Exploration and exploitation of the adjacent possible space for open-endedness

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Introduction

Understanding the mechanisms that create open-ended evolution is considered a grand challenge and a key task in the field of artificial life (Bedau et al., 2000). The source of creating open-endedness is the continuous creation of novel forms. Novel forms are created and evolve as they gain population - understanding this mechanism is key to understanding open-ended evolution. In several models of artificial life, "novelty" has been considered a mutation and has often been assumed to occur randomly. However, recent studies have proposed a model in which novelty does not occur randomly, but rather toward adjacent possible spaces (Tria et al., 2014). The effectiveness of the model is confirmed by the fact that the model simulates the behavior of people with a high degree of accuracy when compared to empirical data constituted from behavioral data on the Internet. The model reveals that the balance between exploration, exploitation, and the search strategy for possible adjacent spaces determines how the network grows.

In this study, we use this agent-based model to analyze how network characteristics differ depending on exploration, exploitation, as well as the search strategy for possible adjacent spaces. The objective is to identify the interactions between nodes that are necessary for the novelty to gain attention and population when they are added to the network.

Agent-based model based on adjacent possible

The idea of *Adjacent Possible* was originally theorized by Stuart Kauffman to explain the evolution of molecules and organisms (Kauffman, 1993). Adjacent possible space refers to the space of possibilities that are one step away from what actually exists and will become reality in the near future. A similar concept can be found in the protein space theory proposed in Smith (1970). The protein space theory argues that gene evolution occurs through the accumulation of minute changes in existing genes and the changes must occur under the restriction that genes can form phenotypes. Kauffman extended and generalized this theory to apply not only to the evolution of genes but also to the evolution of human relationships and many other areas.

Ubaldi et al. (2021) extended Polya's urn model, which incorporates the concept of an adjacency possible space, to an agent-based model to generate a social network. The model generates a network in which agents interact based on two parameters, ρ and ν, and a strategy s, where ρ determines the strength of exploitation, ν determines the strength of exploration, and s is a strategy for exploring Adjacent Possible space.

Each agent has its own urn and is assigned an ID. We select one agent from the environment according to the size of the agent's urn. This agent is the starting point of the interaction, the *caller agent*. Next, one agent (the *called agent*) is drawn from the caller agent's urn to be the interaction partner, and the caller agent's ID is added to the called agent's urn by ρ. This operation gives the model the property of preferential attachment. ρ indicates the strength of exploitation, as it increases the probability of interacting again with a partner with whom one has already interacted.

Next, $\nu + 1$ number of agents are selected from the caller agent's urn according to strategy s and added to the called agent's urn. The operation is performed for called agents. The task of selecting $\nu + 1$ agents from the opponent's agent implies a search for possible adjacent spaces. ν indicates the strength of exploration. How $\nu + 1$ number of agents are selected from the interacting partner agents is defined by the strategy s. Various strategies can be specified, such as selecting randomly (s = *RND*), selecting randomly according to population (s = *WSW*) or exchanging the most recently interacted agents (s = *SSW* or *ASW*). See the original paper for details on the model (Ubaldi et al., 2021).

It has been reported that this model can reproduce real-world data with high accuracy when the parameters are set appropriately. For example, the Twitter mention network has $\rho = 5$, $\nu = 5$ and strategy $s = WSW$ can successfully reproduce its dynamics. Similarly, the American physical society co-authorship network has $\rho = 6$, $\nu = 15$ and strategy $s = SSW$. The mobile phone network has $\rho = 21$, $\nu = 7$ and strategy $s = ASW$.

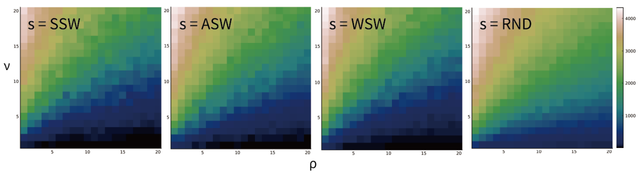

Figure 1: Network size according to different ρ, ν and strategy s.

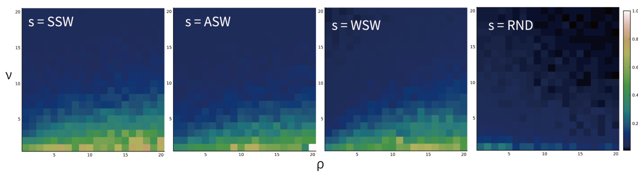

Figure 2: Network cluster according to different ρ, ν and strategy s.

Experiment

We simulated the agent-based model described above and analyzed how the network changes when ρ, ν, and strategy s are changed.

Figure 1 shows the results of how the network size changes. Here, SSW, ASW is the strategy of exchanging the most recently interacted agents, WSW is the strategy of randomly selecting weights on previously chosen agents, *RND* is the strategy of exchanging agents completely at random. If $R = \rho/\nu$, we observe the property that the smaller R is, the larger the size of the network. Observing by strategy, *RND* tends to increase the size of the network compared to other strategies.

Figure 2 shows how the cluster coefficients change. It is observed that the cluster coefficients also correlate with R similar to the network size, but the correlation seems to be smaller. It is also observed that the cluster coefficients in strategy *RND* are very small.

The higher the number of agents randomly selected from the possible adjacency space, the higher the probability of selecting previously less selected agents. Thereby, the network size increases because it acquires many nodes with a small number of edges and the cluster coefficients become smaller. Given open-ended evolution, it is suggested that the value of exploration (ν) is greater than the value of exploitation (ρ) and that randomly selecting agents from the adjacency possible space is important.

Next, with ρ and ν fixed at constant values, we analyzed how the frequency of selection of new nodes (novelty) as they appear differs for different strategies. Figure 3 shows the results for different strategies (*ASW*, *SSW*, *WWS*, *RND*) in the Twitter mentions network ($\rho = 5, \nu = 5$). The selection count of nodes, born at the time signified by the x-axis, is selected at the time on the y-axis. A brighter color indicates a higher selection count. In the figure, a blank space

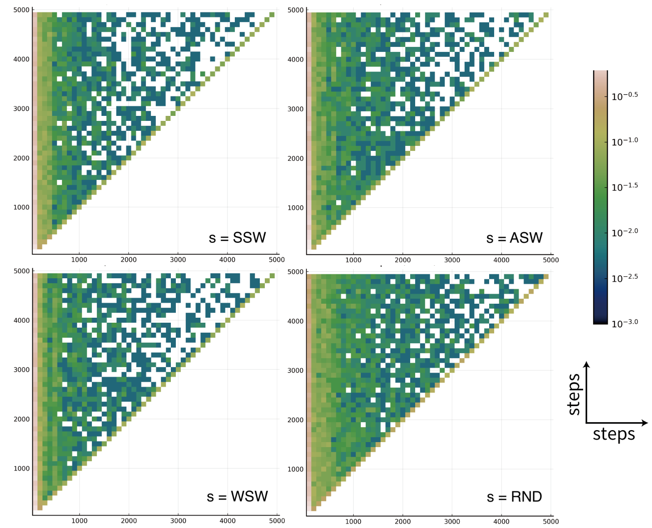

Figure 3: Selection count of nodes, born at the time signified by the x-axis, selected at the time on the y-axis. A brighter color indicates a higher selection count. Twitter mention network ($\rho = 5, \nu = 5$) with four different strategies.

indicates a zero selection. The entire trend is that nodes that have been present since the early steps of network growth are selected more frequently, indicating preferential selection. Compared to *WWS* and *RND*, *ASW* and *SSW* have a stronger preferential attachment effect, and it can be observed that the newer the node is, the less often it is selected. The result that randomly selecting agents to recommend interaction partners contributes to network development is interesting because it is the antithesis of the common social networking service recommendation system, which tends to recommend well-known users.

Conclusion

In this study, we analyzed the nature of interactions to achieve an open-ended network using an agent-based model that incorporates the concept of Adjacency Possible space. The results show that in terms of open-ended evolution, the value of exploration is greater than exploitation and that the more random the search for possible adjacent spaces, the more likely new nodes will be accessed.

It was assumed that all the nodes take the same strategy; however, this is unrealistic. It is common for users to have different ideas about who to recommend to other users. In our future work, we will explore how the obtained population differs when each node has a different strategy, and what kind of network growth will be observed when each node evolves its strategy when obtaining the population.

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