Factored Value Functions for Cooperative Multi-Agent Reinforcement Learning

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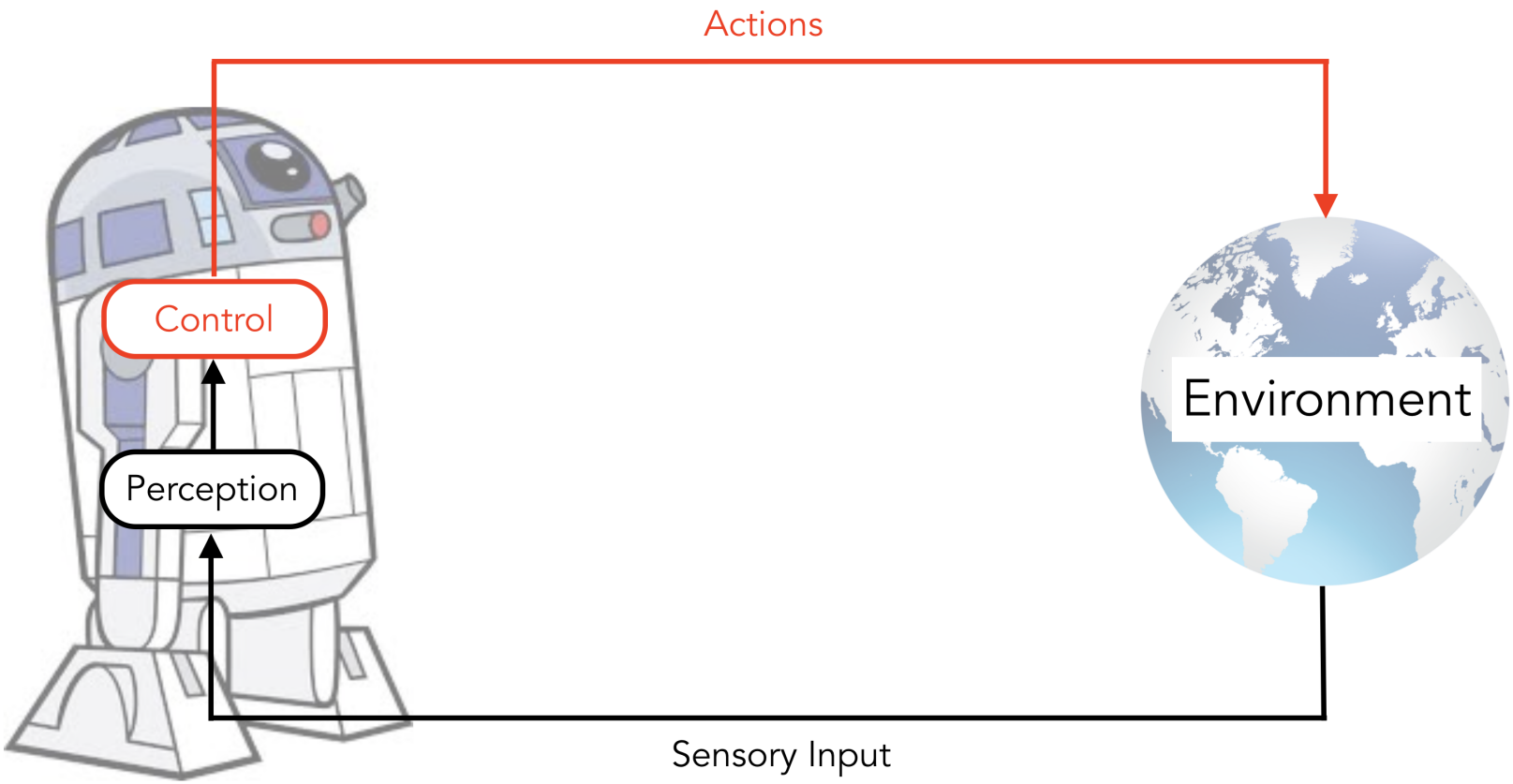
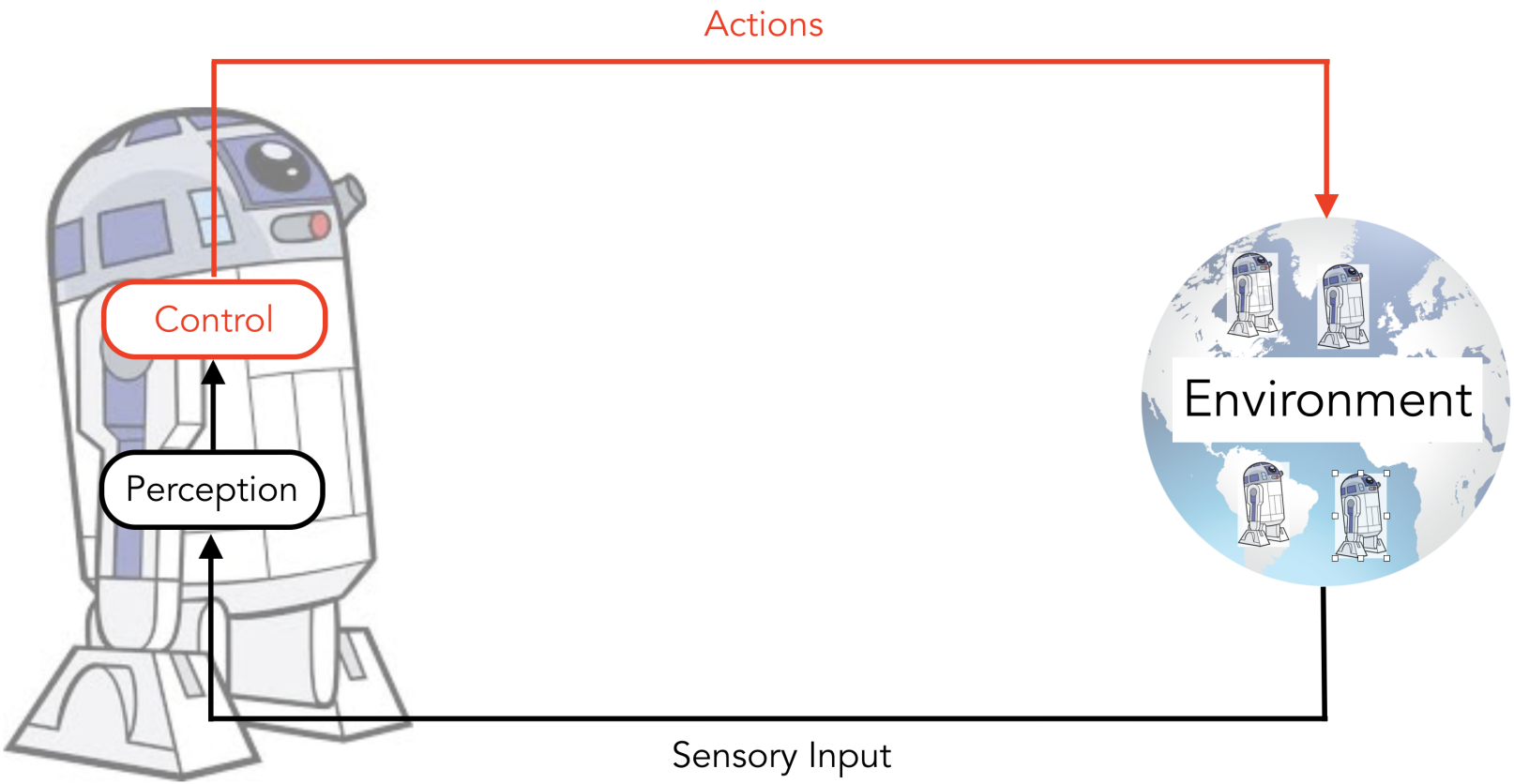
joint work with Jakob Foerster, Gregory Farquhar, Anuj Mahajan, Tabish Rashid, Mikayel Samvelyan, Christian Schroeder de Witt, Nantas Nardelli, Tim Rudner, Chia-Man Hung, and Phil Torr

October 23, 2020

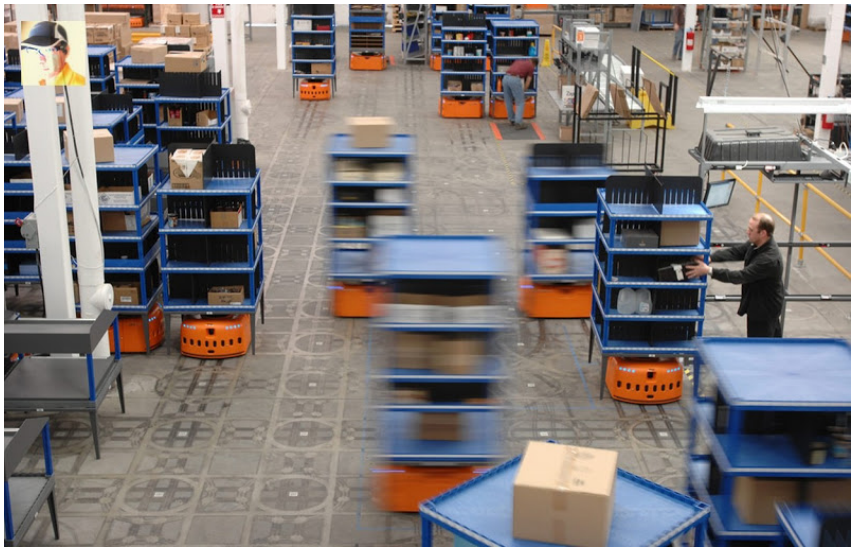
Single-Agent Paradigm



Multi-Agent Paradigm



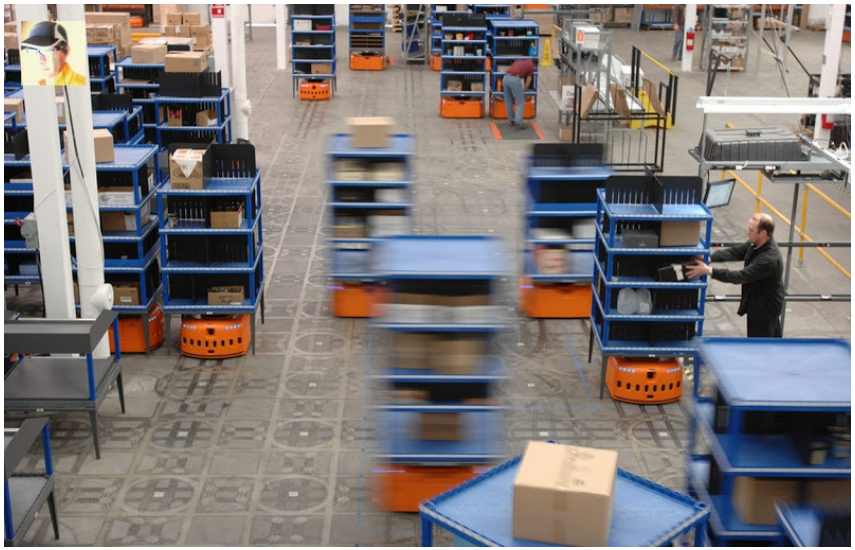
Multi-Agent Systems are Everywhere



Types of Multi-Agent Systems

- *Cooperative:*
  - Shared team reward
  - Coordination problem
- *Competitive:*
  - Zero-sum games
  - Individual opposing rewards
  - Minimax equilibria
- *Mixed:*
  - General-sum games
  - Nash equilibria
  - What is the question? [Shoham et al. 2007]

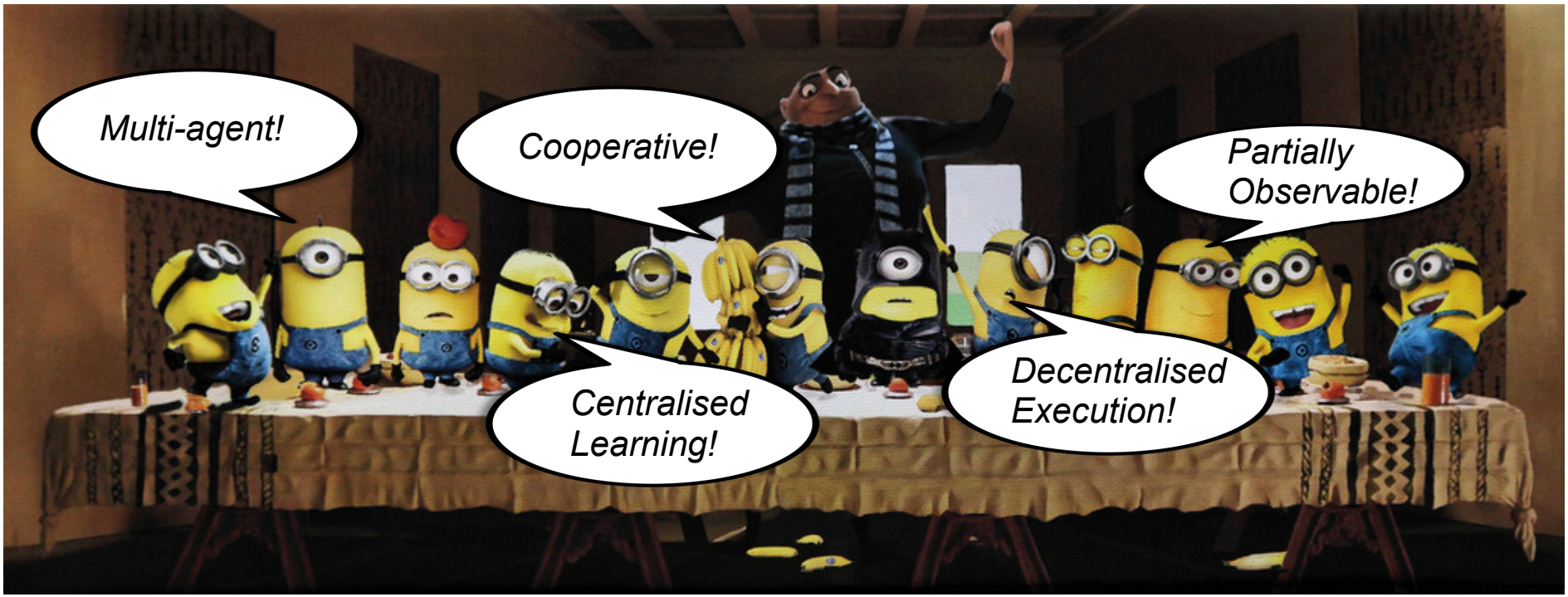
Coordination Problems are Everywhere



Multi-Agent RL Methods from WhiRL

- DIAL [Foerster et al. 2015]
- Multi-Agent Fingerprints [Foerster et al. 2017]
- COMA [Foerster et al. 2018]
- *QMIX [Rashid et al. 2018]*
- LOLA [Foerster et al. 2019]
- SOS [Letcher et al. 2019]
- MACKRL [Schroeder de Witt et al. 2019]
- MAVEN [Mahajan et al. 2019]
- WQMIX [Rashid et al. 2020]
- COMIX [Schroeder de Witt et al. 2020]

Setting



(Figure by Jakob Foerster)

Markov Decision Process

- Agent observes *state* $s \in S$ and selects an *action* $u \in U$
- State transitions: $P(s'|s,u) : S \times U \times S \rightarrow [0,1]$
- Receives *reward*: $r(s,u) : S \times U \rightarrow \mathbb{R}$
- Goal: maximise expected cumulative discounted *return*:

$$R_t = \sum_{k=0}^{\infty} \gamma^k r_{t+k}$$

- *Value functions* given policy $\pi(s,u)$:

$$V^{\pi}(s) = \mathbb{E}_{\pi}\left[R_t | s_t = s\right] \quad \text{and} \quad Q^{\pi}(s,u) = \mathbb{E}_{\pi}\left[R_t | s_t = s, u_t = u\right]$$

Multi-Agent MDP

- All agents see the global state s
- Individual actions: $u^a \in U$
- State transitions: $P(s'|s, \mathbf{u}) : S \times \mathbf{U} \times S \rightarrow [0, 1]$
- Shared team reward: $r(s, \mathbf{u}) : S \times \mathbf{U} \rightarrow \mathbb{R}$
- Equivalent to an MDP with a factored action space

Dec-POMDP

- Observation function: $O(s, a) : S \times A \rightarrow Z$
- Action-observation history: $\tau^a \in T \equiv (Z \times U)^*$
- Decentralised policies: $\pi^a(u^a|\tau^a) : T \times U \rightarrow [0, 1]$
- Natural decentralisation: communication and sensory constraints
- Artificial decentralisation: improve tractability
- Centralised learning of decentralised policies

Setting

CENTRALISED TRAINING OF DECENTRALISED CONTROL

The Predictability / Exploitation Dilemma

- Exploitation:
  - Maximising performance requires collecting reward
  - In a single-agent setting, this requires *exploiting* observations
- Predictability:
  - Dec-POMDP agents cannot explicitly communicate
  - Coordination requires *predictability*: "stick to the plan!"
  - Predictability can require ignoring private information

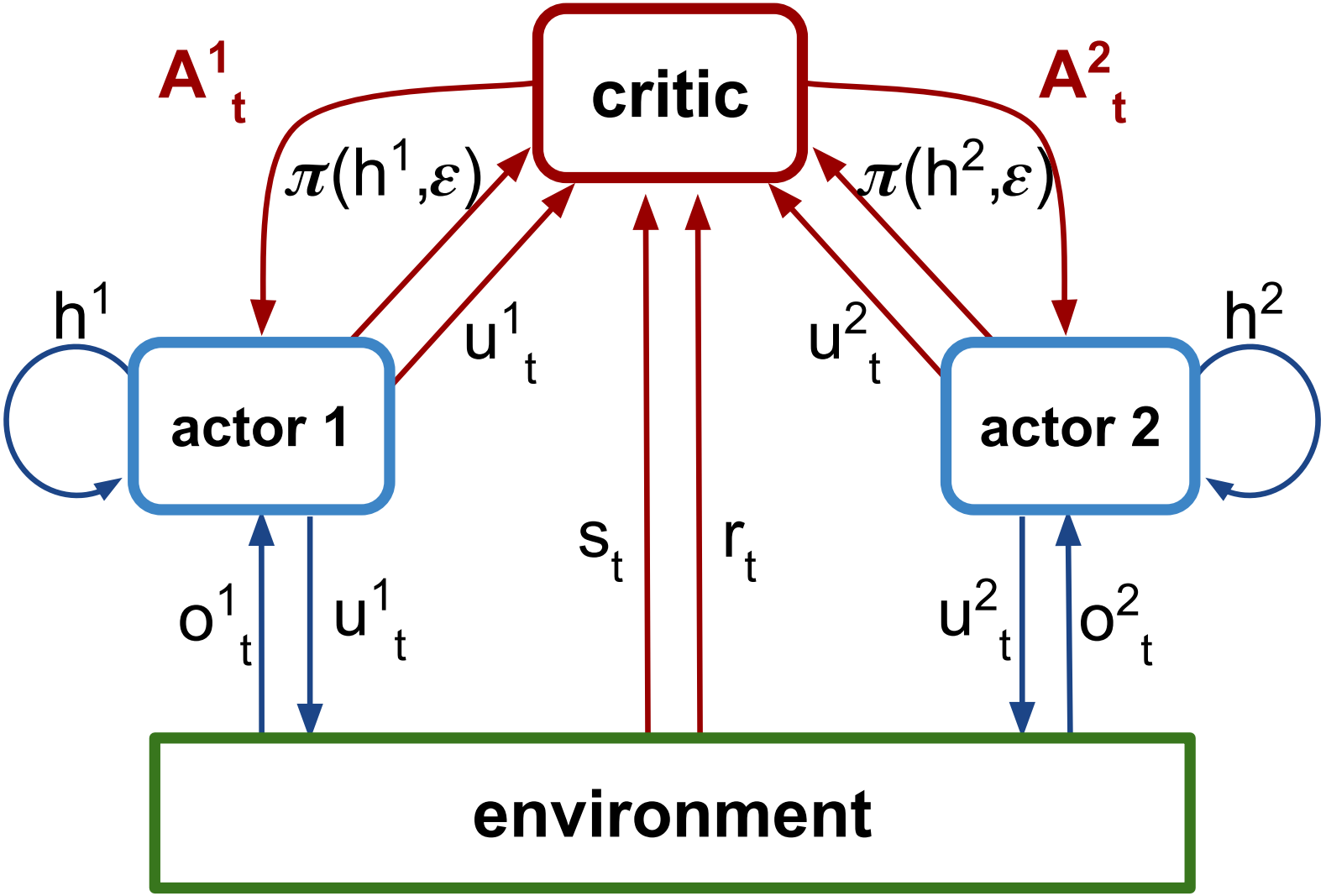
When does the benefit of exploiting private observations outweigh the cost in predictability?

Independent Learning

- Independent Q-learning [Tan 1993]
  - Each agent learns independently with its own Q-function
  - Treats other agents as part of the environment
- Independent actor-critic [Foerster et al. 2018]
  - Each agent learns independently with its own actor-critic
  - Treats other agents as part of the environment
- Speed learning with *parameter sharing*
  - Different inputs, including a, induce different behaviour
  - Still independent: value functions condition only on τ^a and u^a
- Limitations:
  - Nonstationary learning
  - Hard to learn to coordinate

Centralised Critics [Lowe et al. 2017; Foerster et al. 2018]

Centralised $V(s, \tau)$ or $Q(s, \tau, \mathbf{u}) \rightarrow$ hard greedification $\rightarrow$ actor-critic

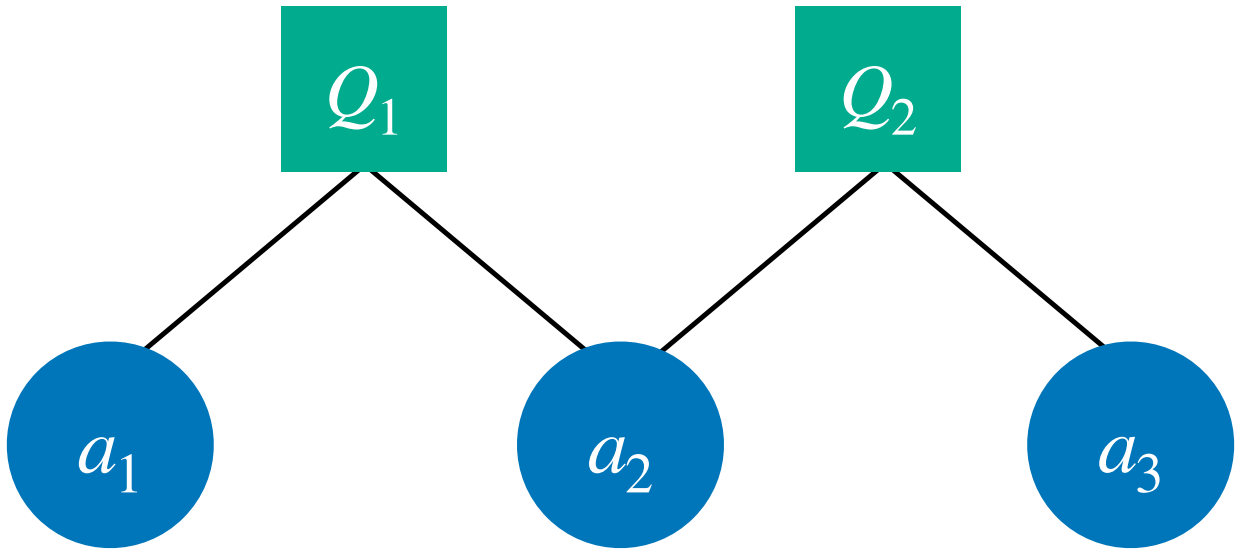


Factored Joint Value Functions

- *Factored value functions* [Guestrin et al. 2003] can improve scalability:

$$Q_{tot}(\boldsymbol{\tau}, \mathbf{u}; \boldsymbol{\theta}) = \sum_{e=1}^{E} Q_e(\tau^e, \mathbf{u}^e; \theta^e)$$

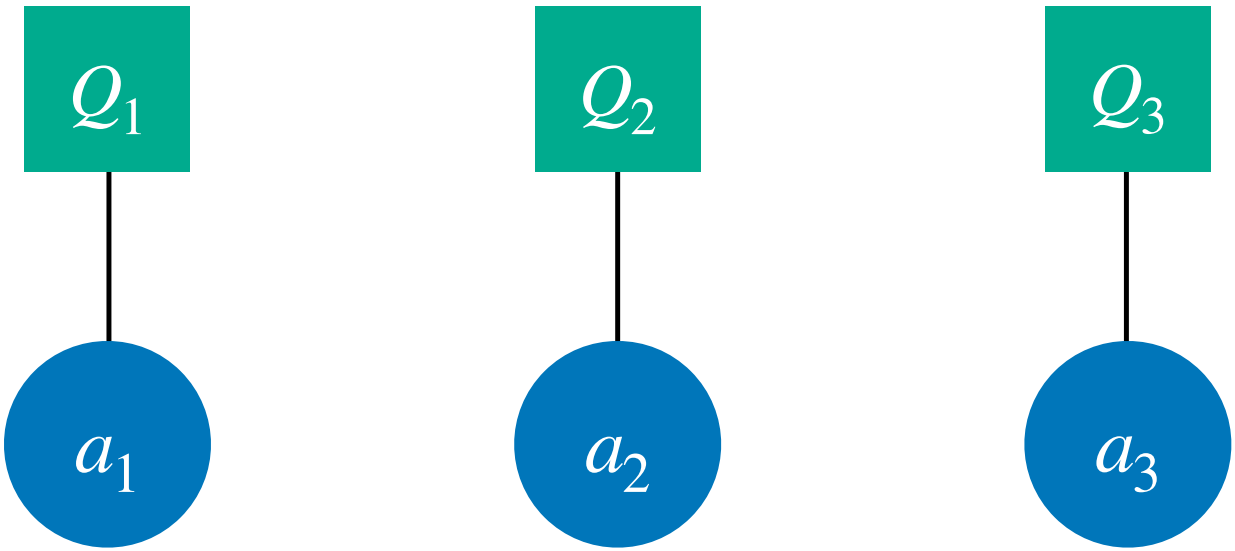
where each e indicates a subset of the agents



Value Decomposition Networks [Sunehag et al., 2017]

- Most extreme factorisation: one per agent:

$$Q_{tot}(\boldsymbol{\tau}, \mathbf{u}; \boldsymbol{\theta}) = \sum_{a=1}^{N} Q_a(\tau^a, u^a; \theta^a)$$



Decentralisability

- Added benefit of decentralising the max and arg max:

$$\max_{\mathbf{u}} Q_{tot}(\boldsymbol{\tau}, \mathbf{u}; \boldsymbol{\theta}) = \sum \max_{u^a} Q_a(\tau^a, u^a; \theta^a)$$

$$\arg\max_{\mathbf{u}} Q_{tot}(\boldsymbol{\tau}, \mathbf{u}; \boldsymbol{\theta}) = \begin{pmatrix} \arg\max_{u^1} Q_1(\tau^1, u^1; \theta^1) \\ \vdots \\ \arg\max_{u^n} Q_n(\tau^n, u^n; \theta^n) \end{pmatrix}$$

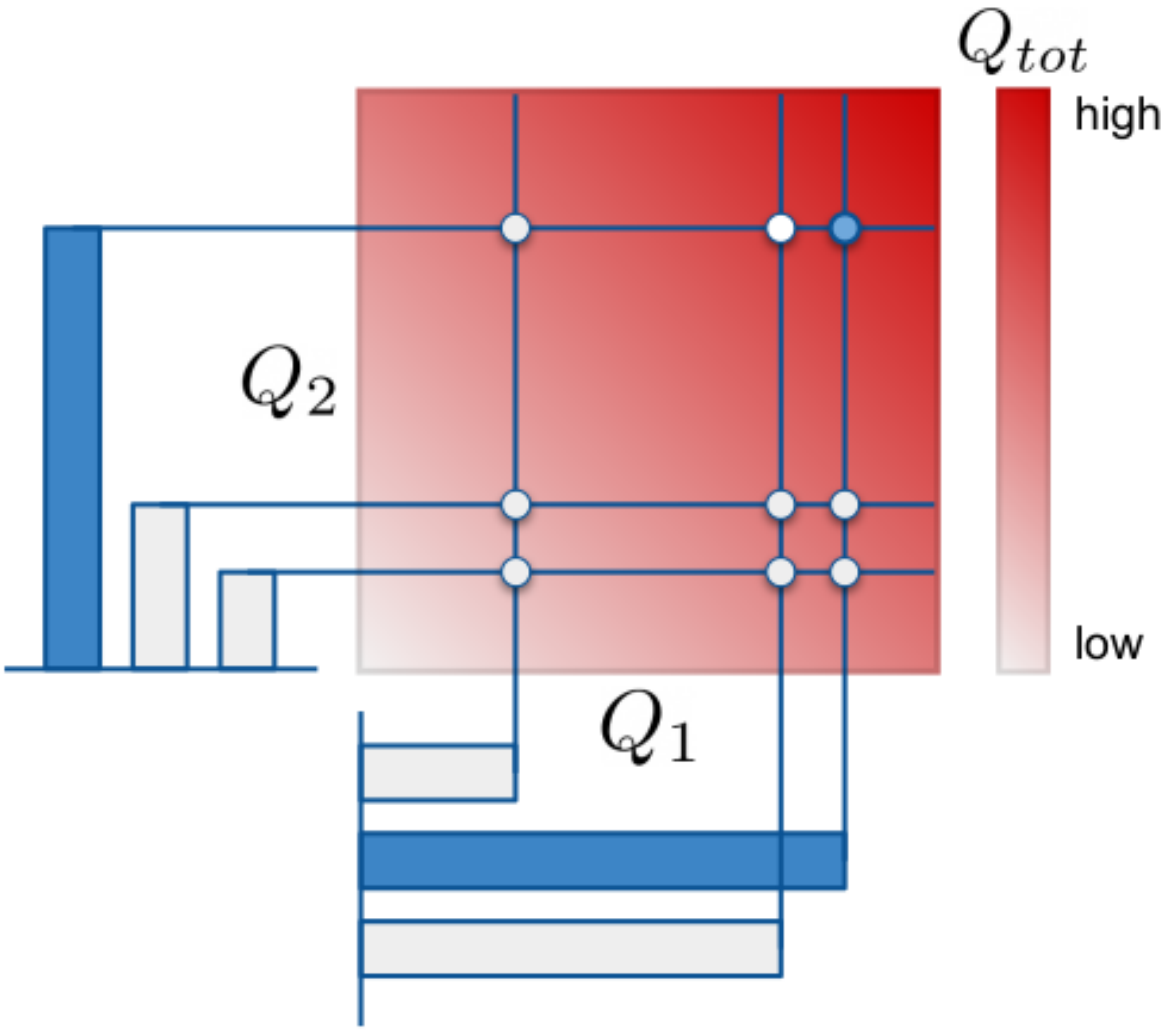
- No more hard greedification $\implies$ Q-learning, not actor-critic:

$$\mathcal{L}(\boldsymbol{\theta}) = \sum_{i=1}^{b} \left[\left(y_i^{\text{tot}} - Q_{tot}(\boldsymbol{\tau}, \mathbf{u}; \boldsymbol{\theta}) \right)^2 \right],$$

$$y_i^{\text{tot}} = r_i + \gamma \max_{\mathbf{u}'} Q_{tot}(\boldsymbol{\tau}'_i, \mathbf{u}'; \boldsymbol{\theta}^-)$$

QMIX's Monotonicity Constraint

To decentralise max / arg max, it suffices to enforce: $\frac{\partial Q_{tot}}{\partial Q_a} \geq 0, \ \forall a \in A$



Representational Capacity

It'll never work: monotonic mixing still can't capture the benefit of coordination

Agent 1 \ Agent 2	A	B
A	0	1
B	1	2

linear & monotonic

VDN & QMIX

Agent 1 \ Agent 2	A	B
A	0	1
B	1	8

nonlinear & monotonic

Just QMIX

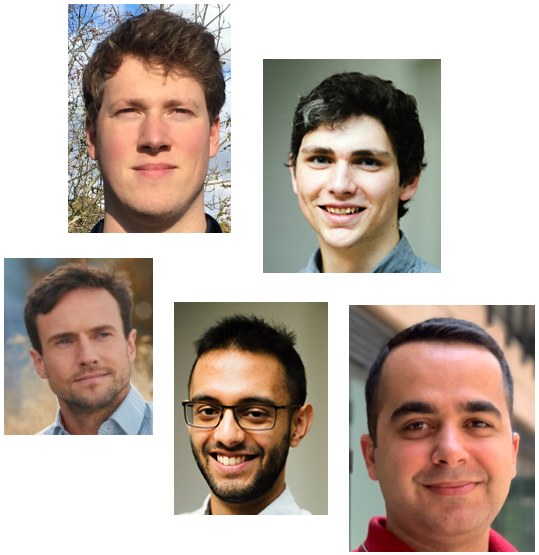
Agent 1 \ Agent 2	A	B
A	2	1
B	1	8

nonlinear & nonmonotonic

Neither

Bootstrapping

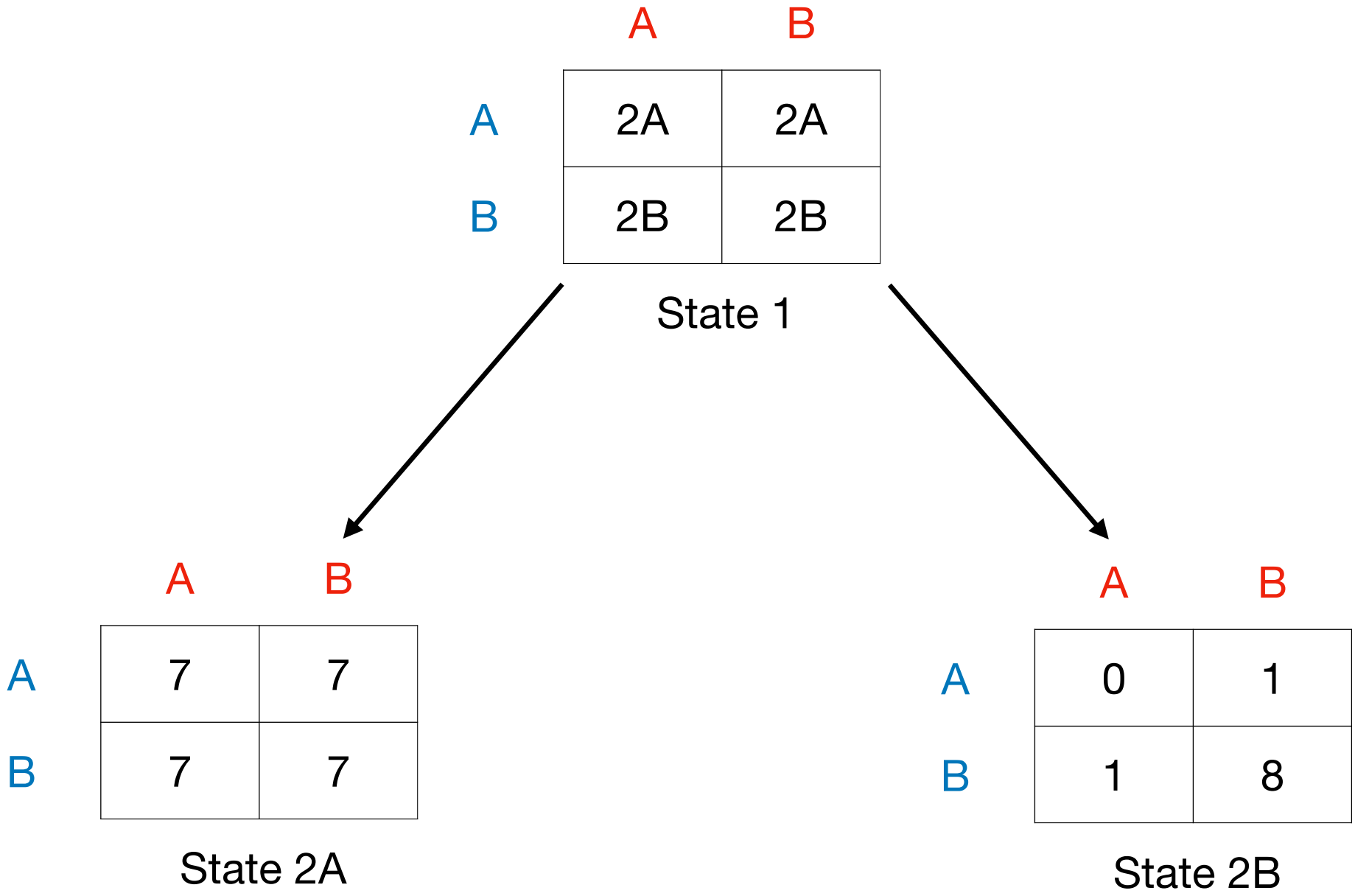
It matters because of *bootstrapping*



$$\mathcal{L}(\theta) = \sum_{i=1}^{b} \left[\left(y_i^{\text{tot}} - Q_{tot}(\boldsymbol{\tau}, \mathbf{u}, s; \theta) \right)^2 \right],$$

$$y_i^{\text{tot}} = r_i + \gamma \max_{\mathbf{u}'} Q_{tot}(\boldsymbol{\tau}'_i, \mathbf{u}', s'; \theta^-)$$

Two-Step Game



Two-Step Game Results

Ground Truth

State 1

	A	B
A	7	7
B	8	8

State 2A

	A	B
A	7	7
B	7	7

State 2B

	A	B
A	0	1
B	1	8

VDN

State 1

	A	B
A	6.94	6.94
B	6.35	6.36

State 2A

	A	B
A	6.99	7.02
B	6.99	7.02

State 2B

	A	B
A	-1.87	2.31
B	2.33	6.51

QMIX

State 1

	A	B
A	6.93	6.93
B	7.92	7.92

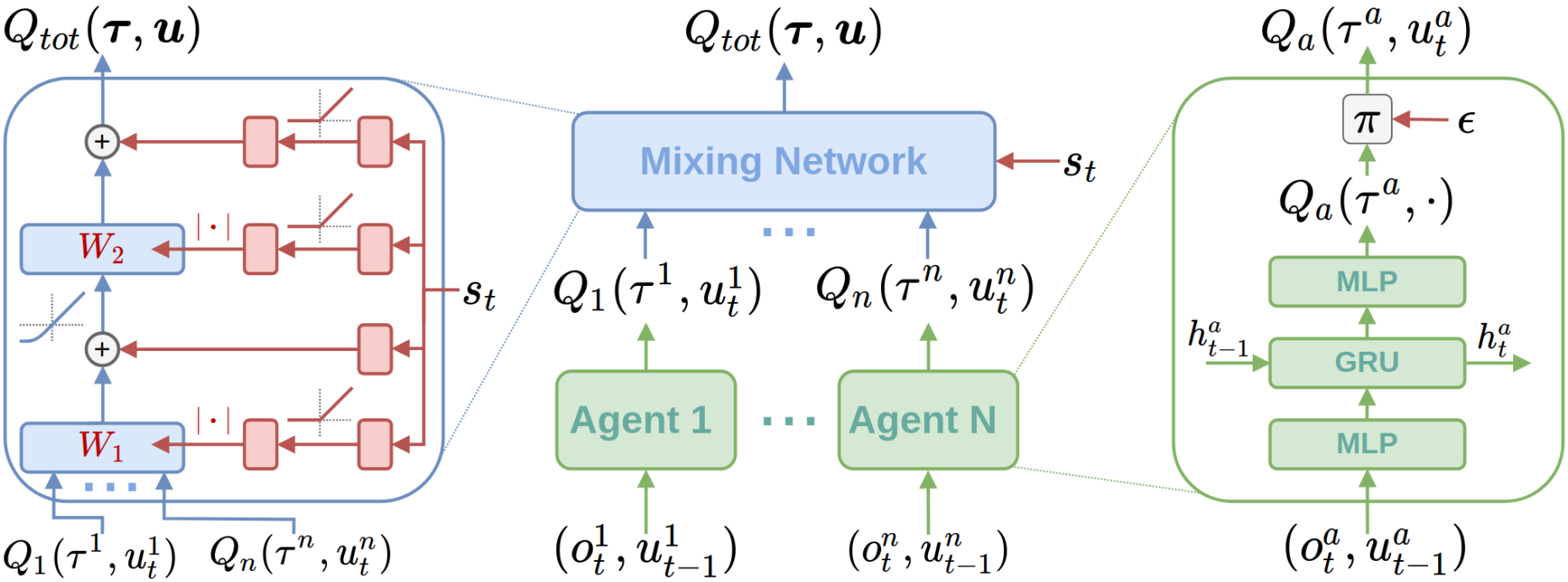
State 2A

	A	B
A	7.00	7.00
B	7.00	7.00

State 2B

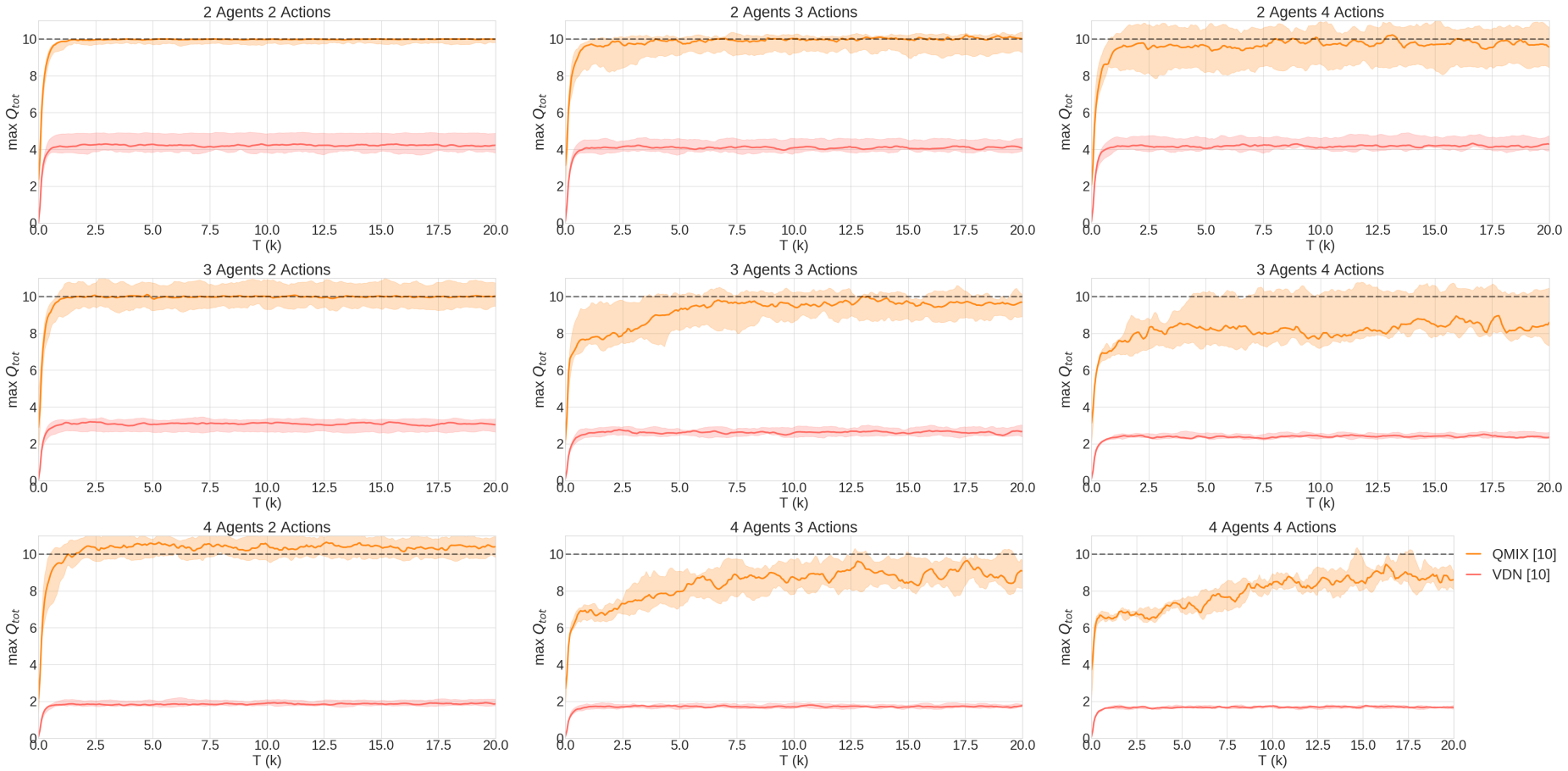
	A	B
A	0.00	1.00
B	1.00	8.00

QMIX [Rashid et al. 2018]



- Agent network: represents $Q_i(\tau^a, u^a; \theta^a)$
- Mixing network: represents $Q_{tot}(\boldsymbol{\tau})$ using nonnegative weights
- Hypernetwork: generates weights of hypernetwork based on global s

Random Matrix Games (The Students Were Right)



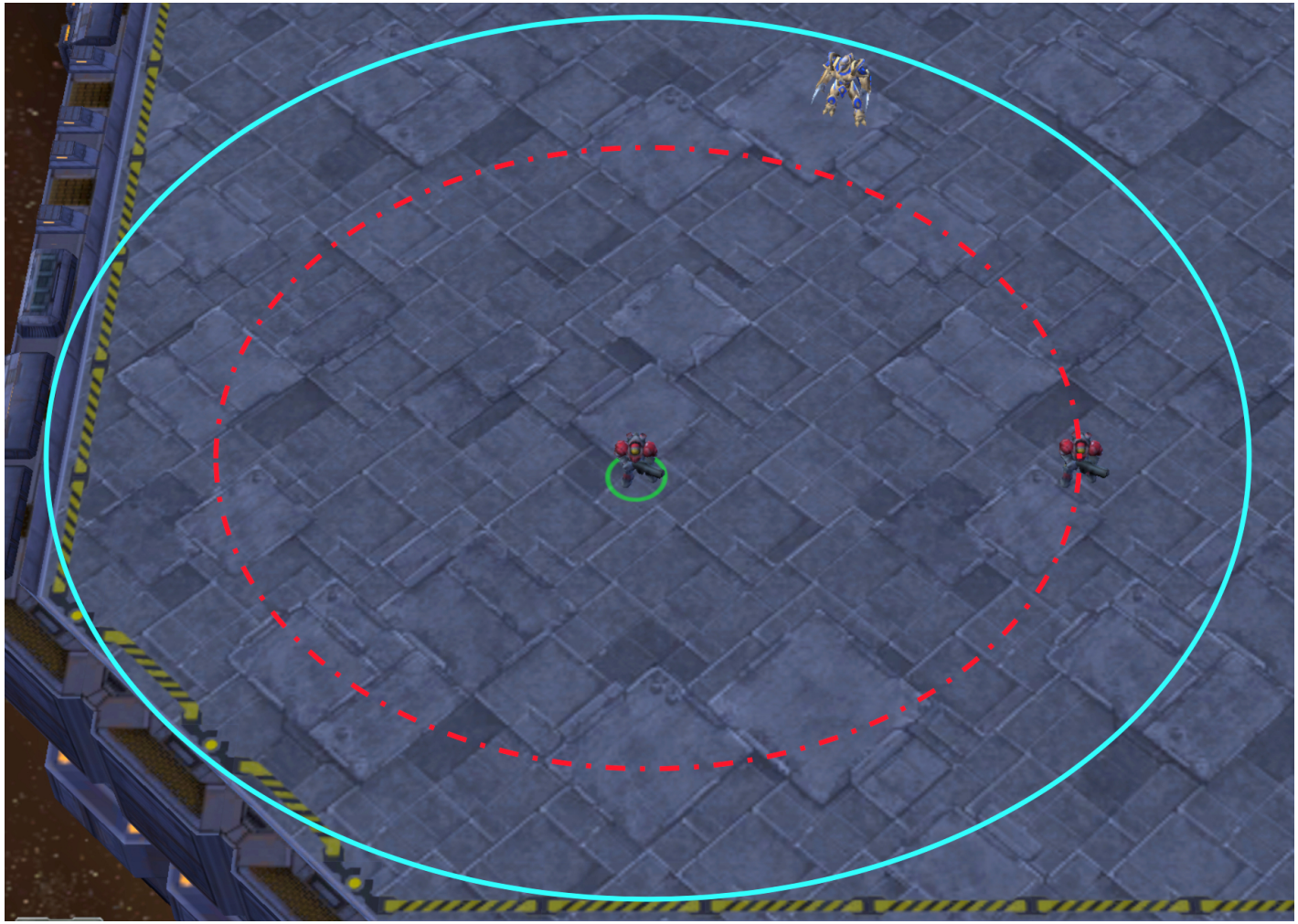
StarCraft Multi-Agent Challenge (SMAC)

[Samvelyan et al. 2019]

https://github.com/oxwhirl/smac

https://github.com/oxwhirl/pymarl

Partial Observability in SMAC

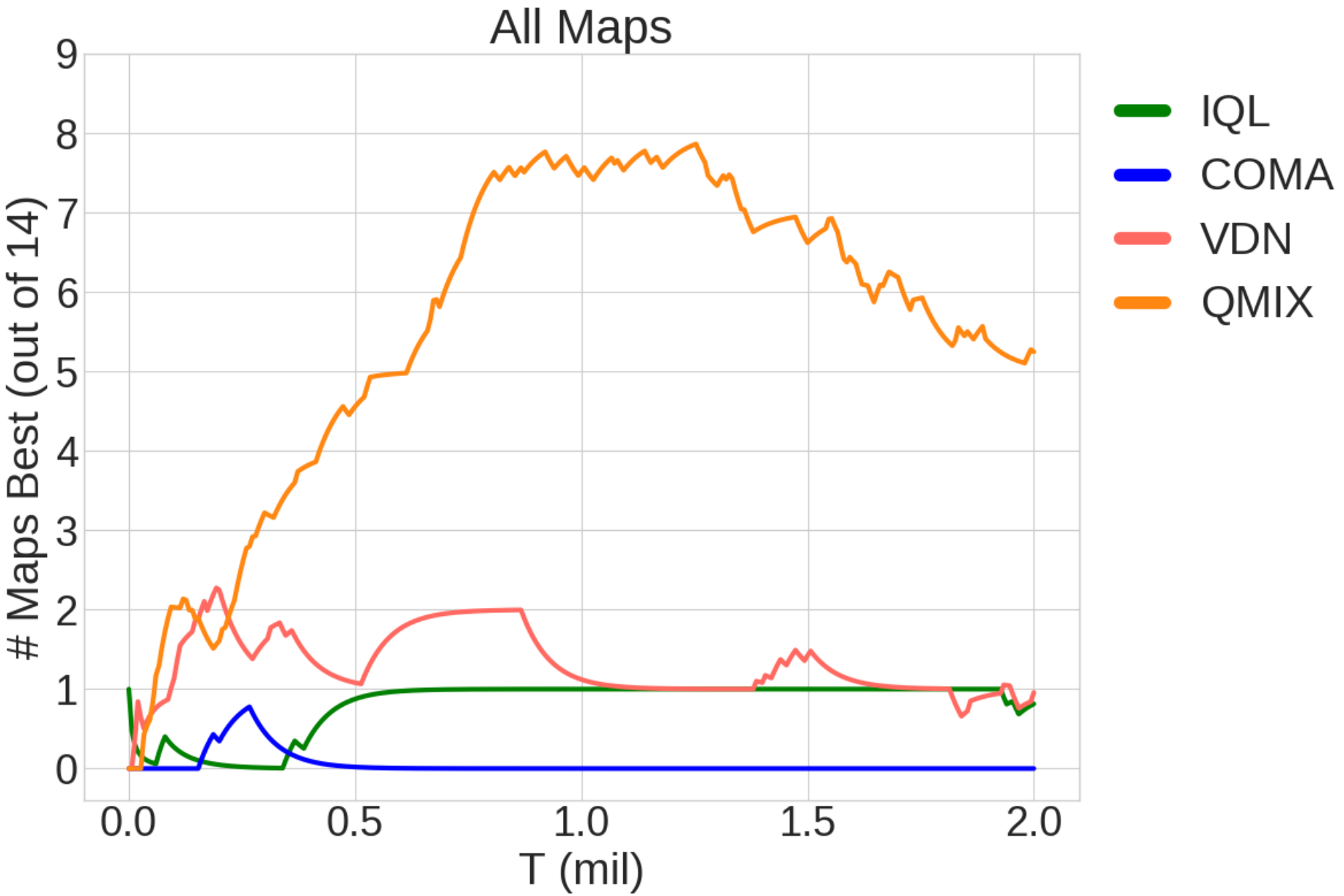


Cyan = sight range Red = shooting range

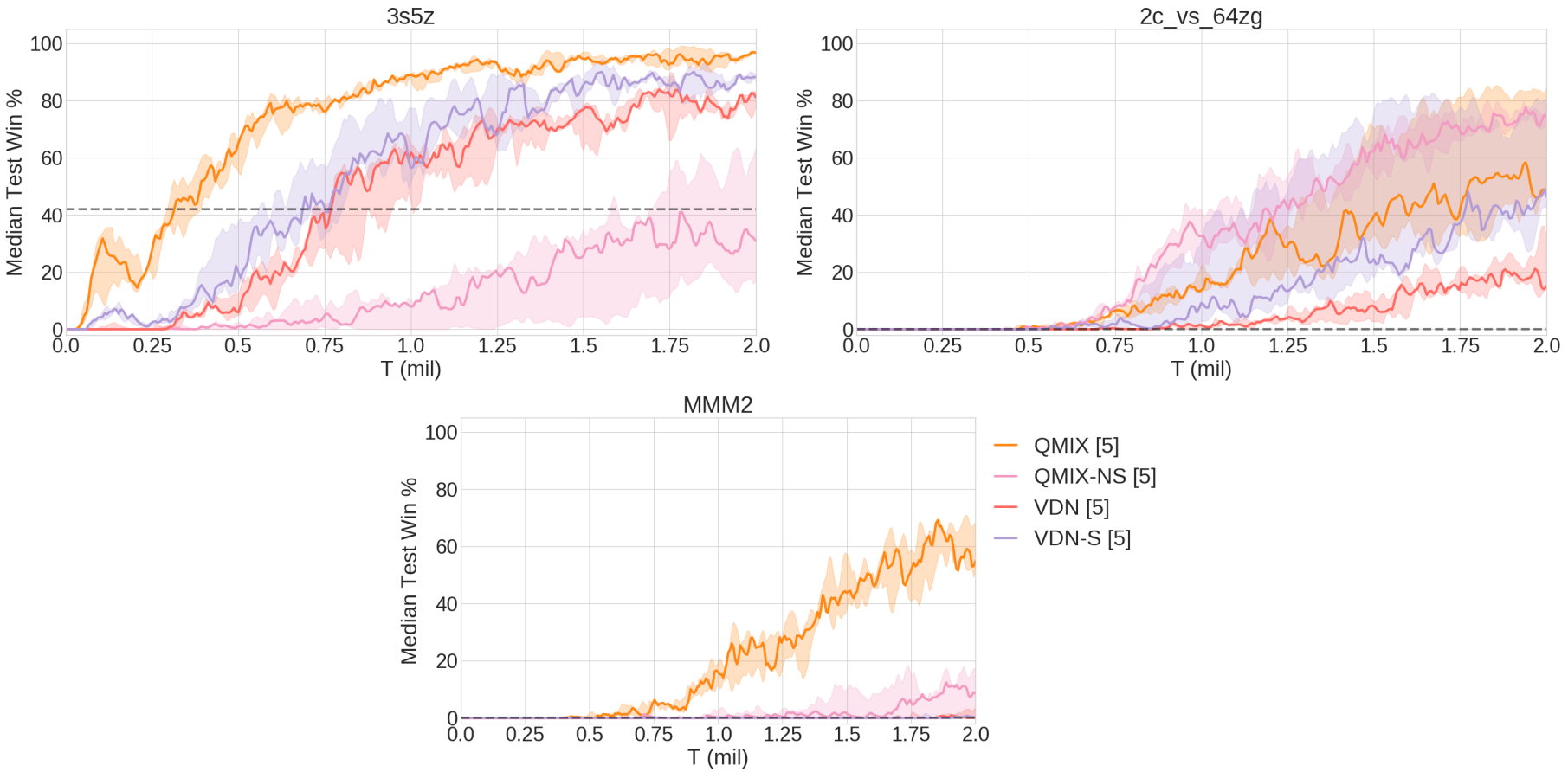
SMAC Maps

Name	Ally Units	Enemy Units
2s3z	2 Stalkers & 3 Zealots	2 Stalkers & 3 Zealots
3s5z	3 Stalkers & 5 Zealots	3 Stalkers & 5 Zealots
1c3s5z	1 Colossus, 3 Stalkers & 5 Zealots	1 Colossus, 3 Stalkers & 5 Zealots
5m_vs_6m	5 Marines	6 Marines
10m_vs_11m	10 Marines	11 Marines
27m_vs_30m	27 Marines	30 Marines
3s5z_vs_3s6z	3 Stalkers & 5 Zealots	3 Stalkers & 6 Zealots
MMM2	1 Medivac, 2 Marauders & 7 Marines	1 Medivac, 3 Marauders & 8 Marines
2s_vs_1sc	2 Stalkers	1 Spine Crawler
3s_vs_5z	3 Stalkers	5 Zealots
6h_vs_8z	6 Hydralisks	8 Zealots
bane_vs_bane	20 Zerglings & 4 Banelings	20 Zerglings & 4 Banelings
2c_vs_64zg	2 Colossi	64 Zerglings
corridor	6 Zealots	24 Zerglings

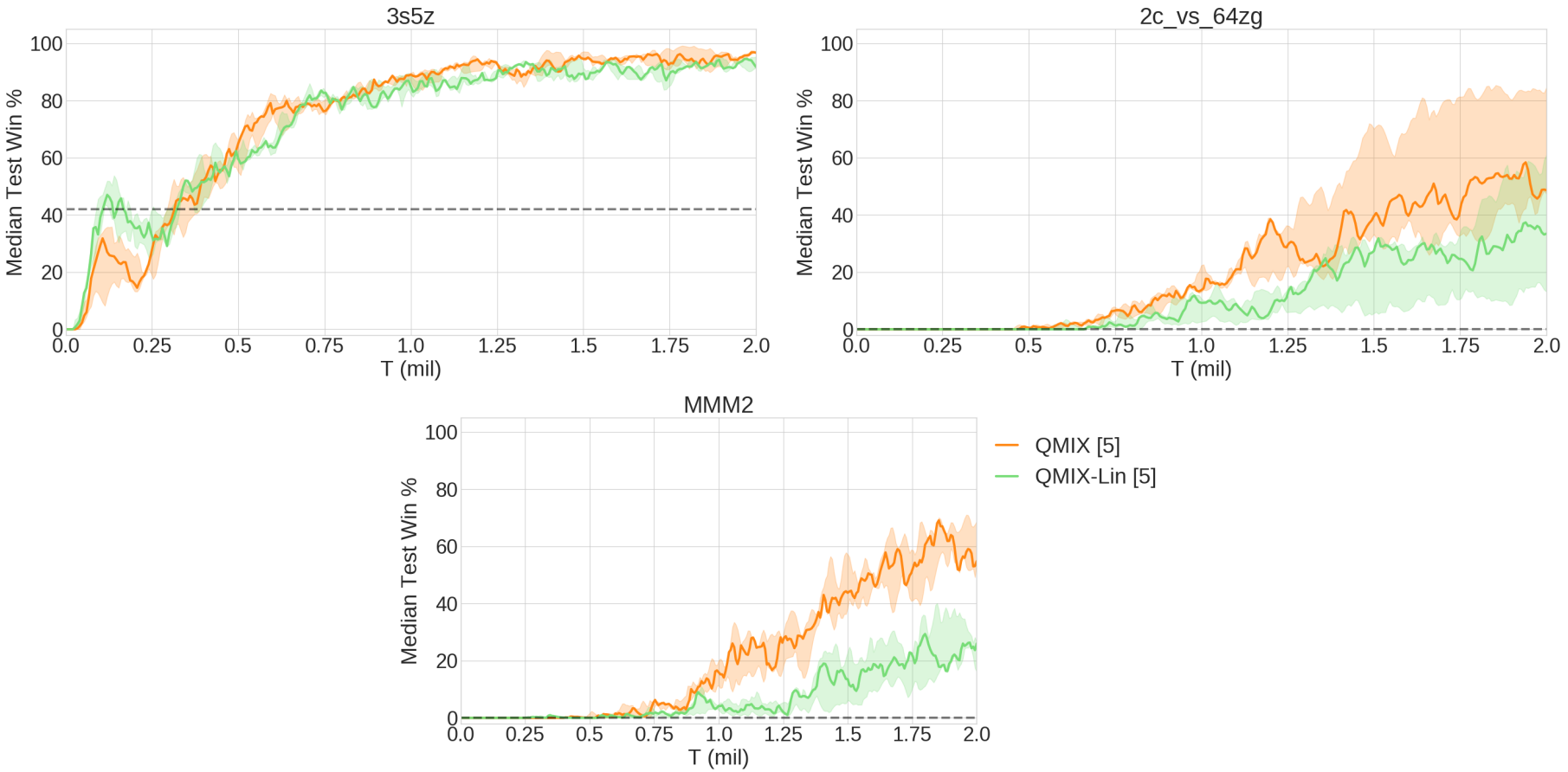
Overall Results (The Students Were Right)



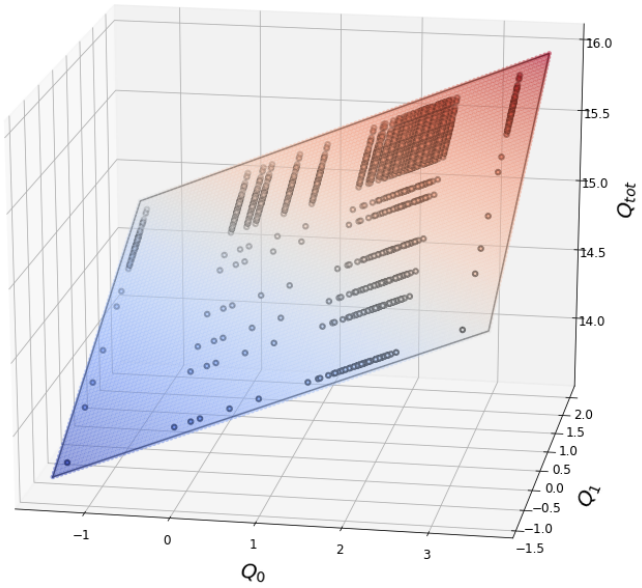
State Ablations



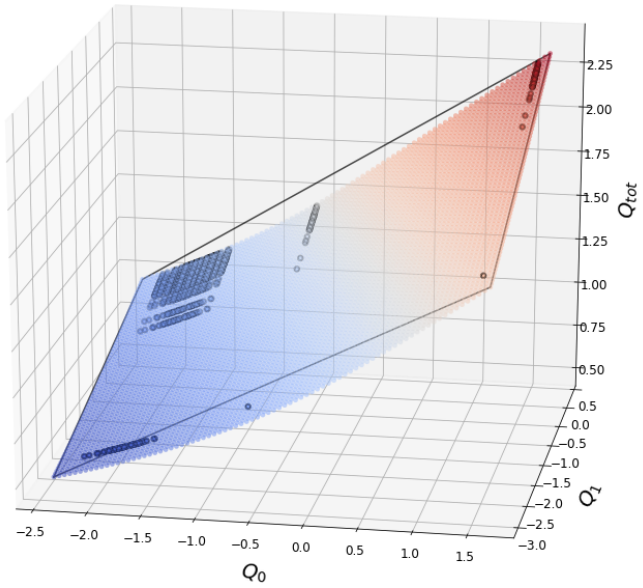
Linear Ablations



Learned Mixing Functions (2c_vs_64zg)

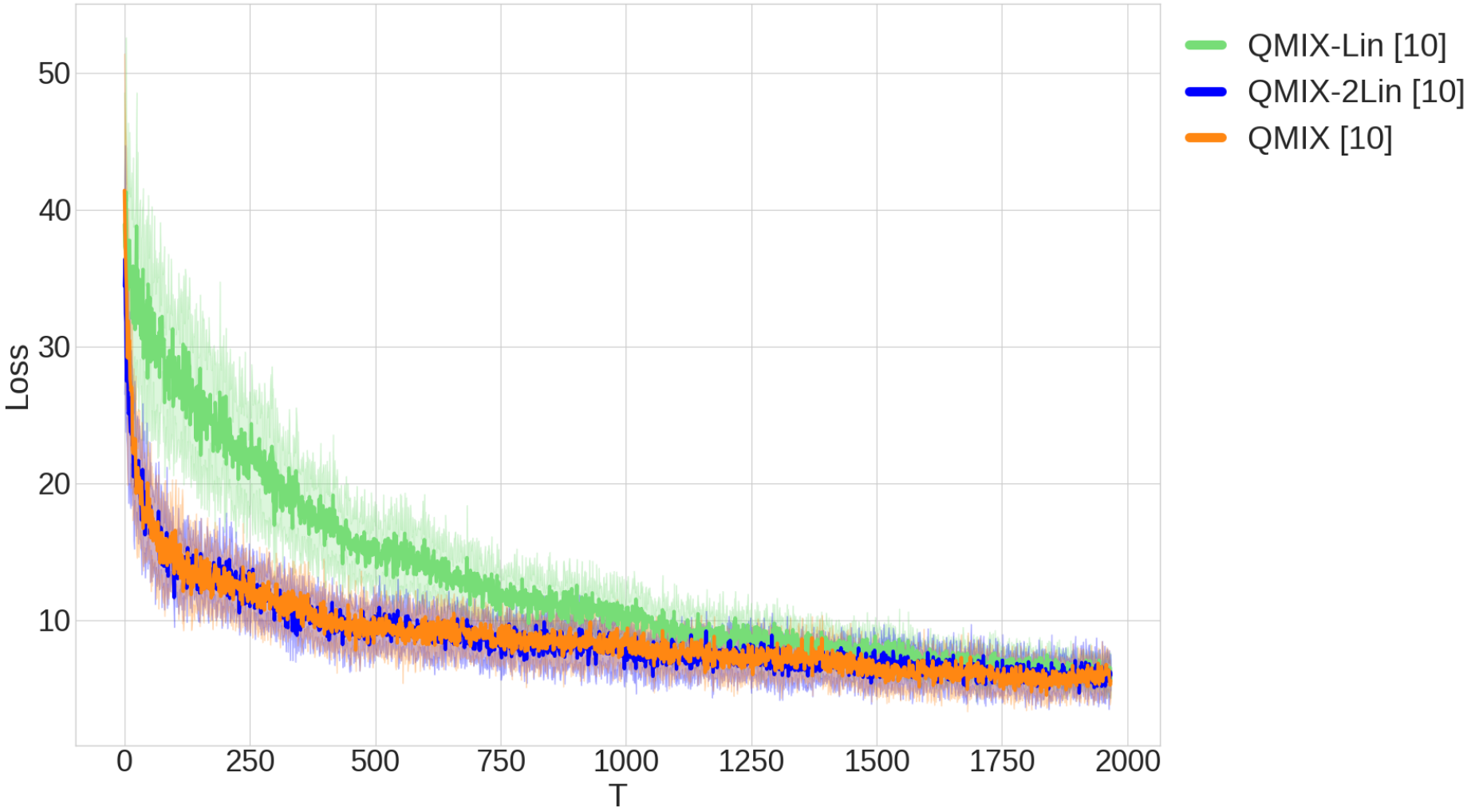


$t = 0$

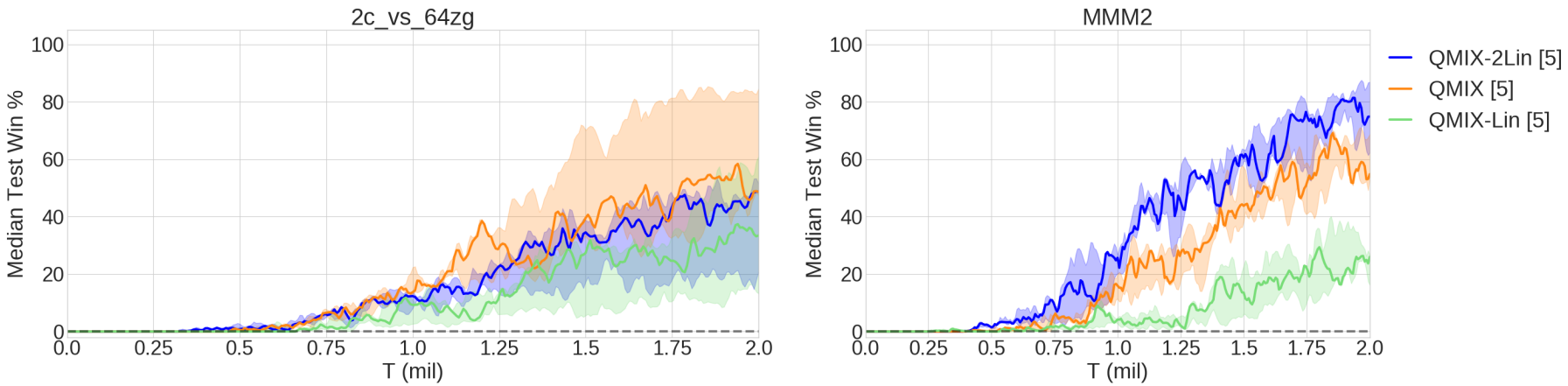


$t = 50$

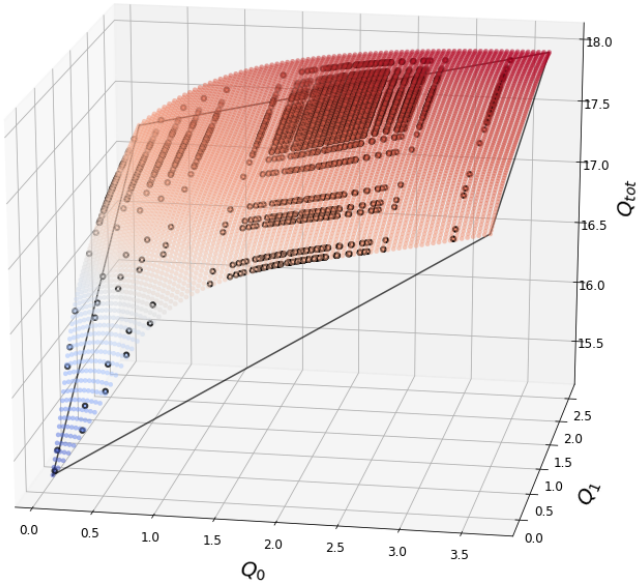
Multi-Layer Linear Mixing (Regression)



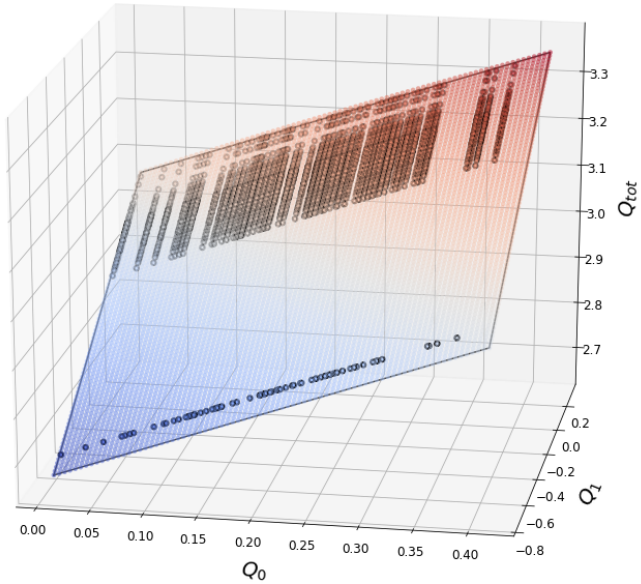
Multi-Layer Linear Mixing (SMAC)



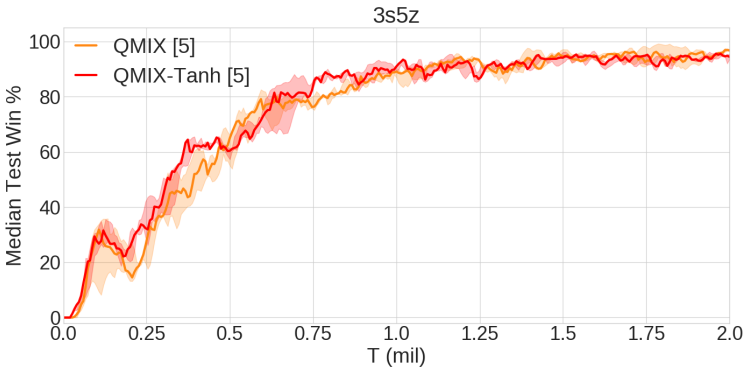
Tanh Activation

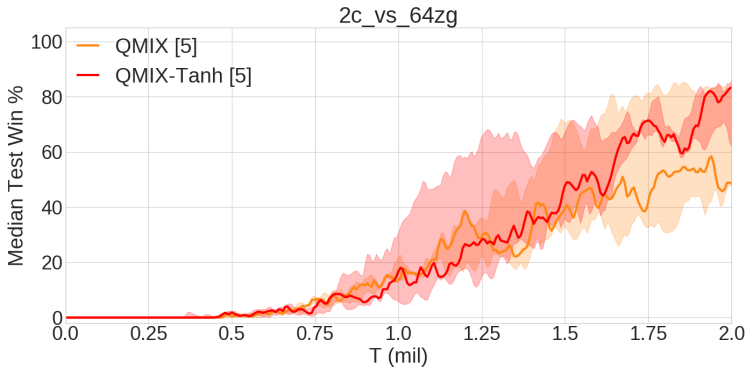


$t = 0$



$t = 50$





QMIX Takeaways

- Value function factorisation is crucial
- Flexible conditioning on central state is crucial
- Richly parameterised mixing is crucial
- Nonlinear mixing is not crucial (on SMAC)

Multi-Agent RL Methods from WhiRL

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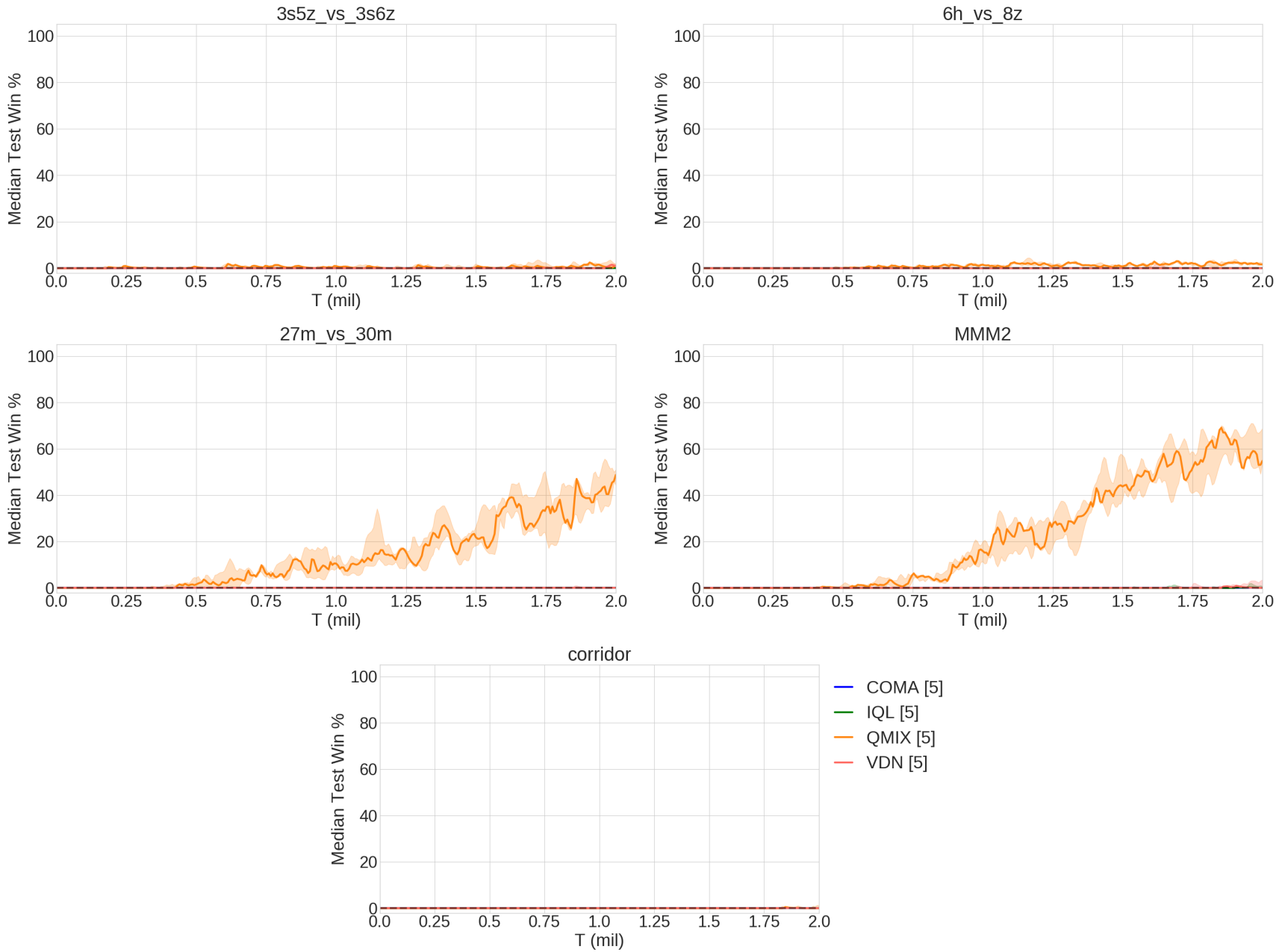
Super Hard Maps



Hypotheses

Hypothesis 1

Super Hard Maps in SMAC require nonmonotonic mixing functions

But then why does COMA also fail?

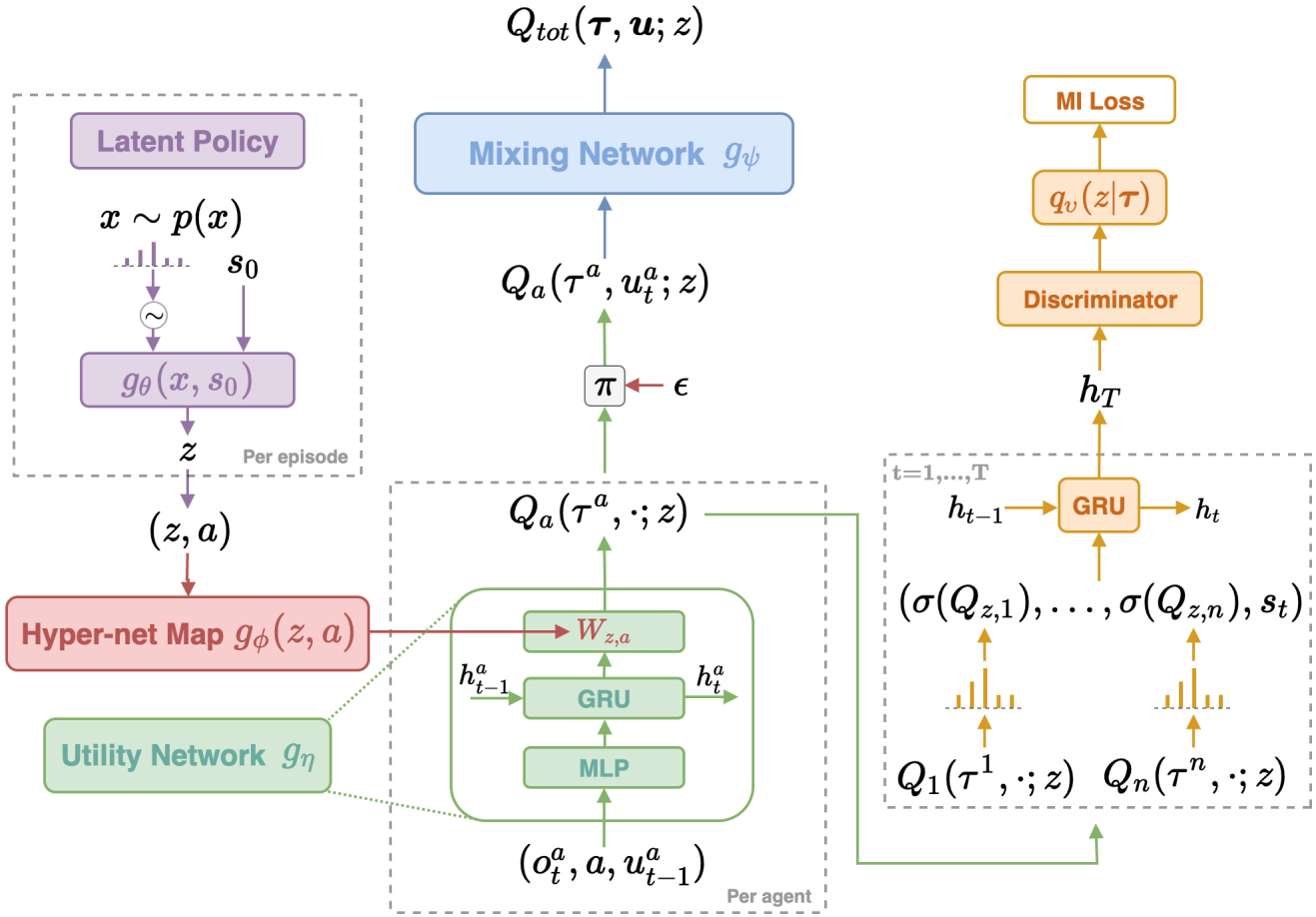
Hypothesis 2

Learning nonmonotonic mixing functions requires smart exploration

QMIX uses naive ϵ-greedy and is sensitive to annealing schedule

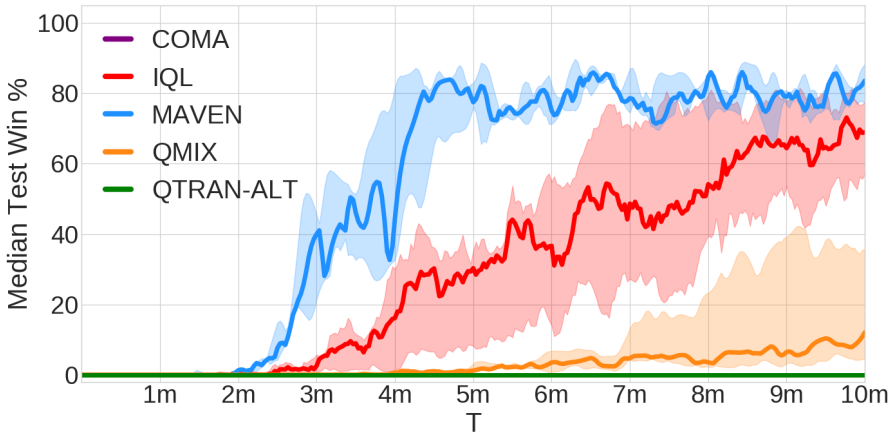
Multi-Agent Variational Exploration (MAVEN)

[Mahajan et al. 2019]

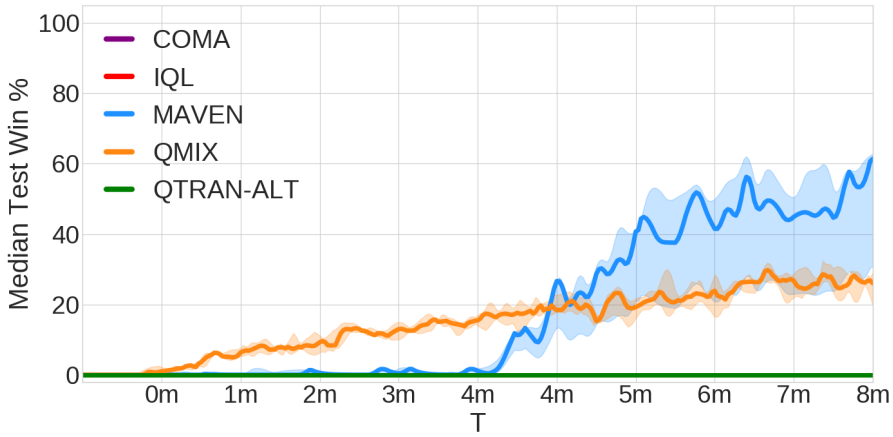


$$\max_{\upsilon,\phi,\eta,\psi,\theta} \mathcal{J}_{RL}(\theta) + \lambda_{MI}\mathcal{J}_V(\upsilon, \phi, \eta, \psi) - \lambda_{QL}\mathcal{L}_{QL}(\phi, \eta, \psi) \qquad (1)$$

MAVEN Results on Super Hard Maps

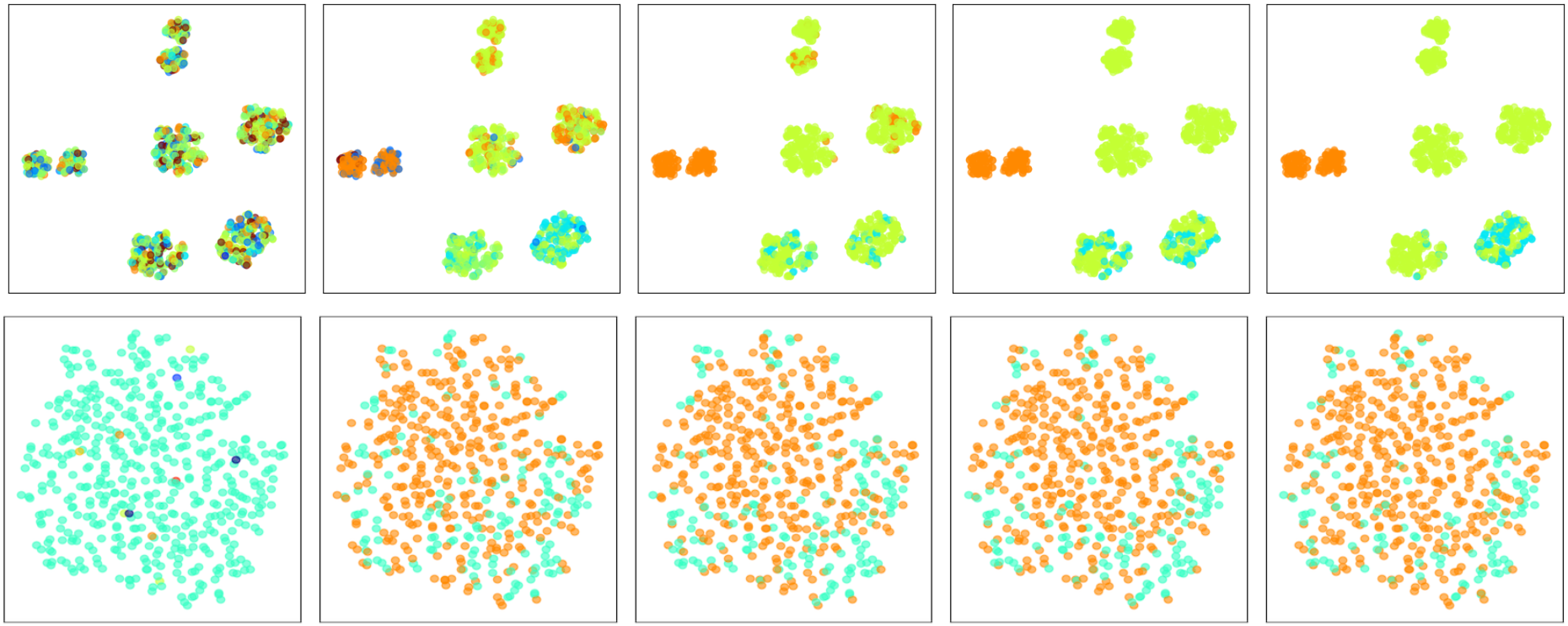


corridor



6h_vs_8z

MAVEN Latent Space



Top: 3s5z Bottom: corridor

Papers

QMIX: Monotonic Value Function Factorisation for Deep Multi-Agent Reinforcement Learning, **ICML-18**

Tabish Rashid, Mikayel Samvelyan, Christian Schroeder de Witt, Gregory Farquhar, Jakob Foerster, & Shimon Whiteson

Monotonic Value Function Factorisation for Deep Multi-Agent Reinforcement Learning, **JMLR-20 (To Appear)**

Tabish Rashid, Mikayel Samvelyan, Christian Schroeder de Witt, Gregory Farquhar, Jakob Foerster, & Shimon Whiteson

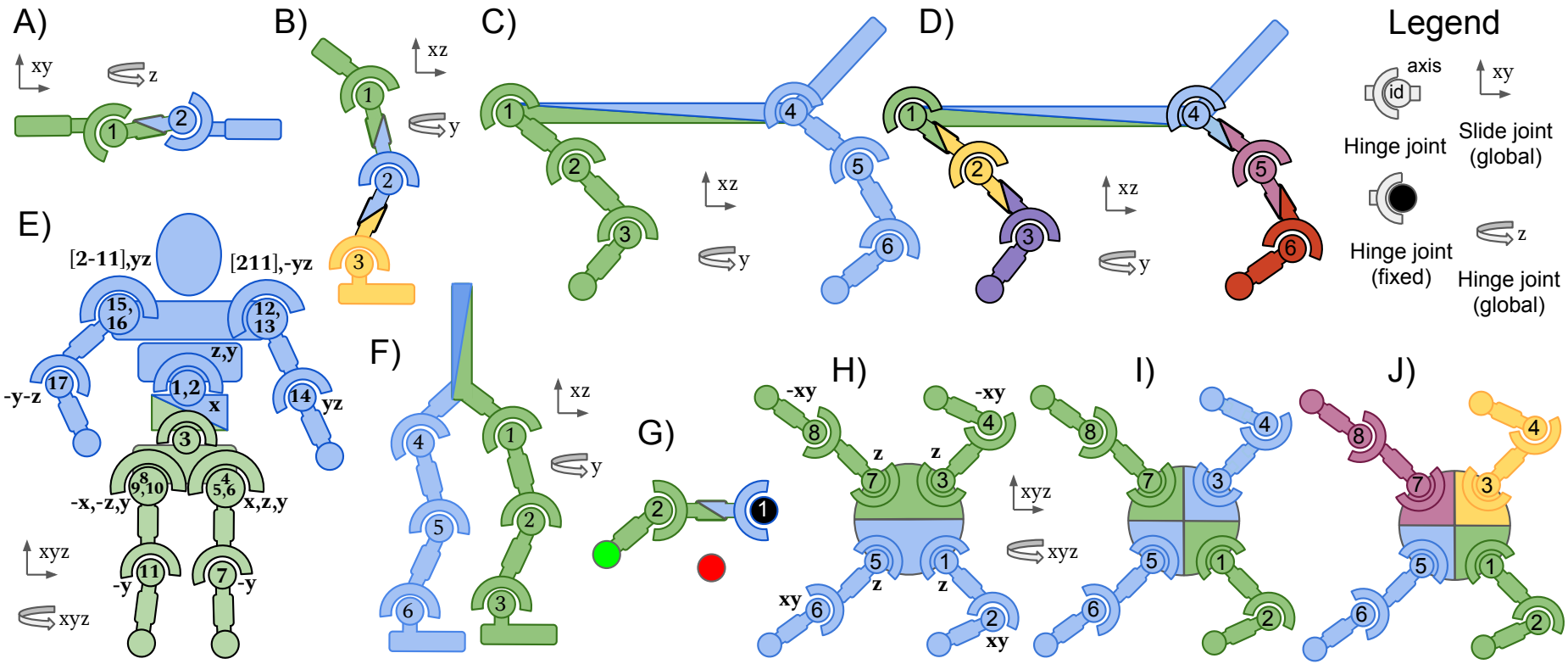
MAVEN: Multi-Agent Variational Exploration, **NeurIPS-19**

Anuj Mahajan, Tabish Rashid, Mikayel Samvelyan, & Shimon Whiteson

Conclusions

- QMIX: simple, effective value factorisation for MARL
- Extensive results suggest factorisation is crucial
- Confounder: COMA is on-policy actor-critic
- Controlled comparisons:
  - COMIX: continuous-action QMIX [Schroeder de Witt et al. 2020]
  - MADDPG: continuous-action off-policy actor-critic [Lowe et al. 2017]

Multi-Agent Mujoco [Schroeder de Witt et al. 2020]



$$COMIX > MADDPG$$

$$COMIX = FacMADDPG$$

New Frontiers

- *New factorisations*: tensor decomposition
- *New algorithms*: PPO-based methods upending SOTA
- *New architectures*: transformer-based approaches for transfer
- *New applications*: Google Research Football

Figure from [Kurach et al. 2019]