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Recommendation System for Product Using User Interest, Social Circle and Location of User

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***Abstract : Recommendation System (RS) is used to discover users interested items. The present testimonial framework is not efficient as desire. It has to require enhancement in framework for current and future necessities to getting best results for recommendation qualities. This paper combines four factors such as users interest, personal interest similarity, interpersonal impact and user's location information. In propose system we add user location in dataset also use PCC similarity method which reduce the RMSE and MAE errors*.**

Keywords : Interpersonal influence, personal interest, recommender system, social networks.

I. Introduction

Recommendation system (RS) has been effectively used to take care of issue overwhelming. Social networks, for example, Facebook, Twitter are dealing with extensive sizeof data user interesting things and items. RS has extensive variety of utilizations, for example, research articles, new social labels, videos, music and so on. By user data and distinctive quality things can be prescribed, which is firmly identified with user interest. Overview demonstrates that more than 25 percent of sales generated through suggestion. More than 90 percent people trust that items suggested by companion are valuable and 50 percent individuals purchase the prescribed items or things of their advantage. Google+ launched Friends Circle with filter the contacts for various activities and methodology. This feature enhances the possibility of a user to come close with each other such as friends.

In a large web space, suggestion discovers things of user hobby. Collaborative and content based filtering are generally utilized strategies for proposal. Cold start is complex issue in Data Mining. Despite the fact, various algorithms are available to work with Data Mining. Cold start is cause, individuals deals in breaking down the usefulness of those algorithms and it is lead somewhat diminishing in imagination and improvements in data mining algorithms. Frosty begin can be depicted as inaccessibility of data for displaying algorithms.

Web is constantly alert, in often expanding web it extremely hard to identify the user interest into the things within time. Personalized RS have some components like interpersonal interest, person's interest and interpersonal impact. Personalized RS is useful to prescribe the things over social networks with the point that suggested things aimed to in light of their previous behavior and interpersonal relationship of social networks.

II. Brief Survey

X. -W. Yang, H. Steck, and Y. Liu[1] have proposed accessible rating information consolidated with social network information based on category specific social trust. Authors also draw a few changes of friends inside of circles depends on their gathered skill levels. Proposed recommendation models based on circle can be better use client's social trust data, convey about extended recommendation precision. Utilization combined social network data which is huge improvement over previous method. But it is still aproblem to encapsulate client's personality in RS.

M. Jiang, P. Cui, R. Liu, Q. Yang, F. Wang, W. -W. Zhu and S. -Q. Yang [2] have study along with social recommendation on the premise of psychology and sociology studies, thatshow two vital components: individual preference and interpersonal impact.At the beginning authorstry to show the particularadvantage of both factors such asitem reception and recommendation in online. At that point author proposed a noveltechnique for factorization of probabilistic matrix to break them in underlying spaces. They include the study on both Facebook style bidirectional and Twitter style unidirectional social community datasets in China. Authors achieve their goal to beat the existing methodologies and can be effectively adjusted by real-world recommendation situations. Components integration in testimonial model to enhance the accuracy of RS is avital issue.

M. Jamali and M. Ester[3] have investigated a model-based methodology for recommendation in social networks, utilizing matrix factorization methods. Enhancing past work, author includes trust propagation strategy into the model. Trust propagation is shown animportant circumstance in the social science, inanalysis social network and in recommendation based on trust. Author tests on two real-world data sets and give the conclusion of their system, public domain Epinions.com dataset and a much bigger dataset that author have recently crawled from Flixster.com. Modeling trust propagation prompts a generous increment in recommendation precision, specifically for cold start clients. But still it is a hugeissue to typify client's behavior in RS and problem that how to createthe social factors be viably incorporated in recommendation model to enhance the precision of RS.

R. Salakhutdinov and A. Mnih[4] have shown the Probabilistic Matrix Factorization (PMF) model which have ability to spread out straightly with number of perceptions and essentially, well efficient on the broad, thin and exceptionally unstable Netflix dataset. Author expanded the PMF model to incorporate a versatile prior on parameters of the model and shows the model limit can be controlled automatically. At long last, author presents anobligate adaptation of the PMF model that depends on the determination that clients who have rated same sets of movies are prone to have same references. Mitigates error rate, It is still an extraordinary issue to exemplify client's behavior in RS.

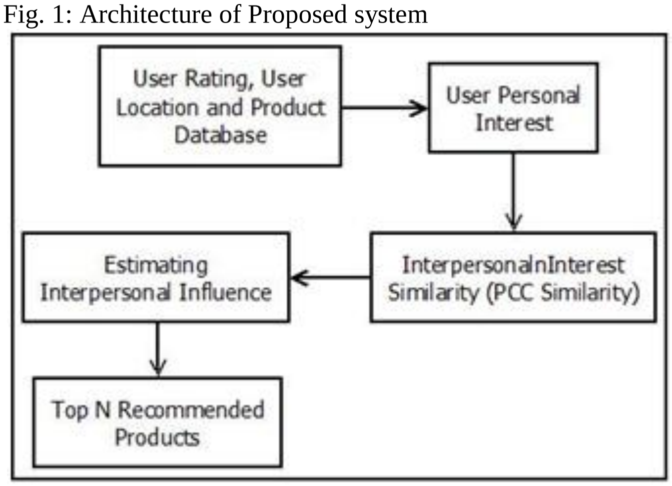
M.E. Tipping and C.M. Bisho [5] have explained how the principal axes of a set of analyzed information vectors might be considered by most extreme probability appraisal of parameters in an idle variable model nearly related with factor analysis. Author assumed the attributes of the related probability function, giving an EM algorithm for calculating the key subspace iteratively and examine, with illustrative examples, the favorable circumstances passed on by this probabilistic way to deal with PCA. They achieve the more effective algorithms for information representation and more proficient systems for image compression.

III. Methodology

A. *System Overview*

The below diagram shows the flow of a propose system. The propose system use user rating, user location and product ad a dataset in a system. The find out the user personal interest from the dataset and apply interpersonal interest similarity using PCC similarity technique. The PCC similarity has high accuracy to find the similarity between numbers of users interests. On the basis of similarity, estimate the interpersonal influence and finally we get top N recommended products.

Fig. 1: Architecture of Proposed system



IV. Algorithms

A. *Algorithm for Proposed system*

Initialization: user rating, user location, products
ListofProduct = null;
While (numOfProduct > 0){
Calculate:
User personal interest (Apply BaseMF);
Interpersonal interest similarity
{PCC similarity:

$$r = \frac{\sum XY - \frac{(\sum X)(\sum Y)}{n}}{\sqrt{\left(\sum x^2 - \frac{(\sum x)^2}{n}\right)\left(\sum Y^2 - \frac{(\sum Y)^2}{n}\right)}}\}$$

usecircleCon model{
Calculate user-to-user trust value;
Combine trust value with rating matrix;}
List OfProduct.add(product(n));n--;}
Return recommended products;

V. Mathematical Model

1. Basic Matrix Factorization

$$\Psi(R,U,P) = \frac{1}{2}\sum_{u,i}\left(R_{u,i} - \hat{R}_{u,i}\right)^2 + \frac{\lambda}{2}(\|U\|_F^2 + \|P\|_F^2)$$

Where,
$\hat{R}_{u,i}$ Denotes the ratings
$R_{u,i}$ Is the real rating values in the training data for item *i* from user *u*,
U and ***P*** are the user and item latent feature matrices that require learning from the training data.

2. CircleCon Model

$\Psi^c(R^c, U^c, P^c, S^{c^*}) =$
$\frac{1}{2}\sum_{u,i}(R_{u,i} - \hat{R}_{u,i})^2 + \sum_{u,i}(R_{u,i} - \hat{R}_{u,i})^2 + \frac{\lambda}{2}(\|U\|_F^2 + \|P\|_F^2) +$
$\frac{\beta}{2}\sum_u((U_u^c - \sum_{v\in F_u^c} S_{u,v}^{c^*} U_v^c)(U_u^c - \sum_{v\in F_u^c} S_{u,v}^{c^*} U_v^c)^T)$

Where the estimated ratings for a user are category regarding that as follows:
$\hat{R}_{u,i}^c = r^c + U_u^c P_i^{cT}$

Where r^c is experimental set as user's average rating value in category c.

$$\begin{aligned}\Psi(R,U,P,S^*,W^*) = {} & \frac{1}{2}\sum_{u,i}\left(R_{u,i} - \hat{R}_{u,i}\right)^2 + \frac{\lambda}{2}(\|U\|_F^2 + \|P\|_F^2) \\ & + \frac{\beta}{2}\sum_u((U_u^c \\ & - \sum_{v\in F_u^c} S_{u,v}^{c^*} U_v^c)(U_u^c - \sum_{v\in F_u^c} S_{u,v}^{c^*} U_v^c)^T) \\ & + \frac{\gamma}{2}\sum_{u,v}(W_{u,v}^* - U_u U_v^T)^2\end{aligned}$$

VI. Results and Tables

A. Dataset

In this proposed system, utilize the user rating, user location and product ad a dataset. It includes number of users, user's interest, number of products and user location.

B. Result

Table I. RMSE Comparison between Existing and Propose System

Modules	Existing System	Propose System
BaseMF	2.846	1.846
CircleCon	1.779	0.7
ContexMF	1.36	0.25

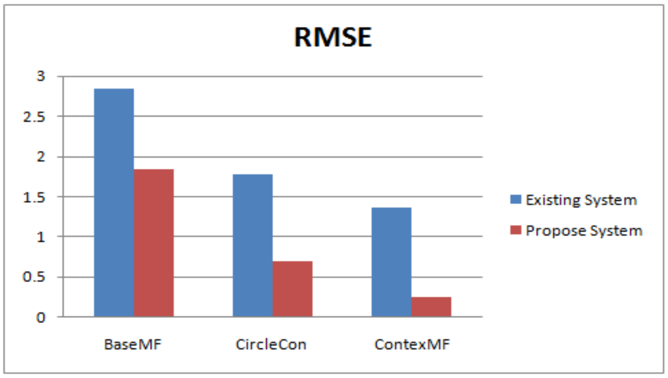


Fig 2: RMSE Comparison between Existing and Propose System

The Fig. 2 graph shows the Root Mean Square Error (RMSE) between existing systems and proposes system. The propose system has low RMSE rate than the existing system and improve the accuracy.

Table II. MAE Comparison between Existing and Propose System

Modules	Existing System	Propose System
BaseMF	2.182	1.182
CircleCon	1.38	0.32
ContexMF	1.026	0.026

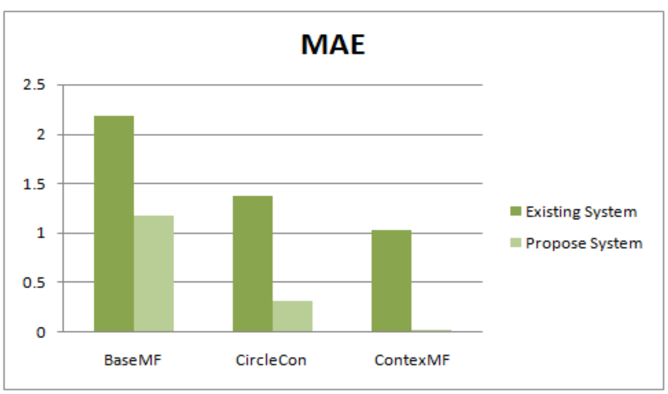


Fig 3: MAE Comparison between Existing and Propose System

The Fig. 3 graph shows the Root Mean Square Error (MAE) between existing systems and proposes system. The propose system has low MAE rate than the existing system and improve the accuracy.

VIII. Conclusion

A personalized recommendation methodology system proposed in this framework. This method developed by mixing social network factors that is personal interest, interpersonal interest similarity, interpersonal influence and user's location information. Specifically, the personal interest indicates user's singularity of rating items, particularly for the accomplished users and these factors, mixture of both used to increase the precision and appropriateness of recommender system. In propose system we add user location in dataset also use PCC similarity method which decreased the RMSE and MAE errors and improve the accuracy.

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