Spatial configurations and learning rules impact on the evolution of cooperative behaviour in the *n*-person iterative prisoner's dilemma

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The *n*-person Iterative Prisoner's Dilemma

The ***prisoner's dilemma*** is a standard example of a game analysed in Game Theory that shows why two completely rational individuals might not cooperate even if it appears that it is in their best interests to do so.

The ***iterated*** prisoner's dilemma is an extension of the general form except the game is repeatedly played by the same participants

The ***n-person iterative prisoner's dilemma*** (NIPD) is a version of the iterative prisoner's dilemma with more than two players. It is a much more general and reliable model for dynamics such as economical and socio-geographical phenomena.

Background research

How does *spatial configuration* affect the evolution of cooperative behaviour across multiple rounds of NPD?

- it is more difficult to evolve cooperation as the ***number of players*** increases
- the ***initial percentage of cooperators*** and defectors as little bearing on the emergence of cooperation
- the mobility of the automata (***scale of interaction***) is a central factor that favours cooperation

References Power, C. *A spatial agent-based model of N-person prisoner's dilemma cooperation in a socio-geographic community*, 2009; Suzuki, R., & Arita, T. *Evolutionary analysis on spatial locality in n-person iterated prisoner's dilemma.* 2003

Can learning rules be a confounding factor in previous analysis on how spatial configurations can affect the evolution of cooperative behaviour in the NIPD?

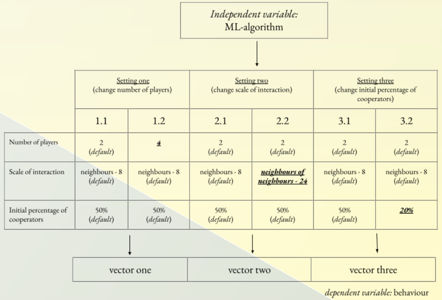
Method

Can the results in the background research be simulated under the assumption of different machine learning based approaches for strategy inference?

In particular:

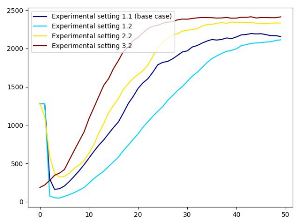
- can the results be replicated while using a ***mimic-last-move*** evolutionary algorithm (MLM-EA) for strategy inference?
- can the results be replicated while using a ***genetic algorithm*** (GA) for strategy inference?
- can the results be replicated while using ***particle swarm optimisation*** (PSO) for strategy inference?

Answers will be given through a series of *controlled experiments*

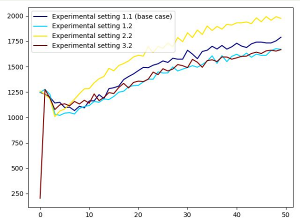


Results

MLM-EA



GA



PSO

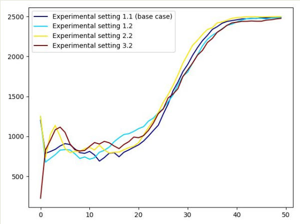


Table 1: Development of cooperation in the controlled experiments

	MLM-EA	GA	PSO
Experimental Setting 1.1	1119.316 ± 47.15	395.67 ± 98.46	1242.89 ± 24.92
Experimental Setting 1.2	895.09 ± 49.55	394.11 ± 91.63	1242.34 ± 25.97
Experimental Setting 2.2	1409.69 ± 29.95	447.54 ± 92.89	1246.50 ± 12.25

Table 2: Final state of the grid in Setting 1.1 (base case) vs Setting 3.2

	MLM-EA	GA	PSO
Experimental Setting 1.1	2368.31 ± 37.9	1644.17 ± 94.21	2492.23 ± 9.50
Experimental Setting 3.2	2407.70 ± 35.01	1662.10 ± 89.33	2486.91 ± 12.60

Conclusions

Although the *generic pattern* identified in previous analysis in ***confirmed***, the *intensity* of the effect that each factor has on the evolution of cooperative behaviour is ***dependent*** on the approach to strategy inference.

In particular:

- The magnitude of the effect established to be caused by the variation of the **number of players** has proven to vary a lot across the three scenarios presented, this may suggest a *shift* or *total cancellation* of the effect under the assumption of a different ML-based approach.
- The impact of the **scale of interaction** on the evolution of cooperation seems to have *little to no effect* when PSO is employed
- The **initial percentage of defectors** is confirmed to have *little bearing* on the evolution of cooperation in the three scenarios presented.

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