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Personalization and Context-awareness in Social Local Search: State-of-the-art and Future Research Challenges

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ABSTRACT

Location-based services (LBS) are now the platforms for aggregating relevant information about users and understanding their mobile behavior and preferences based on the location histories. The increasing availability of large amounts of spatio-temporal data brings us opportunities and challenges to automatically discover valuable knowledge. While context-aware properties quickly became the key of the success of these pervasive applications, information related to user preferences and social signals still lack of adequate capitalization. Local search in LBSs is a peculiar service where recent and current interests, the network of explicit and implicit social interactions between users can be combined for effectively performing fine-tuned and personalized recommendations of points of interest. In this article we present the various and peculiar aspects of local search in mobile scenarios. Then we explore the added value of personalization and the benefits of considering social signals, summarizing open challenges and emerging technologies.
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1. Introduction

Local search in LBSs offers a particular user a set of venues within a geospatial range related to a given location. Different categories of venues are usually indexed such as shopping malls, hotels, restaurants and entertainment venues. Popular LBSs providing local search are Yelp [1] and Foursquare [2], while in recent years Social Network Services (SNS) such as Facebook included the *what's nearby* feature, similar to the local search, gaining advantage by the amount of user-generated content they are able to collect, e.g., geo-tagged photos and videos. People are increasingly using LBSs also to enrich their social lives. The self-reported positioning, more commonly known as *user check-in*, is the feature for users to report their current location and other people being at the same place. Photos, comments and ratings are often associated with each check-in.

Nevertheless, limitations on wireless bandwidth, battery life, and the variety in device capabilities and screen sizes make delivering detailed information about points of interest (POI) complicated in general. In large city areas characterized by high density of venues, developing effective ranking algorithms able to accurately recommend a small number of interesting results is challenging. Current mobile apps' user interfaces struggle to provide users with limited numbers of situation-aware recommendations (see Fig. 3(a)).

Current LBSs provide users with local search based on the current location, customer ratings or characteristics of the venues such as price and free parking, but do not take into consideration the user unique tastes and preferences. Some SNSs use general social signals promoting the most visited or rated POIs, but they do not go further with deep analyses of the user interactions in social networks. *Social local search* often refers to local search affected by explicit or inferred social signals, where the former are based on one's social connections, and the latter depends mostly on the implicit-derived relationships

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between users in the social graph. As a result, the search is not only based on the characteristics of the POIs but also on the individual's prior history, and the likes, dislikes and behaviors of those the individual have some sort of affinity or social relationship.

The combination of these advances opens the door to innovative research and will lead to the development of LBSs able to perceive the environment elements, infer complex context and current user activity features and the potential presence of other people [3]. By understanding the mutual influence between visited venues, user preferences, the network of explicit and implicit relationships between users and other relevant factors, LBSs' local search will be a very long way down the path toward an essential and pervasive service for the increasing number of global mobile subscribers.

The goal of this article is to bring the novice or practitioner quickly up to date with the main outcomes, challenges and research directions in this field. Several approaches have been proposed to model user behavior and are able to make context-aware recommendations or predictions. Given the extent and complexity of this goal, the aspects being discussed are primary focused on attempts for combining context-awareness, personalization and sources of social signals in single frameworks. Further relevant aspects such as middleware design and implementation, context data storage have been well described in the literature [4,5], whereas, further surveys deal with the more general concept and techniques of local search (e.g., [6–9]) without going any further into the issues related to the combination of the above-mentioned factors.

The rest of the article is structured as follows. The first two sections briefly describe the essential notion of POI and its principal characteristics, and the paradigms of interactions to obtain recommendations from the LBSs. We then extend the discussion to the role of context-awareness, user preferences, and explicit and implicit social signals in the local search, respectively, in Sections 4–6. Another direction we touch on is about inferring a rank for a list of POIs, to single users or groups, by combining multiple sources of evidence, in Sections 7 and 8, respectively. The discussion is extended to itineraries in Section 9. The most relevant methods and techniques involved in the considered domain are introduced in Section 10, whereas the categories of experimental settings are summarized in Section 11. Finally, concluding remarks are drawn and relevant research challenges are exposed.

2. Points of interest

A POI is a specific location (e.g., museums and restaurants) or a clearly circumscribed area (e.g., nature reserve) that someone may find useful or interesting in a given circumstance. Special cases of POIs identify physical sites and categories of activities at the same time (e.g., river trips, hunting and bush camps). POIs are usually grouped in categories and sub-categories.

A list of POIs $\Phi = \{p_1, \ldots, p_N\}$ can be typically obtained from online business directories (e.g., Yellow Pages). Popular examples of POI categories in these services are: mechanics, hairdressers, fast foods and beauty salons. A more peculiar category of POIs is related to temporary events, such as gallery exhibitions, local markets or sport tournaments. These events are characterized by a specific location that people might find useful attending, but the validity, that is, the period of time the event will take place, is limited. Yet directories of businesses miss to include these POIs, several event detection approaches aim at identifying these kinds of events by sifting through news and public streams on social networks [10–13]. Recurring events (e.g., sports of festivals) can be identified by analyzing geo-tagged images on online photo sharing services [14].

2.1. Features

The peculiar characteristics of the POIs might alter the estimation of the user's interest. For this reason, LBSs have to distinguish the most relevant features for each category and define proper representations in the system.

Let us take, for example, the restaurant category. Because they are common places of congregation and communication, truly varied in their food, cuisines and delivery, they account for a quarter of the local search queries [15]. Fig. 1 reports examples of features for this POI category. Current LBSs would combine and recommend several popular venues nearby the user. But context features such as the presence of other people call for a different selection approach. Dining with a large group of people, whether business occasions or casual family affairs, might require spacious rooms with adequate seating capacity and quite atmosphere. In the same way, preferences for food might motivate to promote the venues distant from the current location just because they match the user's tastes. It also makes sense that in particular contexts (e.g., lunchtime in office hours) people tend to allot short time, therefore the location is assumed to be one of the deciding factors. These scenarios unveil some limitations of the current local search systems which sort the most relevant POIs essentially according to the relative distance ignoring the influence of the current circumstances.

Additional knowledge about each POI can be collected by analyzing the user behaviors and monitoring the user interaction with SNSs, e.g., [16] and further studies discussed in 4.1.

Besides predefined categories, such as the Foursquare category hierarchy [18], non-hierarchical keywords can be assigned by users to highlight relevant aspects that distinguish a POI from others in the same category. Additional terms can be collected from submitted reviews by means of knowledge extraction approaches. Biancalana et al. employ keyphrase extraction algorithms for identifying topical phrases from user reviews that best describe each POI [17], as shown in Fig. 2. Tags help users to type any word they want, rather than forcing them to navigate hierarchical or controlled vocabularies. Of course, that also makes it far harder to find relevant POIs in particular circumstances. For instance, a search for POIs tagged

POI feature	Sub-feature	Inferred
location	<latitude,longitude>	
	street address	*
category	main	
	sub-category	
features	price range	
	parking	
	average noise level	
	validity time	
user behaviour-derived	current crowd-level	
	average length of stay	*
tags	{tag1, tag2, ...}	**
social signals	reviews	**
	ratings	**
	number of check-ins	**
	friends' check-ins	**

Fig. 1. Some features associated with a POI, stored in the LBS, inferred or retrieved analyzing external sources (*) or both (**).

Name	Category	Sub-category	Address	...	Tags	Semantic Tags
Raavi Pakistani	Restaurant	Indian, Pakistani	533 Jackson St, San Francisco, CA	...	{wine, Pakistani, Indian, Haveli, naan, tikka, Curry, samosa}	{Take-out: yes, *Meal served*: dinner, ...}

Fig. 2. Example of the POI representation proposed in [17] with keywords and semantic tags associated to each venue.

with "Chinese cuisine" will miss relevant venues tagged as "Dim sum". Word sense disambiguation and entity recognition may help to map user-generated keywords to taxonomies of correlated concepts improving the retrieval performances.

The above-mentioned sort of key–value information can be stored in a local knowledge-base and quickly retrieved in two separate steps. The users can explicitly request filters on the available POIs (e.g., availability of parking lot, average price within a predefined range). The LBS can also match peculiar characteristics of the closest venues with the ones visited by the user in the past, in a way that is consistent with the assumption of stable preferences. Section 5 deals with the representation of profiles of user interests and preferences.

3. Interaction paradigms in mobile local search

Whereas a typical keyword search scenarios with optional filters is the most common interaction paradigm with LBSs, it is not the only one. More formally, three types of end-user interactions are feasible in local search:

- Pull, where user takes the initiative to get the list of points of interest by querying a local search service.
- Push, where the service is given the initiative to deliver points of interest.
- Ads, where the points of interest take form of location-enabled mobile ads.

The desktop user interfaces of local search follow a *Pull* approach but the diffusion of mobile applications (or *apps*) enabled different paradigms of interactions.

Because the user query is missing, the *Push* paradigm is often named *context-dependent reaction* because it proactively initiates an interaction according with certain context stimuli or it can be triggered by updates on the user's social network. *Geofencing* usually refers to a wide range of scope, e.g., media recommendation, advertisements, family monitoring, anti-theft installations, geo-caching, recreational activities [19]. *Personalized geofencing* focus on providing users with tailored alerts depending on the individual's interests and other factors beyond the specific query, whether it is submitted or not, as shown in Fig. 3(b). Popular examples are Foursquare's *Radar* and Facebook's *Nearby Friends*.

When a location-aware device enters or exits a predefined set of boundaries, the device receives a generated notification. When the boundary corresponds to one or more POIs stored in a LBS, the notification may correspond to promotions to customers when they enter a store, as shown in Fig. 3(c). Thirteen percent of users are believed to use LBSs for finding deals or special offers [20]. Discounts can be automatically pushed to users if the software detects they are particularly interested in some items. Retailers can capture the benefit of this paradigm to customize their advertisements, rising the flow of crowd into their venues by targeting users that are more keen to redeem discounts and increasing customer loyalty. According to a recent report, this form of mobile *location-based advertising* will grow worldwide from $1.66 billion in 2013 to $14.8 billion in 2018 [21].

While the interaction with the LBS looks similar between the ads and push paradigm, the former aims at establishing communications between the users and companies that send customized, scheduled messages to a large number of customers or to a smaller and targeted group, according to the content of the message they want to communicate. The push paradigm tries to keep the users engaged with their social network, and let them disclosure more interests and preferences by interacting with other peers.

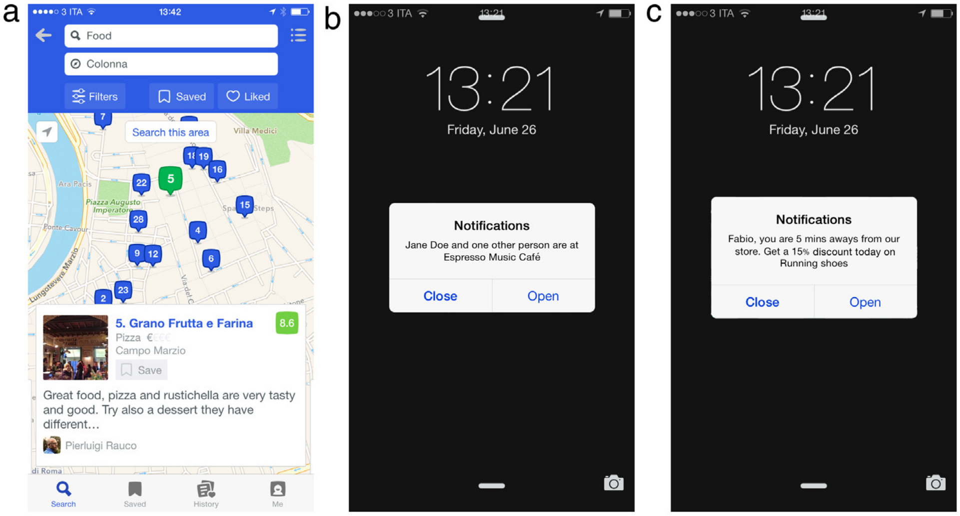

Fig. 3. Three examples of interaction paradigms: Pull, Push and Ads.

Finally, the user may also discover new POIs looking on the habits of their friends in the LBS's social network. This is the case when the local search takes the form of recommendations without any explicit request based on the user needs. For instance, if one user's friend leaves a check-in at a Thai restaurant and the user has never tried one, she might start feeling the desire to give it a try. LBSs play a dual crucial role in this interaction paradigm. By driving the information dissemination between profiles they can alter the subset of POIs that are shown first, promoting the ones that more likely will be visited by the target user in the near future. By modeling how users alter their interests and preferences based on visited POIs of their friends, LBSs can identify forms of *informational social influence* [22], where individuals are strongly influenced by a subset of people they are connected to. In these induction forms, visited POIs can diffuse through the network like an epidemic. While *homophily*, that is the tendency of individuals to choose friends with similar characteristics [23], can partially justify the correlation between the actions of adjacent peers in the network, social induction can arise also through the presence of more heterogeneous factors [24]. Most of the recommendation systems assume stable and subjective preferences but in real scenarios they may be altered as users acquaint themselves with new alternatives discovered by the recent activities of friends [25]. At the present time, frameworks for modeling preference formation and preference change on social networks, evaluated in the POI recommendation domain, are missing.

Section 6 brings back the signals coming from the social networks with the more general purpose of exploiting them when the user explicitly asks for recommendations.

4. The context in the local search

The context $u_i^{(c)}$ is any information that can be used to characterize the situation of the user u_i that is considered relevant to the interaction between the user and the LBS [9]. Context information models have to deal with a large variety of sources that differ in their update rate and their semantic level. Baldauf et al. [26] introduce three principal categories of context factors: *spatio-temporal/environmental*, *task-related* and *personal*. The former factors describe basic attributes such as time, location, direction and the current external circumstances surrounding the user such as the weather condition. The task-related context describes what the user is currently doing, e.g., driving or listening to music. The personal factors are related to the personal state or condition such as her emotional and physical states. Examples of context features are reported in Fig. 4.

Recent smartphones, fitness and health tracker devices provide users with several sensors for monitoring the health status such as blood sugar levels, caloric burn, carb intake and insulin dosage for diabetes patients, besides body's response to specific activities. Monitoring these sensors can also help understand models of human behavior and activities [27]. Well-being state prediction can also be performed in order to identify current and anticipatory stress conditions, sadness, loneliness or depression [28].

In spite of the potential applications in the domain under discussion, since at present there is not any research activity toward recommendation of POIs that exploits this form of personal factors, the following sections will focus the discussion on the remaining two categories.

4.1. Spatio-temporal and environmental context factors

The current user–location is one of the most important elements of user context. Global position system (GPS) receivers are included in almost any recent smartphone. A *trajectory* can be defined as a sequence of GPS points $p_1^{(t_1)} \xrightarrow{\Delta t_1} p_2^{(t_2)} \xrightarrow{\Delta t_2}$

Context feature	Sub-feature	Inferred
SPATIAL/TEMPORAL AND ENVIRONMENTAL		
location	current	
	future	*
time		
traffic	reports	*
	forecasts	*
weather	reports	*
	forecasts	*
audio		
ambient light sensor		
TASK-RELATED AND PERSONAL		
social	with others	*
agenda		*
means of transportation		*
activity		*
emotional state		*
health signals		

Fig. 4. Some relevant context features.

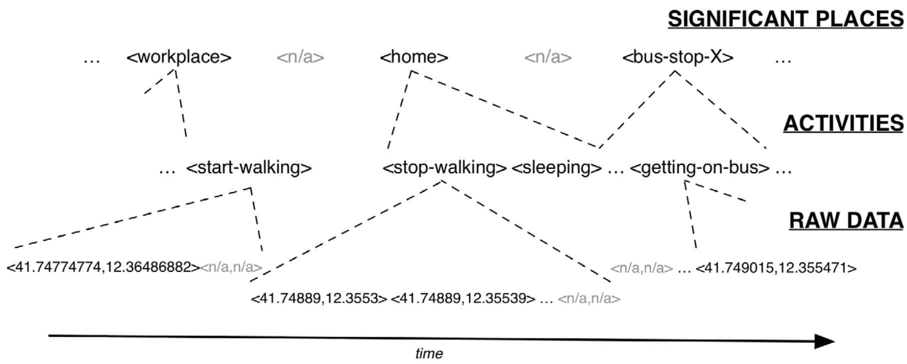

Fig. 5. Activity recognition and significant place extraction performed on raw location data, i.e, latitude and longitude.

$\dots \xrightarrow{\Delta t_{n-1}} p_n^{(t_n)}$, each of which $p_j^{(t_j)}$ contains a latitude, longitude and the time t_j the user has remained on it and the travel time between two consecutive points Δt_j. The merge of all the obtained trajectories defines the *location history* $u_i^{(h)}$ of the ith user.

The GPS receivers use trilateration from satellite signals to determine the current position. LBSs should cope with several issues related to this system. User trajectories are usually generated at low and irregular frequencies leaving the routes between two consecutive points of a single trajectory uncertain. Due to the periodical GPS signal loss, the absence of exhaustive traces of GPS data because of the battery limitations and the low accuracy of GPS, inferring context information is very challenging.

For these reasons mining the *visited POIs* $\Phi(u_i) \subset \Phi$ from the GPS trajectories in urban environments lacks of adequate precision [29], even if alternate geopositioning techniques, e.g. pseudo-satellite technology and wireless signal positioning are employed [30]. *Reverse geocoding*, that is, the conversion of a location's latitude and longitude into a street address that can be matched with the venues' addresses stored in the LBSs does not guarantee reliable outputs. More accurate localization techniques are usually confined to indoor areas, e.g., shopping malls and city airport terminals, where reliable Wi-Fi signals can be exploited [31].

Studies on large groups of mobile phone users over several months have shown how mobility patterns have high degrees of spatial and temporal regularity, with many of the visited locations near the users' home locations [32]. Several approaches aim at recognition of common routes [33–35], future routes [36–42], significant places [43–46], recurrent activities (e.g., working or sleeping) [47–52] and driving commute patterns and transportation routines [53,46]. Most of these approaches are cast to the task of labeling and segmenting sequential locations, as shown in Fig. 5, a well-studied research problem often addressed with generative or discriminative models such as Conditional random fields, Hidden Markov models and Dynamic Bayesian networks trained on the collected GPS data. The following sections discuss several scenarios where the above-mentioned features have the chance to play a key role in the POI recommendation.

Recent research aims at localizing the most significant places in a given region by mining multiple users' GPS trajectories [35]. A similar approach discovers regions of different functions, such as diplomatic and embassy, education and historic interest areas by mining a combination of taxi trajectories and POI data [54,55]. Whereas this sort of *geographical topic modeling* does not uncover novel POIs to be considered in the recommendation and do usually require a large amount of context information from a multitude of people, it provides knowledge tags assigned to areas or places of interest capturing meta-information about descriptions, categorizations, classifications or other meaningful information in the form of factual or conceptual knowledge. A deeper insight into how the obtained descriptions can be used for semantically enriching the representation of the location histories is to be found in Section 5.

Real-time weather reports and forecasts, temperature, traffic flow and alerts can be easily retrieved from online web services. By analyzing the GPS-determined locations transmitted to the remote service by a large number of mobile phone users or public transit data, it is possible to estimate the speed of users and travel times along a length of road [56,57]. This information can be particularly useful during the ranking process (Section 7).

Micro-blog posts can also be analyzed for improving the representation of the mobility behaviors in terms of spatial, temporal and activity aspects for each single user [58–61]. Such short messages offer a good opportunity for studying the behaviors of individuals toward multiple dimensions.

4.2. Task context factors

Besides the relative proximity, people often decide to visit specific POIs based on their current activities. By considering the human behavior and decision making process that motivated each visit makes the prediction more meaningful than mining raw sequences of geo-coordinates. But there are many different underlying interrelated causes to understand for providing accurate recommendations.

Automated processing and interpretation of signals obtained from the device sensors may generate higher layers of context features [62]. Low-level modules such as microphones, accelerometers, and light sensors make available signals about different kinds of personal and environmental characteristics. Feature extraction is an intermediate step at which raw data are transformed to a form suitable for activity inference, which is performed through a classification that connects interesting events and behaviors with context features [63]. Model-based algorithms use the training examples to construct a mathematical model of the target classification function. The training step of these classifiers is usually done offline by selecting the most relevant activities to be considered and collecting the required data from the sensors in real scenarios.

Recent versions of the Android operating system [64] already include an activity recognition tool for developers that automatically figures out if the user is walking, driving, or biking by exploiting inference on GPS and accelerometer data, e.g., [65–67]. Evaluations of transportation mode detection techniques that include knowledge of the underlying transportation network show high accuracy (93.5%) [68]. Examples of recommendations that make explicit use of current user tasks and activities for POI ranking are discussed in Section 10.3.

5. User interests and preferences

Most of the recommender systems are based on measures of correlation between the features associated with each item and the preferences, ratings and interests of the user. By modeling that information into user profiles, LBSs are facilitated to recommend the venues that best meet the expectations, even if they are not in the close proximity of the user. This scenario frequently occurs when people are planning to visit a city and want to collect several preference-aware recommendations taking less care of their physical locations. Because task context factors cannot be established they must be ignored by the LBS. As discussed later in Section 7, profiles of users can also be used for clustering people with similar preferences and let the system share histories of significant POIs between them.

A profile $u_i^{(p)}$ may include demographic information, e.g., name, age, country, education level. Several approaches take inspiration from the content-based approach developed in Information Filtering [69]. Users profiles are built similarly to how documents to filter are represented in such a way that the similarity measure between them is more easily assessed. It has the further advantage that the profiles are built extracting selected content from the documents of interest.

As for LBSs, keywords, semantic tags and other features associated to the venues $\Phi(u_i)$ have the chance to implicitly identify a profile of interests [70,71]. Fig. 6 shows an example of profile proposed in [17] where the information associated to the visited POIs are properly weighted for identifying interests and preferences over different categories.

A relevant issue has to be tackled before following this inferential strategy. Relevant information is collected explicitly, through direct user intervention on the LBS. Normal users visit a limited set of venues in comparison with the potential venues within a geospatial range or in the entire LBSs' database. In addition, users do not typically report their presence in every visited venue. A 2013 study among 2252 adults ages reports that 12% of adult smartphone owners use a social service to checkin at certain locations or share their location with friends [72]. For this reason, check-ins give only a partial representation of the interests.

People often use check-ins to let their friends know where they are or take the chance to redeem special discounts and deals. The semantic associated with check-ins does not always correspond to an explicit interest.

Besides that, user interests cover different categories and sub-categories, and the preference is limited to a binary vote that the user manifests when she generates the check-in. If the user checks-in at the National Gallery in London, Western painting from the mid-13th to 1900 is probably the topic of interest, but it is not clear which collection, artist, painting or

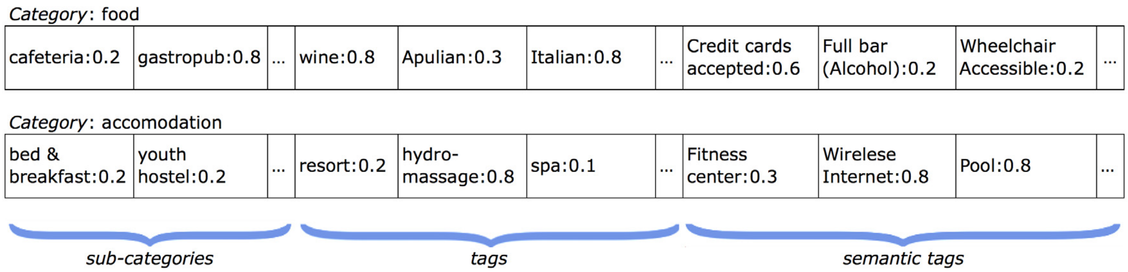

Fig. 6. A diagram of the user profile where the weights of sub-categories, plain tags, and semantic tags are organized according to predefined macro categories.

temporary exhibition is the specific one. Detailed taxonomies of categories are required for accurately representing different interests, but at the same time the training phase would take much more time before identifying specific subcategories and meeting acceptable results.

Statistical topic model approaches, such as Latent Dirichlet Analysis (LDA) [73], analyze large volumes of unlabeled text in order to discover abstract topics, that is, cluster of words that frequently occur together. Community-contributed photos are freely available and with rich context information, e.g., hashtags, comments, geo-tags, time. This information can be treat as a mixture of topics, where each topic is a multinomial distribution over terms in a vocabulary corresponding to a specific semantics. Hao et al. [74] adapt those models in the LBS context with the dual objective of summarizing the representative characteristics of each POI with that multinomial distribution over the abstract topic space, and using those characteristics for mapping the user query in the topic space for enabling partial matches and improve the relevance measurements.

5.1. Preferences and context factors

One drawback of interest-based profiles is that these interests are often affected by the spatio-temporal and task context factors. It also means that users exhibit different check-in preferences at different moments of the day [75]. For example, a person may regularly arrive to the office early in the morning, go to a restaurant for lunch at noon, and watch TV at home after dinner. But if one looks at those behaviors as manifested interests, venues regularly visited by the user might bias the profiles toward a very few specific sub-categories that do not reflect the variety of potential tastes and preferences. Nevertheless location histories $u_i^{(h)}$ may also hide extensive knowledge about individual's interests and behaviors. For example, a person that often goes for a run might like physical exercises and be keener to have healthy food when he goes out for dinner. Activity recognition can be used not only for enriching the context but for implicitly identifying particular user interests.

Strong correlations sometimes exist also between one city and its venues. Take the restaurant example. It is more likely to find an Italian restaurant in Rome than Paris. For this reason, people that live in Rome might show bias toward restaurants that serve Italian food. At the same time, people on vacation are often keen to try local food. More in general, preferences are unique to specific spatial regions [76].

Analyzing data from Foursquare, Citysearch, and TripAdvisor the Georgia Tech research team found that factors such as weather (e.g., temperature, rain, snow, season) also affect user ratings, with reviews more negative when it is raining or snowing [77].

Looking also at the observations discussed in the previous section, current interests and context are to be considered two mutually dependent variables in the recommendation. By exploring and mining the habits of a large collection of users, significant patterns and correlations between explicit preferences, characteristics of the venues and contexts where a particular activity and situation took place have the chance to be revealed.

5.2. Individual traits

The other sources of evidence about user interests are SNSs. They have the advantage of incrementally collecting significant data about the users. For example, analysis of Facebook *likes* may enable LBSs to know more about user preferences on dietary habits and sport activities, and alter accordingly the ranking of selected POIs in the related categories personalizing the recommendation. By analyzing the social network structure it is also possible to predict personality traits of each user [78], such as in the Big-5 model [79]: extraversion, agreeableness, conscientiousness, emotional stability and intellect/imagination; or more elaborated ones [80].

Only recently has personality-related research started to investigate the possibility of exploiting those *stereotype*-based models within the domain of recommendation systems. For instance, psychocentric travelers, whose center of attention is focused on self-doubts and anxieties, are thought to prefer the familiar and is not open to new experiences. On the contrary, allocentric travelers, who exhibit a confident and self-assured behavior, are more likely to choose exotic destinations. Indeed, as things stand at the moment, only introductory studies are available. For example, Gretzel et al. [81,82] explore travel personality categories as a possible shortcut for classifying users and propose a theoretical framework that explicitly includes personality characteristics of the travelers for the recommendation purpose.

5.3. Adaptation to drifting interests

Proper modeling of user interests cannot ignore that interests and preferences evolve, sometimes after visiting recommended venues. Various experiments on different domains show that ratings are also not reliable, that is, users re-rate to their original rating only 60% of the time [83]. User profiles must be kept updated accordingly. At present, studies on how these aspects affect the local search are still to be explored.

6. Social signals in the context

So far we assumed that people tend to visit POIs close to their current location, which better match their preferences and interests but plenty of social signals may alter the decision making process.

Social networks bind nodes (individuals) through ties (interpersonal connections) and allow the former to report geographic positions. Through analysis of check-in datasets extracted from LBSs, significant correlations can be observed. For example, the probability of having a social connection between two individuals is a function of their relative distance [84]. Social influence phenomenon permits that actions of one user induce her friends to behave in a similar way [24]. At the same time, a survey in 2012 estimates that 78% of Internet users considered reviews and ratings from others influential when making buying decisions [85].

Four categories of social signals can be introduced: *general* signals that come from the users' activity and behavior on the web, *personal* signals that are identified in the user's personal circle of friends, relatives or colleagues; *implicit* signals arising from groups of users that share common interests and behaviors, even if there are not any explicit tie that binds them; and finally signals related to the *social context*, that is, any relevant information that characterizes the situation involving a group of people.

6.1. General social signals

The general social signals can be classified as follows:

- User ratings and reviews on LBSs' social networks;
- User ratings and reviews on external sources (e.g., blogs, local online magazines);
- Aggregated number of check-ins for each POI.

Despite the lack of publicly accessible large-scale review aggregators, the tendency of the users to use incorrect spelling and improper use of grammar and punctuation, opinions from other users are valuable information for comparing two or more POIs. Statistical natural language processing techniques extract summaries, opinions, user tags and other features from text reviews [86].

Let us take, for example, three users A, B, and C that have all visited the same restaurant X. User A is very happy because she found the food delicious and the venue very clean and elegant. User B is quite satisfied by the experience and enjoyed the aperitif by the pool. User C enjoyed the food but found the price expensive. These three users would write three completely different reviews for the same venue and would give different ratings. For instance, user A could probably give a rating of 5 out of 5, while user C would give 1 or 2 out of 5. Imagine, now, that user D wants to know if venue X is a good restaurant for a very special occasion. Would the rating information of user A or even the average rating of all reviews be valuable to this user? The answer is obviously no, because user D is interested in the opinion of people who have visited the venue in the same circumstances as she is planning to.

The smaller screens on mobiles tend to make it more difficult for the user to read all of the reviews, compare various options, and remember prior content. *Aspect-based opinion mining* summarizes the user-generated reviews extracting aspects and the corresponding ratings [87]. These aspects consist of relevant and representative attributes, concrete or abstract, describing the POI that is being analyzed. For example, taking several reviews of a restaurant into account, the opinion mining provides users with concise outputs as the following:

Output- POI: *Hakkasan restaurant*		
Aspect: *Low Price*		
	Positive:	7
	Negative:	125
Aspect: *Service*		
	Positive:	52
	Negative:	4
	...	
Aspect: *Overall*		
	Positive:	177
	Negative:	32

Despite the evident advantage of taking the review text into consideration as additional features for the local search, no attempts have been made thus far. Ling et al. [88] successfully improved the recommendation prediction accuracy and partially addressed the cold-start problem by modeling the features of interest through a Gibbs sampling method [89]. The sort of hybrid content-based and collaborative filtering has been evaluated on several datasets related to different types of items available on an e-commerce website but missed to prove the effectiveness in the local search. Moreover, context features have not been considered. By performing statistical analysis on the attributes of the visited venues, it is also possible to describe repeated characteristics that may better represent the interests of the user. If almost all the restaurants visited by the user A are reviewed as top classy and with elegant decor, future recommendations should meet that preference.

A persistent negative phenomenon that significantly hinders the use of social media systems for effective information dissemination and sharing is the presence of spammers. Social spammers behave as active normal users by quickly accumulating a large number of social relations and spreading unwanted or fake content via social networking. For this reason, there are significant efforts to detect and analyze social spammers in various SNSs and LBSs [90–92].

A popular approach for spotting the most relevant content is looking for *local knowledge experts*, namely, users that are generally more capable than others of finding out high quality venues. Those experts are basically active and authoritative users in writing reviews, enjoying positive feedbacks from the community. Expert finding methods, including content-based and link structure-based, have been studied in recent years [93,94]. However, a very few attempts perform social local search considering local experts. Biancalana et al. [17] observe the citation counts of the written reviews, causing some potential experts to be ignored, in particular, if the activity of reviewing of those experts is not prolific or the considered POIs are in niche categories.

A basic local search ranking function that is often implemented in LBSs is based on the *venue popularity*, which can be easily estimated by the number of people that checked in or left a review. However, popularity, taken in isolation at least, is the opposite of personalization. It produces the same POI ranking for two users located in the same place, albeit they may show distinct preferences and activities. While generic recommendations are good for taking a glance at the most popular places in a region, the decision-making process of the users is multifaceted in general.

6.2. Personal social signals

Social ties facilitate the propagation of user-generated information between people, such as visited POIs, opinions and current locations, building up a *familiarity-based network* of people related to the user through explicit familiarity and friendship connections. As has already been mentioned, *social influence* is commonly used for referring to actions taken by one user which are triggered by one of her friend's recent actions [24,95,96].

Further studies prove how social friends tend to share common interests, thus leading to correlated check-in behaviors and, therefore, visited venues in comparison with users without any tie. Using a Facebook dataset of check-in and POI data, Change and Sun develop models for predicting where users will checkin in the future [97,98]. They found out how the number of times any of the user's friends has checked into a place is a good feature to predict if the user will visit the same place. By extending the analysis over the traces of 2 million mobile phone users from a European country, Cho et al. make the distinction between short-ranged travels, less impacted by the user's social network ties, and long-distance traveling, which more likely happens near an existing friend [41]. In other words, the farther people travel the more likely the visited locations are influenced by the friends' check-ins. They also found that users more likely visit a venue where a friend has just checked-in, and that probability drops off following a power law as the elapsed time increases.

Such observations, therefore, initiates an interesting idea that mining cohesive subgroups, in which people have strong friendship ties and hence have common interests, has the potential on targeting a small number of POIs for the recommendation. However, it must also be said that, while people usually perceive positively friends' checking at a venue, *social popularity recommenders*, where the suggested items are the ones more popular among the user's active friends, do not show adequate efficacy [99,32]. Common location ratios between friends is generally very small, with 4% of friends having a common location ratio greater than 10% [100]. By analyzing two popular LBSs, Gowalla and Brightkite, the check-ins that were first visited by a user and then by her friend are in the range between 4.1% to 9.6% [41]. In addition, recommendations based on the friends' check-in behaviors are constrained within the living area of the considered peers.

On the other side of the same coin, because of this small check-in overlap, social tie strength cannot be estimated solely by the common visited venues. Whereas multiple spatio-temporal co-occurrences are strong indicators of a social tie [101], due to the data sparsity and large fractions of users with very few spatio-temporal activity on the network, the similarity weight or social influence score cannot be exactly estimated, especially in urban environments [58].

Further investigation is also required if the location histories $u_i^{(h)}$ are taken into account. Eagle et al. [102] made the first attempt to prove how physical proximity is generally much higher for friends by analyzing 94 subjects over a period of nine months. They also prove how time and visited venues are important factors for predicting self-reported friendship relations. Cranshaw et al. [103] extend the analysis to 489 users making the first attempt to explore the connection between an online social network and the location traces of its users. While the study is still limited in the number of users, the authors show many cases of friendships in the social network with little to no evidence for friendship in the co-location data. Similarly, numerous instances are about users that are not friends in the online social network, yet exhibit comparable co-location patterns. But the authors mention an interesting fact: the *location entropy*, which measures the diversity of unique visitors

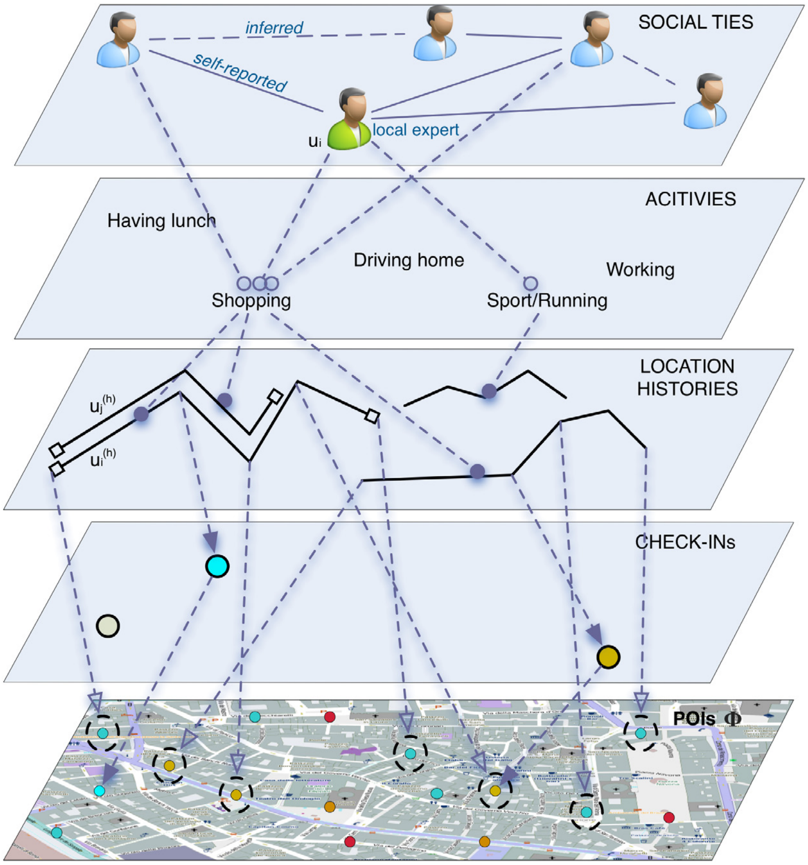

Fig. 7. Personal social signals and other relevant data related to the spatio-temporal context.

of a location, can be used to analyze the context of the social interactions at each location. Being in close proximity to a tattoo studio is quite different from spending several hours in an office building on a Monday morning.

6.3. Implicit social signals

Social ties let us know which are the closest friends of a user or find out the authoritative persons for a determined category of POIs. The familiarity-based network can be expanded considering also people that do not have any explicit relationship provided that some sort of similarity to the user exists as reflected by their social activity and behavior. The so-called *similarity-based network* can then be determined by identifying this sort of *implicit ties*. One of the biggest assets of this approach is the substantial increment of ties and circles of users available for the recommendation. The top layer of Fig. 7 shows a network of users connected through both self-reported and implicit, or inferred, ties.

A large study of 22 million check-ins across 220,000 users indicates how human mobility can be modeled following the Lévy Flight [104], in which a random walk proceeds according to steps drawn from a heavy-tailed distribution characterized by a mixture of short random movements with occasional long jumps, and where one third of the user's check-ins are located in radius of less than 10 miles. It is little wonder that most of the state-of-the-art approaches determine implicit ties looking at the geographic overlapping of visited venues between users.

Lu et al. [40] define a similarity measure between two location histories $u_i^{(h)}$ and $u_j^{(h)}$ according to the distance of two sequences of spatio-temporal features, services or venues that have been selected by the user by querying the LBS at a given time. This measure is then used for groups of users that are not only close to each other at current time, but also likely to move together for a while.

Because of the large dimension of potential distinct spatio-temporal features, Thakur et al. [105] capture the aggregated dominant behavioral patterns by using Singular Value Decomposition (SVD), which helps converting high-dimensional datasets to lower dimensional spaces. The input vectors represent the fraction of time the mobile user spent at one location during a given period. This allows the authors to capture the location visiting and periodic preferences of 8860 users in four major university campuses.

A further elaborated technique makes use of *hierarchical graph modeling* for comparing users with different degrees of similarity [106–108]. The assumption is that users sharing similar location histories and sequences of visited regions on

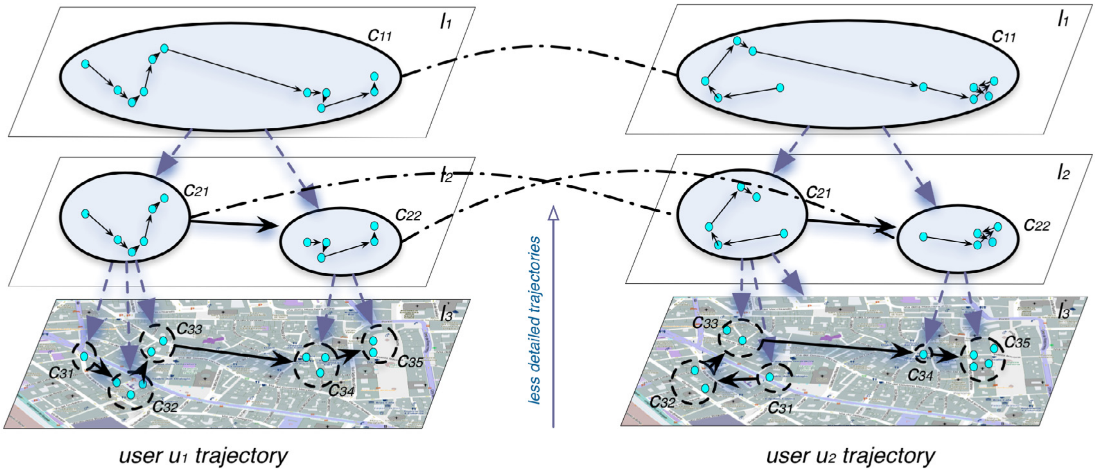

Fig. 8. The hierarchical graph modeling proposed in [106–108].

geographical spaces of finer granularity are more correlated. Fig. 8 shows two user trajectories mostly composed of distinct venues but, if they are clustered according to the geo-distance between them, some sort of similarity can be recognized on the l_3 layer. On the l_2-layer the similar clusters are merged and the similarity between the pair of trajectories is more evident. Higher layers represent more coarse cluster and, therefore, trajectories. Strong graph-based similarity at higher layers means that users are visiting similar regions but not necessary the same visited venues.

In order to better define the similarity between two users, each region can be assigned to a *Inverse Document Frequency* (IDF) weight, similarly to the Information Retrieval task [109]. IDF estimates how distinctive a word is to a corpus of text documents. By analogy, the IDF can be defined as follows:

$$IDF(poi_j) = \log \frac{|\Phi|}{|\{u_i : poi_j \in \Phi(u_i)\}|} \tag{1}$$

where the denominator counts the number of distinct users that checked-in at poi_j. Intuitively, if the venue is visited by many people, it cannot be considered meaningful to distinguish two persons. This approach has roots on the concept of location entropy introduced in the previous section.

The above-mentioned approaches rely on geographic overlapping and, therefore, cannot evaluate the similarity of two people living far away from each other. Let us take the scenario of travelers that are visiting a city that is new to them. It is more likely that they slip back to the general social signals coming from external sources instead of querying the network of their close friends. While those signals differ orders of magnitude from the information that can be collected from the familiarity-based network, the exposure of that amount of information makes it very difficult to take proper decisions efficiently and within reasonable timeframes.

In order to address those scenarios, similarity measures should not limit to consider only geographic features of trajectories but can be extended to their semantics or activities implied by nearby landmarks [110,111]. Then two users can be considered similar if they both wake up early in the morning, performs fitness activity in the afternoon and usually have dinner at hippie restaurants, even though trajectories are entirely different. Fig. 7 depicts an example of activities associated with the location histories.

This sort of *semantic similarities* require a first step where sequences of location histories are transformed to semantic trajectories. *Semantic reverse geocoding* converts spatio-temporal sequences to a predefined set of activities by querying geographic databases storing annotated landmarks [112,113]. Now, the similarity can be estimated by matching semantic trajectories, that is, sequences of common activities.

A similar attempt focuses on the concept of *routine activity* defined in terms of few highly frequented locations visited with regular time intervals [52]. In view of the consideration that the semantic reverse geocoding is only suitable for public places and, therefore, user's home or workplace will be ignored, a routine activity is represented by place distribution vectors belonging to a given time span. Because a user may have multiple routine activities, the similarity between two users is measured by considering the similarities of all their routine activities.

At the moment, surprisingly, attempts to explore hybrid recommendation that make use of both personal and inferred social signals are yet to be examined, whereas empirical evidence proves the effectiveness in the different domain of text document retrieval [114].

6.4. Social context

In particular scenarios, two or more people interact with each other mainly for performing activities collectively, e.g., choosing theme parks, ski resorts or hiking trails when planning for holidays or, quite simply, eating out. The assumption hitherto made is that people are mainly motivated by individual interests in their decision-making process but, in these circumstances, individuals may choose to conform to others and reverse their own opinion in order to reach any sort of consensus and maximizing the average satisfaction. Social networking services provide users with a convenient platform for organizing and participating in such activities and LBSs now face challenges in supporting and exploiting them in local search. Concepts like tie strength or emotional contagion are social factors that potentially improve the accuracy of the predictions when they are included in a group recommendation model.

The *social context* usually refers to any relevant information that can be used to characterize the situation of a group of people, including social ties, past, present and future activities of both individuals and the group; and descriptions or latent factors behind those activities. Several techniques developed for mining context features by analyzing the behaviors of individuals can be easily adapted to groups by taking into account the social ties identifying each person involved. In general, *social signal processing* refers to the technologies for measuring, assessing and modeling signals in order to infer social characteristics such us role, personality and group dynamics by studying laws and principles underlying social interactions [115].

In spite of the paramount role played by the social context and signals, POI recommendation for groups has received little interest with few attempts mostly focused on the identification of the items that are representative of the majority's preferences. In the *aggregate-model* recommendation, the suggestion list is generated by aggregating individual members' preferences and predicting the ratings for the pseudo-user that represents the whole group. In the *aggregate-prediction* recommendation, the generated predictions for each individual are merged to provide the user with a single suggestion list. Both of the models ignore social ties and relevant context and dynamic factors. Social signals from verbal and nonverbal human–human interactions that take place beyond the LBS require sensors like microphones and cameras that are usually not employed in the LBS mobile apps for privacy reasons. On top of that, relationships between social signals and their meaning are intrinsically complex to determine and, therefore, they are simply ignored. Section 8 outlines the few attempts to overcome these issues.

7. Inferring the rank of the venues

Given a geospatial range identified by a geographical position gp and radius r, local search first retrieves the venues $\Phi_{gp,r} \subset \Phi$ which Euclidean distance is located in r. The goal is suggesting the subset $\Phi'_{gp,r} \subset \Phi_{gp,r}$ that maximizes the satisfaction of the user and obeys a set of user-specified constraints, such as POI categories, price range or opening hours.

An effective local search needs to consider the three dimensions previously introduced: the individual's context $u_i^{(c)}$, which includes the location history $u_i^{(h)}$, the profile of interests and preferences $u_i^{(p)}$ and the plethora of social signals representing opinions given by other people and the habits of friends in the individual's social network.

Acquiring an extensive understanding of the rich and comprehensive context in real time, identifying the preferences and their potential alterations and exploiting the large amount of social information are all tasks that mutually influence one another in simulation of the decision-making process of the user. As a consequence, the architecture of a LBS can be decomposed into many interacting modules as shown in the diagram in Fig. 9, and, therefore, the proposed ranking approaches differ considerably.

7.1. Weighted linear combination

An intuitive idea for supporting the POI recommendation is to make use of the *linear combination*, a popular data fusion methodology. The assumption is to consider three distinct ranking systems and merging multiple outcomes in a single rank [99,17]. Each system defines a similarity function that computes the rank assumed independent of the rank of any other recommender. The rank $r(u_i, poi_j)$ for the $poi_j \in \Phi_{gp,r}$ and user u_i is then computed as follows:

$$r(u_i, poi_j) = c_c r_c(u_i, poi_j) + c_p r_p(u_i, poi_j) + c_{ss} r_{ss}(u_i, poi_j) \tag{2}$$

where c_c, c_p and c_{ss} are three constants weighting the scores from the context-based recommender r_c, the interest-based recommender r_p and the recommender based on social signals r_{ss}, respectively.

A significant reduction of the complexity is guaranteed because of the conditional independent assumption between the three categories of features. It also allows leveraging of the component systems in several ways by exploiting a number of effects. Because of the variety of the characteristics of the input features, multiple recommendation techniques can be implemented, each one adapted to the category of analyzed features. For instance, neural networks and vector space models have been exploited in the context-based and interest-based recommendation, respectively, in [17], whereas link analysis algorithms discover relevant patterns of interest on social networks in [108,116].

It is also possible to identify certain circumstances where the relevance of one category of features assumes more accuracy in the recommendation. For instance, by analyzing the distance users travel between successive check-ins, it is

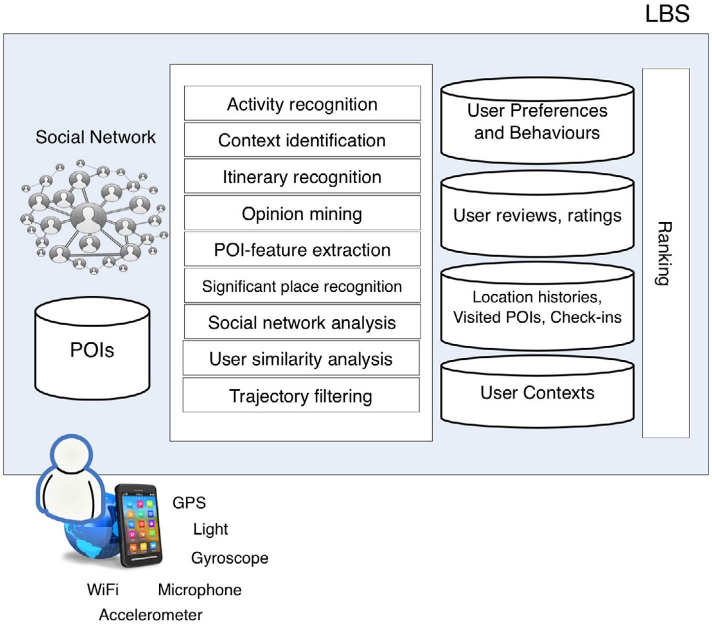

Fig. 9. General architecture of a LBS that implements the local search.

shown how nearly 80% of the total check-ins for a user occur within 10 km of the previous check-in [117], indicating a geographical clustering phenomenon in the visited venues. It may be intuitively explained by the tendency of users to choose POIs near the offices or homes, or in general, the city where they usually live. A power law distribution approximates the check-in probability to the distance between two POIs visited by the same user. Therefore the closeness to previous visited venues is an additional feature to consider for POI ranking. On a different note, some people prefer to drive on familiar routes, so spatio-temporal context factors such as shortest routes or non-traffic ones are less influential. In the first scenario, the recommendation principally based on the distance between the POI and the user, that is to say, a context-aware recommendation, has the chance to better optimize the ranking model. The second scenario requires data mining of location histories to identify fixed-habit users, find out their preferred routes and the venues close to them. Stereotype-based user profiles representing users that have common behaviors are often employed for making the computation less resource-intensive. In order to exploit this effect, a *hybrid* combination model would have to condition its combination technique on the POI being scored, weighting one system more than another based on some characteristics of the current context [118].

The issue of determining the parameters c_c, c_p and c_{ss} does, however, remain open. Supervised or semi-supervised machine learning techniques automatically construct and optimize a ranking model based on given training data. LBSs require to collect large amount of these data in order to represent the potentially unlimited space of combinations of context, preference and social signal features.

7.2. Collaborative filtering-based recommendation

Collaborative Filtering (CF) is a popular recommender approach that has seen considerable success on Internet [119]. It aims at predicting how well a user will like an object given a set of historical preference judgments for a community of users. The general idea behind the CF is that similar users vote similarly on similar items. If the judgment is expressed in form of numeric value r_{ij}, a user–item matrix $R \in \mathbb{R}^{n\times m}$ is computed, where each cell represents the u_i user's rating for the location poi_j (see Fig. 10). In the neighborhood-based method a subset of appropriate users who appear to have similar preferences to the active user is chosen. The ratings from those neighbors are combined for inferring predictions. The system determines which users have similar taste via standard formulas for computing statistical correlations.

Some issues have to be considered before implementing this form of *social information filtering*. When the LBS stores a large number of venues, user–location matrices are affected by the *sparsity* problem. Users log more than 35% check-ins at novel locations each day even after half a year [41]. The ratings are explicitly given by the user after having visited a POI but, in practice, they are often missing or scarce because the user is not always keen to submit them. Insufficient number of visitors to many locations limits the prediction accuracy [99,120]. Even active users visit a few of the available POIs and recommender systems based on traditional nearest neighbor algorithms may be unable to make any recommendation for a particular user. Temporary events, such as amphitheater concerts or street fairs, occur to only a limited extent. LBSs cannot draw any inference for users about which it has not yet gathered sufficient information. This also happens for novel POIs that no user of the community has seen yet, or new users who have no preferences on any POI, a phenomenon known as *cold-start* problem [121].

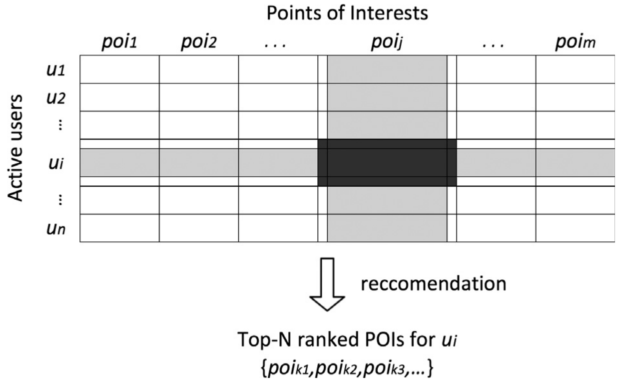

Fig. 10. The user–item matrix R.

This problem can be seen as extreme case of the sparsity where there is no rating for new users or items, making the prediction process impossible. In local search, *friend-based CF* may mitigate the cold-start for new users or people that are traveling to new cities by explicitly combining social ties during the prediction [32].

Interesting experiments show that, as far as temporary events are concerned, the most effective recommenders are based on the popularity among residents of the area where the events takes place, whereas the least effective recommends events that are nearby the user [122]. On the basis of the empirical evidence that proves how user opinions are spatially unique, Levandoski et al. [76] define the concept of *preference locality*. It represents the scenario where users from a spatial region prefer POIs that are perceptibly different than POIs preferred by users from other regions. For this reason, the recommendation should be influenced by location-based ratings which are spatially close to the user. The authors differentiate the ratings and POIs that strongly depend on the relative location from the ones that are independent of the spatial features. An adaptation of the item-based CF considers the different categories of ratings in order to provide users with single sets of top ranked POIs.

7.3. Dimensionality reduction

Latent factor models have the advantage of explaining the ratings by characterizing both items (e.g., visited POIs, activities, social ties and preferences) and users on a limited set of factors, i.e., 20–100, inferred from the rating patterns. These latent factors measure dimensions such as the relative distance, the average price or the popularity. The set of obtained weights indicate how much one user likes the POI high on the corresponding factor. This information can improve the CF system prediction accuracy, especially in case of data sparsity.

Besides the dimensionality reduction, one of the main advantages of latent factor models is that preferences are valid even though the users are traveling to a new city, where the missing CF ratings do not allow the LBS to make any suggestion. The most well known dimensionality reduction techniques are: Latent semantic analysis (LSA) [123], Matrix Factorization (MF) [124], Principal Component Analysis (PCA) [125]; and probabilistic approaches like the probabilistic LSA (PLSA) [126] and LDA [73].

8. Recommendations for groups

Recommendation to groups of people is a challenging task since each individual may show conflicting tastes, whereas user preferences may change due to the presence of other users in the group. Hence, the subset $\Phi'_{gp,r}$ is selected in accordance with the likelihood of the group members choosing the same items. Several research studies on group recommendations assume groups consisting of stable membership, but in POI recommendation they are essentially transient, therefore, adequate activity histories useful for understand the common interests and preferences of the members are usually missing.

Two tasks must be addressed for implementing group recommendation: (1) profiling preferences of individual users, and (2) modeling the decision-making process of the group given the preferences of its members. The former task is usually solved making use of latent topic modeling. A number of latent topics are identified, each of them representing a different distribution over the POIs. Every topic forms a cluster of POIs, where the ones with higher probabilities in the same topic tend to be picked by similar groups. The user preferences are modeled as a mixture of latent topics, that is, a multinomial distribution. Purushotham et al. [127] introduce an elaborate system that combines topic models for groups and location activities in a CF framework. By studying a large dataset of check-ins, they discovered that 27% of groups have visited 75% POIs which the groups' users have never visited before. Traditional aggregate-model and aggregate-preference recommendations, which suggest the most popular venues visited by the group members, do not have chances to provide the users with good suggestions in those scenarios. Since the proposed approach learns relevant activities from other similar groups, accurate recommendations are suggested even though individuals show different preferences.

A group of persons is commonly identified by monitoring the SNS and looking for profiles that: (1) checkin at the same location, (2) within the same interval of time and (3) are connected through social ties. Group identification can be improved by monitoring at the spatio-temporal features and, in particular, by comparing the user trajectories. Indeed, often users do not leave check-ins and, therefore, they would not be recognized by the LBS.

9. Recommending itineraries

Itinerary recommendation extends the local search providing users with trajectories between venues of interest subjected to constraints such as a fixed duration of travel. The trip generation is a challenging problem because of the various trip types and different travel behaviors across demographic characteristics. We can identify three steps in the itinerary recommendation: (1) mining itineraries from user-generated data, (2) revealing distinguishing attributes for each itinerary and (3) providing personalized recommendations.

There are people who take advantage of flights with long layovers by taking public transportation from the airport to the city center and spend a half-day exploring the city. In this scenario, they probably want to focus on a few attractions to save travel time. The LBS should allow plenty of wiggle room for traffic, long airport security lines and unexpected factors. People with physical disabilities might enjoy location paths that maximize the number of interesting places while minimizing effective travel time and multiple modes of transportation. Some people sensitive to the environmental issues might prefer paths that include energy-efficient transportation. In other circumstances, people prefer to have one particular POI included in the itinerary, perhaps as destination, or to maximize the sum of the preference scores that the LBS assigns to each venue in the path, without considering other factors. POIs have a wide range of visiting time, from the quick stop in fast foods to long-lasting visits in large museums. Time constraints are in general more sensitive in itinerary recommendation. Determining the proper visiting time of each place and the proper transit time from one place to another is fundamental for defining route goodness functions [128].

Yoon et al. [144] explicitly model both the available time of the user and the staying time for each POI included in the itinerary. Techniques such as *association rule mining* on user-generated check-in data may suggest repeated sequences of venues, which can be then filtered according to the user preferences and contexts. At the same time, two temporally close check-ins may suggest an important correlation between two locations identifying a partial representation of the current context and the proper visiting order [145].

In urban scenarios with large sets of POIs the complexity of the problem must be deeply examined, especially if the recommendations are tailored to each user [146,147]. In cases where a high-density of POIs are nearby, such as historical sites in ancient cities or attractions in amusement parks, tourists may be crowded in the same sightseeing site at the same time exceeding the venues' capacity. In order to avoid these congestion conditions, LBSs may dynamically alter the relevance of the POIs favoring the less congested ones, as suggested in [148] by means of the Ant Colony Optimization paradigm [149].

Online photo sharing services, such as Flickr, offer real-world public datasets of rich photographers' histories and are often used as sources for mining popular venues [150], travel sequences [108] or, more in general, their attractiveness [151].

The large amount of geo-tagged photos shared on SNS allow LBS to mine also demographic information about the locations by detecting people attributes by means of image analysis techniques. In [142] the authors take into consideration several visual features to classify each photo in one of the following attributes: family, friends, couple and solo traveler. By sorting the geo-tagged photos, the followed itineraries are collected and one of the above-mentioned attributes is identified and assigned to each of them. Finally, a Bayesian learning model sorts out the best itinerary given a query and the attributes representing the profile of the user.

Local travel experts can help populate a knowledge base of popular itineraries. Manual customization of the suggested itineraries by the users can provide valuable feedback for improving the local knowledge base [152].

More complex approaches dynamically suggest new POIs according as the last visited ones, their characteristics and categories, personalizing the recommendation as the current context evolves. Multiple conflicting criteria and undesirable situations that may result in the modification of the current schedule can also be considered by monitoring the behavior of the user [153].

To our knowledge, at the present moment online LBSs that offer personalized itinerary recommendation are still to be rolled out, while approaches that explicitly consider both profiles of user interests and context factors are a very few (see Table 1).

10. Methods and techniques for POI recommendation

Whereas most of the proposed recommendation approaches are based on CF and MF techniques, and exploit check-in and location histories for inferring the relevant POIs for each user, as summarized in Table 1, they considerably differ in terms of peculiar techniques and representations of available data, making the spectrum of potential solutions considerably heterogeneous. This section aims at identifying interesting methodologies and techniques for the POI recommendation, highlighting the most promising for addressing the issues discussed in the previous sections.

Table 1
Comparison between surveyed personalized and context-aware approaches that make use of social signals.

References	Sources of user profiling	Representations of POIs	Context features in addition to user–location	Ranking techniques	Other relevant techniques
POI recommenders					
[99]	CI, PSS			CF, LC	Friend-Based CF
[32]	CI, PSS			CF	
[107]	LH	CAT		CF, GB	Region IDF
[29]	LH			CF	
[129]	UR			CF	Serendipity
[76]	UR			CF	Context-Aware Ratings
[130]	CI			CF	Context Feature Mining
[108]	LH			GB, CF, HITS	Implicit Social Signals, Local Experts
[131]	LH/UR		A	CF, MF	User-Location-Activity Tensors
[120]	CI			CF, PLSA	Venue IDF
[17]	CI/UR	CAT/TAG		LC, CS, NN	Local Experts
[100]	CI/UR			CF	Friend-Based CF
[107]	LH			GB	Implicit Social Signals
[132]	CI			MF	Personal Social Signals
[75]	CI		T	MF	
[133]	CI	CAT		MF	
[134]	CI/PSS	TAG		RT	
[116]	LH	CAT		GB, HITS	Local Experts, Venue IDF
[127]	CI, PSS			CF, LDA	Group-Recommender
[135]	CI, PSS	TAG		TM	Group-Recommender, Social Tie Strength
[136]	CI, PSS	TAG		TM	Group-Recommender, Social Tie Strength
[137]	CI			BI, MF	Sentiment Analysis
[138]	CI		T	CF	
[139]	D	TAG		LC	Aspect-Based Opinion Mining
[61]	CI	TAG	T	HDP	
[140]	LH		A	DC, GB	User Stereotypes, Venue IDF
[141]	CI	CAT	A	MF	
Itinerary recommenders					
[142]	D, CI			BI	Analysis of Face Attributes On Geo-Tagged Photos
[143]	CI			BI	Local Experts

Legend: (A) Activities or Intents, (BI) Bayesian Inference, (CAT) Categories, (CI) Check-ins and Visited POIs, (CF) Collaborative Filtering, (CS) Cosine Similarity measure, (D) Demographic Factors, (DC) Dynamic Clustering, (GB) Graph-based Similarity, (GMC) Generalized Maximum Coverage, (HDP) Hierarchical Dirichlet Process, (HITS) Hyperlink-Induced Topic Search, (LC) Linear Combination, (KL) KL-Divergence, (KM) Keyword-matching, (LH) Location Histories, (MF) Matrix Factorization, (NN) Neural Networks, (PSS) Personal Social Signals, (RT) Regression Trees or Decision Trees, (T) Time, (TAG) Tags, Keywords, Latent Topics or Features, (TM) Topic Model-based Matching, (UR) User Reviews and Ratings.

10.1. POI recommendation based on general social signals

Most of the recommenders assume that location histories and check-ins are the only sources for identifying user preferences. A hybrid user preference model proposed in [137] combines also aspects extracted from the comments left by the visitors, that is, the general social signals. Text-based *sentiment analysis* extracts relevant features converted in the $[-1, 1]$ interval, where the extremes represent really negative and really positive sentiments, respectively. That sentiment classification is obtained querying SentiWordNet [154], an opinion lexicon derived from the WordNet database where each term is associated with numerical scores indicating positive and negative sentiment strength. Check-ins are then combined with sentiment scores in a single *check-in preference matrix* used for the recommendation. Similarly, sentiments can also be considered as implicit ratings for CF approaches, partially addressing the sparsity issue [155]. Levi et al. [139] push forward the sentiment analysis on general social signals by clustering the reviews according to the intent and the nationality of the visitor that wrote them, and the aspects dealt in the review, e.g., location, service, food, facilities. The hypothesis is that users of the LBS are looking for recommendations from travelers with comparable needs so, once they query the LBS, the ratings associated with the reviews more similar to the current request are weighted higher. The drawback of that approach is that, in general, the aspect-based opinion mining is domain-dependent, so that it requires a long investigation for each available category of POIs. The users are also forced to manually specify the intents behind each request carrying the burden of defining each relevant aspect.

In order to tap the vast amount of information from general social signals it is fundamental to determine quality measures and rank the most relevant resources. HITS link analysis algorithm [156] has been initially developed for mining the link structure of the web for discovering and ranking pages relevant for a particular topic. Several authors have used it in different domains. The algorithm defines *hubs* as pages that advertise the authoritative pages, and *authority* pages the one that contain

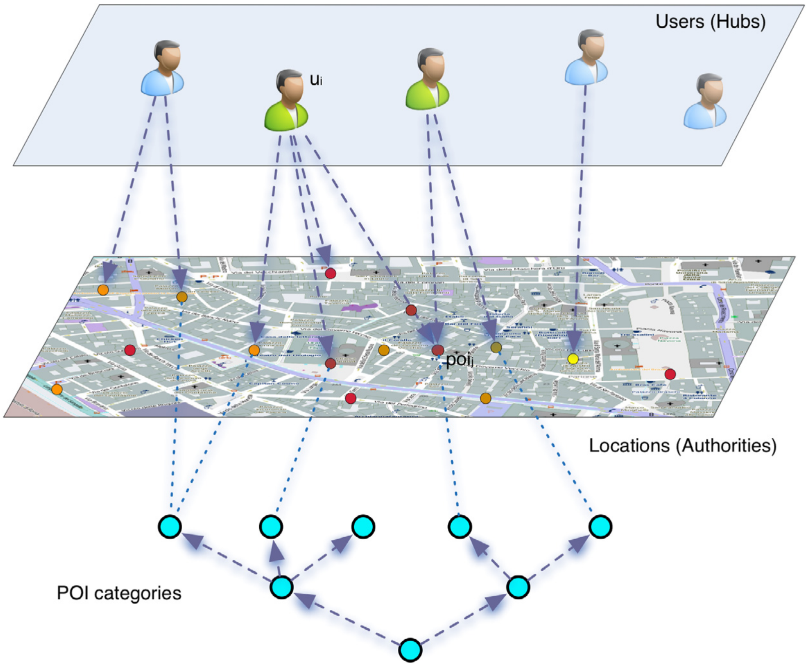

Fig. 11. The HITS paradigm adapted for local search [108,116].

valuable information on the subject. HITS identifies good authorities and hubs for a topic by assigning two weights: authority and hub weights. These weights are defined recursively: a high authority weight occurs if one page is pointed to by many pages with high hub weights, and vice versa, a high hub weight occurs if the page points to many pages with high authority.

Similar to the HITS algorithm, in [108], a hub is a user who has visited many venues, and an authority is a venue that has been visited by many users given geographical radius r. The topic is defined by the set of POIs enclosed in r. Hub users and authority locations have a mutual reinforcement relation that can be formalized as follows:

$$
\begin{aligned}
auth(poi_j) &= \sum_{u_i \in V_{poi_j}} hub(u_i) \\
hub(u_i) &= \sum_{poi_j \in U_{u_i}} auth(poi_j)
\end{aligned}
\tag{3}
$$

where $auth(poi_j)$ and $hub(u_i)$ are the authority value of poi_j and hub value of u_i, respectively, V_{poi_j} is the set of users that have checked-in at poi_j and U_{u_i} is the venues visited by u_i. These values are exploited for ranking both venues and local knowledge experts that are suggested to travelers that query the LBS. Given that HITS is an iterative algorithm that is repeated a specified number of times until the convergence is reached, and the ever-changing nature of the large check-in dataset, the HITS calculus may be time-consuming.

Bao et al. [116] extend the previous approach considering user preferences represented by a weighted hierarchical taxonomy of predefined categories corresponding with the categories and subcategories of the available POIs, as shown in the bottom part of Fig. 11. For each category, the HITS algorithm infers the local experts. Thus, the accuracy of the recommendation is improved because the rank rewards the venues chosen by the local experts sharing the same interests with the user that submitted the query.

10.2. POI recommendation based on personal and implicit social signals

Inspired by the PageRank algorithm and its random walk formalization for estimating transition probabilities between nodes, Noulas et al. [157] represent users and POIs as nodes of a graph. Two users are connected if they have a tie on a SNS (i.e., friendship), and one user is connected to a POI if she visited it. Hence, the graph represents a transition probability that is used to calculate the steady-state probability of the random walk. The recommended POIs are the ones that result more connected to the user, through friends or visited places, or through any combination of these two factors.

Ye et al. [99] performed a comparative evaluation between a random walk-based approach for collaborative item-based recommendation and a CF-based algorithm that includes the geographical influence of check-ins, that is, the phenomenon of proximities of visited POIs discussed in Section 4.1. They prove how geographical influence has more impact on the effectiveness of recommendations than personal social signals used in the random-walk, improving the recommendation

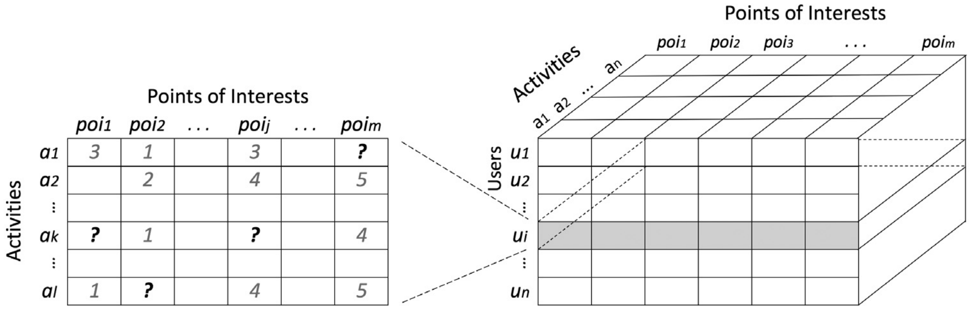

Fig. 12. The user-location-activity matrix proposed in [131].

performance by at least 13.8%. On the other hand, personal signals better address the cold start problem because social friends may supply potentially relevant POIs from their check-ins, especially to new users without location histories.

A more refined approach first defines the geographical influence by modeling the probability of a user's check-in on a location as a Gaussian distribution [132]. A generalized MF framework is developed considering also personal social signals, i.e., explicit social ties. A comparative evaluation between traditional CF approaches and PLSA trained over a check-in dataset confirms the better accuracy of this kind of latent factor models that combine multiple factors [120]. To sum up, the combination of user preferences, geographical influence and personal social signals guarantees the highest performance for the recommendation.

10.3. POI recommendation based on context features and inference

Besides the relative distance with POIs, two relevant context factors are often considered: activities frequently associated with a visit to a POI and the mutual influence between time, preferences and the other context factors.

Activities: An interesting approach makes use of 3-d tensors for representing User-Activity-Location entries [131], where a tensor represents a specific situation. As each user has limited ratings showing Location–Activity information, as shown in Fig. 12, the LBS obtains a 2-d Location–Activity matrix by aggregating the tensor values over the user dimension. This matrix represents what people usually do when they visit a place.

Memory-based CF is exploited for addressing the sparsity issue by predicting the ranking on missing Location–Activity entries based on what it is known by the existing ones. Visited venues are mined by analyzing the comments left from the users on the LBS while the associated activities are identified by manual human labeling. Similarly to the Location–Activity matrix, the following matrices are obtained: Location–Feature, Activity–Activity, User–Location and User–User matrix. Further analyses are performed for addressing the sparsity issue. For instance, a dataset of Activity–Activity correlations is built by querying a web search engine for understanding how likely one activity co-occurs with another (e.g., visiting a shopping mall is usually associated with having some food or drinks). Collective MF [158] finally builds the model which predicts a reasonable ranking on these missing entries in the initial tensors.

A User-Activity-Location tripartite graph data structure has been proposed in [140]. It explicitly models user activities from the user trajectories and consists of three disjoint node sets representing users, activities and locations. The authors define an *activity* in terms of "segments of trajectories within a certain time frame".

A co-clustering algorithm identifies coherent clusters of similar users, activities and locations. The similarity between those entities is defined as follows:

- Two users are similar if they have similar activity patterns and have visited similar locations.
- Two activities are similar if they take place in similar sequence of locations and performed by similar users.
- Two locations are similar if they are visited by similar user and occurred in similar activities.

Sattari et al. [159] employ similar high-dimensional data structures to handle the ternary User-Activity-Location relation. High Order SVD decomposes the order-3 tensor ($User, Location, Activity$) into a core tensor that is of the same shape as the original tensor, together with 3 orthogonal side-matrices. The approach finds similar entries to the initial tensor from the reduced-rank matrices and then refers to original tensor to find corresponding rating values.

Empirical evaluations of the aforesaid approaches prove the benefit of explicitly considering the activity dimension during the ranking.

Temporal Factors: A time-aware CF has been proposed in [138]. Categories of POIs are often visited in certain moments of the day, e.g., at midnight downtown bars can be busy but the public libraries seldom are. The authors add a time dimension to the user–item matrix R for explicitly indicating the preference of the users to visit a POI in a particular time slot of the day. Two users are similar if they share the same temporal behavior, that is, they are likely to visit similar POIs at the same time. An empirical evaluation and improvement of the accuracy by 37%–51% over a CF baseline. Gao et al. [75] take advantage of *temporal patterns* and regularity in check-in behaviors, as discussed in Section 4.1. Time information is considered by many to be a fundamental factor for better tracking user preferences [160]. Indeed, two time-related phenomena frequently occur [161]: (1) *consecutiveness*: closer check-in preferences happen on consecutive temporal state, and (2) *non-uniformness*: different check-in preferences at distinct hours of the day. The recommendation is cast to the optimization problem where MF models the time-dependent user/check-in preferences. Similarly, by studying significant patterns of transitions of the visited venue, it is possible to improve the prediction by restricting the recommended POIs to the most likely categories [133], e.g., having a dinner out after a late-afternoon soccer game.

A general framework able to correlate both user, spatial, temporal and activity aspects is introduced in [61]. The preferences of the users are represented as sets of previously visited regions, which are obtained by retrieving their geo-tagged micro-posts. Instead of PLSA and LDA, in which the number of topics needs to be empirically set, the authors make use of the hierarchical Dirichlet process (HDP) [162], which can automatically determine the latent dimensions from the available data. The activity is determined by the set keywords extracted by the micro-posts. A user query takes the form of a set of keywords and the context consists of the current location and time. A missing evaluation on real scenarios does not yet guarantee the validity of the framework in the local search task.

So far we mentioned approaches based on static sets of spatio-temporal features, but the accuracy of the POI reccomendation may be improved by characterizing the dynamic aspects of the current situations. However, due to the multitude of contingent context factors, it is not clear which parameters need to be explicitly modeled and what are the relationships influencing the recommendation process. Relevant parameters in some circumstances may be disturbing others.

A 2-step methodology has been proposed in [130]. In the first step, a preliminary set of context factors is identified by human experts on real-life datasets covering a broad range of circumstances. During the second step, the methodology investigates how the user behavior is affected by different values of those factors. T-test and Analysis of variance (ANOVA) are used for determining the significance of the factors in each situation. The most relevant factors are then considered in the CF-based recommendation. Because of the manual annotation of the context features, the approach is suitable for well-defined scenarios but is scarcely-scalable to any available category of POI.

10.4. Inferring user interests, preferences and stereotypes

One simple way to estimate the rating r_{ij} in the matrix R is by defining a linear relationship with the number of visits of u_i at the poi_j location. This sort of implicit feedback does not require any cognitive effort by the user and is usually interpreted as a positive rating essentially because it is supposed that negative experiences do not bring the visitors to repeat them in the future.

As has already been said, estimating the visited POIs by mining the location history suffers from two major drawbacks: low recall and large numbers of false alarms. In order to mitigate the latter effect, CityVoyager considers solely POIs frequently visited by the user [29]. The authors prove that the precision improves as the amount of location history data increases because the false alarms do not occur at fixed places, and so they are rarely considered as frequently visited venues, that is, positive ratings. However, the benefits on false alarms come at the expense of the recall, which is negatively affected by the less frequently visited venues ignored by the system.

Similarly, the GeoMF model [141] integrates the user feedback represented by the number of times the user checked-in at a place and POI categories into a MF framework. Users and POIs are so mapped onto a joint latent space in such a way that the preference is modeled as inner product between them in that space. Zheng et al. [107] generalize the implicit positive rating as the user's visit on a geospatial region, where one region is defined in terms of the set of POIs within. As already mentioned in Section 6.3, a hierarchical graph models the user's location histories on different geospatial scales. The finer the granularity of geographical regions shared by two users, the more similar these two individuals are considered by the CF. As a result of that *graph-based similarity*, two users can be similar even though they have not visited the same POIs, increasing the chances to find correlations in R and, therefore, reducing the sparsity. The LBS recommends the top-N regions that might interest the user. The graph-based similarity has been frequently considered for the POI recommendation, e.g., [76,106,108].

Three user *stereotypes* are defined in [140] to represent three classes of behaviors, namely, (1) pattern users, (2) normal users, and (3) travelers, according to the number of different locations they visit in daily activities. Pattern users basically repeat the same trajectories, normal users visit more different location, whereas travelers visit many different venues everyday. Once a user asks for recommendations, the system uses the current location, activity and stereotype for filtering the best matching subclusters in the tripartite graph. The top most visited locations in the subclusters are submitted to the user. Yet again, the location entropy penalizes the really common POIs throughout the community. Stereotypes have the advantage to group similar users even if they have not in common many visited places, partially addressing the sparsity and providing hints to the recommendation.

10.5. POI recommendation for groups

In the previous sections we saw how topic models based on LDA can describe activities that could be performed at a given location. By counting the number of times groups checkin at a given location, the approach also recognizes venues more suitable for group activities. Similarly to single-user recommendations, a community can be also described by means of latent variables representing groups of users with common interests, e.g., Thai food, basketball, volunteering; so that

Name	Type	Website	Users	Period	Date	Data collected
Event Recommendation Engine Challenge	POI/SS	www.kaggle.com/c/event-recommendation-engine-challenge	37K	-	2012	*user profiles and interests for each POI (event), social ties*
FriendsAndFamily	POI/SS	realitycommons.media.mit.edu	140	1y3m	2010/11	*location labels, call logs, proximity data user profile, periodic surveys about social activites, interactions of users, mood, etc.*
GeoLife	UL	research.microsoft.com/en-us/projects/geolife/	182	3y	2007/12	*17.6K user trajectories*
GeoText	UL	www.ark.cs.cmu.edu/GeoText/	9475	7d	2010/03	*377616 geo-located Twitter microposts*
Gowalla	SSL/UL	snap.stanford.edu/data/loc-gowalla.html	200K	20m	2010	*950K SNS social ties, 6M check-ins w/timestamp*
LBSNDR	POI/SS	www.public.asu.edu/~hgao16/dataset.html	33.6K	1y9m	2010/11	*social network, check-ins, hometown location, location category*
LifeMap	UL	crawdad.cs.dartmouth.edu/yonsei/lifemap/mobility	*anonymized*	2m	2011	*user locations, location labels*
Mobility Models	UL	crawdad.cs.dartmouth.edu/ncsu/mobilitymodels/	81	5m	2006/08	*user locations*
myPersonality project	UL/	mypersonality.org	4M	-	2012	*user locations, facebook profiles (e.g. likes), psychometric tests' scores*
nodobo	UL	nodobo.com/release.html	27	5m	2010	*cell towers, call logs, sms*
Reality Mining	SS/UL	realitycommons.media.mit.edu	100	9m	2004	*user locations, location labels, call losg, sms, running apps, social ties*
TREC Contextual Suggestion	POI	sites.google.com/site/treccontext/	182	-		*title, desc, user preferences for each POI*
UMN/Sarwat	POI	archive.org/details/201309_foursquare_dataset_umn	2.1M	-	2013	*1M check-ins, 1.1M POIs, 27M social ties, 2.8M ratings*
Yelp	POI/SS/UL	www.yelp.com/dataset_challenge/	43.8K	-	2013	*11.5K POIs w/metadata, 8.2K aggergated check-ins, 300K reviews*

Fig. 13. Public datasets about Points of interest (POI), Social signals (SS) and User locations (UL).

each user belongs to one or more communities. When latent spaces have been assigned to both groups and locations, the CF framework performs group-activity recommendation.

Due to the lack of quantified strength in friends' relationship, the Purushotham et al.'s approach assigns equal weights to every social tie in the network. But what actually happens is that social influence between individuals is not uniform. In [135] the relationship intensity among friends is evaluated for improving the POI recommendation. A probabilistic generative model is trained for simulating the decision making in the POI selection. The model takes into account both the user preferences and strengths of the social ties. The latent topics representing the domains of interest and the influential friends are inferred by an ad-hoc model parameter learning algorithm that is finally exploited for the recommendation. The notion of social influence and influential users has also been discussed in [136], where a similar group recommendation approach has been proposed. Interestingly, whilst determining the strength of social ties may indeed be beneficial for better filtering information from the user's friends, no attempts have been made for taking advantage of this approach for the single-user recommendation.

Often people are involved in complex human-decision activities that is carried through if recommendations from friends contradict their own opinion. Self-confirmation effects or different levels of social conformity pressures may strongly alter the interaction of users with recommendations [163]. Individuals often choose to conform to other members of the group and reverse their own opinions and preferences in order to restore their sense of belonging, or they may decide to keep to their decisions by taking advantage of their social influence. As things stand, these theoretical studies are yet to be capitalized.

A framework that combines both social factors and content interests of group members, taking into consideration the characteristics that impact group decisions, i.e., the social strength, expertise, and interest dissimilarity among group members; has been proposed in [164]. The social strength is estimated by evaluating the average daily contact frequency between two members, whereas the expertise is determined by the number of items the user has rated. An algorithm automatically analyzes group characteristics and generates the corresponding group consensus function for predicting group preferences. The principal limitations of the framework are that it ignores any context information and the evaluation is restricted to the movie recommendation.

The Consensus model [143] represents each group as a multinomial distribution over latent topics, where each topic attracts a set of users to join. The preference of the user is influenced by both the topic that attracted her, and her personal preferences. The final recommendation is obtained by aggregating the users' recommendations in the group in such a way that, if a user is an expert in the group topics, her selections are taken more into account.

11. Evaluation methodologies

Generally, the evaluation of the user satisfaction is estimated according to the probability that the user visits at least one time one of the top ranked POIs recommended by the LBS in the near future.

Evaluating POI recommenders and their algorithms is inherently difficult for several reasons and standard evaluation methodologies are still missing. The proposed approaches differ considerably in terms of the considered context features, user preferences and social signals. Services such as *Factual* [165] query several online sources and collect millions of POIs worldwide addressing the issue of providing a database of univocal POIs accessible via download or API. Nevertheless, as shown in Fig. 13, at the present time there are not public datasets that provide enough depth for including the required features (namely, context, social signals and user locations) over long periods and, subsequently, experimental results comparing the accuracy of different approaches on the same input dataset are not available.

Two categories of experimental settings are usually followed in the literature, as shown in Table 2. The first is based on location histories collected by GPS-enabled devices over a predefined period, generally lasting months. These devices are set to regularly receive GPS coordinates of each volunteer involved in the experiment, who then requests to map stay-points to specific POIs that she has visited during the day. The recommended POIs are then evaluated by the users that express their feedbacks after the ranking process end. This *field-based* setting guarantees detailed information about the visited locations and additional context features that can be retrieved and elaborated by the devices.

Table 2
Principal pros & cons about the two categories of experimental settings.

	pros	cons
Field-based experiments	• Detailed location histories • Additional context factors	• Require volunteers • Long lasting
	Refs: [107,131,130,29,107,140]	
Lab-based experiments	• Scale to large datasets • Social signals available	• Sparse • Limited data about contexts
	Refs: [75,132,76,120,17,133,134,116,127,135–138,61,141,99]	

Two interesting tools help collect potentially relevant context signals. The *Funf Open Sensing Framework* [166] is an Android-based extensible framework, originally developed at the MIT Media Lab, for simplifying the collection of context data. *Google Map Gps Cell Phone Tracker* project [167] offers clients for iOS, Android, Windows Phone and Java Me/J2ME cell phones for periodically tracking the cell phone location. *AirSage* [168] makes available anonymized consumer locations and population movement data by analyzing cellular-signal data points.

Due to the long time required and the number of participants to recruit in order to collect enough information and feedbacks for reliable significance testings, an alternative evaluation methodology that follows the Cranfield paradigm is often considered. A *lab-based* setting is defined in terms of a large population of users that provide their check-in data. Foursquare and Yelp provide Application programming interfaces (or APIs) in order to easily collect these usage data. Alternatively, geo-located microposts may be extracted from general SNSs such as Twitter [169].

The so-obtained datasets are usually orders of magnitude larger in terms of monitored users than the field-based settings but the extent of information that is possible to collect is limited to check-ins and social ties. The ground truth of this Cranfield paradigm is defined by following a cross-validation methodology, which splits the check-ins of each user in known data (training dataset) and unknown data against which the recommenders aim at predicting the included POIs. The basic assumption is that each user's positive feedback is expressed by a check-in left on the online service, but as already discussed in Section 5, this hypothesis has not been validated. Moreover, APIs do not always guarantee to limit the scope of the retrieved information to a small number of users or geographically bounded regions. The effectiveness of the recommendation for the obtained sparse datasets (i.e., many users and venues having a single check-in) is usually low. The experiments are therefore focused on estimating the relative performance of algorithms instead of their absolute effectiveness measure.

In both of the above-mentioned settings the recommendation is viewed as an information retrieval task where the goal is providing only the good POIs. For this reason, traditional measures such as Precision (the fraction of relevant POIs retrieved out of all POIs retrieved), Recall (the fraction of relevant POIs retrieved out of all relevant POIs) and Mean Absolute Error are considered. In order to take the positions of correct POIs in the ranked list into account, further metrics such as Normalized discounted cumulative gain (nDCG) are also evaluated.

An interesting recent attempt to foster standard evaluation methodologies for the POI recommendation has been proposed by the Text REtrieval Conference (TREC) [170]. The provided user profiles indicate the preferences w.r.t. each training scenario. Contexts contain geographical locations and several pieces of optional data about one hypothetical trip. The required suggestions consist of a ranked list of attractions the user may be interested in based upon the provided context and user profile.

12. Conclusions

Local search on mobile devices has quickly emerged as an essential service to obtain information on points and regions of interest based on the current user–location, taking over functions of traditional Yellow pages.

Besides the recent research activity, several critical scenarios and research challenges about local search have been identified. A number of other research areas outside the local search, which are rapidly developing, have also the potential to stimulate innovation. In the rest of this section, some of the topics that we consider to be promising sources of new perspectives, applications and models are mentioned.

12.1. Improving the push-based interaction

While the current Push-based implementations of LBSs are not able to filter out less attractive POIs, it is likely that in the future the ranking algorithms will take into consideration more signals about the users and the current environment. A number of recently released proactive applications, such as Google Now, Microsoft Cortana, Apple Siri and Yahoo Aviate continually learn about user interests, friends and favorite things, tailoring the suggestions over time to make them personalized. Venue recommendation in the form of push-paradigm is without doubts one of the potential targets of these personal assistants.

Under certain conditions (e.g., user is driving), notifications received through mobile phones may cause distractions or annoyance. While notifications are considered important if they are about significant events and consistent with the current task, they do not always cause immediate attention [171]. For this reason, future implementations should also automatically assess the perceived importance of the notifications for each set of circumstances in which the users find themselves.

The recent field of *anticipatory mobile computing* [172] makes use of machine learning and numerous sensors for monitoring the context and forecasting future events. The ability to predict users' locations, activities or social encounters does not only make the human–computer interaction more effective, but it is also crucial for tracking user intent and providing better recommendations. A pervasive LBS that strives to be a proactive personal assistant has to perform a sort of context prediction and must anticipate the user needs.

12.2. Accurate representations of the user preferences

Models of user interests and preferences are dynamically affected by multiple factors. LBSs must be able to extract accurate preferences from monitored behaviors in complex and ever-changing environments. They should keep the preferences up to date by responding rapidly to changes in user behaviors by selecting the appropriate mining and recommendation techniques.

The presented models do not explicitly consider the transient aspects of the user preferences. In reality, perception and popularity of POIs constantly change, affected by several distinct factors. For example, massive advertising has a profound effect on public taste in clothing, and hence some shops are more appealing than others. Similarly, users' inclinations evolve, leading them to redefine their taste. LBSs should account for the temporal effects reflecting the dynamic, time-dependent nature of the user–venue interaction.

Mobile users are often faced with time constraints and possess limited knowledge about a given region. In these circumstances, they will look for the opinion of friends or online experts before making any decision. When opinions of others influence users' intents facilitating the decision making process, the informational social influence takes place [22]. By identifying this information and modeling the confidence in the user's beliefs and attitudes, LBSs have the chance of more effectively driving the relevant information in the social environment. Positive informational social influence may significantly enhance the relationship between respondents' attitude toward online suggestions obtained from the community.

12.3. Making sense of big data

As the sheer amount of raw data from physical sensors and social signals increases, the computer scientists have started looking for efficient statistical analysis techniques for analyzing current and historical facts and making predictions and recommendations. Big data research has the potential to positively influence this research.

Online local search is mostly based on the current user–location and the popularity of the points of interest. They return maps of points based on the current position but ignore the user's specific interests. Additional relevant signals from the environment, the user's current situation and activities, and signals from his network of friendships or general signals from the social web are ignored.

Single sensor signals can be combined to obtain accurate and high-level context information and facts. The discussion of several user scenarios leads us to recognize a tangle of interrelated explicit or inferred variables which makes it difficult to model and effectively include them in the recommendation process.

Some of those challenges have the chance to be addressed by leveraging learning-to-rank techniques [173]. They refer to machine learning techniques for training the model used for the ranking task. The LBSs collect large amount of usage data such as contexts, location histories and implicit feedbacks represented in the form of user check-ins. They make it possible to train those models and infer the most effective features for each single potential scenario. Whereas recent approaches aim at adapting learning-to-rank to hybrid recommender systems [174], personalized local search has yet to take advantage of them.

Several research findings call for new approaches able to identify the better recommendation strategy by deciding which prediction techniques are most suitable based on the acquired knowledge about the user and the current circumstances. For instance, the time variability of some POI categories requires complex decision making approaches in order to reveal significant correlations when the large sets of data are continuously altered [175]. In order to scale to large populations and supports high numbers of POIs and variable contexts, cloud computing and distributed processing platforms are to be considered [176,177].

While the large variety and heterogeneity of data sources makes it difficult and costly to design robust models, *deep learning* techniques [178] have the chance to identify multi-layer latent factors and extracting meaningful representations for the recommendation task in an unsupervised fashion, such as in neural nets with many hidden layers.

One big obstacle for the development of new prototypes is the absence of adequate public datasets containing large historical records of the disparate facets of the behavior of a large set of users, their social ties and interactions. Only a few public datasets are available today limited to their size and features.

12.4. Serendipity

If the profiles of the users are built by statistically weighting the preferences according with the number of times a user visits a venue, a typical *filter bubble* phenomenon would avoid to suggest venues that do not fail to agree with previously expressed interests [179].

In order to mitigate it, Horozov et al. [129] allow some random POIs to be introduced in the recommendation. The authors assume that this randomness introduces a form of *serendipity*, but also guarantees the capability of generating additional recommendations in the case of insufficient number of ratings. Quercia et al. [180] focused on recommending emotionally pleasing routes in the city. They prove that the paths with highest perceived happiness are not always the shortest ones and, in general, people are keen to discover new ones.

Besides the above-mentioned attempts, current POI-recommendation fails to consider human desires for variety, discovery and change that may balance the effects of a self-reinforcing personalization.

12.5. Privacy

Even though LBSs can be very useful, these benefits come at a cost of users' privacy and those with whom the user comes in contact. Advances in tracking technologies create opportunities for remote services to collect huge amount of sensitive data of a multitude of users. It is speculated that the provided personalized recommendations are associated with privacy risks. An appropriate trade-off exists between privacy and accuracy of these recommendations. A large body of research has focused on developing location privacy protection mechanism that ggallows users to preserve the sensitive information disclosed, e.g., [181–186].

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