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A SURVEY OF CONTEXT-AWARE MOBILE RECOMMENDATIONS

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Mobile recommender systems target on recommending the right product or information to the right mobile users at anytime and anywhere. It is well known that the contextual information is often the key for the performances of mobile recommendations. Therefore, in this paper, we provide a focused survey of the recent development of context-aware mobile recommendations. After briefly reviewing the state-of-the-art of recommender systems, we first discuss the general notion of mobile context and how the contextual information is collected. Then, we introduce the existing approaches to exploit contextual information for modeling mobile recommendations. Furthermore, we summarize several existing recommendation tasks in the mobile scenarios, such as the recommendations in the tourism domain. Finally, we discuss some key issues that are still critical in the field of context-aware mobile recommendations, including the privacy problem, the energy efficiency issues, and the design of user interfaces.

Keywords: Context-aware; mobile recommendations; recommender systems.

1. Introduction

Advances in sensor, wireless communication, and information infrastructures such as GPS, WiFi, and the smart phone technology have exposed users to the massive amount of mobile services at anytime and anywhere. As the quick increase of these services, it becomes more difficult for mobile users to find the right information that is needed to complete a particular task (e.g., planning a trip) .[104] Since recommender systems, which aim at information filtering and user profiling,[3] have been successfully applied for improving the quality of services in a number of fields, [13,31,73,145] it is

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a natural direction to develop mobile recommender systems for recommending the right service or information to the right mobile users at anytime and anywhere.

Recommender systems for mobile users have been studied before.[39,100,150] While the general ideas of mobile recommendations are similar to those in traditional domains, there are still some unique features and domain challenges that need to be dealt with by mobile recommender systems. Among them, one of the most important characteristics of mobile recommender systems is "context-awareness"; that is, the context information (e.g., physical locations) of mobile users at a particular time is usually recorded and the contextual information can be exploited as an important source for enhancing recommendations.[104] In general, mobile recommendation algorithms will achieve better performances if they can use more contextual information properly. As a result, recent years have witnessed increased interests in developing context-aware mobile recommender systems in the literature.

Indeed, in this paper, we provide a focused survey of the current research and development of context-aware mobile recommendations, from *mobile data collection* to *recommendation-oriented mobile contextual modeling* and to *existing mobile recommendation applications*. Specifically, after briefly reviewing the state-of-the-art of recommender systems in Sec. 2, we provide the general notions and the process of context-aware mobile recommendations (Sec. 3), and discuss how the contextual information is collected (Sec. 4). Then, we introduce the existing ways to model context-aware mobile recommendations in Sec. 5, such as location (one of the most basic and widely researched mobile context) pattern mining, context-rich (going beyond location and trajectory) pattern mining and the way of incorporating context into mobile recommender systems. Furthermore, Sec. 6 summarizes several existing recommendation tasks in the mobile scenarios, especially in the areas of social networking, tourism, urban computing, information retrieval and information (e.g., news) recommendation. Before concluding this paper in Sec. 8, we provide a discussion and present some key issues that have strong impact on current context-aware mobile recommendations (Sec. 7), including the privacy problem, the energy-efficient issues, and the design of the user interfaces.

2. Recommender Systems

In this section, we briefly discuss some basic ideas, concepts and techniques for general recommender systems. As is well known, recommender systems attempt to suggest items to users that they may be interested in, where items are used for denoting all the things that the systems recommend (e.g., products or services), and users can be individuals (e.g., customers) or groups of individuals (e.g., groups of tourists), etc. Since the topic of recommender systems is not the major concerns of this paper, we only focus on the materials that are important for readers to quickly understand or review current researches on recommender systems. It is worth noting that this topic deserves much more space than a section, and more detailed information of recommender systems can be found in Ref. 57.

2.1. *Taxonomy dimensions*

There are many candidate dimensions that can be used for classifying and identifying recommender systems, and in the following we focus on three major ones that apply to every recommendation study — the amount of information (data sources) exploited for input, the type of recommendation solutions adopted, and the goal of the algorithm (i.e., the evaluation type). For better illustration, Fig. 1 shows the main categories of the recommendation algorithms based on the above three taxonomy dimensions.

2.2. *Information exploited*

Based on the amount of input information exploited by each algorithm, we classify current recommender systems into nonpersonalized, personalized and context-aware personalized ones.

Among them, nonpersonalized systems can collect user behavior records (e.g., rating or buy history) but cannot capture personalized information (e.g., user ID) of each user, and they usually mine the collective intelligence for recommending popular items.[22] Such applications include the *query suggestions* provided by search engines like Google and Baidu. Further, the applications like Amazon[73] and Youtube[31] have the ability to distinguish each single user and thus they can make personalized item recommendations. Recently, as more and more personalized user profiles (e.g., location, age or sex) have been recorded, it enables us to learn the user

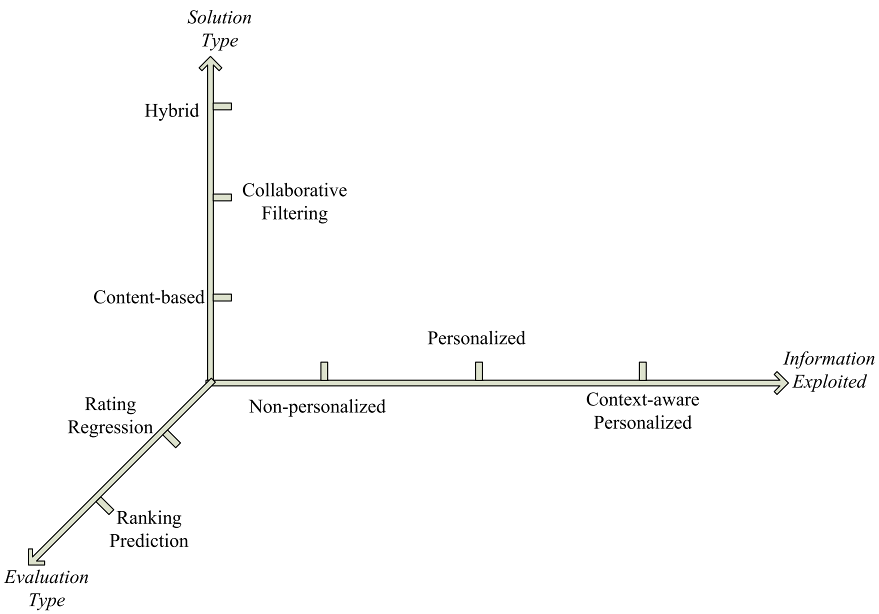

Fig. 1. The main categories of recommendation algorithms.

preferences more accurately (similarly, we can also understand the items better) and thus filter irrelevant items more preciously. In this paper, we note these information-rich applications as the context-aware personalized recommender systems,[4] such as the context-aware mobile recommendations. Worth noting that, different from the other two dimensions, the classifications in this dimension are generally time ordered, for example, nonpersonalized systems are usually the first showing up research works.

2.3. *Recommendation solutions*

Following the classifications given in Ref. 3, we group the current researches under recommendation solutions into content-based methods, collaborative filterings, and hybrid approaches.

Specifically, content-based methods usually recommend the items that are similar to the ones given user preferred in the past.[90] These methods are usually based on information retrieval techniques (e.g., TF-IDF and vector similarity computations) and they focus on recommending the items that contain textual information, such as documents, web sites, and news messages. Though they can deal with the cold-items (the new items without many user actions) problem, content-based methods often lead to the overspecialization problem and they may not recommend the items whose features cannot be easily extracted and represented. In contrast, in collaborative filterings[102] the given user will be recommended the items that people with similar tastes and preferences liked in the past (also noted as user-based collaborative filterings, and similar idea of item-based collaborative filterings[73] proceeding in an item-centric manner). The techniques like graph-based similarity computations[37,121] and matrix factorizations,[61,81,109] are often used for collaborative filterings. Compared to content-based methods, collaborative filtering methods only require the information about user interactions and do not rely on the content information of items or user profiles. Thus they have more broad applications, and massive research studies on collaborative filterings have been reported. However, collaborative filterings often suffer from the cold-item, cold-user and data sparsity problems. For avoiding certain limitations, hybrid approaches which combine content-based methods and collaborative filterings are widely used.[66] For example, the performance of matrix factorization-based collaborative filterings have been improved dramatically by incorporating some kind of additional sources of content information about the users or items. Based on different application scenarios, this content information can be the rating temporal effects,[60] the social connection,[83,91] or even the item's marginal net utility.[129]

2.4. *Evaluations*

In the traditional recommendation scenarios, user's preferences on the items are expressed either by different explicit rating scores (e.g., a 1−5 scale in Netflix and MovieLens, and usually the higher score the better) or by implicit actions (e.g., click the recommended web page). Thus, the corresponding recommender systems formalize the recommendation either as a rating regression problem or a ranking prediction problem.

Thanks for the vast rating-based applications,[61,102] public data sets[a] and many contests,[b] rating regression oriented recommender systems have been widely researched. The task of these recommendation algorithms is usually to fill up the missing entries of the user-item rating matrix with predicted value (as shown in Fig. 2). Correspondingly, the effectiveness of the recommendation algorithms are evaluated by how close the predicted ratings are to the true user ratings, and thus mean absolute error (MAE), which measures the average absolute deviation between a predicted rating and the user's true rating, is an often used metric.[43] Similarly, the root mean squared error (RMSE), whose result has more emphasis on large errors, is another important evaluation metric.

In contrast, there are many scenarios, where the user ratings are usually not conveniently available, but implicitly expressed by users' behaviors such as click or not-click, and bookmark or not-bookmark.[93] In these scenarios, the systems want to find out the items that each user would like to click/bookmark, and then rank them earlier to the given user. Thus, similar to information retrievals, this kind of recommender systems usually choose Precision, Recall (or Top-K, or Hits), mean average precision (MAP),[43] or degree of agreement (DOA)[41,74] as the key metrics.

We briefly summarize some comparisons between rating and ranking oriented recommender systems. Their differences are the following. At first, they are based on different assumptions. For the rating oriented recommender systems, they usually assume that users have the opportunity to see/rate all the items, thus the ratings can be used to represent the user's preferences. For the ranking oriented systems, they

Input

	U_1	U_2	U_3	U_4	…	U_n
I_1	4	?	2	5	…	?
I_2	3	2	1	?	…	3
I_3	?	2	?	3	…	4
…	…	…	…	…	…	…
I_p	5	?	3	4	…	?

Prediction →

Output

	U_1	U_2	U_3	U_4	…	U_n
I_1	4	3	2	5	…	4
I_2	3	2	1	2	…	3
I_3	3	2	4	3	…	4
…	…	…	…	…	…	…
I_p	5	4	3	4	…	5

Fig. 2. The flowchart of the rating oriented recommendation algorithm.

[a] http://www.grouplens.org/node/73, http://www.informatik.uni-freiburg.de/cziegler/BX/, http://goldberg. berkeley.edu/jester-data/.
[b] Netflix,URL:http://www.netflixprize.com/; KDDCup,URL:http://kddcup.yahoo.com/.

usually assume that the users prefer the items that they have seen/clicked than other ones. Then, based on the different assumptions and data records, one of them tries to predict the ratings for users, while the other one wants to generate ranking lists. Thus, they are suitable for different application scenarios. Besides these, both of them have some limitations. For example, the limitations for the rating oriented methods include: Their assumption is too strong, in other words, in real applications the users usually have no chance to interact with all the items; furthermore, rating prediction is just a middle step of the recommendation, and the more important thing should be how to present our recommendation results to the users so as to change the user behaviors (e.g., avoiding low ratings). In contrast, the major limitation for the ranking oriented methods lies in the weakness of their assumption, in other words, user's click behavior does not always mean given user is interested in this item, and it is useful to distinguish the user's positive feedbacks from the negative ones.

Thus, we can see that the high offline performance gained by the metrics like MAE or Precision cannot completely prove the effectiveness of one recommendation algorithm, and in real applications, more sophisticated user studies and online experiments are also required. Meanwhile, beyond the evaluations based on accuracy, there are still many challenges for a successful recommender system as we will discuss later.

2.5. *Discussion*

In summary, we hope all the current recommendation algorithms can be projected to the three-dimensional coordinates as shown in Fig. 1. For instance, Table 1 lists several typical recommendation algorithms and the belonging categories when they were first proposed.

From the above illustration we can see that the classifications of recommender systems shown in Fig. 1 are mainly focused on the classifications of their recommendation algorithms. Worth noting that recommender system is the entire process starting from data collection to the recommendation results evaluation and further adjustments rather than a single algorithm.[3,43,53,57] In real applications,

Table 1. Categories of several typical algorithms.

Algorithm	Information exploited	Solution type	Evaluation type
UCF,[102] ICF,[73]	Personalized	Collaborative filtering	Rating
LIBRA[90]	Personalized	Content-based	Ranking
Slope one[67]	Personalized	Collaborative filtering	Rating
PMF[109]	Personalized	Collaborative filtering	Rating
ItemRank[41]	Personalized	Collaborative filtering	Ranking
LDA[18]	Personalized	Collaborative filtering	Ranking
fLDA[5]	Context-aware	Hybrid	Rating
TrustWalker[48]	Context-aware	Collaborative filtering	Rating
timeSVD++[60]	Context-aware	Hybrid	Rating

many more aspects should be considered for designing, deploying and evaluating a recommender system, such as the scalability, the user interactions (e.g., the explanation of recommendation results), the novelty and the coverage. Therefore, with so many problems to be worthy of attention, the researches on recommender systems remain pretty much open. Meanwhile, these research problems make recommender systems a strongly interdisciplinary field. Thus, the corresponding approaches for solving these recommendation problems are based on methodologies overlapping many disciplines such as data mining, human−computer interaction, natural language processing, psychology, marketing and even sociology.

3. Overview of Context-Aware Mobile Recommendations

In this section, we will first review some general concepts and definitions about mobile contexts and context-awareness. Followed then, we will briefly introduce the main tasks for recommendation-oriented mobile context mining.

3.1. *Concepts*

3.1.1. *Context and mobile context*

Context is a multifaceted concept that has been studied across different research disciplines, including computer science (primarily in artificial intelligence and ubiquitous computing), cognitive science, linguistics, philosophy, psychology, and organizational sciences.[4]

Therefore, there are many definitions about "*Context*". In this paper, we follow the definition by Abowd *et al.,*[1] which is also a commonly used one: "Any information that can be used to characterize the situation of entities (i.e., whether a person, place or subject) that are considered relevant to the interaction between a user and an application, including the user and the application themselves." Based on this definition, it is easy for an application developer to enumerate the context for a given application scenario. Meanwhile, there are also some other definitions. Following the classifications in Ref. 1, they can be roughly classified into three categories.

The first category defines context by enumeration of examples.[20,33,108] For example, Brown *et al.*[20] defined context as location, identities of the people around the user, the time of day, season, and so on. Ryan *et al.*[108] enumerated context as the user's location, environment, identity and time. Dey[33] defined context as the user's emotional state, location and orientation, focus of attention, date and time, objects, and people in the user's environment.

The second category simply provides synonyms for context, such as referring to context as the environment or situation.[19,44,131] For example, Brown[19] defined context to be the elements of the user's environment that the user's computer knows about. Ward *et al.*[131] viewed context as the state of the application's surroundings. Similarly, Hull *et al.*[44] saw context as the aspects of the current situation, including the entire environment.

The third category views context to be the constantly changing execution environment, which includes three pieces: (1) Computing environment, such as network connectivity, communication costs, and communication bandwidth, and nearby resources such as printers, displays, and workstations; (2) User context, such as the user's profile, location, people nearby, even the current social situation; (3) Physical context, such as lighting noise levels. These definitions were mainly provided by Schilit *et al.*,[115] Dey *et al.*[34] and Pascoe.[96] However, Dey argued these definitions are too specific. Since it is impossible to enumerate which aspects of all situations are important, which change from situation to situation.

As context has been studied in multiple disciplines, each discipline tends to take its own idiosyncratic view that is somewhat different from other ones.[4] In this paper, we will focus on the context used by applications in mobile computing, that is "*mobile context*" for short. Based on different taxonomy dimensions, these mobile contexts can be classified into different category sets. In the following, we illustrate two major taxonomy dimensions:

Hierarchy of contexts: Abowd *et al.*[1] simply divided contexts into two levels. They assume that the location, identity, time, and activity, are the primary context types, which can characterize the situation of a particular entity. Thus, they are identified on the first level. All the other types of context are on the second level.

Function of contexts in mobile applications: Chen and Kotz[25] defined two kinds of contexts as: (1) *Active Context* that influences the behaviors of an application, i.e., the characteristics of the surrounding environment that determine the behavior of the mobile applications; (2) *Passive Context* that is relevant but not critical to an application. Given one particular context class, whether it is active or passive depends on how it is used in applications. From the definition, we can claim that "context" in "context-aware" means active context.

3.1.2. *Mobility and context-awareness*

Compared to those traditional PC and web oriented recommender systems, "Mobility" and "Context-Awareness" are two major characteristics in context-aware mobile recommender systems. In the mobile computing field, mobility contains two aspects: (1) users communicate (wireless) "anytime, anywhere, with anyone", and (2) devices can be connected "anytime, anywhere to the network". From the two aspects of mobility, we can see that there are the following three fundamental mobility dimensions to characterize mobile recommender systems:

User mobility refers to the fact that the user can access a mobile information system in different locations.

Device portability reflects that the device used to access the information system is mobile.

Wireless connectivity refers to the fact that the device used to access the recommender system is networked by means of a wireless technology such as Wifi, or UMTS, or Bluetooth.

We can see that the above mobilities also bring in the context-awareness of mobile recommendations. To the best of our knowledge, the first definition of context-aware applications is given by Schilit and Theimer,[116] which restricted the definition from applications that are simply informed about context to applications that adapt themselves to context. In this paper, we adopt a more general definition by Abowd *et al.*[1]: "A system is context-aware if it uses context to provide relevant information and/or services to the user, where relevancy depends on the users task". Besides, some other definitions can be grouped into two categories: using context and adapting to context, which follows the taxonomy provided by Ref. 1.

The first category is a more general case of using context. For example, Hull *et al.*[44] and Pascoe *et al.*[97,108] defined context-awareness to be the ability of computing devices to sense aspects of a user's local environment and the computing devices themselves. Dey[33] limited context-awareness to the human−computer interface. Salber *et al.*[111] defined context-awareness to be the ability to provide maximum flexibility of a computational service based on real-time sensing of context. Comparatively, the second category is the more specific "adapting to context" category, which requires that an application behavior be modified for it to be considered context-aware. Thus, many researchers[20,115,131] define context-aware applications to be applications that dynamically change or adapt their behavior based on the context of the application and the user.

3.2. *Tasks for recommendation-oriented mobile context mining*

As shown in Fig. 3, there are three main steps for recommendation-oriented mobile context mining. This subsection will present an overview of the tasks for each step.

3.2.1. *Mobile context collection*

The first step, context-aware data collection for creating a suitable target data set, is one of the key steps in knowledge discovery in databases.[122] As shown in Fig. 3, mobile devices, such as smart phones, PDA, Pads, are excellent platforms for gathering mobile contextual information.[15] For example, whom the users have been calling and messaging, how often, what images they have been capturing with their

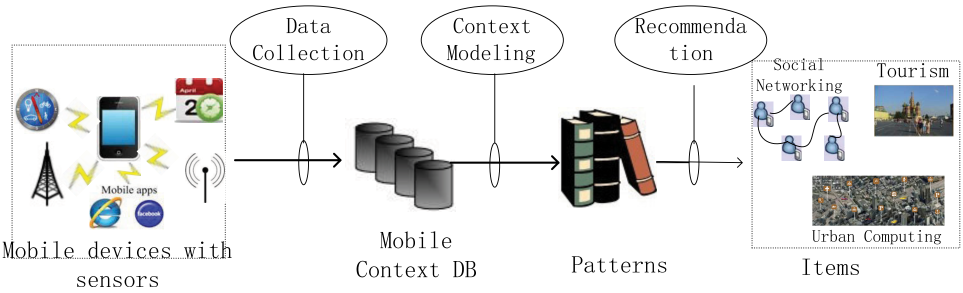

Fig. 3. The process of context-aware mobile recommendations.

camera, what music they have been listening to, and so on. Moreover, as mobile phones are becoming the devices that cover many other features and integrate a plethora of sensors and radios, more rich context data can be captured. For instance, the exact location of the user outdoors can be sensed by GPS, whether there are other devices in proximity can be sensed by Bluetooth technology, user's activity can be mined from motion sensors such as accelerometer. These data can be directly saved in the mobile devices through context logs or uploaded to the server.

3.2.2. *Recommendation-oriented mobile context modeling*

Given the collected mobile context data, we can apply data mining techniques to the discovery of usage patterns, which is denoted as "Recommendation-oriented Mobile Context Modeling". More and more modelings have sprung up and targeted towards various applications in the past years. Since there are many researches focusing on location-based context modeling, we classified the existing mobile context modeling into two categories: (1) location-based context data modeling[36,46,55,134,136,137,139,152] and (2) context-rich modeling.[11,21,58,82,84] In Sec. 5, we will introduce those modelings in more detail.

3.2.3. *Application-dependent recommendations*

We can incorporate the patterns mined in the recommendation-oriented mobile context modeling stage for various recommendation areas (shown in Fig. 3). For example, recommendations for mobile social networking,[27,69,82,127,139,146] tourist guides,[2,9,32,38,42,76] recommendations for urban computing,[142,143,149] context-aware mobile information retrieval,[17,28,62] information recommendation for context-aware mobile users[77,101,132,156] and so on.

4. Mobile Context Collection

Data collection can be classified into data collection using static nodes and data collection using mobile elements.[50] Here we focus on using intelligent and high powered mobile devices as data collectors for sensor data. The mechanisms or technologies of context data collection by using mobile devices have been discussed by a number of researches,[25,50] and we apply two major taxonomy dimensions to classify these technologies: Mobility and Context Types.

Taxonomy Dimension of Mobility: Generally speaking, based on this taxonomy dimension, the work in this literature can be classified into three categories[49,50]: random mobility approach, predictable mobility approach, and controlled mobility approach. For example, Tain *et al.*[47] proposed data mule, a three layer architecture comprising mobile elements, sensor nodes and data sinks, which focuses on modeling a random walk-based data collector and sensor data buffering issues. Cao *et al.*[21] built a data collection system, containing a server and several client ends, for collecting the rich context data and interaction records of mobile users, which is also a random walk-based data collector because of unrestricted user mobility. Chakrabarti *et al.*[24] used the predictable mobility of observers (e.g., buses, shuttles and trains) to collect data from sensor networks that are distributed over an area. These works,[51,56,120] focus on using controlled mobility for collecting data in sensor network. Worth noting that, different from the dimension discussed below, in one project or research work, there is just one mobility collection technology.

Taxonomy Dimension of Context Types: According to this taxonomy dimension, we classify the context data collection mechanisms the same as[25]: (1) sensing the location, (2) sensing low-level contexts beyond location, and (3) sensing high-level contexts. In one project or research work, maybe several or all of these mechanisms need to be applied for collecting rich contexts.

There are pervasive positioning technologies that can be used for location sensing. For example, GPS is the most well known because it provides worldwide coverage, high accuracy and a wide number of nonexpensive available GPS receivers. However it is useless indoors, particularly in the vertical axis.[119] Cell ID positioning, is useful indoors and a very basic form of positioning in GSM (Global System for Mobile Communications) networks, which can be used on the user device and does not require any upgrade to the handsets or network equipment. However, its accuracy depends on the cell size. Besides, there are a number of positioning technologies based on short-range signals like Bluetooth, WiFi, infrared or RFID. According to Ref. 25, there has been no uniform way to track locations with fine granularity that works both indoors and outdoors. Thus, a context-aware mobile system may exploit in conjunction with several kinds of location data sensed by different locators.

Here, we give some examples of low-level contexts beyond location and introduce the possible approaches to sense them. *Time*: this contextual information is from the built-in clock of the computer. *Orientation*: a simple orientation sensor based on two mercury switches can sense the change of the device orientation. Some other low-level types of physical context can be sensed by specially designed sensors.[25] For example, two accelerometers to provide tilt and vibration measurements, an omni-directional microphone to detect sound, and other built-in sensors for measuring temperature and pressure.

Comparatively, it is a big challenge to sense high-level context information, i.e., complex social contexts, such as the user's "current activity". Chen and Kotz[25] provided three available schemes: (1) machine vision, based on camera technology and image processing; (2) consulting the user's calendar to directly find out what the user is supposed to do at certain time; (3) using artificial intelligence techniques to recognize complex contexts by combining several simple low-level sensors.

Finally, these sensory data are usually saved in mobile devices through context logs or uploaded to the service, for further modeling.

5. Recommendation-Oriented Mobile Context Modeling

Mobile context modeling is a process of exploiting contextual information for modeling mobile recommendations, which is critical for the success of context-aware mobile recommender systems. Current research on modeling mobile context draws upon methods and algorithms developed from several fields such as data mining and machine learning. However, worth noting that it is not our intent to describe the details of all the algorithms and techniques that have been used. Alternatively, we would like to summarize several typical kinds of recommendation-oriented context modeling activities that to the best of our knowledge have been applied to the mobile domain. Specifically, we first describe the way of modeling locations and trajectories, due to the fact that so many researches of modeling context focus on location information only. Then, we discuss the techniques used to express rich context information in various context-aware mobile systems. At last, we study the paradigms for incorporating context into mobile recommender systems.

5.1. *Location pattern mining*

Location-based recommendations are among the hottest and fastest-growing mobile applications today. Thus modeling locations and trajectories has attracted more and more researchers' attention.[92,99] Here we group many of these work into some typical modeling tasks, and most of them can serve for the location-based services, such as mobile recommendation.

5.1.1. *Significant place mining*

To the best of our knowledge, significant place mining consists of two sub-tasks: identifying personal significant places by mining personal location history and mining interesting locations in a given geospatial regions based on multiple users' location histories. In the following, we will discuss the related research work in the two sub-tasks, respectively.

Identifying personal significant places is central to understand human mobility and social patterns,[46] which is extremely important for high-level recommendation applications. The modeling method is dependent on the existence of free and pervasive positioning technologies. In the following, we focus on GPS trajectories-based methods[55,87,125] and Cell ID trajectories based methods.[26,88,136] Marmasse and Schmandt[87] identified a salient location by utilizing the disappearances and appearances of GPS signal within a certain radius. The limitation of this work is that false locations are identified due to many possible outdoor GPS shadows. To conquer this limitation, Ashbrook *et al.*[125] considered the time gap between disappearances and appearances of GPS signal for filtering significant places. Moreover, they used clusters of places instead of places for representing the final significant locations because GPS coordinate can vary in the same physical location. Kang *et al.*[55] applied a time-based clustering algorithm to cluster the locations along the time axis. Yang[136] first proposed a closure patterns-based approach for identifying cell ID clusters and then considered two factors for defining significance of cell ID clusters: having a long time of stay and demonstrating a strong recurring pattern. Eagle *et al.*[36] constructed a cellular tower network (CTN) according to the co-occurrence of cell IDs in the trajectory and then segmented CTN based on heuristic rules. Meneses and Moreira[88] processed data in sequence and real time and limited the maximum number of clusters on a mobile device. They also provided a user familiarity level for each of these places.

Mining interesting locations in a given geospatial regions, and in particular tourism regions, can be used as a handbook for individuals to understand an unfamiliar city in a very short period and help them to plan their journeys with minimal effort, i.e., such information would enable mobile guides.[14,95,152] Worth noting that, different from personal significant place mining, this modeling task is based on a set of individuals' trajectories that share the property of visiting the same sequence of places. For instance, Zheng *et al.*[152] use a HITS-based inference algorithm for considering the mutual reinforcement relationship between users' travel experiences (hub scores) and the interests of locations (authority scores).

5.1.2. *Semantics annotation of places*

Automatically annotaing all places with category tags is a crucial prerequisite for location search, recommendation services, and data cleaning.[137] Isaacman *et al.*[46] proposed Home and Work Algorithms, which use logistic regression based on significance factors for home or work. They first define "home" hours to be weekends and weekdays between 7 pm and 7 am, whereas "work" hours are weekdays between 1 pm and 5 pm. The clusters with the largest number of events during the "home" hour is selected as home. There are two dominating factors for work algorithm: rank of the Work Hour Events and percentage of Home Hour Events. Ye *et al.*[137] addressed the task of semantic annotation of places in location-based social networks as a multi-label classification problem. They learnt a binary support vector machine (SVM) classifier for each tag in the tag space to support multi-label classification by extracting features of places from *explicit patterns of individual places* and *implicit relatedness among similar places* based on the check-in behavior of mobile users.

5.1.3. *Location trajectory pattern mining*

Mining location trajectory patterns plays a fundamental role to an increasing number of applications, such as transportation management, urban planning and tourism.[7] Location trajectories are universally defined as a set of *stops* and *moves*, where stops are the important places for the application and moves are transitions between consecutive stops. For example, Fig. 4 shows an example of a location trajectory $C_1 \rightarrow C_2 \rightarrow C_3$ with three stops. In recent years, the notation of *semantic trajectory* has been concerned by a growing number of researchers. Consider Fig. 4, if we have known C_1 indicates a shopping mall, C_2 is a restaurant, and C_3 indicates a cinema, this example can be represented by a semantic trajectory *shoppingmall* $\rightarrow$ *restaurant* $\rightarrow$ *cinema*. In the following, we group the work in this literature into two categories.

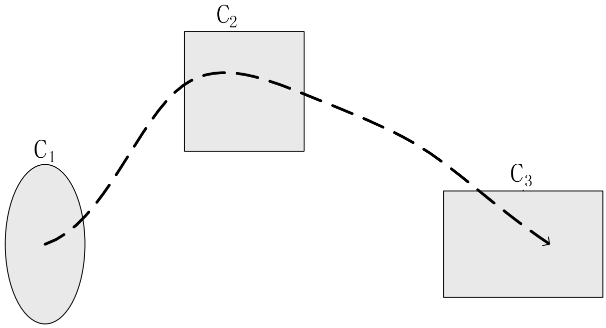

Fig. 4. Example of a location trajectory with three candidate stops.

The first category focuses on modeling geographic patterns of locations. For example, both Li *et al.*[69] and Zheng *et al.*[151] put multiple users' GPS data together and hierarchically clustered them into geographic regions, i.e., stops, in a divisive manner. Lu and Tseng[79] proposed a Personal Mobile Commerce Pattern Mine (PMCP-Mine) algorithm for efficient discovery of mobile users' Personal Mobile Commerce Patterns (PMCPs).

The semantic information of locations is considered in the second category. For example, Alvares *et al.*[7] proposed a novel framework for semantic trajectory knowledge discovery by integrating trajectory sample points to the geographic information. Ying *et al.*[139] first leveraged the geographic information database, Google Map, to implement semantic trajectory transformation, and then mined maximal semantic trajectory patterns by performing the sequential pattern mining algorithm Prefix-Span from each user's semantic trajectory dataset. Xiao *et al.*[134] constructed a feature vector for each stop according to the place of interests fallen in the region.

5.2. *Context-rich pattern modeling*

In this subsection, we discuss the pattern modeling methods used to express rich context information in various context-aware mobile systems. Generally, we group many of these popular methods into the following categories.

5.2.1. *Association rules*

Association rule learning aims at discovering interesting strong relations (rules, patterns[110]) between variables.[6,80] Actually, context-aware associations are very popular in the mobile domain, and mined association rules (patterns) can be used as the basis for improving mobile services. For example, *if a user always listens to popular music between* 8:00 and 9:00AM, *while the user is on the bus on the way to office every weekday morning*, a pop music service can be automatically recommended to the user once such a context for the user is detected.[128]

Along this line, Cao *et al.*[21] proposed to mine the associations between user interactions and contexts captured by mobile devices (or they called as behavior patterns), from context logs to characterize the habits of each single mobile user. This behavior pattern recognition method was recently extended by Wang *et al.*[128] for identifying context-aware roles from multi-user behaviors. Similarly, Lu *et al.*[77] proposed the idea of mining mobile commerce patterns for mobile users, where mobile commerce patterns are the entangling relations between mobile user's purchase (interaction) patterns and moving (context) patterns. Besides the rules between user interactions and contexts, associations between different contexts are also important for modeling users' mobility patterns.[89] Also, Saleh and Masseglia[112] focused on studying the context-aware (time) mobile user behavior associations, and they think these associations should be more informative for understanding users given the context. At last, Baralis *et al.*[12] presented the idea of generalized association rule for providing a high-level domain knowledge abstraction that allows a compact representation of general correlations among context data (e.g., time and location).

5.2.2. *Sequence mining*

Sequence mining discovers frequent subsequences as patterns in a sequential database,[85] and comparing with association rule learning, sequence mining are more focusing on the time-ordered patterns. By using this approach, service providers can predict future trends and change points of mobile users, which will be helpful in placing precautions and targeted services.

Sequence is a frequently happening phenomenon for mobile user behaviors, such as the travel/trajectory patterns. Giannotti *et al.*[40] introduced trajectory patterns as concise descriptions of frequent behaviors in terms of both space (i.e., the regions of space visited during movements) and time (i.e., the duration of movements). Further, Monreale *et al.*[89] took advantage of these trajectory patterns for next location prediction. Given a location sequence of one object (e.g., mobile user, or bald eagle), Li *et al.*[71] aimed at mining their periodic behaviors. Besides the context data collected by the system from GPS and sensor, some user generated data have also been exploited for sequence mining. For instance, Zheng *et al.*[153] analyzed tourist mobility and travel behaviors based on geotagged photos, since these photos become digital footprints marking users' physical presence. Noting that many related works about mobile pattern mining and mobile behavior predictions can be found in Ref. 78.

5.2.3. *Clustering and classification*

In general, clustering tries to group a set of objects (e.g., mobile users) and find whether there is some relationship between the objects. In contrast, we have a set of predefined class labels for classification, and we want to know which class a new object belongs to. Both of these techniques have wide applications in the context-aware mobile domain.[30,154]

There are several kinds of interesting clusters to be discovered, such as context (e.g., location) clusters, user clusters, and item (e.g., pick-up points) clusters. Specifically, Zheng *et al.*[152] clustered multiple individuals' location histories with a tree-based hierarchical graph (TBHG), where the hierarchy of TBHG denotes different geospatial scales (alternatively, the zoom level of a Web map), like a city, a district and a community. This TBHG structure was also adopted by Leung *et al.*[68] for alleviating the stay point sparsity problem. Considering the uncertainty of putting a trajectory into a cluster, Pelekis *et al.*[98] proposed a fuzzy algorithm for clustering mobile trajectories. Wang *et al.*[130] proposed an algorithm for detecting communities (user clusters) in a mobile social network by taking into account information diffusion. Ge *et al.*[39] presented a driving distance-based pick-up points clustering method for taxi drivers, and similarly Yuan *et al.*[144] used a density-based clustering method to discover the same parking places. Also, Lu *et al.*[78] proposed a transaction clustering algorithm that builds a cluster model for mobile transactions.

Classification can be done by using supervised inductive learning algorithms such as decision tree classifiers, naive Bayesian classifiers, K-nearest neighbor classifiers, SVM, etc.[122] For example, Zheng *et al.*[148] provided an approach based on supervised learning to automatically infer transportation mode (e.g., walking, driving) from mobile users' raw GPS data. Ye *et al.*[137] developed a semantic annotation technique for location-based social networks to automatically annotate all places with category tags (labels), and this method supports multi-label classification. Li *et al.*[70] proposed a method to infer the status (e.g., stable or not) of high-energy-consuming sensors according to the outputs of software-based sensors and the physical sensors that are necessary to work all the time for supporting the basic functions of mobile devices. Yuan *et al.*[141] proposed a framework that discovers and annotates regions of different functions (e.g., residential areas, business districts, and educational areas) in a city using both human mobility among regions and points of interests located in a region.

5.2.4. *Low-rank factorizations*

Low-rank matrix factorization is a fundamental building block of machine learning, underlying many popular regression, factor analysis, and dimensionality reduction algorithms.[118] This type of methods are one of most popular solutions in current mobile context modeling.

For alleviating the data sparsity and poor prediction accuracy problems in recommender systems, Ma *et al.*[84] proposed a factor analysis approach based on probabilistic matrix factorization by incorporating social contextual information, such as social networks and social tags. Also, they proposed another framework which fuses the users' tastes and their trusted friends' favors together (social trust ensemble).[83] Similarly, for alleviating the sparsity of the mobile users' behavior pattern space, Ma *et al.*[82] took advantage of a constraint-based Bayesian matrix factorization model for extracting users' latent common habits among behavior patterns and then transforming behavior pattern vectors to the vectors of mined common habits which are in a much more dense space. Based on collective matrix factorization, Zheng *et al.*[147] proposed a method to recommend locations and activities for mobile users, where the missing entries of the location−activity matrix are filled by information from location−feature and activity−activity matrices. By fitting the observed data, tensor factorization (TF) is another effective model-based context-aware recommender system technique. TF extends the classical two-dimensional User-Item matrix factorization problem into an n-dimensional (User-Item-Context) version of the same problem. The multi-dimensional matrix is factored into lower-dimensional representation, where the user, the item and each contextual dimension are represented with a lower dimensional feature vector.[10,58]

As more and more textual context data are being collected, topic models-based pattern mining emerges in the mobile domain.[140] For instance, Bao *et al.*[11] proposed two topic models (MUC and LDAC) to learn personalized contexts of mobile users, in the form of probabilistic distributions of raw context data from the context sessions. Liu *et al.*[76] analyzed the characteristics of the travel package data and developed a Tourist-Area-Season Topic (TAST) model, which can extract the travel topics conditioned on both the tourists and the intrinsic contexts (i.e., locations, travel seasons) of the landscapes. Yuan *et al.*[141] drew an analogy between discovering functions of a region and the topic discovery of a document, i.e., a region having multiple functions is just like a document containing a variety of topics. Along this line, they proposed a DMR (Dirichlet Multinomial Regression)-based topic model.

5.3. *Incorporating context into mobile recommender systems*

Generally, there are two major issues in context-aware mobile recommendations: First, which contextual data should really influence the recommendation procedure[104]; Second, how to incorporate selected context information into the mobile recommendation process.[4]

5.3.1. *Context selection*

For the first issue, current researches either exploit some heuristic context selection methods or use as many contextual data as possible. One of the most popular context selection methods is to use common sense and domain knowledge. For instance, considering the cost sensitivity, Ge *et al.*[38] selected the context of travel cost (including the financial cost and the time) for distinguishing the tour recommendation and traditional recommendations. Saleh and Masseglia[112] claimed that the users' intents will differ from one period to anther, e.g., behaviors over Christmas will be different from those extracted during the summer. Thus, they think time is an essential element of the context for discovering user behaviors. Comparatively, an even more convincing way of context selection is taking advantage of the statistical results. For instance, for predicting the taxis' driving directions, Yuan *et al.*[143] also took the time context into consideration, and the difference is that they split the time slots of one day based on the distributions of the collected data. Liu *et al.*[76] analyzed and illustrated the possible contextual information and their influence on tourists. For the scenarios where there are massive number of dimensions of context, it is impossible to measure the importance of each context manually. Thus, a more reasonable solution is to select all the contextual information for modeling and let the algorithms automatically make choice. For instance, having said that tensor factorizations (TF)[10,58] have the ability to treat different types of context as additional dimensions in the representation of the data as a tensor.

5.3.2. *Context incorporation*

According to Adomavicius and Tuzhilin's[4] classifications, different approaches to using contextual information in the recommendation process can be broadly categorized into two groups: (1) recommendation via context-driven querying and search, and (2) recommendation via contextual preference elicitation and estimation.

The context-driven querying and search approach has been used by a wide variety of mobile (e.g., tourist) recommender systems.[2,126] Systems with this approach typically use contextual information (obtained either directly from the user, e.g., by specifying current mood or interest, or from the environment, e.g., obtaining local time, weather, or current location) to query or search a certain repository of resources (e.g., restaurants) and present the best matching resources (e.g., nearby restaurants that are currently open) to the user.[4]

There are three different algorithmic paradigms of the recommendation via contextual preference elicitation and estimation — contextual pre-filtering, post-filtering, and collaborative modeling — for incorporating contextual information into the recommendation process. In the paradigm of contextual pre-filtering (or contextualization of recommendation input), contextual information drives data selection or data construction for that specific context. In other words, information about the current context is used for selecting or constructing the relevant set of data records (i.e., ratings). Then, recommendations can be predicted using any traditional methods on the selected data. For instance, for travel package recommendation, Liu *et al.*[76] exploited the seasonal collaborative filtering as contextual pre-filtering, i.e., they first found the seasonal nearest neighbors for given tourist, and then collaborative filtering was used for ranking the candidate packages. In the paradigm of contextual post-filtering (or contextualization of recommendation output), contextual information is initially ignored, and the recommendations are predicted using any traditional methods on the entire data. Then, the resulting set of recommendations is adjusted (contextualized) for each user using the contextual information. An experimental comparison of the pre-filtering method versus two post-filtering methods on the real-world datasets can be found in Ref. 94. Last but not least, in the paradigm of contextual modeling (or contextualization of recommendation function), contextual information is used directly in the modeling technique as part of recommendation algorithm. For instance, low-rank factorization-based methods for rating regression, like the extensions of probabilistic matrix factorization,[38,84] can be classified into this category.

More general information on context incorporation can be found in Ref. 4. Noting that our presented methods constitute only the initial approaches to providing recommendations, and for designing realistic useful context-aware mobile recommender systems, more sophisticated methods[123] combining multiple techniques (e.g., pre-filtering, post-filtering) together to achieve some synergy between them should also be developed.

6. Mobile Recommendation Applications

In this section, we present some typical application domains for context-aware mobile recommendations. Different from Sec. 5, where context modeling techniques are highlighted, this section will focus on the recommendation tasks and functions.

6.1. *Mobile social networking*

In this subsection, we illustrate two typical recommendation categories in mobile social networking. The first one is recommending social relationships, i.e., social link prediction, and the second one is exploiting social relationship or locations for item recommendation.

Using cell phone location data, as well as data from two online location-based social networks, Cho *et al.*[27] aimed to understand what basic laws govern human motion and dynamics. They found that humans experience a combination of periodic movement that is geographically limited and seemingly random jumps correlated with their social networks. Since human movement and mobility patterns are impacted by the context of geographic and social constraints, Quercia and Capra[100] provided a framework called *FriendSensing* that automatically recommends personalized social friends by logging and analyzing co-location mobile data (collected from Bluetooth of the mobile phones). More specifically, Scellato *et al.*[113] found and defined some link prediction features based on the properties of the places visited by mobile users which are able to discriminate potential future links among them. Building on the findings, the authors described a supervised learning framework which exploits these prediction features to predict new links among friends-of-friends and place-friends.

Schifanella *et al.*[114] designed a collaborative filtering approach which epidemically spreads recommendations through spontaneous similarities between users, this approach can deal with self-organizing communities, host mobility, wireless access, and *ad hoc* communications. Ye *et al.*[137] developed a semantic annotation technique for location-based social networks to automatically annotate all places with category tags which are a crucial prerequisite for location search and recommendation services. Further, a city offers thousands of social events a day, and upon mobile phone data we have been able to infer which events had been attended by the mobile users.

For dwellers to make choices, Quercia *et al.*[101] carried out a study of the relationship between preferences for social events and geography, and then tested a variety of algorithms for recommending social events. There are some other research works which improve recommender systems by incorporating social contextual information, such as Refs. 48 and 84. Besides the item recommendation for each mobile user, mobile social information are also important for the service providers, since mobile social network plays an essential role as the spread of information and influence in the form of "word-of-mouth". By finding a subset of influential individuals in a mobile social network such that targeting them initially (e.g., to adopt a new product) will maximize the spread of the influence (further adoptions of the new product), Wang *et al.*[130] proposed a new algorithm for recommending top-K influential nodes to the service providers.

6.2. *Tourism*

In Sec. 5.1, we have presented several tasks on location modeling. Many of these tasks are particularly important for the location-based mobile services, among which tourism recommendations have received the largest attention. Thus, in this subsection, we go one step further to give the typical recommendation studies in the tourism domain, and these current work can be divided into two subgroups.[75]

The first subgroup has a focus on the development of intelligent systems and algorithms to the tourists in the pre-travel stage for travel planning,[138] information filtering,[133] inspiration,[105] etc. For instance, Yin *et al.*[138] proposed an automatic trip planning framework by leveraging geo-tagged photos and textual travel logs. Also, Hao *et al.*[42] proposed a Location-Topic model by learning the local and global topics to recommend the travel destinations. Wu *et al.*[133] designed a system using the multimedia technology to generate the personalized tourism summary. By taking the travel cost (e.g., the tourist's budget, the time cost) into the consideration, Ge *et al.*[38] and Xie *et al.*[135] provided focused studies of cost-aware tour recommendation. For travel recommendation and advisory, Ricci *et al.* described case-based reasoning approaches, Trip@dvice[105] and DieToRecs.[106] By exploiting a set of features for each tourist's specific interaction session, these two approaches address a number of travel issues, including mix-and-match travel planning, the new package/tourist problem, etc. Moreover, Liu *et al.*[76] proposed a cocktail approach on personalized travel package recommendation which also combines several contextual constraints.

In the second subgroup, people target on providing more context-aware travel information to the on-tour tourists with mobile devices. For instance, Abowd *et al.*[2] presented the Cyberguide project, in which they built the prototypes of a mobile context-aware tour guide, where user's current location as well as a history of past locations are used. Similarly, Cena *et al.*[23] presented UbiquiTO, a tourist guide which integrates different forms of adaptation for mobile tourist guides. Averjanova *et al.*[9] developed a map-based mobile recommender system that can provide users with some personalized recommendations. Also, Carolis *et al.*[32] developed a mobile recommender system which uses a map for outlining the location and the information of landscapes in a town area. Recently, a more sophisticated on-tour support system, MobyRek, was developed by Ricci and Ngayen.[107] This system employs a dialogue approach whereby a set of candidate items are proposed and the user is asked to critique the recommended items.

More related work on tourists guides about finding/recommending relevant attractions and services can be found in Ref. 104. All the listed mobile systems and algorithms target at helping tourists from different perspectives. In real applications, tourists need support throughout all the travel stages: from pre-travel planning to the on-the-move support during the travel, and even when the travel is finished.[107]

6.3. *Urban computing*

With the rapid progress of urbanization and civilization on earth, urban computing is emerging as a concept where every sensor, device, person, vehicle, building, and street in the urban areas can be used as a component to probe city dynamics to further enable city-wide computing for serving people and their cities,[c] e.g., by providing smart and context-aware recommendations in the urban spaces. Due to a wide range of potential applications, research on the recommendations in urban computing has received a lot of interests from both of the industry and academia. In the following, we use two instances to illustrate the recommendation tasks currently existing: mobile recommendations with shopping and taxis, respectively.

Actually, the idea of providing personalized aids to mobile shoppers was proposed as early as 10 years ago.[63] Recently, more and more work have been designed for tracking the context of mobile customers for providing intelligent recommendation. For instance, Kidokoro *et al.*[59] proposed a method that estimates customer interests by identifying a set of areas at which a customer has stopped in their experimental shop environment and recommends items through robots located on the shop's shelves. Kalnikaitėv *et al.*[54] presented a minimal, mobile and fully functional lambent display that clips onto any shopping trolley handle, intended to nudge customers as an assistance for their weekly shop at a local supermarket. Lu *et al.*[77] proposed a framework, called Mobile Commerce Explorer (MCE), for mining and prediction of mobile users' movements and purchase transactions under the context of mobile commerce (e.g., in shopping center). At last, an overview of some support systems for shopping center environment tracking and recommendations can be found in Ref. 8.

Similarly, GPS-equipped taxis have also enabled us to provide intelligence for helping taxi drivers make more effective and real-time decisions. For instance, Yuan *et al.*[143] mined smart driving directions from the historical GPS trajectories of a large number of taxis, and recommended a driver with the practically fastest route to a

[c] http://research.microsoft.com/en-us/projects/urbancomputing/.

given destination at a given departure time. Considering the context of the drivers (e.g., traffic conditions and driver behavior), an even more powerful project for recommending fast driving routes by a Cloud-based system was recently presented in Ref. 142. Besides these, location traces can also help to maximize the probability of taxi drivers' business success. For instance, Ge *et al.*[39] developed a mobile recommender system which has the ability in recommending a sequence of pick-up points for taxi drivers or a sequence of potential parking positions, and Yuan *et al.*[144] proposed a system to make recommendations for both taxi drivers and passengers expecting to take a taxi.

6.4. *Information retrieval and recommendations*

While on the go, searching and surfing information (e.g., news) on one's phone is becoming pervasive. However, mobile devices and the mobile Internet represent an extremely challenging search environment, such as context-awareness, limited screen-space, restricted text-input and interactivity, etc. In this subsection, we mainly focus on their characteristic of context-awareness.

The effectiveness of context-aware web search has been proved before,[22] and more contextual information such as location has been exploited for better clustering[72] and personalization.[17] Church and Smyth[28] proposed a novel interface to support multi-dimensional, context-sensitive mobile search, combining context features such as location, time, and community preferences to offer a unique search experience that is well adapted to the needs of mobile users. Considering the limited training data and weak relevance features in mobile search, Inagaki *et al.*[45] proposed to leverage the knowledge of Web search to enhance the ranking of mobile search. Further, Lane *et al.*[62] presented another local search technology for mobile phones, Hapori, that not only takes into account location in the search query but also richer context such as the time, weather and the activity of the mobile user. Recently, Tamine-Lechani *et al.*[124] presented a comprehensive survey of contextual information retrieval evaluation methodologies.

Besides the recommendations in tourism, social networking and urban computing, mobile systems can now provide more information recommendations beyond our imagination. For instance, Zhu *et al.*[155] proposed a uniform framework for personalized context-aware mobile (e.g., app, mobile media) recommendation, which can integrate both context independency and dependency assumptions. Lee and Park[64] presented a news recommender for the mobile web, and for recommending mobile music. Lee *et al.*[65] proposed a collaborative filtering-based recommendation methodology based on both implicit mobile user ratings and less ambitious ordinal scales. Woerndl *et al.*[132] designed a hybrid method for recommending mobile applications to users based on what other users have installed in a similar context. Zhuang *et al.*[156] presented an approach to context-aware and personalized entity (e.g., restaurant) recommendation which understands the implicit intent without any explicit user input on the mobile phone.

7. Discussion

As the large majority of our devices will be mobile and wireless, context-aware mobile recommendations are becoming more and more popular in various application domains. Toward this research direction, it will be much easier for data miners to collect massive number of contextual mobile data, and thus we believe more attention worth being paid to the way of data processing and data modeling, and consequently mining much more useful knowledge (as illustrated in Sec. 5 and Sec. 6). Also, deep insights into the evaluation of recommendation results are usually required. Though mobile recommendations are the practical application of recommender system techniques and the evaluation metrics that we gave in Sec. 2.4 are applicable to mobile recommendations, most of these metrics are only useful for offline evaluations. For real-world applications, more sophisticated online experiments (e.g., mobile user studies and feedbacks) are also required.

In summary, compared with traditional recommendations, mobile recommender systems can provide better recommendation results when coupled with personalized contextual information, since they can understand mobile users more accurately. However, there are also some limitations and key issues that should be taken care of when designing context-aware mobile recommender systems. Specifically, in the following we highlight some of them: how to protect the privacy of the mobile users in these context-aware systems, how to tackle the problem of high energy consuming of context-aware mobile applications, and how to conquer the limitations of the small interfaces of mobile devices (e.g., mobile phones and PDA).

7.1. *Privacy issue*

With the benefits having been brought by context-aware mobile applications, the privacy issues have also been paid more and more attentions due to the capability of these applications to collect, store, use, and disclose the contextual information of those who use them. Hence, the success of context-aware services is conditioned to the availability of effective privacy protection mechanisms.[103]

Recently, many privacy protection techniques have been specifically developed for location-based services (LBS), which are mainly in the form of online compared to the traditional offline privacy protection in microdata release due to the dynamic nature of spatio-temporal information. These techniques are often insufficient and inadequate when applied to generic context-aware services. Riboni *et al.*[103] provided a classification of these privacy protection techniques applied in the LBS field and focused on describing available approaches and solutions on those for more complex context-aware services. Even though these techniques are effective in a particular scenario and under particular assumptions, they fail to protect against the different kind of attacks that can be posed to the privacy of users taking advantage of context-aware services. In order to overcome these shortcomings, some research work proposed the combination of techniques from two or more categories. Specifically Riboni *et al.*[103] claimed that a deeper integration is needed and proposed an architecture for a comprehensive framework towards this goal. However, it is still a long way to go in order to refine the architecture and test the framework on real applications. Therefore, studying on the privacy protection mechanisms is still a hot and important direction.

7.2. *Energy-efficiency issues*

With the development of those intelligent context-aware mobile applications, the energy efficiency of context-sensing becomes the bottleneck for the success of these applications limited by the battery capacity. Many studies for energy-efficient context-sensing have been reported.[16,29,52,70]

For example, Li *et al.*[70] proposed to leverage machine learning technologies to infer the status of high-energy-consuming sensors according to the outputs of software-based sensors and the physical sensors that are necessary to work all the time for supporting the basic functions of mobile devices. If the inference indicates the high-energy-consuming sensor is in a stable status. They instead use the latest invoked value as the estimation to avoid the unnecessary invocation. Even though it can improve the energy efficiency of multiple high-energy-consuming context sensors by trading off the sensing accuracy, it is inevitable to result in exhaustion of additional energy by the complex learning approaches. Hence, the energy issue is still a tricky and important problem in context-aware mobile computing field.

7.3. *User interface issues*

Due to the small interfaces of mobile devices, such as mobile phones and PDA, recommendation sessions can be difficult and frustrating for end-users. The limitation of small interfaces for browsing and item recommendations lie in the three aspects: (1) on a small screen the user may be forced to carry out extensive scrolling while browsing a web page, and the more a user has to scroll down, the smaller the chances of an item being clicked; (2) a user on a small screen is less effective in completing an assigned task when compared to users of large screens; (3) mobile devices offer limited input and interaction capabilities. Some techniques have been exploited in mobile recommender systems to address this issue.[104] Here we list some of them as follows:

Starfield Displays.[35,117] A starfield display is basically a mapping of selected attributes of a multidimensional information space onto a two-dimensional representation to reduce clutter. This technique has been proved to be suitable and successful access methods for mobile device information systems.[117]

Displaying Similar Searches.[28] This kind interface support multi-dimensional, context-sensitive mobile search that is well adapted to the needs of mobile users, by integrating the user context, in the form of temporal and location data, with preference information derived from the queries of mobile searchers with similar interests. The main idea is that instead of recommending information explicitly requested by the user the system becomes proactive by presenting information, i.e., searches performed by other users in similar contexts.[104]

Map-based Interfaces. Map-based interfaces are used as intuitive access method to visualize the recommended items, e.g., points of interests (restaurants, or hotels) and various kinds of information related to these points (menus or in-room services). Due to the various limitations of mobile devices, to display large number of objects and their related information on an electronic map is computationally expensive and not effective. Thus, mobile Recommender systems can simplify the usage of map-based interfaces for mobile services.

Many more techniques and detailed illustrations can be seen in Ref. 104. Though there are so many established techniques for addressing this user interface issue, to develop new techniques is still an important topic with the increasing popularity of smart mobile devices.

8. Conclusion

In this paper, we provided a focused survey of context-aware mobile recommendations. Specifically, we introduced the existing studies according to the whole spectrum of context-aware mobile recommendations, including mobile contextual data collection, context-aware modeling of mobile recommendations, and mobile recommendation application scenarios. In this survey, we had a focus on the recommendation applications in social networking, tourism, and urban computing. Also, this study shows that there are still some critical challenges for mobile recommendations, such as the privacy problem, the energy-efficiency concern, and the design of the user interfaces.

In addition to these general technical and domain challenges, there are still some potential future research directions as follows.

- **The complexity of context-aware mobile data.** Indeed, structured and unstructured context-aware data are now quickly being gathered by ubiquitous information-sensing sources. These data are so large and complex that it becomes difficult to process using traditional data analysis tools. It is necessary to develop new solutions for dealing with (e.g., storing, search, sharing, analyzing and visualizing this type of big data),[d] and thus mine more information for personalized mobile recommendations.
- **More diversified applications.** Here, we only focus on some mobile application scenarios. However, the idea of context-aware mobile recommendations can be well incorporated into other application domains. For instance, it has recently caught a lot of attentions from Economics of Information Systems for mobile recommendations. As another example, multi-criteria mobile recommendations[86] (e.g., restaurant guides) also put forth on some challenging research problems.

[d] http://en.wikipedia.org/wiki/Big_data.

- **From demand fulfillment to demand generation.** Current research studies on mobile recommendations mainly focus on fulfilling each single users' direct requirements (e.g., travel route recommendation). When more context-aware data become available, it is possible to understand users more comprehensively, and thus predicting their additional demands which are not currently realized by themselves. For instance, by analyzing the personalized information of mobile users, one company can design targeted marketing campaign programs.
- **Spam/fraud tolerant context-aware mobile recommendation.** Spam or fraud user ratings have become a big challenge for recommender systems for many years. While some measures and detection techniques have been proposed, they usually cannot be directly applied to the mobile domain. With the popularity of context-aware mobile services, we believe that more and more research attention will be focused on designing spam/fraud tolerant context-aware mobile recommender systems in the near future.

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