Trustworthy Social Circle Influenced Location Aware User Centric Recommendation System

Mr. Vishal Jayprakash Kadam[1], Mr. V. S. Gaikwad[2]

[1]PG Scholar, Department of Computer Engineering, JSPM NTC, RSSOER, Pune, MH, INDIA
[2]Asst. Professor, Department of Computer Engineering, JSPM NTC, RSSOER, Pune, MH, INDIA

---***---

Abstract- *Recommender system analyzes available data to make suggestions for user's interest centric decision making. Rapid growth of information generated by online social networks leads to increase in demand of efficient and effective recommender systems to give improved results. Traditional recommendation techniques are limited because they do not consider factors of social relation in the social network for giving recommendation. In this paper, we have fused parameters of social network like personal interest, interpersonal interest similarities and interpersonal influence along with user's location data to build unified personalized recommendation system. The factor of interpersonal influence has been granulized into various levels of trust propagation combined with coefficient of bias and rating magnification to derive cumulative percentile rating which will make final ratings inclined towards rating given by people in inner circle of trust. Interpersonal interest similarity patterns are recognized by applying data stemming technique like LDA on web searches by users to build lifestyle index which is transformed to develop friendship suggestions indirectly helping to solve cold start problem. We also tested ratings calculated by our algorithm for various scenarios by rating simulator.*

Key Words- **Social Circle, Interpersonal Interest Similarity, Interpersonal Influence, Location-aware Search, Recommender System**

1. INTRODUCTION

Recommendation system has been successfully used to solve information clog problem overwhelmingly. Social networks are dealing with huge scale of information by recommending user interested items. RS has variety of applications such as movies, new social tags, music, research articles, etc. as per the user input and distinct attribute items can be recommended, which is closely related to user interest. Surveil shows that more than 25% of sales generated through recommendation. Over 90% peoples believe that products recommended by friend are useful [1] and 50% people buy the recommended products or items of their interest. Google+ introduced "Friends Circle" to filter the contacts according to different activities and strategies [2], which helps users to be closer to their friends. In a magnanimous web space, recommendation systems helps to find items of user interest [7]. Content based filtering and Collaborative filtering are widely used methodologies for recommendation [3]. Cold start problem seem to be a serious problem for data mining works. Even though we have many algorithms to work on Data Mining, cold start has make users to step back in analyzing the functionality of those algorithms lead to slight decrease in creativity and optimizations in data mining algorithms[4][5]. Cold start can be defined as unavailability of data for modelling algorithms [7]. Web is often dynamic, so it very difficult to predict the user interested items in time [13].

Personalized RS comprises factors such as interpersonal interest, person's interest and interpersonal influence [1]. Personalized RS is assistive to recommend the items on social networks with the goal that recommended items should base on their historical behavior and interpersonal relationship of social networks. The popular online social networks provide additive information to enhance pure rating-based RS [2]. Recommendation in conventional system focusing on couplet of (buyer, item) whereas social recommendation focusing on triplet (seller, buyer, item) which enhances the more appropriate items of user interest [10]. The caliber of the recommendation can be attained with the assistance of user interpersonal interest in social network. Numerous social-trust based RS have lately been proposed to improve recommendation precision. The interpersonal relationship among friend's circle in social networks and social contexts assists to solve cold start and sparsity problem.

In this paper, user-item locations information along with three versatile social parameters, personal interest, interpersonal interest similarity, and interpersonal influence, consolidated into integrated personalized recommendation system based on probabilistic matrix factorization to recommend more personalized & real-time items.

2. RELATED WORK

For General Recommendation, most favorite methodologies are content based and item based filtering. Both of these systems are vulnerable to cold start and sparsity problem. To overrun these stumpers, personalized recommendation system uses the interpersonal interest, profile etc. to suggest user interested items. Peoples to a greater extent buy products recommended by their friends from social circle, so personalized recommendation systems helps to make decision. Some of the personalized recommendation system approaches are discussed as below;

Numerous existing approaches to collaborative filtering cannot handle very large datasets and never easily deal with users who have very few ratings. Ruslan Salakhutdinov and Andriy Mnih [5] present the Probabilistic Matrix Factorization (PMF) model which scales linearly with the number of observations and, more significantly, performs well on the large, sparse, and very imbalanced Netflix dataset. Further extension in the PMF model was to include an adaptive prior on the model parameters and show how the model capacity can be controlled automatically. Finally, they introduce a constrained version of the PMF model that is based on the postulates that users who have rated same sets of movies are promisingly to have similar preferences. The resulting model is able to extrapolate considerably better for users with little ratings. But this model does not take any social factors into consideration.

M. Jamali and M. Ester [4] introduced a SocialMF model-based approach for recommendation in social networks, employing matrix factorization techniques. Advancing previous work, incorporated the mechanism of trust propagation into the model. Trust level propagation has been showcasing to be a decisive phenomenon in the social sciences, in social network analysis and in trust-based recommendation. SocialMF achieves significantly reduced recommendation error (RMSE) in particular for cold start users.

Yang *et al*. [2] proposed CircleCon model which use the concept of "inferred trust circle" based on the domain-obvious circles of friends on social networks to recommend user favorite items. Their approach not only fine-tune the interpersonal trust level in the complex networks, but also reduces the load of big data. The CircleCon model has been found to outperform BaseMF [5] and SocialMF [4] with respect to accuracy of the RS. The approach focuses on the parameter of interpersonal trust propagation in social network and deduces the trust circle.

M. Jiang et al. [3] introduced ContextMF model which demonstrate the significance of social contextual factors including interpersonal influence and individual preference for item adopting on real-time datasets. The task of ContextMF model is to recommend acceptable items from sender x to receiver y. Here, the parameter of interpersonal influence is same as to the trust values in CircleCon model [2]. In addition, individual preference is mined from receiver's historical adopted items.

Besides the interpersonal influence (similar to the trust values in CircleCon model, individual preference is a novel factor in ContextMF model. They still execute the interpersonal influence as CircleCon model and omit the topic relevance of items, as here also predict ratings of items in opinions style datasets and use the circle based idea in our experiments. Though individual predilection is proposed in this model, users latent feature is still connected with his/her friends rather than his/her characteristic. As a matter of fact, the parameter of individual preference of this model is obligated by interpersonal preference similarity.

X Qian, H Feng, G Zhao, T Mei [1] proposed unified personalized recommendation model based on probabilistic matrix factorization by rejuvenating three social network parameters; personal interest, interpersonal interest similarity, and interpersonal influence. The personality is signified by user-item pertinence of user interest to the topic of item. To embody the effect of user's personality, they mine the topic of item based on the natural item category tags of rating datasets. Thus, each item is referred by a categorized activity or topic distribution vector, which can reflect the characteristic of the rating datasets. Moreover, they get user interest based on his/her rating behavior. They then assign to the effect of user's personality in personalized recommendation model proportional to their expertise levels. From another point of view, the user-user relationship among circle of social network contains two parameters: interpersonal influence and interpersonal interest similarity. They apply the inferred trust circle of Circle-based Recommendation (CircleCon) model [2] to enforce the factor of interpersonal influence. Similarly, for the interpersonal interest similarity, they infer interest circle to enhance the intrinsic link of user latent feature.

3. PROPOSED SYSTEM

3.1 System Overview

In proposed system, social network factors like personal interest, interpersonal interest similarity, and interpersonal influence along with user-item locations information which improves the accuracy and applicability of recommender system to recommend more personalized and real-time items.

The personal interest denotes user's individuality of rating items.

The interpersonal interest similarity infers the interest circle to enhance the intrinsic links between users latent feature.

The interpersonal relationship or influence denotes especially the circles of friends and the trust propagation among social networks makes it possible to solve the cold start and sparsity problem more efficiently.

To make recommendations more relevant and limit search result flooding we include location information which also serves purpose of tie barker in case ratings for two items are same.

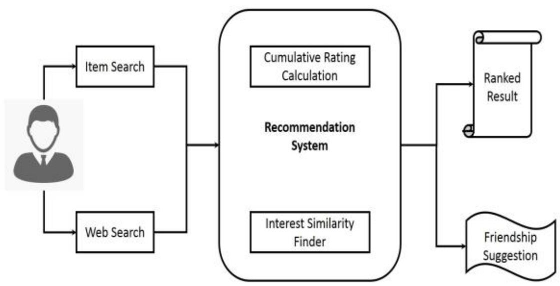


Fig -1: System Architecture

3.2 Implementation

The Implementation of Proposed System has two main components viz. Cumulative rating and Friend suggestion mechanism.

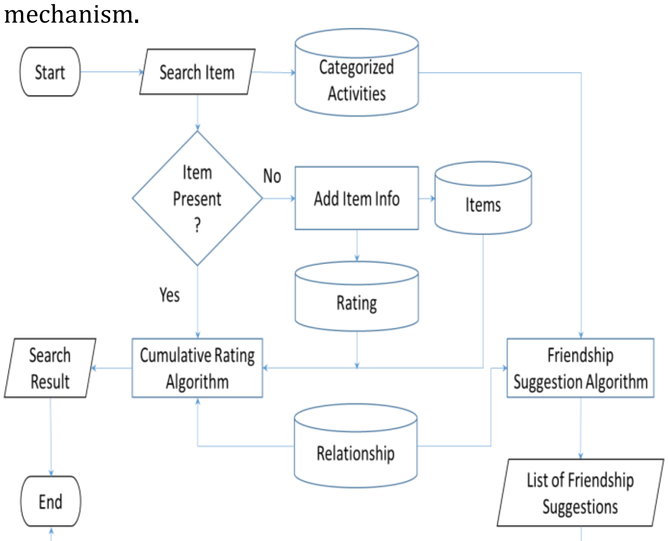


Fig -2: System Flow

Firstly, Cumulative rating calculation process makes use of set of item which has location details, relationship database and rating database to produce cumulative rating. We assign higher weight to rating given by people who are closer friends compared to people who are just acquaintances. This is achieved by using following coefficients in context of user searching an item. Coefficient of Bias (μ_b) indicates users in remaining trust circle type in the form of fractional value. Coefficient of Rating Magnification(μ_m) for a trust level is total number of users in system divided by number of users in that trust circle from current users point of view. This is imitation of real world scenario when a person ask for opinion of people he trusts more first then approaches other. When number of users in inner circle is less then value of (μ_b) and (μ_m) increases for inner circle which in turn increase cumulative rating. If there are large number of people in inner circle of trust then (μ_b) increases (μ_m) decreases for outer circle which achieves higher rating for inner circle

Second part is friend suggestion mechanism which records search activities of person apply data stemming techniques to find out keywords. Then uses LDA models to convert it in to categories and builds lifestyle index. We transform lifestyle index in to reverse life style index which gives list of people who have common interest. Using relationship database we have determine if people with common interest are friend are not, if not then we add them as friend suggestion.

3.3 Mathematical Model

System $S = \{U, L, R_R, R_S, \mu_b, \mu_m, D, C, A, LI, RI, Fs, I\}$ Where,

U = Set of users in system where $u \epsilon U$

L = Set of Location of an item in tuple form <latitude, longitude>

R_S = Items rating set on scale of 1(UK) to 5(CF)

R_R = Relation matrix showing directed relationship between users

$R_{R'} \subseteq R_R \ \forall \ R_R^{uj} \{R_R^{uj} \in R_R$ |Relation in user's u & j is CF $\vee$ F $\vee$ CCF$\}$

$\mu_b = (1 - |R_{R'}| / |U|)$ where μ_b is Coefficient of Bias

$\mu_m = |U| / |R_{R'}|$ where μ_m is Coefficient of Rating Magnification

D = Set of data points <item i, rating r, distance l>

$C = \{c_1, c_2 \ldots c_n\}$ - Set of interest category

$A = \{a_1, a_2 \ldots a_n\}$ - Set of activities

$LI = \{\langle u_1, c_1\rangle \ldots \langle u_i, c_j\rangle \ldots \langle u_m, c_n\rangle\}$

$RI = \{\langle c_1, u_1\rangle \ldots \langle c_j, u_i\rangle \ldots \langle c_n, u_m\rangle\}$

F_s = Set of friendship suggestion $\langle u_i, u_j\rangle$ (suggesting u_j as friend to u_i)

I = Set of Items that can be inquired

R_S^{ij} = Rating score given for i^{th} item by user j

R_R^{uj} = Level of relationship between user's j & u from perspective of u
R_S^{iju} =Rating score for i^{th} item calculated from rating by user j for u

$$R_S^{iju} = \begin{cases} R_R^{uj} * R_S^{ij} * \mu_b * \mu_m \text{ ; If } u_j (R_R^{uj}) = CF \mid F \mid CCF \\ R_R^{uj} * R_S^{ij} \text{ ; Else} \end{cases}$$

3.4 Algorithms

The algorithm of cumulative rating by utilizing the real-time location of the user and the item to be searched, ratings provided by other users and by considering the interpersonal influence or level of trust among users gives the result set of searched items within user specified radius which enhance the real-time personalized recommendation.

Algorithm of Cumulative Rating

Input: u ϵ U, <lat_u, lon_u> ϵ L, d< i, r, l> ϵ D, R_R, R_S, search radius rad

Output: d' (list of top 'k' search results)

Initialize d< i, r, l>

For each item i
  l = Sin (lat_u) * Sin (lat_i) + Cos (lat_u) * Cos (lat_i) * Cos (lon_u – lon_i)
  l = l * 180 / π
  Add l to tuple Set D
Next item i

Merge Sort (D) based on distance
$r_{ti} = 0$;

For each data d_i ϵ D ∧ l ≤ rad
    If $u_j (R_R^{uj}) \in R_R$
        If $u_j (R_R^{uj}) = CF \vee F \vee CCF$
            $R_S^{iju} = R_R^{uj} * R_S^{ij} * \mu_b * \mu_m$
        Else
            $R_S^{iju} = R_R^{uj} * R_S^{ij}$
        End if
        $r_{ti} = r_{ti} + R_S^{iju}$;
    Else if
        $r_{ti} = r_{ti} + 1 * R_S^{ij}$;
    End if
    Add r_{ti} to tuple d for item i
Next tuple d

Merge Sort (D) based on ratings
d' = k list (D);
Return d';

In the Algorithm for Friend Suggestion, we utilize users Lifestyle Index LI and Reverse lifestyle Index RI. This is done by using LDA model which help stemming of user search terms to find out user interest categories and build life style index for user. Then it transform this life style index into reverse life style index which provides list of peoples with common interests. This list is used to provide new friend suggestions when users with similar interest are not in each other's friend list.

Algorithm for Friendship Suggestion

Input = U, C, R_R, List of user activities for each user in tuple form <u_i, a_j>

Output = F_s
Initialize list L with all user activities <u_i, a_j>
For each user u ∈ U
  For each activity a_i ∈ A
    Apply data stemming method to map activity a_i to category c_j
    If <u_i, c_j> ∉ LI
        Add <u_i, c_j> to LI
    End if
  Next activity a_i
Next user u

Transpose LI to RI
For each user u_i ∈ U
  For each c_j ∈ C
    For each u_j ∈ U
      If <c_k, u_i> = <c_k, u_j> and <u_i, u_j> ∉ R_R
        Add <u_i, u_j> to F_s
      End if
    Next user
  Next category
Next user
Return F_s;

4. Experiments & Result Discussion

In our system, we have considered rating on scale of 1 to 5 and social circles of 5 types. Based on different ratings given by number of people, numerous combinations of cumulative rating scores are possible. Here we have chosen 7 scenarios to rate different hotels that represent possibilities of user breakup across user categories

Total User	100	Lay Bhari	Abhi-ruchi	Durv-ankur	Vaish-ali	Suk-anta
CF	1	1	2	3	4	5
F	3	1	2	3	4	5
CCF	5	1	2	3	4	5
ACQ	44	5	4	5	3	1
UK	46	5	5	4	5	1
	Final CR	9.41%	14.71 %	20.00 %	25.29 %	30.59 %

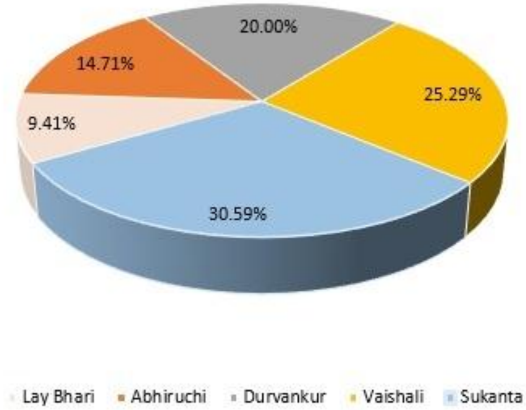
Table -1: Conditional Scenarios

described in table below. For analysis, we have considered system consist of 100 users.

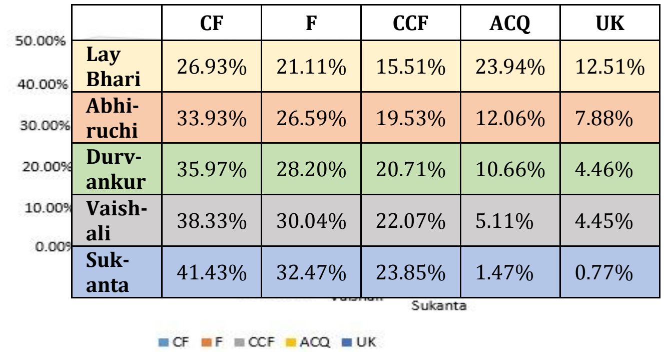
Scenario	Description
UK only	When user registers himself and he has not added any one to his friend list. At this point of time all other users in system are unknown (UK) to him. Here we provide him recommendation based on those unknown persons rating only. (CF=0, F=0, CCF=0,ACQ=0, UK=99)
Min CF	Here user has just added a close friend (CF) and all other users are still unknown to him. (CF=1, F=0, CCF=0,ACQ=0, UK=98)
CF+F	Few close friends and friends are added but there are no Close Friends of Friends (CCF) or Acquaintances (ACQ). (CF=5,F=20,CCF=0,ACQ=0,UK=74)
CF+CCF	Few close friends and Close Friends of Close Friends are added but there are no Friends (F) or Acquaintances (ACQ). (CF=5,F=0,CCF=20,ACQ=0,UK=74)
#IC< #OC	Number of persons in inner circle(s) of trust (e.g. CF, F, CCF) is always less that number of people in outer circle (e.g. F, CCF, ACQ). (CF=1,F=3,CCF=5,ACQ=44,UK=46)
ACQ	User has only Acquaintances (ACQ) in his friends list. (CF=0,F=0,CCF=0,ACQ=25, UK=74)
MAX CF	User has added most of the users as close friend (CF). (CF=90, F=0, CCF=0,ACQ=0, UK=9)

Consider scenario #IC < #OC with following breakup of users and their ratings for illustration purpose. When we calculate cumulative rating then items which get better rating by persons in inner circle of trust get higher cumulative rating scores compared to items which are rated lower by trusted circle. Percentile Rating Breakup and its graphical view is depicted below.

Table -2: Breakup of Users & their Ratings



Weightage given to different trust circles while calculating score is described in table below with its graphical representation.



	CF	F	CCF	ACQ	UK
Lay Bhari	26.93%	21.11%	15.51%	23.94%	12.51%
Abhi-ruchi	33.93%	26.59%	19.53%	12.06%	7.88%
Durv-ankur	35.97%	28.20%	20.71%	10.66%	4.46%
Vaish-ali	38.33%	30.04%	22.07%	5.11%	4.45%
Suk-anta	41.43%	32.47%	23.85%	1.47%	0.77%

The main time consuming factor in calculating cumulative rating is computing R_S^{iju}. Assuming the average number of ratings per user is $\bar{r}$, and the average number of friends in a category per user is $\bar{f}$, then complexity of evaluation of r_{ti} is $O(\bar{r} + \bar{f})$.

For each rating calculation, the algorithm proposed needs to take the ratings provided by user multiplied by weight depending on closeness with current user and coefficient of normalization using formula described in mathematical model.

5. CONCLUSION

In this paper, a trustworthy social circle influenced user centric recommendation system is proposed by blending of social network parameters like personal interest, interpersonal interest similarity, and interpersonal influence along with location based user-item information which improves the accuracy and applicability of recommender system to recommend more personalized and real-time items. In particular, the trust propagation levels in interpersonal relationship or influence, especially the circles of friends, of social networks provide opportunity to reduce the cold start and sparsity problem impacts more efficiently. Coefficient of bias and rating magnification introduced in this paper ensure that cumulative rating generated is always in favor of opinions provided by inner circle of trust similar to process of decision making in real world.

Future Scope will be to include various level s of interests to improve outcome of friend suggestions algorithm. This is to leverage enthusiasm of a person in an interest category. Also, in rating algorithm by using more granular levels of relationship like friend of close friend, close friend of friend and friend of friend leads to improvise cumulative rating.

REFERENCES

[1] X Qian, H Feng, G Zhao, T Mei "Personalized Recommendation Combining User Interest and Social Circle", Knowledge and Data Engineering, IEEE Transactions, 2014.

[2] X. -W. Yang, H. Steck, and Y. Liu. "Circle-based recommendation in online social networks". KDD‟12, pp. 1267-1275, Aug.2012.

[3] M. Jiang, P. Cui, R. Liu, Q. Yang, F. Wang, W. -W. Zhu and S. -Q. Yang. "Social contextual recommendation". CIKM‟12, pp. 45-54, 2012.

[4] M. Jamali and M. Ester. "A matrix factorization technique with trust propagation for recommendation in social networks". In Proc. ACM conference on Recommender systems (RecSys), 2010.

[5] R. Salakhutdinov and A. Mnih. "Probabilistic matrix factorization". In NIPS 2008, 2008.

[6] Y Chen, C Wu, M Xie, X Guo "Solving the Sparsity Problem in Recommender Systems Using Association Retrieval" , Journal of computers, 2011

[7] Q. Yuan, L. Chen, and S. Zhao, "Factorization vs. regularization: Fusing heterogeneous social relationships in top-N recommendation," in Proc. 5th ACM Conf. Recommender Systems, Chicago, IL, USA, 2011.

[8] H Ma, D Zhou, C Liu, MR Lyu, I King. "Recommender Systems with Social Regularization". Fourth ACM international conference on Web search and data mining, 2011.

[9] A Bellogín, P Castells, I Cantador. "Self-adjusting Hybrid Recommenders Based on Social Network Analysis". 34th international ACM SIGIR conference on Research and development in Information Retrieval, 2011.

[10] Xavier Amatriain "Mining Large Streams of User Data for Personalized Recommendations" ACM SIGKDD Explorations, 2012.

[11] P. Cui, F. Wang, S. Liu, M. Ou, S. Yang, and L. Sun. "Who should share what? item-level social influence prediction for users and posts ranking". SIGIR, pp. 185-194, 2011.

[12] J. Huang, X. Cheng, J. Guo, H. Shen, and K. Yang. "Social recommendation with interpersonal influence". In Proceedings of the 19th European Conference on Artificial Intelligence (ECAI), pp.601–606, 2010.

[13] G. Adomavicius, and A. Tuzhilin. "Toward the next generation of recommender systems: a survey of the state-of-the-art and possible extensions". Knowledge and Data Engineering, IEEE Transactions on, pp. 734-749, Jun. 2005.