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Analysis of Collaborative Filtering Algorithm fused with Fashion Attributes

Hua Quanping

Information Engineering Institute, Zhejiang Textile & Fashion College, Ningbo 315211, China
watchping@163.com

Abstract

With analyzing usual collaborative filtering algorithm , a modified collaborative filtering algorithm which fuses with fashion attributes is researched .Firstly , using fuzzy mathematics processes fashion attributes, which include style , color , material , quality , brand , and seasonality , to produce fashion attributes function . Secondly, using fashion attributes function adjusts users appraising matrix parameters of collaborative filtering algorithm to improve fashion recommendation system performance. Lastly, to use experiment proves that performance of modified collaborative filtering algorithm is better than performance of usual filtering algorithm performance in personalized fashion recommendation system.

Keywords*: collaborative filtering, fashion attributes, recommendation system, algorithm, fuzzy mathematics*

1. Introduction

Personalized recommendation system, is one of components in E-commerce website. Personalized recommendation system is defined as following: according to recording and saving users browsing web behavior, collecting data is analyzed and mined, users demands are achieved. When users browse the web, the recommendation system gives suited information according to refined information [1-2]. Recommendation system is a kind of information filtering mechanism which can reduce extra costs when users search information. At present, personalized fashion recommendation system mainly includes new style fashion recommendation system, cut-price fashion recommendation system, popular fashion recommendation system, and so on [3-4].

Collaborative filtering algorithm is one of components in personalized recommendation technology [5-9]. The algorithm can recommend website resources according to users interests similarity, which is that commodities that are browsed by a user or other users are homologous. The algorithm can find new resources which interest users and can not concern resource describing form. There are some faults about current collaborative filtering algorithm if the algorithm is used in special fashion website of E-commerce. The main reason is that usual collaborative filtering algorithm is built in users browsing web interest degree. In some special websites, such as fashion sales website and so on, efficiency of recommendation system based on usual collaborative filtering algorithm is not wonderful .How to improve the recommendation efficiency of special recommendation system, some special collaborative filtering algorithms can be developed to solve these problems. In the paper, a special collaborative filtering algorithm, which fuses with fashion attributes including fashion style, fashion color, fashion material, fashion quality, fashion brand, and fashion seasonality, is researched. With some experiments, the modified collaborative filtering algorithm to improve recommendation efficiency in the fashion website is proved to be feasible.

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2. Personalized Recommendation System Model Based on modified Collaborative Filtering Algorithm

Personalized recommendation system (PRS) model based on modified collaborative filtering algorithm is as follows.

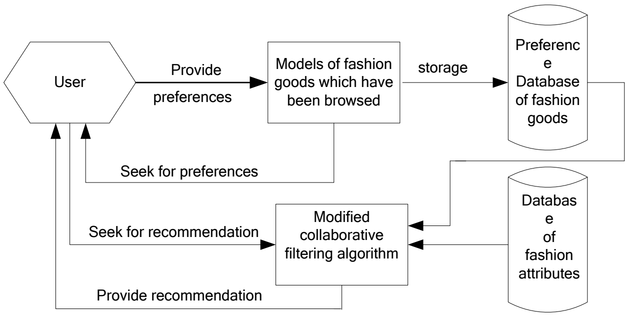

Figure 1. PRS Model based on Modified Collaborative Filtering Algorithm

PRS model based on modified collaborative filtering consists of two core parts basically. They are data refining procedure and recommendation algorithm based on modified collaborative filtering. Firstly, according to the web which is browsed by users, data refining procedure is to process and refine web data. Secondly, modified collaborative filtering executes clustering items, processes and implements self-adaptive recommendation services.

3. Usual Collaborative Filtering Recommendation Algorithm

Usual collaborative filtering recommendation algorithm mainly includes as following parts.

The first step: to choose data resource in the recommendation system. According to some papers, data resource can be defined as follows:

Definition 1[10] Data resource function is $D = f(U, I, R)$, where $U = (User_1, User_2, ..., User_m) \in Z_+^m$, $User_i (i = 1, ..., m)$ is the i -th user , U is m users vector , $I = (Item_1, Item_2 \ , ..., Item_n) \ \in Z_+^n$, $Item_j (j = 1, ..., n)$ is j -th item , I is n items vector, R is matrix that vector U multiplies vector I^T to produce , I^T is vector I transposition .The matrix R is as following formula (1):

$$R = \begin{bmatrix} r_{11} & \cdots & r_{1j} & \cdots & r_{1n} \\ \vdots & & & & \vdots \\ r_{i1} & \cdots & r_{ij} & \cdots & r_{in} \\ \vdots & & & & \vdots \\ r_{m1} & \cdots & r_{mj} & \cdots & r_{mn} \end{bmatrix} \tag{1}$$

Where r_{ij} is that $User_i$ appraises $Item_j$ to produce value.

The second step: to computer correlation based on similarity.

Definition 2 Correlation is based on similarity , another name is Pearson similarity ,where $sim(i, j)$ is correlation , $r_{(i,j)}$ is $User_i$ and $User_j$ appraise elements of vector $I_{(i,j)}$ to produce $r_{(i,j)}$, $I_{(i,j)} \subseteq I$. $sim(i, j)$ is as following formula (2) :

$$sim(i, j) = -\frac{\sum_{k \in I_{(i,j)}} (r_{ik} - \overline{r_i})(r_{jk} - \overline{r_j})}{\sqrt{\sum_{k \in I_{(i,j)}} (r_{ik} - \overline{r_i})^2} \sqrt{\sum_{k \in I_{(i,j)}} (r_{jk} - \overline{r_j})^2}} \tag{2}$$

Where $\overline{r_i}$ is that $User_i$ appraise elements of vector $I_{(i,j)}$ to produce average score, $\overline{r_j}$ is $User_j$ appraise elements of vector $I_{(i,j)}$ to produce average score.

The third step: to produce recommendation.

According to neighbours of current special website users who are browsing the web, two recommendation results , which include that users predict arbitrary items to produce value and top-N recommendation set , can be computed.

(a) Users predict arbitrary items to produce value: according to user u to appraise I_u , $P_{u,k}$ is as following formula (3):

$$P_{u,k} = \overline{R_u} + \frac{\sum_{m=1}^{N} sim(u,m) * (R_{m,k} - \overline{R_m})}{\sum_{m=1}^{N} sim(u,m)} \tag{3}$$

Where $\overline{R_u}$ is that user u has appraised item k ($k \notin I_u$) to produce average score, $sim(u,m)$ is similarity coefficient of user u and neighbours set N . $R_{m,k}$ is that user m appraises item k ,which is not be appraised by user u , to produce score , $\overline{R_m}$ is user m appraises item m to produce score , N is neighbour numbers . If $P_{u,k}$ value is more big, that means users u more likes item k .

(b) Top-N recommendation set is produced : firstly, $P_{u,k}$ is computed , then $P_{u,k}$ values can be arranged from big to small , thirdly , n items is choosed according to $P_{u,k}$ values arrangement , lastly , top-N recommendation set is produced .

Although some collaborative filtering recommendation algorithm can be used in the E-commerce website successfully, there is some faults .The key fault is as following:

Data potential sparsity: with the development of E-commerce system application scope, users and goods numbers become more large. Every user can only appraise small parts of goods based on user interest. Because these small parts of goods are 1%-2% of total goods in website, data potential sparsity is produced. Data potential sparsity makes recommendation efficiency of usual collaborative filtering recommendation algorithm based on users appraising web goods score decrease.

4. Collaborative Filtering Recom-mendation Algorithm based on Fashion Attributes

In order to improve recommendation efficiency of fashion website, to solve data potential sparsity of fashion website in some degree, modified collaborative filtering algorithm based on fashion attributes is researched.

Firstly, using fuzzy mathematics processes fashion attributes to produce fashion attributes function. In the paper, fashion attributes include fashion style, fashion color, fashion material, fashion quality, fashion brand, and fashion seasonality. Let fashion style use fuzzy set A_1 , fashion color use fuzzy set A_2 , fashion material fuzzy use set A_3 , fashion quality fuzzy use set A_4 , fashion brand use fuzzy set A_5 , fashion seasonality use fuzzy set A_6 . Fuzzy sets A_1 , A_2 , A_3 , A_4 , A_5 , A_6 are as following formula (4-9).

$$A_1 = \frac{A_1(u_1^{(1)})}{u_1^{(1)}} + \frac{A_1(u_2^{(1)})}{u_2^{(1)}} + \cdots + \frac{A_1(u_{n1}^{(1)})}{u_{n1}^{(1)}} \tag{4}$$

$$A_2 = \frac{A_2(u_1^{(2)})}{u_1^{(2)}} + \frac{A_2(u_2^{(2)})}{u_2^{(2)}} + \cdots + \frac{A_2(u_{n1}^{(2)})}{u_{n2}^{(2)}} \tag{5}$$

$$A_3 = \frac{A_3(u_1^{(3)})}{u_1^{(3)}} + \frac{A_3(u_2^{(3)})}{u_2^{(3)}} + \cdots + \frac{A_3(u_{n3}^{(3)})}{u_{n3}^{(3)}} \quad (6)$$

$$A_4 = \frac{A_4(u_1^{(4)})}{u_1^{(4)}} + \frac{A_4(u_2^{(4)})}{u_2^{(4)}} + \cdots + \frac{A_4(u_{n4}^{(4)})}{u_{n4}^{(4)}} \quad (7)$$

$$A_5 = \frac{A_5(u_1^{(5)})}{u_1^{(5)}} + \frac{A_5(u_2^{(5)})}{u_2^{(5)}} + \cdots + \frac{A_5(u_{n5}^{(5)})}{u_{n5}^{(5)}} \quad (8)$$

$$A_6 = \frac{A_6(u_1^{(6)})}{u_1^{(6)}} + \frac{A_6(u_2^{(6)})}{u_2^{(6)}} + \cdots + \frac{A_6(u_{n6}^{(6)})}{u_{n6}^{(6)}} \quad (9)$$

According to segmentation of fashion style, fashion color, fashion material, fashion quality, fashion brand, and fashion seasonality, domain $u_i^{(j)}(j \in [1,6], i \in [1,N])$ and $A_j(u_i^{(j)})(j \in [1,6], i \in [1,N])$ are decided. Because segmentation of fashion attributes has not standardized definition and we make programming become easy , uniform form of fuzzy sets A_1 , A_2 , A_3 , A_4 , A_5 and A_6 are given .The explicit form is given in the experiment .

Recommendation efficiency which is produced by fashion attributes function named fashion recommendation efficiency function. In order to research function relationship among fuzzy sets A_1 , A_2 , A_3 , A_4 , A_5 and A_6 further , fashion recommendation efficiency function is defined according to the following way .

Definition 3 For $\forall(x_{i1}^{(1)}, x_{i2}^{(2)}, x_{i3}^{(3)}, x_{i4}^{(4)}, x_{i5}^{(5)}, x_{i6}^{(6)})$, there must be $\exists y_i$ to make $(x_{i1}^{(1)}, x_{i2}^{(2)}, x_{i3}^{(3)}, x_{i4}^{(4)}, x_{i5}^{(5)}, x_{i6}^{(6)}) \xrightarrow{f} y_i$. Where $x_{i1}^{(1)} \in A_1$, $x_{i2}^{(2)} \in A_2$, $x_{i3}^{(3)} \in A_3$, $x_{i4}^{(4)} \in A_4$, $x_{i5}^{(5)} \in A_5$, $x_{i6}^{(6)} \in A_6$. f is mapping between function y_i and variables $(x_{i1}^{(1)}, x_{i2}^{(2)}, x_{i3}^{(3)}, x_{i4}^{(4)}, x_{i5}^{(5)}, x_{i6}^{(6)})$.

According to definition 3, function y_i is as following formula (10).

$$y_i = f(x_{i1}^{(1)}, x_{i2}^{(2)}, x_{i3}^{(3)}, x_{i4}^{(4)}, x_{i5}^{(5)}, x_{i6}^{(6)}) \quad (10)$$

Fuzzy sets A_1 , A_2 , A_3 , A_4 , A_5 and A_6 satisfy following assumption.

$$A_1(u_1^{(1)}) > A_1(u_2^{(1)}) > \cdots > A_1(u_{n1}^{(1)}) \quad (11)$$

$$A_2(u_1^{(2)}) > A_2(u_2^{(2)}) > \cdots > A_2(u_{n2}^{(2)}) \quad (12)$$

$$A_3(u_1^{(3)}) > A_3(u_2^{(3)}) > \cdots > A_3(u_{n3}^{(3)}) \quad (13)$$

$$A_4(u_1^{(4)}) > A_4(u_2^{(4)}) > \cdots > A_4(u_{n4}^{(4)}) \quad (14)$$

$$A_5(u_1^{(5)}) > A_5(u_2^{(5)}) > \cdots > A_5(u_{n5}^{(5)}) \quad (15)$$

$$A_6(u_1^{(6)}) > A_6(u_2^{(6)}) > \cdots > A_6(u_{n6}^{(6)}) \quad (16)$$

Fashion in current markets is defined as set C . Where $C = \{c_1, c_2, ..., c_n\}$, $c_i(i \in [1,n])$ means current markets $l1$-th type fashion whose attributes is in fuzzy sets A_1 , A_2 , A_3 , A_4 , A_5 and A_6 . Assuming $l1$-th type fashion attributes values are $u_{j1}^{(1)}$, $u_{j2}^{(2)}$, $u_{j3}^{(3)}$, $u_{j4}^{(4)}$, $u_{j5}^{(5)}$, $u_{j6}^{(6)}$ and $u_{j1}^{(1)} \in A_1$, $j1 \in [1,n1]$, $u_{j2}^{(2)} \in A_2$, $j2 \in [1,n2]$, $u_{j3}^{(3)} \in A_3$, $j3 \in [1,n3]$, $u_{j4}^{(4)} \in A_4$, $j4 \in [1,n4]$, $u_{j5}^{(5)} \in A_5$, $j5 \in [1,n5]$, $u_{j6}^{(6)} \in A_6$, $j6 \in [1,n6]$.

Let $x_j^{(1)} = u_{j1}^{(1)}$, $x_j^{(2)} = u_{j2}^{(2)}$, $x_j^{(3)} = u_{j3}^{(3)}$, $x_j^{(4)} = u_{j4}^{(4)}$, $x_j^{(5)} = u_{j5}^{(5)}$, $x_j^{(6)} = u_{j6}^{(6)}$.

According to f definition, the $l1$-th type fashion in the current markets is as following formula (17).

$$y_{l1} = \frac{1}{6}(x_{j1}^{(1)} + x_{j2}^{(2)} + x_{j3}^{(3)} + x_{j4}^{(4)} + x_{j5}^{(5)} + x_{j6}^{(6)}) \quad (17)$$

Using same calculation method , we can get to $c_{l1}(l1 \in [1,n]), c_{l2}(l2 \in [1,n]), \cdots, c_{ln}$

$(l\,n \in [1,n])$ whose function are $y_{l1}, y_{l2}, ...,$ and y_n . $y_{lp}(lp \in n)$, which is ultimate value among $y_{l1}, y_{l2}, ..., y_n$, is computed according to the following formula (18) .

$$y_{lp} = y_1 \vee y_2 \vee ... \vee y_n \tag{18}$$

Using y_{lp} adjusts elements values of matrix R to produce matrix $\hat{R}$ according to the following formula (19).

$$\hat{R} = \begin{bmatrix} r_{11} \vee y_{lp} & \cdots & r_{1j} \vee y_{lp} & \cdots & r_{1n} \vee y_{lp} \\ \vdots & & & & \vdots \\ r_{i1} \vee y_{lp} & \cdots & r_{ij} \vee y_{lp} & \cdots & r_{in} \vee y_{lp} \\ \vdots & & & & \vdots \\ r_{m1} \vee y_{lp} & \ldots & r_{mj} \vee y_{lp} & \cdots & r_{mn} \vee y_{lp} \end{bmatrix} \tag{19}$$

The formula (19) is processed further, we can obtain formula (20).

$$\hat{R} = \begin{bmatrix} \hat{r}_{11} & \cdots & \hat{r}_{1j} & \cdots & \hat{r}_{1n} \\ \vdots & & & & \vdots \\ \hat{r}_{i1} & \cdots & \hat{r}_{ij} & \cdots & \hat{r}_{in} \\ \vdots & & & & \vdots \\ \hat{r}_{m1} & \ldots & \hat{r}_{mj} & \cdots & \hat{r}_{mn} \end{bmatrix} \tag{20}$$

where $\hat{r}_{ij} = r_{ij} \vee y_{lp}$.

According to formula (20) and (2) , we can obtain $sim(\hat{i}, j)$ which is computed as following formula (21).

$$sim(\hat{i}, j) = -\frac{\sum_{k \in I_{(i,j)}} (\hat{r}_{ik} - \overline{\hat{r}_i})(\hat{r}_{jk} - \overline{\hat{r}_j})}{\sqrt{\sum_{k \in I_{(i,j)}} (\hat{r}_{ik} - \overline{\hat{r}_i})^2} \sqrt{\sum_{k \in I_{(i,j)}} (\hat{r}_{jk} - \overline{\hat{r}_j})^2}} \tag{21}$$

According to formula (21) and (3) , we can obtain $\hat{P}_{u,k}$ which is computed as following formula (22).

$$\hat{P}_{u,k} = \overline{\hat{R}_u} + \frac{\sum_{m=1}^{N} sim(\hat{u}, m) * (\hat{R}_{m,k} - \overline{\hat{R}_m})}{\sum_{m=1}^{N} sim(\hat{u}, m)} \tag{22}$$

Modified $\hat{P}_{u,k}$ can reflect function relationship between users appraising and current popular fashion attributes in the markets. because $\hat{P}_{u,k}$ values are arranged from big to small in the recommendation system , we can get to n items from the first item to n-th item .The n items produce users recommendation set top-N.

5. Experiment Results and Analysis

5.1. Data Sets and Evaluation Criterion

In order to test feasibility of modified collaborative filtering recommendation algorithm fused with fashion attributes, the fashion shopping website based on the algorithm is developed. Data sets are built on the following the rule.

Firstly, 50 users data is choosed from users database. Secondly, 1500 data, which is 50 users appraised 30 kinds of fashion goods to produce according to first level to 5-th level rule, is choosed from users appraising database. 80% data is training data set, 20% data is test data set.

Appraising recommendation system test criterion is built on mean absolute error (MAE). MAE can test accuracy which is expected according to error between the first kind of users who predict goods of web to produce score and the second kind of users who actually appraise goods of web to produce score .If MAE value becomes more small, that means the recommendation system efficiency is more high. Data set which is to expect goods of web to produce is $\{R_1,...,R_i,...,R_N\}$, data set which is to appraise goods of web to produce is $\{R_1^{'},...,R_i^{'},...,R_N^{'}\}$ .MAE[11] is computed as following formula (23) .

$$MAE=\frac{\sum_{i=1}^{N}\left|R_{ik}^{j}-(R_{ik}^{j})'\right|}{N} \tag{23}$$

In the special test fashion website , there are two kinds of databases .The first kind of database is database of fashion goods attributes .The second kind of database is database of users appraising fashion goods .The modified collaborative filtering recommendation algorithm to process the first kind of database and the second kind of database to produce recommendation results. In the test, fashion attributes are as following tables .

Table 1. Fashion Style Level

style level	1	2	3	4	5
meaning	very fashion	general fashion	fashion	old fashion	very old fashion

Table 2. Fashion Color Level

color level	1	2	3	4	5
meaning	very fashion color	general fashion color	fashion color	old fashion color	very old fashion color

Table 3. Fashion Material Level

material level	1	2	3	4	5
meaning	very fashion material	general fashion material	fashion material	old fashion material	very old fashion material

Table 4. Fashion Quality Level

material level	1	2	3	4	5
meaning	very good	general good	good	a little poor	poor

Table 5. Fashion Brand Level

brand level	1	2	3
meaning	very famous	general famous	usual brand

Table 6. Fashion Seasonality Level

seasonality level	1	2	3
meaning	very matching to current time	matching to current time	poor matching to current time

According to Table 1 to Table 6, fashion attributes fuzzy mathematic programming formulae, which are based on formula (4-16), are as following formula (25-30).

$$A_1 = \frac{0.7}{1} + \frac{0.6}{2} + \frac{0.5}{3} + \frac{0.4}{4} + \frac{0.2}{5} \tag{25}$$

$$A_2 = \frac{0.7}{1} + \frac{0.6}{2} + \frac{0.5}{3} + \frac{0.4}{4} + \frac{0.2}{5} \tag{26}$$

$$A_3 = \frac{0.7}{1} + \frac{0.6}{2} + \frac{0.5}{3} + \frac{0.4}{4} + \frac{0.2}{5} \tag{27}$$

$$A_4 = \frac{0.8}{1} + \frac{0.6}{2} + \frac{0.4}{3} + \frac{0.2}{4} + \frac{0.1}{5} \tag{28}$$

$$A_5 = \frac{0.5}{1} + \frac{0.5}{2} + \frac{0.4}{3} \tag{29}$$

$$A_6 = \frac{0.8}{1} + \frac{0.5}{2} + \frac{0.2}{3} \tag{30}$$

5.2. Experiment Results and Analysis

Two experiments can be designed to test the modified collaborative filtering recommendation algorithm fused with fashion attributes. Firstly, modified Pearson similarity fused with fashion attributes is how to effect the fashion recommendation system function .With the same test situation, cosine, Pearson similarity and modified Pearson similarity fused with fashion attributes are be tested separately. The results are as follows.

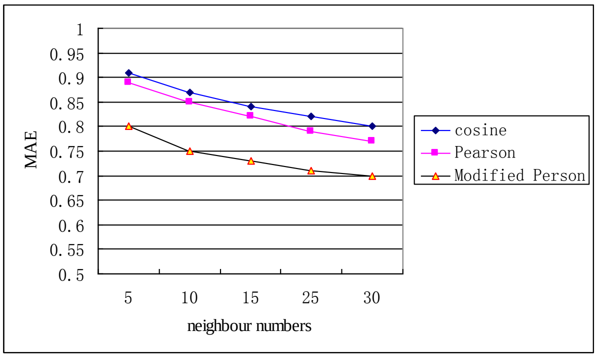

Figure 1. Three Similarity Computer Method Comparison

From Figure 1, MAE values of modified Pearson similarity fused with fashion attributes are smallest among MAE values of cosine, MAE of Pearson similarity and modified Pearson similarity .Therefore, modified Pearson function is best among cosine, Pearson, and modified Pearson .That means modified Pearson function can be adjusted by fashion attributes function effectively.

Secondly, recommendation capability of modified collaborative filtering algorithm (MCFA) and usual collaborative filtering algorithm (UCFA) can be compared . The result is as follows.

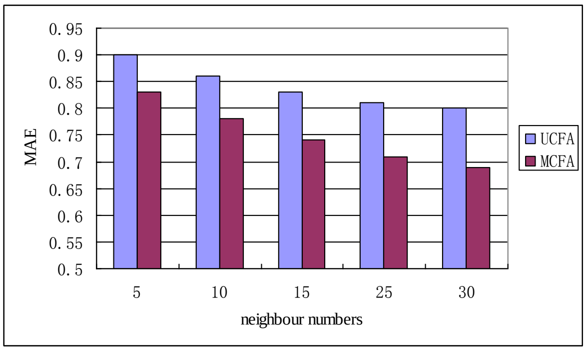

Figure 2. Function between MCFA and UCFA

From Figure 2, with neighbour numbers increasing , with MAE values becoming more and more small, although that means two algorithms is feasible to process fashion goods recommendation in the fashion website recommendation system, MCFA function is better than UCFA function ,because the reason is that MAE values of MCFA is smaller than MAE of UCFA.

6. Conclusion

A modified collaborative filtering algorithm fused with fashion attributes is researched under usual collaborative filtering algorithm. With using fuzzy mathematics to process fashion attributes parameters, fashion attributes function can be produced. Fashion attributes function adjusts R matrix of usual collaborative filtering recommendation algorithm to improve recommendation capability. With experiment results, the modified collaborative filtering algorithm is proved to be feasible to process fashion goods recommendation in fashion goods website.

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Author

Hua Quanping, he received his B. Eng degree in Mathematics from Zhejiang Normal University and M. Eng degree in Computer Science and Technology from Southeast University, China in 1992 and 2005 respectively. He is a dean of Department of Information Engineering in Zhejiang Textile & Fashion College. His current research interests on Intelligence Computation and Database Technology.