GROUP-ORIENTED LOCATION RECOMMENDATION SYSTEM (GOLRS) USING MULTI-AGENT INDUCED COGNITIVE BEHAVIORAL MODEL

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ABSTRACT:

Nowadays, there is a tremendous increase in location recommendation due to the development and use of location prediction process based on social networks. In this approach, a new multi-agent based framework is developed to generate personalized excellent location recommendations. The personalization problem is solved based on a dynamic user profile that includes the permanent and temporary cognitive behavior of the user. A better adaptation to the user's cognitive behavior improves the prediction processes and also improves the overall user experience with better results. Public acceptance of location-based social networking services has been greatly enhanced by the development of smart mobile devices. Location-Based Social Networks (LBSNs) are used as an important approach to exploit users locations based on their needs. Since human beings are very methodical in their behavior, activities are very important in one's life. The variety of human habits and preferences makes it difficult to find comfortable spaces for all people, whether in a group or not. Context-aware group-based location recommendation systems are developed from a random walk algorithm through this approach. The three different contexts considered from the developed approach are: location context (i.e., category, popularity, ability and spatial proximity), environmental context (i.e., weather, day of the week, social relationships, personal preferences). From the results it can be observed that the accuracy, F1 score increases and the total system takes less time to operate.

KEY WORD: Recommender neural network, Point Of Interest (POI), Location Based Social Networks (LBSNs), Information Retrieval (IR), World Wide Web (WWW).

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I. INTRODUCTION

Newly developed technologies have improved our daily work in many ways and made the facilities more usable. In every aspect they can see the newly designed technologies.

This generation follows people to make their activities. This is a method that helps us where they are through newly invented technologies. More useful resources for Information Retrieval (IR) for this purpose play an important role in the World Wide Web (WWW). Appropriate information is derived for IR from any type of data analysis to meet the needs of the user [1]. Location-Based Service (LBS) is commonly used in IR system. In general, geographic data is used to provide its services regardless of the user's proximity.

LBS Recommender System (RS) is referred to as one of the most important features. In this way RS takes information from the user according to the user's needs and interprets it to find the most relevant content [2]. Delivers content from a simple application based on user needs. The presence of GPS technology in mobile devices provides a high level of information for user tasks [3]. As a data source, this information can be used to improve the quality of newly developed RS. Recommender systems are information filtering and knowledge management systems that are responsible for providing accurate recommendations [4].

Context-aware Recommender Systems are other important aspects which recommend to the users by considering other contextual factors such as weather, temperature, geological conditions, etc. Context-awareness-based recommender systems work in various domains, in which computational intelligence is in high demand.

In the current position, the developed GOLRS position takes into account social and personal factors [5]. This GOLRS shows user location from check-in data even earlier. LBSN elements (users, locations) are represented by their relationships using a graph model to obtain them. An unweighted graph model is used in this approach to show a specific LBSN [6]. After constructing the graphs, a modified intuitive application is run on it to multiply the recommended probabilities of the nodes. After ordering nodes, users are presented with lists of locations according to estimated probabilities.

Location-Based Social Networks (LBSNs) have been launched due to the increasing number of mobile devices. Location-Based features are provided by some of these Social Networks for sharing (Govalla, Foursquare, etc.) while others are provided by social networking services (Facebook, Twitter, etc.). Users can also use it to share locations (restaurants, view spots, etc.) with their friends at any time [7]. This application is essential for location recommendation as it also gets to better user needs and is easy to do business.

Wireless communication network technology, hand-held devices, and location-based technology have developed rapidly in recent years. Location-Based Social Networks (LBSNs) services are widely used by people. When people view or check into a place on LBSNs, their locations and check-in information are shared with many other people. This historical check-in data is used to gain a better understanding of user expectations and their locations in LBSNs, helping people find places of interest they need and make new social connections.

Therefore, this check-in data makes event recommendation useful in a wide variety of applications, such as location and friendly recommendation. Providing better location-based services based on LBSNs location recommendation plays an important role.

In fact, the function of Point of Interest (POI) recommendation is to provide personalized recommendations for places of intrest. Location-Based Social Networks are being used to provide better location-based services. POI recommendations are useful for LBSN users and POI owners. Their owners have more customers. Likewise for users to find important relevant POIs that they need and better meet the needs of users. POI recommendation is made differently from conventional recommendation tasks in that it relies on location-awareness and contexts. This can be explained by the following sections. A man named Bob lives in New York City and near home he likes to have his morning coffee at Starbucks and then lunch at an Italian restaurant near his office and chat with his friends at a bar on the way back home.

Developing POI recommender systems is more difficult than developing traditional recommender systems. The reasons for this are as follows. First, the user is more interested in POI recommendation locations at different times. Second, LBSN users' opinions are inherently spatio temporal correlated. The variability of spatiotemporal data has become a major challenge for nature recommendation. The third is usually used to describe POI with categories and tags.

II. LITERATURE SURVEY

Huang, H. Gartner, G.; Krisp, J.M. Raubal, M. Van de Weghe, N et al. [8] process of LBS evolution based on mobile location is found and efforts are made to find out the challenges of LBS development. Some of the challenging features such as interaction between users and decision-making influence privacy services in social media.

Liao, G. Jiang, S. Zhou, Z. Wan, C. Liu, X et al. [9] similarly introduced tensor factorization for Recommendation System to improve the accuracy of user recommendation. First, the Latent Dirichlet Allocation (LDA) model was used to access user's POI information, and the probability distribution for different information was also prepared. The data collected for each user's is divided into different parts and also describes the needs of the users. Singular Value Decomposition (SVD) algorithm is used to find preferences and make recommendations.

W.G.R.M.P.S. Ratnaik et al.[10] based on the previous blog entries, methods are described to focus on blogs as they contain valuable information for potential travelers that is not available on official websites to find specific user travel routes. Populations are interconnected to show multimedia content related to popular travel routes and places. same pattern mining technique for fast mining of sequential patterns using PrefixSpan algorithm is introduced to extract their trajectories. Ensure that the data is in a structured form so that the POI can be generated in the most popular manner provided by the system

Albana, B.; Sakr, M.; Moussa, S.; Mowad, I et al. [11] they used the CaboCha method and the Japanese lexicon as a lexicon for action verbs to describe dependency. The RS system is provided using Jio-tagged places to search for public interest. This work is done to map the user's interests on the score and reduce the problem of new user start in the system.

C. Paola, L. Sergui and C. Carlos et al. [12] Comment Classification (CC) was introduced as a method to recommend hotels from segment online words written by customers. Good, fair and bad are divided into three groups after taking CC comments from TripAdvisor.com. The core modules of ontology design and comment classification are incorporated into this model to gather information. The authors analyzed 686 reviews from 74 hotels for an experiment on the website tripadvisor.com. Recommender system was developed to find itineraries that fit users like and reduce the amount of effort invested in them.

Authors J. Lucas, N. Luz, M. García, R. Anacleto, A. Figueiredo and C. Martins et al. [13] in addition classification methods have also implemented the RS recommendation method for tourism. Classification and association rules are combined to predict this approach. A methodology that can reduce the limitations presented in case study while increasing recommendation quality in RS. It also includes many online writing and social networking services.

[14] R. Anacleto, L. Figueiredo, N. Luz, A. Almeida, and P. Novais et al. Mobile Recommendation and Planning System (PSiS Mobile) was invented to provide effective assistance during tourist visit. Contextually-aware want to use recommendations, tourist preferences, and context to learn about information and points of interest.

A. Almeida, B. Coelho, and C. Martins et al. [15] artificial intelligence based architecture was developed for user modeling and RS segments for tourist guides. A tourist guide application has been using linear models, Neural Networks and several Machine Learning techniques such as classification and text mining.

III. GOLRS USING MULTI-AGENT INDUCED COGNITIVE BEHAVIORAL MODEL

Figure (1) below shows a block diagram of GOLRS using a multi-agent induced cognitive behavioral model. The system should be able to take requirements gathered from their behavior as it is not interested in clearly providing all the needs of users to take recommendations. The recommendations provided to the users should be stored in an appropriate form to assist the user's needs and a preference in future processing that is aggregated. Ontology has been adopted as a suitable method to initiate recommendation stability in many existing systems of personalized recommendation. This approach is that user profiling methods should be capable of addressing changes accordingly as user needs may change in any way.

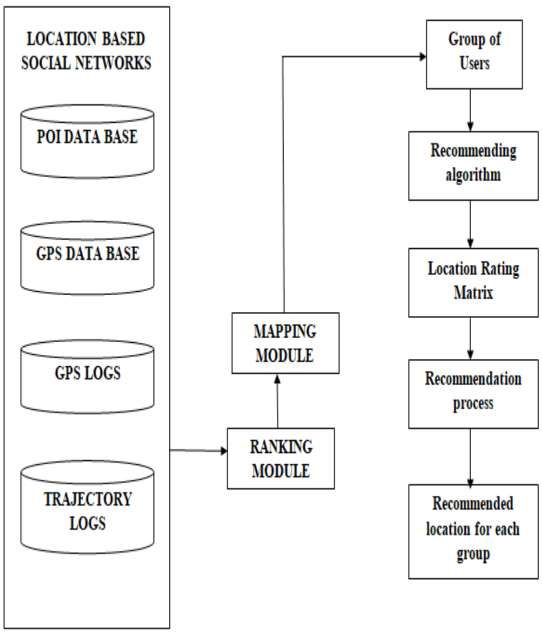

Fig. 1: BLOCK DIAGRAM GOLRS USING MULTI-AGENT INDUCED COGNITIVE BEHAVIORAL MODEL

The ranking module is based on performing the processing of location database in user profiles to generate major performing users and popular location. Each check-in location has their experience and ratings provided by competent users or similar users.

Target users are found based on their Point of Interest profile and interests. Recommending service provider on data batch wise processing is done on requirement. A ranking inference model is defined based on a set of users and locations to assign ranks. Top rank are given to provide better recommendations to the target user for popular locations. After a large number of user visits, the minimum computational time taken by the system to find locations with low ratings is cut from the recommendation processing lists.

Target activations are multiplied by similarities from potential users based on the user's current regions. Finding and initiating like-minded users is said to be the main goal of similarity calculation and it helps a lot in user preference management for that geographic region. Proximity of locations based on real-time geographic distance between locations is calculated as an additional advance to predict travel feasibility by target users.

Annotated lists from locations are generated from the recommendation module by multi-level collaborative filtering that Used to provide optimized recommendations based on scalar optimizations. The recommendation module follows a scalar optimization technique for its convenience and ease of use of objective functions. They follow to help users in appropriate ways to improve the quality of recommendations as well as for multi-level collaborative filtering with multiple constraints.

An algorithm is developed to recommend a personalized list based on location recommendations to the target user by using the ontology profile generated from the multi-agent system. The scalar sum method was used to optimize the recommended lists. Multi-level PCCs are used to perform calculations of single dimensions and set effective user entities. Audience acceptance and proximity criteria are verified after recommending a location to users to ensure that all users are taking advantage of travel utilities. User profile locations with maximum proximity values are returned to close location lists. After the user profile is prepared based on the needs of the potential users it is very useful in generating further recommendations. This results in a list of recommendations described by the user.

Algorithms used in the group recommendation core are used to perform recommendations. (1) content-based recommendation, (2) link analysis-based recommendation, and (3) collaborative filtering (CF) recommendation can be divided into three parts as important methods of recommendation. The recommended method of each has specific disadvantages and advantages. Data sparsity and cold starts are described as major problems in collaborative filtering-based recommender systems, and these problems can be eliminated in link analysis-based recommender systems.

Our recommendation module adopts a scalar optimization technique using scalar optimization for ease and simplicity of using objective functions alike. Weighted scalar optimization is described as follows.

$$\text{Fun (User)} = \sum_{b=1}^{no\ of\ object\ \ function} \mathrm{Weight_b} \times \mathrm{Fun_b\ User}$$

Based on the user’s location biography a users location graph is created. The border between them is bounded by viewing the user's space. Although the view ability rate for a user's location is not in the LBSN-based check-in dataset, it can be assumed that if a user regularly checks in at the same location, the user will be more interested in that location. Not all users have the same check-ins, so check-in times can vary greatly for different users.

User group members can be set in the group recommender system or selects the same groups throughout the system. Although users are largely human-like, users are divided into self-functioning segments. In this approach the proposed method is used for automatic bulk structure. In order to quantify the needs of consumers and prioritizing their needs, spatial proximity, free days and social relations are used in this approach. In a clustering algorithm k-medoids are used to reduce user requirements and generate clusters within a given interval. This method is used to extract the important points to find out the requirements from the users.

In this section, location is recommended and location capability and the ability to access online information from weather forecasts in different time are assumed. Since efficiency depends on location once a day as well as any day of the week, the recommendation can be influenced by the location of these parameters. Location recommendation is shown differently for rainy or dry weather. Only indoor locations are provided for clusters of systems during rainy weather. When segment sizes are large it is difficult to know location efficiency when dates and time periods are defined in advance. Location efficiency can be shown without any problems only when time based recommendations are handled as an important factor. The availability of this data does not limit the applicability of the system. The recommended locations can be used by the concerned groups with temporary flexibility they can move their positions only when they want and free capacity is made available at the recommended locations.

Group-based position scoring is based on the group-position matrix and the ability of the group weather forecast positions to provide the most significant positions at different times for each segment within the system. Only provided when there is no way to show the location in the next alternate position in the ranked location list. The output for each group of this step consists of the top-k ranked positions and the efficiency of recommended positions in each time period. The capacity of locations varies from time to time and as a result the departmental recommendations may also need to change.

IV. RESULT ANALYSIS

Table (1) below shows the comparison table of USTTM and GOLRS using MAICBM (Multi-Agent Induced Cognitive Behavioral Model). In this precision, accuracy, F1-score and time are given in detail. Compared to USTTM, GOLRS using MAICBM increases accuracy, precision, F1-score and reduces time.

To show the results obtained by the system, three types of accuracy measurement parameters are used. The precision rate is shown in the formula as the first parameter of measurement.

Precision = TP/(TP+FP)

The variable defines the number of true references for TP similarly to the number of false references for FP users. A high accuracy rate means that our results are useful.

Accuracy: Proportion of correctly labeled subjects to the total pool of subjects. Accuracy answers the following question: How many users out of all users have labeled correctly?

Accuracy = (TP+TN)/(TP+FP+FN+TN)

The last parameter is given by the F-measure and the formula.

F-Measure = 2*(Recall * Precision) / (Recall + Precision)

The F-measure precision and recall value are defined as the weighted harmonic mean. Accuracy is increased by higher F-measure values even in the system.

Table: 1: COMPARISON TABLE

S.NO	PARAMETER	USTTM	GOLRS USING MAICBM
1	Accuracy	78%	94%
2	Precision	82%	98%
3	F1-Score	65%	87%
4	Time	91%	11%

The below figure (2) shows the comparison of accuracy and precision for USTTM and GOLRS using MAICBM. Compared with USTTM, GOLRS using MAICBM increases the accuracy, precision in effective way.

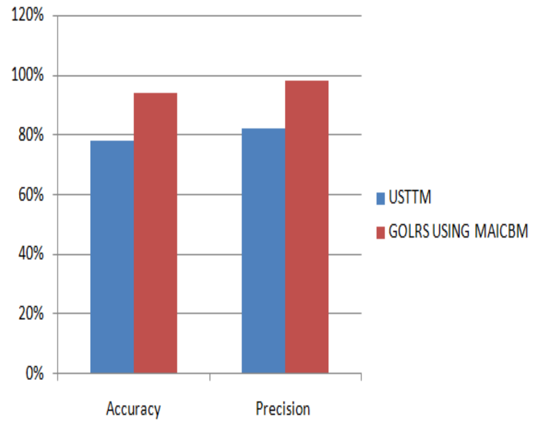

Fig. 2: COMPARISON OF ACCURACY AND PRECISION

The below figure (3) shows the comparison of F1-Score and time for USTTM and GOLRS using MAICBM. Compared with USTTM, GOLRS using MAICBM increases the F1-Score and reduces the time in effective way.

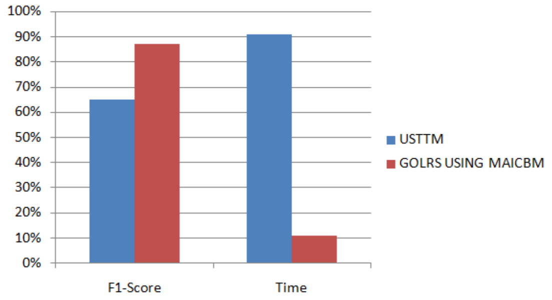

Fig. 3: COMPARISON OF F1-SCORE AND TIME

V. CONCLUSION

Location-Based social networking services have become more popular as the development of smart mobile devices has increased. Recommending locations for Location-Based Social Networks (LBSNs) based on user needs is considered an important task. Most of the approaches already offered to all users are focused on developing a single method or models. In this approach reveal that users' thoughts on visiting places depend on multiple factors and that different user may be influenced differently by these factors by describing social networks as truly location-based. The results show that the algorithm is performing popularity-based collaborative filtering and content-based filtering. In addition, using a crowd profile and people's location preferences can significantly improve the accuracy of the recommendation.

VI. REFERENCES

[1] G. Adomavicius and A. Tuzhilin. Toward the next generation of recommender systems: A survey of the state-of-the-art and possible extensions. TKDE, 17(6):734–749, 2019.

[2] J. Bao, Y. Zheng, and M. F. Mokbel. Location-based and preference-aware recommendation using sparse geo-social networking data. In SIGSPATIAL GIS, 2019.

[3] A. Bar, L. Rokach, G. Shani, B. Shapira, and A. Schclar. Improving simple collaborative filtering models using ensemble methods. In MCS, 2019.

[4] C. Burges, R. Ragno, and Q. V. Le. Learning to rank with nonsmooth cost functions. In NIPS, 2018.

[5] C. Burges, T. Shaked, E. Renshaw, A. Lazier, M. Deeds, N. Hamilton, and G. Hullender. Learning to rank using gradient descent. In ICML, 2018.

[6] E. Cho, S. A. Myers, and J. Leskovec. Friendship and mobility: User movement in location-based social networks. In KDD, 2018.

[8] Huang, H.; Gartner, G.; Krisp, J.M.; Raubal, M.; Van de Weghe, N., Location based services: Ongoing evolution and research agenda. J. Locat. Based Serv. 2018, 12, 63–93.

[9] Liao, G.; Jiang, S.; Zhou, Z.; Wan, C.; Liu, X,. POI recommendation of location-based social networks using tensor factorization, In Proceedings of the 2018 19th IEEE International Conference on Mobile Data Management (MDM), Aalborg, Denmark, 26–28 June 2018; IEEE: Piscataway, NJ, USA, 2018; pp. 116–124

[10] W.G.R.M.P.S. Rathnayake, Google Maps Based Travel Planning and Analyzing System (TPAS), IEEE, Proceeding of 2018 IEEE International Conference on Current Trends toward Converging Technologies, Coimbatore, India, 2018

[11] AlBanna, B.; Sakr, M.; Moussa, S.; Moawad, I., "Interest aware location-based recommender system using geo-tagged social media", ISPRS Int. J. Geo-Inf. 2016, doi:10.3390/ijgi5120245

[12] C. Paola, L. Serguei and C. Carlos, Tourist Information Evaluation Using a Social Network, J. of Advances in Computer Networks, 2(2014)

[13] J. Lucas, N. Luz, M. Garc´ıa, R. Anacleto, A. Figueiredo, and C. Martins. , "A hybrid recommendation approach for a tourism system", Expert Systems with Applications, 40(9):3532–3550, 2013.

[14] R. Anacleto, L. Figueiredo, N. Luz, A. Almeida, and P. Novais., "Recommendation and planning through mobile devices in tourism context", In Ambient Intelligence - Software and Applications, volume 92 of

Advances in Intelligent and Soft Computing, pages 133–140, 2011
[15] A. Almeida, B. Coelho, and C. Martins., "Intelligent hybrid architecture for tourism services", In Max Bramer, editor, IFIP AI, volume 331 of Advances in Information and Communication Technology, pages 205–214. Springer, 2010.

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