Microscopic Analysis of Edge Creation Process in Trust-based Social Networks

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Abstract. In last years, online social networks are enjoying drastic increase in their population and connectivity. Meanwhile, trust is known as essential factor in quality of the connections between diverse nodes in the network. To address the efficiency in the interactions of nodes, we propose in this paper a trust-based architecture applicable to maintain interactions in multi-agent-based social network. We provide a detailed discussion over the network formation by taking into account the edge creation factors classified as homophily, confounding and influence. We systematically inspire different involving factors to observe evolution of the network of trust-based interconnections in a microscopic manner. We also provide a theoretical analysis of the proposed model assessment and discuss the system implementation, along with simulations obtained from a number of executions compared with the broadly known frameworks.
General Terms. Human Factors, Measurement, Experimentation.
Keywords. Trust establishment , Edge Creation, Multi-Agent Systems, Agent Communication, Social Networks.

1 Introduction

Online social networks are drastically being enlarged. Facebook, Flicker, Yahoo Answers are among very popular social networks that are gaining a very high traffic in terms of the users and their conductivities. In general, the impact of the features of these networks and analysis on how they form the behavior of the users have been a hot interest during the very recent years. A number of theoretical and empirical works have been proposed analyzing the users behavior in forming the connection between them. For example, the analysis on the edge creation process [10, 6] related to the sociality of a node led to hypothesis to observe the distribution of a heavy-traffic degree of popular nodes in the network. In [1], the authors address the source of the correlation between agents that led them to extend their activity and create edges. In [2], the correlation between agents are analyzed in an online large scale community. In fact, the relation between the agents that just joined the community and the agents that are already in the community is discussed.

Here we take a different perspective over the social correlation of agents. In edge creation process, we analyze diverse impacts upon the trust that is already established between two nodes and consequently, we generalize to analyze the socializing of the agents that use different trust evaluation systems. To this end, we first discuss the trust evaluating method and upon that, we analyze the activity area extension of agents in a microscopic approach. To maintain a trust-based network, different computational frameworks have been proposed in the literature. Some models consider the direct interaction of two parties [15, 14, 8]. Some models rely, to some extent, on the suggested rating provided by other agents [12, 9, 13]; and some others also consider the suggested rating of the agent being evaluated [4, 8]. Since agents are self-interested, it is hard to analyze an agent's likely behavior based on previous direct interactions given the fact that the collected information from other agents may be non-reliable and could lead to a non-accurate trust assessment. So far, these frameworks do not act properly if selfish agents tend to change their behaviors. Therefore, agents do not properly initiate a social activity in the sense that they cannot maintain a strong control on the adjacent environment.

In this paper, we use the proposed model that is fully presented in [11] and discuss the social network-related affects (classified in [1]) such as influence, confounding, and homophily on the edge creation process of the distributed agents. In the proposed model, we provide an efficient assessment process in a twofold contribution. In the first contribution, agents mutually interact and rate each other based on the interaction done (either satisfactory or dissatisfactory). The obtained ratings are accumulated to assess the direct interaction rating of a particular agent. In the evaluation process, we call the evaluator agent as *the trustor* and refer to him as Ag_a, and the evaluated agent as *the trustee* and refer to him as Ag_b. Also we refer to the involved agents in the trust assessment process as *consulting agents*. In the proposed framework, Ag_a evaluates the credibility of Ag_b by combining his own direct trust rating with the ratings provided by the consulting agents. The computed trust value is used as a doubt to extend the connection between the trustor and the trustee agent. In the second contribution of the proposed model, the trustor agent after a period of direct interaction with the trustee agent performs a retrospect trust adjustment (so-called maintenance) in order to update his belief set about the credibility of the consulting agents that provided information regarding to the trust level of trustee agents. Depending on the accuracy of the consulting agents, the trustor agent would either increase or decrease his trust ratings about consulting agents. By updating the trust values, agents basically would recognize the adjacent agents that are worth to extend the connection with. On the other hand, agents would stay apart from bad agents in terms of social activities. Doing so, gradually agents recognize more reliable consulting agents around in the network, which would form a more efficient social correlation between adjacent agents. This assessment is used in microscopic analysis of edge creation between the interacting agents.

The remainder of this paper is organized as follows. In Section 2, we briefly define our proposed framework as comprehensive trust assessment process, which

is composed of evaluation and maintenance process. In Section 3, we define the social network parameters, and environment that the interactions are initiated. In Section 4, we elaborate the affects of the discussed network properties in the experimental environment. Representing the testbed, we compare our model results with two well-known trust models in terms of efficiency in trust assessment and finally Section 5 concludes the paper.

2 Trust Evaluation Method

In this section, we formalize the trust assessment between interacting parties (customer and provider agents) in the social network. Since the proposed trust assessment model is fully described in [11], in this paper we only refer to the assessment formulation. In general, each customer agent c_i is linked to a set of customers it knows and a set of provider agents it has interacted within the past. Without loss of generality, a customer c_i has to evaluate correlating agents in the environment (could be consumers or providers) in any case of interaction. For instance, a direct evaluation of a provider p_j is possible if the customer had enough transactions with that provider. In the trust model that we use for evaluation [3], three elements are used to characterize the relationship between the trustor Ag_a and trustee agents Ag_b: 1) how much the trustor agent trusts the trustee: $Tr_{Ag_a}^{Ag_b}$; 2) the number of past transactions: $NT_{Ag_a}^{Ag_b}$; and 3) the time recency of the last transactions: $TiR_{Ag_a}^{Ag_b}$. The transactions could taken place caused from homophily, confounding or influence of any other agents in the network. Formally, we define a social network for service selection as follows:

Definition 1. A social network for service selection is a tuple $\langle C, P, \longrightarrow_{tc}, \longrightarrow_{tp} \rangle$ where C is a set of customer services, P a set of provider services, $\longrightarrow_{tc} \subseteq C \times \mathbb{R}^3 \times C$ is a ternary relation (for labelled edges linking customers) and $\longrightarrow_{tp} \subseteq C \times \mathbb{R}^3 \times P$ is a ternary relation (for labelled edges linking customers to providers).

We use the usual notation for the labelled edges: if $c_i, c_k \in C$ and $v \in \mathbb{R}^3$, then $(c_i, v, c_k) \in \longrightarrow_{tc}$ is written as $c_i \xrightarrow{v}_{tc} c_k$. Likewise, we write $c_i \xrightarrow{v}_{tp} p_j$ instead of $(c_i, v, p_j) \in \longrightarrow_{tp}$. Our social network for service selection has two types of nodes: type 1 for customers and type 2 for providers and two types of edges: type 1 for edges between customers and type 2 for edges linking customers to providers. The edges of type 1 represent friendship relations in the network, while edges of type 2 capture business relationships. The existence of an edge of type 1 $c_i \xrightarrow{v}_{tc} c_k$ means that c_i knows (is friend of) c_k such that: $v = (Tr_{c_i}^{c_k}, NI_{c_i}^{c_k}, TiR_{c_i}^{c_k})$. The existence of an edge of type 2 $c_i \xrightarrow{v}_{tp} p_j$ means that c_i had transactions with p_j such that: $v = (Tr_{c_i}^{p_j}, NT_{c_i}^{p_j}, TiR_{c_i}^{p_j})$. We note that there is no edges in this social network between providers. This does not mean that there is no social link between providers, but only the existing links (which could be collaborations or competitions) are not used in our framework.

The direct evaluation of a provider p_j by a customer c_i is based on the ratings c_i gave to p_j for each past interaction (r_l) combined with the importance of that interaction (λ_l) and its time recency. Let n be the number of total transactions between c_i and p_j ($n = NT_{c_i}^{p_j}$), equation 1 gives the formula to compute this evaluation. To perform the indirect evaluation, the customer c_i solicits information about the provider p_j from other customers c_k such that there is an edge $c_i \xrightarrow[cc]{v} c_k$ in the social network. The set of these customers c_k is denoted $\mathcal{T}_{c_i}$. The equation computing the indirect estimation is given by equation 2, where $\alpha Tr_{c_i}^{c_k} = Tr_{c_i}^{c_k}.NI_{c_i}^{c_k}.TiR_{c_i}^{c_k}$.

$$DTr_{c_i}^{p_j} = \frac{\sum_{l=1}^{n}(\lambda_l.TiR_{c_i}^{p_j}.r_l)}{\sum_{l=1}^{n}(\lambda_l.TiR_{c_i}^{p_j})} \tag{1}$$

$$ITr_{c_i}^{p_j} = \frac{\sum_{c_k \in \mathcal{T}_{c_i}} \alpha Tr_{c_i}^{c_k}.Tr_{c_k}^{p_j}.TiR_{c_k}^{p_j}.NT_{c_k}^{p_j}}{\sum_{c_k \in \mathcal{T}_{c_i}} \alpha Tr_{c_i}^{c_k}.TiR_{c_k}^{p_j}.NT_{c_k}^{p_j}} \tag{2}$$

To compute $Tr_{c_i}^{p_j}$, the direct and indirect evaluations are combined according to their proportional importance. The idea is that the customer relies, to some extent, on its own history (direct trust evaluation) and on consulting with its network (indirect trust evaluation). This merging method considers the proportional relevance of each trust assessment, rather than treating them separately. To this end, c_i assigns a contribution value for the trust assessment method (ω for direct trust evaluation and $1 - \omega$ for indirect trust evaluation when $\omega < 1$). The value ω is obtained from equation 3. Basically, the contribution of each approach in the evaluation of p_j is defined regarding to: (1) how informative the history is in terms of the number of direct transactions between c_i and p_j ($NT_{c_i}^{p_j}$) and their time recency ($TiR_{c_i}^{p_j}$); and (2) how informative and reliable the consulting customers are from c_i's point of view ($DTr_{c_i}^{p_j}$). Therefore, consultation with other agents is less considered if the history represents a comparatively higher entropy value ω, which reflects lower uncertainty. Respecting the contribution percentage of the trust assessments, c_i computes the trust value for p_j using equation 4.

$$\omega = \frac{\ln(DTr_{c_i}^{p_j}.NT_{c_i}^{p_j}.TiR_{c_i}^{p_j})}{\sum_{c_k \in \mathcal{T}_{c_i}} \ln(DTr_{c_i}^{c_k}.NI_{c_i}^{c_k}.TiR_{c_i}^{c_k})} \tag{3}$$

$$Tr_{c_i}^{p_j} = \begin{cases} \omega.DTr_{c_i}^{p_j} + (1-\omega).ITr_{c_i}^{p_j} & \text{if } \omega < 1 \\ DTr_{c_i}^{p_j} & \text{if } \omega \geq 1 \end{cases} \tag{4}$$

Generally, the merging method is used to obtain the most accurate trust assessment. However, after a number of transactions, customers should analyze the quality of the received services regarding to what is expected (represented here by $Tr_{c_i}^{p_j}$) and what is actually performed (so-called observed trust value $\widehat{Tr}_{c_i}^{p_j}$). To this end, an adjustment trust evaluation should be periodically performed. The idea is to learn from past experiences, so that witnesses providing bad trust values, which are far from the observed one, will be removed from the list of

potential witnesses in the future. In addition, over the recent interactions, high quality providers are recognized and thus distributed to the adjacent agents. In general, using the maintenance process (for full description of algorithms, see [11]), correlated agents could increase their rate of influence to one another, which eventually would approach to a more active social network. This can be represented by the following equation:

$$\min_{c_k \in \mathcal{T}_{c_i}} |Tr_{c_k}^{p_j} - \widehat{Tr}_{c_i}^{p_j}| \tag{5}$$

3 Social Network Representation

To analyze our social network for service selection, many parameters described in the literature about social networks could be considered. A detailed list of such parameters are presented in [5]. For space limit, we consider only the following parameters and provide equations to compute them in our context of trust for service selection. Without loss of generality, we would like to measure the probability (likelihood) of edge creation between a customer and a provider agent. The focus of this paper is on the study of edge-by-edge evaluation of the social network in microscopic manner. We compare the network formation of different types of agents that are using different trust establishment method and use different strategies. Hence, we effectively analyze the effect of different trust models in socializing a particular agent that joins a network and seeks to increase his overall outcome (so-called utility). We basically distinguish between different models based on their strategy of network formation in agent arrival, edge arrival and interaction maintenance process (how after-interaction parameters affect the strategies that are used in the further actions of agents).

3.1 Outdegree

Outdegree is a parameter for the extent to which an agent in the network conveys information regarding some other agents. Outdegree value from the customer point of view, is to what extent a customer agent knows the providers. The idea is to reflect the fact that a customer that is connected to more reliable providers has a higher outdegree than a customer linked to less reliable ones. In other words, the outdegree value reflects the extent to which an agent tries to set up and strengthen more edges connecting him to other agents. Equation 6 computes this parameter for a generalized agent Ag, that could be a customer or a provider agent, where $\alpha Tr_{Ag}^{c_k} = Tr_{Ag}^{c_k}.NI_{Ag}^{c_k}.TiR_{Ag}^{c_k}$ and $\alpha Tr_{Ag}^{p_j} = Tr_{Ag}^{p_j}.NI_{Ag}^{p_j}.TiR_{Ag}^{p_j}$.

$$D_{out}(Ag) = \sum_{c_k \in \mathcal{T}_{Ag}} \alpha Tr_{Ag}^{c_k} + \sum_{p_j \in \mathcal{T}'_{Ag}} \alpha Tr_{Ag}^{p_j} \tag{6}$$

where $\mathcal{T}'_{Ag} = \{p_j \in P \mid \exists\ c_i \xrightarrow{v}_{cp} p_j$ in the social network$\}$

3.2 Indegree

Indegree is a parameter for the extent to which a customer in the network receives information regarding to a particular agent from some other agents. Indegree value from the customer point of view, is the extent that the agent is known by the close agents in the network. The idea is to reflect the fact that a customer that is connected to more reliable providers has a higher indegree than a customer linked to less reliable ones. Indegree value from a provide point of view, is the extent that a provider agent is popular in the social network that causes higher number of requests from the customer agents. In other words, the indegree value reflects the popularity of an agent in the sense that any agent would like to increase it and thus cares not to distract it. Although the agents that are known by many agents are supposed to be supported by them, however, regarding to their accuracy and quality of service, they may expect a portion of the adjacent agents for support. Equation 7 computes this parameter for a generalized agent Ag, that could be a customer or a provider agent.

$$D_{in}(Ag) = \sum_{c_k \in \mathcal{S}_{Ag}} \alpha Tr_{c_k}^{Ag} \tag{7}$$

where $\mathcal{S}_{Ag} = \{c_k \in C \mid \exists\ c_k \xrightarrow{v}_{cc} Ag$ in the social network$\}$

3.3 Homophily

Homophily is a parameter for the extent to which a customer in the network chooses to interact with a provider that is known and is already evaluated (this is concept is derived from [1]). This basically raises to strengthen the correlation of adjacent agents. In the social network, agents that are known from previous interactions may tend to request for a service, which is expected to be satisfactory. This is the affect of being friend in a network. In general, it is likely that a customer agent re-selects a particular provider agent aiming to request for a new service. Thus, provider agents normally try to provide a quality service to keep their customers. The homophily of agents in the network is a factor that is not directly compared to other choices of the customer agent, that is seeking for a service. Basically it is the matter of how well-quality the provider agent would provide the new service. This means that, the customer agent's concern is to measure the probability of gaining the expected quality in the service given the fact that the provider agent is already provided a similar service to the same customer. This possibility measurement is mainly related to the indegree value of the provider agent in the sense that a provider with high indegree value is known to be popular, so there is less chance of disturbing its popularity by providing a not promised service quality. In Section 4, we analyze this effect in more details showing that the trust models with the after interaction policies could lead to a more accurate friendship evaluations.

Equation 8 computes the probability of selecting a provider with $D_{in}(P_j)$ as indegree value. In this equation, we do not involve the trust measurement that

the customer agent C_i performs for evaluating the provider agent P_j ($Tr_{C_i}^{P_j}$). The reason is that since the customer agent C_i is already in relation with the provider p_j, then based on the previous evaluation, could decide whether it worths to select this provider again. If by any chance, the previous history does not reflect the efficiency of the provider P_j, there is no point for investigating the probability of the provider's efficiency if being selected. In equation 8, the value ω is set to be the entropy value (see equation 3) of the history between the customer agent C_i and the provider agent P_j. And the value β represents the coefficient set for the system inconsistency. In the trust models with after interaction strategies, this value is dynamically modified reflecting the system accuracy level, however without maintenance process, the value is set initially and remains fixed.

$$p(D_{in}(P_j)) = \frac{e^{\omega ln(D_{in}(P_j)+1)+\beta}}{1 + e^{\omega ln(D_{in}(P_j)+1)+\beta}} \tag{8}$$

3.4 Confounding

Confounding is a parameter for the extent to which a provider as an external agent influences a customer agent to request for a particular service (this is concept is derived from [1]). This influence affects some close agents in the network to set up an edge with an unknown provider under the promising conditions that the provider defines. In general, the providers that join the network, seek for the agents that are more likely to request for their providing service. In other words, when a provider agent is being activated, tries to socialize himself in the network. Thus, starting from very close customer agents, the provider agent encourages them to request for his service. To this end, the provider at the beginning acts generously in order to attract the customers and gain more popularity. Moreover, upon high quality service, the customer agents may influence their adjacent agents to request for the same service. So, the provider agent takes the outdegree value of the customer agents into account and based on the interaction span of the customer agents, provides high quality services.

In confounding factor, the probability of activating an agent with a provider agent is computed in equation 9. As it is assumed that the provider P_j is unknown to the customer C_i, so the customer agent would evaluate the social trustworthiness value of the provider. Given the fact that the trust measurement requires some information from the other adjacent agents, the customer agent takes the entropy value into account in order to partially consider the indirect trust value ($ITr_{C_i}^{P_j}$) and the rest for the popularity of the provider agent. Thus, the customer C_i first evaluates the provider P_j and then considers the P_j's indegree value together with the network inconsistency level. If the information obtained for evaluating P_j is not enough, the entropy value ω would be high, so that mostly the trust evaluation part would be considered. This would normally cause to lower the overall probability of activation.

$$p(D_{in}(P_j)) = \omega \times ITr_{C_i}^{P_j} + (1-\omega) \times \frac{e^{ln(D_{in}(P_j)+1)+\beta}}{1+e^{ln(D_{in}(P_j)+1)+\beta}} \tag{9}$$

3.5 Influence

Influence is a parameter for the extent to which an agent is prompted to initiate a request caused by an adjacent agent (this is concept is derived from [1]). This could taken place in a friendship of agents that they distribute the idea of some services to be requested. When an agent in encouraged to think about a particular service from a provider, the agent may have already a set up edge with the provider, by which can evaluate the provider, or may need to set up a new edge upon which could obtain a service. This is the affect of getting encouraged by a friend in a network. In general, it is likely that a person does action because his friend is already done it. Thus it is the matter of activation of a new edge, which is set up between a customer agent and the provider agent, that is already been requested for a service by the customer agent's adjacent agent (friend).

In the confounding factor, we mentioned that when a typical provider advertises his service to a couple of adjacent customer agents, he considers that some of the customers may propagate his quality of service to their adjacent agents, which could lead to more service requests. On the other hand, the customer agent that is being prompted to take a service produced by a particular provider, needs to evaluate both the advertising adjacent agent C_j ($DTr_{C_i}^{C_j}$) and the provider itself P_j ($ITr_{C_i}^{P_j}$). Equation 10 computes the influence-based probability of activation of a customer agent C_i regarding to taking the service produced by a provider agent P_j. In this equation, ω_{C_j} is the entropy value regarding to the information C_i has and thus could rely on, and ω_{P_j} is the entropy value that C_i has regarding to the provider P_j and would consider for interaction.

$$p(D_{in}(P_j)) = \omega_{C_j} \times DTr_{C_i}^{C_j} + (1-\omega_{C_j}) \times \Theta \tag{10}$$

where

$$\Theta = \omega_{P_j} \times ITr_{C_i}^{P_j} + (1-\omega_{P_j}) \times \frac{e^{ln(D_{in}(P_j)+1)+\beta}}{1+e^{ln(D_{in}(P_j)+1)+\beta}}$$

4 Experimental Results and Related Work

In this section, we describe the implementation of proof of concept prototype. In the implemented prototype, agents are implemented as *Jadex*©^{TM} agents. Like in [7], the testbed environment is populated with two agent types: (1) *service provider agents*; and (2) *service consumer agents*. The simulation consists of a number of consequent Runs in which agents are activated and build their private knowledge, keep interacting with one another, and enhance their overall knowledge about the environment. Depending on the agent interactions, agent may extend their connections hoping to be more socialized. However, there is

always the chance of investing on wrong agents that lead to no outcome. Here we distinguish agents by the service (or information) quality that they provide and agents do not know about that. Table 1 represents four types of the service providers we consider in our simulation: good, ordinary, bad and fickle. The first three provide the service regarding to the assigned mean value of quality with a small range of deviation. Fickle providers are more flexible as their range of service quality covers the whole possible outcomes. Upon interaction with service providers, service consumer agents obtain utilities and consequently rate the quality of the providers (for simplicity, we assume only the consumers are interconnected to the provider agents). In the simulation environment, agents are equipped with different trust models in the sense that their edge creation policies are different. In the proposed model, we try to establish a trust mechanism where an agent, firstly can maintain an effective trust assessment process and secondly, accurately updates his belief set, which reflects the other agents likely accuracy. In order to confirm the mentioned characteristics, we compare the proposed model with other trust models in two perspectives. In former comparison view, we use the agents that only perform a direct trust assessment process. We refer to this group of agents as *Direct Trust Group* (DTG). In later overview, we use the agents that (in addition to the direct trust assessment mechanism), perform maintenance process for evaluating the consulting agents in order to increase their information accuracy. We refer to this group of agents as *Maintenance-based Trust Group* (MTG). The reason of decomposing the proposed model to two groups is to focus on the efficiency of each model, which enables us to analyze the impact of each contribution on the accuracy of the agent in edge creation process. In order to discuss the proposed model's overall performance, we compare it with BRS [1] [9] and Travos [2] [13] trust models. These models are similar to the proposed model in the sense that they do consider other agents' suggestions while evaluating the trust of some specific agents and discard inaccurate suggestions aiming to perform best edge creation. The detailed description of these models is provided in [4]. Here we basically distinguish [10] between different models based on their strategy of network formation in agent arrival, edge arrival and interaction maintenance process (how after-interaction parameters affect the strategies that are used in the further actions of agents).

We start the discussion by the probability of selecting the providers over their different popularity values. As we discussed earlier, the indegree value of a node reflects their popularity in the social network. Thus we could conclude that the chance of selection for a particular service provider agent would be proportionally relevant to its indegree value (ordinary selection attitude). However, the trust evaluation method together with its distribution process would affect

[1] BRS trust model collects the after-interaction ratings and estimates the trust using beta distribution method. This trust model ignores the ratings from such agents that deviate the most from the majority of the ratings.

[2] Travos trust model is similar to BRS in collecting the after-interaction ratings and estimating the trust using beta distribution method. But Travos ignores the ratings from agents that provide intermittent reports in the form of suggestions.

Table 1. Simulation summarization over the obtained measurements.

Service provider type	Density in the network	Utility range	Utility SD
Good	15.0%	$]+5,+10]$	1.0
Ordinary	30.0%	$]-5,+5]$	2.0
Bad	15.0%	$]-10,-5]$	2.0
Fickle	40.0%	$]-10,+10]$	–

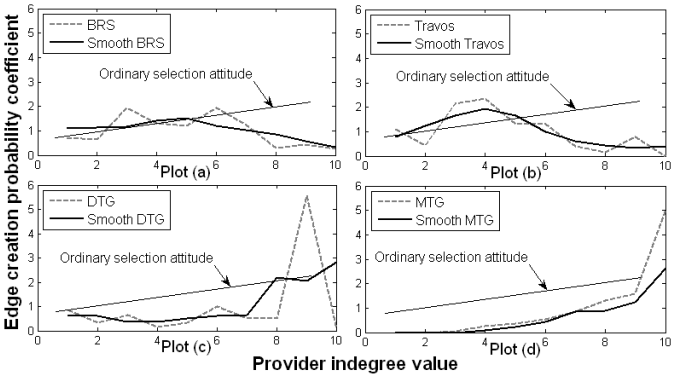

Fig. 1. Probability of edge creation with provider agent vs. the provider's indegree value.

this probability of selection. Illustrated in figure 1, the BRS agents act independently of the mentioned probability as strategically, the BRS agents do not consider the popularity of the provider. Travos agents also do not consider such value, however, the probability of selection of the popular providers increase, as they take less risk of changing their behaviors and thus perform satisfactory services, which would lead to their selection. In general, because of inaccuracy detection feature of Travos agents, the percentage of selection of provider agents with high indegree value increase in a gentle manner. At some certain point, the selection of popular providers are coming down (see *plot b*). This is explained by the fact that a popular provider has large number of recommenders that provide diverse range of information to the agent, that is trying to evaluate the provider. So this diversity would cause to confusion state (the state that this system would generalize the majority of the information that is obtained and could be inaccurate), which in Travos would cause the drop of the suggestions and thus the selection would be less. The proposed model agents (DTG and MTG) follow the information propagation feature as the adjacent agents influence each other to select the high quality providers. There is a difference in the slope of selection graph in MTG and DTG models. This is explained by the fact that the MTG group are characterized by the maintenance process that enable them to recognize high quality provider agents and thus their accuracy in influencing adjacent agents are more than regular DTG agents. In general, since

the maintenance feature does not exist in DTG group, the customer agents loose the track of high quality provider agents, and thus the probability of selection would not increase so fast.

In general in the defined testbed, the agents that are obtaining a high quality service are encouraged to distribute their experience to other adjacent agents (influence others). This activity of agents would basically get increased over the time, or say over the age of the agent. In figure 2, we have compared the activity of different groups of agents by comparing edge extension of the agents (out-degree value). Without loss of generality, the edge extension is proportionally related to the accuracy of agent in detecting the high quality providers. In BRS model, the extension over the time is not increasing as the agent gets involved with high number of adjacent agents and would be difficult to effectively extend the social activity, so more or less would be independent of the age of the agent. Travos and DTG models are increasing, however relatively with small slope. In MTG group, because of the maintenance process the agents would be encouraged to initiate a request to high quality service providers and thus extend their activity. In this graph, the slope is relatively large as over the time, the agent could manage to categorize the providers that could possibly act beneficially for the agent, and thus would enlarge his activity area. In figure 2, the second line represents how fast the agents would drop the previous data and use the recent data for their analysis. This dropping factor is also relevant to how active an agent is and thus, to what extent there would be available resource that agents could drop obsolete data. DTG and MTG group use the same dropping feature ($TiR(\Delta t_{Ag_a}^{Ag_b})$), which is derived in equation 11. Variable λ is an application-dependent coefficient. In some applications, recent interactions are more desirable to be considered (λ is set to relatively large number). In contrast, in some other applications, even the old interactions are still valuable source of information. In that case, a relatively smaller value to λ is used.

$$TiR(\Delta t_{Ag_a}^{Ag_b}) = e^{-\lambda \; ln(\Delta t_{Ag_a}^{Ag_b})} \quad \lambda \geq 0 \tag{11}$$

We would like to go further into the details of the selection history in terms of the microscopic social network affects (homophily, confounding, and influence) and illustrate them in figure 3. in this section, we observe the diverse impacts of homophily, confounding and influence features on each group in the sense that we would capture their edge creation reasons. Note that the edge creation is not the important issue, however, the concern is to extend to the agents that are known to be trustworthy. Therefore, we elaborate the overall outcome of different agents at the following. The homophily aspect would be caused by the friendship relation of the agents that have history interaction between them. This is a very general case in the sense that consumer agents over the time would get to know and select the provider agents. If the interacted service is satisfactory for the agent, then the consumer agent may re-select the same provider agent in some future. BRS agents are the ones that mostly rely on the homophily affect in the sense that they keep the history of the interaction in order to re-evaluate the provider agent. The providers that remain trustworthy would be selected over

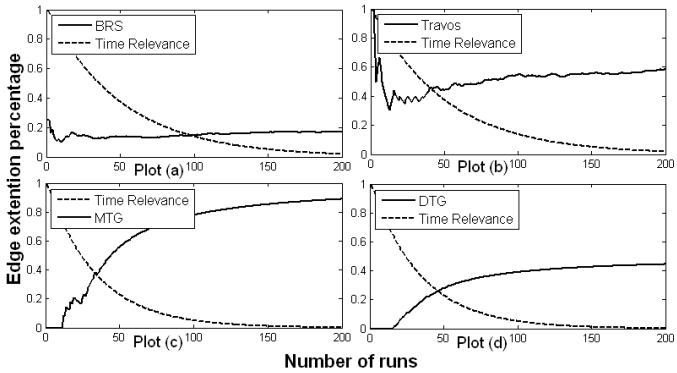

Fig. 2. Agent edge extension vs. the agents age.

the time. As it is clear from plot $a1$, once the providers change their policies, the selection of them would be affected so fast, as the BRS agents recognize that they should start seeking for the appropriate friends. Travos agents also rely on the previous history and re-select the previously interacted service providers (see plot $b1$). However, over the time the reports regarding to the accuracy of the providers would be divergent, which would lead to refuse the selection. The same reason is the case for DTG and MTG group (shown in plots $c1$ and $d1$). These agents to some extent rely on the previous history and select the providers. After some certain time, these agents also recognize the inconsistency in the evaluation process of the history interacted providers. Overall, DTG and MTG agents evaluate the providers in a very accurate manner. The accuracy that Travos, DTG and MTG agents have cause the decremented manner after some certain time.

Confounding factor reflects the extent to which the provider agents advertise their service to the consumers (could be new or previously serviced ones). This feature also affects BRS group, as they start evaluating the advertising provider, and thus extend their activation area. Plot $a2$ indicates that the BRS group are easy to involve in interaction with the advertising provider agent. Travos agents act in the same way as the provider agents could induce them to take their service. However, Travos agents are considering this case less, because they investigate the previous reports related to the advertising provider and doubt on the inconsistent ones (see plot $b2$). In general, the BRS and Travos agents accept the confounding-related interactions over the time, and thus their graph has an increasing manner. But in DTG and specially MTG, the agents would not accept this service all the time, as over the time, once the network inconsistency level increases, these agents would have confusion in accepting the confounding-related affect caused by unknown service providers (see plots $c2$ and $d2$). MTG agents would accept this option from the providers, but since they are equipped with a maintenance process, they would distribute the performance of

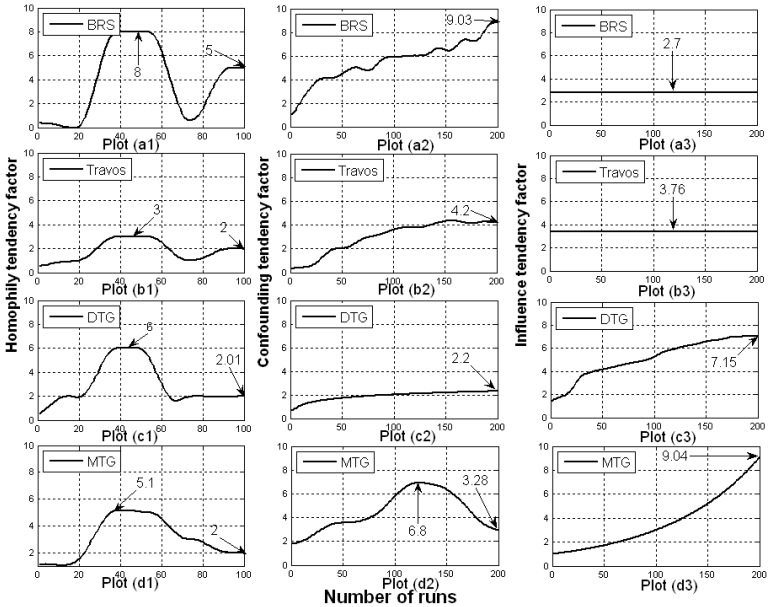

Fig. 3. Overall comparison of the proposed model with BRS and Travos in terms of (a) Homophily; (b) confounding; and (c) influence factors.

the providers to the adjacent agents, which would lead them to get to know the network faster than the other models. This would let the MTG agents to select the best providers, and thus would drop the request from most of the unknown agents while they are already in a good accuracy level.

Influence factor is mostly used by active agents, while they obtain service and tend to distribute the efficiency of the interaction to the adjacent agents. Since BRS agents independently select the providers, the influence is not a factor for these agents (plot $a3$). Treavos agents would act almost independently, however the Travos agents are encouraged by the reports they obtain for the evaluation of a particular provider agent (plot $b3$). DTG group would be encouraged with the same factor as Travos agents. Upon evaluating provides, the DTG agents would consider the reports obtained from adjacent agents and recognize outstanding service provided by the provider that is just served an adjacent agent (see plot $c3$). The influence-related interactions are mostly initiated among MTG group, shown in plot $d3$. This is explained by the fact that the MTG group are equipped with maintenance feature, which enables them to reason about the accuracy and efficiency of the obtained services and propagate the information to the adjacent information.

Considering all the involved features, at the end we compare the models in general perspective, starting good provider selection efficiency. In such a biased environment, the number of good providers are comparatively low. Therefore,

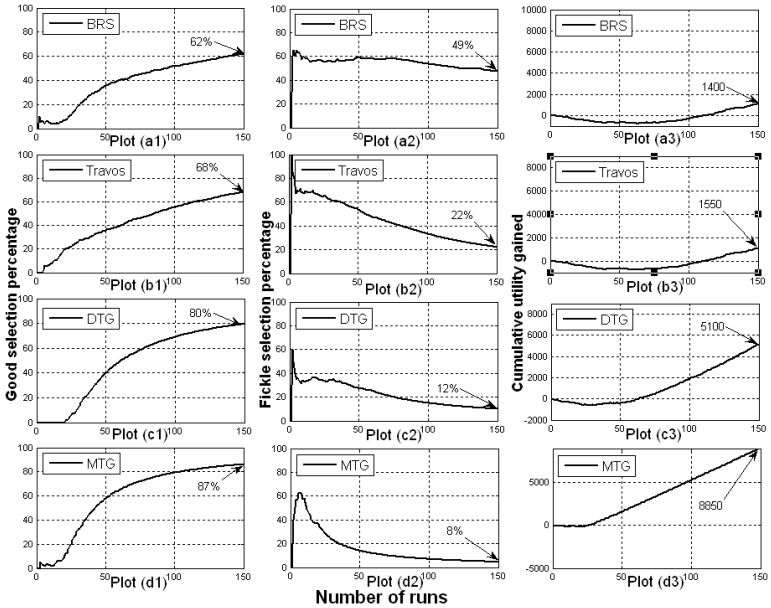

Fig. 4. Overall comparison of the proposed model with BRS and in terms of (a) good selection percentage; (b) fickle selection percentage; and (c) cumulative utility gained.

the agents need to perform an accurate trust assessment to recognize the best providers. As it is clear from the Figures 4, plots $a1$, $b1$, and $c1$, DTG agents function better than other models (Travos and BRS). The reason is that in this model, agents are assessing the credibility of the providers using other agents suggestions depending on their credibility and to what extent they know the provider. Afterwards these agents rate the provider, which would be distributed to other agents upon their request (relatively in plots $a2$, $b2$, and $c2$ the comparison of fickle selection percentage, and in $a2$, $b2$, and $c2$, the gained cumulative utility is shown). Not excluding the fact that DTG agents are considering partial ratings for consulting agents, we state that they weakly function when the environment contains agents that do not truthfully reveal their believes. MTG agents in addition to the direct trust assessment, provide incentives for consulting agents, which encourages them to effectively provide the information aiming to gain more utility. Plot $d1$ shows that MTG agents outperform other models in best provider selection. This is expressed by the fact that MTG agents recognize the best providers ensuring that the best selected provider would provide the highest utility. Relatively plot $d2$ shows an outperform in fickle selection and consequently higher cumulative utility in plot $d3$.

In BRS model, the trustor agent in the assessment process uses beta distribution method and discards the ratings that deviate the most from the majority of the ratings. Concerning this, BRS is comparatively a static trust method,

which causes a low-efficient performance in very dynamic environment. In general, if a BRS agent decides to evaluate an agent that he is not acquainted with, he considers the majority of ratings, which are supposed to be truthfully revealed about the trustee agent. In such a case that the trustee agent has just changed his strategy, the trustor agent would loose in trust assessment and does not verify the accuracy of the gained information. Therefore, as illustrated in figure 4, plots $a1$, the BRS agents would have less percentage of good providers selection, relatively higher percentage of fickle providers selection (plot $a2$), and consequently lower gained cumulative utility (plot $a3$).

Travos [13] trust model is similar to BRS in using beta distribution to estimate the trust based on the previous interactions. Travos model also does not have partial rating. Hence, the trustor agent merges his own experience with suggestions from other agents. However, unlike BRS model, Travos filters the surrounding agents that are fluctuating in their reports about a specific trustee agent. To some extent, this feature would cause a partial suggestion consideration and thus, Travos agents would adapt faster comparing to BRS agents. Rates concerning the good and fickle selection percentage shown in figures 4, plots $b1$ and $b2$ reflect higher efficiency of Travos compared to BRS. However, Travos model considers that agents do not change their behavior towards the elapsing time. These missing assumptions affect the accuracy of trust estimation in a very biased environment (lower gained cumulative utility in plot $b3$).

5 Conclusion

The contribution of this paper is the detailed investigation of a trust-based multi-agent architecture in edge creation and correlation formation in social network. The established trust is provided by the proposed framework, that is briefly explained here. The trust assessment procedure is based on integrating suggestion of consulting agents, objectively enhancing the accuracy of agents to make use of the information communicated to them. The surveillance over the surrounding environment, makes distributed agents eager to extend their activity area by interacting to high quality agents. In the proposed framework, maintenance process considers the communicated information to judge the accuracy of the consulting agents in the previous trust evaluation process. The ex-interacted analysis, makes the agents to propagate the recent and accurate information to their adjacent agents, which is considered as homophily and influence factors in edge creation analysis.

Our model has the advantage of being computationally efficient as it takes into account the important factors involved in extending the activity zone of agents. Moreover, we have done a detailed empirical analysis over the edge creation and behavior of agents over their age, while they are equipped with different trust mechanism protocols. The proposed mechanism efficiency is compared with other related models to prove the capabilities of the proposed model. Our plan for future work is to advance the assessment model to enhance the model efficiency. In the maintenance process we need to elaborate more on the optimization part,

trying to formulate it in the sense to be adaptable to diverse situations. Finally, we plan to maintain more detailed analysis in comparison with other models to capture more results reflecting the proposed model capabilities.

References

1. A. Anagnostopoulos, R. Kumar, and M. Mahdian. Influence and correlation in social networks. Proceedings of the 14'th ACM SIGKDD International Conference on Knowledge Discovery and Data Mining, Las Vegas, USA, KDD2008.
2. L. Backstrom, D. Huttenlocher, J. Kleinberg, and X. Lan. Group formation in large scale networks: membership, growth, and evolution. Proceedings of the 12'th ACM SIGKDD International Conference on Knowledge Discovery and Data Mining , pp.44-54, KDD2006.
3. J. Bentahar, B. Khosravifar, and M. Gomrokchi. Social network-based trust for agent-based services. Proceedings of the 5'th IEEE International Symposium on Web and Mobile Information Services, Bradford, UK, WAMIS2009 (in press).
4. J. Bentahar, B. Khosravifar. Using trustworthy and referee agents to secure multi-agent systems. Proceedings of the 5'th IEEE International Conference on Information Technology: New Generations, pp. 477-482, Las Vegas, USA, ITNG 2008.
5. V. Buskens. Social networks and trust. Kluwer Academic Publishers. 2002.
6. N. A. Christakis, and J. H. Fowler. The spread of obesity in a large social network over 32 Years. The new England Journal of Medicine, 357(4):370-379, 2007.
7. T. Dong-Huynh, N.R. Jennings and N.R. Shadbolt. Fire: an integrated trust and reputation model for open multi-agent systems. Journal of Autonomous Agents and Multi-Agent Systems 13(2):119-154, 2006.
8. T. Dong-Huynh, N.R. Jennings and N.R. Shadbolt. Certified reputation: how an agent can trust a stranger. In Proceedings of the 5'th International Joint Conference on Autonomous Agents and Multiagent Systems, pp. 1217-1224, Japan, 2006.
9. A. Jesang and R. Ismail. The beta reputation system. 15'th Bled Electronic Commerce Conference e-Reality: Constructing the e-Economy, June 2002.
10. J. Leskovec , L. Backstrom , R. Kumar, and A. Tomkins. Microscopic evolution of social networks. In Proceedings of the 14'th ACM SIGKDD International Conference on Knowledge Discovery and Data Mining, pp. 462-470, 2008.
11. B. Khosravifar, M. Gomrokchi, J. Bentahar, and Ph. Thiran. A maintenance-based trust for Open multi-agent systems. Accepted in the 8'th International Conference on Autonomous Agents and Multiagent Systems, AAMAS, Budapest, Hungary 2009.
12. J. Sabater, M. Paolucci and R. Conte, Repage: REPutation and ImAGE among limited autonomous partners. Journal of Artificial Societies and Social Simulation 9(2), 2006.
13. W. T. Teacy, J. Patel, N.R. Jennings, and M. Luck. Travos: trust and reputation in the context of inaccurate information sources. Autonomous Agentsand Multi-Agent Systems, 12(2):183-198, 2006.
14. Y. Wang, and M.P. Singh. Formal trust model for multiagent ststems. Proceedings of the 20'th International Joint Conference on Artificial Intelligence (IJCAI), pp. 1551-1556, 2007.
15. L. Xiong and L. Liu. PeerTrust: supporting reputation-based trust for peer-to-peer electronic communities. Journal of IEEE Transactions on Knowledge and Data Engineering, 16(7):843-857, 2004.