Nearing Stroop Effect Replication via Neuroevolution

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ABSTRACT

We present the next step in our study of cognitive abilities by using evolutionary computation. To this end we use a spatial, developmental, neuroevolution system. We use our existing system to evolve ANNs to perform simple abstractions of the cognitive tasks color identification and reading. We define these tasks to explore hypotheses about the the Stroop effect. Our results show the versatility of our evolutionary system. We successfully replicate many of the qualities of the Stroop effect.

Keywords

Evolutionary Algorithm; Developmental EA; Neuroevolution; Cognitive Simulation

1. INTRODUCTION

Much research in cognitive psychology has been devoted to goal directed behavior or to the mental processes involved in focusing on relevant information. One of the paradigmatic tasks in cognitive psychology is the Stroop task in which people are presented with words in color (e.g., RED in green) and asked to pay attention to the color and ignore the meaning of the word. The current work applies evolutionary algorithms (EAs) to study the mechanisms involved in the Stroop task.

In his original work Stroop presented participants with lists of stimuli on a card and asked them to name the color of the ink as fast as possible. Stroop used two conditions, *Incongruent* (e.g., RED in green) and *Neutral* (i.e., patches of colors). Responding was slower to the incongruent condition than to the neutral condition. Stroop suggested that the difference between incongruent and neutral conditions was an indication for the automaticity of word reading. Importantly, when he asked participants to read the words and ignore their color, word reading was not hampered by the incongruent colors. Modern, computer aided research into the effect also includes *Congruent* trials (i.e., Green in green) that Stroop could not use in his experiments because when one presents a number of stimuli on a card, participants may switch to reading the words rather than naming the colors.

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In this work we present new results from our study of cognitive phenomena following our previous exploration into the Stroop effect [1]. 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.

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 4.

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 30 (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 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 stands 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" grids (*red*, *green* and *blue*) and 1 "task definition" grid which is used to differentiate between different tasks. In order to evaluate evolved individuals we test 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. we refer to inputs where the symbol and color match as congruent to inputs where they conflict incongruent, and to the rest as neutral.

previously [1] we were successful in separately evolving networks to become proficient in both the CP and the CR tasks. We also achieved a bidirectional interference pattern by evolving for reading and color at the same time resulting in networks that did significantly better on congruent inputs than on incongruent ones in both tasks.

3. EXPERIMENT

Following our previous work, we try to evolve ANNs which exhibit more Stroop like behavior. We focus on the asymmetry that exists between the interference when the task is naming colors and the lack of interference when the task is reading words. We do this by manipulating the effect that different types of inputs have on fitness during the evolutionary run. Below we present one of our best results.

In the experiment We calculated the fitness score and the benchmark score using 12 test inputs from The CP Experiment and 21 test inputs from the CR Experiment. Each fitness test-case from the CR test suite affected the fitness result as if it appeared 30 times in the suite. After the runs terminated, we checked the best individuals on congruent and incongruent inputs separately in both tasks. There are 3 congruent inputs and 6 incongruent inputs all in all (These numbers hold for both the CP and the CR tasks). The fitness function, which was weighted to bias evolution in favor of the CR task.

Looking at congruent inputs the best solution in a simulation had a mean benchmark score of 749.9962 ($\sigma = 219.0$) in the CP task. Looking at incongruent inputs the best solution in a simulation had a mean benchmark score of 493.3311 ($\sigma = 141.0$) in the CP task.

Looking at congruent inputs the best solution in a simulation had a mean benchmark score of 746.6633 ($\sigma = 246.7$) in the CR task. Looking at incongruent inputs the best solution in a simulation had a mean benchmark score of 738.3301 (($\sigma = 191.4$) in the CR task.

We conducted one-way ANOVA on the 4 score types ($F(3, 396) = 38.2965$). The difference between the congruent and incongruent is significant in the CP task ($p < 0.0001$), but it is insignificant in the CR task ($p = 0.9915$). This approach successfully creates the desired asymmetry that is an attribute of the Stroop effect.

Among our inputs for the CP task there are 3 neutral inputs. In the experiment results on neutral CP inputs fell somewhere in between the congruent and incongruent scores. The best solution in a simulation had a mean benchmark score of 596.6617 ($\sigma = 202.6$) on neutral inputs. In light of these results we can say that our experiments are Stroop like also in the classical sense using neutral inputs. On the other hand this is also where our results differ somewhat from the Stroop effect as it appears in humans. While in humans the difference in performance between congruent and neutral tests (known as the *Facilitation Gap*) is small to negligible, in our results this gap is quite wide.

4. CONCLUSIONS

We presented a new results in our study of the stroop effect using our developmental spatial neuroevolution system. Our system employs various measures to make developmental process more like natural development. 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, by biasing fitness function in favor of the reading task. We expect that further exploring the conditions that will lead to such better approximations of the Stroop effect 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 [2] we plan to test in more depth the effect of short exposure times on the Stroop effect. We are currently using our system to explore other cognitive effects such as the *Simon Effect* and to explore the evolution of numerical cognition.

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).

5. ACKNOWLEDGMENTS

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6. REFERENCES

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