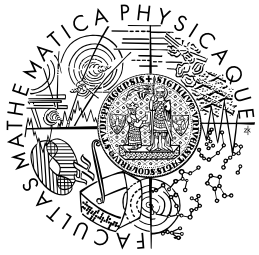

FACULTY
OF MATHEMATICS
AND PHYSICS
Charles University

BACHELOR THESIS

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Playing a 3D Tunnel Game Using Reinforcement Learning

Department of Software and Computer Science Education (KSVI)

Supervisor of the bachelor thesis: Adam Dingle, M.Sc.
Study programme: Computer Science
Study branch: Artificial Intelligence

Prague 2023

I declare that I carried out this bachelor thesis independently, and only with the cited sources, literature and other professional sources. It has not been used to obtain another or the same degree.

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Author's signature

I would like to express my heartfelt appreciation to my supervisor, Adam Dingle, for his invaluable guidance and support throughout my academic journey, beginning with our first Programming 1 class and continuing through to the completion of this project. His patience and assistance were greatly appreciated and played a significant role in the success of this work.

In addition, I am deeply thankful to my mother for her unwavering belief in me and to my grandparents who made it possible for me to be here. Their contributions are greatly appreciated and will never be forgotten.

Title: Playing a 3D Tunnel Game Using Reinforcement Learning

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Department: Department of Software and Computer Science Education (KSVI)

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Abstract: Tunnel games are a type of 3D video game in which the player moves through a tunnel and tries to avoid obstacles by rotating around the axis of the tunnel. These games often involve fast-paced gameplay and require quick reflexes and spatial awareness to navigate through the tunnel successfully. The aim of this thesis is to explore the representation of a tunnel game in a discrete manner and to compare various reinforcement learning algorithms in this context. The objective is to evaluate the performance of these algorithms in a game setting and identify potential strengths and limitations. The results of this study may offer insights on the application of discrete tabular methods in the development of AI agents for other continuous games. (ADD RESULT)

Keywords: tunnel game, reinforcement learning, artificial intelligence, algorithms

Contents

Introduction

Reinforcement learning is a subfield of machine learning that aims to train agents to make decisions that will maximize a reward signal [Sutton and Barto, 2018]. This approach has been widely applied in the field of artificial intelligence, particularly in the context of training agents to play games. In a game setting, an agent's actions can be evaluated based on their impact on the agent's score or likelihood of winning. Through the process of reinforcement learning, the agent learns to make strategic decisions that maximize its reward by receiving positive reinforcement for good moves and negative reinforcement for suboptimal moves. This allows the agent to adapt and improve its performance over time as it plays the game. Research on reinforcement learning in games has demonstrated its effectiveness in a variety of contexts, including board games, video games, and real-time strategy games.

In the field of artificial intelligence, games can be classified as either continuous or discrete based on the nature of the action space and state space. Continuous games have a continuous action space, meaning that the possible actions an agent can take are not limited to a fixed set of options, but can vary continuously within a certain range. In contrast, discrete games have a discrete action space, meaning that the possible actions are limited to a fixed set of options. Continuous games are often characterized by a high-dimensional state space, as they may involve a large number of variables that describe the game state. Discrete games, on the other hand, typically have a lower-dimensional state space, as the number of possible states is limited by the discrete action space. In general, continuous games are more challenging to model and solve than discrete games, as they require more complex decision-making algorithms and may require more computational resources.

In this thesis, we will investigate the application of reinforcement learning to train agents to play a continuous 3D tunnel game, which I designed and implemented myself for this thesis work. The continuous game environment will be discretized into a set of states, and different reinforcement learning algorithms will be applied to train agents to play the game. The goal of this study is to determine whether it is possible for any of the agents to win the whole game, and to compare the performance of different agents that use different reinforcement learning algorithms.

The results of this study will contribute to the understanding of the potential of reinforcement learning for training agents to use discrete algorithms in a naturally continuous environment, and to provide insight into the strengths and weaknesses of different reinforcement learning algorithms in this context.

1. Game Design

For this thesis work I designed and implemented a game called “Space-Run”, which involves attempting to accumulate the highest score possible by navigating through three distinct tunnels while avoiding various obstacles. The game is endless in nature, as the speed increases each time the player successfully completes all three tunnels.

It is worth noting that, in designing this game, I was inspired by the pre-existing “Tunnel Rush” (tun [2022]). “Tunnel Rush” and “Space Run” are both 3D tunnel games that involve advancing through a tunnel to avoid traps. However, there are several key differences between the two games. “Tunnel Rush” is a web-based game played in first-person perspective, while “Space Run” is a desktop-based game played in third-person perspective. “Tunnel Rush” has levels, some of which are inverted with the traps on top of the tunnel and the player outside of it. “Space Run”, since inspired by “Tunnel Rush”, also has levels, but they are all inside the tunnel and features not only traps but also creatures that the player must avoid or shoot. Additionally, “Space Run” has a computer-themed setting, with elements such as battery, bugs, and viruses.

1.1 Player and Movement

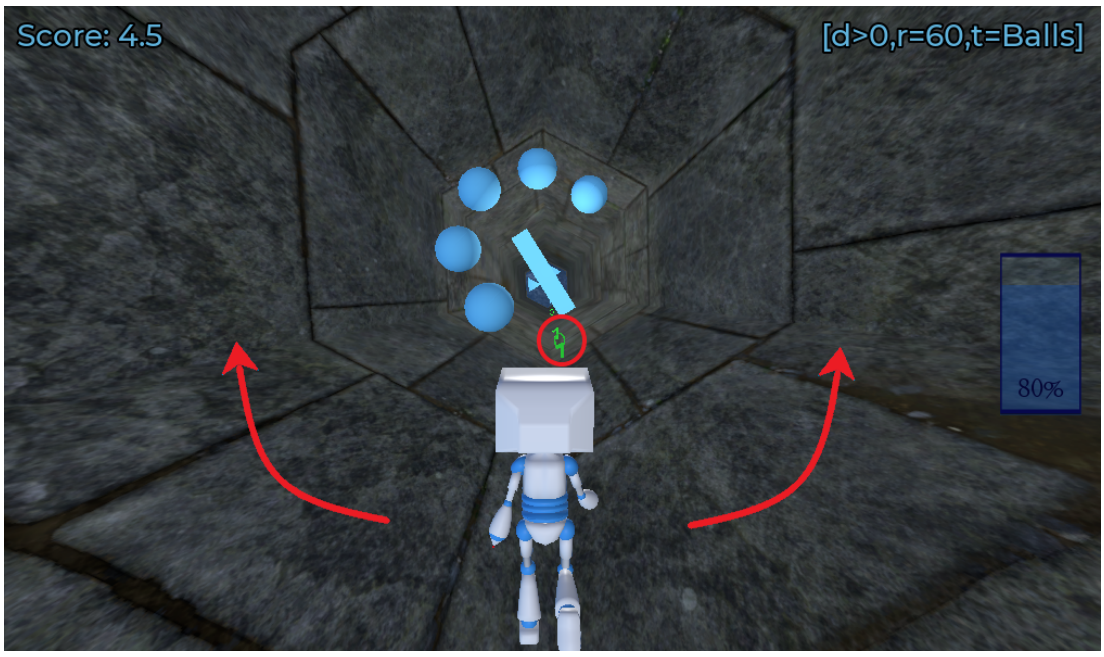


Figure 1.1: Movement

In “Space-run” the player assumes control of a character named Hans (see Figure 1.2) who continually advances at a constant speed through the tunnels. To navigate through the game, the player must use the left and right arrow keys to rotate the current tunnel and avoid obstacles (as shown in Figure 1.1).

In addition to these lateral movements, Hans also has the ability to shoot bullets (also shown in Figure 1.1) by pressing the space key, which can be used to defeat certain in-game creatures and earn a higher score. The player must utilize these abilities in order to progress through the game and achieve a high score.

Figure 1.2: Hans

1.2 Obstacles

As previously stated, the player must navigate through various obstacles in the game. These obstacles can be divided into three distinct categories, and each tunnel contains a unique subset of them. In the subsequent sections, we will delve deeper into these categories in order to better understand the challenges faced by the player.

1.2.1 Traps

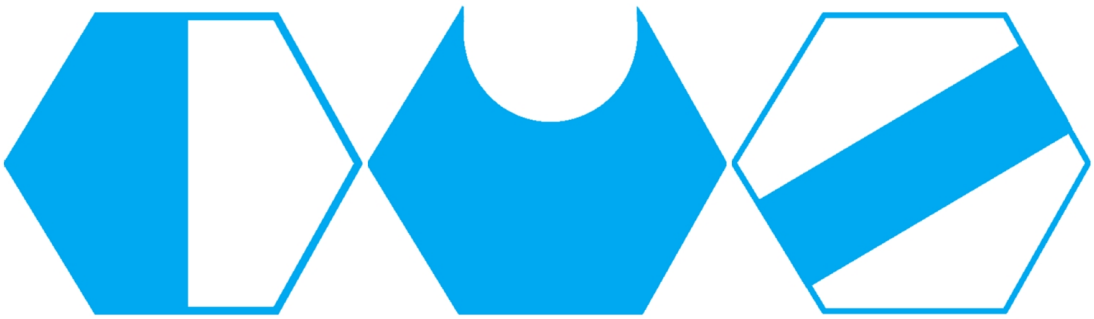


Figure 1.3: Trap examples

As depicted in Figure 1.3, a selection of the various trap types that the character Hans must avoid is presented. These traps, of which there are a total of 10, vary in their level of difficulty and can be either static or animated. These traps can be encountered in any of the three tunnels, and if the player fails to successfully evade them, they result in an instant death.

1.2.2 Bugs

Figure 1.4: Bugs

In addition to traps, the game also features bugs as an obstacle (as shown in Figure 1.4). These bugs typically appear in the second tunnel and are designed to rotate around the tunnel toward the player's position, making them more challenging to evade. However, they can still be avoided by the player. If the player chooses to engage with the bugs, they can be defeated by shooting three bullets at them. If the player collides with a bug, Hans will lose 25% of his battery life (for more information on battery life, see Section 1.3).

1.2.3 Viruses

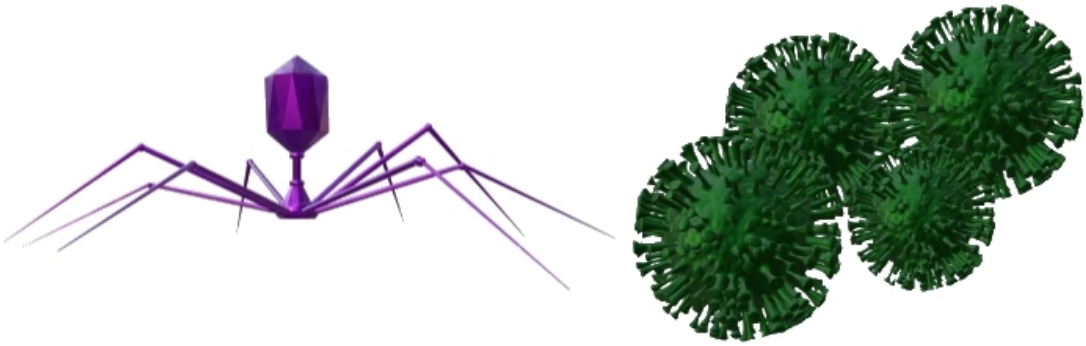


Figure 1.5: Bacteriophage and Rotavirus

The third and final type of obstacle in the game are viruses (illustrated in Figure 1.5). These viruses are typically found in the third tunnel and, similar to bugs, can be eliminated through the use of three bullets. They also, just like bugs, rotate around the tunnel toward the player's position. Bacteriophage, a subtype of virus, will result in an instant death if the player comes into contact with them. Rotaviruses, on the other hand, will cause the player's character to become sick for a brief period of time. During this illness, it is crucial for the player to avoid coming into contact with another Rotavirus, as this will result in the end of the game.

1.3 Additional Features

There are several other features of the game that are worth mentioning. One of the most significant of these is the battery life of the player's character, Hans, which is displayed on the right side of the screen (as shown in Figure 1.6). As Hans is designed to resemble a computer, it is necessary for him to recharge his battery throughout the game by collecting energy tokens (Figure 1.6). This will fully restore his battery capacity. There are three main ways in which Hans can lose battery life: running causes a constant reduction of 1% every 0.5 seconds, each bullet shot costs 1% of the battery life, and coming into contact with a bug results in a reduction of 25% (as described in Section 1.2.2). If the battery reaches 0%, Hans will die and the game will end.

Finally, it should be noted that upon successfully navigating through all three types of tunnels, the game will increase in speed and the player will once again encounter the same tunnels, looping through them indefinitely until the player loses.

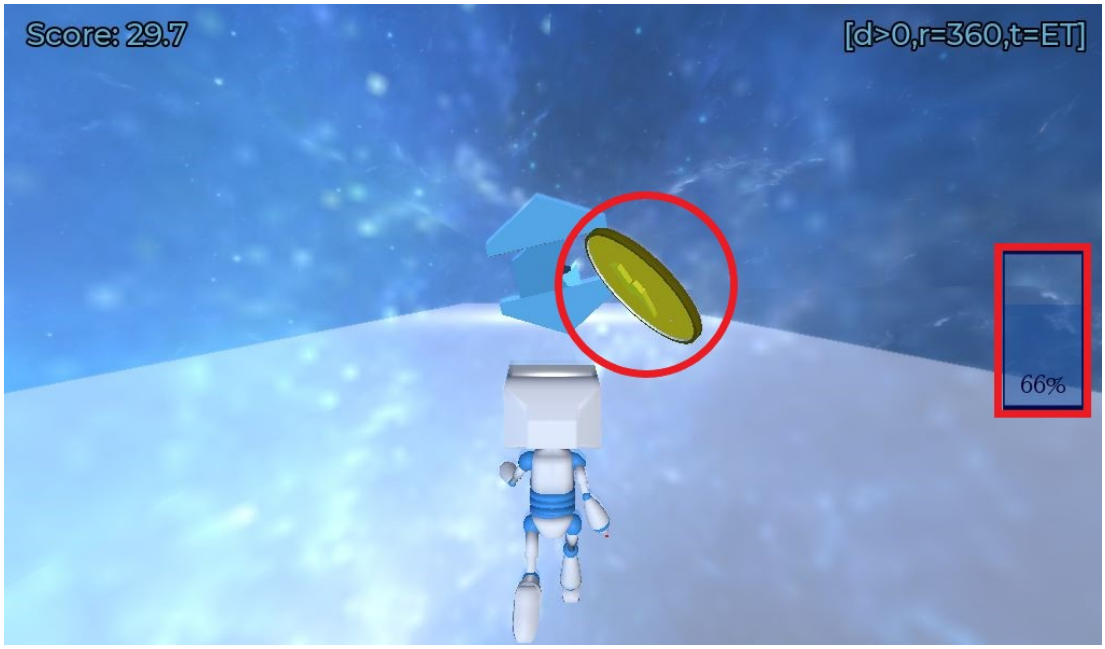


Figure 1.6: Battery and Energy Token

1.4 Score Count and Winning

The score of the game is based on the length of time that the player is able to survive. Additionally, each time a player successfully shoots down a bug or virus, their score increases by 10 points. As previously mentioned, the game is designed to be played indefinitely, but for the purpose of this study, we have set the game to be considered won after an agent successfully completes nine tunnels, reaching level 10.

2. Implementation of the Game

"Space-run" was developed using the Godot Engine (version v3.2.3.stable) , an open-source game engine licensed under the MIT License. It is a cross-platform tool that offers a range of features for game development, including a visual scripting language, 2D and 3D graphics support, and a powerful physics engine. The Godot Engine utilizes a node-based architecture, where nodes are organized within scenes that can be reused, instanced, inherited, and nested. This structure allows for efficient project management and development within the engine. The game was written entirely in GDScript, the primary scripting language of the Godot Engine (et al [2021]).

In addition to using the Godot Engine, I also utilized Blender (version 6.2.0) et al [2022] for creating and animating the characters in the game. Blender is popular open-source 3D modeling and animation software that offers a range of features for creating detailed and realistic characters. The characters were then imported into the Godot Engine using the .glTF 2.0 Group [2022] file format, which is a widely supported file format for exchanging 3D graphics data.

The source code for the game, and for the whole thesis can be found at the following repository online (Adilovic [2022]).

2.1 The top-level organization

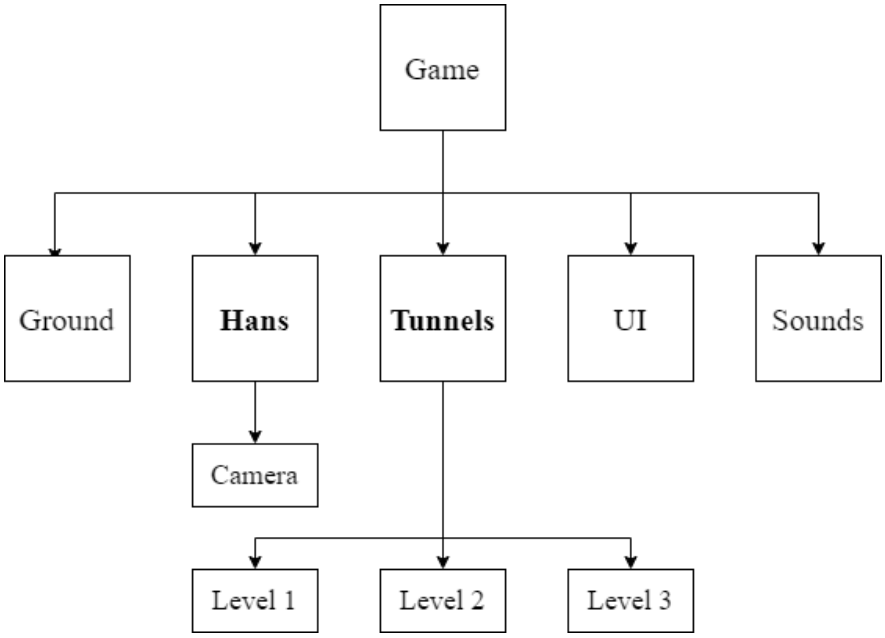


Figure 2.1: Structure of Game.tscn

The main scene for the game, referred to as `Game.tscn`, is depicted in Figure 2.1. It includes several nodes, including Ground, UI, Sounds, Game, Hans, and Tunnels. The Ground node is a CSGBox[1] that serves as the ground in the game,

[1]A CSGBox is a 3D object that represents a box with a Constructive Solid Geometry (CSG) shape.

while the UI and Sounds nodes handle the user interface and audio aspects, respectively. The Game, Hans, and Tunnels nodes contain the majority of the game's functionality. Specifically, the Game node manages the overall gameplay, the Hans node controls the player character, and the Tunnels node manages the movement and appearance of the tunnels.

For a more in-depth understanding, let us examine some of the core aspects of the game in the following sections.

2.2 Game

The script for the Game node is the initial point of the game session and includes both the `_start()` and `_game_over()` methods. It also serves as a link between the game and the agent environment described in Chapter 3, and as such includes all of the necessary set methods for the agent environment. These methods allow for communication between the game and the agent environment, enabling the agent to interact with and influence the game.

The following text describes the core functionalities of the main methods within `Game.gd`:

- The `_ready()` function is called at the start of the game's execution and, after setting up the environment, it triggers the start function. This function initiates the gameplay and sets the necessary conditions for the game to proceed.

- As described in more detail in Chapter 3, the user can specify environment parameters and a starting level for the agent through the command line. These parameters determine the obstacles that the player will face and the starting position of the player character, Hans. The `_start` function incorporates these parameters into the obstacle arrays and positions Hans accordingly. The function also generates the obstacles for the designated starting level. The creation and deletion of obstacles during gameplay is discussed in Section 2.4 of this chapter.

- The `_game_over` function manages the end of the game and sends a signal to the top-level script, `Main.gd` (described in Chapter 3), indicating that the game has ended. It also provides `Main.gd` with the necessary information about the game's status and outcome.

2.3 Hans

The next node we want to examine is Hans. While `Hans.tscn` is a scene with the main character and its necessary animations, what interests us more is the `Hans.gd` and its key components.

```
func _physics_process(delta):
    # code used to update the variables and UI
        ...
```

```
tunnels.delete_obstacle_until_x(curr_tunnel,translation.x -
    tunnels_children[curr_tunnel].translation.x + 50)

# create a trap in the next tunnel every 50 meters
if translation.x < new_trap:
    create_new_trap()

# updating score
score._on_Meter_Passed()

# Hans's movement
var velocity = Vector3.LEFT * speed
velocity = move_and_slide(velocity)

# in case Hans collided with something, handle it properly
check_collisions()

# bugs and viruses need to move torwards Hans
tunnels.bug_virus_movement(delta, curr_tunnel)

if isShootingButtonPressed:
    shoot()

# type needs to be calculated before
# so we know where the next trap is on x axis
var type = calc_type()
state.update_state(calc_dist(),calc_rot(),type)
```

The primary function within `Hans.gd` is the `_physics_process()`, which is called on every tick of the game. It handles the main aspects of the player character through the use of various methods and functions. These include deleting passed obstacles, creating new obstacles every 50 meters, updating the score, handling the movement of the player character, bugs and viruses, and determining the current state of the player. The state label, which is displayed on the upper right corner of the screen (as shown in Figure 2.2), is the primary information that agents receive when making decisions about their next move, as described in Chapter 3. The `_physics_process()` function also handles collisions and shooting if the player chooses to do so. Overall, this function plays a crucial role in the gameplay and management of the player character.

It is also worth noting that this script handles the movement of the tunnels to the back as Hans passes them, with the first tunnel being moved to be after the third one. This feature allows for the game to be infinite, as the tunnels are constantly cycled and reused.

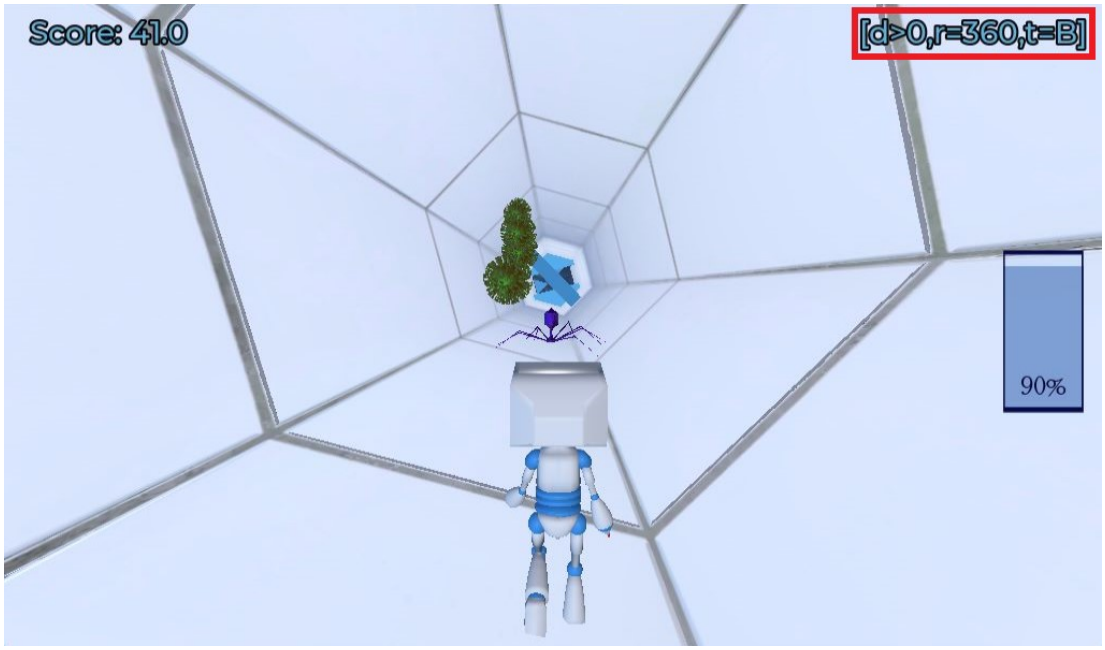


Figure 2.2: State

2.4 Tunnels

The Tunnels node, which is a child of the main scene in the game tree, contains three child nodes of the Spatial type[2] (level1, level2, and level3) and each of these nodes includes a CSGTorus[3] node, which represents the physical appearance of the tunnels. Obstacles are added to the appropriate level node as instances. The `Tunnels.gd` script, which is attached to the Tunnels node, handles many of the previously mentioned functions such as obstacle creation and deletion and tunnel rotation. In the following code snippets, we will examine the `Tunnels.gd` script in greater detail.

```
func _physics_process(delta):
    # gets move from the agent
    # in case we chose the Keyboard agent
    #this will just return input from the keyboard
    var move = game.agent.move(game.state.get_state(),
        game.score.get_score(), game.num_of_ticks)

    #rotates the tunnel
    if move[0] == 1:
        var tunnel = get_child(hans.get_current_tunnel())
        tunnel.rotate_object_local(Vector3.RIGHT,-ROTATE_SPEED * delta)
    elif move[0] == -1:
        var tunnel = get_child(hans.get_current_tunnel())
        tunnel.rotate_object_local(Vector3.LEFT,-ROTATE_SPEED * delta)
```

[2]A Spatial node is a type of node that represents a 3D object or transformation in the game world. It is a versatile node that can be used to create and manipulate 3D objects, including meshes, materials, and lighting. Spatial nodes are often used as the root node for 3D objects in a scene, and they can be nested inside other Spatial nodes to create hierarchical transformations.

[3]A CSGTorus node is a type of 3D object that represents a torus shape in the game world.

```
    # shoot if necesarry
    if not hans == null: # if it is not instanced we can't call the
        function
        hans.switch_animation(move[1] == 1)
```

The _physics_process() function within the Tunnels.gd script serves as the primary connection between the agent and the game. As shown in the provided code, the function retrieves the next move from the agent and rotates the tunnel accordingly, potentially including shooting as well.

```
func create_first_level_traps(tunnel):
    level <- level we are making traps for
    num_of_traps <- randomly pick number of traps to be added
    x <- x position of the first trap

    for n in num_of_traps:
        x <- update x to next position
        if x is outside the tunnel:
            break
        # create one trap at x
        create_one_obstacle(level, x)
```

The function depicted in the code above serves to generate obstacles in the starting tunnel. By periodically creating traps in the tunnel ahead, the game is able to prevent lag caused by an excessive number of objects existing simultaneously. For that reason, this function is used only once, at the beginning of the game.

```
func create_one_obstacle(level,x):
    scene <- pick which kind of obstacle will be added
    tunnel <- get the level we are making traps for
    i <- randomly pick an obstacle

    using previous information, make an instance of the obstacle
    set its position at x and rotate it randomly by n * 60 degrees
```

The tunnels are positioned along the x axis, and this function allows for the creation of obstacles within them at specific x positions and a random rotation.

```
func delete_obstacle_until_x(level,x):
    tunnel <- get current tunnel

    for child in children of the tunnel:
        if child is an obstacle:
            if we passed the child:
                remove it
            else:
                return
```

As previously mentioned, by dynamically deleting passed obstacles, the game is able to maintain a stable performance and avoid overloading the system.

3. Structure of the Experimental Setting

To train an agent on a specific environment, the user must utilize a command-line interface. There are various options available to cater to the user's needs. This chapter will outline all of the provided options and how they are encoded. However, firstly we need to look into a concept called State and its usage for this thesis.

3.1 State

The majority of the implemented agents in the game utilize the concept of state to facilitate learning. The agent will determine its next action based on the current state in which it finds itself. By dividing the game into discrete states, we are able to utilize tabular method algorithms to train an agent to play this continuous game. Once one obstacle is passed, the value of the state indicated refers to the next one. Each state is represented by a triplet consisting of distance, rotation, and obstacle type.

Before further explaining this notion, lets look at the standard unit of distance measurement in Godot - a "meter" .It is used to represent the size, position, and movement of objects in the game world. In Godot, one meter is equal to the size of a standard cube. To better understand the notion, it would be useful to note that Hans is approximately 12m tall and his starting speed is 35 meters per second, while each tunnel has width and height of 12m and depth 2800m.

The distance value indicates the distance of the agent from the next obstacle in meters. For example, if we set the `dists` parameter (indicated by the user, see 3.2.1) to 2, there are two possible distance values for the state: <50, <0, indicating that the agent is 0-49 meters away from the obstacle and at least 0 meters away from the obstacle, respectively. If the `dists` parameter is set to 1, the distance value remains constant at ¿0.

The rotation parameter divides the rotation of the obstacle into `rots` intervals (see 3.2.1). As the tunnel rotates, the state label will indicate the rotation value to which Hans is aligned at the moment. If the `rots` parameter is set to 360, this would correspond to the number of degrees in a circle and result in 360 possible rotations. However, the obstacles in this game do not require such a high number of rotations and agents can be trained to avoid most obstacles using fewer than 10 rotations.

Finally, the type parameter indicates the type of obstacle that Hans must avoid. Each obstacle has its own string representation. With this information, the agent can learn to recognize the safe rotation for different types of obstacles and, along with the distance parameter, decide whether to move left, right, forward, or shoot in combination with any of these actions.

3.2 Command line options

n=int	number of games
agent=string	name of the agent
level=int	number of the level to start from
env=[string]	list of obstacles that will be chosen in the game
shooting=string	enable or disable shooting
dists=int	number of states in a 100-meter interval
rots=int	number of states in 360 degrees rotation
database=string	read the data for this command from an existing file and/or update the data after the command is executed
ceval=bool	performs continuous evaluation
debug=bool	display debug print statements
options	displays options

Note: any of these options can be omitted as they all have default values. If no options are specified, a normal game with the `Keyboard` agent will be run.

3.2.1 Command line option descriptions

n - Number of games the agent will train on in this session. The default is 100.

agent - Name of the desired agent
Options: [`Keyboard`, `Static`, `Random`, `MonteCarlo`, `SARSA`, `QLearning`, `ExpectedSARSA`, `DoubleQLearning`]
Sub-options (only for the listed agents): `MonteCarlo`, `SARSA`, `QLearning`, `ExpectedSARSA`, `DoubleQLearning` =[float, float, float, float] :

[`gam` (range [0,1]), `eps` (range [0,1]), `epsFinal` (range [0,1]), `initOptVal` (range [0,∞))]
Example usage: "`agent=MonteCarlo:eps=0.1,gam=0.2`"
The meaning of the suboptions will be explain in the later section.

level - Number of the level to start from. Default value is 1.
Options: `[1, ... , 10]`
Note: after the 10th level, the agent is considered to have won the game

env - List of obstacles that will be chosen in the game
Options (any subset of): [`Traps`, `Bugs`, `Viruses`, `Tokens`, `I`, `O`, `MovingI`, `X`, `Walls`, `Hex`, `HexO`, `Balls`, `Triangles`, `HalfHex`, `Worm`, `LadybugFlying`, `LadybugWalking`, `Rotavirus`, `Bacteriophage`]
Note: if this parameter is not included, the environment will contain all available obstacles (i.e. the full game). Example usage: "`env=HexO,I,Bugs`"

shooting - Enable or disable shooting
Options: [`enabled`, `disabled`]
Note: this option is disabled by default.

dists - Number of states in a 100-meter interval
This parameter is part of the state label and typical options range from 1 to 3. Default value is 1.

rots - Number of states in 360 degrees rotation
This parameter is part of the state label and the minimum viable option is 6. This is also the default value.

database - Read or write data for this command from/to a file
Options: [`read`, `write`, `read_write`]
Note: these files are typically used to start another session of the agent's training from the last point of the previous session, to run a game with visuals and observe the agent's performance, or for plotting the results. This option does not affect the Keyboard, Static, or Random agents. Default option for this parameter is to neither read nor write.

ceval - Performs continuous evaluation
This parameter indicates that after each training game, a test game will be played using only the policy(s) learned thus far. For example, if the user specifies "n=100", a total of 200 games will be executed, with 100 of them being training games and the remaining 100 being test games. This allows for the assessment of the agent's progress and performance during the training process. Options: [`true`,`false` (default)]

debug - Display debug print statements
Options: [`true`,`false` (default)]

options - Displays all of the mentioned options

3.2.2 Running the program

There are several possibilities for running the game from the command line. In addition to various combinations of the options listed above, the user has the choice of running an experiment with or without the graphical interface. If they opt for the first possibility, the window will open and the game will be played at its normal speed. On the other hand, if the experiment is run without graphics, it will be over 200 times faster and the output will only be displayed in the terminal. It should also be noted that the experiments are fully reproducible since the seed values for all random variables are predetermined.

To run the program in the command line, the user may benefit from adding the Godot executable to PATH environment variable. This will allow them to start the application from the command line simply by entering the command `godot` while inside the same directory as the `project.godot` file.

By default, running the program in this manner will launch a normal game with the graphical interface and the `Keyboard` agent. However, the user can customize their experiment by using a combination of the options listed above. For example, the command:

```
godot database=write agent=SARSA:initOptVal=100.0,eps=0.3 env=HexO
    n=10 dists=1 rots=8
```

Alternatively, the user may choose to train the agent faster by disabling the graphical interface and increasing the speed of the program. This can be achieved by modifying the previous command as follows:

```
godot --no-window --fixed-fps 1 --disable-render-loop database=write
    agent=SARSA:initOptVal=100.0,eps=0.3 env=HexO n=10 dists=1 rots=8
```

To view a list of available options, the user can simply enter the command `godot options`.

3.3 Main

The `Main.tscn` scene is the top level scene in the game and consists of a single Node type node. The script attached to this node, `Main.gd`, is responsible for ensuring that all options specified in the command line (as discussed in Section 3.2) are executed correctly. This script is the starting point of the training and handles the initialization and execution of ore or more game sessions. There are several key functions within the `Main.gd` script that are worth discussing in more detail.

```
func _ready():
    # get args
    var unparsed_args = OS.get_cmdline_args()
    # show options
    if unparsed_args.size() == 1 and unparsed_args[0] == "options":
        display_options()

    # parse args
            ...

    # set param, if something went wrong, show options
    if set_param(args) == false:
        display_options()
    else:
        # make an instance of the chosen agent
        instance_agent()
        # this filename will contain all options
        # and will use as a unique key for the training session
        build_filename()
        # there was a problem while initializing an agent
        if not agent_inst.init(actions, read, write, command, n, debug):
            print("Something went wrong, please try again")
            print(options)

        play_game()
```

The _ready() function is the starting point of the program when run from the command line. It is responsible for parsing all of the arguments and checking their validity. If any issues are encountered, the program will display options and terminate. If the arguments are valid, the first game will be played.

```
func play_game():
    if agent == "Keyboard" and VisualServer.render_loop_enabled: # play
        a regular game
       ...
    # there are still some number of games that need to be played
    elif n > 0:
        n -= 1
        game = game_scene.instance()
        set_param_in_game()
        # prepare the agent
        agent_inst.start_game(is_eval_game)
    # we came to the end of the session
    else:
        agent_inst.save(write)
        print_and_write_ending()
```

The play_game() function is called each time a game is played. If the specified number of games (as defined by the "n" parameter) have already been played, the program will terminate. Otherwise, a single game will be executed.

```
func on_game_finished(score, ticks, win, time):
    # finish up
    print_and_write_score(score, win)
    agent_inst.end_game(score, time)
    # start a new game
    play_game()
```

The game_over() function is called when the game emits a signal indicating that it has finished. Upon execution, this function outputs the necessary information, updates the agent through the end_game() function, and then calls the play_game() function to continue the game session.

4. Applied Algorithms

The algorithms utilized in this thesis fall under the categories of Monte Carlo methods and Temporal Difference (TD) Learning. These methods involve the selection of actions by an agent over time in order to maximize a reward signal. The agents are unaware of the environment dynamics of the game and are only provided with information regarding the current state and score. In this chapter, we will discuss the specific algorithms implemented in the project. Firstly, however, a few key concepts need to be introduced:

A **state** is a representation of the current situation of the environment, and an **action** is a decision made by the agent in response to the current state. A **reward** is a scalar value that represents the immediate feedback received by the agent for its action in a given state. A **policy**, then is a mapping from states to actions that determines the actions an agent takes in each state. An **ϵ-greedy policy** is a type of policy in which the agent takes the action that maximizes the expected reward with probability
(1 - ϵ), and takes a random action with probability ϵ. The `eps` and `epsFinal` were discussed in Chapter 3. With these parameters, the user can indicate starting and ending value of the ϵ which will then adequately decrease after each played game. The **value function** is a measure of the long-term expected return of a given policy. It represents the expected sum of future rewards that the agent will receive when following that policy. The value function is used to evaluate the relative effectiveness of different actions or states in an RL problem.

In the previous chapter, the representation of the state in the game was discussed, and it was briefly mentioned that the set of actions an agent can take are [`left, right, forward, left + shoot, right + shoot, and forward + shoot`]. As for the reward, the most natural choice is the score variable from the game.

Before looking into individual algorithms, there is one more key concept to introduce: **exploration vs exploitation**. In the field of reinforcement learning, the exploration-exploitation trade-off refers to the balancing act between discovering new information or strategies and utilizing existing knowledge to maximize reward. Exploration involves trying out different actions or strategies in order to gather more information about the environment and its rewards, while exploitation involves utilizing the information gathered to maximize reward. Finding the right balance between exploration and exploitation is crucial in reinforcement learning, as excessive exploration or exploitation can result in suboptimal results.

4.1 Monte Carlo

The Monte Carlo method is a type of reinforcement learning algorithm that uses a sample of the past experiences of the agent to estimate the value function. It can be used with either on-policy or off-policy learning, depending on how the samples[1] are collected. On-policy learning means that the agent is using the same behavior policy to collect samples as it is using to improve the value

[1] A sample refers to a single experience or transition that the agent encounters as it interacts with the environment. A sample typically consists of the current state of the environment, the action taken by the agent, and the resulting reward and next state.

function. First visit Monte Carlo is a variant of on-policy Monte Carlo that only considers the first time a state is visited in an episode[2], as opposed to all visits. Optimistic initial values are a technique used in Monte Carlo methods to encourage exploration by setting the initial value of all state action pairs to a high number, encouraging the agent to visit as many states as possible in order to learn their true value [Sutton and Barto, 2018]. A value of the state is defined differently between each algorithm. It serves as a measurement to determine which action is better to be taken in a particular state, and will be further discussed in Chapter 5. For the purpose of this thesis, we have used on-policy first visit Monte Carlo algorithm, with both initial optimistic value and an ϵ-greedy policy as tools to enforce exploration. This method is guaranteed to eventually converge to an optimal policy if the limit as the number of samples goes to infinity. This means that, as the number of samples increases, the estimates of the value function produced by Monte Carlo methods will become increasingly accurate. However, the rate at which Monte Carlo methods converge to the true value function can be slow, and the estimates may be quite noisy (i.e., have high variance) if the number of samples is small.

```
For each episode:
        Initialize value function for all states to a high number
            (optimistic initial value).
    Loop for each step of episode:
        Set state and action to their initial value
        Take the action and observe the next state and reward.
        If the state has not been visited before in this episode
            (first visit):
            update the value function using the reward.
        Choose the next action using the epsilon-greedy policy.

    Update the epsilon-greedy policy based on the results of the
        learning process.
```

Figure 4.1: On-policy first-visit Monte Carlo control (for ϵ-greedy policy)

As seen in Figure 4.1, Monte Carlo algorithm behaves in a way that the policy is being update only after one episode has finished. During the episode, moves are chosen based on the currently known policy. The update for this algorithm discussed in detail in Chapter 5.

4.2 Temporal Difference Learning

Temporal difference (TD) learning is a type of reinforcement learning algorithm that estimates the value function using the difference between the immediate reward and the expected future reward. It can be used with either on-policy or off-policy learning, depending on how the samples are collected. On the other hand, as previously mentioned, Monte Carlo methods require a complete episode

[2]In this project, an episode is a whole duration of one game being played.

to finish before the value function can be updated, whereas TD learning can update the value function incrementally as the agent takes actions. This means that TD learning can start learning and adapting to the environment much earlier than Monte Carlo methods.

```
Initialize Q(s,a) for all states s and actions a, except
   Q(terminal,a) = 0
Loop through each episode:
       Initialize state S
       For each step of the episode
           Pick an action A using epsilon-greedy policy
           Take action A and observe the reward R and the next
              state S'
           Update the policy depending on the algorithm
           S <- S'
       Until S is terminal
```

Figure 4.2: Tabular TD learning

In this section we will introduce four temporal difference learning algorithms: SARSA, Q-learning, expected SARSA, and double Q-learning. The main difference between SARSA, Q-learning, expected SARSA, and double Q-learning is the way in which they estimate the value of the action-value function[3]. The pseudocode above shows us the common core idea for all the TD learning algorithms used in this thesis. Now, we can look at them individually, based on their update functions.

To gain a deeper understanding of the update functions used in temporal difference (TD) learning algorithms, it is helpful to introduce several variables that are commonly used. The variable `Q(S,A)` denotes the action value function, which represents the expected return of taking a particular action in a given state. `R` represents the reward parameter, while the variables `S'` and `A'` denote the next state and next action, respectively, following the current state and action. The variable γ is a discount factor that determines the importance of future rewards relative to immediate rewards. The variable α is a learning rate that determines the degree to which the agent updates its estimates based on new information (for further explanation see Chapter 5).

$$Q(S, A) \leftarrow Q(S, A) + \alpha[R + \gamma Q(S', A') - Q(S, A)$$

Figure 4.3: SARSA update function

SARSA stands for "state-action-reward-state-action", and is an on-policy TD learning algorithm. This means that it uses the same behavior policy to col-

[3]The action value function is a measure of the long-term expected return of taking a particular action in a given state. It represents the expected sum of future rewards that the agent will receive when starting from the given state and taking the specified action. The action value function is used to evaluate the relative effectiveness of different actions i

lect samples as it is using to evaluate the action-value function. In SARSA, the action-value function is updated using the current state, current action, reward, next state, and next action.

$$Q(S, A) \leftarrow Q(S, A) + \alpha[R + \gamma max_a Q(S', a) - Q(S, A)]$$

Figure 4.4: Q-learning update function

Q-learning is an off-policy TD learning algorithm. The policy being learned about is called the target policy, and the policy used to generate behavior is called the behavior policy. In this case we say that learning is from data "off" the target policy, and the overall process is termed off-policy learning. In Q-learning, the action-value function is updated using the current state, current action, reward, and next state, with the next action chosen using the greedy policy.

$$Q(S, A) \leftarrow Q(S, A) + \alpha[R + \sum_a \pi(a|S')Q(S', a) - Q(S, A)]$$

Figure 4.5: Expected SARSA update function

Expected SARSA is an off-policy variant of SARSA algorithm that uses the expected value of the next action, rather than the actual next action, to update the action-value function. This allows the algorithm to take into account the probability of each possible next action, rather than just the action chosen by the behavior policy.

With 0.5 probability:

$$Q_1(S, A) \leftarrow Q_1(S, A) + \alpha[R + \gamma Q_2(S', argmax_a Q_1(S', a)) - Q_1(S, A)]$$

Else:

$$Q_2(S, A) \leftarrow Q_2(S, A) + \alpha[R + \gamma Q_1(S', argmax_a Q_2(S', a)) - Q_2(S, A)]$$

Figure 4.6: Double Q-learning update function

Double Q-learning is a variant of Q-learning that uses two action-value functions to estimate the value of each action. The two functions are updated independently, and the final action-value estimate is the average of the two estimates. In Q-learning, the greedy policy is biased because it always chooses the action with the highest estimated value at each time step, regardless of the uncertainty of the estimates. This can lead to a suboptimal behavior in some cases, however, updating the functions independently helps us reduce this bias.

5. Implementation of the Agents

In this project, the RL agents are designed such that their functionality is encapsulated within a top-level scene called `Main.tscn`. Within this scene, there is an instance of the selected agent, and the code makes use of several functions implemented by the agent in order to interact with the environment. Specifically, the required functions are: `move()`, `init()`, `start_game()`, `end_game()`, `save()`, `set_seed_val()`, `get_and_set_agent_specific_parameters()`, and `get_n()`.

The purpose of most of these functions is self-explanatory. `init()` and `save()` are used to initialize and save the agent's internal state, respectively, and are called only once per experiment. `start_game()` and `end_game()` are called at the beginning and end of each episode, while `move()` is called by the `Tunnels.gd` script, and it is in this function that the agent makes a decision about which action to take based on the current state and score. The remaining functions pertain to the internal structure of the agent and are not relevant to the reader.

5.1 Hierarchy

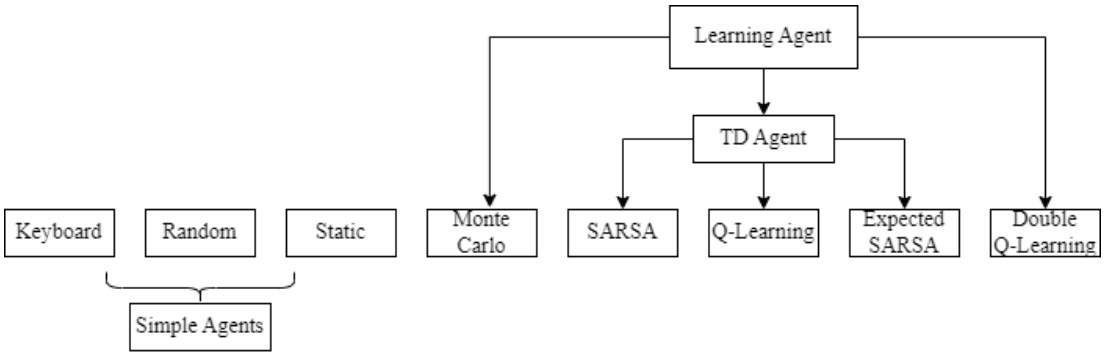


Figure 5.1: Agents hierarchy inside the project

In the current design of the game, there are a total of 8 agents implemented, 5 of which utilize some form of reinforcement learning (RL) algorithm. These RL agents share a common superclass called "Learning Agent", while 3 of them are further subclassed under the "TD Agent" class (see Figure 5.1). As previously discussed, the RL algorithms can be broadly divided into two categories: Monte Carlo methods and temporal difference (TD) learning. The TD algorithms differ only in their update function, and so it was deemed appropriate to group them under the same superclass. However, the Double Q-Learning agent, which utilizes separate policies and requires additional modifications, was implemented as a separate subclass or the "Learning Agent". The implementation details of these agents will be further elaborated upon in the subsequent sections.

5.2 Simple Agents

To facilitate testing of the game environment, several simple agents were implemented. These agents serve as baseline models and are used to ensure that

the environment is functioning as intended before more sophisticated RL agents are developed. There are three simple agents in total: a "Keyboard agent" that receives input from the player via the keyboard, a "Static agent" that always chooses the forward action, and a "Random agent" that chooses a random action at each time step.

5.3 Learning Agent

The Learning Agent class serves as a base class for all the reinforcement learning agents in this project. It provides a set of shared functions and features that are used by all agents, such as reading and writing data to a file and debugging statements. In terms of decision-making, these agents all follow an epsilon-greedy policy, whereby they select the action with the highest value for a given state with a certain probability, or randomly choose any action with the remaining probability. Each of the subclasses of the Learning Agent class then implements specific code that is unique to that particular agent.

5.3.1 Monte Carlo Agent

$$R = next\_step.score - curr\_step.score$$
$$G = \gamma^{next\_step.time - curr\_step.time} * (R + G)$$
$$total\_retun[state\_action] = total\_retun[state\_action] + G$$

Figure 5.2: Total return update for Monte Carlo

The Monte Carlo method is a type of reinforcement learning algorithm that updates its policy only after an episode is completed. This is done by iterating through the entire episode and increasing the number of visits and total return for each state-action pair, if this is their first visit inside this episode. The total return is calculated using the formula shown in Figure 5.2, while the number of visits is simply incremented by 1. To determine the optimal action, the agent compares the ratio of total return to number of visits for each possible action at a given state. This calculation is performed at each state transition during the episode [1]. The γ variable in the equation shown in 5.2 serves as a discount factor, meaning that the last move made, which resulted in the agent's death, will receive the highest penalty. As we move further down the list of moves, their significance decreases. It is important to note that if the value of γ is set to 1, all moves are given equal weight. The `R` variable represents the return value, which is calculated as the difference in scores between two steps.

[1] Instead of calling the move function periodically, the agents will always choose the same action based on the current state. Only once the state has changed, the new action is chosen based on the accumulated score and the new state.

5.3.2 TD Agent

Unlike the Monte Carlo methods, which update their policies only after the completion of an episode, TD agents update their policies in real-time, after each action is taken. To accomplish this, all TD agents have a shared function called `move()`, which contains the update formula shown in Figure 2. However, the specific implementation of this formula varies slightly between the different TD algorithms. As visible on the Figure 5.3 the update of the policy for a particu-

$$alpha = 1.0/visits[state\_action]$$

$$gamma = \gamma^{next\_step.time - curr\_step.time}$$

$$q[state\_action] = q[state\_action] + alpha * (gamma * (R + new\_state\_val) - q[state\_action])$$

Figure 5.3: Policy update for Temporal Difference Learning

lar state value in TD learning requires several variables. The first is the overall number of visits, represented by the variable alpha and divided by 1. The second variable is gamma, which serves the same purpose as in the Monte Carlo method. Lastly, the `new_state_val` variable, which is unique to each agent, is needed for the update. Different methods of calculating the `new_state_val` variable can be seen in Figure 5.4. In SARSA, the `new_state_val` is calculated based

$$\text{SARSA: } new\_state\_val = q[statenew_{a}ction]$$

$$\text{Q-Learning: } new\_state\_val = q[statebest_{a}ction]$$

$$\text{Expected SARSA: } new\_state\_val = \sum_{a} \pi(action|state) Q(state, action)$$

Figure 5.4: new_state_val variable for individual TD Agents

on the value of the next action the agent will take, denoted as `new_action`. On the other hand, Q-learning uses the value of the best action possible in the next state, denoted as `best_action`. These two variables are equal if greedy policy is implemented. However if we consider ϵ-greedy policy, then they might differ based on weather a random action has been chosen. Expected SARSA combines these two approaches by taking the expected value of all possible actions in the next state.

5.3.3 Double Q-Learning Agent

Similar to the agents in the TD class, the update for the Double Q-Learning agent occurs each time the agent changes its state. The update process is slightly different. In this method, two separate action-value functions, denoted as Q1 and Q2, are used to estimate the maximum action value for a given state. At each update step, one of the Q-values is selected randomly and updated using the other Q-value as a reference. This process helps to reduce the overestimation of action values and leads to more stable learning.

$$gamma = \gamma^{next\_step.time - curr\_step.time}$$

if probability <0.5:

$$new\_state\_val = q2[get\_state\_action(state, best\_action)]$$

$$q[state\_action] += alpha * (gamma * (R + new\_state\_val) - q[state\_action])$$

else:

$$new\_state\_val = q[get\_state\_action(state, best\_action)]$$

$$q2[state\_action] += alpha * (gamma * (R + new\_state\_val) - q2[state\_action])$$

Figure 5.5: Policy update for Double Q-Learning

6. Experiments

In this chapter, we will evaluate the performance of the various agents when confronted with different combinations of obstacles. One of the key questions we aim to answer is whether any of the agents are able to successfully learn to play the entire game.

6.1 Individual Traps

Figure 6.1: `rots` value used for each trap type

To start off let us analize each individual type of trap and how the agents perform under the same conditions. For this purpose we have performed experiments for each agent and each trap type with the hope that they can learn to play in such an environment in under 50 games. In figure 6.1 we can see the number of rotations used for each individual trap type. The aim was to minimize this number so that the state space itself would be minimized. To calculate how many states there are in an experiment, it is sufficient to multiply the number of obstacles by the number of possible rotations and distances. However, it is important to mention that throughout this experimentation, `dists` value was always 1 since all the obstacles were successfully trained by at least one agent with that number of distances.

In the Figures 6.2 and 6.3, we can observe the average performance of each agent in 50 games for individual traps and with different initial optimistic values. Both of these experiments utilized an epsilon value of 0.2. It is evident that the Double Q-Learning agent had the lowest performance among the agents tested in these experiments. However, it is important to note that when trained on a larger number of games, this agent demonstrated improved performance (as seen in Figure 6.5[1]).

Once peculiar case while training on individual traps is shown in Figure 4. If we look more closely to the policy the agent has chosen, it is visible that instead of aiming to reach a specific rotation value, it decided to rather quickly switch in between two rotations as, in this case, it will always be a safe option. This is indeed the optimal policy for this trap type under six rotations.

[1]The table on the figure shows the move agent will choose in a certian state. Columns represent rotation value while rows show us which trap and dists value the state has. The value of a particular row and column, then, is an arrow pointing to which direction the agent will move. In case the agent chooses to shoot, a little * will be shown next to the arrow

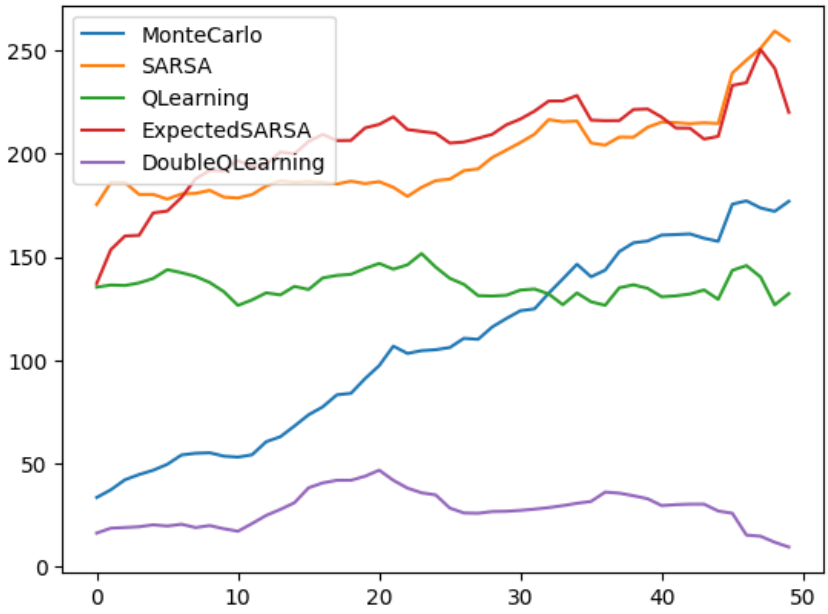


Figure 6.2: Average performance of the agents on individual traps, initOptVal=20

6.2 Bugs

In this section, we will analyze how the Bugs environment responded to training with different agents. As seen in Figure 6.6, the SARSA and Expected SARSA agents had the best overall performance in this environment. Interestingly, when shooting was enabled, the policies trained by these algorithms were the same as when shooting was disabled (see Figures 6.7 and 6.8). This result might be counter intuitive since the shooting gains point for the player and, since we did not have energy tokens in this environment, the agent was allowed to shoot indefinitely.

6.3 Viruses

The results of the experiments on the viruses environment indicate that the Expected SARSA and Q-Learning algorithms performed the best. While Q-Learning resulted in the same policy with both shooting enabled and disabled, the Expected SARSA algorithm produced two distinct policies depending on the presence of shooting (see Figures 6.10, 6.11 and 6.12). Even when given the option to shoot, the agent preferred to avoid the obstacle instead. A comparison of the performance of all algorithms can be seen in Figure 6.9.

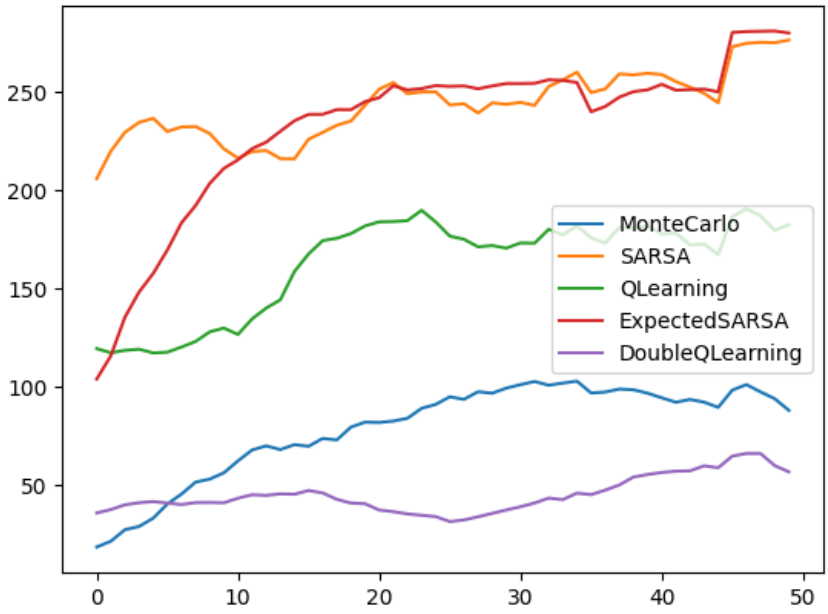


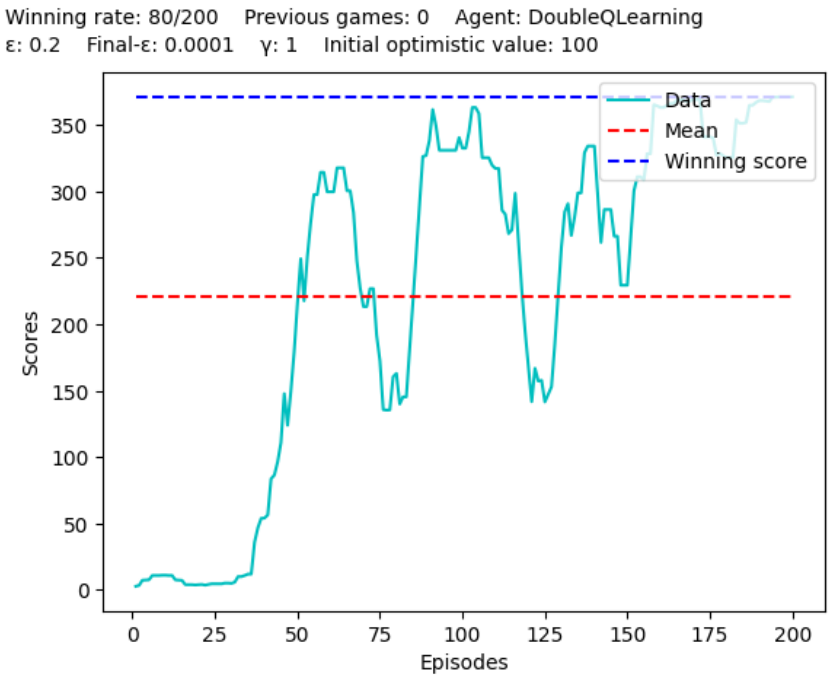
Figure 6.3: Average performance of the agents on individual traps, initOptVal=100

6.4 Combinations

6.4.1 Traps and Tokens

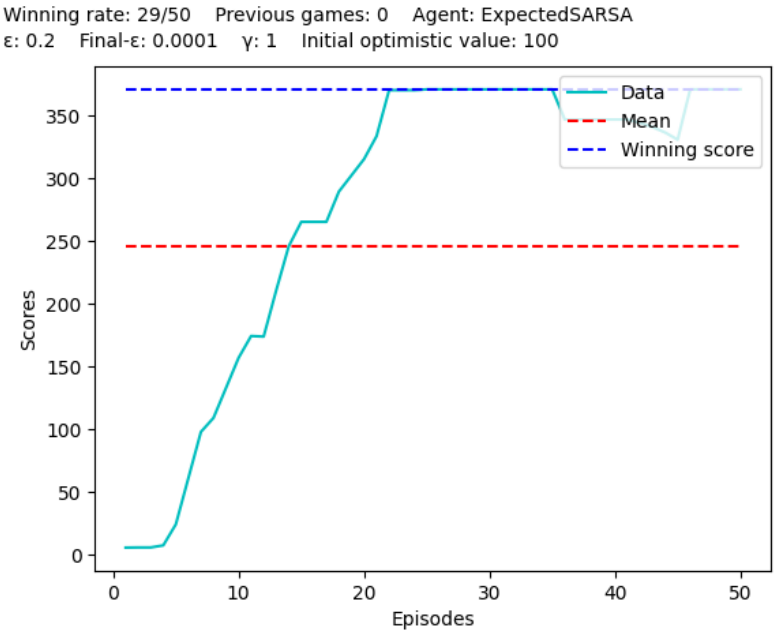
6.4.2 Bugs, Viruses and Tokens

6.5 All obstacles



	60	120	180	240	300	360
(0, I)	↑	→	←	←	←	→

Figure 6.4: Double Q-Learning trained with 200 games on I-type trap



	60	120	180	240	300	360
(0, Triangles)	→	←	→	←	→	←

Figure 6.5: Triangle-type trap with Expected SARSA algorithm

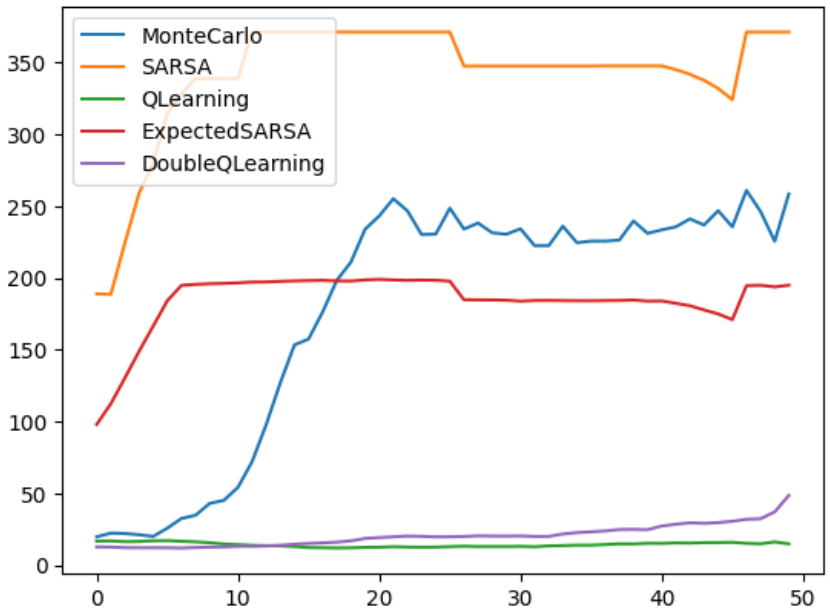
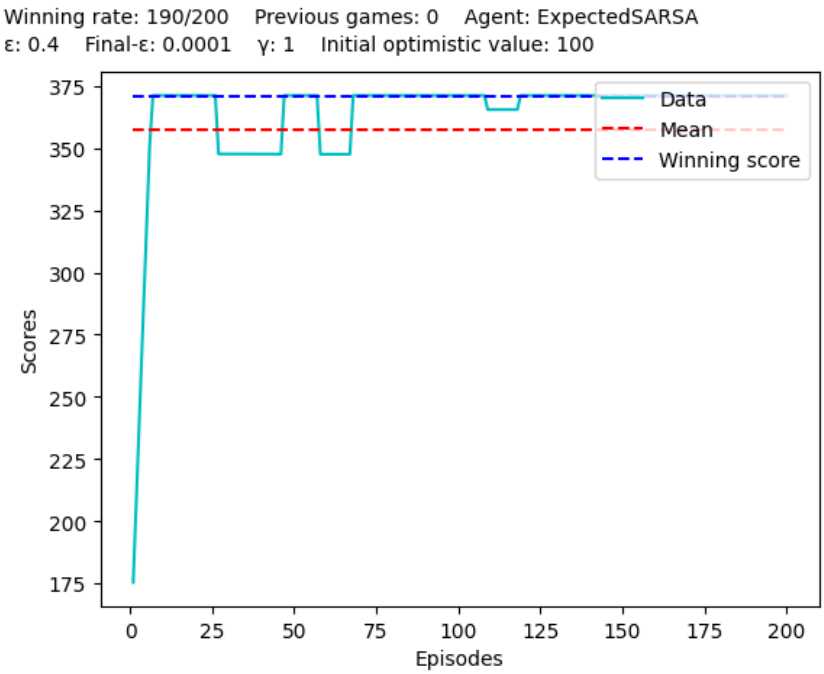
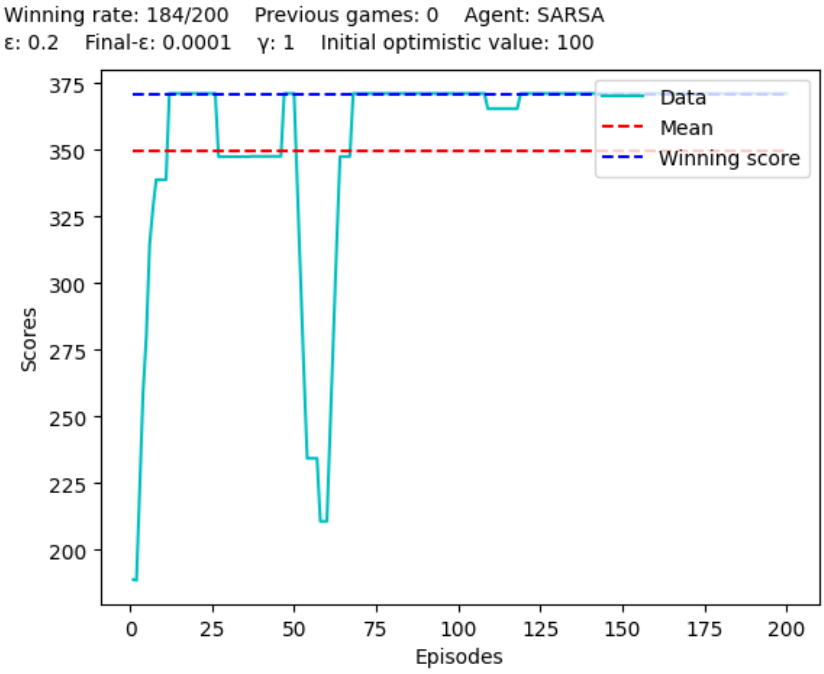


Figure 6.6: Average performance of the agents with Bugs environment



	60	120	180	240	300	360
(0, LBF)	→	→	↑	↑	←	←
(0, LBW)	→	→	→	→	←	←
(0, W)	←	→	→	→	←	←

Figure 6.7: Policy of the Expected SARSA algorithm on the Bugs environment



	60	120	180	240	300	360
(0, LBF)	→	→	↑	←	←	←
(0, LBW)	→	←	↑	←	←	→
(0, W)	→	→	→	↑	↑	←

Figure 6.8: Policy of the SARSA algorithm on the Bugs environment

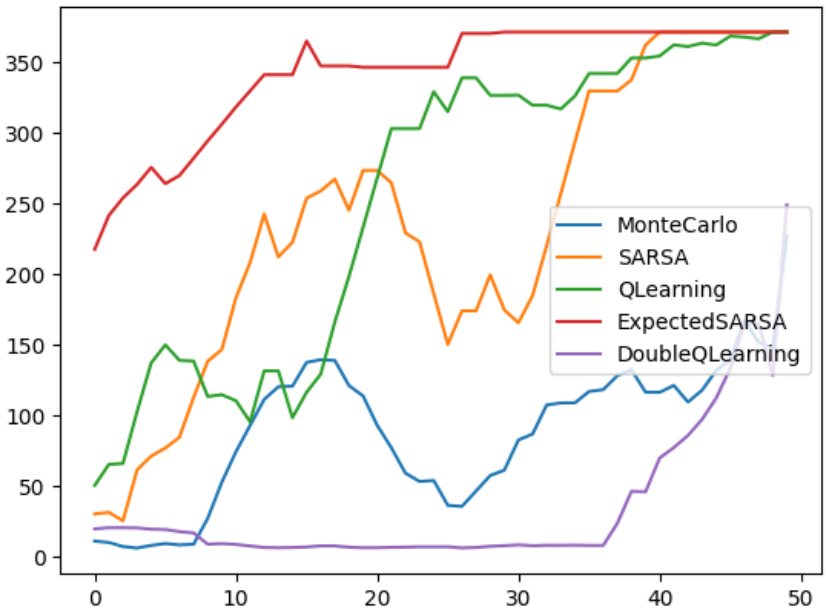
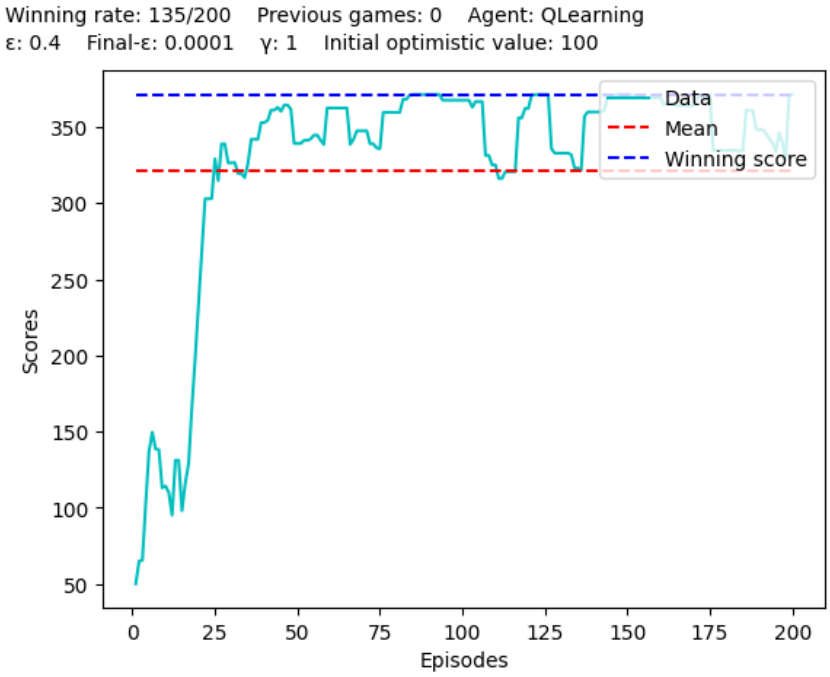
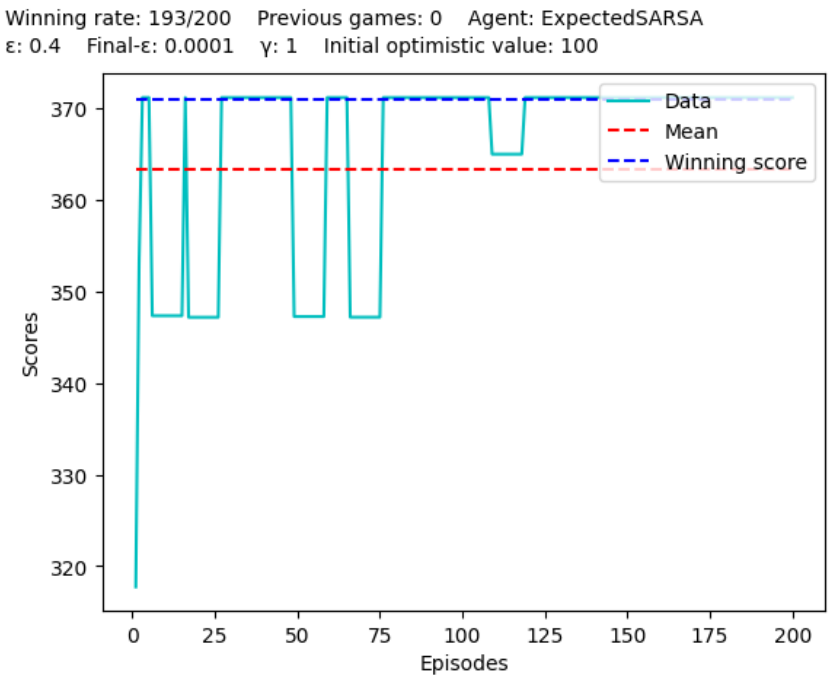


Figure 6.9: Average performance of the agents with Viruses environment



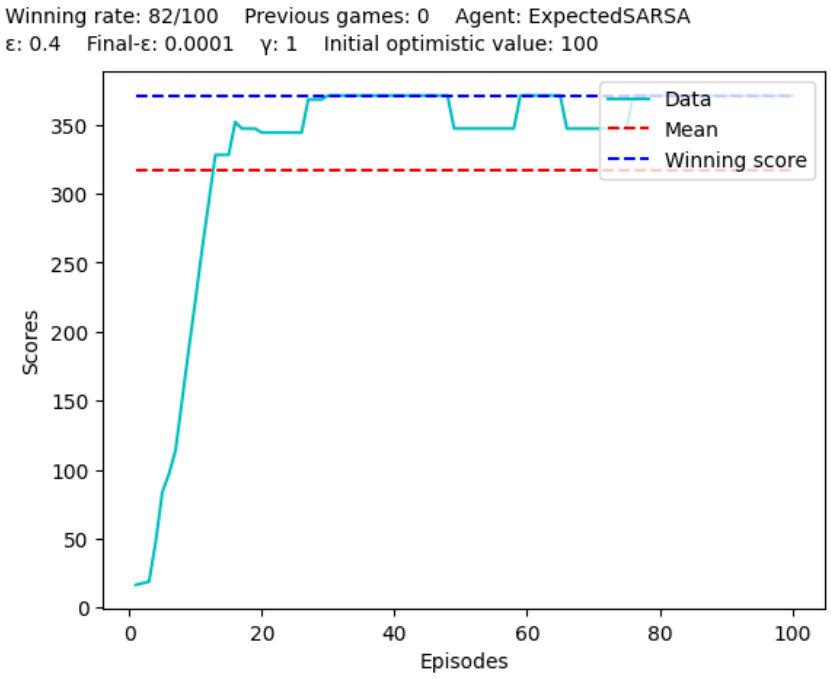
	60	120	180	240	300	360
(0, B)	→	↑	←	←	←	→
(0, R)	→	→	→	←	←	→

Figure 6.10: Policy of the Q-Learning algorithm on the Viruses environment



	60	120	180	240	300	360
(0, B)	→	→	←	←	←	←
(0, R)	→	→	→	→	←	←

Figure 6.11: Policy of the Expected SARSA algorithm on the Viruses environment without shooting



	60	120	180	240	300	360
(0, B)	←	→	→	←	←	←
(0, R)	→	→	↑	←	←	←

Figure 6.12: Policy of the Expected SARSA algorithm on the Viruses environment with shooting

Conclusion

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List of Figures

List of Tables

List of Abbreviations

A. Attachments

A.1 First Attachment