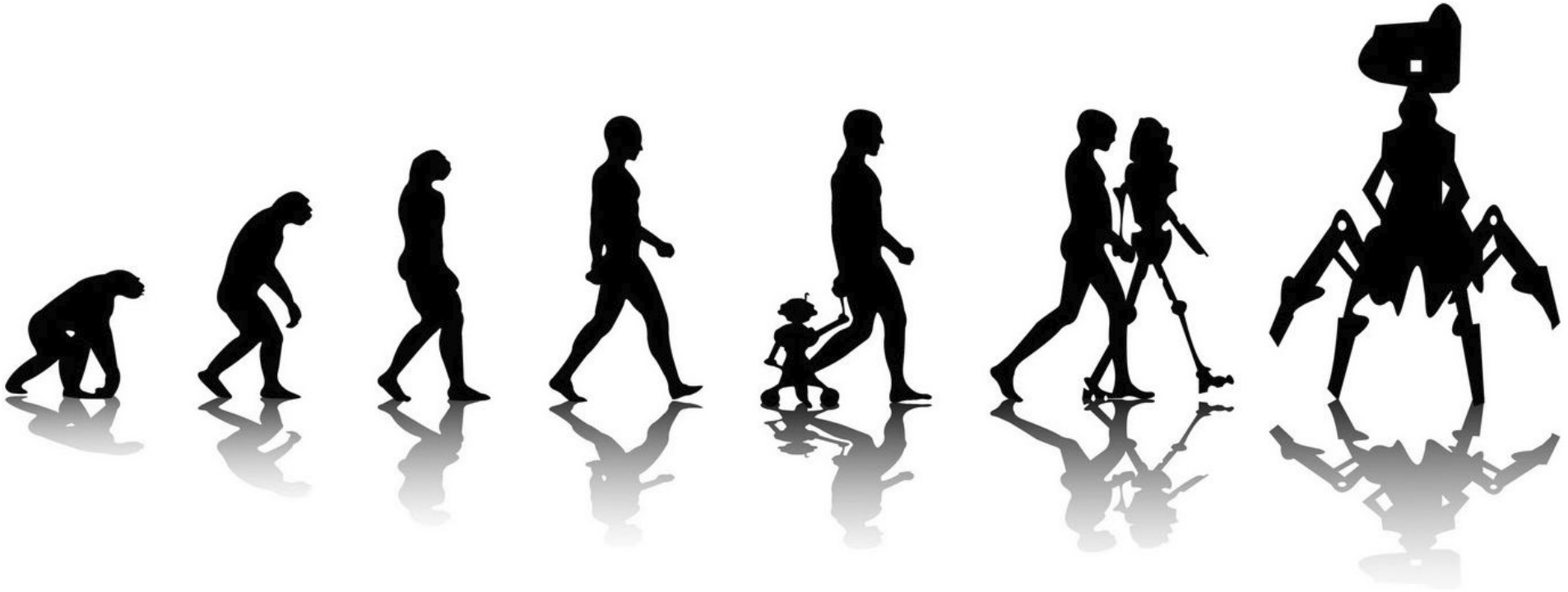


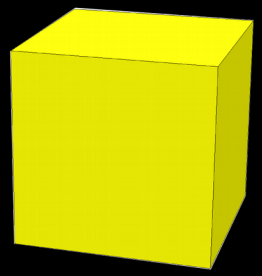
# Modern Robotics: Evolutionary Robotics

COSC 4560 / COSC 5560

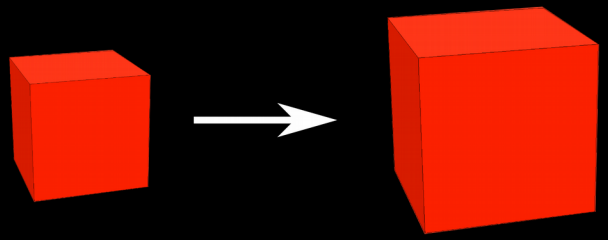
Professor Cheney

3/2/18

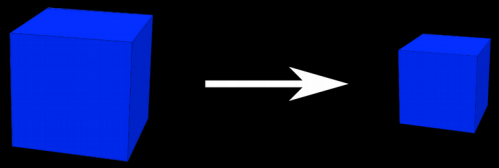
# Morphological Computation (Cont.)



= target (to reach towards)

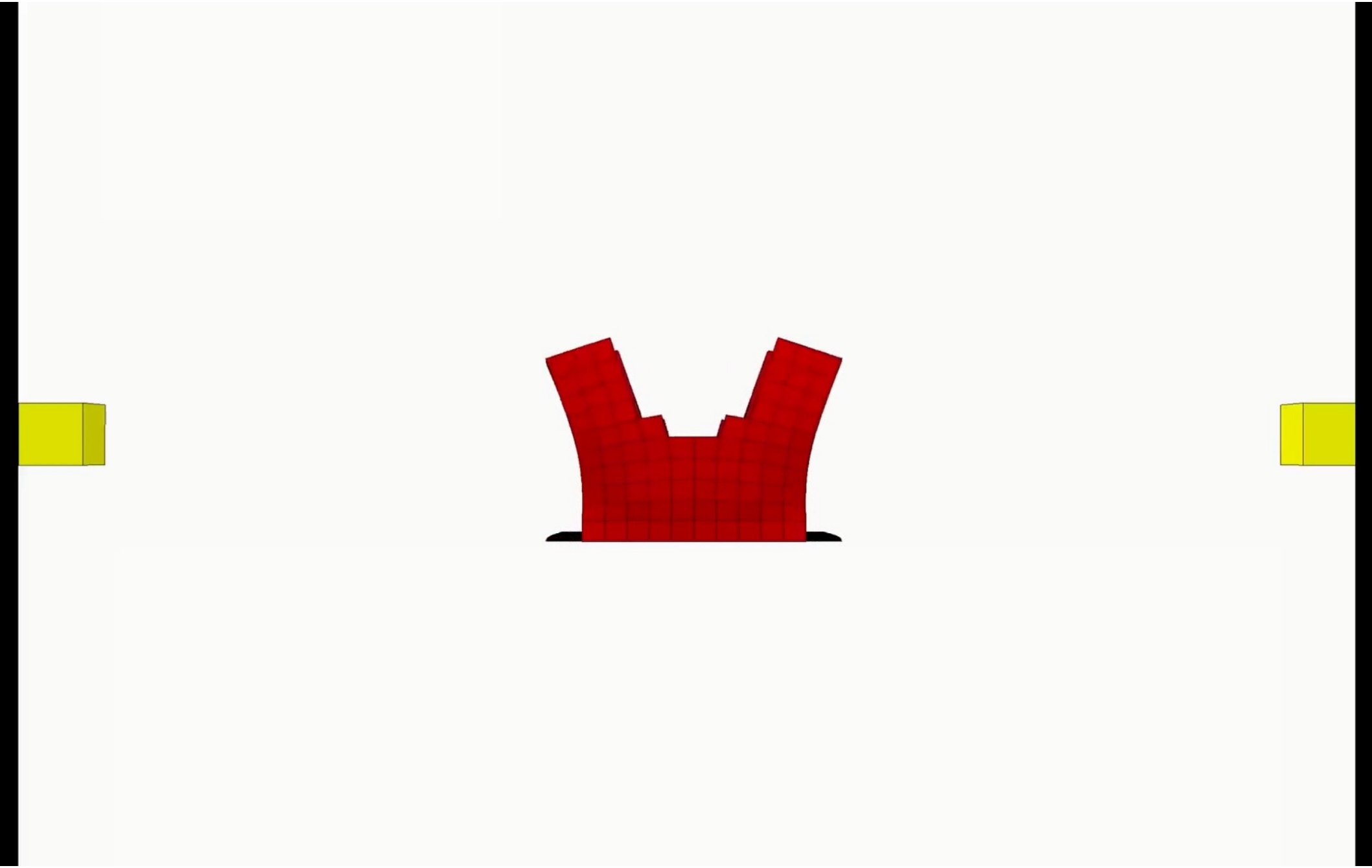


Red tissue expands



Blue tissue shrinks

# Soft materials:



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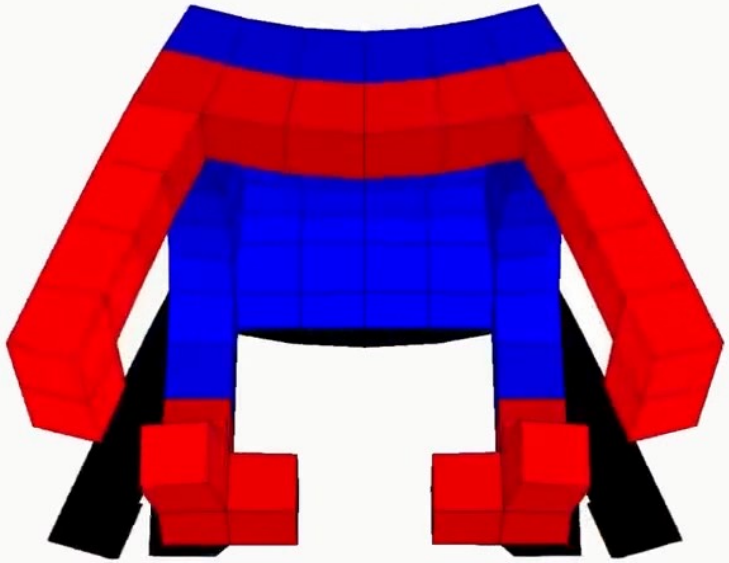


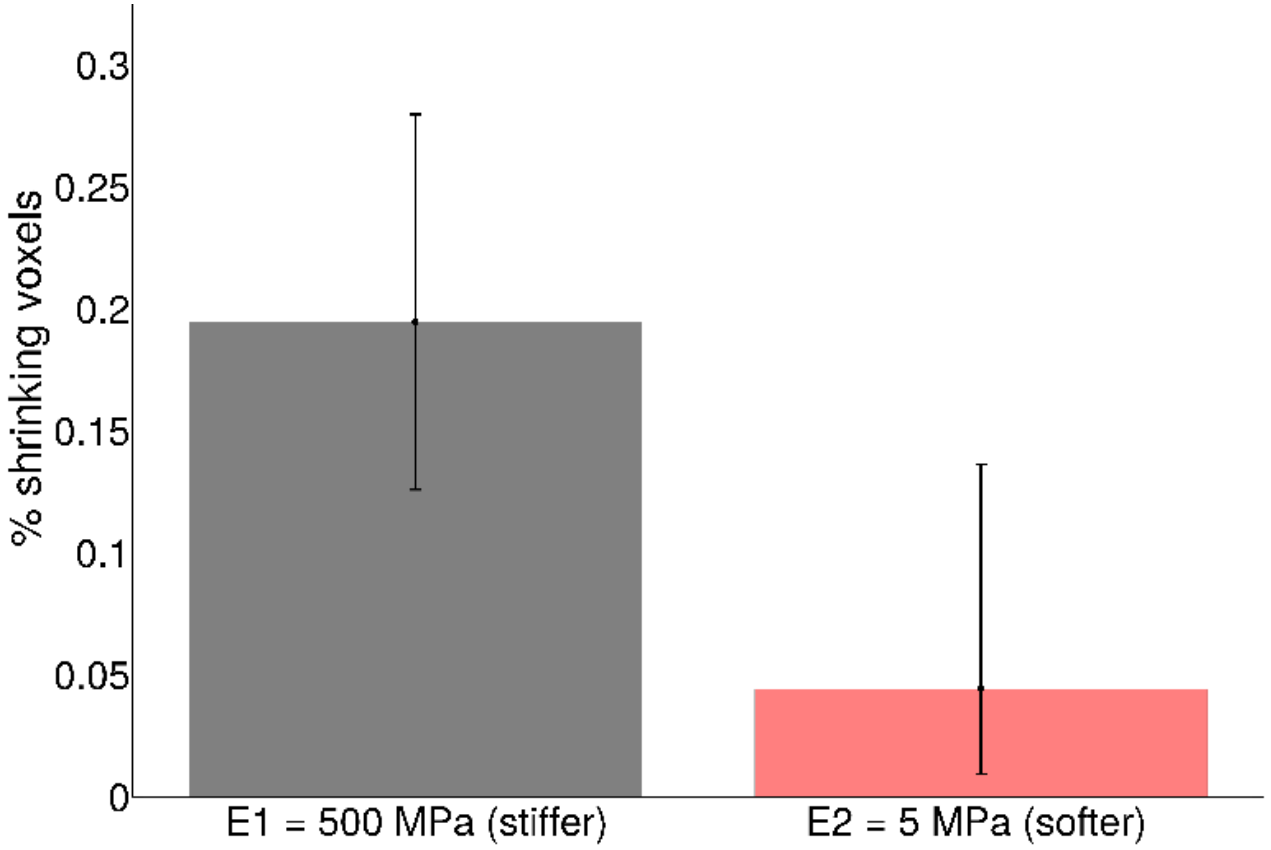
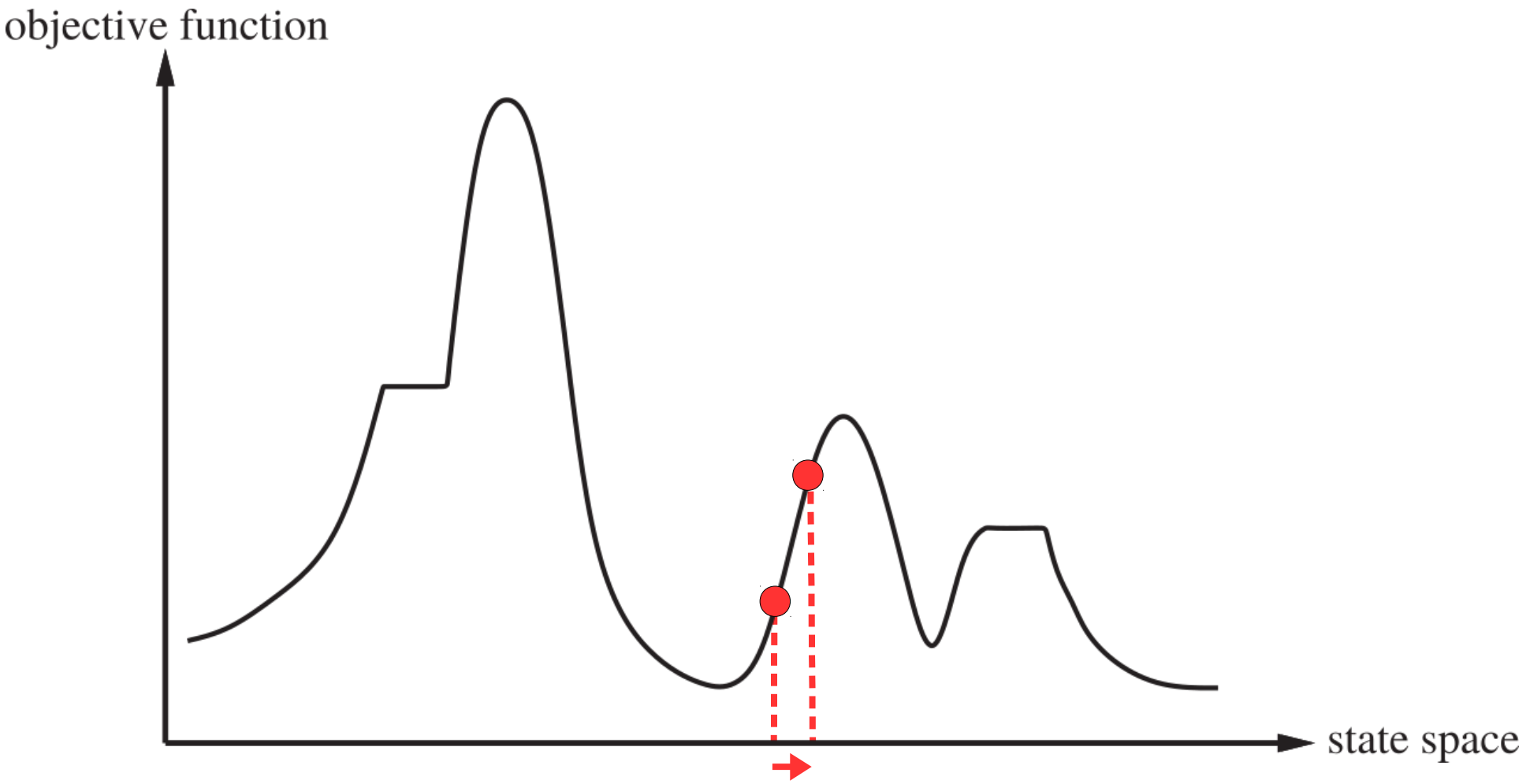
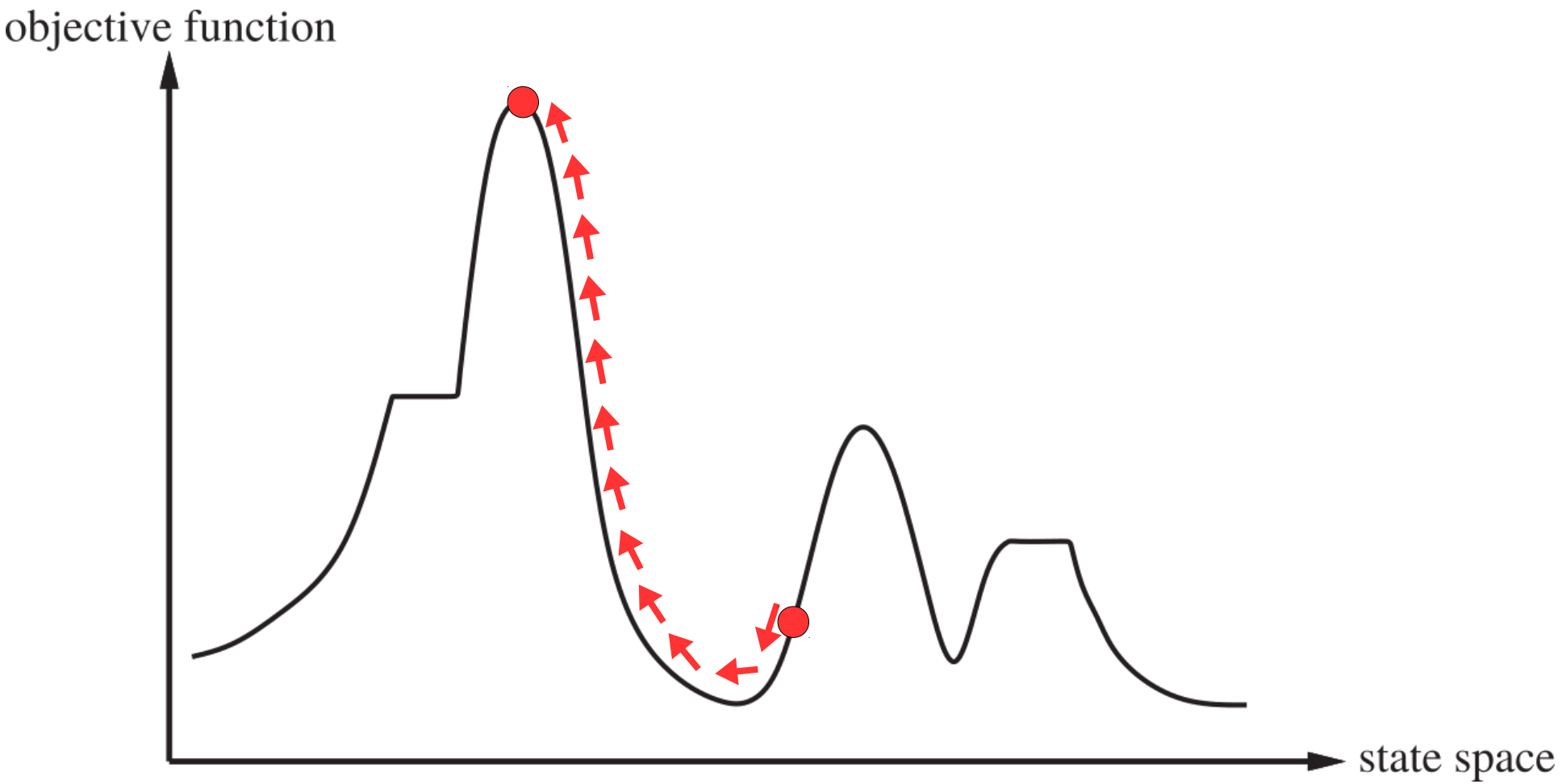


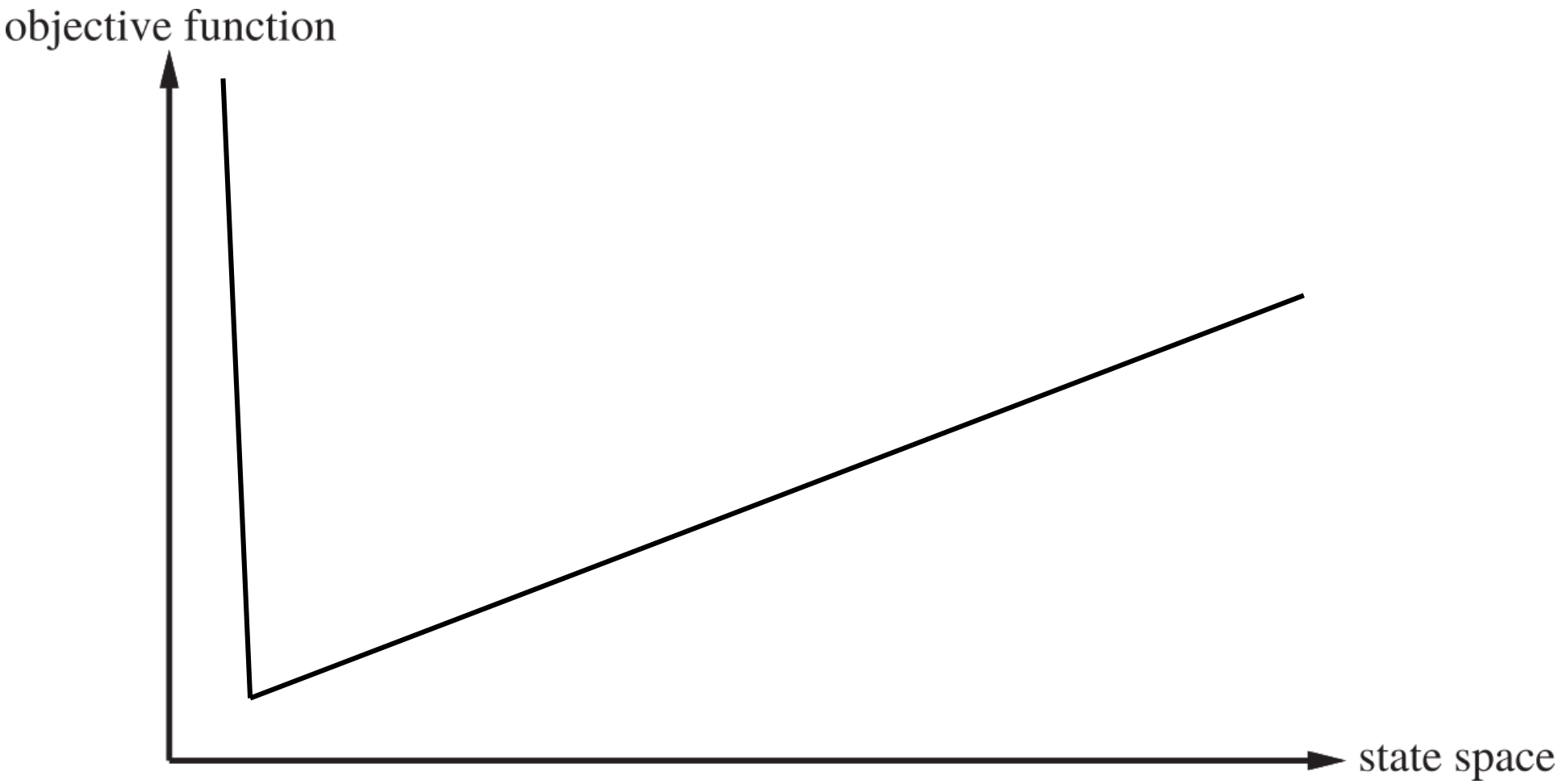

Figure 5: Stiffer robots tend to employ significantly more shrinking voxels than softer ones ($p < 0.002$), in the attempt to actively control the shape.

# Deceptive Fitness Landscapes

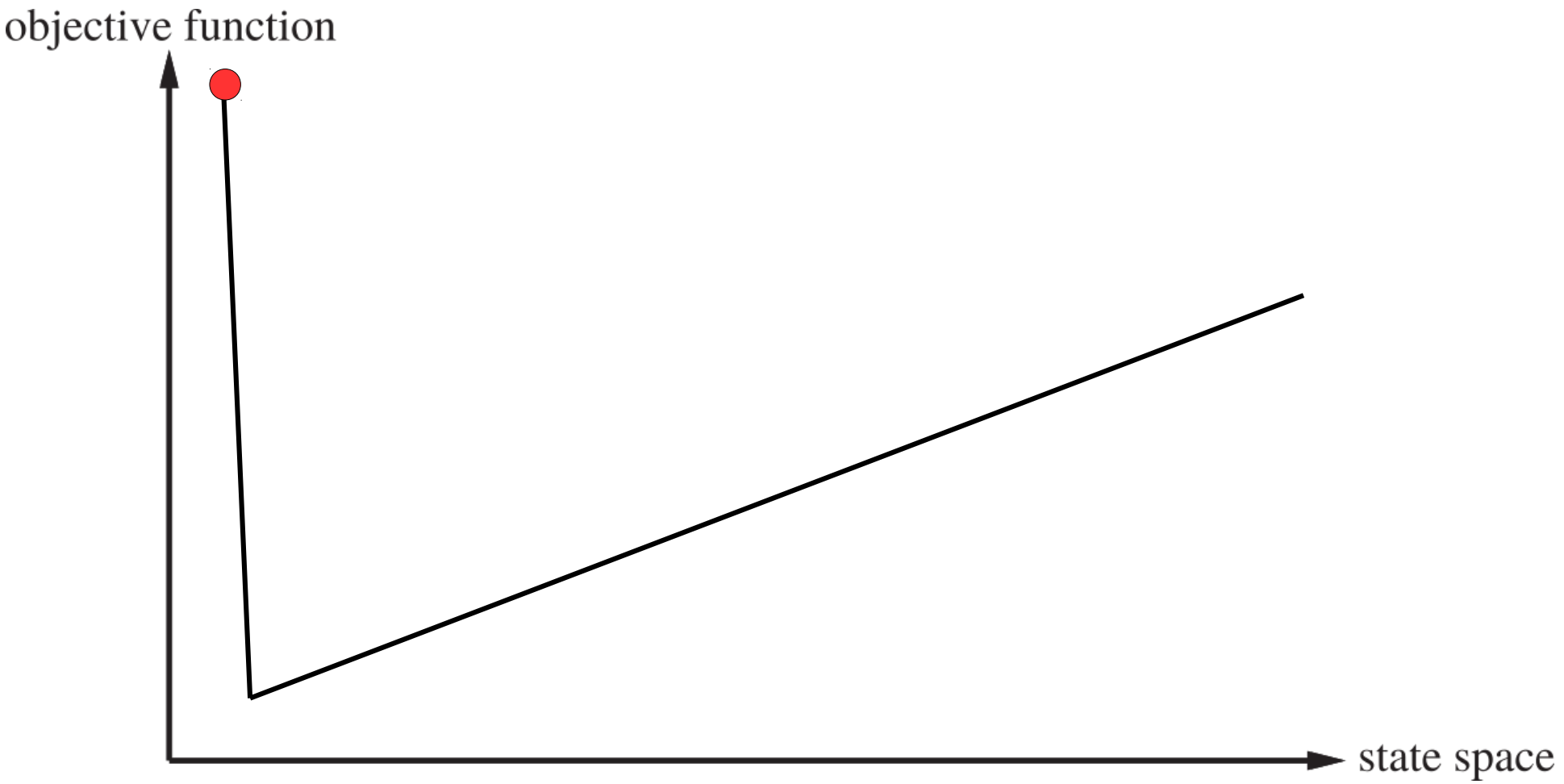

objective function
state space


objective function
state space

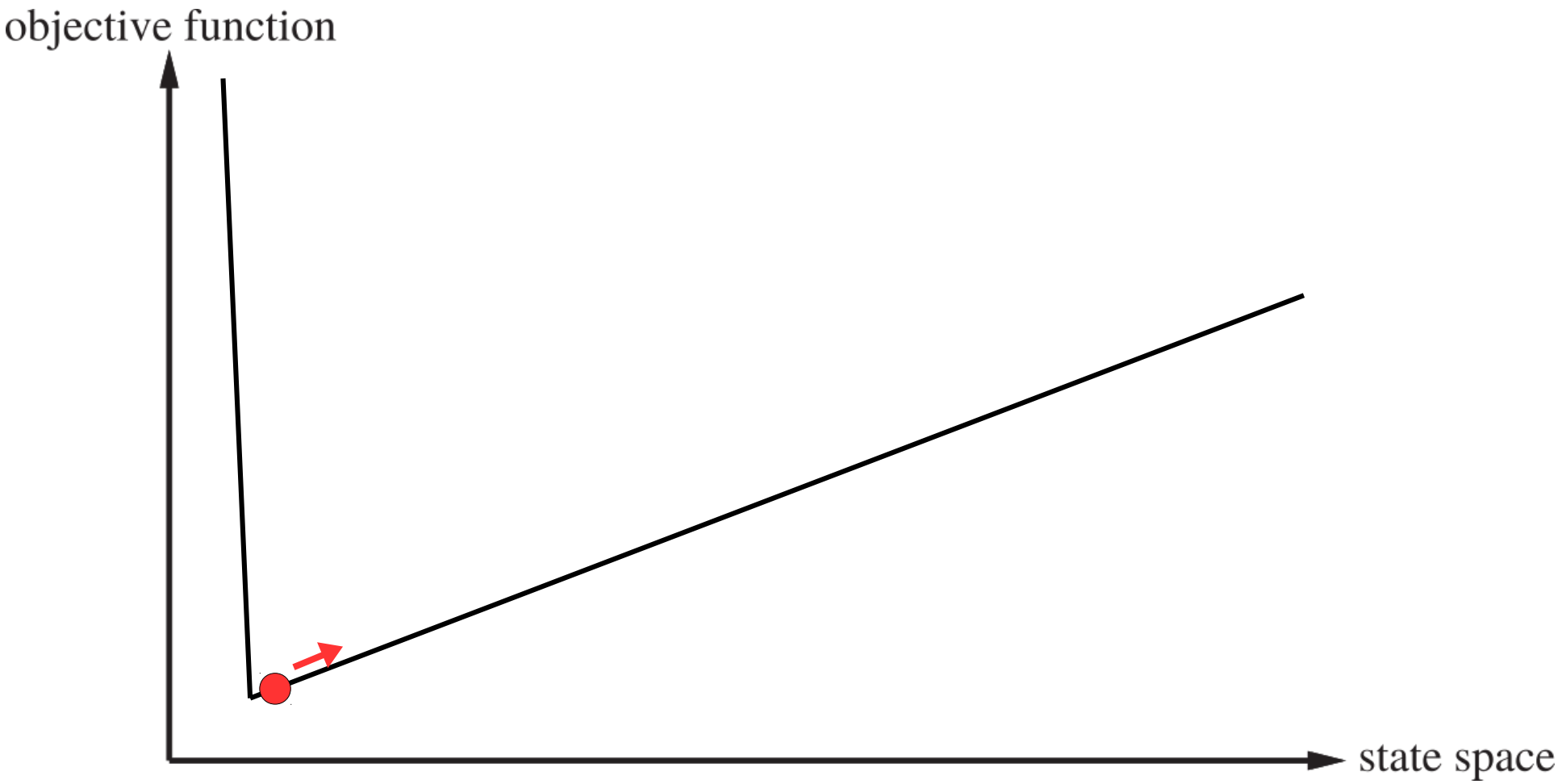
# deceptive fitness landscape

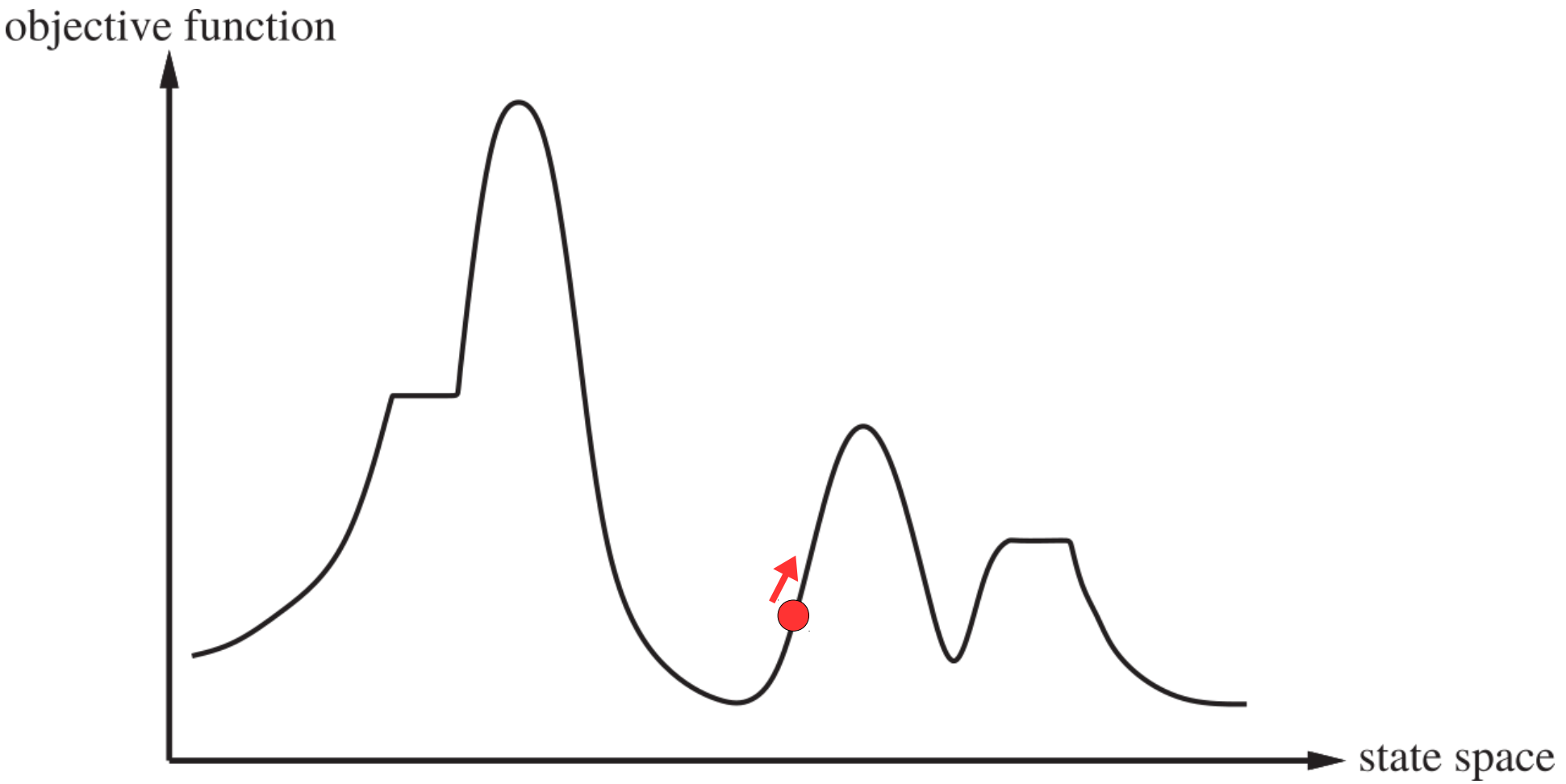


# deceptive fitness landscape



# deceptive fitness landscape




objective function
state space

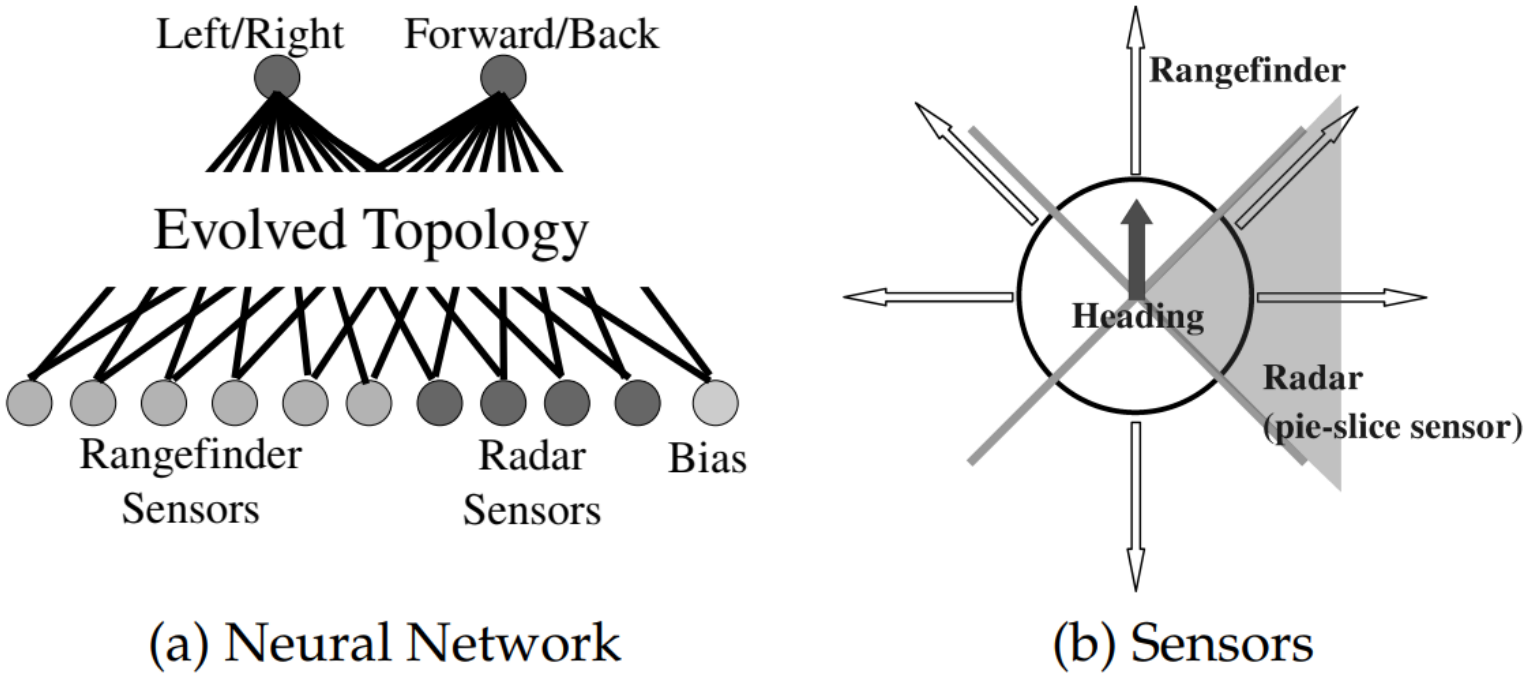
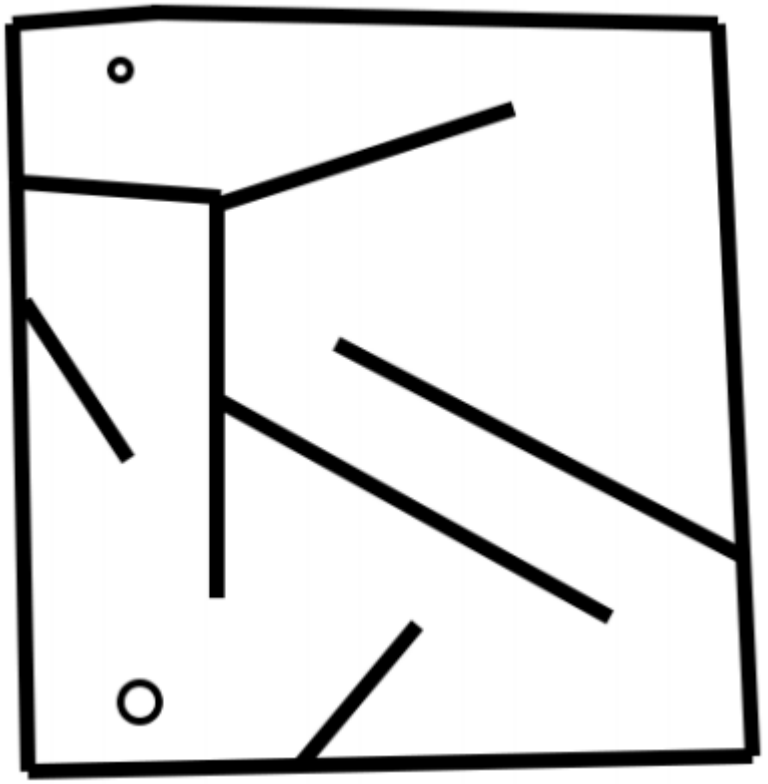
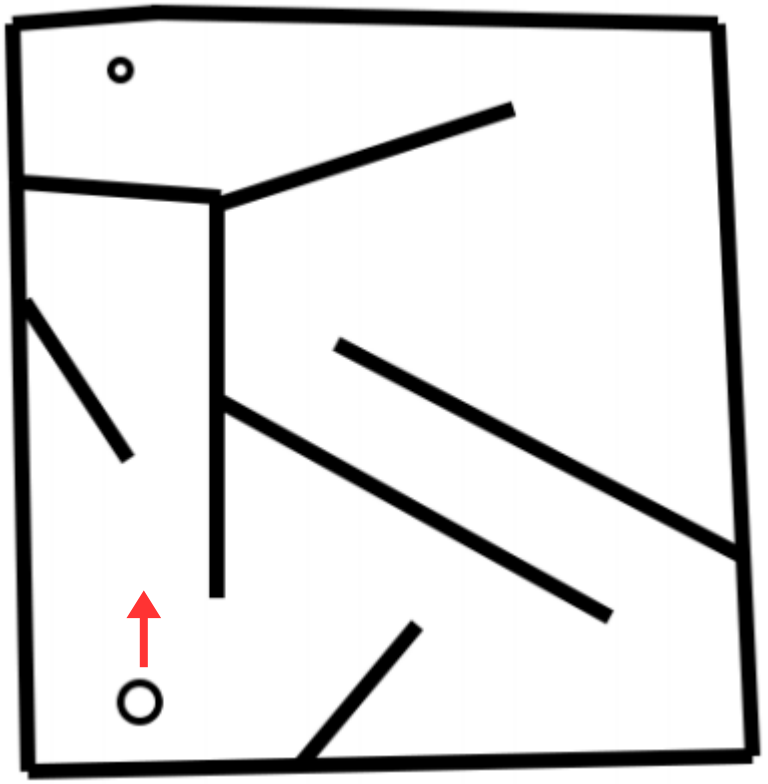
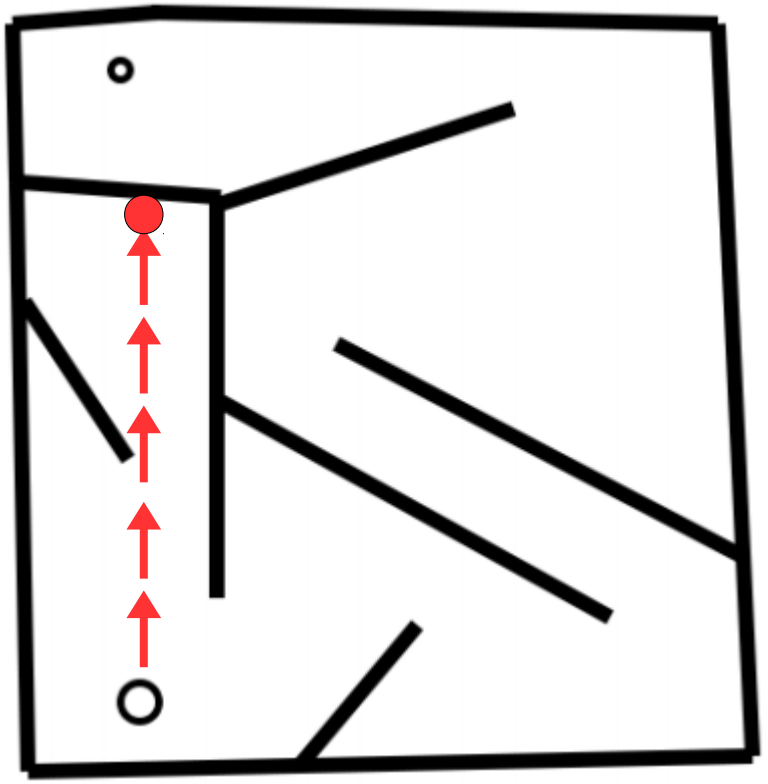
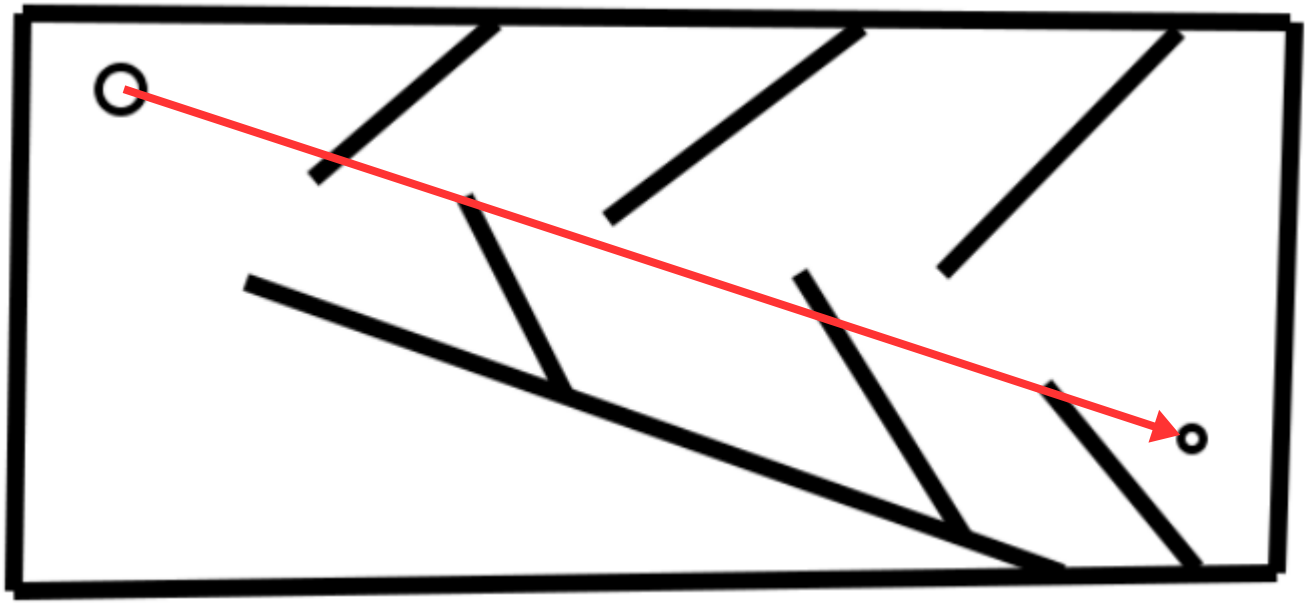


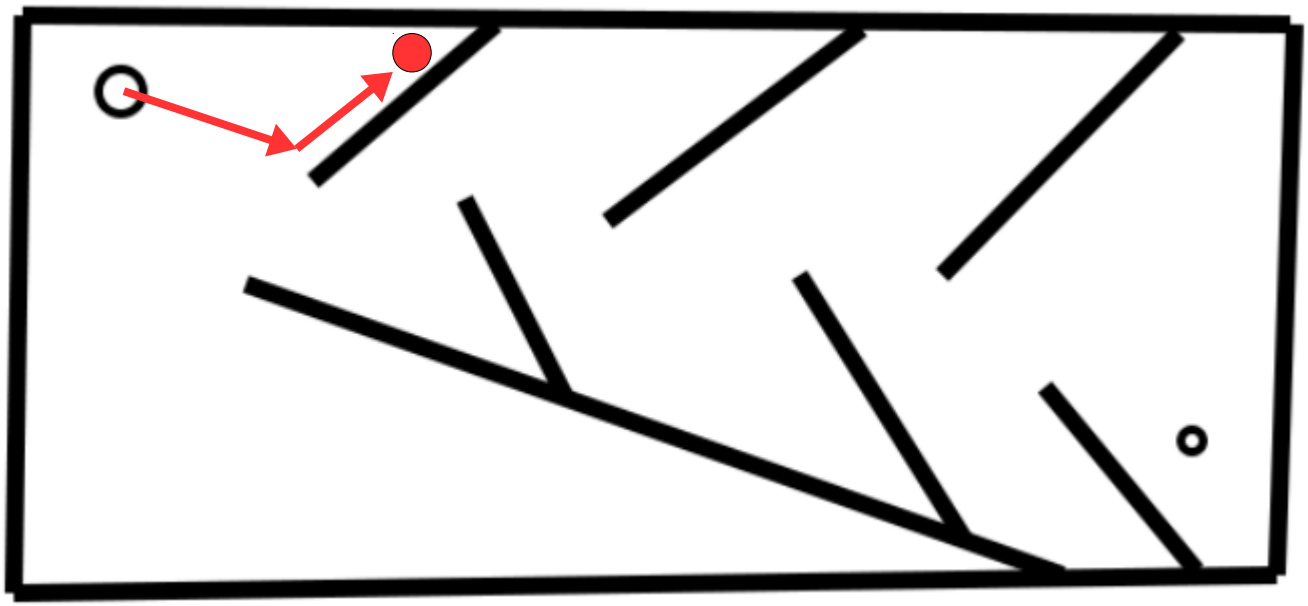

Figure 1: **Maze Navigating Robot.** The artificial neural network that controls the maze navigating robot is shown in (a). The layout of the sensors is shown in (b). Each arrow outside of the robot's body in (b) is a rangefinder sensor that indicates the distance to the closest obstacle in that direction. The robot has four pie-slice sensors that act as a compass towards the goal, activating when a line from the goal to the center of the robot falls within the pie-slice. The solid arrow indicates the robot's heading.

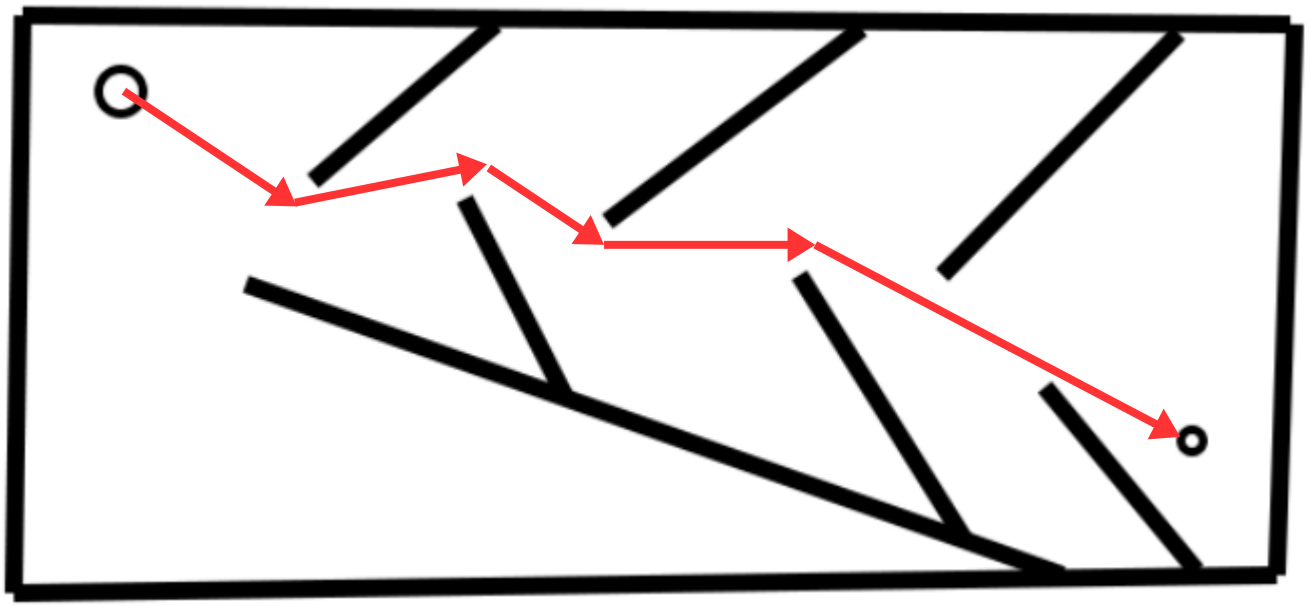




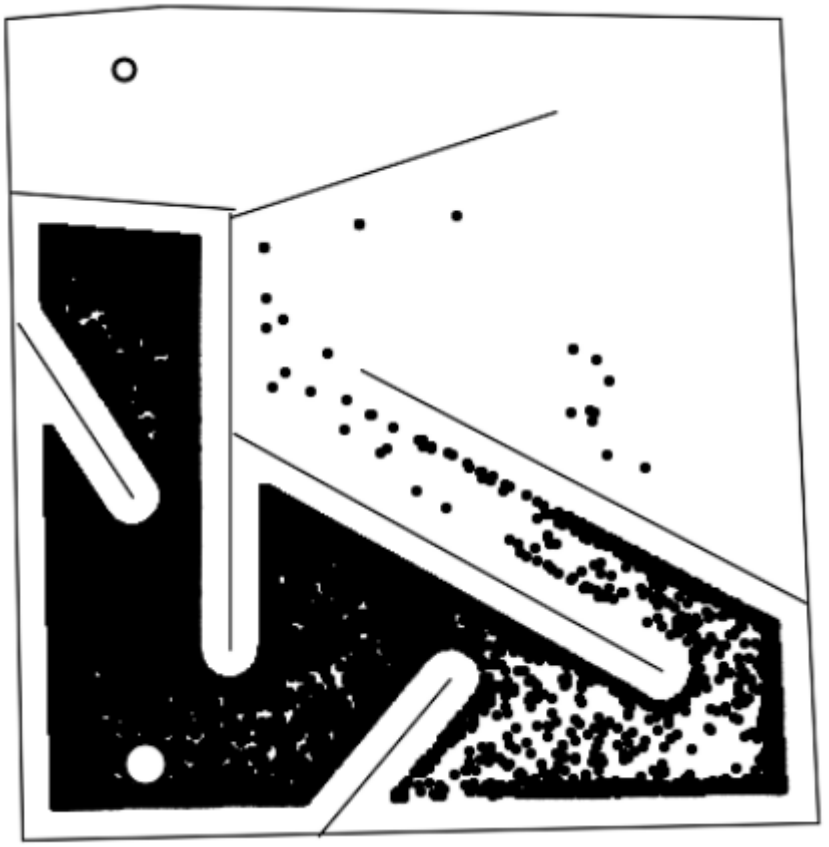








# Hard Map Fitness



# Abandoning Objectives: Evolution through the Search for Novelty Alone

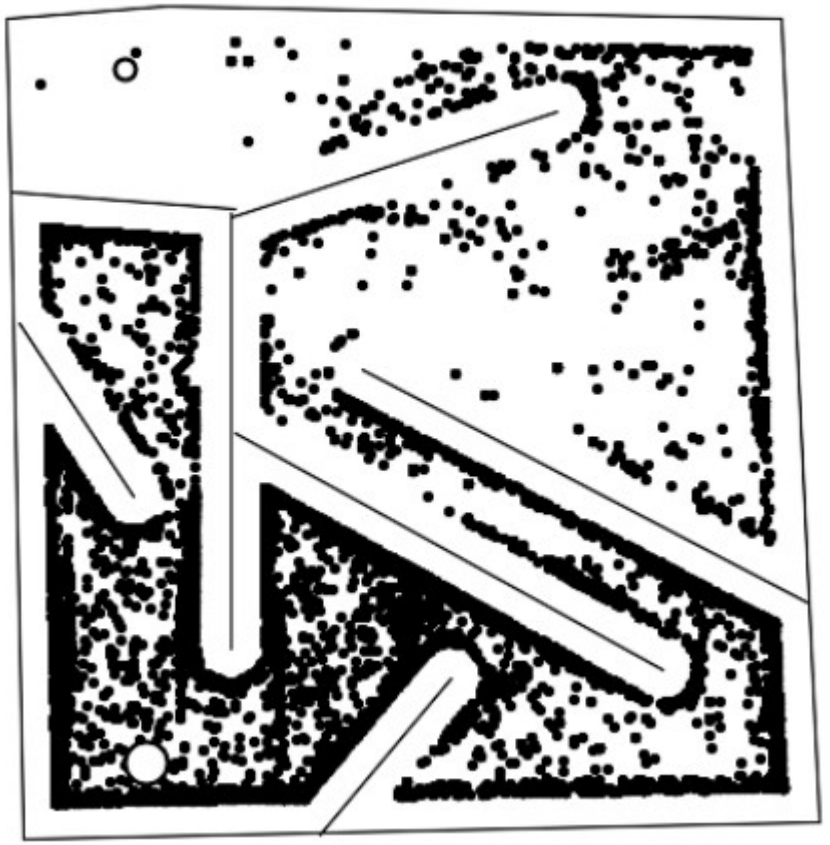
Joel Lehman and Kenneth O. Stanley

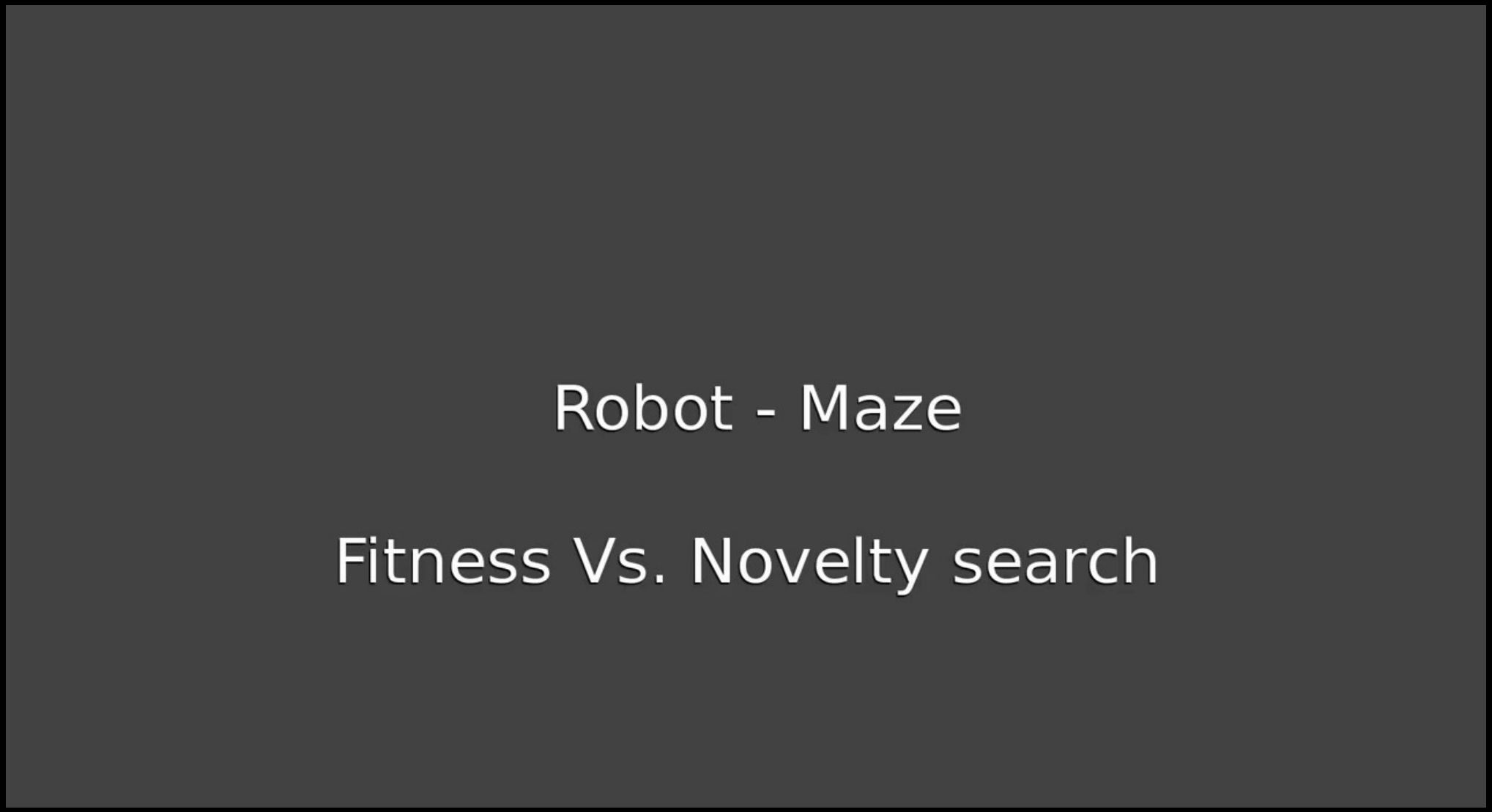
A simple measure of sparseness at a point is the average distance to the $k$-nearest neighbors of that point, where $k$ is a fixed parameter that is determined experimentally. If the average distance to a given point's nearest neighbors is large then it is in a sparse area; it is in a dense region if the average distance is small. The sparseness $\rho$ at point $x$ is given by

$$\rho(x) = \frac{1}{k} \sum_{i=0}^{k} \text{dist}(x, \mu_i), \tag{1}$$

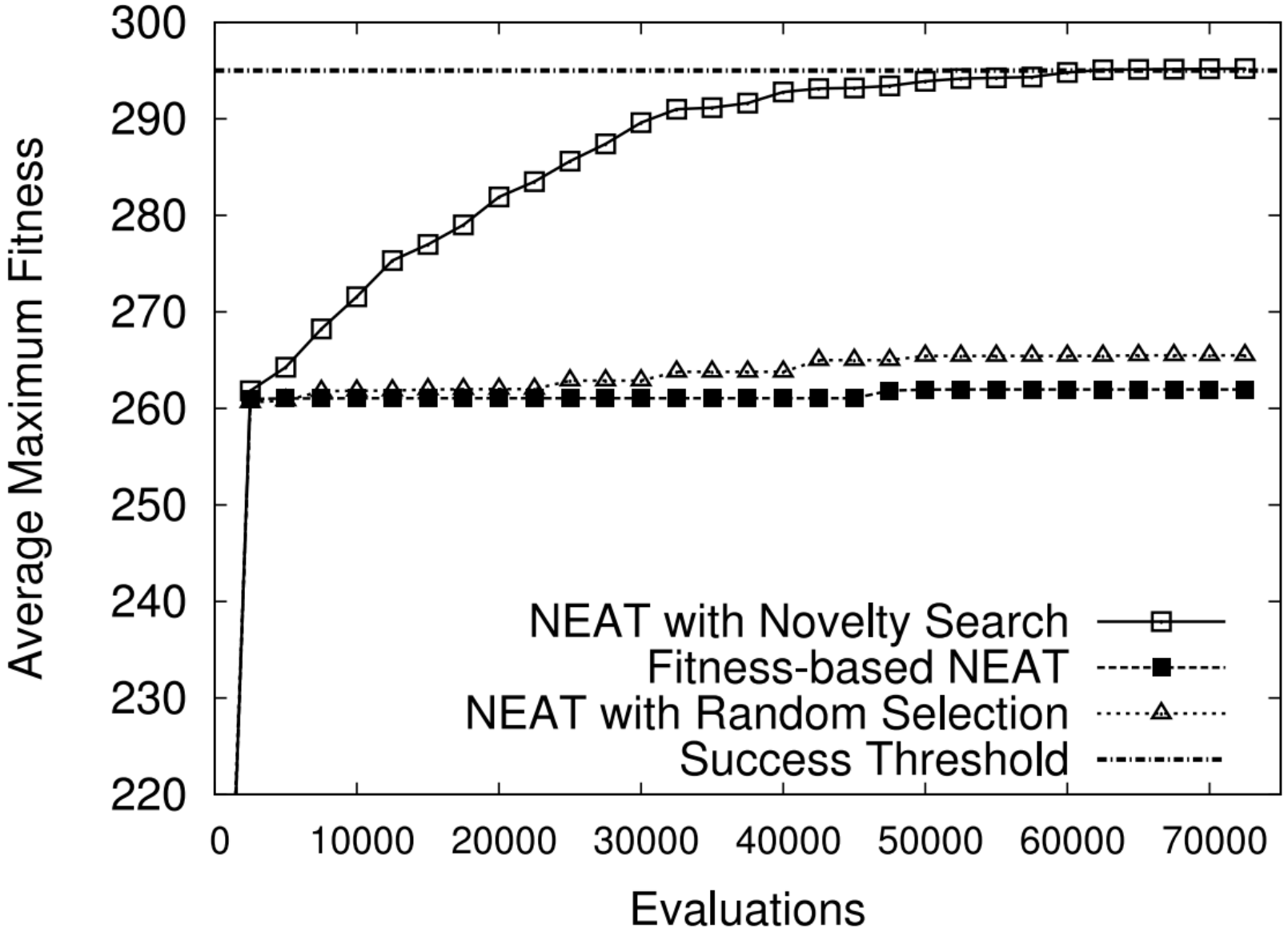
where $\mu_i$ is the $i$th-nearest neighbor of $x$ with respect to the distance metric *dist*, which is a domain-dependent measure of behavioral difference between two individuals in the search space. The nearest neighbors calculation must take into consideration individuals from the current population and from the permanent archive of novel individuals. Candidates from more sparse regions of this behavioral search space then receive higher novelty scores. It is important to note that this behavior

# Hard Map Novelty



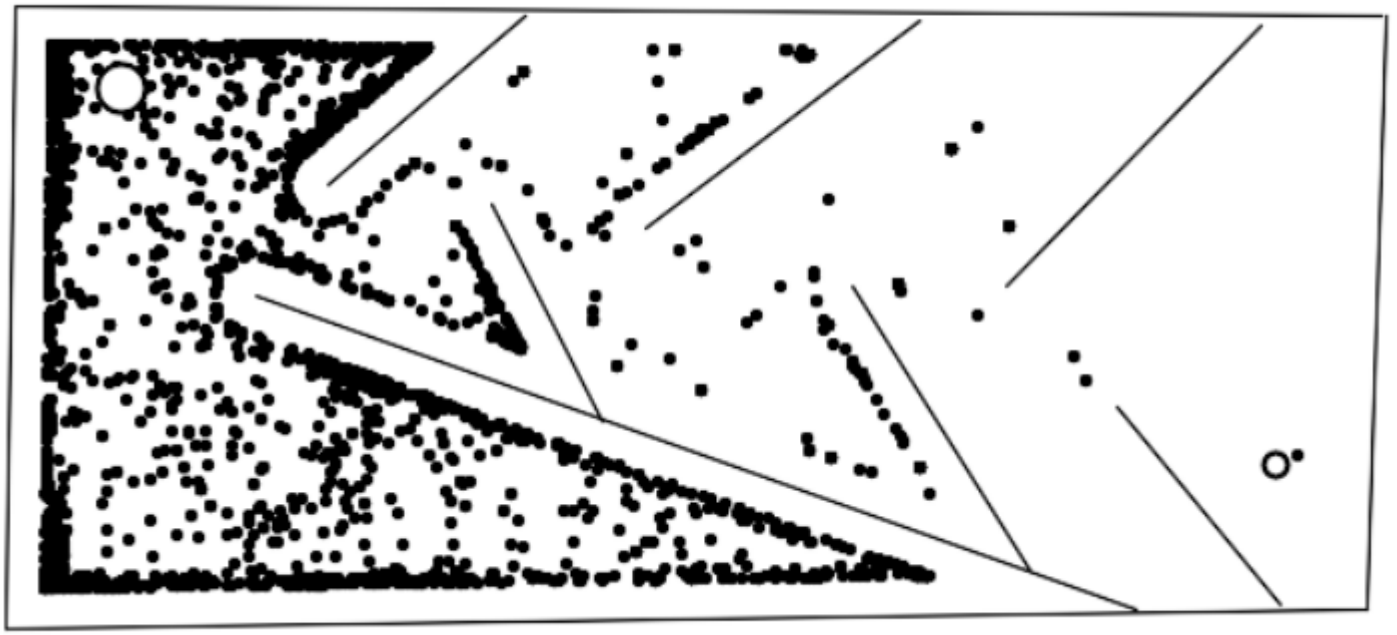



[Methenitis et al 2015]

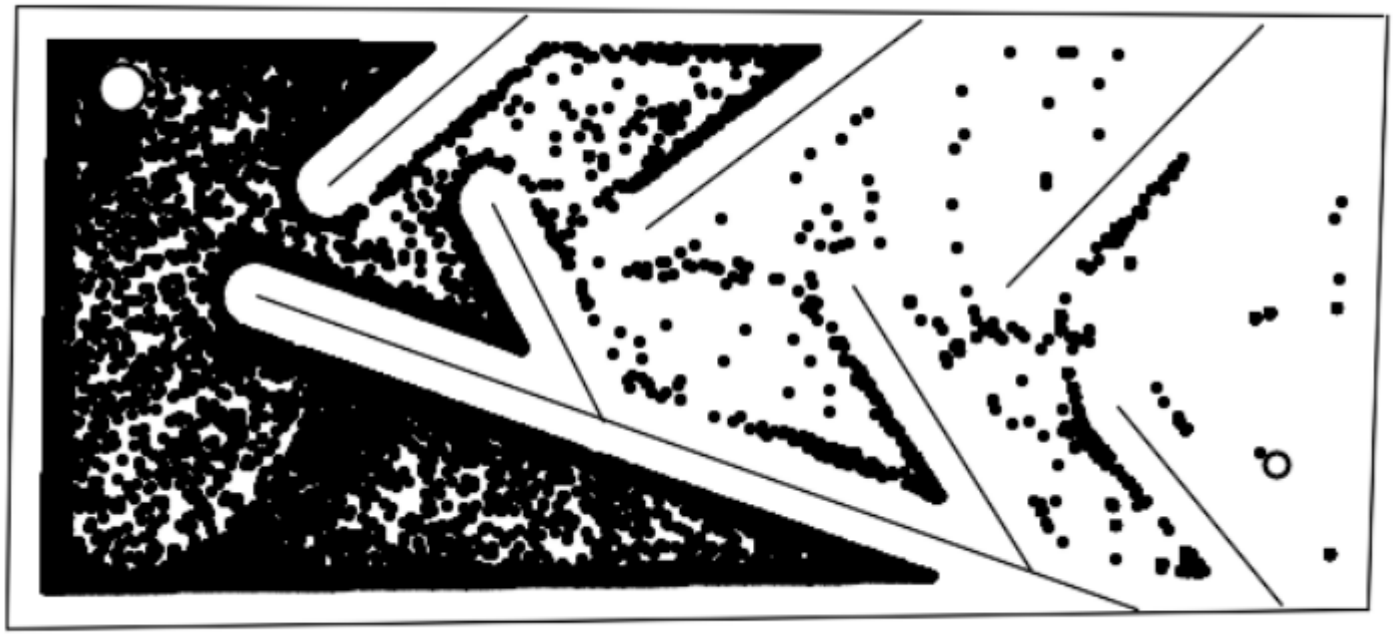

Average Maximum Fitness
300
290
280
270
260
250
240
230
220
0
10000
20000
30000
40000
50000
60000
70000
Evaluations
NEAT with Novelty Search
Fitness-based NEAT
NEAT with Random Selection
Success Threshold

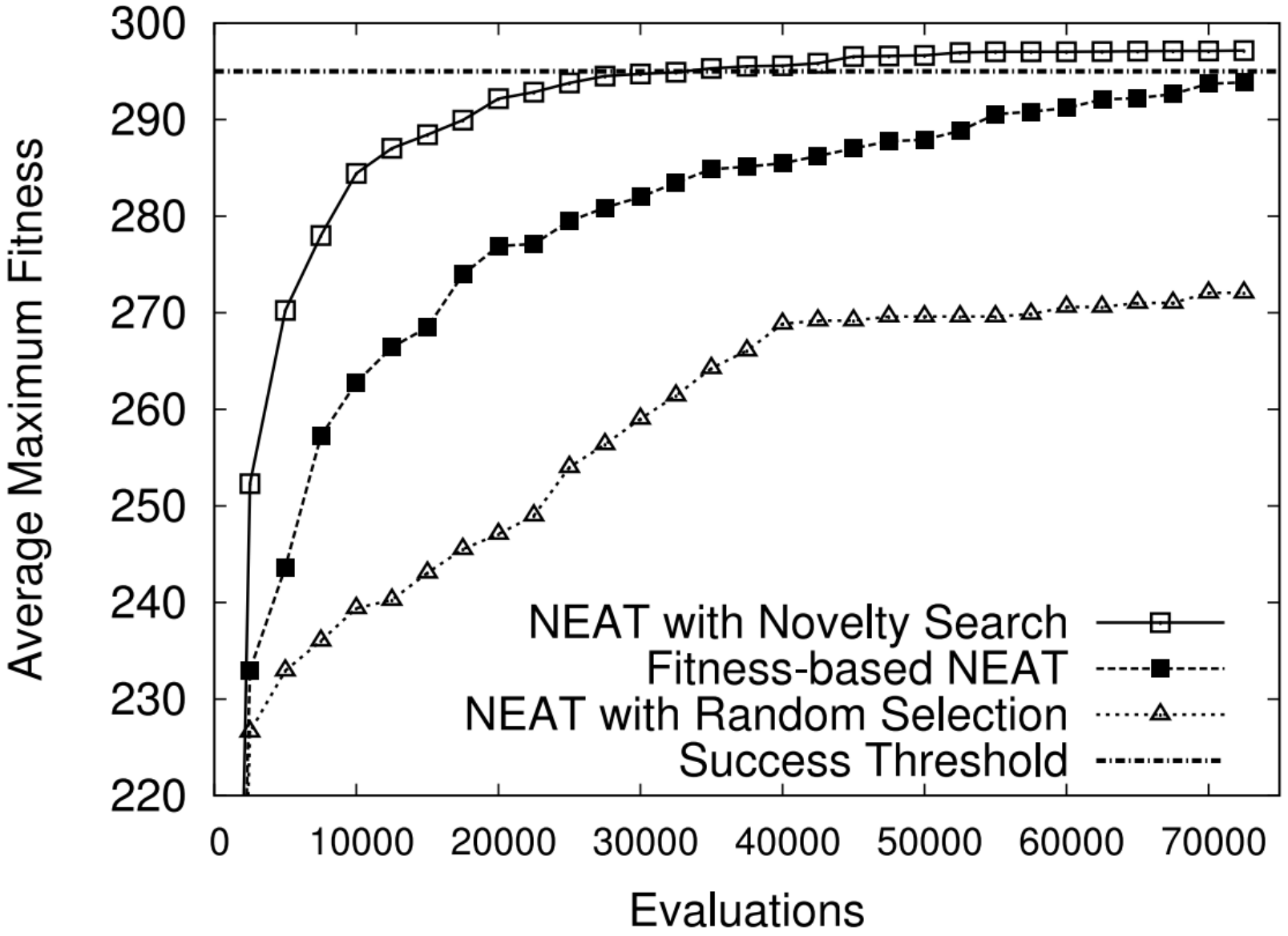
(b) Hard Map

# Medium Map Novelty

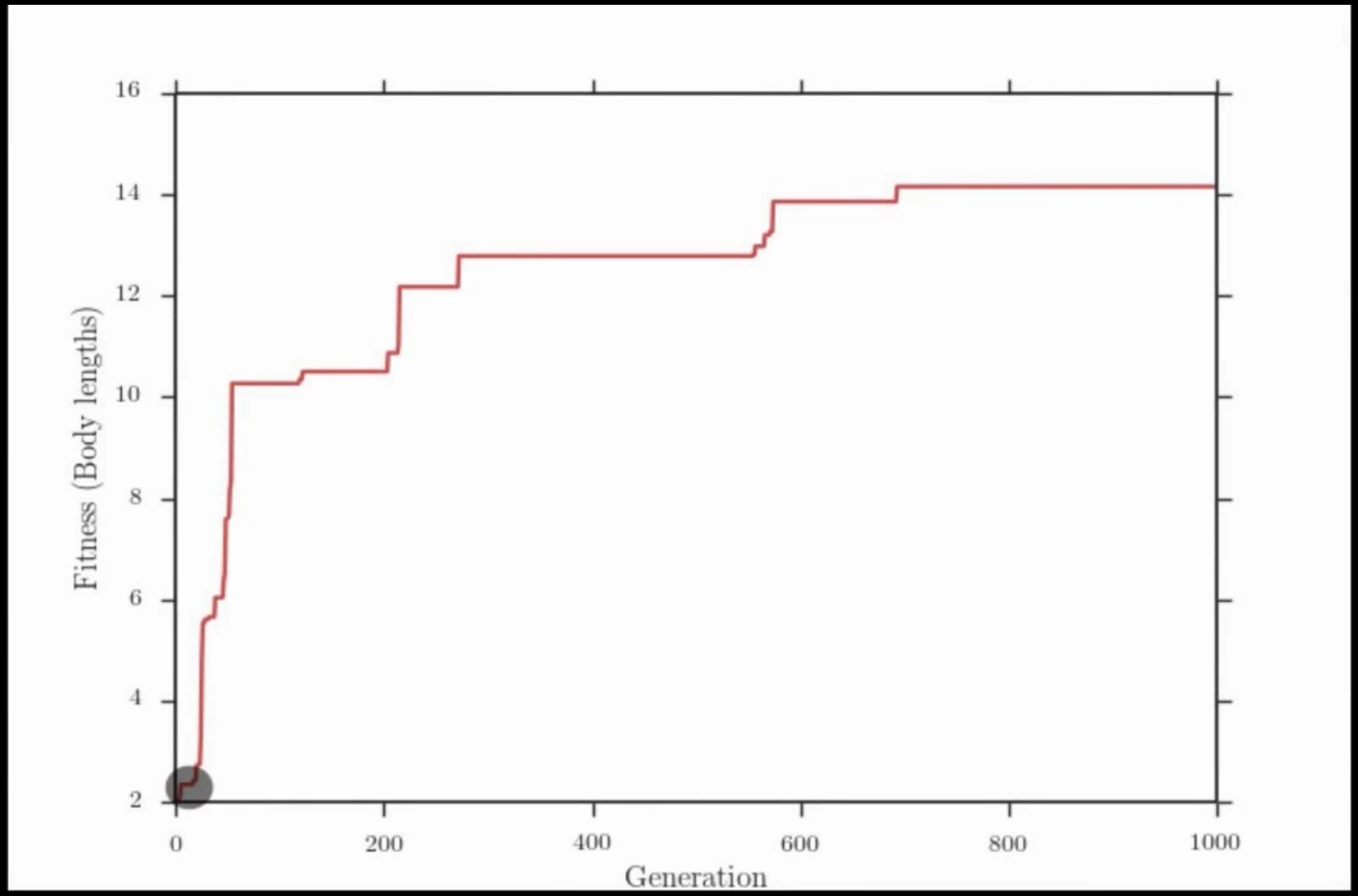


# Medium Map Fitness

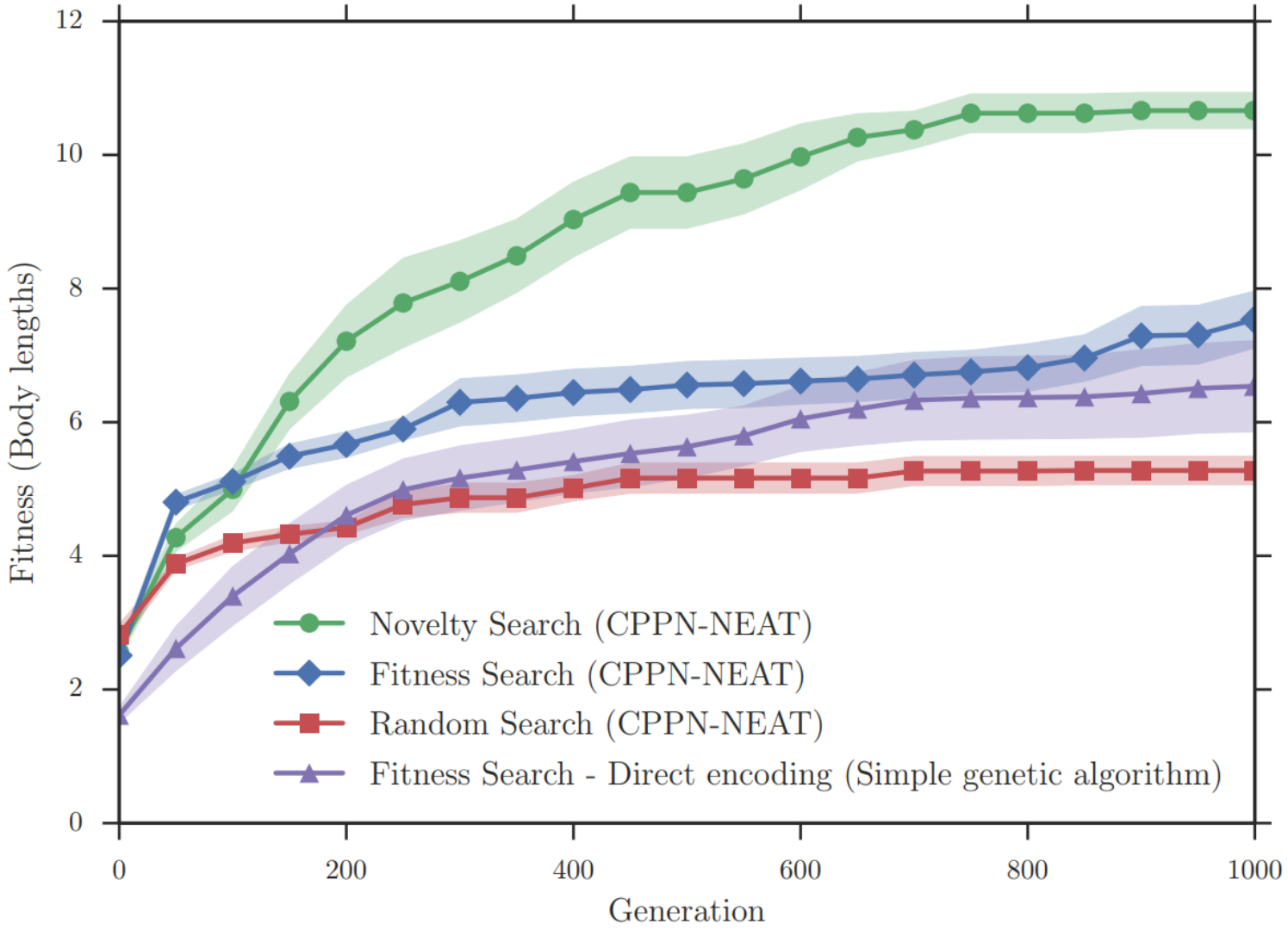



Average Maximum Fitness
300
290
280
270
260
250
240
230
220
0
10000
20000
30000
40000
50000
60000
70000
Evaluations
NEAT with Novelty Search
Fitness-based NEAT
NEAT with Random Selection
Success Threshold

(a) Medium Map




[Methenitis et al 2015]

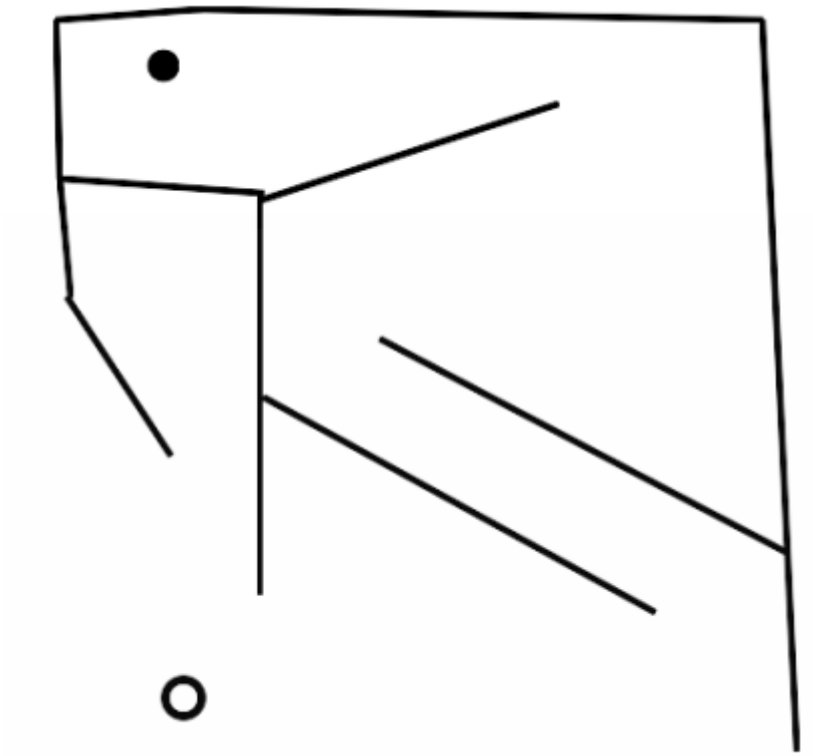


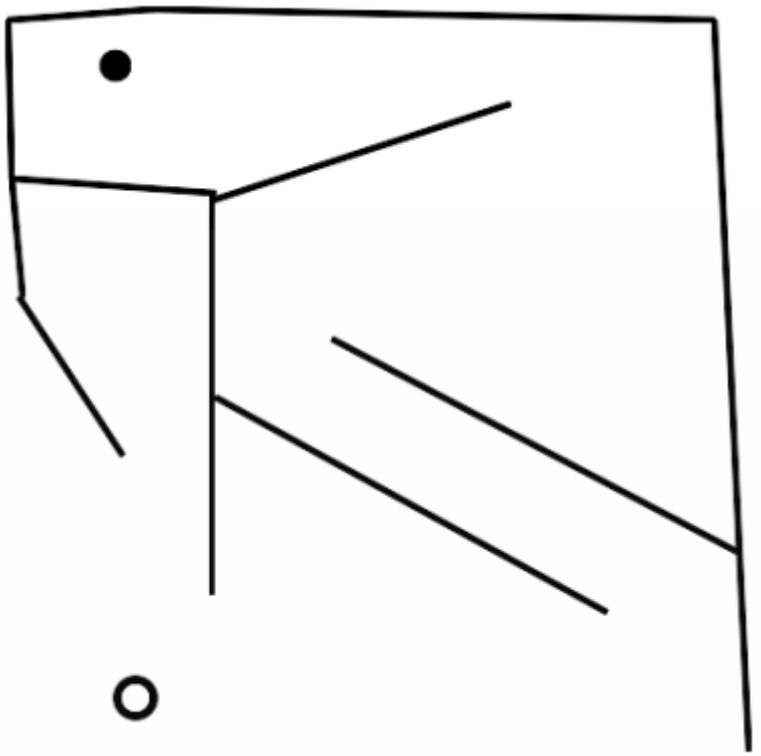

[Methenitis et al 2015]

Space soft robots

Evolution under variant gravity levels

[Methenitis et al 2015]





novelty search solved the maze only five times out of 100, which is not significantly better than fitness-based NEAT, which solved the maze two times out of 100. This result confirms the hypothesis that constraining the space of possible behaviors is important in some domains for novelty search to be efficient. However, fitness fares no better, highlighting that fitness-based search is not necessarily a viable alternative even when novelty search is not not effective.