Offline Pre-trained Multi-Agent Decision Transformer

Anonymous authors
Paper under double-blind review

Abstract

Offline reinforcement learning leverages static datasets to learn optimal policies with no necessity to access the environment. This is desirable for multi-agent systems due to the expensiveness of agents' online interactions and the demand for sample numbers. Yet, in multi-agent reinforcement learning (MARL), the paradigm of offline pre-training with online fine-tuning has never been reported, nor datasets or benchmarks for offline MARL research are available. In this paper, we intend to investigate whether offline training is able to learn policy representations that elevate performance on downstream MARL tasks. We introduce the first offline dataset based on StarCraftII with diverse quality levels and propose a *multi-agent decision transformer* (MADT) for effective offline learning. MADT integrates the powerful temporal representation learning ability of Transformer into both offline and online multi-agent learning, which promotes generalisation across agents and scenarios. The proposed method demonstrates superior performance than the state-of-the-art algorithms in offline MARL. Furthermore, when applied to online tasks, the pre-trained MADT largely improves sample efficiency, even in zero-shot task transfer. To our best knowledge, this is the first work to demonstrate the effectiveness of pre-trained models in terms of sample efficiency and generalisability enhancement in MARL.

1 Inrtoduction

Multi-Agent reinforcement learning (MARL) plays an essential role for solving complex decision-making tasks by learning from the interaction data between machine or autonomous agents and simulated physical environments. It typically applies to self-driving (Shalev-Shwartz et al., 2016), traffic control (Bazzan, 2009), and recommendation system (Xian et al., 2019), and, to specifically mention, surpasses human beings on some video games (Bellemare et al., 2013; Wang et al., 2020). However, the experience-based policy learning scheme requires the algorithms with high sample efficiency because of the limited computing resources and high cost resulting from the data collection (Haarnoja et al., 2018; Munos et al., 2016; Espeholt et al., 2019; 2018). Furthermore, even in domains where the online environment is feasible, we might still prefer to utilize previously collected data instead, for example, if the domain's complex requires large datasets for effective generalization. In addition, a policy trained on one scenario usually cannot perform well on another even though under the same task. Therefore, a universal policy is critical for saving the training time of general reinforcement learning. Offline RL (Levine et al., 2020) attracts more researchers motivated by improving online reinforcement learning with offline datasets (Fu et al., 2020). Those methods like CQL (Kumar et al., 2020), BEAR (Kumar et al., 2019), and BCQ (Fujimoto et al., 2019) conventionally leverage the current off-policy RL algorithms, e.g., DQN (Mnih et al., 2015), with provable constraints (Rashidinejad et al., 2021). They mainly focus on solving the overestimation of Q values learned in offline datasets and the distribution shift between offline and online. However, those constraints limit the performance with insufficiently offline dataset exploitation (Kumar et al., 2019). Recently, the transformer shows its advantage of representing the sequential data for the classification or prediction tasks. Most related to our work, Chen et al. (2021) replace the constrained Q networks in conventional offline RL algorithms with causal transformer and demonstrate the superiority comparing with baselines such as Behavior Cloning (BC) and state-of-the-art offline algorithms in single-agent offline RL. Nevertheless, the overestimation problems emerge in the offline multi-agent RL when one directly applies the sequential modeling method. We propose leveraging

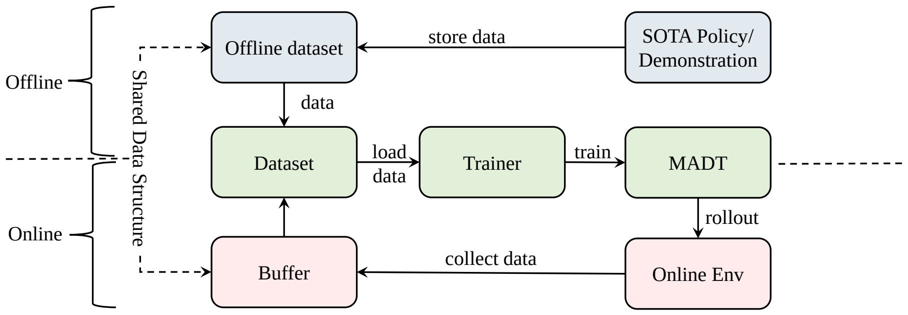


Figure 1: Overview of the pipeline for pre-training the general policy and fine-tuning it online.

the representation capability of the transformer and then load the pre-trained model as part of the policy in the fine-tuning phase.

This paper proposes Multi-Agent Decision Transformers (MADT) for pre-training the general policy on offline datasets, capable of generalizing onto other seen/unseen environments. Firstly, we collect the offline datasets from the well-known, challenging MARL environment, StarCraft Multi-Agent Challenge (SMAC) (Samvelyan et al., 2019), interacting with the state-of-the-art algorithm, multi-agent PPO (Yu et al., 2021). Then we construct transformer variants for multiple agents with parameter sharing or acing as a part. We give the paradigm of pre-training a model with the transformer and fine-tuning it with MARL. We conclude the main contribution as follows:

- We propose a series of transformer variants for offline MARL via leveraging the sequential modeling of the attention mechanism.
- We derive a framework with offline pretraining and online fine-tuning to improve sample efficiency and generality across different scenarios.
- We are the first to apply the pre-trained model across different multi-agent scenarios to validate the transferring ability. Experimental results show fast adaptation and superior performance.
- We build a dataset with different skill-level covering all SMAC scenarios for benchmarking progress in MARL pre-training.

2 Preliminary

Multi-Agent Reinforcement Learning. For the Markov Game, which is a multi-agent extension from the Markov Decision Process (MDP), there is a tuple representing the essential elements $< \mathbb{S}, \mathbb{A}, R, P, n, \gamma >$, where $\mathbb{S}$ denotes the state space of n agents : $S_1 \times S_2 \dots S_n \to \mathbb{S}$. $\mathbb{A}_i$ is the action space of each agent i, $P : S_i \times \mathbb{A}_i \to PD(S_i)$ denotes the transition function emiting the distribution over the state space and $\mathbb{A}$ is the joint action space, $R_i : \mathbb{S} \times \mathbb{A}_i \to \mathbb{R}$ is the reward function of each agent and takes action following their policies $\pi(a|s) \in \Pi_i : \mathbb{S} \to PD(\mathbb{A})$ from the policy space Π_i, where Π_i denotes the policy space of agent i, $a \sim \mathbb{A}_i$, and $s \sim S_i$. Each agent aims to maximize its long-term reward $\sum_t \gamma^t r_t$, where $r_i^t \in R_i$ denotes the reward of agent i in time t and γ denotes the discount factor.

Attention-based Model. Attention-based model has shown its stable and strong representation capability. The scale dot-production attention uses the self-attention mechanism demonstrated in (Vaswani et al., 2017). Let $\mathbf{Q} \in \mathbb{R}^{t_q \times d_q}$ be the quries, $\mathbf{K} \in \mathbb{R}^{t_k \times d_k}$ be the keys, and $\mathbf{V} \in \mathbb{R}^{t_v \times d_v}$ be the values, where t_* are the element numbers of different inputs and d_* are the corresponding element dimensions. Normally, $t_k = t_v$ and $d_q = d_k$. The outputs of self-attention are computed as:

$$\text{Attention}(\mathbf{Q}, \mathbf{K}, \mathbf{V}) = \text{softmax}(\frac{\mathbf{Q}\mathbf{K}^T}{\sqrt{d_k}})\mathbf{V} \tag{1}$$

where the scalar $1/\sqrt{d_k}$ is used to prevent the softmax function into regions that has very small gradients. Then we introduce the multi-head attention process as follows:

$$\text{MultiHead}(\mathbf{Q}, \mathbf{K}, \mathbf{V}) = \text{Concat}(\text{head}_1, \dots, \text{head}_h)\mathbf{W}^O \tag{2}$$

$$\text{head}_i = \text{Attention}(\mathbf{Q}\mathbf{W}_i^Q, \mathbf{K}\mathbf{W}_i^K, \mathbf{V}\mathbf{W}_i^V) \tag{3}$$

The position-wise feed-forward network is another core module of the transformer. It consists of two linear transformations with a ReLU activation in between. The dimensionality of inputs and outputs is d_{model}, and that of the feef forward layer is d_{ff}. Specially,

$$\mathrm{FFN}(x) = \max(0, x\mathbf{W}_1 + \mathbf{b}_1)\mathbf{W}_2 + \mathbf{b}_2 \tag{4}$$

where $\mathbf{W}_1 \in \mathbb{R}^{d_{model} \times d_{ff}}$ and $\mathbf{W}_2 \in \mathbb{R}^{d_{ff} \times d_{model}}$ are the weights, and $\mathbf{b}_1 \in \mathbb{R}^{d_{ff}}$ and $\mathbf{b}_2 \in \mathbb{R}^{d_{model}}$ are the biases. Across different positions are the same linear transformations. Note that the position encoding for leveraging the order of the sequence as follows:

$$\begin{aligned} \mathrm{PE}(pos, 2i) &= \sin pos/10000^{2i/d_{model}} \\ \mathrm{PE}(pos, 2i+1) &= \cos pos/10000^{2i/d_{model}} \end{aligned} \tag{5}$$

3 METHODOLOGY

In this section, we demonstrate how the transformer is applied to our offline pre-training MARL framework. Firstly, we introduce an offline MARL method, in which the transformer maps between the local observations and actions of each agent in the offline dataset via parameter sharing sequentially. Then we leverage the hidden representation as the input of the multi-agent decision transformer (MADT) to minimize the cross-entropy loss. Furthermore, we introduce how to integrate the online MARL with MADT in constructing our whole framework to train a universal MARL policy. To accelerate the online learning, we load the pre-trained model as a part of MARL algorithms and learn the policy based on experience in the latest buffer stored from the online environment. To train a universal MARL policy quickly adapting to other tasks, we bridge the gap between different scenarios from observations, actions, and available actions, respectively. Figure 1 overviews our method from the perspective of offline pre-training with supervised learning and online fine-tuning with MARL algorithms.

3.1 MULTI-AGENT DECISION TRANSFORMER

Algorithm 1 shows the training process of Multi-Agent Decision Transformer (MADT), in which we autoregressively encode the trajectories from the offline datasets in offline pre-trained MARL and train the transformer-based network with supervised learning. We carefully reformulate the trajectories as the inputs of the causal transformer different from those in the Decision Transformer (Chen et al., 2021). Denote that we deprecate the reward-to-go and actions that are encoded with states together in the single-agent DT. We will interpret the reason for this in the next section. Similar to the seq2seq models, MADT is based on the autoregressive architecture with the reformulated sequential inputs across timescale. The left part of Figure 2 shows the architecture. The causal transformer encodes the agent i's trajectory sequence τ_i^t at the time step t to a hidden representation $\mathbf{h}_i^t = (h_1, h_2, \dots, h_l)$ with a dynamic mask. Given $\mathbf{h}_t$, the output at the time step t only based on the previous data then consumes the previously emitted actions as additional inputs when predicting a new action.

Algorithm 1: MADT-Offline: Multi-Agent Decision Transformer

```
Input: Offline dataset $\mathcal{D} : \{\tau_i : \langle s_i^t, o_i^t, a_i^t, v_i^t, d_i^t, r_i^t \rangle_{t=1}^T\}_{i=1}^n$, $v_i^t$ denotes the available action
Initialize $\theta$ for the Causal Transformer;
Initialize $\alpha$ as the learning rate, $C$ as the context length, and $n$ as the maximize agent number
for $\tau = \{\tau_1, \dots, \tau_i, \dots, \tau_n\}$ in $\mathcal{D}$ do
    Chunk the trajectory into $\tau_i = \{r_i^t, s_i^t, a_i^t\}_{t \in 1:C}$ as the ground truth samples, where $C$ is the
    context length, and mask the trajectory when $d_i^t$ is true
    for $\tau_i^t = \{\tau_i^1 \dots \tau_i^t \dots \tau_i^T\}$ in $\tau_i$ do
        Mask illegal actions via $P(a_j|\tau_i, \hat{a}_{<j}; \theta') = 0$ if $v_i^t$ is True
        Predict the action $\hat{a}_t = \arg\max_a P(a|\tau_i, \hat{a}_{<t}; \theta')$
        Update $\theta$ with $\theta = \arg\max_{\theta'} \frac{1}{C} \sum_{j=1}^{C} P(a_j) \log P(\hat{a}_j|\tau_i, \hat{a}_{<j}; \theta')$
    end
end
return $\theta$
```

Trajectories Reformulation as Input. We model the lowest granularity at each time step as a modeling unit x_t from the static offline dataset for the concise representation. MARL has many

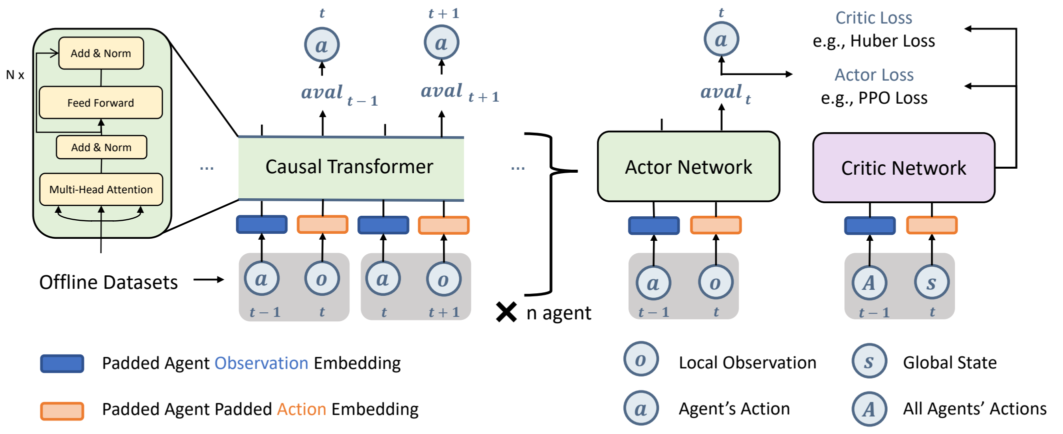


Figure 2: The detailed model structure for offline and online MADT.

elements such as ⟨`global_state, local_observation`⟩, different from the single agent. It is reasonable for sequential modeling methods to model them in Markov Decision Process (MDP). Therefore, we formulate the trajectory as follows:

$$\tau^i = (x_1, \dots x_t \dots, x_T) \quad \text{where } x_t = (s_t, o_t^i, a_t^i)$$

where s_t^i denotes the global shared state, o_t^i denotes the individual observation for agent i at time step t, and a_t^i denotes the action. We take x_t as a token similar to the input of natural language processing.

Output Sequence Constructing. To bridge the gap between training with the whole context trajectory and testing with only previous data, we mask the context data to autoregressively output in the time step t with previous data in $\langle 1 \dots t-1 \rangle$. Therefore, MADT predicts the sequential actions at each time step using the decoder as follows:

$$y = a_t = \arg\max_a p_\theta(a|\tau, a_1, \dots, a_{t-1}) \tag{6}$$

where θ denotes the parameter of MADT and τ denotes the trajectory including the global state s, local observation o before the time step t, p_θ is the distribution over the legal action space under the available action v.

Core Module Description. MADT differs from the transformers in conventional sequence modeling tasks that take inputs with position encoding and decode the encoded hidden representation autoregressively. We use the masking mechanism with a lower triangular matrix to compute the attention:

$$\text{Attention}(\mathbf{Q}, \mathbf{K}, \mathbf{V}) = \text{softmax}(\frac{\mathbf{Q}\mathbf{K}^T}{\sqrt{d_k}} + M)\mathbf{V} \tag{7}$$

where M is the mask matrix which ensures the input at the time step t can only correlate with the input from $\langle 1, \dots, t-1 \rangle$. We employ the Cross-entropy (CE) as the total sequential prediction loss and utilize the available action v to ensure agents taking those illegal actions with probability zero. The CE loss can be represented as follows:

$$L_{CE}(\theta) = \frac{1}{C} \sum_{t=1}^{C} P(a_t) \log P(\hat{a}_t | \tau_t, \hat{a}_{<t}; \theta), \quad \text{where } C \text{ is the context length} \tag{8}$$

where a_t is the ground truth action, τ_t includes $\{s_{1:t}, o_{1:t}\}$. $\hat{a}$ denotes the output of MADT. The cross-entropy loss shown above aims to minimize the distribution distance between the prediction and the ground truth.

3.2 Multi-Agent Decision Transformer with PPO

The method above can fit the data distribution well resulting from the sequential modeling capacity of the transformer. But it fails to work well when pre-training on the offline datasets and improving continually by interacting with the online environment. The reason originates from the mismatch between the objective in MADT and ignore the value of each action. When the pre-trained model is loaded to interact with the online environment, the buffer will only collect actions conforming to the distributions of the offline datasets rather than those corresponding to high reward at this state. That means the pre-trained policy is regarded as good once the selected action is identical to that in the dataset, even though it leads to a low reward. Therefore, we need to design another paradigm, MADT-PPO, to integrate RL and supervised learning for fine-tuning continually in Algorithm 2. Figure 2 shows the pre-training and fine-tuning framework. A direct method is to share the pre-trained model across each agent and implement the REINFORCE algorithm (Williams, 1992). However, only actors result in higher variance, and the employment of a critic to assess state values is necessary. Therefore, in online MARL, we leverage an extension of PPO, the state-of-the-art algorithm on tasks of StarCraft, MPE, and even return-based game Hanabi (Mordatch & Abbeel, 2018).

Algorithm 2: MADT-Online: Multi-Agent Decision Transformer with PPO

```
Input: Offline dataloader $\mathcal{D}$, Pretrained MADT Policy with parameter $\theta$
Initialize $\theta$ and $\phi$ are the parameters of an actor $\pi_\theta(a_i|o_i)$ and critic $V_\phi(s)$ respectively, which
could be inherited directly from pre-trained models.
Initialize $n$ as the agent number, $\gamma$ as the discount factor, and $\epsilon$ as clip ratio
for $\tau = \{\tau_1, \ldots, \tau_i, \ldots, \tau_n\}$ in $\mathcal{D}$ do
    Sample $\tau_i = \{s^t, o_i^t, a_i^t\}_{t\in 1:T}$ as the ground truth, where $T$ is the context length
    Compute the advantage function $A(s, a_i) = \sum_t \gamma^t r(s, a_i) - V_\phi(s)$
    Computing the important weight $w = \pi_\theta(o_i, a_i)/\pi_{\theta_{old}}(o_i, a_i)$
    Update $\theta_i$ for $i \in 1 \ldots n$ via:
        $\theta_i = \arg\max \mathbb{E}_{s\sim\rho_{\theta_{old}}, a\sim\pi_{\theta_{old}}}[clip(w, 1-\epsilon, 1+\epsilon)A(s, a_i)]$
    Compute the MSE loss $L_\phi = \frac{1}{2}[\sum_t \gamma^t r - V_\phi(s)]^2$
    Update the critic network via $\phi = \arg\min_\phi L_\phi$
end
return $\theta$, $\phi$
```

3.3 Universal Model across Scenarios

To train a universal policy for each of the scenarios in the SMAC which might be vary in agent number, feature space, action space and reward ranges, we consider the modification list below.

Parameters Sharing Across Agents. When offline examples are collected from multiple tasks or the test phase owns the different agent numbers from the offline datasets, the difference of agent number across tasks is an intractable problem for deciding the number of actors. Thus, we consider sharing the parameters across all actors with one model as well as attaching one-hot agent IDs into observations, for compatibility with a variable number of agents.

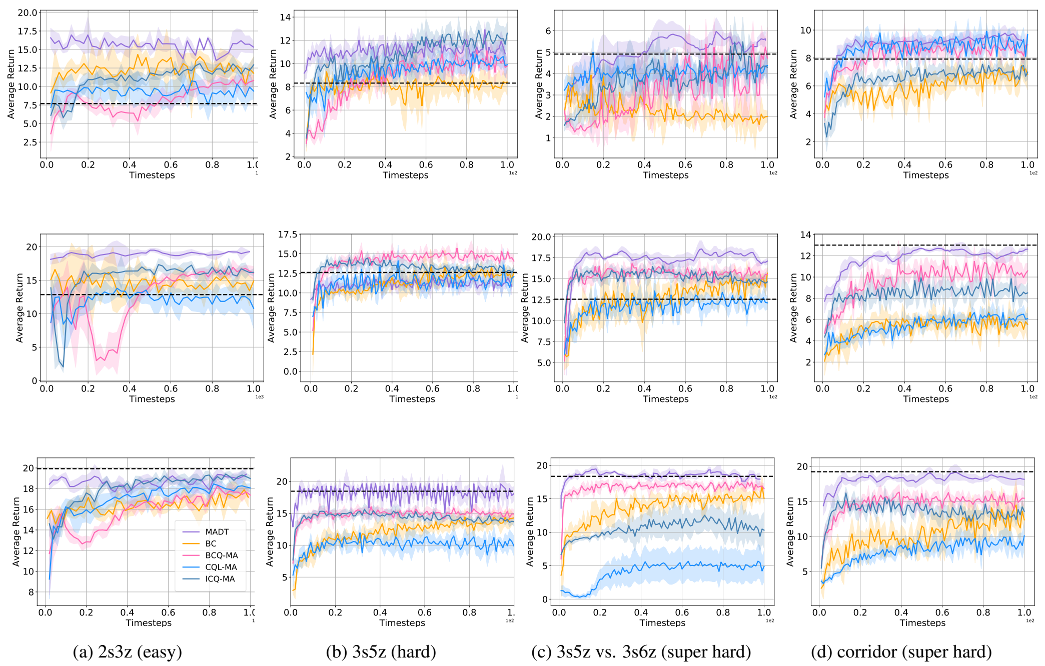
Feature Encoding. When the policy needs to generalize to new scenarios that arises from different feature shapes, We propose encoding all features into a universal space by padding zero at the end and mapping to a low-dimensional space with fully connected networks.

Action Masking. Another issue is the different action space across scenarios. For example, less enemies in a scenario means less potential attack options as well as available actions. Therefore, an extra vector is utilized to mute the unavailable actions so that their probabilities are always zero during both learning and evaluating process.

Reward Scaling. Different scenarios might be vary in reward ranges and lead to unbalanced models during multi-task offline learning. To balance the influence of examples from different scenarios, we scale their rewards into the same range to ensure the output models have comparable performance between different tasks.

4 Experiments

We show three experimental settings: offline MARL, online MARL by loading the pre-trained model, and few-shot or zero-shot offline learning. For the offline MARL, we expect to verify the performance of our method in pre-training the policy and directly testing on the corresponding maps. For the fine-tuning in the online environment, we aim to demonstrate the capacity of the pre-trained policy on the original or new scenarios. Experimental results in offline MARL shows our MADT-offline



(a) 2s3z (easy) (b) 3s5z (hard) (c) 3s5z vs. 3s6z (super hard) (d) corridor (super hard)

Figure 3: Performance of offline MADT comparing with baselines on four easy or (super-)hard SMAC maps. The dotted lines represent the mean values in the training set. Columns (a-d) are average returns from (poor, medium, good) datasets from top to the bottom.

in 3.1 outperforms the state-of-the-art methods. Furthermore, MADT-online in 3.2 can improve the sample efficiency across multiple scenarios. Besides, the universal MADT trained from multi-task data with MADT-online generalize well in each scenario in few-shot even zero-shot setting.

4.1 Offline Datasets

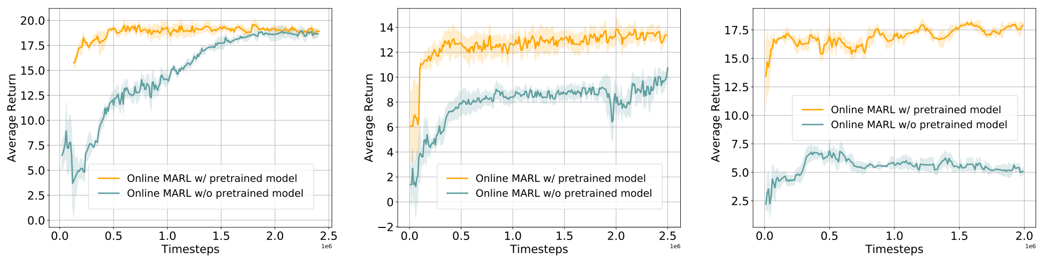
The offline datasets are collected from the running policy, MAPPO (Yu et al., 2021), on the well-known SMAC task (Samvelyan et al., 2019). Each dataset contains a large number of trajectories: $\tau := (s_t, o_t, a_t, r_t, done_t, v_t)_{t=1}^{T}$. Different from D4RL (Fu et al., 2020), our datasets consider the property of DecPOMDP, which owns local observations and available actions for each agent. In Appendix, we list the statistical properties of the offline datasets in Table 2 and Table 3.

4.2 Offline Multi-Agent Reinforcement Learning

In this experiment, we aim to validate the effectiveness of MADT offline version in Section 3.1 as a framework for offline MARL on the static offline datasets. We train a policy on the offline datasets with various qualities and then apply it to an online environment, StarCraft (Samvelyan et al., 2019). There are also baselines under this setting, such as Behavior Cloning (BC) as a kind of imitation learning method showing stable performance on single-agent offline RL. Besides, we employ the conventional effective single-agent offline RL algorithms, BCQ (Fujimoto et al., 2019), CQL (Kumar et al., 2020), and ICQ (Yang et al., 2021), then add the mixing network for multi-agent setting, denoting as "xx-MA". To verify the quality of our collected datasets, we choose data from different level and train the baselines as well as our MADT. Figure 3 shows the overall performance on various quality datasets. The baseline methods enhance their performance stably, indicating the quality of our offline datasets. The results also show that our MADT outperforms the offline MARL baselines and converges faster across easy, hard, and super hard maps (`2s3z`, `3s5z`, `3s5z_vs_3s6z`, `corridor`).

4.3 Offline Pre-training and Online Fine-tuning

The experiment designed in this subsection intends to answer the question: **Is the pre-training process is necessary for online MARL?** Firstly we compare the online version of MADT in Section 3.2 with and without loading the pre-trained model. If training MADT only by online experience, we can view it as a transformer-based MAPPO replacing the actor and critic backbone networks with the



(a) so many baneling (easy) (b) 5m vs. 6m (hard) (c) 3s5z vs. 3s6z (super hard)

Figure 4: The average returns with and without the pre-trained model..

transformer. Furthermore, we validate that our framework MADT with the pre-trained model can improve sample efficiency on most easy, hard, and super hard maps.

Necessity of Pretrained Model. We train our MADT based on the datasets collected from a map and fine-tune it on the same map online with the MAPPO algorithm. For comparison fairness, we use the transformer as both actor and critic networks with and without the pre-trained model. Primarily, we choose three maps from Easy, Hard, and Super Hard maps to validate the effectiveness of the pre-trained model in Figure 4. Experimental results show that the pre-trained model converges faster than the algorithm trained from scratch, especially in the challenging maps.

Improving Sample Efficiency. For validating the improvement of the sample efficiency via loading our pre-trained MADT and fine-tuning it with MAPPO, we compare the overall framework with the state-of-the-art algorithm, MAPPO (Yu et al., 2021), without the pre-training phase. We measure the number of interactions with the environment in Table 1, and our pre-trained model needs much less than the traditional MAPPO to access the same win rate.

Maps	# Samples to Acess the Win Rate					Maps	# Samples to Acess the Win Rate				
	20%	40%	60%	80%	100%		20%	40%	60%	80%	100%
2m vs. 1z (Easy)	8e4/-	1e5/-	1.3e5/-	1.5e5/-	1.6e5/-	3s vs. 5z (Hard)	8e5/-	8.5e5/-	8.7e5/1.5e4	9e5/5e4	2e6/1.5e5
3m (Easy)	3.2e3/-	8.3e4/-	3.2e5/-	4e5/-	7.2e5/-	2c vs. 64 zg (Hard)	2e5/-	3e5/-	4e5/8e4	5e5/1e5	1.8e6/5e5
2s vs 1sc (Easy)	1e4/-	2.5e4/-	3e4/-	8e4/4e4	3e5/1.2e5	8m vs. 9m (Hard)	3e5/-	6e5/-	1.4e6/2e4	2e6/8e4	∞/2.2e6
3s vs. 3z (Easy)	2.5e5/-	3e5/-	6.2e5/1e4	7.3e5/1.5e5	8e5/2.9e5	5m vs. 6m (Hard)	1.5e6/2e5	2.5e6/8e5	5e6/2e6	∞/∞	∞/∞
3s vs. 4z (Easy)	3e5/-	4e5/-	5e5/-	6.2e5/-	1.5e6/1.8e5	3s5z (Hard)	8e5/6.3e4	1.3e6/1e5	1.5e6/4e5	1.9e6/1e6	2.5e6/2e6
so many baneling (Easy)	3.2e4/8e3	1e5/4e4	3.2e5/7e4	5e5/8e4	1e6/6.4e5	10m vs. 11m (Hard)	2e5/-	3.5e5/-	4e5/2.8e4	1.7e6/1.2e5	4e6/2.5e5
8m (Easy)	4e5/-	5e6/-	5.6e5/-	5.6e5e5/1.6e5	8.8e5/2.4e5	MMM2 (Super Hard)	1e6/	1.8e6/	2.3e6/	4e6/	∞/∞
MMM (Easy)	5.2e4/-	8e4/-	3e5/-	4.5e5/-	1.8e6/6e5	3s5z vs. 3s6z (Super Hard)	1.8e6/-	2.5e6/-	3e6/8e5	5e6/1e6	∞/∞
bane vs. bane (Easy)	3.2e3/-	3.2e3/-	3.2e5/-	4e5/-	5.6e5/-	corridor (Super hard)	1.5e6/-	1.8e6/-	2e6/-	2.8e6/-	7.8e6/4e5

Table 1: The sample numbers needed to access the win rate $20\%, 40\%, 60\%, 80\%$, and 100% with (MAPPO/pre-trained MADT). "-" represents that no more samples is needed to reach the target win rate. "∞" represents that policies cannot reach the target win rate.

4.4 Generaliztion with Multi-Task Pre-training

Experiments in this section are to explore the transferability of the universal MADT mentioned in Section 3.3, which is pre-trained with mixed data from multiple tasks. According to whether the downstream tasks have been seen or not, the few-shot experiments are designed to validate the adaptibilty on seen tasks, while the zero-shot experiments are designed for the held-out maps.

Few-shot Learning. The results in Figure 5a shows that our method can utilize multi-task datasets to train a universal policy and generalize to all tasks well. Pre-trained MADT can achieve higher return than the model trained from scratch when we limit the interactions with environment.

Zero-shot Learning. Figure 5b shows that our universal MADT can surprisingly improve performance on downstream task even if it has not been seen before. (3 stalkers vs. 4 zealots).

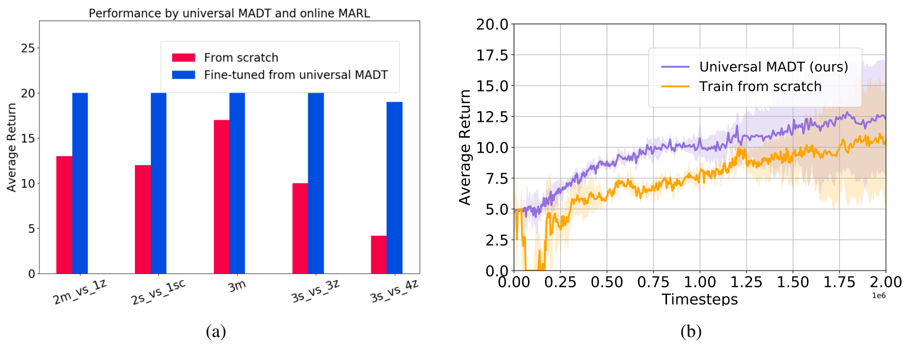


Figure 5: Few-shot and Zero-shot validation results. (a) shows the average returns of the universal MADT pre-trained from all five tasks data and the policy trained from scratch, individually. We limit the environment interaction to 2.5M steps. (b) shows the average returns of a held-out map (`3s_vs_4z`), where the universal MADT is trained from data on (`2m_vs_1z, 2s_vs_1sc, 3m, 3s_vs_3z`).

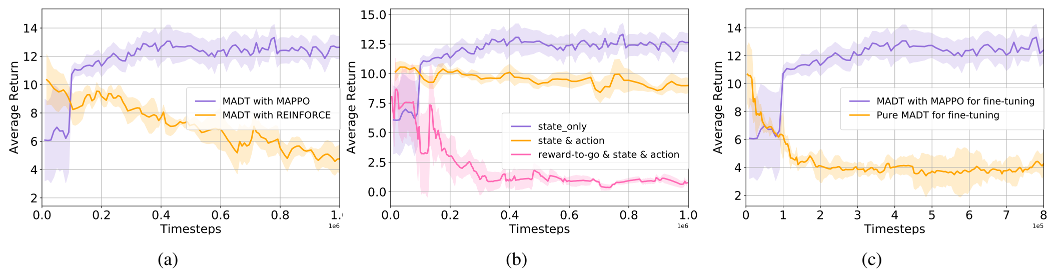


Figure 6: Ablation results on a hard map, `5m_vs_6m`, for validating the necessity of (a) MAPPO in MADT-Online, (b) input formulation, (c) online version of MADT.

4.5 Ablation Study

The experiments in this subsection are designed to answer the following research questions: **RQ1:** Why we choose MAPPO for online phase? **RQ2:** Which kind of input shall we use to make the pre-trained model beneficial for the online MARL? **RQ3:** Why cannot the offline version of MADT be improved in the online fine-tune period after pre-training?

Suitable Online Algorithm. Although the selection of MARL algorithm for online phase should be flexible according to specific task, we design experiments to answer **RQ1** here. As discussed in Section 3, we can train Decision Transformer for each agent and online fine-tune it with a MARL algorithm. An intuitive method is to load the pre-trained transformer and take it as the policy network for fine-tuning with the policy gradient method, e.g. REINFORCE (Williams, 1992). However, for the reason of high variance mentioned in Section 3.2, we choose MAPPO as the online algorithm and compare their performance in improving sample efficiency during the online period in Figure 6a.

Dropping Reward-to-go in MADT. To answer **RQ2**, we compare different inputs embedded into the transformer, including the combination of state, reward-to-go, and action. We find the reward-to-go harmful to online fine-tuning performance, as shown in Figure 6b. We suppose the distribution of reward-to-go is mismatch between offline data and online samples. That is, rewards of online samples are usually lower than offline data due to stachastic exploration at the beginning of the online phase. It deteriorates the fine-tuning capability of the pre-trained model, and based on Figure 6b, we only choose states as our inputs for pre-training and fine-tuning.

Integrating Online MARL with MADT. To answer **RQ3**, we directly apply the offline version of MADT for pre-training and fine-tune it online. However, Figure 6c shows that it cannot be improved during the online phase. We analyze the results from the absence of motivation for chasing higher rewards, and conclude that offline MADT is in fact supervised learning and tends to fit its collected experience even with unsatisfactory reward.

5 Related Work

Offline Deep Reinforcement Learning. Conventionally, offline RL trains a policy based on the static and previously collected data without any environmental interaction (Levine et al., 2020). This policy is then leveraged to interact with the online environment to obtain promising results. A straightforward method for the current reinforcement learning is to use the off-policy algorithm and regard the offline datasets as a replay buffer to learn a policy with good performance. However, experience existing in offline datasets and interaction with online environment have different distributions which cause the overestimation in the off-policy (value-based) method (Kumar et al., 2019). Substantial works presented in offline RL aim at resolving the distribution shift between the static offline datasets and the online environment interaction (Kumar et al., 2020; Fujimoto et al., 2019; Kumar et al., 2019). Yang et al. (2021); Jiang & Lu (2021) constrain off-policy algorithms in offline MARL. Related to our work for the improvement of sample efficiency, Nair et al. (2020) load the pretrained model to generate a weight for actor-critic online RL algorithms. Recently, the Decision Transformer outperforms many state-of-the-art offline RL algorithms via regarding the training process as a sequential modeling phase and test on the online environment (Chen et al., 2021; Janner et al., 2021). In contrast, we show a transformer-based method in the multi-agent field, attempting to transfer across many scenarios without extra constraints.

Multi-Agent Reinforcement Learning. As a natural extension from single-agent RL, MARL attracts much attention to solve more complex problems under Markov Games (Zhang et al., 2021). Related algorithms conventionally enforce multiple agents to interact with the environment online and collect the experience to train the joint policy from scratch (Rashid et al., 2018; Sunehag et al., 2017; Son et al., 2019; Mahajan et al., 2019; Yu et al., 2021). The framework of traditional multi-agent learning employs the centralized training and decentralized execution framrwork due to local observation and increasing action space. We build offline datasets by collecting elements from the DecPOMDP and train the general policy with parameter sharing. We utilize transformer to learn a policy with previously collected data from the golden policy in advance and fine-tune it online.

Transformer. Transformer (Vaswani et al., 2017) has achieved a great breakthrough to model relations between the input and output sequence with variable length, for the sequence-to-sequence problems (Sutskever et al., 2014), especially on machine translation (Wang et al., 2019) and speech recognition (Dong et al., 2018). Recent works even reorganize the vision problems as the sequential modeling process and construct the SOTA model with pretraining, named ViT (Han et al., 2020; Dosovitskiy et al., 2020; Liu et al., 2021). Due to the Markovian property of trajectories in offline datasets, we can utilize Transformer as that in language modeling. Therefore, Transformer can bridge the gap between supervised learning in the offline setting and reinforcement learning in the online interaction because of the representation capability. We claim that the components under Markov Games are sequential then utilize the transformer for each agent to fit a transferable MARL policy. Furhtermore, we fine-tune the learned policy under via trial-and-error.

6 Conclusions

In this work, we propose MADT, an offline pre-trained model for MARL, which integrates the transformer to improve sample efficiency and generalizability. We build an offline MARL dataset based on SMAC. Our method outperforms the state-of-the-art methods in offline MARL, including BC, BCQ, CQL, and ICQ. Our whole framework can also drastically improve the sample efficiency of online MARL via loading pre-trained model. Furthermore, we apply our method to train a universal policy over the multi-task datasets and fine-tune it under the few-shot and zero-shot settings. Results demonstrate that this universal policy adapts fast to new tasks and promises performance on different level maps.

To our best knowledge, we are the first to pre-train the multi-agent model with offline datasets and fine-tune it under the few-shot and zero-shot settings. Future research will pre-train a more general policy, which can transfer across more diverse tasks.

REFERENCES

Ana LC Bazzan. Opportunities for multiagent systems and multiagent reinforcement learning in traffic control. *Autonomous Agents and Multi-Agent Systems*, 18(3):342, 2009.

Marc G Bellemare, Yavar Naddaf, Joel Veness, and Michael Bowling. The arcade learning environment: An evaluation platform for general agents. *Journal of Artificial Intelligence Research*, 47: 253–279, 2013.

Lili Chen, Kevin Lu, Aravind Rajeswaran, Kimin Lee, Aditya Grover, Michael Laskin, Pieter Abbeel, Aravind Srinivas, and Igor Mordatch. Decision transformer: Reinforcement learning via sequence modeling. *arXiv preprint arXiv:2106.01345*, 2021.

Linhao Dong, Shuang Xu, and Bo Xu. Speech-transformer: a no-recurrence sequence-to-sequence model for speech recognition. In *2018 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*, pp. 5884–5888. IEEE, 2018.

Alexey Dosovitskiy, Lucas Beyer, Alexander Kolesnikov, Dirk Weissenborn, Xiaohua Zhai, Thomas Unterthiner, Mostafa Dehghani, Matthias Minderer, Georg Heigold, Sylvain Gelly, et al. An image is worth 16x16 words: Transformers for image recognition at scale. In *International Conference on Learning Representations*, 2020.

Lasse Espeholt, Hubert Soyer, Remi Munos, Karen Simonyan, Vlad Mnih, Tom Ward, Yotam Doron, Vlad Firoiu, Tim Harley, Iain Dunning, et al. Impala: Scalable distributed deep-rl with importance weighted actor-learner architectures. In *International Conference on Machine Learning*, pp. 1407–1416. PMLR, 2018.

Lasse Espeholt, Raphaël Marinier, Piotr Stanczyk, Ke Wang, and Marcin Michalski. Seed rl: Scalable and efficient deep-rl with accelerated central inference. In *International Conference on Learning Representations*, 2019.

Justin Fu, Aviral Kumar, Ofir Nachum, George Tucker, and Sergey Levine. D4rl: Datasets for deep data-driven reinforcement learning. *arXiv preprint arXiv:2004.07219*, 2020.

Scott Fujimoto, David Meger, and Doina Precup. Off-policy deep reinforcement learning without exploration. In *International Conference on Machine Learning*, pp. 2052–2062. PMLR, 2019.

Tuomas Haarnoja, Aurick Zhou, Kristian Hartikainen, George Tucker, Sehoon Ha, Jie Tan, Vikash Kumar, Henry Zhu, Abhishek Gupta, Pieter Abbeel, et al. Soft actor-critic algorithms and applications. *arXiv preprint arXiv:1812.05905*, 2018.

Kai Han, Yunhe Wang, Hanting Chen, Xinghao Chen, Jianyuan Guo, Zhenhua Liu, Yehui Tang, An Xiao, Chunjing Xu, Yixing Xu, et al. A survey on visual transformer. *arXiv preprint arXiv:2012.12556*, 2020.

Michael Janner, Qiyang Li, and Sergey Levine. Reinforcement learning as one big sequence modeling problem. *arXiv preprint arXiv:2106.02039*, 2021.

Jiechuan Jiang and Zongqing Lu. Offline decentralized multi-agent reinforcement learning. *arXiv preprint arXiv:2108.01832*, 2021.

Aviral Kumar, Justin Fu, Matthew Soh, George Tucker, and Sergey Levine. Stabilizing off-policy q-learning via bootstrapping error reduction. *Advances in Neural Information Processing Systems*, 32:11784–11794, 2019.

Aviral Kumar, Aurick Zhou, George Tucker, and Sergey Levine. Conservative q-learning for offline reinforcement learning. *arXiv preprint arXiv:2006.04779*, 2020.

Sergey Levine, Aviral Kumar, George Tucker, and Justin Fu. Offline reinforcement learning: Tutorial, review, and perspectives on open problems. *arXiv preprint arXiv:2005.01643*, 2020.

Ze Liu, Yutong Lin, Yue Cao, Han Hu, Yixuan Wei, Zheng Zhang, Stephen Lin, and Baining Guo. Swin transformer: Hierarchical vision transformer using shifted windows. *arXiv preprint arXiv:2103.14030*, 2021.

Anuj Mahajan, Tabish Rashid, Mikayel Samvelyan, and Shimon Whiteson. Maven: Multi-agent variational exploration. *Advances in Neural Information Processing Systems*, 32:7613–7624, 2019.

Volodymyr Mnih, Koray Kavukcuoglu, David Silver, Andrei A Rusu, Joel Veness, Marc G Bellemare, Alex Graves, Martin Riedmiller, Andreas K Fidjeland, Georg Ostrovski, et al. Human-level control through deep reinforcement learning. *nature*, 518(7540):529–533, 2015.

Igor Mordatch and Pieter Abbeel. Emergence of grounded compositional language in multi-agent populations. In *Thirty-second AAAI conference on artificial intelligence*, 2018.

Remi Munos, Tom Stepleton, Anna Harutyunyan, and Marc Bellemare. Safe and efficient off-policy reinforcement learning. *Advances in Neural Information Processing Systems*, 29:1054–1062, 2016.

Ashvin Nair, Murtaza Dalal, Abhishek Gupta, and Sergey Levine. Accelerating online reinforcement learning with offline datasets. *arXiv preprint arXiv:2006.09359*, 2020.

Tabish Rashid, Mikayel Samvelyan, Christian Schroeder, Gregory Farquhar, Jakob Foerster, and Shimon Whiteson. Qmix: Monotonic value function factorisation for deep multi-agent reinforcement learning. In *International Conference on Machine Learning*, pp. 4295–4304. PMLR, 2018.

Paria Rashidinejad, Banghua Zhu, Cong Ma, Jiantao Jiao, and Stuart Russell. Bridging offline reinforcement learning and imitation learning: A tale of pessimism. *arXiv preprint arXiv:2103.12021*, 2021.

Mikayel Samvelyan, Tabish Rashid, Christian Schroeder De Witt, Gregory Farquhar, Nantas Nardelli, Tim GJ Rudner, Chia-Man Hung, Philip HS Torr, Jakob Foerster, and Shimon Whiteson. The starcraft multi-agent challenge. *arXiv preprint arXiv:1902.04043*, 2019.

Shai Shalev-Shwartz, Shaked Shammah, and Amnon Shashua. Safe, multi-agent, reinforcement learning for autonomous driving. *arXiv preprint arXiv:1610.03295*, 2016.

Kyunghwan Son, Daewoo Kim, Wan Ju Kang, David Earl Hostallero, and Yung Yi. Qtran: Learning to factorize with transformation for cooperative multi-agent reinforcement learning. In *International Conference on Machine Learning*, pp. 5887–5896. PMLR, 2019.

Peter Sunehag, Guy Lever, Audrunas Gruslys, Wojciech Marian Czarnecki, Vinicius Zambaldi, Max Jaderberg, Marc Lanctot, Nicolas Sonnerat, Joel Z Leibo, Karl Tuyls, et al. Value-decomposition networks for cooperative multi-agent learning. *arXiv preprint arXiv:1706.05296*, 2017.

Ilya Sutskever, Oriol Vinyals, and Quoc V Le. Sequence to sequence learning with neural networks. In *Advances in neural information processing systems*, pp. 3104–3112, 2014.

Ashish Vaswani, Noam Shazeer, Niki Parmar, Jakob Uszkoreit, Llion Jones, Aidan N Gomez, Lukasz Kaiser, and Illia Polosukhin. Attention is all you need. *arXiv preprint arXiv:1706.03762*, 2017.

Qiang Wang, Bei Li, Tong Xiao, Jingbo Zhu, Changliang Li, Derek F Wong, and Lidia S Chao. Learning deep transformer models for machine translation. *arXiv preprint arXiv:1906.01787*, 2019.

Tonghan Wang, Tarun Gupta, Anuj Mahajan, Bei Peng, Shimon Whiteson, and Chongjie Zhang. Rode: Learning roles to decompose multi-agent tasks. *arXiv preprint arXiv:2010.01523*, 2020.

Ronald J Williams. Simple statistical gradient-following algorithms for connectionist reinforcement learning. *Machine learning*, 8(3):229–256, 1992.

Yikun Xian, Zuohui Fu, S Muthukrishnan, Gerard De Melo, and Yongfeng Zhang. Reinforcement knowledge graph reasoning for explainable recommendation. In *Proceedings of the 42nd International ACM SIGIR Conference on Research and Development in Information Retrieval*, pp. 285–294, 2019.

Yiqin Yang, Xiaoteng Ma, Chenghao Li, Zewu Zheng, Qiyuan Zhang, Gao Huang, Jun Yang, and Qianchuan Zhao. Believe what you see: Implicit constraint approach for offline multi-agent reinforcement learning. *arXiv preprint arXiv:2106.03400*, 2021.

Chao Yu, Akash Velu, Eugene Vinitsky, Yu Wang, Alexandre Bayen, and Yi Wu. The surprising effectiveness of mappo in cooperative, multi-agent games. *arXiv preprint arXiv:2103.01955*, 2021.

Kaiqing Zhang, Zhuoran Yang, and Tamer Başar. Multi-agent reinforcement learning: A selective overview of theories and algorithms. *Handbook of Reinforcement Learning and Control*, pp. 321–384, 2021.

A Properties of datasets

We list the properties of our offline datasets in Tables 2 and 3.

Maps	Difficulty	Data Quality	# Samples	Reward Distribution (mean (±std))
3m	**Easy**	3m-poor	62528	6.29 (±2.17)
		3m-medium	-	-
		3m-good	1775159	19.99 (±0.18)
8m	**Easy**	8m-poor	157133	6.43 (±2.41)
		8m-medium	297439	11.95 (±0.94)
		8m-good	2781145	20.00 (±0.16)
2s3z	**Easy**	2s3z-poor	147314	7.69 (±1.77)
		2s3z-medium	441474	12.85 (±1.37)
		2s3z-good	4177846	19.93 (±0.67)
2s_vs_1sc	**Easy**	2s_vs_1sc-poor	12887	6.62 (±2.74)
		2s_vs_1sc-medium	33232	11.70 (±0.73)
		2s_vs_1sc-good	1972972	20.23 (±0.02)
3s_vs_4z	**Easy**	3s_vs_4z-poor	216499	7.58 (±1.45)
		3s_vs_4z-medium	335580	12.13 (±1.38)
		3s_vs_4z-good	3080634	20.19 (±0.40)
MMM	**Easy**	MMM-poor	326516	7.64 (±2.05)
		MMM-medium	648115	12.23 (±1.37)
		MMM-good	2423605	20.08 (±1.67)
so_many_baneling	**Easy**	so_many_baneling-poor	1542	9.08 (±0.66)
		so_many_baneling-medium	59659	13.31 (±1.14)
		so_many_baneling-good	1376861	19.46 (±1.29)
3s_vs_3z	**Easy**	3s_vs_3z-poor	52807	8.10 (±1.37)
		3s_vs_3z-medium	80948	11.87 (±1.19)
		3s_vs_3z-good	149906	20.02 (±0.09)
2m_vs_1z	**Easy**	2m_vs_1z-poor	25333	5.20 (±1.66)
		2m_vs_1z-medium	300	11.00 (±0.01)
		2m_vs_1z-good	120127	20.00 (±0.01)
bane_vs_bane	**Easy**	bane_vs_bane-poor	63	1.59 (±3.56)
		bane_vs_bane-medium	3507	14.00 (±0.93)
		bane_vs_bane-good	458795	19.97 (±0.36)
1c3s5z	**Easy**	1c3s5z-poor	52988	8.10 (±1.65)
		1c3s5z-medium	180357	12.68 (±1.42)
		1c3s5z-good	2400033	19.88 (±0.69)

Table 2: The properties for our offline dataset collected from the experience of multi-agent PPO on the easy maps of SMAC.

Maps	**Difficulty**	**Data Quality**	**# Samples**	**Reward Distribution (mean ($\pm$std))**
5m_vs_6m	**Hard**	5m_vs_6m-poor	1324213	8.53 ($\pm$1.18)
		5m_vs_6m-medium	657520	11.03 ($\pm$0.58)
		5m_vs_6m-good	503746	20 ($\pm$0.01)
10m_vs_11m	**Hard**	10m_vs_11m-poor	140522	7.64 ($\pm$2.39)
		10m_vs_11m-medium	916845	12.72 ($\pm$1.25)
		10m_vs_11m-good	895609	20 ($\pm$0.01)
2c_vs_64zg	**Hard**	2c_vs_64zg-poor	10830	8.91 ($\pm$1.01)
		2c_vs_64zg-medium	97702	13.05 ($\pm$1.37)
		2c_vs_64zg-good	2631121	19.95 ($\pm$1.24)
8m_vs_9m	**Hard**	8m_vs_9m-poor	184285	8.18 ($\pm$2.14)
		8m_vs_9m-medium	743198	12.19 ($\pm$1.14)
		8m_vs_9m-good	911652	20 ($\pm$0.01)
3s_vs_5z	**Hard**	3s_vs_5z-poor	423780	6.85 ($\pm$2.00)
		3s_vs_5z-medium	686570	12.12 ($\pm$1.39)
		3s_vs_5z-good	2604082	20.89 ($\pm$1.38)
3s5z	**Hard**	3s5z-poor	365389	8.32 ($\pm$1.44)
		3s5z-medium	2047601	12.61 ($\pm$1.32)
		3s5z-good	1448424	18.45 ($\pm$2.03)
3s5z_vs_3s6z	**Super Hard**	3s5z_vs_3s6z-poor	594089	7.92 ($\pm$1.77)
		3s5z_vs_3s6z-medium	2214201	12.56 ($\pm$1.37)
		3s5z_vs_3s6z-good	1542571	18.35 ($\pm$2.04)
27m_vs_30m	**Super Hard**	27m_vs_30m-poor	102003	7.18 ($\pm$2.08)
		27m_vs_30m-medium	456971	13.19 ($\pm$1.25)
		27m_vs_30m-good	412941	17.33 ($\pm$1.97)
MMM2	**Super Hard**	MMM2-poor	1017332	7.87 ($\pm$1.74)
		MMM2-medium	1117508	11.79 ($\pm$1.28)
		MMM2-good	541873	18.64 ($\pm$1.47)
corridor	**Super Hard**	corridor-poor	362553	4.91 ($\pm$1.71)
		corridor-medium	439505	13.00 ($\pm$1.32)
		corridor-good	3163243	19.88 ($\pm$0.99)

Table 3: The properties for our offline dataset collected from the experience of multi-agent PPO on the hard and super hard maps of SMAC.

B Details of hyper-parameters

Details of hyper-parameters used for MADT experiments are listed from Table 4 to 8.

Hyper-parameter	**Value**	**Hyper-parameter**	**Value**	**Hyper-parameter**	**Value**
offline_train_critic	True	max_timestep	400	eval_epochs	32
n_layer	2	n_head	2	n_embd	32
online_buffer_size	64	model_type	state_only	mini_batch_size	128

Table 4: Common hyper-parameters for all MADT experiments

Maps	**offline_episode_num**	**offline_lr**
2s3z	1000	1e-4
3s5z	1000	1e-4
3s5z_vs_3s6z	1000	5e-4
corridor	1000	5e-4

Table 5: Hyper-parameters for MADT experiments in Figure 3

Maps	**offline_episode_num**	**offline_lr**	**online_lr**	**online_ppo_epochs**
2c_vs_64zg	1000	5e-4	5e-4	10
10m_vs_11m	1000	5e-4	5e-4	10
8m_vs_9m	1000	1e-4	5e-4	10
3s_vs_5z	1000	1e-4	5e-4	10
3s5z	1000	1e-4	5e-4	10
3m	1000	1e-4	5e-4	15
2s_vs_1sc	1000	1e-4	5e-4	15
MMM	1000	1e-4	1e-4	5
so_many_baneling	1000	1e-4	1e-4	5
8m	1000	1e-4	1e-4	5
3s_vs_3z	1000	1e-4	1e-4	5
3s_vs_4z	1000	1e-4	1e-4	5
bane_vs_bane	1000	1e-4	1e-4	5
2m_vs_1z	1000	1e-4	1e-4	5
2c_vs_64zg	1000	1e-4	1e-4	5
5m_vs_6m	1000	1e-4	1e-4	10
corridor	1000	1e-4	1e-4	10
3s5z_vs_3s6z	1000	1e-4	1e-4	10

Table 6: Hyper-parameters for MADT experiments in Figure 4, 6 and Table 1

Hyper-parameter	**value**
offline_map_lists	[3s_vs_4z, 2m_vs_1z, 3m, 2s_vs_1sc, 3s_vs_3z]
offline_episode_num	[200, 200, 200, 200, 200]
offline_lr	5e-4
online_lr	1e-4
online_ppo_epochs	5

Table 7: Hyper-parameters for MADT experiments in Figure 5a

Hyper-parameter	**value**
offline_map_lists	[2m_vs_1z, 3m, 2s_vs_1sc, 3s_vs_3z]
offline_episode_num	[250, 250, 250, 250]
offline_lr	5e-4
online_lr	1e-4
online_ppo_epochs	5

Table 8: Hyper-parameters for MADT experiments in Figure 5b