A Generalized Stereotypical Trust Model

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Outline

Motivation & Objectives

Model trustworthiness of sellers:

- Experienced sellers
  - Sufficient past experience
  - Reputation systems
- Inexperienced sellers
  - No or little past experience
  - Stereotypical trust models

Motivation & Objectives

Stereotypical trust model for a buyer:

- Basic assumptions
  - Seller behavior follows certain patterns
  - Evaluation on a new seller influenced by past experience
- Machine Learning on his own experience
- Cold start problem
  - Insufficient past experience with sellers
  - Can not learn accurate trust stereotypes
  - Collect other buyers' experience
    - Users' subjectivity difference

Motivation & Objectives

A generalized stereotypical trust model for cold start problem:

- Build a semantic ontology
  - Represent sellers' attributes in e-marketplaces
- Fuzzy semantic decision tree (FSDT) with limited experience
  - Fuzzy process: generalize over non-nominal attributes
  - Semantic process: generalize over nominal attributes

Related Work

Stereotypical trust models:

- Burnett et al. (2010) [1]
  - Use M5 tree to learn stereotypes
  - Integrate with probabilistic trust model
- Liu et al. (2009) [2]
  - Apply traditional machine learning tools
  - Directly predict successfulness of transactions
- Collect other buyers' experience for cold start problem
- Limitations
  - Users' subjectivity difference problem
  - Manually identify attributes
- Our approach
  - Only use a buyer's own experience
  - Ontological reasoning

Related Work

Stereotype-based user modeling, e.g.:

- Rich (1979) [3]
  - Manually construct users' stereotypes
  - User's socio-demographic characteristics
- Ardissono et al. (2003) [4]
  - Personalized electronic guides for digital TV
  - Stereotypical user model with machine learning
- Limitations
  - Focus on socio-demographic characteristics
  - Cold start problem
- Our approach
  - Also consider attributes related to sellers' selling behavior
  - Address cold start problem

Semantic Ontology

- Represent the hierarchical relationships among attribute values
- Automatically identify seller attributes and values
- Ontological reasoning technique helps our semantic process

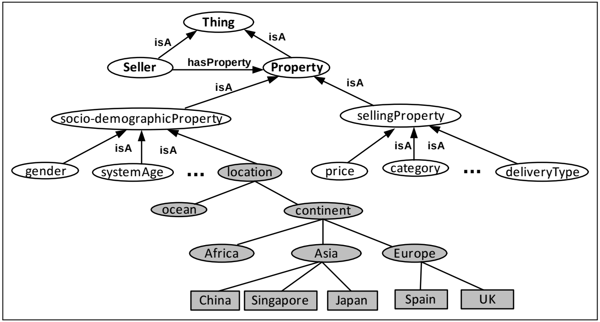


Figure: An Example Semantic Ontology of Seller Attributes in E-marketplaces

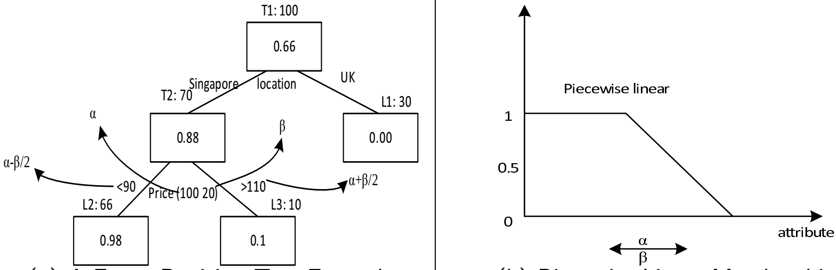
Fuzzy Semantic Decision Tree Learning

- Goal of stereotypical learning
  - $F : \overrightarrow{A} \rightarrow T_s$
  - $\overrightarrow{A}$: attribute vector describing seller information
  - T_s: the trust degree (ranged in $[0, 1]$) for the seller
- Our approach: FSDT to learn function F
  - Basic decision tree learning + two additional processes
    - Fuzzy process for non-nominal attributes
    - Semantic process for nominal attributes

Fuzzy Process

Generate fuzzy decision tree (Figure 2(a)):

- Extend the fuzzy method [5] with non-nominal attributes
  - Piecewise Linear Membership function (Figure 2(b))
  - Instances in $[\alpha - \beta/2, \alpha + \beta/2]$ to both the successors
- Traditional decision tree with nominal attributes



(a) A Fuzzy Decision Tree Example (b) Piecewise Linear Membership

Fuzzy Process

- Split Criterion: minimize the mean square error (MSE)

$$\begin{aligned} MSE(S, a) = \text{mean}[\sum_{i \in S_L} \mu_S(i) \times (T_i - \hat{T}_L)^2 \\ + \sum_{i \in S_R} \mu_S(i) \times (T_i - \hat{T}_R)^2] \end{aligned} \tag{3.1}$$

$$MSE(S, a) = \text{mean}[\sum_{i \in S} \mu_S(i) \times (T_i - \hat{T}_i)^2] \tag{3.2}$$

$$\hat{T}_i = \mu(i, a, \alpha, \beta) \times \hat{T}_L + [1 - \mu(i, a, \alpha, \beta)] \times \hat{T}_R \tag{3.3}$$

where a is a certain attribute;

- Learn (α, β) for each non-nominal attribute a

Fuzzy Process

Contribution of fuzzy process:

- Improve performance of stereotypical learning
- Intuition
  - Both groups with corresponding membership degree
  - Fuzzy area
  - With limited experience
    - Difficult to precisely classify inexperience seller

Semantic Process

Based on fuzzy decision tree:

- Exploit hierarchial relationships among attribute values
- Generalize over the values of nominal attributes
  - Replace specific values with more general one
  - Without significant decrease of classification performance
  - E.g, a location ontology

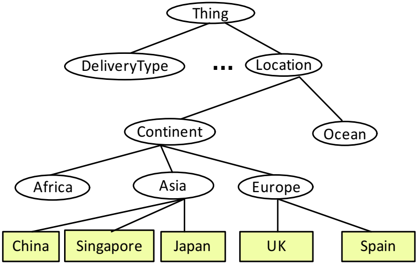
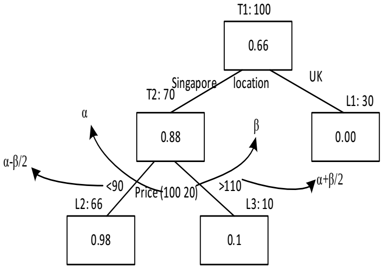
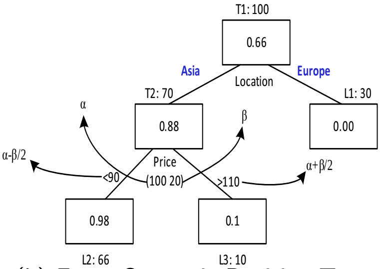


Figure: A Location Ontology

Semantic Process



(a) Fuzzy Decision Tree



(b) Fuzzy Semantic Decision Tree

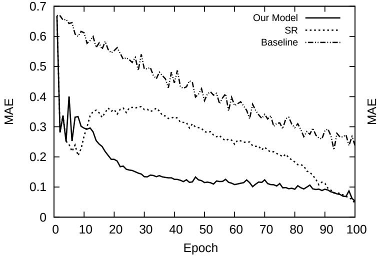
- Contribution of semantic process
  - Can predict the trustworthiness of inexperienced sellers with unmet values for nominal attributes

Simulation

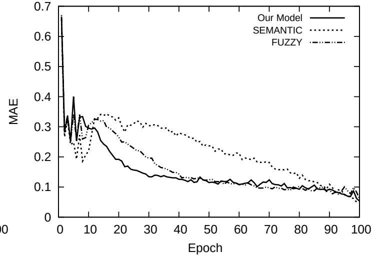
- Simulated e-marketplace: 100 sellers and 20 buyers
  - Sellers provide products of different quality
  - Five attributes: *location*, *system age*, *price*, *delivery type* and *number of items sold*
  - Buyers have different subjectivity
- Benchmark Comparisons
  - Baseline: random with memory
  - SR: Burnett et al.'s approach [1]
  - FUZZY: only fuzzy process
  - SEMANTIC: only semantic process
- Parameters
  - Degree of buyer subjectivity difference
  - Value ranges of non-nominal attributes
  - The number of possible values of nominal attributes

Experimental Results

- Our model performs better than SR and Baseline (*Figure 3(c)*)
- Both the fuzzy and semantic process contribute to performance improvement (*Figure 3(d)*)
- FUZZY and SEMANTIC outperform the SR approach (*Figures 3(c) and 3(d)*)



(c) FSDT vs. SR vs. Baseline



(d) FSDT vs. FUZZY vs. Semantic

Experimental Results

- Worse than Reputation-based method and SR when $|d|$ is small, better when $|d|$ gets larger

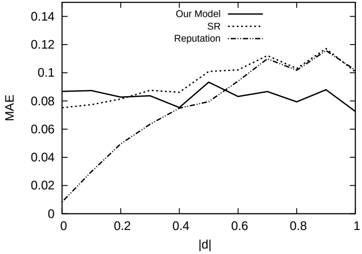
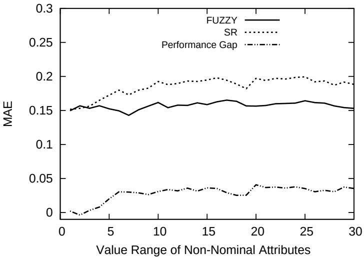


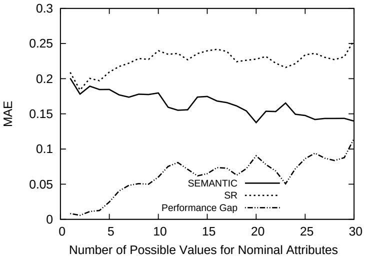
Figure: Varying degree of buyer subjectivity difference

Experimental Results

- Figure 4(a)
  - FUZZY performs better than SR
  - Verify the generalization capability of the fuzzy process
- Figure 4(b)
  - SEMANTIC performs better than SR
  - Verify the generalization capability of the semantic process
  - The generalization capability increases as the number increases



(a) Varying the value ranges of non-nominal attributes



(b) Varying the number of possible values of nominal attributes

Conclusions

Contribution of our approach:

- Propose a novel generalized stereotypical trust model
  - Fuzzy process on non-nominal attributes
  - Semantic process on nominal attributes
- Address the cold start problem for stereotypes learning
  - When buyers have limited experience
- Verify the effectiveness of FSDT by experiments
  - More accurately evaluate trustworthiness of inexperience sellers
  - Robust with regard to the change of training data set

Future Work

- Conduct more experiments
  - More scenarios in the simulated e-marketplaces
  - Real data (e.g., eBay)
- Use other membership functions
  - e.g., triangular and trapezoidal membership function
- Consider multi-nominal trust degrees

Thanks!
Any Questions?

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