An Effective Recommender System by Unifying User and Item Trust Information for B2B Applications

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Abstract

Although Collaborative Filtering (CF) -based recommender systems have received great success in a variety of applications, they still under-perform and are unable to provide accurate recommendations when users and items have few ratings, resulting in reduced coverage. To overcome these limitations, we propose an effective hybrid user-item trust-based (HUIT) recommendation approach in this paper that fuses the users' and items' implicit trust information. We have also considered and computed user and item global reputations into this approach. This approach allows the recommender system to make an increased number of accurate predictions, especially in circumstances where users and items have few ratings. Experiments on four real-world datasets, particularly a business-to-business (B2B) case study, show that the proposed HUIT recommendation approach significantly outperforms state-of-the-art recommendation algorithms in terms of recommendation accuracy and coverage, as well as significantly alleviating data sparsity, cold-start user and cold-start item problems.

Keywords:
Recommender systems, Collaborative filtering, Trust filtering, Hybrid, Data sparsity, Cold-start

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1. Introduction

The volume of data on the web and the number of Internet users have been increasing at an unprecedented rate in recent years. With this exceptional growth, it becomes critical to make the interaction of users with the Internet very efficient and to enhance web users' ability to distinguish relevant information from what is irrelevant [1]. This has prompted a strong interest in personalized recommender systems, which are considered to be the most popular forms of web personalization and have become a promising and important research topic in the field of information filtering. Recommender systems are a kind of information systems that use justifications to generate recommended products to customers and ensure that customers like these products. These justifications can either be obtained from preferences directly expressed by customers, or they can be induced, using data representing the customer experience [2].

More recently, significant steps have been taken in the direction of providing personalized services for a wide variety of web-based applications [3] such as e-business applications [4, 5] recommending news [6], movies [7], books [8], videos [9], bundle purchases [10], resource recommendations in social annotation systems [11], and online research papers [12]. Collaborative Filtering (CF) is the best-known recommendation recommender systems technique for producing recommendations, and there are currently a number of popular online companies such as Netflix.com, Amazon.com, and Last.fm that use CF to offer recommendations to their customers. CF produces recommendations in a given domain based on the ratings of a set of similar users or items known as neighbours [13, 14]. CF can be classified into user-based and item-based CF approaches. In the user-based CF approach, a user will receive recommendations of items liked by similar users. In the item-based CF approach, a user will receive recommendations of items that are similar to items the user has liked in the past [13]. Despite their popularity and success, the CF-based approaches still suffer serious limitations because of insufficient rating information [13, 15, 16, 17]. These limitations include:

Data Sparsity problem This occurs when users typically rate only a small portion of the available items, thus, the number of ratings attained becomes very small compared to the number of ratings that need to be predicted. Due to this problem, CF-based recommendation approaches will face a lot of difficulties when trying to identify successful neighbors in the system and, accordingly, result in low quality recommendations [13, 15].

Cold-Start (CS) Item problem This is also known as the new item problem. New items have only been rated by a few users, which makes it very difficult to find similar users that rated such an item. Thereby, with few or no ratings for CS items, CF-based recommendation approaches cannot properly locate similar item neighbours and will be unlikely to generate personalized recommendations for them [13, 15].

Cold-Start (CS) User problem This is also known as the new user problem. Due to lack of user rating data, CF-based recommendation approaches often face severe difficulties in properly find user neighbours, so they fail in producing adequately personalized recommendations for new users [13, 15].

Researchers have commonly tackled these limitations by incorporating additional external information to the rating information, thereby forming hybrid recommender systems. Examples of this external information include demographic information [18, 19, 20], content-based information [21, 22, 23], explicit trust information [24, 25, 26], semantic information [27, 28, 29] and user's knowledge [30, 31]. The incorporation of such information has proved to be successful in solving the above limitations of the CF-based approaches by allowing recommender systems to make inferences based on additional external sources of knowledge. The incorporation of additional external information is not always practical, however, due to a number of limitations: (1) systems that employ specific types of information are not flexible (e.g., content-based recommender systems that operate on a particular application domain cannot be directly applied to different domains without modifications) [32]; (2) the additional information is not always available and is often difficult to obtain. For example, explicit trust filtering systems require additional manual labor and user effort from the end user (who provides his/her trustworthiness to other users) which prevents the fully automated view of the original proposed CF-based recommender systems [26]; (3) the available information is not considered to be sufficiently reliable, complete or representative [33].

In this paper, we address the rating information insufficiency problem in the CF-based recommendation approach and propose a practical hybrid user-item trust (HUIT) recommendation approach as a possible solution. The proposed HUIT approach aims to improve the quality of recommendations by extending the active user's and target item's neighbourhood using alternative information derived from existing historical ratings. It fuses the implicit trust information of users and items within the CF framework to achieve more effective results in terms of recommendation accuracy and coverage, especially when dealing with data sparsity, CS user and CS item problems. The proposed HUIT approach combines the user-based trust and the item-based trust recommendation approaches. The user-based trust approach utilizes the intuitive properties of implicit trust and trust propagation between users, as well as the users' global reputation, to handle the data sparsity and CS user problems. The item-based trust approach utilizes the intuitive properties of trust between items and the items' global reputation to further reduce the effect of data sparsity and CS item problems. The remainder of this paper is organized as follows: Section 2 briefly describes the research background and related works. In Section 3, we present the main components of the HUIT approach. A case-based mathematical example is given in Section 4 to illustrate the process of the HUIT approach. In Section 4, we also reveal the experimental evaluation results using MovieLens, Yahoo! Webscope and FilmTrust datasets to compare the HUIT approach with existing benchmark algorithms. In Section 5, a case study in which HUIT was applied in B2B practice, using a dataset extracted from the Bizseeker system's prototype, is presented. Finally, we present the conclusions and proposals for future work.

2. Background And Related Work

2.1. CF-based recommender systems

CF is the most widely applied recommendation technique based on user preferences, which are subjective evaluations of users [34, 35, 36]. CF-based techniques can be classified into two basic classes: memory-based and model-based [13]. Memory-based techniques are essentially heuristics that make rating predictions based on the entire collection of previously rated items by the group of users. Memory-based CF techniques can be further divided into user-based and item-based CF approaches [13, 35]. The difference between them depends on whether evaluations are made from similar users or from similar items.

In the user-based CF approaches, the first step is to analyze the user-item matrix and create a vector for each user containing the user's ratings on all the rated items. The similarity of each pair of users' vectors is then computed using similarity measures such as Pearson correlation and Cosine correlation. However, these similarity measures compute the similarity between two users based only on the overlap items defined in their respective rating vectors. Next, for each target item, the most similar users (Top-n) to the active user are selected as the user's nearest neighbours. Predictions are generated using a weighted average of the neighbours' ratings, on the target item. Finally, the items obtaining the highest predicted ratings are recommended to the user [13, 35]. The item-based CF approach is the transpose of the user-based CF approach in which prediction are produced based on the similarity of items. To summarize, the user-based CF approach recommends those items to an active user that are most liked by the user's nearest neighbours, whereas, the item-based CF approach recommends items to an active user that are similar to items the user has liked in the past, and keeps away items that are similar to items the user did not previously like [13, 35, 16].

Nevertheless, as mentioned before, the extensive use of CF-based techniques has uncovered some major limitations; these include data sparsity, CS user, and CS item problems (refer to Section 1 for more details).

2.2. Trust-based recommender systems

In a trust-based recommender system users are aware that the sources of recommendation were derived from people either directly trusted by them, or indirectly trusted by another trusted user through trust propagation. Trust propagation (also known as trust inference) is often in use to infer trust and create new relations between users who have no direct trust links between them [24, 25]. In fact, trust-based recommender systems have greater recommendation efficiency than traditional CF-based techniques because they exploit trust information to alleviate issues concerning data sparsity or CS user problems [24, 37, 25, 38, 39]. Based on the type of trust information, two main trust-based recommendation approaches have been reported in the current literature: explicit trust-based and implicit trust-based recommendation approaches.

Explicit trust-based approaches will ask users to explicitly select or rate other trustworthy users to build an explicit trust network that is used to produce explicit trust-based recommendations [24, 25]. Golbeck [24] developed an online recommender system using explicit trust in web-based social network, called FilmTrust. In this system users can rate films, write reviews and also express trust statements to other users they add as friends. The trust statements referred to how much users trust the movies ratings of their friends. Massa and Avesani [25] developed an explicit trust-aware recommender system in which users were asked to rate items and other users. In this system, users are asked to add other users whose ratings consistently found to be valuable in their web of trust. It also requires users to add those whose ratings they have consistently found offensive, inaccurate, or not valuable to their block list. However, two main problems have been exposed relating to the use of explicit trust-based approaches: (1) they are time consuming and expensive in terms of obtaining the explicit trust as they require additional manual labour and user effort from the end user; (2) since new users have to first build up their web of trust before the filtering is effective, explicit trust-based approaches suffer from the CS user problem [37, 39]. Thereby, these limitations have limited the applicability of explicit trust-based approaches in recommender systems, and have made the use of implicit trust-based approaches more practical [38, 26, 39].

In implicit trust-based approaches, the trust relationships can be expressed based on an assumption that other users' ratings can be considered as recommendations to a certain user. For example, if a user b has delivered highly accurate recommendations to active user a in the past, then user b should acquire a high trust score from active user a [37, 40, 39]. O'Donovan and Smyth [40] indicated that user reliability in delivering accurate recommendations in the past is an important factor for influencing recommendation and prediction in the future. Specifically, the more accurate predictions a given user has produced in the past, the more trustworthy he/she is considered to be. Hwang and Chen [37] utilized the implicit trust values that are directly derived from the user ratings to propose an implicit trust-based approach. Yuan et al. [39] employed the implicit trust values that are generated from user similarities to develop a novel implicit trust aware recommendation model (iTARS). In general, most of the present implicit trust-based approaches share common features: (1) they use ratings or prediction errors between users' profiles as an indication of trust; (2) they do not consider what has not been rated when computing trust but only consider the intersection of users' profiles (i.e., common ratings).

Based on current literature, most of the existing explicit and implicit trust-based recommendation approaches are classified as user-based trust recommendation approaches [24, 37, 25, 40, 38, 39] and very few developments in item-based trust recommendation approaches [41, 40]. Kim, Ji and Jo [41] presented an item-based trust recommendation approach to enhance predic-

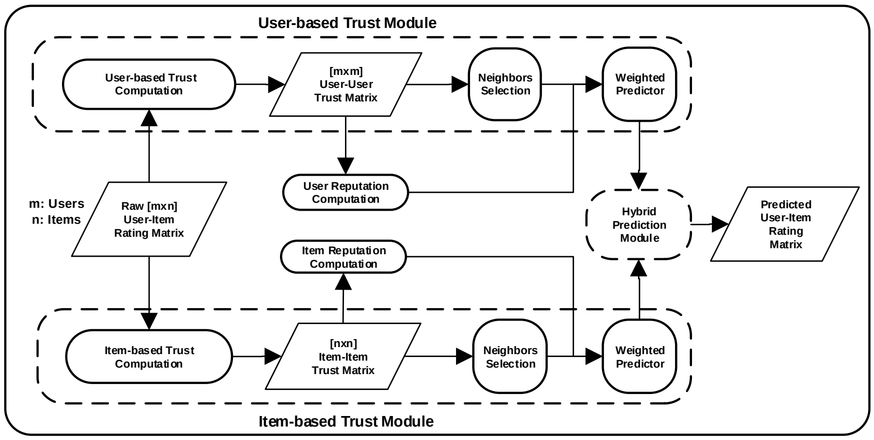

Figure 1: The HUIT recommendation approach architecture diagram

tion quality and overcome sparsity and scalability problems. The proposed approach combines item confidence and item similarity, collectively called item trust, using this value for online predictions. In addition to a user-level trust metric (profile-level trust), O'Donovan and Smyth [40] also proposed an item-level trust metric that is more fine-grained than the user-based trust metric. Item level trust is a representation of a producer's trustworthiness with respect to the recommendation of a specific item. In item level trust, trust values are calculated at the item level in which the proportion of correct recommendations that a producer has been involved in are summarized according to a pre-defined error bound.

3. A Hybrid User-Item Trust-based Recommendation Approach

This section presents the proposed HUIT recommendation approach in detail. First, we describe the structure and each component of the HUIT approach. Then, we introduce a numerical example to illustrate the recommendation process of the HUIT approach.

3.1. The architecture of the HUIT recommendation approach

As shown in Figure 1, the HUIT approach obtains a raw user-item rating matrix $R_{m \times n} = \{r_{ai}, a = 1, 2, \ldots, m, \text{ and } i = 1, 2, \ldots, n\}$, where $r_{ai} \in \{1, 2, 3, 4, 5\}$, five-point scale from 1 (Poor) to 5 (Excellent), m is the number of users and n is the number of items, as inputs, and produces a user-item prediction matrix $P_{m \times n}$ as an output. The HUIT approach has three main modules: user-based trust, item-based trust and hybrid prediction modules. Each module is described in the following subsections.

3.1.1. The User-based Trust (UT) Module

This module exploits users' implicit trust relations in the user-user implicit trust network to make implicit user-based trust recommendations. The module contains four main steps:

UT-Step 1: *Implicit User-based Trust Computation*

This step is divided into two connected sub-steps, trust derivation and trust propagation. Trust derivation takes the user rating matrix $R_{m \times n}$, and calculates the direct implicit trust scores of every pair of users. After computing the direct implicit trust scores, trust propagation exploits the indirect trust relationships to calculate the trust scores between users who are not directly connected.

a) *Trust Derivation*

Based on the paradigm of implicit trust-based approaches, this study measures the trustworthiness of a given user by measuring the prediction accuracy of that user as a past recommender to an active user [37]. For trust derivation, we first compute the predicted rating using the Resnick's prediction method [35]. For any $a, b \in U, i \in I$, the predicted rating of item i for the user a by the only neighbourhood user b, $P_{a,i} \in [1, 5]$, is given as follows:

$$P_{a,i} = \overline{r_a} + (r_{b,i} - \overline{r_b}), \tag{1}$$

where $r_{b,i} \in \{1, 2, 3, 4, 5\}$ denotes the rating of item i by user b, and $\overline{r_a}$ and $\overline{r_b}$ are the mean ratings of users a and b, respectively. However, in the case of only one neighbour is used (Equations (1) and (9) in this study), the Resnick's prediction formula may produce out of bounds predictions. To alleviate this issue and maintain the predicted ratings to be within the range of $[1, 5]$ in Equations (1) and (9), we let:

$$P_{a,i} = \begin{cases} 5, & \textit{if } P_{a,i} > 5; \\ 1, & \textit{if } P_{a,i} < 1. \end{cases} \tag{2}$$

Taking into account that a user's past prediction accuracy is used to measure that user's trustworthiness, the Mean Squared Differences (MSD) method [13, 36] is employed to measure the degree of similarity of user a with respect to user b from the predictions error of co-rated items between them, as shown by Equation (3). To ensure that the value of $MSD_{a,b} \in 1$, we have first to normalize the rating $r_{a,i}$ and predicted rating $P_{a,i}$ values within the range $[0, 1]$ using the $Max - Min$ normalization method [42]. For any $a, b \in U$, the degree of similarity of user a with respect to user b, $MSD_{a,b} \in 1$, based on the predictions error of co-rated items between them $I_{a,b}$, is given by:

$$MSD_{a,b} = 1 - \frac{\sum_{i=1}^{I_{a,b}} (P_{a,i} - r_{a,i})^2}{|I_{a,b}|}, \tag{3}$$

where $P_{a,i}$ refers to the normalized predicted rating of item i for user a, $r_{a,i}$ denotes the normalized rating value of item$i$ with respect to user a, $I_{a,b}$ is the set of co-rated items by both users a and b. $|I_{a,b}|$ is the number of items that have been rated by active user a and potential neighbour user b.

The $MSD_{a,b}$ metric nonetheless still has a major drawback, as demonstrated in previous research work on implicit trust-based approaches [37, 40, 39], since it does not consider what has not been rated between users a and b when computing the implicit trust between them. The impact of this issue can be seen when users who have rated a very small number of items express a high level of trust towards almost all other users. For example, an implicit trust value of 0.90 calculated between two users with only 20 common items is not as trustworthy and reliable as an implicit trust value of 0.70 calculated with 200 common items. In this case, the proportion between the common ratings and the total rated items should be taken into consideration when computing the derived implicit trust. One way to solve this issue is to use the user-based Jaccard similarity metric [43], as shown by Equation (4).

$$UJaccard_{a,b} = \frac{|I_{a,b}|}{|I_a| + |I_b| - |I_{a,b}|}, \tag{4}$$

where $|I_a|$ is the number of items that have been rated by active user a. $|I_b|$ is the number of items that have been rated by potential neighbour user b.

The user-based Jaccard metric is used as a weighting scheme to reflect on the proportion between the common ratings and the total rated items when computing the derived implicit user-based trust, as given by Equation (5). For any $a, b \in U$, the implicit user-based trust derivation metric between user a and user b, $UDtrust_{a,b} : U \times U \to [0, 1]$, is given as:

$$UDtrust_{a,b} = MSD_{a,b} \times UJaccard_{a,b} \tag{5}$$

b) *Trust Propagation* Trust propagation is needed when there are no direct trust relations between users. Thus, from the direct trust network, it is possible to propagate trust and create new relations between users who have no direct trust link between them. For example, assuming that user $a \in U$ (source user) trusts user $b \in U$ (intermediate user) and user b trusts user $c \in U$ (target user), by using trust propagation matrices it can be inferred that user a can trust user c at some level. In case there is more than one intermediate user (bs), a trust aggregation method is needed to combine the different trust beliefs that target user a has received from bs about c to infer a unique trust belief about c. In this study, we use the aggregation method proposed by [44]. The rationale behind the following aggregation method is that it ensures that the inferred trust value is most significantly weighted by the co-rated items between trusted users. Thus, if two users have more co-rated items, their direct relationship is more reliable and requires more weight [37, 44]. For any $a, b, c \in U$, the propagated implicit trust value that indicates to what extent user a implicitly trusts user c, $Ptrust_{a \to c} : U \times U \to [0, 1]$, is computed as follows:

$$Ptrust_{a,c} = \frac{\sum_{b \in adj(a)} (|I_{a,b}| \times UDTrust_{a,b} + |I_{b,c}| \times UDTrust_{b,c})}{\sum_{b \in adj(a)} (|I_{a,b}| + |I_{b,c}|)}, \tag{6}$$

where user a has bs direct trusted adjacent neighbours that trust user c, $UDTrust_{a,b} \in [0, 1]$ is the implicit user-based trust value between user a and user b. $UDTrust_{b,c} \in [0,1]$ is the implicit user-based trust value between user b and user c. $|I_{a,b}|$ is the number of items that have been commonly rated by active user a and potential neighbour user b. $|I_{b,c}|$ is the number of items that have been commonly rated by active user b and potential neighbour user c.

UT-Step 2: *User Reputation Computation*

A user overall reputation is defined as the average combination of implicit user-based trust values received from other connected users in the user-user implicit trust network. For any $b, k \in U$, the reputation score of user b, $UR_b : U \times U \to [0,1]$, is given as:

$$UR_b = \frac{\sum_{k=1}^{l} UTrust_{k,b}}{l}, \tag{7}$$

where user k is an adjacent user neighbour that trust user b, $UTrust_{k,b} \in [0,1]$ is the implicit user-based trust value between user k and user b. l is the number of adjacent neighbours that trust user b.

UT-Step 3: *Neighbour Selection*

The most trusted users to the active user ($N^{UT} \in U$) are selected as a set of neighbours. For the neighbours' selection process, we use the *Top-n* method in which a predefined number of users with greatest correlation are selected [45].

UT-Step 4: *Calculate User-based Weighted Predictions*

The deviation-from-mean approach [45, 35] is used in the weighted predictor component to calculate the implicit user-based trust predicted rating value of the active user $a \in U$ on item $x \in I$, $P_{a,x}^{UT} : U \times I \to [0,5]$, as given by:

$$P_{a,x}^{UT} = \begin{cases} \overline{r_a} + \frac{\sum_{b=1}^{N^{UT}} UTrust_{a,b}(r_{b,x} - \overline{r_b})}{\sum_{b=1}^{N^{UT}} UTrust_{a,b}}, & \textit{if } UTrust_{a,b} \neq 0; \\ \overline{r_a} + \frac{\sum_{b=1}^{N^{UT}} UR_b(r_{b,x} - \overline{r_b})}{\sum_{b=1}^{N^{UT}} UR_b}, & \textit{if } UTrust_{a,b} = 0. \end{cases} \tag{8}$$

where, $\overline{r_a}$ and $\overline{r_b}$ represent the average rating values of the active user a and potential neighbour user b on all items that are rated by each user separately, $r_{b,x}$ denotes the rating value of the potential neighbour user b for target item x. $UTrust_{a,b} \in [0,1]$ represents the implicit user-based trust value between the active user a and potential neighbour user b, and is obtained from the user-user implicit trust matrix. N^{UT} is the set of nearest neighbours of active user a.

3.1.2. The Item-based Trust (IT) Module

This module exploits items' implicit trust relations in the item-item implicit trust network to make implicit item-based trust recommendations. The module contains four main steps:

IT-Step 1: *Implicit Item-based Trust Computation*

This step takes the rating matrix as input and calculates the direct implicit item-based trust scores between every pair of items. We measure the trustworthiness of a given item by measuring the prediction accuracy of that item, as a past recommender, to the target item. For example, if an item y has delivered highly accurate recommendations to a target item x in the past, then item y should obtain a high trust score from target item x. For trust derivation, we again use Resnick's prediction method to compute the predicted rating. For any $x, y \in I, u \in U$, the predicted rating of item x for the user u by the only neighbourhood item y, $P_{u,x} : U \times I \rightarrow [1,5]$, is given as follows:

$$P_{u,x} = \overline{r_x} + (r_{u,x} - \overline{r_y}), \tag{9}$$

where $r_{u,x}$ denotes the rating of item x by user u, and $\overline{r_x}$ and $\overline{r_y}$ are the mean ratings of items x and y, respectively. As shown by Equation (10), the MSD method is then used to measure the degree of similarity of item x with respect to item y from the predictions error of co-rated users between them. The predicted rating $P_{u,x}$ and rating $r_{u,x}$ values are normalized within the range $[0,1]$ using the max-min normalization method to ensure that the value of $MSD_{x,y} \in [0,1]$. For any $x, y \in I$, the degree of similarity of item x with respect to item y, based on the predictions error of co-rated users between them $U_{x,y}$, is given by:

$$MSD_{x,y} = 1 - \frac{\sum_{u=1}^{|U_{x,y}|} (P_{u,x} - r_{u,x})^2}{|U_{x,y}|}, \tag{10}$$

where $P_{u,x}$ refers to the normalized predicted rating of item x for user u , $r_{u,x}$ denotes the normalized rating value of item x with respect to user u, $|U_{x,y}|$ is the number of co-rated users between items x and y.

The ratio of proportion between the common users who rated both items and the total number of users who rated each item individually is very important and should be taken into account when computing the derived implicit item-based trust. The item-based Jaccard similarity metric [43], as shown by Equation (11), is used here to deal with this issue. For any $x, y \in I$, the item-based Jaccard similarity between target item x and potential neighbour item y, $IJaccard_{x,y} : I \times I \rightarrow [0, 1]$, is computed as follows:

$$IJaccard_{x,y} = \frac{|U_{x,y}|}{|U_x| + |U_y| - |U_{x,y}|}, \tag{11}$$

where $|U_{x,y}|$ is the number of users who have rated both target item x and potential neighbour item y. $|U_x|$ is the number of users who have rated a target item x. $|U_y|$ is the number of users who have rated a potential neighbour item y. We use the item-based Jaccard metric as a weighting scheme to consider the ratio of users who have rated two items in common to the total number of users who have rated each item individually when computing the derived item-based implicit trust, as given by Equation (12). For any $x, y \in I$, the implicit item-based trust derivation metric between item x and item y, $IDTrusr_{x,y} : I \times I \rightarrow [0, 1]$, is given as:

$$IDtrust_{x,y} = MSD_{x,y} \times IJaccard_{x,y} \tag{12}$$

IT-Step 2: *Item Reputation Computation*

The overall reputation of an item is defined as the average combination of implicit item-based trust values received from other connected items (i.e, other items rated by the same user) in the item-item trust network. For any $y, z \in I$, the item reputation of item y,$IR_y : I \times I \rightarrow [0, 1]$, is given as:

$$IR_{u,y} = \frac{\sum_{z=1}^{w_u} ITrust_{z,y}}{|w_u|}, \tag{13}$$

where item z is an adjacent item neighbour for item y and is rated by user u, $ITrust_{z,y} \in [0,1]$ is the item-based implicit trust value between item z and item y. $|w_u|$ is the number of adjacent item neighbours that have been rated by user u.

IT-Step 3: *Neighbour Selection*

The *Top-n* method is used to select a set of neighbours that are the most trusted items to the target item ($N^{IT} \in I$) from the item-item implicit trust matrix.

IT-Step 4: *Calculate Item-based Weighted Predictions*

This step computes the rating predictions of all unrated items by an active user. The predicted rating of active user $a \in U$ on a target item $x \in I$, $P^{IT}_{a,x} : U \times I \rightarrow [0,5]$ is calculated using the weighted sum of deviations from the mean item ratings approach [43, 45, 35] as given by Equation (14) :

$$P^{IT}_{a,x} = \begin{cases} \overline{r_x} + \frac{\sum_{y=1}^{N^{IT}} ITrust_{x,y(r_{a,y}-\overline{r_y})}}{\sum_{y=1}^{N^{IT}} ITrust_{x,y}}, & \textit{if } ITrust_{x,y} \neq 0; \\ \overline{r_x} + \frac{\sum_{y=1}^{N^{IT}} IR_{a,y(r_{a,y}-\overline{r_y})}}{\sum_{y=1}^{N^{IT}} IR_{a,y}}, & \textit{if } ITrust_{x,y} = 0. \end{cases} \tag{14}$$

where, $\overline{r_x}$ and $\overline{r_y}$ are the mean rating values of the target item x and potential neighbour item y, respectively. *if* $ITrust_{x,y} \in [0,1]$ represents the item-based implicit trust value between the target item x and neighbour item y, and is obtained from the item-item implicit trust matrix. N^{IT} is the set of nearest neighbours of the target item x in terms of trustworthiness, obtained by neighbour selection. $IR_{a,y}$ is the overall reputation of an item y based on other items rated by user a.

3.1.3. The Hybrid Prediction Module

This module uses the switching hybridization strategy, as shown by using Equation (15), to combine the prediction values of the implicit user-based trust and the implicit item-based trust approaches. The hybrid prediction value ($HP_{a,x} \in [0,5]$) take into account all possible ways to obtain a rating prediction value for an active user a who has not rated the target item x. The weighted harmonic mean method is used to ensure that a high total prediction rating value is obtained only if prediction rating values of both the implicit user-based and the implicit item-based trust approaches are high [40].

$$HP_{a,x} = \begin{cases} 0, & if\ P_{a,x}^{UT} = 0\ and\ P_{a,x}^{IT} = 0 \\ P_{a,x}^{UT}, & if\ P_{a,x}^{UT} \neq 0\ and\ P_{a,x}^{IT} = 0 \\ P_{a,x}^{IT}, & if\ P_{a,x}^{UT} = 0\ and\ P_{a,x}^{IT} \neq 0 \\ \frac{2\times P_{a,x}^{UT} \times P_{a,x}^{IT}}{P_{a,x}^{UT} + P_{a,x}^{IT}}, & if\ P_{a,x}^{UT} \neq 0\ and\ P_{a,x}^{IT} \neq 0 \end{cases} . \tag{15}$$

3.2. A Numerical Example

Presume that there are six "Consumer Goods" Australian supplier businesses (S_1 to S_6) listed in a directory of online suppliers. Also, suppose that there are four overseas buyers (B_1 toB_4) who have conducted business with some of the listed suppliers and have rated them on a numeric five-point scale from 1 (Poor) to 5 (Excellent). A raw Supplier-Buyer rating matrix can accordingly be created as depicted in Table 1. In the following rating matrix, we consider buyer B_4 to be an extreme CS user, and supplier S_3 to be an extreme CS item, since both have only one rating.

Table 1: Raw Supplier-Buyer rating matrix

Buyers	**Suppliers**					
	S_1	S_2	S_3	S_4	S_5	S_6
B_1	*Null*	3	4	*Null*	*Null*	3
B_2	4	*Null*	*Null*	2	4	3
B_3	*Null*	5	*Null*	4	4	2
B_4	2	*Null*	*Null*	*Null*	*Null*	*Null*

Now, suppose that buyer B_4 is looking for "Consumer Goods" Australian supplier businesses. A numerical recommendation example is given to illustrate how the HUIT recommendation approach is used to generate recommendations.

3.2.1. The User-based Trust Module

UT-Step 1: *Implicit User-based Trust Computation*

a) *Trust Derivation:* The direct implicit trust values of each pair of buyers are calculated using Equation (5). Table 2 shows the buyer-buyer direct implicit trust values between the four buyers.

Table 2: Buyer-Buyer direct implicit trust matrix

$UDTrust$	B_2	B_3	B_4
B_1	0.17	0.20	N/A
B_2	-	0.35	0.25
B_3	-	-	N/A
B_4	-	-	-

b) *Trust Propagation:* According to Table 2, there are no direct implicit trust connections between buyers (B_1, B_4) and (B_3, B_4) as they do not co-rate any similar suppliers, thus implicit trust propagation is needed in this situation to infer the indirect implicit trust values between them. For illustration purposes, Figure. 2 shows the calculation process of the propagated implicit trust values between buyers (B_1, B_4).

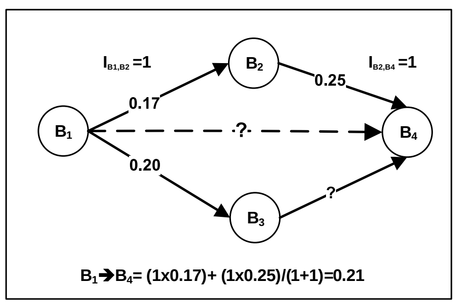

Figure 2: An example of the trust propagation process

Table 3 demonstrates the complete user-user implicit trust matrix of the four buyers after the trust propagation process.

Table 3: Buyer-Buyer propagated implicit trust matrix

$PTrust$	B_2	B_3	B_4
B_1	0.17	0.20	**0.21**
B_2	-	0.35	0.25
B_3	-	-	**0.33**
B_4	-	-	-

UT-Step 2: *User Reputation Computation.* In this step, based on Table 3, we use Equation (7) to calculate the user reputation scores for the four buyers, as given in Table 4.

Table 4: Buyer reputation matrix

UR_B	B_1	B_2	B_3	B_4
Reputaion Score	0.193	0.257	0.293	0.263

UT-Step 3: *Neighbour Selection.* Based on Table 3 and let the number of nearest neighbours $N^{UT} = 3$, we can identify the nearest neighbours to any given buyer in terms of implicit user-based trustworthiness, as shown in Table 5.

Table 5: Buyer neighbour selection

Neigh. order	B_1	B_2	B_3	B_4
1	B_4	B_3	B_2	B_3
2	B_3	B_4	B_4	B_2
3	B_2	B_2	B_1	B_1

UT-Step 4: *Calculate User-based Weighted Predictions.* On the basis of Tables 3, 4 and 5, Equation (8) is used to calculate the implicit user-based trust predicted rating values on each un-rated supplier for all buyers, as shown in Table 6.

Table 6: Implicit user-based trust predicted Supplier-Buyer matrix

Buyers	**Suppliers**					
	S_1	S_2	S_3	S_4	S_5	S_6
B_1	3.67	-	-	2.90	3.81	-
B_2	-	3.99	3.92	-	-	-
B_3	4.14	-	4.42	-	-	-
B_4	-	2.63	2.67	1.60	2.47	1.11

3.2.2. The Item-based Trust Module

IT-Step 1: *Implicit Item-based Trust Computation.* We use Equation (12), based on Table 1, to calculate the item-based trust between the six suppliers, as given in Table 7.

Table 7: Supplier-Supplier implicit trust matrix

UDTrust	S_2	S_3	S_4	S_5	S_6
S_1	0.0	0.0	0.33	0.33	0.25
S_2	-	0.50	0.33	0.33	0.0
S_3	-	-	0.0	0.0	0.33
S_4	-	-	-	0.50	0.0
S_5	-	-	-	-	0.33

IT-Step 2: *Item Reputation Computation.* We use Equation (13), based on Table 2, to calculate the item reputation scores for the six suppliers, as given in Table 8.

Table 8: Supplier reputation matrix

Reputation Score	S_1	S_2	S_3	S_4	S_5	S_6
B_1	-	0.25	0.42	-	-	0.17
B_2	0.31	-	-	0.28	0.39	0.19
B_3	-	0.22	-	0.28	0.39	0.11
B_4	0.0	-	-	-	-	-

IT-Step 3: *Neighbour Selection.* Let the number of nearest neighbours $N^{IT} = 4$; based on Table 7, we identify the nearest neighbours to any given buyer in terms of implicit item-based trustworthiness, as shown in Table 9.

Table 9: Supplier reputation matrix

Neigh. order	S_1	S_2	S_3	S_4	S_5	S_6
1	S_4	S_3	S_2	S_5	S_4	S_3
2	S_5	S_4	S_4	S_1	S_1	S_5
3	S_6	S_5	S_5	S_2	S_2	S_1
4	*N/A*	*N/A*	*N/A*	*N/A*	*N/A*	*N/A*

Table 9 shows that items' reputation scores can indeed be utilized to extend the items' neighbourhood based on the active user ratings, for example, to calculate the prediction score of supplier S_1 for active buyer B_1 , we can use only one neighbour which is S_6 based on Table 9 (as S_4 and S_5 have not been rated by buyer B_1). However, we still can use S_2 and S_3 as neighbours for S_1 based on their global reputations in Table 8. Thus the use of items global reputation will expand the neighbourhood space and thus improves the recommendation accuracy and coverage in cases of data sparsity and CS items.

IT-Step 4: *Calculate Item-based Weighted Predictions.* On the basis of Tables 7, 8 and 9, we use Equation. (14) to calculate the implicit item-based trust predicted rating values on each un-rated supplier for all buyers (Table 10).

Table 10: Implicit item-based trust predicted Supplier-Buyer matrix

	Suppliers					
Buyers	S_1	S_2	S_3	S_4	S_5	S_6
B_1	2.82			2.70	3.79	
B_2		4.03	4.11			
B_3	3.34		4.37			
B_4		0.00	0.00	2.00	3.00	1.67

3.2.3. The Hybrid Prediction Module

On the basis of Tables 6 and 10, we use Equation (15) to calculate the final HUIT predicted rating values on each un-rated supplier for all buyers, as shown in Table 11.

Table 11: Final HUIT predicted Supplier-Buyer matrix

	Suppliers					
Buyers	S_1	S_2	S_3	S_4	S_5	S_6
B_1	3.19			2.80	3.80	
B_2		4.01	4.01			
B_3	3.70		4.39			
B_4		2.63	2.67	1.78	2.71	1.33

As a final step, the most interested suppliers for an active buyer are recommended. Let $k = 3$, according to the final HUIT predicted supplier-buyer rating matrix as shown in Table 11, the top k recommended suppliers for active buyer B_4 are S_5 ($PV_{B_4,S_5} = 2.71$), S_3 ($PV_{B_4,S_3} = 2.67$) and S_2 ($PV_{B_4,S_2} = 2.63$).

4. Experimental Evaluation

This section describes the experimental evaluation and results of the proposed HUIT recommendation approach. The main goal of this section is to show the effectiveness of the approach through comparisons with well-known benchmark recommendation approaches. This section includes the datasets, evaluation metrics, benchmark algorithms, and evaluation results.

4.1. Datasets

Experiments were carried out using three datasets to assess the performance of the proposed HUIT recommendation approach.

(1) *The MovieLens dataset*. This dataset contains 100,000 ratings of 1,682 movies from 943 users (http://www.movieLens.org). The ratings scale is from 1 to 5. The sparsity level of the MovieLens dataset is 93.7% (sparsity level= $1-$ density = $1-(100000/\ (943 \times 1682))$ =0.937).

(2) *The Yahoo! Webscope R4 dataset*. This dataset is provided as part of the Yahoo! Research Alliance Webscope program. The Yahoo! Webscope dataset (http://webscope.sandbox.yahoo.com) consists of two files, a training dataset and a test dataset, where ratings in both sets are discrete values from 1 to 5 on a single criterion (i.e., each user can only make one rating for a specific movie). The training data contains 7642 users, 11915 movies and 211231 ratings. The test data contains 2309 users, 2380 movies and 10136 ratings. The sparsity level of the *Yahoo!R4* training dataset is 99.8% (sparsity level= $1-$density = $1-(211231/\ (7642 \times 11915))$=0.9976).

(3) *The FilmTrust dataset*. This dataset has been created by crawling the FilmTrust website (http://trust.mindswap.org/FilmTrust/). The dataset contains 1592 users, 1930 movies, and 28645 ratings on a floating point scale of 1 (bad) to 10 (excellent). The sparsity level of the FilmTrust dataset is 99% (sparsity level= $1-$ density = $1-(28645/\ (1592 \times 1930))$ =0.99)[46].

4.2. Evaluation Metrics

Different evaluation measures have been used to evaluate the quality of recommendations in current recommender systems. In this paper, we use the most popular measurement metrics: the standard Mean Absolute Error (MAE) and the *Coverage* metrics. The MAE is the most widely used metric in recommendation research [45, 35] for measuring the accuracy of recommendations. MAE measures accuracy by computing the average absolute deviation between the system's predicted rating against the actual rating assigned by the user. Note that a lower MAE value represents higher recommendation accuracy. Given the set of actual/predicted ratings pair (r_{ai}/r_{pi}) for all the n items available in the test set, the measurement for MAE can be given by:

$$MAE = \frac{1}{n}\sum_{i=1}^{n} |r_{ai} - r_{pi}| \tag{16}$$

The *coverage* measure evaluates the ability of a given recommender system to provide recommendations. The *coverage* is computed as the percentage of items for which a prediction is requested and for which the recommender system is able to make a prediction [45]. Let n be the number of available items and I_p be the number of items for which a prediction can be made, the *coverage* can be given by:

$$coverage = \frac{I_p}{n} \tag{17}$$

In all experiments, a hold-out cross-validation method is applied to verify the validity of the experimental results. Through cross-validation, all datasets are divided into a training set and a test set, with the training set consisting of 80% of the data and the test set consisting of 20%.

4.3. Benchmark Algorithms

Taking into consideration that the HUIT recommendation approach is a hybrid of the user-based and item-based trust recommendation algorithms, its results are compared with the results of two user-based and two item-based benchmark recommendation algorithms:

(1) The Resnick user-based CF, where the similarity is computed using the Pearson correlation (denoted as UB-CF) [35].

(2) The Sarwar item-based CF, which employs vector cosine similarity (denoted as IB-CF)[16].

(3) The O'Donovan user-based trust, which combines implicit trust-based filtering and weighting using profile-level trust (denoted as UB-Trust) [40].

(4) The Kim item-based trust, which combines the item confidence and item similarity (denoted as IB-Trust) [41].

4.4. Evaluation Results

We conducted a number of experiments to verify the improvement in the proposed HUIT recommendation approach and its effectiveness against the benchmark algorithms in terms of improving recommendation accuracy and coverage in resolving data sparsity, CS user and CS item problems.

4.4.1. Comparison between the HUIT approach and other benchmark algorithms on different datasets

In this section, we conduct three experiments using the MovieLens, Yahoo! Webscope and FilmTrust datasets to compare the recommendation accuracy performance of the HUIT recommendation approach with respect to the benchmark recommendation algorithms. In all experiments, we varied the number of neighbours and computed the corresponding MAE for all recommendation approaches. Looking into the results shown in Figures 3, 4 and 5, we can see that the HUIT approach achieves the best recommendation accuracy (i.e., lowest MAE) at all neighbourhood sizes. Therefore, it can be concluded that the HUIT approach is a significant improvement in terms of recommendation accuracy compared to the benchmark recommendation algorithms.

4.4.2. Comparison between the HUIT approach and other benchmark algorithms on the data sparsity problem

This section verifies the success of the HUIT approach in alleviating the data sparsity problem. To manipulate different levels of sparsity in this section, we used the sparsity metric to extract and create six sparse datasets from the MovieLens dataset. In these sparse datasets, sparsity levels decrease from the highest level of 99.5% to the lowest level of 97.0% (i.e., 99.5%, 99.0%, 98.5%, 98.0%, 97.5%, and 97.0%). Two experiments have been carried out using the six sparse datasets to measure the recommendation accuracy and

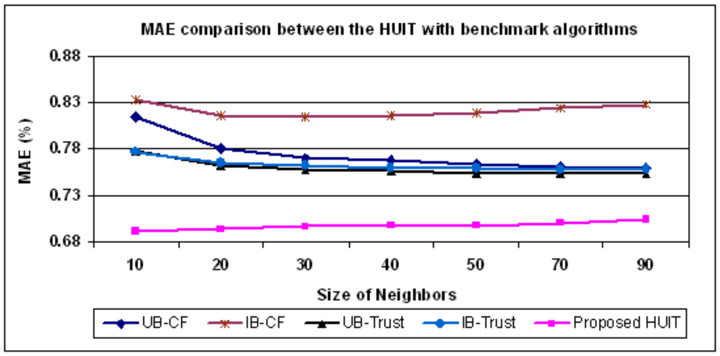

Figure 3: Recommendation accuracy (MAE) comparison between the HUIT approach and other benchmark algorithms on different numbers of neighbours (MovieLens dataset)

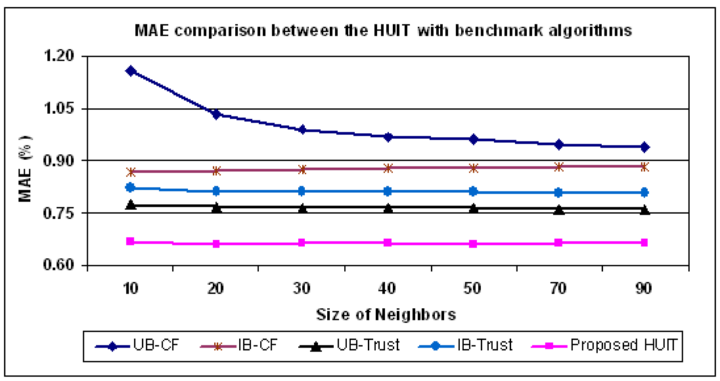

Figure 4: Recommendation accuracy (MAE) comparison between the HUIT approach and other benchmark algorithms on different numbers of neighbours (YahooWebscope dataset)

coverage of the HUIT approach against the benchmark algorithms on different data sparsity levels. Figure 6 indicates that the HUIT approach has the highest recommendation accuracy at all levels of data sparsity, compared to the benchmark algorithms. For example, in the 99.5% sparse dataset, the average percentage improvement of the HUIT approach over the benchmark recommendation algorithms is 50%. Figure 7 validates the HUIT approach as having the highest coverage for all levels of data sparsity, compared to the benchmark algorithms. For example, in the 99.5% sparse dataset, the benchmark user-based CF, item-based CF and item-based trust recommendation algorithms are barely able to make any recommendations for any item in the test set, and the benchmark user-based trust recommendation algorithm

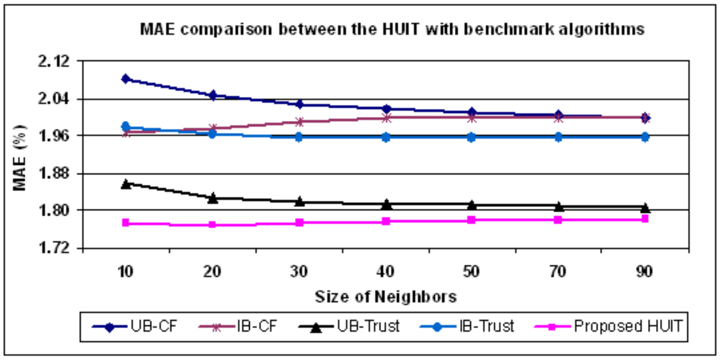

Figure 5: Recommendation accuracy (MAE) comparison between the HUIT approach and other benchmark algorithms on different numbers of neighbours (FilmTrust dataset)

is able to make recommendations for 13% of the available items in the test set, whereas our algorithm can make recommendations of up to 73% of the available items in the test set.

By considering both recommendation accuracy and coverage, it can be concluded that the HUIT approach is a significant improvement in alleviating the data sparsity problem compared to the benchmark recommendation algorithms.

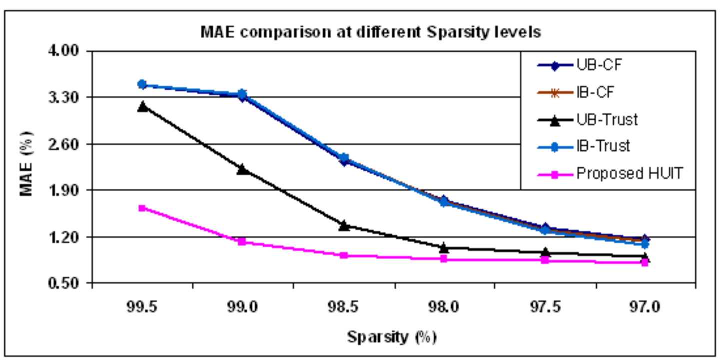

Figure 6: Recommendation accuracy (MAE) improvement at different data sparsity levels

4.4.3. Comparison between the HUIT approach and other benchmark algorithms on the CS user problem

In this section, we present the experimental results to confirm the effectiveness of the HUIT recommendation approach in alleviating the CS user

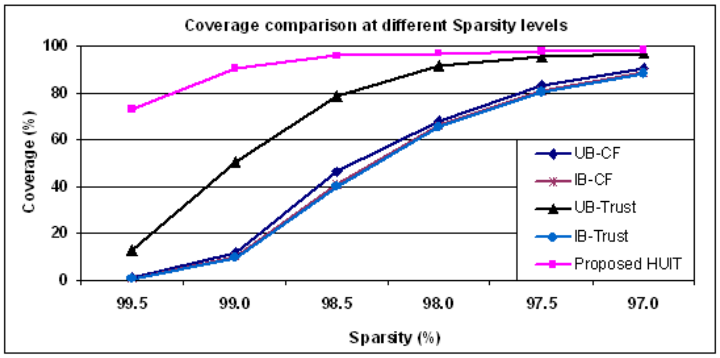

Figure 7: Recommendation coverage improvement at different sparsity levels

problem. Two experiments, shown in Figure 8 and Figure 9, are conducted to measure the recommendation accuracy and coverage of the HUIT approach compared to the user-based benchmark algorithms on a different number of ratings for CS users. It can be seen that when new users receive more ratings, recommendation accuracy and coverage increase gradually. This is expected, because a low number of ratings leads to a poor set of neighbours and hence reduces prediction accuracy and coverage.

Looking into the results shown in Figure 8 and 9, we can see that the HUIT approach has the highest recommendation accuracy and coverage for any given number of CS user ratings compared with the benchmark user-based recommendation algorithms. For example, according to Figure 8, with 5 ratings for CS users, the percentage improvements of the HUIT approach over the benchmark user-based CF and user-based trust recommendation algorithms are 45% and 34% respectively. According to Figure 9, with 5 ratings for CS users, the benchmark user-based CF recommendation algorithm is able to make recommendations for 25% of the available items in the test set, and the benchmark user-based trust recommendation algorithm is able to make recommendations for 52% of the available items in the test set, whereas the HUIT approach can make recommendations for 78.9% of the available items in the test set. Hence, by considering both recommendation accuracy and coverage, it can be concluded that the HUIT recommendation approach is a significant improvement in alleviating the CS user problem compared to the benchmark user-based CF and trust recommendation algorithms.

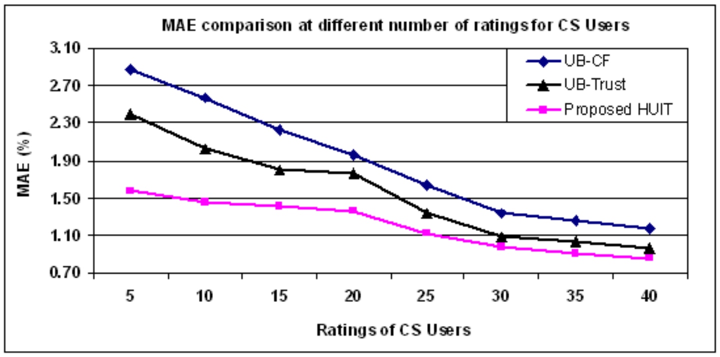

Figure 8: Recommendation accuracy improvement on different numbers of ratings for CS users

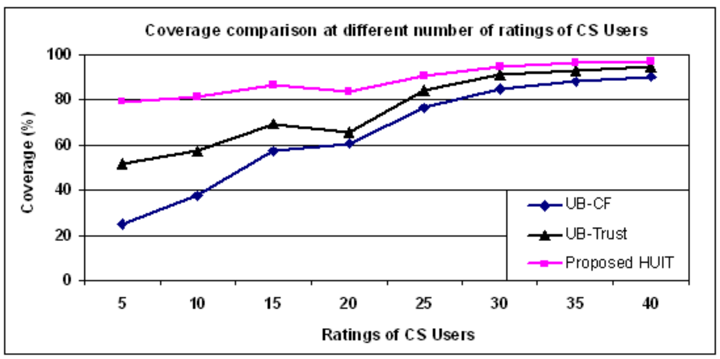

Figure 9: Recommendation coverage improvement on different numbers of ratings for CS users

4.4.4. Comparison between the HUIT approach and other benchmark algorithms on the CS item problem

This section presents the results of two experiments to demonstrate the effectiveness of the HUIT recommendation approach in alleviating the CS item problem. Two experiments are performed to measure the recommendation accuracy and coverage of the HUIT approach and other benchmark item-based recommendation algorithms on different numbers of ratings for CS items, as shown in Figure 10 and 11. Clearly, the recommendation accuracy and coverage increase gradually when CS items obtain more ratings. Figure 10 shows that the HUIT approach has the highest recommendation accuracy for any given number of ratings for CS items compared to the item-based benchmark algorithms. For example, in the extreme case of the CS item dataset (two ratings), the average percentage improvement of the HUIT approach over the benchmark item-based CF and item-based trust recommendation algorithms is 8%. Figure 11 shows that the HUIT approach has the highest coverage of any given number of ratings for CS items in comparison with the item-based benchmark algorithms. For example, the benchmark item-based CF and trust algorithms are unable to make any recommendations when CS items have only two ratings, whereas the HUIT approach can produce recommendations for up to 20.4% of these items. Thereby, it can be concluded that the HUIT recommendation approach significantly alleviates the CS item problem when compared to the item-based benchmark item-based CF and trust recommendation algorithms.

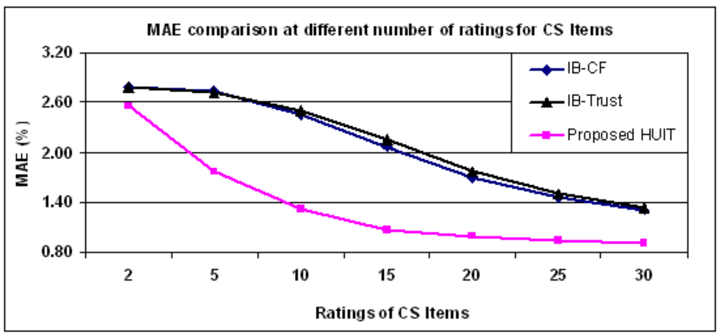

Figure 10: Improvement of recommendation accuracy on different numbers of CS items ratings

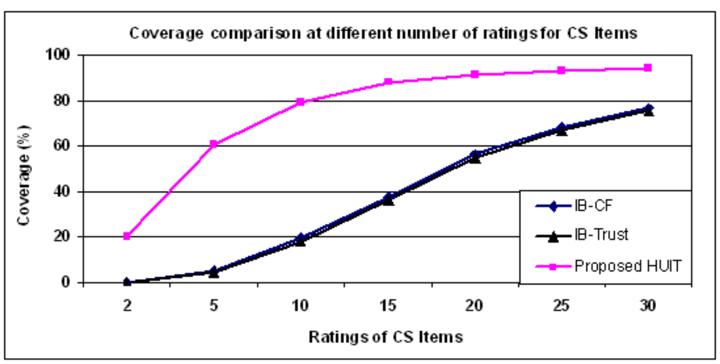

Figure 11: Improvement of recommendation coverage on different numbers of CS items ratings

5. Business-to-Business Recommender System: A Case Study

With the rapid growth of e-Business, companies are finding it harder to survive whereas consumers are unable to effectively select the items that really meet their needs. To reduce the item overload that confronts Internet shoppers, personalized recommender systems are being developed and employed to help users select suitable items that meet their personal needs. A recent study shows that recommender systems are an important part of e-business systems, and websites that make effective use of personalized recommenders have been reported as seeing up to 35% of their sales being generated from recommended products [47]. The main characteristics and motivators of using recommender systems in e-business applications, are converting browsers into buyers, increasing cross-sell, and building customer loyalty [48].

One of the most important applications of B2B is Buyer-Supplier matching. We believe that recommender systems can add value to this application by facilitating business integration and supporting supply chain management. Matching buyers and suppliers (matching business partners) is the first step to achieving successful business integration and/or supply chain management for businesses to strengthen their competitiveness in the marketplace [49, 50]. Buyer-Supplier matching involves a multi-stage decision making process that includes searching for partners, negotiating and signing a contract. The problem of searching for business partners is probably the least explored stage of the business partner selection process in the relevant literature [51]. Because of the information overload and the evolving number of businesses, the task of searching and locating appropriate business partners becomes too costly, inconsistent, and unreliable. This task can, however, be efficiently supported by personalized recommender systems that facilitate the decision process of a business user (e.g., buyer) in selecting qualified business partners (e.g., supplier) based on their preferences. An existing example is the Australian Suppliers Directory (ASD, http://www.austrade.gov.au/ASD/) that promotes Australian goods and services to overseas buyers, as well as assisting overseas buyers to search for suppliers all over Australia. The ASD is full of information about Australian businesses which have export-ready products or services (suppliers), and the list of businesses and information increases considerably day by day. The ASD has a search facility that employs a simple keyword search engine to help overseas companies to retrieve potential Australian business partners. The problem is that the keyword query as a search facility is neither reliable nor efficient, and cannot satisfy users' particular needs [52]. To solve this problem, a recommender system prototype called BizSeeker [28] is implemented to provide business partner recommendation e-services for Small to Medium Businesses (SMBs).

A dataset extracted from the 'BizSeeker' system and related to the domain of business partner recommendations is used as a case study to further validate the feasibility of applying the proposed HUIT approach to a real B2B application. The BizSeeker dataset contains 1602 ratings of 332 businesses from 100 users. The businesses are selected from the Australian Suppliers Directory which is provided by the Australian Trade Commission government trade agency (http://www.austrade.gov.au). Businesses are categorized on the basis of the Austrade classification of industry classes which includes 17 categories. The sparsity level of the BizSeeker dataset is 95.2% (sparsity level= $1-$density = $1-$ (1602/ (100×332)) =0.952). Two experiments have been conducted to: (1) review the applicability of the proposed HUIT approach to a real B2B application; and (2) confirm the effectiveness of the proposed HUIT approach compared to the benchmark algorithms on a B2B related dataset. In the first experiment, we measure the recommendation accuracy, as shown in Figure 12. The experiment shows that the HUIT approach achieves the highest recommendation accuracy at any given neighbourhood size. The second experiment, as shown in Figure 13, measures the recommendation coverage. Figure 13 confirms that the HUIT approach has the highest coverage at any given neighbourhood size. Therefore, by considering both recommendation accuracy and coverage using the BizSeeker dataset, it can be concluded that the HUIT approach is a significant improvement over the benchmark recommendation algorithms.

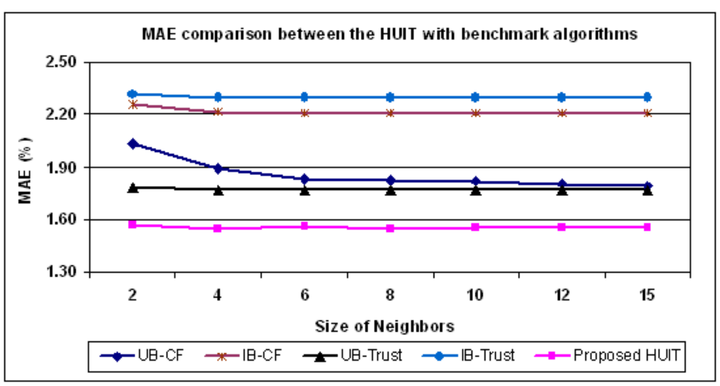

Figure 12: Improvement of recommendation accuracy on different numbers of neighbours

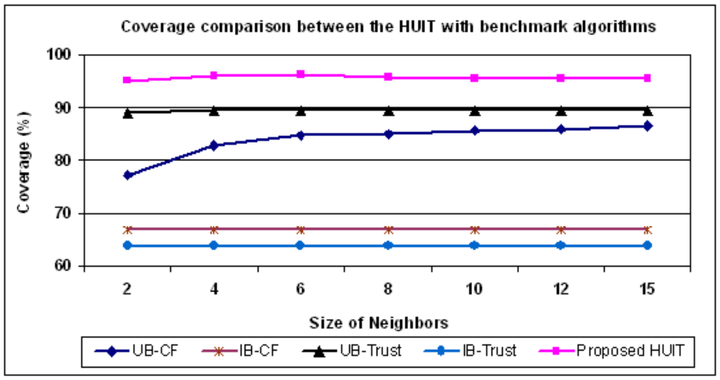

Figure 13: Improvement of recommendation coverage on different numbers of neighbours

6. Conclusions And Future Work

In this paper, we address the most common limitations of recommender systems associated with insufficient rating information without the need for an external knowledge source by proposing a HUIT recommendation approach. The HUIT approach combines the implicit user-based trust and implicit item-based trust approaches to improve the quality of recommendations by extending the active user's and target item's neighbourhood using alternative information derived from historical ratings. The intuitive properties of implicit trust and trust propagation between users in the implicit user-based trust approach, as well as the users' global reputation, is used to address the data sparsity and CS user problems. The item-based trust approach utilizes the intuitive properties of trust between items and the items' global reputation to further reduce the effect of data sparsity and CS item problems. The experimental results verify that the HUIT approach provides recommendations of far higher quality in terms of recommendation accuracy and coverage when dealing with data sparsity, CS users and CS items, than the benchmark trust and CF-based recommendation algorithms. A B2B recommender system case study is also presented to show the feasibility and practicality of using the HUIT approach in real e-business applications.

In the near future, we intend to investigate how to effectively integrate the global reputation of users and items in the recommendation process to improve the quality of recommendations even more. Also, we plan to study and evaluate the impact of using different hybridisation strategies on the recommendation quality of the HUIT recommendations. Additionally, testing and improving the scalability of the proposed algorithm will be carried out. Finally, an extension of the previously proposed 'BizSeeker' prototype system incorporating the HUIT recommendation approach, to be used in real-world practice, will be considered.

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