

ASSESSING THE EDGE SERVER USER'S PERSONAL PREFERENCE FUNCTION UTILIZING SOCIAL NETWORK-BASED RANK

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Abstract-The proliferation of smartphones and other mobile devices has led to the rise of location-based social networks (LBSN). Users may make use of LBSN's geographic information in conjunction with portable edge terminal devices to plan or modify their trips. However, cloud storage is under more strain and has higher operational and maintenance expenses as a result of the contemporary Internet's exponential development in both users and applications. Using such a mountain of unique data to precisely identify user-interested locations and promote them to customers is an important area of location-based recommendation-based research. This study begins by analysing the user's personal preference function on the edge server using the Rank-FBPR matrix decomposition framework based on social networks. The goal is to improve data processing for edge devices. After that, group the POIs by interacting with the cloud-based geographic data. It then incorporates the geographical data into the framework to retrieve the

I. INTRODUCTION

With the fast growth of Internet technology and the continual popularisation of mobile communication devices, Location-based Social Networks (LBSN) have invaded people's lives. An individual's preferred geographic location to access sites of interest may be defined using LBSN's geographic information and social features

potential sites of interest. As a last step, we utilise the personal preference function and power law distribution to forecast the scores of potential points of interest. Then, we sort the points of interest by decreasing score and suggest them to the user. By taking edge devices and the cloud into account holistically, our algorithm suggests a POIs recommendation algorithm and successfully integrates the time and location data of users' check-ins in the LBSN. The results show that the framework works well from both cold and non-cold starts. Results from experiments conducted on the Foursquare and Yelp datasets demonstrate that Rank-FBPR outperforms competing models in terms of recommendation accuracy and recall, while also demonstrating its ability to handle cold start issues.

Keywords--LBSN, edge computing, personal preference.

in conjunction with the Internet connection provided by the portable terminal. The rapid expansion of network edge devices (including smartphones, wearable smart devices, etc.) over the last decade has been driven by the explosion in popularity of cloud computing, big data, and the internet of things (IoT), allowing users to make timely adjustments to their work and travel

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plans while still enjoying the benefits of intelligent perception and the convenience of using all kinds of these technologies. Also, there's no assurance of the high precision or processing power needed for points-of-interest suggestion. Here, the need for the edge computation arises because the centralised processing mode cannot handle the data produced by the edge devices. In edge computation, "edge" means "network edge," which is the location farthest from the data centre and nearest to the user (either physically or in terms of network distance) [1]. Some or all of the computing functions that were once performed in the cloud centre are now handled by the edge computing model. Meanwhile, gadgets in the periphery of networks are experiencing the fast entry of the period. In order to guarantee processing in real time and cut communication costs, the edge computing architecture may decrease data transmission bandwidth while simultaneously improving data transmission performance. At the same time, it may lessen the likelihood of sensitive data from terminals leaking and improve the protection of private data. Edge intelligence is becoming more widespread as computing capabilities at the edge continue to develop. Wang et al. [3] performed a survey that demonstrates the practicality and significance of edge intelligence in everyday life. By integrating mobile edge systems with deep learning and joint learning, Wang et al. [4] proposed the futuristic idea of edge artificial intelligence. The calculation transfer decision is guided by multiple Deep Reinforcement Learning (DRL) agents on the internet of things device (Li et al., 2015). To further reduce the transmission cost between the internet of things device and edge nodes, distributed training on these agents is carried out using Federated Learning (FL). More and more studies in the field of POI recommendation are

concentrating on POIs that are associated with LBSN services. In order to provide efficient points-of-interest guiding service, one of the new paths in the development of POIs recommendation systems is to integrate edge computing in LBSN location service to establish a points-of-interest access model. Users of LBSN may check-in to sites of interest, reveal their precise position, and discuss their experiences with other users. Websites and platforms that provide location-based services, like Foursquare and Yelp, gather and analyse user check-in data, and then they offer suggestion services for points of interest based on their users' current whereabouts [6]. To better serve consumers, most POI recommendation studies in recent years have relied on LBSN user check-in data and multi-source heterogeneous information to provide recommendations. As an example, Ye et al. [7] modelled spatial clustering using a power-law distribution and used the user's interests, social connections, and geography to provide suggestions for sites of interest. Prior to making recommendations for sites of interest, Zhang et al. [8] simulated the user's access behaviours using the Kernel Density Estimation (KDE) approach. In order to forecast the user's score on the POIs, Koren et al. [9] used Matrix Factorisation (MF) to model the possible attributes of each user and POI. They did this by decomposing the user's POI matrix into a person matrix and a points-of-interest matrix. Lastly, customers are provided with a list of suggested sites of interest according to the rating. As a foundational framework for adapting to user behaviours, Lian et al. [10] presented the Weighted Matrix Factorisation (WMF) technique, which gives a lot of weight to activities that have a lot of user interaction. At last, a model for factor augmentation was suggested as a way to include graphic

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factors. While current POIs recommendation algorithms are effective at suggesting a collection of places that are highly relevant to users' interests based on their profile, they rely on a single piece of contextual information to construct their models, which ignores the variety of recommendations and makes it difficult to provide users with a tailored set of points of interest based on their precise geographic location in real-time. The conventional wisdom was that a user should initiate a request to the Cloud server from their client, and the server should then answer. The cloud server won't be able to react quickly enough to changes in user preferences by adjusting recommendation results in such a mode, which causes a domino effect of issues like less client dependence and a lag in real-time perception of user behaviours. In light of this, this research presents a new point-of-interest (POI) recommendation algorithm that incorporates social information into the Bayesian Personalised Ranking (BPR) technique, drawing on the features of edge computing. The technique seeks to achieve reduced processing latency and real-time feedback by extending Cloud operations to edge servers with computing capability, based on the architecture of hybrid Cloud and edge computing. The edge server handles all the terminal data processing, and then it uses the Bayesian ranking algorithm and the user's social ties to deduce their personal preference. The data pertaining to cities is then analysed in the cloud, while the edge servers group sites of interest based on geographic data. Now the algorithm is ready to be produced. The following are the three primary contributions of this paper: First, we suggest an edge-server-based BPR learning model. With the user's preferences and social connections taken into account, the POIs suggestion becomes a ranking challenge.

(2) The BPR framework of social relations (FBPR) is integrated with user geographical data, urban area data is processed in the cloud, and the framework is then combined with clustered point-of-interest data to create a recommendation list of POIs that is both diverse and individualised. (3) We run a plethora of tests on Yelp and Foursquare. Experimental findings comparing this algorithm's accuracy and recall to those of other algorithms demonstrate the validity and superiority of the suggested technique.

II. RELATED WORKS

The suggestion of points-of-interest (POIs) is more involved than the conventional recommendation approach because it must take into account the effect of several aspects, including social information, temporal information, and geographical information. Two important components of the technique suggested in this work are POIs recommendation and points-of-interest clustering. See below for an overview of where these two components are in terms of research.

A. CLUSTERING OF THE POINTS-OF-INTEREST

Data mining, data representation, and data visualisation all make use of clustering. Clustering based on partitions, density, or grids are all examples of classical clustering approaches. Two of the most used clustering algorithms are K-Means and K-MEDOIDS. These two techniques are not well-suited for clustering POIs on a wide scale, but as distance-based heuristics, they sidestep the problem of using up all the clustering-based divisions. Among density-based algorithms, DBSCAN is by far the most used. The basic idea behind this technique is to group similar points together based on how dense they are in the area. It gets over the problem

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that, when using a distance approach, you can only find clusters with regular shapes; however, this isn't always the case, and it often yields results that don't match up with the clustering demands of the points of interest. Before processing any data, grid-based clustering partitions the space into a limited number of grid structures. Although this technique has fast processing speed, it divides the grid very resource intensively and performs poorly in real time. With a more consistent clustering result and less computing required, spectral clustering outperforms the old K-Means algorithm, an old clustering approach. A novel approach to geospatial data clustering, Multi-Reference Clustering (MRC), was put out by Zhong et al. [11]. In order to modify geographical data, this technique augments K-Means clustering with the idea of reference points. The local search approximation approach significantly decreases the temporal complexity of MRC by grouping data points into K clusters; nevertheless, this method is too sophisticated to be appropriate for clustering suggestions for points of interest (POIs). Using the Geo-Social Network (GeoSN) paradigm, Shi et al. [12] established a novel clustering approach called DCPGS, which stands for Density-based Clustering Places in Geo-Social Networks. The clustering findings are more thorough and effective when the social and geographical distance across areas are taken into account. There are two unintended consequences, though: first, that users with no social connections but close geographic proximity may be clustered; second, that users with close

social distance but geographical proximity may be subject to recommendation, implicit feedback, and embedded recommendations.

III. PROPOSED METHOD

Social information, geographical location data, time data, etc. all make up contextual information in the LBSN. Users are more likely to visit nearby spots of interest and locations recommended by friends. Ye et al. [7] developed a model to estimate the likelihood of a user checking in at a certain location in relation to their access to sites of interest by including geographical impact, user choice, and social influence into collaborative filtering recommendations. This prediction model outperforms more conventional collaborative filtering recommendation algorithms, according to the experiments. Since friends clearly have varied interests, the random stroll isn't a good fit for recommending POIs. In order to address the issue of data sparsity and effectively react to real-time POIs suggestions, Qian et al. [13] combined geographic and temporal information and suggested a representation approach called Translation-based, Time and Location aware (TransTL). There are two types of user feedback—implicit and explicit—and both are essential for point-of-interest suggestion. The suggestion may be too biased if it is dependent only on the user's rating or other explicit feedback data. Improving the variety of recommendation results may be achieved by combining the suggestion with implicit feedback, such as appraisal, browsing, and collecting.

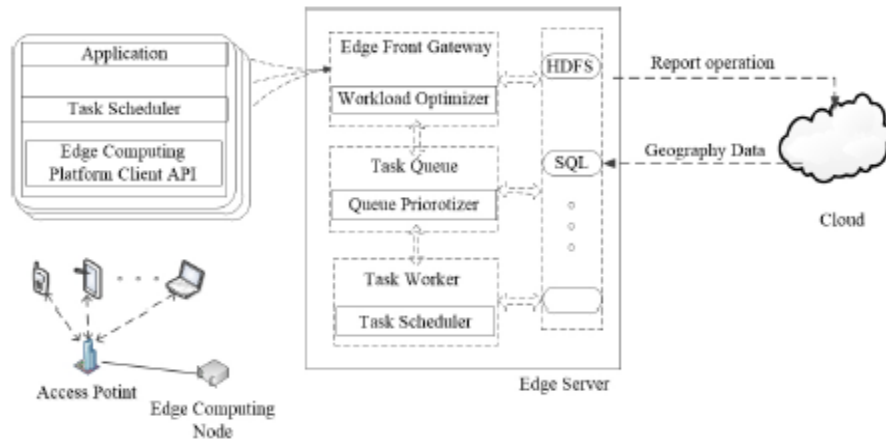


figure 1. The architecture of Rank-FBPR algorithm.

Finally, the personalized ranking list of points of interest is generated. Considering the personal preference and geographical location of the target user, the personal preference function and power-law distribution are used to predict the scores of candidate points, and the ranking list of points of interest is generated according to the descending order of scores.

IV. RESULTS AND DISCUSSION

COMPARISON MODELS AND PARAMETER SETTINGS

1) COMPARISON MODELS

A number of traditional models for suggestion of sites of interest based on geographic location are chosen for comparison studies so that we may assess this algorithm's recommendation performance.

(1) GeoMF [10], which uses an upgraded model that takes into account user and interest potential components based on the weighted matrix decomposition model. Concurrently, the spatial locations of interest are clustered using two-dimensional Kernel density estimation.

(2) MGM [13]: The multicenter Gaussian Model (MGM) captures geographical impacts, and then, to propose locations of interest, geographic information and social factors are combined into matrix decomposition.

(3) BPRMF [17]: In order to provide implicit feedback, we learn the user's interest preferences from their paired item preferences. Then, we utilise matrix decomposition to offer a personalised ranking list of points of interest to the user, all without considering contextual information.

The recommendation model suggested in this study is Rank-FBPR. It starts by creating an FBPR framework of points of interest (POIs) by integrating social interactions and BPR algorithms. Then, it employs the CRP clustering approach to find potential POIs. Finally, it takes into account the user's personal preference and geographical location to provide a ranking list of the top K POIs.

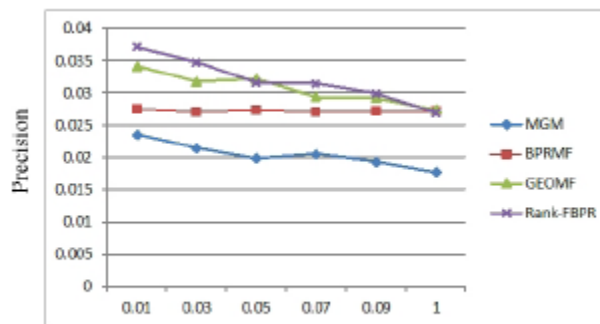
2) PARAMETER SETTINGS

Adjusting the regularisation coefficient in the model may relieve the

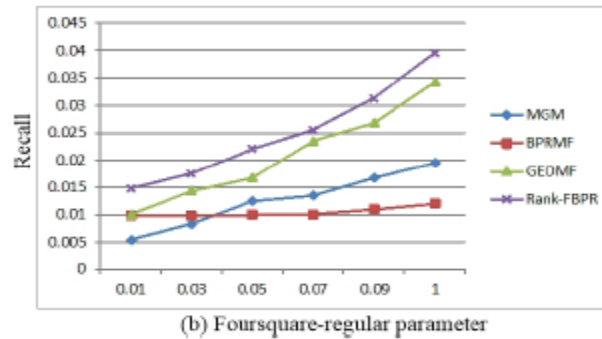
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sparseness of user check-in of POIs, which greatly influences the efficacy and efficiency of the proposed model. In order to compare each comparison model to Rank-FBPR in an ideal setting, this section will analyse the impacts of regularisation coefficients and points-of-interest dimensions. Figure 3 displays the implications of the regularisation coefficient on recommendation performance, whereas Figure 4 shows the effects of the point of interest dimension. Figures 3(a) and 3(b) show that when the regularisation coefficient increases, the accuracy of the suggested outcomes from GeoMF, MGM, and Rank-FBPR diminishes. Every one of the suggested models performs at its best when the coefficient is 0.01. Coefficients have minimal impact on BPRMF because to the absence of a regularisation term; nevertheless, recall improves with increasing coefficients. Figures 3(c) and 3(d) demonstrate that when the number of POI dimensions increases, the suggested model's accuracy and recall also rise. A sufficient amount of data will be available to

characterise social and geographical links until the POIs dimension reaches 50, at which point the growth of all models begins to slow down. Keep an eye on the Yelp dataset after that. Figures 4(a) and 4(b) indicate that when the regularisation coefficient was increased, the accuracy and recall were also dropped. At 50 points-of-interest, the accuracy of all models begins to decline, as seen in Figure 4(c) and 4(d). One possible explanation is that, being the most popular review site in the US, Yelp has more features and information on users. It becomes increasingly difficult to model as the data becomes scarce. From the results obtained by the four models in the two datasets, it can be deduced that GeoMF achieves the best suggested effect when it takes into account all negative feedback and sets the regularisation coefficient to 0.01. Also, the number of users in the MGM and the size of the POIs are also set to 10. For the sake of objectivity, this research sets the parameters of Equation(6) to users $U \ D \ 10$, POIs dimensions $V \ D \ 10$, and the regularisation coefficient $b \ D \ 0.01$.



(a) Foursquare-regular parameter



V. FUTURE SCOPE AND CONCLUSION

In this paper, we provide a novel Rank-FBPR method for hybrid cloud and edge computing. This algorithm can interact with geographic information stored in the cloud and gives users real-time awareness on edge servers. In order to determine the user's personal preference function, the algorithm first splits the points-of-interest in the Cloud and then incorporates the user's social relationship into the BPR ranking criteria. Based on the CRP procedure, the locations of interest are then grouped. Next, a number of potential points of interest (POIs) are chosen based on the user's preferences, clustering results, and geographic location; then, the predicted scores of these POIs are sorted descendingly to provide a suggested set of points of interest. The last step is to return the user's personalised suggestion list. The outstanding efficiency of the edge computing environment is shown by experiments conducted on actual data sets, which demonstrate that the hybrid recommendation approach employed has significant benefits in both the recommendation outcomes and the performance of the framework. Additionally, the technique is able to better address users' individual demands, has a greater accuracy and recall rate, and has more diverse POIs. Time impacts, user variety at the same points-of-interest, and POI consumption

level are some examples of contextual information that might be included to the learning analysis framework in the future. Concurrently, it's important to provide users correct references, make it easier for users to access POIs, and give continual POI recommendations based on correlations between POIs. In addition, we want to implement a more hierarchical approach to enhance recommendation performance and investigate a hybrid network structure that is both simpler and more scalable.

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