iJRASET
International Journal For Research in
Applied Science and Engineering Technology

INTERNATIONAL JOURNAL FOR RESEARCH

IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY

Volume: 9 **Issue:** XI **Month of publication:** November 2021

DOI: https://doi.org/10.22214/ijraset.2021.38836

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.429
Volume 9 Issue XI Nov 2021- Available at www.ijraset.com

COMMTRUST

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Abstract: We propose CommTrust for trust evaluation by mining feedback comments. Our main contributions include: 1) we propose a multidimensional trust model for computing reputation scores from user feedback comments; and 2) we propose an algorithm for mining feedback comments for dimension ratings and weights, combining techniques of natural language processing, opinion mining, and topic modeling. Extensive experiments on eBay and Amazon data demonstrate that CommTrust can effectively address the "all good reputation" issue and rank sellers effectively. To the best of our knowledge, our research is the first piece of work on trust evaluation by mining feedback comments.. 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

I. INTRODUCTION

A well-reported issue with the eBay reputation management system is the "all good reputation" problem [1], [2] where feedback ratings are over 99% positive on average [1]. Such strong positive bias can hardly guide buyers to select sellers to transact with. 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 – aspect ratings are mostly 4.8 or 4.9 stars. 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].

In CommTrust, we propose an approach that combines dependency relation analysis [4], [5], a tool recently developed in natural language processing (NLP) and lexiconbased opinion mining techniques [6], [7] to extract aspect opinion expressions from feedback comments and identify their opinion orientations. We further propose an algorithm based on dependency relation analysis and Latent Dirichlet Allocation (LDA) topic modelling technique [8] to cluster aspect expressions into dimensions and compute aggregated dimension ratings and weights. We call our algorithm Lexical-LDA. Unlike conventional topic modelling formulation of unigram representations for textual documents [8], [9] our clustering is performed on the dependency relation representations of aspect opinion expressions. As a result we make use of the structures on aspect and opinion terms, as well as negation defined by dependency relations to achieve more effective clustering. To specifically address the positive bias in overall ratings, our dimension weights are computed directly by aggregating aspect opinion expressions rather than regression from overall ratings. In CommTrust, access that unites dependency relation analysis 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 an algorithm is proposed to cluster feature expressions into the dimensions and calculate total dimension weights and ratings, called Lexical-LDA. Therefore, the reputation profiles in CommTrust contain dimension reputation scores, weights and complete trust scores for ranking sellers.

II. IMPLEMENTAED WORK

Computational Trust Evaluation The strong positive rating bias in the eBay reputation system has been well documented in literature [1]–[3], although no effective solutions have been reported. Notably in [3] it is proposed to examine feedback comments to bring seller reputation scores down to a reasonable scale, where comments that do not demonstrate explicit positive ratings are deemed negative ratings on transactions. The 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.

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A. *Computing Trust Valuation*

The positive trust score aspect of the Amazon reputation system is well documented. No valid solutions have been reported. As proposed in , 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.

B. *Analying Feedback Comments*

In 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 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 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" given by Amazon feedback comments. The numerical developing model is based on regression about a complete rating.

C. *Opinion Mining and Summarization*

Similar to that buyers and sellers are referred to as individuals in e-commerce applications, terms like peers and agents are often used to refer to individuals in open systems in various applications in the trust evaluation literature. In a comprehensive overview of trust models is provided. The EigenTrust algorithm uses a rating matrix representation for local trust scores and computes the global ratings for peers from the rating matrix. All the above discussed models assume that feedback ratings are readily available and focus on aggregation algorithms. A couple of studies focus on gathering ratings through social networks . Nevertherless ratings are assumed available rather than obtained via data mining.

The multi-dimensional approach to fine-grained trust computation has been studied in agent technologies . In individual, social and ontological reputations are computed and their ratings are combined to form an overall score. In the dimension scores are computed from direct experience of individual agents, and then aggregated by weighted summation. Reece *et al*. presented a probabilistic approach considering the correlation among dimension during aggregation. In all these trust models however, weightings for dimension trust are either not considered or assumed given.

Other approaches to fine-grained trust computation have also been proposed in literature , where specific factors for individual and transaction contexts are considered. However, many factors considered in these models are not readily available in e-commerce applications.

III. COMMTRUST MODEL

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. Lists some sample comments, together with their rating from eBay. For example for comment c_2, 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. Comments-based trust evaluation is therefore multi-dimensional. 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.

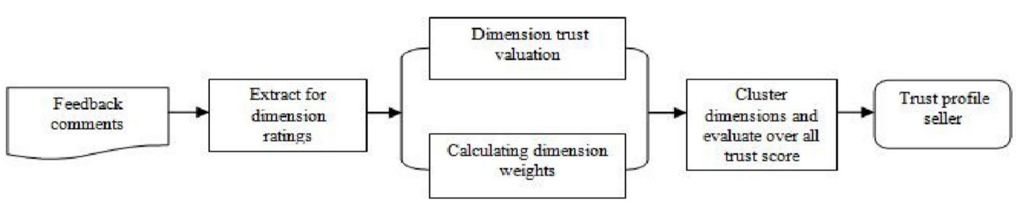

Figure 1: The CommTrust framework

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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.

$$S = \sum \quad _n * w(1)$$

Where = and $= h$ dimensioned where (= 1. .).

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

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

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

The above equation is called m-estimated [12]. = [0.1] and [0.5] which represents a constant trend for truth valuation. In equation 2, is a hyper parameter which may be in peusedo counts 1/2 ∗ 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 . 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.

We make use of two types of lexical knowledge to "supervise" clustering 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.

IV. MINING FEEDBACK COMMENTS FOR RANKING

We propose the Lexical-LDA algorithm to cluster 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.

We make use of two types of lexical knowledge to "supervise" clustering 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.. 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.

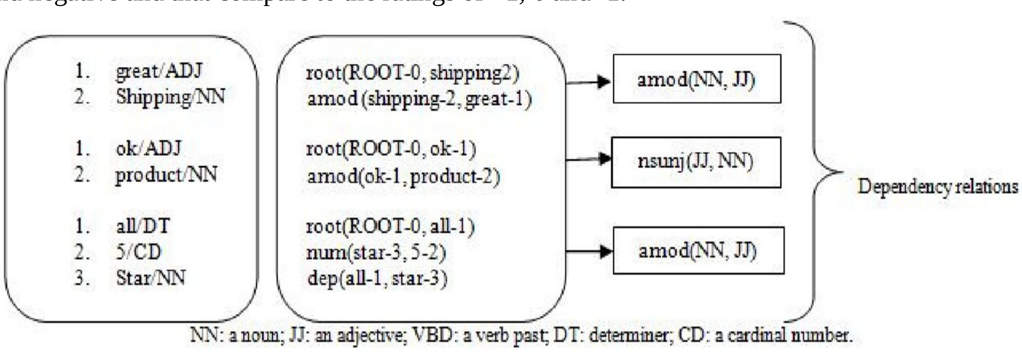

Figure 2: Typed dependency relation analysis

V. 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.

Our application of the second type of lexical knowledge to "supervise" the topic modelling process is motivated by the notion of "cannot links" in [37], although conventional LDA on documents of word tokens is applied there. Their application of constraints at the sentence level potentially can result in a large number of such constraints. In addition to the "cannot-link" constraints, "must-link" constraints are used to state that some phrases with common words likely belong to the same topic. For example "battery power" and "battery life" likely belong to the same topic. Although such phrases may be widespread in product reviews, they are rare in e-commerce feedback comments. It is wroth noting that it is shown in [37] that the cannot-link constraints produce more effectiveness on the clustering results than the must-link constraints. When (modifier, head) pairs and their negations are clustered into dimensions, we compute weights for dimensions.

Intuitively the weight for a dimension is proportional to the total number of positive and negative ratings on the dimension. Specifically we compute the total number of (modifier, head) dimension expressions for the dimension. Indeed only frequent dimension expressions with head terms appearing in at least 0.1% of comments are included. The total number of dimension expressions for dimensions are normalised to produce the dimension weights.

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

1) 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.
2) 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).

A. 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.

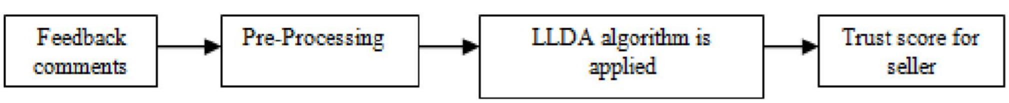

Figure 3: Mining feedback comments

Informal language expressions are widely used in feedback comments. Some pre-processing was first performed: Spelling correction was applied. Informal expressions like *A+++* and *thankx* were replaced with *AAA* and *thanks*. The Stanford dependency relation parser was then applied to produce the dependency relation representation of comments and dimension expressions were extracted. The dimension expressions were then clustered to dimensions by the Lexical-LDA algorithm.

To evaluate Lexical-LDA, the ground truth for clustering was first established. Dimension expressions are *(modifier, head)* pairs, and to remove noise only those pairs with support for head terms of at least 0.1% or three comments (whichever is larger) were considered for manual clustering. Some head terms resulted from parsing errors that do not appear to be an aspect were discarded. Examples of such terms include *thanks*, *ok* and *A+++*.

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In the end a maximum of 100 head terms were manually clustered based on the inductive approach to analysing qualitative data. We first grouped head terms into categories according to their conceptual meaning – some head terms may belong to more than one category, and some orphan words were discarded. We then combined some categories with overlapping head terms into a broader category, until some level of agreement was reached between annotators

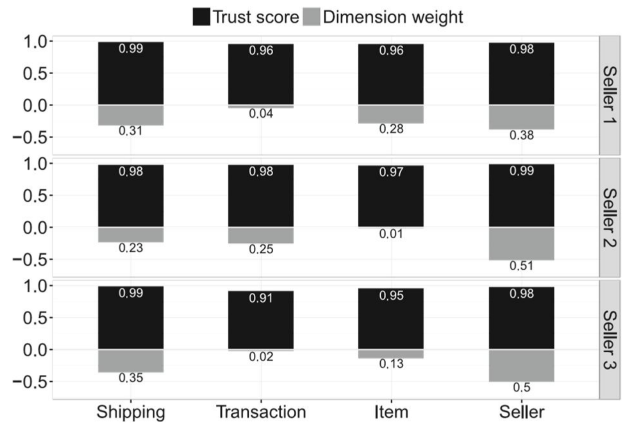

Fig. 4. Dimension trust profiles by CommTrust for sellers.

Fig. 4 depicts the dimensional trust profiles for three eBay sellers Sellers 1, Seller 2 and Seller 3, where they have the same four dimensions, including *shipping*, *cost/response*, *item* and *seller*. For each seller, the upward bars represent trust scores for dimensions while the downward bars represent their weights. For example while having a high overall trust score of 0.9771, Seller 3 has a low dimension trust score of 0.9067 for the *response* dimension (Dimension 2). The figure clearly illustrates the variation of dimension trust for each seller horizontally and those across different sellers vertically. Such comprehensive trust profiles certainly can cater to users preferences for different dimensions and guide users in making informed decisions when choosing sellers.

We evaluate Lexical-LDA against standard LDA for clustering and against the human clustering result. As there are seven categories by human clustering, $K = 7$ for LexicalLDA. Fig. 6(a) plots the RI of Lexical-LDA at different settings of α. Note that the data point for $\alpha = 0$ corresponds to the standard LDA. In addition to the eBay and Amazon datasets, to demonstrate the generality of our approach, the performance of Lexial-LDA on the TripAdvisor dataset is also plotted. For eBay and Amazon data, each plotted data point is the average for ten sellers. On eBay data, RI of Lexical-LDA hovers over 0.78 ~ 0.83, and Lexical-LDA significantly outperforms standard LDA for $\alpha > 0$ except $\alpha = 0.3$ (p-value < 0.05, paired two-tail t-test). Comparable RI is observed on TripAdvisor and Amazon datasets. Our experiment results indicate that Lexical-LDA has steady performance across different domains.

Head Term Clusters Dimensions

Dim	Manual clustering	Lexical-LDA (α=0.5)	Standard LDA
1	item, bag, product, dress, earrings, outfit, top, ring, shoes, coat, necklace, jacket, stuff, one, curtains, handbag, boots, zip, toy, backpack, suit, material, goods, piece, scarf, leggings	item: 532, bag: 146, dress: 70, earrings: 49, outfit:45, coat: 16, top: 16, ring:14, one:11, shoes: 11, jacket:11, necklace: 11, tfit: 8, handbag: 7, look: 7, received: 7, goods: 6, scarf: 3, product: 3	item: 341, bag: 199, dress: 74, earrings: 61, outfit: 50, shoes: 17, coat: 16, ring: 15, necklace: 13, jacket: 11, one: 10, look: 10, curtains: 8, fit: 7, handbag: 6, suit: 6, received: 6, track: 5, toy: 3, piece: 3, leggings: 3, scarf: 3
2	quality, condition, look, size, color, description, fit, described, design	look: 16, size: 10, material: 10, curtains: 8, color: 8, zip: 6, design: 4	size: 11, refund: 8, material: 8, zip: 5, color: 5, design: 5, order: 4, business: 4, post: 3
3	delivery, shipping, postage, dispatch, time, arrived, received, post, shipment, arrival, came	delivery: 1139, payment: 179, shipping: 69, response: 59, postage: 50, dispatch: 25, despatch: 18, deal: 10, came: 10, arrival: 7, arrived: 6, shipment: 5, post: 5	delivery: 1096, shipping: 60, response: 58, postage: 45, dispatch: 22, despatch: 18, deal: 10, came: 10, arrival: 7, arrived: 6, shipment: 5
4	seller, ebayer	seller: 286, ebayer: 286, bayer: 5, described: 4, leggings: 3, track: 3	seller: 519, ebayer: 409, service: 249, communication: 149, product: 138, price: 44, quality: 39, value: 39, buy: 29, condition: 19, looks: 16, top: 15, items: 13, purchase: 13, ebay: 12, time: 11, bayer: 8, stuff: 7, described: 5, boots: 4, description: 4, backpack: 4
5	service, response, track, communication	communication: 142, service: 133, product: 106, quality: 55, price: 46, value: 40, buy: 29, condition: 28, ebay: 11, time: 10, stuff: 8, purchase: 6, boots: 5, description: 5, backpack: 5	goods: 5
6	transaction, buy, deal, purchase, order, business	transaction: 165	transaction: 160
7	payment, price, value, refund	refund: 12, order: 6, business: 5, suit: 4, toy: 4, piece: 1	payment: 147

The accuracy of Lexical-LDA with different settings of α. As can be seen in the graph, accuracies hover over 0.70 ~ 0.74 on eBay data and 0.61 ~ 0.63 on Amazon data. There are not statistically significant differences in accuracies between Lexical-LDA with α > 0 and standard LDA, on either Amazon or eBay datasets. However clustering accuracy only measures how automatic clustering matches the human clustering, rather than the coherence within clusters by clustering algorithms. Table 10 shows the clusters of head terms for seven dimensions for eBay Seller 1 from manual clustering, Lexical-LDA (α = 0.5) and standard LDA respectively. Each head term is grouped to the dimension with the highest frequency. We can see that Lexical-LDA has significantly higher within-cluster coherence than standard LDA.

VI. CONCLUSION

We have proposed effective algorithms to compute dimension trust scores and dimension weights automatically via extracting aspect opinion expressions from feedback comments and clustering them into dimensions. Our approach demonstrates the novel application of combining natural language processing with opinion mining and summarisation techniques in trust evaluation for e-commerce applications.

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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