Slime Mould inspired Neuroevolution

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01 Intelligence: Slime Moulds

Previously part of the kingdom of Fungi, Slime moulds refer to a group of unrelated single-cell eukaryotic entities in the mycetozoan group of the amoebozoa [6]. **To understand how slime moulds relate to AI, understanding the slime mould plasmodial state is paramount.**

In their plasma state, they demonstrate **innate intelligence when foraging for food**. An example is Atsushi Tero et al., who ran an experiment in which slime moulds designed transport networks for Japan. They achieved this by placing food sources in a petri dish corresponding to where the major cities are situated in Japan. Next, Physarum polycephalum, a slime mould, was placed where the capital Tokyo would logically exist. Once the slime mould had stabilised, the research team was left with a vein network that resembled that of the Japan railroad [8]. This experiment was repeated using other countries' layouts, and the **slime moulds managed to rival the logistic networks designed by humans[1].**

Another surprising ability is a slime mould's ability to share knowledge. This ability was discovered in an experiment where a slime mould was split and distributed throughout a maze, where the slime moulds met. They shared the knowledge of areas already searched[4]. **This ability to search for optimal solutions and share knowledge leads to their use in AI.**

02 Reinforcement Learning

Search algorithms provide a powerful tool for solving problems within AI[2].For example, training neural networks. To train neural networks, a search for optimal network weights is required. Usually, this search is gradient descent, but **any meta-heuristic search would work similarly due to the No-Free Lunch Theorem[9].**

Another area of AI where search algorithms are crucial is Reinforcement Learning (RL). RL requires a search algorithm to find a policy, a "rulebook", on how an agent should interact with an environment to achieve a goal[5]. To optimise the agent's policy, its actions must be optimised. **A biologically inspired algorithm for this optimisation process is NEAT (NeuroEvolution of Augmenting Topologies).**

NEAT is based on evolution and uses two genetic operations, crossover and mutation. In mutation, the structure of a neural network is modified. Whereas in the crossover operation, genetic material between neural networks is shared. Through survival of the fittest, networks which are more effective at solving an agent's policy propagate[7]. **NEAT can be combined with slime mould movement to create a new way to find near-optimal policies.**

03 Combine: The Technique

In a paper by Li et al., a model for the movement of a slime mould called **"Slime Mould Algorithm (SMA)" was proposed[3]. This algorithm can be married to NEAT, which produces a neuroevolution technique inspired by slime moulds.** As described by SMA, the model moves a slime model through equations that model the oscillation and approaching food of slime moulds[3]. The movement within a plane is then expanded by adding or removing planes of movement. Because the slime mould's position represents a neural network, the planal movement changes the weights and biases, and the planal shifts represent the adding or removing nodes and connections within the neural network. **This movement provides a substitute for NEAT's mutation operation as well as part of the crossover function.**

Furthermore, slime moulds can share knowledge with their neighbours. **Slime moulds can therefore help one another find the ideal neural network and is the other half of modelling NEAT's crossover function**.

This movement creates a neural network that acts as our near-optimal policy for reinforcement learning to evolve.

This gives us a technique which then can be used to **solve problems in an AI** environment similar to NEAT.

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