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Concept-based learning of human behavior for customer relationship management

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ABSTRACT

In this paper, we apply concept learning techniques to solve a number of problems in the customer relationship management (CRM) domain. We present a concept learning technique to tackle common scenarios of interaction between conflicting human agents (such as customers and customer support representatives). Scenarios are represented by directed graphs with labeled vertices (for communicative actions) and arcs (for temporal and causal relationships between these actions and their parameters). The classification of a scenario is performed by comparing a partial matching of its graph with graphs of positive and negative examples. We illustrate machine learning of graph structures using the Nearest Neighbor approach and then proceed to JSM-based concept learning, which minimizes the number of false negatives and takes advantage of a more accurate way of matching sequences of communicative actions. Scenario representation and comparative analysis techniques developed herein are applied to the classification of textual customer complaints as a CRM component. In order to estimate complaint validity, we take advantage of the observation [19] that analyzing the structure of communicative actions without context information is frequently sufficient to judge how humans explain their behavior, in a plausible way or not. This paper demonstrates the superiority of concept learning in tackling human attitudes. Therefore, because human attitudes are domain-independent, the proposed concept learning approach is a good compliment to a wide range of CRM technologies where a formal treatment of inter-human interactions is required.

1. Introduction

In recent years, it has become clear that it is hard to overestimate the importance of customer support and customer retention in industry. Customer relationship management (CRM) has grown into a significant industrial sector with its own series of technological advancements. A number of computer science algorithms, including optimization and scheduling, have been developed specifically targeting CRM [43,15,60,64]. More areas of Artificial Intelligence are still finding applications in CRM; the current paper addresses the simulation of human reasoning and behavior, the proper and efficient implementation of which can be vital to a series of CRM applications. A state-of-art CRM system must be capable of simulating human behavior to properly address customer needs, facilitate communication, perform customer retention and resolve conflicts should they arise. To solve these problems, a CRM application needs the capability to operate in the realm of the human thoughts, by simulating human reasoning and by learning human behavior. In this paper we propose a concept-based representation technique and an infrastructure to learn customers' behavior.

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One of the main problems to be solved in facilitating customer retention and assisting inter-human conflict resolution is how to reuse previous experience in later situations with similar agents. A business rule system-based architecture is typical for CRM [27]. However, machine learning is required for handling a poorly formalized domain like human behavior [59,42]. Using information about customers' prior behavior and historical patterns to understand buying activities, behaviors, and ticketing characteristics is important. Most companies are new to using such structured information about customer behavior to manage and measure relationships. Such efforts go beyond having a call center for customers to raise complaints; it requires having a modern behavior-simulation based management system that listens to the customers, documents the problem and solution, and changes the behavior of employees and call center interactions to build proper relationships with customers [53].

In a series of previous studies, we focused on various issues surrounding the practical implementation of reasoning in such domains as understanding multiagent scenarios [16,22], determining possible criminal behavior of mobile phone users by means of analyzing the location tracking data [16], and emotional profiling [18]. We have addressed a number of issues with graph learning, simulating reasoning about mental states and communicative actions; and introduced complaint scenarios as graphs, using argumentation-based learning [19]. We explored the contribution of specific sources of information about scenarios as communicative actions, argumentation and meta-argumentation patterns [20], and causal links [17,18].

In this study, we focus on scenario structures as a whole to build a concept learning framework for CRM. Referring to concept learning and concept graphs, we follow Mitchell [36] and Sowa [51]. We will observe how concept learning helps to deal with customer complaints, as well as how it assists in the interactive exploration of product features extracted from customer reviews. We select lattices and formal concept analysis (FCA, [24]) as tools for learning human behavior because they have the following properties:

- flexibility,
- appropriateness for poorly formalized domains like human behavior,
- deterministic structures capable of explicit explanation of decisions proposed by the system, and
- sensitive measure of concept similarity [14].

In the last decade, machine learning features of FCA have been leveraged by a number of industrial applications, and we believe CRM will further demonstrate its capability to handle domains with extremely complex structures. Hence, this paper contributes to the state-of-art by building a concept learning framework to operate on human attitudes for decision support and decision making and thoroughly evaluates this framework. We will demonstrate that concept-based learning is better suited for representing complex patterns of human behavior, including communication, than conventional machine learning mechanisms, such as classification of groups of words extracted from textual descriptions of a conflict or dialogue.

To properly position our work in a family of CRM technologies, we mention the following classes of CRM services, following [11,9]:

(1) aggregation of data to create a single, accessible source (whether physical or virtual),
(2) analysis and presentation of that data as usable information by individuals doing strategic planning or executing strategic sales/marketing initiatives, and
(3) tools and information to provide front-line personnel or systems that are interacting with customers or prospects the ability to make timely, educated decisions that benefit both the customer and company.

In this paper, we focus on the tools mentioned in the third class of CRM services, specifically focusing on facilitating customer interaction through concept learning technologies. The following sequence of problems needs to be solved for predicting and classifying human behavior using a CRM system:

(1) Discover how to *reconstruct behavior patterns* from text. It turns out that communicative actions and their subjects are essential elements of behavior discourse.
(2) Construct a *formal language* to represent communicative actions. Find attributes of communicative actions so that similarity between them can be defined. Analyze how the mental space is 'covered' by communicative actions, and form a substitution matrix for them to measure similarity.
(3) Build a way to *extract information* from natural language for communicative actions (which is relatively easy) and their subjects and parameters (which is significantly harder due to implicit references to these subjects in natural language). In the expression 'He denied that he made an early withdrawal from his account' communicative action = '-deny' and its subject = 'he made an early withdrawal'.
(4) Observe that the sequence of behavior patterns can be packaged as a *scenario*. Define a scenario as a graph including communicative actions and interaction between their subjects, based on causal links and relations for argumentation.
(5) Define relationships between scenarios via subgraphs, with respective operations on vertices and arcs. Define similarity between scenarios based on graphs and similarities between individual communicative actions.
(6) Build a machine learning framework and select a particular learning approach well suited to operate with scenario graphs. Evaluate whether concept learning is an adequate approach.