

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

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# Introduction

- ▶ Discusses algorithms used for evolutionary computation (EC).
- ▶ Previous approaches primarily used objective functions.
  - ▶ Example: Chinese finger trap
  - ▶ Problem: Only finds local optima (deception)
- ▶ New Idea: Search for novelty instead.
  - ▶ Completely ignores the objective
- ▶ How can we use these approaches to model evolution?
- ▶ Main idea: The objective function isn't as perfect as we used to think, sometimes novelty functions work better.



Figure 1: Chinese Finger Trap

## Background

- ▶ Deception – when lower-order building blocks are combined and don't lead to a global optimum.
  - ▶ Multi-Objective Evolutionary Algorithms can sometimes fight deception by training against multiple objectives.
  - ▶ Incremental evolution of objective functions can also help
    - ▶ Implies the need to track the “stepping stones” that lead to the objective
- ▶ Selection pressure restricts the scope and direction of search
- ▶ NeuroEvolution of Augmenting Topologies (NEAT)
  - ▶ Evolves artificial neural networks
  - ▶ Complexifies the network over generations

## The Search for Novelty

- ▶ Learning method is rewarded for finding instances that are significantly different from any found before
- ▶ Biped locomotion example:
  - ▶ Novelty function would reward falling in new ways (maybe eventually walking)
  - ▶ Objective function function would reward falling the furthest
- ▶ Novelty search is different from exhaustive search
  - ▶ Domain typically limits the variety of behaviors
  - ▶ Since NEAT starts simple and complexifies, it is much better than random.
- ▶ Seems naive → where is the pressure to adapt?
  - ▶ Not necessary → stepping stones are rewarded

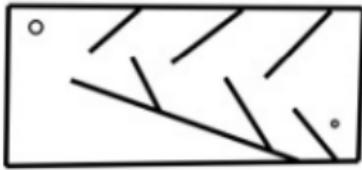
## Novelty Search Algorithm

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

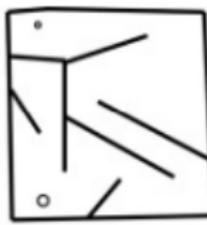
$$\rho(x) = \frac{1}{k} \sum_{i=0}^k \text{dist}(x, u_i)$$

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

## Experiment 1: Maze



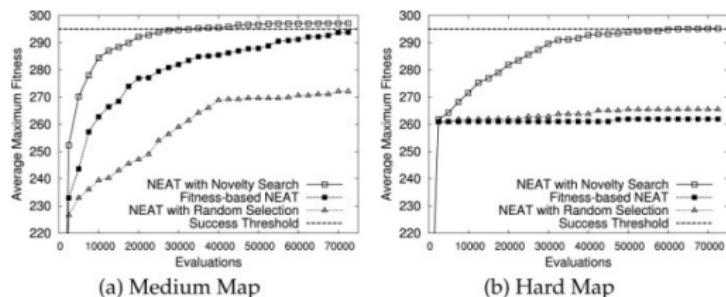
(a) Medium Map



(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

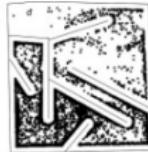


- ▶ Fitness-based NEAT was three times slower (56k evaluations vs 18k)
- ▶ The average genomic complexity of solutions evolved by fitness-based NEAT was almost three times greater than those evolved by Novelty-based NEAT
- ▶ The hard map was solved 3/40 times by fitness-based NEAT and 39/40 times by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

## Biped Experiment

- ▶ A more challenging problem than the Maze Problem
- ▶ Robot needs to walk as far as possible in given time
  - ▶ 6 DOF – pitch and roll in each hip, pitch in knee
- ▶ Novelty metric: each second, sample the offset of the center of mass
- ▶ Average distance traveled for:
  - ▶ Objective Function: 2.88 meters
  - ▶ Novelty Function: 4.04 meters
- ▶ The novelty function produced models that were significantly less complex
- ▶ Video



Figure 2: Biped Robot

## Discussion/Conclusion

- ▶ Novelty and objective functions can be used together so the benefits of both are included.
  - ▶ Search for novelty, optimize with objective
- ▶ Novelty function is not *always* better, but objective functions are not perfect.
- ▶ When does novelty search not work? – Future work
- ▶ Evolution is not explicitly a search for novelty
  - ▶ But, novelty search does appear in natural evolution

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