Examining the Stroop Effect Using a Develomental Spatial Neuroevolution System

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ABSTRACT

We present a novel approach to the study of cognitive abilities by using evolutionary computation. To this end we use a spatial, developmental, neuroevolution system presented here for the first time. We use our system to evolve ANNs to perform simple abstractions of cognitive tasks such as size perception, counting color identification and reading. We define these tasks to explore hypotheses about the evolution of counting and the the nature of the Stroop effect. Our results show the versatility of our evolutionary system. We show that we can evolve it to perform a variety of cognitive tasks, and also that evolved networks exhibit interference behavior when dealing with multiple tasks and incongruent data.

Categories and Subject Descriptors

I.2.0 [**Artificial Intelligence**]: General—*cognitive simulation*; I.2.6 [**Artificial Intelligence**]: Learning—*connectionism and neural nets*

Keywords

Evolutionary Algorithm; Developmental EA; Neuroevolution; Cognitive Simulation

1. INTRODUCTION

A major goal of cognitive science research is understanding how the brain works to create the human mind. To this end researchers use a variety of methods and tools. These include experiments on human subjects, the use of neuroimaging to directly observe human brain activity while performing cognitive tasks, and creation of computer models to explain cognitive phenomena [2].

In this work we present a new approach to the study of cognitive phenomena. We employ an *Evolutionary Algorithm* (EA) on populations of randomly generated *Artificial Neural Networks* (ANNs) in order to evolve them to perform cognitive tasks without directly designing them to fit a given theory. This allows us to explore the specific conditions under which certain phenomena may occur.

In this work we focus on Stroop Effect [4]. It describes the delay identifying the color of a word in the presence of conflicting information (e.g. it takes longer to identify blue color of the word *GREEN* written in blue than it does if with either *BLUE* in blue or *XXXX* in blue). This effect has been one of the most thoroughly researched effects in the field of Psychology for decades and no list of citations can do it justice. Since we just touch on it in this research we will not attempt to do it justice. A comprehensive, if somewhat outdated, review of this the research into this effect was presented by MacLeod [3].

2. THE SYSTEM

We design our evolutionary system with an eye towards nature. We focus on three important traits which we integrate as design features. Our system is ANN based, developmental, and spatial. We chose neuroevolution because the artificial neuron is an abstraction of the biological neuron (though the two are by no means identical). A individual's gene does not map directly to a specific simple element in the final network. Rather, it acts as an instruction to be performed by the neurons in the developing network during its development. Every artificial neuron in our system is located in some point in a virtual space and all actions are location based.

The ANNs in our system consist of three distinct layers: input, output, and hidden. Each one of the layers exists in its own space defined by the user. The user defines the number of dimensions each layer has and the size of each dimension. Our genome is encoded as a linear array of genome atoms (or genes). Each gene is a set of numbers that specify a developmental step. The user controls the attributes of the ANN and the evolutionary algorithm with run parameters.

We used single-point crossover that allows genome size to change by picking crossover location to each parent separately. Mutation is uniform. When a spot in the genome then either the atom itself is randomly changed or a small genome segment beginning with the chosen atom is copied to another random location in the genome. In our runs below we used a mutation rate of 0.02, and a crossover rate of 0.8. Our system uses standard tournament selection that we used with tournament size of 3.

We used a diversity maintenance measure that limits the number of individuals with similar behavior profiles (for brevity we will not explain these profiles here). Our diversity maintenance system allows an individual to be selected only if the number of its neighbors already selected is lower than a 20 (this parameter is tunable by the user). In the runs below the input grid was of size $4 \times 5 \times 5$ the output grid was of size 4×5 and the hidden network grid was of size $8 \times 10 \times 10$. We set the limit on the number of hidden layer neurons and of network links to 400 and 4000, respectively.

Our system supports multiple encoding schemes. There are several different types of actions that a gene can cause. The probability of a gene encoding a certain action is controlled by the user, who chooses how much weight to assign to each of the possible gene

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types. Gene types include genes for adding new neurons, genes for splitting existing neurons, genes connecting neurons with links etc.

The tasks we examine here are classification tasks where the ANN is expected to tell a number of different classes apart. The output is 2-dimensional, and each row stands for one of the possible classes. Decision is made by plurality rule. Our convention is that the first row stand for *red*, the second stands for *green*, the third stands for *blue* and the forth is reserved future use.

We see the 3-dimensional input grid as made up of 4 2-dimensional grids: 3 colored "visual field" boards (*red*, *green* and *blue*) and 1 "task definition" grid which is used to differentiate between different tasks. In order to evaluate evolved individuals we tested their performance on test-cases after the runs, and return the rate in which they return correct outputs (we call this a benchmark score and we normalize it to the [0,1000] range).

Our first task is the Color Perception task (or *CP*). In the CP task we expect the forth grid of the input to contain all -1. Our second task is the Color Reading task (or *CR*). In this task the ANNs are required to read a colored symbol in the input. In the CR task we expect the forth grid of the input to contain all 1. Notice that a symbol can be written in the color it stands for. The kind of inputs where the symbol and color match are called *Congruent* and kind of inputs where they do not are called *Incongruent*.

3. EXPERIMENTS

We present three experiments. In each experiment we ran the same simulation 50 times in order to get sufficient data. Each 50 simulation experiment set took at most about a day.

In Experiment 1 we tested our system on the CP task. We used a population of 300 individuals, running for 400 generations. We calculated the fitness score and the benchmark score with 4 symbols in all 3 base colors (a total of 12 inputs). In this experiment we tested the best individual every 100 generations and not just at the end. After 100 generations the best benchmark score in 48 out of the 50 simulations was already a perfect 1000. Though further analysis of this run may seem redundant at this point by turning to another datum we find that the runs keep improving in a meaningful way. We wish to focus on is the margin by which the correct answer wins over the incorrect answer that is second in the plurality vote. After 100 generations the mean value of this margin is 2.1375 (SD 0.5268), after 200 generations it is 4.1861 (SD 0.8335), after 300 generations it is 4.416 (SD 0.7512) and after 400 generations it is 4.5193 (SD 0.7094).

In Experiment 2 we tested our system on the CR task. We used a population of 500 individuals, running for 750 generations. We calculated the fitness score and the benchmark score with 3 symbols in that stand for the three base colors in the 3 base colors as well as the 4 possible combination colors (a total of 21 inputs). In this experiment we tested the best individual every 250 generations. After 250 generations the best solution in a simulation had a mean benchmark score of 850.4732 (SD 98.0602). After 500 generations the best solution in a simulation had a mean benchmark score of 877.1404 (SD 97.1681). After 750 generations the best solution in a simulation had a mean benchmark score of 885.712 (SD 97.5919591). We look again at the margin by which the correct answer wins the plurality vote. After 250 generations the mean value of this margin is 2.3164 (SD 0.4376), after 500 generations it is 2.6382 (SD 0.4761) and after 750 generations it is 2.7482 (SD 0.5987).

In Experiment 3 we try to create an effect analogous to the Stroop effect. We focus on a striking characteristics of the Stroop effect, namely the difference between and *Congruent* (e.g. the word *RED* in red) and Incongruent (e.g. the word *RED* written in blue color) trials. Typically, congruent trials are easier for people, and they perform them more quickly and (when manipulated to answer fast) more accurately. We used a population of 300 individuals, running for 300 generations. We calculated the fitness score and the benchmark score using the 33 test inputs from the previous experiments. After the runs terminated, we checked the best individuals on congruent and incongruent inputs separately in both tasks.

Looking at congruent inputs the best solution in a simulation had a mean benchmark score of 853.331 (SD 201.7724) in the CP task. Looking at incongruent inputs the best solution in a simulation had a mean benchmark score of 699.9968 (SD 191.4858) in the CP task. The difference is significant ($p < 0.001$). Looking at congruent inputs the best solution in a simulation had a mean benchmark score of 826.6642 (SD 223.5097) in the CR task. Looking at incongruent inputs the best solution in a simulation had a mean benchmark score of 453.3306 (SD 133.4997) in the CR task. The difference is significant ($p < 10^{-15}$).

4. CONCLUSIONS

We presented a new developmental spatial neuroevolution system for cognitive science research. Our system employs various measures to make developmental process more like natural development. We tested our system in the domains of Color Perception and Color Reading. We explored the Stroop effect, and we successfully replicated, in our evolved networks, the phenomenon interference due to conflict between information from two aspects. We also succeeded in establishing that this conflict can be directional. There is still some work required to create a better approximation of the Stroop effect, and we expect that exploring the conditions that will lead to such an approximation may give us better insight into the way such an effect comes to be.

We plan to expand our system further and try to use it to find a way of evolving a pattern more similar to the Stroop effect as it manifests in humans. Later, following work by Dadon et. al [1] we plan to test in more depth the effect of short exposure times on the Stroop effect.

Our system itself is still a work in progress, and we want to expand it and use it to look into some new areas and add more functionality in order to explore more complex behavior. An obvious extension would be to allow for the evolution of recurrent networks for domains with multiple where the network must react according to new input as well as its own output (e.g. navigation tasks).

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6. REFERENCES

[1] G. Dadon, D. Mesika, A. Berger, and A. Henik. The time course of consciousness in the stroop task, 2015. In preparation.

[2] N. De Pisapia and T. S. Braver. A model of dual control mechanisms through anterior cingulate and prefrontal cortex interactions. *Neurocomputing*, 69(10):1322–1326, 2006.

[3] C. M. MacLeod. Half a century of research on the stroop effect: an integrative review. *Psychological bulletin*, 109(2):163, 1991.

[4] J. R. Stroop. Studies of interference in serial verbal reactions. *Journal of experimental psychology*, 18(6):643, 1935.