ROBOT-DISCOVERER: A ROLE MODEL FOR ANY INTELLIGENT AGENT

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We argue that autonomous robots who discover knowledge about their environment are paradigmatic intelligent agents. According to a demanding definition, intelligence is agent's ability to be successful in new situations. Successful operation in a new situation requires new knowledge and effective application of that knowledge. Since an ability to generate new knowledge is characteristic to discoverers, it is clear that intelligent agents must be discoverers. We compare human and robotic discovery and we clarify the notion of robotic agent and the meaning of autonomous pursuit of knowledge. Then we show on several examples how robotic discoverers examine new situations and discover new knowledge. Our examples include exploration of office environment by a mobile robot, experiments made by robot arms, and a robot-scientist who makes chemistry experiments. In these examples we demonstrate the use of the same methods and striking similarity of knowledge discovered in each case. Walking through examples we describe the basic components of machine discoverers, distinguishing (1) a general purpose discovery mechanism, applicable in many domains, and (2) various ways of linking that algorithm with the physical world through robot's sensors and manipulators.

An extended abstract follows:

1 Discovery

A person who is the first to propose and justify a new piece of knowledge K is considered the discoverer of K. Being the first means acting autonomously, without reliance on external authority. This often starts from exploring new situations and recognizing what is new about them. Throughout the history, human were considered discoverers when they did not follow on external authority. Either there was none at the time when the discovery has been made, or the discovery contradicted the accepted beliefs.

Intelligence involves not only discovery of new knowledge but also effective knowledge application. A discoverer must be able to apply knowledge in many ways. As discovery is rarely a one-time event, this process continues through many steps and knowledge available at a given time guides the future steps.

2 Cognitive autonomy of a machine discoverer

Machine discoverers can be viewed as computer systems who autonomously pursue knowledge. Let us clarify the notion of cognitive autonomy to make it useful in machine discovery. Suppose that agent A discovers piece of knowledge K which has been known to others. We can still consider that A discovered K, if A did not know K before making the discovery and was not guided towards K by any external authority. It is relatively easy to trace the external guidance received by a machine discoverer as all details of software are available for inspection. In particular, the initial knowledge and method are available for inspection.

The existing systems would not reach success in making discoveries if we humans did not provide help. However, they are autonomous to some degree, and future research in machine discovery will increase their cognitive autonomy. The agent is more autonomous if it has more means and methods, for instance more sensors and manipulators, more goals and capabilities to achieve them. It is also more autonomous if it can modify its operation so that rather than executing pre-programmed steps, new results can drive further exploration.

One way to satisfy an expanded range of goals is to implement new components of the discovery process. The mere accumulation of new components, however, would not suffice. The components must be strongly integrated and the integration must be supported by the autonomous evaluation of results, so that the next step is selected automatically. As a result, more discovery steps in succession can be performed without external intervention, leading to greater autonomy. A single step rarely permits a sound judgement about the results. A combination of steps provides a more informed feedback on the reasons for acceptance.

3 Applications of a robot-discoverer

We show that the same discovery mechanism can be applied in seemingly different domains. We consider several case studies that result in similar knowledge structures: (1) a discovery in the domain of chemistry, (2) robot arm that discovers physical properties of objects, and (3) exploration of office space by a mobile robot.

3.1 Discovery in a science laboratory

We consider FAHRENHEIT (Żytkow, 1996) application in the domain of differential pulse voltammetry (Żytkow, Zhu, & Hussam 1990) and in exploration of state transition between ice and water. These applications help us to illustrate the repertoire of discovery methods. Experiments involved collection of many thousands data points, detection of maxima in data and the discovery of many regularities on the heights and locations of those maxima. Theory formation tasks involved piecemeal generalization of empirical equations, detection of phase boundaries and understanding of phase space properties.

3.2 Robot arm repeats Galileo's experiment

We set-up a robot arm experiment similar to Galileo's experiments with the inclined plane. The robotic system placed different cylindrical objects, differing by the diameter of an inner cylindrical hole, on the top of an inclined plane and measured the time in which they rolled and reached the bottom. The system collected data, determined empirical error, found empirical equations acceptable within error and generalized them to different angles and different radius of the inner hole (Huang & Żytkow, 1997). By confronting empirical equations developed by FAHRENHEIT with theoretical models based on classical mechanics, two systematic deviations between data and a theoretical model hint at extra processes not captured by the model but accounted for in empirical equations. Possible phase transitions should be confirmed by the continued discovery process.

3.3 Robot arm discovers how to manipulate a box

When a box is lifted at one end by a robot gripper, different outcomes are possible depending on the grasping force. For instance, the box may slip from the gripper. It may tilt so that it is lifted only partially. As the force increases, it can be fully lifted, but then it can be also squashed. By changing location of the gripper and repeating the attempts to lift the box with a various grasping force, a theory is developed that includes several areas and boundaries between them: (1) box falls from the gripper; (2) box is lifted partially, at one end; (3) box is fully lifted; (4) box is lifted but it is also squashed. Each area is limited by a well defined boundary, beyond which the properties of lifting change. Altogether experiments discover a phase space of several different behaviors.

3.4 Exploration of office environment with a mobile robot

Map generation by a mobile robot who explores an unknown office environment, has been yet another application of FAHRENHEIT's discovery methodology. Consider an intersection, traversed by Nomad, and explored with the use of its sonar sensors. Individual readings are generalized to lines that indicate walls. Boundaries on those lines, such as corners and doorways are detected according to the same methodology. A local map, different for a T-intersection, X-intersection, a hallway and other typical details in an office environment, consists of a combination of line segments. It resembles a phase space and is discovered from individual readings by the same methodology as in the previous examples.

Exploration goals combine knowledge discovery and application. We show on examples that goals such as (1) find where I am; (2) match my current situation against the known map; (3) build a map; (4) if I know where I am, use the map as a theory that helps to interpret observations; are common with discoveries made in other domains.

4 Anatomy of a robot-discoverer

We present a robotic discoverer whose architecture has been influenced by various existing systems, primarily small FAHRENHEIT, but also LIVE (Shen, 1993), DIDO (Scott and Markovitch, 1993) and KEKADA (Kulkarni and Simon, 1987). We summarize the basic components of a robotic agent-discoverer, and their interaction with the physical world. The agent consists of "mind" and "body". The mind is a software system, while the body is hardware, which belongs to the physical world. The agent interacts, at any given time, with a small, selected part of the world. We can call it robot's surrounding, immediate environment or an empirical system.

Hardware of the discoverer includes the "brain" part and the "body" part. The brain includes a computer with its processor, memory, input and output, plus processors which drive sensors and manipulators, linked to the computer input/output (Zytkow, Zhu i Hussam 1990). The body includes sensors and manipulators and the platform on which they operate.

The part of the software necessary for contact with the external world includes device drivers which control the available sensors and manipulators, and operational definitions of meaningful laboratory activities and measurements, expressed in terms of elementary actions of sensors and manipulators (Zytkow, Zhu and Zembowicz, 1992). This part of software is application specific. While many operational definitions share common generic structure, each concrete configuration of sensors and manipulators as well as codes understood by their processors are specific, and can be viewed as a physical interpretation of the formalism of machine discoverer.

The discovery method consists of a static, pre-programmed network of discovery goals and plans. Each goal specifies a generic task of discovery. Plans specify how those goals may be accomplished. Because discovery goals require search in different spaces of hypotheses, terms, procedures, and the like, most of the plans are algorithms that can effectively search the corresponding spaces. The same goal can be carried by various plans. For instance, many systems include a module which fits data with empirical equations: BACON, COPER (Kokar, 1986), small FAHRENHEIT, IDS (Nordhausen and Langley, 1989), KEPLER (Wu and Wang, 1989). Goals and plans can be called recursively, until plans are reached which can be carried out directly, without reference to other goals and plans.

Knowledge representation schema contains the tools for constructing, maintaining, and analyzing the network of knowledge emerging in the discovery process. It defines basic types of knowledge and the ways in which they can be connected. Systems such as DIDO (Scott and Markovitch, 1993), FAHRENHEIT, IDS and LIVE (Shen, 1993) use graphs to represent relationships between pieces of knowledge and they use frame-like structures to represent knowledge contained in individual nodes in the graphs.

Static network of goals and plans as well as the knowledge representation schema can be treated as an abstract discoverer. It can be applied in many domains. A concrete discoverer can be formed by augmenting the abstract discoverer with sensors, manipulators and procedures which control their functioning. This way the abstract mechanism reaches a concrete interpretation.

In a concrete application, when a machine discoverer investigates a concrete physical system, the elements of the discovery method are instantiated in concrete ways, forming a run-time agent. Concrete goals and concrete plans of actions change dynamically, following the patterns provided in the static network of goals and plans. Similarly, concrete knowledge is represented in a dynamically changing network (Zytkow 1991; Zytkow and Zhu 1993) which is constructed and maintained based on the patterns taken from the static network. As new discoveries are made, this network grows to include new knowledge. Goals and plans can be selected dynamically, at the runtime, by analysis of the current state of the knowledge network. When a limitation of knowledge is detected, static network of goals and plans can provide a response in the form of a goal and a plan which should overcome that limitation.

FAHRENHEIT's knowledge representation in the form of a knowledge graph (Żytkow, 1996) allows the system to examine any given state of knowledge and seek new goals that transcend that state. Each goal corresponds to a limitation of knowledge. Each state of knowledge can be transcended in different directions, so that goal generator typically creates many goals and is thus supported by goal selector.

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