When is Happy Hour: An Agent's Concept of Time

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Extended Abstract[1]

In *Artificial Life*, agent based modeling is a popular synthetic approach that often studies the evolutionary conditions responsible for adaptive group behavior. For example, emergent social phenomena such as communication and cooperation have been studied using agent models with a spatial distribution of agents and resources (Parisi, 1997), (Arita and Koyama, 1998). However, few studies have focused on the evolution of abstract concepts, such as a *concept of time*, that benefits individual and group behavior. In this study, agents attain a concept of time via learning to benefit from periodicity (cyclic resource growth) in the environment. Notable exceptions include the study of how memory extends an agents temporal horizon and increase its adaptability (Ching Ho et al., 2008). Nehaniv (1999) discusses the concept of narrative intelligence in temporally grounded agents. For example, the impact that stories of the past have upon an agent group's social behavior. In related work, Nehaniv et al. (2002) describe an information-theoretic model for individual and social learning in temporally grounded agents. The capacity to learn from environmental temporal patterns such as periodicity is beneficial to a broad spectrum of organisms, from Amoebae (Saigusa et al., 2008) to human civilizations (Hassan, 1997). This study investigates how an evolved sense of time can be used to adapt agent group behavior. The objective is to use a minimalist simulation model (with a spatial distribution of food and agents) to demonstrate that learning a concept of time facilitates efficient group foraging behavior. The concept of time is embedded into agent signals (indirectly indicating distances to food), and environmental behavior (*seasonal variations* define when food is scarce versus plentiful). Each agent is defined by a *local clock* (it's lifetime), and the environment by a *global clock* (oscillations of resource growth). The hypothesis is that resource growth cycles coupled with agent signaling about resource locations are sufficient conditions for agents to increase the efficiency of group foraging behavior. That is, agents adapt their behavior to exploit altruistic signals, learning when food is plentiful versus when it is not.

Figure 1 presents an example of the environment (left) and the agent *Artificial Neural Network* (ANN) controller (right). Controllers are adapted with an *Evolutionary Algorithm* (EA) that evolves connection weights. Agent fitness equals the food amount consumed during a lifetime. Agents consume U energy units for standing still, and $U + W$ energy units for moving. The EA selects for agent behaviors that stop and conserve energy when food is scarce, and behaviors that cause agents to move about foraging when food is plentiful. The environment is a two dimensional torus consisting of P evenly spaced food patches, governed by cyclic periods of food abundance (*summer*) and scarcity (*winter*). Each iteration, agents (speakers) emit a signal that conveys how many iterations in the past the speaker was on a food patch. From this, receivers (closest agents) learn that a food patch is Y grid spaces away in a given direction (agents receive signals from both directions).

To test the hypothesis that agent groups learn to use the concept of time, a comparative study was conducted. Experiments were executed where agent signalling was *switched on* and *switched off*. Results indicated that agents evolved a meaningful association between signals, cyclic resource growth, and foraging behavior. That is, agents interpret signals differently given different *seasons*, and adapt foraging behavior based on signals received. When there are few resources, agents signal that food has not been eaten (on average) in a long time. This causes agents to conserve energy by moving less. Where as, when resources are plentiful, agents signal that food has been eaten (on average) recently, causing agents to be less energy conservative.

Figure 2 depicts agent controller average hidden layer activation versus signal intensity in *winter* and *summer*. The broad spread of average internal state values is indicative of frequent agent activity in the summer (figure 2, *second figure*). Where as, the relatively compact clustering of average internal state values is indicative of infrequent agent activity in the winter (figure 2, *first figure*). Therefore, this signalling behavior indicates that agents effectively adapt their behavior to the environment's seasonal variation. In simulations without signalling, this disparity in average signal intensity and internal state values is not observed (figure 2, *third* and *fourth figures*). That is, approximate uniformity in the spread of activation values in winter and summer indicate that agents do not adapt their behavior to seasonal variation. Thus, in simulations including the concept of

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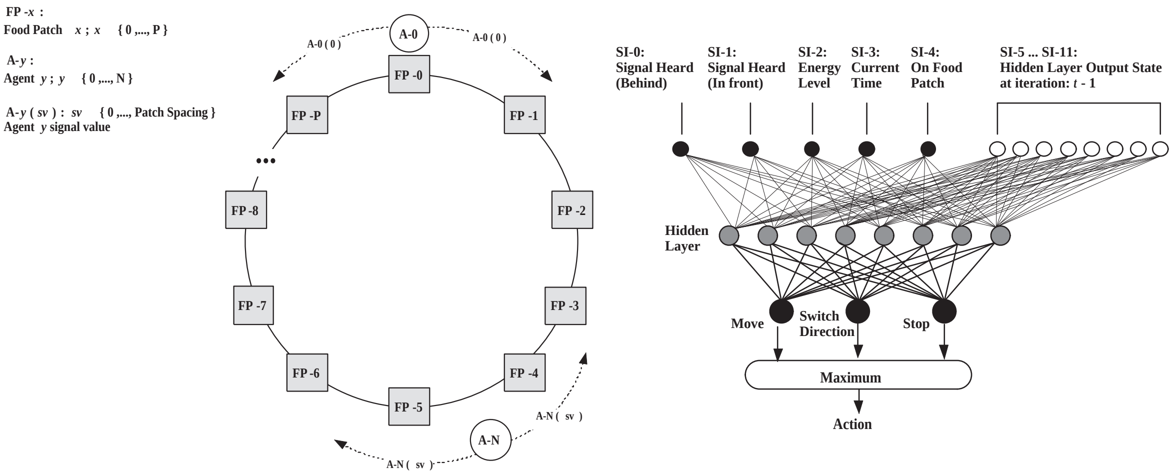

Figure 1: *Ring World Environment (Left):* There are *P*, evenly spaced food patches, and *N* agents. Each iteration, agents emit signals indicating the time (number of iterations) since they were last on a food patch. Signals are broadcast in both directions, at a fixed number of grid spaces. *Right:* Agent controller is a recurrent feed-forward neural network. *SI:* Sensory Input.

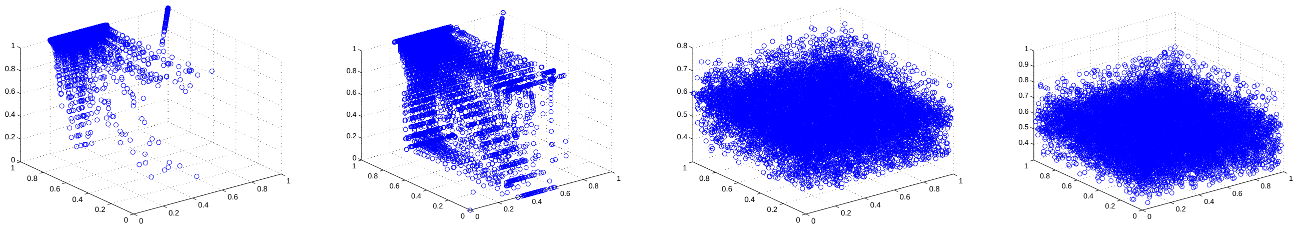

Figure 2: *Internal State of Fittest Agent with (first two plots), without signaling (last two plots):* Average activation values plotted against signal values at generation 500. Average internal controller state is mapped for periods of food *scarcity* (left, both plots) and *abundance* (right, both plots). These periods are known as *winter* and *summer*, respectively.

time (signalling and cyclic resource growth), agents use signals sent under different environmental conditions in order to adapt foraging behavior and attain a higher fitness (compared to simulations where agents do not employ the concept of time).

It is important to note that the concept of time developed in this simulation is different from our notion of time. Thus, future work will investigate defining internal state mechanisms that indicate if agents have acquired a concept of time analogous to our own. Furthermore, we will examine interactions between agents' *local clocks* (for example, each agent's notion of when different seasons occur), and the environment's *global clock* (defining the periodicity of seasons), and if the synchronization of local and global clocks facilitates beneficial adaptive behavior in agent groups.

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