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Communal Stance for Mining E-Commerce Site by Evaluating Customers Review and Feedback

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ABSTRACT: Internet has rapidly distributed in the past few years. Trust computation is pre-eminent for the triumph of e-commerce systems.In order to gain peoples trust we use reputation based trust models and feedback ratings to compute sellers reputation trust scores. It became very difficult to select the trust worthy sellers. One such key issue for any ecommerce application is “all good reputation”. The buyers openly express their opinions in the feedback comments which is observed by the sellers and the ecommerce site management. In this paper the buyers express their opinions genuinely in the feedback comments. Here we propose a Comm Trust approach in this paper that combines dependency relation analysis. A tool recently developed in natural language processing and opinion mining from feedback comments. We further propose algorithm based on dependency relation analysis and Latent Dirichlet Allocation (LDA) topic modelling to cluster expressions into dimensions and then compute aggregated dimension ratings.

KEYWORDS: E-Commerce, text mining, natural language processing, opinion mining and latent Dirichelt allocation

I. Introduction

It is very difficult to find the accurate trust values for any product. Few reporting systems have been implemented in ecommerce system such as eBay and amazon, where the overall reputation scores for sellers are computed by aggregating feedback ratings. The main issue with eBay reputation management system is “all good reputation”. It becomes easy for buyers to select sellers based on strong bias. The DSR’s are aggregated on 1 to 5 star scale as rating scores. One such reason for lack of negative feedback ratings which will damage their own reputation.

In this paper, we propose comment-based multidimensional trust model by mining ecommerce feedback comments. With Comm Trust comprehensive trust profiles are computed for sellers, which include reputation scores and weights, as well as the overall trust score by the aggregation of reputation scores. Here it combine dependency relation analysis (DRA), a tool which is recently developed in natural language processing and lexical based opinion mining based techniques, to extract the opinion expressions from feedback comments.

We further propose an algorithm based on DRA and LDA topic modelling techniques to cluster expressions into dimensions and compute the dimension ratings and weights. The individual trust level models are aimed to compute the reliability of peers and assist buyers in their decision making whereas the system level models are aimed to regulate the behaviour of peers, prevent fraudsters and ensure system security. The rating aggregation algorithm for computing individual reputation score which include the simple positive feedback percentage and the average of individual star ratings as in amazon or any other ecommerce system, many models like Kalman inference[20], which also computes trust score variance and confidence level. With respect to time more factors are involved in feedback ratings, reputation models and comment based trust values.

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II. RELATED WORK

[1] Extracting product features and opinions from reviews

This paper introduces OPINE, which is an unsupervised information extraction system that embodies a solution to identify product features, identify opinions regarding product features, determine the polarity of opinions, and rank opinions based on their strength these OPINE solves the opinion mining tasks and gives an output as set of product features.

Here we compare the most relevant previous mining systems with opine and find whether the opines precision is better than the previous data sets. The other systems are used to identify polarity of documents. But opine is one such system which recalls the opinion phase extraction and opinion phase polarity determination.

[2] Mining and summarizing customer reviews

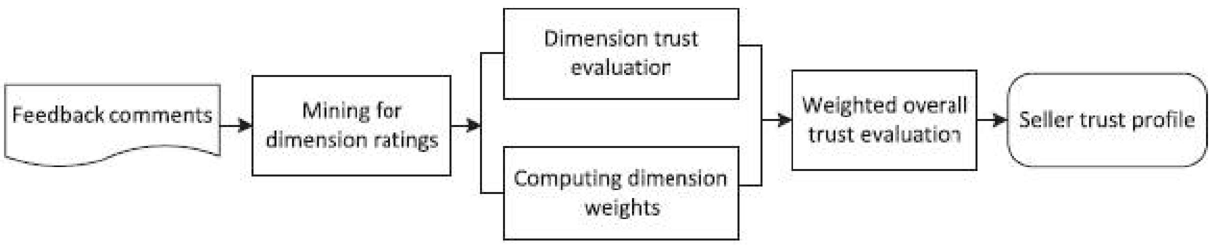
With the rapid growth of ecommerce more and more products are sold on the web in order to satisfy the customers and give them a good shopping experience the online merchants takes review from the customers and mining is done based on the feedback. Some popular products can get more reviews and some may get less reviews .The set of customer review of a product involves three sub tasks.

- Identify the features of the product that customers have expressed their own opinions
- Per each positive and negative opinions, review is made to enhance their product review
- And finally producing the summary using the discovered information.

In this paper our work is classification on reviews they not only focus on classifying each review but they classify the whole sentence positive opinions are review at one time and negative opinions are review at other time. The most important issue of this paper is information gathering behaviour to find how people think. To facilitate future work a discussion is made on available resources, computation of datasets, and evaluating the customer reviews.

III. SYSTEM ARCHITECTURE

This figure shows the scheme of Comm Trust frame work. Here the opinion expressions and associatedratings are first extracted from feedback expressions.Dimension trust scores together with weights are computed by clustering aspect expressions into dimensions and dimensions into ratings.



A. COMM TRUST COMMENT BASED MULTIDIMENSIONAL TRUST EVALUATION:

Buyers express their opinions openly and honestly as feedback comments. Our analysis of feedback comments on ecommerce site reveals if the buyer give positive rating for any transaction and sometimes they leave mixed opinions in order to know the exact opinion of any buyer, the sellers view both the feedback comments and ratings. For example at times he may give positive rating and feedback as bad communication and late shipping. With all these salient features the seller can assume whether there is lack of shipping, customer services or product delivery, with this the ecommerce site management will take care of these factors. If product is not upto the buyers satisfaction. We can know by the ratingsof the product. The overall trust score T for a seller is the weighted aggregation of dimension trust scores for the sellers, where td and wd represent the trust score and weight for dimension d=(d=1……m).

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

B.EXTRACTING ASPECT EXPRESSIONS AND RATINGS BY TYPED DEPENDENCY ANALYSIS:

The typed dependency relation is a NLP tool to perform grammatical relationship in a sentence we can parse the sentence into pair of words in the form of heads. Let us take an example “super quick shipping product work excellent”. The sentence super quick shipping is represented as three dependency relation. The adjective modifier relation and (shipping-3,super-1) and amod (shipping-3,quick-2) indicates that the super modifies shipping and quick modifies shipping words are annotated pos tags as noun(NN),verb(VB), adjective(JJ), adverb(RB).The modified relations thus can be denoted as (modifier,head) pairs. The ratings from the dimension expression for the head terms are identified by identifying the prior polarity of modifier terms by SentiWordNet. In SentiWordNet the prior polarity terms are positive,negative or neutral which corresponds to ratings of +1,-1,0.

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

Fig. 1 plots trust score *td* by Equation 3 in relation to different settings of total number of ratings *n* and pseudo counts *m*. The figure is plotted for y/n = 0.8, and similar trends are observed for other values of y/n. It shows that when the total number of observed ratings *n* is large (n >300), *td* is not very sensitive to the settings of *m* and converges to the observed positive rating frequency of 0.8. When there is a limited number of observed ratings, that is n < 300, an observed high positive rating frequency y/n is very likely an overestimation, and so *m* is set to regulate the estimated value for *td*. With $m = 2$, $td \approx 0.8$ when $n \geq 50$. On the other hand, with $m = 20$, $td \approx 0.8$ only when $n \approx 300$. From our experiments, settings of m = 6..20 typically give stable results. By default, we set $m = 6$. We will first describe our approach based on the typed dependency analysis to extracting aspect opinion expressions and identifying their associated ratings. We then propose an algorithm based on LDA for clustering dimension expressions into dimensions and computing dimension weights.

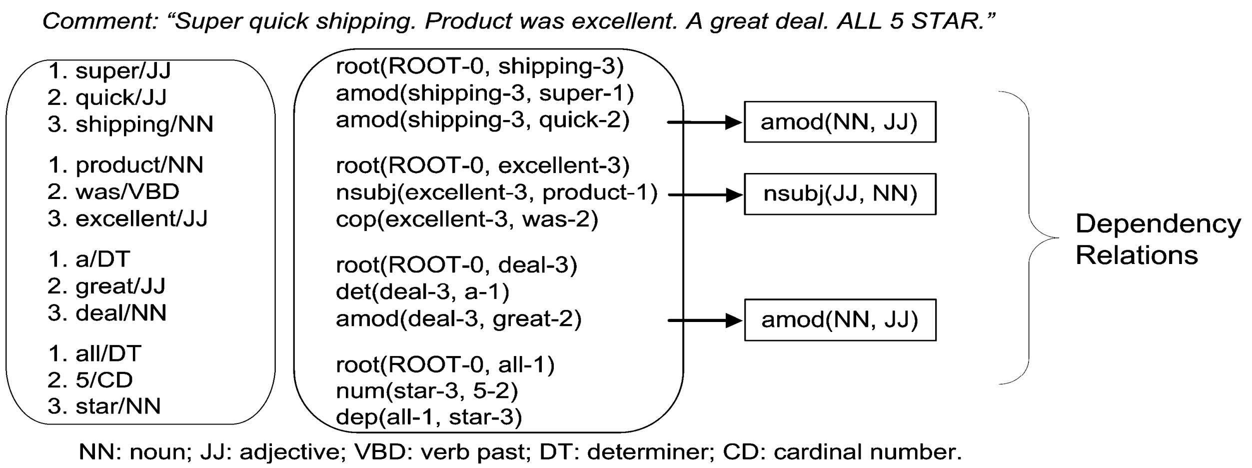

Fig:Typed Dependency relation analysis

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Sample Comments on eBay:

No	Comment	Ebay Rating
C1	Beautiful Item	1
C2	This phone is simply awesome	1
C3	Im not satisfied with delivery of the product	1.2
C4	Best Seller! Thank you.	1.8
C5	Wrong color was sent and item has been damaged	1.3

IV. CLUSTERING DIMENSION EXPRESSIONS INTO DIMENSIONS

In order to cluster aspect expressions into semantically coherent categories, we use lexical LDA algorithm. Here LDA takes document by term matrix as input which differs from conventional topic modelling approach we use two types of lexical knowledge to supervise clustering dimension expression into dimensions so as to form meaningful clusters. As comments are short the co-occurence of hear terms in comments is not very clear.so we use the co-occurence of dimension expression with respect to same modifier across comments which give a meaningful expression b. In some feedback comments we observe that the same aspect of ecommerce transaction is commented more than once. By using this shallow lexical knowledge of dependency relation for dimension expression, the clustering problem is evolved by topic modelling as follows: the input tool lexical LDA or dependency relation for dimension expression in the form of (modifier,head) pairs or their negations like (past shipping) or (not good seller).For LDA, gibbs sampling has been proposed as approximate inference. The detailed description for gibbs sample for LDA is given as below, M,K,V denotes number of documents, number of topics and number of word tokens of vocabulary and α -> and β -> be hyper parameters on mixing component of topics. The distribution of a word token wi for a topic k where i=(m,n) denotes nth word in mth document. w ->={wi=t,wri}, Z->={Zi=k,Zri} and n denotes count.

$$p\left(z_i = k \mid \vec{z}_{\neg i}, \vec{w}\right) \propto \frac{n_{k,\neg i}^{(t)} + \beta_t}{\sum_{t=1}^{V}\left(n_{k,\neg i}^{(t)} + \beta_t\right)} \cdot \frac{n_{m,\neg i}^{(k)} + \alpha_k}{\sum_{k=1}^{K}\left(n_{m,\neg i}^{(k)} + \alpha_k\right)}.$$

V. EXPERIMENT

Experiment is done on two ecommerce data sets and one restaurant review datasets were conducted inorder to evaluate the various aspects of Comm Trust which includes trust model and the lexical LDA algorithm for clustering dimension expressions. Inorder to demonstrate the generality of lexical LAD, the restaurant review dataset is used other than e-commerce.

A. DATASETS

Per suppose take ten eBay sellers where two sellers were taken per each four categories. List out all thecategories in addition to seller products and then extract the feedbackprofile for each seller.

- Feedback score is given as the total number of positive ratings for a seller
- Positive feedback sellers percentage is calculated as
  (positive ratings) / (positive ratings + negative ratings

Likewise take another shopping site and evaluate two items per each four categories. Note that each item illustrates the feedback of the sellers based on their ratings.

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eBay seller product information :

Seller	Category	#comments	Avg. rating
Seller 1	Electronics-Computer	4365	4.8
Seller 2	Electronics-Computer	4786	4.8
Seller 3	Electronics-Camera	3202	4.9
Seller 4	Electronics-Camera	8000	4.8
Seller 5	Electronics-Phone	5097	4.7
Seller 6	Electronics-Phone	2631	4.8
Seller 7	Jewelry-Ring	6281	4.6
Seller 8	Jewelry-Ring	1295	4.5
Seller 9	Baby-Tub	3860	4.8
Seller 10	Baby-Diaper	927	4.7

B.EVALUATE METRICS

Trust evaluation of ecommerce application is to rank sellers and provide a trust worthy sellers to the users. It also helps them in their business. Here large number of sellers are taken for various categories of products. The feedback comments are evaluated in any order and later arranged in high to low manner. Average rating is calculated per each product by clustering the head terms. It gives the exact accuracy of the rating.

$\mathrm{ACC}(H) = \Sigma_{KI} N_I / |V|$

The ultimate goal of trust evaluation for e-commerce applications is to rank sellers and help users select trustworthy sellers to transact with. In this respect, in addition to absolute trust scores, relative rankings are more important for evaluating the performance of different trust models. To this end, we employ Kendall's τ[50] to measure the correlation between two rankings based on the number of pairwise swaps that is needed to transform one ranking into another. τ falls in $[-1, 1]$, a positive value indicates positive correlation, zero represents independence and a negative value indicates negative correlation. τ is the standard metric for comparing information retrieval systems, and it is generally considered that $\tau \geq 0.9$ for a correlation test suggests two system rankings are equivalent. A large value for $|\tau|$ with $p \leq 0.05$ suggests that two rankings are correlated.

C.USER STUDY

A user study was conducted to elicit users ranking of sellers from reading feedback comments, which was also used as the ground truth for evaluating the CommTrust multidimensional trust evaluation model. Inspired by evaluation techniques from the Information Retrieval community [51], experiment participants are asked to judge differences rather than make absolute ratings. For ten sellers, each seller is paired with every other seller and form 45 pairs. The orders for pairs and for sellers within pairs were randomised to avoid any presentational bias. Each pair was judged by five users and a seller preferred by at least three users was seen as a vote for the seller. The total number of preference votes from 45 pairs for each seller were used as the preference score to rank sellers.

It is infeasible to ask participants to read all comments for two sellers and choose a preferred seller. We therefore generated summaries of comments for sellers. The comment summaries for each pair of users were presented side by side to elicit users preference judgements. For a seller, we generated opinionated phrases for four dimensions, where positive and negative phrases for each dimension are ordered by decreasing frequency. The three most frequent positive and negative phrases for each dimension formed the summary for a seller under the column heading of Comment rank is the ranking of sellers by user preferences after participants read the comment summaries for sellers. The correlation between rankings are measured by Kendall's τ. The rank difference between two ranking vectors is defined as:where rank(i) and rank'(i) are respectively the rank for seller *i* by two ranking methods, and N=10. The low Kendall's τ value (0.1111 and 0.4222) and high *p*- value (0.7275 and 0.1083) suggest that on eBay and Amazon, user preference rankings after reading comment summaries are not strongly correlated with the rankings by the respective eBay and Amazon reputation systems. This suggests that the comments contain distinct information for users to rank sellers.

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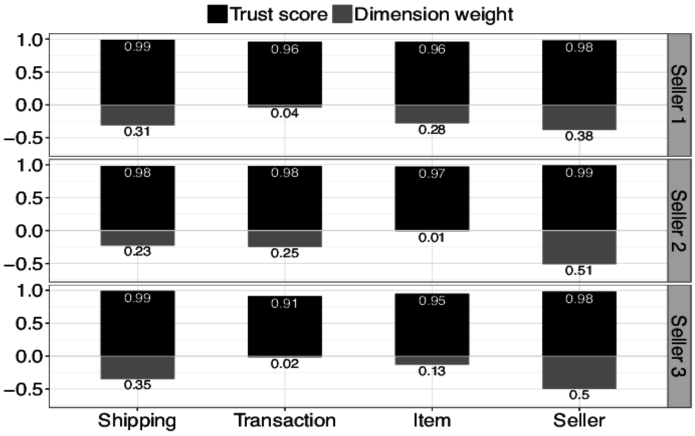

Fig: Dimension trust profiles by CommTrust for sellers

D. EVALUATION OF LEXICAL-LDA

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. The ranking difference of 3 for ten eBay users between rankings by reading comments and by eBay reputation system suggests that on average there is a difference of 3 ranks for sellers by the two approaches. Similarly for Amazon sellers there is difference of 1.8 ranks on average. Our user study demonstrates that it can be speculated that content of comments can be used to reliably evaluate the trustworthiness of sellers.

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+++*. In theend a maximum of 100 head terms were manually clustered based on the inductive approach to analyzing qualitative data [52]. 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. 3 As a result of this manual labelling process for the eBay and Amazon dataset, the feedback comments for each seller finally seven clusters are obtained. A strength of CommTrust is that the relative weights that users have placed on different dimensions in their feedback comments can be inferred. However, it is hard to elicit the weights from users when they write the feedback comments. We therefore evaluate our dimension weight prediction indirectly. To verify the effectiveness of the dimension weights in the overall trust score, we compute the unweighted overall trust scores for sellers, and compare the ranking of sellers by unweighted overall trust scores with the ground truth ranking by users .

Lexical-LDA was implemented based on the Mallet topic modelling toolkit [53]. With aspect expressions in the form of *(modifier, head)* pairs, the modifier term by head term matrix formed the input for Lexical-LDA. In constructing the cannot-link head term list for a head term (c.f. Section 4.2), only head terms appearing together with the head term in at least 0.1% of or three (whichever is larger) comments were considered. The purpose was to remove the otherwise many spurious cannot-link head terms. The Lexical-LDA parameter settings were: prior pseudo counts for topics and terms were set as $\alpha\ k = 0.1$ and $\beta t = 0.01$ (See Equation (5)), the number of topics $K = 4, 7, 10$ for evaluating the trust model and number of iterations was set to1000. 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 Lexical LDA.

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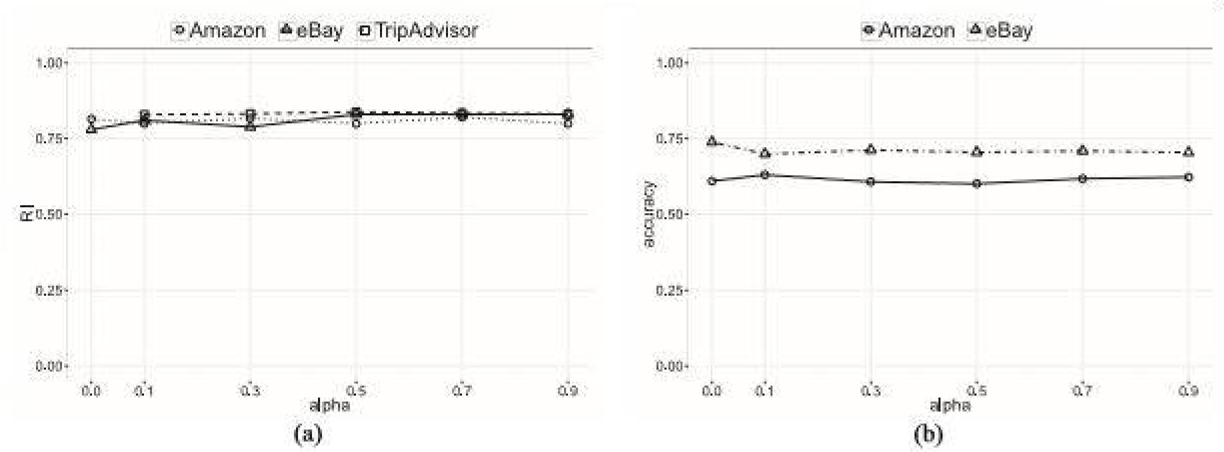

Evaluation of Lexical-LDA dimension clustering. (a) RI of Lexical-LDA. (b) Accuracy of Lexical-LDA.

VI. CONCLUSION

With the rapid growth of ecommerce sites in today's world. It became complex for users to trust the sellers product. Same product may vary in different sites based on sellers opinion. In order to improve their reputation the management need to focus on certain things. The most high reputated products are given ranks based on certain factors. On the other hand, the feedback ratings are taken where positive and negative comments are evaluated for accuracy. In this paper we proposed a multi dimensional trust profile for sellers by taking the ratings of feedback comments. Amazon and eBay are one such fast going sites in this trend. So few dimensions are taken by clustering the expression, NLP,opinion mining and some marisation techniques are involved.

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