# A novel data mining algorithm for mathematics teaching evaluation

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## ABSTRACT

*With relative theory about technology of data mining and recommender model of user's interest, this paper presents the method of MWFP-TREE based on the combination between recommender model idea of user's weight and the minimum weighted FP-TREE method. Compared to traditional method, this method does not only carry out dimension reduction of raw data to improve the efficiency of a constructing tree but it also performs association rule mining and improves mining effect. This method is applied to mathematics teaching evaluation in one university and it finds out different evaluations from different students respectively considering students' information and teachers' information while it is not similar to traditional thought which is only to perform mining direction based on teachers' information. Towards mining regulations and results, it provides significant referential values for objectivity of teaching evaluation and teaching directions.*

**Keywords**:  teaching evaluation, data mining, interest recommendation, MWFP-TREE
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## INTRODUCTION

Educational evaluation research has become one of three fields on current educational scientific research and mathematics teaching evaluation research is the important content in educational evaluation research. mathematics teaching evaluation is an important step for universities to realize mathematics teaching of scientific management and is also an effective measure to promote mathematics teaching reform and improve mathematics teaching quality. With constant penetration and development of mathematics teaching reform, especially, the provision of educational thinking from examination-oriented education to quality-oriented education seems to be more important to perform mathematics teaching evaluation research.Mathematics teaching evaluation system in each university accumulates amounts of data. Most of it is only applied to perform simple data statistics and inquiry but useful information truly hidden in it is rarely used. Thus, it can acquire efficient information through data mining.

Data mining is an interdisciplinary subject mixing many subjects, which attaches researchers' attention from different fields. This subject contains database technology, artificial intelligence, machine learning, statistical analysis, pattern discovery, information retrieval, etc [1-8]. Sun Zhongxinag [9] points that students' evaluation on teaching method as well as teaching achievement from different teaching methods is analyzed by correlation analysis. Association rules method is to judge which method fits specific students or courses, which can also adopt correlation analysis. Many researchers propose to apply association rules [10-13] to find out factors related to students' scores, school performance, employment, etc, to provide effective reference for teaching system in universities.  [14] indicates that using non-objectivity of students' scoring to evaluate teaching and using association rule to acquire information influencing teaching quality are helpful to scientific nature of teaching evaluation. JIANG Yongliang presents [15] that applying FP-growth to perform mining association rule in the course chosen

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system to obtain useful association rule: which students like which courses. It can assist relevant department to carry out reasonable allocation of teaching resource and make corresponding decisions. Qu Shouning [16] in Jinan University raises that using Apriori algorithm based on students' exam scores can analyze internal connection between each subject while users can easily acquire relevant information between courses on the basis of mining result and make decisions, etc.

Aiming at existing problems in college teaching evaluation and based on association rule research, the filtering technology based on content expression is combined with the collaborative filtering technology based on user similarity to present a kind of new mixed improved model concerning existing technological features and research object. This mixed improved model acquires recommending result from the perspective of content and user similarity respectively and improves recommending quality. On this model basis, the thought of weight is added and improved from efficiency and result. From CRM idea, users with different types are regular mining in unit. Different kinds of users carry out corresponding regulation so as to acquire more effective analysis results.

## 2. Relative theory and method improvement in user recommender system
### 2.1. Users recommender system
The method based on content is to suppose that each user is independent. Users' historic data merely of content-based filtering and data based on program features are performed recommendation. Content-based filtering technology mainly adapts to information expressed by text [17] and information which is recommended to users only limits similar information generated by users' historic behavior. Moreover, a pure content-based recommender system faces the problem of excessive individualization. Memory-based algorithm on collaborative filtering (CF) is a successful recommender technology which recommends according to client's historic probability with similar hobby and behavior. However, the defect of this technology lies that: if a new attributive quality appears in the database, there is hardly any recommended possibility due to probability factor. In addition, if a user's hobby is special, he will not find the most adjacency and he is also not recommended correctly.
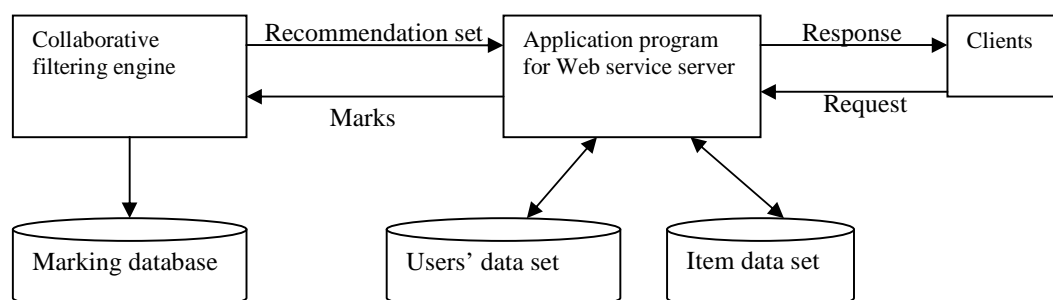


**Figure 1. Collaborative filtering system**

Figure 1 describes recommender system process of classic systematic filtering.User sends out request to web service program, web service program responses and respectively invokes users and program data set. Meanwhile, collaborative system is invoked and historic score database offered by collaborative filtering system carries out comparison and filtering to acquire recommended information to return to client.

### 2.2. Users' interest recommendation combination technique and improvement
At present, the algorithm combining the two methods is on the basis of content-based result to apply collaborative filtering, which only considers similarity between users rather than considering that the proportion of forming content's each attributive quality's deeper influence on users [18]. Therefore, this paper comes up with the weight idea that users evaluate matrix and content matrix to construct users, project, weight matrix of content attribute so as to reveal each project's deeper influence on users to find out projects significant to users at last.

At first, according to selected project matrix R of each user Un and the matrix F of project attribute, the relation matrix P between users and project attribute can be acquired:

$$p(u, f) = \sum_{\forall R(u,i)>0} F(i, f) \qquad (1)$$

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When p(u,f)>0, there has relationship between user u and project attribute F. Table 1 refers to the difference on inner relationship and users between users and project attribute. Column F2 refers that most users prefer this attribute with little difference. Column F4 refers that this attribute only aims at user U3 with large difference. The purpose of this paper's method describing difference, that is, the setting of attributive weight, is to find out better description or expressing user's features. It reveals key attributes on difference between users and removes previous weight setting whose limit is only from professional knowledge and human setting weight.

**Table 1. Users-items weighting matrix p**

|     | F1 | F2 | F3 | F4 |
|-----|----|----|----|----|
| U1  | 2  | 2  | 1  | 0  |
| U2  | 1  | 2  | 0  | 0  |
| U3  | 0  | 0  | 0  | 1  |
| U4  | 0  | 2  | 1  | 0  |

The setting of attribute weight is:

$$w_i = \ln \frac{|U_i|}{|U_{k_i}|} \tag{2}$$

U denotes to user number and $U_{k_i}$ denotes the user number of selecting this attribute at least one time. The lower w is, the more kinds of users are interested in it and the smaller this attribute reflects user's difference. In contrast, if W is larger, it will be easier to distinguish different kinds of users' interest attribute. Especially when $U_i / U_{k_i} = 1$, it means all users will choose this attribute.

### 3. Evaluation algorithm with users' interest
### 3.1. Improved FP-tree based on weight
Before establishing FP-tree and constructing FP-tree condition, user's interest weight model should be utilized to deal with data. On this basis, the association rule algorithm application does not only reduce data dimension, but it can also find out regulations with potential meaning more effectively with considering the influence of user interest weight and support. Weight $|w_i|$ can enlarge user difference but attribute with low support can be kept so that some attributes with high support but little difference could be directly filtered.

The minimum weight support is:

$$MWSP(X) = \underset{j \in X}{Min}(w_j * \sup port(X_j))$$

When constructing tree and condition tree, the minimum weight support can be taken as miming regulation of pruning condition, which narrows regulation scope. The increase of node support number is not purely taken 1 as a unit but to increase as corresponding values in user attribute matrix P in a unit so as to improve mining efficiency. The specific algorithm is shown as:

(1)Constructing MWSP-TREE
Scan transaction database one time and WSP is smaller than the minimized support pruning. F set of frequent item and their support are selected and F is ranked through descending order in support. Root node of tree is constructed, which is marked by nun.
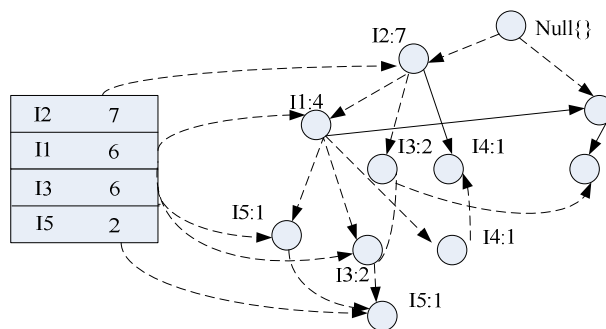
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**Figure 2. Construct MWFP TREE**

Towards each transaction in data, inserttree(p}P,tree) is operated. The process shows: if tree has a child N, then N.itemname=P.itemname. So N counting is increasing p.count, that is, the value in line P and column p in this matrix.

The node counting is not simply taken 1 as a unit but related to user's recommender model matrix. Therefore, support increasing efficiency is increasing with reducing scanning time.

(2) MWFP mining call MWFP-Growth(TREE,a)
If TREE includes single path P then

For each combination of nodes in P

Generate mode $\beta = \alpha_i \bigcup \alpha$ ,its MWPS is the minimum MWPS of nodes number in $\beta$

Else for each $\alpha_i$ in header table of TREE

Generate mode $\beta = \alpha_i \bigcup \alpha$ , support counting MWPS is the minimum MWPS of nodes number in $\beta$

Construct conditional pattern basis for $\beta$ and its conditional tree $tree_\beta$

If $tree_\beta \neq \phi$ then

Call MWFP-Growth($tree_\beta$ , $\beta$ )
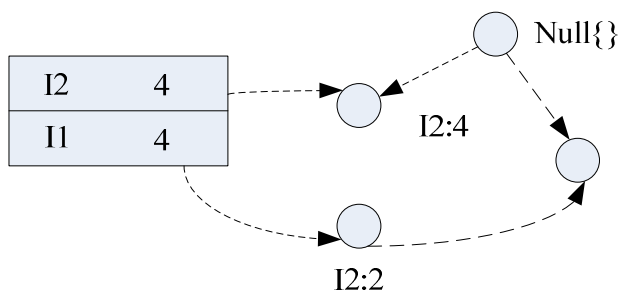
Get conditional tree for I3 as figure 3 shows.



**Figure 3. Condition tree of I4 whose wsp>minwsp**

The conditional tree with conditional nodes I3 is calculated as formula 3 and the minimum weight support is taken as conditional criteria.The flow in detail is :
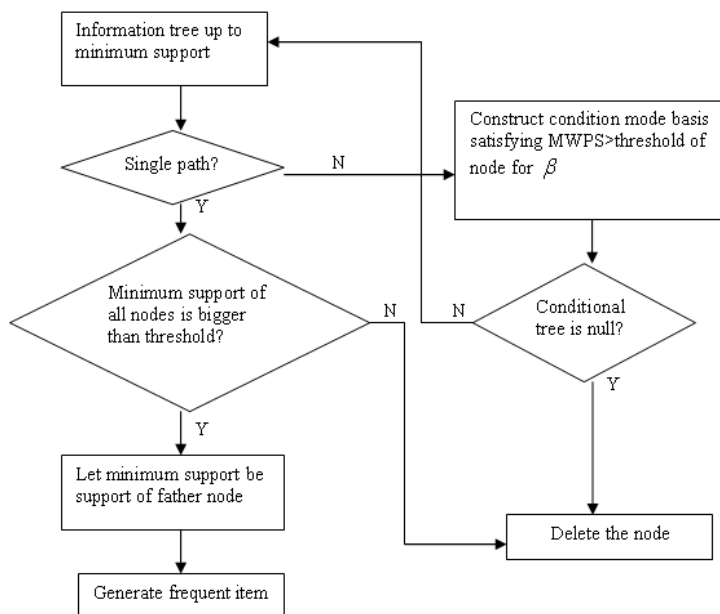
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**Figure 4. Procedure of MWFP mining**

**3.2 The comparison resultsbetween MWFP and original algorithm**
The following shows the comparison between weight of related attribute acquired by table 2 as well as its weight formula and its partial item set under different algorithms.

**Table 2. Items weighting matrix**

| Item | Weight |
|------|--------|
| F1 | 0.3 |
| F2 | 0.12 |
| F3 | 0.3 |
| F4 | 0.6 |

**Table 3. Comparison of itemsets in WIP and MWFP**

| Itemsets | supporting count | Weight | WIP | MWSP-TREE |
|----------|------------------|--------|-----|-----------|
| U3,F4 | 1 | 0.6 | 0.3 | 0.6 |
| U2,F2,F1 | 2 | 0.12,0.3 | 0.5 | 0.24 |
| U2,F3,F1 | 1 | 0.3,0.3 | 0.35 | 0.3 |

In table 3, the support of (u2,f2,f1) is relatively larger in algorithm FP-TREE. However, in algorithm MWFP, since attribute F2 is popularized, which is not functioned to produce association rule towards one user and its weight support is relatively small, it is directly selected or deleted. The support of (u3,f4) is relatively small in algorithm FP. However, since attribute F4 is special to U3, it is kept in algorithm WFP-TREE. Compared to classic WIP algorithm, the weight of WIP is artificial settings and it has large subjective factors. Mining result is influenced largely by subjective factors.

**Table 4. Items weighting matrix**

| Item | Weight |
|------|--------|
| F1 | 0.3 |
| F2 | 0.2 |
| F3 | 0.4 |
| F4 | 0.6 |

For improved algorithm, the number of practical transaction business reduces to user numbers. Simply, if a user chooses 3 projects, the transactional data before handling is 3 while the transactional data after handling is 1. During

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constructing tree and condition tree, node support increase is not purely taken 1 as a unit but to increase as corresponding value in a unit in user attribute matrix, which improves mining efficiency as a whole.

**Table 5. Comparison of itemsets in WIP and MWFP**

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Under the condition of the 10% lowest support and the 40% lowest confidence, each algorithm performs test towards two 12-intensive and sparse data sets. During experiment, data tuple number increases from 100 to 1500, which is used to compare time complexity changes of each algorithm.
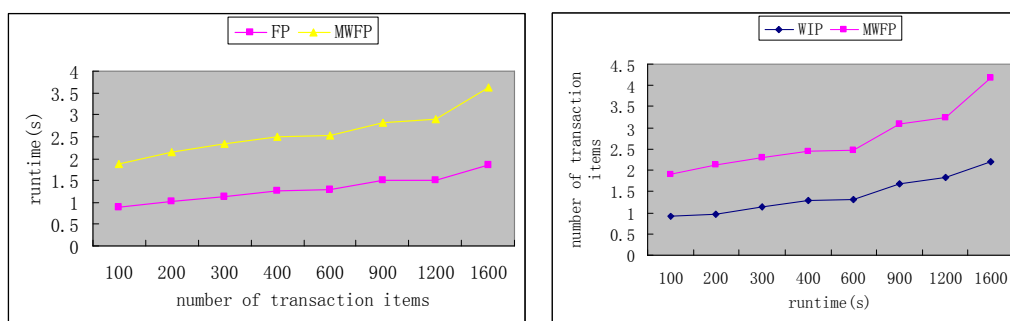


**(a) FP and MWFP algorithm**    **(b) WIP and MWFP algorithm**
**Figure 5. Comparison of experimental efficiency on different algorithms in intensive data dataset**

Data curves on time complexity of MWFP algorithm and WIP algorithm is shown as figure 5. It is discovered that the improved MWFP algorithm's operating time aiming at FP-tree algorithm is fast with increasing data scale. With increasing transaction numbers, operation speed is more quickly. Operation time of MWFP algorithm and FP-tree algorithm is increasing as soon as transaction is increasing. If transaction of MWFP is small with sparse data set, the efficient operation is not superior to the other two algorithms. If transaction of MWFP is smaller with intensive data, operation time is relatively long at the beginning. However, with transaction increasing, MWFP appears to be superior and operation time is quicker than before.
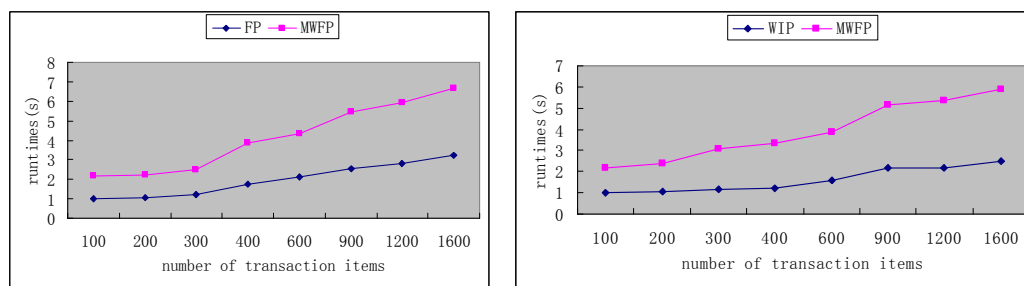


**(a) FP and MWFP algorithm**    **(b) WIP and MWFP algorithm**
**Figure 6. Comparison of experimental efficiency on different algorithms in sparse dataset**

Figure 6 refers to efficiency comparison of sparse dataset. It is shown that the improved algorithm is not suitable towards sparse scale data. Since data are sparse, it cannot be functioned to set corresponding weight and data dimension. Similarly, constructing user's weight model consumes some time, which results in efficiency reduction. Since WIP is artificial weight setting, therefore, even though there is a sparse dataset, it will not affect its efficiency, which can perform pruning and improve mining efficiency according to subjective request.

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**4. Implementation in mathematics teaching evaluation system**
First, scores are divided into excellent, better, good and bad. The scores above better will be selected as interesting teacher evaluation table. The combination between teachers' attribute table and students' attribute table applies the idea of users' interest model to deal with data. Through using handled data, relevant regulations towards different students' influencing teachers' scores are carried out mining. Then, through evaluating data, students' information and teachers' information, weight system hierarchy based on users' interest will be constructed.

The users' attributes of first layer denote the attributes of students:
$S_\mu = \{C_1, C_2, ..., C_n\}$, $C_n$ is the detailed attributes of students;

The teachers' information in second layer denote the evaluation matrix and teachers attributes matrix;
$T_\mu = \{C_1, C_2, ..., C_n\}$, $C_n$ is the detailed attributes of teachers;

$S_\mu = \{T_1, T_2, ..., T_n\}$ .When $T_n = 1$ it means the evaluation for teachers is better; $T_n = 0$ means the evaluation for teachers is lower than good;

The teachers' attributes of third layer denote the teachers attributes which attract the students interest ,that is,the essential reason to select teachers;

$M_\mu = \{(C_1, N_1, W_1), ..., (C_n, N_n, W_n)\}$, $C_n$ is the attributes which attract the students interest and $N_n$ is the times of selection. $W_n$ is the weight of this attribute.

With some main attributive information including teachers' ages, school ages, educational background, students' grades, GPA, gender, etc, the selected sample numbers and representativeness are comprehensively considered to analyze to obtain potential correlation of teaching and its attributive quality, which performs data pre-processing. Teachers' fundamental information table, students' evaluating teaching information table and students' fundamental information table are collected to store in database. The acquired data are performed discretization and generalization transformation so as to get data structure form in unification which is suitable for data mining, which is shown as the following table:

**Table 6. Students and teachers' information**

| Grade | | GPA | | | | Educational background | | | Titles | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| grade 2-3 | grade 4 | < 3.0 | 3.0-3.6 | >3.6 | ... | Master | Doctor | lecturer | associate professor | professor | ... |
| 4 | 0 | 4 | 0 | 0 | ... | 4 | 2 | 2 | 1 | 1 | ... |
| 3 | 0 | 0 | 3 | 0 | ... | 3 | 2 | 1 | 1 | 1 | ... |
| 2 | 0 | 0 | 2 | 0 | ... | 2 | 2 | 2 | 0 | 0 | ... |
| 0 | 3 | 0 | 3 | 0 | ... | 3 | 2 | 1 | 2 | 1 | ... |
| ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... |

In the first line of data, data 4 under student attribute refers one low-grade student's evaluation score is higher than "better" from four out of six teachers. That is, he selects four efficient data in his evaluation table and he evaluates 4 times with this attribute. Therefore, this student's related attribute matches 4. The data under teacher's attribute is, therefore, the matrix data corresponded to this kind of attribute on student and teacher after applying user's interest model.

Before MWFP algorithm handling, there are 560 data totally. However, after handling, there are totally 180 data. The weight above master's degree is 0, that is, all teachers have this attribute. Although the support of this attribute in data is high, it does not have practical mining sense. Therefore, most people's selection attribute is directly deleted. Although they have higher support, there is not any difference. After filtering little weight, it can be selected through statistical method to directly generate regulation. The following table displays the comparison on some results between these two mining algorithms.

The top 5 rules on application of FP-tree in table 7

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**Table 7. Top 5 rules on application of FP-tree**

| NO | Rules |
|---|---|
| 1 | Students with GPA 3.0-3.5→the teacher should have master's degree, doctor's degree or above with humorous teaching style, larger than 5 teaching years and 40 ages. |
| 2 | Boys, relevant majors →the teacher should have master's degree, doctor's degree or above with humorous teaching style, casual teaching environment, larger than 5 school years and 40 ages. |
| 3 | Non-relevant majors, boys→ have master's degree or above with humorous teaching style, larger than 5 school years and 40 ages. |
| 4 | Non-relevant majors, boys→ have master's degree or above with lecturer, associate professor and casual teaching environment. |
| 5 | Students of grade 4, relevant majors→casual teaching, lecturer, associate professor. |
| … | … |

The top 6 rules on MWFP-TREE in table 8

**Table 8. Top 5 rules on application of MWFP-tree**

| NO | Rules |
|---|---|
| 1 | The student with GPA smaller than 3.0, relevant majors and grade 2-3→the teacher with age smaller than 40, lecturer, school year smaller than 5. |
| 2 | The student with GPA smaller than 3.0, related majors, boys→the teacher with casual teaching, lecturer, associate professor, female teacher. |
| 3 | The student with GPA is between 3.0-3.6, relevant major, girls→strict teaching, professor, associate professor, male teachers. |
| 4 | The student with GPA larger than 3.6, relevant major→strict teaching, professor, associate professor, school year is larger than 5, male teacher. |
| 5 | The student with relevant major, GPA is between 3.0-3.6 and grade 4→casual teaching, lecturer, associate professor, female teacher. |
| 6 | The student with non-relevant major and grade 2-3→lecturer, associate professor, casual teaching. |
| … | … |

From table 7, it is shown that, since evaluation is taken as the unit of class, data feature is that boy proportion is large and the number of students belonging to GPA 3.0-3.6 is big, the original algorithm should be applied and most regulations are determined according to boys and students' GPA in 3.0-3.6. Moreover, mining regulation is directly acquired through statistical method. The condition with humorous teaching style, school year larger than 5 and age larger than 40, should not be necessarily applied to construct MWFP-TREE.

From table 8, it can be analyzed that students with non-relevant majors prefer casual teaching environment and relatively simple teaching style. Towards this kind of students, corresponding teachers can be assigned. However, towards senior students with relevant majors, the learning requirement is not as strict as those students with lower grades due to employment and other factors. Meanwhile, various kinds of students will have evaluation deviations towards teachers who are strict in teaching. Thus, the correct analysis should be carried out towards this evaluation. Some teachers with strict teaching and low evaluation scores should increase other factor coefficients to regulate in order to guarantee evaluation objectivity and mobilize teachers' activity.

## CONCLUSION

Aiming at problems in college P. E evaluation system and on the basis of association rule research, this paper presents solution based on data mining algorithm. Towards traditional users' interest modeling which is only simply technological basis application with merely users' similarity consideration, this paper also presents a weight recommender model based on users' interest. Through increasing users' interest weight on the basis of original FP-TREE algorithm, it not only functions as data dimension but it also finds out different regulations which are suitable for different users from the perspective of users' classification. Finally, MWFP is applied to teaching evaluation in one university. Association rule mining based on recommender model of user weight is carried out in teaching evaluation data to provide decision support information for teaching department, improve teaching quality and promote students to keep better learning state.

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