

AGENT CONSUMER REPORTS: OF THE AGENTS, BY THE AGENTS, AND FOR THE AGENTS

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Service matching is critical in large, dynamic agent systems. While finding exact matches is always desirable as long as an agent knows what it wants, it is not always possible to find exact matches. Moreover, the selected agents (with exact match) may or may not provide quality services. Some agents may be unwilling or unable to advertise their capability information at the sufficient level of details, some might unknowingly advertise inaccurate information, while others might even purposefully provide misleading information. Our proposed solution to this problem is the agent “consumer reports”. The broker agent will not only collect the information advertised by the service provider agents, but also learn about the experiences the consumer agents have about their service providers. It might also hire some agents to test certain service providers to see how well they can do what they claim they are capable of doing. Then agent consumer reports will be built based on the information collected. The advanced level of agent consumer reports will also dynamically capture the probabilistic distribution of the services and use it to assess the probability of a match. We plan to extend LARKS and use it as our agent capability description language.

1 Introduction

Finding the right agent(s) for the right task (service) is critical to achieve agent cooperation in large, dynamic agent systems. A popular approach to this problem is to use a broker agent (may also be called matchmaker, or facilitator) to connect the service provider agents and the service consumer agents, via service matching. Typically a broker agent recommends service providers based on the capabilities/services advertised by the service providers themselves. The matching method evolves from the early age, simple KQML performative based matching, to syntax and semantic based matching; from yes/no matches to matches with probabilities. However, we may still have problems since some agents may be unwilling or unable to advertise their capability information at sufficient level of details; some might unknowingly advertise inaccurate information; while others might even purposefully provide misleading information.

We have similar problems in the real world: we don't know whether the colorful, fancy, and even touching commercials are true or not. There is no perfect solution to this real world problem, but consumer reports certainly help a lot (besides the justice system). Consumer reports are created using the information from the manufacture's specification, consumer's feedback, and their test results on the products. It provides

guidance for consumers to choose the right product. We believe that this consumer reports approach should work for the agent world, too. By following a simple brokering protocol (which will not be discussed here because of space limitation), the broker agent will not only collect the information advertised by the service provider agents, but also learn about the experiences the consumer agents have about their service providers. It might also hire some agents to test certain service providers to see how well they can do what they claim they are capable of doing. Based on the collected information and the domain knowledge, consumer reports can be built to assist in service matching. Moreover, the broker agent can dynamically capture the probabilistic distribution of the agent services and use this information to assess the probability of a service match. Finally, our approach goes beyond the simple notion of a “reputation server” in that it discovers and refines a complex, symbolic model of a service provider’s performance.

This rest of this article is organized into two sections. In section 2, we shall describe how the agent consumer reports will be built, and we will discuss some related issues in section 3.

2 Building Consumer Reports

In our model of agent system, there are three types of agents: service provider agents, service consumer agents, and broker agents. A broker agent is the one responsible for building the agent consumer reports. To simplify the problem, but without loss of generality, we make the following assumptions: (1) All the agents (including the broker agent) in a system share a common domain ontology, and (2) the security and/or privacy issues are orthogonal to what we will discuss in this article.

2.1 Representation

We are extending the LARKS framework for use in describing the agent’s capabilities. **LARKS**, Language for Advertisement and Request for Knowledge Sharing, is an agent capability description language developed at CMU. It describes an agent’s service by specifying the context, the data types, the input and output variables, and the input and output constraints. It also has a slot for the definition of the concepts used in the description.

The matchmaking scheme in LARKS is relatively flexible and powerful. It has five filters, each of which addresses the matching process from a different perspective. “Context matching” determines if two descriptions are in the same or similar context; “profile comparison”, “similarity matching”, and “signature matching” are used to check if two descriptions syntactically match; “semantic matching” checks if the

input/output constraints of a pair of descriptions are logically match. Based on the need of a specific application domain, these filters can be combined to achieve different types/levels of matching.

Since LARKS doesn't provide the mechanisms for describing the "ratings" of an agent service, we plan to extend LARKS so that, besides the 7 standard slots described above, a description will also have zero or more "CR" (Consumer Reports) slots. These slots (if any) are typically domain dependent, and will be used to describe the strength of various aspects of the service provided by some specific agent. For example, the integer sort service description can have some CR slots (in *Italic*) as shown in figure 1.

Context	Sort
Types	
Input	Xs: ListOf Integer;
Output	Ys: ListOf Integer;
InConstraints	Le(length(xs), 100);
OutConstraints	Before(x,y,ys) <- ge(x,y); In(x,ys) <- in(x,xs);
ConcDescriptions	
<i>PriceIndex</i>	2 (10 is best)
<i>ResponseTimeIndex</i>	1 (10 is best)

Figure 1. Capability description for integer sort, with CR slots.

Basically we will add another type of filter, the consumer reports filter, to handle the CR related slots. Since these slots are usually domain dependent, the evaluation and comparison of these slots might need to be done in a domain dependent way. A default CR filter can be provided, e.g., to compare integer-typed slots. The system will allow customized CR filters to be plugged-in to handle the CR slots in a domain dependent way during the matchmaking or comparison. It is recommended that the consumer reports filter be applied after all the other designated filters have been applied. The CR filter will then be used to pick the best one(s) from all the candidates.

Please note that while we plan to extend LARKS and use its service/capability description language and its matching filters, we think the approach proposed here is applicable to other representations or systems as well.

2.2 Building Consumer Reports

The consumer reports are built based on the information the broker collects about the service provider agents. The information comes from various channels: The feedback

from service consumer agents, testing results (relevant agents can be asked or "hired" to test the service provider agents, when appropriate), the service descriptions advertised by the service provider agents, the domain knowledge etc. If the broker also performs task brokering (in which the broker receives a query, finds an appropriate agent, forwards the query to that agent, and passes the result back to the requesting agent), the requests and the results are useful sources for learning too.

The building of consumer reports is more than just collecting feedback data and assigning ratings. There are two levels of consumer reports - the basic level and the advanced level. The **basic level** is simply about assigning ratings to each relevant CR slots of the original service descriptions based on the information collected. The **advanced level**, however, goes beyond the originally advertised service descriptions. It might also rate the sub-classes and super-classes of the advertised service class, and captures the probabilistic distribution of the services. Let's use an example to illustrate the basic idea.

Consider selling televisions as a service with three sub-service classes: selling traditional TVs, selling HD-ready TVs, and selling HDTVs. Suppose the broker discovered that 85% of the advertisements/requests are about traditional TVs, 8% are about HD-ready TVs, and the rest (7%) are about HDTVs. Then if an agent requests a recommendation on "selling TV" service, the broker would be able to recommend a traditional TV seller with pretty high confidence, or recommend a HD-ready TV seller or a HDTV seller with low confidence (if there is no better choice). Five years later, the distribution of the 3 sub service classes might change to 30%, 20%, and 50% respectively. The broker agent will then be able to dynamically capture the changes in the probabilistic distribution and change its matching criteria accordingly.

On the other hand, while most of the TV sellers (those who advertise that they sell TVs) sell traditional TVs, not that many TV sellers sell HDTVs. So based on the probabilistic distribution, the broker agent would be more confident to recommend a TV seller if the request is about traditional TV, while it would be less confident (to recommend a TV seller) if the request is about HDTV. When computing the probabilistic distributions, we consider **both** how many sub classes a service class has, and the frequency of the advertisements and recommendation requests on that service. Moreover, the feedback from the consumer agents will also be taken into account.

In large, heterogeneous agent systems, while exact service matches are always desirable (as long as you know what you want), it's not always possible to find exact matches. Therefore, it's important for the broker agent to learn the probabilistic distribution of the services so as to identify the partial matches that have higher probability of success.

3 Discussions

This paper presents some preliminary concepts and plans for an adaptive service broker which learns and refines a model of a service provider's performance. Although we have touched on a number of issues, significant additional issues remain as well as a concrete implementation. The related issues not addressed here include (but not limited to) the security issue, the privacy issue, the fairness issue, and the ontology issue. We believe that the security issue and the privacy issue are orthogonal to what we've discussed here. The fairness issue is more closely related. Though we believe that in general the agent consumer reports provide basis for better service matching, the ratings on specific services may not always be "accurate" - the evaluation of "accuracy" itself is already a big issue. One (partial) solution in mind is for the broker agent to always return a list of service provider agents (instead of the best one(s) only) but will be ordered. For the ontology issue, what if the agents have only a limited subset of shared ontology, or they might use just different ontologies. This issue is somewhat orthogonal, but not cleanly. Employment of ontology translation or ontology negotiation might help.

One of the ideas behind this work is the law of locality. The approach proposed here is meant to capture both the temporal locality (e.g., the distribution may change over time) and the spatial locality (e.g., a sub set of the services may get referenced frequently).

We will develop a prototype implementation of a system which is partly based on the LARK framework. We will incorporate new ideas which are evolving from the semantic web [Berners-Lee, et. Al. 2001] and the DAML [DAML, 2000] language in particular. Some initial work has been done to explore how DAL can be used to represent and reason about web services and agent services [DAML-S 2001, McIlraith and Zeng 2001].

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