AN ENHANCED TRUST-BASED RECOMMENDER SYSTEM USING INFLUENCE OF TRUSTEE ON RATING PROPAGATION

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ระบบแนะนำด้วยความเชื่อที่เพิ่มประสิทธิภาพโดยใช้อิทธิพลของผู้ที่มีความน่าเชื่อถือแบบการแพร่กระจายของความเห็น

นายสัจจวัฒน์ เจริญเหรียญ

วิทยานิพนธ์นี้เป็นส่วนหนึ่งของการศึกษาตามหลักสูตรปริญญาวิทยาศาสตรมหาบัณฑิต
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สัจจวัฒน์ เจริญเหรียญ : ระบบแนะนำด้วยความเชื่อที่เพิ่มประสิทธิภาพโดยใช้อิทธิพลของผู้ที่มีความน่าเชื่อถือแบบการแพร่กระจายของความเห็น (AN ENHANCED TRUST-BASED RECOMMENDER SYSTEM USING INFLUENCE OF TRUSTEE ON RATING PROPAGATION) อ.ที่ปรึกษาวิทยานิพนธ์หลัก: ผศ. ดร.ศรันญา มณีโรจน์, 44 หน้า.

The Recommender System (RS) suffers from sparse data problem, so the trust on social network is gathered to be additional data source. It is called trust based RS. The current trust based RS usually use similarity value between a pair of users generated from their co-rated items as a trust value. This is not applicable in the real world: 1. Similarity value provides symmetry relation, while trust value should be asymmetry relation. 2. Co-rated items are hard to discover, so some pair of users may not have the trust value. 3. Similarity value does not concern about trust level from remoteness between the users. A new asymmetry trust value calculation is produced to eliminate all above problems by applying latent user model. In rating prediction step, the current trust based RSs calculate prediction using weighted average on rating of raters where is the trust value of rater from active user acts as the weight. In this work, a new way to generate weight is proposed by considering the influence level of rater towards active use. In addition, transposed rating is proposed to use instead of directly rater’s rating in order to show the rater’s opinion in perspective view of active user. My enhanced trust based RS is expected to produce more accuracy and coverage recommendations.

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ระบบการให้คำแนะนำมักจะได้รับผลกระทบจากการที่มีข้อมูลไม่เพียงพอที่จะนำมาใช้ในการประมวลผลจึงทำให้ประสิทธิภาพของระบบให้คำแนะนำไม่ดีพอ ดังนั้นจึงได้มีการนำเครือข่ายสังคมเข้ามาใช้เป็นข้อมูลอีกชุดสำหรับการประมวลผล ซึ่งเรียกว่าระบบให้คำแนะนำโดยใช้ค่าความเชื่อระหว่างบุคคล โดยปกติระบบให้คำแนะนำโดยใช้ความเชื่อจะใช้ค่าความคล้ายคลึงกันระหว่างแต่ล่ะคู่ของผู้ใช้งานที่คำนวนมากจาก Co-rated Item เป็นค่าความเชื่อ แต่ทว่าการคำนวนค่าความเชื่อด้วยวิธีนี้นั้นไม่ได้สอดคล้องกับความเป็นจริง โดยปัญหาจากการใช้ค่าความคล้ายคลึงคือ 1. ค่าความคล้ายคลึงจะมีคุณสมบัติของความสมมาตรซึ่งทำให้ค่าความเชื่อระหว่างผู้ใช้สองคนนั้นเท่ากันแต่ทว่าค่าความเชื่อระหว่างผู้ใช้งานนั้นอาจจะไม่เท่ากันก็ได้ 2. การหา Co-rated Item ในชุดข้อมูลนั้นทำได้ยากจึงทำให้ไม่สามารถคำนวนหาค่าความคล้ายคลึงให้กับผู้ใช้งานทุกคนได้ 3. ค่าความคล้ายคลึงไม่ได้คำนึงถึงระดับความเชื่อของความห่างของผู้ใช้แต่ล่ะคนที่อยู่ไกลหรืออยู่ใกล้ การคำนวนค่าความเชื่อที่ไม่สมมาตรแบบใหม่จึงถูกสร้างขึ้นมาเพื่อแก้ไขปัญหาข้างต้นทั้งหมดโดยได้ประยุกต์ใช้รูปแบบจำลองของผู้ใช้แฝง ส่วนการทำนายผลนั้นระบบให้คำแนะนำโดยใช้ความเชื่อจะคำนวนโดยใช้การเฉลี่ยถ่วงน้ำหนักระหว่างค่าประเมินของผู้ใช้ที่ประเมินคะแนนให้กับสิ่งของชิ้นนั้นกับค่าความเชื่อของผู้ขอคำแนะนำที่มีต่อผู้ใช้ที่ประเมินคะแนน ในงานวิจัยชิ้นนี้ได้นำเสนอวิธีคำนวนค่าเฉลี่ยถ่วงน้ำหนักแบบใหม่โดยพิจารณาจากอิทธิพลของผู้ใช้งานในระดับต่างๆที่ส่งผลต่อผู้ขอคำแนะนำ และอีกทั้งได้เสนอใช้การสลับเปลี่ยนค่าประเมินแทนที่การใช้ค่าประเมินที่ได้จากผู้ใช้ที่ประเมินคะแนนโดยตรงเพื่อที่จะได้ปรับเปลี่ยนค่าประเมินของผู้ใช้ที่ประเมินคะแนนให้อยู่ในมุมมองของผู้ที่ขอคำแนะนำ ในการเพิ่มประสิทธิภาพของระบบให้คำแนะนำแบบความเชื่อนี้ถูกคาดหวังว่าสามารถเพิ่มความแม่นยำและสามารถให้คำแนะนำได้ครอบคลุมมากขึ้น

Department:	Mathematics and Computer Science	Student's Signature	....
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CHAPTER I

INTRODUCTION

1.1 Introduction

Amount of Information is growing rapidly. Whenever users will use the search engines or other tools that helps them to find the information from the many sources. However, the information that give back to the user may not related to their mind for example, the users search the movie hat their preferred in search engine website and search engine may give some unwanted movies as the first rank to user.

The Recommendation System (RS) was introduces for another tool to help users find the right answer for them. It will predict what should be attractive for each individual user based on one's personalized characteristics. The RS consists of three major steps. First, collecting rating data representing the user's preference towards different items. Next, generating the user's pattern based on his past experience towards those items. Last step, assigning a prediction value to new items based on the user's pattern and shows the list of top N items as a result. However, there is some problem for the data inside the RS. There are some unwanted data inside, which leads to inaccurate rating prediction that created by sparseness of data.

There are many researchers tried to solve this problem by using additional data source. One of the most popular data source and architecture is Trust-awared recommender (TAR) [1] architecture proposed by Messaet al. TAR merges the original data source called User-Rating Matrix, which collects data from users who have rated the items, with an additional dataset called the trust network.

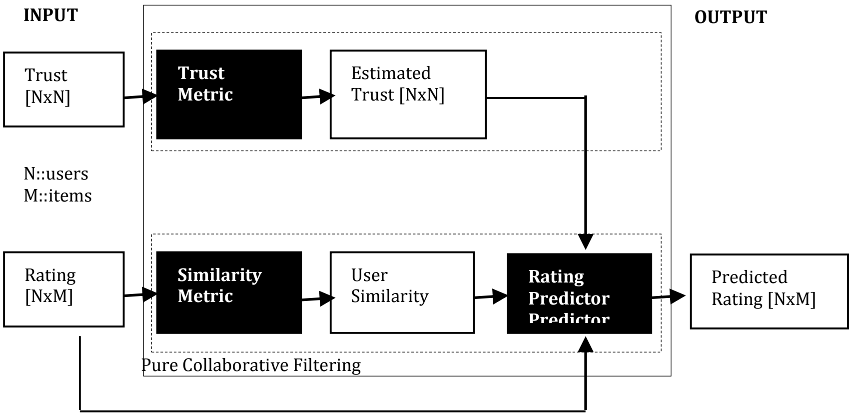


Figure 1.1: Trust-awared recommender system architecture.

From the TAR shows in Figure 1.1, a Rating Predictor uses User Similarity and Estimated Trust to predict a rating. The Estimated Trust can be calculated from Trust Matrix or Trust Network, a simulation of social network in the form of a graph, consisting of nodes (representing users) and edge (representing trust relation between users). Normally, there is only edge to show one user's trust towards another user without any trust value. Consequently, the similarity between each pair of user is often used as a trust value. However, it is difficult to identify the trust value in case of a friend of a friend. In Fig. 1.2, for example, if user A is a friend of User B, while User B is a friend of User C, then what is the appropriate trust value of user A for user C be defined.

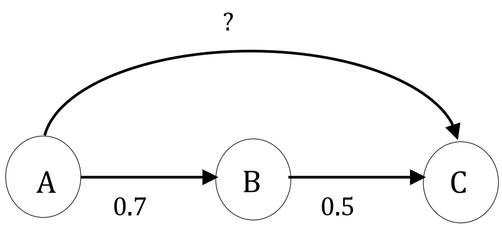


Figure 1.2: The problem of Estimated Trust.

Assigning the values of user A and user C may use two traditional trust-based recommendation methods was proposed namely TidalTrust[2, 3] and MoleTrust[4]. Both techniques use a similarity as a trust value between each pair of users. The

TidalTrust technique uses for estimating the trust value in case of a friend of a friend by selecting the trust value of the previous friend with the maximum trust value in the path. Next, the MoleTrust use the calculation of the trust value by finding the average of the trust values of all previous friends on the path. And the TidalTrust traverses the all-possible paths by using the Breadth-First Search technique to find the maximum trust value that greater than the threshold. This step was called as trust propagation. Meanwhile, MoleTrust uses the same searching technique in this step. It will traverse through any raters who gave the rating on the target items, within the number of maximum length (hop) specified by the researcher. Both TidalTrust and MoleTrust have limitations in trust propagation. TidalTrust uses the same threshold value for all users, and while MoleTrust is limited by the number of hop. However, practically, different users have different characteristics and behaviors. Therefore, a new trust propagation technique without these limitations should be developed.

Moreover, both TidalTrust and MoleTrust use similarity value to represent the trust value between two users. However, trust values generated from similarity value are symmetrical on both directions (i.e. A   B and B   A), making its unpractical. Additionally, the problem of data sparsity also makes it difficult to calculate the trust value. Sometimes there is no co-rated item. For this reason, a new technique to calculate the trust value without co-rated items should be considered. Moreover, until now, trust value calculation does not concern about the length between the finding user or active user and raters on the path. For more accurate prediction, users who have greater number of hops than the active user, should have lesser reliability from the active user. So, the length between the active user and raters should also be taken into account in the trust value generation.

In traditional trust-based methods, the raters' opinions (Rating) are directly used in the prediction[5]. However, in case those raters are not friends of the user, their opinions may not be appropriate for the active user. Therefore, the rating should be transitively related to the previous users' opinions on the path until it relates to the active user, in order that it becomes the rating in perspective of the active user's opinion. For example, Let G = {V1, V2, V3, V4, V5} be user node and E = {(V1, V2), (V2, V3), (V3, V4), (V4, V5)} be the set of edges. User V1 is the active user and user V5 is a rater. When user V1 requires predicted rating of item i, user V1 will walk to user V5 (the rater who rated for item i) via user V2, user V3 and user V4. After that, user V5 usually sends the rating back to the user V1 directly as the predicted rating as shown in Figure. 1.3.

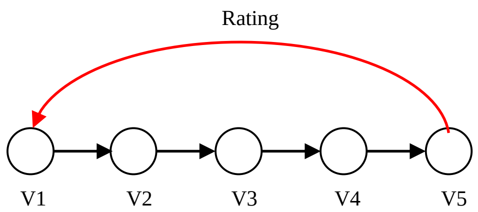


Figure 1.3: User V5 transmits User V5's rating to user V1 directly.

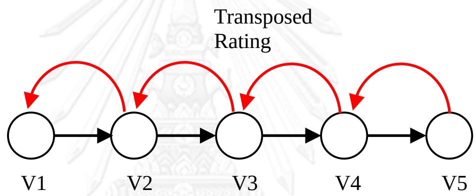


Figure 1.4: Transposed rating from user V5 to user V1

However, user V5 is not user V1's friend. So, user V5's rating is the ratings in perspective view of user V5, which might not be appropriate for user V1. Therefore, user V5's rating must be transposed into the perspective view of user V4 and user V4 must do the same thing to the user V3, V3 > V2 and V2 > V1, respectively, until the rating in perspective view of user V1 is obtained as shown in Fig. 1.4.

After trasversing through the network, there are a group of raters spreading in the trust network. The paths that reach each rater are called distinctive paths. Let G be a set of users in the trust network, E be a set of edges and R be a set of raters.

G = {V1, V2, V3, V4, V5, V6, V7},

E = {(V1, V2), (V2, V3), (V3, V4), (V4, V5), (V1, V6),

(V6, V7)} and

R = {V3, V5, V7}

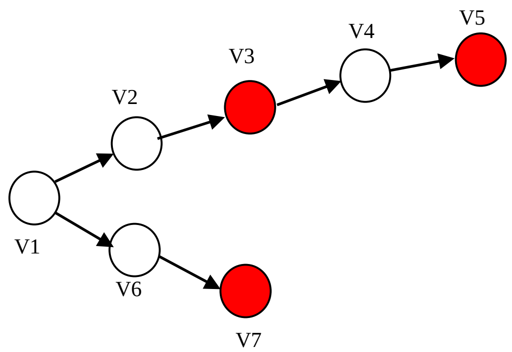


Figure 1.5: Three raters that spread in the trust network

From Figure 1.5, there are three raters in the trust network. So, there are three distinctive paths from V1 to raters. Let P be a set of the path. P = {PV3, PV5, PV7}, PC = {V1, V2, V3}, PV5 = {V1, V2, V3, V4, V5} and PV7 = {V1, V6, V7}. Considering each path, PV3 and PV7, have one rater (V3 and V7 respectively), while PV5 has two raters (V3, V5). The raters (V3, V5) on the same path should not have the same influence level to the active user. The user V5's weight should be greater than that of user V3, because the opinion of the previous rater should be accumulated as the opinion of destination rater. This means the number of raters on the path should affect the weighting of each rater on that path.

1.2 Research Objectives

The research focuses on method of recommender system that will serve the following aspect:

1. To ensure the trust value can be calculate.
2. To improve rating prediction by reflecting the influence of the rater.

1.3 Scope

This research proposed new trust based recommender system technique. It consists three main parts for improving the accuracy and the coverage of the prediction.

1. Trust value calculation; Using the latent feature user to calculate the trust value instead of the user rating matrix

2. Trust Propagation; Select only the target user who can be trusted for propagating.

3. Rating Prediction; Using the transpose rating for scale the rating into the perspective view of the user instead of the target user.

1.4 Research Methodology

In order to achieve the objective of this research, there are five tasks that make this research success and it was described below:

1. Study the concept and related work
2. Define a state of problem
3. Revising the methodology and approach and propose our own method
4. Implement the prototype to experiment the proposed method
5. Write the thesis

Below is a time table covered all of the above tasks.

No	Task	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
1	Study the concept and related work															
2	Define a state of problem															
3	Revising the methodology and approach and propose our own method															
4	Implement the prototype to experiment the proposed method															
5	Write the thesis															

Table 1.1: Research Methodology Time Table

1.5 Benefit

The proposed techniques will offer the following benefits;

1. Enhancement of the accuracy and coverage of rating prediction

2. Ability to generate asymmetric trust value for all pairs of users and to identify the length between each pair of users

3. Elimination of limitations on trust propagation commonly found in the current trust based RS.

4. Ability to transform raters' rating into the active user's perspective view

5. More accurate rating prediction reflecting the influence of the number of raters on the same path on the weight of each rater on each of the path

CHAPTER II
THEORETICAL BACKGROUND

In this chapter, the related work will be discussed. It talks about the Recommender System. Why it was created? How it works? How many researchers are in Recommender System? and What are the problems still remain in the Recommender System?

2.1 Recommender System

In the current era, Information is the most key significant for many business and people. However, the size of information is very large and the most interesting information that business or people interested is hard to retrieve. So, the recommender system was created for solving this issue above. The recommender system[6-8] is used for recommend the items which the user might interest. The three main steps of the recommender system[9, 10] consist the data collection, pattern matching and ranking the item. In order to collect the data, it requires the data from the user who has the past experience with the item. The user must review the item or rate the score for the item. When the user satisfied the product, he or she will give five points or stars for that item and give one point or star for the goods that users are not satisfied. When the users was gave the score to the item, the score is store in the data source, which called User-Rating Matrix. The User-Rating Matrix contains the rating of each item, which provide the users. However, there are some information that does not has the relation between items and users. Table 2.1 is shown the example of User-Rating matrix.

	Item 1	Item 2	Item 3	Item 4	Item 5	Item 6
User 1						
User 2		4				
User 3				5		
User 4				2		
User 5						1

Table 2.1: The example of the User-Rating Matrix

For the example, the user 2 gives 4 points on the item 2. That's mean item 2 is good for user 2. In contrast, user 5 gives 1 point on the item 6. It can assume that user 5 fell bad on this item. When considering user 4 and user 3, user 4 give 2 point on the item 4 but user 3 give 5 point on the same item. Then, the perspective view of two persons on the same item is different. So, the recommender system should make the personalization for each user to recommender the item.

The recommender system is the personalize system which can find the suitable item for each person. The recommend items are based on the personality and the attentiveness on the item. So, the recommender system finds the pattern of each user and match the pattern to the item. The recommender system can be categorized into two methods, which are Content-Based filtering and Collaborative filtering.

2.1.1. Content-Based filtering

Content-Based filtering is the method of the recommender system, which used for matching the pattern. It calculates the similarity value between target user and the user in the User-Rating matrix. After the calculation, it will choose the user who is the most similar the target user. Then, the recommender system uses that user as the pattern data for prediction.

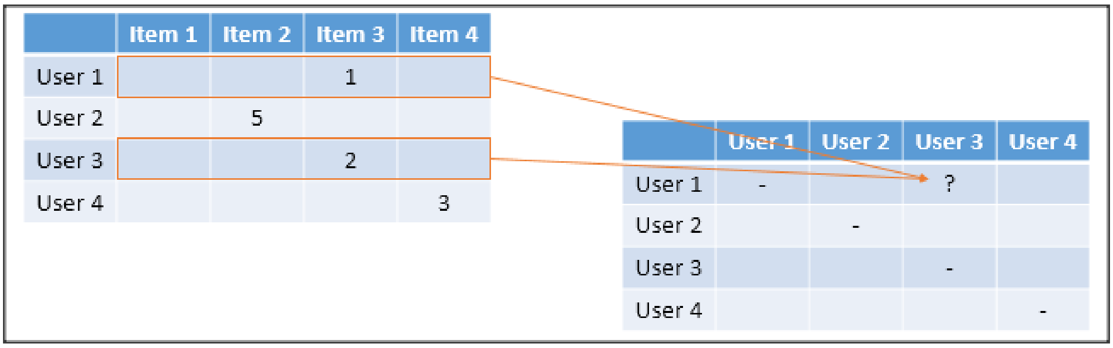


Figure 2.1: The example of Content-Based filtering

In the Figure 2.1, the User-Rating matrixes are selected two users for calculate the similarity value. User 1 and User 3 were selected. Then, apply the similarity equation and give the result in the Similarity matrix between each user. It will use in the prediction step of the recommender system.

2.1.2 Collaborative filtering

Collaborative filtering is the other method of the recommender system. It has the same object as the Content-Based filtering but it has different process. This method uses the item for matching the pattern instead of the user.

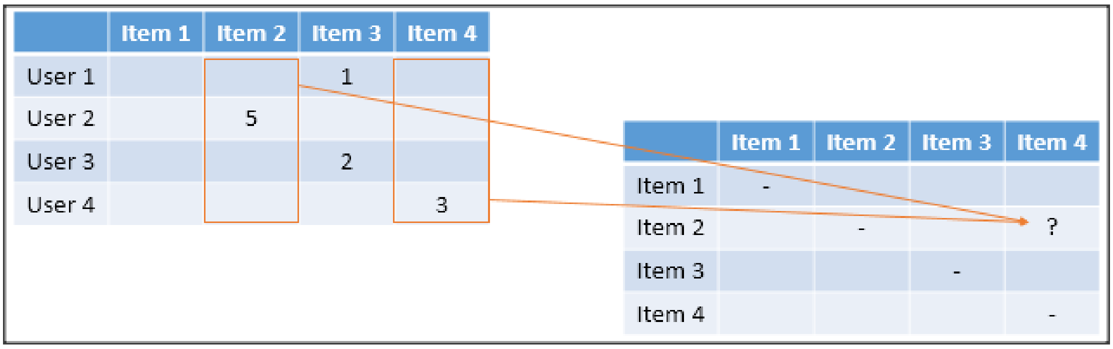


Figure 2.2: The example of Content-Based filtering

From figure 2.2, two items from User-Rating Matrix was selected for calculate the similarity value. They are item 2 and item 3. Then, calculate the similarity value and store it in Similarity matrix.

2.1.3 Hybrid Filtering

The Content-Based Filtering and Collaborative Filtering have their pros and contra. So, the Hybrid Filtering was proposed for improving from the existing approach. It is the method of the recommender system, which combined the Content-Based Filtering method, and Collaborative Filtering method. The objective of the combination is making the Recommender System better than the only one method.

After matching pattern, the next step is the prediction step. The prediction step uses the similarity value, which calculate from User-Rating matrix for predict the rating. The user and items that has the highest similarity value will select. Then, it uses the rating of the item, which rate by them for prediction. The predicted rating is calculated from the average of the selected rating. After predict the rating of all items, rank the item[11], which has the most rating, and represent to the user who uses the Recommender System.

However, there are two problems on the recommender system. They are cold-start problem and sparsity problem. The cold-start is the problem of the new user. He or she does not have any rating in the User-Rating matrix. So, they cannot match the pattern with the other users. The other problem is sparsity problem. The sparsity problem is the problem, which the data is not enough for processing.

	Item 1	Item 2	Item 3	Item 4	Item 5
User 1					
User 2		3			
User 3				7	
User 4					
User 5			1		
User 6					

Table 2.2: The example of the sparsity problem

In Table 2.2, it are shown the sparsity problem. The amount of the rating in the recommender system has small number. So, it cannot use to matching the pattern. When calculate the similarity value, it cannot calculate because it does not have the enough data for calculate. The sparsity problem is the huge problem. Then, there is the Trust-Based Recommender System, which used the additional data source e.g. trust value between two users for solve this problem.

2.2. Trust Based Recommender System

Until now, a lot of researcher tries to use the trust network as the other data source. There are a lot of methods using trust value in the Recommender System but it still has a limitation. Some method has a good reason for propagation but it is fail to improve the accuracy. In this section, the previous trust based recommender system[12] are described and discussed.

2.2.1. Trust Aware Recommender System

The sparsity problem is shown that the only one data source is not enough for prediction in the recommender system. Then, Messa et al. proposed Trust Aware Recommender System (TAR), which is the architecture of the Trust-Based Recommender System. It uses the additional data source with the User-Rating Matrix. The additional data source is the Trust Network. The Trust Network is the collection of the user and the relationship between each user. It represents in many form such as social network or a graph. If the graph is used for represent the Trust Network, the node is represented for the user and the edge is represented for the relationship between each user.

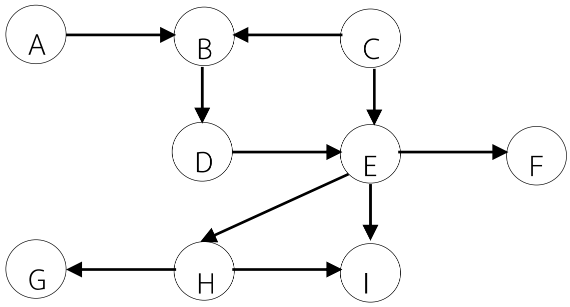


Figure 2.3: Example of the Trust Network

From the figure 2.3, TAR combines the User-Rating Matrix with the Trust Network into the architecture. So, this architecture requires two data source. This architecture has two parts. The first part, the Trust Network is converted into the Trust Matrix. Then, calculate the trust value for each user in the Trust Matrix. However, it user the similarity value for calculate the trust value which has the same problem of the User-Rating matrix when calculate the similarity value. The second part, The User-Rating is used to calculate similarity value same as the Recommender System. After finish this two part, the Rating predictor uses the weight average to combine the trust value and the top N neighbors' rating, which select from the most similarity value in the similarity matrix.

By the way, the additional data source still lead to the new problems which are the trust value cannot calculate and the symmetry property of the trust value. So, the other researchers proposed the other method for eliminate this problem.

2.2.2. Tidal Trust

Tidal Trust[13] is a method of trust propagation that used to find the trust value of the active user to the target user by finding the longest path. This method uses the bread first search algorithm to find the longest path. It traverses through the entire possible path that can propagate to the target user. Then it finds the trust value of the propagation by compare the trust value in each path that has the same destination. After that, the selected path is the path, which has the maximum trust value. The trust value get from this method is not reasonable because it come from the trust value of friend of friend. To understand the problem of this method, please see the Fig. 3 that shows as sub network. When the trust value of user A to B is 0.7 and the trust value of user B to C is 0.5 then user A will trusted user C is 0.5. It equal user B trust user C but in the real world, User A does not need trust user C equal user B that trust user C. And this method uses a resource to process. If the trust network of user is very large and it must calculate all of possible way that can go. It will take a time to process from start user to the last user. The next method is the method that reduces the distance of propagation. It was called Mole Trust.

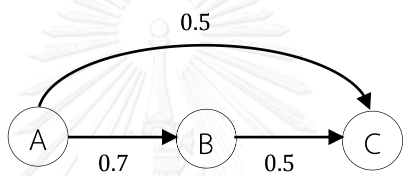
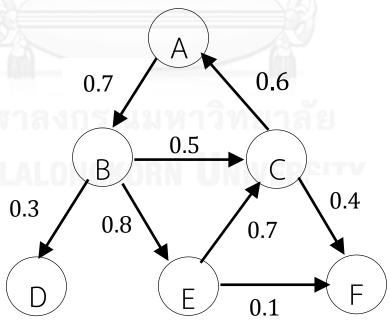
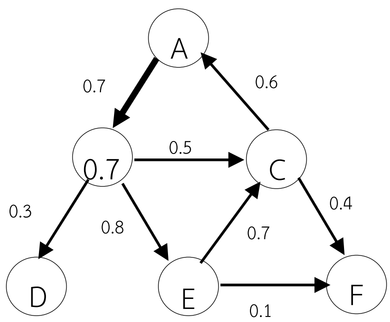
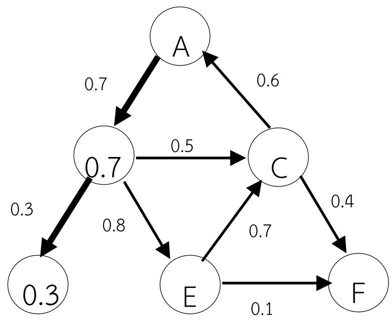


Figure 2.4: A problem of Tidal Trust.



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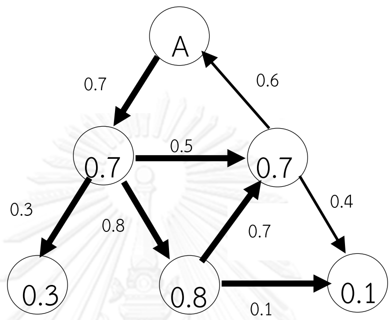
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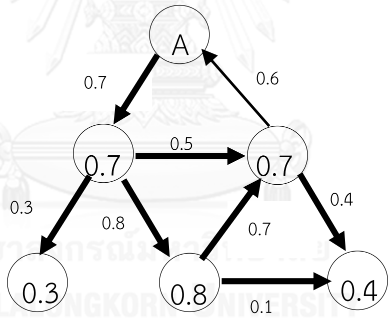
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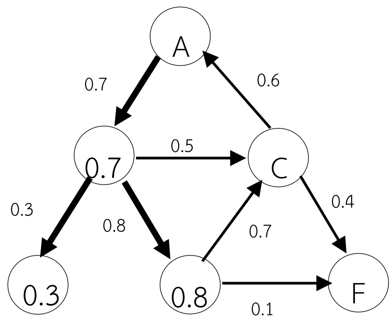
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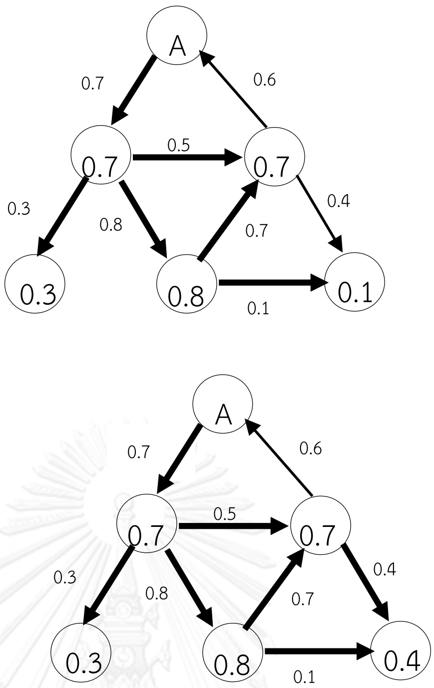

Figure 2.5: Example of Tidal Trust's Propagation

From the above figure, it shows the Tidal Trust's Propagation. It starts from user A to User F. From the graph, user A and User F are not the friend. When, user A wants the information from user F. User A must traversal to user A via his or her friend. Every time of the visiting the friend's node, there is a trust calculation. It calculates until propagate to user F. In the last figure, it finishes the calculation. It gets 0.4. So, the trust value of user A to user F is 0.4.

2.2.3. Mole Trust

Mole Trust is the method that reduces the propagation of the tidal trust. First, this method removes the cyclic in the trust network method by create the new trust network. After that, propagate in the new trust network. In order to remove the cycle of the trust network, it will help to reduce the propagation by not creating the path that was ever go. To make it more understand Fig. 4 and Fig. 5 are described, When the first path go to user C from user A is A > B > C and the other path is A > D > E > F > C. The first path will go to user C shorter than the second path. So the path will not create duplicate path because it was selected the first path. To calculate the trust value, it will calculate by using the weight average of the user that trusts the target user. It more reasonable than tidal trust because it is not using the same trust value and it share the trust value with the other user. But this method is not good enough because it still has a lot process for reducing the cyclic. Another issue is the limited of distance, when traverse in the huge graph is needed to concern.

The next method is T-Index Approach. It is a method that attaches the node that the user should trust to make it has the node for selected more than the trust network.

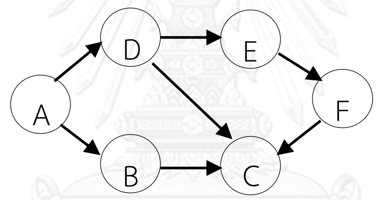

Figure 2.6: Example of a Trust Network that has cycle.

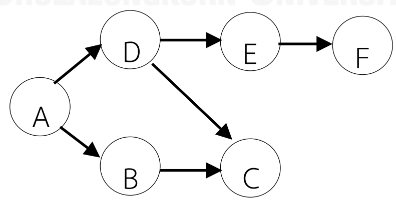

Figure 2.7: Example of a Trust Network that remove the cycle by using Mole Trust.

2.2.4. T-Index Approach

T-Index is the method that defines the word that is called TopTrustee. TopTrustee is the list of the users that the active user should trust but that user is not connected to the active user as a neighbor. TopTrustee is created by apply of the H-Index which uses to find the index of the citation paper. It finds the index of the trust user in the trust network for each user. After get the index of the trust user, the topless index of the trust user will put into the TopTrustee of the active user. Then the trust value is calculated for each user in the TopTrustee by using the trust propagation.

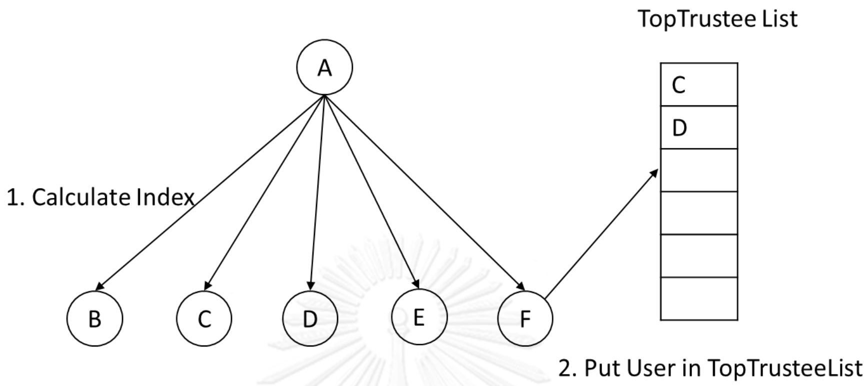

Figure 2.8: The step to put the user in the TopTrustee List

To predict the rating, the transposure of trustee rating is used between the active user and the user in the TopTrustee list. The transposure of trustee rating is used to adjust the rating between two users into the same rating scale. It is used as the rating instead of the rating of target user for prediction. The next method is the method that proof the trust network is a small world network and it can calculate the maximum distance for propagation not like the method from above that propagate until the end of the network. It reduces the computation.

2.2.5. The small world Trust Network

To use the small-worldness theory[14] in the trust network, the thing that must do is the proving that the small-worldness network is existed in the trust network. To proving the small-worldness, it has two steps for proving. First, calculate the cluster coefficient that has enough value. Second, Proof the node in the small-worldness network that can propagate to every node. After proving this, the maximum propagation distance can calculate by using the number of node in the network and the average of edge in the network. While propagation, if the distance of propagation is more than the maximum propagation distance, the propagation will terminate. The next method is the method that applies the small world trust network and tries to improve the accuracy and coverage but reduce the computation.

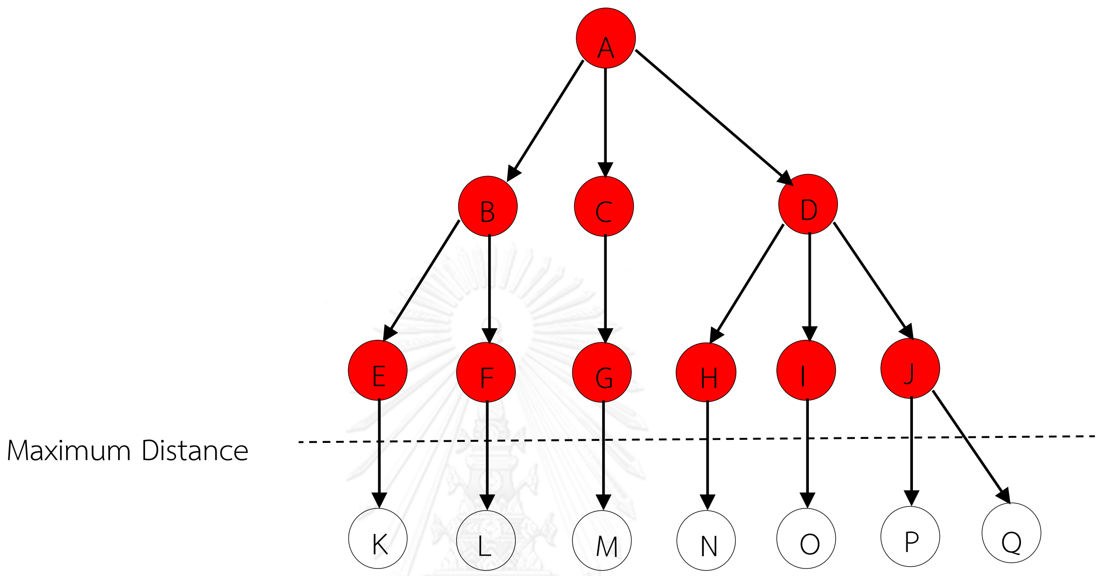

Figure 2.9: The propagation of small-worldness theory

Before the propagation of the small-worldness theory, it calculates the distance of the propagation. Then, it propagates to all possible nodes in the trust network but it does not propagation to the node, which has the distance more than the maximum distance as show in figure 2.9.

2.2.6 T_Protocol

T_Protocal[15] is a method that gets inspiration from solving the problem of Random Walk method and C_Protocol. Random Walk method is the method that calculates all of the possible propagation that can walk in the trust network but it has the most disadvantage because it use a lot of calculation that take a long time to get the path for propagate. In the advantage point of this method is high accuracy and high coverage. C_Protocol method is the opposite of Random Walk method because the accuracy and coverage of C_Protocol is very low but it uses small computation because it selects the node for propagate by choose the node that has the most children.

To solve C_Protocol problem, the researcher develop the C+_Protocol method by select the two nodes that has the most children then select the two nodes of each children for propagation and do this until stop at the node that not has the children. C+_Protocol is better than C_Protocol because it uses the node more than one node that is the cause for make a good result but the result is not good as the researcher expected. Then they postpone T_Protocol. It is a revise of C+_Protocol. T_Protocol will propagate by selected the top two node that has the most children like C+_Protocol but for each children, it selects the top two node of the most children again. And T_Protocol applies small-worldness theory for find the maximum distance of propagation. It will not propagate until the end of the network. The result of this method is better than C_Protocol and C+_Protocol but it is not good enough Random Walk method but it use the computation smaller than Random Walk. The next method is the method that selects only one node for propagation and has a good result as Random Walk but the result is not stable.

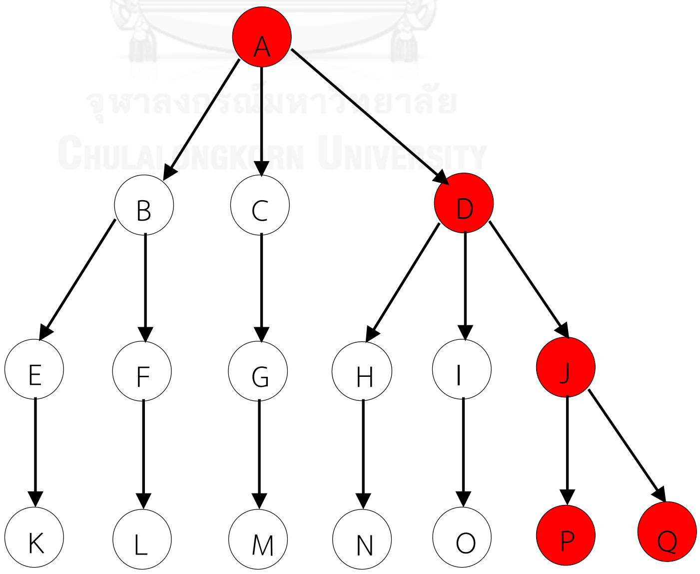

Figure 2.10: Example of C_Protocol

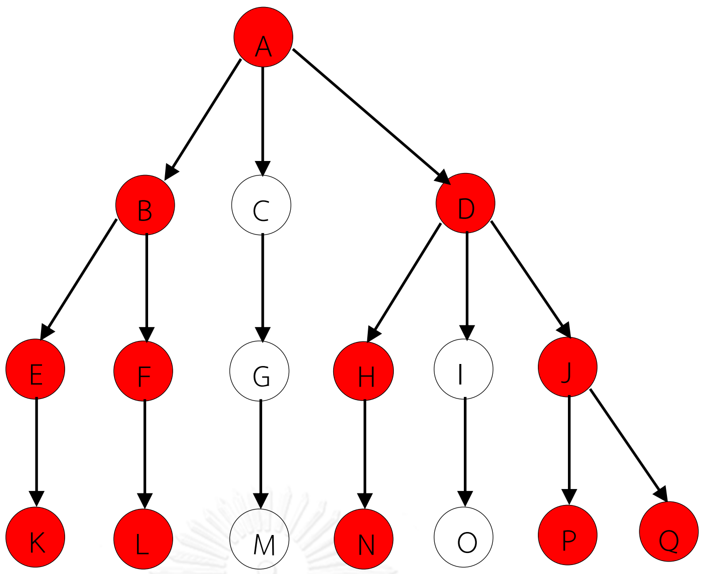

Figure 2.11: Example of C+_Protocol

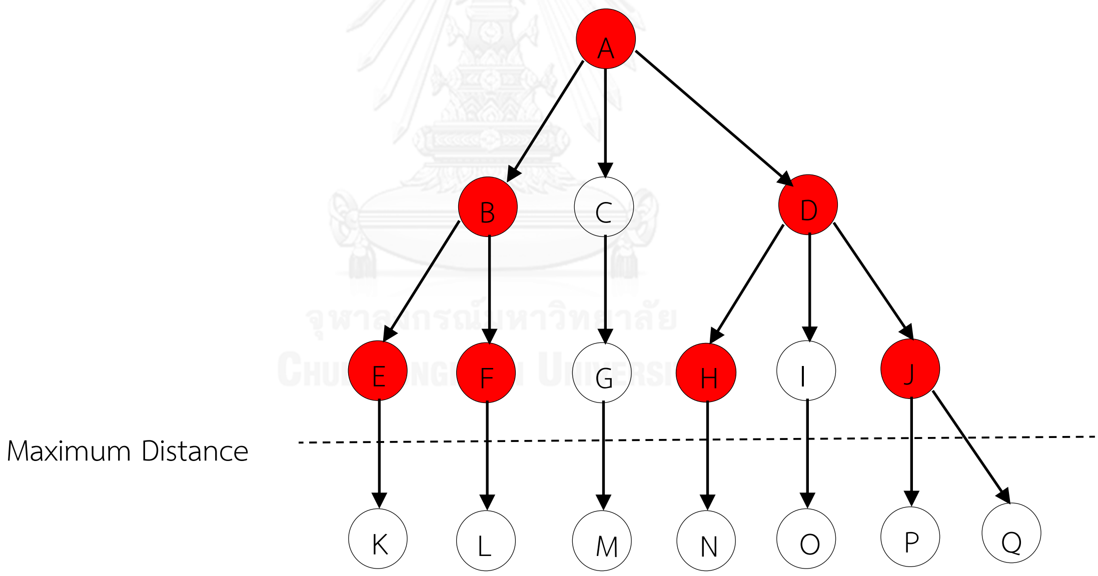

Figure 2.12: Example of T_Protocol

From the above figure, C_Protocol has the small amount of the propagation. It shows the small number of the coverage. Meanwhile, C+_Protocol has the amount of propagation more than the C_Protocol. On the very large Trust Network, C+_Protocol propagates into the deep of the Trust Network, which lack of the performance. So, T_Protocol has the better performance than C+_Protocol because it was defined the number of distance. T_Protocol does not propagate to the end of the Trust Network.

2.2.7 Trust Walker

Trust Walker[16, 17] is the another approach based on Random Walk[18] that tries to reduce the selected node for propagation and reduce the number of computation. First, this method will calculate the probability for select path. Then, random the number that in the bound of the probability and select that path. After that, it checks the node that has the rating for prediction, or not. When it not has rating then calculates the probability for stop and random number again. When the random number is not in the bound of stop, it will do the first step again. But when it stops, it will calculate probability of the selecting the item and then random the number for chooses the item. After get the item or the rated items are in the selected node then send the rating to the prediction formula to get the result rating. The rating that use in the prediction formula is come from the random value that was random. So, this method will not stable for each time that use this method. It will make the question follow this. How this method reliable?

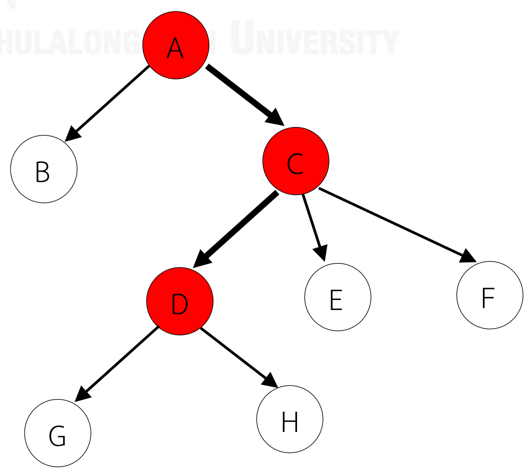

Figure 2.13: Example of Trust Walker

From the figure 2.13, it shows the step of the propagation in the Trust Walker. It randomly selects the node for propagation. When it found the rating, it stops immediately or randomly stops on the node.

2.2.8 An Improved Collaborative Filtering Algorithm Based on Trust

On the very large trust network, the propagation technique is not good. Especially, the exploration on every node on the graph will take a long time depending on the complexity of that the trust network.

Y. Guo et al. proposed trust value calculation without propagation. This model find the trust factor of the rater toward the rating used directly by using the harmonic mean on the number of friends and number of evaluated items. The friends of a user have an effect to the trust factor. When a user has the number of friends more than the others, he will be more reliable.

However, the problems of the Trust-Based Recommender System can summarize by following.

1. The problems of the trust value evaluation: There are three main problems. It includes uncover all of pair of users, symmetry in both directions between a pair of users and unconcern about number of hops.

2. The problem of the propagation: There are two limitations in the Trust Propagations. They are either fix the number of hops or threshold of trust propagation.

3. The problem of the prediction: Rater’s opinion may not relate to active user’s opinion.

In the next Chapter, it shows the method which try to eliminate all of the problems in the Trust-Based Recommender System.

CHAPTER III
RESEARCH METHODOLOGY

In order to solve problem of previous Trust-Based Recommender System methods mentioned in the last section of Chapter II, A new Trust-Based Recommender System method is proposed. In the proposed method, there are three main problems which found in the previous works. First, the trust value evaluation[19]. It consists of three problems. 1) the sparsity problem makes the trust value cannot calculate for every users, 2) the symmetry property of the similarity value which makes the trust value be same between two users, 3) the adjusting of the trust value for remoteness user is not consider in the trust value evaluation. The second main problem, the trust value propagation defined the distance and the threshold for propagation. It might lost the important detail for prediction. The last main problem is the transmitting of the rating. Rating of raters does not related to the perspective view of the active user. To solve three problems, there are three main steps: trust value generation, group of rater searching and rating prediction:

3.1. Trust value generation, Three problems are considered as mentioned in

3.1.1. To guarantee the trust calculation on every pair of user, the new method without using co-rated item is proposed by applying SVD. First, the method extracts the latent feature of the user[20-22].

$$R = USV^t \tag{1}$$

Where R is the user-rating matrix, U is the user matrix, S is the reduced matrix and V^t is the transpose matrix of the item matrix. From matrix U, each row of the matrix is represented to the user feature vector. Each feature vector of user is the latent model, which is used to represent user’s characteristic. In order to find the similarity between a pair user, the cosine similarity on their user feature vectors is applied.

$$sim_{A,B} = \frac{\sum_{i=1}^{n} A_i \times B_i}{\sqrt{\sum_{i=1}^{n}(A_i)^2} \times \sqrt{\sum_{i=1}^{n}(B_i)^2}} \quad (2)$$

The equation can be described as A_i is the ith latent feature of user A (active user), B_i is the ith latent feature of user B and *n* is the number of latent features.

3.1.2. To prevent the symmetry problem of the trust value on both directions of the pair of user[23], the $sim_{A,B}$ is not only used but also the reliability of B in the network is concerned. The reliability of B can be calculated by using the number of in-degree which represents the number of friends who trust B.

$$trustworthiness_B = \frac{\ln(n_{in,B}+e)}{\ln(\max(\{n_{in,C} | C \in \{user\ in\ Trust\ Network\}\})+e)} \quad (3)$$

Where e is a natural number, $n_{in,B}$ is the number of the in-degree edge of the user B and $\max(\{n_{in,C} | C \in \{user\ in\ Trust\ Network\}\})$ reaching the maximum number of the in-degree edge of the user in the trust network. After that, the confidence of B towards A is calculated by merging $sim_{A,B}$ and $trustworthiness_B$ by using harmonic mean as in eq.4.

$$confidence_B = \frac{2 \times trustworthiness_B \times sim_{A,B}}{trustworthiness_B + sim_{A,B}} \quad (4)$$

3.1.3. To concern the number of hops in the trust value calculation, the real situation that contains the confidence reduction of user, who is far from active user, should be considered by the number of hop as in eq.5.

$$trust_{A \to B} = confidence_B \times \frac{1}{d_B} \quad (5)$$

Where *d* is the number of hop from user A to B

3.2. In trust propagation to raters, two limitations of trust propagations is considered including fixing the number of hops and the threshold of trust propagation

3.2.1. To eliminate such 2 limitations, the correct rater without fixing or specifying trust propagation threshold and the number of hop will be walked. The correct rater set is the set of raters who have a trend to predict item accurately. The correct rater refers to the user, who has different between actual rating and predicted rating on the target item.

$$\left|R_{aJ,k} - R_{pJ,k}\right| < \epsilon \tag{6}$$

$R_{aJ,k}$ is the actual rating of user J on target item k, which is rated by user J. $R_{pJ,k}$ is the predicted rating by the user J on target item k and $\boldsymbol{\epsilon}$ is the difference threshold. R_{pJ} is calculated by using latent model, which is extracted from SVD proposed by Badrul et al.[24]

$$R_{pJ,l} = \bar{C}_J + U_z \cdot \sqrt{S_z}'(J) \cdot \sqrt{S_z} \cdot V_z'(l) \tag{7}$$

The parameters can be described as following. R_{pJ} is the predicted rating from user J, $\bar{C}_J$ is the average rating of user J, U_z is the user matrix in z dimension, S_z is the reduced matrix in z dimension, V_z is the item matrix in z dimension, J is the row of user J in the matrix of dot product from $U_z \cdot \sqrt{S_z}'$ and l is the column of item l in the matrix of dot product from $\sqrt{S_z} \cdot V_z'$.

3.2.2. To reduce the number of trust propagation[25], after a set of rater is found, A* Search[26] is used instead of Breadth First Search to get to each correct raters. While breadth first search must visit every user in the network to get to rater, A* combines Breadth First Search and Depth First Search for traversal in the network from the starting node to target node. A* Search has a heuristic function that provides a condition for considering to walk to next level node if the current node has the most weight on the edge. Oppositely, the subject will return to the node that has the most weight on the edge if the current node is not the most weight on the edge.

3.3. Rating prediction

3.3.1. To solve problem about none relating of the rater's rating and active user, the relationship of the rating in the perspective view of user is defined. Rater's rating is transposed into the perspective view of the previous user in the path until getting to the active user.

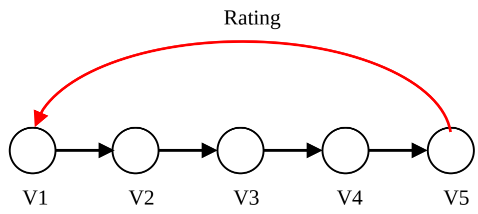

Figure 3.1: User V5 sends the rating to Uesr V1

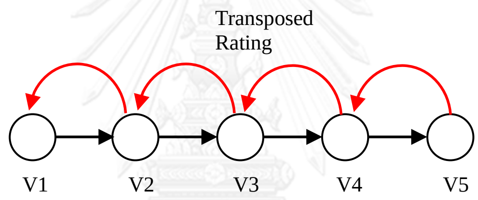

Figure 3.2: User V5 sends the rating to User V1 via User V1's friends.

If consider the figure 3.2, it shows how the user V1 gathering the rating from user V5 directly but they are not related. Both of them has relationship via their friends. When, user V1 wants the rating from user V5. He/She must ask from his/her friends. His/Her friends will ask the others for the rating. Until, they found the rating. After that, the rating should send back to the previous user because both of them have the relationship. The sending back of the rating is called transpose rating. Every time of the transpose rating, the rating might be adjust because the friends of each person know the way to talk with their friends. So, the rating will change into the perspective view of user who send the rating back to his friends. The transpose rating in this step is called back propagation.

To transpose the rating into the perspective view of previous user, the equation is proposed by Neal Lathai et al. [27] is used (eq.8)

$$rating_{Y \to X,k} = \frac{((R_k - 1) \times lower_{R_k}) + \left(R_k \times same_{R_k}\right) + ((R_k + 1) \times higher_{R_k})}{lower_{R_k} + same_{R_k} + higher_{R_k}} \quad (8)$$

The parameter R_k is the actual rating of user Y on target item k, $lower_{R_k}$ is the number of co-rated items that have rating value less than actual rating of user Y, $same_{R_k}$ is the number of co-rated items that has rating value equal to the actual rating of user Y and $higher_{R_k}$ is the number of co-rated items that have rating greater than the actual rating of user Y.

In order to transpose the rating, it must use the co-rated items of two users but the sparsity problem of rating always occurs. Therefore, the co-rated items are difficult to identify between each pair of user.

	User A
Item 1	
Item 2	4
Item 3	3
Item 4	2
Item 5	3
Item 6	
Item 7	

	User B
Item 1	2
Item 2	
Item 3	
Item 4	
Item 5	1
Item 6	
Item 7	5

Figure 3.3: The Co-Rated item between user A and user B

From the figure 3.3. Shows the co-rated item between two users. In the User-Rating matrix, the co-rated item is hard to find on two users. In the worst case, both of them do not have the co-rated item. In this step, the transpose rating cannot be calculated on some pair of users. Then, the rating of the user B should be fill, when user B receive the rating from user A. To fill the rating of users B, The predicted rating of user derived from (eq.7) is used. The rating of user B will be predicted and fill in the table, only items rated by the rater but unrated by user B. When fills the rating, it fills on the item which user A rated. After filled, both of them have the co-rated item. So, the transpose rating can be calculated.

	User A
Item 1	
Item 2	4
Item 3	3
Item 4	2
Item 5	3
Item 6	
Item 7	

	User B
Item 1	2
Item 2	2
Item 3	4
Item 4	5
Item 5	1
Item 6	
Item 7	5

Figure 3.4: After fill the rating on user B

Figure 3.4 show the result of filling the rating on user B. After fill, user B has the rating on the item 2, item 3 and item 4. So, User A and User B have the co-rated more than the past.

3.3.2. To identify the influence level of each rater to the active user, the number of raters on the same path is considered with rater's trust value and farness from active user. The weight of rater is proposed in this research as in eq.9.

$$w_y = \sum_{i \in \{raters\ on\ the\ same\ path\ of\ y\}} \frac{t_i}{d_i} \tag{9}$$

The parameter w_y is a weight of rater y, t_i is the trust value of user i, d_i is the number of hop from user i to user y is a destination rater. In order to predict rating of item k for active user A, the weighted average on transposed rating of all correct raters is calculated in eq.10 where the weight is the weight of correct raters from eq.9.

$$Predict\ Rating_{A,k} = \frac{\sum_{y \in \{rater \mid |r_{ay,k} - r_{py,k}| < \epsilon\}} w_y \times rating_{A \to Y,k}}{\sum_{y \in \{rater \mid |r_{ay,k} - r_{py,k}| < \epsilon\}} w_y} \tag{10}$$

Where $\boldsymbol{Predict\ Rating_{A,k}}$ is the predicted rating for user A on target item k. Normally, both of TidalTrust and MoleTrust determine the trust value between active users as a weight of rater and use the rating of rater directly. In this research, the influence level is proposed as a weight of rater (eq.9) and transposed rating (eq.8), which shows rater's opinion in active user perspective view, is used.

CHAPTER IV
EXPERIMENT AND EVALUATION

In order to prove the proposed method, this Chapter describes the experiment and the evaluation of the proposed method. The experiment splits into two parts. The first part, the experiment compare the new trust value evaluation with two classical methods of Trust-Based Recommender System which are Tidal Trust and Mole Trust. The other is the comparison between the new trust value evaluation and the new trust value evaluation with back propagation. The objective of this experiment is to evaluate the efficiency of proposed method. The evaluation metric are Root Mean Square Error and Rating Coverage.

4.1 Dataset

In this work, the Epinions dataset is used. This dataset consists of user-rating dataset and trust network dataset. However, user-rating dataset has 49,290 users, 139,738 different items and 664,824 reviews. In the trust network dataset has 487,181 issued trust statements

4.2 Evaluation Metric

To evaluate the model, I use RMSE and coverage metrics.

4.2.1 RMSE (Root Mean Square Error)

It represents the accuracy of the prediction rating. If RMSE value is high, it will tell that recommender system provides a low accuracy of predicted rating.

$$RMSE = \sqrt{\frac{\sum_{(u,i)|R_{u,i}}(r_{u,i}-\hat{r}_{u,i})^2}{|\{(u,i)|R_{u,i}\}|}} \tag{11}$$

Where $r_{u,i}$ is an actual rating of user(*u*) on target item(*i*), $\hat{r}_{u,i}$ is a predicted rating of user(*u*) on target item(*i*) and $\{(u,i)|R_{u,i}\}$ is the test set of the users.

4.2.2 Rating Coverage

Coverage is a measure of the percentage of items for which system can provide recommendations.

$$coverage = \frac{|\{(u,i)|\hat{r}_{u,i}\}|}{|\{(u,i)|r_{u,i}\}|} \quad (12)$$

Where $\hat{r}_{u,i}$ is a predicted rating of user(u) on target item(i), $r_{u,i}$ is an actual rating of user u on target item(i), $\{(u,i)|\hat{r}_{u,i}\}$ is the set of the prediction rating and $\{(u,i)|r_{u,i}\}$ is the test set of the user

4.3 Experiment

In this experiment, the proposed method is splitted into two part. The first part, the experiment tests only the new trust value evaluate without back propagation which compares with Tidal Trust and Mole Trust. The second part of the experiment, it compares the trust value evaluation and the trust value evaluation with the back propagation. The objective of this experiment is to evaluate the efficiency of the trust value with back propagation. Can it improve the accuracy and coverage, or not?

4.3.1 To evaluate new trust evaluation, two classical Trust-Based Recommender System is used to compare. They are Tidal Trust and Mole Trust. Both of them are the trust value evaluation. So, they was selected to compare. To predict the rating of the target item, the leave one out technique (blind only actual rating on the target item of the target user of dataset) is used. Instead of all rating in the dataset, I randomly select only one target item per target user and uses only the first 5,000 users are used as the test set. To avoid the bias, I use the same random data with TidalTrust, MoleTrust and proposed methods. The results of the experiment are shown as Table. 3.

	TidalTrust	MoleTrust	New Trust Evaluation
RMSE	1.3037	1.2519	1.1192
Coverage	0.1145	0.7623	0.7673

Table 4.1: The comparable table of three methods.

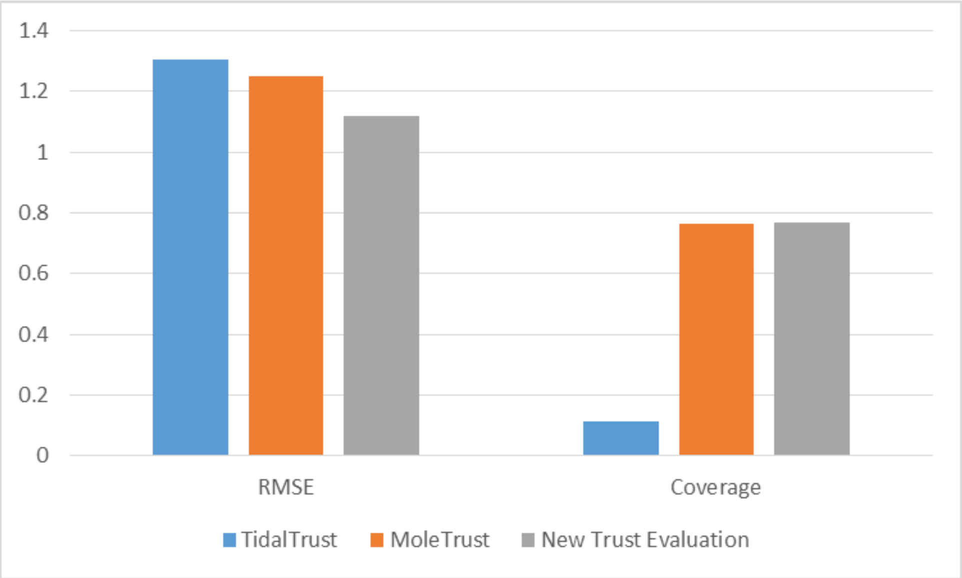

Figure 4.1: The comparable chart of three methods.

From the figure, it shows RMSE value of our proposed method is lower than TidalTrust and MoleTrust. It can be concluded that proposed method provide better accuracy. Similarly, Coverage value of our proposed method is greater than TidalTrust and MoleTrust. It can conclude that proposed method provides more predictable items.

4.3.2 To compare the back propagation, the new trust value evaluation is combined with the back propagation. After the combination, it is compared with the proposed new trust value evaluation without the back propagation mention in the table 3. In order to predict the rating, the leave one out technique is used same as previous topic, while, in this experiment only trust 3,000 users are used, because of time limitation of the prediction calculation which uses the multiply of the 5,000 dimensions matrix. The results of the experiment are shown as Table. 4.2.

	Trust Value	Trust Value with Back Propagation
RMSE	1.0595	2.2707
Coverage	0.5726	0.5286

Table 4.2: The comparable table of Trust Value Evaluation with Trust Value Evaluation with Back Propagation

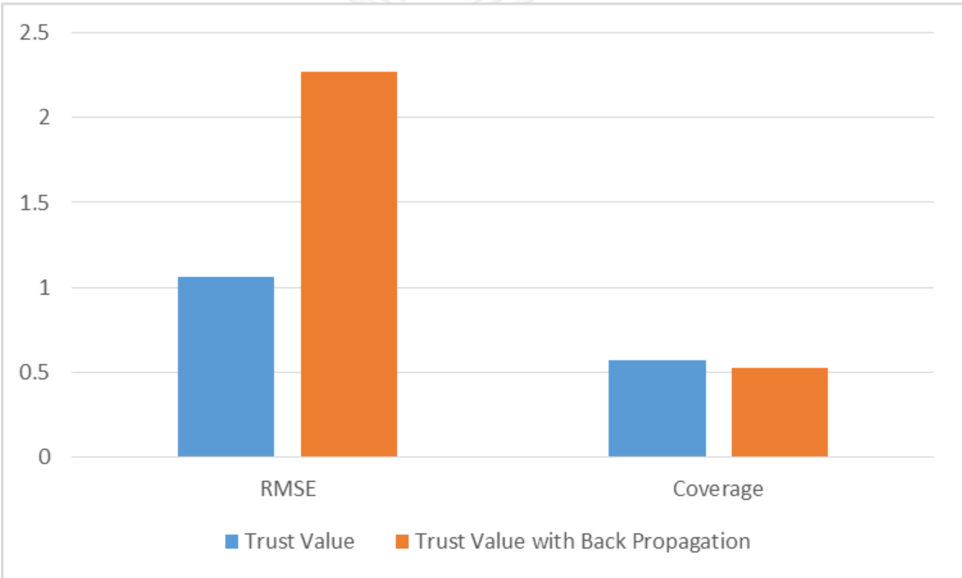

Figure 4.2: The comparable chart of Trust Value Evaluation with Trust Value Evaluation with Back Propagation

From the figure 4.2, it shows RMSE value of trust value evaluation with back propagation is greater than trust value evaluation. It can be concluded that trust value evaluation with back propagation gave lower accuracy. While, Coverage value of the trust value evaluation is greater than trust value evaluation with back propagation. It can conclude that trust value evaluation provides more predictable items.

CHAPTER V
CONCLUSION

In the previous chapter, the results of the experiment show the new trust value evaluation make the better rating prediction than Tidal Trust and Mole Trust. Similarly, the rating coverage evaluation is still better than Tidal Trust and Mole Trust. However, the new trust evaluation with back propagation has low efficiency when compares with the new trust evaluation. It is lower on both accuracy and coverage. The reasons of results of both experiments will be discussed in this chapter.

5.1 Discussion on Trust Value Evaluation

5.1.1 Accuracy

The reasons that the proposed method has better accuracy than both TidalTrust and MoleTrust are following by this:
Both current trust-based RSs calculate the trust value by using the co-rated items which is hard to identify the co-rated items because of the sparseness data. The small number of co-rated item cause low quality of neighbour which leads to low accuracy. While, the purposed method uses latent feature of user without using co-rated items. Moreover, 5,000 users feature are extracted from user-rating matrix, so, it can represent user characteristic more correctly.

The current trust-based RSs do not consider the degree of reliability for each user in trust network while proposed method uses the ratio of the number of friends on a specified user and the most number of friends in the trust network to determine the reliability.

The current trust based RSs are not concern remoteness friend which should have the less trust value than the closet friend, while the proposed method concern about this by reducing the trust value of the remoteness user.

5.1.2 Coverage

The proposed method improves the coverage than Tidal Trust and Mole Trust. The proposed method uses the latent feature of user for calculating the similarity value without using co-rated items. So, it can calculate similarity for all pair of user. However, it cannot provide 100% coverage, because the target item obtains rating from only raters user not from other users. Therefore, there is no rating from rater in the prediction step. This case occurs not only our proposed method, but also in current trust based RS such as MoleTrust and TidalTrust.

5.2 Discussion on Trust Value Evaluation with Back Propagation

5.2.1 Accuracy

The reason why the new trust value evaluation with back propagation provides greater value of the Root Mean Square Error (RMSE) than the new trust value evaluation is psudo rating from transpose step when prediction.

In the prediction step, normally, the real rating is used in the prediction as in the new trust value evaluatio. However, the transpose rating uses psudo rating instead of the real rating. The transpose rating needs the real rating as the facor. Since, sparsity rating problem, the psudo rating are used instead.

	User A
Item 1	
Item 2	4
Item 3	3
Item 4	2
Item 5	3
Item 6	
Item 7	

	User B
Item 1	2
Item 2	
Item 3	
Item 4	
Item 5	1
Item 6	
Item 7	5

	User A
Item 1	
Item 2	4
Item 3	3
Item 4	2
Item 5	3
Item 6	
Item 7	

	User B
Item 1	2
Item 2	2
Item 3	4
Item 4	5
Item 5	1
Item 6	
Item 7	5

Figure 5.1: Fill the rating into the User

From figure 5.1, In order to transpose the rating from user to previous user, both user must have the rating on the same rating. However, the data source has sparsity problem which has small number of rating. It leads to the problem that the rating is not enough for prediction. So, before, transposing, the predicted ratings are created and fill in the table. Then, the co-rated items are used for prediction. Since, the psudo rating are used instead of real rating. It makes the transpose rating low accuracy. Consequently, the result of prediction, also have low accuracy This is the cause of the method with back propagation has RMSE greater than Trust Value Evaluation without Back Propagation.

5.2.2 Coverage

There is factor that cause lower coverage. The coverage is lower than the coverage without back propagation, the coverage is depending on the correct user which act as rater for the prediction. The trust value evaluation use all of rater while the trust value evaluation without back propagation uses correct user, a user who has ability to prediction, as rater. The correct users come from the prediction by using the Resnick's Formula. If the different between the prediction and the rating is smaller than the threshold, the rater will put into the correct user set which describe in Chapter III. While the threshold is 0.5, the number of rater less than the number of the correct rater. So, it found the smaller amount of correct user than the trust value evaluation which selects all of user for prediction.

5.3 Conclusions

The objective of this research is to improve the accuracy and quality of the Trust-Based Recommender System. In this thesis, the two algorithms are proposed. They are the new trust value evaluation and the new trust value evaluation with back propagation.

The new trust value evaluation is calculated on three new factors. First, finds the similarity value on each pair of user by using latent feature model instead of co-rated item. Second, calculates degree of reliability for each user to identify the trustworthiness of the every person in the trust network. The last, it uses the number of hop for adjusting the trust value on the remoteness user who is the expected low trust value which is shown in the real world application concept. From the experiment results, the proposed method is more efficiency than the classical Trust-Based Recommender System (MoleTrust and TidalTrust) methods on both accuracy and coverage.

Whereas, the efficiency of the Trust-Based Recommender System is decrease when using with the back propagation. The back propagation is the changing of the rating's rater into perspective view of the active user via friend of friend by transposing the rating of the rater to the previous user. Until, the active user gets the rating. So, the back propagation method should be adjust to make the better accuracy and quality of the prediction. In the experiment, the low accuracy result comes from the using of the pseudo rating instead of real rating as the factor of the prediction. So, there should be more study on this problem for making the better results of the prediction.

However, only the new trust value evaluation is enough for make the good accuracy and quality of the rating prediction.

5.4 Future work

In order to transpose the rating of user, it needs the rating of two user but the rating is not exist. So, there should has the efficiency method to create the pseudo rating. If the pseudo rating can produce the rating as the real rating, the prediction of the new trust value evaluation with back propagation will be better. Then, it should study more in order to revise the way to get high quality pseudo rating in the transpose rating of process in future work.

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APPENDIX

VITA

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