Evolutionary learning

NEAT & HyperNEAT

JB Mouret

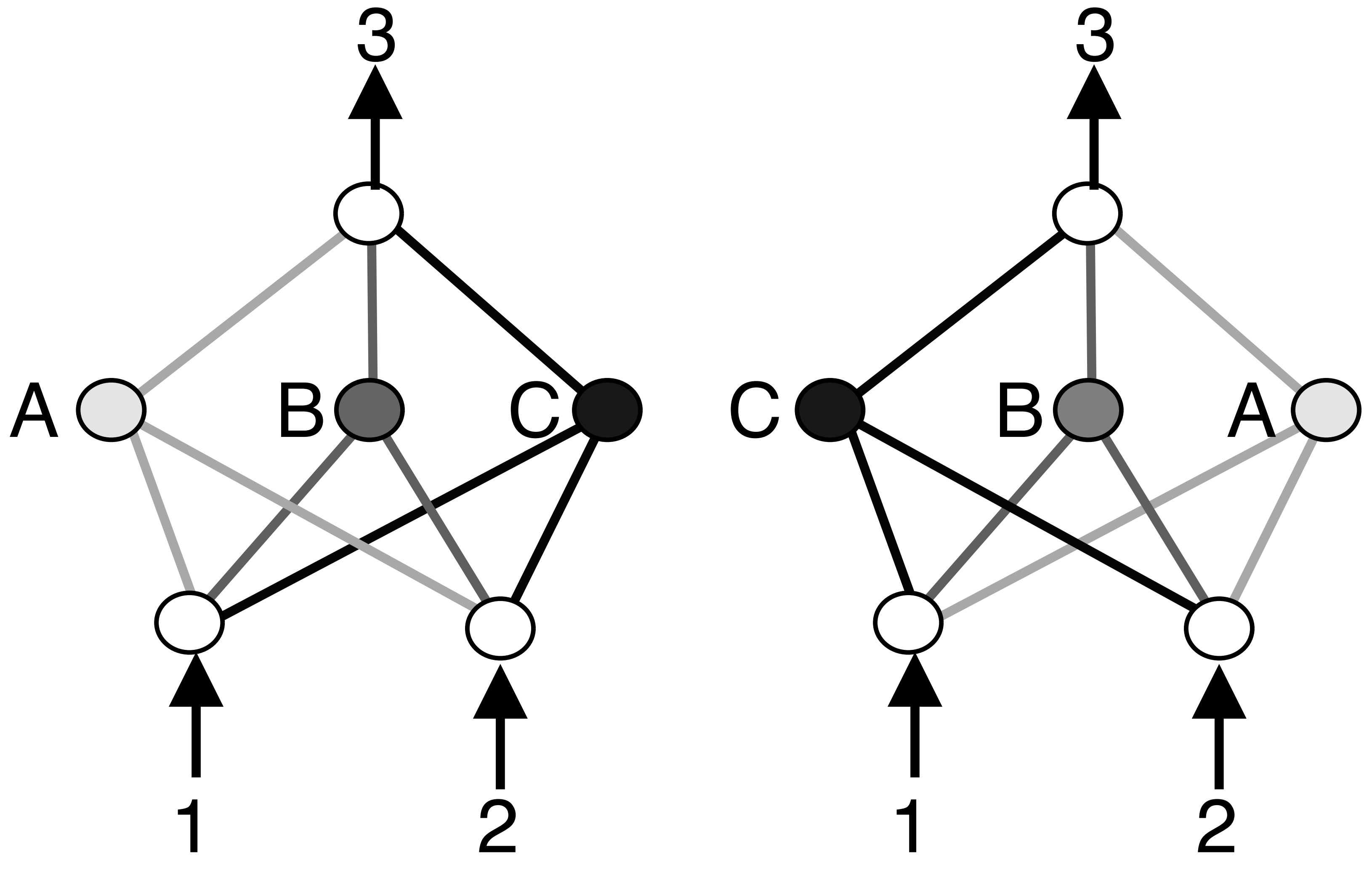
How to evolve both the structure and the weights?

Concept of direct encodings:

- Encode a graph as the genotype
- Labels = weights
- Mutation:
  - add a connection between two random nodes
  - remove an existing connection
  - add a neuron (usually on an existing connection)
  - change a weight (e.g., Gaussian perturbation)

- No cross-over:
  - permutation problem
  - graph matching is hard (complexity)

- Use a standard evolutionary algorithm (not an ES!)

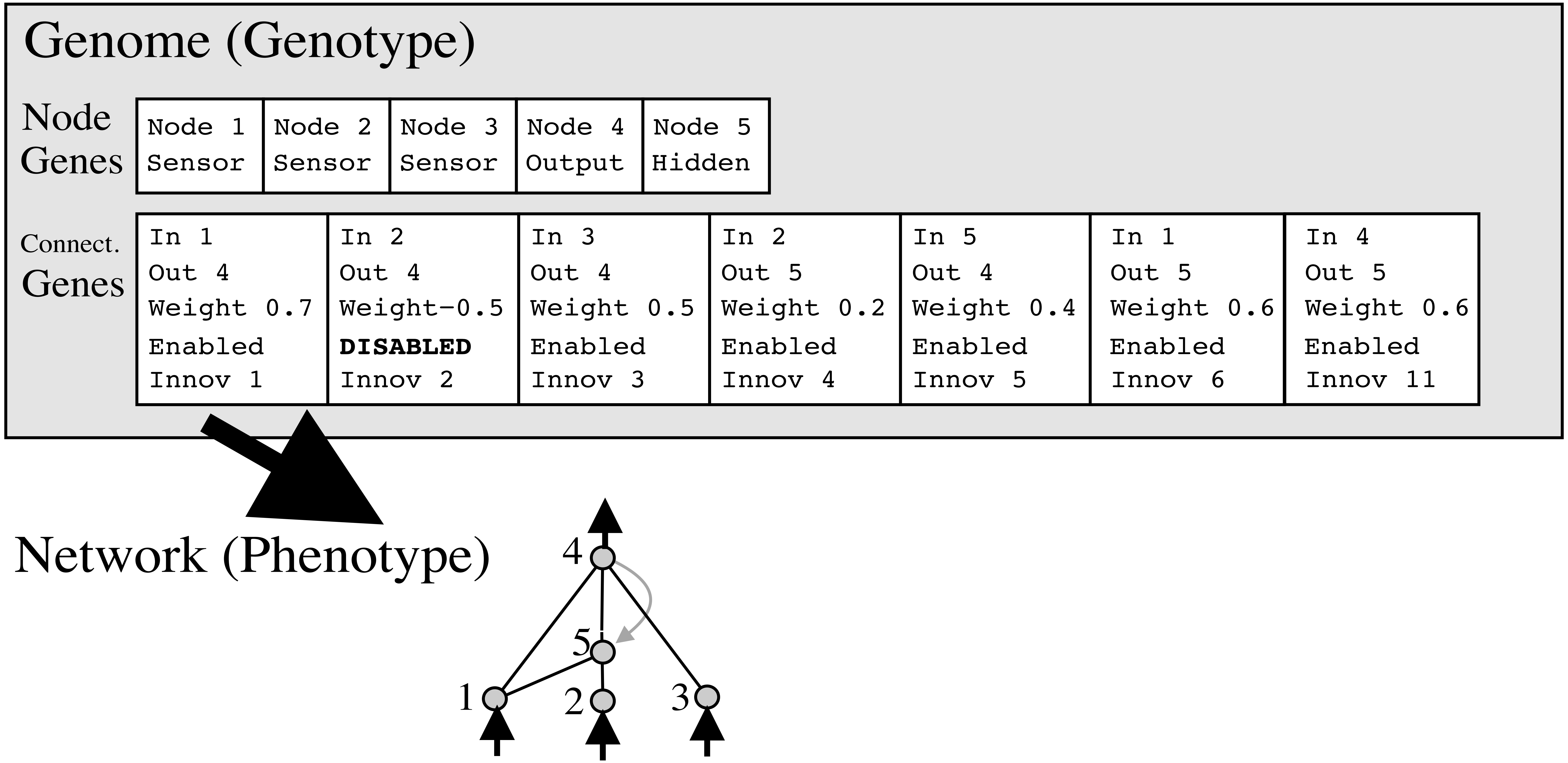


NEAT

Concept of NEAT:

- Grow incrementally: start with always the same topology
- Facilitate the comparison of networks with innovation numbers

➔ A (global) counter for each new connection



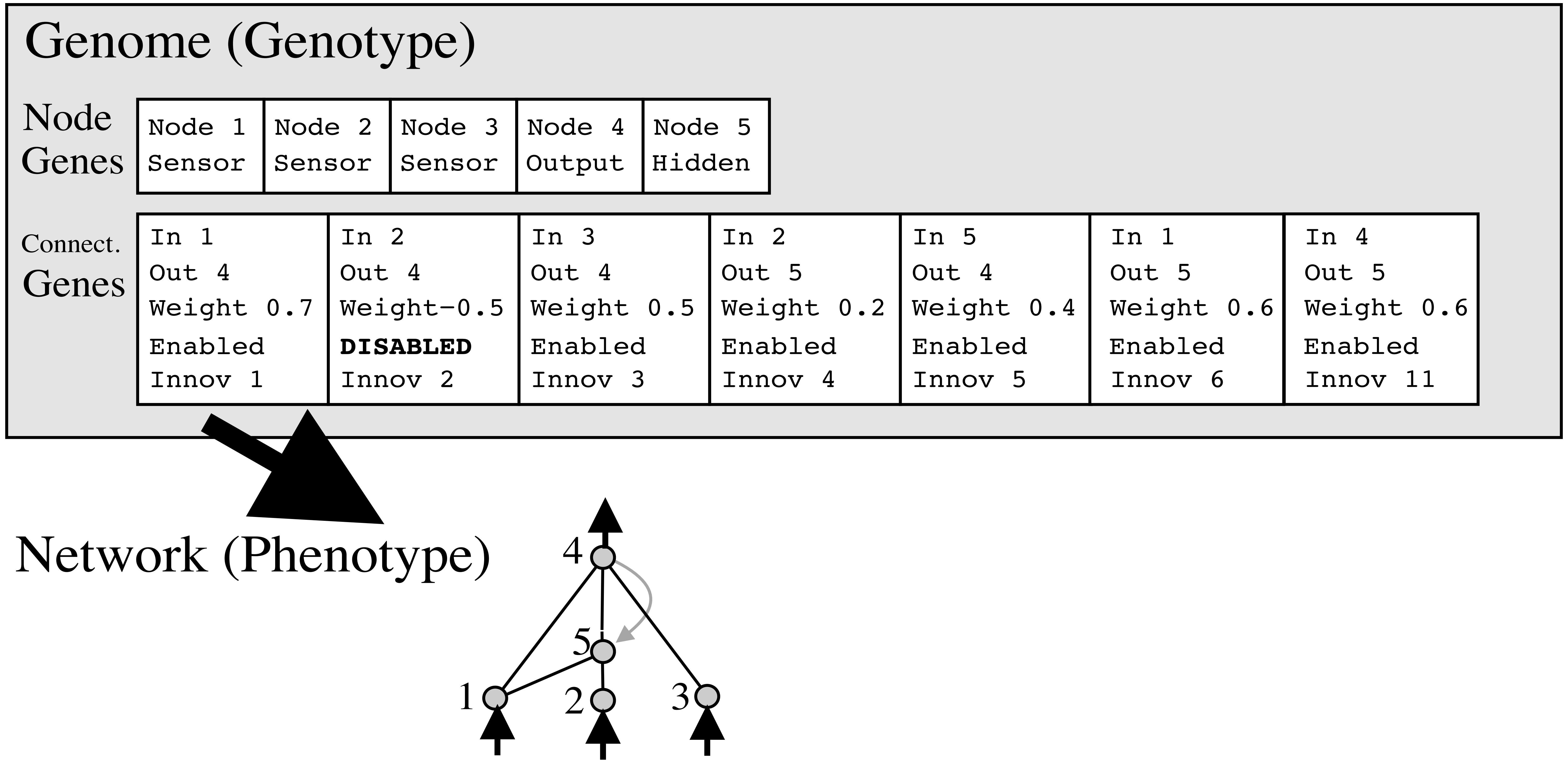
Stanley KO, Miikkulainen (2002) R. Evolving neural networks through augmenting topologies. *Evolutionary computation*. 2002;10(2):99-127.

NEAT

Neuro-Evolution of Augmenting Topologies (NEAT)

- Facilitate the comparison of networks with innovation numbers

➔ A (global) counter for each new connection

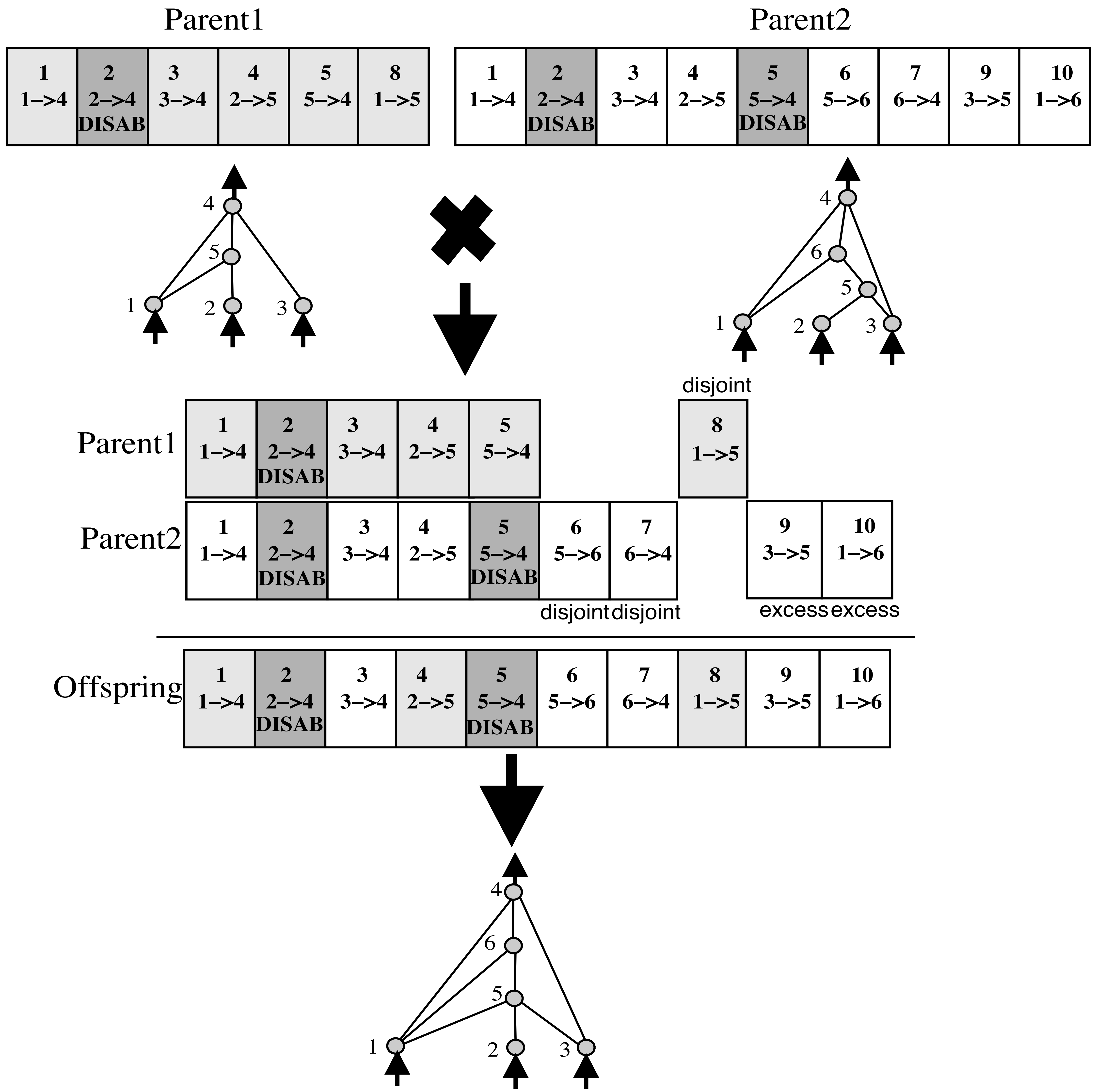


Stanley KO, Miikkulainen R. (2002) Evolving neural networks through augmenting topologies. *Evolutionary computation*. 2002;10(2):99-127.

NEAT: cross-over

Neuro-Evolution of Augmenting Topologies (NEAT)

- Align the genes with the same innovation number
- Matching genes are inherited randomly,
- disjoint genes and excess genes are inherited from the more fit parent



Stanley KO, Miikkulainen R (2002). Evolving neural networks through augmenting topologies. *Evolutionary computation*. 2002;10(2):99-127.

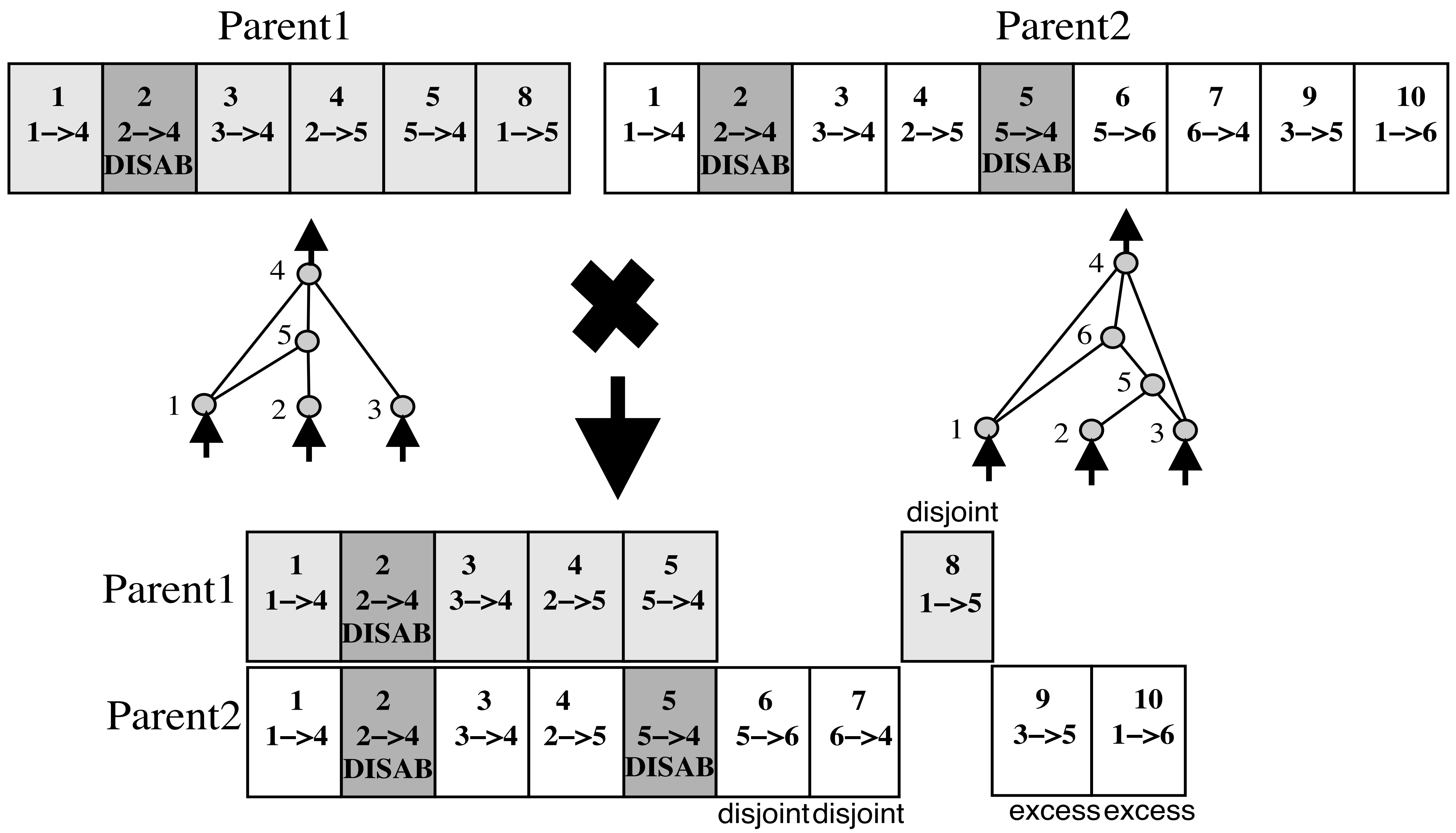
NEAT: speciation

Neuro-Evolution of Augmenting Topologies (NEAT)

Objective: define niches by network topology

(so that a novel topology is “protected")

- Align the genes with the same innovation number
- Compute a distance between individuals:



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

Excess genes

Disjoint genes

Weight difference (joint genes)

Use fitness sharing:

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

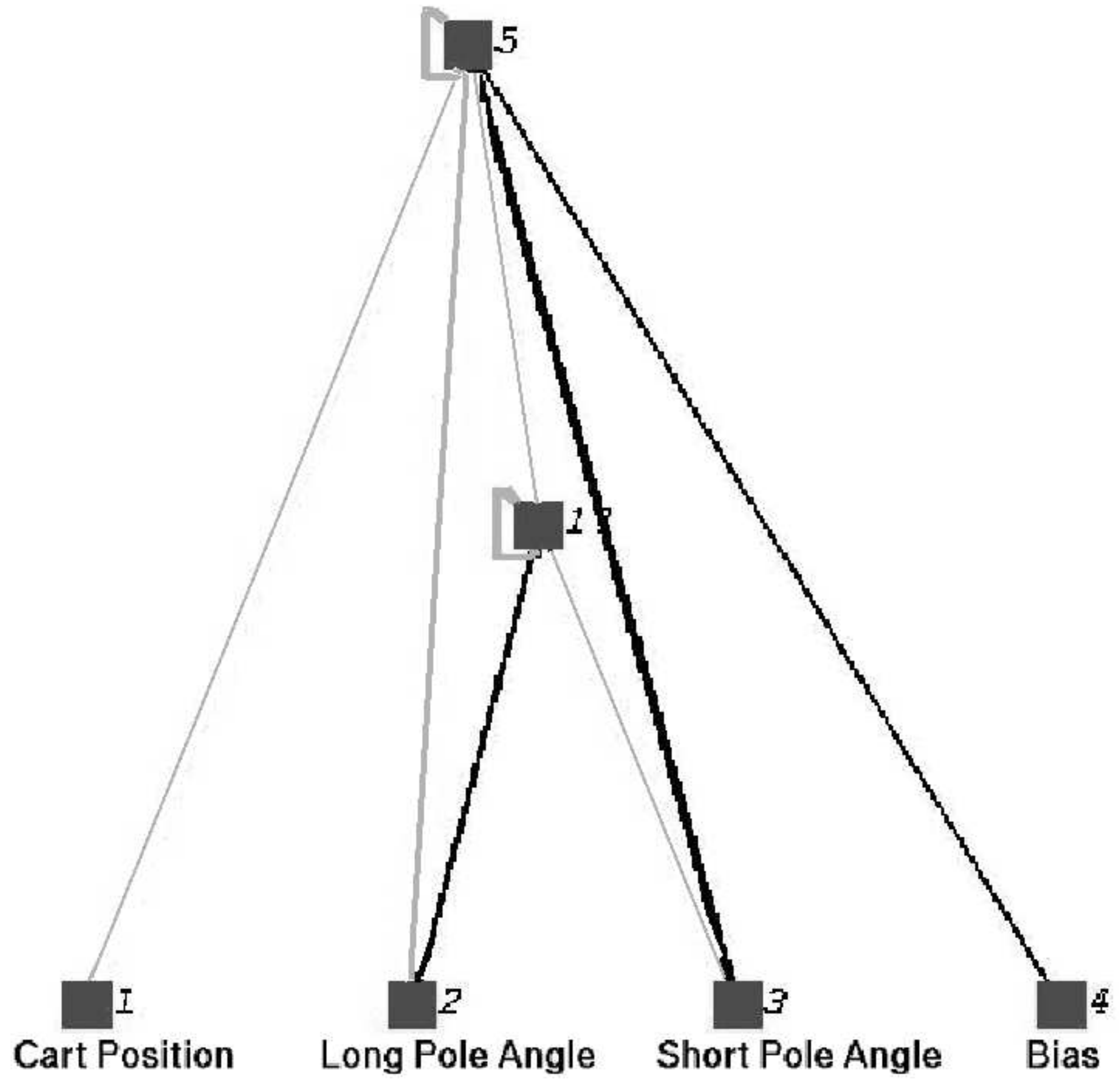
1 if $\delta(i,j) > \delta_{tr}$, 0 otherwise

Stanley KO, Miikkulainen R (2002). Evolving neural networks through augmenting topologies. *Evolutionary computation*. 2002;10(2):99-127.

NEAT: results

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

double pole balancing with velocities



double inverse pendulum
(note the recurrences!)

Stanley KO, Miikkulainen R (2002). Evolving neural networks through augmenting topologies. *Evolutionary computation*. 2002;10(2):99-127.

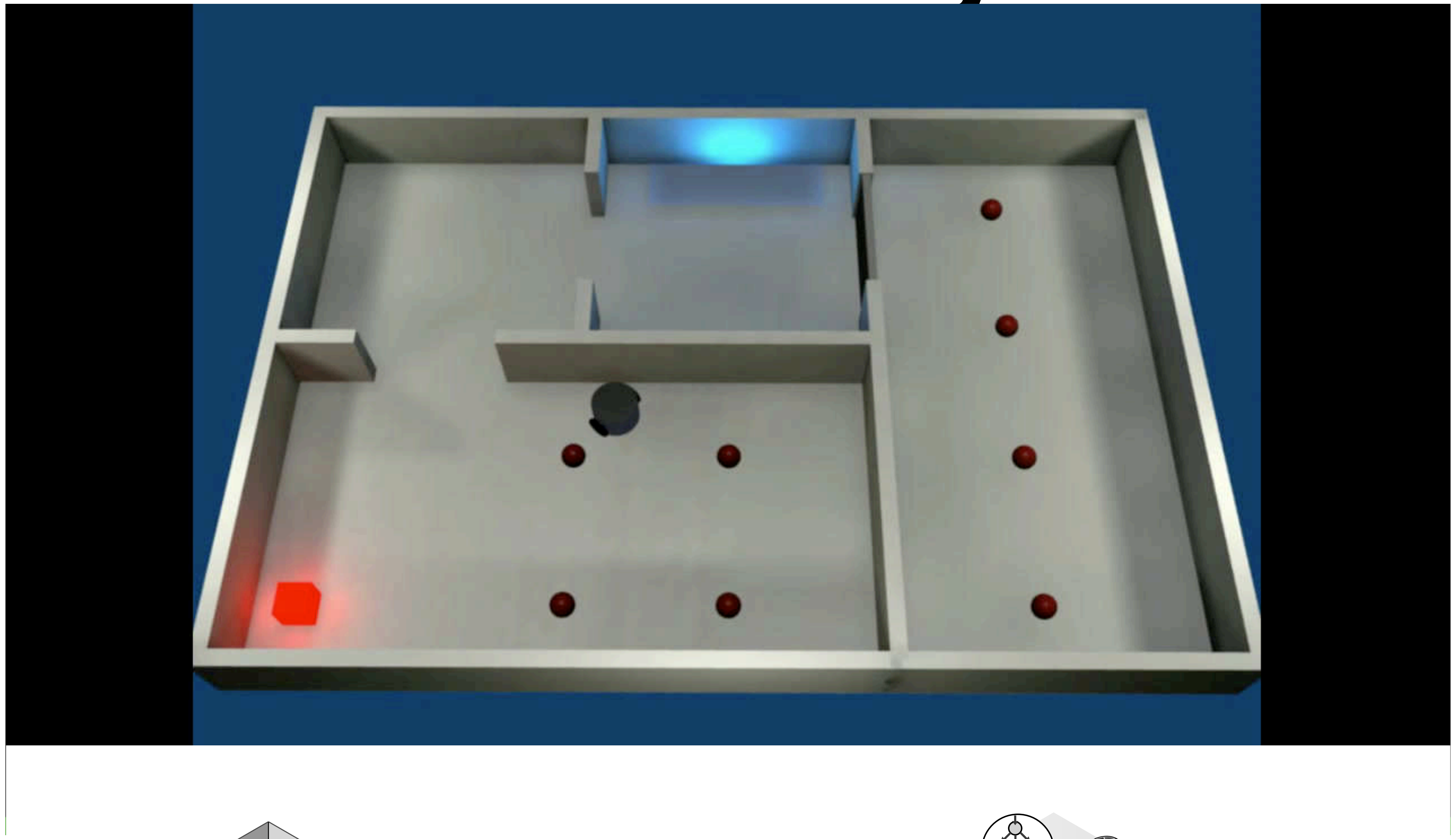
Instead of speciation: behavioral diversity

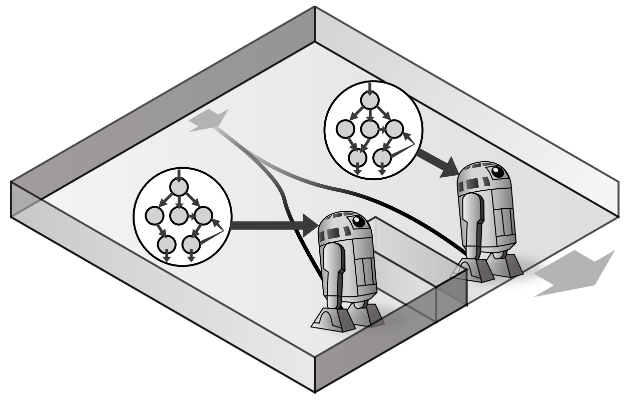
- Define a distance between behaviors
  e.g., diff. in trajectory or sensor streams
- Use NSGA-II to maximize:

$$\begin{cases} Fitness(x) \\ \boxed{\sum_i d(x, P_i)} \end{cases}$$

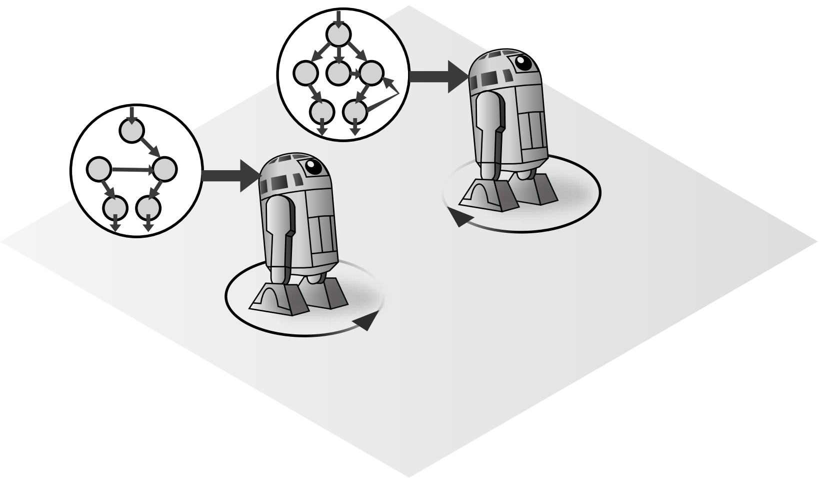
Diversity with regards
to the population

The key for evolving topologies is diversity





Close genotype / different behavior

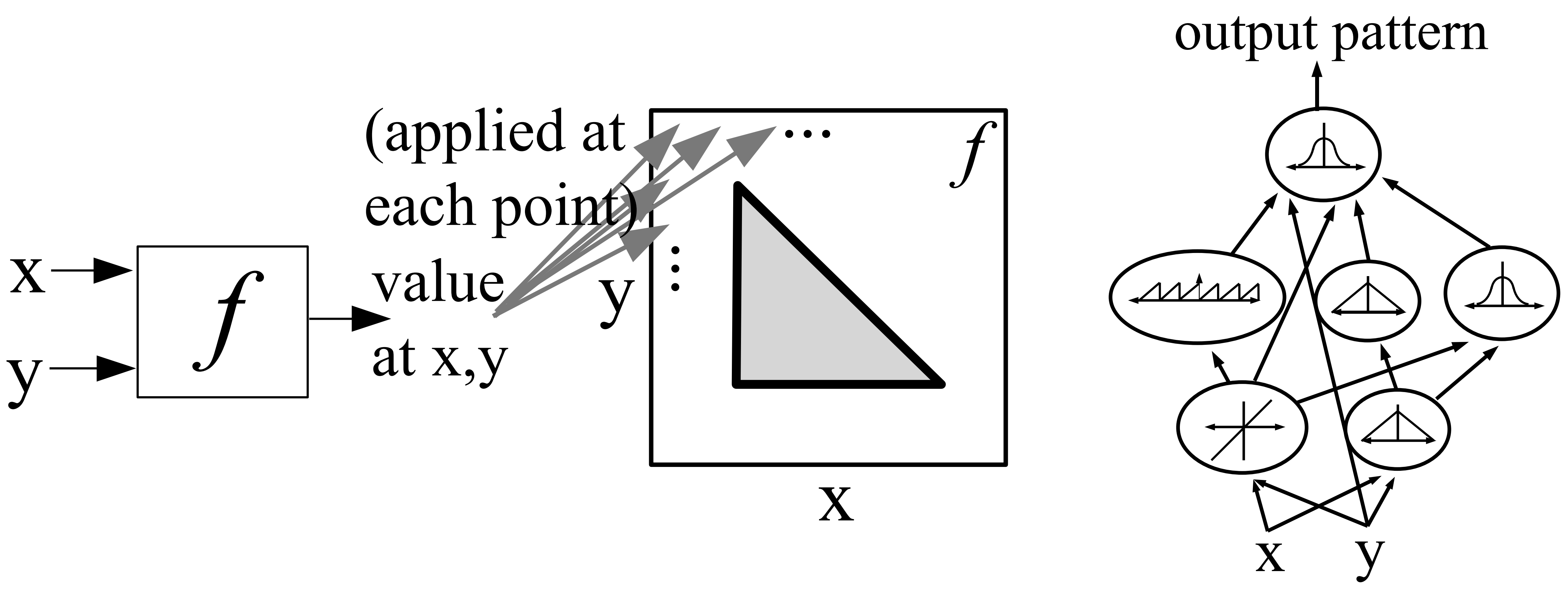


Different genotype / same behavior

Mouret, J. B., & Doncieux, S. (2012). Encouraging behavioral diversity in evolutionary robotics: An empirical study. Evolutionary computation, 20(1), 91-133.

Doncieux, S., & Mouret, J. B. (2014). Beyond black-box optimization: a review of selective pressures for evolutionary robotics. Evolutionary Intelligence, 7(2), 71-93.

Finding natural patterns

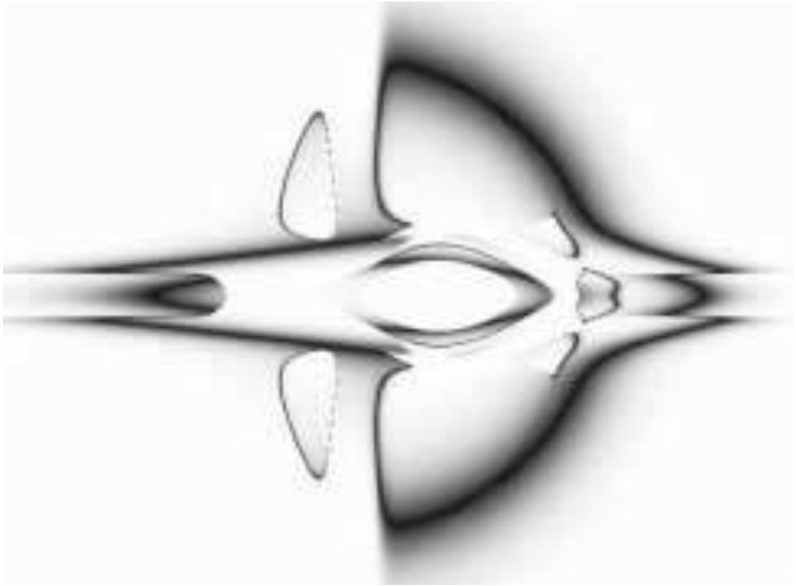


(a) Mapping

(b) Composition

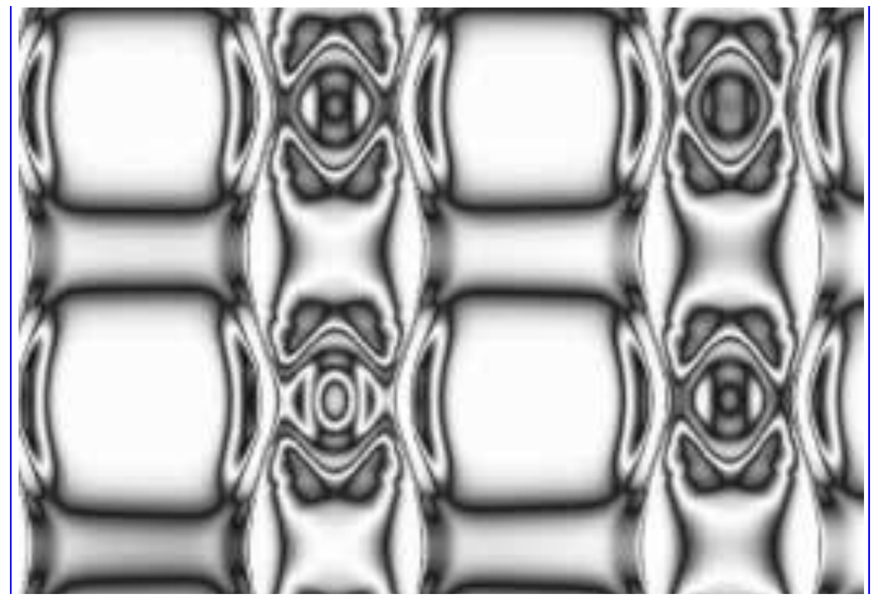
Evolved with NEAT
Additional mutation: change the activation function
Functions:

- sine wave (repetition)
- Gaussian (symmetry)
- sigmoid
- …



Symmetry

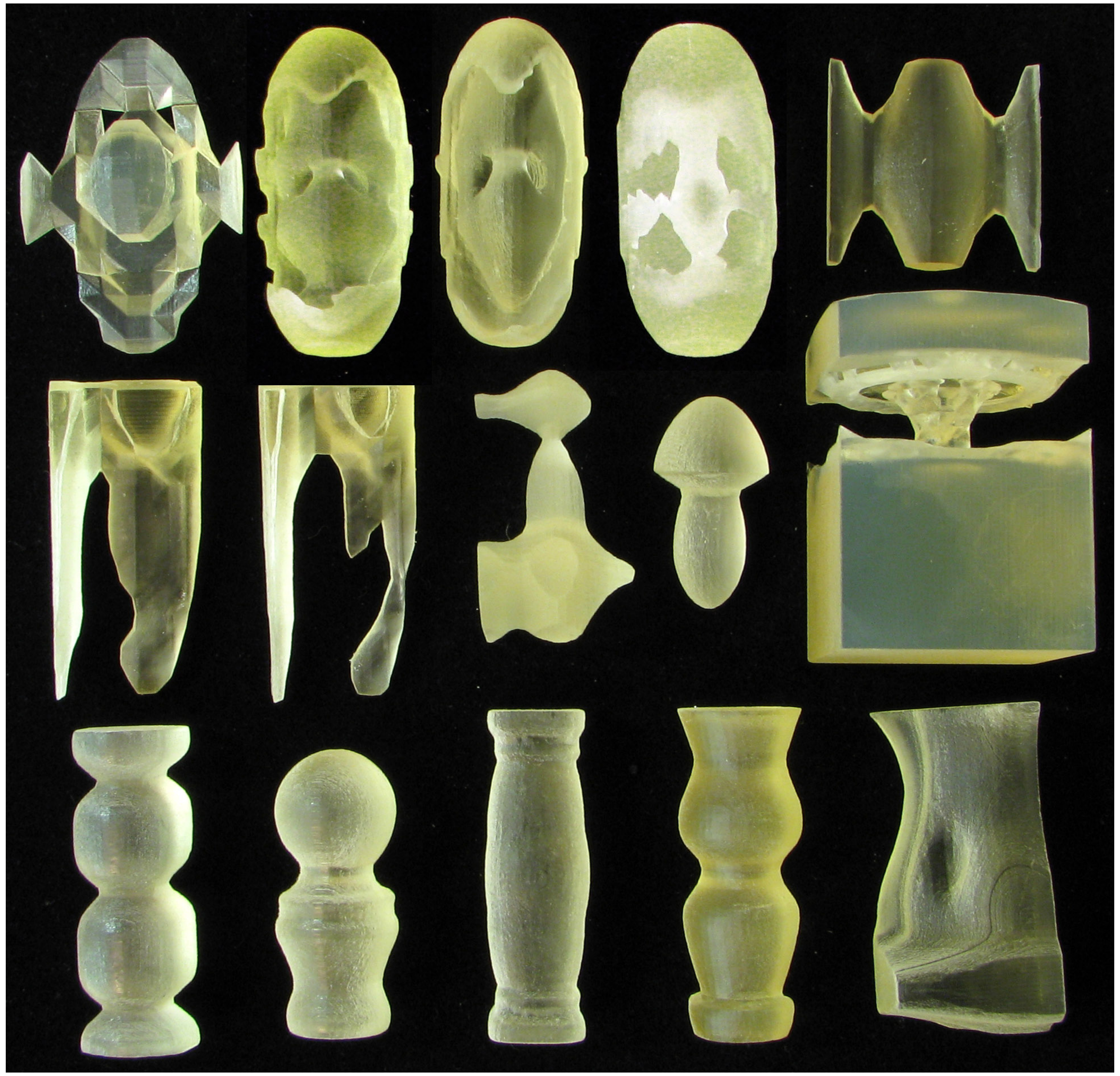
Imperfect symmetry

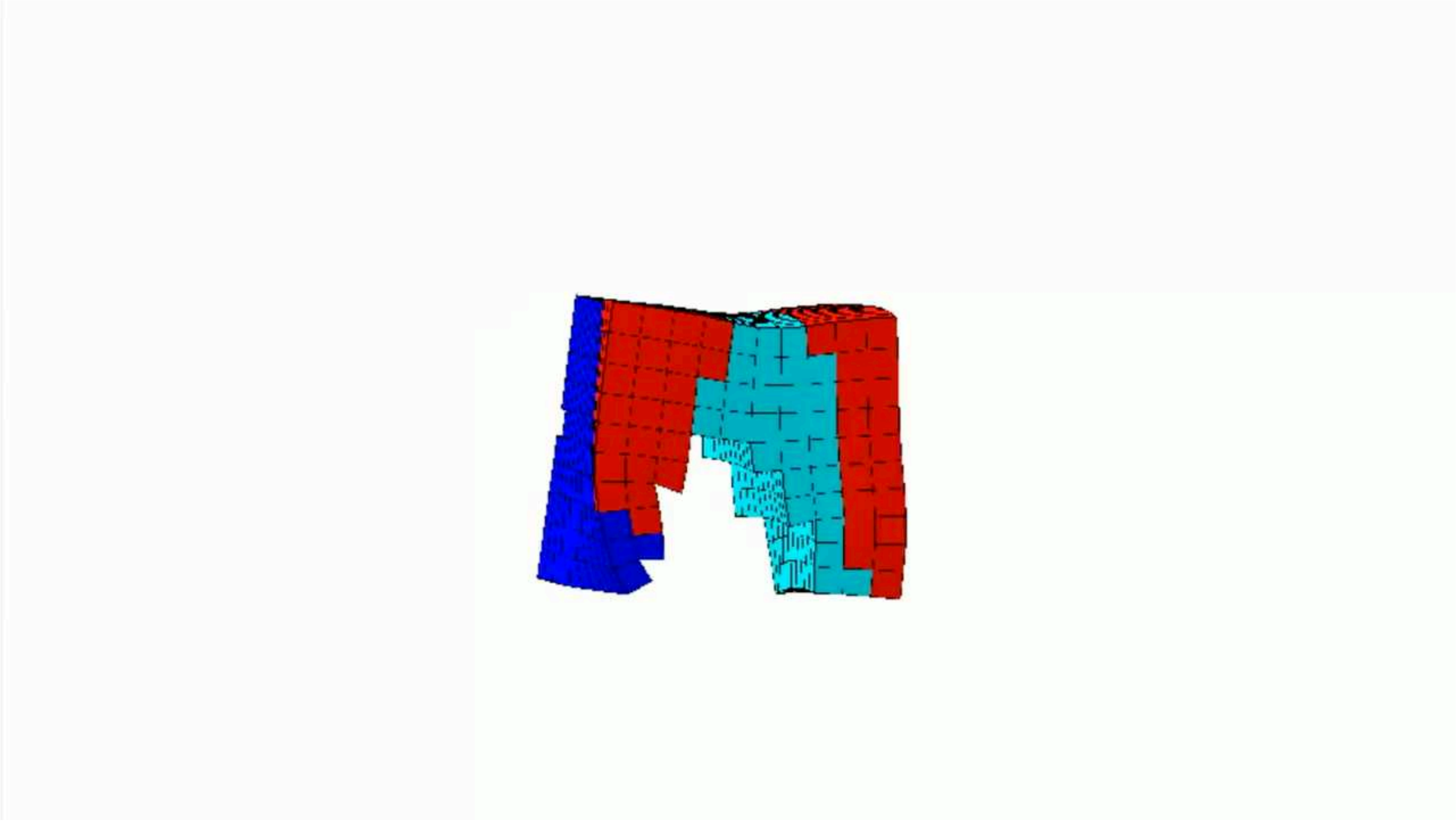


Repetition with variation

Stanley, Kenneth O. (2007) “Compositional pattern producing networks: A novel abstraction of development." *Genetic programming and evolvable machines* 8.2 (2007): 131-162.

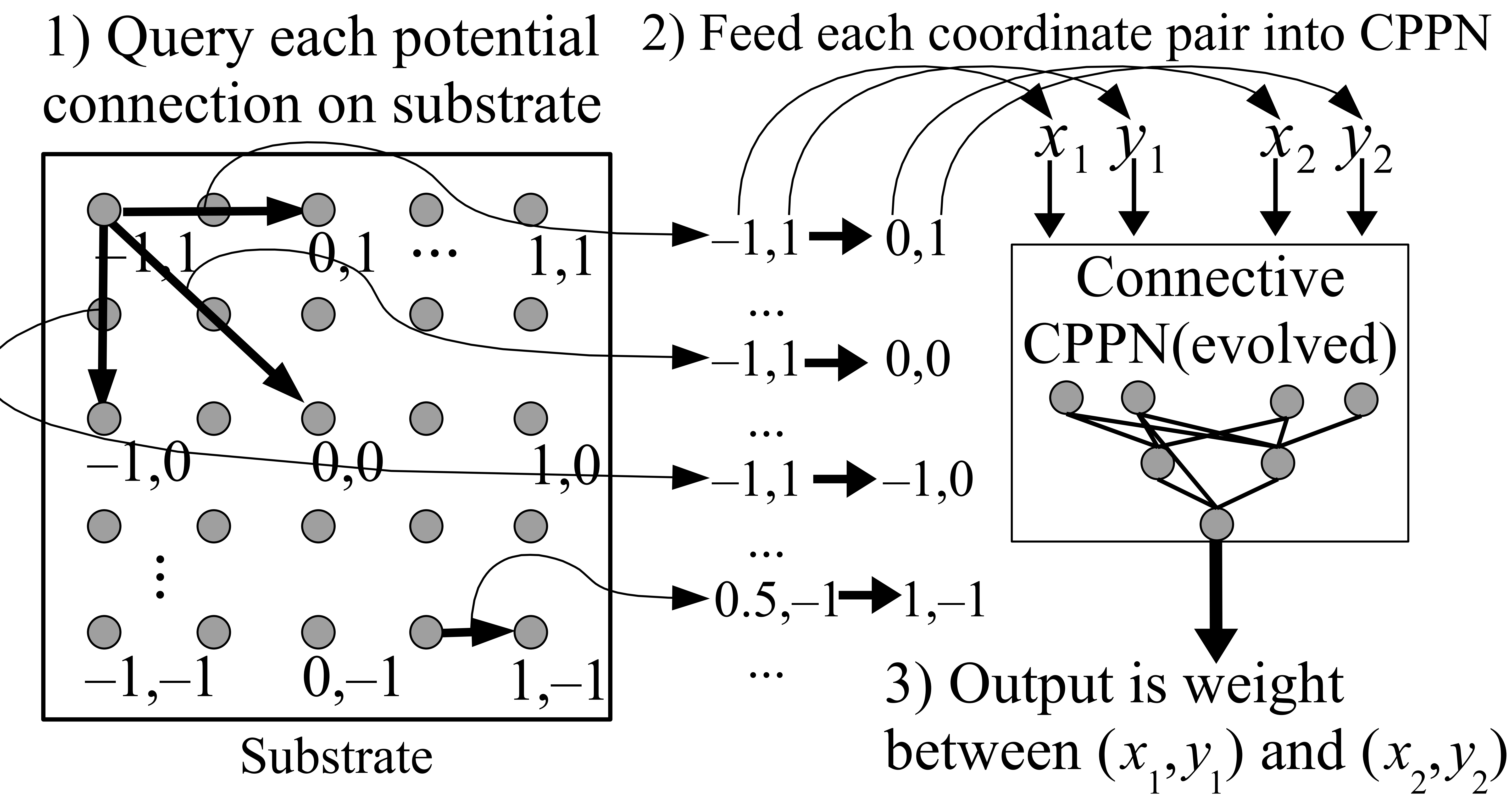
Finding natural patterns

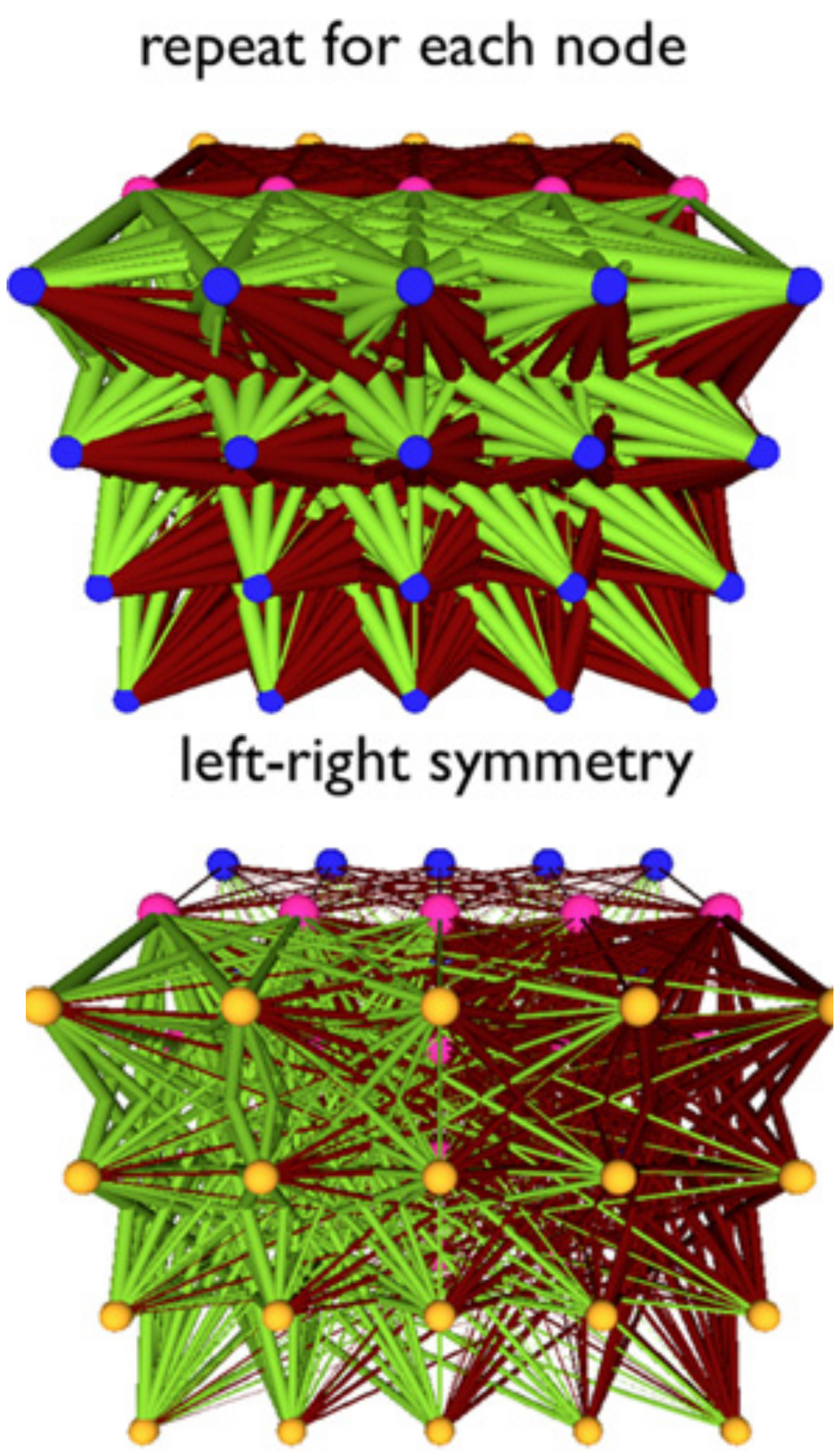




Clune, Jeff, and Hod Lipson. (2011)“Evolving three-dimensional objects with a generative encoding inspired by developmental biology." Proc. of *ECAL*. 2011.
Cheney N, MacCurdy R, Clune J, Lipson H. (2013) Unshackling evolution: evolving soft robots with multiple materials and a powerful generative encoding. In. *Proc of GECCO* 2013

Connection patterns





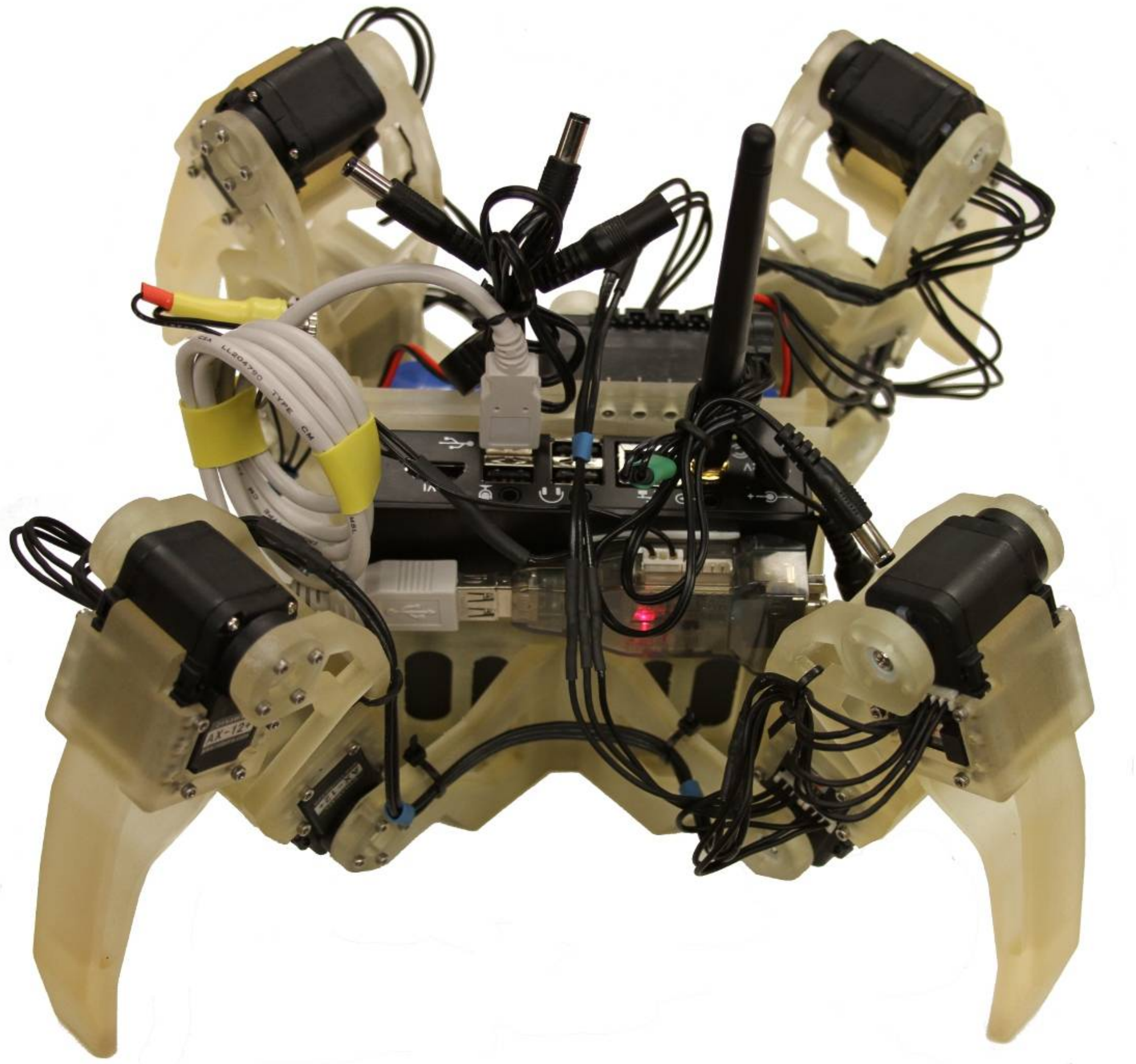
Scales to million of neurons!

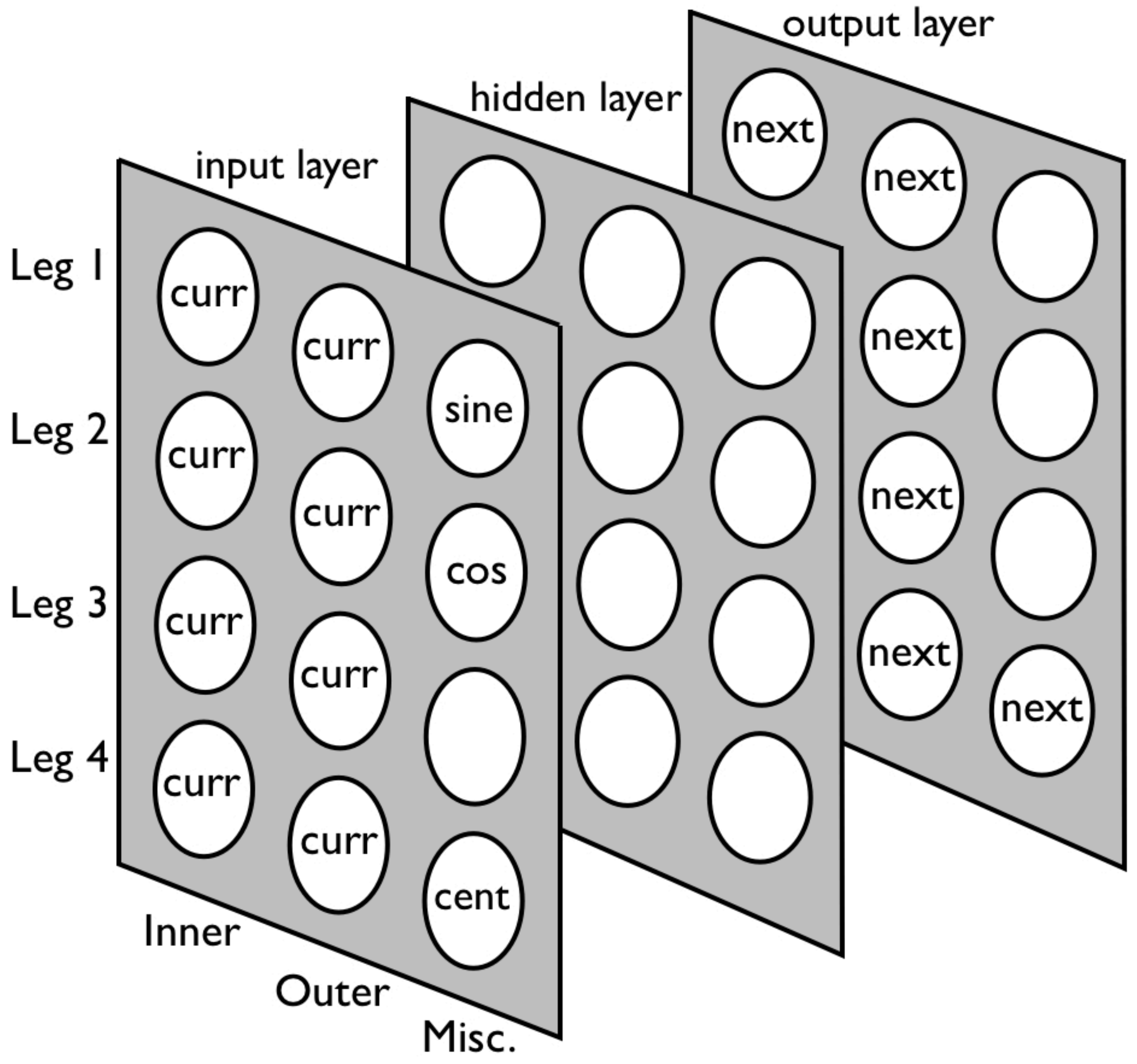
Stanley, Kenneth O., David B. D'Ambrosio, and Jason Gauci. (2009) "A hypercube-based encoding for evolving large-scale neural networks." *Artificial life* 15.2 (2009): 185-212.

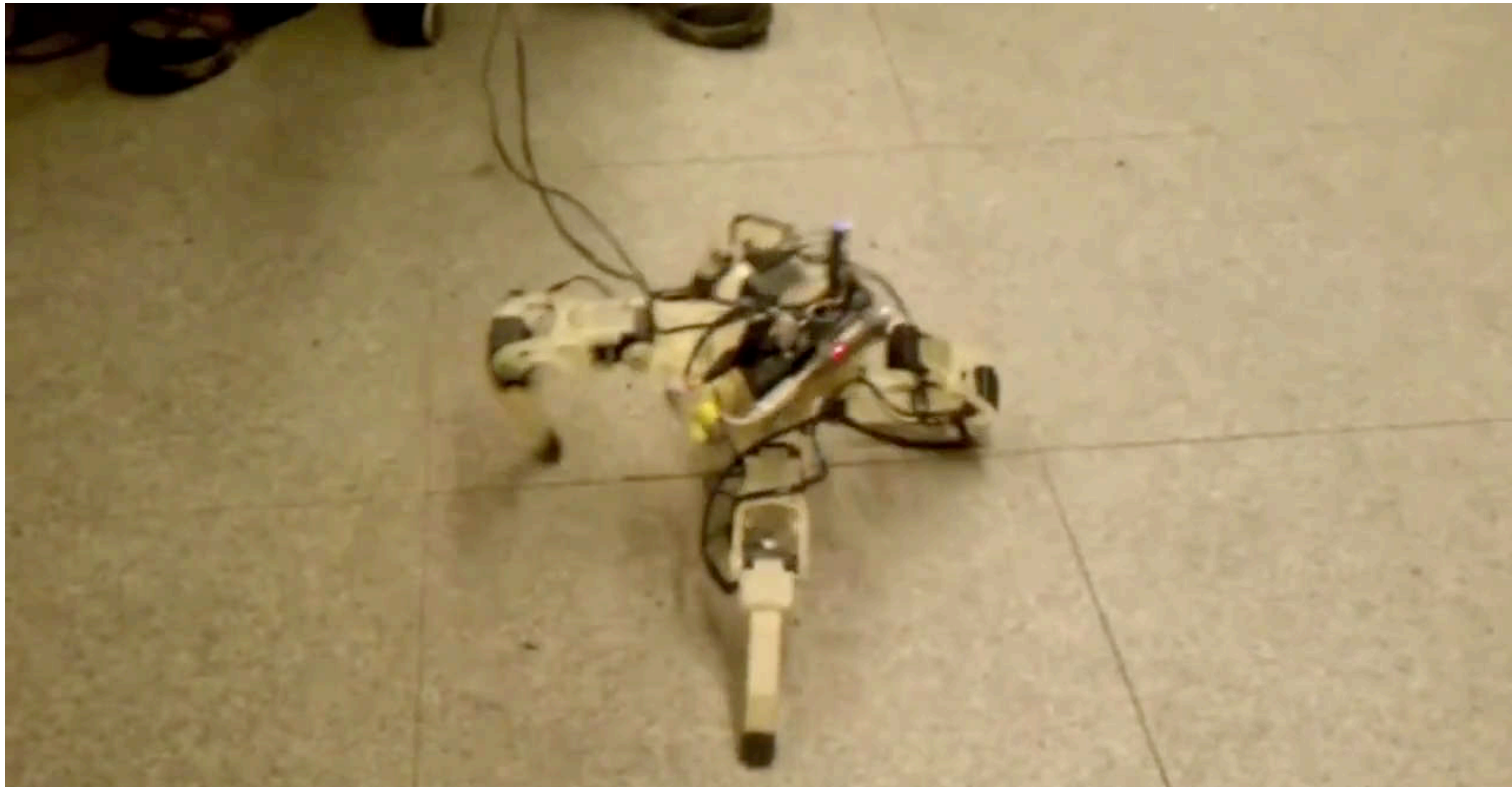
Clune J, Stanley KO, Pennock RT, Ofria C. (2011) On the performance of indirect encoding across the continuum of regularity. *IEEE Transactions on Evolutionary Computation.* 2011 Jun;15(3):346-67.

HyperNEAT: learning gaits

	Average	Std. Dev.
Previous hand-coded gait	5.16	–
Random search	9.40	6.83
Uniform Random Hill Climbing	7.83	4.56
Gaussian Random Hill Climbing	10.03	6.00
Policy Gradient Descent	6.32	7.39
Nelder-Mead simplex	12.32	3.35
Linear Regression	14.01	12.88
Evolved Neural Network (HyperNEAT)	29.26	6.37







Yosinski, J., Clune, J., Hidalgo, D., Nguyen, S., Zagal, J. C., & Lipson, H. (2011). Evolving robot gaits in hardware: the HyperNEAT generative encoding vs. parameter optimization. In ECAL (pp. 890-897).