Geoinformatica (2015) 19:525565
DOI 10.1007/s10707-014-0220-8

Recommendations in Location-based Social Networks: A Survey

Jie Bao · Yu Zheng · David Wilkie · Mohamed Mokbel

Received: 23 September 2013 / Revised: 23 August 2014 /
Accepted: 15 September 2014 / Published online: 6 February 2015

Abstract Recent advances in localization techniques have fundamentally enhanced social networking services, allowing users to share their locations and location-related contents, such as geo-tagged photos and notes. We refer to these social networks as location-based social networks (LBSNs). Location data bridges the gap between the physical and digital worlds and enables a deeper understanding of users' preferences and behavior. This addition of vast geo-spatial datasets has stimulated research into novel recommender systems that seek to facilitate users' travels and social interactions. In this paper, we offer a systematic review of this research, summarizing the contributions of individual efforts and exploring their relations. We discuss the new properties and challenges that location brings to recommender systems for LBSNs. We present a comprehensive survey analyzing 1) the data source used, 2) the methodology employed to generate a recommendation, and 3) the objective of the recommendation. We propose three taxonomies that partition the recommender systems according to the properties listed above. First, we categorize the recommender systems by the objective of the recommendation, which can include locations, users, activities, or social media. Second, we categorize the recommender systems by the methodologies employed, including content-based, link analysis-based, and collaborative filtering-based methodologies. Third, we categorize the systems by the data sources used, including user profiles, user online histories, and user location histories. For each category, we summarize the goals and contributions of each system and highlight the representative research effort. Further, we

Jie Bao
University of Minnesota
E-mail: baojie@cs.umn.edu

Yu Zheng
Microsoft Research
E-mail: yuzheng@microsoft.com

David Wilkie
University of North Carolina
E-mail: wilkie@cs.unc.edu

Mohamed Mokbel
University of Minnesota
E-mail: mokbel@cs.umn.edu

provide comparative analysis of the recommender systems within each category. Finally, we discuss the available data-sets and the popular methods used to evaluate the performance of recommender systems. Finally, we point out promising research topics for future work. This article presents a panorama of the recommender systems in location-based social networks with a balanced depth, facilitating research into this important research theme.

Keywords Location-based Social Networks · Recommender Systems · Location-based Services · Location recommendations · Friend recommendations · Community discoveries · Activity recommendations · Social media recommendations

1 Introduction

With millions of users, social networking services like Facebook and Twitter have become some of the most popular Internet applications. The rich knowledge that has accumulated in these social sites enables a variety of recommender systems for new friends and media.

Recently, advances in location-acquisition and wireless communication technologies have enabled the creation of location-based social networking services, such as Foursquare, Twinkle, and GeoLife [131]. In such a service, users can easily share their geo-spatial locations and location-related contents in the physical world via online platforms. For example, a user with a mobile phone can share comments with his friends about a restaurant at which he has dined via an online social site. Other users can expand their social networks using friend suggestions derived from overlapped location histories. For instance, people who constantly hike on the same mountain can be put in contact.

The location dimension bridges the gap between the physical world and the digital online social networking services, giving rise to new opportunities and challenges in traditional recommender systems in the following aspects:

1. *Complex objects and relations:* A location is a new object in location-based social networks (LBSNs), generating new relations between users, between locations, and between users and locations. New recommendation scenarios, like location and itinerary recommendations, can be enabled using this new knowledge, and traditional recommendation scenarios, such as friend and media recommendation, can be enhanced. However, doing so requires new methodologies for generating high-quality recommendations.
2. *Rich knowledge:* A location is one of the most important components defining a user's context. Extensive knowledge about a user's behavior and preferences can be learned via their location history [113]. The huge volume of location-related data generated by users improves the likelihood that social opinions, e.g., the most favorite dish in a restaurant or the most popular activity at a point of interest, can be accurately assessed by recommender systems.

These opportunities and challenges have been tackled by many new approaches to recommender systems, using different data sources and methodologies to generate different kinds of recommendations. In this article, we provide a survey of these systems, and the publications proposing them, with a systematic review on over sixty articles published over the last five years in the major journals, conferences, and workshops, including but not limited to KDD, WWW, Ubicomp, ACM SIGSPATIAL, LBSN, RecSys, ACM TIST, and VLDB. For each publication, we analyze 1) what a produced recommendation is (i.e., the objective of a recommendation), 2) the methodology employed to generate a recommendation, and 3) the data source it used. According to these three aspects, we propose three taxonomies to respectively partition the recommender systems. This survey presents a panorama of the recommendations in location-based social networks with a balanced depth, facilitating research into this rising topic. The contributions of this article are detailed as follows:

– We distinguish LBSNs from conventional social networks and define their unique properties, challenges, and opportunities.
– We categorize the major recommender systems for LBSNs in three taxonomies, organized by data sources, methodologies, and recommendation objectives. In each category, we summarize the goals and contributions of each system. In addition, we highlight one representative system in each category, providing a more in-depth view of the methodology.
– We summarize the public LBSN datasets and the major methods for evaluating the recommendations in LBSNs.
– We point out promising research directions in LBSN recommender systems, paying special attention to directions that result from the analysis and synthesis of the different recommender system categories.

The rest of the paper is organized as follows: In Section 2, we provide an overview of location-based social networks. We then propose taxonomies for existing recommender systems for LBSNs in the three subsequent sections. In Section 3, we propose a taxonomy organized by objective of the recommendations. In Section 4, we propose a taxonomy organized by the methodology of the recommendation system. In Section 5, we propose a taxonomy organized by the data source used by the recommender systems. In Section 6, we summarize the datasets and major methods for evaluating a recommendation in an LBSN. In Section 7, we present potential future research directions and discuss how they relate to the existing recommender systems. Finally, in Section 8 we present our concluding remarks.

2 Overview

In this section, we first present a formal definition of location-based social networks. After that, we summarize the unique properties of locations as the new data type and discuss the new challenges they bring to recommender systems for LBSNs.

2.1 Concepts of Location-Based Social Networks

A social network is an abstract structure contains different relations between the individuals, such as friendships, common interests, and shared knowledge. An online social networking service is a participatory digital representation of real-world social networks. The social networking services reveal user's real social connections, and also enhance the growth by allowing them to share and communicate about ideas, activities, events, news, and interests in a much easier fashion.

The addition of spatial aspect in a location-based social networking service strengthens the connection between the social networking services and the real-world social networks. Location-based Social Networks or Geosocial Network is formally defined as a type of social networking in which geographic services and capabilities such as geocoding and geotagging are used to enable additional social dynamics [78]. Zheng further elaborate the concept for these location-based social networks [137], as:

"*A location-based social network (LBSN) does not only mean adding a location to an existing social network so that people in the social structure can share location-embedded information, but also consists of the new social structure made up of individuals connected by the interdependency derived from their locations in the physical world as well as their location-tagged media content, such as photos, video, and text. Here, the physical location consists of the instant location of an individual at a given timestamp and the location history that an individual has accumulated in a certain period. Further, the interdependency includes not only that two persons co-occur in the same physical location or share similar location histories but also the knowledge, e.g., common interests, behaviors, and activities, inferred from an individual's location (history) and location-tagged data*."

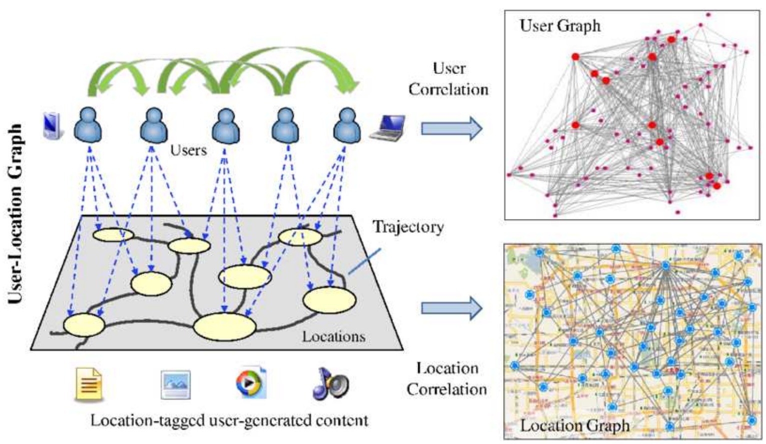


Fig. 1 Concept of location-based social networks. [137]

Figure 1 gives an overview of different networks contained in a typical location-based social networks, in which the addition of locations creates new relations and correlations. As a consequence, conceptually, we can build three graphs within a LBSN as: a location-location graph, a user-location graph, and a user-user graph.

– *Location-location graph.* In the location-location graph (shown in the bottom-right of Figure 1), a node is a location/venue and a directed edge represents the relation between two locations. This relations can be explained in many possible ways. For example, it can indicate the physical distances between the locations, or the similarities between the locations in terms of their functionality/category. Also, it can be connected by the user activities that some users consecutively visited.
– *User-location graph.* In the user-location graph (shown in the left of Figure 1), there are two types of nodes, users and locations. An edge starting from a user and ending at a location can indicate that the user's travel histories, and the weight of the edge can indicate the number of visits or the user's review ratings.

- *User-user graph.* In the user-user graph (shown in the top-right of Figure 1), a node is a user and an edge between two nodes represents the relations between users, as: a) the physical distances between the users, b) the friendship relations in a traditional social networking system. And c) the other relation derived from the users' location histories, e.g., two users may be connected if they have visited the same location, or similar types of places. The latter connection. In other words, we can recommend users to an individual based on the inferred location-based connection. Once the individual accepts the recommendation, the relationship switches from the inferred location-based connection to the traditional social connection.

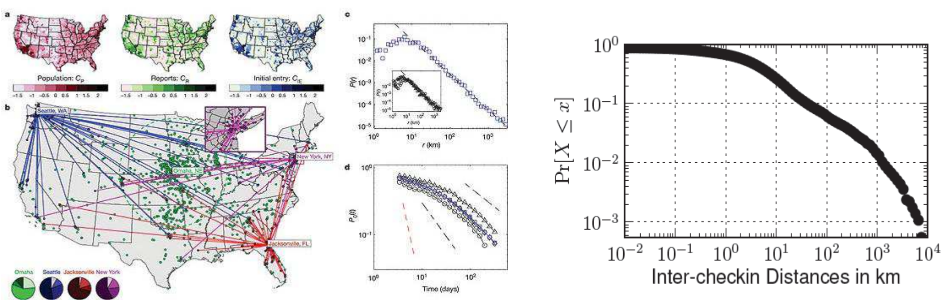
The existing location-based social networking services can be classified into three major groups:

- *Geo-tagged-media-based.* Geo-tagging services enable users to label the media content such as text, photos, and videos generated in the physical world. The tagging can occur passively when the content is created by the device or can be added explicitly as the content by the user. Users can then view the created contents in a map. Representative websites of such location-based social networking services include Flickr, Panoramio, and Geo-twitter. Though a location dimension has been added to these social networks, the focus of these services is still on the media content. That is, location is used only as an additional label to organize and enrich the media contents.
- *Point-location-based.* Applications like Foursquare and Yelp encourage people to share their current locations, such as restaurants or museums, which are the most popular type of location-based social networking services. In Foursquare, points and badges are awarded for users' checking in. With the real-time location of users, an individual can discover friends (from her social network) around their location to enable social activities in the physical world, e.g., inviting people to have dinner or go shopping. Users can also add comments and reviews as tips to venues that other users can read. With this kind of service, a location (or a venue) is the first class citizen in the system, where all the activities like checking in, tipping, and posting photo are all required to be associated with a point location.
- *Trajectory-based.* In a trajectory-based social networking service, such as Microsoft GeoLife and cyclopath [67], is a new type of location-based social networking services. Addition to the point location history, users also record their GPS trajectory route connecting the point locations. These services tell users' basic information, such as distance, duration, and velocity, about a particular trajectory, but they also show users' experiences, represented by tags, tips, and photos along the trajectories. In short, these services provide "how and what" information in addition to "where and when." Other users can reference these experiences (e.g. travel) by browsing or replaying the trajectory on a digital map or in the real world with a GPS-enabled phone.

2.2 Influence of Locations in Social Networks

Users' location histories contain a rich set of information reflecting their preferences, once the patterns and correlations in the histories has been analyzed [30]. Research into location histories found that the distribution of locations often fit a power law, i.e. the closer locations have a much higher probability of being visited, e.g., [21, 11, 49]. In [11], the authors study the location histories of marked currency as it circulates (shown in Figure 2a).

They collect a total of 20,540 trajectories throughout the United States. The authors investigate the probability $P(r)$ of finding a traversal distance r within a number of days. A total of 14,730 (that is, a fraction Q = 0.71) secondary reports occurred outside a short range radius L_{min} = 10 km. The distribution shows power-law behavior $P(r)$ $r^{(1+\beta)}$ with an exponent $\beta = 0.59 \pm 0.02$. Recent investigations found similar patterns in users' location histories in LBSNs. For example, [73] studies a large point-location data set collected from Foursquare that reveals several patterns: a user's activities are different during the weekdays and weekends, and the spatio-temporal patterns of users' check-ins fit the power law distribution. They found that 20% of the user's check-ins occur within a distance of 1 km, 60% occur between 1 and 10 km, 20% occur between 10 km and 100 km, and a small percentage extend to distances beyond 100 km. Analysis such as the above, coupled with investigations into user and location correlations and patterns, provide clues of user preferences that can guide recommender systems.



(a) human mobility study via money circulation [Brockmann et al. 2006]

(b) Human mobility study via user check-ins [Noulas et al. 2011]

Fig. 2 Location Influences in LBSNs [11, 73].

2.3 Unique Properties of Locations

Location information brings the following three unique properties to LBSNs, as shown in Figure 3,:

Hierarchical. Locations span multiple scales: for example, a location can be as small as a restaurant or as big as a city. Locations with different granularities form a hierarchy, where locations on a lower tiers refer to smaller geographic areas. For example, a restaurant belongs to a neighborhood, the neighborhood belongs to a city, the city belongs to a county, and so on (see Figure 3a). Different levels of location granularity imply different location-location graphs and user-location graphs, even given the same location histories of users. These hierarchical relationships need to be considered as, for example, users who share locations at a lower level (such as a restaurant) likely have a stronger connection than those who share locations at a higher level (such as living in the same city). This hierarchical property is unique in LBSNs, as it does not hold in an academic social network, where a conference never belongs to others.

Measurable Distances. Connecting the physical world to a LBSN leads to three new geospatial distance relations, the distance between different users' locations (shown as D1 in Figure 3b), the distance between a user and a location (shown as D2 in Figure 3b), and the distance between two locations (shown as D3 in Figure 3b). According to the first law of geography posed by Waldo Tobler [97], "*everything is related to everything else, but near things are more related than distant things*", we propose that distance affects an LBSN in the following three ways. 1) The user-user distance influences the similarity between users. For example, users with a history of visiting nearby locations are more likely to have similar interests and preferences [56, 105], and users who live close to each other are more likely to be friends [26]. 2) The user-location distance influences the likelihood a user will be interested in a location. For instance, users in Foursquare visit restaurants close to their homes more frequently than others [55]. 3) The location-location distance affects the correlations between locations. For example, car dealerships are often placed close to each other.

Sequential ordering. Subsequent visits by a user to two locations creates a relation with a chronological ordering. For instance, the two users in Figure 3c share a location visiting pattern. From the time of each visit, we can create an ordering which may indicate some similarities between their preferences [129] or may imply traffic conditions [96].

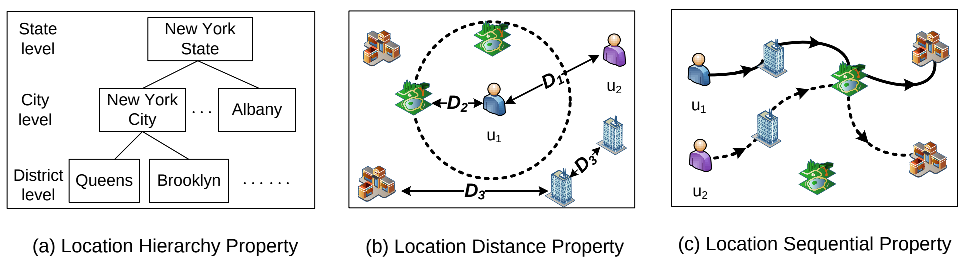


Fig. 3 Unique Properties of Locations.

2.4 Challenges to Recommendations in LBSNs

While creating new opportunities for LBSNs, the unique properties of locations also bring new challenges such as 1) location context awareness, 2) the heterogeneous domain, and 3) the rate of growth.

2.4.1 Location Context Awareness

Recommender systems in LBSNs need to consider how the current location of a user, the location history of the user, and the location histories of other users influences what recommendation to make.

The Current Location of a User. A user's current location plays a vital role in generating recommendations in LBSNs due to the following three reasons.

First, a user's current location can be represented on different levels of granularity (the hierarchical property of locations). Choosing a proper granularity for the recommendation scenario is important and challenging. For instance, we should use a fine granularity when recommending restaurants to a user, while a relatively coarse granularity (like in a city or state) for local news recommendations.

Second, the distance property of locations implies that people are more likely to visit nearby locations than distant ones. However, the quality of a location (like a restaurant) is also important for recommendation-making. Ranking a recommendation based on both the user-location distance and the quality of a location is non-trivial. Further, a location indicates a spatial constraint for generating recommendations, but also influences user preferences. For example, beaches might be given a high recommendation rank to a user traveling to Hawaii, even though the user prefers sporting events more than beaches typically. The same user may be more interested in seeing the status of her friends living in Hawaii. An additional challenge is that fine grain location needs to be taken into account quickly: users often access LBSNs via mobile devices that frequently update their location information. Addressing this requires efficient algorithms to generate recommendations quickly.

Third, due to the sequential property of locations, a user's current location affects future travel decisions. For instance, the majority of people visiting Tiananmen Square will subsequently travel to the Forbidden City, or a dessert or drink recommendation may be appropriate after visiting certain restaurants. Discovering these sequential relations and incorporating them into recommendations presents subtle challenges.

The Historical Locations of the User. Earlier works, e.g., [29, 31], have suggest that a user's historical behaviors is a powerful indicator of the user's preferences. A user's historical locations accumulated in an LBSN (e.g., check-ins and geo-tagged photos) reflect more accurately a user's experiences, living patterns, preferences and interests than the user's online behaviors [137]. However, it is non-trivial to model a user's location history due to the hierarchy, distance, and sequential properties of locations. Moreover, learning a user's personal preferences from the user's location history is very challenging for the following reasons. 1) As users do not share their locations everywhere, a full set of a user's location history does not exist. Learning a user's preferences from sparse location data is challenging. 2) A user's preferences span multiple kinds of interests, such as shopping, cycling, and arts, rather than consisting of binary decisions, e.g., a set of 'like or dislike' statements. 3) A user's preferences have hierarchies and granularity, such as "Food" $\rightarrow$ "Italian food" $\rightarrow$ "Italian pasta". 4) A user's preferences are constantly evolving (and location dependent).

The Location Histories of Other Users. Location histories generated by other users in LBSNs make up the social opinion, which is one of the most important information bases for making recommendations. To extract social opinions from the location histories, however, we are faced with the following two challenges. 1) It is difficult to design a model to consistently represent different users' distinct locations and make these location histories comparable and computable. 2) Users have different degrees of knowledge about different geospatial regions. For instance, local experts of a town are more likely to find high quality restaurants and shopping malls. As a result, weighting different users' data according to their experiences and knowledge is useful when inferring social opinions from the massive user-generated and location-related data. Further, the knowledge of a user is region-related and changes over the granularity of a location. A travel expert in New York City might have less knowledge of Seattle. Likewise, people who are shopping experts in one district of a city might not be the most knowledgeable of the city as a whole. Effectively and efficiently inferring social opinions with respect to users' knowledge of different regions is a difficult problem.

2.4.2 Heterogeneous Domain

The graph representing an LBSN is heterogeneous, consisting of at least two types of nodes (user and location) and three types of edges (user-user, location-location, and user-location).

Table 1 Comparison of three social networks.

	Location Awareness	Heterogeneous Environments	Evolving Speed
Academic Social Networks		√	Slow
General Online Social Networks			Fast
Location-Based Social Networks	√	√	Fast

Alternatively, we can say there are at least three tightly associated graphs that model an LBSN (as mentioned in Section 2.1). If an LBSN is trajectory-based, trajectories can be regarded as another type of node in the social network.

A location is not only an additional dimension of information about the user, but also an important object in the LBSN. Inferring the similarity or correlation between two objects in a heterogeneous graph must incorporate the information from related nodes of other types. For instance, determining the connection between two users in an LBSN needs to involve the user-location and location-location relations. A location shared by two users could be evidence of similarity, or it could simply indicate that a location is very popular. Only careful analysis can determine which case holds, and to what extent it should influence the strength of the connection between the users.

2.4.3 The Rate of Growth

Location-based social networks evolve at a faster pace than traditional social networks in both social structure and properties of nodes and links. Though academic social networks are also heterogeneous, with authors, conferences, and papers, they evolve at a much slower speed than LBSNs do. For example, adding new links in an LBSN is much easier than it is in a academic social network as visiting a new location is easier than publishing a paper. Further, the properties of nodes and links in a LBSN evolve more quickly than those of academic social networks. A user can become a travel expert in a city after visiting many interesting locations over several months, while a researcher needs years before becoming an expert in a research area. The rate of growth and evolution in LBSNs raise the standard of scalability, efficiency, and updating strategy demanded of recommender systems.

We summarize the differences among different types of social networks, e.g., academic networks, such as DBLP, general online social networks, such as Facebook, and location-based social networks, like Foursquare and GeoLife, in Table 1. LBSNs present novel opportunities and challenges given the unique properties of locations, the heterogeneous structure of a network, and their high rate of growth and evolution.

2.4.4 Cold Start & Data Sparsity

Cold start problem happens, when the system encounter some individual users or items with very limited history or activity. For the new user or item, the recommendation model does not have enough knowledge to provide effective suggestion. The cold start problem gets worse in LBSNs, as the growth ratio is very rapid. It is a non-trivial task to recommend the new items ((e.g., geo-tagged photos, activities, and tweets)) in the LBSNs quickly enough for the user. As a result, some novel method/models and hybrid approaches that take advantage of different recommendation models are necessary, e.g., [88, 34].

Data sparsity happens, when the entire data in the recommendation model are insufficient for identifying similar users/items and it is one of the major issues limiting the quality of recommendations. For the recommender systems in LBSNs, it have more significant impact. The main reasons are: 1) a user's location history are limited, as we discussed in Section 2.2, while the number of places in a LBSN is a much larger number even in one city. In this case, the recommender system will generate a very sparse user-location model; and 2) a user's location history is always locally crowded [73]. As a consequence, even if a user has enough location history near her residential area, the recommender system will run into the data sparsity issue, when she travels to some new areas.

2.5 Structure of The Paper

To provide a comprehensive survey on recommendations in LBSNs, we studied over forty related publications from the major conferences and journals from 2008 to 2011, as summarized in Table 2.

For each publication, we study: 1) what is being recommended (i.e. the objective), 2) the methodology employed to generate the recommendation, and 3) the data source used. Based on these three aspects, we propose three taxonomies to partition these recommender systems for LBSNs. Following the framework shown in Figure 4, we further detail the three taxonomies taxonomy as follows.

Recommendation objective. Four types of recommendations are common in LBSNs: 1) location recommendations, which suggest stand-alone locations (e.g., POIs and regions) or sequential locations (such as travel routes and sequences) to a user; 2) user recommendations, which suggest popular users (like local experts and opinion leaders), potential friends (i.e., who share similar interests and preferences), or communities, which a user may wish to join due to shared interests and activities; 3) activity recommendations, which refer to activities that a user may be interested taking into consideration the user's interests and location; 4) social media recommendations, which suggest social media, such as photos, videos, and web contents, to the user taking into account the location of a user and the location metadata of the social media.

Recommender system methodology. We categorize the major methodologies used by the recommender systems in LBSNs into the following three groups: 1) content-based recommendation, which uses data from a user's profile (e.g., age, gender, and preferred cuisines) and the features of locations (such as categories and tags associated with a location) to make

Table 2 Statistics on literatures related to Recommendations in LBSNs.

	Names	2008	2009	2010	2011	2012	2013
Conferences	WWW	0	2	3	2	1	1
	MDM	1	1	1	1	0	2
	KDD	0	0	1	4	3	3
	ACM-GIS	1	1	2	3	2	2
	UbiComp	0	0	4	1	0	2
	LBSN	N/A	3	3	5	4	N/A
	RecSys	0	0	2	1	1	2
Journals	VLDB	0	0	2	0	1	0
	ACM-TIST	0	0	1	1	4	2
	ACM TWEB	0	0	0	1	0	0
Total Numbers		2	7	19	19	16	14

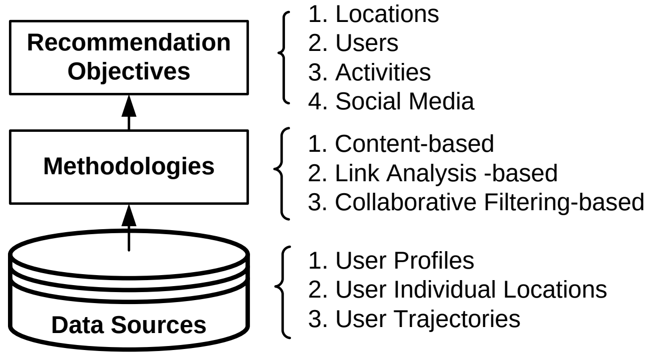


Fig. 4 An overview of recommender system categories in LBSNs.

recommendations; 2) link analysis-based recommendation, which applies link analysis models, e.g., hypertext induced topic search (HITS) and PageRank, to identify experienced users and interesting locations; and 3) collaborative filtering (CF) recommendation, which infers a user's preferences from historical behavior (such as from a location history).
Data sources used. Recommender systems in LBSNs can take advantages of various data sources such as: 1) user profiles, which explicitly specify a user's age, gender, interests, preferences, etc.; 2) user geo-located content, which includes a user's ratings of visited locations, geo-tagged content, check-ins, etc.; and 3) user trajectories, consisting of sequential locations contained in a user's GPS trajectories.

Table 3 provides an overview of some representative publications in regard to the three aspects mentioned above. For instance, Zheng et al. [136] recommend interesting locations and local experts in a city to users based on user location histories in a form of GPS trajectories using a HIST-based link analysis method.

3 Categorization by Objectives

Location-based social networks open new recommendation possibilities. In this section, we categorize the existing recommender systems in LBSNs based on their objectives as 1) locations, including the stand-alone locations and traveling routes, 2) users, including expert users, friends recommendation, and community discovery, 3) activities, and 4) social media.

3.1 Location Recommendations

As location recommendation is a very broad topic, in this paper, we only focus on location recommendations in the context of social networking, where the techniques and methods are based on user's geo-social activities. Figure 5 gives an overview of the existing location recommender system in LBSNs. These systems can be divided into two groups by the objectives of their recommendation: 1) stand-alone location recommender systems, which provide a user with individual locations, such as restaurants or cities, that match their

Table 3 Summary of the existing recommender systems in Location-Based Social Networks.

	Objectives				Methodologies			Data Sources		
	Social Media	Location	User	Activity	Content based	Link Analysis	CF	User Profile	Individual Locations	User Trajectories
Sandholm [83]	√						√		√	
Levandoski [55]	√	√					√		√	
Park [76]		√			√			√		
Horozov [45]		√					√		√	
Ye [111]		√					√		√	
Chow [20]		√					√		√	
Ye[112]		√					√		√	
Tai [94]		√				√			√	
Yoon [121]		√				√				√
Cao [13]		√				√				√
Ye [110]		√			√				√	
Liu [62]		√				√			√	
Zheng [136]		√	√			√				√
Zheng [133]		√	√				√			√
Li [56]			√				√			√
Hung [47]			√				√			√
Xiao [106]			√		√		√			√
Ying [120]			√		√		√		√	
Scellato [87]			√			√			√	
Zheng [127]		√		√			√		√	√
Symeonidis [75]		√		√			√		√	
Yin [114]		√		√		√			√	

preferences, and 2) sequential location recommender systems, which recommend a series of locations (e.g., a popular travel route in a city) to a user based on their preferences and their constraints, such as in time and cost. As shown in Figure 5, each type of location recommender system can be further categorized based on the data sources used.

3.1.1 Stand-alone Location Recommendations

The stand-alone location recommender systems have been a focus of recent research, including the development of multiple prototype systems, e.g., [20, 76, 95, 111, 126, 127, 132,

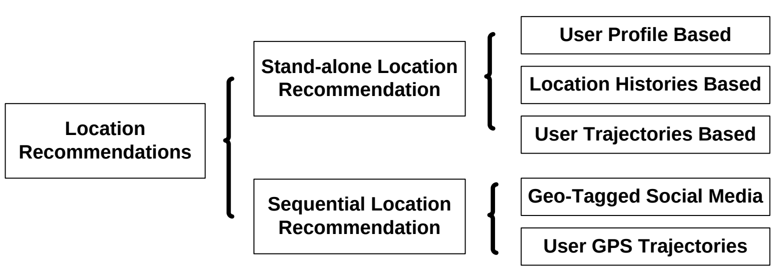


Fig. 5 Location Recommendations in LBSNs.

136]. We can further subdivide and categorize the stand-alone location recommender systems based on the data sources used, as follows.

User profiles. These location recommendation systems suggest locations by matching the user's profile against the location meta data, such as description and semantic text and tags. The first prototype of system proposed in [76] matches user's profile data – including age, gender, cuisine preferences, and income – against the price and category of a restaurant using a Bayesian network model. In [80], Ramaswamy et al., focus on enabling location recommendation on low-end devices capable only of voice and short text messages (SMS). Their approach focuses on using a user's address and 'social affinity', social connections implied by a user's address book, to make recommendations. The social affinity computation and spatio-temporal matching techniques in the system are continuously tuned through the user feedback. In [52], Kodama et al., select location candidates using semantic data and make a final recommendation using a skyline operator [9] that takes into account both the price and the distance of the candidate locations. The advantage of this type of technique is that, the recommendation will not suffer from the cold-start problem, where the users or venues are new and have limited history. As long as the user or venue has a complete profile and category information, the recommendation can be done in an efficient way by matching the keywords and applying some filtering conditions. However, such systems potentially suffer from the recommendation quality issue, because the system may recommend a matching place with poor quality from the social opinion.

User location histories. A user's location history includes a) their online rating history of locations (e.g., hotels and restaurants) and b) their the check-in history in location-based social networking systems. Using users' location histories, as described above, for making recommendations has advantages over relying solely on profile data as location histories also capture the ratings from the other users. It therefore improves the quality of recommendation by ignoring poorly-reviewed locations that otherwise match user's profile.

Many online web services, e.g. Yelp and Yellowpage, allow users to explicitly express their preferences for locations using ratings. Using these ratings, a body of research, e.g., [20,45,111,25], proposes location recommendation systems using Collaborative Filtering (CF) models that give personalized recommendations for locations that take into account other users' ratings. The intuition behind these methods is that a user will share location preferences with similar users. Most of the CF-based location recommender systems undertake three discrete operations, 1) similarity inference, which calculates a similarity score between users based on their historical ratings, 2) candidate selection, which selects a subset of candidate locations using the user's current location, and 3) recommendation score predication, which predicts the rating a user would give to a location. For example, motivated by the observation that "*people who live in the same neighborhood are likely to visit the same local places*", [45] uses the historical ratings from users living close to the user's query location, which significantly reduces the number of users in the user similarity matrix and thus reduces the computational cost of the recommendation. Similarly, Ye et al. 2010 [111] suggest that solely using the ratings of a user's friends is more efficient and just as effective as using the ratings generated by the top-k most similar users. The authors present a set of experiments showing that a user's friends share more preferences than strangers. Ye et al. 2011 [112], use user check-ins to study the effects of the CF-model, geographical distance, and social structures in making location recommendations. The authors find that geographical distance has the largest impact in their model. In their following work [32], they extend the solution to consider the user's social relations and her current position. Zhang and Chow [125] further explore the geographical influences in location recommendation, from the perspective of a user's personalized travel pattern. In their model, each user in the system has a personalized travel distance preferences, which has the biggest impact on choosing the location recommendation. The proposed technique achieves 40% in precision and 25% in recall, which are significantly superior than the conventional user-based collaborative filtering. In paper [119], the recommendation model extended by considering the general popularity of the candidate venues by analyzing the large scale user check-in behavior. Shi et al. 2011 [89] propose a personalized location recommender system to take advantage of the venue category information using on a category-regularized matrix constructed from the user location histories. This type of location recommendations consider both the user's preferences as well as a category-based location similarity. Bao et al. [8] identify the the "new-city" recommendation issue, and propose a solution with three key components in a location recommender system, a) the user's current location, which constrains the location candidates, b) the user's location category histories, which reflects the user's preferences, and c) the opinions from the local experts. Yin et al. 2013 [114] further extend the problem by proposing an LCA-LDA model, a location-content-aware probabilistic generative model to quantify both the local preference and the item content information in the recommendation process. Yang et al. [108] also take advantage of the content information in the users' comments left in the check-ins to build a more fine-grained user preference model for personalized location ranking using tensor factorization techniques. In terms of improving the efficiency of the location recommendations [20, 107], Chow et al., propose a new recommendation algorithm that using the safe region technique to reduce the system communicational and computational overhead for the users moving on their paths. In [25], Del Prete and Capra present a decentralized mobile recommendation service designed for pervasive environments using peer knowledge to avoid the bottleneck of the centralized server.

Representative Research. Ye et al. 2011 [112] present a recommender system which uses CF module to fuse multiple factors as: a) the user's preferences, which are extracted from the check-in history, b) the user's social connections, which are measured by the user's distance to other users in the social network, and c) the geographic distance between the user and the candidate locations, within a collaborative filtering model. As a result, the probability $S_{i,j}$ of a location l_j to be visited by the user u_i can be estimated using the following equation:

$$S_{i,j} = (1 - \alpha - \beta) \times S^{u}_{i,j} + \alpha \times S^{s}_{i,j} + \beta \times S^{g}_{i,j} \tag{1}$$

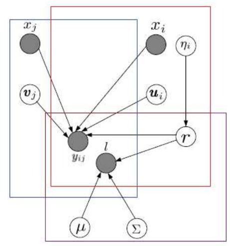
where the two weighting parameters α and β $(0 \leq \alpha + \beta \leq 1)$ denote the relative importance of social influence and geographical influence compared to user preference. Here α = 1 implies that $S_{i,j}$ depends completely on social influences, β = 1 implies that $S_{i,j}$ depends completely on geographical influences, and $\alpha = \beta = 0$ implies that $S_{i,j}$ depends only on user preference.

The authors explore the effect of the different factors in two large data sets from Foursquare and Whrrl. They found their model allowed high precision and recall. Further, they observed that a) geographical influences had a greater impact on the probability of a user visiting a location than did social influences, b) *Random Walk and Restart* may not be suitable for POI recommendations in LBSNs as close social network connections still exhibit significantly different location preferences, and c) the insufficient number of visitors to many locations limits some Collaborative Filtering approaches.

Representative Research. As applying the collaborative filtering approach directly can not capture the insights how these information influence a user's choice over different POIs. Liu et al. [62] proposed a more generative model that integrates the: a) The geographical influence on a users check-in behavior, by taking into consideration of geographical factors, such as the regional popularity and the Toblers first law of geography. b) The latent factor in explicit rating recommendation to implicit feedback recommendation settings by considering the skewed count data characteristic of LBSN check-in behaviors. The proposed model is flexible and could be extended to incorporate different later factor models which are suitable for both explicit and implicit feedback recommendation settings.

1. Draw a region $r \sim \text{Multinomial}(\eta_i)$.
2. Draw a location $l_j \sim \mathcal{N}(\mu_r, \Sigma_r)$.
3. Draw a user preference
   a Generate user latent factor $\boldsymbol{u}_i \sim P(\boldsymbol{u}_i; \Psi_{\boldsymbol{u}_i})$.
   b Generate item latent factor $\boldsymbol{v}_j \sim P(\boldsymbol{v}_j; \Psi_{\boldsymbol{v}_j})$.
   c User-item preference $\alpha(i,j) = \boldsymbol{u}_i^\top \boldsymbol{v}_j + x_i^\top W x_j$.
4. $y_{ij} \sim P(f_{ij})$ where
   $$f_{ij} = \left(\boldsymbol{u}_i^\top \boldsymbol{v}_j + x_i^\top W y_j\right) \cdot \rho(j) \cdot (d_0 + d(i,j))^{-\tau}$$

(a)The geographical probabilistic generative process model for a user *i* to choose a POI *j*



(b) A graphical representation of the proposed model

Fig. 6 An Overview of Geographical Preference Model for POI Recommendation [62]

.

Figure 6 gives an overview of the decision processes captured in the model, where a user i checked in a POI j. First, the user samples a region from all $\mathbb{R}$ regions following a multinomial distribution $r \sim$ Multinomial(η_i), then a POI is selected from the sampled region $l_j \sim \mathcal{N}\ (\mu_{\text{r}}, \Sigma_{\text{r}})$. Finally, based on a) user preferences, b) the POI popularity, and c) the distance between the user and the POI, the user makes a check-in decision following certain distribution. The user is preference for POI j can be represented as a linear combination of a latent factor $\mathbf{u}_i^\intercal \mathbf{v}_j$ and a function of user and item observable properties $x_i^\intercal \mathrm{W} y_i$. Additionally, $\rho(j)$ indicates the popularity of the POI j and $(d_0 + d(i,j))^{-\tau}$ is a power-law like parameter term to model the distance factor for the user's check-in behavior between her current location and the POI location.

In this generative model, **u** and **v** are user and item factors, x_i and x_j are user and item observable properties respectively, and W is a matrix that is used to transfer the observable prosperity space into the latent space to capture the affinity between the observed features and the user-item pair. The results, based on the real data from Foursquare, confirms that they can achieve at least three time better precision and recall ratio over the traditional single value decomposition (SVD), probabilistic matrix factorization(PMF), non-negative matrix factorization (NMF) and Bayesian non-negative matrix factorization (BMF) methods.

User trajectories. Compared to stand-alone check-in data, user-generated trajectories contain a richer set of information, such as the visiting sequence between locations, the path traveled, and the duration of stay at each location. As a result, trajectory data can be used to more accurately estimate a user's preferences. Examples of recommender systems using trajectory data include [54, 95, 135, 136, 58]. In particular, Zheng, et al [135, 136] propose a recommendation framework to find expert users and interesting locations by mining GPS trajectory data. In [13], Cao et al. extend the previous work to consider location-location relations as well as location-user relations. In [54], Leung et al. propose a dynamic clustering algorithm in a collaborative location recommendation framework that takes advantage of user classes.

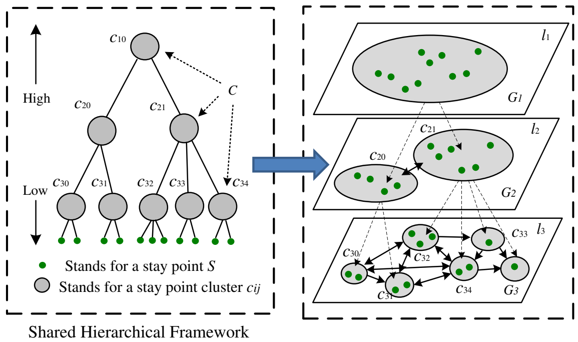


Fig. 7 Tree-based hierarchical graph. [136]

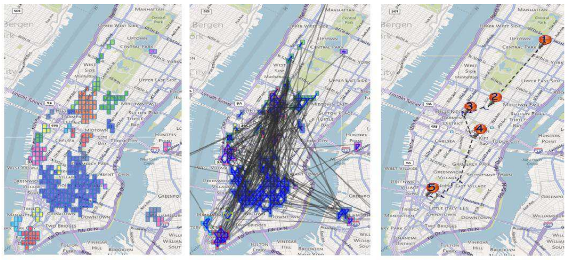
Representative Research. Zheng et al. 2009 [136] extend the hypertext induced topic search (HITS) model to extract interesting locations and experienced users using two approaches, 1) dividing the geographical space into a Tree-based Hierarchical Graph (TBHG), and 2) assigning scores to each user and location that indicate the popularity of the location and the travel experience of the user. Figure 7 gives an example of a TBHG structure, in which the multiple layers on the right side of the figure represent the location clusters at different levels of granularity, and the tree structure on the left describes the relationships between the clusters on each level. The intuition behind the score assignment in (2) is that the more experienced users should be better able to recommend interesting locations, while the interesting locations are likely to be accessed by more experienced users.

In this model, a user's visit to a location is modeled as an edge from the user to the location. Thus, a user is a 'hub' if they have visited many locations, and a location is an 'authority' if it has been accessed by many users. Further, the user's travel experience and a location's interest have a mutually reinforcing relationship. Based on this relationship, a ranking of experienced users and interesting locations can be derived from the model using the following equations:

$$a_{ij}^{l} = \sum_{u_k \in U} v_{jk}^{k} \times h_{lq}^{k} \tag{2}$$

$$h_{lq}^{k} = \sum_{c_{ij} \in c_{lq}} v_{ij}^{k} \times a_{ij}^{l} \tag{3}$$

where the subscripts ij implies that the quantity x_{ij} is of the i^{th} level of the j^{th} cluster in the TBHG, h_{ij}^{k} represents the k^{th} user's experience, a_{ij}^{l} represents the location interest, and c_{lq} is c_{ij}'s parent node on the l^{th} level. The rating is local, as the system rates user experience and location interest at every level of the TBHG, which is consistent with the intuition, for example, that a very experienced user in New York may not have any idea of the interesting locations in Beijing. The authors use this model to extract the top n most interesting locations and the top k most experienced users in a given region using a power



(a) Regions (b) Routable graph (c) Top-1 route

Fig. 8 Construct Popular Routes. [102, 63]

iteration method. Based on the traveling trajectory from 108 users in GeoLife, the solution achieves the score at 1.6/2, which is at least 20% better than the ranking by count method, in a real user study.

3.1.2 Sequential Location Recommendations

Sequential location recommendations can have more complex objectives. For example, a suggested location path could maximize the number of interesting places visited while minimizing travel time or energy consumption. From a user's location history, one can infer how a users preferences for locations are correlated [132]. A number of sequential location recommender systems have been proposed based on either users' geo-tagged social media posts [94, 65, 58, 102, 63] and users' GPS trajectories [28, 15, 35, 36, 121, 122, 133].

1) Mining Geo-tagged social media. A user's geo-tagged social media content can be used as a knowledge base for making sequential location recommendations, e.g., as done in [4, 42]. In [94] the authors use association rule mining [2, 41] and sequence mining [40, 93] over sequences of locations extracted from geo-tagged photos. Based on the user's historical visiting pattern, the system creates an itinerary of scenic locations to visit that are popular among other users. Using a vast amount of geo-tagged photos collected from Panoramio, the authors of [65] propose a Travel Route Suggestion algorithm to suggest customized travel plans that take into account the time spent at each location, the total travel time, and user preferences. In [115], Yin et al. propose a trip recommendation method that focuses on ranking trajectory patterns mined from uploaded photos. In [58], the authors make use of users' historical visiting patterns, including the type of location, to suggest subsequent locations.

Representative Research In [102, 63], the authors propose the Route Inference framework based on Collective Knowledge (RICK) to construct popular routes from uncertain trajectories. Given a location sequence and a time span, RICK constructs the top-k routes by aggregating uncertain trajectories in a mutually reinforcing way. RICK is comprised of constructing a routable graph and inferring popular routes, as seen in Figure 8. First, RICK constructs a routable graph from uncertain trajectories by aggregating user check-in data. Second, a routing algorithm is used to construct the top-k routes according to a user-specified query. The proposed routable graph provides a good model of the uncertain trajectory with an accuracy of 0.9. Also, on average, the system can find the top-3 routes within 0.5 seconds, with a distance error smaller than 300 meters compared to its corresponding ground-truth.

2) Mining GPS trajectory.

GPS trajectories contain a rich set of information, including the duration a user spent at a location and the order of location visits, that can improve sequential location recommendations. In [28], the authors present a graph model for socio-spatial networks that stores information about frequently traveled routes and implement a route recommender system using their query language. In [15], the authors propose a route recommender system that takes into account a user's own historically preferred road segments, mined from the user's historical trajectories. The intuition for this approach is that users may feel more comfortable traveling on familiar roads. In [35], Ge et al 2011. propose an approach to travel recommendation based on the user's cost constraints, where the travel costs are learned using tour data from professional travel agencies. In [36], Ge et al. 2010 integrate energy consumption into a mobile recommender system by learning energy-efficient transportation patterns from trajectories. In [43], the system integrates the real-time information updates from the local community to recommend a better route to avoid the traffic.

Representative Research. The itinerary recommender system [121, 122, 133] further extended the previous works by incorporating additional constraints, such as 1) a total time constraint on the trip, e.g., a user only has 8 hours for traveling, 2) a destination constraint, which indicates that the user wants to end the trip with a selected location, e.g. a user may need to return to a hotel or the airport, and 3) a constraint on specific ratio metrics, including a) the elapsed time ratio (ETR) between the duration of the recommended trip to the total time constraint, which captures a user's desire to utilize as much available time as possible, b) the stay time ratio (STR) between the amount of time a user stays at location to the amount of time spent traveling between locations, which captures a user's desire to maximize the time in the interesting locations, and c) the interest density ratio (IDR), which is the summation of interest scores for all the locations in the trip over the maximum total interest. Figure 9 shows the architecture of the itinerary recommender system, containing the following two components:

Offline model building. The offline system builds the model used to identify interesting locations and estimate travel times. First, it detects points along the user trajectories at which a user has stayed at a location for some significant duration of time. Next, it clusters these points into interest locations. The duration of a user's stay and the travel time between each location is then computed. Finally, the system infers the interest level based on the HITS model.

Online recommendation. The online system receives a user's query, including a starting location, a destination, and a time constraint, and returns an itinerary with a sequence of locations. This computation involves three main steps, 1) query verification, which checks the feasibility of the query with the spatial and temporal constraints, 2) itinerary candidate selection, which collects the candidate itineraries based on the HITS model generated in the model building step, and 3) itinerary candidate ranking, which ranks the candidate trips based on the elapsed time ratio, stay time ratio, and interest density ratio.

3) Temporal analysis of user sequential locations.

Additionally, another branch of ongoing research aims to analyzing the temporal characteristics of users' sequential location history in LBSNs for better recommendations. For example, In [64], the authors explore the spatial and temporal relationships among individual points within trajectories to identify the sub-sequences related to the user's preferred activi-

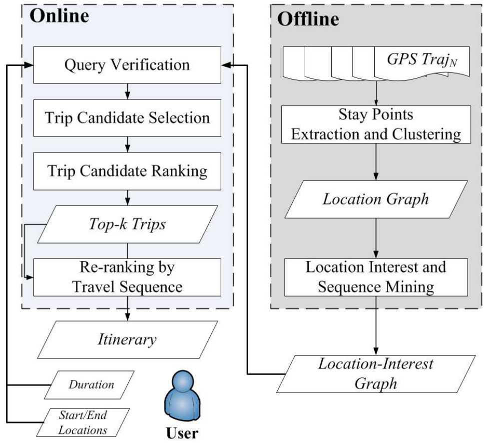


Fig. 9 An overview of itinerary recommender system [121, 122]

ties and assign to them a semantic meaning. Ye et al. 2011 [109] proposes a method to extract location features based on the temporal distributions of users' check-ins. Ye et al. [110] extends their work by considering two additional aspects, 1) a set of explicit patterns, including the total number of check-ins, the total number of unique visitors, the maximum number of check-ins by a single visitor, the distribution of check-in times in a week, and the distribution of check-in times in a 24-hour interval, and 2) implicit relatedness, which captures the correlations between locations in check-in behavior. Based on the temporal characteristics of users' check-in behaviors, recommender systems in LBSNs now recommend locations based on the current time. For example, Cho et al. [19] propose a location recommendation method based on the periodicity of the human movement. They propose two methods PMM (Periodic Mobility Model) and PSMM (Periodic Social Mobility Model) using a temporal probability distribution function and the social relations. [33] further extends the model with using more aggregated temporal functions, such as sum, mean, maximum and voting, over the users' check-in data. Most recently, Rahimi and Wang [79] further extend the existing work by studying the spatial and temporal periodicity activities in the users' check-in data, and propose two novel recommendation algorithms, Probabilistic Category Recommender, which uses the temporal probability distribution to recommend the category of location that would be interested for the user based on her historical behavior, and Probabilistic Category-based Recommender, which further considers the user's spatial traveling behaviors. The experimental results show that they can achieve over 15% improvement in both recall and precision evaluations.

Representative Research. Cho et al. [19] analyzed a large scale user check-in dataset from BrightKite and Gowalla, where they find that humans experience a combination of periodic movement affected by both the geographical location and the social relations. More specifically, their short-ranged travel is periodic both spatially and temporally and not effected by the social network structure, while long-distance travel is more influenced by social network ties. The data reveals that social relationships can explain about 10% to 30% of all human movement, while periodic behavior explains 50% to 70%.

Based on the insights, they propose two methods PMM (Periodic Mobility Model) and PSMM (Periodic Social Mobility Model) to predict/recommend the user's locations. In

PMM model, the authors define a limited number of states for the user that has periodicity activities, like home or work. Based on the different time of the day, they build a temporal component of PMM model as:

$$P[c_u] = H] = \frac{N_H(t)}{N_H(t) + N_W(t)} \tag{4}$$

$$P[c_u] = W] = \frac{N_W(t)}{N_H(t) + N_W(t)} \tag{5}$$

where $P[c_u(t)]$ models the probability distribution over the state of the user over time and $N_W(t)$ and $N_H(t)$ are with a truncated Gaussian distribution parameterized by the time of the day.

The spatial component is generated by modeling the movement when a user is in the home/work state using a 2-dimensional time-independent Gaussian distribution:

$$P[x_u(t) = x_i | c_u(t)] = \begin{cases} \mathcal{N}(\mu_H, \Sigma_H) & \text{if } c_u t = H \\ \mathcal{N}(\mu_W, \Sigma_W) & \text{if } c_u t = W \end{cases} \tag{6}$$

where Σ_H, Σ_w are the home, work check-in position co-variance matrices. μ_H and μ_H are the means of users check-in locations hen she is in home and work state, respectively.

PMMS model further improves the previous model by adding the factor from the user's social relations. To include the social network information to the model, we introduce another check-in classification $z_u(t)$, where $z_u(t) = 1$ implies the check-in is social (non-periodic) and $z_u(t) = 0$ implies that it is periodic. The PSMM mobility model then becomes:

$$\begin{aligned} P_u[x(t) = x] = P[x(t) = x | z_u(t) = 1] \cdot P[z_u(t) = 1] \\ + P[x(t) = x | z_u(t) = 0] \cdot P[z_u(t) = 0] \end{aligned} \tag{7}$$

where $P[x(t) = x | z_u(t) = 0]$ is the Periodic Mobility Model.

3.2 User Recommendations

User recommendations, which includes popular user discovery [98, 12, 38], friend recommendation [16, 5, 82, 104, 117], and community discovery [60, 103], have been extensively studied in the context of traditional social networks. The traditional user recommendation approaches are based on the underlying social structure and user interaction patterns. Location-based social networks provide a new way to make user recommendations by also considering users' location histories. Location histories provide rich contextual information and have significant correlations to real social behaviors [22]. Several studies reveal that geographical information actually plays a vital role in determining user relationships within social networks. For example, by analyzing the spatial dissemination of new baby names, [39] confirms the importance of geographical proximity, despite the interconnectedness of the Internet era. [59] shows that at least 2/3 of the friendships in an online social network are determined by the users' locations. [86] analyzes the data collected from a location-based social networking system (Foursquare) and finds that 1) about 40% of the connections are within 100 km, 2) a strong heterogeneity exists across users regarding the spatial distances of connections between their social ties and triads, and 3) gravity models may influence how these social connections are created. Thus, considering users' location histories in an LBSN can improve the effectiveness and efficiency of user recommendations. In this section, we summarize the existing work in user recommendation for location-based social networks, e.g., [48, 136, 56, 105, 120, 118], categorizing each work by its objective, 1) popular user discovery, 2) friend recommendation, or 3) community discovery.

Popular user discovery. Traditional approaches to popular user discovery [98, 12] find the opinion leaders in a social networking service by analyzing the node degrees within the information diffusion networks. In LBSNs, we consider 'popular users' to be the users with more knowledge about the locations. Finding experienced users is very important for the recommender systems in LBSNs as these users can provide high quality location recommendations. Zheng et al. 2009 [136] finds that a user's traveling experiences are regional, and a user's experience is best determined by considering the qualities of the locations in addition to the number of locations visited. The authors propose a system to identify experienced travelers by applying a HITS inference model over a Tree-Based Hierarchical Graph of users' historical trajectories. Ying et al. 2011 [118] extends the previous work and proposes four metrics that are used for analysis on EveryTrail (a website for sharing trips). They found that users who share more trajectories get more attention from other users, and users who are popular are more likely to connect to other popular users.

Friend recommendation. Traditional friend recommender systems provide a user with promising potential friends based on their user profiles [16, 104], the social structure [27], and the users' interactions [5, 38, 82]. Location information in can significantly improve the effectiveness of friend recommendations. The basic intuition is that user location histories reveal preferences, and thus users with similar location histories have similar preferences and are more likely to become friends. Several publications investigate the impact of users' geographical locations on their social relations. For example, a recent study [26] on MySpace data reveals that users' social connections are highly related to their geographical distances, i.e. that the users living close to each other are more likely to be friends. Moreover, Backstrom et al. [6] observe that at medium to long-range distances, the probability of friendship is roughly proportional to the inverse of the distance. However, at shorter ranges, distance does not play as large a role in determining the likelihood of friendships. Similarly, Scellato et al. 2011 [87] analyze a large set of data from Gowalla (a location-based social networking system), from which they find that the link prediction space can be reduced by 15 times by focusing on location-friends and friends-of-friends. Based on this observation, they propose a link predication model using supervised learning that considers the users' visited locations. Yu et al. [123] builds a pattern-based heterogeneous information network to predict connection probabilities using an unsupervised link analysis model. The connections inside the information network reflect users' geographical histories as well as their social relationships. The connection probability and the friend recommendation score are calculated by a random walk process over the user-location network. Other works, such as [19], study the relationship between user movement and friendships through an analysis of mobile phone communications and check-ins. The authors discover that users' short term periodical movement is irrelevant to social structure, but their long distance movement significantly affects their social structure.

A related body of research proposes to measure the similarity between two users from their historical locations and trajectories. Li et al. 2008 [56] present a user similarity algorithm that builds a tree-based hierarchical graph of locations. A user's detailed trajectory is abstracted as a set of sequentially visited locations. Based on a sequence matching algorithm that takes into account location hierarchies, the system finds users with similar traveling patterns. Xiao et al. [105] extend the user similarity approach by considering the

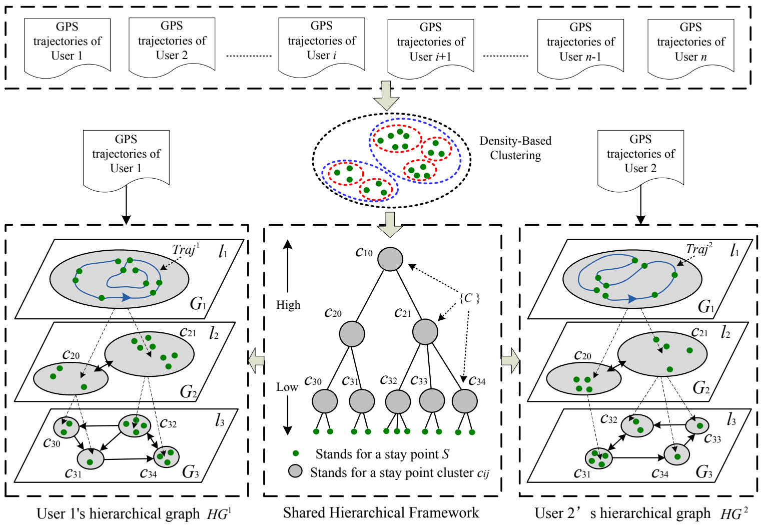


Fig. 10 Hierarchical graph modeling individual location history. [56]

available semantic information for each location, such as its tags and categories. This allows connections between users who have different geographic behaviors, e.g., living in different cities, but share similar semantic behaviors, i.e. they go to the same types of locations. For this approach, the authors transform users' trajectories int location histories with category information. Similarity scores between users are calculated by matching their maximal traveling sequences at different spatial granularities. Ye et al. 2010 [120] expand on the use of location semantic information. Their framework consists of four phases, 1) semantic trajectory transformation, which converts a user trajectory into a sequence of locations with semantic data, such as parks and schools; 2) maximum semantic trajectory pattern mining, which applies the sequential pattern mining algorithm to each user's trajectory to find the most frequent sequence, 3) semantic similarity measurement, which computes a similarity score between users maximum semantic trajectories, and 4) potential friend recommendation, which uses the constructed user similarity matrix to suggest potential friends.

Representative Research. Zheng et al. 2011 [134] further extends the user similarity measure framework presented in [56] by considering the sequences of locations at different spatial granularities. The authors propose a new sequence matching algorithm that divides the location sequences and considers the popularity of each visited locations separately. The newly proposed framework, referred to as a hierarchical-graph-based similarity measurement (HGSM, shown in Figure 10), is proposed to model each individual's location history and measure the similarity between each user. This similarity is based on the users' location histories and is measured using three factors, 1) the shared sequence of users' movements, i.e. the longer the sequence of similar visitations shared by two users, the more similar the two users, 2) the baseline popularity of the locations, e.g. two users visiting a location less traveled might be more correlated than others visiting a popular location, and 3) the hierarchy of geographic spaces, i.e. the finer the granularity of geographic regions shared by two individuals, the more similar these two individuals. The system reports a mean of the precision score at 0.92, which significantly out-performs the conventional cosine similarity measure.

Community discovery. Traditional approaches to community discovery often cluster users with either spectral clustering [68, 100, 57] or tensor factorization [60] based on the social structure (see [37] for a detailed survey). With the availability of location information, community discovery in LBSNs can be extended to discover user communities with similar location preferences. For example, [48] clusters users based on their traveling patterns, which are mined from their trajectories. First, the authors extract each user's frequently visited locations. They then apply a distance based clustering algorithm to discover communities within the social networks. This computation includes 1) constructing profiles, consisting of a probability suffix tree (PST) for each user describing the frequency of location visits, 2) measuring the distance between profiles, and 3) identifying communities using a clustering algorithm.

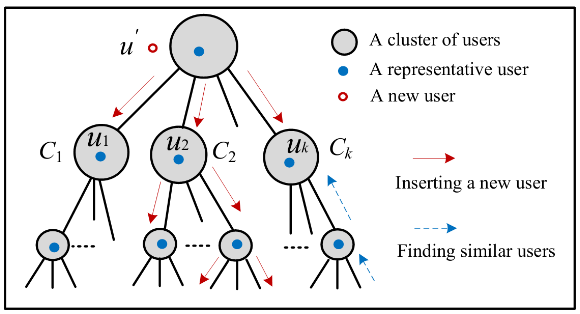


Fig. 11 Hierarchical graph modeling individual location history. [106]

Representative Research. Xiao et al. 2012 [106] present an example of this line of research. They hierarchically cluster users into groups by clustering according to the similarity measure proposed in [105]. Consequently, as depicted in Figure 11, they can build a hierarchy of user clusters, where a cluster denotes a group of users sharing some similar interests, at different levels of similarity. The clusters on the higher layers stand for big communities in which people share some high-level interests, e.g. sports. The clusters occurring at the lower layers denote people sharing some narrower interests, e.g. hiking a particular mountain. During the experiments, the authors find that users sharing (1) a ner semantic location, (2) a longer sequence of locations, and (3) less popular semantic locations would be more similar to each other

3.3 Activity Recommendations

An activity recommendation in an LBSN is an information retrieval operation of one or more activities that are appropriate for a query location. For example, sightseeing, boating, and jogging could be recommended for the Olympic Park of Beijing. A list of possible activities at a location can be obtained directly from user-labeled tags or inferred from users' location histories and the semantic data attached to each location.

3.3.1 Individual Inference-based Approaches

A user's activity at a certain location can be inferred from the user's geo-tagged social media data and the POI dataset. For example, Yin et al. 2011 [116] studied the distributions of some geographical topics (like beach, hiking, and sunset) from the geo-tagged photos acquired from Flickr. Pozdnoukhov and Kaiser [77] studied a large set of geo-tagged tweets to explore the spatial-temporal distribution of the topical content. The authors show that the topics, and thus activities, are often geospatially correlated. Hung et al. 2010 [47] propose a method to automatically detect activities using the spatial temporal attractiveness (STPA) of points of interest (POI). By comparing the sub-trajectories contained in each POI's STPA, the authors show that most likely activities and their durations can be discovered. The accuracy of this method depends on the POIs and trajectories having accurate arrival time, duration, spatial accuracy, as well as other background factors. [72] also combines with the users communication patterns to infer the urban activity in a supervised learning framework.

3.3.2 Collaborative Learning-based Approaches

One shortcoming of individual inference-based approaches is that they have difficulty dealing with data sparsity, which can be a common occurrence in LBSNs as some users may have a limited location history and some locations may receive few visitors. An alternative approach based on collaborative learning uses information from all users to discover activities. This idea was first proposed in [129], which extracts the location semantics from GPS data and uses it in conjunction with user profile data to identify activities. The system exploits the connections between the user activities and profiles in a joint learning process. Further, Zheng et al. 2010 [127] propose a new model for location and activity histories using a user-location-activity rating tensor. Their system uses this model to provide location-specific activity recommendations. [128] proposes a new algorithm that uses a ranking-based collective tensor and matrix factorization model. Separately, [75] extends the previous work by using the Higher Order Singular Value Decomposition (HOSVD) technique to perform dimensionality reduction and semantic analysis. As more data is accumulated by their system, it uses incremental solutions to update a tensor that includes users, locations and activities.

Representative Research. [127] provides location and activity recommendations in LBSNs to answer two questions for the tourists, 1) where to go for activities such as sightseeing or dining in a large city and 2) what activities are available at specific locations, e.g. if someone visits the Bird's Nest in Beijing Olympic park, what can they do there? The major challenge is due to data sparsity, as users in the system have very limited histories. To this end, the authors propose a collaborative-based approach to extract the features for the locations. Three matrices are constructed as the data model, as shown in Figure 12:
Location-activity matrix. A user can log an activity in order to associate it with a point in a trajectory. For example, in Foursquare, users can associate content with venues to share with their friends. The specification of both activity and location in this social media enables the authors to study the correlation between locations and activities and to construct a location-activity matrix. Ideally, the activities associated with a location can be discovered from the location-activity matrix. However, the matrix is typically very sparse as the amount of user-added content is dwarfed by the number of locations. To address this, the paper uses the location-feature and activity-activity matrices to infer missing items in the location-activity matrix, as shown in Figure 12.

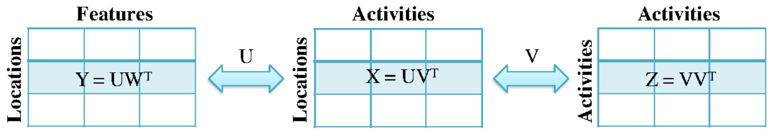


Fig. 12 Collaborative location-activity leaning model. [127]

Location-feature matrix. This matrix connects locations and categories (such as restaurants, cafes, and bars) based on the intuition that locations of the same category are likely to have the same activity possibilities. In this matrix, a location may include multiple categories (or features). For example, a mall would include shops, movie theaters, and cafes. The matrix is built from a POI database, in which each POI is associated with a set of properties such as, name, address, GPS coordinates, and categories.
Activity-activity matrix. This matrix models the correlations between different activities. From this, the authors infer the likelihood of an activity being performed at a location given that a user has performed some other activity. The paper suggests two ways to determine these correlations, (1) by mining the user-created content and (2) by using the number of search engine results for the activity terms (if the user-content is insufficient).

After the system constructs the three matrices, a filtering approach is applied to train the location-activity recommender system using collective matrix factorization [91]. An objective function, shown in Equation 8, is defined to infer the missing values. This function is iteratively minimized using gradient descent.

$$L(U,V,W) = \frac{1}{2} \parallel I \circ (X - UV^T) \parallel_F^2 + \frac{\lambda_1}{2} \parallel Y - UW^T \parallel_F^2 + \frac{\lambda_2}{2} \parallel Z - VV^T \parallel_F^2 + \frac{\lambda_3}{2} (\parallel U \parallel_F^2 + \parallel V \parallel_F^2 + \parallel W \parallel_F^2) \tag{8}$$

Where $\| \cdot \|_F$ denotes the Frobenius norm. I is an indicator matrix with its entry $I_{ij} = 0$ if X_{ij} is missing, $I_{ij} = 1$ otherwise. The operator "$\circ$" denotes the entry-wise product. As shown in Figure 12, the authors propagate the information among $X_{m \times n}$, $Y_{m \times l}$ and $Z_{n \times n}$ by requiring the matrices to share the low-rank matrices $U_{m \times k}$ and $V_{n \times k}$. The first three terms in Equation 8 control the loss in matrix factorization, and the last term controls the regularization over the factorized matrices to prevent over-fitting. From the final location-activity matrix, the top k values are suggested as activities for the location.

One limitation of the proposed activity recommendation approach is that it can not provide personalized recommendations for the users that take into account each user's preferences. Therefore, [126] extends the approach to create a personalized activity recommender system which includes user-user and user-location matrices. Specifically, the authors model the user-location-activity tensor $\mathcal{A}$ under the factorization framework and use additional information to address the data sparsity issue. Figure 13 illustrates the new tensor model. Data scarcity results in missing entries in tensor $\mathcal{A}$ that must be filled. In addition to the location-features, activity-feature, and activity-activity matrices used in the previous system, the matrix $B \in \mathbb{R}^{m \times m}$, which encodes the user-user similarities, and the matrix $E \in \mathbb{R}^{m \times n}$, which models the user's location visiting preferences, are added to the computation. Finally, to fill the entries in tensor $\mathcal{A}$, model-based methods are applied [92,91] to decompose the tensor $\mathcal{A}$ with respect to each tensor entity.

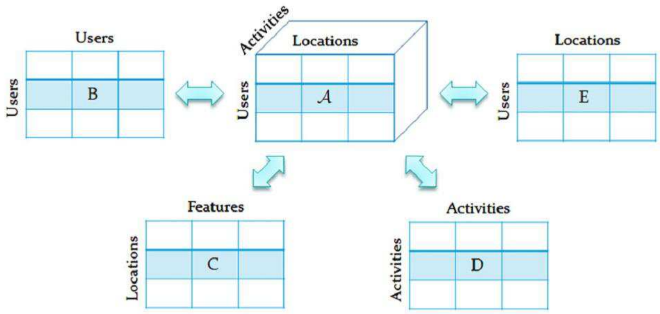


Fig. 13 Personalized Collaborative location-activity leaning model [127].

3.4 Social Media Recommendations

Social media recommendation aims to provide users with suggestions of photos, videos, or other web content they might like. Using location information in LBSNs can improve both the effectiveness and efficiency of traditional social media recommendations. Several works in spatial keyword searching for web content show the effectiveness of this pairing, e.g., [17, 124, 10, 84].

[69] analyzes the rating data from MovieLens [70] and finds that people at different locations have different preferences. For example, users from Minnesota are more interested in crime and war movies, while users from Florida are more interested in fantasy and animation movies. Location-aware image ranking algorithms have been proposed to increase the relevance of the search results, e.g., [3, 50]. [90] improves the quality of the image tags using a recommender system to automatically infer and suggest candidate location tags. [23] discovers events using both social and location information. [46] propose a topic model that considering the spatial and textual aspects of the user's post and build a spatial topic model to capture the relation between the user's location and interests.

The efficiency of recommender systems can be significantly improved by using location data to prune out irrelevant information. [85] improves the efficiency of content delivery networks using a novel caching mechanism based on geographic location. [83] builds a real-time recommender system for online web content using a collaborative filtering method to make more diverse and personalized recommendations within a geographical area. [55] proposes a novel location-aware recommendation framework, LARS, which considers the influences of the spatial ratings and spatial users in the location-aware recommendations. In [84], the authors further extend the viral marketing model in a location-based social network, where they consider the user opinion, spatial distance and the social influences to recommend a best set of customers to the venue owners that may maximize the potential profit.

4 Categorization by Methodology

Although traditional recommendation systems have been successful by using community opinions, e.g., inventories in Amazon [61] and news from Google [24], incorporating location information requires novel approaches. In this section, we categorize the major methodologies used by recommendation systems in location-based social networks as being based on: 1) content, 2) link analysis, or 3) collaborative filtering.

4.1 Content-based Recommendations

Content-based recommendation systems, such as [76, 80], match user preferences, discovered from users' profiles, with features extracted from locations, such as tags and categories, to make recommendations. These systems require accurate and structured information for both the user profiles and the location features to make high quality recommendations.

The major advantages of the content-based approach that such a system is robust against the cold start problem for both new users and locations. As long as the newly added user or location has the appropriate descriptive content, they can be handled effectively. However, content-based recommendation systems have many drawbacks in regard to LBSNs: 1) content-based recommendation systems do not consider the aggregated community opinions (inferred from users), which may result low quality recommendations, and 2) content-based recommendation systems require that the structured information for both users and locations be created and maintained, which can be costly, especially in LBSNs in which the majority of the contents (i.e., user profiles and location tags) are generated by the users.

4.2 Link analysis-based Recommendations

Link analysis algorithms, e.g., PageRank [74] and Hypertext Induced Topic Search (HITS) [14, 51], are widely used to rank the web pages. These algorithms extract high quality nodes from a complex network by analyzing the structure. In LBSNs, there are interconnected networks of different types, e.g., user-user, user-location, and location-location networks. [136] extends the HITS algorithm for discovering experienced users and interesting locations in an LBSN. In their system, each location is assigned a popularity score, and each user is assigned a hub score, which indicates their travel expertise. Based on a mutually reinforcing relationship, a ranking of expert users and interesting locations is computed. Similarly, [81] extends a random walk-based link analysis algorithm to provide location recommendation.

The advantages of link analysis-based methodologies are that 1) they take into account the user's experiences when making recommendations and amplify ratings from experienced users, and 2) they are robust against the cold start problem. However, they have a major drawback: they can only provide generic recommendations for all users, which overlooks users' personal preferences.

4.3 Collaborative Filtering-based Recommendations

Collaborative filtering (CF) is widely used in conventional recommendation systems [1]. The intuition in extending the CF model for recommendations in LBSNs is that a user is more likely to visit a location if it is preferred by similar users. The CF approach used by recommender systems in LBSNs consists of three processes: 1) candidate selection, 2) similarity inference, and 3) recommendation score predication.

Candidate Selections. The first step of CF-based recommendation systems is to select a subset of candidate nodes to reduce the computational overhead. The traditional CF-based recommendation algorithms use the most similar users (or locations, activities, etc.) as the candidates. CF-based recommender systems in LBSNs can also use geographic bounds and associations to constrain the candidate selection process. A spatial range can be computed to prune candidate locations, e.g., [20]. [45] selects candidate users by considering only individuals who live near the user's querying location. Non-geographic criteria can also be used. In [111], the authors select candidates by considering user preference and social influence, but also geographic influence modeled as a power-law probabilistic model.

Similarity Inferences. Similarities between users (or locations, activities, etc.) are inferred from users' ratings and location histories in LBSNs. The traditional CF models can be divided into two subgroups: 1) user-based models, such as [44], that use similarity measures between each pair of users; and 2) item-based models, such as [53], that use similarity measures between each pair of items (media content, activities, etc.). The following equation demonstrates a simple user similarity computation for user u and u' using the Cosine correlation function in a user-based CF model:

$$\mathit{UserSim}(u,u') = \frac{\sum_{o\in\mathcal{O}} r(o,u)\times r(o,u')}{\sqrt{\sum_{o\in\mathcal{O}} r(o,u)^2}\sqrt{\sum_{o\in\mathcal{O}} r(o,u')^2}} \tag{9}$$

where $r(o,u)$ is the rating user u gives to each object o in the set of all objects O. Many of the existing recommendation systems in LBSNs, e.g., [20,45,111,25], provide location recommendations based on the distribution of user's ratings over their visited locations using the above equation.

Similarity inference between users (and locations etc.) can also be done by analyzing the pattern of location co-visitation. Recently, systems have been proposed that use the number of visitations (e.g., tips and check-ins) at locations as an implicit rating of the location, e.g., [95,89]. Location similarity can also be captured using sequential relations [56] or semantic similarities [105].

Recommendation Score Predication. Finally, CF systems predict a recommendation score for each object o_i (locations, social media, etc.) in the candidate set. These scores are calculated from ratings given by the set of users (U) and the similarity measures between individual users. The following equation gives an example of a recommendation score computation:

$$\mathit{RecScore}(o_i,u) = \frac{\sum_{u_j\in\mathcal{U}'} \mathit{UserSim}(u,u_j)\times r(o_i,u_j)}{\sum_{u_j\in\mathcal{U}':r(o_i,u_j)>0} |\mathit{UserSim}(u,u_j)|} \tag{10}$$

The advantages of the collaborative filtering models are that 1) they do not need to maintain well structured descriptions of items (locations, activities, etc.) or users, and 2) they take advantage of community opinions, which provide high quality recommendations. However, CF models also suffers from several drawbacks: 1) when data is sparse, e.g. the number of user ratings is low, the user-item (location, etc.) rating matrix is very sparse and the collaborative filtering model fails to make effective recommendations; 2) due to the large number of users and items in the systems, the similarity model construction process is very time consuming, presenting a scalability challenge that is exacerbated by the rapid growth and evolution of LBSNs, and 3) the CF model deals poorly with the cold start problem, providing recommendations for new users or new items in the system.

5 Categorization by Data Sources

In this section, we summarize the different types of data sources used in recommender systems for LBSNs, including 1) user profiles, 2) user online histories, and 3) user location histories.

5.1 User Profiles

As in the conventional social networks, LBSN users maintain profiles that may include demographic data, interests, and preferences. Such profile information is used by many content-based recommender systems, e.g., [76], to recommend locations based on the location's categories, user generated tags, etc. Other research, e.g. [109, 110], focuses on improving the accuracy of the location tags and categories by extracting user activity patterns for each location.

5.2 User Online Histories

Users' online histories come in three main classes, user ratings, user interaction patterns, and user search histories. Users in LBSNs may leave explicit ratings for locations to express their opinions, just as they can in traditional recommender systems. User ratings in LBSNs are associated with locations and can be used to find similar users or similar locations, e.g., [20, 45, 111]. User interaction patterns in LBSNs include user tags and commenting patterns. The user interaction patterns are used for friend recommendation and community discovery systems, e.g. as in [38, 104]. User search histories include map browsing histories and spatial searching logs. By accumulating such information, recommender systems can estimate the community's knowledge and preferences, e.g., [101, 7, 99].

5.3 User Location Histories

A user location history is a record of a user's previously visited locations accumulated in an LBSN, including for example check-in data and trajectories. A user's location history can be a more accurate data source to study the user's behaviors and preferences as it records where users actually go, rather than what they list as preferences. Location histories can also be used for friend recommendation. For example, when two users share the location history sequence or stay similar amounts of time at a same location, it provides evidence that the users share preferences and interests.

6 Performance Evaluation

In this section, we first summarize several popular location-based social networking datasets. After that, we describe the typical methods used to verify the effectiveness of the recommendation results.

6.1 Datasets

There are many famous benchmark datasets available, like MovieLens [70] and Netflix [71], for evaluating the effectiveness and efficiency of the traditional recommendation techniques. There are also several real location-based social networking datasets available from different online services. In this subsection, we briefly introduce these real-world services, and then describe the basic properties/statistics of the datasets. Table 4 provides an overview of the datasets described in this subsection.

Table 4 LBSN Datasets Used in Recommendation Evaluations.

Name	Type	Statistics
GeoLife [131]	GPS trajectory	17,621 trajectories from 182 users.
Brightkite [19]	Check-ins & Friendships	4,491,143 check-ins from 58,228 users
Gowalla [19]	Check-ins & Friendships	6,442,890 check-ins from 196,591 users
Twitter [18]	Geo-tagged Tweets	22,506,721 tweets from 225,098 users
Foursquare 1 [73]	Check-ins	12,000,000 check-ins from 679,000 users
Foursquare 2 [8]	Check-ins, Friendships, User Profiles & Venue Information	325,606 check-ins from 80,606 users
Foursquare 3 [33]	Check-ins, Friendships, User Profiles & Venue Information	Three sets of check-ins from 33,596 users

GeoLife [131] This trajectory dataset [1] was collected in (Microsoft Research Asia) Geolife project by 182 users in a period of over three years. Each data entry is a sequence of time-stamped points, each of which contains the information of latitude, longitude and altitude, recorded by different GPS loggers and GPS-phones, and have a variety of sampling rates. This dataset recorded a broad range of users outdoor movements, including shopping, sightseeing, dining, hiking, and cycling.

BrightKite [19] Brightkite was a location-based social networking website, where the users were able to ”check in” at places and able to see who has been there before. The service is not available currently, as it was acquired by Limbo. The dataset [2] is collected by BrightKit public APIs, and consists of a social network 58,228 users and 214,078 relations and a series of users’ check-in histories (total of 4,491,143 check-ins).

Gowalla [19] Gowalla was a location-based social networking website where users share their locations by check-ins. However, the service is not available currently, as it was acquired by Facebook in December 2012. This dataset [3] is collected by Gowalla public APIs, including a user friendship network (with 196,591 users and 950,327 relations) and a total of 6,442,890 check-ins from these users.

[1] http://research.microsoft.com/en-us/downloads/b16d359d-d164-469e-9fd4-daa38f2b2e13/

[2] http://snap.stanford.edu/data/loc-brightkite.html

[3] http://snap.stanford.edu/data/loc-gowalla.html

Twitter [18] This dataset [4] contains 22 million geo-tagged tweets collected via Twitter APIs. The geo-tagged information was posted from more than 1,200 applications. More than 53% of the tweets are from Foursquare, and most of the other tweets are from Twitter's applications on mobile platforms like Blackberry, Android, and iPhone. A few hundred thousands are from other location sharing services like Gowalla, Echofon, and Gravity.

Foursquare 1 [73] Foursquare [5] is a location-based social networking website, where the users can check-in/comment at the nearby venues. This dataset contains approximately 12,000,000 user check-ins over a period of 111 days, describing the mobility patterns of more than 679,000 users across about 3 million geo-tagged and categorized venues.

Foursquare 2 [8] This dataset [6] contains 221,128 check-ins generated by 49,062 users in New York City (NYC) and 104,478 check-ins generated by 31,544 users in Los Angeles (LA). This dataset also includes the detailed information about the venue profiles, like the name and category information.

Foursquare 3 [33] This dataset [7] contains three datasets from Foursquare: a) check-in history of 18107 users, b) check-in history of 11326 users, and c) 4163 users who live in the California. Each user in the dataset has the profile, friendship relations, and each venue contains its category information.

6.2 Evaluation Methods

recommender systems in LBSNs have typically used two methods to evaluate the effectiveness of their recommendations, 1) user studies and 2) precision and recall ratios.

User Studies. To conduct a user study of a recommender system, the researchers invite multiple subjects to use the recommender system and evaluate its performance, e.g., [127]. For each recommendation task, the subjects need to evaluate the top-k recommendations suggested by the recommendation system.

To create a baseline for evaluation, researchers aggregate all the feedback provided by the subjects to create an ideal ranking list. As recommendations are based on result rankings, the normalized discounted cumulative gain (nDCG) [66] is used to measure the effectiveness of the recommendation list. nDCG is also commonly used in information retrieval to measure search engine performance. A higher nDCG value means that more relevant items appear first in the results list.

Precision and Recall Ratios. Precision and recall ratios are also used to evaluate the effectiveness of recommendations in LBSNs, e.g., [112, 8]. To use this evaluation method, a user's location history is divided into two parts, 1) the location history generated within a query area, which is used as ground truth, and 2) the rest of the user's location history, which is used as a training set to learn the user's preferences and build the recommendation model. The system is then evaluated by whether it can suggest those sites within the querying region that the user has actually visited based on the training data (the location history outside of the query region).

For example, in the left part of Figure 14, the black dots are the venues the user visited. A system trained with data outside the query region (the dotted square) recommends the

[4] http://infolab.tamu.edu/data/
[5] http://www.foursquare.com
[6] http://research.microsoft.com/en-us/projects/lbsn/default.aspx
[7] http://www.public.asu.edu/ hgao16/dataset.html

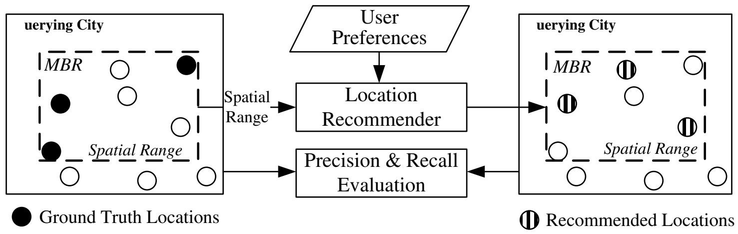


Fig. 14 Evaluate Recommendation using Precision and Recall Ratios. [8]

venues illustrated by the striped dots in the right part of Figure 14. Using the black dots as ground truth, recall and precision can be calculated.

$$precision = \frac{number\ of\ recovered\ ground\ truths}{total\ number\ of\ recommendations} \tag{11}$$

$$recall = \frac{number\ of\ recovered\ ground\ truths}{total\ number\ of\ ground\ truths}. \tag{12}$$

This evaluation measurement may be pessimistic as, for example, a user may still prefer a location even if the user has not yet visited it.

7 Future Work

Although many recommender systems have been proposed in LBSNs, there are still many open questions and challenges to be addressed. In this section, we summarize potential research directions to improve the effectiveness and efficiency of recommender systems in LBSNs.

7.1 Effectiveness of Recommendations

To improve their effectiveness, recommender systems need more accurate estimations of user preferences and social knowledge. Potential paths to achieve this include 1) using diverse data sources, 2) integrating and hybridizing different types of recommendation methodologies, and 3) increasing context awareness.

Diverse Data Sources. Most recommender systems in LBSNs currently use only one type of the data source to make recommendations. However, there are many different types data in LBSNs, e.g., users' friendships, online interactions, and user location histories. By considering more diversified data sources, more effective recommendations can be provided. For instance, the user online interactions, social structures, and location histories are all very relevant to friend recommendation. If two users have more online interactions, are close in the social structure, and have overlapped location histories, these users are likely to be compatible. A friend recommender system that can consider all these factors will make higher quality friend recommendations. In addition, other data sources outside LBSNs, such as POIs, road networks, and traffic conditions, can also be considered in the recommendation.

fusing the knowledge from multiple heterogeneous data sources into a recommendation system is also a challenge [130].

Hybrid Methodologies. The recommendation methodologies used in the existing recommender systems each have their own drawbacks. For example, in collaborative filtering based recommender systems, data sparsity and cold starts are challenging problems. Link analysis-based recommender systems avoid these problems, but only provide generic recommendations that ignore users' personal preferences. By integrating CF and link analysis-based techniques, a hybrid recommender system could overcome the weaknesses of both.

Context Awareness. Current recommender systems in LBSNs use a user's history to extract preferences. However, the user's context is currently ignored. A context aware recommender system in LBSNs would need to consider 1) user context, including static attributes like income, profession, and age, as well as dynamic attributes include current user location, mood, and status, (e.g., at home or in meeting) and 2) environmental context, including information about the surrounding environment, e.g. the current time, weather, traffic conditions, events, etc.

7.2 Efficiency of Recommendations

Recommendations in LBSNs can be computationally costly, especially given the frequency with which users add new location data and content.

User Mobility. Users in LBSNs interact with the services using mobile devices and want up-to-date recommendations based on their current location. However, processing continuous recommendation requests as multiple individual requests is inefficient as many redundant computations are undertaken between the consecutive recommendation queries. To address this, more advanced recommendation algorithms are required that leverage prior computations to reduce the cost of continuous recommendation requests.

Frequent User Updates. Users in LBSNs can be very active. They visit many locations over short time spans, which adds information related to their preferences at a high rate. It is very inefficient to re-compute the user preferences and user similarities every time a user undertakes a new activity. As a result, new recommendation techniques are required to efficiently address the update frequency in LBSNs.

8 Conclusion

Motivated by the prevalence of location-based social networks and the importance of recommender systems, we have provided a systematic survey of the related recent research. We studied over 60 papers published in the last five years, including but not limited to KDD, WWW, RecSys, UbiComp, ACM SIGSPATIAL LBSN, ACM TIST, and ACM TWEB. We provided categorizations of existing systems in regard to their data sources, their methodologies, and their recommendation objective. This survey presents a panorama of this research with a balanced depth and scope. Further, this survey serves as a tutorial, introducing the concepts, unique properties, challenges, representative solutions and systems, evaluation methods, and future work for recommender systems in LBSNs.

References

1. Gediminas Adomavicius and Alexander Tuzhilin. Toward the next generation of recommender systems: A survey of the state-of-the-art and possible extensions. *Knowledge and Data Engineering, IEEE Transactions on*, 17(6):734–749, 2005.
2. Rakesh Agrawal, Ramakrishnan Srikant, et al. Fast algorithms for mining association rules. In *Proc. 20th int. conf. very large data bases, VLDB*, volume 1215, pages 487–499, 1994.
3. Yuki Arase, Xing Xie, Manni Duan, Takahiro Hara, and Shojiro Nishio. A game based approach to assign geographical relevance to web images. In *Proceedings of the 18th international conference on World wide web*, pages 811–820. ACM, 2009.
4. Yuki Arase, Xing Xie, Takahiro Hara, and Shojiro Nishio. Mining people's trips from large scale geo-tagged photos. In *Proceedings of the international conference on Multimedia*, pages 133–142. ACM, 2010.
5. Lars Backstrom and Jure Leskovec. Supervised random walks: predicting and recommending links in social networks. In *Proceedings of the fourth ACM international conference on Web search and data mining*, pages 635–644. ACM, 2011.
6. Lars Backstrom, Eric Sun, and Cameron Marlow. Find me if you can: improving geographical prediction with social and spatial proximity. In *Proceedings of the 19th international conference on World wide web*, pages 61–70. ACM, 2010.
7. Andrea Ballatore, Gavin McArdle, Caitriona Kelly, and Michela Bertolotto. Recomap: an interactive and adaptive map-based recommender. In *Proceedings of the 2010 ACM Symposium on Applied Computing*, pages 887–891. ACM, 2010.
8. Jie Bao, Yu Zheng, and Mohamed Mokbel. Location-based and preference-aware recommendation using sparse geo-social networking data. In *ACM SIGSPATIAL*, 2012.
9. S Borzsony, Donald Kossmann, and Konrad Stocker. The skyline operator. In *Data Engineering, 2001. Proceedings. 17th International Conference on*, pages 421–430. IEEE, 2001.
10. Ourdia Bouidghaghen, Lynda Tamine, and Mohand Boughanem. Personalizing mobile web search for location sensitive queries. In *Mobile Data Management (MDM), 2011 12th IEEE International Conference on*, volume 1, pages 110–118. IEEE, 2011.
11. Dirk Brockmann, Lars Hufnagel, and Theo Geisel. The scaling laws of human travel. *Nature*, 439(7075):462–465, 2006.
12. Ronald S Burt. The social capital of opinion leaders. *The Annals of the American Academy of Political and Social Science*, 566(1):37–54, 1999.
13. Xin Cao, Gao Cong, and Christian S Jensen. Mining significant semantic locations from gps data. *Proceedings of the VLDB Endowment*, 3(1-2):1009–1020, 2010.
14. Soumen Chakrabarti, Byron Dom, Prabhakar Raghavan, Sridhar Rajagopalan, David Gibson, and Jon Kleinberg. Automatic resource compilation by analyzing hyperlink structure and associated text. *Computer Networks and ISDN Systems*, 30(1):65–74, 1998.
15. Kai-Ping Chang, Ling-Yin Wei, Wen-Chih Peng, and Mi-Yeh Yeh. Discovering personalized routes from tejaectories. In *GIS-LBSN*, 2011.
16. Jilin Chen, Werner Geyer, Casey Dugan, Michael Muller, and Ido Guy. Make new friends, but keep the old: recommending people on social networking sites. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*, pages 201–210. ACM, 2009.
17. Yi Chen, Wei Wang, Ziyang Liu, and Xuemin Lin. Keyword search on structured and semi-structured data. In *Proceedings of the 2009 ACM SIGMOD International Conference on Management of data*, pages 1005–1010. ACM, 2009.
18. Zhiyuan Cheng, James Caverlee, Kyumin Lee, and Daniel Z Sui. Exploring millions of footprints in location sharing services. *ICWSM*, 2011:81–88, 2011.
19. Eunjoon Cho, Seth A Myers, and Jure Leskovec. Friendship and mobility: user movement in location-based social networks. In *Proceedings of the 17th ACM SIGKDD international conference on Knowledge discovery and data mining*, pages 1082–1090. ACM, 2011.
20. Chi-Yin Chow, Jie Bao, and Mohamed F. Mokbel. Towards Location-Based Social Networking Services. In *The 2nd ACM SIGSPATIAL International Workshop on Location Based Social Networks*, 2010.
21. Nick Couldry and Anna McCarthy. *Mediaspace: Place, scale and culture in a media age*. Routledge, 2004.
22. Justin Cranshaw, Eran Toch, Jason Hong, Aniket Kittur, and Norman Sadeh. Bridging the gap between physical location and online social networks. In *Proceedings of the 12th ACM international conference on Ubiquitous computing*, pages 119–128. ACM, 2010.
23. Elizabeth M Daly and Werner Geyer. Effective event discovery: using location and social information for scoping event recommendations. In *Proceedings of the fifth ACM conference on Recommender systems*, pages 277–280. ACM, 2011.

24. Abhinandan S Das, Mayur Datar, Ashutosh Garg, and Shyam Rajaram. Google news personalization: scalable online collaborative filtering. In *Proceedings of the 16th international conference on World Wide Web*, pages 271–280. ACM, 2007.
25. Lucia Del Prete and Licia Capra. differs: A mobile recommender service. In *Mobile Data Management (MDM), 2010 Eleventh International Conference on*, pages 21–26. IEEE, 2010.
26. Peter DeScioli, Robert Kurzban, Elizabeth N Koch, and David Liben-Nowell. Best friends alliances, friend ranking, and the myspace social network. *Perspectives on Psychological Science*, 6(1):6–8, 2011.
27. Peter G Doyle and J Laurie Snell. Random walks and electric networks. *Carus mathematical monographs*, 22, 1984.
28. Yerach Doytsher, Ben Galon, and Yaron Kanza. Storing routes in socio-spatial networks and supporting social-based route recommendation. In *Proceedings of the 3nd ACM SIGSPATIAL International Workshop on Location Based Social Networks*. ACM, 2011.
29. Nathan Eagle and Alex Pentland. Reality mining: sensing complex social systems. *Personal and ubiquitous computing*, 10(4):255–268, 2006.
30. Nathan Eagle and Alex Sandy Pentland. Eigenbehaviors: Identifying structure in routine. *Behavioral Ecology and Sociobiology*, 63(7):1057–1066, 2009.
31. Nathan Eagle, Alex Sandy Pentland, and David Lazer. Inferring friendship network structure by using mobile phone data. *Proceedings of the National Academy of Sciences*, 106(36):15274–15278, 2009.
32. Gregory Ference, Mao Ye, and Wang-Chien Lee. Location recommendation for out-of-town users in location-based social networks. In *Proceedings of the 22nd ACM international conference on Conference on information & knowledge management*, pages 721–726. ACM, 2013.
33. Huiji Gao, Jiliang Tang, Xia Hu, and Huan Liu. Exploring temporal effects for location recommendation on location-based social networks. In *Proceedings of the 7th ACM conference on Recommender systems*, pages 93–100. ACM, 2013.
34. Huiji Gao, Jiliang Tang, and Huan Liu. Addressing the cold-start problem in location recommendation using geo-social correlations. *Data Mining and Knowledge Discovery*, pages 1–25, 2014.
35. Yong Ge, Qi Liu, Hui Xiong, Alexander Tuzhilin, and Jian Chen. Cost-aware travel tour recommendation. In *Proceedings of the 17th ACM SIGKDD international conference on Knowledge discovery and data mining*, pages 983–991. ACM, 2011.
36. Yong Ge, Hui Xiong, Alexander Tuzhilin, Keli Xiao, Marco Gruteser, and Michael Pazzani. An energy-efficient mobile recommender system. In *Proceedings of the 16th ACM SIGKDD international conference on Knowledge discovery and data mining*, pages 899–908. ACM, 2010.
37. Lise Getoor and Christopher P Diehl. Link mining: a survey. *ACM SIGKDD Explorations Newsletter*, 7(2):3–12, 2005.
38. Eric Gilbert and Karrie Karahalios. Predicting tie strength with social media. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*, pages 211–220. ACM, 2009.
39. Jacob Goldenberg and Moshe Levy. Distance is not dead: Social interaction and geographical distance in the internet era. *arXiv preprint arXiv:0906.3202*, 2009.
40. Jia-Wei Han, Jian Pei, and Xi-Feng Yan. From sequential pattern mining to structured pattern mining: a pattern-growth approach. *Journal of Computer Science and Technology*, 19(3):257–279, 2004.
41. Jiawei Han, Jian Pei, and Yiwen Yin. Mining frequent patterns without candidate generation. In *ACM SIGMOD Record*, volume 29-2, pages 1–12. ACM, 2000.
42. Qiang Hao, Rui Cai, Changhu Wang, Rong Xiao, Jiang-Ming Yang, Yanwei Pang, and Lei Zhang. Equip tourists with knowledge mined from travelogues. In *Proceedings of the 19th international conference on World wide web*, pages 401–410. ACM, 2010.
43. Mike Harding, Joseph Finney, Nigel Davies, Mark Rouncefield, and James Hannon. Experiences with a social travel information system. In *Proceedings of the 2013 ACM international joint conference on Pervasive and ubiquitous computing*, pages 173–182. ACM, 2013.
44. Jonathan L Herlocker, Joseph A Konstan, Al Borchers, and John Riedl. An algorithmic framework for performing collaborative filtering. In *Proceedings of the 22nd annual international ACM SIGIR conference on Research and development in information retrieval*, pages 230–237. ACM, 1999.
45. Tzvetan Horozov, Nitya Narasimhan, and Venu Vasudevan. Using location for personalized poi recommendations in mobile environments. In *Applications and the Internet, 2006. SAINT 2006. International Symposium on*, pages 6–pp. IEEE, 2006.
46. Bo Hu and Martin Ester. Spatial topic modeling in online social media for location recommendation. In *Proceedings of the 7th ACM conference on Recommender systems*, pages 25–32. ACM, 2013.
47. Lian Huang, Qingquan Li, and Yang Yue. Activity identification from gps trajectories using spatial temporal pois' attractiveness. In *Proceedings of the 2nd ACM SIGSPATIAL International Workshop on Location Based Social Networks*, pages 27–30. ACM, 2010.
48. Chih-Chieh Hung, Chih-Wen Chang, and Wen-Chih Peng. Mining trajectory profiles for discovering user communities. In *Proceedings of the 2009 International Workshop on Location Based Social Networks*, pages 1–8. ACM, 2009.

49. Bin Jiang, Junjun Yin, and Sijian Zhao. Characterizing the human mobility pattern in a large street network. *Physical Review E*, 80(2):021136, 2009.
50. Hidetoshi Kawakubo and Keiji Yanai. Geovisualrank: a ranking method of geotagged imagesconsidering visual similarity and geo-location proximity. In *Proceedings of the 20th international conference companion on World wide web*, pages 69–70. ACM, 2011.
51. Jon M Kleinberg. Authoritative sources in a hyperlinked environment. *Journal of the ACM (JACM)*, 46(5):604–632, 1999.
52. Kazuki Kodama, Yuichi Iijima, Xi Guo, and Yoshiharu Ishikawa. Skyline queries based on user locations and preferences for making location-based recommendations. In *Proceedings of the 2009 International Workshop on Location Based Social Networks*, pages 9–16. ACM, 2009.
53. Daniel Lemire and Anna Maclachlan. Slope one predictors for online rating-based collaborative filtering. In *SDM*, volume 5, pages 1–5. SIAM, 2005.
54. Kenneth Wai-Ting Leung, Dik Lun Lee, and Wang-Chien Lee. Clr: a collaborative location recommendation framework based on co-clustering. In *Proceedings of the 34th international ACM SIGIR conference on Research and development in Information Retrieval*, pages 305–314. ACM, 2011.
55. Justin Levandoski, Mohamed Sarwat, Ahmed Eldawy, and Mohamed Mokbel. Lars: A location-aware recommender system. In *IEEE International Conference on Data Engineering*, 2012.
56. Quannan Li, Yu Zheng, Xing Xie, Yukun Chen, Wenyu Liu, and Wei-Ying Ma. Mining user similarity based on location history. In *Proceedings of the 16th ACM SIGSPATIAL international conference on Advances in geographic information systems*, page 34. ACM, 2008.
57. Yanhua Li, Zhi-Li Zhang, and Jie Bao. Mutual or unrequited love: Identifying stable clusters in social networks with uni-and bi-directional links. In *Algorithms and Models for the Web Graph*, pages 113–125. Springer, 2012.
58. Defu Lian and Xing Xie. Learning location naming from user check-in histories. In *ACM SIGSPATIAL*. ACM, 2011.
59. David Liben-Nowell, Jasmine Novak, Ravi Kumar, Prabhakar Raghavan, and Andrew Tomkins. Geographic routing in social networks. *Proceedings of the National Academy of Sciences of the United States of America*, 102(33):11623–11628, 2005.
60. Yu-Ru Lin, Jimeng Sun, Paul Castro, Ravi Konuru, Hari Sundaram, and Aisling Kelliher. Metafac: community discovery via relational hypergraph factorization. In *Proceedings of the 15th ACM SIGKDD international conference on Knowledge discovery and data mining*, pages 527–536. ACM, 2009.
61. Greg Linden, Brent Smith, and Jeremy York. Amazon. com recommendations: Item-to-item collaborative filtering. *Internet Computing, IEEE*, 7(1):76–80, 2003.
62. Bin Liu, Yanjie Fu, Zijun Yao, and Hui Xiong. Learning geographical preferences for point-of-interest recommendation. In *Proceedings of the 19th ACM SIGKDD international conference on Knowledge discovery and data mining*, pages 1043–1051. ACM, 2013.
63. Hechen Liu, Ling-Yin Wei, Yu Zheng, Markus Schneider, and Wen-Chih Peng. Route discovery from mining uncertain trajectories. In *Data Mining Workshops (ICDMW), 2011 IEEE 11th International Conference on*, pages 1239–1242. IEEE, 2011.
64. Chun-Ta Lu, Po-Ruey Lei, Wen-Chih Peng, and Jiunn Su. A framework of mining semantic regions from trajectories. In *Database Systems for Advanced Applications*, pages 193–207. Springer, 2011.
65. Xin Lu, Changhu Wang, Jiang-Ming Yang, Yanwei Pang, and Lei Zhang. Photo2trip: generating travel routes from geo-tagged photos for trip planning. In *Proceedings of the international conference on Multimedia*, pages 143–152. ACM, 2010.
66. Christopher D Manning, Prabhakar Raghavan, and Hinrich Schütze. *Introduction to information retrieval*, volume 1. Cambridge university press Cambridge, 2008.
67. Mikhil Masli, Landon Bouma, Andrew Owen, and Loren Terveen. Geowiki+ route analysis= improved transportation planning. In *Proceedings of the 2013 conference on Computer supported cooperative work companion*, pages 213–218. ACM, 2013.
68. Nina Mishra, Robert Schreiber, Isabelle Stanton, and Robert E Tarjan. Clustering social networks. In *Algorithms and Models for the Web-Graph*, pages 56–67. Springer, 2007.
69. Mohamed Mokbel, Jie Bao, Ahmed Eldawy, Justin Levandoski, and Mohamed Sarwat. Personalization, Socialization, and Recommendations in Location-based Services 2.0. In *5th International VLDB workshop on Personalized access, Profile Management and context awareness in Databases (PersDB)*. VLDB, 2011.
70. MovieLens. http://www.MovieLens.org/.
71. NetFlix Prize Data. http://www.netflixprize.com/.
72. Anastasios Noulas, Cecilia Mascolo, and Enrique Frias-Martinez. Exploiting foursquare and cellular data to infer user activity in urban environments. In *Mobile Data Management (MDM), 2013 IEEE 14th International Conference on*, volume 1, pages 167–176. IEEE, 2013.

73. Anastasios Noulas, Salvatore Scellato, Cecilia Mascolo, and Massimiliano Pontil. An empirical study of geographic user activity patterns in foursquare. *ICWSM*, 11:70–573, 2011.
74. Lawrence Page, Sergey Brin, Rajeev Motwani, and Terry Winograd. The pagerank citation ranking: Bringing order to the web. *Technical Report*, 1999.
75. Symeonidis Panagiotis, Papadimitriou Alexis., Manolopoulos Yannis., Senkul Pinar, and Toroslu Ismail. Geo-social recommendations based on incremental tensor reduction and local path traversal. In *Proceedings of the 3nd ACM SIGSPATIAL International Workshop on Location Based Social Networks*. ACM, 2011.
76. Moon-Hee Park, Jin-Hyuk Hong, and Sung-Bae Cho. Location-based recommendation system using bayesian users preference model in mobile devices. In *Ubiquitous Intelligence and Computing*, pages 1130–1139. Springer, 2007.
77. Alexei Pozdnoukhov and Christian Kaiser. Space-time dynamics of topics in streaming text. In *Proceedings of the 3rd ACM SIGSPATIAL International Workshop on Location-Based Social Networks*, pages 1–8. ACM, 2011.
78. Daniele Quercia, Neal Lathia, Francesco Calabrese, Giusy Di Lorenzo and Jon Crowcroft. Recommending Social Events from Mobile Phone Location Data In *International Conference on Data Mining*, pages 971–976. IEEE, 2010.
79. Seyyed Mohammadreza Rahimi and Xin Wang. Location recommendation based on periodicity of human activities and location categories. In *Advances in Knowledge Discovery and Data Mining*, pages 377–389. Springer, 2013.
80. Lakshmish Ramaswamy, P Deepak, Ramana Polavarapu, Kutila Gunasekera, Dinesh Garg, Karthik Visweswariah, and Shivkumar Kalyanaraman. Caesar: A context-aware, social recommender system for low-end mobile devices. In *Mobile Data Management: Systems, Services and Middleware, 2009. MDM'09. Tenth International Conference on*, pages 338–347. IEEE, 2009.
81. Rudy Raymond, Takamitsu Sugiura, and Kota Tsubouchi. Location recommendation based on location history and spatio-temporal correlations for an on-demand bus system. In *ACM SIGSPATIAL*. ACM, 2011.
82. Maayan Roth, Assaf Ben-David, David Deutscher, Guy Flysher, Ilan Horn, Ari Leichtberg, Naty Leiser, Yossi Matias, and Ron Merom. Suggesting friends using the implicit social graph. In *Proceedings of the 16th ACM SIGKDD international conference on Knowledge discovery and data mining*, pages 233–242. ACM, 2010.
83. Thomas Sandholm and Hang Ung. Real-time, location-aware collaborative filtering of web content. In *Proceedings of the 2011 Workshop on Context-awareness in Retrieval and Recommendation*, pages 14–18. ACM, 2011.
84. Mohamed Sarwat, Ahmed Eldawy, Mohamed F Mokbel, and John Riedl. Plutus: Leveraging location-based social networks to recommend potential customers to venues. In *Mobile Data Management (MDM), 2013 IEEE 14th International Conference on*, volume 1, pages 26–35. IEEE, 2013.
85. Salvatore Scellato, Cecilia Mascolo, Mirco Musolesi, and Jon Crowcroft. Track globally, deliver locally: improving content delivery networks by tracking geographic social cascades. In *Proceedings of the 20th international conference on World wide web*, pages 457–466. ACM, 2011.
86. Salvatore Scellato, Anastasios Noulas, Renaud Lambiotte, and Cecilia Mascolo. Socio-spatial properties of online location-based social networks. *ICWSM*, 11:329–336, 2011.
87. Salvatore Scellato, Anastasios Noulas, and Cecilia Mascolo. Exploiting place features in link prediction on location-based social networks. In *Proceedings of the 17th ACM SIGKDD international conference on Knowledge discovery and data mining*, pages 1046–1054. ACM, 2011.
88. Andrew I Schein, Alexandrin Popescul, Lyle H Ungar, and David M Pennock. Methods and metrics for cold-start recommendations. In *Proceedings of the 25th annual international ACM SIGIR conference on Research and development in information retrieval*, pages 253–260. ACM, 2002.
89. Yue Shi, Pavel Serdyukov, Alan Hanjalic, and Martha Larson. Personalized landmark recommendation based on geotags from photo sharing sites. *ICWSM*, 11:622–625, 2011.
90. Ana Silva and Bruno Martins. Tag recommendation for georeferenced photos. In *Proceedings of the 3nd ACM SIGSPATIAL International Workshop on Location Based Social Networks*. ACM, 2011.
91. Ajit P Singh and Geoffrey J Gordon. Relational learning via collective matrix factorization. In *Proceedings of the 14th ACM SIGKDD international conference on Knowledge discovery and data mining*, pages 650–658. ACM, 2008.
92. Nathan Srebro, Tommi Jaakkola, et al. Weighted low-rank approximations. In *ICML*, volume 3, pages 720–727, 2003.
93. Ramakrishnan Srikant and Rakesh Agrawal. *Mining sequential patterns: Generalizations and performance improvements*. Springer, 1996.
94. Chih Hua Tai, De-Nian Yang, Lung Tsai Lin, and Ming Syan Chen. Recommending personalized scenic itinerarywith geo-tagged photos. In *Multimedia and Expo, 2008 IEEE International Conference on*, pages 1209–1212. IEEE, 2008.

95. Yuichiro Takeuchi and Masanori Sugimoto. Cityvoyager: an outdoor recommendation system based on user location history. In *Ubiquitous intelligence and computing*, pages 625–636. Springer, 2006.
96. Karen P Tang, Jialiu Lin, Jason I Hong, Daniel P Siewiorek, and Norman Sadeh. 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*, pages 85–94. ACM, 2010.
97. Waldo R Tobler. A computer movie simulating urban growth in the detroit region. *Economic geography*, pages 234–240, 1970.
98. Thomas W Valente. Social network thresholds in the diffusion of innovations. *Social networks*, 18(1):69–89, 1996.
99. Petros Venetis, Hector Gonzalez, Christian S Jensen, and Alon Halevy. Hyper-local, directions-based ranking of places. *Proceedings of the VLDB Endowment*, 4(5):290–301, 2011.
100. Ulrike Von Luxburg. A tutorial on spectral clustering. *Statistics and computing*, 17(4):395–416, 2007.
101. Joe Weakliam, Michela Bertolotto, and David Wilson. Implicit interaction profiling for recommending spatial content. In *Proceedings of the 13th annual ACM international workshop on Geographic information systems*, pages 285–294. ACM, 2005.
102. Ling-Yin Wei, Yu Zheng, and Wen-Chih Peng. Constructing popular routes from uncertain trajectories. In *Proceedings of the 18th ACM SIGKDD international conference on Knowledge discovery and data mining*, pages 195–203. ACM, 2012.
103. Jason Wiese, Patrick Gage Kelley, Lorrie Faith Cranor, Laura Dabbish, Jason I Hong, and John Zimmerman. Are you close with me? are you nearby?: investigating social groups, closeness, and willingness to share. In *Proceedings of the 13th international conference on Ubiquitous computing*, pages 197–206. ACM, 2011.
104. Rongjing Xiang, Jennifer Neville, and Monica Rogati. Modeling relationship strength in online social networks. In *Proceedings of the 19th international conference on World wide web*, pages 981–990. ACM, 2010.
105. Xiangye Xiao, Yu Zheng, Qiong Luo, and Xing Xie. Finding similar users using category-based location history. In *Proceedings of the 18th SIGSPATIAL International Conference on Advances in Geographic Information Systems*, pages 442–445. ACM, 2010.
106. Xiangye Xiao, Yu Zheng, Qiong Luo, and Xing Xie. Inferring social ties between users with human location history. *Journal of Ambient Intelligence and Humanized Computing*, 5(1):3–19, 2014.
107. Wenjian Xu, Chi-Yin Chow, and Jia-Dong Zhang. Calba: capacity-aware location-based advertising in temporary social networks. In *Proceedings of the 21st ACM SIGSPATIAL International Conference on Advances in Geographic Information Systems*, pages 354–363. ACM, 2013.
108. Dingqi Yang, Daqing Zhang, Zhiyong Yu, and Zhiwen Yu. Fine-grained preference-aware location search leveraging crowdsourced digital footprints from lbsns. In *Proceedings of the 2013 ACM international joint conference on Pervasive and ubiquitous computing*, pages 479–488. ACM, 2013.
109. Mao Ye, Krzysztof Janowicz, Christoph Mülligann, and Wang-Chien Lee. What you are is when you are: the temporal dimension of feature types in location-based social networks. In *Proceedings of the 19th ACM SIGSPATIAL International Conference on Advances in Geographic Information Systems*, pages 102–111. ACM, 2011.
110. Mao Ye, Dong Shou, Wang-Chien Lee, Peifeng Yin, and Krzysztof Janowicz. On the semantic annotation of places in location-based social networks. In *Proceedings of the 17th ACM SIGKDD international conference on Knowledge discovery and data mining*, pages 520–528. ACM, 2011.
111. Mao Ye, Peifeng Yin, and Wang-Chien Lee. Location recommendation for location-based social networks. In *Proceedings of the 18th SIGSPATIAL International Conference on Advances in Geographic Information Systems*, pages 458–461. ACM, 2010.
112. Mao Ye, Peifeng Yin, Wang-Chien Lee, and Dik-Lun Lee. 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*, pages 325–334. ACM, 2011.
113. Yang Ye, Yu Zheng, Yukun Chen, Jianhua Feng, and Xing Xie. Mining individual life pattern based on location history. In *Mobile Data Management: Systems, Services and Middleware, 2009. MDM'09. Tenth International Conference on*, pages 1–10. IEEE, 2009.
114. Hongzhi Yin, Yizhou Sun, Bin Cui, Zhiting Hu, and Ling Chen. Lcars: a location-content-aware recommender system. In *Proceedings of the 19th ACM SIGKDD international conference on Knowledge discovery and data mining*, pages 221–229. ACM, 2013.
115. Zhijun Yin, Liangliang Cao, Jiawei Han, Jiebo Luo, and Thomas S Huang. Diversified trajectory pattern ranking in geo-tagged social media. In *SDM*, pages 980–991. SIAM, 2011.
116. Zhijun Yin, Liangliang Cao, Jiawei Han, Chengxiang Zhai, and Thomas Huang. Geographical topic discovery and comparison. In *Proceedings of the 20th international conference on World wide web*, pages 247–256. ACM, 2011.

117. Zhijun Yin, Manish Gupta, Tim Weninger, and Jiawei Han. Linkrec: a unified framework for link recommendation with user attributes and graph structure. In *Proceedings of the 19th international conference on World wide web*, pages 1211–1212. ACM, 2010.
118. Josh Jia-Ching Ying, Wang-Chien Lee, Mao Ye, Ton Ching-Yu Chen, and Vincent S. Tseng. User association analysis of locales on location based social networks. In *GIS-LBSN*, 2011.
119. Josh Jia-Ching Ying, Eric Hsueh-Chan Lu, Wen-Ning Kuo, and Vincent S Tseng. Urban point-of-interest recommendation by mining user check-in behaviors. In *Proceedings of the ACM SIGKDD International Workshop on Urban Computing*, pages 63–70. ACM, 2012.
120. Josh Jia-Ching Ying, Eric Hsueh-Chan Lu, Wang-Chien Lee, Tz-Chiao Weng, and Vincent S Tseng. Mining user similarity from semantic trajectories. In *Proceedings of the 2nd ACM SIGSPATIAL International Workshop on Location Based Social Networks*, pages 19–26. ACM, 2010.
121. Hyoseok Yoon, Yu Zheng, Xing Xie, and Woontack Woo. Smart itinerary recommendation based on user-generated gps trajectories. In *Ubiquitous Intelligence and Computing*, pages 19–34. Springer, 2010.
122. Hyoseok Yoon, Yu Zheng, Xing Xie, and Woontack Woo. Social itinerary recommendation from user-generated digital trails. *Personal and Ubiquitous Computing*, 16(5):469–484, 2012.
123. Xiao Yu, Ang Pan, Lu-An Tang, Zhenhui Li, and Jiawei Han. Geo-friends recommendation in gps-based cyber-physical social network. In *Advances in Social Networks Analysis and Mining (ASONAM), 2011 International Conference on*, pages 361–368. IEEE, 2011.
124. Dongxiang Zhang, Yeow Meng Chee, Anirban Mondal, A Tung, and Masaru Kitsuregawa. Keyword search in spatial databases: Towards searching by document. In *Data Engineering, 2009. ICDE'09. IEEE 25th International Conference on*, pages 688–699. IEEE, 2009.
125. Jia-Dong Zhang and Chi-Yin Chow. igslr: personalized geo-social location recommendation: a kernel density estimation approach. In *Proceedings of the 21st ACM SIGSPATIAL International Conference on Advances in Geographic Information Systems*, pages 324–333. ACM, 2013.
126. Vincent Zheng, Bin Cao, Yu Zheng, Xing Xie, and Qiang Yang. Collaborative filtering meets mobile recommendation: A user-centered approach. In *AAAI Conference on Artificial Intelligence*, 2010a.
127. Vincent W Zheng, Yu Zheng, Xing Xie, and Qiang Yang. Collaborative location and activity recommendations with gps history data. In *Proceedings of the 19th international conference on World wide web*, pages 1029–1038. ACM, 2010.
128. Vincent W Zheng, Yu Zheng, Xing Xie, and Qiang Yang. Towards mobile intelligence: Learning from gps history data for collaborative recommendation. *Artificial Intelligence*, 184:17–37, 2012.
129. Vincent Wenchen Zheng, Yu Zheng, and Qiang Yang. Joint learning user's activities and profiles from gps data. In *Proceedings of the 2009 International Workshop on Location Based Social Networks*, pages 17–20. ACM, 2009.
130. Yu Zheng, Licia Capra, Ouri Wolfson, and Hai Yang. Urban computing: Concepts, methodologies, and applications. *ACM Transaction on Intelligent Systems and Technology (ACM TIST)*, 2014.
131. Yu Zheng, Yukun Chen, Xing Xie, and Wei-Ying Ma. GeoLife2.0: A Location-Based Social Networking Service. In *MDM*, 2009c.
132. Yu Zheng and Xing Xie. Learning location correlation from gps trajectories. In *Mobile Data Management (MDM), 2010 Eleventh International Conference on*, pages 27–32. IEEE, 2010.
133. Yu Zheng and Xing Xie. Learning travel recommendations from user-generated gps traces. *ACM Transactions on Intelligent Systems and Technology (TIST)*, 2(1):2, 2011.
134. Yu Zheng, Lizhu Zhang, Zhengxin Ma, Xing Xie, and Wei-Ying Ma. Recommending friends and locations based on individual location history. *ACM Transactions on the Web (TWEB)*, 5(1):5, 2011.
135. Yu Zheng, Lizhu Zhang, Xing Xie, and Wei-Ying Ma. Mining correlation between locations using human location history. In *Proceedings of the 17th ACM SIGSPATIAL International Conference on Advances in Geographic Information Systems*, pages 472–475. ACM, 2009.
136. Yu Zheng, Lizhu Zhang, Xing Xie, and Wei-Ying Ma. Mining interesting locations and travel sequences from gps trajectories. In *Proceedings of the 18th international conference on World wide web*, pages 791–800. ACM, 2009.
137. Yu. Zheng and Xiaofang. Zhou. *Computing with Spatial Trajectories*. Springer, 2011.