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Modeling Moral Choices in Social Dilemmas with Multi-Agent Reinforcement Learning

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for the Ecological Study of the Brain

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Research Questions

1. How do we develop **morally robust** & **adaptable** AI agents for the real world?

2. How can we **represent** different existing **ethical frameworks** for AI agents?

How can we develop morality in agents?

Top-down: Define specific **rules**, safety **constraints**, moral **principles** to follow.

- E.g. *Asimov's* Three Laws of Robotics; AI / RL Safety constraints.
- ➢ Hard/impossible to define all necessary rules for agents to follow without contradictions.

Bottom-up: Allow agents to **learn morality from interactions** with an environment / humans, without any predispositions.

- E.g. Reinforcement Learning, incl. RLHF.
- ➢ Risks of agents reward-hacking or learning inefficient norms early on.

[Amodei *et al.*. (2016). Concrete problems in AI safety. *arXiv:1606.06565*.]
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→ **Hybrid**: Combine top-down moral objectives with a bottom-up learning approach.

- ➢ Reinforcement Learning via **intrinsic rewards** based on top-down definitions of moral preferences.

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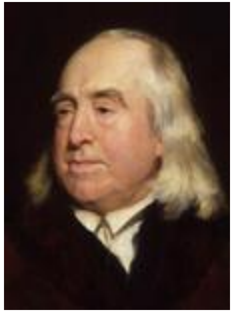
Formalising Moral Objectives - a philosopher's perspective

Consequentialist:
choose actions which maximise some long-term outcome in society.

- E.g. Utilitarianism



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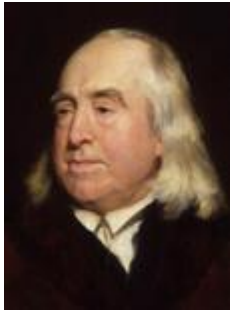

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Norm-based:
choose actions which adhere to a moral norm here & now.

- E.g. Deontological ethics

[Kant (1981). *Grounding for the metaphysics of morals*.]

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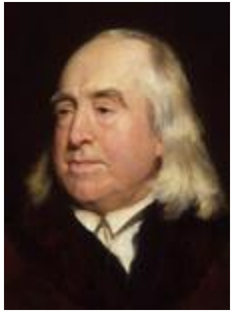

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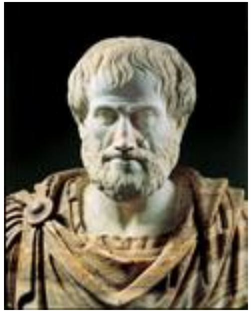
Virtue Ethics:
act according to a set of virtues.

- May be consequentialist / norm-based / multi-objective



[Aristotle. *The Nicomachean Ethics*.]

Multi-Agent Systems & Learning Agents

Any society is a **multi-agent system**.

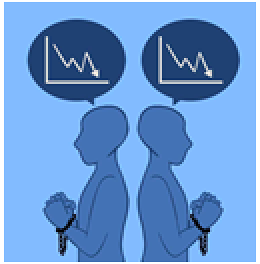
Learning agents affect one another's ‘curriculum’ → outcomes are not fully predictable.

General-Sum Games

Real-world multi-agent scenarios can be modeled using **general-sum games**:

- Both agents may benefit from the interaction (unlike Go/Chess);
- Agents may exploit or deceive each other to gain a greater payoff.

Two-player Social Dilemma games



Repeated dilemma games:

- short-term/individual gain *vs.* long-term cumulative outcomes
- → complex strategies can **evolve** (incl. reputation & punishment)

Iterated Prisoner's Dilemma

	C	D
C	3,3	1,4
D	4,1	2,2

Motivations to Defect:
Greed: 4 > 3
Fear: 2 > 1

[Axelrod, R. & Hamilton, W.D. (1981). The evolution of cooperation. *Science*, 211(4489):1390–1396.]

Image source: Investopedia

Our contributions:

- We design (simplified) **intrinsic moral rewards** inspired by various philosophical theories.
- We evaluate our approach by modeling **repeated dyadic interactions** between **morally diverse** Reinforcement Learning agents.
- We systematically analyse the impact of different types of morality on the **emergence of cooperation/defection/exploitation**, and the corresponding **social outcomes**.

The Reinforcement Learning loop

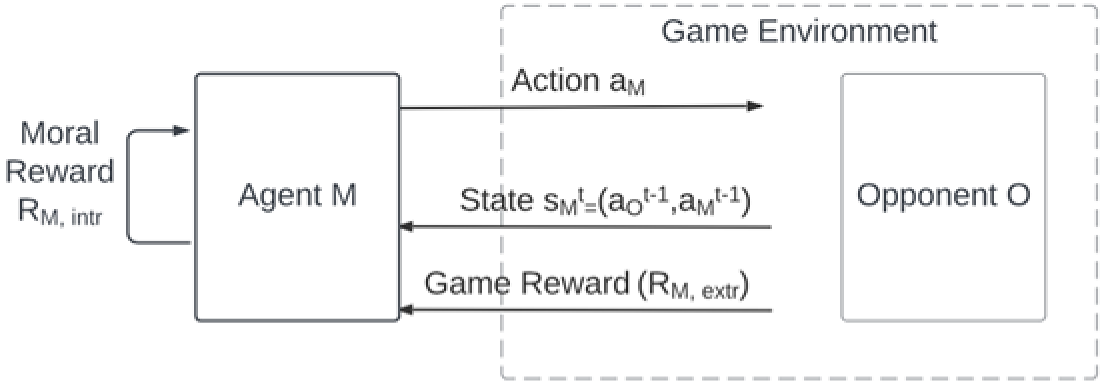
M = moral agent

O = opponent

s^t = state at time t (pair of moves from last iteration)

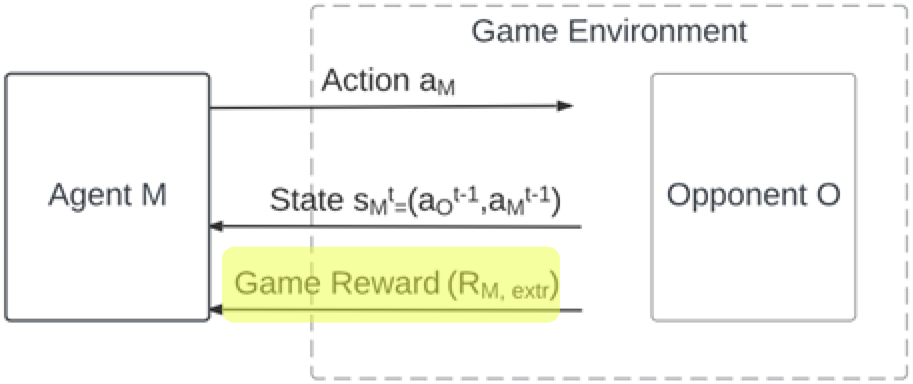
a^t = action at time t (C or D)

R = intrinsic or extrinsic reward



The Reinforcement Learning loop

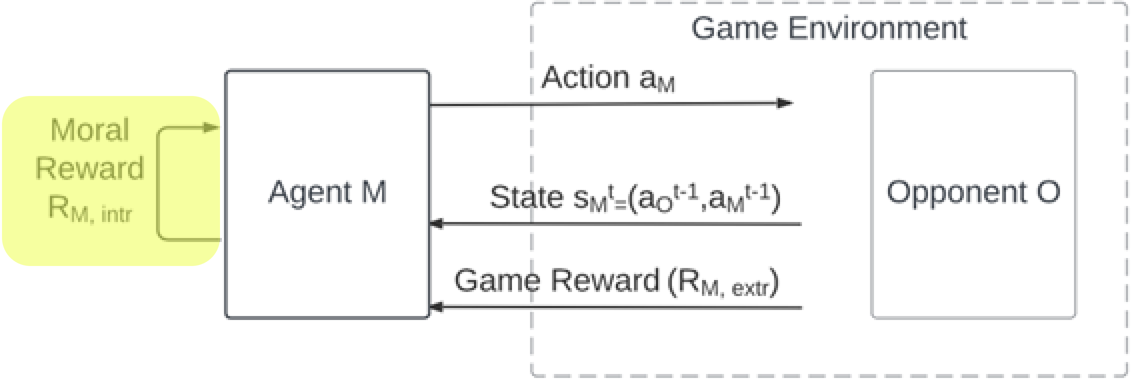
- A traditional, self-interested (*Selfish*) agent learns to maximise the game payoff (extrinsic reward) over time.



The Reinforcement Learning loop

- A traditional, self-interested (*Selfish*) agent learns to maximise the game payoff (extrinsic reward) over time.

- *Moral* agents instead learn to maximise an **intrinsic reward** according to a given moral framework.



[Chentanez, N. et al. (2004.) Intrinsically motivated reinforcement learning. NeurIPS'04.]

Moral Learning Agents

M = moral agent

O = opponent

Agent *M*	Moral Reward (at time *t*)
Utilitarian	*M*'s payoff + *O*'s payoff
Deontological	Punished if *M* defects at time *t* & *O* cooperated at time *t-1*
Virtue-equality	$1 - \frac{\lvert M\text{'s payoff} - O\text{'s payoff}\rvert}{M\text{'s payoff} + O\text{'s payoff}}$
Virtue-kindness	Rewarded for cooperating at time *t*
Virtue-mixed	*equality* reward + normalized *kindness* reward

Reinforcement Learning in Social Dilemmas

- Agents learn in pairs, against a fixed opponent, via **tabular Q-Learning.**
- They repeatedly play one of the dilemma games (10000 iterations) using an **epsilon-greedy** policy (with epsilon decay).
- Both agents learn to **choose actions which maximise cumulative reward.**

[Leibo *et al*. (2017). Multi-agent reinforcement learning in sequential social dilemmas. *AAMAS'17*.]

Evaluation Results

Presented here:

- Actions chosen on final iteration.

Further results available:

- Social outcomes accumulated over training [see paper]
- Rewards & actions over time, etc. [see online Appendix]

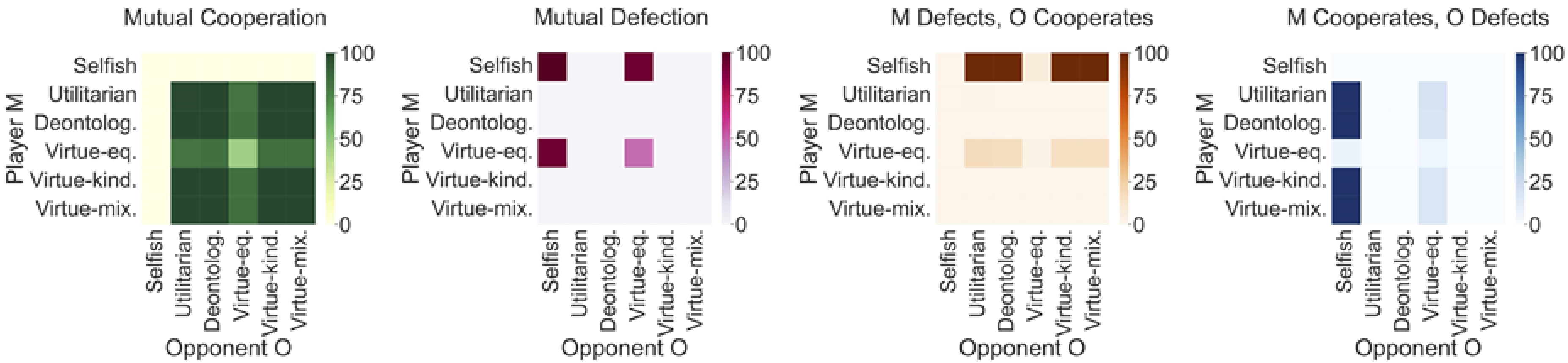
Actions - Iterated Prisoner's Dilemma

M = moral agent

O = opponent

	C	D
C	3,3	1,4
D	4,1	2,2

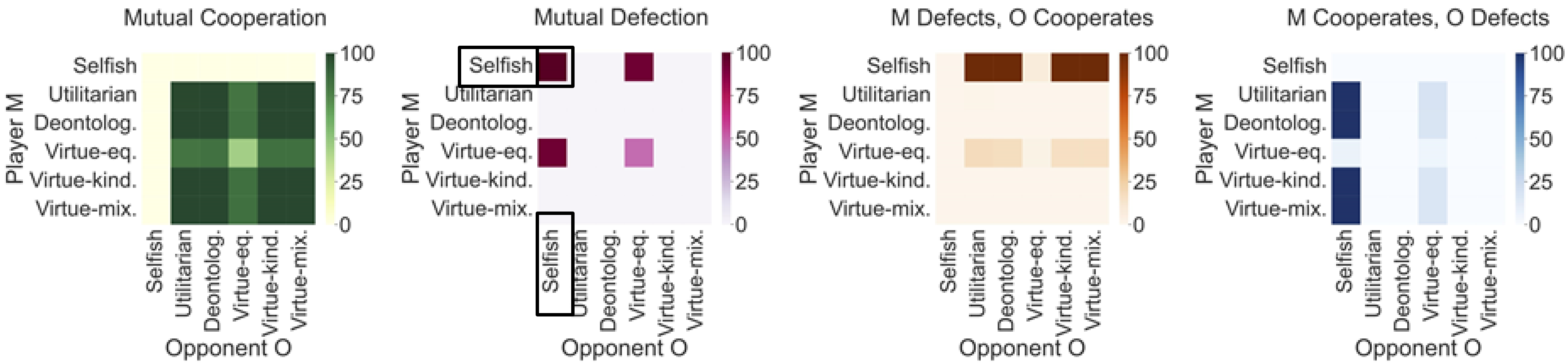
We evaluate **pairs of actions** chosen on the final iteration **by each pair of agents** (as % of times pairs **CC - mutual cooperation**, **DD - mutual defection**, **DC - exploitation**, **CD** were observed over 100 runs).



Actions - Iterated Prisoner's Dilemma

	C	D
C	3,3	1,4
D	4,1	2,2

Selfish vs *Selfish* players learn to **mutually Defect** on 100% of the runs.

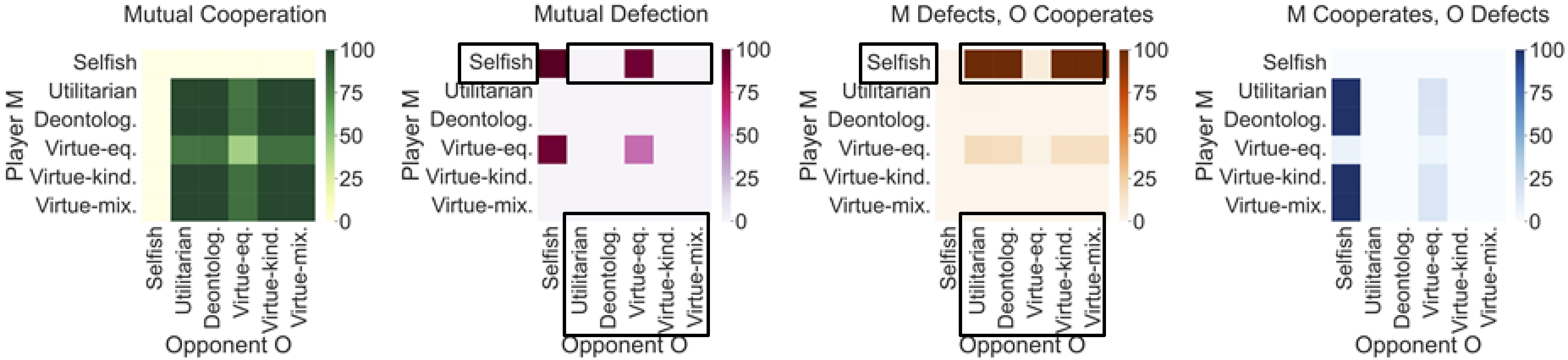


Note, the training was run until the convergence of the Selfish-Selfish pair to a stable policy (here: mutual defection). This occurred over 10000 iterations.

Actions - Iterated Prisoner's Dilemma

	C	D
C	3,3	1,4
D	4,1	2,2

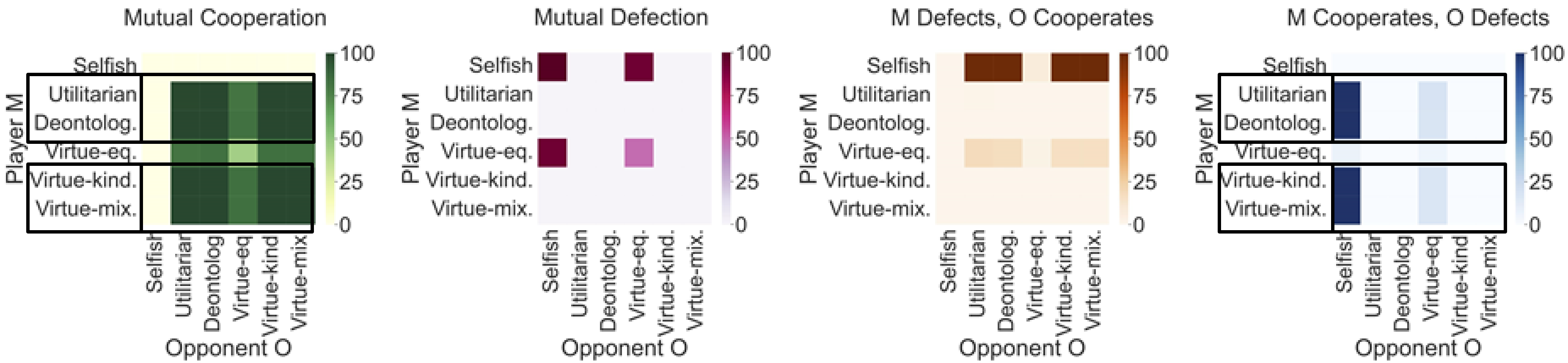
Selfish player achieves **mutual defection** against *Virtue-equality*, *and* learns to **exploit** all other *moral* players.



Actions - Iterated Prisoner's Dilemma

	C	D
C	3,3	1,4
D	4,1	2,2

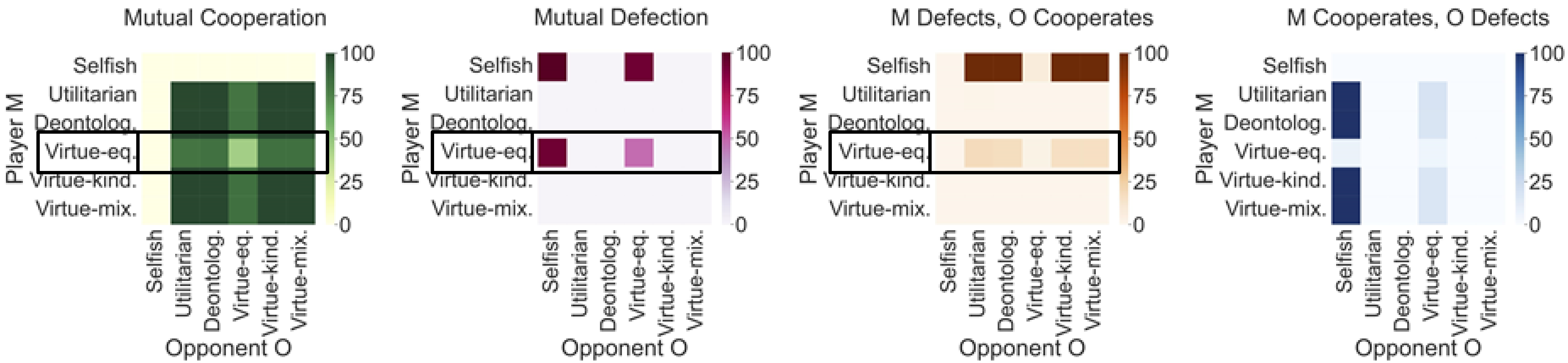
Most *moral* players (*Utilitarian*, *Deontological*, *Virtue-kindness* & *Virtue-mixed*) learn cooperative policies, achieving **mutual cooperation** against one another. However, they get **exploited** by *Selfish* and sometimes *Virtue-equality* opponents.



Actions - Iterated Prisoner's Dilemma

	C	D
C	3,3	1,4
D	4,1	2,2

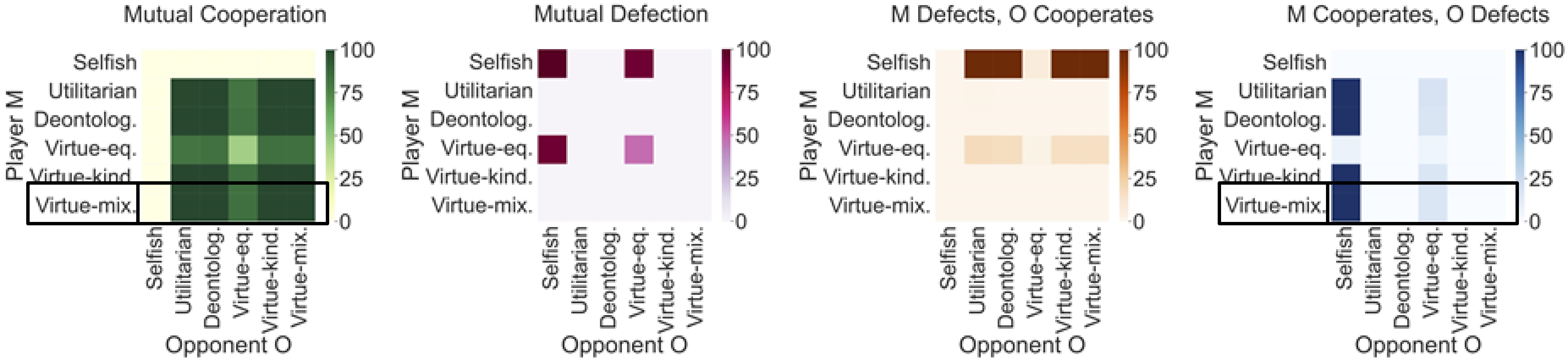
For the *Virtue-equality* player, some **exploitative** behavior emerges (before convergence).



Actions - Iterated Prisoner’s Dilemma

	C	D
C	3,3	1,4
D	4,1	2,2

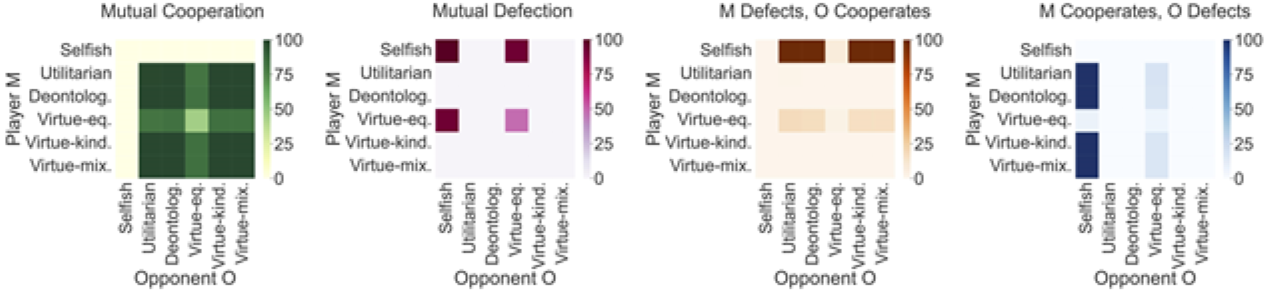
For the *Virtue-mixed* player, the ‘kindness’ signal was stronger than ‘equality’ - hence this agent learnt the **fully cooperative** policy by the end.



Actions - all three games

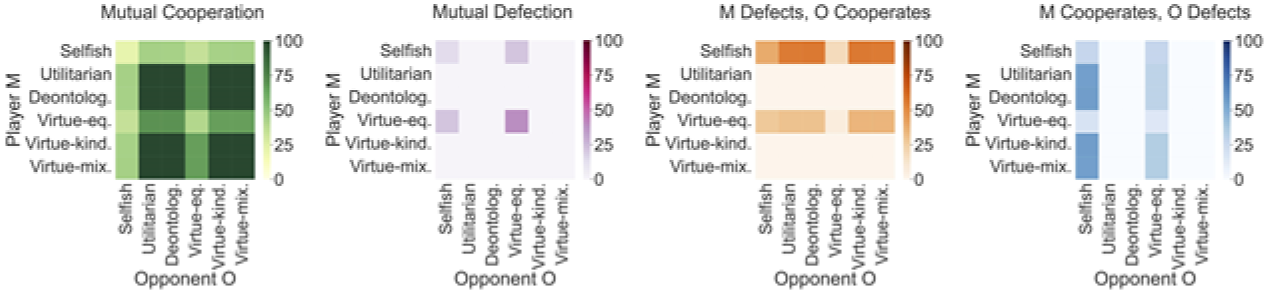
Iterated Prisoner's Dilemma (*greed* & *fear*)

	C	D
C	3,3	1,4
D	4,1	2,2



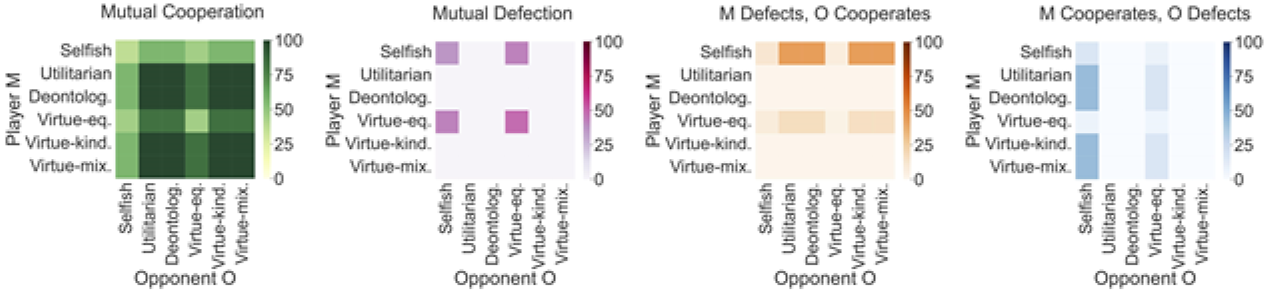
Iterated Volunteer's Dilemma (*greed*)

	C	D
C	4,4	2,5
D	5,2	1,1



Iterated Stag Hunt (*fear/lack of trust*)

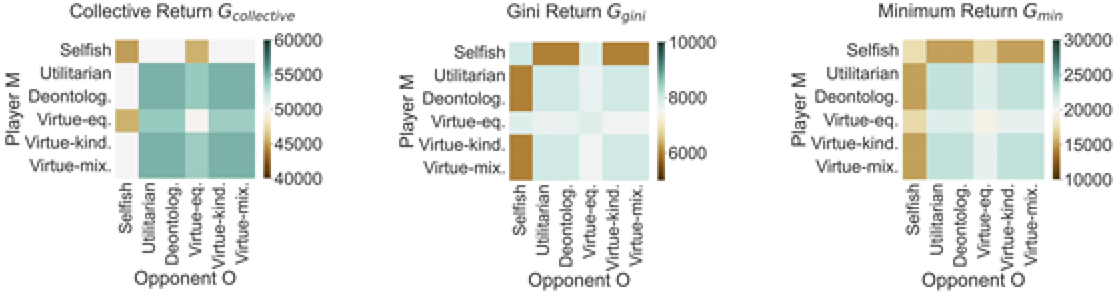
	C	D
C	5,5	1,4
D	4,1	2,2



Social Outcomes - all three games

Iterated Prisoner's Dilemma (*greed* & *fear*)

	C	D
C	3,3	1,4
D	4,1	2,2



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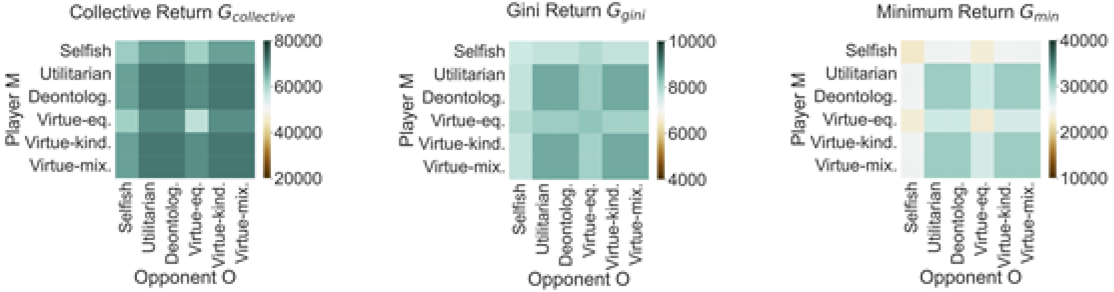

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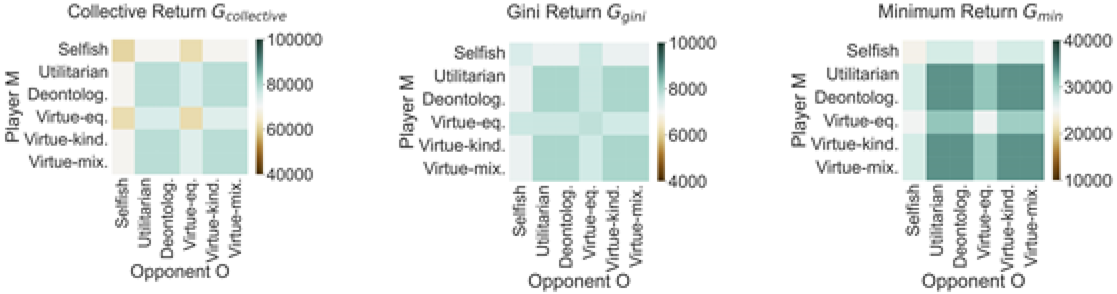

Summary

- It is possible to use top-down inspiration from moral philosophy to design simplified yet representative intrinsic rewards for learning agents, enabling a **hybrid approach** to developing morality.

- We believe that our **approach** can be easily **generalized** to other types of moral agents or games (code available online[1]):
  - large population of agents;
  - agent learning against human opponents.

[1] https://github.com/Liza-Tennant/moral_choice_dyadic

Next Steps

- Study the behavior of these agents in **populations** (rather than dyadic interactions).
    - Partner selection mechanism

- Develop further, perhaps non-consequentialist **metrics** for **evaluating moral behaviours & outcomes** in societies.

Thank you!

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https://liza-tennant.github.io/

Paper with Appendix: https://arxiv.org/abs/2301.08491

Code: https://github.com/Liza-Tennant/moral_choice_dyadic

Appendix

Social Dilemmas

	C	D
C	*R, R*	*S, T*
D	*T, S*	*P, P*

$R > P$: mutual cooperation is preferred to mutual defection
$R > S$: mutual cooperation is preferred to the sucker's payoff
$2R > T+S$: mutual cooperation is preferred to one player exploiting the other (defecting when the other cooperates)
$T > R$ (greed): defection is more tempting than mutual cooperation and/or $P > S$ (fear): mutual defection is preferred to the sucker's payoff

[Macy & Flache. (2002). Learning dynamics in social dilemmas. *PNAS* 99, suppl_3, 7229–7236.]

The Social Dilemma Environments

We compare three different dilemma game structures, with differing motivations to Defect:

Iterated Prisoner's Dilemma

	C	D
C	3,3	1,4
D	4,1	2,2

Greed: 4 > 3

Fear: 2 > 1

Iterated Volunteer's Dilemma

	C	D
C	4,4	2,5
D	5,2	1,1

Greed: 5 > 4

Iterated Stag Hunt

	C	D
C	5,5	1,4
D	4,1	2,2

Fear: 2 > 1

Social Outcomes - all three games

We define the following three outcome metrics:

Collective Return	*M*'s payoff + *O*'s payoff, summed over time
Gini Return	the 'equality' between *M* and *O*'s payoffs, summed over time
Min Return	the min payoff for *M* or *O*, summed over time

Social Outcomes - all three games

Iterated Prisoner's Dilemma (*greed* &

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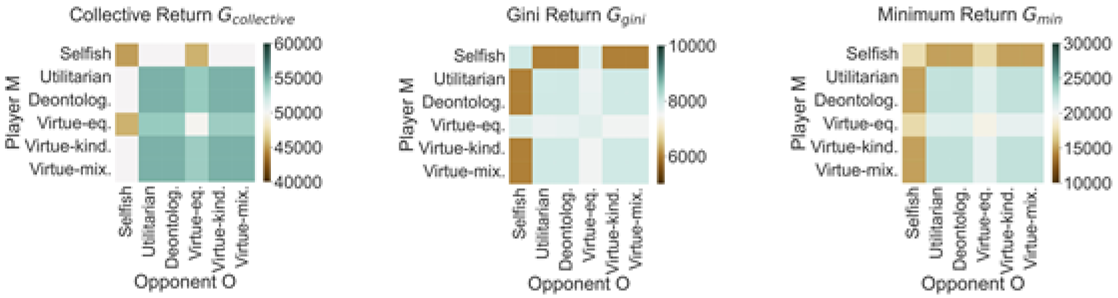

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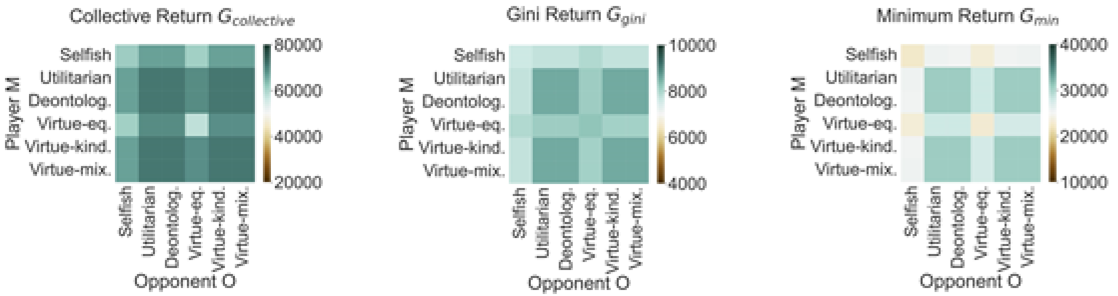

Iterated Stag Hunt (*fear/lack of trust*)

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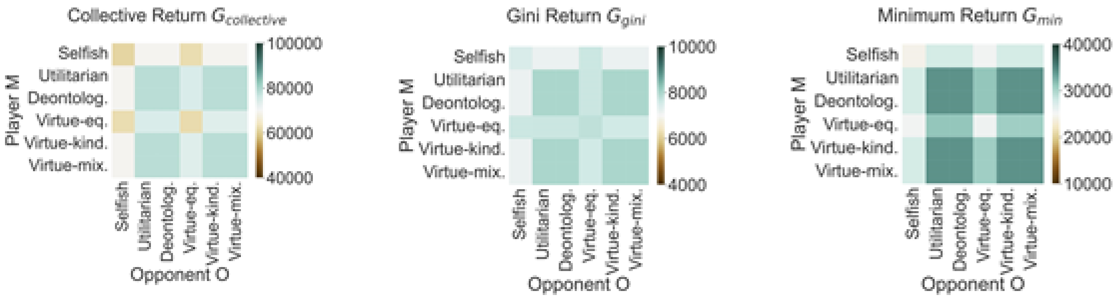

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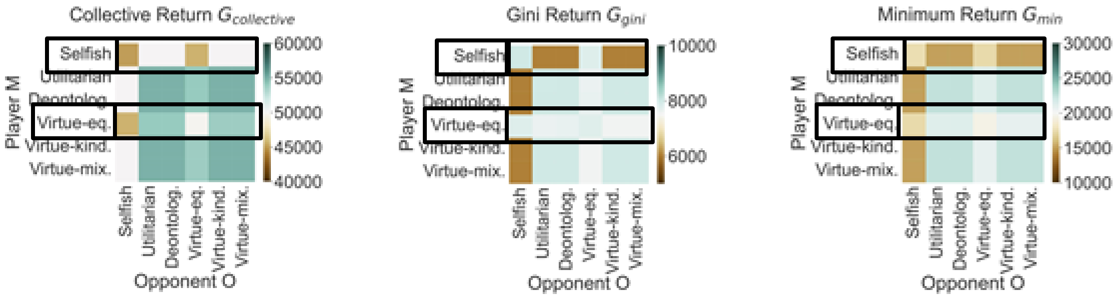

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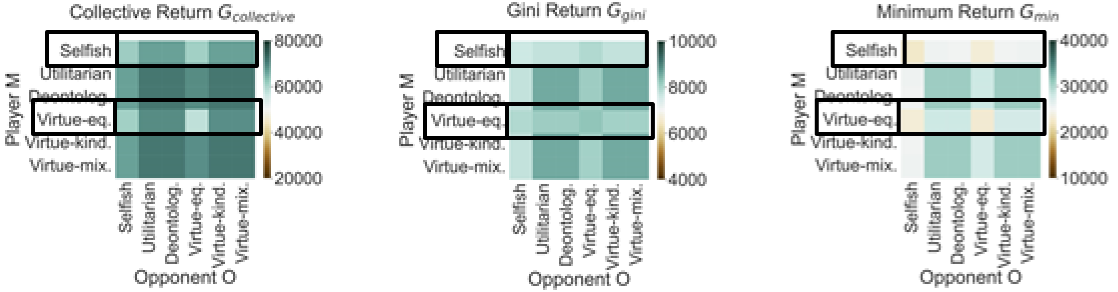

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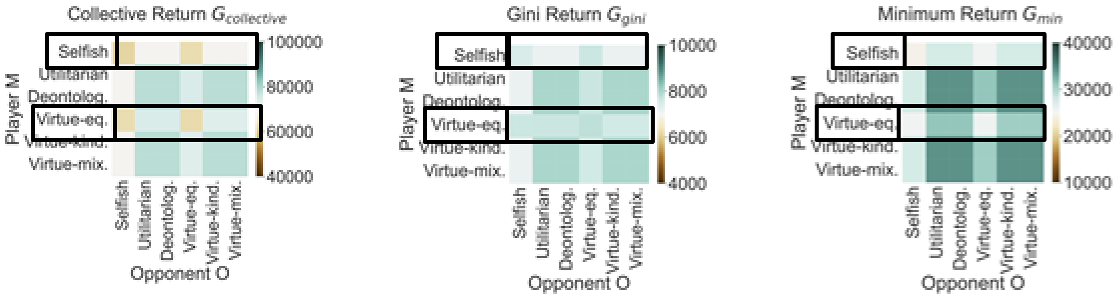

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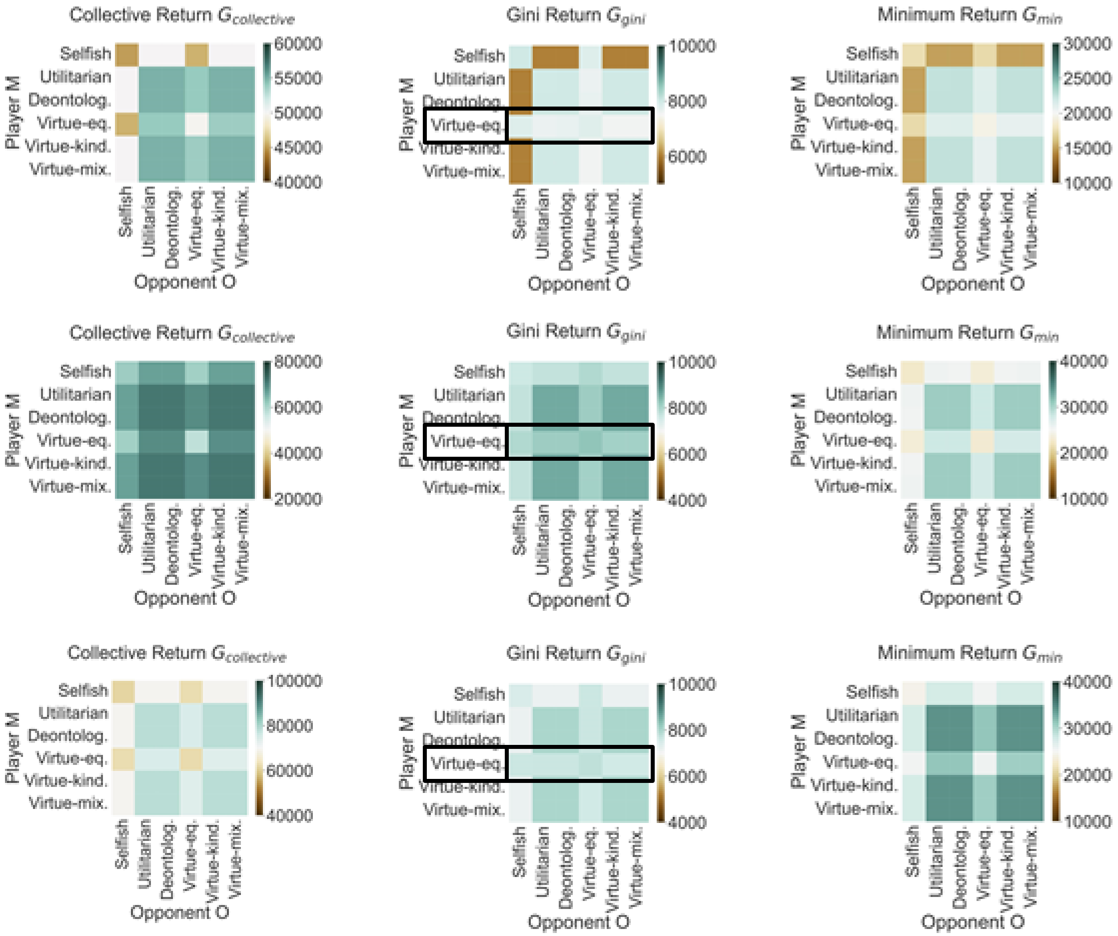

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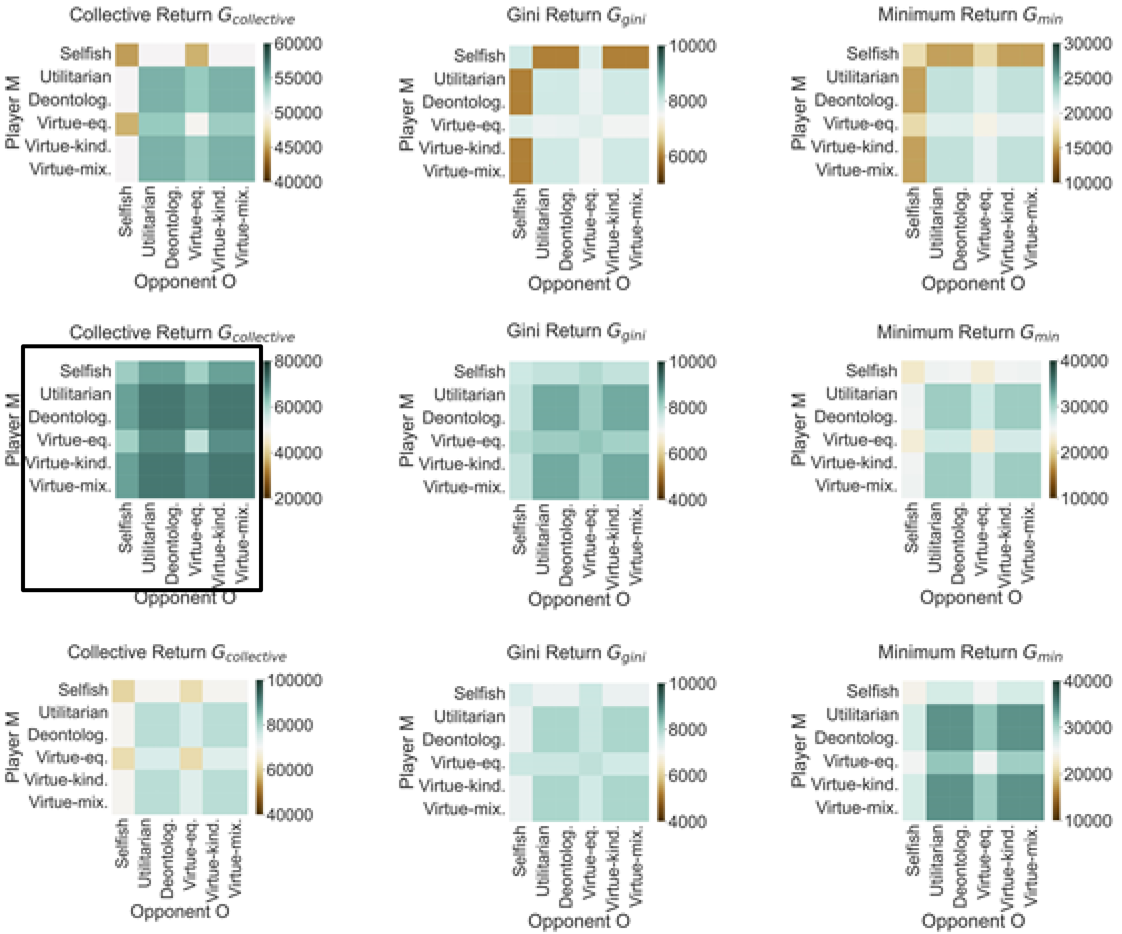

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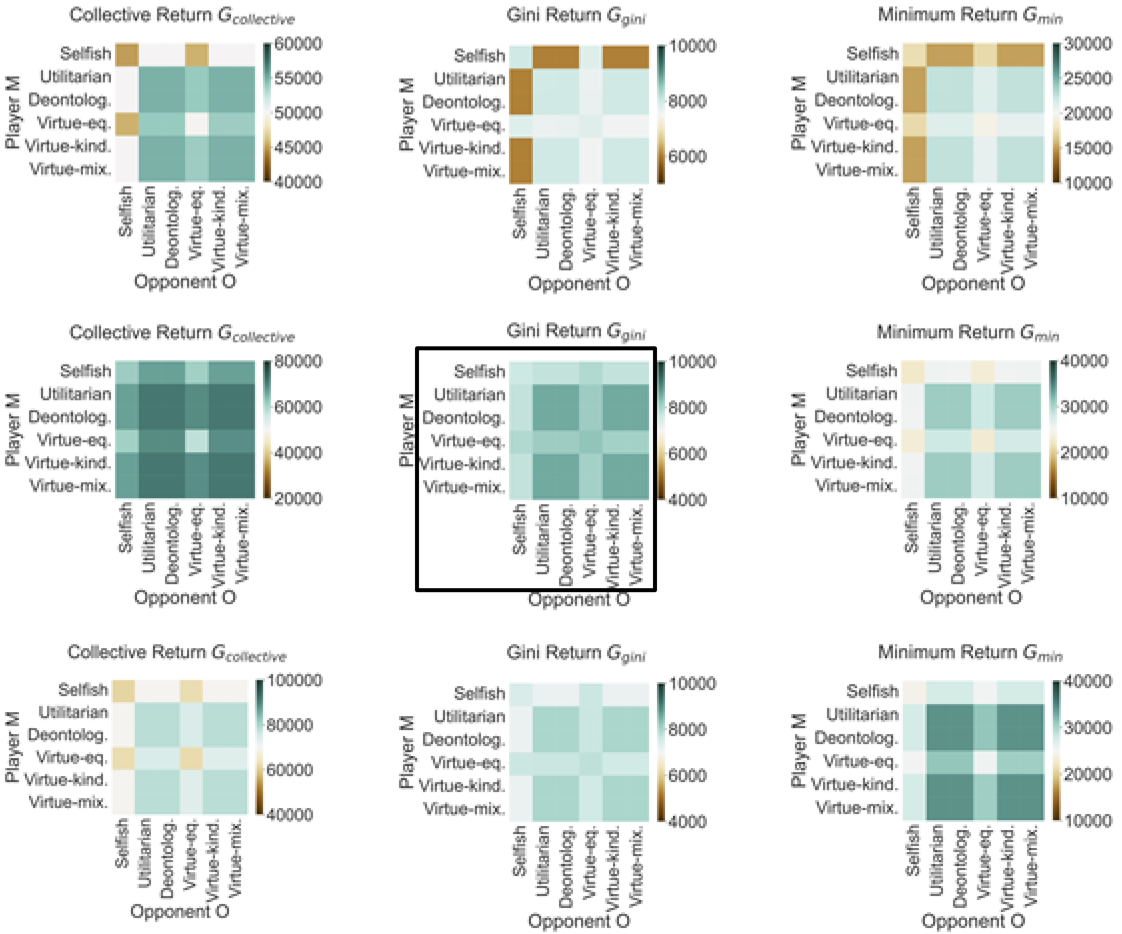

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