# Neuroevolution of Augmenting Topologies

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CONTENTS



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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], though 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 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 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 (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 - therefore 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.

### *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¿:*

#### *2) ¡Variant 2¿:*

#### *3) ¡Variant 3¿:*

## IV. Practical Applications of NEAT

### *A. ¡Application 1¿*

### *B. ¡Application 2¿*

### *C. ¡Application 3¿*

## V. Conclusion

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## References


[1] Yao - Evolving Artificial Neural Networks; 1999; http://avellano.fis.usal.es/~lalonso/compt_soft/articulos/yao99evolving.pdf

[2] Stanley, Miikkulainen - Efficient Evolution of Neural Network Topologies; 2002; http://nn.cs.utexas.edu/downloads/papers/stanley.cec02.pdf

[3] Stanley, Miikkulainen - Evolving Neural Networks through Augmented Topologies; 2002; http://nn.cs.utexas.edu/downloads/papers/stanley.ec02.pdf

[4] Geard, Wiles - Structure and Dynamics of a Gene Network Model Incorporating Small RNAs; Dec 2003; https://ieeexplore.ieee.org/document/1299575

[5] Stanley - Efficient Evolution of Neural Networks through Complexification; Aug 2004; http://nn.cs.utexas.edu/downloads/papers/stanley.phd04.pdf

[6] Reisinger, Miikkulainen - Acquiring Evolvability through Adaptive Representations; Jul 2007; http://nn.cs.utexas.edu/downloads/papers/reisinger.gecco07.pdf

[7] Mattiussi, Duerr, et al - Center of Mass Encoding: A self-adaptive representation with adjustable redundancy for real-valued parameters; Jul 2007; https://infoscience.epfl.ch/record/101405

[8] Floreano, Duerr, et al - Neuroevolution: From Architectures to Learning; Jan 2008; http://citeseerx.ist.psu.edu/viewdoc/summary?doi=10.1.1.182.1567

[9] Mattiussi, Marbach, et al - The Age of Analog Networks; Sep 2008; https://www.aaai.org/ojs/index.php/aimagazine/article/view/2156

[10] Stanley, D'Ambrosio, et al - A Hypercube-Based Indirect Encoding for Evolving Large-Scale Neural Networks; 2009; http://axon.cs.byu.edu/~dan/778/papers/NeuroEvolution/stanley3**.pdf

[11] Risi, Stanley - Enhancing ES-HyperNEAT to Evolve More Complex Regular Neural Networks; Jul 2011; http://citeseerx.ist.psu.edu/viewdoc/summary?doi=10.1.1.365.4332

[12] Lehman, Stanley - Novelty Search and the Problem with Objectives; Oct 2011; https://www.cs.ucf.edu/eplex/papers/lehman_gptp11.pdf
[13] Woergoetter, Porr - Scholarpedia Article on 'Reinforcement Learning'; Sep 2012; http://www.scholarpedia.org/article/Reinforcement_learning
[14] Holland - Scholarpedia Article on 'Genetic Algorithms'; Oct 2012; http://www.scholarpedia.org/article/Genetic_algorithms
[15] Fogel, Fogel, et al - Scholarpedia Article on 'Evolutionary Programming'; Oct 2013; http://www.scholarpedia.org/article/Evolutionary_programming
[16] Lehman, Miikkulainen - Scholarpedia Article on 'Neuroevolution'; Oct 2013; http://www.scholarpedia.org/article/Neuroevolution
[17] Pascanu, Ganguli, et al - On the Saddle Point for Non-Convex Optimization; May 2014; https://www.researchgate.net/publication/262452520
[18] Kim, Rigazio - Deep Clustered Convolutional Kernels; Mar 2015; https://arxiv.org/abs/1503.01824
[19] Fernando, Banarse, et al - Convolution by Evolution; Jun 2016; https://arxiv.org/abs/1606.02580
[20] Miikkulainen, Liang, et al - Evolving Deep Neural Networks; Mar 2017; https://arxiv.org/abs/1703.00548
[21] Xie, Yuille - Genetic CNN; Mar 2017; https://arxiv.org/abs/1703.01513
[22] Negrinho, Gordon - DeepArchitect: Automatically Designing and Training Deep Architectures; Apr 2017; https://arxiv.org/abs/1704.08792
[23] Real, Moore, et al - Large-scale Evolution of Image Classifiers; Jun 2017; https://arxiv.org/abs/1703.01041
[24] Stanley - Neuroevolution: A Different Kind of Deep Learning; Jul 2017; https://www.oreilly.com/ideas/neuroevolution-a-different-kind-of-deep-learning
[25] Brock, Lim, et al - SMASH: One-Shot Model Architecture Search through HyperNetworks; Aug 2017; https://arxiv.org/abs/1708.05344
[26] Salimans, Ho - Evolution Strategies as a Scalable Alternative to Reinforcement Learning; Sep 2017; https://arxiv.org/abs/1703.03864
[27] Jaderberg, Dalibard, et al - Population Based Training of Neural Networks; Nov 2017; https://arxiv.org/abs/1711.09846
[28] Zhang, Clune, et al - On the Relationship Between the OpenAI Evolution Strategy and Stochastic Gradient Descent; Dec 2017; https://arxiv.org/abs/1712.06564
[29] Stanley, Clune - Welcoming the Era of Deep Neuroevolution; Dec 2017; https://eng.uber.com/deep-neuroevolution/
[30] Liu, Simonyan, et al - Hierarchical Representation for Efficient Architecture Search; Feb 2018; https://arxiv.org/abs/1711.00436
[31] Such, Stanley, et al - Accelerating Deep Neuroevolution: Train Atari in Hours on a Single Personal Computer; Apr 2018; https://eng.uber.com/accelerated-neuroevolution/
[32] Such, Madhavan, et al - Deep Neuroevolution: Genetic Algorithms Are a Competitive Alternative for Training Deep Neural Networks for Reinforcement Learning; Apr 2018; https://arxiv.org/abs/1712.06567
[33] Zoph, Vasudevan, et al - Learning Transferable Architectures or Scalable Image Recognition; Apr 2018; https://arxiv.org/abs/1707.07012
[34] Lehman, Chen, et al - ES Is More Than Just a Traditional Finite-Difference Approximator; May 2018; https://arxiv.org/abs/1712.06568
[35] Lehman, Chen, et al - Safe Mutations for Deep and Recurrent Neural Networks through Output Gradients; May 2018; https://arxiv.org/abs/1712.06563
[36] Zhong, Yan, et al - Practical Block-Wise Neural Network Architecture Generation; May 2018; https://arxiv.org/abs/1708.05552
[37] Rawal, Miikkulainen - From Nodes to Networks: Evolving Recurrent Neural Networks; Jun 2018; https://arxiv.org/abs/1803.04439
[38] Conti, Madhavan, et al - Improving Exploration in Evolution Strategies for Deep Reinforcement Learning via a Population of Novelty Seeking Agents; Oct 2018; https://arxiv.org/abs/1712.06560
[39] Real, Aggarwal, et al - Regularized Evolution for Image Classifier Architecture Search; Feb 2019; https://arxiv.org/abs/1802.01548
[40] Sun, Xue, et al - Evolving Deep Convolutional Neural Networks for Image Classification; Mar 2019; https://arxiv.org/abs/1710.10741