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 Algorithms

A evolutionary algorithm is defined as 'a generic population-based and meta-heuristically optimized algorithmic solution to an applied problem' [cite].

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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