

Indirect Encodings of Artificial Neural Networks

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COMPUTATIONAL
INTELLIGENCE
GROUP

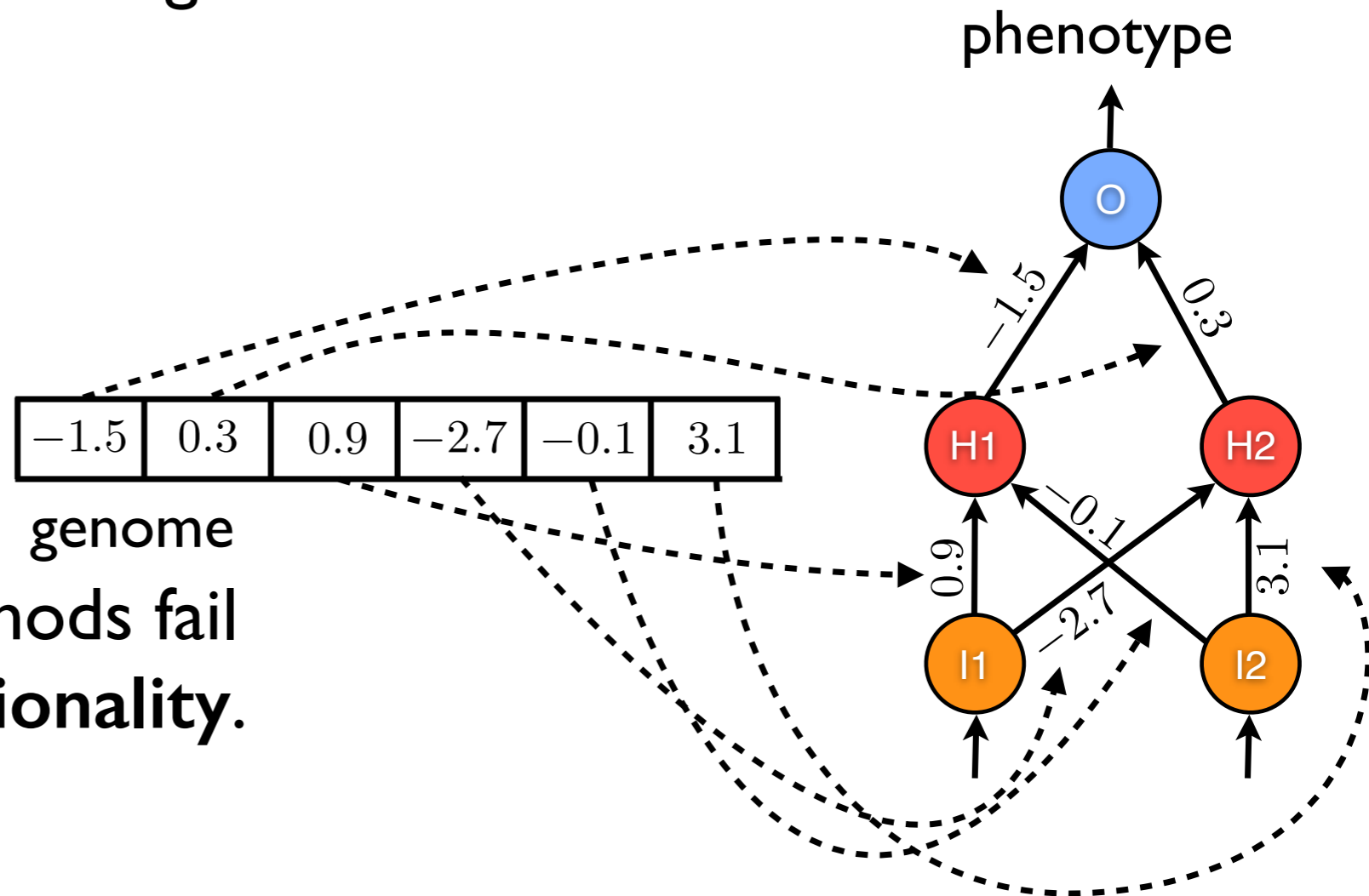
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Overview

- Computational Development.
- Indirect Encodings of ANNs.
- Hyper-cube based encoding.

Direct Encoding

- **Direct encoding** → each structural part (neuron/link) is represented by a dedicated gene.
- Not suitable for Large-scale ANN's:

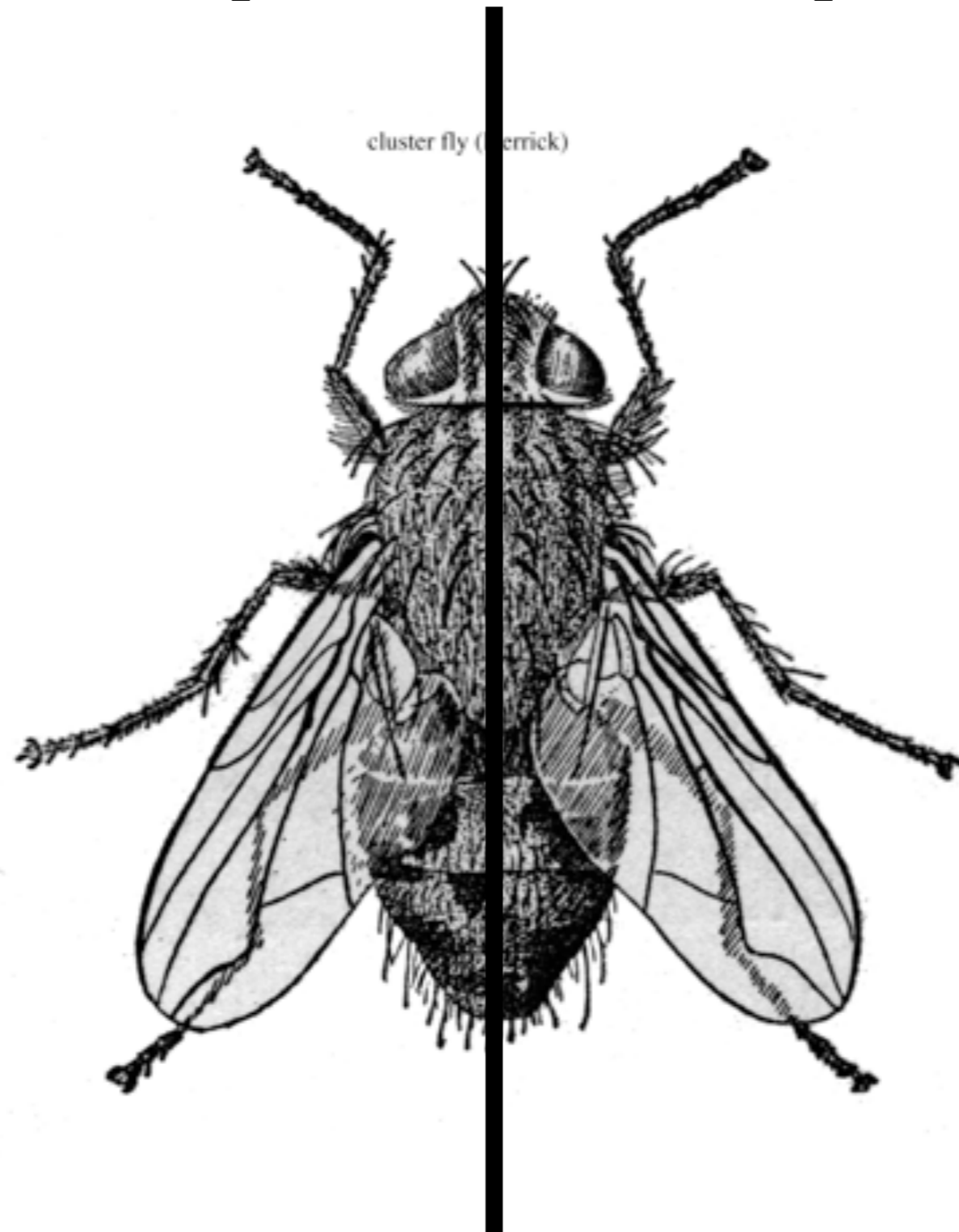


Direct optimization methods fail
→ the curse of dimensionality.

Indirect Encoding: the Way it Works in Nature

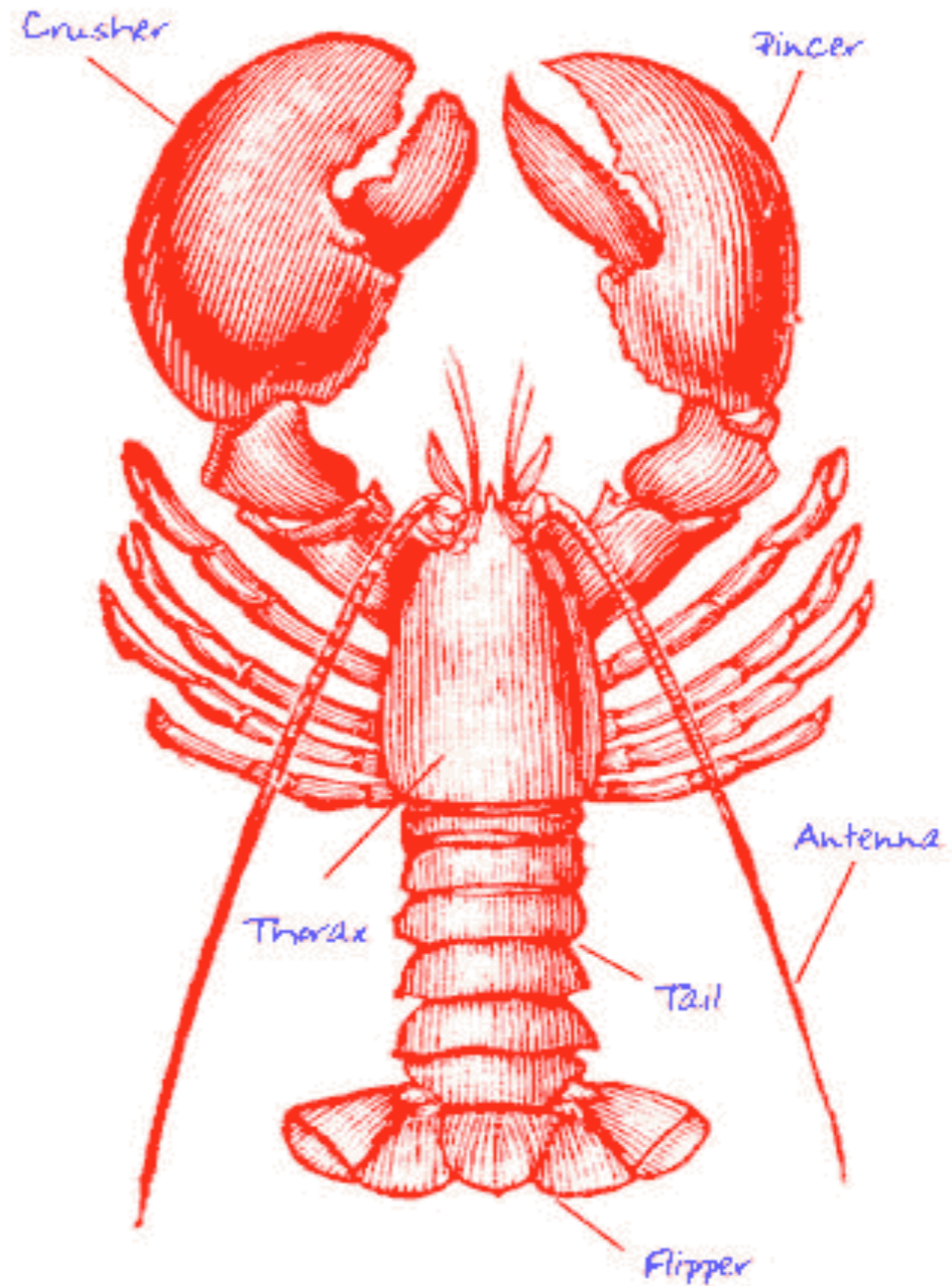
- Human genome → 20 000 - 25 000 genes describing almost 100 billion neurons each linked to as many as 7 000 others (plus the rest of organism!).
- We need some kind of **compression**:
→ **indirect encoding**.
- But we also need a **regularity** in data being compressed.
- **Q**: What are the regularities found in living organisms?

Symmetry



(wikimedia commons)

Imperfect Symmetry

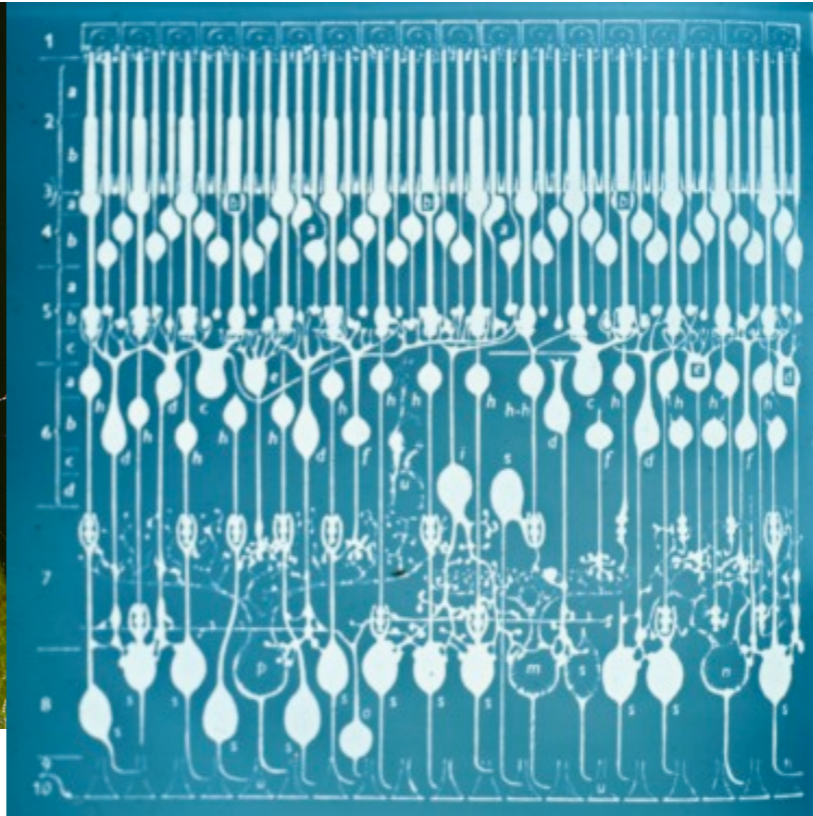


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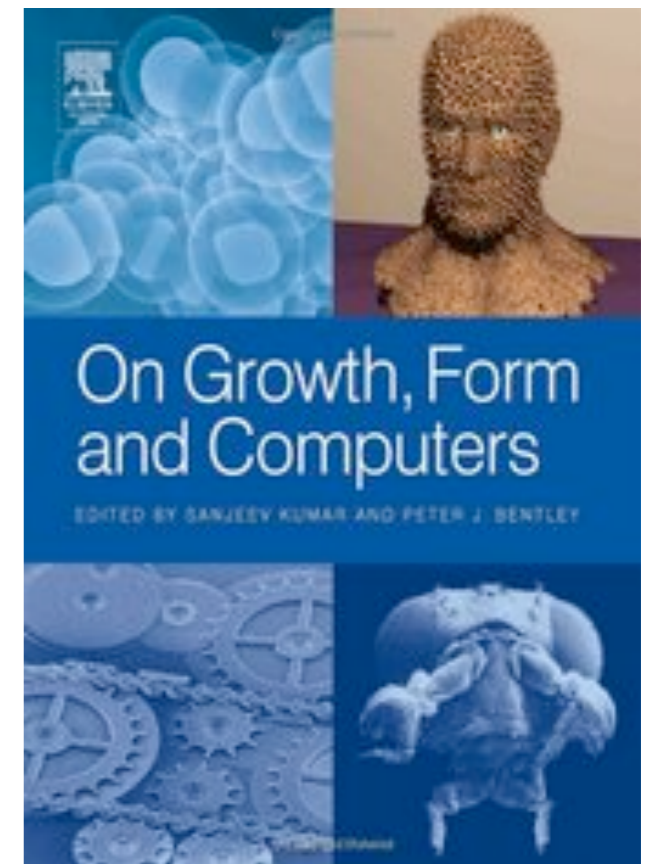
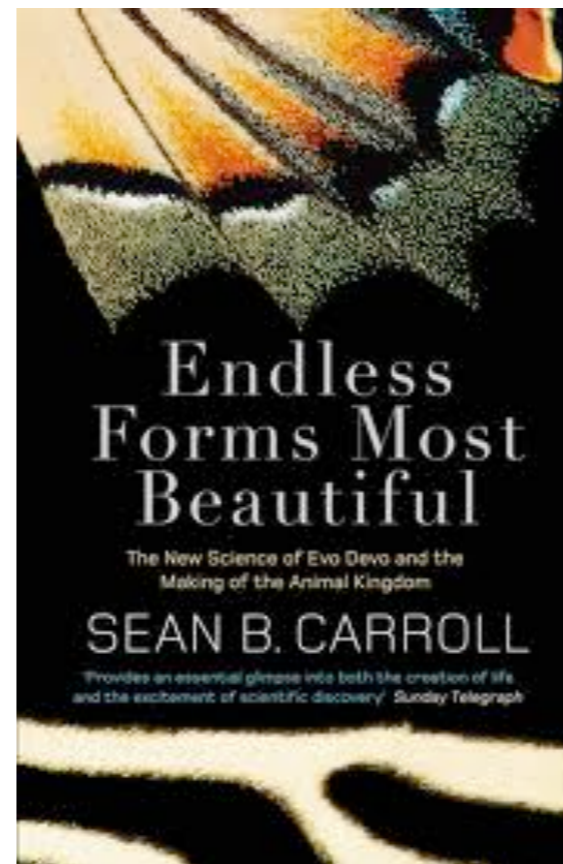
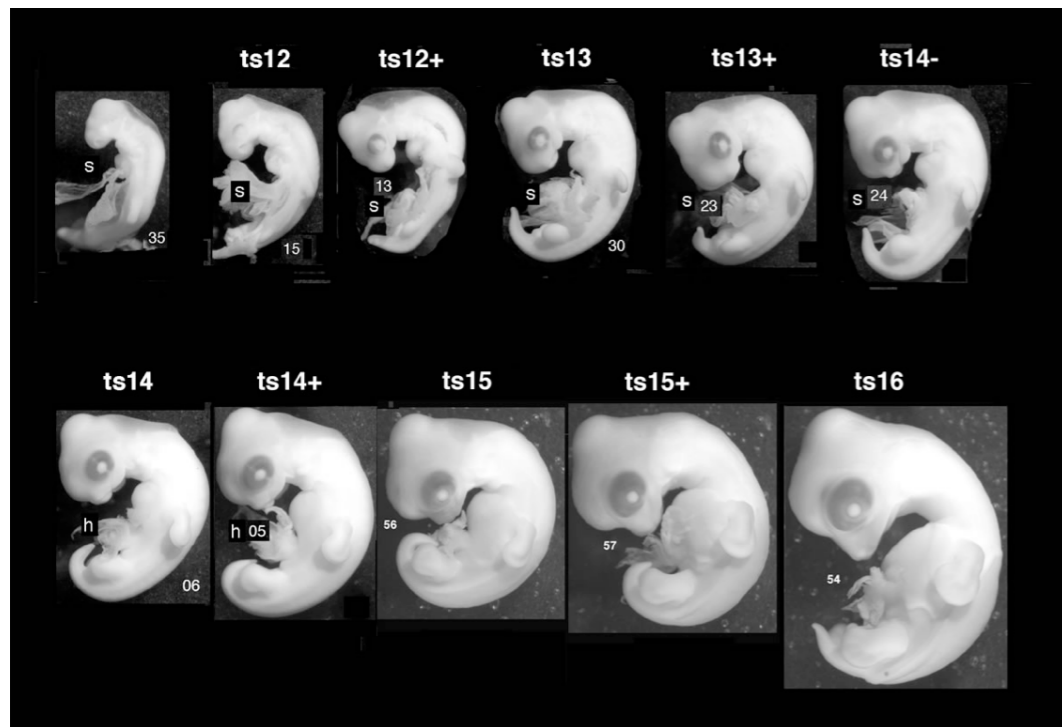
Repetition with Variation



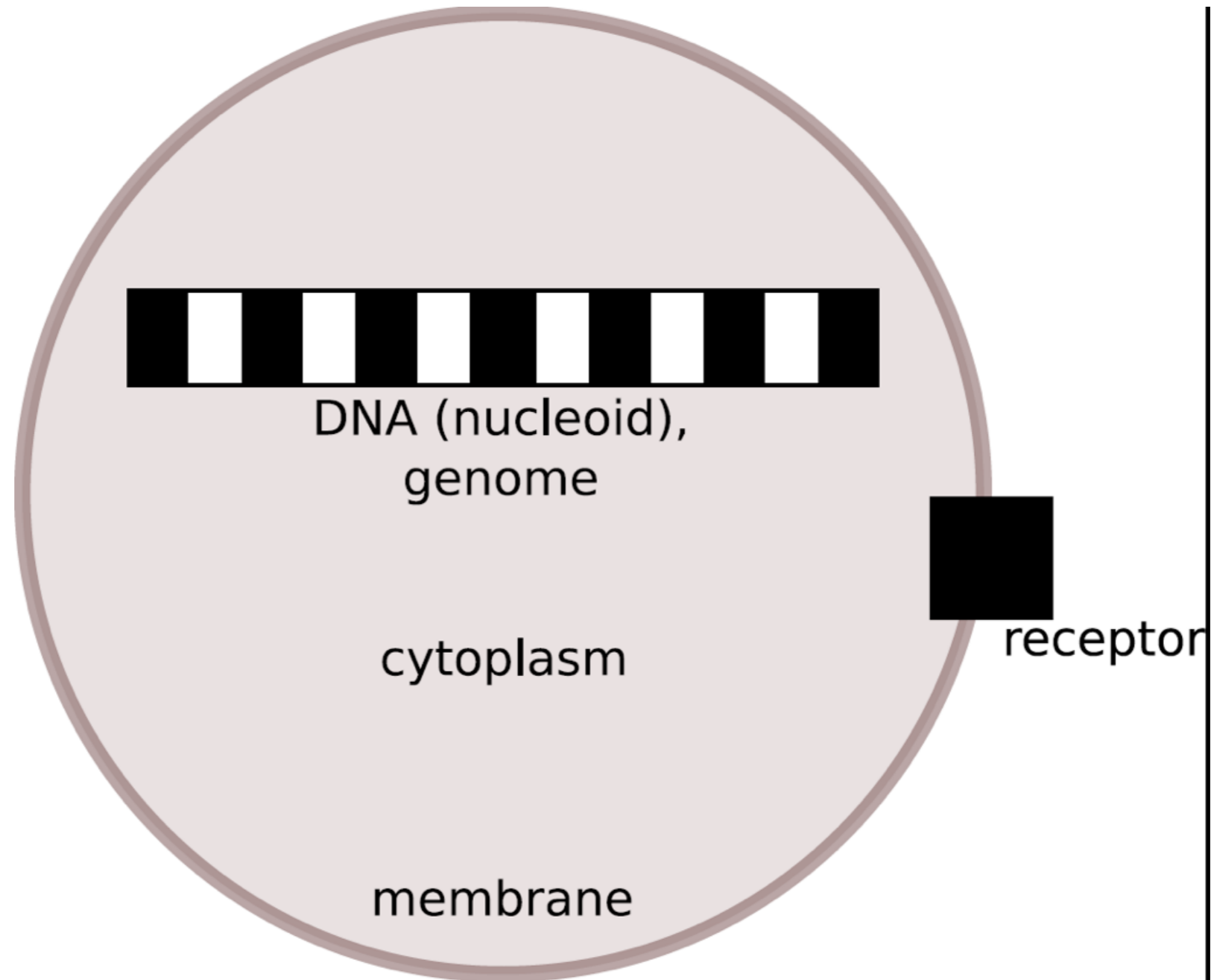
- Note that all these regularities happen at **all scales** of an organism.

How Are Organisms Built?

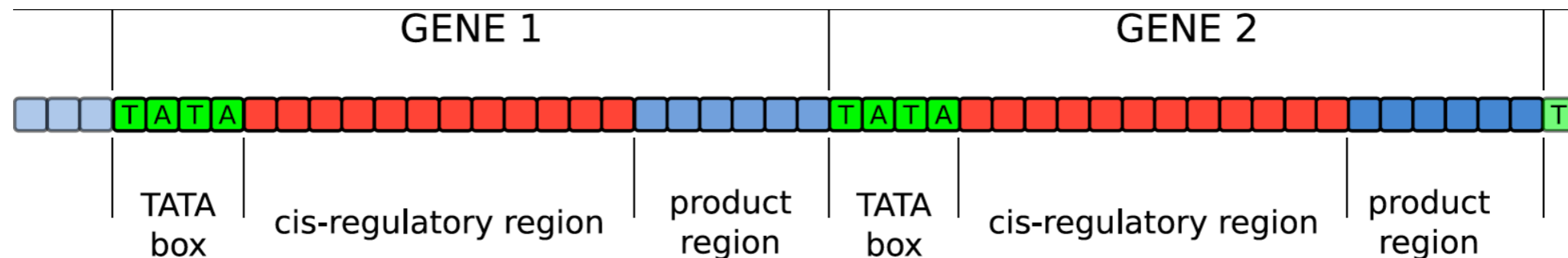
- Development from a single cell (zygote).
- Evolutionary Development “Evo-Devo”.



The Cell



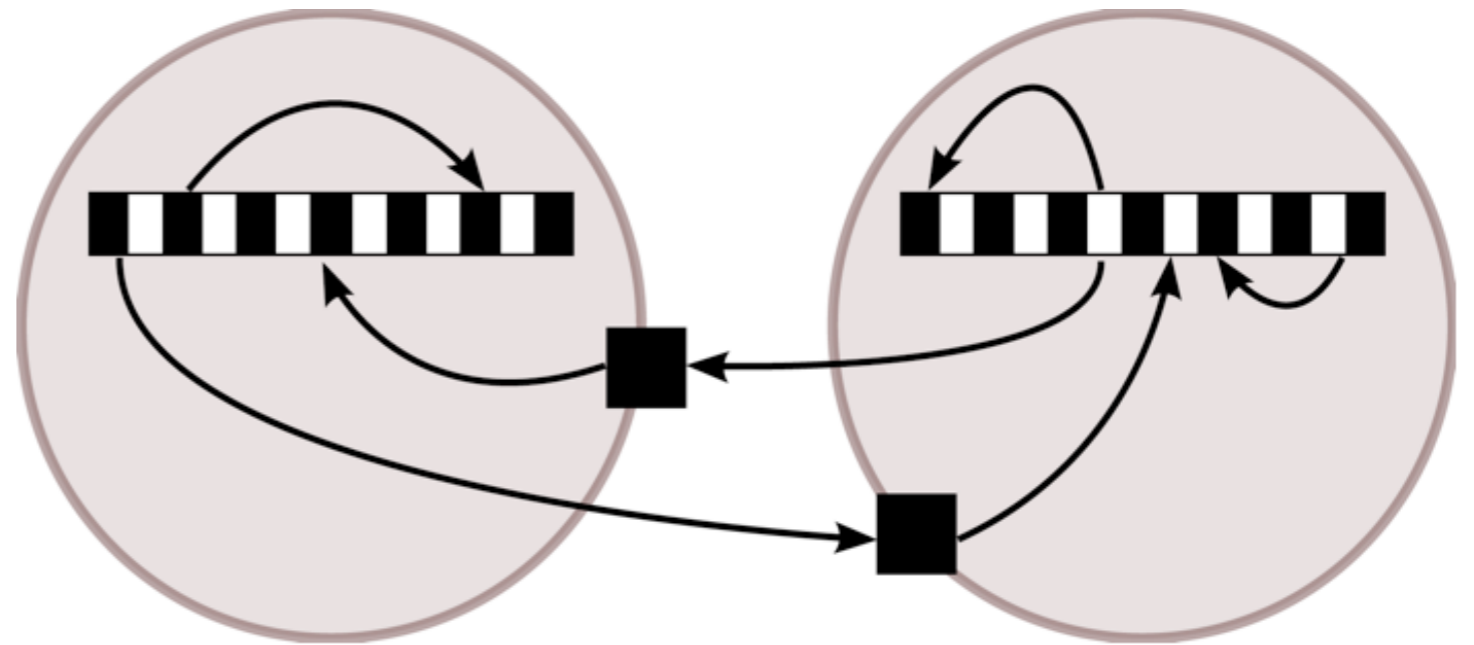
Genome: A Closer Look



- *TATA box* – marks the start of a gene
- *(cis-)regulatory region* – composed of binding sites.
- *binding site* – binds regulatory proteins → gene activation/inhibition
- *product region* – when gene is active a protein is produced:
 - *special*: cell division, differentiation,
 - *regulatory*: can bind to binding sites of other genes,
 - *structural*.

Cell Divisions

- Program same for all cells.
- What differs?
 - Regulatory protein *concentrations*.
- *Receptors* – selectively pass regulatory proteins from inter-cellular space.
- Diffusion, decay, cell differentiation.
- Gene Regulatory Networks (GRNs).



How to Simulate Development?

- Cell program – ANN, FSM or other controller:
 - *inputs*: binding sites,
 - *outputs*: gene activities.
- *Physical simulation*: diffusion, decay, receptors...
- Cell division:
 - *copy cell program* from mother → daughter cell,
 - *different concentrations* for mother/daughter.
- This is called: *Computational Development*.

“French Flag” Organism

- Cell program evolved using Cartesian Genetic Programming (CGP).

CGP encoded adder

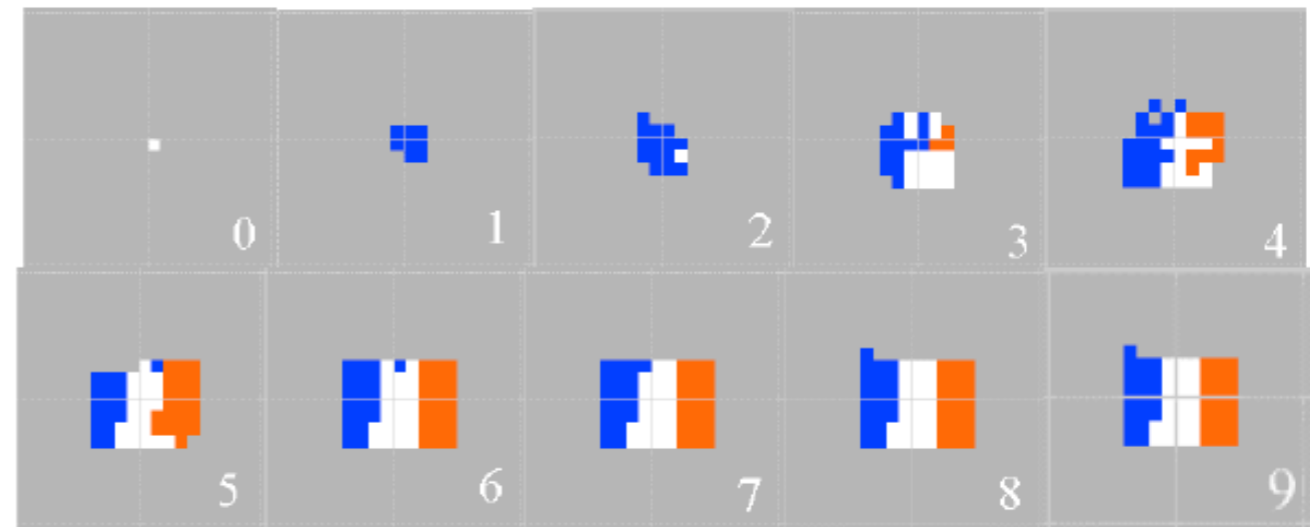
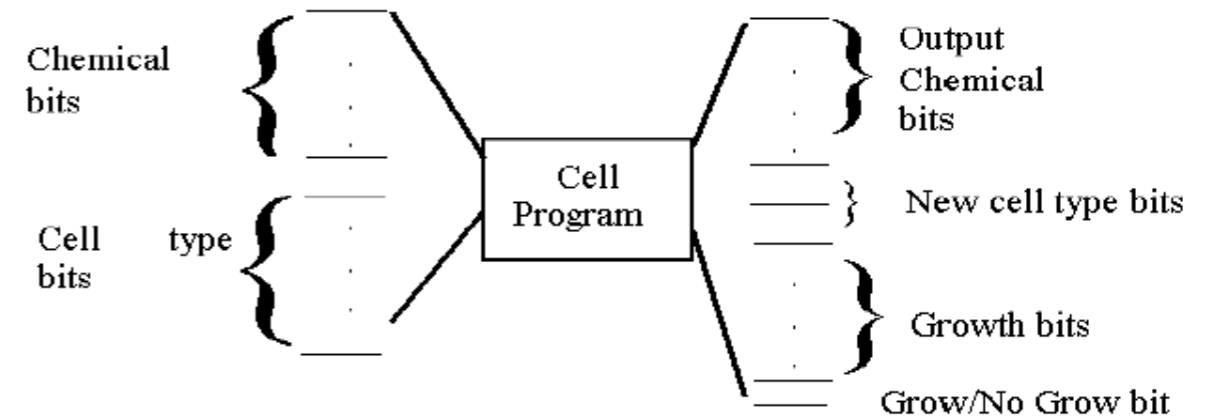
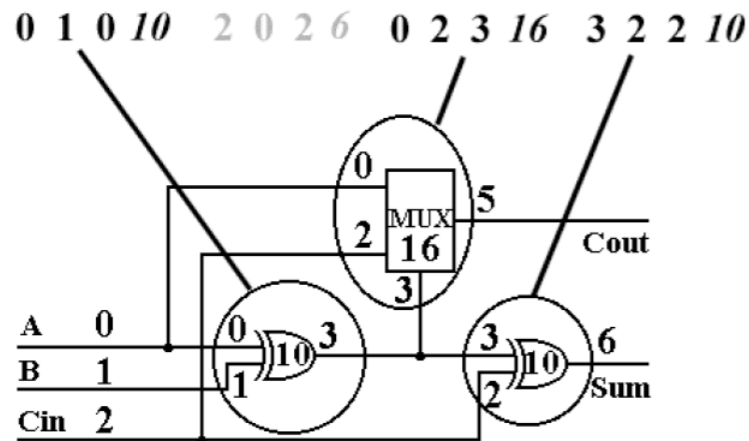


Fig. 4. Growth of fittest cell program from a white seed cell to a mature French flag (two chemicals)

“French Flag” Organism II

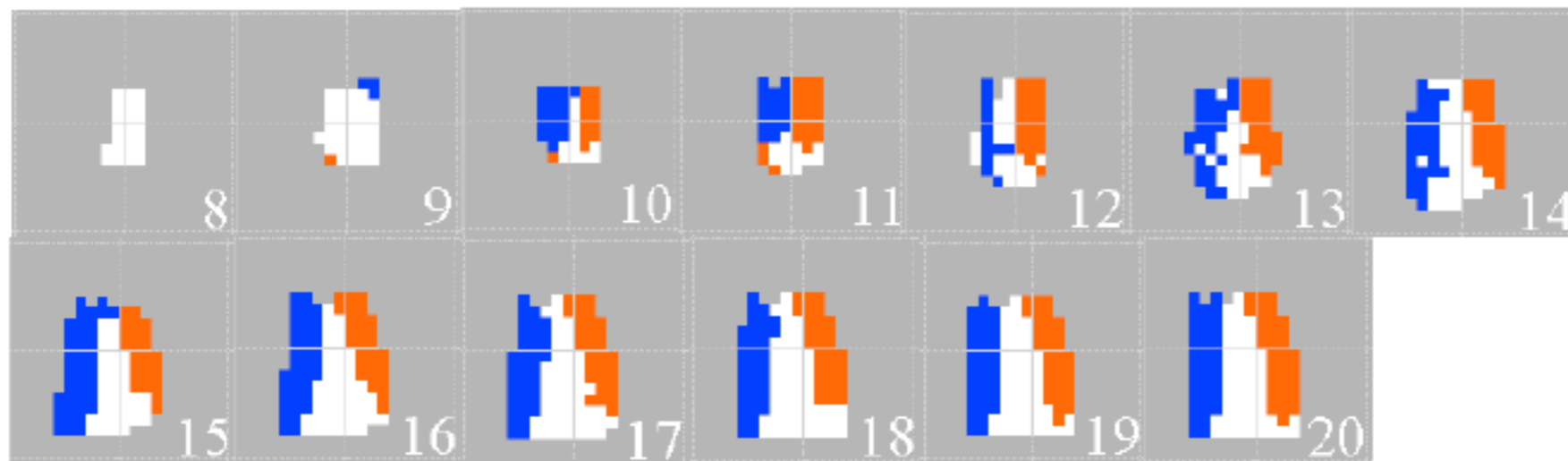


Fig. 7. Autonomous recovery of badly damaged French flag organism conditions (blue and red regions killed at iteration 8 - see Fig. 4). There is no further change after iteration 20

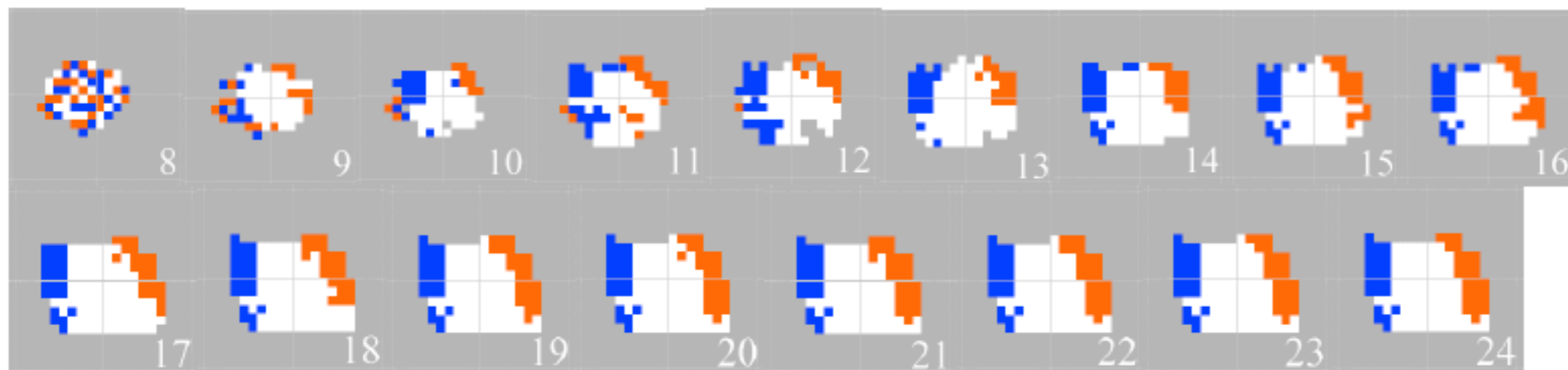
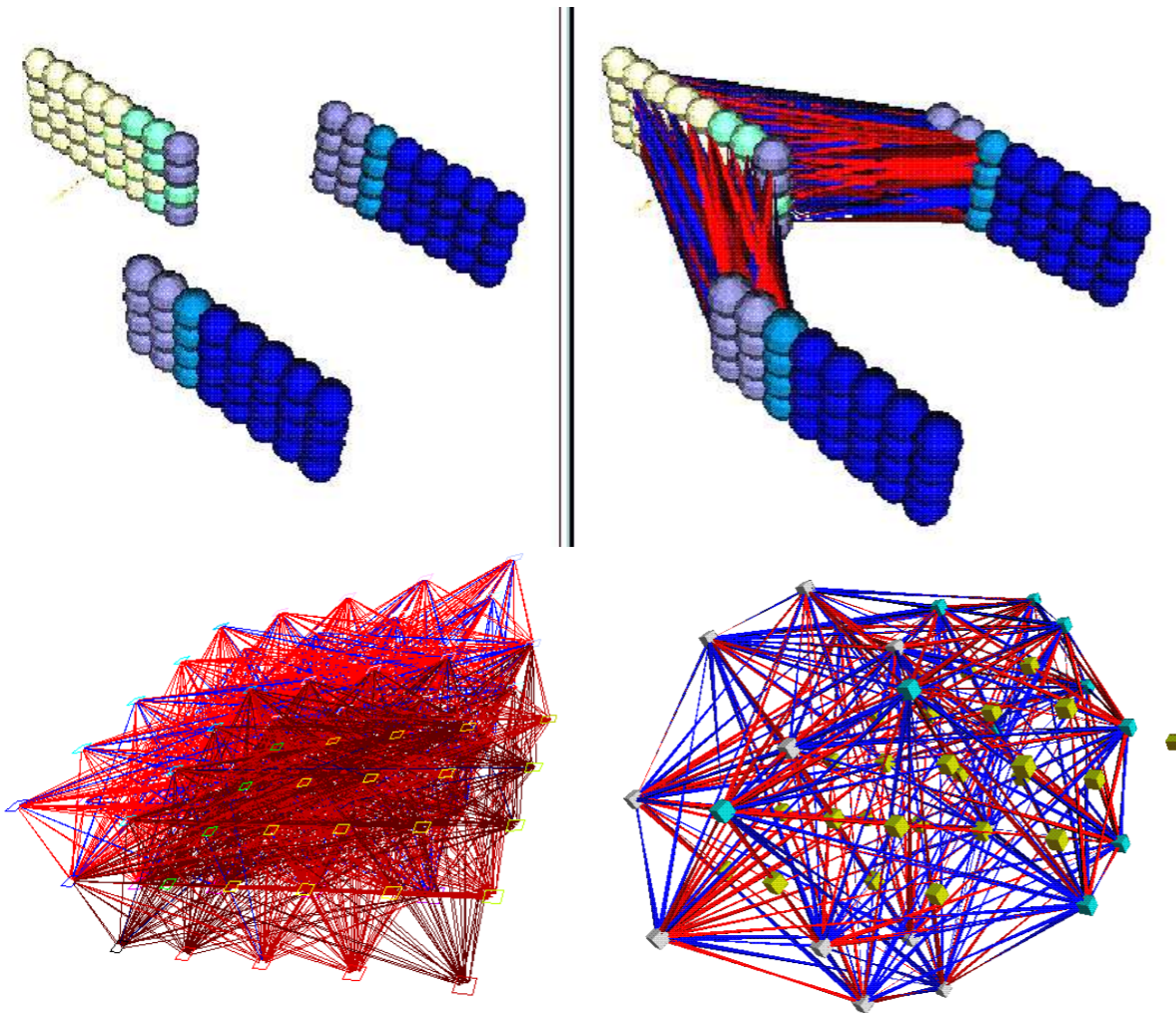


Fig. 8. Autonomous recovery of French flag from randomly rearranged cells (French flag at iteration 8 - see Fig. 4). There is no further change after iteration 24

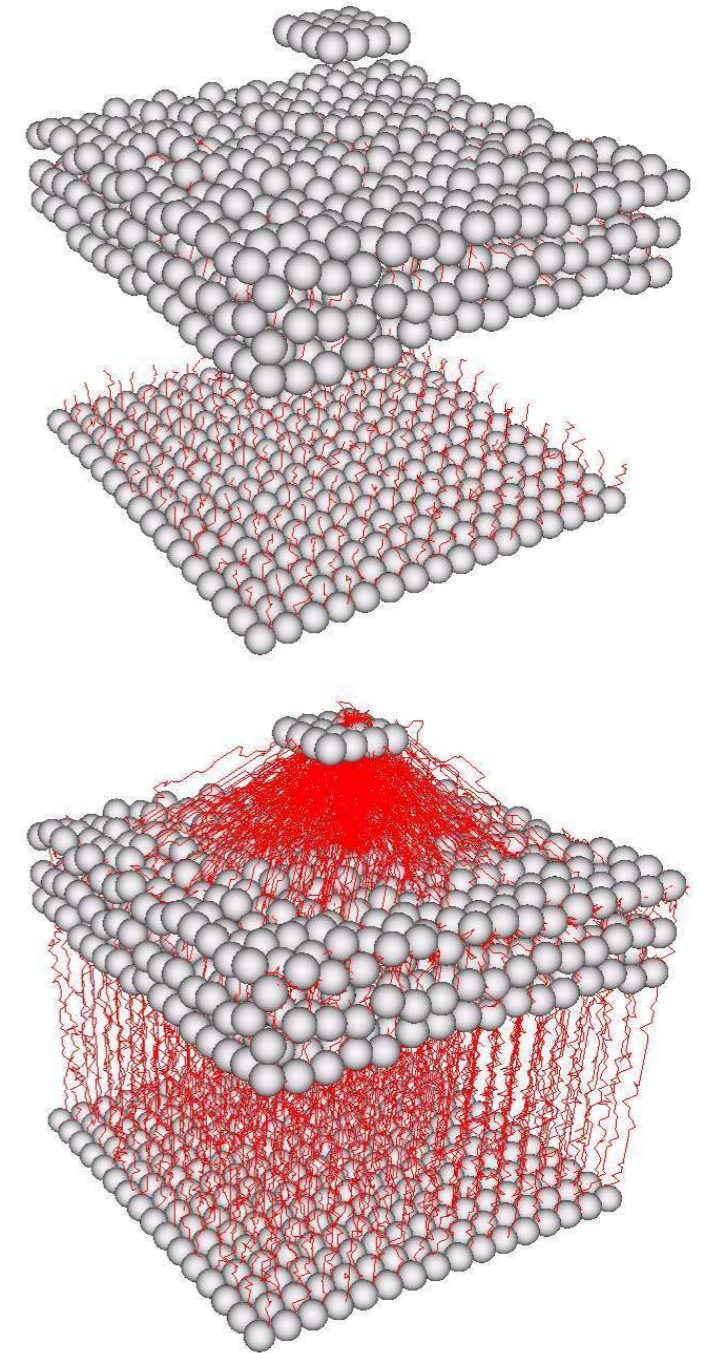
Indirect encodings of ANNs

- GRN-based
- Cellular Encoding
- Hypercube-based
- Other: rewriting rules, L-systems, ...

GRN-based



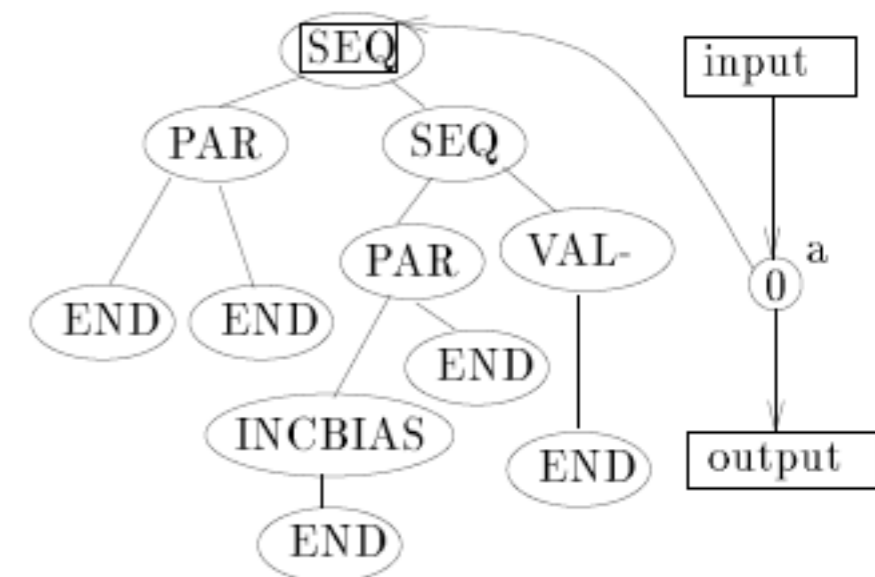
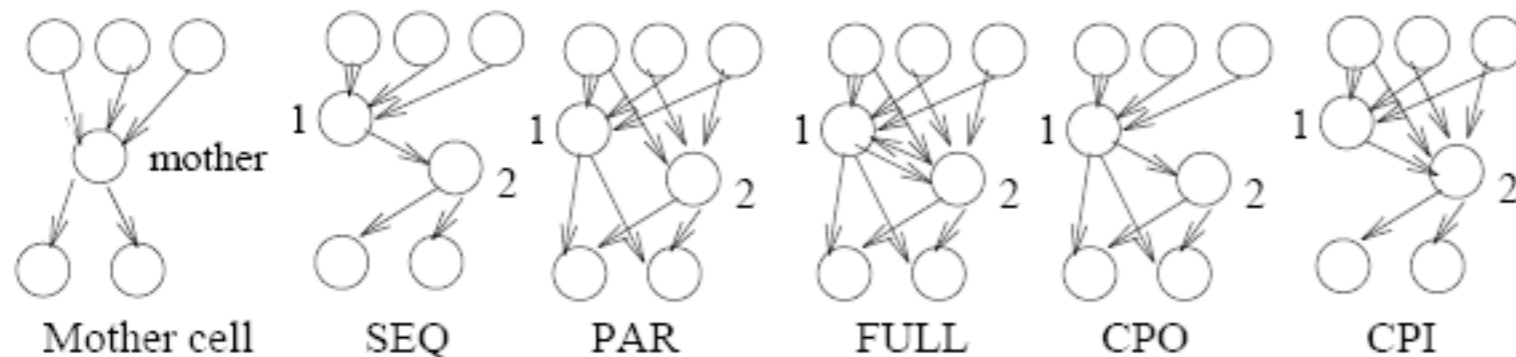
Peter Eggenberger-Hotz (1997):
Creation of Neural Networks Based on Developmental and Evolutionary Principles



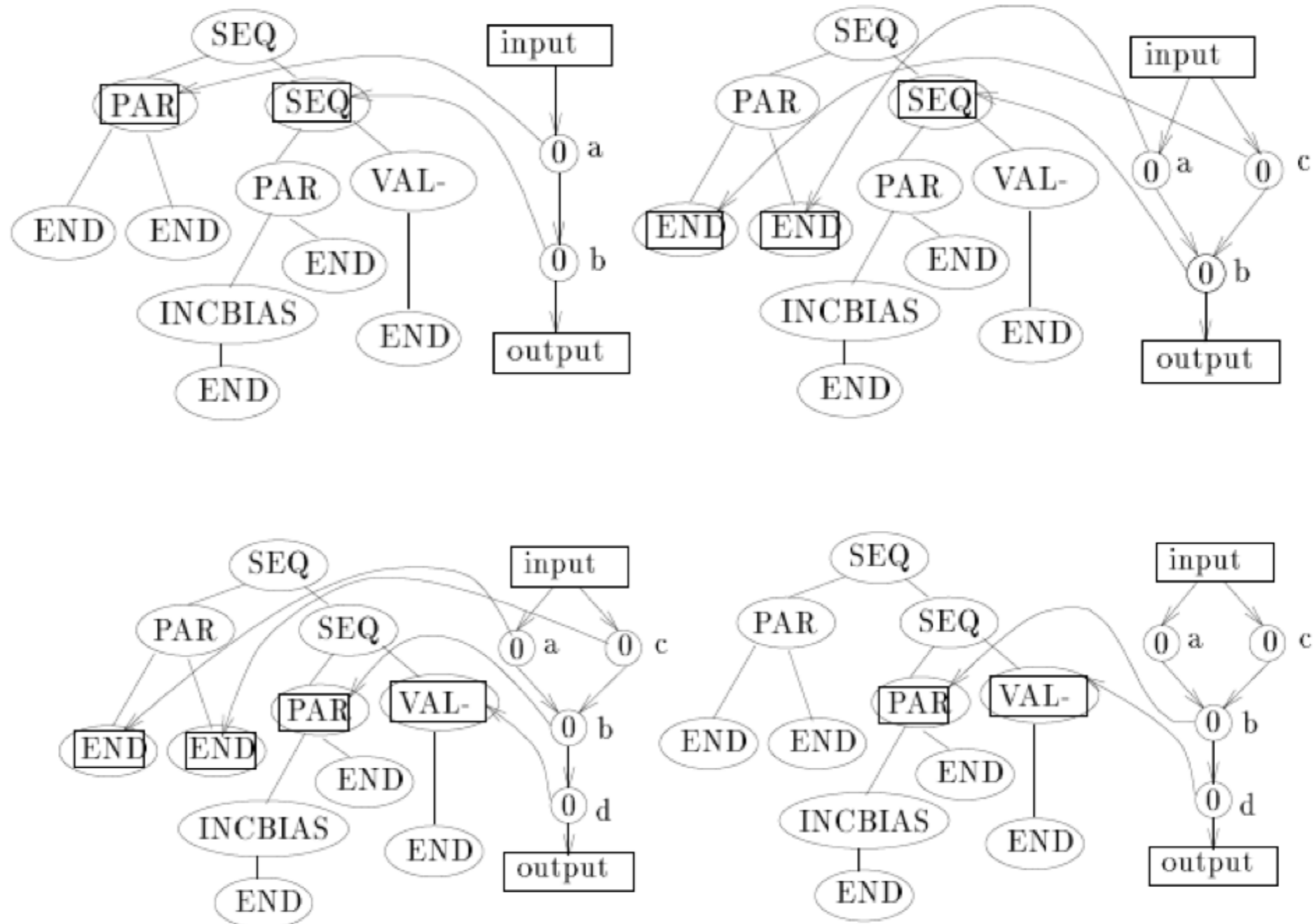
Peter Eggenberger-Hotz (2003):
Evolving the Morphology of a Neural Network for Controlling a Foveating Retina and its Test on a Real Robot

Cellular Encoding (CE)

- 1993, Frédéric Gruau: indirect encoding example.
- Inspiration in embryo-genesis (cell division and differentiation). Cells → neurons.
- Program to “grow” ANN is represented by a tree (Genetic Programming).
- Operations: parallel/sequential divisions, connections change, change of weights/bias...



Cellular Encoding II

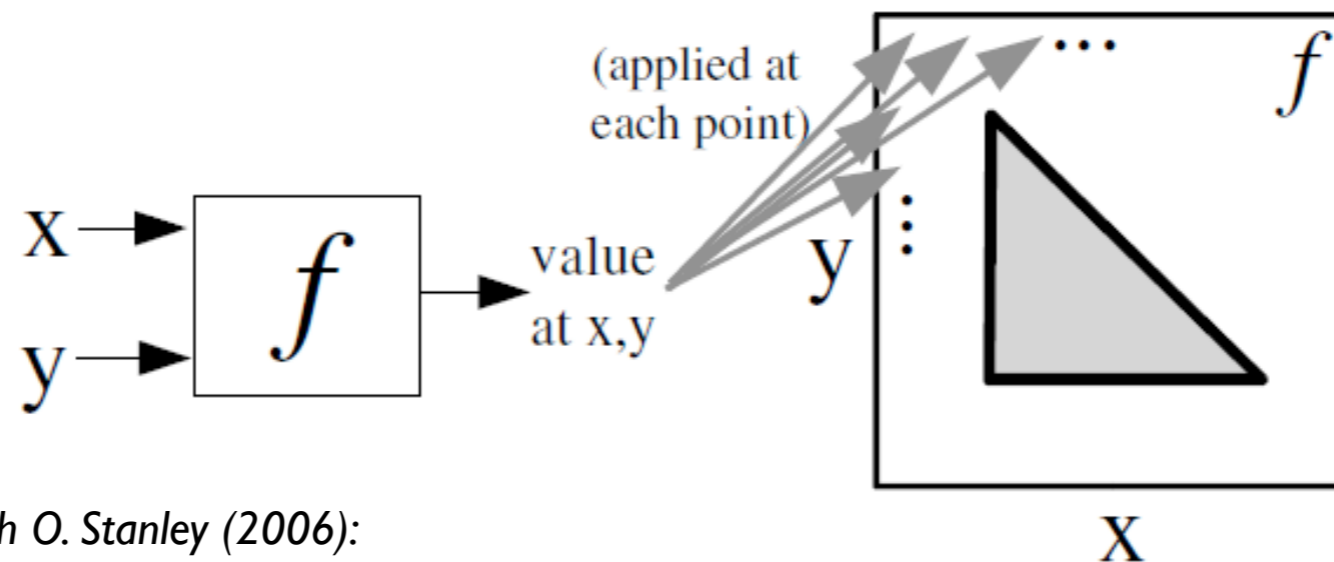


Cellular Encoding III

- May use operation which reads a sub-tree repeatedly → evolved a network representing parity of arbitrary number of inputs.
- Allows ANNs of arbitrary size: *neural module reuse*.

Compositional Pattern Producing Networks (CPPNs)

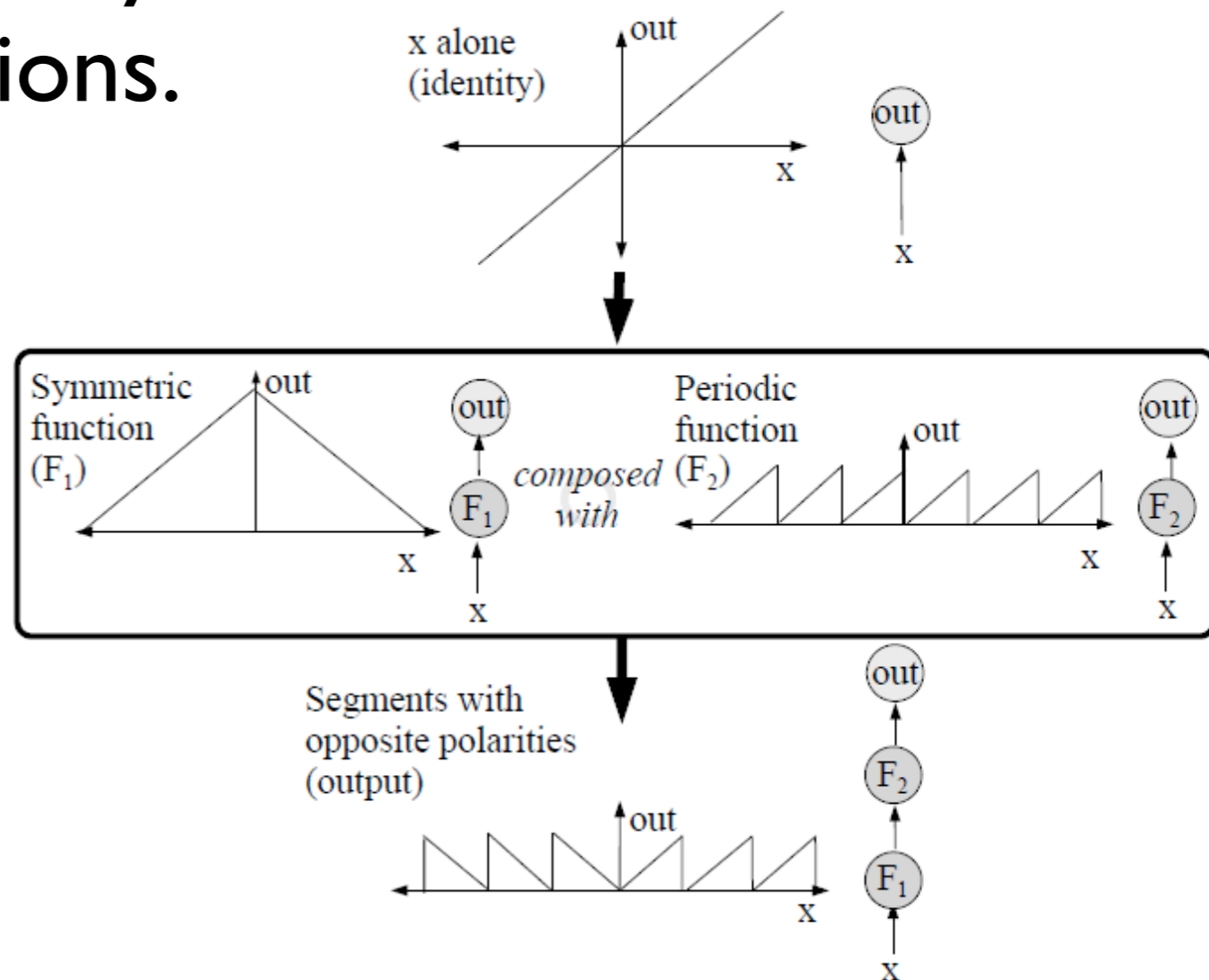
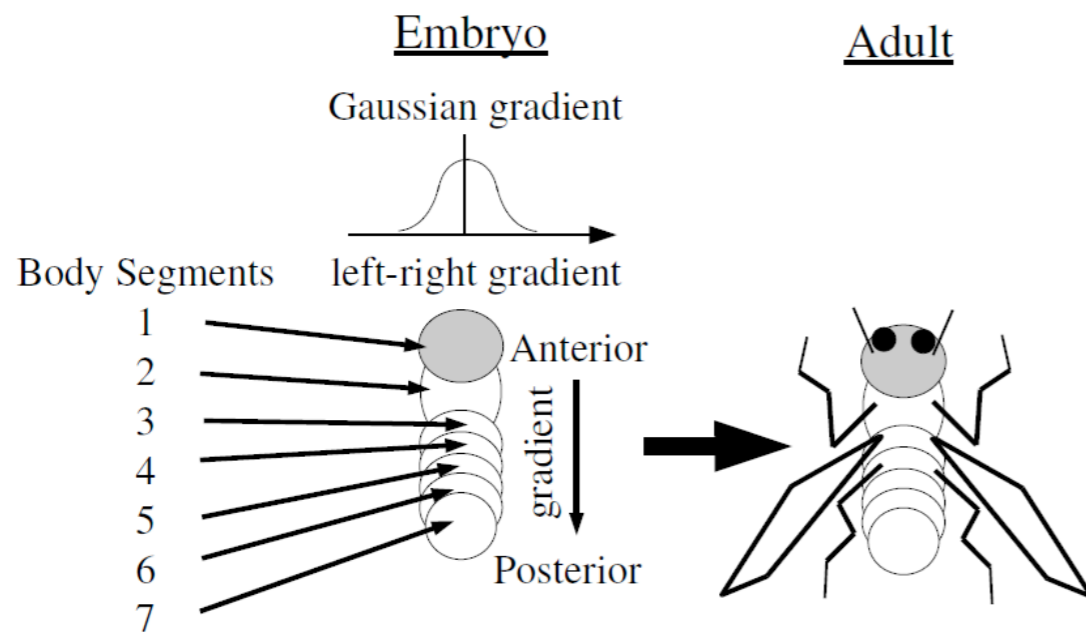
- Stanley 2006.
- Can we create such regular patterns without development in time?
- We can ask a special function called CPPN, where the cells are, using absolute coordinates.



Kenneth O. Stanley (2006):
*Compositional Pattern Producing Networks:
A Novel Abstraction of Development*

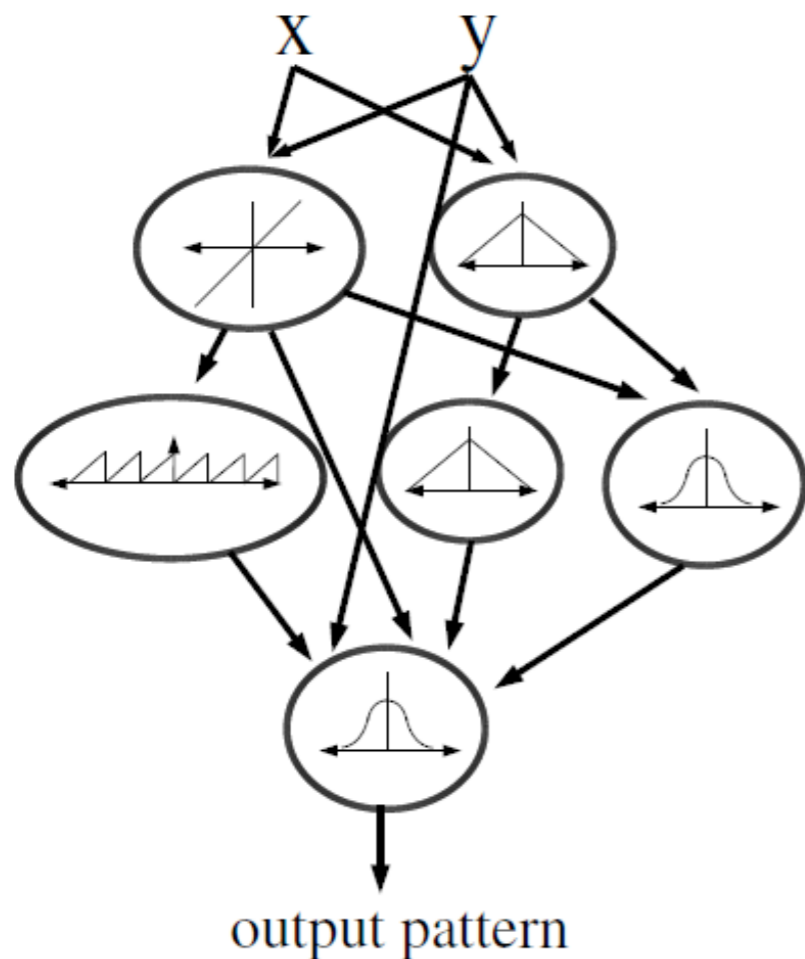
Regularities by CPPN

- Nature uses concentration gradients of regulatory proteins to determine position.
- CPPN is a composition of symmetric, periodic and other functions.



Regularities by CPPN II

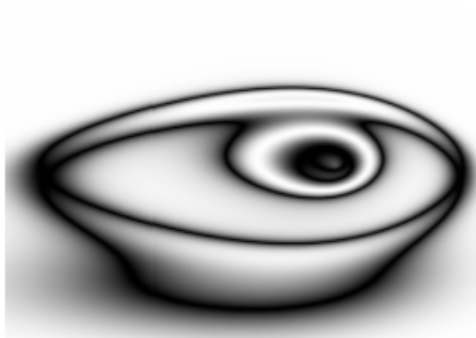
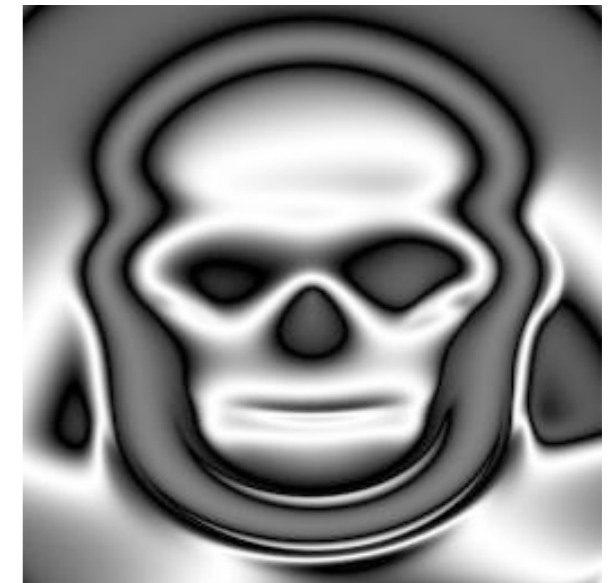
- **CPPN** is a composition of symmetric, periodic and other functions.



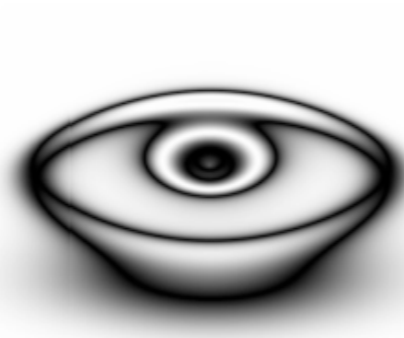
Name	Equation
Bipolar Sigmoid	$\frac{2}{1+e^{-4.9x}} - 1$
Linear	x
Gaussian	$e^{-2.5x^2}$
Absolute value	$ x $
Sine	$\sin(x)$
Cosine	$\cos(x)$

Picbreeder

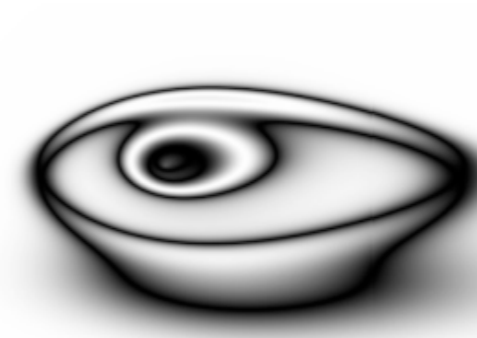
- Interactive evolution of images.
- CPPN output: level of grey.
- CPPNs evolved using NEAT.
- <http://picbreeder.org/>



(a) Eye warped left



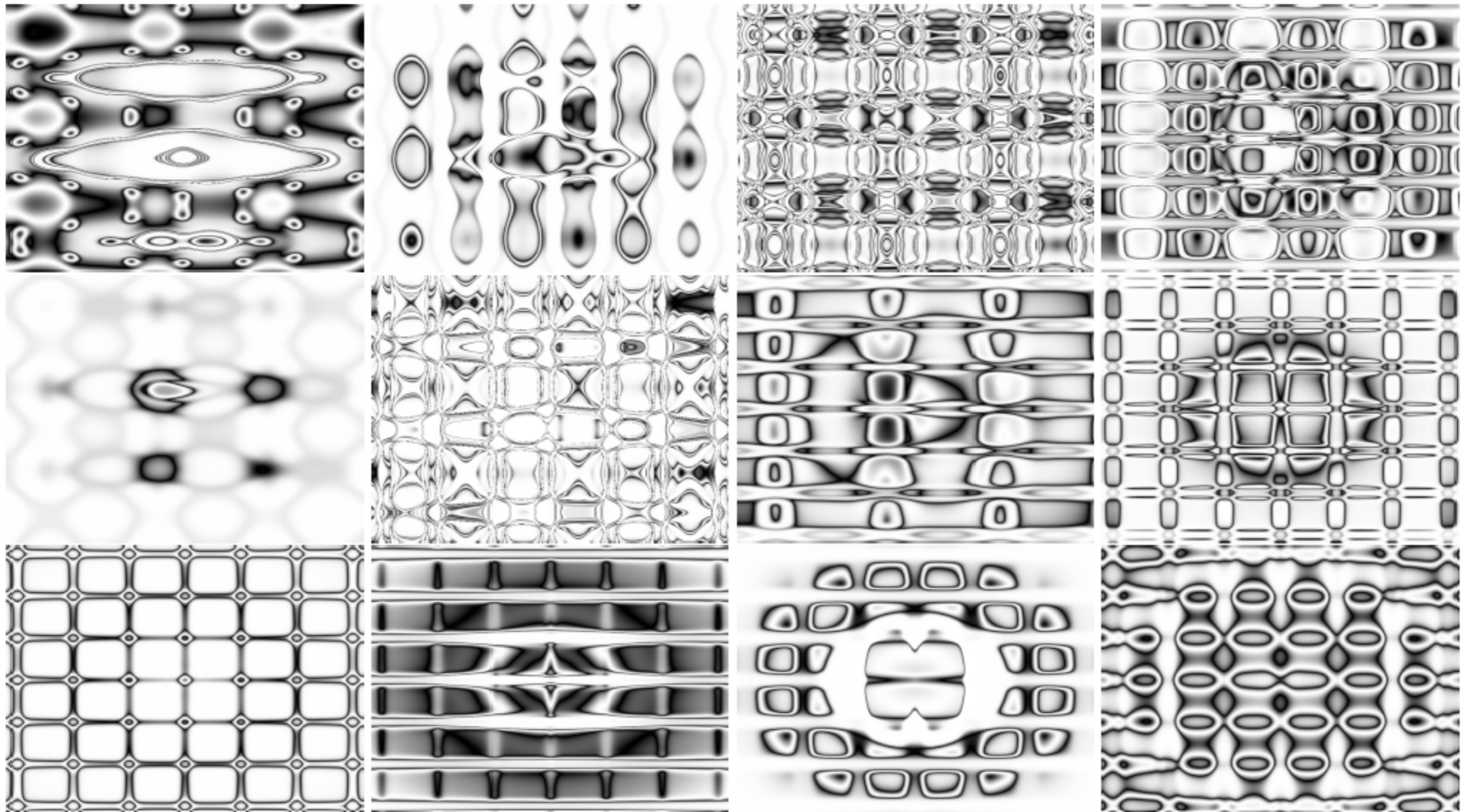
(b) Symmetric eye



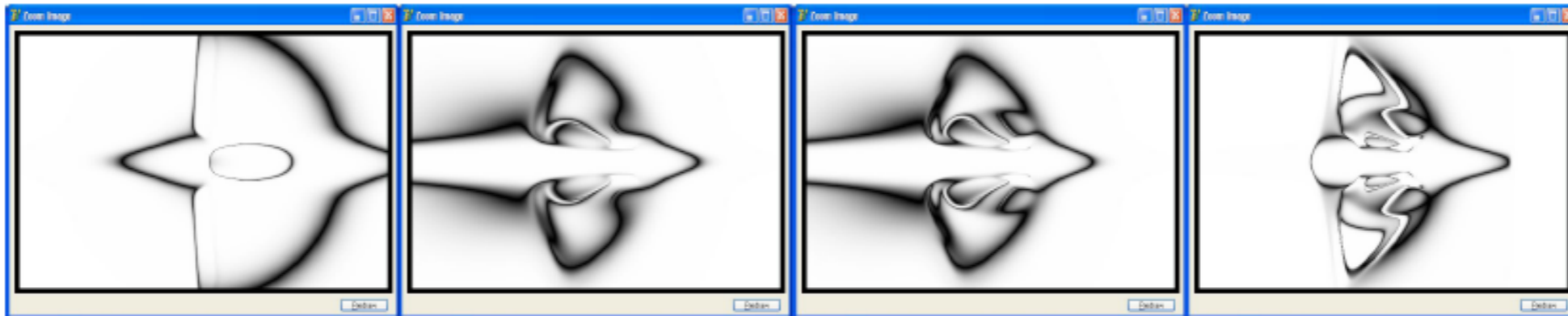
(c) Eye warped right

K. O. Stanley. Compositional pattern producing networks: A novel abstraction of development. *Genetic Programming and Evolvable Machines Special Issue on Developmental Systems*, 2007. To appear.

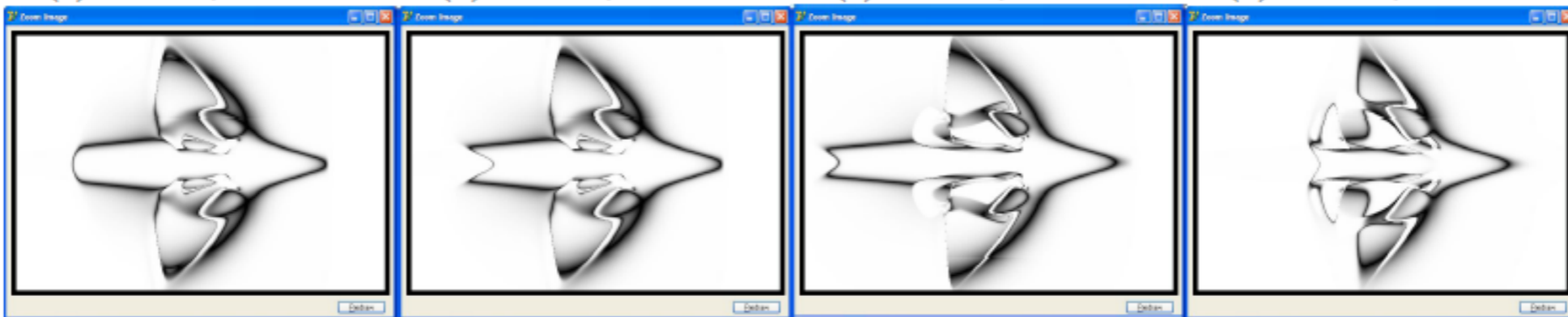
Picbreeder II



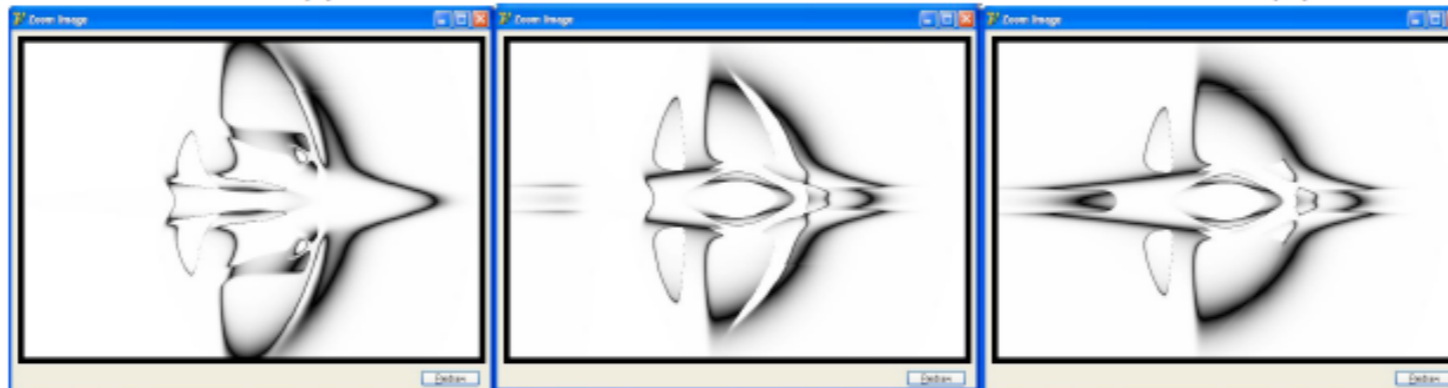
Picbreeder: Space Ship



(a) 4 func., 17 conn. (b) 5 func., 24 conn. (c) 6 func., 25 conn. (d) 8 func., 28 conn.



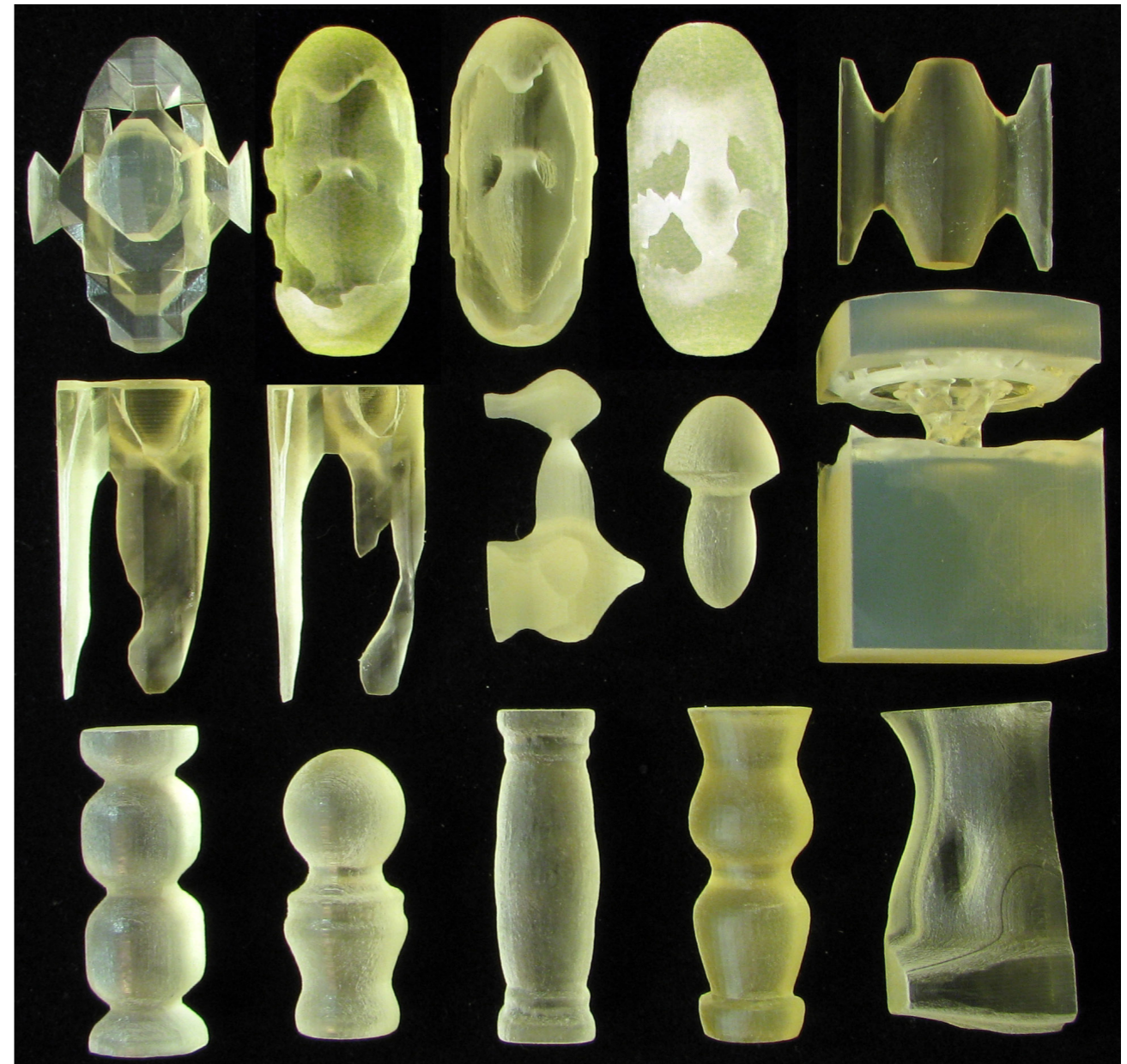
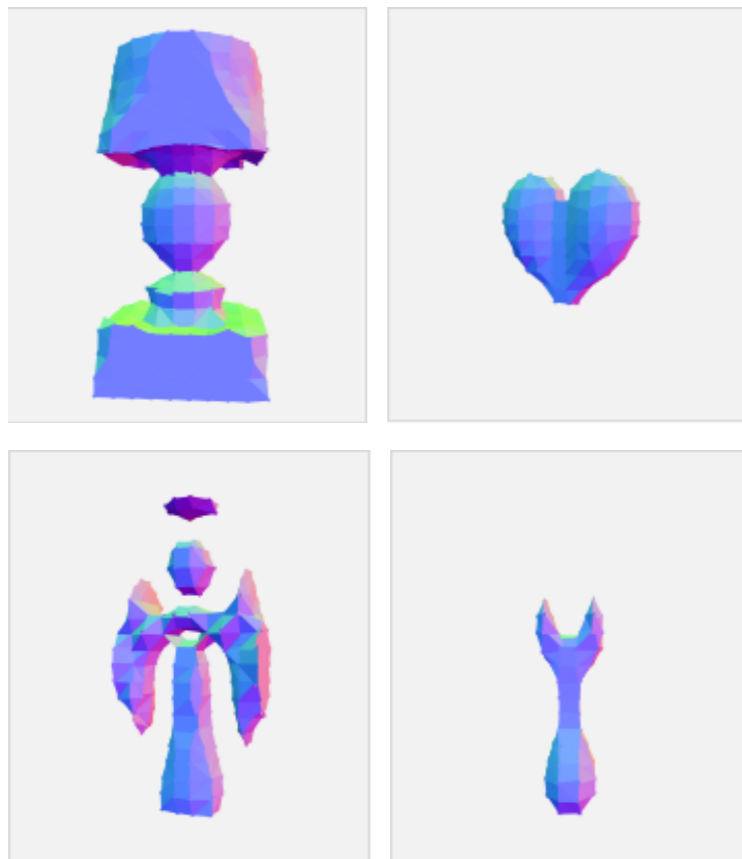
(e) 8 func., 30 conn. (f) 8 func., 31 conn. (g) 8 func., 32 conn. (h) 8 func., 34 conn.



(i) 8 func., 36 conn. (j) 9 func., 36 conn. (k) 9 func., 38 conn.

Endless Forms

- Similar approach in 3D.
- <http://endlessforms.com>



Jeff Clune, Hod Lipson (2011):

Evolving Three-Dimensional Objects with a Generative Encoding Inspired by Developmental Biology

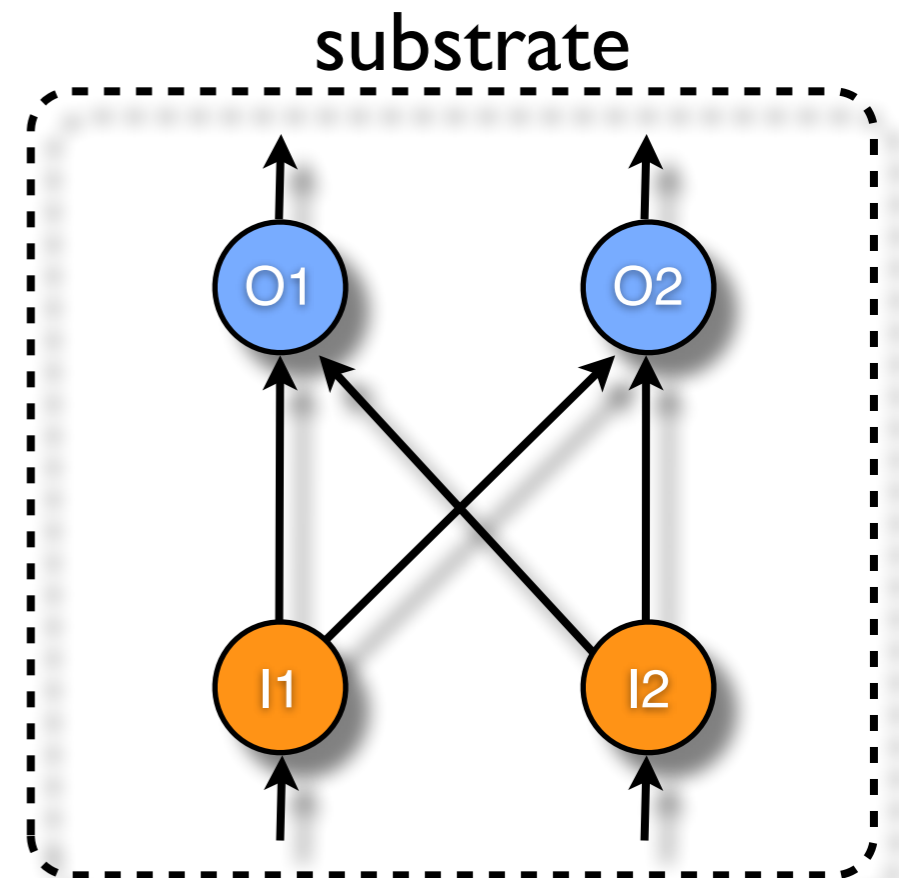
Hypercube-based Encoding

- Stanley 2007.
- Uses CPPNs in a similar way to Picbreeder: evolves **connectivity patterns**.
- Best known for **HyperNEAT** algorithm which evolves ANNs.

HyperNEAT

- Stanley et al. 2007: Hypercube-based encoding.

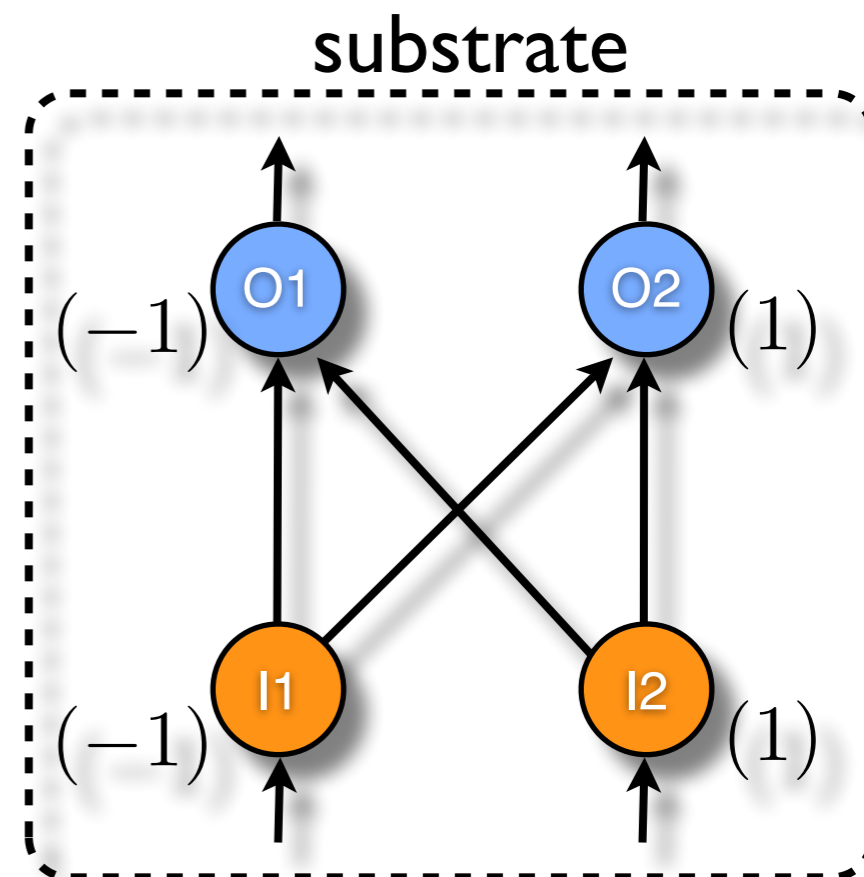
Substrate is a template for a possibly large-scale neural network.



HyperNEAT

- Stanley et al. 2007: Hypercube-based encoding.

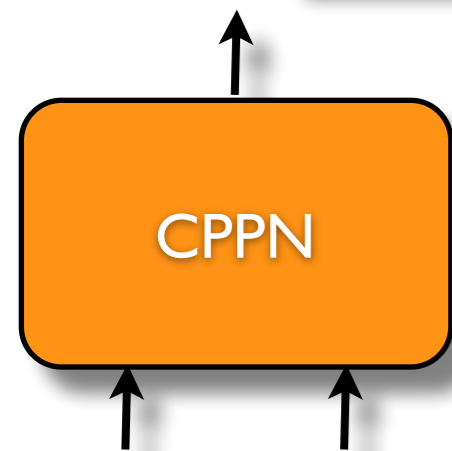
Each neuron is assigned coordinates. The weights of connections are unknown.



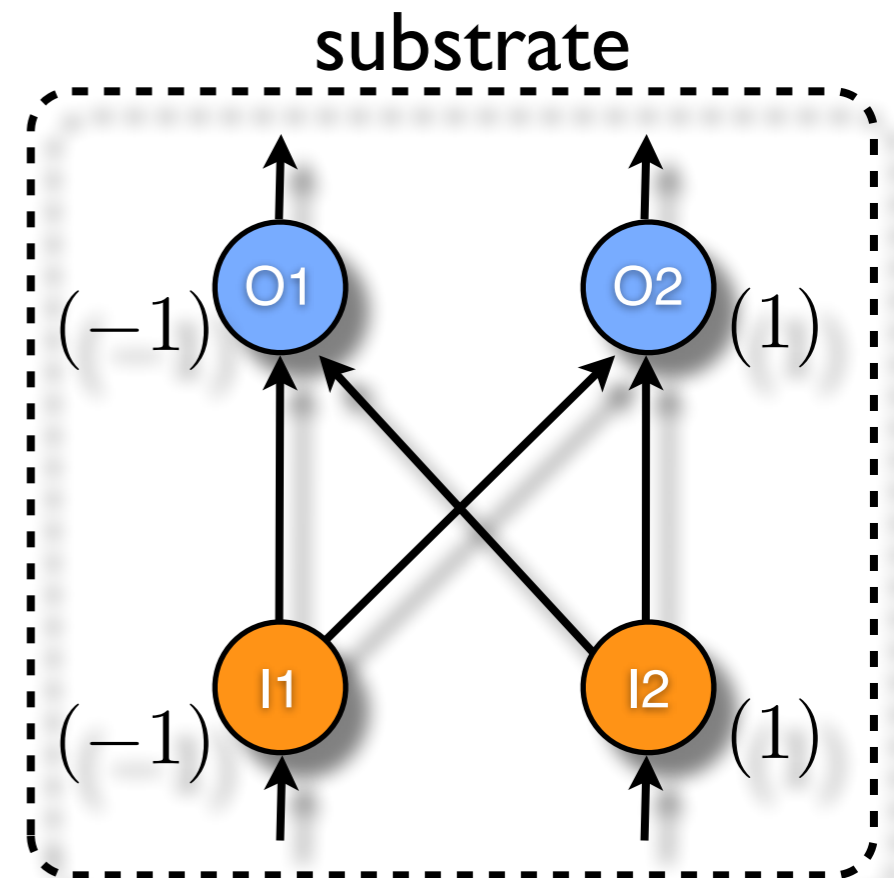
HyperNEAT

- Stanley et al. 2007: Hypercube-based encoding.

The *final network* is constructed out of *substrate* by computing all needed weights. This is done using CPPN.



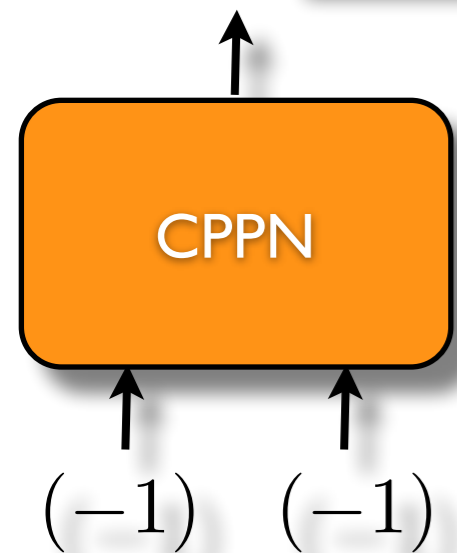
decode weight values



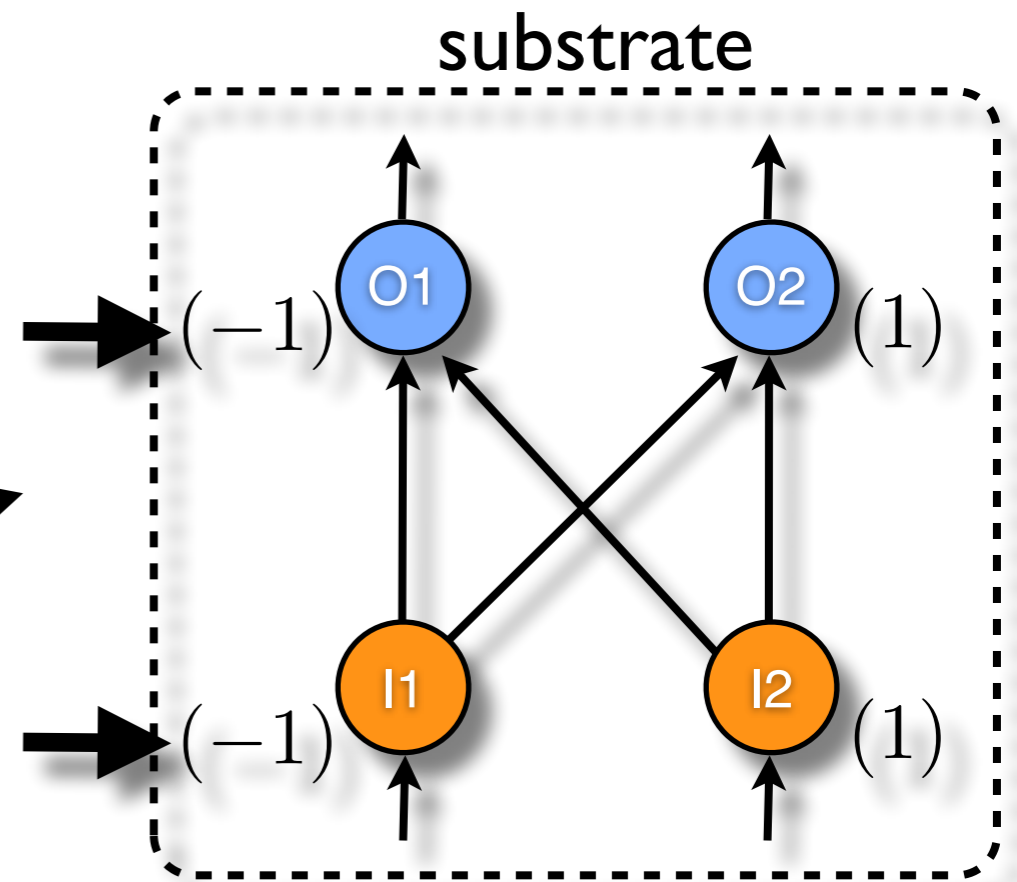
HyperNEAT

- Stanley et al. 2007: Hypercube-based encoding.

CPPN is a function which takes coordinates of both source and destination neuron for each connection ...



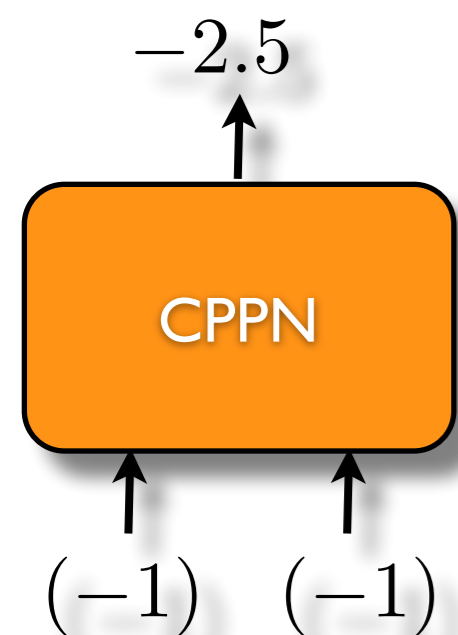
decode weight values



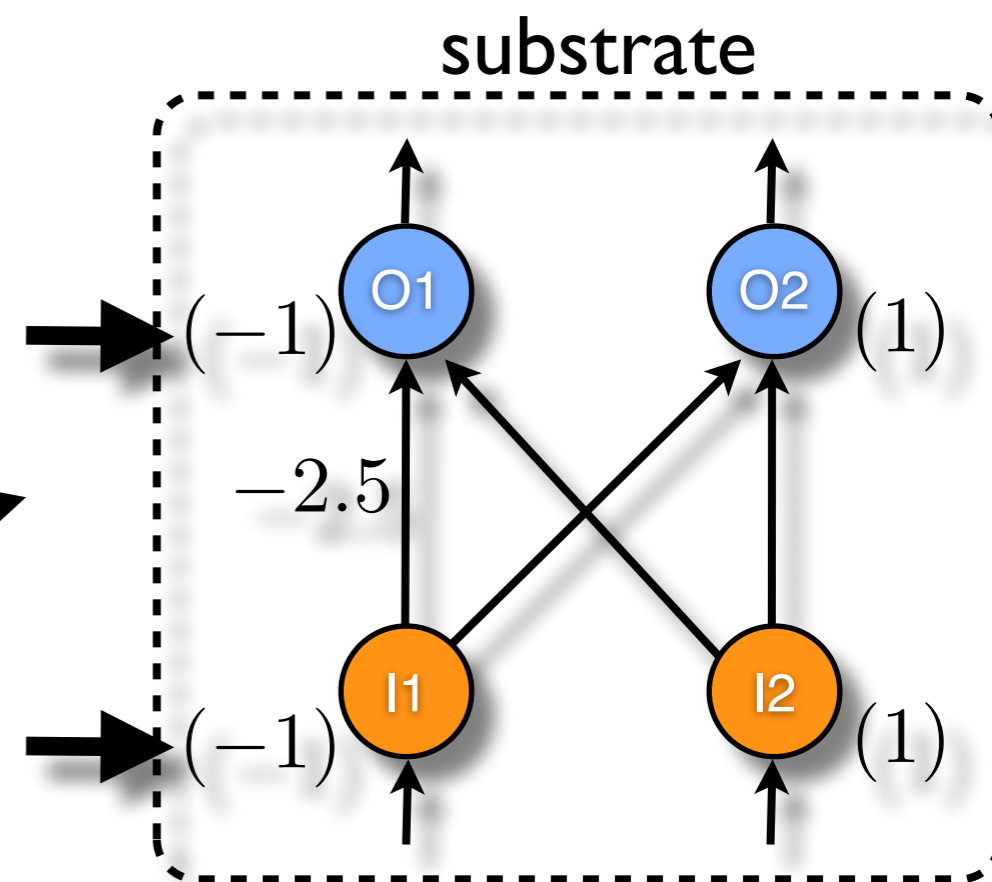
HyperNEAT

- Stanley et al. 2007: Hypercube-based encoding.

... and computes the weight of the corresponding connection.



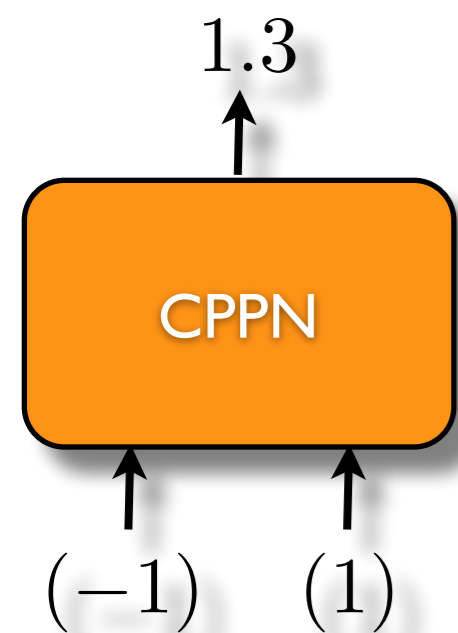
decode weight values



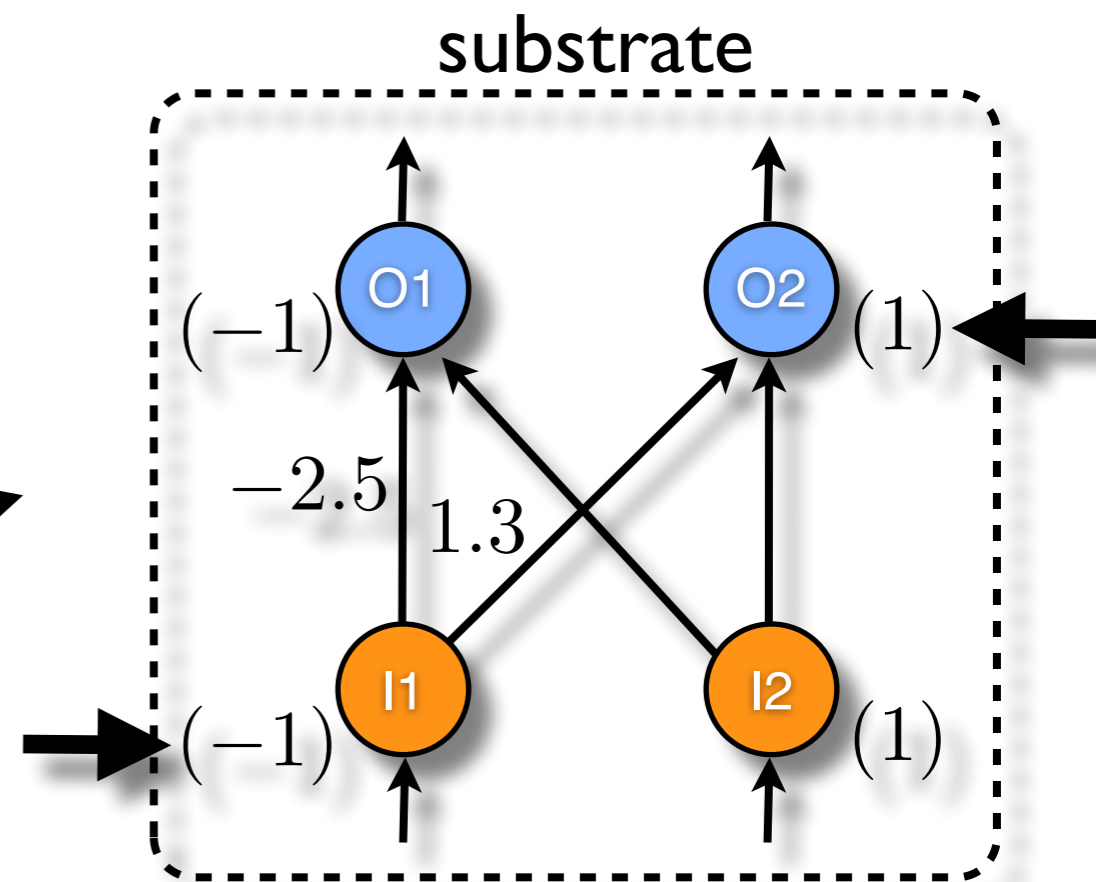
HyperNEAT

- Stanley et al. 2007: Hypercube-based encoding.

All weights are computed in a same way...

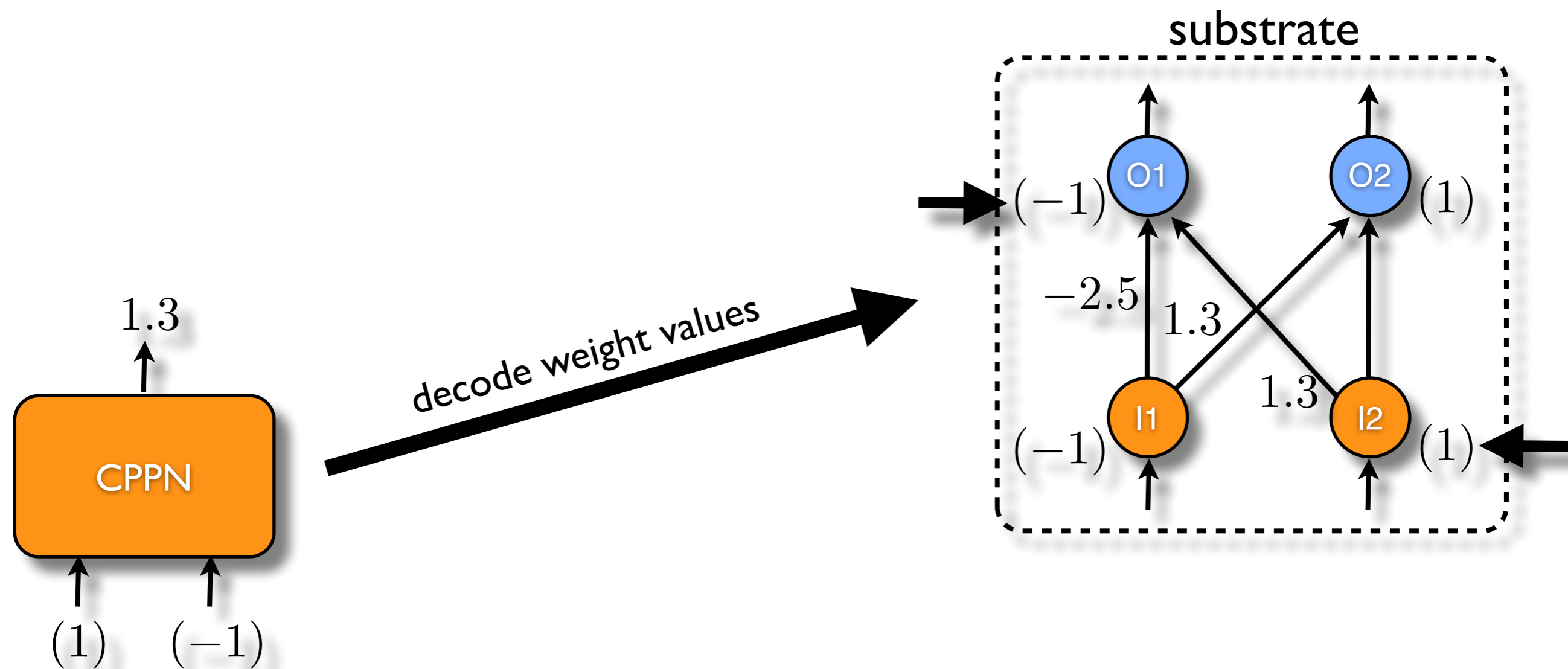


decode weight values



HyperNEAT

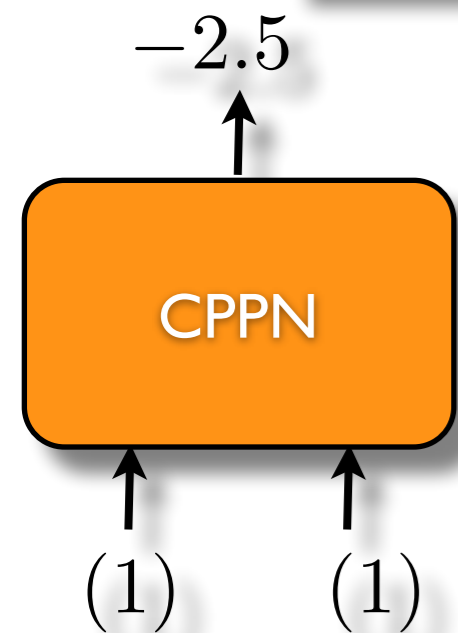
- Stanley et al. 2007: Hypercube-based encoding.



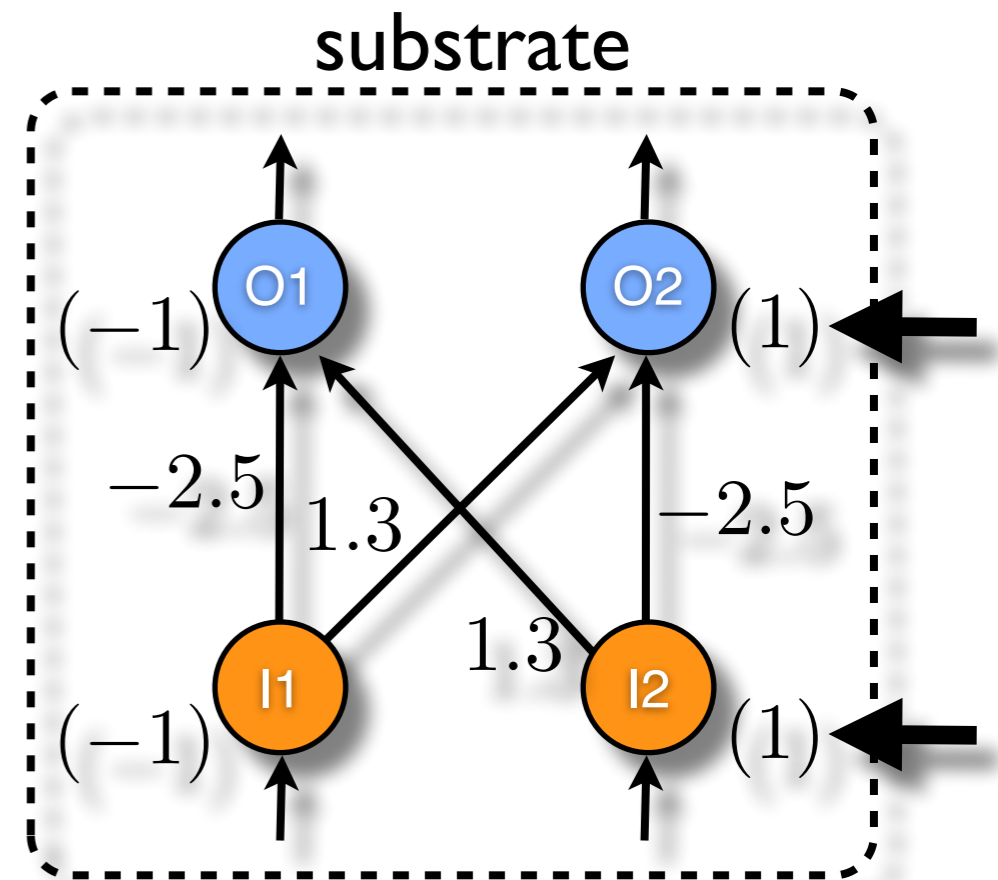
HyperNEAT

- Stanley et al. 2007: Hypercube-based encoding.

Note, that the weights are symmetric. CPPNs promote regular patterns.

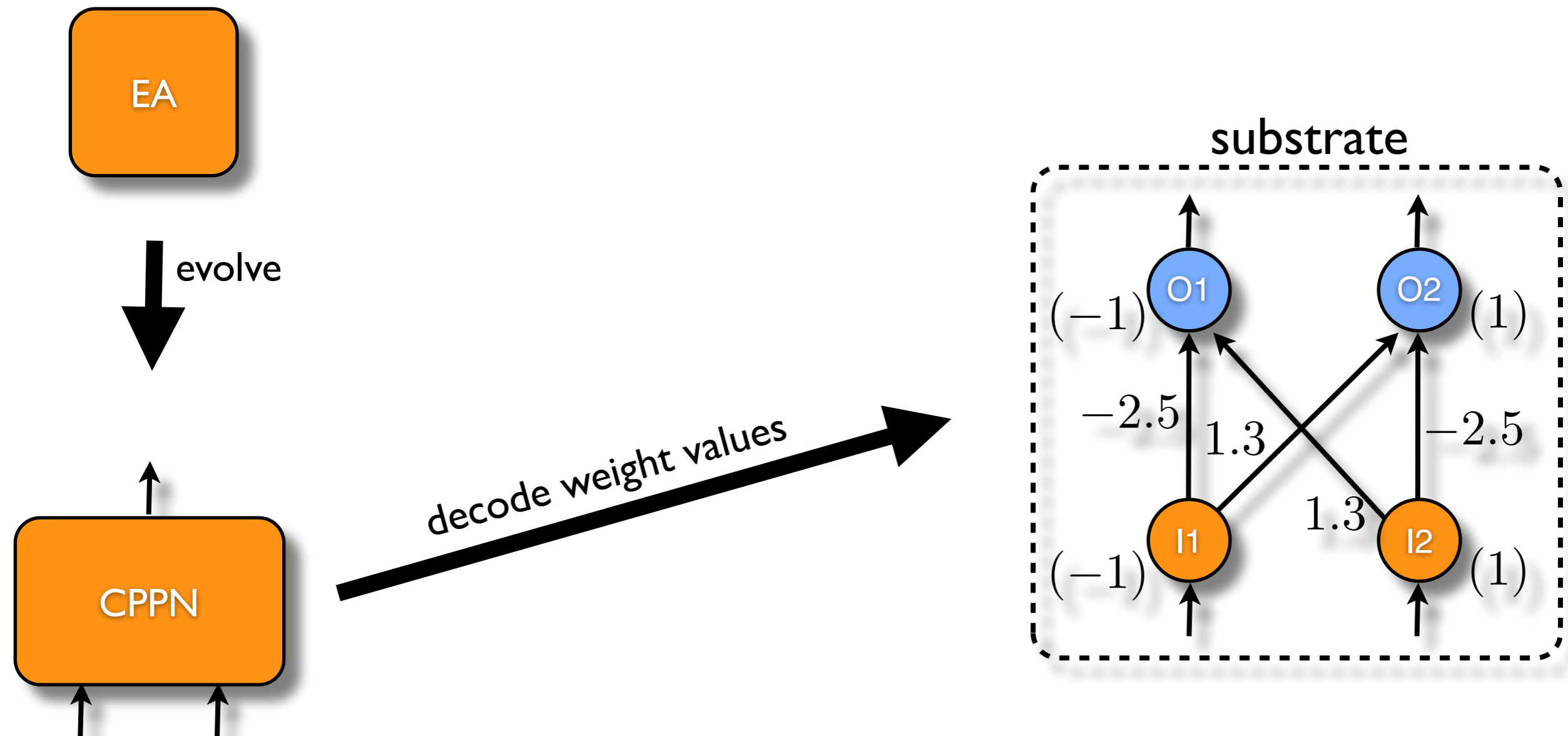


decode weight values



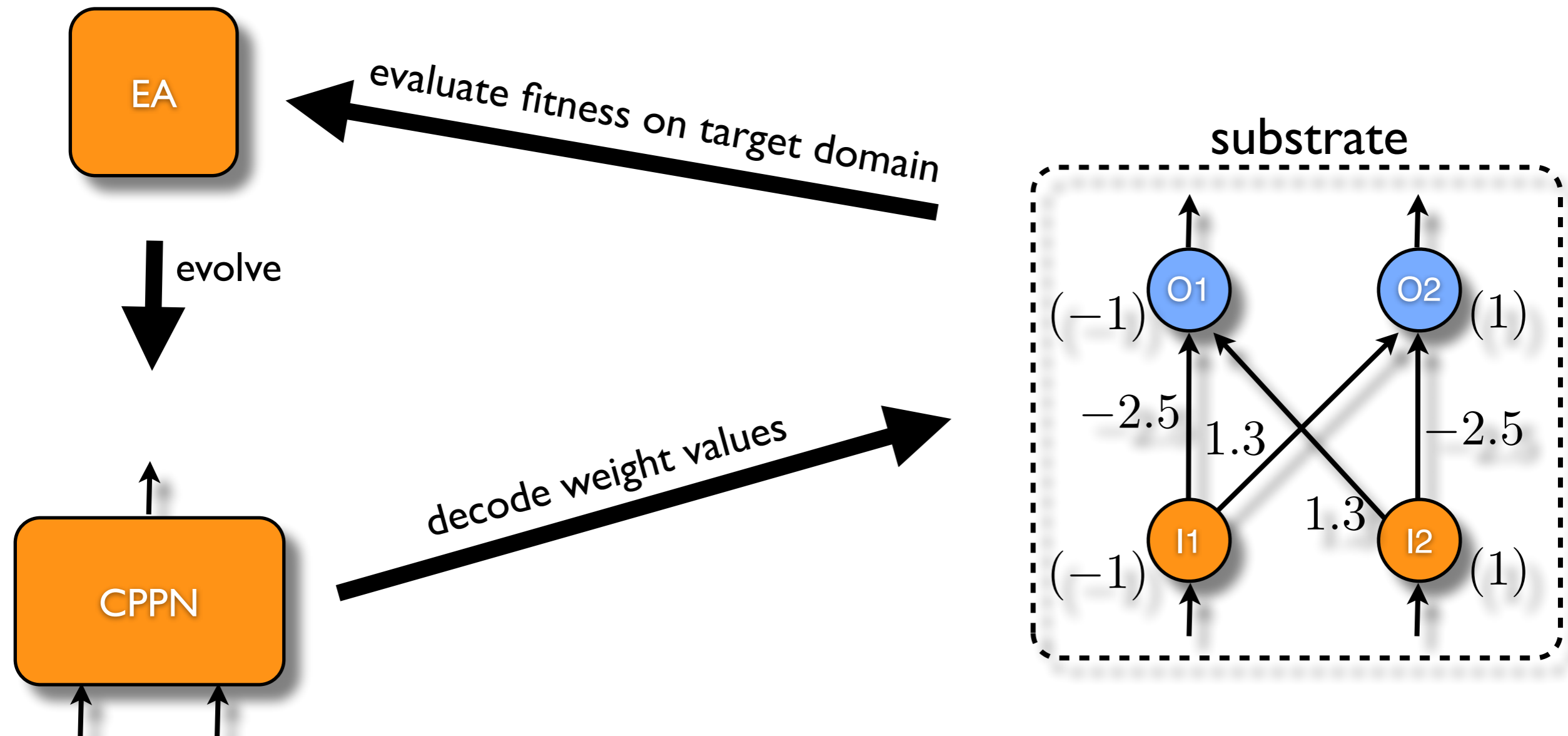
HyperNEAT

- Stanley et al. 2007: Hypercube-based encoding.

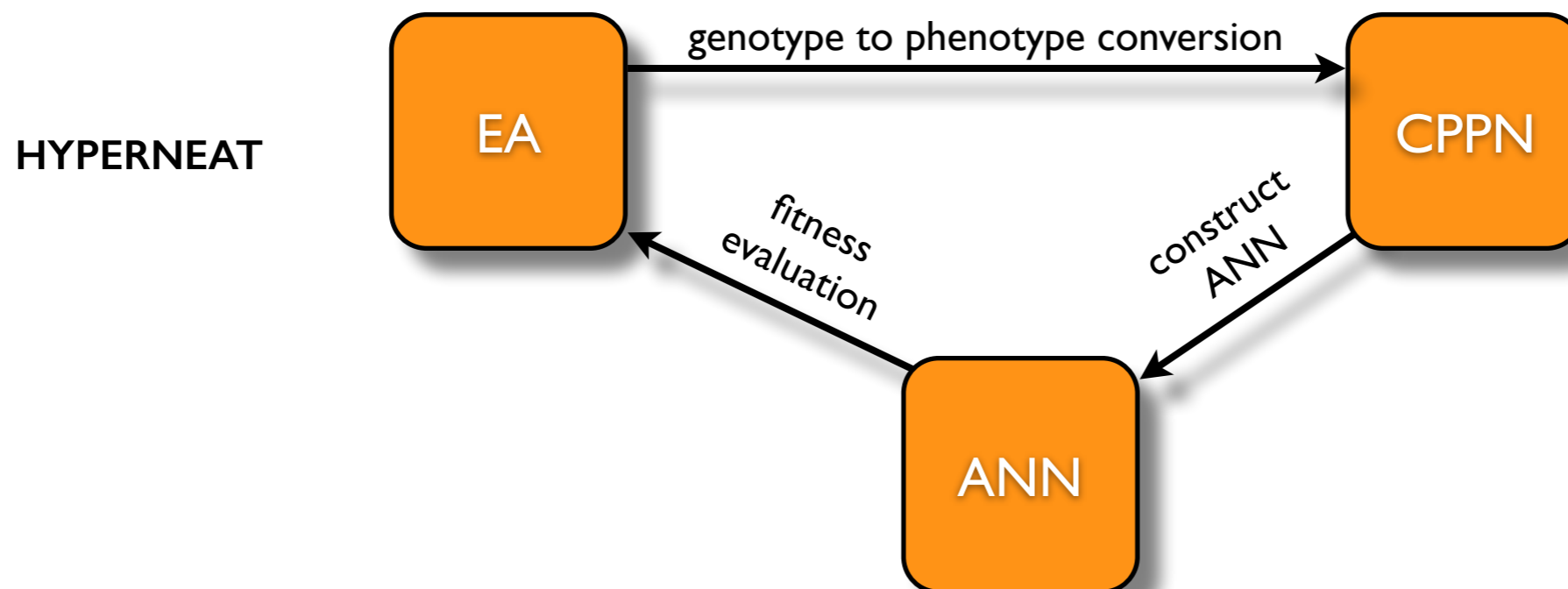
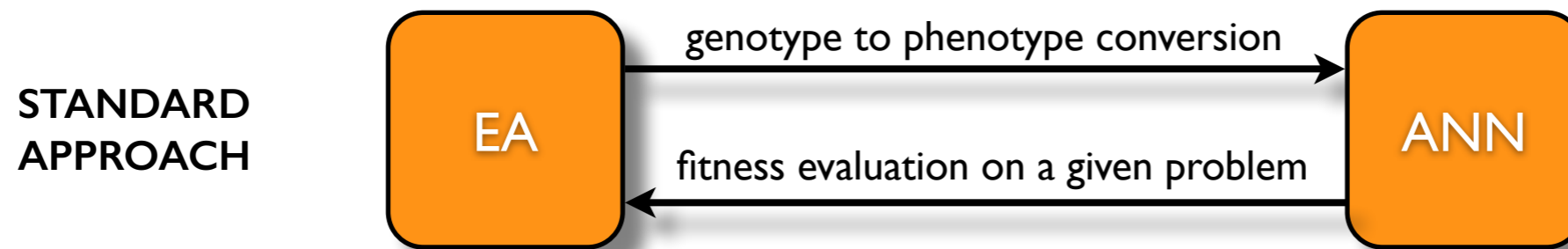


HyperNEAT

- Stanley et al. 2007: Hypercube-based encoding.

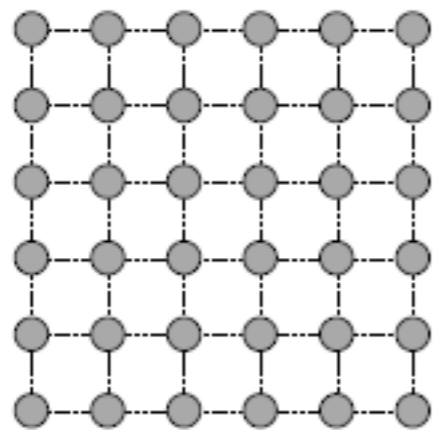


HyperNEAT vs. Standard Approaches

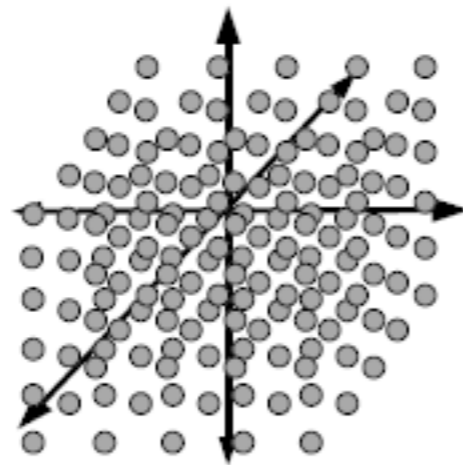


Types of Substrate?

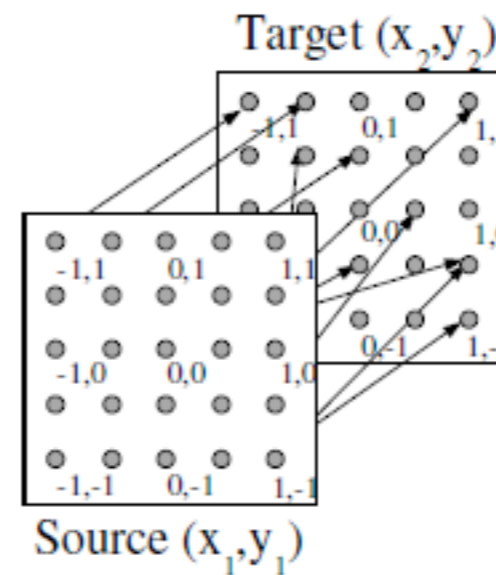
- The list of neurons' coordinates along with possible connections between them.



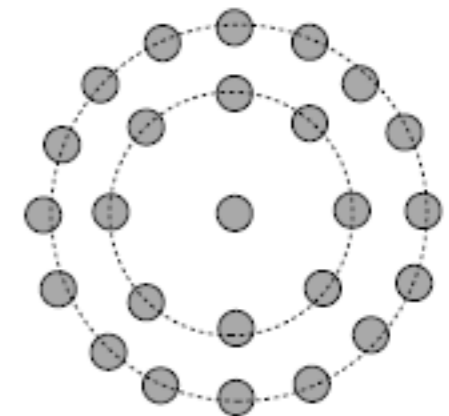
(a) Grid



(b) Three-dimensional



(c) Sandwich



(d) Circular

Create or not Create a Link?

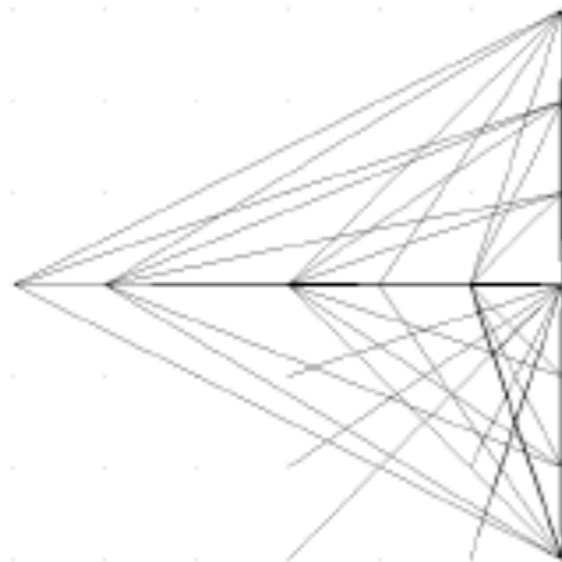
- Substrates are often fully connected → lots of links → computationally infeasible → pruning is used.
- If CPPN outputs weights in range $[-3; 3]$ then
- links with weights < 0.2 are not expressed,
- ≥ 0.2 are scaled to magnitude between 0 and 3.
→ when using this approach the final ANN is a sub-graph of a substrate.

Connectivity Patterns

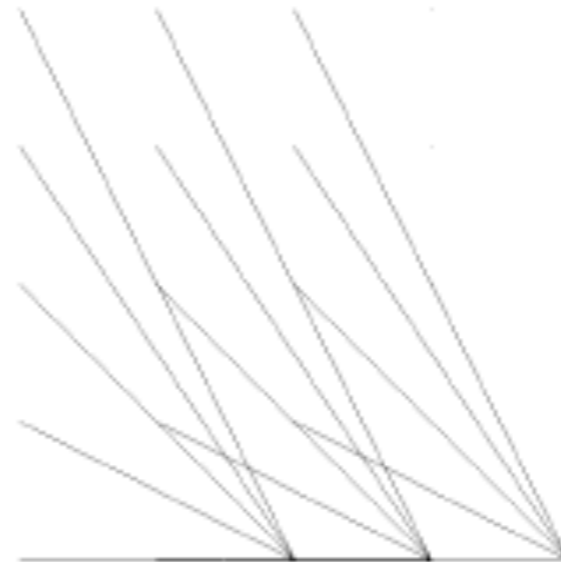
- Patterns evolved using interactive evolution:



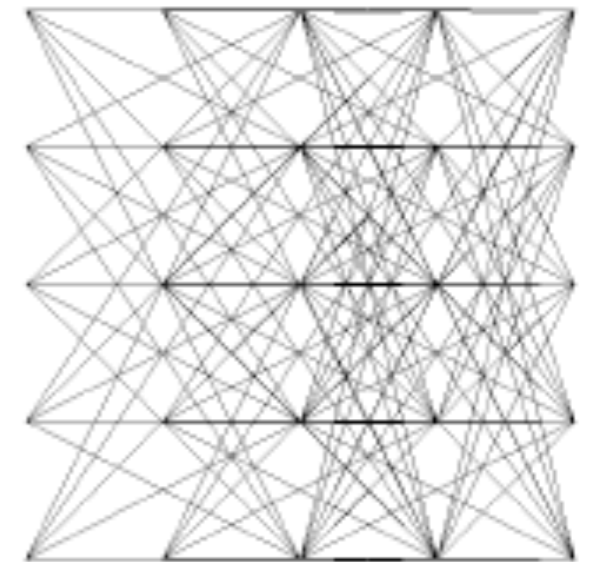
(a) Sym.



(b) Imperf.



(c) Repet.



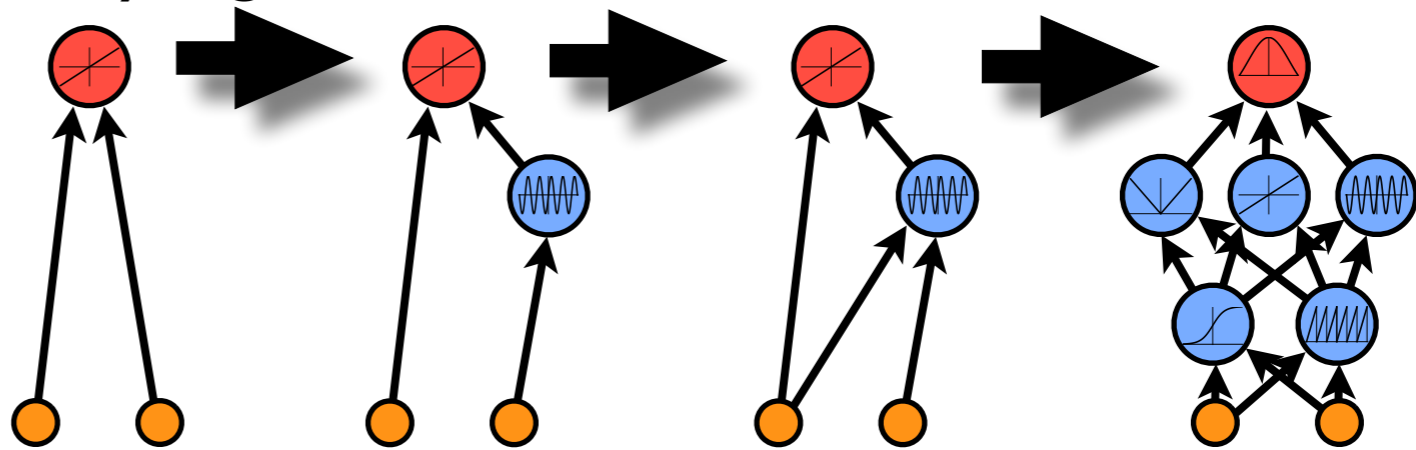
(d) Var.

Spatial Representation

- **HyperNEAT exploits spatial representation of a problem.** The same happens in Nature:
 - connection of eyes to brain hemispheres,
 - similar things processed nearby.
- We have to assign coordinates.
- **Does every problem have a reasonable spatial representation?**
 - It seems that most problems have. The others would not probably benefit from regularities in ANNs.

NEAT in HyperNEAT

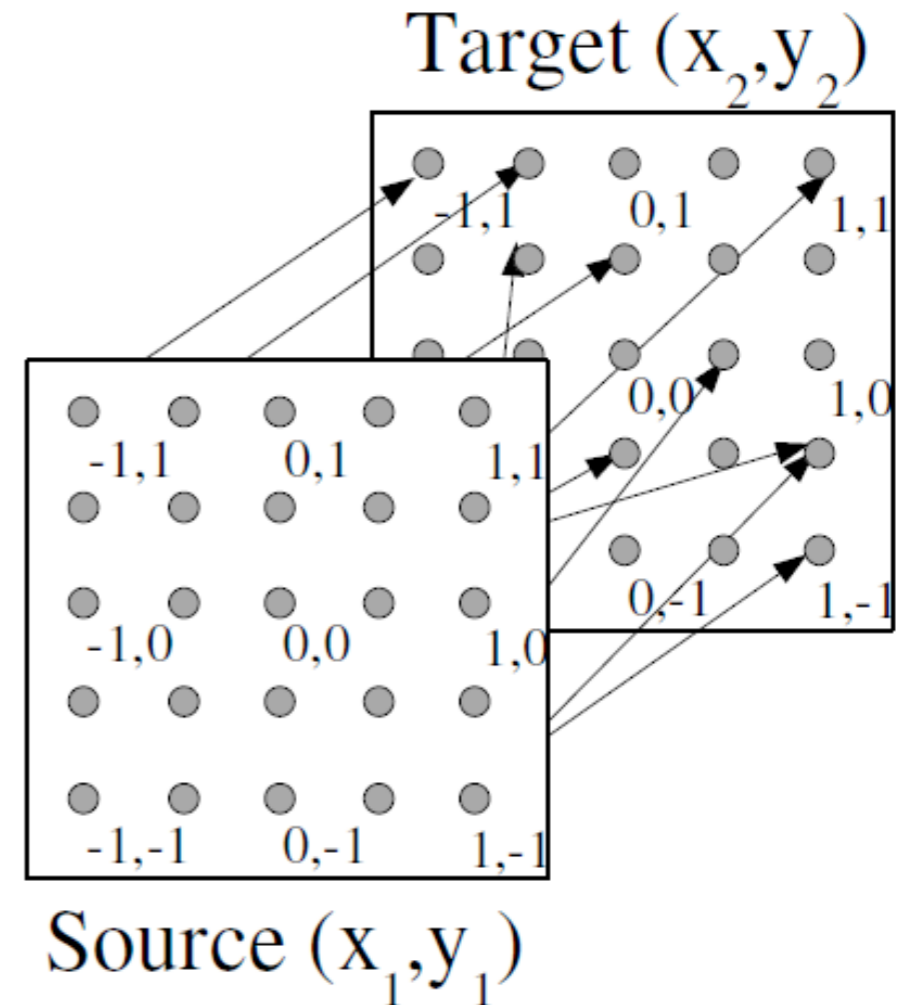
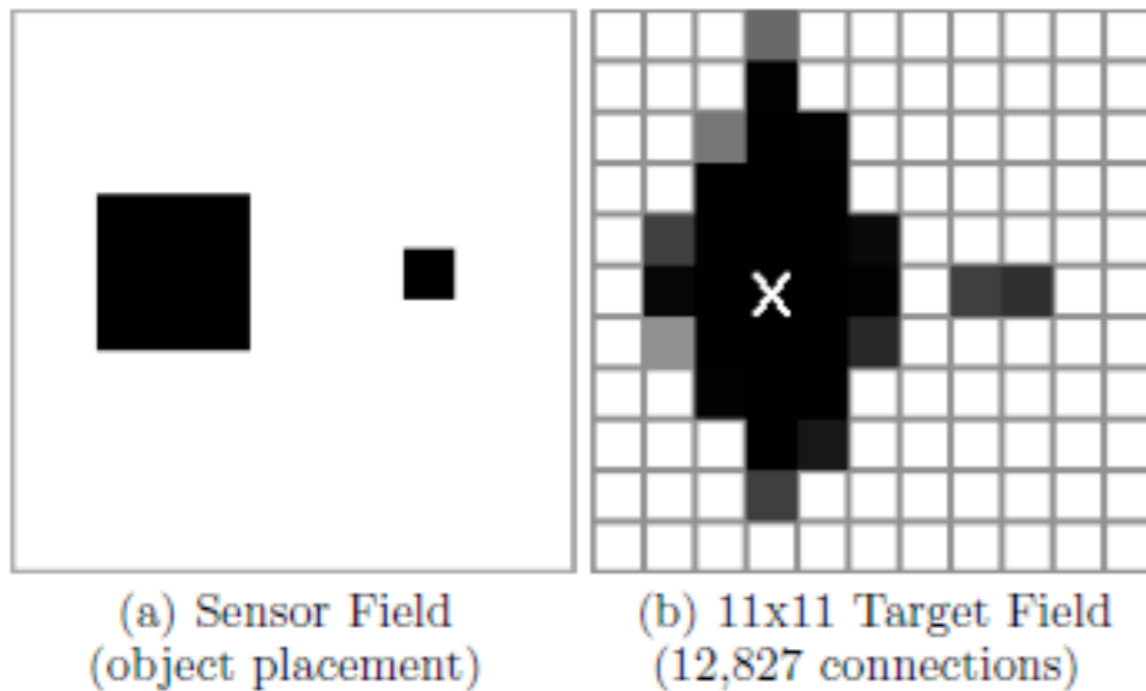
- HyperNEAT uses a slightly modified NEAT (Stanley 2001) as a **base algorithm** to evolve CPPNs.
- NEAT is neuro-evolutionary algorithm able to evolve ANNs of arbitrary topologies.



- It is based on:
 - **complexification** → evolving gradually more complex ANNs,
 - **innovation numbers** → track structural innovations,
 - **niching** → allows simultaneous evolution of small and large ANNs in one population. **Requires to define a distance measure for ANNs.**

Visual Discrimination

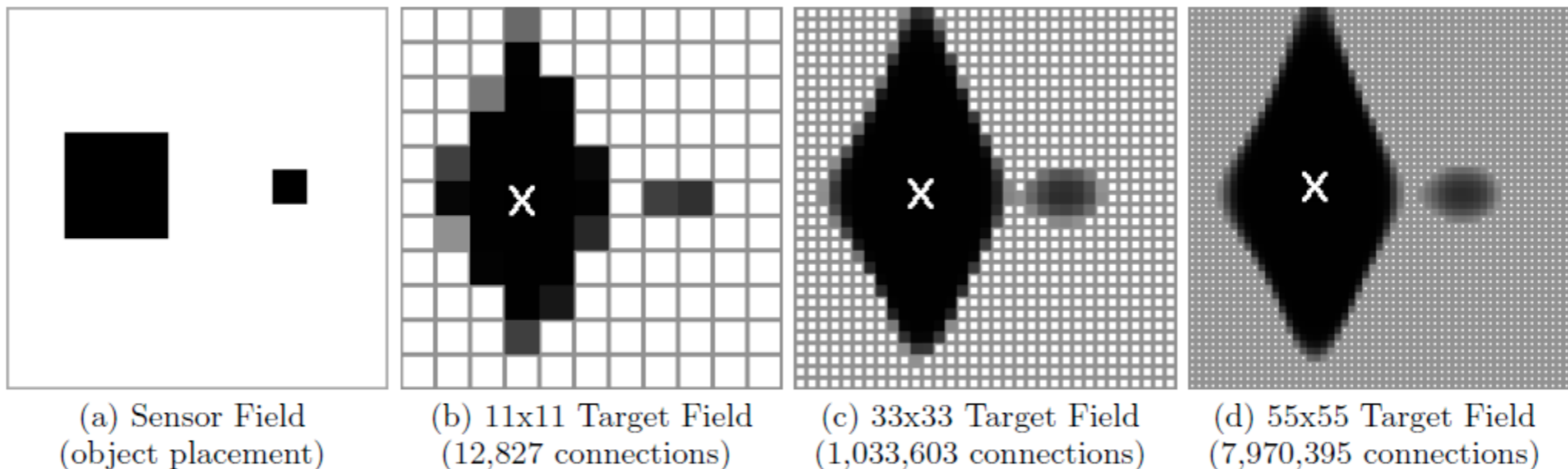
- Visual targeting: distinguish the larger object.
- “Sandwich substrate”.



Jason J. Gauci and Kenneth O. Stanley (2007):
Generating Large-Scale Neural Networks Through Discovering Geometric Regularities

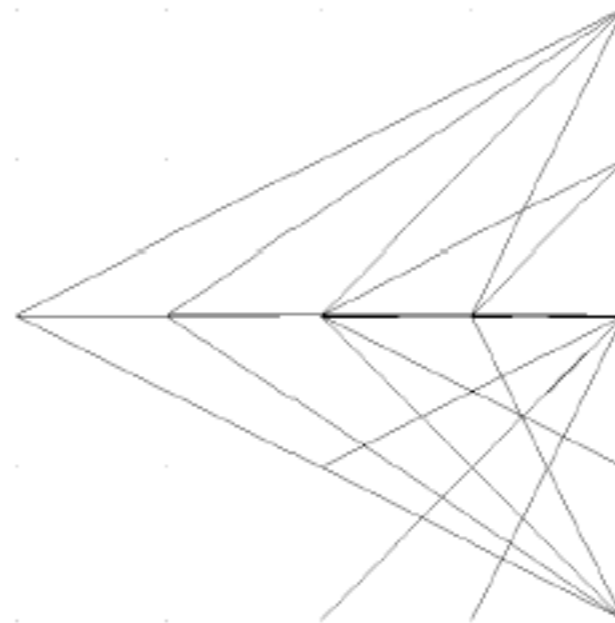
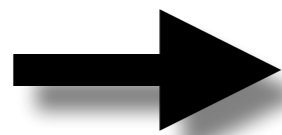
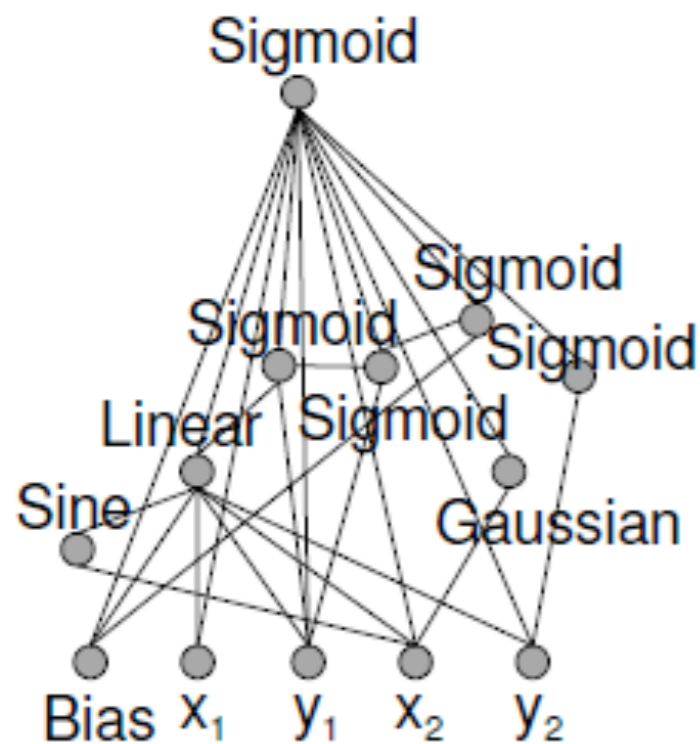
Visual Discrimination II: Scaling the Substrate

- The substrate density can be scaled using the same CPPN.
- The function of the final ANN is approximately preserved.
- We can train on small \rightarrow get large.

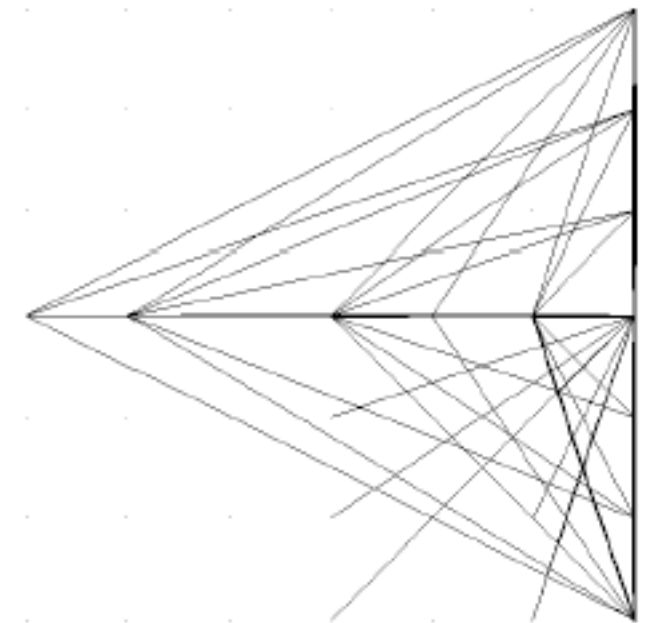


Visual Discrimination III: Scaling the Substrate

- An equivalent connectivity concept at different
- substrate resolutions.



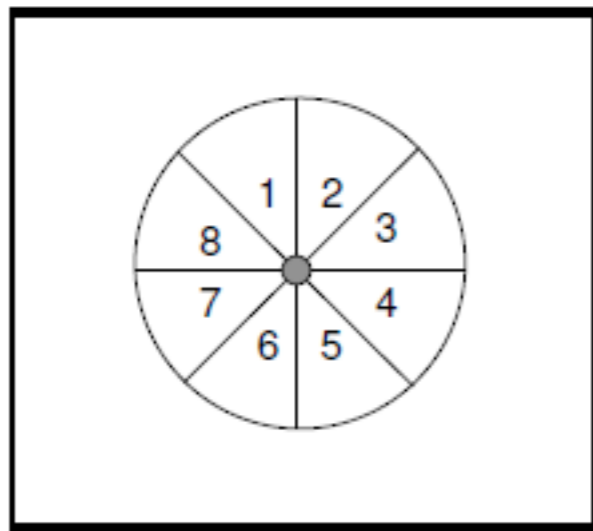
(a) 5 × 5 Concept



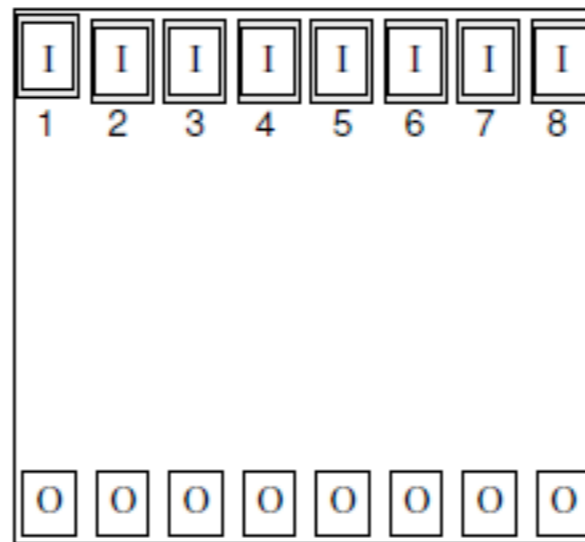
(b) 7 × 7 Concept

Food Gathering Problem

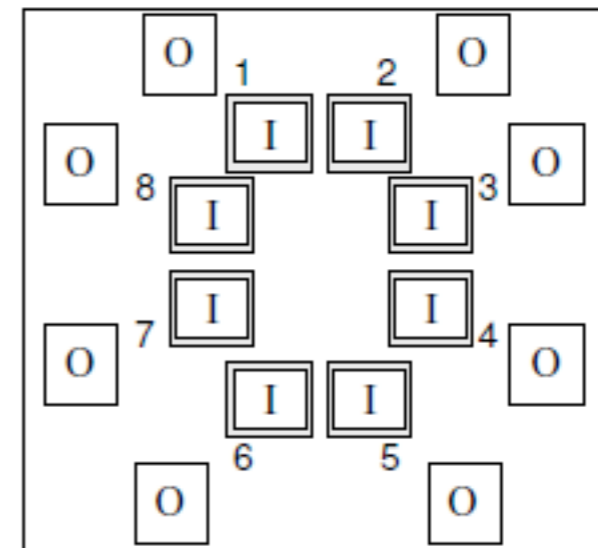
- Range-finder sensors detect food.
- More food eaten → higher fitness.
- Experiments with different sensor/effector placement – exploiting geometric relationships with “outer world”.



(a) Robot



(b) Parallel



(c) Concentric

David B. D'Ambrosio and Kenneth O. Stanley (2007)

A Novel Generative Encoding for Exploiting Neural Network Sensor and Output Geometry

Food Gathering Problem II

- Parallel worked better than Concentric because less computation is needed for CPPN.
- New CPPN inputs added: the *distances*
- $(x1-x2)$ and $(y1-y2)$
- When CPPN is provided the distances, both work the same.

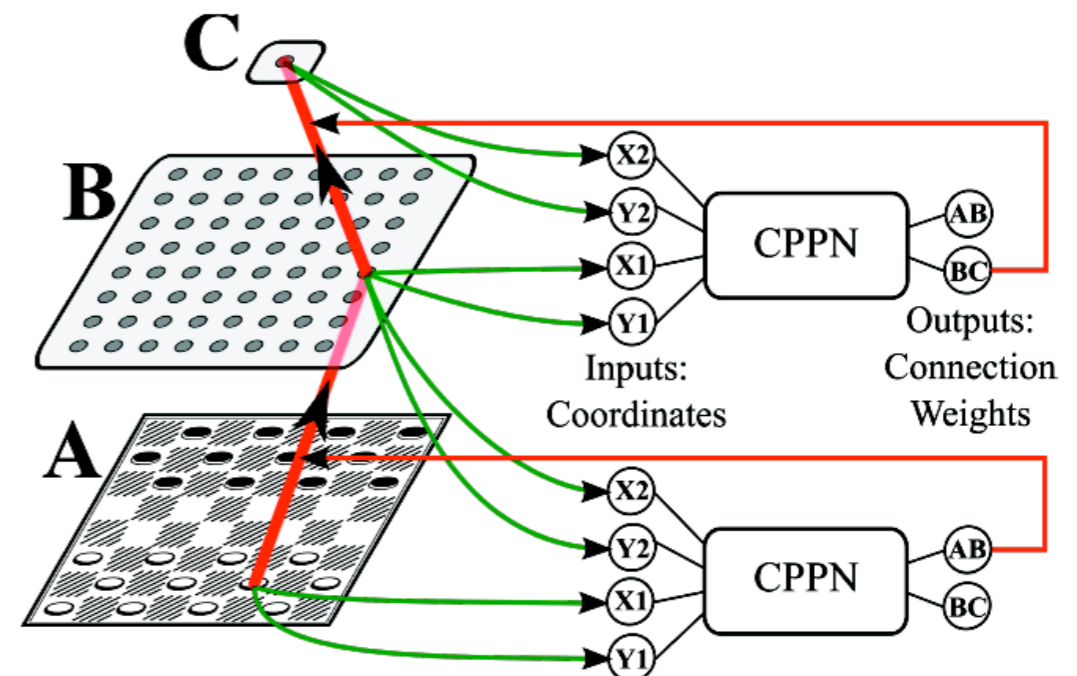
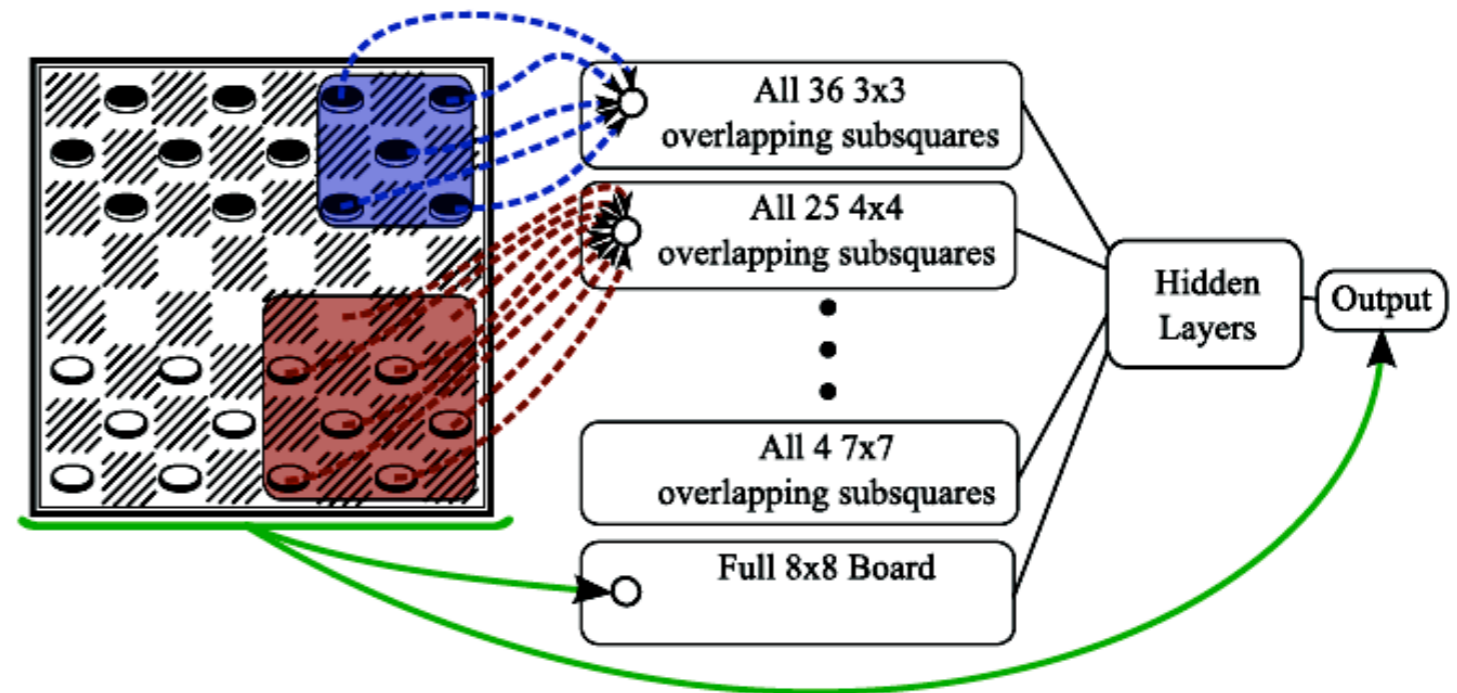
Checkers

- Comparison with classic NEAT.

- HyperNEAT is faster + generalizes.

- Single CPPN with multiple outputs.

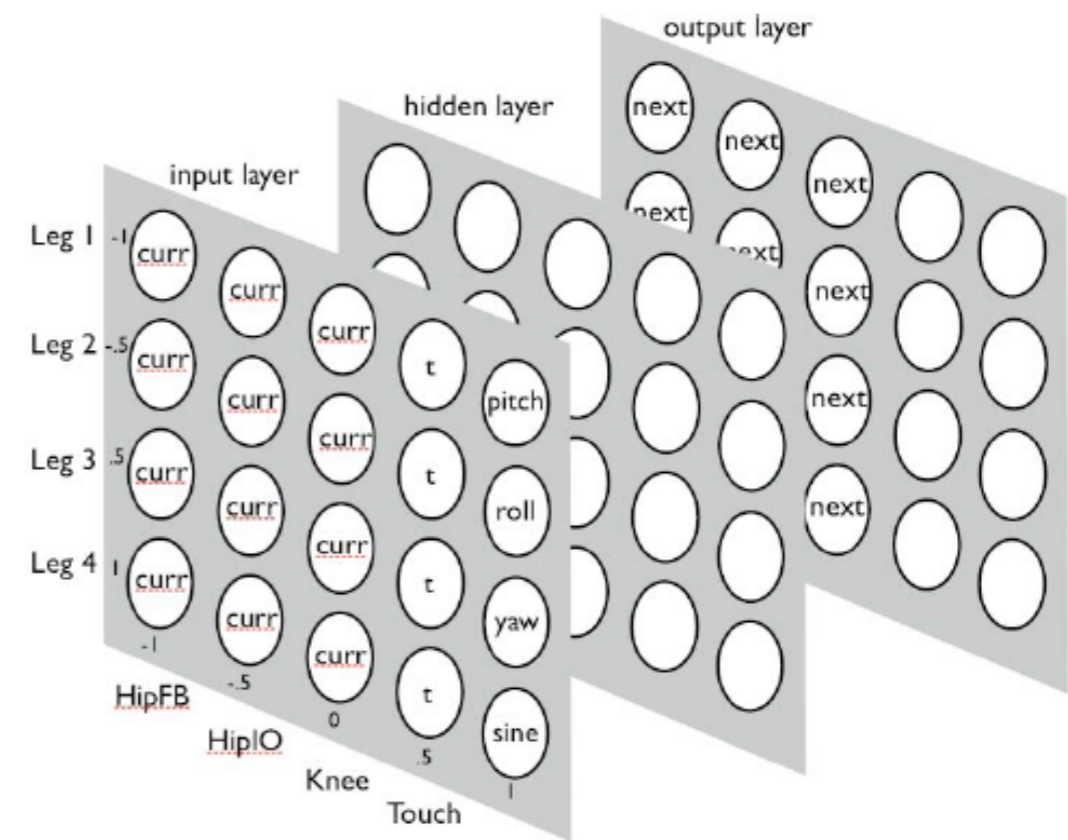
- The output of the final net is a heuristic score for the minimax algorithm.



Jason Gauci and Kenneth O. Stanley (2008):
*A Case Study on the Critical Role of Geometric
 Regularity in Machine Learning*

HyperNEAT Coordinated Quadruped Gaits

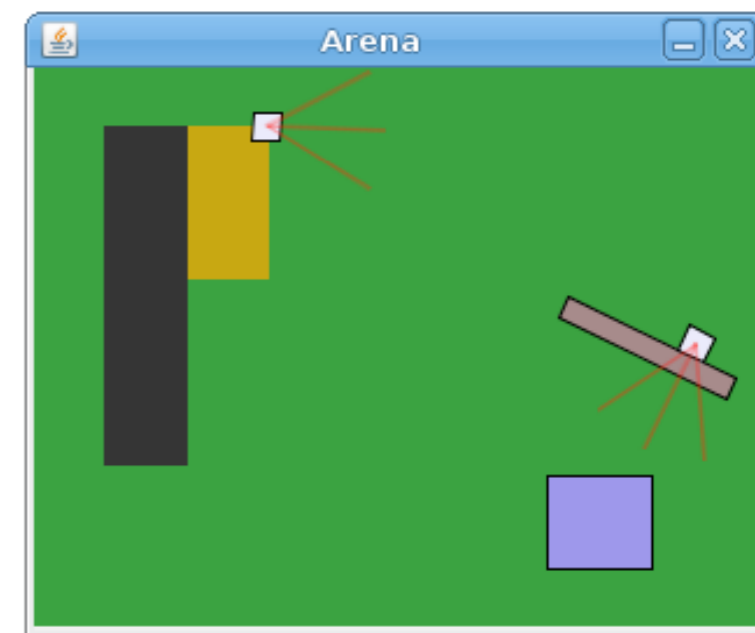
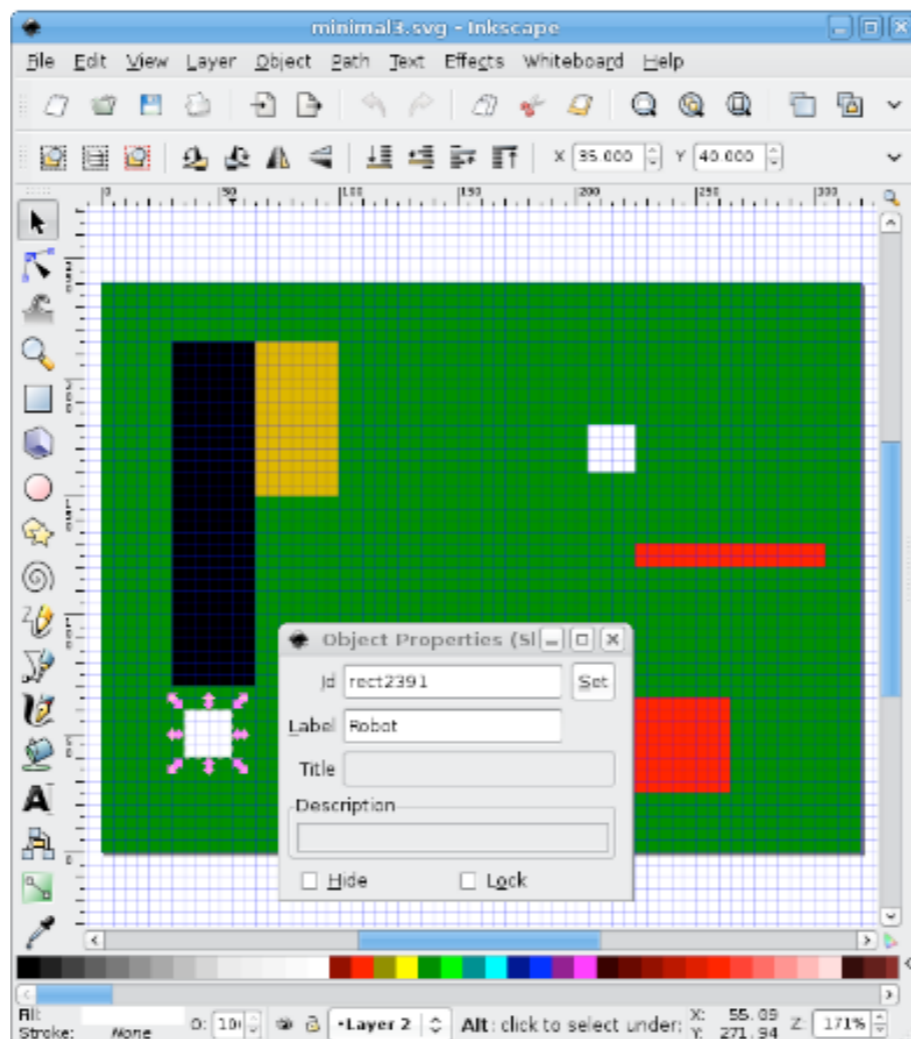
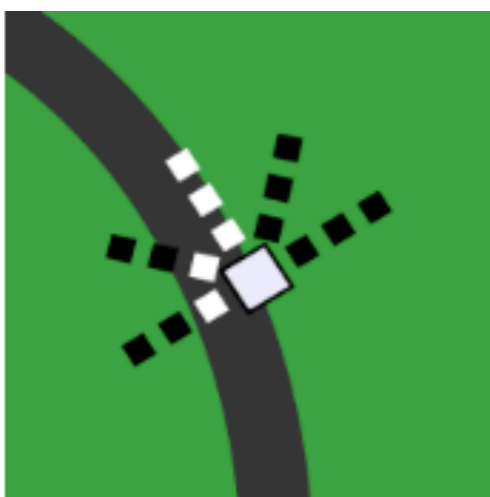
- Simulation of four legged walker robot.
- Comparison with classic NEAT.
- Other experiments show that HyperNEAT can deal with random substrates.



Jeff Clune:
*Evolving Coordinated Quadruped Gaits with the HyperNEAT
Generative Encoding*

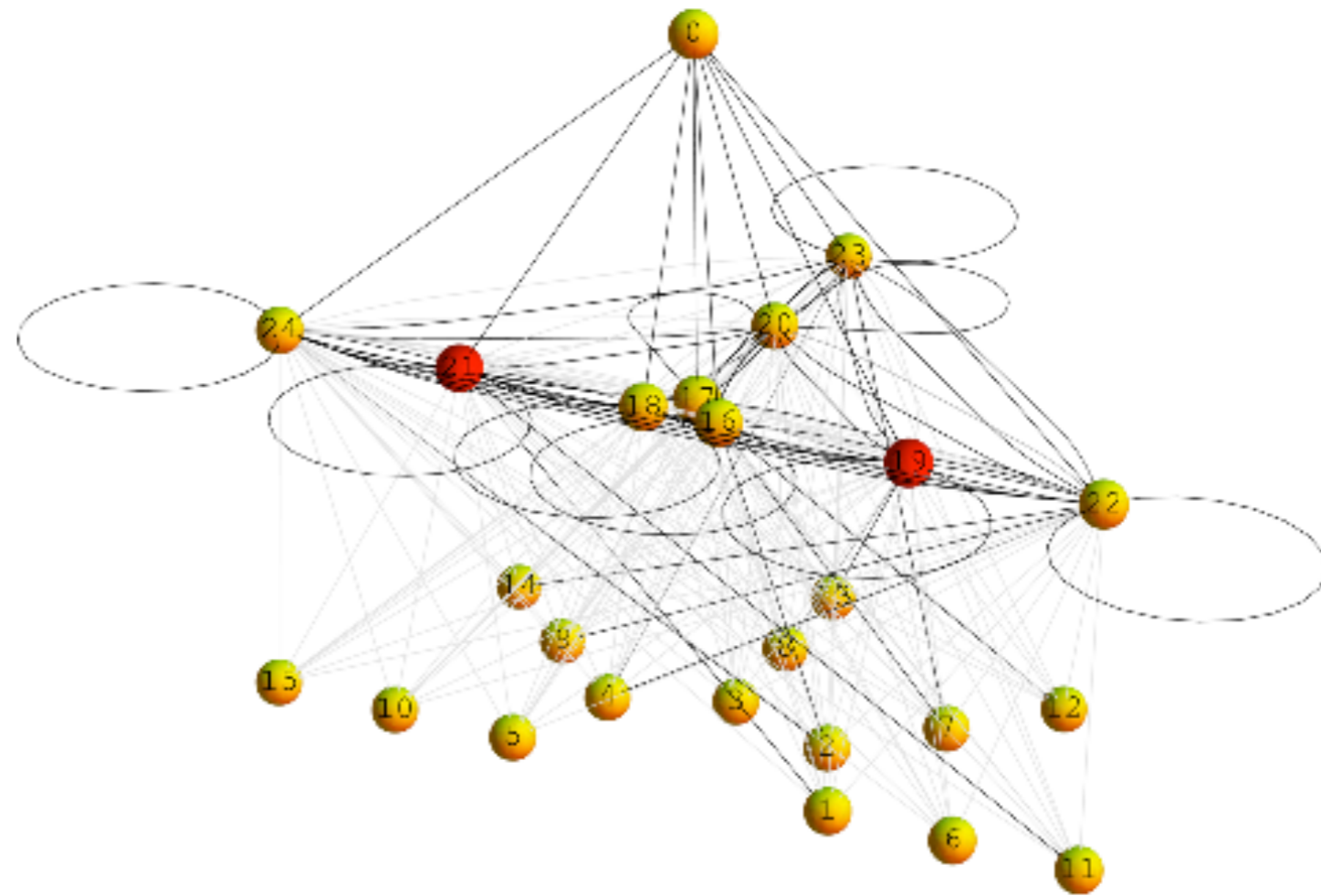
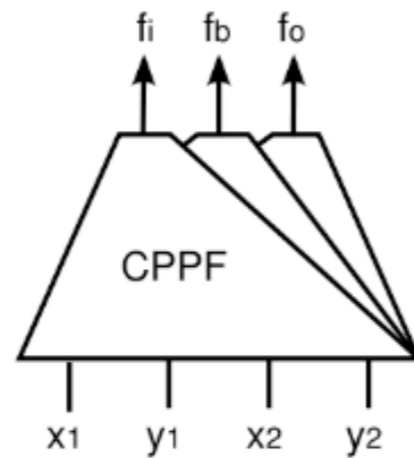
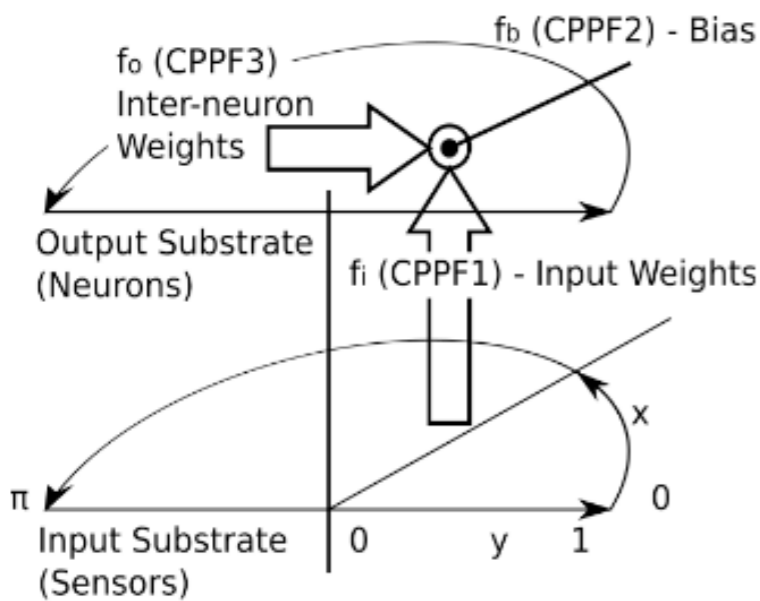
Mobile Robot Navigation

- HyperNEAT/HyperGP for robot control.
- ViVAE Simulated 2D environment with rigid body physics.



Mobile Robot Navigation II

- Substrate uses polar coordinates.
- Input + 1 fully recurrent layer
- See VIDEO...



Q&A