Bipedal Walking - Reinforcement Learning

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Abstract

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Contents

Chapter 1

Introduction

In this chapter the targeted problem, along with the proposed solution will be introduced. To better understand the explored problem, key relevant background concepts will be introduced.

1.1 RoboCup

RoboCup is an attempt to advance the field of robotics by providing a common problem and an environment for sharing knowledge and collaborate. The Objective of RoboCup is to achieve fully autonomous soccer playing robots that are able to defeat the FIFA World Cup champions by 2050.

RoboCup has since evolved from just soccer and now includes multiple fields, Rescue, Soccer, @Home, Industrial and Junior. [4]

1.2 Soccer League

RoboCup Soccer is split into multiple leagues, each with different challenges and focuses. The Small Size league uses small wheeled robots, each team is composed of six robots and play using a orange golf ball while tracked by a top-view camera; This enables the robots to abstract from challenges such as complex vision detection, walking and others, enabling the teams to focus on strategy and multi-robot/agent cooperation and control in a highly dynamic environment with a hybrid centralized/distributed system.

Middle size League assimilates to small size league, but in this case, the robots are of a larger size and must have all sensors on board; The main focus of the league is on mechatronics design, control and multi-agent cooperation at plan and perception levels.

RoboCup also has simulation for most of its leagues, allowing the teams to focus on software and avoid the difficulties originated by using real robots hardware.

The Standard Platform is a step-up from the simulation league as while it uses real robots, NAOs, it allows the teams to focus mainly on software while using real robots and the challenges of using real robots without having to develop custom hardware. Each robot is fully autonomous and takes its one decisions.

The Humanoid league, assimilates the most to humans, using robots assimilating its shape and unlike robots outside the Humanoid League, the task of perception and world modeling is not simplified by using non-human like range sensors, making this, the most transversal league, requiring hardware and software development. In addition to soccer competitions technical challenges take place. Dynamic walking, running, and kicking the ball while maintaining balance, visual perception of the ball, other players, and the field, self-localization, and team play are among the many research issues investigated in the Humanoid League.

1.3 Bold Hearts

The Bold Hearts are the RoboCup team from the University of Hertfordshire. The team researches and develops software and hardware in the Humanoid league, specifically in the teen size league. The robots used by the team are based on the Darwin-OP but incrementally developed using custom 3D printed parts and a new computing unit, Odroid-XU4 and camera, the Logitech C920 Pro. The Robots use ROS2 as an operating system. [10]

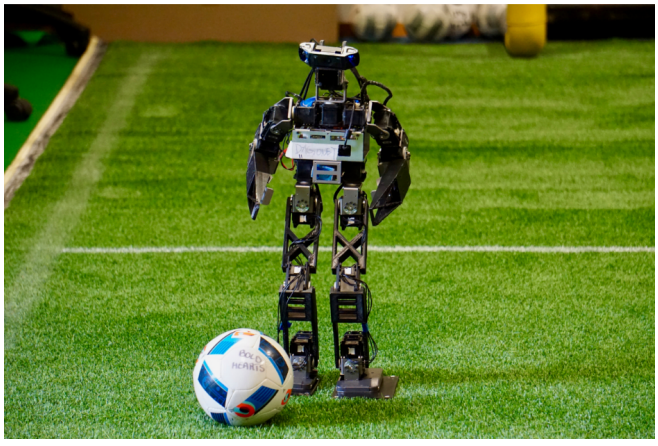


Figure 1.1: Boldbot

1.4 Introduction to the Project

1.4.1 Problem

Robotic locomotion has, until a few years ago, been focused on wheel-based movement. Although it is very stable and easy to implement, it lacks flexibility, the ability to move on uneven, unpredictable terrain and overcome obstacles such as stairs.

As a member of the Bold Hearts team our robots must be able to walk and, in addition to the high complexity of this challenges, RoboCup rules periodically change, these changes are put in place as the RoboCup objective is to achieve the most realistic environment. Rule changes affect both robots, changing the required height, sensors and others, as well as affecting the environment such as moving from flat ground to synthetic grass.

One of the main challenges faced by the team is walking, which is one of the most complex movements performed by humans, requiring simultaneous control of multiple joints to move while maintaining balance. This is one of the most energy and time-consuming problems faced by the team agravated by the rules changes and continuous improvements this requires updates to the robot's structural architecture, leading to new updates to the walking algorithm.

1.4.2 Proposed Solution

Walking algorithms can be developed using various techniques, including explicit programming, supervised learning and unsupervised learning. Walking is very complex as there are a lot of variables involved in it, such as the ground contact, maintaining balance and the complex gait movement. The two main aspects important to highlight are that the walking algorithm requires changes when both the robot or external factors change and that it requires manual work from the team to achieve this.

The best way to solve the first mentioned problem requires having a robot and environment agnostic approach, this is possible by using Reinforcement Learning as the principles of the movement maintains therefore it should be possible to develop an agnostic reward function. From the moment a reinforcement learning solution is successfully implemented, the team should be able to use the same implementation to retrain the policy using the updated robot/environment that has been modeled in the simulator. This also allows to reduce the complexity of the problem as the input into the system is sensory data and the output is a set of actions to execute on the joints.

1.4.3 Aims and Objectives

This project proposes to develop a reinforcement learning implementation for walking, to achieve the objectives of the project, three main topics will be covered, robotics biped locomotion, reinforcement learning algorithms and the training framework.

While achieving a working walking pattern would be desireable, the project aims to develop an implementation of reinforcement learning to achieve walking, along with it aims to develop resourcefull documentation on the process and its results, allowing for reproducibility and further development and adaptations of the current implementation to learn not only walking but any suitable problem.

Chapter 2

Background Research

2.1 Reinforcement Learning

Reinforcement learning is one of the main machine learning paradigms, alongside supervised learning and unsupervised learning. The objective of reinforcement learning is essentialy to map states to actions while maximizing a reward signal, in same cases, actions may affect not only the present but future situations. To learn how to map the states to actions the agent must try them, this charactheristics, trial-and-error and delayed reward are the most distinguishable features of reinforcement learning.

The agent must be able to perform actions affecting the environment followed by a perception, this perception should indicate to what state the robot has transitioned and the reward signal associated with the result of the action taken given the previous state. This interaction is summerized in the following figure.

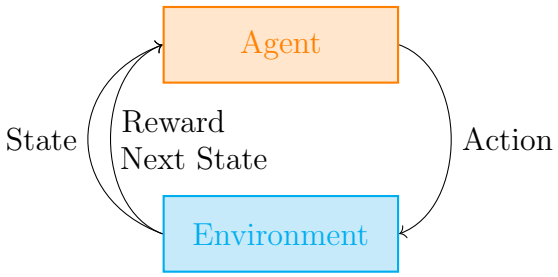


Figure 2.1: Reinforcement learning model

One unique challange in reinforcement learning is balancing exploration and exploitation. To succed a task the agent must exploit actions that, through experience have yielded the most rewards, although, to have experience and perform better in the future the agent must explore new actions. The dilemma is that neither exploration nor exploitation can be pursued exclusively without failing at the task [11]

2.1.1 Markov Decision Process

Reinforcement learning can be described using the Markov Decision Process(MDP). MDP is the final summary concept of the individual elements:

- The Markov Decision Chain
- The Markov Property
- The Markov Reward Process

Markov Decision Chain

A Markov chain is a mathematical system that experiences transitions from one state to another according to certain probabilistic rules. The defining characteristic of a Markov chain is that no matter how the process arrived at its present state, the possible future states are fixed. In other words, the probability of transitioning to any particular state is dependent solely on the current state.

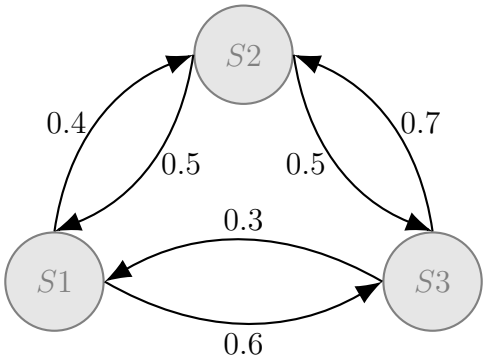


Figure 2.2: Example of a Markov Decision Chain

As can be observed by the example Markov Decision Chain, the transition probabilities are fixed and are only dependent on the current state, this is the Markov property.

$$P(S_{t+1}|S_t)$$

Definition of the probability of transitioning to any particular state given the current state.

Markov Property

This means that the transistion to state t_{+1} from state t is independent of the past, meaning that our current state already captures the information of the past states. Defined by the following equation:

$$P[S_{t+1}|S_t] = P(S_{t+1}|S_1, ..., S_t)$$

Markov Reward Process

As it suggests, the Markov Reward Process is a Markov process with the difference that it includes a reward system that indicates how much reward is accumulated through a particular sequence. An additional factor is applied, the **discount factor** γ that indicates how much the future reward is discounted. if $\gamma = 0$ then the agent will only consider the immediate reward, if $\gamma = 1$ then the agent will consider all subsequent rewards. In practice this extreme rewards are inneffective and γ is usually set to values between 0.9 and 0.99

2.1.2 Bellman equation

The bellman equation is the basis to solve RL problems, it helps us solving the MDP, it is defined as:

$V(s) = max_a(R(s,a) + \gamma V(s'))$

The Bellman equation sums to the present reward the discount factor multiplied by the best next value outputed by the value function.

The optimal value function $V^*(s)$ maximizes the expected reward. To achieve this the Bellman equation is solved by iteratively updating the value function until $V^*(s)$ is reached.

2.2 Learning Algorithms

One of the main decisions in implementing a reinforcement learning algorithm is the learning algorithm, to understand the algorithm decision its important to understand how this differ.

The first major split in RL algorithms is whether it is model-free or model-based, model-based algorithms use a model of the environment, which is capable of mimicking its behaviour, this allows inferences to be made about how the environment will behave given an action and what the next reward will be. This method of reinforcement learning isn't adequate for the current problem due to the high complexity of the environment in which the agent is interacting, making it impossible to model it.

The second decision is between **policy optimization** and **Q-Learning**. While both aproaches have similar concepts and are driven by MDP they are internally different.

In Q-learning, the goal is to determin a single action from a set of discrete actions by finding the action with the highest Q-value. While in policy optimization the goal is to learn a map from state to action, this can be stochastic and, opposed to Q-Learning, workds in continuous action spaces.

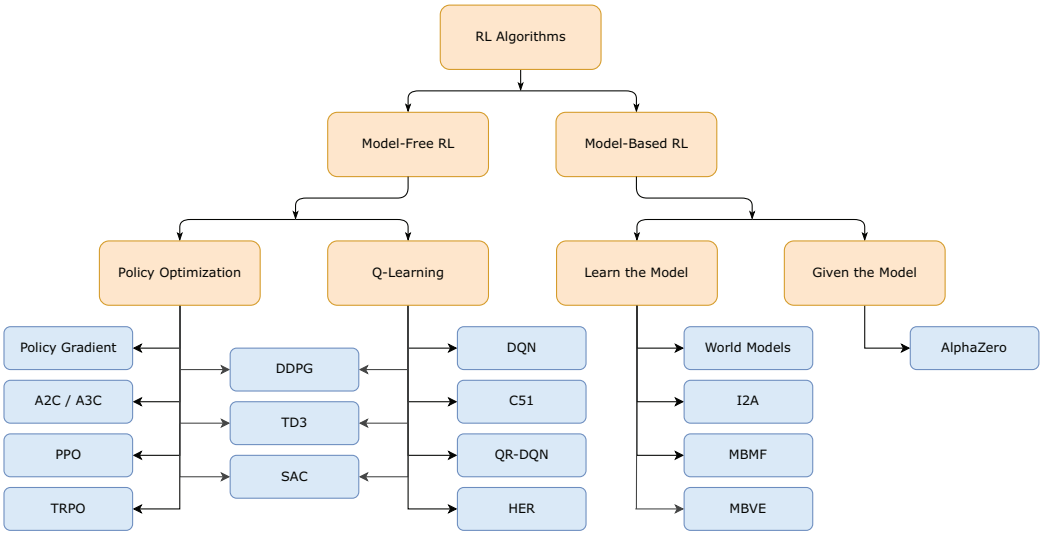


Figure 2.3: A non-exhaustive, but useful taxonomy of algorithms in modern RL. [7]

To the problem in study, Q-Learning was a better fit as the action space was discretized(covered further in chapter 3), apart from the action space, the Implementation of Q-learning is simpler and more common.

The algorithm decision was set on Deep Q-Network (DQN). The main difference between DQN and Q-Learning is that DQN implements a neural network replacing the Q-table. This is a benefit due to the complexity of the environment and the total number of possible states, using standard Q-learning would require a very large q-table, which is a huge memory and computational burden.

2.3 Training Framework

Followed by the new advances in RL there was a growing need for a common benchmarking framework, that would allow for comparing algorithms and implementations.

Gym was releasead by the OpenAI team to enable this, by providing an accessible API and common environments. Gym is now the most widely used tool in RL research, it has a large community and documentation and a growing number of environments.

Gym was choosen as the framwork to standardize the implementation which allows for an easier understanding and comparison, behond this, gym

also facilitates the implementation by using all the pre-built functions.

2.4 Previous Implementations

To develop this project it was important to first study previous implementations, what problems were faced and the reasoning behind there decisions, this brought light to many problems and details of implementing reinforcement learning in special for walking.

One important implementation was the **Deep Q-Learning for Humanoid Walking**[12], an implementation of reinforcement walking on the Atlas platform. this implementation higlits some of the general pre-conceptions regarding the reward system and how to handle the complexity of controlling all the joints simultaneously.

2.5 Logging and Reproducibility

One of the most important aspects of machine learning and Reinforcement Learning in particular is data logging and reproducibility. This project required extensive testing of hyperparameters and reward systems. To understand the results and its correlation with the variables in testing its important to log all the results and to be able to reproduce the results. **Requirements for logging:**

- Hyperparameters
- Performance metrics
- Code
- Models
- Renderings

From previous experiences with machine learning and logging platforms MLflow was the first option analysed, although, Weights & Biases (WandB) was the choosen platform, WandB offered an hosted version option compared to MLflow, WandB also integrates with Keras allowing for a seamless implementation. WandB fills all the requirements and allows for a comparison of the renderedings and performance results between runs.

Chapter 3

Design

3.1 Development Structure

Due to the complexity of the project, a development structure has been put in place, this includes multiple steps of increasing complexity and realism, the increasing complexity allows for detecting problems at earlier, simpler stages, making the transition and understanding the problems easier.

3.1.1 Cartpole

Cartpole is a classic exercise of reinforcement learning, it consists in balancing a pole in a cart moving on an horizontal plane by applying a force on the right or left side of the cart making it move in the oposite direction.

The cartpole environment allowes for the implementation and testing of the reinforcement learning algorithm, different implementations and its comparison, at this stage it was also used to implement the logging and reproducibility interface.

3.1.2 2D Walker

At this stage the complexity of the environment increases as the environment starts to assimilate the target problem. Although, this stage eliminates some of the complexity such as using a more complex 3D environment and implementing the training with the robot controll interface. This allows for the implementation of a neural network, learning algorithm that is capable of handling multiple simultaneous outputs as it is required to control all the joints of the robot and understanding how to efficiently calculate the best action.

To achieve this it is necessary to develop a custom 2D environment of a simplified humanoid in order to train a walking behaviour. New challenges from this stage such as implementing a custom reward system, rendering and step functions are an important step in order to transition to 3D simulation.

3.1.3 3D Walker

The final stage of the project is the implementation on a 3D simulated robot, this is the combination of the previous stage with extre complexity, not only due to the inherited complexity of a higher diensional world but because this should be able to integrate with the real robot from the Bold Hearts team and therefore use its control interface. Robot simulation is the main platform for developing software for robotics, it has many benefits,

developing software and testing it directly on a real robot can be a very slow process and can even lead to breaking the robot.

3d simulation brings new challenges, such as a larger range of motion and more joints to controll, along with a more complex environment, requiring more processing power and more time to solve the problem. Along with this it requires a more complex reward system as a new dimention poses new problems.

3.2 Environment Definition

One of the main reasons for the use of OpenAI Gym in this project is the ability to standardize the environments. In this section each Gym environment will be described.

3.2.1 Cartpole

The cartpole environment is a very simple exercise, consisting of a pole in a cart moving on an horizontal plane, the objective is to balance this pole by applying a force on the right or left side of the cart making it move in the oposite direction. [6]

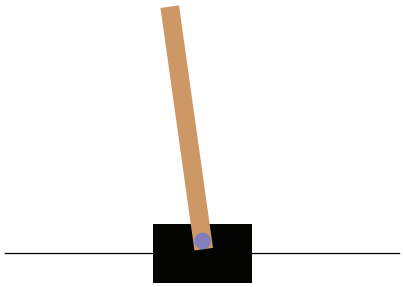


Figure 3.1: Rendered Cartpole Environment - OpenAI Gym

Cartpole Environment definition:

- **Observation Space**

Table 3.1: Observation Space for the Cartpole environment

Num	Observation	Min	Max
0	Cart Position	-4.8	+4.8
1	Cart Velocity	-Inf	+Inf
2	Pole Angle	-24°	+24°
3	Pole Angular Velocity	-Inf	+Inf

- **Action Space**

Table 3.2: Action Space for the Cartpole environment

Num	Action
0	Push cart to the left
1	Push cart to the right

- **Reward:** In the cartpole environment the reward is attributed per timestep survived, being awarded 1 point per timestep.

3.2.2 2D Walker

The 2D environment requires a 2D Humanoid, this has been defined with 8 different joints, 2 in the shoulder, 2 in the hips, 2 in the knees and 2 for the ankles.

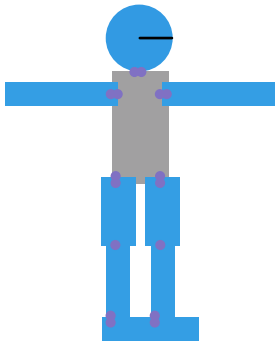


Figure 3.2: Representation of 2D humanoid

Environment definition:

- **Observation Space:** The Observation Space is a vector of size 8, containing the angles for each of the 8 joints of the humanoid.

Table 3.3: Observation Space for the 2D Walker environment

Observation	Min	Max
Joint Position	-20°	+20°

- **Action Space:**

Table 3.4: Action Space for the 2D Walker environment

Num	Action
0	Move the joint counterclockwise
1	Maintain joint position
2	Move the joint clockwise

- **Reward:**

Table 3.5: Reward system for the 2D Walker environment

Action	Points
Moves Back	- 2
Stays in Place	-1
Moves Forward	1
Loses contact with the ground	cumulative -2
Reaches target	10
Falls	-10

3.2.3 3D Walker

In the 3D environment, the robot needs to simulate the one used by the Bold Hearts team, given that the team already uses a simulator, gazebo, this will be used to interact with the robot given that it provides ROS2 integration.

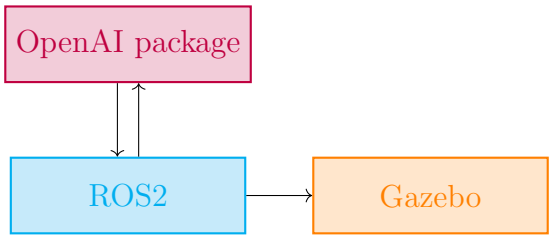


Figure 3.3: Integration of ROS2, Gazebo and OpenAI Gym

To achieve this integration, OpenAI Gym should be able to subscribe ROS2 topics containing the world observations. The OpenAI Gym should also be able to publish to ROS2 topics, allowing it to control the robot's joints, as well as calling services in order to controll the simulation, including, pause and reset the simulation. One of the main aspects of this integration is to allow to train not only walking but also any relevant task by the team, to achieve this the OpenAI Gym package should be split into three different parts:

- Robot
- Environment
- Task

The robot file should contain all the setup required for the Boldbot, the teams robot. On the Environment file all the environment setup should be

defined, such as the observation space, action space, reward system, etc. Finaly the task file should be specific for the task trying to be achieved, allowing the team to setup just the task without requiring setting up the robot and environment everytime. [2]

Chapter 4

Implementation

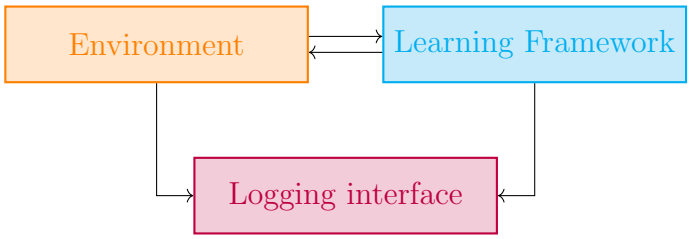
4.1 Cartpole

Cartpole is a pre-built environment from the gym library, therefore, it just has to be imported using:

gym.make('CartPole-v1')

In this experiment the version 1 was prefered over version 0 as it provides more timesteps, setting the limit to 500 timesteps per episode.

There are three main parts in stage 1:



Each of this should interact for a successfull implementation of the first stage. After the environment is imported, the learning framework is imported, this is a framework that is used to train the agent. In this stage, two main implementations were explred, Keras-rl and a manual implementation of the keras API.

Keras-rl

To implement keras-rl[5] in the specific hardware used in this project, it was required to be installed from source inside a miniforge environment. To be able to setup the model used by keras-rl tensorflow was required, once again, the hardware required a custom installation, the instructions can be found on the manufactures website [3].

As the requirements were met, the next step is to setup a model, this was setup using keras, imported from tensorflow.

Listing 4.1: Setting up the model in the cartpole environment

```
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense, Flatten, Input
from tensorflow.keras.optimizers import Adam

states = env.observation_space.shape
actions = env.action_space.n

def build_model(states, actions):
    model = Sequential()
    model.add(Input(states))
    model.add(Flatten())
    model.add(Dense(12, activation='relu', input_shape=(1,4)))
    model.add(Dense(12, activation='relu'))
    model.add(Dense(actions, activation='linear'))
    return model

model = build_model(states, actions)
model.build(states)
```

The code displayed above is used to import the required packages for the model, proceeded by a function where the model is defined, here, we can see that the model receives the inputs, flattens this followed by a fully connected layer with 12 neurons and relu activation function, this layer is followed by another fully connected layer with 12 neurons and relu activation function.

4.2 2D Walker

The 2d environment uses as a physics engine Pymunk [9], a python implementation of Chipmunk[1] in conjunction with pygame [8] to render the simulation.

4.3 3D Walker

Chapter 5

Experimental Results

This chapter will cover the development process, the decisions that have been taken as well as the results and outcomes of the individual development parts.

5.1 Cartpole Outcomes

The first task developed was the classic cartpole environment, this was helpfull in understanding core concepts of reinforcement learning and neural networks, along with it, cartpole was essential in testing and setting up the logging interface as well as testing different implementations of the learning algorithm

Keras-rl

Keras-rl is a community maintained high level implementation of keras agents for reinforcement learning. this was the first implementaiton tested.

The implementation of keras-rl is very easy and doesn't require a deep understanding of reinforcement learning and the leanring structures.

Keras API

The second implementaiton tested was using the plain keras API, while this provides more flexibility it also requires a much deeper understandng of how reinforcement learning works. The implementaiton using the Keras API was essential to develop a necessary knowledge for the project and to progress to the next stage.

While an implementaiton using Keras-rl would be simpler and even possibly ease the itteration process, this implementation provides less flexibility and given the target of the project and desire to develop a deeper understanding of reinforcement learning the implementation using the Keras API was choosen to implemnt the next phases.

Results

The cartpole served as an innitial testing environment for multiple variables and strategies.

The first attempt uses Boltzmann distribution as an exploration policy in this experiment an itteration on the learning rate was performed, along with the number of steps to achieve the target.

Figure 5.1: Reward output for the cartpole experiment - Boltzmann

As can be seen from the above graphs, the learning rate of 0.01 shows much better results when compared to 0.1, although when the model was tested after 5000 steps the results were as follows:

	20 episodes test run	
	Learning Rate: 0.01 Steps 5000	Learning Rate: 0.01 Steps: 10000
Episode 1	126.00	500.00
Episode 2	121.00	500.00
Episode 3	129.00	500.00
Episode 4	124.00	500.00
Episode 5	124.00	500.00
Episode 6	123.00	500.00
Episode 7	122.00	500.00
Episode 8	123.00	500.00
Episode 9	124.00	500.00
Episode 10	123.00	500.00
Episode 11	125.00	500.00
Episode 12	116.00	500.00
Episode 13	125.00	500.00
Episode 14	126.00	500.00
Episode 15	125.00	500.00
Episode 16	127.00	500.00
Episode 17	118.00	500.00
Episode 18	125.00	500.00
Episode 19	122.00	500.00
Episode 20	119.00	500.00
	Average: 123.35	**Average: 500.00**

As we can observe from the table, the training length can have a significant impact on the results, in the case of the cartpole environment it helps to break harmfull correlations, stoping the cart from moving of the boundaries.

The second attempt uses a more common exploration policy, epsilon greedy, in this experiment the epsilon, learning rate and metric used were also varied.

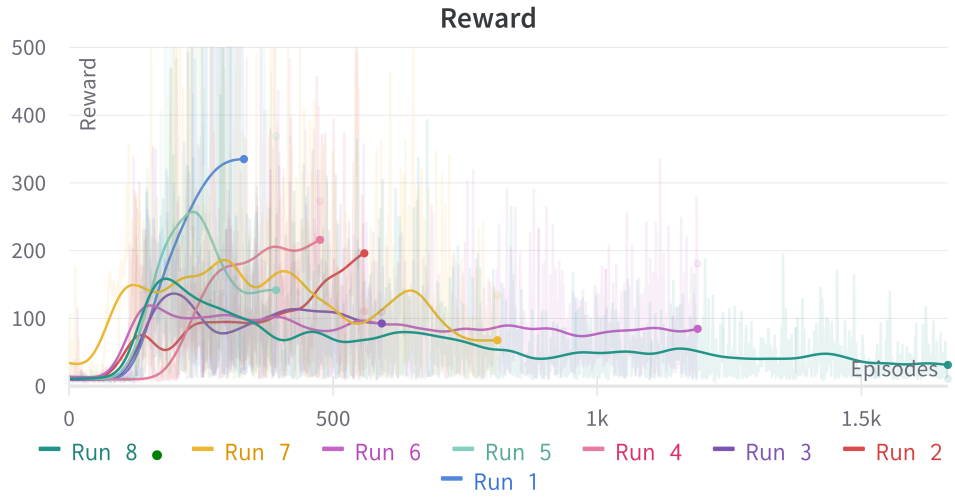


Figure 5.2: Reward output for the cartpole experiment - epsilon greedy

Hyperparameters	Run 1	Run 2	Run 3	Run 4	Run 5	Run 6	Run 7	Run 8
epsilon	0.1	0.1	0.1	0.1	0.1	0.1	0.2	0.3
learning rate	0.01	0.1	0.03	0.001	0.01	0.03	0.01	0.01
metric	mae	mae	mae	mae	accuracy	mae	mae	mae
number of steps	50000	50000	50000	50000	50000	100000	100000	100000

	Run 1	Run 2	Run 3	Run 4	Run 5	Run 6	Run 7	Run 8
Episode 1	500.00	31.00	47.00	390.00	500.00	88.00	500.00	89.00
Episode 2	500.00	28.00	49.00	338.00	500.00	87.00	500.00	95.00
Episode 3	500.00	85.00	33.00	500.00	500.00	84.00	500.00	90.00
Episode 4	500.00	85.00	26.00	166.00	500.00	90.00	500.00	92.00
Episode 5	500.00	28.00	51.00	210.00	500.00	91.00	500.00	88.00
Episode 6	500.00	28.00	57.00	307.00	500.00	88.00	500.00	93.00
Episode 7	500.00	34.00	41.00	335.00	500.00	86.00	500.00	95.00
Episode 8	500.00	27.00	22.00	343.00	500.00	91.00	500.00	92.00
Episode 9	500.00	85.00	80.00	307.00	500.00	86.00	500.00	87.00
Episode 10	500.00	33.00	21.00	500.00	500.00	92.00	500.00	92.00
Episode 11	500.00	28.00	26.00	139.00	500.00	29.00	500.00	90.00
Episode 12	500.00	83.00	90.00	437.00	500.00	87.00	500.00	87.00
Episode 13	500.00	30.00	75.00	341.00	500.00	90.00	500.00	91.00
Episode 14	500.00	33.00	56.00	500.00	500.00	88.00	500.00	90.00
Episode 15	500.00	88.00	41.00	493.00	500.00	87.00	500.00	93.00
Episode 16	500.00	31.00	88.00	500.00	500.00	86.00	500.00	91.00
Episode 17	500.00	29.00	39.00	500.00	500.00	81.00	500.00	93.00
Episode 18	500.00	35.00	33.00	500.00	500.00	87.00	500.00	89.00
Episode 19	500.00	83.00	67.00	340.00	500.00	94.00	500.00	93.00
Episode 20	500.00	32.00	77.00	242.00	500.00	87.00	500.00	92.00
Average	500.00	46.80	50.95	369.40	500.00	84.95	500.00	91.10

Table 5.1: test

When comparing the two approaches, it is clear that the more common epsilon greedy approach was more successfull in solving the cartpole environment, achieving the maximum of 500 points in 50000 steps.

As can be observed by the table containing the average reward for 20 test episodes, we can observe that both run 1 and run 5 were successfull with 50000 steps, followed by run 4 with close scores. Both run 1 and 5 have 0.01 as the learning rate and only vary the metric used, any learning rate above 0.01 tested yelded low scores, when testing varying epsilons it was possible to solve the environment with double the steps, the results also demonstrate that setting random exploration to values higher than 20% couldn't be solved under the 10000 steps.

The conclusion drawn show that the most suitable parameters are:

- **epsilon** = 0.1
- **learning rate** = 0.01

- **metric** = mae
- **number of steps** = 50000

5.2 2D Environment Outcomes

When first implementing the 2D environemnt using the keras-rl library, it was found that the library doesn't support the use of Multidiscrete action spaces, an attempt to implement this environment using tensorflow Agents yelded the same results:

"ValueError: Only scalar actions are supported now"

Given this, it was necessary to implement a custom learning implementation using the Keras API.

The 2D environment was a big challenge to develop, this is due to the big jump in complexity in comparison with a simple, well known and documented environment such as the cartpole. The 2D environment required a custom 2D environment and the implementation of this with the physics engine. When this obstacle was overcome, the second major challenge was to implement the learning algorithm and be able to control the 8 joints simultaniously.

Once the learning algorithm was fully implemented, the reward system and hyperparameters needed to be tested and tuned, this shows the complexity of reinforcement learning. While many itterations over the reward system and hyperparameters were made, given the limited time and resources a full walking motion could not have been achieved. Although, the results obtained with experientation were helpfull in understading the impact of the changes in the reward system.

Results

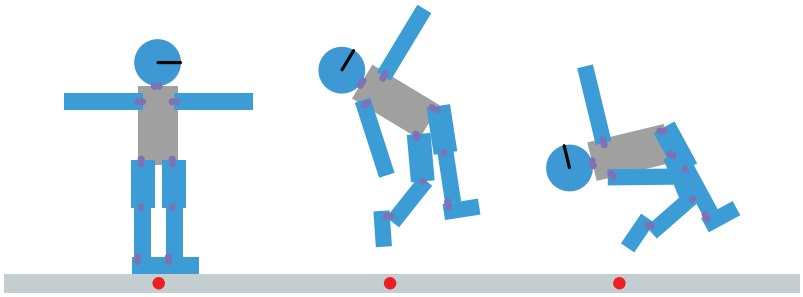


Figure 5.3: Simulation of 2D environment after 199 episodes

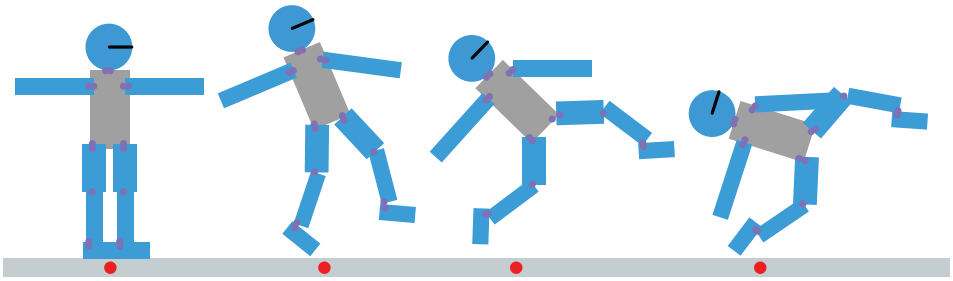


Figure 5.4: Simulation of 2D environment after 10651 episodes

Hyperparameters	
gamma	0.99
learning rate	0.01
epsilon maximum	0.1
epsilon minimum	0.01
batch size	64
units per hidden layer	128
loss function	mean absolute error

After 10000 episodes we start to observe how the agent starts to learn to move forward as it yelds the most rewards as opposed to the example of 199 episodes where the agent would jump and fall almost in the starting position. From performing a parameter importance analysis on a larger number of runs using the wandb logger, the perceived notions are confirmed as can be seen bellow:

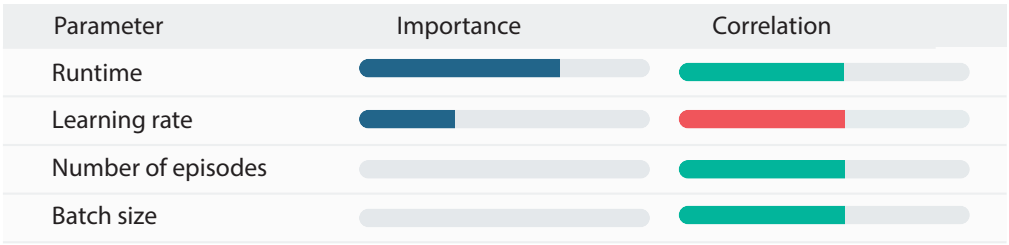


Figure 5.5: Parameter importance analysis of the 2D environment

5.3 3D Environment Outcomes

5.4 Reward Function

Chapter 6

Future Research

6.1 Empowerment

6.2 Reward Function Development

6.3 Policy Gradients

6.4 Mujoco Implementation

6.5 Real Robot Training

Chapter 7

Project Evaluation

Chapter 8

Conclusion

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