Learning with Opponent-Learning Awareness

GTC 2018

Full paper at AAMAS 18

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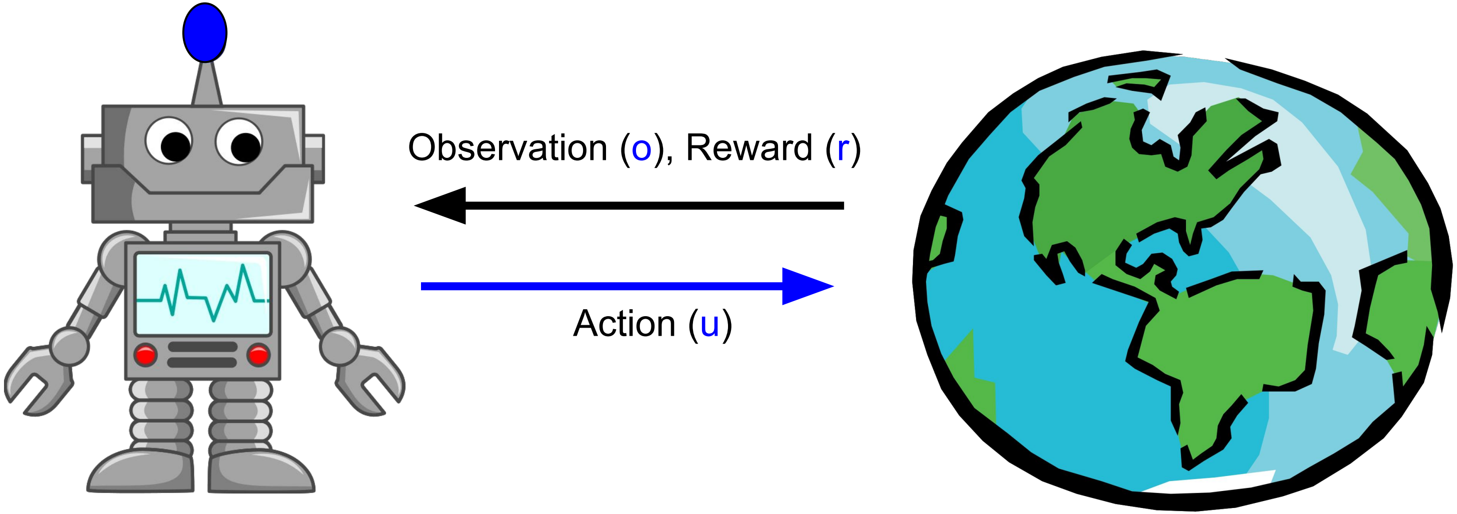
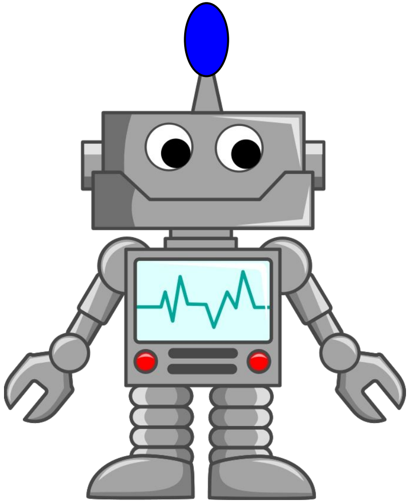
Google

Reinforcement Learning



Goal is to maximise total return per episode: $V = \sum \gamma^t r_t$

Deep Reinforcement Learning



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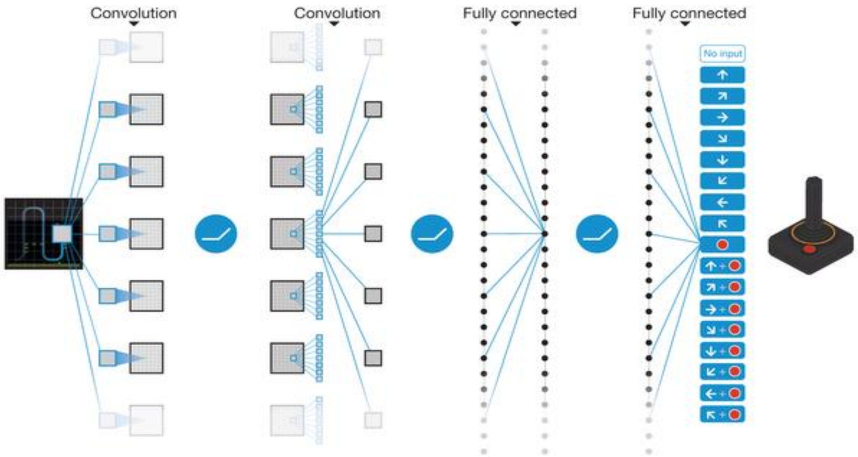

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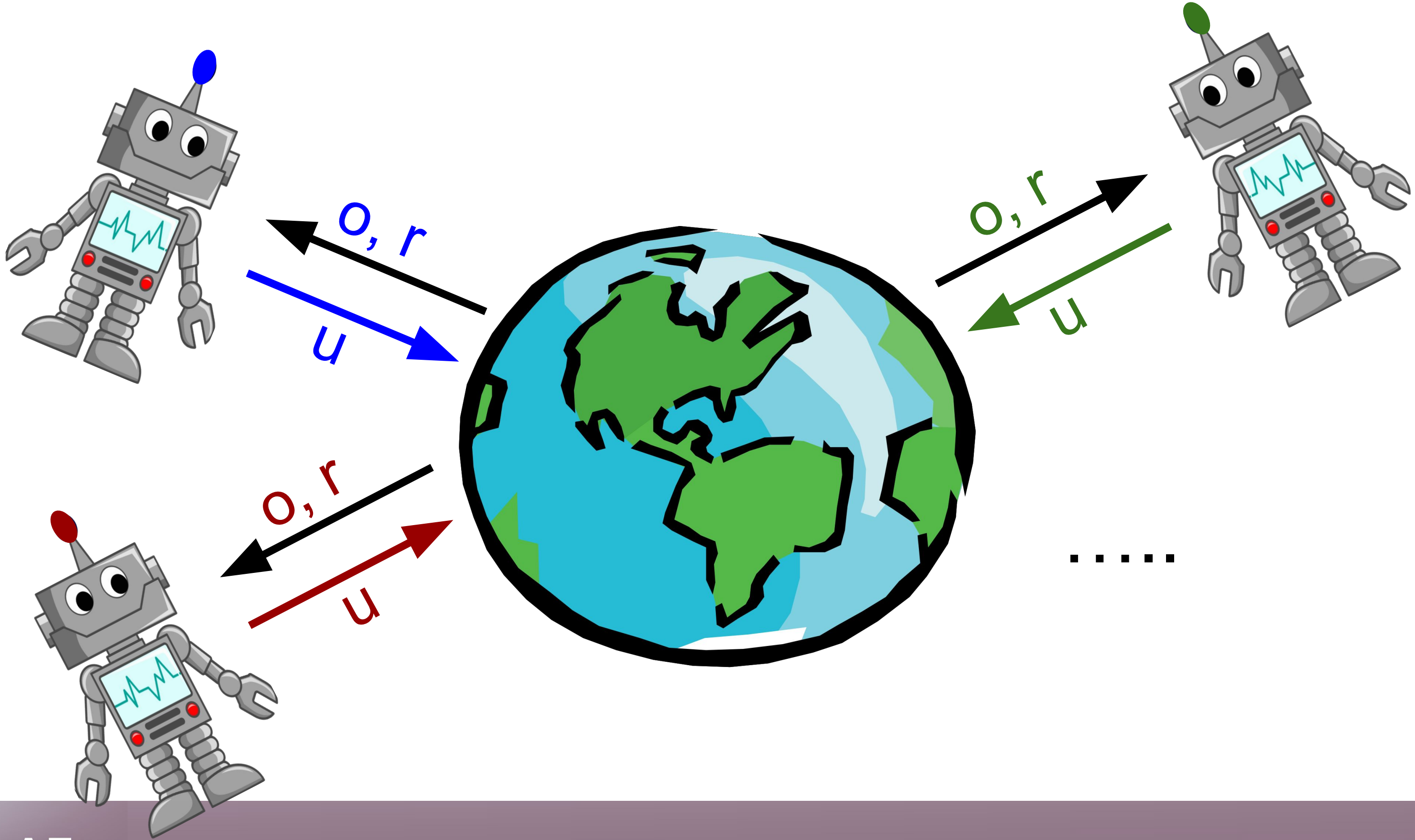
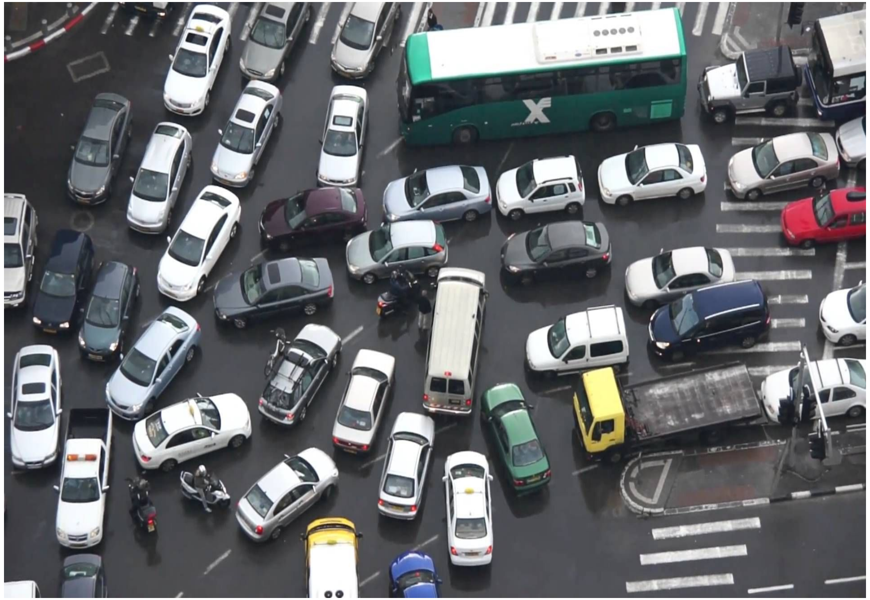
Multi-Agent Reinforcement Learning [MARL]



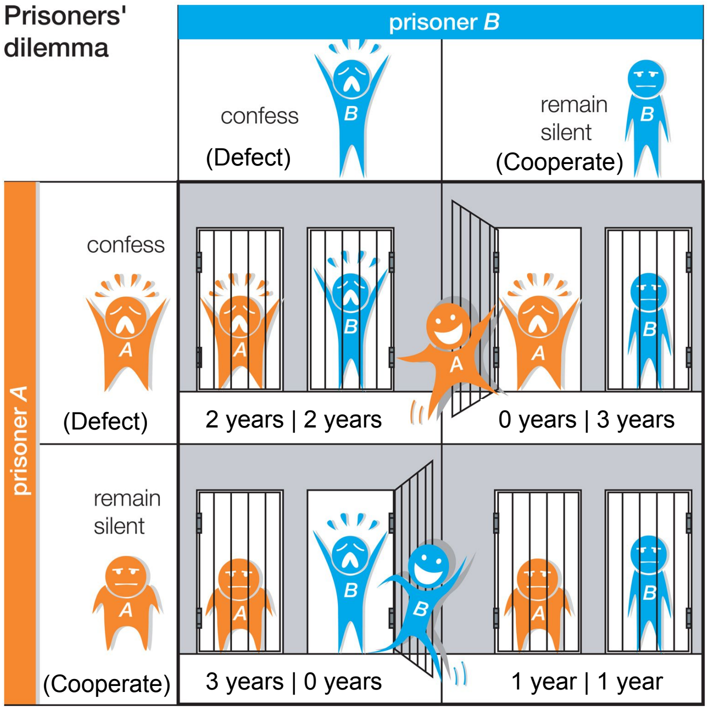
Some “great challenges” of MARL

- Communication
- Non-stationarity
- Credit Assignment
- Reciprocity

LOLA Motivation



Prisoners Dilemma



	D	C
D	(-2, -2)	(0, -3)
C	(-3, 0)	(-1, -1)

Prisoner's Dilemma

Payout matrix:

	D	C
D	(-2, -2)	(0, -3)
C	(-3, 0)	(-1, -1)

Background

- Single shot game:
  - Defection is only Nash equilibrium
- Repeated game (with high gamma):
  - Folk theorem says many equilibria

It's everywhere..:

4 Real-life examples

- 4.1 In environmental studies
- 4.2 In animals
- 4.3 In psychology
- 4.4 In economics
- 4.5 In sport
- 4.6 Multiplayer dilemmas
- 4.7 In international politics

Related Work

Non-cooperative Deep RL:
- Generalization of tit-for-tat with deep RL [Lerer & Peysakhovich, 2017]
- Investigation of pro-social Learners in generalised stag hunt [Peysakhovich & Lerer, 2017]
- Emergence of cooperation and competition [Leibo et al, 2017]
- Centralized actor-critic for training [Lowe et al, 2017]

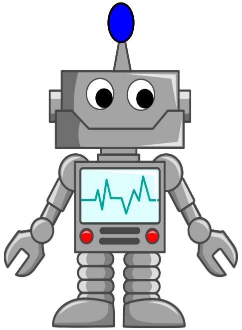
Opponent modeling:
- fictitious play [Brown, 1951],
- action prediction [Mealing & Shapiro, 2013]

Opponent learning:
- Policy prediction under one-step learning dynamics [Zhang & Lester, 2017]
- Unrolled GAN [Metz et al, 2016] differentiates through opponent's update steps

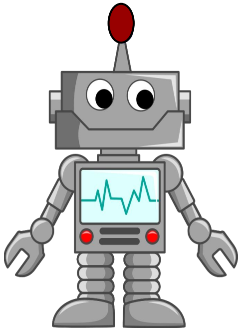
Human-Machine Interaction:
- "Planning for Autonomous Cars that Leverage Effects on Human Action" [Sadigh et al, 2016]

Naive Learning

$$\boldsymbol{\theta}^1_{i+1} = \text{argmax}_{\boldsymbol{\theta}^1} V^1(\boldsymbol{\theta}^1, \boldsymbol{\theta}^2_i)$$



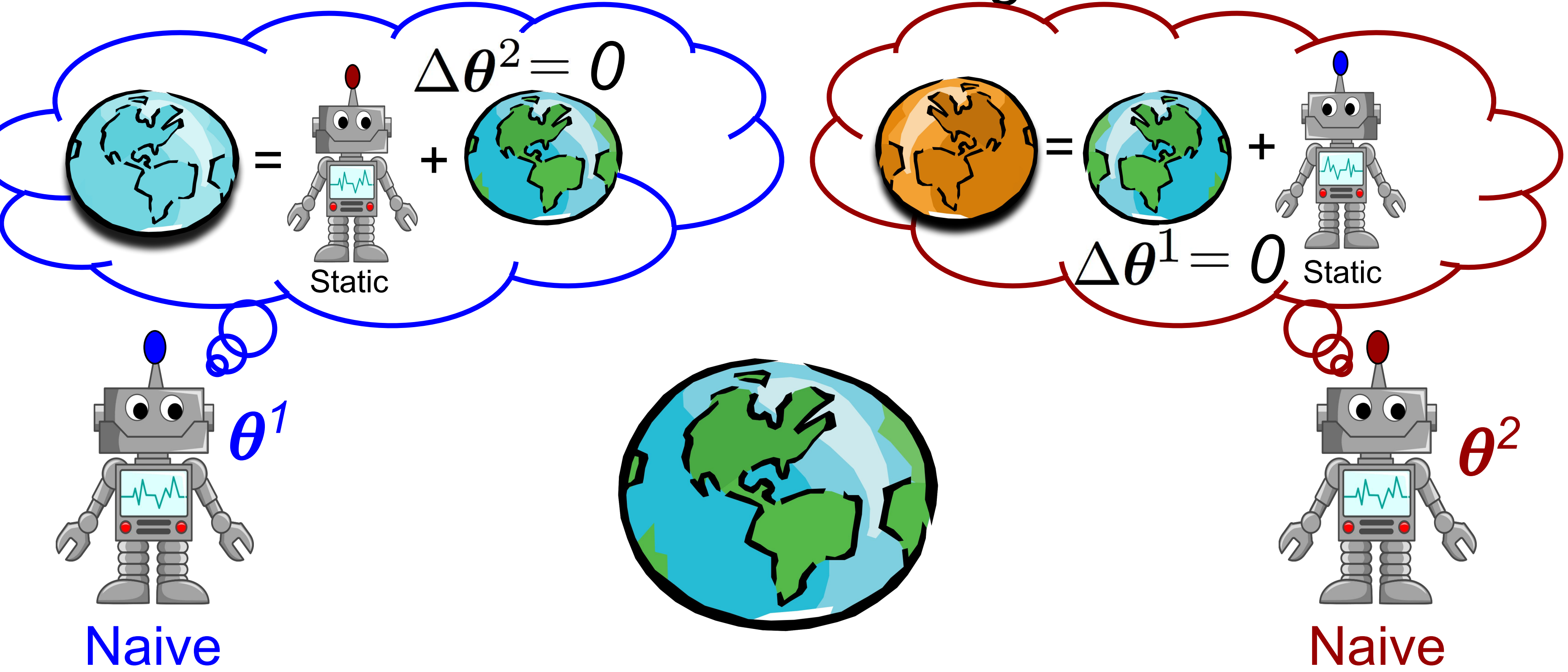
Naive



Naive

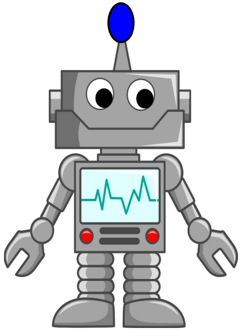
$$\boldsymbol{\theta}^2_{i+1} = \text{argmax}_{\boldsymbol{\theta}^2} V^2(\boldsymbol{\theta}^1_i, \boldsymbol{\theta}^2)$$

Naive Learning

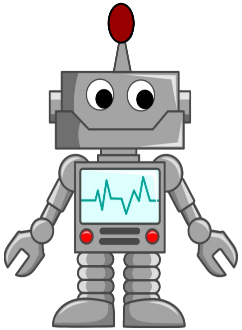


Naive Learning with Gradients

$$\boldsymbol{\theta}^1_{i+1} = \boldsymbol{\theta}^1_i + \nabla_{\boldsymbol{\theta}^1_i} V^1(\boldsymbol{\theta}^1_i, \boldsymbol{\theta}^2_i) \cdot \delta$$



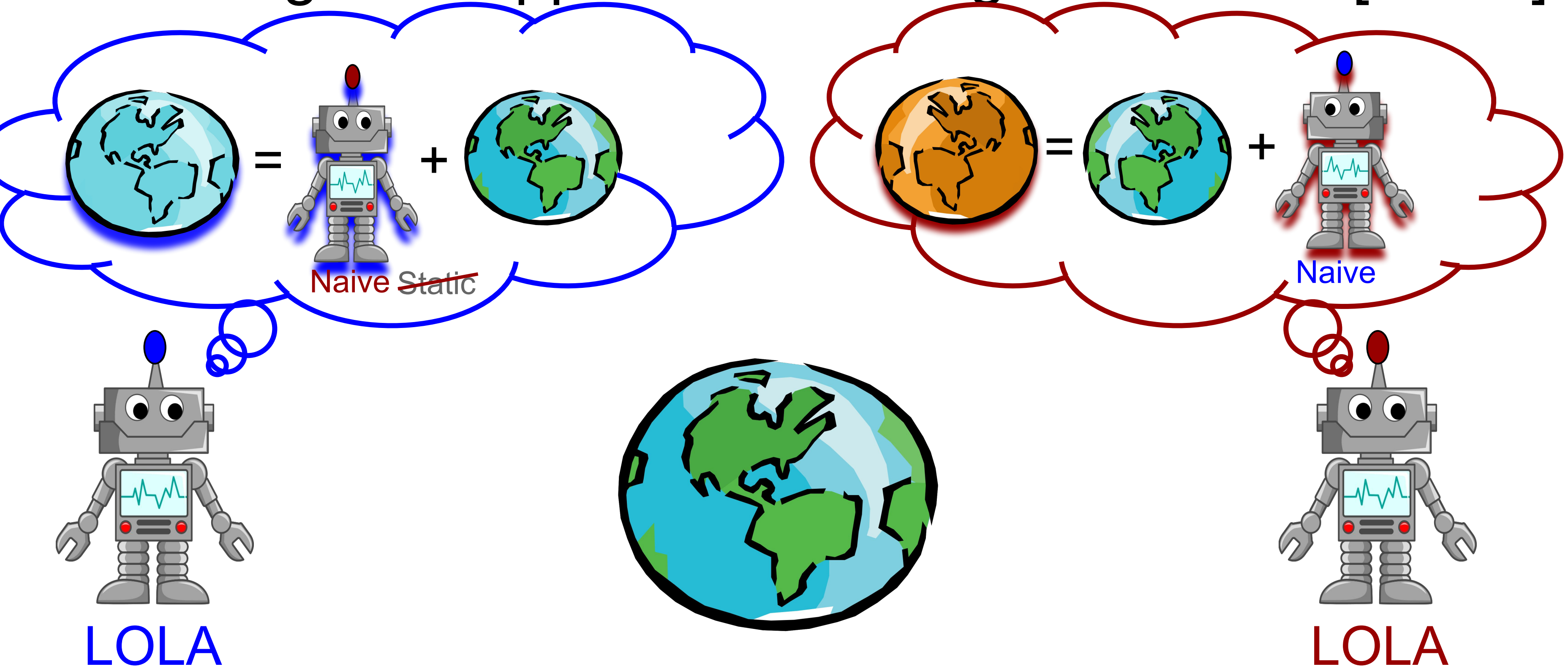
Naive



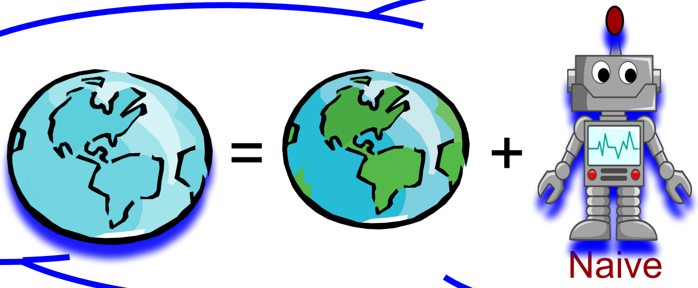
Naive

$$\boldsymbol{\theta}^2_{i+1} = \boldsymbol{\theta}^2_i + \nabla_{\boldsymbol{\theta}^2_i} V^2(\boldsymbol{\theta}^1_i, \boldsymbol{\theta}^2_i) \cdot \delta$$

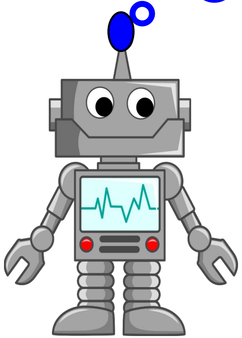
Learning with Opponent Learning Awareness [LOLA]



LOLA with Gradients



$$\Delta\boldsymbol{\theta}^2 = \nabla_{\boldsymbol{\theta}_i^2} V^2(\boldsymbol{\theta}_i^1, \boldsymbol{\theta}_i^2)$$



$$\boldsymbol{\theta}_{i+1}^1 = \boldsymbol{\theta}_i^1 + \nabla_{\boldsymbol{\theta}_i^1} V^1(\boldsymbol{\theta}^1, \boldsymbol{\theta}^2 + \Delta\boldsymbol{\theta}^2) \cdot \delta$$

$$V^1(\boldsymbol{\theta}^1, \boldsymbol{\theta}^2 + \Delta\boldsymbol{\theta}^2) \approx$$

$$V^1(\boldsymbol{\theta}^1, \boldsymbol{\theta}^2) + (\Delta\boldsymbol{\theta}^2)^T \nabla_{\boldsymbol{\theta}^2} V^1(\boldsymbol{\theta}^1, \boldsymbol{\theta}^2)$$

LOLA Maths

Optimize Return after one step of opponent learning:

$$V^1(\theta^1, \theta^2 + \Delta\theta^2) \approx V^1(\theta^1, \theta^2) + (\Delta\theta^2)^T \nabla_{\theta^2} V^1(\theta^1, \theta^2)$$

$$\Delta\theta^2 = \nabla_{\theta^2} V^2(\theta^1, \theta^2) \cdot \eta$$

LOLA learning rule:

$$f^1_{\text{lola}}(\theta^1, \theta^2) = \nabla_{\theta^1} V^1(\theta^1, \theta^2)$$
$$+ \left(\nabla_{\theta^2} V^1(\theta^1, \theta^2)\right)^T \nabla_{\theta^1} \nabla_{\theta^2} V^2(\theta^1, \theta^2) \cdot \delta\eta$$

Health warning:
This requires access to true value function and derivatives

LOLA Policy Gradient

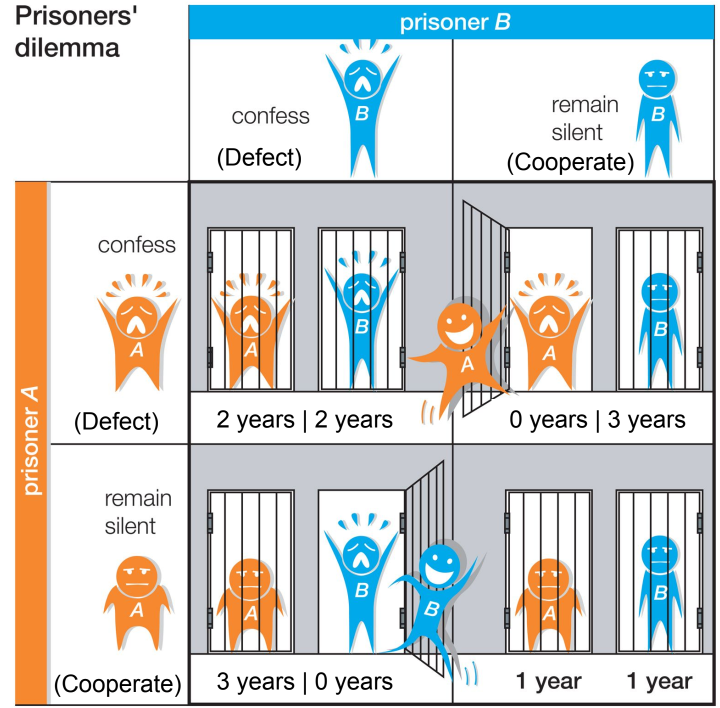
Can use Policy Gradients to estimate all gradients

$$\boldsymbol{f}^1_{\text{lola, pg}} = \nabla_{\boldsymbol{\theta}^1} \mathbb{E}\, R^1_0(\tau) \cdot \delta +$$
$$\left(\nabla_{\boldsymbol{\theta}^2} \mathbb{E}\, R^1_0(\tau)\right)^T \nabla_{\boldsymbol{\theta}^1} \nabla_{\boldsymbol{\theta}^2} \mathbb{E}\, R^2_0(\tau) \cdot \delta\eta.$$

LOLA term is still tractable and exact (in expectation):

$$\begin{aligned}
&\nabla_{\boldsymbol{\theta}^1} \nabla_{\boldsymbol{\theta}^2} \mathbb{E}\, R^2_0(\tau) \\
&\quad = \mathbb{E}\left[R^2_0(\tau) \nabla_{\boldsymbol{\theta}^1} \log \pi^1(\tau) \left(\nabla_{\boldsymbol{\theta}^2} \log \pi^2(\tau)\right)^T \right] \\
&\quad = \mathbb{E}\left[\sum\nolimits_{t=0}^{T} \gamma^t r^2_t \cdot \left(\sum\nolimits_{l=0}^{t} \nabla_{\boldsymbol{\theta}^1} \log \pi^1(u^1_l | s_l)\right) \right. \\
&\qquad \left. \left(\sum\nolimits_{l=0}^{t} \nabla_{\boldsymbol{\theta}^2} \log \pi^2(u^2_l | s_l)\right)^T \right]
\end{aligned}$$

Prisoners Dilemma



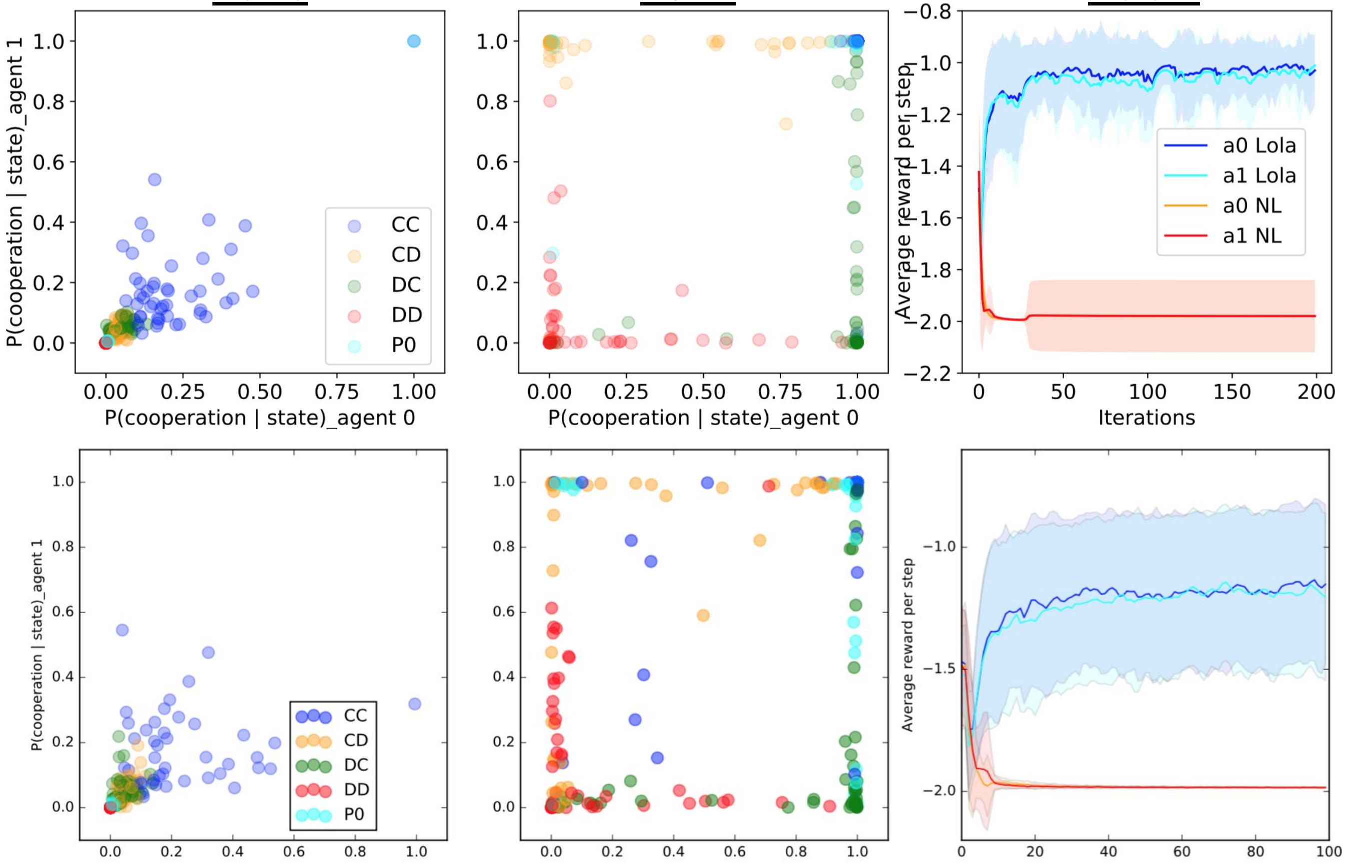
	D	C
D	(-2, -2)	(0, -3)
C	(-3, 0)	(-1, -1)

Iterated Prisoner's Dilemma

Naive | LOLA | Return

Exact

Policy Gradient



Matching Pennies

⇩

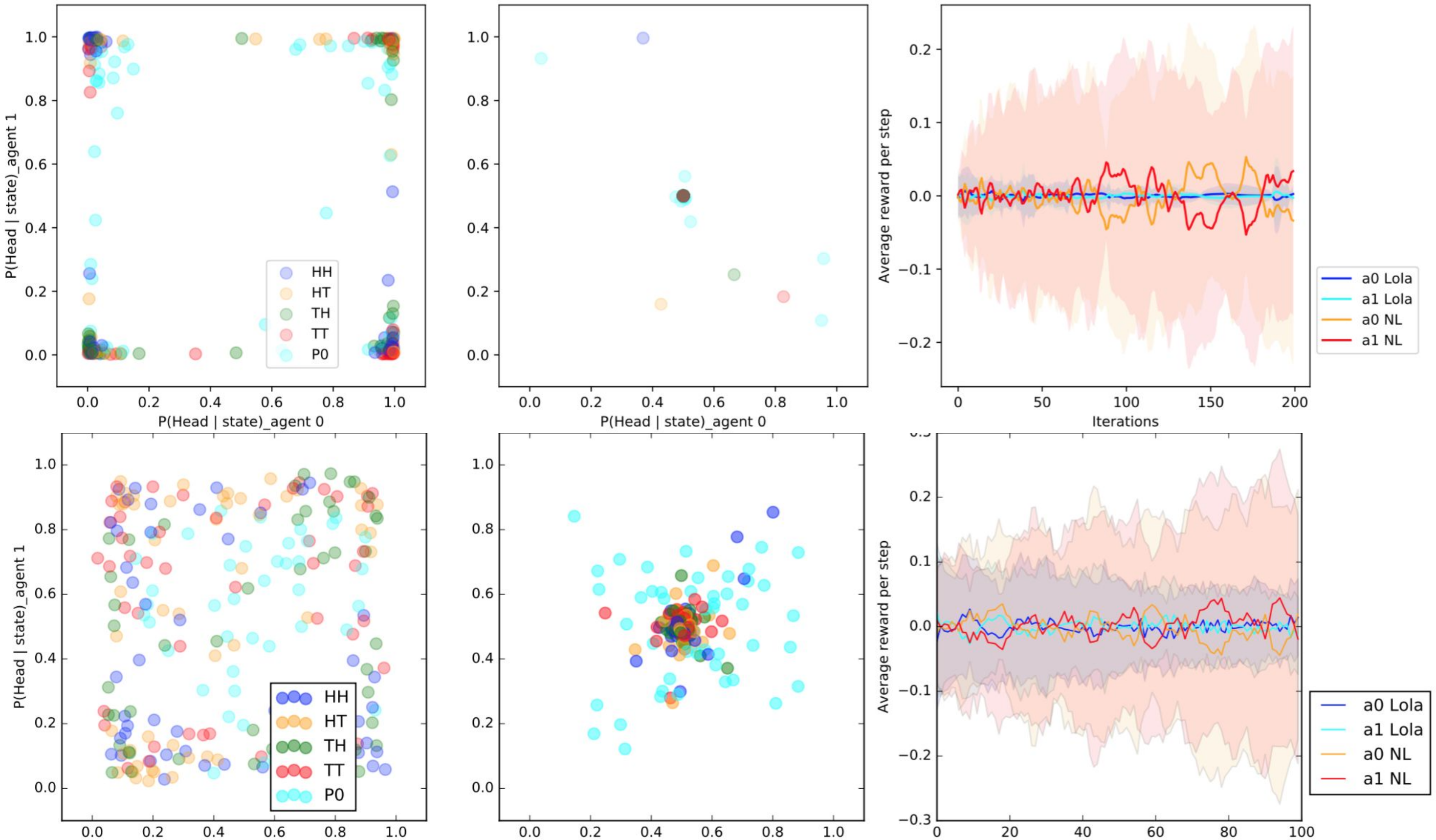
	Head	Tail
Head	(+1, -1)	(-1, +1)
Tail	(-1, +1)	(+1, -1)

Iterated Matching Pennies

Naive | LOLA | Return

Exact

Policy Gradient

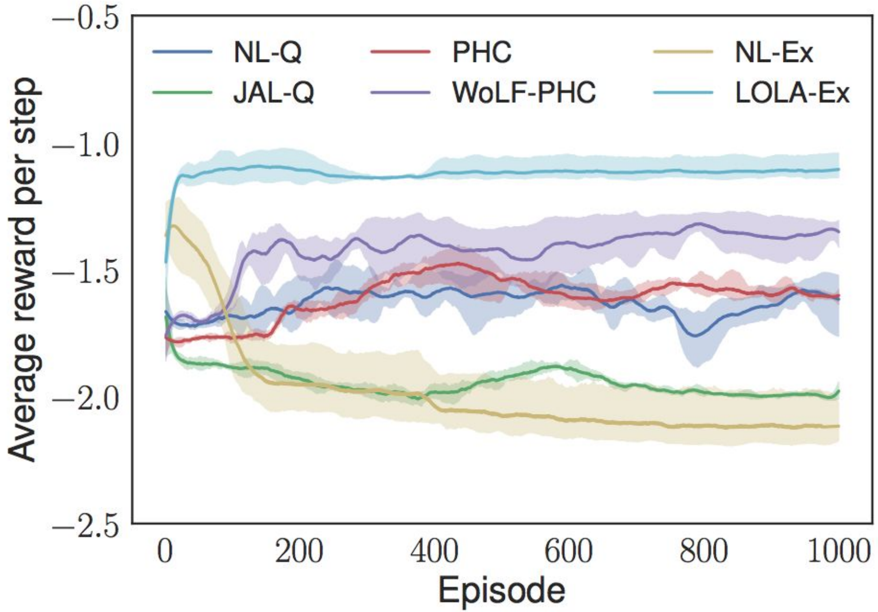


Results

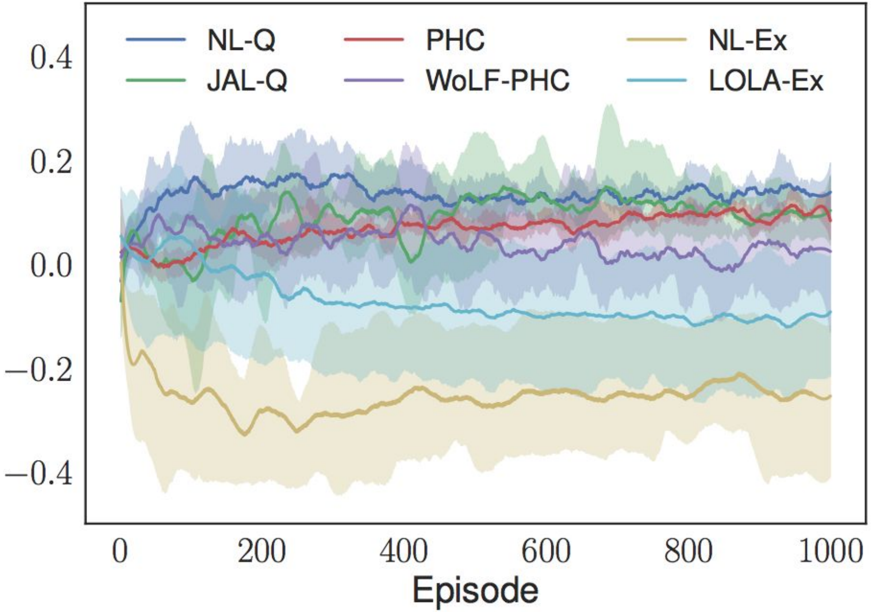
	IPD		IMP	
	%TFT	R(std)	%Nash	R(std)
NL-Ex.	20.8	-1.98(0.14)	0.0	0(0.37)
LOLA-Ex.	81.0	-1.06(0.19)	98.8	0(0.02)
NL-PG	20.0	-1.98(0.00)	13.2	0(0.19)
LOLA-PG	66.4	-1.17(0.34)	93.2	0(0.06)

Round Robin Tournament

Iterated Prisoner's' Dilemma



Iterated Matching Pennies

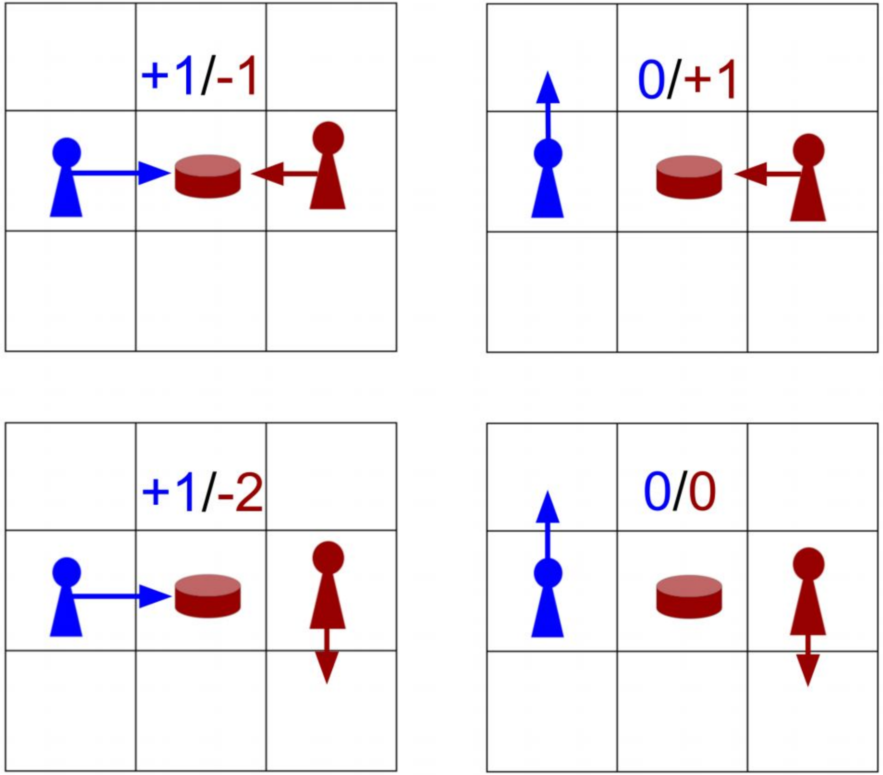


LOLA with Opponent Modelling (LOLA-OM)

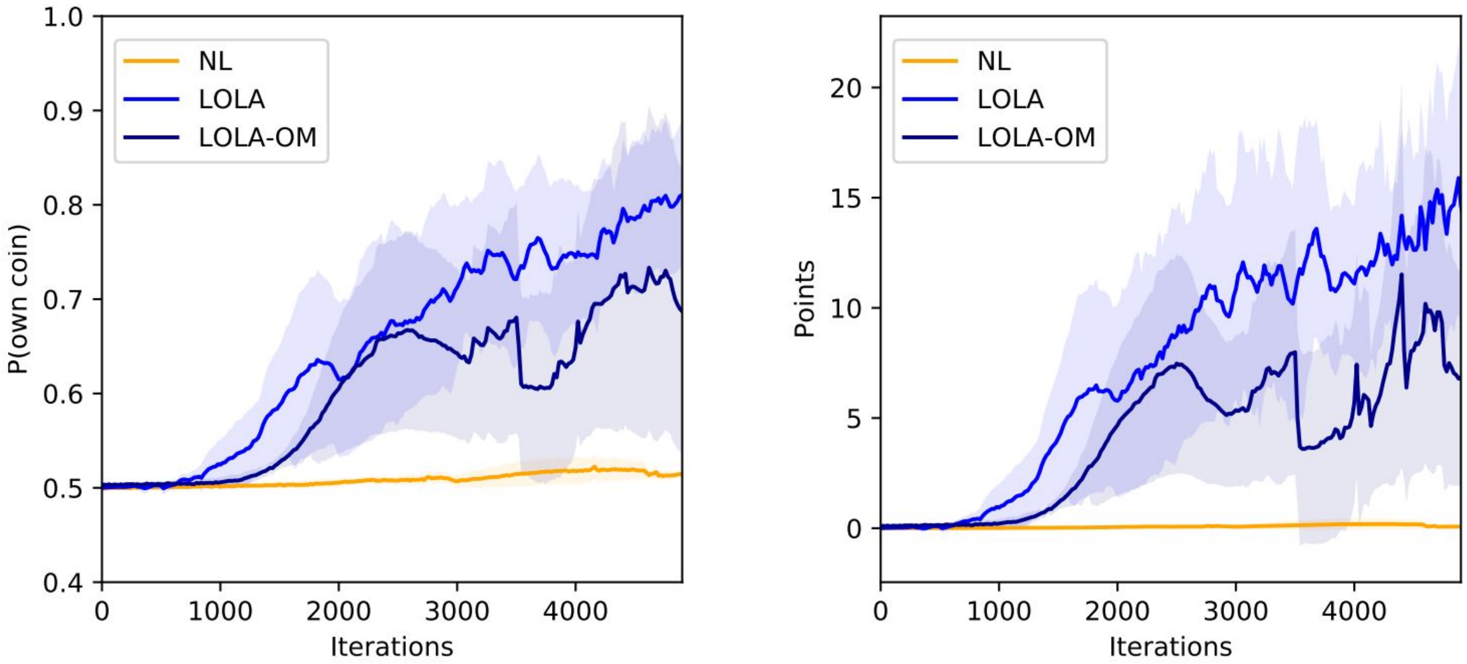
$$\boldsymbol{\theta^2} \quad \Rightarrow \quad \boldsymbol{\hat{\theta}^2}$$

$$\hat{\theta}^2 = \underset{\theta^2}{\operatorname{argmax}} \sum_t \log \pi^2_{\theta^2}(u^2_t | s_t)$$

LOLA with Recurrent Deep RL

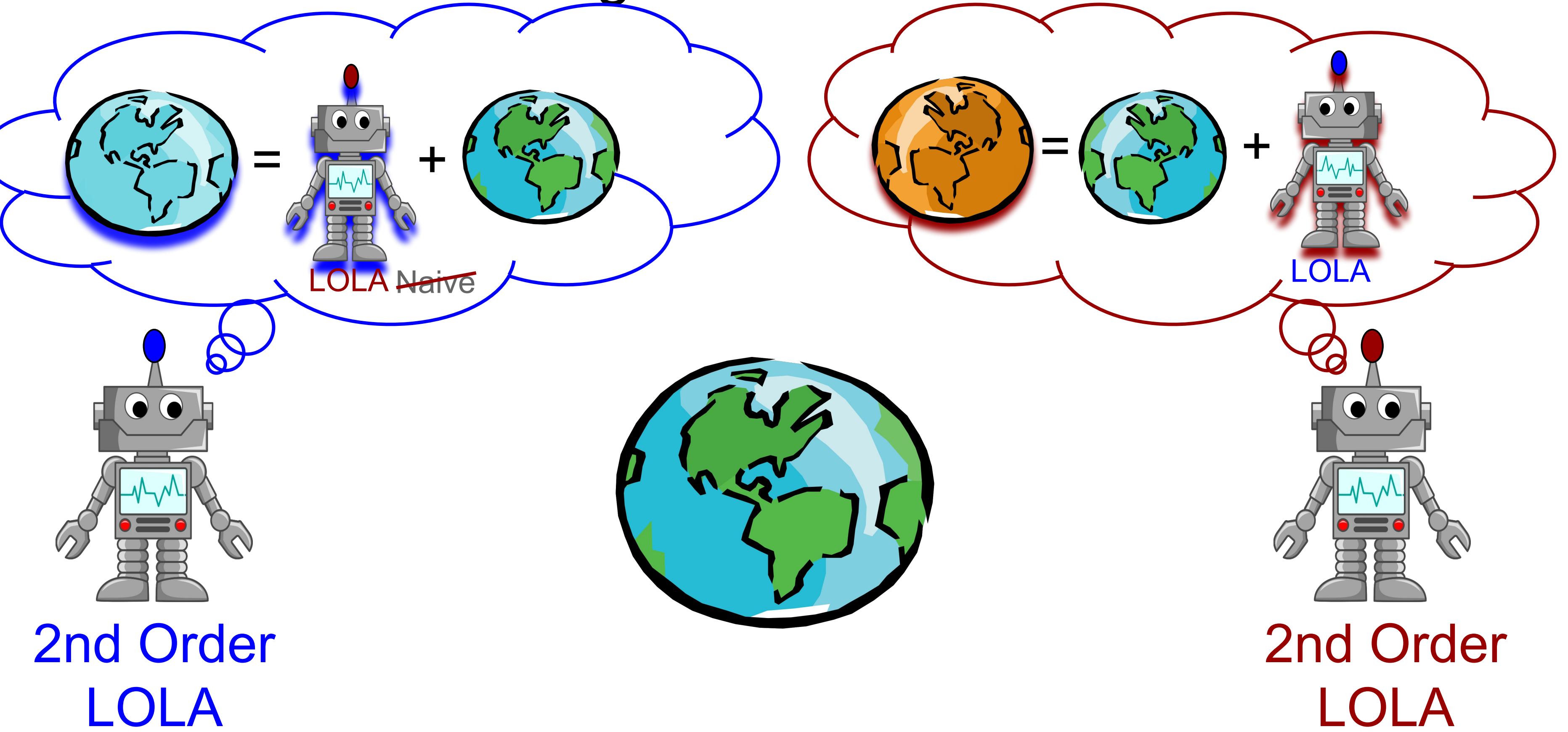


LOLA with Recurrent Deep RL



LOLA with Recurrent Deep RL

Higher Order LOLA



Higher Order LOLA results

	NL	1st order	2nd Order
NL	(-1.99, -1.99)	(-1.54, -1.28)	-
1st	(-1.28, -1.54)	(-1.04, -1.04)	(-1.14, -1.17)

LOLA Open Challenges

- Unknown update rules?
- Adversarial update rules?
- Proofs

LOLA Conclusion

- State of the art Deep-MARL methods lead to defection
- LOLA leads to emergent reciprocity
- Cooperation arises out of selfish interest, considering learning of the opponent
- Works both in an exact setting and in Deep RL using policy gradients

Acknowledgements

OpenAI

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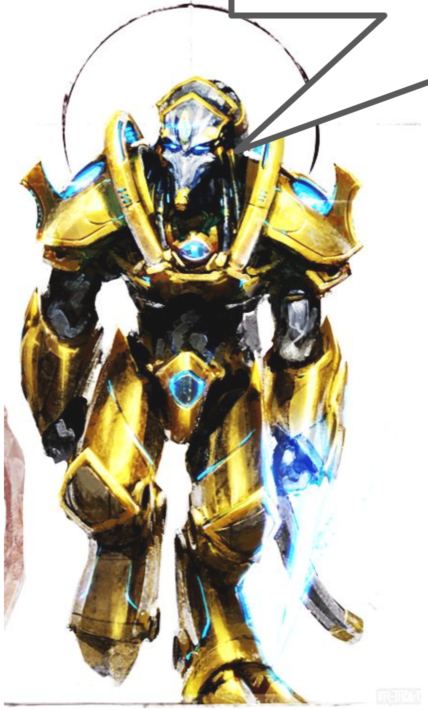
NVIDIA

CARNEGIE MELLON UNIVERSITY PITTSBURGH PENNSYLVANIA 1900

Thank you for listening!!



Any questions?

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