Online Product Recommendation by Utilizing Social Network Features

Archana Singh, Avinash Sharma, S. R. Yadav

Abstract— **with the increase in internet facility most of the market move towards online store, as number of users are spending their time in Online Social Rating or Network websites such as Flixter, facebook, etc. This include new field for researcher to predict user purchasing with the use of digital relation among them. This paper works in this field by utilizing two kind of network first is social product rating and other is social network. Social product rating help in finding product ranking, then fuzzy interval values are generate for calculating user to user trust based on social features. In this work new concept of fuzzy interval value has increase the efficiency of the work. Results are compare with previous methods of product prediction and it is obtain that proposed work has high precision and recall value on different dataset size as compare to previous approach.**

Keywords: - Fuzzy Interval, Product prediction, social media features.

I. INTRODUCTION

As digital world include different facility for the ease of human life, one of its boon is internet. This internet has reduced hundred of works, in terms of managing things, providing information, etc. So number of internet users are increasing day by day, many of different kind of services are developed through which people maintain their social relation buy products, sell old products, etc. Utilization of this traffic is done by researcher by analyzing user reviews and comments for product purchase prediction [2,5,9].

Many of sites like epinion, flixter, etc. are maintaining users ratings for variety of products. Users co-comment on same number of products share its experience which can increase or decrease products rate. On these sites users are from different social networks but communicate each other on the basis of that product relation. Opinion of one lead to one long continuous talk help other for purchasing.

Social networking sites like facebook, twitter, etc. provides good platform to maintain relation among people. On these sites people put their personal life. So utilization of both kind of sites are done in [8, 10]

It is known that people buy those products that are suggested by some other person who has trust on it. As advertisement for particular community increase product selling if target community is correct. So product prediction work will identify those community for advertising. As chance of purchasing that kind of product is high.

Chance of product sale is highly based on product feature. Its sale increases by making proper advertisement. Product prediction accuracy increase by user reviews, while combination of social network in product prediction will also increase accuracy as done in [1, 8].

Problem Identification: This work focus on product recommendation system, where user recommend product by rating products. Utilization of this single recommendation has low efficiency. So some of researcher has included social relation trust value, where user-user trust is present. But direct specifying the trust is difficult as it vary with time. So proper trust calculation is required. In this work use of fuzzy interval value is done for calculating trust from current user social features value with other. So combination of rating and user trust is done in this work for increasing the efficiency of prediction.

II. RELATED WORK

Product recommendation system is done by two main techniques first is content based and other is community-based. Content-based technique is popular as compare to community base although some interest has focused on collaborative filtering [12]. In content base recommendation users own preferences is specify, so retriving decision from this is easy and perfect [19].

In [12] frequency vector of users are maintain by hashtag and entities specify in tweets. Similarly one more vector having URL links of twitter is maintained in separate vector. So Users are then recommended URLs whose vector is most similar to theirs.

In [14] BOW (Bag of word) is maintain for the common words use in URLs and twitter terms specify by the users. Here social network among users is not consider.

In [18] friendship base random walks is done for collecting data from tweets by users. Here similar kind of tweets are utilize for the user-user recommendation.

In [16] similar approach of random walk is adopt but technique use for recommendation is base on collaborative filtering instead of content-based techniques.

In [17] recommendation is done by combining user influence and user recommendation. Based on this probabilistic matrix model prediction is done that is both similar in nature. Here it is obtain that Community-based systems has better accuracy as compare to content-based and collaborative filtering methods.

Social Networks and Purchase Behavior is analyzed by some researcher and has investigated the broader topic of how social network influences users in their purchases. In [13] empirically demonstrate that a user's friends exercise \peer pressure": if friends widely adopt a product, the user is more likely to buy it.

In. [15] study the trading dynamics on the e-commerce social network Taobao. They show that buyers are more likely to purchase from sellers that friends in their network have already bought from (information passing). They prove that when a buyer has to decide from which seller to buy a product, the social network has a bigger inuence on the decision than the sellers' ratings and the price of the product.

Basic Notation

Whole work focus on social feature base trust development and utilize this trust for rated item prediction. As purpose of social network is varying from site to site so number and type of feature also vary. In this work facebook social network is consider and its feature set is consider for trust calculation. Here many events are as comment, like, tag, unlike, write on wall, etc. Here each type of event is act as feature.

III. PROPOSED WORK

In this work product is predict, with the use of different relation such as user product relation user user relation. Base on these relation a new combination of features is use for the prediction of product that will be purchase by user. So fig. 2 represent the steps of proposed work.

User-User Datset: In this dataset user user feature relation is present. This can be understand as user U1 has some relation with U2 in terms of {Like, comment, share image, shar video, message, share comment, friend request, same group, common friends, video chat, text chat, etc.}, then number of time these activity done by the user is count in the dataset for U2 by U1 is store.

Pre-Processing

The dataset contains number of feature between users so conversion of dataset as per working environment should be done. In this step dataset is arranged into matrix in which first two columns represent user-id, while rest of the columns represent the feature count values. If zero present in the column then it shows that the feature is not used by the specified user ids. Different features include in the work are {Like, comment, share image, shar video, message, share comment, friend request, same group, common friends, video chat, text chat, etc.}. So separation and arrangement of features between users is done in this step.

```
Pre-Processing(DataSet)
Loop i=1:m
        DS[1, m] ← Sender(DataSet[m])
        DS[2, m] ← Receiver(DataSet[m])
        Loop j=1:x
                DS[x, m] ←Feature_count(DataSet[m])
        EndLoop
EndLoop
```

Generate Interval

Here a matrix is develop for the network where each user is acting as a node. In this matrix each row is representing number of different combination of possible friends and column represent different feature values between those user. Let that matrix is $M[n\times p_n, f]$ where n represent number of nodes, p_n represent friends of nth user and f represent different features.

For generating interval one need to count number of time each feature use by nth user for p_n user, in the similar fashion number of time p_n user use that same feature for nth user. In the similar fashion each user will generate interval value for the other. So new matrix after calculating the interval value is $M[n\times p_k, f_x,(U,L)]$.

Calculate Membership Degree

Here interval value is use for finding single value for that it is named as membership degree. For this find the upper membership degree by below formula:

$$U_{P_n,fx}=\sum_{k=1}^{n}(M[n\times p_n, f_x,U]-M[n\times p_k, f_x,U])$$

In similar fashion for the calculation of lower membership degree:

$$L_{P_n,fx}=\sum_{k=1}^{n}(M[n\times p_n, f_x,L]-M[n\times p_k, f_x,L])$$

Finally membership degree is obtain by summing this upper and lower degree value.

$$M[n\times p_n, f_x]=L_{P_n,fx}+U_{P_n,fx}$$

Score Relation

In this step one single value is calculate correspond to all features, so this term is called as score relation. It is very simple as above step of membership degree calculation has already resolve the upper and lower membership value into single value of each feature. So summation of all the feature value give final score to the user n correspond to p_n. This can be understand by below formula.

$$S_{p_n} = \sum_{x=1}^{f} M[n \times p_n, f_x]$$

Now this S_{p_n} vector contain score that should cross one threshold value t for analyzing number of friends that may get high trust. So those values in r_{p_n} is above threshold is consider as future edge in the network.

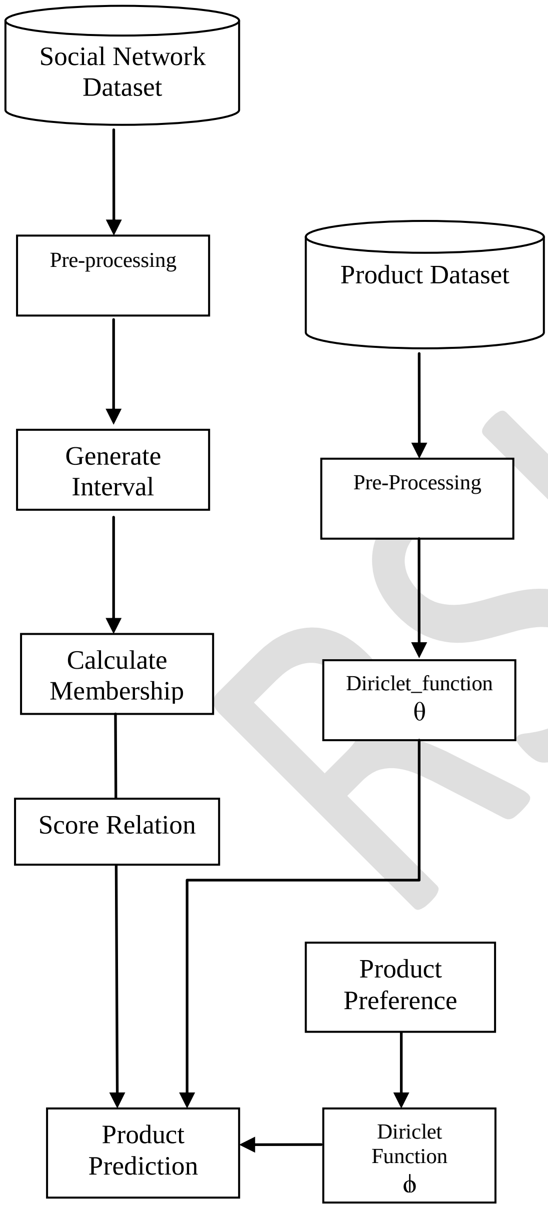

Fig. 1 Block diagram of Proposed Work

Product Rating Datset

In this dataset product rating feature is present. This can be understand as user U1 has either use or have knowledge or its review for any product id P1then rate it on the basis of his thought such as {best, very good, better, good, ok}.

Pre-Processing

As dataset contain number of rating between user and product so conversion of dataset as per working environment is done in this step here dataset is arrange into matrix form where first column represent user-id second represent product-id while third us for rate. For giving rate instead of giving any text rate values are provide for each class. If zero present in the column then it shows that that product is not use by the specify user ids.

UPD ← Pre_processing (UPD)

Latent Dirchlet Algorithm

Here with the help of this function dirrchlet will give a value as a relation between the user and user or item which is base on the UPD rating dataset.

θ← LDA(UPD)

In the similar fashion each product has its own product preference, so by the use of LDA one more relation is introduce.

Φ← LDA(Product_preference)

Product Prediction

This is the final step here user product prediction is done on the basis of social graph (user-user dataset), user-item relation, item preference.
In this step each user Xn who is friend of user Yj where j=1,2….t where t is number of X friends.

P[j] ← θj*ϕ*S[n]

Now this P has j number of entries. So the maximum value index in P will be the final product id.

Proposed algorithm:

Input: SND, UPD, Product_Preference
Output: Product_prediction

1. SND ←Pre-Processing(SND)
2. M←Generate_Interval(SND)
3. M←Membership_Degree(M)
4. S←Generate_Interval(M)
5. UPD ← Pre_processing(UPD)
6. θ← LDA(UPD)
7. Φ← LDA(Product_preference)
8. Loop 1: n
9. Loop 1:j
10. P[j] ← θj*ϕ*S[n]
11. If P[j] > T
12. P[j] = P[j]*(x*C1 + y*C2) // x is n friends using product j while y is not n friend but useing product j

13. EndIf
14. EndLoop
15. EndLoop

IV. EXPERIMENT AND RESULT

Experimental Setup

This section presents the experimental evaluation of the proposed work. All algorithms and utility measures were implemented using the MATLAB tool. The tests were performed on an 2.27 GHz Intel Core i3 machine, equipped with 4 GB of RAM, and running under Windows 7 Professional.

Dataset

The Epinions dataset contains

- 49,290 users who rated a total of
- 139,738 different items at least once, writing
- 664,824 reviews.
- 487,181 issued trust statements.

Users and Items are represented by anonimized numeric identifiers.
The dataset consists of 2 files:first file contains the ratings given by users to items, second file contains the trust statements issued by users.

Evaluation Parameter

To test outcomes of the work following are the evaluation parameter such as Precision, Recall and F-score.

Precision = TP / (TP+ FP)

Recall = TP / (TP + TN)

F-score = 2 * Precision * Recall / (Precision + Recall)

Where TP : True Positive
TN : True Negative
FP: False Positive

Results

Results are comparing with the previous work in [1] which is term as previous work in this paper.

Values	**Previous [1]**					
	300	**600**	**900**	**300**	**900**	**600**
TP	4	8	10	10	15	17
TN	146	228	243	140	221	236
FP	134	340	66	16	24	66
FN	16	24	581	134	340	581

Table. 1. Comparison results of Previous work with proposed work for 600 user and 1000 product.

Values	**Previous [1]**	**Proposed**
Precision	0.2	0.3846
Recall	0.029	0.0694
F-Measure	0.0506	0.1176

Table. 2. Comparison results of Previous work with proposed work for 300 user and 1000 product.

Values	**Previous [1]**	**Proposed**
Precision	0.2500	0.3846
Recall	0.023	0.0423
F-Measure	0.0421	0.0761

Table. 3. Comparison results of Previous work with proposed work for 600 user and 1000 product.

Values	**Previous [1]**	**Proposed**
Precision	0.1176	0.2048
Recall	0.0169	0.0284
F-Measure	0.03	0.0499

Table 4 Comparison results of Previous work with proposed work for 900 user and 1000 product.

It has been observed by table 1, 2, 3 & 4 that product prediction of proposed work is better as compare to previous one, as precision value is higher. It is observed that as the size of the datset increases then number of user and there chance of generating product prediction get less. This due to the confusion or the randomness of user.
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V. CONCLUSION

As the online market increases day by day number of users are also increasing. So target for correct customer is basic requirement of the companies. Keeping this motive paper work for product prediction of the user based on its social network and product rating. It is obtained that combination of both information give highly accurate result. Fuzzy interval technique is implement for social network features relation building. Results shows that proposed approach has high precision value of 0.3846 achieve for different number of users and product. In future combination of multiple social network may produce high accurate recommendation.

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