Single-agent to Multi-agent in Deep Reinforcement-learning

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Abstract—OW QMIX, CW QMIX, QTRAN, QMIX, and VDN are the state-of-the-art algorithms for solving Dec-POMDP domains. OW QMIX, CW QMIX, QTRAN, QMIX, and VDN failed to solve complex agents' cooperation domains such as box-pushing. We give a 2-stage algorithm to solve such problems. On 1st stage we solve single-agent team $\rho_{team}$ problem (POMDP) and get an optimal policy traces $\pi_{single}$. On 2nd stage we solve multi-agent $\rho_{multi}$ problem (Dec-POMDP) with the single-agent optimal policy traces $\pi_{single}$.

Single-agent to multi-agent has a clear advantage over OW QMIX, CW QMIX, QTRAN, QMIX, and VDN on complex agents' cooperative domains.

Keywords—Deep-learning, Deep reinforcement-learning, Machine-learning, Multi-agent reinforcement-learning

I. INTRODUCTION

Reinforcement learning [10] is an area of machine learning concerned with how intelligent agents ought to take actions in an environment in order to maximize the notion of cumulative reward. Reinforcement learning [12] does not require labeled data to make learning. Reinforcement learning algorithms aim to find a balance between exploration and exploitation. A Markov decision-process (MDP) deals with a single agent on a fully-observable world. A Partially-observable Markov decision process (POMDP) deals with a single agent on a partially-observable world. A decentralized partially-observable Markov decision process (Dec-POMDP) deals with a multi-agent on a partially-observable world.

II. BACKGROUND

A. Markov decision process (MDP)

A Markov decision process [14] is a 4-tuple $(S, A, p_a, R_a)$ where

- $S$ is the state space
- $A$ is the action space
- $p_a(s, s') = Pr(s_{t+1} = s'|s = s, a_t = a)$ is the probability that action $a$ in state $s$ at time $t$ will lead to state $s'$ at time $t + 1$
- $R_a(s, s')$ is the immediate reward received after transitioning from state $s$ to state $s'$, due to action $a$

A policy function $\pi$ is a mapping from state space to action space.

B. Partially observable Markov decision process (POMDP)

A discrete-time POMDP [16] models the relationship between an agent and its environment. Formally, a POMDP is a 7-tuple $(S, A, T, R, \Omega, O, \gamma)$, where

- $S$ is a set of states
- $A$ is a set of actions
- $T$ is a set of conditional transition probabilities between states
- $R: S \times A \rightarrow R$ is the reward function
- $\Omega$ is a set of observations
- $O$ is a set of conditional observation probabilities
- $\gamma \in [0, 1]$ is the discount factor

At each time period, the environment is in some state $s \in S$. The agent takes an action $a \in A$, which causes the environment to transition to state $s'$ with probability $T(s'|s, a)$. At the same time, the agent receives an observation $o \in O$ which depends on the new state of the environment, $s'$, and on the just taken action $a$, with probability $O(o|s', a)$.

Finally, the agent receives a reward $r$ equal to $R(s, a)$.

C. Decentralized partially observable Markov decision process (Dec-POMDP)

A Dec-POMDP [15] is a 7-tuple $(S, \{A\}, T, R, \{\Omega\}, O, \gamma)$, where

- $S$ is a set of states
- $A_i$ is a set of actions for agent $i$, with $A_i = \times A_i$ is the set of joint actions
- $T$ is a set of conditional transition probabilities between states, $T(s, a, s') = P(s'|s, a)$
- $R: S \times A \rightarrow R$ is the reward function
- $\Omega_i$ is a set of observations for agent $i$, with $\Omega = \times \Omega_i$
- $O$ is a set of conditional observation probabilities $O(o|s', a)$
- $\gamma \in [0, 1]$ is the discount factor

At each time step, each agent takes an action $a_i \in A_i$, the state updates based on the transition function $T(s, a, s')$, each agent observes an observation based on the observation function $O(s', a, o)$ and a reward is generated for the whole team based on the reward function $R(s, a)$.

D. Q-learning

Q-learning [11] is a model-free reinforcement learning algorithm. It does not require a model of the environment, and it can handle problems with stochastic transitions and rewards without requiring adaptations. For any finite Markov decision process (FMDP), 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.

1. Initialize $Q(s, a), \forall s \in S, a \in A(s)$ arbitrarily.
2. Initialize $Q(terminal - state, \cdot) = 0$.
3. For each episode do
   a. Initialize $S$.
   b. Chose $A$ from $S$ using policy derived from $Q$.
   c. Take action $A$, observe $R, S'$.
   d. $Q(S, A) \leftarrow Q(S, A) + \alpha[R + \gamma \max_{a} Q(S', a) - Q(S, A)]$
   e. $S \leftarrow S'$.
4. Until $S$ is terminal.

E. Value decomposition network (VDN)

VDN [1] is a multi-agent deep reinforcement-learning 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 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 agent sum known as additivity. The multi-agent Q-values formula of VDN is:

$$Q(h_1, h_2, ..., h_d, (a_1, a_2, ..., a_d)) = \sum_{i=1}^{d} \hat{Q}_i(h_i, a_i)$$

Where each $\hat{Q}_i$ depends on the agent's local observations.

F. QMIX

Q MIX [2] is a multi-agent reinforcement-learning algorithm for Dec-POMDP. QMIX is inspired by agent networks representing each $Q_a$, and a mixing network that combines them into $Q_{tot}$ 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 same results as a set of individual argmax operations on each $Q_a$ by enforcing the monotonicity constraint of $\frac{\partial Q_{tot}}{\partial Q_a} \geq 0, \forall a$. QMIX agent's network is DRQN-style and receives single observation and action. The mixing network is a feedforward neural-network that receives agent network output, mixing them monotonically producing $Q_{tot}$. QMIX hypernetwork takes state as input producing mixing network layer weights, and consists of a single linear layer, and then absolute activation function.

G. QTRAN

QTRAN [3] is a multi-agent deep reinforcement-learning algorithm for Dec-POMDP. QTRAN consists of 3 deep neural-networks: joint action value, individual action value, and state value. QTRAN transforms the original joint action value function $Q_{jt}$ to $Q'_{jt}$ to share optimal joint actions with $Q_{jt}$. $Q'_{jt}$ formula is $Q'_{jt}(\tau, u) = \sum_{i=1}^{N} Q_{jt}(\tau, u_i)$.

QTRAN state-value network is a duel network that takes state as input produces the state-value as output. QTRAN combines 3 loss functions by weights: $L_{td}$ the td-error loss, and $L_{opt}$ and $L_{opt}$ losses for factoring $Q_{jt}$ by $Q$. QTRAN uses the DQN algorithm to update networks.

H. Weighted QMIX

Weighted QMIX [4] is a multi-agent deep reinforcement-learning algorithm for Dec-POMDP. Weighted QMIX is based on QMIX, adding weights to the loss with 2 different versions. This weighted projection allows more emphasis to be placed on better joint actions. The Weighted QMIX projection operator is:

$$\pi_{w} Q := argmin_{q \in Q^{min}} \sum_{u \in U} w(s, u)(Q(s, u) - q(s, u))^2$$

Idealized-Centrally Weightening (CW) down-weight every suboptimal action. Optimistic-Weighting (OW) assigns a higher weighting to joint actions that are underestimated relative to $Q$.

I. Curriculum Learning

Curriculum learning [9] 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. DQN [5] 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.

1) Co-learning

Co-learning [9] is a multi-agent curriculum learning in which agents’ interacts each other in the environment to make learning. AlphaGo [6] uses self-play to speed up the learning process. AlphaGo is focused on the game of Go. Single-agent to multi-agent algorithm focuses on general collaborative multi-agent problems.

2) Robust Adversarial Reinforcement learning (RAL)
   a) Hide and seek

Asymmetric self-play [7] focuses on a game of hiding and seek [9]. The Hiders must hide, while the Seekers must find the Hiders. Both teams must use the game’s physics rules. 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 multi-agent policy for multi-agent problem training. Single-agent to multi-agent uses single-agent policy traces for multi-agent problem training.
3) Collaborative Multi-agent reinforcement learning (MARL)
CM3 [8] takes 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. Then in the second stage, cooperation is learned by adding the parameters for the other agents into the network. CM3 choses a single agent out of all agents for training and then adds the parameters of the other agents into the neural-network.
Single-agent to multi-agent uses a single-agent team problem for training and then uses the optimal single-agent team policy traces for the multi-agent problem actions' choosing.

III. Algorithm
A multi-agent problem $p_{\text{multi}}$ which modeled as Dec-POMDP has the following components
- Multi-agent actions vector
- Multi-agent observations vector
- Multi-agent task
The multi-agent problem has the following
1. All agents have the same actions
2. All agents have the same observation variables
A team problem $p_{\text{team}}$ is a single-agent problem which modeled as POMDP has the following components
- Single-agent actions vector
- Single-agent observations vector
- Single agent task
The single-agent problem has the following
1. The agent actions is the same actions of each agent of the multi-agent problem
2. The agent observation variables are the same observation variables of each agent of the multi-agent problem

We use curriculum learning for our algorithm. As task generation we take the existing problem of multi-agent problem defined as Dec-POMDP and make a new problem of single-agent team problem defined as POMDP.

As sequencing we do the following order
1. Solve single-agent team problem defined as POMDP and output a policy traces $\pi_{\text{team}}$.
2. Solve the multi-agent problem defined as Dec-POMDP with policy traces $\pi_{\text{team}}$.

As transfer-learning in the the multi-agent problem we chose an action by a sampled policy from $\pi_{\text{team}}$ policy traces in probability of $\alpha$ where $0 < \alpha < 1$.

A. Single-agent to multi-agent
We solve the single-agent problem using Weighted QMIX and get a policy traces $\pi_{\text{team}}$ as output. We initialize $\alpha$ as the probability of the multi-agent model to choose an action by a sampled policy $\beta$ from $\pi_{\text{team}}$ policy traces. We train the multi agent model with $\pi_{\text{team}}$ policy traces.

1. $\pi = (a, s, o, r) = solve - \text{team()}$
2. while $\text{steps} < \text{total steps do}$
   a. $a_{\text{single}} = \text{true by probability $\alpha$}$
   b. run - episode($a_{\text{single}}$, $\pi$)
   c. for index in range($n - \text{training}$) do
      i. batch = buffer.sample()
      ii. train(batch)

B. Run episode
An episode runs until it terminates by getting an indicator from the environment. At episode running we chooses an action by single agent policy traces $\pi_{\text{team}}$ and by the model actions-selector. On probability $\alpha$ we chose actions with $\pi_{\text{team}}$ policy traces, on probability $1 - \alpha$ we chose actions with a model actions-selector. Finally we return the tuple and the total episode rewards.

1. while not terminated do
   a. update - buffer(s, available - actions, o)
   b. if single - agent - action
      i. actions = select - sa - actions($\pi$)
   else
      i. actions = select - actions()
   d. $r, t = env.\text{step(actions)}$
   e. update - buffer(actions, r, t)
2. update - buffer(s, available - actions, o)

C. Select single-agent actions
We initiate an empty vector of actions actions. We loop over each agent from the total agents. The multi agent state is $s_{\text{multi}}$. The multi agent observation is $o_{\text{multi}}$. We sample a random single agent policy $\beta$ from $\pi_{\text{team}}$. We get the corresponding single agent state $s_i$ for $s_{\text{multi}}$. We get the corresponding single agent observation $o_i$ for $o_{\text{multi}}$. We get the single agent action $a_{i, \text{single}}$ for $s_i, o_i$ and $\beta$. We get the corresponding multi-agent action $a_{i, \text{multi}}$ for $a_{i, \text{single}}$. We append $a_{i, \text{multi}}$ to actions.
1. \[ \text{actions} = \text{empty vector at size of } n - \text{agents} \]
2. \[ \text{for } \text{agent} = \text{index in range}(n - \text{agents}) \text{ do} \]
   a. \[ \beta = \pi.\text{sample}() \]
   b. \[ \text{action} = \text{get - ma - action}() \]
   c. \[ \text{actions.append(action)} \]
3. \[ \text{return actions} \]

IV. Domains
A. Box-pushing
2-agent in a 1-dimensional grid with a state of agents' location and an initial hidden observation of a randomized boxes' location. The agent has an action of move-left and move-right for moving in the grid, a sense action to get the boxes location, and a push action to push the box left. The agents will succeed in pushing the box only if both of them are located at the box location and both of them make the push action at the same time step. The agent's target is to push all the boxes to the right grid edge. The agents get a prize of -1 for each action, a penalty of -10 for taking a push action where one of them is not at the box location, and a prize of 10 if the box is reached to the right grid edge. push action is a stochastic action with probability of success of .8. The grid size is 3. The total boxes is 1.

1) Box-pushing collaborative
   Identical to box pushing with an additional collaborative action of sense.

2) Box-pushing stochastic
   Identical to box pushing with an additional stochastic action of sense with a success probability of .8.

B. Rock-sample
2-agent in a 1-dimensional grid with a state of agents' location and an initial hidden observation of randomized rocks' locations and conditions. The agents have an action of move-left and move-right for moving in the grid, a sense action to get the rocks' location and condition, and a sample action to sample the rock. The agents will succeed sampling the rock only if both of them are located at the rock location and both of them make the sample action at the same time step. The agent's target is to sample all the rocks in good condition. The agents get a prize of -1 for each action, a penalty of -10 for taking a sample action where one of them is not at the rock's location, and a prize of 10 for a good rock's sample. The grid size 5. The total of rocks is 2.

1) Rock-sample stochastic
   Identical to rock-sample with a stochastic sense action. The grid sizes are 3 and 4.

C. Predator-prey
2-agent in a 1-dimensional grid with a state of agents' location and an initial hidden observation of a randomized preys' location. The agents have an action of move-left and move-right for moving in the grid, a sense action to get the prey's location, and a hunt action to hunt the prey. The agents will succeed in hunting the prey only if both of them are located at the prey location and both of them make the hunt action at the same time step. The agents' target is to hunt all the prey. The agents get a prize of -1 for each action, a penalty of -10 for taking a hunt action where one of them is not at the prey's location, and a prize of 10 if a prey is hunted. The hunt action is a stochastic action with a success probability of .8. The grid size is 2. The total prey is 1.

V. Results
Each experiment is composed from 5 different random experiments. Each graph is composed of solid lines and shaded lines. A solid line is the mean. The shaded lines are mean plus standard error and mean minus standard error. Each experiment gives 2 different graphs. The left graphs are single-agent problems of Single-agent to multi-agent. The right graphs are multi-agent problems of Single-agent to multi-agent, OW QMIX, CW QMIX, QTRAN, QMIX, and VDN.

A. Box-pushing
Grid size 3, total agents 2, total boxes 1

Single-agent problem has converged at an 80K time step from Single-agent to multi-agent. Multi-agent problem Single-agent to multi-agent has been converged at 600K time step. Multi-agent problem QMIX has been converged at 600K time step. Multi-agent problems OW QMIX, CW QMIX, QTRAN, and VDN have not converged. There is a clear advantage to Single-agent to multi-agent over competitors.

1) Box-pushing collaborative
Grid size 3, total agents 2, total boxes 1
Single-agent problem has converged at a 50K time step from Single-agent to multi-agent. Multi-agent problem Single-agent to multi-agent has been converged at 600K time step. Multi-agent problems OW QMIX, CW QMIX, QMIX, QTRAN, and VDN have not converged. There is a clear advantage to Single-agent to multi-agent over competitors.

2) Box-pushing stochastic
Grid size 3, total agents 2, total boxes 1

Single-agent problem has converged at a 70K time step from Single-agent to multi-agent. Multi-agent problem Single-agent to multi-agent has been converged at 600K time step. Multi-agent problems OW QMIX, CW QMIX, QMIX, QTRAN, and VDN have not converged. There is a clear advantage to Single-agent to multi-agent over competitors.

3) Box-pushing stochastic collaborative
Grid size 3, total agents 2, total boxes 1

Single-agent problem has converged at an 80K time step from Single-agent to multi-agent. Multi-agent problem Single-agent to multi-agent has been converged at 600K time step. Multi-agent problems OW QMIX, CW QMIX, QMIX, QTRAN, and VDN have not converged. There is a clear advantage to Single-agent to multi-agent over competitors.

B. Rock-sample
Grid size 5, total agents 2, total rocks 2

Single-agent problem has converged at a 30K time step from Single-agent to multi-agent. Multi-agent problem has been converged at a 600K time step from VDN. Multi-agent problems have converged at a 900K time step from Single-agent to multi-agent, OW QMIX, and QMIX. The multi-agent problem has not converged from QTRAN. There is no clear advantage to Single-agent to multi-agent over competitors.

1) Rock-sample stochastic
Grid size 3, total agents 2, total rocks 2

Single-agent problem has converged at a 70K time step from Single-agent to multi-agent. Multi-agent problems have been converted at 300K from QMIX, and VDN. The Multi-agent problem has converged at 600K from Single-agent to multi-agent. Multi-agent problem has not converged from QTRAN, OW QMIX, and CW QMIX. There is no clear advantage to Single-agent to multi-agent over competitors.

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

Single-agent problem has converged at a 60K time step from Single-agent to multi-agent. Multi-agent problem has been converged at 300K from VDN, and QMIX. The Multi-agent problem has converged at 600K from Single-agent to multi-agent. Multi-agent problem has not converged from OW QMIX, CW QMIX, and QTRAN. There is no clear advantage to Single-agent to multi-agent.

C. Predator-prey
Grid size 2, total agents 2, total preys 1

Single-agent problem has converged at a 40K time step from Single-agent to multi-agent. Multi-agent problem has been converged at 200K steps from OW QMIX, QMIX, VDN, and QTRAN. Multi-agent problem has not converged from
Single-agent to multi-agent, and OW QMIX. Single-agent to multi-agent has no clear advantage over competitors.

VI. Discussion
A. Average rewards
Single-agent to multi-agent has a clear advantage on box-pushing domains. Single-agent to multi-agent has no advantage on rock-sample and predator-prey domains. Box-pushing domains require complex agents' cooperation. The optimal policy is both agents sense, then both agents move to the box location, and then both agents push the box collaboratively and move right repeatedly. Predator-prey and rock-sample do not require complex agents' cooperation. The optimal policy of predator prey is both agents sense, then both agents move to the prey location and hunt it collaboratively. The optimal policy of rock-sample is both agents sense, then both agents move to the good rock location and sample it collaboratively.

B. Policies quality
Single-agent to multi-agent has a clear advantage on policy quality on box-pushing domains. Single-agent to multi-agent recover the optimal policy on all the box-pushing domains. There is only 1 case for competitors to recover the optimal policy on box-pushing domain from QMIX. Single-agent to multi-agent has no clear advantage on policy quality on rock sample and predator-prey domains. At rock-sample domains all Single-agent to multi-agent, VDN and QMIX recover the optimal policy. At predator-prey domain CW QMIX, QMIX, VDN, and QTRAN recover a stable optimal policy but Single-agent to multi-agent, and OW QMIX recover a not stable optimal policy.

VII. Conclusion
Single-agent to multi-agent has a clear advantage on complex agents' collaboration domains over CW QMIX, OW QMIX, QTRAN, QMIX, and VDN.

The advantage of Single-agent to multi-agent-based on the complexity gap between single-agent problems to multi-agent problems. Solving a single-agent team problem requires much less resources than solving a multi-agent problem.

VIII. Further work
Single-agent to multi-agent has not been tested on domains with heterogeneous agents. To give good results we suggest training it on multiple single-agent problems, one problem for each agent, and then apply a transfer-learning through action choosing.

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

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