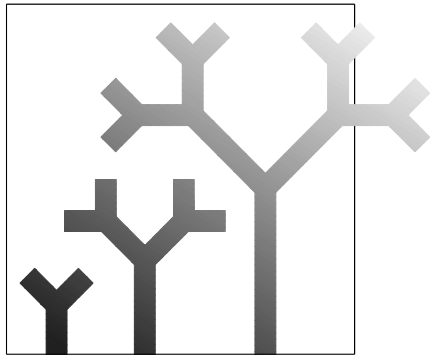
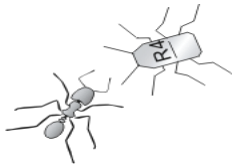
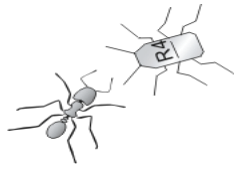
Body-Brain Co-evolution





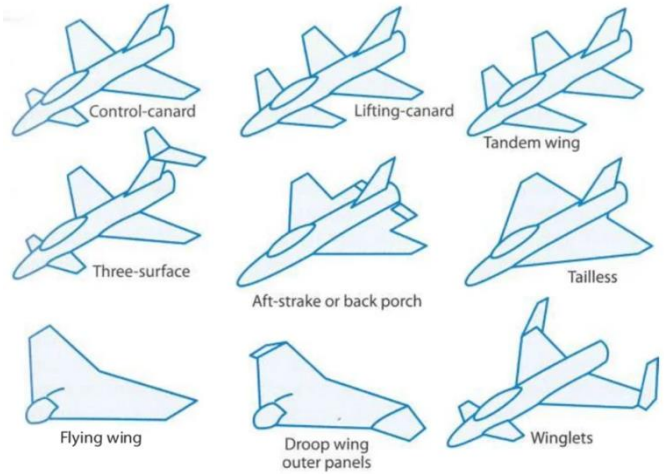
What you will learn in this class

- Direct representations of morphological parameters
  - example: aircraft morphology
- Generative representations of morphologies
  - example: fractals
  - example: plants
  - example: neural architectures
- Encodings and coevolution of robotic morphologies and brains
- Body and/or Brain Encoding by Composition Pattern Producing Networks
- Coevolution of Morphologies and Learning Brains
  - example: body shapes and learning for different tasks
  - example: eye morphology for different tasks

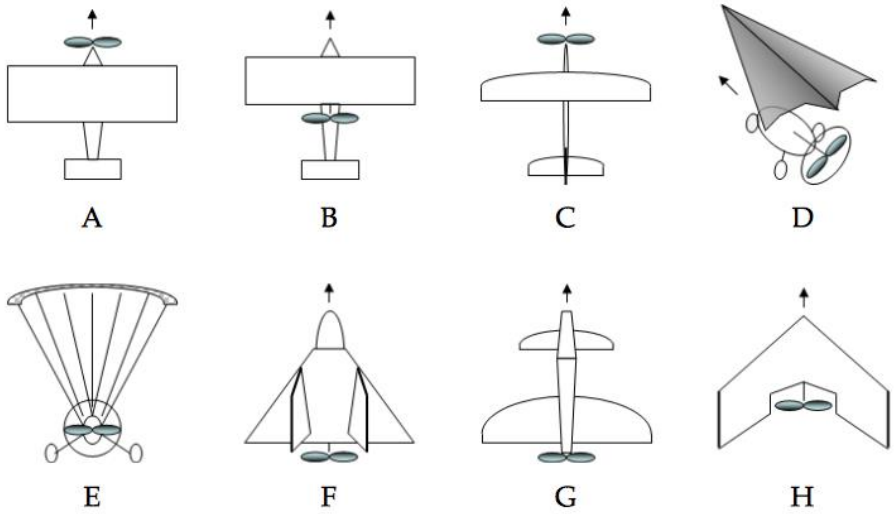


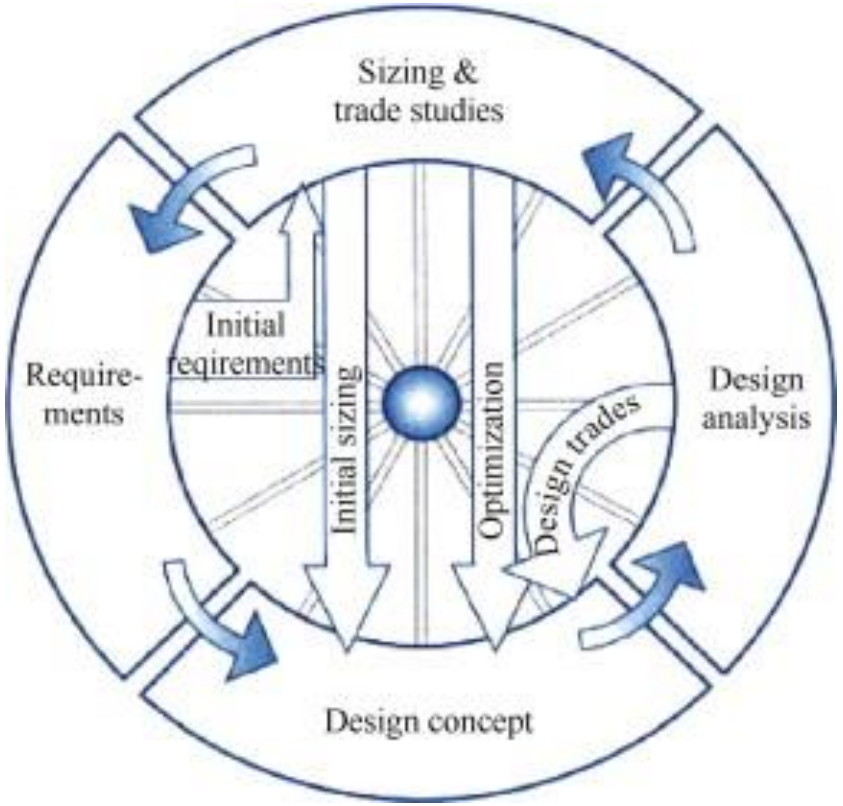
The “art” of aircraft design

Jets: High speed, high payload aircraft



Propellers: Low speed, low payload aircraft and drones

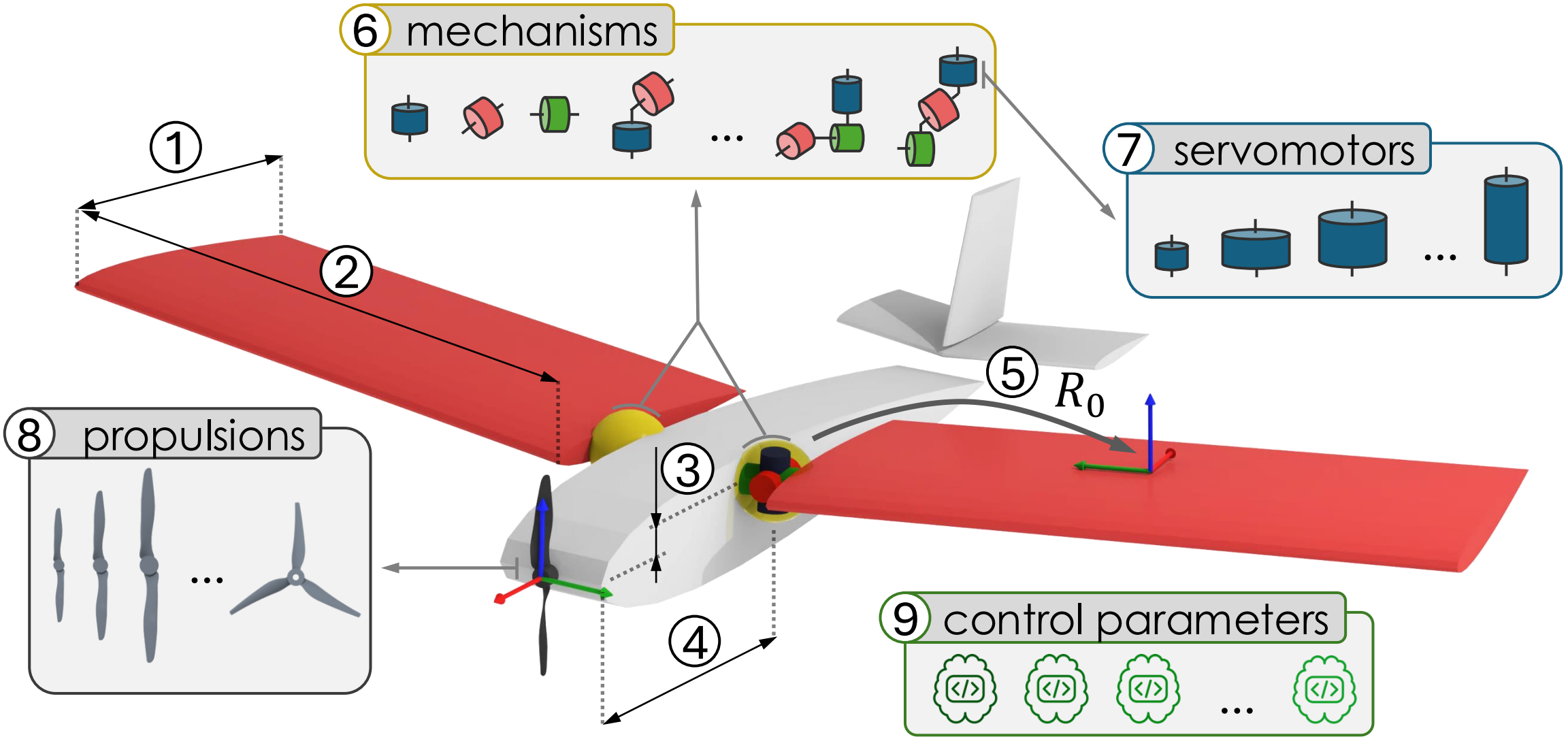




Designing an aircraft, big or small, is an iterative process (Raymer, 2015)

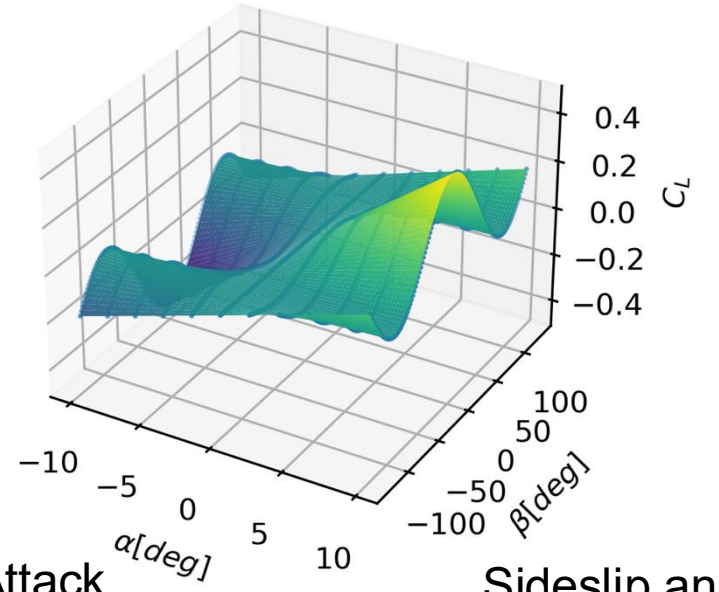
Each design is a compromise of requirements, efficiency, and control

Body Parameters



Bergonti et al. (2024) Co-Design Optimisation of Morphing Topology and Control of Winged Drones, *ICRA*

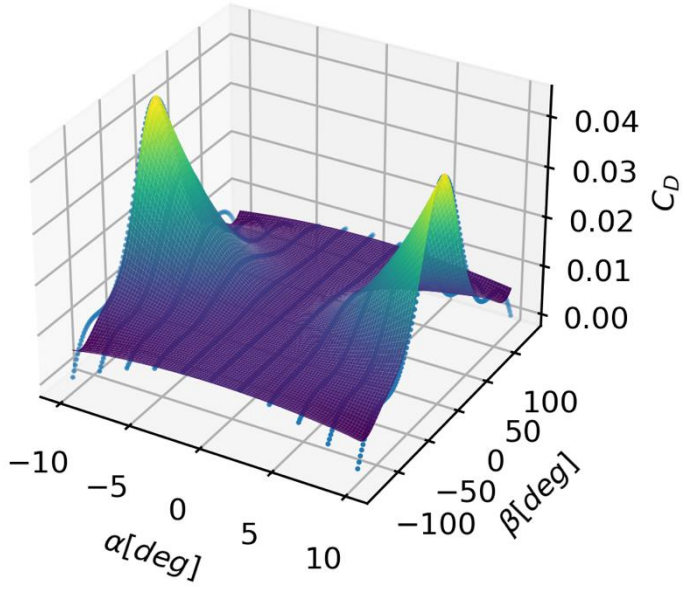
Aerodynamic Model



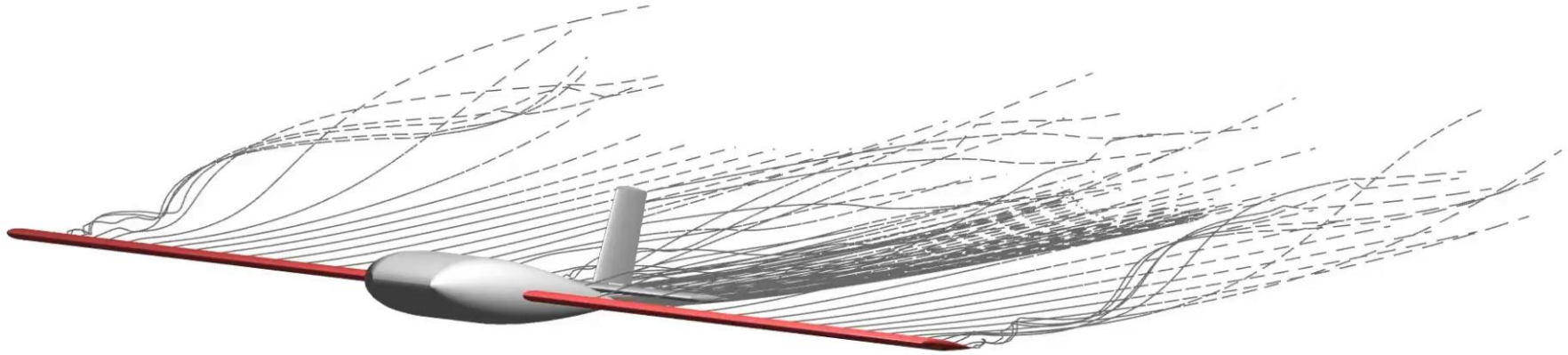
Lift

Angle of Attack

Sideslip angle

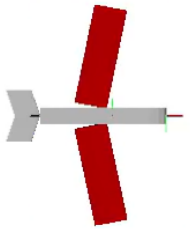


Drag

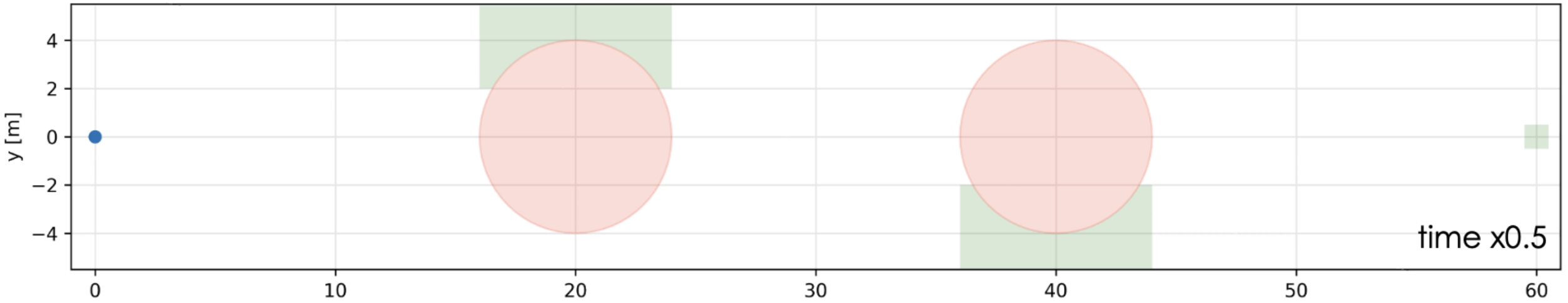


Trajectory Optimisation in Simulation

Identify time-varying control inputs for optimal trajectory with constraints



Mission definition: Collision-Free Flight



Minimise:

Energy Consumption

Flight Time

Constraints:

1) start at blue location;
2) pass through green sides
3) arrive to green target, stay within mechanical limits of aircraft

Evolutionary Loop

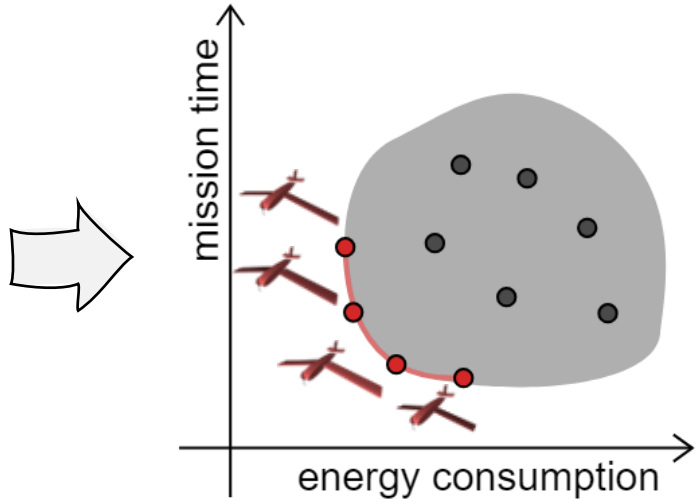
Mission scenarios

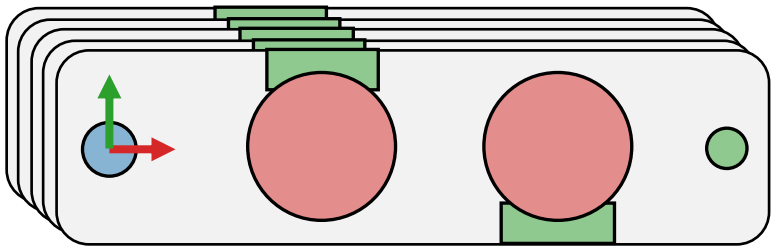
NSGA-II

selection crossover

sorting mutation

evaluation





fitness functions:

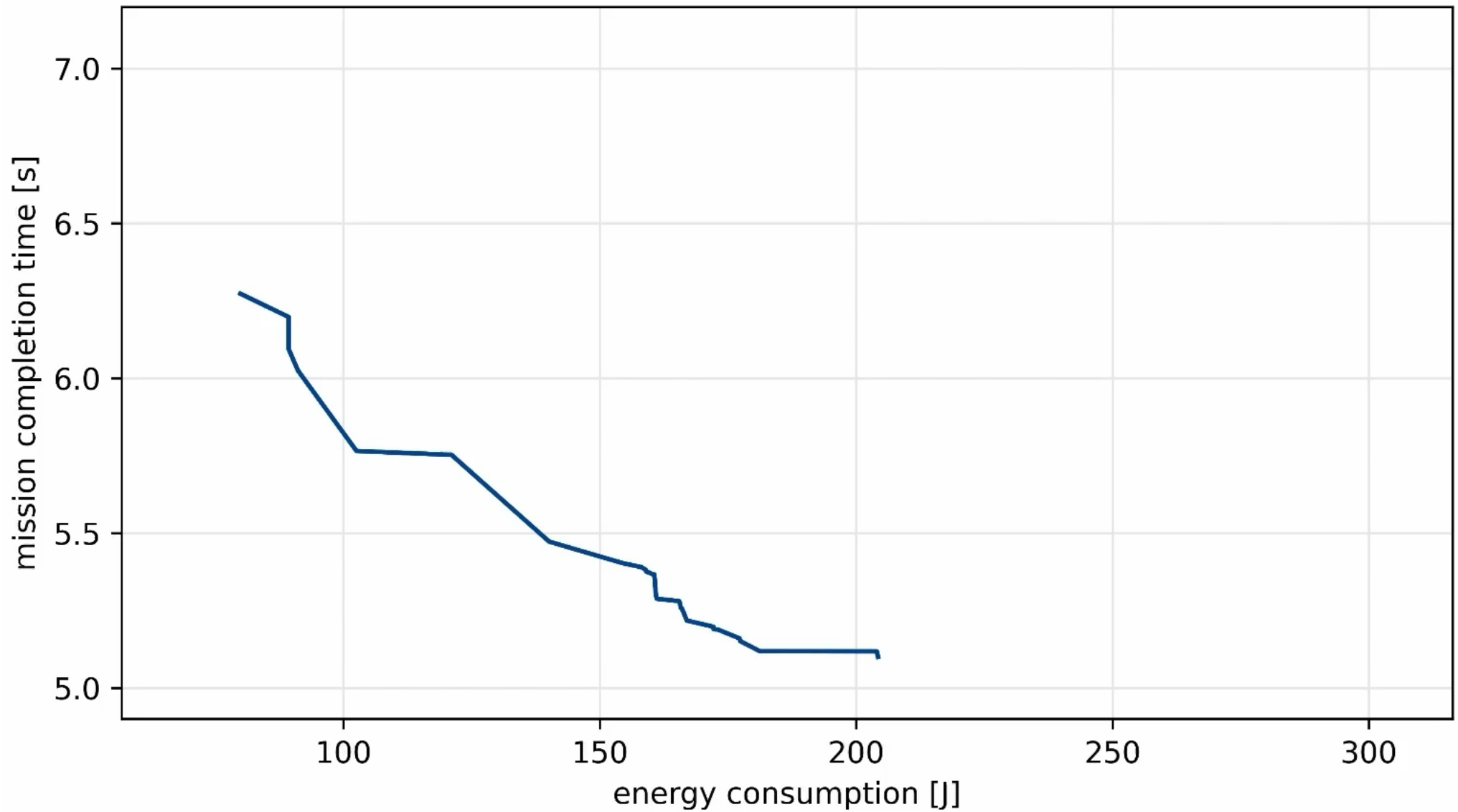
$$\mathcal{L}_1 = \sum_{i=1}^{n_s} \frac{(\text{energy})_i}{n_s}$$

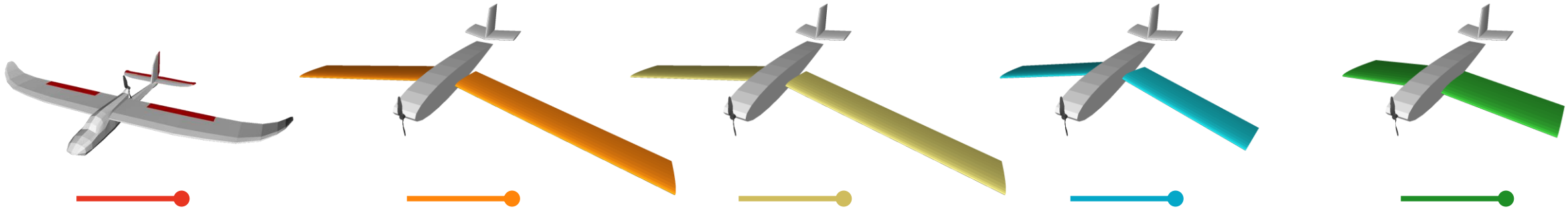
$$\mathcal{L}_2 = \sum_{i=1}^{n_s} \frac{(\text{time})_i}{n_s}$$

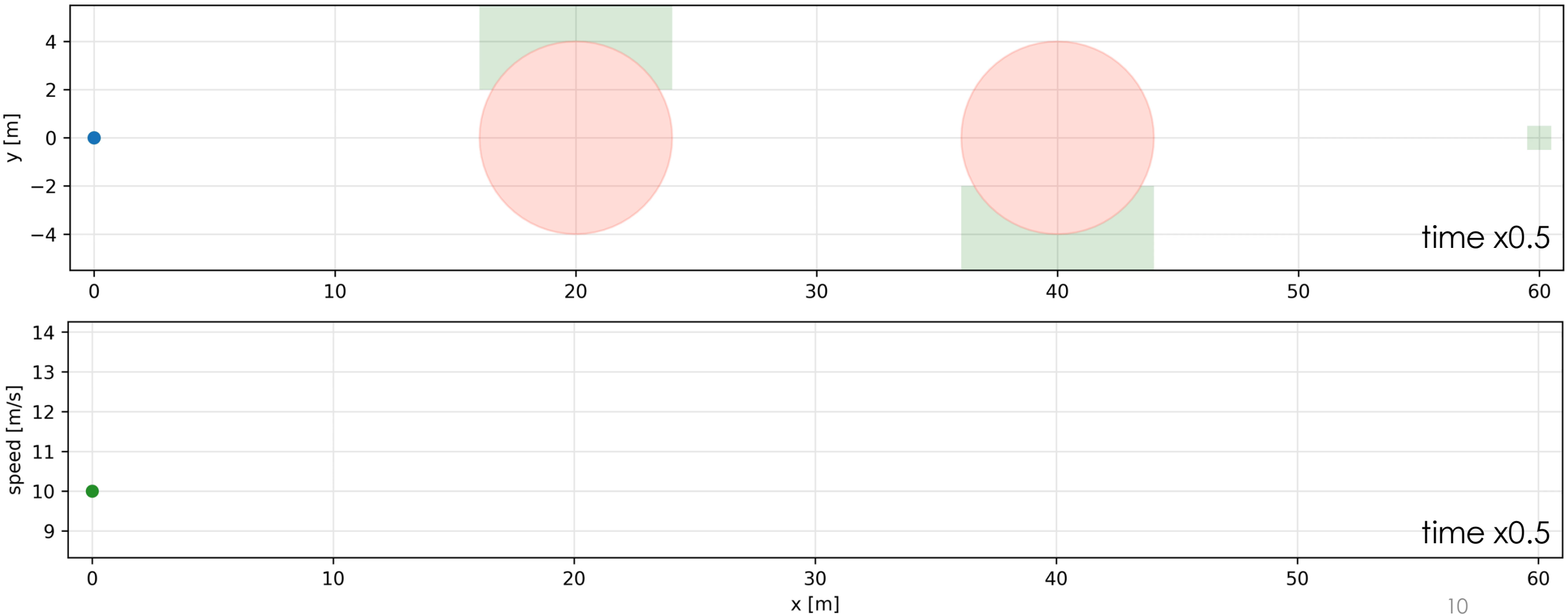
scenario 1 ⇨ modelling ⇨ traj.opt.

⋮ ⋮ ⋮

scenario n_s ⇨ modelling ⇨ traj.opt.

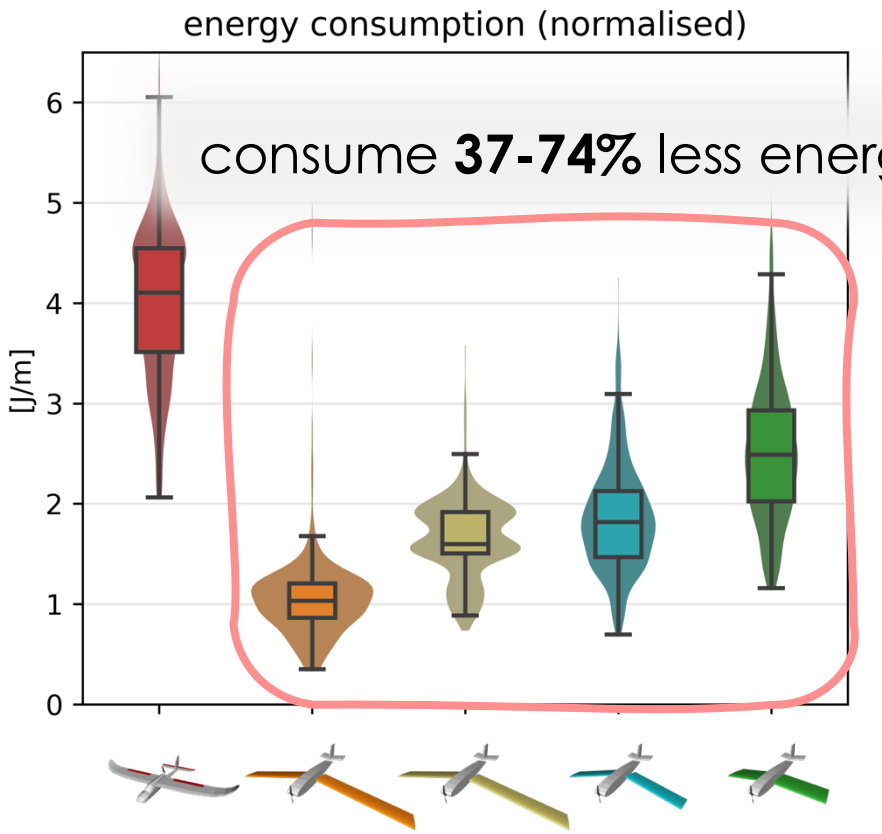

7.0
6.5
6.0
5.5
5.0
mission completion time [s]
100
150
200
250
300
energy consumption [J]

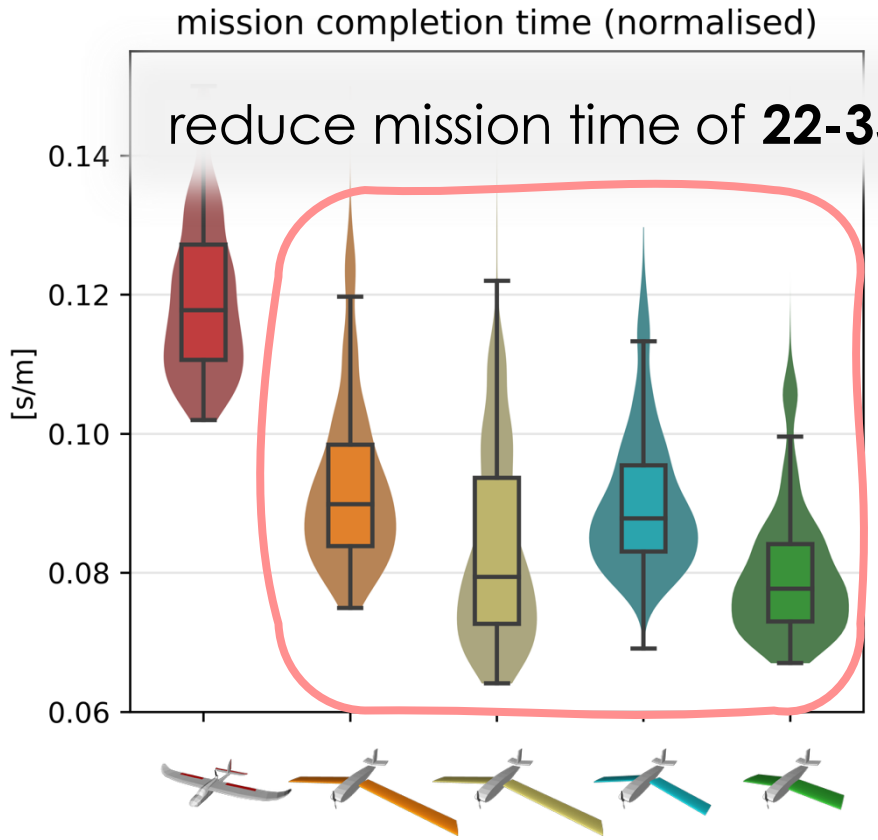


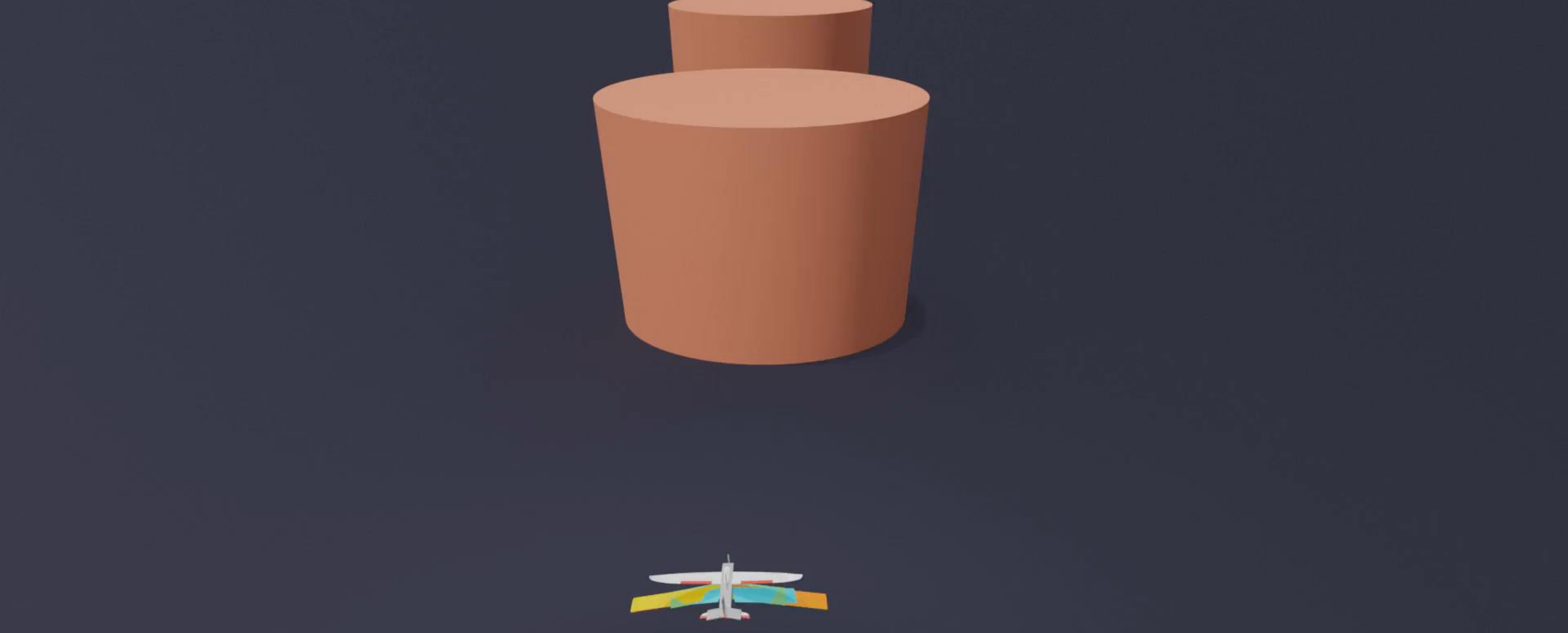

y [m]
4
2
0
−2
−4
0
10
20
30
40
50
60
time x0.5
speed [m/s]
14
13
12
11
10
9
0
10
20
30
40
50
60
x [m]
time x0.5

Validation

Test the drones in 972 scenarios (different from those used for evolution)





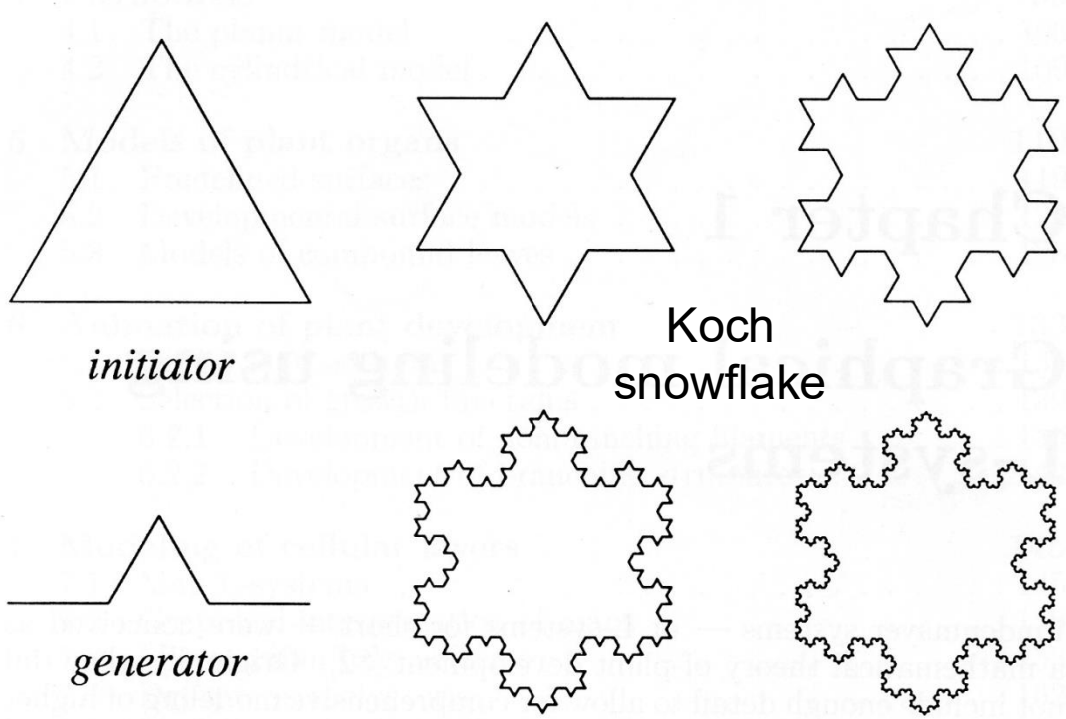


Bergonti, Nava, Wüest, Paolino, L’Erario, Pucci, Floreano (2024) Proceedings of ICRA

Generative representations

Rewriting System: recursively replace a sub-component with another sub-component

Fractals: *Replace edges of a polygon with open polygons and rescale at each iteration [von Koch, 1905]*



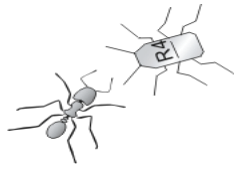
Several types of rewriting systems have been developed. For example:

L-systems (plants)

Cellular automata (anything)

Language systems (language)

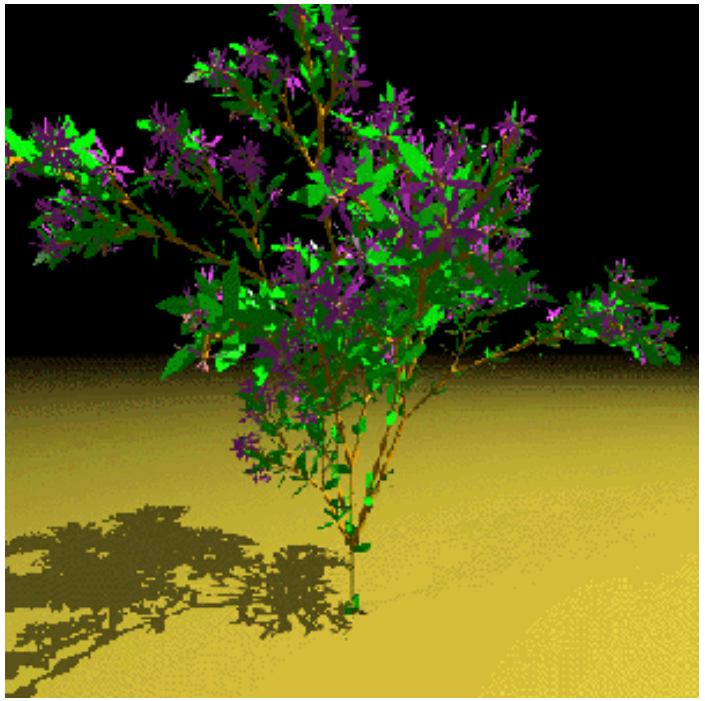
Matrix rewriting (neural networks)



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



Artificially generated tree

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

L-system: Definition

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

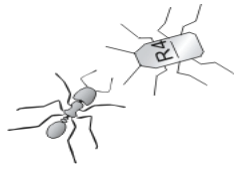
An L-system is composed of:

1. A set of symbols s forming an *alphabet* A
2. An *axiom* ω (initial string of symbols) $s_k, s_z, s_{v,\ldots}$
3. A set $\pi = \{p_i\}$ of *production rules* $p_i : s_k \rightarrow s_z$.

The following assumptions hold:

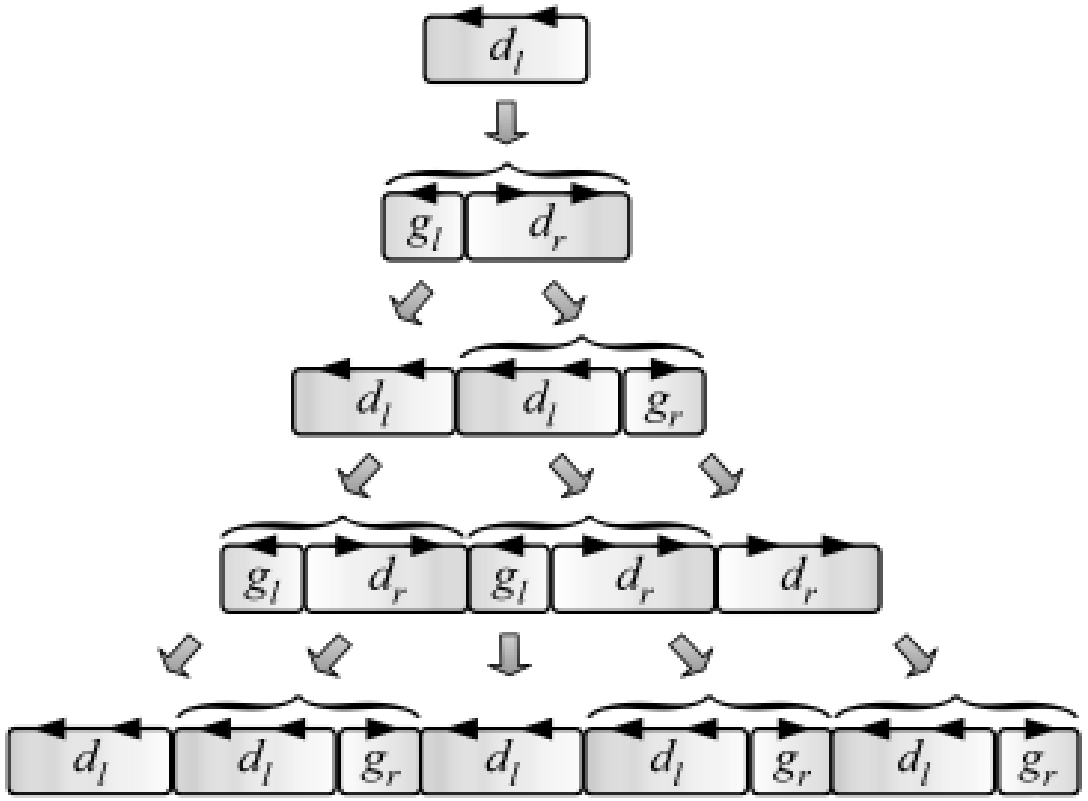
1.Production rules are applied in parallel and replace recursively all symbols in the string.

2.If no production rule is specified for a symbol s, then we assume the identity production rule $p_o : s_k \rightarrow s_k$



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

$$A = \{g_r, g_l, d_r, d_l\}$$

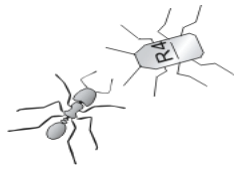
$$\omega = d_l$$

$$p_1 = d_r \rightarrow d_l\, g_r$$

$$p_2 = d_l \rightarrow g_l\, d_r$$

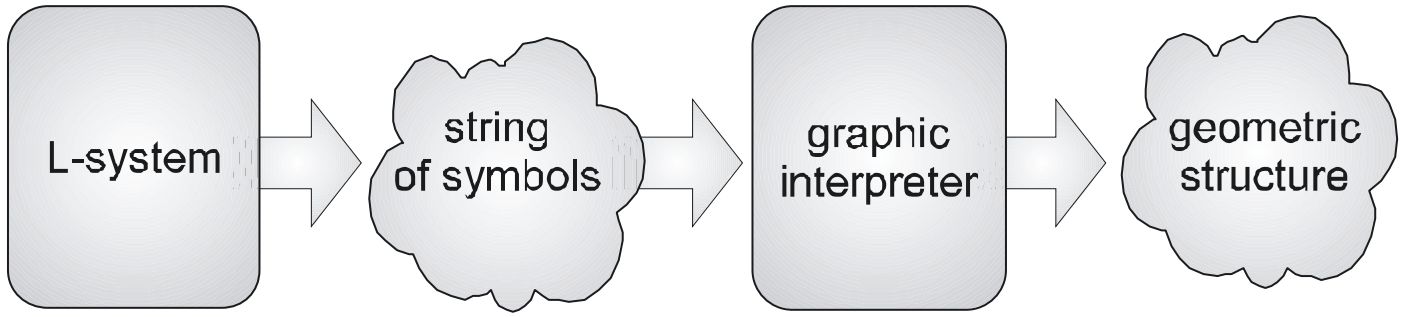
$$p_3 = g_r \rightarrow d_r$$

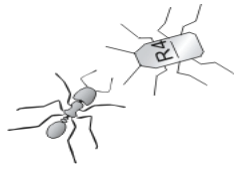
$$p_4 = g_l \rightarrow d_l$$



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.

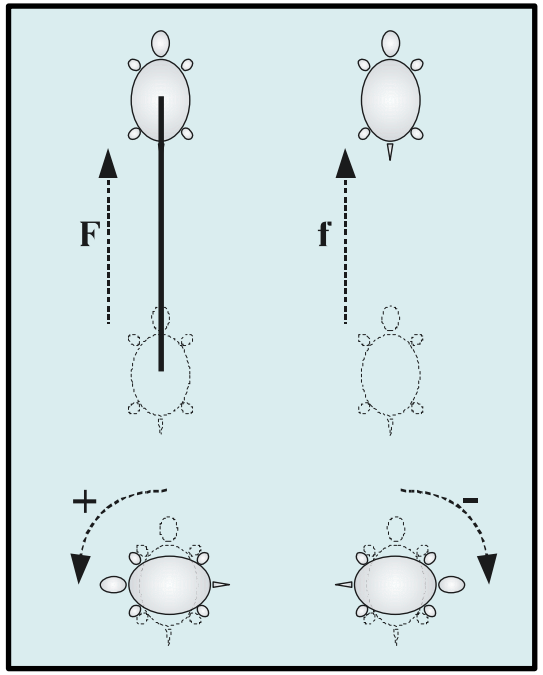
Given the step size d and the angle increment δ, the turtle can respond to the following commands:

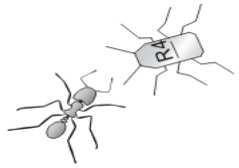
F : move forward by a step while drawing a line.

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

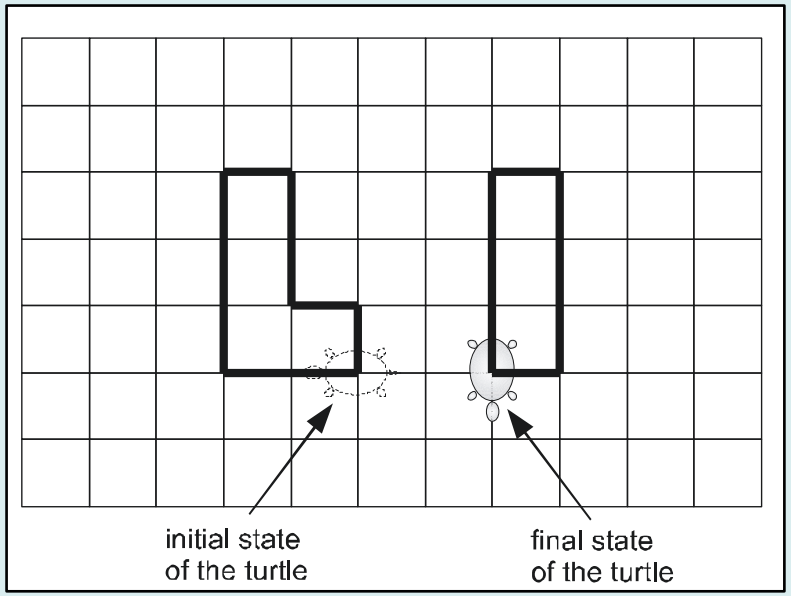
+ : turn left (counterclockwise) by angle δ.

– : turn right (clockwise) by angle δ.



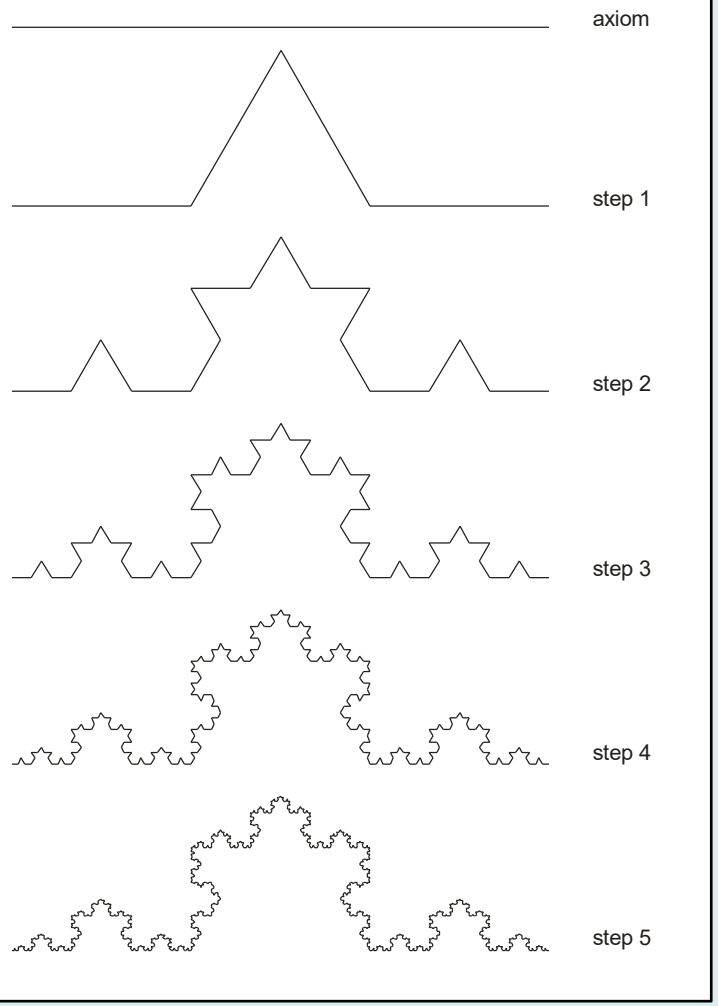


Examples



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

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



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

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

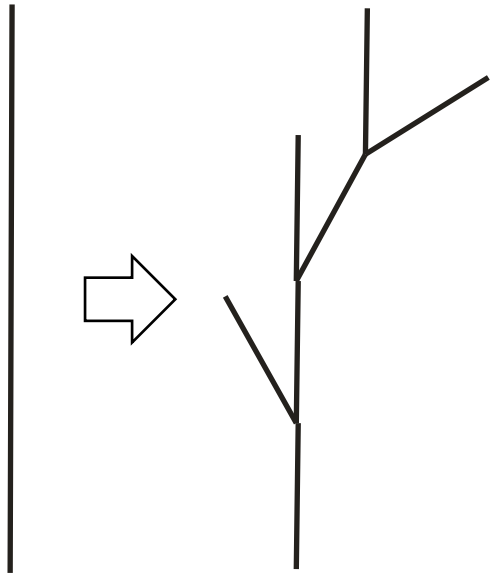
Bracketed L-systems

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.).

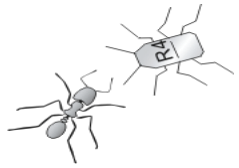
] Restore the state of the turtle using the last saved state (no line is drawn).

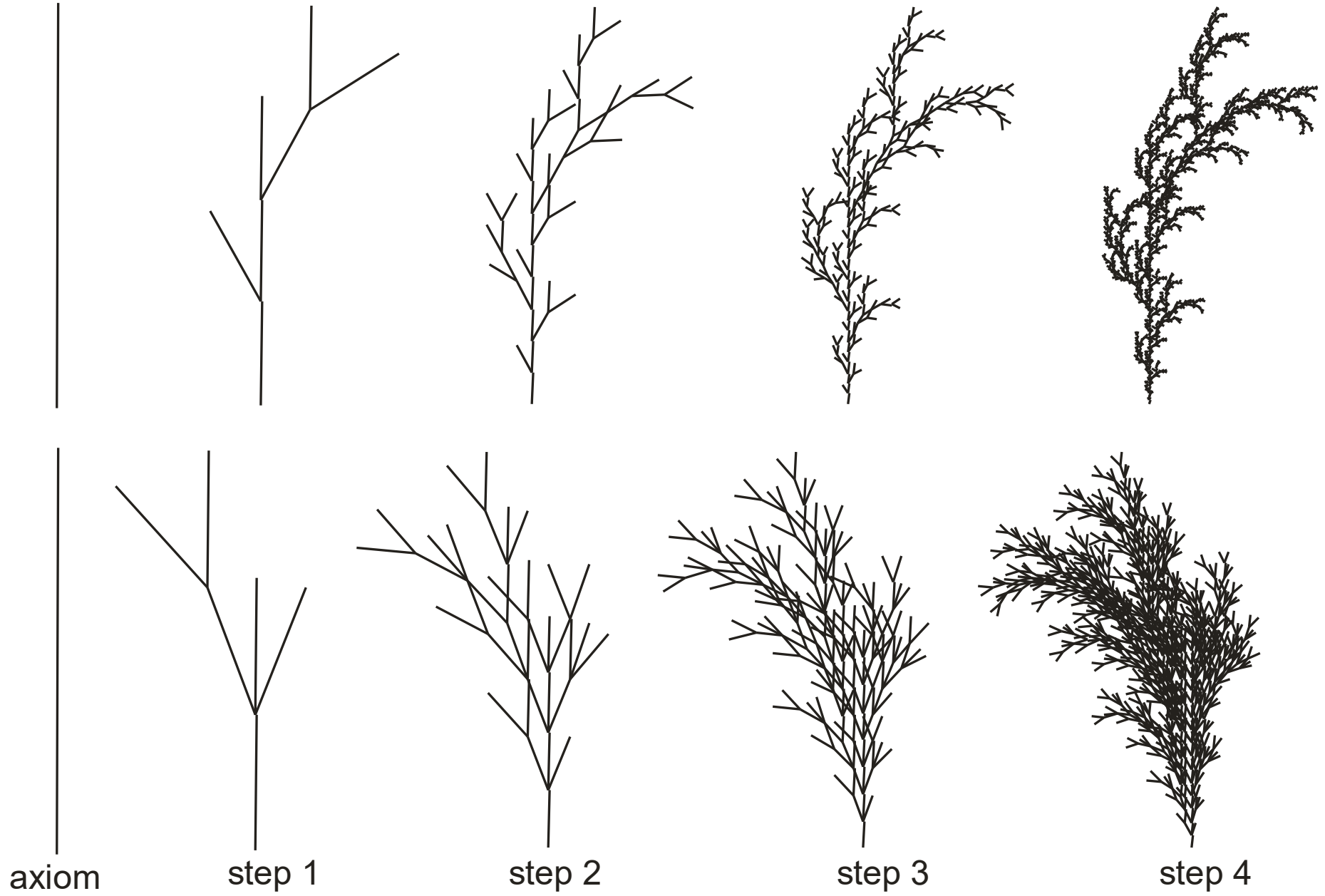


$\delta \quad \delta = 29^\circ \;,\; \mathrm{A} = \{ F, +, -, [,] \}$

$\omega = F$

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




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

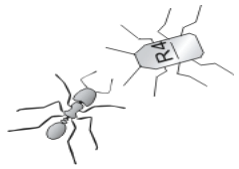
$\delta \quad \delta = 29^\circ \quad , \quad \mathrm{A} = \{ F, +, -, [,] \}$

$\omega = F$

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

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

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



Application to computer graphics

http://gug.sunsite.dk/

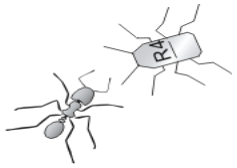
http://www.ii.uib.no/~knute

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

How to identify rewriting rules?

- 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

- With evolutionary algorithms
  - When the morphology serves a function that can be measured: neural network, a gene regulatory network, an electronic circuit, a robotic body, etc.



Neural architecture by matrix rewriting

A *rewriting system* [Kitano, 1990] that encodes a grammar to represent network topologies

Genome encodes the rewriting (grammar) rules, such as: *ABCD adaa cbba baac abad 0001 1000 0010 0100*

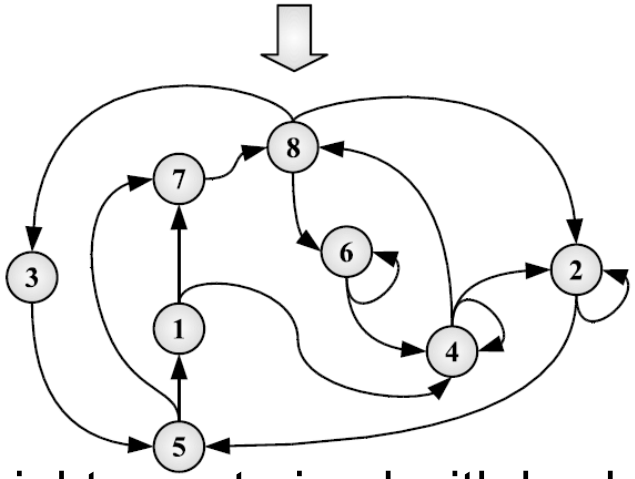
$$\mathcal{E} \rightarrow \begin{bmatrix} A & B \\ C & D \end{bmatrix}$$

$$A \rightarrow \begin{bmatrix} a & d \\ a & a \end{bmatrix} \quad B \rightarrow \begin{bmatrix} c & b \\ b & a \end{bmatrix} \quad C \rightarrow \begin{bmatrix} b & a \\ a & c \end{bmatrix} \quad D \rightarrow \begin{bmatrix} a & b \\ a & d \end{bmatrix}$$

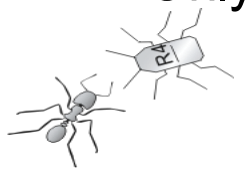
$$a \rightarrow \begin{bmatrix} 0 & 0 \\ 0 & 1 \end{bmatrix} \quad b \rightarrow \begin{bmatrix} 1 & 0 \\ 0 & 0 \end{bmatrix} \quad c \rightarrow \begin{bmatrix} 0 & 0 \\ 1 & 0 \end{bmatrix} \quad d \rightarrow \begin{bmatrix} 0 & 1 \\ 0 & 0 \end{bmatrix}$$

$$\mathcal{E} \Rightarrow \begin{bmatrix} A & B \\ C & D \end{bmatrix} \Rightarrow \left[\begin{array}{cc|cc} a & d & c & b \\ a & a & b & a \\ \hline b & a & a & b \\ a & c & a & d \end{array}\right] \Rightarrow \left[\begin{array}{cccc|cccc} 0 & 0 & 0 & 1 & 0 & 0 & 1 & 0 \\ 0 & 1 & 0 & 0 & 1 & 0 & 0 & 0 \\ \hline 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 1 & 0 & 0 & 0 & 1 \\ \hline 1 & 0 & 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 & 0 & 1 & 0 & 0 \\ \hline 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 \\ 0 & 1 & 1 & 0 & 0 & 1 & 0 & 0 \end{array}\right]$$

$$\begin{array}{c} \\ 1 \\ 2 \\ 3 \\ 4 \\ 5 \\ 6 \\ 7 \\ 8 \end{array} \begin{array}{c} \begin{array}{cccccccc} 1 & 2 & 3 & 4 & 5 & 6 & 7 & 8 \end{array} \\ \begin{bmatrix} 0 & 0 & 0 & 1 & 0 & 0 & 1 & 0 \\ 0 & 1 & 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 1 & 0 & 0 & 0 & 1 \\ 1 & 0 & 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 \\ 0 & 1 & 1 & 0 & 0 & 1 & 0 & 0 \end{bmatrix} \end{array}$$

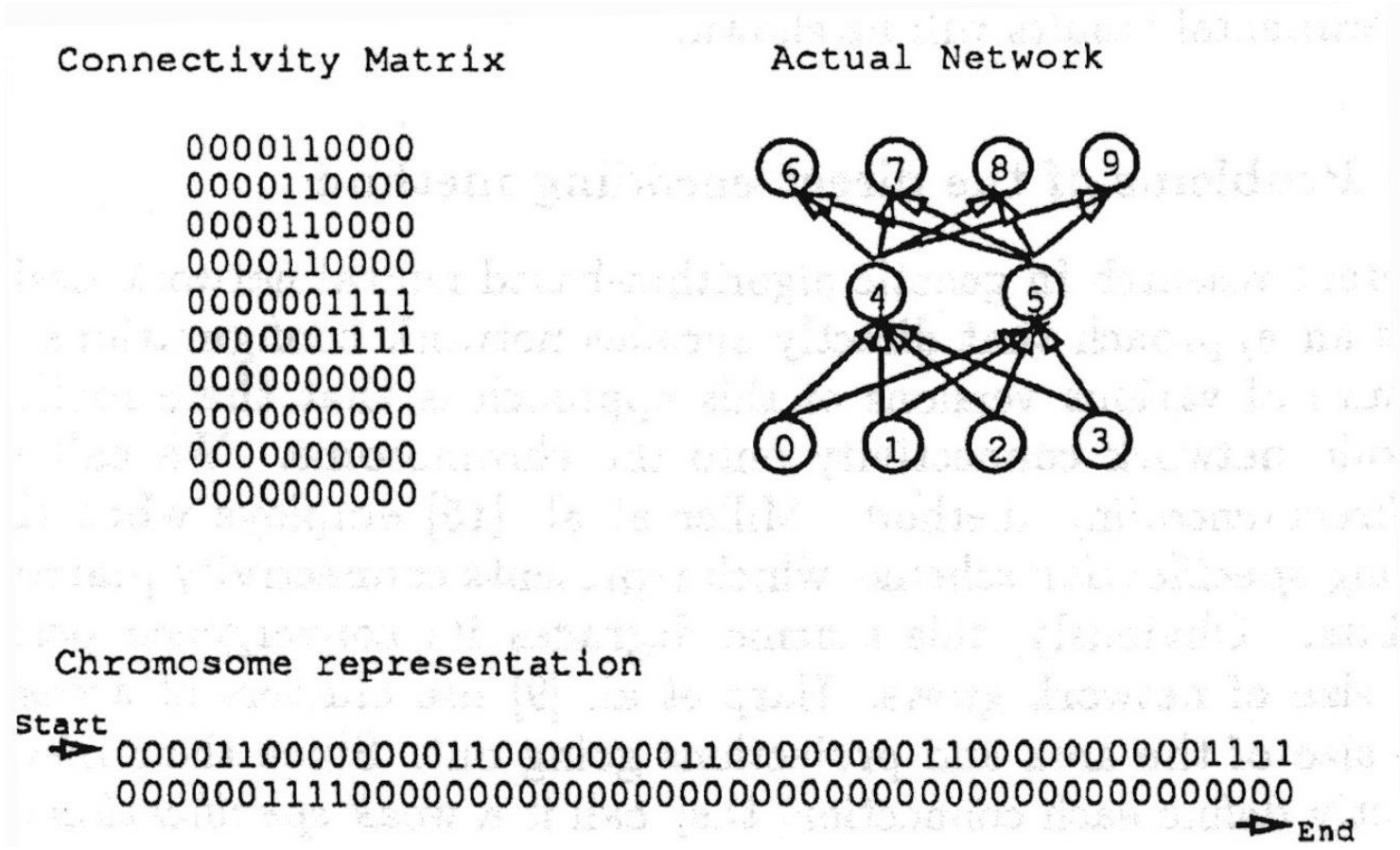


Only the presence/absence of connections is evolved. Weights are trained with backpropagation.



Direct Encoding of Network Topology

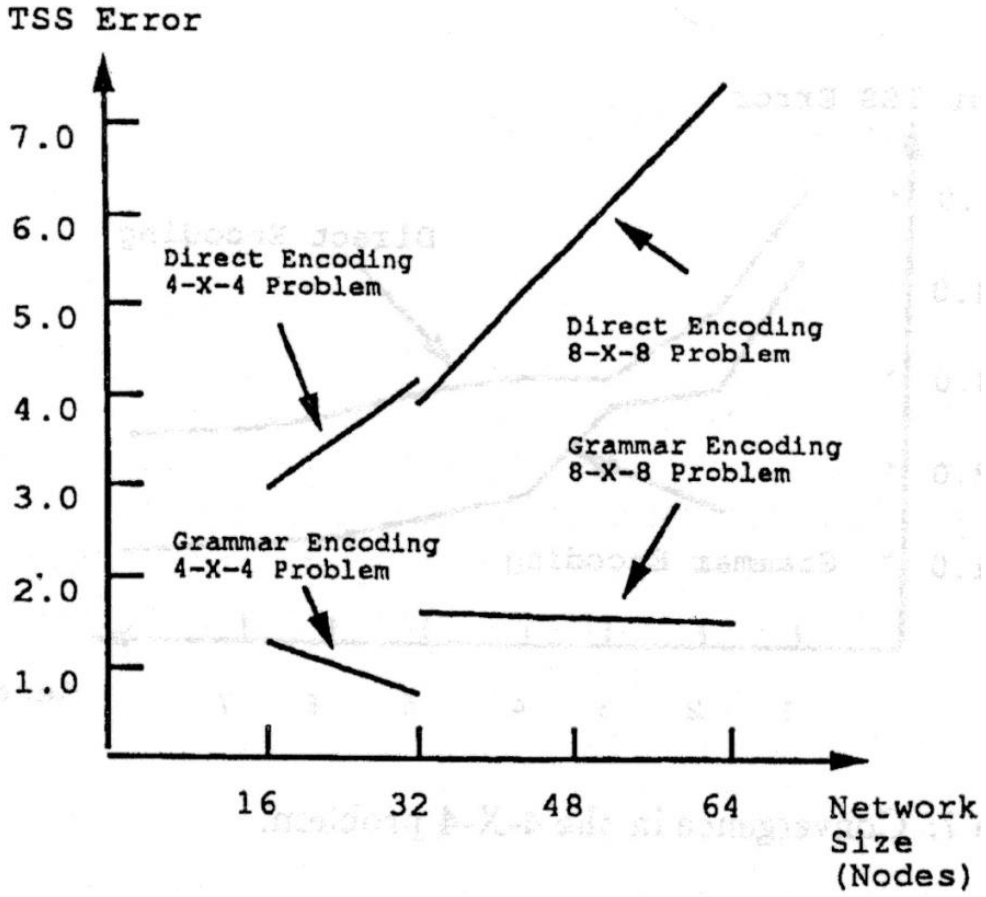
Length of genetic code is proportional to number of neurons in the network



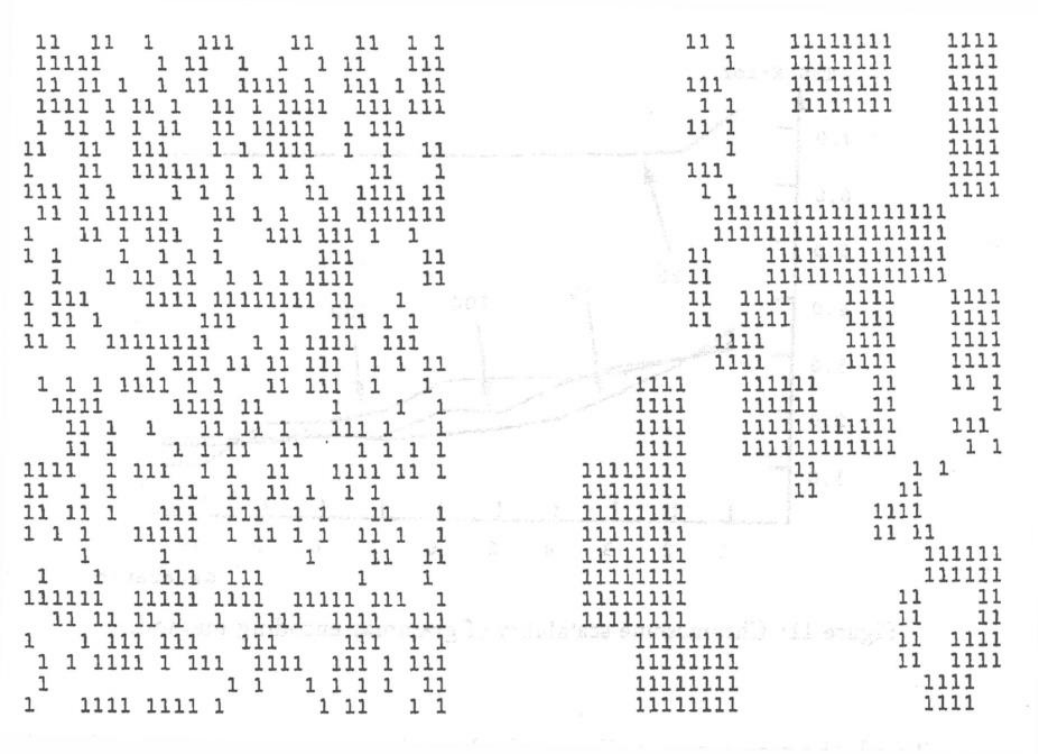
Evolving autoencoder architectures

- Autoencoder performance is worse with direct encoding and worsens with network size
- Topologies evolved with grammar encoding are more regular (good for spatial information processing, such as convolutional neural networks).

Performance comparison



Architecture comparison

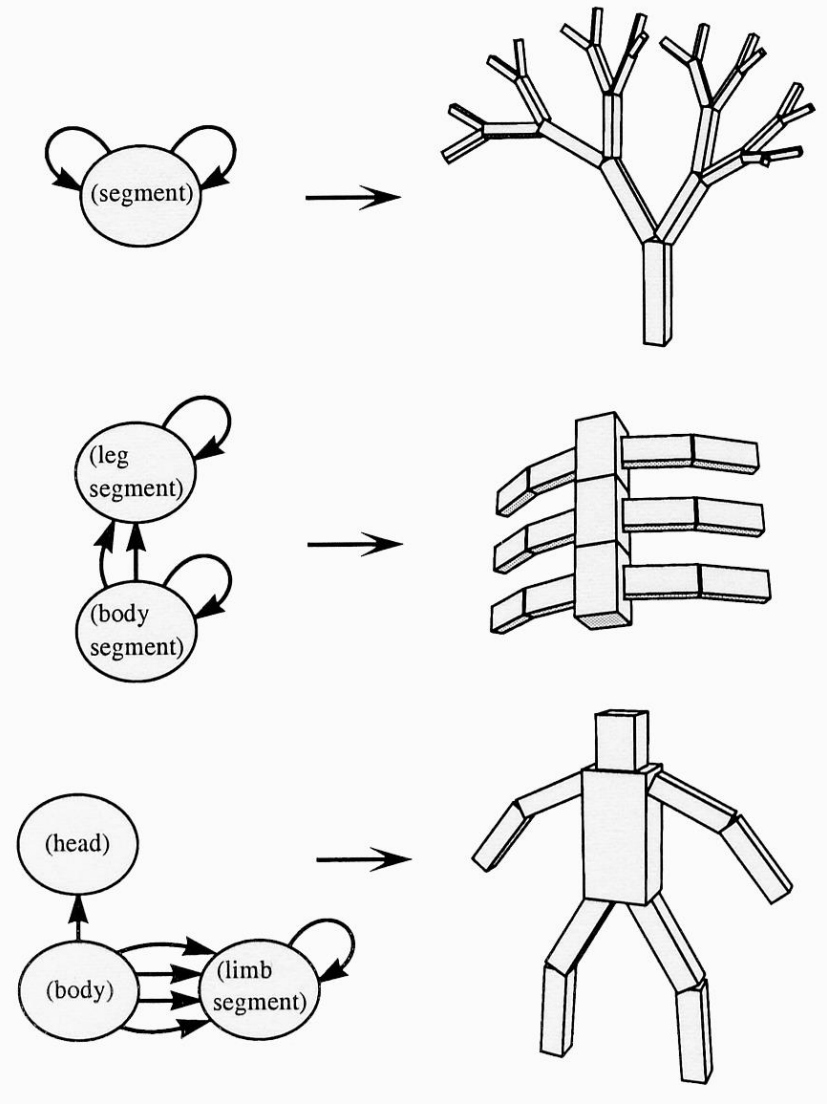


Direct encoding

Grammar encoding

Grammar encoding of robotic bodies and brains

[Sims, 1994]



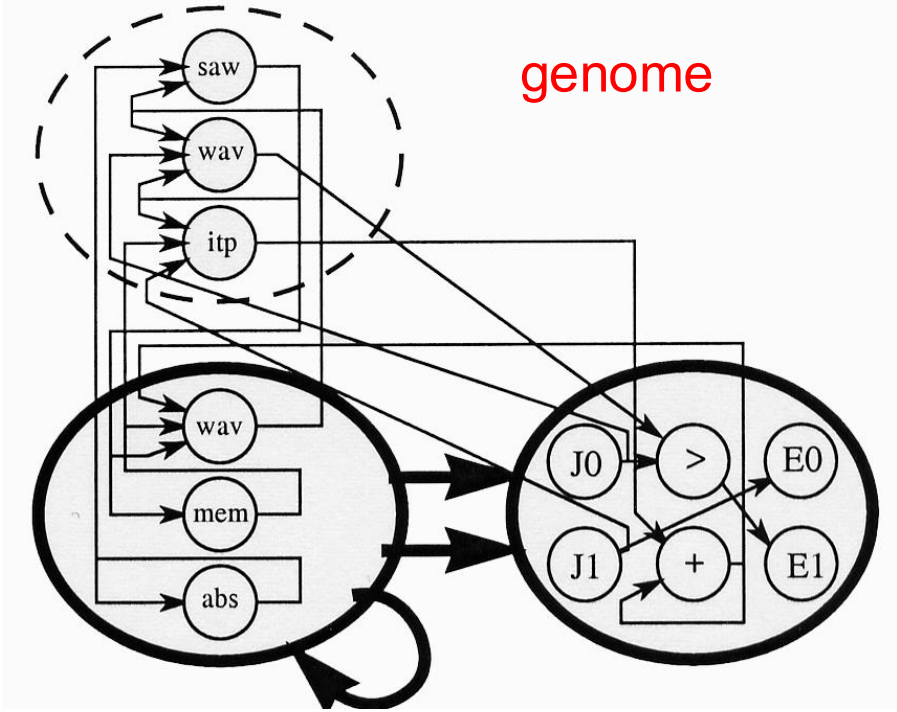
genotype phenotype

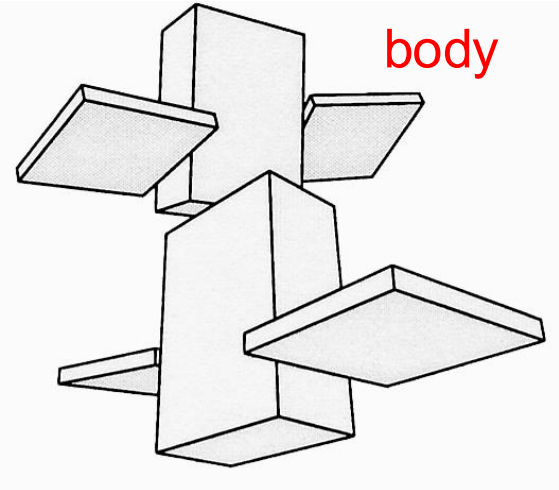
Body components:

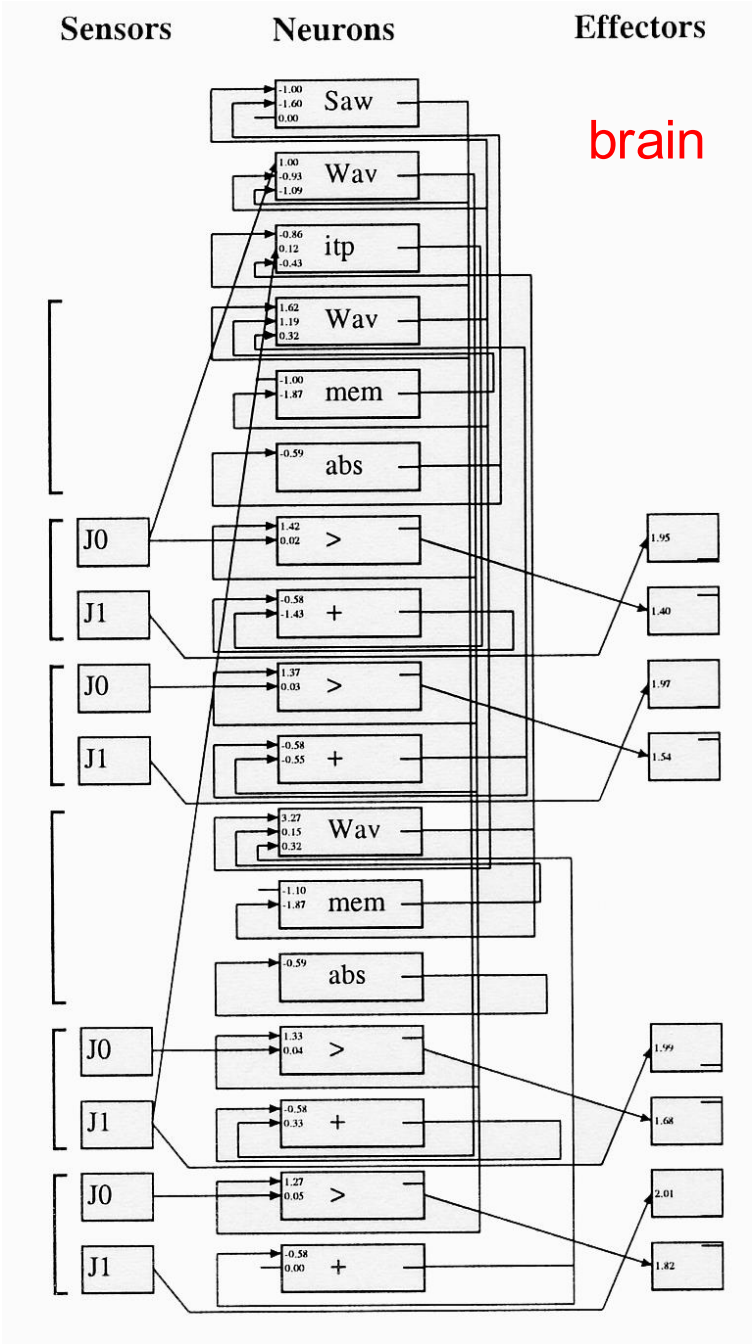
- dimension
- joint type (rigid, twist, revolute, ...)
- recursive-limit
- connection (position, orientation, scale, reflection)
- terminal
- neural circuit

Neural circuit components:

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

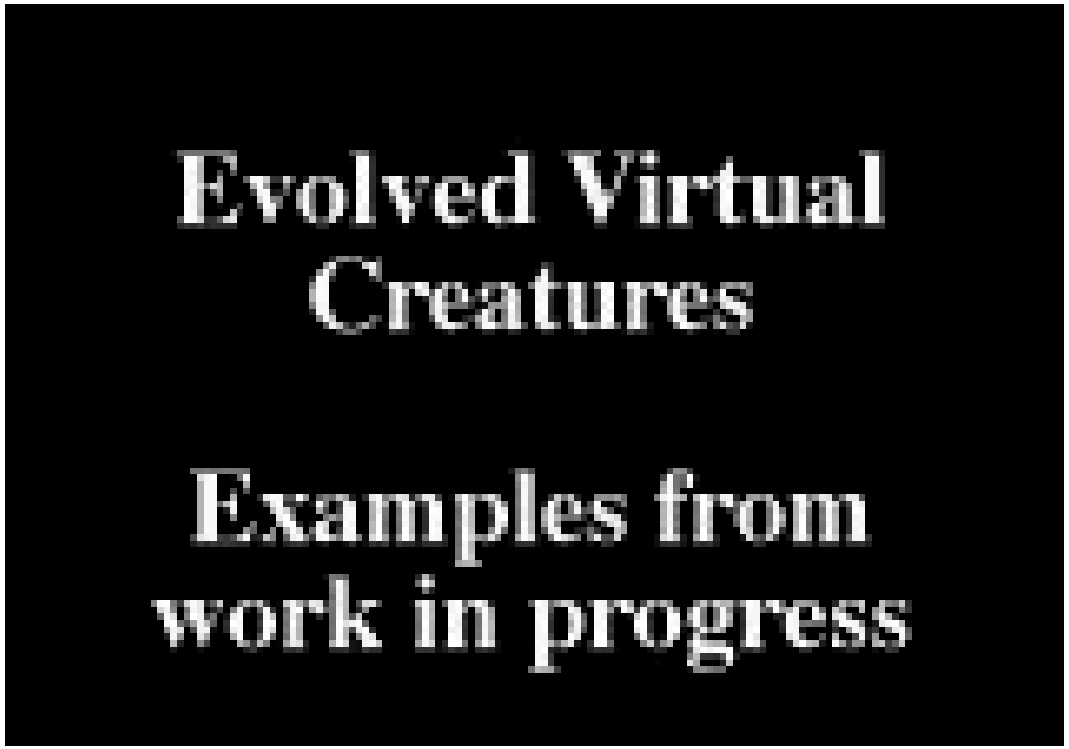

genome
saw
wav
itp
wav
mem
abs
J0
>
E0
J1
+
E1


body

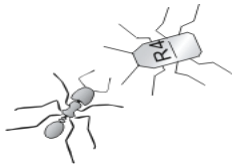

Sensors
Neurons
Effectors
brain
Saw
Wav
itp
Wav
mem
abs
J0
>
J1
+
J0
>
J1
+
Wav
mem
abs
J0
>
J1
+
J0
>
J1
+

[Sims, 1994]

Co-evolved robotic bodies and brains

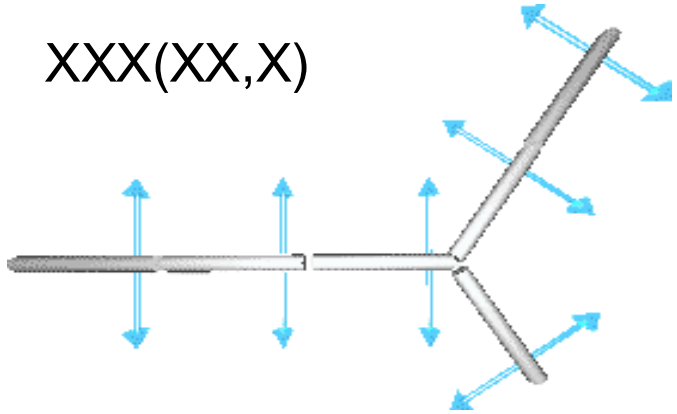


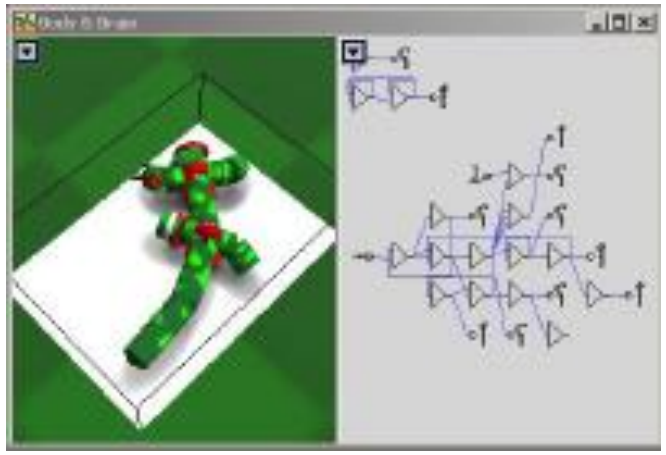
Sims, *1994*

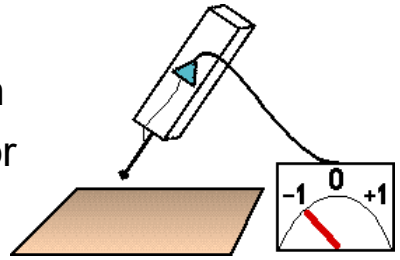


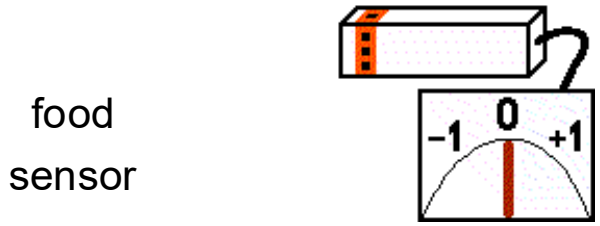
Framstick [Komosinski & Ulatowski, 1999]

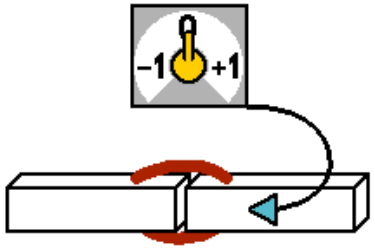
Body parts are joined sticks. Sticks can host sensors and neurons. Joints are actuated by muscles.

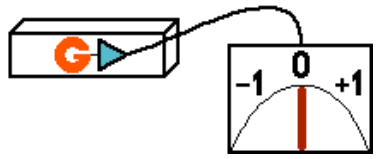




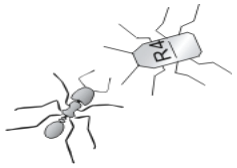




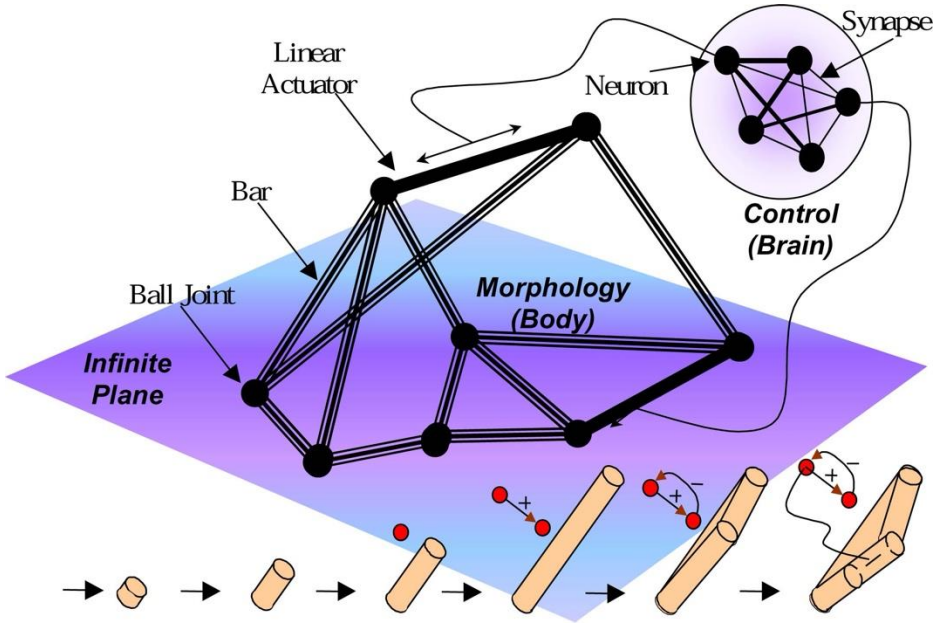


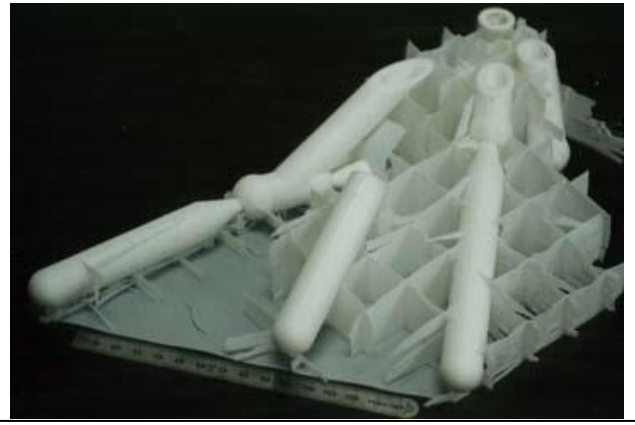


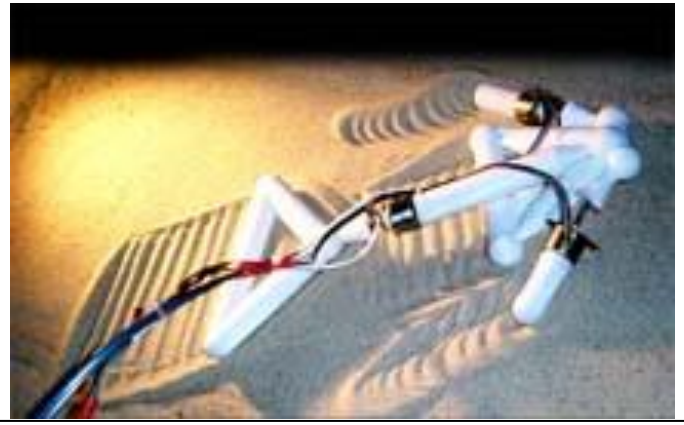
www.frams.alife.pl

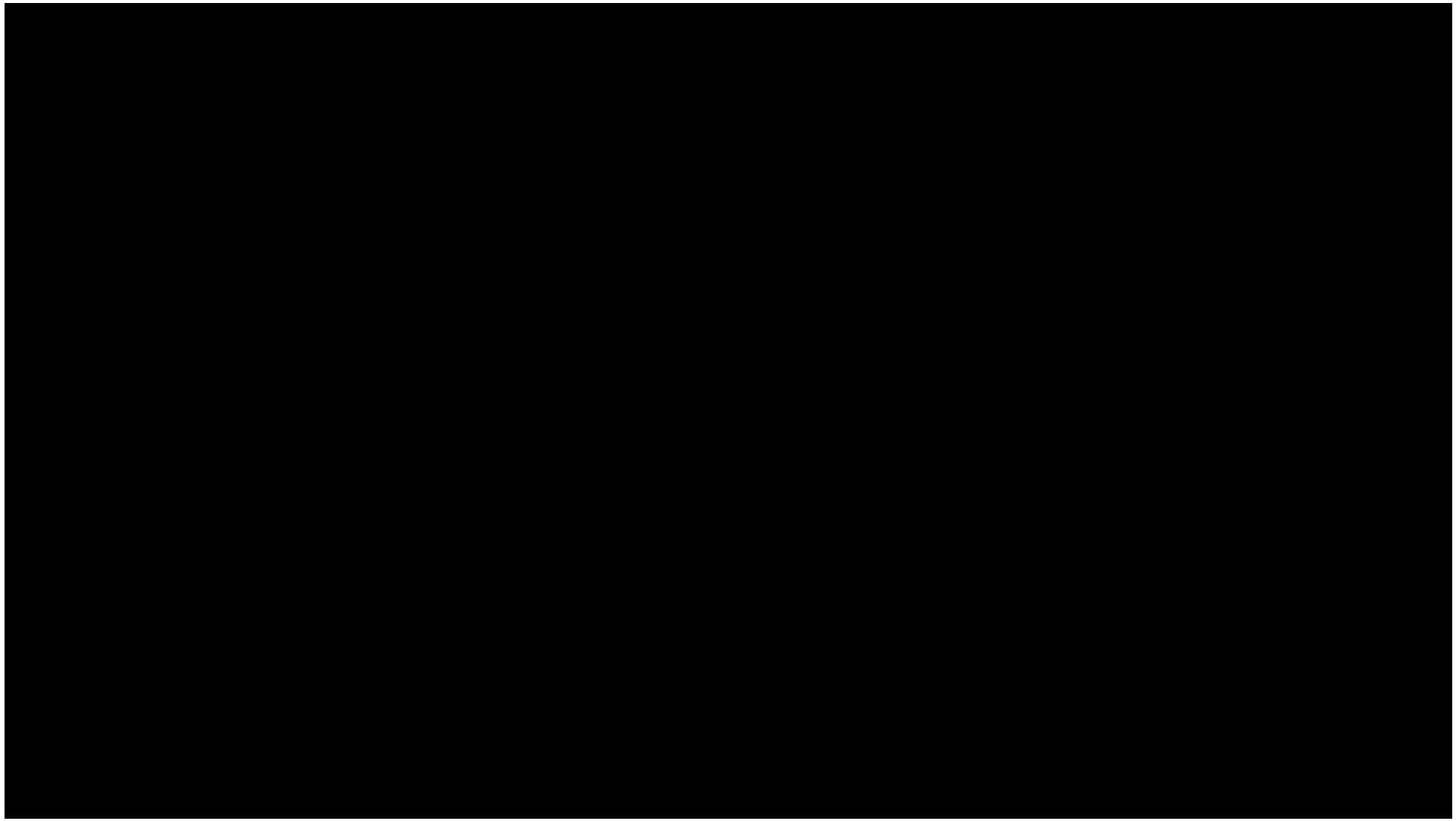


The Golem project (Lipson & Pollack, 2000)

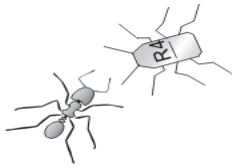


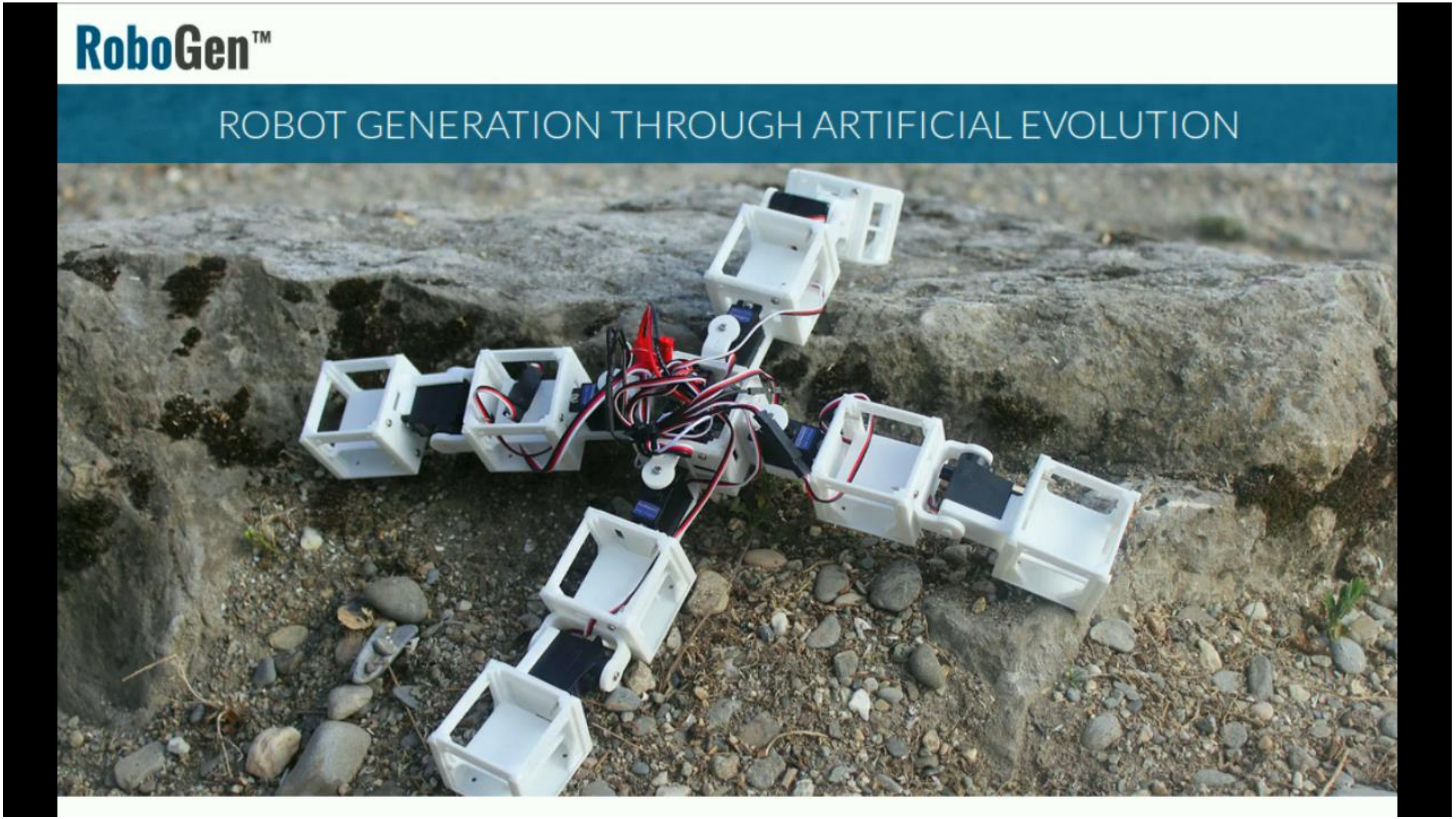






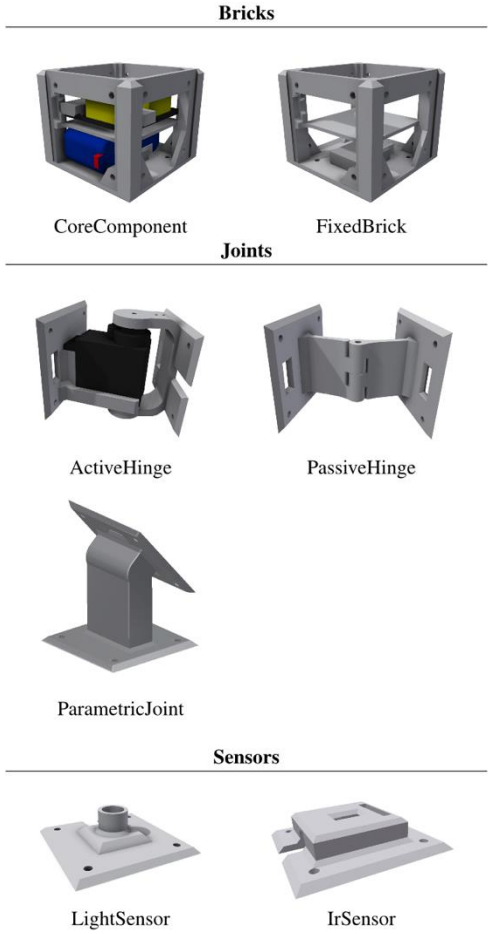
http://www.demo.cs.brandeis.edu/golem/



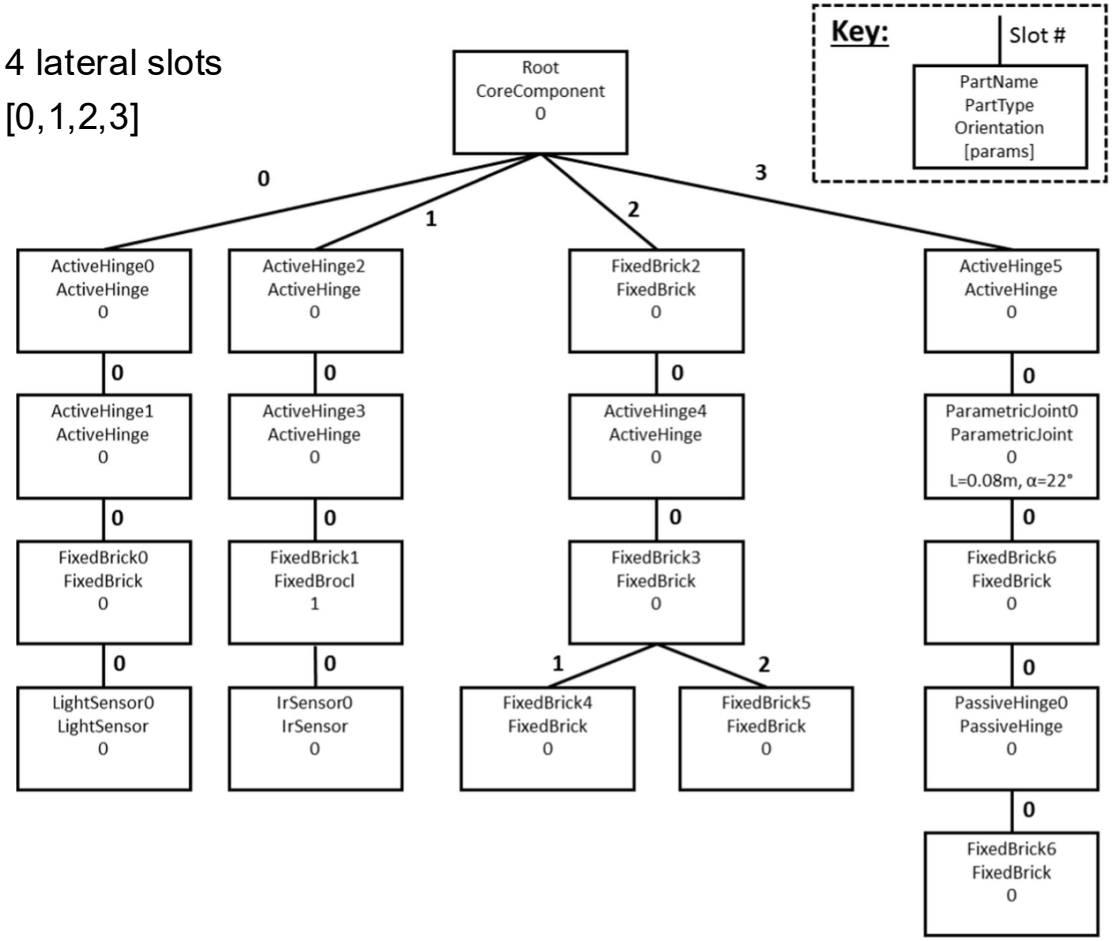


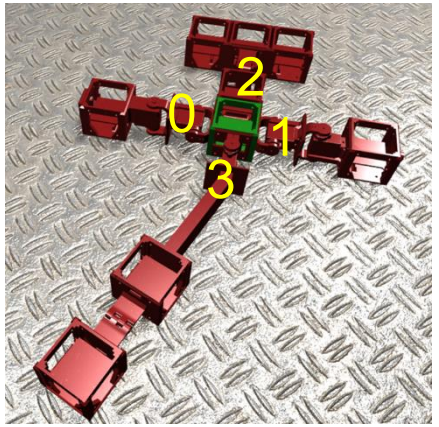
Auerbach, Concordel, Kornatowski, Floreano (2018) *IEEE Transactions on Learning Technologies*

Robogen: Morphology Encoding and Mutations



4 lateral slots
[0,1,2,3]



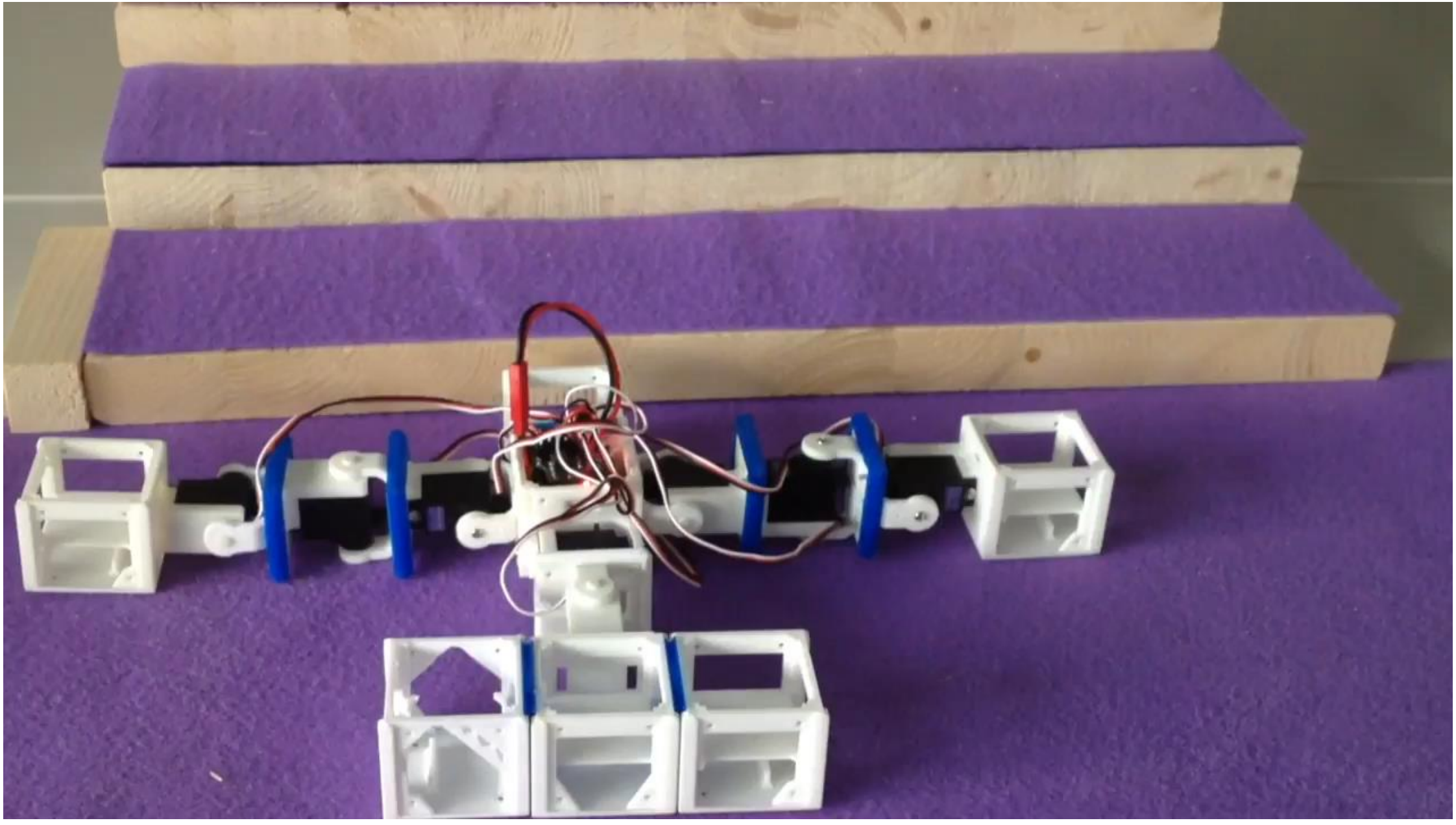


Mutation Operator	Description
NodeInsert	Insert a random node at a random location in the body representation tree.
NodeRemove	Remove a random node from the body tree representation.
SubtreeDuplicate	Duplicate a randomly chosen subtree and insert it at a random location on the body tree.
SubtreeSwap	Swap two randomly chosen subtrees of the body tree representation.
SubtreeRemove	Remove a randomly chosen subtree from the body tree representation. Unlike *NodeRemove* which attempts to remove a node and propagate its children upwards, *SubtreeRemove* removes a node and all of its descendants.
MutateParam	Mutate a randomly chosen parameter of a randomly chosen node. For the purpose of this operator a node's orientation relative to its parent is also consider to be a parameter.

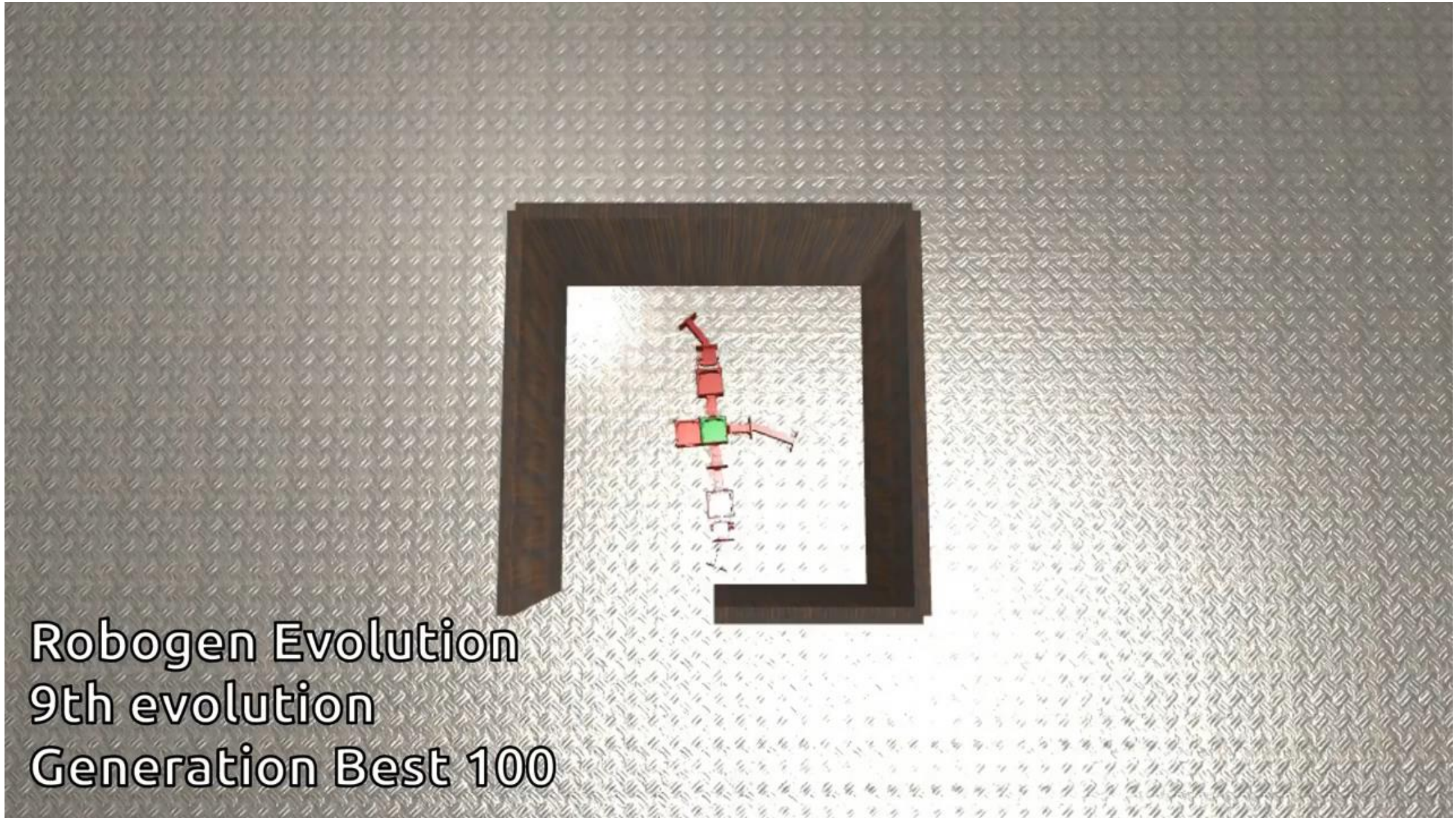
The probability of applying each operator is user-configurable.

www.robogen.org

Robot evolved by EPFL students (2018): the climber

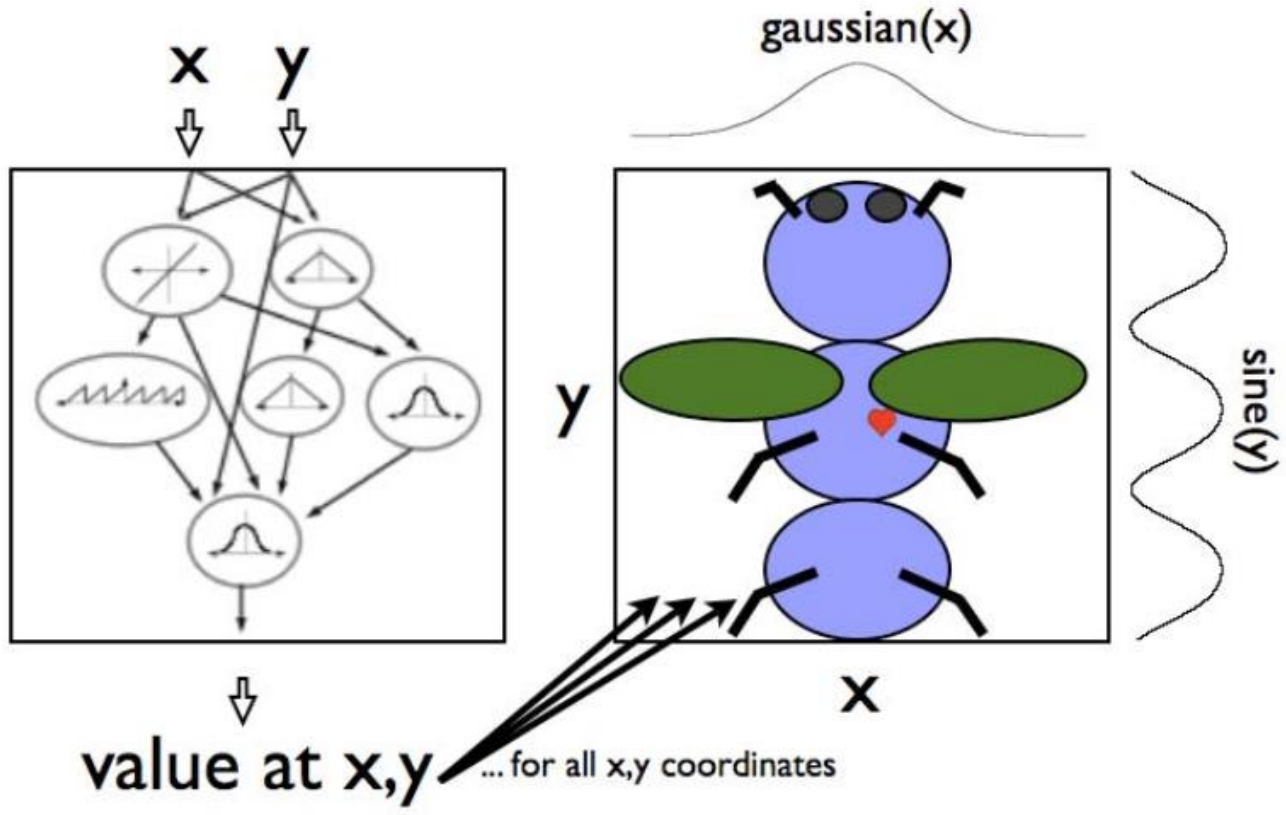


Robot evolved by EPFL students (2018): the jailbreaker

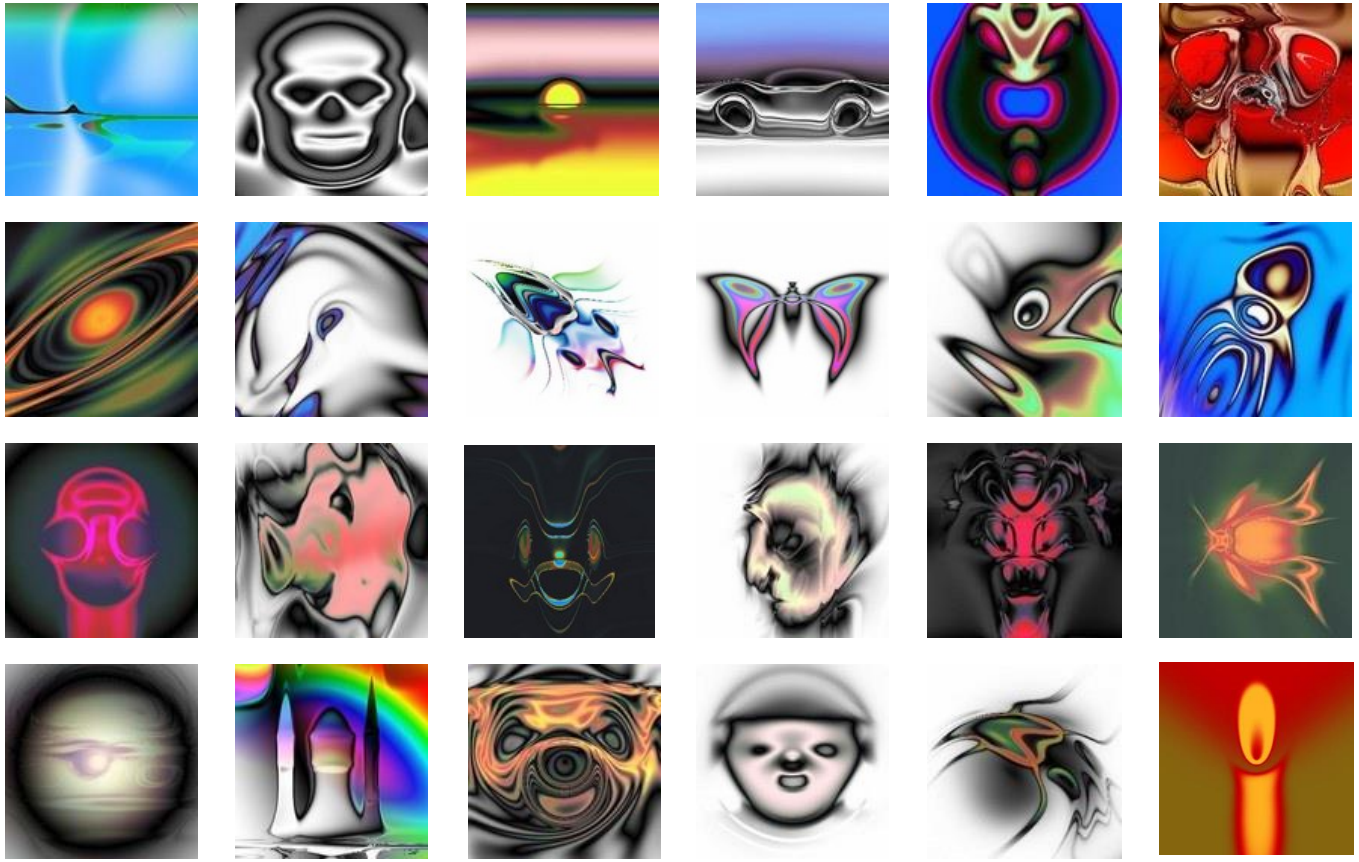


Compositional Pattern Producing Networks (CPPNs)

- 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

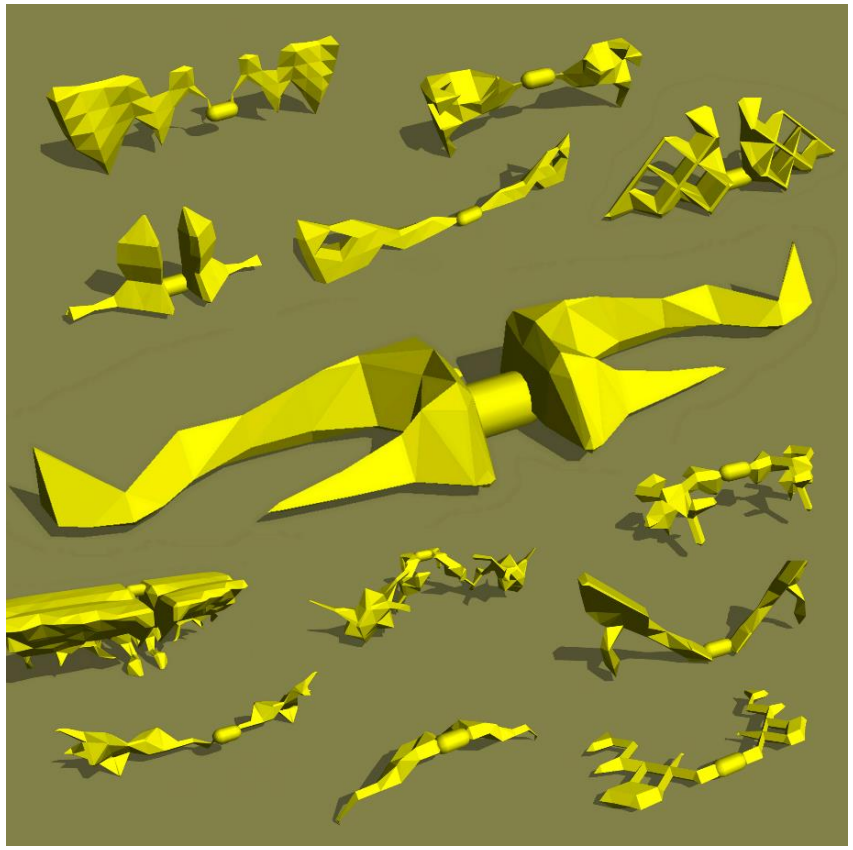


2-Dimensional images

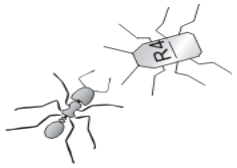


Picbreeder.org
[Secretan et al., 2007]

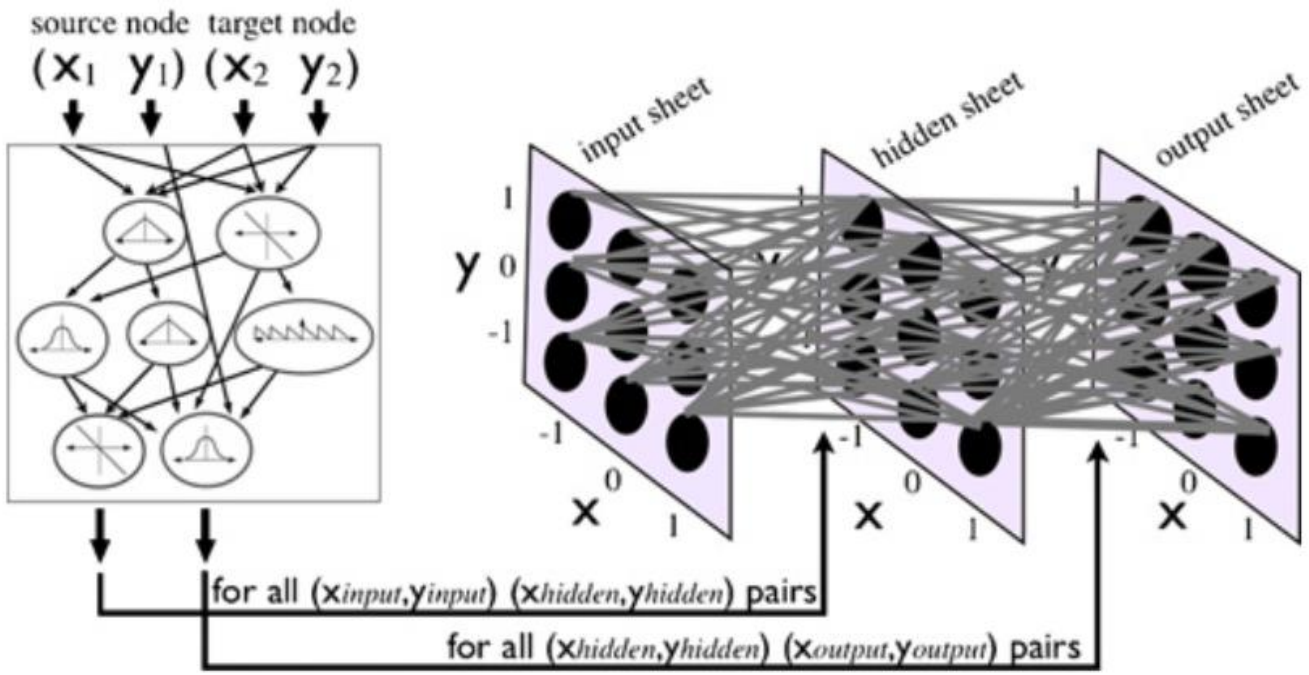
3-Dimensional objects



Robot morphologies
[Auerbach and Bongard, 2014]

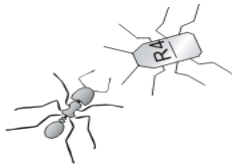


Co-design of neural controllers and robotic bodies by CPPNs



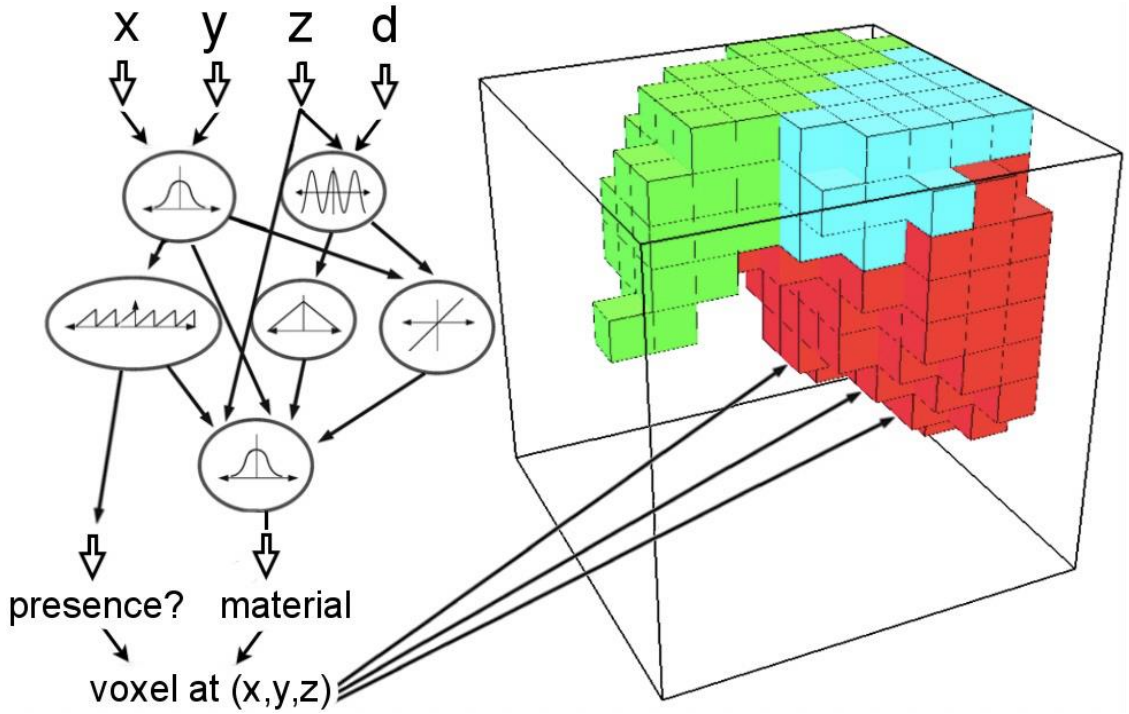
CPPNs can “paint” weights of neural network connections [Stanley et al., 2009], up to several million connections

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

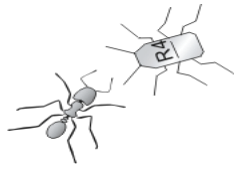


Green voxels undergo periodic volumetric actuations of 20%

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

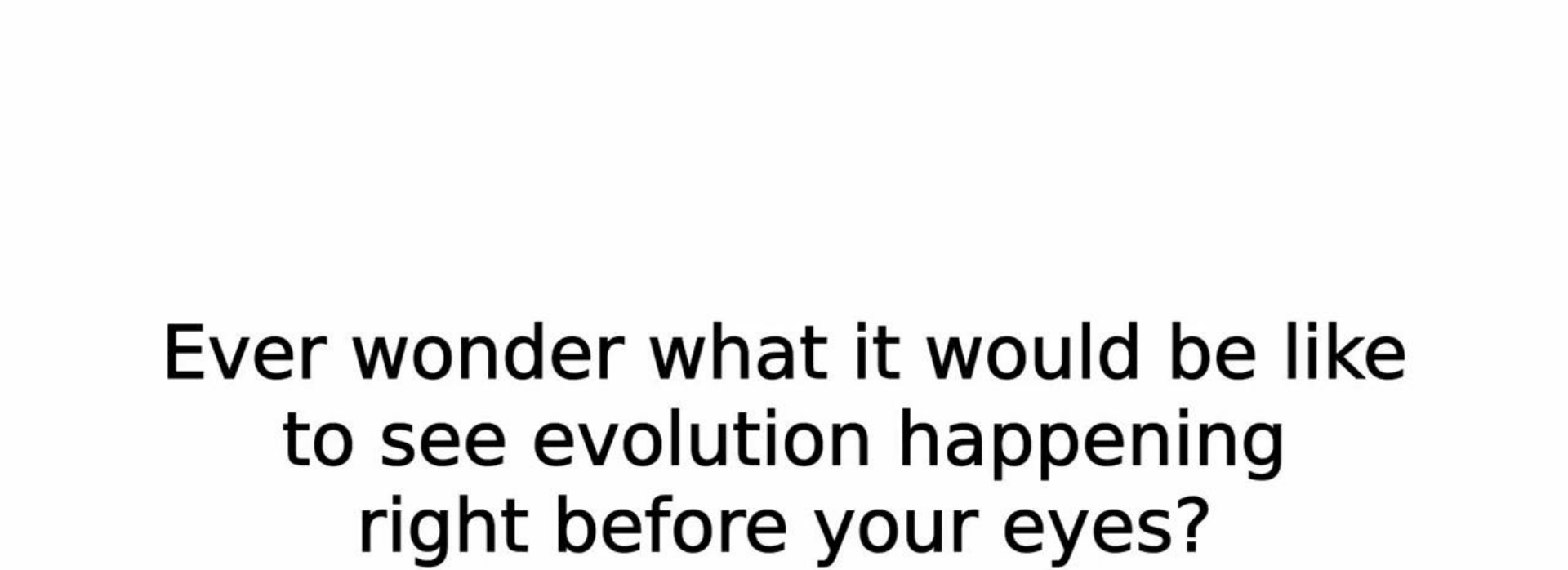
Light blue voxels are soft and passive, having no intrinsic actuation

Dark blue voxels are also passive, but are stiffer



Evolution of soft-bodied robots

Cheney, MacCurdy, Clune, Lipson, 2013

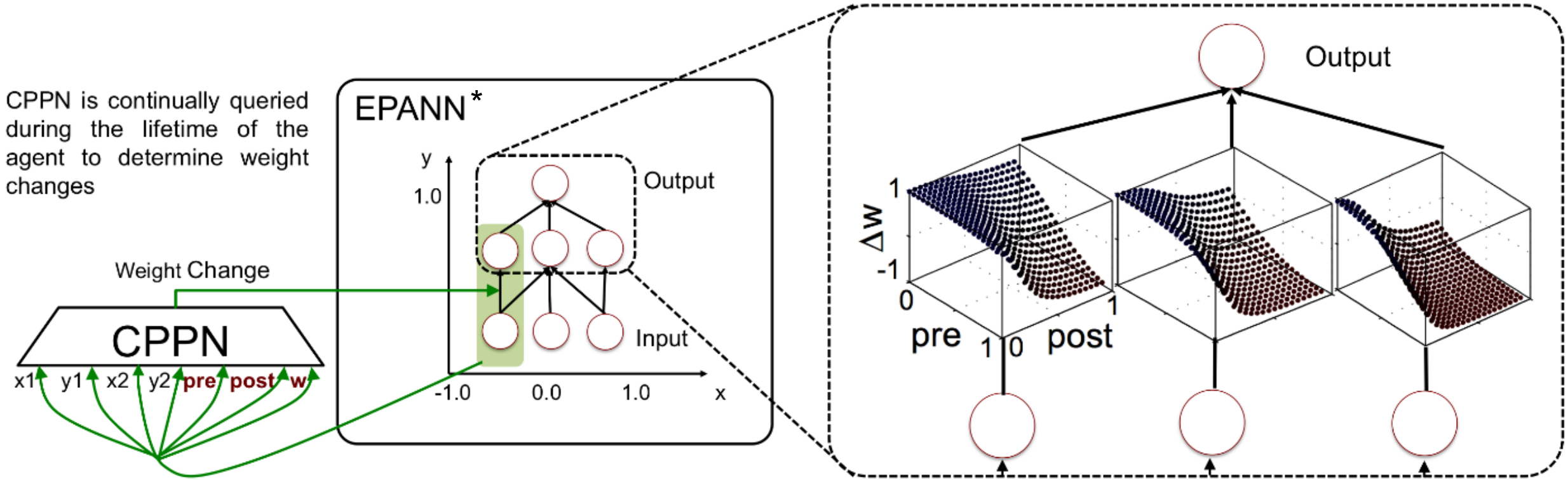


http://jeffclune.com/videos.html

Using CPPNs as learning rules

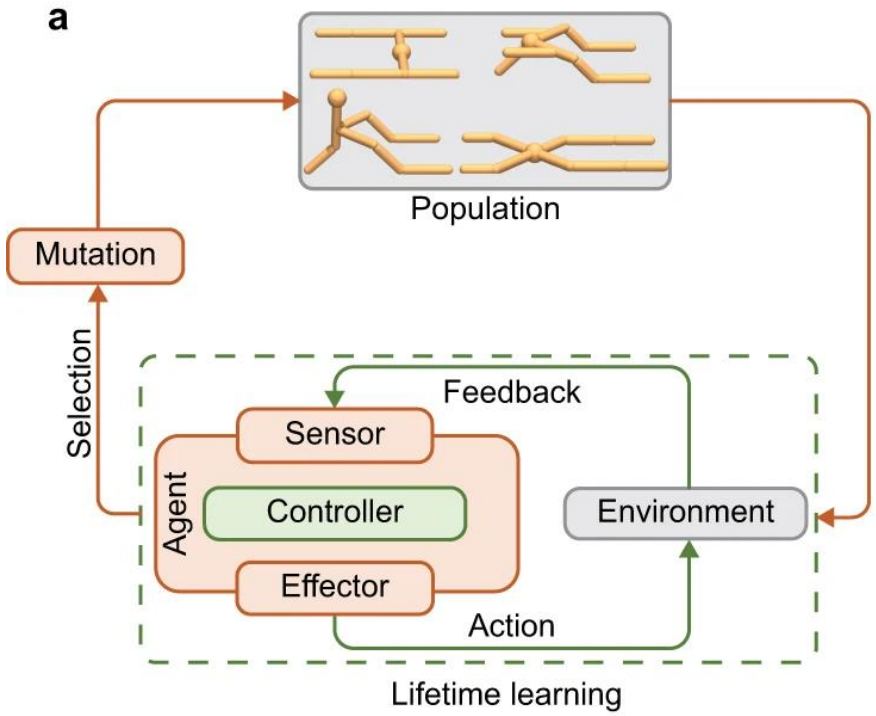
Risi and Stanley, 2010, 2014

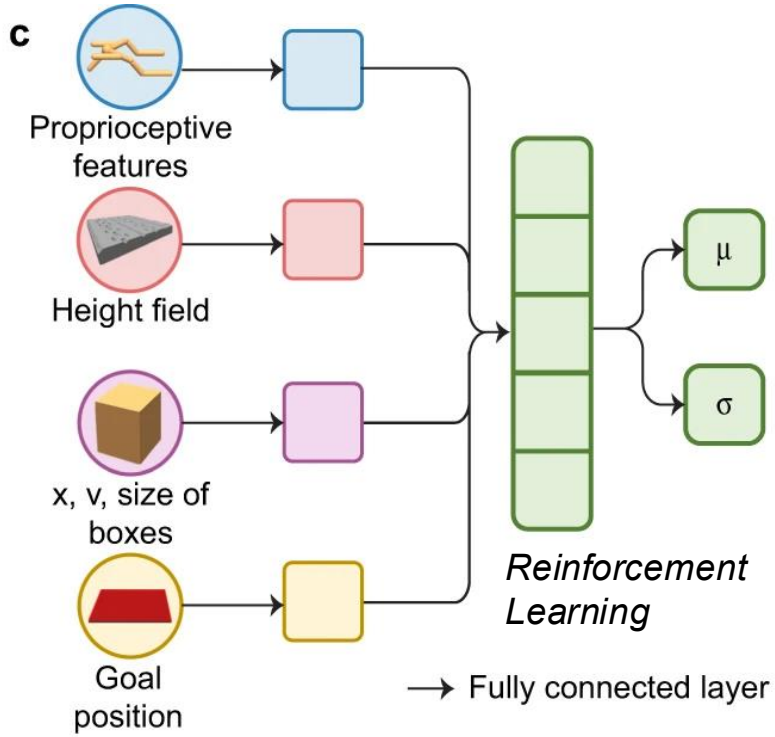
- Genetically encode and evolve the weights of the CPNN
- Use CPNN to compute weight updates of the neural controller at each time step of the robot lifetime
- Use robot's performance to compute fitness of the CPNN for selection

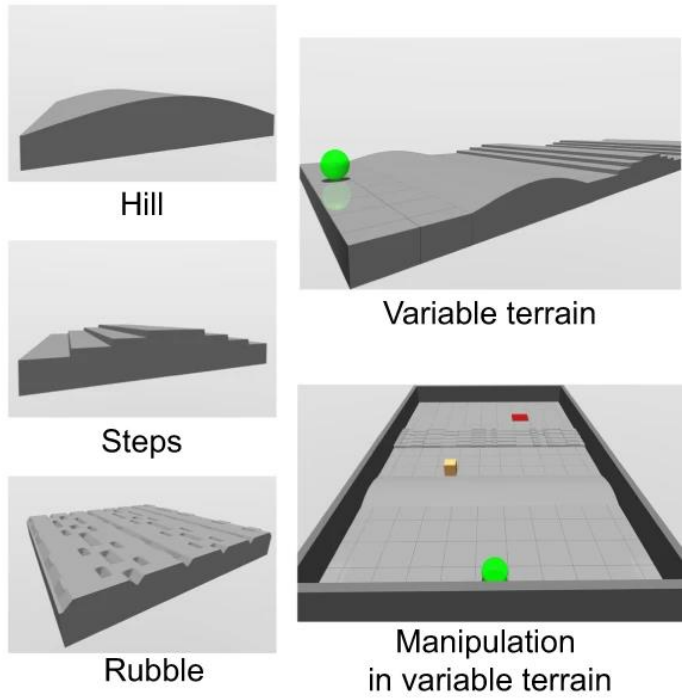


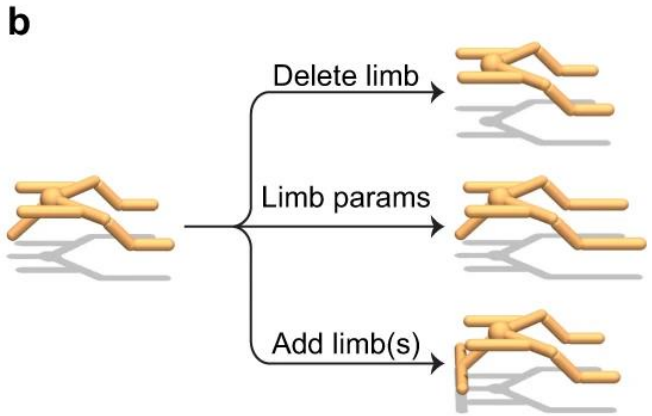
*Evolutionary Plastic Artificial Neural Network

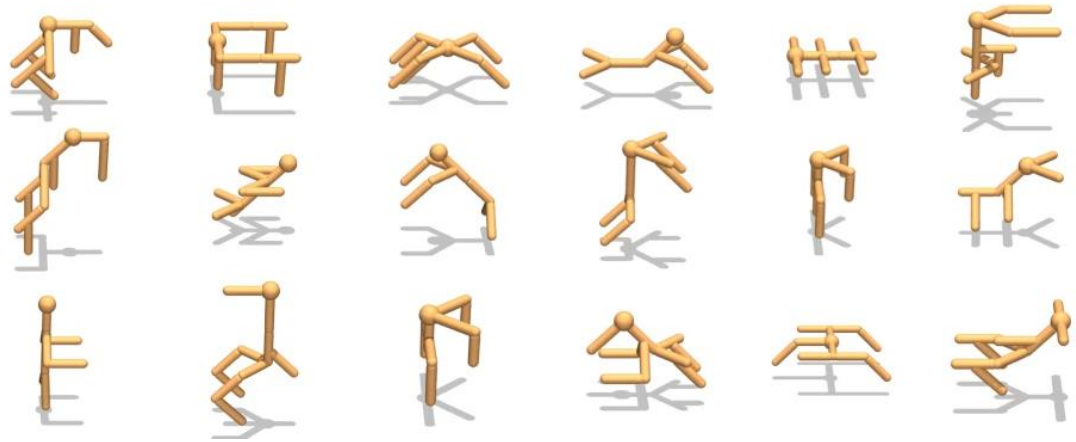
Morphological evolution of learning robots







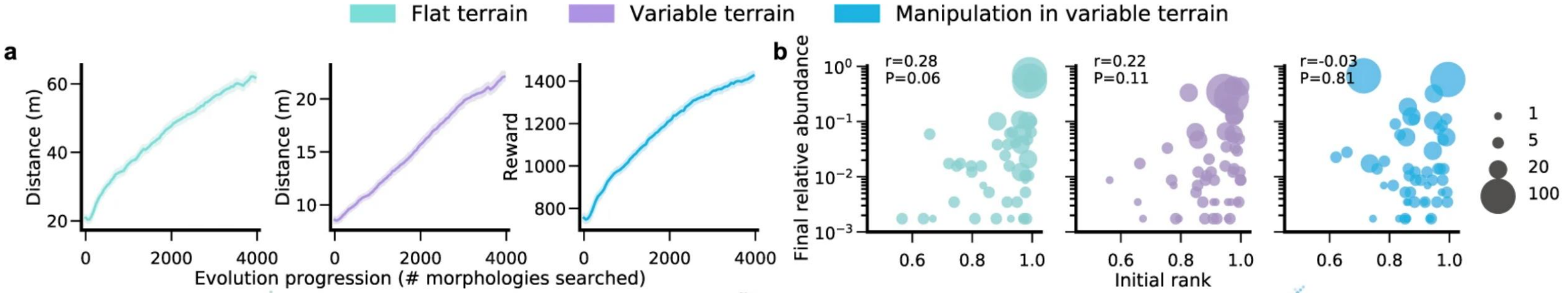


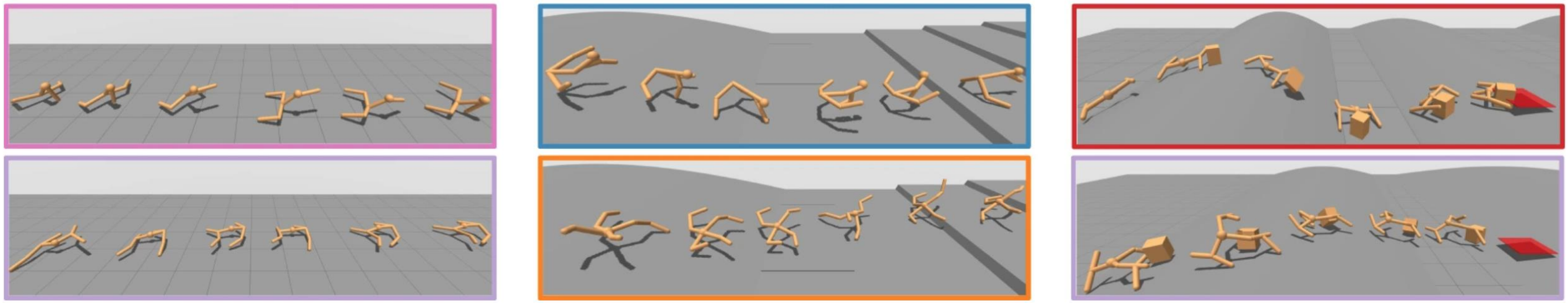


Gupta A, Savarese S, Ganguli S, Fei-Fei L (2021) Embodied Intelligence via Learning and Evolution. *Nature Communications* 12(1), 5721

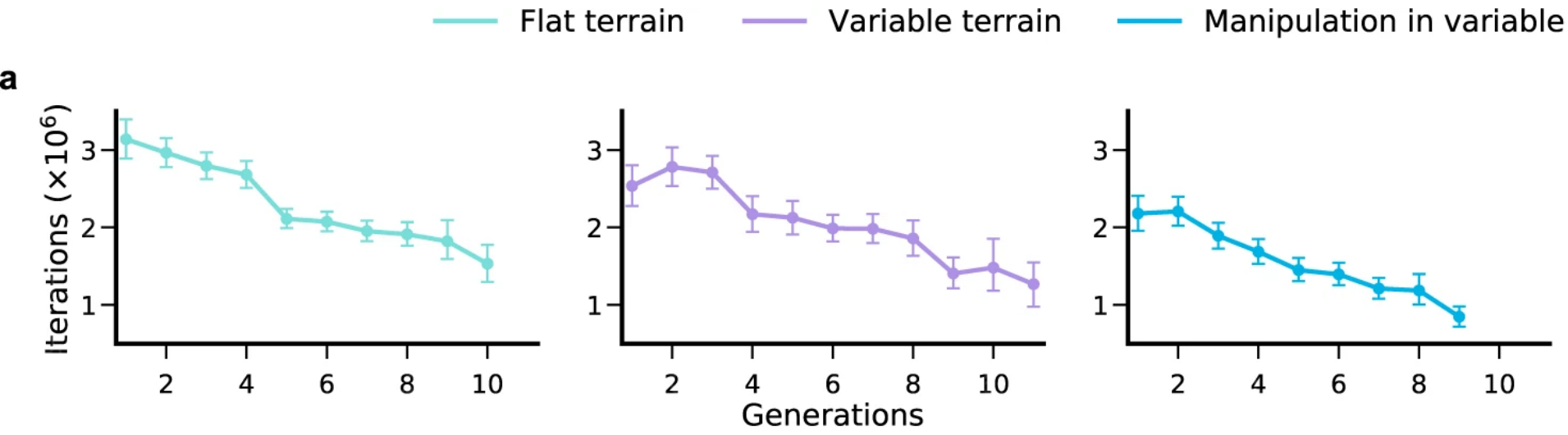
Local tournament selection preserves diversity

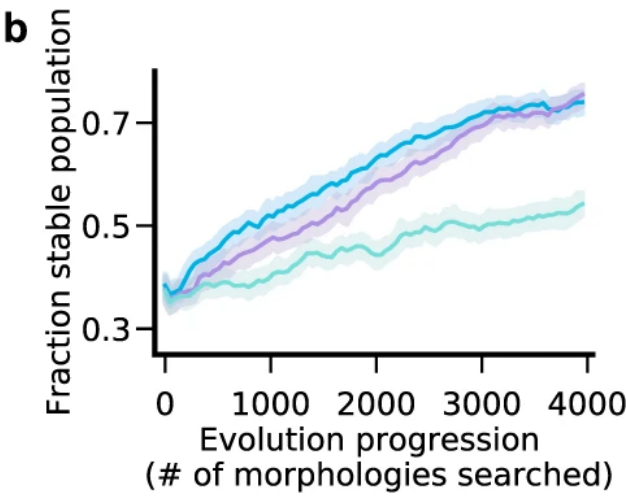
Population spread across 100's of CPU, each simulating 4 individuals and reproducing the best one

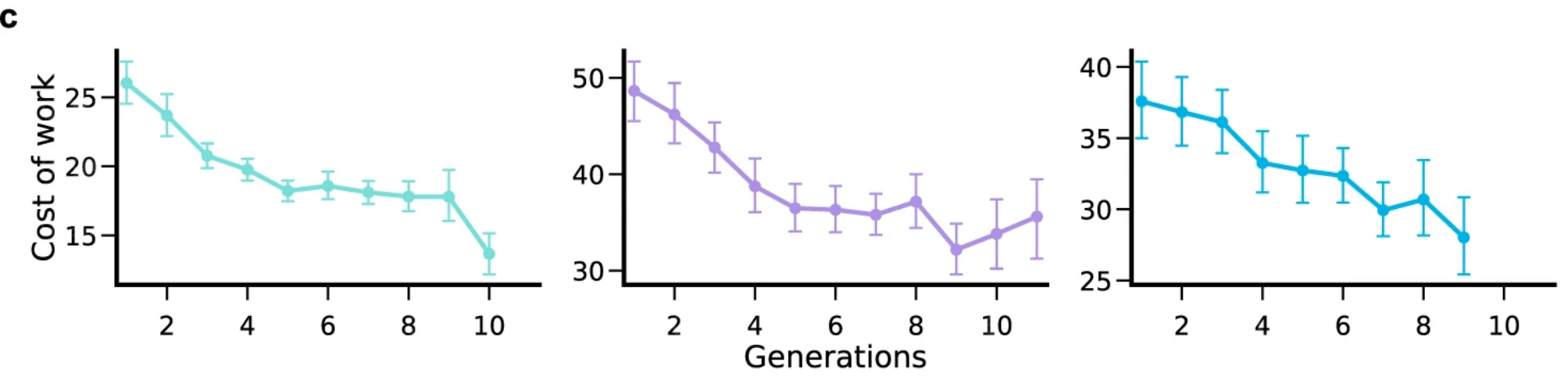


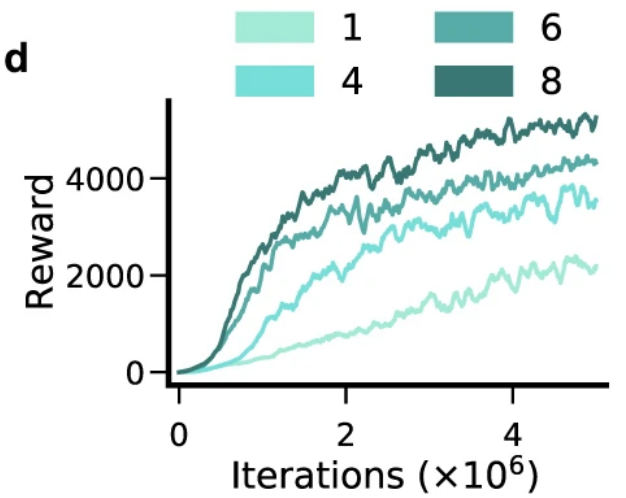


Better bodies learn faster and better

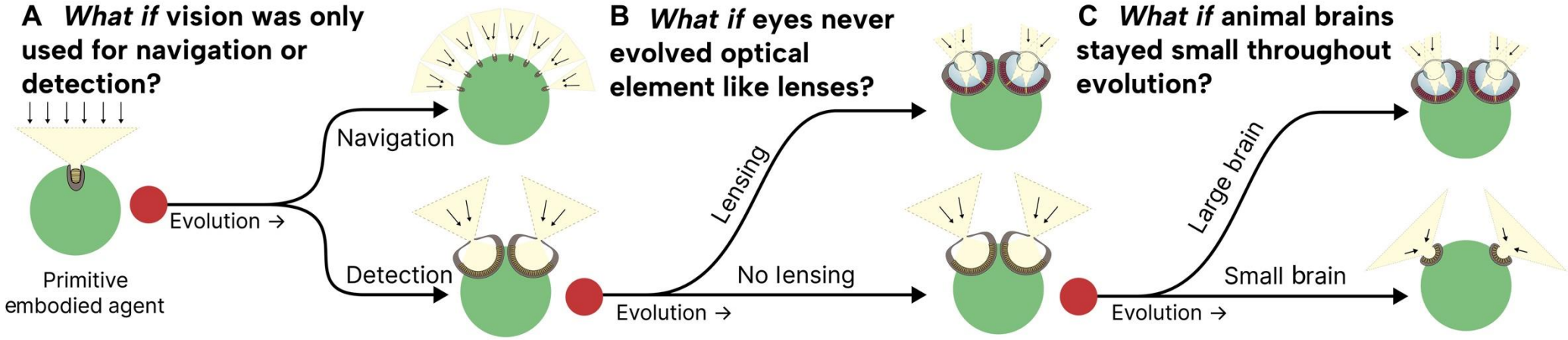




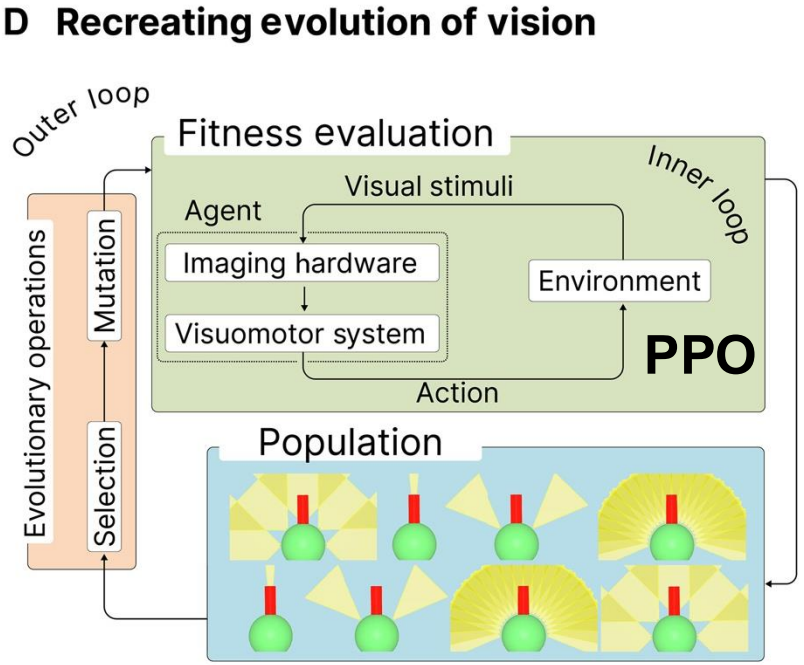


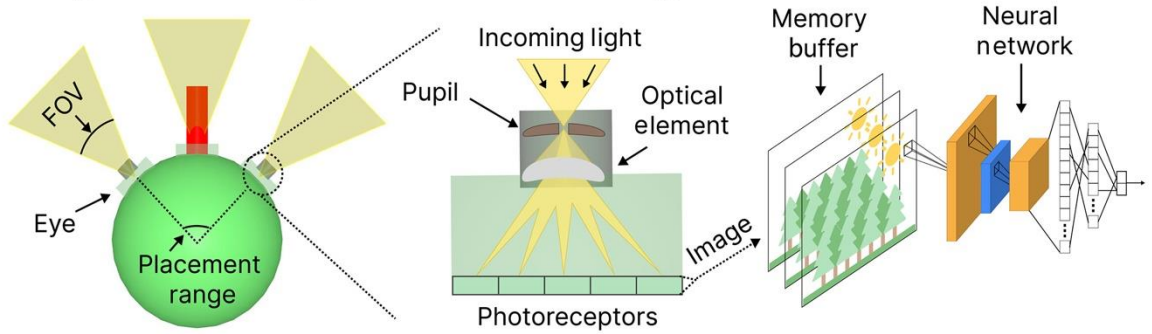


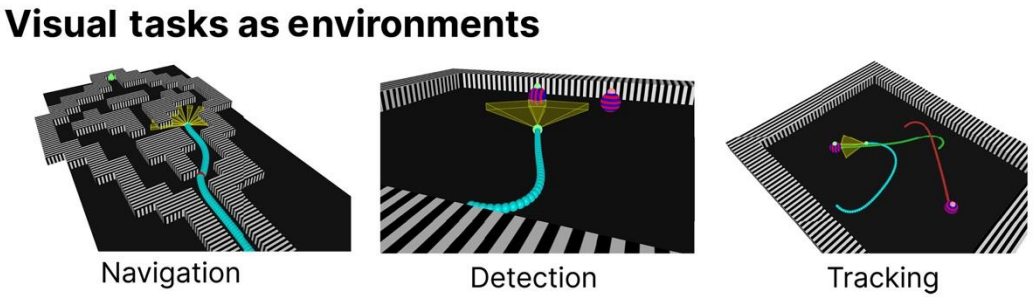
Coevolution of eye morphology and neurocontroller

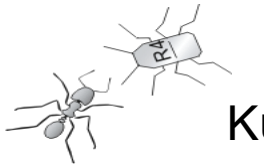


CMA-ES



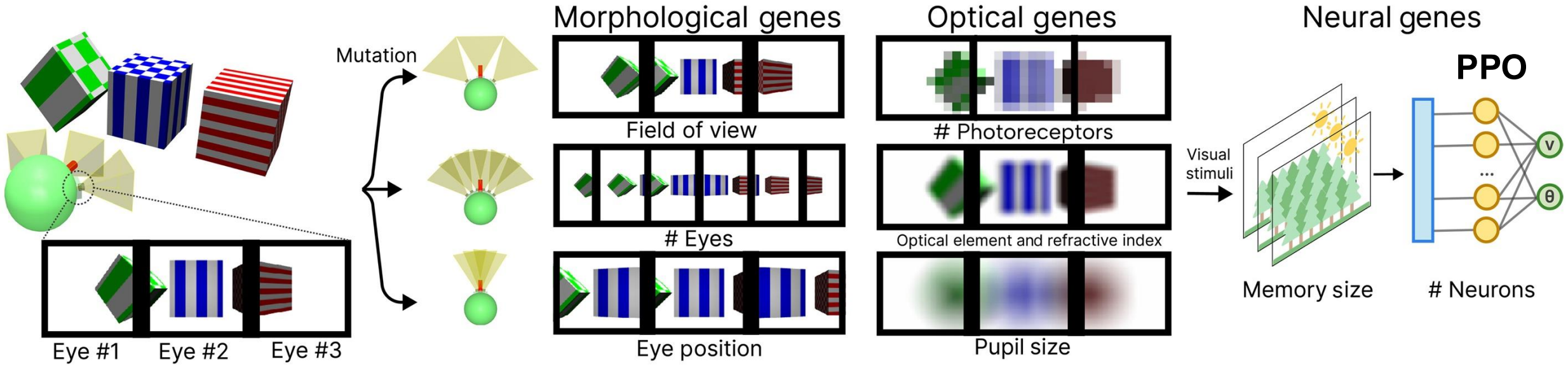






Kushagra et al. (2025) What if eye...? Computationally recreating vision evolution. *Science Advances*

Genetic Encoding and Evolutionary Parameters



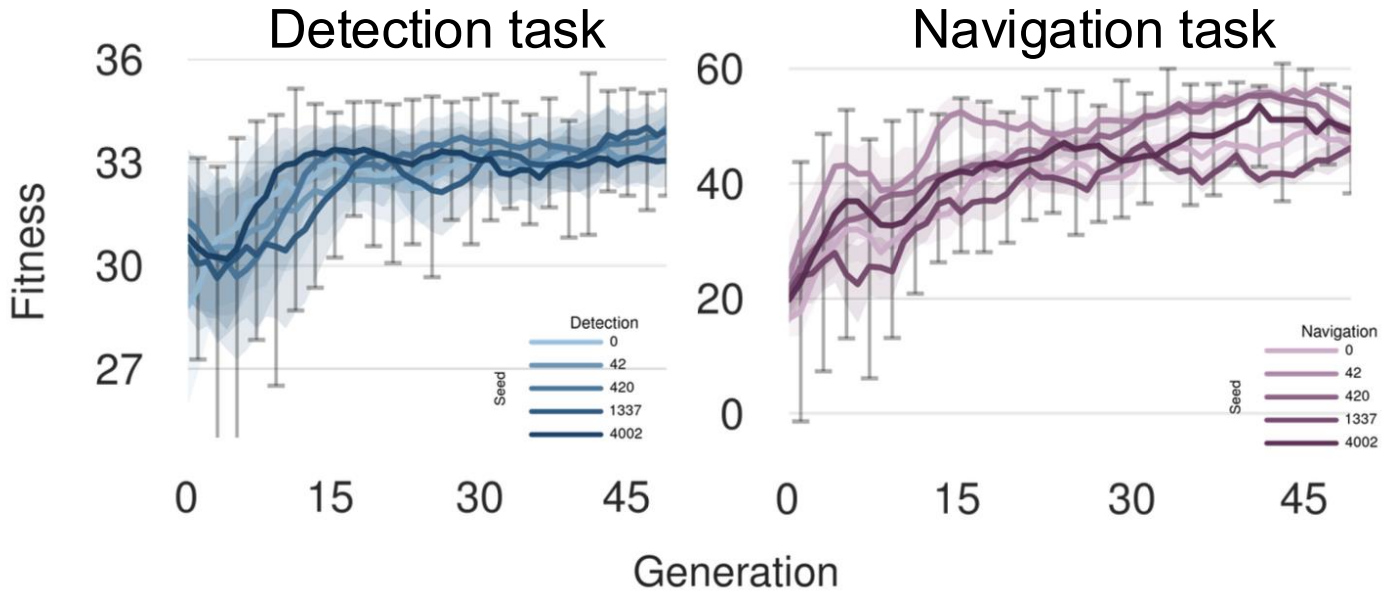
Population size = 16

Generations = 50

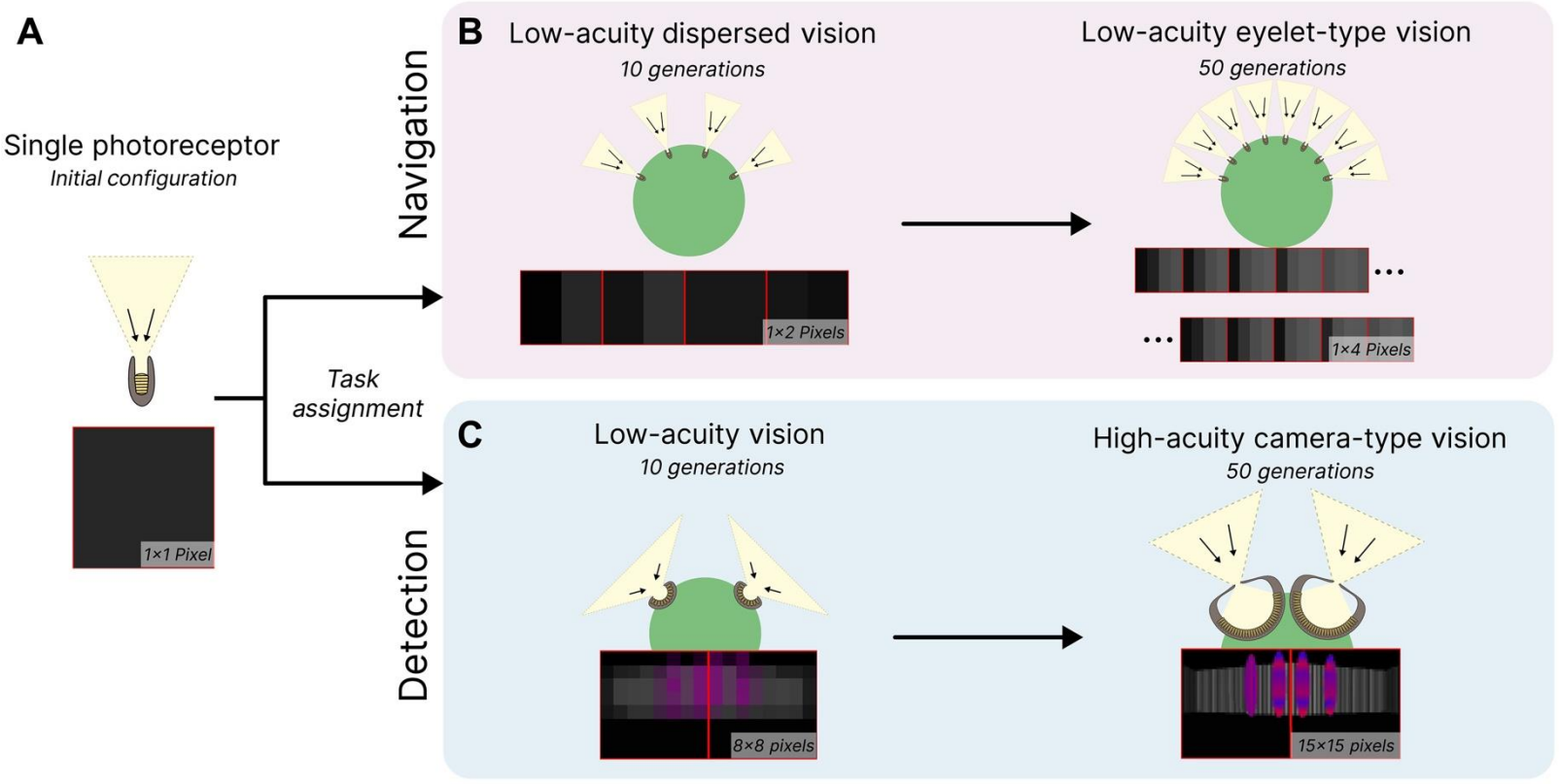
PPO = 1 Mio training cycles, 6 evaluations

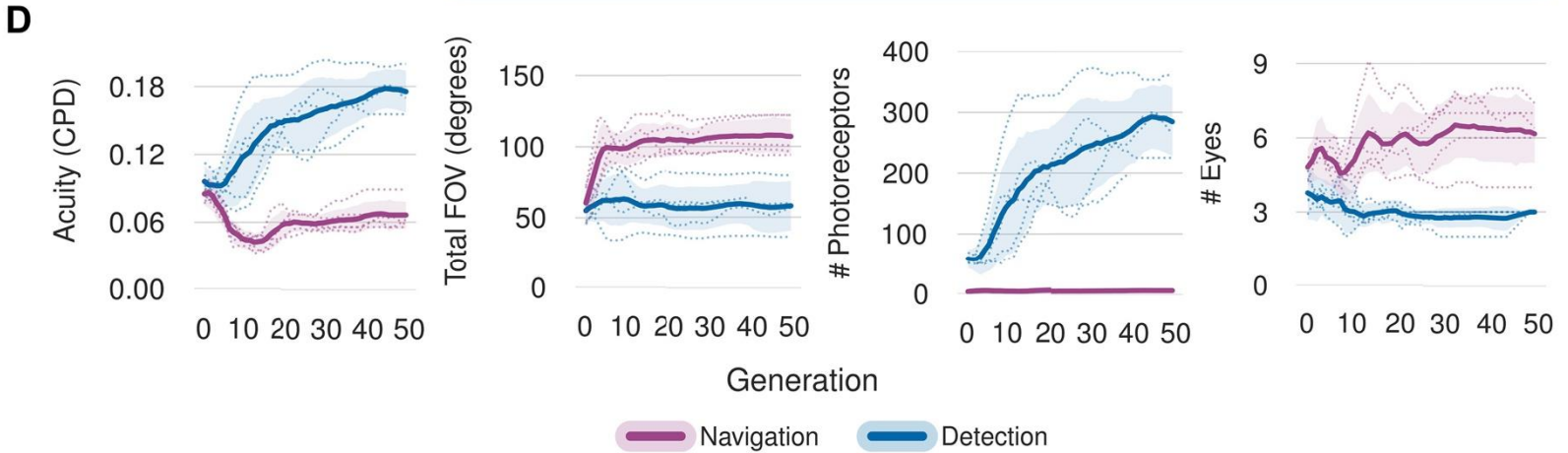
Darwinian evolution

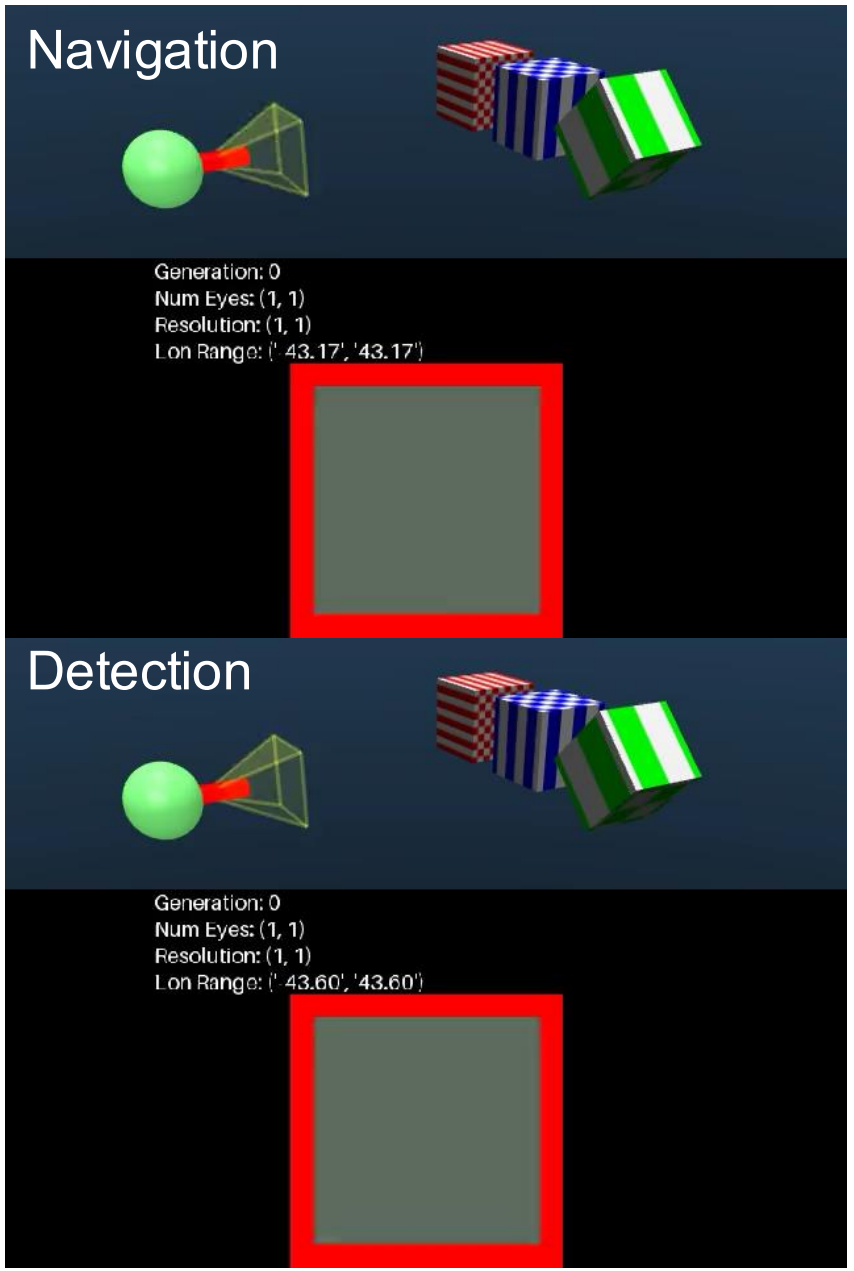
Fitness Function ≈ Reward function



Navigation vs Detection Tasks







Checkpoints

- What is a re-writing system and what can be used for?
- Describe the components of an L-system and its operation
- Describe the turtle interpretation of L-systems
- What is a bracketed L-system and why is it used?
- Describe the matrix rewriting system for evolving neural network topologies
- What are Compositional Pattern Producing Networks and how can they be used to evolve bodies, neural topologies, and learning rules?