

# Motivated Agents

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## 1 Introduction

This poster presents a model for motivated agents with behaviours influenced by an internal, domain independent motivation process rather than domain specific rewards, goals, or examples provided by an external teacher. Internal motivation is desirable in complex, dynamic environments where hard-coded domain theories can only approximate the true state of the world and where pre-programmed goals can become obsolete.

Early work with motivated agents focused on the use of domain specific motives [Sloman and Croucher, 1981] or environment modelling by focusing attention on situations with the highest potential for learning [Kaplan and Oudeyer, 2004]. More recent work with intrinsically motivated reinforcement learning agents [Singh et al., 2005] has produced agents that, rather than learning a model, learn new behavioural *options* [Precup et al., 1998]. An option or simply a *behaviour* is a whole course of action that achieves some sub-goal. Our model extends previous work by defining general structures for events, attention focus and motivation.

## 2 The Motivated Agent Model

Our model for motivated agents is shown in Figure 1. It has three types of structures: sensors, memory and effectors. These structures are connected by four processes: sensation, motivation, learning and action. Agents function in a continuous sensation-motivation-learning-action loop.

*Sensors* receive raw data in the form of an n-tuple of state variables  $\{x_1, x_2, x_3, \dots, x_n\}$  describing the current state of the agent and its environment. The n-tuple has a particular format:  $x_1$  to  $x_k$  comprise data about the state of the agent and  $x_{k+1}$  to  $x_n$  comprise data about other objects sensed by the agent. This includes both absolute and relative data such as the location of an object relative to the agent. This general format is domain independent. Relative values make allow agents to learn general behaviours relative to themselves.

*Sensation* transforms raw data received from sensors into structures called *events*. Events encapsulate two recognisable occurrences among state variables values: increases and decreases between one state and the next.

Individual events and the current state n-tuple are incorporated into *memory*.

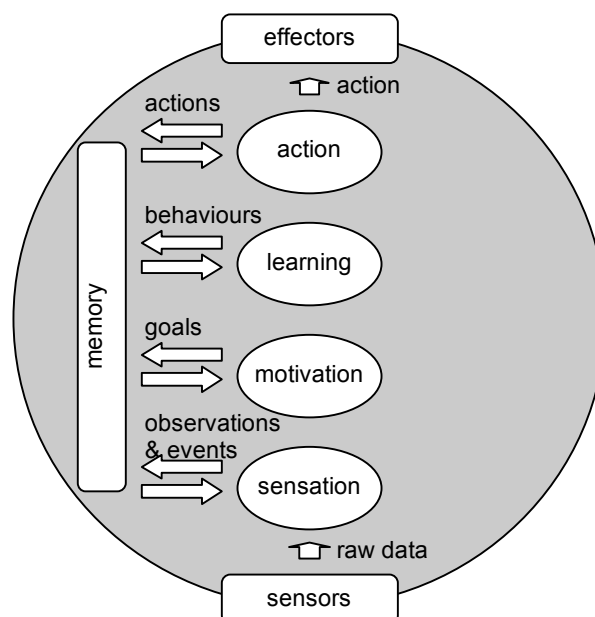


Figure 1 – The motivated agent model.

*Memory* is a cumulative record of events, actions, and goals. Initially, memory is empty save for a set of primitive actions that the agent can perform in the world.

*Motivation* creates goals and stimulates action towards goals. Agents are motivated to create goals to understand and repeat interesting events that occur in their environment. We characterise interesting using the intuition that events that occur infrequently in the world are interesting. Agents act towards goals by identifying situations in which they can learn how to make interesting events recur using a temporal difference Q-learner (TDQL) [Sutton and Barto, 2000]. Goals are *masked* so that events that occur with equal or lesser frequency than the one being pursued are ignored. Masking increases learning efficiency by focusing attention and reducing the size of the state space.

*Learning* encapsulates new knowledge as a *behaviour* once an agent can repeat an interesting event at will. Masking ensures that behaviours are independent of the situation in which they were learned. A behaviour can be reused either as a pre-planned course of action for achiev-

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ing new goals similar to the one from which it was originally created or as a building block when learning to solve more complex goals.

*Action* reasons about which *effectors* will further the agent's progress towards its current goal.

*Effectors* are the means by which actions are achieved. They allow the agent to cause a direct change to the world.

### 3 Motivated Agents in Practice

We demonstrate our agent model using a robot guide. This domain, based on Dietterich's taxi domain [2000] and illustrated in Figure 2, contains avatars who need to be guided to particular locations. Such situations are common in large scale virtual worlds where new citizens can easily become lost. There are four possible sources and destinations for avatars. The robot has twelve effectors controlling the movements of its legs and can choose to start or stop guiding an avatar. The robot's sensors can perceive the absolute co-ordinates of the agent, the elevations of its legs, the co-ordinates of its legs relative to its body and the absolute and relative co-ordinates of an avatar and its destination.

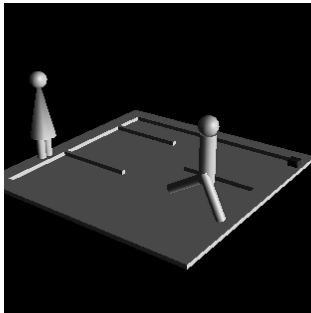


Figure 2 – A guide robot.

After a period of exploration, the robot notices that increases and decreases in its location and the location of other avatars are infrequent. The agent is motivated to create and pursue goals to repeat these changes. Over time the agent learns walking behaviours, such as Behaviour-1, to change its location. These behaviours are independent of the location in which they were learned and the position of other avatars. The agent uses these walking behaviours to develop path-following behaviours, such as Behaviour-2, to change the location of the avatar.

**Behaviour-1** [lift left foot, move left foot forwards, put-down left foot, lift right foot, move right foot forwards, put-down right foot]

**Behaviour-2** [guide, Behaviour-1, Behaviour-1, Behaviour-1, Behaviour-1, Behaviour-1, Behaviour-1, stop-guiding]

### 4 Empirical Results

We measured the performance of the robot guide by graphing the number of primitive actions taken to produce Behaviour-2 in response to some goal G. We then implemented a flat TDQL with a pre-programmed reward for achieving a similar behaviour that satisfies G. Figure 3 shows that the motivated agent learns Behaviour-2 more quickly than a flat TDQL can learn a similar behaviour. This is because the motivated agent can make use of ab-

stract behaviours such as Behaviour-1 while constructing Behaviour-2.

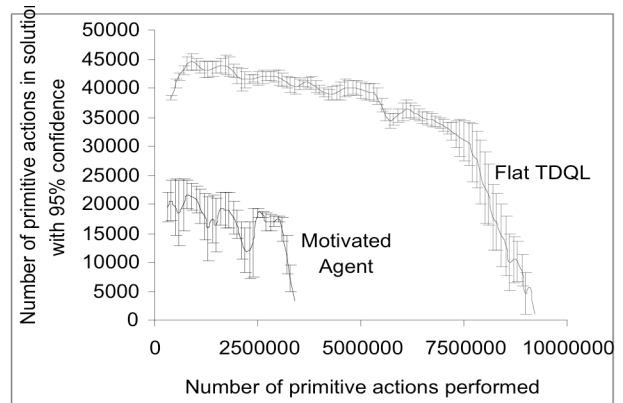


Figure 3 – Learning progress in a guide task.

### 5 Conclusion

Motivated agents are autonomous agents with behaviours influenced by internal, domain independent motivation. In addition to being able to choose their own goals they are able to learn behaviours to satisfy their goals more quickly than agents utilising the TDQL algorithm

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