Reinforcement Learning China Summer School

RLChina 2021

Learning to Collaborate in Complex Environments

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AI Breakthrough in Pattern Recognition

What's the Next?

Intelligent decision-making in multi-agent environments

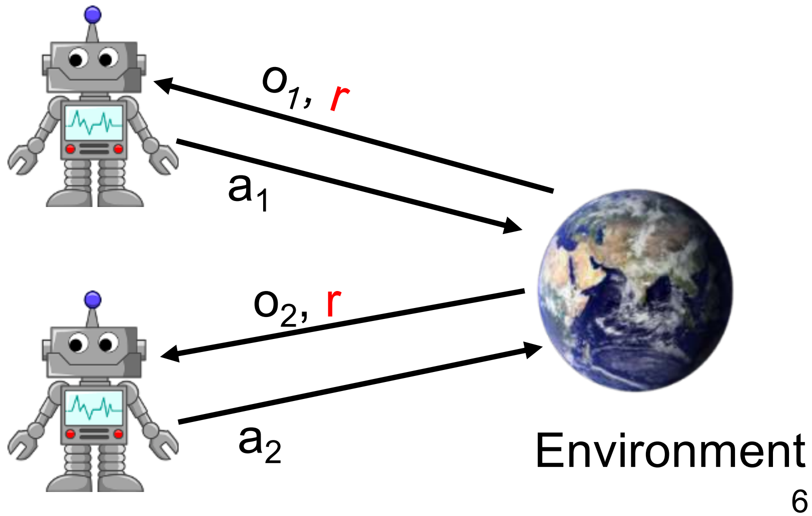
Types of Multi-Agent Systems

- Cooperative
  - Working together and coordinating their actions
  - Maximizing a shared team reward
- Competitive
  - Self-interested: maximizing an individual reward
  - Opposite rewards
  - Zero-sum games
- Mixed
  - Self-interested with different individual rewards (not opposite)
  - General-sum games

An Example in Starcraft II:
3 Stalkers vs 5 Zealots

Collaborative Multi-Agent Decision-Making

- Finding policies for agents to optimize team performance
- Model: decentralized partially observable Markov decision process (Dec-POMPD)
  - Multi-agent sequential decision-making under uncertainty
  - Extension of MDPs and POMDPs
- At each step, each agent *i* takes an action and receives:
  - A local observation o_i
  - A joint immediate reward *r*



Dec-POMDP

- Model
  - Agent: $i \in I = \{1, 2, \dots, N\}$
  - State: $s \in S$
  - Action: $a_i \in A$, $\boldsymbol{a} \in A^N$
  - Transition function: $P(s' \mid s, \boldsymbol{a})$
  - Reward: $R(s, \boldsymbol{a})$
  - Observation: $o_i \in \Omega$
  - Observation function: $o_i \in \Omega \sim O(s, i)$

Dec-POMDP

- Objective: to find policies for agents to jointly maximize the expected cumulative reward
- A local policy π_i for each agent i: mapping its observation-action history τ_i to its action
  - Action-observation history: $\tau_i \in T = (\Omega \times A)^*$
  - State is unknown, so beneficial to remember the history

Dec-POMDP

- Objective: to find policies for agents to jointly maximize the expected cumulative reward
- Joint policy $\boldsymbol{\pi} =< \pi_1, \dots, \pi_n >$
- Value function: $Q_{tot}^{\boldsymbol{\pi}}(\boldsymbol{s}, \boldsymbol{a}) = \mathbb{E}\left[\sum_{t=0}^{\infty} \gamma^t r_t \mid s_0 = s, \boldsymbol{a}_0 = \boldsymbol{a}, \boldsymbol{\pi}\right]$
- Optimal Policy $\boldsymbol{\pi}^*= \mathrm{argmax}_{\pi} \max_{a} Q_{tot}^{\boldsymbol{\pi}}(\boldsymbol{s_0}, \boldsymbol{a})$

Multi-Agent Reinforcement Learning (MARL)

- MARL is promising for solving Dec-POMDPs
  - Dec-POMDP is NEXP (2002)
  - The environment model is often unknown
  - Learning policies by interacting with the environment
- Reinforcement learning in a nutshell
  - Exploration: add some randomness into action selection
  - If an action performs better than expected, do it more in the future; otherwise, do it less.
- MARL: learning policies for multiple agents
  - Where agents are interacting

MARL Challenges

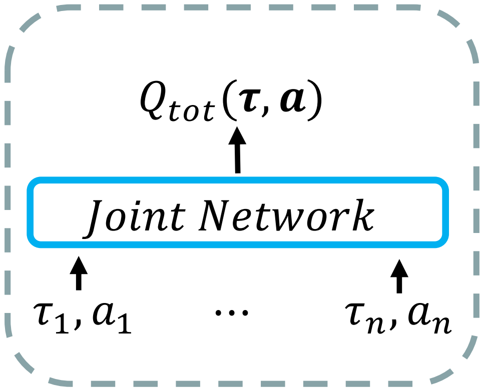
- Scalability
  - A large number of agents
- Credit Assignment
  - each agent's contribution to the team
- Uncertainty
  - Partial and noisy observations
- Heterogeneity
  - Requiring diverse behaviors of agents
- Exploration
  - Coordinated exploration among agents

Outlines

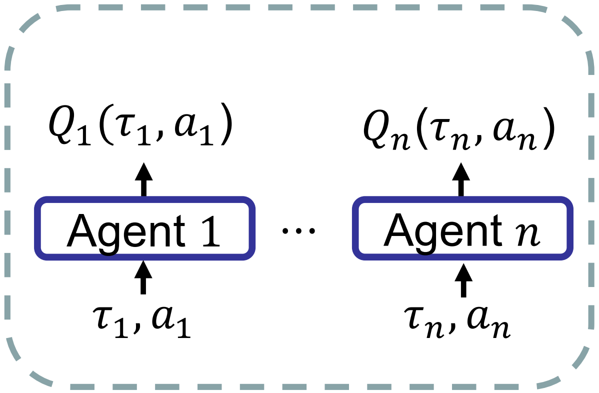
- Linearly factorized multi-agent learning [Arxiv 2020, ICLR 2021a]
  - Simple but scalable and effective
  - Properties: local convergence and implicit credit assignment
- QPLEX: non-linearly factorized learning [ICLR 2021b]
  - Strong representation with global convergence
  - State-of-the-art benchmark performance
- Extensions
  - Learning to communicate [ICLR 2020a]
  - Role-emergence learning [ICML 2020, ICLR 2021c]
  - Effective exploration [ICLR 2020b, Arxiv 2021]

Multi-Agent Reinforcement Learning (MARL)

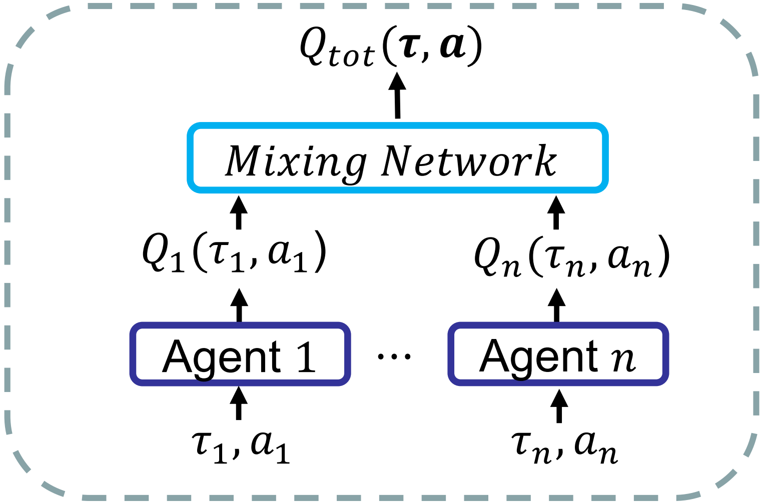
- Paradigms: learning cooperative policies or value functions



Centralized Value Functions



Decentralized Value Functions



Factorized Value Functions

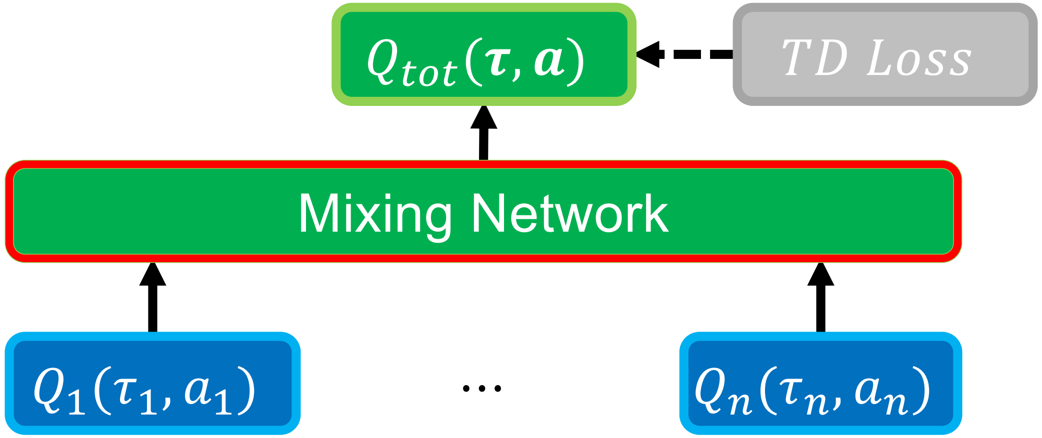
Scalability 

Non-stationarity
Credit assignment 

Centralized training
Decentralized execution 

Factorized Multi-Agent Reinforcement Learning

- Paradigm: centralized training with decentralized execution



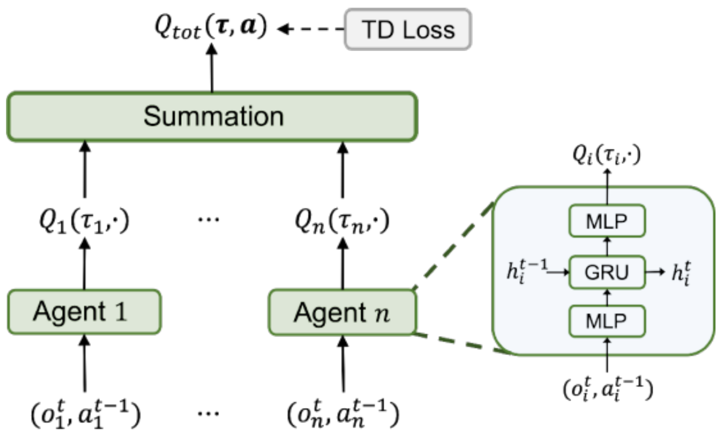
$$\mathcal{L}(\boldsymbol{\theta}) = \mathbb{E}\left[\left(r + \gamma V(\boldsymbol{\tau}'; \boldsymbol{\theta}^-) - Q(\boldsymbol{\tau}, \boldsymbol{a}; \boldsymbol{\theta})\right)^2\right]$$

$$V(\boldsymbol{\tau}'; \boldsymbol{\theta}^-) = \max_{\boldsymbol{a}'} Q(\boldsymbol{\tau}', \boldsymbol{a}'; \boldsymbol{\theta}^-)$$

- Individual-Global Maximization (IGM) Constraint
  - $\operatorname{argmax}_{\boldsymbol{a}} Q_{tot}(\boldsymbol{\tau}, \boldsymbol{a}) = \left(\operatorname{argmax}_{a_1} Q_1(\tau_1, a_1), \ldots, \operatorname{argmax}_{a_n} Q_n(\tau_n, a_n)\right)$
  - Consistent greedy action selection between joint and individuals

Linear Factorized Multi-Agent Learning

- Linear Mixing: $Q_{tot}(\boldsymbol{\tau}, \boldsymbol{a}) = \sum_i Q_i(\tau_i, a_i)$ [Sunehag et. al., 2017]
- Satisfying IGM Constraint
- Parameter sharing
- No specific reward for each agent
- Implicit credit assignment through gradient backpropagation

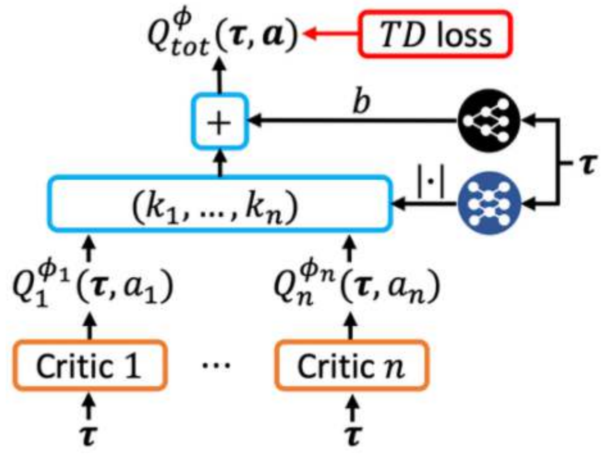


Implicit Credit Assignment Mechanism

- **counterfactual** credit assignment mechanism
  - $Q_i^{(t+1)}(s, a_i) = \underbrace{\mathbb{E}_{a'_{-i}}\left[y^{(t)}(s, a_i \oplus a'_{-i})\right]}_{\text{Evaluation of } a_i} - \frac{n-1}{n} \underbrace{\mathbb{E}_{\mathbf{a}'}\left[y^{(t)}(s, \mathbf{a}')\right]}_{\text{Baseline}}$
  - Target Q-value: $y^{(t)}(s, \mathbf{a}) = r + \gamma \max_{\mathbf{a}'} Q_{tot}^{(t)}(s', \mathbf{a}')$

[Arxiv 2020]

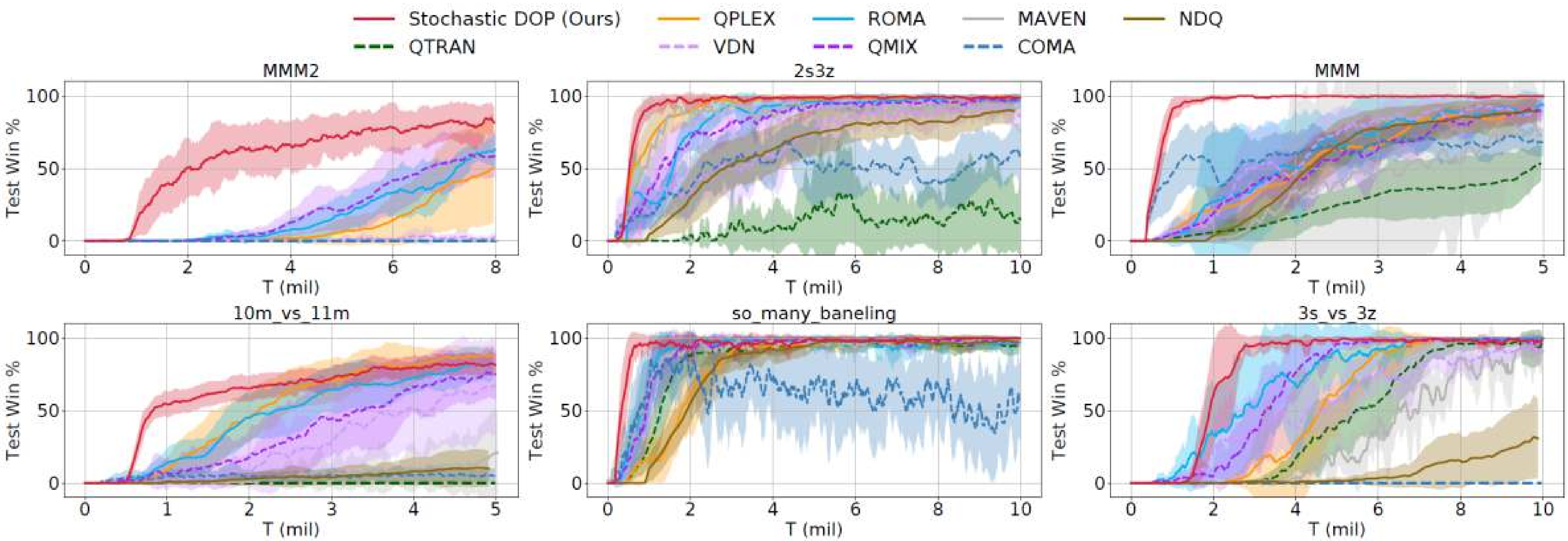
DOP: Off-Policy Decomposed Policy Gradient



- Introducing linearly decomposed critic
  - $Q_{tot}^{\boldsymbol{\pi}}(\boldsymbol{\tau}, \cdot) = \sum_i k_i(\boldsymbol{\tau}) Q_i(\boldsymbol{\tau}, \cdot) + b(\boldsymbol{\tau})$
- Policy gradient theorem
  - $\nabla J(\theta) = \mathbb{E}_{\boldsymbol{\pi}}[\sum_i \nabla_\theta \log \pi_i(a_i|\tau_i) k_i(\boldsymbol{\tau}) Q_i(\boldsymbol{\tau}, a_i)]$
- Benefits:
  - Simple but effective
  - Convergence guarantee with monotonic improvement
  - Work for both discrete and continuous action space

[ICLR 2021a]

Starcraft Micromanagement Benchmark



Learned Kiting Strategy in Starcraft II

Limitations on Linear Value Factorization

- $Q_{tot}(\boldsymbol{\tau}, \boldsymbol{a}) = \sum_i Q_i(\tau_i, a_i)$
- Limited Representation

Agent 1

Agent 2

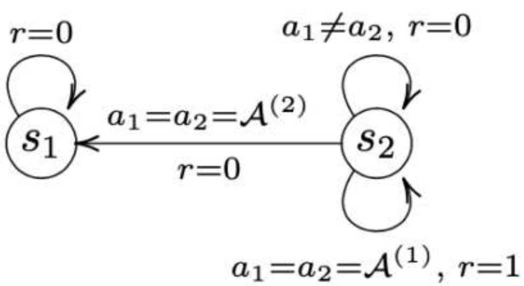
a_2 \ a_1	$\mathcal{A}^{(1)}$	$\mathcal{A}^{(2)}$	$\mathcal{A}^{(3)}$
$\mathcal{A}^{(1)}$	**8**	-12	-12
$\mathcal{A}^{(2)}$	-12	0	0
$\mathcal{A}^{(3)}$	-12	0	0

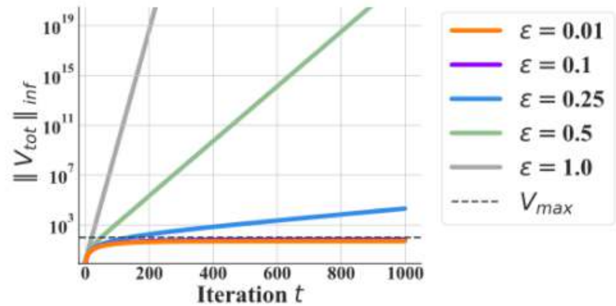
(a) Payoff of matrix game.

a_2 \ a_1	$\mathcal{A}^{(1)}$	$\mathcal{A}^{(2)}$	$\mathcal{A}^{(3)}$
$\mathcal{A}^{(1)}$	-6.5	-5.0	-5.0
$\mathcal{A}^{(2)}$	-5.0	-3.5	-3.5
$\mathcal{A}^{(3)}$	-5.0	**-3.5**	-3.5

(b) Q_{tot} of VDN.

- No global convergence guarantee with value-based learning





[Arxiv 2020]

Outlines

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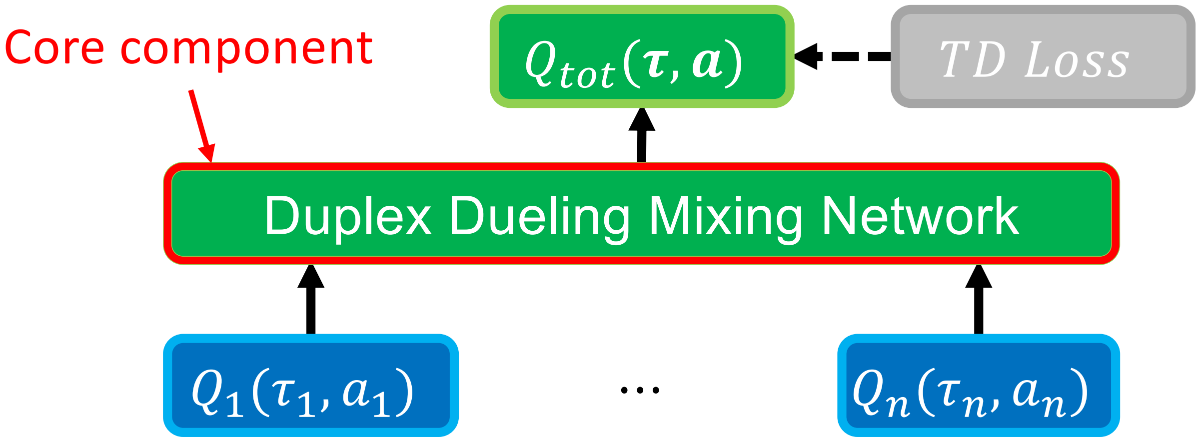
QPLEX: Duplex Dueling Mixing Network

[ICLR 2021b]

- Idea: fitting the maximum value and compensating the rest



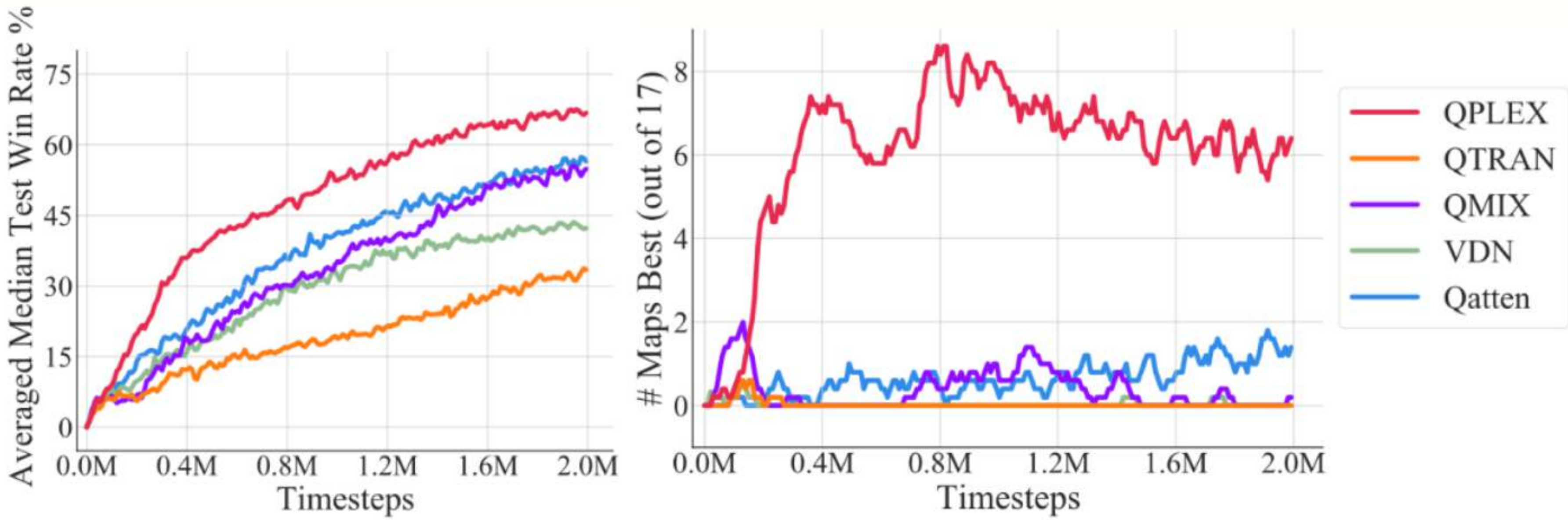
Linear Value Factorization

- QPLEX : $Q_{tot}(\boldsymbol{\tau}, \boldsymbol{a}) = \boxed{\sum_i Q_i(\boldsymbol{\tau}, a_i)} + \boxed{\sum_{i=1}^{n} (\lambda_i(\boldsymbol{\tau}, \boldsymbol{a}) - 1)\, A_i(\boldsymbol{\tau}, a_i)}$
  - Strong representation capacity
  - Easily realized and learned by neural networks

Theoretical Properties

Theorem 1 (Full Representation Capacity): *The joint action-value function class that QPLEX can realize is equivalent to what is induced by the IGM principle.*

StarCraft II Benchmark

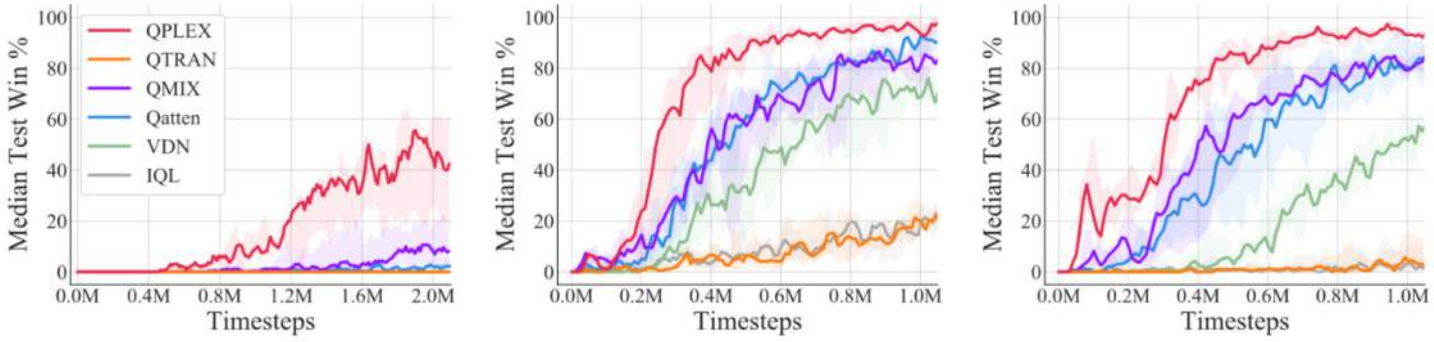


(a) Averaged test win rate

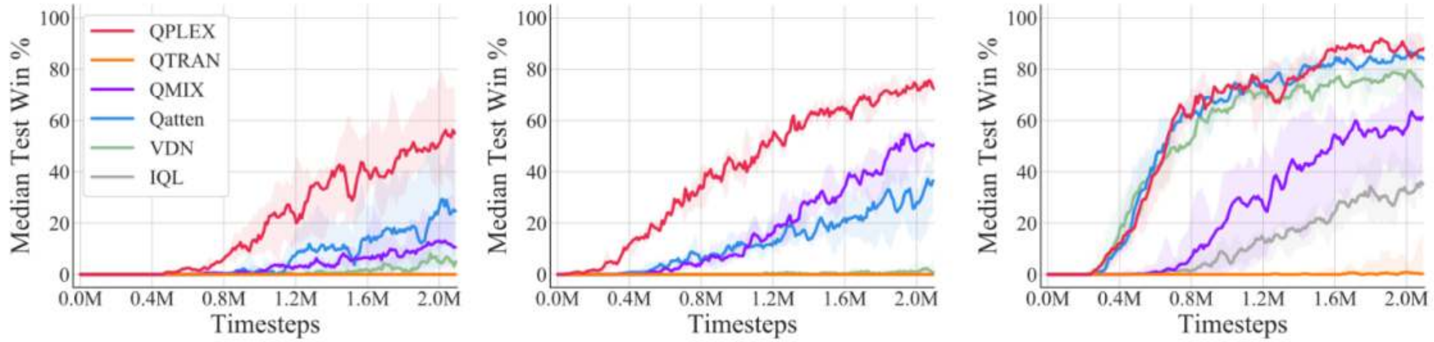
(b) # Maps best out of 17 scenarios

Figure: (a) The median test win %, averaged across all 17 scenarios. (b) The number of scenarios in which the algorithms' median test win % is the highest by at least 1/32 (smoothed).

StarCraft II Benchmark: Online Learning



(a) 5s10z (b) 1c3s5z (c) 3s5z

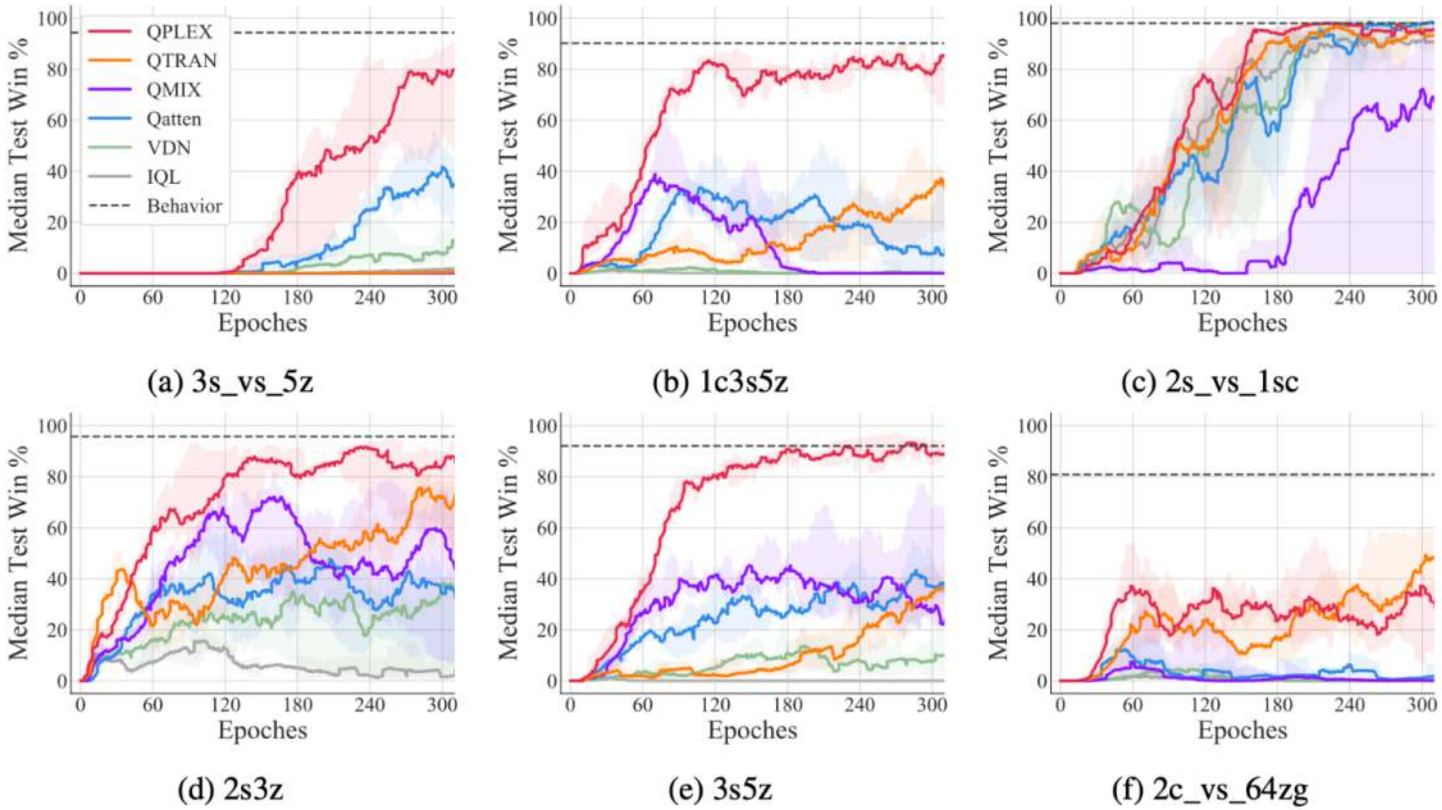


(a) 1c3s8z_vs_1c3s9z (b) 7sz (c) 3s_vs_5z

Learned Interesting Strategy in Starcraft II

StarCraft II Benchmark: **Offline Learning**

Data collected by a behavior policy learned by QMIX



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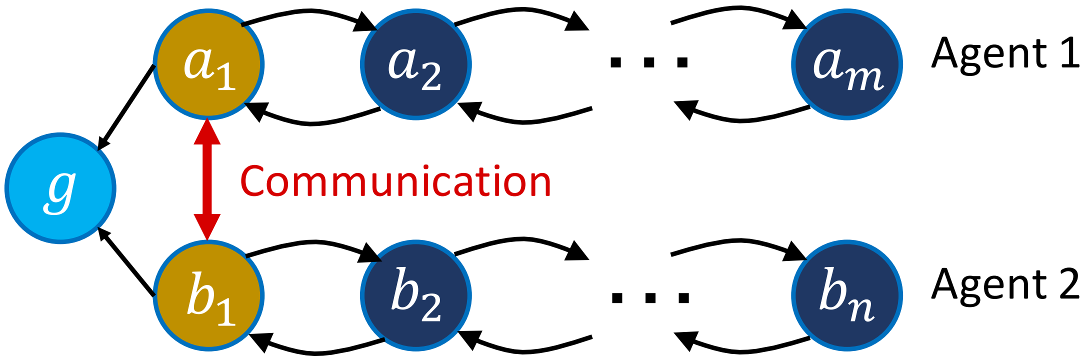
Limitations of Full Value Factorization

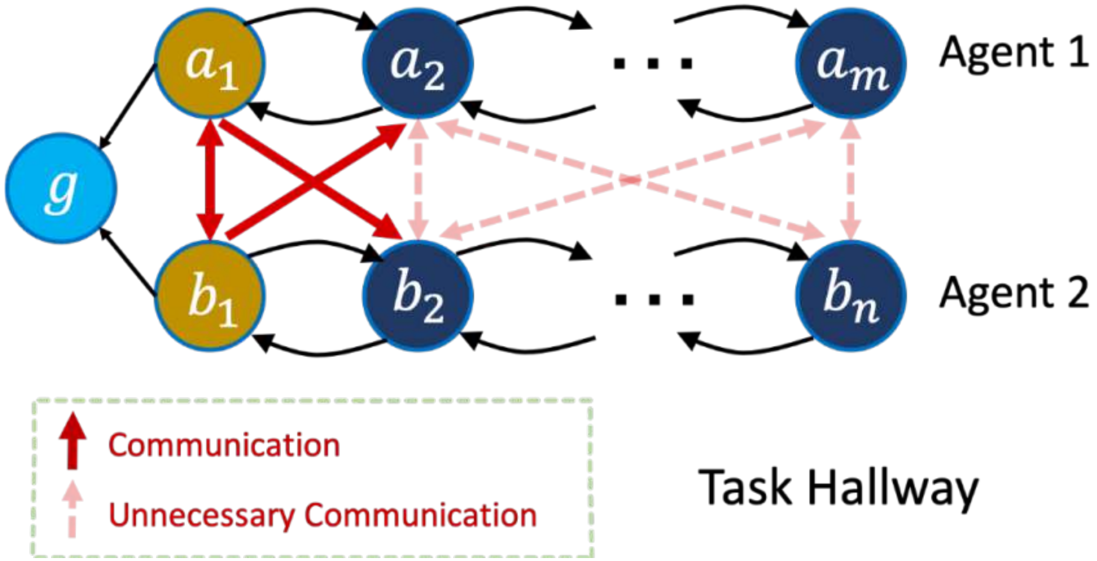
- Can cause miscoordinations during execution
  - Need Communication!



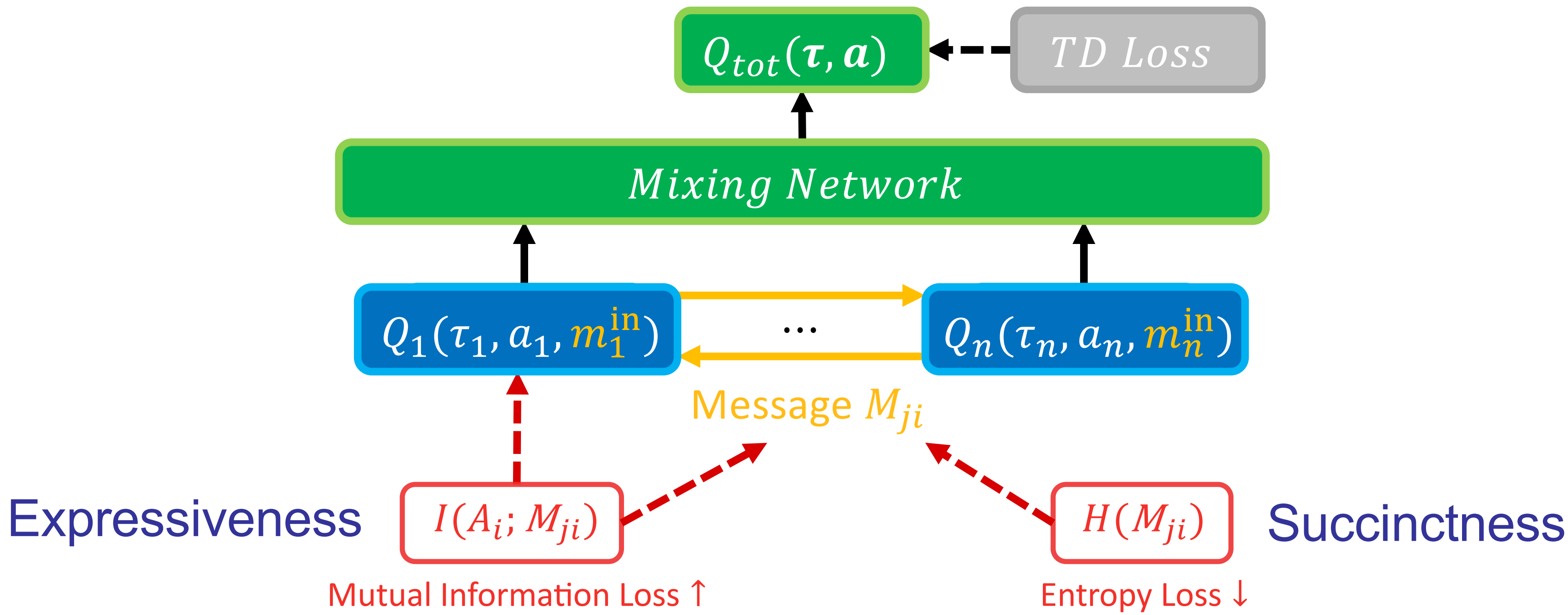
Task Hallway

Nearly Decomposable Q-Value Learning (NDQ)

- Allowing communication, but minimized
- Learn when, what, and with whom to communicate



NDQ Framework: Communication Optimization



Wang, T., Wang, J., Zheng, C. and Zhang, C., 2019. Learning nearly decomposable value functions via communication minimization. *ICLR* 2020

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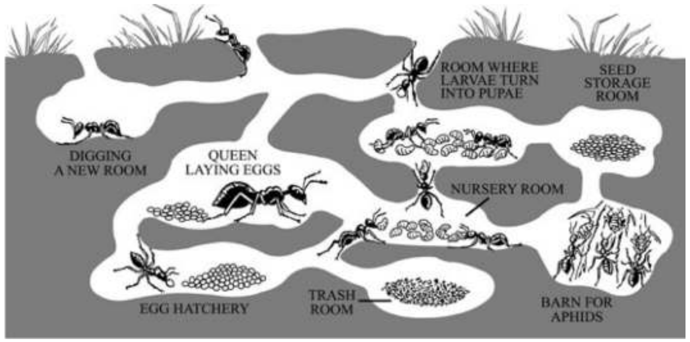
Why role-based learning?

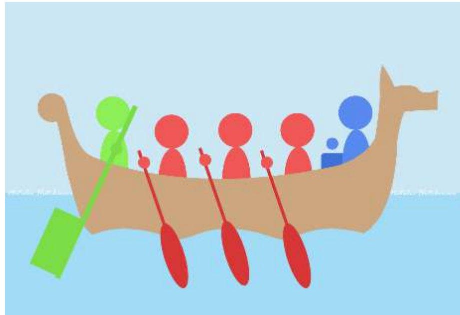
- Complex cooperative tasks require **diverse** behaviors among agents



- Learning a single shared policy network for agents[1-4]
  - Lack of diversity and requiring a high-capacity neural network
  - May result in slow, ineffective learning
- Learning independent policy networks is not efficient
  - Some agents perform similar sub-tasks, especially in large systems

[1] Rashid, et. al. QMIX: Monotonic value function factorisation for deep multi-agent reinforcement learning. (ICML 2018)
[2] Vinyals, et al. Grandmaster level in starcraft ii using multi-agent reinforcement learning. (Nature 2019)
[3] Baker, et al. Emergent tool use from multi-agent autocurricula. (ICLR 2020)
[4] Lowe, et al. Multi-agent actor-critic for mixed cooperative-competitive environments. (NeurIPS 2017)

ROMA: Multi-Agent Reinforcement Learning with Emerging Roles

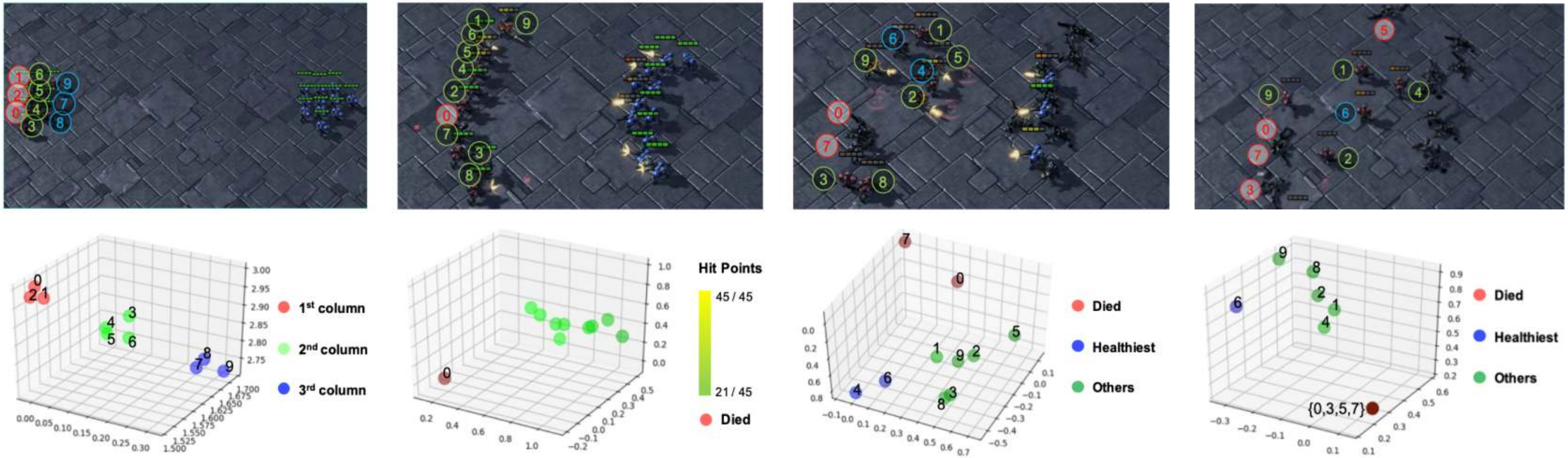


- Agents with similar roles have similar policies and share their learning
  - Similar roles ⟺ similar subtasks ⟺ similar behaviors
- Inferring an agent's roles based on the local observations and execution trajectories
- Agents learn policies conditioned on their roles
- An agent can change its roles in different situations

[ICML 2020, ICLR 2021c]

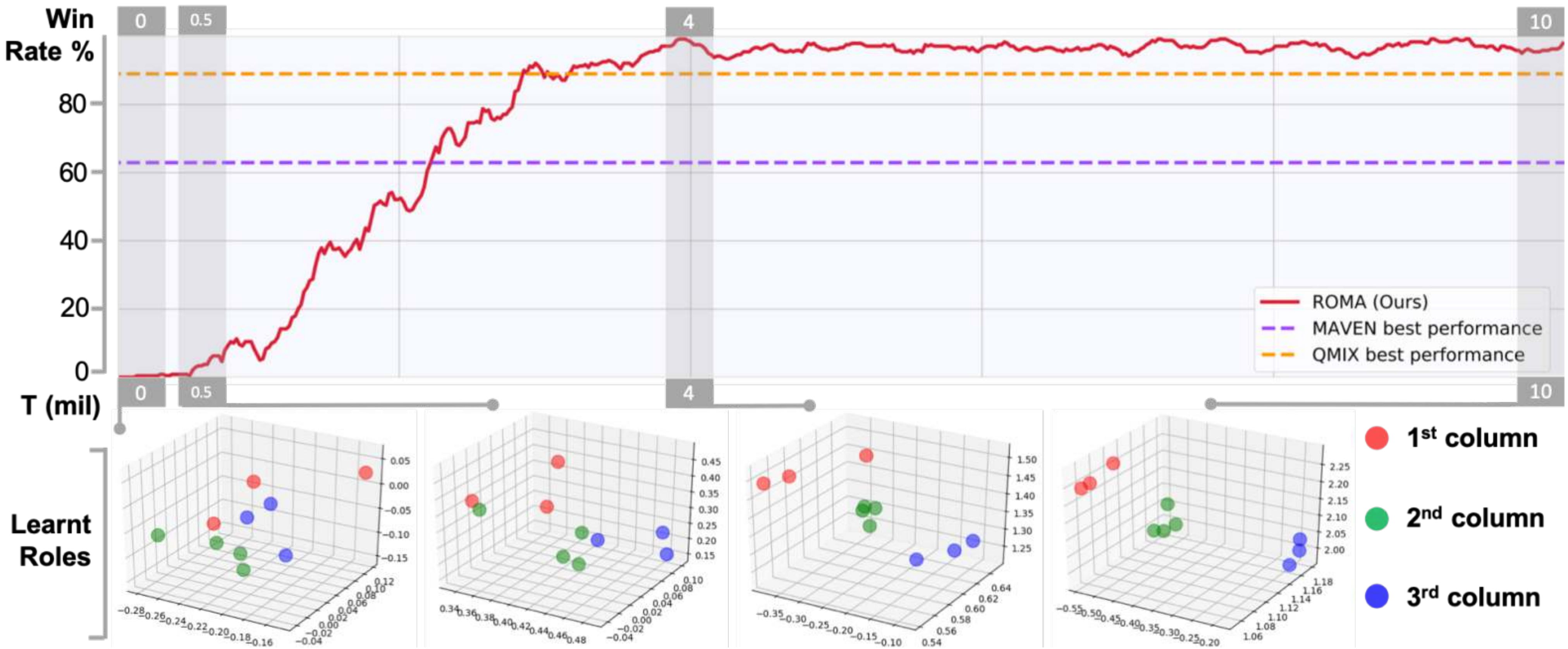
Starcraft II: 27 Marines vs 30 Marines

Dynamic Roles

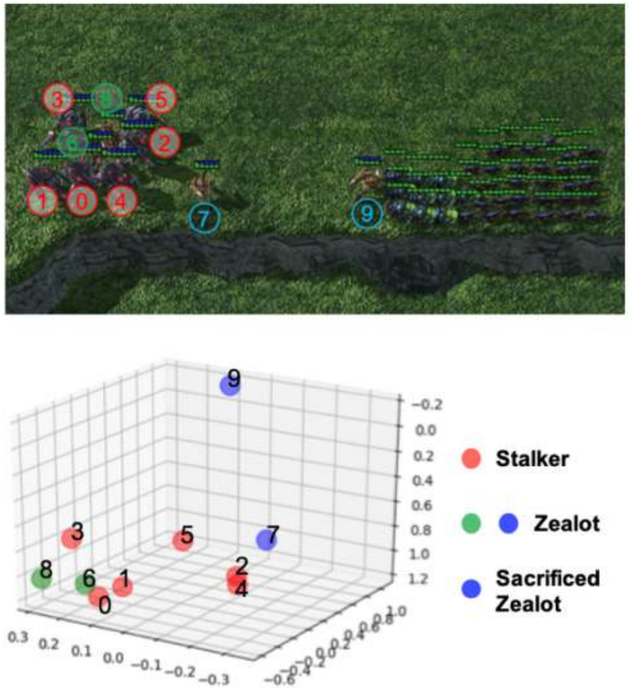


$t = 1$ $t = 8$ $t = 19$ $t = 27$

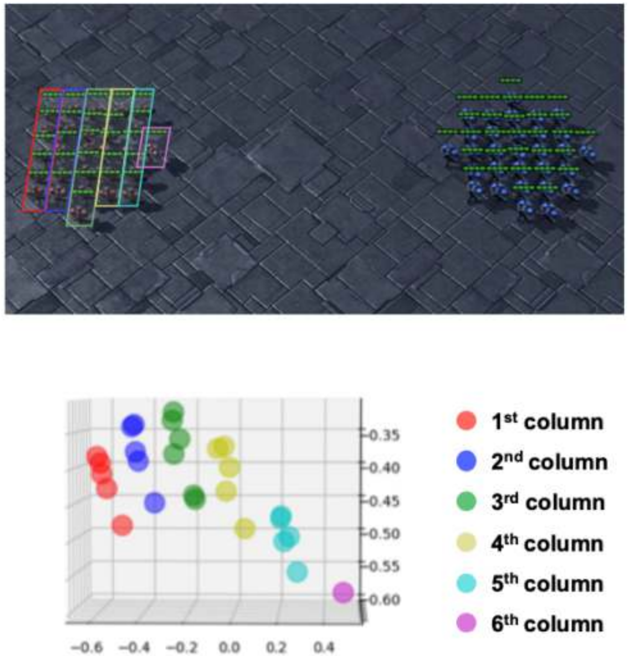
Role Emergence



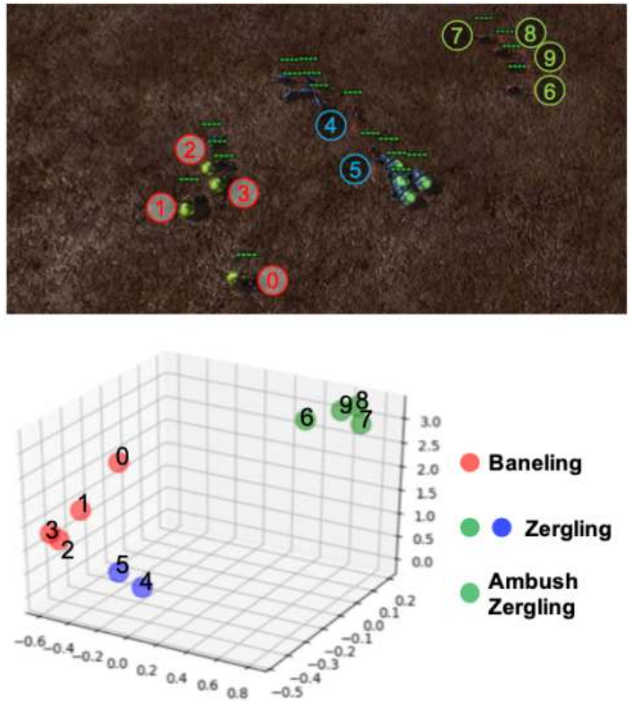
Specialized Roles



(a) Strategy: sacrificing Zealots 9 and 7 to minimize Banelings' splash damage.



(b) Strategy: forming an offensive concave arc quickly



(c) Strategy: green Zerglings hide away and Banelings kill most enemies by explosion.

Google Research Football

[Arxiv 2021]

Summary

- MARL plays a critical role for AI, but is at the early stage
- Value factorization enables scalable and effective MARL
- Communication is essential for dealing with uncertainty
- Role-based shared learning is promising for complex tasks.

- Future work:
  - Safe learning against opponents
  - Meta-learning for fast adaptation
  - Model-based MARL