

# 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 → where is the pressure to adapt?
- ▶ Not necessary → stepping stones are rewarded

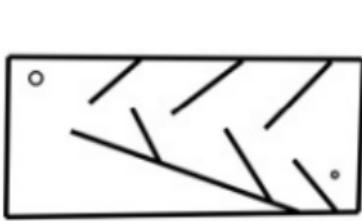
## Novelty Search Algorithm

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

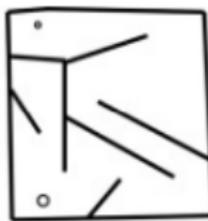
$$\rho(x) = \frac{1}{k} \sum_{i=0}^k \text{dist}(x, u_i)$$

Where  $x$  is the point in question and  $u_i$  is the  $i$ th nearest neighbor of  $x$

## Experiment 1: Maze



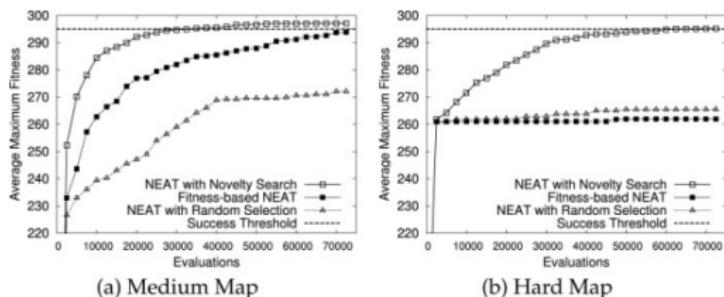
(a) Medium Map



(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

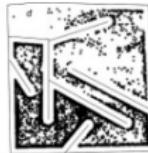


- ▶ Fitness-based NEAT was three times slower (56k evaluations vs 18k)
- ▶ The average genomic complexity of solutions evolved by fitness-based NEAT was almost three times greater than those evolved by Novelty-based NEAT
- ▶ The hard map was solved 3/40 times by fitness-based NEAT and 39/40 times by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