Hybrid User Clustering-Based Travel Planning System for Personalized Point of Interest Recommendation

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Abstract In the recent times, the massive amount of user-generated data acquired from Internet has become the main source for recommendation generation process in various real-time personalization problems. Among various types of recommender systems, collaborative filtering-based approaches are found to be more effective in generating better recommendations. The recommendation models that are based on this collaborative filtering approach are used to predict items highly similar to the interest of an active target user. Thus, a new hybrid user clustering-based travel recommender system (HUCTRS) is proposed by integrating multiple swarm intelligence algorithms for better clustering. The proposed HUCTRS is experimentally assessed on the large-scale datasets to demonstrate its performance efficiency. The results obtained also proved the potential of proposed HUCTRS over traditional approaches by means of improved user satisfaction.

Keywords Recommender systems · Personalization · Point of Interest · Clustering · Prediction · E-Tourism

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1 Introduction

The rapid advancements of internet technologies have drastically increased the information overload and personalization concern, since modern users are provided with plenty of choices [1–3]. The recommender system provides an excellent solution for personalization problem in various application domains. To suggest the list of relevant recommendations to the active user, the recommender system strongly studies the association between the item and target user from existing information like historical purchase record, browser footprint and evaluation information. Some of the commercial applications of recommender system include art, e-commerce, social events, etc. Considerably, personalized recommendation increases the probability of suggesting more interested items when compared to generic recommendations. Further collaborative filtering method helps to provide personalized recommendations by increasing the prediction accuracy [4–6].

Most of the commercial applications are based on collaborative filtering recommender system (CFRS) and gained a tremendous amount of popularity [7, 8]. In CFRS, the relevant item for the active user is suggested on the basis of ratings given by same user for other equivalent items. In general, CFRS uses an item-based or user-based model for guessing ratings. In user-based model, collaborative filtering studies the behavior of target user and predicts the rating for unknown items based on the ratings of identical users [9–15]. Accordingly to boost the accuracy of prediction ratings, clustering techniques were exploited and thereby generate more relevant recommendations [16–18]. Based on the similarity measures, clustering techniques group the user into a single or multiple classes of similar users [19, 20]. In CFRS, many clustering methods such as expectation maximization, K-means clustering, evolutionary clustering, fuzzy c-means clustering, etc., were used to generate personalized recommendations [21–24].

The key applications of clustering techniques in data mining are pattern recognition, image processing, web mining, market research, document classification and spatial data analysis. Though the user clustering-based recommender system provides better results, the information processing becomes more complex. Besides, the conventional clustering algorithms have limitation to provide optimal solution for large-scale datasets [25–28]. Hence, the utilization of such traditional clustering techniques fails to generate efficient recommendations. To overcome the drawbacks of traditional approaches, bio-inspired intelligent clustering algorithms [29–35] have been introduced to generate optimal recommendations in real-time recommender systems. The bio-inspired intelligent clustering algorithms implemented in different application areas such as decision support system, market research, spatial data analysis and pattern recognition have already proved their improved performance efficiency [36–38].

The recommender system generates the recommendations based on the feedback of active target user on previously consumed items. The explicit user ratings together with implicit user behavior are utilized to generate target user's personalized recommendation list [39, 40]. After predicting the ratings for the point of interest (POI), recommender system organizes and ranks the POIs. Finally, the items with high prediction ratings were presented at the top, and first n items were suggested as relevant recommendation to the target user. To enhance the recommendations, hybridization is embraced by combining multiple recent technologies with the traditional recommendation approaches. As an efficient decision-making approach, recommender system was adopted in the field of travel and e-tourism [41–44]. Personalized travel recommendation is a challenging task compared to other recommender problems. Such challenge in the domain of e-tourism can be resolved by adopting user's preferences, opinion mining and contextual features in the recommendation prediction process. Therefore, a new hybrid user clustering-based travel recommender system is proposed using swarm intelligence algorithms through a clustering ensemble approach. To review the prediction accuracy of proposed recommender system, experiments were carried out on large-scale real-time Yelp and TripAdvisor datasets. The experimental result demonstrates the outperformance of the proposed recommender system with more relevant travel recommendations to target users.

2 Hybrid User Clustering-Based Travel Recommender System

A new hybrid user clustering model is designed by integrating three different swarm intelligence algorithms to address the limitations of stand-alone models which are used in the collaborative filtering-based recommender systems. To achieve better POI recommendations, we have exploited P-SSO [45], DPSO [46] and HPSO [47] through an ensemble approach to generate user clusters [25]. The HUCTRS generates a final list with n POIs which are highly relevant to the preference of active target user. It is predicted by utilizing the data acquired from location-based social network (LBSN). The proposed HUCTRS consists of clustering, rating prediction and recommendation generation phase. The structure of the proposed HUCTRS is shown in Fig. 1. Initially, the LBSN data is used to generate clusters through swarm intelligence algorithms. Clusters are formed by training 70% of the dataset, and the remaining 30% are used as testing data. Then on the basis of generated clusters, the active user is mapped to the highly identical user cluster determined through a neighborhood search to predict ratings by DML-PCC metric [48]. Based on the ratings, n POIs listed on the top are suggested to the target user.

The main objective of using ensemble model is to exploit the important features of multiple clustering algorithms and thereby boost the performance efficiency of the recommendations. The user clustering is performed iteratively with different number of clusters to produce better clusters. From the clustering results of the individual smarm intelligence algorithms, similarity matrix is generated for the further processing. Consensus similarity matrix is constructed from the results of individual

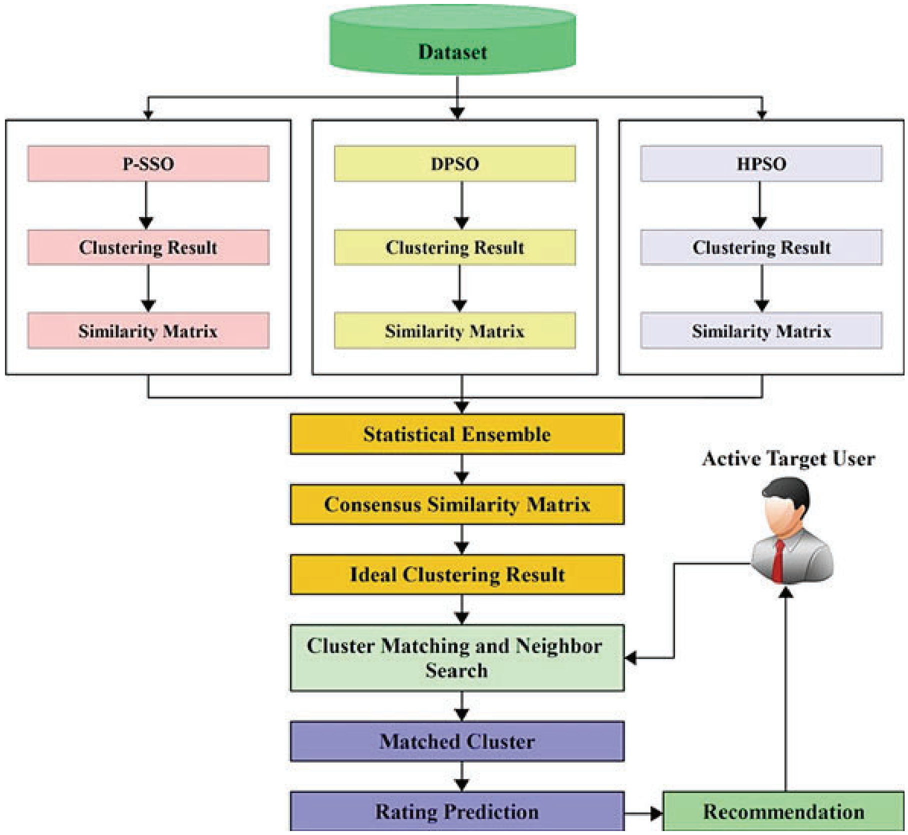

Fig. 1 Proposed system architecture

similarity matrix. From the resultant matrix, ideal user clusters are produced and active user is mapped to the highly relevant cluster.

2.1 Parallel Social Spider Optimization

The swarm intelligent algorithm introduced on the basis of social behavior of the spider in the colony is the social spider optimization (SSO) [49]. The position updating procedure of the SSO is modified with a parallel algorithm to form parallel social spider optimization (P-SSO) [45]. The P-SSO has been proven to be computationally faster than the SSO by nearly ten times. The existing experimental results have clearly presented the clustering capabilities of P-SSO over traditional clustering approaches.

2.2 Density-Based Particle Swarm Optimization

Particle swarm optimization is widely used to address the limitations of clustering algorithms in various domains. The PSO is designed in a better way to withstand premature convergence, and also it requires tuning of learning coefficients to produce better clusters. The popularity-based PSO approach is further hybridized with the kernel density estimation technique as density-based particle swarm optimization (DPSO) to address the premature convergence problem in clustering [46].

2.3 Hierarchical Particle Swarm Optimization

The hybridization of the traditional PSO has been done in a pace to meet the demands of the better solutions for various engineering problems. Especially to address the clustering problem, the PSO algorithm is combined with the hierarchical agglomerative data clustering technique as hierarchical particle swarm optimization (HPSO) to improve the clustering accuracy [47].

2.4 Dynamic Multi-Level Pearson Correlation Coefficient

The considerable concern of the CFRS is the accuracy of the resultant recommendations. Though the traditional cosine and PCC metrics are capable of providing an improved recommendation, yet there is a space that requires improvement in the process. To progress the quality of recommendation process, the traditional PCC is modified as dynamic multi-level Pearson correlation coefficient (DML-PCC) in an efficient way to address the requirement of active user [48].

3 Experimental Evaluation

The recommendation efficiency of the proposed HUCTRS has evaluated experimentally on the large-scale real-time TripAdvisor and Yelp datasets. The experiments were carried out on the PC running with 64-bit Windows 7 OS and Intel Core i7-5500U clocked at 3.00 GHz and 16 GB of memory. The comparative analyses were performed between experimental results of HUCTRS and other relevant recommendation methods. For evaluation process, three metrics such as coverage, *F*-measure and root mean square error (RMSE) were utilized to analyze the recommendation performance of HUCTRS.

3.1 Root Mean Square Error (RMSE)

RMSE is the evaluation metric applied to estimate the error in the resultant recommendations. In general, RMSE is calculated as follows:

$$\mathrm{RMSE} = \sqrt{\frac{\sum_{\mathrm{user,point}} \left(\mathrm{ActualRating}_{\mathrm{user,point}} - \mathrm{PredictRating}_{\mathrm{user,point}}\right)^2}{\mathrm{TotalRatings}_{\mathrm{tested}}}} \tag{1}$$

where *user* is the active target user, *point* is the point of interest (PoI), and actual $\mathrm{rating}_{\mathrm{user,point}}$ is the rating actually provided by the active target user to the particular PoI. Similarly, predict $\mathrm{rating}_{\mathrm{user,point}}$ is the rating calculated by the recommendation approach for the same user and PoI.

3.2 Coverage

An evaluation metric coverage is utilized to determine the percentage of ratings predicted for overall user-POI pairs by the recommendation model.

$$\mathrm{Coverage} = \frac{\text{Number of Ratings}_{\mathrm{Predicted}}}{\text{Number of Ratings}_{\mathrm{Tested}}} \tag{2}$$

3.3 F-*Measure*

Another metric F-measure is utilized to evaluate the resultant point of interest recommendations. To compute F-measure, coverage and precision are required. Precision is calculated as follows:

$$\mathrm{Precision} = 1 - \frac{\mathrm{RMSE}}{4} \tag{3}$$

F-measure is determined using the resultant precision and coverage values as follows:

$$F \text{ - Measure} = 2 \times \frac{\mathrm{Precision} \times \mathrm{Coverage}}{\mathrm{Precision} + \mathrm{Coverage}} \tag{4}$$

3.4 Discussions

The experiments were carried out on large-scale real-time TripAdvisor and Yelp datasets to demonstrate the potential capabilities of the proposed HUCTRS. The experiments were also conducted with the existing baseline approaches [50, 51], namely LBPARS, LBCFRS, LFARS, UPARS, MPCBRS and PBCFRS to make experimental analyses. Figures 2, 3 and 4 present the comparative graph of different recommendation algorithms applied on TripAdvisor and Yelp datasets in terms of coverage, RMSE and *F*-measure values. The effectiveness of the recommended poIs generated by the proposed model is evaluated on the basis of user's previous travel history. Our proposed HUCTRS makes recommendations based on the learning process made on the previously visited venues of the user.

When the recommendation approach is capable of generating more number of location recommendations, the developed approach is considered to be more efficient and effective. The result depicts the enhanced performance of the proposed HUCTRS over existing methods on both TripAdvisor and Yelp datasets. Following the proposed

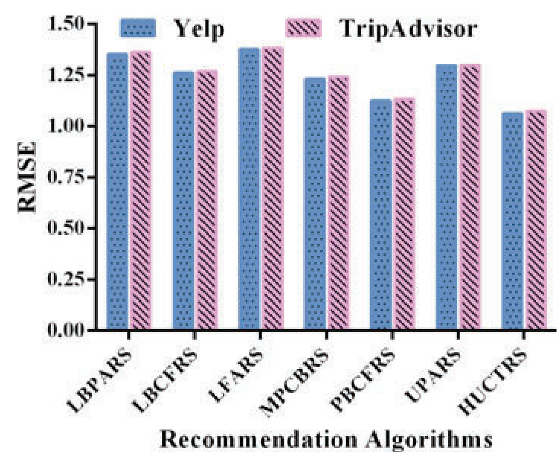

Fig. 2 Comparison of RMSE for various recommendation algorithms

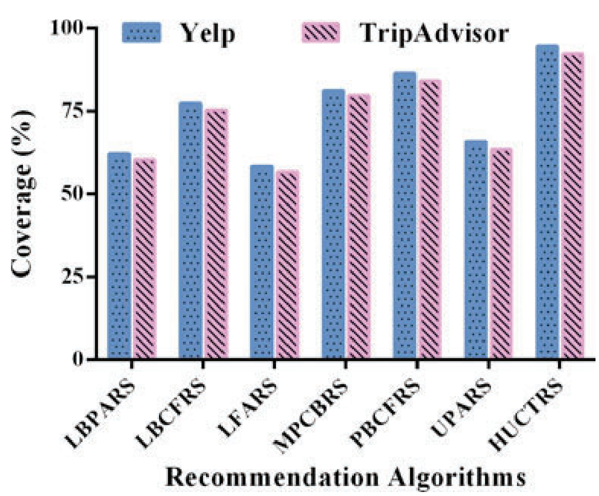

Fig. 3 Comparison of resultant coverage with other recommendation algorithms

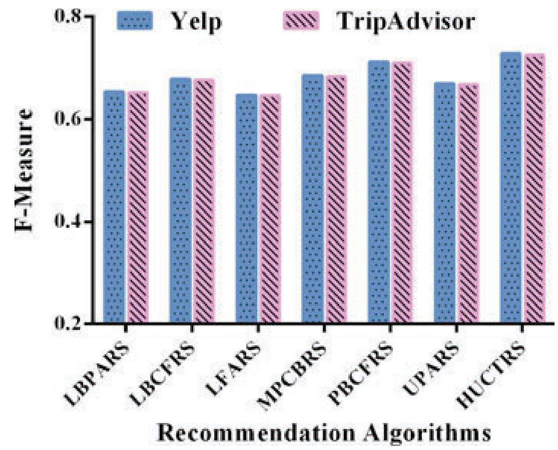

Fig. 4 Comparison of resultant F-measure with other recommendation algorithms

HUCTRS, the PBCFRS recommendation approach has been performed competitively. Compared to all recommendation approaches considered for the experimental evaluation, the LFARS is found to be the least performer on both Yelp and TripAdvisor datasets.

The proposed HUCTRS approach is found to be a better performer due to the global optimization provided by the selected swarm intelligence algorithms. To mention about the RMSE, the proposed HUCTRS has the lesser error rate between the predicted and actual ratings. The ratings prediction function of the proposed HUCTRS utilizes the advantageous feature of DML-PCC to determine ratings for the unknown items. The HUCTRS approach is designed to be location-aware, and the spatial attributes of the POIs play a crucial role in generating final recommendation list. From the overall analysis, it is noticeable that HUCTRS generates user satisfiable recommendations in an efficient and effective manner.

4 Conclusion

Recommender systems are developed to assist users in selecting interesting and relevant services by addressing the information overload problem. In the field of e-tourism, personalization is the research challenge of recommender system in recent times. To address the challenge, we have developed a HUCTRS based on swarm intelligence algorithms. Our proposed hybrid recommendation approach exploits the advantageous features of P-SSO, DPSO and HPSO algorithms through an ensemble model. The developed recommendation approach predicts ratings through an enhanced DML-PCC metric to make recommendations. The proposed HUCTRS outperforms the baseline approaches on both TripAdvisor and Yelp datasets. The results obtained from experiment were assessed by means of standard evaluation metrics, namely RMSE, F-measure and coverage. The HUCTRS provides better POI recommendations due to the tendency of providing global optimization by ensemble swarm intelligent algorithms. The utilization of social network data significantly reduces the interactions between the user and the system. The proposed HUCTRS is designed in a way to be a proficient support tool for the active user. In future, we intend to develop the recommender system with multi-agent technology to accumulate user-generated information from various resources.

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