Robotic Navigation in Simulated Urban Environments

An investigation on the effect of uncertainty in the observed environment

This dissertation is submitted in part requirement for the Master of Science in Spatial Data Science and Visualisation at the Centre of Advanced Spatial Analysis, Bartlett Faculty of the Built Environment, University College London.

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Date: 30/08/2019

MSc Spatial Data Science and Visualisation, TMSSDSAVIS01

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Word count:

# Abstract

# Declaration

I, Kristian Emil Lunow Nielsen, hereby declare that this dissertation is all my own original work and that all sources have been acknowledged. This dissertation is xxx words in length, from introduction to conclusion inclusive, excluding footnotes. Word count by Word.

Date: 30/08/2019

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Table of Contents

[Abstract 2](#_Toc16538183)

[Declaration 3](#_Toc16538184)

[List of tables 5](#_Toc16538185)

[List of figures 6](#_Toc16538186)

[List of acronyms and abbreviations 7](#_Toc16538187)

[Acknowledgements 8](#_Toc16538188)

[1. Introduction 9](#_Toc16538189)

[1.1 Theoretical background 11](#_Toc16538190)

[1.2 Purpose of the Study 13](#_Toc16538191)

[1.3 Significance of the Study 13](#_Toc16538192)

[1.4 Scope of the Study 14](#_Toc16538193)

[2. Literature Review 15](#_Toc16538194)

[2.1 Reinforcement learning 15](#_Toc16538195)

[2.2 Deep reinforcement learning 20](#_Toc16538196)

[2.2.1 Policy Gradient Methods 20](#_Toc16538197)

[2.2.2 Proximal Policy Optimisation 22](#_Toc16538198)

[2.5 Robotic Navigation in Urban Environments 23](#_Toc16538201)

[2.5.1.1.1 Robotic Navigation in Urban Environments using Reinforcement Learning 25](#_Toc16538202)

[3. Prerequisites 26](#_Toc16538203)

[2.1 Notation 26](#_Toc16538204)

[2.2 Autonomous delivery robots today 26](#_Toc16538205)

[2.3 Unity – as a simulation engine for research in DRL 27](#_Toc16538206)

[2.3.1 The environment 29](#_Toc16538207)

[2.3.1.1 Environment 32](#_Toc16538208)

[2.3.1.1.1 Walls & Obstacles 32](#_Toc16538209)

[2.3.1.1.2 Pedestrians 33](#_Toc16538210)

[2.3.1.1.3 Crowded areas 33](#_Toc16538211)

[2.3.1.2 Academy 35](#_Toc16538212)

[2.3.1.3 Agent 38](#_Toc16538213)

[2.3.1.4 Target 42](#_Toc16538214)

[2.3.1.5 Rewards 42](#_Toc16538215)

[2.3.1.5.1 Extrinsic 43](#_Toc16538216)

[2.3.1.5.2 Intrinsic 43](#_Toc16538217)

[2.3.2 Training 44](#_Toc16538218)

[2.3.2.1 Training hyperparameters 44](#_Toc16538219)

[2.3.3 TensorBoard 45](#_Toc16538220)

[2.4 Curriculum Learning 45](#_Toc16538221)

[3. Exploration/Exploitation trade-off 47](#_Toc16538222)

[3.1 The look of learning 48](#_Toc16538223)

[3.2 Learning to learn 50](#_Toc16538224)

[3.2.1 Curriculum 50](#_Toc16538225)

[3.2.2 Maximum steps allowed for agent 50](#_Toc16538226)

[3.2.3 Shared experience 54](#_Toc16538230)

[3.2.4 Observation stacking 56](#_Toc16538231)

[3.2.5 Using visual input 59](#_Toc16538232)

[Insights: 59](#_Toc16538233)

[Thoughts: 60](#_Toc16538234)

[3.4 Discussion 60](#_Toc16538235)

[Stuff for the discussion: 60](#_Toc16538236)

[3.5 Future work 60](#_Toc16538237)

[4. Policy Evaluation 60](#_Toc16538238)

[5. Appendix 61](#_Toc16538239)

[5.1 Effect of invoking maximum steps 61](#_Toc16538240)

[5.2 Effect of parallelisation 61](#_Toc16538241)

[5.3 Tuning of hyperparameters of the environment 62](#_Toc16538242)

[5.4 Training and Curriculum Learning 63](#_Toc16538243)

[5.5 Environment Configuration 63](#_Toc16538244)

[5.5.1 Environment 63](#_Toc16538245)

[5.5.1.1 Pedestrians 65](#_Toc16538246)

[5.5.2 Academy 68](#_Toc16538247)

[5.5.3 Agent 69](#_Toc16538248)

[5.5.4 Target 70](#_Toc16538249)

[5.5 Effect of restricting the number of steps for the agent 71](#_Toc16538256)

[5.5 Reward Shaping 72](#_Toc16538262)

[5.6 Support scripts 73](#_Toc16538270)

[5.6.1 scalarToCSV 73](#_Toc16538271)

[6. References 73](#_Toc16538272)

# List of tables

# List of figures

# List of acronyms and abbreviations

Net – neural network

Ppo – Proximal Policy Optimisation

RL

DL

DRL

# Acknowledgements

# Introduction

The topic for this dissertation is robotic navigation in simulated urban environments, and the purpose of the study is to explore the use of deep reinforcement learning (DRL) in this context. Deep learning (DL) is an area with growing attention within urban analytics, as urban infrastructure is being transformed by the advances in artificial intelligence and robotics. This motivates exploring DL, through DRL, on a use case, with increasing focus from some of the world’s biggest corporations (Nichols, 2019; FedEx, 2019; Scott, 2019). That case of study of this research is DRL’s ability to deal with some of the challenges faced by robotic citizens, the autonomous delivery robots (ADR’s).

Urban environments are complex dynamics of interactions between objects, and navigation herein requires an ability to explore, foresee, adapt and plan.   
Successful prior work on robotic navigation in crowded urban environments (CUE’s) rely on the use of particle filters, for building a probabilistic map of the environment to handle planning, and a combination of human interaction as well as goal-directed exploration for exploration and adaption of/to the environment (Lidoris et al., 2009; Kümmerle et al, 2013). The need for human interaction limits the autonomous degree of the robot, potentially limiting the usages of the robot to a certain time period doing the day.   
Recent advances in DL, implying the rise of DRL, could present a way for a robot to improve spatial awareness. Thereby circumventing the need for human interaction and allowing the robot to operate at any time. The first work on DRL for robotic navigation and obstacles avoidance have seen the daylight (Mirowski et al, 2018; Kahn et al., 2017; Zhou et al., 2019). All three are bound to tackle static obstacles, and so do not address a major challenge of CUE’s, namely dynamic obstacles.

Therefore, the motivation and context of this study is to obtain insights on how a model-free DRL approach with continuous actions and partial observability, tackles the challenges of a simulated ADR navigating a crowded environment with static and dynamic obstacles. The study sheds light on two additional aspects; the effect of uncertainty about the observed environment, and how different training strategies can aid the learning process.

## Theoretical background

The fundamental aspects of robotic navigation can be boiled down to learning and planning, which is also the fundamentals of reinforcement learning (RL) through the tasks of control and prediction. Control tasks are concerned with learning the best policy, while prediction tasks evaluate the policy at hand.

Traditional RL literature distinguish between *model-based* and *model-free* algorithms, where model-based algorithms rely on planning and model-free algorithms rely on learning (Sutton and Barto, 2018).

This study is mainly a control task, on obtaining an optimal policy for locating a target while avoiding obstacles, and not about planning the optimal route to the target given a policy.

The RL algorithm used in this study is called *Proximal Policy Optimization* (PPO) (Schulman et al, 2017a; Schulman et al, 2017b), which belongs to class of *policy gradient methods.* This class of methods essentially extends traditional *model-free* control algorithms, as *Q-learning* (Watkins and Dayan, 1992), into large scale real-world applications.

* + 1. The Reinforcement Learning Problem

The traditional RL set-up consists of an agent (the RL system) and environment in which it operates, see figure 1. Every RL problem is about *solving* the Markov Decision Process (MDP), in the sense of optimizing some objective function given the MDP, as the MDP fully characterise problem. This objective function can either be a *policy* function, *value* functionor the *advantage* function (difference between the policy and value function), depending of the problem and algorithm.

The decision process is a *Markov* decision process because all history of the environment is captured in the most recent value;

*Figure 1 – Markov Decision Process*A screenshot of a cell phone

Description automatically generated *Credit: (Sutton and Barto, 2018)*

Any MDP is made up by a set of actions, , a set of states,, a set of rewards, , and sometimes explicitly, yet rarely in practice, a set of state transition probabilities. The latter won’t be elaborated any further, as they are only relevant for smaller finite[[1]](#footnote-1) MDP’s, which occurs rarely in practice, at least in any interesting applications.

The order in figure 1: The agent observes the initial environment and takes an action at time *t*, transitioning the environment to state *t +1* and emitting a reward to agent. Based on the new observed state and the reward obtained, the agent chooses a new action, and this cycle repeat until the terminal state. An important thing to mention is that the reward does not say directly how good the action was, but how the good the resulting state is.  
The reward signal is often sparse, meaning the agent only receives a reward at the terminal state, i.e. at the end of an *episode*. If the terminal state is good, the agent receives a large positive reward, if bad, a large negative reward, and zero in all states[[2]](#footnote-2) leading up to the terminal state.

## Purpose of the Study

This research aims at addressing the challenges that are surrounding the application of DRL for navigation and obstacle avoidance tasks in CUE’s. The implication hereof is that the conducted research is mainly methodological. This research should be regarded as a preliminary study, to be further extended to generalise to the real world, because of the complex nature of urban environments, and especially crowded areas. This study outlines the basis for filling the gap on DRL for dynamic obstacle avoidance, as this, to the knowledge of the author at the time of writing, is yet to be explored. This study was at the same time an opportunity to explore Unity and the toolkit ML-Agents by (Juliani et al., 2018) for conducting DRL research, under realistic physical settings.

The intention of this study is not to promote DRL to replace existing methods in traditional robotic navigation, but hopefully to aid these, to achieve *smarter* and *safer* cities in the future.

The first objective of this study is to address the challenges emerging when using DRL for navigation and obstacles avoidance in dynamic environments.   
The second objective of the study is to address ways to tackle these challenges and promote meaningful learning in the agent.   
The final objective is to address how uncertainty around the observed environment affects the learning taking place.

## Significance of the Study

This study contributes to the continuing development of DRL for robotic navigation in urban environments, by addressing some of the challenges still present and test novel design methods of the training phase. Addressing the ongoing challenges, hopefully enables focused future research (Irpan, 2018), avoiding rediscovering of known results.  
Most prior research in this area has been concerned with developing novel methods to tackle the challenges at hand, potentially neglecting the design of the training phase.  
Design of the training phase has previously been shown to have a significant effect (Bengio et al., 2009; Mirowski et al., 2018)   
Two ways to design the training phase are *curriculum* and *imitation* learning (CL and IL respectively), where the latter is widely adopted in prior research on robotic navigation (Zhou et al, 2019; Kahn et al., 2017). The former appears overlooked in the context of robotic navigation, especially in the specific context of robotic navigation in CUE’s using DRL.

This study use CL in the training phase, and therefore addresses how the use of CL can aid to manage some of the challenges of robotic navigation in CUE’s using DRL.

## Scope of the Study

The study explores state-of-the-art methods and serves as a framework to evaluate the current state of the field of DRL for robotic navigation in CUE’s through simulation. Simulation is done under realistic physical settings, intending to smoot the future generalisation to real-world applications. The aim is that even though the study is limited to simulation, it could serve as a baseline for future real-world applications.  
The investigated DRL algorithm is based on what is available in the ML-Agents toolkit, and this algorithm is the state-of-the-art for continuous control tasks (Schulman et al., 2017).

The literature review is not intended to be complete on RL/DRL nor robotic navigation. It serves to present the current state of the field, by the most important and latest contributions relevant for robotic navigation in CUE’s using DRL, in order to address the objectives of the study. Furthermore, fundamental concepts in RL, as well as key innovations leading to DRL, and the class of the method used in this study are outlined. That limits the literature review to viewing some concepts of model-free control, see (Sutton and Barto, 2018) for an extensive coverage of RL.

# Literature Review

The following proceeds by first reviewing RL, the emergence of DRL and *the[[3]](#footnote-3)* class of DRL algorithms, before reviewing the literature on robotic navigation in urban environments and the use of RL as well as DRL in this context. The order of the review is to provide some base knowledge of the chosen method, before reviewing the field of application surrounding this study.

## Reinforcement learning

Perhaps the most important discovery within RL is *temporal-difference learning* (TD), originating from animal learning psychology. TD was originally acknowledged in RL context by (Minsky, 1954; Samuel, 1959), and proposed in known format today by (Sutton, 1984; Anderson, 1986). TD methods leverage on both *dynamic programming* (DP) and *Monte Carlo methods[[4]](#footnote-4)* (MC), by using bootstrapping as DP, making TD online, and sampling as MC, making them model-free. Different TD methods for control tasks exists, some being *SARSA*, *Q-learning* and *Expected SARSA*, and they differ by the way they handle the estimate of the objective function in future states.   
The following focuses on Q-learning, see (Sutton and Barto, 2018) for a review of the other two.

Q-learning is an *off-policy* learning method, which mean that the actual action is drawn from a *behaviour* policy, , which is compared to an alternative successor action, drawn from the target policy, . Off-policy learning methods are useful because they allow one to re-use experience from old policies, as we will see is useful, and to learn about the optimal policy while following an exploratory policy.   
Given the two actions, , the online update of the state action-value function is done according to (1).

Both policies are improved, with the target being updated greedily[[5]](#footnote-5) and the behaviour -greedy[[6]](#footnote-6), both w.r.t. , which simplifies the target as seen from (2).

The substituted expression is just the current estimate of the optimal future value.

*Figure 2 – Q-learning algorithm*  
A screenshot of a cell phone

Description automatically generated  
*Credit: (Sutton and Barto, 2018)*

Q-learning converges to the optimal policy and action-value function, with probability 1, under the assumption that all states are visited infinite number of times[[7]](#footnote-7), illustrated in (3).

The Q-learning algorithm showed in figure 2 can seem too simple to work on real-life large-scale control problems. However, it illustrates the high-level idea, about improve an estimate in online fashion – which is essential before covering the policy gradient methods.   
Q-learning is in practical purposes couple with some minor tricks, as *batch* updates, *eligibility* *traces* and *function approximation* for more efficient scalable learning. Batch updates will be explained in a section to come, but the interested reader should consult (Sutton and Barto, 2018: Chapter 12) for a description of eligibility traces.

Doing convergence of (3), the function on the left-side is a so-called *approximate* state action-value function, which is the simple case is look-up table with size . In real-life applications, such a table is often impossible to store in memory. To ensure scalability, function approximations are used, implying the look-up table is replaced with a parameterised function, which could be a linear combination of features, a neural network or something third. The full description of function approximations are covered in (Sutton and Barto, 2018; Chapter 9,10 & 11), but for now it should be noted that the approximate state action-value function changes from to , and updating the weights in the correct direction improves the approximate state action-value function in the desired direction.

Before moving on to policy gradient methods, which are mostly used in the industry today (Karpathy, 2016), it is worth to look at what drove the transition to *deep* RL.

Today’s choice of function approximators are most often neural networks (nets), and the *deep* part of DRL referrers to the structure of the net. A deep net consists of many layers, enabling learning of complex high-dimensional non-linear functions, as each layer learns different aspects of the data passed through (Lecun et al., 2015). *DL*, which is the high-level designation for variations of deep nets, belongs to the class of general-purpose learning procedures (Lecun et al., 2015). General-purpose learning procedures can learn good feature representations directly from the data, avoiding the need for hand-crafted, often non-generalisable, features and at the same time managing the *selectivity-invariance dilemma* (SID). SID in feature engineering is the ability of features to produces representation that are selective to aspects of the image that are essential for discrimination, but that are invariant to irrelevant aspects such as the pose of the animal (Lecun et al., 2015).

Some of the most important advances in DL, leading to DRL, is;

* The adaption of the *rectified linear unit* (ReLU) activation function as the standard.

Activation functions are used to squeeze the output of neurons to a bounded range, typically . ReLU, , bounds the outcome to , which has shown to provide much faster training of deep nets (Lecun et al, 2015; Nair and Hinton, 2010; Krizhevsky et al., 2012).

* Increased GPU power and the possibility of parallelised GPU training.

More powerful GPU’s allows increasing storage of data in memory, and parallel GPU implementations of deep nets allow for faster training and handling of larger amounts of data than ever before (Krizhevsky et al, 2012; Lecun et al., 2015).

* The raise of convolutional nets (ConvNet).

ConvNets are built with an eye for processing data in the form of multiple arrays, and the typical architecture[[8]](#footnote-8) consists of local connections, shared weights, pooling and many layers (Lecun et al., 2015).

ConvNets has been shown to training faster and exhibit greater generalisation ability than stacked nets of fully connected layers (Lecun et al, 2015). The trend is to combine different types of nets in the final deep net, as seen in (Krizhevsky et al., 2012; Sermanet et al., 2013; Mnih et al., 2013).

These advances along with the use of *experience replay[[9]](#footnote-9)* (Lin, 1992), made the difference for the first successful deployment of a DRL model, to learn a control policy directly from high-dimensional sensory input (Mnih et al., 2013). The agent of (Mnih et al., 2013) learned to play 7 ATARI games, with no adjustment between the games, and surpassed previous implementations on six of the games while obtained above human-expert level on three of them. The work of (Mnih et al., 2013) motivated two other important papers, (Mnih et al., 2015) and (Silver et al., 2016).  
(Mnih et al., 2015) extend the work of (Mnih et al., 2013) to 49 ATARI games, beating all previous implementations, obtaining the level of a profession human game-tester across all 49 games and achieving above human performance on 23 games (Mnih et al., 2015).  
(Silver et al, 2016), deploying a combination of deep nets and a tree search algorithm, obtained master[[10]](#footnote-10) level in the boardgame GO, which was regarded as one of the grand challenges, because of its enormous state space consisting of possible moves.

Having reviewed a traditional RL method, as well as the key innovations leading to DRL, including a few key applications, it is now time to review a class of DRL methods. This class is called *policy gradient (PG) methods*, and the method used in this study, *PPO*, belongs to this class.

## Deep reinforcement learning

This section starts out with a simplified example from (Karpathy, 2016), because the example gives a good intuitive idea about how PG methods work. After this example follows a review of the method used in this study.

### Policy Gradient Methods

Modern PG methods seeks to learn a parameterised policy function to select actions, with some approximating a value function as well, to aid the learning process. The latter class are referred to as *Actor-Critic* methods, and the method used in this study belongs to this class.  
The objective of PG methods is to learn the policy parameters based on the gradient[[11]](#footnote-11) of some scalar performance measure, with respect to the policy parameters (Sutton and Barto, 2018). To do that, the parameters of the approximated policy function, most often the weights in a net, are adjusted according to the reward signal . How must to adjust, and so how to update the policy, is determined by the gradient of the scalar signal[[12]](#footnote-13) and called backpropagation[[13]](#footnote-14), seen from (3).

With being the learning rate and the gradient of the reward function.

The task in (Karpathy, 2016) is to learn an agent to play the ATARI game of Pong, from nothing more than the pixels from the emulator[[14]](#footnote-15), using a basic PG.

The structure is as follows; we receive an image, of size 210x160x3[[15]](#footnote-16), and get to decide whether to move up or down. After every action, the agent is rewarded; +1 if the ball went past the opponent, -1 if the ball went past us and 0 otherwise. The objective is to beat the opponent, and so maximising the reward.

(Karpathy, 2016) approximate the policy function with a net, and adjust the weights based on the actions taken. Say an episode consists of 200 steps, implying 200 actions to be taken. If just 101 of the actions are *good* actions, the outcome will be a reward of +1. Overtime, as we adjust the weights in favour of the good actions, the share of good actions within one episode increases, implying that the total number of episodes leading to a positive reward increase.

### Proximal Policy Optimisation

PPO is the embedded DRL algorithm in the ML-Agents toolkit, and it has been shown to outperform far more complex PG methods while being more general and having better sampling complexity (Schulman et al., 2017b).

PPO optimises a surrogate objective function, based on sampled experience (batch updates), from which the policy is updated, and an action is chosen from the updated policy. Simple and effective. See

With the theory outlined, it is now time to review the field of application for this study.



## Robotic Navigation in Urban Environments

Besides limiting this part of the literature review to only consider robotic navigation in urban environments (UE), it is also restricted to only consider navigation in unknown environments as it resembles to the model-free DRL approach studied in this study.  
This part of the literature review is divided into two parts; the traditional literature, which does not include the use of RL, and the DRL-based literature.

Robotic navigation in UE’s obviously comes with a lot of challenges. The four main challenges surrounding robotic navigation in UE’s are mapping, localisation, traversability analysis and planning. Common for all the papers examined on the traditional literature, is that each of the four challenges are handled by separate systems, within the robot.

The consensus to handle mapping appears to be using particle filters, often using a SLAM[[16]](#footnote-17) module (Lidoris et al., 2009; Kümmerle et al., 2013; Maria Bauer et al., 2008; Trulls et al., 2011; Georgiev and Allen, 2004). This approach implies computing an occupancy grid; however, it can be troublesome in terms of memory to store large scale occupancy grid, which is something to consider design-wise.

Localisation is done in different ways; (Maria Bauer et al., 2008; Lidoris et al., 2009; Kümmerle et al., 2013) uses sampled based methods, as Monte Carlo Localisation. (Georgiev and Allen, 2004) uses a combination of GPS coordinates, odometry and visual image processing for localisation and (Trulls et al., 2011) uses an online particle filter implementation based on a 3D geometric model of the environment.

Traversability analysis is usually done using a combination of horizontal and vertical lasers, to measure distance to objects, and potentially changing positions (needed to locate dynamic obstacles as pedestrians) (Trulls et al., 2011; Lidoris et al., 2009; Kümmerle et al., 2013; Maria Bauer et al., 2008).

Planning is done differently; (Lidoris et al., 2009; Maria Bauer et al., 2009;Trulls et al., 2011) use the A\* algorithm to calculate the shortest path through the crowded area. (Kümmerle et al., 2013) uses a hierarchical set-up, which consists of three planners, a high-level agent planning the overall go-to-route, an intermediate-level agent which calculates waypoints and a low-level agent calculating the velocity of the robot based on the waypoints.

The take-aways from the presented literature review is that robotic navigation is a field which has been subject for much research. Some challenges are handled consensually while others are subject for experimentation of novel methods.

#### Robotic Navigation in Urban Environments using Reinforcement Learning

The literature on the use of DRL in the specific field of robotic navigation in UE’s is currently sparse, but it is an area with growing interest from the research community (Zhou et al., 2019). The implication is that no papers exists, at least to the knowledge of the author, which handles all four challenges, mentioned in the previous section, directly.

One paper from DeepMind by (Mirowski et al., 2018) presents an agent, which can navigate through a simulated city based in visual input – and transfer its knowledge to other cities. However, their agent operates with discrete actions and the environment possesses only static obstacles. Their agent uses two interesting additions to the traditional DRL architecture; A method named *Long Short-Term Memory* (Hochreiter and Schmidhuber, 1997) to incorporate memory in the agent, and the use of CL, enabling the agent to be introduced to increasing complexity of the environment doing training.

Another paper from OpenAI by (Kahn et al, 2017) focuses on obstacle avoidance using DRL, and they incorporate uncertainty-awareness in the agent, for safer navigation. The short comings of this article, compared to the traditional literature, is that they only consider static obstacles. Furthermore, they use a model-based DRL model.

The final paper considered here, is a paper by (Zhou et al., 2019) which uses a hierarchical agent to perform goal-directed navigation while being adaptive to changes in the environment. The high-level agent handles the goal orientation and the low-level agent takes care of changes in the environment. They train in a simulated environment and show that the agent generalises to the real world.

All the papers deliver promising insights, but two of them are especially interesting, in terms of this study; (Mirowski et al., 2018) uses CL successfully for navigation, and (Zhou et al., 2019) trains an agent, the low-level one, to be able to deal with changes in the environment, which also is able to transfer to the real world.

# Methodology

This section outlines methods used to address the objectives of this research, and how they are investigated.   
The current state of ADR’s is presented, to provide justification for the choice of software and the environment developed.  
The simulated environment, and its content, is outlined with an eye for the objectives, and a more detailed description is found in appendix.

There are three objectives, as mentioned in section 1.3, namely;

* To investigate the ability of DRL to tackle the most common challenges of CUE’s.
* To explore ways to ease learning of the robotic agent.
* To investigate how uncertainty about the observed environment affects the performance of the robotic agent.

This study simulates an ADR in a simplified urban environment, that possesses the core challenges commonly found in CUE’s. The core challenges are highlighted via the literature review[[17]](#footnote-18) and section 3.1, outlining the current state of ADR’s. The core challenges are found to be static, semi-static and dynamic obstacles, elaborated in section 3.2.1.  
To evaluate the suitability of DRL, to tackle the highlighted challenges, a framework is needed. The framework is developed in Unity, and a justification for choosing Unity is presented in section 3.2.  
An attractive feature of Unity is the degree of realism possible in Unity, which potentially can smooth the transition from the digital twin[[18]](#footnote-19).

Different robotic agents are compared, to evaluate the effect of different inputs on the decision making of the robot. Their performance is evaluated on their *average cumulative reward* (ACR), *average episode length* (AEL) and their ability to avoid obstacles.

Finally, the different robotic agents are compared on their ability to handle uncertainty in the observed environment, elaborated in section 3.2.2.

State hypothesis?



## Autonomous delivery robots today

Delivery robots are not a thing of the future, they are already deployed in a few pilot cities, even in London (Nichols, 2019). An increasing number of companies are putting they attention on autonomous delivery robots (FedEx, 2019; Scott 2019), to meet increasing customer expectations of companies to ride the technology weaves, to enable low-cost-low-emission products.   
Starship, founded by two of the Skype co-founders, are regarded the leader in the ADR race, with their fleet of ADR’s having logged over 100.000 kilometres and more than 25.000 deliveries under the wheels. The fleet has been deployed in cities like London, New York and Washington DC (Merrit, 2019; Nichols, 2019), and the fleet has gained enough experience to surpass the need for any handholding (Nichols, 2019).   
Their newest launch is autonomous delivery of food and beverages at George Mason University, Maryland. The partnership is to accommodate the rising need for smart solutions in a high-paced-high-expectation environment, where nutrition sometimes is overlooked (Nichols, 2019).

The specifications of (FedEx, 2019; Starship, 2019; Scott, 2019) serves as input to the development of the robotic agent, to ensure realism in the simulations, together with realistic physical settings, elaborated in coming section.

*There is no link between the context and the method – what are the opportunities for the research? And why is Unity a good approach?*

## Unity – as a simulation engine for research in DRL

Unity is best described as being a multi-functional platform, enabling development of everything from complex high resolution multiplayer games to less complex mobile games over to VR/AR applications, and increasingly as a challenging set-up to conduct research on artificial intelligence (AI) (Juliani et al, 2018; OpenAI, 2018; Sadeghi & Levine; 2016).

With increasing complexity, sometimes in an exponential manner, comes a need for low latency and distributed computing. Irrespectively of the increasing complexity being a derivative of a high-resolution 3D game consisting of, potentially, thousands of players with widespread interaction patterns, or research on algorithms that roughly needs 18 million video frames to surpass human performance (Hessel et al, 2017), satisfies Unity the need (Juliani, 2019). The underlying engine runs in de-synchronized fashion, supporting simulations at run times at least 100 times faster than real time. This is possible while still maintain physics and frame rendering. A final appealing feature of the computational side is the ability to run concurrent training session, internally in one application as well as externally, enabling the possibility to utilise cloud computing for further increased computational power.

The diversity in the application areas implies that Unity is a serious candidate for modelling the complex dynamics of urban environments. The most appealing feature is the ability to replicate real-life physical complexity, and thereby enabling realistic movement patterns as well as interaction between objects. This is an important factor with an underlying interest in enabling the results to generalise to the real-world, as higher similarity between the environment within the results are obtained and the environment in which the results are deployed, increases the likelihood for generalisation. Unity provides the capabilities to construct a *digital twin* of real-life cities, which is appealing for a wide variety of research areas.   
Another feature of Unity, which makes it appealing for modelling urban dynamics, is the possibility to model complex social interaction. Unity comes with two options to add layers of social interaction to the environment. The *NavMesh* class provides the ability to add AI agents to the environment, useful for spatial queries, as pathfinding. As described in detail later, this class is utilised to model pedestrian behaviour in the constructed urban environment for this paper. NavMesh agents can interact with other NavMesh agents, as well as avoid other moving obstacles, enabling a layer of social interaction with relative ease.   
A more challenging, and perhaps are more interesting way to add social interaction to the environment is by utilising the ML-Agents toolkit, a central part of this paper. The ML-Agents toolkit bridges sophisticated machine learning methods with the graphical interface and complex physical engine of the traditional Unity application, enabling a new setting to push the boundaries for DRL research (Juliani, 2018). The toolkit allows researcher to utilise pre-defined algorithms, based on TensorFlow, or define them themselves, via a Python API. In the light of the NavMesh class, the toolkit puts the control of the interaction in the hands of the researcher, which carries a certain responsibility. It requires the researcher to exhibit a greater understanding of the task and modelling at hand, and so reduces the possibility of headless simulation – limiting the risk of another black box appearance.  
With the introduction of ML-agents, can Unity partly be regarded as the new kid in the class of software’s usable for Agent-Based modelling (ABM). The ML-Agents toolkit makes Unity an appealing contender to the traditional software’s used for ABM, by the fact that the scripting languages are C# and Python. The use of C# and Python implies low latency along with a wide variety of options for further data processing, through open source libraries, and user support, from the enormous communities surrounding the two languages.

Consider the ending of this section, if it should be changed/extended a bit.



### The environment

It is noted that the ADR’s appears to have a height around 0.5-1.5 metre, a width and depth of 0.5 metre, a total weight (including cargo) of 45-50 kgs and a speed around 5 km/h (FedEx, 2019; Starship, 2019; Scott, 2019).

The simulated environment, figure 5, it is intended to simulate areas of a city which are less trafficated with cars, and more dominated by pedestrians. This could be pedestrian streets or campus university (Nichols, 2019).   
A city example could be the area around Carnaby Street in Soho, London.   
Simulating these somewhat simplified urban areas is justified by the current state at which ADR’s are today, i.e. still being in an early stage and facing challenges by the unpredictability of the real world (Nichols, 2019).

The simulated environment needs to possess certain challenges, to reflect the dynamics of a real-life urban environments. These challenges are; static obstacles, dynamic obstacles, crowded areas and varying street sizes.

Static obstacles represent mainly buildings, but they could represent everything static in the built environment.

Dynamic obstacles represent pedestrians, occupying some of the walkable area of the ADR.

The crowded areas represent an area with a lot of potential challenges, which could be a public square or an area on a pedestrian street, where some entertainment unfolds etc. It is an area where the agent can pass through, but it will require a significant amount of additional effort, which implies that it potentially is beneficial for the agent to avoid interaction.

Varying street sizes are represented by the simulated environment having *difficult areas*. The difficult areas are located between the top/bottom static obstacle and the wall, and it is *difficult* because it is narrower that the area between any two static obstacles.

*Figure 5 – The environment*  
A close up of a screen

Description automatically generated  
*The environment contains one moving pedestrians (light green), three crowded areas with varying density (red (high), orange (medium), green (light)), the target (dark green square) and the five static obstacles.*

##### Walls & Obstacles

The walls preresents boundaries for a certain pilot area in a city, and the obstacles represents buildings. Both walls and obstacles serve as a resetting mechanism upon collision with the agent, simulating that it is unacceptable for an ADR to exit the pilot area or to bump into objects of the built environment.

##### Pedestrians

They are *NavMesh agents* (Unity, 2019), which is Unity’s build-in AI configuration, and they are the dynamic obstacles in the environment. The RL agent reset upon collision with them, as it is unacceptable for ADR’s to collide with pedestrians.

##### Crowded areas

The crowded area can attain different densities, to simulate varying complexity of the areas. The densities are used to shape the reward function, which ultimately determines the success of the learning. ELABORATE.  
The crowded area is represented as a circle, which has a certain *density[[19]](#footnote-20)*. The size, as well as the density, of the area is two parameters which determines the complexity of the

***Density***

The density values that a crowded area can possess are based on empirical population density estimates for 2019 from London, see table 1 and figure 8 & 9. The actual values of an area if randomly drawn from the list of possible values, and the density as well as the location of the area is changed every time a new episode begins.

|  |  |
| --- | --- |
| **Table 1 - Population densities, London.** | |
| Max Ward: | 0.0289 |
| Max Boroughs: | 0.0164 |
| Overall:  **Re-create in LaTeX** | 0.0058 |

*Figure 8 – Population density, Boroughs, London  
A close up of a piece of paper

Description automatically generated*

*"Contains National Statistics data © Crown copyright and database right [2015]" and "Contains Ordnance Survey data © Crown copyright and database right [2015]"*

Figure 8 and 9 show the population density in London, at borough and ward level respectively. It is no surprise that the densest areas are close to the city centre, and the densest ward is located within Westminster borough, namely Church Street.

*Figure 9 – Population density, Wards, London   
A close up of a piece of paper

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#### Academy

The academy is one of three cornerstones of the ML-Agents toolkit, and it serves to bridge actions and observations to the TensorFlow-based models in Python. The academy is a Python API, and bridging is done through the *brain*.

***Brain***

There are two types of brains, learning brains and player trains.   
Learning brains learns the policy based on the net implemented in TensorFlow. See figure 10 for the configuration of a learning brain.   
The player brains allow the researcher to test before invoking the learning brain, by giving the researcher the option to control the agent with keys on the keypad.

*Figure 10 – A learning brain*  
A screenshot of a cell phone

Description automatically generated

A brain can take *vector observations* as well as *visual observations* as input, and it outputs an action vector. The size of both the observation vectors and the action vector is specified by the researcher, and it is problem specific.  
The learning brain used this case takes in vector observations, as visual observations requires more computational power than available for this paper. The size of the vector is determined by the observations collected, with an example using sensor information provided in section 2.3.1.3.

Stacking observation vectors equips the agent with short-term memory, which can be beneficial when dealing with dynamic obstacles.

#### Robot Agent

The agent object is by far the most complex, in terms of the number of components and methods contained in the attached script. The content of the agent object is seen figure 12.

The agent GameObject contains a ray perception component along with two custom scripts, other than the familiar components as of the mesh, the rigidbody and the collider components.

Other than the mesh components as well as the rigidbody and collider component, which are previously described, contains the agent a ray perception component along with two custom scripts; one to draw trails and one to hold the necessary methods needed for any agent, to leverage the ML-Agents toolkit.

***Ray perception***

The ray perception component enables the agent to cast rays in specified length and direction and are here used to collect observations about the state of the environment. The rays resemble with LIDAR sensors commonly used for robots (Georgiev and Allen, 2004; Kümmerle et al., 2013; Starship, 2019; FedEx, 2019).

***Brain***

An agent needs a brain to control the movement of the agent, and it is the same brain as specified in the academy. Certain methods control the movement, more specifically; CollectObservations, AgentAction and MoveAgent.

CollectObservations serves to provide the agent with a vector of *observations*, sensor information in this case,and is only needed when the brain uses vector observations*[[20]](#footnote-21)*.   
The agent has 180 degrees sensor vision, in steps of 10 degrees, spanning in front with a length of 50 meters.   
The agent is provided with five tags to recognise, and a ray is casted for each of the tags to recognise, for each of the degrees specified. Furthermore, it keeps track of distance to the objects, and if an object has been missed.   
The observation vector has the dimension , which for the specific case here means that the observation vector is .

Describe partial/full observability.

The agent chooses an action, based on the observations about the current state of the environment. The action/-’s is chosen by the brain, and facilitated to the agent through the AgentAction method, in which the action signal is translated to actual movement via the MoveAgent method.  
The action of the agent is degrees to turn, as the agent is moved forward with a constant speed. The speed of the agent is subject to change, via the public ***speed*** variable.   
The speed of the agent is, by default yet subject for change, set equal to 1 m/s, which is roughly equal to a speed of 3.5 km/t – the average chilled walking speed.

The direction of the movement could, as well, be an action for the agent to learn, subject of investigation in section 3.3.1.

***Max step***

As with the academy, the option to specify a maximum number of steps is present. The agent will be reset when the number of steps surpasses the specified number, which is useful to break unfavourable movement patterns, as is shown later.

***Decisions***

Decisions can be done either at a specific interval or on demand, and this paper here uses decision at a specific interval. The decision interval (DI) should be chosen with the complexity of the environment and the speed at which the agent moves in mind.

As with many of the other parameters of the environment, it is of interest to choose the level at a level which generalises. The default level of DI is chosen to be every fifth step.

#### Target

The target is an important element of the environment, as it is the sparse positive reward signal, which the agent searches for. In this paper, the target is a cube randomly positioned in the environment. As irrelevant as the geometry of the target is, as relevant is the size, relative to the environment. The relative size of the target affects how easily the target is located and can be thought of as the difference in locating a building on a street compared to a specific brick on a specific building, at that same street. The size of the target is fixed here, at a relative size of 3.75%, chosen arbitrary and the effect of the relative size of the target could be a topic for future investigation. 3.75% is equivalent to size of 3 meters.   
The content of the target is seen in figure 21 in appendix.   
The target contains a custom script which serves two purposes; randomly setting a new position of the target and check for collision with static objects in the environment.

Continuously changing the position of the target increases the likelihood of the learning to generalise to unseen environments.

The target is not allowed to be located within another static object in the environment, to prevent conflicting collisions. Having the target located separately from other static objects, simulates the idea about locating a position outside a building for delivery by the ADR.

#### Rewards

Rewards are the fundamental driver of learning, irrespectively of the agent being real or artificial. Rewards occur with varying frequency, yet often distant, and they come in two types; extrinsic and intrinsic.

All characteristics of rewards, referred to as the *reward function* in RL literature, shapes the learned policy function. Headless treatment of the reward function results in poor policies, while careful design of the reward function enables generalisable high-quality policies.

##### Extrinsic

Extrinsic rewards come from outside the agent, and thereby emitted by the environment.

The environment emits a reward of -1 if the agent collides with static obstacles, walls or pedestrians, in hope to disincentive behaviour resulting in these collisions.  
Differently, are collisions with the target rewarded with +1, to incentive goal-seeking behaviour.

To motivate smarter decisions, and thereby quicker learning, is the agent penalised, -0.0005, for every step it takes in the environment. The goal is to obtain a policy which provides the agent with navigational abilities, exhibiting characteristics that resembles with shortest-path-optimisation using A\* search used in traditional robotic navigation research (Maria Bauer et al., 2009; Trulls et al., 2011; Kümmerle et al., 2013).

A subobjective of this study is to learn the agent, that crowded areas require more effort to navigate through. To do so, the agent is penalised for every step in the crowded area, proportionally to the density of the area.

##### Intrinsic

Intrinsic rewards are internal rewards, encouraging curiosity-driven exploration.

A full treatment is given by (Pathak et al., 2017; Juliani, 2018), but the overall idea is to use two nets to predict the next action and observation respectively and compare the predicted values to the observed values. The difference is the intrinsic reward, and the bigger the difference, the bigger the reward.

The agent of this study is trained with curiosity-driven exploration, seen from figure 13, because of the sparse nature of rewards associated with navigational tasks.

### Training

Training can be done either in the editor or by running a build application of the environment. How to carry out training from the command line is described neatly by (Juliani et al., 2019), and is so not described here.

Running training from a build application of the environment provides some desired possibilities, where two of them are running concurrent runs and concurrent environments.

Concurrent runs are independent, which is beneficial for benchmarking.   
Concurrent environments are equivalent to having multiple training areas within one environment, which implies more experience being sampled, which should result in improve learning (Teng et al, 2019). Running multiple environments is a way to speed up training beyond have multiple training areas. It is computationally demanding, and it is usually used together with cloud computing.

Cloud computing is not a possibility here, and this paper is so limited to the use of multiple training areas.

#### Training hyperparameters

As within other areas of machine learning, requires RL algorithms considerations on various hyperparameters. Tuning of the hyperparameters becomes increasingly important as the complexity of the task increases. However, when tuning the parameters to a specific task or environment, some generalisation is lost.   
In this study, the hyperparameters are mostly kept at default values, with some being modified slightly to accommodate continuous actions instead of discrete. The full set of hyperparameters used is seen from figure 13, and for a discussion of the hyperparameters and how they should be set optimally, see (Schulman et al., 2017; Juliani et al., 2019).

*Figure 13 – Training Hyperparameters*  
A black and silver text on a screen

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### TensorBoard

TensorBoard is used to visualise a wide range of statistics related to the training conducted, covering environment, policy and learning statistics. Each of the statistics available is described in detail in (Juliani et al, 2018b).

## Curriculum Learning

The use of CL for machine learning algorithms was formalised by (Bengio et al., 2009), and they specifically studied the use of CL on deep nets, with their experiments showing significant improvements in terms of generalisation.  
(Mirowski et al., 2018) used CL successfully for navigation using DRL, and reported great generalisation properties of their work.

The aim of this paper is not to optimal construction of curriculums, as that is a research question itself, and the curriculum used in this study is specified such that it directly addresses three of the four main challenges equally, namely the static obstacles, the crowded areas and the dynamic obstacles.

Specifying curriculums in Unity is done in a json file, seen in figure 14. For a discussion of each of the parameters in the curriculum, see (Juliani et al., 2018).

*Figure 14 – An example of a curriculum*A screenshot of a cell phone

Description automatically generated

The parameters of the CL are specified through a dictionary, and the keys of the dictionary referrers to the reset parameters[[21]](#footnote-22) of the academy. The dictionary contains at least one variable for each of the three types of obstacles, along with an option to specify the number of training areas, allowing for parallelisation of the training. The latter is described in more detail in section 3.2.2.

The curriculum is designed such that the obstacles are introduced relative to their degree of complexity. The first challenge is the static obstacles, then the semi-static crowded areas and finally the dynamic pedestrians. Each type of obstacle is introduced over three lessons, and the same threshold is required.   
The threshold should be set with two variables of the environment in mind, namely the *average episode length* (AEL) and *the step penalty* (SP), as well as the value of the *minimum number of episodes* (MNE). The AEL and SP form an upper bound on the level of obtainable *average cumulative reward* (ACR)*,* and the relationship between the ACR and the threshold gets stronger the higher the value of MNE.  
If the positive reward is +1, the AEL is 200 and SP is -0.0005, then the upper bound of the ACR is . Furthermore, if one training run consist of 200 episodes, and the MNE is chosen to be 200, then the threshold is equivalent to ACR. Setting the threshold and MNE too higher imply in no progress and setting them too low can result in unstable progress.   
Signal smoothing can be enabled to increase the robustness of the signal.

A common misconception when working with reinforcement learning is the amount of data needed to sustain meaningful learning, the planning fallacy as of (Irpan, 2018). Which means that the MNE and the threshold should be set at a level, which ensures stable learning which generalises.

# Exploration/Exploitation trade-off

Coming of configuring the set-up, it is time to explore the environment, address the challenges and hopefully solve the environment.  
When is the environment *solved*? The environment is solved when the agent can cope with the different type of challenges that the environment processes. As mentioned in section 2.3.1, the environment of this paper processes four main challenges; difficult areas, static obstacles, crowded areas and dynamic obstacles.

## The look of learning

Learning can be expressed in many ways (Juliani et al, 2018b), however, the most intuitive statistics is the average cumulative reward (ACR) and the average length of an episode (ALE), examples are seen from figure 16.

The ACR is expected to converge to the maximum obtainable level of reward within a single episode, when learning has taken place and the agent has solved the environment. The ALE should converge to the minimum number of steps needed to obtain the reward. If a small negative reward is provided at each step, the ALE and ACR develop almost inversely, because the number of steps used bound the maximum obtainable reward.   
The speed of which the convergence takes place is a direct consequence of the complexity of the environment and the degree of assistance provided to the agent, as will be clear doing this section.

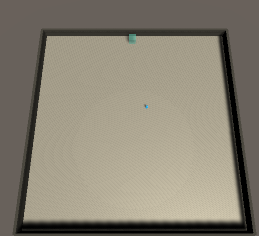
*Figure 15 – The simplest version of the environment.*  
   
*The simple environment contains only a target (darker green square) and the agent (light blue).*

Figure 15 shows the simplest possible environment, without any obstacles. Learning in this environment is straight forward, and this is seen from figure 16, by the red curves. Figure 16 shows how ACR and ALE converges rapidly to their optimal levels, which are obtained after around 75.000 steps in this case.

*Figure 16 – ACR and ALE for the environment from fig. 5 and 14*  
*A close up of text on a white background

Description automatically generated*

The shapes of ACR and ALE seen in figure 16 are ideals, and far from trivial to obtain with the slightest degree of complexity present. The road to meaningful learning requires careful design of the aid provided to the agent to ensure generalisation and so providing the agent with the ability to handle unseen and challenging environments, which is one of the aims of this paper. The blue curves are obtained from the environment from figure 16, and their shapes are quite different from the red counterparts.  
Figure 16 illustrates that learning can take place in complex environments, seen from the increasing ACR, but it is not guaranteed to be meaningful or stable. An ACR-curve fluctuating around zero indicates that the actions of the agent is dominated by random actions. It is not possible to say whether the actions of the agent would continue to be random, or if more learning would take place over time, based on figure 16. Figure 16 contains only 200.000 steps, which in general is regarded as few, and the purpose of figure 16 is to motivate the need for aids, to constitute meaningful and sustainable learning with the ability to generalise to unseen environments.

## Learning to learn

Depending on the environment, it is sometimes necessary to aid the learning process of an agent, as a result of what model-free RL basically are – a function mapping, often high-dimensional, from states to actions. In English, that means that too complex states can result in odd behaviour, if the quality of the function mapping is too poor at the time being.   
This section covers different ways to minimise the occurrence of destructive behaviour, to facilitate meaningful learning.

### Curriculum

The first step towards improving learning is to introduce a curriculum, for the agent to learn from, to gradually add complexity to the environment, as the agent learn to cope with novel challenges. The initial curriculum used in this paper is seen from figure 14, in section 2.4 which contains a full discussion of the parameters.   
Providing the agent with a curriculum to learn from is not enough to avoid destructive behaviour, and another means to limit the presence of destructive behaviour is to regularise the number of steps taken by the agent.

### Maximum steps allowed for agent

The idea is that above a certain threshold, destructive paths is too likely to occur. Destructive paths occur because of too much complexity, which implies that unwounded behaviour becomes optimal at time.

An example of this is that the agent runs in circles, because the target is located in area which is either associated with too high a probability of colliding with obstacles or unexplored, and so uncertain, and because of the size of step penalty, that implies that running in circles is more attractive at the time.

Note, the threshold should be chosen such that it doesn’t circumvents the agent for moving around the entire environment.   
An example of the effect can be seen from figure 17 and 18[[22]](#footnote-24). Figure 17 shows the ACR, AEL and the changes in lessons of two runs of CL-based training, in an environment with static and dynamic obstacles (pedestrians). The blue run does not have a maximum number of steps specified, which the red have. Figure 18 shows the actual number of steps for each episode of blue run, with one episode taking around 35.000 steps. Table 2 shows how many observations lies above certain thresholds. The threshold used on the red run, in figure 17, is , which from table 3, is equivalent to excluding 0.5% of the total observations.

*Figure 17 – The Effect of Restricting the number of steps*  
*A screenshot of a cell phone

Description automatically generated*

Excluding such a tiny fraction of the observations results in a lot more stable training, by reducing the skewness of the steps-distribution[[23]](#footnote-25).

*Table 2 – Fraction of observations lost with maximum steps invoked*A screenshot of a cell phone

Description automatically generated

Figure 18 shows two important findings. Each graph, in figure 18, contains the steps as points and a tiny bar, if the target of an episode where located in a *difficult area[[24]](#footnote-26)* and the target where reached.   
The first important finding is, that the restricted agent (red) reaches targets in the difficult areas continuously throughout training. This indicates that restricting the number of steps to 4000 does not prevent the agent for exploring even the toughest parts of the environment.  
The second important finding is, that the restricted agent seems to learn the difficult areas significantly quicker than its unrestricted fellow.

*Figure 18 – Number of Steps Within Each Episode  
A screenshot of a cell phone

Description automatically generated*

The last point is derived from the concentration of bars in the two graphs. The blue case takes around 2000 episodes before the concentration stabilise, where it, at worst, happens around 500 episodes for the red case. A stable concentration of bars indicates that learning, to locate the target in the difficult areas, has taken place.

Because the targets are randomly placed around the environment, we did expect to see roughly the same number of episodes, with the target located in the difficult areas (TLDA), and this is confirmed from table 3.

*Table 3 – Learning the difficult areas*  
A close up of a keyboard

Description automatically generated

Table 3 reveals an interesting observation, namely that the efficiency, in terms of episodes with TLDA resulting in the target being reached, does not appear to differ, taking the differences in TLDA-shares into consideration. However, the steps needed to reach the target is on average 15% lower for the bounded agent, which results in better performance.

Bounding the steps of the agent appears to result in the agent learning the environment quicker, and taking smarter actions, which over the longer run could materialise in overall improved efficiency because the quality of experience of the agent increases.

The take-away from this section is that avoiding potentially disastrous paths does influence learning, and going forward, a is used.



### Shared experience

Parallelised training is well-known is be beneficial in DL and DRL (Mnih et al., 2013; Silver et al., 2016; Lecun et al., 2015; Teng et al., 2019), to cope with the amount of data needed, and manipulating the training time, to obtain significant results. The main objective of parallelisation is to reduce training time, and where training of deep nets with hundreds of millions of weights and billions of connections between units took weeks two years ago, advances in parallelisation have reduced training time to a few hours (Lecun et al., 2015). Part of these advances in parallelisation comes from novel algorithms, which benefit from parallelisation other than reduced training time. These novel algorithms incorporate experience of the agent to update the function approximation in question, thereby reducing the amount of data needed, and this is exactly what PPO does.   
Parallelisation, at least in Unity, works by running concurrent training environments, either internally or externally. *External* refers to running multiple applications of the same environment, often used when training on GPU’s via cloud computing. *Internal* refers to having multiple environments, with the agents being linked to the same brain, within one application, see figure 19. Internal concurrent training is a way to utilise parallelisation when training on a CPU, and training using GPU’s isn’t a possibility (Teng, 2019).

*Figure 19 – Internal concurrent training*  
 *Four similar environments prior to initialisation, each with an agent, a target and static obstacles. All the agents are linked to the same brain, thereby gathering experience to the same buffer.*

Running concurrent training environments, externally as well as internally, fills the same experience buffer with prior observations. The usual benefit is that training accelerate, because the share of favourable prior observations increases faster with more agents to harvest. However, it can of cause go the other way, if the environment contains too much complexity at the time being. Furthermore, if nothing prevents the agents from wandering around to infinity, a bad spiral unfolds. This spiral is powered by two events; firstly, the agents never benefit from sharing experience because they rarely finish an episode. Secondly, the shared experience is low quality of the wandering. In this way, sharing becomes a burden. This is referred to as the feedback-loop-effect by (Butcher, 2018)[[25]](#footnote-27).

*Figure 20 – Shared Experience  
A screenshot of a cell phone

Description automatically generated*

The power in sharing experience is seen from figure 20. Figure 20 provides a detailed look of the AEL curve, in figure 23[[26]](#footnote-28), from the area bounded by the black line. Figure 20 shows that bad experience of one agent often comes alone, i.e. spikes are often apart. The result is that the experience buffer contains a higher share of good experience to base the policy update on, implying an acceleration in learning, seen in figure 23.

### Observation stacking

Stacking observations provide the agent with a short-term memory, which can be beneficial in dynamic environments where consecutive information enables the agent to better understand the consequences of its action, and thereby better foresee (Juliani, 2018).  
Observation stacking is an alternative to the use of recurrent nets proposed by (Hochreiter and Schmidhuber, 1997), and explored by (Mnih et al., 2015; Borsa et al., 2019), for example to achieve human-level control on 47 ATARI games.

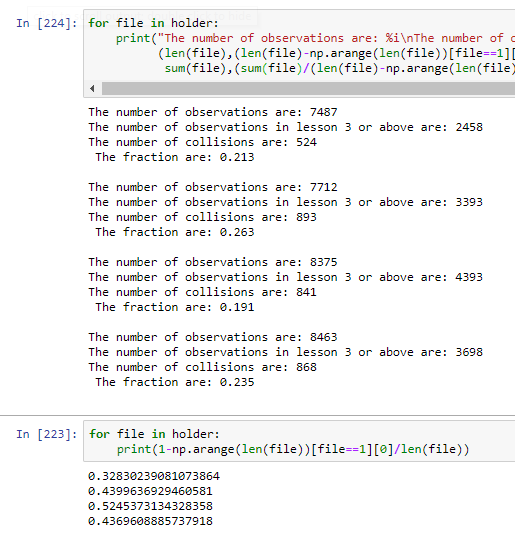
The effect of stacked observations is explored in this study, because recurrent nets have been found not to work well with continuous vector action spaces (Matter et al., 2018), which is used by the agent of this study.

The effect of stacking observations is interesting when the dynamic obstacles are present in the environment, illustrated in figure 21. Figure 21 compares the performance, in terms of ACR and AEL, of the baseline from figure 17 and two unbounded[[27]](#footnote-29) runs with 3 and 6 observations stacked respectively. The comparison starts from the number of steps where the first run progresses to lesson 3, which is where the pedestrians are introduced in the environment. The take-away from figure 21 is the stability of the ACR, but especially the AEL, from the two stacked runs (green and purple).

*Figure 21 - The Effect of Observation Stacking  
A screenshot of a cell phone

Description automatically generated*

Another interesting angle for comparison, between the four runs from figure 21, is to look at the number of collisions with pedestrians, see table 4. Table 5 indicates how stacking consecutive observations, can improve the ability to avoid collisions with pedestrians. The green run spends over half of its episodes with pedestrians present and has the lowest collision rate.

*Table 4 – Pedestrian collisions  
*

*Create in TEX*

### Using visual input

The success of DRL came from the ability to learn directly form raw images, and visual input are widely used in combination with sensory input in traditional robotic navigation.

Remaining structure:

* 3.2.5 to section 3.
* Comparison of performance
* Uncertainty section
* Discussion
* Conclusion

## Insights:

*Randomization of rewards usually poses a problem for the agent - it doesn't know what to do because it doesn't know what reward to expect.*

*.. the agent can't learn a perfect model of how observations correspond to rewards (i.e., they're "noisy")*.

Source: <https://github.com/Unity-Technologies/ml-agents/issues/1680>

## Thoughts:

If it turns out that, no matter the actions taken, it seems impossible for the agent to learn avoiding the sensor clouds, presumably because of the randomness in the penalties of the steps (as derivative of above), one idea can be to let the penalty be fixed but use the density to change timescale/speed.

## Discussion

## Stuff for the discussion:

* As RL is nothing more than a function mapping, either exact or approximative, it follows sort of trivially that randomness makes the mapping blurry, which is the reason why the agents has a hard time dealing with the sensor clouds.
* Indirect addressing the challenges of the difficult areas using CL and parallelisation of training areas.
* Similarity between RL and traditional boosting
  + How the optimisation work, and why we don’t need to run *many* runs of our RL application to get statistically significant results.

## Future work

* Increasing the action space

Increasing the action space of the agent increases the degree-of-freedom of the agent, which be beneficial in navigation tasks with the presence of dynamic obstacles.

# Policy Evaluation

# Appendix

The appendix contains sections of configuration of the environment, tuning of the parameters related to the environment and the agent and illustration of the effect of some of the concepts used to aid the training process.

## Proximal Policy Optimisation explained

The PPO proposed by (Schulman et al., 2017b) and used in the ML-Agents toolkit, is an Actor-Critic styled PG method, and both the approximative policy and value function are approximated by deep nets. For the full argumentation for using an actor-critic styled PG method, see (Schulman et al., 2016), but the simplified argument is to manage the bias-variance trade-off, occurring from the use of stochastic policies in PG methods.  
It is choice of surrogate objective function that differs PPO from other PG methods, with the motivation for a new surrogate objective function being that, existing surrogate objective functions tends to suffer from catastrophic large updates when multiple steps of optimisation is been performed using the same trajectory. The proposed surrogate objective function for PPO bounds the size of the update, eliminating the risk of large updates. The surrogate objective function is seen in (4) and the algorithm is shown in figure 4. Review (Shulman et al., 2017b) for a thorough description of PPO and the difference to other PG methods.

*Figure 4 – PPO Algorithm  
A screenshot of a cell phone

Description automatically generated*

PPO relies on an estimate of the advantage function, , and this estimate is the *generalised advantage estimator* by (Schulman et al., 2016). A full treatment is found in the reference and here it is noted that the estimate is the exponentially weighted average of the empirical returns minus the value function baseline given by (5).

## Effect of invoking maximum steps

Restricting the number steps allowed for the agent to take within one episode, reduces the skewness of the step distribution, which in turn results in a lot more stable training. This is seen from figure 20.

*Figure 22 – Distribution of steps taken by the agent*A screenshot of a cell phone

Description automatically generated

## Effect of parallelisation

Accompanying graph to section 3.2.3.

*Figure 23 – The Effect of Parallelisation  
A screenshot of a cell phone

Description automatically generated*

## Tuning of hyperparameters of the environment

There are three parameters that qualifies as hyperparameters of the environment, when looking back at the outlined environment. These three are; the *speed* at which both the agent and the pedestrians move, the *decision interval* of the agent and the *time scale* at this the simulations are carried out. The reason for these three parameters is because they naturally neither are part of a curriculum nor determined by the desire of having realistic physics in the simulated environment.

|  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- |
| **Table 5. Environment configuration (200.000 steps)** | | | | | | | | |
| Speed | Decision Interval | Time Scale | Training time | Deviation\* | ACR: Mean\*\* | ACR: Std. dev. | AEL: Mean | AEL: Std. Dev. |
| 2 | 5 | 60 | 1650 | 22.2% | 0.663 | 0.65 | 40.32 | 19.41 |
| 1 | 5 | 60 | 1500 | 11.1% | 0.920 | 0.59 | 39.55 | 15.59 |
| 1 | 3 | 60 | 1350 | 0.0% | 0.916 | 0.80 | 101.31 | 198.75 |
| 1 | 7 | 60 | 1750 | 29.6% | 0.896 | 0.63 | 34.07 | 15.86 |
| 1 | 10 | 60 | 1800 | 33.3% | 0.812  **Re-create in Tex** | 0.56 | 26.22 | 9.32 |
| 1 | 5 | 100 | 1350 | 0.0% | 0.908 | 0.62 | 43.03 | 19.58 |
| 1 | 5 | 20 | 2020 | 49.6% | 0.908 | 0.57 | 44.02 | 21.15 |
| \*: Relative to the fastest, \*\*: Mean of converged path | | | | |  |  |  |  |

## Training and Curriculum Learning

~~Figure 16~~ shows ACR and ALE, along with the changes in lessons[[28]](#footnote-30), for a training session with the initial curriculum.

~~Figure 16 -~~ *~~ACR and ALE for first training session using curriculum learning~~*

## Environment Configuration

This section contains all specifications of the environment, which is left out from section 2.3.1.

### Environment

The walkable area is labelled *ground* in figure 6, and it serves two important purposes. Firstly, it defines the extend of the area through its scale, seen in figure 7[[29]](#footnote-31). The extend of the area is used to ensure that random placing, through scripting, of objects happens within the bounds of the traceable area.   
Secondly, it serves as a container for the objects belonging to this training area[[30]](#footnote-32). Initialising new GameObject’s as children of another GameObject is a way to ensure intended interaction with relevant GameObject’s. It allows the researcher to write generic scripts and not instances specific scripts, which are in general good practice, and especially desirable when working with parallelised set-ups.

***Tags***

Every GameObject within the training area is tagged, as seen in the right side of figure 7[[31]](#footnote-33). Tags is an elegant way to differentiate GameObject’s from each other, especially useful in association with collision detection, collecting observations on the state of the environment and random placing of GameObject’s.

***Layers***

Assigning different GameObject’s to different layers is used to either include or exclude certain GameObject’s from some sort of detection. This is useful in the two-brain set-up, ensuring that one brain handles avoidance of dynamic obstacles and one brain takes care of the general navigation towards the target.

***Static Objects***

To the right of the GameObject’s name is the ability to mark a GameObject as static, which is used in connection with NavMesh agents. Static GameObject’s are part of mesh in which a NavMesh agent can navigate (Unity, 2019).

***Geometry of a GameObject***

Any object having a shape contains a Mesh filter, defining the geometry of the object, and a Mesh renderer, which ensures rendering of the object at the position specified in the transform component. Figure 7[[32]](#footnote-34) shows that the *ground* element is a plane, having a size of 80x80x1, positioned at (0,0). The height (size in the y direction) of the *ground* element is not as such important, if it is above 0, to sustain the plane rendering.

Within the bounded *ground,* not necessarily as child objects, is six types of objects placed, two of them elaborated in individual sections below, and the other four are *walls, obstacles, pedestrians* and *crowded areas.*

#### Pedestrians

The pedestrian GameObject is a prefab, which is attached to the academy from where it is initialised. Figure 21 shows the components attached to the pedestrian prefab, of which four are interesting to elaborate on.

***Collider***  
The collider together with the *rigidbody* component, is what that enables collision detection between the object and another object, with a collider and rigidbody component attached as well. The settings in the collider is irrelevant, as they are standard settings matching the scale of the GameObject.

***Rigidbody***  
The rigidbody is the component that enables the physics engine to take control of the movement of the GameObject. The *mass* of the GameObject is specified in kilograms and is set equal to a reasonable average value for a male.

*Figure 21 – The pedestrian prefab*  
A screenshot of a cell phone

Description automatically generated

***RB: Drag***

The *drag* is a force working in the opposite direction to the movement of the object, specifying at what pace the movement of the object is decreased. The value for the drag of the pedestrian prefab is calculated using (1), to ensure realistic behaviour in the simulation, because the default value is zero which is not in accordance with realistic behaviour.

Where is density of the fluid that the object passes through, air in this case here, is the speed (m/s) at which the object moves, is the drag coefficient (unit less) and A is the cross sectional area related to the movement, which is the area of the object normal to the direction of the movement. Table 5 shows the values used, and the calculated drag.

|  |  |  |  |
| --- | --- | --- | --- |
| **Table 5. Drag** |  | Value | Unit |
| Density (air), rho: |  | 1.225 | Kg/m^3 |
| Speed, v: |  | 1 | m/s |
| Drag Coefficient, Cd\*: |  | 1.3 | Unitless |
| Cross sectional area, A: |  | 3.141593 | m^2 |
| *Average of human body in upright position, and at the same time the coefficient of a short cylinder.* | | |  |
|  |
| Drag: |  | 2.501493 |  |

The *angular drag* is how much a rotation is slowed down, and it is kept at standard value, because the default value is within a realistic order.

The rigidbody is marked as being *kinematic*, which implies that the object isn’t influenced by any forces. Why have the rigidbody attached then? Because it ensures better collision properties having both the collider and the rigidbody attached to an object, and all movement is handled by the NavMesh agent component below.

***Nav Mesh Agent***

The Nav Mesh Agent component is what turns an empty GameObject into a Nav Mesh agent. At least initially, is every parameter herein kept default, except speed and angular speed. The speed of the agent is set equal to 1 m/s, the same as the ML agent, which is roughly equal to a speed of 3.5 km/t – the average chilled walking speed.  
The angular speed is set equal to 150, a bit above the default value of 120, as it is equal to the angular speed used in the ML agent.

***Walking around***

The final component is a custom script, written to ensure that the pedestrian walks around the training area continuously doing an episode. The script has two public variables, the radius and frequency. The radius is the distance from the agent, that a new target point is draw within. One target point is drawn within the frequency specified, and there should therefore strike a balance between the radius and the time, such that the agent has time to travel that distance within the specified time.

### Academy

***Configuration***

The width and the height determine the size of the application window when training is done outside the editor.

The quality level is the quality of the camera input, if visual observations are provided to the brain, and is so not relevant for this paper.

The time scale is the speed at which the simulation is carried out – 1 is real time and 100 is 100 times faster than real time. The actual level of time scale does not as such affect the performance of the training, only the training time, yet some physics calculations gets inaccurate with a too high time scale, and so affecting the performance. This should only be relevant if one has objects that travels at high speed, which isn’t the case in this paper.

The time scale is set to 100, based on test simulations shown in appendix A showing no effect on performance, yet ensuring as fast as possible training.

The final configuration parameter is the targeted frame rate, which is the rate at which Unity aim at rendering the frames, which shouldn’t be altered unless one is using visual inputs.

*Initialisation of environment*

Below the reset parameters are the two prefabs, *pedestrian* and *crowded area*, attached in initialising of the environment.

### Agent

***Camera/Render textures***

The agent script contains the option to specify camera/-s and/or render textures, if the brain attached to the agent uses visual observations.

***Draw trails***

The agent script contains the option to enable drawing, and specify the number of trails drawn, which serves to visualise changes in learning patterns doing training. A custom implementation is used, contained in the second custom script of the agent, because the default implementation, *trail renderer,* does not consider the resetting of the agent. *Trail renderer* draws the jump from where one episode ends to the start position of the agent, which minimises the information obtained by visualising the trails.

The custom implementation simply draws a line for each episode, as either a new child element of the agent, if the number of trails is less than the specified number of trails, or by modifying the oldest trails.

***Name of file***

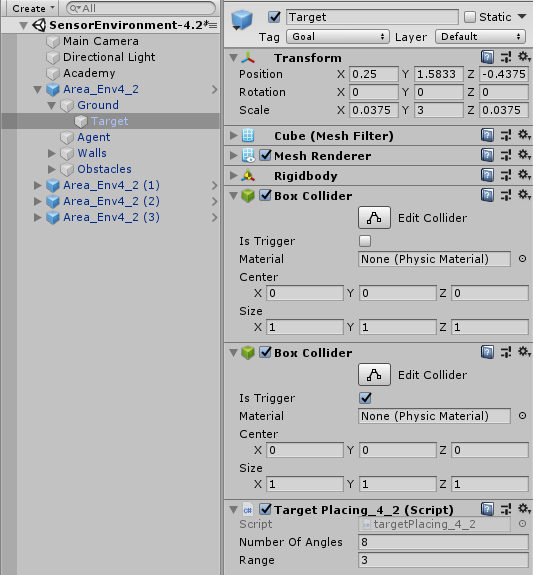
If desired, by checking ***verbose***, the agent collects additional information, compared to the information provided via TensorBoard and writes it to specified files. The additional information provides deeper insights into the progress of the training and highlights potential shortcomings. The additional information is information on the number of collisions with pedestrians and crowded areas, the steps used to locate the goal and the steps taken in the crowded area. However, this can be changed to suite the environment and the need of the researcher.

***Second brain***

The agent script is provided with an option to add a second brain, and potentially many more, which is useful to investigate the effect of separating tasks on individual brains. This is investigated at the later point.

### Target

The content of the target is seen in figure 22.

*Figure 22 – The content of the target object  
*

The target contains, besides the custom target script, only familiar components. The target script has two box colliders .. Check if that is even necessary

~~The custom target script serves two purposes; randomly setting a new position of the target and check for collision with static objects in the environment.~~ Start out with something else. The public parameters of the script are input to the method used to check for collisions. By default, 4 rays are casted with a length of 3, covering all sides.



## Effect of restricting the number of steps for the agent

Equivalent to figure 17 and 18 – yet the worst case seen.

*Figure 23 – The Effect of Restricting the number of steps*  
A screenshot of a cell phone

Description automatically generated

*Figure 24 – Number of Steps Within Each Episode*A screenshot of a social media post

Description automatically generated



## Reward Shaping

The idea of exploring reward shaping (RS) stems from (Mirowski et al., 2018) and is theoretically justified by (Ng et al., 1999; Schulman et al., 2016).  
The basis of RS is that early rewarding of favourable actions increases the likelihood of future actions being in favour of the target, as a sort of guidance of the agent (Ng et al., 1999).  
RS could help to improve the efficiency surrounding episodes with TLDA, discussed in section 3.2.2, by continuously motivating correct actions towards the goal.

(Mirowski et al., 2018) shapes the reward function by providing early rewards to the agent, which are proportional to the distance to the goal within some buffer[[33]](#footnote-35). Furthermore, early rewards are only provided for actions leading to decreasing distance, to prevent the agent form orbiting around the target harvesting early rewards.

This study uses a simpler set-up, based on the lower scale of the environment considered compared to the environment in (Mirowski et al., 2018), which is to provide the agent with an early reward equal to step penalty.

Figure X – Effect of reward shaping



## Support scripts

This section covers some python scripts, which was necessary to enable this analysis and visualising many of the results.

### scalarToCSV

hej

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1. All sets of the MDP are finite [↑](#footnote-ref-1)
2. This is not entirely true, as it is common practice to reward the agent with a minor negative reward at each state (also called *step*), to incentive fast learning. [↑](#footnote-ref-2)
3. A reference to the fact that this class of methods is the most used today (Karpathy, 2016). [↑](#footnote-ref-3)
4. see (Sutton and Barto, 2018) for a description of both methods. [↑](#footnote-ref-4)
5. A greedy policy is a policy, that chooses the action resulting in the maximum outcome. [↑](#footnote-ref-5)
6. A -greedy policy is a policy, which with probability chooses a random action and with probability chooses the greedy action. [↑](#footnote-ref-6)
7. See (Sutton and Barto, 2018), Chapter 9, section 4 for a full description. [↑](#footnote-ref-7)
8. See (Lecun et al., 2015) for a detailed description, of the architecture and each of the components. [↑](#footnote-ref-8)
9. N previous observations are stored, over many episodes, from which T *experiences* are randomly sampled from . Updates are done on the sampled experiences, and the agent chooses an action according to an -greedy policy, i.e. off-line learning, (Mnih et al., 2015). [↑](#footnote-ref-9)
10. Page 5, (Silver et al., 2016). [↑](#footnote-ref-10)
11. The first derivative of a function. [↑](#footnote-ref-11)
12. See (Lecun et al., 2015: P. 436, 2nd paragraph towards the bottom) for a straightforward explanation. [↑](#footnote-ref-13)
13. Training of nets using gradient of the objective function, see (Rojas, 1996: Chapter 7) and footnote 13. [↑](#footnote-ref-14)
14. A piece of software, integrating The Arcade Learning Environment (Bellemare et al., 2013) and the preferred script editor of the researcher. [↑](#footnote-ref-15)
15. Height, width and channels. [↑](#footnote-ref-16)
16. See (Lidoris et al., 2009) for a description. [↑](#footnote-ref-17)
17. Section 2.3 & 2.3.1. [↑](#footnote-ref-18)
18. "A digital twin is a real time digital replica of a physical device" (Bacchiega, 2017) [↑](#footnote-ref-19)
19. See figure Z in appendix. [↑](#footnote-ref-20)
20. Visual observations are provided directly to agent. [↑](#footnote-ref-21)
21. See section 2.3.1.2 and figure 9. [↑](#footnote-ref-22)
22. See section 5.5 for a more extreme case. [↑](#footnote-ref-24)
23. See appendix 5.1 [↑](#footnote-ref-25)
24. One of the four challenges of this simulated CUE, remember? [↑](#footnote-ref-26)
25. ### Section *J.P. Morgan has been using reinforcement learning algorithms to place trades, even though this can cause problems.*

    [↑](#footnote-ref-27)
26. See appendix, section 5.2. [↑](#footnote-ref-28)
27. In terms of maximum steps allowed. [↑](#footnote-ref-29)
28. Each lesson is an entity in the arrays of the parameters in the curriculum. [↑](#footnote-ref-30)
29. P. 32 [↑](#footnote-ref-31)
30. Made up of the *Area* prefab. [↑](#footnote-ref-32)
31. ,29 P. 32 [↑](#footnote-ref-33)
32. [↑](#footnote-ref-34)
33. See (Mirowski et al., 2018) section 5.3. [↑](#footnote-ref-35)