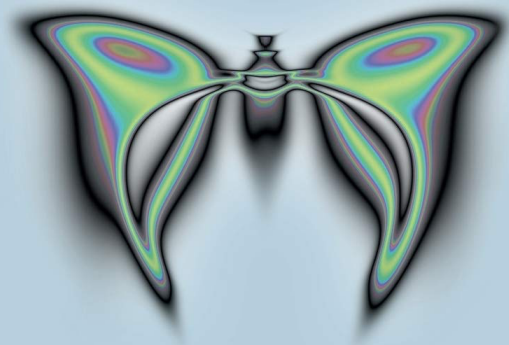


## 25: Novelty Search

- Objectives for AI
- Story of Picbreeder
- Deception in search
- Novelty search
- Novelty search for GP

Kenneth O. Stanley · Joel Lehman  
**Why Greatness  
Cannot Be Planned**

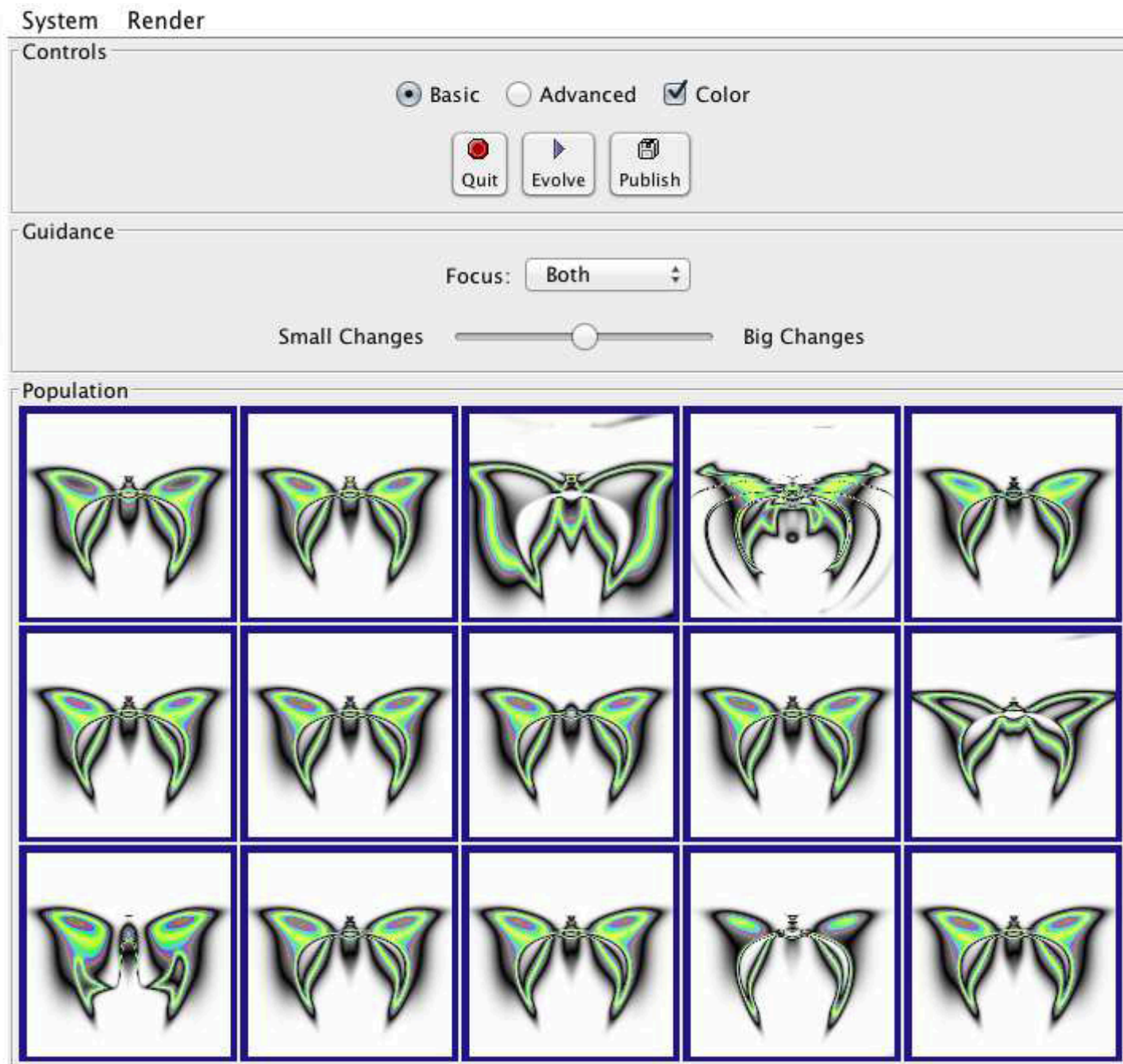
The Myth of the Objective



# The myth of the objective

- Almost all current AI systems are trained based on objectives
- Intelligence should be creative, innovative, and collaborative
- Ambitious objectives can block their own achievement
  - An obstacle to creativity and innovation
  - Without protection for individual autonomy, collaboration can become dangerously objective
- We are infatuated with metrics

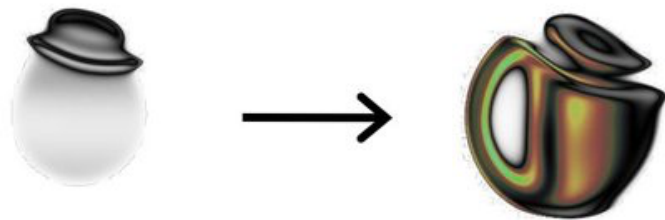
# Picbreeder



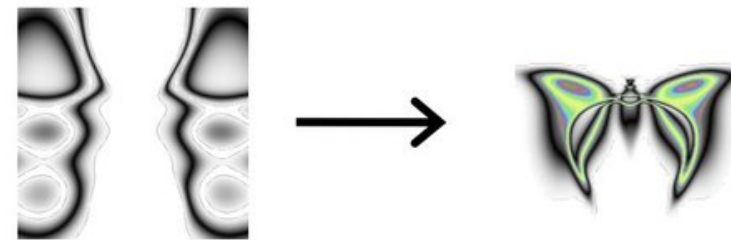
- Online collaborative evolution of images
- No specific goal
- Users choose what is interesting
- Highly subjective

# Picbreeder

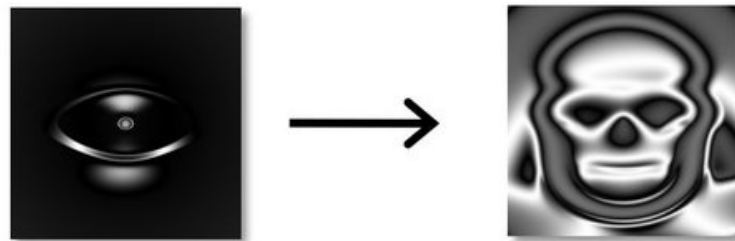
## Most Top Images have the Same Story



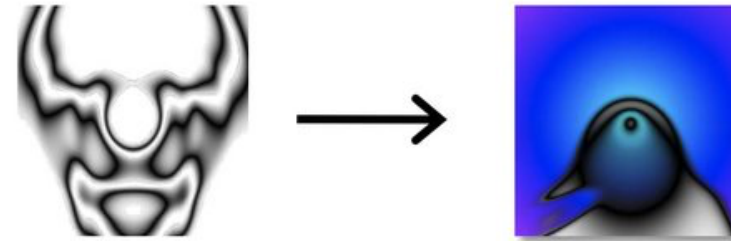
Stepping stone to the Teapot



Stepping stone to the Butterfly



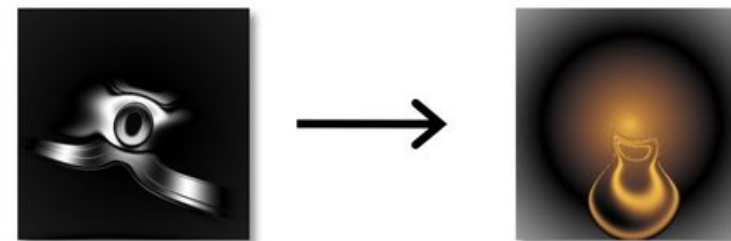
Stepping stone to the Skull



Stepping stone to the Penguin



Stepping stone to Jupiter



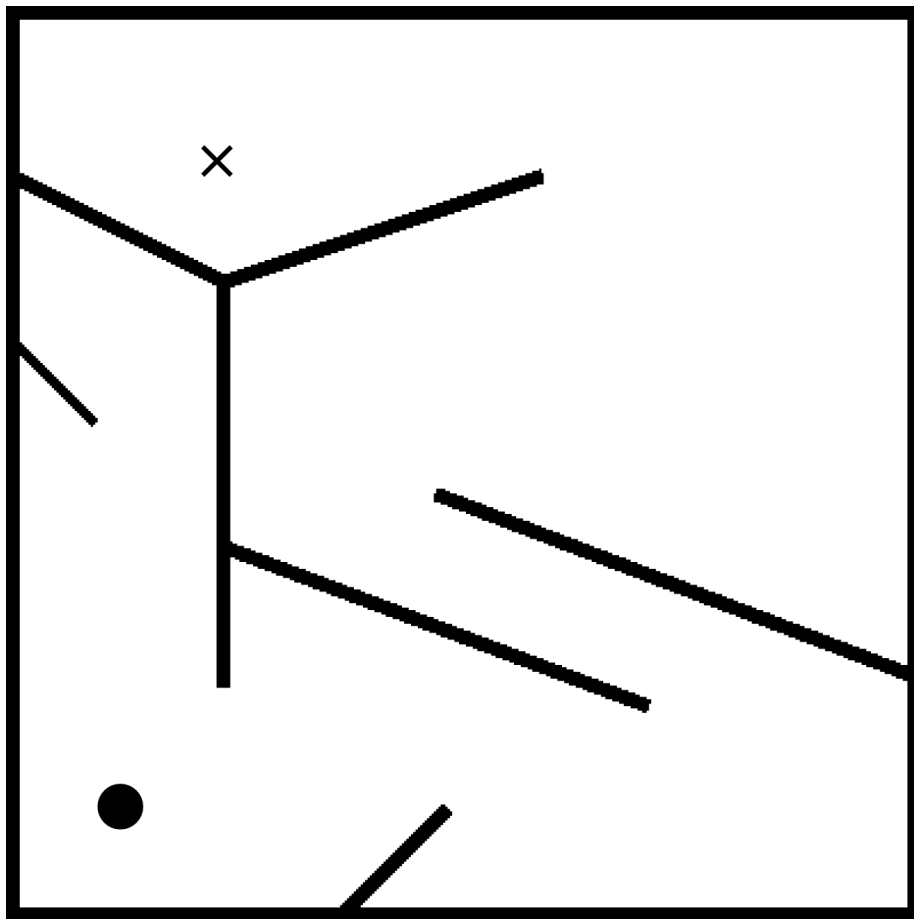
Stepping stone to the Lamp

The stepping stones almost never resemble the final product!  
*You can only find things by not looking for them*

# Implications

- “The path to success is through not trying to succeed”
- “To achieve our highest goals we must be willing to abandon them”
- “It is in your interest that others do not follow the path you think is right”
- “They will lay the stepping stones for your greatest discoveries”
- Convergent consensus vs. divergent treasury hunting

# Deception

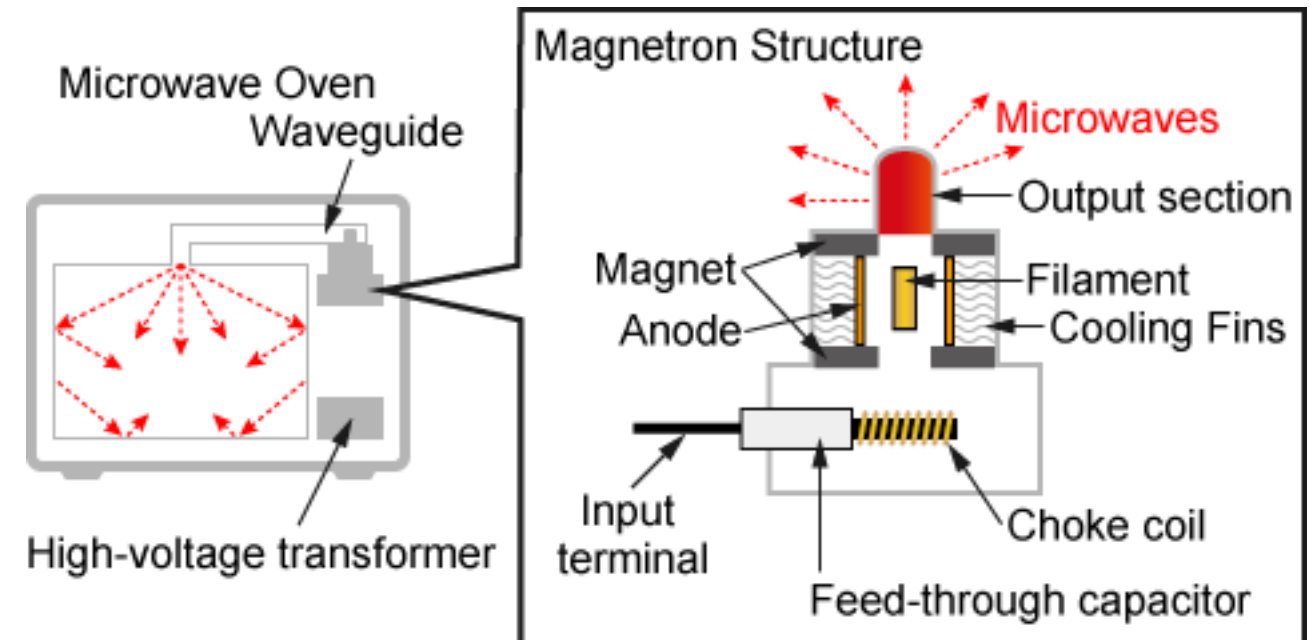
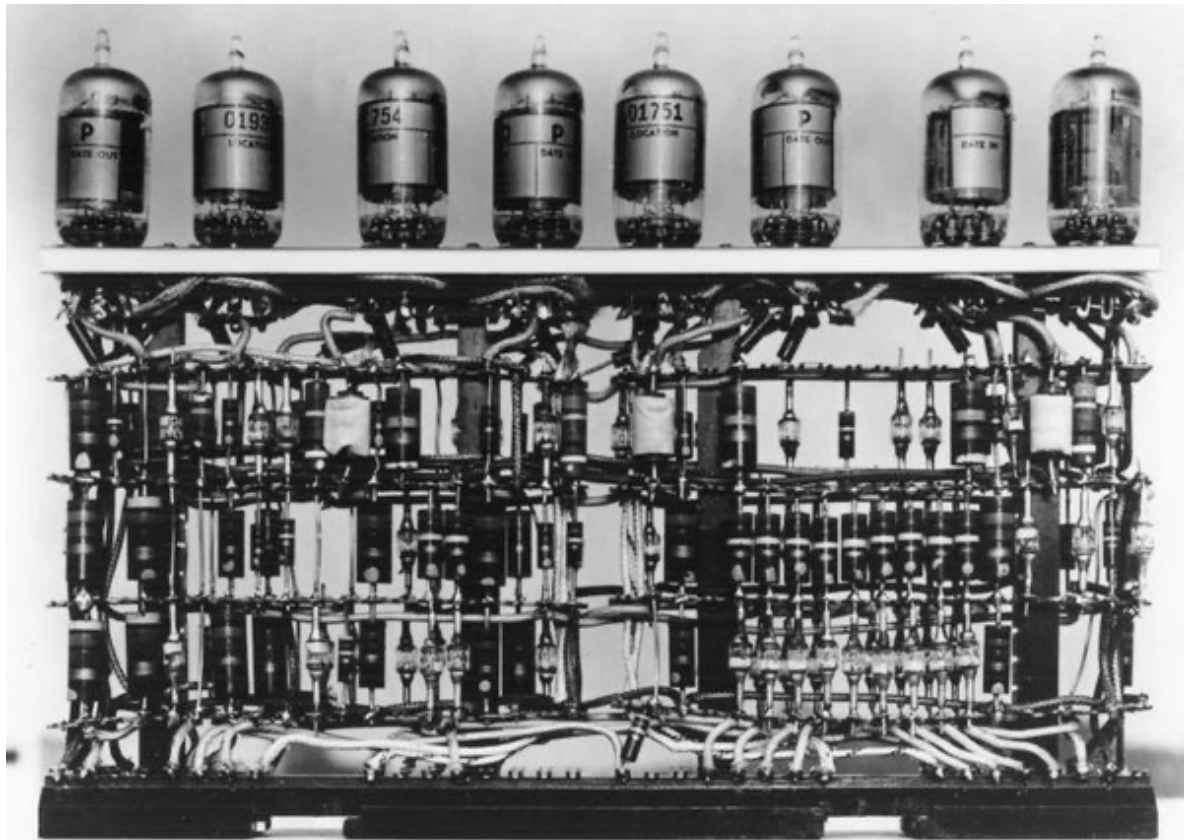


- Deception is the reason one can't find things by looking at them
- The stepping stones to get to the solution are not like the final solution
- Most heuristic base on how close to the goal
- Deceptive search space
- The need for more exploration



# Examples of accidental inventions

- The vacuum tube and modern computers
- Magnetron for radar systems and microwave



# Open-endedness

- Not how to learn something
- But how to learn everything
- Not just a single positive result
- But an ongoing cacophony of surprises
- Natural evolution is the ongoing creation of all the diversity of life



# Interestingness and novelty

- Subjectivity of measuring interestingness
- Divergence is creative
- Novelty reflects divergence and can be quantified
- Fitness creates a gradient towards the objective
- Novelty creates a gradient of behavioral differences

# Novelty search

- What if we ignore the fitness function?
- And search for novel things (behaviors)
- Characterize behaviors with a vector
- Replace fitness by novelty, computed by the behavioral distance to the archive and population

The diagram illustrates the formula for novelty  $\rho(x)$ . It features three colored boxes: a yellow box for  $\rho(x)$ , a cyan box for the summation term  $\frac{1}{k} \sum_{j=0}^k$ , and a green box for the distance term  $d_b(x, \mu_j)$ . Annotations include: a yellow arrow pointing from the yellow box to the text "Novelty of  $x$ "; a cyan arrow pointing from the cyan box to the text "Sum over the  $k$  nearest neighbors from archive and population"; and a green arrow pointing from the green box to the text "behavioral distance between  $x$  and  $\mu_j$ ".

$$\rho(x) = \frac{1}{k} \sum_{j=0}^k d_b(x, \mu_j)$$

Novelty of  $x$

Sum over the  $k$  nearest neighbors from archive and population

behavioral distance between  $x$  and  $\mu_j$

# Efficiently Evolving Programs through the Search for Novelty

Joel Lehman  
University of Central Florida  
4000 Central Florida Blvd.  
Orlando, FL 32816-2362 USA  
jlehman@eecs.ucf.edu

Kenneth O. Stanley  
University of Central Florida  
4000 Central Florida Blvd.  
Orlando, Ohio 32816-2362 USA  
kstanley@eecs.ucf.edu

“Abandoning objectives is often the only way to outperform the direct search for the objective.”

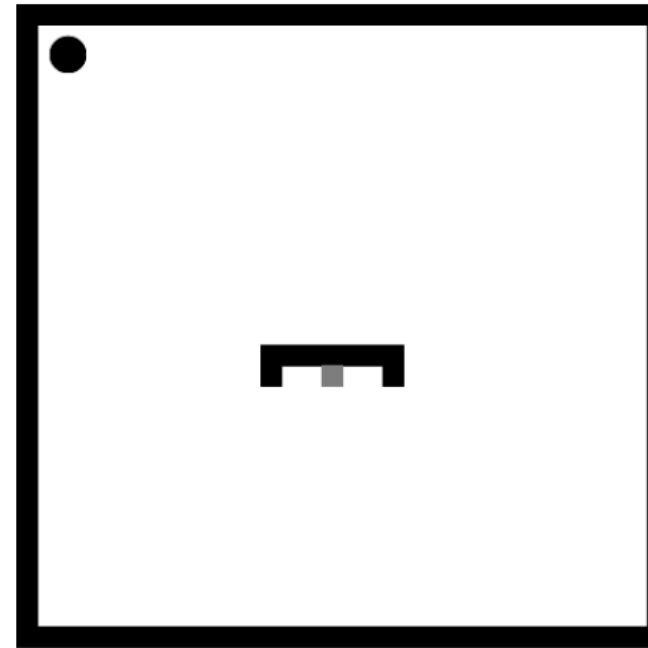
— Kenneth Stanley

# Novelty search for genetic programming

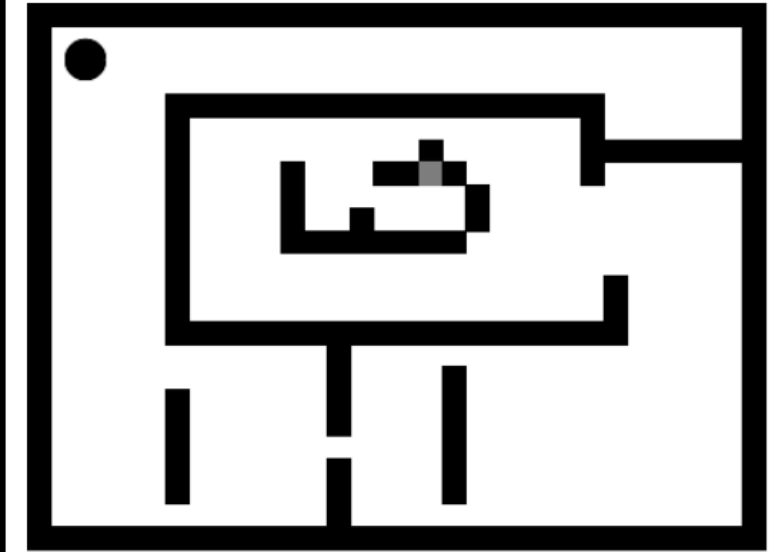
- Premature convergence
- Solving deceptive GP problems
- A measure of sparseness at a point: the average distance to the k-nearest neighbors of that point

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

# Maze experiment



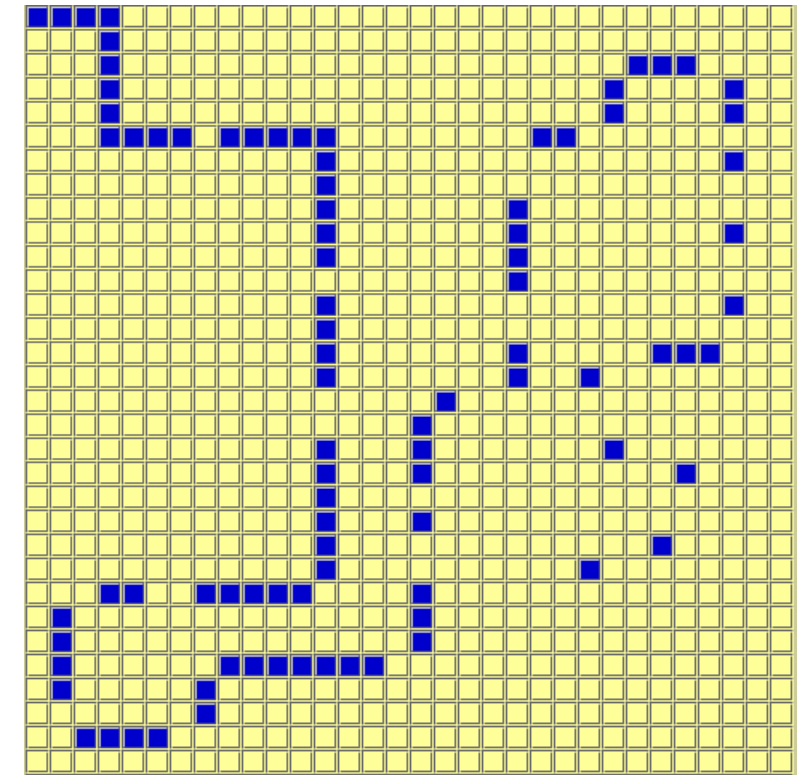
(a) Medium Map



(b) Hard Map

Objective:	Find a robot that navigates the maze
Terminal set:	Left (turn left), Right (turn right), Move (move forward one square)
Functions set:	IfWallAhead (execute one of two child instructions based on whether there is a wall directly ahead), Prog2 (sequentially execute the two child instructions)
Fitness cases:	Medium Maze and Hard Maze
Wrapper:	Program repeatedly executed for 100 time steps for the medium maze or 400 time steps for the hard maze
Population Size:	1,000
Termination:	Maximum number of generations = 1,000

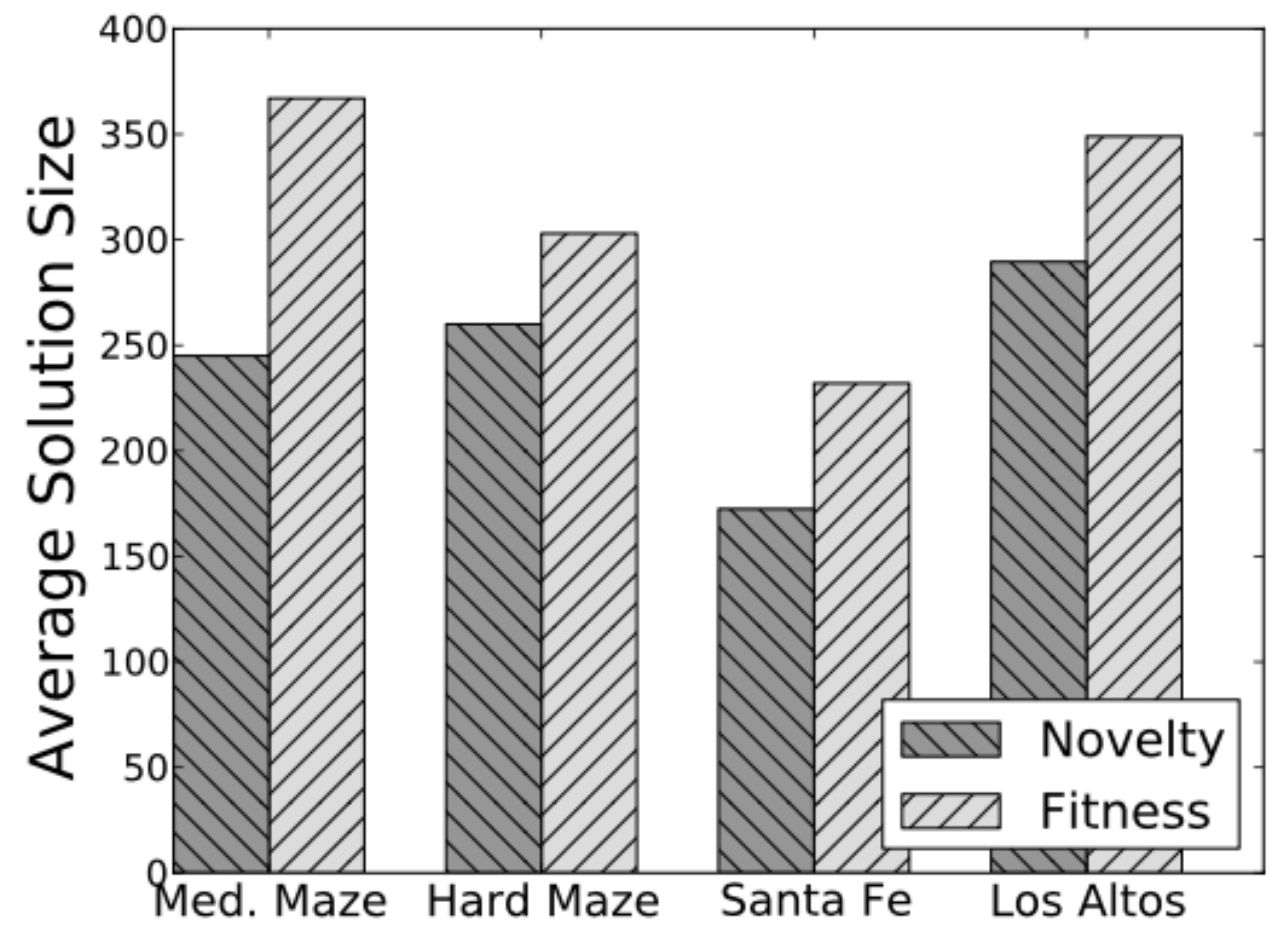
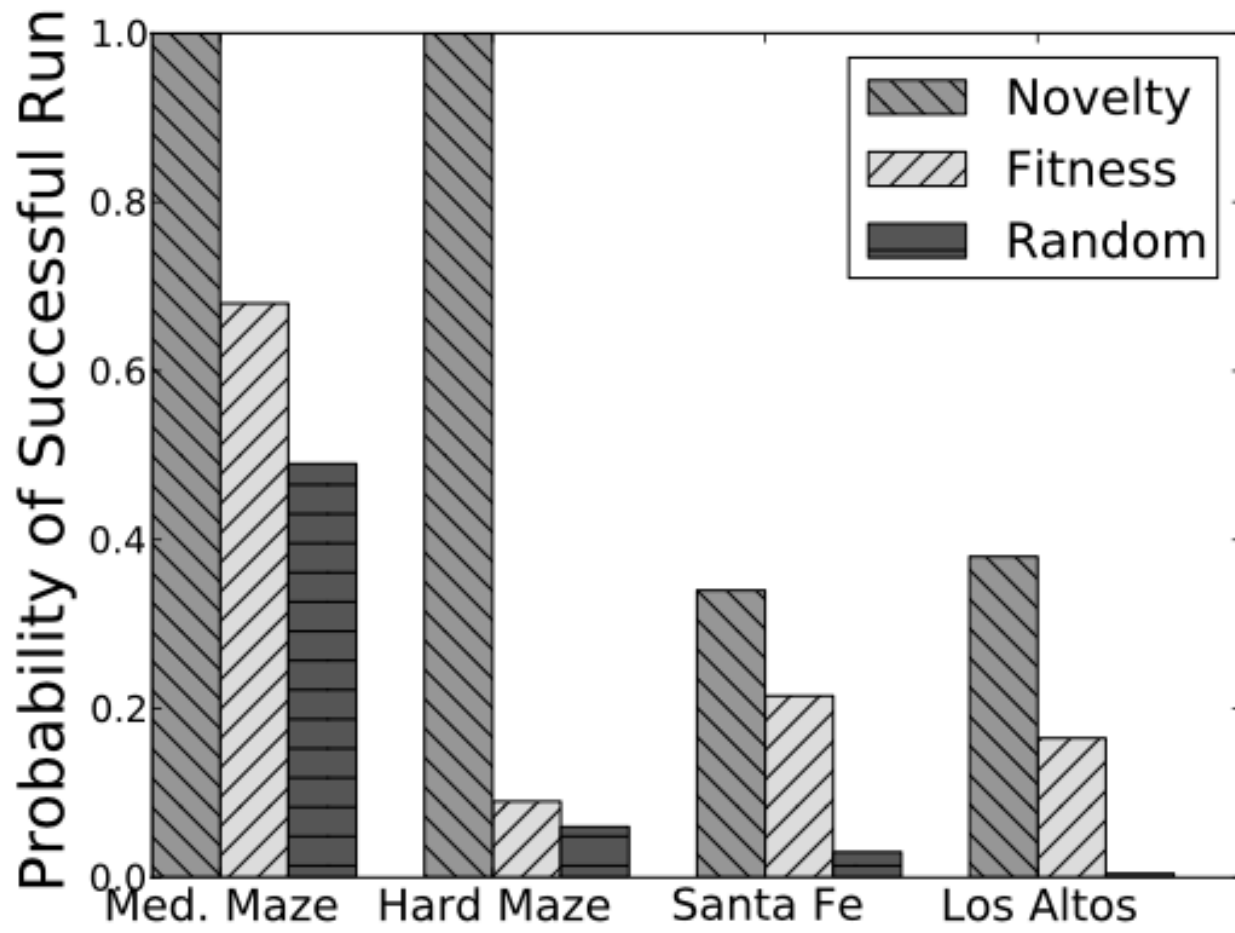
# Artificial Ant experiment



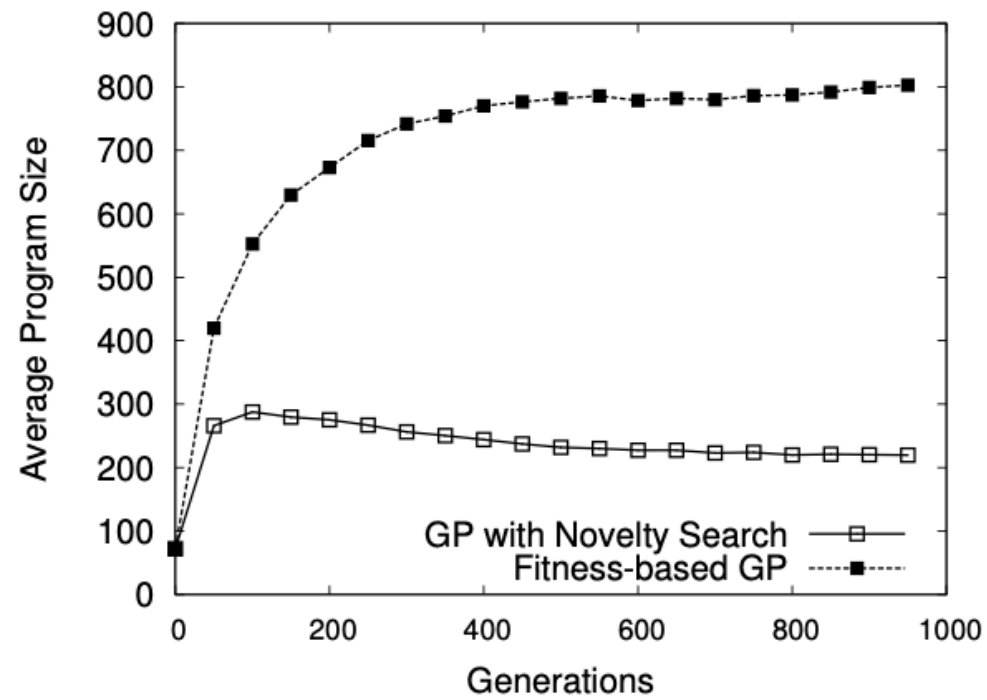
Objective:	Find an ant that follows food trails
Terminal set:	Left (turn left), Right (turn right), Move (move forward one square)
Functions set:	IfFoodAhead (execute one of two child instructions based on if there is food directly ahead), Prog2 (sequentially execute the two children instructions)
Fitness cases:	Santa Fe Trail and Los Altos Trail
Wrapper:	Program repeatedly executed for 400 time steps for Santa Fe Trail or 3,000 time steps for Los Altos Trail
Population Size:	1,000
Termination:	Maximum number of generations = 1,000



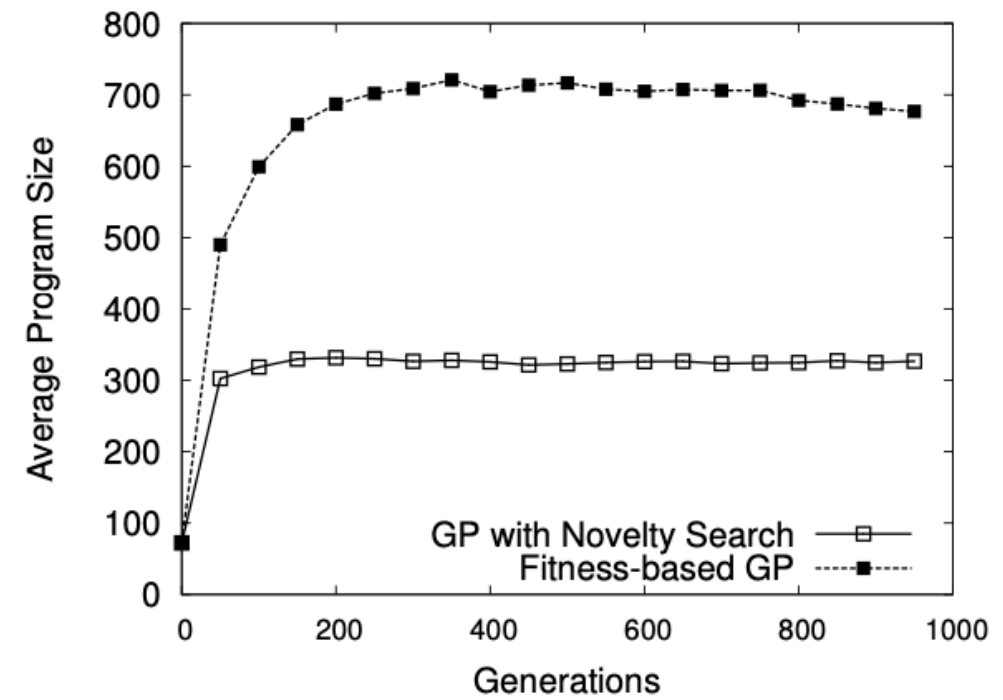
# Results comparison



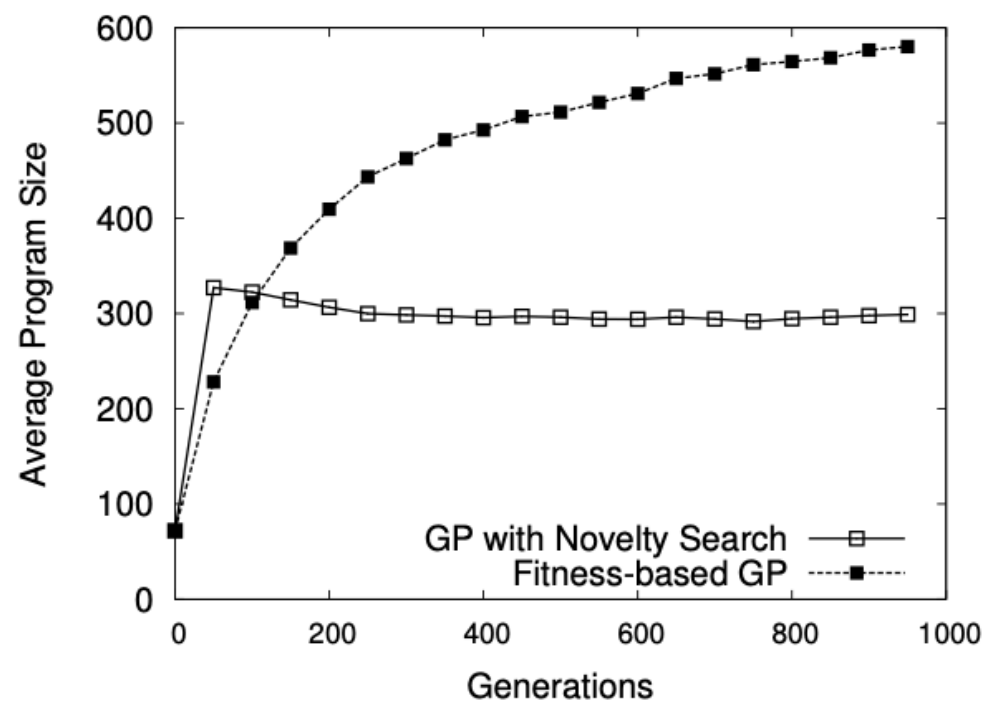
# Results comparison



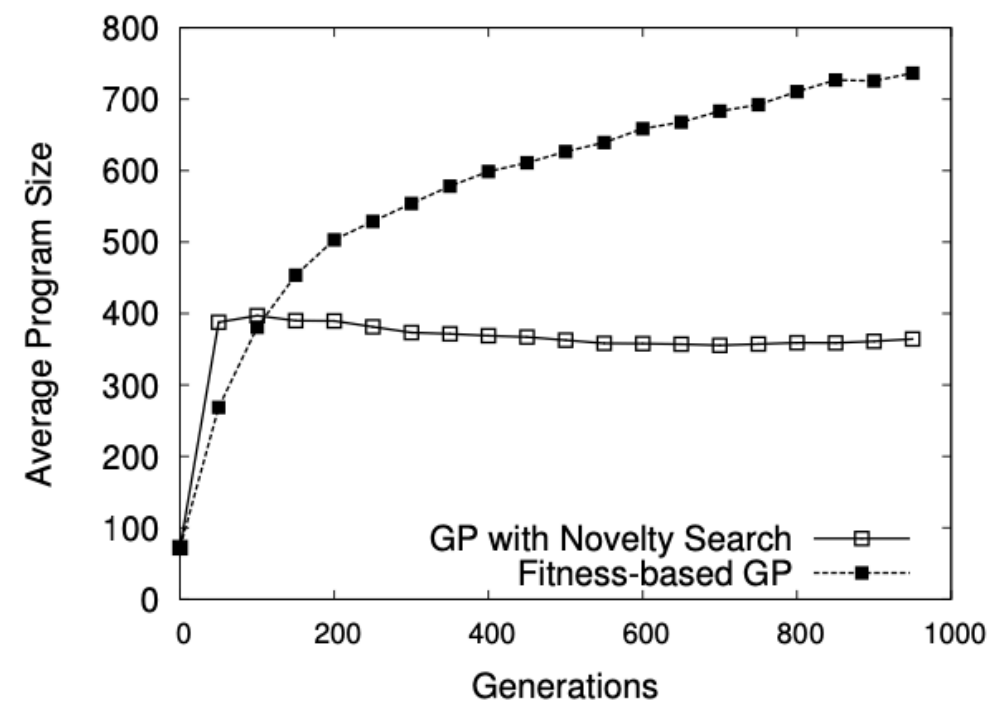
(a) Medium Maze



(b) Hard Maze



(c) Santa Fe Trail



(d) Los Altos Trail