COMMTRUST: A MULTI-DIMENSIONAL TRUST MODEL FOR E-COMMERCE APPLICATIONS

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ABSTRACT

E-Commerce applications use reputation-based trust models based on the feedback comments and ratings gathered. The "all better Reputation" problem for the sellers has become very huge because a buyer facing problem to choose truthful sellers. This paper proposes a new model "CommTrust" to valuate trust by mining feedback comments that uses buyer comments to calculate reputation scores using multi-dimensional trust model. An algorithm is proposed to mine feedback comments for dimension weights, ratings, which combine methods of topic modeling, natural language processing and opinion mining. This model has been experimenting with the dataset which includes various user level feedback comments that are obtained on various products. It also finds various multi-dimensional features and their ratings using Gibbs-sampling that generates various categories for feedback and assigns trust score for each dimension under each product level.

KEYWORDS

E-Commerce, Feedback mining, Trust score, Topic modeling, Reputation-based trust score

1. INTRODUCTION

Accurate trust evaluation plays a vital role in e-commerce systems. A reputation system [2] is implemented to get superior service deals in e-commerce systems like Amazon, eBay etc. To allocate rank for sellers, feedback ratings are calculated which are given by the buyers. The "all better reputation" [2] problem is an issue for all sellers where the feedback rating is above 99% positive on average [2]. Such strong positive bias is not helpful to the buyers to select a right seller or product. At the Amazon, the system uses detailed seller ratings for sellers (DSRs) on four conditions, i.e. item, shipping, communication and cost. In DSRs we find strong positive bias even though there is a little problem with product or delivery. The One potential negative rating is the chance for the absence of negative ratings at electronic commerce websites, it attracts the buyer who provides the negative feedback about the items and it harms their own reputation [2] in purchasing sites.

Buyers express some disappointment and negative opinions about the product in feedback comments. Example: a buyer may have liked an item, packaging, and the overall transaction, but the delivery would have been postponed. For this situation, the buyer may tend to score more 4 on a 5-star scale and comment on the postponement in the content field. In order to overcome the above-mentioned "all better reputation" [2] problem, a Comment based multi-dimensional (CommTrust) is proposed for the trust valuation model accomplished by mining e-commerce comments. CommTrust, trust profile is calculated for a seller that incorporates dimension reputation scores, weights and overall trust scores. Thus, trust profiles for sellers are made by mining feedback comments.

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In CommTrust, access that unites dependency relation analysis [3, 4] and lexicon based opinion mining techniques are proposed to extract feature opinion expressions from feedback comments. Furthermore, based on dependency relation analysis and Latent Dirichlet Allocation (LDA) topic modeling methods [5, 18] an algorithm is proposed to cluster feature expressions into the dimensions and calculate total dimension weights and ratings, called Lexical-LDA [5]. Therefore, the reputation profiles in CommTrust contain dimension reputation scores, weights and complete trust scores for ranking sellers.

2. RELATED WORK

The work focus on three major areas: 1) Computing approach to trust, mainly reputation based trust valuation; 2) Analyzing feedback comment in e-commerce application and usually mining opinions on product analysis and another form of free text documents; and 3) opinion mining and summarization.

2.1. Computing Trust Valuation

The positive trust score aspect of the Amazon reputation system is well documented [1, 6]. No valid solutions have been reported. As proposed in [6] , to observe feedback comments to get seller reputation score below the balanced ratio, where feedback comments do not create the positive rating which allows negative rating for a transaction. Complete trust scores for seller rating on transactions farther aggregated. In this, our focus is on extracting dimensions from buyer feedback comments and these dimension ratings are calculated to find a trust score for dimensions.

2.2. Analying Feedback Commenets

In [13] the e-commerce application, there have been different learning's on analysis feedback comments, even though an inclusive trust valuation is not their focus. The focal point is on the sentiment classification [7, 20] of feedback comments. It concludes that feedback comments are audible by evaluating them as a trail. Omitted conditions for comments are assumed negative, these methods are made from an aspect rating [15, 16] are used to allocate feedback comments may be positive or negative. The approach enhanced to encapsulate feedback comments. It aims to sort out the considerate comments that do not present in actual feedback. It aims at developing "rated aspect summary" [8] given by Amazon feedback comments. The numerical developing model is based on regression about a complete rating.

2.3. Opinion Mining and Summarization

The main performance is relevant to opinion mining and sentiment analysis [9, 10] on free text documents. Aspect Opinion mining on item review is the existing work. In a product description and the opinion towards them are extracted. By choosing and re-constructing sentences according to the extracted characteristics are summarized. Feedback mining and summarization is the mission of generating sentiment summary [17] that consists of sentences from feedback which arrest the buyer's opinion. Feedback summarization is interested in features or aspects on which customers have opinions. It also concludes either the opinions are positive or negative. This creates it from classic content summarization. A comprehensive overview is presented. Most existing works on survey mining and summarization [11, 19] concentrate on item reviews. For example, [14] concentrated on mining and summarizing ratings by extracting opinion sentences with regard to the product features.

3. COMMTRUST: MULTI-DIMENSIONAL TRUST VALUATION FOR COMMENTS

In electronic commerce application, feedback comments are the source in which users state their opinions about the product honestly in a text box. Feedback comment analysis is done on the various e-commerce sites announce that, even if the buyer gives positive comment he/she still gives comments of mixed opinions about the product. For example, the buyer leaves a comment as "Worst response, will not purchase again". So the buyer has a negative opinion towards the customer service and delivery of the product and gave a complete positive feedback score for the purchase. Therefore, a comment based trust valuation is multi-dimensional. The terms are used for opinion and rating correspondently to express their positive, negative and neutral polarity toward entities that expressed in natural language text.

3.1. Commtrust Model

The commtrust framework Figure 1 Shows, Feedback comments are extracted based on opinion expressions and their association ratings. Dimension trust and weights are calculated using cluster form expression into dimensions which accumulate the complete trust score.

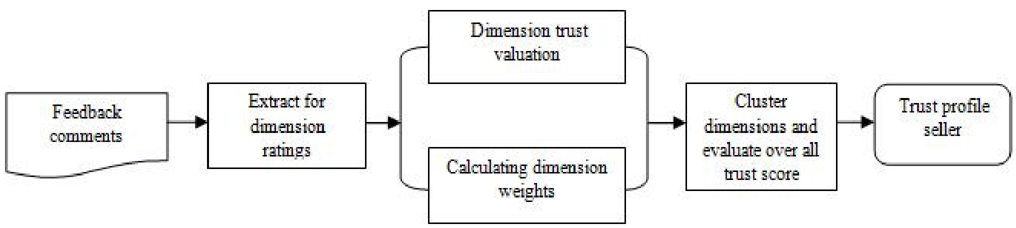

Figure 1: The CommTrust framework

The below equation 1 is used to compute trust score and weights for overall trust score evaluation .

Equation 1: A complete trust score is weighted for a seller is accumulated using dimension trust score.

$$S = \sum_{n=1}^{m} s_n \; * \; w_n \qquad (1)$$

Where $s_n = trustscore$ and $w_n = weight$ dimensioned where $n(n = 1..m)$.

The below equation 2 is used to compute dimensions trust scores.

Equation 2: Given n positive (+1) and negative (-1) ratings towards dimension i, $n = |\{v_d \, | v_d = +1 \, \forall \, v_d = -1\}|$, the trust score for d is:

$$s_d = \frac{|\{v_i = +1\}| + 1/2 * m}{n + m} \qquad (2)$$

The above equation is called m-estimated [12]. s_d = [0.1] and [0.5] which represents a constant trend for truth valuation. In equation 2, m is a hyper parameter which may be in peusedo counts - 1/2 $*\, m$ for the positive and negative. The further genuine considerations are required to review the real, constant trust score of 0.5, which represents the higher value of m. By proposing the previous delivery use the super-parameter m, importantly, the modification may decrease the positive preference in ratings, supremely although a finite number of negative and positive ratings [2].

4. MINING FEEDBACK COMMENTS FOR RANKING

In this section we present the dependency relation analysis for each feedback comment that helps in the generation of trust score for seller products. This also presents an algorithm for LDA which is used to calculate dimension weights and rating.

4.1. Typed Dependency Relation Analysis For Extracting An Expression And Rating

The typed dependency relation analysis [4] tool currently refined in natural language processing (NLP) and it is used to interpret grammatical errors in sentences. With typed dependency relation parsing, a set of dependency relation represented [4] by a sentence between a couple of words in the type of (dependent, head), heads are given as content words and other similar words as turn on the heads as shown in Figure. 2. Whenever a comment indicates an opinion pointing to dimensions, hence opinion words and dimension words must form some dependency relations. Words are additionally commented on their parts of speech tags functioning as an adjective (ADJ), adverb (AVB), noun (NN) and verb (VB). The dimension expressions pointing to head terms by ratings are analyzed by distinguishing the prior polarity changes terms through an opinion of a user's lexicon SentiWordNet. The previous polarity of the words in SentiWordNet consists of Positive, neutral and negative and that compare to the ratings of +1, 0 and -1.

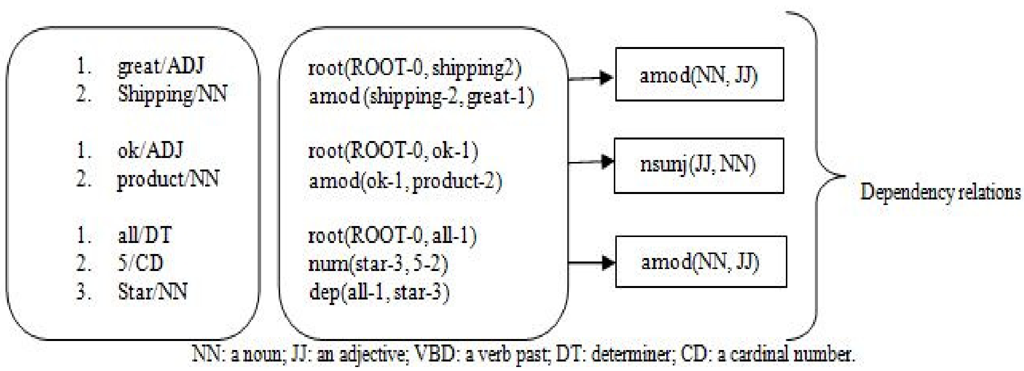

Figure 2: Typed dependency relation analysis

4.2. Clustering Dimensions

The Lexical-LDA algorithm is proposed to cluster expressions into semantically called dimensions. In the topic-modeling technique, it assumes the file as input by using term matrix, for effective clustering Lexical-LDA that allows shallow lexical knowledge in dependency relations for the topic modeling.

Lexical knowledge makes use of two types of supervise clustering dimension expressions that are helpful in the generation of appropriate clusters.

- Comments are small, hence re-occurrence of a head condition are not exact instructive. Rather, re-occurrence of dimension expressions a pone consideration to the same change across comments is used, and it possibly considers other relevant terms for dimension expressions.
- As recognized in few conditions to the similar condition of e-commerce purchases are commented n number of times in feedback comments.

Under this topic modeling, clustering complication is formulated as follows: the distribution of topics generates dimension expressions for the equal change term or negation of a change term. The distribution of head terms generates each and every topic successively. The above confess to adapting the structured dependency relation illustration from the dependency relation parser for clustering. Dependency relations will be input for lexical-LDA for dimension expression in the form of (head, modifier) couples, or their denial like (quick, shipping) or (bad, seller).

4.3. Lexical LDA-Evaluation

In the feedback comments set of informal language, expressions used. Before processing is performed, and then spelling correction is applied. For example: let us consider “thankx” is replaced by “thanks”. Then, the Stanford dependency parser was utilized to generate the dependency relation representation of the comments and dimension expressions were abstracted. Lexical- LDA algorithm is applied to cluster dimension expression into dimensions, then finally after the computing trust score for seller’s figure 3.

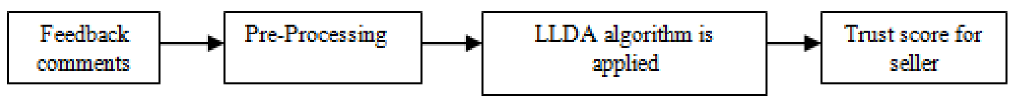

Figure 3: Mining feedback comments

Algorithm 1: Variational inference algorithm for the LDA

Input: A No of cases L
Corpus with P files, Q terms in a file d
Output: A Model parameter: β, θ, z
$\emptyset_{ni}^{0} := 1/l$ for all i and n
$\gamma_i := \alpha_i + Q/l$ for all i
repeat
for $n = 1$ to Q
for $i = 1$ to L
$\emptyset_{dni}^{t+1} := \beta_{iwn} \exp\left(\varphi\left(\gamma_{di}^{t}\right)\right)$
normalize $\emptyset_{dni}^{t+1}$ to sum to 1
$\gamma^{t+1} := \alpha + \sum_{n=1}^{N} \emptyset_{dn}^{t+1}$
until convergence

The varitional inference method in above-shown algorithm 1, γ and $\emptyset_n$ are starting points. The pseudo code is understandable with every iteration in varitional interference requires $O\left((Q+1)L\right)$, in the file number of iterations are necessary required for each and every file on the order of words in the file. Approxmently produced total operations are $Q^2 L$.

5. Experimentation And Results

The model is experimented in Net Beans IDE with MySQL environment. We have taken 1000 users feedback comments extracted from the Amazon for MP3 player products. These feedback comments are based on the item, shipping, communication, and cost. The DSRs are used to rate seller, that helps the customer to buy standard products. In the following figure 4 & 5, dataset information is exported with three buttons, the first button is to browse the user datasets and then click on the view button to view the dataset information and these datasets are extracted and load the data into the database and click on the next button this direct to a dependency analysis page.

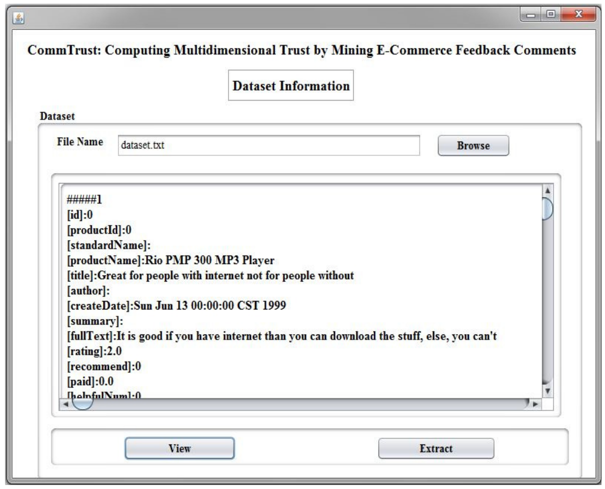

Figure 4: Dataset Information

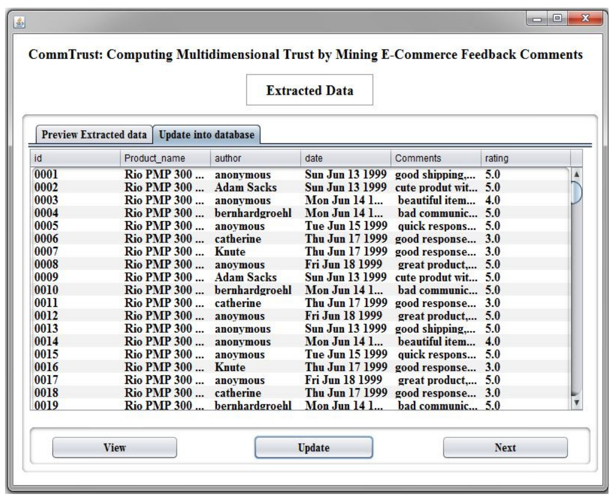

Figure 5: Extracted Data

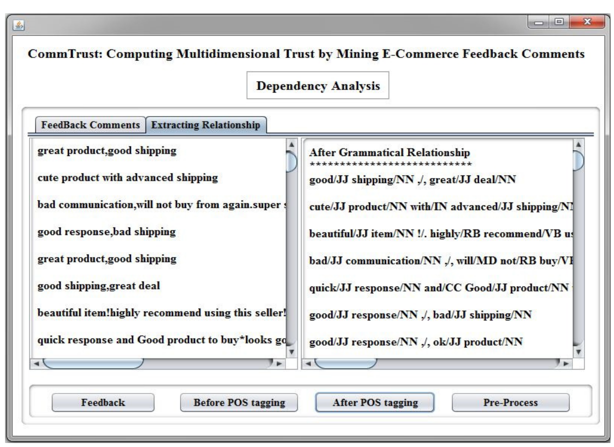

Figure 6: Dependency Relation Analysis

The figure 6 shows the dependency analysis page. In this user feedback comments are viewed because in each comment dependency relation identifies the parts of speech tags for each category like noun, verb, adjective, and adverb etc. For example: as shown below before POS tagging comment like: good shipping, a great deal and after POS tagging comment like: good/ADJ shipping/NN, great/ADJ deal/NN and then click on the pre-process button, this ends with dependency relation.

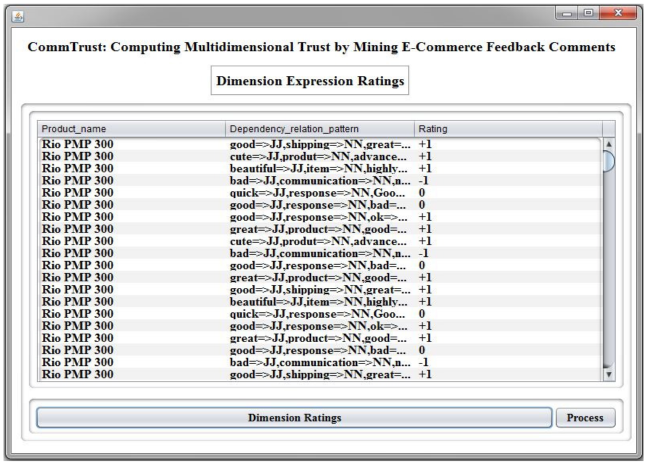

Figure 7: Dimension Expression Rating

The figure 7 shows dimension expression ratings pointing to head terms are analyzing by distinguishing the prior polarity of change terms through an opinion of a user's lexicon SentiWordNet. The pervious polarity of the words in SentiWordNet Consist of positive, neutral and negative and that compare to the ratings of +1, 0 and -1. Here, the +1 rating is given to the positive feedback comments, the 0 rating is given to the neutral feedback comment like a semi-positive and semi-negative and -1 rating is given to the negative feedback. Then click on the process button.

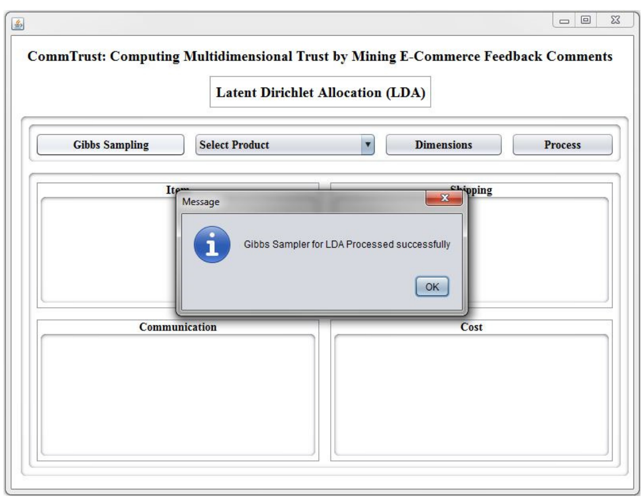

Figure 8: Gibbs Sampling

The figure 8 shows LDA window it consists of four buttons they are Gibbs sampling, product selection, dimensions and process. If we click on Gibbs sampling it is a generative model for

LDA process and the dimensions are divided into four expressions such as item, shipping, communication and cost. This is shown in figure 9. In this process we have to select a product after that click on the dimension button and we can view dimension words. Now click the process button.

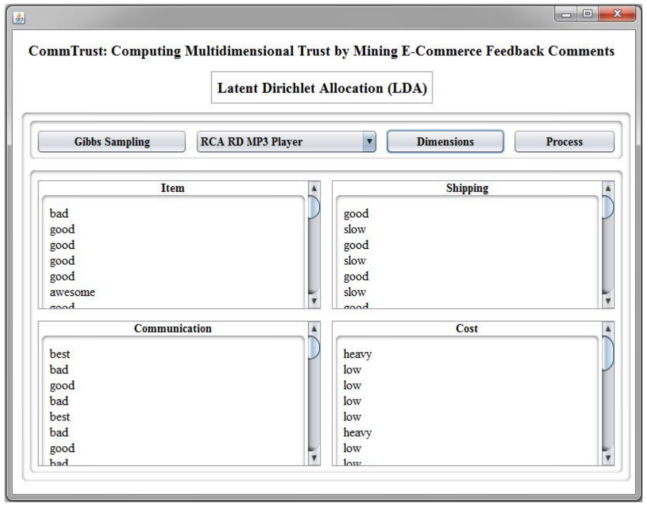

Figure 9: Dimension Expressions

Next, the Lexical-LDA algorithm is used to cluster aspect expression and these dimension expressions are the input for LDA. In this process figure 10 shows a weight and trust score button. It is used to calculate the dimension trust scores and weights for each product and click on the select product and evaluation button then we can view the dimension scores for the product as shown in the figure.

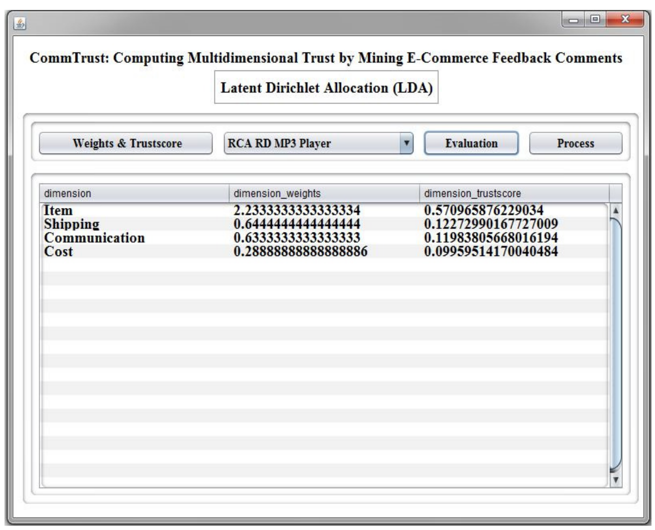

Figure 10: Weights and Trust score

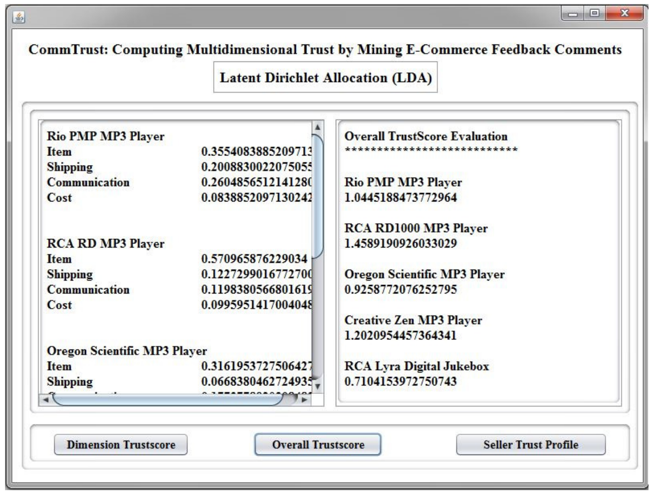

Figure 11: LDA Clustering

The Figure 11 shows the main LDA process, it is carried out in cluster formation for products, in the below screenshot it shows the dimension trust score for different products and these dimensions are clustered, it is called overall trust score evaluation. Now click on the seller trust profile.

The following graphical representation figure 12 shows the trust score for dimension expressions like item, shipping, communication and cost for different mp3 player products.

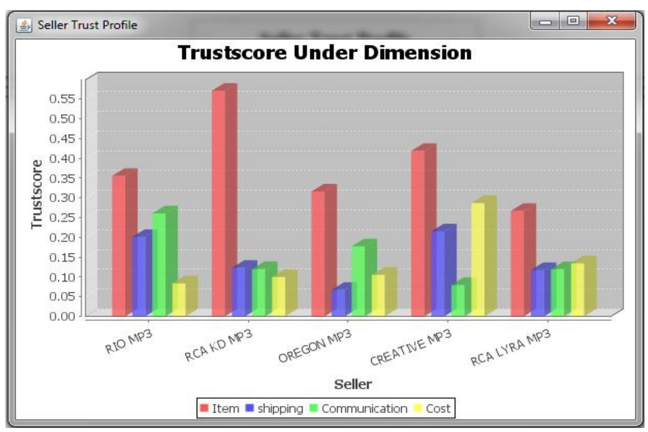

Figure 12: Trust score Dimensions

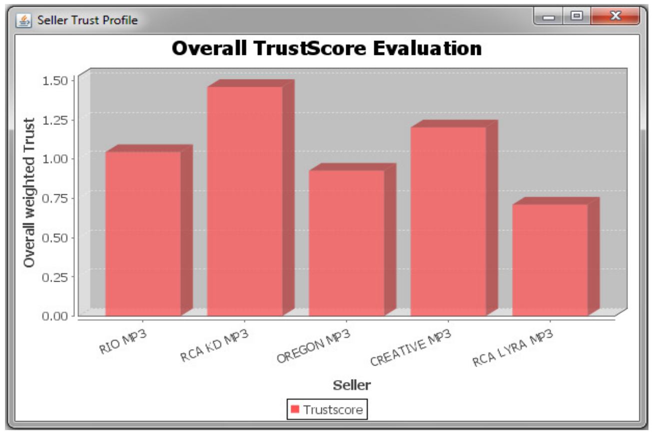

Figure 13: Over all Trust score Evaluation

The figure 13 shows comparison between the products with respect to scores. These scores are assigned for each product now the buyer can choose the trustworthy seller based on the overall trust score.

6. CONCLUSION

The "reputation system" problem is well known on popular websites like Amazon eBay etc. High reputation scores cannot rank sellers effectively so the customers are misguided to select genuine and trustable sellers. As observed that the buyers give their negative opinions in free text feedback comments fields, although they provide higher ratings. In this paper, we presented a multi-dimensional trust valuation model for calculating comprehensive trust profiles for sellers. The trust valuation model also includes an effective algorithm that computes dimension trust scores and dimension weights by extracting feature opinion expressions from feedback comments and clustering them into dimensions. By combining the NLP (natural language processing) with opinion mining can evaluate the trustworthy sellers in the e-commerce application. All inclusive experiments on feedback comments for Amazon sellers determine that our technique figures out trust score in an impressive way and rank sellers.

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