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Decision Making in the Multi-Dimensional Trust by Mining Huge Volume of unstructured E-Commerce Feedback Comments

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ABSTRACT

Information of extreme size, diversity and complexity – is everywhere. This disruptive phenomenon is destined to help organizations drive innovation by gaining new and faster insight into their customers. Market and Technology has its own way of implementation of the strategic decision policy. These days' data mining in the trend o the E-commerce plays the role of the market, as the trend is shifting from classical trend to the electronics trend which in turn we call as E-commerce. If we approach the model of axis model of decision making cannot be without data and information. Hence In this Paper we put forward the concept of the feedback from customer as open text which mined with the specific purpose to study the customer need in the E-commerce market. Vendors like Amazon and Alibaba more customer centric rather to market centric, hence the data will help them what is the trend the customer need rather to the market. In the context, we have implemented the no-sql database based approach to retrieve information in a pattern which the client or customer need. The Divide and Conquer with Map reduced program enables us to reach the destination with the robustness, performance oriented and best of the timely technology solution.

Keywords: Electronic commerce, text mining, Big Data, Hadoop, Volume

I. INTRODUCTION

An incentive mechanism is a system with designed rules ensuring that the actions of big data honestly reporting their information will produce a better outcome for these big data. Mechanism where big data are better off to report truthfully the information of their valuation about requested products. Different incentive mechanisms have been developed by researchers to encourage honesty in the reporting from buying big data in electronic marketplaces, in order to diminish concerns about untruthful ratings. For example, side payment mechanisms offer side payment to buyers that truthfully rate results of business with sellers. The credibility of two participants in their business will be decreased if their ratings about the business result are different.

Figure 1. Decision Making Process Cycle Illustration.

Buying big data will provide truthful ratings in order to keep up their credibility. Trust revelation mechanisms create incentives for big data to truthfully report their own trustworthiness or the trust they have of others. A special kind of social network is called an "affiliation network," in which nodes are actors and events to which the actors belong. Affiliation networks can also be described as collections of subsets of entities. Each event describes the subset of actors who are affiliated with it, and each actor describes the subset of events to which it belongs. Viewing an affiliation network this way is fundamental to the hyper graph approach.

II. RELATED WORK

Social acceptance of trust and reputation systems is another critical factor. For the more widespread and general usage of these systems, social acceptance by all parties is an issue that needs to be considered. The second task is to adjust reputation advice according to its accuracy. The aim of this task is to reduce the effect of inaccurate advice.

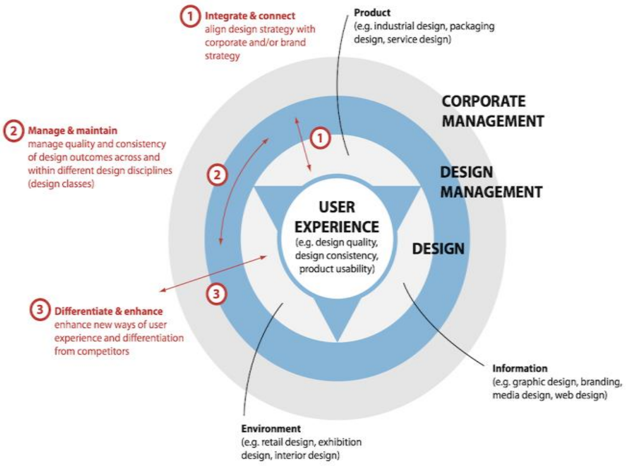

Figure 2. Model View of the E-Commerce Feedback

This task is necessary because it can deal with the situation where an advisor unfairly rates a seller a large number of times Experimental results shows that has better performance in estimating sellers' trustworthiness than the BRS system. However, this model also has some weaknesses. It assumes that selling big data act consistently. This assumption might not be true. A seller may change its behavior from being trustworthy to being untrustworthy. Suppose an advisor has done business with the seller before and their interaction is successful. The fair advice provided by the advisor then indicates that the seller is trustworthy. However, this advice will be incorrectly considered as unfair when a buyer takes this advice and does business with the seller after the seller changes its behavior. The second problem is that this model relies only on the buyer's personal experience with the advisor's advice. Another example is the similarities between collaborative filtering and reputation systems. Both types of systems collect ratings from members in a social network.

III. METHODOLOGY

Universal test beds and evaluation metrics for comparison of the relative efficiency of trust and reputation mechanisms compared to that of more established systems are needed and theory-driven guidelines should be developed to decide which set of mechanisms to use. It proposes a Bayesian network-based trust model in a peer-to-peer file sharing system. In this system, file providers' capabilities are evaluated according to different aspects, including download speed, file quality, and file type. A Bayesian network is constructed to represent conditional dependencies between the trustworthiness of file providers and the aspects. Each user holds a Bayesian network for each file provider. If a user has no personal experience with a file provider, he may ask other users for recommendations. A recommendation provided by an advisor will be considered by the user according to the trust value he has of the advisor. The trust value is updated by a reinforcement learning formula. More specifically, it will be increased decreased after each comparison between the Bayesian networks held by the user and the advisor for the file provider. Therefore, the weights of two pieces of evidence collected one month ago and one year ago have very little difference as long as they have been collected one after the other. Another problem is that this approach determines the preference similarity between two nodes based on only their current reputation ratings to one other node, which is certainly insufficient.

The usefulness of the former arises when the emphasis is on the content, and the latter can be used when the source of information is a more important factor. They are thus complimentary social mechanisms in global open distributed systems. There is significant potential to combine collaborative filtering and reputation systems. Another example is investigating Web-based social networks and its applicability to different tasks such as trust interference within trust networks.

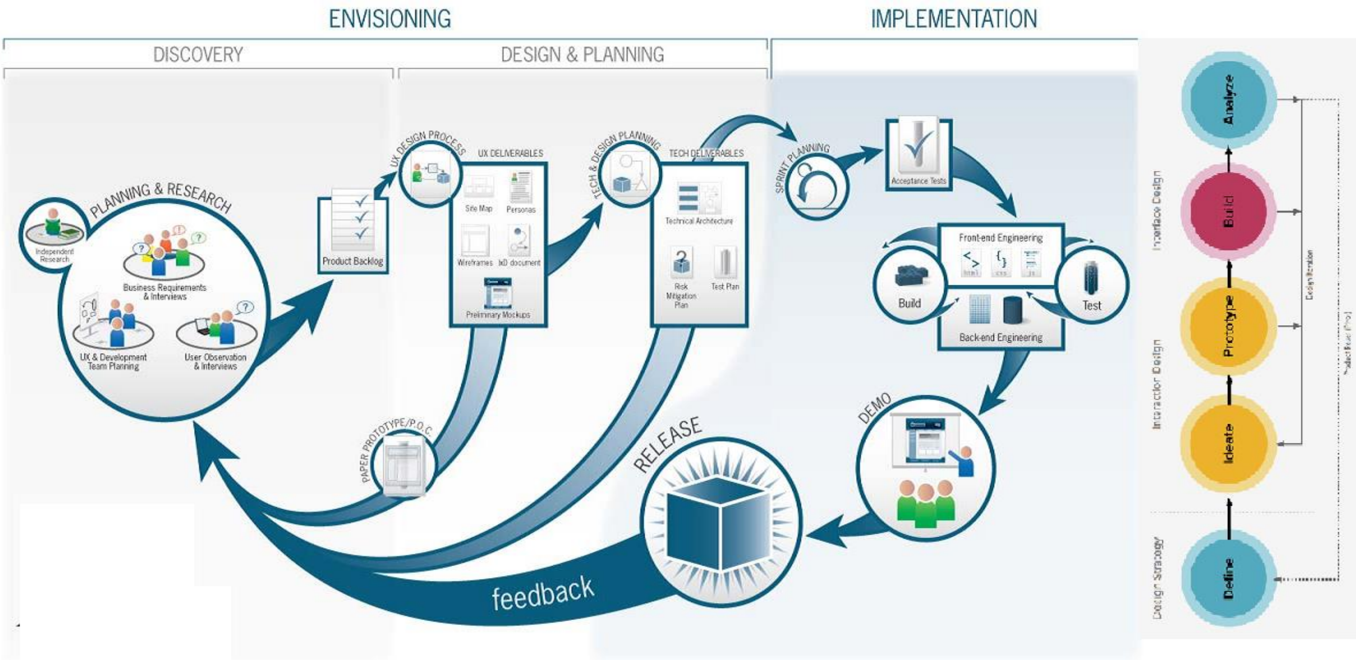

Figure 3. Architectural Model of the Prototype Approach

The third problem concerns the method for integrating advice. The RRSMAN approach updates the reputation rating of a node by considering other nodes' advice. Pieces of advice provided by other nodes are considered equally as long as these nodes are trustworthy or each piece of advice is compatible. Some trustworthy nodes may be more trustworthy and others may be less trustworthy. Their advice about a node should have different impact when updating the reputation rating of the node. Similarly, advice with different compatibility values should also be considered differently. In distributed reputation systems, there is no central location for submitting ratings or obtaining advisors' ratings. A buyer should simply request advice about a seller from advisors. Even though some distributed reputation systems have distributed stores for collecting ratings, it is still costly to obtain all ratings for the seller. Therefore, approaches used in these systems cannot consider all big data' ratings for the sellers. The approaches used in distributed reputation systems, for example TRAVOS, Bayesian and WMA, handle unfair ratings by estimating the trustworthiness of an advisor based on each individual buyer's personal experience with the advisor's advice.

3.1 Evaluation and Analysis

In centralized reputation systems, central servers collect ratings for each selling agent from buying big data after transactions between them have taken place. These systems typically provide the same cumulative rating of a seller to any buyer. The approaches for coping with unfair ratings in these systems.

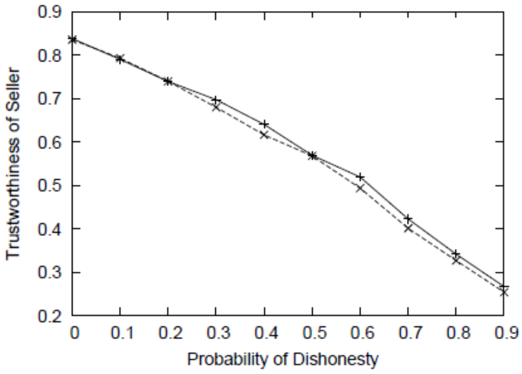

Figure 4. Comparison of the Density of the Seller

Do not consider buyers' personal experience with advisors' advice. These approaches are based on all ratings of sellers and belong to the \public/endogenous" category. Results from those approaches do not differ for different buyers.

IV. CONCLUSION AND FUTURE WORK

A decision to trust is a decision tied with risk. Even when the expectations are well grounded, there is an element of risk in trust, a chance that those who are trusted will not act as expected. The risk should be justified in order to confirm the current trust and to strengthen it, otherwise if the other party defects, trust decreases dramatically. The estimation of this risk remains a problematic area. Game theory is a powerful tool for this purpose.

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