
Evolving Neural Networks through Augmenting Topologies

Evolutionary Computation, 2002

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Presentation by

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Basic Information

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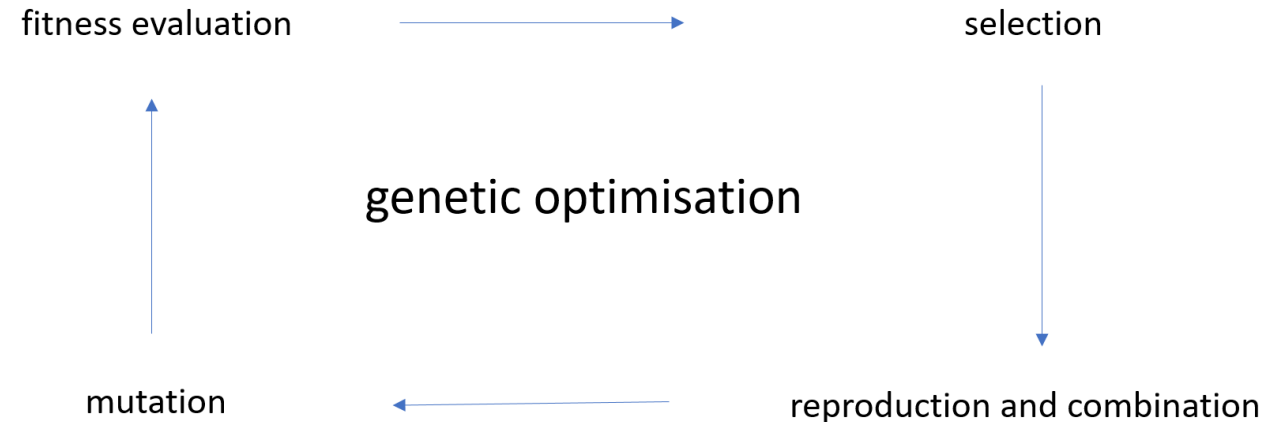
Journal : Evolutionary Computation, 2002, MIT Press

Citations : 3115

- Prior Research
- Theoretic Proposition : NEAT
- Evaluation and Analysis
- Discussion and Conclusion

Introduction

- NEAT : Neuro-evolution of Augmenting Topologies
- Neuro-evolution/Evolution Strategies
 - Evolution strategies to optimize DNNs
 - Optimisation evaluated over population
 - Mutation, crossover
 - Fitness function calculated
- ES vs GD
 - “Scattering” rather than “rolling”
 - Population vs point
 - Mutation vs gradient descent

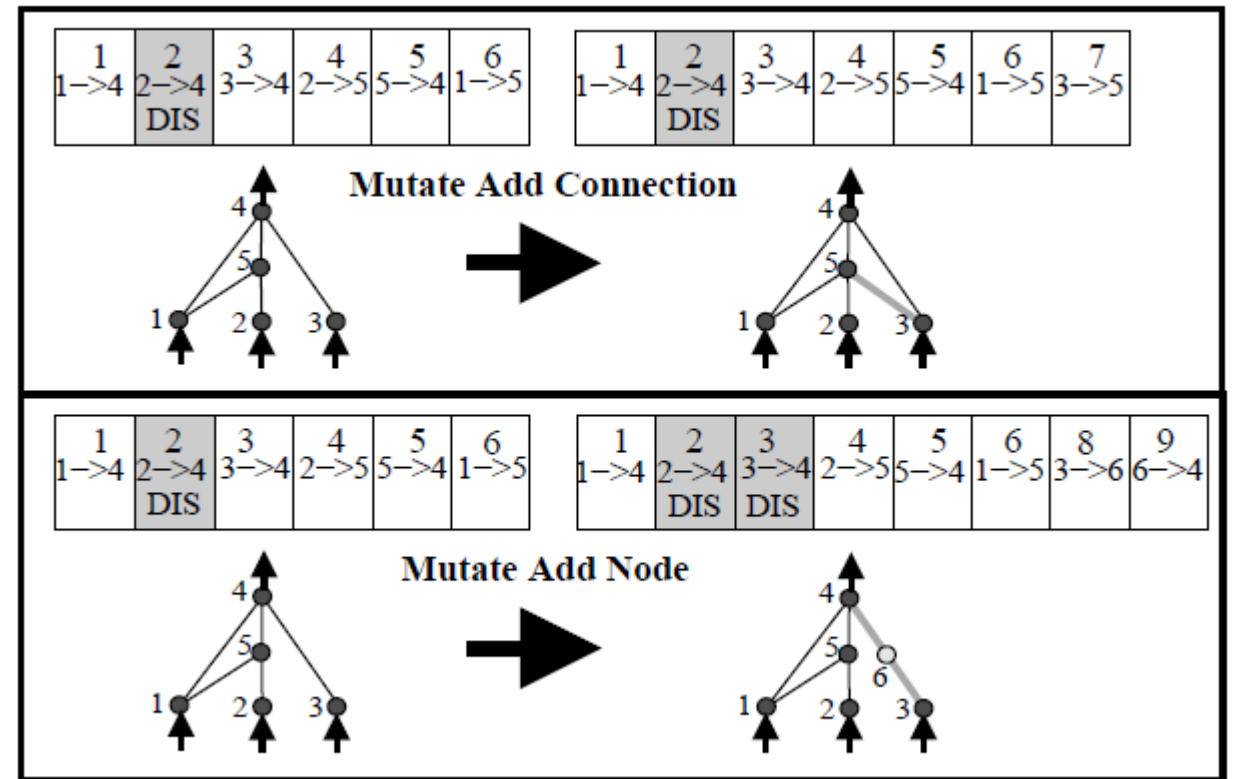


Background : TWEANN

- Topology evolution : TWEANN
- Problems to solve for TWEANN
 - Genetic representation for topology crossover?
 - Protecting topological innovation that takes a few generations to be optimised?
 - Obtaining simple networks without designing 'complexity' functions?
- Key ideas of NEAT
 - Genetic Encoding
 - Crossover method : Historical Marking Crossover
 - Protecting innovations : Speciation, Explicit Fitness Sharing
 - Minimal Structure of Initialisation

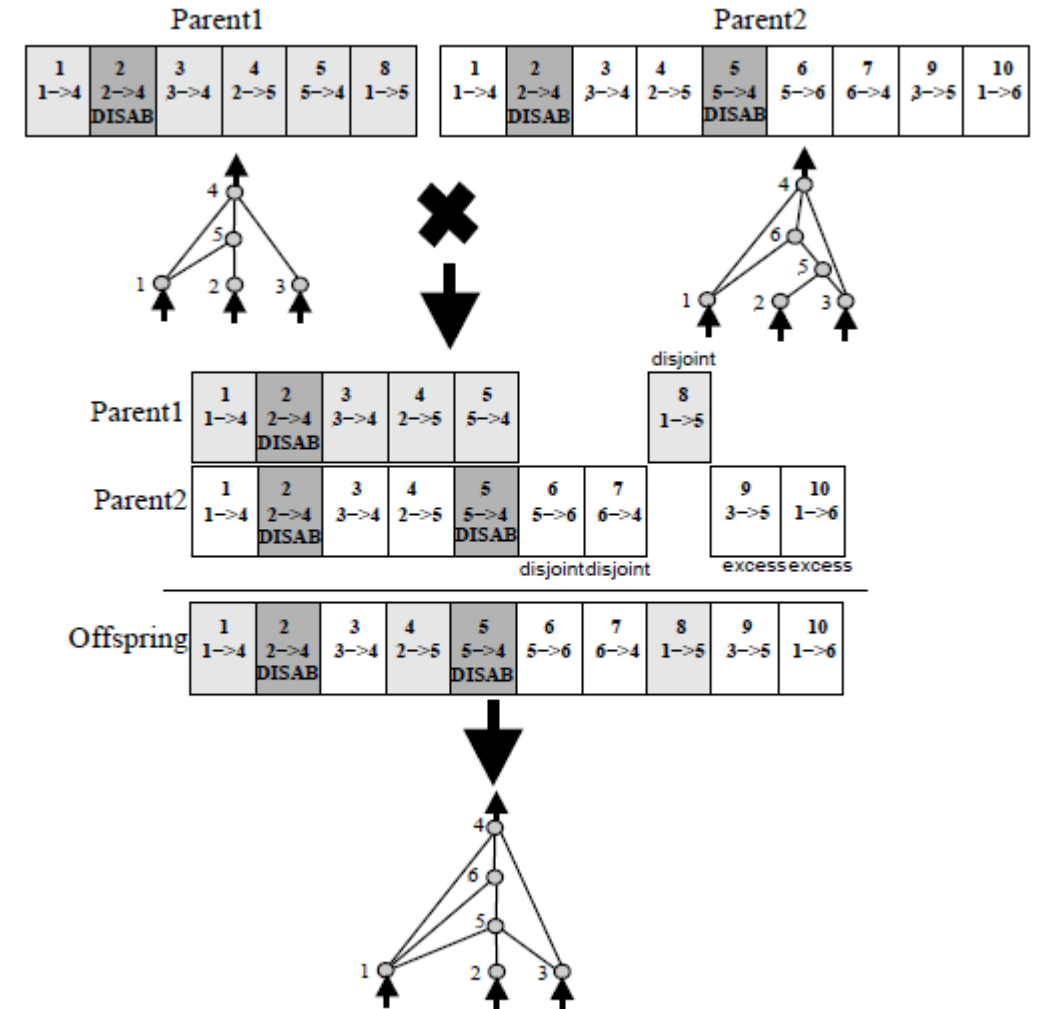
NEAT : Encoding

- Genetic Encoding
 - Genome is linear list of connections
 - In/out node, weight, enable bit, innovation number
- Mutation
 - Add connection
 - Add node (between connection)
 - Nodes are never deleted, just disabled



NEAT : Crossover

- Historical Marking Crossover
 - Crossing over genes : how to solve overlap?
 - Global innovation number to determine parent, historical marking
 - Any possible unique connection is logged as unique value, and accumulated
 - Comparison between genomes simple; common genes/divergent mutations identified, easy to crossover
 - Expensive topological analysis not needed



NEAT : Speciation

- Speciation
 - Adding nodes causes initial loss
 - Classify population by species; protection within a niche
 - Similar topologies into same species; historical markings for efficient solution
- Compatibility Distance
 - Calculated solely from gene comparison
 - Speciate using threshold distance
 - Speciation by recursively selecting random representatives and grouping all compatible genomes

$$\delta = \frac{c_1 E}{N} + \frac{c_2 D}{N} + c_3 \cdot \overline{W}$$

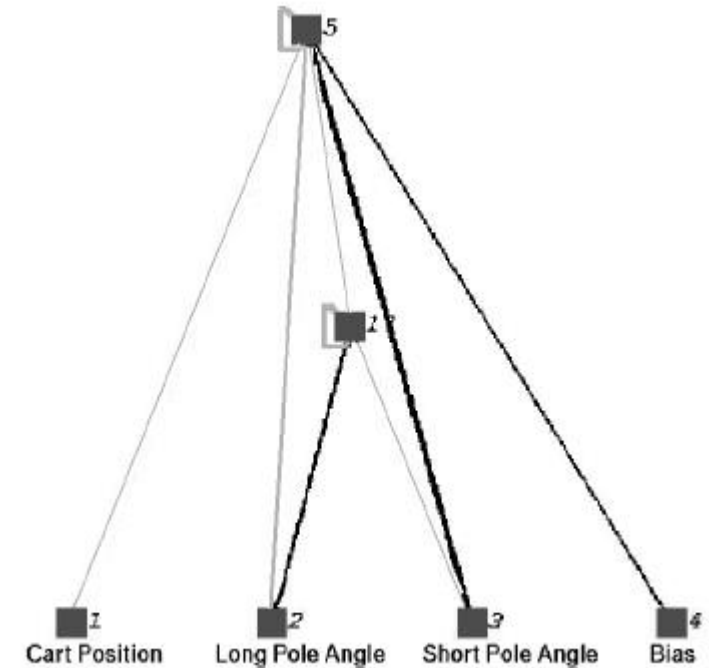
NEAT : Speciation

- Explicit Fitness Sharing
 - Want to prevent one species from dominating population
 - Sharing function : number of genomes of same species
 - Number of offspring assigned to each species dependent on average of fitness in species
 - Lowest performing members eliminated

$$f'_i = \frac{f_i}{\sum_{j=1}^n \text{sh}(\delta(i, j))}$$

NEAT : Minimal Structure

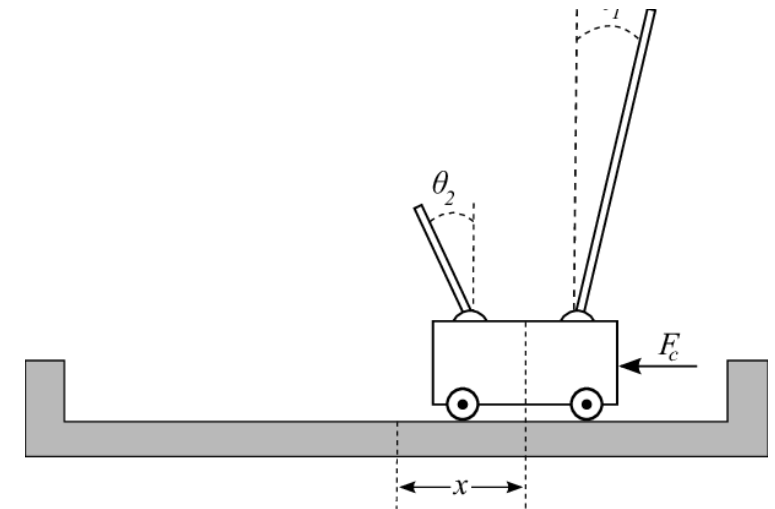
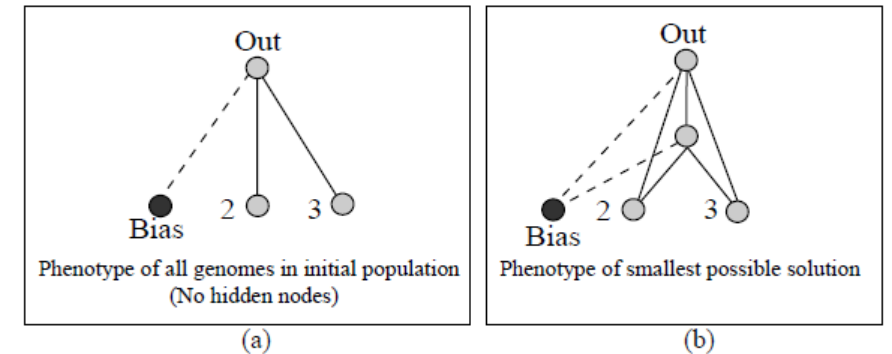
- Minimizing Dimensionality
 - TWEANN : Typically starts with an initial population of random topologies
 - NEAT : Uniform population with zero hidden nodes
 - Makes discovering compact solutions more likely
 - Performance advantage



Evaluation and Analysis

- Does NEAT evolve the necessary structures?
 - XOR network : requires growing hidden units
 - Average : 32 generations, 2.35 hidden nodes
- Is NEAT more efficient than other NE systems?
 - Pole balancing : challenging task for all methods

Method	Evaluations	Generations	No. Nets
Ev. Programming	307,200	150	2048
Conventional NE	80,000	800	100
SANE	12,600	63	200
ESP	3,800	19	200
NEAT	3,600	24	150



Evaluation and Analysis

- Ablations
 - Specific features removed to show TE, Speciation, Minimal Structure, Crossover is required

Method	Evaluations	Failure Rate
No-Growth NEAT (Fixed-Topologies)	30,239	80%
Nonspeciated NEAT	25,600	25%
Initial Random NEAT	23,033	5%
Nonmating NEAT	5,557	0
Full NEAT	3,600	0

Discussion and Conclusion

- Method of applying ES for optimization
 - Topology evolution : not only breeds/mutates/optimises, but complexifies
Strengthens analogy between GAs and natural evolution
Adds new dimensions to weight space, not trapped by local minimas
 - Minimal structure : faster computation, compact solutions
 - Historical marking : easy comparison, crossover between genes
 - Speciation : protecting innovations
- Extensions
 - rtNEAT : evolution occurring in real time rather than by evaluation of fitness per generation
 - HyperNEAT, ES-HyperNEAT, CoDeepNEAT etc.

References

- Websites
 - <https://towardsdatascience.com/gradient-descent-vs-neuroevolution-f907dace010f>
 - <https://eng.uber.com/deep-neuroevolution/>