Effects of Simulation Parameters on Naïve Creatures Learning to Safely Cross a Highway on Bimodal Threshold Nature of Success

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Abstract

A model of simulated cognitive agents (naïve creatures) learning to safely cross a cellular automaton based highway is described. These creatures have ability to learn from each other. We investigate how the creatures’ learning outcomes are affected by the model parameters (e.g., the traffic density, creatures’ ability to change a crossing point, creatures’ fear and desire). We observe and study a bimodal nature in the number of successful creatures in various creature populations at simulation end. This value is either low or high depending on the values of the model parameters.

Keywords: Autonomous robots, agents, cognitive agents, learning, cellular automata, computational intelligence, data visualization

1 Introduction

When modeling and simulating autonomous robots, it may be useful to identify them with autonomous cognitive agents that are capable of: (1) interacting with each other and their environment and (2) performing cognitive acts of perceiving, reasoning, judging, responding and learning [1]- [4].

The purpose of this work is to identify a simple example of a population of minimal (in storage and logical primitives) cognitive agents and to study how the agents’ learning outcomes are affected by model parameters. We consider the model of naïve creatures learning to cross a highway introduced in [5]- [9] and investigate the performance of a simple learning algorithm based on an “observational social learning” mechanism [10] and [11]. Each creature learns by observing the outcomes from the actions of creatures that have already attempted to cross the highway earlier and imitates the successful ones. The creatures use a simple decision making formula and build their knowledge base (KnB) by observing the outcomes of the creatures that attempted to cross the highway earlier. We observe that the transferring of the KnB after building it by many populations of creatures within the

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same environment (i.e., the highway with the same traffic density) results in a number of the initial repeats with low values for the number of successful creatures, leading to the rest of the repeats with high values. This bimodality in data means that the creatures learn how to successfully cross the highway after a number of initial repeats. This learning is enhanced by the access to preexisting knowledge. We investigate how this bimodality/learning is affected by the model’s parameters.

The paper is organized as follows: Section II describes our model; Section III presents an analysis of bimodal nature in the number of successful creatures and Section IV reports our conclusions and outlines future work.

2 Model of Creatures Learning to Cross a Highway

We review here only the main features of the model that have been developed in [5]-[9]. The simulated environment involves, in this case, a single lane highway, cognitive agents (creatures), and vehicle traffic. We model the vehicle traffic on the highway by adopting the Nagel-Schreckenberg cellular automaton model, [12]-[15], in which, as customary in the traffic modeling literature, each cell represents a segment of a highway of 7.5m in length [12].

The creatures have the goal of trying to successfully cross the highway without being struck by a vehicle. The crossing is unsuccessful if they are struck by a vehicle and hence, destroyed/killed. They are simple/minimal (evaluating distances and velocities of the vehicles in only an approximate/qualitative way), but they have the ability to learn from each other via their knowledge base (KnB) tables. For example, if creatures in the past were mainly destroyed (after attempting to cross) by vehicles perceived at close distance and fast velocity, the next creature faced with that scenario will not likely attempt to cross. The creatures’ nature of fear and/or desire will also influence their decision to cross or wait. If the simulator permits (based on the binary parameter, Horizontal Creature Movement (Horiz. Cre.)), the creature may decide to move alongside the highway to a new crossing point (CP) instead of waiting for favorable traffic conditions for crossing. This helps keep the creature queue from being jammed and potentially allows for more creatures to cross at once.

The KnB table is shared with all creatures at the same CP. The table’s rows and columns index the different combinations of the qualitative distance and velocity categories, as perceived by creatures. The KnB table entries are calculated by: (sum of the successful crossings) - (sum of the unsuccessful crossings), for that particular distance and velocity combination. These values are divided by the total number of successful creatures at a given CP to create the success ratio at that CP. The success ratio, when factored in with the creatures’ fear and desire values, determines whether or not the creature will attempt to cross the highway. Each KnB table starts off blank (i.e., with all entries equal to 0), then transfers over to the next population of creatures (repetition), then to a different traffic environment (defined by the parameter, Car Prob.) only if the parameter, KnB Transf. is set to “forward” or “backward” rather than “none”. If KnB Transf. is set to “forward”, the KnB table of each initial CP (i.e., set at initialization) is additionally transferred after the last repeat (30th in this case) from each lower density traffic environment to the next higher one. For example, (because the tested Car Prob. values are 0.1, 0.3, 0.5, 0.7, and 0.9), the KnB tables resulted from the 30th repeat with Car Prob. 0.1 are carried over to the start of 1st repeat in traffic environment with Car Prob. 0.3, and so on. An opposite transferring occurs if KnB Transf. is “backward”. For example, the KnB tables resulted from the 30th repeat traffic environment with Car Prob. 0.9 are carried over to the start of 1st repeat in traffic environment with Car Prob. 0.7, and so on.
3 Analysis of Bimodal Nature in the Number of Successful Creatures

Our interest is in better understanding the learning/transferring of the KnB over multiple populations, i.e. after every repetition. Data based on many configurations of parameters' values first have a number of the repeats resulting in low values for the number of successful creatures that eventually leads to having the rest of the repeats with high values. This reveals the process of creatures learning how to successfully cross the highway. The nature of this jump in the number of successful creatures is examined with focus on the factors that influence its occurrence and, if it occurs, the location (repetition number) at which it occurs.

The data is arranged in such a way that each row uniquely represents a configuration of the parameters (e.g., values of fear, desire, Car Prob., KnB Transf., Horiz. Cre., CP) with columns indicating the number of successful creatures at simulation end for each repetition. A configuration exhibiting a large jump in the number of successful creatures throughout its repetitions is defined as a bimodal case. A threshold value for the maximum of adjacent differences in successful creatures within a configuration determines if that configuration is a bimodal case. Specifically, if a configuration has a maximum adjacent difference in successful creatures of greater than this threshold value, this bimodal nature is flagged for that configuration. A plot of how influential is the choice in the threshold value is shown as Figure 1. Based on the analyses creating clustered histograms for these data (to be published elsewhere), a threshold value near 250 successful creatures appears appropriate. Multiple threshold values: 150, 200, 250, 300, and 350 are considered. From Figure 1, the determined bimodal cases do indeed vary slightly, however, not too much. Additionally, the general results concluded from this analysis are consisted with any of the five considered threshold values.

![Figure 1: A plot displaying the number of determined bimodal cases for different threshold values by different datasets. The sensitivity appears not too severe at the considered threshold values (dotted vertical lines).](image-url)

The main determinant of where the jump in successful creatures occurs is the Horiz. Cre. factor. Figure 2 illustrates this with frequency histograms as function of the repetition number, displaying where the jump in successful creatures is occurring. They are organized in table form, each based on the data filtered for different combinations of KnB Transf. and Car Prob. values. The darker shaded bars represent the data with Horiz. Cre. equal to 1 while the lighter shaded bars represent the data with...
Horiz. Cre. equal to 0. When the creatures are allowed to move to another CP, the jump in success occurs already after the first few repetitions, whereas the jump can occur at any repetition when the creatures are not allowed to change CP. Thus, the creatures are more quickly learning how to successfully cross the highway when the simulator allows them to change the CP.

Allowing for even more learning through continuing to transfer the KnB between different consecutive traffic environments generally reduces the number of bimodal cases (Figure 2). When the creatures are allowed to move to another CP, there is even more of a reduction in bimodal cases if the KnB is transferred (Figure 2).

**Figure 2:** Grouping of frequency histograms on the location of the jump in success under a threshold of 250 successful creatures by Car Prob. and KnB Transf. The darker bars represent the data with Horiz. Cre. equal to 1 (i.e., creatures can to move to another crossing point), while the lighter bars represent the data with Horiz. Cre. equal to 0 (i.e., creatures are not allowed to change the crossing point). The vertical black/grey lines represent the means.
4 Conclusions and Future Work

Our paper contributes to understanding the process of learning by observation, repetition and by using simple learning algorithms. This understanding is important for the development of small, simple autonomous robots, which have limited computational resources and have to learn a task by repeating it many times. We presented a model of simple cognitive agents learning to cross a highway, i.e. the agents learn their task of crossing the highway in a dynamically changing environment. The agents have the ability to learn from each other and have the capabilities to perceive, reason, and judge at a fairly minimal level. They use a simple decision making formula and build their KnB by observing the performance of the other agents. We investigate how the model’s many parameters and their interaction affect the agents’ learning outcomes with focus, here, on the effects of KnB transfer.

In our simulations we observe a number of the initial repeats with low values for the number of successful creatures at simulation end, leading to the rest of the repeats with high values. This bimodality in data means that, after a number of initial repeats, creatures learnt how to cross the highway successfully. Transferring of KnB after building it by many populations of creatures within the same highway traffic environment (i.e., with the same car density) to a highway traffic environment with a different car density enhances creatures’ ability to learn to cross successfully. We investigate how this bimodality/learning is affected by the model’s parameters. We present selected simulation results. More detailed analysis will be presented elsewhere.

References