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Interactional Motivation in Artificial Systems: Between Extrinsic and Intrinsic Motivation

Olivier L. Georgeon, James B. Marshall, and Simon Gay

Abstract—This paper introduces Interactional Motivation (IM) as a way to implement self-motivation in artificial systems. An interactionally motivated agent selects behaviors for the sake of enacting the behavior itself rather than for the value of the behavior’s outcome. IM contrasts with extrinsic motivation by the fact that it defines the agent’s motivation independently from the environment’s state. Because IM does not refer to the environment’s states, we argue that IM is a form of self-motivation on the same level as intrinsic motivation. IM, however, differs from intrinsic motivation by the fact that IM allows specifying the agent’s inborn value system explicitly. This paper introduces a formal definition of the IM paradigm and compares it to the reinforcement-learning paradigm as traditionally implemented in Partially Observable Markov Decision Processes (POMDPs).

Index Terms—Developmental learning, self-motivation, constructivist learning, autonomous agents.

We propose a new form of self-motivation for artificial agents and robots: interaction-centered motivation, or, more concisely, interactional motivation (IM). In essence, we define an IM mechanism as the association of (a) a value function associated with the possible interactions that exist between the agent and the environment, and (b) an unsupervised learning mechanism that learns to select behaviors that maximize this value function over time. The key difference with traditional reinforcement learning resides in the fact that the value function is a function of behaviors (interactions) rather than of states.

Motivation is generally defined as a driving force that initiates and directs behaviors. It is widely acknowledged that an agent that selects behaviors to maximize a value function over time conforms to this definition, and, therefore, implements a form of motivation. Typically, a Partially Observable Markov Decision Process (POMDP) can be used to model an agent that learns to perform actions in search for rewarding situations [1]. The designer of the POMDP defines a set of states $S$, a set of actions $U$, and a reward function $r : S \rightarrow \mathbb{R}$ that assigns values to states. The POMDP framework is represented in Figure 1.

![Diagram of a POMDP showing the underlying Markov Decision Process (MDP), and the stochastic process $\pi(y|x)$ mapping the state $i$ (resulting from action $u_i$) to an observation $y_i$, thus partially hiding the environment’s state from the agent.](image)

The designer of the POMDP interprets a state $i \in S$ as a specific configuration of an agent in a virtual environment, and interprets $u$ as an action that the agent performs in the environment according to the agent’s policy. In this case, the agent’s motivation is said to be extrinsic because the reward function $r(i)$ is defined independently from the agent’s policy. Moreover, from the designer’s perspective, the agent’s motivation seems to come from something rewarding in the environment that is external to the agent itself.

Extrinsic-motivation models, such as POMDPs, would in fact constitute models of animals that learn to act based on states of the world that have been identified a priori by someone else, if such animals existed. Here we argue that animals face a very different problem: the problem of identifying useful states of the world, with regard to the animal’s own motivation. This problem is related to the symbol-grounding problem: grounding the agent’s knowledge in its own activity [5]. Especially in the field of developmental robotics, we expect the meaning of the agent’s knowledge to derive from the agent’s own motivations and experiences rather than from a provided interpretation of the world [10].

The notion of intrinsic motivation has been proposed as a way to implement motivation independently from any specification of the environment. Examples of intrinsic motivation systems are curiosity [7], search for predictability and control [2], and search for simplification of knowledge or compressibility of data [9]. With intrinsic motivation, the value system is generally not made explicit in the form of numerical values. Instead, it is implicitly characterized by the resulting behavior of the system.

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In between extrinsic and intrinsic motivation, we propose here the notion of interactional motivation as a way to specify an inborn value system without referring to the environment. Figure 2 illustrates the IM paradigm with a formalism similar to the formalism used in figure 1, to allow for the comparison with POMDPs.

Another difference with POMDPs is that the distribution $v$ is now a function of the state $i_t$ and the action $u_t$ rather than of the resulting state $i_{t+1}$. With this new definition, $v(y| i_t, u_t)$ specifies the observation $y$ obtained after performing a given action $u$ in a given state $i$. This difference is important because it means that the observation $y$ does not always inform the agent about the same property of the environment each time, in contrast to observations in a POMDP. For example, we have implemented IM agents for which the observation is a single bit [4]. At each time step, the meaning of the observational bit $y_t$ depends on the action $u_t$ that produced it. When $u_t$ corresponds to feel to the left then $y_t$ informs the agent about the presence or absence of an object on the left; when $u_t$ corresponds to try to move forward then $y_t$ informs the agent about the success or failure of this attempt (depending on a possible obstacle). However, the agent initially ignores this meaning. We expect IM agents to demonstrate that they learn this meaning by progressively adapting their behavior to maximize the value function $r$. We show examples of such agents online (http://e-ernest.blogspot.fr/).

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