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Survey on CommTrust: Multi-Dimensional Trust Using Mining E-Commerce Feedback Comments

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ABSTRACT: The Reputation based trust models are very admirable in ecommerce applications .Feedback ratings are gathered together for computing sellers' reputation trust scores. A CommTrust system is proposed where the observation made by buyers are mostly used to express opinions about the product in free text feedback review. These feedback review comments are mined. In CommTrust 1) a multidimensional trust model is proposed for computing reputation scores from user feedback comments, 2) for mining feedback comments which are used for weights and ratings of dimension an algorithm is proposed; natural language processing's combining techniques, opinion mining, and topic modeling. The CommTrust proved to be very effective after testing it on various websites like Amazon and eBay.

KEYWORDS*:* Electronic commerce, CommTrust, text mining, Repudiation based models, Sentiment Analysis.

I. Introduction

1.1 Repudiation system

Reputation systems [2] give a proper path for developing the trust through social control without interference of trusted third parties. Most of the research on reputation-based trust uses information such as community-based feedbacks about past experiences of peers. This is done to help making recommendation and judgment on quality and reliability of the transactions.[2]Community based feedbacks are often simple aggregations of positive and negative feedbacks that peers have received for the transactions they have performed and cannot accurately capture the peer's dependability. Peers can mislead in a different of ways in addition, such as generating bogus feedbacks on additional peers. The challenge of building a trust mechanism is how to effectively cope with such malicious behavior of peers. Other challenge is the trust context changes from communities to communities and from transactions to transactions. It is important to build a reputation based system that is able to adapt to different communities and different situations.

The three challenges should be satisfied by reputation system[3]. The system should: (1) provide information that will allow buyers to differentiate between trustworthy and non-trustworthy sellers (2) encourage sellers to be trustworthy, and (3) discourage participation from those who aren't. In the terminology of asymmetric information, the number 2 and number 3 challenges are that a reputation system must prevent moral hazard and adverse selection on the part of sellers.

EBay is one of the best known Internet reputation systems. The comments from buyers and sellers about each other are collected by it. It collects comments after each transaction. Examination of a huge data set from 1999 reveals several interesting features of this system. It facilitates many millions of sales each month. At very first, without incentives to complimentary ride, more than half the time response was supplied. Further, it is always positive beyond expectations. Third, future performance of reputation profiles was predictive. However, the Pollyanna assessments of reputation are encouraged by net feedback scores those are displayed by eBay. The best predictor available is far from it. Fourthly, although sellers with better reputations were more likely to trade their things, they benefited from no boost in price, at

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slightest for the two sets of objects that were examined. Finally, an elevated correlation between buyer and seller feedback as it suggests that the players reciprocate and retaliate is present.

The eBay reputation system is applicable to buyers also. [4] But, sellers cannot hold goods if they are paid, the reputations matter of buyer is substantially less. The great risk is that they will not get paid, if they can turn to the second high bidder. More, even if sellers wished to rely on reputations of buyers it would do slight well, as it is not at all possible to exclude buyers with bad reputations from one's auction.

It is not worth at the outset that the system need not be theoretically sound in order to work properly. It may only be important that buyers and sellers both believe that the system or some part of the system works. [5]A literature is published on the effective workings of reputation systems on the Internet. Therefore it seems not likely that most of the participants are aware of frequency of feedback, disproportions in feedback among those having positive and negative experiences, and so on. the system's working doesn't matter, but how its participants believe it works, or even whether they believe it works even if they have no concern about why matters the most. The performance of man in a world lacking a God might be fully moral and God fearing if its denizens believed there was a God who would judge them and possibly punish them in the hereafter, in order to invoke an analogy drawn from grander contemplations.

II. COMMTRUST

A fine-grained multi-dimensional trust evaluation model by mining e-commerce feedback comments is projected in[6]; it is called as Comment-based Multi-dimensional trust (CommTrust).

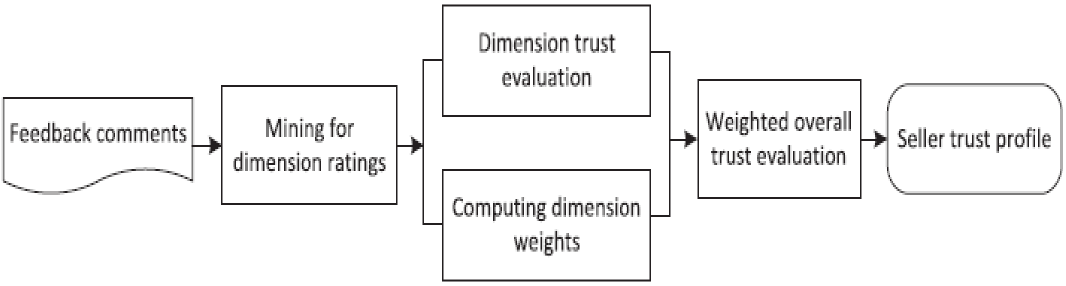

Fig: CommTrust Framework

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) The 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 [7], 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) Sentiment 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

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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.

An umbrella of sentiment analysis or opinion mining covers all of the above. The term sentiment analysis is more commonly used in industry. In academia both sentiment analysis is and opinion mining is frequently used. They basically represent the same field of study. The terminology sentiment analysis at very first appeared in (Nasukawa and Yi, 2003). The term opinion mining was first used in (Dave, Lawrence and Pennock, 2003). However, the earlier research on sentiments and opinions were diverse.

c) Sentiment Analysis Applications

As the opinions are key influencers of human behaviors, 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) Computational 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 behavior of peers, avoid fraudsters and ensure system security was the system level models aim [11].

2) Feedback Comment Analysis

In e-commerce applications feedback comments are examined analyzing in[10] . It says that their focus was not albeit the comprehensive trust evaluation. The main focus of [10] was sentiment classification of 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.Proposed a technique for summarizing feedback. It aims at to filter out courteous comments that do not provide real feedback. Lu. Et al. [elaborates on producing "rated aspect summary" from eBay feedback comments. Its statistical generative model has basis on regression on the overall transaction ratings.

3) Aspect Opinion Extraction and Summarisation

Our work is related to opinion mining, or sentiment analysis on free text documents. In frequent nouns and noun phrases are considered aspects for product reviews, and an opinion lexicon is developed to identify opinion orientations. It is further proposed to apply lexical knowledge patterns to improve the aspect extraction accuracy. The dependency relation parsing is used to mine aspect opinions for movie reviews. However these works do not group aspect opinion expressions into clusters. Some work group's aspects into clusters, assuming aspect opinion expressions. Recently a semi- supervised algorithm was proposed to extract aspects and group them into meaningful clusters as supervised by

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user input seed words. Unsupervised topic modelling- based techniques have been developed to jointly model opinions and aspects (or topics), based on either the probabilistic Latent Semantic Analysis (pLSA) [9] or Latent Dirichlet Allocation (LDA) [8]. The used models differ in granularities and how aspects and opinions interact. All these existing work however are based on the unigram representation of documents and none of them make use of any lexical knowledge.

III. CONCLUSION

A survey studied Repudiation system, various aspects of repudiation system. The high reputation scores for sellers cannot effectively rank sellers and therefore cannot guide potential buyers to select trustworthy sellers to transact with. The most popular eBay repudiation system is studied. A CommTrust system is analyzed. Its aspects like The Stanford typed dependencies representation, Sentiment Analysis, Sentiment Analysis Applications are discussed. Thus the survey will help researchers for further study in repudiation systems.

REFERENCES

1. P. Resnick, K. Kuwabara, R. Zeckhauser, and E. Friedman, “Reputation systems: Facilitating trust in internet interactions,” Commun. ACM, vol. 43, no. 12, pp. 45–48, 2000.
2. P. Resnick and R. Zeckhauser, “Trust among strangers in inter- net transactions: Empirical analysis of eBay’s reputation system,” Econ. Internet E-Commerce, vol. 11, no. 11, pp. 127–157, Nov. 2002.
3. J. O’Donovan, B. Smyth, V. Evrim, and D. McLeod, “Extracting and visualizing trust relationships from online auction feedback comments,” in Proc. IJCAI, San Francisco, CA, USA, 2007, pp. 2826–2831.
4 M.De Marneffe, B. MacCartney, and C. Manning,“Generating typed dependency parses from phrase structure parses,” in Proc. LREC, vol. 6. 2006, pp. 449–454.
5 M. De Marneffe and C. Manning, “The Stanford typed dependen- cies representation,” in Proc. CrossParser, Stroudsburg, PA, USA, 2008.
6 B. Pang and L. Lee, “Opinion mining and sentiment analysis,” Found. Trends Inf. Ret., vol. 2, no. 1–2, pp. 1–135, Jan. 2008.
7 B. Liu, Sentiment Analysis and Opinion Mining. San Rafael, CA, USA: Morgan & Claypool Publishers, 2012. [8] D. M. Blei, A. Y. Ng, and M. I. Jordan, “Latent Dirichlet alloca- tion,” J. Mach. Learn. Res., vol. 3, pp. 993–1022, Jan. 2003.
9 T. Hofmann, “Probabilistic latent semantic indexing,” in Proc. 22nd ACM SIGIR, New York, NY, USA, 1999, pp. 50–57.
10 Y. Lu, C. Zhai, and N. Sundaresan, “Rated aspect summarization of short comments,” in Proc. 18th Int. Conf. WWW, New York, NY, USA, 2009.
11 H. Wang, Y. Lu, and C. Zhai, “Latent aspect rating analysis with- out aspect keyword supervision,” in Proc. 17th ACM SIGKDD Int. Conf. KDD, San Diego, CA, USA, 2011, pp. 618–626.
12 H. Wang, Y. Lu, and C. Zhai, “Latent aspect rating analysis on review text data: A rating regression approach,” in Proc. 16th ACM SIGKDD Int. Conf. KDD, New York, NY, USA, 2010, pp. 783–792.
13 S. Ramchurn, D. Huynh, and N. Jennings, “Trust in multi-agent systems,” Knowl. Eng. Rev., Vol. 19, no. 1, pp. 1–25, 2004.
14 B. Yu and M. P. Singh, “Distributed reputation management for electronic commerce,” Comput. Intell., vol. 18, no. 4, pp. 535–549, Nov. 2002.
15 M. Schillo, P. Funk, and M. Rovatsos, “Using trust for detecting deceptive agents in artificial societies,” Appl. Artif. Intell., vol. 14, no. 8, pp. 825–848, 2000.
16 J. Sabater and C. Sierra, “Regret: Reputation in gregarious soci- eties,” in Proc. 5th Int. Conf. AGENTS, New York, NY, USA, 2001, pp. 194–195.
17 A. Jøsang, R. Ismail, and C. Boyd, “A survey of trust and repu- tation systems for online service provision,” DSS, vol. 43, no. 2, pp. 618–644, 2007.
18 S. D. Kamvar, M. T. Schlosser, and H. Garcia-Molina, “The EigenTrust algorithm for reputation management in P2P net- works,” in Proc. 12th Int. Conf. WWW, Budapest, Hungary, 2003.
19 Z. Zhai, B. Liu, H. Xu, and P. Jia, “Constrained LDA for group- ing product features in opinion mining,” in Proc. 15th PAKDD, Shenzhen, China, 2011, pp. 448–459.
20 P. D. Turney, “Thumbs up or thumbs down?: Semantic orientation applied to unsupervised classification of reviews,” in Proc. 40th ACL, Philadelphia, PA, USA, 2002, pp. 417–424.

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