Article

A Hybrid Artificial Reputation Model Involving Interaction Trust, Witness Information and the Trust Model to Calculate the Trust Value of Service Providers

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Abstract: Agent interaction in a community, such as the online buyer-seller scenario, is often uncertain, as when an agent comes in contact with other agents they initially know nothing about each other. Currently, many reputation models are developed that help service consumers select better service providers. Reputation models also help agents to make a decision on who they should trust and transact with in the future. These reputation models are either built on interaction trust that involves direct experience as a source of information or they are built upon witness information also known as word-of-mouth that involves the reports provided by others. Neither the interaction trust nor the witness information models alone succeed in such uncertain interactions. In this paper we propose a hybrid reputation model involving both interaction trust and witness information to address the shortcomings of existing reputation models when taken separately. A sample simulation is built to setup buyer-seller services and uncertain interactions. Experiments reveal that the hybrid approach leads to better selection of trustworthy agents where consumers select more reputable service providers, eventually helping consumers obtain more gains. Furthermore, the trust model developed is used in calculating trust values of service providers.

Keywords: interaction; witness information; trust; reputation

1. Introduction

The concept of reputation has many applications in real life scenarios. Reputation finds its use in electronic markets such as the websites eBay® and Amazon® [1]. Direct and indirect interaction are the

main sources of information to calculate reputation. Through direct interactions, agents directly interact with other agents who are present in a multi agent system. This is the most reliable means of information source. In case of witness information (word of mouth), agents collect the reputation value from other agents present in community [2]. However, these two sources alone cannot yield the real reputation score of a service provider. This is because, if reputation is based only on interaction trust (direct experience), the agent in that case interacts directly with other agents present in community individually. Due to this, it would require a long time for an agent to reach a satisfying estimation level as he has to come in direct contact with other agents. Therefore, interaction trust alone cannot reach a reliable reputation score. Moreover, in case of witness reports, self interested agents could be unwilling or unable to sacrifice their resources in order to provide reports. As a result, this approach alone could not guarantee a reliable estimation [3].

In this article we have presented a hybrid reputation model and compared its results with other information sources. We used two experimental set ups. In the first we compare a hybrid model developed with the witness information as the source and then we compare a hybrid model with interaction trust as a source of information. We also present a trust model which is used to calculate trust values of service providers from a list of providers.

The structure of article is as follows. In Section 2, we highlight the related work done in this area. Section 3 deals with reputation network architectures. In Section 4 various common information sources to find reputation values are discussed. In Section 5 the hybrid reputation model we developed and its results are discussed. The Section 6 describes trust model to calculate the trust values of service providers. Section 7 discusses the conclusion and future work that can be done in the next step of our study.

2. Related Work

In recent years, many reputation models have appeared in academic researching and online business fields. In these models, transaction takes place between provider and consumer and after a transaction the service consumer rates the service provider. The score is obtained when the consumer agents make a transaction from the provider agent and the score is used to help the service provider and service consumer choose the transaction partner. The reputation models are generally divided into two categories according to the information they collect. These are: centralized reputation mechanism and distributed reputation mechanism. The centralized reputation mechanism collects all the information after every transaction, calculates the reputation score and presents it to all service consumers. This helps service consumers to make a decision regarding with whom should they transact to obtain more benefits. In a distributed reputation mechanism there is no central repository which stores the ratings or obtains reputation scores of others. Instead, there are distributed storages where ratings can be stored or each participant simply records their opinion about the experiences of other parties and provides the required information when asked [1]. The models based on centralized mechanism are eBay® [4], Amazon® [5], *etc*., where the central repository is maintained where all the ratings are stored and updated continuously and models based on distributed mechanisms are similar to AFRAS [6] and Regret [7].

As our hybrid model is also based on a centralized mechanism of reputation, we will discuss reputation models which are related to centralized mechanisms. eBay® [4] and Amazon® [5] are good

examples of online marketplaces that use centralized reputation mechanisms. eBay® has 50 million registered users and is considered as the world's largest online marketplace. eBay® uses English auctions to sell most of its items. The reputation mechanism used is based on the ratings that users perform after the completion of a transaction. The user can give three possible values: positive (1), negative (−1), or neutral (0). The reputation value is computed as the sum of those ratings over the last six months. Similarly, Amazon® also use the mean (in this case of all ratings) to assign a reputation value. The information source used to build the reputation value comes from other agents that previously interacted with the target agent (witness information). As it is only based on a witness information source, which is a third party source, they do not provide explicit mechanisms to deal with users that provide false information. Therefore, we add interaction trust as a source so as to increase reliability. This addition will make a reputation model hybrid as we can differentiate the consumers' data source into two different types which are witness information and interaction trust [2]. Another model based on using a centralized mechanism is Sporas where only the most recent rating between two users is considered. The users with high reputation values have very smaller rating changes after each update compared to users with low reputation. Sporas is the evolved version of online reputation model. Measure of reliability and the preference given to most recent ratings are the two new features added in this model. These features help in improving the model and performing better. This model works better compared to other online reputation models [2].

3. Reputation Network Architecture

3.1. Centralized Architecture

In centralized reputation architecture there is a particular entity called the central repository that is responsible for the activities of gathering information from the community, performing calculations on this information and making the results of its calculations public to everyone in the community. In the Figure 1 below all the interactions between A, B, C and other agents present in a community are stored in reputation center. This reputation center uses computation engine where all the ratings are computed. The ratings stored are globally available to all the members present in a community. This is shown in figure 1 [1].

Figure 1. Framework for centralized Reputation Systems. "Adapted from [1]". (**a**) Past interaction between agents is shown; (**b**) Present interaction between agents is shown.

(**a**) Past   (**b**) Present
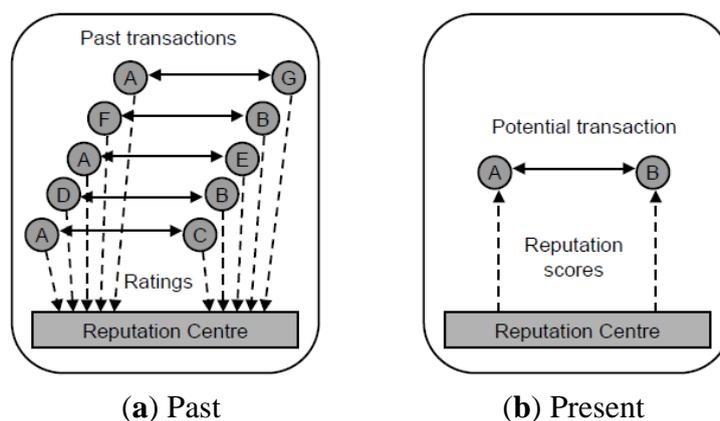
3.2. Distributed Architecture

In this case there is no central repository or storage. The central reputation center is replaced by several smaller distributed ones which means each individual stores its own interactions and when required to retrieve information then that agent has to be asked individually and there is no global access to ratings or reputation scores. This is shown in Figure 2 below [1].

Figure 2. Framework for Distributed Reputation Systems. "Adapted from [1]". (**a**) Past interaction is between agents is shown; (**b**) Present interaction between agents is shown.

(**a**) Past   (**b**) Present
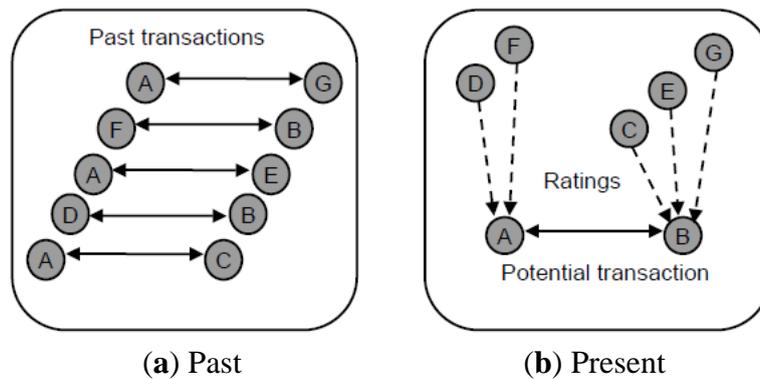
4. Information Sources of Reputation

The various information sources of reputation are direct experiences, witness information, sociological information and prejudice [2].

4.1. Direct Experience

Direct experience is used to calculate reputation among agents in a multi agent system. This is further divided into two types. These are direct interactions in which agents directly interact with other agents present in the system and find out the reputation. The second type is direct observation in which agents directly observe the interaction of other agents present in system and calculate the reputation. The second type, which is direct observation, is a less common source of information, and direct experience is the most reliable source from which to calculate reputation [2].

4.2. Witness Information

Witness information is also known as "word of mouth" as it uses the information gathered from other agents in the community. This is the most abundant in multi agent systems but is not as reliable as direct experience as the other agents may hide information for their own benefits [2].

4.3. Sociological Information

This reputation is based on social relations among agents in a community, such as competition, co-operation, *etc*. This kind of information is possible when there are many agents present in a community and interaction among those agents is good [2].

4.4. Prejudice

The use of prejudice can also help in calculating reputation of agents in multi agent system, but its use is not very common. However, we guess that as the complexity of a multi agent system increases, this feature will also be used for calculating reputation. Prejudice assigns reputation to an individual based on signs that identify the individual to be part of a particular group or community. The use of prejudice in multi agent system will be similar to positive intentions, which is the opposite to real life, as in real life it is as negative intentions. The sign can be anything, such as behavior of agents in a group, and will represent the group [2].

5. Hybrid Reputation Model

The reputation model proposed uses a hybrid approach which will combine both interaction trust and witness information. In this model, two kinds of agents are created: ProviderAgent and ConsumerAgent. Provider Agents act as service providers and provide services to ConsumerAgent. ConsumerAgents act as service consumers, calculating the reputation of providers using the reputation model, consuming services and giving ratings. As in the hybrid model service consumers source of information is differentiated. In this way, the reputation value of service consumer computed will be close to the true reputation of the service provider. Witness information helps gather more information. Interaction trust is more reliable source.

We have used two different settings to perform experiments with the simulation. In the first setting we compare witness information as information source alone with the hybrid model. In the second setting we compare interaction trust as information source alone with the hybrid model. In our hybrid model we are using weighted mean to calculate final reputation value. The value R(a,b,c) will represent final reputation value where "a" rates "b" in terms of c. So it means "a" is a consumer agent who is rating the other agent after the product is delivered and "b" is a provider agent. Depending upon the source of information used, the value of k will be selected which will be either 1 or 2 and R_k (a,b,c) will represent the reputation score using a particular source used. We will average all the scores from time step 1 to time step 100. This average will be a weighted mean as we have two different sources of information used. When $k = 1$ we have value of $w_k = 60\%$ and when $k = 2$ we have value of $w_k = 40\%$. We are multiplying this w_k with R_k(a,b,c) from time step 1 to step 100.

5.1. Hybrid Reputation Model Algorithm

Input: R(a,b,c), is a reputation value which is to be evaluated. Each evaluation with value of c $\in\{0,1,2\}$, a is a service consumer agent and b is a service provider agent.

Input: W_k the rating weight function.

Input: T, is the time difference between current time and time when rating r_i is recorded. Simulation round difference is used to represent time difference.

Process: a will rate b in terms of c and form a set named R_k(a,b,c) ∈ r_i where all ratings are stored and k can be 1 or 2 depending upon the source of information selected.

    for each: R_k recorded in a record r_i at time T **do**

        calculate R(a,b,c) by using weighted mean.

    end for

Output: Reputation value (R(a,b,c))

5.2. Hybrid Model Implementation and Experiments

In this model there are 25 consumer agents and 5 provider agents. This number is enough to give us a brief idea of how our model is calculating a reputation score. However, we are undertaking a further case study by collecting real world data from bestbuy websites. At the beginning stage there is no history of interaction stored, so in the first round of experiments, consumer agents buy products from all five providers and rate them, according to the service provided. This kind of interaction is direct interaction as consumer agents interact directly with providers and make a decision to transact. In this interaction, the value of "k" will be set to 1 and wk will be set to 60%. After transaction and using the product, consumers give ratings to their provider, which can be of value 0, 1 or 2. The value 2 is highest, so it means product provided by provider was good. The value 1 means product provided by provider was fair and value 0 means unsatisfactory. For each consumer there is a set of criteria we have chosen to give ratings. We have chosen three criteria: itemdescribed, performance, arrival time. Now, the providers get ratings from consumers on these three criteria. The consumer gives a rating on these three criteria that can be of value 0, 1 or 2. So if the consumer gives rating (2,2,2) it would mean that provider scored the highest points in criteria itemdescribed, criteria performance and criteria arrival time which shows provider is selling good products since he received maximum value of 2 in all three criteria. Similarly, a provider can get rating in the form (2,1,2) or (1,2,2) or (2,2,1) or (1,1,1) and so on.

After this stage, there is some history of interactions stored. The consumers ask the other consumers and they do not interact with providers any more. Now the interactions in our model are only between consumer agents and this is indirect interaction, also called as witness interaction. The value of "k" will be 2 and value of W_k will be 40%. Consumer agents do not interact with provider agents. Consumer agents interact with other Consumer agents who have already interacted with providers who submitted their ratings. The source of information when one consumer asks other consumer agent about a provider is of the type witness information. After these interactions among consumer agents, consumer agents now trust a particular provider agent based on information from other consumer agents, then make a decision to transact. When the product is received then this consumer updates their beliefs about the provider, and new ratings are stored in a central repository. In the first experimental setup, we had 10 consumer agents who directly interacted with providers from time step 1 of simulation until time step 50. These 10 agents interacted with providers in a direct way, consumed the products and gave the ratings. These ratings were then averaged. However, the remaining 15 agents interacted with these 10 consumer agents in an indirect way known as witness information. They had direct interaction with providers in first 50 time steps. So in the first set we had 10 agents with source of information as interaction trust and 15 agents with source of information as witness information.

These 15 agents interacted from time step 51 to time step 100 and their received ratings were averaged. This is shown in the Table 1 below.

**Table 1.** Variation of Information source in hybrid model for service consumers.

Number of Sets	Number of Agents Having Interaction Trust as Information Source	Number of Agents Having Witness Information Source
Set 1	10 Agents	15 Agents
Set 2	15 Agents	10 Agents

After all interactions among consumer agents, we get the values of ratings and multiply them with their respective weights according to the source of information which was used during interaction between providers and consumers. We calculate the reputation score using the weighted mean method, which means that, if the source of information used was interaction trust, which is a direct source and is the most reliable source of information then it has more weight, namely is 60% as shown in Table 2. If, during the interaction, the source of information was witness then it is weighted as 40%. Here we have assumed the weight to be 60% and 40% for two different information sources. However, we can give weights as 80% and 20% also. However, the weight of data source which involves interaction trust as a source of information should always be more than the information in direct interaction, which is more reliable then witness information. So we gave weight to interaction trust as 60% and witness information as 40%. This is because some data sources are more reliable than others and the direct information source is always more reliable. After getting these ratings we averaged all these ratings which is termed average user gain, which signifies the gain that the user obtained after consuming the products. For calculation of the next sets in our experiments we varied the source of information in other sets. A total of two sets were used and each set had a total of 25 consumer agents and 5 provider agents. In set 1 we already had 10 consumer agents with source of information as direct interaction and the remaining 15 had their information source as witness information. In set 2 of our experiment we increased the number of consumer agents which had direct interaction and decreased the consumer agents which used witness information. So in set 2, 15 consumer agents directly interacted with providers from time step 1 to time step 50 and 10 other consumer agents had witness information as information source among themselves and interacted from time step 51 to time step 100. All of the ratings received were averaged again.

The overview of hybrid interaction is shown in Figure 3. In the figure, both the direct and indirect interactions are taking place. The consumer agent has direct interaction with providers and also indirect interaction with already interacted consumers. This makes the model hybrid as we have differentiated the information sources of interaction among consumers.

The Real Reputation Score is calculated using weighted mean. or average. Average gain is calculated by averaging all the scores or ratings when interaction is hybrid based and then averaging all the scores and ratings with the two other information sources separately. This average gain is represented as Average UG where UG means the gain that users obtain after transaction with providers which is also called reputation score. It was observed that the hybrid approach gives better results combining both the information sources.

Figure 3. Overview of the hybrid model having both direct and indirect sources of information.
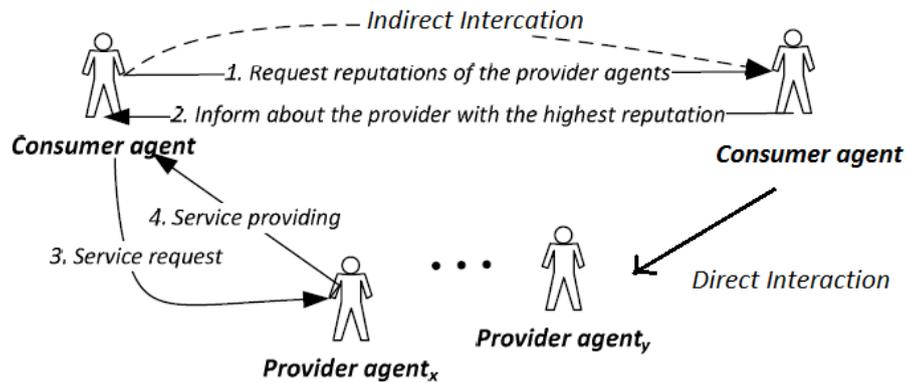
*5.3. Experimental Variables and Parameters*

Table 2. The values of variables and parameters used.

| Simulation Variable	Symbol	Value
Number of Simulation Rounds	T	100
Number of Provider Agents	Np	5
Number of Consumer Agents	NC	25
Direct Experience reputation wt	Q1	60%
Witness Information reputation wt	Q2	40%

5.4. Experimental Results of Hybrid Reputation Model

Figure 4 shows the comparison between the witness-hybrid sources of information and Figure 5 shows interaction between the trust-hybrid sources of information. The dashed line represents the experiment results that involve the source as witness information alone. The continuous line represents the hybrid model that uses both the sources of information, which are interaction trust and witness information. The third line, that is the dotted line, involves interaction trust as a source of information only. The Y-axis represents the average UG (the gain that users obtained), and the X-axis represents the round of experiment. Simulations are run in rounds and the round number is used as the time value. The average user gain here signifies that when consumer agents interact with other consumers present in the simulation environment in a hybrid way, then they tend to obtain better goods or services provided by the provider. This means more benefit for consumers, which leads to more gain. As a result, the average gain computed in the end is more in case of hybrid then individual sources of information. All of these approaches are proved to be beneficial to consumers. It shows that all the information sources discussed above can help consumers to select profitable providers to transact. However, as seen in Figure 4, hybrid outperforms the approach that uses witness information only and in Figure 5 hybrid also outperforms when interaction trust is used alone. As we see in both the cases the continues line (which represents the hybrid approach) is above or in a higher position than the dotted line and dashed line. In conclusion, through experiments we prove that hybrid is more helpful for consumers to select profitable providers. Experiment results are shown in figure 4 and figure 5 below.

Figure 4. Experimental Results involving hybrid and witness as source of information.
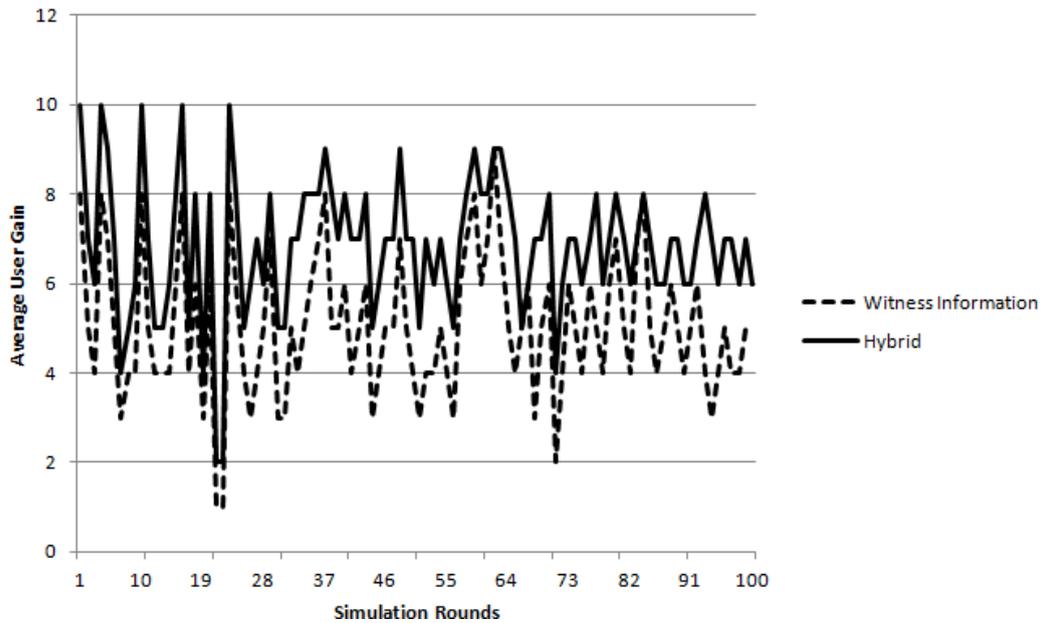
Figure 5. Experimental Results involving hybrid and witness as source of information.
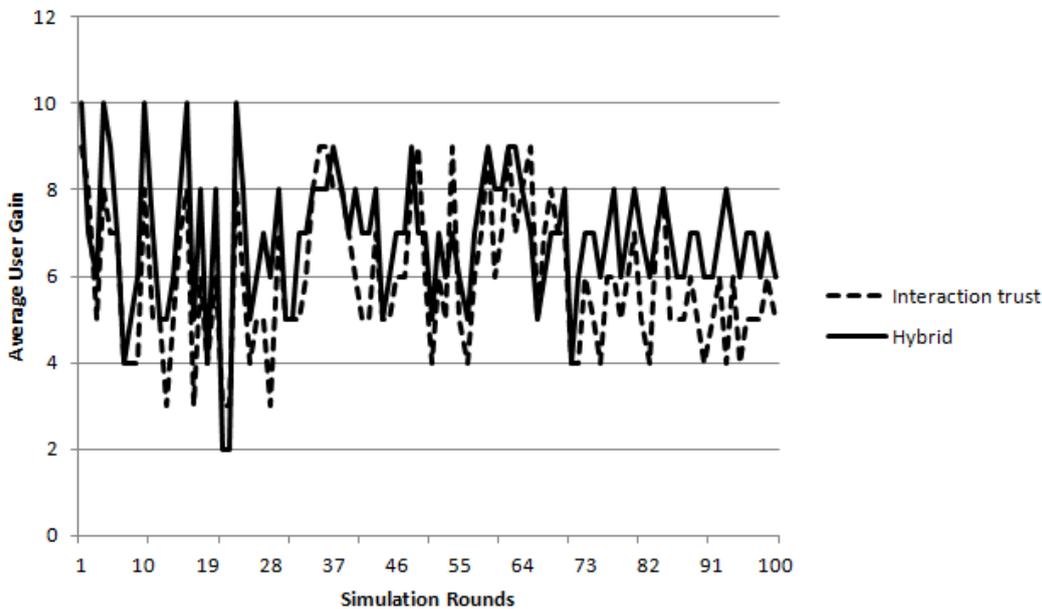
6. Trust Model

6.1. Introduction

With the improvement in technology and increased used of internet at homes, the impact of E-commerce trading is rising rapidly. Due to this, the customers are now comfortably able to search and buy products online. An electronic market platform usually requires buyers and sellers to exchange offers-to-buy and offers-to-sell. However, this business of conducting transaction via a computer platform brings in new challenges. One of the major shortcomings of electronic trade is that consumers have to purchase goods from providers without any personal interaction. So this means there is no direct interaction between the provider and the consumer. This means that consumers may buy goods

from companies which they have not interacted with before, and whom they do not know. Therefore, it leads to uncertainty about the product provided by provider and this platform needs to incorporate issues such as trust and help make the transaction more secure and reduce the uncertainty [9].

6.2. Approach for Trust Model to Calculate the Trust Value of Service Providers

In this model, there are 25 consumer agents and 5 provider agents. This model is based on probability theory.

$$T = \frac{\sum_{i=1}^{n} r_i}{n}$$

where r_i = rating score recieved at each time step; n = total number of interaction; T = Trust Value.

Table 3. Shows the value of all ratings collected from Amazon® website [5] for different providers selling similar product which is camera.

Product Camera	Ratings Received	Number of Interactions	Overall Rating Score
Providers	-	-	-
Camera Depot	4,3,2,4,4,5,5,5	8	4.0
Camera Depot	5,4,2,3,3,2,3,4,5,5,5	11	3.7
Camera Depot	5,3,1,3,2,2,2,3	8	2.6
Camera Depot	4,3,4,4,1,1,1,1,1,1	10	2.1
Camera Depot	2,4,2,2,1,1,3,2,3,1,1,2	12	2.0
Camera Depot	1,1,2,2,1,1,1,1	8	1.2
Camera Depot	5,5,4,5,5,4,2,5,5,5,4,5	12	4.5
Camera Depot	5,5,3,5,5,5,4,4,4,3	10	4.8
Wegio	5,4,3,3,4,4	6	3.8
Wegio	4,4,2,1,1,3,1,1,2,2,1,3,5	13	2.3
Ritz	3,2,3,1,1,1,3	7	2
Ritz	5,5,4,1,3,2,4	6	4.1
Ritz	5,5	2	5
Ritz	2,2,1,1,1,1,2,1,1,1,1	11	1.2
Ritz	4,5,4,3	4	4
Ritz	5,5,4,5,5,4,5,5	8	4.8
Ritz	4,3,4,5,3,4,4	7	4
Ritz	1,1,	2	1
Ritz	5,5,5	3	5
Ritz	2,1,3,2,4	5	2.5
Camera Store	5,5,5,5	4	5
Camera Store	5,5	2	5
Camera Store	4,1,2,1,2	5	2.3
Camera Store	5,4,5,3,3,2	6	3.7
Camera Store	4,4,2,5,5	5	4
Camera Store	2,2,2	3	2

6.3. Case Study in Trust Model

In order to test the formula developed above we collect the data from the amazon® website [5] and test our formula of trust on that data. We used a mozenda [10] software to automate the collection of data. We look at providers who are selling similar products and we have to choose which among those list of providers is the most reliable and trustworthy one so consumers can make a transaction based on the ratings observed. The provider with higher trust value is trustworthy provider. The similar product we are using is "camera". We chose this product for our case study because this product has maximum data available on the amazon® website. Now we see ratings for cameras. We have different providers and the ratings they got over a period of time will help us to decide which is the best provider. The data consisted of three data field values which are "name of the provider", "ratings received", "number of interactions" and the "overall rating score" they got. The ratings observed were given by consumers ranging from 1 to 5. The results are shown in figure 6.

Figure 6. Shows trust values of all providers for camera as a product from Amazon® website.
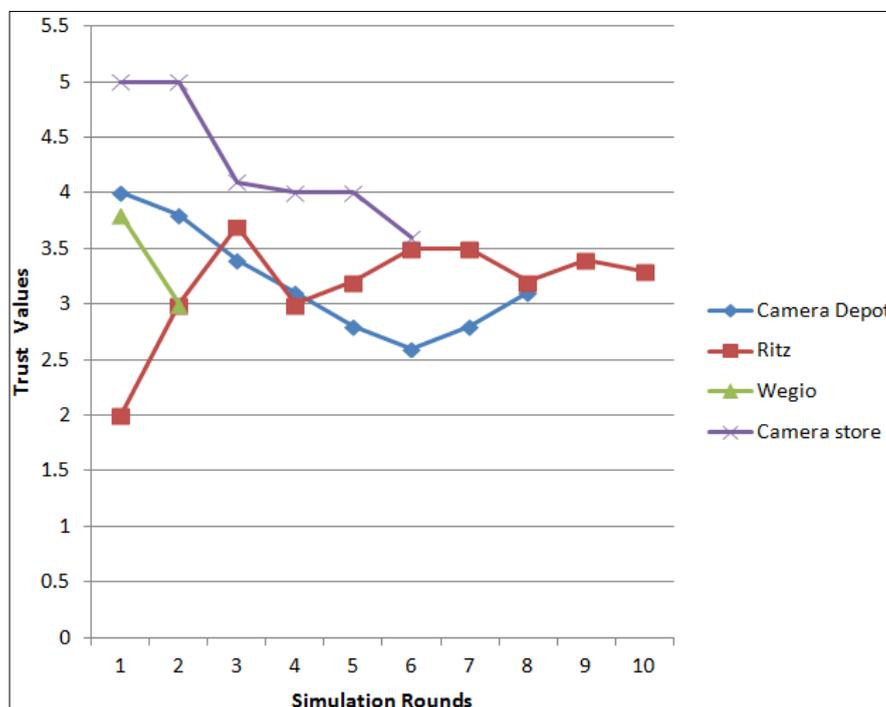
From the above figure we see all the providers with their trust values. Trust value of provider named "Wegio" is lowest which is 3.0 and trust value of provider named "camera store" is highest which is 3.6.

6.4. Data Collection

The mozenda [10] is a data extraction software developed in 2007 to solve the problem of creating a software tool that would allow to quickly and easily extract information from the web. In mozenda we used point-and-click interface, which enables us to build and edit agents that harvest specific information and images from any website. Building an Agent is a process, where we simply type in the

URL of the target website and navigate to the webpage we want to start gathering information from and then we click "Start a new agent from this page". To begin populating our data table, we click on the fields of data that we want to capture. We can either capture the item's text, create a list of items, or tell our agent to follow a link. To capture specific details we simply highlight the parts of text we wanted to capture. Mozenda will automatically recognize these text elements and replicate what we have done across multiple items and pages. Once we have the agent gathering the correct items in our list, we can add a "List Pager" that will navigate through multiple pages capturing similar items in our list. With the help of list pager we will get data from many pages in a short time. All the data collected is in the form of numbers as the ratings given by consumers is of numeric values. After specifying mozenda the data we need to collect we now go to the Mozenda Web Console, where we can run the agent that we created in the Agent Builder. Finally, we can export data captured from the web as CSV, TSV, or XML files which can be downloaded and viewed on our local computer in just seconds.

In the tables below, we see the ratings given by different consumers for the same product that is being sold by different providers. We test our trust model on the "camera" product. Each table has four columns which specifies what is the name of provider who is selling the product, ratings given by consumers over a period of time, the number of interactions taking place and the total rating score.

7. Conclusions and Future Work

In this paper, we presented a hybrid reputation model that combines both the interaction trust and witness information. Interaction trust happens when consumer agents directly interact with provider agents and buy a product. Witness information is an indirect information source where a consumer agent has no interaction with providers but has indirect interaction with other consumer agents present. From experiments we find that the combination of the two leads to better and more reliable result. This model has accomplished the purpose of helping consumers to select reputable providers which finally helps the consumer to obtain more gains. However, in the next step the trust model is used to calculate the trust value of provider agents. From simulation experiment we find that our approach used was successful in finding the provider agent with higher trust values. With the trust model, the consumer agents will have better gains. We can conclude from the results of case study that our formula is successful in calculating the trust values of service providers.

In our future work we can add a group reputation feature. Currently this model deals with individual reputation and asks for ratings from individual consumer agents. Addition of a group reputation [11] feature can help in making improved decisions to select provider agents.

Acknowledgment

Conflicts of Interest

The author declares no conflicts of interest.

References

1. Jøsang, A.; Ismail, R.; Boyd, C. A survey of trust and reputation systems for online service provision. *Decis. Supp. Syst.* **2007**, *43*, 618–644.
2. Sabater, J.; Sierra, C. Review on computational trust and reputation models. *Artif. Intell. Rev.* **2005**, *24*, 33–60.
3. Kravari, K.; Bassiliades, N. Harm: A hybrid rule-based agent reputation model based on temporal defeasible logic. *Res. Appl.* **2012**, *7438*, 193–207.
4. eBay.com, Inc eBay.com [online]. Available online: http://www.eBay.com (accessed on 17 July 2013).
5. Amazon.com, Inc. 17th July, 2013. Available online: http://www.amazon.com (accessed on 17 July 2013).
6. Rubiera, J.; Lopez, J.; Muro, J. A fuzzy model of reputation in multi-agent systems. In Proceedings of the Fifth International Conference on Autonomous Agents, New York, NY, USA, 2001; pp. 25–26.
7. Sabater, J.; Sierra, C. Regret: Reputation in gregarious societies. In Proceedings of the Fifth International Conference on Autonomous Agents, New York, NY, USA, 2001; pp. 194–195.
8. Rahman, A.A.; Hailes, S. Supporting trust in virtual communities. In Proceedings of the IEEE 33rd Annual Hawaii International Conference on System Sciences, Maui, HI, USA, 7 January 2000.
9. Hnativ, A.; Ludwig, S.A. Evaluation of trust in an ecommerce multi-agent system using fuzzy reasoning. In Proceedings of the IEEE International Conference on Fuzzy Systems, Piscataway, NJ, USA, 20–24 August 2009; pp. 757–763.
10. Mozenda, Inc. 17th July 2013, Mozenda.com [online]. Available online: http://www.mozenda.com (accessed on 17 July 2013).
11. Tong, X.; Zhang, W. Group trust and group reputation. In Proceedings of the ICNC'09 Fifth International Conference on Natural Computation, 2001; Volume 5, pp. 561–565.
12. Mui, L. Computational Models of Trust and Reputation: Agents, Evolutionary Games, and Social Networks. Ph.D. Thesis, Massachusetts Institute of Technology, Cambridge, MI, USA, 2002.
13. Sundaresan, N. Online trust and reputation systems. In Proceedings of the 8th ACM Conference on Electronic Commerce, 2007; ACM Press: New York, NY, USA, pp. 366–367.
14. Jordi, S.M. Trust and Reputation for Agent Societies. Ph.D. Thesis, Universitat Autònoma de Barcelona, Cerdanyola del Vallès, Spain, 2003.
15. Ramchurn, S.D.; Huynh, D.; Jennings, N.R. Trust in multi-agent systems. *Knowl. Eng. Rev.* **2004**, *19*, 1–25.
16. Daignault, M.; Shepherd, M.; Marche, S.; Watters, C. Enabling trust online. In Proceedings of the International Symposium Electronic Commerce, 2002; Volume 12, p. 3.
17. Kravari, K.; Kontopoulos, E.; Bassiliades, N. Towards a knowledge-based framework for agents interacting in the semantic web. In Proceedings of the 2012 IEEE/WIC/ACM International Conferences on Web Intelligence and Intelligent Agent Technology (WI-IAT), 2009; Volume 2, pp. 482–485.

18. Riggs, T.; Wilensky, R. An algorithm for automated rating of reviewers. In Proceedings of the 1st ACM/IEEE-CS Joint Conference on Digital Libraries, ACM, New York, NY, USA, 2011; pp. 381–387.