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LUDWIG-MAXIMILIANS-UNIVERSITÄT MÜNCHEN
INSTITUT FÜR INFORMATIK
LEHRSTUHL FÜR MOBILE UND VERTEILTE SYSTEME

MASTER THESIS

Exploring the Impact of Markets on Multiagent Reinforcement Learning

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I hereby affirm that I wrote this Master Thesis on my own and I did not use any other sources and aids than those stated.

Munich, 13. December 2021

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Signature

Abstract

A current research addresses the question of how to get mixed-motive agents to work together to achieve a common goal. Mixed-motive is an agent composition, that describes agents working independently and whose actions do not affect others directly. In most cases, the agents are not able to communicate. The influence to work in cooperation could be established through markets, namely a shareholder market (SM) or an action market (AM). By using markets, agents gain incentives when they act cooperatively. Shares of the SM let agents participate in the reward of others and an AM enables agents to reward others for certain actions.

This thesis introduces the coloring environment and uses it to compare the impact of the two markets in three different agent compositions - cooperation, mixed-motive and competitive. The coloring environment lets agents move around and color the cells they visit. Visiting a cell that is already colored removes its color, unless the competitive setting is set. In this case, the agent can capture opponent cells. The goal is to color the whole environment.

The compositions are established by means of reward distribution. Rewards of competitive and mixed-motive agents are calculated with their individual amount of color presence in the environment. Cooperative agents however, get one shared reward based on the overall coloration, which can lead to the credit assignment problem (CAP). Additionally, all three compositions face organizational challenges of agents getting in each other's way. The effectiveness of markets on these problems are analyzed in this research.

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1. Introduction

Reinforcement Learning (RL) is a popular research topic with many successful and interesting applications. Some popular RL utilizations are in the gaming sector, for example Go [SHM+16][SSS+17], chess [BTW01][SHS+17], poker [Dah01][XCC21] as well as very complex player versus player games such as Starcraft [VBC+19] and Dota [BBC+19]. Usually, such applications can be played by multiple agents, either in a team or against each other.

RL is unique in the fact that agents can learn to solve tasks without prior knowledge. However, having multiple agents try to learn in a shared environment poses several problems. An agent team, i.e. in a soccer game [AT04], either scores a goal or misses its chance. Retracing the game outcome onto the contributions of all agents and assigning credit accordingly is a common problem called the “credit assignment problem” (CAP).

Other game types, such as racing games for example, place players in competitive situations. The common goal is to reach the finish line - the earlier, the better. By using items or strategies, one might start to sabotage others, in order to place first. Although, when time becomes a factor, the goal might shift to finishing as quickly as possible, instead of wasting time disrupting others. Players still compete but keep a neutral behavior towards each other, since the success of one does not affect the achievement of others. This composition is further called mixed-motive. Cooperative, competitive and mixed-motive agent constellations are referred to as compositions.

Mixed-motive and competitive situations can be applied or recreated with RL. However, training competing agents often leads to disorder, since they get in each other’s way or become greedy and self-centered. A new research showed that adding incentives to mixed-motive agents enabled cooperative behavior and helped to align individual goals among each other. Schmid et al. [SBM+21] achieved this through a neutral market. A shareholder market (SM) allows agents to sell shares and let others participate in their success. Action market (AM) is the alternative option and lets agents buy specific actions from others. The following outline presents application details and the research question of this thesis.

1.1. Research Question

Since markets were only applied and analyzed on mixed-motive agent compositions so far, it leaves the question open, how the problems of cooperation and competitive compositions would be affected by them. By using markets on cooperation settings one could assume that agents with higher results contributed positively to the common goal. Therefore, the credit should already be assigned accordingly. In theory, markets in competitive compositions should also improve the results. Through incentives, the individual goals of agents might be aligned, which should reduce competitive behavior.

This research therefore compares the effectiveness of each market applied on all three compositions. Furthermore, to get a bigger picture, agents will be trained with two different learning algorithms and the results will be compared. To enable the research of different compositions, this thesis further introduces the coloring environment. Agents have unique colors and can stand or move in a grid. Agents that move around color the visited cells. However, moving on a colored cell removes the color instead. The different compositions are modeled through a reward schema, which signalizes how good or bad the coloration result is.

Cooperating agents always receive the same reward among each other, based on the overall coloration. In mixed-motive compositions, agents only get rewards based on their own contribution. Competitive settings are similar to mixed-motive, but with the difference that agents can take over colored cells of their opponents. The ending condition of the environment is a fully colored grid.

The training of the agents is executed through the two most popular learning algorithms of RL: proximal policy optimization (PPO) and the training of a deep Q-Network (DQN). PPO is a policy gradient method which allows agents to enhance their decision-making. DQN is an algorithm that utilizes a neural network together with Q-values. Q-values help to evaluate all possible actions of a situation and lets agents choose the best option in regard to possible future outcomes.

Comparing the affects of SMs and AMs in three distinct compositions and using two different learning algorithms results in many executions. To get an overview, scoreboards will be presented that filter the three best trainings, with or without markets, of each composition and algorithm. Based on those scores, the best settings will be challenged in more difficult setups with more agents to see how well they can scale.

1.2. Thesis Structure

The thesis begins by covering the background of this research question. First, the definition of RL is presented, and then the two learning algorithms PPO and DQN are introduced. In the related works chapter the credit assignment problem is analyzed in detail and the most common solution for it is introduced. Markets are the second topic of this chapter, and entails their calculations and trading approach.

Chapter 4 shows the implementation details of the coloring environment, its reward calculations and implementation details of the two learning algorithms and markets. The training results are displayed in the chapter 5 and discussed afterwards. To conclude this research the results are summarized and extensions or changes for future studies are suggested.

2. Background

RL is a process that requires both interactive parts as well as algorithms that improve interactions. The following section 2.1 introduces the general concept of RL and its specifications. Afterwards, two popular learning algorithms for RL problems are presented: PPO and DQN.

2.1. Reinforcement Learning

Sutton and Barto wrote in "Reinforcement learning: An introduction" [SB18] that RL is based on two components that interact with each other: an environment and an agent, see Figure 2.1. Those interactions take part during a time period with discrete time steps $t \in \mathbb{N}_0$ until a goal is reached or the ending condition applies. This process is called an episode. Formally, the journey of the agent to find the goal is described as a Markov Decision Process (MDP) [SB18]. When multiple agents act in the same environment, the Markov decision process is called a stochastic game [BBDS10].

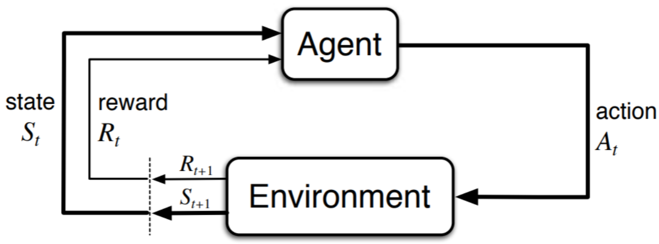


Figure 2.1.: The cycle of agent-environment interaction as shown in "Reinforcement learning: An introduction" [SB18]

One environment state S_t is part of a set S containing all possible states. In most cases, the environment state describes what the agent can see. An agent often only has a small field of view, which turns a MDP into a partially observable MDP [SB18]. During each point in time t, the agent can interact with the environment by executing an action A_t, which changes the environment state. An example would be moving in the environment, which results in a new area that the agent can now see. In a multiagent environment, every agent chooses its action simultaneously and adds it into a joint action set, which is executed collectively during t [BBDS10].

The reward R_t is an element of a set of possible rewards $R \subset \mathbb{R}$ [SB18]. Therefore, the reward can potentially be negative. Depending on the environment, that value can act as immediate feedback to the agents action. Other times, the reward is received as a result of a whole action sequence or the achievement of a certain state, for instance the goal or subgoals. The general concept of RL, as defined by Sutton and Barto [SB18], is for agents to maximize rewards. Unlike machine learning approaches, the agent starts with no knowledge about good or bad actions and enhances the decision-making over time.

Sutton and Barto defines the agents' action selection with respect to the current state as a policy π. They explain further that a policy could be as simple as a lookup table, mapping states to actions, or it could contain a complicated search process for the best decision. However, policies most of the time map action-state pairs to a selection probability, with all actions of a state adding up to 100%. During environment interactions, agents receive rewards which can be used to update the policy accordingly. As an example, the probability of policy $\pi(a \mid s)$ decreases when receiving a negative or low reward, reducing the chances of executing the same action in that specific state again.

While rewards only rate the immediate situation, a value function, i.e. the state-value function $V^{\pi}(s_t)$ for a policy π, can be used to estimate the long-term value of a state s [SB18]:

$$v_{\pi}(s) \doteq \mathbb{E}_{\pi}\left[G_t \mid S_t = s\right] = \mathbb{E}_{\pi}\left[\sum_{k=0}^{\infty} \gamma^k R_{t+k+1|S_t=s}\right] \tag{2.1}$$

The result is the estimated discounted cumulative reward an agent could get following that state and choosing actions based on the current policy. The discount factor is defined by Sutton and Barto as $0 \leq \gamma < 1$ and provides a constant that reduces the importance of future rewards. A high γ symbolizes a greater interest in rewards that are far away, whereas a discount of zero only takes the current reward into account. By setting γ smaller than one, it is ensured that the infinite sum results in a value. Generally, states that offer immediate high rewards could end in a low reward streak. In the opposite case, a low reward state could subsequently yield high rewards. Therefore, value functions are of great use to achieve the maximum reward.

The last part to note about RL is that it entails the problem of balancing exploration and exploitation [SB18]. On the one hand, an agent has to explore different options in order to learn and expand its knowledge. On the other hand, agents strive to maximize the reward, which can lead to greediness. An agent could start to exploit its knowledge too early, choosing actions of which it knows to result in positive rewards. However, if an agent does not explore enough, the best action sequence will stay hidden and the agents knowledge will not improve.

2.2. Proximal Policy Optimization

In 2017, Schulman et al. introduced the concept of PPO in the article "Proximal Policy Optimization Algorithms" [SWD+17]. Policy optimization is the improvement of the action selection strategy π based on the current state s_t. This is achieved by rotating two steps [SWD+17]:

1. Sampling data from the policy and
2. Optimizing the objective with that data through several epochs.

Using those steps results in the agent gathering a small batch of experiences while choosing actions with a policy π. Afterwards, this batch is used once to enhance the current policy. Then, the experiences are discarded and the agent uses the updated policy to gather a new batch. By repeating those two steps the agent can learn to choose better actions. PPO is applied to prevent drastic policy changes, which stabilizes the learning process.

The origin of PPO lies in a similar approach called Trust Region Policy Optimization (TRPO). TRPO also restricts policy updates by defining a trust region [SLA+15]. This is achieved by maximizing the following function [SWD+17]:

$$\underset{\theta}{maximize}\,\hat{\mathbb{E}}_t\left[\frac{\pi_\theta(a_t \mid s_t)}{\pi_{\theta_{old}}(a_t \mid s_t)}\hat{A}_t - \beta\, KL[\pi_{\theta_{old}}(\cdot \mid s_t), \pi_\theta(\cdot \mid s_t)]\right] \tag{2.2}$$

The expectation $\hat{\mathbb{E}}_t$ indicates, that an empirical average over a number t of samples is used for estimation and the algorithm alternates between sampling and executing these calculations. The variable $\hat{A}_t$ describes an estimator of the advantage function. This function was defined in the paper "Trust Region Policy Optimization" [SLA+15] with $A_\pi(s, a) = Q_\pi(s, a) - V_\pi(s)$. The first part calculates the state-action value, estimating the upcoming rewards for an agent, starting at state s and initially selecting action a. Afterwards, the action selection is based on the current policy π.

The second part contains the state value function $V_\pi(s)$, which works very similarly by starting at state s and using π. However, the difference is that the agent always chooses actions according to the policy. The result of the advantage function $A_\pi(s, a)$ shows whether a profit could be gained when deviating from the policy by specifically choosing action a.

The fraction $\frac{\pi_\theta(a_t|s_t)}{\pi_{\theta_{old}}(a_t|s_t)}$ in the Minuend of function (2.2) can be replaced by $r(\theta)$ and represents the probability ratio of an action in the current policy in comparison to the old policy [SWD+17]. θ represents a policy parameter. The result of $r(\theta)$ is greater than one, if an action is very probable in the current policy. Otherwise, the outcome lies between zero and one. Schulman et al. [SWD+17] further extract the first part of function (2.2) as the surrogate objective:

$$L^{CPI}(\theta) = \hat{\mathbb{E}}_t\left[\frac{\pi_\theta(a_t \mid s_t)}{\pi_{\theta_{old}}(a_t \mid s_t)}\hat{A}_t\right] = \hat{\mathbb{E}}_t\left[r(\theta)\hat{A}_t\right] \tag{2.3}$$

If only this part of function (2.2) is maximized on its own, it would result in large outcomes, which in turn leads to drastic policy updates. In order to stay in a trust region, as the name suggests, a penalty is subtracted from the surrogate function (2.3). The penalty is the subtrahend of equation (2.2) and contains the fixed coefficient β. Regardless of the function details and outcome of KL, the coefficient β is hard to choose, since different problems require different penalty degrees [SWD+17]. Even during a training process it could be necessary to adapt the coefficient, due to changes.

Therefore, Schulman et al. introduced

$$L^{CLIP}(\theta) = \hat{\mathbb{E}}_t \left[\min\Big(r(\theta)\hat{A}_t,\ clip(r(\theta), 1-\epsilon, 1+\epsilon)\hat{A}_t \Big)\right] \tag{2.4}$$

which is very similar to equation (2.2) but does not require coefficients. The first min entry contains L^{CPI} (2.3). The second part contains a *clip* function, which narrows the space of policy mutation with the small hyperparameter ϵ. After applying the clip function, $r(\theta)$ lies between $[1-\epsilon, 1+\epsilon]$. Calculating the minimum of the clipped and unclipped probability ratio produces the lower bound of the unclipped $r(\theta)$, preventing the policy to change drastically.

Finally, the following equation is introduced

$$L_t^{CLIP+VF+S}(\theta) = \hat{\mathbb{E}}_t \left[L_t^{CLIP}(\theta) - c_1 L_t^{VF}(\theta) + c_2 S[\pi_\theta](s_t)\right] \tag{2.5}$$

with c_1 and c_2 as coefficients. The authors point out that the loss function $L_t^{VF} = (V_\theta(s_t) - V_t^{targ})^2$ combines the policy surrogate and the value function error term and is necessary once a neural network shares parameters between policy and value function. An entropy bonus S is added to ensure exploration.

Furthermore, Schulman et al. point out that the policy is executed for T time steps, with T being a smaller value than the overall episode duration. Until now, the advantage function calculates values through an infinite loop, see the value function (2.1) for example. Hence, the advantage function needs to be adjusted as well. It is necessary that the future estimations do not exceed that time step limit. In this context, the following advantage function is used [SWD+17]:

$$\hat{A}_t = \delta_t + (\gamma\lambda)\delta_{t+1} + \cdots + (\gamma\lambda)^{T-t+1}\delta_{T-1} \tag{2.6}$$

$$\text{where} \qquad \delta_t = r_t + \gamma V(s_{t+1}) - V(s_t) \tag{2.7}$$

Schulman et al. also showed an example of the PPO algorithm, cf. algorithm 1. The example uses an actor-critic approach, which means that a critic is responsible to approximate the value function of the policy and the actor in turn improves the policy based on the approximation results of the critic [KT03]. N detonates actors collecting data in T time steps in each iteration. Meanwhile, the critic computes the estimations of the advantage values. Afterwards, the policy is replaced with a new one, in which the function $L_t^{CLIP+VF+S}(\theta)$ (2.5) is optimized during K epochs. For the optimization process, a small random batch of the previous time steps is used.

Algorithm 1: PPO, Actor-Critic Style, as shown in "Proximal Policy Optimization Algorithms" [SWD+17]

for *iteration=1,2,...* **do**
  for *actor=1,2,...,N* **do**
    Run policy $\pi_{\theta_{old}}$ in environment for T timesteps
    Compute advantage estimates $\hat{A}_1, ...\hat{A}_T$
  end
  Optimize surrogate L wrt θ, with K epochs and minibatch size $M \leq NT$
  $\theta_{old} \leftarrow \theta$
end

2.3. Deep Q-Network

Another learning approach that is often compared with PPO is the training algorithm of a deep Q-Network with Q-learning and experience replay. Instead of improving a policy, agents improve by maximizing a value function. Hence, this algorithm relies on the action value function, that is formally defined as follows [MBM+16]:

$$Q^{\pi}(s,a) = \mathbb{E}\left[\ R_t \mid s_t = s, a\right] \tag{2.8}$$

R_t represents the discounted cumulative reward $R_t = \sum_{k=0}^{\infty} \gamma^k r_{t+k}$. The estimated outcome is calculated by starting at a state s, executing a specific action a and reaching the next states by using a policy π. Mnih et al. [MKS+15] state, that the optimal action-value can be approximated with a deep convolutional neural network and the following function:

$$Q^*(s,a) = \max_{\pi} \mathbb{E}\left[r_t + \gamma r_{t+1} + \gamma^2 r_{t+2} + \ldots | s_t = s, a_t = a, \pi\right] \tag{2.9}$$

The difference between function (2.8) and (2.9) is, that in the second one, a policy is chosen, which optimizes the outcome. Mnih et al. continue by stating, that in a scenario where the sequence s' of all actions a' are known, the optimal $Q^*(s', a')$ of the next state can be calculated. Then, this Bellman equation could be applied [MBM+16]:

$$Q^*(s,a) = \mathbb{E}_{s'}\left[r + \gamma \max_{a'} Q^*(s', a') \mid s, a\right] \tag{2.10}$$

Many RL algorithms estimate this function through iterative updates, by calculating $Q_{i+1}(s,a) = \mathbb{E}\left[r + \gamma \max_{a'} Q_i(s', a') \mid s, a\right]$, Q_{i+2}, $\ldots$ [MKS+13]. Eventually the optimal Q value is reached with $i \rightarrow \infty$. Those calculations proved to be very impractical, since they require a lot of computational work, which is why Mnih et al. introduced the Q-network at this point. As a result, the parameters of the Q function are extended with θ as network weights ($Q(s,a;\theta)$).

However, the researchers argued that using a neural network in combination with the Q function proofed to be unstable. According to the authors, this is caused by correlating observations that are used to calculate the function. Additionally, small updates to the action value may lead to drastic changes of the policy. Such problems change the connection between Q values and their successive target values $r + \gamma \max_{a'} Q(s', a')$. To overcome these issues, Mnih et al. introduced two new concepts:

1. An experience replay that enables random sampling of observations and
2. An iterative update process of the action values approaching the target values.

The target values are only updated periodically in their implementation.

In algorithm 2, a deep Q-learning approach with an experience replay is shown. The experience replay contains the acquired agent knowledge of each time step in form of a quadruple: (old state, action, reward, new state). The experience values are then stored into the replay memory D across multiple episodes. The states are parameters of Φ_t in the example, since they are preprocessed, to match the network input conditions.

In addition to the action value function Q, the target action-value $\hat{Q}$ is initially defined with the same weights to enable iterative updates. In order to fill the memory, the agent first selects actions and acts in the environment. The action selection here is based on the ϵ-greedy policy, meaning that with a probability of ϵ a random action is chosen [MKS+15]. Otherwise, the best option according to the Q-value is selected.

Algorithm 2: DQN with Experience Replay, as shown in “Human-level control through deep reinforcement learning” [MKS+15]

Initialize replay memory D to capacity N
Initialize action-value function Q with random weights θ
Initialize target action-value function $\hat{Q}$ with weights $\theta^- = \theta$
for *episode=1,M* **do**
    Initialize sequence $s_1 = \{x_1\}$ and preprocessed sequence $\phi_1 = \phi(s_1)$
    for *t=1,T* **do**
        With probability ϵ select a random action a_t
        otherwise select $a_t = \text{argmax}_a Q(\phi(s_t), a; \theta)$
        Execute action a_t in emulator and observe reward r_t and image x_{t+1}
        Set $s_{t+1} = s_t, a_t, x_{t+1}$ and preprocess $\phi_{t+1} = \phi(s_{t+1})$
        Store transition $(\phi_t, a_t, r_t, \phi_{t+1})$ in D
        Sample random minibatch of transitions $(\phi_j, a_j, r_j, \phi_{j+1})$ from D
        Set $y_j = \begin{cases} r_j & \text{if episode terminates at step j + 1} \\ r_j + \gamma \text{max}_{a'} \hat{Q}(\phi_{j+1}, a', \theta^-) & \text{otherwise} \end{cases}$
        Perform a gradient descent step on $(y_j - Q(\phi, a_j; \theta))^2$ with respect to the network parameters θ
        Every C steps reset $\hat{Q} = Q$
    end
end

Executing the selected action results in a memory entry in the form of the earlier described quadruple. Afterwards, a minibatch of the replay memory is randomly sampled to calculate the difference between the values. The action values with the current weights are subtracted from y_i. This variable calculates estimated Bellman equation by using the target action values with the old weights. The parameter y_i contains just the reward value of the sample, if the sampled entry was the last step the episode of the entry. A gradient descent step is performed on the function, which means that the local minima of the function is searched by tweaking the parameter θ.

Finally, every certain amount of steps C the target network is set to the current Q-Network. The suggested process offers several advantages [MKS+15]: the replay memory leads to a smaller deviation or fluctuation in the parameters. The random samples of minibatches can be efficient, since an experience might be used multiple times to update the network weights. Furthermore, through the randomness in the samples, the correlation of steps is interrupted. This leads to a decrease of variance in between updates. Lastly, updating the target network periodically improves the stability of the learning process.

3. Related Work

Realistic RL scenarios often involve multiple agents solving problems together, for example robots working in warehouses and factories. Such multiagent environments come with many difficulties. On the one hand, in a scenario where agents work independently, it is very probable that they get in each other's way. They aim to achieve the highest score or finish their individual tasks, preventing the overall goal to be achieved.

In cooperative environments, on the other hand, agents share the reward and therefore cannot tell who contributed useful actions. The difficulties of agents working independently is discussed in chapter 3.2, whereas the cooperation challenge is the focus of the next chapter.

3.1. Credit Assignment Problem

Sutton and Barto [SB18] define a RL environment as cooperative, when agents execute their actions collectively each time step but receive one overall reward in return. In this case, individual learning is difficult or even impossible. Collective actions may contain bad choices that would be rewarded or, in case of a penalty, good actions that would be punished. Deciding which agent deserves more of the common reward is referred to as the CAP [Min61].

The CAP originated in a one-agent environment that only returned reward once the goal is reached or the terminating condition applies. A popular example of this is a chess game. In 1961, Minsky [Min61] elaborated, that a player wins or loses the game, but cannot retrace which decision got him there. Later on, Sutton decomposed the CAP into subproblems, namely the structural and temporal CAP [Sut84]. He suggests, that the temporal problem lies in assigning credit to each chess move by determining when the position improves or worsens, rewarding or penalizing that action. On the contrary, the structural CAP is assigning credit to the internal decision that leads to each particular action.

Transferring the single-agent CAP into a multiagent environment, Agogino and Tumer [AT04] show that the problem shifts from being a temporal to a structural type. They explain that while a single agent faces the temporal CAP due to many steps taken within an extended time period, in the multiagent case it becomes a structural CAP, because of multiple executed actions in a single-time-step. Since the actions are executed all at once, the challenge is now evaluating the decision that lies underneath.

Over the years, many solutions and theories emerged in order to solve CAPs in multiagent environments [RB09], [ZLS+20], [AT04]. A popular example for a simple approach to solve the problem is the difference reward (DR) [NKL18], [YT14], [AT04]. The idea is to calculate the overall reward with the joint multiagent actions as usual. Then, another reward is calculated for one agent if that agent would not have submitted its action. The difference between those two values indicates how profitable the action of the analyzing agent is. A high DR indicates a lucrative action, since excluding it leads to a small subtrahend value. With this method, each agent has the opportunity to learn how their actions contribute to the global reward, enabling individual learning.

Formally, in order to find the DR $D_i(z)$ for an agent i and the joint action set z, the following function applies [AT04]:

$$D_i(z) = G(z) - G(z_{-i}) \tag{3.1}$$

The first part of the equation $G(z)$ represents the overall reward of the action set of one time step. The second part $G(z_{-i})$ demonstrates the result of the same actions and time step, excluding only the action of agent i. Another approach to find the DR is to select a default action in $G(z_{-i})$ for the analyzing agent i, instead of dropping its action completely [VG96]. Calculating the equation (3.1) results in $D_i(z)$ of one agent i.

An example for this approach contains two agents, i and j, that act in an environment. In a time step t agent i executes a good action and j a bad action. For this scenario, good actions produce 0.6 as reward and bad choices result in -0.5 as punishment. In this example, the cooperation reward is the sum of the rewards, which is 0.1. Therefore, agent j is rewarded for selecting a bad action through the positive reward of 0.1 and ends up learning this strategy. However, using the DR function, a reward of $D_j(z) = 0.1 - 0.6 = -0.5$ is calculated for agent j and $D_i(z) = 0.1 - (-0.5) = 0.6$ for agent i. Thus, the credit is assigned to each agent depending on their contribution. Since there are only two actors, their DRs match the actual environment rewards of the actions.

As a downside, this approach is often inefficient or even infeasible [NKL18]. Nguyen et al. [NKL18] imply that large domains could make this calculation impossible. Sometimes, environment states need to be stored and replayed for every agent in order to calculate $G(z_{-i})$. Agogino and Tumer [AT04] claim that this simple function is not always applicable, since it can get difficult to exclude agents' actions. Nevertheless, this formula is often coupled with the CAP in research papers and builds a base for many advanced solutions of this topic.

3.2. Markets

As described before, agents that share an environment and act independently can often hinder each other from reaching the common or individual goal. Sutton and Barto defined a game to be competitive, when agents receive varying reward signals [SB18]. In most cases, agents follow a mixed-motive, meaning that their individual rewards could sometimes align and sometimes be in conflict. An environment is purely competitive, when the increase in reward of one agent leads to reward decrease of the others [SBM+21].

In "Stochastic Market Games" [SBM+21] Schmid et al. introduced concepts that add incentives when agents act cooperatively in mixed-motive settings, to improve the overall rewards for all participants. The idea of a Stochastic Market Game (SMG) is to enable dominant cooperative strategies through a global and impartial trading market. According to the researchers, a stochastic game becomes a SMG if two conditions are met: First, the environment actions of agents are extended with market actions. Second, the reward function adjusts the calculated rewards based on agreements met in the market executions. Furthermore, Schmid et al. defined two types of markets: unconditional and conditional markets.

3.2.1. Shareholder Market

They compare the concept of unconditional markets to companies and shareholders, since shareholders do not need to fulfill any conditions to receive the dividends. In unconditional SMGs, both companies and shareholders are agents that buy and sell shares as market actions. Figure 3.1 shows such a SM. During each time step, every agent has the possibility to put their share on the market or to announce a buying offer directed to another agent.

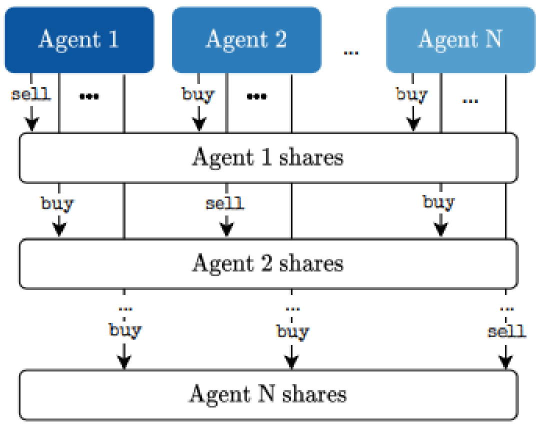


Figure 3.1.: Shareholder Market as presented in "Stochastic Market Games" [SBM+21]

If the buying offer coincide with a share that is up for sale in the same step, a market transaction is registered. Now, the shareholder participates in the reward of the current step of the transaction agent by a fixed dividend d. Schmid et al. mention that an optional price p can be defined as an amount a seller receives from the buyer upon each share purchase. However, they claim that agents with high rewards are very likely to gift their shares in order to align the goals of the other agents with their own. Shareholders profit from the success of the selling party through the dividends.

An example is an agent i who wants to sell a share and agent j that wants to buy a share specifically from agent i with both being in time step t. In this scenario, the offers coincide and a share of i is now claimed by j. If i now receives a reward of one and the dividend is 20%, agent j obtains a reward of 0.2 in addition to its own reward. However, in a scenario where agent i decided not to sell, agent j is not be able to claim the share and does not profit from the reward of agent i. After each step, the shares are resolved and the matching starts again.

3.2.2. Action Market

On the contrary, the authors define conditional markets similar to purchase contracts, where buyers pay a fixed price p to sellers when they in turn meet the buyers' demand. A proposed conditional SMG is the AM. In this case, actions are extended with a buying offer, containing one expected action from one specific agent, see Figure 3.2.

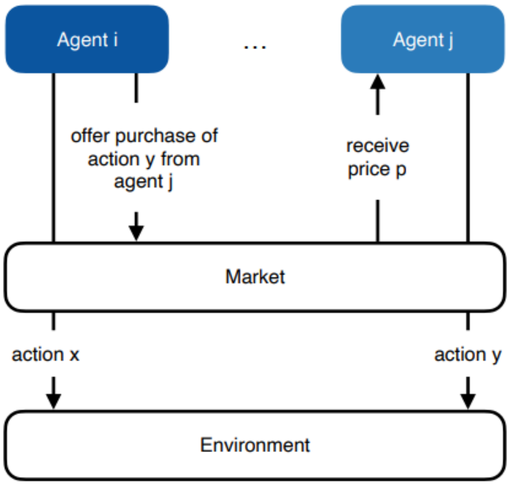


Figure 3.2.: Illustrated Action Market

In an example with two agents, i and j, i needs a resource that is currently occupied by j. Hence, agent i would profit from j giving up the resource and therefore offers to buy from j the action "release". Formally, agent i executes action $\vec{a}_{i,t}$, containing an environment action $a_{i,t}^{\text{env}}$ and the offer to agent j $a_{i,j,t}^{\text{offer}}$ [SBM+21]. The offer proposal shows that agent i is willing to buy from j at time step t a specific action $a_{j,t}^{\text{env}}$. If agent j fulfills the conditions and releases the resource in the same step t, it would receive a fixed price from agent i in form of a reward. However, if that is not the case, the market conditions do not apply and j is not paid by agent i.

In both market settings, a purchase is established if the specified agent happens to execute an action that matches with a buyer. It is important to emphasize that the matching is performed during a time step, leaving it to chance, whether purchases take place. For instance, in an AM, agents do not know in advance if and what action another agent is buying from them. Despite this uncertainty, the researchers show that both market implementations yield promising results. An increase of the overall rewards of participating agents in mixed-motive games is observed.

4. Approach

This chapter introduces the functionality and calculations of the “Coloring Environment”. The first section focuses on the key components: the environment itself and its agents. The agent compositions, which defines how they behave towards each other, is also part of section 4.1. Section 4.2 presents the reward calculations, which is tightly coupled with the behavior of the agents. Subsequently, the process of learning and how PPO and DQN are implemented is the topic of section 4.3. Lastly, the two market implementations and their influence on the rewards are presented.

4.1. Coloring Environment

A RL environment is a versatile and unbiased instance that can visualize changes and agent behavior. In Figure 4.1, the environment used in this work is presented. It originated from an openAI project called “Minimalistic Gridworld Environment” [CBWP18], which is designed for one agent whose main goal is to solve labyrinth puzzles. However, for the purpose of this research, the environment is changed heavily, becoming the “Coloring Environment”. Multiple agents can act in the new instance to try and achieve a common goal - to color all walkable cells.

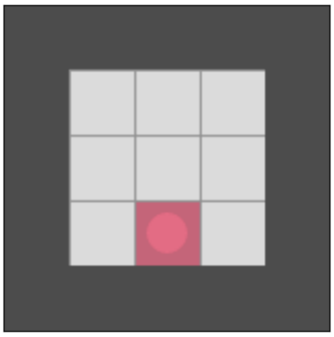


Figure 4.1.: The coloring environment.

In Figure 4.1 walls are visualized as outer dark cells and floors as white cells. The agent is represented with the red dot and the cell on which it is located is marked with the same color. By moving around, the agent can color cells. The environment is successfully solved once all fields are colored within a certain amount of steps. If a cell is already colored and the agent walks over it again, the color is removed. Therefore, the cell is reset and ready to be colored again.

Besides moving up, down, left and right, an agent can also execute the action wait to stay in place. Agents can not walk onto walls and if they try they stay in place instead. In a multiagent setting, each agent has a different random color. Cells adopt the color of the agent that walks over it. Multiple agents can occupy one cell, however, the cell can only contain one color at a time. In such a case, the color is decided by the order of the agents.

The coloration status of the cell is internally just managed with a bit switching function. This status changes from zero to one and vice versa every time an agent moves onto it. Theoretically, Figure 4.1 could also hide a blue agent underneath the red dot. If an agent were to move away from the cell, its color would not change, regardless whether another agent is still standing on it. Cells are always reset, if an agent moves on a colored cell, regardless of other agents being there. When two agents move on the same cell, the bit is just switched twice, which means that the coloration state stays the same.

4.1.1. Compositions

When multiple agents are placed in the coloring environment, there are several ways how they will behave towards each other. Depending on the setting, even the environment distinguishes how certain actions affect the state. Per default, agents will try to work together to reach the environment goal. Alternatively, they could work independently or even compete with each other.

The primary focus in cooperative agent compositions is only the overall coloration. The agents always receive the same reward, regardless of the specific colors on the grid. An extreme example would be one agent that colors the whole environment blue. Naturally, this would result in a high reward and in cooperation this means that all other agents would get the same amount.

In a DR setting however, agents are able to estimate their contribution, in order to improve their actions. This implementation executes the default action wait to find $G(z_{-i})$, see equation (3.1). By choosing wait as the default action, agents can learn what the environment outcome and general coloration percentage would be if they had not participated in the current step. It is important to note, that DR settings are always an extension of the cooperation mode and are never used with other compositions and markets.

In mixed-motive settings the colors are of importance. Agents only gain rewards based on their individual contributions. Thus, the rewards are generated by looking up each percentage a color is present and assigning that value to the same colored agent as reward. For example, if a red agent colored 60% of the grid red, the reward for that agent would be 0.60. A blue agent, that did not color any cells would get a reward of zero.

In a fully competitive mixed-motive scenario, the reward calculations stay the same. The difference lies in the reset behavior of colored cells. In this mode, agents can capture already colored cells when they walk over them. However, one condition applies: the color of the cell in the new position can not match the agent color. If they match, the cell is reset instead. Hence, taking over the cells of the opponents is beneficial, since it increases the presence of the own color, leading to a higher reward.

In comparison, the basic mixed-motive composition shows no advantages of resetting the opponent cells. Resetting cells is always punished with a small negative reward, regardless of the composition. Therefore, mixed-motive agents gain no benefit of doing so. This should lead to a neutral or independent behavior between the agents.

4.1.2. Observation

The observations agents receive from the environment are always generated individually and from their own point of view, with them in the center. The observation only contains a restricted area around them, making the environment a partially observable MDP. In large environments, this feature increases the difficulty. An example for an observation of an agent is shown in 4.2. This observation depicts the internal state of the environment visualization of Figure 4.1.

```
[
  [ [2 1 0] [2 1 0] [2 1 0] [2 1 0] [2 1 0] [2 1 0] [2 1 0] ]
  [ [2 1 0] [2 1 0] [2 1 0] [2 1 0] [2 1 0] [2 1 0] [2 1 0] ]
  [ [2 1 0] [3 0 1] [3 0 1] [3 0 1] [2 1 0] [2 1 0] [2 1 0] ]
  [ [2 1 0] [3 0 1] [3 0 1] [4 1 2] [2 1 0] [2 1 0] [2 1 0] ]
  [ [2 1 0] [3 0 1] [3 0 1] [3 0 1] [2 1 0] [2 1 0] [2 1 0] ]
  [ [2 1 0] [2 1 0] [2 1 0] [2 1 0] [2 1 0] [2 1 0] [2 1 0] ]
  [ [2 1 0] [2 1 0] [2 1 0] [2 1 0] [2 1 0] [2 1 0] [2 1 0] ]
]
```

Figure 4.2.: The internal agent observation

Per default, the agent has a view size of a seven by seven grid, represented in a three-dimensional array, similar to a RGB picture. All highlighted entries are part of the grid that is shown in Figure 4.1 and the red array shows the agent. The row entries of the observation can be mapped to the columns of 4.1, starting from the top left of the visualization.

The first dimension of the observation array contains the whole internal observation of an agent. The second array dimension represents the environment grid. Since the view size of the agent exceeds the dimension of the 5x5 visual grid, the additional rows and columns are filled with placeholders, in this case walls.

The last array dimension contains cell information, which is always composed of three elements. The first cell element defines the object type with one being just an empty cell, two shows a wall, three a floor tile and four an agent. The second element stores the coloration status as a bit. This defines whether a cell is colored, with zero signalizing an uncolored cell. Since agents can not walk onto walls, represented as [2 1 0], that object type always has a coloration state of one. The third cell encoding describes the color of a cell.

To better distinguish the object types in the visual representation, walls are zero for the color black and floors are initially white with encoding one. Each agent is assigned a number from two upwards which in turn stands for a randomly generated RGB color. The floor color encoding is overwritten with the agents color code when the cell is captured. For example, if the agent moves to the left, the cell of the previous position changes to a colored floor cell [3 1 2]. The new position of the agent is row three and column four with cell encoding [4 1 2].

4.2. Reward Calculations

The allocation of rewards is closely related to the composition of the agents, which can be specified by the user in training or visualization runs. In addition, the environment shape can be set, a number of agents placed and more. A basic example command for a training run is shown in listing 4.1.

Code Listing 4.1: Exemplary command to execute training with three agents in a coloring environment using PPO as algorithm

```
1 $ python -m scripts.train
2       --algo ppo
3       --model ppo-training
4       --env Empty-Grid-v0
5       --grid-size 7
6       --agents 3
7       --max-steps 20
8       --setting mixed-motive
```

The `--algo` parameter can be either “ppo” or “dqn” to choose a learning algorithm. This argument is the only required setting for training. All other configurations, including those not listed in 4.1, have default values and are shown in Appendix A.

With `--model` the destination path is defined, in which all logs, recordings and status updates are stored. Line 4 and 5 configures the environment. In alternative to the empty grid option of `--env`, as shown in Figure 4.1, four homogeneous rooms can be generated with “FourRooms-Grid-v0” to increase the difficulty.

The rooms are always of the same size and each room is accessible to all adjoining neighbors by one wall opening, which is random and changes in each episode. The overall size of the grid is set in Line 5. However, all grids in every layout option have outer walls that narrow the area in which agents can move. Hence, in a grid of size seven the agents can only move in a five by five field, due to the surrounding walls.

The amount of agents that act in the environment is set through the argument `--agents` and the maximum quantity of steps they can execute is defined with `--max-steps`.

To reach the highest reward, the agents need to color the whole field before they run out of steps. Lastly, the argument `--setting` specifies the composition of the agents. If no setting is set the agents work cooperatively. In the example of 4.1 the setting "mixed-motive" is chosen. The last two options for this parameter are "mixed-motive-competitive" and "difference-reward".

Regardless of the composition, agents initially generate separate rewards in each step based on their individual environment change. For instance, agents that color a field produce a positive reward of 0.1, whereas agents that reset a field contribute a penalty of negative 0.1. Agents that just wait generate a reward of zero. The only exception is the setting "mixed-motive-competitive", where agents can capture opponent cells. If that is the case, they get a positive reward of 0.1 otherwise the rules stay the same.

Rewards are always written into a list, which is initially returned by the environment, see algorithm 3, line 1. The position in the list indicates the accountable agent, i.e. a reward list of $[0.1, 0, \cdots]$ shows that agent zero is responsible for a reward of 0.1 and so forth. In algorithm 3, the update process of the initial environment rewards during each step is summarized. This step function takes the training arguments of Appendix A into account, which leads to the four conditions below.

Algorithm 3: Reward calculation each step

```
1  observations, rewards, done, info = environment.step(actions)
2
3  if difference reward setting then
4  |  rewards = calculate difference reward for each agent
5  else if cooperative setting then
6  |  rewards = calculate one cooperative reward
7  end
8
9  if market specified then
10 |  rewards = execute market actions and return transaction rewards
11 end
12
13 if done then
14 |  rewards = calculate final rewards
15 end
16
17 return observations, rewards, done, info
```

The first condition checks for a "difference-reward" setting. In this case, the agents work in cooperation, but try to solve the CAP by calculating the DR, see function (3.1). To achieve that, the current reward array is summed up to summarize the overall reward. As a result, the variable $G(z)$ of the DR equation is now set to the sum. To find the subtrahend of the equation, the agents are iterated and their individual calculations take place. The environment rewards are added up again, but this time the reward of the current agent is set to zero. This sum is the value of $G(z_{-i})$ for agent i. The function (3.1) is now applied for each agent and the initial reward list is updated with the individual DRs.

The last step of the DR reward update is checking, whether any value exceeds an upper or lower bound. If that is the case, then the value is set to the corresponding limit. Otherwise, the reward remains unchanged. The upper and lower bounds are necessary, due to more participating agents possibly leading to an enormous positive or negative sum. For example, a large positive sum without bounds could in turn decrease the importance of the final reward for reaching the environment goal. The other extreme is a high negative sum demotivating agents to move. The bounds in this implementation are set to 0.1 and -0.1.

If the setting is set to the standard cooperation, the reward needs to be changed to a new homogeneous value for each agent, due to the shared outcome. Again, the sum of the initial environment reward is calculated and reassigned to each agent position in the rewards array. The values must be clamped again in the same procedure as for the DR values. However, all rewards of the array are changed to the same value, should the bounds be exceeded. Settings that contain “mixed-motive” skip all previous reward updates, since in this case each agent keeps the individual value.

As third condition the market argument is checked for a SM or AM. In this case the market transactions changes the rewards. Details of the market process are discussed in section 4.4. One thing to note here is, that agents can execute market transactions in each step. For example, they can spend their current reward on actions or shares that are for sale or receive the purchase price from buyers, which in turn modifies the rewards.

The last condition depends on the done flag which signalizes the end of an episode. The flag is true, once either the grid is fully colored or the maximum step amount is reached. In this case, the final reward calculations are applied, see algorithm 4. The current rewards are passed as an argument to this calculation, since the list is modified again.

During the final reward calculations, the different agent compositions are checked again. In a “mixed-motive” or “mixed-motive-competitive” setting, each grid color percentage is extracted and added to the reward of the same colored agent. Otherwise, the composition is based on cooperation and the general grid coloration, regardless of the colors, is looked up and added to each reward value.

Additionally, the presence of a DR setting needs to be checked. For the final DR calculations the environment supplies information in the `info` variable of algorithm 3 Line 1. Namely, what the general coloration percentage of the environment would be for each agent, if this agent had executed action wait. Those percentages are subtracted from the cooperative coloration percentage to generate the DRs. Finally, the last market calculations are taken into account, see chapter 4.4 for details.

Algorithm 4: Final reward calculation

```
if mixed in setting then
    for each agent do
        rewards[agent] += agent color percentage on the grid
    end
else
    // cooperative setting
    rewards += overall coloration percentage of the grid
    if difference reward setting then
        rewards = calculate difference rewards
    end
end

if market specified then
    rewards = final market adjustments executed on rewards
end

return rewards
```

4.3. Learning Process

In order to compare different settings and agent compositions, each agent manages its own learning improvement, observation and action selection. Therefore, all calculations and estimations are executed independently, for instance, policy updates and value estimations. They also set up their own neural networks and optimizers and update them only with their own values. However, the environment still connects the agent experiences, by reacting to all agent actions simultaneously in each step and including visible agents in the observations.

Depending on the learning algorithm, the corresponding class is instantiated by the training script, as shown in Figure 4.3. The PPO and DQN classes both extend a base class that provides some abstract methods and a multiprocessing operation to execute actions on several environments at once. The base class returns data, allowing the training script to create recordings and log files to enable evaluation.

First, the training of agents begins by generating n environments based on the `--procs` setting of the training command, see Appendix A for the parameter list. Each environment has the same configurations, for example `--grid-size`, `--agents` and `--agent-view-size`. Second, the amount of `--frames` is taken from the parameters, defining a general training loop, which ends once this number is reached or exceeded. During the loop, the defined training algorithm `--algo` is executed.

Since both algorithms have similar procedures, they share the base class. This class implements a second iteration, that loops over the amount set for `--frames-per-procs`. During a time step, the agents execute different actions in the parallel environments.

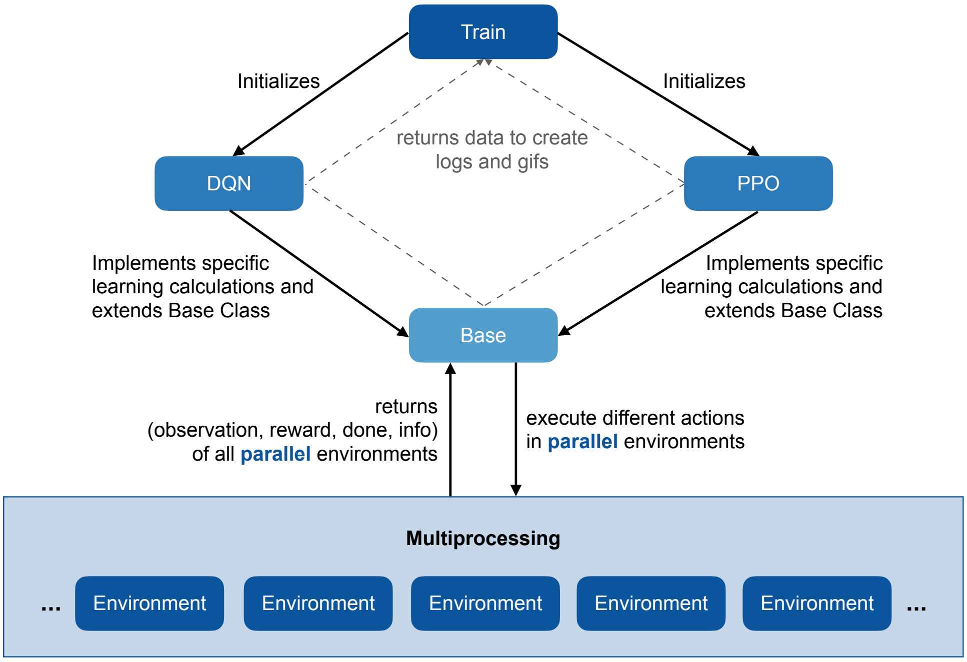


Figure 4.3.: The training structure

Therefore, each step in the `--frames-per-procs` iteration produces a frame in every environment. The action selection of the learning algorithms generate different decisions based on the state of each environment.

During the inner iteration, data such as rewards, observations, actions and more are stored in base class variables that are accessible by the learning algorithms. When this iteration is done, the base variables are reset and log values of all episodes that reached the done state are returned to be logged, as shown in Figure 4.3. The training loop keeps track of a frames counter, which sums up all frames that were produces by the parallel environments in the inner iteration. The training loop ends, when the frames counter is greater or equal to `--frames`. Otherwise, more experience batches are gathered.

Both learning algorithms include their own action selection methods. The PPO implementation relies on an actor-critic neural network, with an action space containing a probability distribution. In case of the DQN implementation, the target network assigns Q values to actions, and agents choose one based on the maximum value with an epsilon greedy probability. In both variants, the action selection results in one action for each agent and for each environment.

Unlike the PPO algorithm, in the DQN approach a quadruple of information is saved each frame into a replay memory. The four parts of the quadruple consist of the executed actions during that time step, the returned rewards and both the previous and new observation of the parallel environments. Until the frame amount of `--initial-target-update` is reached, DQN agents only gather the quadruples but do not use them yet.

After exceeding the `--initial-target-update`, the DQN learning starts. Each frame a batch of size `--batch-size` is selected by randomly picking entries from the replay memory. Then, this batch is used to apply Q-learning updates to the experience samples, enhancing the training network. Every `--target-update` amount of frames this training network is copied into the target network to enhance the action selection while keeping the algorithm stable.

The action selection itself is also improved during the training, by decreasing the ϵ gradually through $\epsilon = \epsilon_{end} + (\epsilon_{start} - \epsilon_{end}) * e^{-\frac{frames}{decay}}$. This ensures exploration in the early phase. A high ϵ leads to actions that are picked at random. In the later course, as the amount of frames increase, the ϵ gets smaller. In this case, the chance to select actions based on their Q values rises, which exploits the gathered experiences. Through `--epsilon-start` and `--epsilon-end` min and max values are set, and `--epsilon-decay` defines the speed of reduction.

In the DQN implementation, learning happens during the base class batch creation, whereas in the PPO algorithm the learning process is triggered after the creation of each base class experience batch. Basically, every time the inner loop finishes, the gathered values are reshaped and saved into a PPO experience buffer. Additionally, the advantage values are calculated and added to the buffer. With that buffer, the PPO model is now optimized. A small number of `--epochs` are iterated and during each iteration random batch entries are selected. With those entries the entropies, values and losses are calculated. Afterwards, the calculation results are used to update the policy and network, as suggested in the code of algorithm 1.

4.4. Market Settings

To include a market into the training process, the `--market` parameter can be set accordingly. The user has a choice to include an AM through the string "am" or a SM with "sm". In either case, the environment needs to adjust the action space, since agents now have the option to conduct market transactions.

Per default, the environment action space is discrete and only contains one element with five options: moving up, down, left, right or wait. Adding a market expands that discrete space into a multi discrete space. Hence, both markets require actions in form of arrays that contain three elements. However, they use different information in the action array slots. This and further distinctions and detailed procedures of each market are explained separately in the following.

4.4.1. Shareholder Market

A coloring environment that includes a SM constrains the first element of the action array to one of the five environment actions. The next position contains an agent index, towards which a buying offer will be made. Although, if this number is higher than the amount of agents in the game, the action intends no buying transaction. The last array position contains either a zero or a one, with one signalizing that the agent wants to sell its share. An abstract representation of a shareholder action array is: `[environment_action, agent_index, sell_share]`.

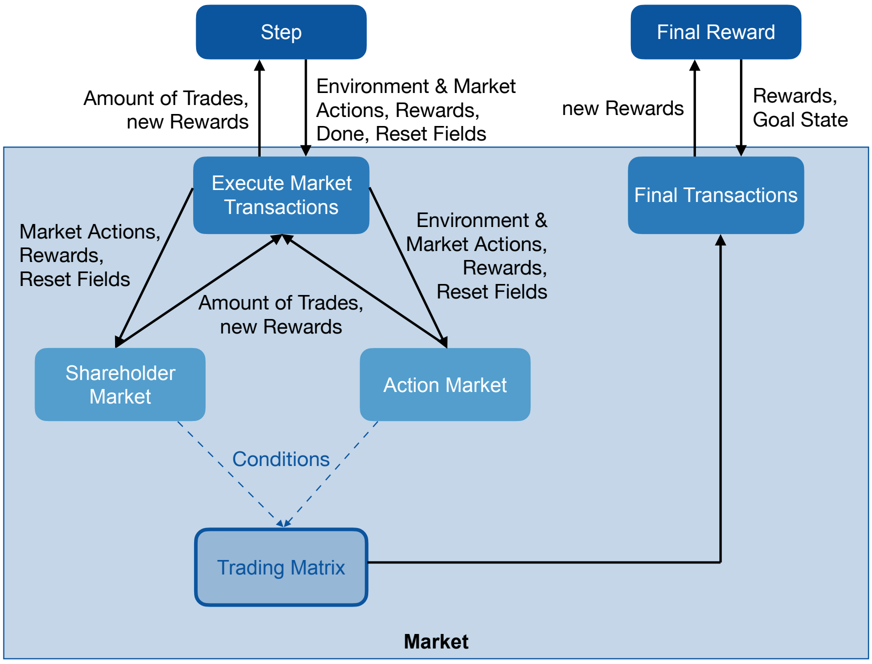


Figure 4.4.: The market elements

In Figure 4.4 market elements are visualized. On the left, the process that takes place during each step is shown, see algorithm 3 line 10. The market always receives an action array that is already divided in two parts, one part only containing the first array position and the other part includes the buying and selling information in this case.

In the course of the market calculations a trading matrix is altered. This matrix is quadratic with dimensions equal to the amount of agents. In a shareholder trading matrix, the diagonal contains ones, since every agent starts with the full ownership over their own shares. All other matrix slots are filled with zeros. An example for an initial trading matrix is shown below.

$$trading\_matrix = \begin{pmatrix} 1 & 0 \\ 0 & 1 \end{pmatrix}$$

As displayed in Figure 4.4, the market type is checked first. The type is defined by the `--market` parameter and the market receives this setting during initialization. If the market type includes the string "sm" the SM matches and the corresponding function is called. Inside the shareholder function two additional matrices are created in each step, a buying matrix and a selling matrix. Both matrices are always initially filled with zeros, are quadratic, and their dimensions are equal to the amount of agents, similar to the trading matrix. Depending on the market action, the buying matrix is altered to contain a one in the row of the buyer and the column of the agent that the offer is directed to. Each agent can only buy one share at a time, therefore, the rows contain at maximum one entry. The same applies to the selling matrix, which contains ones on the diagonal, showing which agent wants to sell according to the market actions.

After setting up and filling out the two matrices they are iterated, extracting the row entries of each matrix and defining the corresponding indices as buyer and seller. A transaction takes place, if the following conditions are met:

- the buyer is not equal to the seller
- all entries of the buyer row and the seller row match
- the sellers shares are greater than the `--trading-fee`

If all conditions are true, the trading matrix is updated, by changing the share of the selling agent, adding the subtracted amount to the buyer. The amount can be set with `--trading-fee`, which is 0.1 per default. The last condition ensures that agents still receive some of their own rewards and do not trade everything off.

An example for a transaction could be two agents acting in an environment. If agent two buys a share from agent one, the trading matrix is updated. The second row stores the shares of agent two, which increases by 0.1 on the first position. This signalizes that agent two is owner of some shares of agent one and still has 100% of its own shares. In response, the shares in the first row and column of agent one decreases to 0.9.

$$trading\_matrix = \begin{pmatrix} 1 & 0 \\ 0 & 1 \end{pmatrix} \xrightarrow[\text{from Agent 1}]{\text{Agent 2 buys}} trading\_matrix = \begin{pmatrix} 0.9 & 0 \\ 0.1 & 1 \end{pmatrix}$$

Additionally, the rewards of the current step calculation would be updated, if shares had prices. In this implementation, however, the shares have no price since agents are willing to give them away for free. Otherwise, the price would be subtracted from the buying agents reward and that value would be added to the reward of the selling agent.

In any case, the SM triggers a reward calculation according to the trading matrix in every step. This means that for the example above, agent two will receive 10% of the rewards from agent one in every step, until the episode ends. However, this is only the case in the steps in which agent one is not in debt. Further details of the reward calculations in markets will be discussed in section 4.4.3. Lastly, the transaction count is documented for evaluation purposes. At this point, the market execution for the current step is done and the number of executed trades and the updated rewards are returned in algorithm 3, line 10.

4.4.2. Action Market

The agent action shape of an AM environment is similar to the shareholder action array. Again, an action has three slots, with the first being the environment execution and the second being the index of an agent a buying offer is directed to. The difference to a shareholder action is the last array position. Instead of setting a bit to signalize the willingness of selling shares, the agent chooses an environment action that is expected from the agent of position two. Hence, an abstract representation of an action in the AM is the following: `[environment_action, agent_index, expected_action]`.

The market elements and general process of visualization 4.4 also apply to an AM setting. However, the trading matrix is initially filled with zeros. To establish a transaction, the market actions are examined and the following conditions checked:

- the buyer differs from the receiving agent
- the environment action of the receiving agent matches the expected action

When the two conditions are met, a market transaction takes place. The `--trading-fee` parameter decides the price the buyer pays the receiving agent. Both the rewards and trading matrix are altered, by subtracting the price from the buyer and adding it to the receiver. An example of the trading matrix update in this market setup is shown below. In this example agent two is purchasing from agent one again.

$$trading\_matrix = \begin{pmatrix} 0 & 0 \\ 0 & 0 \end{pmatrix} \xrightarrow[\text{from Agent 1}]{\text{Agent 2 buys}} trading\_matrix = \begin{pmatrix} 0 & 0.1 \\ 0 & -0.1 \end{pmatrix}$$

The trading matrix stores the market balance of both agents in each row. For agent two, this means that the negative value was spent. The first row shows that agent one still has a neutral balance and gained the `--trading-fee` of 0.1 from agent two. To conclude, the market returns the number of transactions that took place in this step and the new rewards, equal to the SM implementation.

4.4.3. Reward Calculations

During each step, agents can update the trading matrix by acting on the market. With each update, the rewards are also changed. In Figure 4.5 a detailed example of the reward update in a market is shown. It is worth mentioning that it is not possible to execute both markets simultaneously, but rather one can be set for a training process at maximum. This illustration shows both calculations in one image for convenience. Equal to the previous examples, the red agent two buys a share or action from the blue agent one. For both market scenarios the `--trading-fee` is set to the default value and both agent rewards start at 0.1. On the top half of the image, the internal market calculation of a SM is shown, and the bottom half illustrates the calculation of an AM.

In a SM, the trading matrix represents the distribution of agent shares. Each matrix column adds up to one, representing a 100% share of an agent. As mentioned earlier the diagonal of the matrix is initially set to one. For this example the trading matrices are configured according to the trade. The first matrix row implies that agent one is owner of 90% of its own shares and is not owner of any shares from agent two. Whereas the second row shows that agent two claims 10% of the shares of agent one and has full ownership over its own.

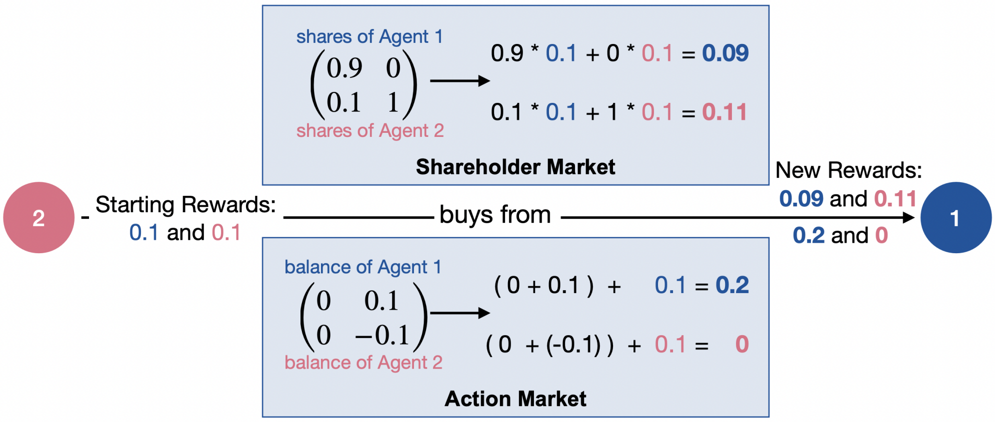


Figure 4.5.: Exemplary reward calculations of both market types

To generate the new rewards of the agents, the market multiplies all current rewards with each matrix rows. The resulting products of each row are then summed up to represent the new reward of the corresponding agent. For the example, agent one gets a new reward value of 0.09 and agent two claims 0.01 from agent one and adds that to its full value of 0.1, resulting in a new reward of 0.11.

In contrast to an AM, the rewards in a SM are just reassigned based on the current shares of the trading matrix. An exceptional case is, when agents have negative rewards. Then, their share will be skipped during the redistribution, since shares are used to participate in profits. Another difference to AMs is that the shown SM reward redistributions are executed in each step, and it is irrelevant whether market actions were executed. The only exception however is the last step, when the done flag is set to true. In this case the final rewards (see algorithm 4) need to be calculated first, before the shares are taken into account.

AMs, in most cases, update the rewards directly and only once, when a transaction is executed. The trading fee is immediately subtracted from one agents' reward and added to the counterpart during the trade. If an agent cannot afford the fee, the process is completed anyway and the agent goes into debt. This means that the AM implementation does not need a trading matrix. Nonetheless, the matrix is always updated, since a specific scenario requires the calculations to be executed at the end, see section 4.4.4. In this case, the agents market balance, stored in the matrix rows, is summed up and added to the reward. This procedure is illustrated in the bottom half of Figure 4.4.3. The fee of 0.1 is subtracted from agent two and added to the reward of agent one, leading to new rewards of 0.2 for agent one and zero for agent two.

4.4.4. Additional Conditions

The `--market` string for both types can be extended to add more conditions, namely with "no-reset", "no-debt" and "goal". The "no-reset" string enables the check whether the buyer has recently reset a cell. If that is the case, the corresponding buyers are ignored on the market for the current step. Hence, their market actions will not be applied. However, in a SM the penalized agent can still sell its shares.

With the “no-debt” flag, transactions only take place if buyers can afford to pay the price. In this implementation with AMs and the default fee, this is solely the case if agents have colored a cell in that step. Waiting or misbehaving agents are excluded as buyers, since their rewards result in 0 or -0.1, which does not meet the fee of 0.1. For SMs, this depends on the presence of a share price. Per default, the price is zero, similar to the approach of Schmid et al. [SBM+21], making this condition irrelevant for the SM setting.

The last addition, “goal”, lets the market process run as usual, removing the reward changes during the steps. All transactions are just documented into the trading matrix during an episode. Eventually, the transactions are executed once the final rewards of algorithm 4 is calculated. As shown on the right side of Figure 4.4, the market obtains those rewards and a Boolean describing whether the environment goal was reached.

The rewards are updated with the trading matrix content when either of the two conditions is satisfied:

- “goal” addition is present and environment goal was reached
- no “goal” addition and market type is a SM

Otherwise the rewards are returned as they are and will not be processed further. The “goal” addition specifies, that the grid needs to be fully colored, in order to execute trades. For goal oriented markets, regardless of the type, the final environment state needs to equal the overall aim. Thus, the whole grid has to be colored, to execute the final market transactions.

If the first condition applies and an AM is present, the rewards are updated by using the trading matrix. For a SM, either condition must be met in order to generate the final reward. The calculations for both cases are equal to the example of chapter 4.4.3. After the final market updates to the rewards the new values are returned, as shown in Figure 4.4. The last thing to point out is that the additional market conditions can be used in combination, making “sm-goal-no-reset-no-debt” for example a valid `--market` setting.

5. Results

In this chapter, the results of various training executions with different parameters are compared. All possible combinations of markets, agent compositions and learning algorithms in an easy setup are shown in section 5.2. The best combinations are then extracted and applied in more challenging environments, which are compared in section 5.3 and 5.4. Furthermore, Appendix B shows all generated training plots of the presented results.

5.1. Preset

The results of this research compare multiagent trainings with varying settings, namely acting in different compositions and markets. In this case, the amount of agents stays fixed and is greater than one. The agents use either of the two learning approaches PPO or DQN to train. Hence, the overall possible comparisons include a total amount of 102 executions. This number results from the calculation of multiplying the two learning algorithms with the three possible agent compositions (cooperative, competitive and mixed-motive) and additionally two optional markets that can contain three modular additions.

The market options are for example the following SM instances:

- “sm”
- “sm-goal”
- “sm-no-debt”
- “sm-no-reset”
- “sm-no-reset-no-debt”
- “sm-goal-no-debt”
- “sm-goal-no-reset”
- “sm-goal-no-reset-no-debt”

The 8 options above are also applied on the AM and lastly the option of no market needs to be considered, leading to 17 market scenarios. Calculating the total amount of executions now with those 17 market possibilities results in the 102 executions.

Yet, not all market arrangements are needed. For example, the mix of “no-reset” and “no-debt” is not of use in this implementation. An agent that has reset a field has a reward of -0.1 and therefore already is in debt, which means that “no-debt” includes “no-reset”. This subtracts four compositions from the 17 market scenarios. Additionally, shares are free of charge, making the options “sm-no-debt” and “sm-goal-no-debt” irrelevant. Agents can always afford to buy shares in this case. The SM is therefore left with four combinations and the overall market scenario count is now 11:

- “am”
- “am-goal”
- “am-no-debt”
- “am-no-reset”
- “am-goal-no-debt”
- “am-goal-no-reset”
- “sm”
- “sm-goal”
- “sm-no-reset”
- “sm-goal-no-reset”
- no market

In total, the analyzation now only includes 66 training results.

In order to compare the market approach with a credit assignment solution in the cooperation composition, the training with a DR setting is also included. This in turn, adds another execution to each learning algorithm. Furthermore, to ensure that the environment is generally solvable, one agent first trains in the environment setup with each learning algorithm using similar hyperparameter as in the multiagent case. The execution count is therefore 70 in total.

For an easy setup, those 70 executions are mostly run with the default parameters that can be looked up in Appendix A. The agents solve an empty five by five grid, in which they can only walk inside a three by three area, due to the surrounding walls, see Figure 5.1. The maximum amount of steps the agents are allowed to take is set to 25, if not manually specified otherwise. This count is generated by squaring the grid size. For the one agent execution the step size is reduced to 10.

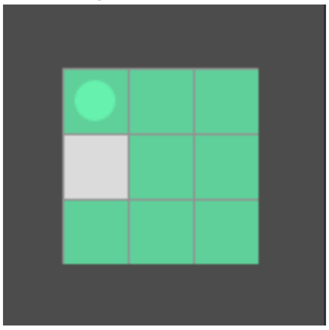


Figure 5.1.: Visualization of a small environment with one agent

Setting	Fully colored
1 ppo	3383
1 dqn	650

Table 5.1.: Number of times the agent fully colored the environment during training with each learning algorithm

Table 5.1 shows the amount of times the grid on the left (Figure 5.1) was fully colored by one agent using each learning algorithm during approximately 80.000 `--frames`. The PPO agent colored the whole grid a total amount of 3383 times and the DQN agent 650 times. This means that at least 3383 PPO and 650 DQN episodes were played through. A fixed upper episode number does not exist, since it depends on the amount of steps agents need to reach the goal. The less they need, the more episodes they could play. The 80.000 frames are an approximation of the overall step count the agents can execute. The number of goals is a way to compare similar executions, and will be used as a general score to filter the best settings of the 70 executions.

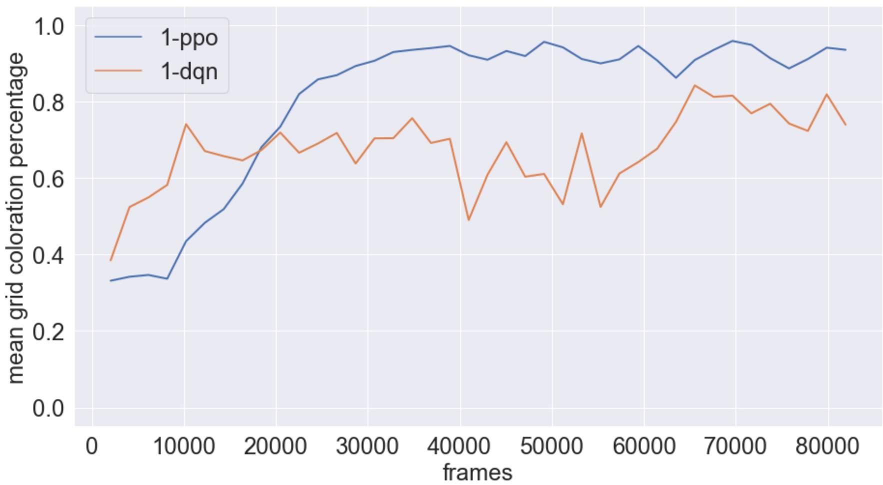


Figure 5.2.: The mean coloration percentage in a 5x5 grid and one acting agent

The average grid coloration percentage during the training is shown in plot 5.2. The plot lines start at around 2048 frames, since this marks the first time an entry is saved. This specific number originates from the 128 `--frames-per-proc` with `proc` referencing the parallel environments. This in turns means that 128 steps in 16 environments are executed. During those 128 steps, with 10 `--max-steps` in the worst case, 12 episodes could be completed in each environment. All data of such completed episodes are gathered and mean values are calculated.

The plot depicts the average grid coloration percentage of the end of completed episodes. For the DQN line, this means, that the first entry at 2048 frames contains a final mean grid coloration of 40%. The plot also exceeds the 80.000 default `--frames`, since the last data entry includes the last 2048 frames. This and more training plots are shown in Appendix B.

Plots and tables that refer to the fully colored grid values is the only case, in which the occurrences are counted instead of calculating mean values. Hence, in the table 5.1 the total sum of all finished episodes with a fully colored grid is presented. Both training runs solve the environment and the plot illustrates that in both cases, a high percentage of the grid is colored. The DQN execution yields a better performance in the early stage, whereas the PPO agent gradually improves over time. In both cases, an average final coloration of over 70% is eventually reached. This concludes that the grid is solvable with the default parameters.

5.2. Easy Setup

Now the multiagent scenario is compared. A set of two agents are trained to color the field of the same default dimensions, see Figure 5.3. However, every agent executes an action during a step and with 10 steps and two agents in theory 20 cells could be visited. Hence, the `--max-steps` count is reduced to eight. This should leave enough space for agents to make mistakes and still have a chance to solve the grid.

In order to get an overview of the overall 70 training results, the remaining 68 multiagent executions are divided into three different `--setting` values. The first data division only covers the cooperation compositions, including "difference-reward". Table 5.2 illustrates the scoreboard of the top three executions in this specification for each learning algorithm, measured by the total amount of complete colorations.

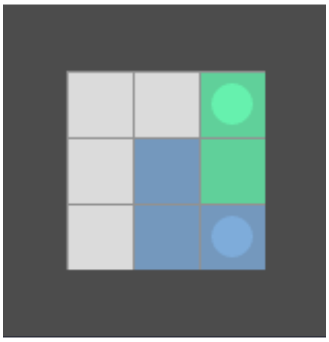


Figure 5.3.: Visualization of a small environment with two agents

	Top PPO Cooperation Settings	Fully colored
1	cooperation difference-reward	1683
2	cooperation	1109
3	cooperation sm-goal-no-reset	533

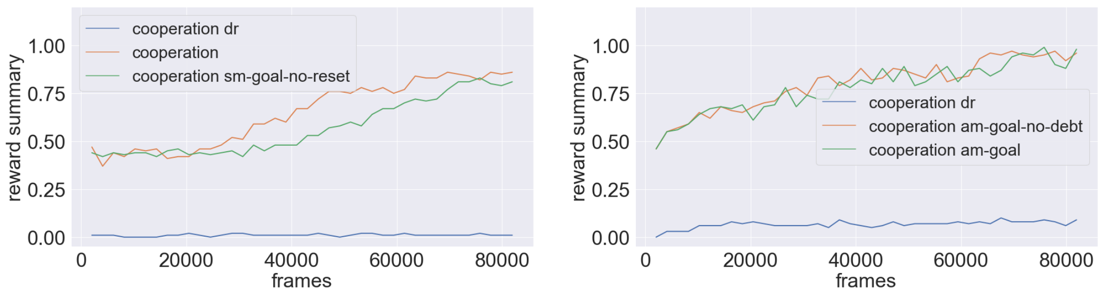
	Top DQN Cooperation Settings	Fully colored
1	cooperation difference-reward	5949
2	cooperation am-goal-no-debt	3197
3	cooperation am-goal	2880

Table 5.2.: Number of times two agents working in cooperation fully colored the environment during training.

In both cases, the agents with the DR setting scored best, 1683 times with the PPO algorithm and 5949 times by using DQN. The PPO scores continue with the default cooperation scenario on second and the SM with the "goal-no-reset" condition on third place. On the contrary, the DQN results show AM settings on the remaining places, with the additions "goal-no-debt" on second place and "goal" on the third place. It is visible that in both scoreboards the second and third executions are far behind the corresponding DR setting in terms of fully coloration counts.

In the two plots of Figure 5.4, the reward summary of the top scores are displayed (see table 5.2). The term reward summary is used, since the rewards of cooperating agents are equal and sometimes contain only slight changes through markets. However, in other agent compositions, the rewards are rather specific to each agents' contribution. In any case, the logged training data contains the mean reward of every agent separately.

In order to summarize cooperation rewards, the average value of those separate agent rewards is calculated for each data entry and the results are then plotted here. For reward summaries of all other compositions, each data entry is summarized with the sum of the separate agent rewards. The maximum y-axis label is set to 1.2, since agents



(a) Reward summary of PPO agents

(b) Reward summary of DQN agents

Figure 5.4.: Reward Summaries of the top three cooperation compositions using PPO (left) and DQN (right)

get a reward of one, if they color the whole field, and additionally could get a reward of 0.1 for the final step. Through the reward summary calculations rounding errors may occur, which could in turn exceed the maximum reward of 1.1. Furthermore, markets could also contribute to bigger rewards.

Even though, the executions with the DR configuration scored highest in terms of reaching the goal, the reward lines in this case stay around 0.1. The reason for that is that agents get the difference of two rewards, leading to very small values. All rewards, except the DRs, show a continuous increase and at least reach a summary reward of 0.8.

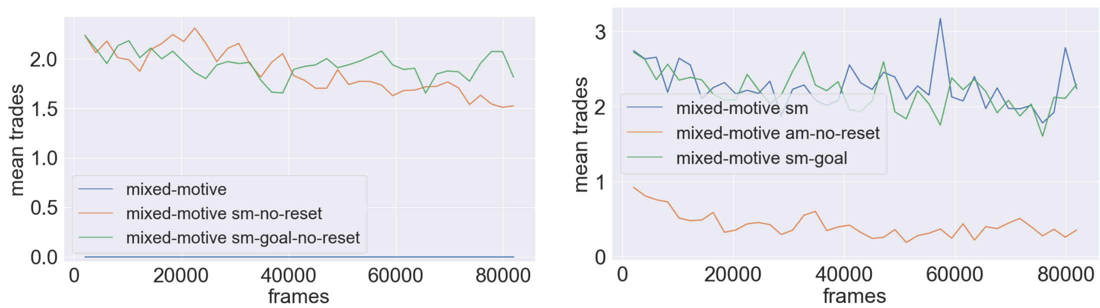
The next training executions to look at are "mixed-motive" settings. Again, a scoreboard listing the top three results of each learning algorithm, is shown in table 5.3.

	Top PPO Mixed-Motive Settings	Fully colored
1	mixed-motive	1734
2	mixed-motive sm-no-reset	1422
3	mixed-motive sm-goal-no-reset	1377

	Top DQN Mixed-Motive Settings	Fully colored
1	mixed-motive sm	5417
2	mixed-motive am-no-reset	5379
3	mixed-motive sm-goal	5302

Table 5.3.: Number of times two agents working in a mixed-motive setting fully colored the environment during training.

The PPO scoreboard shows that the plain "mixed-motive" setting is on the top with a score of 1734. Subsequently, SM configurations follow, with the addition of "no-reset" on second and "goal-no-reset" on third place. The DQN scores also show two SM settings, the default market occupies the first place and the SM with the "goal" addition is on the last place, both however colored the grid a total of over 5300 times. The AM with the "no-reset" condition is on the second place in the DQN statistics.



(a) Mean trades of PPO agents **(b)** Mean trades of DQN agents

Figure 5.5.: Mean trades of the top three mixed-motive compositions using PPO (left) and DQN (right)

In Figure 5.5, two plots are shown, visualizing the trading behavior of the agents during training. The plots display the mean amount of trades in the parallel environments. In plot 5.5a, the blue line stays at zero, since this execution does not contain a market extension. The other two lines are slightly decreasing and move between 2.2 and 1.5. Both lines represent a SM interaction with the values showing that on average two market transactions occurred. This in turn means that about two shares were bought in the completed episodes of all parallel environments.

In the right plot 5.5b, an AM is represented with the orange line. The mean trades are less compared to the other two SM lines. This is often the case for the two markets, since action purchases subtract a bigger value at once, whereas selling shares reduces a minor value of the payout continuously. Comparing the SM executions between PPO and DQN shows, that the restriction of “no-reset” lowers the average trades to around two, whereas without this specific condition the trade count is between two and three.

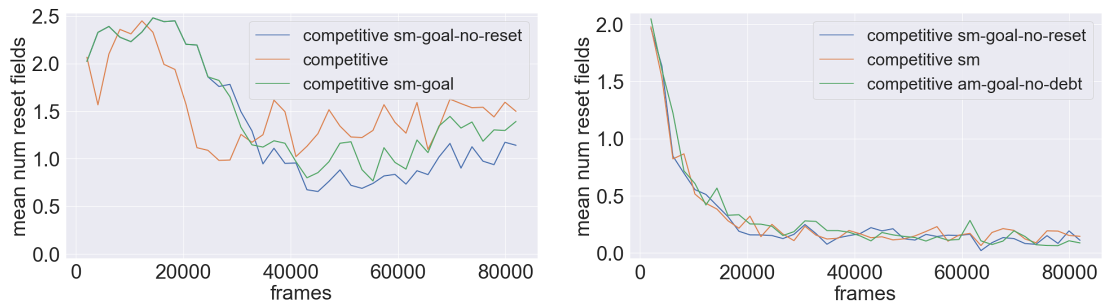
The last dataset division only includes executions of competitive agent compositions. Table 5.4 shows the scoreboards of this setup.

	Top PPO Competitive Settings	Fully colored
1	competitive sm-goal-no-reset	3614
2	competitive	3461
3	competitive sm-goal	3225

	Top DQN Competitive Settings	Fully colored
1	competitive sm-goal-no-reset	7877
2	competitive sm	7842
3	competitive am-goal-no-debt	7560

Table 5.4.: Number of times two agents working in a competitive setting fully colored the environment during training.

For both learning algorithms, the most fully colored grids result from executions specifying a SM with the condition “goal-no-reset”. In the DQN table the execution using the standard SM follows on second place and the last place is occupied by an AM with the specification “goal-no-debt”. For PPO, however, the second place is the normal competitive mode without any additions and on third place is a SM execution with the “goal” restriction. Overall, the score differences within the tables are not significant, at most a difference of around 300 goal states is observed. Furthermore, the scores of the first places in these two boards are the best values achieved by a multiagent setup so far, with 3614 fully colored grids in the PPO table and 7877 in the DQN table.



(a) Mean number of reset fields of PPO agents

(b) Mean number of reset fields of DQN agents

Figure 5.6.: Mean number of reset fields of the top three competitive compositions using PPO (left) and DQN (right)

The plots to those scoreboards are displayed in Figure 5.6. In this case, the average amount of reset fields are visualized. All lines start at a value two, which means, that during the first 2048 frames an average of two cells are reset during the completed episodes. In both cases the graphs eventually drop, however for PPO executions this takes around 20.000 frames and in the later half a small increase in all lines can be observed. Meanwhile, the three DQN trainings rapidly reduce the average resets to around 0.3. This value is never reached by PPO executions, here the lowest score is approximately 0.6.

5.3. Difficult Setup

To see how the results change when it becomes more challenging to reach the goal, all top executions shown before are now repeated in a bigger environment. The grid size is increased to seven, which provides an area of 25 cells for the agents to color. Also, since the grid offers more room, the amount of agents is increased to three.

To give the agents more time to learn, the `--frames` are set to 200.000 and the value of `--frames-per-proc` is changed to 256. With the increase to 256, the training data entries are now 4096 frames apart instead of the 2048 before. The number 4096 comes from multiplying the number of environments with the `--frames-per-proc`. To successfully solve the grid with one agent, some DQN specific parameters needed to be tuned. As a result, the adjusted values of `--replay-size`, `--epsilon-decay` and `--target-update` are 700.000, 20.000 and 10.000.

In Figure 5.7, the one agent learning scenario during training in a difficult setup is shown. The agent view size is also noticeable, with the lighter floor and wall colors three tiles around the agent. In this case, the agent cannot see the two top rows of the grid. This, of course, also contributes to the difficulty of this setup.

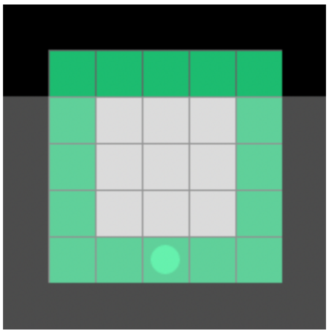


Figure 5.7.: Visualization of a 7x7 Environment with one agent

Setting	Fully colored
1 ppo	2924
1 dqn	394

Table 5.5.: Number of times the agent fully colored the environment during training with each learning algorithm.

The results of the training executions with one agent are shown in table 5.5. In this case, the maximum step amount is again the default value of 49, since the grid size of seven is squared. Similar to the easier setup, the PPO training yields more fully colored grids compared to the DQN execution. While the PPO agent reaches the goal 2924 times, the DQN agent only achieves 394 goal states. Comparing those numbers with their corresponding easy equivalent, it is also obvious that the scores of both learning algorithms have decreased.

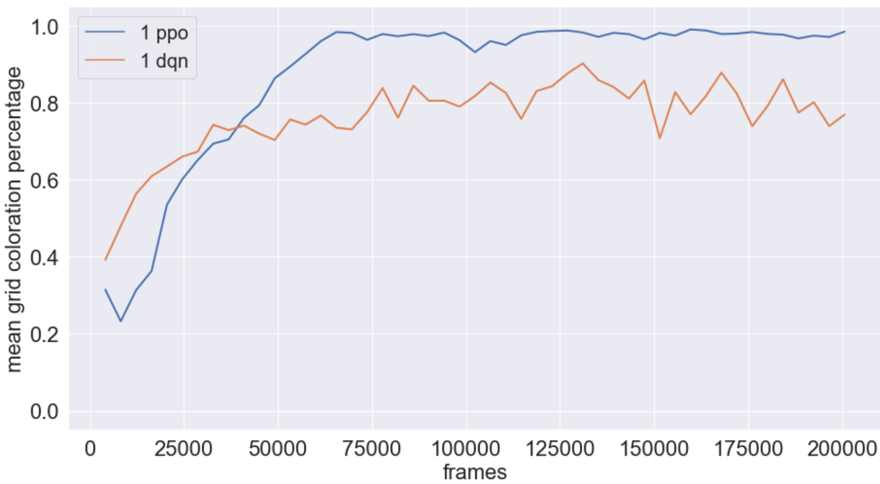


Figure 5.8.: The mean coloration percentage of a 7x7 grid and one acting agent

Looking at the mean coloration percentage plot 5.8 however, both executions show an increase to a relatively high percentage. The DQN agent training reaches an average of 80% grid coloration with only minor deviations. In comparison, the training with PPO has a steep incline from 20% to 95% and after 60.000 frames, this high percentage is maintained until the end of training. This proves that both algorithms learned strategies to color the environment with the set parameters.

For the training in this setting with three agents, the maximum step amount is set to 20. In Figure 5.9, a training frame is visualized. In this time step, the observation of the top agent does not include the two agents on the bottom. The two agents in turn also cannot see the top agent, but are aware of their neighbor.

The results of the cooperation executions with three agents are listed in table 5.6.

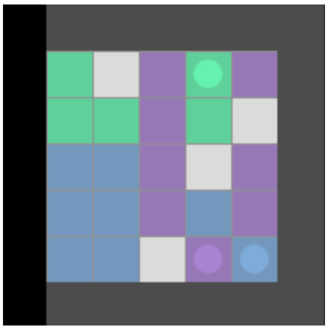
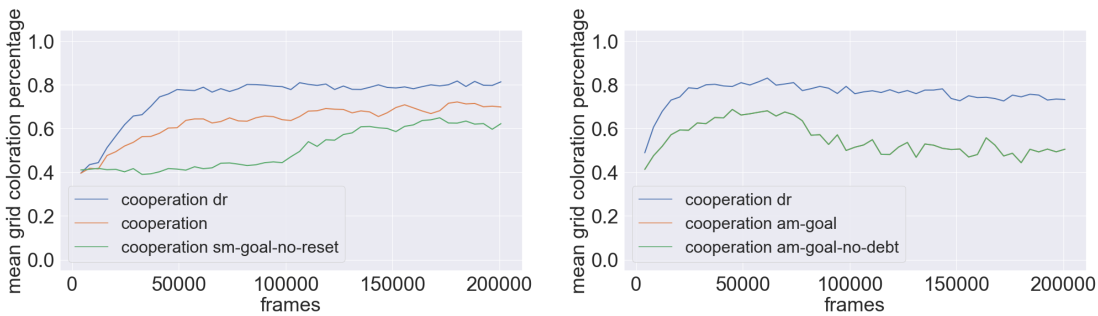


Figure 5.9.: Visualization of a 7x7 environment with three agents

	Top PPO Cooperation Settings	Fully colored
1	cooperation difference-reward	166
2	cooperation	10
3	cooperation sm-goal-no-reset	0

	Top DQN Cooperation Settings	Fully colored
1	cooperation difference-reward	115
2	cooperation am-goal-no-debt	0
3	cooperation am-goal	0

Table 5.6.: Number of times three agents working in cooperation fully colored the environment during training.



(a) Mean coloration percentage of PPO agents

(b) Mean coloration percentage of DQN agents

Figure 5.10.: Mean grid coloration percentages of the top three cooperation compositions using PPO (left) and DQN (right)

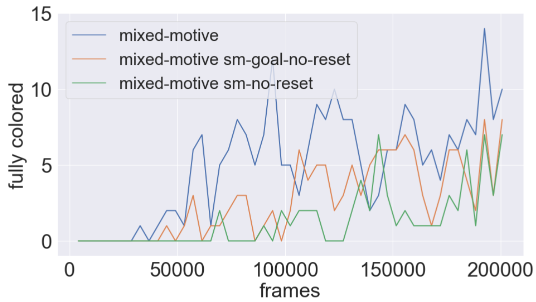
This table shows that all cooperative settings with specified markets yielded no goal achievements. In the DQN scoreboard, only the DR approach resulted in 115 complete colorations. The PPO table also lists the DR training result as first place with a total score of 166. The standard cooperation training ranks second in this regard, but only with 10 fully colored states. Overall, the scores have significantly decreased in comparison to the small environment results.

In the plots of Figure 5.10, it is visible that both DR trainings result in a similar average coloration percentage of around 80%. In the DQN plot, only two lines are visible due to the "goal" addition of the market execution. Since the goal is never reached, the final market payout with the trading matrix could not be applied. Hence, both trainings yielded the same decisions and overlap in this graph.

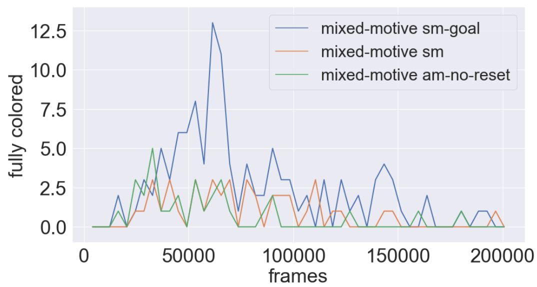
	Top PPO Mixed-Motive Settings	Fully colored
1	mixed-motive	247
2	mixed-motive sm-goal-no-reset	133
3	mixed-motive sm-no-reset	66

	Top DQN Mixed-Motive Settings	Fully colored
1	mixed-motive sm-goal	116
2	mixed-motive sm	42
3	mixed-motive am-no-reset	31

Table 5.7.: Number of times three agents working in a mixed-motive setting fully colored the environment during training.



(a) Fully colored grid achievements of PPO agents



(b) Fully colored grid achievements of DQN agents

Figure 5.11.: Environment goal achievements of the top three mixed-motive compositions using PPO (left) and DQN (right)

Continuing with the mixed-motive executions, table 5.7 shows the goal achievements. The PPO board still has the default mixed-motive composition on first place, with 247 fully colored counts. Comparing this board with the results of the smaller environment, it is clear that the next two position have swapped places. Also in the DQN board, the order has changed. The previous last placed "sm-goal" setting is now on the first place with 116 colorations and the other two executions moved down.

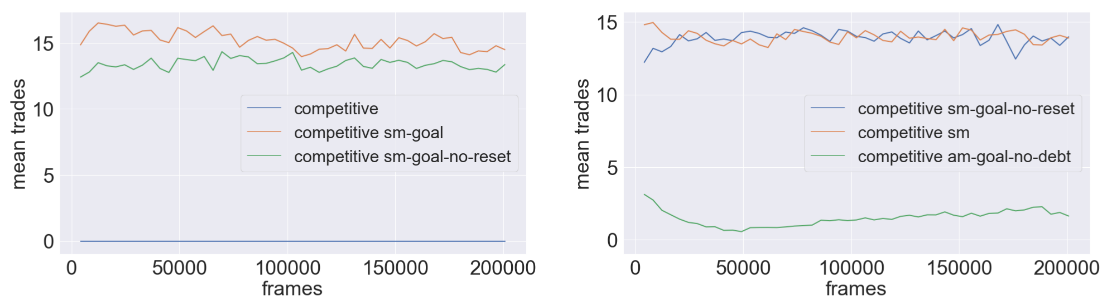
Figure 5.11 displays the two plots that show how the fully coloration numbers are generated. On the left-hand side, the PPO based trainings show an increase of reaching the goal state towards the end, with a maximum of around 14. This means, that in a data point, which extracts over 4096 frames and 16 parallel environments 14 episodes ended with the grid fully colored. Looking at the DQN plots it is evident that the highest point of the learning curve lies at approximately 60.000 frames and then it levels off.

	Top PPO Competitive Settings	Fully colored
1	competitive	277
2	competitive sm-goal	165
3	competitive sm-goal-no-reset	111

	Top DQN Competitive Settings	Fully colored
1	competitive sm-goal-no-reset	367
2	competitive sm	240
3	competitive am-goal-no-debt	198

Table 5.8.: Number of times three agents working in a competitive setting fully colored the environment during training.

Finally, the last table 5.8 shows the top scores of competitive compositions in a seven by seven coloration environment. While up to this point the first places of PPO executions in the difficult setting resulted in higher scores than their DQN counterparts, in this table this is not the case. The top competitive DQN training resulted in 367 completely colored fields, whereas the highest PPO score is only 277. Furthermore, the order of the DQN board stayed the same, while the PPO scores changed, with the previous first placed “sm-goal-no-reset” now being on the last place.



(a) Mean trades of PPO agents

(b) Mean trades of DQN agents

Figure 5.12.: Mean trades of the top three competitive compositions using PPO (left) and DQN (right)

The last thing to point out are the mean trade counts in those trainings. Plot 5.12a and 5.12b display how many market transactions on average were executed. The two plots show similarities of building the strategy to sell around 15 shares on average. For the AM in the DQN execution the mean amount is only at approximately 3 trades.

5.4. Rooms Setup

To further stress test the learning abilities of agents, the environment is now also divided into rooms. In order to set up a reasonable room division, the environment size needed to be increased to a 9x9 grid. A visualization of this setting is shown in Figure 5.13. The maximum step count in trainings with one agent is, again, not set manually, which results in 81. Other than changing the `--env` parameter to "FourRooms-Grid-v0" and the grid size to 9 the same parameters of the previous seven by seven settings were used.

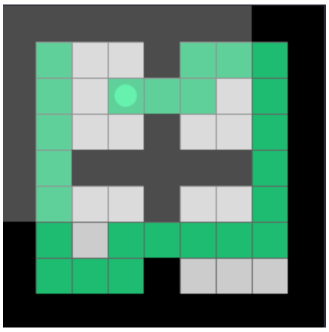


Figure 5.13.: Visualization of an environment with rooms and one agent

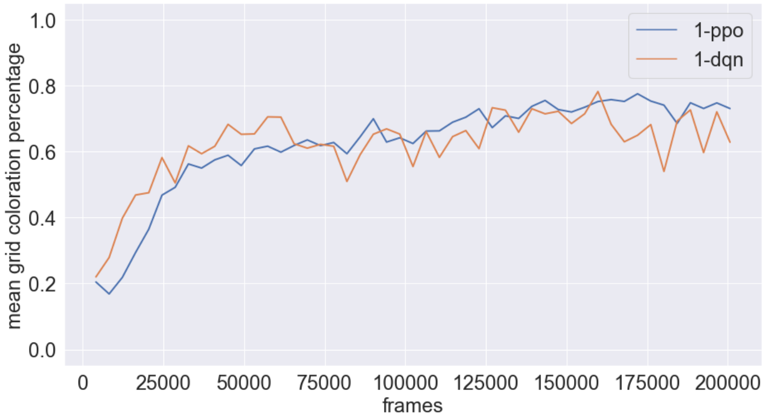


Figure 5.14.: The mean coloration percentage in a 9x9 Rooms Environment and one acting agent

Figure 5.14 replaces the score table, since both ppo and dqn trainings with one agent never reached the goal. However, the plot shows potential, due to the increase from 20% average coloration to around 70%.

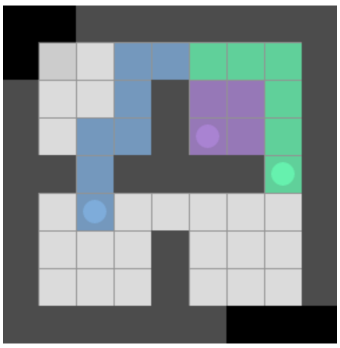


Figure 5.15.: Visualization of an environment with rooms and three agents

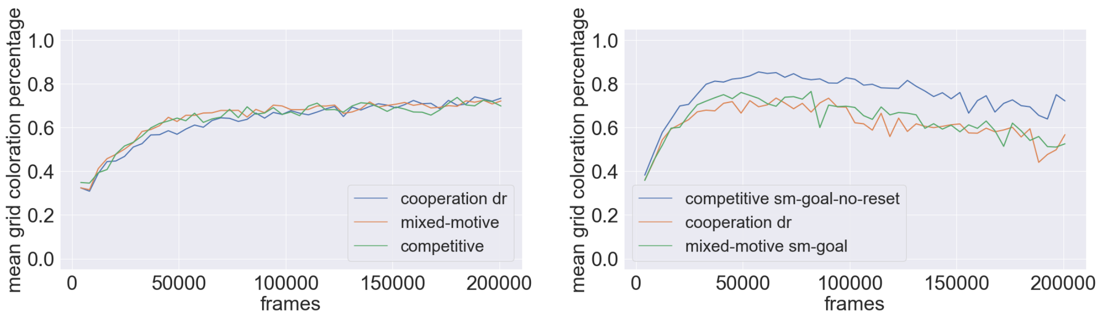
For the multiagent training with three agents, the step amount is set to 30. A visualization of this setup is shown in Figure 5.15. Furthermore, only the first places of the scoreboards of chapter 5.3 were trained in this environment, because of long execution times. As a result these six settings are analyzed, for PPO:

- cooperation dr
- mixed-motive
- competitive

and for DQN:

- cooperation dr
- mixed-motive sm-goal
- competitive sm-goal-no-reset.

Unfortunately, all but one of the training executions never fully colored the environment. Only the top DQN competitive training managed to reach the goal state a total of 10 times. In Figure 5.16a, it is shown that the PPO agents learn to color 70% of the grid over time. In the DQN plot however, they reach the peak of 80% early on and drop the coloration percentage slowly afterwards, with the lowest point in the DR setting to 40%.



(a) Mean coloration percentage of PPO agents **(b)** Mean coloration percentage of DQN agents

Figure 5.16.: Mean grid coloration percentages in a 9x9 Rooms Environment using PPO (left) and DQN (right)

6. Discussion

Appendix B shows all training plots of the settings covered in the previous chapter 5, which will be used to discuss the results. In general, increasing or decreasing lines can be interpreted as learning improvements of the agents, depending on the attribute. For example, an increase in the grid coloration plot shows that agents learn to color more cells. A decrease in the mean number of reset fields signalizes the understanding that resetting fields is a bad choice in most cases. The plot titled "mean num frames per episode" shows how many frames a completed episode produces on average. If the agents for example are not able to solve the environment, the values of the plot equals the maximum amount of steps.

Decreasing number of reset fields, but consistent high numbers of frames per episode and few if any fully colored grids point out that agents often execute the waiting action. If they explore, more fields would be reset. On the contrary, would they often reach the goal, a number smaller than the maximum amount of steps can be expected as the average frames per episode. Furthermore, this plot can be used to see how efficient the agents solve the problem. Reaching the goal and simultaneously using many episode frames signalizes inefficient step use, whereas less episode frames show the opposite.

The plots that present the amount of fully colored grid achievements during training also often increase steadily. This can be interpreted as a learning curve for the trained agents, see Figure B.3 as an example. Other times, a global maximum can be observed where the amount decreases afterwards. This behavior could result from overtraining the networks, due to sampling of similar optimal experiences/batches [ZVMB18], or overestimation [HMVH$^+$18], or simply a growing disorganization between agents.

The reward summary plots are very similar to the grid coloration percentages, because of the reward assignments, see chapter 4.2. Most of the time the agents receive the coloration percentage as reward. Markets only adjust those values slightly. Besides, by calculating the reward summaries, market changes of the rewards are not traceable in this plot. The only setting that changes the reward summaries significantly is the DR condition, which result in very small values, due to the difference calculation.

The following two chapters focus on the results of each algorithm separately. First the DQN scoreboards and their corresponding plots are discussed. Subsequently, all PPO scores are analyzed. Additionally, the PPO chapter 6.2 briefly covers the differences between the two learning algorithms and the poor results of the most challenging setup.

6.1. DQN Results

A learning curve can often be observed in the results of the easy setup. However, in the plots of the one agent training B.1, the DQN setting does not show good results for the full coloration values. The agent reaches the goal, but does not keep a steady amount. A drop back to zero is often the case in this plot. The reset fields decrease to around 0.3, but the number of frames per episode do not deviate significantly from the default 10. Another signal is the coloration coverage, which shows a general increase to 80%. To interpret the behavior of that agent, one can assume, that the agent colors a big patch of the grid and might get stuck at some point. In order to achieve the goal it would need to reset fields. Instead, it seems to wait until the episode ends. To improve this behavior, the epsilon decay could be slowed down to ensure more exploration.

However, looking at the multiagent compositions with DQN in the easy setup, it is obvious that in every case the plot lines of reset fields and number of frames per episode decrease. This means, that the DQN agents learn not to reset fields and instead color them. The parameters seem to be perfectly adjusted for the multiagent scenario, due to the enormous amount of goals. The only improvement possibility that remains, are the average frames per episode. Two organized agents would only need four to five steps to fully color the grid, which is never accomplished. Overall, the DQN agents reach the goal and learn to do so fairly quick.

Another interesting feature of the top DQN scoreboards shown in chapter 5.2 is that every table listed executions with market setting, the only exception is the cooperation board, with the DR execution on first place. A closer inspection reveals that the DQN cooperation board only listed AMs beside the DR execution. The mixed-motive scores then included SMs, but show one AM on second place. Finally, the competitive scoreboard placed an AM training on last place.

The first interpretation that can be drawn from this is that in each DQN composition trainings without a market never achieved better results than those listed in the tables. Second, AMs without additional conditions are also never listed in the score tables. The second and third placed cooperation trainings, for example, use AMs with the addition of “goal”. The second placed execution also restricts the market with the “no-debt” addition. This means that agents who bought actions during training also colored a cell, otherwise their market action would be ignored. With the “goal” condition, all market actions were documented during training and the payout happened at each episode end.

The DQN cooperation plot of the easy setup shows very low average trading counts (see B.5). For example, at the 80.000 frames point the debt restricted action market registered only around 0.5 trades. Hence, every second episode contained a trade. This assumption results from looking up the value of average frames per episode at the 80.000 frames mark, which is approximately 7, and dividing that into the amount of mean trades. The result is 14 which is the double of the average episode duration.

Generally, all the trading plot lines of the easy setup using DQN and an AM tend to stay or at least develop to values below one. Therefore, it is clear that every other episode contained one AM trade at best. The most trades with AMs can be observed in the cooperative mode with only the goal restriction that shows one trade on average per episode. But this number is not steady and drops below one most of the time. The reason for that could be that the default `--trading-fee` of 0.1 for this market type is too high. Schmid et al. [SBGP18] pointed out, that another reason for decreasing AM trades is speculation of agents. Agents may withhold their offer in the anticipation that the other agents may still perform the expected action.

Furthermore, a low chance of executing exactly that one action other agents want to buy in the same step may cause the small amount of trades. One agent has an action set of 75 actions to choose from, with one action containing:

- One of five possible environment actions (wait, left, right, up, and down) on first place.
- On second place is the agent to whom an offer will be made to. In this case the option of two is given (1 and 2 - agents can make offers to themselves, but markets ignore such requests) and one additional choice (3) to not act on the market.
- Finally, one of the five possible environment actions again, which is expected by the targeted agent.

The probability, that a transaction between two agents takes places, is only 1%.

As an example, if agent two wants to buy from agent one the action "wait", then the probability for that action to be executed by agent one is $P([wait, X, X]_1) = \frac{15}{75} = 0,2$. X presents a placeholder for the action elements that are not of interest. The 15 results from 15 actions in the set with "wait" on the first place, i.e. $[wait, 1, wait], [wait, 2, wait], [wait, 3, wait], [wait, 1, left]$,... Continuing with the probability of agent two directing the buying offer to agent one and expecting action "wait" is only $P([X, 1, wait]_2) = \frac{5}{75} = 0,066$. Only the environment action of agent two is variable in this case, leading to five possibilities for that constellation.

The actions of each agent do not affect the probabilities and actions of the other, which means that the two values 0,2 and 0,07 are stochastically independent. To calculate the overall percentage of those two agents executing one action each to achieve a market transaction is:

$$P([wait, X, X]_1 \cap [X, 1, wait]_2)) = P([wait, X, X]_1) * P([X, 1, wait]_2) = \frac{15}{75} * \frac{5}{75} \approx 0.01 \tag{6.1}$$

With an increasing amount of agents, the chances of establishing a transaction decrease.

Proceeding with the difficult setup for the same one agent DQN execution, it is evident that the training has similar setbacks to the easy setup. A decrease of reset fields and an increase in grid coloration percentages is visible, but at the same time the number of frames do not lower much. This can be interpreted with many waiting actions and a rather flat learning curve. Nonetheless, due to the long episodes with 81 steps in this training, the amount of goals increases slowly towards the end.

The DQN cooperation results show, that the AM executions failed to reach the goal. Naturally, the "goal" condition never applied and with both executions containing this addition, the market was never properly executed. As a result, the two AM trainings were plain cooperation executions. The only difference to the normal cooperation setting is the action shape, which still contains three elements instead of one. In theory, a market still applied, and the agents executed the market actions in the background, but the final reward of the AM calculations were never conducted.

Looking at the trades, it is also apparent that agents were more active on the market in comparison to the easy setup results. This might be due to the missing consequences of actually giving up reward through transactions in combination with a higher amount of steps leaving room for more exploration. Comparing the cooperation results of the two setups, it is clear that the DR execution is more stable, since the goal was still reached, whereas training with markets seem to struggle the more agents join the game and the bigger the environment gets. Nonetheless, the DR training did not result in many fully colored grids, since the agents face organizational challenges.

The SM executions of the DQN agents show obvious signs that the training without additional market conditions performed well. In the easy setup mixed-motive agents colored the most grids with only the SM and also in the competitive mode this market scored the second place. The first place in the competitive scoreboard is reached with “sm-goal-no-reset” and the third placed SM in the mixed mode adds the “goal” condition. Hence, the only SM implementation never listed is the “no-reset” addition on its own.

The longer episodes get, the better the SM with “goal” conditions in those two compositions using DQN performed. A reason is the reward calculations of this market type. In every step the agents give away the percentage they sold off, which adds up after a while. Overall, the environment goal is reached in all DQN SM executions, regardless of the environment difficulty, and present a learning curve (excluding the rooms setup in this comparison).

6.2. PPO Results

The PPO one agent executions of both difficulty setups showed steep learning curves and a high amount of fully colored grids. In both cases, the reset fields dropped significantly and the amount of frames per episode also reduced. This generally means that agents are able to learn with the parameters set.

In contrast to DQN scores, all PPO scoreboards of multiagent scenarios included compositions without markets. The PPO cooperation and competitive scoreboards showed the corresponding plain setting on second place and in the mixed-motive board the mixed-motive setting placed first.

Another observation is, that PPO scoreboards never listed AMs. Schmid et al. [SBM+21] explained, that the reason for that lies in the bigger action space of markets in general, but especially of the AM. Instead of choosing between selling a share or not, agents need to choose an expected action of five options. The authors state that the DQN algorithm can handle the increased action spaces of both market types, whereas PPO showed performance loss in those executions. This also explains why in the PPO scoreboards the default compositions performed better than those with market executions.

The average trade amount of all easy setup PPO executions with a SM are around two shares per episode. Considering the odds of establishing a transaction, it becomes obvious that this is plausible. The action space for this market type contains only 30 variations, with one action consisting of:

- One of five possible environment actions.
- On second place is the agent to whom an offer will be made to or the number three here, to not act on the market, equal to the AM definition.
- Finally, the last place contains an option of two, to either sell the own shares in the current step or not.

A transaction only occurs if an agent decides to sell and another agent chooses the selling agent to direct its offer to. Hence, the probability of agent one, for example, selling its share is $P([X, X, 1]_1) = \frac{15}{30} = \frac{1}{2}$ and the probability of agent two to buy from agent one is $P([X, 1, X]_2) = \frac{10}{30} = \frac{1}{3}$. Calculating the overall stochastically independent probability of actions that result in a SM trade is therefore:

$$P([X, X, 1]_1 \cap [X, 1, X]_2) = P([X, X, 1]_1) * P([X, 1, X]_2) = \frac{1}{2} * \frac{1}{3} \approx 0.166 \qquad (6.2)$$

With a probability of about 17%, shares are traded, which decreases further, the more agents participate on the market.

The plot for competitive PPO trainings in the difficult setup (see B.11) shows that a maximum of approximately 16 trades in the “sm-goal” execution was reached. The reason for that might, again, be the longer episodes that allows more exploration. Furthermore, the “goal” condition might encourage agents to sell, because rewards are redistributed only at the end. The maximum amount of trades per episode in a SM is 27 for training with three agents, since agents are prohibited to give away all their shares, see chapter 4.4.1.

Another fact to point out for the PPO scores is that the first placed “competitive sm-goal-no-reset” execution lose performance in the seven by seven environment setup and gets demoted. As a result, all PPO executions without markets are placed in the first ranks of the difficult setup scoreboards. Only in the cooperation board, the DR still ranks before the plain cooperation setting. This shows that the markets in combination with PPO do not perform well, let alone solve the CAP or organizational challenges.

Furthermore, it is necessary to mention the major goal differences between the PPO and DQN scoreboard tables within a composition. For example, the cooperation table 5.2 of the easy setup listed 1.683 coloration goals with the PPO DR training, whereas DQN DR reached nearly 6.000 completely colored grids. A speculation for those differences might emerge from the data efficiency of the DQN using a replay memory. A small environment together with two agents produces a relatively small variation of states and experiences. The results of the two learning algorithms become more similar as the environment increases in difficulty.

The most difficult setup, the environment divided into rooms, could not be solved by any PPO execution. Only one DQN training managed to reach the goal, but only 10 times in total during a duration of approximately 200.000 frames. All settings of both algorithms generally managed to color a good amount of the grid in this scenario, by reaching about 70% average coloration at some point. However, through the layout of the rooms and a limited amount of 30 steps the agents need to organize efficiently. If a room still has some uncolored cells left, agents might need to reset numerous fields on their way back to that spot.

A good example of uncolored patches in rooms can be seen in Figure 5.13. Here, only one agent is placed on the grid, with a setting containing three agents the amount of field resets and organizational challenges increases. An exception is the competitive setting, which always achieves better results than the other compositions in all setups, due to the modified field resetting rules. Agents can capture colored cells of opponents, instead of resetting them, which simplifies the aim of coloring the entire grid. It is more likely to reach that goal, especially if they have enough steps to explore with. This might also be the reason, why the competitive setting of DQN agents achieved the goal in the most challenging setup.

7. Conclusion

Each of the three compositions presented in chapter 4.1 lead to learning problems or game losses. Cooperation may reward misbehavior, namely field resetting, resulting in the CAP of chapter 3.1. In mixed-motive or fully competitive settings, the overall goal may never be reached, due to greediness or disorder. This research compared the effects of markets not only on mixed-motive settings as suggested by Schmid et al. [SBM+21], but on all three agent compositions.

During the thesis, the coloring environment was presented. It enables agents to color cells by moving around. Stepping on colored cells removes the color and penalizes the agent, coloring cells rewards them. In competitive agent compositions, agents can take over cells and do not reset them. The goal was to color the whole grid in order to get the highest reward. The thesis aims to compare the effect of markets in the three agent compositions and whether SMs or AMs could solve the problems multiagent environments face.

Overall, the CAP does not seem to be solvable through markets applied in the coloring environment. The performance of the DR executions could not be met by any market type. Increasing the grid size and amount of agents also showed that cooperative settings with markets failed to reach the goal completely. This could be an indicator for agents struggling to understand how their actions contributed to the observations and shared rewards. In the mixed-motive and competitive compositions, trainings with markets achieved fully colored grids, even in the difficult setup. This shows an alignment and organization between the agents. Nonetheless, in the most challenging environment, a nine by nine room divided grid, none of the compared settings helped the agents learn how to solve the task.

All in all, one could argue, that the parameters need some adjustments for the different challenges to achieve better results. For instance, reducing the fee in AMs and increasing it for SMs, and generally fine-tuning the hyperparameters of the learning algorithms for each setup. Another point is to conduct all 70 training executions in all challenges, rather than filtering the best settings through the results of an easy training setup. It would also be interesting to compare the results of agents, who always have the full view of the environment with this partially observable implementation.

The coloring environment also leaves room for expansions. More environment shapes could be defined, instead of just a quadratic instance. It would be interesting to see how different reward values for good or bad actions might affect the learning. Another addition that comes to mind would be a supplementary small bonus reward for completely coloring the grid. This should increase the urge of reaching that goal across all compositions.

In regard to the markets, one point to note for future implementations is: the integration of markets into observations. This could enable some sort of micromanagement or at least improve market transparency. Agents could declare in AMs, for example, which action they expect for the next or future time steps. By adding the market actions into the observation, agents in turn could specifically react to the current offer. This also applies for declaring the selling of shares. Agents would know when shares are up for sale and can decide to buy them.

Another idea for applications of SMs is to use the observation to show the acquired shares an agent has from others, so that the relation to higher rewards is more obvious. Generally, the concept of SMGs, as defined by Schmid et al. [SBM+21], is that agents do not communicate directly, but still find a way to cooperate in mixed-motive compositions. By extending the observation, this concept in theory still holds true.

Lastly, a variable market price could be introduced. This would enable agents to decide how much something is valued. Going back to the AM example, where an agent needs a resource that another agent occupies, depending on the current urgency, the agent in need might be willing to pay a higher price. In SMs, agents could decide to pay a certain share price and, based on that amount, the targeted agent might decide to sell after all. Overall, the subject of markets in RL is a very exciting research topic, due to its wide range of possibilities.

Appendix A.

Training Parameters

```
required arguments:
  --algo ALGO           Algorithm to use for training. Choose between 'ppo'
                        and 'dqn'.

optional arguments:
  -h, --help            show this help message and exit
  --seed SEED           Generate the same set of pseudo random constellations,
                        colors, positions, etc. every time the algorithm is
                        executed. (default: 1)
  --agents AGENTS       Amount of agents. (default: 2)
  --model MODEL         Path of the model inside the storage folder, if none
                        is given then a random name is generated. (default:
                        None)
  --capture CAPTURE     Boolean to enable capturing of the environment. The
                        outcome are in form of gifs. (default: True)
  --env ENV             Environment ID, choose between Empty-Grid-v0 for an
                        empty environment and FourRooms-Grid-v0 for an
                        environment divided into equal sized rooms. (default:
                        Empty-Grid-v0)
  --agent-view-size AGENT_VIEW_SIZE
                        Grid size the agent can see. Agent Observation is
                        based on that field of view. For example, 7x7 grid
                        size means agent can see three tiles in each
                        direction. (default: 7)
  --grid-size GRID_SIZE
                        Size of the environment grid. (default: 5)
  --max-steps MAX_STEPS
                        Maximum amount of steps an agent has to reach a goal.
                        If none is given then this max count is set to: grid
                        size * grid size. (default: None)
  --setting SETTING     Setting can be either: '' for cooperation, 'mixed-
                        motive' for a mixed motive environment, 'mixed-motive-
                        competitive' for a competitive composition or
                        'difference-reward' for a setting that calculates
                        difference rewards. Cooperation means all agents get
                        the same reward. If set to mixed-motive or mixed-
                        motive-competitve the reward is not shared and each
                        agent is responsible for its own success. In
```

```
                        competitive mode, agents can take over opponent
                        coloration without resetting the cells, otherwise
                        cells are always reset when colored and walked over.
                        The last option 'difference-reward' is a cooperation
                        setting but calculates the reward for each agent by
                        subtracting a new reward from the total reward. The
                        new reward just excludes the action of this one agent.
                        A high difference reward means, that the action of
                        that agent was good. (default: '' for cooperation)
  --market MARKET       There are three options: 'sm', 'am' and '' for none.
                        SM = Shareholder Market where agents can sell or buy
                        shares on the market. AM = Action Market where agents
                        can buy specific actions from others. (default = '')
  --trading-fee TRADING_FEE
                        If a market transaction is executed, this value
                        determines the price, i.e. in an action market this
                        defines the price the buyer pays. In a shareholder
                        market this value defines the share value. (default:
                        0.1)
  --frames FRAMES       Number of frames of training. (default: 80.000)
  --frames-per-proc FRAMES_PER_PROC
                        Number of frames per process. In case of PPO this is
                        the number of steps, before the model is optimized.
                        (default: 128)
  --procs PROCS         Number of processes/environments running parallel.
                        (default: 16)
  --recurrence RECURRENCE
                        Number of time-steps the gradient is back propagated.
                        If it is greater than one, a LSTM is added to the
                        model to have memory. (default: 1)
  --batch-size BATCH_SIZE
                        Batch size that is used for sampling. (default: 64)
  --gamma GAMMA         Discount factor with 0 <= gamma < 1, specify how
                        important future estimated rewards are. High value
                        means high importance. (default: 0.99)
  --log-interval LOG_INTERVAL
                        Number of frames between two logs. (default: 1)
  --save-interval SAVE_INTERVAL
                        Number of times the --frames-per-proc amount of frames
                        needs to be reached, to log the current training
                        values, i.e. rewards, into a csv file. (default: 10, 0
                        means no saving)
  --capture-interval CAPTURE_INTERVAL
                        Number of times --frames-per-proc amount of frames
                        needs to be reached, to capture the last --capture-
                        frames amount of steps into a gif. Warning: --capture
                        needs to be set to True as well. (default: 10, 0 means
                        no capturing)
  --capture-frames CAPTURE_FRAMES
```

```
                      Number of frames that are captured. (default: 50, 0
                      means no capturing)
--lr LR               Learning rate. (default: 0.001)
--optim-eps OPTIM_EPS
                      Epsilon value for the Adam optimizer. (default: 1e-8)
--epochs EPOCHS       [PPO] Number of epochs for PPO optimization. (default:
                      4)
--gae-lambda GAE_LAMBDA
                      [PPO] Lambda coefficient in GAE formula, used for
                      calculation of the advantage values. (default: 0.95, 1
                      means no gae)
--entropy-coef ENTROPY_COEF
                      [PPO] Entropy term coefficient. (default: 0.01)
--value-loss-coef VALUE_LOSS_COEF
                      [PPO] Value loss term coefficient. (default: 0.5)
--max-grad-norm MAX_GRAD_NORM
                      [PPO] Maximum norm of gradient. (default: 0.5)
--clip-eps CLIP_EPS   [PPO] Clipping epsilon for PPO. (default: 0.2)
--epsilon-start EPSILON_START
                      [DQN] Starting value of epsilon, used for action
                      selection. (default: 1.0 -> high exploration)
--epsilon-end EPSILON_END
                      [DQN] Ending value of epsilon, used for action
                      selection. (default: 0.01 -> high exploitation)
--epsilon-decay EPSILON_DECAY
                      [DQN] Controls the rate of the epsilon decay in order
                      to shift from exploration to exploitation. The higher
                      the value the slower epsilon decays. (default: 5.000)
--replay-size REPLAY_SIZE
                      [DQN] Size of the replay memory. (default: 40.000)
--initial-target-update INITIAL_TARGET_UPDATE
                      [DQN] Frames until the target network is updated,
                      Needs to be smaller than --target-update! (default:
                      1.000)
--target-update TARGET_UPDATE
                      [DQN] Frames between updating the target network,
                      Needs to be smaller or equal to --frames-per-proc and
                      bigger than --initial-target-update! (default: 15.000)
```

Appendix B.

Detailed Results

B.0.1. Easy Setup

The following plots show details of the best training results in a small 5x5 grid. The default parameters of Appendix A are used for all executions. Only the agent amount, setting and market value change. In the first Figure B.1, one agent is acting in the environment, all other trainings are executed with two agents. An example command how to run a training process with two agents in the cooperation composition and with PPO is shown below. The cooperation mode is set as default, when no `--setting` is specified, see Appendix A. The amount of steps is restricted to 8 for the two agent executions. Trainings with one agent have a step restriction of 10. All example commands of this Appendix can be executed with either learning algorithm by just switching the `--algo` value.

Code Listing B.1: Exemplary command to execute training with two PPO agents in a easy setup

```
$ python -m scripts.train
    --algo ppo
    --agents 2
    --max-steps 8
```

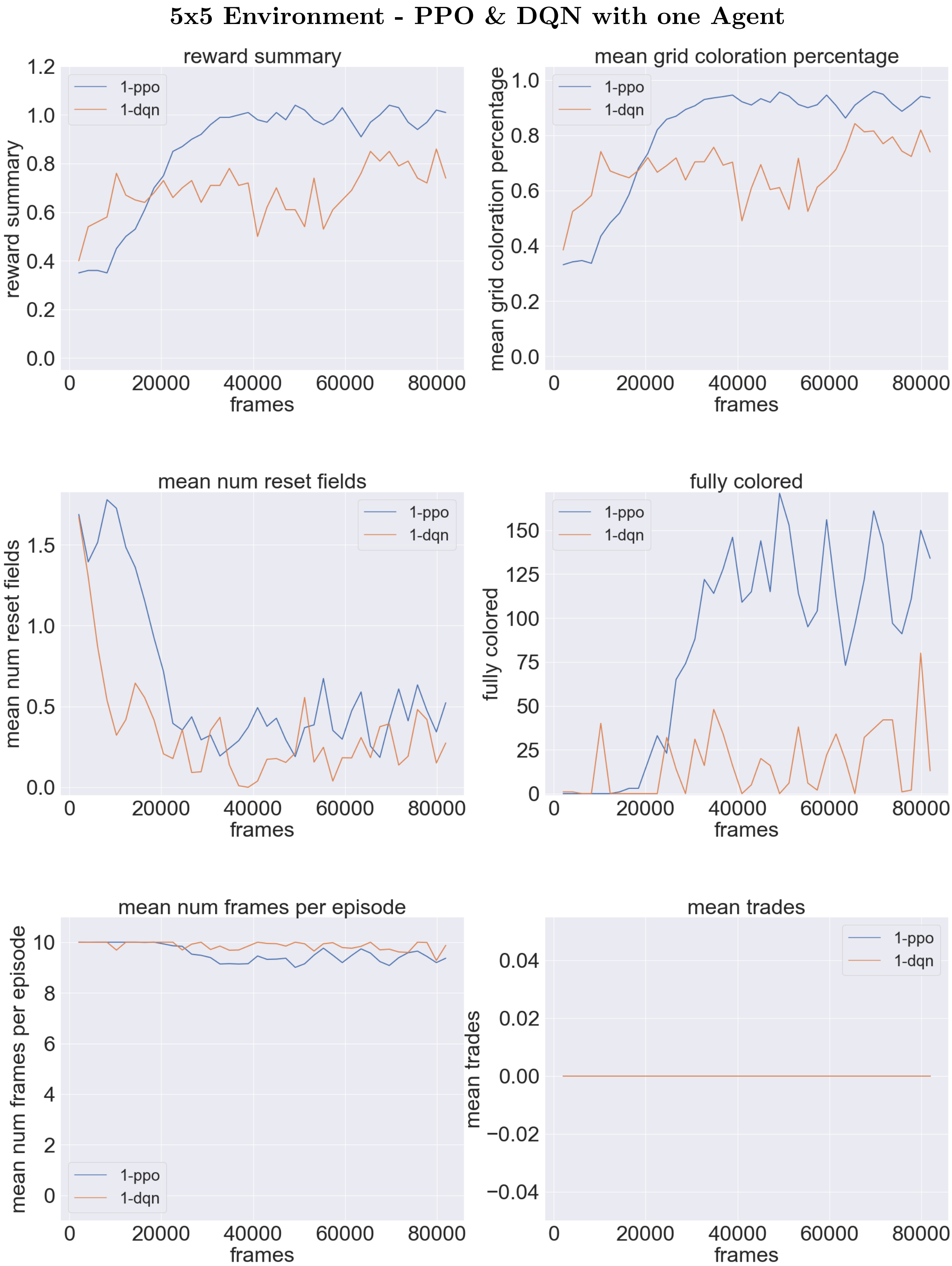


Figure B.1.: Details of the training in a 5x5 Environment with one agent using PPO and DQN

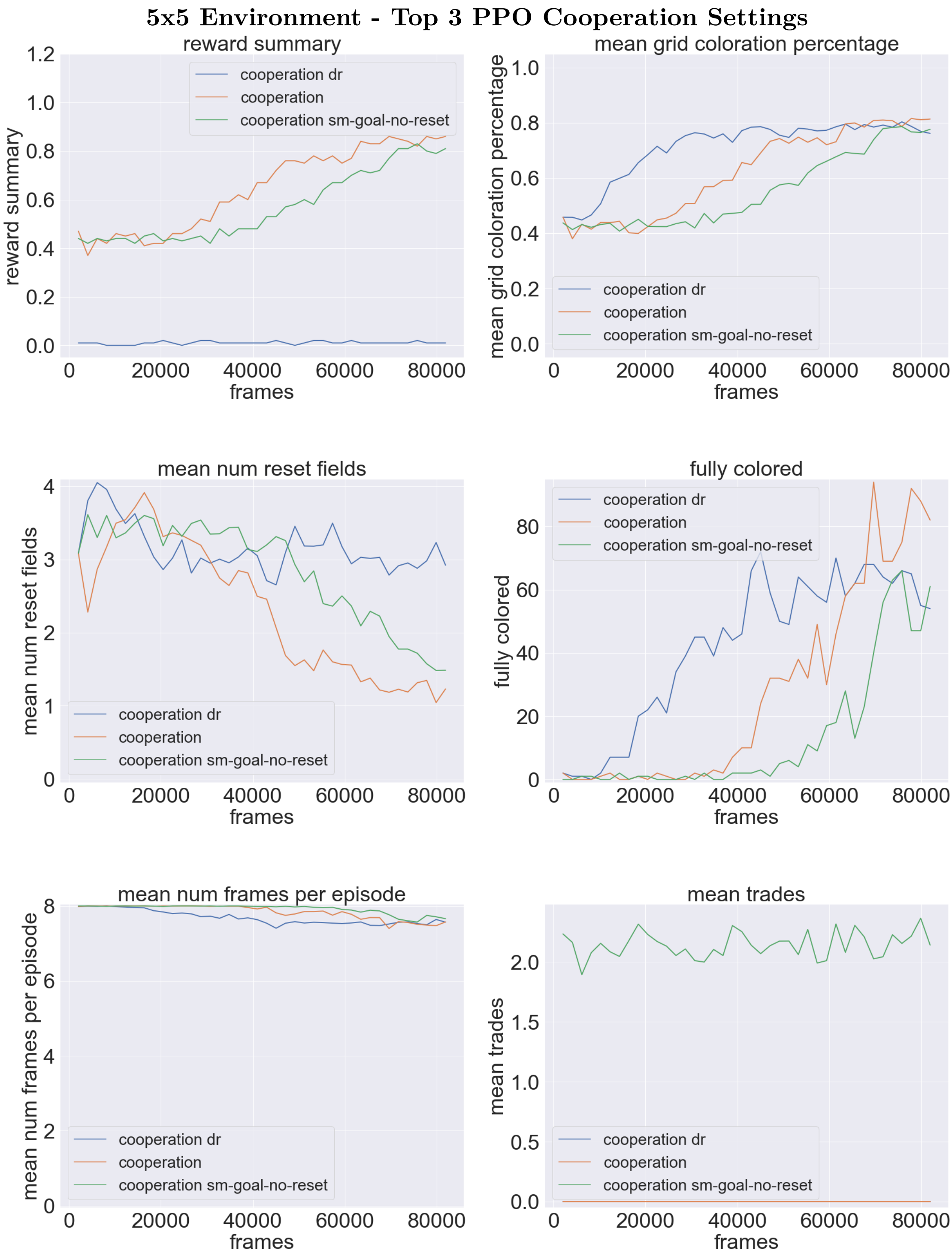


Figure B.2.: Details of the top executions with two cooperative PPO agents in a 5x5 Environment

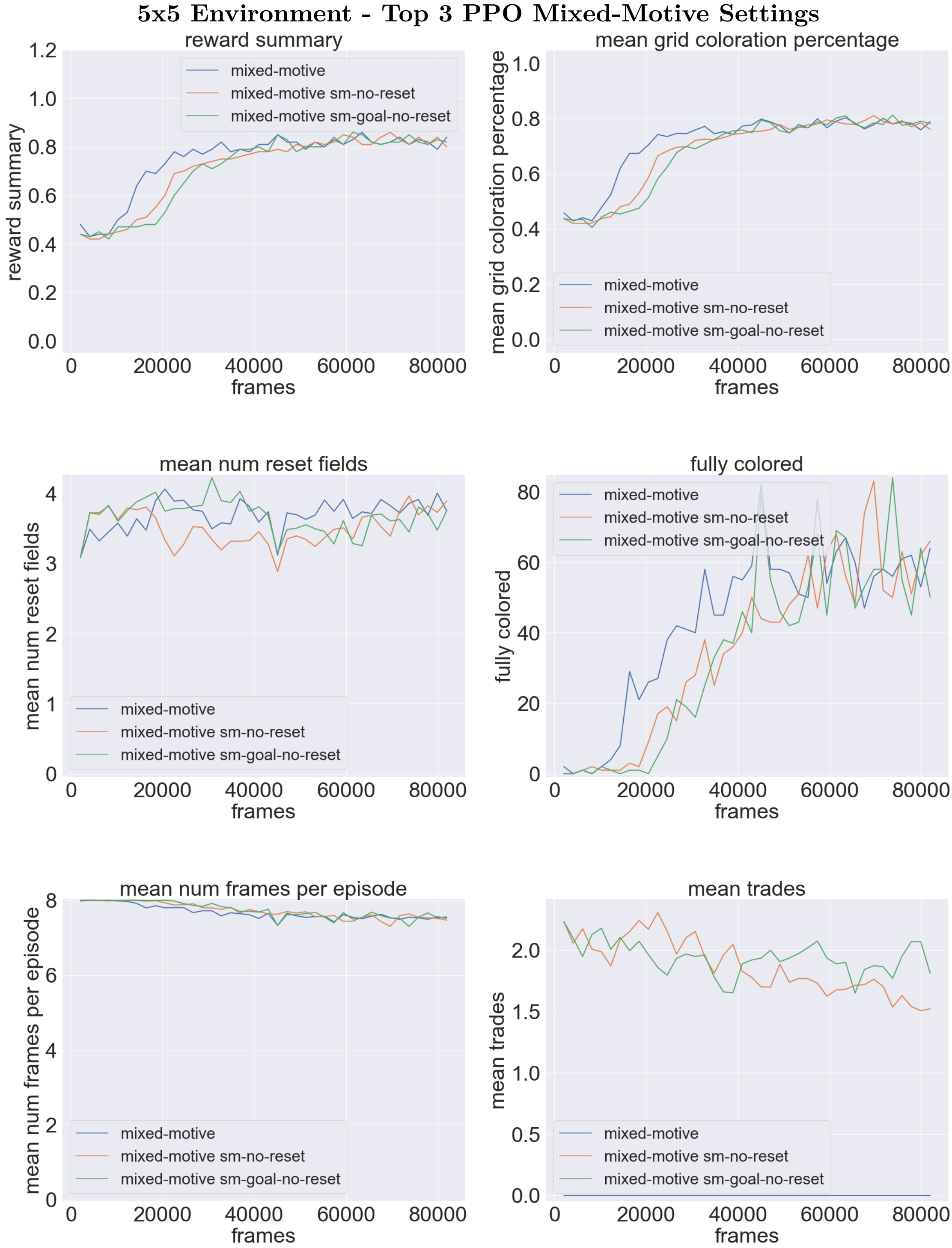


Figure B.3.: Details of the top executions with two mixed-motive PPO agents in a 5x5 Environment

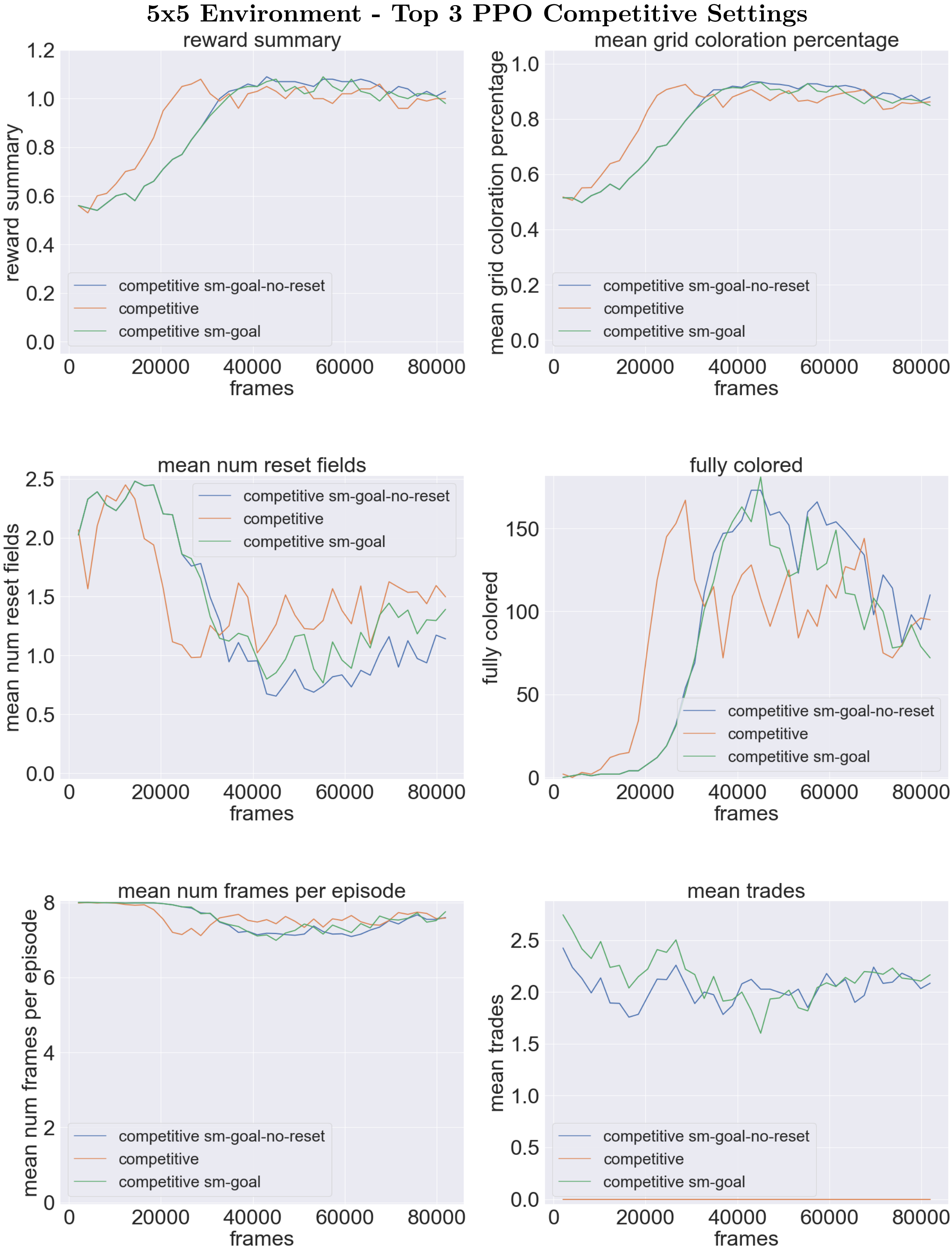


Figure B.4.: Details of the top executions with two competitive PPO agents in a 5x5 Environment

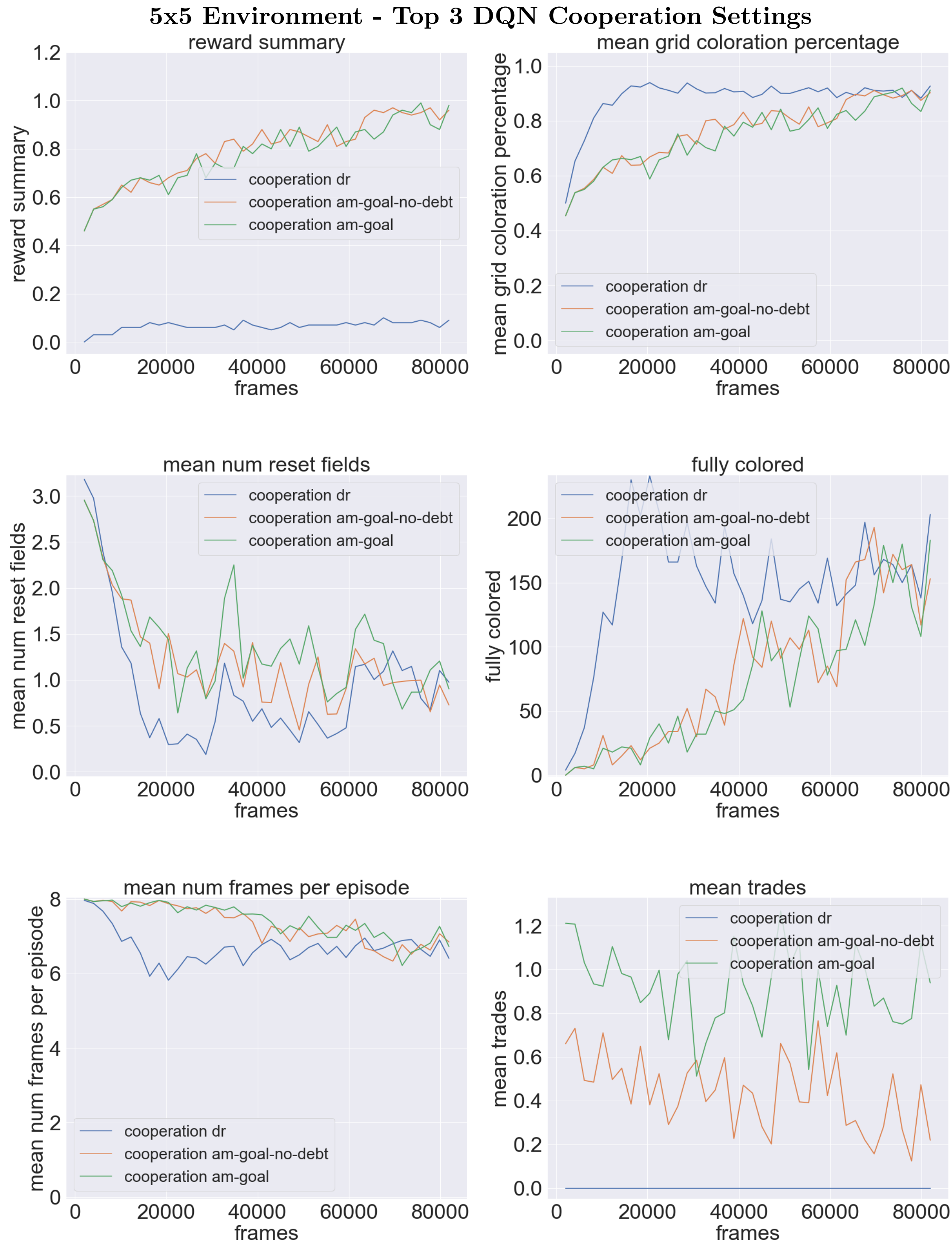


Figure B.5.: Details of the top executions with two cooperative DQN agents in a 5x5 Environment

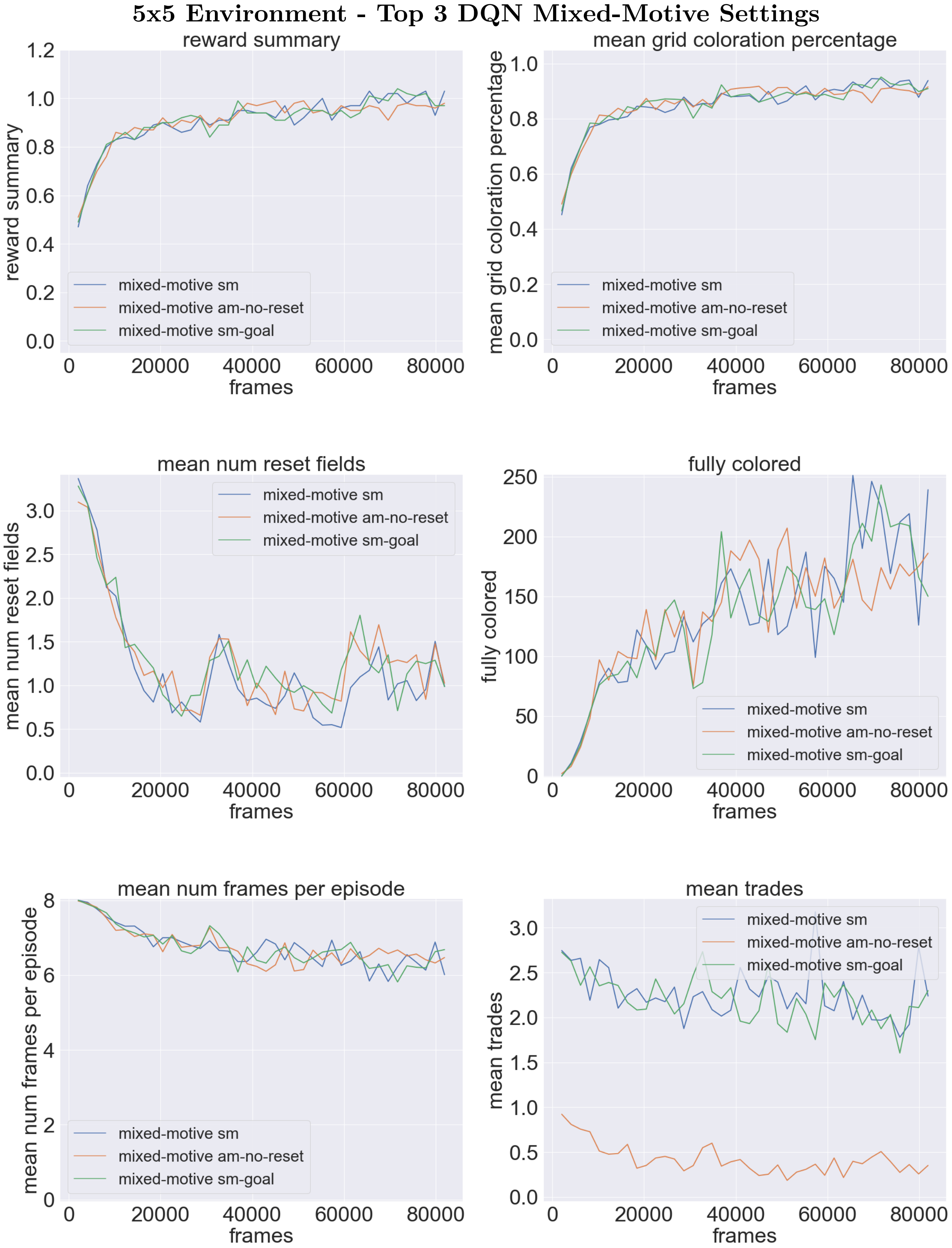


Figure B.6.: Details of the top executions with two mixed-motive DQN agents in a 5x5 Environment

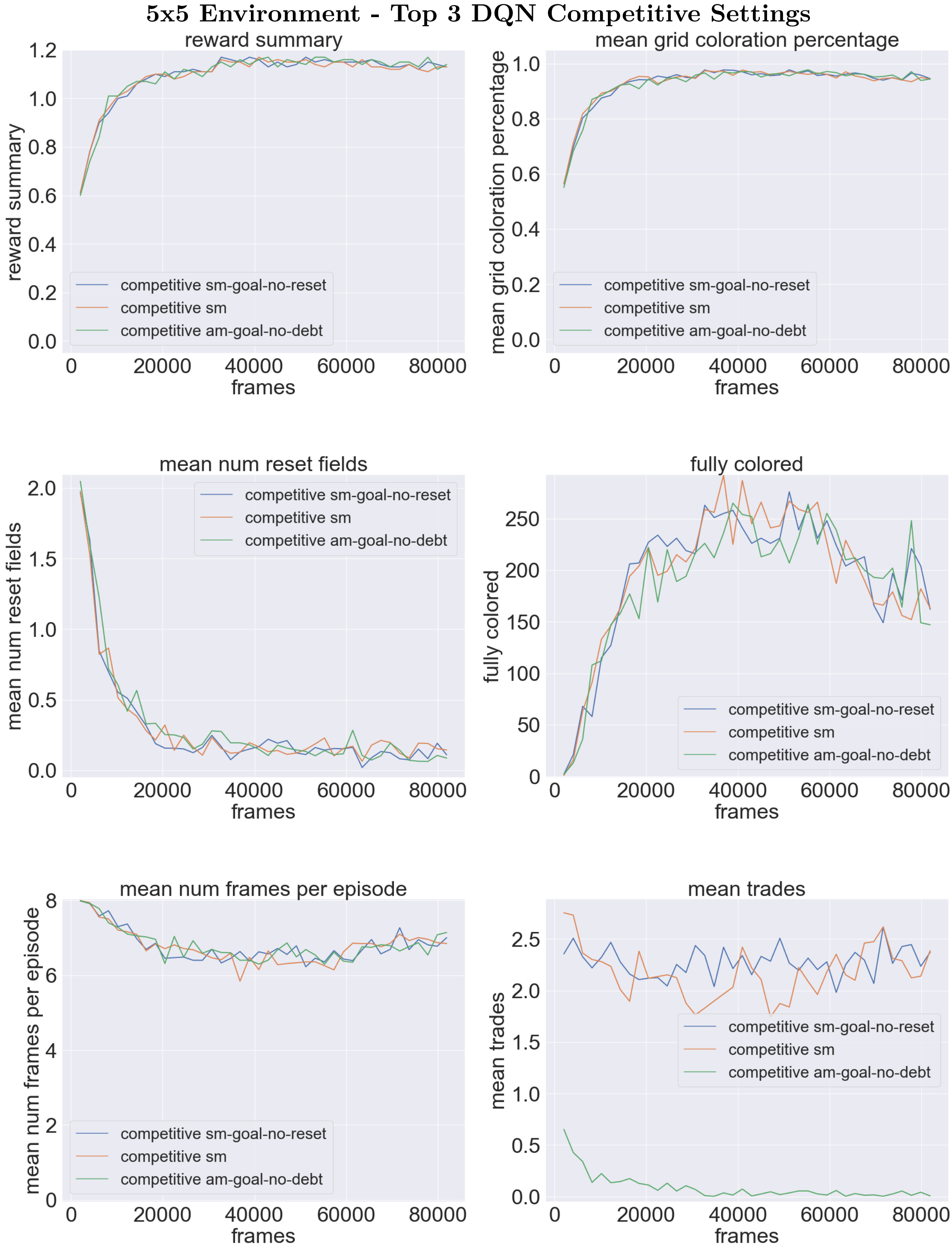


Figure B.7.: Details of the top executions with two competitive DQN agents in a 5x5 Environment

B.0.2. Difficult Setup

The difficult setup trains three agents in a seven by seven environment. The challenge here is on one hand, the larger number of agents, which causes more disorganization, and on the other, the field size, which requires more work. The following plots show the same executions as in the previous easy setup, trained in the bigger environment and with one more agent.

An example to run a training process in a difficult setup is shown below. The example presents a DQN command for a cooperation composition with three agents in a seven by seven grid. The maximum step amount is restricted to 20. In the training with one agent the `--max-steps` parameter is not set, which results in a step count of 49. For details, see the training parameter list of Appendix A.

Code Listing B.2: Exemplary command to execute training with three DQN agents in a difficult setup

```
$ python -m scripts.train
    --algo dqn
    --agents 3
    --target-update 10000
    --replay-size 700000
    --epsilon-decay 20000
    --grid-size 7
    --max-steps 20
    --frames-per-proc 256
    --frames 200000
```

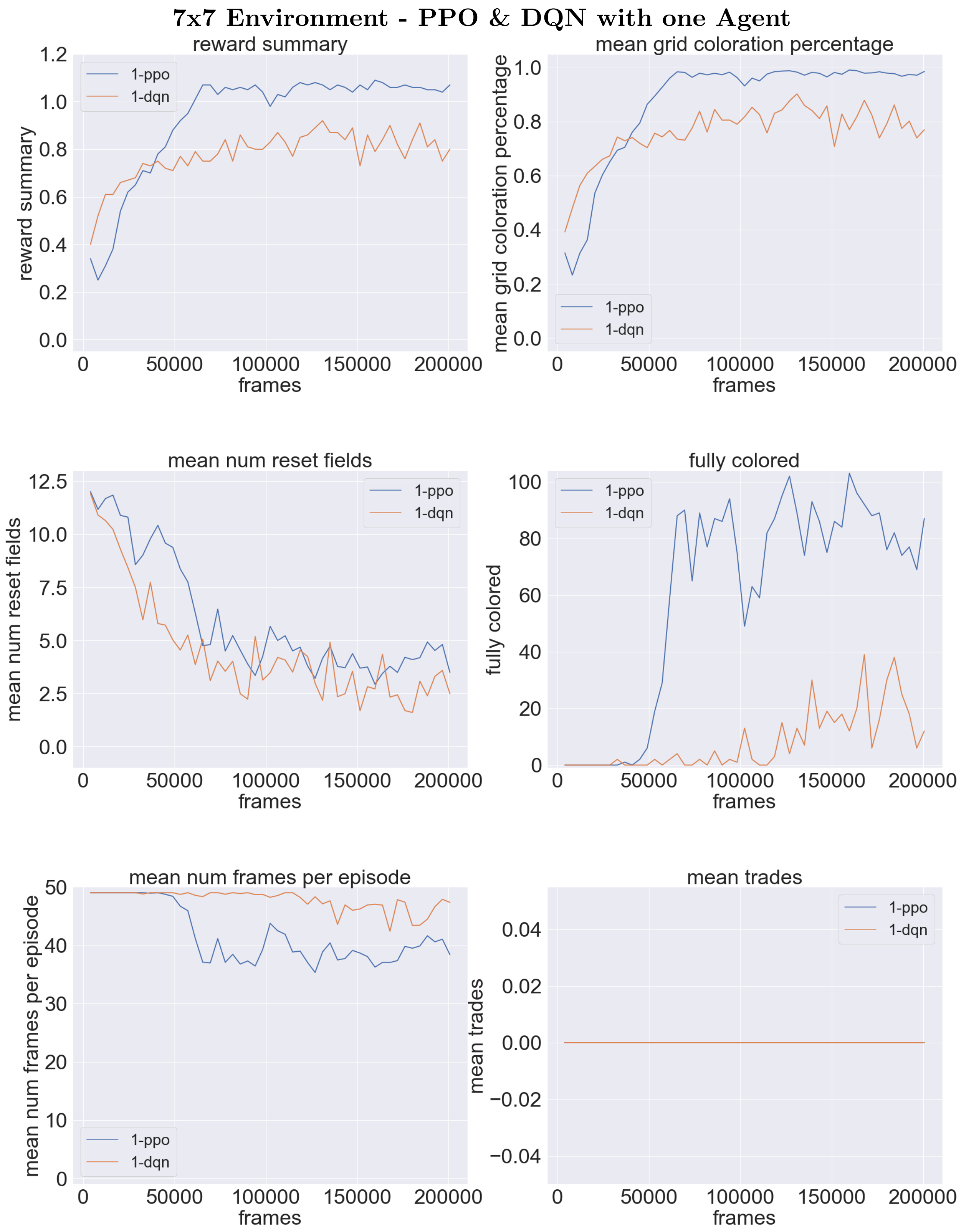


Figure B.8.: Details of the training in a 7x7 Environment with one agent using PPO and DQN

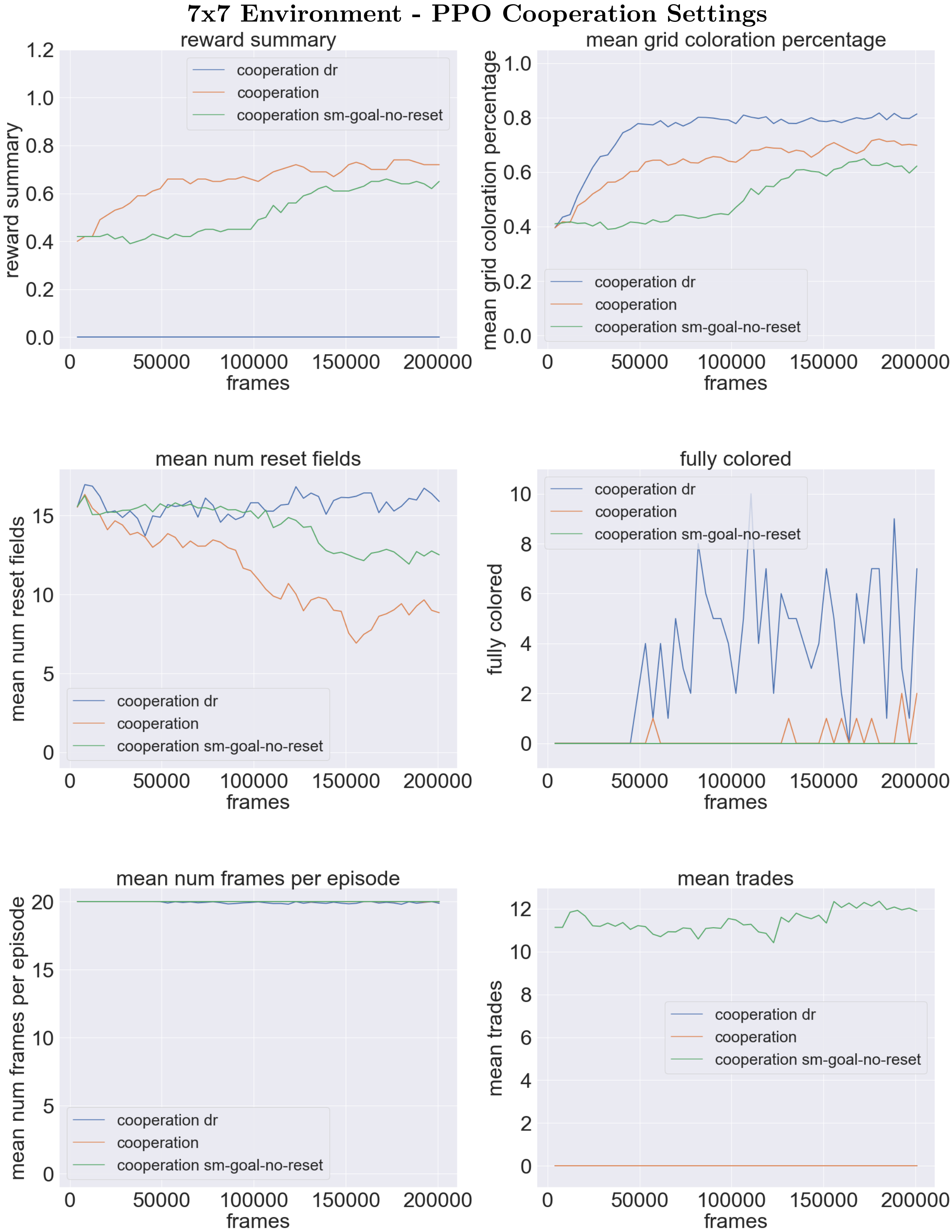


Figure B.9.: Details of the training executions with three cooperative PPO agents in a 7x7 Environment

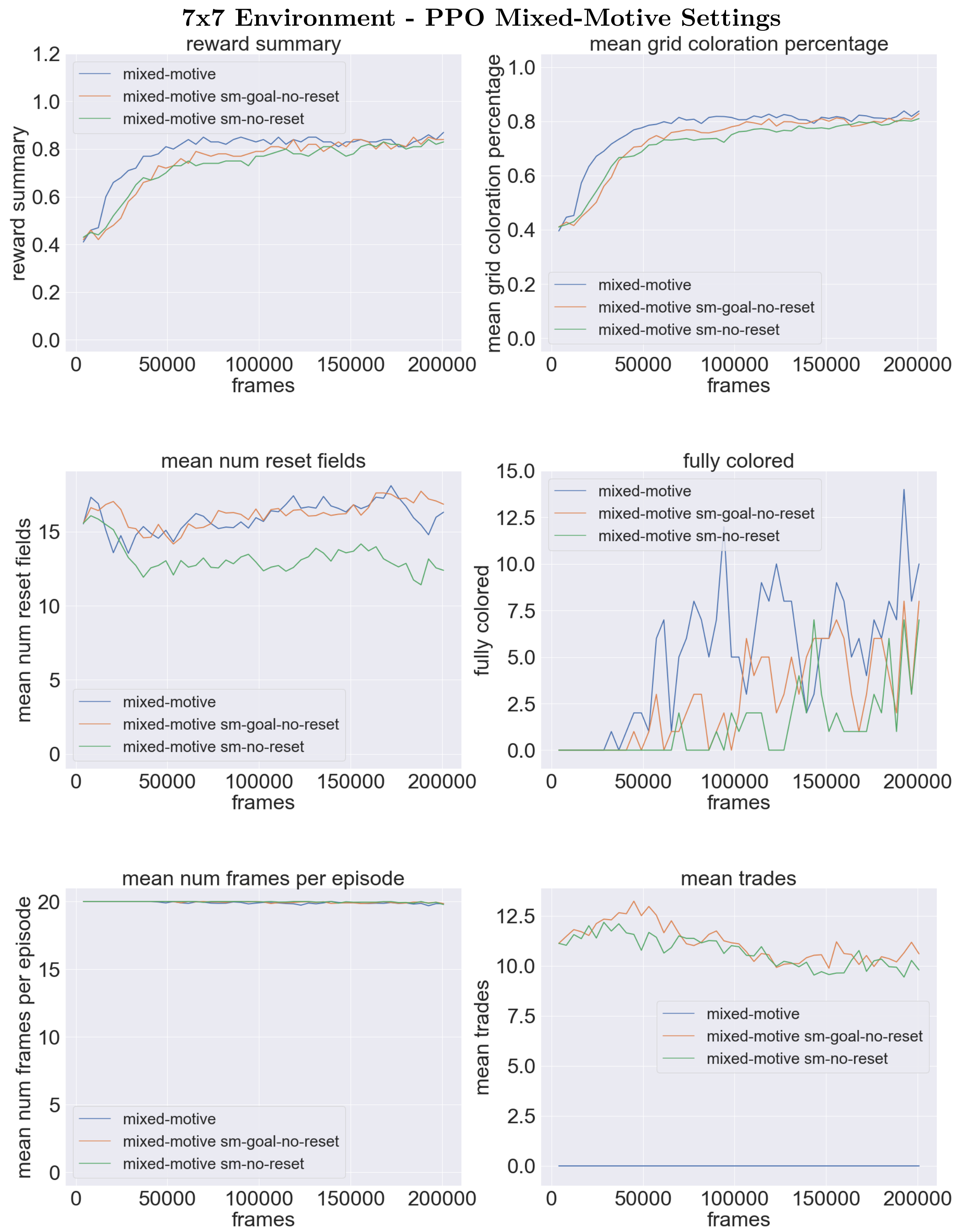


Figure B.10.: Details of the training executions with three mixed-motive PPO agents in a 7x7 Environment

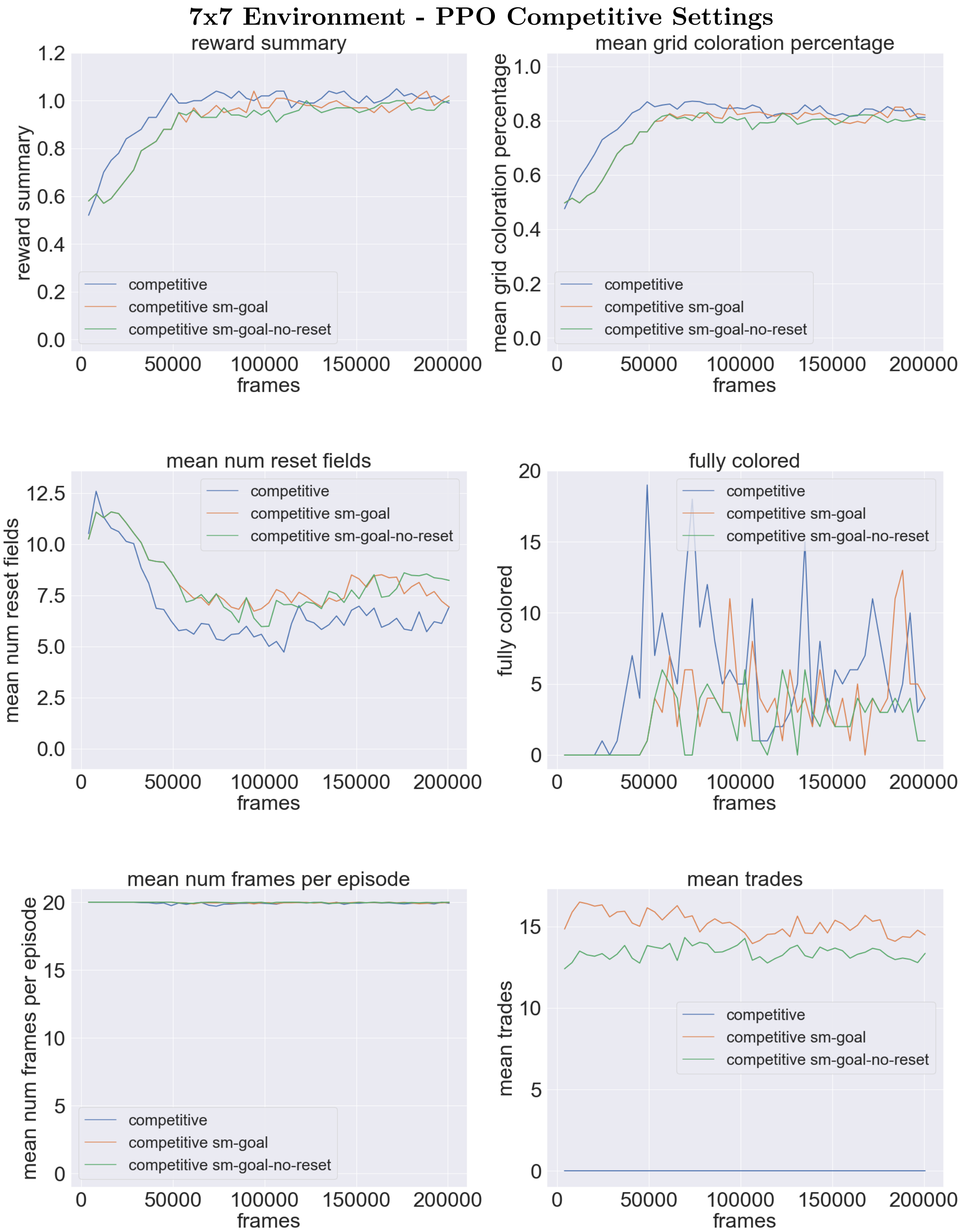


Figure B.11.: Details of the training executions with three competitive PPO agents in a 7x7 Environment

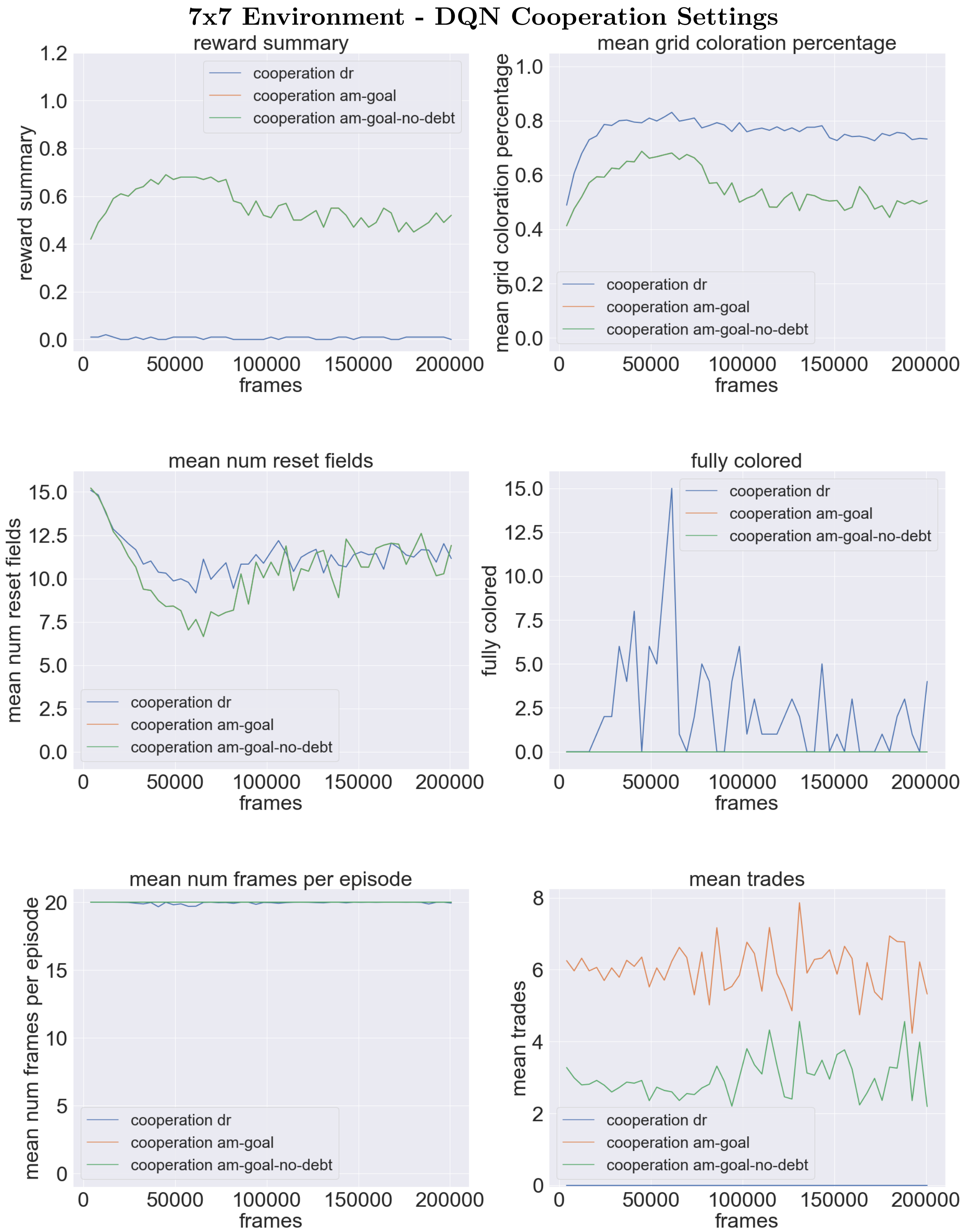


Figure B.12.: Details of the training executions with three cooperative DQN agents in a 7x7 Environment

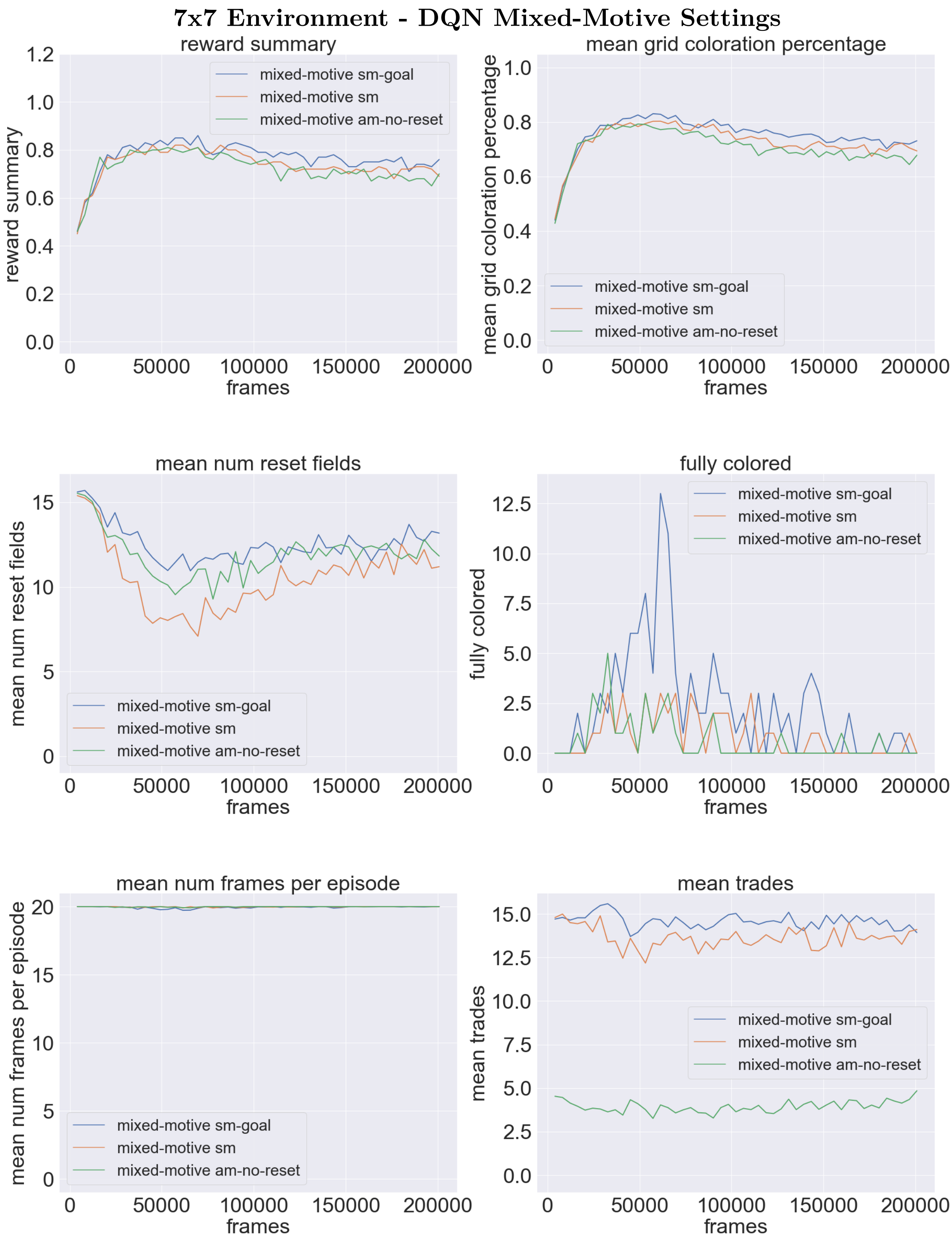


Figure B.13.: Details of the training executions with three mixed-motive DQN agents in a 7x7 Environment

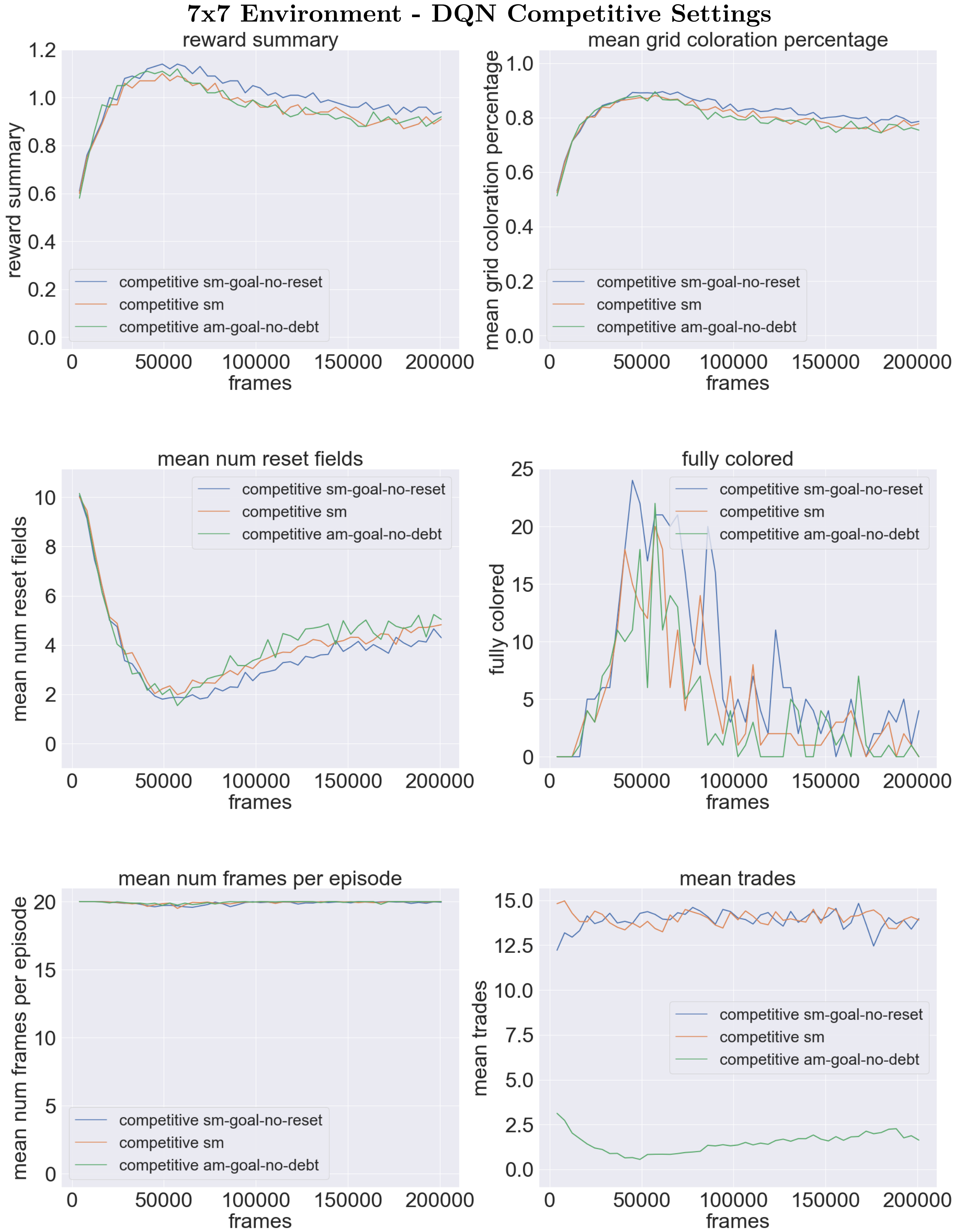


Figure B.14.: Details of the training executions with three competitive DQN agents in a 7x7 Environment

B.0.3. Rooms Setup

The first places and hence the best results of each multiagent plot of the difficult setup are now set in a room divided environment. To create a good layout the grid needed to be extended by setting a size of nine. An example to run a training process in such a nine by nine environment with rooms is shown below. This defines a cooperation composition with three agents using DQN to learn. Training with one agent has no specific max steps set, which leads to a default step restriction of 81 per episode.

Code Listing B.3: Exemplary command to execute training with three DQN agents in a rooms setup

```
$ python -m scripts.train
    --algo dqn
    --agents 3
    --env FourRooms-Grid-v0
    --target-update 10000
    --replay-size 700000
    --epsilon-decay 20000
    --grid-size 9
    --max-steps 30
    --frames-per-proc 256
    --frames 200000
```

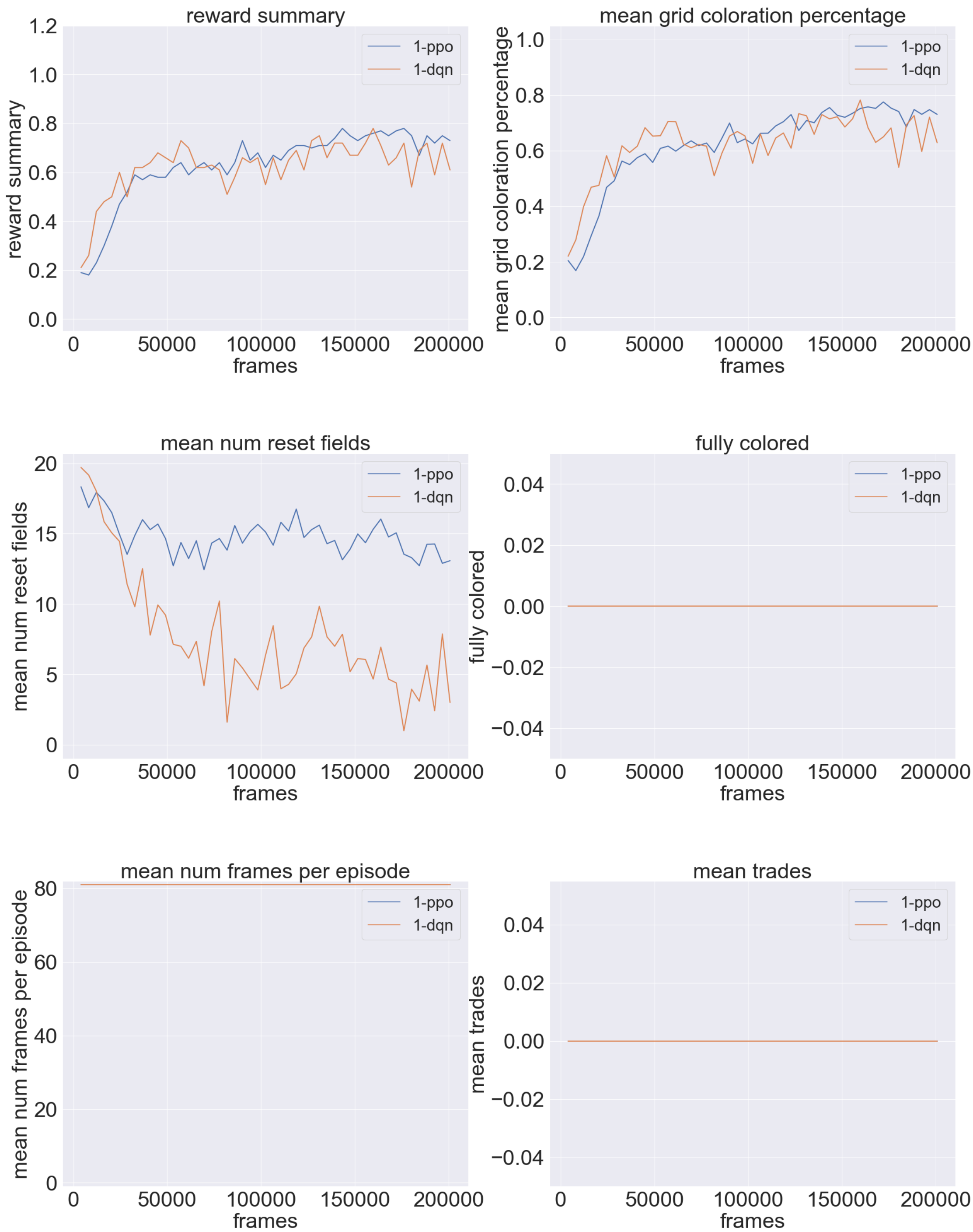


Figure B.15.: Details of the training in a 9x9 Rooms Environment and one agent using PPO and DQN

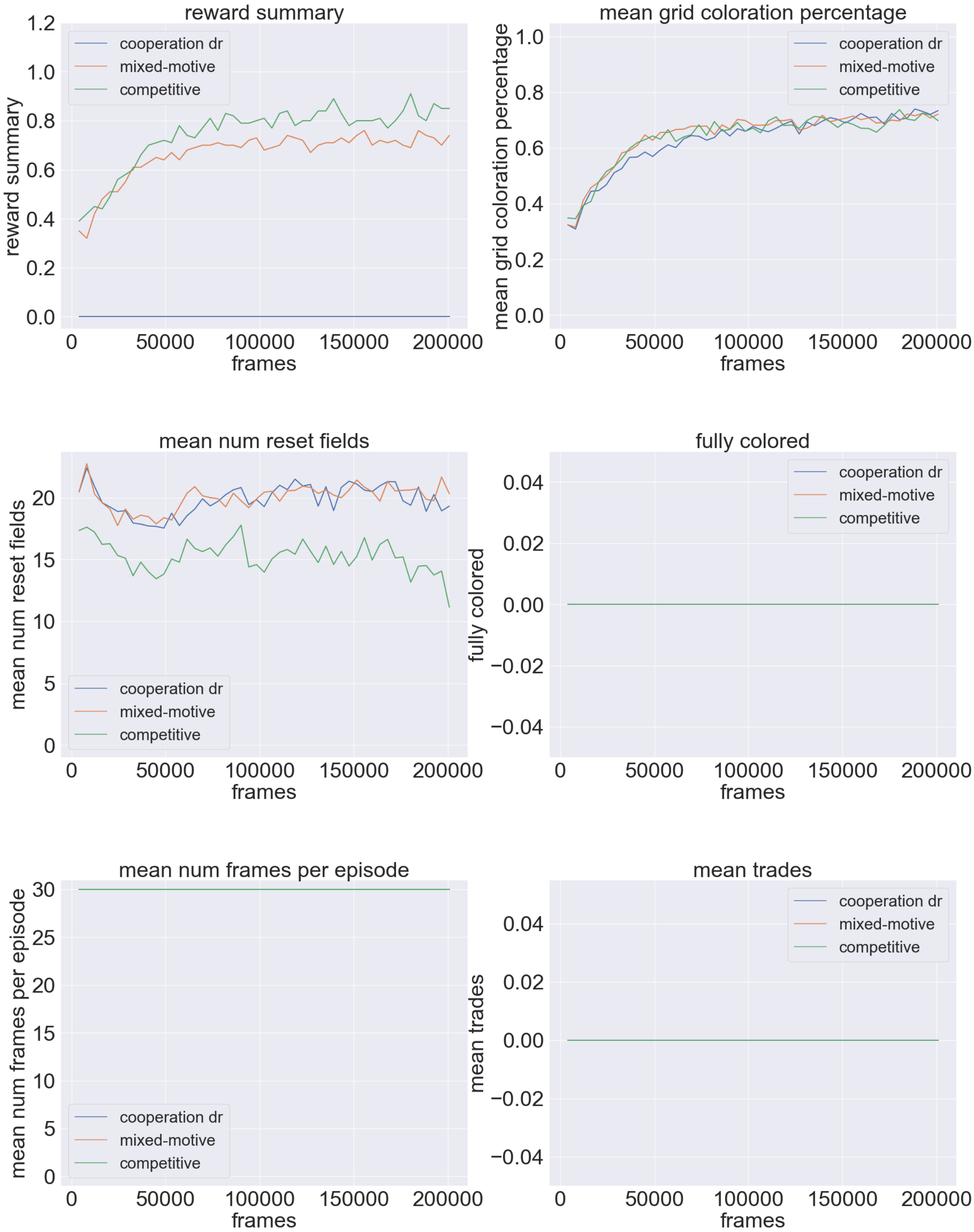


Figure B.16.: Top score details of three PPO agents in a 9x9 Rooms Environment

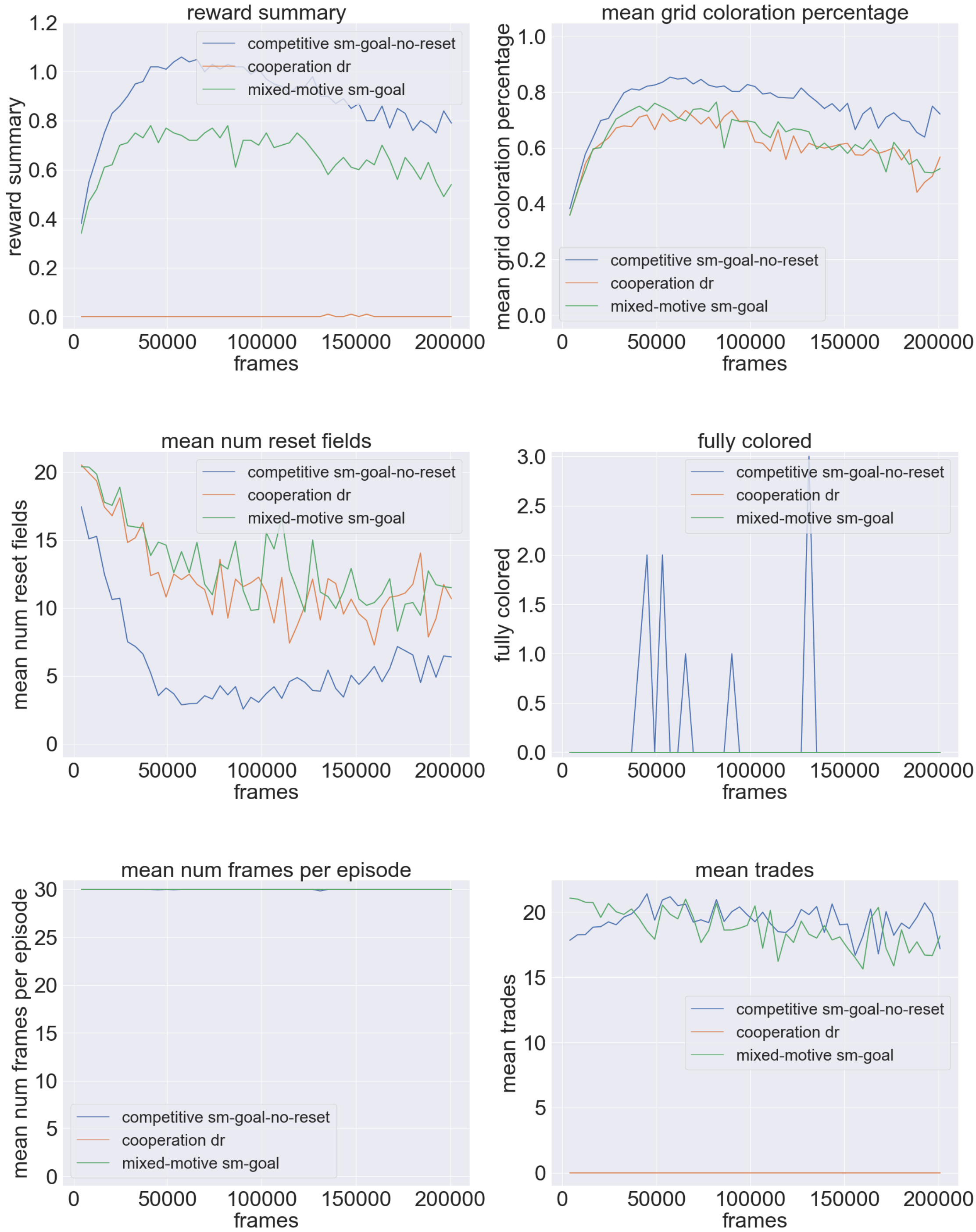


Figure B.17.: Top score details of three DQN agents in a 9x9 Rooms Environment

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