New perspectives for Recommendations in Location-based Social Networks: Time, Privacy and Explainability

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ABSTRACT

Online social networks have attracted users' attention in the last decade. Recommendation services constitute a critical functionality of such social platforms: users receive recommendations about resources (documents, pieces of music) and potential friends (people with the same interests). Recently, technological progressions in smart phones enabled the exploitation of geographical data information in social networks. Users can now receive recommendations about new Points of Interest (POIs), and new activities in POIs. Eventually, Location-based Social Networks (LBSNs) may become the 'Next Big Thing' of the Internet industry. This paper surveys the related work and current state-of-the-art algorithms in LBSNs. We also provide three new perspectives that concern recommendations in LBSNs: time-awareness, user's privacy issues, and explainability of recommendations. We present the latest work in LBSNs by comparing real systems and by categorizing them in multiple ways (platforms, personalization, etc.).

Categories and Subject Descriptors

H.3.3 [**Information Search and Retrieval**]: Information filtering

General Terms

Recommender systems, Algorithms, Performance

Keywords

Recommender systems, Location-based Social Networks

1. INTRODUCTION

Online Social Networks (OSNs) allowed users to connect and share their interests to each other. Nowadays, smart phones and tablets let users to be connected to Internet from anywhere (ubiquitous computing), sharing their location, geo-tagged notes, photos, videos, text etc. This subset of OSNs is known as Location-based Social Networks (LBSNs), where location is a new dimension that integrates our physical with our digital lives.

OSNs such as Facebook[1], Twitter[2], Linkedin[3], and MySpace[4] have attracted the attention of millions of users. Recommender systems applied to these OSNs provide recommendations to users for new friends, items etc. Recently wireless technologies via smart phones and tablets gave new perspectives in recommendations in LBSNs, which are addressed in the following:

1. *Time factor:* Time is an important factor of LBNSs that may provide more accurate recommendations. For example, users periodically perform daily activities in specific locations (e.g. home, work, etc.). Therefore, the hidden relation between time and location could leverage the recommendations in LBSNs.

2. *Privacy:* Another important factor is privacy, which has not been addressed adequately in related work of LBNSs. LBSNs reveal sensitive information about the locations that a user has visited. This sensitive information can expose users to unpleasant situations. That is, user's location privacy can prevent phenomena as assaulting, stalking, burglary etc.

3. *Explainability:* Explainability is the third important factor in LBSNs. Explainability of the recommendations can provide a more transparent system and thus can increase the users' system acceptance.

The paper is organized as follows. In Section 2, we will provide the problem definition. Section 3 presents the basic characteristics of the most popular LBNSs. Section 4 deals with the new perspectives in LBSNs, i.e. time, privacy and explainability. Finally, Section 5 concludes our paper.

2. PROBLEM DEFINITION

In this section, we provide a description of the basic possible entities of an LBSN, i.e. users, locations, activities and groups and the connections among them.

Figure 1 shows the relations among the aforementioned entities. In our running example of Figure 1, we have four layers (one layer for each entity). In particular, we have five users who belong in three groups (Recsys, KDD and LBSN

[1]http://www.facebook.com
[2]http://www.twitter.com
[3]http://www.linkedin.com
[4]http://www.myspace.com

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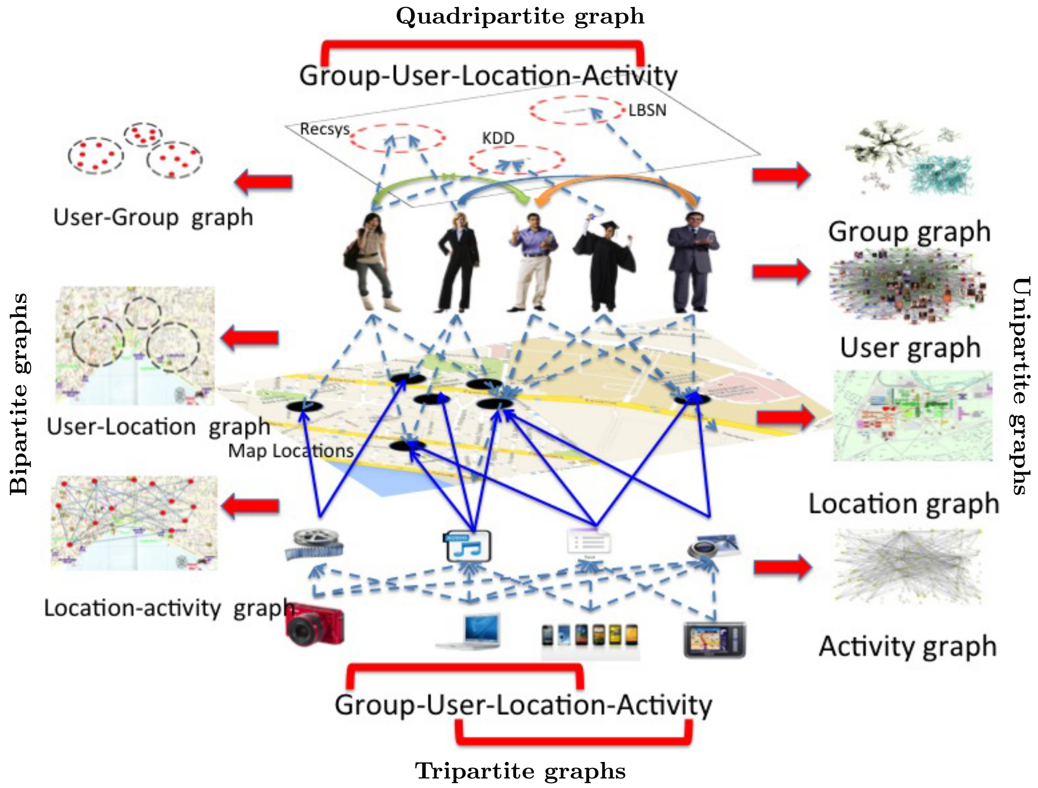


Figure 1: Group, User, Location, and Activity entities and their correlations in LBSNs.

conferences). These users have also visited some places (see Map Locations) and have performed activities such as photos, music text or video containing geo-tagged information.

In our running example of Figure 1, there are eleven graphs of different participating entities (i.e. unipartite, bipartite, tripartite, and quantripartite). On the right side of Figure 1, we can see the four generated unipartite graphs (Group, User, Location, Activity). On the left side of Figure 1, we can observe the three bipartite graphs (User-Group, User-Location, Location-Activity). On the bottom of Figure 1, we show the two constructed tripartite graphs (Group-User-Location, User-Location-Activity). Finally, on the top of Figure 1, we present the quadripartite graph(Group-User-Location-Activity). In the following, we describe each one in details.

1. **Unipartite graphs:** On the right side of Figure 1 we have four graphs:
   (a) *Group graph:* The Group graph is a group-group unipartite graph, which consists of the relations among groups (i.e. RecSys, KDD, and LBSN conference).
   (b) *User graph:* The User graph is a user-user unipartite graph, which indicates the social relations among the five users. Each node represents a user connected with another user.
   (c) *Location graph:* The Location graph is a location-location unipartite graph, which presents relations among locations. Each location is represented as a node and is connected with another location.
   (d) *Activity graph:* The Activity graph is an activity-activity unipartite graph, which presents relations between activities. Each node represents an activity, which users have performed in the past.

2. **Bipartite graphs** On the left side of Figure 1, we have three graphs:
   (a) *User-Group Graph:* User-group is a bipartite graph that indicates the groups where users belong to.
   (b) *User-Location Graph:* User-location is also a bipartite graph presenting locations that users have visited. There are two types of nodes. One type of node represents the user, whereas the second represents the location.
   (c) *Location-Activity Graph:* Location-activity graph is a bipartite graph that consists of two types of nodes, i.e. the activity that is performed in a given location.

3. **Tripartite graphs** On the bottom side of Figure 1, we have two tripartite graphs which are the following:
   (a) *Group-User-Location Graph:* The group-user-location graph is a tripartite graph, which presents information about what locations have been visited by users who belong in specific groups.
   (b) *User-Location-Activity Graph:* The user-location-activity graph is also a tripartite graph that indicates what activities have been performed in a specific location by the users.

4. **Quadripartite graph** On the top of Figure 1, we have one quadripartite graph, which is the following:

    (a) *Group-User-Location-Activity Graph:* The group-user-location-activity graph is a quadripartite graph that includes all four dimensions. In this way, we have knowledge about user preferences for activities and groups in POI's. It is obvious, that this graph is the most enriched one.

3. REAL LIFE LOCATION-BASED SOCIAL NETWORKS

In this section, we present fourteen selected real-life LBSNs that provide recommendations, as shown in Table 1. Our goal is to discover the strengths and the weaknesses of these systems.

Firstly, we divide these systems based on the platform (desktop, mobile/tablet) they run, as shown in the third column of Table 1. As we can see, half LBSNs support both platforms. It is obvious, that LBSNs should allow the user mobility. Thus, it is a drawback for LBSNs that do not support the mobile/tablet platform.

Moreover, we categorize recommender systems based on the fact that they support personalization or not, as shown in the fourth column of Table 1. Notice that there is a balance between the number of systems that support generic or personalized recommendations. It is notable, that only three systems support both of them. Generic recommendations do not exploit any knowledge about the user. On the other hand, personalized recommendations are based on the user's profile such as her log history, her friend's suggestions etc. Systems should be able to provide recommendations to new/unregistered users. Thereupon, it is a huge advantage for LBSNs to support both types.

Next, we examine the internal features that are supported by the recommender systems. As shown in the fifth column of Table 1 there are six features (i.e. cross-system connectivity, wish list, to do list, duplicates correction, map visualization, and check-ins). In the following, we discuss each feature in detail.

Cross-systems connectivity allows users to connect to other social networks, by using the login name and password of another network. For example, Facebook Connect [5] in cooperation with Netflix allows users to carry their friendship network from facebook to Netflix. Thus, a user can take movies recommendations by using the movies likes of her friends in facebook.

The second feature is the 'wish list'. By using the wish list users can keep notes of places that want to visit or events that want to attend. This feature helps the recommendation engine to provide location recommendations by interrelating common events/places of users.

The third feature is, 'to do list'. This feature is similar with the previous one. The difference lies on the fact that users can keep notes of things they must do.

The fourth feature is the 'duplicates correction'. In LBSNs, millions of users check-in in different locations, but tag them with the same word (synonimity). As an example, one of the most used words to tag a location is the term 'home'. LBSNs have many locations tagged with this word, which makes it difficult to distinguish them. To solve this problem, some LBSNs have adopted the duplicates correction feature. By using this feature, a user can determine if a given tag is correct and if not, she proposes a correction. Thus, the system is purified by the duplicated names as time goes by.

The fifth feature is the 'map visualization', which is supported by all systems. This feature allows users to visually locate their current location. Thus, it supports users' mobility, which is essential in LBSNs.

Finally, the sixth feature is the 'check-in'. This feature allows users to declare their location, by using also geo-tagged information (i.e photo, text, video etc.). By using this feature, users are able to check-in to POIs. At the same time, LBSNs keep information about users' preferences, their activities, and the events they attend.

Furthermore, we divide systems based on the recommendation types (i.e. location, friend, activity, event-local, event-non local), as shown in the sixth column of Table 1.

The first type of recommendation is location. As shown in the sixth column of Table 1 all LBSNs support location recommendations. The second type is friend recommendations. Please notice that only few LBSNs provide friend recommendations, missing to have adequate knowledge about their users social network and their social behavior. Next, there is activity recommendation. Each activity belongs to an activity type (i.e. bar, sightseeing, clubbing, etc.). Notice that this kind of recommendation is available only in six systems. That is, users can not get good recommendations about their daily activities. Finally, there are event recommendations, which are divided in local and non-local. On the one hand, local recommendations concern events that take place in a physical location. On the other hand, non-local recommendations concern events that take place on the internet (as for example an internet lecture or webinar).

The seventh column of Table 1 concerns the explanation styles of recommendation (i.e., 'User', 'Activity' and 'Location'). Explanations are the mirror of each LBSN, because they reflect in a transparent way the logic behind a recommendation. Recommendations should be justified to users, so that they can understand the reason of the recommendation. Most of LBSNs support user and activity explanation to justify their recommendations. However, distance proximity is the most important factor and should be also considered in explanations. An example of a user explanation would be as follows: 'I recommend you this location because twelve of your friends have been there in the past'. In the same direction, an example of an activity explanation would be as follows: 'I recommend you this activity because it has average rating 4.8 in the rating scale of 1-5'.

[5] `https://blog.facebook.com/blog.php?post=41735647130`

[6] `https://www.foursquare.com`
[7] `http://www.yelp.com`
[8] `http://www.getnowapp.com`
[9] `https://www.everplaces.com`
[10] `http://www.fieldtripper.com`
[11] `http://www.tagwhat.com`
[12] `http://www.zagat.com/Austin`
[13] `http://www.raved.com`
[14] `https://www.snoox.com`
[15] `http://www.google.com/+/learnmore/local`
[16] `http://delab.csd.auth.gr/geosocialrec`
[17] `http://www.wisdom.com`
[18] `https://www.facebook.com/about/location`
[19] `http://sindbad.cs.umn.edu`

Table 1: Selected location-based Social Networks

		Platform		Persona-lization		System features						Recommendation types					Explanation			Impact
	Systems	Web	Mobile/tablet	Generic	Personalized	Cross-system connectivity	Wish list	To do list	Duplicates correction	Map visualization	Check-ins	Location	Friend	Activity	Event (Local)	Event (Non-local)	User	Activity	Location	Number of registered Users
1	foursquare[6]	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	-	✓	✓	-	✓	✓	-	20 M
2	yelp[7]	✓	✓	✓	-	✓	-	-	-	✓	-	✓	-	✓	✓	-	-	✓	-	10 M
3	getnowapp[8]	-	✓	✓	-	✓	-	-	-	✓	-	✓	-	-	✓	-	-	-	-	3 M
4	everplaces[9]	-	✓	✓	-	✓	-	-	-	✓	-	✓	-	-	-	-	-	✓	-	4 K
5	fieldtripper[10]	-	✓	✓	-	✓	-	-	-	✓	-	✓	-	-	-	-	-	-	-	NA
6	tagwhat[11]	-	✓	-	✓	✓	-	-	-	✓	✓	✓	-	-	-	-	-	-	-	NA
7	zagat[12]	✓	✓	✓	✓	-	-	-	-	✓	-	✓	-	-	-	-	-	✓	-	4 M
8	raved[13]	-	✓	-	✓	✓	✓	-	-	✓	-	✓	-	✓	-	-	-	-	-	8 M
9	snoox[14]	✓	✓	✓	✓	✓	-	-	-	✓	✓	✓	-	✓	-	-	✓	-	-	NA
10	google+ [15]	✓	-	-	✓	✓	-	-	-	✓	✓	✓	-	-	-	-	✓	✓	✓	500 M
11	geosocialrec[16]	✓	-	-	✓	-	-	-	-	✓	✓	✓	✓	✓	-	-	✓	✓	✓	30 K
12	wisdom[17]	✓	✓	✓	-	✓	-	-	-	✓	✓	✓	✓	✓	✓	-	✓	-	✓	NA
13	Facebook Places[18]	✓	✓	✓	-	-	-	-	✓	✓	✓	✓	✓	-	✓	✓	✓	-	✓	1.15 G
14	Sindbad[19]	✓	✓	✓	✓	-	-	-	-	✓	✓	✓	-	-	-	-	✓	-	✓	NA
	Number of systems that support the feature	9	12	10	8	10	2	1	2	14	8	14	3	6	5	1	7	6	4	+1.75 G

The last column of Table 1 presents the impact of each LBSN. As you can see, there are over 1.75 billion registered users. That is, LBSNs are everywhere and keep the interest of over 1/5 of the world population.

4. NEW PERSPECTIVES: TIME, EXPLAINABILITY, AND PRIVACY

In this section, we survey the state-of-the art work that concerns the new perspectives in LBSNs (i.e. time, explainability and privacy), which have not been addressed adequately in the real life LBSNs.

4.1 Time

Time is a crucial dimension in LBSNs, which has not been addressed enough by the research community yet. It is true that time plays an important role in LBSNs to provide accurate recommendations, based on the periodicity of user's mobility per day, per week, or even per month. For example, in different hours of a day, users are engaged in different kind of activities (go to work, go home, etc.). Let's assume that a user is located in Tsimiski Street of Thessaloniki city (Greece) at 4 a.m. He has just finished clubbing and he asks for another activity recommendation. It is obvious, that he cannot be recommended an activity such as visiting the city's library, even if it is near his current location and is very popular place, since it is closed at that time of the day. That is, users' time mobility patterns must be treated in a different way (e.g. different weighting schema for each time slot of the day), to leverage recommendations in LBSNs.

Concerning time dimension, Yuan et al. [10] exploited spatio-temporal characteristics of POIs by using a unified framework, which consists of the spatial and temporal dimensions.

As far as the temporal dimension is concerned, they split time in multiple slots. Then, they fill these slots with check-in values that users made at each specific hour of the day. Moreover, they use a User-Time-POI (UTP) cube to present check-in records. An element $C_{u,t,l}$ of UTP cube, denotes a user u, who visited a location l at time slot t. They incorporate temporal dimension in their model, by predicting the probability that a user u will check-in a location l at a specific time t, as shown by Equation (1):

$$\widehat{C^{(t)}_{u,t,l}} = \frac{\sum_v w^{(t)}_{v,t} * C_{v,t,l}}{\sum_v w^{(t)}_{v,t}} \quad (1)$$

where, $w^{(t)}_{v,t}$ is the temporal behavior similarity between users u and v.

As far as the spatial dimension is concerned, they claim that locations, which are in distance from the current user's location, are not probable to be visited. Thus, given a user u, and the history of his check-ins L_u in locations, they calculate the conditional probability $P(l|L_u)$ as the ranking score for each candidate location l and propose the top ranked locations by using the Bayes rule, as shown by Equation (2):

$$\widehat{C^{(s)}_{u,l}} = P(l) \prod_{l' \in L_u} P(l'|l) \quad (2)$$

Next, they use linear interpolation to compute the final recommendation score for each location l, by normalizing the two scores ($\widehat{C^{(t)}_{u,t,l}}$ and $\widehat{C^{(s)}_{u,l}}$), which correspond to the temporal and spatial information accordingly. Finally, they use the tuning parameter α to compute the final probability that a user u will check-in a location l at a specific time t, as shown by Equation (3):

$$C_{u,t,l} = \alpha * C^{(t)}_{u,t,l} + (1 - \alpha) * C^{(s)}_{u,t,l} \quad (3)$$

Another similar work is presented by Ho et al. [2]. This paper extracts spatio-temporal information for future events from news articles. They also perform sentimental analysis of each news article to identify the positive or negative perception of the article. They combine all the aforementioned information to predict and then recommend suitable events for a user to attend or avoid. That is, a prediction of a traffic jam situation can prevent unpleasant delays of the users near that location. Another example could be a car accident that took place nearby the target user's location. If the system early recognized it by mining web news article, then it can recommend to the user to follow a different route. In general, their mining model consists of two steps. The first step is the key words recognition, where toponyms and temporal patterns are identified. The second step is matching, where spatio-temporal disambiguation, de-duplication, pairing, and sentiment classification analysis are performed.

Xiang et al. [9] proposed a framework that models users' long-term and short-term preferences over time. Their model is built on a Session-based Temporal Graph (STG), which incorporates user, location and session information, as shown in Figure 3.

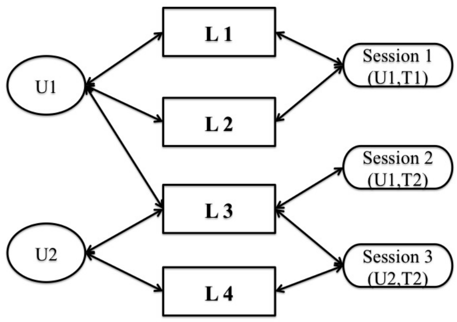
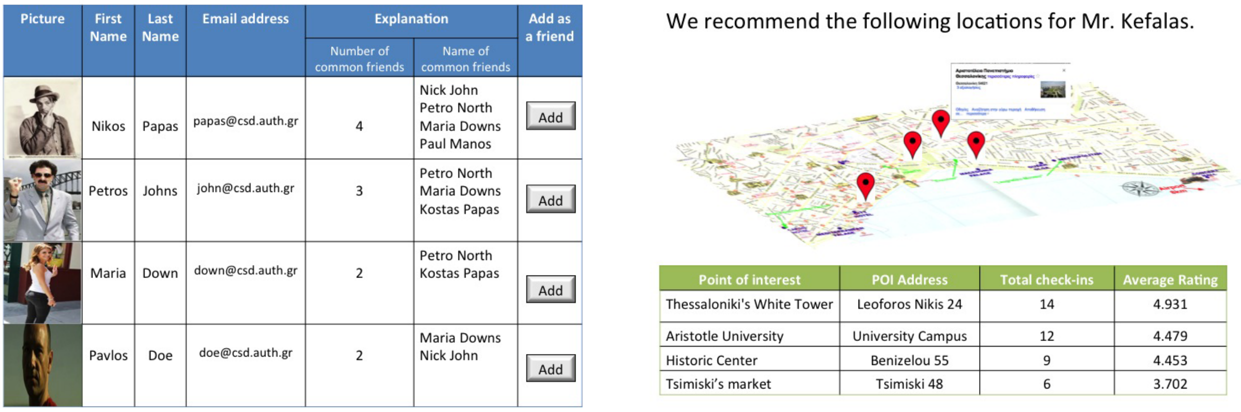


Figure 3: An example of STG graph

Figure 3 shows an example of a STG graph. As shown, there are 2 user, 4 location and 3 session nodes. User U1 has visited locations L1, L2 and L3, whereas user U2 has visited locations L3 and L4. Notice also that locations L1 and L2 are linked to session 1 node. This means, both locations (L1 and L2) were co-visited by U1 at the same t1 period (e.g. during the morning of Thursday 19 September 2013).

Based on the aforementioned STG graph, the user-location bipartite graph denotes the long term preferences of a user, whereas the location-session bipartite graph denotes the short term preferences of a user. Moreover, Xiang et al. [9] proposed also a novel recommendation algorithm named Injected Preference Fusion (IPF) and extended the personalized Random Walk for temporal recommendation.

As far as the IPF is concerned, the preferences that are injected into the user node will be propagated to locations visited by the user at all time, and then tend to propagate to unknown locations approximate to u's long-term prefer-



(a) 1-D explanation

(b) 2-D explanation

Figure 2: Two different Explanation styles examples.

ences; while preferences injected into the session node will propagate to locations visited by the user at session t, and then tend to propagate to unknown locations approximate to u's short-term preferences.

Finally, Raymond et al. [5] proposed a method to provide location recommendations for users that use buses. Their method is based on users' location histories and spatio-temporal correlations among the locations. By combining collaborative filtering algorithms with link propagation, they are able to predict origins, destinations and arrival times of buses.

4.2 Explainability

By providing explanations along with the recommendations, LBSNs can adequately justify the reasons behind a recommendation. Papadimitriou et al. [3] classified the explanation styles based on the number of dimensions that are used such as 'Users', 'Activities', and 'Locations'. That is, an explanation style of a recommender system can solely depend either on a user, or a location, or an activity (denoted as 1-Dimensional explanation style). This happens because the main information, which is stored in the heart of a recommender system's database refers to users, locations, and activities/ratings.

An example of a 1-D explanation style is shown in Figure 2(a). As shown, the target user has received 4 recommendations as possible friends (Nikos Papas, Petros Johns, Maria Down, Pavlos Doe). For each one of the 4 recommended friends, he has also taken the number of common friends, which is the explanation behind the recommendation. For instance, Nikos Papas is recommended to the target user as a friend because they have 4 friends in common (i.e. Nick John, Petro North, Maria Downs and Paul Manos).

Figure 2(b) shows a 2-D explanation style example. As shown, this explanation style includes two of the basic dimensions ('Users', and 'Activities/ratings') as a hybrid explanation. Mr. Kefalas is recommended four locations (Thessaloniki's White Tower, Aristotle University, Historic Center and Tsimiski's market). For each one of the 4 recommended locations, Mr. Kefalas has also taken a 2-D explanation. For instance, Thessaloniki's White Tower is recommended to Mr. Kefalas as a location to visit because 14 users have checked-in that place and has an average users' rating of 4.931 in the rating scale of 1 to 5.

Thirumuruganathan et al. [7] presented an explanation system called MapRat. MapRat helps users to significantly improve their decisions by providing them meaningful explanations and visualizing them in a map. Their method follows a two-step procedure. In the first step denoted as Similarity Mining, they identify groups of reviewers with same ratings on items. In the second step denoted as Diversity Mining, they identify groups of reviewers with non-similar ratings on items. Thus, a user can ask for meaningful explanations of the users' perception over items. For example, a user can explore the perception of users over a movie. He can insert into the MapRat some constraints (i.e. movie name, time period of users' ratings, number of clusters, etc.) and he will get a Map that shows the clusters that follow a similar rating behavior. He can also see the clusters that present complimentary behavior.

Finally, Symeonidis et al. [6] proposed a system named GeoSocialRec [20], which makes location, friend and activity recommendations and simultaneously provides an explanation for each recommendation. They have conducted a user study, which has shown that users tend to prefer their friends opinion more than the overall users' opinion. Moreover, in friend recommendation, the users' favorite explanation style is the one that uses all human chains (i.e. pathways of more than length 2) that connect a person with his candidate friends.

4.3 Privacy

User's privacy in LBSNs is even more important than OSNs since user's location can be revealed. The nature of LBSNs imposes strong privacy barriers. Nowadays, user geo-location can be inferred even for people who keep their GPS signal private. For example, as shown in Figure 4, we have a male and a female user. The male user uses a GPS-enabled device, whereas the female user does not. For the male user, a LBSN can identify his absolute location

[20] http://delab.csd.auth.gr/geosocialrec

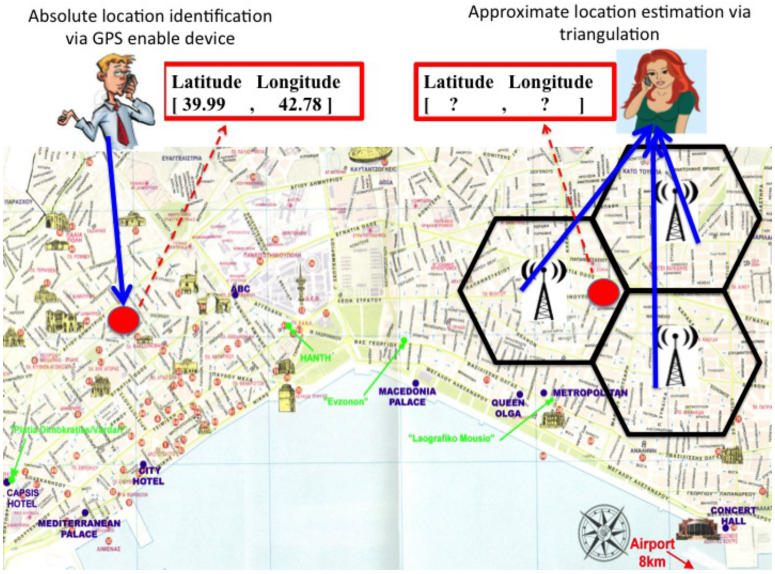


Figure 4: Users' privacy vulnerability example

(geographical latitude and longitude). For the female user, the LBSN can only estimate approximately her location via triangulation (through the antennas of the mobile telecommunication network). It is obvious that, the first case raises important issues of the user's privacy.

Users who publish their location may give access of their sensitive information to strangers. For example, let's assume a user who has an open profile (everyone can see it) and posts geo-tagged information about the places that she visits. Let's also assume that a bugler watches her posts. In this case, she is vulnerable, since the bugler is aware of the time periods of the day that she is away from home.

In general, users let the social network services to concern about their privacy policy by using only the default system's configuration. In literature, there are some works [1, 4, 8] that deal with the privacy issues in LBSNs.

Freni et al. [1] proposed some privacy techniques, which can define the user's privacy preferences easier. Their method allows users to define regions along with time periods that should and should not be published. They also proposed the Wyse (Watch Your Social stEp) technique, which provides a safe way to publish a location. Wyse checks user's profile for a restriction on a location, it retrieves the preferences of her friends, it retrieves relevant locations, and publishes other locations (if there are no restrictions preventing the target location).

Puttaswamy et al. [4] argued that smart phones now act as simple clients and send out user locations to untrusted third-party servers of LBSNs (e.g. foursquare, facebook places etc.). However, this design is susceptible even if several location cloaking techniques are employed. They argue that LBSNs should adapt an approach where the untrusted third-party servers are given encrypted data, and the application functionality will be moved to the client devices. The location coordinates should be encrypted, when shared, and could be decrypted only by the users that the data is intended for. Their main idea lies on the fact that, users should exchange cryptographic keys in an off-line social network with their friends storing these keys in their smart phones. Thus, if a user wants to exchange location information with a friend, this should be done through encryption keys between their devices.

Wei et al. [8] provided also a privacy management system for LBSNs, called MobiShare. MobiShare tackles the problem of users' location privacy, by using two different servers, i.e. the social network server and the location server. Mobishare shares the user's location among trusted social relations, and excludes it from untrusted strangers. Their system supports also an easy user-defined access/privacy control. In particular, MobiShare stores users' identity information to an untrusted third-party social network server. Moreover, it stores encrypted the users' location to an untrusted third-party location server. Their main idea relies on the fact that an attacker cannot identify the current location of a user, because he cannot get control to these two distinguished entities (social network and location server). As an example, assume John logs in his social network and wants to post geo-tagged information. His smart phone sends encrypted location data to the location server. John's friends can see his current location because an authentication process can be in advanced performed by the social network server. However, a stranger could not see his current location because his authentication by the social network server would fail.

The nature of geo-location data raises undesirable side effects during the user experience and can make any LBSN vulnerable. These privacy issues should get the attention of the research community along with the development of better recommendations in LBSNs.

5. CONCLUSIONS

In this paper, we revealed the strengths and weaknesses in LBSNs. We provided a description of the basic possible entities of an LBSN, i.e. users, locations, activities and groups and the connections among them. Moreover, we have brought in surface new perspectives in LBSNs, i.e. time, explainability and privacy, which can leverage the quality of service in LBSNs. This paper also surveyed the related work and current state-of-the-art algorithms in LBSNs.

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