Trust-based Service Provider Selection in Open Environments

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ABSTRACT

The problem of selecting correct counterparts to interact with is of particular relevance in open and dynamic environments. This problem increases when third parties may vary their behaviour at will. In this paper we examine the problem of service provider selection using trust and reputation techniques. Most approaches to service provider selection are based on the client's proper experiences about particular services from particular providers. A problem arises when no previous experience is available. To solve this problem, previous approaches have proposed that clients obtain the required reputation information from their acquaintances. In contrast, our work advocates an experience-based approach for service provider selection, in which clients use trust and reputation mechanisms to infer expectations of future providers' behaviour from past experiences in similar situations. We present some experimental results that support our proposal.

Categories and Subject Descriptors

H.3 [**Information Storage and Retrieval**]: Miscellaneous

Keywords

Service-Oriented computing, Trust mechanisms, Multiagent systems

1. INTRODUCTION

It is commonly agreed that service-oriented computing (SOC) has changed the way of building software in last few years [7]. SOC provides a way of building software focusing on open systems where new services, clients and providers may join or leave the system continuously.

Several authors have investigated trust and reputation mechanisms that provide agents with *expectations* about the future behaviour of their counterparts based on their history within the system [8, 1, 14]. Most mechanisms aim at supporting the emergence of overlay networks of trust relations in otherwise poorly structured systems. Such mechanisms are quite useful for an agent's decision making when choosing a counterpart to interact with. This is particularly true for agents that are part of regulated open systems with "soft" enforcement mechanisms [6].

There are many recent proposals for reputation mechanisms and approaches to evaluate trust in *peer-to-peer* systems in general (e.g. [20, 1]), and multiagent systems in particular (e.g.[8, 19, 14, 6]). Sabater and Sierra [13] consider reputation to have two different dimensions of influence: an *individual dimension* measuring local reputation – evaluated from direct interactions– and a *social dimension* evaluated from direct interactions and from the opinions from the society. In this paper, we will follow the proposal by Ramchurn et al. [12] regarding basic concepts of trust-based systems: *confidence* is a local rating based on direct interactions; *reputation* is a rating based on opinions of others; and *trust* is a rating built as a result from combining.

Most of work in the field of SOC has investigated how to improve service selection [4] above all researching about service matchmaking [2] in which clients use different approaches to obtained the most similar service they have requested for, and service composition [21] as well. On the other hand we find some other works that focus on service discovery techniques [11, 18].

In this paper we propose to combine SOC and trust and reputation mechanisms in order to achieve a better performance when clients need to select the best provider to interact with when services properties are well-known, endowing clients with trust mechanisms that are complemetary with other service-oriented techniques. Section 2 outlines our proposal for building up and mantaining a trust model that takes into account some previous ideas applied to multiagent systems in [6], and shows how it can guide a client's decision making process so as to select good providers for a specific service. We present experimental results with a simulated scenario comparing our approach with others in Section 3. After discussing related work in Section 4, we conclude summarizing our approach and pointing to future lines of work.

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2. TRUST MECHANISMS IN SERVICE-ORIENTED ENVIRONMENTS

In order to improve their performance, clients in a service-oriented (SO) environment are confronted with the problem of deciding appropriate service providers for their requests according to their own beliefs and goals. Hence, trust and reputation mechanisms should be added as an additional step after traditional phases in services environment as it is presented in Figure 1. These mechanisms do not substitute current techniques, as service discovery or service matchmaking, etc., but are complementary, so that once a client has decided which providers perform the service that it requested, trust mechanisms may be quite useful in order to achieve to select best provider for that service. The reason is twofold: i) with an additional trust layer, a client may discern which provider (among potential service providers) is expected to better perform the requested service and ii) clients' local views are totally subjective, since they base their expectations only on their own perceptions of how good a provider is (even if they ask for extra information about providers to external entities – as other clients or any specified service dedicated to it), so different clients could expect non-similar values of *quality* from the same provider. Another problem emerges from the providers' autonomy, since these could vary their behaviour at will, giving different results to different clients for the same service query. Trust and reputation mechanisms propose solutions that tend to alleviate the effect of these *dishonest* providers (ii) and also take into account the effect of *incompetent* providers (i).

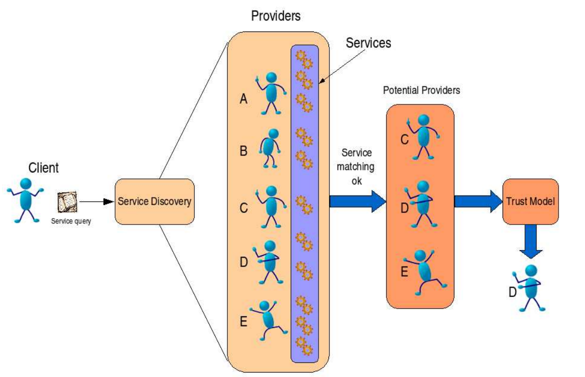

Figure 1: Trust integration in a service-oriented scenario

In the following sections we present, first, an adaptation of standard trust and reputation mechanisms to SO environments. Then we show how a client can use additional knowledge, e.g., a shared taxonomy of services, to infer confidence in a provider if no previous experience is available.

2.1 Basic Trust Model for SO Environments

In line with other approaches [9, 19, 13, 12], a basic trust model for SO environments can be built on the notions of confidence and reputation. A typical situation is that a client C wants to evaluate the trustworthiness of some provider P performing some service S. This trustworthiness is denoted as $t_{C\to\langle P,S\rangle}$, with $t_{C\to\langle P,S\rangle} \in [0..1]$, and it measures the trust C has in P being a "good" service performer – a "good provider" – of service S. In order to build trust, clients can rely on two different measures: their own confidence, and the social reputation of a provider.

Confidence, $c_{C\to\langle P,S\rangle}$, is obtained from C's own experience in receiving a service of type S from provider P. Confidence values regarding past service performings are stored in the client's *Local Interactions Table* (LIT). This table contains one entry for each provider performing a particular service. LIT_C denotes client C's LIT. An example is given in table 1.

$\langle P,S\rangle$	$c_{C\to\langle P,S\rangle}$	$r_{C\to\langle P,S\rangle}$
$\langle p_2,s_5\rangle$	0.5	0.3
$\langle p_4,s_2\rangle$	0.7	0.8
$\langle p_2,s_1\rangle$	0.9	0.5
$\vdots$	$\vdots$	$\vdots$
$\langle p_9,s_5\rangle$	0.4	0.7

Table 1: A client's Local Interactions Table

Each entry in a LIT contains the following elements: i) the provider/service identifier $\langle P,S\rangle$, ii) the client's (C) confidence value for the issue ($c_{C\to\langle P,S\rangle}$), and iii) a reliability value ($r_{C\to\langle P,S\rangle}$). We suppose $c_{C\to\langle P,S\rangle} \in [0..1]$ and higher values to represent higher confidence. Initially, the table is empty. A new entry is added, with default values for $c_{C\to\langle P,S\rangle}$ and $r_{C\to\langle P,S\rangle}$, after the client has had its first experience with the service/provider pair $\langle P,S\rangle$, that is, after the client has used this service from this provider for the first time. Subsequent direct experiences with the same provider/service pair change the confidence value $c_{C\to\langle P,S\rangle}$. In this sense, we suppose that a client has some kind of mechanism to evaluate the quality of a particular service it has recieved from a particular provider. Let $g_{\langle P,S\rangle} \in [0..1]$ be such a quality value for the provider/service pair $\langle P,S\rangle$. In our work, we use the following equation to update confidence:

$$c_{C\to\langle P,S\rangle} = \epsilon \cdot c'_{C\to\langle P,S\rangle} + (1-\epsilon)\cdot g_{\langle P,S\rangle}, \tag{1}$$

where $c'_{C\to\langle P,S\rangle}$ is the confidence value in C's LIT before $g_{\langle P,S\rangle}$ is obtained and $\epsilon \in [0..1]$ is a parameter specifying the importace given to C's past confidence value. Thus, confidence is defined as a meassure for the quality value a client has assigned to a particular service/provider pair in it's own past experiences with that pair.

Reliability ($r_{C\to\langle P,S\rangle}$) measures how certain a client is about its own confidence in a particular provider P performing a service S. We suppose $r_{C\to\langle P,S\rangle} \in [0..1]$. Furthermore, we assume that $r_{C\to\langle P,S\rangle} = 0$ for any tuple $\langle X,Y\rangle$ not belonging to LIT_C.

In our approach we propose to calculate reliability by using the approach proposed by Huynh, Jennings and Shadbolt [8, 9], by taking into account the number of interactions a confidence value is based on and the variability of the individual values across past experiences.

A client may build trust directly from its confidence value or it may combine confidence with the social reputation of an issue. The latter is especially necessary if a client has no experience on an issue or if its confidence is not sufficiently reliable. A client can obtain the social reputation of an issue by asking other clients about their opinion on a provider/service pair. Clients that have been asked for their opinion return the corresponding confidence and reliability values from their LIT. Based on confidence and reputation, the trust that client C has in the issue $\langle P,S\rangle$ (provider P performing the service S) can be defined in the following way:

$$t_{C\rightarrow\langle P,S\rangle} = \begin{cases} c_{C\rightarrow\langle P,S\rangle}, & if \;\; r_{C\rightarrow\langle P,S\rangle} > \theta \\ \frac{\sum\limits_{X\in NC\cup\{C\}} c_{X\rightarrow\langle P,S\rangle}\cdot w_{X\rightarrow\langle P,S\rangle}}{\sum\limits_{X\in NC\cup\{C\}} w_{X\rightarrow\langle P,S\rangle}} & otherwise \end{cases} \tag{2}$$

Using this formula, trust will be measured at a scale [0..1]. θ is a threshold for the reliability of C's own confidence values. If the reliability is below this threshold, $t_{C\rightarrow\langle P,S\rangle}$ is calculated as the weighted mean of the confidence values received from a set of *neighbour clients* (NC) – a set of other clients C knows and asks about their opinion. Client C's own confidence value is also taken into account. $w_{X\rightarrow\langle P,S\rangle}$ is the weight given to client X's confidence in the pair $\langle P,S\rangle$. This weight can be calculated as follows:

$$w_{X\rightarrow\langle P,S\rangle} = \begin{cases} r_{X\rightarrow\langle P,S\rangle}\cdot\alpha, & if \;\; X = C \\ r_{X\rightarrow\langle P,S\rangle}\cdot(1-\alpha), & otherwise \end{cases} \tag{3}$$

where $\alpha \in [0..1]$ is a parameter specifying the importance given to C's own confidence value. For values of $\alpha > 0.5$, a client relies stronger on its own experience than on the opinions obtained form others.

2.2 Confidence Inference using Service Similarities

Applying trust mechanism in service selection may improve the overal utility of clients. This is because out of a set of multiple providers for the same service the clients tend to select the provider that potentially offers the best service. In the framework proposed in section 2.1, as a first choice a client selects the provider based on its own experiences. However, if no direct experiences are available then a client relies on the opinion of others. The second choice, that is, the use of third party information, may have several shortcomings, especially in open environments. First, it is not easy to determine who should be asked for its opinion. Second, it is not clear how reliable the responses are. Thus, a client should avoid asking others if possible. In this section we propose a way to estimate confidence (and trust) values for particular provider/service pairs based on past experiences with similar services. These values can be used as an alternative or in combination with social reputation if no direct experiences are available.

Our approach has been introduced in [6] for agents acting in virtual organisations. It is based on the claim that, in general, agents behave in a similar way in similar interactions and playing similar roles. We believe that the same idea applies to service-oriented computing:

- Services from the same provider will have a similar quality.
- Considering a single provider, the more similar its services the more similar will be the quality of these services.

Formally, we assume that for any service S', with $S' \neq S$, the value $c_{C\rightarrow\langle P,S'\rangle}$ is an approximation for $c_{C\rightarrow\langle P,S\rangle}$. Furthermore, the more similar S' and S the more similar will be the values $c_{C\rightarrow\langle P,S'\rangle}$ and $c_{C\rightarrow\langle P,S\rangle}$. Based on this assumption, we propose the following equation for calculating confidence:

$$c_{C\rightarrow\langle P,S\rangle} = \frac{\sum\limits_{\langle X,Y\rangle\in LIT_C} c_{C\rightarrow\langle X,Y\rangle}\cdot r_{C\rightarrow\langle X,Y\rangle}\cdot sim(\langle X,Y\rangle,\langle P,S\rangle)}{\sum\limits_{\langle X,Y\rangle\in LIT_C} r_{C\rightarrow\langle X,Y\rangle}\cdot sim(\langle X,Y\rangle,\langle P,S\rangle)} \tag{4}$$

Using equation 4, each entry from client C's LIT has an influence in the calculation of $c_{C\rightarrow\langle P,S\rangle}$. The weight given to an entry is determined by the similarity of the provider/service key to the key $\langle P,S\rangle$ and by the reliability of the confidence value. $sim(\langle X,Y\rangle,\langle P,S\rangle)$ can be computed as the product of the similarities of the individual elements (provider and service), as defined in the following equation:

$$sim(\langle X,Y\rangle,\langle P,S\rangle) = sim_p(X,P)\cdot sim_s(Y,S) \tag{5}$$

where $sim_p(X,P)$, $sim_s(Y,S) \in [0..1]$ measure the similarity between providers and services, respectively, and the expression $sim_p(X,P)$ is defined as follows[1]:

$$sim_p(X,P) = \begin{cases} 1, & if \;\; X = P \\ 0, & otherwise \end{cases} \tag{6}$$

As many other organisational models, a SO system may provide shared taxonomies to describe services in a hierarchy. If this is the case, $sim_s(S,S')$ can be implemented by some *closeness functions* that estimates the similarity between two services on the basis of their closeness in the service hierarchy. In particular, we can use a simple formula – as described in the next section – or some other, more complex equations like those described in [10] or [5].

3. EXPERIMENTAL RESULTS

In this section we present some experiments that show how the overall utility of a client improves over time if it selects service providers out of a set of possible candidates by using confidence information. Furthermore, we evaluate the confidence inference model presented in section 2.2 and compare it to a basic confidence model.

In the experiments, we used a testbed which has been developed in the framework of our work on trust and reputation mechanisms for virtual organizations. This testbed simulates a client/provider environment where a number of providers are offering different services and a number of clients want to use those services. A client/provider interaction is simulated as follows:

1. A goal is generated for a client and in order to reach that goal the client has to use a particular service.
2. The client obtains all providers that are offering the required service.
3. Out of the set of possible providers, the client selects one by using a specific confidence model.
4. The service provisioning is simulated. This step basically consists in the generation of a quality value for the selected provider/service pair ($g_{\langle P,S\rangle}$) which can be used by the client as an evaluation meassure for the received service.

[1] Equations 4 and 5 allow for the use of a proper similarity function between service providers. This corresponds to the assumption that similar providers will provide a similary quality of service.

As it can be seen, our testbed simplifies the problem of service provider selection. A client only concentrates on selecting a provider out of a set of providers that are offering a requested service. That is, given a client's service request, the testbed returns a relation of all providers that offer this service. In a real world SO scenario, obtaining such a list is a very difficult problem itself and would require service discovery and service matching techniques.

The quality value ($g_{\langle P,S\rangle}$) which is generated in step 4 represents a concrete experience of a client regarding a particular provider/service pair $\langle P, S\rangle$. The values are generated from a normal probability distribution which is assigned at startup to each provider/service pair[2].The values of $g_{\langle P,S\rangle}$ are cut to the intervall [0..1]. In this way, the testbed simulates that the quality of a service from a provider is always similar with some variations.

The next subsections specify the test scenario and explain the experimental setup. Afterwards, we present some graphical results.

3.1 The Tourism Scenario

As a test scenario we use different services that are provided by different travel agencies and clients who look for such travel services. As described in section 2.2, in order to evaluate our confidence inference approach we need a similarity meassure for services. In this regard, we suppose that a taxonomy is provided which presents a conceptual hirarchy of the different services. Figure 2 presents the services and the taxonomy we used.

3.2 Metrics and Models

In the experiments we tested the following three different confidence models:

- *Random Model*: this model makes clients choose a provider randomly among potential candidates – those which provide the service that client is looking for. Thus, the selection is not based on any experience at all.

- *Basic Model*: in this model a client makes its decision by evaluating the potential providers based on its confidence values stored in its LIT. If a client has sufficient experience about a provider/service pair, it uses this confidence to evaluate the provider. If no previous experience is available, a provider is selected randomly.

- *Inference Model*: this model implements our confidence inference approach as described in section 2.2. Similar to the *basic model*, if a client has sufficient experience about a provider/service pair, it uses its confidence value to evaluate the provider. However, if insufficient previous experience is available (e.g., the reliability of a provider/service pair in a client's LIT is lower than Θ), then the client uses equation 4 to infer a confidence value based on its experience with the same provider but for different services.

Given a service taxonomy as the one presented in Figure 2, we use the following formula to calculate the similarity between services in the inference model:

$$sim_s(x, y) = 1 - \frac{h}{h_{MAX}} \tag{7}$$

where x, y are services, h is the number of hops to reach concept y from x in the services taxonomy, and h_{MAX} is the longest possible path between any pair of concepts in the taxonomy.

The probability distributions assigned at startup to each provider/service pair is generated according to the service taxonomy. Given a provider P offering two services S and S', the closer S and S' are in the taxonomy the more similar will be the probability distributions assigned to the pairs $\langle P, S\rangle$ and $\langle P, S'\rangle$. Thus, the more similar will be the quality of the services S and S' from provider P.

3.3 Results

This section summarizes the experimental results. We ran the same experiment for all three models with the same scenario, using the same number of clients, goals, services and providers. In particular, we used a collection of 20 clients and 20 providers. Results for this paper have been obtained from a collection of 40000 generated goals (service requests). In the *inference model* we used $\Theta = 0.3$. Furthermore, we repeated each experimental run 5 times with an different random seed. The presented results correspond to the average of these five runs.

Figure 3 shows the evolution of the overall system utility over the number of interactions that have taken place. The overal system utility is calculated as the average of the utilities of all individual clients. As utility values we use the quality values a client obtains after using a service. As it can be observed, that the utility improves with the number of interactions if a confidence model is used to select the "best" out of a set of possible providers for a requested service. Both confidence models are clearly better than a random provider selection. Furthermore, it can be observed that the utility improves as the clients gain more experience, that is, as more interactions take place. Regarding the difference between both confidence models, the inference model performs better than the basic model. As it was expected, this holds especially at the beginning, e.g., when the clients have no or very few direct experience. It is in this case that the clients can use experiences about similar services in order to evaluate an unknown provider/service pair.

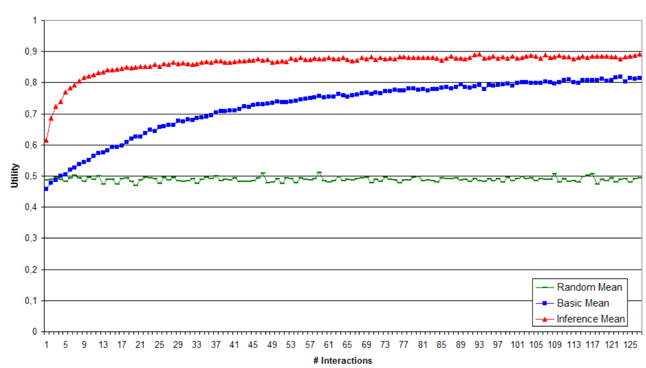

Figure 3: Overall simulation results for the settings: 20 clients, 20 providers and 40000 service requests

[2]The mean and variance of a provider/service pair is selected randomly such that $\mu \in [0..1]$ and $\sigma^2 \in [0..0.25]$.

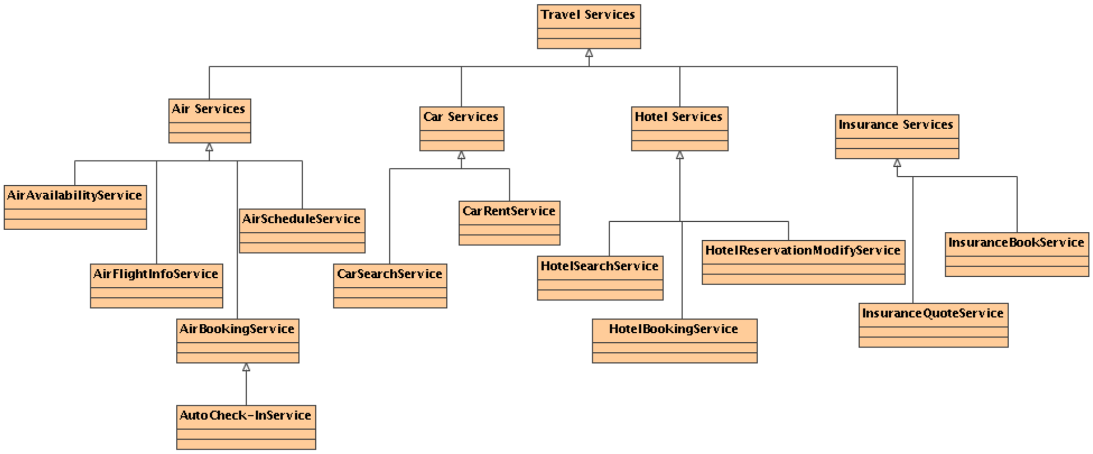

Figure 2: Services taxonomy for tourism scenario

As it is reasonable to hope, client utility behaves in a similar way as global utility. An example of the curves for just one individual client is given in figure 4. As it can be seen in this figure, the difference between the inference model and the basic model degrades as the client carries out more interactions, e.g., it gains more experience. In fact, both curves tend to the same maximum.

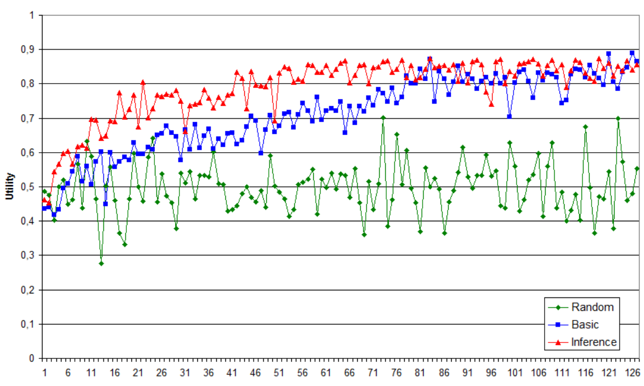

Figure 4: Client utility using three different models

4. DISCUSSION

Previous approaches for service provider selection are mostly based on service matching, the received service, etc. However, our proposal focuses on (as a first step) endowing agents with a local and faster way of evaluating expectations about providers behaviour, quite important when entities (clients and providers) are living in changing and heterogeneous environments.

In contrast to other approaches to trust systems (most of them based on reputation distribution), we have presented a way of evaluating trust at a local level that emphasizes the different experiences of agents from past interactions. The FIRE model proposed by Huynh, Jennings and Shadbold [8] is also concerned with *interaction trust* and *role-based trust*. As in our approach, the former is built from direct experience of an agent, while the latter is the rating that results from role-based relationships between agents. Nevertheless, the FIRE model does not consider inference in similar situations.

In the approach proposed by Sen and Sajja [15] a trust model for selecting processor agents for processor tasks is put forward. Agents select the best processor taking into account others' opinions about it. We suggest using past experiences first, since they are more reliable and a provider that is trustworthy for one client need not be so for another.

The model proposed by Sabater and Sierra [14] also exploits ontologies to make up trust values. Nevertheless, it does not consider taxonomies (or ontologies in its work) in the sense we do, and thus they do not use them to infer trust from past client's experience.

The trust model by Ramchurn et al. [12] is based on direct and indirect multi-agent interactions for establishing contracts between agents in electronic institutions[3]. Still, it does not account for systems with "soft" enforcement mechanisms, where norms and behaviour rules can be transgressed.

Sensoy and Yolum [16] propose an approach for distributed service selection that allows clients to capture their experiences with the service providers using ontologies. This is based on the exchange of detailed experiences of different clients. However, we argue that clients should first use their own past experiences before asking for the expertise from others.

5. CONCLUSION

In this paper we have presented results of applying our previous work in [6] to service-oriented computing, aimed at using trust and reputation mechanisms in clients which have to decide which service providers to request. We have emphasised the problem of finding "good" service providers, even if no previous services have been perfomed before. We have endowed our model with inference capabilities exploiting a shared *taxonomy* of services.

In future work, we plan to extend our model with social reputation capabilities, and study the problem of dishonest and non-cooperative providers. Furthermore, we will focus on developing an extension of our testbed to study evolutionary situations where a huge number of entities perform interactions within a system. Finally, we will look into different ways of applying more accurate similarity functions to use with structural taxonomies, e.g., [10, 5, 17] as well.

Acknowledgements

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