Location-Aware Recommendation Systems: Where We Are and Where We Recommend to Go

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ABSTRACT

Recommendation systems have been successfully used to provide items of interest to the users (e.g., movies, music, books, news, images). However, traditional recommendation systems do not take into account the location as a relevant factor when providing suggestions. On the other hand, nowadays, there exist an increasing amount of geo-referenced data and users are usually interested only in nearby items (e.g., restaurants, museums, cinemas). Hence, the emergence of location-aware recommendation systems have acquired a great attention by the research community in the last decade.

In this paper, we provide a survey of location-aware recommendation systems in mobile computing scenarios. Firstly, we describe briefly the fundamentals of recommendation systems. Then, we introduce some of the most relevant existing approaches for location-aware recommendation. Moreover, we present the main applications of this type of systems in several recommendation scenarios, such as music, news, restaurants, etc. Finally, we discuss new avenues and open issues in the area.

Categories and Subject Descriptors

H.3 [**Information Storage and Retrieval**]: Information filtering

Keywords

Location-aware recommendation systems, mobile computing, open issues

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1. INTRODUCTION

The progressive development of mobile computing technologies has allowed the emergence of *Location-Based Services* (*LBS*). LBS attempt to provide useful and customized information in contexts where the location is an important factor to bear in mind, such as scenarios related to health issues, working environments, entertainment, personal life, and so on. The locations of moving objects are typically obtained by using information obtained by the mobile devices through the communication network used for data transmission or by exploiting geographical positioning systems (e.g., GPS sensors, beacon techniques).

Recommendation Systems (*RS*) have been a main focus of research, as these systems gradually reduce the existing information overload (information available on the Internet, data provided by sensors of different types or other users, etc.), by recommending to the users personalized items of interest (e.g., movies, music, books, news, images) based on their preferences. With the advent of e-commerce, the combination of recommendation system techniques and LBS has been of significant interest for researchers. The inclusion of the location dimension in these types of systems allows obtaining more effective recommendations, so bringing about the emergence of a new field of research called *Location-Aware Recommendation Systems* (*LARS*).

In this paper, we provide a survey on location-aware recommendation systems for mobile computing. The rest of the paper is organized as follows. Section 2 provides some fundamentals about the technological context. In Section 3, we present an overview of related works. Then, we classify different approaches by application domain in Section 4. In Section 5, we discuss future perspectives of LARS. Finally, we present our conclusions in Section 6.

2. BACKGROUND

2.1 Traditional Recommendation Systems

Recommendation Systems (*RS*) are applications aimed at suggesting items of interest to users (e.g., products, services). Recommendations are considered an important support for users' decision making (e.g., decide which products to buy, which book to read next, which movie to watch) [17]. They are important from both the business perspective and from the user's perspective, as they can boost purchases but also alleviate the information overload experienced by the users.

Based on how recommendations are calculated, RS are generally classified into three well-known categories [2], as explained in the following.

Collaborative filtering: the user is provided with items consumed in the past by other users with similar tastes and preferences (*user-based collaborative filtering*). Another possibility is to recommend items based on the similarity with other items that the user has liked in the past (*item-based collaborative filtering*); this similarity is computed by analyzing the ratings given to the items by the users.

Content-based recommendation: recommendations are based on the similarity between the searched item and other items the user liked in the past. As opposed to the case of item-based collaborative filtering, this item similarity is computed by comparing the contents (features) of the items.

Hybrid recommendation approaches: these methods combine both collaborative and content-based algorithms, to benefit from the advantages of each paradigm while trying to avoid their specific disadvantages.

Although major advances have been accomplished by using, fine-tuning, and extending traditional recommendation techniques, they can fail when estimating the relevance of a certain item in some situations (e.g., where the users are interested only in nearby items). In particular, they run into severe problems when tackling scenarios with dynamic variables, such as the location of the user, time, weather, or other users' opinions.

2.2 Location-Aware Recommendation Systems

To alleviate the problems of traditional RS mentioned above, considerable efforts have been invested in the last years, creating a new research line called *Context-Aware Recommendation Systems* (*CARS*) [3]. These novel methods take into consideration the need of including the context of the user and/or the context of items in the process followed to calculate accurate recommendations. Among the different aspects that can be considered to represent the context of a recommendation process, the location of users and/or items has been proved to be of special importance to suggest relevant recommendations [16].

Location-Aware Recommendation Systems (*LARS*), illustrated in Figure 1, take into account the spatial properties (locations) of users and/or items to calculate proper recommendations. The emergence of LARS comes from the fact that users typically prefer nearby items (e.g., restaurants, museums, cinemas), as the effort needed to reach items close to their physical positions will be smaller. Moreover, it may happen that only nearby items are relevant or that items located far have a short spatio-temporal relevance. For example, a suggestion about a specific parking space provided to a driver searching for parking could become obsolete in a short time if the parking space is not nearby (while the user drives towards the parking spot, it can be occupied by another vehicle). In general, LARS can be considered as an extension of traditional recommendation systems, and an important subset of CARS that focuses on the dimension *location* in the multidimensional context. In LARS, the rating is modeled as a function in terms of the item, user and location $f : U \times I \times L \rightarrow R$. Notice that not only the users can be continuously moving but also the items (e.g., if the items are taxi cabs).

The *location* can be associated to the physical position of the user when he/she rates an item (e.g., a book rated by a user from home), to the location of an item (e.g., the position of a restaurant rated), or to both. The framework proposed in [19] classifies location-based ratings in three categories:

- *Spatial ratings for non-spatial items.* Represented by the tuple $(user, ulocation, rating, item)$, where *ulocation* is the user's location.
- *Non-spatial ratings for spatial items.* Stated by the tuple $(user, rating, item, ilocation)$, where *ilocation* represents an item's location.
- *Spatial ratings for spatial items.* Represented by the tuple $(user, ulocation, rating, item, ilocation)$. In this case, the location of the user and the location of the item are both relevant.

The users of LARS can receive implicit or explicit recommendations. On the one hand, *implicit recommendations* (*push-based recommendations*) are proactive recommendations that the user receives without submitting explicit requests to the system. On the other hand, *explicit recommendations* (*pull-based recommendations*) are reactive recommendations, obtained as an answer to a query explicitly submitted by the user (e.g., "I need a restaurant"). In both cases, the set of recommendations provided to the user should be monitored and kept up-to-date, as the relevant recommendations may change due to movements of the user and/or target items.

Currently, several real-world recommendation systems use the location as an important parameter for the suggestion of relevant items. Well-known examples are Google Now (`http://www.google.com/landing/now/`), Foursquare (`http://foursquare.com/`), and Yelp (`http://www.yelp.com`).

Finally, it is interesting to indicate that GPS trajectories obtained from the user's mobile logs can facilitate the discovery of interesting patterns about the user [9, 32, 33], that may be further used to calculate recommendations.

3. DOMAIN-INDEPENDENT APPROACHES FOR LARS

In the recent years, thanks to advances of mobile devices, ubiquitous computing, and wireless communication technologies, a significant number of works have been carried out in the field of LARS. An example is the system presented in [19, 29], which exploits location-based ratings to provide recommendations. To obtain spatial ratings, the authors applied an approach of user partitioning based on the user locality, the scalability to large numbers of users, and the influence of the users, to control the size of the neighborhood. For spatial items, a travel penalty was applied (favoring the closest items). The collecting process of the spatial ratings was motivated by the study carried out on the MovieLens dataset (`http://grouplens.org/datasets/movielens`), that associates the locations with the user's ZIP codes (i.e., spatial ratings), and the Foursquare dataset (`https://developer.foursquare.com/`), which contains information about the places visited by users (i.e., spatial ratings for spatial items). Recently, and along the same vein,

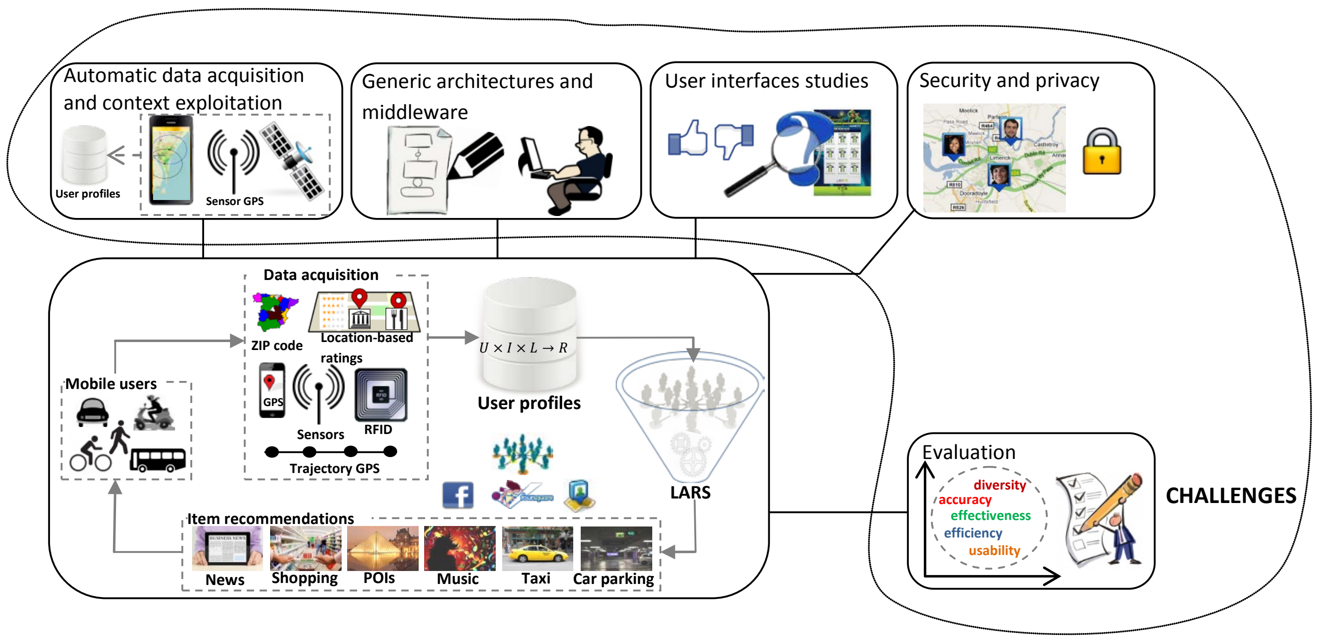

Figure 1: Overview of LARS

the authors of [5] presented LARS*, that also recommends items based on location-based ratings, by using user partitioning and travel penalty techniques. In this case, the location is obtained from the IP address of the user's mobile device.

A similar goal was pursued in [39], where the authors presented LA-LDA, a location-aware probabilistic generative model that uses location-based ratings to model user profiles to produce recommendations (e.g., suggestions about restaurants) as well as to mitigate the well-known cold start problem. They considered the three types of location-based ratings proposed in [19] (i.e., spatial user ratings for non-spatial items, non-spatial user ratings for spatial items, and spatial user ratings for spatial items). In [18], the authors proposed a location-based service recommendation model (LBSRM) that combines relevant elements of LBS and recommendation technologies. Firstly, the model filters information based on the user's location, and then it recommends relevant mobile information services by using clustering techniques. With a similar spirit, the authors of [13] recently integrated LBS with recommendation techniques to present a hybrid recommendation model.

Other approaches consider the impact of the locations not only as a pre-filtering step but directly on the application of collaborative filtering. For example, [11] uses Voronoi diagrams to decompose the user's space and then it uses them in a spatially-aware collaborative filtering algorithm; specifically, they explored the concept of spatial autocorrelation to cluster similar values on a map, by using statistical measures. In this approach, the ZIP code of the area is used to identify the user's location. A location-aware collaborative filtering was also proposed in [27], which uses the user's location to recommend web content in real-time, increasing the diversity of recommendations; specifically, the authors determine the diversity using the Levenshtein edit distance between attributes of items (e.g., locations, tags, titles and URLs) to try to address the handicap of popularity bias without affecting the performance. Moreover, recently, the authors of [37] proposed a location-sensitive recommendation approach in ad-hoc social network environments.

With the development of the Web 2.0, some works focus on the combination of mobile technologies with traditional social networks, giving rise to Location-Based Social Networks (LBSN) [7], such as Foursquare, Facebook Places (`https://www.facebook.com/places/`), and others. The emerge of this new kind of social networks allows to connect with friends, share locations (and/or photos, videos, etc.), receive recommendations of places (e.g., restaurants), etc. The main research topic covered is how to effectively combine the information provided by social networks to offer more accurate recommendations. For example, a user could trust particularly the recommendations offered by his/her friends, but not all the user's connections are necessarily real friends. Analyzing in depth how information about the user's social interactions in real-time (e.g., a tweet or photo published by the user, a conversation with a friend) could be exploited in the context of LARS is an issue that has not been explored in depth so far.

We conclude this section with some final examples. First, a Markov-based technique presented in [1] improves the quality of location-aware recommendation systems by using the location information of items. In the Markov model, the authors consider each item as a state. The states are defined as the history of items viewed (or visited) by the users, and the transition probability is calculated according to the preferences (likes) of items by the users in the past. In general, the recommendation approach suggests the items with the highest likelihood estimation, by taking account the location (i.e., a greater geographical distance among the items decreases the probability estimation). In [23], a collaborative filtering recommendation approach is presented, focusing on the specific case of suggesting geospatial locations (e.g., latitude and longitude) where mobile users can take photos. The final list of locations to recommend must be within a (user-defined) suitable distance from the physical position of the user. Instead of exploiting the users' locations, the authors used three million geotagged photos taken from smartphones (i.e., photos implicitly containing geocoordinates). In [31], data mining techniques (e.g., clustering models) were used to recommend items to the mobile users by considering the user's location. Finally, [24, 25] presented an improvement of collaborative filtering that combines the user's geographical information and the content of items in order to learn location-based user group preferences, considered by the authors as a rating distribution of a group of items. According to the study performed with the MovieLens dataset, the user group preference has strong correlation with the location of the user.

4. LARS IN SPECIFIC DOMAINS

In this section, we discuss several domains where location-aware recommendation systems have been applied. Firstly, we consider the recommendation of generic POIs (Points of Interest) in Section 4.1. Then, we analyze in Section 4.2 relevant references for the tourism domain. Afterwards, Section 4.3 focuses on news recommendation, and we mention in Section 4.4 several approaches proposed in the literature for the shopping domain. Finally, we present in Section 4.5 works related to other domains.

4.1 LARS for the Recommendation of POIs

One of the most common application domains of LARS is suggesting interesting points (e.g., restaurants) around the user. For instance, a collaborative location-aware filtering approach to recommend POIs to mobile users was proposed in [16], which exploits the location as a relevant element for the recommendation of items (e.g., restaurants) near the user's current location. The approach proposed is the result of combining user-based collaborative filtering techniques with a location-based partitioning method (i.e., it allows an adequate rating database partitioning based on the location), with the goal of achieving a high scalability. That work validates the hypothesis that users who live nearby tend to visit the same local places. The proposal in [10] attempts to solve the problem of location-based context-aware recommendations of POIs by using a multiagent system architecture [36]; the use of agents facilitates the collection of POIs' information available on the Web. Another example is the location-dependent collaborative filtering system presented in [34], that analyzes the mobile user's moving features (e.g., moving direction, position, and speed, obtained through a GPS receiver) and the POIs, in order to recommend to the mobile user those items of interest that are in a region near the user's current position and in the same direction. In the rest of this section, we mention some other examples.

An ubiquitous location-based recommendation algorithm that suggests relevant places to mobile users is presented in [30]. The system, named "I'm feeling LoCo", considers the user profile and the places near him/her during the recommendation process. It automatically infers the user's preferences (by mining social network profiles) and considers spatio-temporal constraints in the recommendation process. The physical constraints are delimited by the user's location and the transportation way (e.g., driving a car, riding a bicycle, or walking).

A location-based and preference-aware recommendation system that suggests venues (e.g., restaurants and shopping malls) within a geospatial range was presented in [6]. It learns the user preferences automatically from the user's location history and infers the user's expertise (e.g., in categories such as Chinese food and shopping mall) in several cities. During the recommendation process, the system filters the candidate local experts in a geospatial range (defined by the user) and suggests the venues that match the user's preferences and the social opinions of the selected local experts. This type of system has the advantage of providing venues not only near the area where users live, but also in cities unknown to them. A similar goal was pursued in the Location-Content-Aware Recommendation System (LCARS) proposed in [40], which recommends venues (e.g., restaurants) or events (e.g., concerts and exhibitions) within the city of the query initiator, by using the probability of influence of the personal interests and local preferences of the users. One of the main goals is to alleviate the data sparsity problem (the new city problem) based on the location and content information of spatial items.

Specifically focused on the restaurant domain, [15] proposed a location-based recommendation architecture for dynamic and ubiquitous environments. The authors combine, in the proposed architecture, the ideas of location, personalization, and content-based recommendation. As a final example, the PECITS system [35] provides location-aware recommendations of POI paths (e.g., a list of several connections that the user could take to reach a certain POI, by using public transportation and by foot) in Bolzano (Italy).

4.2 LARS for the Tourism Domain

In the tourism domain the recommendation process implies suggesting a set of products or services that support traveling and tour planning (e.g., attractions, accommodations, restaurants, and activities). For example, the authors of [20, 22] integrated tourism mobile commerce and location-aware features into a traditional recommendation system to provide real-time recommendations for visitors, by taking into account the locations and the ratings of the attractions. Similarly, an architecture for location-based recommendation was proposed in [41], which supports personalized tour planning for mobile tourism applications by using rule-based recommendation techniques. Along the same line, the authors of [9] present a system that recommends touristic places based on the user's visiting history in different regions (e.g., cities or countries). To recommend locations, a set of geotags (manually set on a map or automatically obtained form the GPS device) representing the latitude and longitude where a user took a photo is exploited. This is considered useful to plan a touristic visit to a new city or country.

4.3 LARS for the Recommendation of News

Most LARS use the user preferences and the distance between the current user's location and the positions of the items for the recommendation of relevant items. However, it is not usual to enrich the previous approach by using existing relations between items and tagged locations (e.g., geographical metadata of news articles), which could have an impact on the recommendations.

Thus, the authors of [4] proposed an interesting spatial model for location-based serendipitous recommendation of news articles. For that purpose, they studied the existing associations between the user's current location and the location data available in the geographical metadata of the news articles. The introduction of serendipity in traditional collaborative filtering implies modifying the recommendation approach to discover the novelty (or the surprise) and useful items for the user, by sacrificing accuracy.

A location-based social networking system for mobile devices, named Sindbad, was proposed also in the field of news [28]. With Sindbad, the user can receive friends' news based on their locations, as well as messages posted by his/her friends. Moreover, its recommendation system also suggests spatial items (e.g., restaurants) and non-spatial items (e.g., movies) based on the users' locations, the items' locations, and the ratings provided by friends. For that purpose, the location-aware recommendation module LARS proposed in [19] was used.

4.4 LARS for Shopping Recommendation

In the field of mobile commerce (m-commerce), several types of LARS have been designed and presented in the literature to suggest a variety of products and services that may be of interest to users. An example is the location-aware recommendation system presented in [38], that recommends vendors' web pages to interested customers in mobile shopping. Another example is *CityVoyager* [33], a recommendation system based on the user's location history, which is obtained by using a GPS device. It recommends shops to the users based on the locations of previous shops visited.

In order to avoid the need to type text, along with the associated spelling problems and possible ambiguity, when the user needs to specify the types of items he/she is interested in, an interesting proposal was presented in [42]. Specifically, the location-based shopping recommendation system proposed uses an image of the desired item (e.g., shoes, clothes) provided by the user, as the query, as well as the smartphone's GPS coordinates, to recommend retail shops (with information including their GPS coordinates, promotions, and special offers) to mobile users.

4.5 LARS for Other Scenarios

Finally, it should be highlighted that, although the domains examined in the previous subsections are the most common ones, there are other possible use cases. For example, in the area of music, the authors of [8] tackled the problem of providing location-dependent music recommendations by using emotional tags related to the music and the places of interest. With this idea, they developed a mobile location-aware recommendation system named *Playing-Guide*, that suggests and plays appropriate music for a place of interest for the user (e.g., the user might hear a specific music while visiting a place of interest in a city).

Another interesting work is *Motivate* [21], which presents a context-aware mobile recommendation system that promotes a healthy lifestyle. It recommends different kinds of useful advices to the user (e.g., take a break, walk/cycle to a park, go to a museum), by considering the location of the user, the activities in the user's agenda (e.g., go to work, work, have lunch, go home, have dinner, and busy), the time (e.g., the start and end time of an activity), and the weather (e.g., bad, fair, and good) as context parameters. The location of the user is determined by using GPS.

There exist also some attempts to use the location for recommendation in e-learning environments. The approach in [14] recommends educational materials and peer learners who are nearby, by using RFID to detect the learner's environmental objects and his/her location. The system also allows the learners to share knowledge, interact, collaborate, exchange individual experiences, and visualize the objects that surround the learner, the space of learning resources, and the distance to possible peer helpers.

5. FUTURE PERSPECTIVES

In the following, we discuss some perspectives of interest that should attract further research in the near future (see Table 1 for a summary).

Automatic data acquisition and context exploitation.

Overall, we believe that location-aware recommendation systems could be more effective if the characteristics of the dynamic environment were effectively exploited. In a mobile environment, the location information of the items and/or users is dynamic, and therefore constantly changing. Hence, such information should be updated with a certain frequency, using external sources such as sensors (e.g., GPS, RFID). However, the use of sensors to obtain the dynamic information needed is not sufficiently exploited in some cases. For example, [11, 16] consider the ZIP code to identify the user's location, which is a coarse-grain location. Furthermore, most works related to LARS, despite using locations during the recommendation process, do not detail how they were acquired (e.g., see [13, 18, 27, 31]). The acquisition and automatic discovery of user preferences (which may change from one location to another) from several external data sources (e.g., social networks, sensors), based on the use of data mining techniques, is a major research challenge. Thus, a process that automatically acquires a rich set of data would allow improving the effectiveness of the recommendations, as well as alleviating the cold start problem.

Finally, the quality of the recommendations could be further improved by enriching the user profile with additional context features besides the location dimension (e.g., the transport way, the weather, the time). The intuitive idea is that, by exploiting more information about the user preferences in different contexts, the recommendations obtained can be more appropriate for the current user's context. However, more research work is needed to explore this path. For example, the impact of having more or less context information should be analyzed, and automatic methods are needed to capture the context variables (e.g., we cannot expect that the user will explicitly provide all his/her contextual information when rating an item).

Evaluation.

Regarding evaluation, there are still significant research challenges to be addressed. Firstly, over time, RS have become more complex, by considering new parameters during the recommendation process, such as the location. In the same way, the metrics for the evaluation of these systems should also probably be more complex. However, researchers continue using traditional measures (e.g., MAE, RMSE, precision, recall, and F1 score) to evaluate location-aware rec-

Challenges	State of the art
1) **Automatic data acquisition and context exploitation**: representation, acquisition, and enrichment of data dynamically.	LARS could be more effective if the characteristics of the dynamic environment were effectively captured and exploited. Examples of related contributions: -Exploiting GPS trajectories: [9, 32, 33] -GPS sensing: [6, 8]
2) **Evaluation**: evaluation measures adjusted to dynamic environments, context-enriched data sets.	There is a need to use evaluation measures different from the classical ones, adjusted for the evaluation of LARS. Moreover, the datasets used for evaluation are usually still the same datasets used to evaluate traditional recommendation systems (e.g., MovieLens and Foursquare). Examples of related contributions: -Diversity measure: [27] -Usability questionnaire: [8, 18, 30] -Continuous query processing performance: [19]
3) **User interfaces**: proper design of user interfaces for mobile devices and dynamic environments.	It is necessary to design suitable user interfaces (i.e., simple and intuitive) for LARS, in order to avoid overloading the user with information. Examples of related contributions: -Usability evaluation of interfaces: [8, 30]
4) **Security and privacy**: ensuring the location privacy and user security.	The study and application of techniques to ensure location privacy and user security are important challenges to consider in the development of LARS. Examples of related contributions: -For recommendation systems in general: [26] -No relevant work specific to LARS has been identified
5) **Generic architectures and middleware**: emerge of generic architectures.	Despite the efforts, there is still no implemented architecture that facilitates the development of LARS for mobile environments. An adaptable architecture that could be extended and customized for several application scenarios would be really useful. Examples of related contributions: -Proposal of a generic framework: [12].

Table 1: Summary of challenges related with LARS

ommendation systems. So, we believe that an interesting research direction could be the emergence of new evaluation measures. For example, combining metrics, such as the accuracy and the diversity with the latency, or including location parameters in existing measures, could be an interesting area to analyze. Moreover, most works focus on the evaluation of the effectiveness of the recommendations, but in mobile environments the usability and efficiency are also relevant aspects to evaluate: timely suggestions could be more important than perfect suggestions but with a long delay.

Secondly, the datasets used for evaluation are usually the same datasets used to evaluate traditional recommendation systems (e.g., MovieLens and Foursquare). Hence, it is necessary to generate new datasets containing location information (related to items, users, or both) to evaluate LARS. The problem aggravates if we consider the evaluation of CARS, which require datasets enriched with significant context information. Real datasets could be collected more easily by a mobile recommendation system if the user's context data are automatically detected, as suggested in the previous research challenge. Furthermore, the definition of realistic synthetic data generators, or even crowdsourcing data collection through videogames (gamification), could be explored.

Bridging the gap between mobile computing and LARS.

The fields of mobile computing and recommendation systems have evolved in a quite independent way. However, when considering LARS, it is clear that traditional recommendation techniques should be completed with other data management techniques applied in mobile computing. As an example, it should be noted that a location can refer to the current continuously-changing physical position of a user, an item, or both. This is particularly relevant in typical mobile environments, where the user and/or the item can be moving [8, 30, 34]. For example, consider the case of a user who is walking down the street and uses a mobile application that suggests to him/her an appropriate taxi in real-time; in this case, both the user and the target items may be moving. As another example, if we consider applications such as the recommendation of parking spaces to drivers, estimating the spatio-temporal relevance of the parking spaces is a key issue (parking spots released recently and close to the location of the user should be preferred).

User interfaces.

From the perspective of mobile applications, user interfaces designed for recommendation purposes (explicit or implicit recommendations) should be simple and easy to understand. However, very few studies have evaluated the usability of interfaces in the context of recommendations [8, 30], or have studied in depth the best way to present the information. Hence, we believe that this could be a relevant research line to take into account during the design of location-aware recommendation systems. For example, location-aware recommendation systems are usually designed for mobile phone's screens. So, an important element to consider is the need to visualize only a few recommendations (not a long list of suggestions), to avoid overloading the user by crowding the screen with information, but at the same time those recommendations should be representative and diverse. Similarly, another problem is how to allow the user to easily specify his/her needs regarding the type of items that he/she requires (in pull-based recommendations), for example by using a keyword-based search interface which correctly interprets the user's intention.

Generic architectures and middleware.
In this field, most works are location-aware recommendation approaches and prototype systems that focus on a specific application domain (e.g., music, tourism, POIs, news, shopping). Despite some efforts to generalize this, there is no implemented architecture that facilitates the development of location-aware recommendation systems for mobile environments. We believe that this aspect should be analyzed, given the interest of having a generic solution that can be extended and adapted to different application domains [12].

The previous list does not intend to be exhaustive. For example, *security and privacy* is another hot topic of research which has not been extensively studied so far in the field of LARS, even though the user's location may need to be shared to retrieve suitable recommendations.

6. CONCLUSIONS

In this work, we have provided a survey of location-aware recommendation systems for mobile environments. We first described the basics of LARS and some generic approaches. Then, we presented a number of location-aware recommendation systems for several scenarios. Finally, several future perspectives and challenges, that we believe should guide upcoming research steps, were discussed.

In the last decade, location-aware recommendation approaches made an important progress thanks to significant efforts developed by the research community. Nevertheless, more research is needed to solve existing difficulties and design systems able to obtain more effective recommendations. We hope that this survey will encourage further efforts.

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8. REFERENCES

[1] A. Abbasi, A. Javari, M. Jalili, and H. R. Rabiee. Enhancing precision of markov-based recommenders using location information. In *International Conference on Advances in Computing, Communications and Informatics (ICACCI)*, pages 188–193. IEEE, 2014.

[2] G. Adomavicius and A. Tuzhilin. Toward the next generation of recommender systems: A survey of the state-of-the-art and possible extensions. *IEEE Transactions on Knowledge and Data Engineering*, 17(6):734–749, 2005.

[3] G. Adomavicius and A. Tuzhilin. Context-aware recommender systems. In F. Ricci, L. Rokach, B. Shapira, and P. B. Kantor, editors, *Recommender Systems Handbook*, pages 217–253. Springer, 2011.

[4] Y. A. Asikin and W. Wörndl. Stories Around You: Location-based serendipitous recommendation of news articles. In *2nd International Workshop on News Recommendation and Analytics (NRA)*, pages 1–8. CEUR Workshop Proceedings, 2014.

[5] S. S. Avhad and S. R. Durugkar. Lars∗: Location-aware recommendation system. *International Journal Of Engineering, Education And Technology*, 3(2):1–6, 2015.

[6] J. Bao, Y. Zheng, and M. F. Mokbel. Location-based and preference-aware recommendation using sparse geo-social networking data. In *20th International Conference on Advances in Geographic Information Systems (SIGSPATIAL)*, pages 199–208. ACM, 2012.

[7] J. Bao, Y. Zheng, D. Wilkie, and M. F. Mokbel. A survey on recommendations in location-based social networks. *GeoInformatica*, 19(3):525–565, 2015.

[8] M. Braunhofer, M. Kaminskas, and F. Ricci. Location-aware music recommendation. *International Journal of Multimedia Information Retrieval*, 2(1):31–44, 2013.

[9] M. Clements, P. Serdyukov, A. P. de Vries, and M. J. T. Reinders. Personalised travel recommendation based on location co-occurrence. *CoRR*, abs/1106.5213:1–30, 2011.

[10] H. Costa, B. Furtado, D. Pires, L. Macedo, and A. Cardoso. Context and intention-awareness in POIs recommender systems. In *6th ACM Conference on Recommender Systems, 4th Workshop on Context-Aware Recommender Systems (RecSys)*, 2012.

[11] J. Das, S. Majumder, and P. Gupta. Voronoi based location aware collaborative filtering. In *3rd National Conference on Emerging Trends and Applications in Computer Science (NCETACS)*, pages 179–183. IEEE, 2012.

[12] M. del Carmen Rodríguez-Hernández and S. Ilarri. Towards a context-aware mobile recommendation architecture. In I. Awan, M. Younas, X. Franch, and C. Quer, editors, *Mobile Web Information Systems*, volume 8640 of *Lecture Notes in Computer Science*, pages 56–70. Springer, 2014.

[13] R. Duan, R. S. M. Goh, F. Yang, Y. K. Tan, and J. F. B. Valenzuela. Towards building and evaluating a personalized location-based recommender system. In *IEEE International Conference on Big Data (Big Data)*, pages 43–48. IEEE, 2014.

[14] M. M. El-Bishouty, H. Ogata, and Y. Yano. Perkam: Personalized knowledge awareness map for computer supported ubiquitous learning. *Educational Technology & Society*, 10(3):122–134, 2007.

[15] A. Gupta and K. Singh. Location based personalized restaurant recommendation system for mobile environments. In *International Conference on Advances in Computing, Communications and Informatics (ICACCI)*, pages 507–511. IEEE, 2013.

[16] T. Horozov, N. Narasimhan, and V. Vasudevan. Using location for personalized POI recommendations in mobile environments. In *International Symposium on*

Applications and the Internet (SAINT), pages 124–129. IEEE, 2006.

[17] P. B. Kantor, L. Rokach, F. Ricci, and B. Shapira. *Recommender Systems Handbook*. Springer, New York, USA, 2011.

[18] M.-H. Kuo, L.-C. Chen, and C.-W. Liang. Building and evaluating a location-based service recommendation system with a preference adjustment mechanism. *Expert Systems with Applications*, 36(2):3543–3554, 2009.

[19] J. J. Levandoski, M. Sarwat, A. Eldawy, and M. F. Mokbel. LARS: A location-aware recommender system. In *28th International Conference on Data Engineering (ICDE)*, pages 450–461. IEEE, 2012.

[20] X. Li, Z. Mi, Z. Zhang, and J. Wu. A location-aware recommender system for tourism mobile commerce. In *2nd International Conference on Information Science and Engineering (ICISE)*, pages 1709–1711. IEEE, 2010.

[21] Y. Lin, J. Jessurun, B. de Vries, and H. Timmermans. Motivate: Towards context-aware recommendation mobile system for healthy living. In *Fifth International Conference on Pervasive Computing Technologies for Healthcare (PervasiveHealth)*, pages 250–253. IEEE, 2011.

[22] J. M. Noguera, M. J. Barranco, R. Segura, and L. Martínez. *A Location-Aware Tourism Recommender System Based on Mobile Devices*, chapter 7, pages 34–39. World Scientific, 2012.

[23] T. Phan, J. Zhou, S. Chang, J. Hu, and J. Lee. Collaborative recommendation of photo-taking geolocations. In *3rd ACM Multimedia Workshop on Geotagging and Its Applications in Multimedia (GeoMM)*, pages 11–16. ACM, 2014.

[24] Z. Qiao, P. Zhang, Y. Cao, C. Zhou, and L. Guo. Improving collaborative recommendation via location-based user-item subgroup. *Procedia Computer Science*, 29(0):400–409, 2014.

[25] Z. Qiao, P. Zhang, J. He, Y. Cao, C. Zhou, and L. Guo. Combining geographical information of users and content of items for accurate rating prediction. In *23rd International Conference on World Wide Web Companion (WWW Companion)*, pages 361–362. ACM, 2014.

[26] N. Ramakrishnan, B. J. Keller, B. J. Mirza, A. Y. Grama, and G. Karypis. Privacy risks in recommender systems. *IEEE Internet Computing*, 5(6):54–62, 2001.

[27] T. Sandholm and H. Ung. Real-time, location-aware collaborative filtering of web content. In *Workshop on Context-awareness in Retrieval and Recommendation (CaRR)*, pages 14–18. ACM, 2011.

[28] M. Sarwat, J. Bao, A. Eldawy, J. J. Levandoski, A. Magdy, and M. F. Mokbel. Sindbad: A location-based social networking system. In *ACM SIGMOD International Conference on Management of Data*, pages 649–652. ACM, 2012.

[29] M. Sarwat, J. J. Levandoski, A. Eldawy, and M. F. Mokbel. LARS∗: An efficient and scalable location-aware recommender system. *IEEE Transactions on Knowledge and Data Engineering*, 26(6):1384–1399, 2014.

[30] N. S. Savage, M. Baranski, N. E. Chavez, and T. Höllerer. I'm Feeling LoCo: A location based context aware recommendation system. In G. Gartner and F. Ortag, editors, *Advances in Location-Based Services*, Lecture Notes in Geoinformation and Cartography, pages 37–54. Springer, 2012.

[31] N. Shabib and J. Krogstie. The use of data mining techniques in location-based recommender system. In *International Conference on Web Intelligence, Mining and Semantics*, pages 28:1–28:7. ACM, 2011.

[32] Y. Takeuchi and M. Sugimoto. An outdoor recommendation system based on user location history. In *1st International Workshop on Personalized Context Modeling and Management for UbiComp Applications (UbiPCMM)*, pages 91–100. CEUR Workshop Proceedings, 2005.

[33] Y. Takeuchi and M. Sugimoto. CityVoyager: An outdoor recommendation system based on user location history. In J. Ma, H. Jin, L. T. Yang, and J. J. P. Tsai, editors, *Ubiquitous Intelligence and Computing*, volume 4159 of *Lecture Notes in Computer Science*, pages 625–636. Springer, 2006.

[34] C.-C. Tuan, C.-F. Hung, and T.-C. Kuei. Location dependent collaborative filtering recommendation system. In *International Conference on Future Network Technologies, Qingdao, China*, 2011.

[35] G. Tumas and F. Ricci. Personalized mobile city transport advisory system. In W. Höpken, U. Gretzel, and R. Law, editors, *Information and Communication Technologies in Tourism*, pages 173–183. Springer, 2009.

[36] G. Weiss. *Multiagent Systems*. MIT Press, Cambridge, MA, USA, 2013.

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

[38] W.-S. Yang, H.-C. Cheng, and J.-B. Dia. A location-aware recommender system for mobile shopping environments. *Expert Systems with Applications*, 34(1):437–445, 2008.

[39] H. Yin, B. Cui, L. Chen, Z. Hu, and C. Zhang. Modeling location-based user rating profiles for personalized recommendation. *ACM Transactions on Knowledge Discovery from Data*, 9(3):19:1–19:41, 2015.

[40] H. Yin, B. Cui, Y. Sun, Z. Hu, and L. Chen. LCARS: A spatial item recommender system. *ACM Transactions on Information Systems*, 32(3):11:1–11:37, 2014.

[41] C.-C. Yu and H. ping Chang. Personalized location-based recommendation services for tour planning in mobile tourism applications. In T. D. Noia and F. Buccafurri, editors, *10th International Conference on E-Commerce and Web Technologies (EC-Web)*, volume 5692 of *Lecture Notes in Computer Science*, pages 38–49. Springer, 2009.

[42] T. Zuva, O. O. Olugbara, S. O. Ojo, and S. M. Ngwira. Image content in location-based shopping recommender systems for mobile users. *Advanced Computing: An International Journal*, 3(4):1–8, 2012.