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Effective Web Service Selection via Communities Formed by Super-Agents

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***Abstract*—In this paper, we propose a novel community-based approach for web service selection where super-agents with more capabilities serve as community managers. They maintain communities and build community-based reputation for a service based on the opinions from all community members that have similar interests and judgement criteria. The community-based reputation is useful for consumer agents in selecting satisfactory services when they do not have much personal experience with the services. Experimental results show that our approach results in more effective service selection. A practical reward mechanism is also introduced to create incentives for super-agents to contribute their resources and provide truthful community-based reputation information, as strong support for our approach.**

I. Introduction

Web services provide a flexible way for applications to interact with each other over the Internet in two aspects. The language-/platform- independence allows applications to invoke each other's services no matter what platforms or languages they are using. A web service is also self-describing so that applications can examine the functionality of a web service at runtime and generate corresponding code to automatically invoke the service. The flexibility has made web services well accepted and seen as a promising solution for system integration. A web service system is often an open system where some services may be of low quality. In addition, some providers may be malicious and provide services worse than what they advertise. Thus, trust and reputation mechanisms play an important role in web service systems in helping consumer agents select satisfactory services to consume.

In a distributed web service selection environment, consumer agents have to cooperate and share their experience with services so that they can build reputation about services. For instance, in Yu and Singh's approach [1], in order to know the reputation of a service s, an agent a has to seek many other agents' opinions[1] about s and then combine their opinions together. Nevertheless, during this process, the agent a may not be able to find the information it needs. In addition, agents are often different in their interests and judging criteria. The opinions provided by other agents may not fit the agent's needs. For example, if an agent is in a minority, reputation information provided by others may mislead the agent to make wrong decisions. It would be more desirable to have opinions from agents that have similar interests and judging criteria.

In this paper, we propose a novel community-based service selection approach. Forming communities brings together like-minded agents that share similar interests and judging criteria. These agents in a community will share their information about services they have interacted with, which is useful for other agents to make effective selection of services.

We also exploit the idea of using super-agents to manage communities and build reputation for services. This idea is inspired by studies in peer to peer (P2P) networks. In practice there is a great heterogeneity in the capability of peers - between three and five orders of magnitude [2]. Peers with poor capabilities become bottlenecks, which degrades the system. With the awareness of the great heterogeneity, pure P2P networks have evolved to super peer networks, such as Kazaa and Gnutella (v0.6) [3]. Super-peers are peers with more capabilities. Peers with poor capabilities are connected to super-peers. Each super-peer acts as a server for a small group of clients (i.e. peers with poor resources) to store their information, and to send and receive messages for them. Super peer networks work more efficiently than pure P2P networks in terms of searching resources and passing messages. Similarly, we make use of the more capabilities of super-agents. A super-agent creates a community and acts as the manager of the community. It carefully selects members and maintains community-based reputation for services based on reputation opinions about the services shared by the members of the community. The community-based reputation information will be valuable for other members when selecting services.

In order for our community-based approach to work effectively, super-agents have to contribute resources to maintain communities, build reputation information and answer queries about reputation of services. These super-agents may be malicious in providing reputation information. They may provide false good reputation for some services to promote them or provide false bad reputation to bad-mouth some other services. We design a practical reward mechanism inspired by real world examples where service providers offer rewards for agents that bring consumers to consume their services. Super-agents that are honest and contribute more resources will attract a larger number of consumers to join their communities and follow their advice about services. These super-agents will

[1]A statement of the trustworthiness of service s calculated and given by another agent b will be called a "reputation opinion".

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then be able to obtain more rewards from the service providers.

We simulate a service selection environment where some services are of low quality and some agents may be malicious. Experimental results confirm that forming communities results in more effective service selection, show the incentives for super-agents to contribute more resources and share truthful reputation information about services and for consumers to honestly provide reputation opinions, and indicate that our approach outperforms the experience-based approach [4] and the model of Yu and Singh [1] when consumers do not have much experience with services.

II. Background, Motivation and Related Work

Communities exist in human societies where people with common interests or purposes will get together, share their resources and benefit from each other. The word "community" also often appears in the multi-agent systems literature and has been used to refer to a group of agents that tend to communicate or interact with each other more often than with the remaining agents in the system. In such communities, agents have some kind of proximity and can reach each other within a few hops so that they can easily cooperate. The proximity that defines communities can be identified according to, for example, the neighborhood of agents [1]. This type of communities is often represented in an implicit way.

Our term of "community" is used to denote an explicitly existing organization that facilitates a group of agents with a common goal, interests and preferences to get together, share their knowledge, learn and benefit from one another. For example, in a P2P network, a community can serve as an information center to provide agents with information that would otherwise be distributed in each agent. It brings together like-minded agents and helps them find each other and share information. In the community, there are some agents called community managers responsible for organizing community members and storing community-based information. Community members do not have to be linked close to each other. They are also free to interact with non-members. This is beneficial for the community to locate potential new members.

A. Benefit of Forming Communities

As the strong movitation for our work, forming communities can help agents to find more valuable information. Users often have different opinions about the same thing because of subjective differences (different judging criteria). A community is composed of like-minded agents with similar interests and judging criteria. The opinions from the community members are more valuable than the general public's opinion.

Different approaches have been proposed for coping with subjective differences among consumer agents. For example, Regan et al. [5] propose a Bayesian modeling approach to allow a consumer to learn other consumers' evaluation functions on different features of the services delivered by providers. This is done by analyzing ratings that are provided by the other consumers for the services. The authors claim that this makes it possible to adjust provided ratings for any subjective differences. Sensoy et al. [4] develop an approach for distributed service selection that allows consumers to represent their experiences with the service providers using ontologies. An experience is a record of what service the customer has requested and received in return. In this way, the experience-based approach allows the objective facts of the experiences (other than subjective opinions, i.e. ratings) to be communicated to the other party and thus eliminates subjective differences among consumers. However, these two approaches require consumer agents to either learn complicated models of other consumers or represent their experiences using ontologies. Our proposed community-based approach does not require extra effort from consumers. In Section V, we will demonstrate the benefit of forming communities and compare with the experience-based approach of Sensoy et al. [4] through experiments.

B. Methods for Community Formation

A community can be formed based on a pre-defined ontology about interests [6]. When an agent joins the system, it can be automatically designated into a community by matching its declared interests with the pre-defined ontology. This approach requires experts' effort on building ontology and agents' effort on clearly expressing their descriptions of interests.

Alternatively, communities can be built automatically during the process of agents' interactions. Agents will gradually link with the other agents that they intend to interact with more often and get detached from the agents that they do not cooperate with. If agents interact more often with other agents that are like-minded, gradually, communities will be formed. For example, in Yu and Singh's model [1], two kinds of trust are modeled respectively for each agent, expertise and sociability. An agent's expertise refers to the agent's ability to provide required services. An agent's sociability is the agent's ability of suggesting other agents that can provide the required service. Implicit communities are formed, where each agent keeps a list of neighbors from which it can gain good services or referrals. However, it may take a long time for agents to learn each other and form effective communities.

Different from the above approaches, we allow super-agents to create and maintain explicit communities that will benefit themselves and other agents. Our super-agent based approach offloads duties from consumers and can form communities more quickly, which will be demonstrated through the experiments of comparing with the implicit community formation approach of Yu and Singh [1] in Section V. A similar framework called Surework is proposed in [7] to have super-peers forming clusters of ordinary peers. However, the authors did not provide any computation details nor explore the benefit of providing more valuable information for peers.

III. Community-based Web Service Selection

A super-agent, also called community manager, forms a community based on its interested services and judging criteria for the services.[2] It selects consumer agents as members for the community and updates the community periodically. More importantly, it builds community-based reputation values for the services and shares the information with the community members. The detailed formalization of these responsibilities and processes will be provided later in Section III-C.

In this section, we first provide a description about our community-based service selection approach. When a consumer agent wants to find a service, it issues a search query using keywords to the managers of the communities it belongs to. The super-agents check whether their communities are building reputation for services matching the search keywords. If yes, they will send to the consumer the services' information (e.g. the names and descriptions of the services). They may also be asked for community-based reputation values of the services. Based on the received reputation values of the services, the consumer can then model the trustworthiness of the services. The formalization for calculating the trustworthiness of a service will be presented in the next section.

A. Trustworthiness of a Service

When a consumer agent c judges the trustworthiness of a service s, it will first use its own experience. After each time of using the service, c evaluates the service based on QoS (Quality of Service), which may involve several different metrics, such as response time, accuracy, and reliability. The W3C group provides a summarized guide about defining QoS and its metrics [8]. The overall evaluation of an interaction between a consumer and a service is a combination of the evaluation for each quality metric related to the interaction. How to combine the evaluations of each quality metric depends on the application and a consumer's requirement. The result of the overall evaluation about an interaction with the service is either "satisfying" or "not satisfying", which is used to update the consumer's trust in the service after the interaction according to the following reinforcement learning formula [9]:

$$T_c(s) = \alpha T'_c(s) + (1-\alpha)e(s) \tag{1}$$

where $T_c(s)$ denotes the trust value of the service after the update based on the consumer's personal experience, which is also c's reputation opinion shared with the managers of the communities it belongs to (see Section III-C); $T'_c(s)$ denotes the trust value before the update; $\alpha \in (0,1)$ is the learning rate; $e(s)$ is the evaluation of the interaction represented by either 0 for "not satisfying" or 1 for "satisfying".

If consumer c does not have enough personal experience with service s, it will consider community-based reputation information about the service provided by super-agents. If $w = 1$, it has enough experience. If $w < 1$, it does not have enough experience. The agent sorts the list of super-agents according to its trust in them from high to low. The modeling of the trustworthiness of super-agents will be described in Section III-B. If the agent's trust in a super-agent is higher than a threshold, the super-agent will be regarded as trustworthy and will be asked for community-based reputation of the service, which is a value in the interval [0,1] where 0 means that the service is totally disreputable and 1 means that the service is completely reputable. Once the consumer receives all community-based reputation values of the service from all trustworthy super-agents $\{sp_1,\ sp_2,\ ...,\ sp_n\}$, the consumer agent will calculate an aggregated reputation value according to the following weighted average formula:

$$R_{sp}(s) = \frac{\sum_{i=1}^{n} T_c(sp_i) R_{sp_i}(s)}{\sum_{i=1}^{n} T_c(sp_i)} \tag{2}$$

where $T_c(sp_i)$ is the consumer agent's trust in super-agent sp_i, and $R_{sp_i}(s)$ is the community-based reputation of service s provided by sp_i formalized in Section III-C2.

The trustworthiness of service s is calculated based on the combination of the consumer agent's trust $T_c(s)$ in the service calculated using its own experience and the aggregated reputation value $R_{sp}(s)$, as follows:

$$T(s) = w' T_c(s) + (1-w') R_{sp}(s) \tag{3}$$

where w' represents how much weight should be put on $T_c(s)$. It is determined based on the number of interactions between the consumer agent c and the service s. We first determine the minimum number of interactions needed for c to be confident about the trust value it has of s computed using c's personal experience, based on the Chernoff Bound theorem [10]:

$$N_{min} = -\frac{1}{2\varepsilon^2} ln \frac{1-\gamma}{2} \tag{4}$$

where ε is the maximal level of error that can be accepted by c, and γ is the confidence measure. If the total number of interactions is N_{all}, the weight w' can be measured as follows:

$$w' = \begin{cases} \frac{N_{all}}{N_{min}} & \text{if } N_{all} < N_{min}; \\ 1 & \text{otherwise.} \end{cases} \tag{5}$$

When $w' = 1$, the trustworthiness of the service is the same as the trust value calculated using only the consumer's personal experience with the service (Equation 3). When $w' < 1$, the aggregated reputation value $R_{sp}(s)$ of the service also plays a role in the calculation of the trustworthiness of the service.

Note that there may be the case where a consumer agent does not have enough experience with a service, and it also cannot find trustworthy super-agents to ask for community-based reputation information about the service. In this case, the consumer agent will also ask advice about the service from other community managers or consumer agents.

B. Trustworthiness of a Super-Agent/Community

The trustworthiness of super-agents is calculated to determine which super-agents will be asked by a consumer agent for community-based reputation of a service. It is also used to determine how much weight should be put on each community-based reputation value in Equation 2. The trustworthiness of super-agents is also considered as the consumer's trust in the communities managed by the super-agents.

[2] Note that a community may be maintained by several super-agents. These agents share information about and responsibilities for the community, and can be treated as one single super-agent in later formulations.

If the communities the consumer belongs to are untrustworthy, the consumer may want to leave the communities.

When consumer c asks a super-agent sp_i for a community-based reputation value of a service, it can develop trust in the super-agent or community based on its experience of using the service. After each time of using the service, c can evaluate its experience $e(s)$ as "satisfying" or "not satisfying" (1 or 0 respectively). Another reinforcement learning formula is used to model the trustworthiness of the super-agent, as follows:

$$T_c(sp_i) = \alpha T'_c(sp_i) + (1 - \alpha)e(sp_i) \tag{6}$$

where $T_c(sp_i)$ denotes the consumer agent's trust in the super-agent sp_i after the update, and $T'_c(sp_i)$ denotes the trust value before the update. $e(sp_i)$ is the evaluation of the consumer agent's current experience with the advice provided by the super-agent sp_i about the service. It is determined based on the community-based reputation value $R_{sp_i}(s)$ of the service provided by the super-agent, as follows:

$$e(sp_i) = \begin{cases} R_{sp_i}(s) & \text{if } e(s) = 1; \\ 1 - R_{sp_i}(s) & \text{if } e(s) = 0. \end{cases} \tag{7}$$

To explain, the value of $e(sp_i)$ is determined by comparing the consumer agent's own experience of using the service, $e(s)$, with the community-based reputation about the service provided by the super-agent. If the consumer agent's experience of using the service is satisfying ($e(s) = 1$), $e(sp_i)$ is equal to the reputation value provided by the super-agent about the service, which is $R_{sp_i}(s)$. If the consumer agent's experience of using a service is not satisfying ($e(s) = 0$), $e(sp_i)$ equals $1 - R_{sp_i}(s)$. For example, if the community-based reputation value of a service provided by a super-agent is 0.9 and the consumer agent's experience is satisfying, the reputation value is consistent with the consumer agent's experience with the service. In this case, $e(sp_i)$ equals 0.9. However, if the reputation value is 0.9 and the consumer agent's experience with the service is not satisfying, it indicates that there is a mismatch between the community-based reputation and the consumer agent's own experience. Therefore, $e(sp_i)$ equals 0.1. A super-agent can gain more trust if the community-based reputation value it provides matches more closely the consumer agent's experience. The initial value of a consumer agent's trust in a super-agent may be set to 0.5, which means that the super-agent is neither trustworthy nor untrustworthy.

C. Super-Agent Based Community Formation

Since a super-agent (manager) has limited resources, its community can only contain a limited number of members. Therefore, the manager has to be selective and choose as members only the agents that it regards the most trustworthy. These agents are more likely to provide valuable information that can benefit the manager and other community members.

1) Selecting Community Members: A consumer agent can request to join a community. A community member can also recommend other agents that it considers trustworthy to the community manager. In this way, the community can grow quickly. The manager evaluates a requesting agent according to its reputation in the community, which is a collective measure of how much the agent is trusted by all the community members. If its reputation value exceeds a predefined threshold, the agent will be regarded as reputable and selected as a member. An invitation will be sent to the agent.

Suppose that a consumer agent c requests to join a community managed by a super-agent sp. The consumer submits to sp its reputation opinion ($\in [0, 1]$) for each encountered service formalized by Equation 1. The consumer agent's reputation in the community is then determined by two components, the super-agent's trust $T_{sp}(c)$ and the average trust of community members in the consumer, as follows:

$$R(c) = wT_{sp}(c) + (1 - w)\frac{\sum_{i=1}^{n} T_{c_i}(c)}{n} \tag{8}$$

where $T_{c_i}(c)$ denotes a community member c_i's trust in c, and n is the total number of community members. The super-agent also assigns different weights ($w \in [0, 1]$) on the two components. It may rely more on its own trust value of the consumer in the beginning when there are not many members in the community. Later on when there are more community members, the weight w will be reduced over time. Super-agent sp models the trustworthiness of the consumer agent c based on their ratings for their commonly rated services. The similarity between the two rating vectors may be used to represent $T_{sp}(c)$. The way of calculating $T_{c_i}(c)$ can be similar.

2) Updating Community: A super-agent will update the list of the community members periodically. This is necessary, because a community member may be reputable before joining the community but may become less reputable afterwards, due to the change of its interests or judging criteria. Another reason is that the community manager may find other more reputable agents and want to add them into its community. Because of the limited space in the community, the manager may have to remove some less reputable members. The super-agent sorts all the agents by their reputation values. The number of agents in the community that can be supported by the manager then defines the reputation threshold for membership in the community. If a community member's reputation falls below the threshold, a request for leaving the community will be sent to the agent, so that no further updates from this agent will be considered by the community manager and members.

For each service s, the community manager aggregates all community members' reputation opinions for s to have a community-based reputation value. The way of calculating this value is similar to Equation 8 after replacing $T_{sp}(c)$ and $T_{c_i}(c)$ by the super-agent's reputation opinion $T_{sp}(s)$ and the member's reputation opinion $T_{c_i}(s)$ about s respectively. The manager may also maintain a general public's reputation value of s by also aggregating reputation opinions of non-members and will share this information with all non-members.

IV. A Practical Reward Mechanism

In the system, super-agents have to contribute more resources to maintain communities, model community-based reputation of services, and answer queries of consumer agents. They need incentives for contributing resources. In addition, some super-agents may be dishonest in providing reputation information. They may provide false good reputation for some services to promote these services or provide false bad reputation to bad-mouth some other services. To address these two problems, we design a reward mechanism to create incentives for super-agents to contribute resources and share truthful reputation information about services. Inspired by real world examples, this mechanism is designed to be rather simple but practical, demonstrated by our experiments in Section V.

More specifically, in the reward mechanism, web service providers will provide rewards to super-agents. Each provider can issue its own "virtual points". This idea is similar to "store credits" in the real world. When a customer accumulates enough "store credits", these credits can be used to redeem goods in the store. For each consumer agent that consumes a service provided by a service provider, the consumer agent will also tell the provider a list of trustworthy super-agents that have provided community-based reputation of the service. A number of "virtual points" will be awarded to these super-agents. The number of "virtual points" may be dependent on the value of the service consumed by the consumer and the total number of trustworthy super-agents reported by the consumer agent. To keep our reward mechanism simple, we assume that the "virtual points" will be equally distributed among the trustworthy super-agents. This simplification is reasonable because the total number of trustworthy super-agents providing reputation information to a consumer agent about a service is not expected to be large. The simplification has also often been applied in the real world. The "virtual points" issued by a service provider can be used to redeem services offered by this provider. These "virtual points" may also be used to provide super-agents higher priorities to consume services or provide them with higher quality of services. Service providers in our system have obvious incentives to provide rewards to super-agents. Super-agents' communities building reputation for services offered by the service providers will help the service providers propagate their service information and therefore potentially bring them more consumers.

For super-agents, if their communities build reputation for good services, they can gain "virtual points" from the providers of these good services. The super-agents can then redeem the points for their future interactions with the service providers, i.e. consuming the good services. If some services are bad, super-agents may not gain "virtual points" from the providers of these services because consumer agents will likely not consume these services. But, it is still beneficial for super-agents to build reputation for bad services. They can gain trust from consumer agents by reporting honestly the bad service's reputation. This can potentially increase the super-agents' chance of being asked for advice by the consumer agents and the ability to gain points from good service's providers (in case the super-agents also build reputation for these good services). Generally speaking, if a super-agent contributes more resources to maintain communities, build reputation information about services, and truthfully shares the reputation information with consumer agents, it will be trusted by many consumer agents and have a larger number of community members. It is then able to bring more consumer agents to consume good services. Their good behavior will be rewarded by the service providers providing these good services with virtual credits that the super-agent itself can use to consume the good services for which it builds reputation.

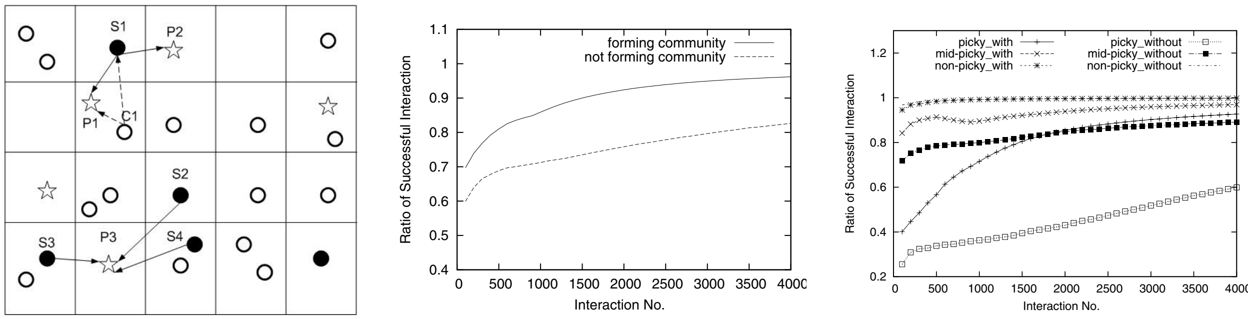
V. Experimental Validation

In this section, we carry out sets of experiments to evaluate our community-based service selection approach. We demonstrate the benefit of forming community for more effective service selection. We also show the incentives created by our system for super-agents to contribute more resources in forming communities and building community-based reputation for services, and for consumer-agents to be honest. We finally compare our community-based approach with the experience-based approach [4] and the model of Yu and Singh [1].

We simulate a service selection environment involving service providers and consumers, some of which are super-agents. Consumer agents and super-agents both consume services provided by service providers. A matrix with 4×5 cells is used to simulate a peer to peer (P2P) system as shown in Figure 1(a). The accessibility of peers in P2P environments is mapped to the matrix. Agents in the same cell are neighboring peers that can reach and communicate with each other by one or more hops. Originally, service providers (shown as stars), consumer agents (shown as white circles) and super-agents (shown as black circles) are randomly located in the cells. Consumer agents and super-agents are different in their ability in discovering service providers. Consumer agents can only find directly the service providers in their own cell. Super-agents are able to directly find the service provides not only in their own cells, but also in the cells adjacent to their own cells. For example, in Figure 1(a), consumer agent C_1 can only find directly provider P_1 but not P_2. Super-agent S_1 can directly find both P_1 and P_2. This simulates that super-agents have more searching power than ordinary consumer agents in the network. Super-agents create communities and build community-based reputation for services provided by the service providers within their searching scope. Thus, one service provided by a service provider may have several super-agents/communities build reputation for it. For example, in the figure, super-agents S_2, S_3 and S_4 all build community-based reputation for a service provided by P_3. In our simulation, super-agents also connect with the consumer agents in their own cells as well as the cells adjacent to them. In this way, consumer agents are able to join communities of the super-agents and find through them the service providers that are not in the consumers' own cells. For example, consumer C_1 can only find P_2 through super-agent S_1.

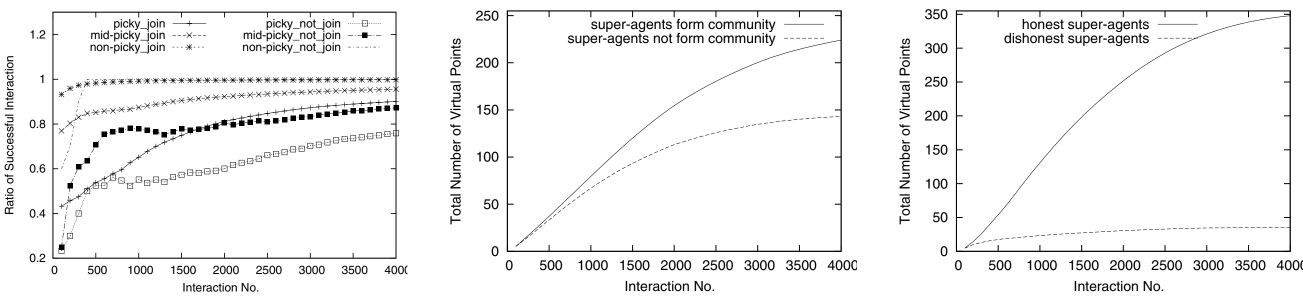
TABLE I
Service Quality and Consumer's Judgement

Service Quality	Very Low	Low	Moderate	High
Non-picky Agent	Bad	Good	Good	Good
Middle-picky Agent	Bad	Bad	Good	Good
Picky Agent	Bad	Bad	Bad	Bad



(a) **(b)** **(c)**

Fig. 1. (a) A Simulated Service Selection Environment; (b) Overall Performance with vs. without Communities; (c) Performance of Different Consumers



(a) **(b)** **(c)**

Fig. 2. (a) Consumers Join vs. not Join Communities; (b) Incentives for Super-Agents to Form Communities; (c) Incentives for Super-Agents to be Honest

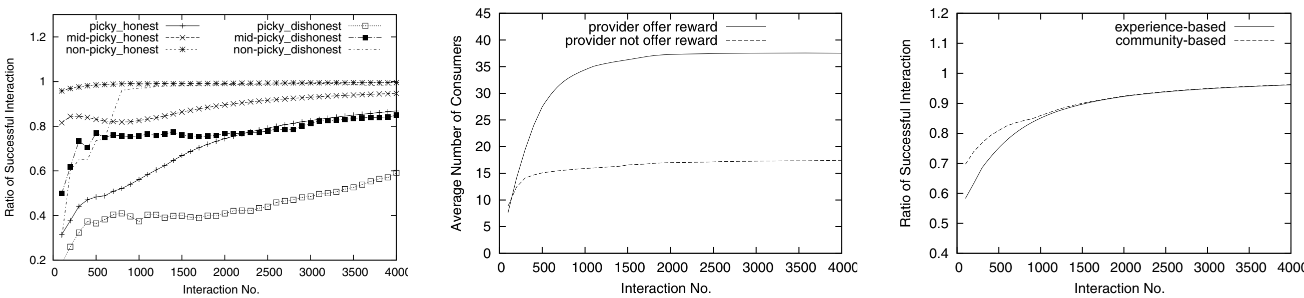
There are four types of services provided by service providers, and 2 services for each type. Different types of services have different service qualities varying from very low quality to high quality. There are three types of consumer agents, non-picky, middle-picky and picky consumers. Each type of consumers judges the quality of each type of services differently according to Table I. For example, picky consumers consider as good only services of high quality. For non-picky consumers, almost all the services except the services in very low quality are good. The simulation involves 100 consumer agents, including 30 picky consumer agents, 40 middle-picky consumers, and 30 non-picky consumers, among which there are 3 picky super-agents, 4 middle-picky super-agents and 3 non-picky super-agents. In the initial state of our simulation, consumers have no knowledge of the service qualities. There are 4000 interactions in the simulation. In each interaction, a consumer agent selects and uses a service. We set $\alpha = 0.9$ in Equation 1, $\gamma = 0.7$ and $\varepsilon = 0.3$ in Equation 4. A consumer's initial trust for each service and super-agent is set to 0.5. We run each experiment for 10 times and present the average of the results produced by each experiment.

A. Demonstrating Benefit of Forming Communities

We first carry out a set of experiments to demonstrate the benefit of forming communities. In the first experiment, we compare the overall performance of two systems. One system uses super-agents to form communities, build reputation for services, and share the community-based reputation of the services with other consumer agents. The other system does not form communities. In this system, each super-agent collects reputation opinions about services from all its neighboring consumers, and builds a general public's reputation value for services by averaging the reputation opinions provided by the consumers. We measure the performance of a system based on the ratio of successful interactions. A successful interaction means that a consumer agent selects a service to use, and finds it satisfying. By using this measure, we can find out whether forming communities can actually help consumer agents find satisfactory services to consume. Figure 1(b) shows the ratio of the number of successful interactions over the total number of interactions. From this figure, we can see that our community-based system performs better than the system that does not form communities. Forming communities can help consumer agents more accurately find satisfactory services.

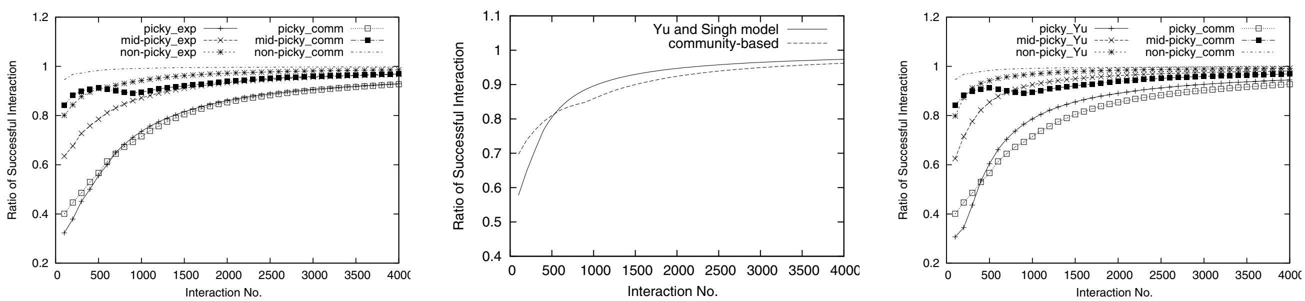
We further check the performance of each type of consumer agents in the two systems. The results in Figure 1(c) show that picky and middle-picky consumers perform better in the system with communities. The non-picky consumers perform almost the same in the two systems, which is expected because almost every service is good for this type of consumers.

The second experiment is to show the benefit for consumers to join a community when communities are formed. We measure the successful interaction ratio in two situations where consumers join and do not join communities respectively. If a consumer agent does not join a community, it cannot acquire community-based reputation information about services from super-agents. The results in Figure 2(a) show that consumers joining communities will gain higher successful interaction



(a) **(b)** **(c)**

Fig. 3. (a) Incentives for Consumers to be Honest; (b) Incentives for Providers to Offer Rewards; (c) Community-based vs. Experience-based



(a) **(b)** **(c)**

Fig. 4. (a) Community-based vs. Experience-based; (b) Community-based vs. Yu and Singh's Model; (c) Community-based vs.Yu and Singh's Model

ratio. It is thus beneficial for consumers to join communities. We can see that picky and middle-picky consumers benefit the most from joining communities. Non-picky agents also benefit in the beginning by joining communities.

B. Incentives

We also carry out a set of experiments to show the incentives created by our system. In the first experiment, we show the greater gain for super-agents to contribute more resources and build community. We compare the average rewards that super-agents receive when building and not building communities respectively. In our reward mechanism, when a super-agent helps a consumer agent find a satisfactory service to consume, the consumer will report to the service's provider. The provider will then reward the super-agent. Note that when a super-agent does not build a community, it still provides a general public's reputation value about services to consumer agents, in order to gain some rewards. The results in Figure 2(b) show that building communities can bring more rewards to super-agents because consumers can benefit from communities and gain a larger number of successful interactions with services. Therefore, clearly, our reward mechanism creates incentives for super-agents to contribute resources to form communities and build and share community-based reputation of services.

Another important purpose of our reward mechanism is to create incentives for super-agents to provide truthful community-based reputation information about services. In this experiment, we involve 50% of super-agents that are dishonest. We measure the average number of virtual credits gained by honest super-agents and dishonest super-agents respectively. As shown in Figure 2(c), honest super-agents can gain many more virtual credits than dishonest super-agents. Dishonest super-agents do not have much chance to be asked by consumer agents for advice about service providers and cannot gain many virtual credits. Therefore, it is better off for super-agents to provide truthful community-based reputation.

In the third experiment, we show that forming communities actually promotes the honesty of consumer agents. We compare the successful interaction ratio when a consumer agent acts honestly and dishonestly respectively. When a consumer agent acts dishonestly, it will provide false feedback to super-agents. It is shown in Figure 3(a) that it is not beneficial for consumer agents to act dishonestly. When a consumer agent is dishonest, it has a higher chance to join a wrong community or be excluded from a right community. Therefore, it will lose valuable information from the right communities, no matter whether it is non-picky, middle-picky or picky.

In the fourth experiment, we measure the number of consumer agents that trust a service provider. Given a trust threshold, if a consumer agent's trust value in a service provider is greater than the threshold, the service provider is trusted by the consumer agent. We simulate two systems. In one system, all service providers offer rewards to super-agents. In another system, service providers do not offer rewards and therefore super-agents do not build reputation for their services. The experimental results in Figure 3(b) show that the providers that offer rewards to super-agents are trusted by a larger number of consumer agents than those that do not offer rewards. Therefore, it is beneficial for providers to provide rewards. The great advantages for providers to offer rewards to super-agents provide incentives for super-agents to build reputation for their services, which is the important foundation for our reward mechanism to work.

C. Comparative Results

We finally carry out a set of experiments to compare our community-based approach with the experience-based approach [4] and the model of Yu and Singh [1]. The experience-based approach allows consumer agents to share experience with services expressed using pre-defined ontologies, in order to cope with subjective differences among consumers. The model of Yu and Singh relies on consumer agents themselves to model other consumers and form implicit communities.

The results shown in Figures 3(c) and 4(a) indicate that our community-based approach outperforms the experience-based approach in the beginning when consumer agents do not have many interactions with services. Later on when consumers have a larger number of interactions with services, these two approaches produce the similar results. These results confirm that our community-based approach can effectively cope with subjective differences of consumers but requires less effort from experts and consumers.

The results shown in Figures 4(b) and 4(c) indicate that our community-based approach outperforms Yu and Singh's model in the beginning when consumer agents do not have many interactions with services. Later on when consumers have more interactions with services, our approach is slightly worse than Yu and Singh's model. However, when consumers have a larger number of interactions (i.e. more than 3000) with services, these two approaches produce similar results. To explain, Yu and Singh's model relies only on consumer agents to build their own neighborhood lists, in order to form implicit communities. Consumer agents do not have much experience with services in the beginning. The communities built by them are therefore not very accurate. Our approach makes use of super-agents to form communities. These agents have more capabilities and can build effective communities from the beginning. Later on when consumer agents have more experience with services and share with super-agents, the super-agents can build more effective communities. Because in the model of Yu and Singh consumer agents rely only on their personal experience to create communities, these communities are more personalized and can help the consumers find more satisfactory services. However, after consumers have enough personal experience with services, they do not rely on other consumers' opinions or community-based reputation information about services. In this case, the performance of our community-based approach is similar to that of Yu and Singh's model. Another important point is that the model of Yu and Singh also requires much effort from consumer agents to model many other consumers. Comparably, in our approach, consumers only need to model super-agents managing the communities that they belong to, thus minimizing the effort required from consumers.

VI. Conclusion and Future Work

In conclusion, our work has several unique features. First, forming explicit communities brings consumer agents the benefit of receiving more valuable information about services shared by like-minded agents in the same communities. Second, the proposed practical reward mechanism encourages incentives for super-agents to contribute their resources, form communities, and truthfully share their reputation information. Third, as other existing trust and reputation mechanisms in decentralized systems do not consider the role of super-agents and cannot take advantage of the extra power of super-agents, our idea of using super-agents fills the gap and holds good promise when more super-agents are emerging in the networks with the advance of technology, easy access of internet, and lower price for high-performance computers.

For future work, we will refine our approach by considering the case where strategic super-agents may be honest for some services but dishonest for others. We may also allow consumer agents to ask advice about super-agents from other consumer agents. The honesty of the other consumers in providing information about the trustworthiness of super-agents may also need to be modeled. We will also look into the idea of sharing information about community members among different communities by super-agents (community managers). This will be helpful to effectively grow communities [11].

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