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.

Contents

1. Introduction

- Motivation
- Goal
- Research Question
- Structure

2. Background

- Describe the technical basis of your work
- Do not tell a historical story - make it short

2.1. Reinforcement Learning

rl components

Sutton and Barto wrote in "Reinforcement learning: An introduction"[SB18] that Reinforcement learning (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 timesteps $t \in \mathbb{N}_0$ 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). When multiple agents act in the same environment the Markov decision process is called a stochastic game [BBDS10].

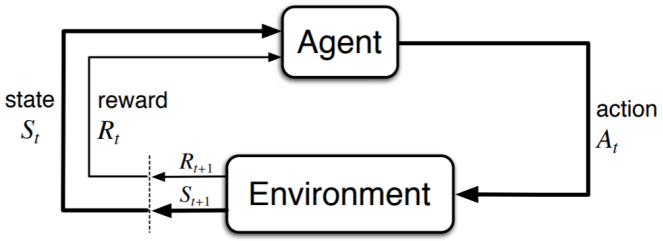


Figure 2.1.: The cycle of agent-environment interaction as shown in "Reinforcement learning: An introduction"[SB18]

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. Since it is possible that not all actions are valid in each environment 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 $v_\pi(s)$ for a policy π, can be used to estimate the long-term value of a state s. The result is the total accumulated reward an agent could get following that state and choosing actions based on the current policy. States that offer immediate high reward could end in low reward streaks. 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 Proximal Policy Optimization (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, Advantage func

The origin of PPO lies in a similar approach called Trust Region Policy Optimization (TRPO). TRPO strives to maximize the following function:

$$\underset{\theta}{maximize}\, \hat{\mathbb{E}}_t \left[\frac{\pi_\theta(a_t \mid s_t)}{\pi_{\theta_{old}}(a_t \mid s_t)} \hat{A}_t - \beta\, KL[\pi_{\theta_{old}}(\cdot \mid s_t), \pi_\theta(\cdot \mid s_t)] \right] \tag{2.1}$$

with $\hat{A}_t$ as an estimator of the advantage function. The advantage function is often calculated with the state-value function $V(s)$, a reward r and a discount coefficient λ over a period of Time t

$$\hat{A}_t = -V(s_t) + r_t + \lambda r_{t+1} + \ldots + \lambda^{T-t+1} r_{T-1} + \lambda^{T-t} V(s_T) \tag{2.2}$$

r(theta)

The fraction in the Minuend of (2.1) can be replaced by $r(\theta)$ and represents the probability ratio of an action in the current policy in comparison to the old policy, with θ being 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 describe that TRPO maximizes 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

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 (2.1) 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. TRPO PPO

Therefore Schulman et al. introduced

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

which is very similar to equation (2.1) 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. PPO Algo

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. 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 timesteps 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 NT timesteps 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-Learning

q value function

Another algorithm that is often compared with PPO is deep Q-Learning (DQN). This Algorithm originated from a simple equation called Q-value [JJR19], expanding the common value function of chapter 2.1 with an action. Therefore the expected reward is calculated starting at a state s, executing a specific action a and following the next states by using a policy π. Mnih et al. [MKS+13] define the optimal action-value with the following:

$$Q^*(s,a) = \max_{\pi} \mathbb{E}\left[r_t + \gamma r_{t+1} + \gamma^2 r_{t+2} + \ldots | s_t = s, a_t = a, \pi\right] \tag{2.6}$$

Bellmann

Here, the maximum sum of rewards is calculated. By using a γ coefficient, future rewards are discounted, putting greater importance on the next few values. They proceed by explaining that if all $Q^*(s', a')$ values of the next timestep are known then the following Bellman equation can be calculated:

$$Q^*(s,a) = \mathbb{E}_{s' \sim \epsilon}\left[r + \gamma \max_{a'} Q^*(s', a') | s, a\right] \tag{2.7}$$

However, in reality the optimal $Q^*(s', a')$ values are not known, thus Mnih et al. continue with the basic idea of RL - iteratively updating this Q function:

$$Q_{i+1}(s,a) = \mathbb{E}\left[r + \gamma \max_{a'} Q_i(s', a') | s, a\right] \tag{2.8}$$

Q network

They conclude that an increasing $i \to \infty$ will allow the functions to converge, resulting in $Q_i \to Q^*$.

Nonetheless, Mnih et al. argue, that this iterative approach is impractical and suggest using a neural network to approximate the action-value function instead. Hence, the new Q function is $Q(s, a, \theta) \approx Q^*(s, a)$, with θ representing all network weights [JJR19]. They refer to this network as a Q-network, which can be trained using the following loss

function:

$$L_i(\theta_i) = \mathbb{E}_{s,a\sim p(\cdot)}\left[(y_i - Q(s,a;\theta_i))^2\right] \tag{2.9}$$

$$y_i = \mathbb{E}_{s'\sim\varepsilon}\left[r + \gamma \max_{a'} Q(s',a';\theta_{i-1})|s,a\right] \tag{2.10}$$

Jafari et al. [JJR19] explain that the loss function shows how much the estimated values deviate from the target values y_i (2.10). Mnih et al. emphasize that y_i holds the network parameters of the previous iteration, due to θ_{i-1}, and therefore it depends on the network weights. Finally, the differentiation of the loss function with respect to θ results in the gradient function below.

$$\nabla_{\theta_i} L_i(\theta_i) = \mathbb{E}_{s,a\sim p(\cdot);s'\sim\varepsilon}\left[\left(r + \gamma \max_{a'} Q(s',a';\theta_{i-1}) - Q(s,a;\theta_i)\right)\nabla_{\theta_i} Q(s,a;\theta_i)\right] \tag{2.11}$$

Algorithm 1 Deep Q-learning with Experience Replay

Initialize replay memory $\mathcal{D}$ to capacity N
Initialize action-value function Q with random weights
for episode $= 1, M$ **do**
  Initialise sequence $s_1 = \{x_1\}$ and preprocessed sequenced $\phi_1 = \phi(s_1)$
  for $t = 1, T$ **do**
    With probability ϵ select a random action a_t
    otherwise select $a_t = \max_a Q^*(\phi(s_t), a; \theta)$
    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 $\mathcal{D}$
    Sample random minibatch of transitions $(\phi_j, a_j, r_j, \phi_{j+1})$ from $\mathcal{D}$
    Set $y_j = \begin{cases} r_j & \text{for terminal } \phi_{j+1} \\ r_j + \gamma \max_{a'} Q(\phi_{j+1}, a'; \theta) & \text{for non-terminal } \phi_{j+1} \end{cases}$
    Perform a gradient descent step on $(y_j - Q(\phi_j, a_j; \theta))^2$ according to equation 3
  end for
end for

Figure 2.3.: DQN with Experience Replay, as shown in "Playing atari with deep reinforcement learning"[MKS+13]

3. Related Work

- Definition of field of research
- Scientific Scope
- Which comparable work in research exists?
- Separation from other works

3.1. Credit Assignment Problem

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 in order to score highest or finish a task, 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. Hence, all agents receive the same reward regardless of their contribution, which aggravates learning. The independence problem is discussed in chapter 3.2 whereas the cooperation challenge is the focus point of this chapter.

coop and problem

Sutton and Barto [SB18] define a RL environment as cooperative, when agents execute their actions collectively each timestep but receive one overall reward in return. In this case individual learning is difficult or even impossible. Collective actions may contain bad choices that could 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. Sutton later on decomposed the CAP into subproblems, namely the structural and temporal CAP [Sut84]. He suggests, that the temporal CAP is 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 various CAP scenarios. An example for a simple approach is the difference reward (DR) [AT04],[NKL18]. The idea is to calculate the reward with the joint multiagent actions as always. In every step however, each agent decomposes that reward by calculating the difference between a new reward and the old one. The new reward is generated with the same actions, only modifying the action of the current agent, setting it to a default or waiting value. With this method each agent has the opportunity to learn how they contributed to the resulting state and reward, enabling individual learning. High DR values indicate lucrative actions of the analyzing agent. The opposite case applies for low valued DRs.

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.

SMG details

Schmid et al. introduced in "Stochastic Market Games" [SBM+21] concepts adding 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. 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 timestep, every agent has the possibility to put their share on the market or to announce a buying offer directed to another agent.

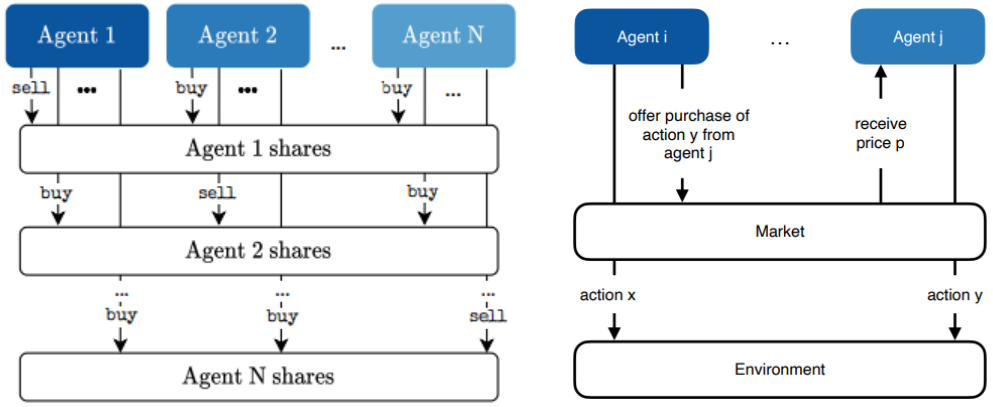
sm transaction

If the buying offer coincide with a share that is up for sale in the same step, a market transaction is registered. From there on out the shareholder participates in the reward of the transaction agent by a fixed dividend d. Schmid et al. mention that an optional price p can be defined as a price 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.

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



(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]

transactions by chance

In both market settings a purchase is established if the specified agent happens to execute a selling action that matches with a buyer. It is important to emphasize that the matching happens during one timestep, 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.

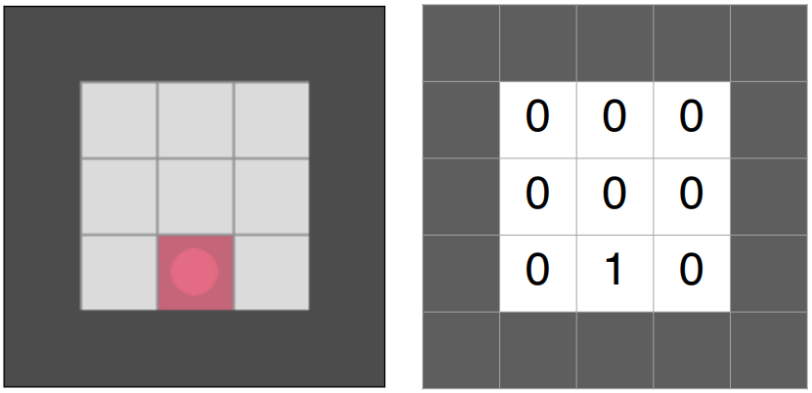
4. Approach

- 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 moves 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 timestep. 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 or not 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 keep 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 its coloration. 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. In the human representation (figure 4.1a) cells adopt the color of the agent that walks over it. The primary focus in cooperative agent compositions is only the binary state. All agents receive the same maximum reward when the grid is fully colored, making it irrelevant what colors the cells have.

mixed-motive multiagents

The opposite is the case in competitive scenarios. In mixed-motive settings for example, agents only gain high rewards once the grid is fully colored, with the twists that it depends on their contribution. The final reward is generated by looking up the percentage a color is present and assigns that value as reward to the corresponding agent.

competitive multiagents

In a fully competitive scenario the reward calculations stay the same, only disabling the bit switching. Therefore, agents can directly capture already colored cells when they walk over them. Hence, taking over the cells of the opponents is beneficial, since it increases the color presence of the own color, leading to a higher final reward.

comparison multiagents

In comparison, the mixed-motive scenario shows no advantages resetting colored cells of others. In this case the cell is not captured and the agent is also punished with a small penalty when doing that. Hence, the mixed-motive setting represents the independent agent composition.

4.1.2. Observation

what the agent sees

The observations agents receive from the environment are always generated from their individual point of view and only contain a restricted area around them. In large environments this feature increases the difficulty but at the same time reflects the reality. An example for a proper observation of an agent is shown in 4.2. This observation represents the internal state of the human representation of image 4.1a.

description

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 bold entries are part of the grid and the colored array is the agent position. All remaining grayed out elements are additions to the observation in order to standardize the observation size.

dimensions

The first dimension of the array contains the whole observation, the second dimension represents each grid column of 4.1a, starting from the top left and the third dimension

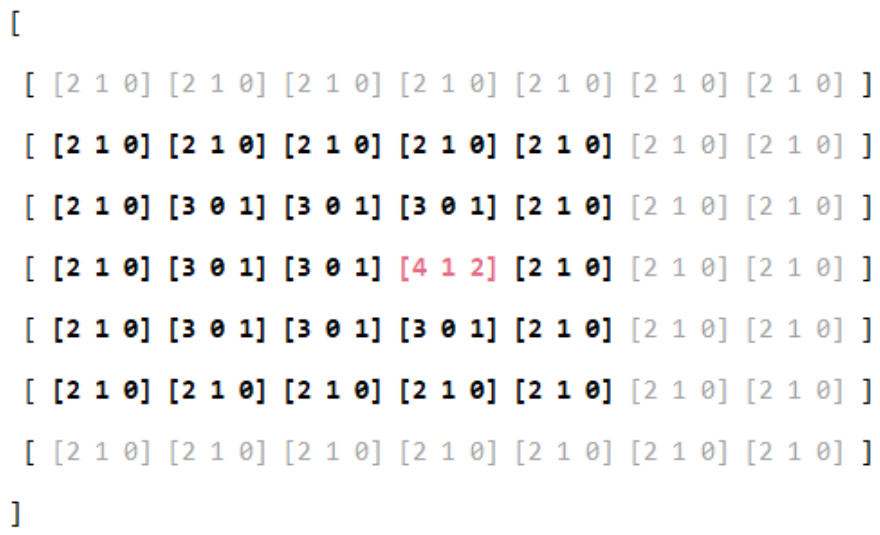


Figure 4.2.: The internal agent observation

encodes each cell. The encoding first defines the object type with 1 being just an empty cell, 2 shows a wall, 3 a floor tile and 4 an agent. Second, the coloration status is visible. Since agents can not walk onto walls, that object type has a coloration state of 1 per default.

cell encoding

The third encoding signalizes the color of a cell. To better distinguish the types in the human 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 color. The Floor color encoding is overwritten with the agents color when the cell is captured.

colors

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.

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 discussed in the sections 4.3 and 4.4. An overview of all training parameters and their default values is listed in Appendix A. The model defines the name for a destination folder, in which all logs, recordings and status updates are stored.

command env

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 of the same size and

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 9
6     --agents 3
7     --max-steps 350
8     --setting mixed-motive
```

each room is accessible to all adjoining neighbors by one 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.

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 maximum 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 option here is "mixed-motive-competitive".

environment reward

In each step agents get separate environment rewards based on their coloration. Agents that color a field receive a reward of 0.1, whereas agents that reset a field get a penalty of -0.1. In the competitive mode agents can not reset fields and therefore receive no penalty. In this case the contrary happens, capturing cells of other agents, yield a positive reward of 0.1. Agents that just wait get a reward of 0. All rewards are written into a list and returned by the environment. The position in the list indicates the receiving agent. In algorithm 1 the process of adapting the initial environment rewards with the specified training arguments is summarized.

Algorithm 1: Reward calculation each step

```
observations, rewards, done, info = environment.step(actions)
if cooperative setting then
    rewards = calculate one cooperative reward
end
if market specified then
    rewards = execute market actions and return transaction rewards
end
if done then
    rewards = calculate final rewards
end
return observations, rewards, done, info
```

coop reward

First, for a cooperative setting a new homogeneous reward needs to be calculated out

of the environment rewards. The calculation for that is summing up all list values and checking if they exceed an upper or lower bound. If that is the case then the new reward is set to the corresponding limit, otherwise the sum is taken as is. This step is necessary, due to more participating agents possibly leading to a really big or really small sum. This in turn could decrease the importance of the final reward for reaching the environment goal. For settings that contain "mixed-motive" this calculation is skipped, since here each agent is responsible for its own environment reward.

market actions

Second, the market transactions are executed, if a SM or AM is specified. The market details are discussed in Section 4.4. One thing to note here is that agents can execute transactions in each step, spending their current reward on items for sale or receive the purchase price from buyers. Therefore the rewards change in this step too.

done calculations

Lastly, the final reward is calculated when done is set to true. That is the case when the environment goal is reached or all steps are used up. Algorithm 2 shows the executed calculations of that case. Again the first thing to check is whether the agents work together. If not, each agents' grid coloration percentage, based on their color presence, is added to the individual reward. Otherwise the environment goal condition is checked for the cooperation mode. If the grid is fully colored the value one is added to each agent reward, since everyone gets the same feedback. Finally, the last market calculations are included into the rewards, see chapter 4.4 for details.

Algorithm 2: Final reward calculation

```
if mixed setting then
    for each agent do
        rewards[agent] += agent color percentage on the field
    end
else
    // cooperative setting
    if grid fully colored then
        for each agent do
            // add the maximum value of 1 to each agent reward
            rewards[agent] += 1
        end
    end
end
if market specified then
    rewards = final market adjustments executed on rewards
end
return rewards
```

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 calcula-

tions 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.

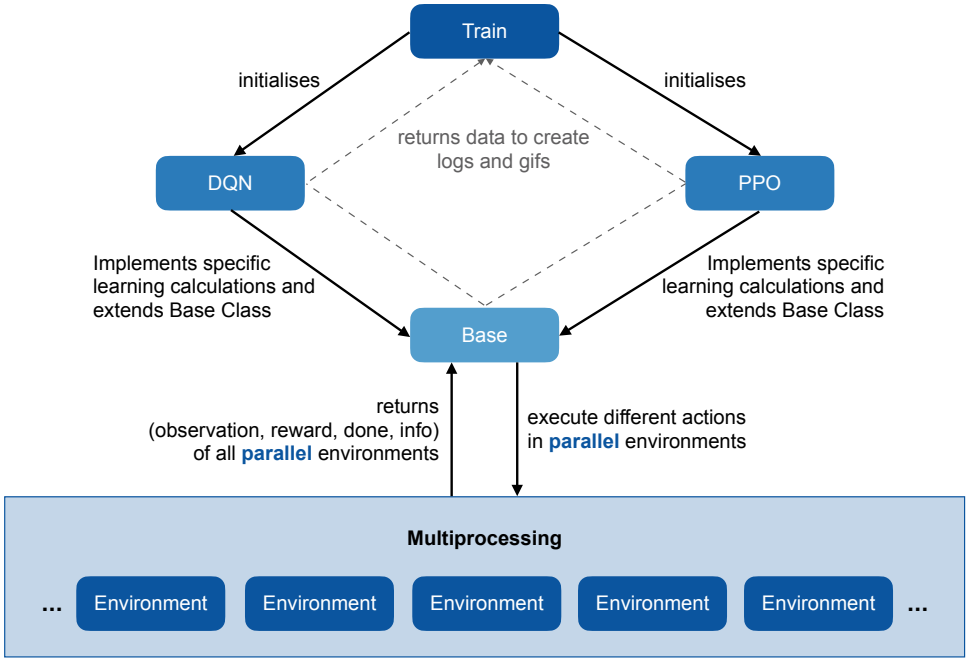


Figure 4.3.: The training structure

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 loop until that number is reached. In this case frames are equivalent to agent steps. 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 through a certain amount of actions which are executed on parallel environments. The action amount is set with `--frames-per-procs`. During that period details like gained rewards, observations, actions and more are stored in base class

variables that are accessible by the learning algorithms. When all experience actions are executed, the base variables are reset and log values are returned, as shown in Figure 4.3. Afterwards the frame counter in the training script is updated with the amount of `--frames-per-procs`. The training loop ends when the frames counter is greater or equal `--frames`. Otherwise more experience batches are gathered.

action selection

Both learning algorithms include their own action selection method. The PPO implementation relies on an actor-critic neural network, letting the actor part calculate a probability distribution of the action space. In case of the DQN implementation a linear neural 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.

4.3.1. DQN

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 the executed actions during that timestep, 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 such memory entries.

target update

After exceeding the `--initial-target-update`, the 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 enhanced 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.

4.3.2. PPO

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 pseudo code of 2.2.

4.4. Market Settings

initialization

TODO: SHAREHOLDER CALCULATIONS CHANGED TO INCLUDE SHARE IN EVERY STEP!

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.

Trading matrix

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 happens in each step is shown, as mentioned in Algorithm 1. Here, the market always receives an action array that is already divided in two parts, one part only containing the environment action and the other the buying and selling information.

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.

execute market transactions

The first thing to check in a market step execution is the market type. If the SM matches, the corresponding function is called. In this case the environment actions are not of importance so the function receives all other parameters instead. Inside the shareholder function two additional matrices are created from the market actions, a buying matrix and a selling matrix.

buying and 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.

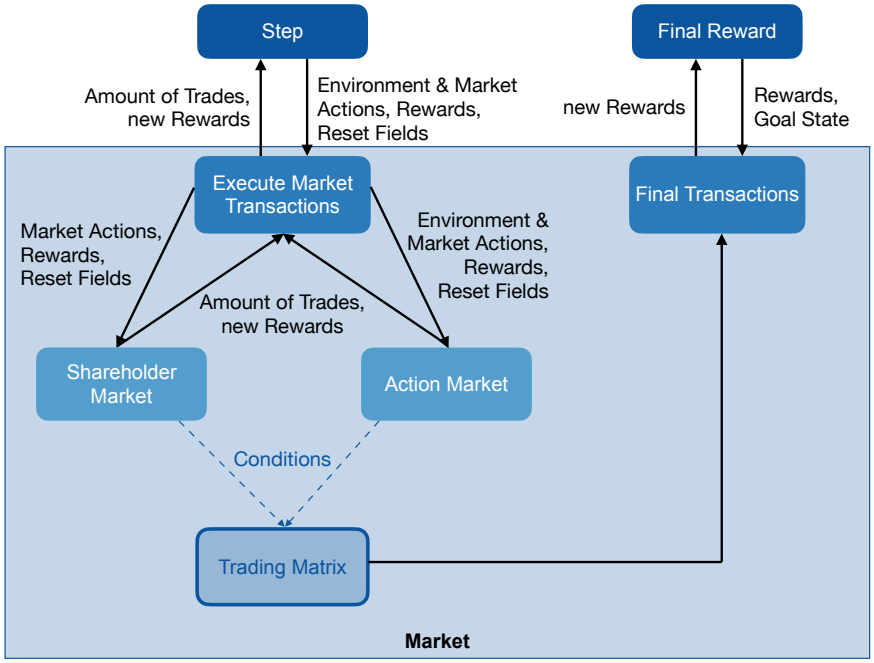


Figure 4.4.: The market elements

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

Inside the shareholder function both matrices are now 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 and seller matrix rows match
- the seller still has enough shares left

transaction

If all conditions of the shareholder function are true, the rewards are updated by optionally substracting a small price from the buying agent and adding that value to the selling agent. Similarly, 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`. Lastly, the trading count is documented for evaluation purposes. At this point the SM step transactions are done and the number of executed trades and the updated rewards are returned from the market.

4.4.2. Action Market

action space

The 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. Furthermore, the AM function needs all parameters, including the environment actions. This information is crucial to the transaction conditions, which are:

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

success

When all 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 here, by substracting the price from the buyer and adding it to the receiver. This concludes an AM step calculation, returning the number of transactions that took place and the new rewards.

4.4.3. Additional Conditions

reset and debt

The AM or SM `--market` string 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 punished by ignoring their market actions. With the "no-debt" Flag, transactions only take place if buyers can afford to pay the price. In AMs, this is solely the case if agents have colored a cell in that step. Waiting or misbehaving agents are excluded as buyers. For SM this depends on the presence of a transaction price. Per default the price is zero, similar to the approach of Schmid et al. [SBM+21].

goal

The last addition, "goal", lets the market process run as usual, excluding the reward change of the SM or AM functions. Here, all transactions are just documented during an episode. The transactions are executed once the final reward is calculated, see Algorithm 2. As shown on the right side of Figure 4.4, the market obtains the current final rewards and a Boolean describing whether or not 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. Since the goods of a SM are shares, naturally the payout takes place at the end of an episode.

In an AM however, each step is self-contained in regards to transactions and payouts. Nonetheless, with the "goal" addition, the payout also shifts to the end of episodes. For goal oriented markets, regardless of the type, the final state needs to equal the environment 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, each agent reward is iterated and added to the sum of the corresponding trading matrix row. For a SM either condition must be met in order to generate the final reward. Again, the trading matrix rows and rewards are iterated here. Each row element is multiplied with the reward of the same index and added to the new reward of that agent. An example of both operations is shown in Figure 4.5.

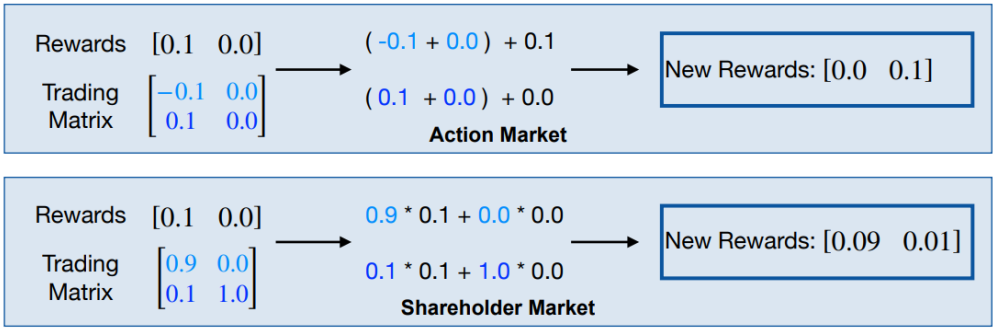


Figure 4.5.: Exemplary reward redistribution of both market types

negative share rewards

An exception occurs in SMs, when agents received negative rewards. In this case their share will be skipped during the redistribution, since shares are used to participate in profits. After the reassignment of rewards the results are returned, as shown in Figure 4.4, and the learning process can continue. 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

- Result presentation
- Description of images and charts
  - One Agent Environment vs MARL
  - Best cases of reward, trades, grid coloration, field resets
  - Worst cases of above
  - influence of markets

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           random seed (default: 1)
--agents AGENTS       amount of agents
--model MODEL         Name of the (trained) model, if none is given then a name is
                      generated. (default: None)
--capture CAPTURE     Boolean to enable capturing of environment and save as gif
                      (default: True)
--env ENV             name of the environment to train on (default: empty grid)
--agent-view-size AGENT_VIEW_SIZE
                      grid size the agent can see, while standing in the middle (default:
                      5, so agent sees the 5x5 grid around him)
--grid-size GRID_SIZE
                      size of the playing area (default: 9)
--max-steps MAX_STEPS
                      max steps in environment to reach a goal
--setting SETTING     If set to mixed-motive the reward is not shared which enables a
                      competitive environment (one vs. all). Another setting is
                      percentage-reward, where the reward is shared (coop) and is based
                      on the percanted of the grid coloration. The last option is
                      mixed-motive-competitive which extends the normal mixed-motive
                      setting by removing the field reset
                      option. When agents run over already colored fields the field
                      immidiatly change the color the one of the agent instead of
                      resetting the color. (default: empty string - coop reward of one if
                      the whole grid is colored)
--market MARKET       There are three options 'sm', 'am' and '' for none. SM =
                      Shareholder Market where agents can auction actions similar to
                      stocks. AM = Action Market where agents can buy specific actions
                      from others. (Default = '')
--trading-fee TRADING_FEE
                      If a trade is executed, this value determens the price (market type
                      am) / share (market type sm) the agents exchange (Default: 0.05)
--frames FRAMES       number of frames of training (default: 1.000.000)
--frames-per-proc FRAMES_PER_PROC
```

```
                      number of frames per process before update (default: 1024)
--procs PROCS         Number of processes/environments running parallel (default: 16)
--recurrence RECURRENCE
                      number of time-steps gradient is backpropagated (default: 1). If >
                      1, a LSTM is added to the model to have memory.
--batch-size BATCH_SIZE
                      batch size for dqn (default: ppo 256, dqn 128)
--gamma GAMMA         discount factor (default: 0.99)
--log-interval LOG_INTERVAL
                      number of frames between two logs (default: 1)
--save-interval SAVE_INTERVAL
                      number of updates between two saves (default: 10, 0 means no saving)
--capture-interval CAPTURE_INTERVAL
                      number of gif caputures of episodes (default: 10, 0 means no
                      capturing)
--capture-frames CAPTURE_FRAMES
                      number of frames in caputure (default: 50, 0 means no capturing)
--lr LR               learning rate (default: 0.001)
--optim-eps OPTIM_EPS
                      Adam and RMSprop optimizer epsilon (default: 1e-8)
--epochs EPOCHS       number of epochs for PPO (default: 4)
--gae-lambda GAE_LAMBDA
                      lambda coefficient in GAE formula (default: 0.95, 1 means no gae)
--entropy-coef ENTROPY_COEF
                      entropy term coefficient (default: 0.01)
--value-loss-coef VALUE_LOSS_COEF
                      value loss term coefficient (default: 0.5)
--max-grad-norm MAX_GRAD_NORM
                      maximum norm of gradient (default: 0.5)
--clip-eps CLIP_EPS   clipping epsilon for PPO (default: 0.2)
--epsilon-start EPSILON_START
                      starting value of epsilon, used for action selection (default: 0.9
                      -> high exploration)
--epsilon-end EPSILON_END
                      ending value of epsilon, used for action selection (default: 0.05
                      -> high exploitation)
--epsilon-decay EPSILON_DECAY
                      Controls the rate of the epsilon decay in order to shift from
                      exploration to exploitation. The higher the value the slower
                      epsilon decays. (default: 1000)
--replay-size REPLAY_SIZE
                      Size of the replay memory (default: 100000)
--initial-target-update INITIAL_TARGET_UPDATE
                      Frames until the target network is updated, Needs to be smaller
                      than target update! (default: 10000)
--target-update TARGET_UPDATE
                      Frames between updating the target network, Needs to be smaller or
                      equal to frames-per-proc and bigger than initial target update!
                      (default: 100000 - 10 times the initial memory!)
```

List of Figures

List of Tables

Code Listings

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