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

MASTER THESIS

Exploring the impact of markets on the credit assignment problem in a multiagent environment

Zarah Zahreddin

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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

Hier kommt der Abstract hin. Hier kommt der Abstract hin.

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1. Introduction

- Motivation
- Goal
- Research Question
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2. Background

Reinforcement learning (RL) is a process that requires on one hand interactive parts and on the other 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: Proximal Policy Optimization (PPO) and the training approach of a deep Q-Network (DQN).

2.1. Reinforcement Learning

rl components

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. Formally, the journey of the agent finding the goal state is described as the Markov Decision Process (MDP). Often, an agent can only see a small field of view, which turns an MDP to a partially observable MDP. When multiple agents act in the same environment the Markov decision process is called a stochastic game [BBDS10].

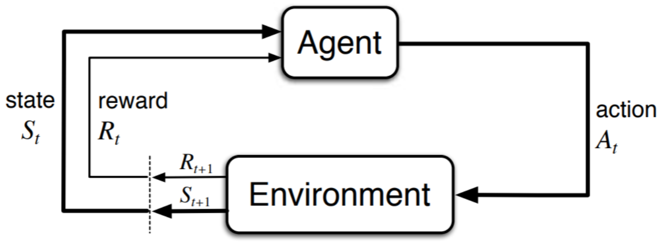


Figure 2.1.: The cycle of agent-environment interaction as shown in "Reinforcement learning: An introduction" [SB18]

sets and values

One environment state S_t is part of a set S containing all possible states. During each point in time t the agent can interact with the environment by executing an action A_t, which in turn changes the environment state. Since it is possible that not all actions are valid in each state the agents action selection is based on a restricted set $A_t \in A(S_t)$. In a multiagent environment, every agent chooses its action and adds it into a joint action set, which is executed collectively during t [BBDS10].

The reward R_t is element of a set of possible rewards R, which is a subset of real numbers $R \subset \mathbb{R}$. Therefore, the reward can potentially be negative or very low. Depending on the environment, that value can act as immediate feedback to the agents action.

The general concept of RL, as defined by Sutton and Barto, 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.

policy

Sutton and Barto continue by defining 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. In most cases however, policies 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 then can be used to update the policy accordingly. For a negative or low reward as an example, the probability of policy $\pi(a \mid s)$ decreases, reducing the chances of executing that same action in that specific state again.

value function

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 immediate 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.

exploration vs exploitation

The last part to note about RL is that it entails the problem of balancing exploration and exploitation. On one hand, an agent has to explore the options given 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 exploiting 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

intro

In 2017 Schulman et al. introduced the concept of PPO in the article "Proximal Policy Optimization Algorithms" [SWD+17]. This section is solely based on that article in order to explain the Algorithm. 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: 1. Sampling data from the policy and 2. Optimizing that data through several epochs.

TRPO

The origin of PPO lies in a similar approach called Trust Region Policy Optimization

(TRPO). TRPO strives to maximize the following function:

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

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.

TRPO advantage func

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.

TRPO advantage func 2

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

r(theta)

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. Here, 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. further extract the first part of function (2.2) as the surrogate objective:

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

However, maximized on its own without a penalty, this results in a large outcome and leads to drastic policy updates.

problem TRPO

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. Even during a TRPO run it could be necessary to adapt the coefficient, due to changes.

PPO

Therefore Schulman et al. introduced

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

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

PPO Algo

unclipped probability ratio produces the lower bound of the unclipped $r(\theta)$, preventing the policy to change drastically.

Finally, PPO is introduced with the following equation

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

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. Additionally, 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 that run over an infinite loop, see the value function (2.1) for example. Therefore, 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:

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

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

AC

Schulman et al. also showed an example of the Algorithm using PPO with an actor-critic approach, see Fig. 2.2. According to Konda and Tsitsiklis [KT03], 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.

PPO pseudo

Here, 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

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

Figure 2.2.: Exemplary use of PPO, as shown in "Proximal Policy Optimization Algorithms" [SWD+17]

2.3. Deep Q-Network

q value function

Another learning approach often compared with PPO is the training of a deep Q-Network with Q-learning and experience replay. 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 $R_t = \sum_{k=0}^{\infty} \gamma^k r_{t+k}$. Here, the estimated outcome is calculated 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] define the optimal action-value with the following:

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

Bellmann

The difference between those two functions is, that a policy is selected in the later formula, which optimizes the outcome. Mnih et al. continue by stating, that in a scenario where the optimal $Q^*(s', a')$ of a sequence s' at the next time step is given, for all actions a' then this Bellman equation applies:

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

This recursive function can be iterated by calculating Q_{i+1}, Q_{i+2}, ... Mnih et al. now imply that this iteration eventually converge to Q^* for $i \rightarrow \infty$. At this point a network is introduced to enhance those calculations, extending the parameters of the $Q(s, a; \theta)$ function with θ as network weights.

problems

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 and small updates to the action value that may lead to drastic changes of the policy. This in turn changes the connection between the Q values and their successive target values $r + \gamma \max_{a'} Q(s', a')$.

dqn solution

To overcome these problems, 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.

experience replay

In Figure 2.3 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 across multiple episodes. The states are parameters of the preprocessed sequences Φ_t in the example, since they are changed, to enable their use as network inputs.

action selection

In addition to the action value function Q, the target action-value $\hat{Q}$ is initialized 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. Otherwise, the best option according to the Q-value is selected.

Algorithm 1: deep Q-learning with experience replay.
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 $\left(\phi_j, a_j, r_j, \phi_{j+1}\right)$ from D
    Set $y_j = \begin{cases} r_j & \text{if episode terminates at step } j+1 \\ r_j + \gamma \max_{a'} \hat{Q}\left(\phi_{j+1}, a'; \theta^-\right) & \text{otherwise} \end{cases}$
    Perform a gradient descent step on $\left(y_j - Q\left(\phi_j, a_j; \theta\right)\right)^2$ with respect to the network parameters θ
    Every C steps reset $\hat{Q} = Q$
  End For
End For

Figure 2.3.: DQN with Experience Replay, as shown in "Human-level control through deep reinforcement learning" [MKS+15]

enhance network

Executing the selected action results in a memory entry in form of the earlier described quadruple. Afterwards a minibatch of the replay memory is randomly sampled and used to perform a gradient descent step. The parameter y_i holds information about the target values, if the episode is not about to end. Otherwise, only the reward is assigned to y_i. The outcome of the subtraction contains the difference of the target values with the old weights and the current action values with the current network weights.

minibatch advantages

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 for instance, leads to a smaller deviation or fluctuation in the parameters. The random samples of minibatches can proof to 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, leading to a decrease of variance in between updates. And lastly, updating the target network periodically improves the stability of the learning process.

3. Related Work

intro and comp. problems

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 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.

coop problems

In cooperative environments on the other hand, agents share the reward and therefore can not tell who contributed useful actions. The independence problem is discussed in chapter 3.2 whereas the cooperation challenge is the focus point of the next chapter.

3.1. Credit Assignment Problem

coop and 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 or less of the common reward is referred to as the credit assignment problem (CAP) [Min61].

CAP definition and kinds

The CAP originated in a one-agent environment that only returned reward once the goal is reached or the terminating condition applied. A popular example of this is a chess game. In 1961, Minsky [Min61] elaborated on this by explaining 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 certain action. On the contrary, the structural CAP is assigning credit to the internal decision that leads to each particular action.

CAP multi

Transferring the single-agent CAP into a multiagent environment Agogino and Tumer [AT04] imply that the problem shifts from being of temporal to 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 actions in a single-time-step. Since the actions are executed all at once, the problem is now evaluating the decision that lies underneath.

cap solution dr

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 always. In order to find the DR $D_i(z)$ for an agent i and the joint action set z, the following function applies:

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

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. A high DR indicates a lucrative action of the analyzing agent, since excluding its action or picking something else leads to a small subtrahend. With this method each agent has the opportunity to learn how their actions contribute to the global reward, enabling individual learning.

An example for this approach would contain 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. The overall reward the agents would get would be 0.1 here, with 0.6 as reward for good choices and -0.5 as punishment for bad ones. At this point agent j would be rewarded for selecting a bad action through the positive reward of 0.1 and could end up learning this policy. However, using the DR function instead results in a reward of $D_j(z) = 0.1 - 0.6 = -0.5$ 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 and since there are only two actors the new rewards comply with the reward distribution of the environment.

This approach however, is sometimes inefficient or even infeasible [NKL18]. Nguyen et al. [NKL18] imply, that large domains could make this calculation impossible. Agogino and Tumer [AT04] claim that this simple function is not always applicable, since it can get difficult to exclude agents. 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

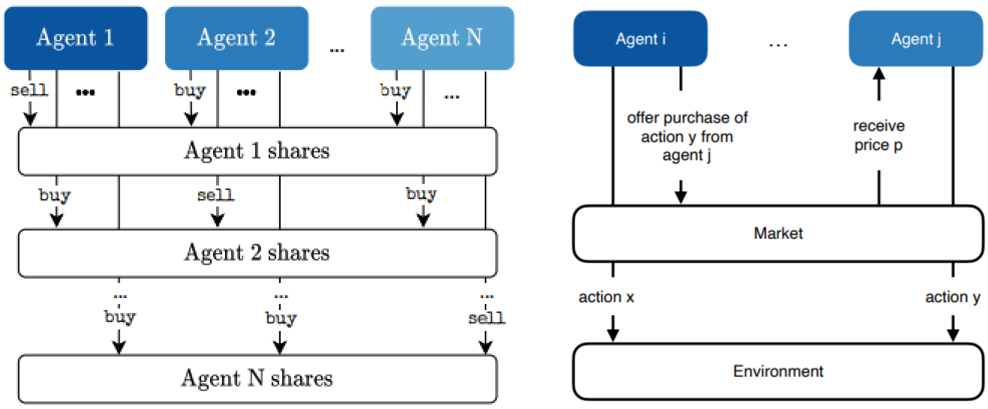
intro mixed motive

As described earlier, 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].

SMG details

Schmid et al. introduced in “Stochastic Market Games” [SBM+21] 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. sm

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 3.1a shows such a shareholder market (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.



(a) Shareholder market (taken from "Stochastic Market Games" [SBM+21])

(b) Action market

Figure 3.1.: Illustrated Markets as defined in "Stochastic Market Games" [SBM+21]

sm transaction

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. They claim however, 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. sm example

—— ist das beispiel ok oder soll das raus?
An example here would be 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. 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 would get a reward of 0.2 in addition to its own reward. However, in a scenario where agent i decided not to sell, agent j would not be able to claim the share and would not profit from the reward of agent i. After each step the shares are resolved and the matching starts again. am

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 so-called action market (AM). In this case actions are am example

extended with a buying offer, containing one expected action from one specific agent, see figure 3.1b.

Again, in an example with two agents i and j, i could need 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 $\overrightarrow{a}_{i,t}$ here, 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 reward. However, if that is not the case, the market conditions do not apply and j would not be paid by agent i.

transactions by chance

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. Hence, in case of an action market agents do not know in advance if and what action another agent could be buying from them. Despite this uncertainty, the researchers showed, that both market implementations yielded promising results. An increase of the overall rewards of participating agents in mixed-motive games was seen.

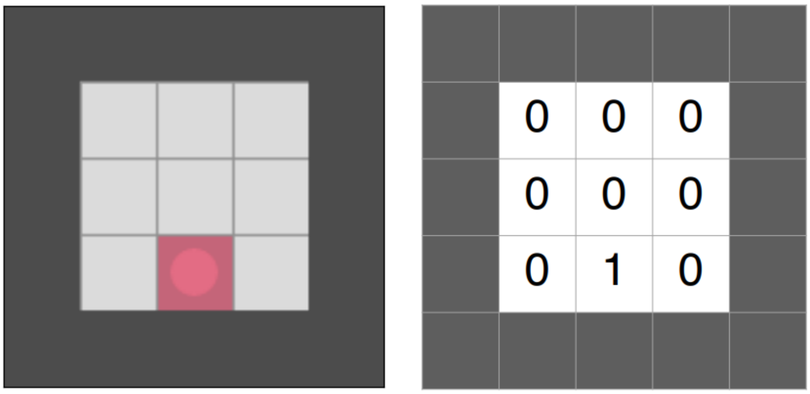
4. Approach

- What is your plan?
- How do you proof that it worked? -> Metric and Experiments

4.1. Coloring Environment

origin and intro

A RL environment is a versatile and unbiased instance, that can can be used to visualize agent behavior and environmental changes. In figure 4.1a, 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. For the purpose of this research however, the environment is changed heavily, becoming the "Coloring Environment". Multiple agents can act in the new instance to try and achieve a new goal - to color all walkable cells.



(a) Human visualization of the coloring environment. A dot represents one agent. Cells change their color when agents move on them.

(b) Simplified agent observation of the current environment state. The number 1 represents a colored cell.

Figure 4.1.: Representations of the coloring environment

cell objects

Figure 4.1b shows a simplified environment observation an agent processes each time step. Every environment cell holds information about the object it represents, being either Walls, Floors or Agents. Furthermore, each object class contains information about its current color, whether it is accessible for an agent and, in case of a floor tile, if it is colored.

4.1.1. Compositions

compositions

When multiple agents are placed in the coloring environment together, 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.

floor coloration

Floor cells manage the coloration state in binary form, as displayed in 4.1b, with a 1 signalizing that the cell is colored. The environment reacts to agent movements by coloring the cells they visit. Agents successfully solve the environment once all fields are colored. Otherwise, agents loose by using up a limited amount of steps.

bit switching

If a cell is already in coloration state 1 and an agent walks over it again the bit is switched, and the cell is reset to 0, removing the color. Besides moving up, down, left and right an agent can also execute the action wait, to stay in place.

cooperative multiagents

Each agent has a different random color. Cells adopt the color of the agent that walks over it. The primary focus in cooperative agent compositions however, is only the binary state. All agents always receive the same reward, regardless of the coloration. An extreme example would be one agent that color the whole grid on its own, and all other agents would profit from the same high reward.

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 not here, that DR settings are always an extension of the cooperation mode and are never used together with market additions.

mixed-motive multiagents

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 the red agent 1 colored 60% of the grid red the reward for that agent would be 0.60. All other agents receive their individual color percentages.

competitive multiagents

In a fully competitive mixed-motive scenario the reward calculations stay the same, only disabling the bit switching for opponent colors. Therefore, agents can directly capture already colored cells when they walk over them. However, if the captured cell contains the same color as the agent the cell is reset instead. Hence, taking over the cells of the opponents is beneficial, since it increases the color presence of the own color, leading to a higher reward.

comparison multiagents

In comparison, the basic mixed-motive composition shows no advantages resetting colored cells. This implementation punishes the resetting of cells with a small negative reward. Since the cell is not captured, the agent won't receive more reward. Hence, it is not likely that the agents work against each other yielding an agent composition with neutral or independent behavior.

4.1.2. Observation

what the agent sees

The observations agents receive from the environment are always generated from their individual 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 image 4.1a.

```
[
  [ [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

description and dimensions

Per default the agent has a view size of a seven by seven grid, represented in a three-dimensional array, similar to a picture with RGB information. Here, all highlighted entries are part of the grid that is shown in Figure 4.1a and the red array shows the agent. 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. All highlighted row entries can be mapped to the columns of 4.1a, starting from the top left of the visualization. The last dimension contains cell information, which is always composed of three elements.

cell encoding colors

The first cell element defines the object type with 1 being just an empty cell, 2 shows a wall, 3 a floor tile and 4 an agent. The second element stores the coloration status, showing 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 1. The third cell encoding describes the color of a cell. To better distinguish the types in the visual representation, walls are 0 for the color black and floors are initially white with encoding 1. Each agent is assigned a number from 2 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, should the agent move to the left, the cell of the previous position is now a colored Floor cell [3 1 2]. The new position of the agent is now in row three and column four with cell encoding [4 1 2].

4.2. Reward Calculations

activation line

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 Coloring.scripts.train
2       --algo ppo
3       --model ppo-training
4       --env Empty-Grid-v0
5       --grid-size 7
6       --agents 3
7       --max-steps 350
8       --setting mixed-motive
```

command algo and model

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 listed 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. Alternatively to the empty grid option of `--env`, as shown in figure 4.1a, 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 7 the agents can only move in a 5 by 5 field, due to the surrounding walls.

settings

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 gain 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 here are “mixed-motive-competitive” and “difference-reward”.

environment 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 0. The only exception is the setting “mixed-motive-competitive”, since 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 1, line 1. The position in the list indicates the accountable agent, i.e. a reward list of $[0.1, 0, \cdots]$ shows that agent 0 is responsible for a reward of 0.1 and so forth. In algorithm 1 the adaptation process of the initial environment rewards during each step is summarized. This process is executed in an environment wrapper, as link between learning or visualization function and the environment itself. The step function of the wrapper takes the training arguments into account, which leads to the four conditions below.

Algorithm 1: 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                                                                    dr rewards
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 content is summed up, to summarize the overall current reward. As a result the variable $G(z)$ of the DR equation is now set to the summed value. To find the subtrahend of the equation, the agents are iterated, and their individual calculations take place. Here, 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. sum clipping

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 individual reward is set to the corresponding limit. Otherwise, the current value stays as is. The upper and lower bounds are necessary, due to more participating agents possibly leading to a really big or very small sum. For example, very large sums without bounds could in turn decrease the importance of the final reward for reaching the environment goal. The other extreme are high negative sums demotivating agents to move. coop

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

market actions

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.

done

The last condition depends on the done flag which signalizes the end of an episode. The environment sets done to true, once either the goal is reached or the maximum step amount is executed. In this case the final reward calculations are applied, see algorithm 2. The result of those calculations is the final update of the reward variable.

Algorithm 2: Final reward calculation

```
if mixed 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
```

done calculations

During the final reward calculations, see algorithm 2, the different agent compositions are checked again. In a mixed setting each agents’ grid coloration percentage, based on their color presence, is added to the individual reward. Otherwise, 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 here. For the final DR calculations the environment supplies information in the `info` variable. 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.

4.3. Learning Process

Independent learning

In order to compare different settings and agent compositions easily, 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, observations still connect the agent experiences, by including the positions of all agents on the grid and reacting to their joint actions in each step.

process structure

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.

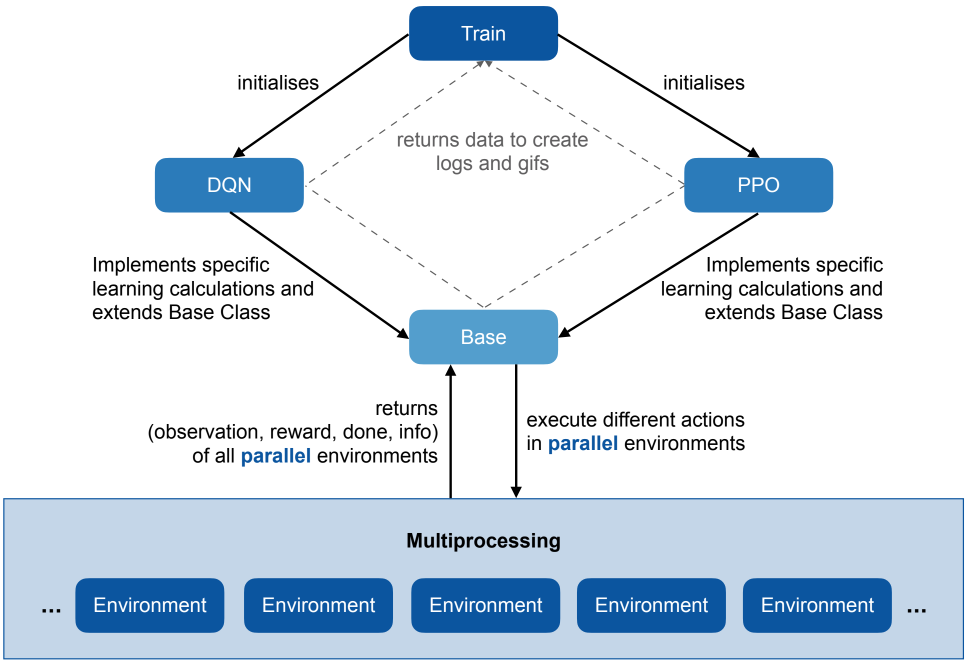


Figure 4.3.: The training structure

training setup

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 suceeded. During the loop, the defined training algorithm `--algo` is executed.

base class

Since both algorithms have similar procedures, they share the base class. In it experiences are gathered by iterating over `--frames-per-procs` and executing actions on the parallel environments. Therefore, each step in the `--frames-per-procs` iteration produces a frame for every environment. The action selection of the learning algorithms generate different decisions based on each state of those parallel environments.

During the iteration data like rewards, observations, actions and more are stored in base class variables that are accessible by the learning algorithms. When the 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. The overall training loop ends when the frames counter is greater or equal to `--frames`. Otherwise, more experience batches are gathered.

action selection

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.

replay memory

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.

target update

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.

fill and reshape experiences

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. The gathered values are reshaped and saved into a PPO experience buffer. Additionally, the advantage values are calculated here and added to the buffer.

optimize model

With that experience 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 2.2.

4.4. Market Settings

initialization

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 have the option to conduct market transactions.

action space

Per default, the environment action space is discrete and only contains five elements: 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

sm - action space

A coloring environment that includes a SM constrains the first position 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]`.

shareholder market step

In Figure 4.4 market elements are visualized. On the left, the process that takes place during each step is shown, see algorithm 1 line 10. Here, 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 the buying and selling information in this case.

trading matrix

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.

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

market transactions - matrices

The first thing to check in a market step execution is the market type. If the SM matches, the corresponding function is called. Inside the shareholder function two ad-

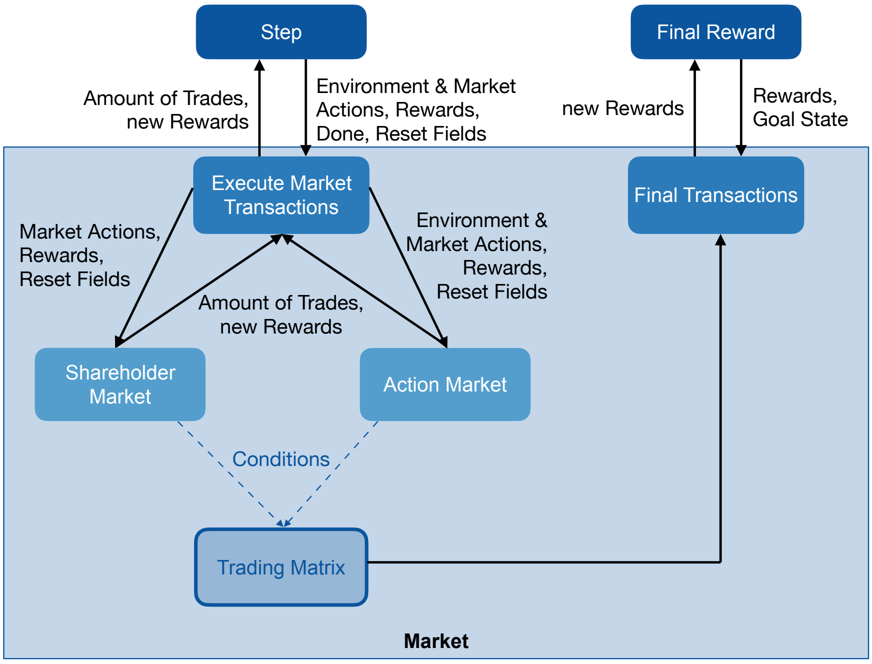


Figure 4.4.: The market elements

ditional matrices are created from the market actions, a buying matrix and a selling matrix. Both matrices are initially filled with zeros, are quadratic, and their dimensions depend on the amount of agents, similar to the trading matrix. The buying matrix contains 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 selling matrix may contain ones only on the diagonal and only for the agent that wants to sell according to the market actions.

iteration

After setting up the two matrices they are iterated, extracting buyer, seller and the corresponding matrix rows. 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`

transaction

If all conditions are true, the trading matrix is updated here, 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.

example

An example for a transaction could be two agents acting in an environment. If agent 2 buys a share from agent 1, the trading matrix is updated. The second row stores the shares of agent two, which increase by 0.1 on the first position. This signalizes that agent

2 is owner of some shares of agent 1 and still has 100% of its own shares. In response, the shares in the first row and column of agent 1 decreases to 0.9.

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

rewards

Additionally, the rewards of the current step calculation, would be updated here, if a price for the shares are set. 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. Nonetheless, in this implementation the SM triggers a reward redistribution according to the trading matrix in each step.

The details of this calculation will be discussed in 4.4.3. Lastly, the transaction count is documented for evaluation purposes. At this point the market execution is done and the number of executed trades and the updated rewards are returned.

4.4.2. Action Market

action space

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 will be directed to. The difference to a shareholder action is the last array position. Instead of setting a bit here 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]`.

transaction

The market elements and general process of visualization 4.4 also apply to an AM setting. Here however, the trading matrix is initially filled with zeros. To establish a transaction in this market setting the following conditions must be met:

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

success

When the two conditions apply 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 here, 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. Here again Agent 2 is purchasing from Agent one.

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

The trading matrix stores the market balance of both agents in each row. For agent 2 this means that the negative value was spent. The first row shows that agent 1 still has a neutral balance and gained the `--trading-fee` of 0.1 from agent 2. To conclude, the market returns the number of transactions that took place in this step and the new rewards.

4.4.3. Reward Calculations

intro

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 or none must be set for a training process. This illustration shows both calculations in one image for convenience. Equal to the previous examples, the red agent 2 buys a share or action from the blue agent 1. 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.

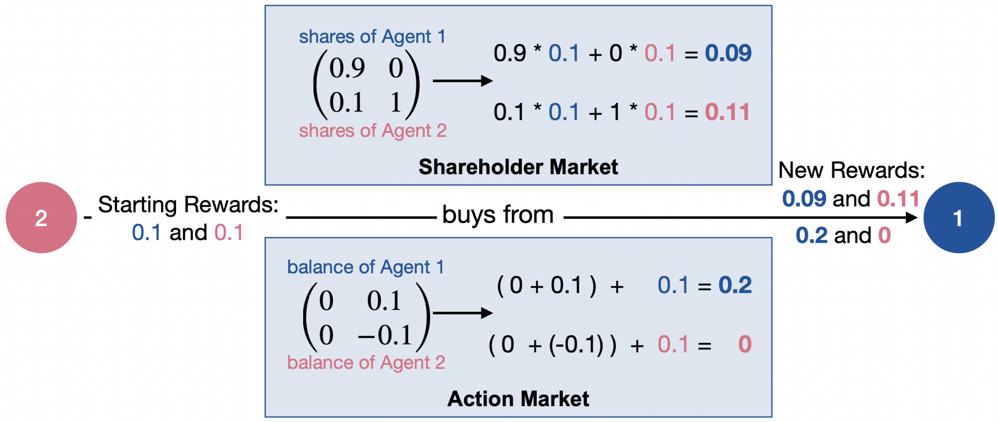


Figure 4.5.: Exemplary reward calculations of both market types

sm matrix

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 1 since agents start with complete ownership over their shares. For this example the trading matrices are configured accordingly. The first matrix row implies that Agent 1 is owner of 90% of its own shares and is not owner of any shares from agent 2. Whereas the second row shows that agent 2 claims 10% of the shares of agent 1 and has full ownership over its own.

sm calculations

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 1 gets a new reward value of 0.09 and Agent 2 claims 0.01 from agent 1 and adds that to its full value of 0.1, resulting in a new reward of 0.11.

sm calculations

In contrast to an AM in a SM the rewards are just reassigned based on the current shares of the trading matrix. An exception occurs, when agents have negative rewards. In this case their share will be skipped during the redistribution, since shares are used to participate in profits.

sm calculations

Another difference to AMs is that the shown SM reward redistributions are executed in each step, and it is irrelevant whether market action 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 2, need to be calculated first, before the shares are taken into account. am calculations

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 can not afford the fee the process is completed anyway and the agent goes into debt. am trading matrix

Thus, this market type makes no use of the 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 current reward. This procedure is illustrated in the bottom half of figure 4.4.3. Here, the fee of 0.1 is subtracted from agent 2 and added to the reward of agent 1, leading to new rewards of 0.2 for agent 1 and zero for agent 2.

4.4.4. Additional Conditions

reset

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. debt

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. 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. goal

The last addition, "goal", lets the market process run as usual, only removing the reward changes during the steps. Here, all transactions are just documented into the trading matrix during an episode. Eventually, the transactions are executed once the final rewards of algorithm 2 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. conditions

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 return as they are and will not be processed further.

For such 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. trading matrix

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. returns

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 environment are shown in section 5.1. The best combinations are then extracted and applied in more challenging environment setups, which are compared in section 5.2.

5.1. Easy Environment Setup

was wurde untersucht

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 2 learning algorithms with the 3 possible agent compositions (cooperative, competitive and mixed-motive) and additionally 2 optional markets that can contain 3 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 by using those 17 market possibilities results in the 102 executions.

was wurde nicht untersucht

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 4 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 4 combinations and the overall market scenario count is now 11. In total the analyzation only includes 66 training results.

wie wurde untersucht / zahlen

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. To summarize the execution count is therefore 70 in total.

Those 70 executions are mostly run with the default parameters that can be looked up in Appendix A. The agents solve an empty 5 by 5 grid, in which they can only walk inside a 3 by 3 field, 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 specified otherwise. This count is generated by squaring the grid size.

Overall the training with default parameters expands over 80.000 frames, of which every 128 (`--frames-per-proc`) are processed in each of the parallel environments. In this case the amount of parallel environments is set to 16 with the parameter `--procs`. All the data that is returned by the environments is saved in one entry. Most of the time the data is summarized into mean values or occurrences are counted. Furthermore, the data entries are always 2048 frames apart, since all 16 environments process 128 actions before a new data entry is logged. After saving each entry the variables containing mean values or counters are reset to produce new values in the next frames.

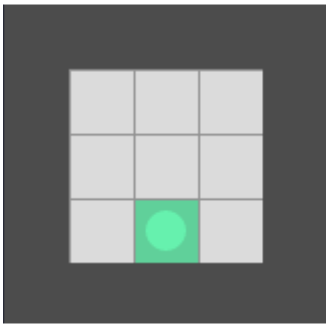


Figure 5.1.: Visualization of level easy with one agent

Setting	Fully colored
1 ppo	2130
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 training algorithm. It is important to mention here, that the maximum step amount is set to 10 in both cases. Additionally, this and all following dqn executions have a `--batch-size` set to 64 instead of the default 256. The ppo agent colored the whole grid a total amount of 2130 times and the dqn agent 650 times.

The average grid coloration percentage of those settings is shown in plot 5.2. The plot lines start at around 2048 frames, since this marks the first time a data entry of the parallel environments is returned. Furthermore, the plot exceeds the 80.000 default `--frames`, since the last data entry includes the last data batch of the environments. The table shows, that both training runs solve the environment and the plot illustrates

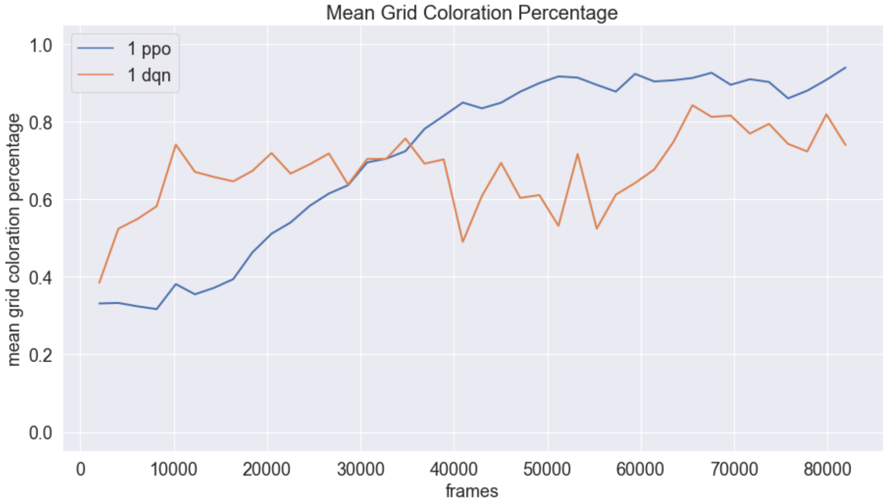


Figure 5.2.: The mean coloration percentage of a 5x5 grid and one acting agent

that in both cases generally 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 coloration of over 70% is eventually reached.

Now the multiagent scenario is compared. Here 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 8.

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.

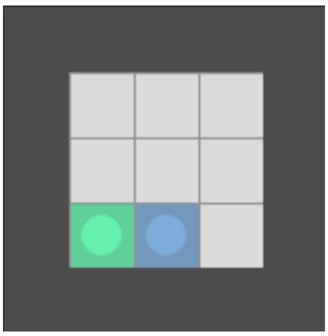


Figure 5.3.: Visualization of level easy with two agents

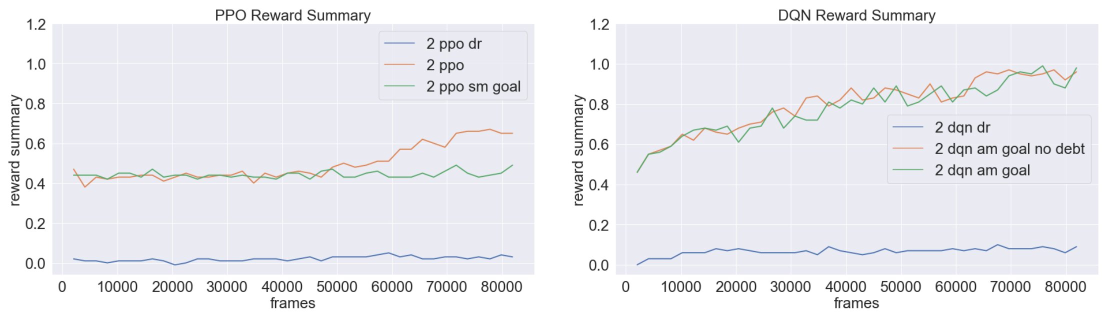
Top 3 PPO Cooperation Settings	Fully colored
2 ppo difference-reward	889
2 ppo	125
2 ppo sm-goal	32

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

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

The measured attribute here is again the overall amount of fully colored states. In both cases the agents with the DR setting scored best, 889 times with the DQN algorithm and 5949 times by using PPO. The PPO scores continue with the default cooperation scenario on second and the SM with the goal condition on third place.

On the contrary, the DQN results show AM settings on the remaining places, with the additions "goal-no-reset" 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.



(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)

In the two plots of Figure 5.4 the reward summary of the top scores, see table 5.2, are displayed. The term reward summary is used here, 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 here is set to 1.2, since agents can get a reward of 1.1 if they color the whole field and additionally 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 thought, the executions with the DR configuration scored highest in terms of reaching the goal, the reward line in this case stays around 0.1. The reason for that is, that agents get the difference of two rewards, leading to very small values. The rewards of the dqn executions show a continuous increase and almost exceed an average summary reward of 1. On the contrary, the ppo executions, excluding the DR setting, only show a small reward increase at the last third half of the training. The DR execution shows now striking changes here.

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

Top 3 PPO Mixed-Motive Settings	Fully colored
2 ppo mixed-motive	1006
2 ppo mixed-motive sm-no-reset	764
2 ppo mixed-motive sm	680

Top 3 DQN Mixed-Motive Settings	Fully colored
2 dqn mixed-motive sm	5417
2 dqn mixed-motive am-no-reset	5379
2 dqn 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.

While the default SM configuration occupies the first place of the DQN scoreboard, in the PPO board it is only on the third place. In fact, the first place of the ppo training is the plain "mixed-motive" setting without any additions. On the second place here is a SM training with the "no-reset" condition. The fully colored counts are very similar between the PPO trainings. The same applies to the values of the DQN board. The second place here is also occupied by a "no-reset" addition, however in this case it is applied to an AM. On the third place of the DQN executions is a SM with the "goal" addition.

Top 3 PPO Competitive Settings	Fully colored
2 ppo competitive	3178
2 ppo competitive sm-no-reset	2645
2 ppo competitive sm	2437

Top 3 DQN Competitive Settings	Fully colored
2 dqn competitive sm-goal-no-reset	7877
2 dqn competitive sm	7842
2 dqn 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.

5.2. Difficult Environment Setup

6. Discussion

- Are the findings as expected?
- Why are the things as they were observed?
- New experiments that provide further insights
- Make your results more comprehensible
    - challenges of markets (i.e. agents didn't need to sell shares/buy actions)
    - final reward is not necessary easy to interpret (did agent do good actions or did he just pick good market actions that sold)?
    - maybe markets need to be more specific (let agents know what others want to buy before choosing action!) and less based on chance - and/or more dynamic, i.e. instead of fixed prices agents can decide what to pay for actions/shares, so that they can for them self decide how important the trade is, and in case of shareholder market, maybe enable multi share purchase?

7. Conclusion

(Briefly summarize your work, its implications and outline future work)
- What have you done?
- How did you do it?
- What were the results?
- What does that imply?
- Future work

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

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. Different values
                        required as default between the two algorithms. The
                        default value here is specific to PPO. For DQN use 64!
                        (default: 256)
  --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)
```

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