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A generalized stereotype learning approach and its instantiation in trust modeling

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ABSTRACT

Owing to the lack of historical data regarding an entity in online communities, a user may rely on stereotyping to estimate its behavior based on historical data about others. However, these stereotypes cannot accurately reflect the user's evaluation if they are based on limited historical data about other entities. In view of this issue, we propose a novel generalized stereotype learning approach: the fuzzy semantic framework. Specifically, we propose a fuzzy semantic process, incorporated with traditional machine-learning techniques to construct stereotypes. It consists of two sub-processes: a fuzzy process that generalizes over non-nominal attributes (e.g., *price*) by splitting their values in a fuzzy manner, and a semantic process that generalizes over nominal attributes (e.g., *location*) by replacing their specific values with more general terms according to a predefined ontology. We also implement the proposed framework on the traditional decision tree method to learn users' stereotypes and validate the effectiveness of our framework for computing trust in e-marketplaces. Experiments on real data confirm that our proposed model can accurately measure the trustworthiness of sellers with which buyers have limited experience.

1. Introduction

In large, open, and uncertain online communities, users often encounter entities (e.g., people, products, and information) with which they have no previous experience or prior knowledge. To make a an appropriate evaluation of an unknown entity, a user usually relies on the experience or knowledge of other users who have previously interacted with the entity, e.g., in the form of online reviews describing the experience. However, there might also be a scenario where the entity has no or few historical interactions for reference (called an *inexperienced* entity). By contrast, in real-life interactions among users, when a person meets an unknown entity, she usually relies on her "instinct", i.e., essential stereotypes developed from her past interactions with similar "entities". A stereotype defines a mapping between observable features of an entity and the expected interaction outcome with this entity (Liu et al., 2009). For the unknown entity, its observed properties are used to match the developed stereotypes of the user, and thus to predict the possible outcome of a potential interaction between the user and the entity.

Stereotypes have been widely used in the user-modeling field (Courtney, 1992; Di Lascio et al., 1999; Michaud and McCoy, 2004) since the work of Rich (1979). The method of constructing stereotypes has undergone the process from manual construction (Rich, 1979; Brajnik and Tasso, 1994) to machine learning (Ardissono et al., 2003; Paliouras et al., 1999; Rodŕguez et al., 2011), i.e., the field of stereotype learning in the past nearly fifteen years. In traditional user modeling, stereotypes are derived from community modeling, which learns stereotypes from past interactions by all the users in a community. In contrast, stereotype learning currently takes a personalized approach in the sense that the stereotypes are learned for each user, mainly from her own previous experience. This is primarily because of two reasons. First, it is very difficult to come up with common rules that satisfy all users in a *dynamic* online system, or for users in a particular *short-term* community. An online community is very dynamic, as users may join and leave the community with a high frequency. Therefore, the stereotypes learned in the past might not work well for the newly joined users. Furthermore, users may be assembled into short-term communities to achieve temporary goals. In this case, stereotypes learned from

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these communities might reveal little about the corresponding users. Second, it is not so easy and suitable to derive stereotypes of entities that can satisfy all users, especially in distributed environments. Subjectivity difference exists among users (Fang et al., 2012b). Different users might have different evaluations of the same entity. It is therefore worthwhile to learn the stereotypes of entities for each user.

For the aforementioned personalized stereotypical modeling, accurate stereotypes can only be built when a user has sufficient past interactions with other entities. When the user only has limited historical interactions, the stereotypes learned based on these historical interactions may not be as accurate. In online environments, the data sparsity problem for stereotype learning becomes particularly serious as there are a large number of categories/items, and users are more likely to encounter enormous entities of different categories (contexts), most of which they have never interacted with before. For example, as indicated by a sample dataset from Amazon (Johri et al., 2011), the median number of reviews per user and the median number of reviews per product are both 2. The review count distributions for users and products follow power laws, where most of users and products have few reviews. Therefore, stereotype learning requires a powerful and effective technique that can learn user stereotypes from relatively small data sets, and there is a great chance of generating classifiers that overfit the training data of a small size with traditional machine-learning tools.

To address the data sparsity problem in stereotype learning, in this paper, we propose a novel fuzzy semantic framework. To clearly demonstrate the framework, we incorporate the framework into the traditional decision tree approach (fuzzy semantic decision tree, FSDT) as our exemplar (Fang et al., 2012a). In addition to decision trees, we argue that this framework can be adopted by other traditional machine-learning approaches, such as Bayesian networks and clustering techniques. To be more specific, in our fuzzy semantic framework depending on a predefined ontology (Fang et al., 2012a), we introduce a novel fuzzy semantic decision tree method to improve the learning and prediction performance of the traditional decision tree learning algorithms (Frank et al., 1998; Burnett et al., 2010) by incorporating two processes: a *fuzzy* process and a *semantic* process. The fuzzy process generalizes stereotypes over the non-nominal (continuous) attributes of entities by splitting the values of these attributes in a fuzzy manner using a piecewise membership function instead of splitting them in the crisp manner. In so doing, some user experience cases may belong to two nodes in the decision tree simultaneously, each with a corresponding membership degree (the sum of these two membership degrees is 1). The semantic process generalizes stereotypes over the nominal attributes of entities by applying ontological reasoning. It exploits the hierarchical relationships between attribute values and replaces some specific values in the decision tree by more general ones. This allows the user to predict the potential interaction outcomes with entities that have previously unseen attribute values.

To validate the effectiveness of our framework, we instantiate FSDT into the computational trust area, specifically in the context of e-marketplaces. In an e-marketplace, it is important for a buyer to model the trustworthiness of sellers to select the most trustworthy sellers with which to do transactions, because dishonest sellers may deliver low-quality products or services (Josang et al., 2007). To evaluate the performance of the proposed trust model, we conduct a set of experiments on a real dataset obtained from eBay (www.ebay.com). We mainly compare our model with those of Burnett et al. (2010) and Liu et al. (2009), which are also stereotypical trust models. Experimental results confirm that both the fuzzy and semantic processes contribute to the success of our model. Our model can predict the trustworthiness of inexperienced sellers (who may be a new comer in the e-marketplace, or may only sell unpopular products and have previously received little attention) more accurately than the currently existing models.

The contributions of our work are three-folds: (1) our research framework combines the fuzzy process and semantic process, with which traditional machine learning techniques can generalize their performance on both non-nominal and nominal attributes; (2) we have successfully implemented the framework on the traditional decision tree method, which has been very popular and useful in stereotype learning, and have instantiated it for computing trust in e-marketplaces; and (3) experiments on a real data verify that the fuzzy semantic decision tree can well measure the trustworthiness of sellers when buyers have limited experience, validating the effectiveness of our fuzzy semantic framework in addressing the data sparsity problem in traditional machine learning.

The rest of this paper is organized as follows. The Related Work section provides an overview of existing work on stereotype learning in both the trust modeling and user-modeling areas, and summarizes the data sparsity problem in the machine-learning area. In the Generalized Stereotype Learning section, we first present an overview of the fuzzy semantic framework and then provide detailed descriptions of the proposed FSDT method. After that, we instantiate FSDT into the computational trust area, and conduct experiments to verify the effectiveness on real data in the following section. Finally, we conclude our current work and propose the future work.

2. Related work

Our work is related to the three research areas: (1) stereotype learning, (2) stereotypical trust modeling, and (3) the data sparsity problem in machine learning.

2.1. Stereotype learning

Stereotype-based user modeling has existed for quite a long time. The user-modeling community employs the stereotyping method as a means of addressing the cold-start problem (also called the ramp-up problem), which was first proposed by Rich (1979). Based on a user's socio-demographic characteristics (obtained from predefined questions) and already-constructed user stereotypes (manually constructed by the system designer), Rich developed a system called Grundy to recommend novels to a user by acknowledging the user's individual differences from other users rather than recommending the same set of novels to different users. The recommendation can be made to new users without collecting their ratings for user modeling. Rich's work has inspired many other researchers who consider using stereotypes to cope with the cold-start or new-user problem. For example, Di Lascio et al. (1999) presented a stereotype-based user model for adaptive hypermedia systems. The model uses a suitable algebraic fuzzy structure to represent certain features of each user and is applied to adapt the navigation and hypermedia content to the user's needs. Based on the fuzzy structure, each user is approximated to the best of a set of predefined stereotypes. In contrast, in our approach, instead of representing each user by fuzzy attributes, we use the fuzzy method to directly represent users' evaluations on non-nominal attributes of entities and aim to address the data sparsity problem by generalizing stereotypes over these attributes.

For learning stereotypes using machine-learning techniques instead of manual construction, Ardissono et al. (2003) presented a personal program guide (PPG) that generates personalized electronic program guides for digital TV. PPG recommends TV programs by using a heterogenous user model including three components, one of which is a stereotypical user model. Unlike Grundy, PPG automatically constructs stereotypical user models by using machine-learning methods. Aiming to deliver effective personalization for digital library users, Frias-Martinez et al. (2007) examined three key human factors (cognitive styles, levels of expertise, and gender differences), and then utilized three individual clustering techniques, k-means, hierarchical clustering, and fuzzy clustering, to explore and stereotype user behavior and perception. Paliouras et al. (1999) explored the acquisition of user stereotypes in the communities automatically from user data by using a $C4.5$ decision tree algorithm on personal data, which is extracted from a