DEDUCTIVE LEARNING

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Synonyms

Explanation Based Generalization, Explanation Based Learning, Chunking

Definition

We can formally define three types of reasoning mechanisms: deduction, induction and abduction. Let define the rule: "if we are in the morning then the sun rises", and the facts "we are in the morning" and "the sun rises". Deduction consists in asserting the fact "the sun rises" given the rule "if we are in the morning then the sun rises" and the fact "we are in the morning". Induction consists in asserting the rule "if we are in the morning" and "the sun rises" from the facts "we are in the morning" and "the sun rises". Abduction consists in guessing the fact "we are in the morning" from the fact "the sun rises" and the rule "if we are in the morning then the sun rises" and the rule "if we are in the morning" from the fact "the sun rises" and the rule "if we are in the morning then the sun rises" and the rule "if we are in the morning" from the fact "the sun rises" and the rule "if we are in the morning then the sun rises" and the rule "if we are in the morning then the sun rises" and the rule "if we are in the morning" from the fact "the sun rises" and the rule "if we are in the morning then the sun rises" and the rule "if we are in the morning then the sun rises" and the rule "if we are in the morning then the sun rises" and the rule "if we are in the morning then the sun rises".

A large number of works in the field of machine learning deal with induction. In this entry we are not dealing with inductive learning but rather with learning from deduction.

Deduction is an important area of Artificial Intelligence. Many Artificial Intelligence systems rely on deduction to solve problems. This is particularly true for systems written in Prolog. Prolog enables to write systems using first order logic. It provides a built-in deduction mechanism and a program can be written declaratively as a set of facts and rules. Deduction is also used in expert systems that also rely on fact and rules to solve problems. Backward chaining consists in starting with a goal expression that the system tries to deduce and to find the rules that conclude on this goal expression, these rules contain sets of conditions that have to be true in order to prove the goal expression and these conditions are set as the new goal expressions that the system tries to deduce. On the contrary, forward chaining consists in starting from a set of facts and to deduce new facts applying the rules that match the set of facts (i.e. a rules matches a set of facts if its all its conditions match some facts). The main difference between Prolog and usual expert systems is that Prolog uses backward chaining while expert systems usually use forward chaining.

Using first order logic to represent rules means that the conditions of the rule can contain variables and not only facts. The example rule of the beginning of the entry about the sun that rises in the morning does not contain variables. A similar rule that may contain a variable could be: "if the variable Hour is greater than 9 and lower than 12 then the sun

rises". The goal of deductive learning is to speed up systems that use deduction in first order logic to solve problems.

Deductive learning (Laird, Rosenbloom & Newell 1986; Mitchell, Keller & Kedar-Cabelli 1986; DeJong & Mooney, 1986) consists in creating rules that deduce rapidly some facts that have taken time to be deduced by a rule based system. If the system fires these learned rules directly, he may find solutions faster than the original system. The goal of deductive learning is to speed up problem solving. One possible drawback of learning rules this way, is that the system can be slower after learning than before learning. This undesired behavior can be caused by the time used to match the learned rules (Minton 1990). To avoid this, an operationality criterion (DeJong & Mooney, 1986) can be used to decide which learned rules are kept and which ones are discarded.

Deductive learning is particularly efficient in games that have threats (Cazenave 1998). Knowing the rules of a game, a system can find the set of facts that enable one player to win if he plays first in a particular position. It can then generate a rule that deduces the game can be won in similar cases where the rule matches. Moreover, since the system knows all the conditions of a rule that enable one player to win, he can analyze these conditions and find a small subset of the possible moves for the other player that invalidate one of the conditions. This small subset of moves contains all the relevant moves to prevent the first player to win, it is also established that no other move can prevent the first player to win. Therefore using these rules in a problem solver for games reduces a lot the branching factor of the games and enables to solve problems that would be unsolvable with a brute force approach.

Theoretical Background

The correctness of deductive learning comes from the equivalence between firing rules with variables and proving theorems in first order logic. A learned rule is a generalization of a set of facts that have been deduced. The generalization consists in replacing in the conditions of the learned rules the binded variables with true variables. The first order learned rule is a theorem in the theory formed by the initial set of rules. Therefore learned rules are consistent with the theory and deduce correct facts provided the initial theory is also correct.

Important Scientific Research and Open Questions

Deductive learning can be used to find rules to direct the search of a problem solver. It is also related to meta-knowledge and to machine consciousness since the system has to observe and analyze its own behavior in order to create new knowledge (Pitrat 2009).

Cross-References

- \rightarrow Metacognition and learning
- \rightarrow Deductive reasoning and learning
- \rightarrow Problem solving

References

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