An Agent-Based Predator-Prey Model with Reinforcement Learning

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In population dynamics we generally analyze either how a single population changes over time, or how two populations interact and influence their population sizes over time. Population dynamics are studied using a wide variety of computational models, from differential equations such as Lotka-Volterra, to individual-based models such as either cellular automata or agent-based models (ABM).

Agent-based simulations allow the agents to learn from their experiences, and adapt their behaviors so they are better suited to their environment. With that level of flexibility, agent-based modeling allows for a variety of discipline applications. From modeling insect behavior (Luke, 2005) to modeling the fall of ancient civilizations (Kohler et al, 2005), agent-based modeling brings understanding and clarity to complex natural interactions by allowing them to develop through the individuals. This individual development can provide added realism over other modeling approaches.

We explore the evolution of agents in a predator-prey system. Although ABM has been used in population dynamics previously, the agents rarely learn from their experiences. We study population dynamics with evolution, where agents in both the predator and prey populations learn from their experiences in the environment. Our agents learn through TD-learning, a type of reinforcement learning.

Reinforcement Learning (RL) is a machine learning technique based on the psychological area of study of the same name. It is very similar in premise: the desired behaviors are rewarded, whereas the undesirable behaviors are either ignored or punished. An RL-agent has a goal state that it is trying to reach. After attempting some action, the agent will receive a value or level of reward or punishment (negative reward). The agent tries to maximize the sum of these reinforcement values from the initial state until its end state. The mapping from state or action to value allows for reinforcement of certain actions over others, until the agent learns the desired behavior.

We analyze our agent-based learning model of predator and prey in three scenarios: only the prey learn, only the predators learn, and both species learn. In addition to prey and predator we also have a non-evolving food source. The food source can be removed from the grid by prey and replenishes slowly over time. Agents move by biased random movement in their Moore neighborhood, and update their probability of movement based on the reinforcement from their previous action. Agents pass their learned biases to the new generation. Our results show that in all three cases each species is able to evolve to show increases in the expected behavior. We observe the expected chasing patterns of predator-prey in visualization, and movement learning on the agent level: prey learn to avoid predators, and predators learn to chase prey through rewards. With the introduction of food growing in clusters instead of randomly, prey learn to stay in the food areas unless threatened by a predator. We also observed the highest learning rate (70.8%) occurring when a species' population was at its highest level, and the lowest learning rate (<1%) when a species' population was at its lowest level.

The results of our work indicate that reinforcement learning can be beneficial in population dynamics models to increase the realism of the model. We show through our framework how to successfully use TD-learning for agent-based simulations in which agents must learn how to move in their world without moving toward a specific goal location. We are unaware of any other research resulting in an agent-based population dynamics model using TD-learning in which the agents are learning general movement strategies in response to actions taken by competitor agents. We propose that this framework can be incorporated into other agent-based models in which learned movement habits are desired.

References

Luke, S., Cioffi-Revilla, C., Panait, L., Sullivan, K., Balan, G. (2005). MASON: A Multi-Agent Simulation Environment. Simulation: Transactions of the society for Modeling and Simulation International. 82(7), 517-527.

Kohler TA, Gumerman GJ and Reynolds RG (2005). Simulating ancient societies. Scientific American. 293(1): 77–84.