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Michel De Glas

LAFORIA, IBP
CNRS - Université Pierre-et-Marie-Curie
Paris, France

Zdzislaw Pawlak

Warsaw University of Technology
Warsaw, Poland

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Learning and Cognition

Ryszard S. Michalski
George Mason University
USA
e-mail : michalsk@aic.gmu.edu

Abstract

This presentation consists of three interelated parts: 1) a discussion of the relationships among several concepts fundamental to understanding intelligent behavior, such as the intelligent system, learning, cognition and inference, 2) a review of the Inferential Theory of Learning that provides a unifying framework for learning processes, and 3) an introduction to research on the theory of guessing that aims at providing a computational foundation for understanding human plausible reasoning and "educated" guessing.

Extended Summary

It is a commonly held belief that the ability to learn is an indispensable component of an intelligent behavior. To consider such a view as being more than an intuitive opinion, one needs to have an operational definition of of intelligence and learning. While several definitions of these concepts have been proposed in the past, they often lack "operationality," by which we mean that they are defined in terms that themselves need to be defined. Also, any satisfactory definition of these concepts should state conditions that are not inherently biological, but would allow any system – biological or not – be viewed as intelligent, as long as it satisfies these conditions. To satisfy the above criteria, the following definition of the intelligent system is proposed.

A system is called intelligent, if it can:

C1. Generate and store information about its environment and its state
(i.e., is equipped with senses that measure/perceive properties characterizing its environment and its internal state, and with memory for storing information about these properties)

C2. Create knowledge from this information
(i.e., can classify, organize, abstract and/or generalize information obtained from the senses)

C3. Can use this knowledge for achieving its goals
(i.e., can access and reason with its knowledge in order to achieve externally or internally created goals, or to perform associated with them functions, such as self-preservation, danger avoidance, service, problem solving, planning, decision making, object recognition, prediction, etc.)

In this definition, knowledge is defined as organized, abstracted and generalized information; information is defined as interpreted data; and data as a collection of symbols. Intelligence can thus be described by an "equation":

Intelligence =
Information Gathering + Knowledge Generation + Knowledge Utilization

In the above definition intelligence is considered as a property that can have a degree, rather than a yes-no property. Specifically, the degree of to which the above three conditions are satisfied by a system determines the degree of its intelligence. Thus, for example, a desk would be viewed as intelligent, if it is equipped with sensors, can create knowledge from the information obtained by them (e.g., knowledge about what height, tilt, shape, etc. of the desk is most desirable or suitable for various people), and then can use that knowledge to automatically adjust its height, tilt, shape, etc., accordingly to the person that seats at it.

The ability to learn is incorporated in the second condition (C2) of the above definition, since learning can be viewed a process of creating knowledge/skill and memorizing it for future use. The input information to a learning process may include any sensory perception, teacher-provided facts and/or knowledge, the learner's prior knowledge, beliefs, feelings, results of learner's reasoning or imagination. Deriving knowledge from the given information and/or knowledge can be viewed as a process of inference. Thus, learning can be described by an "equation":

Learning = Conducting Inference + Memorizing

When applied to human learning, this definition requires some explanation. Human learning can be of two types, depending on the type of knowledge that is being generated. There are two fundamental types of human knowledge, each being represented, accessed and used differently. There is explicit knowledge (conceptual, declarative) and implicit knowledge (skill, procedural). The terms "explicit" and "implicit" knowledge have been introduced by psychologists, such as Neal Cohen from the University of Illinois, Larry Squire from the University of California at San Diego, and Daniel Schacter from the University of Toronto. Terms "declarative" and "procedural" knowledge have been used mostly by AI researchers to characterize different knowledge structures (order-independent or order-dependent, respectively), regardless of whether they relate to human mind or computer.

The fundamental aspect of human memory organization is that explicit knowledge is stored in the prefrontal cortex, while implicit knowledge is manifested through activation of particular motor or sensory system. In a computer, both declarative and procedural knowledge can be represented using the same memory structures. Moreover, the transfer from one form of knowledge to another can be done in a computer automatically, at least in principle, while such a transfer can not be done automatically by human brain. No matter how well we "know" how to perform a certain skill we cannot do it well (or at all) until we practice.

The view of learning as knowledge creation (in the learner's mind) is the basis for the Inferential Theory of Learning that aims at providing a unifying framework for all learning processes. The theory views learning as a process of traversing knowledge spaces using knowledge operators, called transmutations or transforms (such as generalization, abstraction, similization, prediction, selection, agglomeration, etc.) The major contribution of the theory is the distinction between knowledge transmutations that change various aspects of knowledge and usually occur as pairs of opposites, and the type of inference (such as deduction, induction or analogy) that are methods for knowledge transform and that characterize knowledge changes along the truth-falsity dimension. The theory has introduced 43 named knowledge transmutations, in addition to a range of knowledge derivations that determine one piece of knowledge from another on the basis of some logical or statistical dependency between them.

In contrast to typical machine learning methods, which are "monostrategy," human learning is multistrategy, which means that it uses multiple learning strategies in a goal-oriented fashion. Multistrategy learning may involve different types of inference and/or knowledge representations. Because any type of inference may derive knowledge that is potentially useful and worth remembering, the complete theory of learning must to encompass the theory of inference. Thus, learning and inference are two intertwined processes that are mutually dependend on each other (e.g., Gaines and Boose, 1990; Michalski, 1990, 1994).

The last part of the presentation reviews recent ideas on the development of a theory of guessing that attempts to explain how people are able to derive useful knowledge from logically incomplete, insonsistent or uncertain premises. This theory is based on the core theory of human plausible inference (Collins and Michalski, 1989; Collins, Burstein and Baker, 1990), the Inferential Theory of Learning (Michalski, 1993, 1994), knowledge representation based on Dynamic Interlaced Hierarchies (Hieb and Michalski, 1993; Alkharouf and Michalski, 1995) and two-tiered knowledge representation that explains how people represent imprecise concepts (Michalski, 1993).

The two outlined theories – the Inferential Theory of Learning and the Theory of Guessing – are viewed as a contribution to the development of the emerging science of learning and inference.

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