A Multi-Dimensional Trust Model and Fuzzy Decision System for E-Commerce

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Abstract— Reputation-based trust models are widely used in E-Commerce applications, and feedback ratings are aggregated to compute sellers reputation trust scores. Based on the observation that buyers often express opinions openly in free text feedback comments, it have proposed Comm Trust, a multi-dimensional trust evaluation model, for computing comprehensive trust profiles for sellers in E-Commerce applications. Different from existing multi-dimensional trust models, here compute dimension trust scores by extracting dimension ratings from feedback comments. Based on the dependency relation parsing technique, it have proposed DR-mining approaches to mine feedback comments for dimension rating profiles. Also when a new product arrives in the E-Commerce application, it doesn't have any feedback associated with it. Hence it also introduces fuzzy logic into rule definition for preferences of venders and designs a novel agent-based decision system using fuzzy rules and reasoning mechanisms to find the right product from a trustworthy vender according to users preferences.

Key words: Trust Model, Fuzzy Decision System, E-Commerce

I. INTRODUCTION

There has been a tremendous growth in E-Commerce applications, where buyers and sellers conduct transactions on the web. Users are attracted to online-shopping not only due to the convenience in accessing the information of items on-sold, but also because of the availability of other buyers feedback on their purchasing experience, item-related and/or seller-related. All major online-shopping websites encourage buyers to provide feedback, often in the form of ratings along with some textual comments, to facilitate potential transactions.

Reputation reporting systems have been implemented in E-Commerce systems such as eBay and Amazon (for third-party sellers), where overall reputation trust scores for sellers are computed by aggregating feedback ratings. In E-Commerce environments, reputation mechanisms are related to the ratings that a seller received from buyers. The ratings indicate the ability of the seller to provide satisfactory transactions in the future, which is beneficial to new buyers. For example on eBay, the reputation score for a seller is computed by aggregating buyer feedback ratings in the past 12 months, such as either the total number of positive ratings minus the total number of negative ratings or the percentage of positive ratings out of the total number of positive ratings and negative ratings.

A well-reported issue with the eBay reputation management system is the "all good sellers" problem [1], [2] where feedback ratings are over 99% positive on average. Such strong positive bias can hardly guide buyers to select sellers to transact with them. At eBay detailed seller ratings for sellers (DSRs) on four aspects of transactions, namely item as described, communication, postage time, and postage and handling charges are also reported. DSRs are aggregated rating scores on a 1 to 5 star scale. Still the strong positive bias is present. One possible reason for the lack of negative ratings at E-Commerce web sites is that users who leave negative feedback ratings can attract retaliatory negative ratings and thus damage their own reputation [1]. The textual comments can provide detailed information that is not available in ratings. Even though buyers leave positive feedback ratings, they still express some disappointment and negativeness in free text feedback comments [3] often towards specific aspects, or dimensions of transactions. For example, a comment like "The products were as I expected." expresses positive opinion towards the Product dimension, whereas the comment "Delivery was a little slow but otherwise, great service. Recommend highly." expresses negative opinion towards the Delivery dimension but a positive rating to the transaction in general. There are several reasons why comments provide more reliable information. First, ordinal ratings are interpreted differently by different users. Some users tend to rate higher while others tend to rate lower. Secondly, most online shopping websites also allow sellers to rate the buyers to counter-balance the impact of malicious buyers. Since the average rating could affect the sales greatly, sellers may use this mechanism as a weapon to defend their business, rating down buyers who provide low ratings on their purchase. As such, the mechanism effectively leads to pseudo high ratings than what comments are reflecting. From the buyer's perspective, while the average rating may not be a fully reliable measure, it is the only easily accessible measure. Browsing through tens of pages of comments can be time consuming, and to digest the information is a daunting task, as well. This calls for a better measure to represent the reputation of seller accurately. Such reputation is sometimes referred to as trust, which is defined as "the extent to which one party measures the other party's willingness and ability to act in the measuring party's interest".

By analyzing the wealth of information in feedback comments it can uncover buyers embedded opinions towards different aspects of transactions, and compute comprehensive reputation profiles for sellers. Specifically using the positive and negative subjectivity of opinions towards aspects of transactions as dimension ratings, it can propose Comment-based Multi-dimensional trust (Comm Trust),a fine-grained multi-dimension trust evaluation model for E-Commerce applications. Unlike conventional topic modelling formulation of unigram representations for textual documents [4], [5] the proposed method is based on the dependency relation representations of aspect opinion expressions.

Here it propose to use Comment-based Multi-dimensional trust (Comm Trust), a fine grained multi-dimension evaluation model [6] ,to calculate the trust for e-commerce applications. While the model is potentially extensible to target item-specific trust, in this study mainly focus on computing comprehensive trust profile for sellers. With the dimension words it propose Dimension Rating mining (DR-mining) [7] a knowledge-based approach that incorporates domain knowledge, meta-data, and general grammatical patterns to accurately identifying dimension rating expressions from feedback comments. It also introduces a fuzzy decision system to recommend sellers for a new product that arrives in the Ecommerce application in which no feedback comments are associated with it.

II. RELATED WORK

Lishan Cui, Xiuzhen Zhang, YanWang, and Lifang Wu, “Mining E-Commerce Feedback comments for dimension rating profiles” introduced opinion mining on regular documents like movie reviews and product reviews has been intensively studied. It mainly focus on opinion mining on short e-commerce feedback comments [7].

The main aim is to compute a comprehensive rating profile for sellers comprising of dimension ratings and weights. Thus it propose an algorithm to mine feedback comments for dimension ratings, combining opinion mining and dependency relation analysis, a recent development in natural language processing and formulate the problem of computing dimension weights from ratings as a factor analytic problem and propose an effective solution based on matrix factorization. Dimension words are learned from DR-patterns annotated with dimension labels and ratings. For example the dimension-rating pairs (shipping, super) and (shipping, quick) are labelled with the Delivery with rating of +1 (positive).Given a dimension and the candidate dimension words, apply association rule mining to decide a set of dimension words for the dimension.

A. Mukherjee, B. Liu, “Aspect Extraction through Semi-Supervised Modeling” stated aspect extraction is a central problem in sentiment analysis [8]. Current methods either extract aspects without categorizing them, or extract and categorize them using unsupervised topic modeling. By categorizing, they mean the synonymous aspects should be clustered into the same category. However solve the problem in a different setting where the user provides some seed words for a few aspect categories and the model extracts and clusters aspect terms into categories simultaneously. This setting is important because categorizing aspects is a subjective task. For different application purposes, different categorizations may be needed. Some form of user guidance is desired. Hence it propose two statistical models to solve this seeded problem, which aim to discover exactly what the user wants.

I. Titov, R. McDonald , “Modeling Online Reviews with Multi-grain Topic Models” introduced a novel framework for extracting the ratable aspects of objects from online user reviews is proposed [9]. Extracting such aspects is an important challenge in automatically mining product opinions from the web and in generating opinion-based summaries of user reviews. Their models are based on extensions to standard topic modeling methods such as LDA and PLSA to induce multi-grain topics. Hence it argue that multi-grain models are more appropriate for our task since standard models tend to produce topics that correspond to global properties of objects (e.g., the brand of a product type) rather than the aspects of an object that tend to be rated by a user. The models here present not only extract ratable aspects, but also cluster them into coherent topics. The next major step in this work is to combine the aspect extraction methods presented here with standard sentiment analysis algorithms to aggregate and summarize sentiment for products and services. Currently there exist the investigation of a two-stage approach where aspects are first extracted and sentiment is then aggregated.This differentiates it from much of the previous work which extracts aspects through term frequency analysis with minimal clustering.

L. Zhuang, F.Jing, X.Zhu, L.Zhang, “Movie Review Mining and Summarization” proposed the review mining and summarization subtasks [10].The subtasks are Identifying feature words and opinion words in a sentence, Determining the class of feature word and the polarity of opinion word, For each feature word, first identifying the relevant opinion word(s), and then obtaining some valid feature opinion pairs, Producing a summary using the discovered information. A multi-knowledge based approach is needed to perform these tasks. It uses WordNet, movie casts and labeled training data were used to generate a keyword list for finding features and opinions .Grammatical rules between feature words and opinion words were applied to identify the valid feature opinion pairs. Reorganizing the sentences according to the extracted feature opinion pairs to generate the summary.

Z. Zhai, B. Liu, H. Xu, P. Jia, “Constrained LDA for Grouping Product Features in Opinion Mining” introduced opinion mining of product reviews, one often wants to produce a summary of opinions based on product features/attributes [11]. However, for the same feature, people can express it with different words and phrases. To produce an effective summary, these words and phrases, which are domain synonyms, need to be grouped under the same feature. Topic modeling is a suitable method for the task. However, instead of simply letting topic modeling find groupings freely, they believe it is possible to do better by giving it some pre-existing knowledge in the form of automatically extracted constraints. In this paper, they first extend a popular topic modeling method, called LDA, with the ability to process large scale constraints. Then, two novel methods are proposed to extract two types of constraints automatically. Finally, the resulting constrained-LDA and the extracted constraints are applied to group product features.

M. Hu, B. Liu, “Mining and Summarizing Customer Reviews” proposed a set of techniques for mining and summarizing product reviews based on data mining and natural language processing methods [12]. The objective is to provide a feature-based summary of a large number of customer reviews of a product sold online. The experimental results indicate that the techniques are very promising in performing their tasks. Hence it can believe that this problem will become increasingly important as more people are buying and expressing their opinions on the Web. Summarizing the reviews is not only useful to common shoppers, but also crucial to product manufacturers

III. PROPOSED SYSTEM

The feedback comments are considered as a source where buyers express their opinions more honestly and openly. The analysis of feedback comments on eBay and Amazon reveals that even if a buyer gives a positive rating for a transaction, s/he still leaves comments of mixed opinions regarding different aspects of transactions in feedback comments. Unlike existing trust models (including the one used on eBay) where explicit transaction feedback ratings (positive or negative) are used to compute overall trust scores for sellers. Aspect opinion expressions, and their associated ratings (positive or negative) are first extracted from feedback comments. Dimension trust scores together with their weights are further computed by aggregating dimension ratings.

A. The Comm Trust Model

Figure 1 depicts the Comm Trust framework. Aspect opinion expressions, and their associated ratings (positive or negative) are first extracted from feedback comments. Dimension trust scores together with their weights are further computed by clustering aspect expressions into dimensions and aggregating the dimension ratings. The algorithms for mining feedback comments for dimension ratings and for computing dimension weights will be described in the following section. In addition to the overall ratings of transactions, potential buyers often read the feedback comments to solicit opinions and ratings about sellers at finer granular levels. For example, a comment like "The products were as I expected." expresses positive opinion towards the Product dimension, whereas the comment "Delivery was a little slow but otherwise great service. Recommend highly." expresses negative opinion towards the Delivery dimension but a positive rating to the transaction in general.

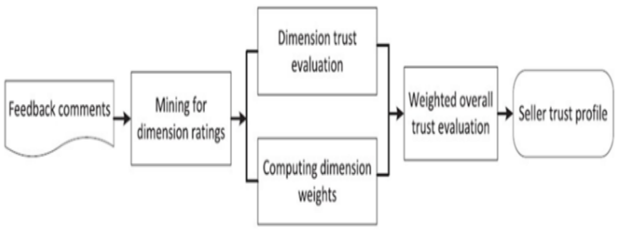

Fig. 1: Comm Trust framework.

By analyzing the wealth of information in feedback comments it can uncover buyers' embedded opinions towards different aspects of transactions, and compute comprehensive reputation profiles for sellers. Hence call the aspects of transactions dimensions and the aggregated opinions towards dimensions dimension ratings. To compute a comprehensive reputation profile for sellers for E-commerce applications, comprising dimension ratings and dimension weights is the main aim.

B. DR mining algorithm

The complete dimension-rating mining (DR-mining) algorithm for identifying dimensions and associated ratings from feedback comments is shown in Figure 2. Each comment is first analyzed .To identify dimensions in comments, the dependency relations resulted from parsing are first matched against the DR-patterns shown in Table 1.

Table 1: Dimension Rating Pattern

Dependency Relation	Patterns	Example
amod(NN, JJ) *adjective modifier*	amod(price/NN, great/JJ) amod(postage/NN, quick/JJ)	*Great price and quick postage,justgorgeous*
advmod(VB,RB)*adverbial modifier*	advmod(shipping/VB, fast/RB)	*very pretty, fast shipping.*
nsubj(JJ, NN) *nominal subject*	nsubj(prompt/JJ, seller/NN)	*this seller was very prompt.*
acomp(VB,JJ) *adjectival complement*	acomp(arrived/VB, quick/JJ)	*Great CD, arrived quick.*
dep(NN, RB) *dependent*	dep(shipping/NN, fast/RB)	*very fast shipping.*

If a DR pattern is found, first the dimension is identified. Dimension words are usually taken as the nouns and verbs in a comment. Modifiers are the adjectives and adverbs which are the associated words of nouns and verbs.

A dimension cluster is formed such that modifiers corresponding to each dimension are grouped in to corresponding dimension cluster. The opinion word and polarity for this modifiers of each dimension cluster is identified using the SentiWordNet opinion lexicon. If either the head or dependent word of a DR-pattern involves the negation relation, the relevant polarity is inverted. The opinion polarities positive and negative correspond to ratings +1 and -1, and nil opinion is deemed a neutral rating of 0. DR-mining thus produces a set of dimension ratings for a comment.

If a comment expresses opinion towards dimensions then the dimension words and the opinion words should form some grammatical dependency relations expressing the modifying relationship. It has been reported that phrases formed by adjectives and nouns, and verbs and adverbs express subjectivity. Among the dependency relations expressing grammatical relationships, select the relations that express the modifying relation between adjectives and nouns, and adverbs and verbs, as determined by the dimensions rating pattern table.

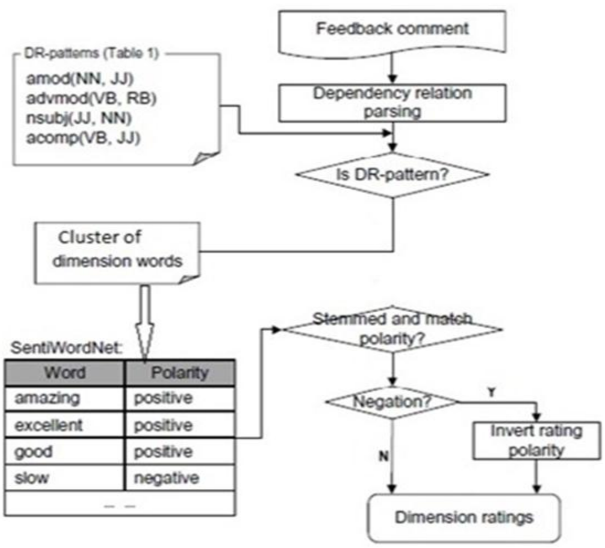

Fig. 2: DR mining algorithm

Based on the analysis of a sample dataset of eBay feedback comments for 10 eBay sellers, five types of dependency relations are found to frequently express dimension rating patterns (DR-patterns), as listed in Table 1. It can be seen that with the modifying relations generally the noun or verb expresses the target concept under consideration whereas the adjective or adverb expresses opinion towards the target concept. Thus it also call dimension word as head term, opinion word as modifier term, and the pair of (head term, modifier term) as dimension expression or aspect expression. For example, with the DR-pattern amod (price/NN, great/JJ), "price" is the head dimension word while "great" is the dependent opinion word.

C. Rating evaluation

Ratings from DR-patterns towards the head terms are identified by identifying the prior polarity of the modifier terms by SentiWordNet, a public opinion lexicon. The prior polarities of terms in SentiWordNet include positive, negative or neutral, which corresponds to the ratings of +1, -1 and 0. Hence apply a general opinion word lexicon SentiWordNet which is a widely used public domain NLP resource to identify opinion polarities. When (modifier, head) pairs are grouped into dimensions, the associated modifier terms express the opinion priority of dimensions.

It is well known that whether a word expresses opinion and the polarity associated with a word depend on context and vary for domains. SentiWordNet is a general opinion lexicon compiled from several application domains and their word annotations need to be reviewed to be applied to the e-commerce domain.

The overall trust score T for a seller is the weighted aggregation of dimension trust scores for the seller.

$$T=\sum_{d=1}^{m} t_d * w_d$$

Where t_d and w_d represent respectively the trust score and weight for dimension d (d = 1..m). The trust score for a dimension is estimated from the number of positive and negative ratings towards the dimension.

D. Fuzzy decision system

Rating of sellers is not possible when a new product arrives in ecommerce application. Hence Users are allowed to express their policies of the sellers of corresponding product. Fuzzy decision system will recommend a seller by applying fuzzy rules based on given policies.

This fuzzy decision system proposes a model of uncertainty based on fuzzy logic to handle uncertainty and fuzziness in decision process for e-shopping activities based on trustworthiness. The model identifies different sources of uncertainty in trustworthiness, and finds that this uncertainty cannot be simply treated as a probability and thus cannot be described by a simple probability model. This paper introduces a general categorization to describe various types of trustworthiness in practical e-commerce environments.

Membership function value of modifiers= ({Number of specified modifier in dimension cluster} / {Total number of modifiers in dimension cluster}) *100, where modifiers are the words in each dimension cluster. During the implementation of fuzzy recommendation system it used an open source library jFuzzy Logic. jFuzzy Logic supports many membership functions, many defuzzifiers, rule aggregation, rule implication and rule connection operators. It can create arbitrarily complex membership functions as well as variable parameterized ones. Mamdani model is utilized here for the developing of fuzzy recommendation system. Mainly triangular membership functions are used. Fcl file is generated for each sellers based on the fuzzy rules. Then a defuzzified value is generated for each seller. The seller who got the maximum defuzzified value will be recommended.

IV. EXPERIMENTAL RESULTS AND ANALYSIS

The experimental analysis are based on mainly five datasets. The datasets contains users reviews about the purchase of different products. Performance analysis is conducted to determine the dimension identification accuracy of the proposed DR mining algorithm and accuracy of the fuzzy recommendation system. Dimension words are usually taken as the nouns and verbs in a comment. Modifiers are the adjectives and adverbs which are the associated words of nouns and verbs. A dimension cluster is formed such that modifiers corresponding to each dimension are grouped in to corresponding dimension cluster.

Figure 3 shows the average accuracies of dimension identification for DR-mining and Hu&Liu mining on 2000 feedback comments related with tv dataset.

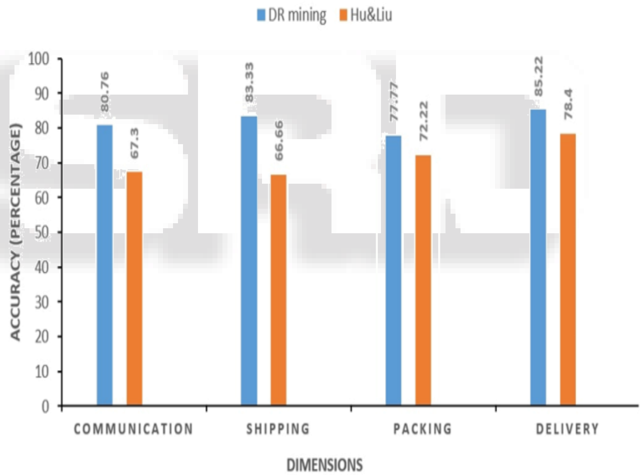

Fig. 3: Accuracy dimensions graph 1

DR-mining achieves accuracies up to 80.76% on the communication dimension, 83.33% on the shipping dimension, 77.77% on the packing dimension and 85.22% on the delivery dimension whereas Hu&Liu achieves accuracies up to 67.3% on the communication dimension , 66.66% on the shipping dimension, 72.22% on the packing dimension and 78.4% on the delivery dimension. Table 2 shows the actual rank and rank of sellers obtained from fuzzy system for the product tv of brand Sony. The rank of sellers for the product tv of brand Sony have identified first. Then the brand Sony of the product tv have removed from the database. The rank of sellers for the brand Sony of the product tv have identified again in fuzzy recommendation system. The variation of the ranks of the sellers can be used to evaluate the fuzzy recommendation accuracy.

Performance analysis shown in Table 2 indicates that fuzzy recommendation system achieves about 80% accuracy than that of actual value computed using DR-mining algorithm.

Table 2: Dimension Rating Pattern

Seller	Actual rank	Recommended rank
Bigbox	Rank 1	Rank 1
Saholic	Rank 2	Rank 2
Techmantra	Rank 3	Rank 3
Rc Deals	Rank 4	Rank 4
Ws Retail	Rank 5	Rank 4

Fig.4. shows the average accuracies of dimension identification for DR-mining and the Lexical LDA algorithm. Here also DR-mining significantly outperforms the Lexical LDA approach for identifying all dimensions.

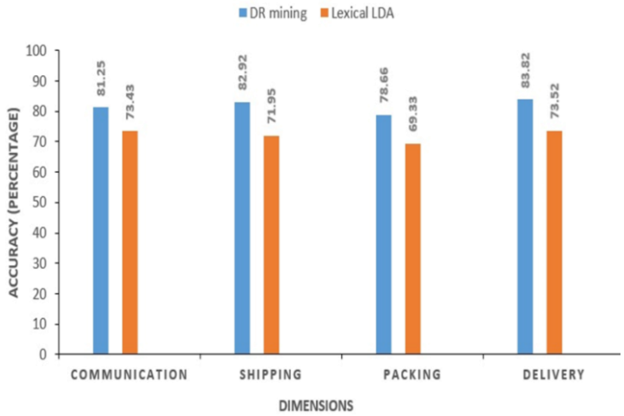

Fig. 4: Accuracy dimensions graph 2

DR-mining achieves accuracies up to 81.25% on the communication dimension 82.92% on the shipping dimension, 78.66% on the packing dimension and 83.82% on the delivery dimension whereas Lexical LDA achieves accuracies up to 73.43% on the communication dimension , 71.95% on the shipping dimension, 69.33% on the packing dimension and 73.52% on the delivery dimension. It have proposed an effective algorithm for mining short feedback comments for dimension ratings. Hence the DR mining approach achieves significantly higher accuracy for discovering dimension ratings in comments than a commonly used opinion mining approach.

V. Conclusion and Future Enhancements

The proposed model can distinctively identify the reputable sellers in E-commerce sites using feedback comments provided by the buyers. Moreover, the ratings are more reasonable, acceptable and not all sellers have high scores as compared to other reputation system. It can significantly reduce the strong positive bias in E-Commerce reputation systems and hence solve the “all good sellers” problem. The model is good assistance to the buyers while doing online transaction since it shields them from being a victim of fraud and untrusted sellers.

It have proposed DR mining algorithm which can effectively identify the dimensions for the trust score calculation of sellers. Rating of sellers is not possible when a new product arrives in ecommerce application. Hence Users are allowed to express their policies of the sellers of corresponding product. Fuzzy decision system will recommend a seller by applying fuzzy rules based on given policies.

The Comm Trust proposed here can be used to reliably evaluate the trustworthiness of sellers, however, it still need improvement to mine more detailed information from feedback comments. In on-line feedback comments, casual language is commonly used to express user’s opinion. For example, some users type in “prod” to refer as “product”. As the results of dimension terms, “prod” and “product” may both have to be identified. In future work, it can improve mining techniques to identify terms more accurately. Future work can explore the possibility of understanding the contents more in depth.

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