

A Survey on Reputation Systems in E-Commerce

Gigi Mol¹, Sincy John²

¹ PG Student, Department of Computer Science and Engineering, A.P.J Abdul Kalam University, Kerala, India

² Professor, Department of Computer Science and Engineering, A.P.J Abdul Kalam University, Kerala, India

Email address: ¹gigimx123@gmail.com

Abstract— A crucial factor for the success of e-commerce system is accurate trust evaluation. Reputation based trust models are widely used in e-commerce systems, where the ratings are used to calculate the trust score. These ratings, also referred as recommendations, referrals and feedback, is the most important factor in building the trust relationship. Ratings will guide the potential buyers to choose the most trustworthy seller. Different rating system may adopt different methods to calculate the reputation trust score, which in turn rank the sellers to guide the buyers. A comprehensive survey on different reputation system in e-commerce applications are presented in this paper.

Keywords— Reputation system, trust score, peer-to-peer, feedback.

I. INTRODUCTION

The most important factors to be considered in an e-commerce system are trust and reputation. Reputation based trust models are used in e-commerce applications to help the users or customers to choose the best seller by letting them rate each other.

In e-commerce system there exists different models such as individual model, system model and reputation model. In individual model, the seller from whom they are going to do a transaction is chosen by the buyer themselves. In the case of system model, the sellers are selected based on their trustworthiness. For reputation model, the trust score is used to rank the sellers and the buyer will choose the one with high rank.

Different reputation models are implemented in e-commerce system to calculate the trust and reputation score. The “all good repute problem” is predominant in most of these reputation models. The trust score is very high for most of the sellers as there is no provision to provide negative ratings in most of the reputation models. A main reason for lack of negative ratings is that, if they leave negative votes their reputation itself may be affected. So, they do not express their real ideas about sellers, which always results in a high positive rating for all of them. This trust and reputation score is considered as the decisive factor in making online purchasing decisions. These scores are evaluated to rank the sellers as per their services and qualities. This helps the buyers to choose the seller as per their requirements.

II. REPUTATION MODELS

Reputation systems can be classified according to four main areas:

- a. Trust computation approaches.
- b. Analysis of e-commerce comments.
- c. Summarization and opinion extraction.
- d. Matrix Factorization technique applications.

A. Trust Computation Approaches

Positive biasing system [1] is used for trust computation in eBay reputation system. It is a simple system in which the individual reputation score is computed for each seller. A

positive feedback percentage is calculated based on the average number of positive and negative feedback in a specified period of time for a particular transaction. All good repute problem occurs in this system as it cannot express the negative aspect towards a transaction [2]. To bring the reputation score to a reasonable level, feedback comments are analyzed and the one which do not explicitly expresses positive opinion is considered as negative. The trust score is computed by aggregating the ratings of all the transactions. Its main focus is on extracting dimensional rating and to calculate overall dimension scores.

Computational trust evaluation is important for open system operations. The terms used to refer individuals in open systems are peers and agents as buyers and sellers in applications of e-commerce. Trust is used by an individual to assess the performance of another individual by his actions [3]. Individual trust models aim to assist users in decision making by computing the reliability of sellers [4]. System models aim to prevent the influence of fraud people by controlling the behavior of peers [5].

The average ratings of customers for a particular product is termed as reputation. It aims to create a trust profile for the sellers and enables the users to choose the most trustworthy sellers for them to transact with. It ensures reliable and secure attitude of open systems. It has been used in variety of applications such as e-commerce, peer-to-peer networks [6], multi-agent systems etc. the accurate computation of reputation score requires effective mechanisms to collect and aggregate those ratings. There are several algorithms for rating aggregations such as star rating system, positive percentage system, beta reputation system, kalman inference system etc.

PeerTrust system is used in peer to peer online communities. It calculates reputation score based on trust parameters and general trust metric. Trust parameter includes feedback scope, transaction context factor, community context factor and credibility factor. The trust metric evaluates these parameters to calculate the reputation score. The advantages of this system includes minimizing security weakness and have less computation time. Its disadvantages includes ranking of seller is not effective and the users are not given enough provision to choose different transactional aspects.

EigenTrust system is a reputation management system for peer to peer network. In this, a unique global trust value is computed for each peer by local trust value assigned to them by other peers weighted by their global trust value. Those having high value will be having high reputation score. The advantages includes self-policing, anonymity and the overhead is less. Its disadvantages includes that a malicious peer can be given a high local trust value to other malicious peers and a priori notion of trust in which the first few peers in the network is considered trustworthy.

In order to obtain a fine grained trust computation, a multi-dimensional approach is used in the area of agent technologies [7]. In this, the overall trust reputation score is computed by aggregating the individual dimension score for each agents. This system computes individual, ontological and social reputation by considering the factors such as timely delivery and quality of item. All these scores are aggregated to form trust reputation score.

The dimension scores can be calculated from an individual agent's direct experience and weighted summation techniques are used to aggregate these scores [8]. It can also be computed by using a probabilistic approach that depends on the correlation between them. In these systems, the weighting for individual dimensions are given to be assumed. The dimensions associated with these systems includes attributes related to items or the communication between the seller and the buyer [9].

CommTrust system is a multidimensional trust model in which the reputation score is computed based on the feedback comments from the user. It is based on the idea that users feel free to express their opinions about different aspects of transaction in the free text feedback comments. The dimensional score is calculate based on the number of positive and negative ratings towards a particular dimension. The advantages of this system includes self-improvement, more accurate and effectively rank the sellers for assisting the potential buyers to choose the most trustworthy seller for doing transactions.

B. Feedback Comment Analysis

The user interaction is one of the main reason for the success of e-commerce applications. A seller having high reputation score will attract a large number of users for doing transactions with them and may leave comments. For identifying the service quality of a seller, the potential buyers may check their reputation score. Most of the reputation system does not provide any provision for considering the negative aspects of the user [10]. So, they feel free to express their actual opinion about a transaction in an open text feedback comments. Therefore, by analyzing the wealth of information in the feedback comments one can generate the actual trusted reputation score for a seller.

This analysis is actually a challenging task as the feedback comments are noisy and unstructured. The problem of all good reputation can be solved by analyzing those comments and extracting the negative aspects towards each seller. Comments those do not express a direct positive opinion towards a dimension is considered negative. Sentiment classification can

be used for analyzing the feedback comments. It uses text characterization for properly analyzing these feedback comments.

For summarizing feedback comments, a technique known as Social Summarization (SS) is used which filter out the unwanted comments that do not express any opinion towards the transactional aspects [10]. This includes courtesy comments such as 'thanking the sellers'. This technique uses the social relationships in online process for summarizing the feedback comments for a particular seller. Its main focus is on the buyer who brought the item from the sellers and not on the sellers. This method performs comparison between the feedback comments by a particular buyer on the target seller to the feedback comments by the same buyer for the sellers other than the target seller. By extracting the descriptions of those two, one can obtain a summary about the transaction. By this method, the courtesy descriptions can be eliminated without deleting the descriptions that actually express their real feelings.

Rated aspect summarization of short comments can also be used for analyzing the feedback comments which aims to identify the various aspects towards the aggregated ratings [11]. This form of decomposition is very useful because the users may have various requirements and the overall ratings may not be informative enough for satisfying their needs. A structured Probabilistic Latent Semantic Analysis (PLSA) based on statistical approach was used to identify the aspects and rating for that from the comments of the user. This statistical generative model is based on the factor of regression on the overall ratings of the transaction.

The CommTrust (Comment base Multi-dimensional Trust model) not only simply classifies the comments from the user into positive and negative but also identifies the dimension in them by mining it and determines the orientation hidden in the text of associated feedbacks [12]. So, it is able to solve the all good reputation problem which is prevalent in most of the reputation systems. Apart from the statistical approach, it uses knowledge based approach such as Stanford dependency parse for identifying the relationship between each words in the sentence and makes an opinion about each phrases in that open text feedback comments. Rather than making a summary of the comments, it aims at calculating the individual dimension scores and their corresponding weights. It improves the computation efficiency compared to all other reputation models.

C. Aspect Opinion Extraction and Summarisation

Opinion mining and sentiment analysis are mostly used to analyze the comments given by the users on the free text documents. According to the extracted features, by selecting and reorganizing sentences, summaries of comments are generated. Sentiment summary can be produced by proper mining of the reviewed comments, which is mainly used for summarizing the user's opinion about a particular transaction. While summarizing the opinions, it also determines whether the opinion about a transactional dimension is positive or negative which makes it different from the traditional summarization of text comments given by the user.

Most of the systems working on summarization of opinion and mining of reviews depends only on the review of products i.e. for extracting opinion towards different aspect of transaction, they concentrate mainly on the summarization and mining of product reviews [13]. In some systems, all the reviews of users towards a particular product is summarized which can help the potential user on making a decision on whether they could buy that product. They consider the transactional candidate aspects as nouns and noun phrases and uses association rule mining methods to evaluate the appropriate opinion towards each aspects that are chosen as its candidates. Then the NLP (Natural Language Processor) is used to parse the comments and to identify those noun and noun phrases associated with each aspect of product reviews by obtaining the part-of-speech tag for each word in that comment statement. For this, NLPProcessor 2000 is used, which parses the comments and identify the opinion about each aspect of product in the transactions.

To find all the commonly used item sets i.e. the set of words or phrases that occur together, association rule mining is used [14]. It identifies the relationship between the words in the text feedback comments. It provides minimum threshold support and minimum constraints in confidence while finding the frequent item pairs. These opinion word are adjectives in a sentence that describes the nouns which represents the transactional aspects for a particular product.

For identifying the orientation of adjective in that feedback comments, WordNet is used. If a particular adjective cannot be identified by the WordNet, then it will be considered as an invalid one and can be rejected from that comment [15]. For a particular adjective, there may be synonyms and antonyms which may have different orientation. It may also check for the negative word that expresses negativeness towards a particular aspect and then reverses its orientation. For identifying the negative opinion, there is a threshold on the distance between the aspect and its opinion.

To extract nouns and noun phrases from the review towards a transaction, OPINE is used. It retains all those having frequency higher than the threshold set experimentally. The assessor of OPINE computes a Point-wise Mutual Information score between the noun phrases and discriminators associated with a particular product and then makes an evaluation on it. Syntactic information uses dependency analysis to extract the various aspects of products and its associated opinions. In this aspect opinion pair can be identified using dependency analysis and the distance between those two is not a matter of concern while analyzing the review of products [16].

A multi-knowledge based approach is used for opinion extraction which combines WordNet, statistical analysis and previous knowledge obtained for that product. In order to find opinion and the corresponding aspect of a product, a keyword is generated depending on the WordNet and the labeled training data. To identify this pair, analyze the grammatical relationship between each and every words or phrases in the sentence by using some natural language processing tools. For this, it is assumed that the aspect and opinion description for that aspect will occur within a certain distance. These product

aspects and their opinions will be bounded in any of the four regions such as full sentence, between the words of opinion and aspect, plus or minus two words and the word next to the aspect till its end.

Manual extraction rules can also be used to extract the opinion words [17]. Instead of setting a threshold distance, it uses some rules to find the opinion words of various aspects. These rules are based on the dependency relation analysis. Some semi-supervised algorithm can also be used to extract the aspect and form some meaningful clusters by using supervised user input. According to LDA (Latent Dirichlet Allocation) and pLSA (probabilistic Latent Semantic Analysis), unsupervised topic modelling techniques can be used to group aspects and opinions together [18]. These models may differ in their granularities and the way how aspects and opinions interact.

Most of these systems depends on the representation of documents and does not utilize any lexical knowledge. Word sentiment classification method is based on the assumption of grouping a fixed number of aspect words and then sorting its opinion into two lists such as positive and negative and grow this using WordNet. It considers synonyms of a particular word as positive and its antonyms as negative. The antonyms of a negative word can be added into list containing positive opinion and its synonyms into list containing negative opinions for a word.

The lexicon based opinion derivation method is SentiWordNet [19]. In this each word corresponds to a numeric score to indicate whether it is positive or negative. It can be considered as the most important resource for automatic sentiment classification [20]. CommTrust uses both Lexical-LDA and DR- mining approaches for identifying the dependency relation between each and every phrases and to identify the dimension ratings for each aspect from the feedback comments of the user.

D. Matrix Factorisation

Matrix factorization is an analytic technique mainly used in the areas of retrieval of information and recommender systems [21]. Latent Semantic Indexing (LSI) is an information retrieval method which is mainly used for indexing and retrieving the required information by applying a singular value decomposition (SVD) to split the document matrix into terms by using a set of factors through which the original matrix can be approximately reproduced using linear combinations. Matrix algebra is used to represent the similarity between the documents, its terms and the queries.

For recommender systems, the commonly used technique is collaborative filtering (CF) which uses matrix factorization algorithm. It will recommend items to the user depending on the preferences of other user having a similar taste with the user. So, there will be having a higher probability for that user to choose that item. The ratings are given to each item by the users and the latent factor model reveals the item and user factors depending on the pattern of rating given to that item by the user. Vector representation is used for representing the user and product interactions. If there is a high correspondence between the item and the user, then it will be chosen for

recommendation to other users. For effective prediction of ratings in collaborative filtering, standard SVD is used.

In comment based multi-dimensional trust model, the application of singular value decomposition (SVD) is entirely different. It computes the relative weights of the original objects using this SVD algorithm. In this the unwanted noises can be removed and it also considers the correlations between the data items. So, it will be more accurate among all other systems.

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