

Multi-Dimensional Trust Evaluation from Mining of E-Commerce Feedback Comments

Priyanka Kumbhar
Computer Engineering Department
G.H.Raisoni college of
engineering,Wagholi,Pune
Maharashtra,India

Manjushree Mahajan
Computer Engineering Department
G.H.Raisoni college of
engineering,Wagholi,Pune
Maharashtra,India

ABSTRACT

Generally Electronic commerce or E-commerce applications such as EBay and Amazon use reputation reporting system for trust evaluation where they gather overall feedback ratings from the sellers to compute the reputation score for a seller. The main issue raised with the reputation conduct system is “all good reputation” problem where most of feedback ratings are positive leading to high reputation scores for all sellers. In this case it is difficult for buyers to select the best or accurate seller that he/she can buy from. So in order to overcome this issue we propose an approach called the Comm Trust which evaluates the multidimensional trust for seller by analyzing buyer’s opinions on free text feedback comments. The main idea behind reputation analyzer is an algorithm CommTrust algorithm which is a topic modeling technique proposed for mining the online feedback comments by grouping aspect expressions into dimensions and compute dimension ratings for a seller.

Keywords

NLP, Topic Modeling, Social network, Recommendation System, Similarity graph, etc.

1. INTRODUCTION

In e-commerce applications, the fundamental goal is consolidates towards generating the accurate trust. Various popularity methods are exist which provides the entire trust ranking to support the buyer to select sincere dealer out of a set of dealers. So here we need the exact trust evaluation which is important for each e-commerce system for its acquirement. However the current methods fail to generate the precise trust ranking because these only concentrate on the advantageous scores. Here in these systems the all magnificent goodwill is fundamental problem for these methods. If we consider an example of EBay which is immensely one-sided towards the positive review these advantageous preconception cannot data buyers to prefer the dealer to handle with. By studying the data in the feedback comments posted by users we can approximate users opinions to evaluate whole trust in user profile for supplier. For example of opinions “Mobile is good but Battery Backup is poor” intimates the positive opinions towards elements part and also show the Negative part in feedback comments. So here with exploration e-commerce reviews comments comprehensive trusts in data are prepared for Sellers by combining dimension ratings and weights plus general trust ratings by collecting dimension ratings. By using data mining on e-commerce reviews feedback is the initial bit of task that numbers fine-grained multidimensional believe in profiles sequentially by exploration reviews comments.

To concentrate on opinion view point case from review and cluster their opinions with preprocessing and calculates

trustworthy relation by using natural language processing. We are using here CommTrust algorithm computation concentrated around trustworthy concerned analysis to cluster based prospective assert into computation and sign-up collect dimension evaluation and weights. Classification is operates on the trustworthy regards demonstration of situation viewpoints elucidation. And finally find the best sellers profiles and comparisons between them.

The main objective of project is a comprehensive trust profiles for sellers that allows users to conduct their online shopping based on past experience. We are mainly working on extracting dimension ratings from feedback comments and further aggregating, preprocessing, clustering these dimension ratings to compute dimension trust scores of particular sellers.

2. PROBLEM STATEMENT

In e-commerce applications sellers provide products and services to buyers and buyers pay for them. While the process of finishing these transactions firstly the quality of products second communication of sellers (whether the seller has friendly communication with buyers), third delivery time (whether the seller delivers items on time) and fourth shipping charges (whether the charges are reasonable).

These are some of the dimensions which buyers are interested mostly. In online feedback comments various customers describe different aspects of dimensions in the comments. So in order to accurately identify these dimensions expressed in natural language textual comments is our second task. for that we used the dataset and do mining on that dataset. And getting result in the form of best sellers profile.

3. LITERATURE REVIEW

There have been rise of different models to find out the ranking of sellers from the customer feedback comments. Customer feedback can be of any type like rating, second grading or through textual comments. So based on the feedback taken into consideration there are number of models are classified.

3.1 Centralised Reputation Systems

In centralized reputation systems the information about the performance of a participant is collected from other members in the community who have had transacted with this given participant as ratings. Here the central authority is the main that collects all the ratings and derives a reputation score for every participant in the reputation systems, and then these scores are made publicly available to all users. So based on this scores participants can choose between the other members to transact with. Ratings are given to the central authority after each transaction. The main functioning of the reputation centre is to collect all the ratings and continuously

updates the scores of the participants and is made visible to all other members of system.

3.2 Distributed Reputation Systems

In distributed reputation system, as the name implies, there is no central location for submitting ratings or for obtaining scores of others. Here the concept of Distributed stores [8] is present where ratings are collected or each participant records their experience with every other member they transacted with and further this information will be shared to relying parties requesting this information. These parties should get ratings from other members who had transacted with the target parties before committing various transactions. Here the relying parties compute the reputation scores solely based on the received ratings from other members. In case if the relying party has got any direct previous experience with the target party then that experience can be taken as private information and it has more weights as compared to the received rating of other members.

3.3 Rating Aggregation Systems

In rating aggregation systems trust relationship [12] is build using ratings. We can also called this as recommendations or feedbacks. The main user of the Rating aggregation algorithms are used to build up trust relationship. There have been so many applications have been proposed using rating aggregation algorithms. Out of these algorithms complex algorithms are not always cost effective and resistant to fake ratings by users. There is one system named Review aggregator which is o using rating aggregation algorithm [10]. In this system it stores different reviews and makes use of these to support websites where the users can read the reviews about the products, and also company databases are created to evaluate their customers and many other activities can be done. Each review would be assigned a numeric value based on the positive expression or polarity expressed in that particular review and based on that an average score is made.

3.4 Opinion Mining Systems

Sentiment analysis or opinion mining refers to natural language processing (NLP) and computational linguistics which identify and extract subjective information [9] from the respective source. This also involves methods like text analysis, feature extraction. The opinion mining targets to determine the polarity of a document with respect to some context. It mainly looks in determining different opinions expressed by different authors about specific topics. The sentiments can be of different types for the same topic. Here we can find the accuracy in each opinion by measuring from human judgment activities.

So there are many researches done on reputation calculation, here in our proposed work, for the first time, we are looking to calculate the multidimensional trust score for sellers. Users can view the multidimensional scores of sellers and selects the best sellers.

Another concept come into the picture such as Opinion mining is also called sentiment analysis which is a part of natural language processing and computational linguistics which identify and extract subjective information [7] from the source like comments, reviews. The main part of these systems is text analysis. Here the concept opinion mining targets to determine the polarity of a document with respect to some context of the text. Further it determines the different

opinions expressed by different authors about some topics. The methods used for Accuracy measurement are precision or recall functions.

4 IMPLEMENTATION DETAILS

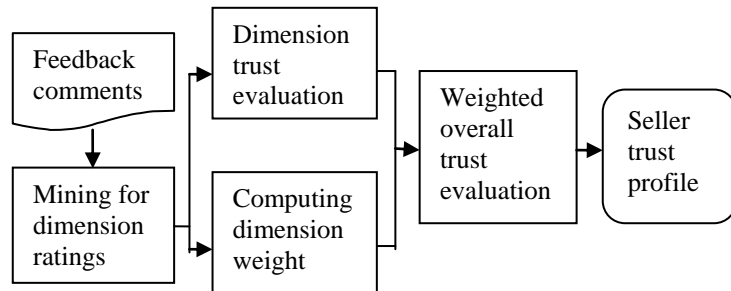


Fig1: System Architecture

Our approach consisting of number of modules, first starting with typed dependency relation parsing analysis to extracting aspect opinion expressions and identifying their associated ratings from feedback comments for each seller by using a sentiwordnet tool. Further based on these dimension expressions we implement our LDA based algorithm for clustering dimension expressions into dimensions, preprocessing the review comments and computing dimension weights [1].

Next we described these modules in detail

4.1 Preprocessing And Type Dependency Relation Parsing

The preprocessing and parsing on review comments is also main part ,type dependency relations parsing [12][13] is a method where we can represent a sentence as a set of dependency relations between pairs of words in the form of (*head, dependent*) expressions, In this content words are chosen as heads whereas other related words depend on the heads. Consider an example In order to parse this we are using standard library named Stanford NLP parser.

The output of NLP parser is dependency relations expressing grammatical relationships. Out of these grammatical relations, we select the relations that express the modifying relation first adjectives and nouns, second adverbs and verbs. The adjectives, verbs, nouns are already we get through standford parser. As we gone through the comments we can say that the modifying relations generally the noun or verb expresses the target concept under consideration, and the adjective or adverb expresses opinion towards the target concept. So here we are representing the modifying relations as (*modifier, head*) pairs. These pairs can be called as Dimension expression in our work.

4.2 Dimension Rating finding

Further from these dimension expressions we are looking to find out the ratings towards the head terms are identified by identifying the prior polarity of the modifier terms by SentiWordNet library. Sentiwordnet is a public opinion lexicon library used for polarity finding. The different polarities given by Sentiwordnet are positive, negative and neutral. These polarities can be represented as ratings of +1, -1 and 0.

4.3 Clustering aspect Expressions

Next we used LexicalLDA algorithm in order to cluster aspect expressions that is modifier head pairs in Dimensions. We are naming this algorithm as Lexial LDA because we are providing input to the LDA as dimension expressions which are in the form of (Modifier, Head).

The overall commtrust algorithm pseudo code for the proposed work is shown below

Algorithm

CommTrust Algorithm Pseudo code: -

Input: - Sellers S, User feedbacks C, input dimension training dataset D

Output: - Seller trust profile

For each seller $s \in S$ do

For each comment $c \in C$ do

$c_sentences \leftarrow divide_into_sentences(C)$

for each $c_sent \in c_sentences$ do

$s_tokens \leftarrow tokenization(c_sentence)$

$d_score \leftarrow match(s_tokens, D)$

$where d_score - dimesion_score$ for sentence

end for

$m_d_score \leftarrow cal_multidimesion_comment_score(d_score, c_sent)$

where $m_d_score - multidimensional$ score of each comment

end for

overall_seller_profile =

$$\frac{\sum m_d_score1 + m_d_score2. + \dots + m_d_score n}{n}$$

end for

All above modules we can represent mathematically as follows:

4 MATHEMATICAL MODEL

The system W can be represented as,

$$S = \{ U, S, C, D, W, TD \} \quad (1)$$

Consider a set U as a set of users registering with our system which is represented as,

$$U = \{ U_1, U_2, U_3, \dots, U_n \} \quad (2)$$

Where U_n - users of system

Now consider another set S, a set of sellers selling their products through e-commerce application. Which can be represented as,

$$S = \{ S_1, S_2, S_3, \dots, S_n \} \quad (3)$$

Various users can buy products through this shopping portal , these products posted by various sellers. After getting a product users give feedback to the seller related to various dimensions such as quality, shipping.

Here we are considering a set C as feedback comment set we are using to analyze multidimensional trust of a seller which can be represented as,

$$C = \{ C_1, C_2, C_3, \dots, C_n \} \quad (4)$$

$$D = \{ D_1, D_2, D_3, \dots, D_n \} \quad (5)$$

which is a set of dimensions which we are using to evaluate the trust score of each seller.

Now each dimension have a certain weight w which can be represented in setW as follows,

$$W = \{ W_1, W_2, W_3, \dots, W_n \} \quad (6)$$

For mining the comments we are using multidimensional comment mining algorithm presented above.

The set

$$TD = \{ TD_1, TD_2, TD_3, \dots, TD_n \} \quad (7)$$

which is a set of dimension trust score for each seller.

In order to find out the overall trust score of a seller we have to aggregate the dimension trust scores of each dimension as,

$$T = (\sum TD_1 + TD_2 + \dots + TD_n) / (n) \quad (8)$$

This score T represents the overall trust score of seller .So we are here showing the multidimensional as well as the total overall score of a seller to the user of a system.

5 RESULTS

We have developed our project using Core Java, Swing and mysql database. In order to test our results we are using feedback datasets, crawled from <http://feedback.ebay.com/ws/eBayISAPI.dll?ViewFeedback2> for different sellers.



Fig 2: The project GUI

The graph following shows the different sellers trust profile consisting of positive and negative score per dimension calculated using above proposed mechanism. One of the sellers trust score and the various dimensions we are showing here are Shipping, Service and Quality

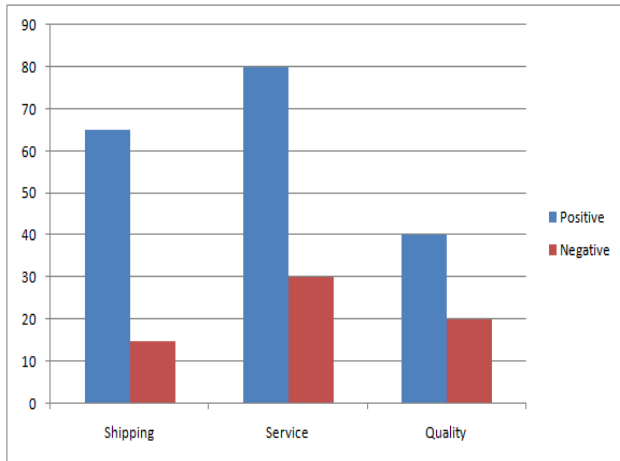


Fig 3: Different sellers trust profile consisting of positive and negative score per dimension

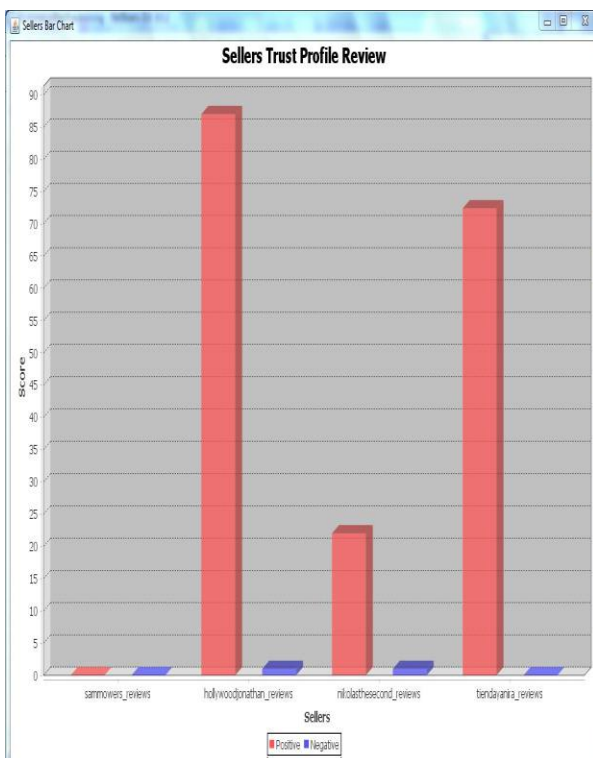


Fig 4: Different sellers dimension trust score comparison graph

6 CONCLUSION

We have proposed a multi-dimensional trust evaluation model for computing comprehensive trust profiles for sellers in E-commerce sites. Here we compute dimension trust scores and dimension weights automatically via extracting dimension ratings from feedback comments and aggregating with feedback rating using on sentiwordnet library and LDA algorithm. Based on this trust scores we can distinctively identify the reputable sellers from another seller that have had bad history with previous buyers. Another important thing here that we have overcome is “All good reputation” as the ratings are more reasonable and acceptable not like all sellers have high scores. So our proposed work can significantly reduce the strong positive bias in e-Commerce reputation systems. This model is good assistance to the buyers when

doing online shopping in order to get prevented from being a victim of fraud and untrusted sellers.

7 FUTURE WORK

In future work, we can improve mining methods to identify terms more accurately and the comments with more word count by storing them in database and Review can be multi languages so that can more efficient to users and which would improve the overall accuracy of the rating system.

8 REFERENCES

- [1] Xiuzhen Zhang, Lishan Cui, and Yan Wang, "Computing Multi-Dimensional Trust by Mining E-Commerce Feedback Comments " IEEE TRANSACTIONS ON KNOWLEDGE AND DATA ENGINEERING VOL:26 NO:7 YEAR 2014
- [2] P. Resnick and E. Friedman, "Reputation Systems: Facilitating Trust in Internet Interactions," *Communications of the ACM*, vol. 43, pp. 45–48, 2000
- [3] P. Thomas and D. Hawking, "Evaluation by comparing result Set in context," in Proc. 15th ACM CIKM, Arlington, VA, USA, 2006, pp. 94101. Department
- [4] X. Wang, L. Liu, and J. Su, "RLM: A general model for Trust representation and aggregation," *IEEE Trans. Serv. Comput.*, vol. 5, no. 1, pp. 131143, Jan-Mar, 2012.
- [5] H. Zhang, Y. Wang, and X. Zhang, "Efficient contextual transaction trust computation in e-commerce environments," in Proc. 11th IEEE TrustCom, Liverpool, UK, 2012.
- [6] S. D. Kamvar, M. T. Schlosser, and H. Garcia-Molina, "The EigenTrust algorithm for reputation management in P2P networks," in Proc. 12th Int. Conf. WWW, Budapest, Hungary, 2003.
- [7] G. Qiu, B. Liu, J. Bu, and C. Chen, "Opinion word expansion and target extraction through double propagation," *Comput. Linguist*, vol. 37, no. 1, pp. 927, 2011.
- [8] M. Hu and B. Liu, "Mining and summarizing customer reviews," in Proc. the fourth Int. Conf. on KDD, 2004, pp. 168–177.
- [9] G. Qiu, B. Liu, J. Bu, and C. Chen, "Opinion word expansion and target extraction through double propagation," *Computational linguistics*, vol. 37, no. 1, pp. 9–27, 2011.
- [10] L. Zhuang, F. Jing, X. Zhu, and L. Zhang, "Movie review mining and summarization," in Proc. the 15th ACM Int. Conf. on Information and knowledge management, 2006, pp. 43–50.
- [11] J. O'Donovan, B. Smyth, V. Evrim, and D. McLeod, "Extracting and visualizing trust relationships from online auction feedback comments," in Proc. IJCAI'07, 2007, pp. 2826–2831.
- [12] M. De Marneffe, B. MacCartney, and C. Manning, "Generating typed dependency parses from phrase structure parses," in Proc. LREC, vol. 6, 2006, pp. 449–454.
- [13] M. De Marneffe and C. Manning, "The stanford typed dependencies representation," in Proc. the workshop on Cross- Framework and Cross-Domain Parser Evaluation, 2008.