

Multi-agent Communication Disorders: Dynamic Breeding Networks in Genetic Algorithms

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Summary

In an ABM, agents communicate.

These interactions form a social network.

We are interested in how the properties of these networks affect group problem solving abilities.

Outline

- **Genetic algorithm model**
- Diffusion of innovation model
- Show and tell
- Experiment
- Results
- Future work


Standard genetic algorithm (GA)

- Start with a tricky problem
 - e.g. scheduling elephant bath time



- Represent possible solutions as bit strings



Bubs & Candy first, then Dumbo alone, then ...

= 101001010111101101110 = 

Dumbo & Moony, then Bubs & Goober, then ...

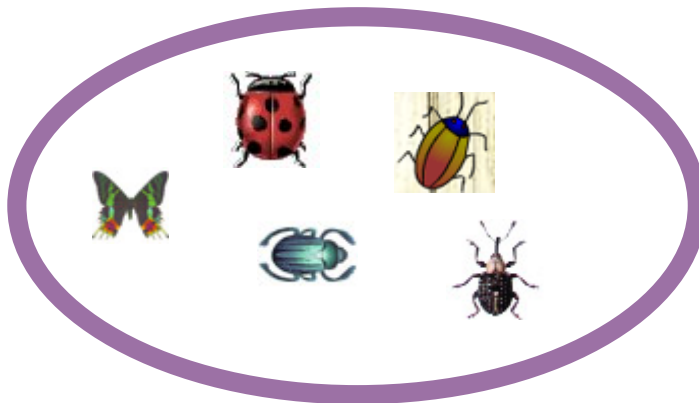
= 001111011011011011011 = 

“Bath Schedule” creatures

101001010111101101110 = 
001111011011011011011 = 



Population










Fitness function:

How good is each bath schedule?

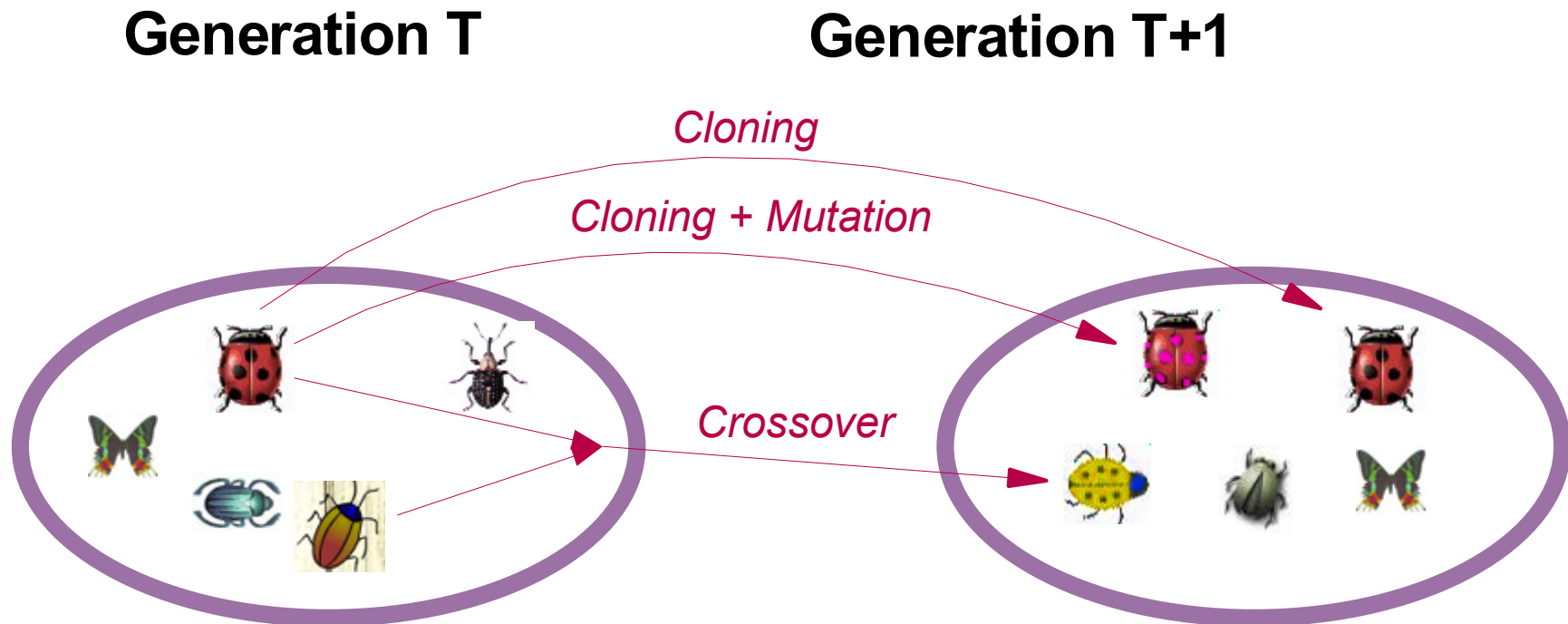
$f(\text{Red Ladybug}) = \text{fair} = 0.7$

$f(\text{Yellow and Blue Beetle}) = \text{poor} = 0.3$

Genetic operators

<i>Crossover</i>	$101001010111101101110 = $ 
	$001111011011011011011 = $ 
	$1010010101111011011011 = $ 
<i>Cloning</i>	$101001010111101101110 = $ 
	$101001010111101101110 = $ 
<i>Mutation</i>	$101001010111101101110 = $ 
	$101001010111100101110 = $ 

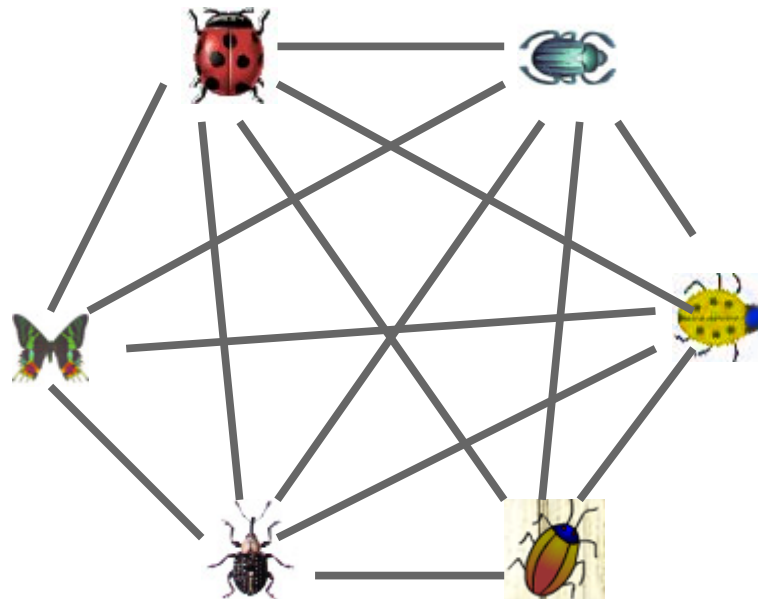
“The Next Generation”



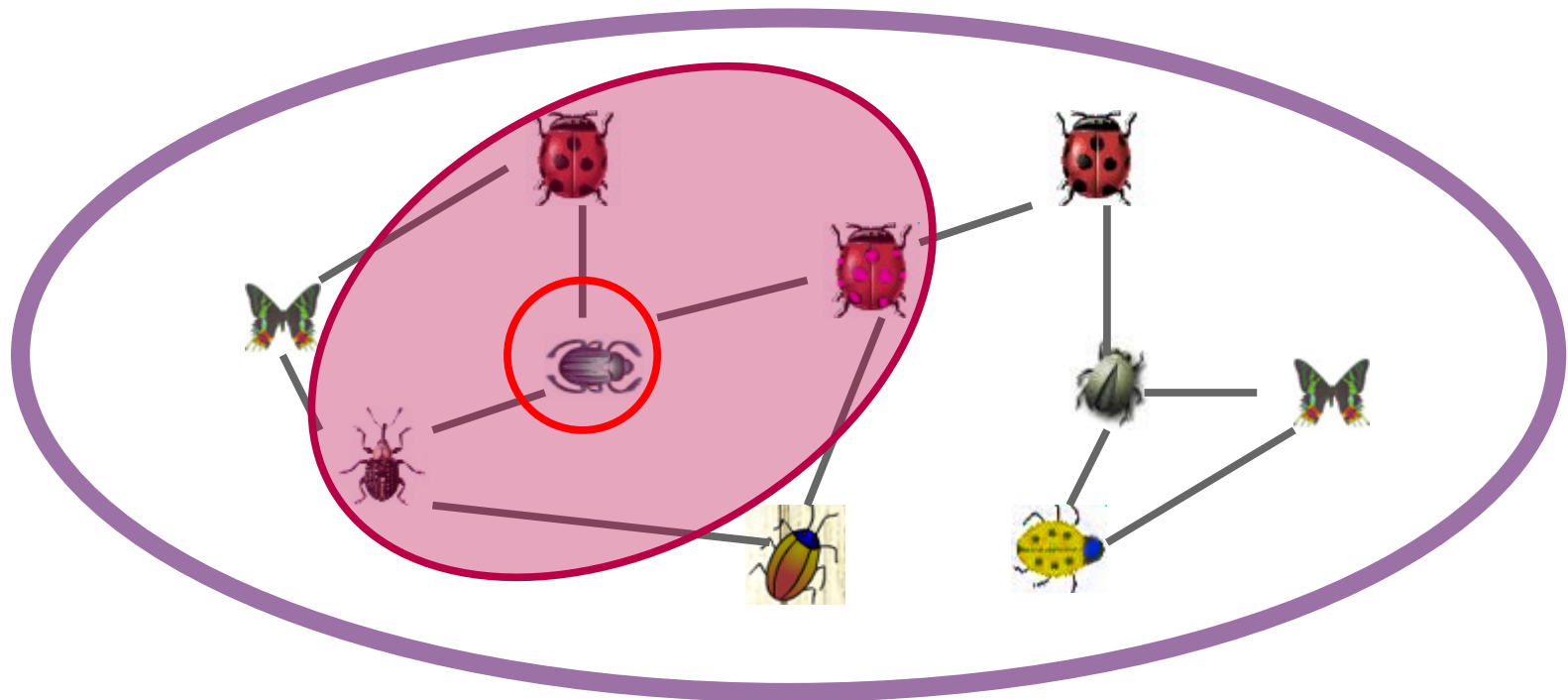
and repeat until satisfied...

Complete Breeding Networks

- In the standard genetic algorithm, every agent can breed with every other agent.
- This can be represented by a complete graph.



Restricted Breeding Networks

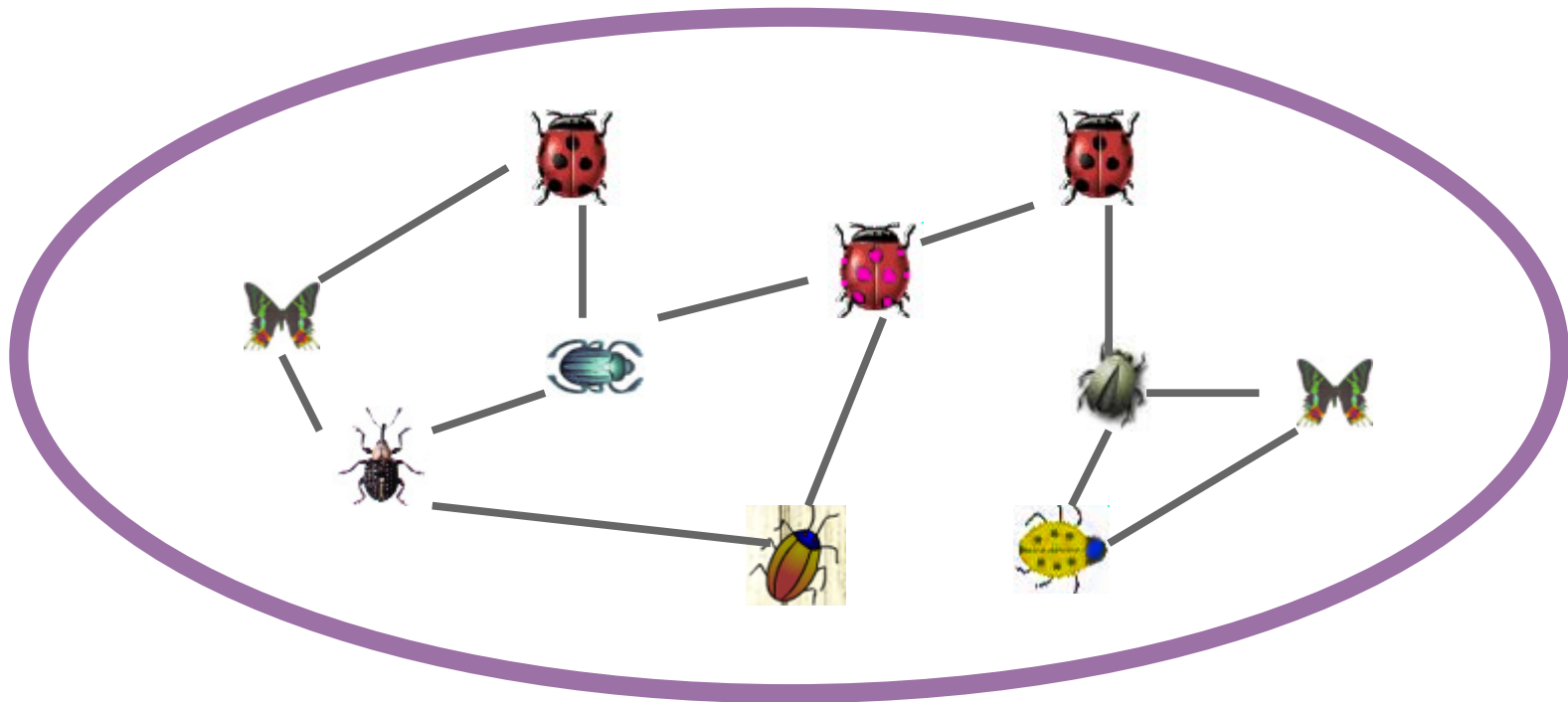


Why should we care?

- Theoretical knowledge in machine learning
 - They might perform better than standard GAs
 - Understanding evolutionary processes
- Applications (parallel GAs)
 - Peer to peer computing
 - Mobile and ad-hoc networks
 - Swarm robots, smart dust?

Primary Question

How sparse can the breeding networks be, such that the genetic algorithm still works?



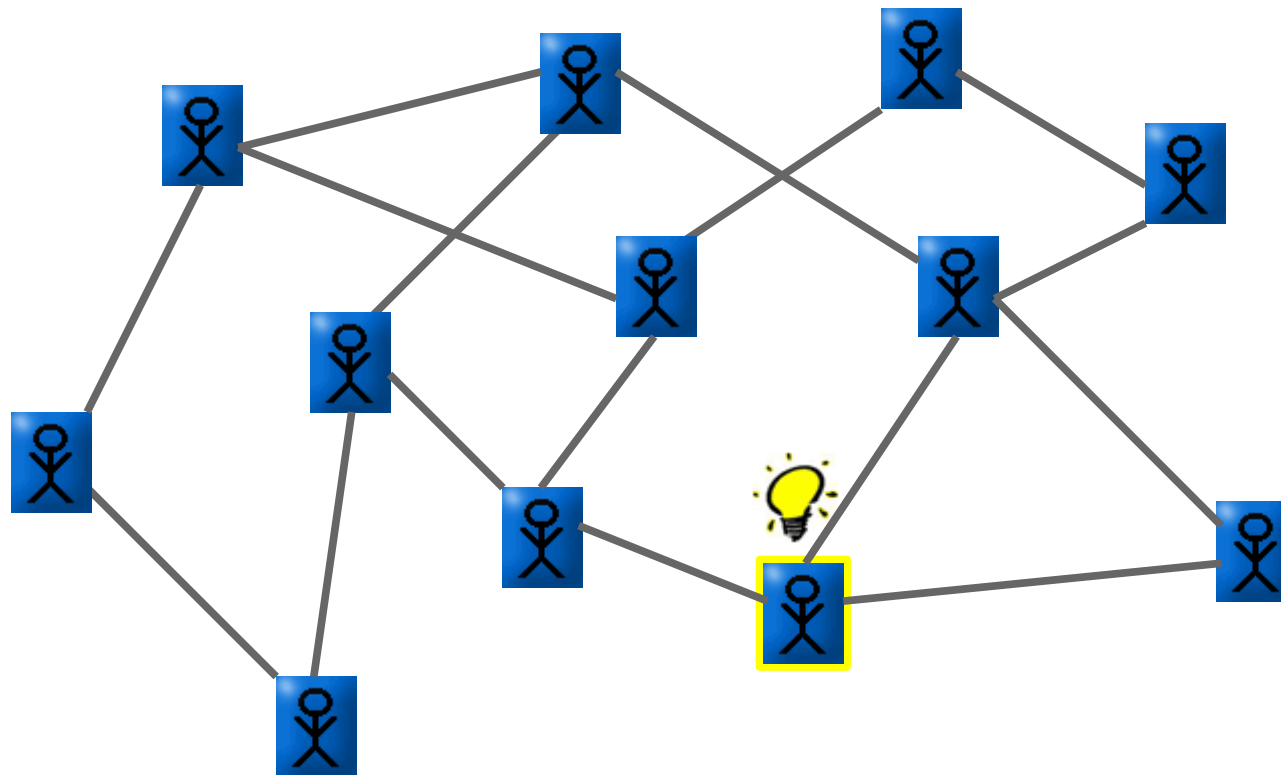
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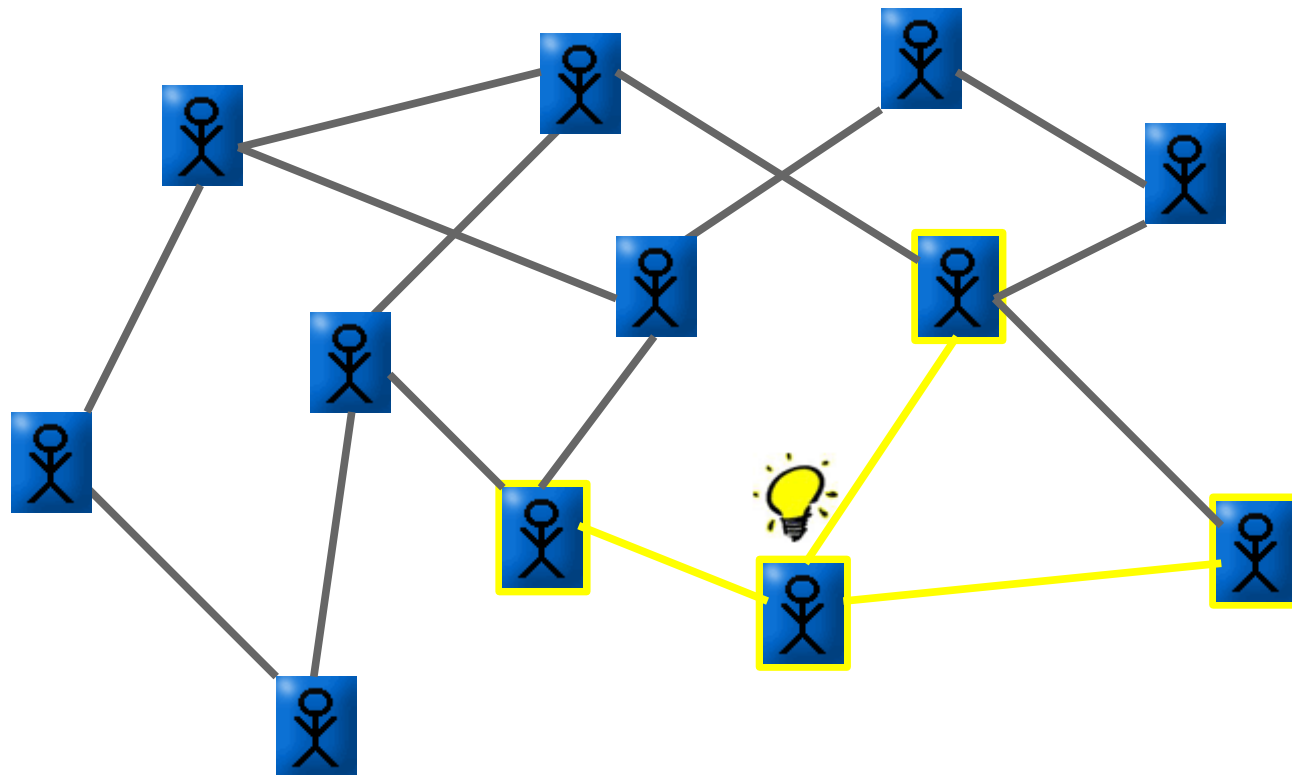
Diffusion of Innovation

- Organizations have social structure
- Individuals follow policies
 - ideas, problem-solving methods, etc
- Better “more innovative” policies diffuse through the social network, as individuals adopt those policies.

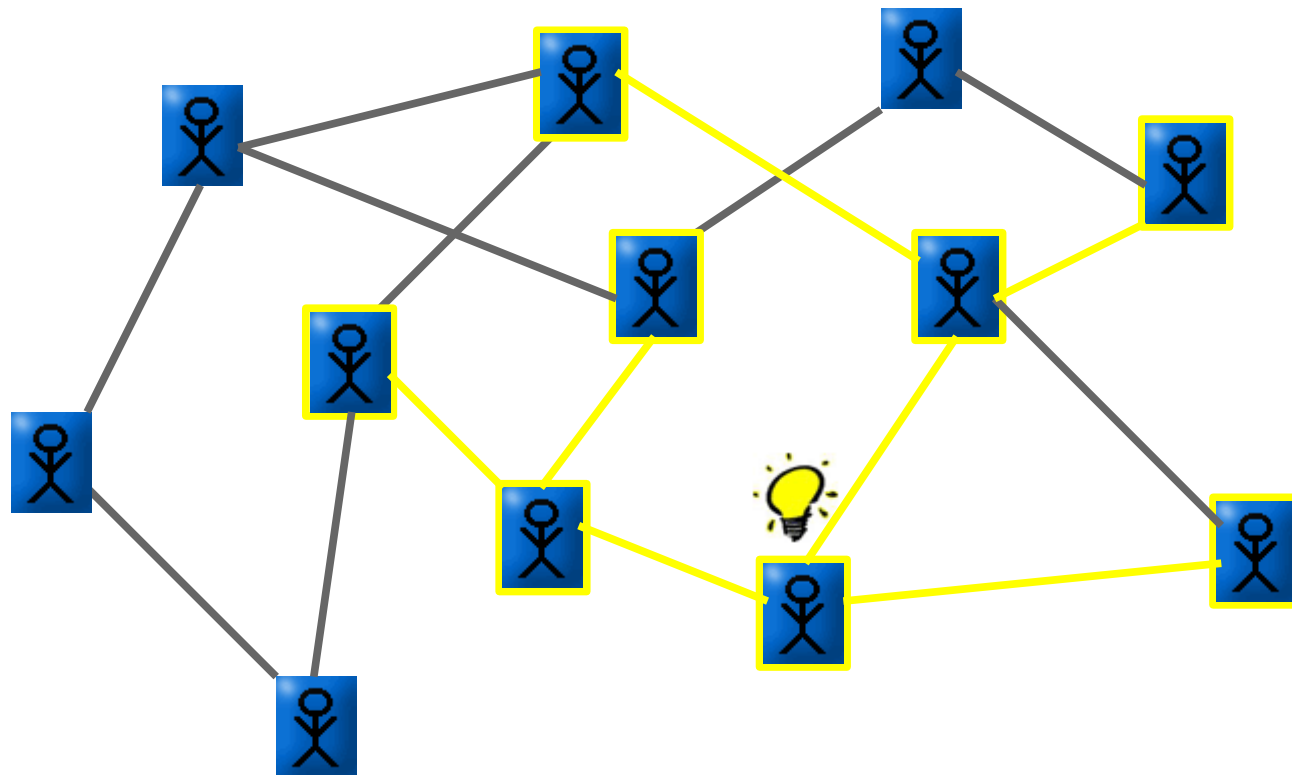
Diffusion of Innovation



Diffusion of Innovation



Diffusion of Innovation



Complexifications

- Policies could be multi-faceted
- Agents could take pieces of policies from other agents
- Adoption shouldn't be deterministic

A Model of Diffusion

- Each person may:
 - Keep their own policy
 - Copycat a neighbor's policy
 - Combine two policies
 - Slightly change their policy

A Genetic Model of Diffusion

- Each person may:
 - Keep their own policy
 - Copycat a neighbor's policy } **Cloning**
- Combine two policies **Crossover**
- Slightly change their policy **Mutation**

Bringing it together

Our model can be viewed from multiple perspectives.

Hopefully it captures generic aspects of information dispersal in the context of solving some problem.

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- **Show and tell**
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Network Topologies

- Spatial (fixed):
 - Breeding neighborhood defined by “in-radius”
- Spatial (dynamic):
 - The agents move in the world
- Random (fixed):
 - Erdős-Renyi random graphs
- Random (dynamic):
 - Network “rewired” each generation.

Model Demo

Outline

- Genetic algorithm model
- Diffusion of innovation model
- Show and tell
- **Experiment**
- Results
- Future work

What's the “problem”?

- We used hyperplane-defined functions (HDFs).
- Goal: produce a certain pattern of bits.

... *****11100**00101***** ...

- In the fitness function:
 - some sub-patterns are rewarded (schemata)
 - some sub-patterns are penalized (pot-holes)

Constant parameters

- Population size: 256
- Crossover rate: 0.7
- Mutation rate: $1 / [2 \times \text{length_of_bitstring}]$
- Tournament selection with tournament size 3
- “Spatial dynamic” specific parameters
 - wiggle-angle amount = between -15 and 15 degrees
 - forward-step amount = 1% of world diagonal.

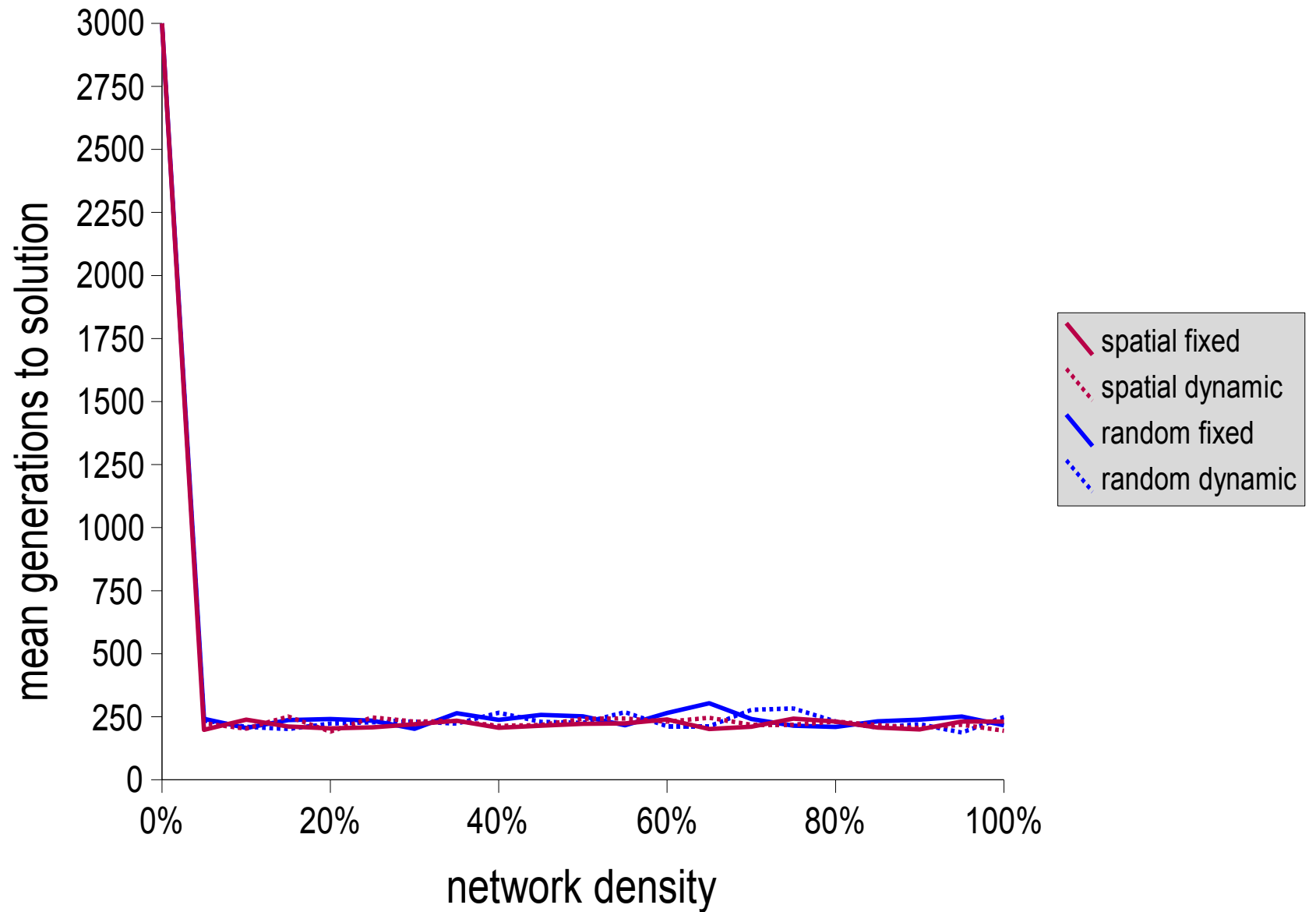
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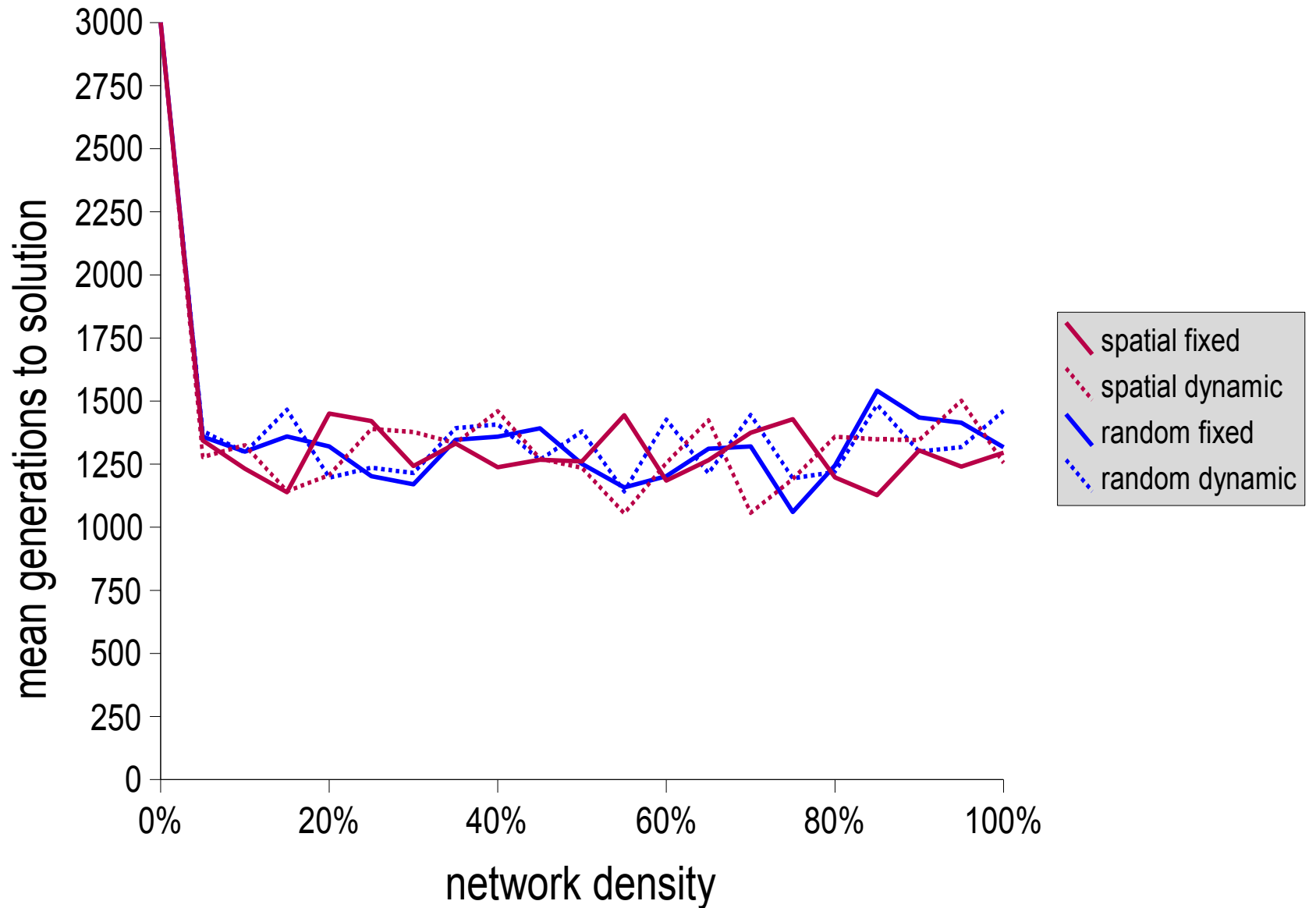
Experiment 1

- Vary the network density from 0% to 100%
 - Run the model until a “perfect” solution is found.
 - Measure how many generations it took.
 - (Give up after 3000 generations.)
- We ran 60 repetitions for each network density, and present the average.

Easier Problem (HDF100)



Harder Problem (HDF200)



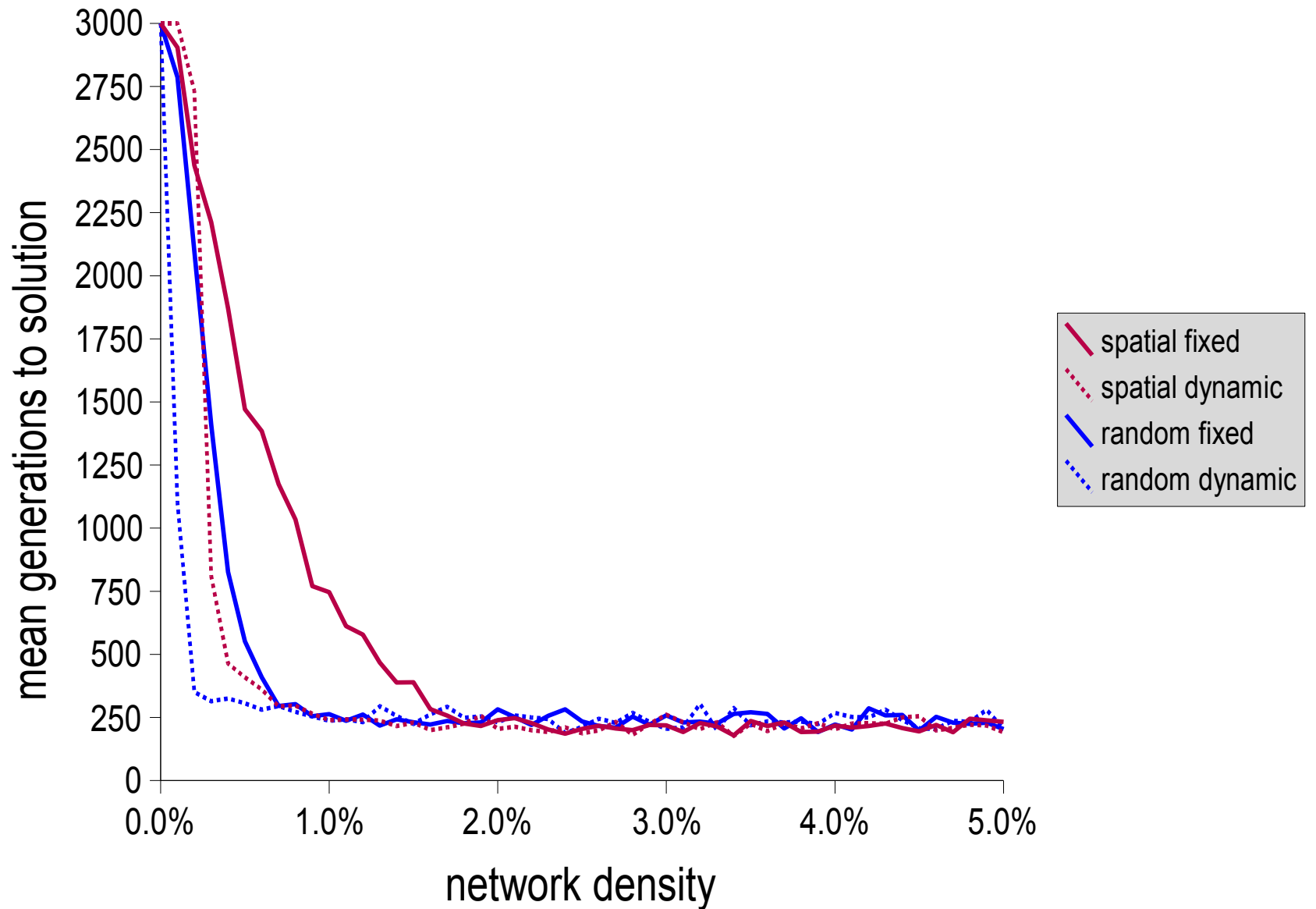
Observations

- The genetic algorithm is robust, even for sparse networks ($\leq 5\%$ density).
- We can't see much else.

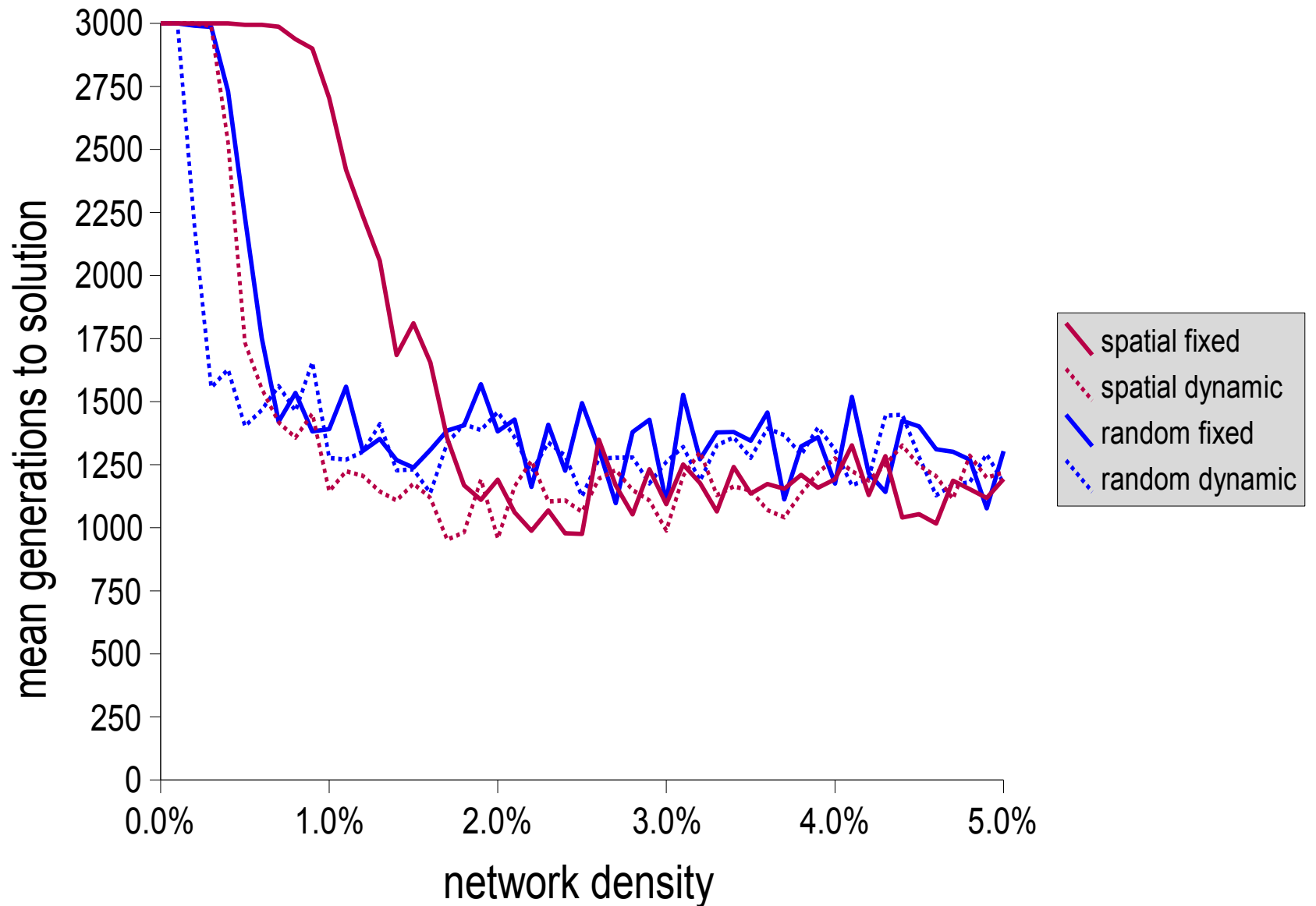
Experiment 2

- Vary the network density from 0% to 5%
 - Run the model until a “perfect” solution is found.
 - Measure how many generations it took.
 - (Give up after 3000 generations.)
- We ran 60 repetitions for each network density, and present the average.

Easier Problem (HDF100)



Harder Problem (HDF200)



Primary Question (revisited)

How sparse can the breeding networks be,
such that the genetic algorithm still works?

Answer:

**It depends somewhat on the network topology,
but our results suggest $< 2\%$**

New Question

- It appears that at very low densities:
 - **random** is better than **spatial**
 - **dynamic** is better than **fixed**

Why?

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Why?

- Giant component?
 - Spatial fixed in particular is segmented.
- (Dynamic) average path length
 - Less time to spread good news everywhere.
- (Dynamic) clustering coefficient
 - Faster rate of initial dispersion.

Extensions

- More network topologies
 - Small world networks (*Watts/Strogatz*)
 - Scale-free networks (*Barabasi*)
- Explore mutation rate
 - Do destructive mutations kill innovation before it has a chance to spread?
- Vary the rate of agent movement

Acknowledgments

- To my co-author, William Rand.
- To my advisor, Uri Wilensky, for his support.

Questions?