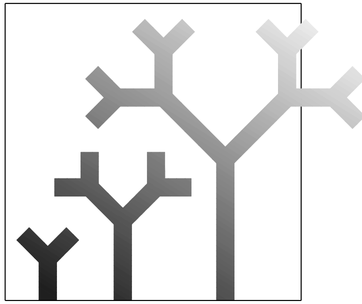
Morphological development and evolution



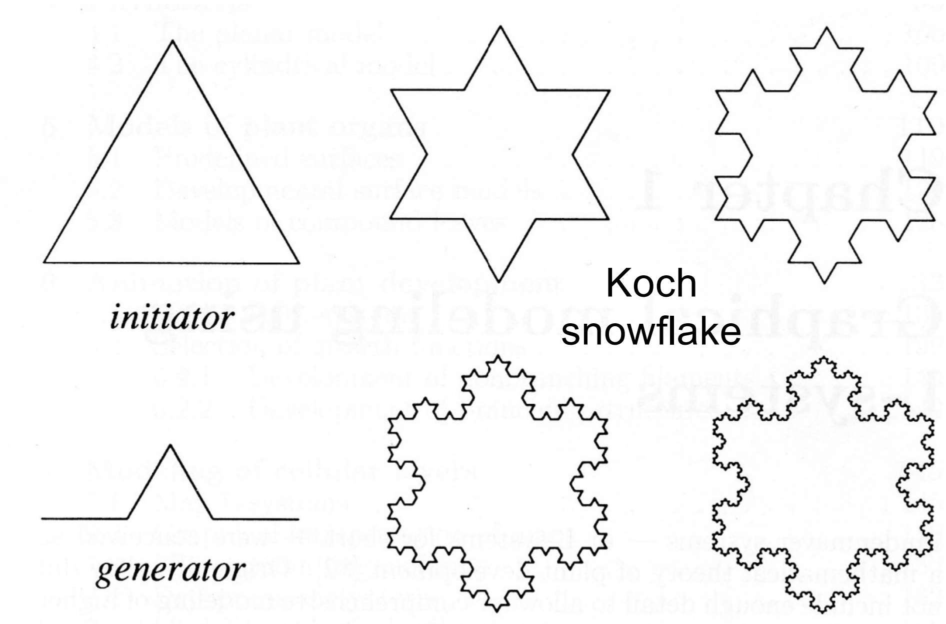
What you will learn in this class

- Describing complex geometries by Rewriting Grammars
- How to describe plant-like structures
- Encoding and evolution of neural architectures
- Encoding and evolution of robotic bodies and brains
- Composition Pattern Producing Networks
- Morphological computation: how bodies simplify control
- Co-evolved bodies make learning faster and better

Growth by Rewriting

Rewriting: recursively replace a sub-component with a more complex sub-component

Fractals are generated by replacing edges of a polygon with open polygons [von Koch, 1905]. At each iteration, the polygon is rescaled.

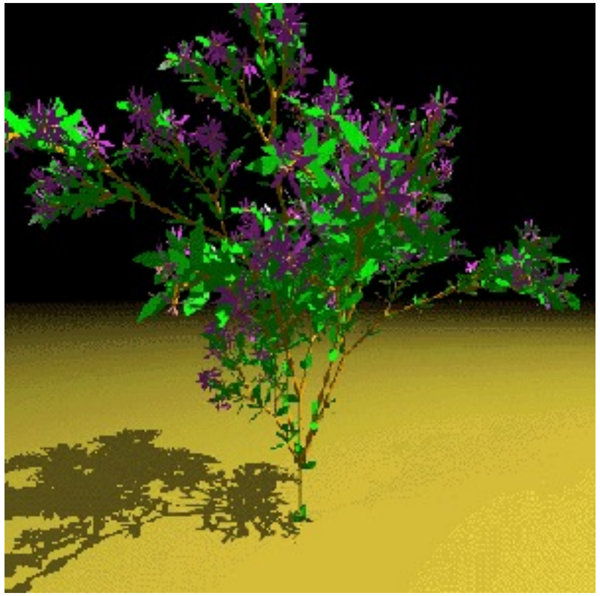


Several types of rewriting systems have been developed. These include *L-systems*, variations of *cellular automata*, and *language systems*.

L-systems [Lindenmayer, 1968]

Lindenmayer systems, or L-systems for short, are mathematical models to describe biological morphologies through a growth process. They were originally applied to model growth of plants.

Aristid Lindenmayer



http://local.wasp.uwa.edu.au/~pbourke

Artificially generated tree

L-system: Definition

L-systems are rewriting systems that operate on symbol strings.

An L-system is composed of:

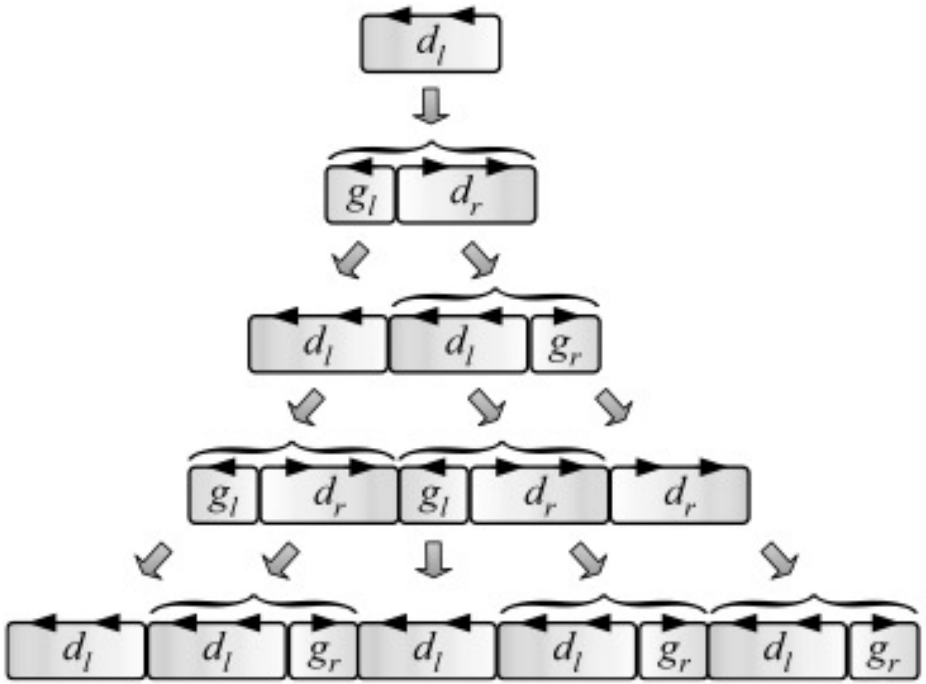
1. A set of symbols s forming an *alphabet* A
2. An *axiom* ω (initial string of symbols)
3. A set $\pi = \{p_i\}$ of *production rules*.

The following assumptions hold:

1. Production rules are applied in parallel and replace recursively all symbols in the string.
2. If no production rule is specified for a symbol s, then we assume the identity production rule $p_o : s \rightarrow s$.

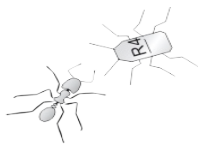
L-system: 1D Example

Development of a multicellular filament of blue-green bacteria *Anabaena catenula* [Lindenmayer 1968]



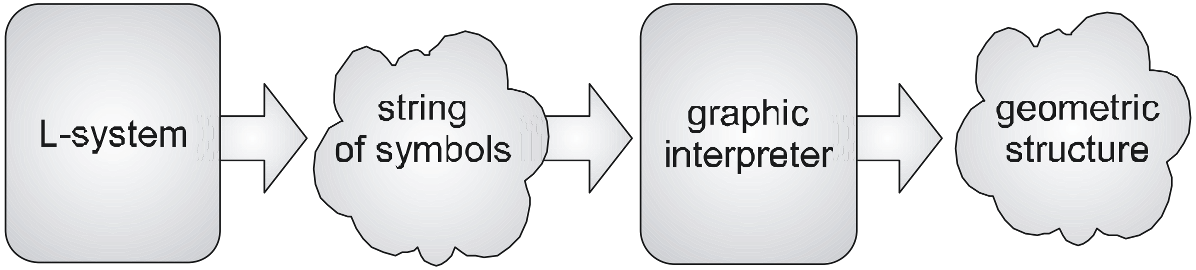
Cells can be in a "growing" state g or in a "dividing" state d with left or right polarity

$$A = \{g_r, g_l, d_r, d_l\}$$
$$\omega = d_l$$
$$p_1 = d_r \rightarrow d_l\, g_r$$
$$p_2 = d_l \rightarrow g_l\, d_r$$
$$p_3 = g_r \rightarrow d_r$$
$$p_4 = g_l \rightarrow d_l$$



Graphics Interpretation

- Using symbols that represent directly geometric entities such as 1D or 2D cells becomes rapidly impractical.
- We can increase the graphic potential of L-systems by following the phase of production of strings of symbols with a phase of graphic interpretation of the strings



Turtle Graphics Interpretation

In 2D, the turtle (printer) state is defined by the triplet x, y, α where the Cartesian coordinates (x, y) represent the turtle's position and the angle α, also known as heading, represents the facing direction.

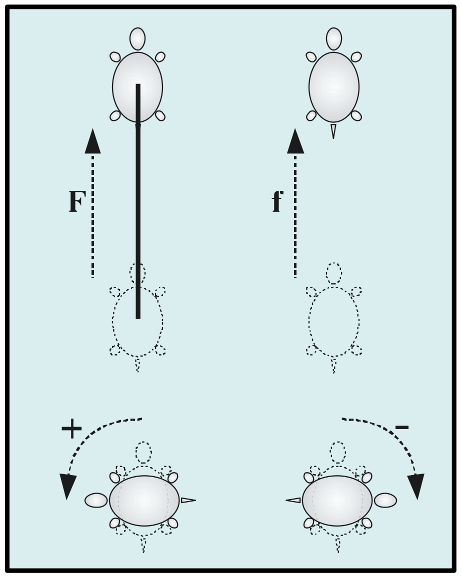
Given the step size d and the angle increment δ, the turtle can respond to the following commands:

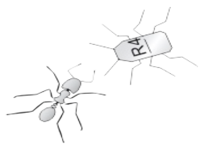
F : move forward by a step while drawing a line.

f : move forward by a step without drawing a line.

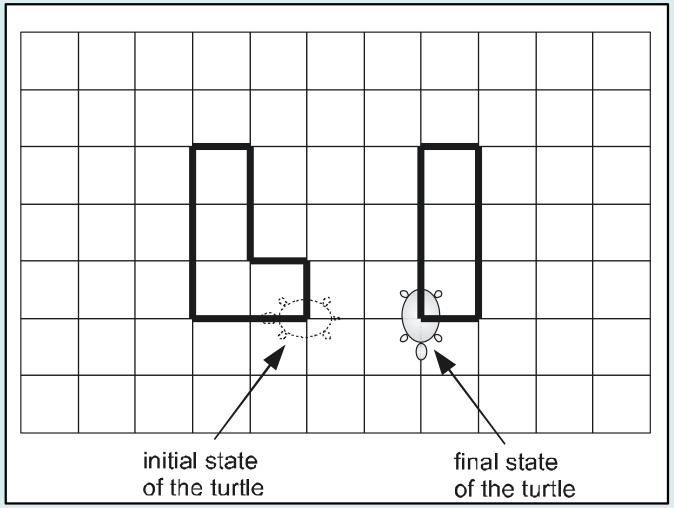
+ : turn left (counterclockwise) by angle δ.

– : turn right (clockwise) by angle δ.



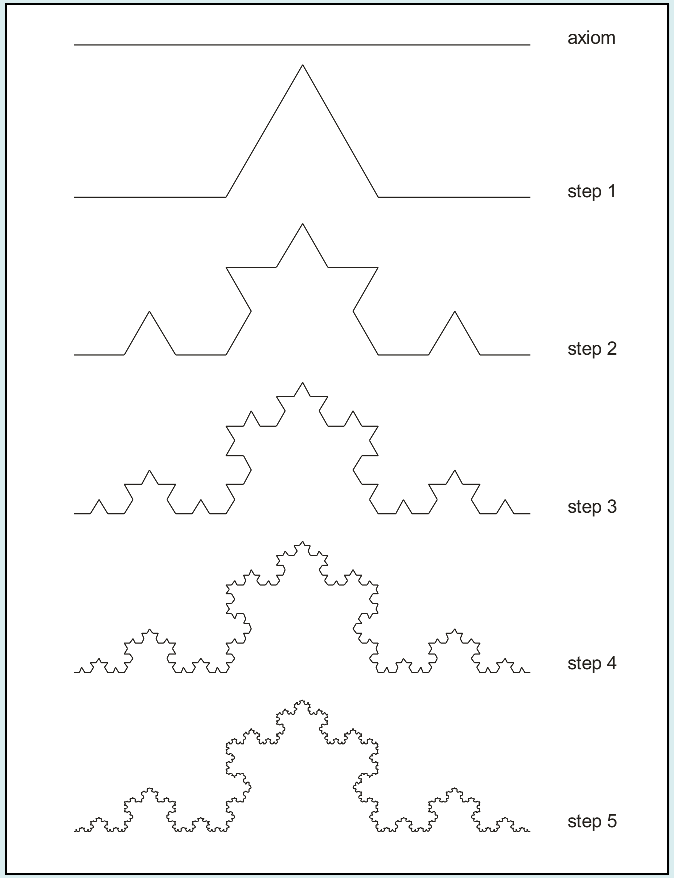


Examples



$\delta = 90^\circ$, $A = \{ F, f, +, - \}$

$\omega = FF - FFF - F - FF + F - F + ffF + FFF + F + FFF$



$\delta = 60^\circ$, $A = \{ F, f, +, - \}$, $\omega = F$

$p = F \rightarrow F+F--F+F$

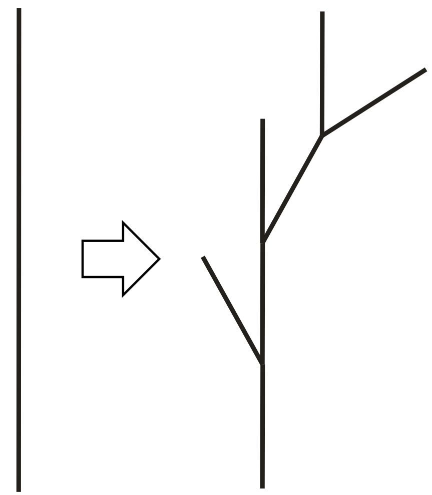
Bracketed L-systems

In drawing branching structures using the turtle interpreter it is necessary to reposition the turtle at the base of a branch after the drawing of the branch itself

- Two new symbols:

[Save current state of the turtle (position, orientation, color, thickness, etc.).

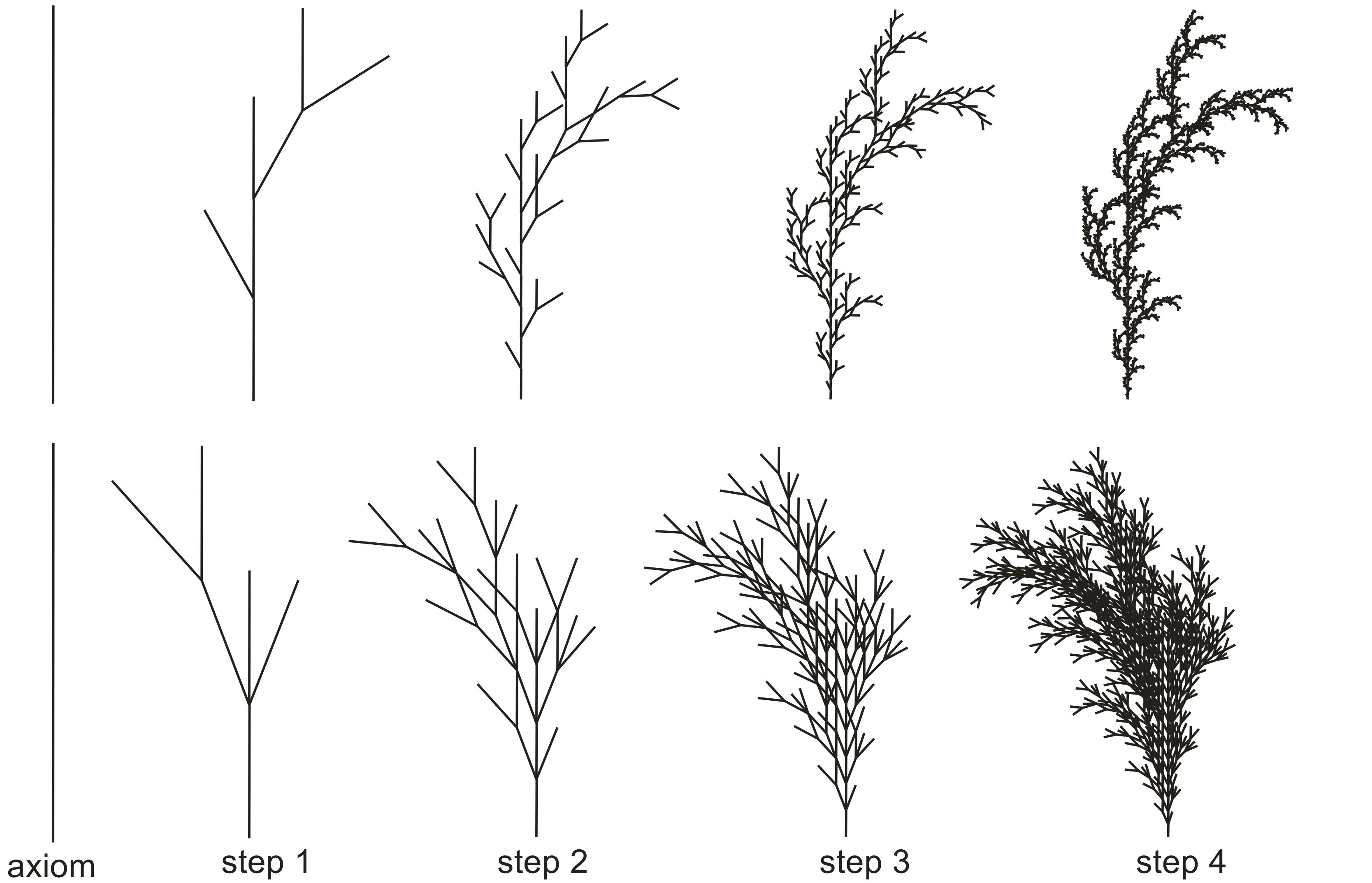
] Restore the state of the turtle using the last saved state (no line is drawn).



$\delta \quad \delta = 29^\circ$, $A = \{ F, +, -, [,] \}$

$\omega = F$

$p = F \rightarrow F\ [+F]F\ [-F\ [+F][-F]]F$


axiom
step 1
step 2
step 3
step 4

Stochastic L-systems

- In nature individuals of the same species are not identical.
- Specimen variability can be modeled by associating probabilities to production rules
- The sum of all probabilities over the same symbol must be 1

δ $\delta = 29^\circ$, $A = \{ F, +, -, [,] \}$

$\omega = F$

$p_1 = F \xrightarrow{1/3} F[+F]F[-F]F$

$p_2 = \mathrm{F} \xrightarrow{1/3} F[-F]F[+F]F$

$p_3 = \mathrm{F} \xrightarrow{1/3} F[-FF-F]F$

Application to computer graphics

http://gug.sunsite.dk/

http://www.ii.uib.no/~knute

http://www.uweb.ucsb.edu/~svetlin

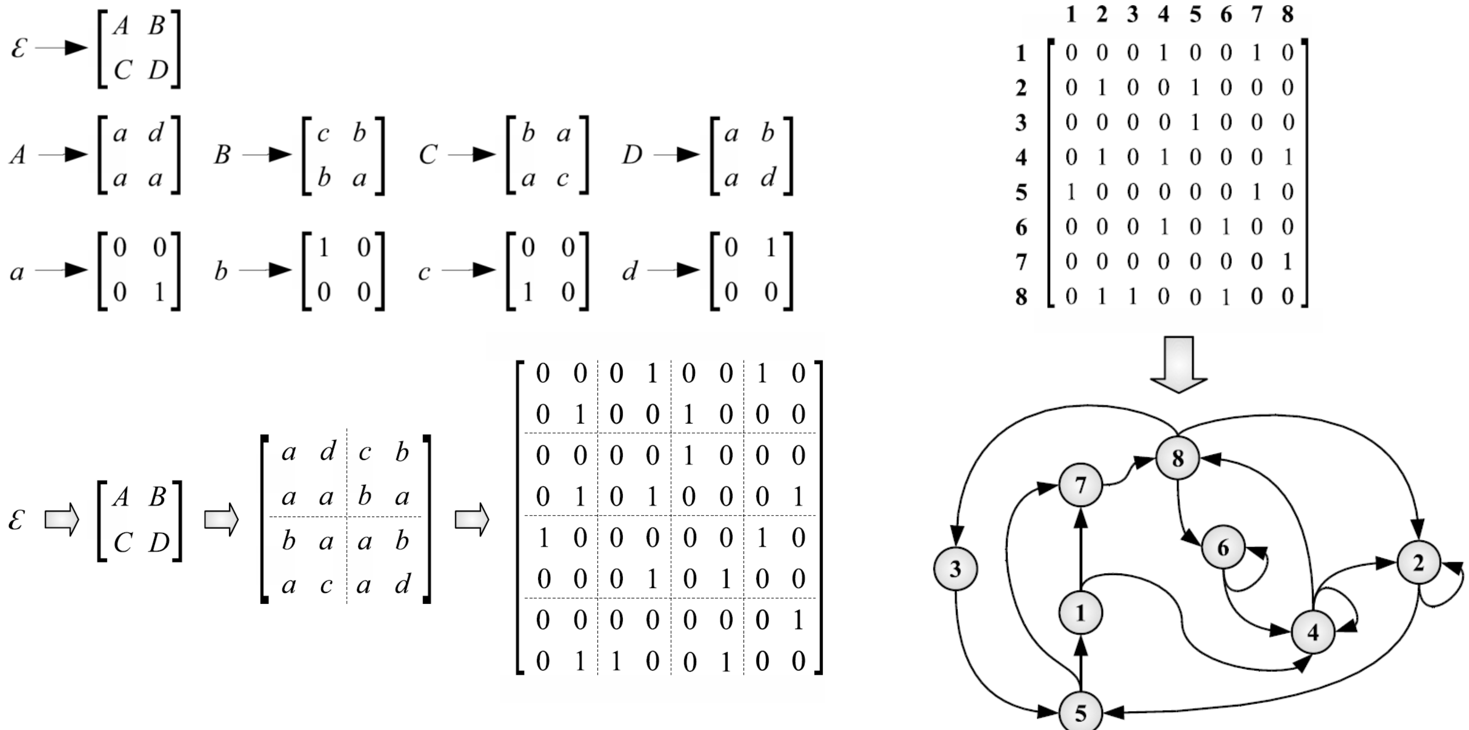
How to design rewriting systems

- It can be done by hand
  - When the rewriting rules are explicitly given (e.g., fractal curve)
  - When the rewriting rules can be easily deduced from the description of the developmental process (e.g., development of bacteria filaments and moss leaves)
  - When the resulting morphologies have only an aesthetic function
- It requires heuristic search methods
  - When the details of the resulting morphology have a functional role, such as a neural network, a gene regulatory network, an electronic circuit)

Neural architecture by matrix rewriting

Matrix rewriting is a *rewriting system* [Kitano, 1990] to describe and evolve neural network morphologies

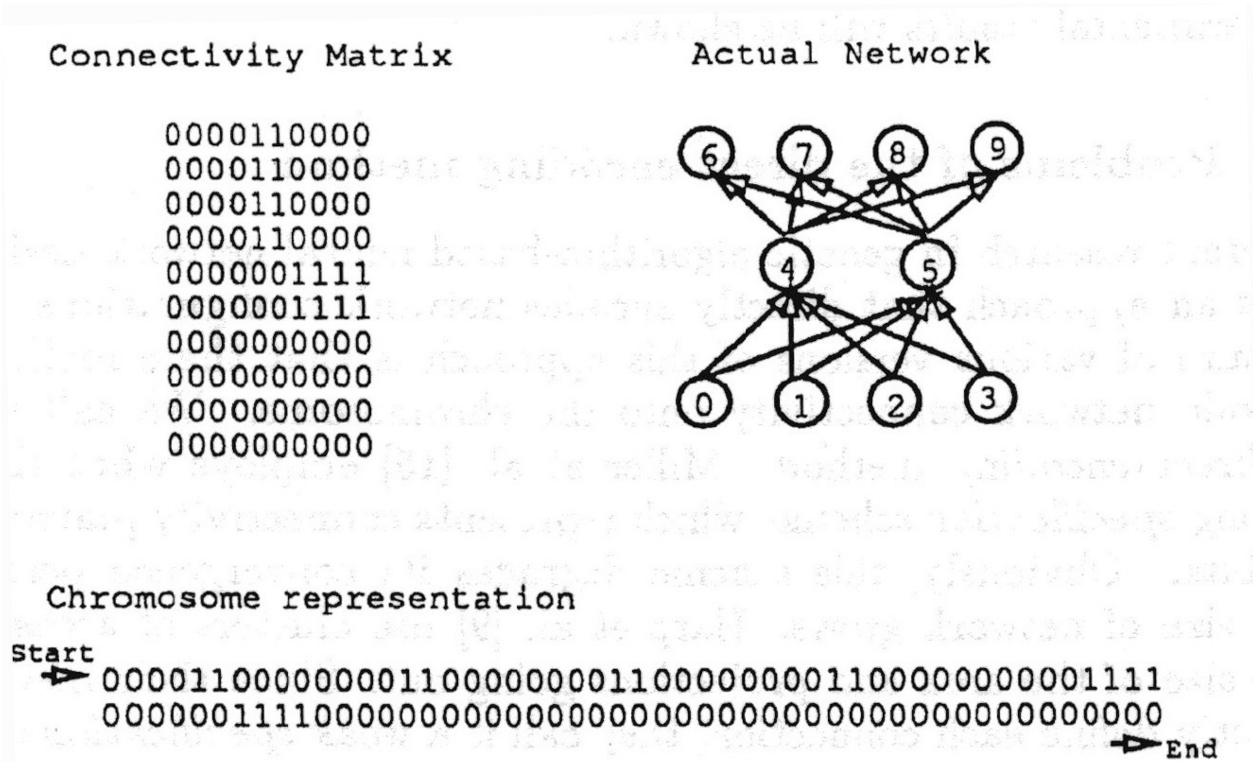
Genome describes rewriting rules, for example: *ABCD adaa cbba baac abad 0001 1000 0010 0100*



Only the presence/absence of connections is evolved. Weights are trained with backpropagation.

Comparison with Direct Encoding

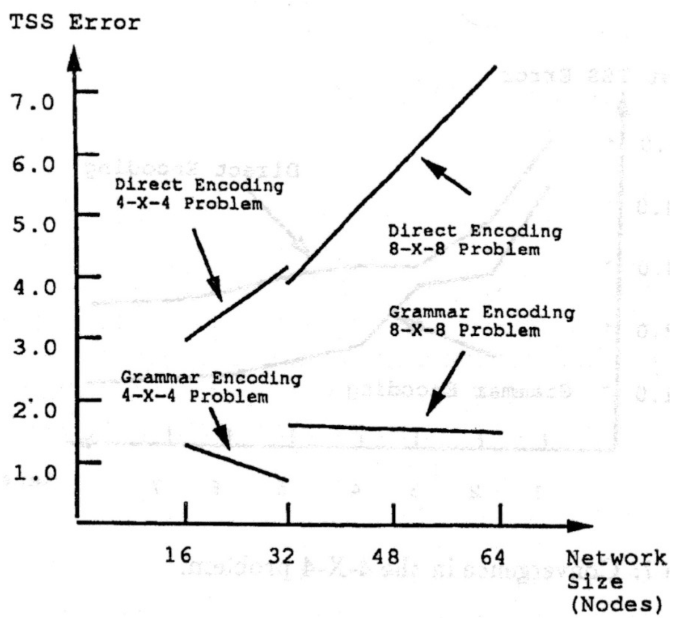
Direct encoding of neural network connection weights does not scale up and can produce irregular connection patterns.



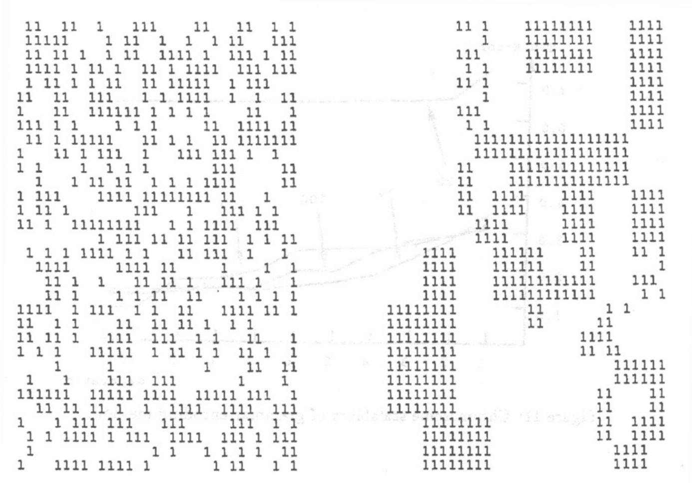
Evolving neural autoencoder architectures

The performance of developmental networks evolved using matrix rewriting does not suffer from network size, as direct encoding networks do, and resulting architectures are more regular (good for spatial information processing, such as convolutional neural networks).

Performance comparison



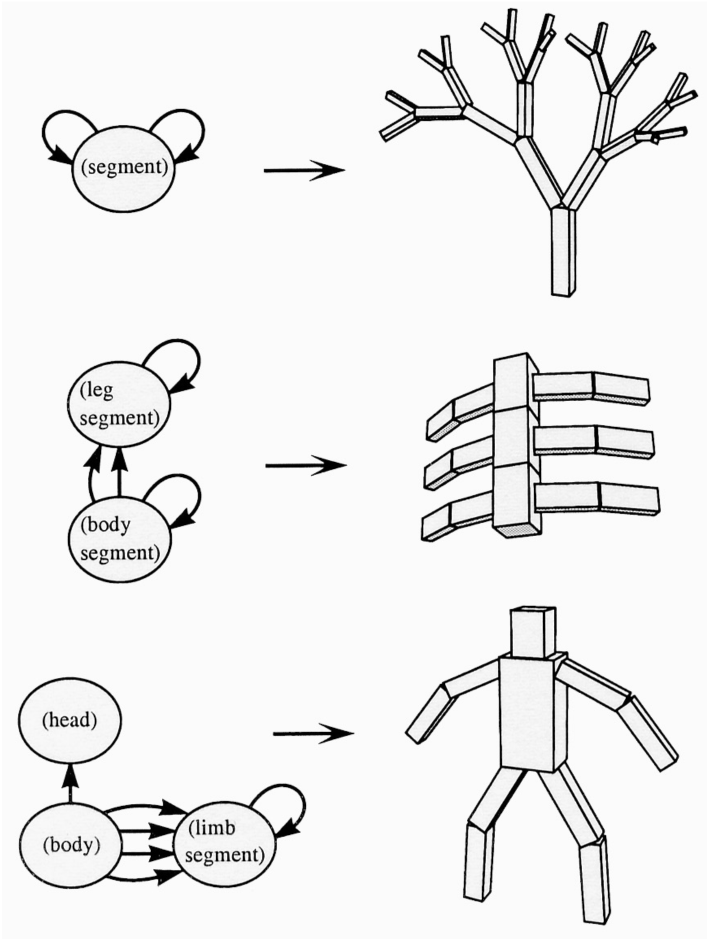
Architecture comparison



Direct encoding Grammar encoding

Grammar encoding of robotic bodies and brains

[Sims, 1994]



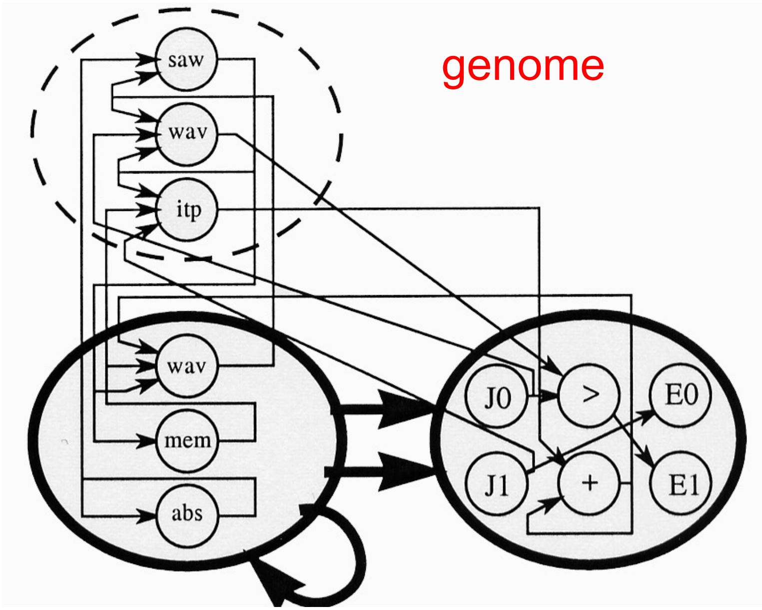
genotype phenotype

<u>Body components</u>:

- dimension
- joint type (rigid, twist, revolute, ...)
- recursive-limit
- connection (position, orientation, scale, reflection)
- terminal
- neural circuit

<u>Neural circuit components</u>:

- sensors: rotation, contact, light
- neurons: sum, memory, oscillator, max, etc.
- effectors: push, pull


genome
saw
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abs
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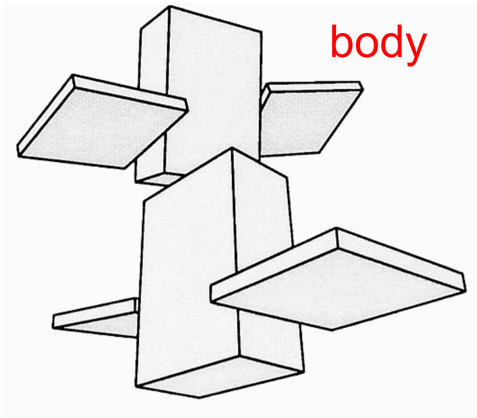
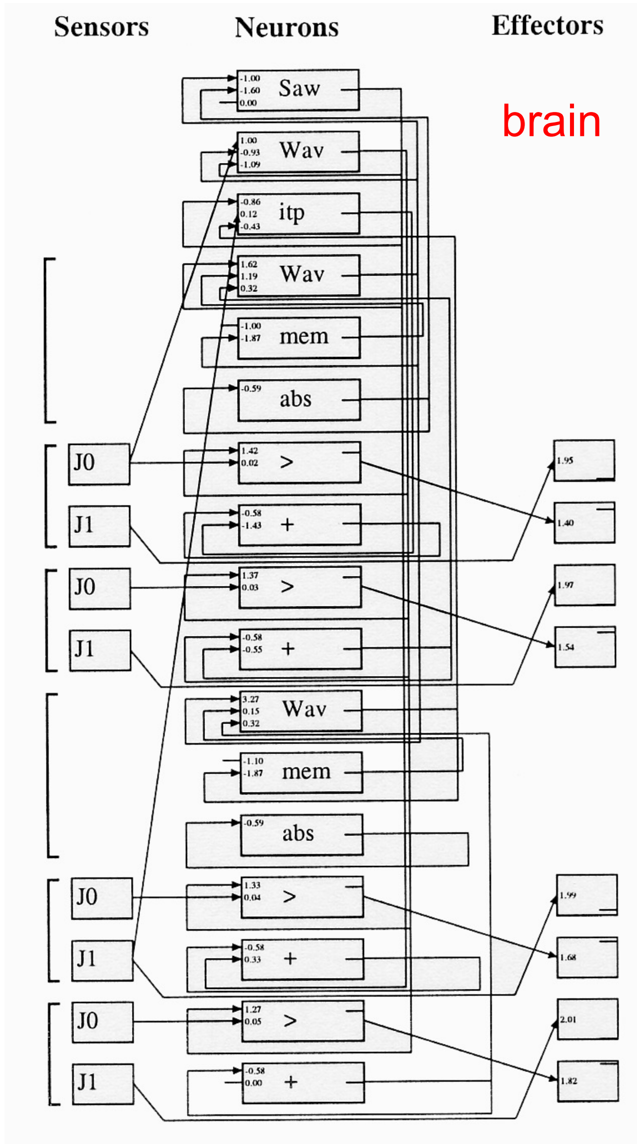
+
E0
E1


body


Sensors
Neurons
Effectors
brain
Saw
Wav
itp
Wav
mem
abs
J0
J1
>
+
Wav
mem
abs

[Sims, 1994]

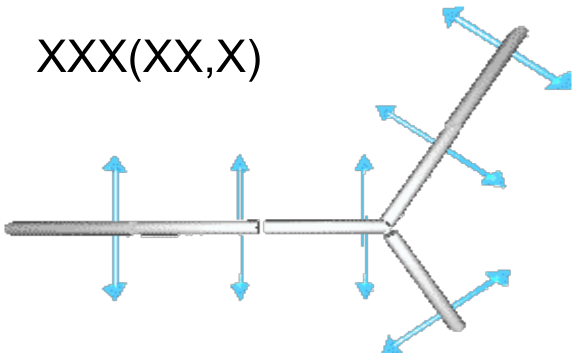
Co-evolved robotic bodies and brains

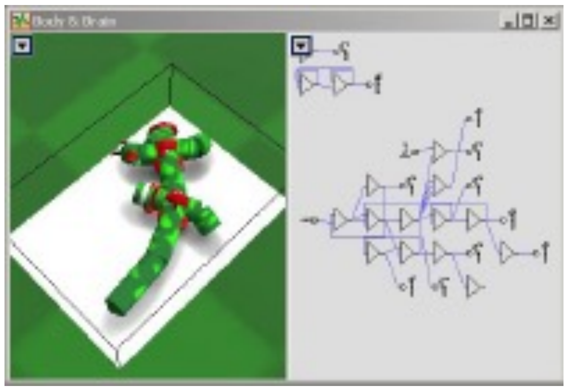
Sims, *1994*

Framstick [Komosinski & Ulatowski, 1999]

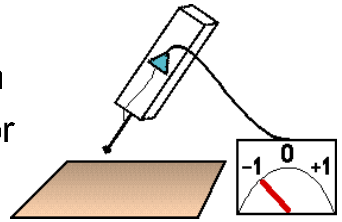
Body parts are joined sticks. Sticks can host sensors and neurons. Joints are actuated by muscles.

XXX(XX,X)

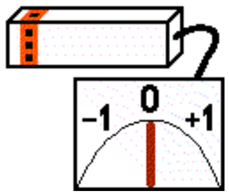


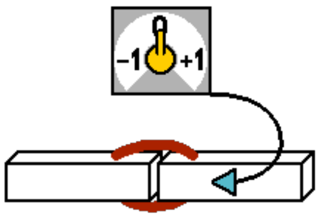


touch sensor

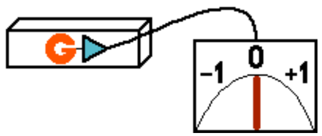


food sensor





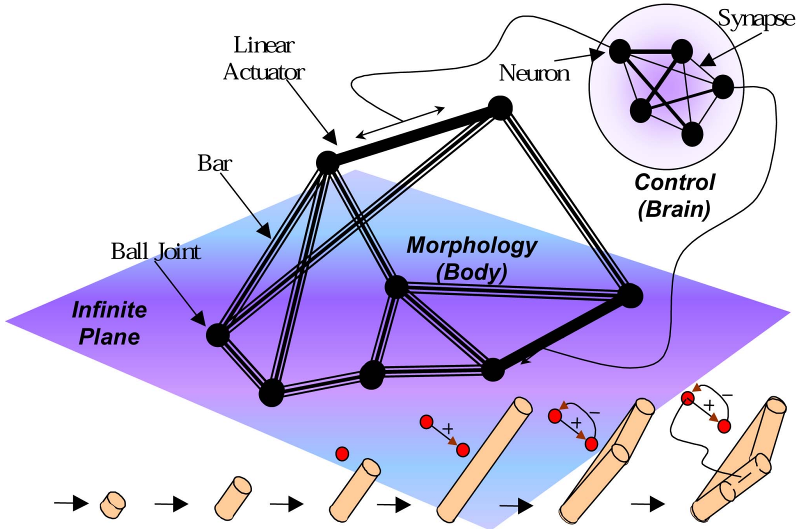
muscle

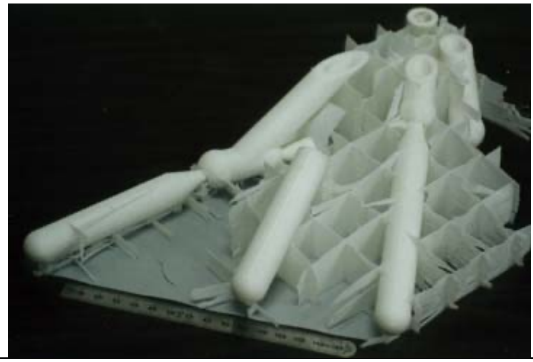


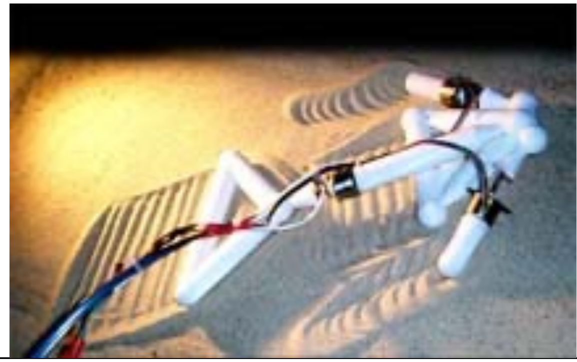
gyroscope

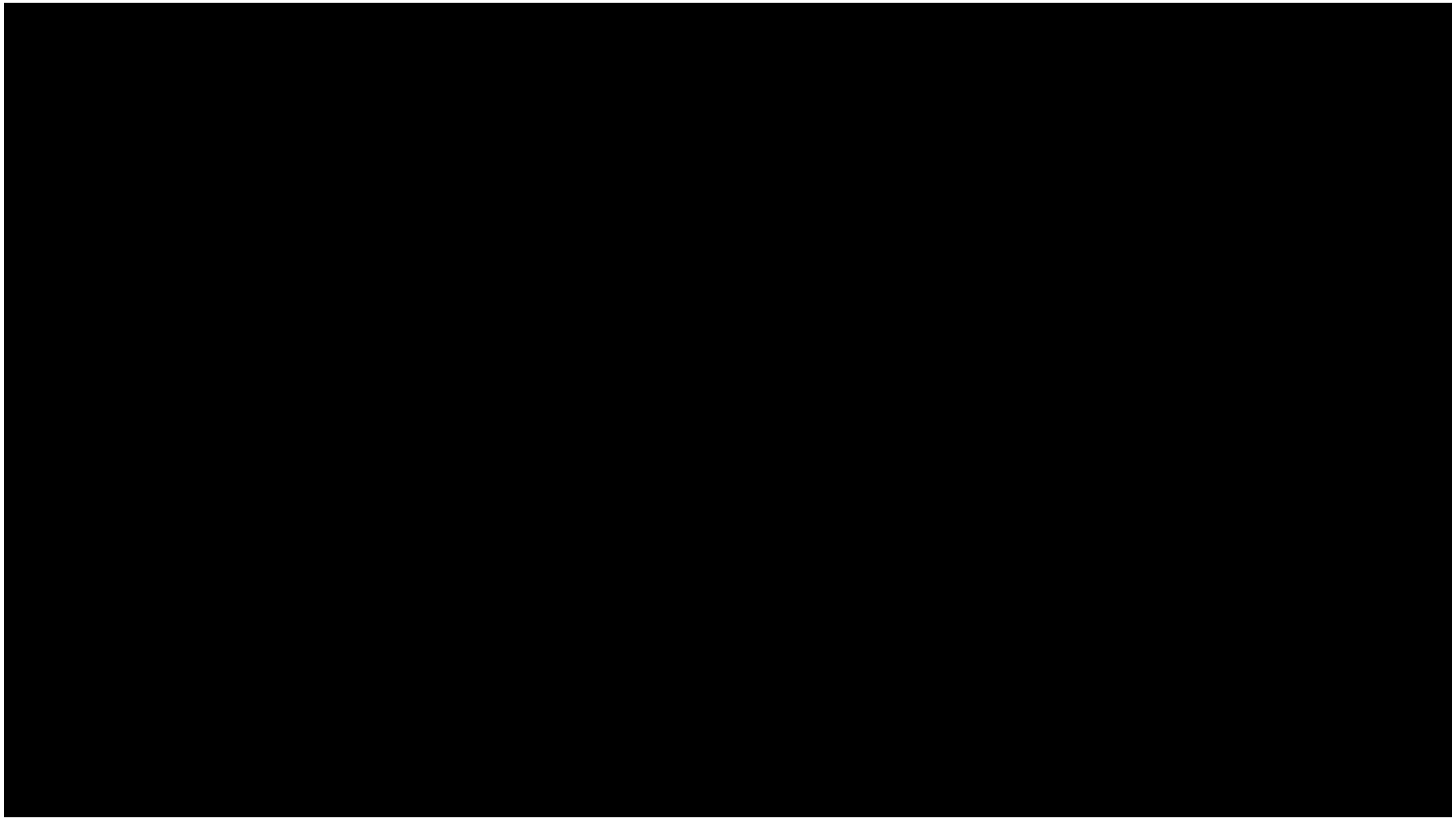
www.frams.alife.pl

The Golem project (Lipson & Pollack, 2000)









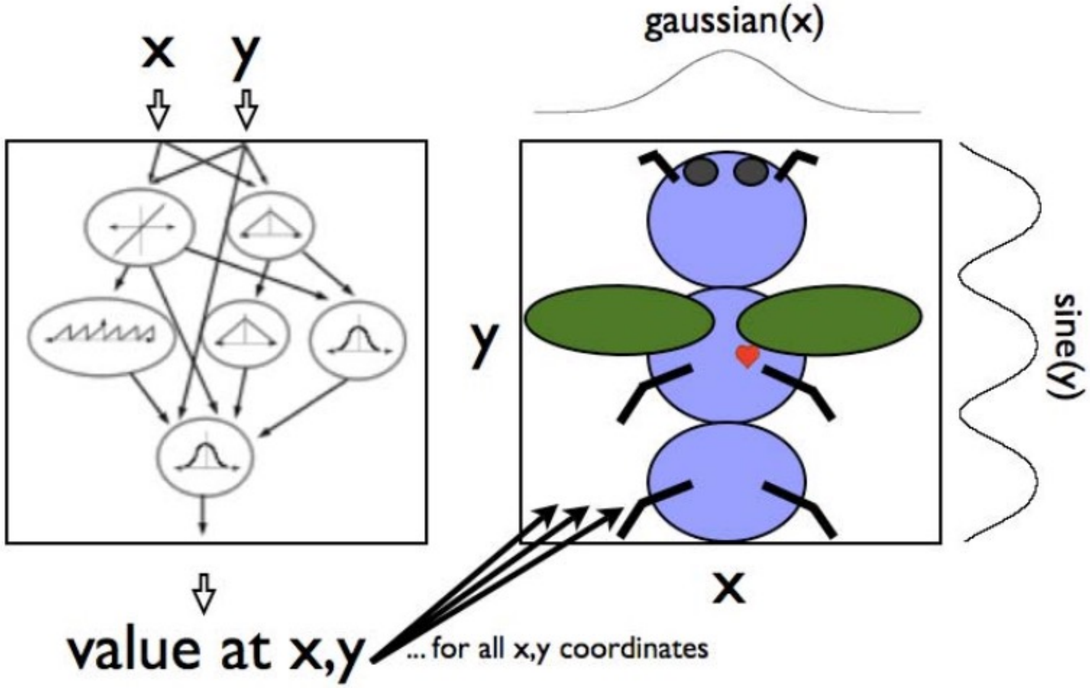
http://www.demo.cs.brandeis.edu/golem/

Robogen

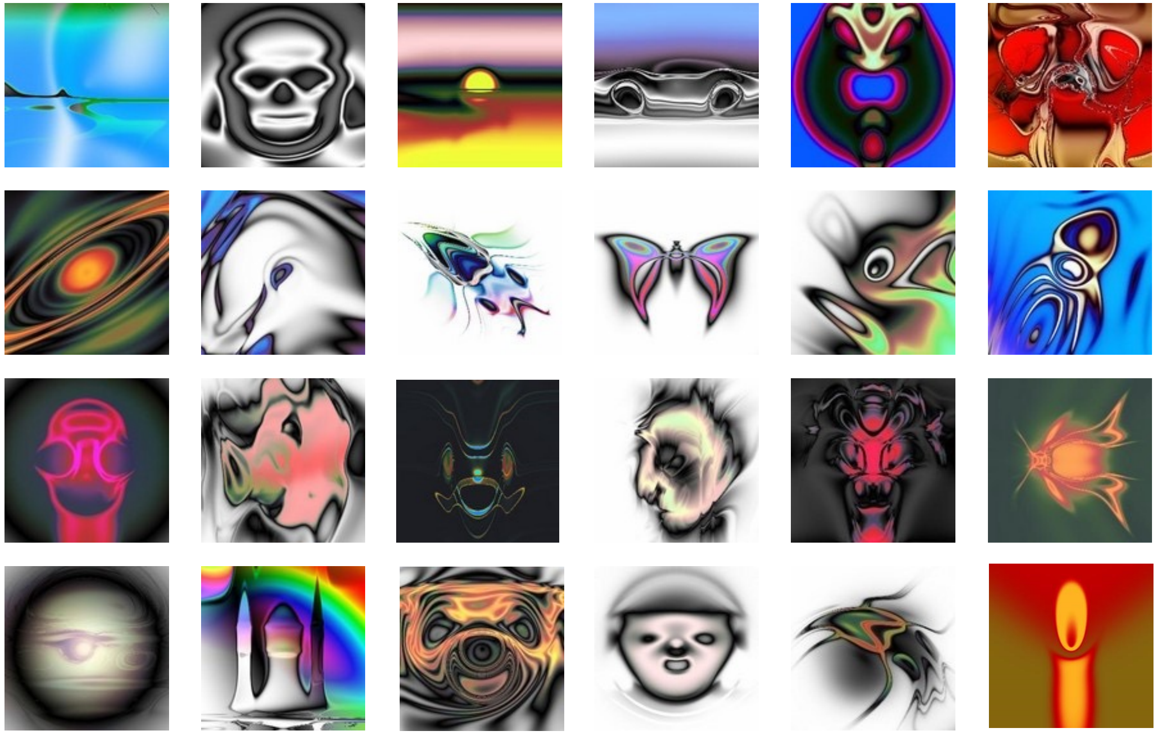
Auerbach J. E., Concordel A., Kornatowski P. M., Floreano D. (2019) Inquiry-Based Learning with RoboGen: An Open-Source Software and Hardware Platform for Robotics and Artificial Intelligence. *IEEE Transactions on Learning Technologies* (12, 3), 356-369.

Compositional Pattern Producing Networks (CPPNs)

- CPPNs were devised by Stanley [2007] as an abstraction of development.
- A CPPN is a neural network that generates object properties as a function of position
- CPPN neurons can have a variety of activation functions suitable for geometric descriptions.
- CPPN produce symmetry, repetition, and repetition with variations, as observed in biological development

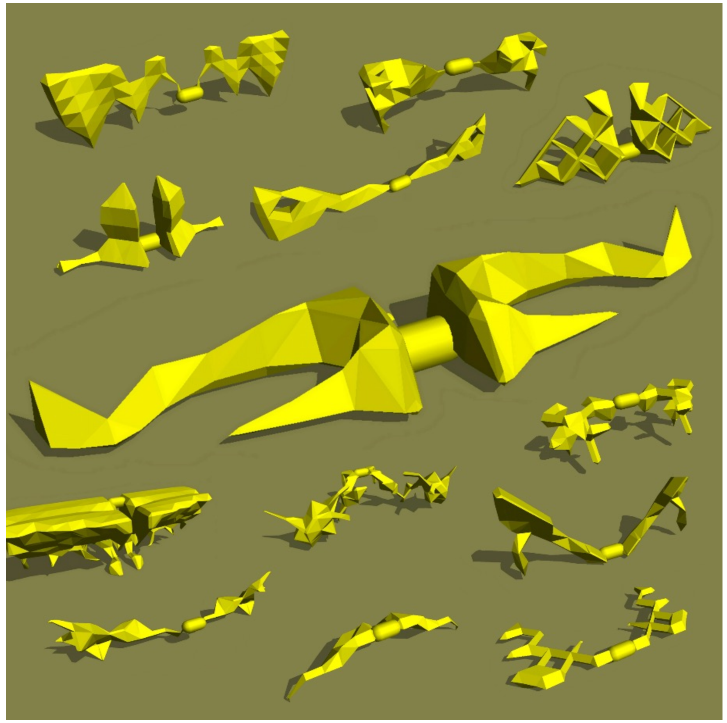


2-Dimensional images



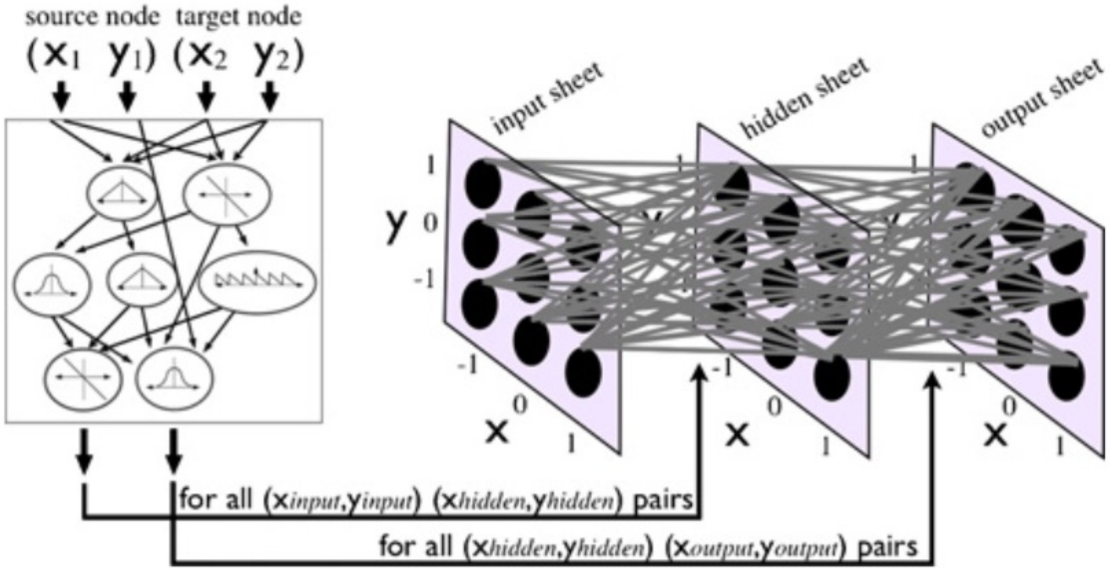
Picbreeder.org
[Secretan et al., 2007]

3-Dimensional objects



Robot morphologies
[Auerbach and Bongard, 2014]

Co-design of neural controllers and robotic bodies by CPPNs

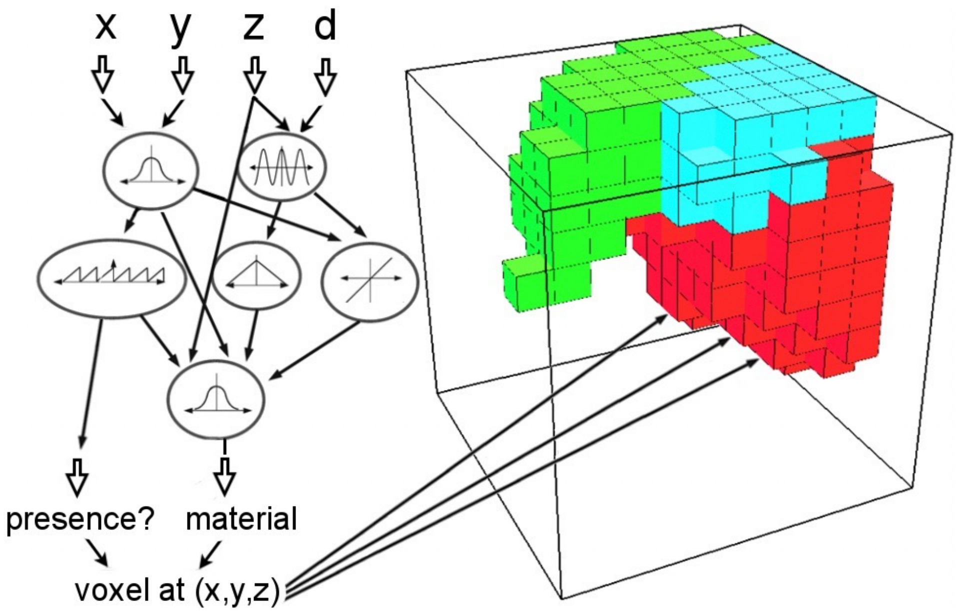


CPPNs can “paint” weights of neural network connections [Stanley et al., 2009], up to several million connections

CPPNs can be used to paint both the robot morphology and the weights of the neural controllers [Clune et al., 2013].

Encoding of soft-bodied robots

Cheney, MacCurdy, Clune, Lipson, 2013



Green voxels undergo periodic volumetric actuations of 20%

Red voxels behave similarly to green ones, but with counter-phase actuation

Light blue voxels are soft and passive, having no intrinsic actuation

Dark blue voxels are also passive, but are stiffer

Evolution of soft-bodied robots

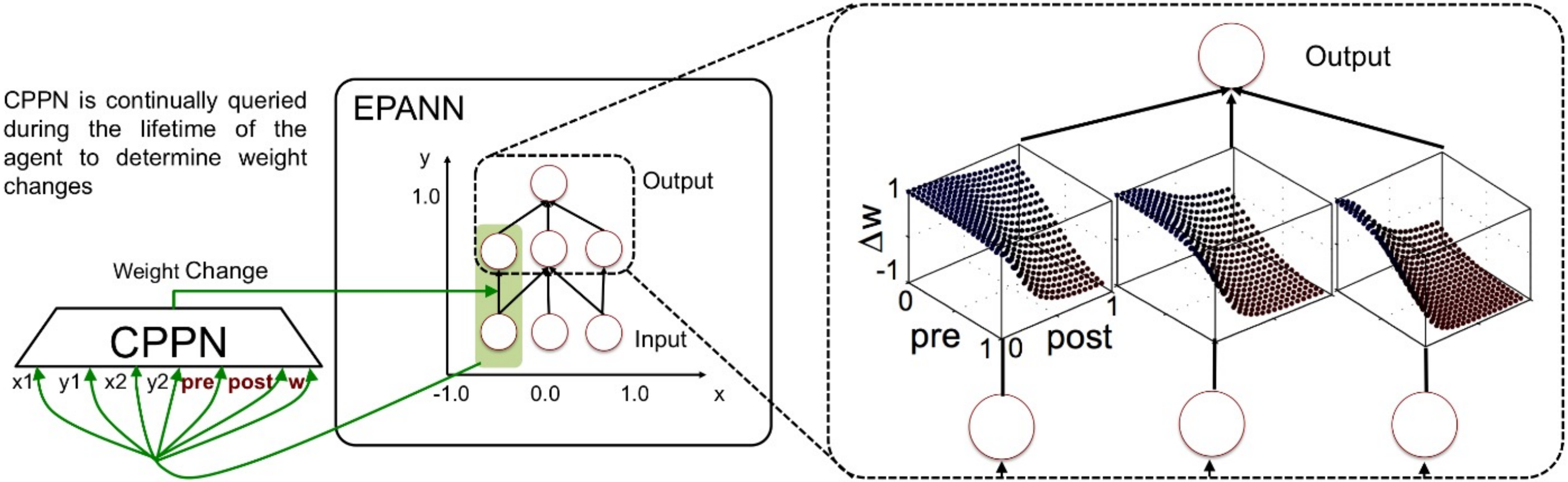
Cheney, MacCurdy, Clune, Lipson, 2013

Ever wonder what it would be like
to see evolution happening
right before your eyes?

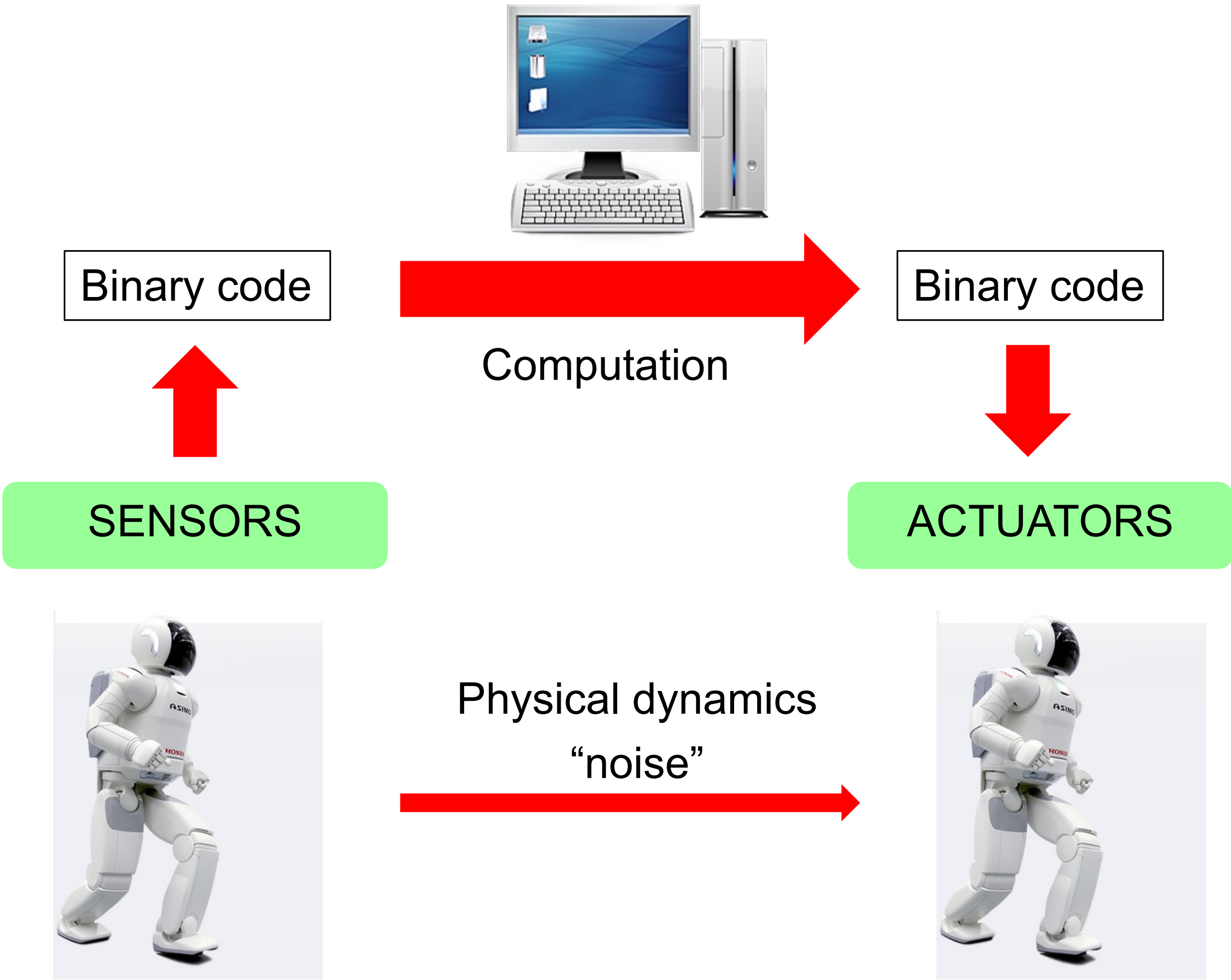
http://jeffclune.com/videos.html

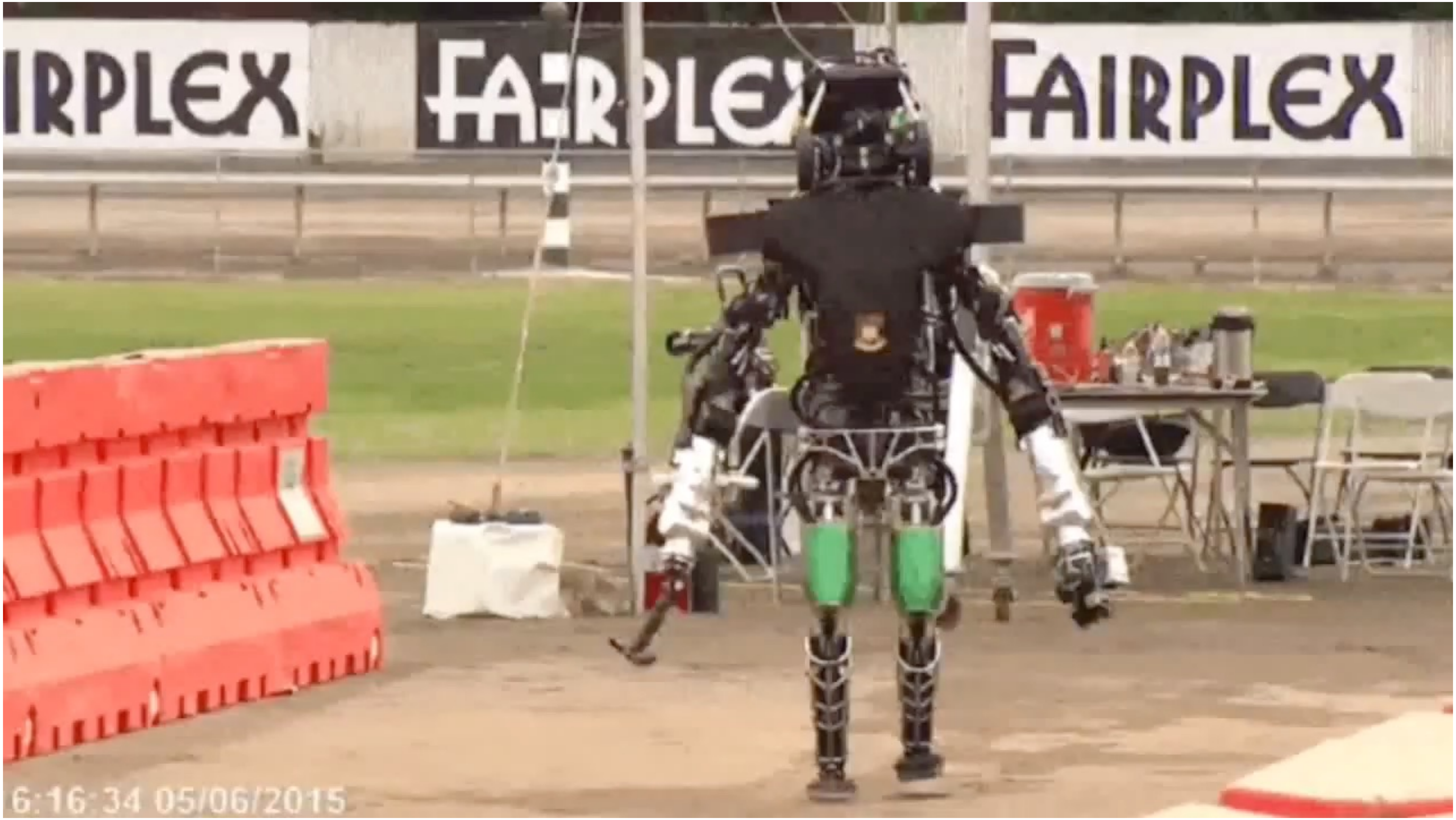
Using CPPNs as learning rules

Risi and Stanley, 2010, 2014



Conventional Control

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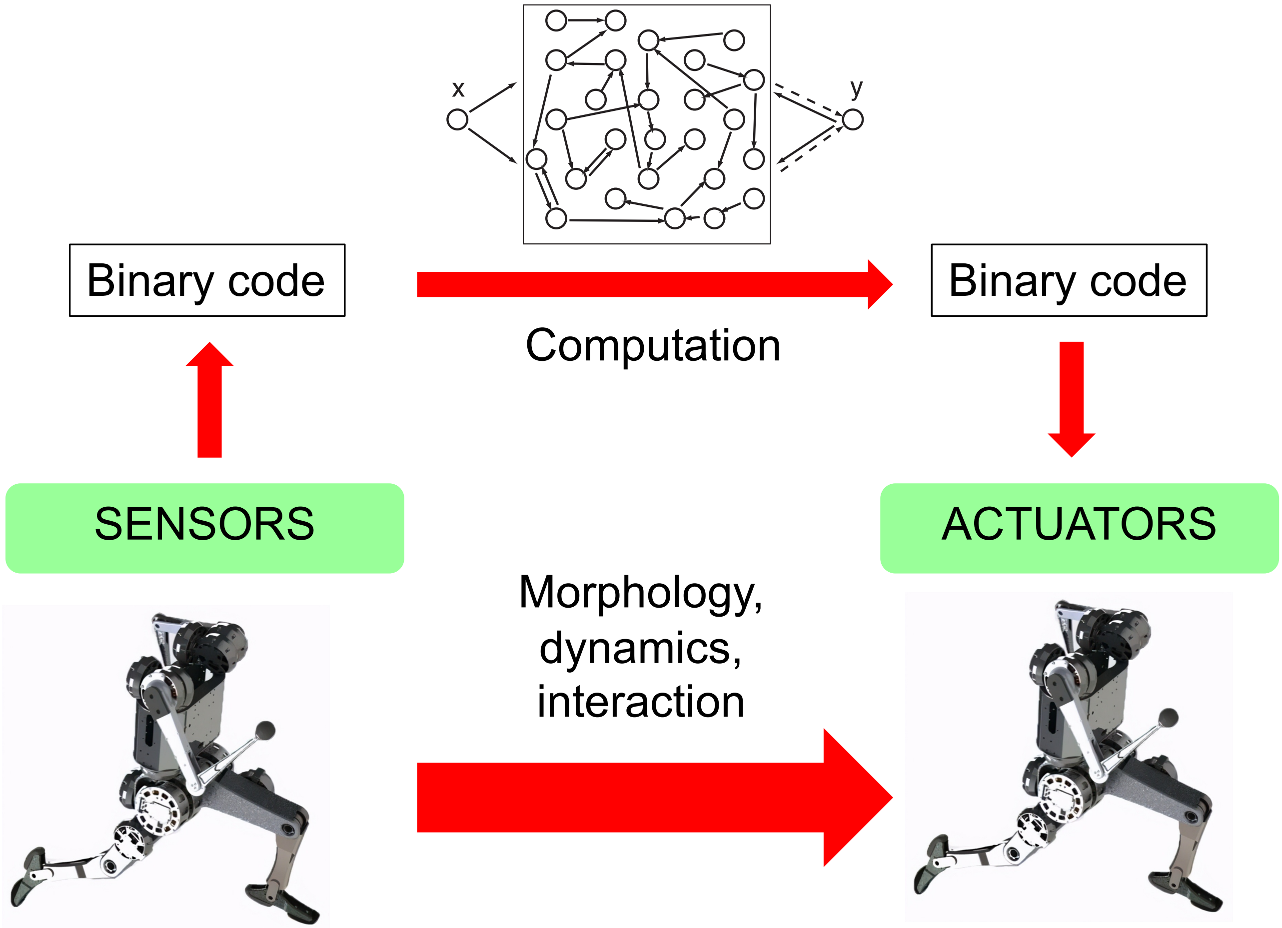
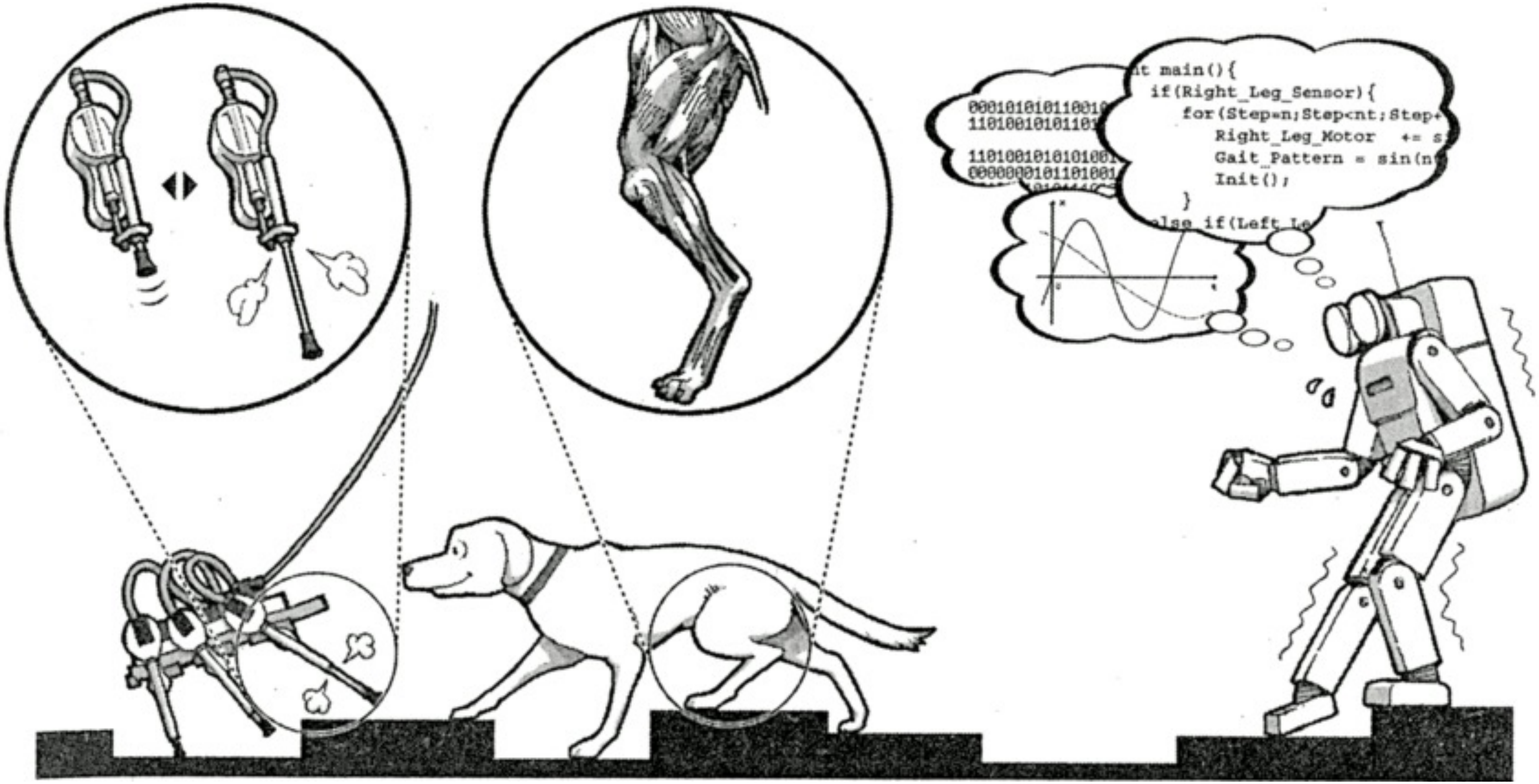
Morphological Computation



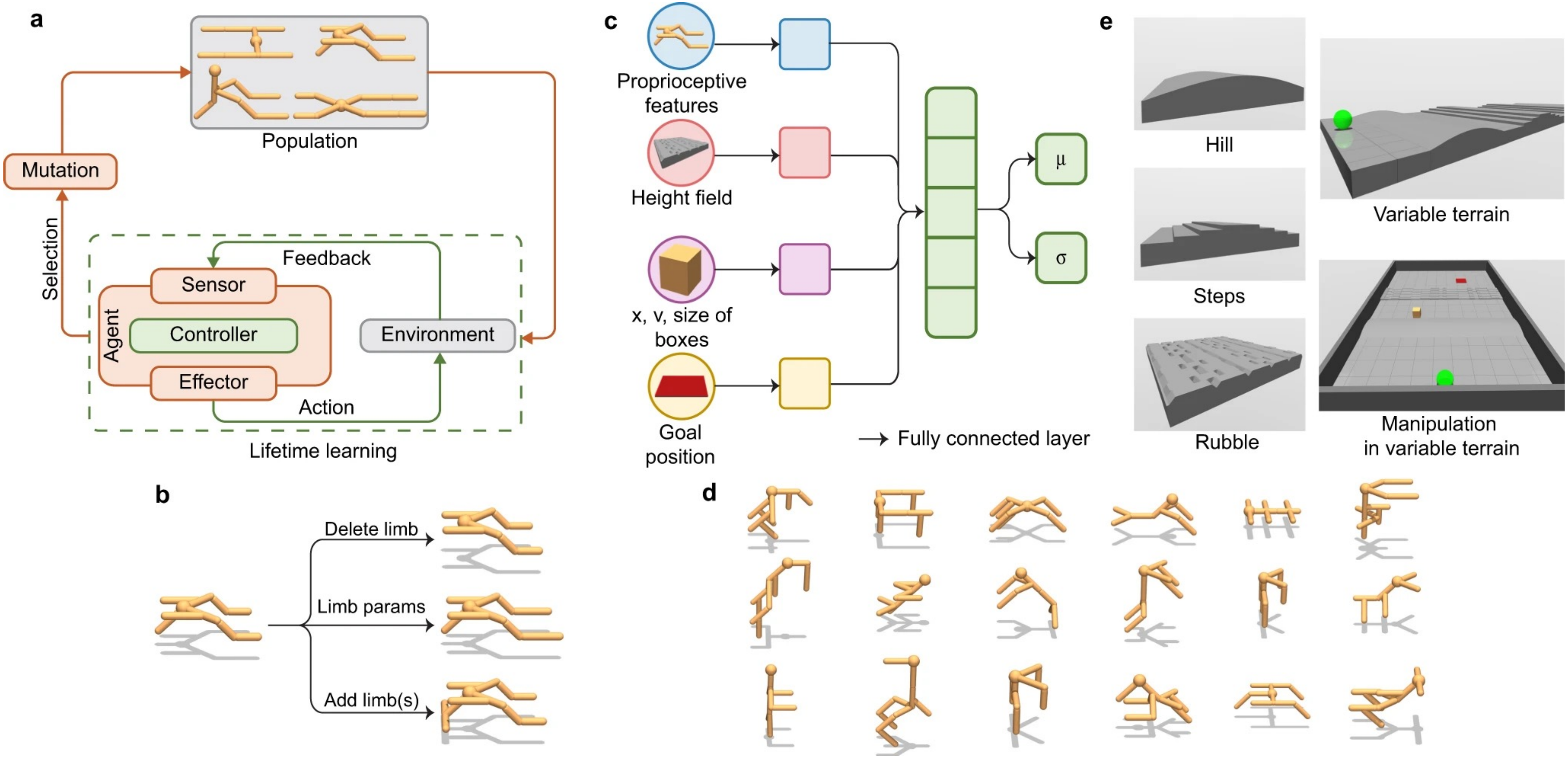
Pfeifer, Rolf, Max Lungarella, and Fumiya Iida (2007) Self-Organization, Embodiment, and Biologically Inspired Robotics. *Science* 318(5853), 1088–93.


Boston Dynamics
Boston Dynamics

Morphological computation simplifies control



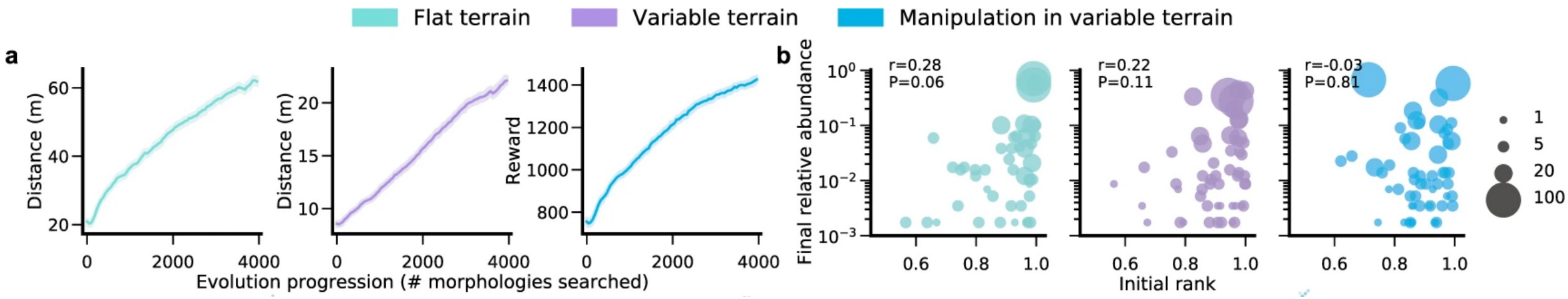
Morphological evolution of learning robots

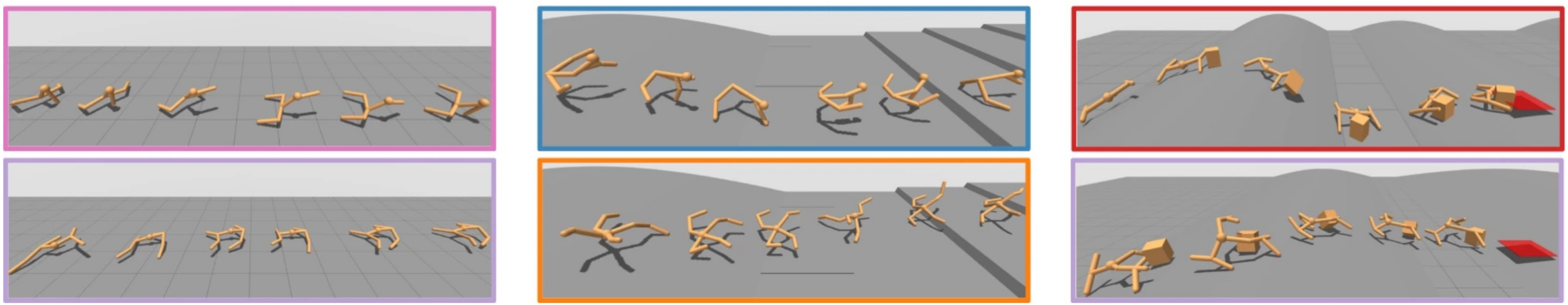


Gupta A, Savarese S, Ganguli S, Fei-Fei L (2021) Embodied Intelligence via Learning and Evolution. *Nature Communications* 12(1), 5721

Local tournament selection preserves diversity

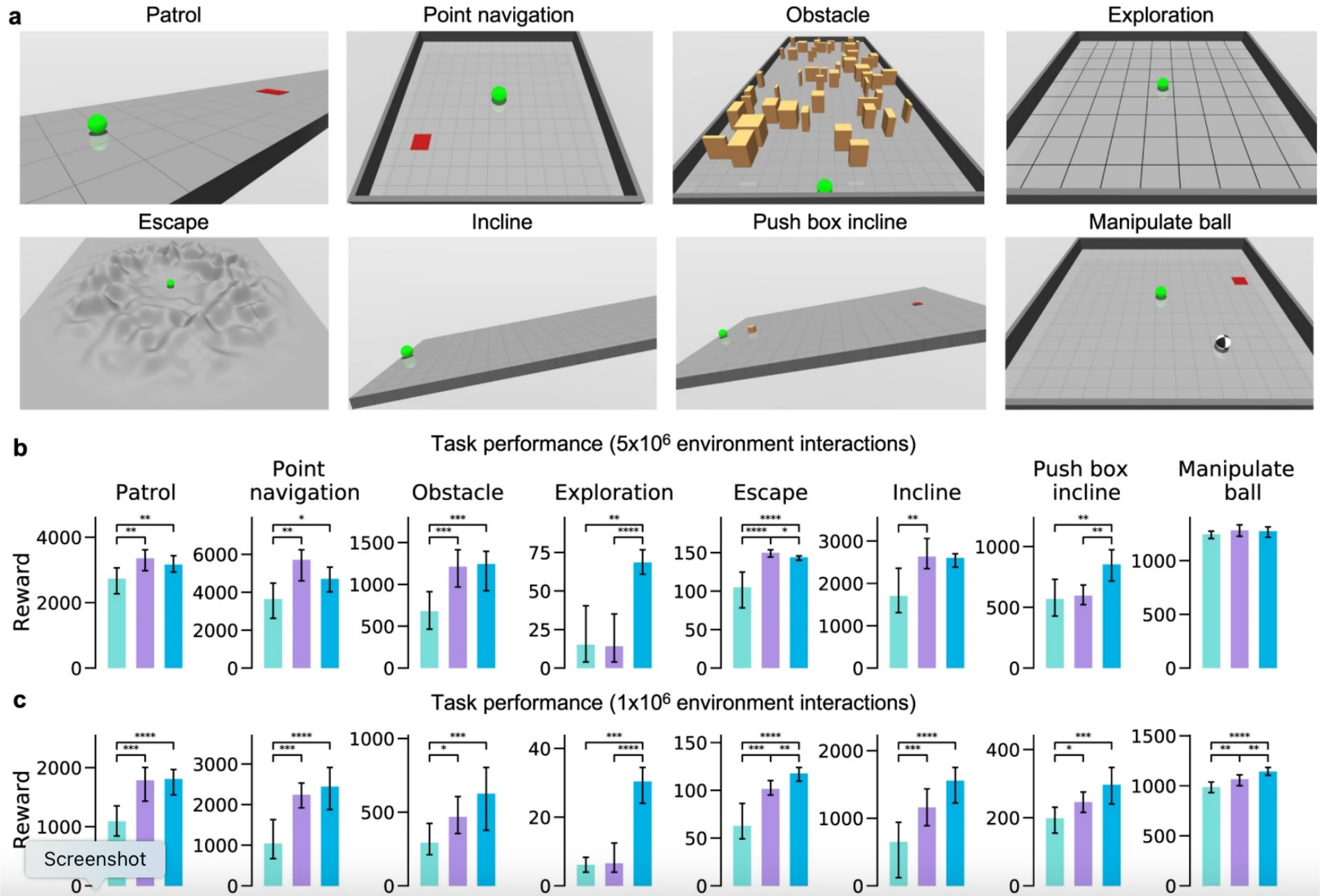
Population spread across 100’s of CPU, each simulating 4 individuals and reproducing the best one





[redacted]

Difficult environments generate robots that learn faster



Better bodies learn faster and better