

Evolutionary algorithms and Novelty Search

Dominika Zogatová

FJFI ČVUT

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Evolutionary algorithms

- Natural evolution
- Selection, reproduction, recombination and mutation
- Simplistic from biology point of view, these algorithms are complex enough to provide powerful search tool
- Optimize for fitness value

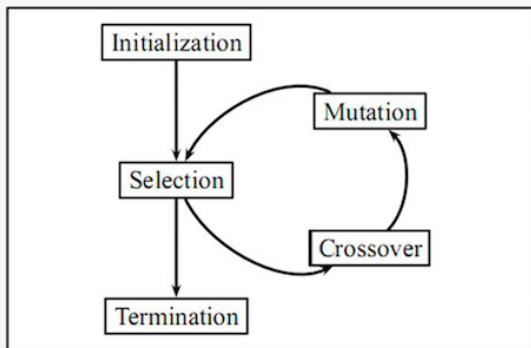


Figure: Evolution Process

- Evolutionary algorithms are known to converge to non-evolving populations rather quickly
- Reliance on fitness function is believed to be the problem
- Questions:
 - Does nature optimize for anything?
 - How to measure novelty?
 - Does natural evolution optimize for novelty?

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Novelty Search

- Rewarding with respect to an objective does not improve overall performance
- Difficult to define an appropriate fitness function
- Some goals are unreachable when optimizing for a single or even multiple objectives alone
- Focuses on finding novel behaviours

- Behavioural novelty is described by measuring the distance to the nearest k neighbours
- The nearest neighbours are computed from all the individuals from the current population and from all members from the archive
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$$\rho(x) = \frac{1}{k} \sum_{i=0}^k \text{dist}(x, \mu_i),$$

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Our approach

- Randomly distributed rewards
- More collected *sugars* = higher the fitness value
-

$$\rho(x) = \frac{1}{k} \sum_{i=0}^k \text{pick}(x, s_i),$$

- Agent is rewarded for exploring the environment

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Tasks (Stanley et al)

● starting position

■ goal

Medium map



Hard map

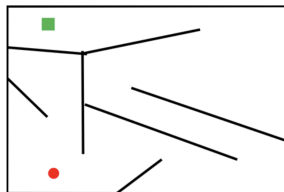


Figure: Maze environments

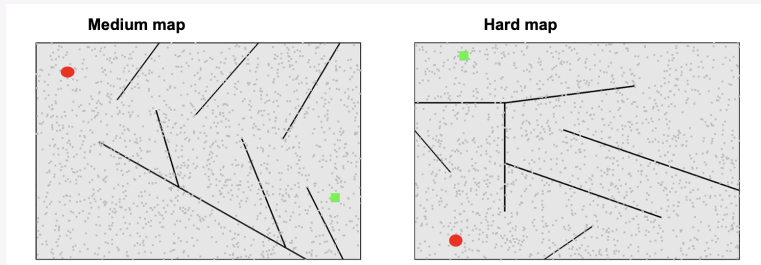


Figure: Maze environments - sugars

- Goal: reach the finish point
- Fitness: distance to the goal
- Novelty: Euclidean distance between k nearest neighbours
- Our approach: number of sugars collected

Table: Results of our implementation

	Medium Map	Hard Map
Fitness	17.6	-
Novelty Search	10.4	237.7
Sugar Approach	11.7	86.6

- Average number of generations needed to reach the goal

Benefits of our approach

- Less hyper parameters
- Better results on more complicated mazes
- Less ad-hoc, no need for archive
- Easy implementation - simpler approach

Animations on Google Slides