The Method of Personalized Recommendation with Ensemble Combination

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Abstract

Nowadays trust and reputation models are becoming more and more important to make the decision through various industries. Trust-based system is vulnerable to sparse relations, so there are attempts to combine the trust and reputation models. In this paper, we propose a method in which the trust and reputation models are harmonized through an ensemble combination. It can be applied to not only the personalized recommendations but also the detection of malicious insider users which attack with unfair rating. The proposed method enables both the models to complement each other and provides the reliably personalized service.

Keywords: Trust and reputation model, Recommendation system, Ensemble combination

1 Introduction

Supporting decision making is becoming more and more important in various industry fields. However, it is difficult to help customers to decide the decision because a lot of information occurs more frequently these days than ever before. In addition, there can be unnecessary information and malicious information. So, among this information, customers must choose the appropriate information according to their personal tastes and their needs. They are also faced with the problem of selection in order to maximize their satisfaction to limited resources.

When facing these problems, trust and reputation models which are based on the Word-of-Mouth (WoM) can support their decision-making by using relations between users. The WoM seeks an advice from people who had hands-on experience and supports a decision-making. Both models are similar in that they infer the reliability using a virtual network which is composed of users who had hands-on experience. However, the trust model infers relations from a subjectively reliable notion of trust established among individuals, while the reputation model infers the relations from an objectively trustworthy notion of reputation established among groups [1].

If trust and reputation models are utilized, we will be able to establish applications used in various industry fields. For example, using these models, a security system can deduce malicious users from analyzing the relations. And personalized service system uses both models for analyzing the taste of users and providing appropriate services for each user. Especially, trust and reputation models are widely used in recommendation systems. Recommendation system produces a recommendation list of appropriate items for the users through using various methods to collect and analyze information, which can support decision-making based on the various information such as cost, performance and prior transactions.

A recent study suggests a method to provide a personalized recommendation list of items based on the analysis and cognition of the user rather than items favored by many people [2, 3]. Previous studies

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on a personalized recommendation system have analyzed their prior activities or transactions to provide customized recommendation services. Other approaches include social network and Collaborative Filtering-based recommendation systems (CF) [2, 4] which utilize the analysis and evaluation of similarities among users. Particularly, CF approach produces more reliably personalized recommendation than other approaches because it conducts in-depth analysis of personal tastes and utilizes the relations between users.

Establishing a recommendation system based on trust or reputation models has both pros and cons. Trust model is appropriate for a customized recommendation in that it is based on a subjective confidence value, but is limited due to the cold-start problem which occurs at the early stage and the sparsity problem caused by insufficient relations. The performance of recommendation system based on trust model will decrease by both of these problems. On the other hand, the reputation-based recommendation system effectively deals with the above-mentioned problems as it draws inference for the reliability value from people's opinion. However, it is not appropriate for a customized inference than trust-based model because it does not consider personal information about each user. Additionally, if the inference is made based on dishonest ratings by malicious insider users, the reputation model may face the unfair rating problem which undermines credibility of reputation-based recommendation system.

In addition, recommendation system has a risk problem, which means the system would pose unsatisfactory outcome for some users while bringing a desired outcome for others. Particularly, this situation occurs when users are given intensive machine learning with existing data. In other words, a training data-based model leads to quality performance, whereas an evaluation data-based model results in significant deterioration in performance.

This paper proposes the ensemble combination method with trust and reputation. It can be utilized to recommend movies and also treat the attacks which occur by malicious users. Intelligently combining trust and reputation model provides to make up for weaknesses which are owned by each model. Also, the proposed method overcomes the risk problem caused by intensive machine learning through ensemble combination. In the end, the proposed system can produce a personalized recommendation for each user.

This paper is organized as follows: Section 2 presents studies relevant to the topic. Section 3 elaborates on the structure and the phased process of an ensemble combination-based recommendation system that this paper intends to suggest. Section 4 presents an analysis and evaluation of the performance of the suggested method utilizing the actual Movie Lens data. Section 5 discusses how to treat when malicious users occur. Section 6 concludes and discusses future research directions.

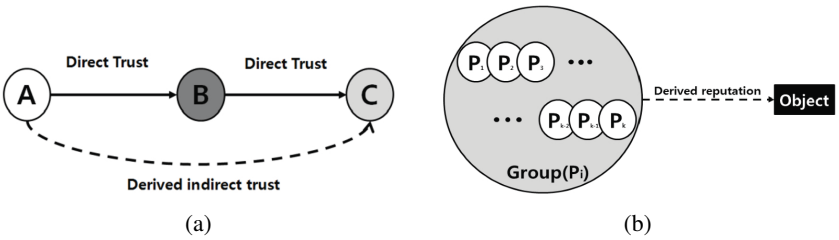
2 Related Work

2.1 Trust and Reputation Model

As regards online service, it is difficult to obtain the reliability which has to be based on first-hand experience. That is why people face 'the risk of prior performance' that they should pay for the goods prior to receiving them [1]. The risk of prior performance is created in the situation where customers generally have no hands-on experience of seeing and trying products online and make a choice for consumption only relying on the information provided by 3rd-parties, which leads to an unsatisfying choice due to the information fallacy or misunderstanding.

The WoM mechanism can be utilized to solve this problem arising frequently in online [5, 1, 6]. This mechanism enables raters with direct experiences of items to establish a virtual network and collects information from them which benefits decision-making.

The trust and reputation models are cases in point. They are similar in that both infer the reliability using a virtual network which consists of users who had information of target items. However, they



(a) (b)

Figure 1: Trust Model(a) and Reputation Model(b)

differ in that the trust model derives a subjective reliability notion of trust value from personal experiences, while the reputation model derives an objective reliability notion of reputation value from group experiences as follows.

Both models are utilized as a framework tool to establish a reliable online service. Marsh suggested a confidence computation model which was applied to Distributed Artificial Intelligence (DAI) community [7], while Jøsang proposed reputation model using probability density [8], and based on this, further suggested a method of controlling unfair rating problem [9]. In addition, Golback proposed a reputation and trust inference model for users in a semantic web-based social network [10]. In this respect, trust and reputation value can be derived through a variety of methods, and studies should continue to establish a reliable online environment. As a result, improving the trust and reputation models contributes to variety of fields because both tools were used by tools for solving problems which occurred in many fields.

2.2 Ensemble Combination with Ensemble Classfication

In general, a prediction model which is established on the basis of thousands of features or small size of training data produces unstable results [11]. In particular, a prediction model which is developed through an intensive training would have not to guarantee its performance if new data appears. To solve this problem, a simple model averaging [12] method can be utilized. This method controls the problem using the average of various classification models based on the information statistics theory. Accordingly, this approach infers prediction results applying a variety of prediction models, thereby producing more stable outcomes compared to a single prediction model.

The ensemble classification method is the next step to the simple model averaging. Ensemble approach has a motive to create a strong decision-making group through combining lots of weak classifiers [13]. In order to support an ensemble-based decision-making, results of single classification method are induced through various methods such as majority or averaged prediction method [14, 15, 16, 17].

The two key parts of establishing ensemble model are the process of selecting major features and effectively combining the results obtained through a single classifier [18]. Ensemble-based prediction model usually presents less generalization fallacy than a single prediction model even though the extent might vary depending on the kinds of classifier, the size of ensemble, a diversity of or a correlation between classifiers. Therefore, improved prediction results can be achieved through combining optimized results of a single classification method using ensemble model. Moreover, this approach can be designed for the high-level data set to have strengths in dealing with the issue of dimensionality increase. This paper is to combine different single recommenders based on the ensemble classification method.

2.3 Research of Trust and Reputation Model for Controlling the Problems

Recommendation systems are used to support decision making in many industries, such as security, e-commerce, and wireless communication systems. However, such systems include risk and sparsity

and cold-start problems. Recent research proposed a variety of methods to address these problems and improve trust- and reputation-based systems [19, 20, 21]. Many papers have proposed the hybrid method, which combines trust and reputation, to address the different strengths and weaknesses of trust models and reputation models [22, 23, 24]. However, these papers propose using a simple combination method or just use the reputation model as a complement to the trust model. In addition, these proposed methods well operate at only specific situation when was defined by author. Therefore, trust and reputation models need to be combined using the intelligent method to address the individual weaknesses of these models. Also, to increase utilization of recommendation systems for general situation, new combination method should continually be researched and proposed. The ensemble combination can provide not only the intelligent combination method but also new method for establishing the general-proposed system.

3 Trust and Reputation Model with Ensemble Combination

This paper suggests a method of intelligently combining trust and reputation models utilizing ensemble combination, which overcomes the weaknesses of both models. Moreover, this method is capable of controlling the risk problem that arises when the customized services are provided to the user. Using trust and reputation models, we can establish various applications such as security system, personalized service system and recommendation system. In this paper, we construct the recommendation system with real movie rating data for evaluating the proposed method. The suggested system follows the process as follows.

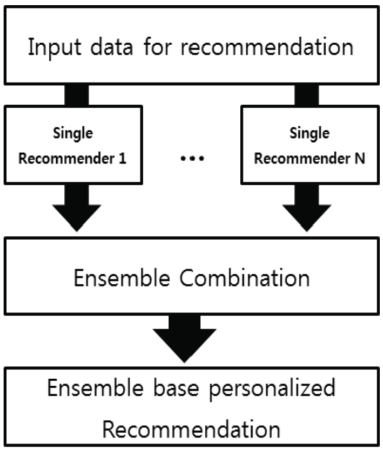


Figure 2: System of Ensemble-based personalized recommendation

First, in order to establish single recommenders, the system employs the Collaborative Filtering method which is often used to establish a recommendation system. Second, a feature set of CF conducts a modeling of relations between the users based on the trust and reputation model and utilizes them. Third, it makes personalized recommendation on the basis of the combined results. The remaining parts of this section contain a detailed account of the suggested method.

3.1 Making Features with Trust and Reputation Model

Trust and reputation model are based on the notion of reliability which can be built between individuals or between an individual and a group. The two values of trust and reputation can be used for modeling based on a variety of information including tastes of users, prior transactions, and similarities among user profiles. As this study is to establish the system based on the actual movie rating data, it defines

Table 1: Three kinds of Relation

UserB \ UserA	1∼2	3	4∼5
1∼2	Trust	Ambiguous	Distrust
3	Ambiguous	Trust	Ambiguous
4∼5	Distrust	Ambiguous	Trust

three kinds of relation which can be seen during rating activity, and based on this, it further develops a trust model. Trust relation means a relationship between the users who give similar ratings on the same item, while distrust relation means a relationship between users who give different ratings on the same item. Ambiguous relation refers to an inexplicable relationship between users as defined under the below Table 1.

The defined relations can be utilized immediately as features of CF. The recommendation system established based on these, opinions of audiences who have similar preferences for certain movies can be utilized. However, meaningful relation can be induced through combining the three kinds of relation, and diversity for the ensemble combination can be ensured when this relation is utilized as a feature. Eventually this will contribute to improving performance of ensemble combination. This paper suggests an Enhance Trust relation based on three kinds of relation and it is inspired by a TF-IDF concept which is frequently used in Information Retrieval (IR). TF-IDF analyzes the number of terms in many documents and provides the values about similarity between each document. This concept used the logarithmic function for normalizing. Like our enhanced trust, three kinds of relation are combined by using logarithmic function.

$$\begin{aligned} EnhancedTrust(a,b) &= [1-\log(AmbiguousTrust(a,b)+1)] \\ &\times \frac{[\log(Trust(a,b)+1)+1-\log(Distrust(a,b)+1)]}{2} \end{aligned} \tag{1}$$

Utilizing the above formula, the result ranges from 0 to 1. The lower the each level of ambiguous relation or distrust relation is and the higher the trust relation is the closer to 1 the value provided.

According to the inference engines, reputation value can be classified into different groups such as a simple computation model, simple model averaging model, individual trust model, and probabilistic model-based reputation model. This study is to utilize Bayesian reputation system which draws a reputation inference based on beta probability density function. Reputation value can be obtained through the following equation. The parameters of r and s represent the number of people who give positive ratings and negative ratings respectively.

$$p^t(Z) = E[beta(p^t(Z))] = \frac{r+1}{r+s+2} \tag{2}$$

In this study, if a trust value about specific target higher than the average of trust value about the target, this trust is considered positive. Whereas a trust value lower than the average is considered negative. This method relatively easily achieves the outcome with high accuracy rate and handles well the unfair rating problem [9]. Moreover, the reputation model is conducive to solving the cold-start problem which is caused by lack of hands-on experience. Because reputation value can be derived from some people who have direct-experience even if another people have lack of information.

Furthermore, trust and reputation inference can be made from different perspectives using various methods. Utilization of inferred information on diverse relations contributes to ensuring diversity of ensemble system, thereby improving performance of ensemble system.

3.2 Collaborative Filtering-based Single Recommender

One of the methods recently and the most frequently used in order to establish a recommendation system is a Collaborative Filtering (CF) algorithm. CF systems have many forms, but common CF consists of two steps. They look for users who had similar rating patterns (step1), and then the systems derive the predicted rating from those like-minded users found in previous step (step2). These CF systems fall under the category of user-based collaborative filtering and these are user-based Nearest Neighbor algorithm. The K-Nearest Neighbor algorithm (K-NN) calculates the similarity between users, and selects the k number of users who exhibit the most associative relationship.

The proposed recommendation system in this paper is made by group which consisted of single recommender based on CF algorithm. In order to implementation CF algorithm, a method should be set on how to select features and deriving the similarity between the users from selected features. In this paper, we use the trust and reputation values which are inferred on the previous stage for features, and further use the following two methods to measure the user-to-user similarities. The first method is to select the users who demonstrate the most associative relationship based on Euclidean distance. For example, when trust infers Euclidean distance based on feature, the model selects the k number of people whose rating information is most similar to users. If the referrals can be made by these people, the model can provide appropriate recommendation for the users. The second method is to infer the level of similarity based on cosine similarity. When certain users represent a vector as a confidence relation with other users, k number of people who have associative relationship with the users would be selected. Finally, the k number of people in CF is determined by the number of people who had first-hand experience about target item i. $r_{u,i}$ means the value of rating about item i by user u and $\overline{r_u}$ is the average rating of user u for all the items rated by that user. n is a normalizing factor.

$$CF(r_{u,i}) = \overline{r_u} + n\sum similarity(u,u')(r_{u',i} - \overline{r_{u'}}) \tag{3}$$

Both methods are similar in that they extract users who have similar tastes. However, despite using the same feature, they produce different outcomes because k number of people is selected through different measurement methods, which helps to ensure the diversity of ensemble system.

If the method employs reputation as feature, it cannot measure the level of similarity through the employment of cosine similarity as it has only simple reputation value on the item. Therefore, reputation-based single recommender produces a list of recommendation based on Euclidean distance. Each single recommender produces a list of recommendation for movie utilizing the selected k number of people. To recommend movies, it employs a simple rating averaging method. In other words, it recommends movies which record high ratings in average among k number of audiences who already watched the movies. Ratings averaging method is relatively easy to use and provides meaningful outcomes.

Moreover, other various feature or associative relation measurement methods can be used to establish the CF, and recommendation methods other than CF can be employed to establish a single recommender. Through this process, diversity of ensemble system can be ensured.

3.3 Ensemble Combination with each single recommender

Even though providing appropriate results for some users, personalized recommendation system has a risk of providing inappropriate results for others. In other words, personalized recommendation system goes through the process of identifying preferences of users, while it does not always work properly for all users. Particularly, this situation often occurred when the recommendation system processed intensive learning with the training data.

However, this risk can be reduced by utilizing various recommenders. For instance, while some recommenders fail to produce an accurate analysis on users' tastes, other recommenders would be able to

do. Therefore, based on training data, this paper calculates the performance of each single recommender as weight values for combination. We can use the concept of Mean Absolute Error (MAE) for calculating performance of each single recommender. The more MAE is low, the more prediction which is derived from recommendation system is accurate. If each MAE is same, it is simple average combination which is previous combination method in ensemble combination. If there are three single recommenders, we can use the formula for the combination as follows. α, β, γ are value of weight which are derive from MAE.

$$Ensemble\_CF() = \frac{\alpha \times Singlerecommender_1 + \beta \times Singlerecommender_2 + \gamma \times Singlerecommender_3}{\alpha + \beta + \gamma} \tag{4}$$

As a result, if each single recommender presents a good performance using training data, it obtains high weighed value, and if it shows a poor performance, then it receives low weighed value.

In addition, variety of information is used for calculating the weight values. When using the MAE as weight value, the recommender which predicts more accurate than others increases the weight. On the other hand, when using the precision or recall which is widely use information retrieval system for evaluating, the recommender which provides more accurate result than others increases the weight.

4 Experiments and Evaluation

4.1 Evaluate Function

In order to evaluate 'Ensemble-base Personalized Recommendation System' suggested by this study, Mean Absolute Error (MAE) which is commonly used in the recommendation field is employed as an evaluation indicator. The MAE can be computed based on the following formula. The MAE compares the actual ratings of customers with the predicted ratings obtained through a recommendation algorithm and evaluates how similar the predicted ratings are to the actual ratings. A_i represents actual ratings on the item i, while F_i represents the predicted ratings on the same item which are inferred through the system.

$$MAE = \frac{\sum_{i=1}^{q} |A_i - F_i|}{q} \tag{5}$$

However, the MAE has a limitation in that low MAE does not guarantee high accuracy of recommendation. In other words, the MAE considers only the level of similarity between the system-based recommendation rating and the actual ratings of users. It does not consider the number of difference between actual preferring list of users and recommended list by the system. Therefore, this study utilizes not only the MAE, but also F-measure which is widely used to evaluate algorithm in information retrieval field. This indicator is compounded of two parameters which are recall and precision. Both parameters are calculated by the number of false negative, false positive, true negative and true positive. The F-measure can be computed based on the following formula.

$$F - measure = 2 \times \frac{Precision \times Recall}{(Precision + Recall)} \tag{6}$$

4.2 Experiments data

This study utilizes Movie Lens data which is information gathered from the movie ratings website. It limits the number of users to 1000 and utilizes 150,000 ratings set of information as well as 3,000 set

of related movie information. Even though it could have used the training data construction methods of traditional ensemble system as like bagging in order to ensure diversity, but we didn't use those methods in this paper. This paper sets a reasonable timestamp and considers it as the present. It also considers remaining parts as the future, and then conducts experiments. In order to carry out the experiment, 90 percent of 1000 people's data is used as training data, while the remaining part is utilized as correct answers which have to be predicted by system.

4.3 Evaluation

The ensemble-based recommendation system in this study consists of five kinds of single recommenders. Five different relations, which are trust, distrust, ambiguous, enhanced trust relations and reputation relation, are employed as features for constructing the CF. Using the three different ways, single recommenders calculate the similarity between each user. One is Euclidean distance similarity, another is using the cosine similarity, and the other is to not use anything for calculating the similarity. In this case, the trust and reputation relations are used as similarity without any processing. Each single recommender infers the predicted ratings by using CF which is based on the features and similarity. The difference between an actual rating and the predicted rating is MAE, and the performance of recommendation system is good when this value is lower.

We combine each single recommender by using four different ways. First, each single recommender is combined in the same proportion, which called a simple average method. Using the training data, the system calculates the average of MAE about each user. The system weighs appropriate single recommenders which have smaller MAE than other single recommender and values of MAE-1 is used as these weights. This way is the second way for combining each recommender and this is a weighted average method by using MAE. Using Root Mean Square Error (RMSE) and user defined values as weights are third and fourth ways for combination. RMSE is frequently used measure of differences between values predicted by a model and actually observed. The difference between MAE and RMSE is the same as the difference between deviation and mean.

As a result, the lower MAE values mean the recommendation system is well predicted the ratings, the higher F-measure values mean system well recommended the items, the lower RMSE the predicted ratings are stably provided for user. Following tables are results of evaluating between each recommendation system.

The comparative analysis of the performance of the single recommenders and the ensemble recommenders is presented in Table 2, 3 and 4 respectively.

Table 2 indicates the result of recommendation system based on Euclidean distance as similarity for CF. In first part which named Euclid_CF_before, the results of MAE and RMSE are calculated by using training data. These results are used as weights when we combine single recommenders for establishing ensemble-based recommendation system. Utilizing the evaluation data set for evaluating, Euclidean similarity-based CF and Euclidean similarity-based ensemble system predict the ratings. As a result, the difference between actual ratings and predicted ratings are recorded in second and third parts which named Euclid_CF_after and Euclid_ensemble. In Euclid_ensemble part, column of simple means the result of MAE, RMSE and F-measure by using simple average method for combination. And columns of MAE, RMSE mean the results of weighted average method-based ensemble recommendation system using MAE and RMSE as weights. Column of user means the results of user-defined weighted average method-based ensemble system. We define each user defined weight as 1, 0.8, 0.9, 1, 1. These values are selected though results of single recommenders by using evaluation data.

According to the results of Table 2, results of CF using the trust-based relations have lower RMSE than reputation-based CF. This means reputation-based CF has weakness to provide the personalized inference for user. In this table, enhanced trust-based CF is best performance in MAE and RMSE re-

Table 2: The result of experiment by using Euclidean similarity

		MAE	RMSE	precision	recall	f
Euclid_CF_before	trust	0.65609	0.11528	0.71084	0.75088	0.69932
	distrust	0.51204	0.09375	0.69272	0.83232	0.72468
	ambiguous	0.65904	0.11582	0.71092	0.74920	0.69875
	Enhanced	0.67402	0.11857	0.71294	0.74180	0.69658
	reputation	0.70446	0.12522	0.71760	0.72915	0.69288
Euclid_CF_after	trust	0.81936	0.22922	0.68646	0.66082	0.64153
	distrust	0.81917	0.22920	0.68657	0.66599	0.64221
	ambiguous	0.81924	0.22917	0.68665	0.66366	0.64163
	Enhanced	0.81875	0.22903	0.68467	0.66509	0.64153
	reputation	0.81922	0.23000	0.67880	0.65733	0.63723
Euclid_ensemble	simple	0.81889	0.22923	0.68500	0.66608	0.64208
	MAE	0.81895	0.22922	0.68531	0.66626	0.64224
	RMSE	0.81890	0.22924	0.68490	0.66600	0.64198
	user	0.81889	0.22924	0.68503	0.66605	0.64208

spects. In the respects of precision and recall, which are widely used in information retrieval system, enhanced trust based CF does not work well. However, ensemble recommenders provide lower MAE than some single recommenders, and give higher precision and recall than enhanced trust-based CF. Although not shown in these tables, sometimes distrust or enhanced trust relation based CF does not infer the predicted ratings because of sparse relations between each user. Whereas the ensemble-based recommendation system can deduce all of ratings because of using the relation of reputation. In this respect, the ensemble-based personalized recommendation system controls the risk problem. Moreover, employing both the trust model and the reputation model simultaneously controls the cold-start problem, the sparsity problem, and the risk problem, which arise when only the single model is used.

The ensemble-based recommender does not necessarily guarantee a good performance than all of single recommenders. However, the ensemble-based recommendation system overcomes the weakness of each single recommender with the intelligent combining method. Also, the results of ensemble-based recommendation systems are changed by what to utilize as the weights. So, it is important to select the appropriated value of weights for optimizing the results. In this experiment, the result of reputation-based CF is relatively good performance. We think that distribution of movie rating and major role are related this situation. We think that the distribution of ratings is biased by 3. Because results of ambiguous-based recommendation using trust and reputation as similarity and training data have the most of small MAE in Table 4.

Both models have problems when malicious user attacks the system. Especially, reputation model has weakness about collaborative unfair rating attack because this attack does not abide by major role. So, we discuss this problem in next chapter. Table 3 and 4, are results of recommenders based on cosine similarity or trust and reputation relations as similarity between each user. Both tables also showed a similar tend like as Table 2.

As a result, the ensemble-based recommendation system does not guarantee a good performance in every time. And three tables showed that an optimized combination using training data does not always guarantee good performance in terms of prediction. But each single recommender will be able to

complement each other through ensemble combination.

Table 3: The result of experiment by using Cosine similarity

		MAE	RMSE	precision	recall	f
Cosine_CF_before	trust	0.68012	0.11755	0.71590	0.73315	0.69521
	distrust	0.62349	0.09671	0.69933	0.76414	0.69925
	ambiguous	0.66074	0.11262	0.71129	0.74224	0.69722
	Enhanced	0.69920	0.12296	0.71738	0.72781	0.69309
	reputation	0.70446	0.12522	0.71760	0.72915	0.69288
Cosine_CF_after	trust	0.81942	0.22988	0.68580	0.66385	0.64267
	distrust	0.82218	0.22352	0.68221	0.65991	0.63881
	ambiguous	0.81989	0.23022	0.68876	0.66457	0.64486
	Enhanced	0.81895	0.22897	0.68515	0.66687	0.64269
	reputation	0.81922	0.23000	0.67880	0.65733	0.63723
Cosine_ensemble	simple	0.81939	0.22992	0.68763	0.66380	0.64397
	MAE	0.81926	0.22992	0.68747	0.66357	0.64385
	RMSE	0.81939	0.22992	0.68766	0.66378	0.64397
	user	0.81935	0.22988	0.68767	0.66374	0.64395

Table 4: The result of experiment by using Trust and Reputation relations

		MAE	RMSE	precision	recall	f
Non_CF_before	trust	0.39752	0.05703	0.67784	0.88720	0.73964
	distrust	0.82436	0.15535	0.69718	0.68315	0.66089
	ambiguous	0.34370	0.04766	0.67152	0.89560	0.74160
	Enhanced	0.73578	0.13016	0.72160	0.70764	0.68704
	reputation	0.70446	0.12522	0.71760	0.72915	0.69288
Non_CF_before	trust	0.82001	0.23164	0.70444	0.66797	0.65682
	distrust	0.85817	0.23731	0.66228	0.64341	0.62869
	ambiguous	0.83322	0.23641	0.69672	0.67490	0.65628
	Enhanced	0.81827	0.22845	0.68544	0.66411	0.64272
	reputation	0.81922	0.23000	0.67880	0.65733	0.63723
Non_ensemble	simple	0.81946	0.22964	0.69282	0.66917	0.64946
	MAE	0.82081	0.22999	0.69547	0.67528	0.65265
	RMSE	0.81905	0.22953	0.69238	0.66964	0.64906
	user	0.81907	0.22959	0.69267	0.67025	0.64940

5 Discussion for Treating Attack

Since trust and reputation models have started to be used for providing reliable service in various fields, there were trials to attack both models to achieve personal profits or malicious goals [25, 26, 27, 1, 6]. These attacks were disturbing to infer the accurate relations between each user, and trust and reputation-based system could not provide the appropriate services. These attacks to deteriorate the reliability of trust and reputation models can be variously defined by their methods [25, 26, 27]. For example, there are the playbook that attacks after getting stable reliability from both models, unfair rating that gives higher or lower ratings than actual status and re-entry that undervalue the rating with multiple ID creation.

Because all of attacks eventually conduct giving higher or lower ratings, the unfair rating attack is biggest problem among every type of these attacks. The unfair rating has most difficult problems to be recognized, since people can have various opinions for an evaluating target. Also, previous unfair rating controlling methods are based on the major role, which assumes that there are more fair evaluators than unfair evaluators. However, the collaborative unfair rating, which instigates many persons or creates multiple ID for a person so that the major role is not valid any more, can easily happen in progressive internet. For this case, the existing method based on the major role cannot effectively filters unfair ratings.

The various methods for solving the unfair rating and collaborative unfair rating problem have been proposed [26, 27, 1, 6]. However, they are designed for a certain situation, thus not working well when the situation is changed. Each of these methods has pros and cons.

Utilizing the proposed method in this paper, we can make the two step ensemble recommendation system for recognizing unfair users and providing reliably personalized recommendation. The first step in the system consists of single recognizers which look for the malicious users by each method and combines each single recognizer by using ensemble combination. Modifying the values of trust and reputation using previous results, the system decreases the influence of malicious users in this step. In next step, we can establish the ensemble recommendation system by using modified relations. As a result, the system provides reliable and appropriate recommendation for each user.

However, this system needs to a lot of computing power because it is composed of both ensemble systems. Morever, CF algorithm, which is used for recommendation, needs considerable computations because it has iterative calculations for prediction. To solve these problems, we can utilize the distributed and parallel system which is spotlighted in these days.

6 Conclusion and Future Work

The trust and reputation models are widely used for establishing various applications, however each one has weaknesses. While the trust model does not provide a reliable service when people haven't enough information, the reputation one cannot provide the personalized service. In addition, the recommendation has the risk problem which means that some users take appropriate service but the other users take inappropriate one. These weaknesses decrease the reliability of the trust and reputation-based systems.

This study suggested that the intelligent combination method based on an ensemble combination technique can be used to address these problems. We also established a recommendation system based on the proposed method with actual data set. Using this recommendation system, we demonstrated that the proposed method overcame weaknesses of the trust and reputation models. Moreover, this study showed that the risk problem posed by each single recommendation system could be controlled through an intelligent combination method. As a result, the proposed system could provide the personalized recommendations and control the aforementioned problems. We also discussed a method for treating the unfair rating problem by using this proposed system.

However, we used only simple techniques of ensemble combination for constructing our system, so we need to further study for improving the performance. To enhance the performance of the ensemble system, a combination of optimized feature selection and the intelligent method are needed. Future studies should aim to improve the performance through optimized parameters and to combine trust and reputation models intelligently and to establish a reliable and appropriate system for users.

We also plan on applying the proposed method to distributed and parallel systems because CF algorithm and ensemble combination have a lot of iterative calculating and need to a lot of computing power. In this further study, we will propose powerful decision-making systems based on distributed and parallel systems.

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