A Survey on Mobile Tourism Recommender Systems

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***Abstract*—*Recommender Systems (RS) have been increasingly common in web applications seeking to predict content items of potential interest to users. Among others, RSs have been successfully applied in e-tourism applications, offering travel recommendations. The emerging mobile RSs are tailored to mobile users and promise to substantially enrich tourist experiences. New developments in mobile and pervasive computing technologies leverage massive opportunities to provide accurate personalized tourist recommendations that capture several contextual parameters. This article presents a state-of-the-art in the field, proposing a classification of mobile tourism RSs and providing insights on their offered services. It also highlights promising research opportunities with respect to mobile RSs employed in tourism.*

I. Introduction

Recommender Systems (RS) have proven to be a valuable tool for online users to cope with the information overload, which makes information search and selection increasingly cumbersome. RSs use registered user profiles and habits of the whole user community to compare available information items against reference characteristics and present meaningful item recommendations [23]. Typically, a RS compares a user profile to some reference attributes and seeks to predict the 'rating' or 'preference' that a user would give to an item she has not yet considered.

RSs are classified in several types, based on the knowledge used, the way they formulate recommendations and the algorithms they implement. The most widely utilized amongst them are [23]: collaborative filtering (users are recommended items similar to those chosen by other users with similar preferences); content-based filtering (recommendations depend on content that the target user has opted for in previous interactions); knowledge-based filtering (they pursue a knowledge-based approach, reasoning about what items meet the user's requirements); hybrid (combination of the abovementioned methods).

Lately, RSs have been increasingly employed in the field of electronic tourism, providing services like trip and activities advisory, lists of points of interest (POIs) that match user preferences, recommendations of tourist packages, etc. Existing RSs in e-tourism correlate user needs, interests and constraints with catalogued destinations annotated using the same vector of parameters.

A relatively recent development in e-tourism lies in the use of mobile devices as a primary platform for information access, giving rise to the field of mobile tourism. Mobile tourism brings forward new challenges and opportunities for innovative personalized services. The most prominent outcome of recent research in mobile tourism has been the proliferation of mobile electronic guide systems [17]. Most incorporate personalization features and take advantage of the sensing capabilities of mobile devices to infer user, social and environmental context to provide context-aware services.

The first systems that coupled mobile guides functionality with RS technologies appeared soon after (we use the term 'mobile tourism RSs' to refer to those systems). Mobile RSs increase the usability of mobile tourism applications providing personalized content, hence limiting the information overload [22]. Mobile tourism RSs may also take advantage of usage and application context in providing improved, context-aware recommendations for attractions or tourist services [13].

Most existing mobile tourism prototypes are web-based (e.g., [9],[13],[14]), wherein the recommendation logic is maintained on the server (hence, continued network connectivity is required). Some standalone systems have been reported (e.g., [19]), typically downloaded and installed on mobile devices thereafter functioning in disconnected mode.

This article presents a state-of-the-art report in the field of mobile tourism RSs, offering insights on recommendation tasks commonly offered by existing mobile tourism RS prototypes. We also propose a classification scheme for mobile tourism RSs, undertaken on the basis of the criteria taken into account for deriving recommendations). Last, we highlight challenges and promising research directions with respect to mobile RSs employed in tourism.

II. Services Offered by Mobile Recommender Systems in Tourism

Mobile RSs represent a relatively recent thread of research applied in numerous application fields (e.g., mobile shopping, advertising/marketing and content provisioning) [22]. Notably,

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mobile tourism is a privileged application field for mobile RSs, which leverages massive opportunities to provide highly accurate and effective tourist recommendations that respect personal preferences and capture usage, personal and environmental contextual parameters.

Below, we focus on typical recommendation tasks commonly offered by existing mobile tourism RSs. The tasks presented herein are not intended to be exhaustive, but provide a reasonable coverage of recent research in the field.

A. Attractions (POIs) recommendations

Most prototyped tourism-relevant mobile RSs are utilized to recommend city attractions (e.g., museums, archaeological sites, monuments, churches, etc.). The recommendations are typically visualized either in a hierarchical list-based interface [16] or by superimposing attraction icons on a map [3], [20].

Recommended attractions are computed on the base of session-specific and long-term preferences stored in the user profile, often using current user location to filter the results (e.g. [15],[20]). However, mobile recommendation engines increasingly take into account additional contextual parameters, including time [9], attractions already visited [9],[13], user mobility pattern [5],[9], weather [13], transportation mode in use [25], user's mood [25], social environment [8],[13], etc.

As regards the type of informative content, this varies from text and images [9] to sound/video [16], 2D maps [3], 3D maps [20], VRML models [18] and augmented reality views [19]. Some map-based systems incorporate GIS servers [18], [20] to improve interactivity with geo-references attractions.

B. Tourist services recommendations

This refers to functionality rather similar to that described above. The user typically receives information relevant to travel services such as restaurant, hotel, transportation services, etc [15],[24],[25]. Most systems use constraint-based filtering approaches to control which services are suggested. The user specifies constraints and the system retrieves and ranks services which satisfy those constraints. For instance, hotel recommendations may be based on offered facilities, customers' reviews, room availability, check-in/checkout times and price, while restaurant recommendations on location, opening hours, customer ratings, menu and price [28].

C. Collaborative user-generated content and social networking services for tourists

A number of systems enable recommendations aiming at discovering attractions or services. Those systems are largely inspired by features often offered by popular social networking platforms, providing access to repositories of user-generated content; as such, they are designed to support visitors to explore a city as well as share their visit experiences [8],[12],[13],[25]. User activity (e.g., movement pattern, visited attractions, pages browsed, etc) is automatically logged, while tourist-relevant content (e.g., comments, attractions ranking, photographs/videos) may be collaboratively managed and shared. Moreover, some systems visualize the positions of nearby visitors and support direct VoIP communication (e.g., in [8]).

Social networking services are either supported as integral part of the RS [8],[13] or based on third-party social networks to extract user profile information [12],[25].

D. Routes and tours recommendations

A number of transportation and navigation tools offer routing services based in the geographical location of mobile users. Route (i.e., point-to-point) recommendation services are integrated in many mobile guide applications to assist users finding their way from their current location to a recommended attraction. Some projects also exploited information retrieved from social networks (through collaborative rating/tagging) to provide personalized route recommendations (e.g., [21]).

Several mobile RSs focused on deriving personalized tourist tours, i.e. ordered lists of intermediate locations (visits to attractions) along an origin-destination path, subject to several user's preferences and constraints such as current location, available time and interests [10]. Some projects offer personalized walking tours, wherein problematic paths with respect to environmental burden (e.g., routes along streets with high traffic) are substituted by more appropriate paths (e.g., by routes through pedestrian zones) [18].

Several projects deal with a more challenging problem, generating multiple-day personalized tours via a subset of available POIs (each tour corresponds to each day of stay at the destination). In addition to user-defined restrictions and preferences, several constraints are considered, such as the opening hours of POIs, the number and duration of desirable breaks (e.g. for lunch), etc. In the relevant literature, this problem is known as the tourist trip design problem (TTDP).

TTDP is a far more algorithmically challenging task compared to generating single tourist tours. High quality TTDP solutions feature POI recommendations that match user preferences (thereby maximizing user satisfaction) and near-optimal feasible route scheduling. Recommended tours are visualized on maps [14],[19], allowing users to browse informative content on selected POIs. Some tools also offer augmented reality views of recommended attractions [19].

Another popular line of research involves mobile tourism RSs that incorporate transport advisory services, considering all available transportation modes (e.g. walking, cycling, bus, tram, metro, etc). Those systems either derive point-to-point multi-modal routes via a set of POIs [26] or first derive a tourist tour and subsequently provide multi-modal route generation among successive recommended POIs [11].

III. CLASSIFICATION OF MOBILE RECOMMENDER SYSTEMS IN TOURISM

The landscape of mobile RSs employed in tourism is extremely diverse in terms of their architectural, technological and functional aspects. Fig.2 illustrates a generic architecture for mobile tourism RSs.

Herein, we propose a classification of existing mobile tourism RSs with respect to the criteria taken into account for deriving recommendations. Notably, a considerable number of prototypes solely rely on user constraints and preferences, either explicitly stated or implicitly inferred, to derive content recommendations (e.g. [9]). Those systems (known as constraint-based systems) typically exploit contextual information to determine the appropriateness of POIs. Strictly speaking though, they lack an actual recommendation engine [20]. Hence, those systems are not surveyed herein.

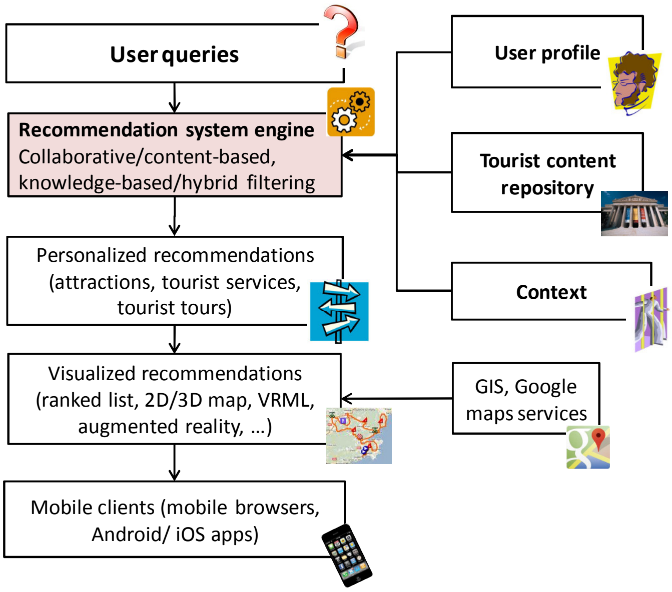

Fig. 1. A generic architecture of a mobile tourism RS.

Pure Location-Aware Recommender Systems (LARS)

In effect, mobile LARSs represent a special case and early versions of context-aware RSs (see following subsection), as their recommendation logic solely relies on location among the many potential contextual parameters. LARSs constituted a major breakthrough over traditional RSs, utilizing the ability of modern (including early) mobile devices to capture their geographical position and seamlessly convey it to the recommendation engine.

GeoWhiz [15] employs a collaborative filtering-based solution that uses location as a key criterion for generating restaurant recommendations. GeoWhiz utilizes a 'convenience' metric in making recommendations, i.e. recommended restaurants are conveniently-situated nearby the user's current location, unless there is an overriding criterion (e.g., restaurant offering discount coupons) that warrants the recommendation.

Biuk-Aghai et al. [7] presented a LARS, which takes into account user preferences and feedback information (ratings) for delivering recommendations (using a collaborative filtering-based engine). The proposed system employs a genetic algorithm for generating travel itineraries and a fuzzy-logic based module for calculating visit/stay times at each stop of the entire trip. Itineraries are calculated on the basis of the user's stated preferences, the user's visit history, official spot ratings and peer users' feedback ratings.

The PECITAS system [26] offers location-aware recommendations for personalized point-to-point paths. The paths are illustrated by listing the various connections that the user must take to reach the destination using public transportation and walking. Although an optimal shortest-path facility is incorporated, users may be recommended longer routes that pass through several attractions, given that their specified constraints (e.g. latest arrival time) and travel-related preferences (maximum walking time, maximal number of transport transfers, sightseeing preferences, etc) are satisfied.

Yu and Chang proposed a LARS [28] which supports personalized tour planning using a rule-based recommendation process. This system packages 'where to stay' and 'where to eat' features together with 'typical' tourist recommendations for sightseeing and activities. For instance, recommended restaurants (selected based on their location, menu, prices, customer rating score, etc) are integral part of the tour and the time spent for lunch/dinner is taken into account to schedule visits to attractions or to plan other activities.

Noguera et al. [20] proposed a 3D-GIS mobile LARS based on a hybrid recommendation engine. Content item recommendations are restricted to an 'influence area' around the user's location. The system visualizes 3D virtual representations of the world where the users are physically located (based on a custom 3D GIS architecture).

Context-Aware Recommender Systems (CARS)

Pure LARSs employ unidimensional logic in recommending items as they only consider a single dimension (i.e. location) of the multi-dimensional contextual and situational space. Multi-criteria ratings allow users to express more differentiated opinions by allowing separate ratings for different aspects or dimensions of an item. Adomavicius et al. [2] proposed a contextualized view on ratings, giving rise to CARS. Although the users still provide unidimensional ratings, the situational context of users (e.g., age, time or weekday) introduces additional dimensionality to the ratings.

The concept of context-awareness agrees with the ubiquitous nature of mobile devices. Mobility adds several contextual dimensions, either implicitly fed (e.g. change of location) or inferred (e.g. multiple visits or spending more time than average in a POI may be regarded as a positive 'vote'). A recent survey revealed that recommendations offered by CARS may significantly improve the appreciativeness of tourists compared to 'plain' RSs [4]. For instance, the recommendation of a music club to young, male users that visit a city in August is presumably more accurate if the system exploits ratings submitted by young, male users, who rated the club in the summertime.

Context values may be captured by mobile devices' built-in sensors (e.g. GPS unit, accelerometer, timer, compass, gyroscope, camera), web services (e.g. weather report or public transportation information service), supporting infrastructure (e.g. measure crowdedness from presence sensors) or peer users. Potentially useful context parameters are location, distance from POI, budget, time, weak day, season, time available for sightseeing, means of transport, weather conditions, mobility history (e.g. POIs already visited), social environment, etc.

One of the early mobile CARS examples employed in tourism is the Cyberguide project [1], which encompassed several tour guide prototypes for different handheld platforms. Cyberguide provided tour guide services to mobile users, exploiting the contextual knowledge of the user's current and past locations in the recommendation process.

Barranco et al. [5] proposed a context-aware system for mobile devices that incorporates the user's location, trajectory and speed (while driving) to personalize POIs recommendations. POIs are chosen among those located within a radius around the user's location; the radius is calculated based on the user's trajectory and speed. The contextually-filtered POIs are then fed into a hybrid RS as an input, which selects the most appropriate ones.

The concept of 'context-aware rating' was introduced in [13] to denote the higher credibility of users that upload reviews, ratings and comments while onsite (via their mobile devices) in comparison with others that perform similar actions through standard web interfaces. In this context, MTRS assigns increased weights to ratings/content provided by tourists actually visiting a POI compared to ratings submitted by web users. Hence, MTRS captures context-aware user evaluations and ratings and uses such data to provide recommendations to other users with similar interests. Further, MTRS delivers personalized recommendation services to mobile users, taking into account contextual information such as the user's location, the current time, weather conditions and user's mobility history (e.g. POIs already visited by the user). A similar approach in taken in the iTravel system [27], which adopts a peer-to-peer (P2P) communication model (powered by WiFi or Bluetooth) to enable detection of nearby tourists and cost-effective information exchange among them.

I'm feeling Loco [25] considers inferred user preferences and spatiotemporal constraints for sites recommendations. The system learns user preferences by mining a person's social network profile. The physical constraints are delimited by the user's location and mode of transportation (walking, bicycle or car), which is detected based on measurements taken by a smartphone's accelerometer sensor.

Magitti [6] is a mobile leisure guide system that detects current user context, infers current and likely future leisure activities and recommends content about suitable venues (e.g., stores, restaurants, parks, movies). Magitti supports three key features: context-awareness (current time, location, weather, venues opening hours, user patterns); activity-awareness (it filters items not matching the user's inferred or explicitly specified activity modes); serendipitous, relaxing experience (users do not need to enter profile, preferences or queries).

ReRex [4] is a CARS that takes a new approach for assessing and modeling the relationship between contextual factors and item ratings, whereby users are asked to judge whether a contextual factor actually influences the rating given under a certain contextual condition (e.g., whether escorting children influences the decision to visit a museum). The application presents the recommendations generated by a predictive model and justifies the recommendations. ReRex also offers assistance in the preparation and modification of a complete itinerary according to occurring circumstances.

Critique-Based Recommender Systems (CBRS)

Critiquing is a form of minimal feedback which helps conversational RSs to narrow the search space and help the user find the product they are looking [22]. A critique is a directional rating feature supplied by the user (typically on a 1-5 scale) with respect to a recommendation. For example, a user suggested a holiday package may specify that she is looking for a similar cheaper holiday by critiquing the price feature.

CBRSs take into account user critiques in addition to 'typical' contextual factors to further improve the accuracy and effectiveness of recommendations. User critiques are incorporated in the user's model. Eliciting user preferences through critiques particularly suits the mobile scenario. Firstly, the preferences are explicitly stated by the user, and hence, are more reliable. Secondly, the user effort to make a critique is low, as compared to methods utilizing standard survey pages.

A critique-based approach has been adopted in MobyRek [24], which aims at supporting travelers in the selection of an appropriate restaurant using a hybrid (content-based/ collaborative filtering) RS. The user critiques a feature of a recommended product when that is somewhat unsatisfactory. A search function lets the user formulate both 'must' and 'wish' conditions and returns a ranked list of products.

IV. RESEARCH CHALLENGES AND FUTURE PROSPECTS

Although mobile RSs have been applied in various application fields, tourism is undoubtedly the most crowded field among them [22]. The emergence of mobile devices with increased sensing, computational and visualization capabilities raises new challenges and opens unprecedented research opportunities. This section highlights challenges, open issues and promising research directions in the field.

Improved context inference mechanisms and elicitation of user preferences: Context-aware recommendations often fall short as user context may be incorrectly interpreted (e.g. spending more time than anticipated while visiting a POI does not necessarily connote user satisfaction), hence, leading to inappropriate recommendations. Therefore, sophisticated context inference mechanisms are required to remove uncertainty and improve the accuracy of recommendations. Those mechanisms may combine hand-crafted knowledge bases, advanced machine-learning techniques, elicitation of user feedback and interpretative user models.

Metrics and formal evaluation methods for assessing the effectiveness of recommendations: Although user experience evaluations are of critical importance to measure the success and perceived usefulness of web and mobile RSs, very little has been done in executing formal field studies and evaluation tests on mobile RSs. Some first evaluation reports have appeared (e.g., [4],[20]), yet, there is still a long way to go.

Certainly, the exercise of user trials in realistic environments calls for the participation of large groups of evaluators and is known to comprise a lengthy process, which engages a considerable amount of resources in the execution of trials and compilation of evaluation reports. To this end, the ‘simulation’ of contextual situations has been proposed as a means to measure how context-aware recommendations are perceived by users (participants may be asked to imagine that a given contextual condition holds and then assess the context-aware recommendation). However, it has been argued that this method must be used with care, as users tend to act differently in real and supposed contexts [4].

Future research should aim at gaining deeper understanding in questions concerning methods, theories and techniques that assess the trust, efficiency, effectiveness, accuracy, satisfaction and perception of mobile tourism RS recommendations [23]. The question of how the above parameters can be defined, evaluated and measured needs to be answered.

Unified attractions/tourist services recommendations: Notably, the majority of mobile RS prototypes focuses either in recommending tourist attractions (see Section A) or on tourist services (see Section B). We argue that those two recommendation service types should not by approached separately, as the selection of restaurants or accommodation largely affects tourist decisions with regards to POI visits (due to time or budget constraints). Hence, RS prototypes offering a unified perspective are in need.

New prospects in tourist route/tour planning services: The state-of-the-art presented in Section D reveals that not much has been done with respect to problems that closely match realistic TTDP requirements. This highlights a promising field of research which calls for modeling and solving problems that take into account TTDP aspects like:

- Tourists are commonly under inflexible budget restrictions when considering accommodation, meals, means of transport or visits to POIs with entrance fees. Hence, next to the time budget, money budget further constrains the selection of POI visits.
- Tourists typically enjoy relaxing and having breaks as much as they enjoy visits to POIs. A realistic route/tour should therefore provide for breaks either for resting or for a coffee and meal. Coffee and meal breaks are typically specific in number, while respective recommendations may be subject to strict time window and budget constraints.
- Tourists commonly prefer to walk along routes featuring buildings and squares with historical value or routes with scenic beauty. Such routes are likely to be preferred also when moving among POIs, e.g. a detour through a street along a castle walls would be more appreciated than following a shortest path though streets with car traffic.
- The use of public transportation services is common among individuals touring a tourist area. Tourist route/tour planners should, therefore, incorporate online multimodal public transportation route planning facilities, tailored to tourist needs.

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