ISSN: 2321-8169
1364 – 1369

Service Recommendation System using Social User's Rating Behaviors

Atul K. Jamnekar
3rd sem, M.E. Department of CSE
PRPCEM, Amravati

Prof. P. B. Sambhare
Asst. Prof. , Department of CSE
PRPCEM, Amravati

Prof. P. D. Soni
Asst. Prof. , Department of CSE
PRPCEM, Amravati

Abstract: The research communities of information retrieval, machine learning and data mining are recently started to paying attention towards Service recommendation systems. Traditional service recommendation algorithms are often based on batch machine learning methods which are having certain critical limitations, e.g., mostly systems are so costly also new user needs to pay the certain cost for new login, can't capture the changes of user preferences over time. So that to overcome from that problem it is important to make service recommendation system more flexible for real world online applications where data arrives sequentially and user preferences may change randomly and dynamically. This system present a new website of online social recommendation on the basis of online graph regularized user preference learning (OGRPL), which incorporates both collaborative user-services relationship as well as service content features into an unified preference learning process. Also provide aggregated services in only one application (social networking) which increases user's interest towards the services. This system also provides security about subscribed services as well as documents/photos on online social network application. This system will utilizes services like Education, adventure, Home Services, Hotels & Travel, Restaurants and Shopping.

Keywords: *Online social recommendation, user preference learning, low rank.*

*****

1. INTRODUCTION

With the increasing popularity of social media, social recommendation has attracted a lot of attention recently in the research communities of information retrieval [1], machine learning [2] and data mining [3], due to the potential value of social relations [4], [5], [6]. We have witnessed the many popular commercial social recommender systems such as Douban [6] and Epinions [7]. A variety of social recommendation models are proposed, which can be generally grouped in two categories: matrix factorization based methods and probabilistic model based methods. The methods of both categories are trained from the partially observed user-service matrix and users' social relations. The matrix factorization based approaches [8], [9], [10] factorize the partially observed user-service matrix into two latent low-rank matrices with the regularization of users social relations, and then fill the missing data entries by spanning two low-rank matrices. On the other hand, the probabilistic model based approaches [11], [12], [13] infer the probabilistic model from the partially observed user-service matrix and then predict the missing entries based on the probabilistic model. Despite the extensive studies of social recommendation systems [8], [10], [11], [12], [13], most traditional social recommendation algorithms are based on batch training techniques which assume all user ratings are provided in the user-service matrix. Such assumption makes them unsuitable for real-world online recommendation applications. First, the user ratings arrive sequentially in an online application. Moreover, if the size of training data is too large, it is difficult for handling all the data. Second, it is common that user preference could drift over time in real-world online application, which makes the batch learning processes fail to capture such changes on time.

1.1 Motivation

In this era, as the humans are being social and spend most of their time on social sites, they always try to find places, products, services online. But users always wants a things in easy way, like if user wants information regarding any place, product or service they can get it by visiting lots of web sites. But this process takes lots of time.

By considering this, the system will help the user to find the service and also recommends services on the basis of their friend and friend of friend's comments as well as rating. Analyzing this rating and comments and the user preferences this system will recommend the various services to the new as well as old users as per there point of interest.

1.2 Objective

1. To develop a secure web application in which we automatically find User-Service Rating and recommend services accordingly
2. To develop reports based on decision support system to increase performance of the service.
3. To provide aggregated services in only one application(social networking) which increases user's interest towards the services
4. To maintain security about subscribed services as well as documents/photos on online social network application.

ISSN: 2321-8169
1364 – 1369

1.3 Scope

Exponential growth of information on the web is the result of growing trend of pervasive computing of "information anywhere, anytime". There are zillions of different items/services available; users cannot be expected to browse through all of them to find what they might like,

As Humans are prone to make rating errors and the rating data always contain noise in practice. Thus, the direct learning of user preference may be over-fitting and is therefore not robust. Users mostly trust their friends so using social relation and their friends ratings will be more trust worthy for recommendation.

2. LITURATURE SERVEY

2.1. Social Recommendation

The social recommendation models are trained from the partially observed user-service matrix and users' social relations. Gao et. al. [8] study the point of interest recommendation based on the content information from the location-based social networks. Qian et. al. [11] incorporates the CircleCon model with probabilistic matrix factorization method for social recommendation. Wang et. al. [14] design a joint social content recommendation framework to suggest users which video to import or re-share in the online social network. Jiang et. al. [12] present the social contextual information based probabilistic matrix factorization for recommendation. Qiao et. al. [15] study the event recommendation by combining both online and offline social networks. Luo et. al. [16] advise the social-based collaborative filtering recommendation using users' heterogeneous relations. Lu et. al. [17] models the dynamic user interest evolving effect and suggestions made by the recommender instigate an interest cascade over the users. Ding et. al. [6] study the celebrity recommendation based on collaborative social topic regression. Wang et. al. [13] presents the tag recommendation based on social regularized collaborative topic regression. Tang et. al. [10] proposes the global and local regularization for social recommendation. Gao et. al. [9] studies the location recommendation on location-based social networks with temporal constraints. Liu et. al. [18] proposes point of interest recommendation system with topic and location awareness in social networks. Zhang et. al. [19] presents the domain specific recommendation system TopRec, which mines community topic in social networks. Hu et. al. [14] proposes a framework MR3 to jointly model ratings, item reviews and social graph for rating prediction. Wang et. al. [20] studies the news recommendation in social media. Zhou et. al. [21] studies the user recommendation in social tagging systems based on users' personal interests.

2.2 Existing System

In the task of online recommendation, the number of user ratings collected at each timestamp is much smaller than the ratings in the offline recommendation, which means all the items have to be recommended in a cold-start manner. Currently, social networking and knowledge sharing sites like Twitter and Douban are popular platforms for users to generate shared opinions for the items like item review and summary [14]. Thus, the user generated content provides the auxiliary information for the items, which has been widely used to tackle the problem of cold-start item [9]. Unlike the existing online collaborative filtering methods [11], OGRPL is a hybrid model utilizing both CF information via the partially observed user service matrix as well as the auxiliary content features for each service. Given a stream of user ratings, OGRPL incrementally learns the user preference on the content features of the items. However, humans are prone to make rating errors and the rating data always contain noise in practice. Thus, the direct learning of user preference may be over fitting and is therefore not robust.

2.3 Limitations of Existing System

1. There is no secure web application in which we automatically find User-Service Rating and recommend services accordingly
2. Existing System does not have any Decision support system to increase the performance of the system as well as to find out user's requirements

3. IMPLEMENTED SYSTEM

3.1 System Flow Chart

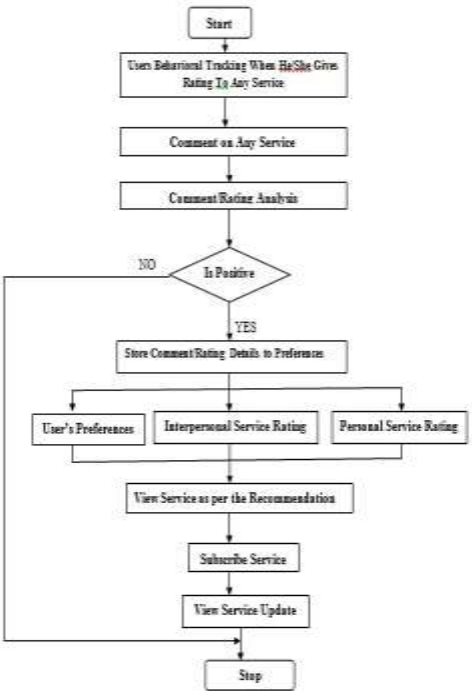

Fig. 1 System Flow chart

 ISSN: 2321-8169
1364 – 1369

1. At first the user will register himself on the website, the system will recommend the various services on the basis of the users profile and also on the basis of his/her social relationship. If no matching profile will be found then the system will recommend the most popular services to the user.

2. After using any service by user he/she will rate/comment to the service about the experience. If the comment and rating is positive/negative it will be store to the database.

3. The user rating will be stored in three matrix like user's preferences, interpersonal rating, personal service rating.

4. System will recommend the user various services on the basis of his profile as well as his/her social relationship.

5. Then the user will subscribe for the particular service user will be able to see new updates and also users rating and comments will stored to the database for preference learning.

6. User can also manages permission to view his/her post that who can see the post and who cannot, also upload articles ,images, documents etc.

3.2 DFD (data flow diagram)

Admin panel DFD

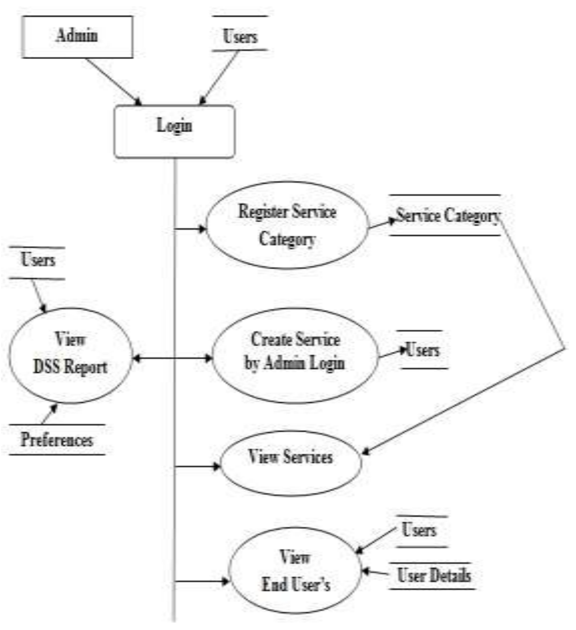

Fig 2 Admin Panel DFD

Admin panel can allows admin to register service categories, create service admin login, View service administrator details and View end user details log. The figure 2 shows admin panel DFD which shows that firstly admin has to log in on to our website then System will checks the details of the user with the users details available in the database. After login admin can add new service category which will be stored in the database, admin can create a new service admin login, also view the list of services available, and users details.

If the user login with the service admin the service admin can register category wise services, Edit service details, Upload service related ads and offers, Upload service related articles. Which are visible to the all users.

User Panel DFD

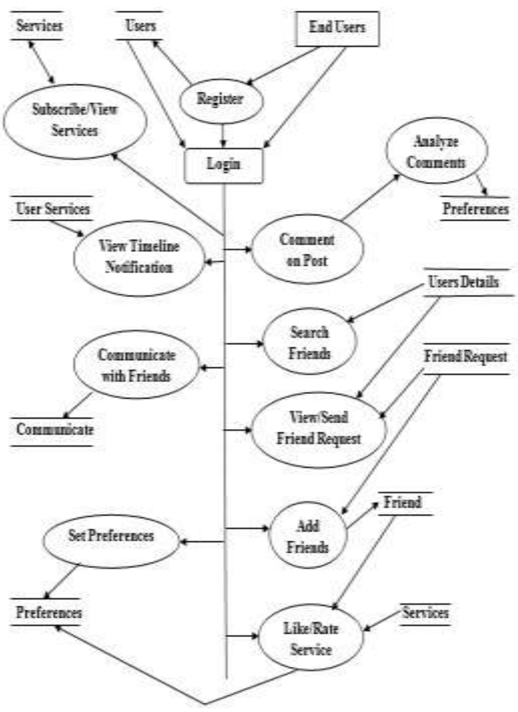

Fig 3 User Panel DFD

Figure 3 shows User DFD user can do the Registration, Change password, Password recovery, Upload articles, images, Set security settings, View friend uploads as per access permission, edit profile. Also user can Search friend, Send friend request, View friend requests, Add friend , View friends , Like/rate services, View notifications on timeline, Like/rate friend's subscribed services, Communicate with friends, Comment on any post.

3.2 Modules

Admin Panel:

System's admin panel can allows admin to register service categories, create service admin login, View service administrator details, add comment keys and View end user details log.

ISSN: 2321-8169
1364 – 1369

Social activities:

Social activity module allows user to Search friend, Send friend request, View friend requests, Add friend , View friends , Like/rate services, View notifications on timeline, Like/rate friend's subscribed services, Communicate with friends, Comment on any post.

User management:

User management module allows user for Registration, Change password, Password recovery, Upload articles, images, Set security settings; View friend uploads as per access permission, edit profile.

Services Management:

Service management module provides facilities like Register category wise services, Edit service details, Upload service related ads and offers, and Upload service related articles.

User-Service Rating Prediction

User-Service Rating Prediction module allows to Track users behavior when user rate any service/ comment on any service**,** When user comment on any service, system will automatically analyze the comments and find out whether the comment is positive/negative**,** Depending on comments and ratings, user's preferred services will be predicted automatically**,** User can view current updates of preferred services and User can set his preferences any time.

Interpersonal rating prediction

Interpersonal rating prediction provides facilities for new users whose preferences are not available, system will consider preferences of other users with similar profile as that of logged in user**,** System will suggest services related to other user's preferences for new users and If users with similar profile are not available, system will suggest most popular services as well as profile wise services.

DSS (Decision Support System)

DSS System will develop graphical and textual reports on the basis of user rating, profile & requirements.DSS reports will help admin and service admin to improve service performance

4. RESULT ANALYSIS

This section show the performance analysis of the system and the result gathered. While comparing with existing system which uses only ratings given by the users and recommend the service accordingly, the proposed system uses the users rating and positive comments by combining them the system generates results and recommend the service accordingly. During the analysis phase of this research, three techniques were analyzed, finding direct trust between user for recommendation, finding preferences on the basis of ratings, positive comments, negative comments given by the users to the service, number of users rated to the service. All these parameters are analyzed for recommendation.

Service	Shopping
Positive Comments	2
Negative Comments	0
Ratings	3
People Rated	16

Table 1 Parameter Analysis

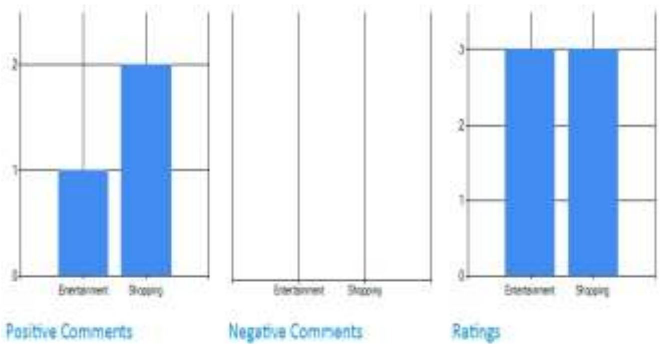

Fig 4 Graph showing positive comments, negative comments and rating given by the users to the service

Rating	Number of users
Rated 1	1
Rated 2	2
Rated 2	2
Rated 4	7
Rated 5	4

Table 2 Ratings given by number of users to the service

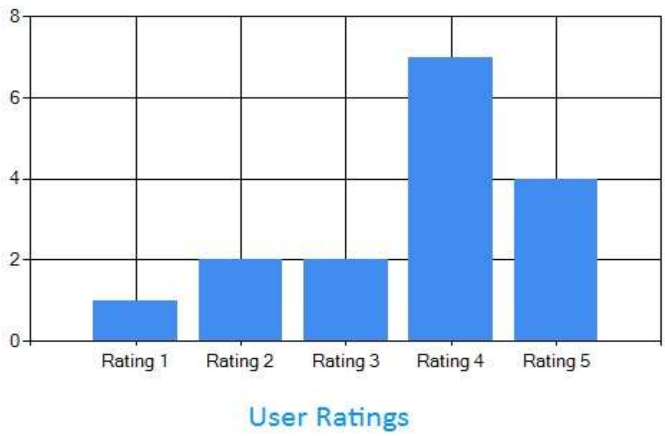

Fig 5 Graph showing ratings given by number of users

 ISSN: 2321-8169
1364 – 1369

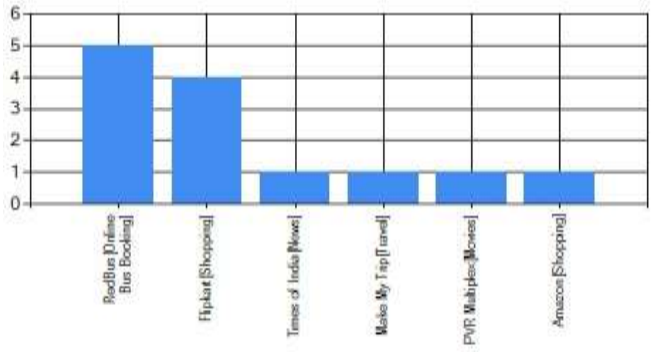

Fig 6 Graph showing recommendation using ratings only

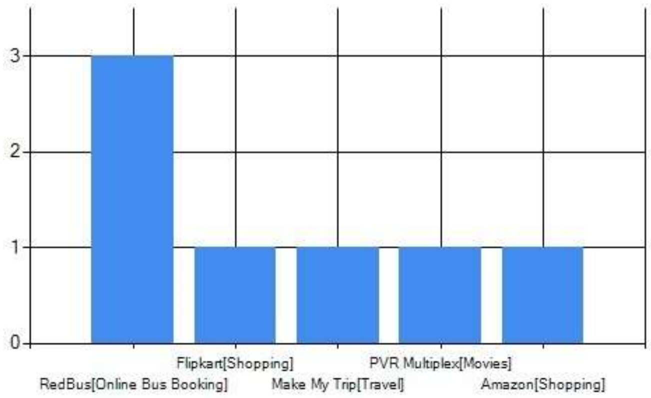

Fig 7 Graph showing recommendation using ratings and positive comments

The above table and graph shows the recommendation by existing system using only ratings and implemented system using ratings and comments. Existing system recommendation is done by ratings only as shown in graph (figure 6) of existing system, where one service (Flipkart) is having second highest rating but less positive comments. Newly developed uses the user rating and positive comments for recommendation figure 7 shows recommendation graph of newly developed system which uses users ratings and user's positive comments given by users to the service which gives more accuracy in recommendation.

3 CONCLUSIONS AND FUTURE SCOPE

This work presented a new approach of online service recommendation from the view point of online user preference learning, by using user's social relations and rating given by them for services, which incorporates both collaborative user-service relationship as well as service content features into a unified preference learning process.

In future the system will explore Non-linear user preference learning function as the user model for the problem of online social recommendation. Also use the implicit user information for recommendation.

REFERENCES

[1] X. Yang, H. Steck, and Y. Liu. "Circle-based recommendation in online social networks". In Proceedings of the *18th ACM SIGKDD international conference on Knowledge discovery and data mining*, pages 1267–1275. ACM, 2012.

[2] J. Zhu, H. Ma, C. Chen, and J. Bu. "Social recommendation using lowrank semidefinite program". In *AAAI*, pages 158–163, 2011.

[3] X. Qian, H. Feng, G. Zhao, and T. Mei. "Personalized recommendation combining user interest and social circle". Knowledge and Data Engineering", *IEEE Transactions on*, 26(7):1763–1777, 2014.

[4] J. Tang, J. Tang, and H. Liu. "Recommendation in social media: recent advances and new frontiers". In Proceedings of the *20th ACM SIGKDD international conference on Knowledge discovery and data mining*, pages 1977–1977. ACM, 2014.

[5] M. Ester. "Recommendation in social networks". In *RecSys*, pages 491– 492, 2013.

[6] H. Ma. "An experimental study on implicit social recommendation". In Proceedings of the *36th international ACM SIGIR conference on Research and development in information retrieval*, pages 73–82. ACM, 2013.

[7] H. Ma, D. Zhou, C. Liu, M. R. Lyu, and I. King. "Recommender systems with social regularization". In Proceedings of the *fourth ACM international conference on Web search and data mining*, pages 287– 296. ACM, 2011.

[8] H. Gao, J. Tang, X. Hu, and H. Liu. "Content-aware point of interest recommendation on location-based social networks". In *AAAI*, 2015.

[9] H. Gao, J. Tang, X. Hu, and H. Liu. "Exploring temporal effects for location recommendation on location-based social networks". In Proceedings of the *7th ACM conference on Recommender systems*, pages 93–100. ACM, 2013.

[10] J. Tang, X. Hu, H. Gao, and H. Liu. "Exploiting local and global social context for recommendation". In Proceedings of the"*Twenty-Third international joint conference on Artificial Intelligence"*, pages 2712– 2718. AAAI Press, 2013.

[11] M. Blondel, Y. Kubo, and U. Naonori. "Online passive-aggressive algorithms for non-negative matrix factorization and completion". In Proceedings of the *Seventeenth International Conference on Artificial Intelligence and Statistics*, pages 96–104, 2014.

[12] M. Jiang, P. Cui, F. Wang, W. Zhu, and S. Yang. "Scalable recommendation with social contextual information. Knowledge and Data Engineering", *IEEE Transactions on*, 26(11):2789–2802, 2014.

[13] H. Wang, B. Chen, and W.-J. Li. "Collaborative topic regression with social regularization for tag recommendation". In Proceedings of the*Twenty-Third international joint conference on Artificial Intelligence*, pages 2719–2725. AAAI Press, 2013.

[14] Z. Wang, L. Sun, W. Zhu, S. Yang, H. Li, and D. Wu. "Joint social and content recommendation for user-

ISSN: 2321-8169
1364 – 1369

generated videos in online social network". Multimedia, *IEEE Transactions on*, 15(3):698–709, 2013.

[15] Z. Qiao, P. Zhang, Y. Cao, C. Zhou, L. Guo, and B. Fang. "Combining heterogenous social and geographical information for event recommendation". In *Twenty-Eighth AAAI Conference on Artificial Intelligence*, 2014.

[16] C. Luo, W. Pang, and Z. Wang. Hete-cf: "Social-based collaborative filtering recommendation using heterogeneous relations". *arXiv preprint arXiv*:1412.7610, 2014.

[17] W. Lu, S. Ioannidis, S. Bhagat, and L. V. Lakshmanan. "Optimal recommendations under attraction, aversion, and social influence". In Proceedings of the *20th ACM SIGKDD international conference on Knowledge discovery and data mining*, pages 811–820. ACM, 2014.

[18] B.LiuandH.Xiong. "Point-of-interestrecommendationinlocationbased social networks with topic and location awareness". In *SDM, volume 13*, pages 396–404, 2013.

[19] X. Zhang, J. Cheng, T. Yuan, B. Niu, and H. Lu. "Toprec: domain-specific recommendation through community topic mining in social network". In Proceedings of the *22nd international conference on World Wide Web*, pages 1501–1510. International World Wide Web Conferences Steering Committee, 2013.

[20] J. Wang, Q. Li, Y. P. Chen, J. Liu, C. Zhang, and Z. Lin. "News recommendation in forum-based social media". In *AAAI*, 2010.

[21] T. C. Zhou, H. Ma, M. R. Lyu, and I. King. "Userrec: A user recommendation framework in social tagging systems". In *A AI*, 2010.