An Approach to Credibility Enhancement of Automated Collaborative Filtering System through Accommodating User's Rating Behavior

Jang-Hwan Sung[a] and Jong-Hun Park[b]

[a] *Graduate Program in Technology Management, Economics and Policy, Seoul National University*
56-1, Sinlim-dong Gwanack-gu, Seoul 151-742, Korea
Tel: +82-010-2715-8205, Fax: +82-2-872-8359, E-mail: beda0525@hotmail.com

[b] *Department of Industrial Engineering, Seoul National University*
56-1, Sinlim-dong Gwanack-gu, Seoul 151-742, Korea
Tel: +82-2-880-7174, Fax: +82-2-872-8359, E-mail: jonghun@snu.ac.kr

Abstract

The purpose of this paper is to strengthen trust on the automated collaborative filtering system. Automated collaborative filtering system is quickly becoming a popular technique for recommendation system. This elaborative methodology contributes for reducing information overload and the result becomes index of users' preference. In addition, it can be applied to various industries in various fields. After it collaborative filtering system was developed, many researches are executed to enhance credibility and to apply in various fields. Among these diverse systems, collaborative filtering system which uses Pearson correlation coefficient is most common in many researches.

In this paper, we proposed new process diagram of collaborative filtering algorithm and new factors which should improve the credibility of system. In addition, the effects and relationships are also tested.

Keywords:

Collaborative filtering; Evaluation; Recommendation; Pearson correlation coefficient; Credibility

1. Introduction

Growing of electronic business is one of the most significant changes in 1990's. Among them, online shopping mall and search portal become the kernel of changes. In 2000's these two fields faced significant change by technology evolution which called web 2.0. Some of the changes in web 2.0 are user participation and individual customization. Because of information overload like many kinds of products in online shopping mall, customers need customized recommendation of products or services based on their own preference. To recommend best products or services to customers, history of purchase is used. Most of information is provided by evaluation of previous users.

Many kinds of algorisms are developed to predict accurate preference of users to recommend best products or services. Among them, collaborative filtering system is most popular in individual recommendation. It calculates individual user preference of specific item based on preference information of active user and other neighbors. For calculating predicted preference of user, collaborative filtering system uses similarity of users in weighting process. Pearson correlation coefficient is most widely used methodology in this process. Following the increase of important of recommendation system, collaborative filtering system become more poplar and many researchers tried to research about this algorism. There are many research directions of system. Among them, the most significant direction is credibility enhancement of algorism.

In research investigation of Kyu-Sang Kim and Hong-Kyu Lee [7], online transaction can't confirm credibility like existing offline shopping because of 'lack of physical access with product' and 'lack of interaction with clerk' [4] [3]. To resolve this problem, we use the after-purchase evaluation system which actively use interactive characteristic of internet communication. But sometimes these evaluation systems have low credibility because it depends on few numbers of data or users' subjective dispositions [3]. So if these factors can be considered in algorism, credibility of system should be enhanced. Moreover, if system is modified by its application, credibility should be enhanced in each case.

Based on literature reviews of papers about collaborative filtering system, we proposed three factors which should enhance credibility of collaborative filtering system. Then the effects of these factors and relationships with other variables are tested using movie evaluation data.

2. Design of CF Process Diagram

Because of lots of extended researches, it is hard to define the fundamental algorism. So before we use collaborative filtering system, we will design new basic collaborative filtering process diagram for clearly understanding of this system. The process is divided by six steps. In most of researches, only step 3, 4, 5 are introduced because they are core of algorithm. But we add other steps because they also affect to the accuracy of prediction. Explanation of each steps are following.

2.2.1. Selecting Target

In step 1, experiment targets are selected. In other word, you have to define the purpose of the experiment. Selection criteria of active user, comparison users, and target items are defined. Moreover, application method is also designed. (Application of system will be explained in step 6.)

2.2.2. Controlling Database

The next step of is database control. Based on criteria which are defined in step 1, appropriate number of data sets are collected. Different with other steps, this step is first introduced in this research. In previous researches, they skip this step because database is controlled after similarity weightings are calculated. But we suggest that database is also controlled before similarity weightings are calculated because it is hard to calculate all similarity weightings between active user and comparison users.

There are two things that have to be decided in this step. They are number of items and number of users. At first, number of items has to be decided. In other word, representative item pool is selected. Then number of users is decided. In some collaborative filtering researches, number of users is decided before number of items. But we suggest that selection of representative item pool is first executed because representative level of data sets is higher.

2.2.3. Weighting Similarity

Third step of is weighting similarity between active user and comparison users. When you recommend movies or books, you prefer to trust those that come from users who have historically proven themselves as providers of appropriate evaluation data. So collaborative filtering system weight comparison users based on how they provide similar data compared with active user. Several different techniques are developed. Among them, we introduced Pearson correlation coefficient which is most common.

$$w_{i,j} = \frac{\sum_{\alpha}(r_{i,\alpha} - \bar{r}_i)(r_{j,\alpha} - \bar{r}_j)}{\sqrt{\sum_{\alpha}(r_{i,\alpha} - \bar{r}_i)^2 \sum_{\alpha}(r_{j,\alpha} - \bar{r}_j)^2}} \quad (1)$$

In Equation (1), similarity between user **i** and **j** is calculated using only the case of both users evaluated item α. This is derived from linear regression model which relies on several assumptions that regarding the data. These are that the relationship must be linear and the errors must be independent and have a probability distribution with mean 0 and constant variance for every setting of the independent variable [1]. Pearson correlation coefficient technique is powerful in calculating exact similarity only when these assumptions are satisfied. But these assumptions are not always satisfied so other techniques are used.

Other similarity techniques include Spearman rank correlation coefficient, and vector similarity. But these techniques are used in special cases so we focus only on Pearson correlation coefficient.

2.2.4. Selecting Neighborhoods

Based on the similarity weightings which are calculated using Pearson correlation coefficient, second database control is executed. It can select all neighbors which are used in calculating similarity weightings with active user. But in most of cases, additional database control is executed. In normal process, this step is necessary because it is hard to calculate prediction score with all neighbors [13]. But in our algorithm process, all neighbors can be used in calculation because first database control is executed in step 2. But addition of this step sometimes can generate more accurate predicted score. So we introduced two most widely used techniques.

The first technique used by Shardanad and Maes, is to set an absolute correlation-threshold, where all neighbors with absolute correlations greater than a given threshold that are decided by researcher [13]. The second technique is best-**n**-neighbors which is to pick the best **n** correlates for a given **n**. Both of techniques have pro and cons so it is important to use appropriate technique in each case. Sometimes all neighbors are selected or both of correlation-thresholding and best-**n**-neighbors techniques are combined [6].

2.2.5. Calculating Predicted Score

After that the rating differences of other neighbors are combined to compute a predicted score. In collaborative filtering system, predicted score of active user are calculated based on some partial information regarding the active user and a set of weightings which are calculated in step 2. If user **i** is active user and comparison user **j** is one of neighbors, predicted preference score of user **i**, $p_{i,\alpha}$, is:

$$P_{i,\alpha} = \bar{r}_i + \tau \sum_{j=1}^{n} w_{i,j}(r_{j,\alpha} - \bar{r}_j) \quad (2)$$

n is the number of users in data sets with nonzero weights. $w_{i,j}$ is similarity weight. τ is normalizing factor which make sum of absolute values of the weights as 1.

2.2.5. Application

The final step is application. In many papers which published in infancy, application step is not introduced but many of further researches focused. So we add this application step to the process algorism. Many of applications are introduced in previous researches. Among them, we selected two applications which are most widely used and the basic purpose of collaborative filtering system.

First application is recommend specific item by using preference score ranking. This method is original purpose of collaborative filtering system and widely used for companies in online shopping business. They use this method for sale promotion of products. Second application is to find exact predicted preference score for statistical purpose. When researchers need statistical data of preference score, they use this algorism to find preference scores which are not rated by users. They can eliminate sparsity problem of evaluation data sets.

Based on explanation of each step in above, we proposed new extended process diagram. By following this process, you should generated more accurate predicted preference score which is proper to your research purpose.

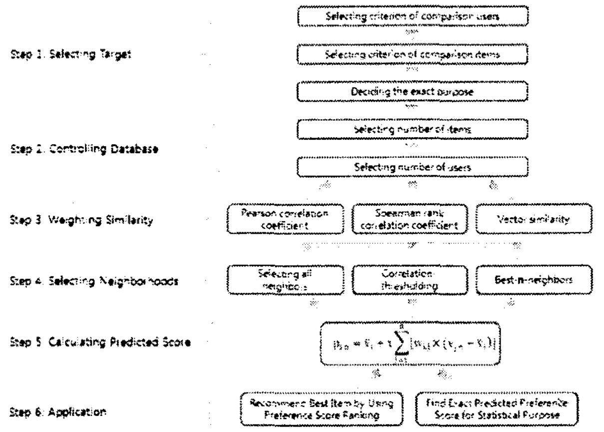

Figure 1 - Extended process diagram of collaborative filtering algorism

3. Design of New Factors

3.1. Commonly Rated Items Weighting

One of the issues that have not been controlled in original collaborative filtering system is the amount of trust to be placed in a correlation with neighbors. The more rated scores that we have to compare the opinions of two users, the more we can trust that the calculated correlation is representative of the true correlation between the two users.

In Equation (2), $w_{i,j}$ of movie α is zero when there is no relationship between user **i** and **j**. It has zero value when user **i** review movie α and user **j** didn't, user **j** review movie α and user **i** didn't, and neither user **i** and **j** review movie α. Only comparison values of commonly rated items are used in system. So we hypothesized that expected score is more credible when number of commonly rated items is increased. This can be significant problem when number of commonly rated items is too small.

J. L. Herlocker, et al. researched about this problem [5]. If two users had fewer than 50 commonly rated items, they applied a significance weight of c/50, where c is the number of commonly rated items. If there were more than 50 commonly rated items, then a significance weight of 1 was applied. In this manner, correlations with small number of commonly rated items are appropriately devalued. They argued that correlations with 50 or more commonly rated items are not dependent on this number. But this method based on inductive logic. In other word, they find criteria from calculated result of data. So it is hard to apply basic algorithm. We suggested new significance weighting method which can apply to basic algorithm and analyze relation with other valuables.

$$P_{i,\alpha} = \bar{v}_i + \tau_{com}\sum_{j=1}^{n}[w_{i,j} \times \frac{c_{i,j}}{\sum_{j=1,\alpha\in I_j}^{n} c_{i,j}} \times (v_{j,\alpha} - \bar{v}_j)] \tag{3}$$

$c_{i,j}$ is the number of commonly rated items between two users and $\sum_{j=1,\alpha\in I_j}^{n} c_{i,j}$ is sum of $c_{i,j}$ that considered only the case that neighbor **j** rate item α. In addition, constant variable τ is also changed because similarity weight is changed. New normalization constant variable is τ_{com}.

3.2. Evaluation Preference

The second issue is about evaluation preference. Each user has different evaluation preference. So if this difference is considered, the accuracy should be improved.

In Equation (2), user **i** has low average evaluation score when if he purchased many low-quality items in the past. On the other hand, user **j** has high average evaluation score when he purchased many high-quality items in the past. This difference make problem in trust of system.

This problem is first discussed in research of Young-Chae Na [9], but he focus on the performance enhancement of application of collaborative filtering algorithm in evaluation system. So even though he discussed and proposed new factor, he didn't use this factor in collaborative filtering system. We hypothesized that this factor gives positive effect in collaborative filtering system and this hypothesis is tested in next chapter.

$$P_{i,\alpha} = \bar{v}_i + \tau\sum_{j=1}^{n} w_{i,j} \times [v_{j,\alpha} - (\bar{v}_j + \frac{\sum_{\alpha=1,\alpha\in I_j}^{k}(v_{j,\alpha} - v_{i,\alpha})}{N})] \tag{4}$$

To eliminate evaluation preference error, $\bar{v}_j + \frac{\sum_{\alpha=1,\alpha\in I_j}^{k}(v_{j,\alpha}-v_{i,\alpha})}{N}$ is inserted instead of $\bar{v}_j$. In Equation (4), $\frac{\sum_{\alpha=1,\alpha\in I_j}^{k}(v_{j,\alpha}-v_{i,\alpha})}{N}$ is average error of pairs of rated scores about commonly rated items between two users. In other word, it indicate level of high or low evaluation preference between user **i** and **j**.

In original collaborative filtering systems, calculated rated score is cut down because $\bar{v}_j$ is relatively large when users purchase items selectively. This problem can be occurs in two cases. First case is occurred when users purchase specific items that they prefer and rate high scores to these items. Second case is occurred when users randomly purchase items and only rate high score to preferred items. In both cases, error is occurred.

But if $\bar{v}_j + \frac{\sum_{\alpha=1,\alpha\in I_j}^{k}(v_{j,\alpha}-v_{i,\alpha})}{N}$ is used, when user **i** rate higher scores about items than user **j**, effected evaluation value is decreased and when user **i** rate lower scores about items than user **j**, effected evaluation value is increased. We hypothesized this can be eliminate error by users who have high and low evaluation preference and enhance trust on collaborative filtering systems.

3.3. Max. Min. Calibrating

Last issue of this paper is about maximum and minimum calibration of calculated scores. One of the advantage of collaborative filtering systems is it can be applied to any data sets which use diverse evaluation scopes. In this research, experiment data sets use evaluation scope from 0 to 1. But collaborative filtering systems cover all the other evaluation scopes, for example, from 1 to 10 or from 10 to 100, etc. Even though data sets use diverse evaluation scopes, evaluation scopes always have maximum and minimum value. But original system sometimes derives predicted score which is larger than 1 or smaller than 0.

Extended predicted score is useful when collaborative filtering system is used in ranking recommendation method because it give differentiation among maximum and minimum scores, but cut down accuracy when it is used in predict exact preference score. So this factor is effective only when system is used in predict exact preference score.

$$p_{i,a} = \begin{cases} 1 & \text{if } p_{i,a} >= 1 \\ p_{i,a} & \text{if } 0 < p_{i,a} < 1 \\ 0 & \text{if } p_{i,a} <= 0 \end{cases}$$

(Applied only when CF is used to predict exact score of each target.)

(5)

3.4. Apply All Three Factors

We designed new model which applied all three factors.

$$P_{i,a} = \bar{r}_i + \kappa_{...} \sum_{j=1}^{n} w_{i,j} \times \frac{c_{i,j}}{\sum_{j=1, a \in I_j}^{n} c_{i,j}} \times [v_{j,a} - (\bar{r}_j + \frac{\sum_{a=1, a \in I_j}^{k} (v_{j,a} - c_{i,a})}{N})]$$

$$p_{i,a} = \begin{cases} 1 & \text{if } p_{i,a} >= 1 \\ p_{i,a} & \text{if } 0 < p_{i,a} < 1 \\ 0 & \text{if } p_{i,a} <= 0 \end{cases}$$

(Applied only when CF is used to predict exact score of each target.)

(6)

We hypothesized all three factors are mutually exclusive and expect credibility of system is enhanced much better.

4. Experimental Evaluation

4.1. Data Set & Evaluation Method

Original data which used in this research is generated by DECSystems Research Center for movie recommendation service called EachMovie. This data was collected during 18 months. 72,916 reviewers reviewed 2,811,983 times about 1,628 movies. Average review per each reviewer is 39 times and average reviewer per each movie is 1,727.

Random data sampling was used in this research because original data set is too big to control in calculating program. 422,677 times of reviews about 1,628 movies by 10,000 reviewers are randomly sampled from original data set. Average review per each reviewer changed 42 times and average reviewer per each movie changed 260 by sampling.

Mean Absolute Error, which is widely used in performance test of evaluation system, is used to evaluate performance of new developed model [12].

$$MAE = \frac{\sum_{i=1}^{N} |p_i - q_i|}{N} \tag{7}$$

In Equation (7), p_i is predicted value which calculated by collaborative filtering system and q_i is real value from the original data set. If MAE value is relatively low, it means proposed model is very elaborate, and vice versa.

4.2. Experimental Results

4.2.1. Relation with Number of Reviewers

In first part of test, performance of new proposed model by changing number of reviewers is calculated. As a result, new model has higher accuracy than original. Credibility enhancement is observed in all three factors and credibility of combined model is much more enhanced. Figure 3 compare MAE of new model and that of original model.

[illegible]		[illegible]	[illegible]	[illegible]	[illegible]
Original Collaborative Filtering	MAE	0.1258	0.1254	0.1267	0.1263
Apply Commonly Rated Items Weighting Factor	MAE	0.1027	0.1167	0.1220	0.1240
	Percentage	22.42%	7.43%	3.81%	1.90%
Apply Evaluation Preference Factor	MAE	0.1208	0.1216	0.1231	0.1231
	Percentage	4.15%	3.12%	2.86%	2.60%
Apply Max. Min. Calibrating Factor	MAE	0.1243	0.1249	0.1263	0.1260
	Percentage	1.18%	0.39%	0.27%	0.25%
Apply All Three Factors	MAE	0.0980	0.1130	0.1185	0.1207
	Percentage	28.29%	10.95%	6.84%	4.65%

Figure 2 - Experiment results by change number of reviewers.

Experiment is executed 10 times; Number of reviewers is changed from 100 to 1000 with step 100. Among them, Figure 2 shows four sampling cases. According to these result, all MAEs are decreased. But the degrees of decrease are different in each case. To analysis the relationship between the number of reviewers and the degree of MAE decrease, results are plotted in 2 dimension graph.

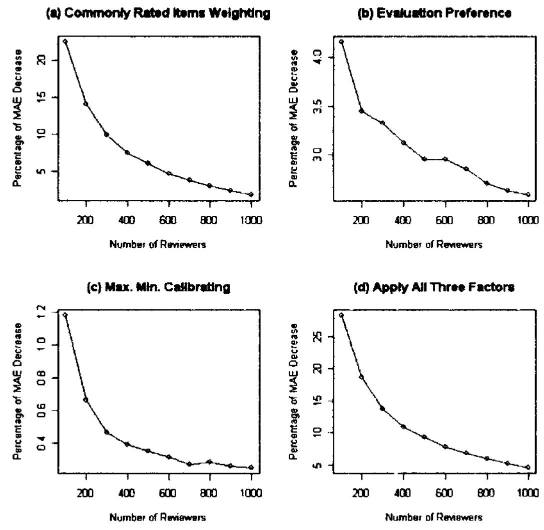

Figure 3 - Relationship between percentage of MAE decrease and number of reviewers

Graph **(a)** in Figure 3 shows inverse proportion between number of reviewers and percentage of MAE decrease. Increase number of reviewers means number of comparison neighborhoods is increased. In Equation (3), if number of comparison neighborhoods is increased, $c_{i,j}$ is constant but $\sum_{j=1,\alpha\in I_j}^{n} c_{i,j}$ is increased and $\frac{c_{i,j}}{\sum_{j=1,\alpha\in I_j}^{n} c_{i,j}}$ become smaller. So proportion of commonly rated items weight is decreased and effect of commonly rated items weighting factor is also decreased. But even the number of comparison neighborhoods is increased, commonly rated items weighting factor derive more accurate predicted score than original model. In conclusion, effect of commonly rated items weighting factor drive more accurate predicted score in all scope of test and most effective when number of comparison neighborhoods is small.

Graph **(b)** and **(c)** in Figure 3 need little different interpretations. In instinctive aspect, effects of factors are also comparatively decreased when number of reviewers is increased. But there are some reasons that these relationships are not the inverse proportion.

First, difference of percentage of MAE decrease is too small. In graph **(b)**, y component is changed only 1.55%. In graph **(c)**, y component is changed only 0.93%. They are too small compare with 20.52% of graph **(a)**. Second, in graph **(b)**, it is hard to find the component which is affected by change of number of reviewers, like $\sum_{j=1,\alpha\in I_j}^{n} c_{i,j}$ in Equation (3). In addition, in graph **(c)**, Equation (5) is also applied after $p_{i,a}$ is calculated.

In conclusion, it is hard to convince that relationship is inverse proportion. So this research didn't give any means to this relationship but if experiment program can control larger amount of data, we can research more about this issue. Even though, it is hard to define as inverse proportion, shape of two graphs is instinctively similar. So we remained this part as future research area.

However, percentage of MAE decrease has positive number in all area in graph **(b)** and **(c)**. It means two factors are always effective. So we confirmed our hypotheses in Equation (4) and Equation (5) are valid.

Graph **(d)** in Figure 3 shows inverse proportion relationship. Difference of percentage of MAE decrease in graph **(b)** and **(c)** is too small compared with graph **(a)** but values in graph **(b)** and **(c)** have positive value and graph **(d)** shows higher credibility enhancement compare with graph **(a)**. So we confirmed our hypothesis that all factors are mutually exclusive and enhance credibility of system.

4.2.2. Relation with Number of Movies

In second part of test, performance of new model by changing number of movies is calculated. The results are similar with that of first part of experiment. New model has higher accuracy than original model. Credibility enhancement is observed in all three factors and credibility of combined model is much more enhanced.

Number of Movies		100	400	700	1000
Original Collaborative Filtering	MAE	0.1401	0.1243	0.1258	0.1245
Apply Commonly Rated Items Weighting Factor	MAE	0.1391	0.1182	0.1170	0.1135
	Percentage	0.75%	5.16%	7.55%	9.70%
Apply Evaluation Preference Factor	MAE	0.1354	0.1208	0.1221	0.1208
	Percentage	3.48%	2.96%	3.08%	3.06%
Apply Max. Min. Calibrating Factor	MAE	0.1388	0.1239	0.1252	0.1239
	Percentage	0.96%	0.38%	0.48%	0.45%
Apply All Three Factors	MAE	0.1341	0.1145	0.1132	0.1098
	Percentage	4.52%	8.61%	11.14%	13.37%

Figure 4 - Experiment result by changing number of movies.

As same with first part, experiment is executed 10 times; Number of movies is changed from 100 to 1000 with step 100. Among them, Figure 4 shows four sampling cases. According to these result, all MAEs are decreased. But the degrees of decrease are different in each case. To analysis the relationship, results are plotted in 2 dimension graph.

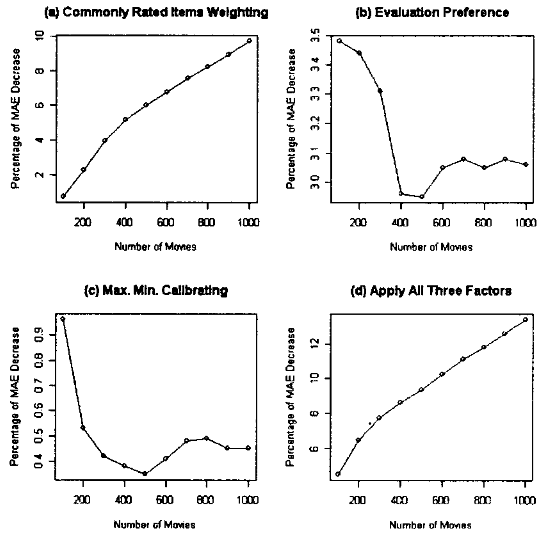

Figure 5 - Relationship between percentage of MAE decrease and number of movies

Different with first part, first graph have proportion relationship. The reason is that the average number of commonly rated items is increased when number of movies is increased because total number of evaluated items is increased. Instead of increase the number of neighborhoods, increase the number of movies means increase the number of comparison items. So in Equation (3), $c_{i,j}$ is increased. Even though $\sum_{j=1,\alpha\in I_j}^{n} c_{i,j}$ is also increased, total accuracy of $\frac{c_{i,j}}{\sum_{j=1,\alpha\in I_j}^{n} c_{i,j}}$ is enhanced. In other word, proportion of commonly rated items weight is increased and effect of commonly rated items weighting factor is also increased. In conclusion, effect of commonly rated items weighting factor drive more accurate predicted score in all scope of test and effect of factor is increased when number of comparison items is increased.

Graph **(b)** and **(c)** in Figure 5 need little different interpretations. In instinctive aspect, it is hard to find the relationship. There are some reasons of these results.

First, in graph **(b)** and **(c)**, difference of percentage of MAE decrease is too small. In graph **(b)**, y component is changed only 0.53%. In graph **(c)**, y component is changed only 0.61%. They are too small compare with 8.95% of graph **(a)**. Second, in graph **(b)**, it is hard to find the component which is affected by change of number of movies, like $c_{i,j}$ in Equation (3). In Equation (4), if the number of α is increased, $\sum_{\alpha=1,\alpha\in I_j}^{k}(v_{j,\alpha} - v_{i,\alpha})$ is increased. But it divided by **N**, so the average is applied. In addition, in graph **(c)**, Equation (5) is also applied after $p_{i,a}$ is calculated.

In conclusion, it is hard to find the relationship. So this research didn't give any means to this relationship but if experiment program can control larger amount of data, we can research more about this issue. Even though, it is hard to find relationship, shape of two graphs is instinctively similar and some hypotheses are considered. But in this research, we remained this part as future research area.

However, percentage of MAE decrease has positive number in all area in graph **(b)** and **(c)**. It means two factors are always effective. So we confirmed our hypotheses in Equation (4) and Equation (5) are valid.

Graph **(d)** in Figure 5 shows proportion relationship. Difference of percentage of MAE decrease in graph **(b)** and **(c)** is too small compared with graph **(a)** but values in graph **(b)** and **(c)** also have positive value and graph **(d)** shows higher credibility enhancement compare with graph **(a)**. So we confirmed our hypothesis that all factors are mutually exclusive and enhance credibility of system.

5. Conclusion and Future Research

There are some contributions in this paper. First, it proposed well organized process diagram of collaborative filtering algorism which divided in six steps. Second, it proposed new factor which consider the number of commonly rated items between active user and other neighbors. Third contribution is that it proposed new factor which consider evaluation preference of users. Forth contribution is that it proposed new factor which consider limitation of evaluation scope problem. Fifth and final contribution is that the relationship between these factors and other variables are analyzed. From these analyses, we confirmed effects of those factors and find relationships.

In the process of design and experiments, some limitations are existed and they gave issues for future researches. The first limitation is that it was hard to extend the scope of number of variables because of memory limitation of statistic program. So we used randomly sampling method to decrease the number of data sets. If the restriction is diminished, full data sets can be experienced and decrease step of variables. Then we could derive more accurate conclusions about our hypotheses. The second limitation is that our experiment was only experienced using movie evaluation data sets. Most of experiments about collaborative filtering system using data sets which are from movie or book industries. But if future researches apply it in other industry fields, they could find characteristics or differences of each result using different industry data. Moreover, we expect more factors which could improve credibility enhancement of system.

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