Reputation-based Provider Incentivisation for Provenance Provision

(Extended Abstract)

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ABSTRACT

Knowledge of circumstances under which past service provisions have occurred enables clients to make more informed selection decisions regarding their future interaction partners. Service providers, however, may often be reluctant to release such circumstances due to the cost and effort required, or to protect their interests. In response, we introduce a reputation-based incentivisation framework, which motivates providers towards the desired behaviour of reporting circumstances via influencing two reputation-related factors: the *weights* of past provider interactions, which directly impact the provider's reputation estimate, and the overall *confidence* in such estimates.

Keywords

Reputation; Circumstances; Incentivisation; Provenance

1. INTRODUCTION

A service-oriented marketplace can be seen as a dynamic marketplace where individuals interact to achieve their goals. Besides the outcomes of past interactions, knowledge of the *circumstances* under which interactions took place gives individuals useful (more sufficient) information to support their decision making in selecting a future interaction partner. The PROV standard [3] (published by W3C as a standard for interoperable provenance) provides a suitable solution for exposing information on various circumstances underlying a service provision. A PROV document describes in a queryable form the causes and effects within a particular past process of a system as a directed graph with annotations. The contents of a provenance graph can be collated from data recorded by a set of independent agents, and clients have a standard means to query the data.

Providers are the obvious source of such provenance data, as it is a record of how they provided a service, but they may not be willing to release such records for several reasons. This may be due to the additional burden incurred on the provider side (the process of provenance recording and documentation could be tedious and expensive), or for competitive grounds (e.g. it may be against provider interests to release records showing that they performed poorly). Targeting providers with relevant *incentives* is a promising way to encourage them to release provenance data. In the context of service-oriented marketplaces, *reputation* is a particularly attractive (extrinsic) incentive for service providers since it has a direct effect on their chances of being selected by clients. Based on this, a reputation-based incentivisation framework is investigated in this paper.

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2. INCENTIVISATION FRAMEWORK

To influence a provider towards provision of (true) circumstances reports, the incentivisation mechanism in place (reputation-based in our case) should allow the provider to gain some utility in response. Existing reputation mechanisms provide a reputation score to compare providers, usually estimated from ratings given by past customers. An intuitive approach would thus be to allow the circumstances given by the provider to influence such a score via influencing the *weight* of these ratings. In fact, when circumstances are available, such an approach seems necessary to ensure accurate assessments of provider reputation for clients. In many cases, this also brings benefits to reputation from the provider perspective. Consider a provider who fails to deliver some goods on time on a day when an unexpected transport strike occurs. Such a failure can potentially harm the provider's reputation, but is out of the provider's control. Thus, it is advantageous for the provider to justify this failure via revealing the mitigating circumstances that occurred, to allow for its effect on reputation to be discounted.

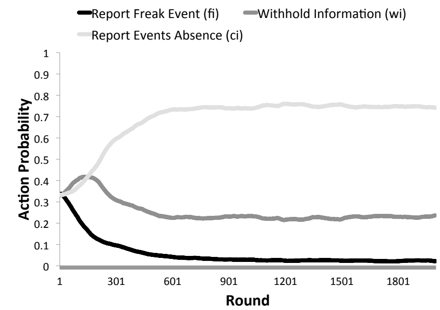
Yet, there may be other cases where exposure of circumstances would not benefit a provider's reputation (e.g. the provider consistently delivers a good performance, so reporting circumstances or reporting their absence would only incur an additional cost without additional benefit). Moreover, such an approach (i.e. weighting past ratings by released circumstances) may also motivate providers towards the undesired behaviour of supplying untrue information (e.g. a provider may claim untrue mitigating circumstances in order to justify their occasional poor performance and thus avoid reputation losses).

To discourage these deception opportunities (i.e. omitted or misleading information by providers), a provider's circumstances provision behaviour should have an effect on another reputation related factor. We argue that a plausible factor is the *confidence* in the *weights* assigned to ratings, influencing in turn the *overall confidence* in the reputation score. The intuition behind this is as follows. When the circumstances underlying a rating are withheld, the rating's relevence for the current situation is uncertain, which should be reflected via a low confidence in the weight assigned for the rating. Similarly, if the circumstances report is provided, but is *suspicious* (suspicious reports can be detected by confirming them against those provided by others in the population), the confidence in the respectively calculated weight for the rating should also be reduced. The overall confidence in the reputation score for a provider could have an important impact on the decision making of the client, and a provider with a low confidence could potentially be placed lower in the ranking list despite having a good reputation score.

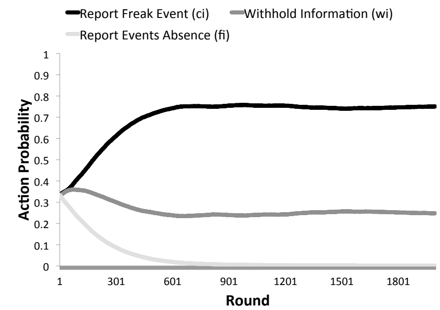
3. EVALUATION

We conducted an agent-based simulation, which proceeds in rounds, each involving three phases: client reconsideration; service provision; and provider reconsideration. In the *client reconsideration* phase, each client selects an interaction partner for the current round from the n most reputable service providers (with an exploration probability). To determine a provider reputation, the client utilises FIRE [2] as the base reputation mechanism, augmented with the proposed extension, with the overall ranking score of a provider being a combination of the provider's respective reputation and confidence scores. In the *service provision* phase, each client receives a service from the selected provider, and rates this service according to their satisfaction. Here, we consider *freak events* as potential circumstances affecting provision of services, as a result of which providers deliver their services at lower quality levels. In the *provider reconsideration*, each provider observes the profit achieved (in terms of the number of client requests received) in the current round following its previous circumstances provision decision, compares this profit against the cost incurred (0 if no circumstances report is provided, and a negative cost otherwise), and adjusts its action policies accordingly through a form of q-learning [1]. Here, we assume two possible states, *occurrence of a freak event*, denoted by s^+, and no occurrence of freak events, denoted by s^-, with three possible provider actions at each state: reporting correct information (ci), reporting false information (fi), and withholding information (wi). The goal is to push the provider's behaviour towards action ci, which corresponds to reporting a freak event occurrence (for state s^+), and reporting no freak event occurrence (for state s^-).

Figures 1(a) and 1(b) illustrate the results obtained (averaged over 100 simulation runs, each involving 50 service providers and 100 clients, with a duration of 2000 rounds). The proposed incentivisation strategy achieves the desired provider behaviour, increasing the probability of action ci to a high level in both states s^+ and s^-. In particular, in state s^- (Figure 1(a)), withholding information is not a favourable action since it lowers the confidence in the provider's reputation estimate, and consequently decreases the provider's overall ranking. Action fi is not beneficial in this state, leading to favouring action ci (i.e. reporting freak events absence), where the boost in confidence achieved via reporting correct information (verified by comparing this information with other providers) compensates for the negative utility of information provision. The same applies for state s^+ (Figure 1(b)). Here, the decrease in confidence from chosing actions wi or fi further lowers the ranking (and thus the selection chances) of the provider affected by the freak event, while choosing action ci (i.e. reporting the freak event) provides a double benefit (discounting the impact of affected interactions on reputation, and increasing confidence).



(a) Negative State (No Freak Event)



(b) Positive State (Freak Event)

Figure 1: Incentivisation with Circumstance-aware Weighting and Circumstance-aware Confidence

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