Optimizing Local Rules in Ant Colony Optimisation

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First: Ant Colony Optimisation

- Inspired by ants
- Ants are agents
- Leave pheromones
- Pheromones evaporate over time
- Ants have a heuristic in what direction the target is
- How likely the ants are to follow this is variable alpha
- How likely they are to follow this is beta
- We will apply to a real map to find the shortest route
- No central control

Ant Colony Optimisation

$$p_{ij} = pheromone^{\alpha} * heuristic^{\beta}$$

Our research in two parts

1. Is it possible to optimize the local rules of individual ants in ant colony optimisation to reduce the number of iterations needed to find an optimal solution on a static real world map by using an evolutionary algorithm? How does the best ant colony compare to an ant colony optimised using grid search? And how does the final ant population compare to an ant colony population that was initialised random?

2. Can an evolutionary ant colony with two genomes outperform a regular ant colony in terms of adaptation to a dynamic network?

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2. Can an evolutionary ant colony with two genomes outperform a regular ant colony in terms of adaptation to a dynamic network?

Part 1: What we will do, in easier terms

- We will evolve ant colonies on a real static map
- Every ant holds their own pheromone importance and heuristic importance
- 100 ants in a colony
- Can evolution create ant colonies that outperform randomized colonies
- And can our best colony outperform two-variable grid searched colonies?
- We expect difference between evolutionary and static colonies

Part 2: What we will do, in easier terms

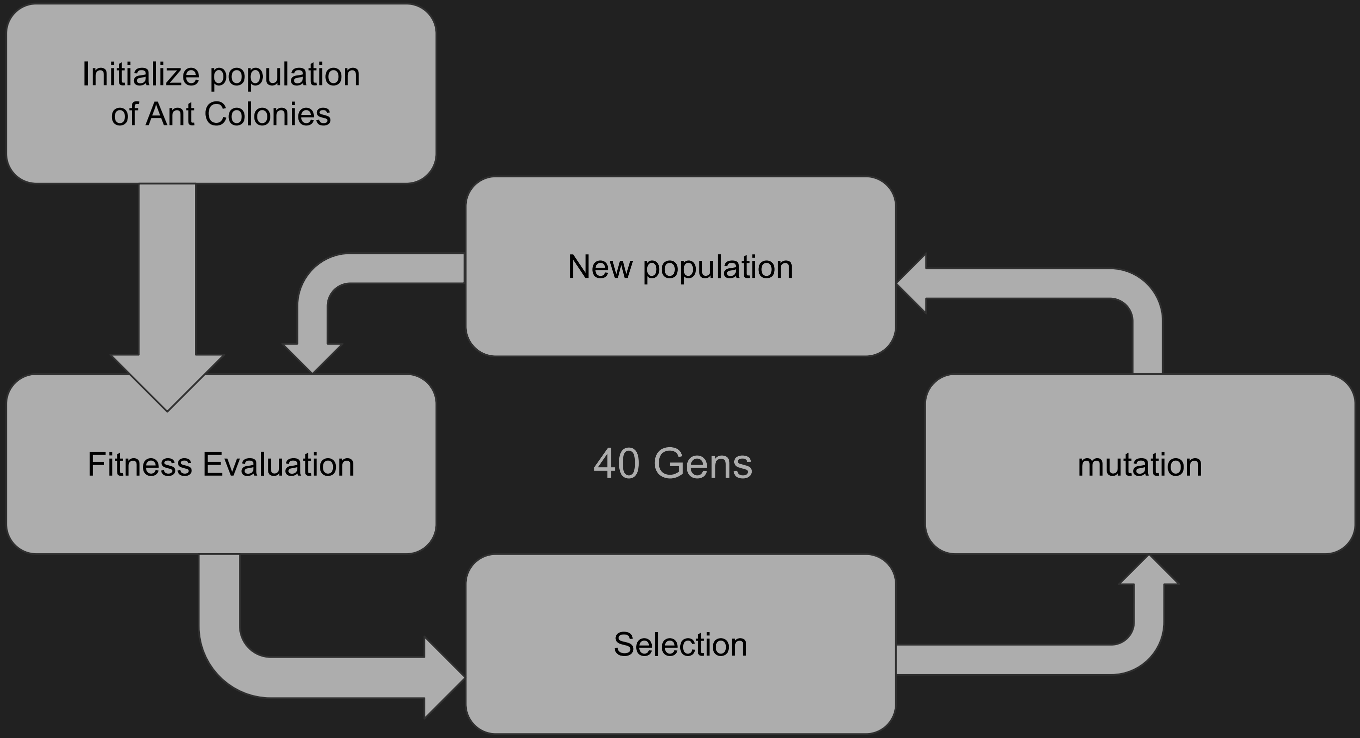
- Dynamic edge costs (traffic)
- Optimise for adaptability
- Only two genomes
- Expect increased adaptability compared to regular ant colony

How do we measure performance?

- Standardized start and finish points will be used to evaluate performance
- Overfitting risk, but less noisy
- Lower iterations to reach optimal path = better fitness
- Shortest distance ratio

Part 1

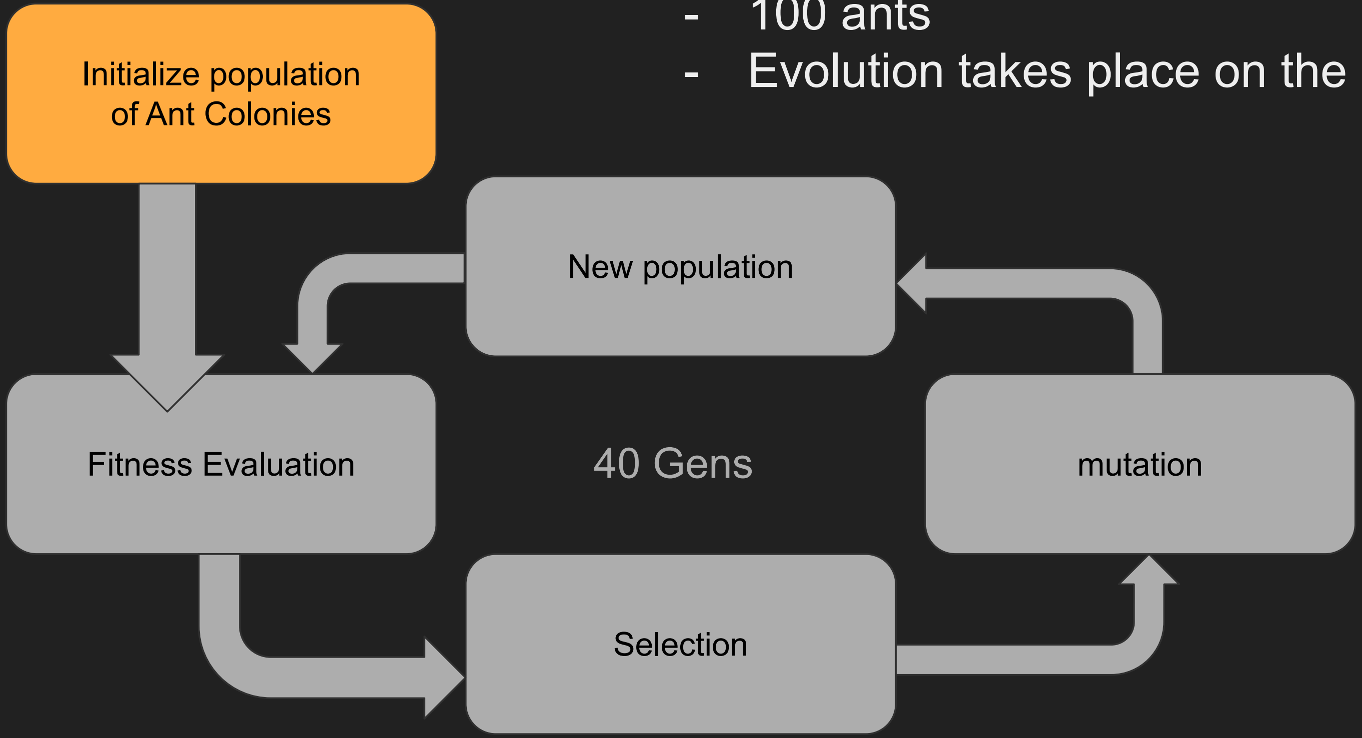
Evolutionary loop



Evolutionary loop

START: Initialise Population

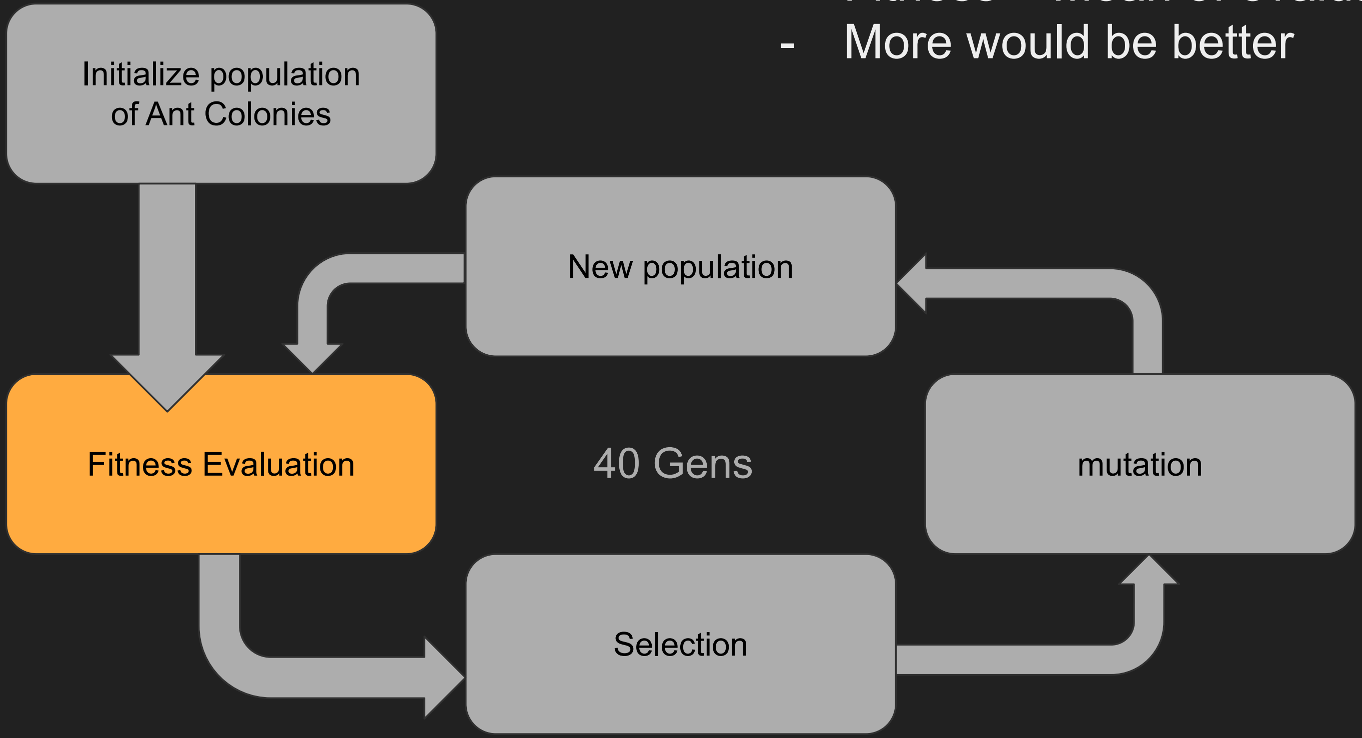
- Create a population of 40 Ant Colonies
- The genotype of a colony is [alpha, beta] for each ant
- 100 ants
- Evolution takes place on the level of colonies



Evolutionary loop

Evaluate Population

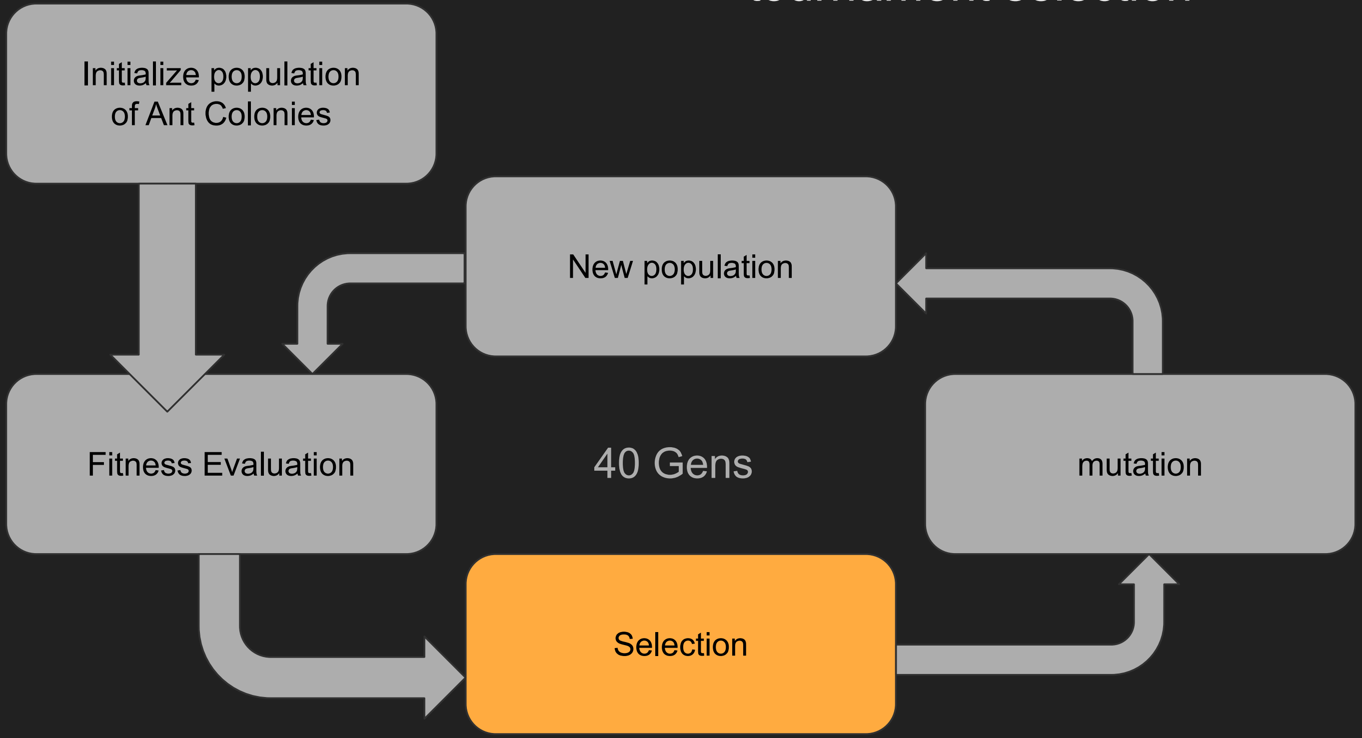
- For each colony:
  - 5 evaluations
  - Fitness = Mean of evaluations
  - More would be better



Evolutionary loop

Selection

- Best colony is always preserved
- tournament selection



Evolutionary loop

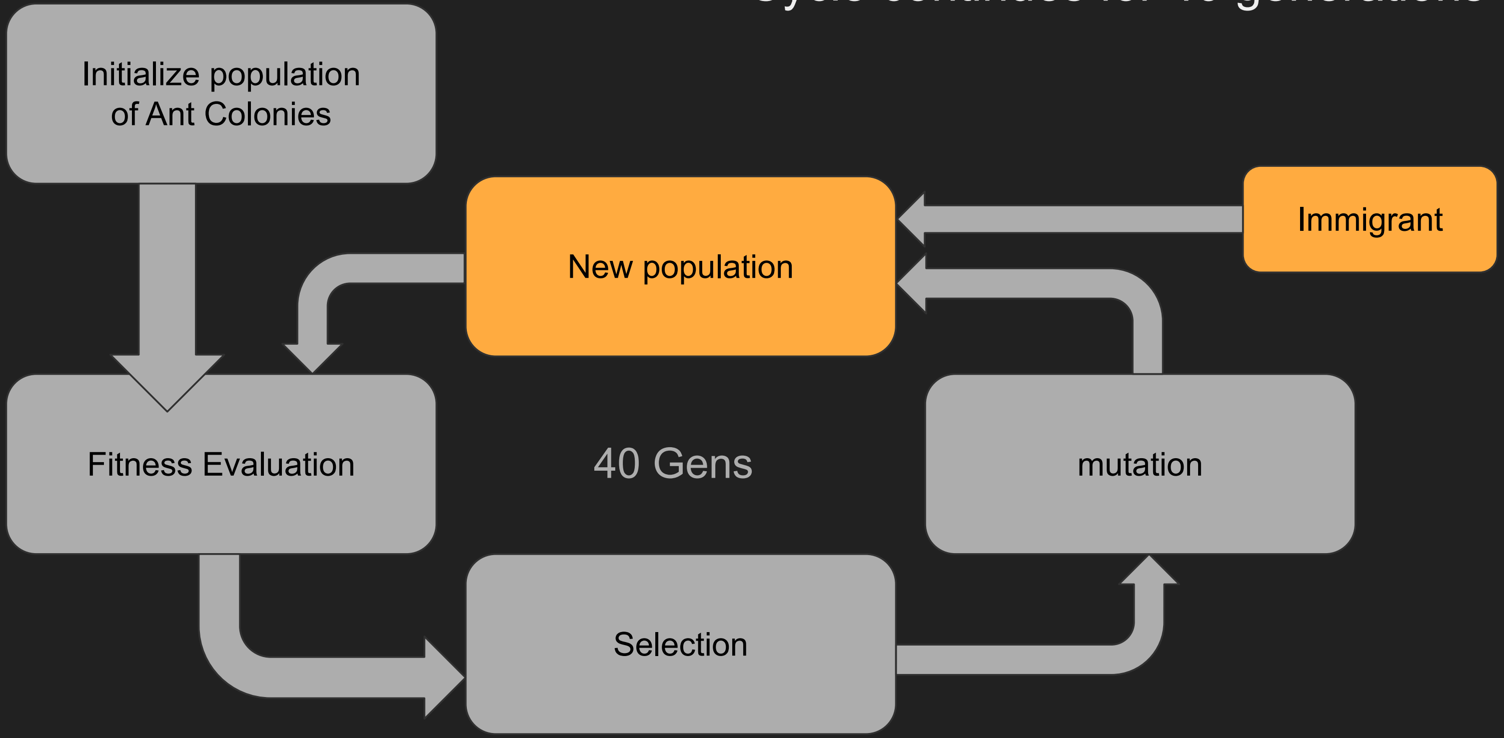
Mutation

- Changes some ants' alpha/beta values
- With some probability
- Best colony not mutated

Evolutionary loop

New population formed

- Random immigrant
- Cycle continues for 40 generations

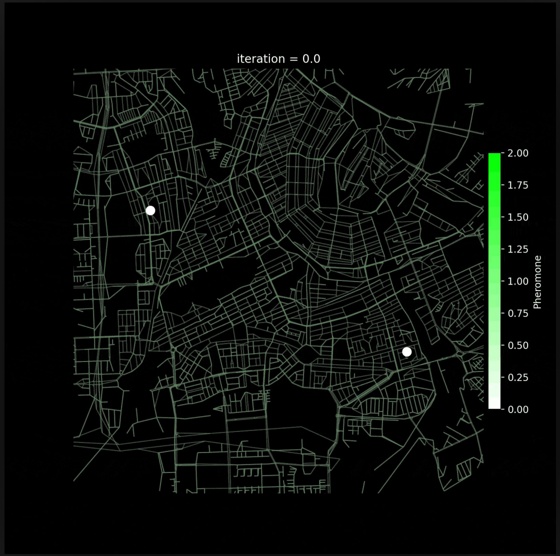


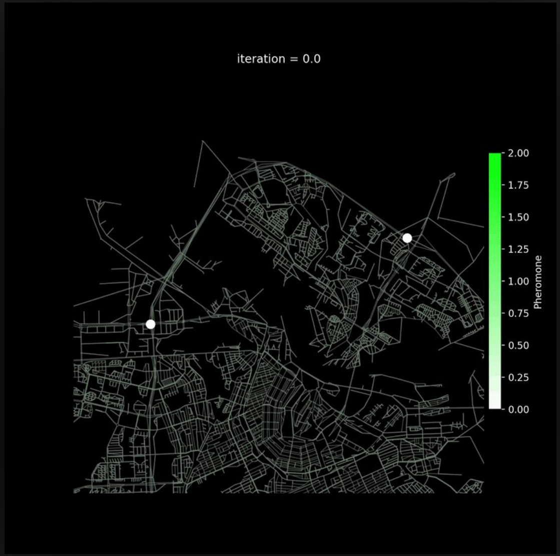
No crossover!

- We tried
- Destroys the performance of a colony

Evaluation not trivial

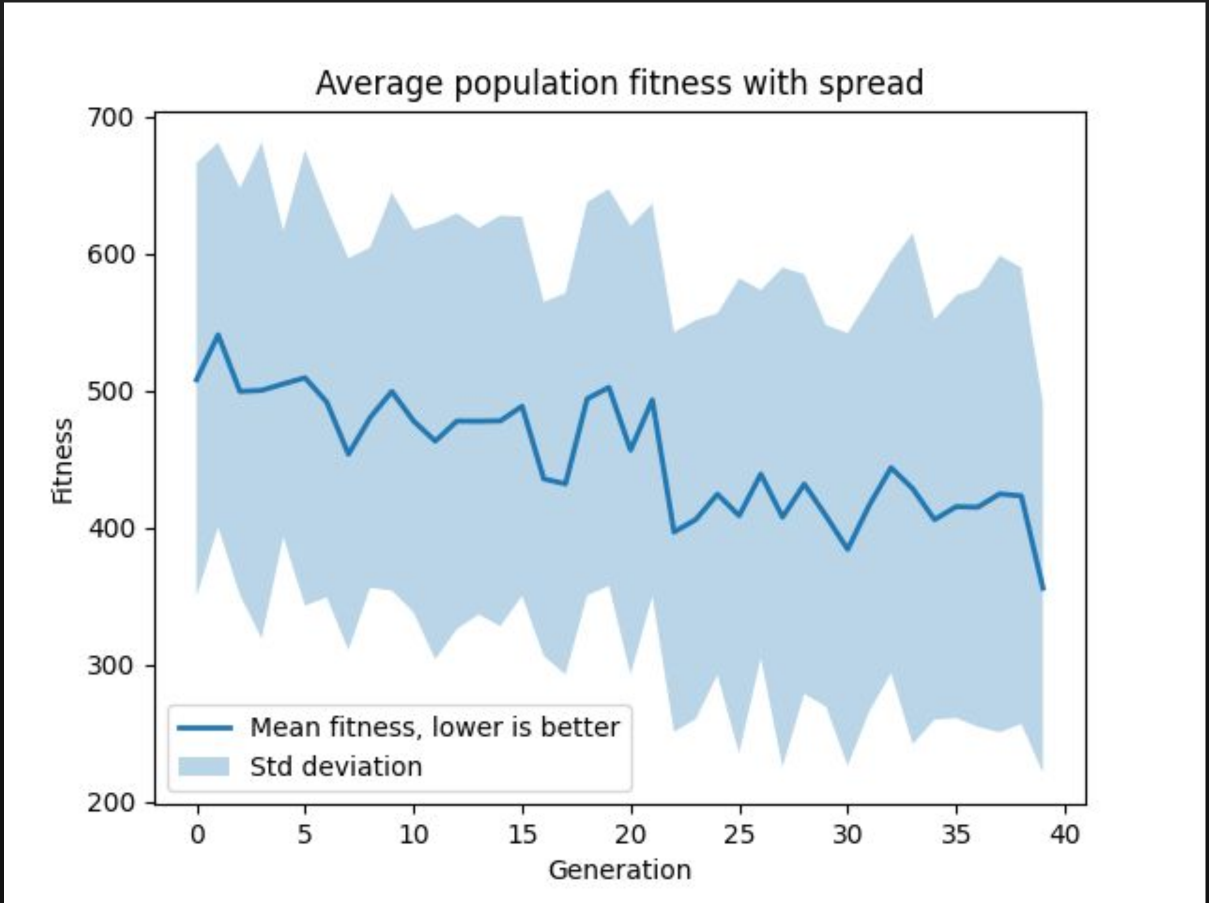
- Some routes too easy, others too hard
- Too low selection pressure





Fitness over gens

- downward trend
- Can't quantify yet



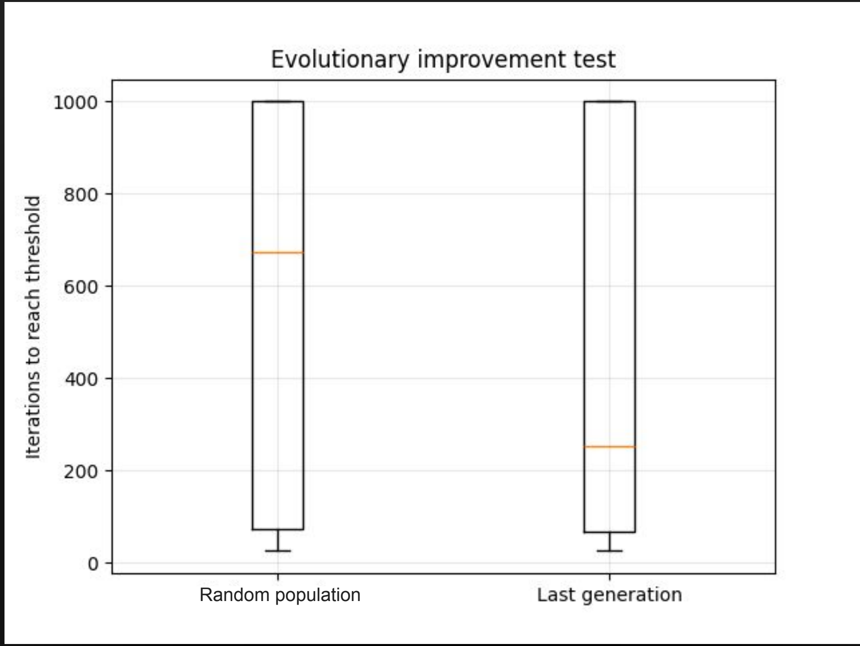
Part 1: test setup

- Test 1: We will compare our full final population to a random population, to proof if evolution worked
  - 100 evaluations per colony in both populations

- Test 2: To further justify our approach, we will then compare our best colony to a two parameter grid-search ant colony.

Results test 1

- Comparing populations:
  - Mann–Whitney U: 363006.50
  - p-value: 8.4928e-07
  - Cliff's delta: 0.134
- Significantly better, but small effect.
- Lot of randomness: spread



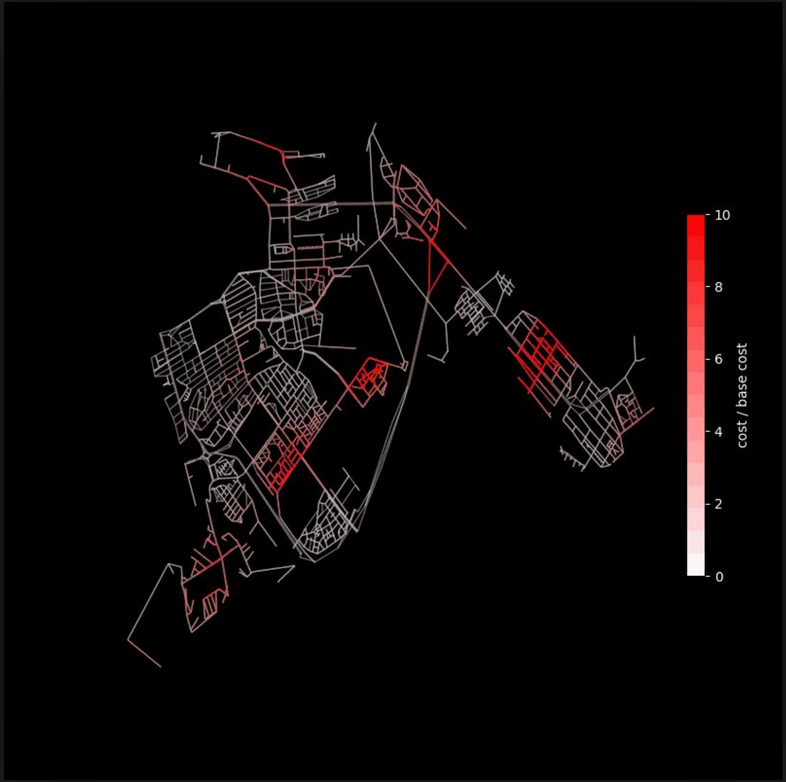
Results test 2: best colony VS best grid searched colony

- Mann–Whitney U: 4548.5
- p-value: 0.800
- Cliff’s delta: -0.0366
- **Insignificant** difference
- We can not say if our approach is better than two-variable grid search to optimize local rules

Part 2: dynamic map

- Why use ant colony optimisation?
- Information is not free
- Traffic simulation

$$M(\vec{x}, t) = 1 + \sum_{i=1}^{10} \alpha_i \sin(\vec{K}_i \cdot \vec{x} + \omega_i t + \phi_i)$$



The concept

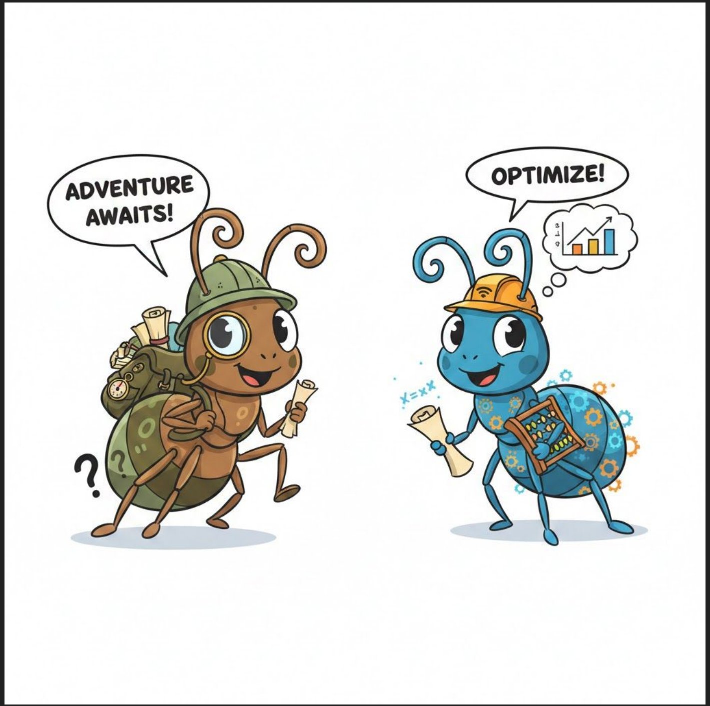
-Two genotypes: explorers and non-explorers

-Natural selection: top 10 performers

-Room for improvement?

-We expect increased adaptability compared

to a single genome colony

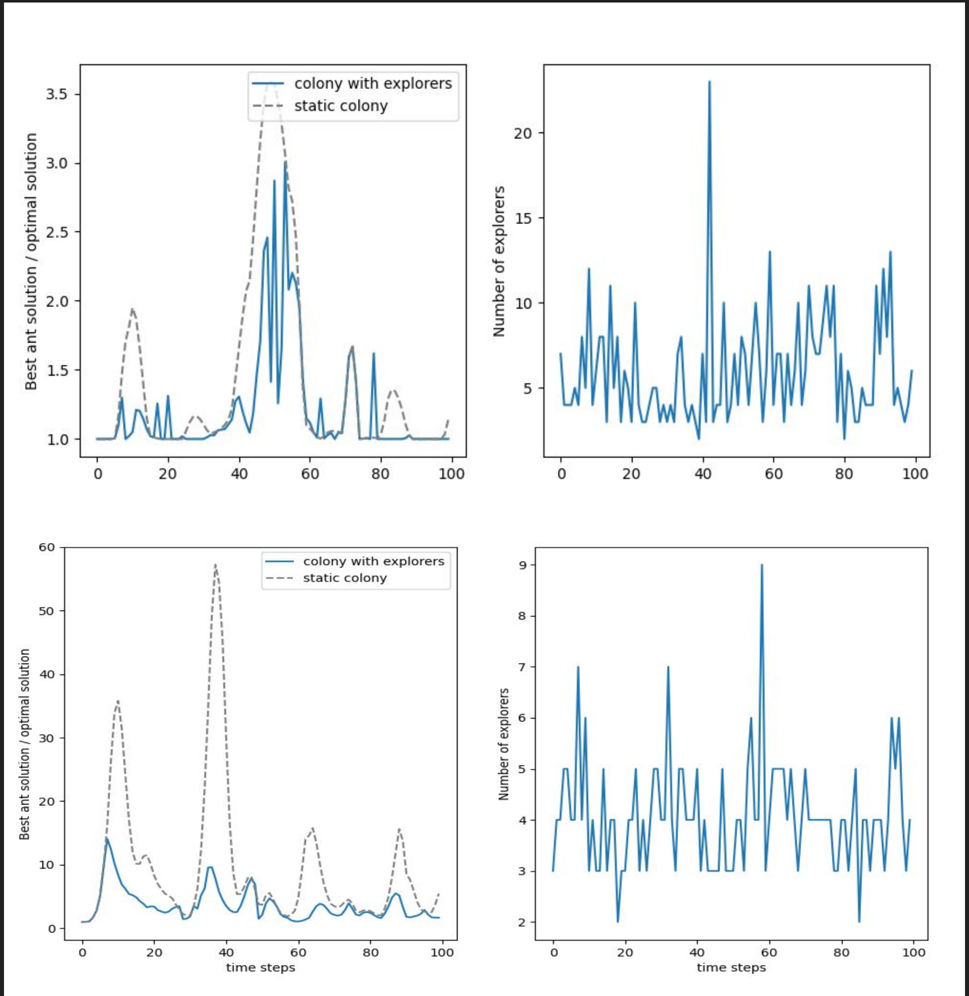


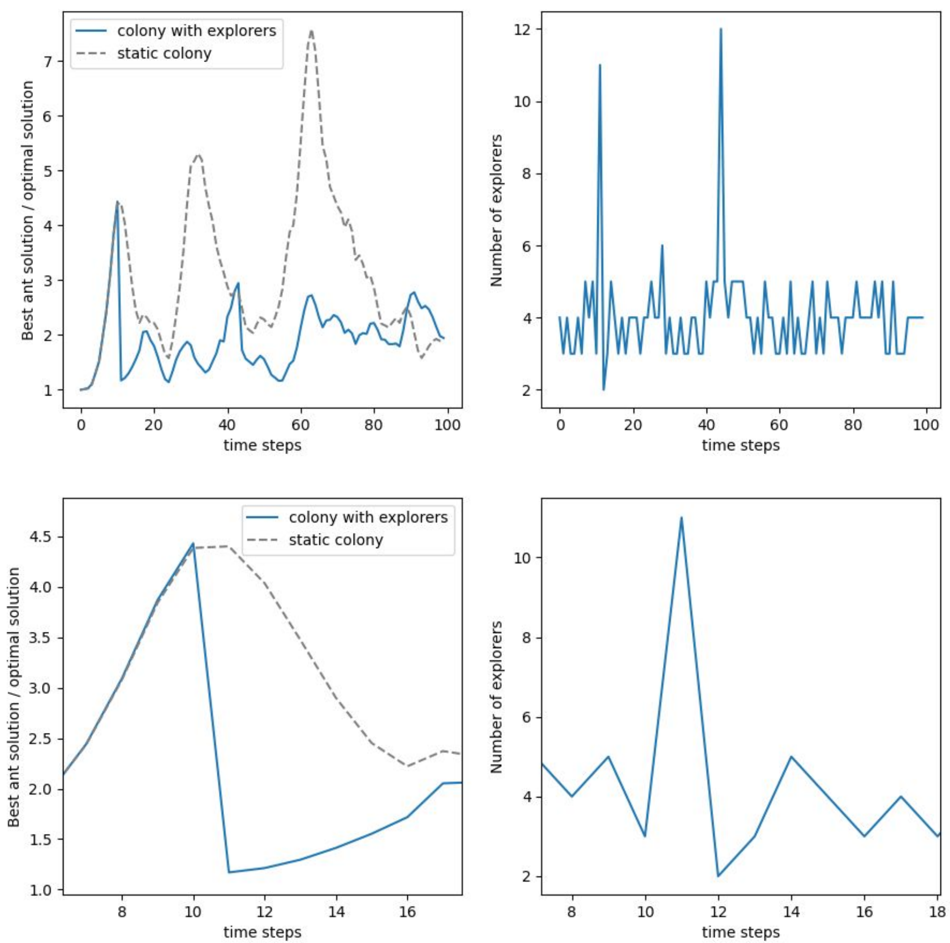
Results

-Consistent outperformance

-Worse performance could

 be relearning




colony with explorers
static colony
Best ant solution / optimal solution
time steps
Number of explorers
time steps
colony with explorers
static colony
Best ant solution / optimal solution
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time steps

Discussion

-Lots of ‘magic numbers’

-Exploration =/=> adaptation

-More genotypes?

-Alpha
-Beta
-Number of ants
-evaporation
-max_pheromone
-Q (deposition)
-Fertility ratio
-Reproduction ratio
-Mutation ratio

Take-away

- It is possible to use evolution to optimize local rules for ants to increase the rate of convergence, but two-variable grid search performs similar.
- A colony with two genomes can outperform a single-genome colony in a dynamic environment.

This project

Future work