ETH zürich

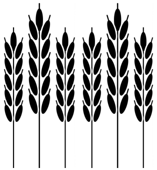
Evolution of Strategies for Prisoner's Dilemma

Gleb Fedorovich, Jan Heldmann, Lukas Schmitt, Fengshi Zheng

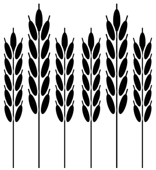
Historical background

Bob

Today



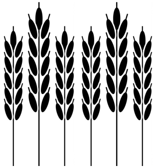
Tomorrow



Alice

Historical background

Tomorrow



Alice

Bob

	A Cooperates	A Defects
B Cooperates	(3,3)	(0,5)
B Defects	(5,0)	(1,1)

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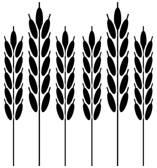
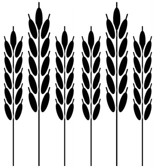


Historical background

Tomorrow



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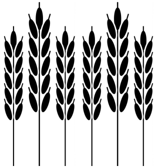

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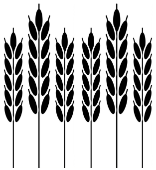
Tomorrow



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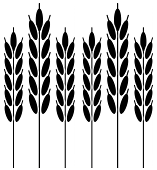
Nash Equilibrium

Today



Axelrod’s tournament

- Participants played the Iterated Prisoner's Dilemma (IPD)
- Tit For Tat (TFT) was the winning Strategy

Axelrod's tournament

	A (C)	A (D)
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TFT											
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rand.	C	D									

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TFT	C	C	D	D	D	C	C	D	C	C	
rand.	C	D	D	D	C	C	D	C	C	D	

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TFT	C	C	D	D	D	C	C	D	C	C	Total = 21
rand.	C	D	D	D	C	C	D	C	C	D	Total = 26

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Important:

- TFT can never get more points than the opponent
- TFT is not the best but the most robust strategy

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rand.	C	D	D	D	C	C	D	C	C	D	Total = 26

Important:
- TFT can never get more points than the opponent
- TFT is not the best but the most robust strategy

4 Reasons TFT won:
- 1. Starts with cooperation which is nice and prevents trouble
- 2. Punishes the defection of its opponent which stimulates cooperation
- 3. Forgives the opponent when they cooperate again
- 4. TFT is a clear strategy which is easy for an opponent to anticipate

Description of Agents

The agents implemented in our model have various types of strategies

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- Always cooperating
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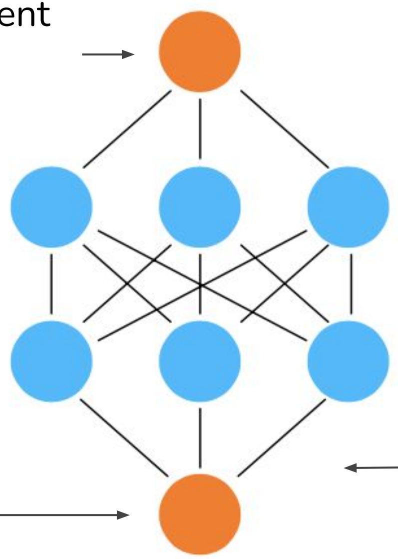
- Neural-Agents: cooperate or defect depends on the result of a neural network
- String-Agents: follow a set of deterministic rules of action

Neural-Agents

Take the history(ies) of the last tournament (0 - cooperating, 1 - defecting)

Feed the action through a forward network

Take the output of the network (float point number from 0 to 1) as the tendency to defect (stochastic)



Each layer applies a linear transform of the previous layer's output, followed by a non-linear activation function:

$$\boldsymbol{y}_{out} = \boldsymbol{\sigma}\left(\boldsymbol{W} \cdot \boldsymbol{x} + \boldsymbol{b}\right)$$

Sigmoid function applied, to make the output between 0 and 1

String-Agents

Histories	Decision
(CC), (CC)	C
(CC), (CD)	D
(CC), (DC)	C
(CC), (DD)	D
…	…
(DD), (DD)	D

- A lookup table that tells the agent which action to take;
- Histories: a list of (my action, opponent's action)

String-Agents

Histories	Decision
(CC), (CC)	C
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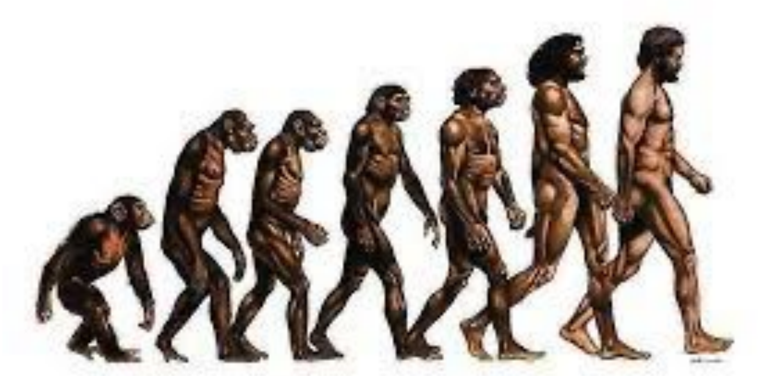
(CC), (DD)	D
…	…
(DD), (DD)	D

- A lookup table that tells the agent which action to take;
- Histories: a list of (my action, opponent's action)
- Take all the decisions in the lookup table, we obtain a **string-representation** for the agent: CDCD…D (TFT)

Genetic Algorithm

- An algorithm to find the maxima of a system
- Inspired by the evolution in nature



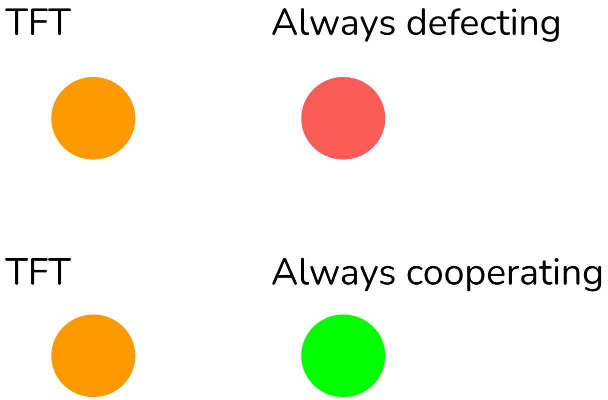
Always cooperating

Always defecting

TFT

Genetic Algorithm

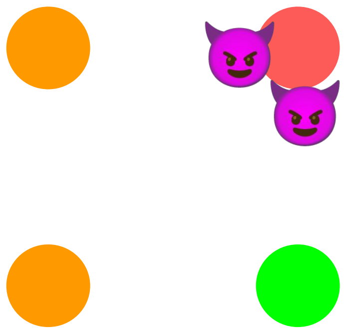
- Agents are born with different genes, which determines their behavior totally
  - E.g. String-Agents' string
  - Neural-Agents' weights and biases



Genetic Algorithm

- Agents are born with different genes
- In each generation, the agents play against neighbors. Their **payoffs** determine their "fitness in the nature"

First round



Genetic Algorithm

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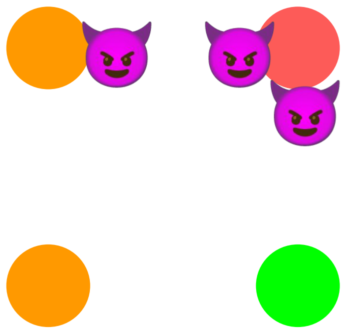
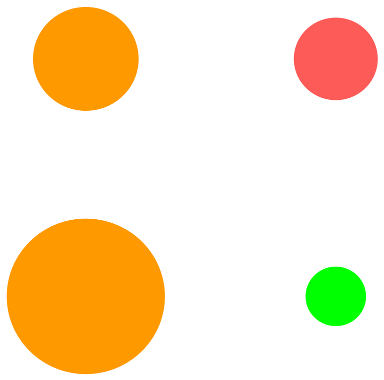
Subsequent rounds



Genetic Algorithm

After last round of the generation

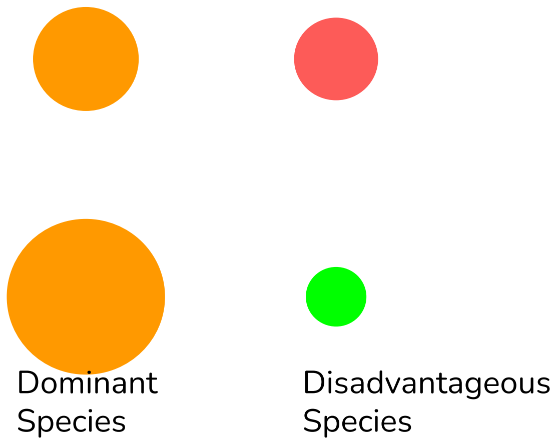
- Agents are born with different genes
- In each generation, the agents play against neighbors. Their **payoffs** determine their "fitness in the nature"



Genetic Algorithm

- Agents are born with different genes
- In each generation, the agents play against neighbors. Their **payoffs** determine their "fitness in the nature"
- The fitter agents will survive, whereas the weaker ones die

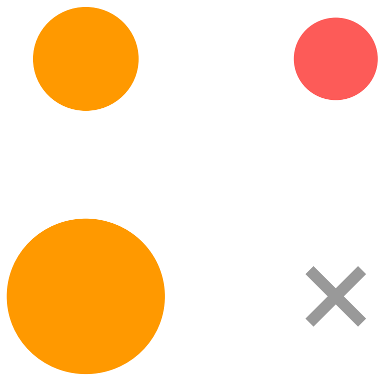
After last round of the generation



Genetic Algorithm

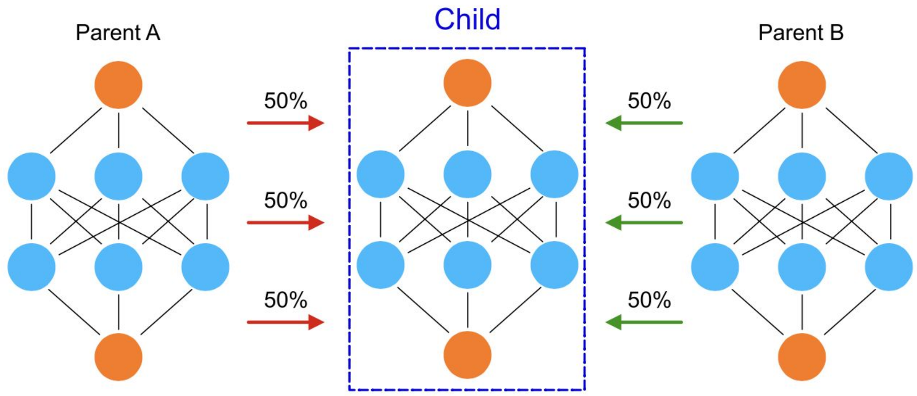
After last round of the generation

- The fitter agents will survive, whereas the weaker ones die
- The fittest agents reproduce with each other



Genetic Algorithm

- The fitter agents will survive, whereas the weaker ones die
- The fittest agents reproduce with each other
    - Parents cross over their genes (or swap weight matrices) to create the children



Genetic Algorithm

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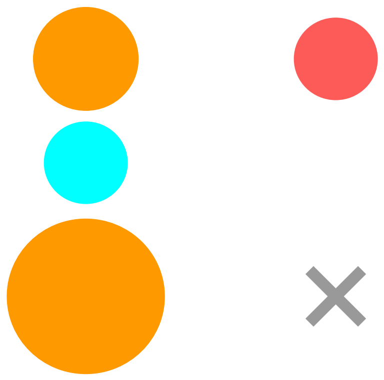
  - Random mutations can happen to children's genes



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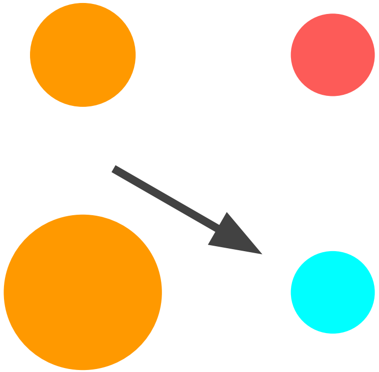
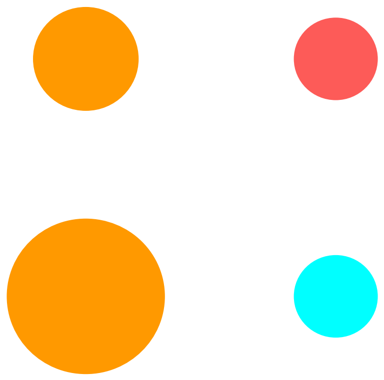


Genetic Algorithm

- The fittest agents reproduce with each other
    - Parents cross over their genes (or swap weight matrices) to create the children
    - Random mutations can happen to children’s genes
    - The child replace the weakest neighbor
- Redo the former process for next generations



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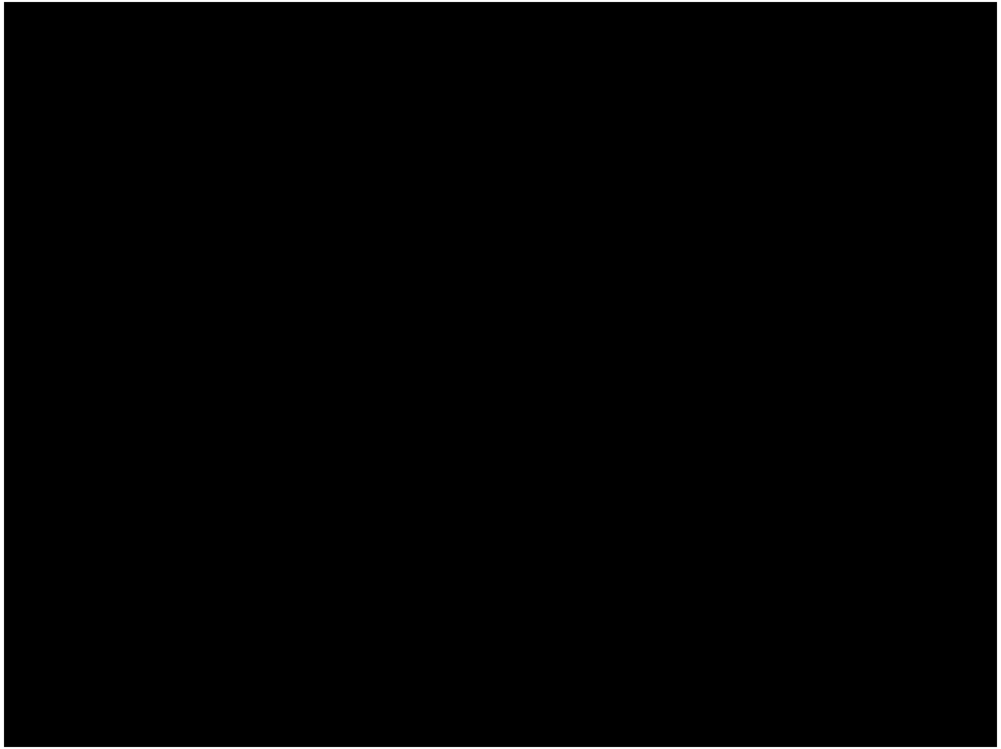


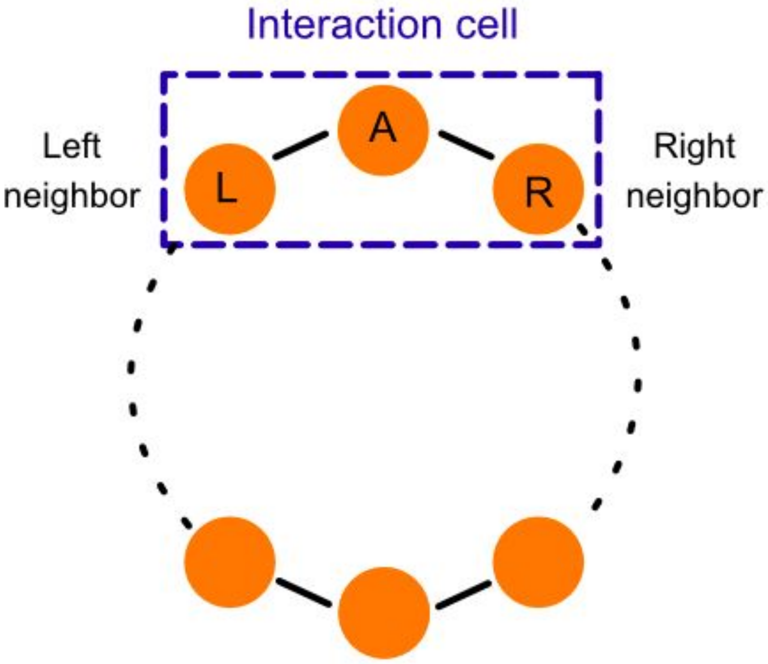
Project goals

Can the Agents learn Tit for Tat

Investigating the behavior of Agents in different settings

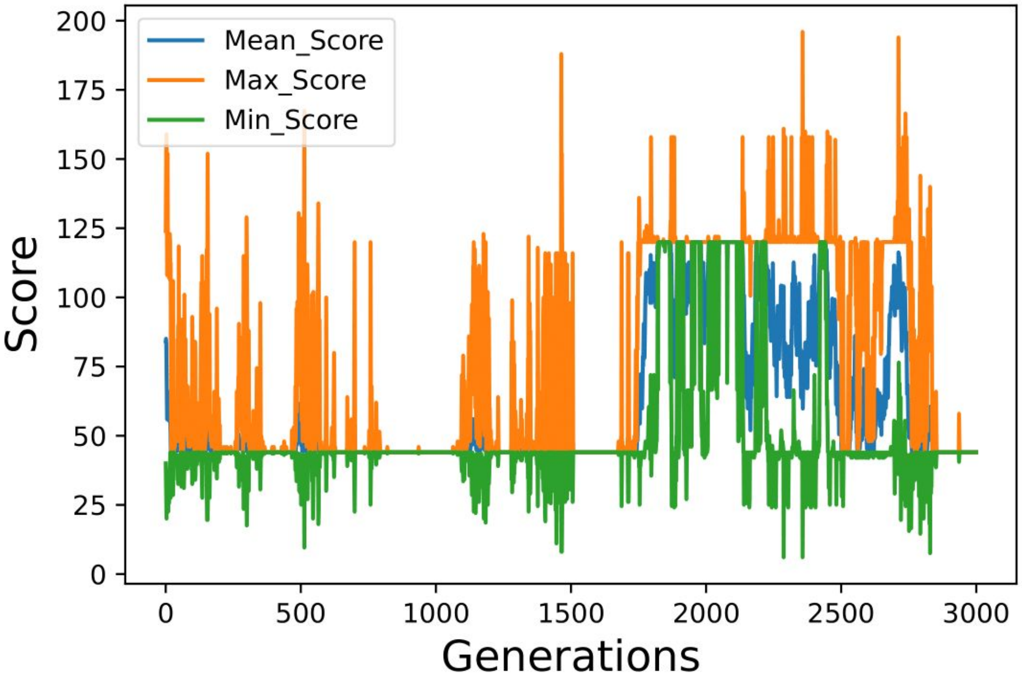
Analyzing the formation of cooperation

Ring Structure



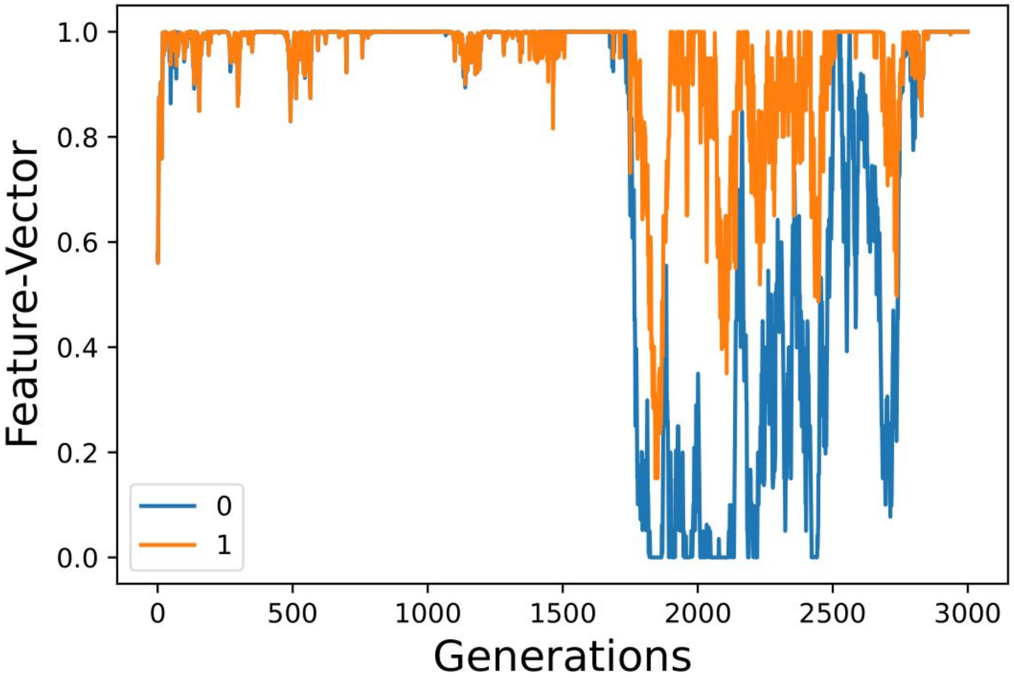
Ring Structure

- 20 Agents
- Nearest-Neighbor-Interaction
- 20 Rounds of PD
- Global-Genetic-Algorithm



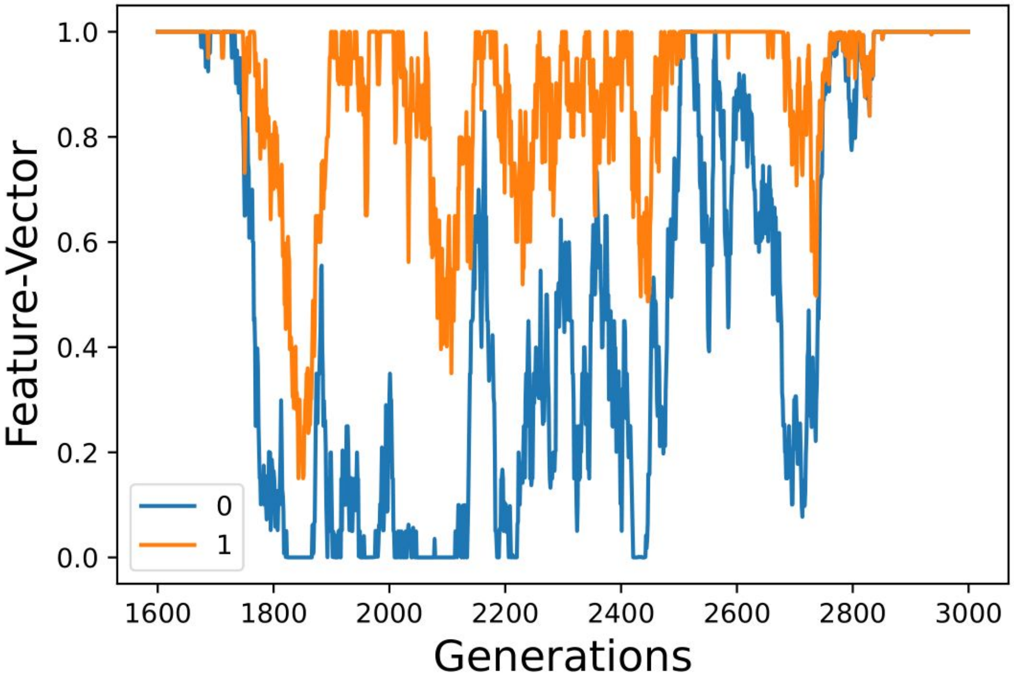
Ring Structure - Feature Vectors

- **FV0**: Output, given C of opponent
  - FV0 = 0: Cooperating
  - FV0 = 1: Defecting
- **FV1**: Output, given D of opponent
  - FV1 = 0: Forgiving
  - FV1 = 1: Punishing
- Phase of cooperation from 1700 to 2500



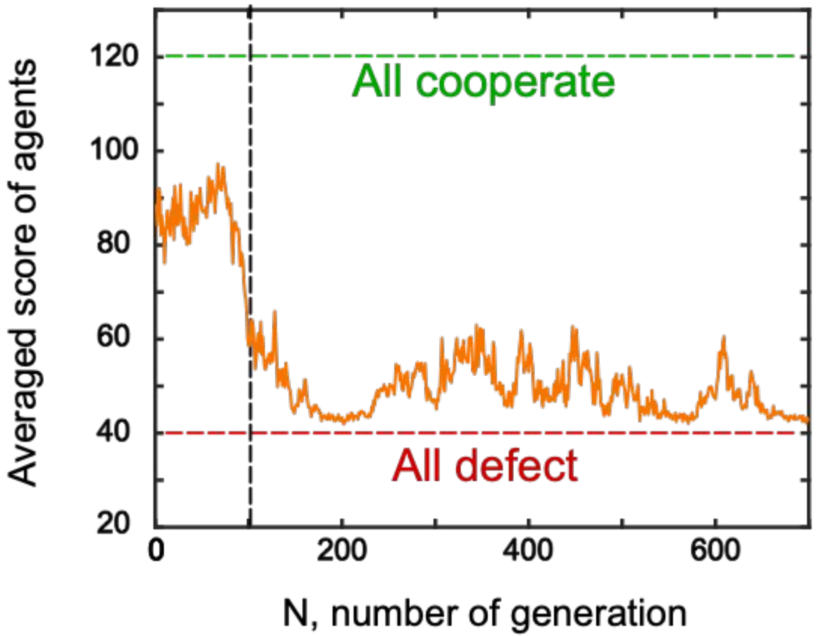
Ring Structure - Feature Vectors

- Starts with Tit for tat
- Always Cooperating
- Defectors spread
- Tit for Tat again



Ring - Influence from outside

What we already know
For Neural-Agents?



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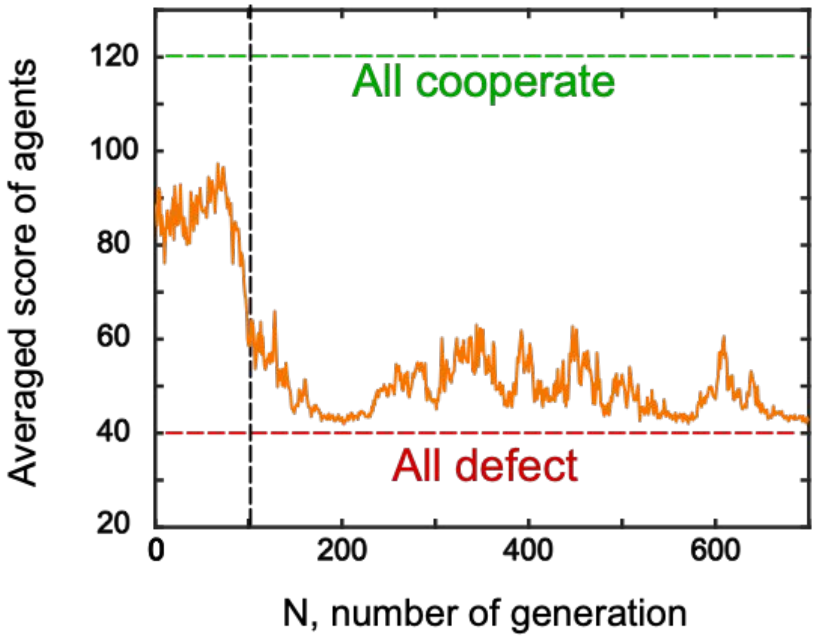

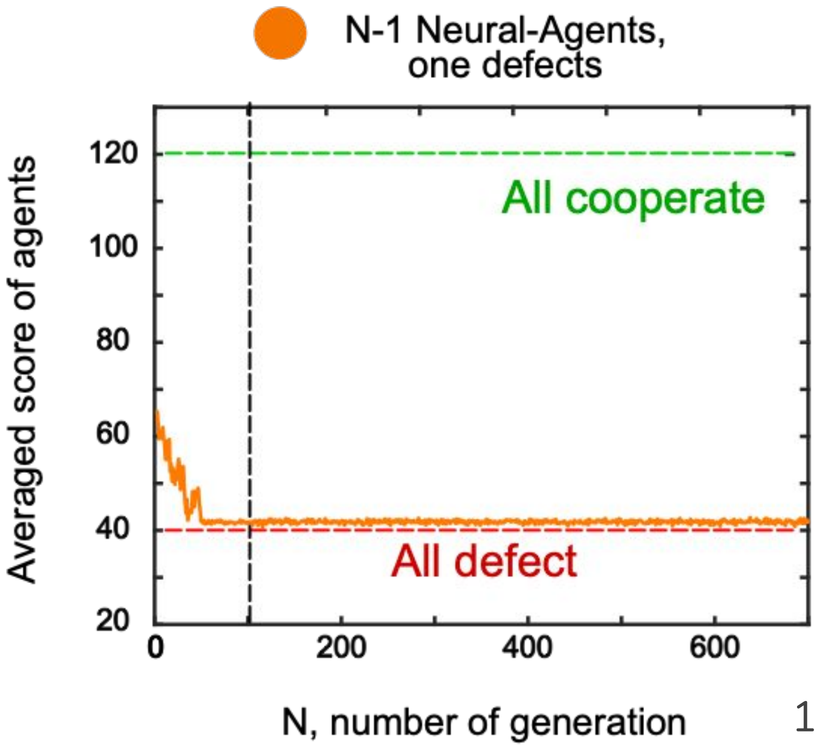

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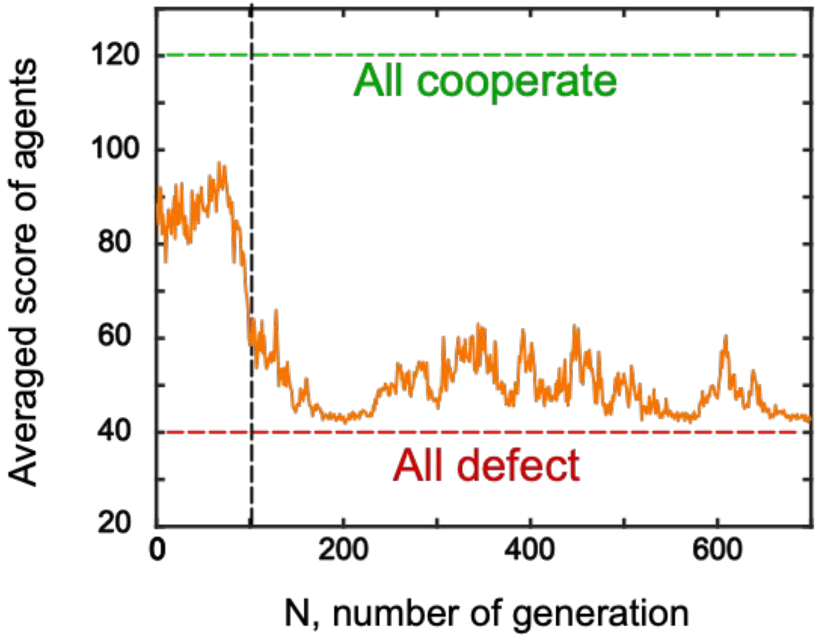

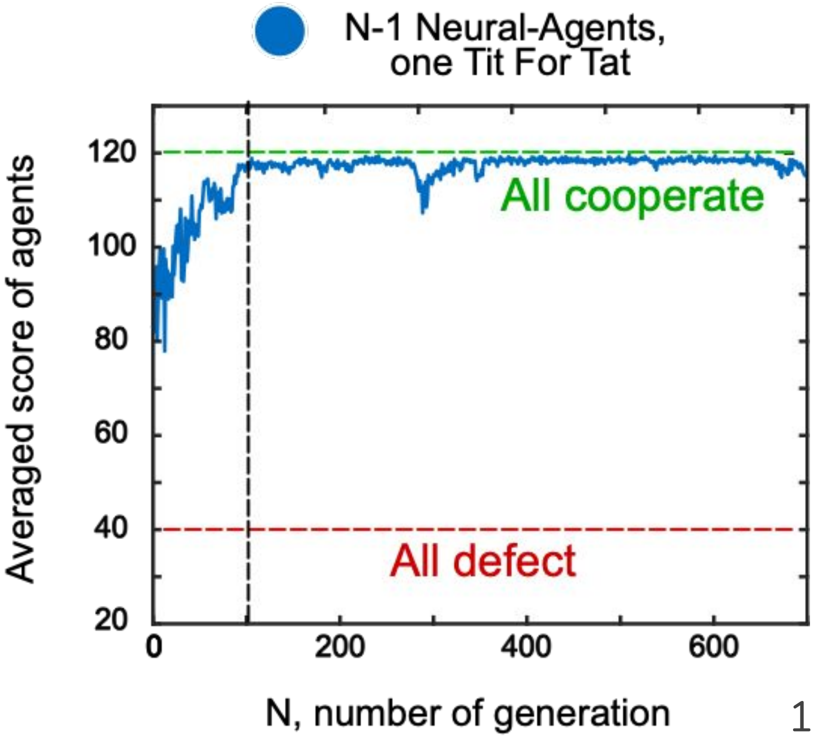

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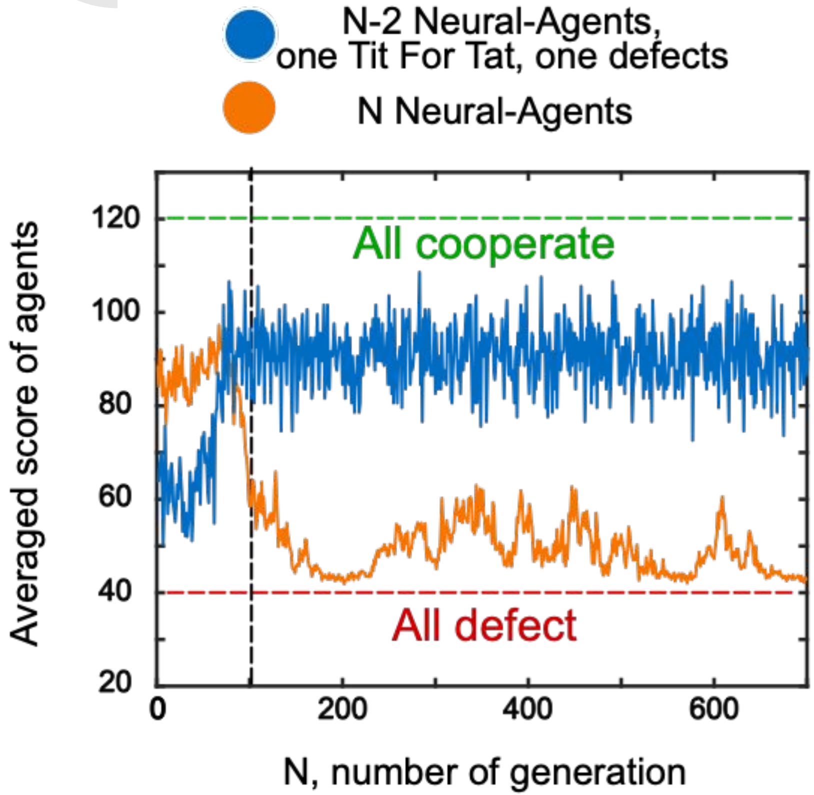

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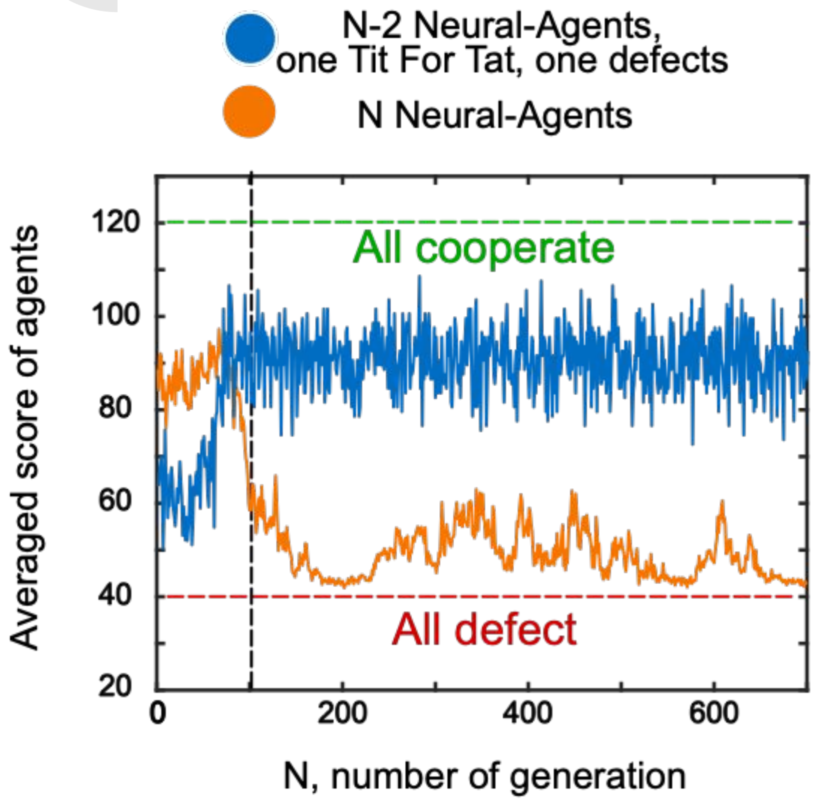

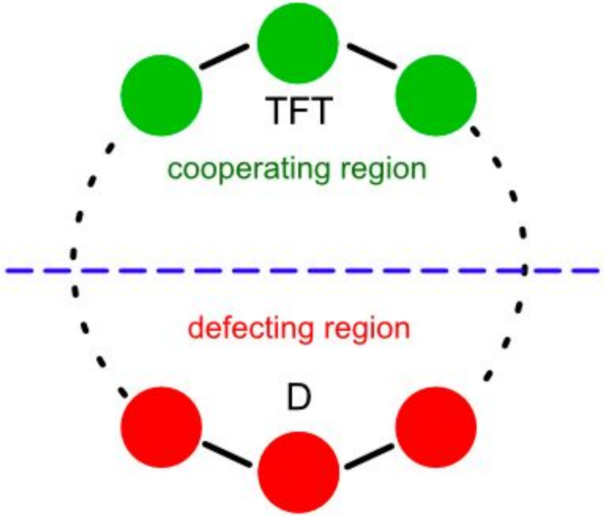

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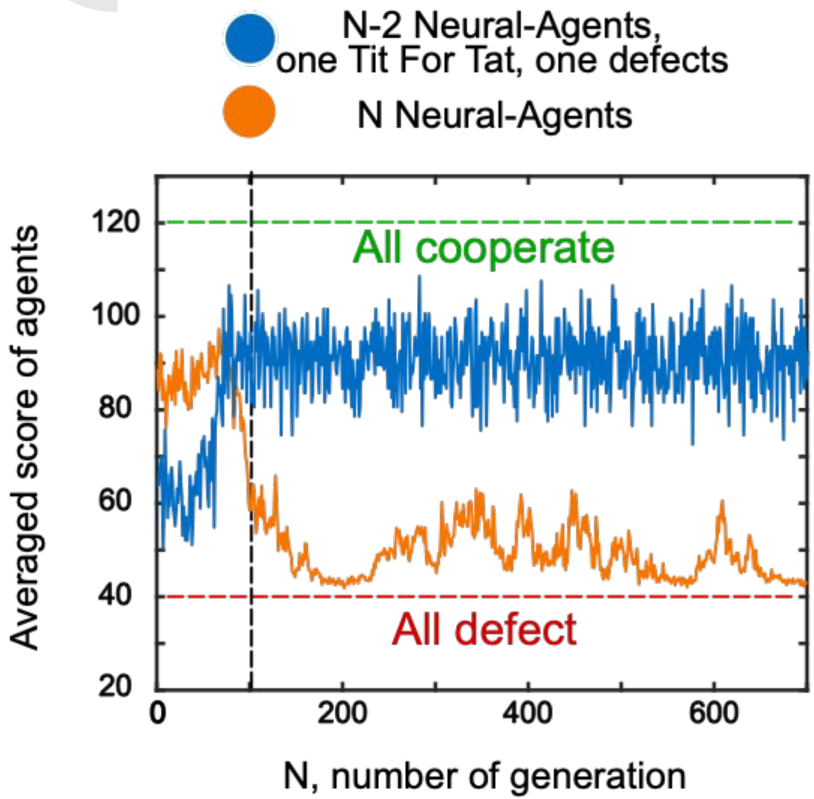
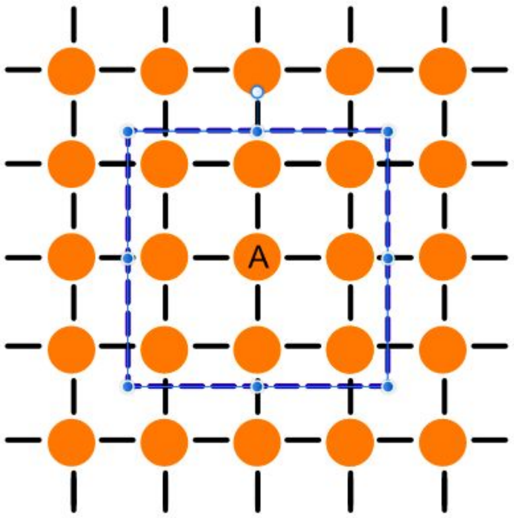
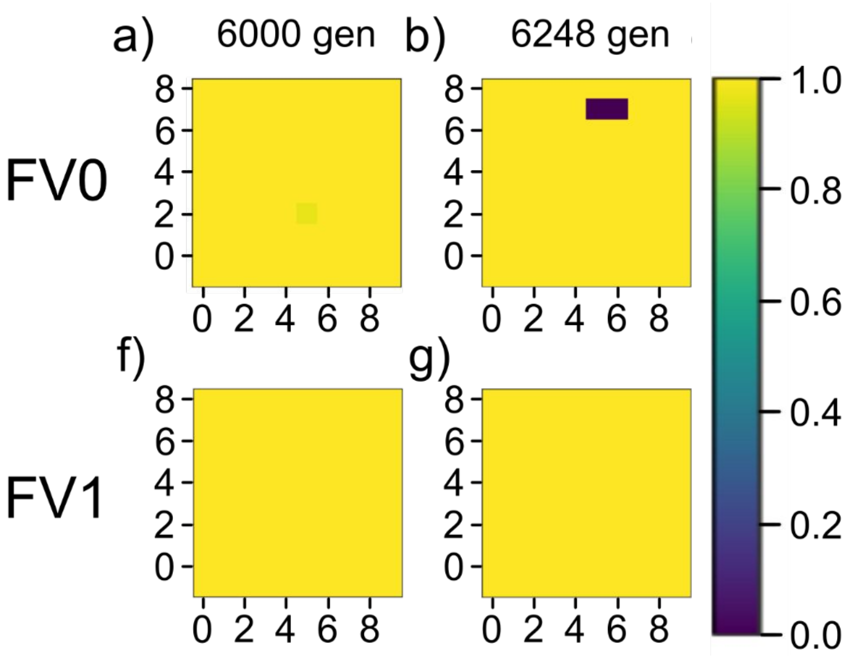


! Let’s go to 2D !



Grid - Formation of Cooperation



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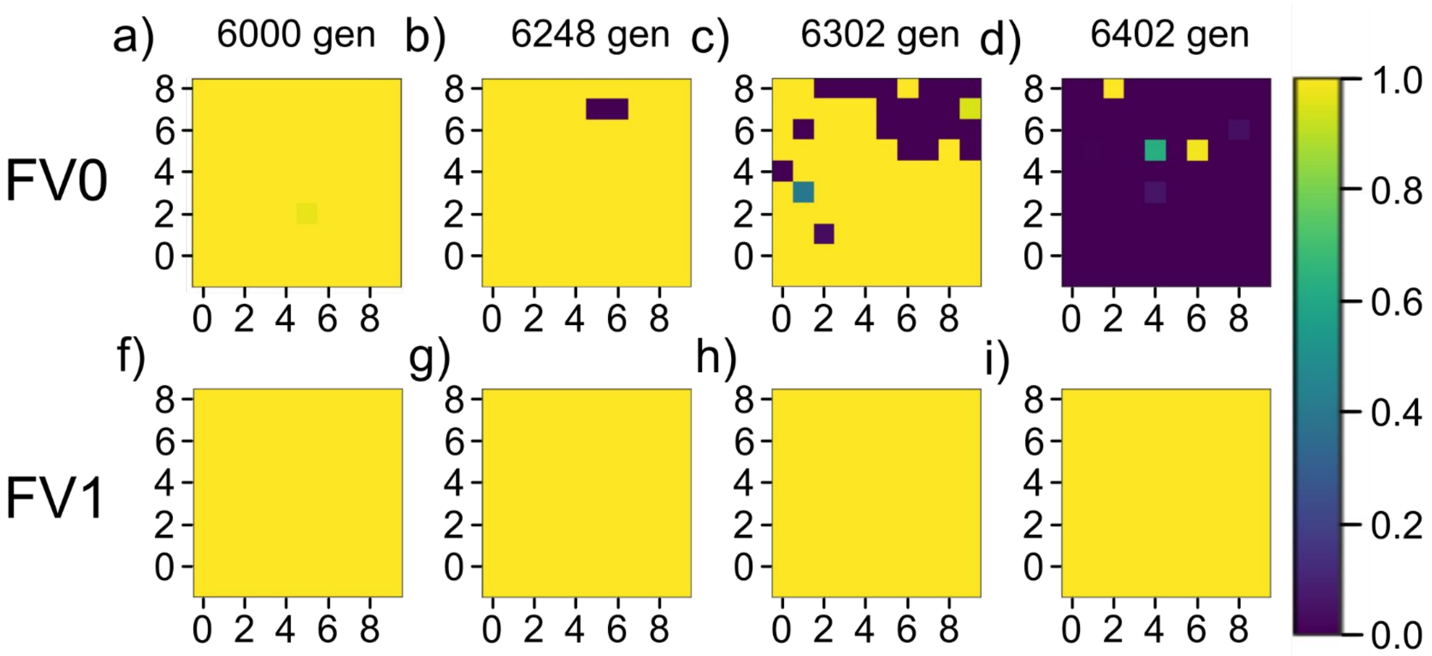

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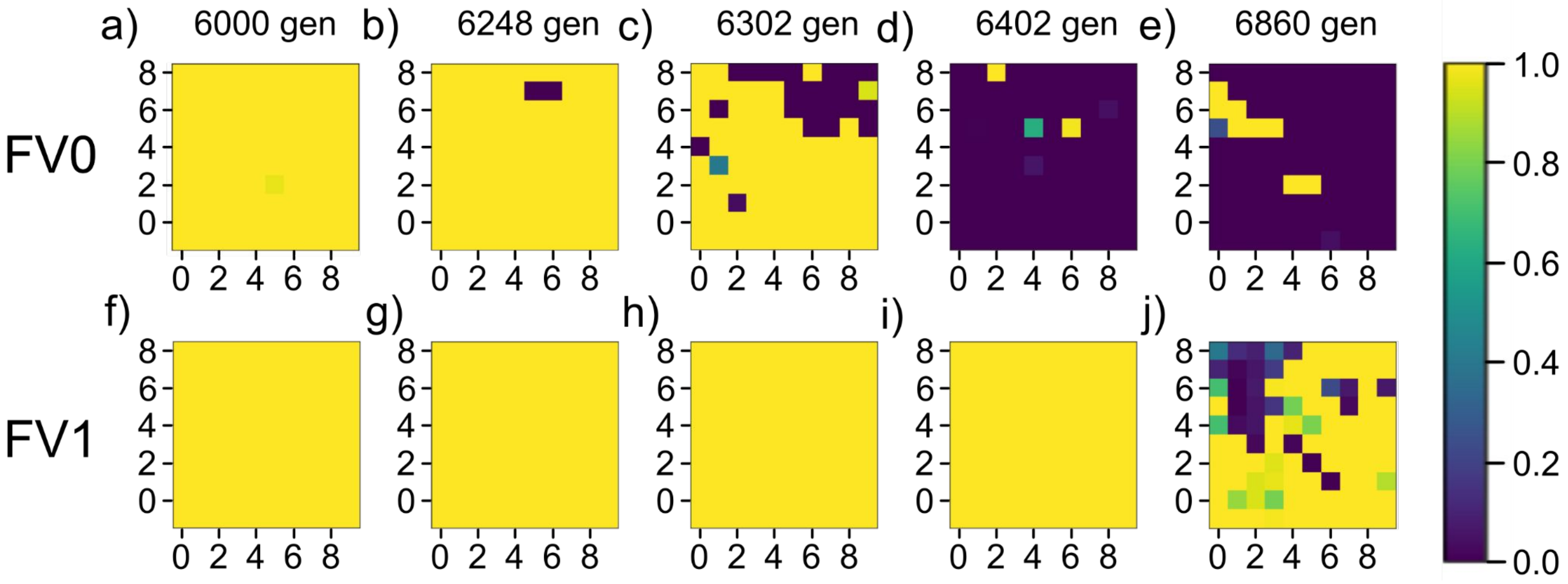


Config.py

```python
# 0 cooperating, 1 defecting
# Map (my_action, other_action) to payoff
PAYOFF_MAP = [
    [3, 0],
    [5, 1],
]

# Neighbors of each agent: can be 8 (everyone around), 4 (left right top bottom), or 2 (left right)
NEIGHBOR_TYPE = 4
NEIGHBOR_RADIUS = 1  # interaction radius

NUM_SUBSTEPS = 10  # rounds in a generation

# Genetic Algorithm parameters
USE_LOCAL_GA = True  # weather to use the localized version of GA
FITNESS_MULTIPLIER = 2  # parameter used for scaling fitness function, see P15 of the java manual
EPS = 1e-3  # for fitness scaling
MUT_PROB = 0.2  # mutation probability for NeuralAgent and StringAgent
MUT_STRENGTH = 1.0  # how strong to perturb the weights of NeuralAgent
TFT_REPRODUCABLE = False  # does TFT participate in the reproduction
NEURAL_REPRODUCABLE = True  # does NeuralAgent participate in the reproduction
STRING_REPRODUCABLE = True  # does StringAgent participate in the reproduction

# Network topology for NeuralAgent
# e.g. [6, 1] means a network with 6 inputs (i.e. memory size 3), fully connected to the output
DEFAULT_NEURAL_STRUCTURE = [6, 1]

# StringAgent's memory size
MEM_LEN = 2
```

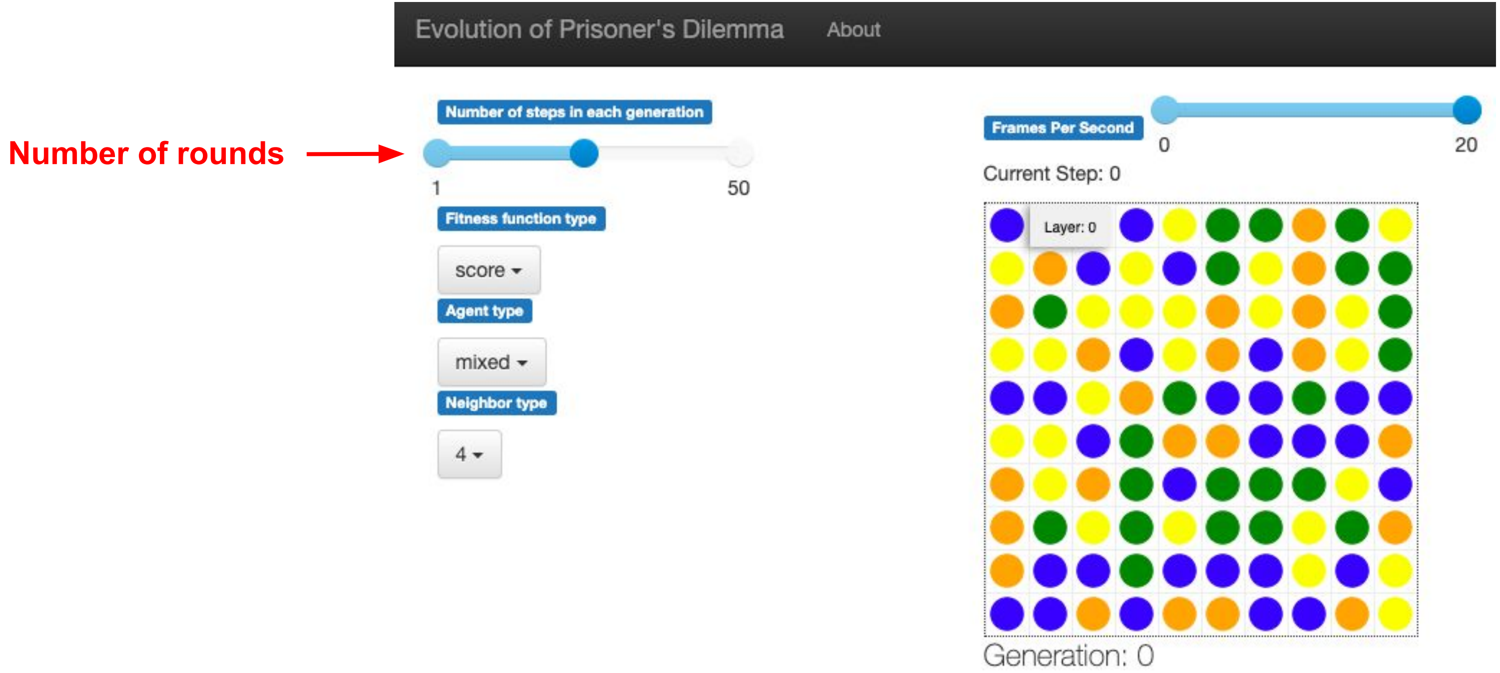
```python
# StringAgent's memory size
MEM_LEN = 2

# Settings for PDModel
DEFAULT_WIDTH = 10
DEFAULT_HEIGHT = 10
TORUS_GRID = True
CANVAS_DX = 30

# Random seeds
MESA_SEED = 4
NUMPY_SEED = 3

# The way agents are rendered in the We
# 'agent_type': the colors indicate whi
# 'defecting_ratio': visualize how defe
# 'inherited_attr': visualize who are t
VISUALIZE_GRID_TYPE = 'inherited_attr'
```

Website application via Mesa package



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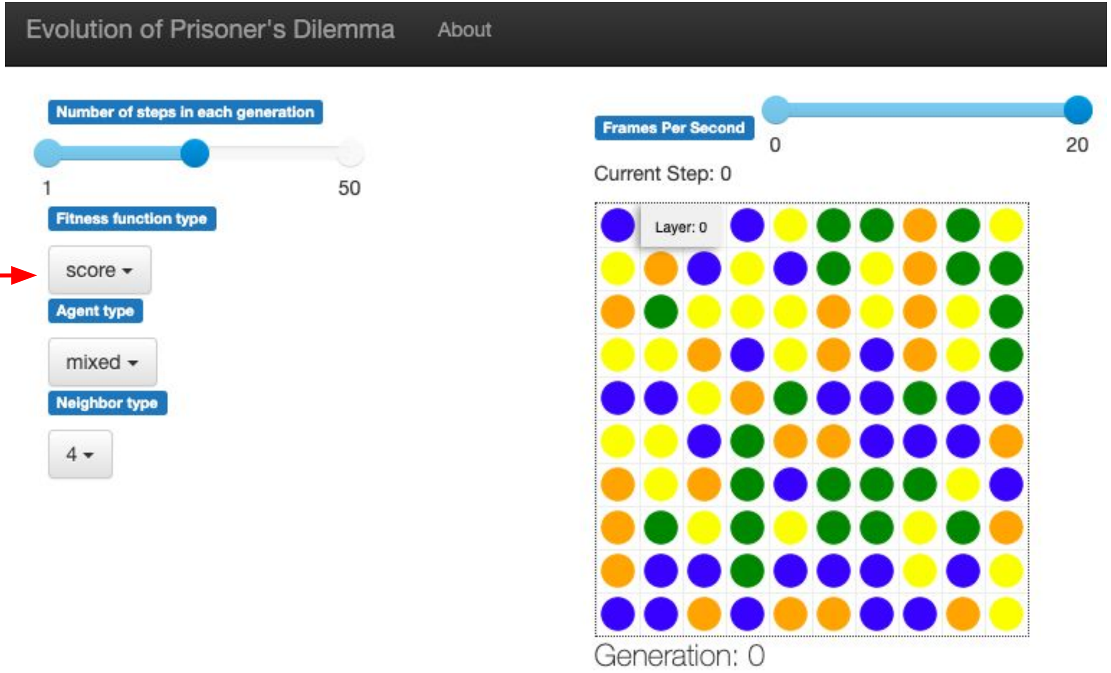
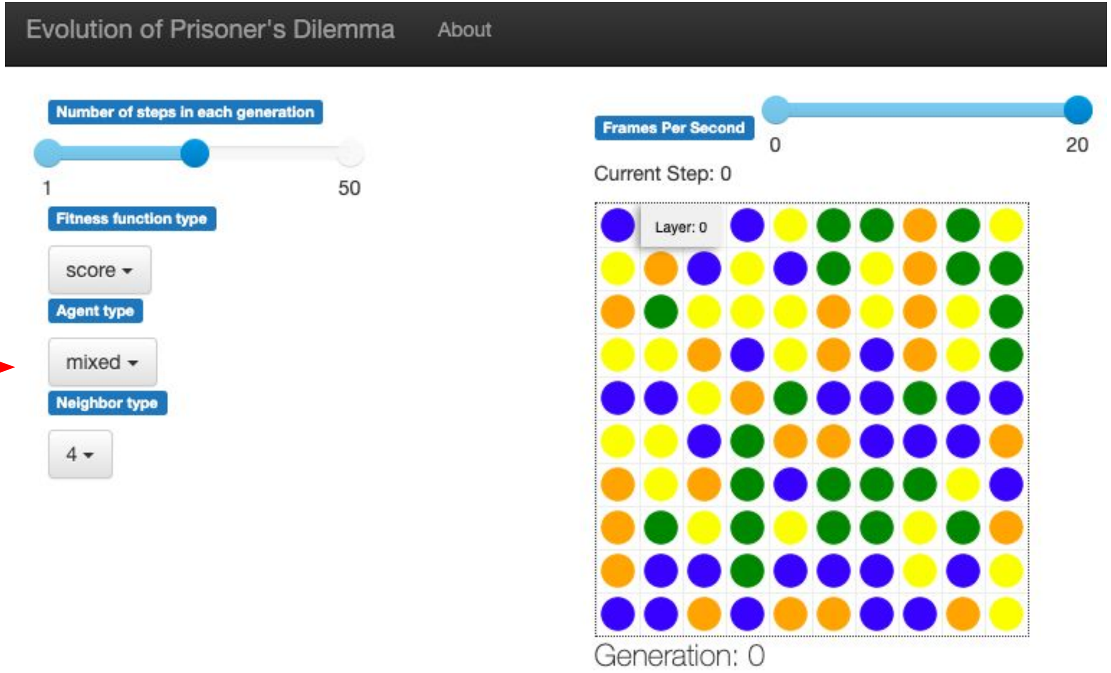


Fitness function type

score
cooperating_ratio
defecting_ratio

Website application via Mesa package



Agent type

neural

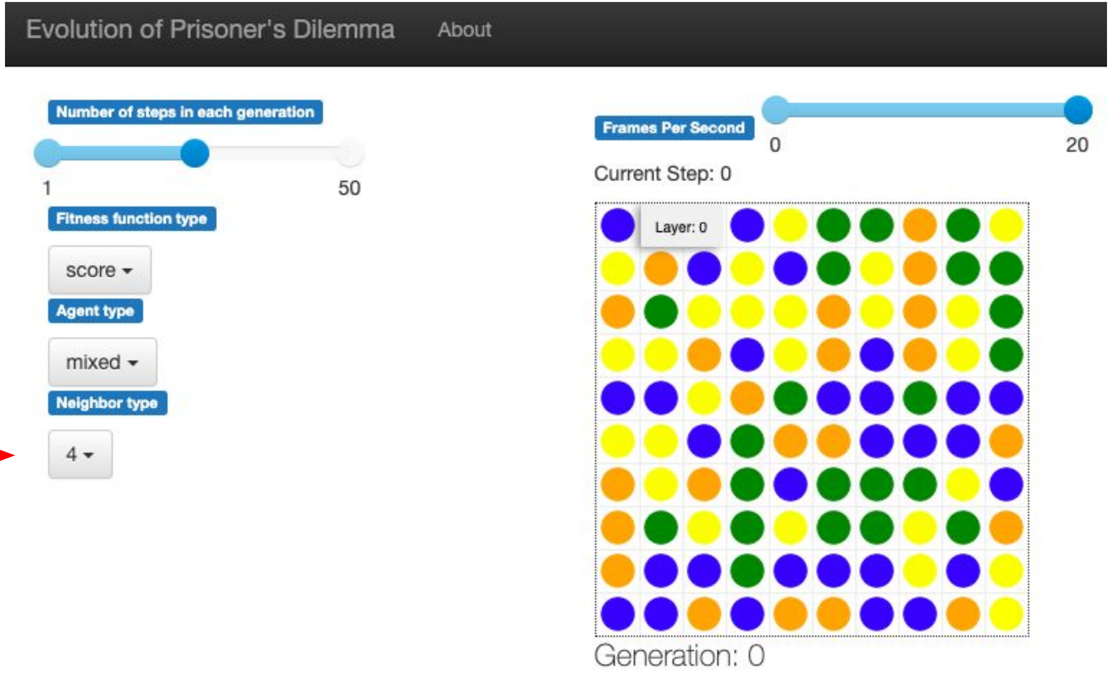
string

tit_for_tat

simple

mixed

Website application via Mesa package



Number of neighbors

8

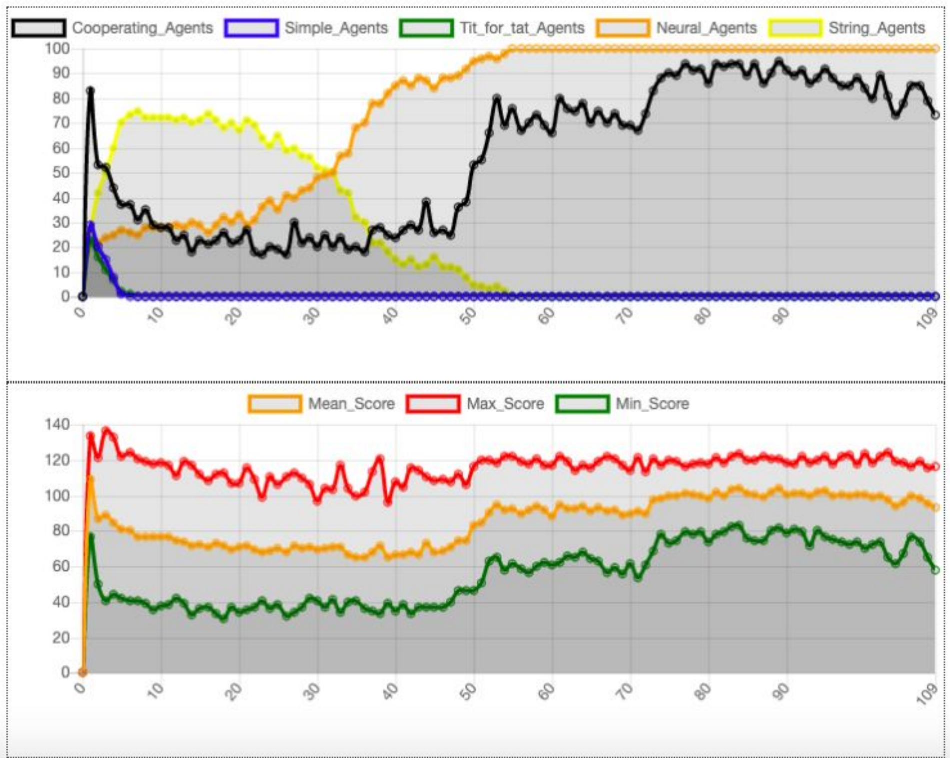
4

2

Website application via Mesa package

Generation: 109 Fittest feature vector: 0.4918, 0.6789

Distribution of agents



Distribution of scores

Execution panel

Results

Agents have to learn TFT for cooperation

Cooperation could be achieved by adding punishers

Local interaction + reproduction are important for cooperation

Larger Agent memory leads to stable cooperation

Questions

References

1. R. M. Axelrod and W. D. Hamilton, *The Evolution of Cooperation*. Basic Books, 1984, isbn: 0-465-02121-2.
2. R. Axelrod, *The Evolution of Strategies in the Iterated Prisoner’s Dilemma*. Lawrence Davis, London: Pitman, and Los Altos, CA: Morgan Kaufman, 1987, pages 32–41.
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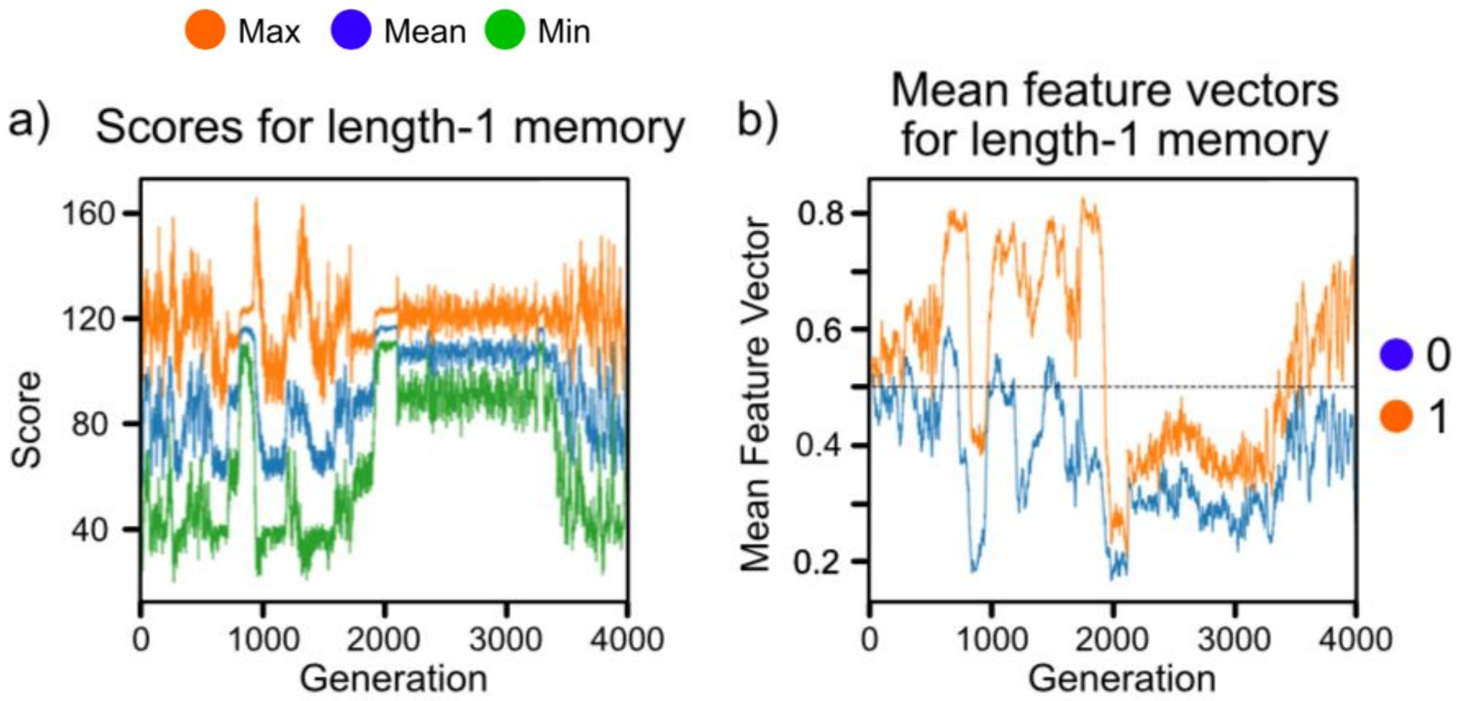
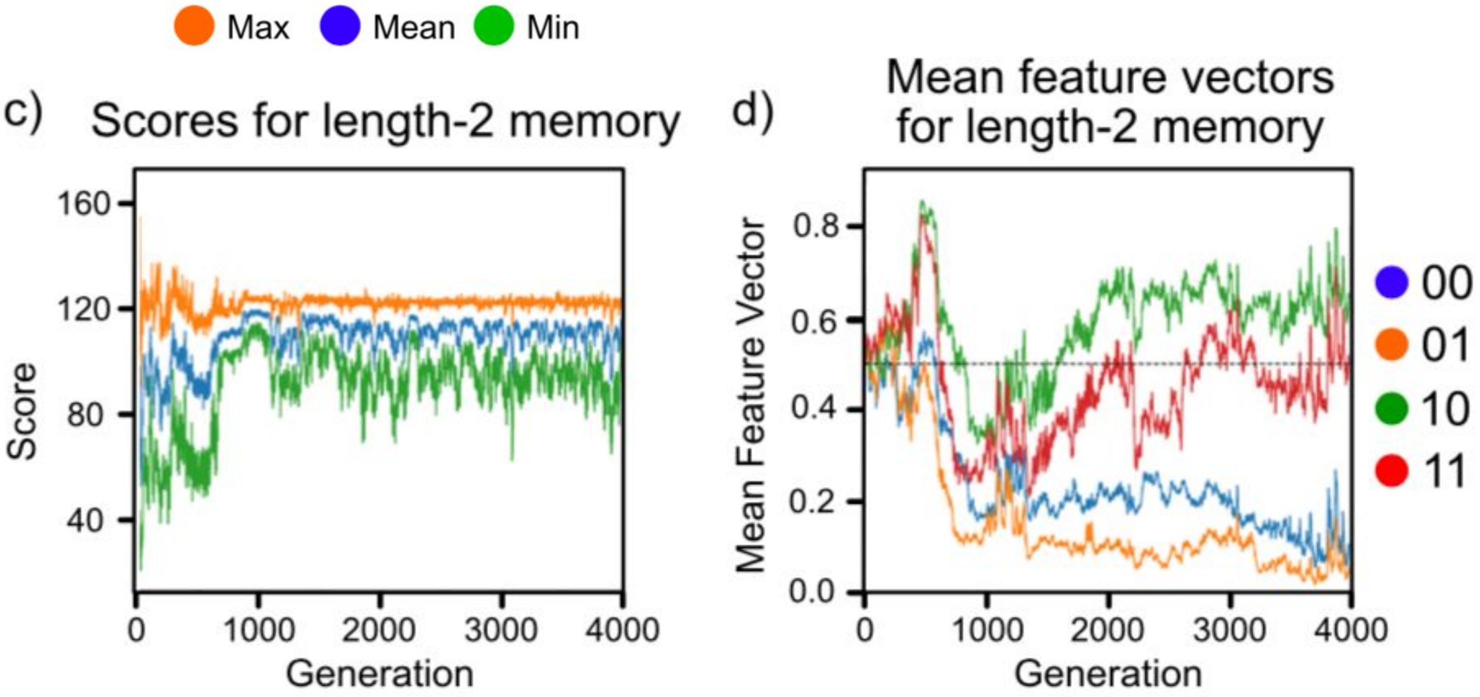
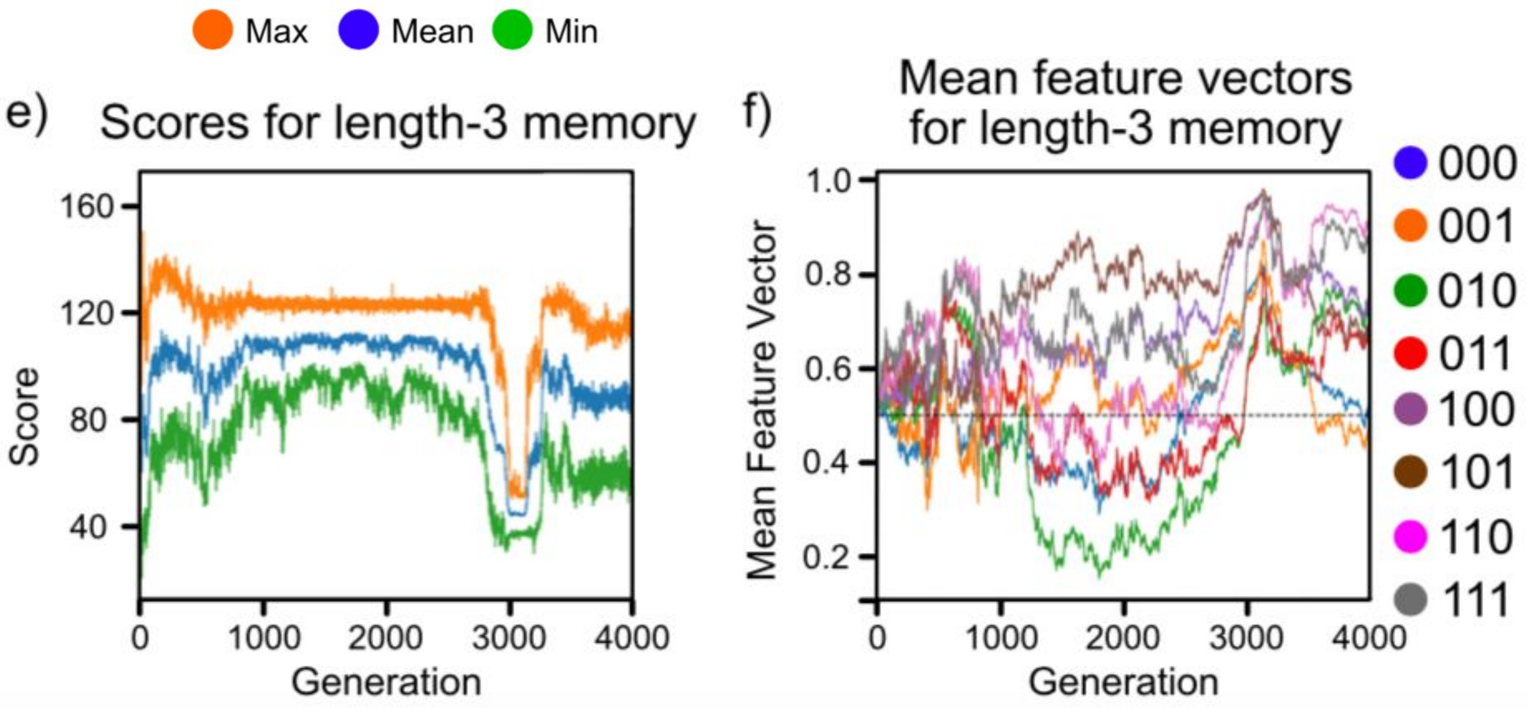
Memory-length tests



Memory-length tests

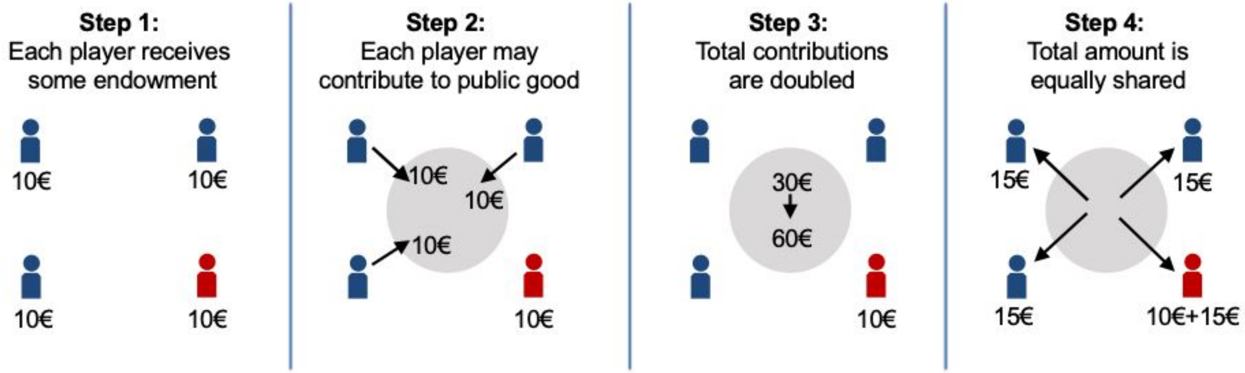


Memory-length tests



Connection to society?

- Public Good Game



- Examples: Tax evasion, climate change, cleaning shared apartment, Cross-Code-Checking
- Defectors lead to tragedy of the common
- Punishment and Reputation key for avoiding the tragedy of the commons