

GECCO



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Novelty Search for Soft Robotic Space Exploration

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SOFT ROBOTIC SPACE EXPLORATION

Exploration of extraterrestrial bodies

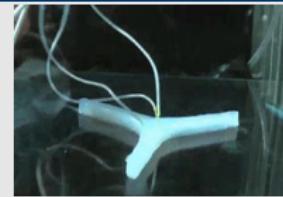
- ▶ One challenge, mobility
- ▶ Find ideas inspired by biology
- ▶ Locomotion strategy and morphology rarely connected

Soft Robots

- ▶ Inspired by nature
- ▶ Gravity-independent
- ▶ No restrictions in locomotion strategy



Soft Robots can have passive or active actuation



SOFT ROBOTS IN SIMULATION



VoxCad Simulator¹

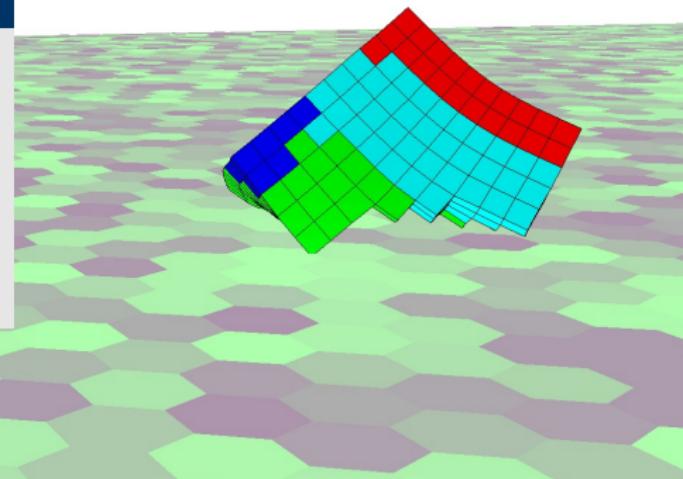
- ▶ Voxel modeling and analyzing software
- ▶ Physics engine extracted and used for the simulations

Simulation

- ▶ 3-D Grid, Voxels, Materials, Temperature

Possible solution space:

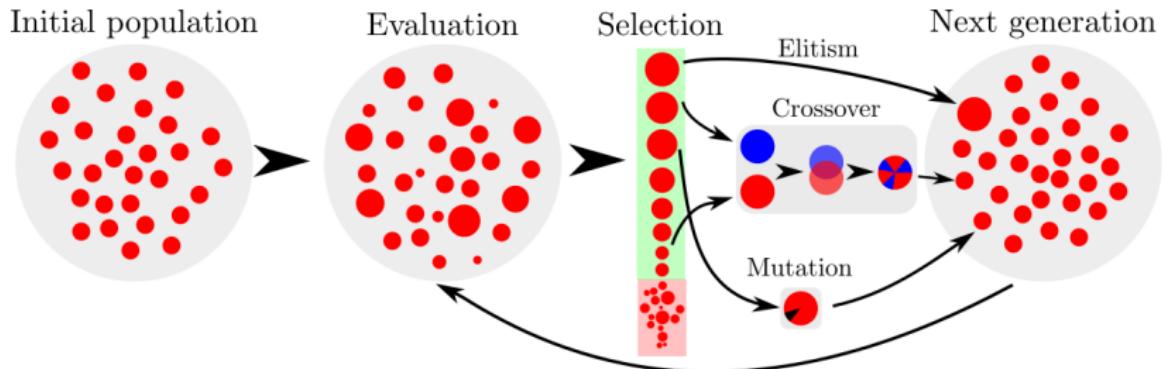
- ▶ for size 10^3 : **9.3×10^{698}**



¹ hiller2012dynamic.

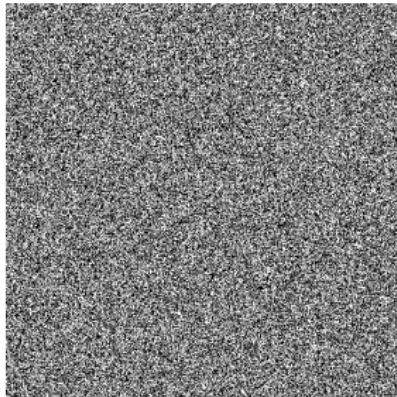
EVOLUTION OF SOFT ROBOTS BY NOVELTY SEARCH

Evolutionary algorithms

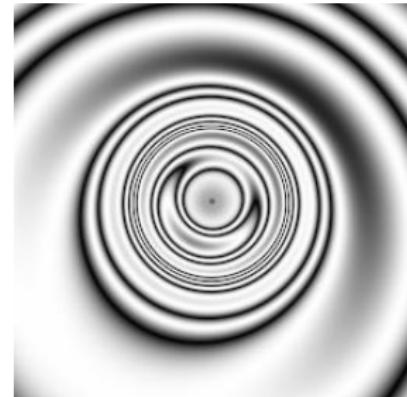


ENCODING SCHEMES

Direct Encoding



Generative Encoding

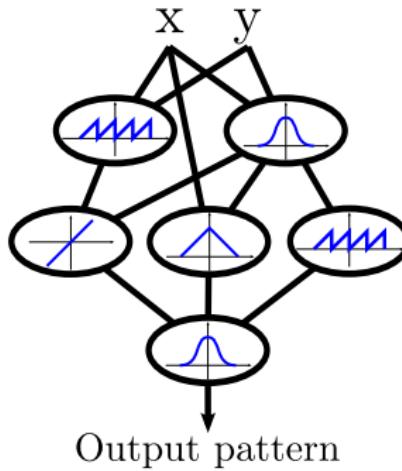


010101...111101
number of pixels

$f(\underbrace{x, y})$ = pixel value
coords.

COMPOSITIONAL PATTERN-PRODUCING NETWORK²

- ▶ Similar to artificial neural networks
- ▶ Large set of canonical activation functions



- ▶ Produce symmetrical and repetitive patterns
- ▶ Appropriate for problems with geometrical structure

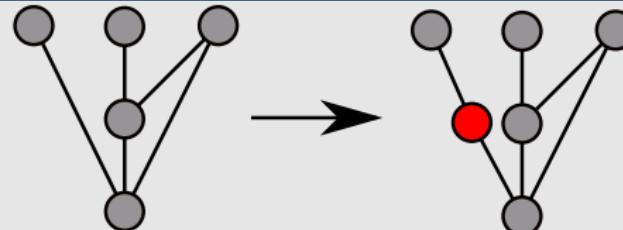
²stanley2007compositional.

NEUROEVOLUTION OF AUGMENTED TOPOLOGIES (NEAT)³

Some key points of this method are:

- ▶ Evolving neural network topologies along with weights
- ▶ Crossover between different topologies
- ▶ Structural innovation through speciation

Genetic Operations in NEAT:



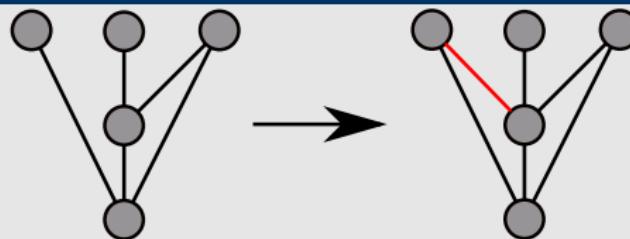
³stanley2002evolving.

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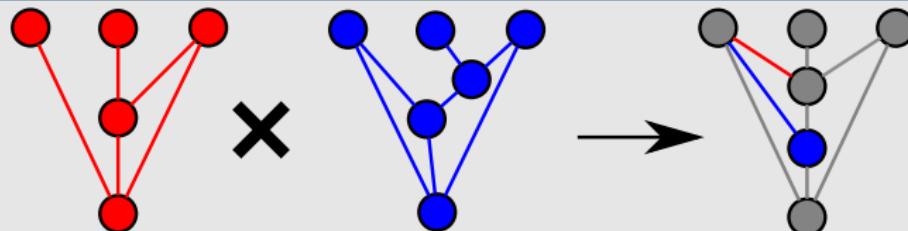


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Genetic Operations in NEAT:



EVOLUTION OF SOFT ROBOTS BY NOVELTY SEARCH⁴

What is novelty search:

- ▶ Traditionally fitness measures how good an individual is.
- ▶ Objective function can prevent evolution reaching the target.
- ▶ Abandon the objective
- ▶ Define a behavior metric
- ▶ Try finding novelty in behavior space

How to define novelty: Sparsity

$$s(x) = \frac{1}{k} \sum_{i=0}^k dist(x, b_i)$$

⁴lehman2011abandoning.

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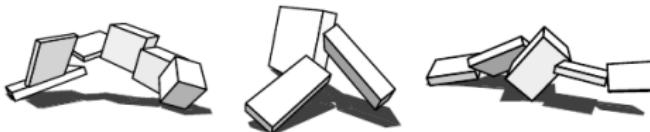
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RELATED WORK

*Evolving virtual creatures*⁵

- ▶ Rigid body parts, joints
- ▶ Evolution of the morphology and the control



*Evolving a diversity of virtual creatures through novelty search and local competition*⁶

- ▶ Novelty < Fitness
- ▶ Novelty search with global fitness competition > Fitness

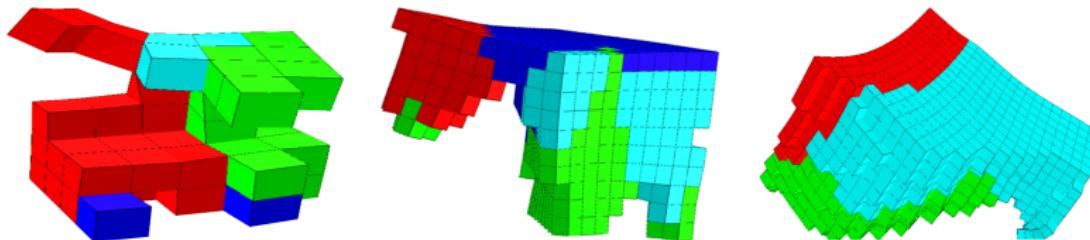
⁵sims1994evolving.

⁶lehman2011evolving.

RELATED WORK

Evolving soft robots with multiple materials and a powerful generative encoding⁷

- ▶ Generative encoding, Compositional pattern-producing network, CPPN
- ▶ Neuroevolution of augmenting topologies, NEAT



Evolution of soft robots by novelty search

⁷cheney2013unshackling.

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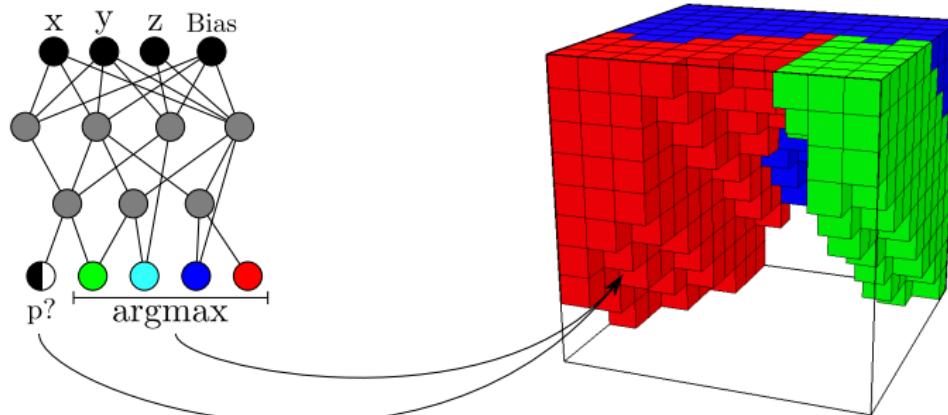
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CPPN-NEAT

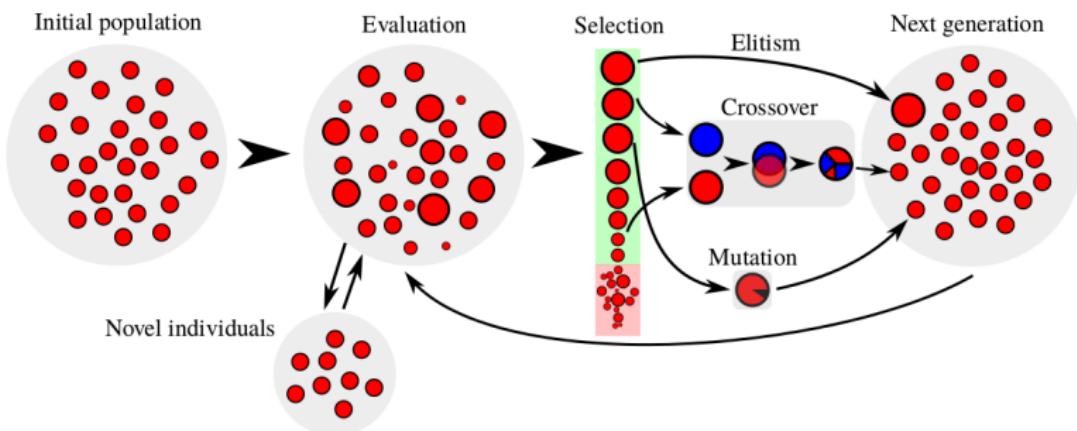
Evolving CPPNs with NEAT

- ▶ Each genome is represented by a CPPN
- ▶ This CPPN is queried for each input coordinate to output the existence and the type of the material.
- ▶ NEAT evolves these CPPNs



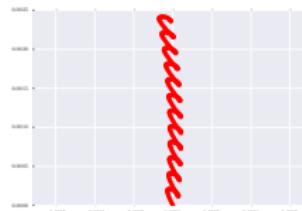
EXTENDING CPPN-NEAT WITH NOVELTY SEARCH

- ▶ Novelty takes the place of fitness
- ▶ Novel individuals stored in a list
- ▶ For each new individual in the population, check its novelty in respect to the stored novel individuals.

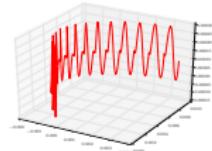


BEHAVIORS

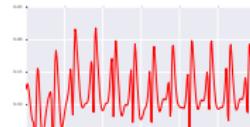
2D-traj.



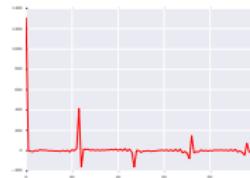
3D-traj.



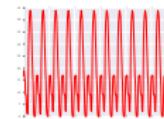
Pace



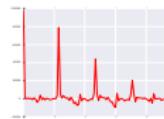
DFT-Pace



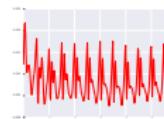
VTG



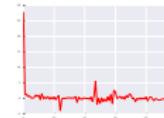
DFT-VTG



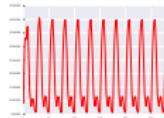
Pr



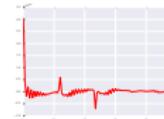
DFT-Pr



KE



DFT-KE



EXPERIMENTAL PHASE

Experiments:

- ▶ Population size: 30, Max. generations: 1000
- ▶ For lattice size/resolution: 5^3 , 7^3 , 10^3
- ▶ 10 different behavior metrics
- ▶ 4 variant gravity levels
- ▶ For both fitness and novelty search

Held at:

- ▶ $2 \times$ Servers (16-core & 8-core)
- ▶ $2 \times$ Desktops (4-core)

~ 22.500 hours of CPU time (single-thread)

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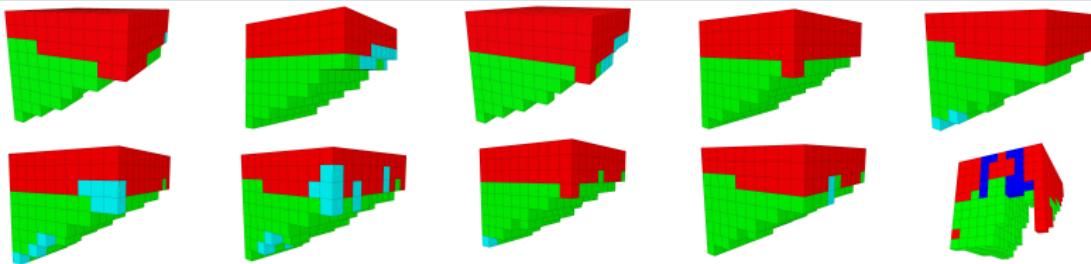
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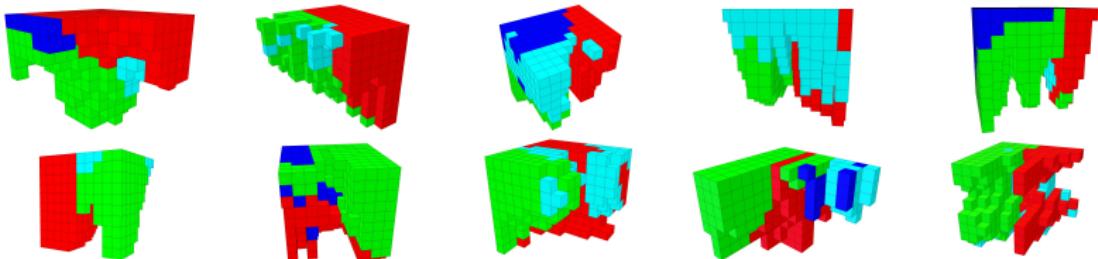
Conclusion

INCREASED DIVERSITY

Fitness-based Search - Champions every 100 generations:

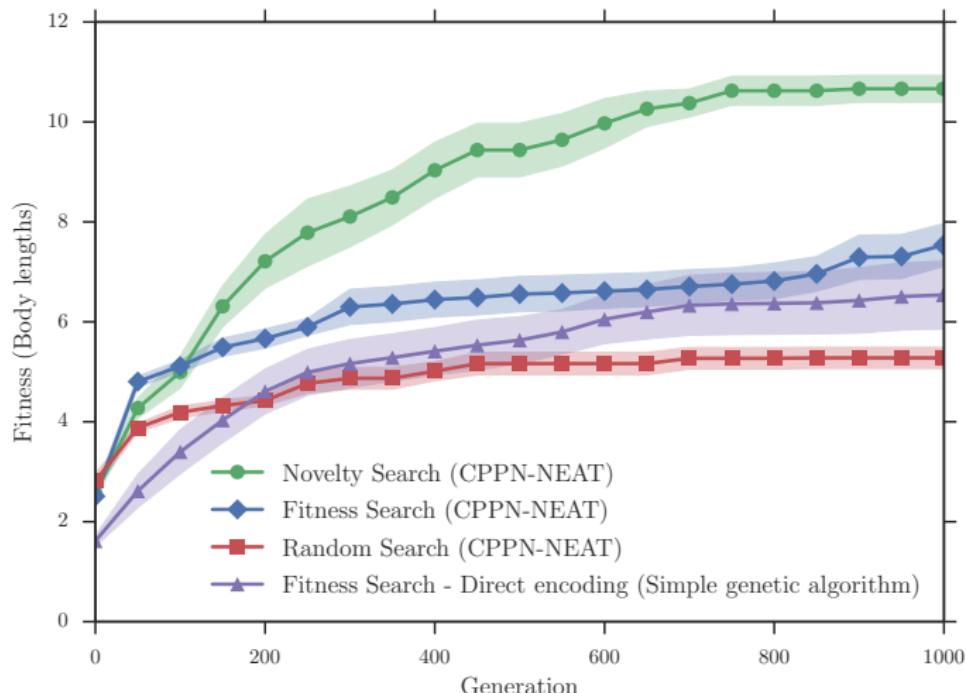


Novelty Search - Champions every 100 generations:



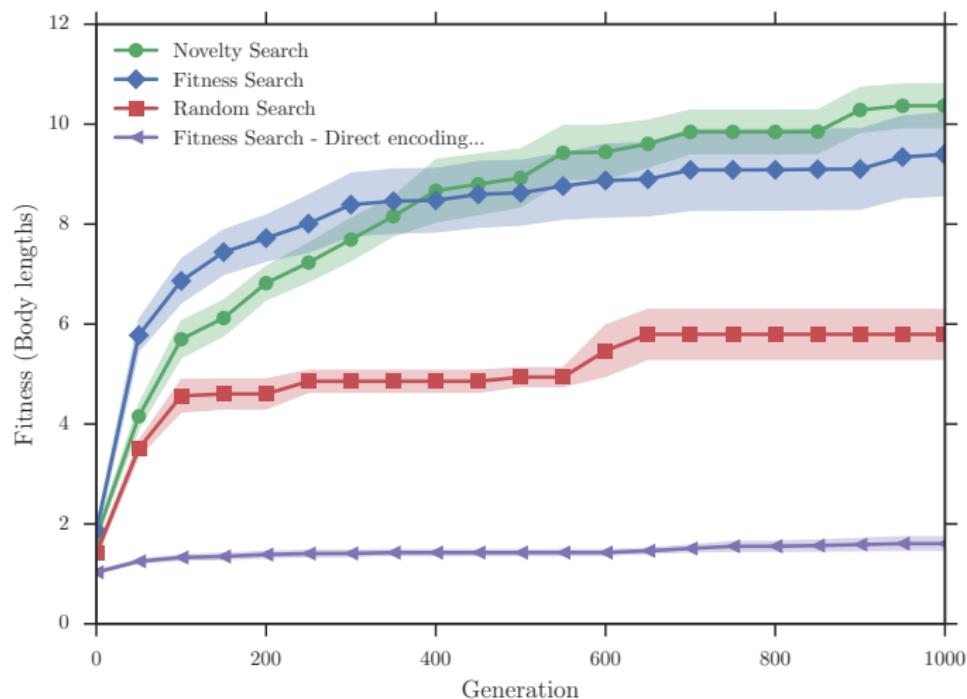
INCREASED PERFORMANCE

Best fitness so far, low-res. 5^3



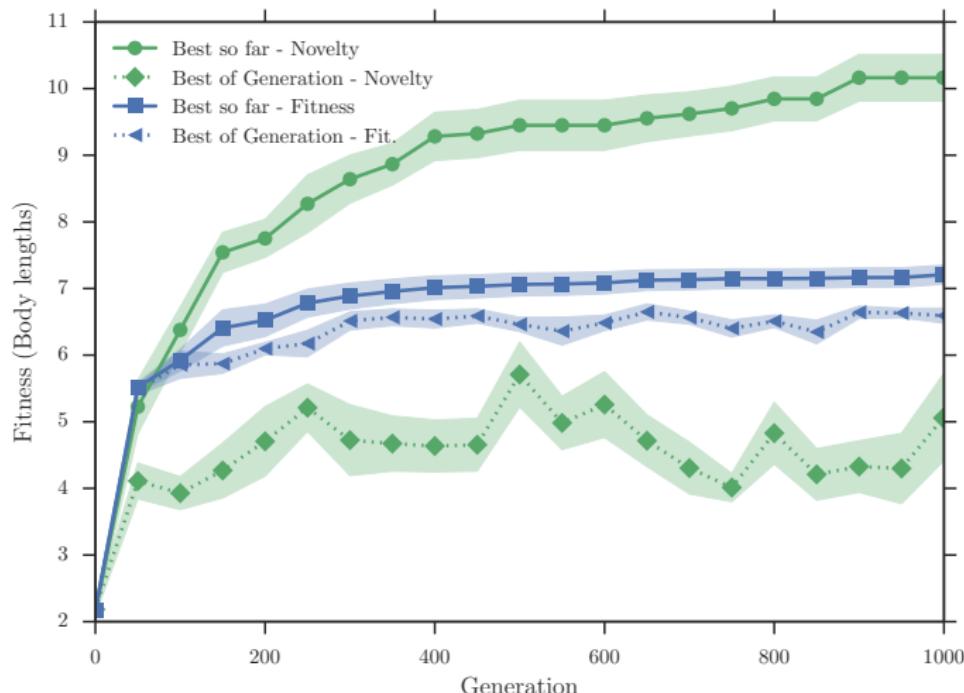
INCREASED PERFORMANCE

Best fitness so far, high-res. 10^3



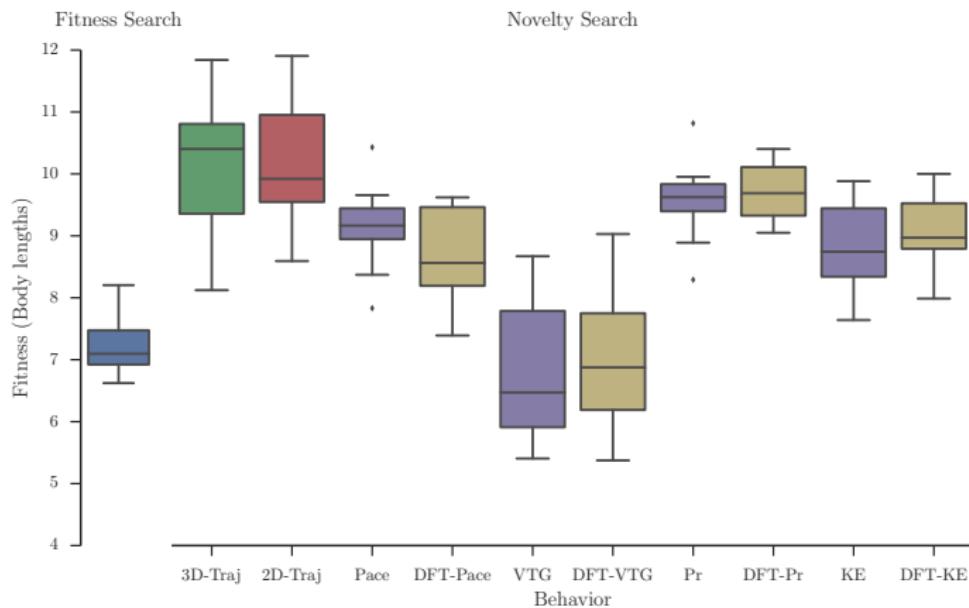
POPULATION COMPARISON

Best fitness so far Vs. Generation best fitness, med-res. 7^3

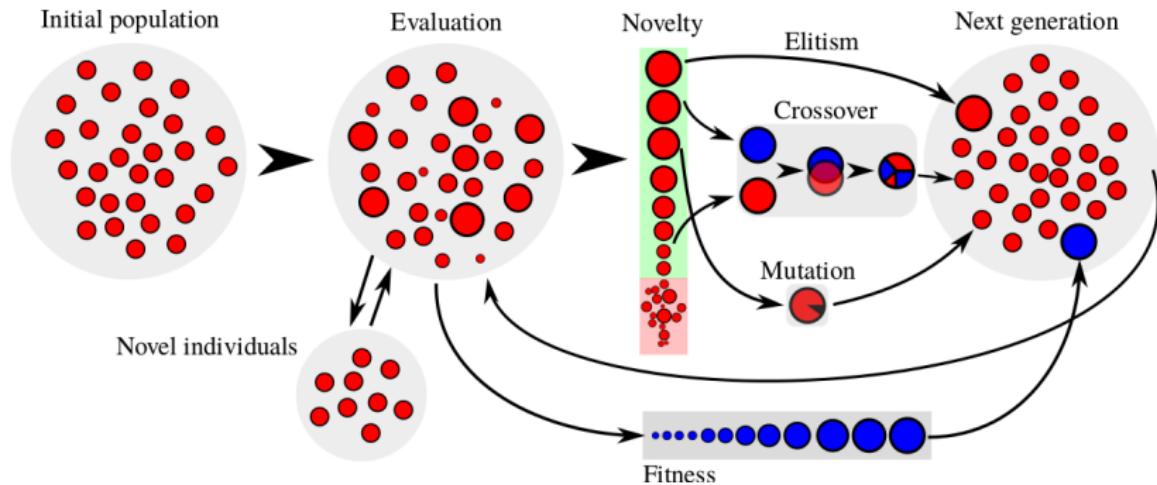


BEHAVIOR SELECTION

Novelty with 10-behavior metrics Vs. Fitness search, med-res.
 7^3



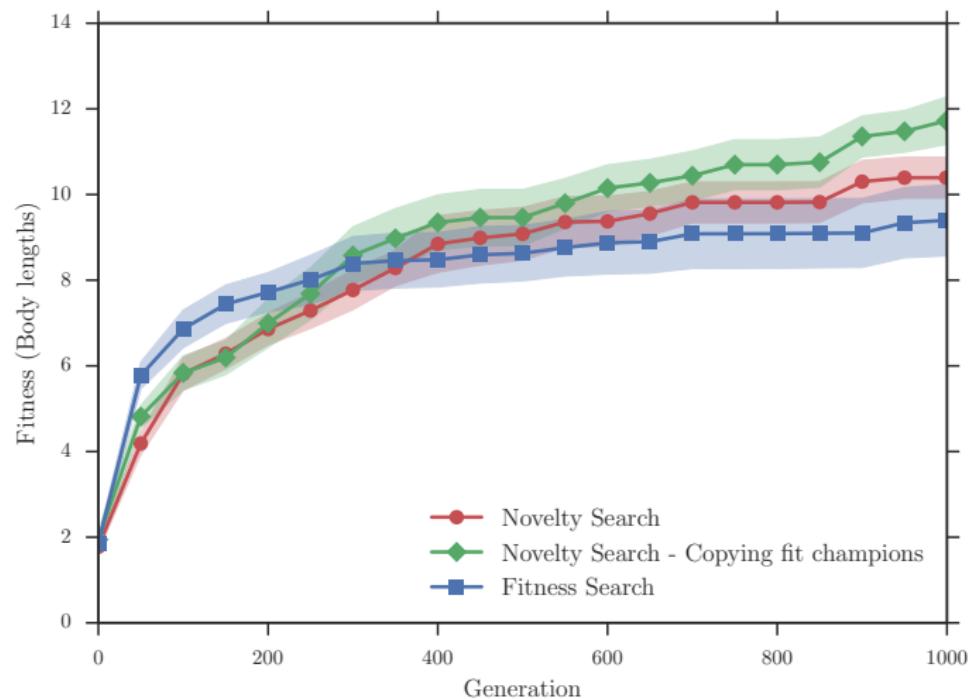
INCORPORATING FITNESS INFORMATION INTO NOVELTY SEARCH



- ▶ Keeping properties of novelty search

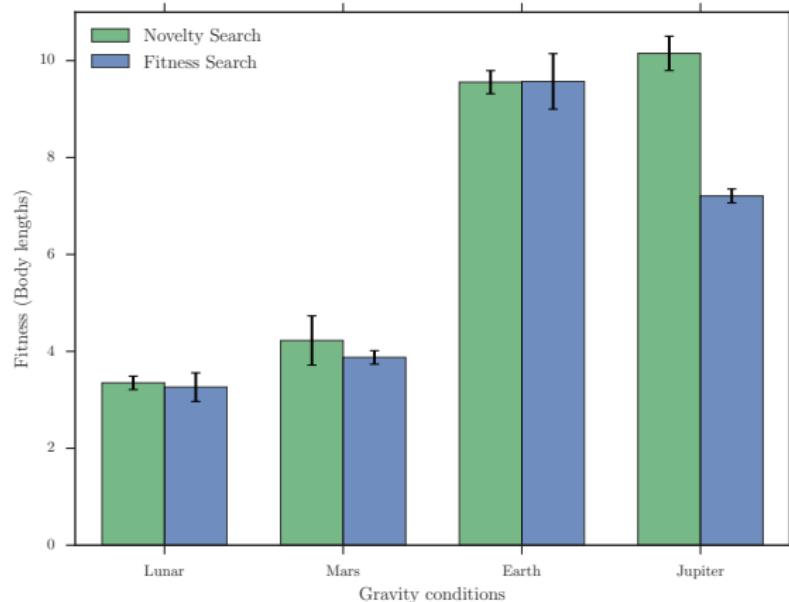
FITNESS ELITISM IN NOVELTY SEARCH

Best fitness so far, high-res. 10^3



EVOLVING SOFT-ROBOTS FOR OUTER SPACE

Displacement achieved in variant gravity levels, med-res. 7^3



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CONCLUSION

- ▶ Novelty search performs better in respect to fitness
- ▶ Increased performance on different settings
- ▶ Performance is not much affected by the behavior metric
- ▶ Fitness elitism further improves performance
- + Co-evolution of materials alongside morphology
- + Develop methods to combine both searches

Thank you!

