An intelligent location recommender system utilising multi-agent induced cognitive behavioural model

Logesh Ravi, Malathi Devarajan, Vijayakumar V, Arun Kumar Sangaiah, Lipo Wang, Sasikumar A & V Subramaniyaswamy

To cite this article: Logesh Ravi, Malathi Devarajan, Vijayakumar V, Arun Kumar Sangaiah, Lipo Wang, Sasikumar A & V Subramaniyaswamy (2020): An intelligent location recommender system utilising multi-agent induced cognitive behavioural model, Enterprise Information Systems, DOI: 10.1080/17517575.2020.1812003

To link to this article: https://doi.org/10.1080/17517575.2020.1812003

Published online: 09 Sep 2020.
An intelligent location recommender system utilising multi-agent induced cognitive behavioural model

Logesh Ravi**, Malathi Devarajanb, Vijayakumar Vc*, Arun Kumar Sangaiahd, Lipo Wange, Sasikumar Aa and V Subramaniyaswamyb

aDepartment of Computer Science and Engineering, Vel Tech Rangarajan Dr.Sagunthala R&D Institute of Science and Technology, Avadi, Chennai, India; bSchool of Computing, SASTRA Deemed University, Thanjavur, India; cSchool of Computer Science and Engineering, University of New South Wales, Sydney, Australia; dSchool of Computing Science and Engineering, Vellore Institute of Technology, Vellore, India; eSchool of Electrical and Electronic Engineering, Nanyang Technological University, Singapore

ABSTRACT
In recent times, location recommendation has received significant attention from the researchers due to emerging utilisation of Location Based Social Networks in the prediction process. In this paper, we present a new multi-agent based framework to generate better-personalised location recommendations. We address the personalisation problem through the dynamic user profile that incorporates the user’s long-term and short-term cognitive behaviour. The better adaptation of user cognitive behaviour enhances the prediction process and improves overall user experience with better recommendations. A detailed user study is conducted to reveal the improved performance of proposed approach through enhanced recommendations in comparison with other approaches.

ARTICLE HISTORY
Received 30 January 2019
Accepted 15 August 2020

KEYWORDS
Cognitive model; collaborative filtering; computational intelligence; multi-Agent Systems; recommender Systems; user behaviour

1. Introduction

The rapid growth of information on the internet has created information overload problem and as an effect, the discovery of specific information has become complex and time consuming (Challam, Gauch, and Chandramouli 2007). Recommender Systems (RSs) have emerged in recent years to address this problem in various application domains through providing personalised experience to the users based on their needs, interests and preferences (Vairavasundaram et al. 2015; Ravi and Vairavasundaram 2016; Khedr et al. 2018; Zhang, Zhang, and Guo 2017; Maleszka 2019; García-Sánchez, Colomo-Palacios, and Valencia-García 2020). In the travel domain, many RSs have been developed to assist users in their travel based on their previous visits or check-ins (Zhong et al. 2020). To provide better personalised services, the RSs need to maintain updated user information such as previous historical data, interests, demographic data and preferences. The main challenge of the RSs is that the interests, requirements and preferences of the users
are static and they change from time to time. The fixed information regarding the user preferences in the user profile may lead to the recommendation of unrelated locations to them. To address this issue, user’s behaviour has to be learned for understanding them in a better way to get adapted for the recommendation of relevant items (Da’u et al. 2020).

In this paper, to capture the user’s interests we use ontological structures to generate personalised recommendations. As our contribution, we collect implicit preferences of the users and use multi-agent based learning technique to adapt recommender system to generate personalised recommendations based on user’s current behaviour. Through this methodology, we have identified the user’s change in interest and respond to it accordingly. The multi-agent system coordinates the user adaptation process and keeps the user profile up-to-date. To demonstrate the potential of our recommendation framework, we employ it in the travel domain for location recommendation. Scalability is considered to be a major addressing issue in the Travel Recommender Systems (TRS). To address this issue, we introduce a cloud-based recommendation framework to generated optimised recommendations.

The remainder of the paper is organised as follows: The next section presents the related works. Section 3 describes our proposed recommendation framework and illustrates the algorithm of proposed RS and Section 4 presents the experimental evaluation and discussions on the obtained results. Later Section 5 describes the surprising location recommendations and finally Section 6 concludes the paper and provides future work directions.

2. Related works

With the effect of the growth of internet technologies, the information on web proliferates in a rapid manner. As an inverse effect, the users find difficulty in searching relevant information to them. To help the users avoid this time-consuming task, RSs had proved their efficiency as a digital assistance tool by organising relevant information in various domains. RSs are mainly classified into three main categories based on the techniques used. They are Collaborative Filtering (CF), Content Based (CB) and Hybrid. In the recent years, the research on personalised recommendations has produced numerous techniques to discover and recommend apt items to the active target user. To make better recommendations, various user profile modelling techniques such as spreading activation (Subramaniyaswamy and Chenthurpandiyan 2012), content-based models (Liu, Jin, and Zhang 2008) and classification techniques (Xu et al. 2008) were used. In (Weng and Chang 2008), to build the user profile, the search and browsing activities of the user are collected and processed for ontology-based learning. Two hybrid RSs employed ontology-based user profiles to recommend research papers to the students and academic staff (Middleton, Shadbolt, and deRoure 2004). PHB (Page History Buffer)-based short-term model is proposed in (Cantador et al. 2008) to emulate the functionalities of database disk buffer and the cache.

In 2008, an adaptation strategy has been proposed in (Cantador et al. 2008) to model a dynamic user profile. In this work, reference ontology is utilised to map user’s preference with the current user context to provide personalised content to the user. Though the user’s preferences can be considered as long-term interests, meanwhile the current context of the user represents the present or short-term or updated interests. Generally,
these user’s interests are considered as weights in the prediction process of recommendation approaches. In the context detection process, there is no consideration given for user’s contexts in previous sessions. Providing some significance to the user’s historical contexts may help the RS to identify the user’s preferences in a better way.

In the development of RSs for the travel domain, most works are mainly focused on trajectory-based approaches (Majid et al. 2013; Barranco et al. 2012). Generally, RSs with the trajectory-based approach trace the user’s travel pattern to the different locations with the corresponding time. Modelling of the user profile based on their travel behaviour pattern is a complex task (León et al. 2013). In Zheng et al. (2009), machine learning and data mining techniques on the user trajectory data to generate the personalised list of locations as recommendations. There some approaches, that utilise the ratings of the users to provide personalised recommendations to them (Ravi and Vairavasundaram 2016; Zheng et al. 2009; Campos, Diez, and Cantador 2014). Few initiatives have been taken to exploit social relationship of users with the locations and friends to make predictions for the generation of relevant venues to the users (Ravi and Vairavasundaram 2016; Doytsher, Galon, and Kanza 2011). A context-aware recommendation framework has been developed in (Irfan et al. 2015) for the venue recommendation using decision variables. In Huang, Tseng, and Chen (2016), a relationship between the characteristics and the decision making outcomes from the tourist perspective is explored. Rough set based ranking approach is presented to ensure the robustness of the decision rules. A dynamic user profile modelling approach has been proposed in Hawalah and Fasli (2015) for the effective understanding of user behaviour and adaptation of the system to varying user’s interests.

Though the above studies to provide recommendations succeed based on some aspects, they fail to address the problem of user’s changing interests over time. Especially in the travel domain, the user’s interests changes frequently as they travel to different locations. Hence the development of low-level dynamic user profile will not help to provide personalised recommendations to achieve user satisfaction. Based on temporal attributes, the user’s interest can be classified as long-term and short-term interests. The consideration of user’s interests as a uniform value may mislead the RSs in the generation of personalised recommendations. The RSs for in the travel domain mostly experiences the scalability issues as the huge volume of data need to be processed to generated recommendations. To address the limitations of the existing RSs, we proposed a dynamic user profile based hybrid recommendation framework over the cloud to benefit users through efficient recommendations. Our proposed recommendation framework provides the solution for the personalisation and scalability issues in the RSs in a better way.

3. Proposed multi-agent-based location recommendation framework (MABLRF)

In this section, we present our proposed multi-agent-based location recommendation framework. To overcome the limitations of the existing works, we propose a new dynamic user profile based recommendation model. Our proposed recommendation framework comprises of five modules to generate personalised recommendations to the users. In the development of our proposed framework, we have considered following factors as desirable attributes.
As users are unenthusiastic in explicitly providing all their interests as preferences to get recommendations, the proposed system should be capable of capturing the updated interests from their behaviour.

To enhance the recommendations provided to the users, the updated user’s interests and preferences should be stored in a suitable format that helps in the future processing. Ontologies have been adopted in an efficient manner to maintain recommendation consistency in many existing personalised recommendation systems.

As user interests can be changeable over time, the user profiling methods of our proposed recommendation approach should be capable of tackling the changes to adapt accordingly.

Based on the aforementioned factors, we present our multi-agent based location recommendation framework with the following five modules as depicted in Figure 1:

- Information Gathering module
- Learning and Adaptation module
- Ranking module
- Mapping module
- Recommendation module

The following subsections explain in detail about the working of the modules of our proposed framework.

Figure 1. Proposed multi-agent based location recommendation framework.
3.1. Information gathering module

The main goal of this module is to collect and organise the user behaviour to identify their interests. The personalisation of recommendations can be achieved only when the target user is satisfied with the tailor-made recommendations lists are provided to them based on their current interests. The changing user interests are determined in three phases. As the first phase, the user’s travel behaviour and online activity data are collected from the social networks. The social networks act as a valuable resource in the collection of user’s current interests. In the second phase of the module, based on the collected user behaviour data, reference ontology is developed. This reference ontology is modelled accordingly to describe the particular application domain with super classes and sub-classes in a hierarchical way. The reference ontology represents the domain information explicitly with semantic and structural relationships. As the third phase of the module, the collected user travel data and check-in information are mapped to the developed reference ontology. The weights are computed for the each user check-in location based on their features and attributes. Here features and attributes refer to the additional information or speciality of a particular location. For instance, the location is good for architecture, religious, food or tourism, etc. Based on the features and attributes of locations and also target users’ interests, the weights are computed for each location. The similarity between the user travel activities and online activities are computed using vector similarity computation approach for the mapping process. For the better mapping process, we adopt a weight based mapping process for better modelling of dynamic user profile.

3.2. Learning and adaptation module

The changing interest of the active target user is tracked and the user profile for the recommendation generation is modelled in this module. We adopt multi-agent intelligence to discover the changing interests of the user to define the updated user profile. The input from the activity mapping process is utilised by the six different agents of the multi-agent system. Three agents are dedicated to insert, delete and forget the interests of the user. These three agents are organised by the session-based agent. The session-based agent is responsible for monitoring the current activity tracking and updating of user’s interests to the session-based user profile. Two agents, namely long-term and short-term agents maintain the user’s long-term and short-term interests accordingly. The short term interests are given higher priority with higher weights as it corresponds to the user’s current interests. After the discovery of user interests by the multi-agent system, the updated user profile is produced with the help of the reference ontology.

3.3. Ranking module

The ranking module performs the processing of user profiles and location database to discover expert users and popular locations. Expert users or similar users are the one who feeds their experience and ratings about each check-in locations. Based on their profile and interests, target users’ point of interests will be discovered. The data is processed batch-wise on the requirement of recommendation service provider. The ranking inference model is applied to assign ranks to the users set and locations based on the
relationships. The popular locations are giving top ranks to provide better recommendations to the target user. The locations with the very low ratings after the considerable number of user visits are pruned from the recommendation processing list to ensure minimum computation time taken by the system.

3.4. Mapping module

The similarities between the expert users were computed based on the current region of the active target user. The main goal of similarity computation is to discover and organise like-minded users, which will much helpful in the management of user preference for that geographical region. As an additional advancement, the locations closeness is computed based on the real-time geographical distance between the target user and locations to estimate the travel feasibility.

3.5. Recommendation module

The recommendation module generates the personalised list of locations through multi-level collaborative filtering. Scalar optimisation is used to provide optimised recommendations.

3.5.1. Scalar optimisation

Our proposed recommendation module adopts scalar optimisation technique to aggregate the objective functions for ease of use and simplicity. The weighted scalar optimisation is defined as follows.

\[
\text{fun}(\text{user}) = \sum_{b=1}^{\text{no_of_obj_fun}} \text{weight}_b \times \text{fun}_b(\text{user}) \quad (1)
\]

where, \( \text{weight}_b \) is the corresponding weight of aggregate functions and the \( \text{fun}(\text{user}) \) is the aggregate objective function. For our recommendation generation process, we consider dual objective of location preference and location closeness.

3.5.2. Multi-level collaborative filtering

To assist users in better way and to improve the quality of our recommendations we adopt multi-level collaborative filtering with multiple constraints (Polatidis and Georgiadis 2016). The multi-level collaborative filtering is based on Pearson Correlation Coefficient (PCC) similarity measure and it is defined as follows.

\[
\text{Sim}_{x,y}^{\text{PCC}} = \frac{\sum_{\text{item}\in ITM} (\text{rat}_{x,\text{item}} - \bar{\text{rat}}_x)(\text{rat}_{y,\text{item}} - \bar{\text{rat}}_y)}{\sqrt{\sum_{\text{item}\in ITM} (\text{rat}_{x,\text{item}} - \bar{\text{rat}}_x)^2} \sqrt{\sum_{\text{item}\in ITM} (\text{rat}_{y,\text{item}} - \bar{\text{rat}}_y)^2}} \quad (2)
\]

Where, \( x \) and \( y \) are the two users and \( \text{rat}_{x,\text{item}} \) is the ratings provided by the user \( x \). \( \text{rat}_{y,\text{item}} \) is the ratings provided by the user \( y \). \( \bar{\text{rat}}_x \) is the average rating of the user \( x \). \( \bar{\text{rat}}_y \) is the average ratings of user \( y \). The computed similarity ranges between \(-1\) to \(1\) and the higher value represents better similarity.

The above PCC similarity measure is modified as a multi-level function and it is represented as follows:
\[ Sim \ MIPcc_{x,y} = \begin{cases} 
Sim \ PCC + c, \text{if } \frac{|ITM_x \cap ITM_y|}{TTL_{coRLTD}_itms} \geq th1 \text{and } Sim \ PCC \geq d \\
Sim \ PCC + c, \text{if } \frac{|ITM_x \cap ITM_y|}{TTL_{coRLTD}_itms} < th1 \text{ and } \frac{|ITM_x \cap ITM_y|}{TTL_{coRLTD}_itms} \geq th2 \text{and } Sim \ PCC \geq d \\
Sim \ PCC + c, \text{if } \frac{|ITM_x \cap ITM_y|}{TTL_{coRLTD}_itms} < th2 \text{ and } \frac{|ITM_x \cap ITM_y|}{TTL_{coRLTD}_itms} \geq th3 \text{and } Sim \ PCC \geq d \\
Sim \ PCC + c, \text{if } \frac{|ITM_x \cap ITM_y|}{TTL_{coRLTD}_itms} < th3 \text{ and } \frac{|ITM_x \cap ITM_y|}{TTL_{coRLTD}_itms} \geq th4 \text{and } Sim \ PCC \geq d \\
0, \text{ Otherwise}
\end{cases} \]

Where \( x \) and \( y \) are the users and \( TTL_{coRLTD}_itms \) represents the total number of correlated items. The threshold values are represented by \( th1, th2, th3 \) and \( th4 \). \( c \) and \( d \) are positive real numbers. The predefined threshold values are used to represent the constraints on correlated items at various levels.

### 3.6. Multi-level collaborative filtering based location recommendation algorithm

We have developed a personalised location recommendation algorithm based on multi-level collaborative filtering utilising the knowledge of expert users and location closeness feature.

**Algorithm:** Multi-Level CF-based location recommendation algorithm

**Input:** \(TU\) (Target User), \(OntoProf\) (Ontological profile with ratings)

**Output:** \(TopnRecList\) (Top-N recommendation list)

\[ \text{RecomList} \leftarrow \text{Null}; \]
\[ \text{SimExpUsrSet} \leftarrow \text{MIPcc}(TU, \text{ExpUsrs}); \]
\[ \text{for each } \text{SimExpUsr} \in \text{ExpUsrSet} \text{ do,} \]
\[ \quad \text{LocSet} \leftarrow \{\text{Loc}_i | \text{Loc}_{SimExpUsr} \in \text{Loc}_i \}; \]
\[ \quad \text{closeness}_{TU, \text{ExpUsr}} \leftarrow \text{max}(\text{MLPcc}(\text{NN}_{TU, \text{LocSet}})) \]
\[ \quad \text{AggSet}[\text{ExpUsr}] \leftarrow \text{ComputeAgg} (\text{LocSet}_{TU, \text{ExpUsr}}, \text{closeness}_{TU, \text{ExpUsr}}) \]
\[ \text{end for} \]
\[ \text{RecList}_{TU} \leftarrow \text{GenerateRec} (\text{OntoProf}_{TU}, \text{AggSet}); \]
\[ \text{TopnRecList} \leftarrow \text{Sort}(Rc-List_{TU}); \]
\[ \text{Return TopnRecList}; \]

The above collaborative filtering algorithm generates the personalised list of location recommendations to the target user through utilising the ontology profile generated by the multi-agent system. The scalar sum method is used to optimise the recommendation list. The multi-level PCC similarity measure is used make similarity computations and expert users set organisation. The popularity and closeness measure is validated before recommending a location to the user to ensure better adaptation of user’s travel possibilities. The locations with the maximum closeness values are added to the list of close location in the user profile. The user profile is updated based on the similar expert users’ interest which is very much useful in the generation of next set of recommendation generation. As an outcome user receives the sorted list of recommendations as a result.

### 4. Experiments and discussions

In this section, we describe the experiments conducted with our proposed MABLRF to demonstrate its improved recommendation potential over existing methods.
4.1. Experimental design

The proposed MABLRF experimentally evaluated for the analysis of effectiveness, performance, and efficiency for the location recommendation. Experiments were conducted on a PC running on 64-bit Windows 7 operating system with Intel core i7-5500 U clocked at 3.00 GHz and 16 GB of memory. Gowalla dataset is utilised to evaluate the proposed MABLRF for location recommendation generation. Gowalla is the LBSN and it is acquired by Facebook in 2011. The Gowalla dataset is rich in user data and used in the evaluation of location recommender systems. The obtained results are compared with existing approaches such as SPTWA (Ravi and Vairavasundaram 2016) and CFS-HGA (Vairavasundaram et al. 2015) for the evaluation of recommendation performance. The analyses of the obtained results are presented neatly.

4.2. Dataset

Generally, the evaluation of the recommender systems is difficult and expensive. In most studies, the datasets are used to evaluate the proposed work to compare its efficiency over existing methods. The utilisation of datasets in the evaluation process is proven to be an efficient and enables reusability of user data for future enhancements. In this work, we use Gowalla dataset to evaluate our proposed MABLRF for the recommendation generation. It is a location based social network acquired by Facebook, rich in users’ check-in details and point of interests which is used in the evaluation of location recommender systems. The dataset is pre-processed to remove lethargic users and users with fewer ratings and feedbacks. The pre-processed Gowalla dataset contains 1,50,734 users, 12,80,969 venues/POIs and 64,42,890 check-ins. Table 1 portrays the statistics of the Gowalla dataset utilised in the evaluation of our proposed recommendation framework.

The proposed collaborative filtering algorithm uses the target users’ profile data to achieve personalised recommendations. Initially, the recommendation list is defined as null. Then multi-level Pearson Correlation Coefficient is applied to generate the SimExpUsrSet based on the similarity between target user and expert users. For each SimExpUsr, location set and closeness set is estimated and aggregated to produce aggregate set of expert user. Finally, with the help of aggregate set and target users’ ontological profile, recommended list is generated for target user. And then the list is sorted and highly ranked top-n recommendations are suggested as personalised recommendations which are likely to be accepted by target user.

4.3. Evaluation metrics

The main aim of the conducted experiments is to evaluate the performance of the proposed MABLRF for its location recommendations. Experiments are conducted on Gowalla dataset

<table>
<thead>
<tr>
<th>Table 1. Statistics of Gowalla dataset.</th>
<th>Gross units</th>
</tr>
</thead>
<tbody>
<tr>
<td>Users</td>
<td>1,50,734</td>
</tr>
<tr>
<td>Locations/POIs/Venues</td>
<td>12,80,969</td>
</tr>
<tr>
<td>User check-ins</td>
<td>64,42,890</td>
</tr>
</tbody>
</table>
and users’ historical check-ins are exploited to make locations as recommendations. We use four evaluation metrics precision, recall and f-measure to evaluate the generated recommendations.

(A) Precision
The commonly known positive predictive value is also known as precision. Precision is the percentage of recommended locations relevant to the user and it is defined as follows:

\[
Precision = \frac{\sum \text{True Positive}}{\sum \text{True Positive} + \sum \text{False Positive}}
\]

(B) Recall
The percentage relevant locations that are recommended is known as recall. Recall is also known as sensitivity and it is defined as follows:

\[
Recall = \frac{\sum \text{True Positive}}{\sum \text{True Positive} + \sum \text{False Negative}}
\]

(C) F-Measure
The f-measure metric is the harmonic mean of recall and precision computed and is defined as:

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

4.4. Discussions
The experiments were conducted to evaluate the recommendation performance of our proposed MABLRF on Gowalla dataset. The Figures 2 and 3 portrays the results obtained by MABLRF, SPTWA, and CSF-HGA with respect to precision, recall and f-measure. The obtained results depict the improved performance of our proposed MABLRF over other recommendation approaches. The utilisation of multi-agent based framework is experimentally evaluated and the results demonstrate the advantageous quality of the generated recommendations by the proposed MABLRF over existing approaches of SPTWA and CSF-HGA. As we use multi-level collaborative filtering for the optimised recommendations generation, we have evaluated the proposed approach with both traditional PCC and multi-level PCC. In the comparison of the results obtained, multi-level PCC performs better with constraints. Our proposed MABLRF adopts with the multi-level PCC in a better way to generate efficient and effective recommendations with utilisation the dynamic user profile. The proposed MABLRF addresses the personalisation problem in the location recommender systems through exploiting user’s long-term and short-term interests for the prediction of personalised list of locations. The bi-objective function employed for the recommendation generation ensures the optimal and feasible recommendations as results.

The popularity and closeness constraints enhance the user acceptability ratio as the probability of user’s check-in at the recommended location is high. The scalability issue in the location recommender system is considered to be a huge barrier for its growth. To address this issue, we have proposed to implement our recommendation framework in the cloud. We have implemented our MABLRF in the cloud infrastructure within our institution for the generation and accessibility of recommendations from multiple
devices. We have conducted our experiments for the generation of top-n recommendations. From the results we inferred a pattern, as the number of location increases, the precision decreases gradually on all approaches. The results obtained from the experiments clearly demonstrate that the proposed MABLRF is significantly effective to generate personalised locations recommendations with dynamic user interests.

5. Surprising location recommendations

In the current scenario, Travel RSs are designed to discover new locations based on their interests. But, users may be also interested in the familiar locations and we intend to explore the possibilities of making better recommendations useful to the users. As the most locations are avoided in the generation process due to the familiarity of the user, the unexpectedness and serendipity factors were missed by the end users. We have evaluated our proposed MABLRF based on the Top-N location recommendation. We have analysed the recommendation performance based on the user survey with the help of questionnaire about the location recommendations. The proposed MABLRF is designed to produce recommendations with unexpected known locations and present the suggestions as

![Figure 2](image_url) Performance evaluation results with PCC based recommendations (a) Precision, (b) Recall and (c) F-measure.

![Figure 3](image_url) Performance evaluation results with multi-level PCC based recommendations (a) Precision, (b) Recall and (c) F-measure.
a surprising list. We have performed an extensive user study to discover the perceived value of the provided recommendations. A new user survey is designed to evaluate the MABLRF recommendations on the mobile platform.

The survey is presented to each participant with three different recommendation approaches and asked to respond the questionnaires regarding the provided recommendations. The positive feedback of the user depicts the performance of the recommendation approach and found to be more satisfying. The Figure 4 presents the analysis of user feedback over different recommendation approaches and from the results users prefer MABLRF over SPTW and EIUCF in most aspects. The questionnaire survey proves the recommendation performance of the MABLRF which satisfies the needs of users. The proven practical effectiveness of the location recommendation approach is much helpful in the investigation of producing highly user satisfiable recommendations.

The proposed algorithm is statistically significant and it is notable from the Figure 4. The difference in performance between proposed recommendation algorithm and other related recommendation algorithms were utilised for evaluation purpose. The proposed MABLRF performs well than SPTW and EIUCF by recommending items equal to users’ interests, providing diverse recommendations, percentage of recommended items liked by the user and users’ willingness to use the system in future. The overall evaluation of the system is presented in the Figure 4(e). This indicates that the proposed MABLRF suggests items which are highly liked by the target user by minimising the likelihood of suggesting irrelevant items to the target user.

5.1. **Limitations of existing recommendation algorithms**

Recommendation algorithms are habitually characterised into collaborative filtering, content-based filtering and hybrid algorithms. Collaborative filtering identifies harmony between users or items on the source of implicit or explicit knowledge. User-based collaborative filtering algorithm recognises similar users on the basis of their ratings on common items. An item-based collaborative filtering algorithm analysis similarity between items and then identifies the new item to be recommended based on the analysed similar item ratings. The most widely accepted and commonly used recommendation algorithm is collaborative filtering algorithm. Content-based filtering algorithm identifies items to be recommended based on active user’s preferences and interests. It ignores the perception of similar users and their contributions to generate comparative recommendations. Hybrid recommendation algorithm integrates both collaborative filtering and content-based filtering algorithm to achieve enhanced performance and produce more precise recommendations.

These conventional recommender systems involve simple user models, whereas the recent proposed recommender system incorporates the contextual information as an additional factor to enhance the eminence of recommendations to construct more suitable suggestions. Technically, context is defined as a predefined set of noticeable features such as geographical location, time, weather, social relationships, user activity, etc. By employing one or more of these contextual features explicitly or implicitly into the recommender system aids to achieve better performance. User’s emotion is considered as one of the most admired contextual features. Some of the important challenges of the traditional recommender system that we have concentrated on our research are:
Collaborative filtering method frequently undergoes cold start problems

When recommender system fails to comprehend user’s preference and interest, it can lead to trust issues

In order to predict the active user’s preference, hybrid approach is in demand to provide input in an iterative and interactive manner.

Figure 4. Analysis of user feedback over different recommendation approaches of MABLRF, SPTW and EIUCF.
5.2. Interactive recommender system

Interactive recommender system facilitates active user to incorporate feedback with the recommender system for personalised recommendation generation. In general, active user’s profile, browsing history and item ratings acts as a basis for recommendation generation. In addition, by employing contextual information such as geographical location, time, user activity and preferences as a supplementary factor helps to generated more personalised recommendations. Our proposed recommender system makes use of this information collected implicitly and explicitly from active user and contextual features aids to acquire the set of similar users. Then the collaborative filtering techniques put forward the set of top-N recommendations on the basis of these similar-minded user’s ratings and interests. Finally, active user’s feedback is then transmitted to the recommender system as an input in order to regenerate the more precised and personalised recommendations. The major utilisation of user interactive recommender system is to achieve transparency, justification, diversity, controllability, cold-start problem and contextual features.

5.3. Transparency and trustworthiness

Transparency explains the logic behind the recommender system to end users. For instance, the representation of similar-minded user’s preferences and interests can be used to express personalised recommendation about end users and assist active user to identify whether the interest of neighbourhood go with their own desire or not. By analysing similar-minded user’s interests and ratings of the common items and by understanding the logic behind the recommender system, it may help active user to amplify the confidence in the recommendation model. In order to achieve optimal performance, the recommender system needs to learn both the implicit behaviour and explicit feedback information from the user. If the active user is not aware of how the recommendation model works, he/she may not be able to train the model properly. Transparency helps to increase understanding of the system logic to improve user-system interaction.

Trust-aware recommendation model is used to solve the data sparseness problem as it suggests the item on the basis of trust. Even if there is no straight trust association between the active user and the recommender, the active user can construct some meandering trust relationship with the recommender for a specific situation. Thereby, trust network is a dynamic social network where users are connected by their trust relations and the distance between them are relatively short. This contributes to elevated rating prediction accuracy for dynamic trust network, where new user can enter the network at anytime by declaring his/her trust on any active user in the trust network.

5.4. Justification for recommendations

Unlike transparency, justification helps active users to recognise the reason behind the certain recommendation generation rather than the logic behind the recommendation model. It only substantiates the recommendation by mapping the descriptions of active user’s profile, preferences, interests, browsing history, previously purchased items and ratings. Highly advantageous characteristic of a recommender system allows to mechanically generating justification to enhance user experiences and amplify user trust.
5.5. Diversity of recommendations

While evaluating the quality of recommender systems, prediction accuracy was recognised as an exclusive criterion. On the other hand from the active user’s point of view, other than prediction accuracy, diversity is also considered as an important characteristic to generate more precise recommendations. Diversity of items could widen user’s awareness and recommender systems are expected to assist active users to find out fresh items of interest but are diverse from the objects which are purchased formerly. Recommendation diversity is considered as the major challenge for accurate and précised recommendation generation as it involves large coverage of the information space. Moreover, it is indispensable for a recommender system to influence active user that the recommended thing is best suitable for their point of interest. In order to satisfy active user’s need, various diversity boosting techniques have been introduced to enhance diversity while building personalised recommendations to active users.

Recommendation diversity makes every user to access huge amount of objects for their item of interest and cause the active user to choose the interesting item in a sensible quantity of time. Therefore item selection process has become burdensome and problematic. To address the diversity problem, the proposed system is developed by making required amount of interactions or questionnaires with active users. The collected information is then feed as an input to the recommendation model which is used to filter relevant item in order to suggest more appropriate items. Recommendation diversity not only resolves over-fitting problem but also necessitates user-centric involvement than other recommender system-associated problems.

5.6. Controllability

The main objective of the proposed recommender system is to assist a user or a set of users to select a desired location from a huge information space based on implicit user behaviour or explicit preferences. Controllability strengthens active user’s contribution in the recommendation process by incorporating feedback and reviews in order to fine-tune the recommending parameters and its relative weights. Active user’s control can be achieved at any step of recommendation process by providing location/POI ratings, review comments, tuning user preferences and adjusting recommendations. By understanding the clear relationship between the location of interest and the location recommended, active users are able to revise the weight of the input parameter and thereby increase the accuracy of the recommendations. The objective of user controllability is to enhance the recommendation process by incorporating feedback and review ratings.
Through visualisation, active user can control the recommendation process via uncomplicated interactive and instructive explanation interface.

5.7. Cold-start problem

Recommender system suggests items on the basis of active user’s preferences either explicitly or implicitly. When new user or item enters the recommender system, the inability to predict and suggest relevant information to the new user without prior experience about the active user leads to a cold-start issues. The collaborative filtering recommender system cannot facilitate cold-start problem, since it has no earlier knowledge or experience about the new user or item such as item ratings, user preferences and interests. Though Content-based filtering recommender system produce recommendations based on item description, they are likely to accomplish lower precision. Moreover, cold-start problem is related to density and diversity of information and it is categorised into recommendations for new users, new items and new items for new users.

It is difficult to understand the process and predict the item of interest for an average user who demonstrates smaller amount of performance and has fewer associations with others. Thereby it leads to entrust about the recommendation generation. The content-based approach attempts to assist the cold-start problem by collecting side information such as user’s gender, age, geographical location, occupation, social relationships as a key feature to study about the active user. The recommender system can suggest some interesting items relevant to active user’s side information, but there is a possibility to drop the personalised recommendation. In this scenario, the cold-start problem can be alleviated by interactive recommender system by clustering similar users or items based on the conversational or questionnaire approach. Then by utilising active users answer as an input measures, the recommendation process helps the system to generate set of top-N recommendations. In interactive or questionnaire based approach, global questions are involved to group the users and local questions are used to optimise the recommendation model.

5.8. Contextual features

Acquiring contextual features and employing it into the recommender system has gained enlarged interest over the personalised recommendations. Among various contextual features, user’s emotional experience is considered as an important factor and plays a significant role in human learning and decision making process. Research discloses that the user’s emotion compose of both beneficial and sometimes harmful decision making. The covert biases correlated to active user’s prior emotional knowledge of the equivalent circumstances support the reasoning process and assist the efficient decision making. Integrating such feature into the recommendation process is a challenging task, for the reason that assessment of such feature is very difficult. By capturing active user’s feedback such as emoticons, text message or review ratings as an input measures to the recommendation process aids to enhance the quality of personalised recommendations. For instance, a rating for location visited on the basis of five stars indicates that the five star rating is for more-liked and one star for less or disliked item.
5.9. Mobile recommendation

Recommendations on the smartphones are considered to be most preferred medium for the location recommendations. The capability of the proposed recommendation approach to present the produced list of top-N recommendations on the mobile phone increases the user acceptance ratio. We have utilised the XplorerVU mobile recommendation framework for the evaluation of the location recommendation the smart city scenario (Logesh et al. 2018). The Figure 5 presents the user interface of XplorerVU mobile recommendation framework. For any mobile recommendation application, user interface and design are the key cognition factors that influence the quality of recommendations. At present, XplorerVU mobile recommendation framework is designed for Smart City Scenario only. The proposed MABLRF on XplorerVU mobile recommendation framework is evaluated for the real-time recommendations in the smart cities of Tiruchirapalli and Thanjavur, India.

6. Conclusions

In this paper, we present a new recommendation framework, utilising multi-agent systems for creating the dynamic user profile. As the main advantage, our proposed RS is capable of
identifying the user’s changing interests and it efficiently classifies the short-term and long-term interests of the user. The better understanding of the user’s changing interests helps our recommendation framework to generate more satisfiable recommendations to users. We have utilised multi-level CF mechanism to generate more relevant and optimal location recommendations. The conducted experiments on the Gowalla dataset depict the improved performance of our proposed MABLRF in the location recommendation problem through precision, recall, and f-measure. Experiments are conducted with traditional PCC and multi-level PCC similarity measures. The multi-level PCC performs far better than traditional PCC with the dynamic user profiles. The significance of the proposed work is the adaptation of multi-agent system with multi-level collaborative filtering for the generation of the optimised location recommendations. In future, we intend to explore the possibilities of utilising multi-agent systems to analyse the user’s travel pattern to develop a preference-aware location recommender system. Further, we also consider in addressing the privacy issues in the location recommender systems.

Acknowledgements
The authors gratefully acknowledge the Science and Engineering Research Board (SERB), Department of Science & Technology, India for the financial support through Mathematical Research Impact Centric Support (MATRICS) scheme (MTR/2019/000542). The authors also acknowledge SASTRA Deemed University, Thanjavur for extending infrastructural support to carry out this research work.

Disclosure statement
No potential conflict of interest was reported by the authors.

Funding
This work was supported by the Science and Engineering Research Board [MTR/2019/000542].

References


