SA2MA in Deep RL

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Abstract

WQMIX, QMIX, QTRAN, and VDN are SOTA algorithms for Dec-POMDP. All of them cannot solve complex agents’ cooperation domains. We give an algorithm to solve such problems. In the first stage, we solve a single-agent problem and get a policy. In the second stage, we solve the multi-agent problem with the single-agent policy. SA2MA has a clear advantage over all competitors in complex agents’ cooperative domains.

1 Introduction

RL [Wikipedia contributors, 2022d] is an area of ML concerned with how intelligent agents ought to take action in an environment in order to maximize the cumulative reward. RL algorithms aim to find a balance between exploitation and exploration.

2 Background

2.1 MDP

An MDP [Wikipedia contributors, 2022a] is a 4-tuple \((S, A, P, R)\) where \(S\) is the set of states, \(A\) is the action space, \(P\) is the probability that action \(a\) in state \(s\) will lead to the next state, \(R\) is the immediate reward received after transforming from a state to the next state. A policy function \(\pi\) is a mapping from state space to action space.

2.2 POMDP

A POMDP [Wikipedia contributors, 2022b] is a 7-tuple \((S, A, T, R, \Omega, O, \gamma)\) where \(S\) is the set of states, \(A\) is the set of actions, \(T\) is a set of transition probabilities between states, \(R\) is the reward function, \(\Omega\) is a set of observations, \(O\) is a set of observation probabilities, \(\gamma \in [0, 1]\) is the discount factor. At each time period, the environment is in some state. The agent takes an action \(a\), which causes the environment to transition to the next state with probability \(T(s|s', a)\). At the same time, the agent receives an observation \(o\) which depends on the new state of the environment, and on the just taken action \(a\), with probability \(O(o|s', a)\). Finally, the agent receives a reward \(r\) equal to \(R(s', a)\).

2.3 Dec-POMDP

A Dec-POMDP [Wikipedia contributors, 2020] is a 7-tuple \((S, \{A_i\}, T, R, \Omega_i, O, \gamma)\) where \(S\) is the set of states, \(A_i\) is the set of actions for agent \(i\), \(\{A_i\}\) is the set of joint actions, \(T\) is a set of transition probabilities between states, \(\Omega_i\) is a set of observations for agent \(i\), \(\{\Omega_i\}\) is the set of joint observations, \(O\) is a set of observation probabilities, \(\gamma \in [0, 1]\) is the discount factor. At each time step, each agent takes an action \(a\), the state updates based on the transition function \(T\), each agent observes an observation based on the observation function \(O\), and a reward is generated for the whole team based on the reward function \(R\).

2.4 Q-learning

Q-learning [Wikipedia contributors, 2022c] is a model-free RL algorithm. For any finite MDP, Q-learning finds an optimal policy in the sense of maximizing the expected value of the total reward over any and all successive steps, starting from the current state.

2.5 VDN

VDN [Sunehag et al., 2017] is a multi-agent deep RL algorithm for Dec-POMDP. VDN studies the problem of cooperative MARL with a single joint reward signal. VDN is built on purely independent DQN-style agents using a deep neural network of LSTM. The main assumption of VDN is that the joint value function of the system is decomposed into a value function of agents sum. The multi-agent Q-values formula of VDN is \(Q((h_1, h_2, ..., h_d), (a_1, a_2, ..., a_d)) \approx \sum_{i=1}^{d} \hat{Q}_i(h_i, a_i)\) where each \(\hat{Q}_i\) depends on the agent local observations.

2.6 QMIX

QMIX [Rashid et al., 2020a] is a multi-agent deep RL algorithm for Dec-POMDP. QMIX consists of agent networks representing each agent’s value function \(Q_a\), and a mixing network that combines them into the multi-agents value function \(Q_{tot}\) in a complex non-linear way that ensures consistency between the centralized and decentralized policies. QMIX ensures that global argmax performed on \(Q_{tot}\) yields the same results as a set of individual argmax operations on each \(Q_a\) by enforcing a monotonicity constraint.
2.7 QTRAN

QTRAN [Son et al., 2019] is a multi-agent deep RL algorithm for Dec-POMDP. QTRAN transforms the original joint action-value function $Q_{jt}$ into a new one $Q_{jt}^*$ that shares the optimal joint action with $Q_{jt}$.

2.8 WQMIX

Weighted QMIX [Rashid et al., 2020b] is a multi-agent deep RL algorithm for Dec-POMDP. WQMIX is based on QMIX but adds weights to the loss in two versions. This weighted projection allows more emphasis to be placed on better joint actions. CW QMIX down-weights every suboptimal action and OW QMIX assigns a higher weight to joint actions that are underestimated relative to Q.

2.9 Curriculum Learning

Curriculum learning [Narvekar et al., 2020] is a 3-part approach consisting of task generation, sequencing, and transfer learning. Task generation is the problem of creating intermediate tasks to be part of a curriculum. As sequencing, DQN [Mnih et al., 2013] uses a reply buffer to store past state action reward experience tuples. In transfer learning, the agent is first trained on source tasks and transferred the knowledge acquired to aid in solving the target.

Co-learning

Co-learning [Narvekar et al., 2020] is a multi-agent curriculum learning in which agents interact with each other in the environment to make learning. AlphaGo [Silver et al., 2017] uses self-play to speed up the learning process. AlphaGo is focused on the game of Go but SA2MA focuses on collaborative multi-agent problems.

Robust adversarial RL

Asymmetric self-play [Sukhbaatar et al., 2017] focuses on a game of hide and seek [Sukhbaatar et al., 2017]. The Hiders must hide, while the Seekers must find the Hiders. Both teams must use the physics rules of the game. The authors show that as one team converged on a successful strategy, the other team was pressured to learn a counter-strategy. This process was repeated. Asymmetric self-play uses a multi-agent policy for the multi-agent training while SA2MA uses a single-agent policy.

Collaborative MARL

CM3 [Yang et al., 2018] is a two-stage approach. In the first stage, a single agent is trained without the presence of other agents. This is done by inducing a new MDP that removes all dependencies on agent interactions and training a network on this subspace. In the second stage, cooperation is learned by adding the parameters for the other agents into the network. CM3 chooses a single agent out of all agents for training and adds the parameters for the other agents into the network while SA2MA trains a single-agent problem for actions choosing in the multi-agent problem.

3 Algorithm

3.1 Mapping

A multi-agent problem has a multi-agent actions vector, multi-agent observations vector, and multi-agent task. In the multi-agent problem, all agents have the same actions and all agents have the same observation variables. A team problem is a single-agent problem with a single-agent actions vector, single-agent observations vector, and single-agent task. For the mapping, in the single-agent problem, the agent actions are the same actions of each agent from the multi-agent problem, and the agent observation variables are the same as each agent from the multi-agent problem.

3.2 Curriculum Learning

We use curriculum learning for our algorithm. In the task the generation we take the multi-agent problem and make a new single-agent team problem. In sequencing, we solve a single-agent team problem and output a policy $\pi$ for solving the multi-agent problem. In transfer learning, in the multi-agent problem, we chose an action by a policy sample from $\pi$ in probability $\alpha$.

3.3 SA2MA

First, solve the single-agent problem using WQMIX and output a policy $\pi$. Then train the multi-agent problem with the policy $\pi$.

3.4 Actions chose

At episode run, we choose an action from the single agent policy $\pi$ or from the WQMIX actions-selector. In probability $\alpha$ we chose actions from the policy $\pi$, otherwise from WQMIX actions-selector.

3.5 Mapping

We iterate over all agents. For each agent, we get the corresponding single-agent state and observation, sample a single-agent policy $\beta$ from $\pi$, and get a single-agent action. Then we map the single-agent action into a multi-agent action and save the action. Finally, we return all actions.

4 Domains

4.1 Box-pushing

Multiple agents are located in a grid, the state is the agents’ location, and the observations are the boxes’ locations. Each agent has an action of moving left and right, a sense action to get the box location, and a stochastic push action to push the box. The agents will succeed in pushing the box only if both are located at the box location and both make the push action at the same time. The target is to push all the boxes to the edge.

Box-pushing collaborative

A box pushing with an additional collaborative constraint for the sense action which allowed only collaboratively.

Box-pushing stochastic

A box pushing collaborative with an additional noise for the sense action.
4.2 Rock-sample
Multiple agents in a grid, the state is the agents’ location, and the observations are the rocks’ locations and conditions. The agents have an action of moving left and right, a sense action to get the rocks’ location and condition, and a sample action to sample a rock. The agents will succeed in sampling a rock only if both of them are located at the rock location and both of them make the sample action at the same time. The target is to sample all the rocks that are in good condition.

Rock-sample stochastic
A rock sample with an additional noise for the sense action.

4.3 Predator-prey
Multiple agents in a grid, the state is the agents’ location, and the observations are the prey’s locations. The agents have an action of moving left and right, a sense action to get locations of preys, and a stochastic hunt action to hunt prey. The agents will succeed in hunting prey only if both of them are located at the prey location and both of them make the hunt action at the same time. The target is to hunt all the prey.

5 Results
Each experiment is composed of 5 different random experiments. Each graph is composed of solid lines and shaded lines. A solid line is the experiment’s mean. The shaded lines are the experiments’ mean plus standard error and mean minus standard error. Each experiment has two graphs. The left graph is a single-agent experiment of SA2MA. The right graph is a multi-agent experiment of all algorithms.

5.1 Box-pushing
Grid size 3, total agents 2, total boxes 1
The single-agent problem has converged at the 80K time step. In the multi-agent problem, SA2MA has converged at 600K time step. QMIX at 800K, OW QMIX, CW QMIX, QMIX, QTRAN, and VDN have not converged.

Box-pushing collaborative
Grid size 3, total agents 2, total boxes 1
The single-agent problem has converged at 70K time step. In the multi-agent problem, Single-agent to multi-agent has been converged at 600K time step, OW QMIX, CW QMIX, QMIX, QTRAN, and VDN have not converged.

Box-pushing stochastic
Grid size 3, total agents 2, total boxes 1
The single-agent problem has converged at 80K time step. In the multi-agent problem, SA2MA has been converged at 600K time step, OW QMIX, CW QMIX, QMIX, QTRAN, and VDN have not converged.

Box-pushing stochastic collaborative
Grid size 3, total agents 2, total boxes 1
The single-agent problem has converged at an 80K time step. In the multi-agent problem, Single-agent to multi-agent has been converged at 600K time step, OW QMIX, CW QMIX, QMIX, QTRAN, and VDN have not converged.

Rock-sample
Grid size 5, total agents 2, total rocks 2
The single-agent problem has converged at 30K time step. In the multi-agent problem, SA2MA has converged at 600K time step. QMIX at 800K, OW QMIX, CW QMIX, QTRAN, and VDN have not converged.

Rock-sample stochastic
Grid size 3, total agents 2, total rocks 2
The single-agent problem has converged at a 30K time step. The multi-agent problem has been converged at a 600K time step with VDN, SA2MA, OW QMIX, and QMIX at 900K. QTRAN has been not converged.
The single-agent problem has converged at a 70K time step. The multi-agent problems have converged at 300K with QMIX and VDN, 600K with SA2MA and has been not converged with QTRAN, OW QMIX, and CW QMIX.

**Rock-sample stochastic**
Grid size 4, total agents 2, total rocks 2

The single-agent problem has converged at a 60K time step. The multi-agent problem has converged at 300K with VDN and QMIX, at 600K with SA2MA, and has not converged with OW QMIX, CW QMIX, or QTRAN.

**Predator-prey**
Grid size 2, total agents 2, total preys 1

The single-agent problem has converged at a 40K time step. The multi-agent problem has converged at 200K steps with OW QMIX, QMIX, VDN, and QTRAN but has not converged with SA2MA or OW QMIX.

6 Discussion

6.1 Average rewards
SA2MA has a clear advantage on box-pushing domains which require complex agents’ cooperation but has no advantage on rock-sample or predator-prey which do not. The optimal policy for box-pushing is for both agents to make sense, then both agents to move to the box location, then both agents to push the box collaboratively while moving right repeatedly. The optimal policy of predator-prey is both agents make sense, then both agents move to the prey location and hunt it collaboratively. The optimal policy of rock-sample is for both agents to make sense, then both agents move to the location of the good rock and sample it collaboratively.

6.2 Policies quality
SA2MA has a clear advantage in policy quality on box-pushing domains. SA2MA recovers the optimal policy in all the box-pushing domains. There is only one case for the competitors to recover the optimal policy on the box-pushing domain which is done by QMIX. SA2MA has no clear advantage on policy quality on rock sample domains or predator-prey. At rock-sample domains, SA2MA, VDN, and QMIX recover the optimal policy. At the predator-prey CW QMIX, QMIX, VDN, and QTRAN recover the optimal policy but SA2MA and OW QMIX do not.

7 Conclusion
SA2MA has a clear advantage in complex agents collaboration domains over all competitors.

The advantage is based on the complexity gap between the single-agent problem to the multi-agent. Solving a single-agent problem requires much fewer resources than solving a multi-agent problem.

8 Further work
SA2MA has been not tested on domains with heterogeneous agents.

9 Source code
https://github.com/nitsansoffair/rwqmix/tree/heuristics_plus

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