A Cognitive Tutoring Agent with Automatic Reasoning Capabilities

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Abstract

In this paper, we show how to make a cognitive tutoring agent capable of precise causal reasoning by integrating constraints with data mining algorithms. Putting constraints on recorded interactions between the agent and learners during learning activities allows data mining algorithms to extract the causes of the learners' problems. Subsequently, the agent uses this information to provide useful and customized explanations to learners.

Introduction

Reasoning is considered crucial for many characteristics of cognition such as selection, abstraction, and planning (Gopnik and Schulz, 2007, Leighton, 2004). One important type of reasoning, among others, is inductive reasoning. In inductive reasoning, either one tries to generalize rules from a set of examples; or from a set of probable or inadequate premises, one decides the likeliness that a conclusion is true. Among the various aspects of inductive reasoning, researchers investigate the existence of causal relations between various events (Kemerling, 2005). We assume that it is possible to discover the cause of a particular effect by observing the occurrence of regularities for particular events.

Different methods are proposed for finding causal relations between events: scientific experiments, statistical relations, temporal order, prior knowledge, etc (Gopnik and Schulz, 2007). Most of the researchers propose the use of probability approach to causal reasoning. However, in this paper we use a data mining approach to discover causal relations between events.

In this paper, we first briefly explain the functioning of the Conscious Emotional Learning Tutoring System (CELTS), a cognitive agent that was created to provide assistance to learners in learning activities (Faghihi et al., 2010a, Faghihi et al., 2009). We then explain how we improved CELTS' causal learning by integrating constraints in our data mining algorithm.

CELTS

CELTS is a hybrid artificial intelligent tutor which is based on Baars' (1997) theory of consciousness. It performs through cognitive cycles. Cognitive cycles in CELTS start by perception and usually end by the execution of an action. CELTS uses its Behavior Network (BN) for action selection. The BN, implemented based on Maes' Behavior Net (Maes, 1989), is a network of partial plans that analyzes the context to decide what to do and which type of behavior to set off. Given that CELTS is a tutor, an expert can define different solutions in the BN to help learners. Thus, BN's nodes are messages, hints, demonstration, etc to assist learners while they manipulate Canadarm2 in the virtual environment. The virtual environment is a simulation of Canadarm2, the robotic telemanipulator attached to the International Space Station (ISS). Using the virtual world, CELTS helps astronauts learn how to manipulate Canadarm2 before going to space (for more details readers are referred to (Faghihi et al., 2010b)). The learners' manipulations of the virtual world simulator, simulating Canadarm2, constitute the interactions between them and CELTS. In particular, the virtual world simulator sends all manipulation data to CELTS, which, in turn, sends advice to learners to improve their performance (Faghihi et al., 2010b). Canadarm2 manipulation on the ISS is a very difficult task, because there is a constant risk of collision. Our team has now added different types of learning such as Emotional, Episodic and Causal learning in CELTS (Faghihi et al., 2010b, Faghihi et al., 2009).

Causal knowledge is generated in CELTS after a) the information is broadcast in the system; b) a decision is made about the ongoing problem, which c) is reinforced by future experiences while CELTS receives information from the virtual world and interacts with learners. Using these three mechanisms, CELTS can memorize learners' errors and find the causes of the errors.

In the next section we explain how our algorithm is improved.

Causal learning

To extract causal rules, we chose RuleGrowth, a data mining algorithm that we have developed in previous work (FOURNIER-VIGER et al., 2011).

Each rule discovered by RuleGrowth has the form X⇒Y, where X and Y are unordered sets of events. The interpretation of a rule is that if events from X occur, the events from Y are likely to follow. Two interesting measures are used for ranking rules: *support* and *confidence*[1]. This information can be interpreted as an estimate of the conditional probability P(Y | X) (Hipp et al., 2002, Deogun and Jiang, 2005). However, one problem when applying RuleGrowth in CELTS is that there can be up to several thousands of rules that are found when the sequence database is large. At any given moment, only a few rules are generally relevant. If too many rules are found, it degrades the performance of CELTS, which has too many rules to consider for reasoning. To reduce the number of rules and to extract only the most precise and relevant ones, we have adapted RuleGrowth to add constraints on events that a rule can contain so that only the rules that are relevant to CELTS are extracted in any situation (the interested reader can refer to (FOURNIER-VIGER et al., 2011) for technical details).

In what follows, we first present these constraints and then explain how they are useful for the reasoning of CELTS. The constraints are the following:

- C1: the set of events that the left part of a rule can contain,
- C2: the set of events that the right part of a rule can contain,
- C3: the set of events that the left part of a rule has to contain,
- C4: the set of events that the right part of a rule has to contain.

We modified RuleGrowth to ignore events that are excluded according to constraints C1 and C3, or C2 and C4 when searching for events that can extend the left or right parts of a rule. The above constraints can be combined to achieve more complex reasoning. For instance, CELTS can detect why some learners don't know which joint must be chosen to achieve a specific goal on the ISS (the event "don't_know_right_joint" and "goal#21") (e.g., goal#21= moving Canadarm2 from point A to point B). To do so, while CELTS interacts with learners, it seeks all the rules whose left part contains the following information: {don't_know_right_joint, exercise_goal#21} and find: {not_perform_distance_evaluation, did_not_performed_camera_adjustement}⇒{doesn't_know_right_joint, goal#21}.

This means that the cause may be that the learner forgot to make a distance evaluation or forgot to adjust camera. According to constraints C3, CELTS can then search the following information "What is the best camera for observing ISS" or "What is the distance between Canadarm2 and ISS" given the cause found and {don't_know_right_joint,goal#21}. Asking these questions, CELTS can help learners to solve the problem by providing explanations to the learner. This also helps CELTS to predict the results of its action and the learner's response and helps it to choose the best action to help the learner.

[1] The support of a rule is defined as the number of sequences that contain the rule. The confidence of a rule is defined as the ratio between the number of sequences where the rule appears and the number of sequences containing its left part.

Conclusion

Reasoning is crucial to many characteristics of cognition such as planning, imagination, and inference (Gopnik and Schulz, 2007). In this paper, by integrating constraints to data mining algorithms, we improved CELTS' performance and capacity of causal reasoning. The constraints help CELTS to construct more precise knowledge and consequently provide better assistance to the learners.

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