

Evolvability of Minimally Cognitive Agents

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Extended Abstract

This work investigates evolvability of continuous-time recurrent neural networks to support the behavior of model-agents subject to fitness criteria that changes over the evolutionary timescale. A population of agents is alternately evolved to perform two tasks with inverted fitness awards. Evidence of evolvability is reported; it is shown that the population locates a region of "meta-fitness" in the landscape in which sub-regions of optimality for each task are easily accessible from one another.

This work investigates evolvability of continuous-time recurrent neural networks (CTRNN) to support the behavior of model-agents subject to fitness criteria that changes over the evolutionary timescale. In this way, two broad thrusts of interest in recent computational approaches to artificial life and cognitive science are synthesized. On the one hand, evolvability is a hot topic of interest in and of itself – what kinds of developmental and phenotypic characteristics enable organisms to successfully adapt to changing environments? This question was raised by Richard Dawkins (1989), and has since received attention in paradigms ranging from binary circuits, discrete-time feed forward neural networks and toy developmental scenarios (Kasthan and Alon, 2005; Kovitz, 2015).

On the other hand there is work motivated by the joint perspectives of situated and embodied cognition, in which CTRNNs are embedded in agents with basic sensory-motor capacities. These agents are themselves embedded into dynamical environments, and genetic algorithms are used to evolve their nervous systems for *minimally cognitive behavior*, a term borrowed from Randall Beer to indicate “the simplest behavior that raises issues of genuine cognitive interest” (Beer, 1996). This methodology facilitates an investigation of cognition as it manifests in adaptive behavior occurring in dynamically coupled brain-body-environment systems. Furthermore, using stochastic search methods to configure nervous systems supporting cognitively interesting behaviors minimizes *a priori* assumptions about the kinds of cognitive and representational capacities an agent needs to support said behaviors.

More specifically, this work is inspired by two projects on either side of the aforementioned motivational fault line. Kasthan and Alon (2005) demonstrated that evolvability (via modularity) can be achieved in a connectionist network by alternately evolving it to perform two separate but related

tasks over many epochs. Their work was conducted with feed forward binary networks evolved to perform discrete logical operations and association tasks. Motivated by the joint perspectives of embodied and situated cognition, we apply a similar methodology to a model-agent controlled by a CTRNN. Here the different tasks correspond to cognitively interesting behaviors carried out in a dynamical environment.

This evolvability study extends an object discrimination task first developed by Beer (1996), in which an agent with an array of distal sensors is required to distinguish circles from lines – moving towards the former and away from the latter in a simulated 2D environment. As in previous work (Beer, 1996), fitness is assigned on a scale of 0-100%, where 50% corresponds to a random solution and 100% is assigned to an optimal solution. Here, a population is evolved to perform this task (Task A) until the best individual reaches a fitness threshold of 80%, at which point the fitness criteria is reversed so that agents have to move towards lines and avoid circles (Task B); these fitness reversals will henceforth be called *swaps*. Note that Task A and Task B are mutually exclusive - an agent with high fitness for one of them has proportionately low fitness for the other. The population is evolved in this alternating fashion, which we refer to as *evolutionary swapping*, for 2500 generations.

To benchmark success of evolutionary swapping, both tasks were first evolved for in isolation. For each task, 20 evolutionary runs were performed over 500 generations with a population of 240. Across all 20 runs, the average value for the fitness of the best individual was 79.1% in Task A and 70% in Task B, suggesting that Task B is more difficult than Task A. More importantly, this indicates that the 80% threshold used in our swapping paradigm is non-trivial - in 500 generations only 8 of 20 runs in Task A produced agents exceeding this threshold, while no agents reached 80% fitness on Task B. In line with this, out of 20 evolutionary swapping runs, only 8 achieved one or more swaps. This is not so surprising, as the first swap corresponds to achieving 80% on Task A given a random starting population, which we know is not guaranteed to occur.

While there is not enough positive data to say that in general the swapping methodology makes it easier to reach the fitness threshold, particular swapping runs do show clear evidence of evolvability. Figure 1 shows the fitness trajectory for one such run. This trajectory is best characterized as periods of ascent up a fitness gradient up to a peak, at which point fitness suddenly

drops off. Peaks correspond to the fitness threshold (indicated by the dotted black line) being reached; the subsequent drop-offs are a result of task swapping - recall that fitness measures of each task are inversions of one another, so we should expect a population with high fitness with respect to one task to have a sudden drop in fitness when tasks are swapped. 12 swaps were achieved (marked by dotted red lines), the first 4 are labeled for the sake of discussion.

The horizontal distance between successive swaps corresponds to the number of generations taken to reach the fitness threshold for one of the tasks starting with the population of the previous swap (i.e. of the opposite task); this will henceforth be called the *swapping interval*. To the extent that evolvability is achieved in this paradigm, the swapping interval should be less than the number of generations it takes to reach 80% when either task is evolved for in isolation. We would also expect swapping intervals to generally decrease over the course of a run. Both of these properties are demonstrated in Figure 1. Starting from a random population, 80% fitness with respect to Task A is reached after 245 generations (*A1*). It then takes 1408 generations to achieve 80% fitness on Task B (*B1*), followed by a 198-generation swapping interval for the second evolution on Task A (*A2*), and then a 45-generation swapping interval for the second evolution on Task B (*B2*). The average swapping interval for the 8 remaining swaps is about 73 generations. That these short swapping intervals occur successively marks a huge improvement over evolving for either task in isolation, where for the most part the 80% threshold is not achievable in 500 generations.

How did such a dramatic increase in evolutionary efficiency occur? One possibility is that a highly diffuse population, which simultaneously contains high fitness individuals for both tasks is generated. This would result in small swapping intervals during which the population could remain relatively static. Alternatively, it could be that the population locates an area of “meta-fitness” in the landscape, in which sub-regions of optimality for each task are easily accessible from one another. This would allow for the population to cluster around a region of optimality for a given task and then quickly transition to a region of optimality for the other task in the following swapping interval. These two explanations are not mutually exclusive, but it is useful to differentiate between them, as one could be more at play than the other.

To help answer this question, principal component analysis (PCA) was performed on the 47-dimensional set of all genotypes in populations at *A1*, *B1*, *A2* and *B2*. Figure 2A shows these populations in a reduced 2D space. The first thing to notice is that populations at each swap are clustered around roughly distinct regions of parameter space (*A2* and *B2* appear to be overlaid but on closer examination it becomes evident that they are clustered in distinct regions, see Figure 2B). This provides support for the second explanation, that the population as a whole is moving through parameter space during swapping intervals, as opposed to a static and highly diffuse population. Furthermore, the proximity of the population clusters to one another sheds light on the swapping intervals displayed in Figure 1. The long duration of *A1*-*B1* corresponds to a large distance in parameter space separating *A1* and *B1*, while the relatively close proximity of *B1* to *A2* is consistent with the short evolutionary duration of *B1*-*A2* necessary to make such a transition in parameter space. Following in this manner, *A2* and

B2, which have the shortest reported swapping interval, also appear to be closest in parameter space.

Thus it appears that the search found a region of meta-fitness in the landscape, in which sub-regions of optimality for either task exist closely to one another. Presumably the close proximity between these sub-regions translates to important structural relations between agents with high fitness on either task. Identifying what these relations are, and investigating how they underpin the dynamical behaviors conducive to success in each task constitutes promising work for the future.

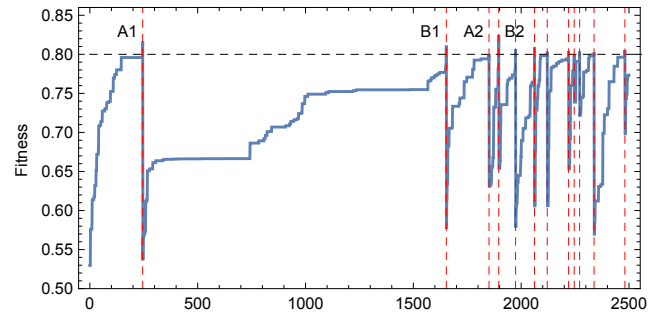


Figure 1: Evolutionary swapping run. Red-dotted vertical lines mark task swaps, the black-dotted horizontal line represents the 80% fitness threshold. The first 4 task swaps are successively labeled *A1*, *B1*, *A2* and *B2*.

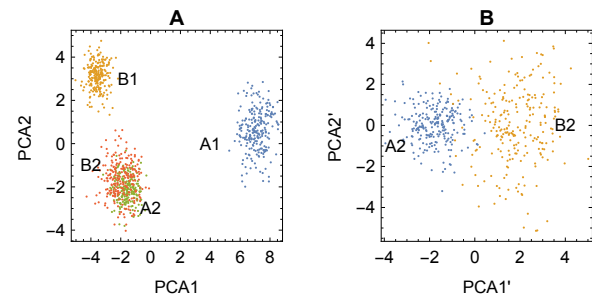


Figure 2: Populations at task swaps projected onto reduced 2D spaces. Figure 2A depicts populations of *A1* (blue), *B1* (yellow), *A2* (green) and *B2* (red) in a 2D space obtained by from a PCA on their union. Figure 2B depicts *A2* (blue) and *B2* (yellow) in a separate 2D space, obtained from a PCA on their union.

References

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