SARC: Subjectivity Alignment for Reputation Computation (Extended Abstract)

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ABSTRACT

Current deployed reputation systems simply aggregate numerical ratings provided by buyers, but overlook the buyers' subjectivity difference in evaluating the transactions with a seller. To address this problem, we propose a subjectivity alignment approach for reputation computation (SARC).

Categories and Subject Descriptors

I.2.11 [**Distributed Artificial Intelligence**]: Intelligent agents; K.4.4 [**Electronic Commerce**]: Trust, Reputation

General Terms

Algorithms; Design

Keywords

Subjectivity Alignment; Reputation System; Bayesian Learning; Intelligent Buying Agent

1. INTRODUCTION

Reputation systems [3] have been proposed to model the trustworthiness of sellers in e-marketplaces where buyers who previously bought products from a seller share their experience, normally in the form of a numerical rating. These ratings are aggregated to represent the seller's reputation. However, a rating is subjective evaluation of a seller by a buyer within the context of a specific transaction. Different ratings could be given for the same transactions by different buyers. Two aspects contribute to the subjectivity difference among buyers: 1) *intra-attribute subjectivity*, the subjectivity in evaluating the same attribute of a transaction; 2) *extra-attribute subjectivity*, the subjectivity in evaluating different attributes of a transaction.

To address the subjectivity difference issue, we propose a subjectivity alignment approach for reputation computation (SARC). In SARC, buyers' subjectivity is learned based on the ratings and detailed reviews they provide about the objective attributes of their transactions with sellers. More specifically, SARC separately learns the *intra-attribute subjectivity* and *extra-attribute subjectivity* of buyers. Buyers' *intra-attribute subjectivity* is modeled using Bayesian learning. Their *extra-attribute subjectivity* is learned using a regression analysis model. Ratings provided by one buyer can then be aligned (converted) for another buyer according to the two buyers' subjectivity.

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2. THE SARC APPROACH

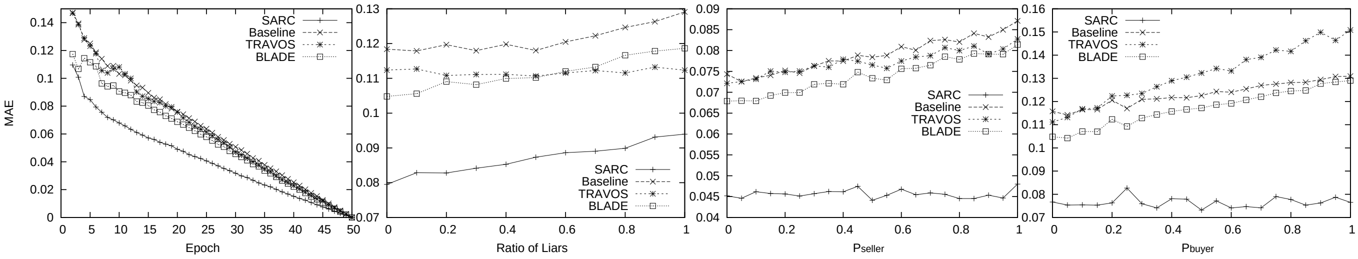
In an e-marketplace, each buyer is equipped with an intelligent (buying) agent. We denote the set of buyers by $\mathcal{B} = \{b_1, b_2, \ldots\}$. The set of agents equipped by corresponding buyers is denoted by $\mathcal{A} = \{a_1, a_2, \ldots\}$, and the set of sellers are referred to as $\mathcal{S} = \{s_1, s_2, \ldots\}$. The set of objective attributes for describing a transaction between a buyer and a seller is denoted as $\mathcal{F} = \{f_1, f_2, \ldots, f_m\}$. Each rating provided by a buyer for a seller is from a set of predefined discrete rating levels $\mathcal{L} = \{r_1, r_2, \ldots, r_n\}$. For a buyer $b_i \in \mathcal{B}$, the goal of her buying agent $a_i \in \mathcal{A}$ is to accurately compute the reputation value of a target seller $s_j \in \mathcal{S}$, according to b_i's subjectivity. To achieve the goal, a_i needs to consider the ratings of other buyers (advisors) that evaluate the satisfaction levels about their past transactions with seller s_j. Due to the possible subjectivity difference between buyer b_i and the advisors, agent a_i also needs to align/convert ratings of each advisor (for example b_k) using our SARC approach.

More specifically, at the beginning of buyer b_i's interactions with the system, agent a_i asks b_i to provide a rating for each of her transactions with a seller (which can be any seller in $\mathcal{S}$). Buying agent a_i also asks b_i to provide detailed review information about each transaction containing the values of the set of objective attributes in $\mathcal{F}$. Based on the provided information (rating-review pairs), agent a_i models a set of correlation evaluation functions (CEFs) for buyer b_i, capturing b_i's *intra-attribute subjectivity.* Each correlation evaluation function is represented by a *Bayesian conditional probability density function* that models the correlation between each rating level and each objective attribute:

$$\mathrm{CEF}^{b_i}_{u,v} = p^{b_i}(f_u \mid r_v) = \frac{p^{b_i}(r_v \mid f_u) \times p^{b_i}(f_u)}{p^{b_i}(r_v)} \quad (1)$$

where $\mathrm{CEF}^{b_i}_{u,v}$ is the correlation function between attribute $f_u \in \mathcal{F}$ and rating level $r_v \in \mathcal{L}$ for buyer b_i; $p^{b_i}(r_v)$ refers to the probability that buyer b_i provides a rating r_v; $p^{b_i}(f_u)$ is the probability distribution of the values for attribute f_u, and $p^{b_i}(r_v \mid f_u)$ is the conditional probability of rating level r_v given the distribution of the values for attribute f_u.

The learned CEFs of buyers will be shared with each other buyer's agent. For a rating provided by the buyer (advisor) b_k, agent a_i can then derive a rating for each attribute $f_u \in \mathcal{F}$, based on the CEFs shared by b_k's agent a_k and those of buyer b_i's own. We use a Naïve Bayesian Network model to learn the mapping from r^{b_k} of buyer b_k to the ratings of b_i for the attributes. Take any $f_u \in \mathcal{F}$ as an example attribute, agent a_i first estimates the conditional probability of a rating level in $\mathcal{L}$ for attribute f_u, given rating r^{b_k} provided by buyer



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

Figure 1: (a) Performance Comparison in the Basic Environment; (b) Performance When Varying Ratio of Lying Buyers; (c, d) Performance for Sellers' Changing Behavior and Buyers' Changing Subjectivity

b_k. Take any rating level r_v as an example, a_i computes $p^{b_i}(r_{v,f_u}|r^{b_k})$, the conditional probability that buyer b_i will assign the rating level r_{v,f_u} to attribute f_u given the rating r^{b_k} of buyer b_k:

$$p^{b_i}(r_{v,f_u}|r^{b_k}) = \frac{p^{b_i}(r_v \mid f_u) \times p^{b_k}(f_u \mid r^{b_k})}{p^{b_i}(f_u \mid r_v)} \qquad (2)$$

where $p^{b_k}(f_u \mid r^{b_k})$ is learned by agent a_k of buyer b_k using Equation 1 and shared by agent a_k to agent a_i, $p^{b_i}(f_u \mid r_v)$ is learned by a_i itself using Equation 1, and $p^{b_i}(r_v \mid f_u)$ is obtained by agent a_i from the rating-review pairs provided by its buyer b_i. What is derived for f_u is a set of probability values, each of which corresponds to a rating level in $\mathcal{L}$. The rating level with the highest probability will be chosen as the rating for f_u, $r^{b_i}_{u,k}$.

Based on the provided rating-review pairs by b_i, agent a_i also learns the *extra-attribute subjectivity* of buyer b_i, which is represented by a set of weights for corresponding attributes in $\mathcal{F}$. The weight of f_u is determined by two factors: 1) the probability value of the rating derived earlier, C_u; and 2) the importance of the attribute learned using a regression analysis model, I_u. These weights will not be shared with other buyers. Once they are learned, the aligned rating ($r^{b_i}_k$) from that of advisor b_k can be computed as the weighted average of the derived ratings for the attributes:

$$r^{b_i}_k = \frac{\sum_{u=1}^{m} r^{b_i}_{u,k} \times C_u \times I_u}{\sum_{u=1}^{m} C_u \times I_u} \qquad (3)$$

3. EVALUATION

We simulate an e-marketplace involving 50 sellers and 200 buyers. Sellers may provide different products with different attribute values. Buyers may have different subjectivity in evaluating their transactions with (the products of) sellers. We also set several important parameters for our simulations, including *information availability*, *dynamic behavior of sellers*, *dynamic subjectivity of buyers*, *ratio of liars* (dishonest buyers), and *granularity of rating scale.* We vary the values of these parameters to simulate basic, deceptive and dynamic environments, respectively. In the experiments, we compare our approach with some representative competing approaches: a baseline approach without subjectivity alignment, TRAVOS [2] and BLADE [1].

In the basic environments without deception, seller dynamic behavior or buyer dynamic subjectivity, SARC can more accurately model sellers' reputation than the other three approaches (Figure 1(a)). We also test some parameters including the ratio of objective attributes, the number of detailed reviews, the granularity of rating scale, and the ratio of shared interactions. We find that in different settings, SARC still has better performance than BLADE. In the deceptive environments where some buyers may intentionally lie about their past experience with sellers (Figure 1(b)), SARC still performs much better than the other approaches. It is not dramatically affected by buyers' deception because it treats deceptive buyers as the ones with different subjectivity, and aligns the ratings from them effectively. In the dynamic environments where sellers may change their provided products (Figure 1(c)), SARC performs consistently and is independent of sellers' behavior change. The performance of other three approaches gets worse as sellers become more probably to change their behavior. When buyers may vary their subjectivity during a certain period of their interactions with sellers, Figure 1(d) shows that SARC continues to perform positively, while the performance of BLADE gets closer to the baseline approach, and TRAVOS performs worse than the baseline approach as P_{buyer} increases.

4. CONCLUSIONS

We proposed a subjectivity alignment approach for reputation computation, SARC, to address the subjectivity difference problem. It performs better than the other three approaches, and can more accurately and stably model sellers' reputation. It is capable of coping with environments with deception and dynamic buyer and seller behavior. The requirement of detailed reviews and objective attributes is not very restrictive. For future work, we will conduct experiments on real data to further verify the robustness and efficiency of SRAC in addressing the subjectivity difference problem for reputation computation.

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