NEAT

Evolving Neural Networks through Augmenting Topologies

Fall 2018

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Intuition

- Easy to understand
- Easy to trace
- GPU friendly

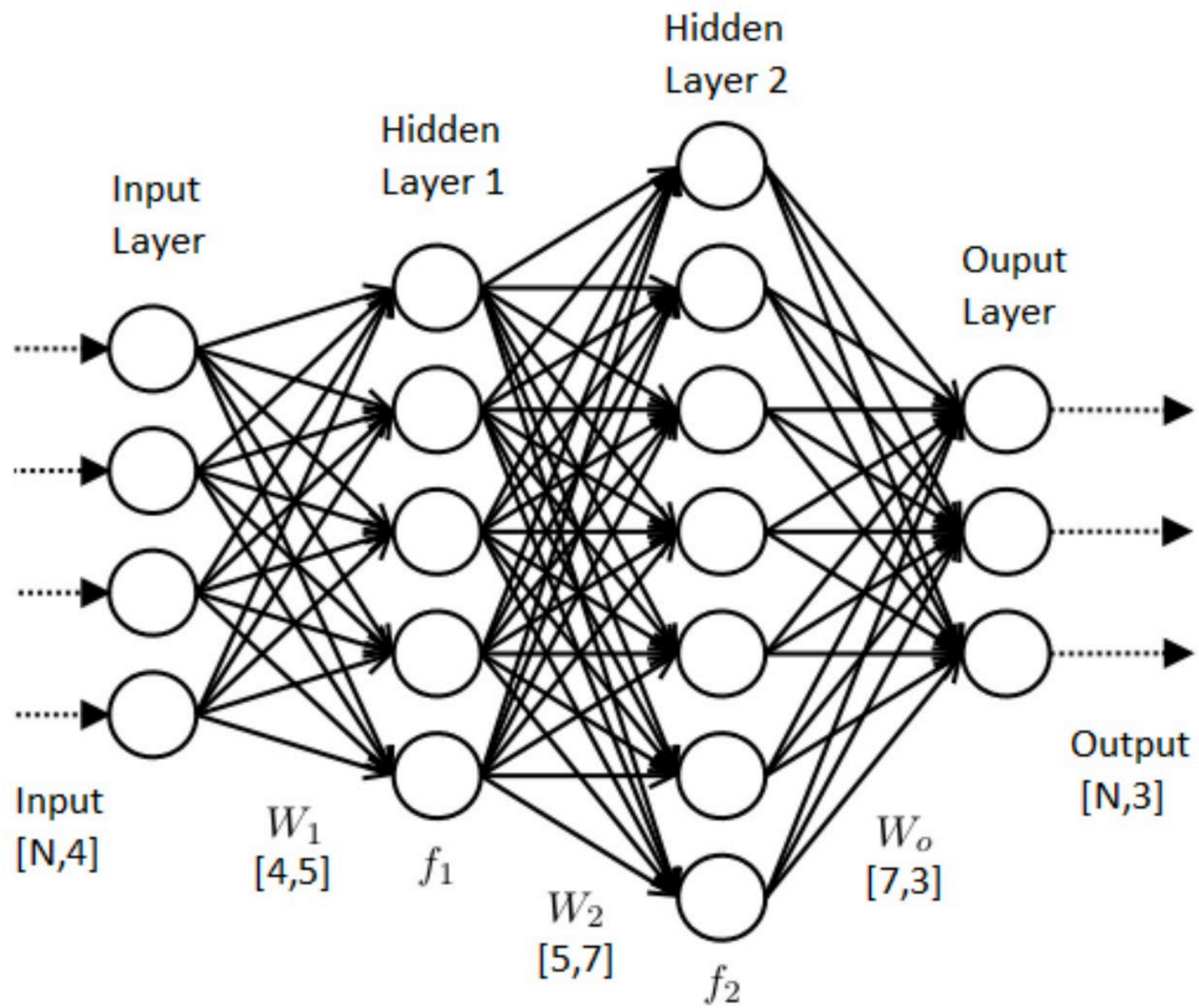


Image From: http://medium.com/

Intuition

- More Optimized
- Fewer calculations
- Reinforcement Learning application

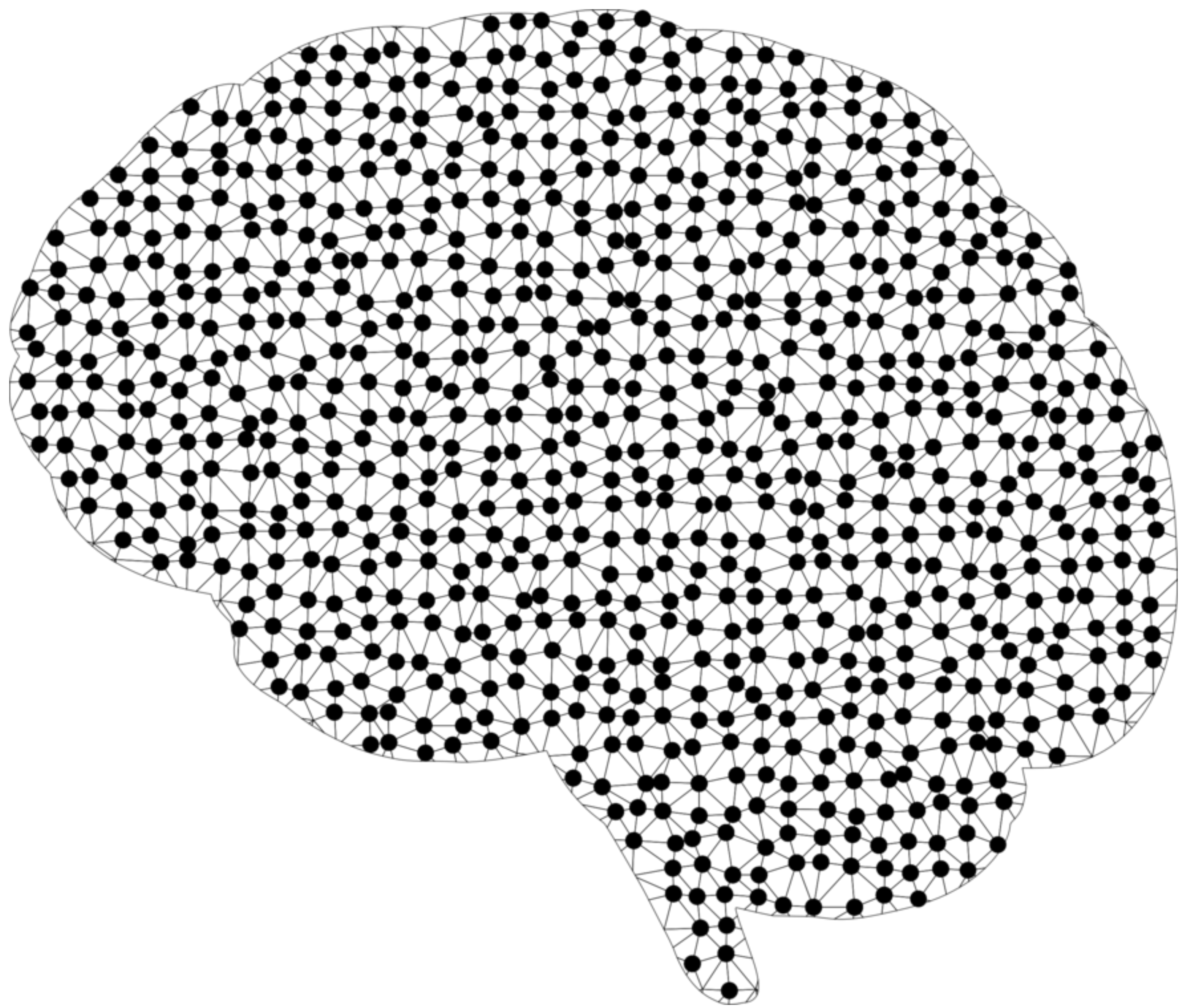
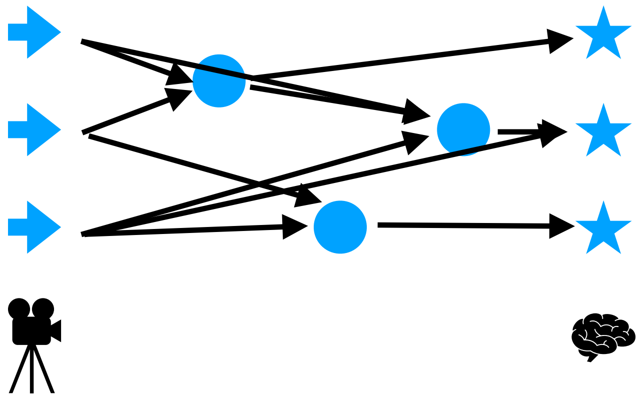


Image From: https://kisspng.com

Basic Idea

1. Select an Empty Network
2. Randomly add Connections
3. Randomly mutate Connections
4. Optimize via **Genetics Algorithms**



By the way, Why?

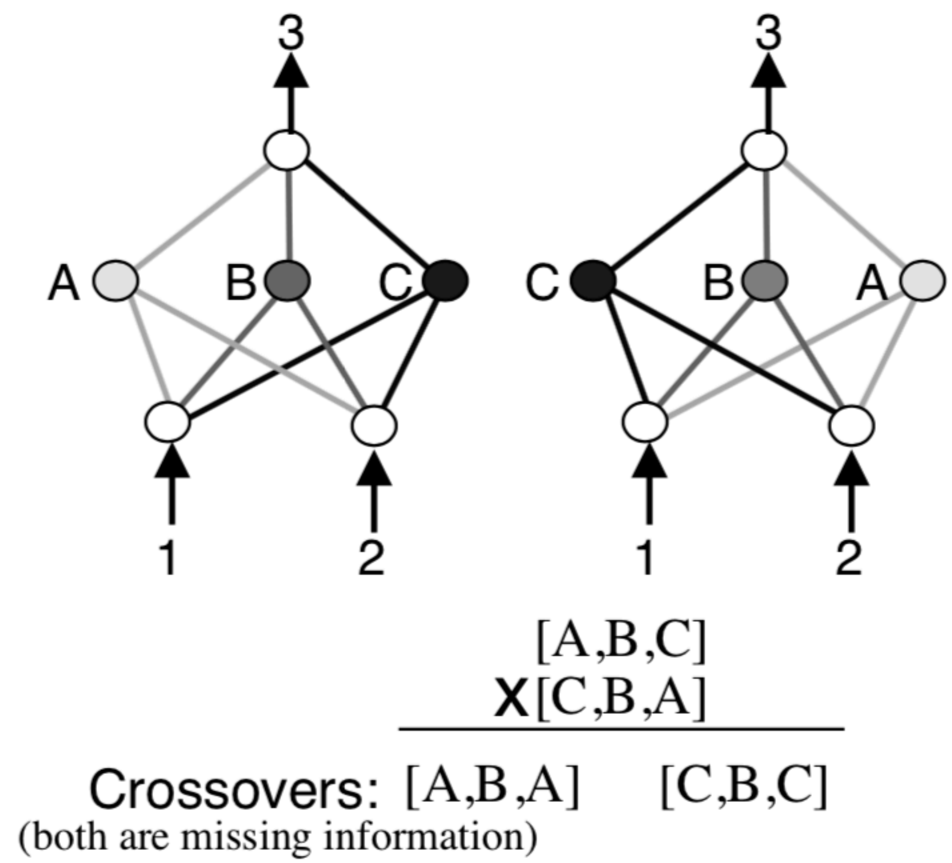
- Can evolving topologies along with weights provide an advantage over evolving weights on a fixed-topology?
- A fully connected network can in principle approximate any continuous function.
- So why waste valuable effort permuting over different topologies?

Encoding

- TWEANNs Encoding
- Binary Encoding
- Graph Encoding
- Indirect Encoding

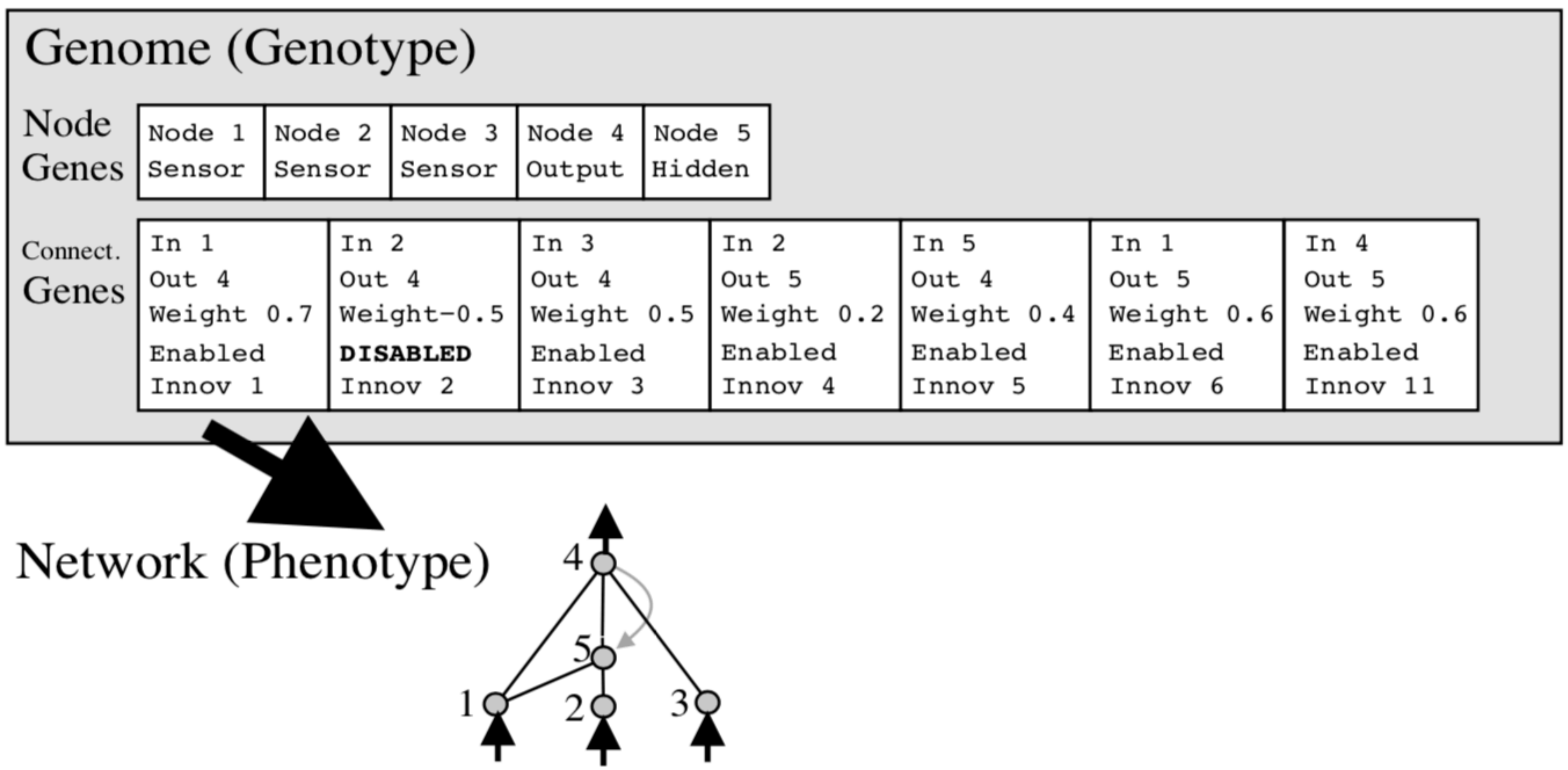
Problems

- Mating between different genes.
- Initial Populations
- Protecting Speciation



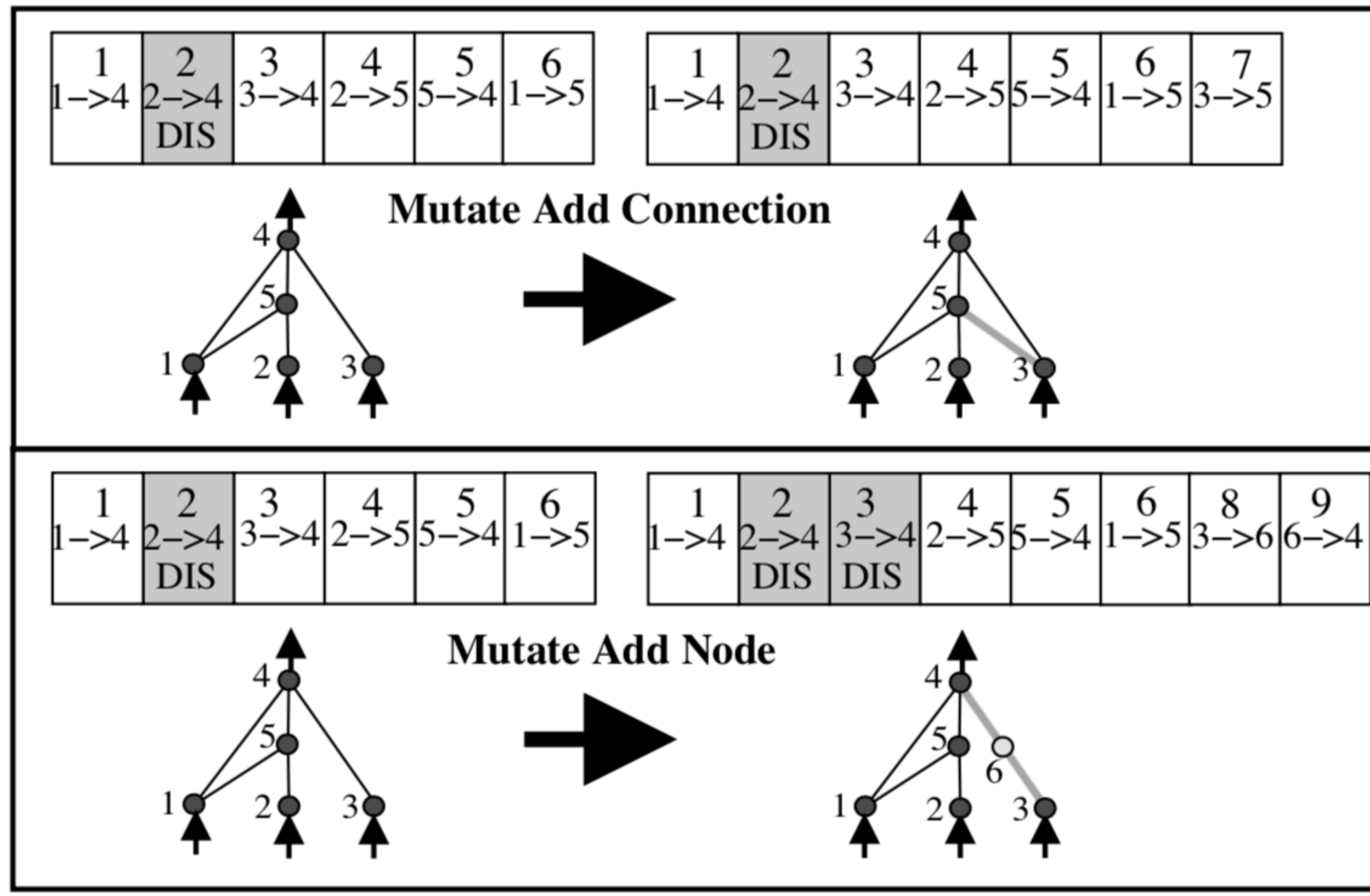
NEAT

Genetic Encoding



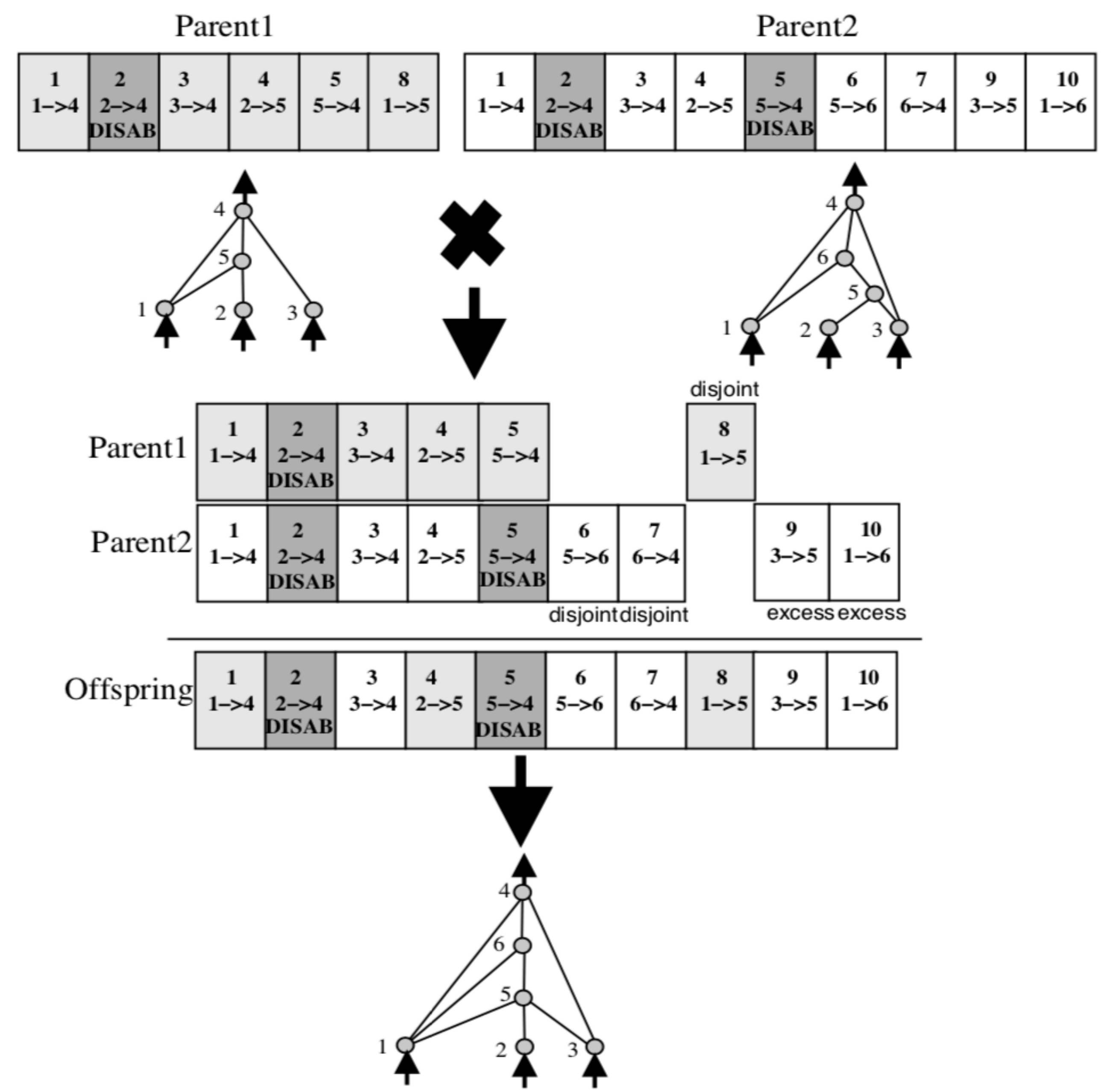
Mutation

- Add Connection
- Add Node



Tracking Genes through Historical Markings

- When Structural Mutation Happens
- Global Innovation Number incrementally increases.
- Crossover within same GIN
- Crossover with a Gene with different GIN



Speciation

- δ: distance of different structures
- E: the number of excess genes
- D: the number of disjoint genes
- W: the average weight matching genes (including disabled genes)

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

Explicit Fitness Sharing

- Organism in same niches share same fitness.
- a species cannot afford to become too big even if many of its organisms perform well.
- sh = 0 : if δ(i, j) < δt

  sh = 1 : otherwise

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

Minimal Solution

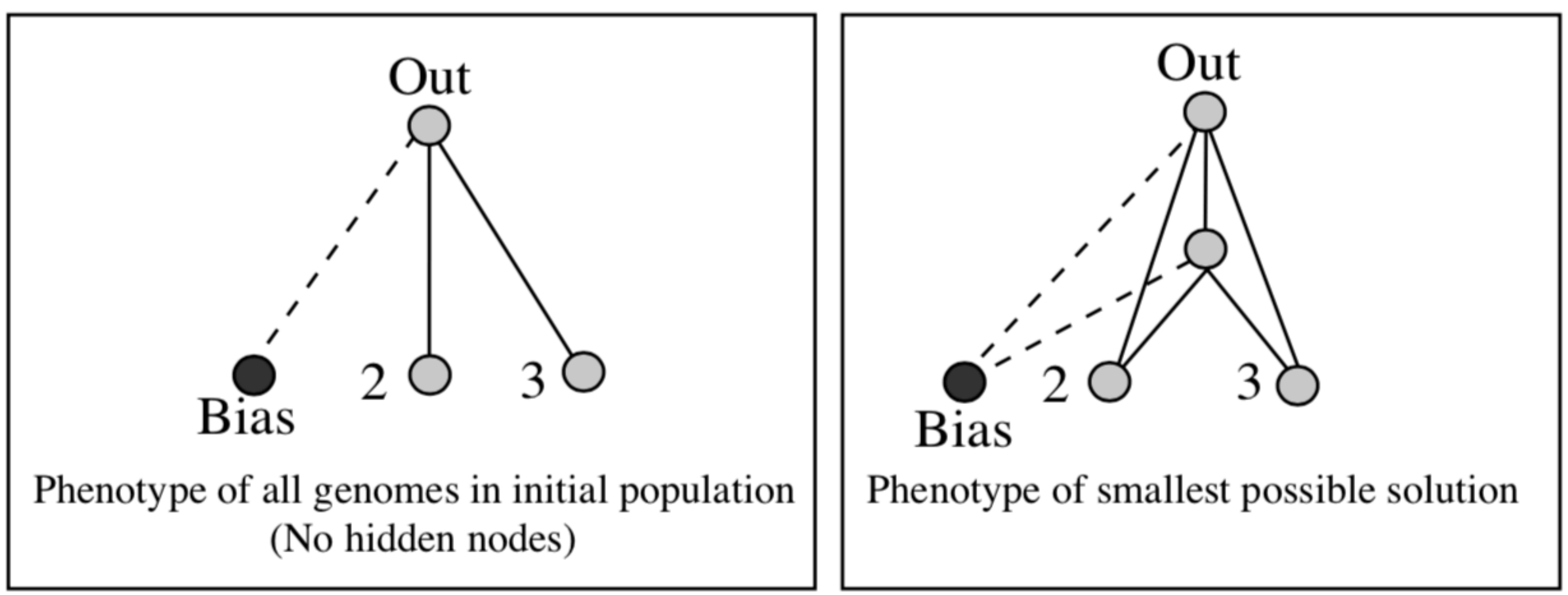
- Minimizing Dimensionality through Incremental Growth from Minimal Structure
- only those structures survive that are found to be useful through fitness evaluations

Performance Evaluations

- Can NEAT evolve the necessary structures?
- Can NEAT find solutions more efficiently than other Neuro-Evolution systems?

Performance Evaluations

- Evolving XORs
- Pole balancing



(a) (b)

Bench-marks

- Pole Balancing as a Benchmark Task
- Pole Balancing Comparisons
- Double Pole Balancing with Velocities

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

Analysis of NEAT

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

Conclusion

- Evolving topology along with weights
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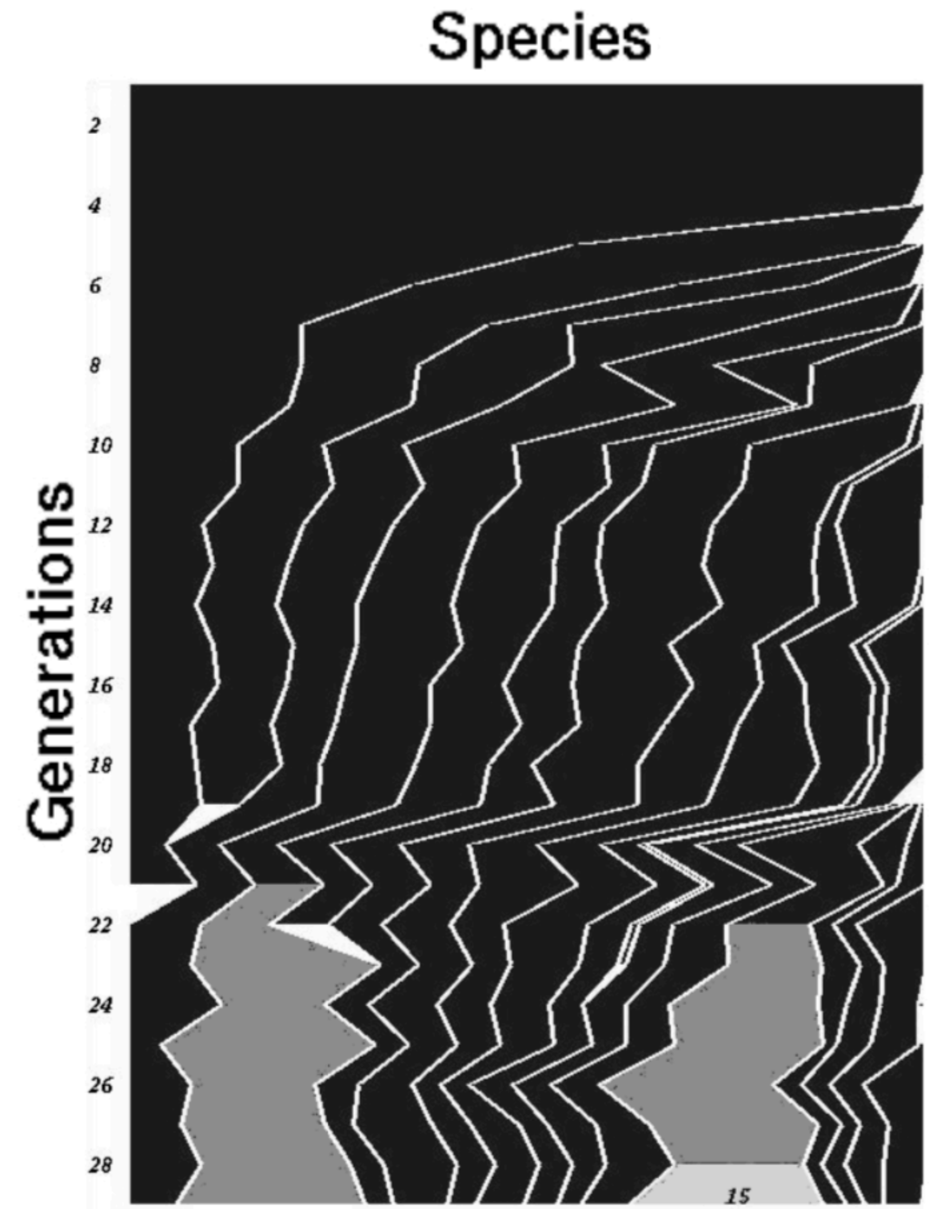

Any Question?

- Paper: *Evolving Neural Networks through Augmenting Topologies, K. O. Stanley, et.al., 2006, MIT Press Journal*
- Find this presentation online: https://arefmq.github.io/downloads/NEAT-Presntation.pdf
- Link of Video: https://www.youtube.com/watch?v=qv6UVOQ0F44&t=31s
- Find me on web: https://arefmq.github.io/
- Read More: https://en.wikipedia.org/wiki/Neuroevolution_of_augmenting_topologies