# 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
- 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
- Seems naive $\rightarrow$ where is the pressure to adapt?
  - Not necessary $\rightarrow$ stepping stones are rewarded
- 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.

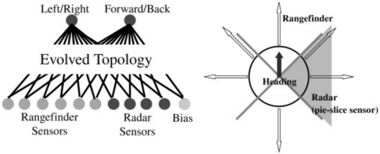
# Novelty Search Algorithm

- 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)

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

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

# Experiment 1: Maze

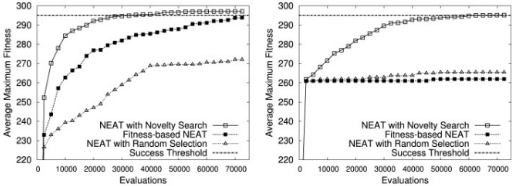



(a) Neural Network (b) Sensors

(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

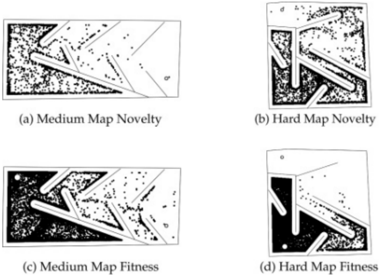
# Experiment 1: Maze Results




(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

# 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

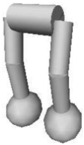


Figure 2: Biped Robot

# Discussion/Conclusion

- Novelty function is not *always* better, but objective functions are not perfect.
- Novelty and objective functions can be used together so the benefits of both are included.
  - Search for novelty, optimize with objective
- 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