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Provenance Based Trust Boosted Recommender System Using Boosted Vector Similarity Measure

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Abstract. As users in an online social network are overwhelmed by the abundant amount of information, it is very hard to retrieve the preferred or required content. In this context, an online recommender system helps to filter and recommend content such as people,items or services. But, in a real scenario, people rely more on recommendations from trusted sources than distrusting sources. Though, there are many trust based recommender systems that exist, it lag in prediction error. In order to improve the accuracy of the prediction, this paper proposes a Trust-Boosted Recommender System (TBRS). Since, the provenance derives the trust in a better way than other approaches, TBRS is built from the provenance concept. The proposed recommender system takes the provenance based fuzzy rules which were derived from the Fuzzy Decision Tree. TBRS then computes the multi-attribute vector similarity score and boosts the score with trust weight. This system is tested on the book-review dataset to recommend the top-k trustworthy reviewers.The performance of the proposed method is evaluated in terms of MAE and RMSE. The result shows that the error value of boosted similarity is lesser than without boost. The reduced error rates of the Jaccard, Dice and Cosine similarity measures are 18%, 15% and 7% respectively. Also, when the model is subjected to failure analysis, it gives better performance for unskewed data than slewed data. The models fbest, average and worst case predictions are 90%, 50% and <23% respectively.

AMS Subject Classification 2020: 91D30; 03B52; 03E72; 15A03
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1 Introduction

The social network is overloaded with a huge number of posts such as blogs, reviews, opinions, images, videos, etc. People use such web information, to make decisions about what to buy, how to spend free time, what to study, etc. An online recommender system helps to retrieve the desired information from this crowded network. For example, to recommend an item in Amazon's recommender system [19], an item-to-item collaborative filtering approach is used. Similarly, Facebook, LinkedIn and other social networking sites examine the network of connections between a user and their friends to suggest a new group, based on interest. Such a recommendation does not guarantee an accurate recommendation, since it is received from an anonymous person. Therefore, people tend to rely more on a trusted person's recommendation than an untrusted online recommendation [27]. Consequently, the quality of recommendations is ensured by exploiting the trust

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values among recommenders. For example, some of the single rating or single preference based trust models [1, 10, 13, 15, 21], represent the trust value '2' as low trust, while trust value '5' represents very high trust in the five rating scale. With a single rating or preference, the multiple features of the user or item cannot be stated which will either directly or indirectly reduce the recommendation quality. Therefore, if the trust rating is derived using multiple features, for example 'Food Quality', 'Food Service', and 'Cleanliness' rated as (4, 3, 2) to recommend a hotel, then evidently the quality of recommendation is improved. Therefore, the proposed recommender system considers multiple attributes or preferences (here 5).

Although many researchers have been successfully working on the integration of trust networks in recommender systems, some more directions are yet to be explored. The issues that are addressed in this work are stated below.

- The derivation of the trust score plays a vital role in any trust based recommender system. Only, countable number of approaches exist that derive the trust score using provenance, but fail to prove the reduced prediction rate.
- Next is, many trust based recommender systems handle only the crisp input (trust score) i.e. 5 (highly trusted) and 1 (meagerly trusted) but unable to handle the vague trust score effectively.
- The final issue that is addressed here is the recommendation of top-k trustworthy reviewers with reduced prediction error.

The first issue is handled by adopting the W7 provenance model to compute the trust score. The second issue is handled by generating fuzzy rules from the Fuzzy Decision Tree based classifier. The first two issues are solved in [31]. This work is an extension of the above two works and solves the last issue. The TBRS works by first extracting the conditional and decision attributes from fuzzy rules and forms a Fuzzy Vector Space (FVSP). Then it finds the similarity between trusted users using the vector based similarity measures, namely Jaccard, Dice and Cosine [8]. Then computes the weighted similarity score by taking the attribute gain as a weight component. Finally, this similarity is boosted by the user's respective trust degree and Top-k similar users are recommended to the target user. The three major contributions of this paper are as follows:

- User profile Modeling
- Formation of Fuzzy Vector Space
- Prediction and Recommendation

This paper is organized as follows. Section 2 briefs about the existing trust based recommender systems. A detailed discussion of the proposed recommender system is given in section 3. Performance evaluation and results are discussed in section 4. Finally, the conclusion and future works are stated in section 5.

2 Related Research

This section discusses the various related articles in the field of trust based recommender systems. The taxonomy of background work is graphically represented in Figure 1. Based on the information collected from an online trust network, recommendation is generated in trust enhanced recommender systems. The most common trust enhanced recommender strategy is, asking the users to explicitly mention the trust statements about other users. For instance, the Moleskiing recommender system [4] uses FOAF files that contain trusted information scales ranging from 1 to 9. The Trust model proposed by A. Abdul Rahman and S. Hailes [1] for virtual communities is grounded in real-world social trust characteristics, reputation or word-of-mouth. Falcone et.al. proposed a fuzzy cognitive map model [10] to derive the trust based on the belief value of an agent. This model shows how different components (belief) may change and how their impact can change depending on the specific situation and from the agent's personality. The aim of a Golbeck's trust model [13] is, to determine how much one person in the network should trust another person to whom they are not directly connected. This algorithm accurately analyses the opinions of the people in the system. TidalTrust algorithm works based on trust-based weighted mean which uses the trust value of users as a weight for the ratings of other users. Hang et al. [14] used a graph-based approach to recommend a node in a social network using similarity in trust networks. Massa and Aversani [21] proposed a trust-based recommendation system where it is possible to search for trustable users by exploiting trust propagation over the trust network. Andersen et. al. [2] explored an axiomatic approach for trust-based recommendation and proposed several recommendation models, some of which are incentive compatible. In the MoleTrust method the similarity weight is attributed to ratings by users.

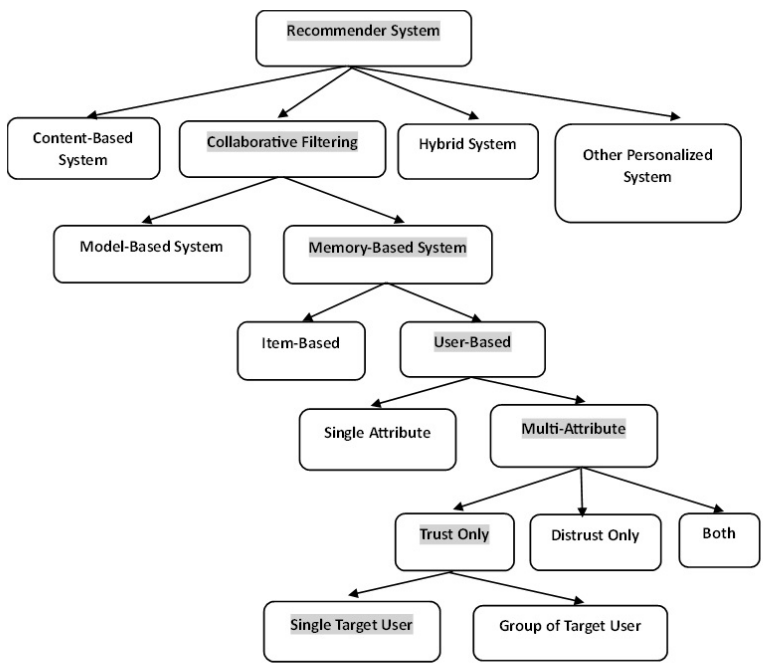

Figure 1: Taxonomy of related work

A trust-filtered collaborative filtering technique is used by O'Donovan and Smith in [29]. Here, the trust value is used as a filtering mechanism, to choose only, the item raters who are trusted above a certain threshold. An Ensemble trust technique proposed by Victor et al. [32] aims to take into account all possible ways to obtain a positive weight for a rater of an item while favoring trust over similarity. Tomislav Duricic et al. [9] proposed a solution to solve the cold start problem in a collaborative-filtering method using regular equivalence. This regular equivalence is applied to a trusted network to generate a similarity matrix using the Katz similarity measure. Abdelghani Bellaachia & Deema [6] proposed a recommendation algorithm called Averaged Localized Trust-Based Ant Recommender (ALT-BAR) to increase the prediction accuracy. The base for this algorithm is Ant Colony Optimization (ACO). To overcome the cold start problem (lack of ratings), ALT-BAR emphasizes the significance of trust between users by modifying the initial pheromone levels of edges. Vahid Faridani et al. [11] proposed a method called effective trust to solve the data sparsity and cold start issues by combining the ratings of trusted neighbors to complement and represent the preferences of active users. Liaoliang et al. [16] proposed a slope one algorithm based on the fusion of trusted data and user similarity. The procedure for the above recommendation algorithm consists of selecting trusted data, calculating the similarity between users and adding this similarity to the weight factor. To address the data sparsity and the cold start problem, Bo Yang et al. [35] proposed a social-collaborative filtering by utilizing the trust data to give high quality recommendations. The author used the matrix factorization technique which maps users into small dimensional latent feature spaces a trust relationship (trustee and truster model). This mapped model is combined into TrustMF model.

Usually e-commerce sites face a large amount of information which leads to sparsity in the data. This causes low accuracy during recommendation. To solve this issue Li Ye et al. [36] proposed a collaborative filtering recommendation which is based on a trust model with fused similar factors. This is nothing but combining the trust model with the user similarity. Modified cosine similarity is introduced in this fused similar factor. One of the key challenges in a recommender system is an accurate prediction of unknown ratings of the target user. During prediction, selecting an appropriate set of users is the major issue in Collaborative Filtering (CF). Hashem Parvin et al. [23] proposed a novel CF method called Trust-aware CF by Ant Colony Optimization (TCF-ACO) to predict missing ratings. First using available ratings and social trust relationship, the users are ranked. Next, proper weight values are assigned to users using ACO. Finally, a set of top-k similar users are filtered out and are used for predicting unknown ratings of the target user. To solve the sparsity and low recommendation accuracy in CF, Kejia & Junyi [34] proposed an improved CF algorithm. This algorithm calculates the user's attribute preference, trust relationships and weight of interest based on time and recommends the items with the highest prediction score. A Graph Convolutional Network via a Reliable and Informative Motif-based Attention Model (CNRIM) [20] is developed to investigate user-user heterogeneous trust relationships and user-item heterogeneous interactivity. Varying reliability and informative motifs introduce heterogeneity. The experiments on publicly available real-world datasets, and empirical analyses present the superiority of our model over popular baselines.

Rad D et al. [24] focus on the study of how socioeconomic status affects trust in recommender systems. It shapes users' perceptions of accuracy, fairness, and transparency in recommender systems. This study is done by exploring the curvilinear effects of the predictor variables on the outcome variable using quadratic regression analysis. The positive and negative aspect of traditional recommendation approaches namely collaborative, content-based and Demographic filtering as discussed in [18]. Also, the potential biases, theoretical insights, design implications and practical solutions for the cold start problem are discussed. Richa and Punam developed a Cross Domain Recommender System (CDRS) [25], which employs data from multiple domains to reduce the problem of sparsity. This model uses a combination of trust as well as distrust which helps in improving trustworthiness of generated recommendation. By incorporating knowledge about the malicious users, the distrust measure shows higher accuracy. This CDRS is developed using JADE and Java technology for the tourism domain. Knowledge graph based trustworthy recommendation system was developed by Nidhi and Richa [7]. Pu Li et al. proposed a scholarly recommendation method by high-order propagation of knowledge graph (HoPKG) [17]. This HoPKG analyzes the high-order semantic information in the KG and generates richer entity representations to obtain users' potential interest by distinguishing the importance of different entities. In current scenario, the demand for senior care services is high. From the crowded data, it has become more difficult to get matching services. This paper proposed a service recommendation framework PCE-CF [33] based on an embedded user portrait model. An automated and personalized meal plan generation was introduced by George and Tekli [26]. This method adapted to the transportation optimization problem. This is a simulation of the human thought process in generating a daily meal plan. The relation between nodes in online social network is filtered out with the help of an ontology. This paper proposed a recommender system using ontology [3]. Choosing a best fit elective course for a student is a challenging task especially at the higher education level. This issue is solved in this paper by utilizing the versatile ontology and sequence prediction algorithm and compact prediction tree [12].

Many works on trust-based collaborative filtering have been carried out to solve the cold start and data sparsity problem. There exist only a few works that attempt to improve accuracy and error minimization.

Most of the work simply uses the similarity score for recommendation without enhancing it. The proposed trust-boosted recommender system recommends the top-k users with minimized error.

3 Proposed Trust Boosted Recommendation System

An architecture of the proposed TBRS is shown in Figure 2. It consists of two major modules. The first module is the provenance based user classification using Fuzzy Decision Tree (FDT) and second module is the recommendation of Top-k trustworthy users. Here users refer to book reviewers. This article depicts an overview of the first module which is given in the following subsection and subsequent section discuss about the proposed trust boosted recommender system.

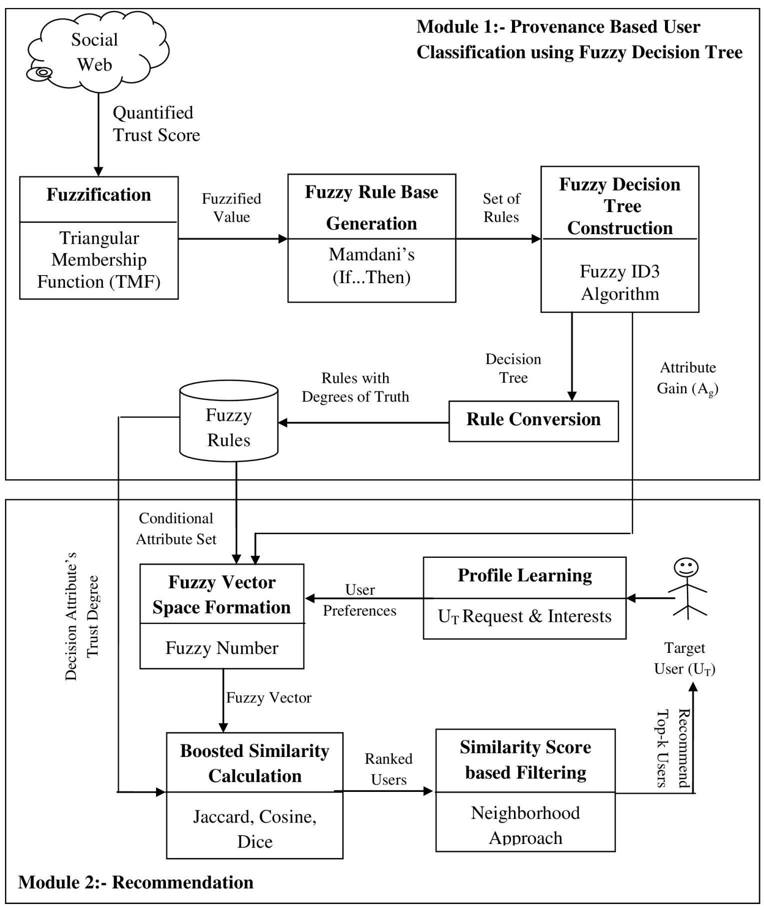

Figure 2: Architecture of trust boosted recommender system

3.1 Overview of Provenance Based User Classification Using Fuzzy Decision Tree (FDT)

This section gives an overview of a classifier built using FDT [31] which is able to solve the first two issues mentioned in the introduction section. The process flow is shown in the top portion of Figure 2.

3.1.1 Provenance Based Trust Quantification

The user's trust in social networks is guaranteed by provenance of web resources [5] The W7 is a provenance model which examines the data in semantic perspective. The plus point of W7 model is that, domain specific provenance requirements are easily adapted. The seven provenance elements are ($WHAT, WHEN, WHERE, WHO, HOW, WHICH, WHY$) [30]. Therefore the trust value of the content creator is assessed using this model. From Goodreads book domain, the reviewer's data are collected by invoking ad-hoc APIs (Application Programming Interface) and HTML scrapping. The Table 1 shows the sample data collected.

Table 1: An example provenance relevant fields

S.No	Field_Name	Example
1	Review Text(RT)	Ever hear people talk about wanting to write the "'Great American Novel"'? Well, it's already done and this is it.This novel is one of my longest standing favorites. It's a profound meditation on the nature of freedom,full of clever Southern folk wisdom, deeply sensitive and insightful.
2	Year Month of Joining(YMJ)	August 2006
3	Review Postdate(RPDT)	September 27, 2013
4	Rate of Review (RVR)	5
5	Likes Received(NLK)	14
6	Post Count(PCNT)	1
7	Comments Received(NCMT)	0
8	Reply Received(NRPY)	90
9	Average Review Rate(ARR)	3.79
10	Key Terms(KT) (Since the terms are exhaustive, only partial terms are given here)	slouch, blame, bowie, buckle, bullyragged, cairo, doxolojer, erysipelas, fan, tod, rod, fox, fire, gabble, gingham, barlow, knife, bars, bilgewater, black, galoot, gar, habob, allycumpain, harrow, teeth, toned, hived, irish, potato, jackstaff, jimpson, weed, juice, harp, langudoc, ambuscade, liberty, pole, melodeum, mesmerism, methusalem, mud, cat, muddy, mug, mulatter, mullen, stalk, mushmelon,calico,camp, capet, bag ,congress, water, corn, consumption, pone, curry, comb,dauphin, delirium, tremens, dog, fennel, doggery, irons, bills, nation, navarre, ...
11	Matched Reviews(MR)	I was surprised by how much I liked this book.There were a couple of parts that dragged for me a bit, but all in all I though it was a very clever, entertaining read. I'm glad I read it as an adult, because I think I liked a lot more now than I would have in high school, especially being the mother of a boy. And I can only hope that my son never is, or has a friend, like Tom Sawyer.
12	Matched Review Postdate(MRPDT)	March 26,2011
13	Time of System Initialization(TSI)	January 2007

The actual description of provenance element as per Bunge's Ontology is given in Table 2. The Table 3 shows the description in the context of trust and its relevant fields are given in Table 4.

P_{WHAT}**:** The trust score of the reviewer is assessed based on the review(s) that are relevant to the title of the book.

Table 2: Description of provenance elements as per Bunge's ontology

Provenance Elements	Description
WHAT	An event that occurred to the data during its lifetime.
WHEN	The time of the event.
WHERE	Location of the event.
WHO	An organization or agent involved in the event.
HOW	The one or more actions that lead to the event.
WHICH	The software or instruments used in the event.
WHY	The reason behind the occurrence of an event.

Table 3: Description of provenance elements in the context of trust

Provenance Elements	Description
P_{WHAT}	Describes the review content that is relevant to the topic.
P_{WHEN}	Represents the effective time spent by the reviewer.
P_{WHERE}	Refers to the location (IP_Address, Domain_name) from where review is posted.
P_{WHO}	Refers to the reviewer who is an author (creator) of the review (originator).
P_{HOW}	Describes how review content is deviated from the rating given by the reviewer.
P_{WHICH}	Refers to the application or device used to post the review.
P_{WHY}	Describes the intention behind the post of review content.

P_{HOW}**:** The reviewer's the trust score of is judged based on how much the RT is deviated from the RVR.

P_{WHO}**:** Here, based on the originality of the review, the trust score of the reviewer is evaluated.

P_{WHY}**:** The trust score of the reviewer is assessed based on the truthfulness of the review.

P_{WHEN}**:** Here, trust scores of the reviewer is assessed based on following three factors.These are

- **Activity_Factor** ($P_{WHEN_{AF}}$):- Measures the active participation or involvement of the reviewer
- **Presence_Factor** ($P_{WHEN_{PF}}$):- Measures how long the reviewer is present in the domain.
- **Frequency_Factor** ($P_{WHEN_{FF}}$):- Calculates how frequently reviewer makes an interaction at awaited frequency constant (π). The π can take the value as one week, two week, three week and upto seven week.
- **Final trust score** ($P_{WHEN_{TF}}) : -(Wt_1)P_{WHEN_{AF}} + (Wt_2)P_{WHEN_{PF}} + (Wt_3)P_{WHEN_{FF}}$.
  Here, Wt_1, Wt_2 and Wt_3 are weight values of $P_{WHEN_{AF}}$, $P_{WHEN_{PF}}$, and $P_{WHEN_{FF}}$ respectively. The weight values can be from 0 to 1 and sum of weight should be 1. For eaxmple, $Wt_1 = 0.6$, $Wt_2 = 0.25$ and $Wt_3 = 0.15$.

A sample quantified value (trust score) of these five provenance elements is shown in Table 5. The score P_{WHAT}=0.222 means RT is highly relevant to the title or concept. The trust score P_{HOW}=0.827 shows that there is not much deviation between RT and his/her RVR whereas P_{HOW}=2.836 shows the more deviation. The P_{WHEN} = 0.3296 and P_{WHEN} =0.1222 means that the effective time spent by the reviewer is more in former case and less in latter case.

Table 4: Required fields of provenance elements

Provenance Elements	Required Fields
P_{WHAT}	RT, KT
P_{WHEN}	RPDT, YMJ, NLK, NCMT, NRPY, TSI, PCNT
P_{WHO}	RT, RPDT
P_{HOW}	RT, RVR
P_{WHY}	RT, RVR

Finally, the trust score of each reviewer is given as input to the learning model to classify reviewers with gradual trust levels.

Table 5: Sample quantified value

Reviewer_ID	P_{WHO}	P_{HOW}	P_{WHY}	P_{WHAT}	P_{WHEN}
1	0.0403	2.761	1.351	0.094	0.3296
2	0.0125	2.831	1.421	0.11	0.1222
3	0.0896	0.827	1.417	0.182	0.1344
4	0.0062	2.836	1.426	0.222	0.2812
5	0.0023	1.791	1.799	0.066	0.1278

3.1.2 Fuzzy Decision Tree Based Classification

The classification process comprises of four major steps.

- Fuzzification of Trust Score
- Fuzzy Rule Base Generation
- Fuzzy Decision Tree Construction and
- Rule Conversion

(a) Fuzzification of Trust Score The quantified trust value derived above is taken as a training data for fuzzification process which converts it into linguistic terms. The proposed model uses the Triangular Membership Function(TMF) for fuzzification process, since it allows a maximum number of instances to fall into this class than any other MF. Each attribute (P_{WHAT}, P_{WHAT}, P_{WHAT}, P_{WHAT}, P_{WHAT}) is partitioned into 5 regions as R_1 to R_5 and the corresponding linguistic space is given in Equation 1.

$$LinguisticSpace = \begin{pmatrix} P_{WHAT} = [HIR, MIR, NR, MR, HR] \\ P_{HOW} = [HSM, MSM, NSM, MD, HD] \\ P_{WHEN} = [HITM, MITM, NETM, METM, HETM] \\ P_{WHY} = [HTR, MTR, NTR, MUTR, HUTR] \\ P_{WHO} = [HDSML, MDSML, NDSML, MSML, HSML] \end{pmatrix} \tag{1}$$

(b) Fuzzy Rule Base Generation Fuzzy sets and fuzzy logic are used as tools for representing the knowledge in Fuzzy Rule Based System (FRBS). The fuzzy knowledge base comprises vague facts and vague rules. Each rule contains an antecedent ('IF' part) and a consequent ('THEN' part). Now, this fuzzy input is then transformed into a set of fuzzy rules (rule base) using Mamdani's 'If...Then' interpretation. The two major steps for deriving a rule base are (i) T-norm to evaluate the firing strength of a rule and (ii) S-norm to compute the qualified membership value. The sample fuzzy rule base is as follows.

$$P_{WHO}(\text{HSML}) \wedge P_{WHEN}(\text{HITM}) \wedge P_{HOW}(\text{HD}) \wedge P_{WHY}(\text{MUTR}) \wedge P_{WHAT}(\text{HR}) \implies U_{TRUST}(\text{LT})$$

(c) Fuzzy Decision Tree Construction FDT takes the rule base and generates decision trees using a fuzzy ID3 [22] algorithm. In FDT, provenance element having highest information gain is chosen as a root node and trust decisions are denoted in a leaf node. Each distinctive path from root to a leaf gives distinct rule. The predecessor part ('IF') of the rule contains node(s) and edge(s) of a path excluding leaf. If more than one node exists in 'IF' part, then they are joined by AND/OR operator or both. The consequent part ('THEN') of the rule contains a leaf node alone. A Degree of Truth (DoT) [28] is assigned to each generated rule to state that how much truth value it holds. DoT is computed using (i) Certainty Factor and (ii) Subsethood based approaches. The range of DoT from 0 to 0.5 represents the false degree and 0.6 to 0.9 denotes the truth degree. If DoT is 1, it means the rule is absolutely true which (i) takes a minimum number of nodes and hence reduced rule generation time and (ii) acquire the knowledge with the least number of feature itself. The sample decision tree is shown in Figure 3.

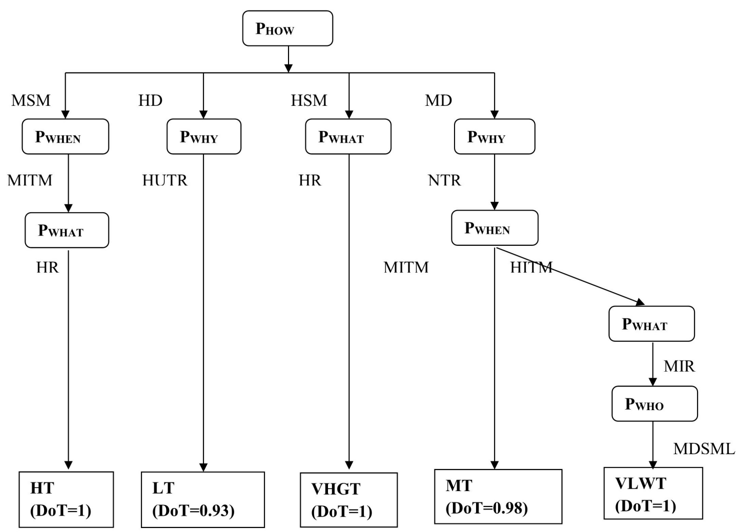

Figure 3: Sample fuzzy decision tree

(d) Rule Conversion The rule is an easy and comprehensive form of knowledge representation than any other representation The corresponding fuzzy rule is shown in Figure 4. Each distinct path from a root to a leaf is called a rule.

3.2 Recommendation of Top-k Trustworthy Users

The three major steps of the recommendation process are (i) User profile modeling, (ii) Formation of FVSP and (iii) Prediction and recommendation. Let the user U_T is a target user who sends a request for recommendations. If U_T is an existing user then the details such as name, number of ratings given, number of

Rule 1: If P_{HOW} is MSM and P_{WHEN} is MITM and P_{WHAT} is HR Then Trust is HT (DoT=1)

Rule 2: If P_{HOW} is HD and P_{WHY} is HUTR Then Trust is LT (DoT=0.93)

Rule 3: If P_{HOW} is HSM and P_{WHAT} is HR Then Trust is VHGT (DoT=1)

ule4: If P_{HOW} is MD and P_{WHY} is NTR and P_{WHEN} is MITM Then Trust is MT (DoT=0.98)

Rule 5: If P_{HOW} is MD and P_{WHY} is NTR and P_{WHEN} is HITM and P_{WHAT} is MIR and P_{WHO} is MDSML Then Trust is VLWT (DoT=1)

Figure 4: Corresponding Fuzzy rules

reviews given, average rating, the interest and trust score of the user are known and can directly access the trust network. If U_T is new user then profile of the user needs to be learned prior to network access. The contents of the profile learned are name, location, join date, favorite books. Initially U_T's area of interest and training example, or already labeled items are collected and sent to the profile learner. Then the set of feedback and request are merged with the output of profile learner. This forms the U_T's file database and sets as user preference.

3.2.1 Formation of FVSP

The fuzzy rules extracted from the trust network as discussed in section 3.1 are partitioned into conditional attribute sets and decision attributes set. The conditional attributes consist of all the trust attributes $P_{HOW}, P_{WHY}, P_{WHEN}, P_{WHAT}, \text{ and } P_{WHO}$. The decision attributes consists of trust decision VLWT, LT, MT, HT and VHGT. The following steps explain how to form FVSP using conditional attribute set.

Step 1: For each trust attributes in the conditional attribute set, assign attribute grade. This is based on the position of the TMF. For example, in P_{WHAT} attribute the position of 'HIR' has low grade, i.e. 1 and 'HR' has high grades, i.e. 5. Similarly, for other trust attributes.

Step 2: Now, assign the fuzzy number for each linguistic term based on the grade. Since it follows the triangular fuzzy logic, the fuzzy number assigned for each grade is shown in Table 6.

Table 6: Fuzzy number for each grade

Grade	Fuzzy Number
1	(0.0, 0.0, 0.25)
2	(0.0, 0.25, 0.50)
3	(0.25, 0.50, 0.75)
4	(0.50, 0.75, 1.0)
5	(0.75, 1.0, 1.0)

For example, the fuzzy number of the linguistic term for the attribute P_{HOW} is shown in Table 7. Similarly for other attributes, fuzzy number is same as that shown in Table 7. The corresponding fuzzy number line is given in Figure 5.

Step 3: The fuzzy number for each attribute is now represented as a vector in FVSP. The FVSP for each rule is represented as $< A_K, FN_{AK} >$.
where,

Table 7: Linguistic values of P_{HOW} Fuzzy number

Linguistic Term	Fuzzy Number
HSM (Highly Same)	(0.0, 0.0, 0.25)
MSM (Moderately Same)	(0.0, 0.25, 0.50)
NSM (Neutrally Same)	(0.25, 0.50, 0.75)
MD (Moderately Deviated)	(0.50, 0.75, 1.0)
HD (Highly Deviated)	(0.75, 1.0, 1.0)

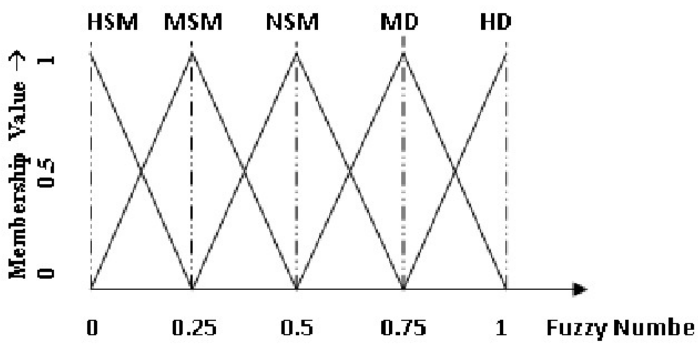

Figure 5: Fuzzy line of P_{HOW} attribute.

- K is the number of attributes (Here, 5)
- A_K is the current attribute and
- FN_{AK} is the fuzzy number for the specified attribute A_K

That is FVSP $= < A_1, (a_{11}, a_{12}, a_{13}) >, < A_2, (a_{21}, a_{22}, a_{23}) > \cdots < A_5, (a_{51}, a_{52}, a_{53}) >$. The (a_{11}, a_{12}, a_{13}) is a triplet used in TMF to define the fuzzy number and the range of value is $0 \leq a_{11} \leq a_{12} \leq a_{13} \leq 1$.

For example, consider the following fuzzy rule.

If P_{HOW} is MD $\wedge$ P_{WHY} is NTR $\wedge$ P_{WHEN} is HITM $\wedge$ P_{WHAT} is MIR $\wedge$ P_{WHO} is MDSML $\rightarrow T_{VLWT}$.

The FVSP for the above fuzzy rule is $< P_{HOW}, (0.5, 0.7, 1) >, < P_{WHY}, (0.25, 0.5, 0.7) >, < P_{WHEN}, (0, 0, 0.25) >, < P_{WHAT}, (0, 0.25, 0.5) >$ and $< P_{WHO}, (0, 0.25, 0.5) >$. Here, MD (Moderately Deviated), NTR (Neutrally Truthful), HITM (Highly Ineffective Time Spent), MIR (Moderately Irrelevant) and MDSML (Moderately Dissimilar) are the linguistic terms of the P_{HOW}, P_{WHY}, P_{WHEN}, P_{WHAT}, and P_{WHO} attributes respectively.

This FVSP is taken as input to calculate the vector similarity and to suggest the top-k trustworthy users.

3.2.2 Prediction and Recommendation

Some of the similarity measures in vector space have been positively applied in fields such as pattern recognition, decision making problems and classification complex objects. The familiar vector similarity measures are Jaccard, Dice and Cosine. The proposed recommender system uses these three measures separately to compute the similarity score between two vectors as shown in Equations 2, 3 and 4. The weighted similarity is obtained by taking the gain value of each attribute (A_G) as weight.

Let $X = U_T = (a_1, a_2, a_3)$ and $Y = U_N = (b_1, b_2, b_3)$ be the fuzzy number of the target user U_T and the other user U_N from the trust network respectively, then

$$S = Jaccard(U_T, U_N) = \sum_{k=1}^{5} A_{G_k} * \frac{\sum_{f=1}^{3}(FN_{A_{Tkf}}.FN_{A_{Nkf}})}{\sum_{f=1}^{3}(FN^2_{A_{Tkf}}) + \sum_{f=1}^{3}(FN^2_{A_{Nkf}}) - \sum_{f=1}^{3}(FN_{A_{Tkf}}.FN_{A_{Nkf}})} \tag{2}$$

$$S = Dice(U_T, U_N) = \sum_{k=1}^{5} A_{G_k} \frac{2\sum_{f=1}^{3}(FN_{A_{Tkf}}.FN_{A_{Nkf}})}{\sum_{f=1}^{3}(FN^2_{A_{Tkf}}) + \sum_{f=1}^{3}(FN^2_{A_{Nkf}})} \tag{3}$$

$$S = Cosine(U_T, U_N) = \sum_{k=1}^{5} A_{G_k} \frac{\sum_{f=1}^{3}(FN_{A_{Tkf}}.FN_{A_{Nkf}})}{\sqrt{\sum_{f=1}^{3}(FN^2_{A_{Tkf}})}.\sqrt{\sum_{f=1}^{3}(FN^2_{A_{Nkf}})}} \tag{4}$$

where,

- A_G- Represents the attribute gain
- f - Represents the fuzzy number of values in each fuzzy number
- a_1, a_3, b_2, b_3 are the endpoints and a_2, b_2 are the peak point of fuzzy numbers

After finding the similarity (S), boost this value by corresponding trust score (T_{wt}) of the user U_N as shown in Equation 5.

$$S_b = S * S^{T_{wt}-1} \tag{5}$$

Using this boosted similarity (S_b), prediction of the target user's trust score is carried out. The prediction formula is given in Equation 6.

$$Pred(U_T, I_j) = \begin{cases} tr_{U_T}, \quad if\ S_b = 0\ or\ if\ tr_{U_N,I_j}\ =\ \bar{tr_{U_N}} \\ \\ tr_{U_T} + \frac{\sum U_N \in NB S_b(U_N,U_T) x (tr_{U_N,I_j} - \bar{tr_{U_N}}}{\sum U_N \in NB |S_b(U_N,U_T)|},\ Else \end{cases} \tag{6}$$

where,

- t_r - Represents the trust value
- I_j – Represents items (books) which are not given any review
- NB – Represents the number of neighbors chosen

Consider the randomly chosen reviewer say reviewer 631 (R_{631}) requesting for the recommendation of k users (Let k=15) as shown in Table 8. The similarity (S) between the requester and the rest of the users is calculated. Then it is boosted using Equation 5. The Table 8 shows the similarity and boosted similarity (S_b) score of the top-15 reviewer where the reviewers are sorted based on similarity scores from highest to lowest. Though both similarities show the highest score for the top reviewers, the trust level differs. The trust level of highly matched reviewer with R_{631} is 'LT'. The top 2 reviewers for both the case, i.e. with and without boost are same. In the case without boosting, top 3rd to 11th and 13th reviewers have other trust level ('MT') instead of 'LT'. But, in case of boosting 3rd to 6th and 13th reviewer has 'VLWT' trust level. Also, 8th and 12th reviewer has 'MT' trust level. This shows that there is an error while carrying out the prediction of trust levels.

Though both without boost and with boost method shows some kind of prediction error, the percentage of the prediction error is less in a later case (46.66%) than the former case (66.66%).

Table 8: Similarity score with and without boost

Without Boost			With Boost			Top-k Reviewer
Reviewer Number	S	Trust Level	Reviewer Number	S_b	Trust Level	
531	0.86012	LT	50	0.94150	LT	1
50	0.86012	LT	531	0.94150	LT	2
630	0.83144	MT	837	0.92353	VLWT	3
26	0.80813	MT	988	0.92353	VLWT	4
1123	0.78135	MT	618	0.90491	VLWT	5
973	0.77931	MT	947	0.90491	VLWT	6
942	0.77931	MT	453	0.90411	LT	7
842	0.77931	MT	630	0.89515	MT	8
356	0.77931	MT	500	0.89250	LT	9
257	0.77931	MT	650	0.89250	LT	10
236	0.77931	MT	678	0.89250	LT	11
453	0.77725	LT	26	0.88001	MT	12
119	0.76748	MT	662	0.87366	VLWT	13
678	0.75253	LT	637	0.87018	LT	14
650	0.75253	LT	679	0.87018	LT	15

3.2.3 Illustrative Example

Let us take random users for whom the recommendation need to be done. The fuzzy rule for Target User (U_T) and user from the trust network (U_N)is given below.

Rule of U_N If P_{HOW} is MD $\wedge$ P_{WHY} is HUTR $\wedge$ P_{WHEN} is NETM $\wedge$ P_{WHAT} is MIR $\wedge$ P_{WHO} is HDSML $\rightarrow T_{LT}$.

Rule of U_T If P_{HOW} is HD $\wedge$ P_{WHY} is HUTR $\wedge$ P_{WHEN} is NETM $\wedge$ P_{WHAT} is NR $\wedge$ P_{WHO} is HDSML.

The Table 9 shows the fuzzy number of U_N and U_T. The similarity calculations are given in Table 10. The attribute gain value of P_{HOW}, P_{WHY}, P_{WHEN}, P_{WHAT} and P_{WHO} are 0.3393, 0.2363, 0.1825, 0.1696 and 0.0723 respectively. The GainWtSim is calculated using these values. FinalSim is the sum of GainWtSim of all the attributes. Finally, BoostedSim is calculated using Equation 5.

Table 9: Fuzzy number for sample input

LingValue (U_N)	Fuzzy Number			LingValue (U_T)	Fuzzy Number		
MD	0.5	0.75	1	HD	0.75	1	1
HUTR	0.75	1	1	HUTR	0.75	1	1
NETM	0.25	0.5	0.75	NETM	0.25	0.5	0.75
MIR	0	0.25	0.5	NR	0.25	0.25	0.25
HDSML	0	0	0.25	HDSML	0	0	0.25

Table 10: Vector similarity score calculation

Similarity Measure	Similarity	GainWtSim	FinalSim	BoostedSim
Cosine	0.986	0.335	0.988	0.995
	1.00	0.236		
	1.00	0.186		
	0.956	0.162		
	1.00	0.072		
Dice	0.971	0.329	0.963	0.985
	1.00	0.236		
	1.00	0.1825		
	0.842	0.143		
	1.00	0.072		
Jaccard	0.944	0.320	0.935	0.973
	1.00	0.236		
	1.00	0.183		
	0.727	0.123		
	1.00	0.072		

4 Performance Evaluation and Result Discussion

To evaluate the performance of the proposed TBRS, experiments are conducted on the popular book based social network called Goodreads.com. The performance measures such as Mean Absolute Error (MAE), Root Mean Squared Error (RMSE) and Average Precision (AP) are defined in the following subsection. Then, an evaluation is carried out with other weight strategies and results are discussed. The proposed TBRS is compared with other trust based recommender systems and the outcomes are described. Finally, the failure scenarios of the proposed recommender system are discussed.

4.1 Performance Measures

The performance of the proposed recommendation strategy is measured with respect to quality of predictions and quality of recommendations. The quality of prediction is done by measuring MAE and RMSE given in Equation 7 and 8 respectively. Similarly the quality of recommendation is done by measuring AP as shown in Equation 9. The TBRS uses the Leave-one-out method to evaluate recommendation systems. This technique involves withholding one rating and trying to predict it with remaining ratings. Then the predicted rating can be compared with the actual rating and the difference will be considered as the prediction error.

$$MAE = \frac{1}{NB}\sum_{i=1}^{NB} \mid Y_i - \hat{Y}_i \mid \tag{7}$$

$$RMSE = \sqrt{\frac{1}{NB}\sum_{i=1}^{NB}(Y_i - \hat{Y}_i)^2} \tag{8}$$

where,

- y_i – Represents the actual value and $\widehat{y_i}$ - Represents predicted value

$$AP@N = \frac{1}{m}\sum_{k=1}^{N} P(k).rel(k) \tag{9}$$

AP is an average of the precision value obtained after each relevant document is retrieved and corresponds to the area under the precision-recall curve. Here, N be the number of items to be recommended, m be the number of relevant items and P(k) refers to precision at k^{th} item.

4.2 Evaluation of Different Weight Approaches

The different weight approaches considered for evaluation are expected weight, preference based weight and proposed gain weight. The three vector similarity measures, namely Cosine, Dice and Jaccard are carried out on the above mentioned weight approaches. The Figures 6, 7 and 8 shows the MAE value obtained from the above three similarity measures. The RMSE value obtained for the above three similarity methods is shown in figures 9, 10 and 11. From the Figures 6, 7 and 8, it is observed that the proposed gain based method shows the less MAE than the other two methods in all the three similarity cases. Also, the RMSE value of the proposed method is less when compared with the expected weight method in all the three cases. The preference based method shows more error rate than the other two methods.

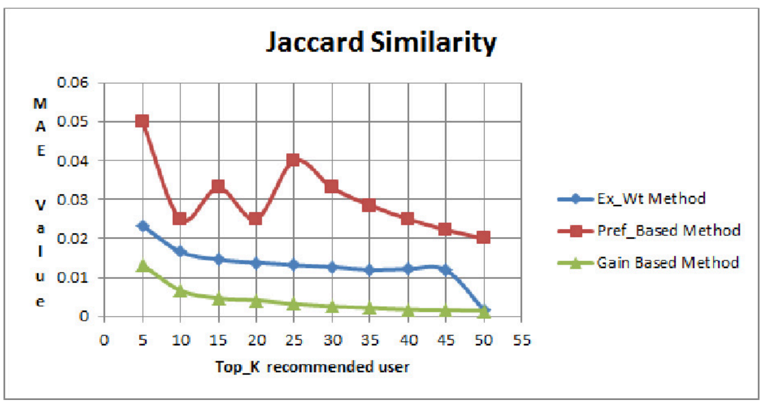

Figure 6: Jaccard MAE measure

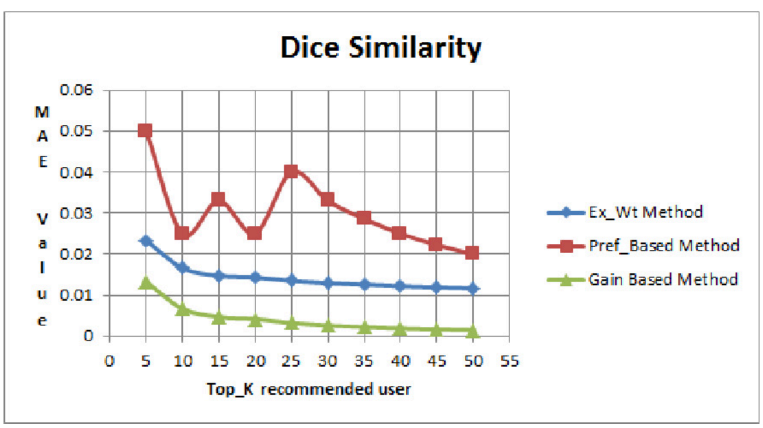

Figure 7: Dice MAE measure

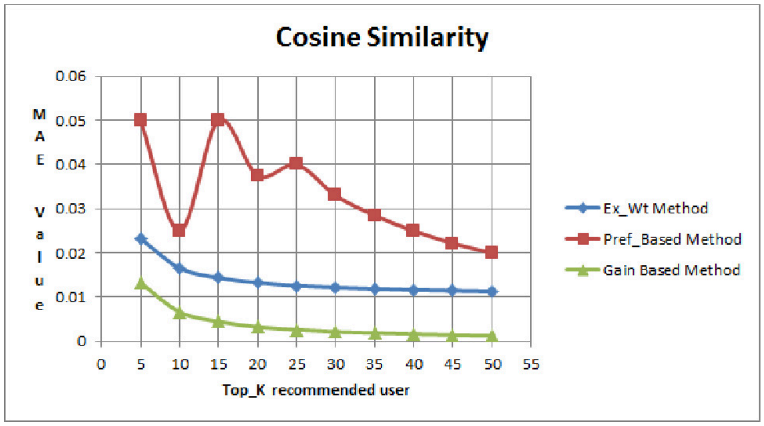

Figure 8: Cosine MAE measure

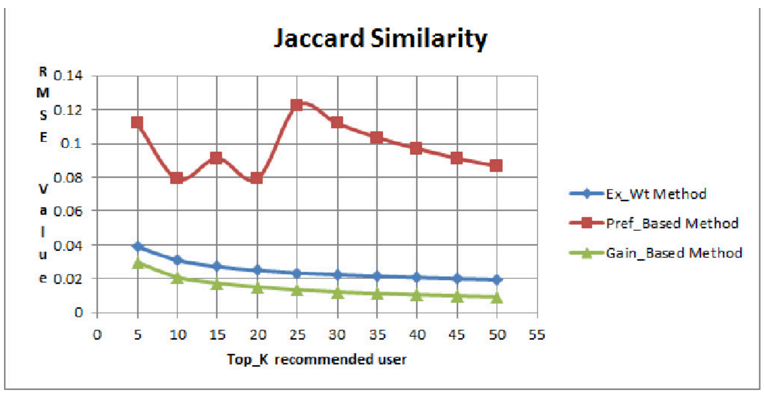

Figure 9: Jaccard RMSE measure

The average precision value is shown in Figures 12, 13 and 14 for all the three similarity methods. The precision value for the proposed method is higher than the other two methods. In all the three cases the average precision is almost same for top-5 and top-10 users. Up to top 20 users precision value is greater than or equal to 0.90. After that the precision value is started decreasing gradually. For top-50$^{\text{th}}$ user, the precision value is very less in preference based method.

The reason for low MAE, lowest RMSE and high AP in proposed gain based method is as follows.

- In preference based method, fuzzy numbers are ranked based on surface area measurement method. The magnitude of the surface area depends on the location of each fuzzy number on the real line. Possible surface values are $0, 0.25, 1, 2, \cdots n-2$. An overall evaluation of edge is calculated by arithmetic average of the fuzzy weight of all the values of involved edges. The value of an edge is adjusted, i.e. rounded-up or rounded-down to one of the above possible surface values. This result in almost equal weight for all the five attributes.

- The expected weight method assigns a weight or grade for each linguistic term of an attribute on the real line. For example, HSM, NTR, HITM, NR, HDSML assigned the weight of 5, 3, 1, 3, 5 as per position on the real line. This method also results in almost equal weight for all five attributes.

- The proposed gain based method uses the information gain value as a weight. The information gain is derived while constructing a fuzzy decision tree. This results in maximum gain for more significant

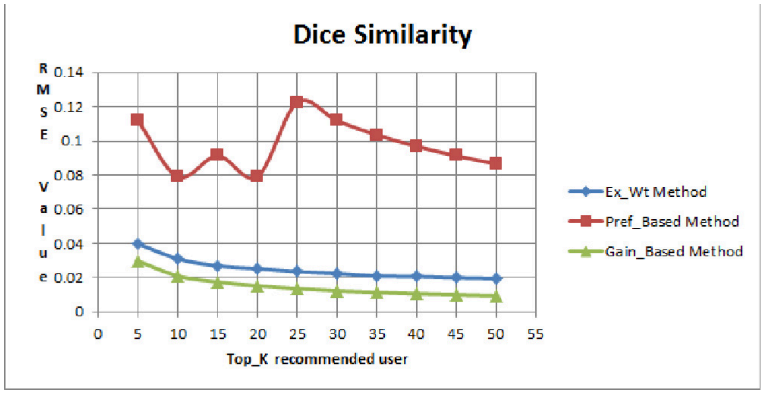

Figure 10: Dice RMSE measure

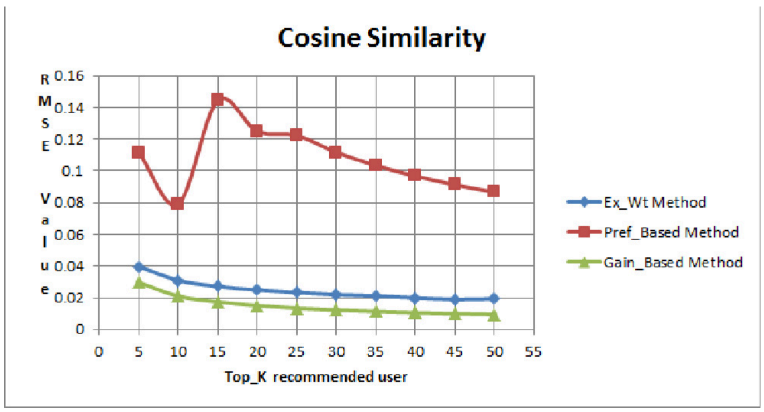

Figure 11: Cosine RMSE measure

attribute P_{HOW} and minimum gain value for least significant attribute P_{WHO}.

Equal weights treats all the attributes as either most significant or least significant. But this is not the case in fuzzy real time data. Therefore, the preference based and expected weight method unable to predict the highly matched reviewer accurately. This compromises the quality of the prediction and hence it leads to prediction error.

4.3 Comparing with Other Trust-Based Recommender System

The proposed recommender system is compared with other trust based recommender system. The evaluation is done on MAE and RMSE measures. First, the proposed method (Boost) is compared against without boosting the similarity. The MAE value of this comparison is shown in Figure 15. In case of NoBst the MAE value for all the three measures are larger than a Boost (Proposed). In the Boost (proposed) the MAE value is very less in Jaccard , slightly higher MAE in Dice followed by Cosine. The MAE and RMSE values of the proposed approach when compared with other trust-based classifier is shown Figure 16 and 17 respectively. The compared methods are Tidal Trust, Mole Trust, Fuzzy Trust Filtering (FTF), Ensemble and Hybrid.

The MAE value of the proposed method is minimized when compared to other methods. When compared to mole trust the error value of the proposed method is slightly lesser. Similarly, the proposed approach results in minimum RMSE value when compared with other approaches. The reason for lesser MAE and RMSE of the proposed method is as follows.

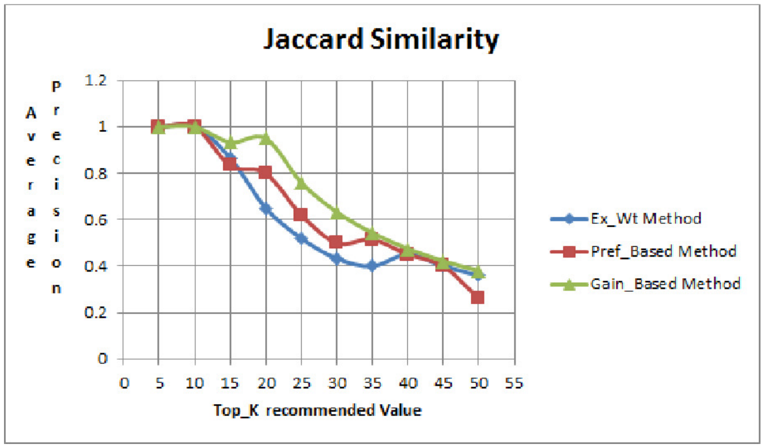

Figure 12: Jaccard AP measure

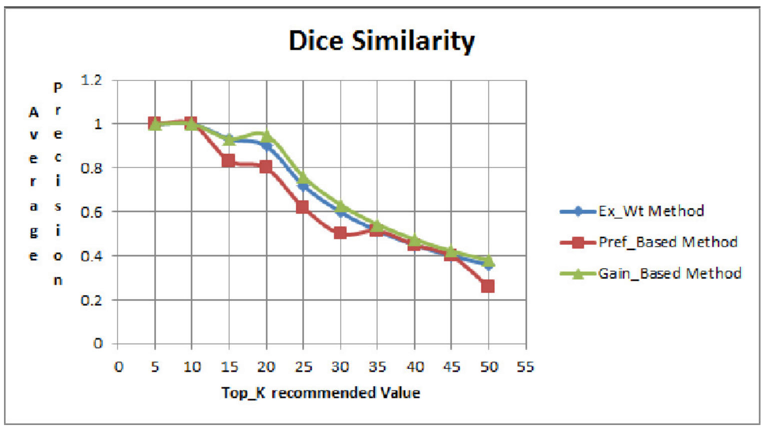

Figure 13: Dice AP measure

- The Tidal Trust method assigns greater weight for more trustworthy users in the prediction process. For example, the trust score of Average Trust, High Trust, Very High Trust and Completely Trust are 0.50, 0.67, 0.83 and 1.00 respectively. This weight is based on the core of the corresponding triangular fuzzy set. The proposed method also assigns more weight to higher trust users and less weight to the low trust user, but the weights are uniformly assigned.

- Mole Trust works by aggregating all the trust statements to produce a trust network. The trust metric is computed based on the maximum propagation distance (MPD). If MPD is 4, then trust metric is 1 (High Trust), 0.75, 0.5, 0.25 (Low Trust). If MPD is 5, then trust metric is 1 (High Trust), 0.833, 0.666, 0.5, 0.33, 0.16 (Low Trust). Since the trust weights are more or less same as proposed, the MAE and RMSE values are slightly closer. But, if MPD is greater than 5, then certainly Mole Trust shows higher MAE and RMSE.

- FTF chose only item rater who are above a certain threshold. That is, it filters neighbors prior to recommendation so that, only the High Trust, Very High Trust and Completely Trust users can participate in the recommendation process. Because of the threshold restriction, the MAE and RMSE values are very large.

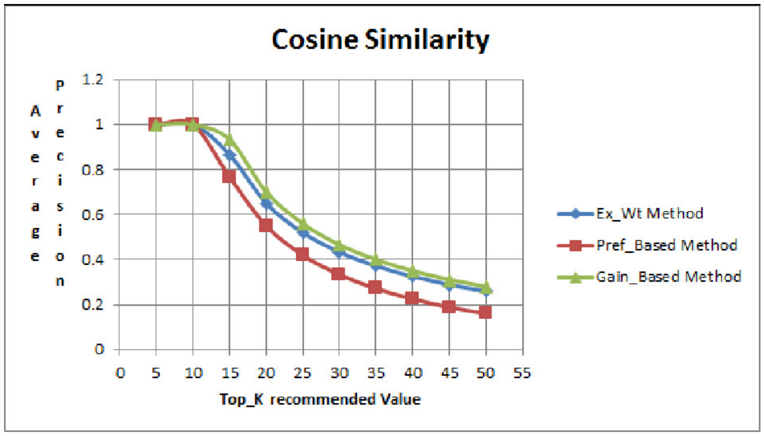

Figure 14: Cosine AP measure

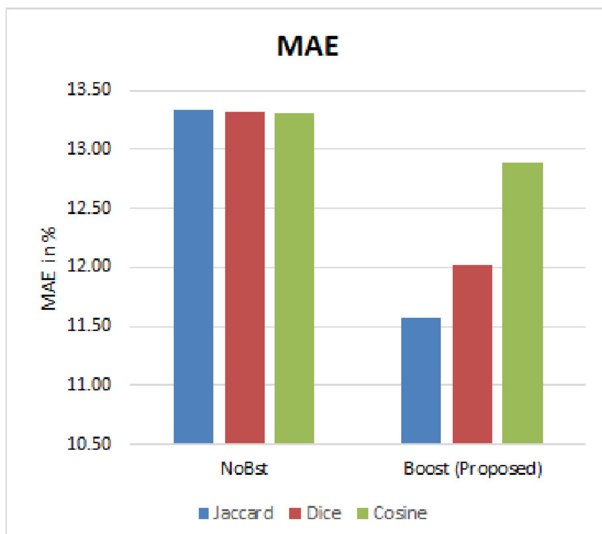

Figure 15: MAE with and without boost

- The ensemble method takes all possible ways to obtain a positive weight for the rater. Thus, it aims to increase the percentage of predictions made by the RS called coverage.

- The hybrid method combines explicit and implicit ratings. Explicit ratings are derived using the Mole Trust method. An implicit rating is computed based on similarity and knowledge factors. It finds the rating difference between two users and assigns weights. If the difference is 0 to 0.5 then weights of 5 is assigned. If the difference is 2 to 3 then weights of 2 is assigned. If it is >3 then weights of 1 is assigned.

To conclude, each method applies a different trust metric for different level of trust. Since the trust metric is not uniformly distributed in the compared trust based recommender systems, it shows the higher MAE and RMSE than proposed.

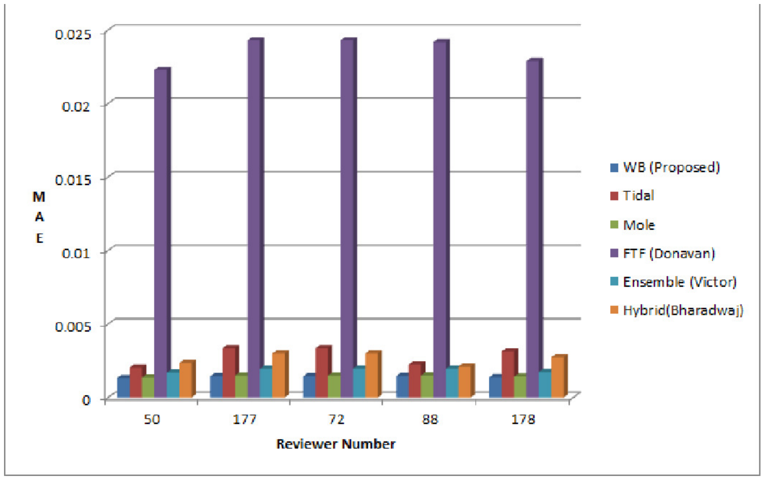

Figure 16: MAE compare

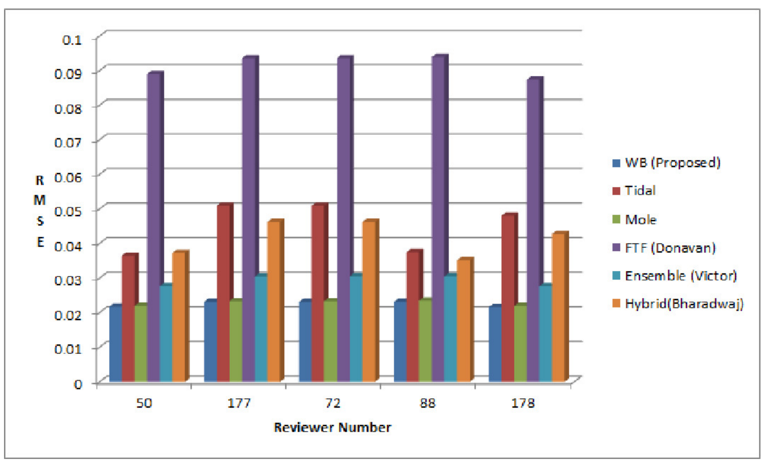

Figure 17: RMSE compare

4.4 Failure Scenarios of Recommender System

To analyze the failure of prediction, let us take a sample from the population. With the margin of error 5% and confidence interval of 95%, the required sample size is obtained. The Figures 18, 19 and 20 shows the prediction score of Best Case, Average Case and Worst Case scenario respectively. The x-axis represents the active users (here, reviewers), y-axis refer to percentage of correct prediction, BJ refers to Boosted Jaccard, BD refers to Boosted Dice and BC refers to Boosted Cosine.

The best prediction score is obtained when the recommendation is made for the Moderately Trusted Users. Here more than 90% of score is achieved in all the three similarity measures. The reason for high prediction score is the highest number of reviewers are classified into this category. An average prediction score is attained when the recommendation is made from Low Trusted and High Trusted users. In this scenario maximum of 50% data is correctly predicted. Because, the number of reviewers classified into LT and HT is lesser when compared with MT.

The recommendation made from the Very Low Trust and few cases of Low Trust users gives the worst prediction score. The maximum of 23% and a minimum of 0% of data can be predicted here. For the user

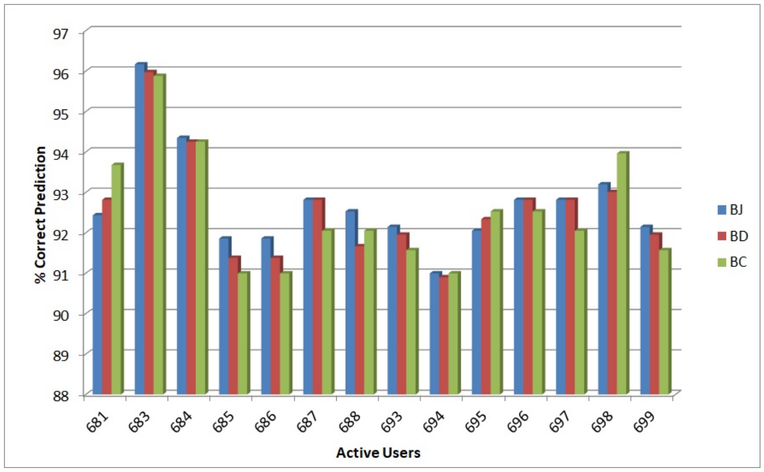

Figure 18: Best case scenario

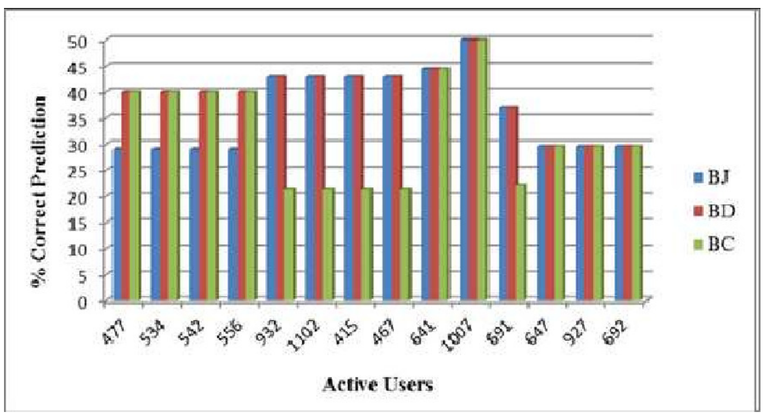

Figure 19: Average case scenario

120 given in Figure 20, the recommender system is unable to recommend a none of the user. As the number of VLWT users is very, very minimum the class becomes skewed and hence worst prediction performance.

To conclude, when the skewness of the data is normal, Jaccard similarity gives the excellent output (Best Case). Similarly, when the data has less skewness, Dice similarity measure performs better than Jaccard and Cosine (Average Case). All the three similarity measures perform poorly (Worst Case) when the skewness of the data is more.

5 Conclusion and Future Work

The proposed TBRS aimed to recommend top-k trustworthy users using a vector similarity measure. To model the user, the contents of the user profile are extracted and formed into a profile database. To find the similarity the fuzzy rules are converted into fuzzy vector space by assigning a fuzzy number for each linguistic term in the rule. To compute the similarity score, the proposed model uses the Jaccard, Dice and Cosine vector similarity measures with information gain as weight. This weighted similarity score is boosted by the trust level of the decision attribute. The performance of the proposed recommender system shows better results in terms of MAE, RMSE and AP when compared with preference based method and expected weight

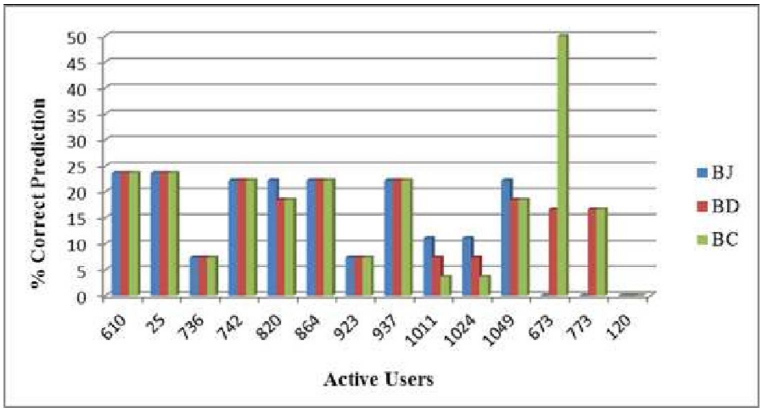

Figure 20: Worst case scenario

methods. Also, the proposed recommender system shows less MAE and less RMSE when are compared with other trust based recommender system. When the data is highly skewed the proposed system fails to give better results.

The limitation of the proposed TBRS is that it needs to be improved to handle the highly skewed data. For example, by applying the log transformation of the skewed data. Also, the TBRS can be extended to recommend a group of users than a single user. For example, recommending the top-5 or top-10 restaurant to the family members.

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