



Controlling Self-Driving Race Cars with Deep Neural Networks

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Abstract

State-of-the-art self-driving cars rely on handcrafted algorithms to control the car's movement. As those systems rely on complete understanding of the environment, tactical decisions such as optimizing its speed are not considered as factor in their driving profile. In this thesis, a realistic racing simulation will be paired with state-of-the-art deep learning techniques to investigate how to maximize a self-driving car's operational capabilities. The racing simulation was given as a game implemented with the Unity game engine, to which this thesis adds the capabilities to be played and learned using artificial agents. After discussing the implementation of environment and agent, first experiments are conducted concerning the best reward-function, the effect of supervised pre-training and required inputs to the agent.

Preface

This document was written as the author's bachelor thesis at the department of neuroinformatics at the University of Osnabrück during summer 2017 and is an original and independent work by the author Christoph Stenkamp.

Christoph Stenkamp
Osnabrück, 5th September, 2017

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Thanks to my parents, Marie, my supervisors, and my friends...

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List of Abbreviations

The abbreviations used throughout the work are compiled in the following list below. Note that the abbreviations denote the singular form of the abbreviated words. Whenever the plural forms is needed, an s is added. Thus, for example, whereas ANN abbreviates *artificial neural network*, the abbreviation of *artificial neural networks* is written ANNs.

ANN	Artificial Neural Network
API	Application Programming Interface
CNN	Convolutional (artificial) Neural Network
CPU	Central Processing Unit
DDPG	Deep Deterministic Policy Gradient - Network
DQN	Deep-Q-Network
FPS	Frames Per Second
GUI	Graphical User Interface
MDP	Markov Decision Process
POMDP	Partially Observed Markov Decision Process

List of Symbols

For my friends, family, and especially Marie.

Chapter 1

Introduction

"sollte etwa 10% der Gesamtarbeit ausmachen"

1.1 Motivation

Self-driving cars are becoming more and more a center of public attention.

Google's self-driving car, Tesla autopilot, die vision von Ubers autonomous taxis,
...

1.1.1 Problem Domain

1.1.2 Goal of this thesis

As put forward by *Lex Fridman* in his MIT lecture "*Deep Learning for Self-Driving Cars*"¹ the tasks for self-driving cars can be sub-divided into the following categories:

- **Localization and Mapping**
- **Scene Understanding**
- **Movement Planning**
- **Driver State**

[rrt* macht halt sowas von 3., end-to-end macht die kiste insgesamt nen bisschen anders]

- von wegen dass hier nur der task von einem auto alleine auf einem track -
convert game into RL problem, and compare performances.

1.2 Research Questions

-pretraining -how to reward braking if needed -others, like how to optimize speed
of communication und wie sieht gutes software development aus?

1.3 noclue

<https://arxiv.org/pdf/1704.03952.pdf>

Semi-autonomous vehicle components: Radar, Visible-light-camera, LIDAR, infrared-camera, stereo vision, GPS/IMU, CAN, Audio

¹MIT 6.S094, course website: <http://selfdrivingcars.mit.edu/>

Localization and Mapping: eg. *file : ///C : /Users/Marie/Downloads/VISAPP2015_145.pdf*
Scene Understanding/Object Detection: Scene Segmentation Network (SegNet) Move-
ment Planning: Previously by stuff like RRT* (optimization-based control), however
reinforcement learning!

End-to-End: NVIDIA Paper

dass Reinforcement Learning ja eigentlich nicht so der beste approach ist

Normally when dealing with self-driving cars, there are countless additional is-
sues, each making up a whole new challenge on their own, like wheather conditions
(snow, rain, fog), pedestrians, other cars, reflections, merging into ongoing traffic, ...
we make it easier here.

Or, according to the Torcs-paper: The racing problem could be split into a num-
ber of different components, including robust control of the vehicle, dynamic and
static trajectory planning, car setup, inference and vision, tactical decisions (such as
overtaking) and fi- nally overall racing strategy. With only a single car on the track,
the overall problem can be formalised as a partially observable Markov decision
processes.

→ Because we only consider the case of a single car on the track it definitely is a
POMDP! seeee next chapter yay

Chapter 2

Reinforcement Learning

As the task at hand was not only to provide a reinforcement learning agent, but also to convert a game itself into something the agent can successfully play, In this chapter I will go into detail about reinforcement learning in general, giving insights on the specific approach chosen. The descriptions will be kept as general as possible at first, with detailed explanations following in the sections about specific algorithms.

2.1 Reinforcement Learning Problems

Machine Learning can mainly be subdivided into three main categories: Supervised Learning, Unsupervised Learning, and Semi-supervised learning. The first deals with direct classification or regression using labelled data which consists of pairs of datapoints with their corresponding category or value. In unsupervised learning, no such label exists, and the data must be clustered into meaningful parts without any knowledge, for example by grouping objects by similarity in their properties. In this thesis, a certain kind of semi-supervised learning will mainly be considered: *Reinforcement learning (RL)*. In RL, instead of labels for the data, there is a *weak teacher*, which provides feedback on actions performed by the learner.

Markov Decision Processes

RL can be understood by means of a decision maker (*agent*) performing in an *environment*. The agent makes observations in the environment (its input), takes actions (output) and receives rewards. In contrast to the classical ML approaches, in RL the agent is also responsible for exploration, as he has to acquire his knowledge actively. Thus, a reinforcement learning problem is given if the only way to collect information about the *underlying model* (the environment) is by interacting with it. As the environment does not explicitly provide actions the agent has to perform, its goal is to figure out the actions maximizing its cumulative reward until a training episode ends.

In the classical RL approach, the environment is divided into discrete time steps. If that is the case, the environment corresponds to a *Markov Decision Process (MDP)*. Formally, a MDP is a 5-tuple $\langle S, A, P, R, \gamma \rangle$, consisting of the following:

S – set of states $s \in S$

A – set of actions $a \in A$

$P(s'|s, a)$ – transition probability function from state s to state s' under action $a : S \times A \rightarrow S$

$R(r|s, a)$ – reward probability function for action a performed in state $s : S \times A \times S \rightarrow \mathbb{R}$

γ – discount factor for future rewards $0 \leq \gamma \leq 1$

In general, both the state transition function and the reward function may be indeterministic, meaning that neither reward nor the following state are in complete control of the decision maker. Because of that, only expected values are examinable, depending on the random distribution of states. Given both s and s' however, the reward is assumed to be deterministic. I will refer to the actual result of a state transition at discrete point in time t as s_{t+1} and to the result of the reward function as r_t . If no point in time is explicitly specified, it is assumed that all variables use the same t .

While an *offline learner* receives the problem definition as input in the form of a complete MDP, where the only task left is to classify actions yielding high rewards from actions giving suboptimal results, the task for an *online reinforcement learning* agent is a lot harder, as it has to learn the MDP itself via trial and error. In the process of reinforcement learning, the agent will encounter states s of the environment, performing actions a . The future state s_{t+1} of the environment may be indeterministic, but depends on the history of previous states s_0, \dots, s_t as well as the action of the agent a_t . It is assumed that the *Markov property* holds, which means that a state s_{t+1} depends only on the current state s_t and current action a_t : $p(s_{t+1}|s_t, a_t) = p(s_{t+1}|s_0, a_0, \dots, s_t, a_t)$

Throughout interacting with the environment, the agent receives rewards r , depending on his action a as well as the state of the environment s . In many RL problems, the full state of the environment is not known to the agent, and it only perceives an observation depending on the environment: $o_t := o(s_t)$ ¹. This is referred to as *partial observability*, and the corresponding decision process is a *partially observable MDP*. Additionally, the agent knows when a final state of the environment is reached, terminating the current training episode. For the agent, an episode therefore consists of observations, actions and rewards ($\mathcal{S} \times \mathcal{A} \times \mathbb{R}$) until at time t_t some terminal state s_{t_t} is reached:

$$\text{Episode} := ((s_0, a_0, r_0), (s_1, a_1, r_1), (s_2, a_2, r_2), \dots, (s_{t_t}, a_{t_t}, r_{t_t}))$$

Value of a state

In the process of reinforcement learning, the agent tries to perform as well as possible in the previously unknown environment. For that, it uses an action-policy π , depending on some parameters θ . The policy maps states to actions, which in the case of a *deterministic* policy leads to $\pi_\theta(s) = a$. Though a stochastic policy is possible, it will not be considered for now². As the agent does not have supervised data on which actions are the ground truth, it must learn some kind of measure for the value of being in a certain state or performing a certain action. The commonly used measure for the value of a state when using policy π can be calculated by the immediate reward this state gives, summed with the expected value of the discounted future reward the agent will achieve by continuing to follow its policy π from this

¹From now on, when the state of the environment is meant, it will be explicitly referred to as s_e , while s is reserved for the agent's observation of the environment $o(s_e)$

²It is obvious, that the result of both the reward function and the state transition function depend on π . To be explicit about that, I will refer to a reward dependent on π as r^π and a state transition dependent on π as s^π . If state or reward depends on an explicit action instead, I refer to it as r^a and s^a . Whenever not necessary for clarity, I will also drop π 's dependence on θ .

state on:

$$V^\pi(s_t) := \mathbb{E}_{s \sim \rho^\pi} \left[\sum_{t'=t}^{t_t} (\gamma^{t'-t} * r_{t'}^\pi) \right] \quad (2.1)$$

As the future rewards depend on future states, it can only be talked about the expected value depending on the actual state distribution. This distribution depends on the agents policy, but may still be indeterministic³. The discounted state visitation distribution, which assigns each state a probability of visiting it according to policy π , is denoted ρ^π .

The actual, underlying value of a state $V^*(s)$ could accordingly be defined as the value of the state when using the best possible policy, which corresponds to the maximally achievable reward starting in state s_t :

$$V^*(s_t) := \max_{\pi} V^\pi(s_t)$$

While *passive learning* simply tries to learn the value-function V^* without the need of action selection, an *active reinforcement learner* tries to estimate a good policy that can actually reach those high-value states. If the value of every state is known, then the optimal policy can be defined as the one achieving maximal value for every state of the MDP: $\pi^* := \operatorname{argmax}_{\pi} V^\pi(s) \forall s \in \mathcal{S}$. Knowing what an optimal policy does, the definition of the value $V^\pi(s)$ 2.1 can be written recursively as

$$\begin{aligned} V^\pi(s_t) &= \mathbb{E}_{s \sim \rho^\pi} \left[\sum_{t'=t}^{t_t} (\gamma^{t'-t} * r_{t'}^\pi) \right] \\ &= r_t^\pi + \gamma * \mathbb{E}_{s \sim \rho^\pi} \left[\sum_{t'=t+1}^{t_t} (\gamma^{t'-t} * r_{t'}^\pi) \right] \\ &= r_t^\pi + \gamma * V^\pi(s_{t+1}) \end{aligned} \quad (2.2)$$

This relation is known as the *Bellman Equation*, which allowed for the birth of dynamic programming⁴.

Value of an action

While the definition of a state-value is useful, by itself it does not help an agent to perform optimally, as neither the successor function $P(s'|s, a)$, nor the reward function $R(r|s, a)$ is known to the agent. While so-called *model-based* reinforcement learning (also referred to as *Certainty Equivalence*) tries to learn both of those explicitly to reconstruct the entire MDP, *model-free* agents use a different measure of quality: the *Q-value*. It represents the expected value of performing action a_t in a state s_t , afterwards following the policy π :

$$Q^\pi(s_t, a_t) := \mathbb{E}_{s \sim \rho^\pi} [r_t^{a_t} + \gamma * V^\pi(s_{t+1}^{a_t})] \quad (2.3)$$

³That is one of the reasons to discount future rewards: The agent cannot be fully sure if it actually reaches the states it strives for. Also, using the discounted reward hopefully helps making the agent perform good actions as quickly as possible.

⁴Dynamic programming is another solution strategy for MDPs. In contrast to RL however, it requires the complete MDP as input to find an optimal policy, which cannot be given in many relevant situations.

With the Q-value Q^* of the optimal policy accordingly

$$\begin{aligned} Q^*(s_t, a_t) &= \mathbb{E}_{s \sim \rho^\pi} [r_t^{a_t} + \gamma * V^*(s_{t+1}^{a_t})] \\ &= \max_{\pi} Q^\pi(s_t, a_t) \end{aligned}$$

For the Q-value, the Bellman equation holds as well: If the correct Q-value under policy π , $Q^\pi(s_{t+1}, a_{t+1})$, was known for all possible actions at time t , then the optimal action is the one maximizing the sum of immediate reward and corresponding Q-value. This is because of the definition of Bellman's *Principle of Optimality*, which states that “An optimal policy has the property that whatever the initial state and initial decision are, the remaining decisions must constitute an optimal policy with regard to the state resulting from the first decision” (quote [3]). Thanks to the principle of optimality, the value of our decision problem at time t can be re-written in terms of the immediate reward at t plus the value of the remaining decision problem at $t + 1$, resulting from the initial choices:

$$Q^\pi(s_t, a_t) = \mathbb{E}_{s \sim \rho^\pi} [r_t^{a_t} + \gamma * Q^\pi(s_{t+1}, \pi(s_{t+1}))] \quad (2.4)$$

As the value of a state is defined as the maximally achievable reward from that state, the relation between Q and V can be expressed as

$$V(s_t) = \max_{a_t} Q(s_t, a_t) \quad (2.5)$$

Quality of a policy

Any agent's goal is to find a policy that can follow the trajectory of the state distribution with the highest expected reward. If the actual Q-value for each action of each state is known, then the optimal policy can be defined as the one taking the optimal action in each state:

$$\pi^* = \operatorname{argmax}_a Q^*(s, a) \forall s, a \in \mathcal{S} \times \mathcal{A} \quad (2.6)$$

This policy guarantees maximum future reward at every state. Note however, that finding $\operatorname{argmax}_a Q(s, a)$ is only easily possible if \mathcal{A} is discrete and finite (more on that later).

As for the actual performance of a policy, a useful measure is the *performance objective* $J(\pi)$, which stands for the cumulative discounted reward from the start state using the respective policy. To measure the performance objective, it is necessary to integrate over the whole state space \mathcal{S} with each state s weighted by its distribution due to π . As only non-stochastic policies are considered here, integration over the action space \mathcal{A} is not necessary. The integral can, as shown by [15], be expressed by the expectation of the value of states following the distribution $s \sim \rho^\pi$:

$$\begin{aligned} J(\pi) &= \int_{\mathcal{S}} \rho^\pi(s) V^\pi(s) ds \\ &= \mathbb{E}_{s \sim \rho^\pi} [V^\pi(s)] \\ &= \mathbb{E}_{s \sim \rho^\pi} [Q^\pi(s, \pi(s))] \end{aligned} \quad (2.7)$$

We assume for now that once an agent knows Q^* , it can simply follow the policy that always takes the action yielding the highest value for every state (the *greedy policy*)⁵.

⁵in fact, the agent cannot act only according to the greedy policy, as it will need to *explore* the environment first. The problem of exploration will be considered later in this thesis.

Thus, the goal of a model-free RL agent is to get a maximally precise estimate of Q^* . To do that, it does not need to explicitly learn the reward- and transition function, but instead can model the Q-function directly. In RL settings with a highly limited amount of discrete states and actions, the respective Q-function estimate can be specified as a lookup table, whereas for areas of interest, the function is estimated using a nonlinear function approximator. The agent's approximation of Q^π will be denoted \hat{Q}^π .

Throughout exploration of the environment, the agent collects more information about it, continually updating its estimate \hat{Q}^π . For that, it uses samples from its episodes of interacting with the environment.

2.2 Temporal difference learning

Throughout the process of reinforcement learning, the agent continually improves its estimates \hat{Q}^π of Q^π . The loss of its current estimate could be seen as the squared difference $(\hat{Q}^\pi - Q^\pi)^2$, however, as the agent has no knowledge of Q^π , it needs some way of approximating it. For that, a Q-learning agent performs *iterative approximation*, using the information about the environment, to continually update its estimates of Q^π . Using the recursive definition of a Q-value given in the Bellman equation 2.4 allows for a technique called *temporal difference learning*[16]: At time $t + 1$, the agent can compare its estimate of the Q-function of the last step, $\hat{Q}^\pi(s_t, a_t)$, with a new estimate using the new information it gained from the environment: r_{t+1} and s_{t+1} . Because of the newly gained information from the underlying MDP, the new estimate will be closer to the actual function Q^π than the original value:

$$\hat{Q}^\pi(s_t, a_t) = r_t + \mathbb{E}_{s \sim \rho^\pi} [\gamma * \max_{a_{t+1}} \hat{Q}^\pi(s_{t+1}, a_{t+1})] \quad (2.8)$$

$$\approx r_t + \gamma * r_{t+1} + \mathbb{E}_{s \sim \rho^\pi} [\gamma^2 * \max_{a_{t+2}} \hat{Q}^\pi(s_{t+2}, a_{t+2})] \quad (2.9)$$

Keeping in mind that \hat{Q}^π is only an estimator of the Q^π -values of the underlying model, it becomes clear that equation 2.9 is closer to the actual Q^π , as it incorporates more information stemming from the model itself.

In temporal difference learning, the mean-squared error of the *temporal difference* from this Bellman equation, $r_t + \gamma * Q(s_{t+1}, a_{t+1}) - Q(s_t, a_t)$, gets minimized via iterative approximation. Even though $r_t + \gamma * \hat{Q}^\pi(s_{t+1}, a_{t+1})$ also uses an estimate, it contains more information from the environment, and is thus a *more informed guess* than $\hat{Q}^\pi(s_t, a_t)$. That makes it reasonable to substitute the unknown $Q^\pi(s_{t+1}, a_{t+1})$ by $\hat{Q}^\pi(s_{t+1}, a_{t+1})$.

It is noteworthy, that each update of the Q-function using the temporal difference will affect not only the last prediction, but all previous predictions.

SARSA

The new knowledge about the environment can be incorporated in two different ways. For the first method, the agent samples a full tuple of $\langle s_t, a_t, r_t, s_{t+1}, a_{t+1} \rangle$ from its interaction with the environment, to then calculate the temporal difference error in non-terminal states as $TD := (r_t + \gamma * \hat{Q}^\pi(s_{t+1}, a_{t+1})) - \hat{Q}^\pi(s_t, a_t)$. This algorithm of calculating the temporal difference error is known as SARSA, and it is an example of *on-policy* temporal difference learning. In on-policy learning, the

agent uses its own policy in every estimate of the Q-value. If the policy of the agent is not stochastic, this method can however lead to it getting stuck in local optima.

Q-learning

The *Q-learning* algorithm [19] stands in contrast to SARSA. Q-learning does not need to sample the action a_{t+1} , as it calculates the Q-update at iteration i using the best possible action in state s_{t+1} ⁶.

As the previous definition of Q-values was only correct in non-terminal states, a case differentiation must be introduced for terminal- and non-terminal states. In the following, y_t will stand for the updated estimate of the Q-value at t , sampling the necessary states, rewards and actions from interaction with the environment, almost resulting in the formula found in [10]. To express its dependence on the policy π , it will be superscripted:

$$y_t^\pi = \begin{cases} r_t & \text{if } t = t_t \\ r_t + \gamma * \max_{a'} \hat{Q}^\pi(s_{t+1}, a') & \text{otherwise} \end{cases} \quad (2.10)$$

The temporal difference error for time t is accordingly defined as

$$TD_t := y_t^\pi - \hat{Q}^\pi(s_t, a_t) \quad (2.11)$$

A Q-learning agent must thus observe a snapshot of the environment, consisting of the following input: $\langle s_t, a_t, r_t, s_{t+1}, t + 1 == t_t \rangle$ (where the last element is the information if state s_{t+1} was a terminal state). That information is then used to calculate the temporal difference error.

In very limited settings, using the above error straight away allows for the update-rule in simple Q-learners: Consider an agent, specifying its approximation of the Q-function (his *model*) with a lookup-table, initialized to all zeros. It is proven by [20] that for finite-state Markovian problems with nonnegative rewards the update-rule for the Q-table (with $0 \leq \alpha \leq 1$ as the learning rate)

$$\hat{Q}_{i+1}^\pi(s_t, a_t) \leftarrow \alpha * (r_t^{a_t} + \gamma * \hat{Q}_i^\pi(s_{t+1}^{a_t}, a_{t+1})) + (1 - \alpha) * \hat{Q}_i^\pi(s_t, a_t) \quad (2.12)$$

converges to the optimal Q^* -function, making the greedy policy π^* optimal⁷. Note, that the same update rule as for the Q-function could be performed for the V-function.

In contrast to SARSA, Q-learning is an *off-policy* algorithm, meaning that the policy it uses in its evaluation of the Q-value is not necessarily the one it actually uses: When calculating the temporal difference error, the agent considers Q-values $\hat{Q}^{\pi_{greedy}}(s, a)$, based on $\pi_{greedy}(s) = \operatorname{argmax}_{a'} \hat{Q}(s, a')$, as better approximation of the real action-value function $Q^\pi(s, a)$. Therefore, it learns about π_{greedy} , which is to always take the action promising maximum value. Because following the deterministic π_{greedy} does not allow for *exploration*, this is not the policy the agent actually pursues.

When using off-policy algorithms with π as the policy we learn about and β as the policy we act upon, our performance objective $J(\pi)$ (equation 2.7) must change,

⁶A slight deviation from this is *double-Q-learning*, an architecture I will go into detail about later on.

⁷Of course the agent will need some kind of exploration technique first, more on that later

as it must incorporate that while the value of a state is calculated using our deterministic π , the distribution of states follows from stochastic policy β :

$$\begin{aligned} J_\beta(\pi) &= \int_{\mathcal{S}} \rho^\beta(s) V^\pi(s) ds \\ &= \mathbb{E}_{s \sim \rho^\beta} [Q^\pi(s, \pi(s))] \end{aligned} \quad (2.13)$$

The process of reinforcement learning consists of two steps: *policy evaluation*, where the agent evaluates its current policy according to the knowledge gained from the environment, and based on that *policy improvement*. In the standard Q-learning considered here, those steps are interleaved, leading to a form of *generalized policy iteration*: the Q-learner learns its action value-function and its policy simultaneously. After updating its Q-function estimate via the temporal difference error, the agent updates its policy to be a *soft* version of the greedy policy $\pi_{i+1}(s) := \arg\max_{a'} Q^{\pi_i}(s, a') \forall s \in \mathcal{S}$, while keeping a mechanism allowing for exploration. Learning with this approach is however generally limited: $\arg\max_{a'} Q(\cdot, a')$ can only easily be found in settings where the action space \mathcal{A} is finite and discrete, as it requires a global maximization over all possible actions. In a later section, I will go into detail about another architecture which does circumvents those problems by splitting up policy evaluation and policy improvement explicitly.

As there are also relevant situations in which discrete actions $\mathcal{A} \subseteq \mathbb{N}^n$ are sufficient, I will stick to those situations for now. Also in these circumstances, a Q-learner using tables as Q-function-approximator reaches its limits really fast, as the state space \mathcal{S} may also be continuous or simply too big for a table to be useful. If that is the case, an update rule like in equation 2.12 becomes irrelevant quickly. Instead, a better idea is to use the definition of the temporal difference error to define a loss function, which is to be minimized throughout the process of RL. A commonly used loss-function is the *L2-Loss*, which allows for gradient descent, updating the parameters of the Q-function into the direction of the newly acquired knowledge. In this case, it may also be useful to calculate the loss of a batch of temporal differences simultaneously, which will be elaborated later on in more detail. The L2-Loss for batch *batch* with model-parameters θ_i , making up the policy π_{θ_i} is thus defined as the following:

$$L_{batch}(\theta_i) := \mathbb{E}_{s,a,r \sim batch} \left[(y_{batch}^{\pi_{\theta_i}} - \hat{Q}_{batch}^{\pi_{\theta_i}}(s, a))^2 \right] \quad (2.14)$$

2.3 Q-Learning with Neural Networks

To understand this section, basic knowledge on how *Artificial Neural Networks* (ANNs) work and what they do is presupposed. Specifically, knowledge of *Convolutional Neural Networks* (CNNs)[22], mainly used in image processing, is required. As mentioned before, it is (in theory) not only possible to use a Q-table to estimate the Q^π -function, but any kind of function approximator. Thanks to the universality theorem, it is known that ANNs are an example of such⁸. The defining feature of ANNs

⁸For a proof of the universality theorem, I refer to chapter 4 of Michael A. Nielsen's book "Neural Networks and Deep Learning", Determination Press, 2015. The referred chapter is available at <http://neuralnetworksanddeeplearning.com/chap4.html>

in comparison to other Machine Learning techniques is their ability to store complex, abstract representations of their input when using a *deep* enough architecture.

2.3.1 Deep Q-learning

The reason to use neural function approximators instead of a simple Q-table approach for reinforcement learning problems is easy to see: While for a Q-table the states and actions of the Markov Decision Process must be discrete and very limited, this is not the case when using higher-level representations. If the agent's observation of a state of the game is high-dimensional (like for example an image), the chance for an agent to observe the exact same observation twice is extremely slight. Instead, an Artificial Neural Network can learn a higher-level representation of the state, grouping conceptually similar states, and thus generalize to new, previously unseen states. It is no surprise that the success of *Deep-Q-Networks* started its journey shortly after the introduction of CNNs, which are able to learn abstract representations of similar images and by now used in countless Computer Vision Applications.

Deep-Q-Network (DQN) refers to a family of off-policy, online, active, model-free Q-learning algorithms for discrete actions using Deep Neural Networks. Using ANNs as function approximators for the agent's model of the environment requires a Loss function depending on the Neural Network parameters, specified by θ . These weights correspond to the parameters of the \hat{Q} -function of the agent. As previously mentioned, this kind of Q-learning defines its policy straight-forward, depending on the $\arg\max_a$ of the Q-function. I will therefore replace the dependence of $\hat{Q}^\pi(s, a)$ on π by a dependence on its parameters: $\hat{Q}(s, a; \theta_i)$. The update rule in Deep Networks depends on the gradient with respect to its loss, $\nabla_{\theta_i} L(\theta_i)$. As the DQN-architecture only considers discrete actions, there is one change that can be made in the definition of the Q-function: instead of giving both the state s and the action a as input to the network, in DQNs only the state is input to the network, with the network returning a separate Q-value for each action $a \in \mathcal{A}$. This speeds up the inference, as one forward step is enough to calculate the Q-value of all actions in a certain state.

While there are attempts to use Artificial Neural Networks for Q-learning as early as 1994[12], some key components of modern Deep-Q-Networks were missing, leading to satisfactory performance only in very limited settings. In standard online RL tasks, the update step minimizing the loss specified in 2.14 is performed not for a batch, but for each time t right after the observation occurred to the agent. In those situations, the current parameters of the policy determine the next sample the parameters are trained on. It is easy to see, that those consecutive steps of MPDs tend to be correlated: It is very likely, that the maximizing action of time t is similar to the one at $t + 1$. Consecutive steps of an MDP are not representative of the whole underlying model's distribution. ANNs require independent and identically distributed samples, which is not given if the samples are generated sequentially. As shown by [7], the update using gradient descent is prone to feedback loops and thus oscillation in its result, thus never converging to an optimal Q^π -function.

It was not until *Deepmind's* famous papers in 2013[9] and 2015[10], that those issues were successfully addressed. One important step when using ANNs instead of Q-tables is to perform stochastic gradient descent using minibatches. In every gradient descent step of the Neural Network, neither only the last temporal difference error TD_t is considered (leading to oscillations), nor the entire sequence TD_0, \dots, TD_t

(because batch updates are not time-efficient in ANNs). Instead, as usual when dealing with ANNs, minibatches are sampled from the set of all observations. When performing the gradient descent step, the weights for the target y_t are fixed, making the minimization of the temporal difference error a well-defined optimization problem (with clear-cut target values as in supervised learning) during the learning step.

The two important innovations introduced in the DQN-architecture were the use of a *target network* as well as the technique of *experience replay*, which in combination successfully solved the problem of oscillating and non-converging action-value functions, even though still no formal mathematical proof of convergence is given.

Experience Replay

As mentioned above, learning only from the most recent experiences biases the policy towards those situations, limiting convergence of the Q-function. To address this issue, the DQN uses an experience replay memory: Every percept of the environment (the $\langle s_t, a_t, r_t, s_{t+1}, t+1 == t_t \rangle$ - tuple) is added to a limited-size memory of the agent. When then performing the learning step, the agent samples random minibatches from this memory to perform learning on a maximally uncorrelated sample of experiences. In the original definition of DQN, those minibatches are drawn uniformly at random, while as of today, better techniques for sampling those minibatches are available[13], increasing the performance of the resulting algorithm significantly.

Target Networks

During the training procedure, the DQN-algorithm uses a separate network to generate the target-Q-values which are used to compute the loss (eq. 2.14), necessary for the learning step of every iteration. Intuitively speaking, this is necessary because the Q-values of the *online network* shift in such a way, that a feedback loop can arise between the target- and estimated Q-values, shifting the Q-value more and more into one direction. To lessen the risk of such feedback loops, the DQN algorithm introduced the use of a second network for calculating the loss: the *target network*. This is only periodically updated with the weights of the online network used for the policy, which reduces the risk of correlations in the action-value Q_t and the corresponding target-value y_t (see equation 2.10).

The use of these two techniques leads to the Q-learning update rule, using the loss as put forward in [10]:

$$L_i(\theta_i) = \mathbb{E}_{\langle s_t, a_t, r_t, s_{t+1} \rangle \sim U(D)} \left[\left(r + \gamma * \max_{a_{t+1}} \hat{Q}(s_{t+1}, a_{t+1}; \theta_i^-) - \hat{Q}(s_t, a_t; \theta_i) \right)^2 \right] \quad (2.15)$$

Where i stands for the current network update iteration, θ_i for the current weights of the target network (updated every C iterations to be equal to the weights of the online network θ_i), $Q(\cdot, \cdot; \theta)$ for the Q-value dependent on a ANN using the weights θ , $\mathbb{E}[\cdot]$ for the expected value in an indeterministic environment, D for the contents of the replay memory of length $|D|$ containing $\langle s_t, a_t, r_t, s_{t+1} \rangle$ -tuples, and $U(\cdot)$ for a uniform distribution.

As is the case with the experience replay mechanism, the usage of a target network was improved as well – modern algorithms do not perform a hard update of the target network every C steps, but instead perform *soft target network updates*, where every iteration, the weights of the target network are defined as $\theta_i^- := \theta_i * \tau + \theta_i^- * (1 - \tau)$ with $0 < \tau \ll 1$, first introduced in [8]. This improves the stability of the algorithm

even more.

As a pseudocode for the DQN-architecture is already stated in the corresponding paper [10], listing it again here would be superfluous. Instead, I try to compare the pseudocode with the code of my actual implementation using Python and Tensorflow in appendix A.1. In the first two pages of the appendix, the necessary definitions of agent and network structure are introduced, before in page 50 there is the actual comparison between the pseudocode and its correspondences in the actual code, namely the `__init__`, `inference` and `q_learn`-functions of the model-class. Note that the blue lines of the pseudocode correspond to difference from the original DQN in favor of later improvements.

2.3.2 Double-Q-Learning

It is well known that Q-learning tends to ascribe unrealistically high Q-values to some action-state-combinations. The reason for this is, that to estimate the value of a state s_j it includes a maximization step over estimated action values $Q(s_j, a)$, where naturally, overestimated values are preferred over underestimated values. It is not possible that Q-value-estimates are completely precise: estimation errors can occur due to environmental noise, inaccuracies in function approximation (consider a flexible ANN trained on only a small sample so far - the ANN will overfit by covering all samples precisely. This overfitting leads to steep curves, over- or underestimating many values in between) and many other issues. Because Q-learning uses the maximum Q-value of state s_{j+1} in every estimate of the value of state s_j , only those estimates are propagated where the noise of the estimation is in a positive direction. Because of that, state s_{j-1} will have the accumulated upward noise from both state s_j and s_{j+1} , and so forth. This leads to unrealistically high action-values. While this would not constitute a problem if all Q-values would be uniformly overestimated, [5] showed that its very likely that the Q-value $Q(s_j, a)$ for only some actions a is overestimated – which changes the result of the $\arg\max_a$ operation and thus leads to biased policies. They also show that the drop in DQN performance correlates with this overestimation of actions.

The solution suggested by [5] is called *Double-Q-learning*. In its original definition without using Neural Networks as function approximators, a double-Q-learner learns two value functions in parallel, by letting each experience update only one of the two value functions at random. For each update then, one function is used to determine the greedy policy, while the other is used to determine the value of this policy⁹. The authors proved that the lower bound for the overestimation of action-value, $\max_{a'} Q^\pi(s, a') - V^*(s)$, is > 0 for the standard Q-learning update rule, whereas it is 0 in the case of DoubleQ. Additionally they showed that these overestimations are indeed harmful by showing the superiority of a DoubleQ-learner in comparison with a normal Q-learner.

Deep-Double-Q-Learning (DDQN) takes the Double-Q idea to the existing framework of Deep-Q-learning: Overestimations are reduced by decomposing the *max*-operation into *action selection* and *action evaluation*. Instead of introducing a second value function, DDQN re-uses the target-network of the DQN architecture in place

⁹“In DoubleQ, we still use the greedy policy to select actions, however we evaluate how good it is with another set of weights”. The intuition behind that is, that the probability of both value-functions always over-estimating the same actions is basically zero.

of the second value function. Although online network and target network are not fully decoupled, experiments showed that it provides a good candidate for independent action evaluation, without the need of additional functions. The technique of DDQN is thus to still use the online network to choose an action (evaluate the greedy policy according to the online network), but the target network to generate the target Q-value for that action (to estimate its value, instead of the max-operation in DQN). As shown by [5], DDQN improves over DQN both in terms of value accuracy and in terms of the actual quality of the policy.

When using Double-Q-Learning, the target-value of the calculation of the temporal difference error (y_t from equation 2.10 must thus be re-defined as

$$y_t^\pi = \begin{cases} r_t & \text{if } t = t_f \\ r_t + \gamma * Q(s_{t+1}, \operatorname{argmax}_{a'} Q(s_{t+1}, a'; \theta_i^-); \theta_i^-) & \text{otherwise} \end{cases} \quad (2.16)$$

It can be seen in appendix A.1 how small the actual change to normal DQN is: The only difference is the usage of the target network in line 21 (marked in blue).

2.3.3 Dueling Q-Learning

In many situations encountered during Q-learning, the value of all possible actions a_t in a state s_t is almost equal. Consider a simulated car, driving with full speed towards a wall, already so close that breaking or steering can't stop the car from driving into the wall. As all actions will end in the episode will end by the car hitting the wall, all actions will have roughly the same Q-value.

The idea of the *dueling architecture* [18] for DQN is to learn the action-state-value function more efficiently. For that, it splits up the Network into a *value stream* and separate *advantage streams*. As mentioned earlier, though the ANN resembles the $\hat{Q}(s, a)$ -function, the actions are not input to the network, but instead it outputs $|\mathcal{A}|$ Q-values, one for each action. A *Dueling Double Deep-Q-Network (DDDQN)* works by splitting an early layer of its corresponding network in half. One of the resulting streams is the value-stream, which results in one value, intuitively corresponding to the value (\hat{V}_{s_t}) of a state s_t , irrespective of the action that can be taken in this state. The other stream is the advantage stream, which has as output $|\mathcal{A}|$ values, standing for the *Advantage (A)* of taking a certain action in this state – it can be seen as a relative measure of the importance of each action. The relation between Q , V and A is the following:

$$Q(s, a) = V(s) + A(s, a)$$

In the very last layer of the ANN those two streams are combined again, so that a DDDQN also outputs one Q-value for each action. Thanks to this, any DDQN can be transformed into a DDDQN by simply changing the structure of the used ANN. It is important to mention however, that the last layer can't simply calculate $V(s) + A(s, a)$ – If that was done, then the network could simply set the V-stream to a constant, negating any advantage gain in splitting them up in the first place. However, as explained in equation 2.5, it holds that $\operatorname{argmax}_{a'} Q(s, a') = V(s)$ – when using deterministic policies, then the value of the state corresponds to the Q-value of the best action that can be taken in this state. Therefore, it must be the case that the *argmax*-action has an advantage of zero. This can be used to calculate the $Q(s, a)$ using the value-stream and the advantage-stream according to the following equation (where θ corresponds to the shared weights, θ^A to the weights specific to the

advantage-stream and θ^V to those specific to the value-stream):

$$Q(s, a; \theta, \theta^A, \theta^V) = V(s; \theta, \theta^V) + (A(s, a; \theta, \theta^A) - \max_{a'} A(s, a', \theta, \theta^A))$$

Actually, during testing it turned out that normalizing the advantage not with respect to the best action, but with respect to the average of all actions, $\frac{1}{|\mathcal{A}|} \sum_{a'} A(s, a'; \theta, \theta^A)$ lead to better stability. By splitting up into separate advantage- and valuestream and combining the two streams in a fully-connected layer using the formula stated above, the authors achieved far better performance than their predecessor, DDQN, on the same dataset [18].

The reason to split into two streams is obvious: In the learning step of a DQN, the derivative is taken with respect to difference in the expected Q-value of an action and the better estimate of that Q-value. In normal DQNs, the network can thus only update the parameters responsible for one of its outputs. A DDDQN learns more effectively, as it learns a shared value of multiple actions: A temporal difference in one Q-value likely changes the value-stream of the network, which also changes the Q-value of other actions. Thanks to this, learning generalizes better across actions, without any changes to the underlying reinforcement learning algorithm. As shown by the authors [18], the difference is especially drastic in situations where many actions have similar outcomes.

In appendix A.1, I listed an exemplary source code of the implementation of an agent using python and tensorflow. The agent stands alone without an environment, and some crucial parts of it, like an implementation of its memory, are missing. However, all aspects mentioned in the previous sections are found in it, which is the algorithm of the actual Q-learning as described above and in [5], as well as the computation graph of the network using precisely the DDDQN-architecture as described above and in [18]. The last page of it (page 50) consists of a comparison of the Pseudocode of the DDDQN (as found in [10], with the changes from [5] and [8] incorporated in and marked blue), where each line of the pseudocode (to the left) corresponds precisely to the respective line of the actual python-code (to the right).

2.4 Policy Gradient Techniques

Policy Gradient (PG) techniques are in principle a far more straight-forward approach to reinforcement learning than temporal difference-methods like Q-learning. The idea behind PG techniques is really simple: The policy $\pi_\theta(a|s) = \mathbb{P}[a|s; \theta]$ of an agent is explicitly modeled using a differentiable function approximator, like a neural network with weights θ . There is no need to approximate the value-function of states or actions explicitly. The quality of the policy is again measured by its performance as in equation 2.13.

Before continuing to explain PG techniques, it makes sense to define another measure of the quality of an action: The *advantage*. The advantage will be what PG methods optimize for, and it can be defined analogously to the value of a state in equation 2.1, with the difference that this time, as we do not explicitly model the value of following states, we can only calculate it after having measured all of the

respective rewards from the environment:

$$A_t := \sum_{t'=t}^{t_t} (\gamma^{t'-t} * r_{t'}) \quad (2.17)$$

To use the policy gradient, the agent must calculate the advantage of every state it visited so far, to then set this advantage as the gradient of the output of its policy function of the corresponding state, to then train the network using backpropagation with respect to this gradient. If the reward is positive, gradient *ascent* will make the network more likely to produce this action in this state, and if the gradient was negative, it will lead to gradient *descent*, discouraging the network to repeat this action in the given state. Thus, the network will learn to repeat actions giving high rewards and to avoid those with negative rewards.

This may sound unintuitive at first, because there is no specific loss function the ANN can optimize for. However in fact, using the gradient with respect to the advantage corresponds to the loss $\sum_t A_t \log p(a_i|s_i)$ – If A_t is positive, we want to increase the probability of action a_t for state s_i , and decrease it otherwise.

The main problem of purely using this approach is however the huge amount of exploration that is needed – the agent does not have any knowledge about what states are good or bad, but only increases the probability of individual actions that turned out to have a good score. Because of this, it can find good policies only by chance, after millions of iterations. If the agent knew the value of a state, it could optimize its policy in the direction of actions that it knows produce a high-valued state. For that, the policy network must get the gradient information of the action from something estimating this value-function, giving rise to *actor-critic architectures*.

2.4.1 Actor-Critic architectures

The technique introduced in the previous sections is a direct adaption of the Q-learning algorithm [16][19], adapted for higher-level function approximators. Standard Q-learning is a kind of *generalized policy iteration*, where the policy evaluation and policy improvement happen in the same step. The algorithm learns via temporal differences the state-action value $Q^{\pi_{greedy}}(s, a)$ for the states it encountered with its current policy π . It then updates π to a soft version of that greedy policy: $\pi_{i+1}(s) := \text{soft}(\argmax_a Q^{\pi_{greedy}}(s, a) \forall s \in \mathcal{S})$, where the *soft*-function ensures appropriate exploration. Learning the Q-function and the policy simultaneously is however generally limited: $\argmax_a Q(\cdot, a)$ can only easily be found in settings where the action space \mathcal{A} is finite and discrete, as it requires a global maximization over all possible actions. While discretizing the action space is possible, it gives rise to the *curse of dimensionality*, especially when the discretization is fine grained. An iterative optimization process like the *argmax*-operation would thus likely be intractable.

However in a lot of scenarios, the action space is not discrete, but continuous: $A \subseteq \mathbb{R}^n$. In such situations, the alternative is to move the policy into the *direction of the gradient of Q*. For that, it is necessary to model the policy explicitly with another function

approximator. This gives rise to *actor-critic* architectures, where both policy and Q-function are explicitly modeled: The *critic* corresponds again to a Bellman-function-approximator, using temporal differences to estimate the action-value $Q^\pi(s, a)$ ¹⁰. In contrast to the previous approach however, the policy is now explicitly modeled by the *actor*. In the case of a stochastic policy, it would be represented by a parametric probability distribution $\pi_\theta(a|s) = \mathbb{P}[a|s; \theta]$, however here we only consider the case of deterministic policies $a = \pi_\theta(s)$, which takes the necessity of averaging over all possible actions when calculating its performance objective according to equation 2.7 or equation 2.13. Note however, that using deterministic policies will (again) lead to the necessity of off-policy algorithms, as a purely deterministic policy does not allow for adequate exploration of state-space \mathcal{S} or action-space \mathcal{A} . Thus, to measure the performance of our policy, we must use function 2.13, which averages over the state distribution of our behaviour policy $\beta \neq \pi$.

To train both actor and critic, actor-critic algorithms rely on a version of the *policy gradient theorem*, which states a relation between the gradient of the policy and the gradient of its performance function. The idea behind actor-critic policy gradient algorithms is accordingly to adjust the parameters θ of the policy in the direction of the performance gradient $\nabla_\theta J(\pi_\theta)$, as moving uphill into the direction of the performance gradient corresponds to maximizing the global performance of the policy¹¹. The DPG technique is the policy gradient analogue to Q-learning: It learns a deterministic greedy policy in an off-policy setting, following a trajectory of states due to a noisy version of the learned policy.

Deterministic Policy Gradient

The idea in the *Deterministic Policy Gradient (DPG)* technique is to use a relation between the gradient of the (deterministic) policy (represented by the actor), and the gradient of the action-value function Q. The existence of a relation is easy to see, because as introduced in equation 2.13, the performance of our policy π is measured using Q.

The *off-policy deterministic policy gradient theorem*, put forward in [15], states the following relation between the gradient of the performance objective of a policy $J(\pi)$ (see equation 2.13) and the gradients of the policy-function π and the action-value function Q.

$$\begin{aligned} \nabla_\theta J_\beta(\pi_\theta) &\approx \int_{\mathcal{S}} \rho^\beta(s) \nabla_\theta \pi_\theta(a|s) Q^\pi(s, a) ds \\ &= \mathbb{E}_{s \sim \rho^\beta} \left[\nabla_\theta \pi_\theta Q^\pi(s, \pi_\theta(s)) \right] \\ &= \mathbb{E}_{s \sim \rho^\beta} \left[\nabla_\theta \pi_\theta(s) \nabla_a Q^\pi(s, a) \Big|_{a=\pi_\theta(s)} \right] \end{aligned} \quad (2.18)$$

There are two important things about this relation: first, it can be seen that the policy gradient does not depend on the gradient of the state distribution. Second, the approximation drops a term that depends on the action-value gradient, $\nabla_\theta Q^\pi(s, a)$. Since the position of the optima are however preserved, the term can be left out, making the approximation no less useful. Both claims are shown in [15].

¹⁰In that, it corresponds precisely to the previous approach. However, as we now allow for a continuous action-space \mathcal{A} , the network cannot return multiple Q-values at once, for each action $a \in \mathcal{A}$. Instead, the actions must also be inputs to the critic, which then outputs one $Q(s, a)$ -value.

¹¹The original policy gradient, introduced in [17], assumes on-policy learning with a stochastic policy. However, to derive the stochastic policy gradient, one must integrate over the whole action-space, making its usage less efficient and requiring more training than the DPG, introduced here.

The practical implication of this relation is the following:

When updating the policy, its parameters θ_{i+1} are updated in proportion to the gradient $\nabla_{\theta} J(\pi_{\theta})$. In practice, each state suggests a different gradient, making it necessary to take the expectation w.r.t. the state distribution ρ^{β} :

$$\theta_{i+1} = \theta_i + \alpha * \mathbb{E}_{s \sim \rho^{\beta}} [\nabla_{\theta} J(\pi_{\theta})]$$

The deterministic policy gradient theorem (2.18) shows that to improve the performance of the policy, it makes sense to move it into the direction of the gradient of Q , where the gradient of Q can be decomposed into the gradient of the action-value with respect to the actions, and the gradient of the policy with respect to its parameters:

$$\theta_{i+1} = \theta_i + \alpha * \mathbb{E}_{s \sim \rho^{\beta}} \left[\nabla_{\theta} \pi_{\theta}(s) \nabla_a Q^{\pi_i}(s, a) \Big|_{a=\pi_{\theta}(s)} \right]$$

In other words, to maximize the performance of the policy, one can re-use the gradient of those actions leading to maximal Q -values. In practice, the true function $Q^{\pi}(s, a)$ is unknown and must be estimated.

The off-policy deterministic actor-critic algorithm learns a deterministic target policy $\pi_{\theta}(s)$ from trajectories generated by an arbitrary stochastic policy, $\beta(a|s) = \mathbb{P}[a|s]$. For that, it uses an actor-critic architecture: The critic estimates the Q -function using a differentiable function approximator, using Q -learning as explained in the sections above, with the weights specified as w . The actor updates the *policy* parameters θ in the direction of the gradient of Q (instead of maximizing it globally as in the sections above¹²). Note that for the update of the policy parameters, only the gradient w.r.t. the weight of the actions as input of the Q -functions are relevant, not the trained weights of the approximator Q^w itself. Figure 2.1 visualizes the idea behind the algorithm graphically.

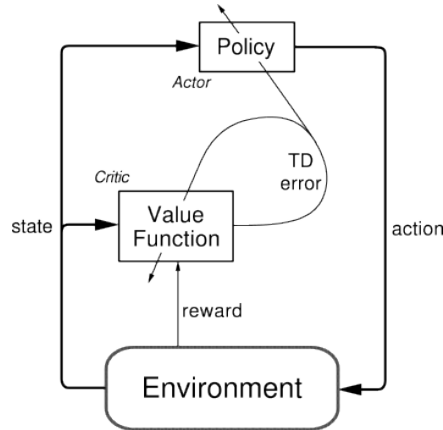


FIGURE 2.1: The actor-critic architecture. Reprinted from [11].

Using the above knowledge, one can derive the *off-policy deterministic actor critic* algorithm. In the first step of this algorithm, the critic calculates the temporal difference error to update its own parameters like in previous sections, and then the actor

¹²“The critic estimates the action-value function while the actor ascends the gradient of the action-value-function” (quote [15])

updates its parameters in the direction of the critic's action-value gradient:

$$TD_i = \mathbb{E}_{s,a,r} [(r_t + \gamma * Q^{w_i}(s_{t+1}, \pi_\theta(s_{t+1}))) - Q^{w_i}(s_t, a_t)] \quad (2.19)$$

$$w_{i+1} = \mathbb{E}_{s,a} [w_i + \alpha_w * TD_i \nabla_w Q^w(s_t, a_t)] \quad (2.20)$$

$$\theta_{i+1} = \mathbb{E}_{s,a} [\theta_i + \alpha_\theta * \nabla_\theta \pi_\theta(s_t) \nabla_a Q^w(s_t, a_t)|_{a=\pi_\theta(s)}] \quad (2.21)$$

With α_w and α_θ as the learning-rates of the critic and the actor, respectively.

As stated by [15], these algorithm may have convergence issues in practice, due to a bias introduced by approximating $Q^\pi(s, a)$ with $Q^w(s, a)$. It is thus important, that the approximation $Q^w(s, a)$ is *compatible*, preserving the true gradient $\nabla_a Q^\pi(s, a) \approx \nabla_a Q^w(s, a)$. This is the case when the gradients are orthogonal, and w minimizes $MSE(\theta, w)$. However, the necessary conditions are approximately fulfilled when using a differentiable critic that finds $Q^w(s, a) \approx Q^\pi(s, a)$.

Deep DPG

The *Deep DPG Algorithm* is an off-policy actor-critic, online, active, model-free, deterministic policy gradient algorithm for continuous action-spaces. The basic idea behind *Deep DPG (DDPG)* [8] is to combine the ideas of the DQN (section 2.3.1) with the architecture and learning rule using the deterministic policy gradient. For that, they also use parameterized deterministic actor function $\pi_\theta(s) = a$, as well as a critic function $Q^w(s, a)$. As the algorithm is also off-policy, it will learn the policy π_{θ^*} , while following a trajectory arising through another, stochastic policy β . This policy will again be a *soft* version of the learned policy π that allows for adequate exploration: $\beta := \text{soft}(\pi)$.

The update of the critic is performed analogously to the Q-value approximator in the Deep-Q-Network architecture. A minibatch of $\langle s_t, a_t, r_t, s_{t+1}, t = t_t \rangle$ -tuples is sampled from a replay memory of limited size, to then perform Q-learning via temporal differences (see 2.14 and 2.15). An obvious difference to the Q-learning in the above sections is however, that not the greedy $\arg\max_{a'} Q(s, a')$ -policy is used in the determination of the targetvalue, but the agent's own parameterized policy $\pi_\theta(s)$. Just like in Deep-Q-Learning, it is necessary to use target networks to ensure convergence of Q – in fact, Lillicrap et. al. [8] were the first to use the previously mentioned soft target updates.

The update of the actor then follows the deterministic policy gradient theorem from equation 2.18: Its estimation of the policy gradient bases on the minibatch-samples used in the critic. For that, it calculates the expectation of the action-gradients it adopted from the critic network. This expectation is an approximation of its policy gradient, allowing the actor to perform a stochastic gradient ascent step to optimize its performance objective.

In practice, it turned out that the usage of target networks for both actor and critic is necessary to ensure stability of the algorithm, such that in practice, there are four different networks: the actors $Q(s, a; \theta^Q)$ and $Q(s, a; \theta^{Q^-})$ as well as the critics $\pi(s; \theta^\pi)$ and $\pi(s; \theta^{\pi^-})$. Incorporating all those changes leads to the following pseudocode snippet of the agent's learning step, adopted from [8]:

Target-value of the critic:

$$y_t := \begin{cases} r_t & \text{if } t = t_t \\ r_t + \gamma * Q(s_{t+1}, \pi(s_{t+1}; \theta^{\pi^-}); \theta^{Q^-}) & \text{otherwise} \end{cases} \quad (2.22)$$

Loss the critic minimizes:

$$L_i(\theta_i^\pi) := \mathbb{E}_{\langle s_t, a_t, r_t, s_{t+1} \rangle \sim U(D)} \left[\left(y_t - Q(s_t, a_t; \theta^Q) \right)^2 \right] \quad (2.23)$$

Sampled policy gradient the actor maximizes for:

$$\nabla_{\theta^\pi} J_\beta(\pi_\theta) \approx \mathbb{E}_{\langle s_t, a_t, r_t, s_{t+1} \rangle \sim U(D)} \left[\nabla_a Q(s_t, \pi(s_t); \theta^Q) \nabla_{\theta^\pi} \pi(s_t; \theta^\pi) \right] \quad (2.24)$$

The correspondences of this ANN implementation and the correspondences of the general definitions can easily be seen: Equations 2.22 and 2.23 correspond to definitions 2.19 and 2.20, whereas equation 2.24 corresponds to equation 2.21.

For a complete code of the DDPG-implementation, I refer to appendix A.2. Analogously to the DQN-agent, an exemplary source code of the implementation of an agent with a DDPG-model can be found there, using python and tensorflow. The agent stands alone without an environment, and some crucial parts of it, like an implementation of its memory, are missing. On page 53, there is again a comparison of the pseudocode (as provided in [8]) and the correspondences in actual-python code, where each line of the pseudocode (to the left) corresponds precisely to the respective line of the actual python-code (to the right).

2.5 Exploration techniques

There is one main difference between supervised learning and reinforcement learning, which I mentioned right at the beginning of this chapter: in RL, the only way to collect information about the environment is by interacting with it. In supervised learning it is no problem to shuffle the dataset beforehand, giving the learner i.i.d. samples, which are sure to be representative about the dataset. In RL however, this is not possible: Consider the situation where the agent drives a car around a track – as long as the agent doesn't drive the car well enough, it will probably not reach high speeds, and will thus learn nothing about situations in which it drives at high speeds. Another problem which was also mentioned before is that so far, only deterministic policies $\pi(s) = a$ were considered. It is obvious that in practice, purely using deterministic policies leads to a complete lack of *exploration* of the state space \mathcal{S} of the MDP: Once the agent found one path to a terminal state, it will continue *exploiting* this path, which almost guarantees a suboptimal solution. In order to explore the full state space instead of sticking with the first local optimum found, a stochastic, non-greedy policy is necessary.

The two algorithms considered here were both variants of Q-learning, which is an off-policy algorithm. In practice that means that the agent learned about some greedy, deterministic policy while following another policy, which I said was a *noisy* version of that greedy policy. A noisy version helps ensuring adequate exploration. The big advantage of off-policy algorithms is thus, that the problem of exploration can be treated independently of the learning algorithm – whatever the mechanism for exploration will be, it is easy to incorporate it in both of the explained algorithms by letting it implement the previously mentioned *soft*(π) method, which takes as input a greedy, deterministic policy and yields a version of it that accounts for adequate state space exploration.

In the following subsection, I will start with exploration techniques for discrete actions, before then explaining methods that can be used in the case of continuous action spaces \mathcal{A} .

2.5.1 Exploration for discrete action-spaces

Chapter 3

Related work

[as mentioned before, there are two levels in the thesis - on the abstract level, the aim is to build a good agent for self-driving cars. On the practical level, it is still one specific simulation of a game, and one at first has to make the given game a RL problem, before you can even talk about trying to solve that. To show how that is normally done, there is the first section. In the second section I will then talk about successful approaches of self-driving cars in reality. That is at first subdivided into real-life and games. Our game is (like so many others) supposed to work as a bridge between real-life and games. As for that, I will also talk about what data is normally available, ...

3.1 Reinforcement Learning Frameworks

In the previous chapter, I outlined the general structure of a reinforcement learning problem. In summary, it consists of agent and environment, where the environment is discretized into timesteps and only partially observed by the agent (POMDP). Each timestep, the agent gets an observation of the environment's state (making up its *internal state* and a scalar reward, and chooses an action to return to the environment. A graphical description of this interaction is depicted in figure 3.1.

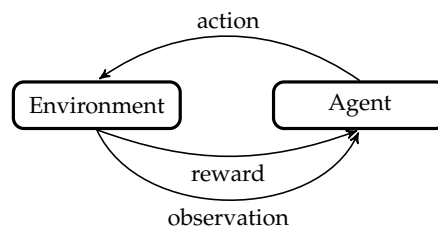


FIGURE 3.1: Interaction between agent and environment in RL

When developing RL agents, it is not enough to create algorithms, but also to have a specification of agent and environment that allows for a dataflow as described above. The original Deep-Q-Network [9] as well as its follow-ups [5][18] trained their agents on several ATARI games using the *Arcade Learning Environment* (ALE) [2], which was developed with the intention to evaluate the generality of several AI techniques, especially general game playing, reinforcement learning and planning. The important contribution of [2] was to provide a testbed for any kind of agent, by providing a simple common interface to more than a hundred different tasks – converting games into reinforcement learning problems. Doing that, it provided the accumulated score so far (corresponding to the reward), the information whether game ended (indicating the end of a training episode), as well as a 160×210 2D array of 7-bit pixels (corresponding to the agent's observation). As the game screen

does not correspond to the internal state of the simulator, the ALE corresponds to a POMDP.

Environments with discrete actions only are however severely limited, and most of the interesting real-world applications, as for example autonomous driving, require however real-valued action spaces. The test scenarios for the Deep-DPG algorithm consisted thus of a number of simulated physics-tasks, using the MuJoCo physics environment.

Both of the above mentioned environments are by now, among many others, merged into the *OpenAI gym*¹ environment [4], a toolkit helping reinforcement learning research by including a collection of benchmark problems with a common interface. Aside the previously mentioned ALE as well as a number of physics tasks using the MuJoCo physics-engine, the openAI gym contains the boardgame Go, two-dimensional continuous control tasks (*Box2D games*), a 3D-shooter by the name of *Doom*, and several other tasks, varying in complexity, input and output.

The goal of openAI gym is to be as convenient and accessible as possible. For that, one of their design decisions was to make a clear cut between agent and environment, only the latter of which is provided by OpenAI. The exemplary sourcecode found in algorithm 1, taken from <https://gym.openai.com/docs>, outlines the ease of creating an agent working in the gym framework.

Algorithm 1 Interaction with the openAI gym environment

```
import gym
env = gym.make('CartPole-v0')
for i_episode in range(20):
    observation = env.reset()
    for t in range(100):
        env.render()
        print(observation)
        action = env.action_space.sample()
        observation, reward, done, info = env.step(action)
        if done:
            print("Episode finished after {} timesteps".format(t+1))
            break
```

The code outlines how the general dataflow between agent and environment usually takes place: After a reset, the environment provides the first *observation* to the agent. Afterwards, it is the agent's turn to provide an action. Even though not featured in this easy example, the action is performed by usage of the observation. Once an agent has calculated the action and provided it to the environment, it can perform another simulation step, returning $\langle observation, reward, done, info \rangle$, which is a tuple consisting of another observation of the environment's state, a scalar reward, the information if the episode is finished and it is time to reset the environment, as well as some information for debugging, typically not used in the final description of an agent. In the remainder of this work, I will refer to this dataflow as a baseline on how the interaction of environment and agent should look like.

It is worth noting, that the openAI gym is not even

¹<https://gym.openai.com>

Name	Paper/Link	Trained on Game	Used as inputs	Used as reward	Furhter distinctivenesses
Tensorkart	Link	Mariokart	Y	Z	only pretraining
original DDPG	[8]	Torcs	vision	bla	ne
original DDPG	[8]	Torcs	lowdim	bla	ne
Thatguy	irgendowonmedium	Torcs	vision	besser	ne
NVIDIA	paperlink	real data	vision	bla	ne

3.2 Self-driving cars

3.2.1 real-life

Nvidias deep-drive RRT* Tesla

available data in real-life

Lidar <https://arxiv.org/pdf/1704.03952.pdf>

3.2.2 games

Leon wollte hier ne Tabelle von verschiedenen games und den respective inputs die sie nutzen...! im DDPG-paper steht "Torcs has previously been used as a testbed in other policy learning approaches (Koutnik et al., 2014b).

Tensorkart hier in den fußnoten die ganzen non-scientific quellen wie tensorkart undso

Das Aufteilen von autonomous driving into the subcomponents, wie bei der vorlesung von Julian... oder, as quoted by TORCS-Paper: "The racing problem could be split into a number of different components, including robust control of the vehicle, dynamic and static trajectory planning, car setup, inference and vision, tactical decisions (such as overtaking) and finally overall racing strategy"

DDPG auf torc hat übrigens im pixel-case nen sehrsehr ähnlichen punktestand wie im low-dimensional case (1840 vs 1876 im best case, -393 vs -401 im average case).

TORCS!!!!!!UNBEDINGT ERWÄHNEN DASS die geschrieben haben dass TORCS ein POMDP ist!!

Chapter 4

Program Architecture

As explained in the introduction (1), the aim of this thesis is to convert a given racing game into an environment that can be played by reinforcement learning agents and to analyze the performance of different agents. In this chapter, I will explain the implementation that was developed throughout this process. I will start by explaining the design decisions that shaped this implementation in section 4.1. In the following section (4.2) I will explain the particular source code. I will start with the game as it was given as starting point, most parts of which are not implemented by the author of this thesis. Then the implemented extensions of the game are explained, before leading over to the agent. In the last section of this chapter (section 4.3), I will explain what kind of data the game provides that can be used by an agent.

4.1 Characteristics and design decisions

As stated in chapter 3.1, the usual framework for solving reinforcement learning tasks is fairly rigid. However, the task of this work differed in some respects from the usual implementation of a reinforcement learning agent, which led to the necessity of differing from the usual framework in numerous situations. In the following sections, I will provide an overview of the difference between this project and other work in the reinforcement learning domain. Furthermore, I will discuss some of the design decisions that found their way into the final version of the program as well as challenges that occurred during its implementation and their respective solution. For that, I will explain general principles in the first section of this chapter, and go into detail about some of the specific details about the implementation in the subsequent section.

4.1.1 Characteristics of this project

There are several differences from this project to others in the reinforcement learning community. The most important difference to the agents presented in chapter 2 is, that those are developed as general-purpose problem solvers, with the intention to solve any arbitrary task given to them. In this approach, that is not the case – the goal is to solve the specific, given game. This allows in principle to incorporate expert knowledge of the task domain, to for example forbid certain combinations of the output or to use particular types of exploration, which are specifically useful in this scenario. The game which is supposed to be played is a racing game, which has implications in several domains, for example making the standard ϵ -greedy approach for exploration much worse as in many other domains. Next to that, the game which is supposed to be played is, in contrast to games solved in openAI's gym-environment (3.1), live. While the game could in theory be manually paused for every RL step, it is worth trying to let the agent run “live”, such that it runs

fluently and its progress can manually be inspected. Another challenge was the fact, that the game is coded in a programming language for which no efficient deep learning architectures exist, which led to the necessity of a proprietary communication between the environment and its agent.

The fact that there is a game that is supposed to be *solved* also extended the entire problem domain: While usually the focus of developing RL agents can lie purely on the agent, assuming that the environment and consequently its definition of state/observation and reward is fixed, the focus of this work was to learn this one game as well as possible – in other words it is also necessary to test what a useful definition of observation or reward looks like. Many of the subsequent design decisions are made with the idea in mind, that it must be as easy as possible to compare different agents using a unique combination of state-definition, reward-definition, model and exploration technique.

Furthermore, the question of how important supervised pretraining is will be addressed in this thesis. For that, the game must provide a way of recording manual actions and their corresponding observation and to record that in a way, that a learner can read it and train on this data. The natural questions arising are how good an agent relying purely on supervised training performs in comparison to others. Another important question is if there is a way to combine pre-training with reinforcement training in racing tasks, as famously done in the board game Go[14].

4.1.2 Characteristics of the game

The given game is a simple but realistic racing simulation. As of now, it consists of one car driving one track. While it possible to implement additional AI drivers or different tracks, no such thing is considered in the current implementation. The main focus of the given simulation lies on realistic physics, which make the game far harder to predict and master than many of those implemented for the Atari-console, on which the original DQN was tested.

The input expected from an agent consists of three continuous actions: The *throttle* increases the simulated motor-torque, which leads faster rotation of the tires and thus applying forward force to the car. The *brake* simulates a continuous brake force slowing down the rotation of the tires. It is not possible to complete a lap while constantly accelerating as much as possible without braking. It is important to note that slip and spin is also simulated: While the rotation of the tires can be accelerated or decelerated fairly abrupt due to their small mass, the car itself has a higher mass and thus more inertia, with forbids abrupt changes in movement. As the tires are rigidly attached to the car, they lose grip on the street, which lessens the impact of consequent forces applied to the tires. The last command an agent must output is the *steering*, which turns the front tires of the car, leading the car applying force to the respective side the tires steered towards.

It is the task of an agent to provide commands for the values of throttle, brake and steering, which are continuous in their respective domains: $throttle \in [0, 1]$, $brake \in [0, 1]$ and $steer \in [-1, 1]$. Of course, as is the general case in reinforcement learning problems, the agent does not know the implications of its actions in advance but must learn them via trial and error. It should however also be kept in mind that the agent provides those actions *to the car*, and that the car must be seen as part of the environment as well, as the actions do not have a reliable impact on its behaviour. For instance, if the car is moving at fast paces, hitting the brake will not lead to an abrupt stop, as the car's inertia still applies a forward force. Also, the impact of the steering changes with the movement of the car. For example, the turning circle of the

car has a much slower radius in smaller speeds. Another consequence of the realism of the physics implemented in this simulation is the fact that simultaneous braking and steering at high velocities has almost no effect: Because of the high speed, the car has a strong forward force. That leads in combination with the braking to the front tires slipping a lot, which reduces the impact on forces applied to them on the car – it will not follow the direction of the steering but continue its forward pace determined by the stronger force, namely the inertia.

The track itself is a circular course with a combination of unique curves, requiring the car to steer left as well as right. Along every point of the course, there are three different surfaces providing different friction – the *track* (inside) itself provides the most grip, while the *off-track* (outside) surface is far more slippery. Between the track-surface and the off-track-surface there is the *curb*, which manifests as a small bump with separate friction properties. The track, curb and off-track each have a consistent width throughout the circuit. To the outside of the off-track there is a wall that cannot be traversed.

The game as a reinforcement learning problem

As detailed in chapter 2, reinforcement learning agents are solvers for (possibly only partially observed) Markov Decision Processes with unknown transition relations. In other words, for the agent to successfully learn how to operate in an unknown environment, this environment must correspond precisely to a tuple of $\langle S, A, P, R, \gamma \rangle$ (details explained in section 2.1). Because in this simulation only the case of a single agent without any other cars on the track is considered, the racing problem can be formalized as a Markov Decision Processes with a similar reasoning than Wymann et al. [21, chapter 4] put forward for TORCS. As is the general case in simulations, while every update-step of the physics aims to simulate a continuous process, those updates must be discretized in the temporal domain. As however both agent and environment run live, the temporal discretization of the agent can not always correspond to that of the environment if an update-step in the agent takes longer than in the environment. To put that into numbers, the fixed timestep for the environment's physics is at 500 updates per second, while the agent discretizes to maximally 20 actions per second.

As mentioned in the previous section, the action space required by the agent is continuous with $\mathcal{A} \subset \mathbb{R}^3$.

The environment's state is a linear combination of different factors, as for example the car's speed, absolute position, current slip-values and much more. While certainly finite, it consists of many high-dimensional values: $\mathcal{S}_e \subset \mathbb{R}^{n \in \mathbb{N}}$. Because of certain factors in the implementation of the environment itself, the environment is indeterministic¹, while the start-state is always equal. As can in principle be argued that the environment's state corresponds to all information stored in the game's section of the computer's RAM, the game trivially fulfills the markov property. As the environment is only a single-agent system, the transition function of the environments can be expressed as a stochastic function of state and action: $\mathcal{S}_e \times \mathcal{A} \rightarrow \mathcal{S}_e$.

¹The game is programmed in Unity, which has non-predictable physics. As discussed for example in <https://forum.unity3d.com/threads/is-unity-physics-is-deterministic.429778/>, this is because of the fact that any random-number-generator depends on the current system time, which is never fully equal in subsequent trials. Because the calculation of some states can be more complex than others, this effect can snowball even more – longer calculation in one step leads to later timing of a subsequent update step, which can lead to a whole other trajectory along the state space, even though the start state was equal.

There is no formal definition of a reward returned by the environment in the game. While it could in theory be argued that the inverse of the time needed to complete a lap could be taken as the reward, it is obvious that this is infeasible due to many reasons: Finishing one lap takes several seconds, which means there are hundreds of iterations between start state and final state. Next to the obviously arising *credit assignment problem*, the chance of an agent even getting to the finish line without crashing, is practically zero without rewarding intermediate progress. Instead, it makes sense to give more dense rewards. As mentioned in section 4.1.1, the reward also is subject of experiments in the scope of this thesis. For the game to correspond to a proper environment, this reward must be a scalar value depending on state and action.

Though it is in theory possible to implement an agent that takes the entire underlying state of the environment as its input, an approach like that is far from feasible, as this state also contains much information only necessary for rendering the game. Instead, in the chosen approach the agent only receives an *observation* of the environment's state.

Summarizing all those factors, it becomes obvious that the given game can clearly be defined in terms of a *Partially Observed Indeterministic Markov Decision Process*.

It is worth noting, that while the dimensionality of the observation is likely much smaller than the dimensionality of the state, any feasible observation will be high-dimensional or real-valued. The chance for any particular combination of parameters to appear multiple times is vanishingly low, which makes the use of function approximation necessary.

While the notion of *POMDPs* itself contains no definition of final states, it is necessary to have use those, as they provide hard limit of the horizon in the calculation of Q-values. Another design decision in the course of the implementation of this project was, that the agent itself can define what it wants to see as the end of an episode. It is a matter of testing after how many seconds the agent shall give up on a trial, or if steering into a wall should be viewed as the end of a training episode. Because of that, the environment provides only candidates of what could terminate an episode to the agent, such that the agent can decide to reset the environment or not.

The game itself has three different game modes the user can choose between at the start of the game: In the Drive mode, users can manually drive the car with the computer's keyboard. If the Train AI supervisedly mode is activated, the car must still be driven manually, while the game exports information about the driving episode that can be used as (pre-) training data for artificial driving agents. The last mode is the Drive AI mode, where car can be controlled by an agent, as long as the User doesn't actively interfere. A screenshot of the start menu can be found in figure B.1 in appendix B. Note that the background of the menu provides a bird-eye view of the track.

4.1.3 Characteristics of the agent

As stated above, it was a design decision to leave as many options open to the agent as possible, such that several agents can each have their own respective definitions of certain features. To summarize from the above chapters, the features unique to every agent are:

- The definition of the agent's *observation-function*, providing its internal state:

$$s = o(s_e)$$

- Definition of the *reward-function*, returning a scalar from state, action and subsequent state: $\mathcal{S}_e \times \mathcal{A} \times \mathcal{S}_e \rightarrow \mathbb{R}$
- Definition of its internal *model*, basing on which it calculates its policy
- Under which conditions an episode is considered to be terminated
- Definition of the agent's *exploration technique*
- If and how the agent relies on pretraining with supervised data

In the following sections, I will refer to the definitions of these functions/options as the *features* of the agent. In the implementation, there are many possible features, not all of which are actually used by an agent. I will refer to those as *possible features*. When I talk specifically about the possible observations influencing the observation-function, I refer to those as (*possible*) *vectors*.

It is due to this design decision that the program flow of this project cannot follow the exact same structure than the one put forward in algorithm 1. One big structural difference is for example that the outer loop (line 3) becomes obsolete, as the agent decides under what conditions the environment must be reset. A further advantage of an implementation like this is also, that it can be experimented with rewards that change over time, such that an agent can for example first learn how to move forward, and only later to always stay on track.

Because there are many features in which agents can differ, it makes sense to use the object-oriented programming concept of inheritance for the different agents. In such an implementation, the main methods common to every agent as well as basic definitions of the features are implemented in a superclass. Particular agents inherit from this class, while overwriting the attributes/functions for the feature in which they differ.

I will go into detail about the implemented features and vectors in a later section after describing the implementation of agent and environment, as the data relies on functions and data specific to this implementation.

4.2 Implementation

The associated programs are, as will be explicitly stated, written by the author of this work as well as its first supervisor, and are licensed under the GNU General Public License (GNU GPLv3). Their source codes can be found digitally on the enclosed CD-ROM as well as online:. Version control of this project relied on GitHub², and was split into three repositories: The source code of the actual game written with the game engine Unity 3D (*BA-rAIce*³), the source code of the implementation, written in Python (*Ba-rAIce-ANN*⁴), as well as the present text, written in L^AT_EX (*BAText*⁵). To ease connections between the following descriptions and their correspondenced in the actual source code, footnotes will refer as hyperlink to the files on GitHub (the relative path on the enclosed CD is equal to those on GitHub). In order to ensure that no work after the deadline is considered, it is referred to the signed commits

THE, SIGNED, COMMITS.

²<https://github.com/>

³<https://github.com/cstenkamp/BA-rAIce>

⁴<https://github.com/cstenkamp/BA-rAIce-ANN>

⁵<https://github.com/cstenkamp/BAText>

The game is programmed using Unity Personal with a free license for students⁶. It is tested under version 2017.1.0f3⁷. Scripts belonging to the game are coded using the programming language C#. The agent was programmed with Python 3.5, relying on the open-source machine learning library TensorFlow[1]⁸ in version 1.3. For a listing of all further used python-packages and their versions, it is referred to the [BA-rAIce-ANN/requirements.txt](#)-file.

While the author of this work contributed most of the work to change the given game such that it can be learned and played by a machine, the original version of the game was given in advance, coded by the first supervisor of this work. While it will be explicitly stated what was already given later in this chapter, it is also referred to the respective branch on Github (*Ba-rAIce – LeonsVersion*⁹). The implementation of the agent was however not influenced by any other people than the author of this work.

As already hinted at, the program flow of the implementation differs from that of other implementations. The game, making up the environment, is completely independent of the agent and runs as a separate *process* on the machine. The agent is written in another programming language and must thus make up a distinct process as well. Because of that, it is necessary that agent and environment communicate over a protocol that allows inter-process-communication. In this work, it was decided to use *Sockets* as means of communication. While explained in following section, it is for now important to know that sockets are best implemented as running in a separate *thread*, where they can send textual information to another socket running in another process.

4.2.1 The game as given

The program flow of the game is encapsulated by the framework that the Unity 3D provides: To ease the implementation of games, Unity provides numerous game objects with pre-implemented properties like friction or gravity, as well as drag-and-drop functionality to add 3D components or cameras to the Graphical User Interface (GUI). Another advantage of Unity is, that it targets many graphics APIs, which takes a lot of work from the programmer to implement an efficient graphics pipeline.

To implement additional behaviour or features not predefined by Unity, it allows for scripts, written in object-oriented C#. Scripts that are supposed to be used by Unity must provide a class that extends¹⁰ its class `MonoBehaviour` or be used by such a one. For the file to be instantiated during runtime, it must be specified in Unity's Object Hierarchy. After starting the program, Unity will create all objects specified in the hierarchy. To enable the possibility of instantiations knowing each other during runtime, they must provide public variables of the type of the respective subclass

⁶<https://store.unity.com/products/unity-personal>

⁷As of now, 5th September, 2017, there is a bug in Unity that causes it to crash due to a memory leak if UI components are updated too often (which happens after a few hours of running). Because of that, in the current release of this project, all updates of the Unity UI are disabled in AI-Mode. A bug report to Unity was filed (case [935432](#)) on 27th July, 2017, and it was promised that this issue will soon be fixed. Once that is the case, the variable `DEBUG_DISABLEGUI_AI_MODE` in [BA-rAIce/AiInterface.cs](#) can be set to `false`.

⁸<https://www.tensorflow.org/>

⁹<https://github.com/cstenkamp/BA-rAIce/tree/LeonsVersion>

¹⁰In the following sections, I will use the terms *extends*, *implements*, *knows* and *has*. When I use those, I mean them in the strict sense in the context of object-oriented programming languages (and the concepts inheritance, interfaces, and references).

of `MonoBehaviour`, which can via drag-and-drop be assigned to the respective future instance specified in the Object Hierarchy. `MonoBehaviour` provides a number of functions that are automatically called by Unity at different times during runtime. The most important ones are `void Start()`, called when first instantiating the respective object, as well as `void Update()` and `void FixedUpdate()`, called every Update-step or Physics-update-step, respectively¹¹. If a subclass of `MonoBehaviour` is attached to a game object, it can provide specific additional functions that are called when specific events occur during runtime – an example would be `OnCollisionEnter(Collision)`.

In the following, I will describe the game in chunks corresponding roughly to an implemented class, to which the footnote in the headline refers. In appendix C, I also provide an informal table of each class and its important methods. Keep in mind that the structure of this files as well as most of their content is not created by the author of this thesis. Note also, that I will sometimes mention optimal features. As those options are relevant not to a User of the game but to its developers, those options are specified in the code, more precisely in a static class called `Consts` in `AiInterface.cs`¹².

Game modes¹³

On the surface, the game has three different game modes that can be active: Drive, Drive AI and train AI supervisedly. These are the three modes the User can choose from in the game's main menu (the UI of which can be seen in figure B.1 in appendix B). In the actual implementation however, the game mode is handled a bit different. `mode` is a public string-array of the globally known object `Game` (an instantiation of a `GameScript`, a subclass of `MonoBehaviour` specified in `GameScript.cs`¹³). `mode` contains one or more strings of the following group: "driving", "menu", "train_AI", "drive_AI" and "keyboarddriving". If the game's main menu is opened, `mode = ["menu"]`, and in all other cases it is a set consisting of `driving` as well as the respectively obvious elements. This implementation is advantageous, because some behaviour needs to be triggered in multiple modes – the car's movement is for instance calculated if `Game.mode.Contains("driving")`, which is the case in all three of the above mentioned modes. The current implementation also makes it easier to add further behaviour: If for example an AI-agent shall also function to generate supervised data, one can simply add the respective mode in the `Gamescript.cs` file.

The functionality for switching the game mode is specified in the `SwitchMode(newMode)` function, found in `GameScript.cs`. After setting the respective mode as described above, this function disconnects any connected Sockets and activates the required cameras for the mode, updates the UI's Display indicating the mode and calls some further initializing functions (`AiInt.StartedAIMode()` or `Rec-StartedSV_SaveMode()`), if applicable. Because particularly the initialization of the `drive_AI`-mode involves connecting with an external Socket, it is done in part in a side thread. This means that the main thread does not wait for the initialization to be finished – because of

¹¹Concerning the difference between Update and FixedUpdate: **Update** is called once per frame, in other words as often as possible. It is generally not used to update physics, as its call frequency depends on the current FPS – if calculations here take too long, the FPS of the game will decrease. **FixedUpdate** is called precisely in a fixed interval of game-internal time. If calculations in FixedUpdate are too slow, the progress of the game-internal time is delayed until FixedUpdate catches up. The update-interval of FixedUpdate can be freely chosen and is 0.002 seconds in the current implementation. If Unity's `Time.timeScale` is set to zero, FixedUpdate() will not be called at all.

¹²<https://github.com/cstenkamp/BA-rAIce/blob/master/Assets/Scripts/AiInterface.cs>

¹³<https://github.com/cstenkamp/BA-rAIce/blob/master/Assets/Scripts/GameScript.cs>

that, the `StartedAIMode()` -function sets the variable `AiInt.AIMode` to `true` once it is done. Any behaviour that depends on a successful initialization of the can thus simply check for this variable instead.

The object `Game` is responsible for switching the `mode` to `menu` in its `Start()` -method or after the press of the `[Esc]` -button at any time during the runtime of the game. Besides this, its definition in `GameScript.cs` also contains the methods `QuickPause(string reason)` and `UnQuickPause(string reason)`. The purpose of `QuickPause` is to pause all physics processes of the game, such that other functionalities running in parallel to it get time to catch up with their calculations. For that, the `QuickPause(string reason)` -function sets the `Game's Time.timeScale` to zero, which freezes all of Unity's internal physics, as well as stopping future `FixedUpdate()` -calls. Further, this function removes `driving` from `mode`, so that other driving-related functions in `Update()` are also stopped. Lastly, the `QuickPause`-mode changes the game's GUI to make the difference visible to the User. While the public function `QuickPause()` could in principle be called from every method of the game, it contains functionalities that are (due to design concepts of Unity) not thread safe, meaning that only the main-thread can call them safely. To enable the possibility of asynchronous threads activating the `QuickPause`-mode, `Game` contains a public variable `shouldQuickpauseReason`. This variable can be set to a value from asynchronous threads, and the `Game` checks every `Update()` -step (guaranteed to be main-thread and to also be called if `QuickPause` is active) if another side thread requested to invoke this method. Once the method that originally invoked `QuickPause` wants the game to continue its normal process, it must call `UnQuickPause(string reason)` (or request for it to be called). However, `QuickPause` could have been enabled by another method as well, that is not ready for the normal game process yet. To prevent such a scenario, the methods to start and to end `QuickPause` must both be called with a string `reason`. In every call of `QuickPause(string reason)`, the function pushes `reason` on `Game's List FreezeReasons`, and in every call of `UnQuickPause(string reason)`, it removes the respective reason from the list and only continues the normal game process if the list becomes empty.

User Interface¹⁴






The job of the `Game's UI` (an instance of type `UIScript`) is to update the user interface. This UI is overlayed over the current scene, such that its components can be seen simultaneously to the image of an active camera. In its `MenuOverLayHandling()` -Method, `UI` specifies the view of the game's menu-mode (as can be seen in figure B.1 in appendix B), as well as the key bindings to activate the required mode. In the method `DrivingOverLayHandling()`, it sets visibility, content, color or position of numerous UI components (defined in Unitys Object Hierachy), that are seen in non-menu-modes. Both `DrivingOverLayHandling()` and `MenuOverLayHandling()` are called every `Update()`, such that the view elements are always contemporary. Further, the `UI` specifies the `void onGUI()` -function, which Unity calls every time it re-renders the GUI. This function overlays Debug information on the screen and changes the view if the `QuickPause`-mode is activated.






The User Interface of the game while driving can be seen in the figures B.2 and B.3 in appendix B, which are screenshots for the `keyboarddriving` and `drive_AI` mode,





¹⁴<https://github.com/cstenkamp/BA-rAIce/blob/master/Assets/Scripts/UIScript.cs>

respectively. The latter of those screenshots is annotated with labelled boxes around each UI component, with page 55 explaining each component a bit further¹⁵.

Controls

If `Game.mode.Contains("keyboarddriving")`, the game is steered with the arrow keys  and . The throttle is triggered via the -key, whereas the brake is called via . The  - key flips the reverse gear. Note that as long as the `pedalType` in `CarController` is set to `digital`, throttle and brake are binary when controlled via keyboard.

If `Game.mode.Contains("drive_AI")` the car is usually controlled by the agent. It is however possible to re-gain control over it via pressing the -key. Once that occurs, the variable `AiInt.HumanTakingControl` is set to true, indicating the program that keyboard-inputs must be accepted. This is useful for example if one wants to check if rewards or Q-values are realistic. If human interference of the `drive_AI` mode is active, it is possible to simulate speeds to the agent (meaning that not the actual speed of the car, but a specified value is sent to the agent). This can be done with the number keys, where the pretended speed is evenly spread between 0 *kph* () and 250 *kph* (). The  key is reserved to simulate a full throttle value. To hand control back to the agent,  must be pressed again.

In the `drive_AI`-mode, a user can also manually disconnect or attempt a connection-trial with an agent. The keys to do that are  and , respectively. During any `mode` containing `driving`,  can be pressed to activate the QuickPause-mode, which allows to spectate the current screen. QuickPause is ended with another hit of .

The car¹⁶

The `car` itself is a `Rigidbody`, which is a Unity-gameObject with certain properties like spatial expanse, mass and gravity. Attached to the `car` is, next to no further mentioned visible components, a Unity `BoxCollider` as well as four `WheelColliders` gameObjects. While the `BoxCollider`'s purpose is to trigger the call of particular functions in scripts attached to other gameObjects upon simulated physical contact, the `WheelColliders` are predefined with certain physical properties, allowing for precise simulation of the behaviour of actual tires. How the car moves is specified in an instance of the class `CarController`, which is attached to the respective `Rigidbody`.

All functions of the `CarController` are only called in modes containing `driving`. In its `FixedUpdate()`-step, the script adjusts the wheelCollider's friction according to the current surface the wheels are on, and it is checked if the car moved outside the street's surface. Furthermore the car's velocity as well as some other values are calculated. Finally, the torques for acceleration and braking are applied and the front wheels are turned according to the steering-value. The amount of those torques and angles depend on three values: $steeringValue \in [-1, 1]$, $throttlePedalValue \in [0, 1]$ and $brakePedalValue \in [0, 1]$. If `Game.mode.Contains("keyboarddriving")` or `AiInt.HumanTakingControl == true`, those values depend on the User's keyboard input. Otherwise, if `AiInt.AIMode` is enabled, the values are defined as known values from the `AiInt`, namely `nn_steer`, `nn_throttle` and `nn_brake`.

In `CarController.Update()`, the outer appearance of the car is updated, consisting of wheel height, wheel rotation and wheel rotation.

¹⁵Note that the entire UI, besides the content behind labels **A**, **F**, **H** and **I**, was already implemented like this by the first supervisor.

¹⁶<https://github.com/cstenkamp/BA-rAIce/blob/master/Assets/Scripts/CarController.cs>

As explained in section 4.1.3, a connected agent must be able to reset the car at any time during runtime. To allow for that, the `CarController` provides a `ResetCar` method. Additionally, there is a `ResetToPosition`-function that resets the car to any specified position and rotation. Because the car must stand still after a reset, it is necessary to completely kill its inertia. To do so, it is not enough to apply zero motorTorque and infinite brakeTorque to the car and call `car.ResetInertiaTensor()` inside `ResetToPosition`, because those values would simply be overwritten in the next call of `FixedUpdate()`. This is why in the given implementation the function `ResetToPosition` sets a boolean variable `justrespawned` to `true`. In every call of `CarController.FixedUpdate()`, it is checked if the car did just reset, and performs the necessary forces to remove all of the car's inertia right there, before setting `justrespawned = false`.

Position tracking¹⁷

To successfully learn useful driving policies, the agent must get precise knowledge of the car's position which goes beyond its mere coordinates. Additional useful information is for example the car's position in relation to the street, or information about the course of the road ahead of the it. To allow for that, the game incorporates a `TrackingSystem`, which is an instance of the class `PositionTracking`). The `TrackingSystem` knows the gameObject `trackOutline` and converts it to an array of coordinates located regularly along the track, each one respectively located at the middle of the street – the `Vector3[] anchorVector`. Using this array, much high-level information about the track can be calculated. As almost all of the respective functionality was however not implemented was not implemented by the author of this thesis, a short scetch of how it can be used shall suffice.

To calculate the progress of the car in percent, one needs the total length of the track as well as the distance the car advanced so far. The first of those can be calculated by summing up the distances between a coordinate and its successor. To get the approximate distance the car advanced, one needs iterate through the `anchorVector`-array to find the one closest to the car (which happens in `GetClosestAnchor(Vector3 position)`). The cumulated distance of successive vectors until the one closest to the car corresponds roughly to its progress in percent.

As every successive coordinate in `anchorVector` is in the middle of the street, one can calculate the direction of the street at position `p` by calculating the vector `anchorVector[GetClosestAnchor(p)+1] - anchorVector[GetClosestAnchor(p)]`. This can be used as basis for many further calculations: For instance, the car's distance to the center of the street can be found via by calculating the norm of the orthogonal projection from the car's coordinate onto this vector. The direction of the car relative to the street can be found by calculating the angle between its `direction`-vector and the previously explained vector.

Besides defining the `anchorVector`-array and other helper-arrays depending on it in its `Start()`-method, the `TrackingSystem` calculates the car's current `progress` at every `Update()`-step and triggers the `UpdateList()`-method of the `RecordingSystem` in regular progress-intervals. Furthermore, the `TrackingSystem` provides certain public methods that can be used by an agent, namely `getCarAngle()`, `GetSpeedInDir()` and `GetCenterDist()`, the precise content of which will be explained in a later section.

¹⁷ <https://github.com/cstenkamp/BA-rAIce/blob/master/Assets/Scripts/PositionTracking.cs>

Tracking time¹⁸

As visible in the game's screenshots (more precisely annotations **B**, **C**, **P** and **Q** of Figure B.3), the game displays information about the current laptime, the last laptime as well as the time needed for the fastest lap. Furthermore the game provides a visual feedback basing on the time needed for a specific section of the street in comparison to the time that was needed for this section in the fastest lap so far (annotation **E**). This is possible because the game records current laptime multiple times throughout the course. As mentioned above, `RecordingSystem.UpdateList()` gets called regularly by the `TrackingSystem`. `RecordingSystem` is an instance of the type `Recorder`. It contains three lists of `PointInTime`s, for `thisLap`, `lastLap` and `fastestLap`. A `PointInTime` is a serializable object (also defined in `Recorder.cs`) that contains two floats, for a progress and a corresponding time.

An instance of a separate class, `TimingScript` (found in `TimingScrip.cs`¹⁹) is attached to a permeable Collider right on the start/finish line that functions as trigger. As a subclass of `MonoBehaviour`, `TimingScript` has a `void OnTriggerExit(Collider other)`, that is invoked as soon as another Collider stops contact with it. As the only movable collider is the car's boxCollider, this method is called as soon as the car starts a lap. A lap is considered valid under two conditions: First, the car needs to pass a second collider (confirmCollider, with its attached `ConfirmColliderScript`²⁰), which ensures that the car did in fact drive a complete lap instead of backing up right back on the start/finish line. The second condition for validity is, that at no time all four tires of the car hit left the street's surface.

If a lap is considered valid, the `TimingSystem's` `onTriggerExit`-procedure calls `RecordingSystem's` `Rec.FinishList()`-method. Afterwards and under no restrictions, it prepares the start of a new lap by calling `Rec.StartList()`. Once `StartList` is called, the `RecordingSystem` creates a new List of `PointInTime`s, to which the `TrackingSystem` then regularly adds new tuples of progress and corresponding time. Once `FinishList` is called, the `RecordingSystem` checks if the lap just now is a new record, and saves it on the computer's disk if so. In its methods `GetDelta()` and `GetFeedback()`, which are called every `Update()`-step of the `UI`, it can then compare the time of the currently latest progress with the corresponding time of `fastestLap`.

4.2.2 The game – extensions to serve as environment

The code explained so far is sufficient for the game to work in the `keyboarddriving`-mode. The framework for this mode was working entirely when the author of this thesis received it, as it was implemented by the first supervisor. The major additions implemented in the scope of this thesis that were mentioned so far is the behaviour following game modes other than `keyboarddriving` or `menu`, the QuickPause-functionality, the mentioned additions to the User Interface, the means to reset the car as well as the functions `GetCarAngle()` and `GetSpeedInDir()` of the `TrackingSystem`, which will be more thoroughly explained lateron.

¹⁸<https://github.com/cstenkamp/BA-rAIce/blob/master/Assets/Scripts/Recorder.cs>

¹⁹<https://github.com/cstenkamp/BA-rAIce/blob/master/Assets/Scripts/TimingScript.cs>

²⁰<https://github.com/cstenkamp/BA-rAIce/blob/master/Assets/Scripts/ConfirmColliderScript.cs>

The minimap cameras²¹

The content of the minimap cameras can be seen behind annotations **H** and **I** of figure **B.3**. They are implemented to serve as an exclusive or additional input to agents, in the hope of providing enough information to learn successful policies. As can be seen, the minimap cameras provide a bird-eye view of the track ahead of the car, by filming vertically downwards. In contrast to the foreshortened main-camera, the minimap cameras are orthogonal, which means that distances are true to scale, irrespectively of their position. Because the cameras are attached to the car's Rigidbody, they are always in the same position relative to the car. In the current implementation, up to two cameras can be used (it is however possible to disable one or both cameras by setting a corresponding value in the class `Consts` in `AiInterface.cs`). When both cameras are active, one of them is mounted further away from the car, such that one provides high accuracy whereas the other provides a greater field of view. If only one camera is enabled, its distance is set for tradeoff of accuracy and field of view. As both cameras must be handled separately, this happens in the `Start()`-method of the `Gamescript.cs`, which knows both cameras.

While a previous implementation of a similar functionality was provided by the first supervisor using a complex and inefficient ray-tracing, in this implementation the minimaps base on Unity `Camera`-objects, which are efficiently calculated on the computer's GPU. Attached to each camera is a respective instance of `MiniMapScript`. While ordinarily the content of Unity's cameras is directly rendered to the game's main screen, this script contains methods to convert the image of the camera to a format that can be sent to an agent. That is made possible by the usage of a `RenderTarget` as well as a `Texture2D`, which are created as private objects in `MiniMapScript's PrepareVision(int xLen, int yLen)`-method. This method is called from outside and expects as parameter the dimensionality of the produced matrix, which is set in the class `Consts` in `AiInterface.cs`.

Both cameras provide the public function `GetVisionDisplay()`. When this function is called, it sets the above mentioned `RenderTarget` as the camera's `targetTexture`, forces the camera to `Render()` to this texture, and then reads the rendered contents into the specified `Texture2D`. After this process, it must reset the camera's `targetTexture`, such that it renders back to the game's main display, such that it can be inspected visually. The `Texture2D` however can be then be read pixel by pixel and thus converted to an array or string. As it was decided that the resulting display only differentiates between track, curb and off, the cameras use a `Culling Mask` that visually filter out all other gameObjects.

Recording training data²²

For the game to be played by an AI agent, data of the environment must be recorded in regular intervals, to either be sent to the agent in the case of it playing the game or learning via reinforcement learning, or to be exported to a file, which an agent can perform pretraining on. In the following sections, I will not talk about what those data exactly looks like, but only how it is saved and sent. Because of that, I will refer to this data under the name vectors, which are in detail explained in section **4.3.1**. Collecting the latest vectors happens in the function `GetAllInfos()` of `AiInterface.cs`, which calls a number of functions and returns a string containing the combined result of those.

²¹<https://github.com/cstenkamp/BA-rAIce/blob/master/Assets/Scripts/MiniMapScript.cs>

²²<https://github.com/cstenkamp/BA-rAIce/blob/master/Assets/Scripts/Recorder.cs>

As calculating the data that needs to be exported can take relatively much time, this process cannot be performed every `FixedUpdate()`-step. Because of that, the following function is used to perform a function in regular time intervals:

```
1 long currtime = AiInterface.UnityTime();
2 if (currtime - lasttrack >= Consts.trackAllXMS) {
3     lasttrack = lasttrack + Consts.trackAllXMS;
4     SVLearnUpdateList ();
5 }
```

Where `AiInterface.UnityTime()` returns Unity's internal time by calling `Time.time * 1000`. Using this definition of time has the advantage that it is maximally precise inside Unity, as the time of calling `FixedUpdate()` is likewise dependant on `Time.time`. A disadvantage of this measurement of time is however, that it can only be used in the main thread and asynchronous methods must rely on the system's time, for which no conversion method exists.

Once user selects the Train AI supervisedly mode, Recorder's `void StartedSV_SaveMode()` gets called, which enables the minimap-cameras and sets `SV_SaveMode = true`. If that variable is `true`, the recorder will in its `StartList()` create a new `SVLearnLap = new List<TrackingPoint> ()`. `TrackingPoint` itself is a class defined in `Recorder.cs`, that contains certain values about the state of the game, if provided at creation. While driving, the recorder checks every `FixedUpdate()`-step with the mentioned method if it calls `SVLearnUpdateList()`. This method then collects the recent values for the currently performed actions, laptime, progress and speed as well as the respectively latest Vectors, creates a `TrackingPoint` from those and updates the `SVLearnLap` with it. When the RecordingSystem's `FinishList` function is called upon the next crossing of the start/finish line, the `SVLearnLap` is saved to a file. As the vectors can contain multiple pixel matrices from the minimapcameras, this may however take quite long. To prevent the game from freezing everytime the car passes the start/finish line, the saving of the actual file is performed in a separate thread.

Because the agent using this exported data is written in another programming language than the environment, the data cannot be exported as binary file. In this implementation, it was decided to save the data in the XML-format. It is worth mentioning that not only the List of `TrackingPoint` is exported, but also additional meta-information, stating among others the interval of how often a `TrackingPoint` was exported, which can be interpreted and used by an agent as well as manually inspected.

Communicating with an agent^{23,24}

As already mentioned, the game is running live and is in general not stopped by the agent, as done for example when interfacing with the openAI gym (section 3.1). Because of that, the speed of communication between agent and environment is a bottleneck in how good an agent can perform, and needs to be as fast and efficiently implemented as possible. To ensure quick reaction times, it was also decided that agent and game must run on the same machine, as sending the data to another machine increases the needed time drastically²⁵.

²³<https://github.com/cstenkamp/BA-rAIce/blob/master/Assets/Scripts/AiInterface.cs>

²⁴<https://github.com/cstenkamp/BA-rAIce/blob/master/Assets/Scripts/AsyncClient.cs>

²⁵This is the reason this project was implemented entirely under Windows: There is no stable Unity Editor for Linux, and there is no contemporary GPU-supporting TensorFlow under Mac. The only common ground for which both are available is therefore the Windows platform.

In the scope of this thesis, it was experimented a lot with the flow of communication between agent and environment, with the current version as its most efficient one so far. While there are multiple possibilities of how two different programming languages can communicate with each other (for example *zero-mq*, *named pipes* or *shared memory*), it was decided to use Sockets for the communication. In most use cases, sockets are used to communicate over the internet, which is why they normally abstract data over several layers, before being sent to another machine. When both sockets are on the same machine and communicate over localhost however, the unnecessary layers are skipped, making a connection over sockets very efficient²⁶. Using the current implementation, reaction times with an average of 30ms were archived (including the network inference), which is fast enough for all purposes.

Communication over sockets generally asymmetric: There must always be a Server and one or more Clients, both of which contain instances of the class `Socket`. Upon being started, the server registers a server-socket at a certain Port of the machine, where it can be found by clients. It is only possible for clients to connect to it as long as the server keeps up this socket, which is why it is advisable to do so in a separate thread. When a client is started, it needs to know the IP-adress of the server (in this case localhost), as well as the number of the port the corresponding socket waits at. Once the client finds a waiting server-socket behind the port, it is common practice that the server creates a new socket at another port. While this new socket represents a stable connection between server and client, the original server-socket can keep on waiting for new clients to connect to in the future. One characteristic when using sockets as means of communication is, that the communicating sockets need to know the length of a message, to know when to stop reading the input stream. To do that, the length of each message will be transmitted with it.

In this project it was decided that the game functions as a client, whereas the server is written in python. This fits the scheme of the implementation, where the main loop happens in python, with the game only considered as an additional thread providing the agent's input (as can be seen in figure 4.1).

If the Drive AI mode was selected in the game's `menu`, the `AiInt` (an instance of the class `AiInterface`¹²) calls its function `StartedAIMode()`, which, next to calling the known `PrepareVision` of the cameras, creates two instances of `AsynchronousClient`, a class defined in `AsyncClient.cs`²⁷

the function `LoadAndSendToPython`.

-warum ich senden und empfangen mit nem DIFFERENT socket mache (dann ist in 2 threads und kann asynchrhon sein aka nichta ufgehalten werden) -dass es entweder raw data oder special commands schickt

-nochmal drauf eingehen dass das spiel live ist -das von leon gemalte ablaufdiagramm

4.2.3 The agent²⁸

As already explained, the implementation at hand differs in its program flow from other implementations, as the environment cannot be specified in a separate class,

²⁶As is explained by alleged former Microsoft networking developer Jeff Tucker in this Stackoverflow-thread: <http://stackoverflow.com/questions/10872557/how-slow-are-tcp-sockets-compared-to-named-pipes-on-windows-for-localhost-ipc>

²⁷<https://github.com/cstenkamp/BA-rAIce/blob/master/Assets/Scripts/AsyncClient.cs>

²⁸I will rely heavily on UML sequence diagrams and class diagrams to explain program flow and classes of agents. In case a reader is unfamiliar with the standards of UML 2.0, it is referred to e.g. <https://www.ibm.com/developerworks/rational/library/3101.html> for sequence diagrams and <https://www.ibm.com/developerworks/rational/library/content/RationalEdge/sep04/bell/index.html> for class diagrams.

on which the agent can perform a function like `step()` (as in line 9 of algorithm 1). As the closest equivalent to such a class, the file `server.py`²⁹ (from now on called `server`) contains the thread-safe class `InputValContainer` that provides explicit functions to read its state. Upon executing the server, an instance `inputval` of type `InputValContainer` is created. This instance is known to objects that read or write from it through `containers`, an instance of the class `Containers`. This class contains references to several objects and settings that must be known to multiple objects and functions, which can thus for example easily access the mentioned input-value as `containers.inputval`.

It is further important to keep in mind, that the server receives *raw data* from the client, and not a tuple consisting of `observation`, `reward`, `done`. The raw data is forwarded to the agent, which calculates the respective *features* on its own. The next section will detail how the server initiates threads needed for the communication with the environment, before leading over to the main loop of the learning process.

Communicating with an environment

The behaviour that will be explained is represented graphically in the sequence diagram in figure 4.1.

The main loop of the agent is started by the `main`-method of the server. Upon execution of the this file, it interprets any passed arguments and starts the method. To allow a fast communication with the game, the main loop of the server is multi-threaded, such that a stable socket-connection to Unity can be preserved while the agent performs its actions in another thread. This may lead to some objects being accessed by different threads (like for example `outputval`), which requires a thread-safe implementation of them.

In its `main`-method, the server creates two server-sockets³⁰, one on the receiver-port (which is equal to Unity's sender-port), and another one on the sender-port (Unity's receiver-port). Afterwards, the server creates an agent (which one will be explained later), the `InputValContainer` `inputval` as well as an `OutputValContainer` termed `outputval` and assigns all their references to `containers`. Once those are created, the server starts two threads, more precisely a `ReceiverListenerThread` and a `SenderListenerThread`. These threads use their respective server-socket they know through `containers`, and wait on their port by calling the socket's `accept()`-method over and over.

Once a client connects to one of those listener-sockets, a new connected socket is created. Using this socket, a `receiver_thread` or `sender_thread` is created respectively, representing a stable connection to Unity. After creating this thread, the `ListenerThread` lets `containers` know about its reference (by appending it to `containers.receiverthreads` or `containers.senderthreads`) and starts its listening-loop over again. This means that during runtime, the two `ListenerThreads` are always active. If for some reason the old `receiver_thread` or `sender_thread` loses its connection, the `ListenerThreads` will simply establish a new one and create a new thread. Both `receiver_thread` and `sender_thread` contain a method to destroy themselves if needed, such that at any time there is exactly one thread responsible for the connection with Unity.

It was experimented with an explicit learn-thread, which runs in parallel to all other threads. As however the very same TensorFlow-model is needed for learning

²⁹<https://github.com/cstenkamp/BA-rAIce-ANN/blob/master/server.py>

³⁰More precisely, the server uses a wrapper-class called `MySocket` (defined in `server.py`), which provides the additional behaviour of prepending the length of the future message to it, such that the socket on the other end knows how much it needs to read.

and inference, doing so in parallel emerged to increase the reaction time of the server from about 30ms to about 300ms. While forcing the inference to run on the CPU and the learning to run on GPU decreased the delay a bit, the performance was still far from satisfactory and the idea was dropped.

While the main thread is constantly running, it does not contribute to the agent's process after initializing all threads and objects. Instead it can, if the agent provides methods to fill it, run the mainloop of the GUI (defined in `infoscreen.py`³¹), which is programmed with the package `tkinter` and must be in the main thread. To allow for side threads to write content to the GUI, its respective widgets (`Text` and `Canvas`) are replaced by thread-safe wrapper-classes using queues. When a side thread wants it to print information, it appends the new content to the queue, whereas the main thread always pops the latest element from that queue to print it. Side threads know those wrappers over the dictionary `containers.screenwidgets` and can call the `write` or `updateCol`-method of the respective element.

The main-thread listens for a termination of the user with `CTRL+C`. Once that occurs, it notifies all other threads to shut down by setting `containers.KeepRunning = False` and waits for their termination by `joining` them, such that the main thread is guaranteed to be the last to finish.

The main loop

In the `receiver_thread`, the socket is constantly waiting for data. When it receives data, it first checks if it was the usual raw data used for the agent's observation/reward or a *special command*. If it was the latter, the `receiver_thread` calls the function `handle_special_commands` from the agent which will, according to its preferences, terminate the episode (for which it resets `inputval` and `outputval` and notifies the environment to reset itself, more on that later).

If the data was no such command, the `receiver_thread` updates the `inputval` and starts an inference of the agent by calling its method `performAction`, passing the latest content of the `inputval`. This method is where the agent calculates its observation/reward, adds this to his replay memory, calculates the action on basis of its model and performs learning steps as appropriate. Immediately after the action is calculated, the agent updates the `outputval` with the the result. Upon being updated, the `outputval` informs the `sender_thread` of this update. This thread can then read the latest `outputval` and send it back to the client using its socket, which may be simultaneous to the agent performing its learning-step³².

As mentioned above, the `inputval` is the server's closest correspondance of the environment. Every time new raw data from the game is sent to the server, `inputval.update` is called, which then incorporates the new information as well as timestamps of when they were send (used to calculate how long an inference took). Because the information that is sent over the sockets is textual, the method `cutoutandreturnvectors` from the file `read_supervised.py`³³ is called to convert this text back to python-arrays. Note, that there will consistently be made a difference between the content of the minimap-cameras (vision-vector, see 4.2.2) and the other vectors, as they are stored

³¹<https://github.com/cstenkamp/BA-rAIce-ANN/blob/master/infoscreen.py>

³²Note that all of the agent's inference runs thus in the receiver-thread. It was experimented to use an additional agent-thread that in regular intervals looks if the `inputval` was filled with new data, such that the inference of the agent and a waiting to receive new data can occur simulatenously. However, as the agent's inference runs fast enough if it does not perform a learning-step after an inference and too slow in any case if it does, this concept was abandoned.

³³https://github.com/cstenkamp/BA-rAIce-ANN/blob/master/read_supervised.py

solely by index. This allows to add new vectors easily, as only a name of the new feature must be added in the definition of `otherinputs` in the file `read_supervised.py`

The `inputval` contains arrays to store the history of vision-vectors (`vvec_hist`), `otherinputs` (`otherinput_hist`) as well as an array for the history of performed actions (`action_hist`). In its `update`-method, it normalizes the `otherinputs` and appends it as well as the latest vision-vectors, where it merges both into the `vvec_hist`. To reduce the computational load, the `inputval` does not contain the entire history of the game. As already explained, it contains a superset of the observations of the actual agent, which likely contains much superfluous information. To reduce the working memory load it causes, the `inputval` only saves the latest information send from the game, which corresponds to the maximum of information an agent *could know* about the last or second to last state. After appending the newest vectors to the value, the `inputval` also checks if the car faced into the wrong direction for a certain amount of time and notifies the agent if so, such that the agent can optionally reset the environment.

Furthermore, the `inputval` defines a `read(pastState=False)`-method, such that an agent can access the information needed for its observation of the latest two states. This method unpacks and returns the respective vision-vector history of both minimap-cameras, the `otherinput_hist` as well as the `action_hist`. It is necessary that also the information about the penultimate state can be obtained, as the agent must add a full tuple of $\langle s_t, a_t, r_t, s_{t+1}, t + 1 == t_t \rangle$ to its replay memory (see chapter 2.3.1) to perform Q-learning.

The `outputval` is less complex than the `inputval`, and only contains the latest result of the inference. When its `update`-method is called, it adds the action to the `inputval` (because the corresponding action to the environment could otherwise not be known) and goes on notifying a `sender_thread` that new information can be sent to Unity in its method `send_via_senderthread`. This method is also called when the client needs to be paused (by sending "pleaseFreeze"), needs to continue (`pleaseUnFreeze`) or needs to reset (by sending "pleasereset"). The function `resetUnityAndServer` combines sending the reset-command to Unity and resetting `inputval` and `outputval`.

Agent-independent features

All of the above explained functionality is necessary for the agent to learn the given game, and has turned out this way due to certain design choices (like the agent deciding itself when to reset the environment) and peculiarities of the necessary proprietary communication with the game. As the game is its own thread, it is constantly running and does not wait while the agent calculates the action (the space between `send(data)` and `send(content)` in the leftmost column of figure 4.1). While this makes it necessary for the agent be quick, it provides the advantage that a user inspect the live environment and inspect it at will. If inside Unity the `[H]`-key is pressed, the actions the agent suggested are overwritten, however the agent still gets input from the environment. If an agent features a GUI, the Q-values and rewards of the states a user drives will be printed to screen, including the agent's suggested action.

When talking about the `inputval`, it was mentioned that it contains as much information as an agent *could* know. In this implementation, there are some features that are clearly specific to an agent, while others are general settings independent of the current agent. Those are stored in the file `config.py`³⁵, while the settings of the agent are saved in the respective file of the agent. Note that the value `msperframe`,

³⁵<https://github.com/cstenkamp/BA-rAIce-ANN/blob/master/config.py>

which specifies in what interval the agent performs actions, must always equal to its correspondance in Unity, `Consts.updatepythonintervals`. The value for the maximum number of history frames, `history_frame_nr`, is currently set to four.

The agents

Until it gets to the agent, neither the observation nor the reward is set. Thus, the agent needs to specify its own functions for its observation (given environment-state) and reward (given state and action). Furthermore, the server notifies the agent of specific events that happened in the game, to which the agent could react by resetting the environment and starting a new episode. These methods, next to the obvious ones of performing an action or conducting a learning-step, must thus be specified by an agent. When describing the agent in this section, only those functions are relevant, as the inner workings of the server are hidden to the agent.

To ease the implementation of agents, they all inherit from a superclass called `AbstractAgent` as well as a class termed `AbstractRLAgent`, both of which are defined in `agent.py`³⁶. The key idea is, that all functions and features mutual to all agents are set in these classes, such that any specific agent must only implement/overwrite the functions in which it differs from its superclasses. Because not all agents use reinforcement learning, it was decided to use two superclasses instead of only one – the class `AbstractAgent` does for example not specify a memory, as a purely pre-trained agent does not need it.

In the scope of this thesis, multiple agents where developed, using different models, vectors and approaches. In the final version of the implementation there are five exemplary agents left, which can all be found in the folder `agents`³⁷. These agents differ in the model they use, if they use the vision-vector and if they rely on supervised pretraining, as will be detailed in chapter 5. Figure 4.2 depicts the inheritance-relation of an agent and its super-classes using an UML-diagram.

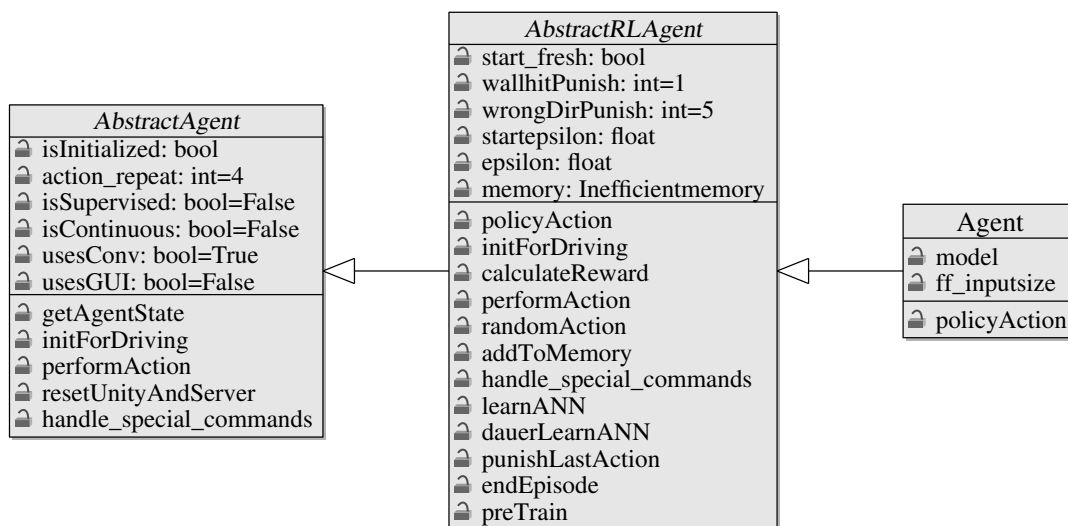


FIGURE 4.2: incomplete UML-diagram of an agent and its super-classes

-Hier im Fließtext nur kleine Versionen der UML-Diagramme, und im Anhang dann die vollständigen versionen!

³⁶<https://github.com/cstenkamp/BA-rAIce-ANN/blob/master/agent.py>

³⁷<https://github.com/cstenkamp/BA-rAIce-ANN/tree/master/agents>

Challenges and Solutions

Pretraining

-damit die pretraining-daten genutzt werden können muss ne methode existieren die die gleich macht wie die methode vom memory

The different agents

DQN vs DDPG, sehend vs nicht-sehend, ...

getstatecountfeaturevec macht für das was ich mache mit meiner netzwerk-struktur keinen sinn (256 neurons direkt bevor es in die actions geht)

Models

-die uml-diagramme sind fertig

Network architecture

1. dqn-algorithm - anzahl layer, Batchnorm, doubles dueling - clipping wieder rein, reference auf das dueling - grundsätzlich gegen batchnorm entschieden, siehe reddit post - MIT GRAFIK - Adam und tensorflow quoten, siehe zotero 2. ddpG - anzahl layer, Batchnorm - MIT GRAFIK

-mo -schöne grafik. -auf meinen DQN-config eingehen und(!!!) ne DDPG-config machen, using the "experiment details" vom ddpG paper

In the original DDPG-algorithm [8], the authors used *batch normalization* [6] to have the possibility of using the same network hyperparameters for differently scaled input-values. In the learning step when using minibatches, batch normalization normalizes each dimension across the samples in a batch to have unit mean and variance, whilst keeping a running mean and variance to normalize in non-learning steps. In Tensorflow, batchnorm can be added with an additional layer and an additional input, specifying the phase (learning step/non-learning step)³⁸. Though Lillicrap et al. seemed to have success on using batch normalization, in practice it lead to unstability, even on simple physics tasks in openAI's gym. As I am not the only one having this issue ³⁹, I left out batch normalization for good.

4.3 Possible features

4.3.1 The vectors

-die mit * oder so markieren die von leon kommen!! -auf den screenshot eingehen für walldistvec!

4.3.2 Exploration

4.3.3 Reward

4.3.4 Pre-training

4.3.5 Performance measure

³⁸cf. https://www.tensorflow.org/api_docs/python/tf/contrib/layers/batch_norm

³⁹redditlink

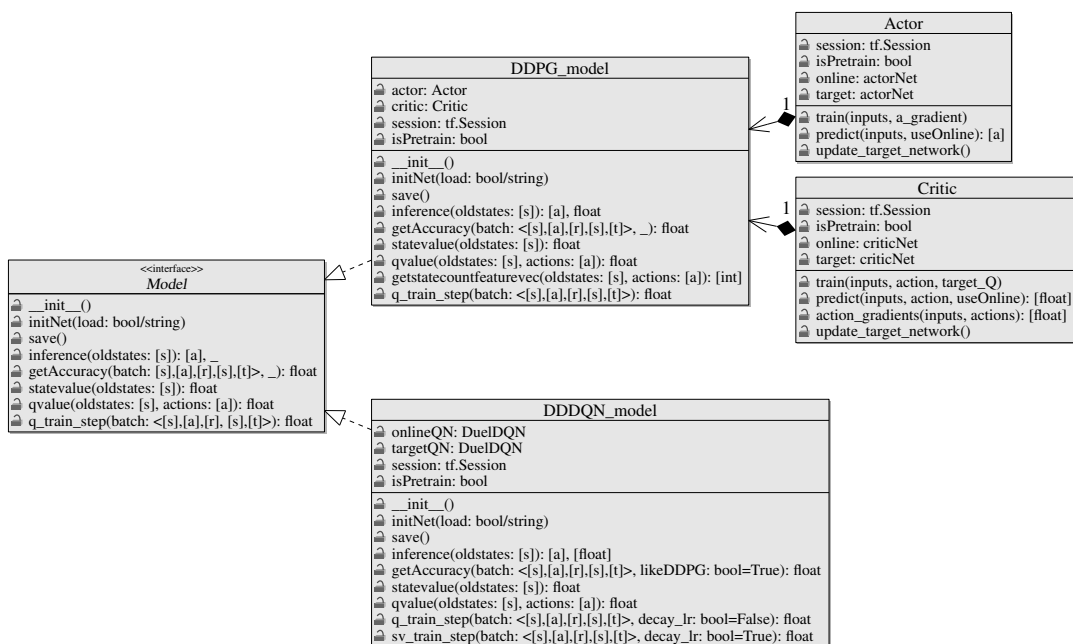
Chapter 5

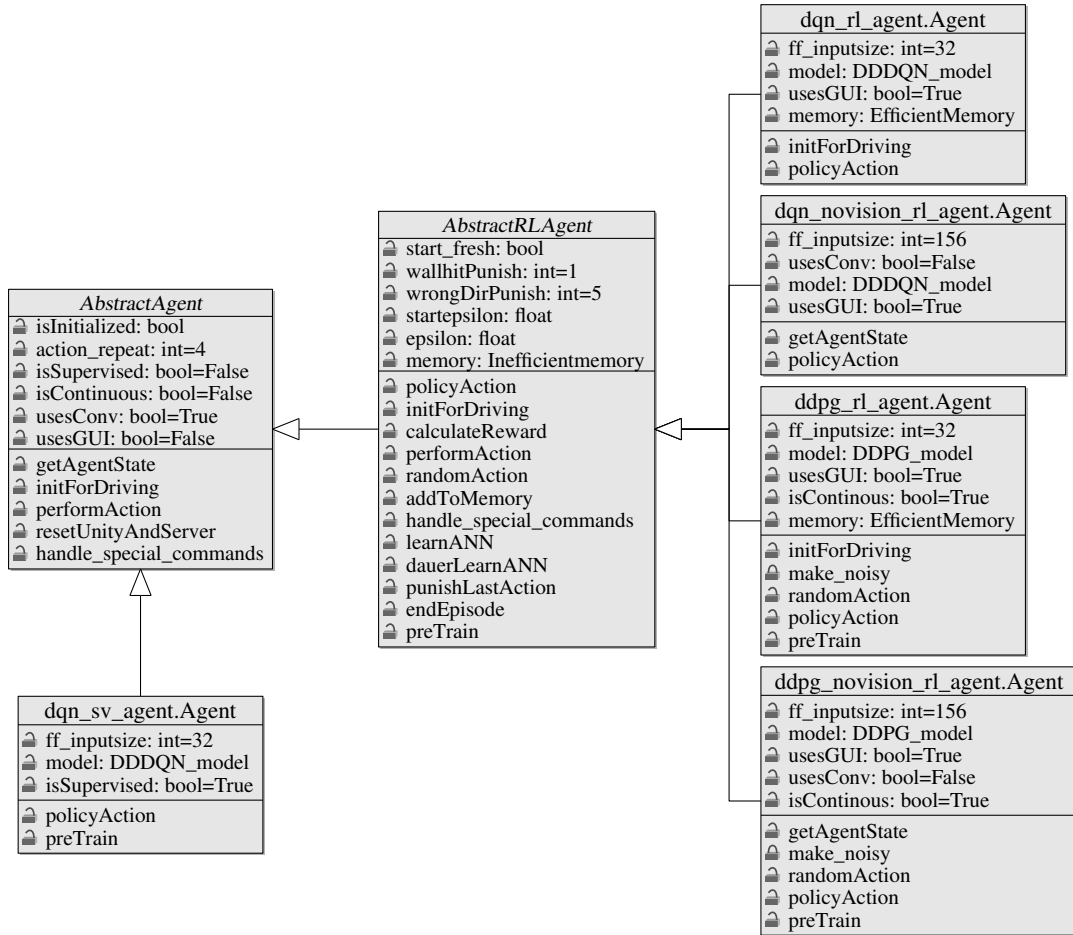
Analysis, Results and open Questions

testing took place on a win10 machine, ... Answer all of the research questions explicitly!!!

-result: mein way of incorporating pretraining -dass ein supervised agent nicht lernen kann da er immer in die wand brettet -parameter selection gehört hier rein!!

filename	uses model	uses visionvector	performs RL
ddpg_novision_rl_agent.py	DDPG	no	yes
ddpg_rl_agent.py	DDPG	yes	yes
dqn_novision_rl_agent.py	DQN	no	yes
dqn_rl_agent.py	DQN	yes	yes
dqn_sv_agent.py	supervised network with DQN-structure	yes	no





Chapter 6

Discussion

-dass es zur beschleunigung möglich wäre mehrere aggregatoren zu haben, die immer die recht aktuellste policy haben und mit unity interagieren und das nem learn-thread schicken, auf verschiedenen Maschinen

"Fragestellung aus der Einleitung wird erneut aufgegriffen und die Arbeitsschritte werden resümiert" Zusammen mit der Conclusion 10% der Gesamtlänge

Chapter 7

Conclusion and future directions

Die paper die bei openAI erwähnt waren die das ganze in viel kreasser sind, die Dota spielen können etc!

Appendix A

Comparison Pseudocode & Python-code

A.1 DQN

The following section describes the structure of an actual reinforcement learning agent, using a **Dueling Deep-Q-Network** as its model (as described in [18]), performing **Double Q-learning** (as described in [5]). The last page consists of a comparison between the pseudocode of the general program flow of a DDQN-network (taken from [10], with changes from [5] and [8] in blue) to the left and its corresponding python-code to the right, where each line of the pseudocode corresponds exactly to the respective line of the python-code. For information on which python- and tensorflow version are used, please see chapter+4. This code is extracted from the actual implementation within the scope of this thesis, with some changes abstracting away irrelevant details.

```

1  class Agent():
2  def __init__(self, inputsize):
3      self.inputsize = inputsize
4      self.model = DDDQN_model
5      self.memory = Memory(10000, self) #for definition see code
6      self.action_repeat = 4
7      self.update_frequency = 4
8      self.batch_size = 32
9      self.replaystartsize = 1000
10     self.epsilon = 0.05
11     self.last_action = None
12     self.repeated_action_for = self.action_repeat

14     def runInference(self, gameState, pastState):
15         self.addToMemory(gameState, pastState)
16         inputs = self.getAgentState(*gameState)
17         self.repeated_action_for += 1
18         if self.repeated_action_for < self.action_repeat:
19             toUse, toSave = self.last_action
20         else:
21             self.repeated_action_for = 0
22             if self.canLearn() and np.random.random() > self.epsilon:
23                 action, _ = self.model.inference(inputs)
24                 toSave = self.dediscretize(action[0])
25                 toUse = "["+str(throttle)+", "+str(brake)+", "+str(steer)+"]"
26             else:
27                 toUse, toSave = self.randomAction() #for definition see code
28             self.last_action = toUse, toSave
29         self.containers.outputval.update(toUse, toSave)
30         self.numsteps += 1
31         if self.numsteps % self.update_frequency == 0 and len(self.memory) > self.replaystartsize:
32             self.learnStep()

34     def learnStep(self):
35         QLearnInputs = self.memory.sample(self.batch_size)

```

```

36     self.model.q_learn(QLearnInputs)

38     def addToMemory(self, gameState, pastState):
39         s = self.getAgentState(*pastState) #for definition see code
40         a = self.getAction(*pastState) #for definition see code
41         r = self.calculateReward(*gameState)#for definition see code
42         s2= self.getAgentState(*gameState) #for definition see code
43         t = False #will be updated if episode did end
44         self.memory.append([s,a,r,s2,t])

47     class DuelDQN():
48     def __init__(self, name, inputsize, num_actions):
49         with tf.variable_scope(name, initializer = tf.random_normal_initializer(0, 1e-3)):
50             #for the inference
51             self.inputs = tf.placeholder(tf.float32, shape=[None, inputsize], name="inputs")
52             self.fc1 = tf.layers.dense(self.inputs, 400, activation=tf.nn.relu)
53             #modifications from the Dueling DQN architecture
54             self.streamA, self.streamV = tf.split(self.fc1,2,1)
55             xavier_init = tf.contrib.layers.xavier_initializer()
56             neutral_init = tf.random_normal_initializer(0, 1e-50)
57             self.AW = tf.Variable(xavier_init([200,self.num_actions]))
58             self.VW = tf.Variable(neutral_init([200,1]))
59             self.Advantage = tf.matmul(self.streamA,self.AW)
60             self.Value = tf.matmul(self.streamV,self.VW)
61             self.Qout = self.Value + tf.subtract(self.Advantage,tf.reduce_mean(self.Advantage,axis=1,keep_dims=
                ↳ True))
62             self.Qmax = tf.reduce_max(self.Qout, axis=1)
63             self.predict = tf.argmax(self.Qout,1)
64             #for the learning
65             self.targetQ = tf.placeholder(shape=[None],dtype=tf.float32)
66             self.targetA = tf.placeholder(shape=[None],dtype=tf.int32)
67             self.targetA_OH = tf.one_hot(self.targetA, self.num_actions, dtype=tf.float32)
68             self.compareQ = tf.reduce_sum(tf.multiply(self.Qout, self.targetA_OH), axis=1)
69             self.td_error = tf.square(self.targetQ - self.compareQ)
70             self.q_loss = tf.reduce_mean(self.td_error)
71             q_trainer = tf.train.AdamOptimizer(learning_rate=0.00025)
72             q_OP = q_trainer.minimize(self.q_loss)
73             self.trainables = tf.get_collection(tf.GraphKeys.TRAINABLE_VARIABLES, scope=name)

76     def _netCopyOps(fromNet, toNet, tau = 1):
77         op_holder = []
78         for idx,var in enumerate(fromNet.trainables[:]):
79             op_holder.append(toNet.trainables[idx].assign((var.value()*tau) + ((1-tau)*toNet.trainables[idx].
                ↳ value())))
80     return op_holder

```

```

1 Initialize replay memory  $D$  to capacity  $N$ 

5 Initialize action-value function  $Q(s, a; \theta)$  with random weights  $\theta$ 

8 Initialize target action-value function  $Q(s, a; \theta^-)$  with weights  $\theta^- = \theta$ 
For episode = 1,  $M$  do
10 Initialize sequence  $s_1 = \{x_1\}$  and preprocessed sequence  $\phi_1 = \phi(s_1)$ 
For  $1 = 1, T$  do
12 With probability  $\epsilon$  select random action  $a_t$ 
13 otherwise select  $a_t = \operatorname{argmax}_a Q(\phi(s_t), a; \theta)$ 

15 Execute action  $a_t$  in emulator and observe reward  $r_t$  and image  $x_{t+1}$ 
16 Set  $s_{t+1} = s_t, a_t, x_{t+1}$  and preprocess  $\phi_{t+1} = \phi(s_{t+1})$ 
17 Store transition  $(\phi_t, a_t, r_t, \phi_{t+1})$  in  $D$ 

19 Sample random minibatch of transitions  $(\phi_j, a_j, r_j, \phi_{j+1})$  from  $D$ 
20 Define  $a^{max}(\phi_{j+1}; \theta) = \operatorname{argmax}_a Q(\phi_{j+1}, a'; \theta)$ 
21 Define  $Q^{j+1} = Q(\phi_{j+1}, a^{max}(\phi_{t+1}; \theta); \theta^-)$ 

23 If episode terminates at step  $j + 1$  then set  $y_j = r_j$ ,
     $\hookrightarrow$  Otherwise set  $y_j = r_j + \gamma * Q^{j+1}$ 

24 Perform a gradient descent step on  $(y_j - Q(\phi_j, a_j; \theta))^2$  with respect
     $\hookrightarrow$  to the network parameters  $\theta$ 
25 Update target network:  $\theta^- \leftarrow \tau * \theta + (1 - \tau) \theta^-$ 
End For
26 End For

```

```

1 #see agent
2 class DDDQN_model():
3     def __init__(self, sess, inputsize, num_action):
4         self.sess = sess
5         self.onlineQN = DuelDQN("onlineNet", inputsize, num_action)
6         self.targetQN = DuelDQN("targetNet", inputsize, num_action)
7         self.sess.run(tf.global_variables_initializer())
8         self.sess.run(_netCopy0ps(self.targetQN, self.onlineQN))
9
10    #see agent
11    def inference(self, statesBatch): #called for every step t
12
13        return self.sess.run([self.onlineQN.predict, self.onlineQN.Qout], feed_dict={
14             $\hookrightarrow$  self.onlineQN.inputs: statesBatch})
15
16        #see agent
17        #see agent
18        def q_learn(self, batch): #also called for every step t
19            oldstates, actions, rewards, newstates, terminals = batch
20            action = self.sess.run(self.onlineQN.predict, {self.onlineQN.inputs:newstates
21                 $\hookrightarrow$  })
22            folgeQ = self.sess.run(self.targetQN.Qout, {self.targetQN.inputs:newstates})
23            doubleQ = folgeQ[range(len(terminals)),action]
24            consider_stateval = -(terminals - 1)
25
26            targetQ = rewards + (0.99 * doubleQ * consider_stateval)
27            self.sess.run(self.onlineQN.q_OP, feed_dict={self.onlineQN.inputs:oldstates,
28                 $\hookrightarrow$  self.onlineQN.targetQ:targetQ, self.onlineQN.targetA:actions})
29            self.sess.run(_netCopy0ps(self.onlineQN, self.targetQN, 0.001))
30        return

```

A.2 DDPG

The following section describes the structure of an actual reinforcement learning agent, using an **actor-critic architecture** as its model, basing on the Deep Deterministic Policy gradient, as described in [15] and [8]. The last page consists of a comparison between the pseudocode of the general program flow of a DDPG-agent (taken from [8]) to the left and its corresponding python-code to the right, where each line of the pseudocode corresponds exactly to the respective line of the python-code. For information on which python- and tensorflow version are used, please see chapter 4. This code is extracted from the actual implementation within the scope of this thesis, with some changes abstracting away irrelevant details.

```

1  class Actor(object):
2  def __init__(self, inputs_size, num_actions, action_bounds, session):
3      with tf.variable_scope("actor"):
4          self.online = lowdim_actorNet(inputs_size, num_actions, action_bounds)
5          self.target = lowdim_actorNet(inputs_size, num_actions, action_bounds, name="target")
6          self.smoothTargetUpdate = _netCopyOps(self.online, self.target, 0.001)
7          # provided by the critic network
8          self.action_gradient = tf.placeholder(tf.float32, [None, num_actions], name="actiongradient")
9          self.actor_gradients = tf.gradients(self.online.scaled_out, self.online.trainables, -self.
           ➡ action_gradient)
10         self.optimize = tf.train.AdamOptimizer(1e-4).apply_gradients(zip(self.actor_gradients, self.online.
           ➡ trainables))
11 def train(self, inputs, a_gradient):
12     self.session.run(self.optimize, feed_dict={self.online.ff_inputs:inputs, self.action_gradient:
           ➡ a_gradient})
13 def predict(self, inputs, which="online"):
14     net = self.online if which == "online" else self.target
15     return self.session.run(net.scaled_out, feed_dict={net.ff_inputs:inputs})
16 def update_target_network(self):
17     self.session.run(self.smoothTargetUpdate)
18
19 class Critic(object):
20 def __init__(self, inputs_size, num_actions, session):
21     with tf.variable_scope("critic"):
22         self.online = lowdim_criticNet(inputs_size, num_actions)
23         self.target = lowdim_criticNet(inputs_size, num_actions, name="target")
24         self.smoothTargetUpdate = _netCopyOps(self.online, self.target, 0.001)
25         self.target_Q = tf.placeholder(tf.float32, [None, 1], name="target_Q")
26         self.loss = tf.losses.mean_squared_error(self.target_Q, self.online.Q)
27         self.optimize = tf.train.AdamOptimizer(1e-3).minimize(self.loss)
28         self.action_grads = tf.gradients(self.online.Q, self.online.actions)
29 def train(self, inputs, action, target_Q):
30     return self.session.run([self.optimize, self.loss], feed_dict={self.online.ff_inputs:inputs, self.
           ➡ online.actions: action, self.target_Q: target_Q})
31 def predict(self, inputs, action, which="online"):
32     net = self.online if which == "online" else self.target
33     return self.session.run(net.Q, feed_dict={net.ff_inputs:inputs, net.actions: action})
34 def action_gradients(self, inputs, actions):
35     return self.session.run(self.action_grads, feed_dict={self.online.ff_inputs:inputs, self.online.
           ➡ actions: actions})
36 def update_target_network(self):
37     self.session.run(self.smoothTargetUpdate)
38
39 def _netCopyOps(fromNet, toNet, tau = 1):

```

```

40 op_holder = []
41 for idx,var in enumerate(fromNet.trainables[:]):
42     op_holder.append(toNet.trainables[idx].assign((var.value()*tau) + ((1-tau)*toNet.trainables[idx].
        ↳ value())))
43 return op_holder

45 def dense(x, units, activation=tf.identity, decay=None, minmax = float(x.shape[1].value) ** -.5):
46     return tf.layers.dense(x, units,activation=activation, kernel_initializer=tf.
        ↳ random_uniform_initializer(-minmax, minmax), kernel_regularizer=decay and tf.contrib.layers.
        ↳ l2_regularizer(1e-2))

48 class lowdim_actorNet():
49     def __init__(self, inputs_size, num_actions, actionbounds, outerscope="actor", name="online"):
50         tanh_min_bounds,tanh_max_bounds = np.array([-1]), np.array([1])
51         min_bounds, max_bounds = np.array(list(zip(*actionbounds)))
52         self.name = name
53         with tf.variable_scope(name):
54             self.ff_inputs = tf.placeholder(tf.float32, shape=[None, inputs_size], name="ff_inputs")
55             self.fc1 = dense(self.ff_inputs, 400, tf.nn.relu, decay=decay)
56             self.fc2 = dense(self.fc1, 300, tf.nn.relu, decay=decay)
57             self.outs = dense(self.fc2, num_actions, tf.nn.tanh, decay=decay, minmax = 3e-4)
58             self.scaled_out = ((self.outs - tanh_min_bounds)/ (tanh_max_bounds - tanh_min_bounds)) * (
        ↳ max_bounds - min_bounds) + min_bounds)
59             self.trainables = tf.get_collection(tf.GraphKeys.TRAINABLE_VARIABLES, scope=outerscope+"/"+self.
        ↳ name)

61 class lowdim_criticNet():
62     def __init__(self, inputs_size, num_actions, outerscope="critic", name="online"):
63         self.name = name
64         with tf.variable_scope(name):
65             self.ff_inputs = tf.placeholder(tf.float32, shape=[None, inputs_size], name="ff_inputs")
66             self.actions = tf.placeholder(tf.float32, shape=[None, num_actions], name="action_inputs")
67             self.fc1 = dense(self.ff_inputs, 400, tf.nn.relu, decay=True)
68             self.fc1 = tf.concat([self.fc1, self.actions], 1)
69             self.fc2 = dense(self.fc1, 300, tf.nn.relu, decay=True)
70             self.Q = dense(self.fc2, 1, decay=True, minmax=3e-4)
71             self.trainables = tf.get_collection(tf.GraphKeys.TRAINABLE_VARIABLES, scope=outerscope+"/"+self.
        ↳ name)

```

4	Randomly initialize critic network $Q(s, a \theta^Q)$ with weights θ^Q	1	class DDPG_model():
5	and actor $\pi(s \theta^\pi)$ with weights θ^π .	2	def __init__(self, session):
7	Initialize target network Q' weights $\theta^{Q'} \leftarrow \theta^Q$	3	self.session = session
8	and π' with weights $\theta^{\pi'} \leftarrow \theta^\pi$	4	self.critic = Critic(self.session)
9	Initialize replay buffer R	5	self.actor = Actor(self.session)
10	for episode = 1, M do	6	self.session.run(tf.global_variables_initializer())
11	Initialize a random process \mathcal{N} for action exploration	7	self.session.run(_netCopyOps(self.actor.target, self.actor.online))
12	Receive initial observation state s_1	8	self.session.run(_netCopyOps(self.critic.target, self.critic.online))
13	for t = 1, T do	9	#replay buffer defined by the agent
14	Select action $a_t = \pi(s_t \theta^\pi) + \mathcal{N}_t$ according to the current policy and ➔ exploration noise	11	#exploration noise added by the agent
15	Execute action a_t and observe reward r_t and observe new state s_{t+1}	12	#agent samples all observations
16	Store transition (s_t, a_t, r_t, s_{t+1}) in R	13	def inference(self, oldstates): #called for every step t
18	Sample a random minibatch of N transitions (s_t, a_t, r_t, s_{t+1}) from R	14	return self.actor.predict(oldstates, "target", is_training=False)
19	targetActorAction = $\pi'(s_{t+1} \theta^{\pi'})$	15	#agent adds exploration noise afterwards
20	targetCriticQ = $Q'(s_{t+1}, \text{targetActorAction} \theta^{Q'})$	16	#done by the agent
21	Set $y_i = r_i + \gamma * \text{targetCriticQ}$ #only in nonterminal states	17	#done by the agent
23	Update critic by minimizing the loss: $L = \frac{1}{N} \sum_i (y_i - Q(s_i, a_i \theta^Q))^2$	18	def train_step(self, batch): #also called for every step t
24	Find the sampled policy gradient:	19	oldstates, actions, rewards, newstates, terminals = batch
25	a.i = $\pi(s_i \theta^\pi)$	20	targetActorAction = self.actor.predict(newstates, "target")
26	$\nabla_{\theta^\pi} J \approx \frac{1}{N} \sum_i \nabla_a Q(s_i, a_i \theta^Q) \nabla_{\theta^\pi} \pi(s_i \theta^\pi)$	21	targetCriticQ = self.critic.predict(newstates, targetActorAction, "target")
27	Update the actor policy using the sampled policy gradient	22	cumrewards = np.reshape([rewards[i] if terminals[i] else rewards[i]+0.99* ➔ targetCriticQ[i] for i in range(len(rewards))], (len(rewards), 1))
28	Update the target networks:	23	_, loss = self.critic.train(oldstates, actions, cumrewards)
29	$\theta^{Q'} \leftarrow \tau * \theta^Q + (1 - \tau) \theta^{Q'}$	25	onlineActorActions = self.actor.predict(oldstates)
30	$\theta^{\pi'} \leftarrow \tau * \theta^Q + (1 - \tau) \theta^{\pi'}$	26	grads = self.critic.action_gradients(oldstates, onlineActorActions)
31	end for	27	self.actor.train(oldstates, grads[0])
32	end for	28	#updating the targetnets
		29	self.critic.update_target_network()
		30	self.actor.update_target_network()
		31	return

Appendix B

Screenshots of the game

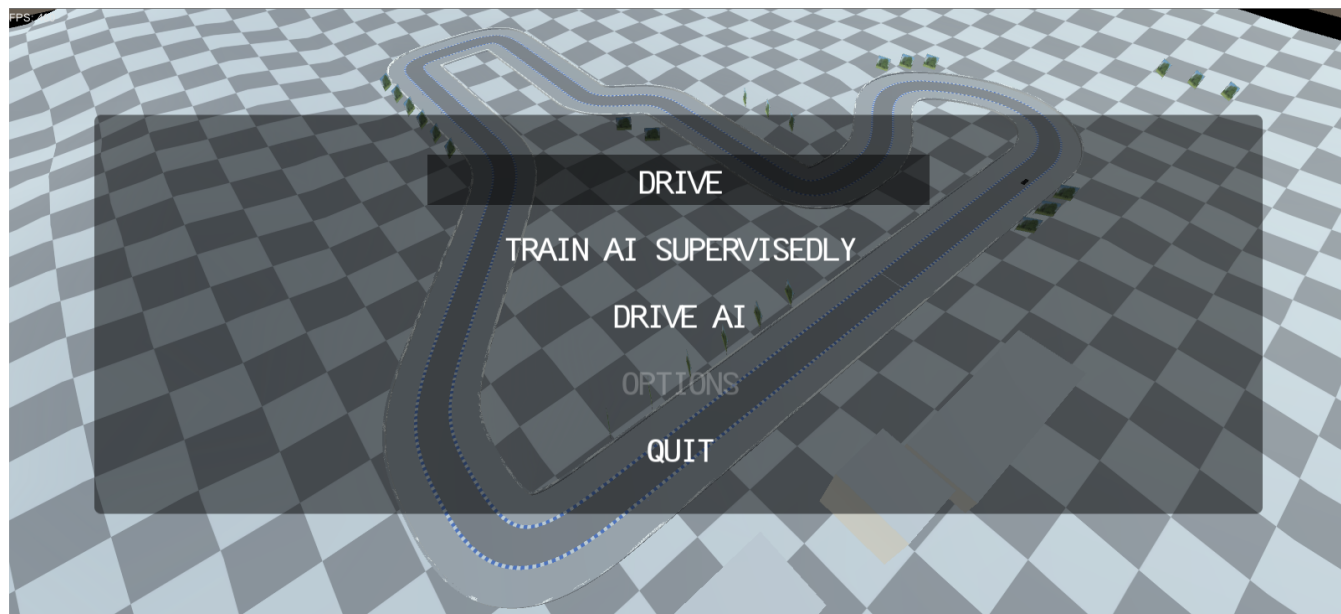


FIGURE B.1: Start screen / menu of the game, also showing a bird-eye view of the track



FIGURE B.2: **Drive** mode. For a description of the UI components, it is referred to section [4.2.1](#)

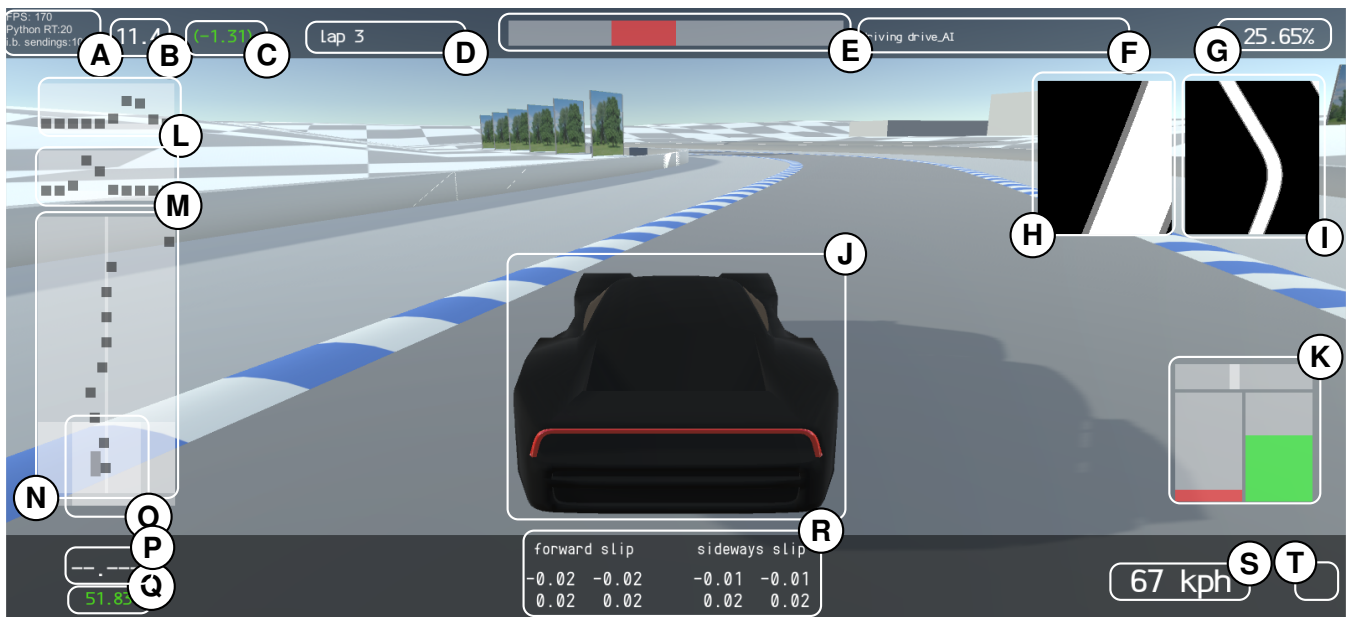


FIGURE B.3: **Drive AI** mode, showing many additional information directly on the screen.
For a description of those, it is referred to sections 4.2.1 and 4.3.1

- **A:** Debug information. Shows FPS, the agent's response time and the time in between two sendings to the agent (the latter two only visible in drive_AI mode).
- **B:** The current lap time in seconds.
- **C:** The time difference of the current lap in comparison to the fastest lap so far.
- **D:** Indicator of the current lap. Also shows if a lap is invalid.
- **E:** Feedback bar, graphically visualizing the time difference of only the current course section in comparison to the fastest lap so far.
- **F:** Indicator for the current game mode. Also indicates if QuickPause is active or if a human interferes in the drive_AI mode.
- **G:** Current track progress in percent.
- **H:** Field of view of the first minimap-camera.
- **I:** Field of view of the second minimap-camera, if enabled.
- **J:** The car. As the main camera is fixed behind it, it will always be in this precise position.
- **K:** Visual representation of the values for steering (top), brake-pedal (bottom left) and throttle pedal (bottom right).
- **L:** Visual representation of the game's `progress-vector`. Only visible in drive_AI and train_AI.
- **M:** Visual representation of the game's `centerDist-vector`. Only visible in drive_AI and train_AI.
- **N:** Visual representation of the game's `lookahead-vector`. Only visible in drive_AI and train_AI.
- **O:** Alternative representation of car's distance to the lane center. Only visible in drive_AI and train_AI. Overlapping with N due to low screen resolution on the machine used for the screenshot.
- **P:** Time needed for the last valid lap in seconds.
- **Q:** Time needed for the fastest valid lap (throughout different sessions) in seconds.
- **R:** Information about slip-behaviour of the car's tires.
- **S:** Speed of the car in kilometers per hour.
- **T:** Indicates a "P" if the car is in reverse gear.

Appendix C

Informal description of the files belonging to the game

Filename	attached to	knows	Start()	Update()	FixedUpdate()	Other behaviour	other functions
UIScripts	Object Hierarchy	all UI components	enable drivingOverlayActive	<ul style="list-style-type: none"> DrivingOverlayHandling: update GUI while driving MenuOverlayHandling: update GUI and listen for input while menu 		onGUI(): Print Debug Information on screen	
GameScripts	Object Hierarchy		<ul style="list-style-type: none"> Sets MiniMapCamera distances Sets menu to menu 	<ul style="list-style-type: none"> enable/disable quit pauses if other threads demand it switch menu to menu on [ESC] 			<ul style="list-style-type: none"> enabling and disabling QuickPause switchboard inclusive the respective calls to initialize the mode
CarController.cs	Car		Sets Car's position	<ul style="list-style-type: none"> Rotates and adjust height of visible wheels Enable reverse gear on R 	<ul style="list-style-type: none"> Sets Car's Forces to zero after a reset handles friction, checks if lap invalid, applies forces to Car 		<ul style="list-style-type: none"> ResetCar and ResetFullPosition AdjustFriction GetSurface
TimingScripts	TimingSystem's Box Collider					OnTriggerExit(): <ul style="list-style-type: none"> sets fast and last lap time calls ResetFinalist and if applicable, Alert EndRound resets activeLap, increases lapcount, ... Starts new lap for Rec 	Other timing-related functions
ConfirmColliderScripts Recorder	TimingSystem's Confirm Collider					OnTriggerExit(): Calls TimingFlipCCTPassed()	

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Declaration of Authorship

I, Christoph Stenkamp, hereby certify that the work presented here is, to the best of my knowledge and belief, original and the result of my own investigations, except as acknowledged, and has not been submitted, either in part or whole, for a degree at this or any other university.

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