Choosing Trust Models for Different E-Marketplace Environments[1]

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[1] Athirai A. Irissappane, Siwei Jiang and Jie Zhang, A Framework to Choose Trust Models for Different E-Marketplace Environments, 23rd International Joint Conference on Artificial Intelligence (IJCAI), 2013

Overview

1. Introduction and Motivation

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Introduction

Reputation Systems

- facilitate trust in internet interactions
- calculate the reputation of an entity using the ratings given by other entities

Existing Reputation Systems (Trust Models)

Many trust models have been proposed in the past [Sabater and Sierra, 2005; Jøsang *et al.*, 2007]

- BRS [Whitby and Jøsang et al., 2004]
- TRAVOS [Teacy *et al.*, 2006]
- Personalized [Zhang and Cohen, 2008]
- WMA [Yu and Singh, 2003]
- iCLUB [Liu *et al.*, 2011]
- BLADE [Regan *et al.*, 2006]

Motivation

How to Choose the Best Trust Model for an Environment?

Performance of trust models depend on,

- environmental settings (of the market) such as frequency of transaction, honesty of seller/buyer, accuracy of advisors ratings, etc [Fullam and Barber 2007]
- tuning parameters of the trust model (*e.g. quantile* parameter in BRS)

- **Simulated Environments**: easy to choose best trust model
  - honesty of sellers/buyers is known (known ground truth)
- **Real Environments**: challenging to choose best trust model
  - no ground truth is available.
  - time consuming and costly to manually inspect and determine best trust model for such environments

Existing Framework to Choose Trust Models

- [Wang and Singh, 2010]: evaluate trust models using real data by their accuracy of predicting ratings of given transactions
  - ground truth about whether the ratings of those transactions are unfair may be unknown
- [Hang *et al.*, 2009]: evaluate trust models using explicitly indicated trust relationships by users in real data
  - users may lie about their trust relationships

- **Personalized Trust Framework** [Huynh, 2009]: selects trust models based on users choice. Users specify how to select a trust model based on information about whose trustworthiness is to be evaluated and the configuration of trust models
  - relies on human intervention
  - humans cannot figure out which trust models will perform best

- **Case Based Reasoning** [Sormo *et al.*, 2005]: CBR is the process of solving new problems based on the solutions of similar past problems. The four major steps of CBR are,
  - retrieve
  - reuse
  - revise
  - retain
- Our approach is similar to Case Based Reasoning

Proposed Framework

- the framework consists of a number of simulated environments (SE) with known ground truth
- given an unknown environment, the most similar simulated environment is identified
- the trust model performing the best in the most similar simulated environment is the most suitable trust model for the unknown environment

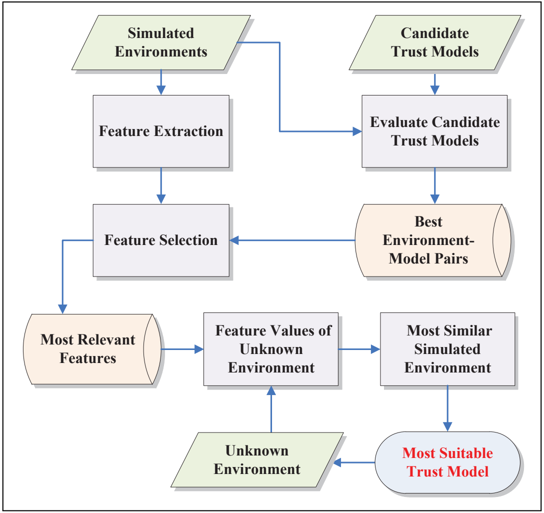


Figure : Procedural Design of the Framework

Major Components of the Framework:

- **E-market Environments**: each environment contains buyers, sellers, transactions and ratings. Each environment is represented by a set of features
  - **Simulated environments**: environments with known ground truth (honesty of buyers and sellers is known)
  - **Unknown environments**: environments where ground truth is not known

- **Candidate Trust Models**: trust models with specific values for each of its parameters. *e.g.* For BRS *quantile* parameter $q \in \{0.05, 0.1, 0.3, 0.5\}$
- **Best Environment-Model Pairs**: pairs of simulated environment and candidate trust model which performs the best in that environment
- **Feature Extraction and Selection**: selecting only the most influential features using correlation and regression techniques

- **Most Similar Simulated environment**: simulated environment with least Euclidean distance (based on the most influential features) with unknown environment
- **Most Suitable Trust Model**: trust model of most similar environment is chosen from best environment-model pairs and is the most suitable for unknown environment

Experimental Settings

Simulated environments (972**)**

- **No.of Sellers** $\in \{10, 25, 50\}$
- **Total Ratings** $\in \{50, 100, 250\}$
- **Honest Buyer Behavior**
  - **Sparse**: buyer rates seller once
  - **Intensive**: buyer rates seller more than once
  - **Mixed**: sparse and intensive
- **Dishonest Buyer Behavior**
  - **Individual Attack Frequency**: sparse, intensive or mixed
  - **Attack Period**: concentrated or distributed $\in \{7, 100\}$
  - **Attack Target**: sellers with reputation $0/1$
  - **Overall Attack Rate**: ratio of unfair ratings $\in \{0.25, 1, 4\}$

Candidate Trust Models (45)

- BRS with *quantile* parameter $q \in \{0.05, 0.1, 0.3, 0.5\}$
- iCLUB with *minPts* $\in [1, 6]$, *maximum neighbor distance* $\theta \in [0.3, 0.7]$ and $\epsilon \in [3, 6]$
- TRAVOS with number of *bins bin* $\in \{2, 3, 5, 8, 10\}$
- Personalized with *error level* $\epsilon \in \{0.3, 0.5, 0.7\}$ and *confidence level* $\gamma \in \{0.3, 0.5, 0.7\}$
- Referral Networks with *number of neighbors* $\in \{2, 4, 6\}$ and *depth limit* of referral networks $\in \{4, 6, 8\}$
- Prob-Cog with *incompetency tolerance threshold* $\mu \in \{0.1, 0.2, \ldots, 0.9\}$
- BLADE

Best Environment-Model Pairs

- find mean absolute error (MAE) for each trust model
- MAE is the difference between predicted trustworthiness of sellers and actual honesty of the sellers
- select the one with the lowest MAE value

Feature Extraction and Selection

- 18 features are used to represent each environment
- select the most relevant features using correlation and regression analysis techniques
    - Pearson correlation, Kendall rank correlation coefficient, Spearman rank correlation coefficient, linear regression (backward) and linear regression (stepwise)

Most Relevant Features

- average number of ratings provided by each buyer for each seller
- variance of percentage of ratings provided by each buyer
- skewness of number of ratings provided by each buyer
- percentage of satisfactory sellers
- average number of ratings for each seller
- variance of number of ratings provided by each buyer
- total number of ratings
- variance of number of ratings for each seller
- skewness of number of ratings for each seller
- average number of transactions in each day
- total percentage of sellers rated by buyers
- total percentage of buyers who are active in the marketplace

Unknown Environments

- **Unknown Random Environments**: generated using parameter values different from simulated environments
- **Unknown Real Environments**: real environments (*IMDB.com*) with simulated unfair rating attacks (RepBad, RepSelf and RepTrap)
- **Large Environments**: environments with number of sellers larger than 50, number of ratings larger than 100, number of buyers larger than 80
- **Extremely Sparse Environments**: buyers do not provide sufficient ratings (each buyer gives an average of 0.1 ratings to sellers)
- **Environments with Dynamic Seller Behavior**: sellers change their behavior dynamically
- **Environments with Many Attacks**: environments where attack rate is larger than 10

Experimental Results

Table : Accuracy of Choosing Most Suitable Models (with Parameters) for Unknown Environments

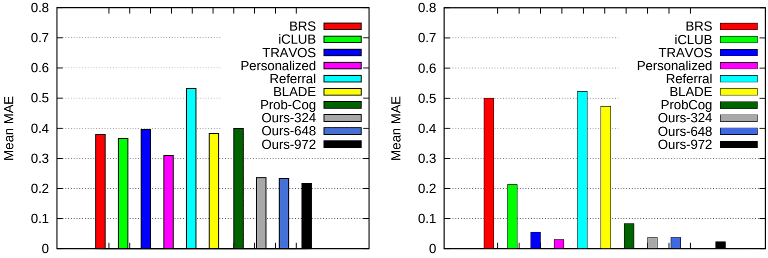
Unknown Random Environments	324 SE	648 SE	972 SE
Correct Models	81.0%	84.0%	92.0%
Correct Models with ϵ	87.0%	89.0%	95.0%
Correct Models and Paras	72.0%	76.0%	82.0%
Correct Models and Paras with ϵ	85.0%	86.0%	94.0%

Unknown Real Environments	324 SE	648 SE	972 SE
Correct Models	81.3%	83.3%	83.3%
Correct Models with ϵ	89.6%	95.8%	95.8%
Correct Models and Paras	72.9%	75.0%	77.1%
Correct Models and Paras with ϵ	89.6%	95.8%	95.8%

Accuracy of the framework increases with,

- number of simulated environments (SE) in the framework.
- tolerance ($\varepsilon = 0.05$), such that difference in MAE of the chosen trust model and that of the truly most suitable model is within ε

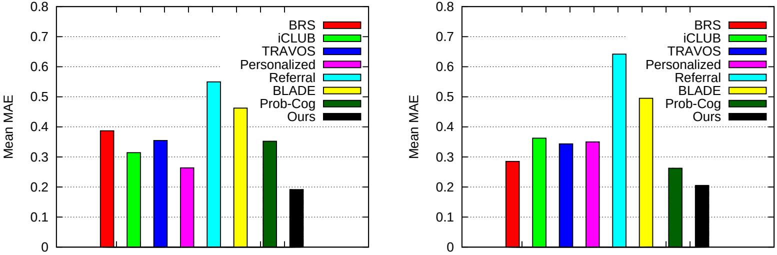
Mean Absolute Error in Determining Seller Reputation



(a) Random (b) Real

- Our framework (Ours-972) obtains the lowest MAE.

Mean Absolute Error in Determining Seller Reputation

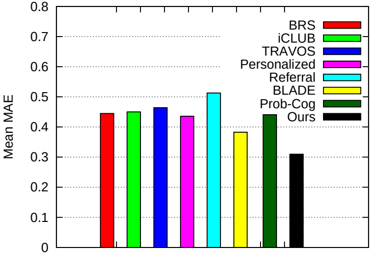


(c) Large

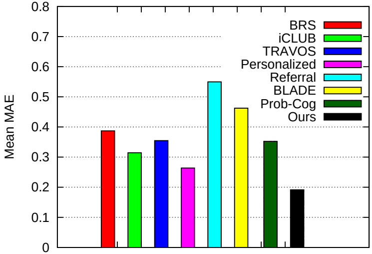
(d) Sparse

- iCLUB, TRAVOS and Personalized get sufficient rating sources, hence perform better in large environments
- BRS (majority rule) and Prob-Cog (incompetency threshold) are less restrictive in accepting advisors' opinions, hence better in sparse environments

Mean Absolute Error in Determining Seller Reputation



(e) Dynamic



(f) Many Attacks

- Personalized and BLADE model changing behavior, hence fare better in dynamic environments
- Personalized and TRAVOS use personal experience of buyer and are able to cope with attacks

Conclusion

- we develop a framework to choose trust models in unknown real environments.
- given an unknown environment, we find a similar simulated environment and the trust model performing the best in the simulated environment is the solution
- as future work, we plan to use machine learning techniques (decision trees, etc.) to find the most suitable trust model
- we will also add more trust models and environments to the framework

Thank You

Questions ?