Title

Abandoning Objectiv Abandoning Objectives: Evolution Through Through the Search for Novelty Alone

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Background

- point

The Search for Novelty

- Objective fitness functions don't reward intermediate stepping stones that lead to the objective
- Instead, reward instances whose functionality is significantly different from what has been discovered before
- Seems naive $\rightarrow$ where is the pressure to adapt?
- Not necessary $\rightarrow$ stepping stones are rewarded

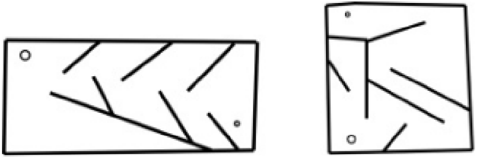
Novelty Search Algorithm

- Key idea: reward divergence from prior behavior
- Create a spatial mapping of evolved solutions
- Use k-means to measure sparsity (higher is better)

$$\rho(x) = \frac{1}{k}\sum_{i=0}^{k} \mathrm{dist}(x, u_i)$$

Where x is the point in question and u_i is the ith nearest neighbor of x

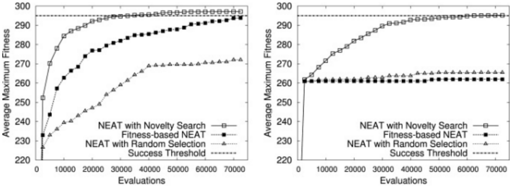
Experiment 1: Maze



(a) Medium Map (b) Hard Map

- Great for deception problems because dead ends that lead close to the goal are local optima
- Fitness-based NEAT metric is defined as the distance from the robot to the goal at the end of an evaluation
- Novelty-based NEAT metric rewards the robot for ending in a place where none have ended before; the method of traversal is ignored

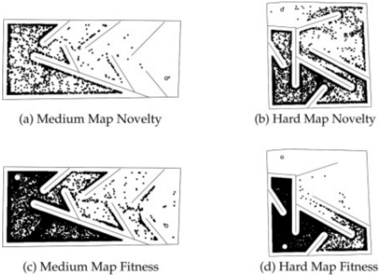
Experiment 1: Maze Results



(a) Medium Map (b) Hard Map

- Fitness-based NEAT was three times slower (56k evaluations vs 18k)
- The average genomic complexity of solutions evolved by fitness-based NEAT was almost three times greater than those evolved by Novelty-based NEAT
- The hard map was solved 3/40 times by fitness-based NEAT and 39/40 times by novelty-based NEAT

Experiment 1: Maze Behaviors



(a) Medium Map Novelty
(b) Hard Map Novelty
(c) Medium Map Fitness
(d) Hard Map Fitness

- Bounding the Size of the Archive in the Maze Domain
  - Possible to limit the archive size, and thus additional computational effort, without significantly decreasing the performance of novelty search
- Removing Walls in the Maze Domain
  - Fitness fares no better; fitness-based search is not necessarily a viable alternative even when novelty search is not effective

Experiment 1: Maze Behaviors

- Lengthening the Behavioral Characterization
  - High-dimensional behavior characterization is not a sufficient basis for predicting that novelty search should fail
- Reducing the Precision of the Behavioral Characterization
  - Archive size can be limited without significant loss of performance
- Characterizing Behavior as the Fitness Measure
  - This type of conflation can be disruptive to novelty search

Experiment 2

- point

Discussion & Conclusion

- Objective Limitations
- Domain-Independent Open-Endedness
- Novelty Search and Natural Evolution
- The Arrow of Complexity
- Further Results on Novelty Search

Novelty search suggests a surprising new perspective on achievement:
To achieve your highest goals, you must be willing to abandon them