Week 6: Intelligent Agents

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# Intelligent Agents

The North American electrical network is the world’s most massive machine, spanning across the continent (Wildberger, 1996). Making predictions across this example system is exceptionally complex due to the variability and inter-relationship of black box decisions. Traditionally, physicists and statisticians approach these issues with very sophisticated equations that seek to model the problem domain. However, those methods are challenging to scale, expensive to operate, and updates require expertise. In contrast, businesses desire elegant solutions that promote agility through experimentation with low entry barriers and minimal economic overhead. Meeting those expectations requires a different paradigm for simulating the environment.

# Definitions and Terminologies

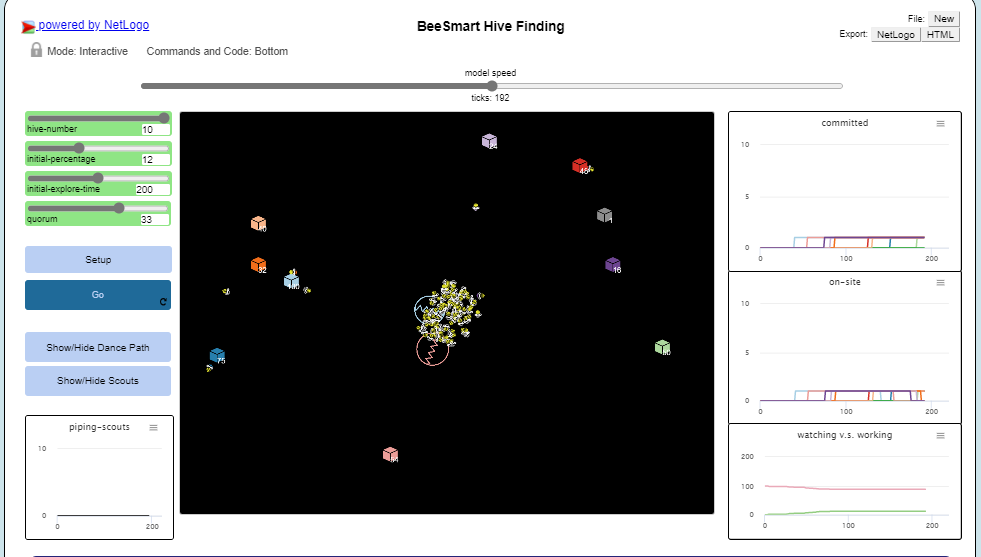
Engineers consistently find that maintaining monolithic technologies requires substantial overhead. Alternatively, using microsystem architectures enables them to build and replace components rapidly in isolation. A similar idea exists with simulations with a decomposition of the environment into multiple intelligent agents (see Table 1).

Table 1: Principal Components

|  |  |
| --- | --- |
| Aspect | Definition |
| Intelligence | The ability to reason about a problem |
| Simulation | An experiment that produces a statistical model |
| Environment | The universe contains the agents |
| Agent | An automaton that follows a predefined script |
| Objective | The goal of the agent |
| Tasks | The steps necessary to complete the objective |
| Notification | A collaborative or competing message between agents |
| Swarm | A group of agents |
| Choice | The random decision of an agent within its action space |
| Aggregate Choice | The net effect of multiple independent agent decisions |

A simulation experiment first identifies the environment, participants, and one or more objectives. Each participant, called an agent, attempts to complete its objective under a set of guiding rules and principles. For instance, NetLogo’s BeeSmart environment contains multiple bees that attempt to maximize food production from various honey pots within a given scene (Wilensky, 2014). Initially, the swarm fumbles around until discovering a couple of locations. After some time, the colony will divide across multiple honey pots and compare site values with neighboring peers. Eventually, the bees converge to the optimal configuration that provides the maximum food for the hive.

Figure 1: BeeSmart Simulation (Wilensky, 2014)



While no individual agent understands the ideal distribution across the environment, the aggregate of independent decisions enables analysts to extract sophisticated observations about the broader objectives. It is also possible to quickly expand upon this simulation by designing expert agents, such as communication specialists, to propagate messages twice as fast. After defining the role and its local rules, the existing simulation can immediately incorporate those customizations.

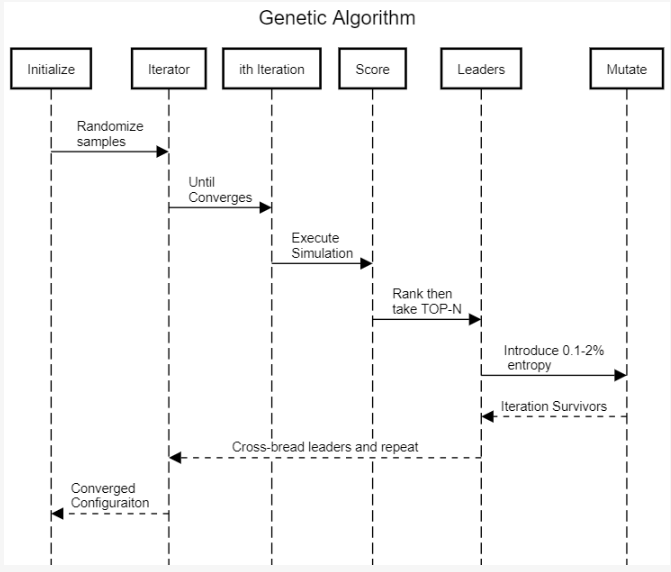
# Theoretical and Practical Perspectives

In addition to executing rapid experimentation at scale, organizations require algorithms that enable their agents to evolve. Traditionally evolutionary computation leverages Genetic Algorithms (GA) and Cellular Automata (CA) (Keller et al., 2016; Wildberger, 1996). Others have extended these strategies, such as Multi-Level Agent-Based Modeling (ML-ABM), to create more adaptive simulations (Hijorth et al., 2020).

## Genetic Algorithms (GA)

The Traveling Salesman is a classical graph puzzle the attempts to find the most efficient route through N-cities. Even with ubiquitous access to cloud computing, enumerating through an exhaustive search is not practical due to the combinations growing at (Keller et al., 2016). As the simulation continues to scale-out, it requires a mechanism to prune that search space and quickly discover the optimal answers. The Theory of Evolution states that biology weeds out inferior strains through the Natural Selection Process (Darwin, 1859). Computers can replicate this model through Genetic Algorithms to converge on optimal configurations (see Figure 2).

Figure 2: Genetic Algorithm



The solution begins by modeling a potential answer as a vector of classification features. First, hundreds to thousands of randomly initialized instances run through the simulation to compute a per-instance score. Then a TOP-N ranking keeps the best instances and discards any other instances. Next, a cross-breeding and mutation process mixes features from winning combinations to produce the offspring. Those offspring cycle through this system thousands of times until only superior specimens remain.

## Cellular Automata (CA)

## Multi-Level Agent-Based Modeling (ML-ABM)