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# E-Commerce Solutions to Increase Retrieval Quality in Conversational Recommenders

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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 paper, based on the observation that buyers often express opinions openly in free text feedback comments, 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 modelling. 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.

**KEYWORDS:** K.4.4 Electronic commerce; H.2.8.I Text mining.

### I. INTRODUCTION

ACCURATE trust evaluation is crucial for the success of e-commerce systems. Reputation reporting systems [1] have been implemented in ecommerce systems such as eBay and Amazon (for third-party sellers), where overall reputation scores for sellers are computed by aggregating feedback ratings. For example on eBay, the reputation score for a seller is the positive percentage score, as the percentage of positive ratings out of the total number of positive ratings and negative ratings in the past 12 months. 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] Although buyers leave positive feedback ratings they express

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some disappointment and negativeness in free text feedback comments [3], often towards specific aspects of transactions.

For example, a comment like “The products were as I expected.” Expresses positive opinion towards the product aspect, whereas the comment “Delivery was a little slow but otherwise, great service recommend highly.” expresses negative opinion towards the delivery aspect but a positive opinion to the transaction in general. By analysing the wealth of information in feedback comments we can uncover buyers’ detailed embedded opinions towards different aspects of transactions, and compute comprehensive reputation profiles for sellers.

We propose Comment-based Multi-dimensional trust (CommTrust), a fine-grained multi-dimensional trust evaluation model by mining e-commerce feedback comments. With CommTrust, comprehensive trust profiles are computed for sellers, including dimension profiles are computed for sellers, including dimension profiles are computed for sellers, including dimension reputation scores and weights, as well as overall trust scores by aggregating dimension reputation scores. 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. In later discussions, we use the terms reputation score and trust score interchangeably.

## II. EXISTING SYSTEM

In the existing system structured survey are the expense and difficulty of question design and lack of participation because many customers do not like to participate in a question-based structured survey. Opinion polling has been traditionally done via customer satisfaction studies in which questions are carefully designed to gather customer opinions about target products or services. Another challenge of aspect-based opinion polling lies where people often express differing opinions on multiple aspects simultaneously in the same reviews and even in the same sentence this is called a multi-aspect sentence. A multi-aspect sentence as a single-aspect mention for aspect-based opinion polling would not lead to satisfactory results. Traditional document-level classification techniques may not always produce meaningful aspect-based opinion polling in many cases.

## III. PROPOSED SYSTEM

The proposed system studies the aspect-based opinion polling from unlabeled free-form textual customer Reviews without requiring customers to answer any questions. A multi-aspect bootstrapping method is proposed to learn aspect-related terms of each aspect that is used for aspect identification. An aspect based segmentation model is proposed to segment a multi-Aspect sentence into multiple single- aspect units as basic units for opinion polling. The proposed opinion polling method does not require Labelled training data. The proposed system easy to implement and can be applicable to other languages (e.g., English) or other domains such as product or movie reviews. The proposed system explores the problem of aspect-based opinion polling from unlabeled free-form textual customer reviews. This paper proposes an automatic method of aspect-based opinion polling from unlabeled textual customer reviews. Produce meaningful aspect-based opinion polling in many cases.

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## ADMIN:

Administration is the owner of the site. He can have all the privileges in this system. He can add Country, district, state, service and specialization. He can also view user comment reports.

## USER:

He is the authentication user. He can have all the privileges in this system. He can view the item details in restaurant and write the comment Particular item.

## COMM-TRUST:

Comments Based Multi Dimensional Trust Evolution, 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 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. Comments-based trust evaluation is therefore multi-dimensional.

## AUTHENTICATION:

This module provides security to the application. Every user should enter correct user name and password to proceed. This request will go to database and check the user existing. If you entered wrong user name and password then it prompts you "Incorrect Username or Password..."

## REGISTRATION:

The system has a process of registration. Every user need to submit their complete details including user name and password in the form of registration. Whenever a user registration completed then only a user can get log in into the system by using his user id and password.

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## PATTERN MATCHING ALGORITHM:

### Algorithm 3: Multi-Aspect Segmentation (MAS)

**Input:** a multi-aspect sentence  $C=c_1c_2...c_n$  consisting of  $n$  sub-sentences

**Initialize:** Set  $U_0=\text{null}$ ,  $J(C, U_0)=0$ .

**Loop:** FOR  $i = 1, 2, \dots, n-1$

FOR  $j = 1, \dots, n-i$

1) Select a new candidate segmentation position

$u$ ;

2) Calculate  $J(C, U_{i-1} + \{u\})$  (Equation 8)

ENDFOR

$u^* = \arg \max_u J(C, U_{i-1} + \{u\})$

IF  $J(C, U_{i-1} + \{u\}) > J(C, U_{i-1})$

THEN  $U_i \leftarrow U_{i-1} + \{u^*\}$

OTHERWISE break;

ENDFOR

**Output:** The final generated segmentation  $U^*$ .

## IV. CLUSTERING DIMENSION EXPRESSIONS INTO DIMENSIONS

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, 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. 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. With the shallow lexical knowledge of dependency relation representation for dimension expressions datasets 180,788 feedback comments were crawled for ten eBay sellers on ebay.com, where two sellers were randomly selected for each of five categories on the “Shop by category” list on eBay.com, including Cameras & Photography, Computers & Tablets, Mobile Phones & Accessories, Baby, and Jewellery & Watches.

Dataset was mainly used to evaluate the applicability of Lexical-LDA for dimension clustering in domains other than e-commerce. 246,399 reviews were in the original dataset and the following pre-processing was applied: Reviews with any missing aspect rating or with less than 50 words were removed so that all reviews have coverage of all aspects. Reviews that Stanford parser cannot parse were also removed. After pre-processing we have a total of 52,805 reviews.

Dimensions, the rankings by CommTrust are strongly correlated with the ground truth rankings, as demonstrated by the high Kendall’s  $\tau$  and low p-values (less than 0.05). The negative Kendall’s  $\tau$  values are a result of that the ranks are inversely ordered in relation to trust scores. This is suggesting that CommTrust has computed the dimension ratings from comments and they match users’ preferences after reading the comments. The number of dimensions does not affect how well the trust scores are correlated with the user rankings.

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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. Table 7 shows the result. It can be seen that without weightings for dimensions, the trust scores for sellers are not correlated with the ground truth ranking of sellers, as demonstrated by low Kendall's  $\tau$  with all p-value greater than 0.05. This result holds for eBay and Amazon sellers, and all 4, 7 and 10 dimensions. The dimension trust scores and weights together form the dimensional trust profiles for sellers. The dimensional trust profiles for ten eBay sellers for four dimensions are shown in Table 8. Note that the four dimensions discovered by CommTrust for a seller are the statistically important dimensions that users expressed opinions on in their feedback comments and may not necessarily correspond to the four aspects as specified by eBay DSR ratings. Nevertheless item and shipping indeed are the dimensions where users comment the most on. In Table 8 the dimensional trust score and weight for the item dimension has been underlined. It can be seen that users have substantially different ratings on the item dimension for different sellers and put on different weights.

The "all good reputation" problem is well known for the reputation management systems of popular ecommerce web sites like eBay and Amazon. The high reputation scores for sellers cannot effectively rank sellers and therefore cannot guide potential buyers to select trustworthy sellers to transact with. On the other hand, it is observed that although buyers may give high feedback ratings on transactions, they often express direct negative opinions on aspects of transactions in free text feedback comments. In this paper we have proposed to compute comprehensive multi-dimensional trust profiles for sellers by uncovering dimension ratings embedded in feedback comments.

Extensive experiments on feedback comments for eBay and Amazon sellers demonstrate that our approach computes trust scores highly effective to distinguish and rank sellers.

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 summarization techniques in trust evaluation for e-commerce applications.

## V. EVALUATION METRICS

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  $\tau$  [50] to measure the correlation between two rankings based on the number of pair wise swaps that is needed to transform one ranking into another  $\tau$  falls in  $[-1, 1]$ , a positive value indicates positive correlation, zero represents independence and a negative value indicates negative correlation.  $\tau$  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, and a small value for  $|\tau|$  with  $p > 0.05$  suggests that two rankings are generally independent. Reviews that Stanford parser cannot parse were also removed. After pre-processing we have a total of 52,805 reviews.

### A 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 multi-dimensional 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.



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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 randomized 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 was used as the preference score to rank these approaches; we also carried out a tradeoff analysis of our schemes to illustrate how application- centric requirements influence the applicability of the eight protocol variants explored in this paper.

Seller rankings by reading comments in user studies

eBay seller	eBay rank	Comment rank	Amazon seller	Amazon rank	Comment rank
Seller 1	6	6	Seller 1	5	5
Seller 2	8	5	Seller 2	4	6
Seller 3	10	10	Seller 3	7	2
Seller 4	4	2	Seller 4	1	1
Seller 5	7	3	Seller 5	3	8
Seller 6	5	1	Seller 6	8	7
Seller 7	9	7	Seller 7	2	4
Seller 8	1	9	Seller 8	9	9
Seller 9	2	4	Seller 9	6	3
Seller 10	3	8	Seller 10	10	10
Kendall's $\tau=0.1111$ , $p$ -value=0.7275			Kendall's $\tau=0.4222$ , $p$ -value= 0.1083		
rank-diff=3			rank-diff=1.8		

## EVALUATION OF THE TRUST MODEL:

Above table lists the CommTrust overall trust scores for ten eBay sellers and ten Amazon sellers for 4,7 and 10 dimensions respectively. As the ground truth, the rankings by reading comment summaries for sellers are also listed (under the heading Comm. rank). For both eBay and Amazon sellers, on all 4,7and10.

## FUNCTIONAL REQUIREMENTS:

Manage State, City, Products, Menu and Menu Items by Admin. Maintain User Details. View Comments like Environment, Discount, Policy, Product, Charge, Service for Particular Restaurant. Registration required for authenticate user. User Change Password and Profile. User can also view others comments and given to the particular Product.

## NON-FUNCTIONAL REQUIREMENTS:

Non-functional requirements describe user-visible aspects of the system that are not directly related to functionality of the system.

**User Interface:** A menu interface has been provided to the user to be user friendly.

**Performance Constraints:** Requests should be processed within no time. Users should be authenticated for accessing the requested data.

**Error Handling and Extreme Conditions:** In case of User Error, the System should display a meaningful error message to the user, such that the user can correct his Error. The high level components in proposed system should handle exceptions that occur while connecting to various database servers, IO Exceptions etc.

## QUALITY ISSUES:

Quality issues mainly refers to reliable, available and robust system developing the proposed system the developer must be able to guarantee the reliability transactions so that they will be processed completely and accurately. The ability of system to detect failures and recovery from those failures refers to the availability of system.

## FUTURE ENHANCEMENT:

In this system we can put comments only once, fatherly changing the comment cannot be possible (editing). In future Enhancement we can give number of words like a paragraph (MULTIPLE COMMENTS). In future we can provide digital signature also.

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## VI. CONCLUSION

The “*all good reputation*” problem is well known for the reputation management systems of popular ecommerce web sites like eBay and Amazon. The high reputation scores for sellers cannot effectively rank sellers and therefore cannot guide potential buyers to select trustworthy sellers to transact with. On the other hand, it is observed that although buyers may give high feedback ratings on transactions, they often express direct negative opinions on aspects of transactions in free text feedback comments. In this paper we have proposed to compute comprehensive multi-dimensional trust profiles for sellers by uncovering dimension ratings embedded in feedback comments.

Extensive experiments on feedback comments for eBay and Amazon sellers demonstrate that our approach computes trust scores highly effective to distinguish and rank sellers. 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 summarization techniques in trust evaluation for e-commerce applications.

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