COMMTRUST SURVEY: Multidimensional Trust Computing

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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. The "all good reputation" problem however is prevalent in current reputation systems reputation scores are universally high for sellers and it is difficult for potential buyers to select trustworthy sellers. In this thesis, based on the observation that buyers often express opinions openly in free text feedback comments, we have proposed CommTrust, a multi-dimensional trust evaluation model, for computing comprehensive trust profiles for sellers in e-commerce applications. Different from existing multi-dimensional trust models, we compute dimension trust scores and dimension weights automatically via extracting dimension ratings from feedback comments. Based on the dependency relation parsing technique, we have proposed Lexical-LDA (Lexical Topic Modelling based approach) and DR-mining (Lexical Knowledge based approach) approaches to mine feedback comments for dimension rating profiles.

Keywords: E-commerce, CommTrust, text mining, Repudiation based models, Sentiment Analysis, Trust evaluation , Parse.

1. Introduction

We have proposed CommTrust, a multi-dimensional trust evaluation model, for computing comprehensive trust profiles for sellers in e-commerce applications. Our work aims to provide a comprehensive trust profiles for sellers that allows buyers to conduct their online shopping based on past experience. Our focus is on extracting dimension ratings from feedback comments and further aggregating these dimension ratings to compute dimension trust scores. The motivation of our research is that online feedback comments contain distinct information for users to rank sellers; therefore content of comments can be used to reliably evaluate the trustworthiness of seller.

The contributions of this thesis are:

- We propose to use Comment-based Multi-dimensional trust (CommTrust), a fine-grained multi-dimension evaluation model, to calculate the trust for e-commerce applications. While the model is potentially extensible to target item-specific trust, in this study we focus on computing comprehensive trust profile for sellers.
- We propose an algorithm to identify dimension rating expresses from feedback comments by applying lexicon-based opinion mining techniques in combination with dependency relation analysis, a tool recently developed in natural language processing.

We tackle the four research questions by two approaches:

1. The topic modeling approach is applied to develop the Lexical-LDA algorithm for grouping dimension rating extraction and trust computation. Lexical LDA makes use of two types of lexical knowledge based on dependency relations for clustering dimension expressions into dimensions so as to produce meaningful cluster. first lexical knowledge is that the co-occurrence of dimension expressions with respect to a same modifier across comments can provide more meaningful contexts for dimension expressions, compare to add on counts of dimension expressions by comments. The second knowledge is that the dimension expressions extracted from the same comment are very unlikely about the same topic. Based on these two types of lexical knowledge, we revised Latent Dirichlet Allocation (LDA) to develop the Lexical-LDA algorithm.
2. With the seed dimension words we propose Dimension Rating mining (DR-mining), a knowledge-based approach that incorporates domain knowledge, meta-data, and general grammatical patterns to accurately identifying dimension rating expressions from feedback comments. The matrix factorization technique applied to automatically compute trust weights. To

the best of our knowledge, CommTrust is the first piece of work that computes fine grained multidimensional trust profiles automatically by mining feedback comments.

we propose a knowledge-based approach that incorporates domain knowledge, meta-data, and general grammatical patterns to mining feedback comments for dimension rating profiles. By analyzing the wealth of information in feedback comments we 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*, we propose *Comment-based Multi-dimensional trust (CommTrust)*, a fine-grained multi-dimension trust evaluation model for e-commerce application.

2.Survey COMMTRUST

A fine-grained multi-dimensional trust evaluation model by mining e-commerce feedback comments is projected; it is called as Comment-based Multi-dimensional trust (CommTrust). Comprehensive trust profiles are computed for sellers using CommTrust. It includes dimension reputation scores and weights and overall trust scores by aggregating dimension scores of reputation. The first system which calculates fine-grained multidimensional trust profiles automatically by mining feedback comments is CommTrust. Later, we use the terms reputation score and trust score interchangeably.

a) **Representation of Stanford typed dependencies**

To have a simple description of the grammatical relationships in a sentence which could very easily be understood and effectively used by people without linguistic expertise who wanted to extract textual relations, The representation of the Stanford typed dependencies was deliberated. As explained in , the representation was not designed for the intention of parser evaluation; Researchers agree that with the widespread sentiment that dependency-based evaluation of parsers avoids many of the problems of the traditional Perceval measures. Also to the extent that the Stanford dependency representation is an efficient representation for the tasks envisioned. It is perhaps closer to an appropriate task based evaluation than some of the alternative dependency representations available.

b) **Analysis**

Restraining mining is also means the Sentiment. It is the turf of study which examines and analyzes beliefs, emotions, and assessments of people towards entities like products, services, associations, persons, questions, events, subjects, and their attributes. A large problem space is represented by it. There are various names and slightly diverse tasks, e.g., feeling analysis, view mining, view extraction, emotion mining, partisanship analysis, influence analysis, sentiment analysis, appraisal mining, etc.

c) **Sentiment Analysis Applications**

As the opinions are key influencers of human behaviours, they are central. Whenever someone needs to take some decision, he/she wants to know the opinions of others. The products and services are always found by businesses and organizations all over the world by the opinions of consumer or public. Individual consumers also desire to know the opinions of users of a product before purchasing it. Even voters want to know others' opinions about political candidates before making a voting decision in election. In the past years, when someone needed opinions, he/she used to ask friends and family. When an organization or a business wanted public or consumer opinions, it performed surveys, view polls, and spotlight groups. Acquiring public and consumer opinions has long been a huge business itself for advertising, community relationships, and political movement companies.

Related work divided into three main areas:

1) Computational approaches to trust, especially reputation based trust evaluation and recent developments in fine grained trust evaluation;
2) E-commerce feedback comments analysis and
3) Aspect opinion extraction and summarization on movie reviews, product reviews and other forms of free text.

1) Trust Evaluation

In literature [8]-[10], the effective rating bias in the eBay reputation system is well documentation. As proposed in [10], to examine feedback comments to bring seller reputation scores down to a rational scale. There comments that do not demonstrate explicit positive ratings are deemed negative ratings on transactions. Similar to that buyers and sellers are referred to as individuals in e-commerce applications. Peers and agents are terms always used to indicate the individuals in open systems in various applications in the trust evaluation literature. The comprehensive overview of trust model is provided in [11]. Individual level trust models aims to compute the reliability of peers and assist buyers in their work of decision making [12]–[14]. To regulate the behaviour of peers, avoid fraudsters and ensure system security was the system level models aim [11].

2) Feedback Comment Analysis

[10], [15], [16], [17] examined analyzing feedback comments in e-commerce applications. It says that their focus was not albeit the comprehensive trust evaluation. The main focus of [10] and [16] was sentiment classification of feedback comments. It is proved that feedback comments feedback comments. It is proved that feedback comments are noisy and hence analyzing them is a challenge. [10] States that the missing aspect comments are deemed negative. Models built from aspect ratings are used to classify comments into positive or negative. [16] Proposed a technique for summarizing feedback. It aims at to filter out courteous comments that do not provide real feedback. Lu. Et al. [15] elaborates on producing “rated aspect summary” from eBay feedback comments. Its statistical generative model has basis on regression on the overall transaction rating.

3. Model Analysis

We view feedback comments as a source where buyers express their opinions more honestly and openly. Our 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. Table 3.1 lists some sample comments, together with their rating from eBay. For example for comment c2, a buyer gave a positive feedback rating for a transaction, but left the following comment: \bad communication, will not buy from again. super slow ship(ping). item as described.". Obviously the buyer has negative opinion towards the communication and delivery aspects of the transaction, despite an overall positive feedback rating towards the transaction. We call these salient aspects dimensions of e-commerce transactions. Comment-based trust evaluation is therefore multi-dimensional. Hereafter we will use the terms opinion and rating interchangeably to express the positive, negative and neutral polarities toward entities that expressed in natural language text.

The CommTrust framework defines the working of proposed system. 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.

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No	Comment	eBay rating
c_1	beautiful item! highly recommend using this seller!	1
c_2	bad communication, will not buy from again. super slow ship(ping). item as described.	1
c_3	quick response	1
c_4	looks good, nice product, slow delivery though.	1
c_5	top seller. many thanks. A+	1
c_6	great price and awesome service! thank you!	1
c_7	product arrived swiftly! great seller.	1
c_8	great item. best seller of ebay	1
c_9	slow postage, didn't have the product asked for, but seller was friendly.	1
c_{10}	wrong color was sent, item was damaged, did not even fit phone.	1

Note: 1 = Positive, 0 = Neutral, -1 = Negative

Table 3.1 : Sample Comment On EBay

The algorithm for mining feedback comments for dimension ratings and the technique for computing dimension weights. CommTrust can significantly reduce the strong positive bias in eBay reputation systems, and solve the \all good sellers" problem. With CommTrust, seller ratings are regulated to a more reasonable level and truly reputable sellers are effectively differentiated from irreputable sellers.

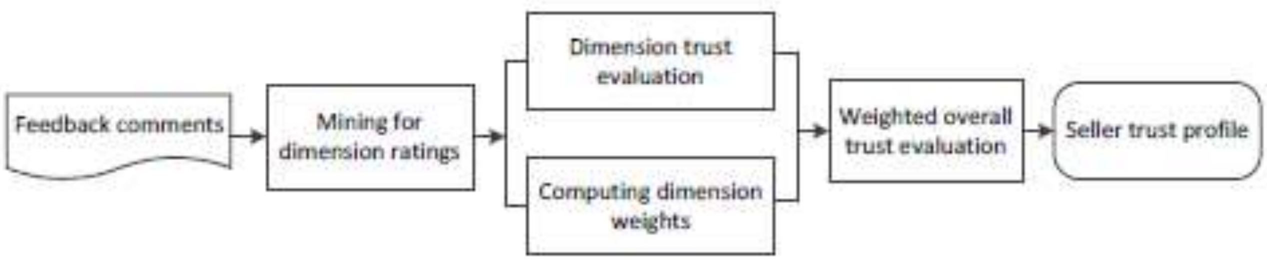

Figure 1: CommTrust Framework

The trust score for a dimension is the degree or probability that buyers express positive opinion towards the dimension, and roughly is positively correlated with the proportion of positive ratings towards the dimension. However, buyers only express limited positive or negative opinions towards some dimensions in feedback comments. Computing the trust score from a limited number of samples has a high chance of over estimate. The trust score on a dimension for a seller is the probability that buyers expect the seller to carry out transactions on this dimension satisfactorily. The trust score for a dimension can be estimated from the number of observed positive and negative ratings towards the dimension.

4. Lexical-LDA

We proposed an algorithm based on popular topic modelling method that Latent Dirichlet Allocation for grouping dimension expressions into dimensions and computing dimension weights. This approach can achieve stable performance across domains, and the features used are more transparent to a human user. This system based on the typed dependency analysis to extracting dimension expressions and identifying their associated ratings.

We propose the Lexical-LDA algorithm to group aspect expressions into semantically coherent categories, which we call dimensions. Different from the conventional topic modelling approach, which takes the document by term matrix as input, Lexical-LDA makes use of shallow lexical knowledge of dependency relations for topic modelling to achieve more effective clustering.
Figure depicts the Lexical-LDA framework.

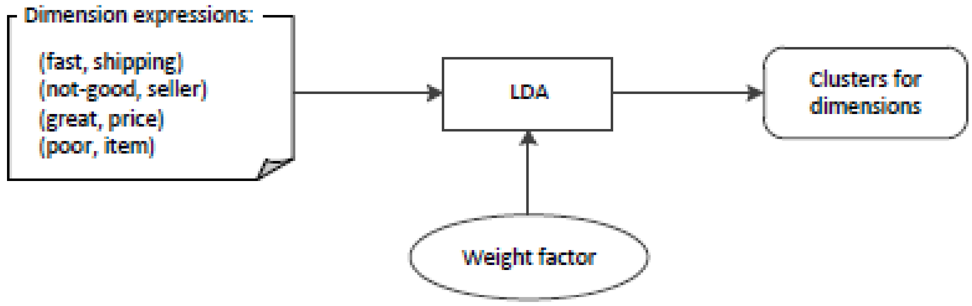

Figure 2: Lexical LDA

We make use of two types of lexical knowledge to \supervise" grouping dimension expressions
into dimensions so as to produce meaningful clusters.

- Comments are short and therefore co-occurrence of head terms in comments is not very informative. We instead use the co-occurrence of dimension expressions with respect to a same modifier across comments, which potentially can provide more meaningful contexts for dimension expressions.
- We observe that it is very rare that the same aspect of e-commerce transactions is commented more than once in the same feedback comment. In other words, it is very unlikely that the dimensions expressions extracted from the same comment are about the same topic.

5. DR-Mining

We will first describe our approach based on the typed dependency analysis to extracting dimension opinion expressions and identifying their associated ratings. We then propose a matrix factorisation technique to automatically compute weights for dimensions from the sparse and noisy dimension rating matrix.
To more accurately identify dimensions, we further extract meta-data on the product hierarchy from eBay to
identify ratings on the product dimension.
Based on eBay Detailed Seller Ratings on four aspects, we define five dimensions:

- Product: the quality or condition (new or used) of the product bought.
- Delivery: delivery is on time or not.
- Communication: how the seller communicates with buyers.
- Cost: item price, handling charges, and other associated cost.
- Transaction: the overall satisfaction of the transaction.

The complete dimension-rating mining (DR-mining) algorithm for identifying dimensions and associated ratings from free text comments is shown in below figure. Each comment is first analysed using the Stanford dependency relation parser. To identify dimensions in sentences, the dependency relations resulted from parsing are first matched.

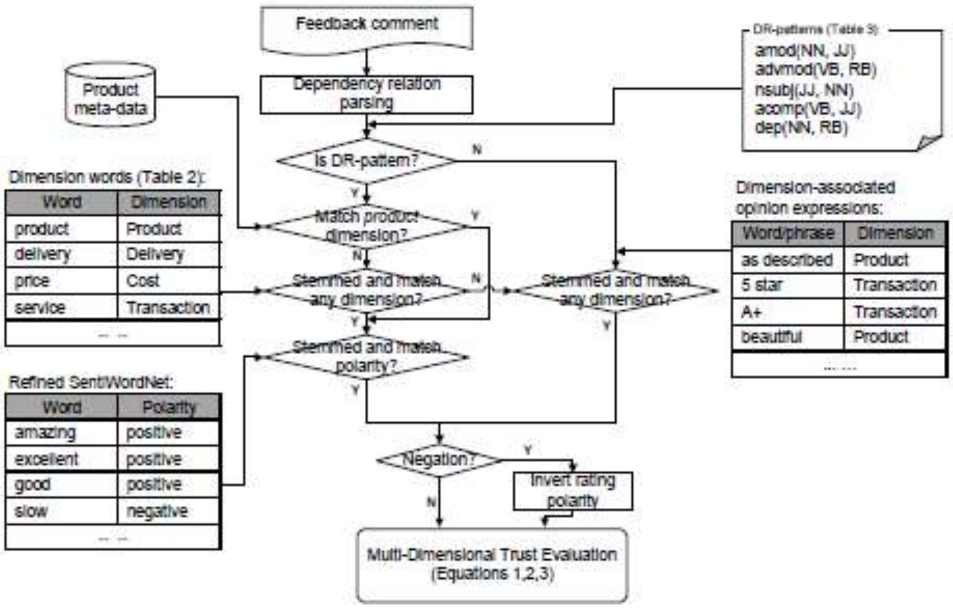

Figure 3: CommTrust DR-Mining Algorithm

Transaction dimension is not considered in the trust model of CommTrust ,identifying ratings on the transaction dimension is important for analysing feedback comments. The accuracy of DR-mining algorithm is conducted to evaluate the dimension accuracy and the dimension rating accuracy on eBay and Amazon datasets. This shows our algorithm can achieve reasonable results on identifying dimension and dimension ratings.

6. Conclusion

We have proposed a multi-dimensional trust evaluation model CommTrust for computing comprehensive trust profiles for sellers in e-commerce applications. Different from existing multi-dimensional trust models, we compute dimension trust scores and dimension weights automatically via extracting dimension ratings from feedback comments.

The reputation systems used in commercial and online applications are prone to vulnerabilities. Thus the reliability is being questioned. When the area of ecommerce is taken into consideration [6], the sellers need to be ranked accurately so that the customers could find it easy to choose between trustworthy sellers in e-commerce applications. This ranking can be done with the help of the feedback given by the buyers. There are different models to put forward the reputation of the sellers. But the methods adopted by them in reputation score calculation are different. Depending on such methods the rankings given to each seller also vary. The ranking which relate more closely to the manual ranking is the most effective and efficient method i.e. if the correlation between manual and automated rankings is strong enough, then it can be concluded that the corresponding automated ranking is much efficient and effective in ranking sellers and can be used widely as reputation systems in e-commerce applications.

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