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Biomimicry Based Learning Outcomes of Simple Cognitive Agents

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Abstract

We discuss a model of a complex system that could be used as an experimental virtual reality platform to study learning outcomes of a population of simple cognitive agents unable to express concepts analytically and unable to use crisp values. In modeling the cognitive agents, called "creatures", and their learning process we pursue the route of biomimicry and steer away from formal methods and established learning algorithms, too complex for minimal creatures. The creatures use "social observational learning", that is each creature learns from the behaviour of other creatures. The creatures may experience fear and/or desire, and are capable of evaluating if a strategy has been applied successfully and of applying this strategy again with small changes to a similar but new situation. The creatures are born as "tabula rasa"; i.e. without built-in knowledge base of their environment and as they learn they build this knowledge base. We study learning outcomes of a population of such creatures when they are learning how to safely cross various types of highways. The highways are implemented as a modified Nagel-Schreckenberg model and each creature is provided with a mechanism to reason to cross safely the highway. We present selected simulation results and their analysis.

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1. Introduction

An autonomous agent is an abstraction of an autonomous entity capable of interacting with its environment and other agents, [1], [2], [3], [4], [5], [6]. A cognitive agent is an agent capable of performing cognitive acts; i.e. a sequence of the following activities: "*Perceiving*" information in the environment and provided by other agents, "*Reasoning*" about this information using existing knowledge, "*Judging*" the obtained information using existing knowledge, "*Responding*" to other cognitive agents or to the external

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environment, as it may be required, and "*Learning*"; i.e. changing (and, hopefully augmenting) the existing knowledge if the newly acquired information allows it. The most common implementation of the cognitive agent abstraction in virtual reality is a software program. In [2] we studied functionality & performance requirements of cognitive agents and proposed the architecture of an application independent software implementation of a generic cognitive agent able of providing the required functionality and performance. The goal of this work is to identify and discuss a simple example that could be used as an experimental platform to identify a minimal cognitive agent. We use *biomimicry* as our approach and our emphasis is on minimal entities, both in terms of storage and in terms of logical primitives (e.g., conjunction, disjunction, and negation). Thus, on purpose, we steer away from formal methods and from established algorithms such as reinforcement learning algorithms.

In the presented work we study the performance of a population of simple cognitive agents, called *"naïve creatures*" (in short "*creatures*"), unable to express concepts analytically and unable to use crisp values (i.e., precise or even approximate numbers). The naïve creatures are capable of evaluating if a strategy has been applied successfully and capable of applying this strategy again with small changes to a similar but new situation. Thus, they are capable of adoption or rejection of the strategy as the result of a learning mechanism. We have chosen as a learning mechanism that is called "social learning", that is, each agent learns from the behaviour of other agents [6]. In this paper, we explore the type of social learning that is known as "observational learning" (i.e., *"If this situation worked well for somebody else, it will probably work for me, and thus I will imitate that somebody else. If this situation did not work well for somebody else, it will probably not work for me, thus I will not imitate that somebody else.*", [6]). In the presented work, the very first naïve creature attempting to learn has nobody to learn from, thus it has a high probability of failing. However, as time goes on, each creature can analyze more and more examples of behaviours of other creatures and draw its conclusions. Hence, it can refine its knowledge acquisition and it can improve its learning outcomes.

We call "*naïve algorithm*" the learning algorithm used by the naïve creatures. This learning algorithm may be considered as one of the simplest possible learning functions of primitive cognitive agents, in our case the naïve creatures learning to cross successfully a highway; i.e. first a unidirectional single-lane highway and later, when the environment changes, multi-lane unidirectional highways and multi-lane bi-directional highways. The naïve creatures are born as "*tabula rasa*"; i.e. a "blank slate" and they are provided with mechanism to reason to cross safely the highway but they do not have a built-in knowledge base of their environment. Their knowledge base is initialized with all variables set to zero. However, the naïve creatures have a built-in template to classify the environmental conditions and a reasoning method to make good use of this classification in deciding whether to cross or not to cross the highway. As the simulation of the model progresses, the full knowledge base table is populated with values representing the evolution of the system.

We use the developed model to study how the naïve creatures' population success of crossing a highway is influenced by the creatures' emotional states of fear and/or desire, their ability to change a crossing point and the environmental traffic conditions. Also, we study how the transfer of the knowledge base acquired in one learning environment to another one affects creatures' population learning outcomes of successfully crossing a highway. The presented research is an extension of our works [7], [8], and [9].

The paper is structured as follows: Section 2 describes our model of naïve creatures learning to cross a highway, their learning algorithm and their virtual environment. In Section 3 we present selected simulation results. In Section 4 we provide our conclusions.

2. Virtual universe of naïve creatures learning to cross a highway

Our model of naïve creatures learning to cross a highway is developed under several assumptions about the creatures, their process of learning and their environment. In our experimental virtual universe we assume that: (1) the environment is a single lane unidirectional highway (the case considered here), or multi-lane unidirectional or bi-directional vehicular traffic, without any intersection; (2) a creature is "*an autonomous entity capable of interacting with its environment and other agents*"; (3) the creature has a strong instinct to survive; (4) all creatures are born on one side of the highway; (5) each creature must cross the highway without being struck by the oncoming vehicles in order to reach the opposite side of the highway.

We assume that each creature is capable of: (1) matching simple patterns; (2) evaluating distances in an approximate way; (3) evaluating the velocity of moving vehicles in an approximate way; (4) assigning a discrete number (i.e., class identifiers) to an approximate class; (5) understanding when another creature has been successful in crossing the highway; (6) repeating the action that has previously resulted in success. We equip each creature with a simple mechanism to evaluate the outcome of the crossing of creatures that crossed previously. Each creature will try to imitate the successful crossings. If unsuccessful crossings outnumber the successful ones, then under similar circumstances the creature will not cross and will wait for better conditions or will try to find a better location to cross from.