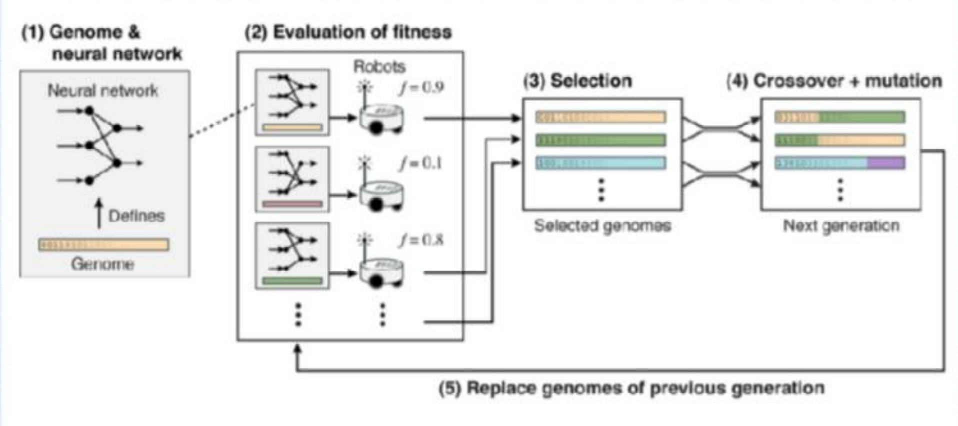
Evolving Robotics

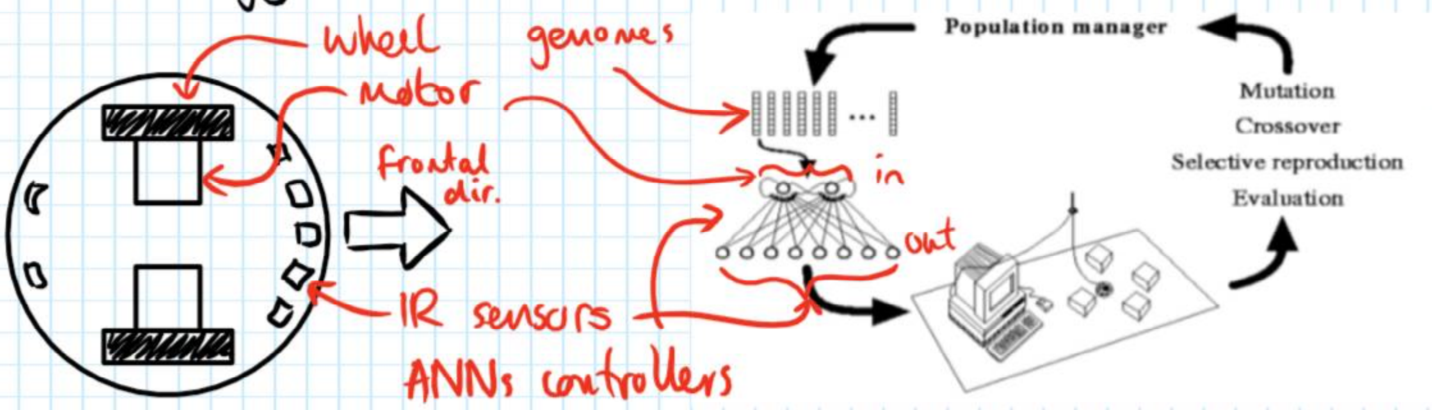
23 May 2017 18:05

Goal: Use artificial evolution to automatically generate control systems and morphologies for autonomous robots.



Example: Obstacle Avoidance

Morphology: Evolutionary Cycle:

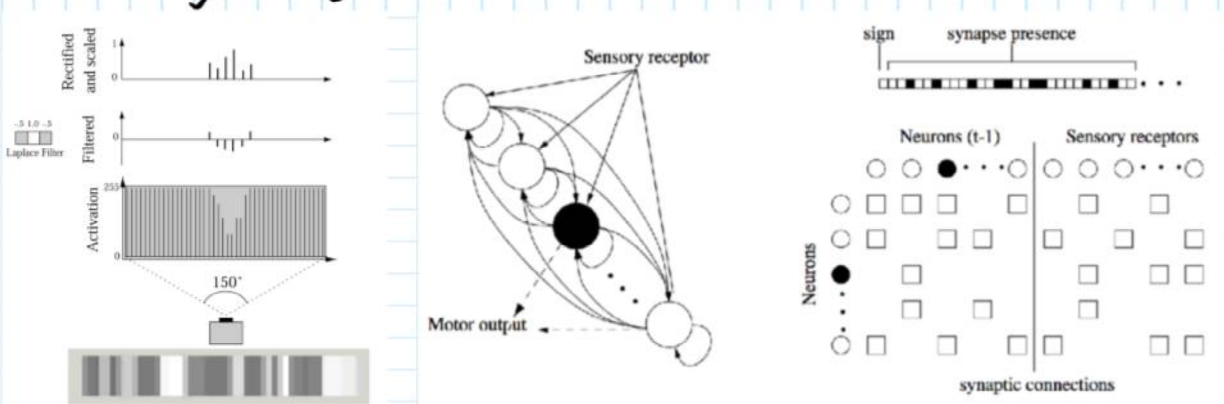


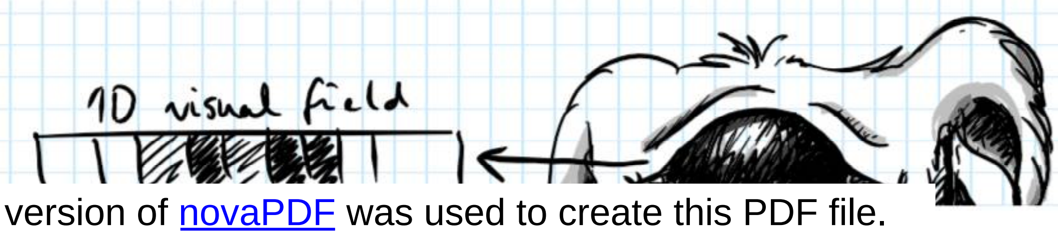
Evolving Sustainability:

Robot is equipped with battery that last 20s, and is put in an environment with a charging station. After 240 generation, Floreano et al. had a robot capable of moving around and recharging every 18s. Fitness could be max distance across 150s trial.

Evolving Vision:

One dimensional visual field fed into learning algorithm





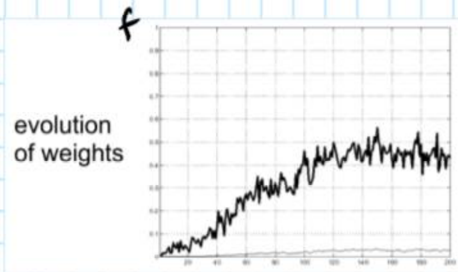
Complex, recurrent
NN measures optic
flow across contrast

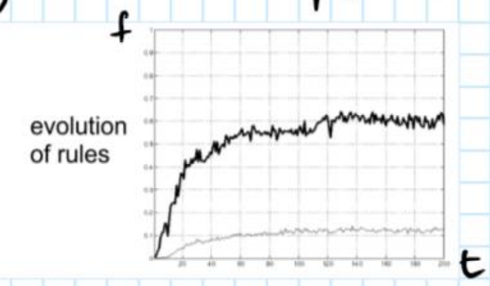
Evolving Learning Procedural:

Genetically encode and evolve different types of learning rules, such as standard Hebbian rules, presynaptic, postsynaptic and covariant rules. The network can have neurons with differing learning rules. This method can be unsupervised.

Hebbian	If connected a, b fire, increase $w_{a\to b}$
Postsynaptic	If neuron b fires, inc $w_{a\to b}$, other way dec
Presynaptic	If neuron a fires, inc $w_{a\to b}$, other way dec
Covariance	balance of increasing and decreasing $w_{a\to b}$

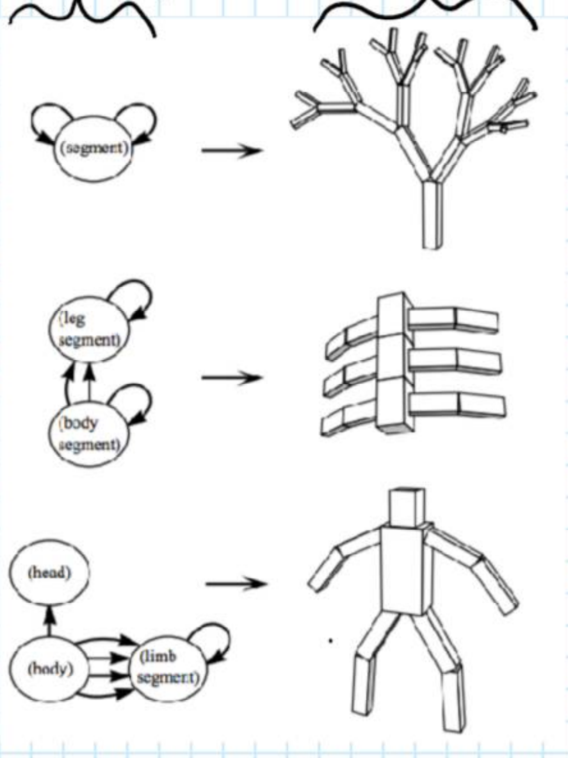
Systems with learned learning rules perform better when switching between problems.





Evolving Morphology

Genotypes Phenotypes



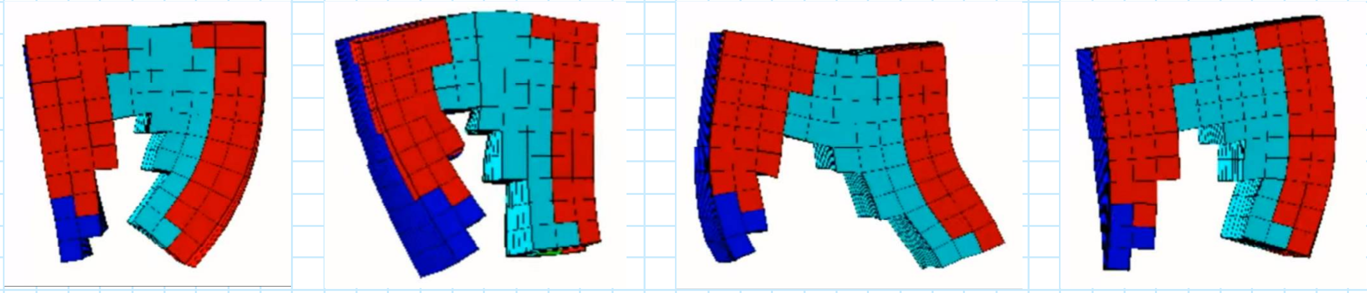
Each phenotype is constructed from a genotype with a starting seed.

- Each segment connects to two segments.
- Each body connects to another body and a segment, each segment connects to another segment.
- A body connects to a head and four limbs. Each limb connects to another limb.

Framsticks

- Evolve stick agents and their neural controllers
- Interesting environment for testing fitness functions

Evolving Soft Robotics



An evolved soft robot galloping

- The dark blues is bone - i.e. hard support
- The light blue is tissue - i.e. soft support that will deform elastically under a force.
- Red is muscle, which expands and contracts given input

The morphology and controller were evolved concurrently using HyperNEAT, a version of NEAT designed for larger networks.

The Reality Gap

Early Example: The Golem Project (2000):

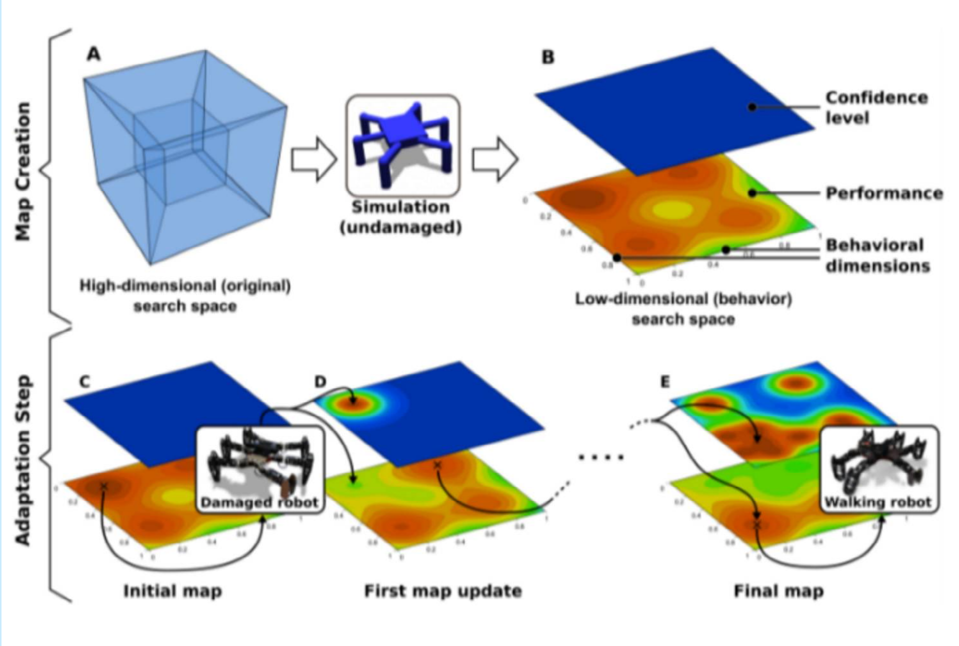
Physically construct creatures using 3D printers. Creatures are evolved artificially in simulation, then printed. Morphology and controller evolved.
Limitation: not self assembling and too slow.

Research is pushing to bridge the "reality gap", current approach involves "co-evolution" of simulated creatures and physical ones. The idea is to constantly adjust the simulated fitness function in accordence with real-world data.

Expected Fitness Maps

In simulation a reduced-dimensionality search space of the robot parameters is maintained, and fitness values are stored for different parameterisations. Therefore the physical robot can try the best controller parameters and see what bridges the gap most sucessfully.

An interesting side effect of this approach is increased adaptability for the physical controller. Suppose the robot becomes damaged, the fitness map will have regions that account for the damaged part being unused, so the space can be re-explored with this consideration.



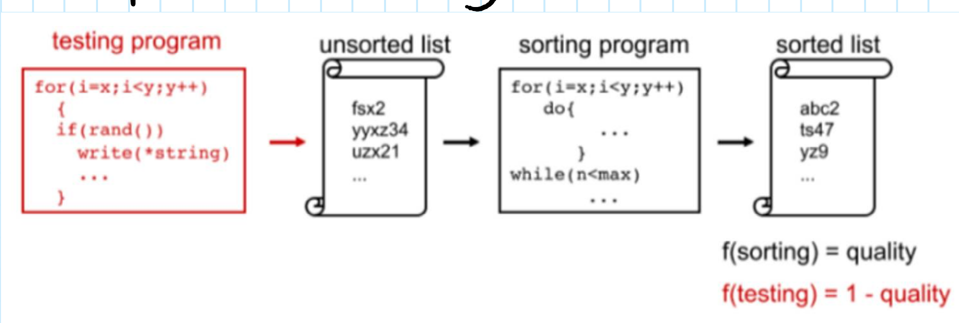
Competitive Co-evolution

Species has fitness functions that are inversely related to one another.

The motivation is to incur an "arms race" to accelerate innovation.

The continuously changing fitness landscape may help prevent stagnation in local minima.

Example : Sorting

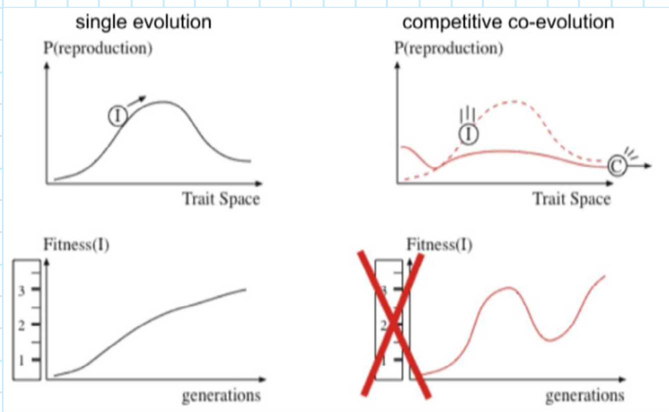


It was shown the evolving a sorting species against a testing species yeild better sorting programs.

The testing program is rewarded by spotting errors in the sorted list, and the sorting algorithm was rewarded for correctly ordered items.

Monitoring Evolution

Unlike for single species evolution, the fitness landscape is dynamic so monotonic increasing fitness cannot be expected

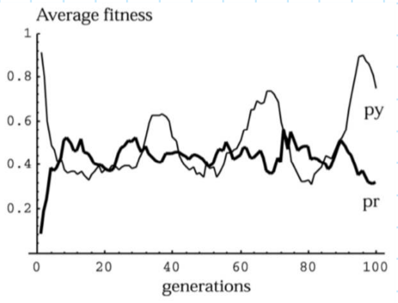


Hall of Fame (HoF):

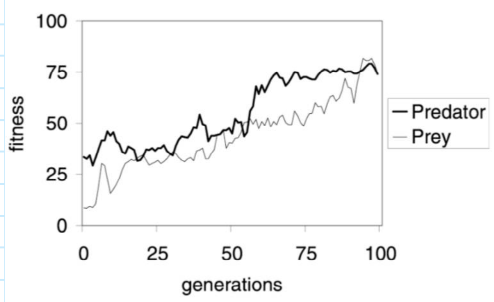
To avoid cycling dynamics of competitive co-evolution, the Hall of Fame [illegible] tests new individuals

To avoid cycling dynamics of competitive co-evolution, the Hall of Fame approach tests new individuals against the previous best individuals from the other species.

Without HoF:



With HoF:

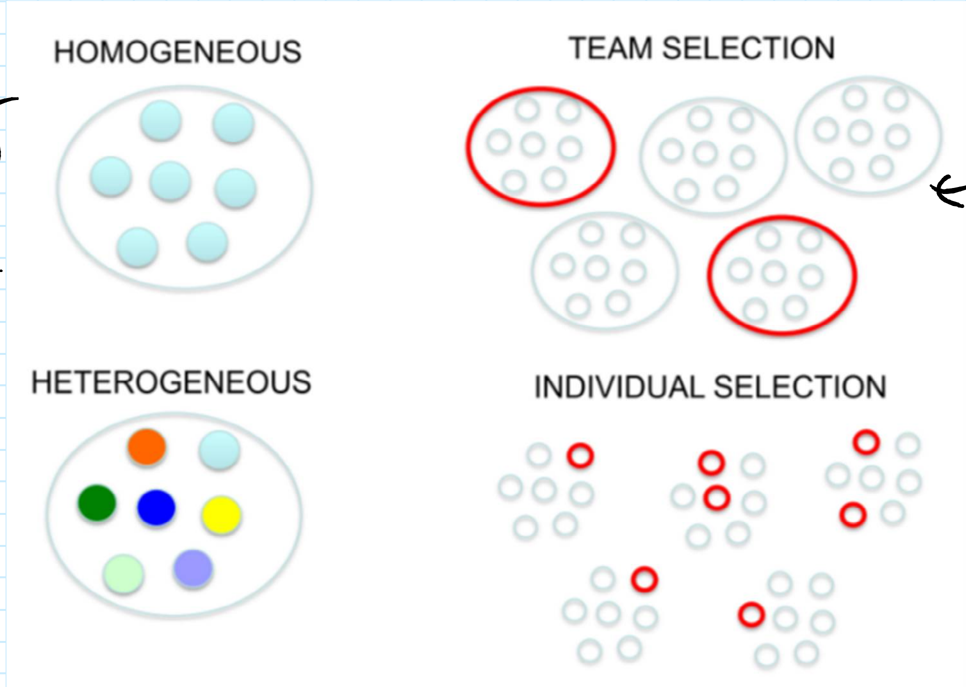


However this approach converges to constantly testing against the same individuals, which makes it exactly equal to the single species approach. In other words, the potential for creative new solutions decreases with time.

Cooperative Co-evolution

Hamilton's rule: The degree of agent cooperation depends on their relatedness.

more cooperative



scores given to teams, not individuals