

The Effects of Environment Complexity on Agents in A-Life

T6 - Existential Dread

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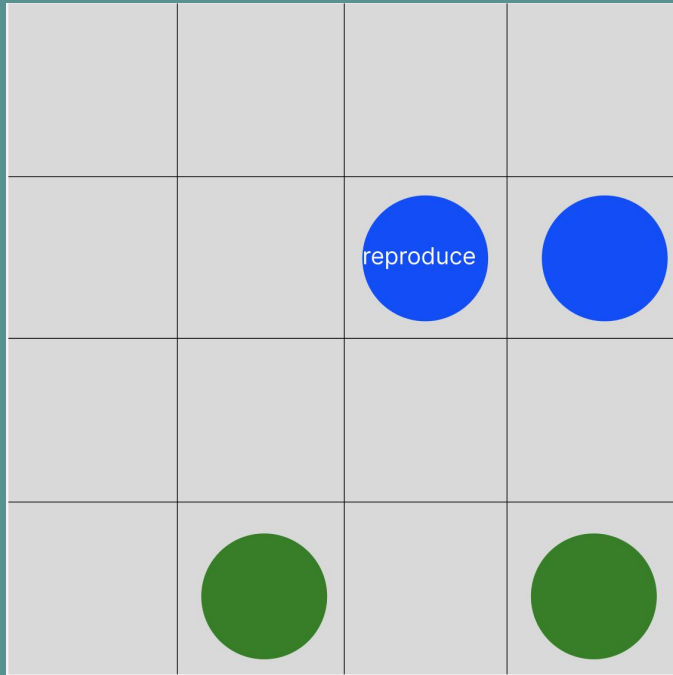


Background

Problem Formulation
Rejected Approaches
Our Approach
Results
Reflection



Back to the mushroom kingdom



- **Green:** Mushrooms (Resources)
- **Blue:** Turtles (Agents)

30 x 30 grid

Simulation goes on until all agents die

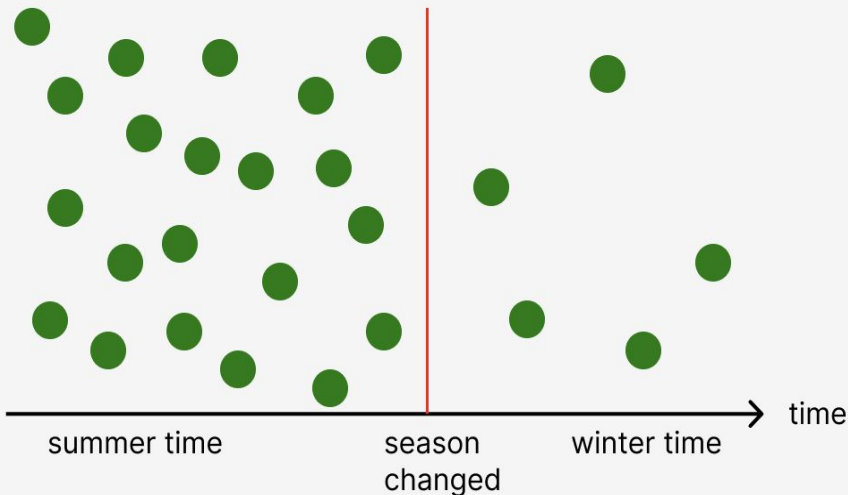
Each timestep, each agent:

- Observes the adjacent eight tiles
- Uses its brain to choose a direction to move in (**costs energy**)
- Moves one step in a NESW direction (**costs energy**)
- Consumes the resource if it has moved onto a tile with a resource (**replenishes energy**)
- If it has been alive for long enough and has enough energy, reproduces (**costs energy**)

Environment settings

- Enough resources for agents to gain energy and reproduce
- Make agents evolve and produce a better brain
- Observe if agents are able to fit the environment

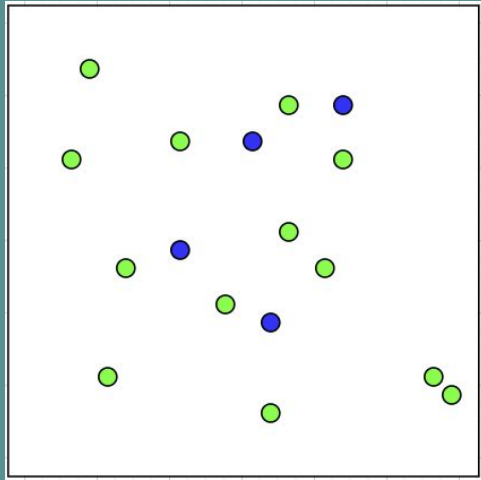
```
env = Grid()  
env.randomPopulate()
```



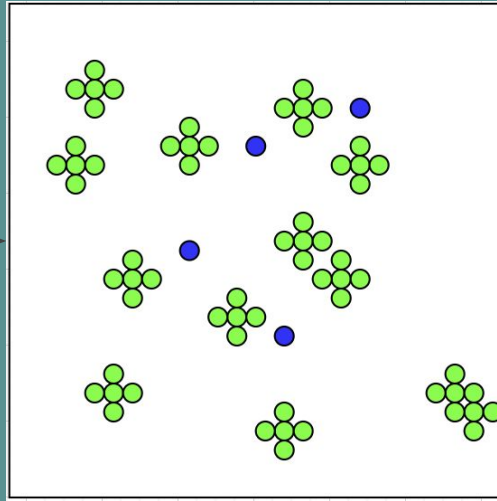
kill resource

EXAMPLE

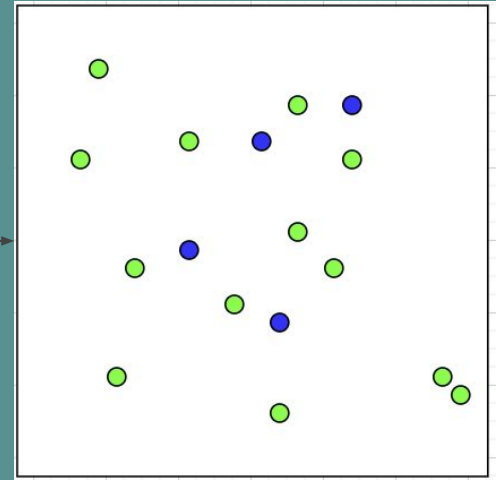
INITIAL ENVIRONMENT



SUMMER SEASON



WINTER SEASON



- Agents
- Food

Synthesized agent brain

- Very simple
- Able to evolve
- Reverse polish notation (RPN) for ease of reading
 - Also known as postfix notation

```
Agent Brain: N E S W argmax  
Agent Brain: N E S remember1 W argmax
```



```
arg maxi [N, E, S, W]  
arg maxi [N, E, remember1(S), W]
```

1 square vision

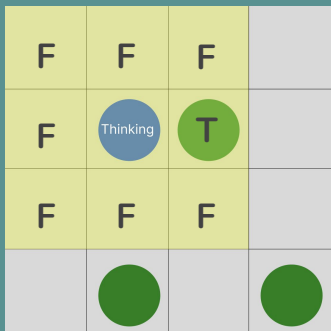
Remember
operator

- Argmax returns index relating to actions (up, right, down, left)
- If argmax doesn't return anything, the (stay) action is used

The Remember Operator

Memory: Whether or not a tile has a resource on it (tiles stored as global coordinates)

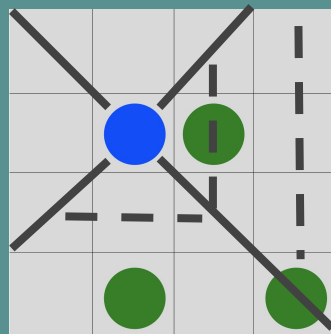
Each timestep, agent updates memory with 8 adjacent tiles.



$\text{remember}\langle X \rangle(\text{direction})$, where X = memory depth, $\text{direction} \in \{N, E, S, W\}$

Returns number of resources X steps in given direction

However, when choosing an action, agents with a higher memory depth consume **more** energy



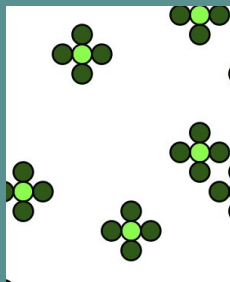
$\text{remember2}(E) = 2$

$\text{remember1}(S) = 0$

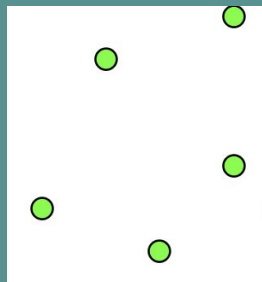
Why is it helpful?

- In winter, resources begin to die out
- **However**, the resource clusters are shrinking toward the initial resource positions
- So, in winter, memory will often be outdated, but it will lead the agent toward the cluster locations, and thus toward the few resources that are left

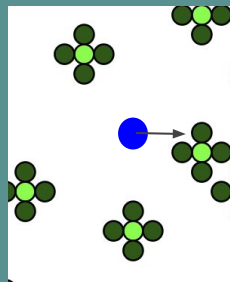
Memory



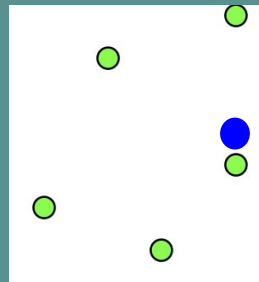
Actual



Remembers
resources in
this direction



Memory was
partially incorrect,
but still gets close
to a real resource



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The Problem

**Within artificial life,
how does increasing
environment complexity
affect agent complexity?**

INPUT Environment Complexity

- Summer/Winter cycle
- Complexity knob that we defined

OUTPUT Agent Complexity

- Memory usage

HYPOTHESIS

Agent complexity increases **linearly** as environment complexity increases.

In other words, as the rate of season changes increases, we expect to see more agents use memory operators

Why this is important

- Calvin's "A Brain for All Seasons"¹
 - Hypothesis that humans developed more complex brains due to changes in the environment
 - Simplified to memory alone
 - A-life approaches can help reason about human evolution, without requiring real-life testing

¹ William H. Calvin, A Brain for All Seasons: Human Evolution and Abrupt Climate Change (University of Chicago Press, 2002)

Background
Problem Formulation

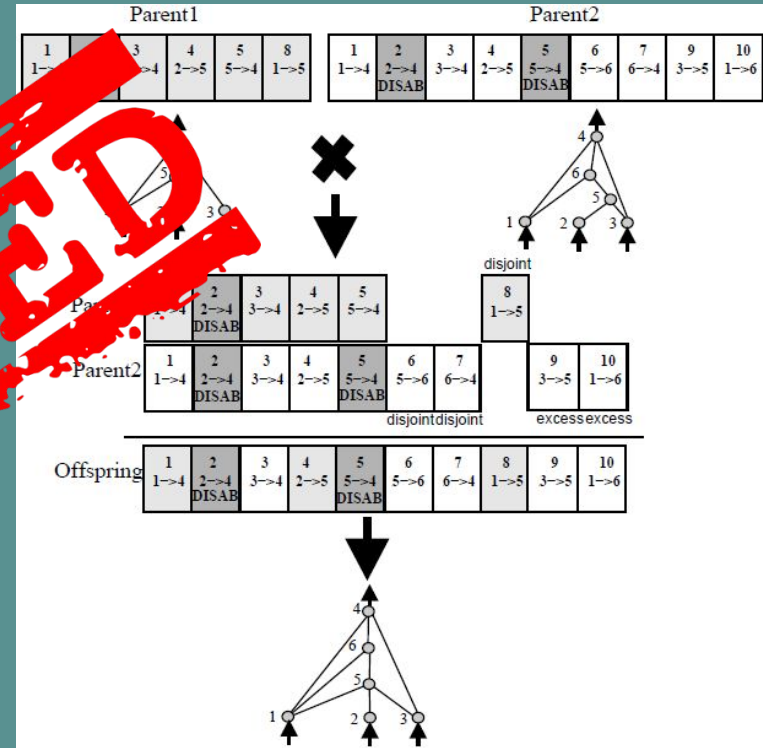
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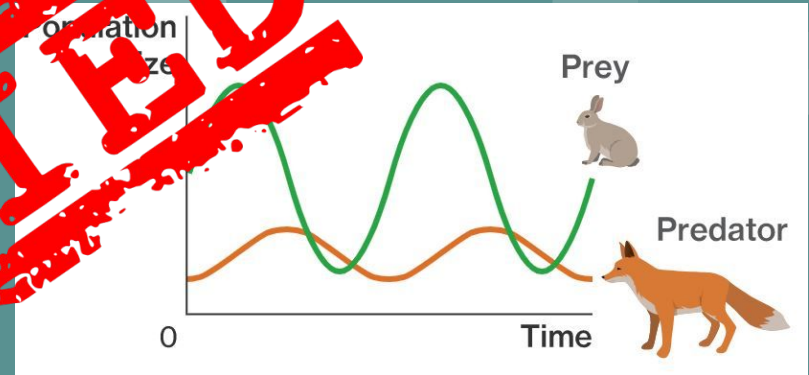
Approaches (NEAT)

- Difficult to implement and impossible to run with large population of agents
- We don't know what Neural Networks are actually doing



Approaches (Prey and Predator)

- Prey as agent (done before... a lot)
- Predator as agent (evolve into a super predator)
 - Moving resources with behavior being environment complexity
 - Lack of resources
 - Leads to lack of evolution



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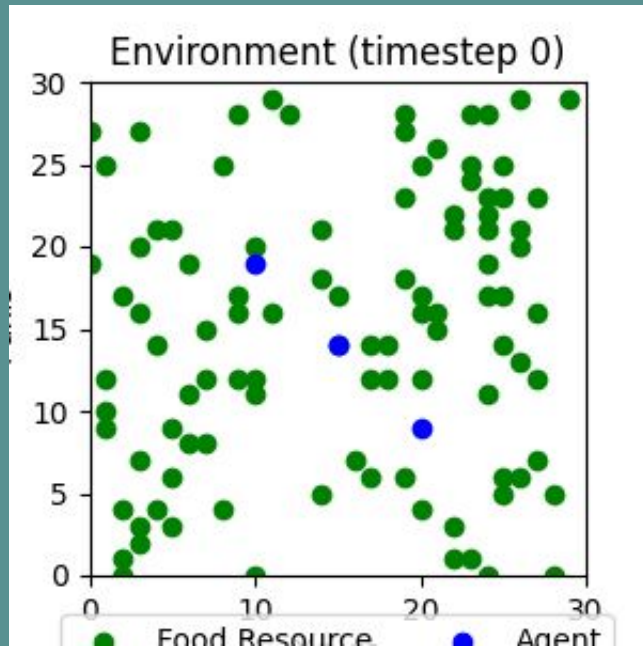
Our Approach

- Agent brain: program synthesis using reverse polish notation for simplicity
- Environment complexity through seasons
- Agent complexity through memory

The experiment (outline)

- Initialize Environment and Agents
 - Random brains
- Let the world do it's thing
 - Summer time different between environments, winter time is constant
- When an agent reaches a suitable energy level, reproduce (mutation)
- Over generations, we observe the lifespan and gather data

Initialize environment and Agents



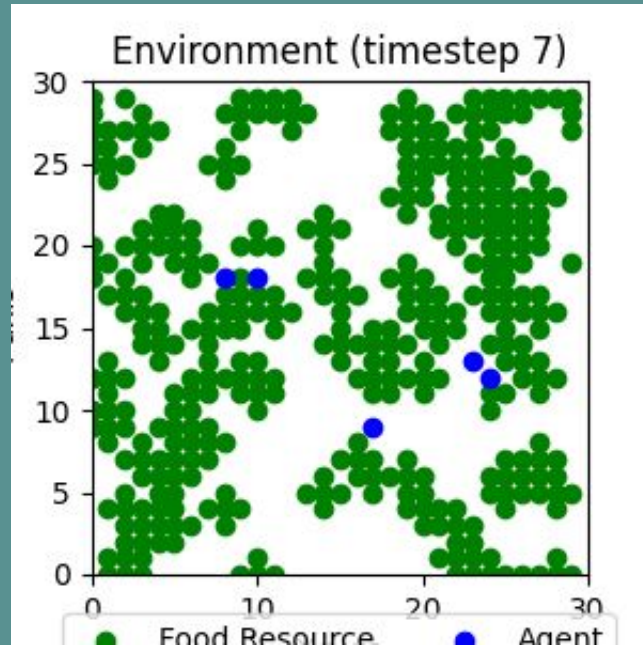
Brains:

Agent 1: N N S E argmax

Agent 2: E N S W argmax

Agent 3: N S S E argmax

World runs and reproduction happens

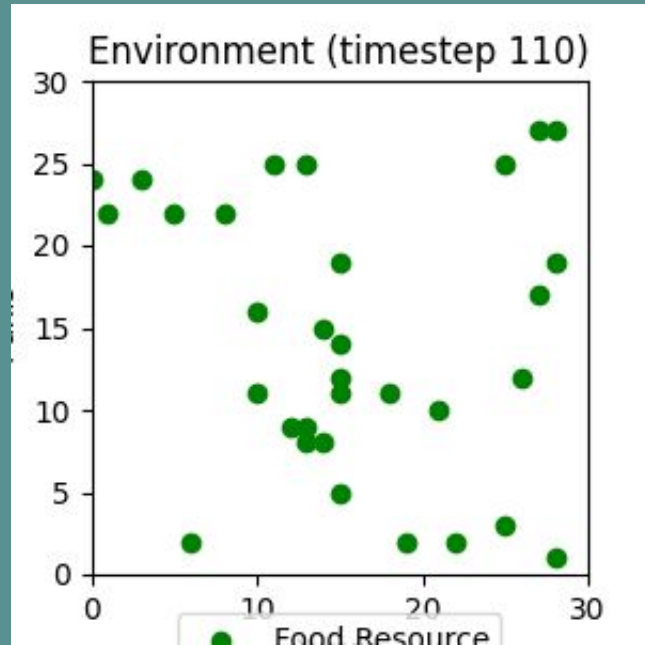


Brains:

```
Agent 1: N N S E argmax
Agent 2: E N S W argmax
Agent 3: N S S E argmax
Agent 4: N E S W argmax
Agent 5: N S S remember1 E argmax
```

- Mutation: With a small probability, change certain variables in the agent's brain formula.
- Ex. Agent 3 → Agent 5

Eventually, death



Start to look at extinction percentage

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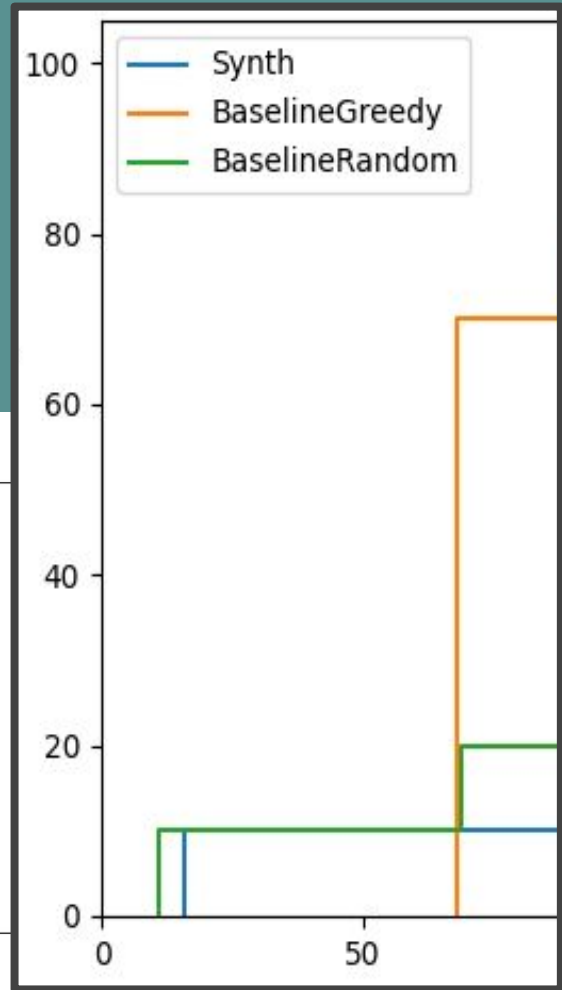
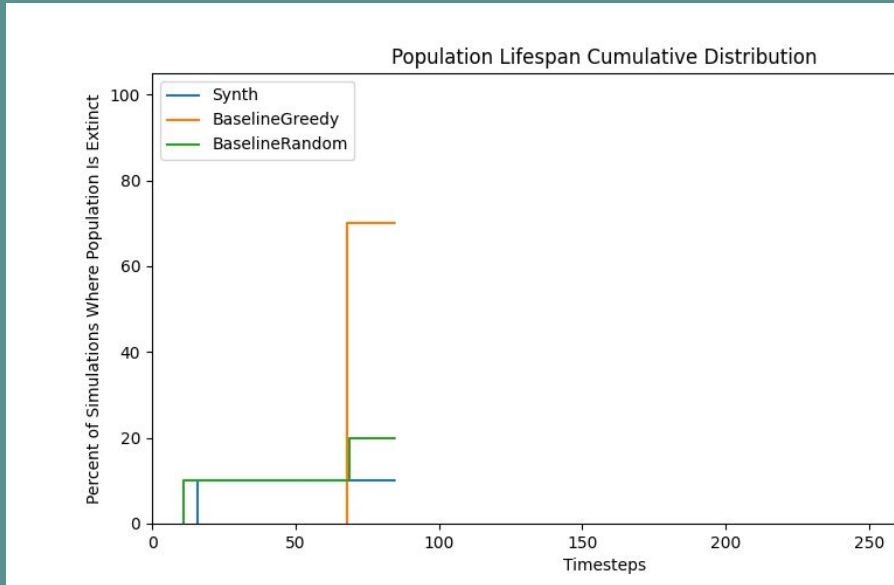
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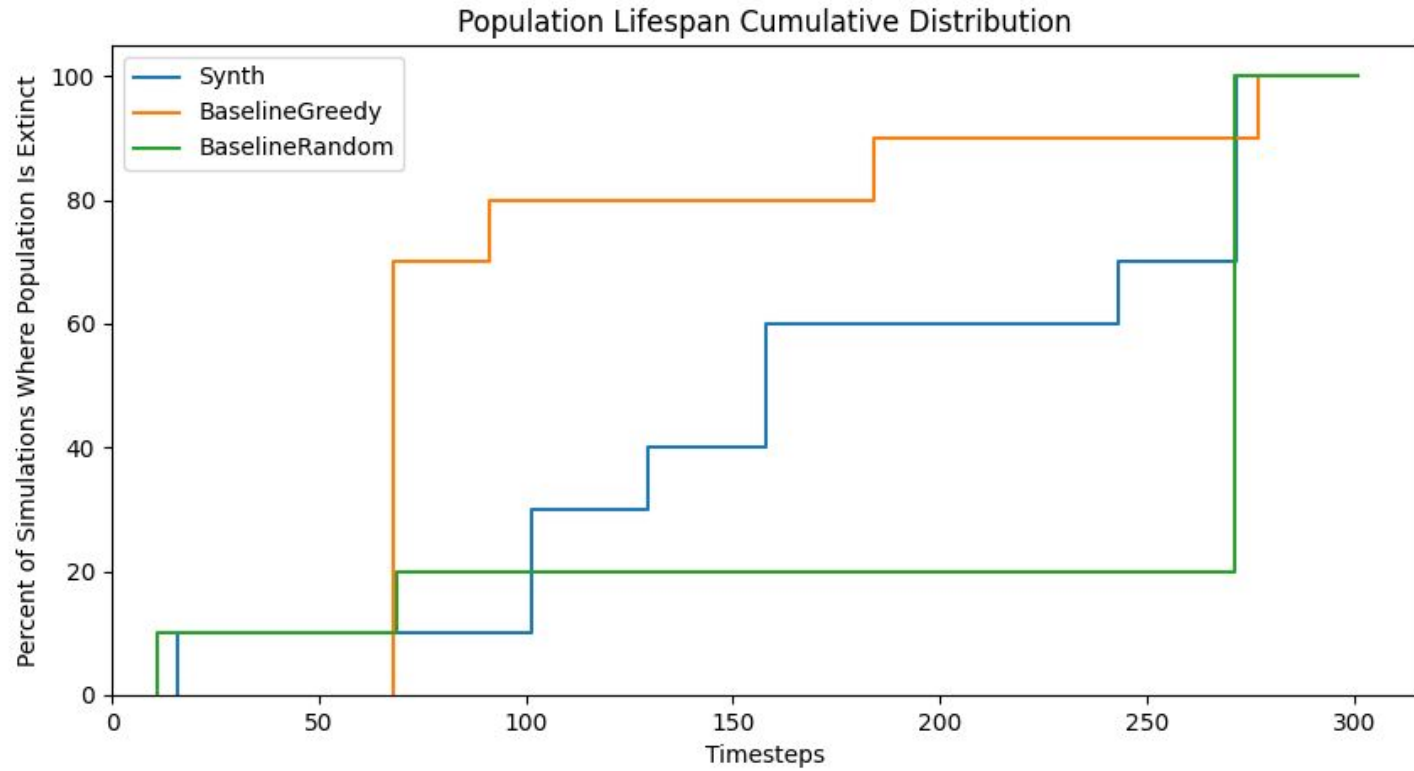


Cumulative Distribution Plots

- Answer: At a given timestep, how many populations (simulations) are extinct?
- Ideal plot stays **low** for as long as **possible**

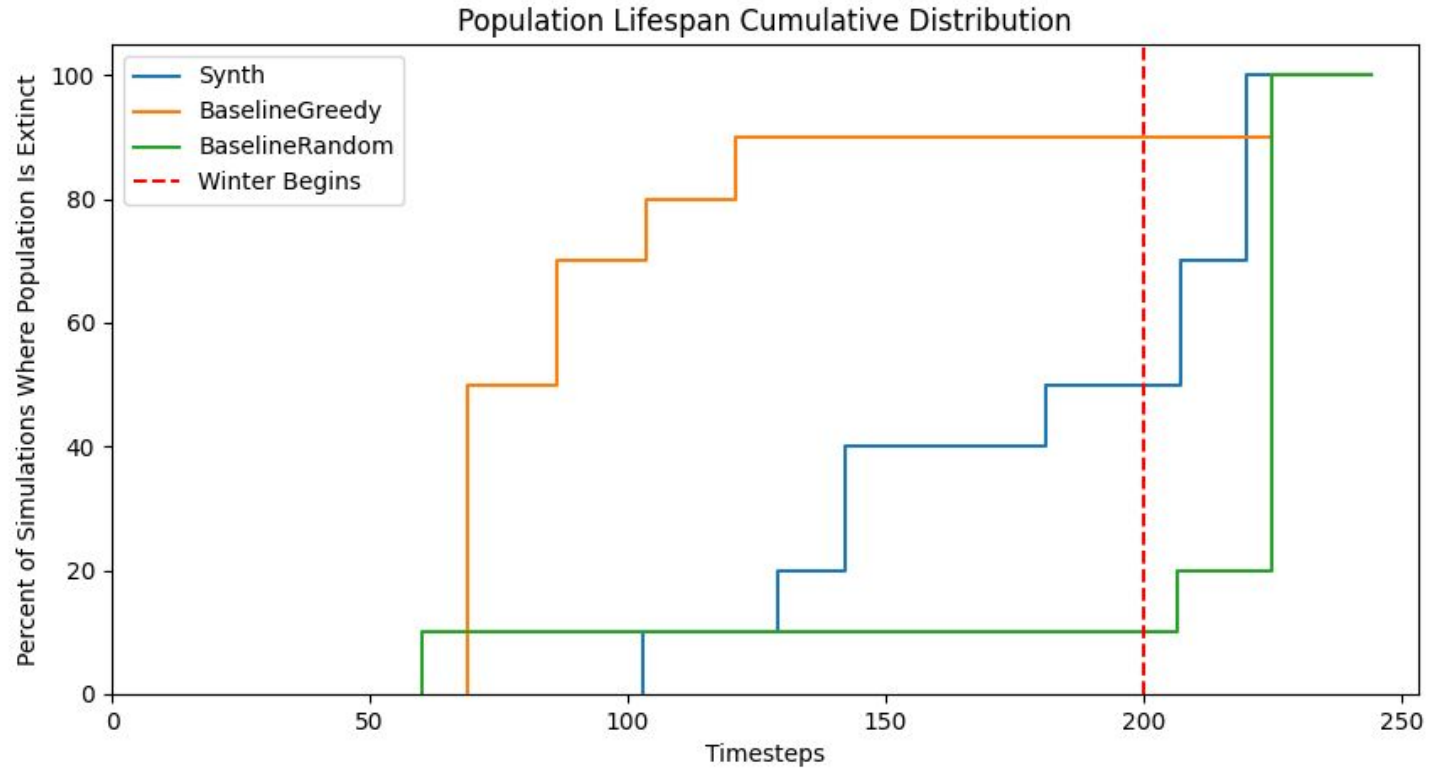


Agent Performance



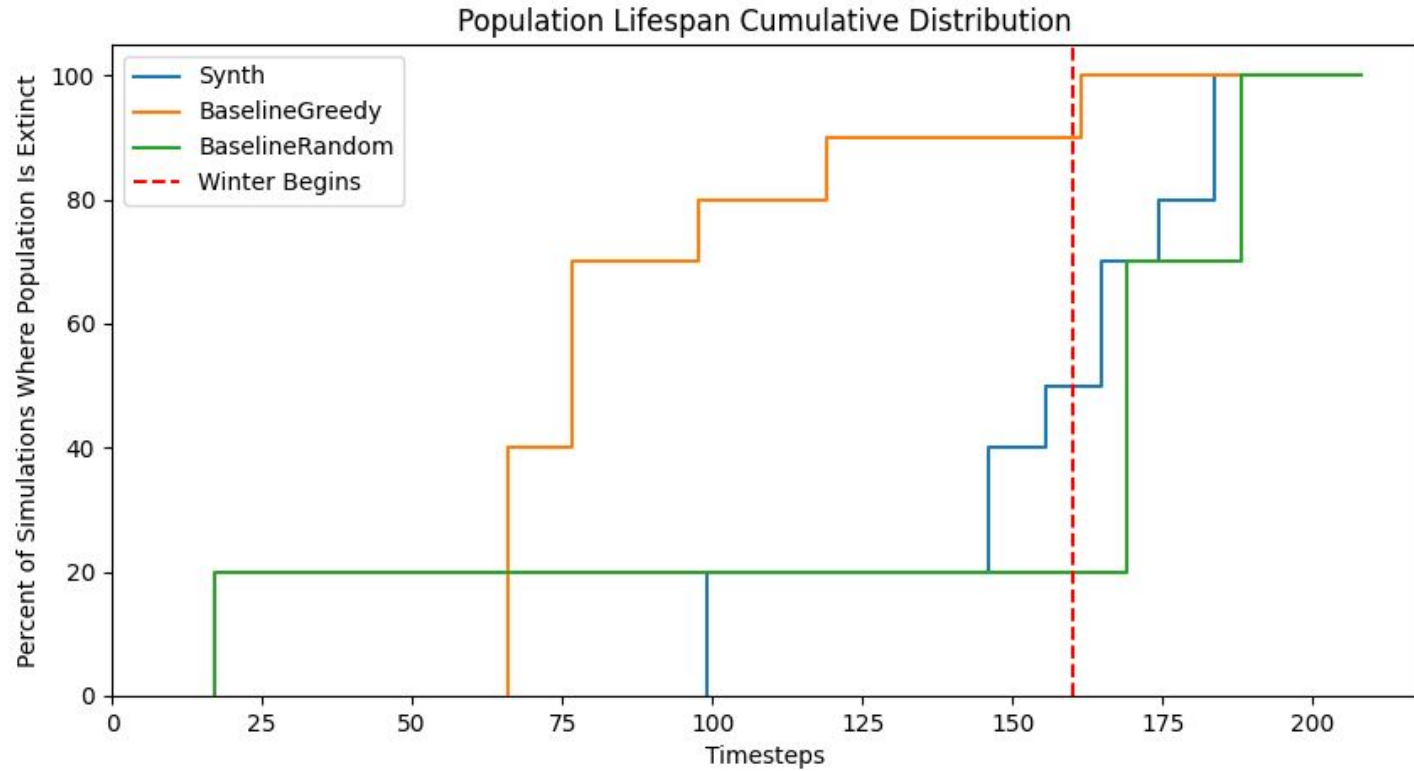
Static Environment ($s = \infty$)

Agent Performance



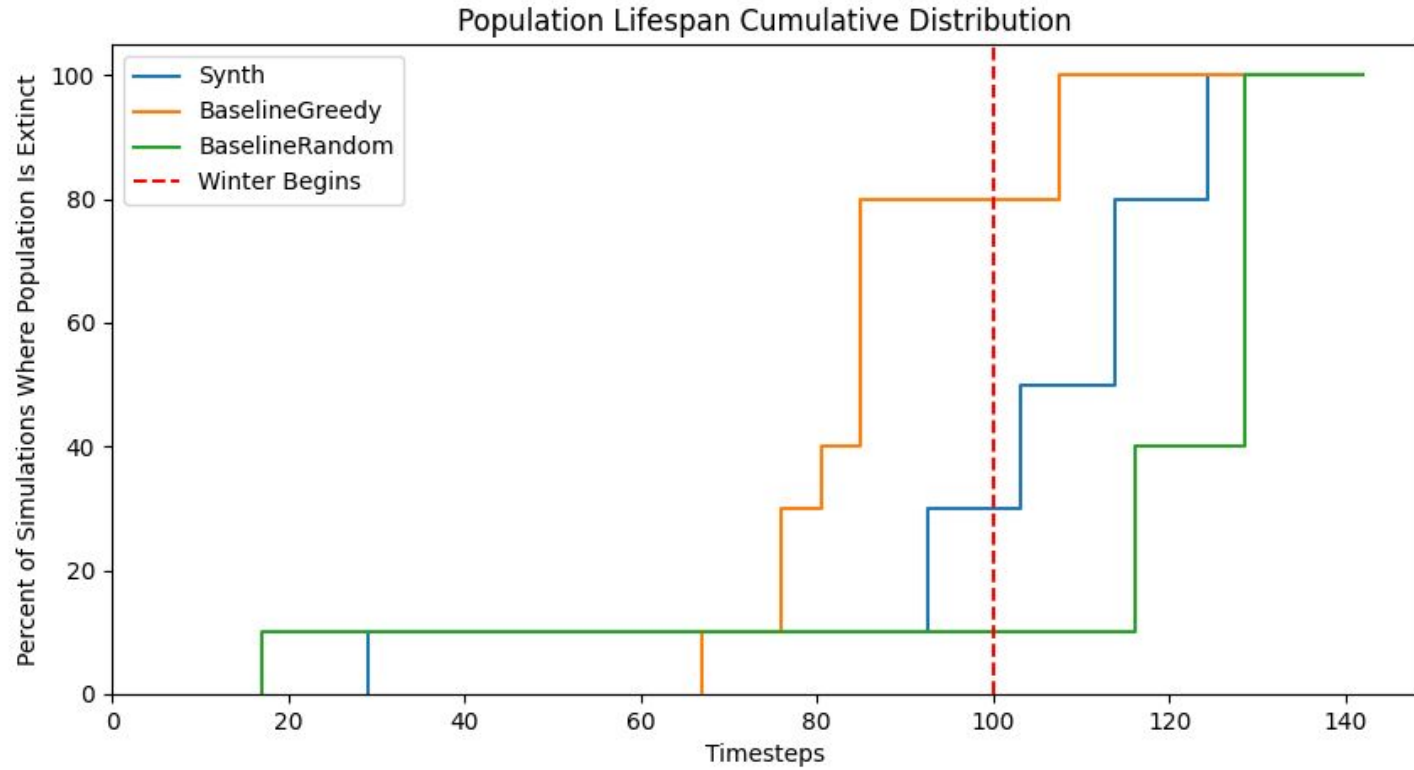
Slowly Changing Environment ($s = 200$)

Agent Performance



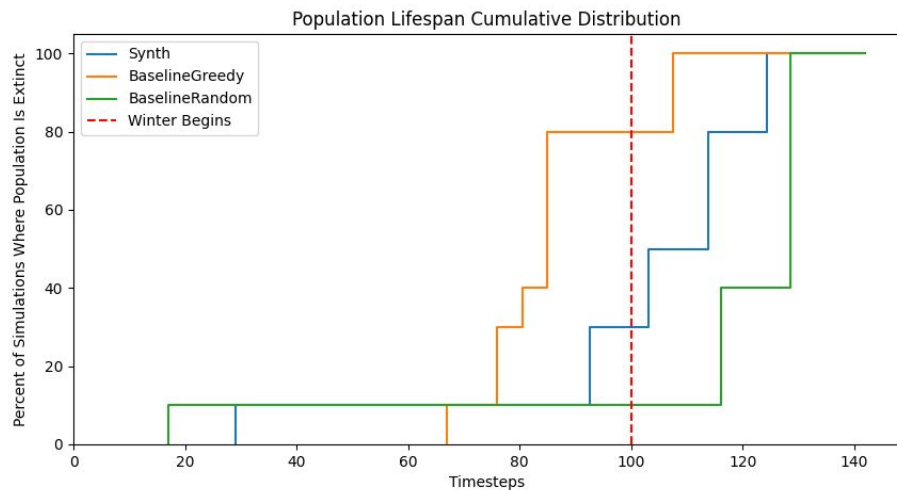
Faster Changing Environment ($s = 160$)

Agent Performance



Rapidly Changing Environment ($s = 100$)

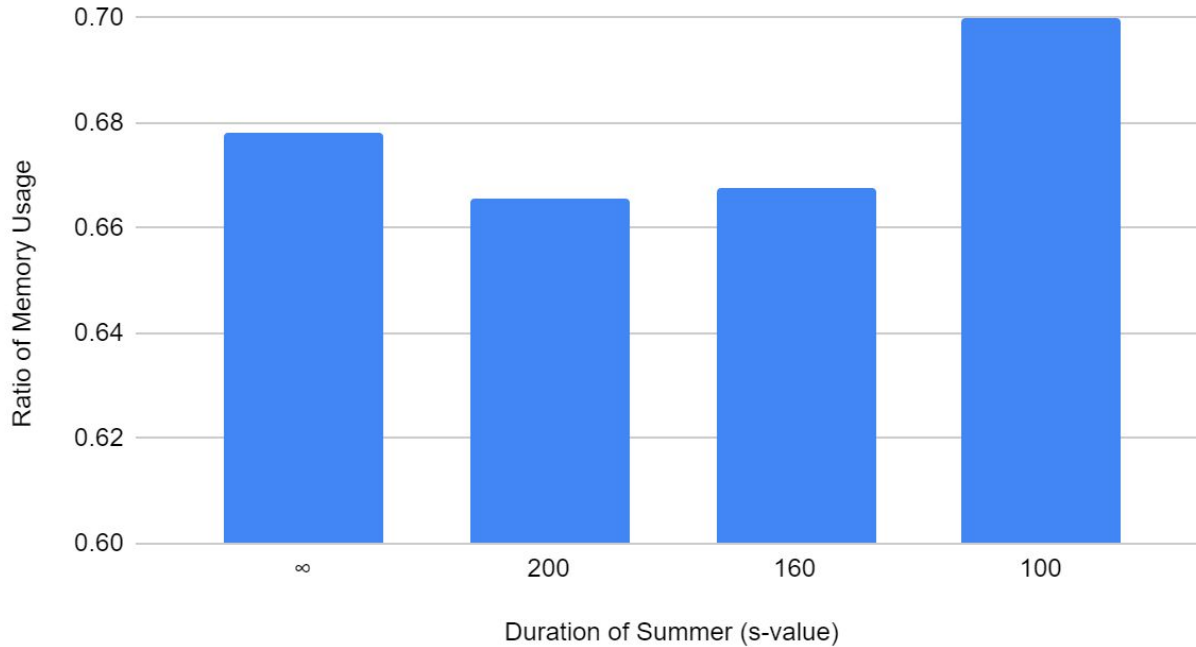
Agent Performance



Notes on results:

- Poor greedy agent performance likely due to being too optimal (overeating)
- Performance of Synth agent does not change significantly

Memory Usage in Different Environments



Static and rapidly changing environments → memory useful

Conclusion: relationship is not linear

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What actually worked

- Some individual agents are able to survive longer.
- Agents are able to use memories to take actions.
- Sufficient resources are making agents to evolve.

Example of evolved agent brain
(21 predecessors):

```
N W remember1 E S argmax
```

What did not work

- Enough resources & without tuning parameters
- Design the environment without enough food resources
- Look at results without visualization



<https://devrant.com/rants/464533/its-more-annoying-for-me-when-my-code-works-and-i-dont-know-why-when-actually-it>

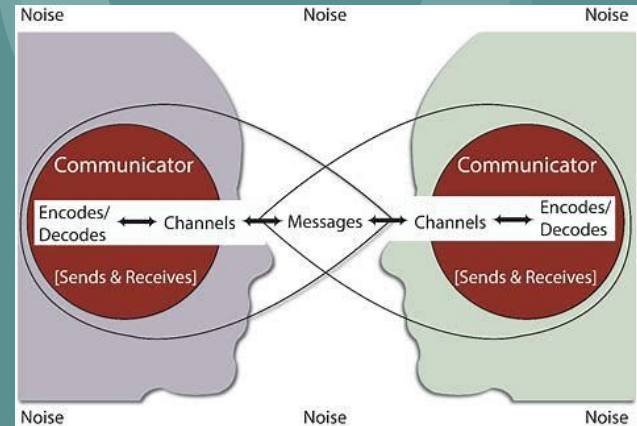
What we learned

- Environment complexity (intuitively) increases Agent complexity, but not linearly
- Greedy agents overeat
 - Build an environment without competition
 - Random agents perform better than greedy



Approaches to explore in the future

- Different environment settings
 - With or without competition
- Neural network type brain
 - With better explainability
- Communication between agents
 - Due to there being multiple agents
 - It increases the survival rate of the population



https://www.shortform.com/summary/communication-skills-training-summary-james-williams?utm_source=bing&utm_medium=cpc&msclkid=b7899c318dc9143432cfa2698e951a8

Questions?