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

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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
- 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) and every method that leads the agent there is a reinforcement learning method. When multiple agents act in the same environment the Markov decision process is called a stochastic game [BBDS10].

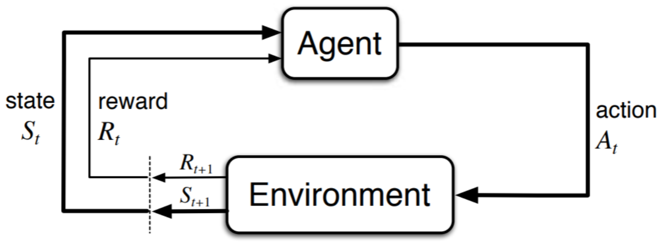


Figure 2.1: The cycle of agent-environment interaction as shown in “Reinforcement learning: An introduction”[SB18]

sets and values

The state S_t is part of a set S containing all possible environment states. Since its likely 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 however, every agent chooses its action and adds it into a joint action set, which is executed collectively on the environment [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 to emphasize a bad action. The general concept of RL, as defined by Sutton and Barto, is to maximize rewards. Thus, unlike machine learning approaches the agent starts with no knowledge about good or bad actions and enhances the decision-making by aiming to improve the reward.

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.

TODO reformulate!!! In most cases it is of stochastic nature, mapping actions and states with probabilities.

During environment interactions agents gain rewards, which then can be used to update the policy accordingly. For example, should the reward be low or negative it could be interpreted as a penalty. In return the policy $\pi(a \mid s)$ could then be adapted to set a very low probability for that action in combination with that certain state. So next time the agent finds itself in that state the bad action is not very likely to be chosen 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. In order to learn, an agent has to explore the options given. However, since maximizing rewards is the goal an agent could become greedy and exploit its knowledge by choosing actions of which it knows to result in small but positive rewards. If an agent doesn't explore enough the best action sequence will stay hidden. Whereas when an agent always explores without exploiting its knowledge, chances are that the reward will not be optimal.

2.2 Proximal Policy Optimization

intro

TODO: introduce PPO as learning algorithm!

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:

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

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

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

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

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

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 (2.1) 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 in a single problem it could be necessary to adapt the coefficient, due to changes within the setting. PPO

Therefore Schulman et al. introduced

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

which is very similar to (2.1) but does not require coefficients. The first part of min 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

PPO is defined by the following equation

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

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. Finally an entropy bonus S is added to ensure exploration. Schulman et al. continues to show an example of an Algorithm using PPO, see Fig. 2.2. N detonates (parallel) actors collecting data in T timesteps in each Iteration. Afterwards the policy is optimized in K epochs by computing the Loss function (2.5) on the corresponding NT timesteps of data, using a minibatch.

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

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

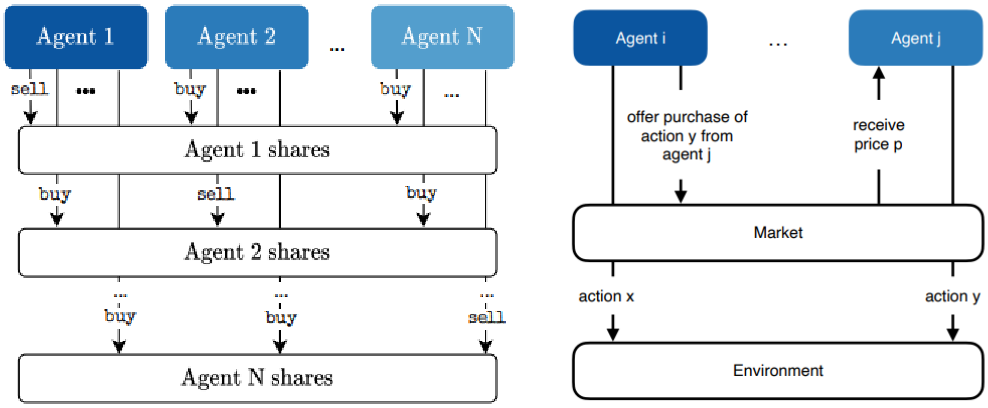
They compare the concept of unconditional markets to companies and shareholders, since shareholders do not need to fulfill any conditions to receive the dividends. In unconditional SMGs both companies and shareholders are agents that buy and sell shares as market actions. Figure 3.1a shows such a shareholder market (SM). 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 timestep, 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]

am transaction

A purchase is established if the specified agent happens to execute the environment action the buyer expected. It is important to emphasize that the matching happens during one timestep, leaving it to chance, whether purchases take place. Hence, 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 Concept

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

4.1 Gridworld

Introduce Gridworld, Agent actions, goal etc.

4.2 MARL Challenges

MARL Problems in Gridworld, i.e. field reset, in comp and CAP in coop.

changing of rewards to solve problems i.e. through markets and percentages

4.3 Market Settings

- am
  - am-goal
  - am-goal-no-reset
  - sm
  - sm-goal
  - sm-goal-no-reset

5 Implementation

- How exactly did you do it?
- Experiment parameters
- Experiment setup
- No need to mention framework, software libraries or tools

5.1 Learning Algorithms

PPO, DQN

5.2 Agent Compositions

env setting: coop vs mixed vs mixed competitive and how the Gridwold/reward calculation behaves

5.3 Reward Calculations

normal/percentage based and market

6 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

7 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?

8 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

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