Chapter 9
Location-Based Social Networks: Locations
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Abstract While chapter 8 studies the research philosophy behind a location-based social network (LBSN) from the point of view of users, this chapter gradually explores the research into LBSNs from the perspective of locations. A series of research topics are presented, with respect to mining the collective social knowledge from many users’ GPS trajectories to facilitate travel. On the one hand, the generic travel recommendations provide a user with the most interesting locations, travel sequences, and travel experts in a region, as well as an effective itinerary conditioned by a user’s starting location and an available time length. On the other hand, the personalized travel recommendations find the locations matching an individual’s interests, which can be learned from the individual’s historical data.

9.1 Introduction

The increasing availability of location-acquisition technologies and Internet access in mobile devices is fostering a variety of location-based services generating a myriad of spatio-temporal data, especially in the form of trajectories [45, 42, 41, 6]. These trajectories reflect the behavior and interests of users, thereby enabling us to better understand an individual and the similarity between different individuals [20, 34, 7, 15, 36]. Research and applications were introduced in Chapter 8 in which the users are the focus and locations are employed as enhanced information for better understanding them. Instead, this chapter discusses the research topics that aim at understanding locations based upon the collective social knowledge of users (e.g., the knowledge contained in their GPS trajectories) starting with generic travel recommendations [48, 44, 37, 38, 40] and then looking at personalized recommendations [46, 43, 39, 13, 33].

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Regardless of an individual’s preferences, the generic travel recommender systems mine a vast number of trajectories (generated by multiple users) and provide an individual with travel recommendations following a paradigm of “trajectories → interesting locations → popular travel sequences → itinerary planning → activities recommendation.” Specifically, these recommender systems first infer the most interesting locations in a region from the given trajectories, and then detect the popular travel sequences among these locations [48]. An interesting location is defined as a culturally important place, such as Tiananmen Square in Beijing or the Statue of Liberty in New York (i.e., popular tourist destinations), and commonly frequented public areas, such as shopping malls/streets, restaurants, cinemas, and bars. With these interesting locations and travel sequences, an ideal itinerary can be planned for a user according to her departure location, destination, and available time [37, 38]. Finally, the generic travel recommendations provide users with some popular activities, e.g., dining and shopping, that could be performed in a location [40]. All these recommendations mentioned above facilitate a user to travel to an unfamiliar place and plan a journey with minimal effort.

However, the personalized recommender systems learn an individual’s interests from her personal location data (e.g., GPS trajectories) and suggest locations to the individual matching her preferences. Specifically, the personalized recommender uses the times that a particular individual has visited a location as her implicit ratings on that location, and estimates an individual’s interests in unvisited places by considering her location history and those of other users [46, 44]. As a result, some locations with high ratings that might match the user’s tastes can be recommended.

Two collaborative filtering (CF) models are individually used to infer a user’s ratings of these unvisited locations. First, the personalized location recommendation is equipped with a user-based CF model, which employs user similarity introduced in Section 8.3 as a distance function between different users [46]. This model is able to capture people’s mobility, such as the sequential and hierarchical properties of human movement in the physical world, while suffering from poor scalability caused by the heavy computation of user similarity. This user-based CF model is detailed in Section 9.3.2. Second, to address the problem of scalability, a location-based CF model is proposed [44]. This model uses the correlation between locations mined from many users’ GPS traces [43] as a distance measure between two different locations. The location-based CF model is slightly less effective than the user-based one while being much more efficient. Refer to Section 9.3.3 for details.

9.2 Generic Travel Recommendations

This section describes the generic travel recommendation following the paradigm of “trajectories → interesting locations → popular travel sequences → itinerary planning → activities recommendation.” Specifically, Section 9.2.1 introduces the detection of interest locations and travel sequences [48]. Section 9.2.2 then presents