

Neuroevolution of Augmenting Topologies

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I. INTRODUCTION

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II. NEUROEVOLUTION AND EVOLUTIONARY ALGORITHMS

Neuroevolution is a form of evolutionary algorithm that generates specific artificial neural networks (short form: ANN) through modification of its parameters, topology and rules in order to maximize the ANN's accuracy or fitness score. The neuroevolution algorithm seeks to modify the ANN in an evolutionary process similar to the Darwinian process that produced human brains and its process-summarizing maxim 'survival of the fittest'. First methods using neuroevolution can be traced back to the 1980s and 1990s [cite], while the first evolutionary algorithms were conceived in the 1950s by Alan Turing and Nils Barricelli. [cite]

To better characterize neuroevolution is it best to first roughly categorize it, whereupon in the following sections the categories are defined in detail. A *neuroevolution algorithm* is a *genetic algorithm*, whose search-space (or genotypes) consist only of artificial neural networks. A *genetic algorithm* in turn is a *evolutionary algorithm* that evolves genotypes - genetically encoded representations of the actual solution (phenotype) - through reproduction, mutation, recombination, and selection.

A. Evolutionary and Genetic Algorithms

A evolutionary algorithm (short form: EA) is defined as 'a generic population-based and meta-heuristically optimized algorithmic solution to an applied problem' [cite]. When breaking this complex definition down into simpler terms, is the first thing that should be clarified about EAs the fact that they are no algorithmic solution to the applied problem in and of themselves per se, but rather that they are meta-algorithms that create another optimized algorithm, which then solves the applied problem. An evolutionary algorithm therefore encodes a method of how to come up with the best solution to an algorithmic problem.

Evolutionary algorithms set out to finding this best algorithmic solution through a *population-based* method. This means that EAs manage an arbitrary variety of algorithmic solutions - all of which differ and solve the applied problem with various grades of accuracy or fitness scoring. Each of these algorithmic solutions is called a *member* of the evolutionary algorithms' population and is potentially the best algorithmic solution - the best member - that is eventually returned. To determine the best member of the population does the evolutionary algorithm assign each member a *fitness score* after it is created. In the

context of neuroevolution for example is this fitness score calculated by judging the accuracy of the artificial neural network or it is calculated by the fitness function in case of an environment embedded agent.

However, the question remains how the members of the population are created in a sensible way so that they may represent a reasonable algorithmic solution to the problem and eventually an optimized one. This is the point at which the EAs' aspect of *meta-heuristic optimization* comes into play. Each new member in a population is conceived by recombining and/or mutating a single or multiple existing members of the population. Presuming that additionally the single or multiple existing members that are recombined and/or mutated to create the new member are chosen to be the highest fitness scoring members (a.k.a. the *fittest* members), does the process constitute an optimization procedure resembling Darwinian evolution. Therefore can be said that evolutionary algorithms breed increasingly optimized algorithmic solution through evolutionary intercombination of existing algorithmic solutions - hence representing the mentioned optimization process.

The possible methods of intercombination between existing members are also inspired by biological evolution, such as reproduction, mutation, recombination and selection. For the sake of brevity will only the following chapter II-B explain those intercombination methods as they apply to neuroevolution algorithms and no general explanation of those methods be given. The mentioned optimization process achieved through these intercombination methods is considered *meta-heuristic* because the optimization process is possible with incomplete or imperfect information or limited computational capacity. Thus even when the feedback - meaning the ability to determine a sensible fitness score through accuracy measurement or similar - of the applied problem is limited or sparse, is fruitful traversal across the search-space through e.g. a lucky mutation feasible.

Finally can be said that the evolutionary algorithms population-based methodology is considered *generic* because it does not dictate how the members of the population are encoded. Though an evolutionary algorithm needs to eventually return an algorithmic solution to the applied problem, does it not dictate that the members are algorithms in memory, nor that they even need to be in algorithmic form when they are given a fitness score. This is where genetic algorithms come into play.

Genetic algorithms (short form: GAs) are evolutionary algorithms whose members are not saved as algorithms in memory, but as genetic-like encodings which can then be translated into algorithms by a user-specified component of the genetic algorithm. To give an example, a genetic algorithm trying to find the best search algorithm would not represent a member as e.g. the Quicksort algorithm itself in memory, but e.g. as a series of four different digits which would then in turn translate into the Quicksort algorithm.

The defining advantage of genetic algorithms by representing members as a genetic-like encoding instead of an algorithm in memory is that intercombination methods like mutation and recombination - central aspects of evolutionary algorithms -

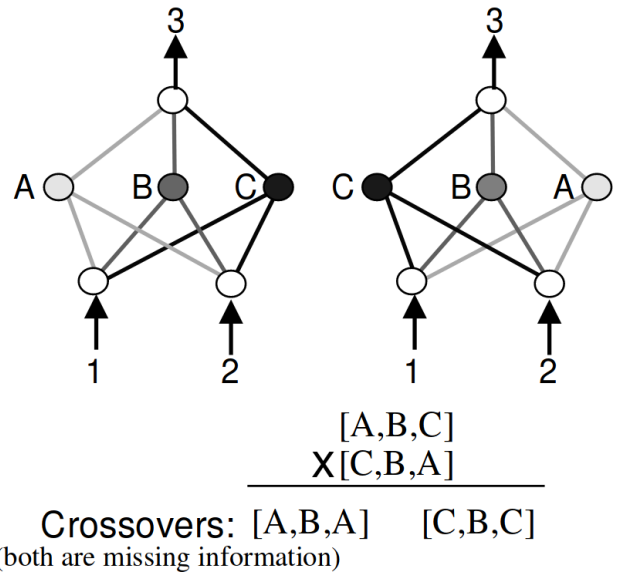


Fig. 1. Illustration of the 'Competing Conventions Problem'. (Source: [3])

are vastly easier on relatively simple genetic encodings than on complex specified algorithms. Figure 1, though actually illustrating the 'Competing Conventions Problem', also illustrates well how such a complex algorithm as an artificial neural network is significantly simpler represented as a genetic encoding and how such a genetic encoding can be vastly easier recombined than the algorithm itself.

B. Neuroevolution

C. Landmark Research in Neuroevolution

III. NEUROEVOLUTION OF AUGMENTING TOPOLOGIES (NEAT)

§Section Introduction§

Neuroevolution of Augmenting Topologies (short form: NEAT) was first introduced in the paper "Evolving Neural Networks through Augmenting Topologies" by Kenneth O. Stanley and Risto Miikkulainen in the year 2002. [cite] It was finalized and shown to be superior to any preceding neuroevolution algorithm in Stanley's PhD thesis "Efficient Evolution of Neural Networks through Complexification" in 2004. [cite]

At time of envisioning of NEAT was Neuroevolution most promising learning approach. Still is powerful today (see rea17/19) "NE is a promising approach to learning behavioral policies and finds solutions faster than leading RL methods on many benchmark tasks (Gomez 2003; Moriarty and Miikkulainen 1997)" [5]

"In highly complex domains the heuristics for determining the appropriate size are not very useful, and it becomes increasingly difficult to solve such domains with fixed-length encodings." [5]

[See all notes write down about stanleys PhD thesis]

A. Key Aspects of NEAT and Differences to Preceding Neuroevolution

B. Performance of NEAT

C. Variants and Advancements of NEAT

- 1) *Variant 1_i*:
- 2) *Variant 2_i*:
- 3) *Variant 3_i*:

IV. PRACTICAL APPLICATIONS OF NEAT

A. Application 1_i

B. Application 2_i

C. Application 3_i

V. CONCLUSION

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