

Effects of communication expressiveness in agent reputation models interoperability: a multivariate analysis approach

Luis G. Nardin¹, Anarosa A. F. Brandão¹, Elisabeti Kira², and Jaime S. Sichman¹

¹ Laboratório de Técnicas Inteligentes (LTI)
Escola Politécnica (EP)

Universidade de São Paulo (USP)
Av. Prof. Luciano Gualberto, 158 trav. 3 – 05508-970 – São Paulo – SP – Brasil
luis.nardin@usp.br, {anarosa.brandao, jaime.sichman}@poli.usp.br

² Departamento de Estatística
Instituto de Matemática e Estatística (IME)
Universidade de São Paulo (USP)
C.P. 66281 – 05311-970 – São Paulo – SP – Brasil
betikira@ime.usp.br

Abstract. SOARI is a service oriented architecture that provides support to the semantic interoperability among agents that implement heterogeneous reputation models. Using this architecture, several experiments and analyses were previously conducted in order to show the effects of a more expressive communication on the reputation evaluation accuracy. However, such analyses were conducted using a univariate statistical approach which disregards possible correlations among reputation models' attributes. Therefore, in order to consider the influence of such possible correlations, this paper analyzes the effects of a more expressive communication among agents with different reputation models using a multivariate statistical approach.

1 Introduction

The number of available online services, in domains such as e-Commerce, e-Government and e-Science has increased in the last years due to the expansion of Internet use [15]. Agent-based computing has been advocated as the natural computational model to automate the interaction with these services, since agents may act autonomously at some extent and they may engage in social activities such as cooperation, coordination, and negotiation [21] on behalf of a user. The engagement in any of these social activities implies that the agents will exchange information, thus becoming exposed to non-knowledgeable or malevolent agents.

In order to reduce the risks associated with such interactions, some solutions were proposed, whose were based on different trust and reputation models, like Histos and Sporas [22], MMH (Mui, Mohtashemi and Halberstadt) [9], ReGreT

[17], FIRE [6], RePage [16] and L.I.A.R.³ [10]. Therefore, since there is no consensus about a single unifying reputation definition, the semantics associated with reputation differs from one model to another. This heterogeneity raises a semantic interoperability issue, which is addressed by SOARI (Service Oriented Architecture for Reputation Interaction) [11] architecture.

In a previous work [12], we developed some experiments using SOARI, whose analyses showed that enabling a more expressive communication improves the agents' reputation evaluation accuracy. Those analyses were conducted applying a nonparametric univariate statistical hypothesis test method, thus a hypothesis was elaborated and tested for each reputation model attribute in isolation. Moreover, the improvement conclusion was based on the fact that the attributes that presented some improvement were the ones influenced by communication.

Therefore, this paper aims to conduct a multivariate statistical analysis, using the same experimental data used in the univariate analysis case, in order to verify the hypothesis that a more expressive communication about reputation is sufficient to improve the reputation evaluation accuracy for the experiments as a whole.

The rest of the document is organized as follows. Section 2 briefly presents SOARI architecture as well as the simulation platforms used to run the experiments. In Section 3, the multivariate method used to analyze the experimental results is described. Then, in Section 4, we present and analyze the obtained results. Finally, conclusions and future work are presented in Section 5.

2 Background Work

In this section, we present the tools used to run the experiments shown in this paper. First, SOARI's main characteristics and functionalities are briefly described. Then, we present the characteristics and differences between the ART (Agent Reputation and Trust) [3] and the FOREART [19] testbeds.

2.1 SOARI

SOARI (Fig. 1) is a service oriented architecture that provides support to the semantic interoperability among agents that implement heterogeneous reputation models. Its main underlying idea is that the mapping among different reputation models, represented as ontologies, may be executed externally to the agents and be available online as a service for agents' use.

This architecture uses the hybrid semantic interoperability approach proposed by [20], which allow the interoperation of agents with different reputation models based on a common vocabulary. In this approach, each agent has its own internal ontology to represent its own reputation model and uses a common reputation ontology, namely FORE [2], to interact with other agents. Therefore, interoperability is possible if each agent has the mapping of its own internal reputation model ontology to the common reputation ontology. By adopting this

³ *Liar Identification for Agent Reputation.*

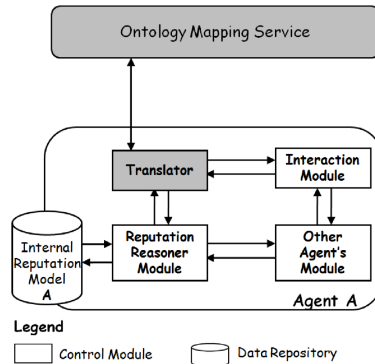


Fig. 1. Service Oriented Architecture for Reputation Interoperability.

approach, agents are prevented from requiring to know other agents' internal reputation models which avoids the use of such information in a hazardous way. Other advantages claimed by the SOARI architecture are: (i) agent simplification, (ii) agent workload reduction, and (iii) ontology mapping reuse.

SOARI is composed of two distinct and specialized modules (in grey in the Fig. 1), the *Ontology Mapping Service* (OMS) and *Translator Module* (TM), whose are responsible for the mapping and translation ontology functions [8]:

- The OMS module is a service outside the agent that implements the mapping and translation ontology functions and presents two main functionalities: (i) it maps concepts from the target's reputation model ontology to the concepts of the common ontology; and (ii) it answers concept translation requests from the TM.
- The TM resides inside the agent and it translates reputation messages. It has four main activities: (i) it translates the reputation messages from the common ontology to the target agent's reputation model ontology whenever the message comes from another agent; (ii) it translates the reputation messages from the agent's reputation model ontology to the common ontology whenever sending a message to another agent; (iii) it triggers some internal reputation function based on the interpretation of messages written using the reputation model ontology; and (iv) it creates a message using the internal reputation model ontology.

A more detailed description of SOARI can be found in [11].

2.2 Simulation Testbeds

The ART [3] and FOREART [19] testbeds are currently the only simulation platforms freely available that provide a common environment to compare different agent reputation models and implementations. They simulate an iterative

art appraisal game, in which agents have different knowledge (expertise) about different painting eras. During the game, agents are asked to evaluate paintings by a pool of clients. In order to overcome their intrinsic knowledge limitation, agents may buy reputation information about third-parties, as well as opinions about paintings, from other agents to produce more accurate appraisals.

Despite both testbeds implement the same art appraisal game, they differ in the way they enable interoperability among agents. In the ART testbed, interoperability is obtained by mapping the agent’s reputation model evaluations into a single value in the domain [0:1]. Although not explicitly defined, it is assumed that value 0 refers to the lowest reputation value and 1 to the highest reputation value. This value representation model may incur in loss of expressiveness, since it is usually required to map complex internal reputation models into a simplistic one.

On the other hand, the FOREART testbed, which is an extension of the ART testbed, enables agents to communicate through symbolic messages. In this work, the SOARI architecture was used to implement the FOREART testbed agents, thus enabling a more expressive communication about reputation among them. A more detailed description about the ART and FOREART testbeds can be found in [4,1].

3 Nonparametric Multivariate Analysis Method

Multivariate analysis is designed to elicit information from a set of stochastic vectors that include simultaneous measurements on many different variables [7]. Multivariate hypothesis tests are methods of group comparisons using such multivariate data, and they may be divided in two groups: *parametric* and *non-parametric* methods.

The *parametric* methods assume that the data have come from an underlying probability distribution and make inferences about the parameters of the distribution. For instance, the Hotelling T^2 test [5] is a multivariate generalization of Student’s T for tests about a location parameter.

The *nonparametric* methods do not rely on assumptions about the data’s probability distribution. One nonparametric alternative to the Hotelling T^2 test is the multivariate permutation test [13], where the only assumption is the exchangeability among the multivariate data vectors.

In this work, we are interested in *nonparametric* multivariate two-sample hypothesis tests, since (i) the reputation models are inherently multivariate, (ii) the experimental data for analysis are not normally distributed, and (iii) we want to perform group comparison between two experimental samples at a time.

Consider that $\mathbf{X}_1, \dots, \mathbf{X}_{n_1}$ are n_1 independent and identically distributed (*iid*) random vectors with a continuous distribution function $F(x)$ defined on R^p for some $p \geq 1$, and $\mathbf{Y}_1, \dots, \mathbf{Y}_{n_2}$ are n_2 *iid* random vectors with a continuous distribution function $G(x)$, also defined on R^p . Thus, \mathbf{X} and \mathbf{Y} denote the vectors of estimated reputation model attributes’ values that we will compare. In that

respect, it is assumed that

$$G(x) = F(x - \Delta), x \in R^p, F \in \mathcal{F} \quad (1)$$

where Δ is a p -vector of real (unknown) elements, and \mathcal{F} is the class of all continuous (not necessarily symmetric) distribution functions on R^p . Therefore, the hypothesis testing may be stated as

$$H_0 : \Delta = \mathbf{0} \text{ vs } H_1 : \Delta \geq \mathbf{0}, \Delta \neq \mathbf{0}. \quad (2)$$

As already informed, when the assumption of multivariate normality is not reasonable, hypothesis testing based on permutation offers one possible solution [18]. Therefore, writing $\Delta = (\delta_1, \dots, \delta_p)^T$, we may write the null hypothesis of equality in multivariate distributions as

$$H_0 = \bigcap_{j=1}^p H_{0j} \quad (3)$$

where each univariate null hypothesis H_{0j} tests the equality between the univariate distributions for the j^{th} reputation model attribute and H_0 represents the global null hypothesis test. Thus, the global alternative hypothesis test may be represented as

$$H_1 = \bigcup_{j=1}^p H_{1j} \quad (4)$$

where $H_{0j} : \delta_j = 0$ and $H_{1j} : \delta_j > 0, j = 1, \dots, p$.

For the j^{th} marginal distribution function for $F (F_j)$ and $G (G_j)$, we have by Eq. 1 that $G_j(x) = F_j(x - \delta_j), x \in \mathbb{R}$, therefore, we may construct a test statistic for H_{0j} vs H_{1j} based on appropriate two-sample linear rank statistics, for $j = 1, \dots, p$. Under H_0 , we may consider that the two samples are from a common population, so that the joint distribution of all the n -vectors $(\mathbf{X}_1, \dots, \mathbf{X}_{n_1}, \mathbf{Y}_1, \dots, \mathbf{Y}_{n_2})$ remains invariant under any permutation of them.

The observation n -vectors $(\mathbf{X}_1, \dots, \mathbf{X}_{n_1}, \mathbf{Y}_1, \dots, \mathbf{Y}_{n_2})$ then gives rise to the rank vector \mathbf{R}_n , where R_{ij} is the rank among the n observations $X_{1j}, \dots, X_{n_1j}, Y_1, \dots, Y_{n_2j}$ for $i = 1, \dots, n$ and $j = 1, \dots, p$. Hence, assuming the two samples are from the same common population, the columns of the rank-collection matrix \mathbf{R}_n are exchangeable vectors, where $n = n_1 + n_2$.

$$\mathbf{R}_n = \begin{pmatrix} R_{11} & \dots & R_{1n} \\ \vdots & & \vdots \\ \vdots & & \vdots \\ R_{p1} & \dots & R_{pn} \end{pmatrix} \quad (5)$$

We denote by \mathcal{P}_n the permutational (conditional) probability generated by the $n!$ (equally likely) possible permutations of the columns of \mathbf{R}_n . Then, a test statistic T_{nj} may be defined as

$$T_{nj} = \frac{1}{n_2} \sum_{i=n_1+1}^n a_{nj}(R_{ij}) - \frac{1}{n_1} \sum_{i=1}^{n_1} a_{nj}(R_{ij}), \quad 1 \leq j \leq p \quad (6)$$

where $a_{nj}(r), r = 1, \dots, n$ denotes the scores for the j^{th} \mathbf{R}_n matrix row. The null hypothesis is rejected for T_{nj} values larger than the critical value. Therefore, in order to obtain the critical value for T_{nj} , we may calculate $\mathcal{L}_{n_1 n_2}$ (Eq. 7) for all possible $n!$ permutations of \mathbf{R}_n .

$$\mathcal{L}_{n_1 n_2} = [n_0 \mathbf{T}_n^T \mathbf{V}_n^{-1} \mathbf{T}_n - \inf\{(\mathbf{T}_n - \mathbf{b})^T \mathbf{V}_n^{-1} (\mathbf{T}_n - \mathbf{b}) : \mathbf{b} \geq \mathbf{0}\}] \quad (7)$$

where $n_0 = n_1 n_2 / n$, \mathbf{T}_n represents the vector of all the T_{nj} values, and the \mathbf{V}_n is the covariance matrix calculated as

$$\mathbf{V}_n = \frac{1}{n} \left[\sum_{i=1}^n \{a_{nj}(R_{ij}) - \bar{a}_{nj}\} \{a_{nl}(R_{il}) - \bar{a}_{nl}\} \right]_{j,l=1,\dots,p} \quad (8)$$

where $\bar{a}_{nj} = \{a_{nj}(1) + \dots + a_{nj}(n)\} / n, 1 \leq j \leq p$.

If \mathbf{T}_n is exactly $N(\theta, \mathbf{V}_n)$ and \mathbf{V}_n is treated as non-stochastic, we may consider it numerically equal to the likelihood ratio statistic. Hence, $\mathcal{L}_{n_1 n_2}$ may be easily computed using a quadratic program.

Since for large values of n the number of permutations may become computation prohibitive, in order to obtain the permutational (conditional) probability \mathcal{P}_n , we may select x , arbitrarily chosen, randomly possible permutations of the columns of \mathbf{R}_n and for each one compute $\mathcal{L}_{n_1 n_2}$. One may notice that for larger x the permutational (conditional) probability becomes more accurate. In order to obtain the critical value for statistical test, all the values of $\mathcal{L}_{n_1 n_2}$ should be sorted

$$\mathcal{L}_{n_1 n_2}(1) \leq \mathcal{L}_{n_1 n_2}(2) \leq \dots \leq \mathcal{L}_{n_1 n_2}(x) \quad (9)$$

and the value $\mathcal{L}_{n_1 n_2}(x - (x * \alpha))$ is selected as the critical value for statistical testing, where α is the level of significance expected for the test. Therefore, if $\mathcal{L}_{n_1 n_2}$ computed for the \mathbf{R}_n rank-collection not permuted matrix is greater than the critical value, then the null hypothesis (H_0) is *rejected* accepting the alternative hypothesis (H_1), otherwise we cannot *reject* H_0 .

4 Experiments

In this section, we briefly describe the simulations performed using ART and FOREART testbeds, as well as the multivariate analysis conducted using the methodology described in Section 3.

More specifically, in this section we intend to present a multivariate analysis obtained from the simulations in order to verify the hypothesis that a more expressive communication about reputation is sufficient to improve the reputation evaluation accuracy. As mentioned earlier, we have already performed a univariate analysis and concluded that there is an improvement of using a more expressive communication, however, in this work we extend this analysis using a method that consider the correlations among all the reputation model attributes.

4.1 Simulations

The experiments were extensively described in a previous work [12], and hence readers interested in the details are encouraged to read it. In this paper, we will provide a brief overview, sufficient to provide the necessary information for the statistical analysis.

The main objective of the experiments was to compare the reputation assigned by *Honest* agents to a *Dishonest* agent obtained from different simulation scenarios of painting appraisal. *Honest* agents answer to the requests only when they have expertise about the corresponding painting era and using information coherent to their internal state. On the other hand, *Dishonest* agents answer to all reputation and opinion requests, even when they do not have expertise about that painting era and they never answer the requests using information coherent to their internal state.

In order to test the improvement when communication expressiveness is higher, we proposed several simulation scenarios, which were classified based on three dimensions: (1) reputation models used by the *Honest* agents (Repage, L.I.A.R., MMH or a combination of them), (2) reputation model of the *Dishonest* agent (in the case of mixed reputation models) and (3) reputation communication method (numeric, when using ART, or symbolic, when using FOREART). The two first dimensions are shown in Table 1⁴.

Table 1. Summary of ART and FOREART simulation scenarios.

Honest Agent Reputation Model	Dishonest Agent Reputation Model	Number of Attributes
L.I.A.R.	L.I.A.R.	3
Repage	Repage	2
MMH	MMH	3
L.I.A.R. and Repage	L.I.A.R.	5
L.I.A.R. and Repage	Repage	5
Repage and MMH	Repage	5
Repage and MMH	MMH	5
MMH and L.I.A.R.	MMH	6
MMH and L.I.A.R.	L.I.A.R.	6
L.I.A.R., Repage and MMH	L.I.A.R.	8
L.I.A.R., Repage and MMH	Repage	8
L.I.A.R., Repage and MMH	MMH	8

We executed 10 runs ($p = 10$) of each simulation scenario with 100 cycles each. Each scenario was composed of 21 agents ($n = 21$), where 20 agents were

⁴ For conciseness, we didn't represent explicitly the third dimension in Table 1.

*Honest*⁵ and 1 agent was *Dishonest* ($i = [1, 20]$ and $j = 21$). The mean reputation value of the *Dishonest* agent by each *Honest* agent (r_j) was taken as the one obtained in the last simulation cycle ($l = 100$ and $m = 100$), because we considered it as the most accurate reputation evaluation.

Formally, consider a set of n agents, where $i = \{1, 2, \dots, n - 1\}$ are *Honest* agents and $j = n$ is a *Dishonest* agent. Moreover, consider that r_{ij}^{sk} is the reputation value assigned by the agent i to the agent j in cycle k on simulation run s . Typically, the reputation value assigned by agent i to agent j on simulation run s corresponds to the mean reputation value of a set of cycles, which is calculated

as $r_{ij}^s = \frac{\sum_{k=l}^m r_{ij}^{sk}}{m - l + 1}$, where l and m represents, respectively, the lower and upper cycle limits. The mean reputation value assigned by the *Honest* agents to the

Dishonest agent on each simulation run s is $r_j^s = \frac{\sum_{i=1}^{n-1} r_{ij}^s}{n-1}$. Finally, given a set of simulation run $s = 1, \dots, p$ that compose a simulation scenario, the mean value

of the *Dishonest* agent is $r_j = \frac{\sum_{s=1}^p r_j^s}{p}$.

Such computation was performed for each reputation model attribute that composes the simulation scenario. Thus, at the end of each simulation scenario run, a vector of size z was generated, where z correspond to the number of reputation models attributes considered on the simulation scenario (see Table 1). Table 2 presents the attributes used by each reputation model in the simulations.

Table 2. Reputation models attributes.

Reputation Model	Attribute Name
L.I.A.R.	<i>Direct Interaction-based Reputation (DIbRp)</i> <i>Indirect Interaction-based Reputation (IIbRp)</i> <i>Reputation Recommendation-based Reputation (RpRcbRp)</i>
Repage	<i>Image Reputation</i>
MMH	<i>Encounter Derived Reputation (EncRep)</i> <i>Observed Reputation (ObsRep)</i> <i>Propagated Reputation (PropRep)</i>

⁵ In mixed experiments, we adopted the following policy: when two reputation models were considered, we used 10 *Honest* agents of each model; when three reputation models were considered, we used respectively 7, 7 and 6 *Honest* agents of each model.

4.2 Results Analysis

Since we are interested in identifying improvements when communications expressiveness increases, we applied the methodology presented in Section 3 using the simulation scenarios differing only in the testbed that was used. In other words, we have compared each of the lines presented in Table 1 using the ART (less expressive) and the FOREART (more expressive) testbeds.

Moreover, we performed the analysis considering 10,000 permuted rank-collection matrices \mathbf{R}_n to compute the permutational (conditional) probability and significance level (α) of 5% to compute the critical $\mathcal{L}_{n_1 n_2}$. This analysis was performed using the statistical software R [14], and the results are presented in Table 3.

Table 3. Experimental analysis results.

Honest Agent Reputation Model	Dishonest Agent Reputation Model	Computed $\mathcal{L}_{n_1 n_2}$	Critical $\mathcal{L}_{n_1 n_2}$	Test Result
L.I.A.R.	L.I.A.R.	5.391	7.235	ACCEPTED
L.I.A.R. and Repage	L.I.A.R.	10.999	9.629	REJECTED
L.I.A.R. and Repage	Repage	11.759	9.600	REJECTED
Repage	Repage	11.077	5.676	REJECTED
MMH	MMH	15.666	6.789	REJECTED
MMH and L.I.A.R.	L.I.A.R.	15.047	10.839	REJECTED
MMH and L.I.A.R.	MMH	14.856	10.827	REJECTED
MMH and Repage	Repage	15.613	9.443	REJECTED
MMH and Repage	MMH	15.504	9.702	REJECTED
L.I.A.R., Repage and MMH	L.I.A.R.	14.014	12.758	REJECTED
L.I.A.R., Repage and MMH	Repage	13.184	12.698	REJECTED
L.I.A.R., Repage and MMH	MMH	14.846	12.626	REJECTED

We want to verify that the reputation value of the *Dishonest* agent attributes using ART is *greater* than the one obtained when using FOREART; in our case, a greater reputation value means that the *Dishonest* agent is less accurately detected in ART. Hence, we would like H_0 to be rejected.

When observing Table 3, we may notice that the only scenario that did not reject H_0 was the homogeneous L.I.A.R. simulation scenario. Therefore, despite that most of the experiments benefits of a more expressive communication, we could not confirm the general hypothesis that it is sufficient to improve the reputation evaluation accuracy.

However, analyzing the attribute values for the homogeneous L.I.A.R. simulation scenario, using both ART and FOREART testbeds, we had detected in [12] that the attribute influenced by communication (*Reputation Recommendation-based Reputation*) shows some improvements in the evaluation accuracy when

analyzed in isolation. However, since multivariate analysis considers all the attributes together, the improvement of the influenced attribute was not sufficient enough to compensate the other attributes values, which did not show any improvement, and therefore the integrated analysis failed to reject H_0 in this specific case.

5 Conclusions

In this paper, we applied a nonparametric multivariate statistical method in order to analyze the experimental data considering the correlation between reputation models attributes. The analyses were performed to verify if a more expressive communication is sufficient to improve reputation evaluation accuracy. The results have shown that most of the experiments benefits of more expressiveness, except in the homogeneous simulation scenario where all the agents use the L.I.A.R. reputation model.

Although this multivariate analyses could not show that there is an improvement for all the simulation scenarios, it does not invalidate the results we obtained in our previous work, since the latter identified improvements in the reputation evaluation accuracy for the L.I.A.R. attributes specifically related to communication.

In further work, we intend to perform other multivariate analysis in order to identify if there is an improvement in the reputation evaluation accuracy when comparing homogeneous and heterogeneous simulation scenarios. We also intend to perform some qualitative analysis in order to better explain the quantitative analysis results, thus enabling a better understanding of the reputation models interdependence. Finally, we intend to study the costs incurred when using a more expressive communication, such as processing and bandwidth resources.

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