Cartesian Genetic Programming of Artificial Neural Networks

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NeuroEvolution

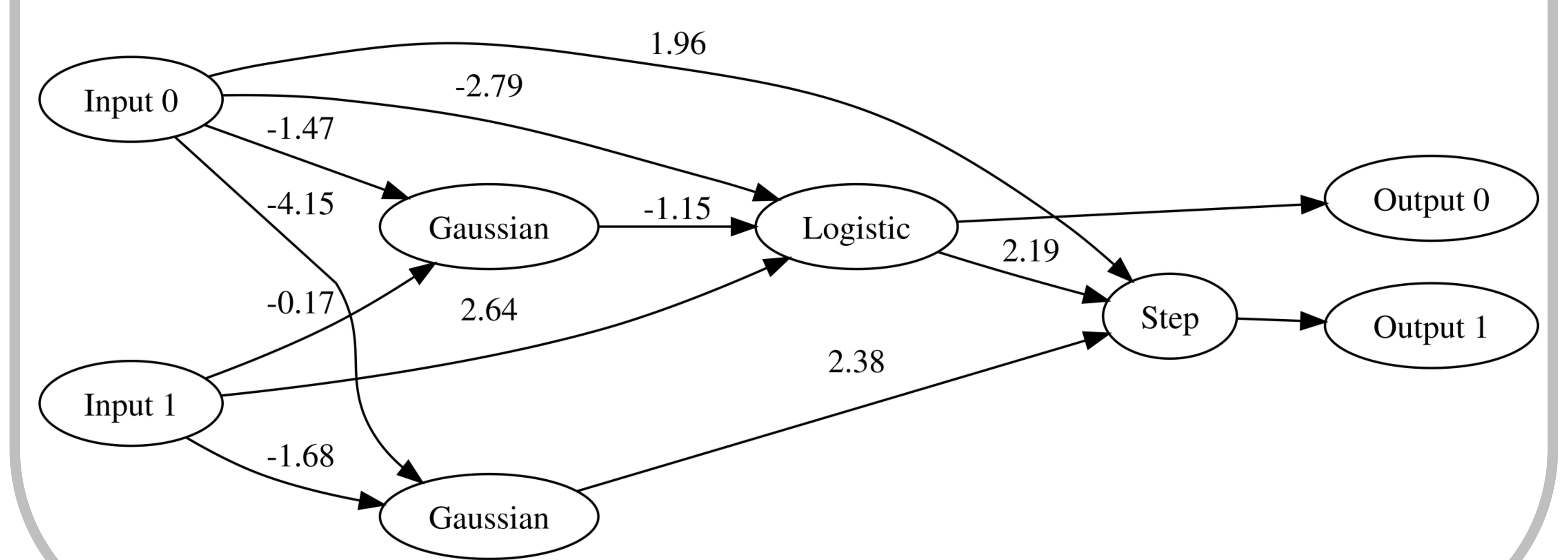
NeuroEvolution is the application of Evolutionary Algorithms to the training of Artificial Neural Networks. NeuroEvolution has a number of key advantages over traditional methods:

- No restriction on topology
- No restriction on neuron transfer functions
- Naturally escapes local optima
- Applicable to reinforcement learning

Cartesian Genetic Programming of Artificial Neural Networks

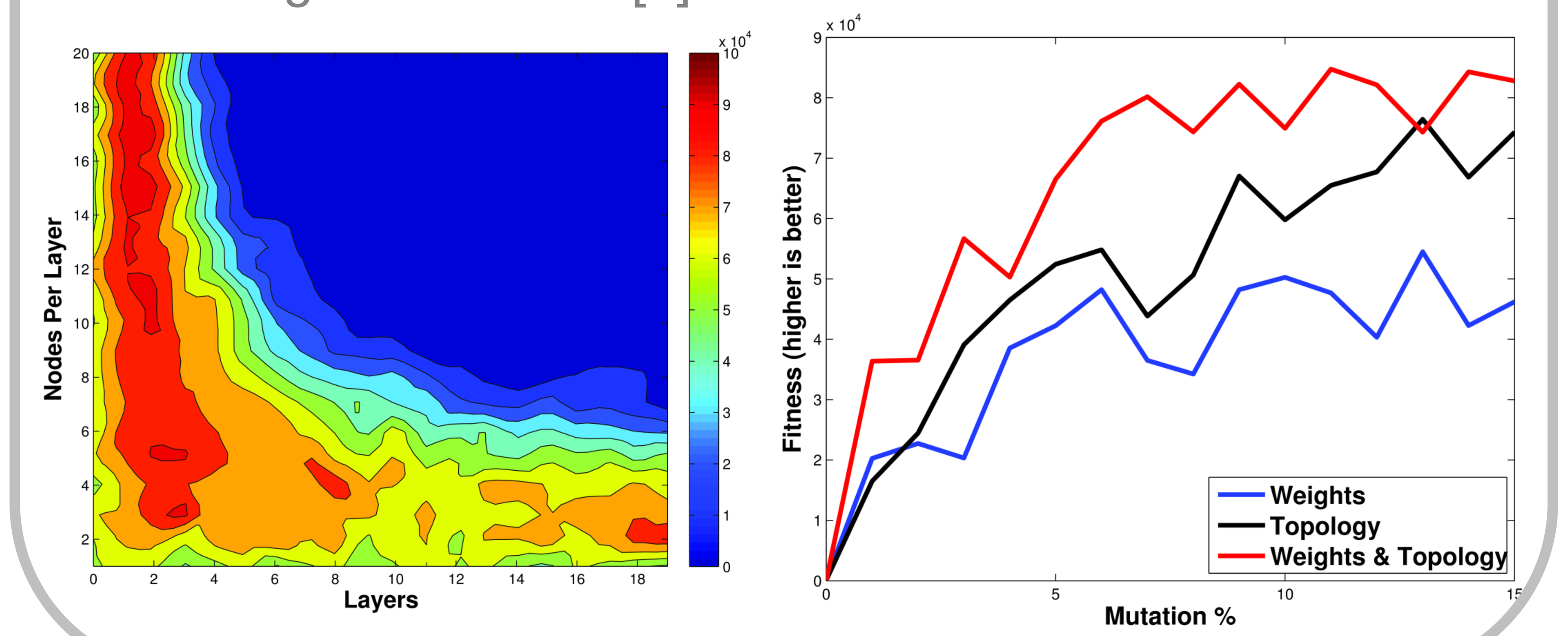
Cartesian Genetic Programming of Artificial Neural Networks (CGPANN) is a form of NeuroEvolution based on Cartesian Genetic Programming. CGPANN also has a number of advantages:

- Creates feed-forward / recurrent networks
- Evolves homogeneous and heterogeneous networks
- Evolves less restricted topologies
- Can optimise deep networks
- Exhibits neutral genetic drift
- Can be combined with gradient based methods



The Importance of Topology

The choice of topology has a large influence on the effectiveness of NeuroEvolution; and neural networks in general. This can be seen in the figure below (left) where the topology is swept for Conventional NeuroEvolution (CNE). In fact optimising topology has been shown to be more significant than optimising connection weights! As is seen in the figure below (right) when using CGPANN. Both figures show the achieved fitness on the double pole balancing benchmark. [1]



Heterogeneous Neural Networks

Unlike gradient based methods, NeuroEvolution places no restrictions on the type of neuron transfer functions which can be used. As opposed to back propagation which can only use non-differentiable transfer functions. As NeuroEvolutionary algorithms are not dependant upon the type of transfer functions, they can easily be used to create heterogeneous networks of many different transfer functions. Furthermore, heterogeneous networks have been shown, on average, to outperform homogeneous networks using multiple NeuroEvolutionary methods over a wide range of benchmark problems. [2]

Double Pole Balancing

The double pole balancing benchmark is a classic reinforcement control task which has become popular for comparing NeuroEvolutionary methods. In the majority of cases below suitable topologies were found by the user. However for CGPANN the topology was also evolved. [3]

NeuroEvolution Method	Number of Evaluations
CNE	22100
SAIN	12600
ESP	3800
NEAT	3578
NEvA	2177
CGPANN	**1111**
CoSyNE	954
CMA-ES	895
DirE*	410

*DirE included an extra bias input not used by the other methods.

References

[1] A. J. Turner and J. F. Miller. **The Importance of Topology Evolution in NeuroEvolution: A Case Study using Cartesian Genetic Programming of Artificial Neural Networks**. Research and Development in Intelligent Systems XXX, pages 213-226, Cambridge, England, 2013.

[2] A. J. Turner and J. F. Miller. **NeuroEvolution: The Importance of Transfer Function Evolution and Heterogeneous Networks**. Fiftieth annual conference of Artificial Intelligence and Simulation of Behavior, pages 158-165, London, England, 2014.

[3] A. J. Turner and J. F. Miller. **Cartesian Genetic Programming encoded Artificial Neural Networks: A Comparison using Three Benchmarks**. GECCO'13, Proceedings of the Genetic and Evolutionary Computation Conference, pages 1005-1012, Amsterdam, The Netherlands, 2013.