations: (1) the quality of recommendations in LBRS can be improved by using all kind of additional information such as check-in data, geographical information, social relationships, and temporal information. (2) Model-based approaches are more effective and efficient than memory-based approaches, and the performance of model-based approaches are also consistent. (3) Quality recommendations in LBRS can only be achieved by using user-based location recommendation approaches rather than item-based approaches. (4) Among criteria for recommendations, we have noticed the following observations: a) accuracy alone is not sufficient for the selection of related algorithm; b) the users are more likely interested in the familiar items rather than unfamiliar ones; c) users like diverse recommendations as compared with more accurate recommendations. For improving the performance of LBRS, rich additional information should be used, like check-ins, social relationships, temporal, and geographical information. An integrated framework is needed to

[11] `www.ratemyprofessors.com/`
[12] `https://foursquare.com/`

enhance the performance of LBRS by integrating all this additional information. Finally, the number of users, locations, routes, POIs, real-world factors, media contents with locations, and all this rapidly growing amount of data make the worst scalability problem for LBRS. Therefore, parallel computing methods like MapReduce need to be considered.

Acknowledgment

The authors would like to acknowledge Dr. Osman Khalid and Dr. Sajjad Ahmad Madani for providing their valuable suggestions, feedback, and precious time.

References

Abbas, A., Bilal, K., Zhang, L. & Khan, S. U. 2015. A cloud based health insurance plan recommendation system: a user centered approach. *Future Generation Computer Systems* **43**, 99–109.

Adomavicius, G. & Kwon, Y. 2012. Improving aggregate recommendation diversity using ranking-based techniques. *IEEE Transactions on Knowledge and Data Engineering* **24**(5), 896–911.

Adomavicius, G. & Zhang, J. 2012. Stability of recommendation algorithms. *ACM Transactions on Information Systems (TOIS)* **30**(4), 23.

Arora, G., Kumar, A., Devre, G. S. & Ghumare, A. 2014. Movie recommendation system based on users similarity. *International Journal of Computer Science and Mobile Computing* **3**(4), 765–770.

Avazpour, I., Pitakrat, T., Grunske, L. & Grundy, J. 2014. Dimensions and metrics for evaluating recommendation systems. In *Recommendation Systems in Software Engineering*, Robillard, M. P., Maalej, W., Walker, R. J. & Zimmermann, T. (eds). Springer, 245–273.

Balakrishnan, S. & Chopra, S. 2012. Collaborative ranking. In *Proceedings of the Fifth ACM International Conference on Web Search and Data Mining*, 143–152. ACM.

Baltrunas, L., Makcinskas, T. & Ricci, F. 2010. Group recommendations with rank aggregation and collaborative filtering. In *Proceedings of the Fourth ACM Conference on Recommender systems*, 119–126. ACM.

Bao, J., Zheng, Y. & Mokbel, M. F. 2012. Location-based and preference-aware recommendation using sparse geo-social networking data. In *Proceedings of the 20th International Conference on Advances in Geographic Information Systems*, 199–208. ACM.

Bao, J., Zheng, Y., Wilkie, D. & Mokbel, M. 2015. Recommendations in location-based social networks: a survey. *Geoinformatica*, **19**(3), 525–565.

Bedi, P. & Sharma, R. 2012. Trust based recommender system using ant colony for trust computation. *Expert Systems with Applications* **39**(1), 1183–1190.

Bellogín, A., Castells, P. & Cantador, I. 2013. Improving memory-based collaborative filtering by neighbour selection based on user preference overlap. In *Proceedings of the 10th Conference on Open Research Areas in Information Retrieval*, 145–148. LE CENTRE DE HAUTES ETUDES INTERNATIONALES D'INFORMATIQUE DOCUMENTAIRE.

Berjani, B. & Strufe, T. 2011. A recommendation system for spots in location-based online social networks. In *Proceedings of the 4th Workshop on Social Network Systems*, 4. ACM.

Bobadilla, J., Ortega, F., Hernando, A. & Alcalá, J. 2011. Improving collaborative filtering recommender system results and performance using genetic algorithms. *Knowledge-Based Systems* **24**(8), 1310–1316.

Bobadilla, J., Ortega, F., Hernando, A. & Gutiierrez, A. 2013. Recommender systems survey. *Knowledge-Based Systems* **46**, 109–132.

Bobrow, J. 2014. *Representation and Understanding: Studies in Cognitive Science*. Elsevier.

Bostandjiev, S., O'Donovan, J. & Höllerer, T. 2012. TasteWeights: a visual interactive hybrid recommender system. In *Proceedings of the Sixth ACM Conference on Recommender Systems*, 35–42. ACM.

Burke, R., OMahony, M. P. & Hurley, N. J. 2011. Robust collaborative recommendation. In *Recommender Systems Handbook*, 805–835. Springer.

Cacheda, F., Carneiro, V., Fernandez, D. & Formoso, V. 2011. Comparison of collaborative filtering algorithms: limitations of current techniques and proposals for scalable, high-performance recommender systems. *ACM Transactions on the Web (TWEB)* **5**(1), 2.

Cantador, I., Castells, P. & Bellogín, A. 2011. An enhanced semantic layer for hybrid recommender systems: application to news recommendation. *International Journal on Semantic Web and Information Systems (IJSWIS)* **7**(1), 44–78.

Cao, X., Cong, G. & Jensen, C. S. 2010. Mining significant semantic locations from GPS data. *Proceedings of the VLDB Endowment* **3**(1–2), 1009–1020.

Cechinel, C., Sicilia, M.-Á., SáNchez-Alonso, S. & GarcíA-Barriocanal, E. 2013. Evaluating collaborative filtering recommendations inside large learning object repositories. *Information Processing & Management* **49**(1), 34–50.

Chang, K.-P., Wei, L.-Y., Yeh, M.-Y. & Peng, W.-C. 2011. Discovering personalized routes from trajectories. In *Proceedings of the 3rd ACM SIGSPATIAL International Workshop on Location-Based Social Networks*, 33–40. ACM.

Chen, L. & Pu, P. 2012. Critiquing-based recommenders: survey and emerging trends. *User Modeling and User-Adapted Interaction* **22**(1-2), 125–150.

Chen, X., Zheng, Z., Liu, X., Huang, Z. & Sun, H. 2013. Personalized QoS-aware web service recommendation and visualization. *IEEE Transactions on Services Computing* **6**(1), 35–47.

Cheng, C., Yang, H., King, I. & Lyu, M. R. 2012. Fused matrix factorization with geographical and social influence in location-based social networks. In *AAAI*, **12**, 17–23.

Cheng, X., Yao, Q., Wen, M., Wang, C.-X., Song, L.-Y. & Jiao, B.-L. 2013. Wideband channel modeling and intercarrier interference cancellation for vehicle-to-vehicle communication systems. *IEEE Journal on Selected Areas in Communications* **31**(9), 434–448.

Chiang, H.-S. & Huang, T.-C. 2015. User-adapted travel planning system for personalized schedule recommendation. *Information Fusion* **21**, 3–17.

Chon, J. & Cha, H. 2011. Lifemap: a smartphone-based context provider for location-based services. *IEEE Pervasive Computing* **10**(2), 58–67.

Chow, C.-Y., Bao, J. & Mokbel, M. F. 2010. Towards location-based social networking services. In *Proceedings of the 2nd ACM SIGSPATIAL International Workshop on Location Based Social Networks*, 31–38. ACM.

Christensen, I. A. & Schiaffino, S. N. 2014. A hybrid approach for group profiling in recommender systems. *Journal of Universal Computer Science* **20**(4), 507–533.

Cremonesi, P., Garzotto, F., Negro, S., Papadopoulos, A. & Turrin, R. 2011. Comparative evaluation of recommender system quality. In *CHI'11 Extended Abstracts on Human Factors in Computing Systems*, 1927–1932. ACM.

Dakhel, G. M. & Mahdavi, M. 2011. A new collaborative filtering algorithm using k-means clustering and neighbors' voting. In *2011 11th International Conference on Hybrid Intelligent Systems (HIS)*, 179–184. IEEE.

Denstadli, J. M. & Jacobsen, J. K. S. 2011. The long and winding roads: perceived quality of scenic tourism routes. *Tourism Management* **32**(4), 780–789.

DeScioli, P., Kurzban, R., Koch, E. N. & Liben-Nowell, D. 2011. Best friends alliances, friend ranking, and the MySpace social network. *Perspectives on Psychological Science* **6**(1), 6–8.

Desrosiers, C. & Karypis, G. 2011. A comprehensive survey of neighborhood-based recommendation methods. In *Recommender Systems Handbook*, 107–144. Springer.

Doytsher, Y., Galon, B. & Kanza, Y. 2011. Storing routes in socio-spatial networks and supporting social-based route recommendation. In *Proceedings of the 3rd ACM SIGSPATIAL International Workshop on Location-Based Social Networks*, 49–56. ACM.

Esparza, S. G., OMahony, M. P. & Smyth, B. 2012. Mining the real-time web: a novel approach to product recommendation. *Knowledge-Based Systems* **29**, 3–11.

Evangelopoulos, N., Zhang, X. & Prybutok, V. R. 2012. Latent semantic analysis: five methodological recommendations. *European Journal of Information Systems* **21**(1), 70–86.

Felfernig, A., Jeran, M., Ninaus, G., Reinfrank, F. & Reiterer, S. 2013. Toward the next generation of recommender systems: applications and research challenges. In *Multimedia Services in Intelligent Environments*, 81–98. Springer.

Gan, M. & Jiang, R. 2013. Improving accuracy and diversity of personalized recommendation through power law adjustments of user similarities. *Decision Support Systems* **55**(3), 811–821.

Gao, H., Tang, J., Hu, X. & Liu, H. 2015. Content-aware point of interest recommendation on location-based social networks. In *AAAI*, 1721–1727. Citeseer.

Golbandi, N., Koren, Y. & Lempel, R. 2011. Adaptive bootstrapping of recommender systems using decision trees. In *Proceedings of the Fourth ACM International Conference on Web Search and Data Mining*, 595–604. ACM.

Gong, S. 2013. Research on attack on collaborative filtering recommendation systems. *Advances in Information Sciences and Service Sciences* **5**(10), 938.

Guo, G., Zhang, J. & Yorke-Smith, N. 2013. A novel Bayesian similarity measure for recommender systems. In *IJCAI*.

Guy, I. 2015. Social recommender systems. In *Recommender Systems Handbook*, Ricci, F., Rokach, L. & Shapira, B. (eds). Springer, 511–543.

Hao, F., Li, S., Min, G., Kim, H.-C., Yau, S. S. & Yang, L. T. 2015. An efficient approach to generating location-sensitive recommendations in ad-hoc social network environments. *IEEE Transactions on Services Computing* **8**(3), 520–533.

Hernando, A., Bobadilla, J., Ortega, F. & Tejedor, J. 2013. Incorporating reliability measurements into the predictions of a recommender system. *Information Sciences* **218**, 1–16.

Hoens, T. R., Blanton, M., Steele, A. & Chawla, N. V. 2013. Reliable medical recommendation systems with patient privacy. *ACM Transactions on Intelligent Systems and Technology (TIST)* **4**(4), 67.

Hoffman, M., Bach, F. R. & Blei, D. M. 2010. Online learning for latent Dirichlet allocation. In *Advances in Neural Information Processing Systems*, 856–864.

Hsu, F.-M., Lin, Y.-T. & Ho, T.-K. 2012. Design and implementation of an intelligent recommendation system for tourist attractions: the integration of EBM model, Bayesian network and Google Maps. *Expert Systems with Applications* **39**(3), 3257–3264.

Hurley, N. & Zhang, M. 2011. Novelty and diversity in top-n recommendation-analysis and evaluation. *ACM Transactions on Internet Technology (TOIT)* **10**(4), 14.

Jannach, D., Zanker, M., Felfernig, A. & Friedrich, G. 2010. *Recommender Systems: An Introduction*. Cambridge University Press.

Jäschke, R., Hotho, A., Mitzlaff, F. & Stumme, G. 2012. Challenges in tag recommendations for collaborative tagging systems. In *Recommender Systems for the Social Web*, 65–87. Springer.

Javari, A. & Jalili, M. 2015. A probabilistic model to resolve diversity-accuracy challenge of recommendation systems. *Knowledge and Information Systems* **44**(3), 609–627.

Kaleli, C. 2014. An entropy-based neighbor selection approach for collaborative filtering. *Knowledge-Based Systems* **56**, 273–280.

Khalid, O., Khan, M. U. S., Khan, S. U. & Zomaya, A. Y. 2014. Omnisuggest: a ubiquitous cloud-based context-aware recommendation system for mobile social networks. *IEEE Transactions on Services Computing* **7**(3), 401–414.

Khribi, M. K., Jemni, M. & Nasraoui, O. 2015. Recommendation systems for personalized technology-enhanced learning. In *Ubiquitous Learning Environments and Technologies*, 159–180. Springer.

Kim, H.-N., Ji, A.-T., Ha, I. & Jo, G.-S. 2010. Collaborative filtering based on collaborative tagging for enhancing the quality of recommendation. *Electronic Commerce Research and Applications* **9**(1), 73–83.

Kolomvatsos, K., Anagnostopoulos, C. & Hadjiefthymiades, S. 2014. An efficient recommendation system based on the optimal stopping theory. *Expert Systems with Applications* **41**(15), 6796–6806.

Konstan, J. A. & Riedl, J. 2012. Recommender systems: from algorithms to user experience. *User Modeling and User-Adapted Interaction* **22**(1-2), 101–123.

Lampropoulos, A. S., Lampropoulou, P. S. & Tsihrintzis, G. A. 2012. A cascade-hybrid music recommender system for mobile services based on musical genre classification and personality diagnosis. *Multimedia Tools and Applications* **59**(1), 241–258.

Le, Q. T. & Pishva, D. 2016. An innovative tour recommendation system for tourists in Japan. In *2016 18th International Conference on Advanced Communication Technology (ICACT)*, 717–729. IEEE.

Lemke, A. 2014. *Technique for Order Preference by Similarity to Ideal Solution*. GRIN Verlag.

Levandoski, J. J., Sarwat, M., Eldawy, A. & Mokbel, M. F. 2012. LARS: a location-aware recommender system. In *2012 IEEE 28th International Conference on Data Engineering*, 450–461. IEEE.

Lewis, D. D. 2014. Learning in intelligent information retrieval. In *Machine Learning: Proceedings of the Eighth International Workshop*, 235–239.

Liu, L., Xu, J., Liao, S. S. & Chen, H. 2014. A real-time personalized route recommendation system for self-drive tourists based on vehicle to vehicle communication. *Expert Systems with Applications* **41**(7), 3409–3417.

Liu, Q. 2014. Accurate and diverse recommendations via integrated communities of interest and trustable neighbors. In *2014 International Conference on Management of e-Commerce and e-Government (ICMeCG)*, 132–137. IEEE.

Lops, P., De Gemmis, M. & Semeraro, G. 2011. Content-based recommender systems: state of the art and trends. In *Recommender Systems Handbook*, Ricci, F., Rokach, L., Shapira, B. & Kantor, P. B. (eds). Springer, 73–105.

Lü, L., Medo, M., Yeung, C. H., Zhang, Y.-C., Zhang, Z.-K. & Zhou, T. 2012. Recommender systems. *Physics Reports* **519**(1), 1–49.

Lyakhov, A. O., Oganov, A. R. & Valle, M. 2010. How to predict very large and complex crystal structures. *Computer Physics Communications* **181**(9), 1623–1632.

Majid, A., Chen, L., Chen, G., Mirza, H. T., Hussain, I. & Woodward, J. 2013. A context-aware personalized travel recommendation system based on geotagged social media data mining. *International Journal of Geographical Information Science* **27**(4), 662–684.

Marin, A. & Wellman, B. 2011. Social network analysis: an introduction. In *The SAGE Handbook of Social Network Analysis*, Scott, J. & Carrington, P. J. (eds). 11–25. Sage.

Masthoff, J. 2011. Group recommender systems: combining individual models. In *Recommender Systems Handbook*, Ricci, F., Rokach, L., Shapira, B. & Kantor, P. B. (eds). Springer, 677–702.

Middleton, B., Bloomrosen, M., Dente, M. A., Hashmat, B., Koppel, R., Overhage, J. M., Payne, T. H., Rosenbloom, S. T., Weaver, C. & Zhang, J. 2013. Enhancing patient safety and quality of care by improving the usability of electronic health record systems: recommendations from AMIA. *Journal of the American Medical Informatics Association* **20**(e1), e2–e8.

Noulas, A., Scellato, S., Lathia, N. & Mascolo, C. 2012. A random walk around the city: new venue recommendation in location-based social networks. In *2012 International Conference on Social Computing (SocialCom) and 2012 International Conference on Privacy, Security, Risk and Trust (PASSAT)* and, 144–153. IEEE.

Noulas, A., Scellato, S., Mascolo, C. & Pontil, M. 2011. Exploiting semantic annotations for clustering geographic areas and users in location-based social networks. *The Social Mobile Web* **11**, 2.

Oh, J., Jeong, O.-R. & Lee, E. 2013. Collective intelligence based place recommendation system. In *Advanced Infocomm Technology*, 169–176. Springer.

Park, D. H., Kim, H. K., Choi, I. Y. & Kim, J. K. 2012. A literature review and classification of recommender systems research. *Expert Systems with Applications* **39**(11), 10059–10072.
Parra, D., Brusilovsky, P. & Trattner, C. 2014. See what you want to see: visual user-driven approach for hybrid recommendation. In *Proceedings of the 19th International Conference on Intelligent User Interfaces*, 235–240. ACM.
Pirasteh, P., Hwang, D. & Jung, J. J. 2015. Exploiting matrix factorization to asymmetric user similarities in recommendation systems. *Knowledge-Based Systems* **83**, 51–57.
Preoţiuc-Pietro, D. & Cohn, T. 2013. Mining user behaviours: a study of check-in patterns in location based social networks. In *Proceedings of the 5th Annual ACM Web Science Conference*, 306–315. ACM.
Pu, P., Chen, L. & Hu, R. 2011. A user-centric evaluation framework for recommender systems. In *Proceedings of the Fifth ACM Conference on Recommender Systems*, 157–164. ACM.
Pu, P., Chen, L. & Hu, R. 2012. Evaluating recommender systems from the users perspective: survey of the state of the art. *User Modeling and User-Adapted Interaction* **22**(4–5), 317–355.
Rana, C. & Jain, S. K. 2015. A study of the dynamic features of recommender systems. *Artificial Intelligence Review* **43**(1), 141–153.
Ren, G., Long, T. & Juebo, W. 2011. A novel recommender system based on fuzzy set and rough set theory. *Advances in Information Sciences and Service Sciences* **3**(4), 100–109.
Rikitianskii, A., Harvey, M. & Crestani, F. 2014. A personalised recommendation system for context-aware suggestions. In *European Conference on Information Retrieval*, 63–74. Springer.
Sarwat, M., Levandoski, J. J., Eldawy, A. & Mokbel, M. F. 2013. LARS*: a scalable and efficient location-aware recommender system. In IEEE Transactions on Knowledge and Data Engineering (TKDE).
Shani, G. & Gunawardana, A. 2011. Evaluating recommendation systems. In *Recommender Systems Handbook*, Ricci, F., Rokach, L., Shapira, B. & Kantor, P. B. (eds). Springer, 257–297.
Sharma, L. & Gera, A. 2013. A survey of recommendation system: research challenges. *International Journal of Engineering Trends and Technology (IJETT)* **4**(5), 1989–1992.
Shi, Y., Larson, M. & Hanjalic, A. 2014. Collaborative filtering beyond the user-item matrix: a survey of the state of the art and future challenges. *ACM Computing Surveys (CSUR)* **47**(1), 3.
Su, H., Zheng, K., Huang, J., Jeung, H., Chen, L. & Zhou, X. 2014. Crowdplanner: a crowd-based route recommendation system. In *2014 IEEE 30th International Conference on Data Engineering*, 1144–1155. IEEE.
Symeonidis, P., Ntempos, D. & Manolopoulos, Y. 2014. Location-based social networks. In *Recommender Systems for Location-Based Social Networks*, 35–48. Springer.
Tang, K. P., Lin, J., Hong, J. I., Siewiorek, D. P. & Sadeh, N. 2010. Rethinking location sharing: exploring the implications of social-driven vs. purpose-driven location sharing. In *Proceedings of the 12th ACM International Conference on Ubiquitous Computing*, 85–94. ACM.
Vanetti, M., Binaghi, E., Carminati, B., Carullo, M. & Ferrari, E. 2010. Content-based filtering in on-line social networks. In *International Workshop on Privacy and Security Issues in Data Mining and Machine Learning*, 127–140. Springer.
Vargas, S. & Castells, P. 2011. Rank and relevance in novelty and diversity metrics for recommender systems. In *Proceedings of the Fifth ACM Conference on Recommender Systems*, 109–116. ACM.
Verbert, K., Manouselis, N., Ochoa, X., Wolpers, M., Drachsler, H., Bosnic, I. & Duval, E. 2012. Context-aware recommender systems for learning: a survey and future challenges. *IEEE Transactions on Learning Technologies* **5**(4), 318–335.
Wang, H., Terrovitis, M. & Mamoulis, N. 2013. Location recommendation in location-based social networks using user check-in data. In *Proceedings of the 21st ACM SIGSPATIAL International Conference on Advances in Geographic Information Systems*, 374–383. ACM.
Wei, L.-Y., Zheng, Y. & Peng, W.-C. 2012. Constructing popular routes from uncertain trajectories. In *Proceedings of the 18th ACM SIGKDD International Conference on Knowledge Discovery and Data Mining*, 195–203. ACM.
Wei, S., Ye, N., Zhang, S., Huang, X. & Zhu, J. 2012. Item-based collaborative filtering recommendation algorithm combining item category with interestingness measure. In *2012 International Conference on Computer Science & Service System (CSSS)*, 2038–2041. IEEE.
Whitley, D. 2014. An executable model of a simple genetic algorithm. *Foundations of Genetic Algorithms* **2**(1519), 45–62.
Wiesner, M. & Pfeifer, D. 2014. Health recommender systems: concepts, requirements, technical basics and challenges. *International Journal of Environmental Research and Public Health* **11**(3), 2580–2607.
Xia, P., Zhang, L. & Li, F. 2015. Learning similarity with cosine similarity ensemble. *Information Sciences* **307**, 39–52.
Xiao, X., Zheng, Y., Luo, Q. & Xie, X. 2010. Finding similar users using category-based location history. In *Proceedings of the 18th SIGSPATIAL International Conference on Advances in Geographic Information Systems*, 442–445. ACM.
Xiao, X., Zheng, Y., Luo, Q. & Xie, X. 2014. Inferring social ties between users with human location history. *Journal of Ambient Intelligence and Humanized Computing* **5**(1), 3–19.

Yang, D., Zhang, D., Yu, Z. & Wang, Z. 2013. A sentiment-enhanced personalized location recommendation system. In *Proceedings of the 24th ACM Conference on Hypertext and Social Media*, 119–128. ACM.

Ye, M., Yin, P. & Lee, W.-C. 2010. Location recommendation for location-based social networks. In *Proceedings of the 18th SIGSPATIAL International Conference on Advances in Geographic Information Systems*, 458–461. ACM.

Ye, M., Yin, P., Lee, W.-C. & Lee, D.-L. 2011. Exploiting geographical influence for collaborative point-of-interest recommendation. In *Proceedings of the 34th International ACM SIGIR Conference on Research and Development in Information Retrieval*, 325–334. ACM.

Yin, H., Cui, B., Li, J., Yao, J. & Chen, C. 2012. Challenging the long tail recommendation. *Proceedings of the VLDB Endowment* **5**(9), 896–907.

Ying, J. J.-C., Lu, E. H.-C., Lee, W.-C., Weng, T.-C. & Tseng, V. S. 2010. Mining user similarity from semantic trajectories. In *Proceedings of the 2nd ACM SIGSPATIAL International Workshop on Location Based Social Networks*, 19–26. ACM.

Zarrinkalam, F. & Kahani, M. 2012. A multi-criteria hybrid citation recommendation system based on linked data. In *2012 2nd International eConference on Computer and Knowledge Engineering (ICCKE)*, 283–288. IEEE.

Zhang, D., He, T., Liu, Y., Lin, S. & Stankovic, J. A. 2014. A carpooling recommendation system for taxicab services. *IEEE Transactions on Emerging Topics in Computing* **2**(3), 254–266.

Zhang, W., Wang, J. & Feng, W. 2013. Combining latent factor model with location features for event-based group recommendation. In *Proceedings of the 19th ACM SIGKDD International Conference on Knowledge Discovery and Data Mining*, 910–918. ACM.

Zheng, V. W., Zheng, Y., Xie, X. & Yang, Q. 2010. Collaborative location and activity recommendations with GPS history data. In *Proceedings of the 19th International Conference on World Wide Web*, 1029–1038. ACM.

Zheng, V. W., Zheng, Y., Xie, X. & Yang, Q. 2012. Towards mobile intelligence: learning from GPS history data for collaborative recommendation. *Artificial Intelligence* **184**, 17–37.

Zheng, Y. 2012. Tutorial on location-based social networks In *Proceedings of International conference on World Wide Web*.

Zheng, Y., Zhang, L., Ma, Z., Xie, X. & Ma, W.-Y. 2011. Recommending friends and locations based on individual location history. *ACM Transactions on the Web (TWEB)* **5**(1), 5.

Zuva, T., Ojo, S. O., Ngwira, S. & Zuva, K. 2012. A survey of recommender systems techniques, challenges and evaluation metrics. *International Journal of Emerging Technology and Advanced Engineering* **2**(11), 382–386.