

# Multi-Agent Reinforcement Learning for Coordinated Block Transportation

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## Abstract

Multi-agent block transportation is a problem that has been used as a way to compare different machine learning algorithms. It can be complicated because agents have to find a way to cooperatively execute a task in an unknown environment. In this paper, we will use this task to compare the performances of the Q-learning and team Q-learning algorithms. While Q-learning is an algorithm that has previously been very successful, team Q-learning might be better at tasks where agents have to use coordination. To test the performances of the algorithms, we created a simulation in which two agents have to move a block to a goal area. **ADD SOMETHING ABOUT RESULTS**

## 1 Introduction

One of the returning issues in machine learning is that it is often hard to decide which learning algorithm should be used for a certain application. Over the years, a lot of valid learning algorithms have emerged, each with their own advantages and disadvantages. Some algorithms might be faster, while others might be more precise, and an algorithm that is better in one area usually performs worse in another. Matching the right task with the right algorithm is not always a straightforward task.

In this paper we will look at the problem of multi-agent box-transportation. For this task, two virtual robots will have to cooperate to transport a box to a certain goal area, while avoiding certain obstacles. This is a problem that has already garnered some attention in machine learning research. In 2006, Wang and de Silva tried to solve this problem with reinforcement learning techniques [4]. They compared the performance of a Q-learning algorithm with the performance of team Q-learning in a dynamic environment. In 2010, a team at the University of Deft also showed how you could use Q-learning, team Q-learning and the WoLF-PHC algorithm to accomplish a similar task in a static environment [1].

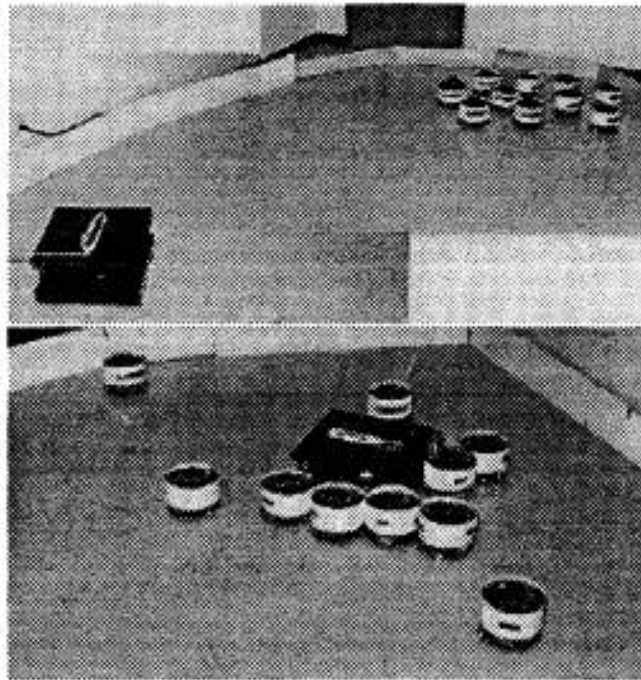
We will also compare the Q-learning and team Q-learning algorithm, since they seem most suitable for a task like this. For our initial task, two agents have to transport a box in a two dimensional static environment. We will compare the performance of our two reinforcement learning algorithms by looking at the time it takes for them to converge to the optimal solution (given that they find it). We have created a simulation to do so, which will provide us with the results we need.

## 2 Application

The box-transportation problem is significant in both the theoretical and practical domain. From a theoretical point of view, it is a relatively simple problem with clear boundaries. Although there are multiple versions of this problem, the basic idea is intuitively easy to understand. Because of its simplicity, it is not hard to extend it to more complicated, real-life situations. It is also a good task to observe the effects of different learning algorithms since, in the more simple, stripped down versions of this task, there are not a lot of parameters that influence the outcome. Finally, it is an interesting way of studying cooperation between multiple autonomous agents.

Although we use a simulation in this paper, the task has successfully been completed by physical robots. For example, in [2] a team of two Pioneer 2 mobile robots was used to physically push a box to a goal area while a third robot served as an observer. In [3] they took a different approach, where they used a swarm of smaller custom robots to collectively move a box to a designated spot (as can be seen in figure 1).

Figure 1: Robots from [3] locating a lit box



It is not hard to come up with practical applications for these kind of systems. In the future, they might for example be useful in construction, or to clear the rubble after a building has collapsed.

## 3 Method

To compare the various learning algorithms, we have written a multi-agent simulation in Python in which agents have to move an object to a certain goal area. In this section, the various components of the simulation will be explained.

### 3.1 The Environment

The environment consists of an **x by y** grid in which the agents can move around. There are a few different types of cells:

**Free cells** These are cells that agents can freely move to. Once an agent or a block moves to a free cell, this cell becomes occupied. They are denoted by dots in the visual representation of the simulation.

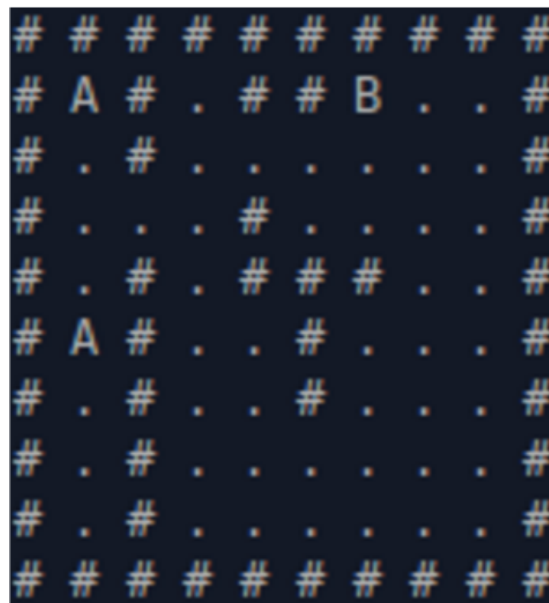
**Walls** These cells are occupied, so an agent can never move to them. They are initialized at the start of the simulation and will not change during the simulation. There are outer walls, which are on the edges of the grid, and some walls inside the grid to make the environment more complex. They look like hash tags in the visualization.

**Block** The block is an item that has to be transported to a certain goal area by the agents. It occupies one cell, and agents cannot move through it. It can only be moved if it is grasped by all of the agents present in the simulation, and those agents move in the same direction. If the block reaches the goal, an epoch ends. In the simulation, it is denoted by a B.

**Goal** The goal cell is basically the same as a free cell, with the exception that if the block reaches the goal a reward is given to the agents and the run of the simulation ends. Agents can freely move on and over the goal, just like with free cells. The goal is represented by a B in the simulation.

**Agent** We'll talk about these in more detail in the next subsection. They occupy one cell, so other agents cannot move through each other. In the simulation they are represented by A's. In figure 2 you can see what the visual representation of the simulation looks like.

Figure 2: The initial state of the simulation. The  $A$ ’s are agents, while the  $B$  is the block



### 3.2 The Agents

For our initial simulation, we start out with two agents. At the start of a run, the agents are spawned at their respective start locations which are defined in the algorithm. Each step, an agent can perform one of five actions: **Stay**, **Left**, **Right**, **Up**, **Down** or **Grab**. The actions mostly speak for themselves. The agent can stay where it is, move in one of four directions or grab the block. The *grab* action can be performed at any step, but will only do something when an agent is next to the block. Once an agent has grabbed the block it will not let go. The move actions *left*, *up*, *right* and *down* only do something when the cell the agent wants to move to is actually free. So, for an action to be performed successfully, the algorithm has to check a few things: do the agents move into a space that is occupied? Have the agents grasped the block? And if they have grasped the block, are they moving in the same direction? Each step, an agent chooses the best action based on its learning algorithm. Then, the agents perform their actions and update the values related to their learning algorithms (usually these are the values in their Q-tables). This process repeats itself until the block has reached the goal. After that, a new run starts and the agents are reset to their starting positions. There are two ways for an agent to get a reward: they can either grab the block to get a reward of 10, or they can get the block to the goal for a reward of 100. These rewards are used to calculate the Q-values, which we will talk about more in the next section.

### 3.3 The Learning Algorithms

For this paper, we compared two machine learning algorithms: Q-learning and team Q-learning. Both are reinforcement learning algorithms, and they are based on the same principles. The goal of both algorithms is, in our case, to make sure that the agents find the optimal policy that will result in the highest reward. It can be found through a value iteration method.

*Q-learning* was first introduced by Watkins in 1989 [5]. It is a model free reinforcement learning technique for multi-agent systems. In our simulation, the agents begin with a Q-table filled with zeros. Each step, they choose one of the five actions with certain probabilities, which are based on the different Q-values. The probabilities are calculated as follows:  $P(a_k) = \frac{e^{Q(s, a_k)/\tau}}{\sum_{l=1}^m e^{Q(s, a_l)/\tau}}$ . In this case,  $s$  is the current state,  $m$  is the total number of Q-values for the current state,  $a_k$  is the  $k^{th}$  action and  $\tau$  is a parameter that gradually decreases during the simulation. After an action is chosen and a new state  $s'$  is reached, the value in  $Q(a_k)$  is updated as follows:  $Q(s, a_k) = (1 - \epsilon)Q(s, a_k) + \epsilon(r + \beta \max_{a'} Q[s', a'])$  (where  $\epsilon$  is the learning rate between 0 and 1). From this formula, it becomes apparent that in order to calculate the Q-value for a certain action in a certain state, both the outcome of that action and the outcome of the best possible action in the next state are considered. After each epoch, to make sure the algorithm converges, we update  $\tau$ :  $\tau_i = \tau_i - (\tau_i - 0.1/N)$ , where  $\tau_i$  is the value of  $\tau$ -value in epoch  $i$  and  $N$  is the total number of epochs.

After the agents have reached the goal with the block, their Q-tables are transferred to the next run. This should result in the fact that the agents learn to choose the path that gains them the highest reward. One notable thing in our simulation is that the agents have two separate Q-tables: one for when the agents have grasped the block, and one for when they have not. This is necessary because the best actions change when the agents start moving the block. Thus, they have to optimize two separate paths.

*Team Q-learning* is based on the same principles as Q-learning, and is actually an extension of the Nash Q-learning algorithm. One of its drawbacks is that it does not have a very good theoretical foundation. The primary difference between the two algorithms is that in team Q-learning, the agents share a single Q-table, and the Q-values are based on their joint actions.

In this case, each step the best action pair is chosen based on the current position of both of the agents. So, after both agents have taken an action, the Q-value for the joint position and joint action of the agents is still updated with the same formula, but in this case,  $Q(s, a_k)$  is the Q-value for the shared action  $a_k$  in the combined state  $s$ . The probability that a certain action is taken is calculated in a way that is very similar to Q-learning. The main difference is that the probabilities for shared actions are calculated, instead of probabilities for the actions of the individual agents. So, in team Q-learning the agents share a Q-table and action probabilities. With this algorithm, it is like the agents try to cooperate with each other.

## 4 Results

## 5 Discussion

## References

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