Neuroevolution of Augmenting Topologies

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***Abstract*—Lorem ipsum dolor sit amet, consectetuer adipiscing elit. Etiam lobortis facilisis sem. Nullam nec mi et neque pharetra sollicitudin. Praesent imperdiet mi nec ante. Donec ullamcorper, felis non sodales commodo, lectus velit ultrices augue, a dignissim nibh lectus placerat pede. Vivamus nunc nunc, molestie ut, ultricies vel, semper in, velit. Ut porttitor. Praesent in sapien. Lorem ipsum dolor sit amet, consectetuer adipiscing elit. Duis fringilla tristique neque. Sed interdum libero ut metus. Pellentesque placerat. Nam rutrum augue a leo. Morbi sed elit sit amet ante lobortis sollicitudin. Praesent blandit blandit mauris. Praesent lectus tellus, aliquet aliquam, luctus a, egestas a, turpis. Mauris lacinia lorem sit amet ipsum. Nunc quis urna dictum turpis accumsan semper.**

I. INTRODUCTION

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II. NEUROEVOLUTION AND EVOLUTIONARY ALGORITHMS

A. Evolutionary Algorithms

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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