Location Based Point-Of-Interest Recommendation System Using Co-Pear Similarity Measure

R. Vinodha, R. Parvathi

Abstract: A new recommendation strategy is proposed to enhance the location-based point of interest (POI). The POIs such as Four square, Gowalla create a curiosity to share their experience and location which they visited. This Recommendation system seems to know everything about the people's interests, passions and stays up to date with modern trends. The POIs recommendation is based on the past check-in activities of the user. The user can't review the rating of any new cities which he/she doesn't check-in. Even though the collaborative filtering (CF) possess numerous advantages but it suffers from some disadvantages also. It can't predict any new (items, users), if the product or users aren't in the training then it can't be embedded in the query thus it creates a cold start problem. To overcome this problem, we introduced a Hybrid Co-pear Collaborative Filtering algorithm integrated into the POIs system. The combination of Cosine and Pearson similarity measures develop the multimodal hybrid method. To upgrade this system, we added a pear review analysis technique that analyses the location and provides valuable information to the new user. The similarity measure is taking place by modifying the data into the vector. During the comparison, we can precisely detect the angle variation between any two non- zero vectors. The cold start problem is overcome and represents a better recommendation for the new users. User GPS trajectories is utilized to calculate the latitude and longitude of the users location from Geo-life dataset. The result showed a variation among the existing and proposed location recommendations and proved that the proposed system provides an optimum solution to the new users.

Index Terms: Cold Start Problem, location-based social network (LBSN), Hybrid Co-pear Collaborative Filtering algorithm, Point of interest (POI), Collaborative Filtering (CF).

1. INTRODUCTION

The rapid development of technology causes urbanization and the evolution of new technologies. The urbanization creates numerous points of interest for visitors. There are enormous data is overloaded from social media, it is enough to predict each user's interest. The Recommender system [1, 19] acts as a technological proxy for social media and its support for decision making. Through a collaborative filtering process, the recommended location is predicated and traced out in GPS [2]. The selection of similar users is obtained from the ranking rate where the query of the user has to match with any of the users who are sorted in a group [5]. The user got recommendations/suggestions from the system based on their last check-in activities [4, 6]. In a traditional system, it is concern about the POI's location rather than the user content. After some analysis, they conjoin the content of the users and nearby location data [6, 7]. Based on the content and location of the users, the filtering process is carried on. Initially, gather all points of interest value from the data history. The process of CF is classified into three categories such as candidate selection, similarity interference, and recommendation score prediction. To resolve the new user's recommendation problems [13] they tried online and offline modeling, where the local expertise experience and personal preference. Each data is weighted and arranged in a hierarchal manner. The location-acquisition and wireless communication enable the users to recommend the dimensions of the location-based on their preferences and they can be sharing their own experience through social media [23]. The Similarity measure is taken among the users based on the activities and locations of the users. The traditional CF model is categories into two subgroups they are 1) User-based models, 2) Item-based models where similarity is measured among the pairs of objects. Finally, recommendation scores are calculated for the set of users based on the similarity measure of the individual users [24]. The e-commerce site [24] contains this type of recommendation system where it shows the relevant information/product to the users based on user preferences. The system analysis the history of the customers and retrieve some products to the users. Millions of user's check-in data are available in the LBSN which is used to determine the mobility and social behavior of the users [25]. Compare to the traditional recommendations, the POIs are usually associated with the rich context of data. Based on the evaluation, the recommendation system provides a suggestion over a vast distribution of POIs.

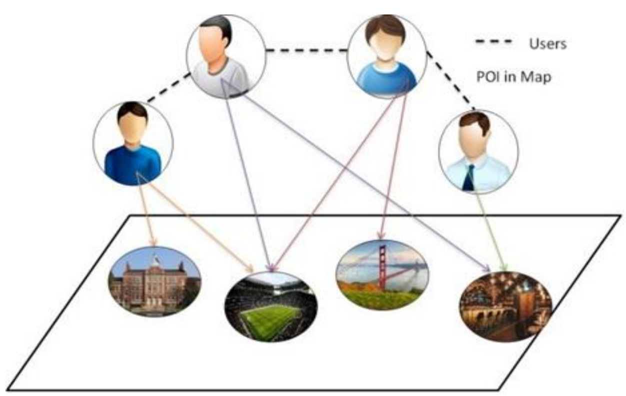

Fig.1: *Concept of Location-Based Social Network*

The location context awareness, heterogeneous domain, and data growth provide deterministic information for the classification process. Different users are connected in an interdependency manner where the internet acts as a medium to share their friendship, common interest, and knowledge, etc. The mobile devices [26] are embedded with location

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sensors, GPS and Wi-Fi. By the combination of the online social network and geographical information has evolved the location-based social networks (LBSN) which are illustrated in Fig.1. The main objective of the POIs domain is to estimate the top list of data for the target users based on his/her interests. To provide a recommendation to the users based on their historical data. To achieve this, result many researchers put forth different recommendation algorithms by combining the references and unique attributes estimated from the user's data. We investigate many results and methods at last, we constructed a hybrid method which provides a better recommendation for the users and rectifies the cold start problem in the recommendation system.

2 RELATED WORK

Ananta et al [1], proposed a paper where he recommends a Point of interest for the tourist. To reduce the burden of tourist he estimates a system which exploits the multi- criteria decision making and information. The system filters the unique data and recommends for the tourist to visit the POIs. He implements systems that improve satisfaction and promote tourism. RongGao et al [2] proposed a method to rank the recommendation data based on Geo-Social Bayesian Personalized Ranking Model. The novel pairwise ranking method was developed by injecting the geo-social preference of the users. Fei Yu et al [3], presented a paper on Location promoting in LBSN where they tried to promote the business location. They also tried to solve the normalization problem. They worked on the real LBSN dataset to achieve this location promotion. Uriwan et al [4], proposed a paper to automatically detect the point distribution in each dataset for the DBSCAN algorithm. Justin et al [5] proposed a paper for the Location-Aware Recommender System to the users. Chenyi et al [6], proposed a paper where the past check-in activities of the users are tracked and utilized for recommendation purposes. Vincent et al [7], presented a paper on point of interest where the system provides a collaborative location and activity recommendation to the users. Based on the GPS history of the users. Zhang et al [8] proposed a paper on cross-region collaborative filtering where probabilistic and topic model-based methods are utilized. Through which location of POI is determined. Zheng et al [9] presented a paper in detecting the mining location and travel sequences using GPS trajectories. HITS and Tree-based hierarchical graph- based algorithm is utilized to make the travel experience an interesting one for the users. Based on the location histories the recommendation where determined. Xuelian et al [18] presented a paper on Location-based social networks. They analyzed the four-square datasets and explore the features from it and utilize the HITS (Hypertext induced Topic Search) based on the POIs recommendation algorithm. Even though the result is better than the other POIs recommendation algorithm it suffers from recommending the irrelevant recommendation data to the users. We analyzed the data sources, a methodology to generate the recommendation and objectives for the recommendation. The existing system only provides the generic recommendation that may not be a choice of the users. Xie et al [27], predict the location based on the HITS algorithm. It provides baseline approaches like rank by count and rank by frequency. This approach is better than the weighted slope of one algorithm. The rest of the paper is arranged as follows in section 3 described the methodology of the recommendation system, section 4 presented the result and discussion of the project whereas section 5 concluded the paper.

3 METHODOLOGY

In this paper, we concentrate on the past check-in activity of the users. In the existing system, the user can view the rating of the already visited cities and places. But they can't view the rating for new cities which he/she not yet visited. So, we develop a hybrid method to reduce the irrelevant POIs. The combination of Cosine and Pearson similarity measures evolve the Co-pear multimodal method. The user pear review analysis technique about the location also adds extra features to this system. The irrelevant data recommendation is caused due to the data sparsity. Based on the GPS log data, the stay point is calculated and detected. Using the stay point a density- based clustering takes place.

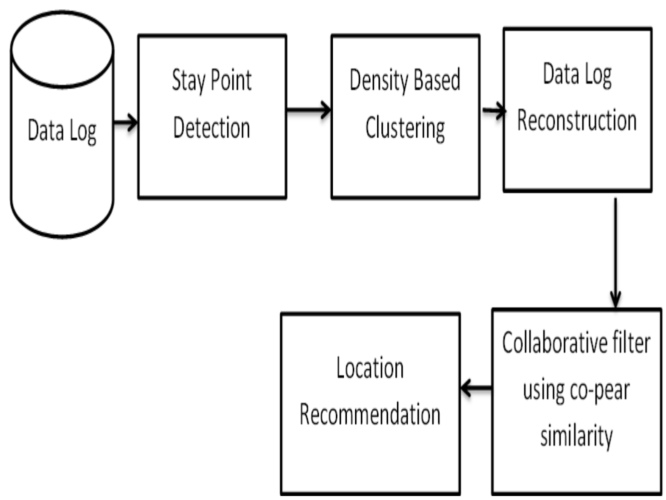

Fig.2: *Block Diagram of Proposed System*

The collaborative filtering is done using Co-pear similarity measure Sim^k. Finally, Location is recommended for the user which is illustrated in Fig.2. The Geo-life Dataset log α is utilized in this system.

GPS Trace (Ta^k) - is the sequences of time-stamped points, Ta^k=p0 – p1-…- pk. The each point p contain (x, y, t) dimension which represent the latitude, longitude and time stamp where pi=(x,y,t) (i=0,1,…k);(x,y). $\forall 0 \leq i \leq k$ p_{i+1}.t>p_i.t

Distance (p_i, p_j)- p_i and p_j represent the geological distance from each point. Int (p_i, p_j)=| $p_i.t - p_j.t$| explain the time stamp difference between two points.

Stay point - A stay point is a geographical region where the user stayed for a while which is represented in Fig.3. s is the consecutive points which indicate the traces of the users and T_t be the threshold time he/she took to cross the region and D_t be the threshold distance. x and y be the co-ordinates of collections where p is the user who's arriving and leaving time is calculated. From fig 3 we can visualize the movement of p (p1, p2…….pn) whereas the trace is tracked out between (p3 to p6) based on the condition of d D_t and Int (p3, p6) Tr. Each stay point represents places where the user visited like he may visit a hotel or park in that region. C is the consecutive points C=(x,y, t_a, t_l) where

$$C.x = \sum_{i=m}^{n} \frac{x.p_i}{|p|} \quad (1)$$

$$C.y = \sum_{i=m}^{n} \frac{y.p_j}{|p|} \quad (2)$$

The C. ta and C. tb represent the arrival and leaving time of the user in that point. Location History - The individual user traveling data is collected separately and calculates the time he/she spend at the same point. It represents as h

$$h = s0(t)- s1(t)- s2(t)-\ldots sn(t) \quad (3)$$

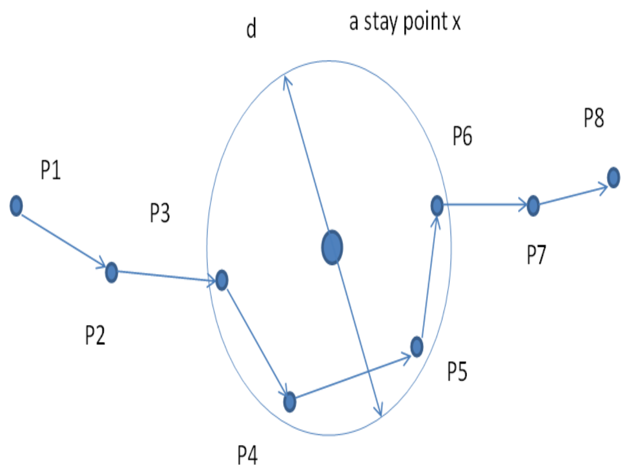

Fig.3: *GPS Trace and Stay Points*

Those data are illustrated in the form of stay points in Fig.3. Each user stay point and time taken is evaluated and determines the favorite stay points of each user SP^k .
Trip: It evaluates the users' favorite place location where he/she want to spend more time rather than other points. The location is calculated based on some threshold value.

COLLABORATIVE FILTERING

The collaborative filtering is a method used by the recommender system. It plays a vital part in finding the structure of the non- linear shape in density-based clusters. Density-based spatial clustering and Noise (DBSCAN) worked on the density clustering. The density reachability and connectivity are the two concepts utilized in the Density algorithm. Density Reachability Dr, consider p is the user who has to reach d point from a point.

Algorithm 1: Hybrid Co-pear Collaborative Filtering algorithm

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Input: The collection of users GPS log α = { $Ta^k, 1 \le k \le |U|$ }, a Distance threshold D_t and Time threshold T_t for stay point detection.
Output: $g_s \leftarrow$ Recommended Location

1. Parsing GeoLife GPS log data
2. For each user $u_k \in U$ do
3. $SP^k \leftarrow$ StayPoint Detection (Ta^k, D_t, T_t) //collection of users staypoints
4. Return
5. $R_s = reshape(SP^k)$ // Reshape stay point data
6. Loop: Assign eps=600; minsample=1
7. $C^k \leftarrow$ DBSCAN Clustering$(R_s, eps, minsample)$
8. $P^k \leftarrow$ Reconstruction (C^k, r) //Reconstruction of data with r Random ranking
9. Return Loop
10. $P^c \leftarrow$ Collaborative filtering (P^k, k_1, r) //Apply collaborative filtering with(Geo data, Ranking, User)
11. $Sim^k \leftarrow$ Algorithm 2 // Co-pear similarity measure algorithm
12. $R_{sim} \leftarrow$ Ranking all user location score (Sim^k)
13. $S_{sim} \leftarrow$ Sorting all user location score (R_{sim})
14. IF d > d_r //Recommended distance condition
15. $g_s \leftarrow$ Fetch recommended location

The trajectories from dataset α are subjected as input to the recommendation system which is depicted in algorithm 1. The dataset of all users is processed to $Ta^k, 1 \le k \le |U|$ to calculate the stay points (SP^k). C^k DBSCAN clustering is evaluated based on the stay points and minimum samples. The data are sorted based on collaborative filtering (P^c). After that, Sim^k Co-pear similarity measure is calculated for two different users through Algorithm 2. At last ranking and sorting are done R_{sim} &S_{sim} based on the recommended distance d_r. finally g_s recommended locations are fetched to the user.
Density connectivity Dc - the connective points between a and d. The neighbor points which provides a path to reach b. Thus, it creates a connective network and represents the stay point for the user.

To implement the DBSCAN algorithm [4], we utilized log data's X{x1, x2, x3,….., xn}, the distance among the points and min point require to cluster (mp)

- Let start from the new location as a starting point.
- Then measure the distance from this point to the neighboring point.
- If enough neighboring points occurred then it can form a cluster or else it considers as a noise.
- After that all the points have to be clustered among the neighboring point. The step will be repeated until all the points got the cluster.
- Till all the points are visited the clustering will proceed.
- It forms an arbitrary shape and arbitrarily size of the clustering.

CO-PEAR SIMILARITY MEASURE

In Pearson similarity measure, initially, we find the Pearson correlation score is equal to the ratio between the covariance and standard deviation of the objects or else the ratio between the two predicted data. Then we took the similarity measure among the objects. If the distance is small then the similarity is high and vice versa. The similarity measure is in the range of [0, 1]. The cosine similarity measure depends upon the cosine angles where cosine of 0 is 1 and less than 1 for other angles. It finds the normalization dot products of the two attributes.

The similarity measure takes place based on the orientation not magnitude. If the orientation of vectors is the same then the cosine value is 1 or else the value will be -1. Two vectors at 90 having a similarity of 0. The cosine similarity is highly recommended for the space vectors where it is easy to evaluate and use in positive space. The outcomes are neatly bounded between [0, 1]. The equation of Co-pear similarity measure Sim^k is given below,

Co-pear

$$(sim^k) = \frac{1}{2N}\sum_{i=1}^{N=2}\left[\frac{2\sum_{i=1}^{n} x_i y_i}{\sqrt{\sum_{i=1}^{n} x_i^2 \sum_{i=1}^{n} y_i^2}} + \frac{2N[\sum xy - \sum x \sum y]}{\sqrt{[N\sum x^2 - (\sum x)^2] + [N\sum y^2 - (\sum y)^2]}}\right] \quad (4)$$

Where

N=no. of similarity measure

X=user or item 1

Y=user or item 2

D=no of pairs of score

$\sum xy$= Sum of the product of paired score

$\sum x$=sum of x score

$\sum y$=sum of y score

$\sum x^2$=sum of squared x score

$\sum y^2$=sum of squared y score

$\sum_{i=1}^{n} x_i y_i$=dot product of two item or user

2- Constant bias

$\sqrt{\sum x_i^2 \ \sum y_i^2}$ = magnitude

Algorithm 2: Co-pear similarity measure algorithm

Input : Users = k_1, k_2, a ranking and location data of all users P^c

Output: Sim^k ← Similarity score

1. For each user $u_k \in U$ do
2. $B_r = k_1 P^c \cap k_2 P^c$
   //Calculate both user rated location
3. $n_r = Length(B_r)$
   //calculate length of both rated location
4. $a = [k_1, P^c, B_r]$, $b = [k_2, P^c, B_r]$
5. $dot = a . b$
6. $Cos = \frac{dot}{||a|| \, ||b||}$
7. IF $n_r == 0$
8. Return 0
9. $x = [k_1, P^c, B_r]$, $y = [k_2, P^c, B_r]$
   // User1 and User 2 square preferences
10. $Num = 2N[\sum xy - \sum x \sum y]$
    //Sum up the squares of preferences of each user and product and Sum up the product value of both preferences for each location
11. $Den = \sqrt{[N\sum x^2 - (\sum x)^2] + [N\sum y^2 - (\sum y)^2]}$
12. IF $Den == 0$
13. Return 0
14. $Per = \frac{Num}{Den}$
15. $Sim^k = \frac{1}{2N}\sum_{i=1}^{N=2}(Cos + Per)$
    //Finally find Co-pear similarity measure

Let k_1, k_2 are two users and P^c contain all the location histories of the users. Sometimes the users may rate the same location B_r as preference where length n_r is determined for that location. At last Co-pear similarity measure/score Sim^k is calculated and substituted in algorithm 1. The dataset is clustered into some geospatial region in a divisive manner. C is the set of Clusters in the region. Finally, the cluster is generated as output. The formation of the cluster takes place with the GPS as a log point which is assumed as the center. Then collecting the sufficient neighborhood for the clusters. R is the distance between the center point and the neighborhood points. After the collaboration, the users are grouped based on their similarity values. The score of the individual user determines the closeness of their interest. The user gets a location to recommend from the different users who are all having the same interest but the high preference is taken from the user who scores high ranking in the group. The group members are sorted based on their values.

4 RESULTS AND DISCUSSION

We conducted a series of experiments between the existing algorithm and the proposed algorithm. A Geo life dataset is utilized for analysis purposes. We plot the graph for 10 users and 20 users for location recommendations which are depicted in Table-1.

***Table-1**: Between existing and proposed system*

Particulars	No of Users	Total Stay Points	Total Clusters
Existing System	10 users	4502	405
	20 users	7495	604
Proposed System	10 users	4502	494
	20 users	7495	494

The graph is plotted for the aforementioned table-2, the stay points, DB graph for existing and proposed system is plotted in Fig.4 to 7. The co-pear similarity also measured and plotted in Fig.8.

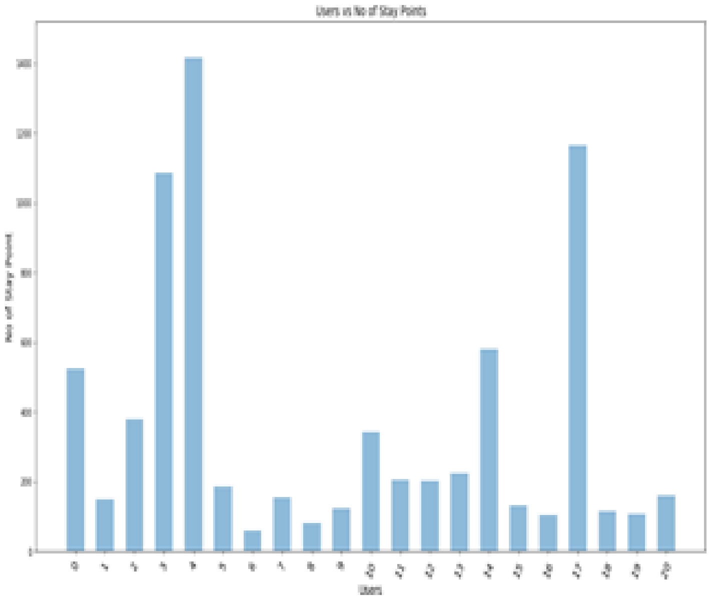

Fig.4: *Existing stay point Graph*

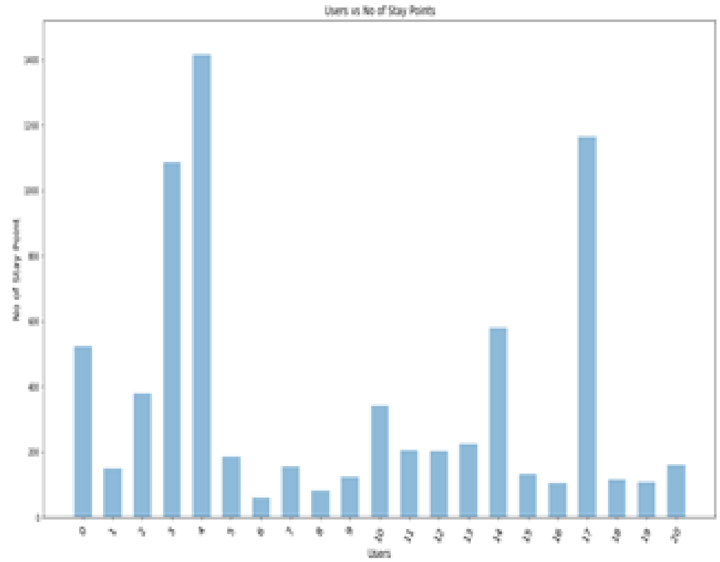

Fig.6: *Proposed stay point Graph*

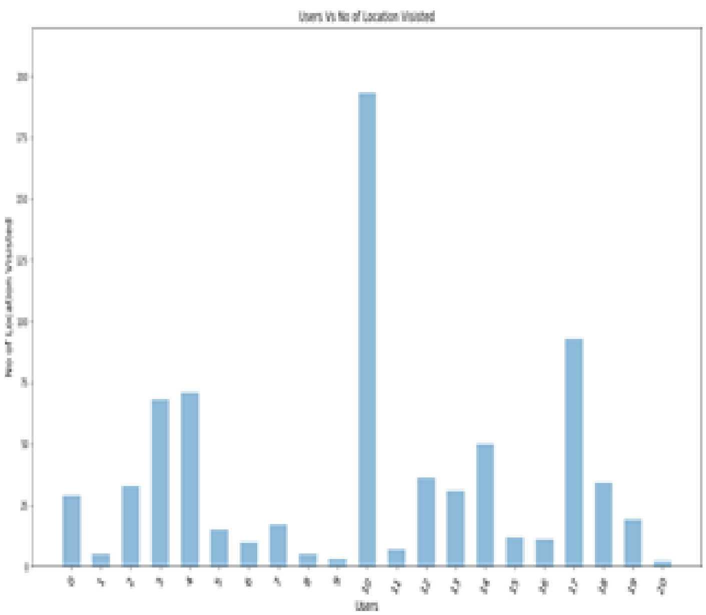

Fig.5: *Existing DB Scan Cluster Graph*

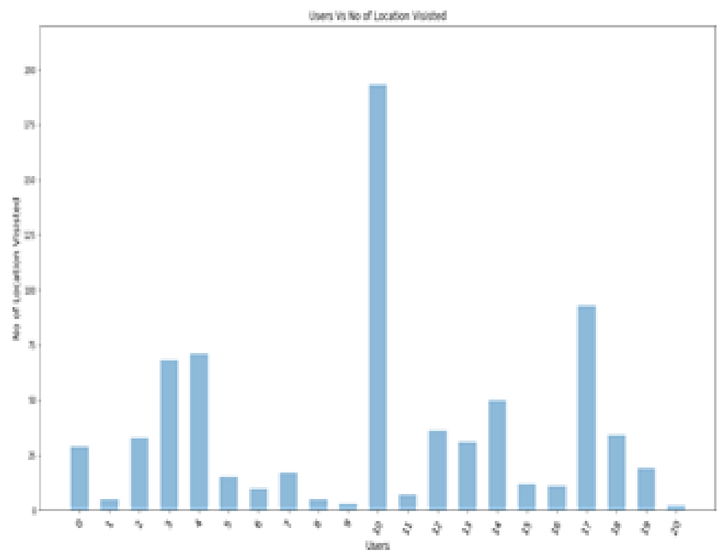

Fig.7: *Proposed DB Scan Cluster Graph*

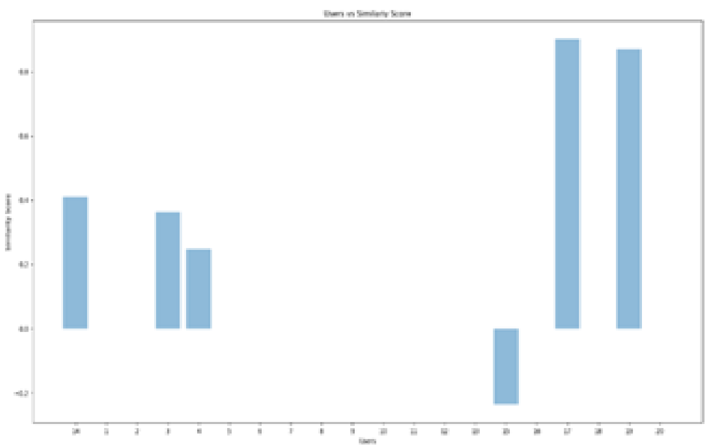

Fig.8: *Proposed Co-pear Similarity Graph*

Table-2: *Location Recommendation*

No of Location Recommended					
S.No	Cities	HITS based Recommendation		Collaborative Filter based Recommendation	
		10 users	20 users	10 users	20 users
1	xiaoguan residential district	127	140	182	137
2	balizhuang residential district	136	150	0	0
3	Changing	118	124	170	130
4	china international exhibition center	131	143	182	137
5	Hepingli	128	141	182	137
6	majiapu residential district	125	138	182	136
7	jiu gong zhen	134	145	183	138
8	shuguang residential district	122	129	175	133

DATASET

We took Geo life dataset [28] for demonstrating the working progress of the Co-pears and HITS algorithms. The dataset is collected by Microsoft Research Asia where they collected a GPS trajectory of 178 users in over 4 years. The dataset represents the sequences of a timestamp, latitude, longitude, and altitude of the users. It contains 17,621 trajectories with a total distance of 1,251.654 km and the total duration is 48,203 hrs. This trajectory is utilized in different fields such as user activity recognition, LBSN, and location privacy, etc...

COMPARISON BETWEEN EXISTING AND PROPOSED SYSTEM

The HITS algorithm provides a random recommendation for the users but Co-pears collaborative filter provides unique recommendations for each user.

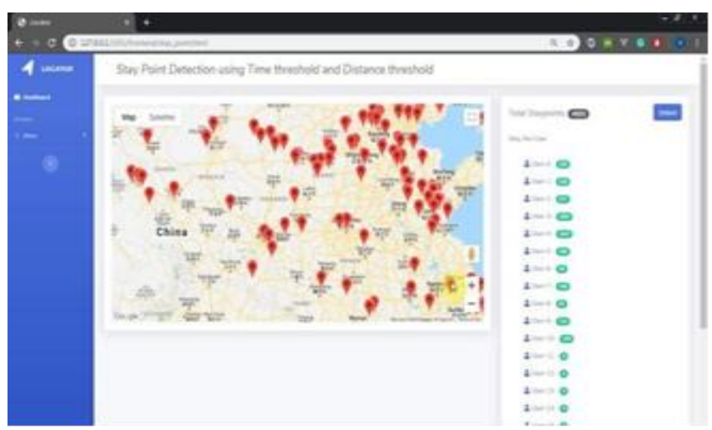

Fig.9: *Total Stay Point Detection*

It overcomes the cold start problem whereas the HITS algorithm still suffers from the cold start problem. The ranking and sorting are done for selecting similar users. Compare to HITS algorithm the Co-pear method is highly efficient. In Fig.9 to 11, the proposed system is illustrated where stay points and clustering data is visualized.

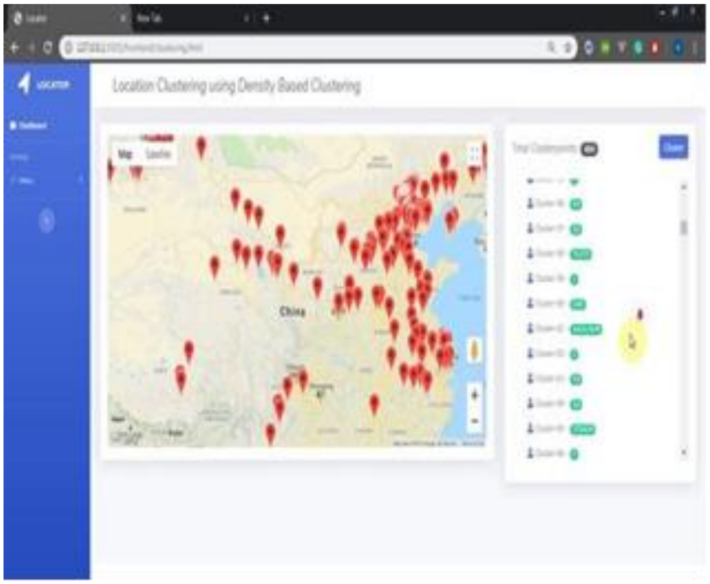

Fig.10: *DBSCAN Cluster*

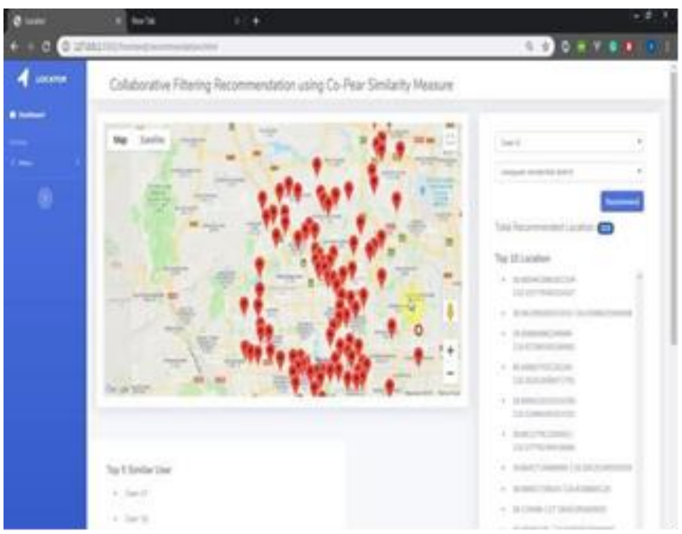

Fig.11: *Collaborative filtering using Co- pear Similarity Measure*

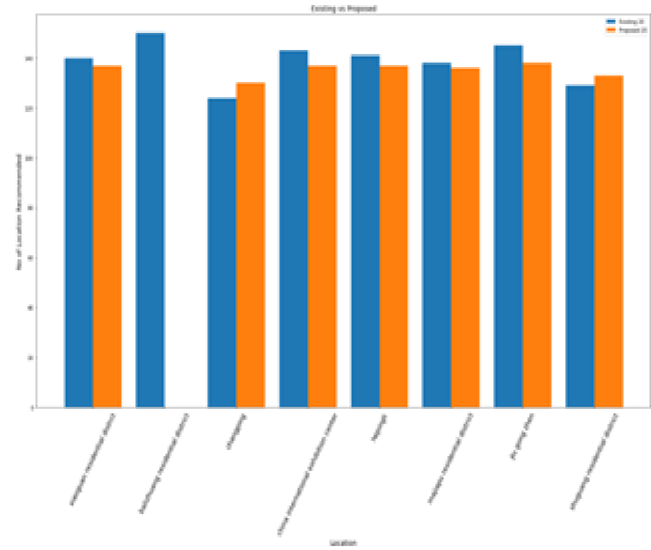

Fig.12: *Existing vs Proposed Recommendation graph*

The clustering value of proposed and existing system is plotted and depicted in Fig.12

5 CONCLUSION

In this paper, we addressed the data sparsity and cold start problem which creates an irrelevant POI for the users. Due to this sparsity, the entries in the rating matrix are missing leads to poor prediction quality of the CF algorithm. To overcome this problem, we implemented the Hybrid Co-pear Collaborative Filtering algorithm where user-based and location-based predicated is takes place. Collaborative filtering based on the Co-pears similarity measure approach provides high-quality recommendations for the users. It also improves the accuracy of prediction. The combination of location interest, user content and mutual relationship among the users helps to reduce the irrelevant POIs. Thus, our system contributes relevant POIs for the users than the existing systems.

REFERENCES

[1] AnantaCharan, Ojha and Jibitesh Mishra, “Interest-Satisfaction Estimation Model for Point-of-Interest Recommendations in Tourism”, published in International conference on Information Technology, 2018.
[2] RongGao, Jing Li, Bo Du, Xuefei Li, Jun Chang, Chengfang Song and Donghua Liu, “Exploiting geo-social correlations to improve pairwise ranking for point-of-interest recommendation” published in China Communications, Volume: 15, Issue: 7, July 2018.
[3] Fei Yu, Zhijun Li, Shouxu Jiang and Shirong Lin, “Point-of-interest Recommendation for Location Promotion in Location-based Social Networks” IEEE 18th International Conference on Mobile Data Management, 2017.
[4] Uriwan Angkhawey and VeeraMuangs, “Detecting Points of Interest in a City from Taxi GPS with Adaptive DBSCAN”, Seventh ICT International Student Project Conference (ICT-ISPC) 2018.
[5] Justin J. Levandoski, Mohamed, Ahmed Eldawy and Mohamed F. Mokbel, “LARS: A Location-Aware Recommender System”, National Science Foundation under Grants IIS-0811998, IIS-0811935, CNS-0708604, IIS-0952, 2012.
[6] Chenyi Zhang and Ke Wang, “POI recommendation

through cross-region collaborative filtering", 13 February 2015Knowl InfSyst, 46:369–387, 2016.
[7] Vincent W. Zheng, Yu Zheng, Xing Xie and Qiang Yang, "Collaborative Location and Activity Recommendations with GPS History Data", In Proceedings of the 19th international conference on World wide web (WWW '10). ACM, New York, NY, USA, 1029-1038. May 2010.
[8] Y. Zheng, L. Zhang, X. Xie and W. Y. Ma, "Mining interesting locations and travel sequences from GPS trajectories", In Proceeding of the 18th International Conference on World Wide Web. ACM, 791-800, 2009.
[9] Yu Zheng and Xing Xie, "Learning Travel Recommendations from User-Generated GPS Traces, ACM Transactions on Intelligent Systems and Technology", Vol. 2, No. 1, Article 2, 2011.
[10] Chenyi Zhang, Ke Wang, Ee-peng Lim, et al, "Are Features Equally Representative? A Feature-Centric Recommendation", AAAI Conference on Artificial Intelligence, 2015.
[11] Bao J, Zheng Y and Mokbel MF, "Location-based and preference-aware recommendation using sparse geo-social networking data", In: GIS, pp 199–208, 2012.
[12] Konstan JA and Riedl J, "Recommender systems: from algorithms to user experience", User Model User-Adapt Interact, 22:101–23, 2012.
[13] Pan C and Li W, "Research paper recommendation with topic analysis", In Computer Design and Applications IEEE 2010;4, pp. V4-264
[14] Cheng C, Yang H, Lyu MR and King I, "Where you like to go next: successive point-of-interest recommendation", In: IJCAI, AAAI Press, pp 2605–2611, 2013.
[15] J.Cibia and D. VidyaBharathi, "Personalized POI Travel Recommendation from Social Media", International Journal of Emerging Technology and Advanced Engineering, Vol-6, Issue 2, 2016.
[16] Xuelian Long and James Joshi, "A HITS-based POI recommendation algorithm for Location-Based Social Networks", Published in: 2013 IEEE/ACM International Conference on Advances in Social Networks Analysis and Mining (ASONAM), 2013.
[17] G. Adomavicius and A. Tuzhilin, "Toward the Next Generation of Recommender Systems: A Survey of the State-of-the-Art and Possible Extensions," IEEE Transaction on Knowledge and Data Engineering, vol. 17, no. 6, pp. 734–749, 2005.
[18] L. Lü, M. Medo, HY. Chi, YC. Zhang and ZK. Zhang, "Recommender systems", Physics Reports, pp. 1-49, 2012.
[19] G. Linden, B. Smith and J. York, "Amazon.com Recommendations:itemto-item collaborative filtering", IEEE Internet Comuputer Society, pp. 76-80, 2003.
[20] B. Sarwar, G. Karypis, J. Konstan and J. Riedl, "Analysis of Recommendation Algorithms for E-Commerce", In: Proceedings of the 2nd ACM Conference on Electronic Commerce, pp. 158- 167, 2000.
[21] Y. Zheng, X. Xie, and W.Y. Ma, "Geolife: A collaborative social networking service among user, location and trajectory", IEEE Data Engineering Bulletin, 33(2):32–40, 2010.
[22] Ammar Jabakji and Hasan Dag, "Improving item-based recommendation accuracy with user's preferences on Apache Mahout", IEEE International Conference on Big Data, 2016.
[23] Kunhui Lin, Jingjin Wang, Zhongnan ,Yating Chen and Zhentuan Xu, "Adaptive Location Recommendation Algorithm Based on Location-Based Social Networks", The 10th International Conference on Computer Science & Education (ICCSE 2015),July 22-24, 2015.
[24] S. Ali, S. Khusro, A. Rauf and S. Mahfooz, "Sensors and Mobile Phones: Evolution and State-of-the-Art", In Pakistan journal of science 66(4):386-400, December 2014.
[25] Yu Zheng and Xing Xie, "Travel Recommendations from User-Generated GPS Traces", ACM Transactions on Intelligent Systems and Technology, Vol. 2, No. 1, Article 2, Pub. date: January 2011.
[26] https://www.microsoft.com/en-us/research/publication/geolife-gps-trajectory-dataset-user-guide/