ISSN(Online): 2320-9801
ISSN (Print): 2320-9798

International Journal of Innovative Research in Computer and Communication Engineering

(A High Impact Factor, Monthly, Peer Reviewed Journal)

Website: www.ijircce.com

Vol. 6, Issue 7, July 2018

Point of Interest Tourist Location and Hotel Recommendation System Based on Deep Learning Model

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ABSTRACT: POI (Point-of-interest) recommendation is a best method to provide more catching travelling locations and hotels. The recommendation system is useful to those peoples who want to travel out of town. User feedback is very important to recommend locations and hotels with different location areas, cultures and environment. For solving all issues in Location and Hotel recommendation we have proposed deep learning concept for multiple levels of representation and model spacial aware hierarchical collaborative deep learning algorithm. This algorithm togetherly perform deep representation study of point of interest from heterogeneous properties and hierarchically mixed information getting from spacial wise individual performance. All preferences of the users in a particular area and the individual preference of the candidate. For facing the multi-modal heterogeneous properties of the point of interests, we have proposed a late feature fusion strategy in a spacial wise hierarchical collaborative deep learning method.

KEYWORDS*:* Point Of Interest, Recommendation System, Deep Learning, Cold start, Data Sparsity, Sentiment analysis

I. INTRODUCTION

In location based social network each user will post current location in check in data on social network and share their location experience on it. By leveraging users check in information to achieve their point of interest in location based social network is used for helping users to explore new point of interests related to regions and hotels [5]. We developed a SHCDL model for facilitating tourist location and hotel recommendations. In personalized point of interest recommendation is more essentially helpful and important whenever people travel to unknown area. This scenario is good recommendation system for home city and out of home town peoples to easily using their check in information [1]. There are two things are challenging in this recommendation task:

A. User Data Sparsity

The more Point of interests visited by a single user is usually less than the total number of Point Of Interests in an Location Based Social Network, which gives very rare user-Point of interests. We have studied number of times persons checkin occurs in the current local area (for example, home town location). That's why the data shortage issue occurs in out of town Point Of Interests recommendation.

B. User Cold Start issue

In point of interest recommendation system cold start is very usual issue. The point of interests which not received any of the ratings from user are known as Cold Start point of interests. Also, peoples who have not rated any of the point of interests are known as Cold Start persons. Apart from new peoples, out of town peoples will face the same issue like Cold Start peoples.

To resolve cold start problem, we have used (DBN) Deep Belief Network for getting Point of Interest semantic representations from a bunch of large no. of features. To accomplish different types of Point Of Interest and study semantic representations of single Point Of Interests, we growing the conventional Deep Belief Network into the multimodal Deep Belief Network (MDBN) by proposing a late feature fusion strategy. At the end we have introduced a

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probabilistic model that is Spatial-Aware Hierarchical Collaborative Deep Learning (SHCDL), to together execute factorization of matrix and to automatically extract the Point Of Interests semantic representations. This SHCDL extract the Point Of Interests semantic representations to be given by each person's ratings.

II. RELATED SURVEY

J. Bao, Y. Zheng, and M. F. Mokbel have introduced a recommender system which is location based and preference aware and offers to individual user no. of locations between a geospatial area. It considers following two scenarios: 1) Users private preference, which automatically learned from their location histories and 2) Users opinions from socialized media which all mined from locations history of city travelling expert. They are also contains two models: Offline model and Online model for recommendation. The Offline model denotes every persons individual preferences with a Weighted Category Hierarchy (WCH) and inferred experts for every person in a city within distinct groups of location based on their location histories using an Iterative Learning models. The online recommendations make a selection of users local experts with user specified geospatial area that matches the users preferences using a preference aware users selection algorithms and at the end inferred totals of the user location on the basis of opinions by selected local experts.[1]

T. Chen, W. Zhang, Q. Lu, K. Chen, Z. Zheng, and Y. Yu. Svd feature introduced SVD Feature, it is a toolkit for machine used for feature based Collaborative Filtering(CF). SVD Feature is modeled to easily solve the feature based matrix factorizations. The feature based toolkit enables to model factorization scenarios by collecting all data like Temporal dynamic, neighbored relationships, and hierarchical data.[2]

P. Covington, J. Adams, and E. Sargin used a deep learning concept to provide the highly focused performance. They introduces two different stages to retrieve data: at first stage they contains a deeply user generation algorithm and in second they describes a another model for deep ranking.[3]

R. Das, M. Zaheer, and C. Dyer replaced LDAs parameterization model for category wise distribution over Opaque word types. They used Multivariate Gaussian Distributions which is extension of LDA to replace categoricalon the embe disovtr eworrd types ibutionsddi ng space. This is motivational to model the group words that are a prior knowning related topics semantically.[4]

G. Ference, M. Ye, and W.-C. Lee introduced location recommendation only for out of town persons by making use of user preferences, social influences and proximity within geographical area so named (UPS-CF) collaborative filtering to make location recommendation for mobile users in Location Based Social Networks. By comparing baseline algorithms, UPS-CF exhibits the best performance. They have introduced the problems in making location recommendations for out of town peoples by making use of user preferences, influences from social media and geographical proximity information.[5]

G. E. Hinton, S. Osindero, and Y.W. Teh accomplish a rapid, Greedy algorithm for deep learning used directed belief networks. Here one level at a time, provided the top two levels form an un-directed memory. The greedy algorithm is used to show slow learning process that makes tuning of weights. After fine tuning, designed three hidden layers to form a best generative model of joint distributions of digit images and their labels. This model of generative provides classification for digits.[6]

G. E. Hinton and R. R. Salakhutdinov presented algorithms to easily learn and infer the system. Monte Carlo based methods used in this system for log probability estimation. They have proposed Replicated Softmax model which is two layer graph based model and graphs are not directed. Here extraction of representations from large size are done by softmax model.[7]

D. Kim, C. Park, J. Oh, S. Lee, and H. Yu studied that the Latent Factors effective because of sparsed behavior of neighboured data. Such issues overcomed by authors by proposing effective latent representation with deep learning concept. They have proposed a novel context wise recommendation model and matrix factorizations convolutional model integrated by Convolutional Neural Network(CNN) into probabilistic matrix factorization. ConvMF catches context data from documents and improves the prediction of ratings by accuracy.[8]

S. Li, J. Kawale, and Y. Fu introduced a deep learning concept for collaborative filter which tightly coupled matrix factorization base collaborative filter in deep learning algorithm and Marginalized Denoising Autoencoders (MDA). Authors proposed architecture for Collaborative Filtering using integrated matrix factorizations along with learning of Deep Feature. They used large dataset to provide recommendation for booking of movie and prediction of user responses.[9]

X. Li, G. Cong, X.-L. Li, T.-A. N proposed factorization model, which is used for ranking, identified as Rank-GeoFM. This model used for Point Of Interests recommendations, considers frequency of check ins characterized by users visited preferences and taking factorization of ranked Point Of Interests exactly. Also the model efficiently assembles distinct types of data, like Temporal and Geographical influences. The developed methods are done with settings of user Point Of Interests and user time Point Of Interests on the Dataset.[10]

III. SYSTEM OVERVIEW

In this proposed system, the main purpose is to provide highly qualified recommendation system for both home town peoples and out of town peoples according to their Place of Interests. In recommendation system we used deep learning model that have been demonstrated great possibility for getting accurate representation and to deliver a good performances in recent recommendations and developed a spacial aware hierarchical collaborative deep learning algorithm. In this model collectively perform deep representation learning for point of interest from heterogeneous feature and hierarchical additive information learning from special aware individual performance. All preferences of the users in a particular area and the individual preference of the candidate in neighboring areas are applied in the form of social regularization and spatial smoothing. For facing the multimodal heterogeneous properties of the point of interests, we have proposed a late feature fusion strategy in a special wise hierarchical collaborative deep learning method. We have maintained a database of users sentiment based keywords which contains positive or negative weight in DB and then mining in user reviews are ranked. After the users lo-gin to the system they can search locations and system provides recommendations for different places and hotels. System would use DB and encounter the review with the keyword in DB and ranked the reviews. Based on the rank of reviews this system recommends hotels. System is developed for those who wants to visit new places and also useful for those who travel out of town. By using such systems, users will getting which hotel is best and suitable for them. User can decide which hotels to accommodate before they reach the city.

A. System Architecture

System Architecture introduces, peoples can post their current places on LBSNs in the form of check-in and introduces personal travelling experiences. There are multiple users post their locations so architecture contains number of users and location in list. Leveraging persons rating information to find out physical Point Of Interests recommendations in location based social network is difficult to helping peoples for exploring up to date Point Of Interests and areas. In this system we have uploaded Foursquare dataset. We applied spatial-aware hierarchical collaborative deep learning algorithm on review rating of location history, visited POI, and check-ins. This recommendation system togetherly make deep representations study of point of interest from heterogeneous properties and hierarchically mixed information getting from spacial wise individual preferences. By using location based review and rating record this system will generate user POI recommendation.

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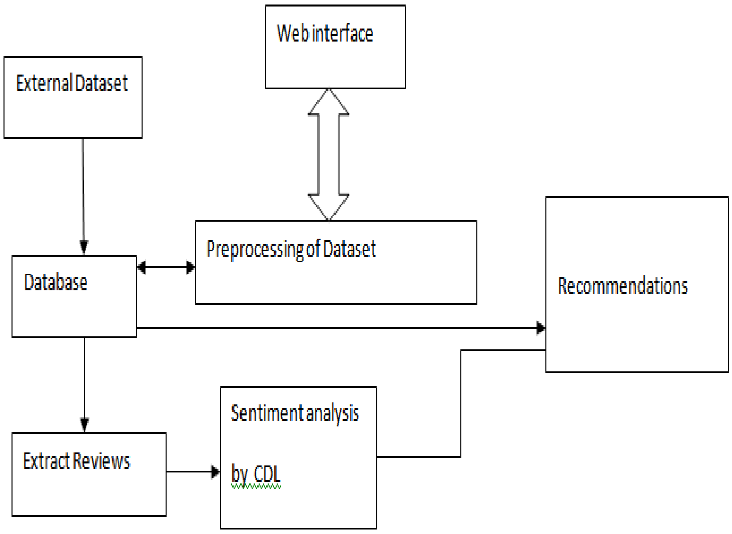

PROPOSED ARCHITECTURE

IV. PROPOSED ALGORITHM

A. SH-CDL Algorithm

Step 1) Input query is q, q = (uq; rq; sq)
Where, uq =user query,
rq =targeted region,
sq=user role.

Step 2) Compute the ranking score of every unvisited POI v in region rq

$$S(q, v) = g(P^T_{uq,rq} qv)$$

then select the top-k POI with highest ranking scores as recommendation.

Step 3) A latent factor vector qv is approximately hidden property vector

$$DBN(Xv, \psi)$$

so the rank scores of the cold start POI can be calculated as:

$$S(q, v) = g(P^T_{uq,rq} DBN(Xv, \psi))$$

Step 4) For new user, SHCDL contains accurate recommendation according to collective preferences of the crowd with same role Sq at target region rq as follow:

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$$S(q, v) = g(\Theta^T_{sq,rq} qv)$$

A. EXPERIMENTAL RESULTS

I have studied the effect of the spatial pyramids height and the parameters of regularization's for personal preferences of users on the Foursquare dataset. Foursquare dataset size is 190mb. Foursquare dataset contains 34,552 POIs and 72,346 check-ins generated by 41,450 users. Each check-in is stored as user-ID, POI-ID, time-stamp.

height	Out-of-Town Scenario		Home-Town Scenario	
	Ac@1	Ac@10	Ac@1	Ac@10
1	0.078	0.142	0.144	0.252
2	0.082	0.161	0.146	0.256

Table1: Impact of spatial pyramid Height

We tested the performance of the SHCDL algorithm by checking the height of spatial pyramids from 1 to 2. The result analysis are introduced in table 1. If height pyramid setting to 1, then it contains that there is no partitions in space, and model of SHCDL degraded where private choices are considered as constant. The result analysis concluded that the accuracy of recommendation system from SHCDL model once increases with increasing height and then going to certainly decrease, even as the height is exceeding than 1. Another conclusion for the rapidly increasing is that increase the height, increases the development of spatial dynamics of private choices and made the area aware private preferences more large.

λu	Out-of-Town Scenario		Home-Town Scenario	
	Ac@1	Ac@10	Ac@1	Ac@10
0.01	0.092	0.166	0.150	0.263
1	0.097	0.170	0.155	0.272

Table2: Impact of Regularization parameter

λu is intrinsic hyper parameter in SHCDL. The greater the λu more allied to the individual preferences $\rho\mu$; r. The corporate choices of the crowde with the similar task θs, r and the much stronger $\rho\mu$, r are regularized. When value of λu contains small in size, then SHCDL will once again generated to SHCDL thats why corporate choices are not developed. For getting effect, we tested the performance of SHCDL model by varying the value of λu from 0.01 to 1, result analysis mentioned in table 3. By the results, we have concluded that the recommendations accuracy of SHCDL first increases with the increasing λu and after that going to decrease.

We first select Point Of Interests less than 12 check ins as cold start Point Of interests, and after that choosed persons with at least 1 cold start check ins as test users. For every test user, we first select their check ins associating with cold start Point Of Interests as the set for test, and the other check ins as the set for training. Here we completed task for measures whether the marked off cold start Point Of Interests in the test set can be correctly recommended to the appropriate persons in the Top-k result.

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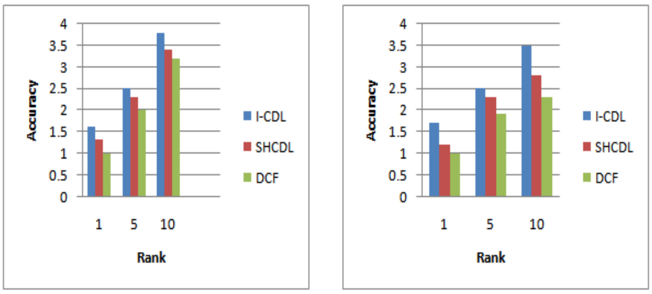
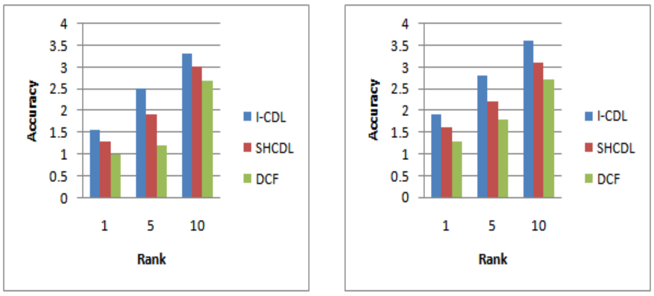


a) Out of town Recommendation b) Home town Recommendation

Fig2) Top-N performance on Hotel dataset



a) Out of town Recommendation b) Home town Recommendation

Fig3) Top-N performance on Location dataset

V. CONCLUSION

We have developed a Point Of Interest Tourist location and Hotel recommendation model which togetherly perform a deep learning for Point Of Interests by using users rating and review information. The proposed system successfully recommends the top 5 recommendations for every user. Ranking matrix factorization has given us the best results for our dataset as compare to other algorithms. From old users rating and review information system represent data from heterogeneous features to defeat the problems with cold start users and data shortage problem for recommendation.

Limitation to this recommendation system is high speed internet required to run the system.

In future work we can add offline recommendation module to this system. Also multi-criteria rating system will use in this recommender engine to better learn users' preferences.

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