A personalised travel recommender system utilising social network profile and accurate GPS data

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Abstract: Recent developments in internet technologies have created a massive demand for online services with the rapidly growing users. Travel recommender systems have been embraced by many researchers due to recent developments and significant requirements in the e-tourism domain. Generating personalised recommendations with minimal interactions is a key challenge and predicting personalised list of locations with the available ratings alone cannot achieve effective recommendations. To address this issue, we develop an intelligent real-time user-specific travel recommender system (IRTUSTRS) through incorporating users’ social network profile and current location by exploiting global positioning system (GPS) data for travel recommendation generation. The proposed IRTUSTRS approach helps end users through enhanced travel recommendations with improved accuracy. The experimental evaluation portrays the improved performance of IRTUSTRS over baseline approaches. The presented work helps to understand the performance of recommender systems by utilising online social network profile of users with the current location through the GPS data.

Keywords: recommender systems; location-based social networks; social networks; travel recommendation; user-location prediction; GPS.


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1 Introduction

More than one number of individuals connected together with more than one type of relations (for example: friends, family, common interests, groups, etc.), is known as a social network. A real-world social network service can be digitally represented. The social network not only mentions the user’s network but also enhance their activities. The activities of user depend on their actual ideas, share post, events and likes.

The user location-based social network data strengthens the social network activities and also the locations mention in the social network services. In the location-based social network consists of the people physical location in their social structure and also to share the information by location embedded system. The location of the user derived from their location tagged media content and other activities (such as their photos, video and text). The user physical location consists of the individual location at the current time and their location history with a specific period of time. One or more person has the same location and also similar location histories it will not affect our Social Network structure. The structure of social network also contains individual behaviours, activities and other information.

The concept of locations-based networks comprises of three types of graphs such as location-location graphs, user-location graph and user-user graph.

• Location-location graph. In the Location-location graph, users consecutively visit the edge between two locations that indicate the node location of the location-location graph. The correlation between the two location strength represented by edge weight.
User-location graph. Users and locations are the two types of the user-location graph. The visited location of the users indicated by the edge starting from the users and ending at a location, the number of visits calculated by weight of the edge.

User-user graph. Basically, a node is a user and edge between two nodes represents two relations. The two relations are existing social network between two users and a new location of the users.

Three groups of previous location-based social networking services are Geo-tagged-media-based services, Point-location-based services and Trajectory-based services.

Geo-tagged-media-based. Location label to media content of users added by geo-tagging services. The new content of users passively added to the physical world and also the content in the geographic context viewed by the users. The location-based social networking services included in the website (Flickr, Panoramio, and Geotwitter). The social network services still focus on media content because the connections between users are based on media itself.

Point-location-based. Some applications like Foursquare and Google Latitude mainly focusing on people current locations, such as hotel or park. In Foursquare application used to point out the individual with the most number of check-ins at a place is crowded. The users’ real-time location can discover by social network and also it enables the social activities of the users in the real world. These real-time location social activities useful for inviting people to have dinner or go shopping with users.

Trajectory-based. The point locations and the route connecting the point location recorded by users are called trajectory-based social networking services (such as Bikely, SportsDo, and Microsoft GeoLife). Normally the users’ experiences represented by their tags, such as photos, media, and tips along the trajectories and also these services used to record users basic information, such as distance, duration, and velocity. In addition to these services provides where and when information of users.

Our main contributions in this paper are as follows.

we have developed an intelligent real-time user-specific travel recommender system (IRTUSTRS) for personalised recommendations

we have exploited the users’ social network profile and GPS data for the generation of travel recommendations

we have experimentally evaluated our developed IRTUSTRS through two real-time large-scale datasets of Yelp and TripAdvisor.

The remainder of the paper is organised as follows: The next section describes the task of the recommender systems and Section 3 explains the additional recommender system objectives. Section 4 portrays the location-aware recommender systems and Section 5 presents the social circles for the recommender systems. Later, Section 6 depicts
the proposed IRTUSTRS approach and Section 7 presents the experimental results and discussions. Finally, Section 8 concludes the paper with the summary and the future work directions.

2 Task of recommender systems

A recommender system generally provides items recommendation as a list, according to the interests of the user. The System also predicts the user’s response for each recommended items. Recommender systems help users in the decision process to choose the particular item and make the process easier. User ratings for the items are represented in the user-item rating matrix \( R \in \mathbb{R}^{u \times i} \), where \( u \) denotes the number of users and \( i \) denotes the number of items. Table 1 demonstrates the sample rating matrix five users and six items. Generally, ratings are represented on a five-star scale. One- and two-star ratings are usually considered as the negative ratings, three-star rating is unbiased and four- or five-star rating denotes the ratings as a positive. Recommender systems algorithm predicts the missing ratings in the rating matrix \( R \) and it recommends the item \( i \) to the user \( u \), only if the predicted rating is positive. Predicted user ratings are represented in the predicted rating matrix \( R' \in \mathbb{R}^{u \times i} \). The traditional evaluation process of the recommender system is represented in Figure 1. The accuracy of the recommender system is assessed using two traditional evaluation metrics. They are the root mean square error (RMSE) and mean absolute error (MAE).

![Evaluation process of recommender system](image)

In real time, the recommender systems were evaluated through its prediction capabilities and accuracy of items suggestions to the users. Though prediction of accuracy is fundamental, recommender systems should also concentrate on the extraction of user’s feel and interests in discovering new items. While providing good recommendations to the users, recommender systems should also protect the privacy of the users. The success of the recommender systems is in identifying the relevant properties of the items, which helps the system by increasing the responsiveness during recommendations of new items.
Table 1  User-item rating matrix

<table>
<thead>
<tr>
<th>User/Item</th>
<th>I_1</th>
<th>I_2</th>
<th>I_3</th>
<th>I_4</th>
<th>I_5</th>
<th>I_6</th>
</tr>
</thead>
<tbody>
<tr>
<td>U_1</td>
<td>–</td>
<td>3</td>
<td>1</td>
<td>5</td>
<td>–</td>
<td>2</td>
</tr>
<tr>
<td>U_2</td>
<td>5</td>
<td>–</td>
<td>1</td>
<td>5</td>
<td>5</td>
<td>1</td>
</tr>
<tr>
<td>U_3</td>
<td>3</td>
<td>2</td>
<td>1</td>
<td>–</td>
<td>–</td>
<td>1</td>
</tr>
<tr>
<td>U_4</td>
<td>4</td>
<td>–</td>
<td>5</td>
<td>–</td>
<td>3</td>
<td>–</td>
</tr>
<tr>
<td>U_5</td>
<td>2</td>
<td>2</td>
<td>–</td>
<td>1</td>
<td>2</td>
<td>5</td>
</tr>
</tbody>
</table>

3  Additional recommender systems objectives

High competition between commercial recommender systems takes place by means of providing high-quality recommendations, best content and variety of services to the users. Recommender systems for the groups of users (Jameson and Smyth, 2007; Ravi and Vaivaniaswamy, 2016) were started to spread out and used in different domains (e.g., web (Pazzani and Billsus, 2007), music (Chao et al., 2005), television (Yu et al., 2006) and tourism (Abilash Reddy and Subramaniyaswamy, 2015; Ardissono et al., 2003; Logesh et al., 2017; Logesh and Subramaniyaswamy, 2017; Patelis et al., 2005). A joint recommendation to the group of users is enhanced by the recommendations to the user group (Jameson and Smyth, 2007). For a recommender system, there are four design approaches. They are

- calculating similarity measures (Meghana Ramya Shri and Subramaniyaswamy, 2015; Ortega et al., 2013)
- obtaining neighbours (Bobadilla et al., 2012a; Subramaniyaswamy and Logesh, 2017)
- obtaining predictions (Christensen and Schiaffino, 2011; Subramaniyaswamy et al., 2012, 2015a, 2015b, 2017; Indragandhi et al., 2017)
- creating recommendations (Baltrunas et al., 2010; Vaivaniaswamy et al., 2015).

From the research results (Ortega et al., 2013), it is very clear that the quality of recommendations from the different approaches does not differ greatly, but the time of execution is reduced. Figure 2 describes the four levels of group user data namely, similarity metric, neighbourhood establishment, prediction and recommendation generation of items.

The recommendations generated should be explained in a simple, accurate and convincing manner to be considered as valuable for users. Explaining recommendations is very important part of recommender systems. It builds the user confidence in the recommendations generated by the system. Generally, explanation types are divided into four categories. They are:

- human manner (user to user approach)
- item manner (item to item approach)
- feature manner (item features)
- hybrid.
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Additionally, recommender systems integrate geo-social information (Yang et al., 2008) and uses conversational techniques (Mcsherry, 2005).

**Figure 2** Four classifications of group recommendation approaches

3.1 **Recommender systems trends**

From the existing recommender systems, it is very clear that these systems collect different types of data and integrate and use it to generate suggestions. The recommender system trend is parallel to the growth and evolution of the web. It can be classified into three stages:

- In the origin of the web, recommender systems used only users’ ratings and demographic data of the user.
- In web 2.0, along with the above information, recommender systems use social information like, friends (both trusted and untrusted), followers, etc. It also includes information from blogs, comments, tags, photos and videos.
In web 3.0, along with the above information, recommender systems may use many sensors to collect context-aware information.

At present, only geographic data is included. In future, recommender systems may incorporate information such as radio frequency identification (RFID) data, health parameters from health gadgets, shopping and food habits.

Context-aware recommender systems (Abbar et al., 2009; Adomavicius and Tuzhilin, 2011), concentrates on the more related information, like location, time and sensor data (Gavalas and Kenteris, 2011). By using data mining or with some hybrid methods, the related information can be acquired both implicitly and explicitly. Presently, mobile applications are very well-known for using geographic location information and such information leads to the efficient recommendations provided by the geographic recommender systems. Since location plays a vital role in the recommendation process in the geographic recommender systems (Matyas and Schlieder, 2009; Oku et al., 2010), these systems are also known as location-aware recommender systems. As recommender systems control large information of users in huge numbers, privacy is considered as main issue. Protection of user’s privacy to certain level must be assured while making predictions (Mcsherry and Mironov, 2009). Privacy must be concentrated along with the maintenance of accuracy of predictions (Machanavajjhala et al., 2011).

Currently, recommender systems are mostly deployed in the e-commerce to help users in choosing items according to their interests and preferences. Recommender systems are vulnerable to attacks (Ray and Mahanti, 2009), by which a product gets many positive user ratings and the product of competitors gets negative ratings. Such attacks on recommender systems for profit are known as Shilling attacks (Chirita et al., 2005; Lam and Riedl, 2004).

In the development recommender systems, integration of knowledge-based filtering has gained more importance. Though it is emerging, it uses knowledge about the items and users to track the reasonable recommendations through the knowledge-based approach (Burke, 2000). The generated recommendations are based on the assumption about the user’s needs. There are several knowledge-based recommender systems models available. They are ontology-based (Middleton et al., 2004), reasoning based on constraints (Felfernig and Burke, 2008), reasoning based on cases (Bridge et al., 2005), structures based (example: queries) (Jannach, 2009), social knowledge-based (Carrer-Neto et al., 2012). The gradual improvement in the integration of different information (e.g., social relations, ratings, locations and user knowledge) has made a clear path towards the research and development of hybrid recommender systems. The combination of several methods such as social, memory-based and location-aware has created a new trend in the development of recommender systems based on combining existing methods. The recent research has produced limited developments for the recommendations and predictions from single information. The results from the algorithms which combined with the personal data have been improved.

4 Location-aware recommender systems

The drastic growth in the usage of mobiles has increased the need for the development of location-aware systems to provide location-based services. These location-aware recommender systems were also called as geographic recommender systems. The
geographic recommender systems utilise the location of the user in the two stages (rating and recommendation) of recommending the process. The recommender systems and its type can be easily identified through following terms.

- **RS**: It is the traditional recommender system, in which the ratings and recommendations are generated without using the geographical information/location of the user.

- **RS + G**: It is also traditional recommender system and it adds the geographical information of the items. But it generates the ratings and recommendations without using the geographical information (Martínez et al., 2009; Schlieder, 2007).

- **GRS**: It is completely geographic recommender system, where the ratings were calculated traditionally and recommendations are generated by using the geographical information of the user. Restaurant recommendation is the best example for GRS (Wan-Shiou et al., 2008).

- **GRS+**: It is the advancement of GRS and in this type of recommender systems, the ratings are generated using by calculating the distance between the user and items. Hybrid filtering mechanisms were deployed to make recommendations. Though the GRS+ looks complete theoretically, but there is lots of semantic difficulty in the rating process which needs more research. Due to the difficulty, GRS+ is less used as the recommender system (Zheng and Xie, 2012; Zheng et al., 2011).

There is a possibility to collect GPS traces of a user and such database can help in the generation of recommendations to the user. User’s GPS data with the social information can provide excellent recommendations to them.

### 4.1 Bio-inspired approaches

Mostly model-based recommender systems were based on bio-inspired approaches such as neural networks (NNs), artificial immune networks (AINs) and genetic algorithms (GA). In recommender systems, a genetic algorithm is mainly used in two different aspects: hybrid user models (Al-Shamri and Bharadwaj, 2008; Gao and Li, 2008; Ho et al., 2007) and clustering (Kim and Ahn, 2004; Zhang and Chang, 2006). Hybrid user models of recommender systems use multiple combinations of filtering techniques such as collaborative filtering with content-based filtering or collaborative filtering with demographic filtering, to utilise virtues of these filtering techniques. By using such mechanisms, the demographic characteristics or features extracted from content-based filtering easily influence the structure of the chromosome. Combination of user’s preferences and relation environment is exploited by a model-based collaborative filtering method using the genetic algorithm (Dao et al., 2012). This model deals with location-based advertisement problem. Though weighing simple similarity measures and genetic algorithm is used to create similarity metric (Bobadilla et al., 2012b). The genetic algorithm also helps in the process of learning the customer’s preferences (Hwang et al., 2010). Recommender systems consist of a common technique called clustering, by which flocking of all users as a group of classes. For each cluster of similar users, collaborative filtering techniques were applied to obtain similar results in a short time of calculation. Commonly used algorithm for genetic-based clustering is Genetic algorithm based K-means algorithm (Kim and Ahn, 2008).
The model of simulating the brain’s information processing scheme to enable the computer to learn is called as a neural network model. This model intends to observe the performance of biological neurons. Generally, a neural network comprises of numerous interconnected nodes. Every node manages assigned knowledge domain, which has inputs from the network of nodes. On the basis of the inputs from the nodes, it learns the association between the data sets and pattern. Based on the feedback from the operation, the pattern is defined to produce needed results. Recommender system development based on the neural networks focuses on the research of hybrid recommender systems. These types of hybrid recommender systems concentrate on learning of the user profiles through neural networks. In some recommender systems, neural network models were used in its clustering process. The hybrid perspective of recommender systems enables neural networks to add more information to the ratings of the items. Widrow-Hoff (Widrow and Hoff, 1960) algorithm of a hybrid recommender system approach (Ren et al., 2008) learns the profiles of every user from the contents of the rated items by which graininess of profiling of the user is improved. Along with the neural network, the usage of collaborative filtering and content-based filtering techniques in the movie recommendation systems generates specific recommendations to the users (Christakou and Stafylopatis, 2005). Self-organising map neural network (SOMNN) clusters the users by exploiting the demographic characteristics of the users and the preferences of items (Lee and Woo, 2002). Extended versions of SOMNN examined the unsupervised learning in neural networks. Its main goal is to discover the fundamental structure of data in the neural network.

The common training method, backpropagation is used to train the neural network to generate related rules from the transactional database (Huang et al., 2008). The hybrid recommender system model solves the unsupervised clustering problem by combining the collaborative filtering algorithm with SOMNN and case-based reasoning (CBR). The utilisation of above two machine learning process solves the problem and converts it into a supervised user preference reasoning problem (Roh et al., 2003).

The creation of pedagogical rules in e-learning is designed through neuro-fuzzy implication (Severac et al., 2012). Neural learning based optimisation perfectly formed the cold-start similarity measure (Bobadilla et al., 2012a). Artificial immune systems are derived from the human immune systems and they are distributive and adaptive in nature. Since it uses the principles and models of human immune systems, the system model is very similar to the defence system of the human body against the infections. Collaborative filtering model based on Artificial Immune Network tackles the problem of recommender system sparsity and makes the algorithms more scalable (Acilar and Arslan, 2009). Artificial Immune Network is used to recommend websites (Morrison and Aickelin, 2002) and in general recommendations (Caizer and Aickelin, 2005).

5 Social circles for recommender systems

Circle-based suggestions based on the user’s social network information is proposed Yuan (Yuan et al., 2009), it is different from conventional methods that mine from the whole social network. The social life of the users involves different aspects and the user may often shift between online and offline modes (Srivastava, 2016). A user \( u \) may trust a
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v with respect to one item or category but may not for another. Thus it is important to
determine the user’s trust circles that corresponding to different items. But in most of the
existing systems, the trust circles of a user are mixed up. Even in some of the circles that
can be known explicitly such as in Facebook or Google+, the users trust with respect to
different items that can be suggested may not exist. Figure 3 depicts the graphical
representation of social networks with users.

Yang et al. (2012) propose a set of algorithms to determine the trust value of user
links by analysing the user’s rating history in different categories and to determine the
trust circles specific to a category. The user’s feedbacks on items which can be grouped
into categories are analysed to set the different circles. It is based on the idea that a user
may trust a friend only in terms of certain items but not in terms of others. The social
network S is divided with respect to different trust relations into sub-networks S(c), where
c is the concerned item.

The inferred circle of user u concerning category c includes user v, i.e., v ∈ C_u,c
if and only if the following two conditions are satisfied:

- S_u,v > 0 in the actual network analysed
- N_u(c) > 0 and N_v(c) > 0 in the rating information collected.

Here N_u(c) is the number of ratings allocated to items by user c in category c. Or the user v
is absent from the circle of u with respect to category c, v ∉ C_u,c. Figure 4 illustrates these
concepts. A set of methods for the construction of trust value of a user u S_u,v(c) with
respect to each of the other users v in the trust circle C_u,c. The social information fed as
input consists of only the corresponding trust circle of a particular item category while
processing to predict the user ratings. The algorithms used in recommender systems
hence may not consider the entire social network but might involve only the trust
information with respect to a social circle.

Figure 3 Graphical representation of social network (see online version for colours)
5.1 Social knowledge-based recommender system

Now we explore the different methods that have used to develop a semantic recommender system. The users’ preferences with respect to the profiles are managed either by the addition and classification of items or by the creation of links with other known users in the network. The information collector module monitors and collects these data in accordance with the IMDB website, thereby instantiating the ontology. The recommender module is responsible for the analysis of user likings and preferences and the generation of suitable suggestions. Now we explain the three modules, ontology repository, data collector and the recommender system.

5.2 Ontology repository

The amount of data that has to processed is large, hence an efficient method for storage and managing the derived ontologies is an important part of the framework. The storage system chosen should be persistent, and the availability of APIs, and support for querying tools and languages should be considered. The storage system should also have good performance in terms of accessing speed, scalability, search capability and reading/writing. Also, the supported inference techniques and the cost of the system should also be analysed.
Data persistence in most of the existing repositories of ontology functions over a relational database such as PostgreSQL or MySQL. There are various other tools available such as OWLIM, Sesame, OWLDB, Redland, Mulgara, and KAON, though they are used less often. The open source ontology repositories are inefficient and suffer from scalability issues when the data is large. Hence a storage system that is simple yet optimal can be developed using relational databases and OWL files. The ontologies and instances are also stored in the relational database, since it is more efficient than most of the ontology repositories. The class descriptions, properties, relationships and the available resources and individuals are also stored in the system database.

5.3 Information collector

The suggestion mechanism involves the extraction of relevant information from the social network information and corresponding update of the ontology. It is termed as ontology population, and involves the extraction and classification of the various relationships, concepts and their instances as per the definitions made in the ontology (Ruiz-Martínez et al., 2011). The value of the recommender service which based on ontology knowledge is maintained by the process of instantiating the ontologies and updating the new knowledge.

The ontology population can be differentiated into two types:

- free text-based ontology population (such as in Ruiz-Martínez et al. (2011))
- semi-structured document-based ontology population (such as HTML, XML, etc.).

A method for ontology population that is based on structured data is proposed in the work (García-Manotas et al., 2010).

6 Proposed personalised travel recommender system

The strategy for predicting user-specific travel recommendation is broadly divided into two steps. In the first step RS understands the user behaviour through SNA data and analyses it with the user preferences. The second step deals with the travel recommendation based on the first step. As the main part, POI is generated for the user purely based on his or her interests.

The framework of a Travel recommender system comprises of various modules such as interaction interface, constraints, personal characteristics and decision task etc. Figure 5 describes the framework adapted for the proposed travel recommender system as an IRTUSTRS. The proposed system is an interaction model between recommender system and user. The application interface acts as an interaction tool between the user and the system. The characteristics of the user, their situational needs, decisional requirements, nature of travel and involvement are crawled through the information collection model. The data can be further analysed to improve the results and the interaction between the user and system.

In-depth, the adapted framework can be elaborated into a proposed model as it is described in Figure 5. In the below model, There are four units namely
user’s preferences learning unit
modelling unit
recommendation unit
feedback unit.

The user’s preferences learning unit organizes the users’ preferences along with the current location and in the modelling collects the list of all available locations in the social networks with its characteristics. The work of the recommendation unit is to discover related POI to the specific user and plan a travel route for him or her. The feedback unit collects the feedback from the user and stores it as a rating for a future use.

The features considered for the recommendation algorithm is users’ check-in history, user’s social network preferences, the mood of the user (this can be obtained by analysing the type of places currently he or she is visiting) and current location with transportation mode. The proposed system comprises of a model used to detect the transportation mode and it is explained in Figure 5. The data of GPS speed and accelerometer variance from the Smartphone is used as an input to decision trees. The decision trees are used as a classifier and it distinguishes the inputs into user transportation activity such as driving, walking or biking.

The workflow operations in the proposed model are depicted in Figure 5. The individual’s user model is updated constantly by a server through LSBN’s API calls and stores the information in a database. The mobile application which acts as an interface of...
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interaction, discover and analyse the transport mode of the user. The developed mobile application also acts an interface between user and system to make a query/ request of location recommendation. While the user requests the system through the mobile application, it sends the query to the server along with the context information (i.e., current location, transport mode and user interactions). On the server side, the received contextual information is used as additional input to the recommendation algorithm with the existing user available data model to recommend the related places. The server responses as a list of \( N \) locations along with the plan of travel to the user to visit and the mobile application visualise the recommendation on the map. Based on the profile of the user and the nearest places; the proposed recommender system suggests top-N locations to visit. Though all locations are considered for recommendation, the places are filtered through comparing the nearest places alone. The meaning of nearness varies by the transportation mode of the user. The filtering of places is also done on the basis of the category of the location and the level of similarity between the places already visited by the user. The top-N places with the highest degree of similarity value are suggested to the user.

6.1 Accurate prediction of user location using GPS data

The rapid developments of the data acquisition models have enhanced the utility of the GPS traces to learn the relationships between the users and locations. To facilitate the recommendation prediction model of the proposed IRTUSTRS we employ the rank-based POI recommendations incorporating the GPS data for the probability prediction of the user location visits. For a location zone \( zo \in FZO \), the probability of the user \( usr \) moving from \( zo_1 \) to \( zo_2 \) is defined in Noulas et al. (2012) as,

\[
P[zo_1 \rightarrow zo_2] \propto \frac{1}{\text{rank}_{zo_1}(zo_2)^{\text{TuneParam}}}
\]

Here, \( \text{rank}_{zo_1}(zo_2) \) is the rank of \( zo_1 \) with respect to \( zo_2 \) and \( \text{TuneParam} \) is the adjustable parameter.

In the traditional rank-based prediction models, the spatial distance between the locations are given priority and the behaviour of the user are neglected. As the user’s behaviour is a dynamic component, it has more value in determining the mobility of the user (Abbasi et al., 2017). To address the above-said issues in the rank-based probability determination approaches, we exploit the hybrid LBSN-based ranking approaches to incorporate user’s online behaviour as follows:

- **Distance-based ranking**: In the distance-based ranking approach, we compute the ranking for the POIs with respect to the distance between the current location of the user and the POI.

- **Threshold-based ranking**: In the threshold-based ranking approach, ranking computation for the POIs is made only for the POIs within the threshold limit of the user.

- **Popularity-based ranking**: In the popularity-based ranking approach, the POI’s are provided weights based on their total number of check-ins in the LBSN. The POIs are ranked based on the weights provided from overall check-ins. The popularity-
based ranking approach is further enhanced by incorporating the ratings provided to
the POIs. Figure 6 portrays the schematic representation of all three types of POI
ranking approaches.

**Figure 6** Schematic representation of different POI ranking approaches (see online version
for colours)

6.1.1 Mobility profiling for the user location prediction

Among various location-based services, prediction of user’s future locations using mobile
traces is considered as a flourishing research area. For many user location-based services,
the location of the active target user is considered to be most valued information.
In a typical real-time scenario, a user during the travel move periodically and the movement of the user is updated with the help of their smart phones as GPS traces with their current location. The user’s GPS traces are used to build the mobility profile based on the user’s movements in the specific areas with respect to temporal instances. The mobility profile of the user comprises of the spatio-temporal point sequences. We adopt GPS traces extraction process from Trasarti et al. (2017) to build user mobility profile.

Algorithm: Mobility Profile Builder

Input: Mobility\_usr Historical mobility pattern of the user usr, dist\_fn distance function, thres\_size minimum size threshold, thres\_dist maximum distance threshold.

Output: MP\_usr mobility profile of the user usr

//Initialize the Mobility Profile Builder algorithm

MP\_usr ← Null;
CollectiveGroup = Group(Mobility\_usr, thres\_size, dist\_fn, thres\_dist);
For TrajCluster ∈ CollectiveGroup do,
  routine ← Medoid (TrajCluster, dist\_fn);
  MP\_usr ← add(routine);
end For

return MP\_usr;

The GPS traces of the active target user are used to build the mobility profile. Then the generated mobility profile is exploited by our proposed IRTUSTRS to make personalised travel recommendations. After generating the relevant list of POIs, the final list of top-n POI list is organised with the help of hybrid POI ranking approaches.

7 Experimental evaluations and discussions

In this section, the proposed travel recommendation approach IRTUSTRS is experimentally evaluated for the efficiency, performance and the recommendations effectiveness with the existing approaches. Experiments are carried out in Python 3.6.0 on Intel core i7-5500U@3.00 GHz system with 16 GB of memory running 64-bit Windows operating system. We utilise Yelp and TripAdvisor datasets for the evaluation of our proposed travel recommendation approach. The experimental results are compared with the existing approaches (Bao et al., 2012; Zhu et al., 2017) such as LBPARS, UPARS, LFARS, MPCBRS, LBCFRS, PBCFRS to demonstrate the recommendation capabilities of proposed IRTUSTRS.

7.1 Evaluation metrics

The main aim of the conducted experiments is to evaluate the performance of the proposed recommendation approach for its travel recommendations. Experiments are conducted on Yelp and TripAdvisor datasets. We use three standard evaluation metrics RMSE, Coverage, f-measure to evaluate the generated recommendations.
(A) RMSE

RMSE is a standard evaluation metric used to evaluate the error in the generated recommendations. Generally, RMSE is computed as follows.

\[
\text{RMSE} = \sqrt{\frac{\sum_{usr,poi}(\text{Actu}_{usr,poi} - \text{Pred}_{usr,poi})^2}{\text{Total}_\text{Tested}_\text{Ratings}}}
\]

Here, \( usr \) represents the user and \( \text{Actu}_{usr,poi} \) is the actual rating provided to the Point of Interest \( poi \). Similarly, \( \text{Pred}_{usr,poi} \) is the predicted rating computed by the recommendation algorithm for the point of interest \( poi \).

(B) Coverage

Coverage is the evaluation metric used to determine the percentage of user-poi pairs to which the ratings can be predicted by the recommendation algorithm.

\[
\text{Coverage} = \frac{\text{Number}_\text{of}_\text{Predicted}_\text{Ratings}}{\text{Number}_\text{of}_\text{Tested}_\text{Ratings}}
\]

(C) F-Measure

The F-Measure is the traditional evaluation metric to evaluate the generated recommendations. To determine the F-Measure, the precision metric has to be utilised to compute the precision values. The precision can be computed with the help of RMSE as follows.

\[
\text{Precision} = 1 - \frac{\text{RMSE}}{4}
\]

Based on the computed precision and coverage values, F-Measure can be computed as follows.

\[
\text{F-Measure} = 2 \times \frac{\text{Precision} \times \text{Coverage}}{\text{Precision} + \text{Coverage}}
\]

7.2 Discussions

We evaluate the efficiency and the effectiveness of the proposed approach for the generated recommendations. Table 2 depicts the comparison of the RMSE, the coverage and F-measure of the different recommendation approaches. The effectiveness of the location-based POI recommendations is evaluated based on the location history of the user. The user preferences are learned based on the venues the user has been visited earlier.

If the recommendation approach generates the more number of user visited locations, then the recommendation approach is said to be more effective. The efficiency of the recommendation approach is effectively evaluated with the help of standard evaluation metrics such as RMSE, coverage and F-Measure. Figures 7–9 portrays the comparison of the RMSE, coverage and F-Measure metrics for both Yelp and TripAdvisor datasets.
The experimental results demonstrate the improved performance of the proposed IRTUSTRS over the existing recommendation approaches. Compared to IRTUSTRS, the PBCFRS approach has a competitive recommendation performance in terms of F-Measure and RMSE. LFARS has very less coverage, while comparing to the other recommendation approaches. The proposed IRTUSTRS has better coverage over other approaches on both Yelp and TripAdvisor datasets. The proposed IRTUSTRS has a lesser RMSE value which represents the reduced recommendation error. As our proposed recommendation approaches are location-aware in nature, spatial constraints of the locations play an important role in the selection of POIs for the recommendation lists. From the overall analysis of the experimental results, the proposed IRTUSTRS approach has been proven to be effective and efficient.

**Table 2** Comparison of RMSE, coverage and F-Measure of recommendation approaches

<table>
<thead>
<tr>
<th>Recommendation approaches</th>
<th>Yelp</th>
<th>TripAdvisor</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>RMSE Coverage</td>
<td>F-Measure</td>
</tr>
<tr>
<td>LBPARS</td>
<td>1.3534</td>
<td>62.28</td>
</tr>
<tr>
<td>LBCFRS</td>
<td>1.2635</td>
<td>77.48</td>
</tr>
<tr>
<td>LFARS</td>
<td>1.3794</td>
<td>58.42</td>
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<tr>
<td>MPCBRS</td>
<td>1.2341</td>
<td>81.32</td>
</tr>
<tr>
<td>PBCFRS</td>
<td>1.1257</td>
<td>86.54</td>
</tr>
<tr>
<td>UPARS</td>
<td>1.2964</td>
<td>65.94</td>
</tr>
<tr>
<td>IRTUSTRS</td>
<td>1.0643</td>
<td>94.73</td>
</tr>
</tbody>
</table>

**Figure 7** Comparison of RMSE of different recommendation algorithms (see online version for colours)
8 Conclusions and future works

In this paper, we have presented an in-depth overview on the role of recommender systems in the various application domains. Based on the recent requirements in the travel recommendation domain, the paper addresses the travel recommendation problem in the real-time scenario. For the generation of the travel recommendation as a service,
we have proposed a personalised travel recommender system through utilising the user’s social network profile as IRTUSTRS. As the additional context for the generation of recommendation, we also incorporate the user’s current location through the GPS data. The hybrid recommendation model of IRTUSTRS for the travel recommendation has better adaptability with the users of all ages. The presented recommender system has proved its efficiency and effectiveness through the generation of accurate recommendation over Yelp and Trip Advisor. The experimental results are evaluated with the help of standard evaluation metrics of RMSE, coverage and F-Measure. From this study, it is clear that the utilisation of users’ context data can help recommender systems in the real-world application that improves the accuracy of the generated recommendations. The exploitation of user’s social network profile has considerably reduced the interaction process between the user and recommender system interface. The personalised recommendation with the lesser interaction proves the intelligent capability of the presented IRTUSTRS system, which is profit for both system and the user. As the future work, we intend to incorporate user’s current emotion for the generation of personalised recommendation. The future work also includes the tailor-made trip recommendation through exploiting multi-agent systems to collect user data from multiple sources. The multi-source data aggregation model for the recommendation generation improves the recommendation accuracy and user satisfaction.

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References


A personalised travel recommender system utilising social network profile


