Reinforcement Learning Explains Conditional Cooperation and Its Moody Cousin

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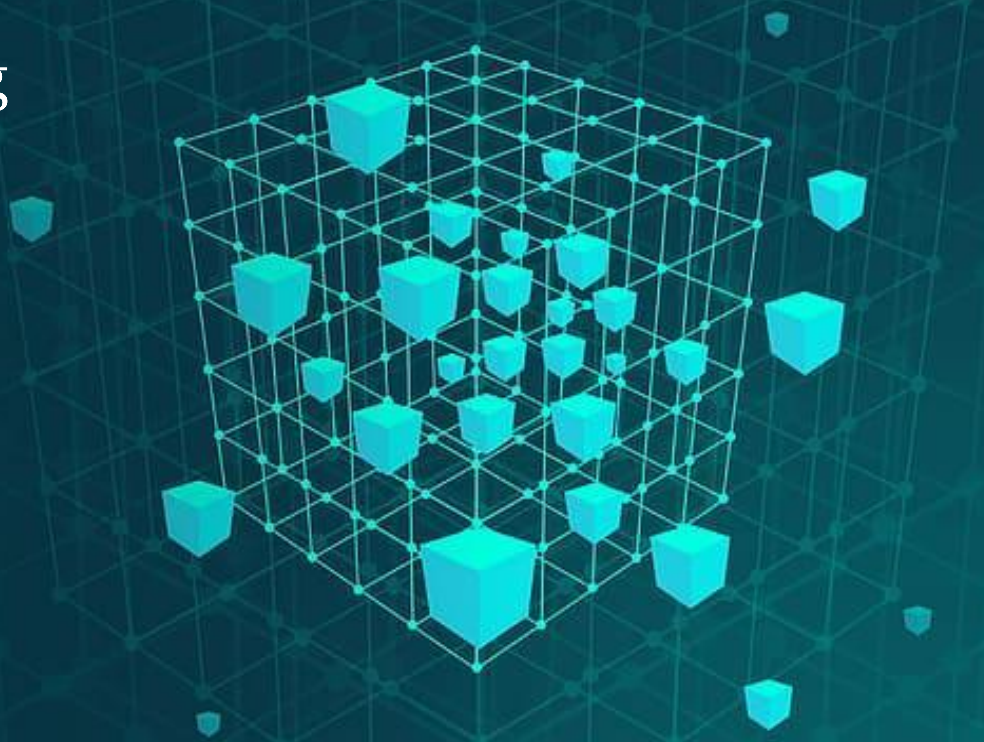
2025-2026



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I. Introduction

EGT
(Evolutionary Game Theory)

RL
(Reinforcement Learning)

Conditional Cooperation (CC)

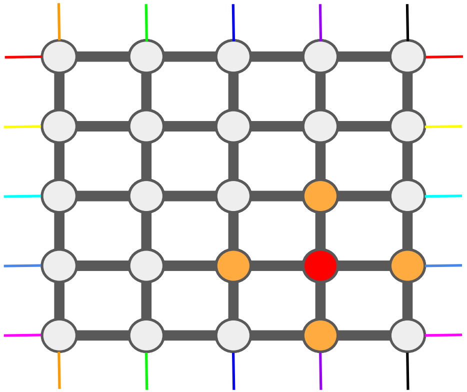
neigh C ⇒ agent C

Moody CC (MCC)

neigh D ⇒ independant agent

II.i PDG Environment

Prisoner Dilemma Game



neighbouring

	C	D
C	3	0
D	5	1

Payoff Matrix

1) Bush-Mosteller

$$p_t = \begin{cases} p_{t-1} + (1 - p_{t-1})s_{t-1} & (a_{t-1} = \mathrm{C}, s_{t-1} \geq 0), \\ p_{t-1} + p_{t-1}s_{t-1} & (a_{t-1} = \mathrm{C}, s_{t-1} < 0), \\ p_{t-1} - p_{t-1}s_{t-1} & (a_{t-1} = \mathrm{D}, s_{t-1} \geq 0), \\ p_{t-1} - (1 - p_{t-1})s_{t-1} & (a_{t-1} = \mathrm{D}, s_{t-1} < 0), \end{cases}$$

$$s_{t-1} = \tanh\left[\beta(r_{t-1} - A)\right],$$

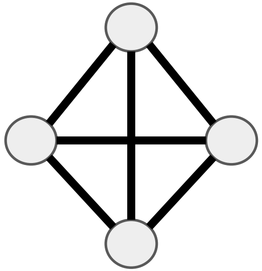
2) Misimplement the decision (ε)

$$\tilde{p}_t \equiv p_t(1 - \epsilon) + (1 - p_t)\epsilon$$

3) Payoff Reward

II.ii PGG Environment

<u>Public Good Game</u>



neighbouring

1) Bush-Mosteller

$$p_t = \begin{cases} p_{t-1} + (1 - p_{t-1})s_{t-1} & (a_{t-1} \geq X \text{ and } s_{t-1} \geq 0), \\ p_{t-1} + p_{t-1}s_{t-1} & (a_{t-1} \geq X \text{ and } s_{t-1} < 0), \\ p_{t-1} - p_{t-1}s_{t-1} & (a_{t-1} < X \text{ and } s_{t-1} \geq 0), \\ p_{t-1} - (1 - p_{t-1})s_{t-1} & (a_{t-1} < X \text{ and } s_{t-1} < 0). \end{cases}$$

$$s_{t-1} = \tanh\left[\beta(r_{t-1} - A)\right],$$

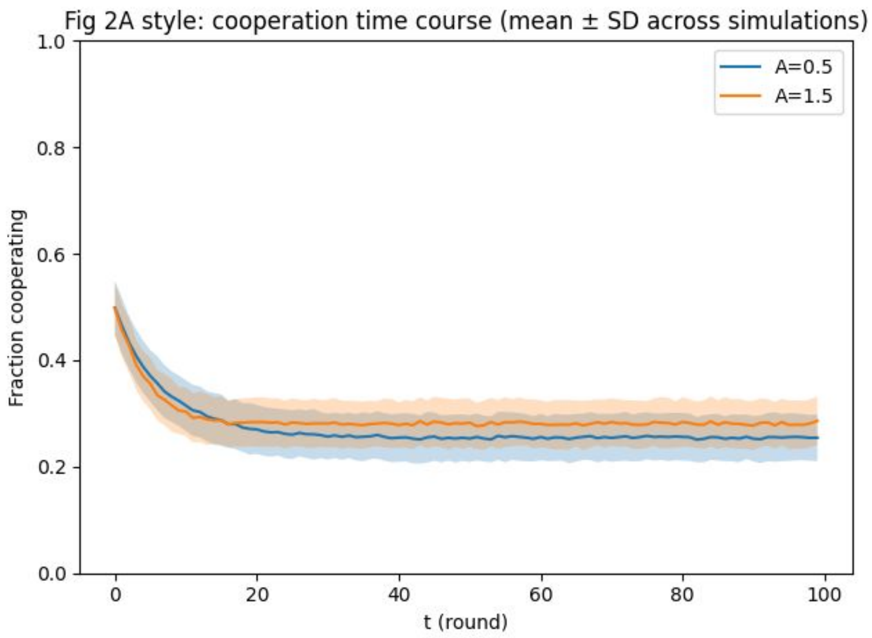
2) staked amount ε [0,1]

$a_t = \eta(p_t, 0.2)$

3) Reward

$r = 1 - a_t + 0.4(a_t + \sum_{j=1}^{3} \tilde{a}_{j,t})$

III.i Simulations PDG



A = 0.5 / 1.5

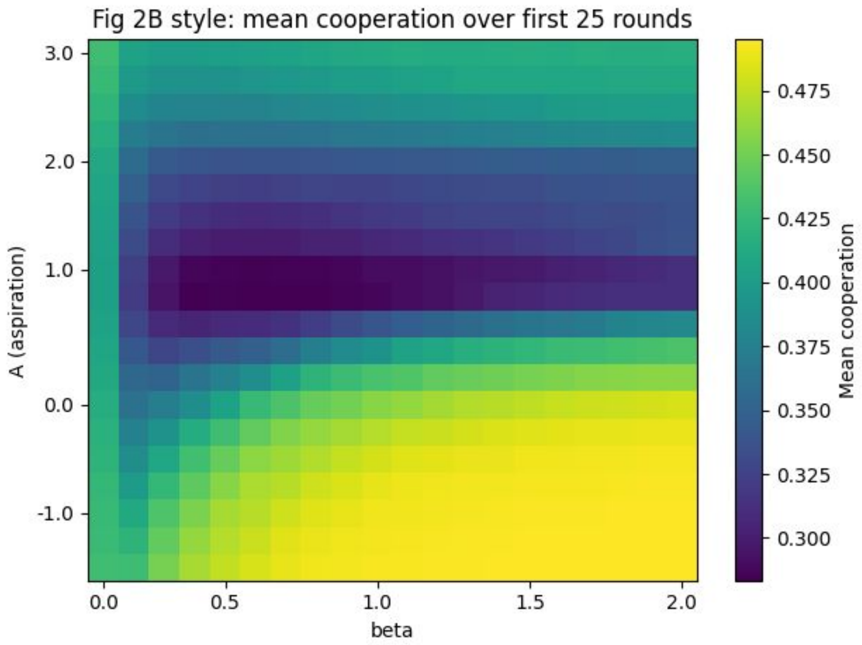
β = 0.2

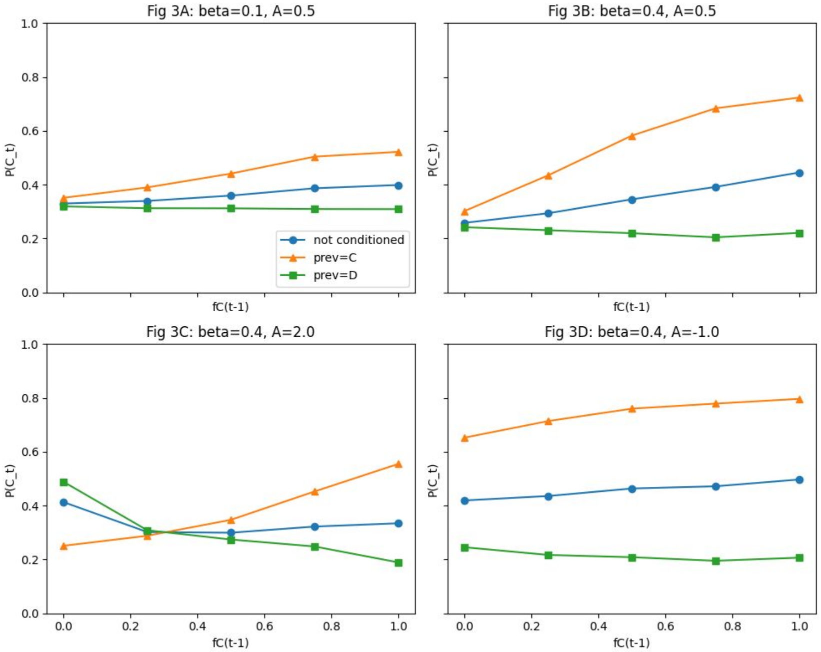
p_0 = 0.5

grid = 10 x 10

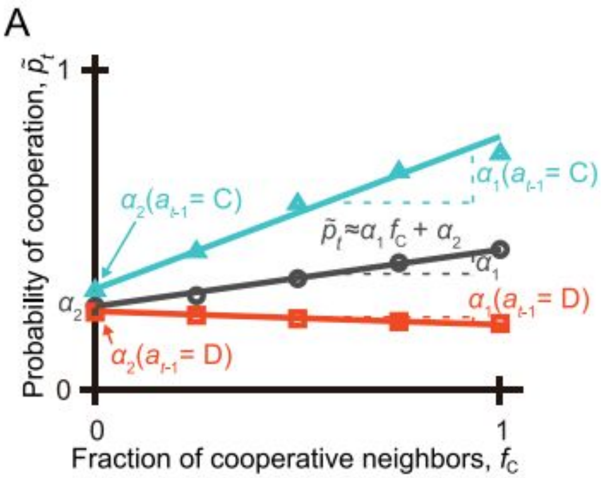
ε = 0.2

III.i Simulations PDG



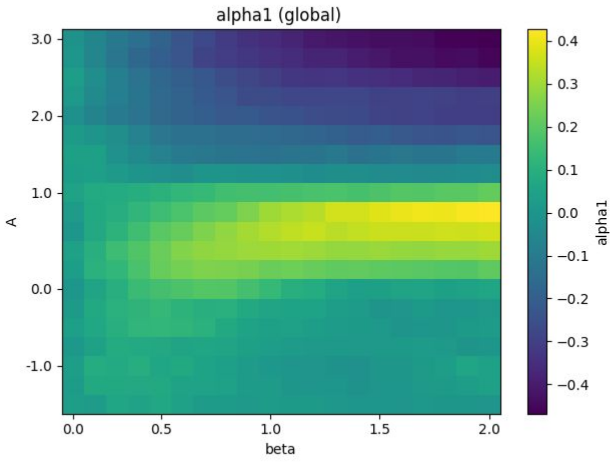


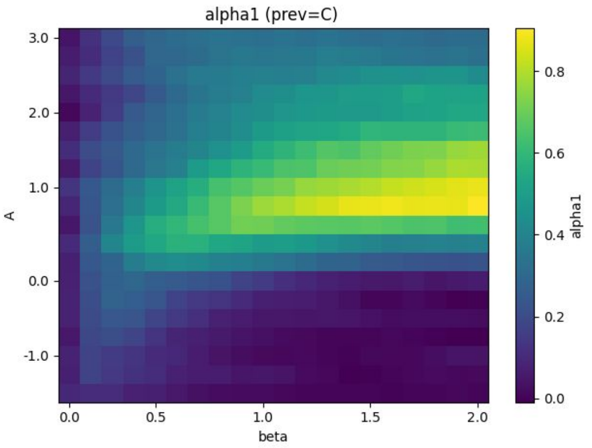
III.i Simulations PDG

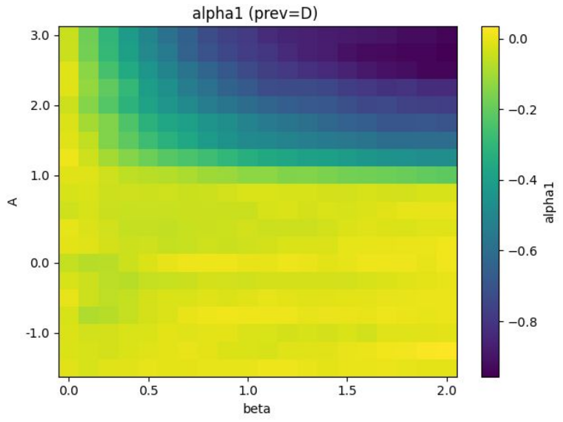


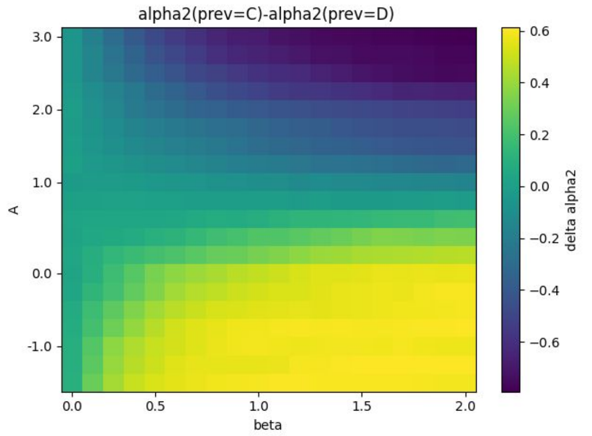
$A < \sim 1$

$\beta > 1$









III.ii Simulations PGG

A = 0.9

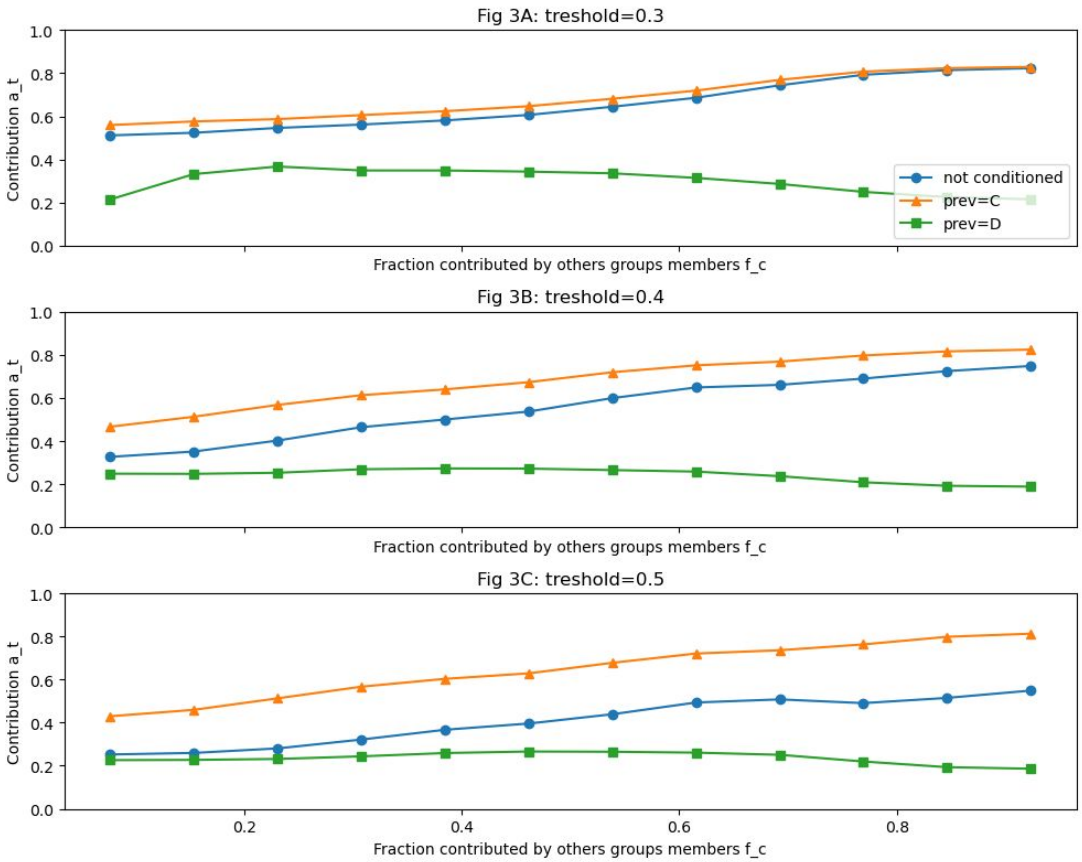
β = 0.4

p_0 = 0.5

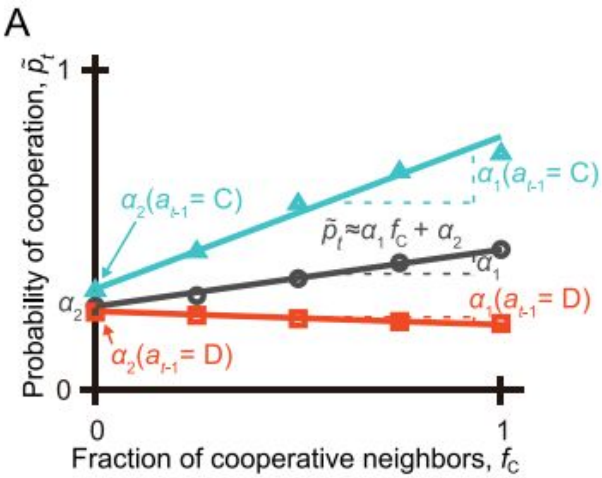
number player = 4

ε = 0.2

Treshold = 0.3 / 0.4 / 0.5

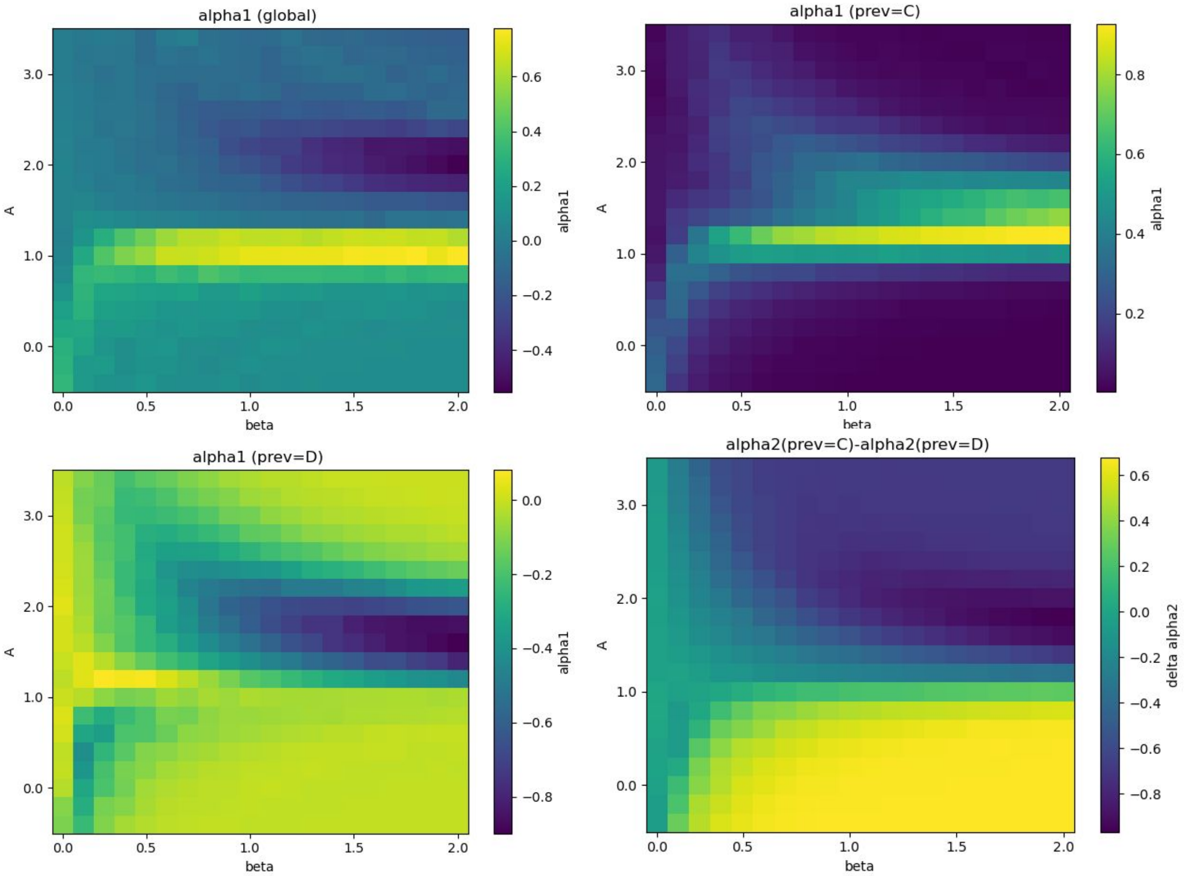


III.ii Simulations PGG



$0 < A < 1$

$\beta > 0.5$

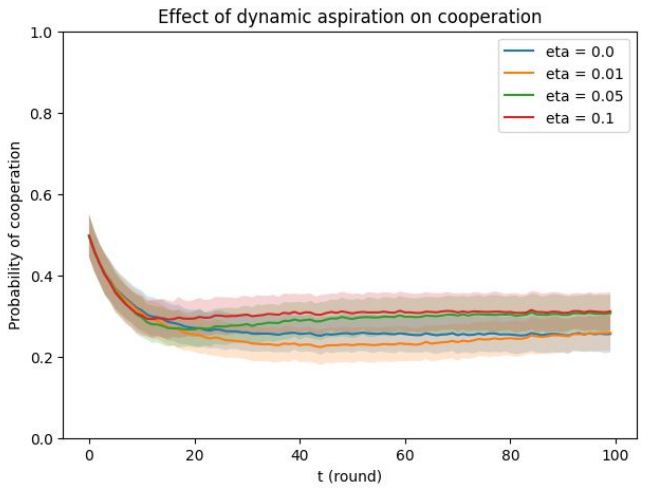


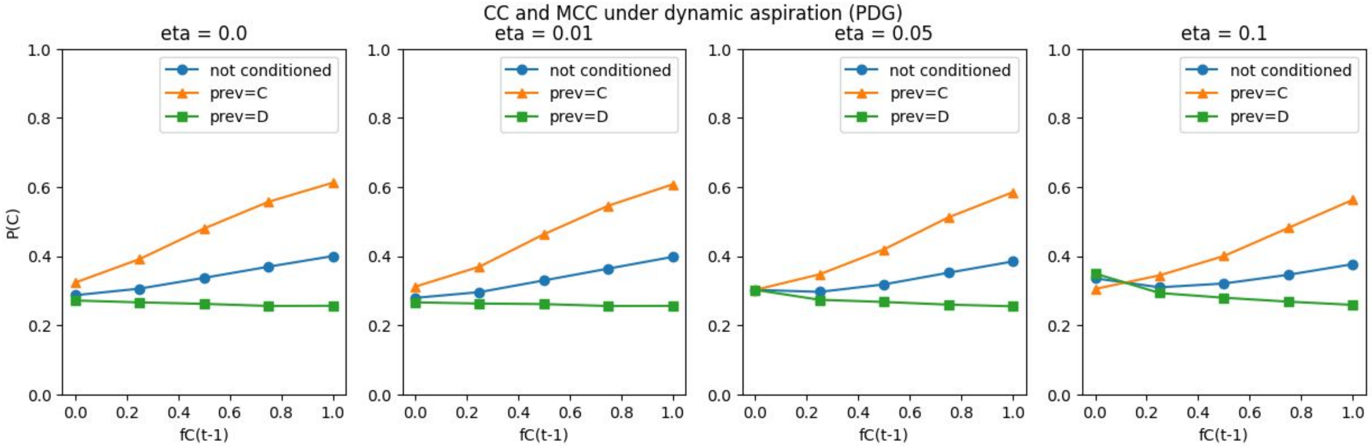
IV.i Dynamical Aspiration

PDG

$$s_{t-1} = \tanh[\beta(r_{t-1} - A)],$$

$$A_{t+1} = (1-\eta)A_t + \eta r_t$$





IV.i Dynamical Aspiration

PGG

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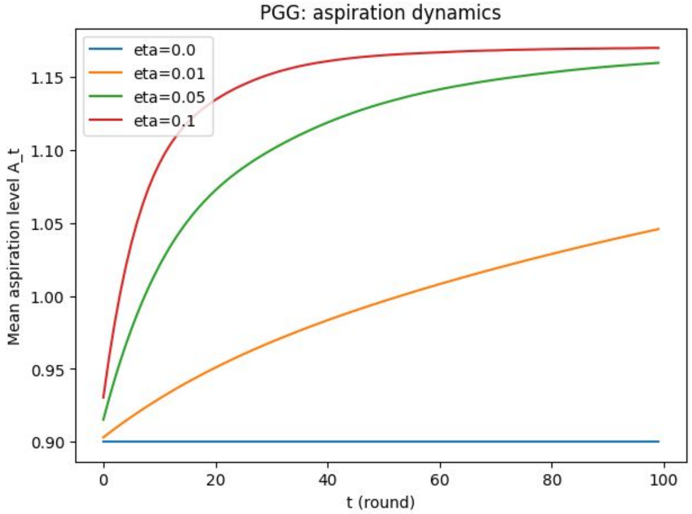
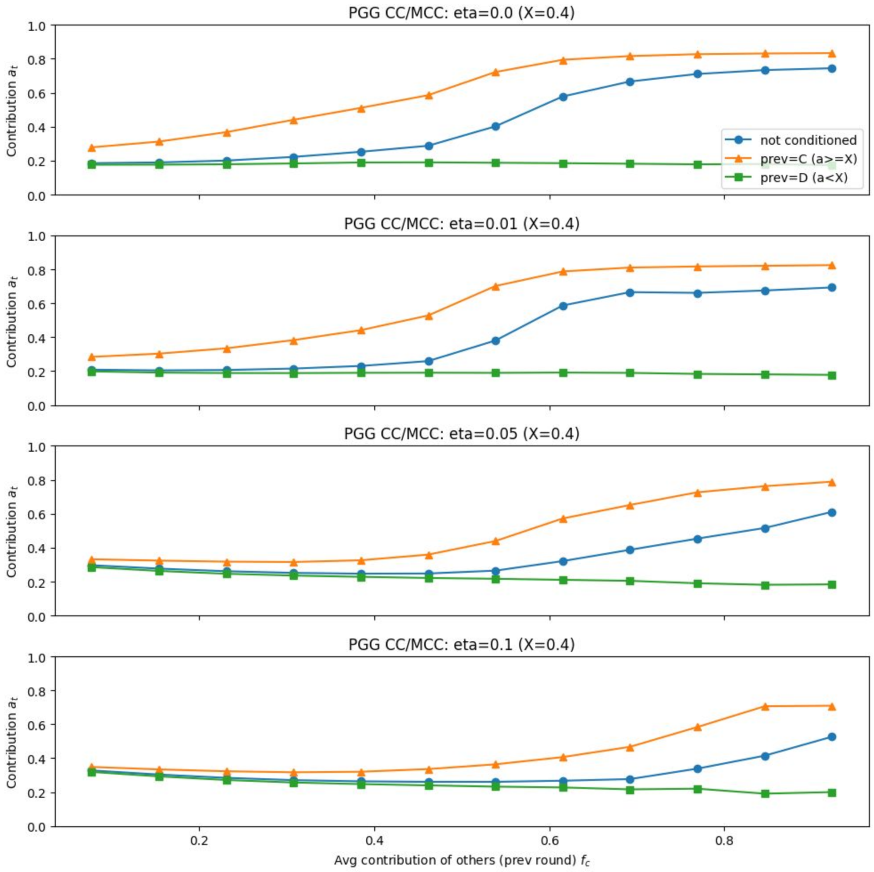
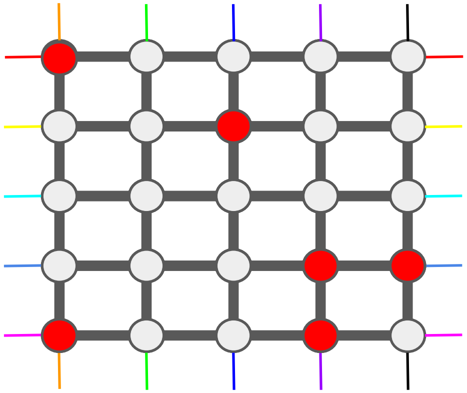


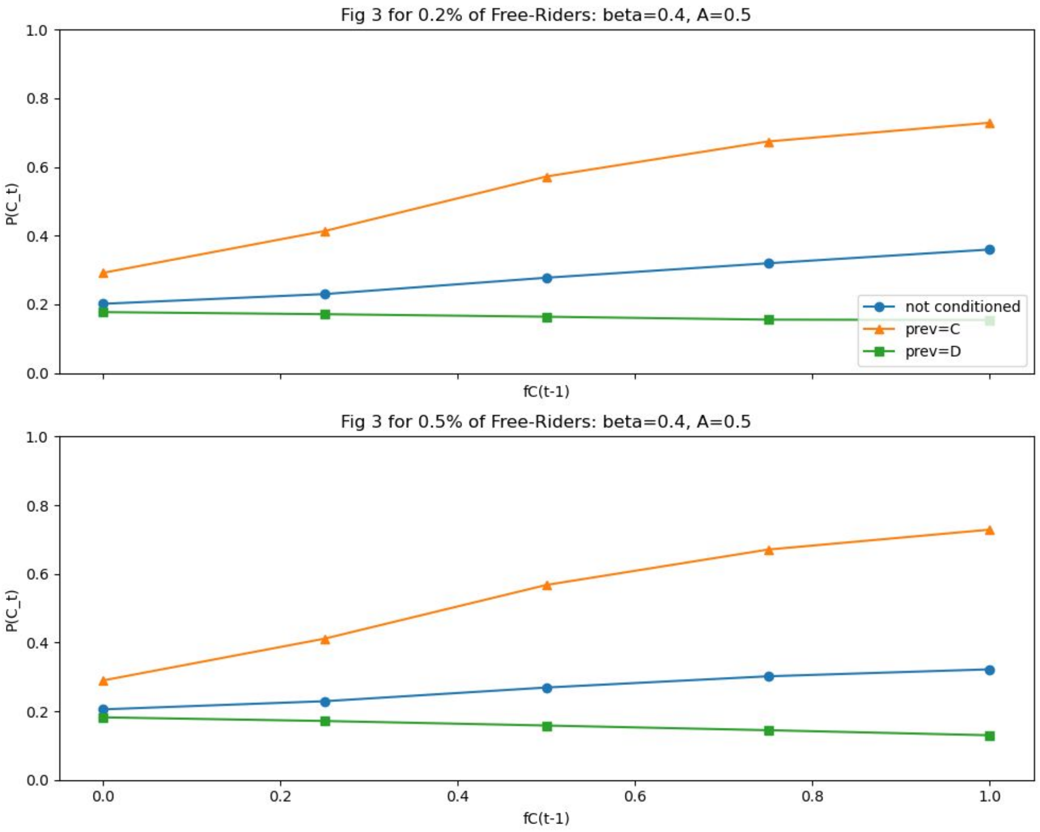


IV.ii Free Rider

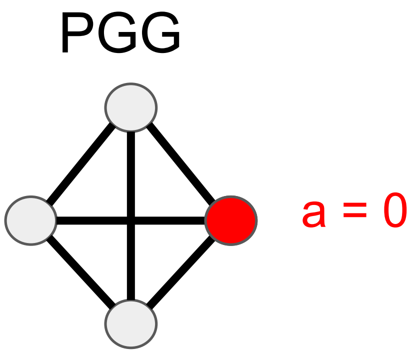
PDG

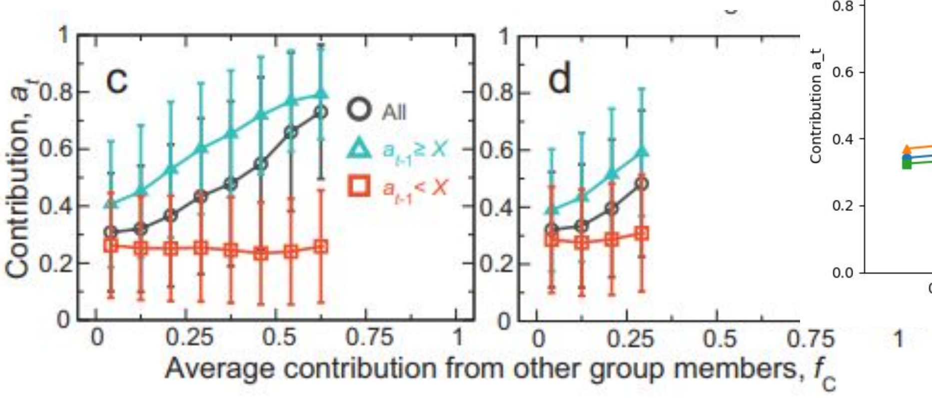


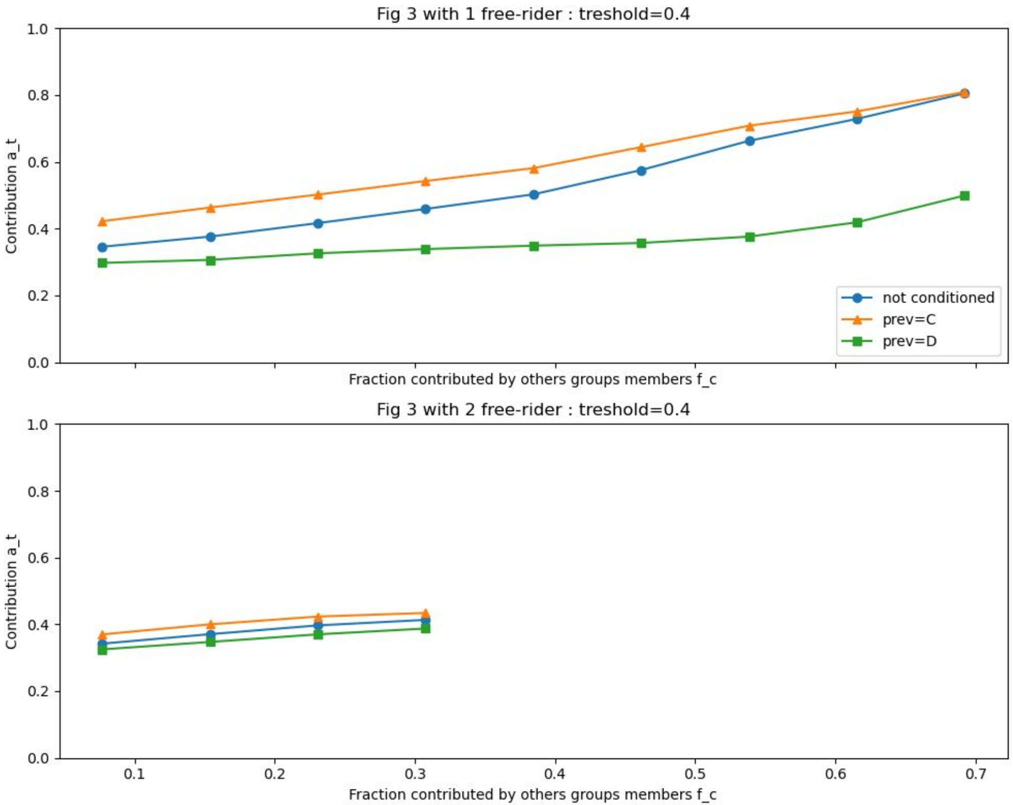
a = 0



IV.ii Free Rider







V. Conclusion

- Reconstruction of paper indicating that CC and MCC are behaviors naturally observable in dynamic learning

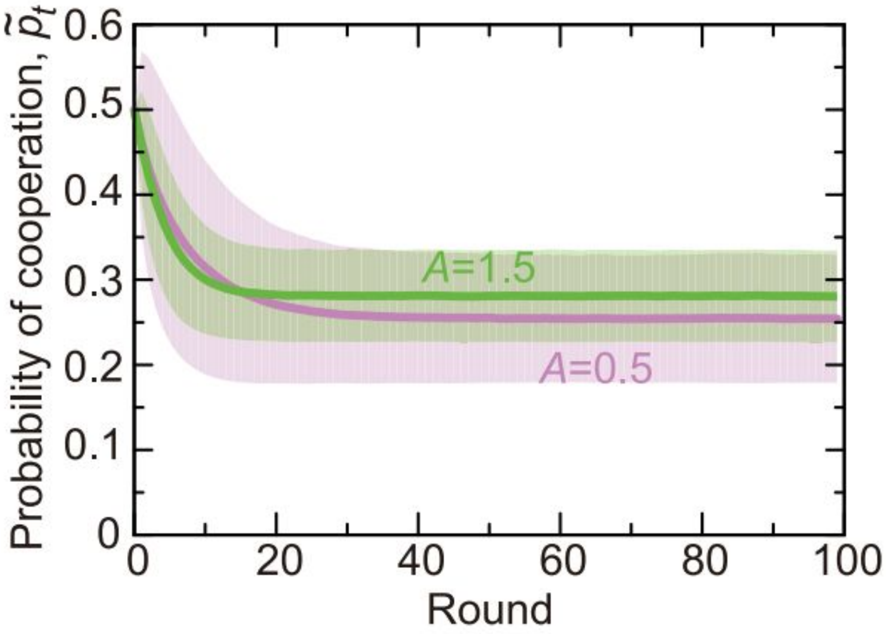
- The parameters do not have a significant impact (convergence speed changes but behavior remains observable).

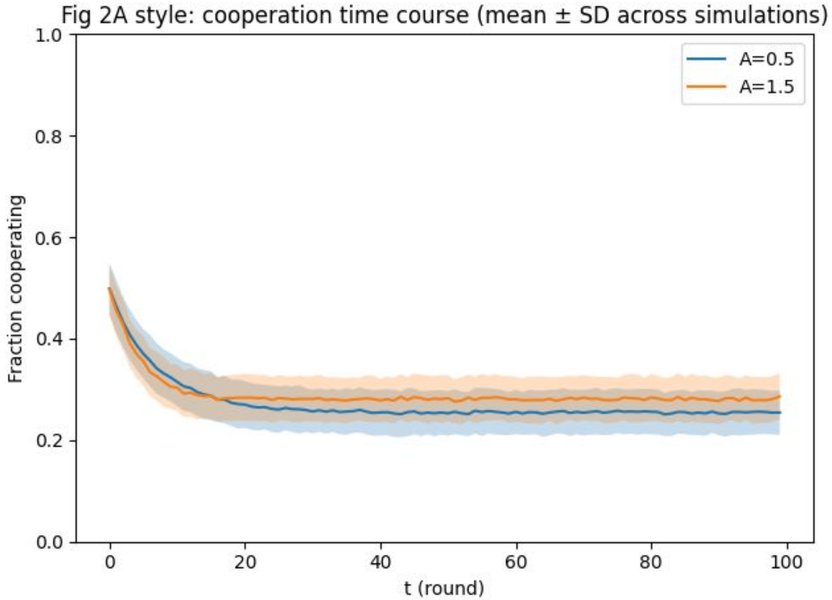
- It is easier to force cooperation than defection.

- Study interaction with neighbors (more neighbors for the PDG or no interaction with all neighbors for the PGG)

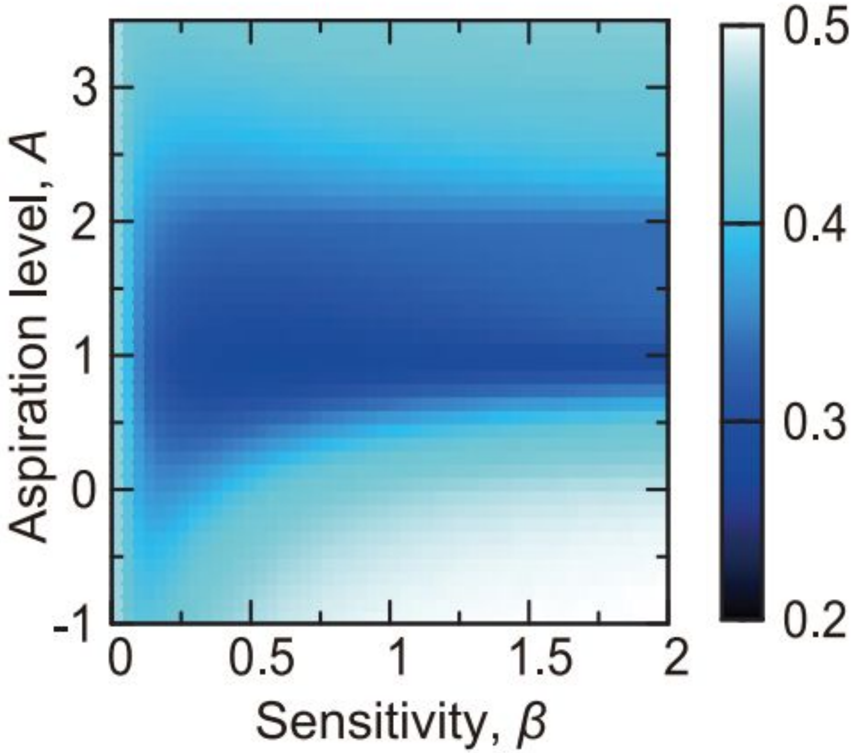
- Use heterogeneous parameters (one variable for each agent) and for other social dilemmas.

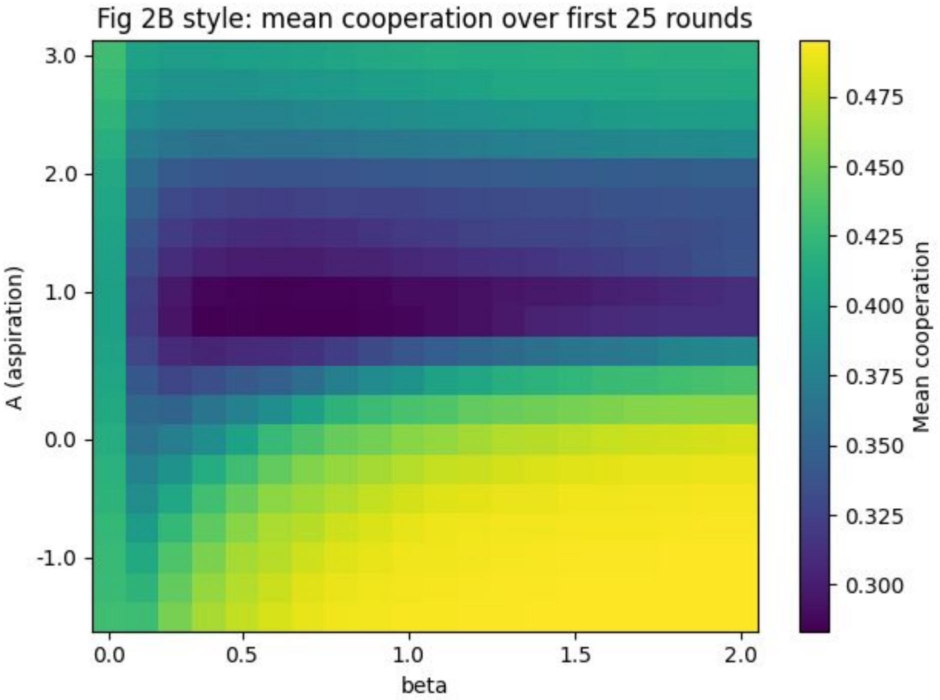
Appendix : Fig 2A



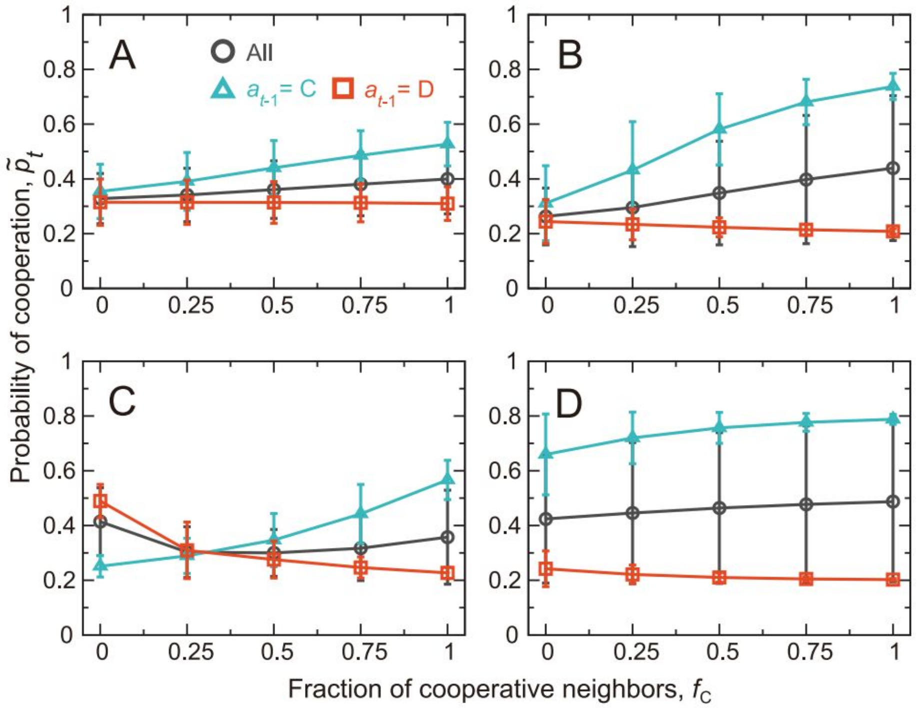


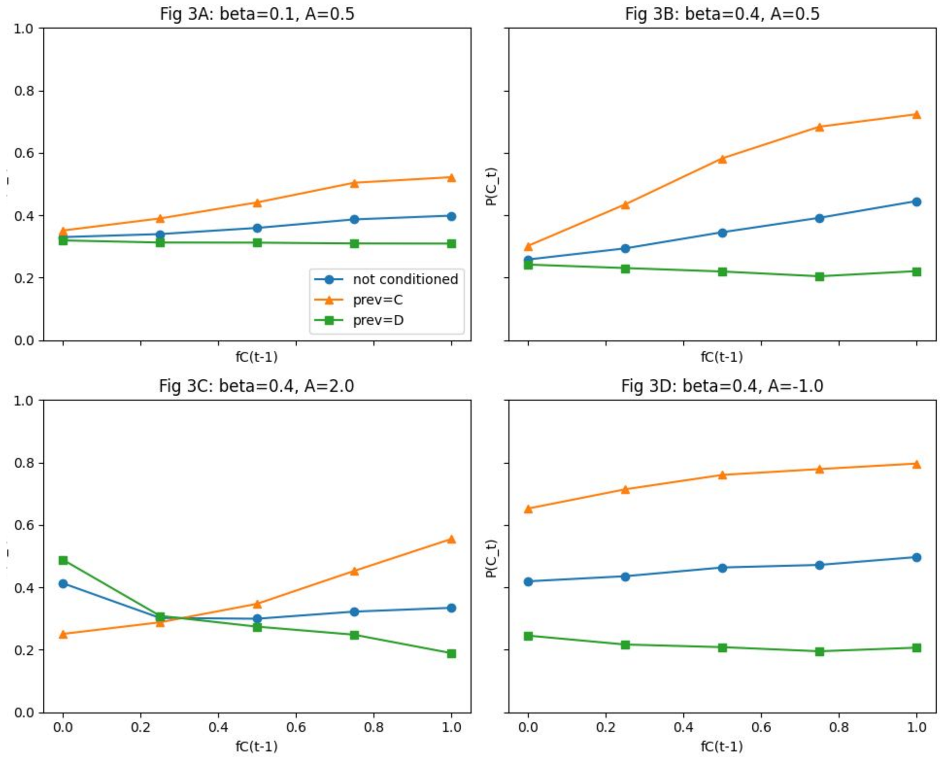
Appendix : Fig 2B



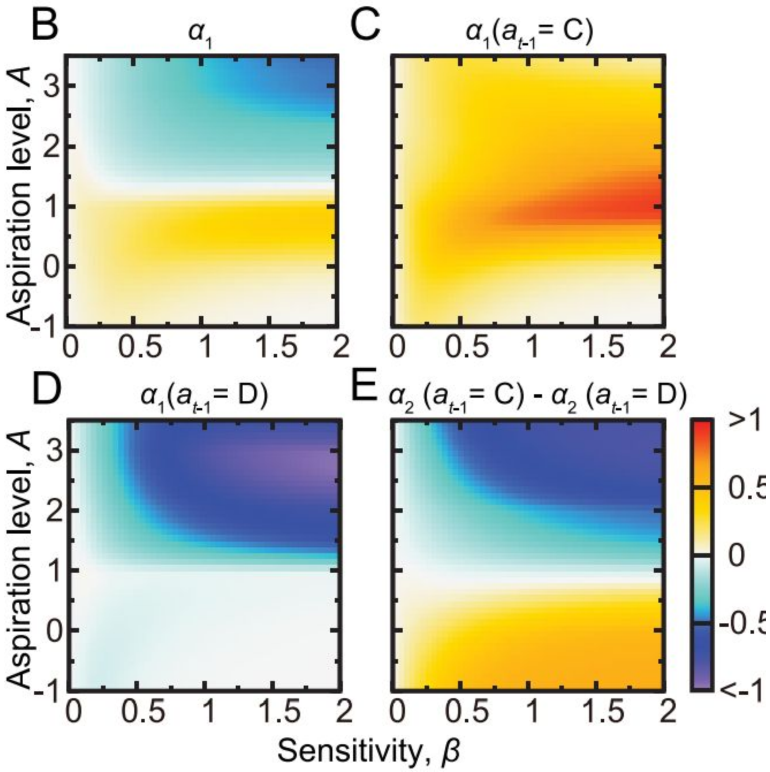


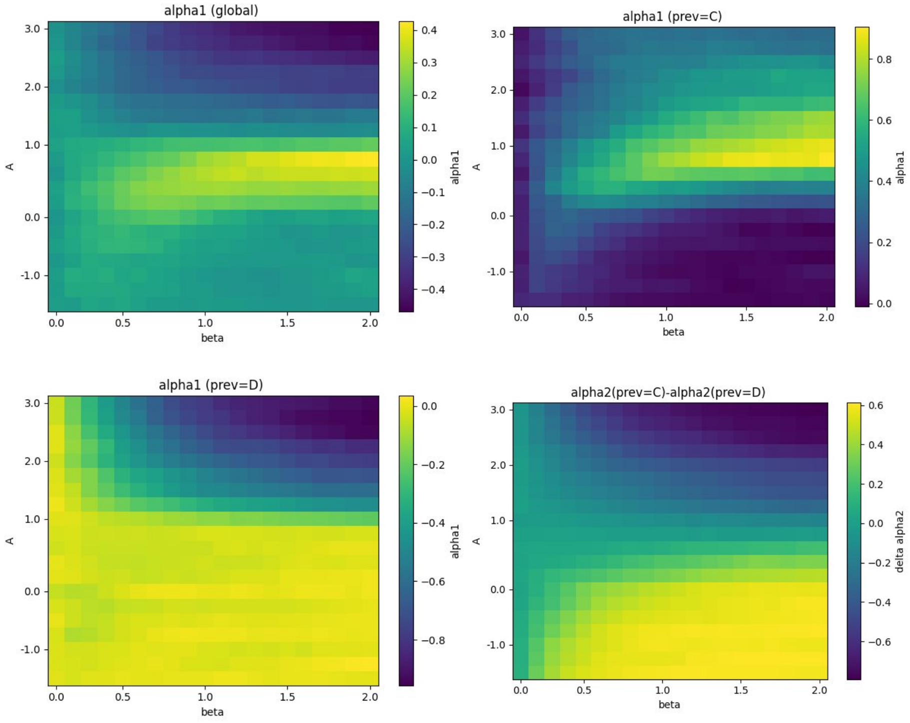
Appendix : Fig 3



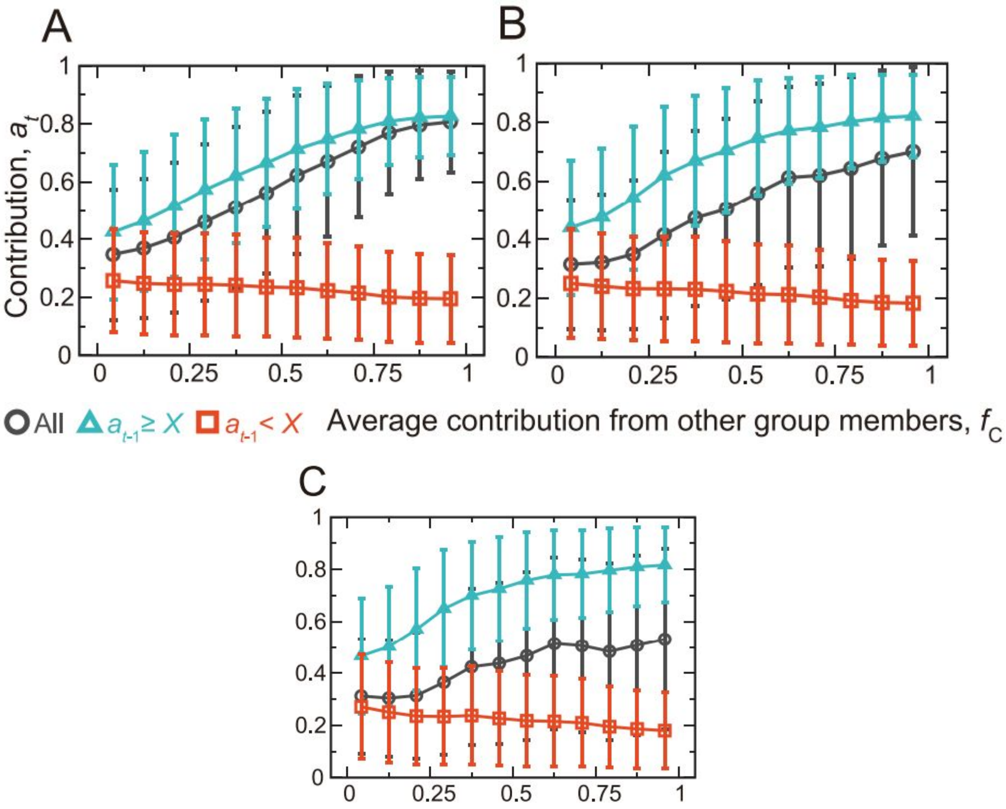


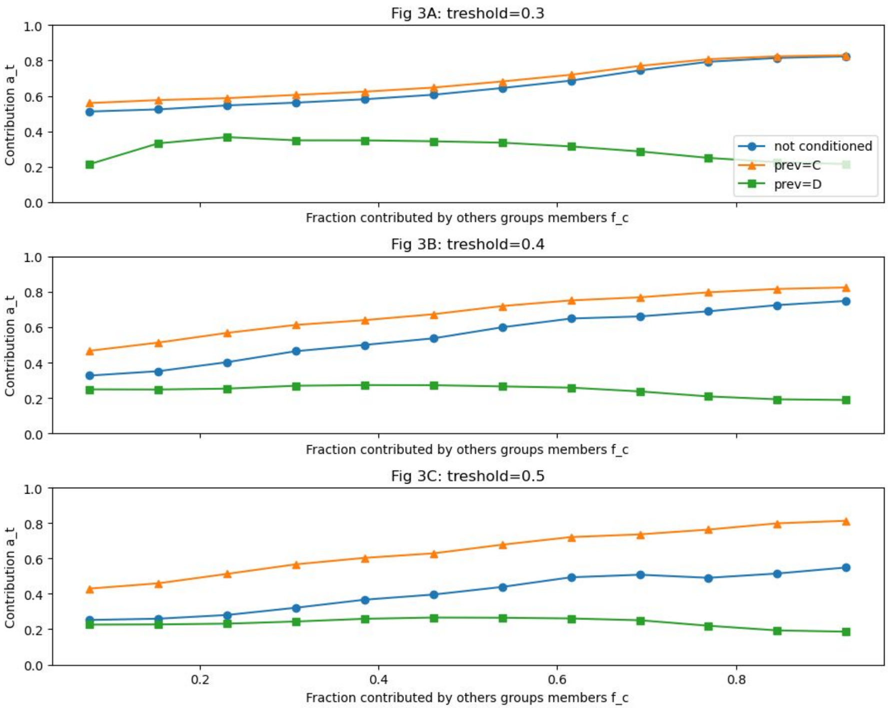
Appendix : Fig 4





Appendix : Fig 5 A-B-C





Appendix : Fig 5 D-E-F-G