A Product Recommendation System using Fuzzy Preference Tree for E-Commerce

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Abstract--- The Recommender systems have now become an important part of web based systems. They aim to automatically products/services to customers; there are still three challenges in e-services: (1) items or user profiles often present complicated tree structures (2) online users' preferences are often indefinite (3)same product getting recommended repeatedly leaving other equal quality products under starvation. This studyproposes a method for modeling fuzzy tree-structured user preferences, in which fuzzy set techniques are used to express user preferences. We are using comprehensive tree matching method which can match two tree-structured data and identify their corresponding parts by considering all the information about tree structures, node attributes and weights. The proposed fuzzy tree-structured user preference profile reflects user preferences effectively, and the recommendation approach demonstrates excellent performance for tree-structured items. The other main idea of this study is that we have included group recommendation through which we can recommend a product to a group of people.

I. INTRODUCTION

The recommender system is a web based support system that suggests a group of particular products from a list of available items to satisfy the necessity of the customers without any direct input from the user. It also rank them with considering some preferences and the product attributes as the deciding point. The recommending systems are used in many fields now-a-days. Before making any recommendation to the user,the recommendation system uses the user history and some product details to select the item for recommendation.

The main problem in recommending a product is that the item attributes and the user preference for a particular item are frequently changing and are uncertain. It is difficult for the system to predict the correct preference of the user for an item at any point of time.It is difficult for user to express their interest in exact numbers.Fuzzy set theory lend themselves well to handle these uncertain issues. User preferences anditem features have been represented as fuzzy sets in the previous research which made it more difficult to handle the bulk of item history. This research is now mainly focusing on making most of the good products getting recommended to the user without spoiling the user preference. As in web,here we are to handle bulk amount of information even for making a small recommendation to the user. These many information will surely lead us to overload problem. The effective solution for this is to develop a personalized recommender system. This recommender system can also be used in e-governance where we could give chance to our own Indian products which are equally good in quality as compared to many other country products.For example- in Kadar industries, or in other fertilizer product and so on.

In order to solve the challenges that we have encountered in the previous recommender systems - namely uncertainty in user preference,tree structure item,sameproduct getting recommended multiple times. This study proposes a method for modeling fuzzy tree structure user preference, presents a tree matching method, develops an innovative fuzzy preference tree and suggest the product from the tree based on CFR-robin algorithm. It

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also proposes a group recommendation using Average Aggregation technique.

II. RELATED WORKS

This section will review the literature on recommender system,tree matching method, fuzzy set technique, preference prediction and displaying suggested products to the user.

A. Recommender Systems

Recommendation techniques have attracted much attention and many recommendation approaches have been proposed. The three main recommendation techniques are collaborative filtering (CF), content-based (CB) and knowledge-based (KB) techniques. The CF technique is currently the most successful and widely used technique for recommender system. It helps people to make choices based on the opinions of other people who share similar interest. The major limitations of CF methods are data scarcity and cold start problems. The data scarcity problem occurs when the number of available items increases and the number of ratings in the rating matrix is insufficient to generate accurate predictions. When the ratings are very small compared to the number of ratings that need to be predicted, a recommender system becomes incapable of locating similar neighbors and produces poor recommendations. The cold-start (CS) problem consist of CS user problem and the CS item problem. The CS user problem also known as new user problem, affects users who have small number of ratings or none. When the number of rated items for the user is small, the CF approach cannot locate similar neighbors. The CS item problem, also known as new item problem,affects items that have small rating or none.

The CB recommendation technique recommend item that are similar to those that are previously preferred by a specific user. The major limitations of CB approaches are item content dependency problem, over specialization problem and new user problem. The KB recommender system offers item to the user based on the knowledge about the user and items. In contrast to the CB and CF approaches, KB approach have no CS problems because a new user can based on knowledge of his/her interest. The KB approach have some limitations however: for instance, it needs to retain some information about item and user, scalability problem, as well as functional knowledge, to make recommendations. Each recommendation techniques have itsown merits and drawbacks, thus hybrid recommendation techniques have been proposed. The underlying semantic properties and attributes associated with users and items have beenexploited to develop recommendations in certain type of recommender system called semantic based recommender system. The semantic information about the items consist of attributes of the items, the relationship between the items and the relationship between the items and metainformation.

The usage of this semantic information can provide some additional information as to why particular items have or have not been recommended, and provide better recommendation effective than current CF techniques, particularly in case where little or no rating information is available. In this study, the attribute information of tree structured data should be fully considered to make accurate recommendations.

B. Group Recommendation

The recommender systems are usually designed to suggest product to a single user. But in many situations the recommended products are consumed by a group of people. For instance- A tour with friends, a movie with family or the music to be played in car for passengers. In this paper we aimed to create a group of people under similar name as a friend group, and then suggest a product to that group. This method of recommending a product to a group of people is what called group recommendation. Thus in this paper groups are created and then the product is recommended to that group. For recommending a product to a group we should keep in mind the preferences of all the members of the group.

C.Fuzzy Set Technique

The fuzzy method is used in the recommender system to overcome the problem of uncertainty. In both the user preference tree and item tree the preference for the particular item is represented as a fuzzy set over an assertion set. The user's international preferences are represented as a basic preference module, which is the ordered weightedaveraging of components that can evaluate items. The user's extensional preferences are expressed as a fuzzy set over the user's experienced items whose membership degrees are the ratings. Based on the representation, the preference for an itemby the user can be inferred. Four kinds of fuzzy set based similarity measures: fuzzy set theoretic, cosine, proximity and correlation like are introduced. The item similarity is computed by integrating CB similarity which is a fuzzy relation within an item set, and item based CF similarity, which is computed on the basis of user preferences.

III. ALGORITHMS

1. Conceptual Similarity Computation Algorithm

SCT(T_u[j],T_i[k],M)
input: two trees T_u[j],T_i[k] and tha mapping setM
output: the conceptual similsrity between T_u[j] and T_i[k]

1. mapping set M_1← {(t_u[j],t_i[k])}
2. if F_u[j]=ϕ, F_i[k]=ϕ
3. SC_{T1}←sc(a(t_u[j]),a(t_i[k]))
4. elseif F_u[j]= ϕ , F_i[k]≠ ϕ
5. sc_{T1}←α .sc(a(t_u[j]),a(t_i[k]) +

$$(1-)\sum_{t=0}^{nk} \mathrm{Wk1.\,scT(Tu[j], Ti[kt],)}$$

6. else if F_u[j]≠ ϕ, F_i[k]= ϕ
7. sc_{T1}←α .sc(a(t_u[j]),a(t_i[k]) +

$$(1-)\sum_{t=1}^{nj} \mathrm{Wk1.\,scT(Tu[jt], Ti[k],)}$$

8. else if F_u[j]≠ ϕ , F_i[k]≠ϕ
9. V_j← {$t_u[j_1]$,$t_u[j_2]$,...$t_u[j_{nj}]$}
10. V_k← {$t_i[k_1]$,$t_i[k_2]$,...$t_i[k_{nk}]$}
11. for s=1 to nj
12. for t=1 to nk
13. new mapping set $M_{s,t}$
14. $ew_{s,t}$←sc_T($T_u[j_s]$,$T_i[k_t]$,$M_{s,t}$)
15. m←compute matching(V_j U V_k,ew)
16. for each ($t_u[j_s]$,$t_i[j_t]$) Єm
17. M_1← M_1 U $M_{s,t}$
18. sc_{T1}← a.sc(a(tu[j])
19. sc_{T0},mapping setM_2←Ø
20. for t=1 to nk
21. new mapping set $M_{j,t}$
22. sc_{T1} ← w_t.sc_T(T_u[j],$T_i[k_t]$,$M_{j,t}$)
23. SC_{T2}< SC_t
24. SC_{T3}←SC_t,M_2←$M_{j,t}$
25. sc_{t2}←0,mapping set M_3 ←Ø
26. for i=1 to nj
27. new mapping set $M_{t,k}$
28. sc_t ← w_t.sc_T($T_u[j_t]$,$T_i[k_t]$,$M_{j,t}$)
29. if SC_{T3}<SC_1
30. SC_{T3}←SCt,M_3←$M_{t,k}$
31. for p=1,2,3
32. if SC_{TP}=max{sc_{T1},sc_{T2},sc_{T3}}
33. M←M U M_p
34. return max{sc_{T1},sc_{T2},sc_{T3}}

2.Fuzzy Preference Tree Merging Algorithm

In order to combine the users intentional preference with the extensional one this algorithm is used. The users preference for the newly experienced items are integrated with the user fuzzy preference tree.

input: user fuzzy preference tree t_u,
item tree t_i,
preference value p_i

1. if$M_{u,i}$=Ø
2. create a tree node r
3. insert(r,T_u)
4. treeT_{ni}←CopyTree(n_i)
5. SetLeafValues(T_{ni},P_{ui})
6. insert(r,T_{ni})

7.T_u←r

8.else

9.n_p←GetMapped Node(n_i,$M_{u,i}$)

10.ifn_p≠null

11.if a(n_p)≠a(n_i)

12.treeT_{ni}←CopyTree(n_i)

13.SetLeafValues(T_{ni},P_{ui})

14.insert(parent(n_p),T_{ni})

15.else

16.ifn_i has no children

letn_p.P_u be($f_{1,unp}$,$f_{2,unp}$,...,$f_{r,unp}$),n_p,count be c,

P_{ui} be ($f_{1,ui}$,$f_{2,ui}$,...,$f_{r,ui}$)

17.$f_{k,unp}$←($f_{k,unp}$.c+$f_{k,ui}$)/(c+1),k=1,2,...,r

18.n_p.count←c+1

19.else

20.for each child node n_{ic} of n_i

21.merge(T_u,n_{ic},P_{ui},$M_{u,i}$)

22.else

23.n_p←GetMappedNode(parent(n_i),$M_{u,i}$)

24.ifn_p≠null

25.treeT_{ni}←CopyTree(n_i)

26.SetLeafValues(T_{ni},P_{ui})

27.insert(n_p,T_{ni})

28.else

29.n_i←SearchMappedDescendant(n_i,$M_{u,i}$)

30.n_p←parent(n_i)

31.remove(n_i,n_t)

32.treeT_{ni}←CopyTree(n_i)

33.insert(n_p,T_u)

34.T_u←T_{ui}

35.merge(T_u,n_i,P_{ui},$M_{u,i}$)

3.Average Aggregation

Let r*(u,i) be either the predicted rating of u for i, or r(u,i) if this rating is present in the data set. Then the score of an item for a group g_i

$$r^*(g,i) = AVG_{u \in g}\{r^*(u,i)\}$$

Items are then sorted by decreasing values of their group scores r*(g,i)

4.Rating Prediction Algorithm

let the root node of T_u be Root(T_u). The predicted rating for the item i by the user is calculated as Pr(root(T_u),$M_{u,i}$).

Pr(t_u[j],$M_{u,i}$)

input: fuzzy preference tree node,

the maximum conceptual similarity tree mapping.

output: the predicted rating.

1.mc←MatchedChildren(t_u[j],$M_{u,i}$)

2.if v(t_u[j])≠null and mc=null

3.return 0;

4.else if v(t_u[j])≠null and mc = null

5.let the preference value be

p_{ui}= {$f_{1,uj}$,$f_{2,uj}$,..,$f_{r,uj}$}

return ∑r k,$f_{k,ui}$

6.else if v(t_u[j])=null and mc(t_u[j])≠null

7.return ∑w_x.pr(t_u[j_x],$M_{u,i}$)

t_u[j_x]Єmc

8.else if v(t_u[j]≠nulland mc(t_u[j]≠null

9.return β_j. ${}^{r}_{k=1}$ k.$f_{k,uj}$

+(1-β_j).∑W_x.pr(t_u[j_x],$M_{u,i}$)

Using this algorithm the preference of the user for a particular item is calculated.

5.CFR-Robin Method

ThismethodincorporatesthefusiontechniqueRound RobinmethodtotheCFtechniquetogenerateasetof candidate products. By using the CF technique, we can generate a set of neighborsfor the target user. Let {B1,B2,....,BR}be these tof neighbors of the target user,SB_i={P_{i2},P_{i2},....,p_i{s_{Bi}}} represents a set of products viewed by a neighbor Bt. Instead of using the products in as the candidates for recommendations, the attributes of each of the products are used as a query to retrieve products from the database that have similar attributes.

That is, P_{IJsbi},Qij={A_1=a_{1ij},A_2=a_{2ij},......A_n=a_{nij}]is a query containing the attributes of a product that the neighbor B_i is interested in. A set of products,{b_1,b_2,....}, whose attributes match the attributes in can be retrieved and also ranked based on the similarity sim(b_k,Q_{ij}) between the products b_k

and the query Q_{ij}. Generally,the attribute values are not necessarily numerical values, they can be nominal attributes. For numerical attributes, the cosine similarity can be used to measure the similarity. For nominal attributes, let $b_k=\{A=a_1,A_2=a_2,...,A_n=a_n\}$,the following method can be used to measure the similarity:

$$sim(b_k,Q_{ij})=\sum sim_A(a_l,a_l^{ij})$$
$$sim=(a_t,a_{tij})=1,a_l==a_l^{ij},$$
$$= 0,a_l\neq a_l^{ij}$$

P_{ij} Є SB_i,based onthesimilarity,alistof ranked products can be generated,

$L_{ij}=<b_1^{ij},b_2^{ij},b_3^{ij},\ldots,b_r^{ij}>$. Therefore, from the neighbor B_i,| SB_i| lists of products are generated: $L_{i1},L_2,...,L_i|SB_i|$. All the products in these lists are similar to the products preferred by in terms of the product attributes. By applying the Round Robin method to the lists, we can rankall the products in L_{i2} U..U $L_t|SB_t|$. The Round Robin method selects a product from the top of each L_{ij} for each round, and then starts again from the top of the list for the remaining products in each L_{ij}. From the ranked products in $L_{i1}U....UL_i|SB_i|$, the top *N* products are chosen as the candidates generated from neighbor B_i, denoted as C_i. Thus, by combining the products in CB_i for all neighbours, we obtain a set of candidate products.

N
$\Gamma=UCB_i$
i-1

IV. Result

Experimental results show that high recommendation accuracy is obtained by representing the user preferences with our proposed fuzzy tree-structured preference model. This reflects the effectiveness of the fuzzy tree-structured user preference model and the proposed recommendation approach based on it. The round robin technique that has been used in our paper helps us to list not only the frequently used products, and also to recommend other new products to the user.

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