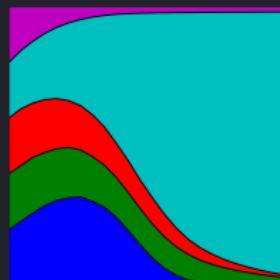


A computational approach to cooperation

Tuesday Lunch





Kirsty MacLeod
@kirstyjean

Following



Me: sets up flawless heat competition trial,
lizards will fight over hot podium, there can
only be one winner!

Lizards:

#Allizards2017



Kirsty MacLeod
@kirstyjean

Following



Me: sets up flawless heat competition trial,
lizards will fight over hot podium, there can
only be one winner!

Lizards:

#Allizards2017



$$\begin{pmatrix} (3, 3) & (0, 5) \\ (5, 0) & (1, 1) \end{pmatrix}$$

D D

1

D D

1

D C

2

D D

1

D C

2

C D

3

D D

1

D C

2

C D

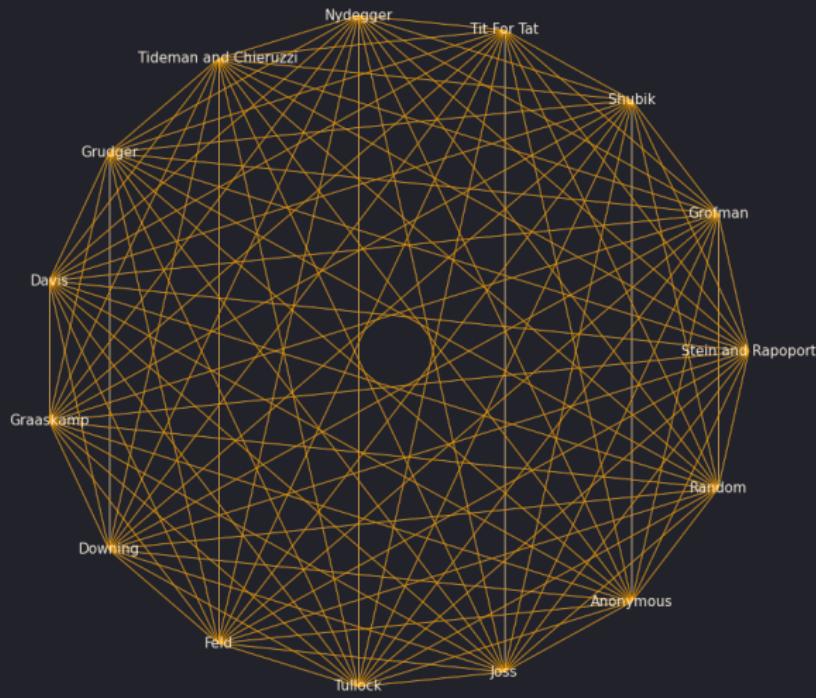
3

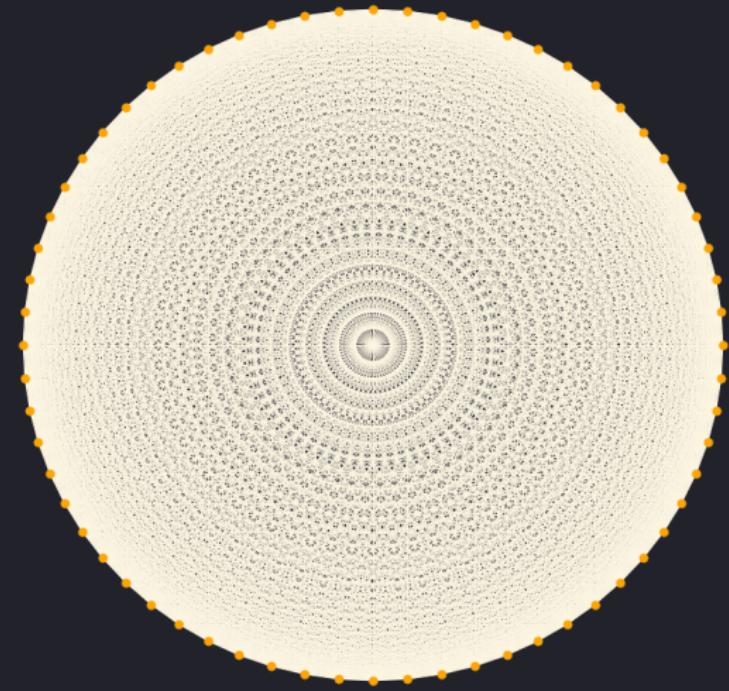
...

C C

n









Tit For Tat

“A strategy that starts by cooperating and then mimics the previous action of the opponent.”

1. Be “nice”; Do not be the first to defect
2. Do not be envious; by striving for a payoff larger than the opponent’s payoff
3. Do not be too clever
4. Reciprocate both cooperation and defection; Be provable to retaliation and forgiveness

Reverse Tit For Tat

Suspicious Tit For Tat

Omega Tit For Tat

Adaptive Tit For Tat

Hard Tit For Tat

Reverse Tit For Tat

Suspicious Tit For Tat

Gradual

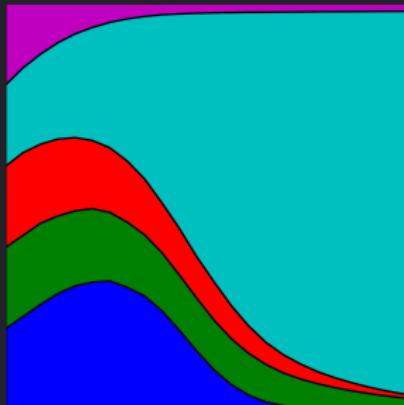
Omega Tit For Tat

Win Stay Lose Shift

Adaptive Tit For Tat

Nice and Forgiving

Hard Tit For Tat



An open framework for the reproducible study of the Iterated prisoner's dilemma. Vincent
Knight, Owen Campbell, Marc Harper et al. Journal of Open Research Software

150 strategies from the literature

150 strategies from the literature

239 strategies available today

```
import axelrod as axl

players = [axl.SuspiciousTitForTat(),
...
           axl.HardTitForTat(),
...
           axl.OmegaTFT(),
...
           axl.Gradual(),
...
           axl.WinStayLoseShift()]

tournament = axl.Tournament(players,
...
                           turns=200,
...
                           repetitions=5)

result = tournament.play()
```

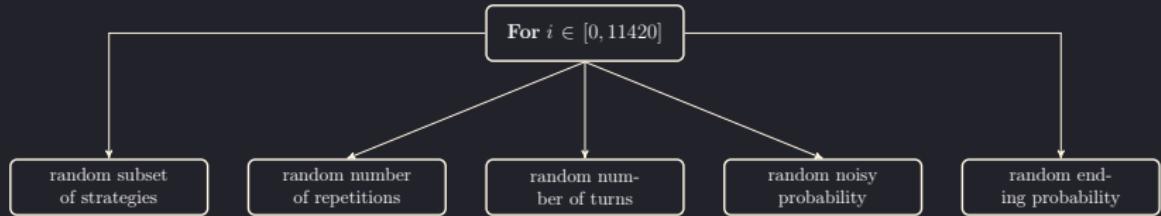
A meta analysis of tournaments and an evaluation of performance in the Iterated Prisoner's Dilemma.

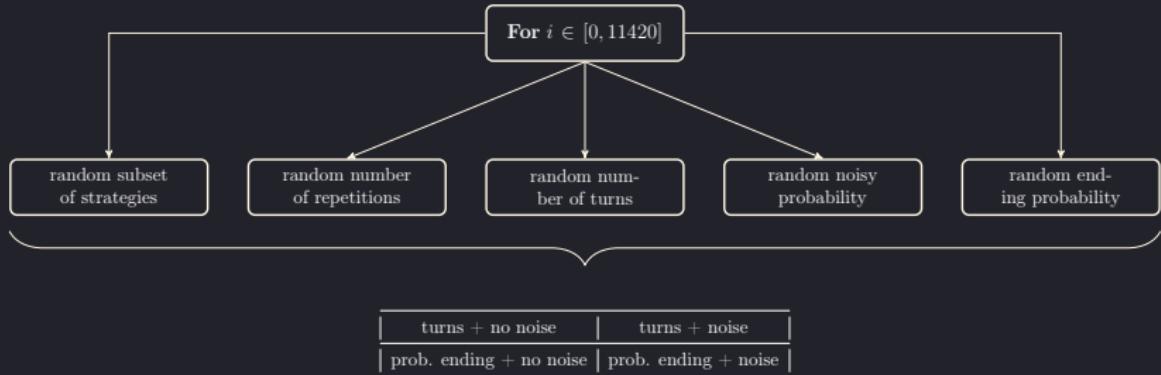
Nikoleta E. Glynatsi, Vincent A. Knight, Marc Harper

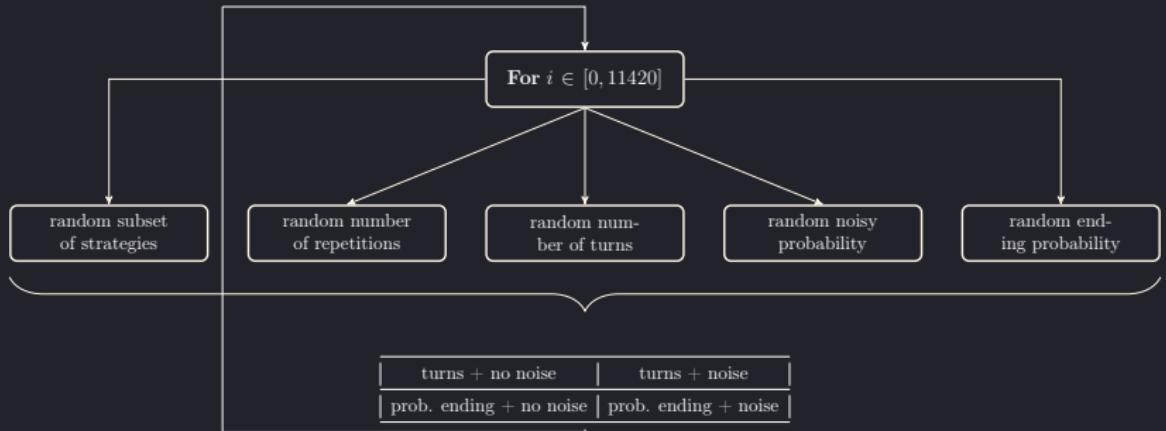
arxiv.org/abs/2001.05911

Axelrod-Python v.3.0.0. - 195 strategies

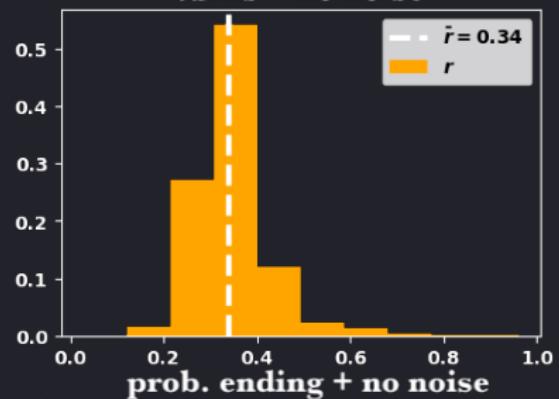
For $i \in [0, 11420]$



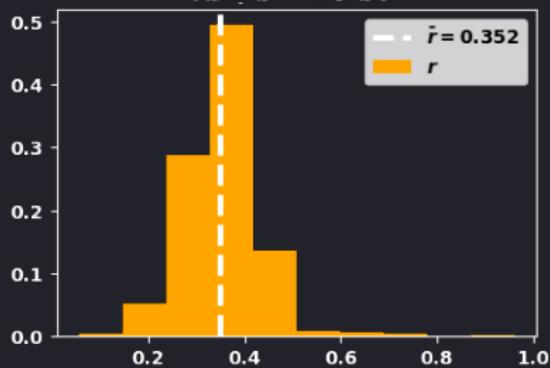




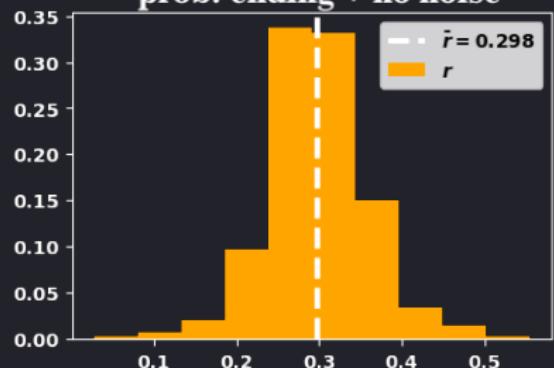
turns + no noise



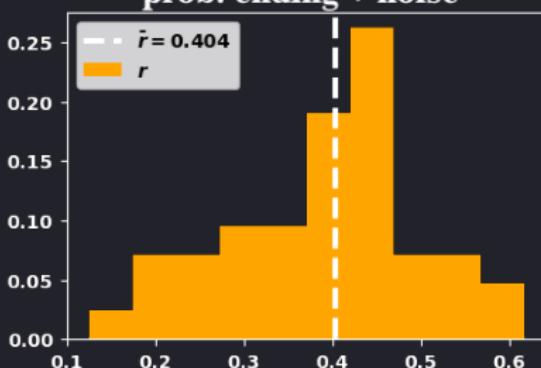
turns + noise

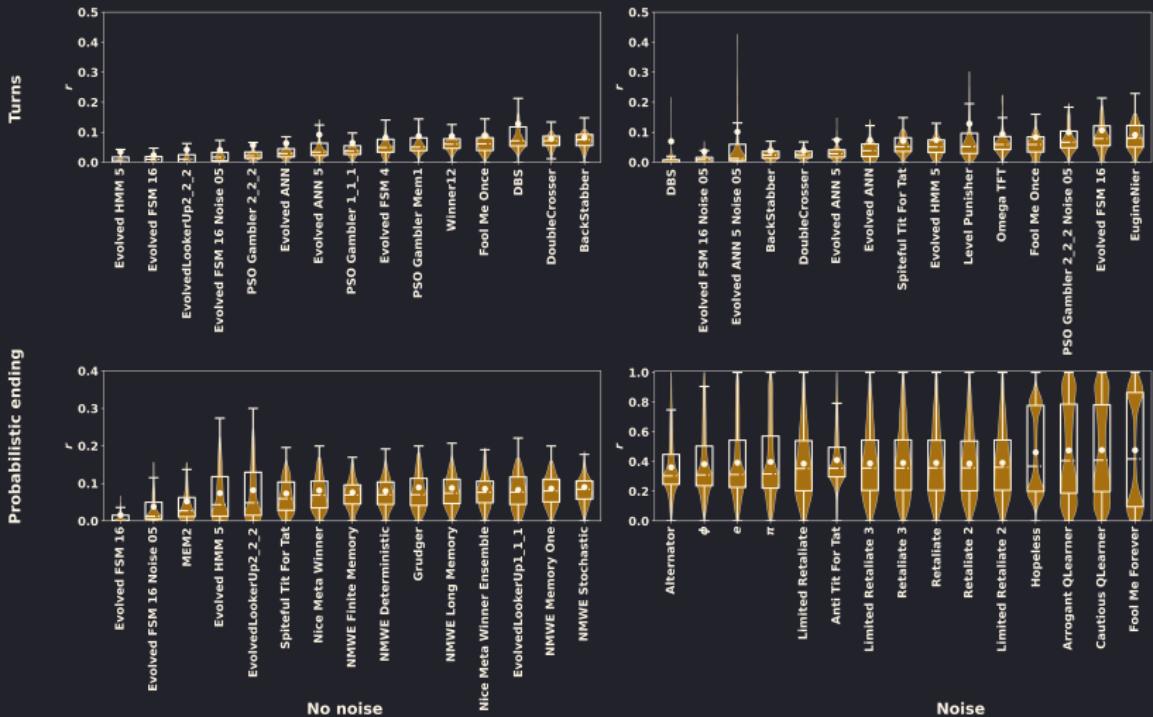


prob. ending + no noise



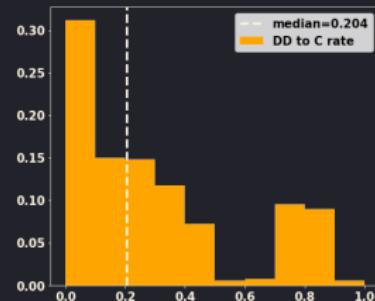
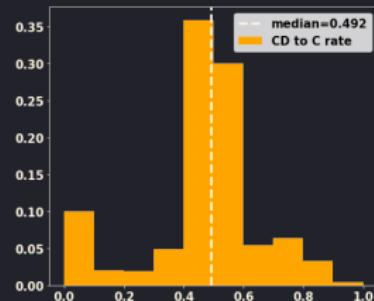
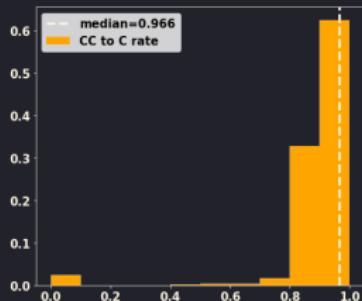
prob. ending + noise



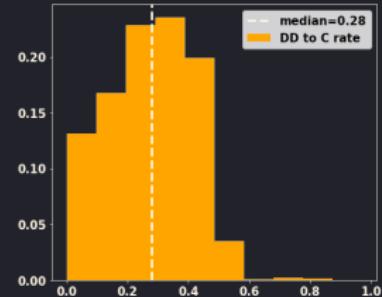
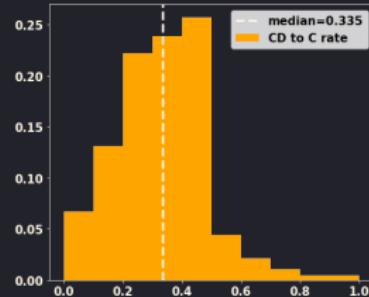
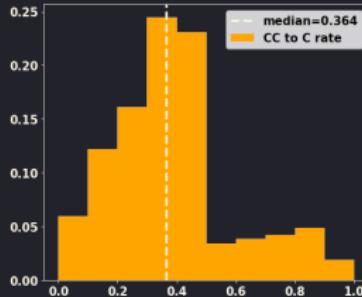


- ▶ ~~Do not be the first to defect~~ Do not defect on the first turn
- ▶ ~~Do not be envious~~ It's okay to be envious
- ▶ ~~Do not be too clever~~ Be clever

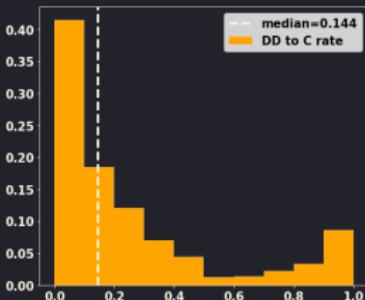
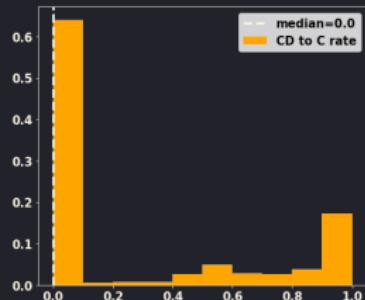
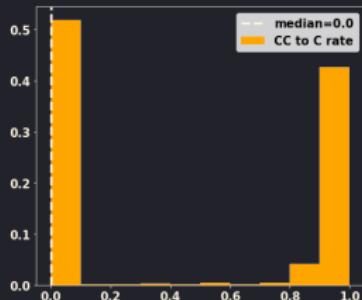
Turns + no noise



Turns + noise



Probabilistic ending + no noise



- ▶ ~~Do not be the first to defect~~ Do not defect on the first turn
- ▶ ~~Do not be envious~~ It's okay to be envious
- ▶ ~~Do not be too clever~~ Be clever
- ▶ ~~Be provable~~ Be provable in tournaments with short matches, and generous when matches are longer

Reinforcement Learning Produces Dominant Strategies for the Iterated Prisoner's Dilemma.

Marc Harper, Vincent Knight, Martin Jones, Georgios Koutsovoulos, Nikoleta E. Glynatsi,
Owen Campbell

doi.org/10.1371/journal.pone.0188046

Axelrod-Python v.2.2.0 - 176 strategies

- ▶ LookerUp
- ▶ Gambler
- ▶ Artificial neural network
- ▶ Finite state machines
- ▶ Hidden markov models
- ▶ Meta strategies

Player Opponent

C
C
D
D

:

D
C
C
C

C
D
C

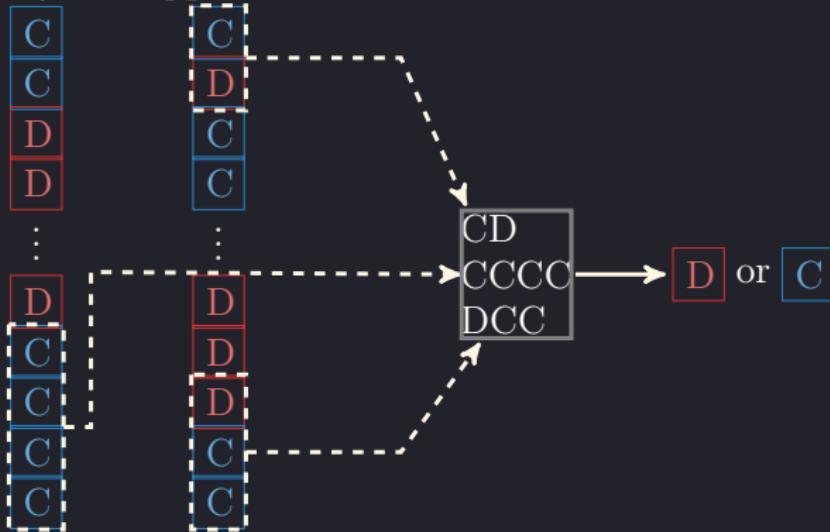
:

D
D
C

CD
CCCC
DCC

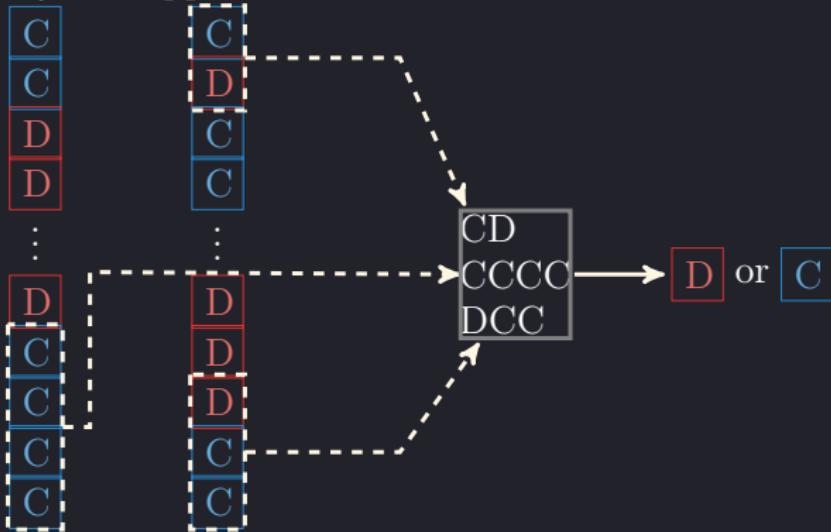
→ [D] or [C]

Player Opponent



$$n_1 = 2, m_1 = 4, m_2 = 3$$

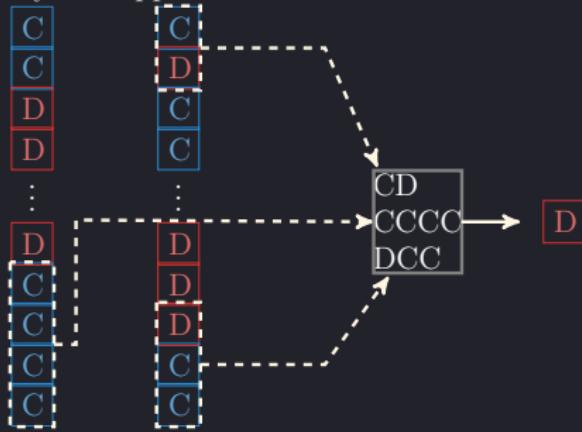
Player Opponent



$$n_1 = 2, m_1 = 4, m_2 = 3$$

EvolvedLookerUp2_4_3

Player Opponent

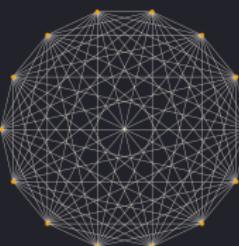


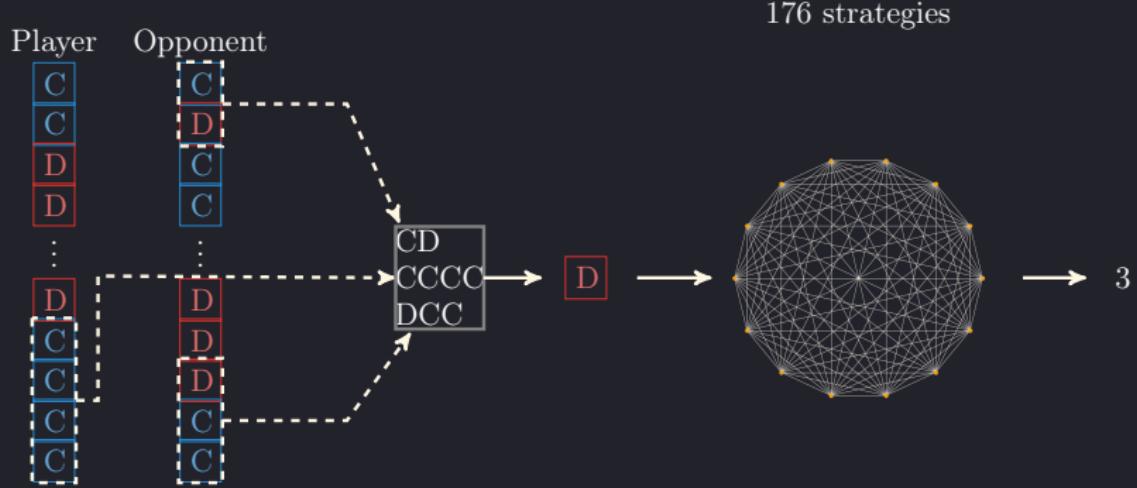
Player Opponent

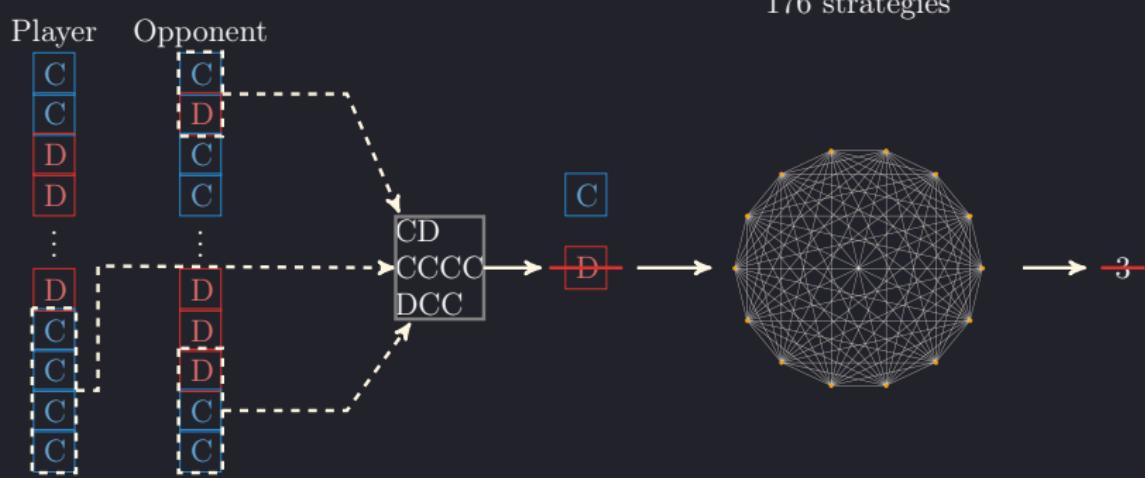
C	C
C	D
D	C
D	C
⋮	
D	D
C	D
C	D
C	C
C	C

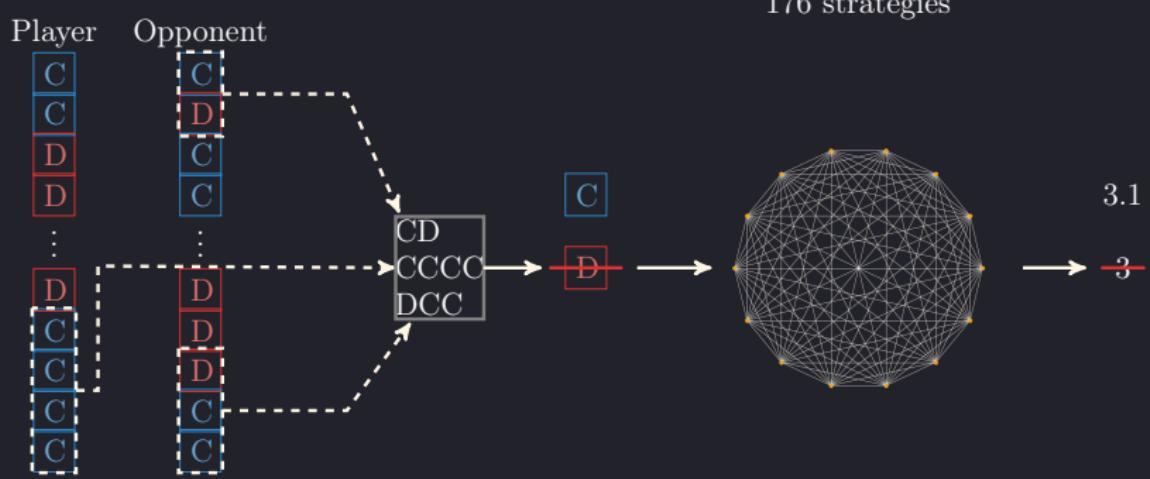
176 strategies

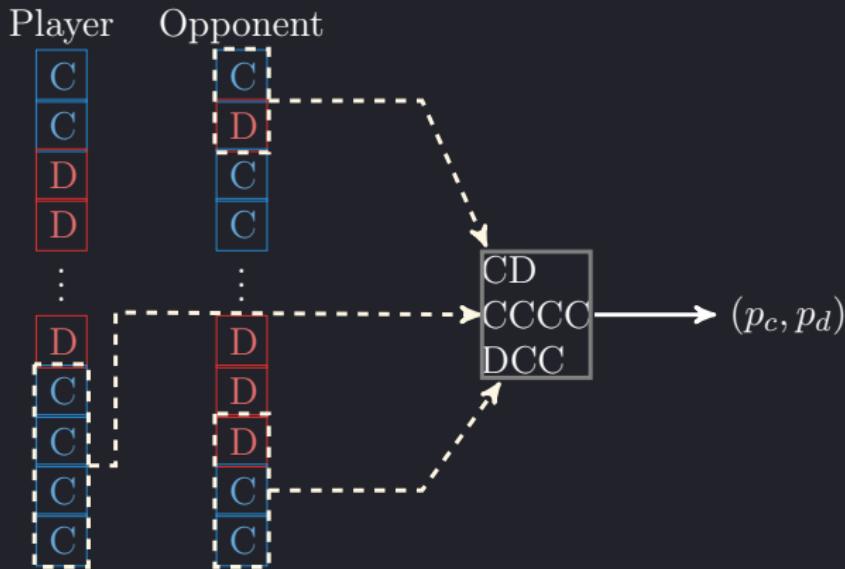
CD
CCCC
DCC









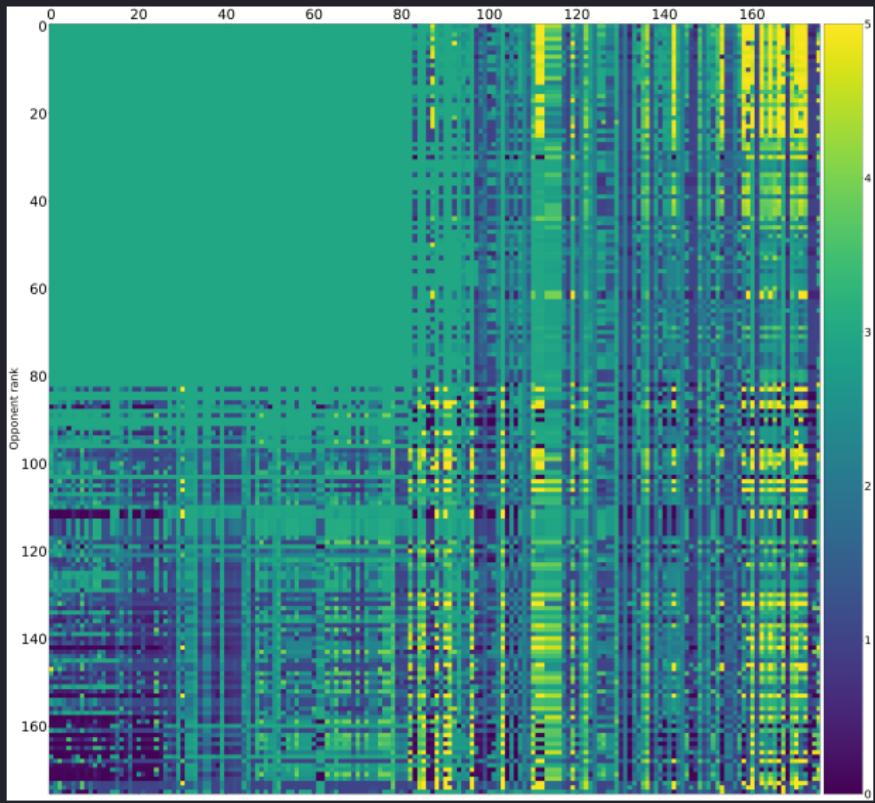


	mean	std	min	max
EvolvedLookerUp2_2_2*	2.173	1.070	1	8
Evolved HMM 5*	2.321	1.275	1	10
Evolved FSM 16*	2.489	1.299	1	10
PSO Gambler 2_2_2*	3.961	1.525	1	10
Evolved FSM 16 Noise 05*	6.300	1.688	1	11
PSO Gambler 1_1_1*	7.082	2.499	1	17
Evolved ANN 5*	7.287	1.523	2	11
Evolved FSM 4*	7.527	1.631	2	12
Evolved ANN*	7.901	1.450	2	12
PSO Gambler Mem1*	8.222	2.535	1	20
Evolved ANN 5 Noise 05*	11.362	0.872	8	16
DBS	12.197	1.125	9	16
Winner12	13.221	1.137	9	17
Fool Me Once	13.960	1.083	9	17
Omega TFT: 3, 8	14.275	1.301	9	19

Table: Turns + no noise tournament: Rank in each tournament of top 15 strategies (ranked by median over 50000 tournaments) * indicates that the strategy was trained.

	mean	std	min	max
DBS	1.205	0.468	1	3
Evolved ANN 5 Noise 05*	2.184	0.629	1	5
Evolved FSM 16 Noise 05*	2.626	0.618	1	9
Evolved ANN 5*	6.371	2.786	2	31
Evolved FSM 4*	7.919	3.175	3	33
Evolved HMM 5*	7.996	3.110	3	26
Level Punisher	8.337	3.083	3	26
Omega TFT: 3, 8	8.510	3.249	3	32
Spiteful Tit For Tat	9.159	3.772	3	40
Evolved FSM 16*	10.218	4.099	3	56
PSO Gambler 2_2_2 Noise 05*	10.760	4.102	3	47
Evolved ANN*	11.346	3.252	3	32
Adaptive	11.420	5.739	3	63
Math Constant Hunter	14.668	3.788	3	43
Gradual	15.163	3.672	4	49

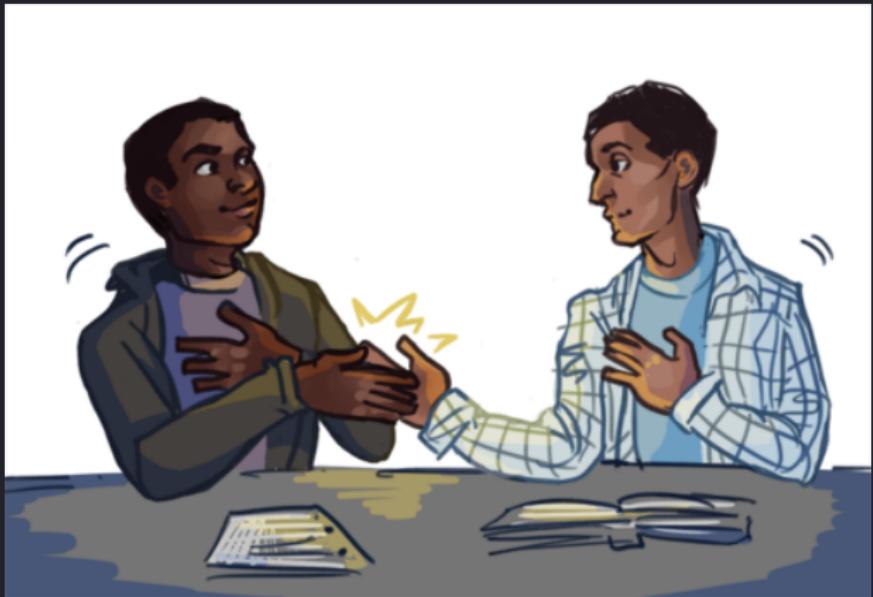
Table: Turns + noise tournament: Rank in each tournament of top 15 strategies (ranked by median over 50000 tournaments) * indicates that the strategy was trained.

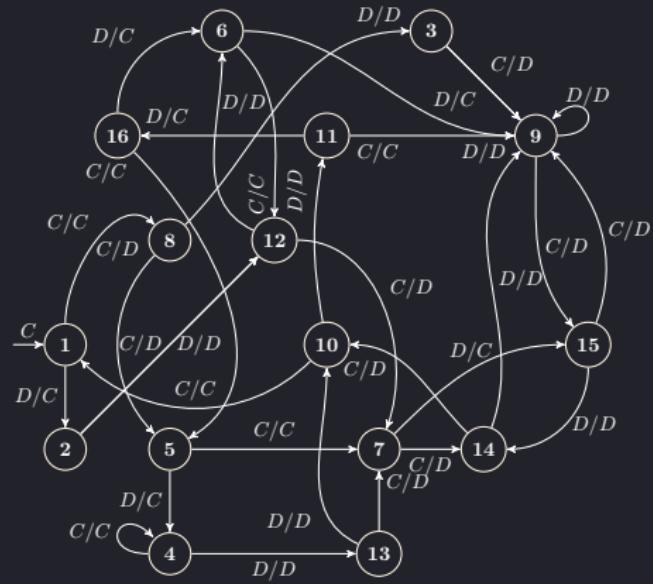


Evolution Reinforces Cooperation with the Emergence of Self-Recognition Mechanisms: an empirical study of the Moran process for the iterated Prisoner's dilemma

Vincent Knight, Marc Harper, Nikoleta E. Glynatsi, Owen Campbell

doi.org/10.1371/journal.pone.0204981





	TF1 #1	TF1 #2
1: C	1: C	
8: C	8: C	
5: D	5: D	
4: C	4: C	

- ▶ ~~Do not be the first to defect~~ Do not defect on the first turn
- ▶ ~~Do not be envious~~ It's okay to be envious
- ▶ ~~Do not be too clever~~ Be clever
- ▶ ~~Be provable~~ Be provable in tournaments with short matches, and generous when matches are longer
- ▶ Self recognition mechanism

 @NikoletaGlyn

<http://web.evolbio.mpg.de/social-behaviour/>

- ▶ Vincent Knight
- ▶ Owen Campbell
- ▶ Georgios Koutsovoulos
- ▶ Marc Harper
- ▶ Martin Jones