LEARNING MODELS FOR A CURIOUS PLACE

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Abstract. A Curious Place is modelled on the concept of an intelligent room, with an added capacity for behaving in a curious manner. Intelligent rooms are responsive physical spaces in which human activities are monitored and responses generated which facilitate or augment these activities. Recent trends in intelligent agent research towards intrinsically motivated learning agents allow physical places to respond with curiosity and exhibit adaptive learning behaviour. This paper presents learning models for curious places for modelling curiosity, curious agents, and curious agent societies. These models are demonstrated with reference to a Curious Research Space as an example of a Curious Place.

1. Introduction

A Curious Place is modelled on the concept of an intelligent room, with an added capacity for behaving in a curious manner. Intelligent rooms are responsive physical spaces in which human activities are monitored and responses generated which facilitate or augment these activities. A current application of intelligent environments is the C-Bus home automation package, in which computational processes monitor activities within the home and respond by turning lights on and off, locking and opening doors, and other actions usually performed by the inhabitants of the home. Home automation systems are possible with sensors and effectors that are programmed to respond as expected.

Other architectures for intelligent rooms use an agent approach to the computational processes which monitor activity. Agents reason about the use of the room in order to facilitate human activity. This research started with the intelligent room project (Brooks et al., 1997; Coen, 1998) and has progressed in several directions, from sensor technology and information architectures, to possible agent models for intelligent reasoning (Hammond et al., 2002). While these systems go beyond the home automation systems to proactively support human activities, they still respond with programmed reflexes to predefined states of the environment.

Recent trends in intelligent agent research towards intrinsically motivated learning allow the design of places able to respond with motives such as interest and curiosity to support and enhance human activities. Maher et al (Maher et al., 2006) introduced three motivated learning agent models for intrinsically motivated intelligent sensed environments which incorporate computational models of motivation with reinforcement learning (RL), supervised learning (SL) and unsupervised learning (UL). These models aim to achieve adaptive responses using motivation to direct learning towards useful or interesting behaviour.

This paper draws on the concept of motivation to design curious places in which responses are governed by agents which use curiosity as motivation for guiding action and learning. We identify learning as a key component of agents in curious places, not only at the agent level, but at the motivation level for representing curiosity. We also consider the roles of agents with different learning models in a curious agent society. Section 2 considers general learning models for curious places at each of these levels of abstraction. Section 3 discusses learning models and an agent society for a Curious Research Space as an example of a Curious Place application.

2. Learning Models for a Curious Place

Maher et al (Maher et al., 2006) introduced three motivated learning agent models for intrinsically motivated intelligent sensed environments which incorporate computational models of motivation with RL, SL and UL. They model motivated learning agents using four processes: sensation $\mathcal{S}$, motivation $\mathcal{M}$, learning $\mathcal{L}$ and action $\mathcal{A}$ as shown in Figure 2(c). Their models focus on the use of different types of learning algorithms in the learning process $\mathcal{L}$ for learning patterns of actions as behavioural responses to the inhabitants of a physical space. In the following sections we consider, in addition, the role of learning for modelling curiosity in the motivation process $\mathcal{M}$ and the way in which agents using different learning models can interact in a multi-agent society.

2.1. THE ROLE OF LEARNING IN CURIOSITY

Saunders (Saunders, 2001) identifies learning as a key component of curiosity as a means of modelling experiences as a baseline for establishing curious stimuli. He postulates that two reasonable assumptions for modelling experiences are firstly that recent experiences are likely to be the most relevant at the current time and secondly that similar experiences from any time in the past are likely to be relevant for determining what actions to take in the present. These assumptions are well modelled by existing machine learning algorithms. Specifically, we identify incremental SL and UL algorithms as potential models for curiosity, extending previous work which focused on UL techniques such as Self-Organising Maps (SOMs) and ART maps. SL and UL algorithms classify or cluster input data and produce an error value representing the similarity of new data to existing categories or clusters. The classification or clustering processes weight new data most heavily while retaining some information about older data, satisfying the two assumptions for modelling experiences. The error value provides a numerical measure of similarity.

In this paper we model curiosity as inversely proportional to the similarity of environmental stimuli to previous experiences. Figure 1 shows two general models for the interaction between the sensation and motivation processes for modelling motivation as curiosity. Figure 1(a) shows the UL case in which the entire sensed state $S_{(t)}$ is used as input for the motivation process which could comprise UL algorithms such as a SOM or K-Means clustering. In contrast, Figure 1(b) shows the SL case where the sensed state is broken into two parts, an observation and a category. These are used as input for a combination of SL algorithms such as Naïve Bayes classification or K-Nearest Neighbour (KNN) classification. The use of elements of the sensed state as categories ensures that categories, and thus curiosity, can adapt to changes in the environment.

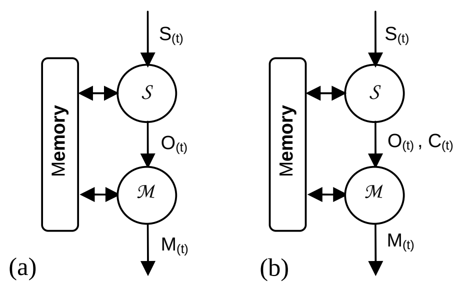

Figure 1. Models of motivation as curiosity using (a) unsupervised learning and (b) supervised learning to model experiences.

2.2. LEARNING MODELS FOR CURIOUS PLACE AGENTS

Previously, motivated learning agents have been considered in isolation for curious place applications such as the Curious Information Display and controlling the hardware of intelligent environments (Maher et al., 2007). Taking the approach that learning models are a key component of both the motivation and learning processes in a curious agent, we extend agent models for curious places to include agents with reasoning processes of differing complexity in terms of their learning ability as shown in Figure 2. The first model, shown in Figure 2(a) is a reflex agent incorporating only pre-defined rules and no learning. This model has been commonly used in existing intelligent room research. The models in Figure 2(b) and Figure 2(c) extend reflex agents with motivation and learning to create motivated agents and motivated learning agents respectively. Agents using these models differ in their ability to adapt and learn, with each type of agent nonetheless relevant to the development of curious places. Reflex agents are useful for performing critical tasks such as turning off a projector to conserve the bulb. Motivated agents extend reflex agents with the ability to trigger behaviours only when they are motivating, for example when it would be interesting to do so. Motivated learning agents extend motivated agents with a further capacity to learn patterns of behaviours from primitive actions. As such, we see curious places as a layered society of agents which interact with different levels of reasoning to achieve adaptive, responsive behaviour. In the next section we present a Curious Research Space as a society of such agents.

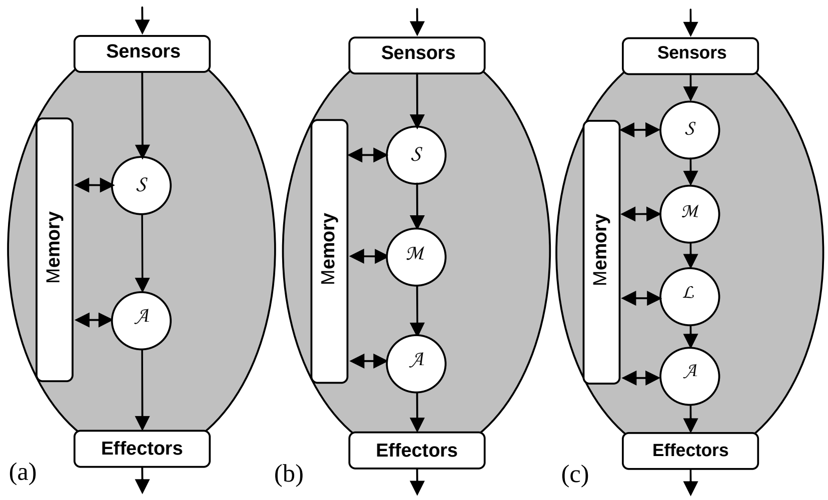

Figure 2. (a) Reflex agents, (b) motivated agents, (c) motivated learning agents.

3. Learning Models for a Curious Research Space

Curious research spaces transform a physical space into a curious place using a society of agents which monitor humans and research material presented in seminars and meetings and compile MS PowerPoint presentations of material from the world-wide web that is relevant and interesting to researchers using the room. This is achieved by a society of agents with different sensors, effectors and reasoning capabilities. A diagram of the curious research space is shown in Figure 3. In this paper we briefly describe each type of agent but focus on learning models for the curious researcher agents.

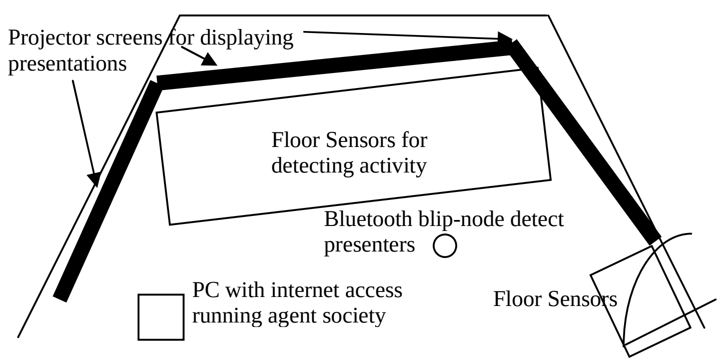

Figure 2. The curious research space.

3.1. SEARCH AGENTS

The search agent is a reflex agent which senses research data in the environment and searches for associated data on the web. Research data is sensed from PDF files as word vectors (Raghavan and Wong, 1986). Word vectors associate each word in a document, with the exception of stop-words such as 'the' and 'and', with a value indicating the frequency of its occurrence. For example, a word vector for the title of this paper might look like:

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<learning:1><models:1><curious:1><place:1>
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The search agent uses the words with the highest frequency of occurrence as keywords for a web search using the Yahoo! API[1].

3.2. CURIOUS RESEARCHER AGENTS

Curious researcher agents are motivated agents which reason about research data produced by both human users of a curious research space and by search agents in order to identify information found by search agents that is interesting and relevant to humans. Curious researcher agents use computational models of curiosity to compute interest and relevance in terms of research data previously presented in the room by humans. We have experimented with two approaches to modelling curiosity for these agents using UL and SL algorithms from the MALLET toolkit (McCallum, 2002), with the aim that different types of curious researcher agents may work together as a society to identify different types of interesting data.

3.1.1. Modelling Curiosity using K-Means Clustering

Currently we have implemented one curious researcher agent which uses K-Means clustering to cluster word vectors of research data produced by humans. When the agent encounters word vectors from a search agent it compares them to each cluster by finding the normalised dot product distance to each cluster. The closest cluster represents the most similar human presentations. We model curiosity using the intuition that less distant documents found by a search agent will be more closely related to human research and should thus stimulate stronger curiosity. Documents within some curiosity threshold are passed to presentation agents for display.

3.1.2 Modelling Curiosity using K-Nearest Neighbour Classification

As a SL alternative we have also implemented one curious researcher agent which uses K-NN classification to classify word vectors from by human research data according to the name of the presenter. This extends the UL approach with the ability to identify specific human researchers to whom new data may be relevant. When the agent encounters word vectors from a search agent it compares them to the K nearest neighbouring word vectors. The category (human presenter) that is best represented within the K nearest neighbours is used as the classification. The error in the classification is the number of non-occurrences of the classification in the neighbourhood divided by the size of the neighbourhood. Error is again inversely proportional to curiosity with the lowest error indicating the most relevance to some human researcher and thus stimulating the highest curiosity. Documents within some curiosity threshold are passed to presentation agents for display.

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[1] http://developer.yahoo.com/

3.1. PRESENTATION AGENTS

Presentation agents are reflex agents that sense data identified as interesting by curious researcher agents and used grammars to produce new presentations based on that data. These grammars describe principles for good presentation design as if-then rules and automate the production of presentations. Space precludes us from going into further detail in this paper.

5. Conclusion

This paper has presented learning models for curious places for modelling curiosity, curious agents, and curious agent societies. These models are demonstrated with reference to a Curious Research Space as an example of a Curious Place. Two models of curiosity were presented based on SL and UL algorithms which model curiosity using learning error.

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