Recommender for Reputation Assessment

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Abstract
In this digital world, E-commerce business is boosting at a tremendous rate. It provides the convenience of choosing the best product from anywhere and at any time. It gives the details of products and services without visiting brick and mortar stores. The problem arises when the customer must choose one product from the pool of digital libraries. There are many e-commerce websites which use recommender systems to assist the customers in buying the best option. Websites like buyhatke.com and Pricedekho.com etc. compare the products from different websites and give recommendations based on price and features only. In this paper we consider recommender system named "Get the Best, Leave the Rest" (GBLR) that compares the product from different websites at the backend and then give the ranking based on different trust factors. Hence the user gets the most reputed website in the increasing order with its product details. This system makes the shopping experience easy and enjoyable.

Keywords: E-Commerce, Digital World, Get Best Leave the Rest

I. INTRODUCTION

In this digital world, e-commerce business is boosting at a tremendous rate. It allows the customer to buy products online without having any limitation imposed by time and distance. Convenience, offers, discounts, better prices add the reason for its popularity. With the growing popularity of online shopping, an increase in the number of shopping websites is observed. Customers find it difficult to select a suitable website which produces good quality products at lower prices. Customers must switch from one website to another to compare the price of products. With the arousal of such an issue, various websites emerged that compare the products from various websites. These websites compare the features and cost of products while the quality of product and reputation of website is generally ignored. For example- Consider two websites. Website A is well regarded and offers high prices for products (P). On the other hand, website B offers lower prices for the same product (P) due to bad quality. The traditional approach tends to recommend the product from website B since product quality is not considered as one of the factors. Moreover, some of the websites offer reliable services while the others may tend to fraud or cause inconvenience to the customers. Different types of frauds can occur if Website A takes the payment from the customer but does not deliver the product or it delivers the product of low quality compared to the product shown on the website. Therefore, there is a significant need to add trust factors while giving recommendations. All the websites cannot be trusted due to privacy, frauds, and security concerns.

Inspired by the above problem, this paper proposes a recommendation system (GBLR) that recommends the products after calculating the reputation of the websites. Initially, the system takes the input from the user in the form of product details. The reputation is determined by the user requirements because every user has his own choices and preferences. The service suitable for one user may not be relevant for others. The recommender searches for the website that fulfills the user requirements using locality sensitive hashing (LSH) technique. All the selected websites are ranked based on Jaccard similarity. Different trust factors are considered i.e., Direct trust, indirect trust, security, quality, satisfaction and later the overall trust is calculated. Finally, it recommends the list of products arranged in increasing order based on ranking.

The main objectives of the paper are-

I. It selects the web service based on security, reliability, performance, and trust.

II. It takes input from the user in the form of requirements and then compares websites to give the most trusted website according to desirability.

III. It compares the products from every website available on the internet rather than comparing them from specific websites.

IV. It evaluates the reputation of websites by using comparison algorithms.

V. It calculates the overall trust of the websites and arranges it in ascending order for the user.

The rest of the paper is organized as follows. Section 2 provides the survey on related work. Section 3 defines the proposed framework. Section 4 evaluates the proposed system experimentally. Section 5 concludes the paper. The trend of shopping is changing from brick-and-mortar stores to online stores. It allows the customer to buy without having any limitation imposed by time and distance. Convenience, offers, discounts, better prices and variety add the reason to its popularity. There are hundreds of online shopping websites. Due to the wide competition different websites offer different prices for the same product. It is obvious for the customer to buy the product after comparing it from different websites. The approach of comparing and then choosing the best is very complex and time consuming. There are some existing websites which provide the convenience of comparing the product from different merchants and then display the prices of the same product from different websites. The main problem is the way of comparison which is based on prices and features of the product. The reputation of the websites is not considered. It leads to incorrect and irrelevant recommendations to the users. For example- Consider two companies. Company A is well regarded and offers high prices for products (P). On the other hand, Company B is lowly reputed, and it offers very less prices for the same product (P) due to the bad quality. The existing system recommends the product from Company B without considering the reputation of the websites. Incorrect recommendations may lead to frauds, inconvenience to the customers. There is a significant need to add the trust factors while giving the recommendations. All the websites cannot be trusted due to privacy, frauds, and security concerns.

Inspired by the above problem this paper proposes a recommendation system (GBLR) that recommends the products after calculating the reputation of the websites. The system takes the input from the user in the form of product details. The reputation is determined by the user requirements because every user has his own choices and preferences. The service suitable for one user may or may not be relevant for others. The recommender searches for the websites that fulfill the user requirements using locality sensitive hashing (LSH) technique. All the selected websites are ranked based on Jaccard similarity. The Jaccard similarity is the proportion of size of intersection to the size of union of two sets. Different trust factors are considered i.e., Direct trust, Indirect Trust, Security, Quality and Satisfaction and the overall trust is calculated. Finally, it recommends the list of products arranged in increasing order based on ranking. The main objectives of the paper are 1. To give the most trusted website to the user based on the requirements.2.To evaluate the reputation of the website by using a comparison algorithm.3.Compare the product from different websites and give ranking on the basis of requirements.4.To save the time of the users in comparing the websites.5. It calculate the overall trust of the websites and arranges it in descending order. The proposed model can overcome the problems of existing recommenders by adding trust factors and reputation measurement techniques.

It focuses on satisfying the user requirements in terms of quality, reliability, satisfaction, security etc.

The rest of the paper is organized as follows: section 2 provides the survey on the related work; section 3 defines the proposed framework. Section 4 set up the facts of the experimental evaluation. It also gives the performance metrics of Accuracy, mean absolute Error (MAE), Root means square error (RMSE), Precision, Recall, F-Measure. Section 5 concludes the paper.

II. RELATED WORK

The current studies on Recommendation system in E-commerce area propose various solutions to problems of trust and reputation in online shopping. The work in this field is presented in the following two parts: related work on the Recommender System and related work on Trust and reputation.

A. Online shopping and Recommender System

In 2013, Kaur et al. [1] give factors that affect the online shopping in India. The factors are different culture, different psychology, and different characters. In 2010, Azzedin and Farag [2] proposed a model of identifying honest recommenders in reputation system. The objective is to detect dishonest recommenders. The paper shows the effect of malicious behavior of the dishonest recommenders which changed the performance of the system**.** In 2008, Hsu and Jung [3] discuss the factors for online trust. The seven dominant factors are reputation, third party assurance, customer service, propensity to trust, website quality, system assurance and brand. The survey was conducted on the respondents because of 172 questionnaires. In 2014 ,Bizhanova et al. [4] presents the product details that are Extracted from Twitter. It classifies Twitter messages using emoticons and preprocessing steps to achieve high accuracy. In 2012, Lieber [5] gives comparison of offline and online approaches. Both have certain strengths and limitations as well. In 2012, Yan et al. [6] proposed a new recommender model for mobile applications. It proposes TruBeRepec recommender system for mobile applications. Algorithms are used to evaluate the trust and reputation of the system through trust behavior observations.

B. Trust and reputation

Trust and reputation is a very important and relevant factor to give the correct recommendation to the user. Various concepts have already been introduced by the scholars. In 2007, Josang et al. [7] analyze a survey of Trust and Reputation Systems . The Basic idea is to rate different parties based on various factors such as quality, transactional details, and past behavior. In 2014 , Kraounakis et al. [8] design a Reputation-Based Model for the evaluation of trust in the systems. A model is prepared in which system entities are classified into two main categories. One is the service resource requestor that consumes the services available, and the other category is service resource provider that provides different services for the user. In 2015, Wahab et al. [9] suggest a survey on reputation model. It divides the web services into three architectures-single, composite and communities. The purpose, model, advantage and limitations of each architecture is discussed .The effect of malicious users are classified in the form of attacks such as DOS, Request drop attack, sinkhole attack etc. In 2012, Broutsou and Andromachi [10] discuss e-commerce websites. The success or failure of many e-business companies depends upon trust and reputation. It analyzes the reputation and trust of the company for online transactions.

In 2001, Chen and Mao[11] evaluate the comments on the basis of reputation of rater. The endorsement matrix and weight propagation is used to build the trust hierarchal structure. Automated methods are suggested to evaluate the text comments. In 2009, Tian et al. [12] suggest model for network selection. The main network is divided into different domains based on trust values. A binary tree is made according to trust values. It is evaluated by past behavior and the values change periodically and updates its position in tree. The node which is at the peak is having highest trust values.

In 2010 H.Trang et al. [13] proposed the Bayesian network to evaluate Trust values for web services. Direct experience, user ratings and quality are the different metrics to evaluate the overall reputation of web services. In 2002 Josang et al. [14] presented Beta reputation system (BRS) that combines different feedbacks and use gamma function to evaluate the reviews of the user. BRS obtain valuable reviews by subtracting positive feedback from the negative feedback. In 2013 Z.Yang et al. [15] proposed a system to establish the trust in social chatting domains. It evaluates its reputation by combining local and global experience. PerChatRep is implemented through smart phones and mobile Adhoc network (MANET) to boost the business potential. In 2014 Britto N Arockiasamy [16] discuss different factors to calculate the trustworthiness of web services.

The factors are Security, Reliability, Experience, Authenticity, Service cost, Accuracy, Performance and the overall trust is calculated by considering the weight factors. In 2009 Wand and Vassileva [17] classify the trust into three types. They are centralized or decentralized, person or resource, global or personalized. It also highlights different Quality of service metrics and reputation mechanism for web service selection. In 2011, Zang et al. [18] proposed different trust functions such as NICE, evidence based model, Peer Trust, Eigen Trust etc. These are evaluated based on Direct interactions and feedback. These functions calculate the reputation of web services. In 2004, Xiong and Liu[19] discuss the trust functions of different members or peers.

The metrics are used to evaluate the reputation such as feedback, number of transactions and credibility of feedback. Peers' opinion is related to similarity measures. In 2007, Hwang and Zhou [20] proposed a trust overlay network and select some power nodes. The relation is formed between users and feedback. The nodes are rated after each transaction and trust value is updated at regular intervals. It uses the concept of Bayesian method and Distributed ranking mechanism to evaluate overall trust. In 2009, Malik and Bougettaya [21] discuss the credibility of rater by assessing the service provider reputation. The honest recommenders are selected on the basis of past behavior and transaction details. In 2013, Han yu et al. [22] discuss the trust models. It evaluates trust on the basis of Direct interactions, indirect interactions and social relationships among the different domains. It also gives a solution to the reputation damage problem. In 2010, Kamwar et al. [23] proposes the Eigen trust values. It works like Google page rank algorithm and calculates local reputation by assessing the positive and negative ratings. Global reputation is calculated from trust matrix.

III. PROPOSED FRAMEWORK

Figure 1 depicts the proposed architecture of the recommender for reputation assessment of different web services. All the websites cannot be trusted due to fraud and security issues. It is very important to consider the reputation of the website before making any transaction with it. The proposed system works as follows:

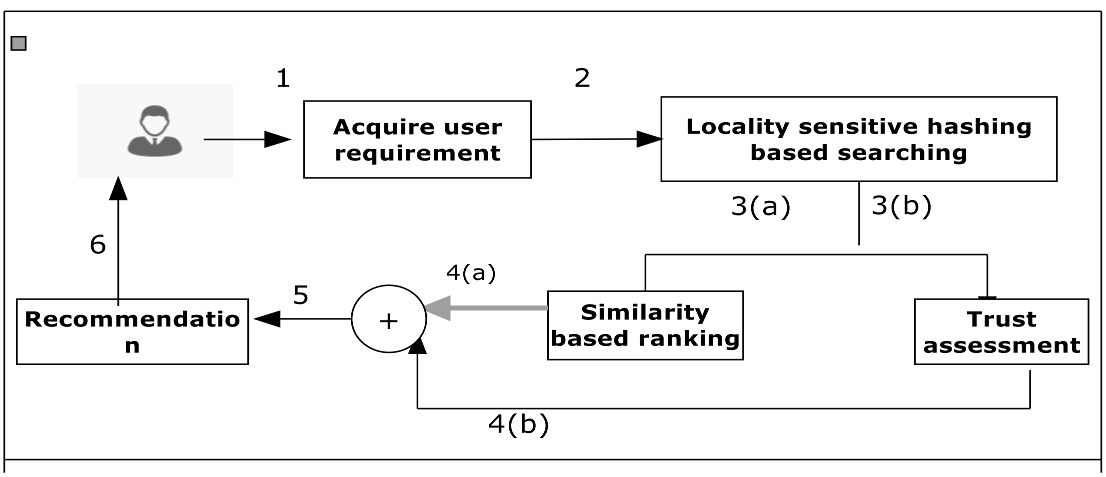

Fig 1. Proposed Model

When the user must buy a product, he enters the product details in the system. For example, if a user wants to buy a mobile phone, then the product details can be price, brand, model, color, memory etc. All these details are input to the system and system searches from different websites to fulfill the requirements of the user. Linear search is performed in case of randomly stored data and portioning search is performed in case of already sorted data, but both are very time consuming. The exact matching of desired information is very rare, so we use similarity measures which are more beneficial for searching. Locality sensitive hashing technique is used to find similar sets. In locality sensitive hashing (LSH) comparisons are performed and the pairs that hash to same bucket are considered similar to each other. These pairs are called candidate pairs and only these pairs are compared rather than every pair**.** The LSH gives those websites which satisfy the user requirements. Suppose the websites are w1, w2,w3,w4,w5. Now the extracted websites are compared and ranked by using Jaccard similarity. The ranking of websites depends upon the similarity level of the document with the actual document by the user. Let the ranking of websites in descending order is w2, w5,w1,w4,w3. It is also important to check the trust values of the ranked websites. Different factors to evaluate the reputation of the website are Direct trust, Indirect trust. quality, satisfaction, payment options and security. Finally, the overall trust is calculated by combining the ranking based on similarity and trust factors. Figure 2 shows system flow in the model.

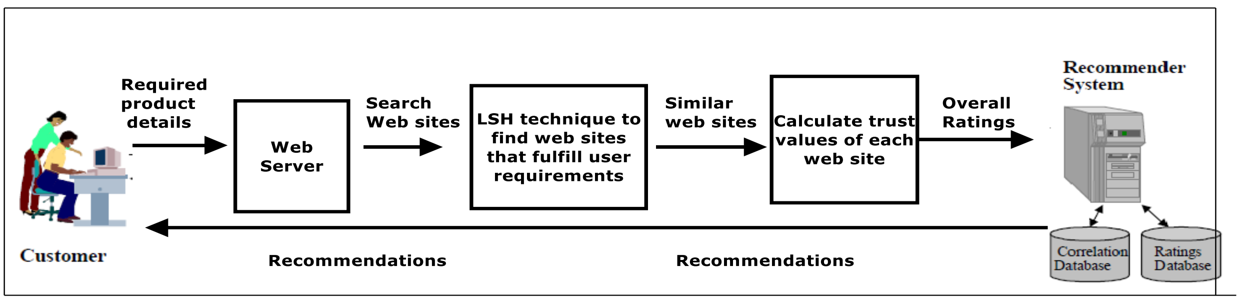

Fig 2. System flow in model

Detailed explanation of the model

A. To find similar sets- The requirements of the user are considered in a text document. Shingling is used to convert the text document into sets by using k shingles and the similarity between the sets is calculated by Jaccard similarity. Shingling gives the characteristics matrix which is created by searching shingles and hash functions in every document. For example the requirements of the user are as follows: Brand-samsung, Range-10,000-15,000, Color-white,Memory-16gb,Camera-12mpx.

Table1: Characteristics Matrix

Shingles	W1	W2	W3	W4	W5
Brand	1	1	0	1	1
Range	0	1	1	0	1
Color	1	0	1	0	1
Memory	0	1	0	1	1
Camera	0	0	1	1	0

Table2: Characteristics Matrix with hash

shingles	W1	W2	W3	W4	W5	Hash1	Hash2
Brand	1	1	0	1	1	1	2
Range	0	1	1	0	1	2	3
Color	1	0	1	0	1	3	4
Memory	0	1	0	1	1	4	0
Camera	0	0	1	1	0	0	1

The size of the matrix is m*n where m is the number of rows and n is sets. The entry Mij=1 if I shingle is present in j set otherwise Mij=0. Suppose W1 satisfies features and of brand and color. It can be represented as W1 (Brand, Color) W2(Brand ,Range, Memory) W3(Range, Memory, Camera) W4(Brand, Memory, Camera) W5(Brand, Range, Color, Memory).

The characteristics matrix is very complex and large. Another technique called minhashing is used to reduce the size of the matrix by creating a signature matrix which is very less in size and gives the same results as a characteristics matrix. In minhashing different hash functions are applied on rows. These hash functions are used to create minhash signature matrix. The hash function is used to generate random permutations of shingle number. Every hash function gives different permutations. Signature matrix consists of h rows that are the number of hash functions and numbers of columns are same as in case of characteristic matrix Each row of the signature matrix is scanned to get the signature matrix. For all the sets for which the entry is “1” in characteristic matrix, for that set the corresponding hash values are compared with the existing hash functions values in Signature matrix. If the value is found to be less it is updated in signature matrix, otherwise no changes are performed.

Table 2.1: After scan of first row

	W1	W2	W3	W4	W5
Hash1	1	1	-----	1	1
Hash2	2	2	-----	2	2

Table 2.2: After scan of second and third row

	W1	W2	W3	W4	W5
Hash1	1	2	0	0	2
Hash2	2	0	1	0	0

Table2.3: After scan of fifth row

	W1	W2	W3	W4	W5
Hash1	1	2	2	1	2
Hash2	2	2	3	1	2

Table 2.4 Matrix After scanning all the rows.

	W1	W2	W3	W4	W5
Hash1	1	2	2	1	2
Hash2	2	0	3	0	0

The signature matrix shows that w2 and w4 are like each other. In this way we can find the similarity between the different websites by applying hash functions on it. The output of this process is all the websites that satisfy the user requirements.

B. Ranking of websites

Suppose we get the number of websites as w1, w2, w3, w4, w5. It is also important to rank the websites on the basis of similarity between the two sets. One set is the website features, and the other set is the required product details by the user**.** The similarity is taken as 1 (or 100%) if there is overall similarity among the two sets and similarity is taken as 0 if there is no similarity between the sets. To calculate similarity between two sets Jaccard concept is used. Jaccard Similarity of two sets is the ratio of the size of the intersection to the size of the union of the two sets.

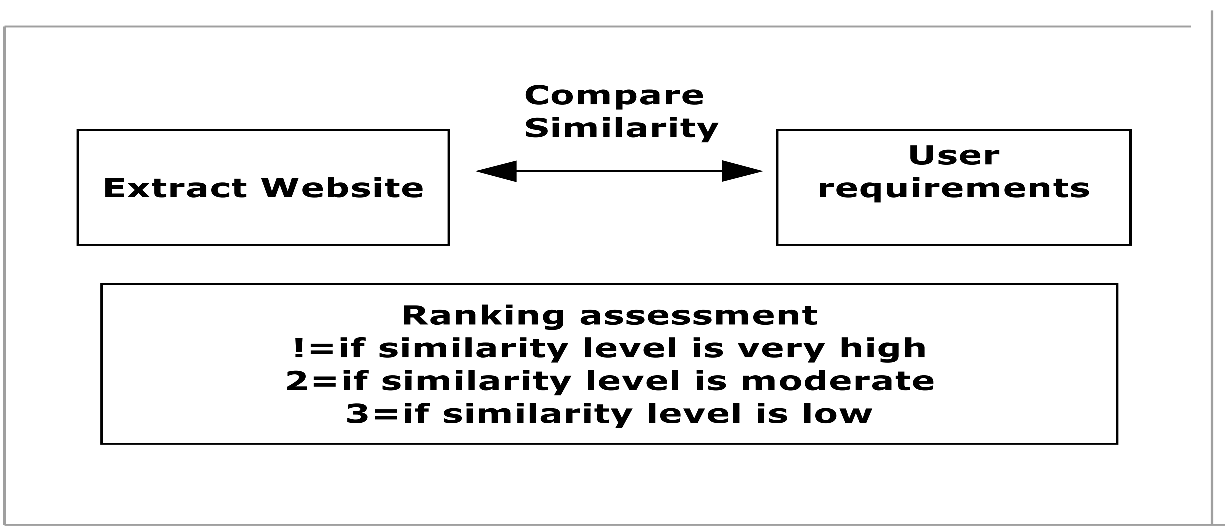

Figure 3 : Jaccard Simmilarity

C. Trust factors

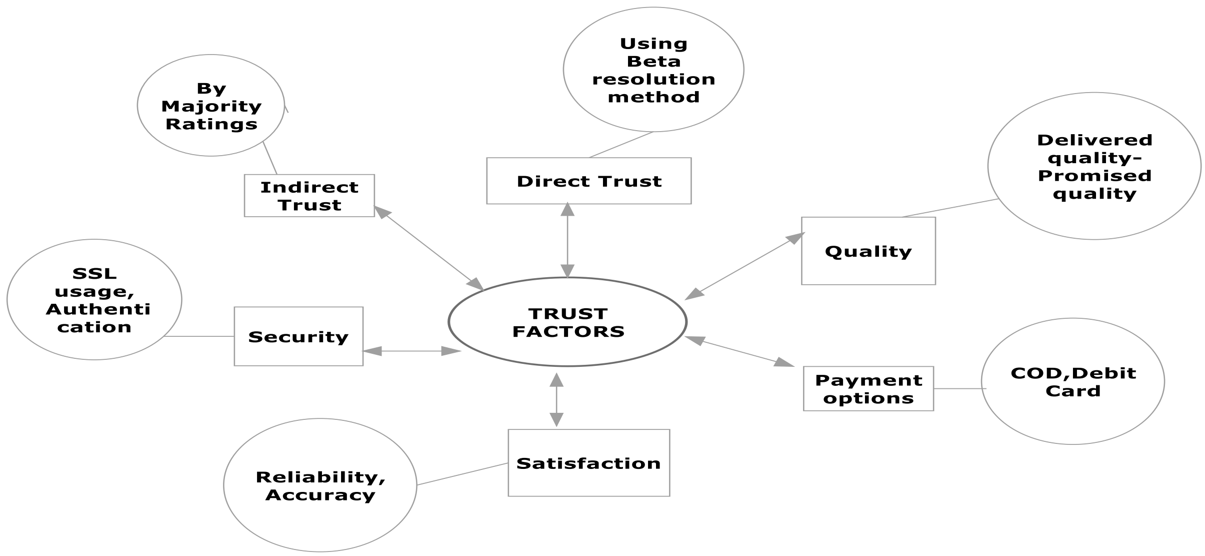

Figure 4: Trust Factors

1. Direct Trust

Direct trust is based on the direct experience of the user. It depends upon past interactions with the third party. To calculate the direct trust we use beta reputation technique (BRS) to estimate the trustworthiness of website by calculating its reputation by difference of positive and negative feedbacks. BRS is based on beta probability density function.

Reputation Function

Let A_t^x and B_t^x be the positive and negative feedback about target t.

$\Psi(\mathrm{p}|A_t^x, B_t^x) = \frac{\Gamma(A_t^x - B_t^x + 2)}{\Gamma(A_t^x+1)\Gamma(B_t^x+1)} * p\, A_t^x (1 - p) B_t^x$

Where $0 \le p \le 1$ and $0 \le A_t^x$ and $0 \le B_t^x$.

The probability expectance value of reputation function is

$(\mathrm{E}\,(\,\Psi(\,\mathrm{p}\,|A_t^x, B_t^x)) - 0.5).2 = \frac{A_t^x - B_t^x}{A_t^x + B_t^x + 2}$

Combining feedbacks

Let $\Psi(p|A_t^x, B_t^x) and\, \Psi(p|A_t^y, B_t^y)$be two different reputation function on T resulting from X's and Y's feedback. The reputation function is defined as:-

1. $A_t^{x,y} = A_t^x + A_t^y$ //// Combining positive feedback.
2. $B_t^{x,y} = B_t^x + B_t^y$ //// Combining negative feedback.

2. Indirect Trust

It is also called recommendations trust. If the reported rating matches with the majority rating then the credibility of rater is increased. The technique of clustering is used by grouping together the similar feedback ratings. The most populated cluster is called majority cluster. It is given as: - M= centroid (maxR_k) ɏ K

Where M- is the majority ratings

K- is the no of clusters.

Max(x)-It gives cluster R with largest membership.

The Euclidian distance between majority ratings (M) and reported rating (N) is computed to adjust the rater credibility. The change in credibility due to majority rating denoted by M_f.

M_f= 1- $\frac{\sqrt{\sum_{k=1}^{n}(M-N_k)^2}}{ς}$ if $\sqrt{\sum_{k=1}^{n}(M-N)}^2 < ς$

1- $\frac{ς}{\sqrt{\sum_{k=1}^{n}(M-N)^2}}$ otherwise

3. Quality

Quality is defined as its ability to fulfill the customers' needs. The quality is always preferred over other factors while making online purchases. Quality is determined by comparing the delivered QOS values and promised values. Let Qd =delivered quality, Qp =promised quality

Cj [-1,1] =compliance value of quality j

Case1: High Quality

If the delivered quality of service is more than promised quality, then it is considered as high quality. The higher value of Cj means the better performance and the compliance value is calculated as follows:

If (Qd> Qp)

Cj= (Qd-Qp)/Qp

Case2: Low Quality

If the delivered quality of service is less than promised quality, then it is considered as product with low quality. And the compliance value is calculated as follows:

If (Qd<Qp)

Cj= (Qp-Qd)/Qp

Cj=1	very bad	if -1<Cj<0.5
Cj=2	bad	if 0.5<Cj<0
Cj=3	satisfactory	if Cj=0
Cj=4	good	if 0<Cj<0.5
Cj=5	Excellent	if 0<Cj<1

4. Satisfaction

It measures the feedback of the customer after interaction with any web service. It uses an average function that stores the value of satisfaction, and an update operation is applied after every interaction.

Let $s_n^t(r,s)$ represent the amount of satisfaction agent r has on agent s based on the services up to n transactions in t time. The satisfaction function is defined as: -

$$s_n^t(r,s) = \propto \times\, s_{cur} + (1-\propto) \times s_{n-1}^t(r,s)$$

Where s_{cur} is the satisfaction value for the most recent transaction. Here s_0^t(r,s)=s_{last}^{t-1}(r,s) that is the satisfaction value at the start of t time is equal to last computed satisfaction (t-1) time interval and the initial value of satisfaction is $s_0^0(r,s) = 0$

s_{cur}

$= 0\ if\ transaction\ is\ fully\ unsatisfied$

1 if the transaction is fully satisfied.

E (0,1) otherwise

5. Payment Options

Payment methods are very important when dealing with online shopping. Payment gateway allows merchants to accept the money through various forms and to ensure security while the transaction is taking place. The various forms of payment are:

1. Cash on delivery (COD)
2. Debit/Credit cards (DC)
3. Net banking (NB)

4. Paypal (PP)

We can use an algorithm to calculate the reputation of a website based on the payment options. Reputation is directly dependent on the payment options.

If (COD==True|| DC==True|| NB==True|| PP=True)
Rating=1.
Else if (DC==True|| NB==True|| PP=True)
Rating=2;
Else(NB==True|| PP=True)
Rating=3.

6. Security

It is one of the most important features when selecting a website for online purchases.

To check the security of the website some of the important concepts are as follows: -

1. SSL usage-: SSL means Secure socket layer. It uses the concept of encryption to maintain the secrecy of the transaction. The usage of SSL can be identified by URL. If the website is using SSL, then it uses HTTPs protocol instead of HTTP. If SSL is used by the website, then it is given value of 1 while absence of SSL is given value of 0.

2. Authenticity-: The concept of authenticity is used to verify the service provider. Due to various threats to security the third-party authentication is very important to rate the website. Authentication is being checked by certificates that are issued to clients from servers. The presence of third-party authentication is given a value of 1 while the absence of authenticity is given a value of 0.

3. Virus protection-: This is one the most common attacks. To deal with this, the web service provider uses a proxy server in front of provider component that will handle such type of risks. The presence of proxy server is taken as 1 while its absence is taken as 0.

Calculating Overall Trust

The overall trust (T) is calculated by adding the ranking of the websites and different trust factors. It is multiplied with the weighting factor (W) and represented as follows:

$$T = W_1 * \text{Rank} + W_2 * \text{Trust values} \quad (1)$$

The trust values are calculated by considering different trust factors along with their weight assigned by user's preference. The weight value can change according to the desirability of the user. One user may give more preference to the security whereas other users give more importance to the cost. Thus, the weight can change based on the user's desirability. The weight can vary in the range of 0 and 1. The total weight of all the factors should be equal to 1.

$$w_1 + w_2, + \ldots\ldots\ldots\ldots + w_{n-1} + w_n = 1 \quad (2)$$

Suppose the total trustworthiness for calculating the trust values is denoted by T_t. The individual factors are denoted by F_1. The corresponding weight value for that factor is denoted by w_1. Thus, the total contribution of that factor is denoted as multiplication of these two factors$W_1 * F_1$. Suppose Quality factor is denoted by F_1, Satisfaction factor is denoted by F_2, Security factor is denoted by F_3 and so on. Thus, the trust values are calculated as:

$$T_t = W_1 * F_1 + W_2 * F_2 + \ldots\ldots\ldots + W_n * F_n \quad (3)$$

IV EXPERIMENTAL SET UP AND COMPARATIVE ANALYSIS

To prove the performance of the new proposed recommender system, we conduct an experimental evaluation and different metrics are considered to evaluate the efficiency and reliability of system [23], [24] . Please find below the experiments conducted on different datasets. The dataset can be collected from real time users or from the Internet. There are various websites that provide random datasets online related to the domains of online shopping products, food and restaurants, movies, hotels etc.

In our experimental evaluation we are using both the real time user's data as well as datasets from the Internet. The requirements about the product are taken directly from the real time users. The user is requested to enter all the desirable features of the product. The dataset of product details can be extracted via crawling on Scraper wiki website. The automatically generated datasets are available from Scraperwiki and are used to extract valuable data from public web pages. All the experiments were conducted on a computer with Intel core i7 processor with 3 Ghz and 16 Gb RAM running on windows 8.

Metrics

To measure the performance of recommender the most important factor is Accuracy. Accuracy decides the success or failure of the recommender system. There are two ways to measure the Accuracy. First and foremost is Prediction Accuracy which consists of Mean absolute error (MAE) and Root Mean Square error (RMSE). The other is classification accuracy which consists of Precision, Recall and F-measure.

A. Prediction Accuracy

It measures the satisfaction of customers with the recommendation provided. The aim is to evaluate the performance of the system to correctly predict the user feedback for the recommended product.

1. Mean Absolute Error (MAE)

It is calculated as difference between predicted ratings(p) and actual ratings(r). The predicted ratings are given by system and actual ratings are given by the user after a purchase is made based on the recommendation provided by system.MAE and accuracy are inverse relation with each other. A lower value of MAE represents higher Accuracy rate.

MAE=$\frac{1}{n}\sum_{i=1}^{n}|p-r|$

2. Root Mean Square Error (RMSE)

It is square root of the difference between predicted and real ratings that is the mean size of error. It is similar to MAE but has more emphasis on larger deviation. The lower value of RMSE means better performance of Recommender.

RMSE=$\frac{1}{n}\sum_{i=1}^{n}((p-r)^2)$

Tale 3: Performance for different Users

User	Ratings by user	Prediction Ratings by system	|p-r|	$(p-r)^2$
A	3	4	1	1
B	5	4.5	0.5	0.25
C	4	4.3	0.3	0.9
D	5	5	0	0

E	3.5	4.2	0.7	0.49
			MAE=2.5	RMSE=2.64

B. Classification Accuracy

Its aim is to identify the most relevant items for a given user. Precision, Recall, F-Measure indicate the performance of recommender regarding items recommended or not recommended.

1. Precision

It calculates the number of relevant items correctly recommended. It measures the ability of the system to retrieve as many relevant documents as possible. Example-Proportion of recommended products that are good**.**

Precision= $\frac{Correctly\ Recommended\ Products}{Total\ Recommended\ Products}$

2. Recall

It measures the ability of the system to retrieve as few non relevant documents as possible in response to request. Recall is ratio of good products recommended over all good products in test set. Example-Proportion of all good products recommended.

Recall= $\frac{Correctly\ Recommended\ Products}{Relevant\ Products}$

3. F-Measure

It is a measure of harmonic mean of precision and recall.

F-Measure=$\frac{2*Precision*Recall}{Precisio+Recall}$

The different metrics of Accuracy that is MAE, RMSE, Precision, Recall, F-Measure are affected by richer datasets. The recommender will perform better if the number of executions per user increases. Let's take a metrics ie Mean Absolute Error (MAE). When there is one rating per user the value of MAE is 0.99. When two ratings per user are added, MAE value decreases to 0.97. Similarly, by increasing the number of executions per user, MAE value can be decreased. Hence the performance of the recommender can be better and more efficient. This behavior is the same for other metrics that is Precision, Recall, F-Measure. Therefore, in our experiment we took 3 executions per user for better results.

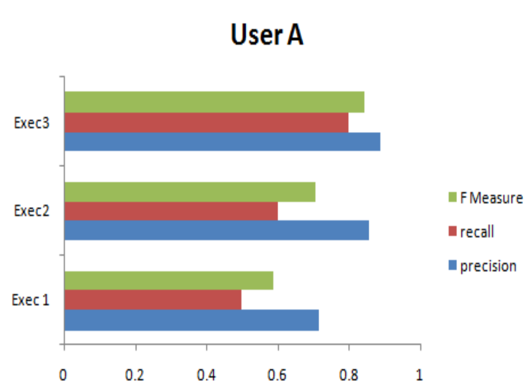

Figure 5: Performance of user A

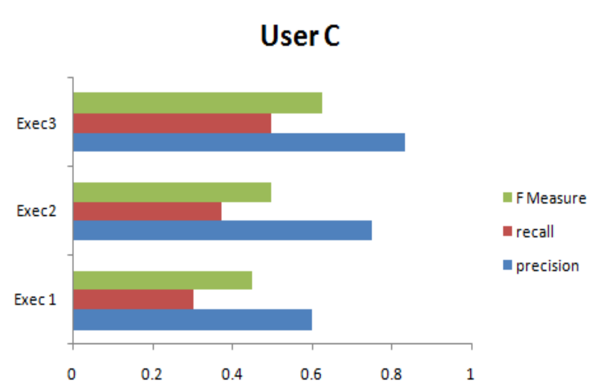

Figure 6: Performance of user C

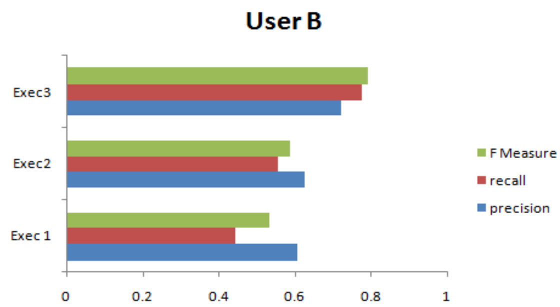

Figure 7: Performance of user B

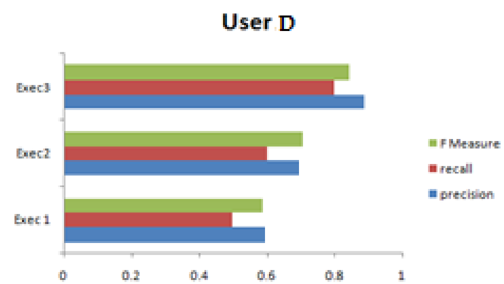

Figure 8:Performance of user D

Table 4: Performance for different users

User	Execution	No of Recommended by system	No of relevant items in test set	Relevant items by user	Non Relevant items by user	Precision	Recall	F-Measure
A	1	7	10	5	2	0.7142	0.5	0.5881
	2	7	10	6	1	0.8571	0.6	0.7058
	3	9	10	8	1	0.8888	0.8	0.8424
B	1	6	9	4	2	0.6666	0.4444	0.5332
	2	8	9	5	3	0.625	0.5555	0.5881
	3	9	9	7	2	0.7777	0.7777	0.7776
C	1	5	8	3	2	0.6	0.375	0.4615
	2	4	8	3	1	0.75	0.375	0.5
	3	6	8	5	2	0.8333	0.5	0.6249

Effect of Parameters on Recommender System

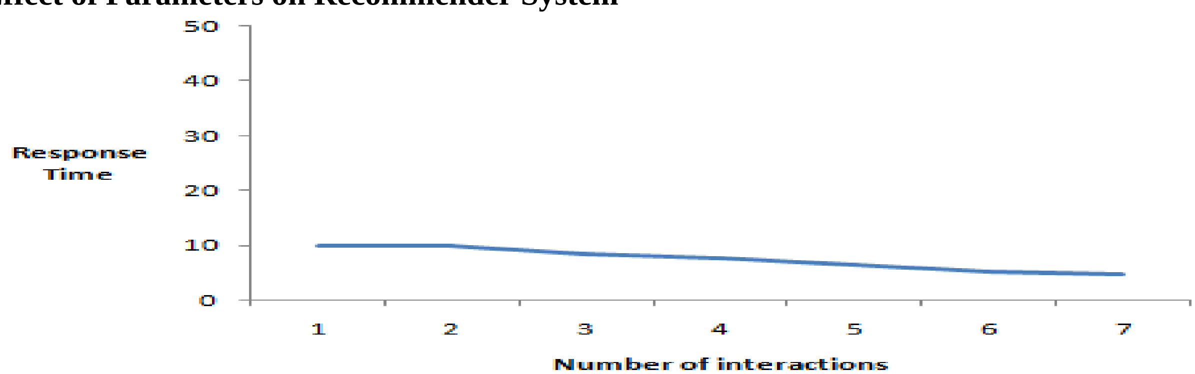

Fig 9: - Response time VS no of interactions

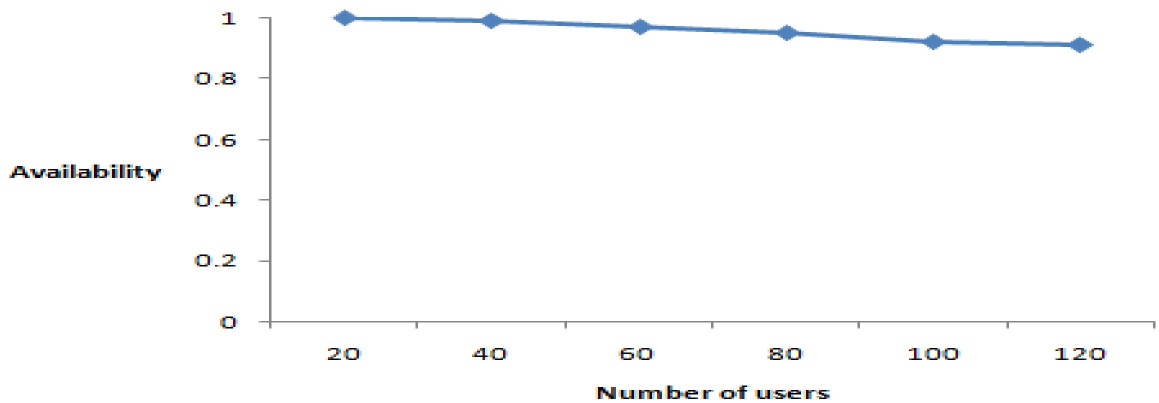

Fig 10: Availability VS no of users

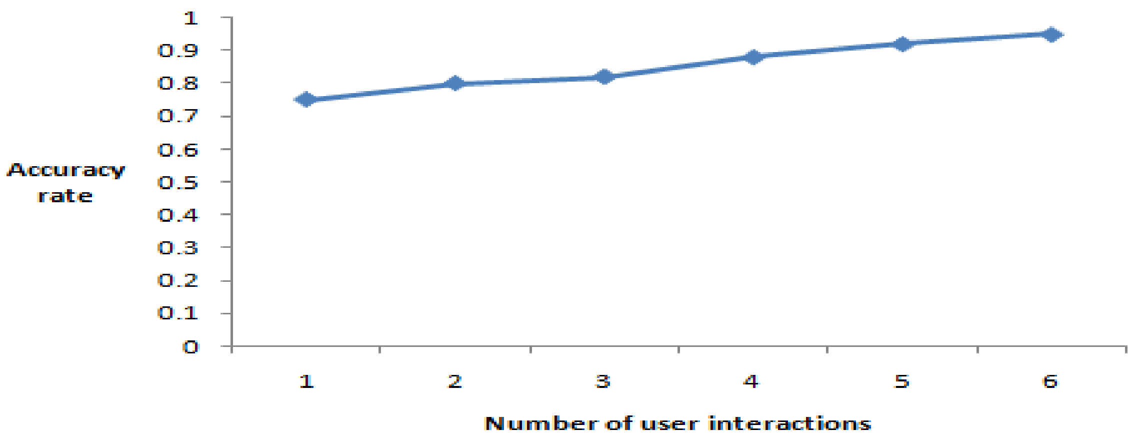

Fig 11: Accuracy rate VS no of interactions

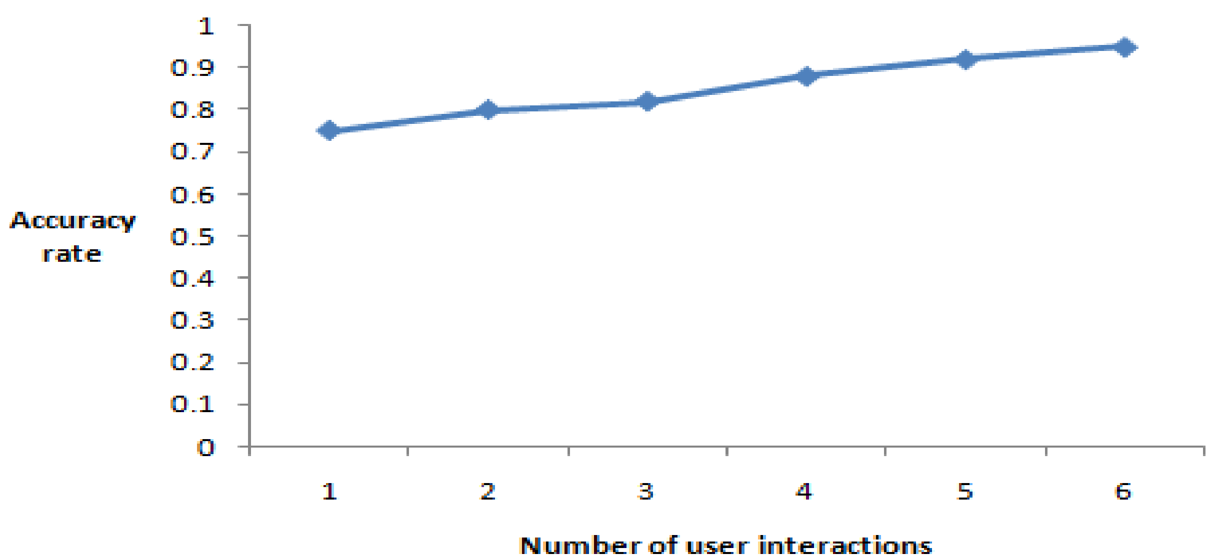

Fig 12: Time VS no of features

REFERENCES

[1] B. Kaur and S. Madan, "Factors Influencing Trust in Online Shopping : An Indian Consumer ' s Perspective," vol. 5, no. 29, pp. 132–139, 2013.

[2] F. Azzedin, "Identifying honest Recommenders in Reputation Systems," *Int. J.*, vol. 3, no. April, pp. 111–117, 2010.

[3] C. J. Hsu, "Dominant factors for online trust," *Proc. 2008 Int. Conf. Cyberworlds, CW 2008*, pp. 165–172, 2008.

[4] A. Bizhanova and O. Uchida, "Product Reputation Trend Extraction from Twitter," *Soc. Netw.*, vol. 3, no. 3, pp. 196–202, 2014.

[5] E. Lieber and C. Syverson, "Online vs. Offline Competition," *Oxford Handb. Digit. Econ.*, no. January, p. 189, 2012.

[6] Z. Yan, P. Zhang, and R. H. Deng, "TruBeRepec: A trust-behavior-based reputation and recommender system for mobile applications," *Pers. Ubiquitous Comput.*, vol. 16, pp. 485–506, 2012.

[7] A. Josang, R. Ismail, and C. Boyd, "A survey of trust and reputation systems for online service provision," *Decis. Support Syst.*, vol. 43, no. 2, pp. 618–644, 2007.

[8] S. Kraounakis, I. N. Demetropoulos, A. Michalas, M. S. Obaidat, P. G. Sarigiannidis, M. D. Louta, and S. Member, "A Robust Reputation-Based Computational Model for Trust Establishment in Pervasive Systems," vol. 9, no. 3, pp. 1–14, 2014.

[9] O. A. Wahab, J. Bentahar, H. Otrok, and A. Mourad, "A survey on trust and reputation models for Web services: Single, composite, and communities," *Decis. Support Syst.*, vol. 74, pp. 121–134, 2015.

[10] A. Broutsou, "Online Trust: The Influence of Perceived Company's Reputation on Consumers' Trust and the Effects of Trust on Intention for Online Transactions," *J. Serv. Sci. Manag.*, vol. 05, no. 04, pp. 365–372, 2012.

[11] M. Chen, "Computing and Using Reputations for Internet Ratings," 2001.

[12] J. Tian, J. Li, and L. Yang, "A Reputation-Based Multi-Agent Model for Network Resource Selection," vol. 2009, no. November, pp. 764–774, 2009.

[13] H. T. Nguyen, "A trust and reputation model based on bayesian network for web services," pp. 251–258, 2010.

[14] A. Jøsang, "The Beta Reputation System," pp. 1–14, 2002.

[15] Z. Yan, Y. Chen, and Y. Shen, "Journal of Computer and System Sciences A practical reputation system for pervasive social chatting," *J. Comput. Syst. Sci.*, vol. 79, no. 5, pp. 556–572, 2013.

[16] B. N. Arockiasamy, "Trustworthiness of Web Services," 2014

[17] Y. Wang and J. Vassileva, "A Review on Trust and Reputation for Web Service Selection University of Saskatchewan Key words."

[18] Q. Zhang, T. Yu, and K. Irwin, "A Classification Scheme for Trust Functions in Reputation-Based Trust Management."

[19] I. Transactions and O. N. Knowledgedata, "PeerTrust: Supporting Reputation-Based Trust for Peer-to-Peer Electronic Communities," no.

November, 2015.

[20] R. Zhou, K. Hwang, and I. C. Society, "PowerTrust : A Robust and Scalable Reputation System for Trusted Peer-to-Peer Computing," vol. 18, no. 4, pp. 460–473, 2007.

[21] Z. Malik and A. Bouguettaya, "RATEWeb : Reputation Assessment for Trust Establishment among Web services," pp. 885–911, 2009.

[22] H. A. N. Yu, Z. Shen, C. Leung, C. Miao, and V. R. Lesser, "A Survey of Multi-Agent Trust Management Systems," 2013.

[23] L. O. Colombo-mendoza, R. Valencia-garcía, A. Rodríguez-gonzález, G. Alor-hernández, and J. J. Samper-zapater, "Expert Systems with Applications RecomMetz : A context-aware knowledge-based mobile recommender system for movie showtimes," *Expert Syst. Appl.*, vol. 42, no. 3, pp. 1202–1222, 2015.