RLereWolf – Reinforcement Learning Agent Development Framework For The Social Deduction Game Werewolf

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Declaration

No portion of the work contained in this document has been submitted in support of an application for a degree or qualification of this or any other university or other institution of learning. All verbatim extracts have been distinguished by quotation marks, and all sources of information have been specifically acknowledged.

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Signed: Georgi Velikov

Date: 2021

Abstract

Unlike complete information games, which are games whose game state is visible to all players, at any given point of time, incomplete information games rely on the player's ability to infer the "missing" information from the provided to them game state. The information inference is targeted towards other players and their personal player state, or role. Due to the inherent nature of complete information games, which do not require any assumptions to be made on the players or the game state, computers are able to beat the best players at those games, such as – Chess, Go, and Checkers by *Deep Blue*, *AlphaGo Zero*, and *Chinook* respectively. In order to beat the best players in incomplete information games, the software built to play them has to be able to adapt to the dynamically changing game state and "fill-out" any of the game state gaps with assumptions based on previous experience and contextual game knowledge, effectively *learning* what the best action to some previously encountered position. RLereWolf aims to provide developers with the framework required to build, observe, and improve existing *Agents*, which are non-human players designed to play the game, as well as introduce *trust*, honesty, and *Q-learning* into the domain of *beating* Werewolf.

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Chapter 1

Introduction

In this chapter, the author will go over the project subject, background information on the topic, alongside any relevant literature. Moreover, the author will define the project's research question and provide a short description of the contributions which RLereWolf has made.

1.1 Context

The game of Werewolf is a social deduction which is based on Dimitry Davidoff's *Mafia* (Braverman et al., 2008) where players are randomly assigned specific roles, at the start of a game, which fall under one of the general factions – *evil*, *neutral*, and *good*. The game is split into two times of the day – *day* and *night*. In order for a game of Werewolf to start, there needs to be at least 5 players, with a maximum of 75 players (BGG, 2016). Whilst the complete game of Werewolf provides players with the three factions, in the implemented base game, only two factions will be used – *evil* and *good*. In the base version of Werewolf, there exist four roles:

- *Villager* – The core role within the game. Part of the *good* faction and has no special actions. They can only vote during the *day* in order to execute a *Werewolf* suspect. Goal of the role is to kill off all *evil* faction players.

- *Guard* – A member of the *good* faction. The *Guard* can protect players during the *night* from being attacked, including himself. The goal of the role is to kill of all *evil* faction players.

- *Seer* – A member of the *good* faction. The *Seer* can find out the role of a player during the *night* time and has the ability to share or withhold any information they learn through divining.

- *Werewolf* – *Villagers* that turn into *Werewolves* during the *night*. They are a member of the *evil* faction and have the ability to attack other players during the *night* in their werewolf form. Their goal to kill off all *good* faction players.

Players must *deduce* and make assumptions about other players, based off of previous experiences and partial game knowledge, that is – incomplete knowledge of the game. The *deduction* is aided by having players question each other and communicate in the village forum, conducted during the *day* time, where a player is voted off for execution. During the *night* time, some roles either form a conclave with their team members and vote on an action, i.e. *Werewolves* voting on who to attack during the night, alternatively some roles have an individual deicing process – *Guard* deciding who to protect during the *night*.

1.2 Literature Review

To the extent of the author's knowledge, the only existing framework that offers similar characteristics is *AiWolf* (Toriumi et al., 2016) which hosts annual competitions amongst the developed agents, by its users (aiW, 2017, 2020). However, whilst *AiWolf* provides a *Java* version of the client and server, their implementation does not provide users with any analytic data, has a limited communication protocol, and a limited reach to its core audience – the machine learning community.

Moreover, although covering 50% of the in-game communications used in actual Werewolf matches (Toriumi et al., 2016), the author believes that this can be further improved upon with *conflict resolution messages*, which has proven beneficial other research which uses the Java iteration of *AiWolf* (Wang et al., 2018) . *AiWolf* does have bindings to Python[1] – however, at the time of writing, Python is the de facto language used in the machine learning domain.

Consequently the largest machine learning community has no access to the core implementation of the framework and are unable to do any changes to the game implementation or inherent functionality, in their primary programming language. Moreover, the *AiWolf* project's primary natural language is Japanese, consequently not all of its functionality is accessible to English speaking users.

All "solved" or "partially-solved" games, that is – games which have an artificial intelligence agent who has mastered the game and is equal or better in skill than human players, are not classified as *incomplete information games*, but rather are known as *complete information games* (Kline, 2015). In *incomplete information games*, also known as *Bayesian games* (Dekel et al., 2004; Ely and Sandholm, 2005), the players do not know the entire game state and have access to a subset of the full game state, where the game state can contain information about the other players or the current player's "view" of the game world. The reason why "solving" *Bayesian games* is hard is because one of the core mechanics in *incomplete information games* – the ability to infer the "missing" from your knowledge, based on partial contextual knowledge and experience, is not trivial to replicate on a computer system.

Nagayama et al. (2019) aims to improve upon the *AiWolf* project, but they mostly targeted a specific role as opposed to the entire set of available roles, i.e. an *Agent* that is proficient only as a Werewolf (Nagayama et al., 2019), whereas the author aims to create multi-role built-in *Agents*. Moreover, the proposed *Agent* in Nagayama et al. (2019) does not inherently learn, and is rather a *rule-based Agent* who tries to "swingle" other players, by communicating accross to other players that they are a *good faction* role. The rules which the "stealth werewolf" follow are based on thresholds values, forming a decision tree (Nagayama et al., 2019), which is hard-coded into the *Agent*. Whilst their *Agent* does provide an improvement on the win-rate of the Werewolf by 65% (Nagayama et al., 2019) to the default *AiWolf Agents* (Toriumi et al., 2016), it is not an *Agent* that covers all roles, supported by the game and does not "learn" or adapt to the current game state.

Wang et al. (2018) shows an implementation of physical *Agents*, i.e. robots, which can play

[1]*AiWolfPy* – `https://github.com/aiwolf/AIWolfPy`

the real world game of Werewolf. However, it relies on the *AiWolf* framework and does not provide any further improvements on the core *AiWolf* framework, other than the addition of *conflict resolution messages* – which add an agreement/disagreement option in the communication protocol. Consequently their framework is only targeted towards hardware implementations of *AiWolf Agents*.

Gillespie et al. (2016) used semantic natural language classifiers to try and understand the communication protocol and have a counter-action based on those player communications. However, this relies on having players consistently sending communications on what their action is. Moreover, if players are not cooperating by sending out frequent communications, then the *Agent* will rely on "observations" which are part of the project's proposed future work.

1.3 Motivation

The process of deduction based on partial contextual knowledge is a relatively trivial task for humans. However, it is a difficult computing science problem which has been historically solved with complicated reasoning using various rules, which aim to translate one's reasoning to its core – sequential if blocks (Kautz et al., 1996; Büning and Lettmann, 1999). Whilst a framework with similar functionalities exists – *AiWolf* (Toriumi et al., 2016), the framework's usability is limited specifically to artificial intelligence development on a specific iteration of the *Werewolf* game (see Section 1.2 for more information), which this project will improve on. Moreover, *AiWolf* targets individual roles with separate *Agents*, whereas the proposed framework will apply a single *Agent* to all, included in the game implementation, roles.

The goal of the framework is to expedite artificial intelligence research and development, by providing the necessary tools and foundation. Moreover, the project aims to explore the addition of *trust* and *honest* which the agents can use to further mimic the real-life decision making process which would occur in the the context of Werewolf.

1.3.1 Research Question

The framework proposes a new framework which aims to provide analytic tools and built-in *Agents* which can play all supported by the game roles. Moreover, the improvements to the communication protocol and the addition of *trust* and *honesty* factors should perform better than a stochastic player approach and worse or equal to the optimised *Q-learning* approach. Consequently the project's goal is to answer the following questions:

RQ1. Can the author offer a framework for both multiple non-expert *Agents* to play the game, and *developers* to train *Agents*?

RQ2. How can the author improve the existing *communication protocol* for the *Agents*?

RQ3. How do the proposed *Agent* behaviour models affect the winning rate?

1.3.2 Contributions

The project aims to improve on the functionality of its existing counterparts, namely *AiWolf*, and provide a more open API to developers and researchers alike. It does that by providing users with:

- Client – A distributable *Game* client which connects to a target *Server* and allows users to play with other human *Players* or *Agents* over the internet.

- Development Framework – A development framework which provides the Werewolf *Game* implementation alongside the analytic utilities which give an insight on the *Players'* behaviours and *Game's* metrics, i.e. turn count, day count, and winning faction. The framework also includes comprehensive *Server* and *Game* activity logging, providing users with a detailed account of the *Player's* actions and the *Game* state. The development framework consists of four sub-systems – *Client*, *Server*, *Game*, and *Environment*.

- Built-in *Agents* – Three distinct built-in *Agents* which target three distinct behavioural models:

  - *Dummy Agent* – A stochastic *Agent* that does random *valid* actions.
  - *Rule-based Agent* – An *Agent* with an *honesty* factor who votes for the least *trustworthy*, according to them, *Player*.
  - *Trainable Agent* – An *Agent* that can learn from playing multiple games of the current Werewolf *Game* implementation. Has no pre-existing knowledge of the game and needs to *train* in order to learn the game's rules and how to optimally play it.

The contributions of this thesis also include an evaluation of the three built-in *Agent* behavioural models which takes into account the *speed*, *win-rate*, and *accuracy performance* of the *Agent* over a series of 1000 *Games* with varying *Game* lobby sizes (see Chapter 6 Empirical Evaluation for more information).

Chapter 1 in a Nutshell

- *Incomplete information games are difficult to "beat" because of the need of inference, based on partial game state knowledge, as opposed to complete information games, i.e. Chess.*

- *Multi-role Agents are a novelty as the primary research focus has been a single-role Agent and the communication protocol.*

- *RLereWolf contributes to beating the Werewolf game by providing a developmental framework which aims to expedite AI research*

Chapter 2

Requirements

The author will go over the possible scenarios that arise whenever a *developer* or *user* is using RLereWolf. The identified scenarios are the basis for both functional or non-functional requirements.

2.1 Scenarios

The Scenarios the author will frame are based on two user groups:

- **Client users** – The users whose primary focus is being able to play Werewolf with their friends and/or *Agents* (see more information in Subsection 4.3.4 Players).
  - Play Werewolf with other people from some network using an open *Transmission Control Protocol* (TCP/IP) connection.
  - Play Werewolf with *Agents*
  - Communicate with other *Players* (see more information in Subsection 4.3.4 Players) in a game of Werewolf
- **Developers** – The developers are users whose primary focus is the development of a Werewolf game & reinforcement learning (RL) artificial intelligence (AI) development for Werewolf. The *developers* might be researchers that investigate incomplete information games.
  - Use reinforcement learning to train "agents" to play an iteration of the Werewolf game.
  - Analyze Werewolf game outcomes with game metrics.
  - Develop expansion packs for the base Werewolf game.
  - Deploy a server that can host multiple Werewolf games.
  - Deploy a client that can connect to a server and play Werewolf.

2.2 Functional Requirements

The functional requirements the author has identified are based on the expected scenario outcomes, as well as any subsequent implied behaviours – exception handling, recovery, and analysis data generation. As RLereWolf contains four subsystems, the author has split their functional requirements into four subsections, namely: *Server*, *Client*, *Game*, *Environment*.

2.2.1 Server

The functional requirements for the *Server* reflect their ability to manage multiple instances of the Werewolf *Game*, as well as support multiple connections from *Clients*. The *Server* should be able to keep track of all connections and requests, and keep a historic log.

SFR1. The server can host multiple *Games* – RLereWolf must be able to *host* multiple *Game* lobbies of Werewolf, each independent of the other.

SFR2. Multiple clients must be able to establish a TCP/IP connection – *Clients* targetting the server should be able to connect to it without any artificial limit connection limit. However, the connection limit is based entirely on the available to the server's available resources – internet speed and CPU speed.

SFR3. Must accept only valid client requests – The *Server* should validate any incoming requests and only *accept* requests which are sourced from an active TCP/IP connection. The requests must be full and non-malicious, that is – not modified by any third-party, other than the *Client* itself.

SFR4. Keep track of active TCP/IP connections – All *Clients* which are connected to the *Server* are logged and kept track of. At any given point of time, the *Server* is able to tell which *Client* is connected to the server by keeping track of their: *Client name*, *Client identifier*, IP, and Port.

SFR5. Disconnect inactive TCP/IP connections – The *Server* checks whether or not a connection it has logged is still able to receive data from it. If the connection is unable to receive data from the server, meaning it is no longer active, then the connection is disconnected and no longer *tracked* by the *Server*.

SFR6. Log connection activity – Every time a *Client* connects to the *Server*, an entry is logged on the *Server* logs, stating the IP and port pair, alongside the number of active connections.

SFR7. Log request activity – Every time a *Client* makes a request to the *Server*, an entry is logged on the *Server* logs, stating the "type of request" a *Client* has sent.

SFR8. Can be built into a single executable package – The *Server* can be built into a single executable as a mean of *deploying* it to a target host.

2.2.2 Client

The functional requirements for the *Client* are targeted towards the client user base, whose primary focus is being able to play the Werewolf *Game*, hosted on some *Server*.

CFR1. Has a graphical user interface (GUI) – The *Client* has a graphical user interface which provides users with the means to connect to a *Server* and play a *Game* (See Section 4.2 for more information).

CFR2. Can connect to a *Server* – The *Client* is able to connect to its target *Server* after specifying a name, which the *Server* and other *Clients* can use as identification, when paired with the *Client* identifier and their corresponding IP & port pair.

CFR3. Can disconnect from a *Server* – The *Client* can disconnect from the *Server* “gracefully” at any given point of time, that is – without any run-time errors on the *Client* machine.

CFR4. Must be able to create a *Game* – Once connected to a *Server*, *Clients* will be able to create a *Game* lobby on that *Server* which other *Players* can join.

CFR5. Must be able to join a *Game* – *Clients* are able to join any *Game* hosted on the *Server*, as long as the maximum *Player* count for the *Game* has not been exceeded.

CFR6. Must be able to recover from any *minor* run-time failures – The *Clients* should be able to recover from a failed request to the *Server*, or minor *Client* run-time exceptions, which do not break the connection between the *Server* and the *Client*. Any *Client* specific exceptions related to the GUI or *Game* & *Player* state handling, can be recovered from.

CFR7. Can *play* Werewolf with other people – Once a *Client* joins a *Game*, other *Clients* can also join it and play the hosted version of the Werewolf *Game* together.

CFR8. Can set themselves as *ready* or *unready* in a *Game* – Once a *Client* joins a *Game*, their readiness state is set to *unready*. They can set their status to *ready*, whenever they would like to start the *Game*. All *Players* must be ready for the *Game* to start.

CFR9. Can *play* Werewolf with other *Agents* – Once a *Client* joins a *Game*, the *Client* can add *Agents* to the *Game*, before a *Game* has started. The *Agent Players*, which join the *Game*, have a readiness state of “ready”.

CFR10. Can be built into a single executable package – The *Client* can be built into a single executable as a means of distribution to users.

CFR11. Can communicate with other *Players* – The *Client* should be able to send preset messages from a finite set of “classified” messages to other *Players* within the same *Game*.

2.2.3 Game

The functional requirements for the *Game* reflect on the base Werewolf game (BGG, 2016) implementation element and what its *Players* can do.

GFR1. Allow multiple *Players* to be in a *Game* – The *Game* instances should be able to support multiple *Players* concurrently playing the *Game*, with a set maximum per instance.

GFR2. Have the base four roles in Werewolf (*Villager*, *Guard*, *Seer*, *Werewolf*) – The *Game* must have the base *Werewolf* roles included which are assigned, randomly, to *Players* in a *Game*, on its start.

GFR3. Roles have different *abilities* – Each of the base roles in the *Game*, should have their distinctive features and abilities that can be used at different times of the day/night within the *Game*.

GFR4. *Players* can only make *valid* actions – The *Game* should validate any action, such that every *Player* can only do permitted by the game rules action, at the current state of the *Game*.

GFR5. Can have humans and *Agents* in a single *Game* instance – The *Game* instances should be able to have humans and *Agents*, both referred to as just *Players*, in a single *Game*, in which they can play together.

GFR6. Log *Game* & *Player* states – Every action done by a *Player* is logged within a *Game* log, alongside the "complete" game state, that is – all information about the *Game* and its *Players*. The log must be stored on the *Game* host machine, if the *Game* is on a *Server* – then the logs will be on the *Server* machine.

2.2.4 Environment

The functional requirements for the *Environment* are based around the reinforcement learning aspect of the framework, and what it must provide *developers* with.

EFR1. Allow multiple *Agents* within the same environment – The RL training *Environment* must support multiple different *Agents* within it. This is because RLereWolf aims to support *Agent* exclusive games in which the *Agents* are able to train in games without the need of a human *Player*.

EFR2. Provide developer with game metrics, used to analyze the *Player* performance – The *Environment* must provide useful *Game* metrics, which can be used for *Agent* analytics under diverse conditions.

EFR3. Training *Environment* should be optional – The training *Environment* needs to be an optional element as the framework aims to provide a modular package for its *developer* user base. This means that only some *Games* will allow for *Agent* training and analysis.

EFR4. Have a default stochastic *Agent* – RLereWolf must come in with an integrated *Agent*, which does random actions.

EFR5. Have a default rule-based *Agent* – RLereWolf must come in with an integrated *Agent*, which does deterministic actions, based on some arbitrary rules.

EFR6. Have a default trainable *Agent* – RLereWolf must come in with an integrated *Agent*, which can *learn* to play the Werewolf *Game* iteration that the *Agent* is in.

2.3 Non-functional Requirements

The non-functional requirements describe the inherently expected behaviour from the system with regards to features such as usability, scalability, and the performance of RLereWolf's components.

NFR1. *Server* and *Game* reliability – Run-time errors on the *Server* & Game must be handled and logged, to avoid the possibility of having a crash whenever *Clients* are connected to the *Server* and/or *Game*. Both *Server* and *Game* will always try and recover from run-time errors.

NFR2. *Client* reliability – Whilst the reliability of the *Client* is not nearly as important as the *Server*'s or the *Game*'s, all run-time errors should be either prompted to the user or recovered from.

NFR3. Maintainability of all modules – Each module should have well documented code, with easy to navigate classes and structures so that it is easily expandable on.

NFR4. RLereWolf must work on modern operating systems – As RLereWolf is written entirely in Python 3.7, the framework's compatibility with operating systems is equivalent to that of Python – capable of supporting modern and legacy systems – Linux, Windows Vista and newer, FreeBSD 10 and newer, and MacOS 10.6 and newer (PythonDev, 2018).

NFR5. Portability of the *Client* & *Server* – The *Client* and *Server* should be in a portable format that is compatible with all, supported by Python 3.7, operating systems.

NFR6. Games should never get stuck other than on awaiting *Players*' actions and should conclude after some finite amount of time – There should be no situation in which the *Game* gets stuck in a state of awaiting someone who is no longer viable for an action with a game turn. That is, the *Game* should reliably track the *Player* actions and record each one, so that it never gets stuck.

Chapter 2 in a Nutshell

- *RLereWolf provides a framework with four comprehensive and independent subsystems – Client, Server, Game, Environment.*
- *RLereWolf's target audience is Werewolf players and Werewolf/Incomplete information game AI researchers.*
- *All four subsystems must have their core functionality implemented, as well as be resistant to run-time issues.*

Chapter 3

Technologies

In this chapter, the author will go over the technologies and methodologies used for RLereWolf, accompanied by a discussion for each technological decision, its implications, and future.

3.1 Programming Language

In the beginning of the project, the author had two primary candidates for a programming language with which the initial iteration of RLereWolf would be built with, namely:

- **C#** – A compiled, general-purpose, type-safe programming language, which has access to the *.NET framework* and its multitude of GUI, asynchronous programming and *language integrated query* (LINQ) utilities (Hejlsberg et al., 2003, 2008). As a result, the author would have access to highly optimised frameworks for building a Server-Client infrastructure, a GUI client and would be assisted with the aforementioned type-safety and immutability, which – in the author's experience, is essential for large projects, such as RLereWolf. Moreover, the author has had 2 years of professional experience with C# and the *.NET* stack.

- **Python** – An interpreted, general-purpose, dynamically-typed programming language whose philosophy is heavily based around code readability, by sticking as close to natural languages as possible (Van Rossum and Drake Jr, 1995; Oliphant, 2007). Although Python's "out of the box" frameworks and packages are enough for the development of RLereWolf, it would need to greatly rely on open-source frameworks to aide the author in the framework's development. Furthermore, Python's vast selection of machine learning frameworks allows for the framework's use in multiple machine learning fields, other than the targeted reinforcement learning field (Pedregosa et al., 2011; Raschka, 2015). Although the author has no professional experience with Python, they have 4 years of academic experience which mostly revolved around Python's usage.

Even though there is the possibility of using both languages for the different modules of RLereWolf, the author decided to stick with a single language for consistency in the initial iteration of the framework. Given the two potential language candidates, the author's decision for an initial programming language was Python.

Although, the performance of Python is sub-par to C#'s (KARACI, 2015; Fourment and Gillings, 2008; Srinath, 2017), the author's decision to go with it is entirely based on the potential user base and their focus – machine learning. More specifically, the author has chosen Python

3.7 instead of the latest available, at the time, Python 3.9 – due to the lack of necessary package support[1].

The aforementioned issue was spotted during the development of RLereWolf and underlines one of the author's concerns with using Python – the inherent dependencies accross various packages and their potential downfall. Consequently, the author has kept the external packages usage to a minimum coupled with a comprehensive list of the required packages (see Appendix B Developer Manual for more information) and their exact version, with the aim of keeping the Python RLereWolf iteration maintenance to a minimum.

3.2 Packages

In this section, the author will discuss the "direct" packages used in the implementation of RLereWolf and their role within the project. By "direct" the author means that they will only look at packages as a whole, without any of their inherent dependencies.

3.2.1 Serialization

A big part of RLereWolf is the client-server infrastructure and the "communication" between the two subsystems. Consequently, the need for a standardised & reliable byte serialization framework which supports the usage of classes, functions, and lambda functions arose, as both client and server subsystems have significant overlap in the used by them data transfer objects (DTOS) (see Chapter 4 RLereWolf Architecture for more information). An example of such a data transfer object is the game state information, which contains the *known* to some *Player* information for the current state of the game. For the task, the author chose *cloudpickle*, which is an extension of the Python integrated *pickle* object serialization framework.

3.2.2 Names & Locale

The framework's game implementation allows for multiple *Players* to play together or with *Agents*. As the game is heavily focused around communication and assumptions for other *Players*, the author decided to use a random name generation package, which is based off of the locale of the game host, typically this would be the server, which would generate names whose players can easily remember and uniquely identify within a game. The names, generated by *Faker*[2], are assigned to *Agents* which have been added to some game lobby. Whilst in the current iteration RLereWolf does not use *Faker* for anything more than name generation, the author has planned, at a later stage, the addition of "profiles". The "profiles" can be generated by the *Faker* library for the *Agents*. The *Agent* "profiles" will give an estimate, to other *Players*, what their game personality might be, that is – how they are likely to behave in the game.

3.2.3 Graphical User Interface

As the time scale of the project did not allow for a fully-fledged "game-like" graphical user interface, the author decided to go with the standard in Python GUI framework – TKinter (see Section 4.2 for more information).

However, the author has additionally relied on Pygubu, which is a *Rapid Application Development* (RAD) (Beynon-Davies et al., 1999; Mackay et al., 2000) tool whose purpose is to

[1]PyTorch issue with Python 3.9 – This is due to the lack of wheels support for Python 3.9 `https://github.com/pytorch/pytorch/issues/47776`

[2]Faker – `https://faker.readthedocs.io/en/master/`

increase implementation speed by providing a GUI builder tool, which creates descriptions of the graphical user interface as *Extensible Markup Language* (XML) Bray et al. (2000) files. The author has also additionally supplemented Pygubu, by adding in renderers for the generated by it XML files. Moreover, Pygubu allows the majority of the design to be primarily designed and laid out in its builder (see Figure 3.1), whilst functionality and complex behaviours are defined in the aforementioned renderers (see Section 4.2 for more details).

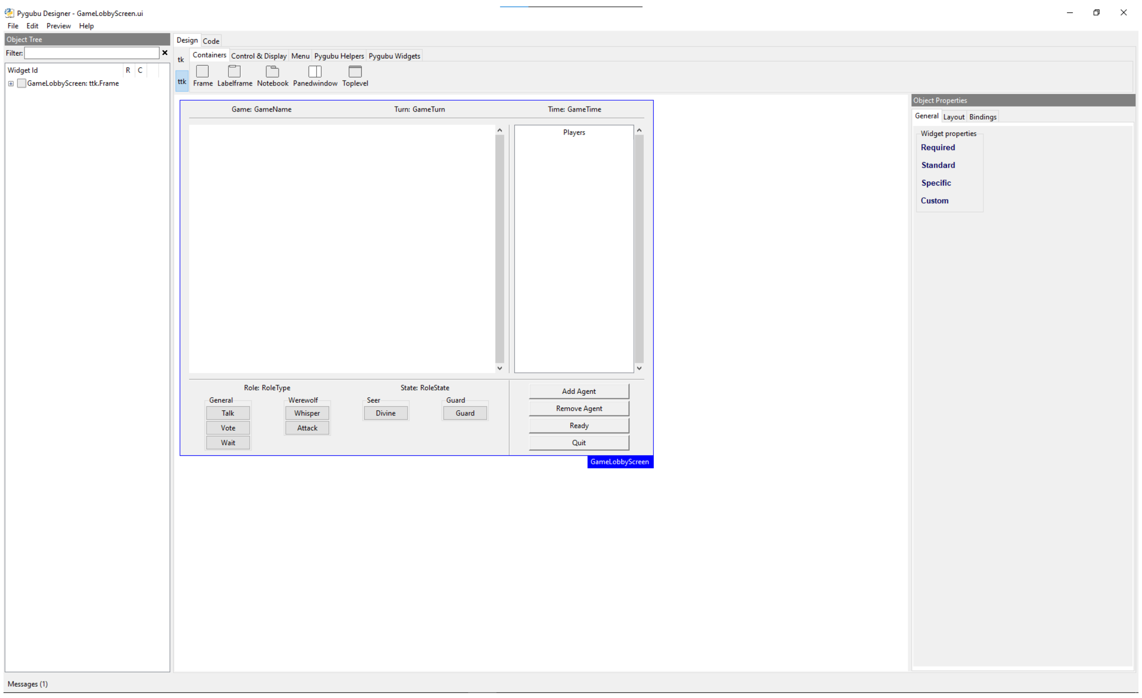


Figure 3.1: Pygubu Designer – the *RAD* graphical user interface builder tool

3.2.4 Machine Learning

Whilst *RLereWolf* comes with the tools for further development of the *Werewolf* game and a client-server infrastructure for it, the primary target user base are researchers and machine learning developers. Whilst RLereWolf could be used with other machine learning techniques, due to its modular design (see Chapter 4 RLereWolf Architecture for more information), its target is *reinforcement learning* (RL).

As such, the author is including a reinforcement learning training environment and a trainable agent (see Sections 4.4 and 5.3 for more information), which can be used as an introduction to the framework, by machine learning enthusiasts. Consequently, the author's choice for a reinforcement learning framework is *OpenAI Gym* and its open-source extension *Ray RLlib* (RLlib, 2020). They provide the author with the necessary environment-agent loop functionalities, alongside the ability to create multi-agent training environment in which multiple *Agents* can play against each other and *optimise* against their individually learned styles of play.

Moreover, the *RLlib* application support can easily be integrated in the framework's built-in *reinforcement learning* algorithms, as well as allow for the further development of RL-based custom algorithms for some multi-agent environment (see Figure 3.2).

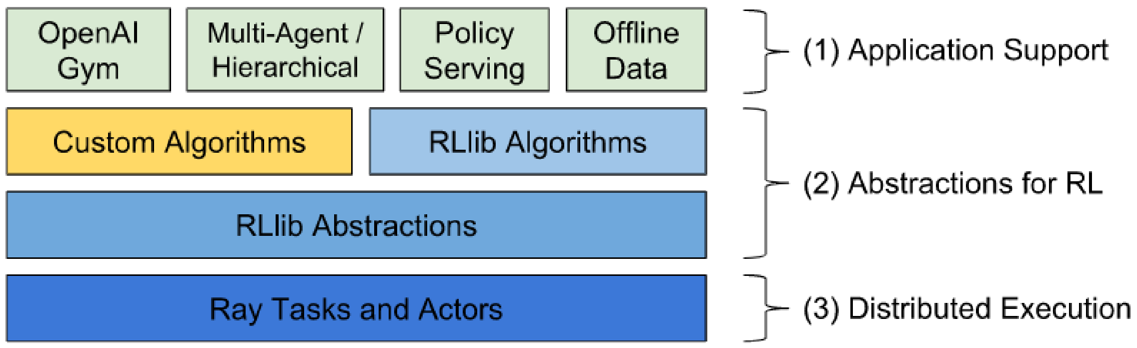


Figure 3.2: Ray RLlib Architecture (RLlib, 2020)

3.2.5 Distribution

Although the framework consists of four subsystems, namely – *Client*, *Server*, *Game*, and *Environment* (see Chapter 4 RLereWolf Architecture for more information), only the *Client* and *Server* subsystems are targeted as distributed packages in the current iteration of RLereWolf. As such, the author has decided to use *pyinstaller*[3], in order to create ease to distribute executable files, which are a "frozen" copy of the Python application. *Pyinstaller* can create create executables for most modern operating systems, including the supported by the author – *Windows*, *Linux*, and *Mac* (Pyi, 2007). The creation of the executables is aided with built-in "build scripts" (see Appendix B for more information on distribution).

3.3 Methodologies

The development approach chosen by the author was an iterative approach with a focus on providing the *minimal viable product* (MVP) (Moogk, 2012; Lenarduzzi and Taibi, 2016). Consequently, the author's focus was to provide a framework which covers the functional requirements, on an at least partial state, such that none of the non-functional requirements. This means effort has been put into all of the functional requirements and are concurrently addressed, which was managed with the assistance of the author's supervisor.

The author proposed a loosely agile-based approach which consisted of week-long *sprints* in which the author would focus on a particular RLereWolf sub-system and its core functionalities which implementation details were split onto several *tickets* (Schwaber and Beedle, 2002; Schwaber, 2004). Each *ticket* had well-defined & small task which combined with the other *sprint tickets*, would complete parts of the functional requirements for some sub-system.

The author relied on *git* version control to keep a record of all changes and *GitHub*'s metrics to keep track of their progress. The repository, owned by the author, which RLereWolf is hosted on can be found on the following address: `https://github.com/GeorgeVelikov/RLereWolf`. The metrics provided by *GitHub* were an important part of making sure the project's development timeline was followed. Furthermore, they provide a complete list of the design decisions the author has made, as a frequent commit principle was followed – i.e. the author would split up tasks into small sub-tasks and make commits for each one. The separation of the tasks inherently leads to numerous small commits (see Figure 3.3 where the orange graph represents the commit count over the period of 17th January to 2nd May).

[3]PyInstaller – `https://www.pyinstaller.org/`

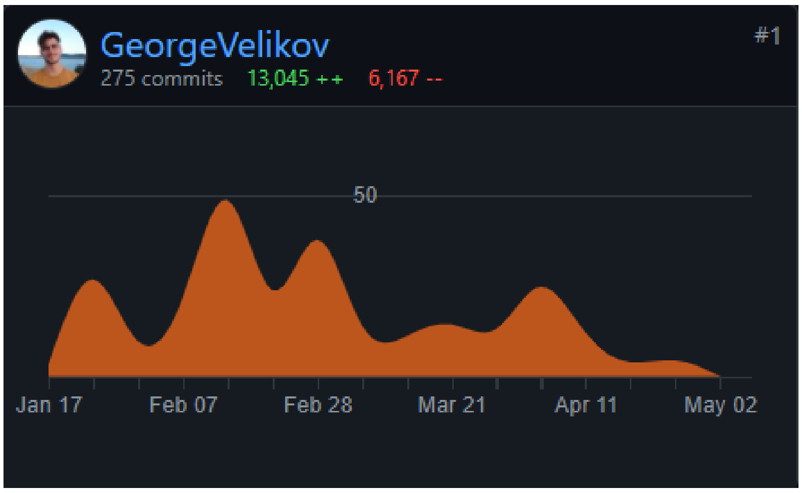


Figure 3.3: *GitHub* metrics – commit count and line modification (adds in green & deletes in red) counts

Alongside detailed and frequent commits, the author has also employed the software engineering industry standard method of *verbose coding* (Buse and Weimer, 2009; dos Santos and Gerosa, 2018). This standard states that the code written by a developer should be clear and coherent enough to be understood as functionality, whereas any code comments should act as a documentation for the reasoning behind the design choices. However, employing *verbose coding* does lead to some possible issues – whilst easily readable and understandable by developers, it does mean that developing will take longer and code files will require more disk space in comparison to a more "minimal" or *cryptic* approach. That being said, the author's decision on employing *verbose coding* was not only a personal choice, but an inherent design choice, as the code within RLereWolf itself, is the tool that is offered to developers.

3.4 Development Hardware & Software

The development of the framework was done on a single machine with the aide of the preferred by the developer *Integrated Development Environment* (IDE) – *Visual Studio*, and a graphing tool – *Draw.io*[4]. Whilst, the framework has no inherent system requirements other than the requirements for Python 3.7 and *Tkinter*, development speed with RLereWolf is highly dependent on the CPU of the host machine.

As development of RLereWolf was done with an IDE, maintanance on the framework would be done, ideally, with the same configuration as the author (see Table 3.1) which is described in-depth both in Appendix B Developer Manual and on the project's *GitHub* repository – `https://github.com/GeorgeVelikov/RLereWolf`.

[4]Draw.io – https://drawio-app.com/

Component	**Description**
Hardware	
CPU	Intel Core i7 6700, 4 cores, 3.4 GHz (up to 4.00 GHz)
GPU	Nvidia Quadro P2000, 5 GB GDDR5
RAM	4x8 DDR4 2133 MHz
OS	Windows 10 Pro
Software	
IDE	Visual Studio Professional 2019 16.8.6
Graphing Tool	Draw.io

Table 3.1: Hardware used during the development of RLereWolf

Chapter 3 in a Nutshell

- *RLereWolf is a Python 3.7 based framework which employs a loose interpretation of the Model-View-ViewModel design pattern.*
- *Client relies on Tkinter for its graphical user interface (GUI) which has a dedicated GUI development pipeline.*
- *The framework has employs multi-agent environment as opposed to the commonly used single-agent environments.*
- *The development of RLereWolf was focused on a minimal viable product and weekly iteration showcasing.*

Chapter 4

RLereWolf Architecture

In this chapter, the author will describe the architecture of RLereWolf, its logical separation into components and how the components interact with another, to create a request-response loop (Mozilla, 2015; FMC, 2004) between the server and the client .

The overall architecture of the framework (represented in Figures 4.1 and 4.2) consists of four major components, which create a request-response loop, namely:

- Server – The *Controller* and middle-man between clients and the game who validates that the actions specified by the client are valid and obey the game rules. As a middle-man, the server accepts data from the clients, checks its validity and passes it to the game. Once the game replies to the server, the server serializes the reply and sends it back to the client (see Section 4.1 for more details about the server).
- Client – The Graphical User Interface (GUI) which acts as the input for the user to send requests to the server in order to *play* a game hosted on the server (see Section 4.2).
- Game – An implementation of the base Werewolf game which is moderated by the server. Multiple Werewolf games can be hosted on the server (see Section 4.3).
- Environment – The training environment and agents supported by the framework (see Section 4.4). The training environment is an extra layer wrapped around the Game. The environment keeps track of the game state and assigns rewards to *Agent Players*. It is an additional feature that any game hosted on the server can have.

The request-response loop of RLereWolf starts with the client sending a *Packet* to the server, which is either redirected to the packet handlers (bottom of Figure 4.3) or discarded by the *Packet Handler Context* (bottom of Figure 4.3), depending on whether the *Packet* is successfully validated. Each color in Figure 4.1 represents the request-response flow for some client, e.g. orange is the packet transfer of *Client Beta*, blue is the packet transfer of *Client Alpha*, and magenta is the packet transfer of *Client Gamma*. Once validated, the *Packet* gets redirected to its corresponding *Packet Handler* and is unwrapped by it. Once the *Packet* is processed, it is targeted as an *Action* on the *Game*, the client is in. For example, *Client Beta* can be seen wanting to send a message in *Game Y* (the orange lines in Figure 4.1).

The Client connects to a specifically targeted server which hosts multiple Games and any associated Environments with them. Each of the aforementioned components is treated as a separate, self-contained *project*. By *project*, the author means the code package separation of RLereWolf.

This is done with the intention of providing developers with an easy way to just use parts of the framework that they are interested in, e.g. someone purely interested in AI development would opt to only use the *Werewolf* project, which contains the Game and Environment modules.

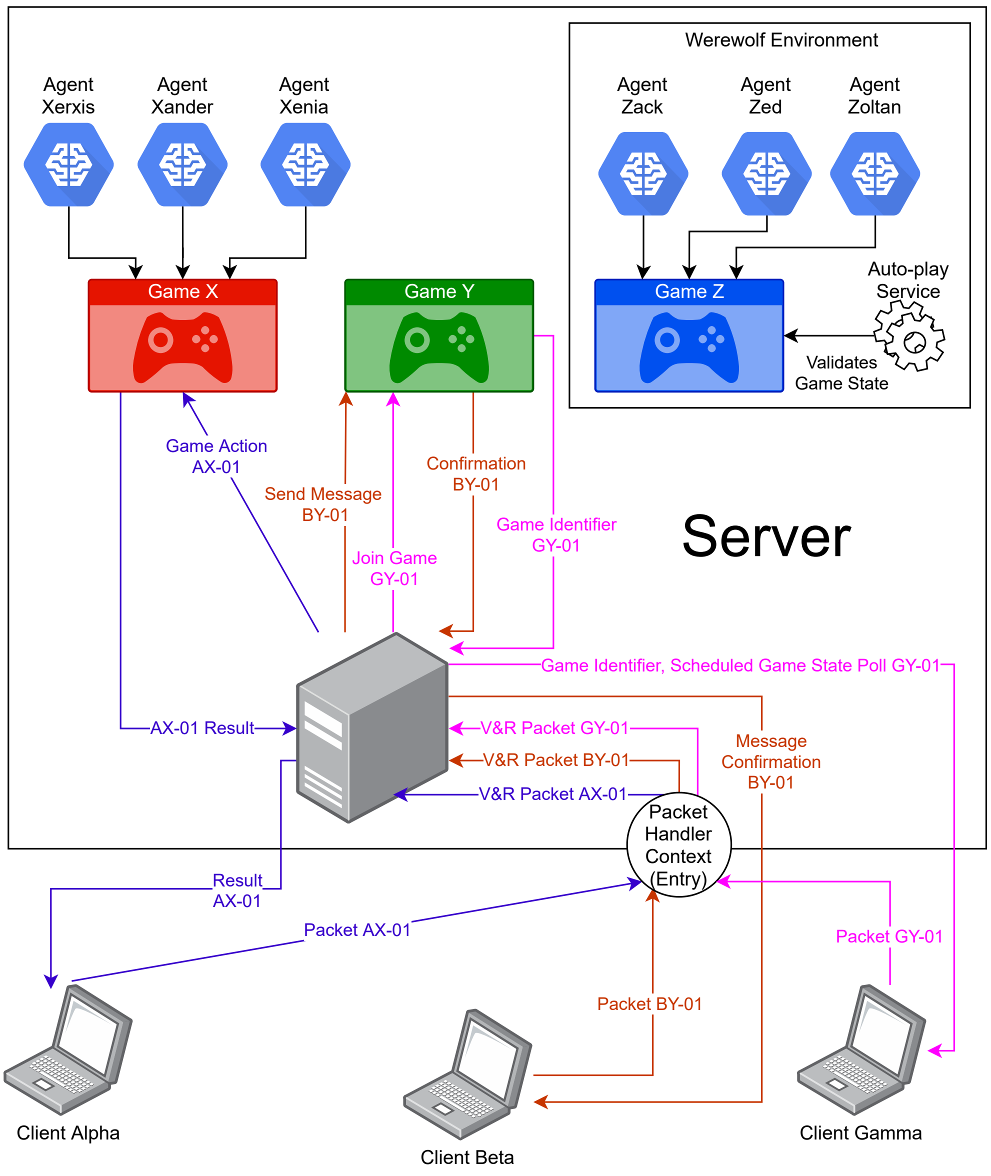
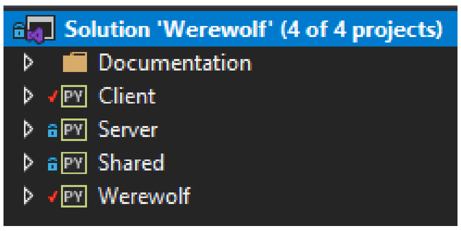


Figure 4.1: Client-Server-Game architecture.

The Client-Server architecture uses TCP/IP sockets and the communicated data is wrapped in serialized "Packets" which contain various metadata about the TCP/IP request and response, which includes data for the validation and redirection of the request (see packets after the Entry in Figure 4.1).

The packets also contain *Data Transfer Objects (DTOs)*, which are miniature models that are serialized and contain the minimum amount of required shared data between some sender and receiver, whose purpose is the decoupling of the sender and its data source, i.e. some data store/database (MSDN, 2014). The DTOs are shared between the server and client and are the minimum functionally required data by either side in order to handle a request/response. The usage of DTOs allows the shared data to be used as a read-only entity (see Figure 4.4, where each property marked with x is immutable), without exposing the source entity, which the server uses, further increasing the service security.



Solution 'Werewolf' (4 of 4 projects)
Documentation
Client
Server
Shared
Werewolf

Figure 4.2: Project Layout – as seen in Visual Studio 2019's Solution Explorer.

4.1 Server

The RLereWolf server instance can moderate multiple Werewolf games which are concurrently ran with diverse combinations of players – be it entirely human players (Game Y, Figure 4.1), entirely "Agent" players (Game Z, Figure 4.1), or a mixture of the two (Game X, Figure 4.1).

The server's abstraction of received data and the Handler Context allows it to only work with "valid" data and reduce the potential for any sort of *corrupt* or invalid requests being processed. Consequently, this reduces the possibility of run-time failure and increases server stability.

Moreover, the server instance keeps track of its connections and automatically disconnects *dead* connections which may be a result of some unhandled run-time client exception or a communication failure – be it loss of internet connection or loss of a *disconnect packet*.

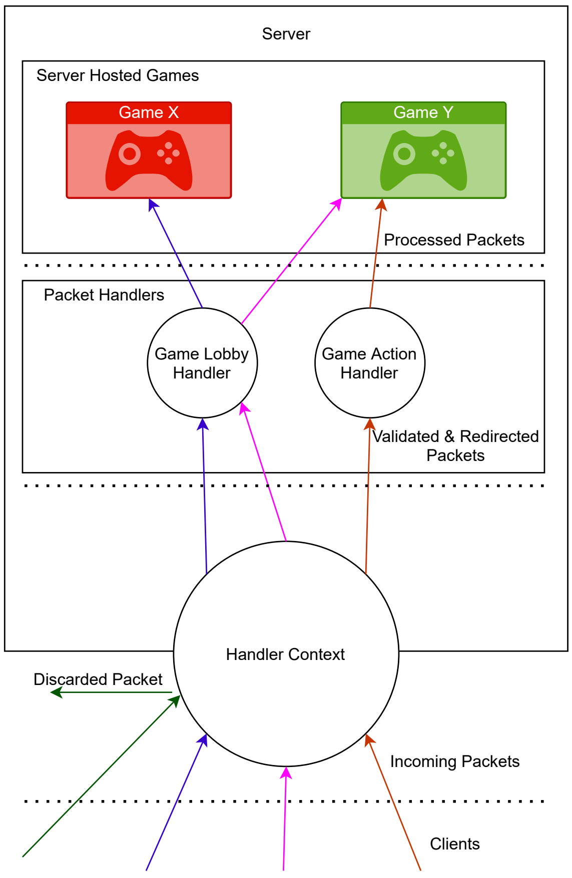


Figure 4.3: Server architecture – receiving packets.

4.1.1 Packets

The data passed between the client and the server is wrapped in *Packets* which allows for easy expansion and debugging, as tracking the "movement" of each of the data packet is well defined and easily traceable. Since each packet is identifier by a *PacketTypeEnum* (see Figure 4.4), the framework can log what is received by the server (see Figure 4.7).

The wrappers allow for consistency in terms of validating and redirecting specific packets in the server. This is needed as the framework aims to provide developers with an easily modifiable and expendable implementation of the Werewolf game. *Packets* usually contain the source (Client) connection identifier, the target (server) connection identifier and the *packet type*, e.g. *VotePlayer Packet* (as seen in Figure 4.5), as they are primarily used to encapsulate data from the Client, to the server.

Moreover, the encapsulation in Packets, inherently adds the support for backwards compatibility in versions. To elaborate, version *X+1* of the server will inherently support version *X* of the client, as long as the Packet type has the same data properties, where any new properties will be defaulted to their default type value upon deserialising and validating on the server.

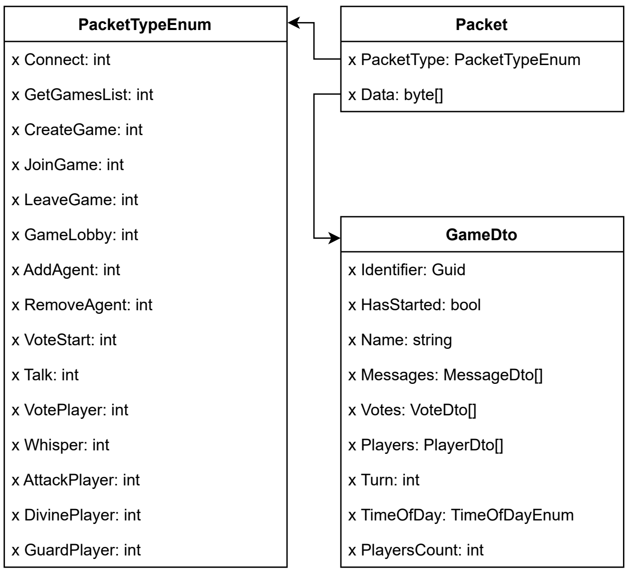


Figure 4.4: Game State Packet (GameDto) structure.

4.1.2 Handler Context

The *Handler Context* is a wrapper that contains all of the registered server packet handlers and is also responsible for the validation and redirection of packets received by the server. It can be described as the traffic controller for a machine that is running a RLereWolf server instance.

The registered packet handlers within are "business logic"(McLaughlin, 2002) units which are separated by general functionality. Whilst the hierarchy can span multiple levels, the author has implemented a two-level hierarchy. The hierarchy consists of the Packet Handlers and Handler Context (as seen in Figure 4.3) for RLerewolf, as further abstraction and nesting does not provide a huge benefit, due to the relative small scale of the needed packet handlers for the functionality of the base Werewolf game. Expanding this into a three-level hierarchy will result in creating sub packet handlers, which will divide the functionality of one specific packet handler. The implemented structure, closely resembles a tree data structure, where the Handler Context is the *root* node.

The handlers also exist in the service in a *global space*, meaning that all the hosted games use the same handlers. This is done because of performance reasons, such that creating a handler context for each game will greatly reduce the load times. The trade-off is that the packets sent by the clients must contain valid metadata which hold a valid game identifier they want to do some action in. Furthermore, handlers are coupled with the server and its handler context. This coupling servers as a means of "registering" handlers to a specific server-context pair. As a result, expanding the framework with additional handlers is a trivial task.

4.1.3 Packet Handlers

The packet handlers, as previously mentioned, handle the validated and redirected packets. Each packet handler then processes each packet by "breaking" it down and acting upon the specified metadata and value data.

The server contains a "Handler Context" which is the formal entry point for the server and it serves as a validation and redirection point to the various specific handlers, i.e. "Game Lobby Handler" or "Game Action Handler". The modular design of the server allows for a formal separation of concerns, similar to how a client would have separate.

Each packet type is redirected to a specific method in some *Packet Handler*. However, there could be the scenario where the framework can also accept the use case of having various *PacketTypeEnum*s (see Figure 4.4) going to a single method within a *Packet Handler*. An example of this in the *GameActionHandler*, where a *Wait* action is dealt as, the appropriate for the player type, an empty Action. This enables the framework to react dynamically to some *Packet*, as the framework could be easily programmed to redirect packets differently, based on some variable – be it the game state or the player state.

4.1.4 Logging

Due to the nature of the tools included in the framework, the author has also developed a basic logging infrastructure to record any errors and general operations on the server and any of its hosted games. The logging tool has a few default distinctions in the messages it logs, namely:

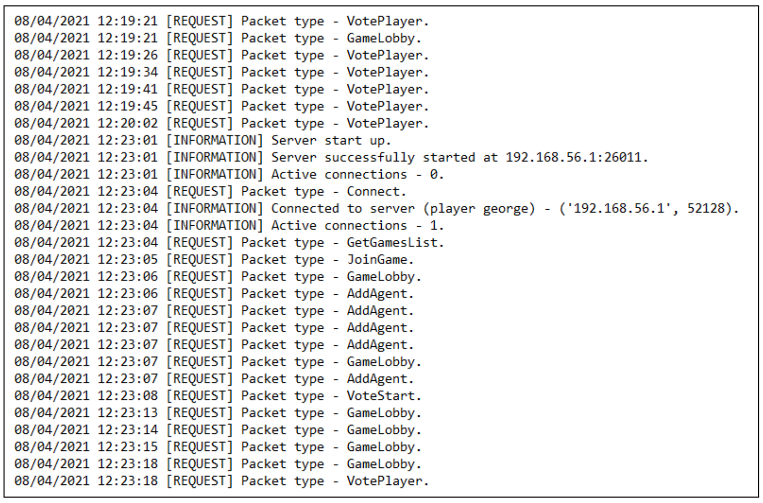
- Error – Logs created by the server whenever a run-time exception is hit which contains a timestamp and a server stack trace. An error message can also be manually logged on specific events within the server.

- Warning – Logs which warn the developer that there might be some, potentially instance breaking, error. As of the time of writing, the framework's only warning messages are logged whenever the intrinsic game rules are broken, e.g. having no villagers in a game. Another warning message is whenever some user has tried to join a full game.

- Information – Logs which are used to just record the state of either game or server. These are mostly used to keep track of dynamically changing values, e.g. the active connections counter (see Figure 4.5).

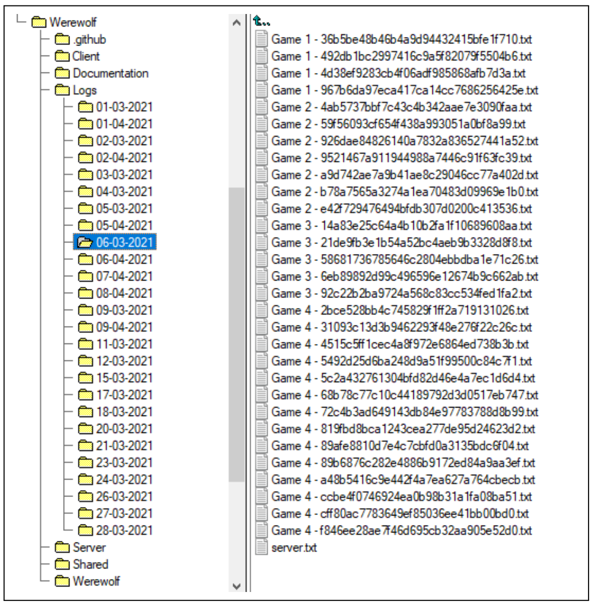
- Request – Logs which keep track of the *Packet* types received by the server at any given time. These messages can be quite chatty and can easily be disabled in the server's initialization calls. However, they are useful in tracking user behaviours and having a rough log of steps in order to recreate some exception.
- Message – This log message type is treated individually and it records any messages sent from either server or any of the players, be it Agent or human (see Figure 4.7).

The logging is split up into folders within the server instance directory. The server creates a folder "Logs" if there does not exist one already and creates a directory for the day it is logging for, e.g. "17-03-2021" (see Figure 4.6). Each folder contains the log files of the server, which records general connect/disconnect calls, any handled and unhandled run-time exceptions, as well as a count of all of the *active* connections to the server.



```
08/04/2021 12:19:21 [REQUEST] Packet type - VotePlayer.
08/04/2021 12:19:21 [REQUEST] Packet type - GameLobby.
08/04/2021 12:19:26 [REQUEST] Packet type - VotePlayer.
08/04/2021 12:19:34 [REQUEST] Packet type - VotePlayer.
08/04/2021 12:19:41 [REQUEST] Packet type - VotePlayer.
08/04/2021 12:19:45 [REQUEST] Packet type - VotePlayer.
08/04/2021 12:20:02 [REQUEST] Packet type - VotePlayer.
08/04/2021 12:23:01 [INFORMATION] Server start up.
08/04/2021 12:23:01 [INFORMATION] Server successfully started at 192.168.56.1:26011.
08/04/2021 12:23:01 [INFORMATION] Active connections - 0.
08/04/2021 12:23:04 [REQUEST] Packet type - Connect.
08/04/2021 12:23:04 [INFORMATION] Connected to server (player george) - ('192.168.56.1', 52128).
08/04/2021 12:23:04 [INFORMATION] Active connections - 1.
08/04/2021 12:23:04 [REQUEST] Packet type - GetGamesList.
08/04/2021 12:23:05 [REQUEST] Packet type - JoinGame.
08/04/2021 12:23:06 [REQUEST] Packet type - GameLobby.
08/04/2021 12:23:06 [REQUEST] Packet type - AddAgent.
08/04/2021 12:23:07 [REQUEST] Packet type - AddAgent.
08/04/2021 12:23:07 [REQUEST] Packet type - AddAgent.
08/04/2021 12:23:07 [REQUEST] Packet type - AddAgent.
08/04/2021 12:23:07 [REQUEST] Packet type - GameLobby.
08/04/2021 12:23:07 [REQUEST] Packet type - AddAgent.
08/04/2021 12:23:08 [REQUEST] Packet type - VoteStart.
08/04/2021 12:23:13 [REQUEST] Packet type - GameLobby.
08/04/2021 12:23:14 [REQUEST] Packet type - GameLobby.
08/04/2021 12:23:15 [REQUEST] Packet type - GameLobby.
08/04/2021 12:23:18 [REQUEST] Packet type - GameLobby.
08/04/2021 12:23:18 [REQUEST] Packet type - VotePlayer.
```

Figure 4.5: Server log – recording the connections it replies to, alongside the request packet types the server receives.



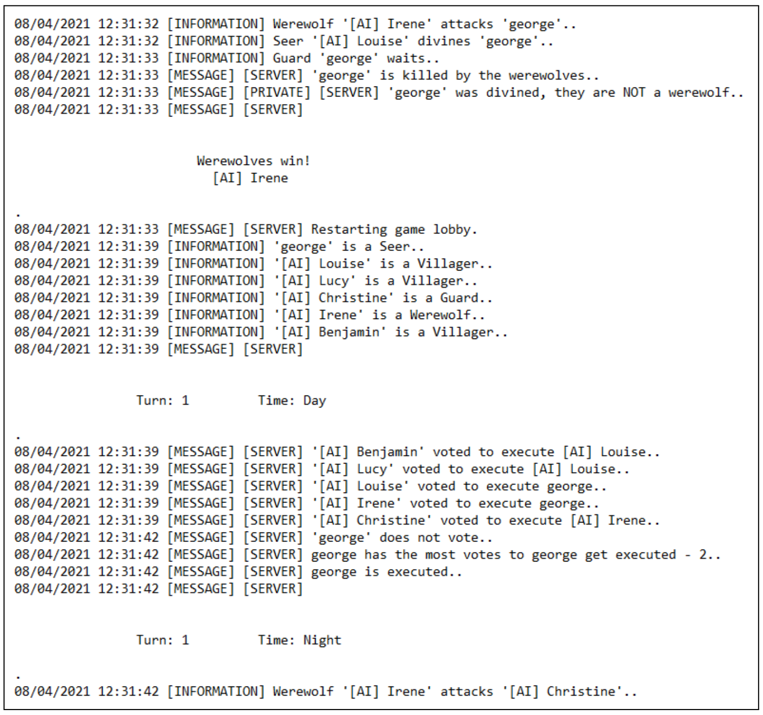
```
Werewolf
  .github
  Client
  Documentation
  Logs
    01-03-2021
    01-04-2021
    02-03-2021
    02-04-2021
    03-03-2021
    04-03-2021
    05-03-2021
    05-04-2021
    06-03-2021
    06-04-2021
    07-04-2021
    08-04-2021
    09-03-2021
    09-04-2021
    11-03-2021
    12-03-2021
    15-03-2021
    17-03-2021
    18-03-2021
    20-03-2021
    21-03-2021
    23-03-2021
    24-03-2021
    26-03-2021
    27-03-2021
    28-03-2021
  Server
  Shared
  Werewolf
```

```
..
Game 1 - 36b5be48b46b4a9d94432415bfe1f710.txt
Game 1 - 492db1bc2997416c9a5f82079f5504b6.txt
Game 1 - 4d38ef9283cb4f06adf985868afb7d3a.txt
Game 1 - 967b6da97eca417ca14cc7686256425e.txt
Game 2 - 4ab5737bbf7c43c4b342aae7e3090faa.txt
Game 2 - 59f56093cf654f438a993051a0bf8a99.txt
Game 2 - 926dae84826140a7832a836527441a52.txt
Game 2 - 9521467a911944988a7446c91f63fc39.txt
Game 2 - a9d742ae7a9b41ae8c29046cc77a402d.txt
Game 2 - b78a7565a3274a1ea70483d09969e1b0.txt
Game 2 - e42f729476494bfdb307d0200c413536.txt
Game 3 - 14a83e25c64a4b10b2fa1f10689608aa.txt
Game 3 - 21de9fb3e1b54a52bc4aeb9b3328d8f8.txt
Game 3 - 58681736785646c2804ebbdba1e71c26.txt
Game 3 - 6eb89892d99c496596e12674b9c662ab.txt
Game 3 - 92c22b2ba9724a568c83cc534fed1fa2.txt
Game 4 - 2bce528bb4c745829f1ff2a719131026.txt
Game 4 - 31093c13d3b9462293f48e276f22c26c.txt
Game 4 - 4515c5ff1cec4a8f972e6864ed738b3b.txt
Game 4 - 5492d25d6ba248d9a51f99500c84c7f1.txt
Game 4 - 5c2a432761304bfd82d46e4a7ec1d6d4.txt
Game 4 - 68b78c77c10c44189792d3d0517eb747.txt
Game 4 - 72c4b3ad649143db84e97783788d8b99.txt
Game 4 - 819fbd8bca1243cea277de95d24623d2.txt
Game 4 - 89afe8810d7e4c7cbfd0a3135bdc6f04.txt
Game 4 - 89b6876c282e4886b9172ed84a9aa3ef.txt
Game 4 - a48b5416c9e442f4a7ea627a764cbecb.txt
Game 4 - ccbe4f0746924ea0b98b31a1fa08ba51.txt
Game 4 - cff80ac7783649ef85036ee41bb00bd0.txt
Game 4 - f846ee28ae7f46d695cb32aa905e52d0.txt
server.txt
```

Figure 4.6: Logs file structure

Furthermore, alongside storing the general server operations in a log file, the framework also logs all of the actions and effective game states, that is - all known game information that has been distributed amongst players. Each log file consists of the game name followed by the unique game identifier e.g. “Game Beta - f56974e2c1dc4e1da363d1d6feeaeee9”. It must be noted that the game identifier does not change on a game restart, it is an effective constant that is created once a *game lobby* is created by either clients or the server itself.

Using identifiers allows for multiple games with the same name to be created, without having any identification issues, as the game names are only used for display purposes. Internally the framework refers to players and games by their assigned *university unique identification* (UUID) (Leach et al., 2005), also known as a *globally unique identifier* (GUID) (MSDN, 2017) (see Figure 4.6).



```
08/04/2021 12:31:32 [INFORMATION] Werewolf '[AI] Irene' attacks 'george'..
08/04/2021 12:31:32 [INFORMATION] Seer '[AI] Louise' divines 'george'..
08/04/2021 12:31:33 [INFORMATION] Guard 'george' waits..
08/04/2021 12:31:33 [MESSAGE] [SERVER] 'george' is killed by the werewolves..
08/04/2021 12:31:33 [MESSAGE] [PRIVATE] [SERVER] 'george' was divined, they are NOT a werewolf..
08/04/2021 12:31:33 [MESSAGE] [SERVER]


                        Werewolves win!
                          [AI] Irene

.
08/04/2021 12:31:33 [MESSAGE] [SERVER] Restarting game lobby.
08/04/2021 12:31:39 [INFORMATION] 'george' is a Seer..
08/04/2021 12:31:39 [INFORMATION] '[AI] Louise' is a Villager..
08/04/2021 12:31:39 [INFORMATION] '[AI] Lucy' is a Villager..
08/04/2021 12:31:39 [INFORMATION] '[AI] Christine' is a Guard..
08/04/2021 12:31:39 [INFORMATION] '[AI] Irene' is a Werewolf..
08/04/2021 12:31:39 [INFORMATION] '[AI] Benjamin' is a Villager..
08/04/2021 12:31:39 [MESSAGE] [SERVER]


                Turn: 1         Time: Day

.
08/04/2021 12:31:39 [MESSAGE] [SERVER] '[AI] Benjamin' voted to execute [AI] Louise..
08/04/2021 12:31:39 [MESSAGE] [SERVER] '[AI] Lucy' voted to execute [AI] Louise..
08/04/2021 12:31:39 [MESSAGE] [SERVER] '[AI] Louise' voted to execute george..
08/04/2021 12:31:39 [MESSAGE] [SERVER] '[AI] Irene' voted to execute george..
08/04/2021 12:31:39 [MESSAGE] [SERVER] '[AI] Christine' voted to execute [AI] Irene..
08/04/2021 12:31:42 [MESSAGE] [SERVER] 'george' does not vote..
08/04/2021 12:31:42 [MESSAGE] [SERVER] george has the most votes to george get executed - 2..
08/04/2021 12:31:42 [MESSAGE] [SERVER] george is executed..
08/04/2021 12:31:42 [MESSAGE] [SERVER]


                Turn: 1         Time: Night

.
08/04/2021 12:31:42 [INFORMATION] Werewolf '[AI] Irene' attacks '[AI] Christine'..
```

Figure 4.7: Game log stored on the server, recording the *full* game state.

The logging functionality built-in to the framework aims to easy development work by giving a verbose description of any game actions to ease state recreation, and any run-time exceptions will also be logged with their appropriate full stack-trace. Although the server should continue working on some run-time exception, it might be the case that it *breaks* the normal state flow of the server. Having the verbose logs helps development by pinpointing the exact failure point.

4.2 Client

The RLereWolf client provides end users with a Graphical User Interface to the base game implementation and relies on the supported functionality by the server.

The client operates on a “screen-swapping” basis, such that there exists a main window to the client with a content frame which we can regard as the display buffer (see Figure 4.8). Every view of the client is then displayed on the screen by swapping out any existing view on the display buffer. This buffer approach allows for an instant transition between the various client pages as a transition only happens once the new page has been fully initialised.

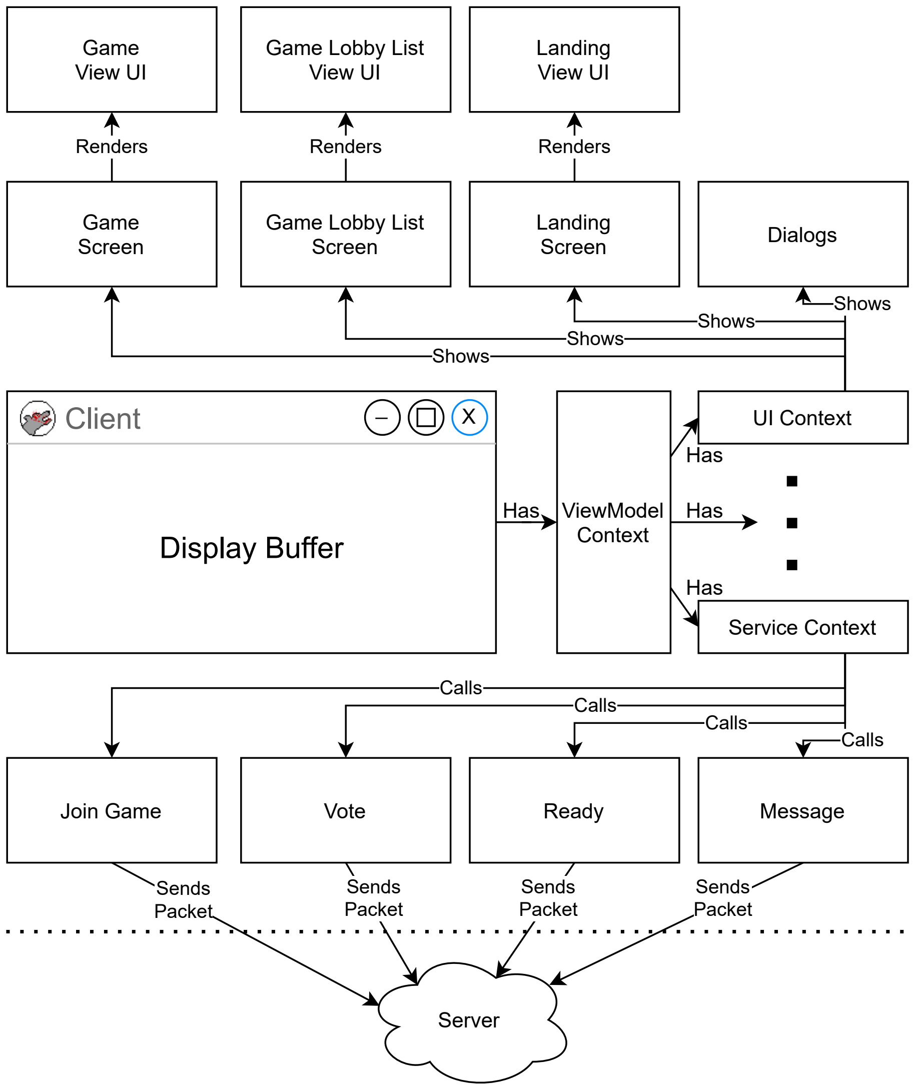


Figure 4.8: Client architecture.

4.2.1 Graphical User Interface

The client's graphical user interface is built with the help of Pygubu[1], an *extension* of Python's integrated bindings to the open-source, cross-platform Tk Graphical User Interface (GUI) kit – Tkinter (Python, 2012). The Tk toolkit is based on *widgets*[2] and it comes with various, commonly-used, *widgets*, e.g. *button*[3], *label*[4], *listbox*[5] etc., alongside a layout hierarchy, which allows the construction of various grid, list or absolute layouts.

The use of Pygubu helps the mimicking of the Model-View-ViewModel (MVVM) (MSDN, 2009) design pattern as it separates any User Interface (UI) definition elements from the code files,

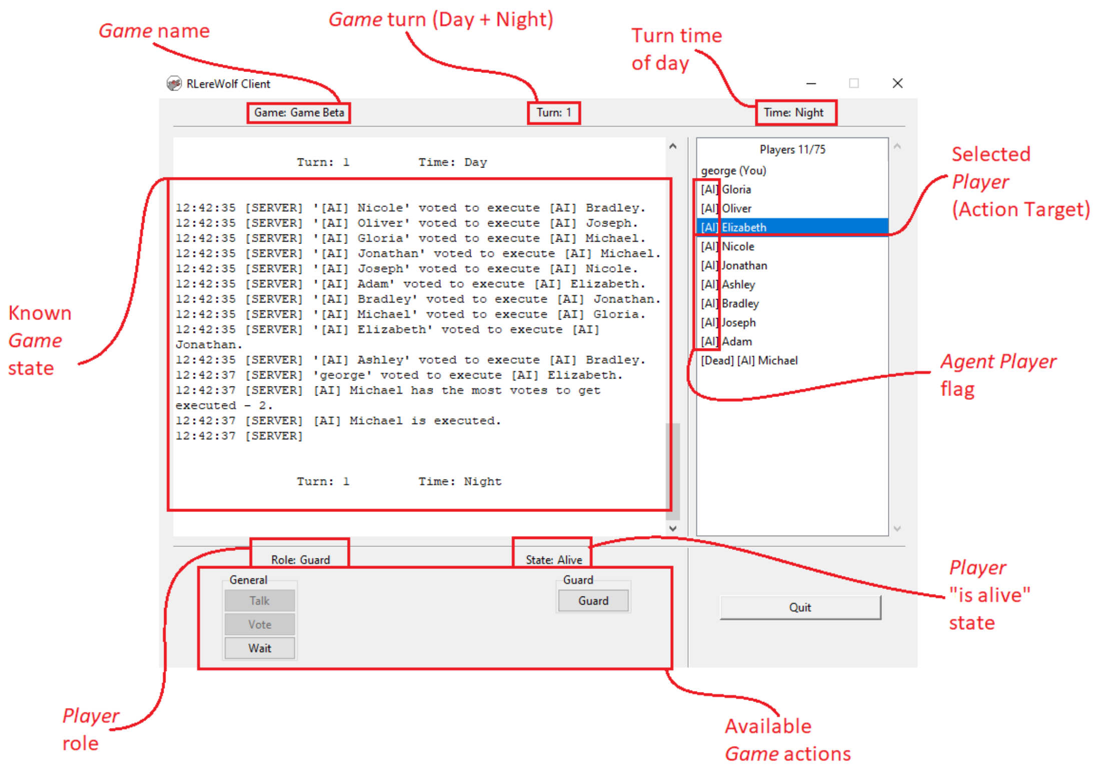
[1]Pygubu Designer – `https://github.com/alejandroautalan/pygubu`
[2]Widget – a small self-contained component, usually digital.
[3]Tkinter Button – `https://tkdocs.com/widgets/button`
[4]Tkinter Label – `https://tkdocs.com/widgets/label`
[5]Tkinter Listbox – `https://tkdocs.com/shipman/listbox`

by defining the user interface in a .ui file, whilst providing basic *data binding* to most of the UI controls.

These UI files are then processed and rendered on run-time by the Pygubu Builder and the accompanied infrastructure created by the author and act as the *View*. The infrastructure consists of renderer classes, acting as *ViewModels*, and the *Models* are the appropriate client-server shared DTOs, i.e. the game state or individual player state.

The written by the author renderers, create the GUI during the framework's runtime, based off of the preemptively created .ui files (see Appendix A User Manual for more information on the GUI). The design of the graphical user interface pipeline is based on *Windows Presentation Foundation's* (WPF) functionality, where the MVVM pattern is preferred (Sells and Griffiths, 2007; Sorensen and Mikailesc, 2010).

The GUI consists of three major screens – *Main Menu*, *Game List*, and *Game Lobby* (see Appendix A User Manual for more information). The *Game Lobby* screen is the actual *Game* which users can play (see Figure 4.9 for the layout and its elements).



```
                Turn: 1         Time: Day

12:42:35 [SERVER] '[AI] Nicole' voted to execute [AI] Bradley.
12:42:35 [SERVER] '[AI] Oliver' voted to execute [AI] Joseph.
12:42:35 [SERVER] '[AI] Gloria' voted to execute [AI] Michael.
12:42:35 [SERVER] '[AI] Jonathan' voted to execute [AI] Michael.
12:42:35 [SERVER] '[AI] Joseph' voted to execute [AI] Nicole.
12:42:35 [SERVER] '[AI] Adam' voted to execute [AI] Elizabeth.
12:42:35 [SERVER] '[AI] Bradley' voted to execute [AI] Jonathan.
12:42:35 [SERVER] '[AI] Michael' voted to execute [AI] Gloria.
12:42:35 [SERVER] '[AI] Elizabeth' voted to execute [AI]
Jonathan.
12:42:35 [SERVER] '[AI] Ashley' voted to execute [AI] Bradley.
12:42:37 [SERVER] 'george' voted to execute [AI] Elizabeth.
12:42:37 [SERVER] [AI] Michael has the most votes to get
executed - 2.
12:42:37 [SERVER] [AI] Michael is executed.
12:42:37 [SERVER]

                Turn: 1         Time: Night
```

Figure 4.9: Game Screen – Annotated elements

All of the navigation and GUI manipulation is abstracted through a UI Context which serves as the effective controller for the client. The UI Context itself is part of the overall ViewModel Context (top part of Figure 4.8) of the application. For readability purposes, the author will refer to the ViewModel Context as *Context*.

4.2.2 ViewModel Context

The client's Context is similar to the aforementioned server's Handler Context (4.1.3 Packet Handlers), in the sense that it aims to separate the various concerns into *contexts*. The defined by the author contexts, accessible to all ViewModels, so far are as follows:

- UI Context – GUI navigation
- Service Context – server API calls

The architecture is such that it can easily be broken down into multiple *child* levels (Figure 4.8). The service context can grow to a larger scale and be be separated into multiple services which are instantiated in the service context. This allows for a verbosely targeted and coherent API structure. Whilst it does not inherently provide any performance benefits, it does provide the framework with a modular design so that it is easy to *plug* and *unplug* various context functionalities.

The Context is shared between all screens of the client and is one of the first entities to be created once a client run, as the context holds all of the logic, neatly separated into corresponding sub-contexts.

4.2.3 Identification

At the current state of the framework, the clients are not remembering their identifier and subsequently create a new one on each launch. The identifiers are a crucial part in the server-client communication protocol.

Once a client connects to the server, the server keeps a reference of the client connection details and their identifier, which is how the client and server can effectively *recover* from minor run-time errors. A particularly important handling was the failure of complete packet transmission on either client-to-server or server-to-client route. This is because there exists the possibility of a request-response loop getting preemptively broken as a result of some run-time exception and the receiving side would end up being *stuck* on awaiting some *Packet*.

All awaited calls are done on background threads which are interrupted if they exceed their allocated time frame. This allocated time frame in which a request-response loop should succeed is based on the poll rate. The reason for awaited calls as opposed to *"fire and forget"* type calls is because the receiver requires the data for some functionality.

4.2.4 Polling

Due to the nature of the client, there needs to be a clear separation between main (UI) thread actions and background (child) thread actions. Most actions are done on the main thread as the usual client expectation is as follows:

1. Press button
2. Start event
3. Optionally get a result by awaiting the event handler

However, whenever the client asks for updates on the game state or the player state, those updates should be done in the background as they are not explicitly started from the user. As a result, the update calls are scheduled by default to happen once every second in order to keep the client synced with the server, which acts as the game moderator.

Consequently, due to having to poll at a specific time delta, the clients are prone to *desyncing*[6] (Cronin et al., 2001; McAnlis et al., 2014). This can be a direct result from an unhandled run-time error, temporary connection loss or corrupt *Packet*s. However, desynchronisiation in RLereWolf is not a huge issue in its current iteration, as the client interface is not complex, in the sense that it does not prompt any real-time dynamic animations as a result of the data transfer. The only noticeable effect of a desync is that the client will *skip* an update frame, only to catch up on the next successful sync call.

The game state polling retrieves data to the user that they do not have. This is done with a timestamp of the last sync time. Every time a client polls for data, the server serializes and packages all game state within a *GameDto* (see Figure 4.4) with data that is created after the provided by the client UTC timestamp, and grabs the current server UTC time as soon as the *GameDto* is created. The server then packages the *GameDto*, the game state snapshot timestamp and other miscellaneous meta data, e.g. target client identifier, and sends it back to the client. Once the client receives the *UpdateEntityDto* (see Figure 4.10), which is a layer between the *Packet* and *GameDto*, it sets a client global value of a timestamp, which records the last time the client has received a snapshot of the game state, for their current game. Then once a client has to poll for data again, it sends off a *Packet* with that timestamp, which is used by the server to package the game/player state into the miminal possible package.

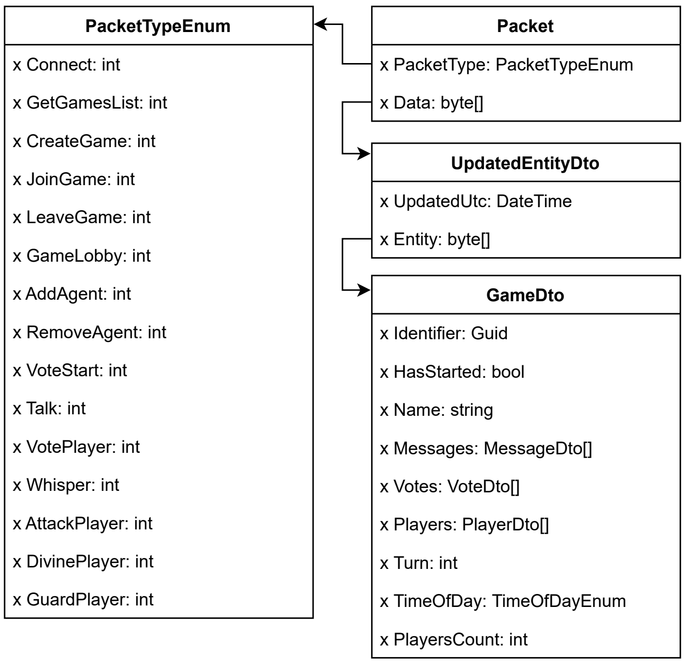


Figure 4.10: Packet Updated Entity DTO.

Keeping a track of the time where the last snapshot was created allows for the server to send the bare minimum of data required to the client. This increases performance and increases general server stability, as the server wouldn't need to send the entire history of messages, as the client is responsible for storing those in their game lobby instance. This means that once a client leaves the

[6]Desyncing - Originates from desynchronisation (desync) and describes the state where a client does not hold the most up-to-date data.

game lobby, that message history is lost.

Moreover, all regular polling events need to have a timestamp which indicates when that particular entity is form – be it the game state or player state. Having a generic **UpdatedEntityDto** wrapper allows for its usage with multiple types of data objects that are part of a polling process.

4.3 Game

The *Game* is the implementation of Werewolf that comes in the current iteration of RLereWolf. *Games* can either be hosted on the server, or played locally with agents. This was an important part of the architecture design, because the author's target was to create an easily modifiable game structure, which can be *played* offline, online and used for training, which would usually be done *offline* as to reduce overheads and training time from some client-server connection. The *Game* is the base Werewolf game, which consists of four roles, namely:

- Villager – A villager in the town, with no special abilities.
- Guard – A villager in the town, capable of protecting someone during the Night from an attack. However, *Guards* have a limited amount of uses on their special ability. RLereWolf has defaulted it to one.
- Seer – A villager in the town with the capabilities to look into their crystal ball at night, and tell whether a certain villager is a werewolf.
- Werewolf – A villager in the town who transforms into a werewolf at night and attacks other villagers.

Each role contains the basic description for it in the form of *flags* and counters. The flags specify whether a role can do a specific action, usually separated by *day* and *night* actions. However, there exist roles which have a limit to their actions. An example of such roles is the Guard, who can only protect other players in the night time a fixed amount of time, usually just once. This behaviour is managed through each of the roles classes as they serve as a configuration for the role itself in that specific implementation of Werewolf.

Role	**Day Action**	**Night Action**
Villager	✓	✗
Guard	✓	✓
Seer	✓	✓
Werewolf	✓	✓

Table 4.1: Base Werewolf game roles – possible time to act

Moreover, the game's default configuration is to distribute roles and allow a *start* whenever there are at least 5 players and at most 75 players, as per the game rules (BGG, 2016). The role distribution and player count can be modified by the game constants configuration file, which defines the minimum, maximum amount of players, alongside the villager : *X* ratio, where *X* is a non-villager role (Guard, Seer, Werewolf).

Whilst this could introduce role distribution issues, such as a distribution in which there would be no villagers due to overlapping ratios, this is entirely down to the developer to consider, as the current iteration of the framework does not support the standard point-based role allocation technique, commonly used in Werewolf games (BGG, 2016).

4.3.1 Roles

The roles in the framework are built using a common *Role* class. This allows for easy expansion and addition of new roles, as the only requirement is adding in the role specific definition "rules", which are inherited from the common *Role* class as abstract behaviour. As briefly mentioned previously, RLereWolf does not support a point-based role distribution system in its current iteration.

This could be a problem as the role type count for some game will not be as diverse. This is because RLereWolf will have a consistent role distribution mapping for some player count and some role distribution ratio configuration – which can be modified within the *GameConstants* and *GameRules* files. However, due to the target of the framework – the development and training of reinforcement learning agents, the author has decided to use the consistent approach of using a ratio-based system. That is, each role will have an additional member from it, based on some overall player count (see Table 4.4 for currently used ratios). It must be noted that the *Villager* has no inherent ratio, as it is assigned to the remainder of the non-special role assigned *Players* in the *Game*.

Role	Ratio (Role:Players)
Villager	N/A
Guard	1:10
Seer	1:15
Werewolf	1:6

Table 4.2: Role-ratio values used by RLereWolf

Using a point-based distribution system will mean that summing up the distributed points a role gives, has to be as close to 0 as possible, to insure a theoretical state of equilibrium between the *bad* and *good* roles, where they are categorised as *negative* and *positive* points respectively (see Table 4.3).

Reaching 0 points is not always possible with a role-point distribution, particularly with a small set of playable roles, due to the nature of the point values, each of the roles has. For example:

- *Scenario* 1 – A *Game* with two *Werewolves*, one *Guard*, and one *Seer* is *valid* provides the *Game* with a point sum of -2, meaning the *Werewolves* will have a slight advantage;
- *Scenario* 2 – Alternatively, a *Game* with two *Werewolves*, two *Guards*, and one *Seer* is also *valid*, with a point sum of $+1$, with an even slighter advantage for the *Villagers*.

As there is no way to reach 0 points in this scenario, the *Game* will pick the option with the smallest advantage to either side, in this example – with *Scenario* 2.

With a point-based system, the role distribution can vary greatly, as all roles that do not have a 0 value, provide some form of effect that helps either *bad* or *good* sides. Whilst the *Villager* role is part of the *good* side, it does not provide any ability that aides either side.

Role	**Points**
Villager	0
Guard	+3
Seer	+7
Werewolf	-6

Table 4.3: Base Werewolf role-point values

4.3.2 Actions

All of the possible actions a *Player* can do are encapsulated as an action. This allows for the handling messages, votes, attacks etc. as a common entity – an action. This results in code simplicity and ease of expansion. The game specific actions currently supported by the framework are:

- Vote – Vote for a player to be executed during the day time.
- Talk – Send a preset communication message to everyone.
- Whisper – Send a preset communication message only to your teammates. Currently accessible only by Werewolves, as they are the only role that concretely *know* who their teammates are.
- Attack – Attack a player during the night as a Werewolf.
- Divine – Reveal whether or not a specific player is a Werewolf to yourself as a Seer, during the night time.
- Guard – Protect a player during the night time from an attacking Werewolf.
- Wait – An empty action in either day or night time which *skips* the user's turn.

A limitation the framework currently has is that each role will have at most one *special action* per time of day phase in the game. By *special action*, the author identifies actions which are required for the game to evaluate the next game state. The special actions in this iteration of Werewolf are *Attack*, *Divine*, *Guard*, and *Vote* (see Table 4.4).

However, the action *Wait* is an exception, as it is treated as the *Empty* action, meaning player *X* targets no player *Y* for the current time of day. To elaborate, a *Wait* action is registered if the player targets no one with an *Attack*, *Divine*, *Guard*, or *Vote* action.

Role	**Vote**	**Talk**	**Wait**	**Guard**	**Divine**	**Whisper**	**Attack**
Villager	✓	✓	✓	✗	✗	✗	✗
Guard	✓	✓	✓	✓	✗	✗	✗
Seer	✓	✓	✓	✗	✓	✗	✗
Werewolf	✓	✓	✓	✗	✗	✓	✓

Table 4.4: Base Werewolf game roles – possible actions

4.3.3 Communication

RLereWolf's implementation of Werewolf also supports a range of preset communication messages which players can send within the game. These messages can be broken down to four message types, namely:

- Conflict resolution messages – Agreement or disagreement with a statement or observation made by a different player, about a specific event or scenario, e.g. whether or not a player is *some* role *X*.
- Asserting messages – Messages that declare whether a player is a particular role. These can be both certain and uncertain, e.g. "I know **player** is a **role**" and "I think **player** is a **role**" respectively.
- Declarative messages – Used by players to announce what their action or *state* is, e.g. "I am a **role**".
- Special messages – Additional messages that are available to particular roles. These would usually be used as a message between *known* teammates, e.g. a werewolf can say who they will attack during the night as a *Whisper*.

The communication protocol proposed by the author aims to improve on the minimalist communication protocol created in *AiWolf* (Toriumi et al., 2016), which covers 50% of all possible messages used in the tested games, by adding conflict resolution messages. The conflict resolution messages can be used to *sway* votes into a particular direction if there are uncertainties who to vote for. The ability to *agree* and *disagree* with players, openly to everyone, can create a scenario, similar to a *chain of trust* (see Figure 4.11), where *trust* can be split into two forms of trust:

- Local trust – An instance trust factor, based on the actions solely in the current game's context.
- Global trust – A trust factor which takes into account all previous interactions with some player.

In this *chain of trust* structure, you could players that can get swayed to do a specific action, if someone they trust has also done it. Taking a look at figure 4.11, the author proposes a scenario in which *Cindy* is a seer and knows that *Diego* is a werewolf. *Ben* trusts *Cindy* a lot and is consequently swayed to do the same action as *Cindy*, because they were uncertain what to do in this round. This chain of trust can proceed to go indefinitely or can break when some player at the end of chain, in this case *Alex*, is certain about their action, or just does not trust *Ben* enough to get swayed.

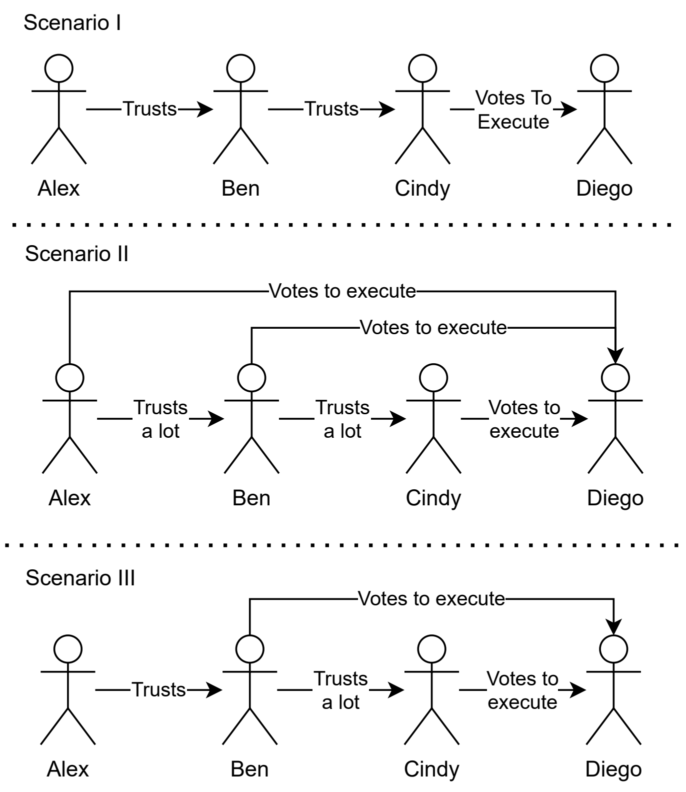


Figure 4.11: Communication – Conflict resolution.

Whilst the framework does not provide with an "out of the box" *Agent* experiment with swaying and conflict resolution messages, the author provides the reader with the framework, client and data to implement the aforementioned scenario.

The provided by the author communication protocol is broken down into multiple DTOs which are created by the server, either by prompted by a client request to send a message, or an intrinsic message that is created by the server, e.g. sending a message of the game state to all players. Each *MessageDto* contains a *MessageMetaDataDto*, which is information about the message itself and is used when determining who the target for some message is. This replaces the need for *Natural Language Processing* (NLP), as all of the messages are strictly defined presets based on three variables:

- The source – The entity that created the message. The entity can be a player or the server in the current iteration of RLereWolf.
- The target – The target player who the message is directed to.
- The message type – This is the identifier of the message preset. It represents the key value if we represent the communication presets as a key-value pair.

Moreover, the implemented by the author communication protocol is easily expandable by adding the preset in the *CommunicationPresetConstants* file and *classifying* it. That is, describing which role can use it and when it can be used, which is done in the *TalkMessageUtility*. At the current iteration of RLereWolf, the supported classification filters are based on the time of day and the player's role.

4.3.4 Players

A *Player* in the framework is regarded as either *Agent* or human player and is a common modelling object between the actions of an agent and a human player. *Players* are the entities that *play* the games hosted on RLereWolf's servers and are tightly coupled with the game implementation. A *Player* can is an entity that is used exclusive within the context of a Werewolf game and cannot exist when not in used by some game. Furthermore, a *Player* can only exist within the context of a single game. Generally, in the current implementation of Werewolf within the framework, a player is characterised by the following features:

- Identifier – The UUID that is either generated or assigned by the *Client*. Players can be instantiated without a reference to an identifier, in which case they just generate a new UUID. The identifier is often used in the framework as a reference of individuals, particularly when handled by a *Client*, as the identifier does not over-expose information about some *Player*, which might reveal their status within the game's context, e.g. their role.
- Name – All *Players* must have a name to be assigned one. *Clients* will provide the name they assign within the *Client* instance itself, whereas *Agents* will have a randomly generated name.
- Role – The role a *Player* has within a game. This is defaulted to Python's null valie – *None*, until the game starts and the role distribution process has finished.
- IsReady – Indicates whether or not the *Player* is *ready* to play the game. By default, all *Agents* which are used in the server hosted games are always ready, as to remove the possibility of getting a game lobby getting *stuck* in a state where it cannot ever start, as the *Agents* cannot toggle their readiness state.
- IsAlive – Indicates whether a player has been killed or executed within the game.

In RLereWolf, the author has separated *Players* into two groups (see Figure 4.12), namely:

- Agent – A stochastic, rule-based or *artificial intelligence* (AI) who is not *directly* controlled by a human player. However, the actions of other players may influence the agent's overall behaviour. Agents can be the following types (see Figure 4.12):
  - Dummy – An agent which does stochastic actions with minor action validation, in order to make sure *valid* game moves are done within the current game state, without doing any logical decision making (for further information see Section 5.1 Dummy Agent).
  - Rule-based – An agent which does deterministic actions based on a trust factor it keeps for each other *Player* in the current game. (for further information see Section 5.2 Rule-based Agent).
  - Trainable – An agent which *learns* from playing multiple games of Werewolf and bases their actions on "previous experiences" (for further information see Section 5.3 Trainable Agent). A *Trainable Agent* has no inherent knowledge of the game, and as such will attempt all possible actions within the game space until they have learned the *rules* of the game by considering the potential reward.

- Human – A human player that is running an instance of the RLereWolf client. This can be used interchangeably with *Client* as their relationship is one-to-one (see Figure 4.12).

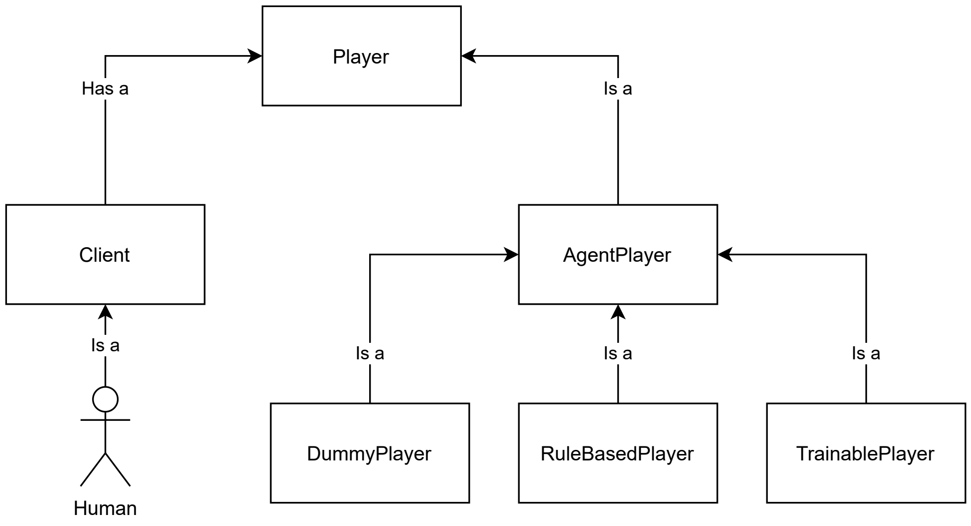


Figure 4.12: Players architecture – The distinction between humans and *Agents*.

Whilst having a common derivative interface for both *Agents* and *Clients* can lead to *shotgun surgery* (Li and Shatnawi, 2007; Olbrich et al., 2010), that is – the change or addition of features of child classes being a direct result by some change on a parent class, its effect is drastically mitigated by enforcing abstract classes. *Shotgun surgery* is a very likely scenario due to Python's lack of type safety and lack of strictly checked abstract class usages, this is because Python is an interpreted language and those mistakes can only be recognised during the framework's run-time.

The enforcement of abstract classes is done through having the derivative class have no functionality whatsoever, but only serve as an interface which throws exceptions whenever the base class is called. Alternatively, users can user Python's *Abstract Base Class*[7] (ABC). However, its behaviour and interface is variable on the Python version at use and could have massive implementation implications. As a result, the author has decided to use self-governed abstract classes by, as previously mentioned, throwing exceptions when the base functionality is called. Consequently, this enforces any children classes to override the base methods if they are to be used at any given point.

Having a shared *Player* derivative for both *Agents* and *Clients* allows for the framework's game implementation to easily be expanded with additional features which may or may not be included in their children classes. This also inherently applies to any of the *AgentPlayer* derivatives – where more *Agents* can be added, or their functionality can be easily modified to target all or just some of the *Agents* (for further information see Chapter 5 Agents).

4.4 Environment

In RLereWolf's architecture, the *Environment* is the "training ground" for some *Agent*. The environment is a wrapper that can optionally be put around a game. This keeps the Werewolf implementation lightweight and implies that not all games will serve a game that *trains Agents* (see top

[7]Abstract Base Class – `https://docs.python.org/3/library/abc`

of Figure 4.1). The environment uses *RLlib* (RLlib, 2020), which uses *OpenAI Gym* (Gym, 2016) and is an effective *wrapper*, encapsulating *OpenAI Gym*. The author's decision to use *RLlib* is due its integrated support for the creation of a multi-agent environment, as opposed to plainly using *OpenAI Gym*. The only supported environment types by *OpenAI Gym* is a *single-agent environment*. This means that in a game, you can only have one single *Agent* entity, this could mean that you have 10 *Agents* in a single game – however, they would all be using the same *brain*.

Having a multi-agent environment allows for the training of multiple *Agents* in a single game. Each *Agent* is responsible for individually taking a decision in each *step* of the game, which in RLereWolf's case, a step is a *time of day* within some game turn, where each turn consists of a *day* and *night* time. Having a *multi-agent environment* also allows for the definition of individual *policies*, which are the intrinsic rules that define an *Agent* and its consideration of the various potential rewards for some action. In the current iteration of RLereWolf, the *TrainableAgent* aims to be the "jack of all trades" within the game's context – that is, be able to learn all four currently supported roles. An immediate consequences of the author's decision is that the training process will be longer as a consequence. The alternative approach is to have a role-specific *TrainableAgent*, e.g. *WerewolfTrainableAgent* and *VillagerTrainableAgent*. Although not provided in the default configuration of RLereWolf, creating *TrainableAgents* for each individual role is possible, due to the hierarchical structure used in the framework (see Figure 4.12).

The training environment in the framework is regarded as the *TrainableEnvironmentWrapper* and it can hold any combination of *Agents* in it. However, its primary target in the current iteration of RLereWolf is the *TrainablePlayer*. However, the environment can also be used in multiplayer games which have multiple players in them, as the *Client* allows for the addition of various *Agent* types to the game lobby. Moreover, the environment contains the *auto-play service* which makes sure training never gets stuck by some invalid action, by keeping a close track of the *Agents* which have attempted an invalid game action. Once an invalid game action is attempted, the *auto-play service* makes sure to discount their identifier as a *Player* who needs to make a play in the current turn.

The environment's functionality heavily relies on the game implementation, as each of the game actions a *Player* can do, will have a return value which indicates the result of an action. A limitation to the framework's action request results is that there can only ever be one result. A scenario in which this could be a problem is whenever a *werewolf* attacks another *werewolf*, which happens to be dead. RLereWolf's training environment keeps track of the following action results:

- Wait action – A wait action result is treated individually as the author can see the importance of recording the only *passive* action, as *Agents* could get into a state where they have learned that waiting would be a viable strategy. Moreover, the incentive to wait should be different than the incentive to actively *vote*, *attack*, *guard* and *divine* someone.

- Successful action – A successful action result is given whenever an *Agent* has decided to do a game action, e.g. *vote*, *attack*, *guard* or *divine*, and their request has gone through successfully.

- Cannot act during time of day – A result given whenever an *Agent* with a particular role that cannot act during the current time of the day, attempts to do an action during that time (see

Table 4.4). In the current iteration of the game, this could be *Villagers* attempting an action during the night time or a *Guard* attempting to *guard* someone during the night once they have reached their maximum guard limit.

- Dead player targeted – A result given whenever an *Agent* targets a dead *Player*. This could be a result of either *day* or *night* game actions. However, *Seers* can target dead *Players* during the night, as it is a valid game action.

- Werewolf cannibalism – A result given whenever a werewolf targets another werewolf of their attack. However, this will be preceded by the *Dead player targeted* result, as only one action result can be retrieved in the current iteration of RLereWolf.

- Invalid action – An invalid action result is used whenever an *Agent* attempts to do an action that their role does not allow them to. This differs from the "cannot act during time of day" result, as an *attack* and *guard* options are both possible during the night. However, they are possible to the *werewolf* and *guard*, respectively.

Each of the action results are used in the observation space generation and are an important part which determines which reward an *Agent* will receive. The action results are part of the description of the observation space, that is – the game state and all of its known, by some player, parameters. Each *Agent* action prompts a reaction from the *Environment*, by providing the *Agent* with an *observation* of the current game state, alongside a reward – which is based off of their action and its consequences. This is also known as the "agent-environment loop" (Gym, 2016; Kong and Mettler, 2013), which is also known as the *Markov Decision Process* (MDP) (Littman, 1994). The loop can be seen in Figure 4.13, in which the *Environments* receives some action (A_x) from an *Agent*, to which the *Environment* replies with an observation space (S_{x+1}) and a reward (R_{x+1}).

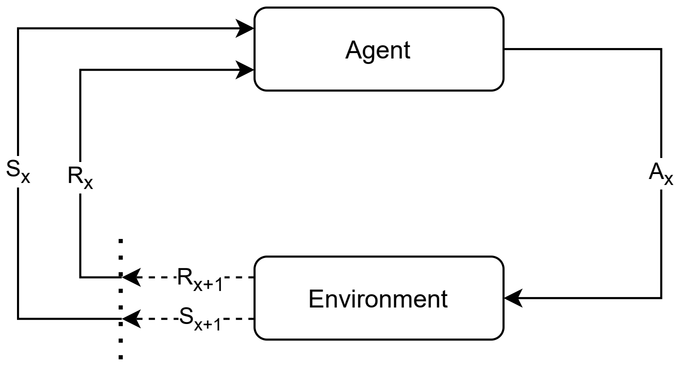


Figure 4.13: Agent-environment loop

4.4.1 Observations

The *observation space* for each *Agent* is calculated on each *Agent* step. Due to the nature of the game and being able to work only with incomplete game state knowledge, the observation space is constructed based on information the *Agent* knows at the current point of some *Player* acting. Whenever an action is made in an *Environment*-wrapped game, the observation space is generated and distributed to each *Agent*. Without the complete game state information it is impossible to reach *pure Nash equilibrium* (Fabrikant et al., 2004; Gottlob et al., 2005) in Werewolf as it is a social deduction, *finite Bayesian game* (Cheon and Iqbal, 2008).

However, the aim of the observations is to provide *Agents* with enough information to reach *Bayesian Nash equilibrium* (Christodoulou et al., 2008) – that is, the state in which a *Player*'s action is based around the highest probable payoff, given their knowledge and *beliefs* of the game and player states. To elaborate, this means that every *Player*'s decision for their current turn will not be based on some predetermined strategy, but would instead be based on all *available* to them information at the current state of the game.

The knowledge of the game state is included in the observation, whereas the player state observations are based entirely off of the *Agent* in the current iteration of RLereWolf (see Section 5.3 for more information). The game state information given to each *Agent* in the current iteration of RLereWolf's *Environment* consists of:

- Role – The current player role, this is provided in the observation as it can be changed by the game whenever a game is restarted.
- Players – The list of players currently in the game. The information for the *Players* is minimal, as it only contains the identifiers and the names of the *Players*
- Votes – The visible by everyone actions for the current time of day and turn in Werewolf. An example of an *invisible* action is the seer's *divine* ability.
- Messages – The messages created by other *Players* or the game itself, which are descriptions of the game state accompanied by message metadata, in order to aide the developer in recognising what the message is and who it is targeted to.

RLereWolf's observation size for some turn is, at the moment, uncapped. As a result there is the possibility of having an infinitely long observation for some turn. What this means is that the framework will get stuck in a state where the *Players* are generating observation data indefinitely. A solution to this problem would be to limit the amount of possible messages an *Agent* can generate within a given turn. Consequently, this would result in a limited observation space which removes the potential for infinite loops within the framework. The reason for allowing infinite observation spaces within RLereWolf is because the author aimed at having the *Agents* define their own game logic – resulting in more freedom when defining the training environment as some *Agents* could be more "chatty" than others.

Furthermore, it mimics the possible behaviour in a real Werewolf game, where some *Players*' behaviour is variable, all whilst obeying the core game rule. In the current iteration of RLereWolf, the observation space not represented in exclusively discrete values, this is a by-product of leaving the *Agents* to process the game state provided to them.

4.4.2 Rewards

Alongside the *observation space*, the *Agents* receive a *reward* at the end of each turn. The rewards are based on various action results, game state conditions and general game *motion*, that is – the advancement of the game in its turn value (see Table 4.5). The values of the *rewards*, represent whether or not a result is deemed favourable or unfavourable (see Section 4.4 for more information on *results*).

Result	**Reward**
Day Passed	-1.0
Vote	+1.0
Wait	+0.5
Incorrect Vote Multiplier	-0.5
Death	-5.0
Victory	+20.0
Lost	-20.0
Werewolf Cannibalism	-7.5
Dead Player Targeted	-35.0
Incorrect Action	-35.0

Table 4.5: RLereWolf *Environment* rewards

The default RLereWolf *rewards* are loosely based on AiWolf (Toriumi et al., 2016) which the author has expanded on, due to the higher amount of possible action results. The design for the *rewards* take into account a possible *Agent* who does not have any understanding of the intrinsic game rules whatsoever and is able to "break" the game rules by doing some *invalid* or *malicious* action. The author describes an *invalid* action as the action which the current *Player*'s state is unable to do, e.g. A *Villager* attacking another *Player* at day time; or A *Guard* divining another *Player* at night. A *malicious* action can be seen as an action in which an *Agent* actively acts against their own role's *nature*, e.g. a *Werewolf* attacking another *Werewolf*. The result-reward justification is as follows:

- **Day Passed** – At the end of each turn (day & night), *Agents* gets a -1.0 penalty. The reasoning behind the penalty is so that *Agents* can get trained to finish the game as quickly as possible.

- **Vote** – Each time an *Agent* votes (this includes *attacking*, *guarding*, *divining*), and that *Player* is the most voted one, the *Agent* gets a $+1.0$ reward. In the case that the vote the *Agent* has cast is on the non-executed *Player*, an *Incorrect Vote Multiplier* is applied. This logic will be based on internal *Agent* design estimations (see Section 5.3 for more information), as this might not have to apply to a *Werewolf*, as they would inherently be targeting the opposite player group.

- **Wait** – There is a need for an explicit reward for *waiting*, as it is a "delaying" tactic, which accompanied with the *Day Passed reward* should lead to either a neutral or negative reward value. In the current iteration of RLereWolf, the author has chosen a reward of $+0.5$, as this pushes *Agents* into making *valid* and *non-malicious* actions on their turn. Whilst usually actively voting will lead to a higher overall *reward* for the *Agent*, sometimes a *wait* action might be lead to the higher overall reward. This is because the voted *Player* might not be the executed one and consequently lead to a higher penalty, as given by the *Incorrect Vote Multiplier*.

- **Incorrect Vote Multiplier** – At the end of each *time of day*, the *Agents*' rewards are applied a -0.5 multiplier, based on how *far* from the most voted *Player* the *Agents* were. This reward acts as a meta-communication protocol, which will eventually align *Agents* to unanimously target the same *Players*. The multiplier gets added on to the final reward by taking into account the order of the most-voted *Players* in some *time of day*, e.g. *Agents* who have voted for the second most-voted *Player* will receive an additional reward of $1 \times (-0.5)$, *Players* who vote for the third most-voted *Player* will receive an additional reward of $2 \times (-0.5)$. Generally speaking, the act of voting will lead to the following reward (R) for some turn and *time of day* ($R_{Turn_{TimeOfDay}}$):

$$R_{Turn_{TimeOfDay}} = R_{Vote} + (Index_{VotedPlayers} \times R_{IncorrectVoteMultiplier})$$

Equation 4.1: Reward calculation for a turn and *time of day* whenever an *Agent* votes

- **Death** – The death of an *Agent*, although sometimes can be seen as a viable strategy, is generally regarded as a negative result which should be avoided. However, the death result is not something an *Agent* will directly have control over. As a result, the author has determined that a penalty of -5.0 will be sufficient in the standard use case, where suicidal strategies are to be generally avoided.

- **Victory/Lost** – Both the *Victory* and *Lost* rewards are applied to all *Agents* within a game, independently of their current *Player state* – dead or alive. The reward/penalty is ± 20.0, depending weather a positive or negative outcome is achieved by the *Players* role archetype. The reward is relative high as it keeps *Agents* focused on winning.

- **Werewolf Cannibalism** – In the current version of the framework, the only recognised *malicious* action is the act of a *Werewolf* attacking another *Werewolf*. Whilst this could be a viable strategy to confuse other players and cast doubt on self-proclaimed *Seers*, the author has set the penalty for cannibalism as -7.5, as to reduce cannibalism actions, due to their niche viability.

- **Dead Player Targeted** – Targeting dead players is considered an *invalid* action by most roles in Werewolf. In the base game of Werewolf, the only role that can target dead players is the *Seer* and this penalty does not apply to them. However, the other currently supported roles (*Villager*, *Werewolf*, and *Guard*) should not be able to target dead players and are consequently penalised with -35.0 points. The need for such a high penalty is because all game breaking actions must be put into the highest priority, as having a higher reward for a *Victory* will prompt *Agents* to "cheat" in the game in order to achieve a Victory.

- **Incorrect Action** – The attempt of acting as other roles than the currently assigned one, or doing an action that is not possible in the current time of day of the turn, will prompt an *Incorrect Action* penalty of -35.0 points. The reasoning is the same as the *Dead Player Targeted* reward – not allowing *Agents* to "cheat" to achieve a *Victory*.

The rewards in RLereWolf are configurable within a single file. However, expanding the possible rewards will prompt the creation of more action-results which the game implementation will need to *recognise*. Once the game implementation recognised the result of a specific *Player* action and replies with the newly implemented result, then the *Environment* will be able to use the result-reward when going over the *step* for some *Agent*.

4.4.3 Auto-play

The *Environment* in RLereWolf is an optional wrapper that can be used for a game instance (see Game Z in Figure 4.1). As the framework can support games with and without human *Players*, the need for an automated playing service arose. The auto-play service aims at simulating games which consist only of *Agents* and ensures the validity of the game state at any given point of time. The auto-play service can be present both in server hosted games and in locally instantiated games, whose current target is games dedicated for training *Agents*.

This service is not manageable by *Clients* within the GUI, but rather by the server administrator's preference, reflected in the server instance configuration. This design choice was due to the fact that a malicious *Client* can get the server into an infinite training loop which can only be handler by a server restart or a computational resource threshold on each game. Consequently, the author has decided to keep the auto-play configuration, primarily targeted for offline training games as the server hosted games will use the training data generated from the offline ones.

4.4.4 Metrics

The *Environment* keeps a log of all of its games under a csv file format and keeps a record of the following metrics within each game:

- **Number of players** – Shows the number of *Players* in the game. These *Players* can be either humans or *Agents*.
- **Dead *Players* voted** – The number of times a *Dead Player Targeted* action-result has been achieved during the ***day***.
- **Dead *Players* attacked** – The number of times a *Dead Player Targeted* action-result has been achieved during the ***night***.
- **Teammate attacked** – The number of times a *Werewolf Cannibalism* action-result has been achieved.
- **Incorrect action** – The number of times an *Incorrect Action* action-result has been achieved.
- **Werewolf wins** – Used as an indicator whether the game was won by the *Werewolf* role archetype. This is a boolean value, displayed as a number (0 or 1).
- **Villager wins** – Used as an indicator whether the game was won by the *Villager* role archetype – *Villager*, *Guard*, and *Seer* in the current iteration. This is a boolean value, displayed as a number (0 or 1).
- **Total turns** – The number of *time of day* phases that occurred in the game (*day* & *night*).
- **Total days** – The total number of days that have passed in the game. Combined with the *total turns* metric, it is possible to determine which *time of day* the game has ended, as an odd *total turns* value implies that the game has ended during the *day*, where as an even *total turns* value implies that the game has ended during the *night*.

- **Total games** – Used as an indicator whether a game has successfully finished, or something has gone wrong within the game, which has prompted the auto-play service to continue. This is a boolean value, displayed as a number (0 or 1).
- **Game time** – How much overall time the *Game* has lasted. This metric is important when designing *Agents* whose primary target is to have shorter *Games*, preferably classified as wins.

The metrics are stored within the root *Werewolf* project folder (see Figure 4.2). Each of the metrics get stored within the same "Statistics.csv" file. An issue with this design is that it would be hard to differentiate between the metrics accross different games which are concurrently running games with the *Environment* wrapper on either a server, or locally. This is a result of the time constraints the author was limited to, and a suggested architecture would be one similar to logging (see Section 4.1.4 and Figure 4.6), in which each game with an *Environment* wrapper will create a csv file within a "Metrics" folder which will be named after the game name and its identifier.

Chapter 4 in a Nutshell

- *Server can accept only legitimate packets sent from the Client.*
- *Server keeps track of all traffic and logs it.*
- *Client has a graphical user interface which can easily be extended with the help of the GUI development pipeline.*
- *Clients are uniquely identified.*
- *Werewolf game implementation supports four roles – Villager, Guard, Seer, and Werewolf.*
- *Each role has special "abilities" that distinguish them.*
- *The players are able to communicate with a "closed" communication protocol, that is – able to communicate with predefined messages.*
- *The Environment is a wrapper over a Game instance.*
- *The built-in Environment provides rewards to the players.*
- *The built-in Environment generates analytic and training data.*
- *The built-in Environment ensures that a Game between Agents is never "stuck".*

Chapter 5

Agents

Agents are the artificial *Players* which humans can play Werewolf with. In this chapter, the author will go over the built-in *Agents* within RLereWolf and what purpose they serve within the context of the framework. Users of the framework can develop additional *Agents*, independently of their decision making capabilities – stochastic, rule-based or machine learning. Whilst the framework can support various machine learning methods, the built-in example provided by the author is using reinforcement learning (see Section 5.3 for more information).

5.1 Dummy Agent

The *Dummy Agent* is the first built-in *Agent* which was introduced into the framework and primarily serves as a means to test the framework and the supported *Game* functionality. The *Dummy Agent* does stochastic actions during both *day* and *night* time, which are valid within the game rules. To put the *Dummy Agent* into prespective:

- If a *Dummy Agent* is a *Villager*, they will only randomly vote for other *Players* (excluding themselves) during the *day* time.
- If a *Dummy Agent* is a *Werewolf*, they will randomly vote for other, non-Werewolf, *Players* during the day time and *attack* a random non-Werewolf *Player* during the night time.

Dummy Agents are not swayed by any of the communications and they themselves are not capable of sending *Messages* or *Whispers*. The *Dummy Agent* serves as a baseline for a *Player* doing random actions within the games' rules and its behaviour serves as a starting point for future *Agents'* performance.

5.2 Rule-based Agent

The *Rule-based Agent* in RLereWolf has a simple understanding of *trust* (Marcus and Davis, 2019) it keeps towards all the players they play against. Each *Rule-based Agent* keeps a record of *global trust* and *local trust* which reflects how trustworthy a *Player* is throughout all of the games played with them and how trustworthy they are in the current game instance. Moreover, each *Rule-based Agent* has an "honesty factor" which is a value from -1 to 1, which provides the *Agent* with a deterministic approach as to what communication the *Agent* will convey to *Players*, if any.

In the current iteration of RLereWolf the *Rule-based Agent* is not fully implemented and behaves similarly to the *Dummy Agent*, such that all of the actions it takes are stochastic with minor *validity* and "common sense" checks. However, the *Rule-based Agent* is not purely stochastic and does select the least trustworthy *Player* to vote for in the current game. This *trust factor*, however, is not fully implemented and is expected to behave similarly to the purely stochastic approach. The *validity* of an action is determined by the game implementation and means that the action “makes sense” within the context of the game, e.g. A *Guard* cannot *divine*. As such, in the current implementation of the framework, the *Rule-based Agent* will perform similarly to the *Dummy Agent* when observing the metrics provided by RLereWolf (see Section 4.4.4 for more information).

However, the aim of the *Rule-based Agent* is to observe communications made by other *Players* in the game and get *swayed* or potentially *sway* other players (see Figure 4.11), based on their observed *trust factor*, which gets recalculated on every game event, in which the *Agent* has made an assumption on.

The *global trust* each *Rule-based Agent* keeps gets recalculated at the end of every game and is a rolling average of the *local trust* for all games played with that *Player*. Due to the limited time of the project, the author could not fully implement this feature. However, the author suggests a similar approach to *Q-learning* (Watkins and Dayan, 1992; Hasselt, 2010) where a *discount factor* is used for the *trust factor*. The role of the *discount factor* is such that the more recent *local trust* values hold more “weight” than older *local trust* values when determining the *global trust* for some other *Player*. Semantically this means that *Players*’ behaviour can change over time, and *Rule-based Agents* should be able to adapt to it.

The *Rule-based Agents* currently do not persist the *trust factor* they observe about other *Players*, and are instead stored in the game host machine’s memory. However, this can be easily implemented as each *Player* in the framework has a corresponding *UUID* (see Section 4.12 for more information) which can be used to reference *Players* across multiple *Game* instances and game lobbies. The persistence model will be similar to the logging architecture (see Section 4.1.4 and Figure 4.6 for more information), in which the host machine will have a folder of files named under the following format: “**Agent Name – Agent Identifier**”.

5.3 Trainable Agent

RLereWolf comes with a built-in reinforcement learning *Agent* alongside its multi-agent environment (see Section 4.4 for more information). The *Trainable Agent*, unlike the *Dummy Agent* and the *Rule-based Agent*, has no knowledge of the intrinsic game rules and is capable of making any move within the context of the game, be it *valid* or *invalid*. However, the *Trainable Agent* can *learn* strategies based on rewards (see Section 4.5 for more information on *Rewards*).

The *Quality Learning* (*Q-learning*) algorithm is used for the *Trainable Agent* as the Werewolf game has a finite action space and will eventually lead to an “optimized” agent for some set of *Players* and their corresponding *behaviours*. In the current iteration of RLereWolf, the *Trainable Agent* is not fully implemented and can consequently not exhibit any emergent behaviours, as the *Trainable Agent* does not formally “learn” in the current iteration. However, the *Trainable Agent* should have a *Q-table*, which represents a map of some unique tuple consisting of the game *State* (S_T) and the *Action* (A_T) which leads to some *Reward* ($\mathbb{R}_T$) at some turn/time (T) within the *Game’s* context (see Equation 5.1), which can be as the following function, for some time T: $\mathbb{R}_T = Q(S_T, A_T)$.

$$Q : S \times A \rightarrow \mathbb{R}$$

Equation 5.1: *Q-learning* function

To elaborate that, the goal of a *Trainable Agent* is to do an *Action* for the current game *State*, such that the highest expected *Reward* "route" is picked, as the *Agent* will try to score the highest *Reward* value it can, for some game instance (see Section 4.5 for more information on *Rewards*). The *Q-table* is the effective data a *Trainable Agent* will acquire after playing a sufficient, finite amount of Werewolf games. The "learned" data will be highly dependent on the game implementation, game rules and *Player* role distribution mechanics.

Consequently, the *Trainable Agents'* perception of the potential *Reward* for some *Action* and game *State* will change over time, which can be further supplemented by a *learning rate* (α) and a *discount factor* (γ) (see Equation 5.2).

$$Q^{new}(S_T, A_T) = Q^{old}(S_T, A_T) + \underbrace{\alpha}_{learning\ rate} \times$$

$$\left(\mathbb{R}_T + \underbrace{\gamma}_{discount\ factor} \times \underbrace{\max Q(S_{T+1}, A)}_{optimal\ future\ value\ for\ all\ actions} - Q^{old}(S_T, A_T) \right)$$

Equation 5.2: *Q-learning* algorithm – "weighted" *Q-value*

The *Trainable Agent* is able to play as any role which is implemented in the Werewolf game, as a result the training time for the built-in *Trainable Agent* will be substantially longer that of a role-specific *Agent*. That is – an *Agent* model designed to play as a single role, as opposed to the full set of supported roles: *Villager*, *Guard*, *Seer*, and *Werewolf*.

Moreover, as the author has briefly mentioned, the *Trainable Agent* has no understanding of the intrinsic *Game* rules and will, consequently, make *invalid* actions at the beginning of the training process. Over time, the *Trainable Agent* will correlate *invalid* actions with a very high negative reward and will get discouraged from attempting the specific $Q(S_T, A_T)$ tuple which will consistently provide it with a negative reward. Furthermore, the *Trainable Agent* has no understanding of *trust* and does not keep *honesty values* for the *Players* they have played with, instead all the observable behaviours, exhibited from the *Trainable Agent*, are learned with *Q-learning*.

In the current iteration of RLereWolf, the "weighted" *Q-learning* (see Equation 5.2) is not fully implemented as the author's allocated time slot for the development of the built-in *Agents* was not sufficient enough. Consequently, each *Agent* has partial completion, but not fully implemented for the initial iteration of the framework. This will be observed in **Chapter 6 Empirical Evaluation**, where the author will go over a set of tests with the built-in *Agents* and discuss their results.

Trainable Agents can be "used" both in *Agent*-only games, which are designed for simulating games and training, as well as games with human *Players* in them (see Figure 4.1). A limitation to *Trainable Agents* in the current iteration of RLereWolf is that they cannot be trained in server hosted games as it would require the usage of the auto-play service and *Environment* (see

Section 4.4 for more information), which cannot be dynamically added to a *Game* instance.

Chapter 5 in a Nutshell

- *The RLereWolf framework provides three built-in Agents.*
- *The Dummy Agent does random actions which are considered valid by the game and its rules.*
- *The Rule-based Agents employs honesty and trust factors which it uses to determine who to vote/attack next. A fall-back is the stochastic approach used in Dummy Agents. All actions considered valid by the game and its rules.*
- *The Trainable Agent uses Q-learning in order to learn on what the best action for some game state is.*

Chapter 6

Empirical Evaluation

In this chapter the author will evaluate the built-in *Agents'* performance with the help of the provided by the *Environment* metrics. The experiments the author will carry out are multiple "runs" of the Werewolf *Game* with an *Environment* wrapper around them. Once the set of experiments are complete, the author will discuss the results with the aide of graphs and tables.

6.1 Experiment Design

The experiments the author will carry over a set of *Games*, each consisting entirely of a single type of *Agent* (*Dummy*, *Rule-based* or *Trainable*). Each of the *Game* "lobbies" will be wrapped with the *Environment*, which not only "trains" the *Trainable Agents*, but it also provides the metrics, which the author will use for the experiment analysis.

The games will be a populated with a variable range of *Players* for each set of "runs". For the purposes of the experiment, each "run" will consist of 1000 games. And the *Agent* count to be observed at minimum, 25%, 50%, 75%, maximum and *AiWolf* equivalent capacities, namely:

- 5 *Agents* (minimum capacity) – The minimum amount of *Players* required in a *Game* of the base version of Werewolf, as stated in the rule book (BGG, 2016).
- 15 *Agents* (roughly 25% capacity) – A small-sized *party*, the same *Player* count used in the *AiWolf* conferences (Toriumi et al., 2016).
- 20 *Agents* (*AiWolf* capacity) – The one quarter point between the minimum and maximum amount of *Players* that can play in a *Game* of Werewolf.
- 35 *Agents* (roughly 50% capacity) – The mid-point between the minimum and maximum amount of *Players* that can be in a *Game* of Werewolf.
- 55 *Agents* (roughly 75% capacity) – The three quarter point between the minimum and maximum amount of *Players* that can play in a game of Werewolf.
- 75 *Agents* (maximum capacity) – The maximum amount of *Players* allowed in a *Game* of Werewolf, as stated in the rule book (BGG, 2016).

The amount of *Players* was, such that, a wide range of possible capacities is tested and analysed, alongside the *Player* capacity tested in *AiWolf* – 15 *Agents*.

As the current iteration of RLereWolf is using a ratio-based role distribution system, the roles for some number of *Players* in a *Game* will be consistent. The role counts for the currently implemented ratios (see Table 4.2) can be seen in Table 6.1. The hardware the author used for the experiments is the same as the development machine (see Table 3.1).

***Player* count**	***Villagers***	***Guards***	***Seers***	***Werewolves***
5	2	1	1	1
15	11	1	1	2
20	14	2	1	3
35	25	3	2	5
55	38	5	3	8
75	51	7	5	12

Table 6.1: RLereWolf role distributions for experimented *Player* counts

The experiments were carried out on the author's development machine (see Section 3.4 for more information on the hardware used) and took a total of 16 hours to complete. The complete recorded data from the $3 \times 6 \times 1000$ ($AgentCount \times PlayerQuantityVariants \times RunGameCount$) set of games, can be found on the project's public repository[1].

6.2 Results Discussion

From the metrics provided to us by the *Environment* we can extract the general win-rate and "speed" performance of each *Agent* (see Table 6.1 and Figure 6.2). However, these results abstract from the *validity* of the *Agents'* actions in the *Games* which were part of the experiment. The *validity* of the *Agent* actions is measured with the amount of times an *Dead Agent Voted*, *Dead Agent Attacked*, *Teammate Attacked*, and *Incorrect Action* action-results (see Section 4.4.2 for more information on action-results and rewards) are given to the *Agents* throughout an entire experiment "run" (see Table 6.2).

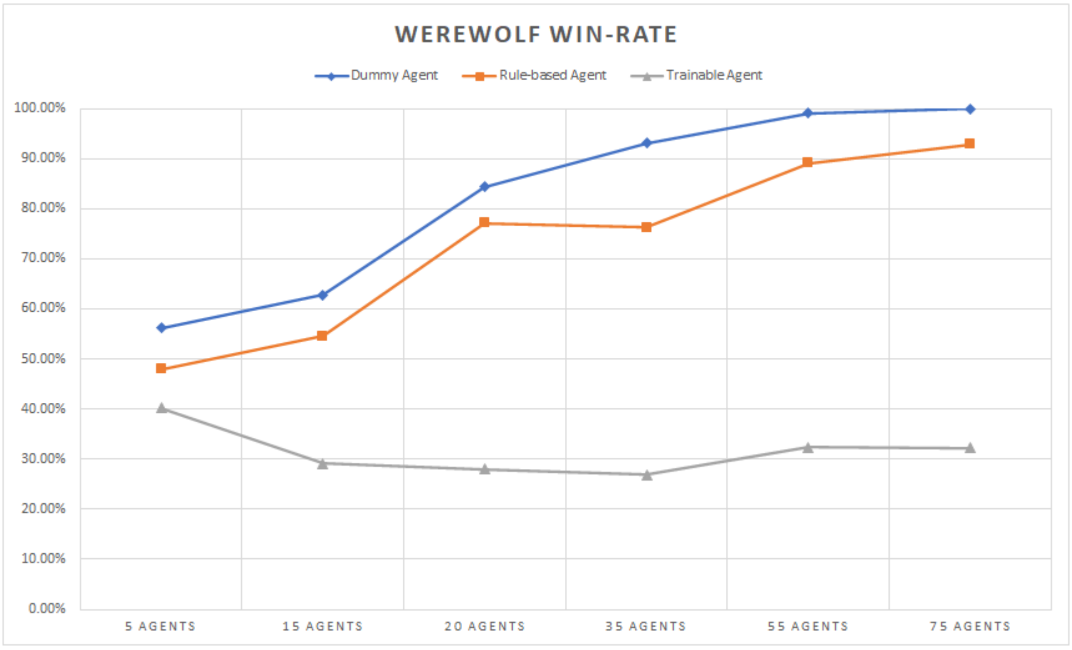


Figure 6.1: Experiment metrics graph – Win-rate and *Game* speed

[1]Recorded experiment metrics – `https://github.com/GeorgeVelikov/RLereWolf/tree/main/Stats`

*A*T	*P*#	*E*WR	*G*WR	A*G*L	A*G*TL	A*G*TC	D*A*V	D*A*A	TA	IA
D	5	56.2	43.8	0.038	0.014	2.74	0.00	0.00	0.00	0.07
D	15	62.8	37.2	0.248	0.022	11.52	0.00	0.07	0.00	2.23
D	20	84.4	15.6	0.511	0.033	15.71	0.00	0.13	0.00	6.38
D	35	93.1	6.9	1.245	0.044	28.64	0.00	0.17	0.00	18.55
D	55	99.1	0.9	3.292	0.079	41.90	0.00	0.16	0.00	50.93
D	75	100.0	0.0	7.741	0.136	57.14	0.00	0.16	0.00	99.95
RB	5	47.9	52.1	0.037	0.013	2.72	0.00	0.00	0.00	0.07
RB	15	54.6	45.4	0.179	0.016	11.55	0.00	0.07	0.00	2.21
RB	20	77.1	22.9	0.458	0.028	16.24	0.00	0.16	0.00	6.45
RB	35	76.3	23.7	1.573	0.051	30.64	0.00	0.19	0.00	19.20
RB	55	89.1	10.9	4.570	0.095	48.22	0.00	0.23	0.00	54.93
RB	75	92.8	7.2	8.777	0.132	66.65	0.00	0.24	0.00	107.50
T	5	40.2	59.8	0.045	0.012	3.78	0.63	0.38	0.15	2.07
T	15	29.1	70.9	0.292	0.017	17.27	11.71	4.50	0.56	48.10
T	20	28.0	72.0	0.601	0.024	25.13	22.91	8.25	1.11	89.68
T	35	26.9	73.1	1.627	0.033	48.66	73.10	20.62	2.68	282.80
T	55	32.4	67.6	3.525	0.043	82.28	177.25	42.55	7.76	675.52
T	75	32.2	67.8	6.560	0.058	114.92	319.30	70.72	13.10	1224.63

Table 6.2: Experiment win-rates, average *Game* length, and average invalid actions for a "run" of 1000 *Games*
A*T* = *Agent* type; *D* = *Dummy Agent*; *RB* = *Rule-based Agent*; *T* = *Trainable Agent*; ***P*#** = *Player* count; ***E*WR** = *Evil* (*Werewolf*) win-rate percentage; ***G*WR** = *Good* (*Villager*, *Guard*, and *Seer*) win-rate percentage; **A*G*L** = Average *Game* length (seconds); **A*G*TL** = Average *Game* turn length (seconds); **A*G*TC** = Average *Game* turn count; **D*A*V** = Average Dead *Agents* voted per *Game*; **D*A*A** = Average Dead *Agents* attacked per *Game*; **TA** = Average Teammates attacked per *Game*; **IA** = Average Incorrect actions per *Game*

***Player* count**	***Villagers***	***Guards***	***Seers***	***Werewolves***	**Points**
5	2	1	1	1	+4
15	11	1	1	2	-2
20	14	2	1	3	-5
35	25	3	2	5	-7
55	38	5	3	8	-12
75	51	7	5	12	-16

Table 6.3: Points for the current ratio-based role-distribution counts

From the results (see Table 6.2), it is visible that the *Agents* have a different win-rate as *Werewolves*, consequently as *Villagers* as well (see Figure 6.1). This is attributed to the different behaviours all three built-in *Agents exhibit*. However, if we take a look at the *Dummy* and *Rule-based Agents*' win-rate as a *Werewolf* (see Figure 6.1), it is visible that both *Agents* exhibit similar behaviour, such that with the rise of *Player* count within the *Game*, their performance as *Werewolves* increases, even reaching 100% win-rate as *Werewolves*. The author believes that this is an inherent flaw of using a ratio-based distribution approach as the intrinsic role-distribution is unbalanced in the current iteration of the *Game* (see Tables 4.3, 6.1 and 6.3).

The upward trend of having *Werewolves* winning as the *Agent* count increase, can also be seen in Table 6.2, which shows the inverted points advantage for both factions, that is – the points each role provides is multiplied with by -1. However, examining the *Werewolf* win-rate of the *Trainable Player* shows that the opposite trend occurs – with the increase of the *Werewolf* advantage, the *Villagers*' win-rate rises, albeit not as drastically as the the change occurring for the *Dummy* and *Rule-based Agents*. This is likely a result of having *Trainable Players* being able to *Wait*, as opposed to *Dummy Agents* and *Rule-based Agents* – who must always act.

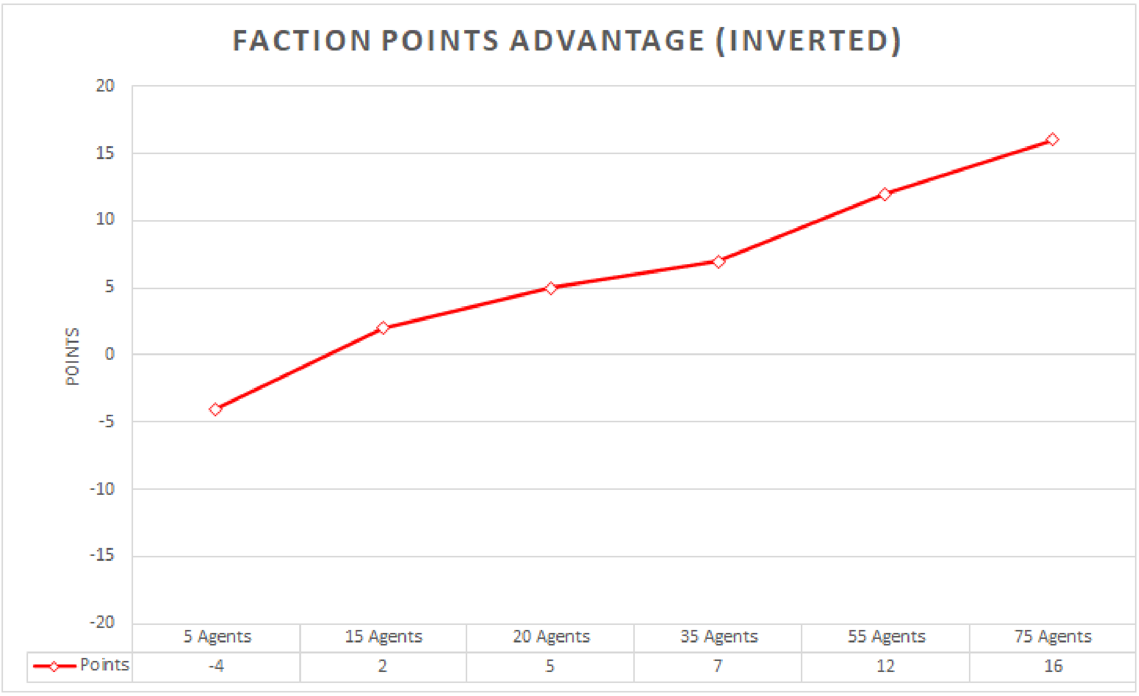


Figure 6.2: Experiment metrics graph – Sum of Points for existing role distribution (inverted). The the *bad* and *good* faction have inverted points, that is – their advantage is multiplied by -1.

It must be noted that the *Trainable Agent* iteration used in the experiments has no pre-existing training data as it is not complete in this iteration. Consequently, a lot of its *Game* actions will be *invalid* (see Figure 6.4), which will in hand increase the experiment time. This can be seen in all of the experiment "runs" where the *Trainable Agent* took from 35% to 100% more turns for a single *Game* on average (see Table 6.2 column **AGTC**).

The *Dummy* and *Rule-based Agents* have some *invalid* actions recorded, which are likely a result of faulty action validation checks as the **DAA** and **IA** values for both are roughly the same with minor differences which are attributed to the stochastic, but mostly *valid*, nature of the *Agents'* actions. Moreover, both *Agents* share the same action validation logic, which further justifies their *validity* performance.

The *Trainable Agent* "runs" have a higher *invalid* actions count, due to them having no inherent action validation whatsoever. .

However, observing the average *Game* length in time, we can see that the timings are relatively consistent (see Figure 6.3). The *Rule-based Agent* took the most time for a *Game*, which was expected by the author, as the *Rule-based Agent* will need to go the trust and honesty values it keeps, in order to make a decision on their action. Surprisingly to the author, the *Trainable Agent* had the lowest average *Game* time, although the longest *Games* in turns, were the *Trainable Agent* ones (see Table 6.2 – low **AGL**, high *AGTC*).

Moreover, it can be seen that the *Dummy Agent* ends up being slower than the *Trainable Agent* after the increase of *Agents* from 55 to 75 (see Figure 6.3), this could be attributed to the extra action *validity* checks a *Dummy Agent* must do, in order to complete their turn. This is further supported by the different in average *Game* turn length (**AGTL**) in Table 6.2 as the *Trainable Agent* "runs" have an equal or smaller **AGTL** value when compared to the *Dummy* or *Rule-Based Agent* "runs". As the time delta between the *Games* ran by the built-in *Agents* follows the same curve and any variations they have can be attributed to their decision making process, the author states that the framework's performance is consistent, independently of the *Agent* type used. However, these minor variations on an average *Game* length in seconds can add up to the overall "run" time. To put into perspective, the time difference between the *Rule-based* and the *Trainable Agent* "runs" at a *Game Player* count of 75 is $2,217$ seconds – roughly equating to a 37 minutes difference for a "run" of 1000 *Games*.

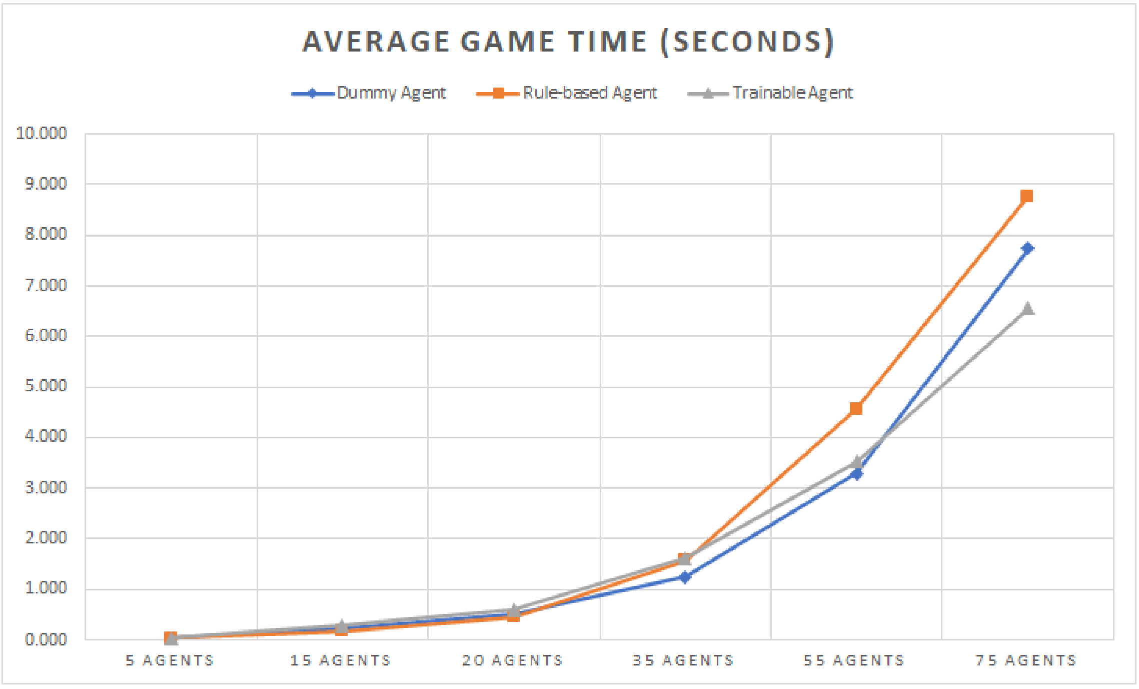


Figure 6.3: Experiment metrics graph – Average *Game* time (seconds)

Whilst RLereWolf does have an improved communication protocol over AiWolf (Toriumi et al., 2016; Nakamura et al., 2017) (see Section 4.3.3 for more information), RLereWolf's communication protocol has had no use in the carried out experiment, as the functionality of *swaying* other *Agents* is not implemented in the framework's current iteration (see Section 4.3.3 for more information). However, observing at the win-rate for the *Villager* and *Werewolf* faction, its average value is closely matched to the final results of the 2^{nd} AiWolf competition (aiW, 2020).

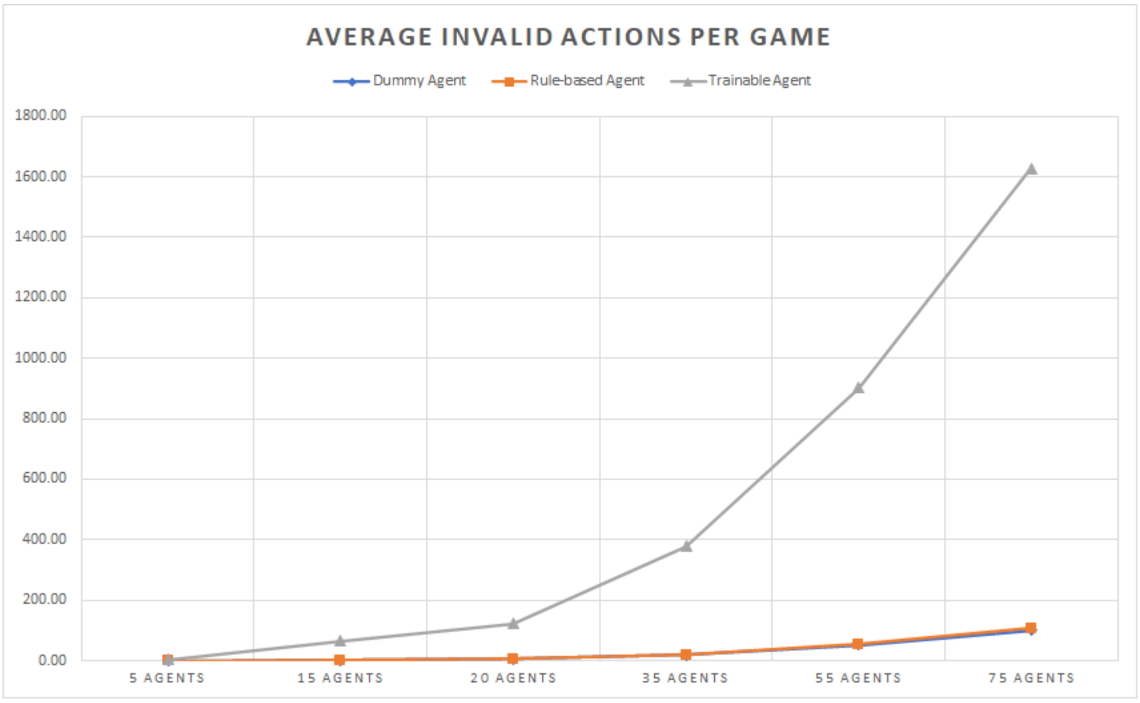


Figure 6.4: Experiment metrics graph – Average invalid actions per *Game*

Chapter 6 in a Nutshell

- *The experiments consist of* 18,000 *games which are only with non-human players.*
- *The recorded data shows a fault within the game implementation's ratio-based role distribution.*
- *The Dummy and Rule-based Agents have an inherent validation fault which could not be observed during initial testing.*
- *The Dummy and Rule-based Agents behave differently, although the same performance trajectory is followed.*
- *The average game time stays roughly equivalent until the 55 player game lobby mark. Implies the stability of the framework and its correlation with the Agent implementation.*
- *Trainable Agent does not learn from their mistakes and commits the most invalid actions, due to the lack of the action validation, present in both Dummy and Rule-based Agents.*
- *The ability to Wait as an action has a big detrimental impact on the overall win-rate of the Trainable Agent when playing as a Werewolf.*

Chapter 7

Conclusion & Future Work

In this chapter, the author will present the formal conclusion they have made from the experiment results and inherent work with RLereWolf, alongside a detailed list of future work elements, which they author has planned for future iterations of the framework, which aim to improve on the GUI, *Agents*, overall analysis tools provided by the *Environment* and accessibility to developers.

7.1 Conclusion

The framework, RLereWolf, has shown its potential for the development of *Agents* whose performance is not entirely bound on the *Game* implementation. Furthermore, the metrics and analysis tools the framework provides are not currently provided by any existing framework. Moreover, RLereWolf provides users with:

- *Client* – An access point for users to play the game Werewolf with other humans or *Agents* on the targeted RLereWolf *Server*. The *Client* has a an easily expandable Tk based GUI which is rendered on run-time by the built-in Pygubu builders and renderers.
- Development Framework – The development framework consists of the code base for the Werewolf game implementation, the analytic utilities provided by the built-in training *Environment*, comprehensive server & game activity logging, and the modular implementation of the four subsystems: *Client*, *Server*, *Game*, and *Environment*.
- Built-in *Agents* – Three built-in *Agents* which allow the framework's users to use them as a foundation for future *Agents*. The three *Agents* are:
  - *Dummy Agent* – A stochastic *Agent* that does random *valid* actions.
  - *Rule-based Agent* – An *Agent* with an *honesty* factor who votes for the least *trustworthy*, according to them, *Player*.
  - *Trainable Agent* – An *Agent* that can learn from playing multiple games of the current Werewolf *Game* implementation. Has no pre-existing knowledge of the game and needs to *train* in order to learn the game's rules and how to optimally play it.

The importance of RLereWolf is that it will expedite the further development and research of artificial intelligence in *Bayesian games* whose real-life application can be easily translated to. This is due to the problem's core nature – working with incomplete information about the environment and making a decision on what the best course of action is, based off of your limited contextual knowledge and past experiences.

The current three, distinct, built-in *Agents* provided the author with experiment results which, unfortunately, prove that the RLereWolf *Agents* do not reach the performance of *AiWolf's Agents*. Consequently, the project could not manage to achieve its goals of providing the entirety of the promised framework, as the three built-in *Agents* are not in a finished state (see Chapters 5 and 6 for more information).

Whilst, the RLereWolf *Agents* bring similar results as previous research (Toriumi et al., 2016; aiW, 2017, 2020), as well as theoretical improvements over its competitor – *AiWolf*. The current framework iteration does not provide the functioning communication channel improvements and are unused by any of the *Agents*.

Moreover, the current framework has a faulty *Game* implementation, which has resulted in non-balanced *Game* lobbies, which is an inherent issue with using ratio-based distribution systems, as opposed to the standard point-based system.

The negative result of project has largely been a result due to the scope of the project and its allocated time. The author aims to complete the framework and add additional improvements in future releases. However, the the machine learning and development concepts learned by the author during the development of the RLereWolf framework will aide them with the planned future work and provide useful in both academic and career contexts.

7.2 Future Work

In this section, the author will discuss some of the future work that has been planned for the framework, be it as a result of truncated functionality, due to the size of the project and its deadline, or – work that was eventually perceived as beneficial to the project.

7.2.1 *Agents*

In the current iteration of RLereWolf, not all of the *Agents* are fully completed. The author has planned the completion of the *Rule-based Agent* and the *Trainable Agent*, alongside the addition of more *Agents*, namely a *Stochastic Agents* – An *Agent* that does completely random actions, similarly to the *Dummy Agent*. However, the *Stochastic Agent* is not guaranteed to make *valid Game* actions.

Consequently, there should be a base for some untrained *Agent* – the *Stochastic Agent*, and a base for some trained *Agent* that only does *valid* actions – the *Dummy Agent*. As a result, *Agent* performance analysis should prove easier, due to the additional performance reference point.

7.2.2 Multiple *Game* Action Results

In its current state, RLereWolf can only record one *Game* action result, per *Player* action. This can be improved upon by returning a set of results as there is the possibility of overlapping action results. This can be beneficial when training *Agents* which have violated more than one game rule, e.g. an *Agent* whose role is a *Villager*, *attacks* another *Player*, during the *day* time. This would prompt two *InvalidAction* rewards – one for the attempt at *attacking* as a *Villager* and one for attempting a *Werewolf* action as a *Villager* (see Section 4.4.2 for more information on rewards).

7.2.3 Point-Based Role Distribution

As briefly mentioned in Section 4.3, the current version of the framework employs a ratio-based approach when distributing the roles, at the start of a *Game* (see Section 4.3.1 for more information on existing role distribution).

The author intends to implement the standard point-based role distribution, as per the Werewolf game (BGG, 2016) (see Section 4.3.1 for more information on point-based role distribution). Users of the RLereWolf framework will have the option to choose between the standard point-based role distribution, or the bespoke ratio-based role distribution.

7.2.4 RLereWolfSharp (C# Iteration)

As mentioned, the author's other programming language choice was C#, which they are proficient in, and is gaining popularity in the field of machine learning with the release of *ML.NET* (Csh, 2018) – an open source machine learning framework for the *.NET* stack. Furthermore, C#'s package manager – *NuGet*, has access to popular machine learning frameworks such as *TensorFlow* and *Keras*.

The immediate challenge with having a C# iteration of RLereWolf is the possibility of code duplication and its avoidance. The author proposes a shared code C# project which uses *Python.NET*[1], which allows Python code to run within the *Common Language Runtime* (CLR) (Meijer and Gough, 2001; Box and Sells, 2003), in order to run Python code within the C# implementation. That way the initial iteration of RLereWolf will become the primary code base which can get reused and referenced from other, future, implementations – in this case RLereWolfSharp.

7.2.5 Expand Communication Protocol & Natural Language Processing

Although the currently implemented communication protocol covers more than 50% of the real world communications (Toriumi et al., 2016), the author aims at improving the communication protocol by adding additional messages into the already established message classifiers (see Section 4.3.3 for more information on existing communication protocol) by expanding the *Conflict resolution* and *Asserting* messages. This will be done with the intention of adding a *spectrum* of certainty, i.e. the messages for *Conflict resolution* could have presets with adjectives which enforce or minimise the agreement/disagreement.

Moreover, the author plans on having an "open" communication protocol for the human *Players*. This would inherently mean that there needs to be some sort of mechanism to allow for *Agents* to comprehend the free text, entered by the human *Player* – i.e. with *Natural Language Processing* (NLP) (Liddy, 2001; Chowdhury, 2003; Indurkhya and Damerau, 2010).

However, problem of *Natural Language Processing* is complex and as such, the author proposes the "open" communication protocol, only being applicable to human *Players*. This is in accordance to popular *Games* which use preset communications, in order to communicate with *Agents*, commonly referred to as *Bots*. This separation of "open" and preset communications can be seen in games in the *Counter-Strike* series, where *Bots* would only react to the "radio commands", which are preset communication messages (CSGO, 2021). Consequently, human *Players* would need to use the preset communication messages, whenever they intend to convey a message to the *Agents*, present in their *Game*.

[1]Python.NET – `http://pythonnet.github.io/`

Appendix A

User Manual

This appendix will go over the functionality of the *Client* and serves as a guide as to how its users should interact with the graphical user interface. In its current iteration – RLereWolf consists of only three major screens – the *Main Menu*, *Game List*, and *Game Lobby*.

A.1 Main Menu

Once a user starts up the *Client*, either by double-clicking on the distributed *Client* executable, or by debugging the *Client* (see Appendix B for more information) – they will be greeted with the main menu screen which shows them the options to:

- Connect – Establish a connection with the *Server*, which will change the *Client* screen to the game list screen – showing all *Games* which the *Client* can join.
- Set Name – This is a mandatory action before connecting to the *Server*. This sets the displayed to other *Clients* name. It serves as a user alias, as the *Clients* are identified by their unique *Client Identifier*.
- Help – Shows a dialog with basic information on how to use the *Client* (see Figure A.2).
- Quit Game – Closes the *Client*.

Before a user is able to *Connect* to the *Server*, they must set their name (see Figures A.1 to A.3).

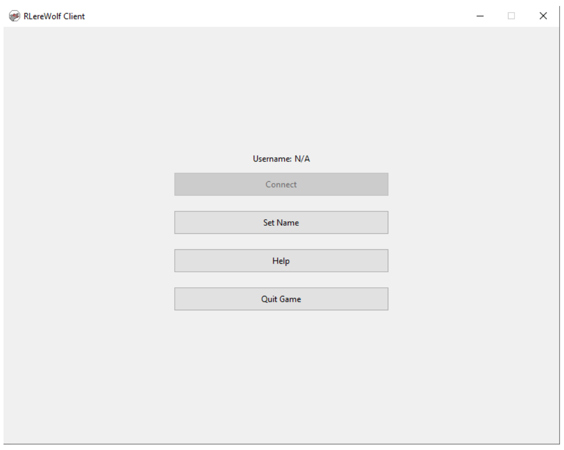


Figure A.1: Main menu – No *Client* name provided

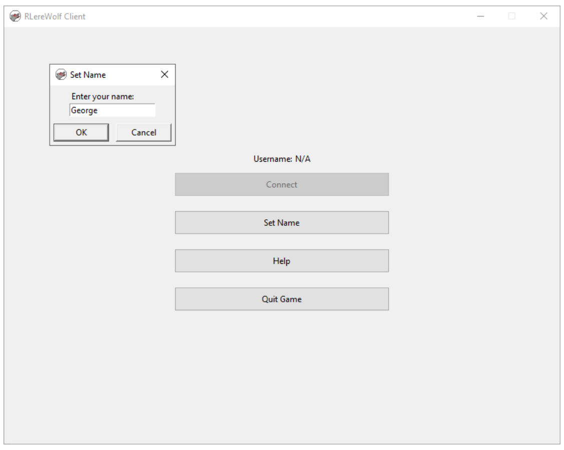


Figure A.2: Main menu – *Set Name* dialog

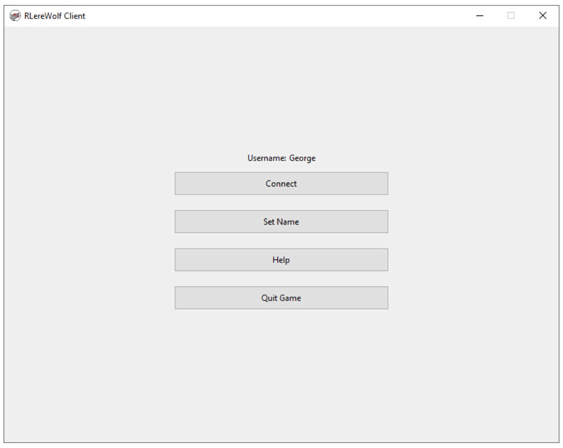
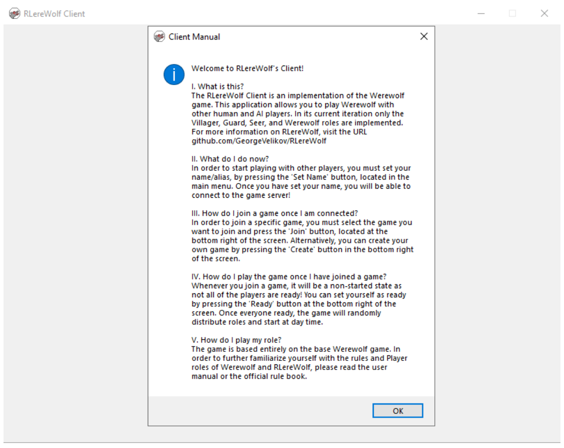


Figure A.3: Main menu – *Client* has a name, ready to connect



Welcome to RLereWolf's Client!

I. What is this?
The RLereWolf Client is an implementation of the Werewolf game. This application allows you to play Werewolf with other human and AI players. In its current iteration only the Villager, Guard, Seer, and Werewolf roles are implemented. For more information on RLereWolf, visit the URL github.com/GeorgeVelikov/RLereWolf

II. What do I do now?
In order to start playing with other players, you must set your name/alias, by pressing the 'Set Name' button, located in the main menu. Once you have set your name, you will be able to connect to the game server!

III. How do I join a game once I am connected?
In order to join a specific game, you must select the game you want to join and press the 'Join' button, located at the bottom right of the screen. Alternatively, you can create your own game by pressing the 'Create' button in the bottom right of the screen.

IV. How do I play the game once I have joined a game?
Whenever you join a game, it will be a non-started state as not all of the players are ready! You can set yourself as ready by pressing the 'Ready' button at the bottom right of the screen. Once everyone ready, the game will randomly distribute roles and start at day time.

V. How do I play my role?
The game is based entirely on the base Werewolf game. In order to further familiarize yourself with the rules and Player roles of Werewolf and RLereWolf, please read the user manual or the official rule book.

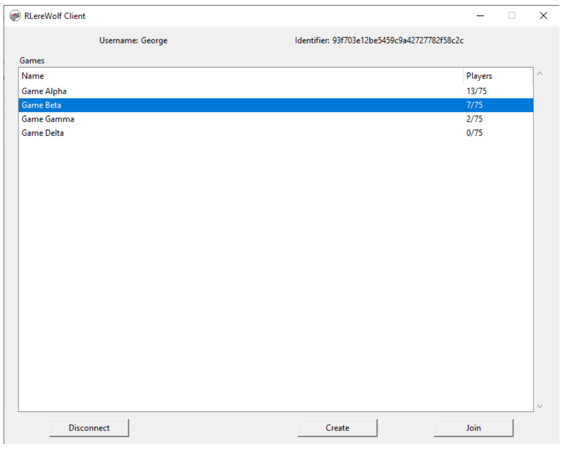
Figure A.4: Main menu – Help dialog

Once a user has set their name, they are able to connect to the *Server*. When the user is successfully connected to the *Server*, that is – whenever they get a successful connect response back from the *Server*, they will be redirected to the *Game List* screen.

A.2 Game List

The *Game List* screen contains all "joinable" by the *Client Games*. The "joinable" *Games* are defined as *Games* which have not started. The "unjoinable" *Games* are those which will not be visible in the list in first place, or *Games* which are full. In this screen, the *Client* user has the following options:

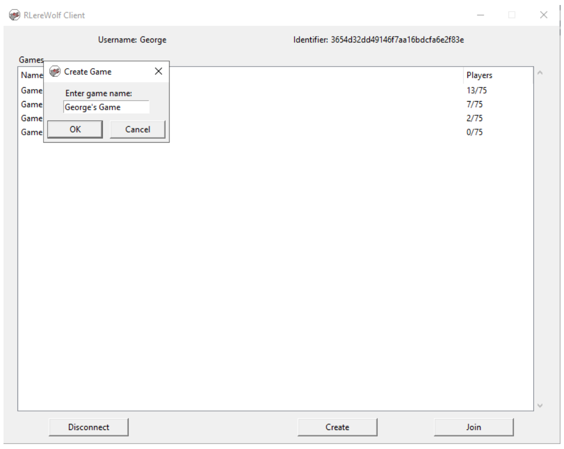
- Disconnect – Disconnects from the *Server* and returns the *Client* back to the *Main Menu*.
- Create – Opens up a dialog (see Figure A.6) so that a *Client* can create a new *Game*. Once a *Game* name is specified, the *Client* automatically joins the newly created *Game*.
- Join – Joins the selected (see Figure A.5, highlighted *Game*) by the *Client* user *Game*, provided it is "joinable". If no *Game* is selected, then the *Client* will stay on the *Game List* screen. Once a *Game* is joined, the *Client* changes the screen to the *Game Lobby* screen.



Username: George   Identifier: 93f703e12be5459c9a42727782f58c2c

Name	Players
Game Alpha	13/75
Game Beta	7/75
Game Gamma	2/75
Game Delta	0/75

Figure A.5: Game List screen



Username: George   Identifier: 3654d32dd49146f7aa16bdcfa6e2f83e

Name	Players
Game	13/75
Game	7/75
Game	2/75
Game	0/75

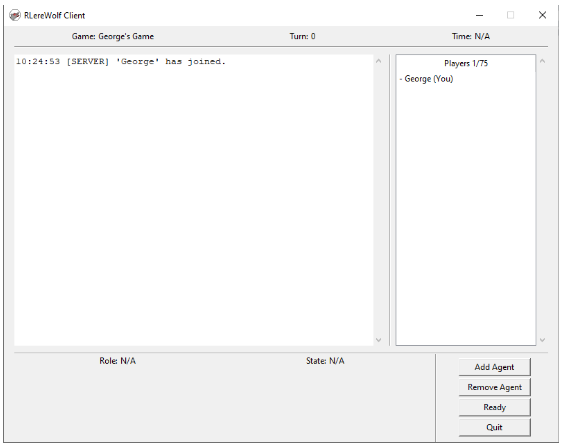
Enter game name: George's Game

Figure A.6: Game List – Create a *Game*

A.3 Game Lobby

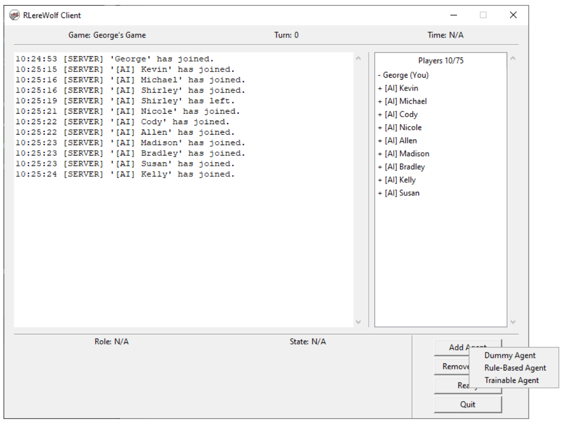
The *Game Lobby* screen is the effective *Game* the *Clients* will be able to play. This screen has two modes:

- Non-started *Game* – A non-started *Game* is a *Game* in which at least one *Player* has not set their status as *Ready* (see Figures A.7 and A.8). The state of readiness of a *Player* is notated as a "+" and "−" on the left of the *Player's* name for being *Ready* and being *not Ready* respectively (see Figures A.7, A.8, and A.14). These *Games* are visible in the *Game List* screen and can be joined by other *Players*, as long as the *Player* limit is not reached. During this phase, all human *Players* in the lobby are able to add *Agents* from a set of three possible *Agent* types – *Dummy Agent*, *Rule-based Agent*, or *Trainable Agent*.
- Started *Game* – A started *Game* is when all the *Players* within the lobby have marked their status as *Ready*, after which the *Game* initiates, by randomly distributing roles to the *Players* in the *Game* (see Figures A.9, A.11, and A.13).



```
10:24:53 [SERVER] 'George' has joined.
```

Figure A.7: Game Lobby – Newly created *Game*



```
10:24:53 [SERVER] 'George' has joined.
10:25:15 [SERVER] '[AI] Kevin' has joined.
10:25:16 [SERVER] '[AI] Michael' has joined.
10:25:16 [SERVER] '[AI] Shirley' has joined.
10:25:19 [SERVER] '[AI] Shirley' has left.
10:25:21 [SERVER] '[AI] Nicole' has joined.
10:25:22 [SERVER] '[AI] Cody' has joined.
10:25:22 [SERVER] '[AI] Allen' has joined.
10:25:23 [SERVER] '[AI] Madison' has joined.
10:25:23 [SERVER] '[AI] Bradley' has joined.
10:25:23 [SERVER] '[AI] Susan' has joined.
10:25:24 [SERVER] '[AI] Kelly' has joined.
```

Figure A.8: Game Lobby – Non-started *Game* with *Agents*

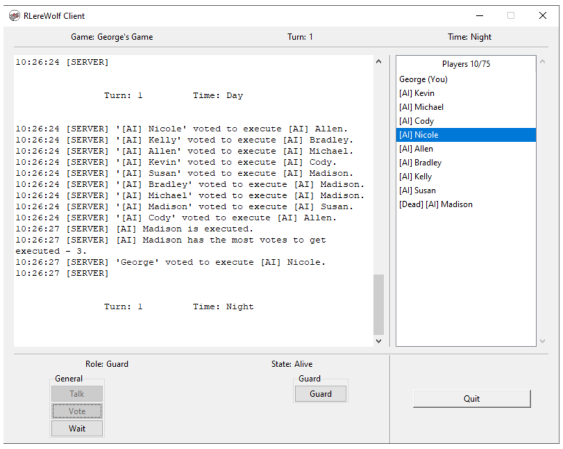
Once a *Game* has started, the *Players* are provided with a random *role* from the set of currently supported roles – *Villager*, *Guard*, *Seer*, and *Werewolf*. The *Game* starts off with the day time, where *Players* must *Vote* to execute or *Wait*, that is – skip their turn and do nothing (see Figure A.9).

Moreover, once a *Game* has started, all *Players* are able to *Talk*, using a set of preset messages, during the day time. In order to *Talk*, a *Player* must select another *Player*, whose "targeted" message is intended to. A "targeted" message is that which references another *Player*, i.e. "Accuse a *Player* of" (see Figure A.11).

Whenever the time of day is changed – *day* or *night*, certain *Game* actions the *Player* can do become unavailable. This is because as a *Player* of your specific role, you are incapable of doing the disabled action within that turn, i.e. *Voting* during the *night* as any role. Furthermore, a *Player* can only see the *Actions* their role can do (see Figure A.9 for a *Guard* and Figure A.11 for a *Villager*).

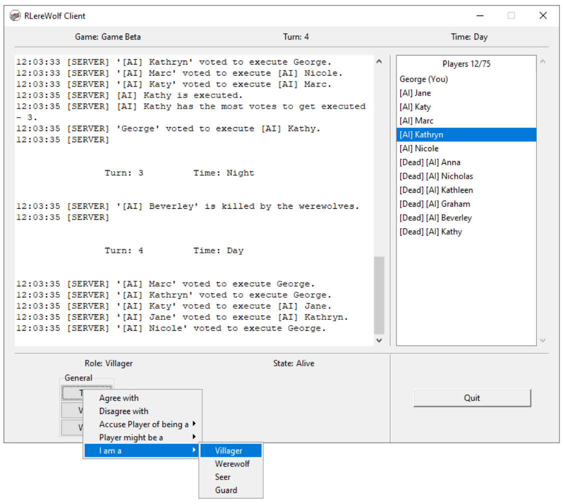
Once a *Game* has finished, then the lobby will automatically "reset" and mark all human *Players* as not *Ready*. *Players* can then mark themselves as *Ready* and start another *Game* of

Werewolf with the same *Players*, or alternatively, add more *Agents*, or wait for new human *Players*. See Figures A.9, A.10, A.11, A.12, and A.13 for more examples on playing Werewolf.



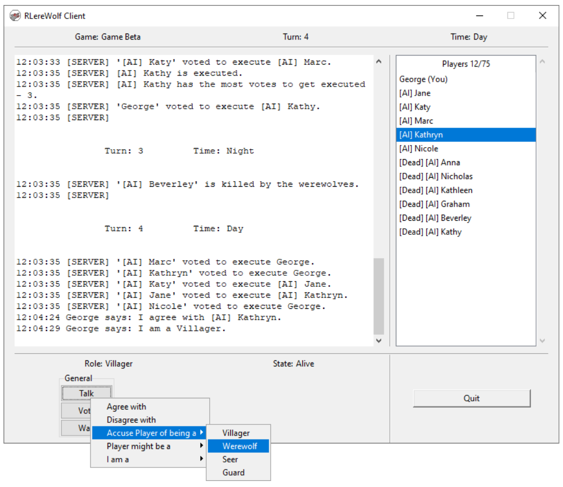
```
10:26:24 [SERVER]


            Turn: 1        Time: Day


10:26:24 [SERVER] '[AI] Nicole' voted to execute [AI] Allen.
10:26:24 [SERVER] '[AI] Kelly' voted to execute [AI] Bradley.
10:26:24 [SERVER] '[AI] Allen' voted to execute [AI] Michael.
10:26:24 [SERVER] '[AI] Kevin' voted to execute [AI] Cody.
10:26:24 [SERVER] '[AI] Susan' voted to execute [AI] Madison.
10:26:24 [SERVER] '[AI] Bradley' voted to execute [AI] Madison.
10:26:24 [SERVER] '[AI] Michael' voted to execute [AI] Madison.
10:26:24 [SERVER] '[AI] Madison' voted to execute [AI] Susan.
10:26:24 [SERVER] '[AI] Cody' voted to execute [AI] Allen.
10:26:27 [SERVER] [AI] Madison is executed.
10:26:27 [SERVER] [AI] Madison has the most votes to get
executed - 3.
10:26:27 [SERVER] 'George' voted to execute [AI] Nicole.
10:26:27 [SERVER]


            Turn: 1        Time: Night
```

Figure A.9: Game Lobby – Night time as a *Guard*



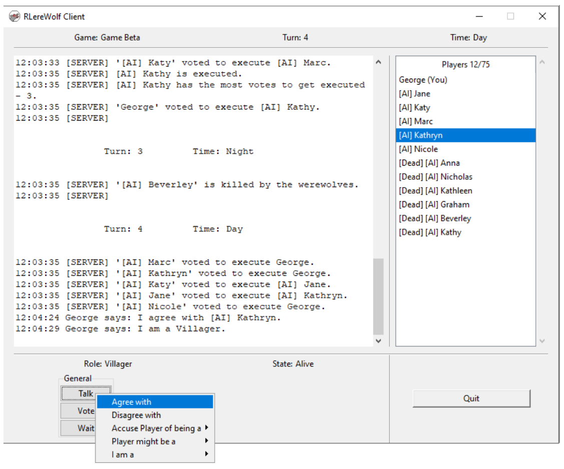
```
12:03:33 [SERVER] '[AI] Kathryn' voted to execute George.
12:03:33 [SERVER] '[AI] Marc' voted to execute [AI] Nicole.
12:03:33 [SERVER] '[AI] Katy' voted to execute [AI] Marc.
12:03:35 [SERVER] [AI] Kathy is executed.
12:03:35 [SERVER] [AI] Kathy has the most votes to get executed
- 3.
12:03:35 [SERVER] 'George' voted to execute [AI] Kathy.
12:03:35 [SERVER]


            Turn: 3        Time: Night


12:03:35 [SERVER] '[AI] Beverley' is killed by the werewolves.
12:03:35 [SERVER]


            Turn: 4        Time: Day


12:03:35 [SERVER] '[AI] Marc' voted to execute George.
12:03:35 [SERVER] '[AI] Kathryn' voted to execute George.
12:03:35 [SERVER] '[AI] Katy' voted to execute [AI] Jane.
12:03:35 [SERVER] '[AI] Jane' voted to execute [AI] Kathryn.
12:03:35 [SERVER] '[AI] Nicole' voted to execute George.
```

Figure A.10: Game Lobby – Declare your own role as a *Villager*



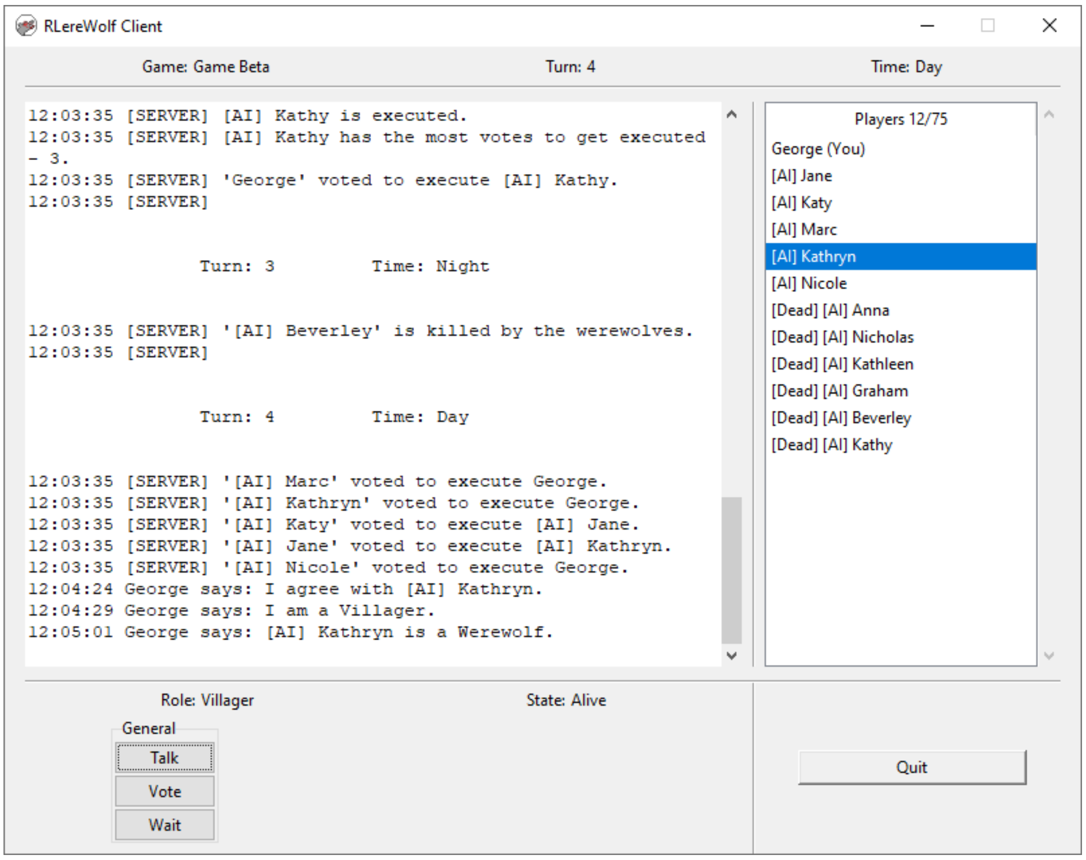
```
12:03:33 [SERVER] '[AI] Katy' voted to execute [AI] Marc.
12:03:35 [SERVER] [AI] Kathy is executed.
12:03:35 [SERVER] [AI] Kathy has the most votes to get executed
- 3.
12:03:35 [SERVER] 'George' voted to execute [AI] Kathy.
12:03:35 [SERVER]


            Turn: 3        Time: Night


12:03:35 [SERVER] '[AI] Beverley' is killed by the werewolves.
12:03:35 [SERVER]


            Turn: 4        Time: Day


12:03:35 [SERVER] '[AI] Marc' voted to execute George.
12:03:35 [SERVER] '[AI] Kathryn' voted to execute George.
12:03:35 [SERVER] '[AI] Katy' voted to execute [AI] Jane.
12:03:35 [SERVER] '[AI] Jane' voted to execute [AI] Kathryn.
12:03:35 [SERVER] '[AI] Nicole' voted to execute George.
12:04:24 George says: I agree with [AI] Kathryn.
12:04:29 George says: I am a Villager.
```

Figure A.11: Game Lobby – Send a message to accuse a *Player* of being a *Role*



```
12:03:33 [SERVER] '[AI] Katy' voted to execute [AI] Marc.
12:03:35 [SERVER] [AI] Kathy is executed.
12:03:35 [SERVER] [AI] Kathy has the most votes to get executed
- 3.
12:03:35 [SERVER] 'George' voted to execute [AI] Kathy.
12:03:35 [SERVER]


            Turn: 3        Time: Night


12:03:35 [SERVER] '[AI] Beverley' is killed by the werewolves.
12:03:35 [SERVER]


            Turn: 4        Time: Day


12:03:35 [SERVER] '[AI] Marc' voted to execute George.
12:03:35 [SERVER] '[AI] Kathryn' voted to execute George.
12:03:35 [SERVER] '[AI] Katy' voted to execute [AI] Jane.
12:03:35 [SERVER] '[AI] Jane' voted to execute [AI] Kathryn.
12:03:35 [SERVER] '[AI] Nicole' voted to execute George.
12:04:24 George says: I agree with [AI] Kathryn.
12:04:29 George says: I am a Villager.
```

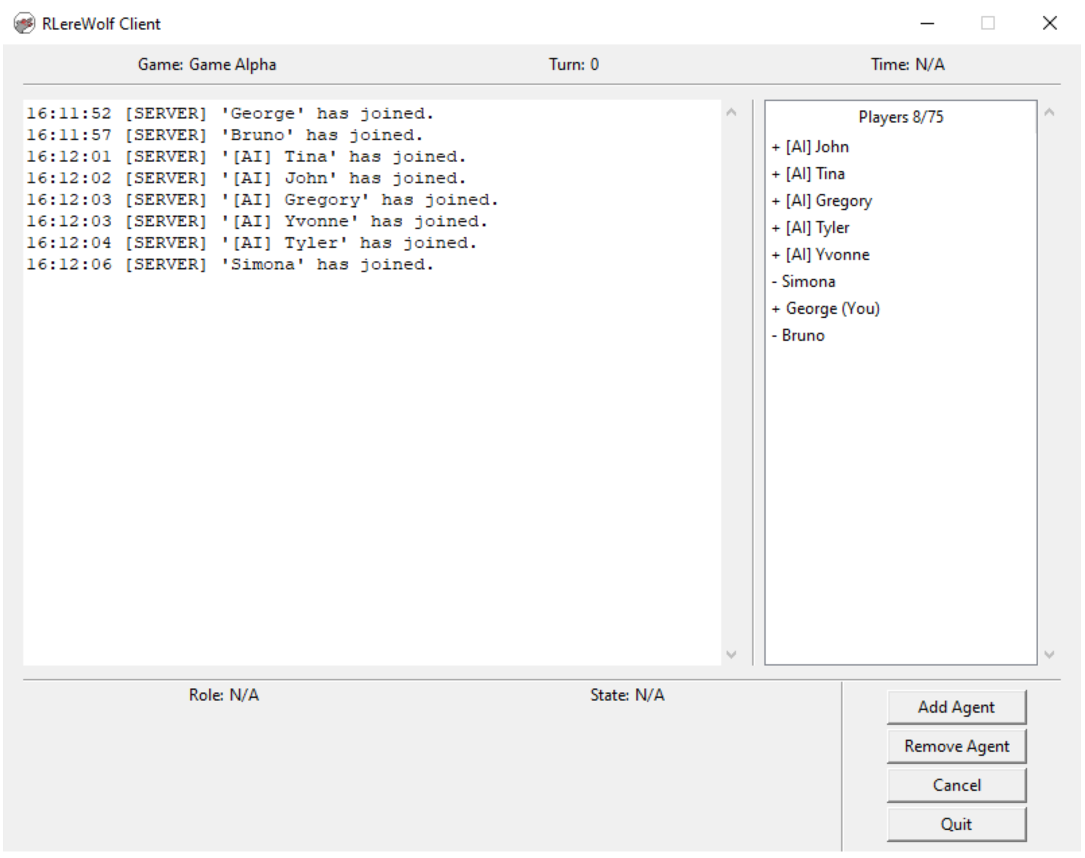
Figure A.12: Game Lobby – Agree with a different *Player* on a statement they have made



```
12:03:35 [SERVER] [AI] Kathy is executed.
12:03:35 [SERVER] [AI] Kathy has the most votes to get executed
- 3.
12:03:35 [SERVER] 'George' voted to execute [AI] Kathy.
12:03:35 [SERVER]


                Turn: 3         Time: Night


12:03:35 [SERVER] '[AI] Beverley' is killed by the werewolves.
12:03:35 [SERVER]


                Turn: 4         Time: Day


12:03:35 [SERVER] '[AI] Marc' voted to execute George.
12:03:35 [SERVER] '[AI] Kathryn' voted to execute George.
12:03:35 [SERVER] '[AI] Katy' voted to execute [AI] Jane.
12:03:35 [SERVER] '[AI] Jane' voted to execute [AI] Kathryn.
12:03:35 [SERVER] '[AI] Nicole' voted to execute George.
12:04:24 George says: I agree with [AI] Kathryn.
12:04:29 George says: I am a Villager.
12:05:01 George says: [AI] Kathryn is a Werewolf.
```

George (You)
[AI] Jane
[AI] Katy
[AI] Marc
[AI] Kathryn
[AI] Nicole
[Dead] [AI] Anna
[Dead] [AI] Nicholas
[Dead] [AI] Kathleen
[Dead] [AI] Graham
[Dead] [AI] Beverley
[Dead] [AI] Kathy

Figure A.13: Game Lobby – Overview of a *Started Game*



```
16:11:52 [SERVER] 'George' has joined.
16:11:57 [SERVER] 'Bruno' has joined.
16:12:01 [SERVER] '[AI] Tina' has joined.
16:12:02 [SERVER] '[AI] John' has joined.
16:12:03 [SERVER] '[AI] Gregory' has joined.
16:12:03 [SERVER] '[AI] Yvonne' has joined.
16:12:04 [SERVER] '[AI] Tyler' has joined.
16:12:06 [SERVER] 'Simona' has joined.
```

+ [AI] John
+ [AI] Tina
+ [AI] Gregory
+ [AI] Tyler
+ [AI] Yvonne
- Simona
+ George (You)
- Bruno

Figure A.14: Game Lobby – Overview of a *Non-started Game*

Appendix B

Developer Manual

The development of RLereWolf has been done with Visual Studio 2019 and Python 3.7, as such – the author recommends the usage of the Visual Studio IDE for the maintenance and further development of RLerewolf. The Visual Studio solution comes with integrated helpers, which aide the development work. An example of such a helper is *SwitchStartupProject*[1], which has been set up with the various project combinations that can be launched (see Figure B.1 for the currently set up project combinations). The framework has a few development rules, which are as follows:

- **Maximum line length** – All code files of RLereWolf are to have a line length less of 120 characters when not a comment, and less than 125 characters when a comment. This aims to support users of 3:4 monitor users and increase code readability. A useful Visual Studio Package to keep this in mind is *Editor Guidelines*[2]

- **Code style** – The code style applied by developers much match that of the existing RLereWolf code base. This implies that classes should always have an individual file for them, alongside the continued practice of defining *getters* and *setters* for the appropriate properties.

- **Naming convention** – Developers should be mindful of the naming conventions they apply. The in-use naming convention is *camelCase* whereas public getters and all methods should be using *UpperCammelCase*.

- **Naming philosophy** – The developers should aim for the coding philosophy in non-documented code should be enough to convey the functionality, whereas any comment blocks should only convey the reason why a certain piece of functionality works the way it does.

Once a developer has a copy of RLereWolf's solution & Visual Studio installed, they can open up the ***Werewolf.sln*** file, which contains the various sub-systems, separated as different Visual Studio projects.

Within the root framework folder, there is a ***requirements.txt*** file, which contains the needed by Python 3.7 packages & their dependencies, in order to run the framework in its entirety. To

[1]SwitchStartupProject – `https://marketplace.visualstudio.com/items?itemName=vs-publisher-141975.SwitchStartupProject`

[2]Editor Guidelines – `https://marketplace.visualstudio.com/items?itemName=PaulHarrington.EditorGuidelines`

install the requirements, the developer should run one of the following commands, where ***pip*** targets the developer's Python 3.7 environment:

pip *install -r requirements.txt*

python3.7 *-m* ***pip*** *install -r requirements.txt*

The currently set up start up configurations can be seen on Figure B.1 and are defined as follows:

- **Client** – Starts a single instance of the **Client.ClientInstance.py** file, which brings up the Tkinter GUI.

- **Server** – Starts a single instance of the **Server.ServerInstance.py** file, which is a black box, containing a log of all actions & requests. The default *ServerInstance* is configured at localhost:26011, details of this can be seen in **Shared.constants.NetConstants.py**

- **Client + Server** – Starts off both *Client* & *Server* projects.

- **Werewolf** – Starts off a configured *Game*, entirely populated with *Agents*, which is set in **Werewolf.Environment.py**. The *Game* has an *Environment* wrapper around it, which saves game metrics and allows for the "training" of *Agents*.

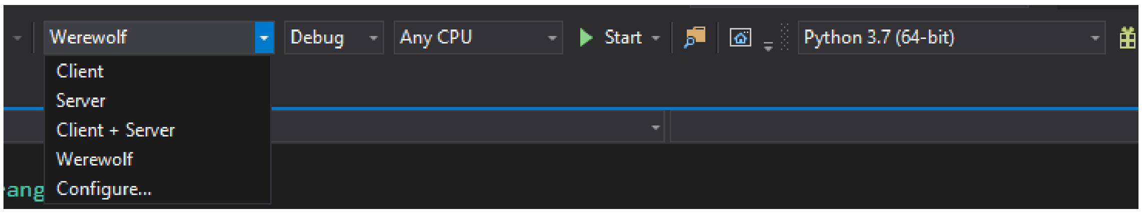


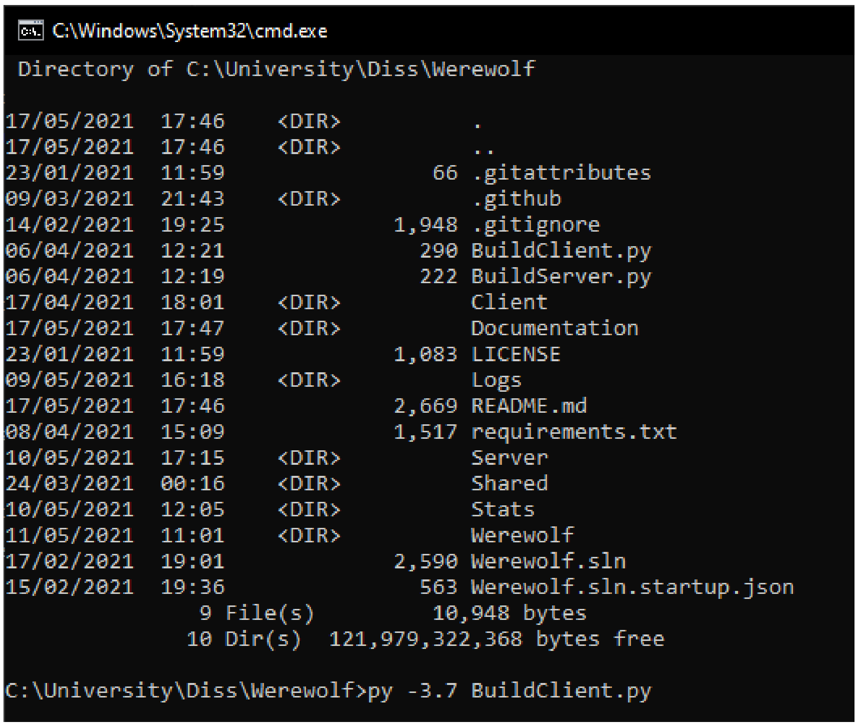
Figure B.1: Project startup options in Visual Studio 2019

B.1 Deployment

RLereWolf comes with a set of "build scripts" for the *Client* and *Server*. They are located in the root project directory and are called *BuildClient.py* and *BuildServer.py* respectively. Each file contains calls to *PyInstaller* which "freezes" and packages the project as executables for some target operating system, which is defaulted to the current host machine OS.

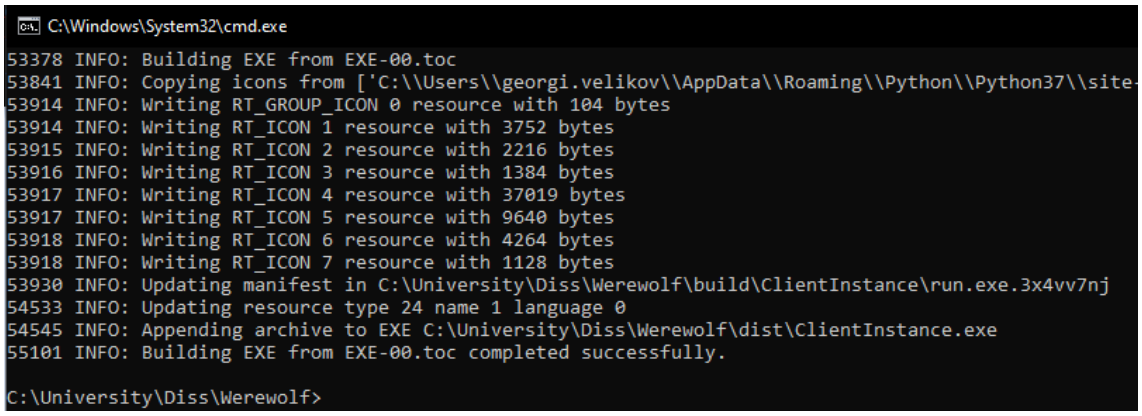
In its current form, the build scripts are not complete as they do not include all of the necessary files. However, these should manually call any non-Python files which are inherently required by the project. An example of this can be the .ui files which are used in the *Client*.

Once the scripts are finished, developers should be able to run either of the "Build" files and have an executable provided to them which they can distribute to either *Client* users or a host machine, to act as a *Server* (see Figures B.2 and B.3 on building the executables).



```
C:\Windows\System32\cmd.exe
 Directory of C:\University\Diss\Werewolf

17/05/2021  17:46    <DIR>          .
17/05/2021  17:46    <DIR>          ..
23/01/2021  11:59                66 .gitattributes
09/03/2021  21:43    <DIR>          .github
14/02/2021  19:25             1,948 .gitignore
06/04/2021  12:21               290 BuildClient.py
06/04/2021  12:19               222 BuildServer.py
17/04/2021  18:01    <DIR>          Client
17/05/2021  17:47    <DIR>          Documentation
23/01/2021  11:59             1,083 LICENSE
09/05/2021  16:18    <DIR>          Logs
17/05/2021  17:46             2,669 README.md
08/04/2021  15:09             1,517 requirements.txt
10/05/2021  17:15    <DIR>          Server
24/03/2021  00:16    <DIR>          Shared
10/05/2021  12:05    <DIR>          Stats
11/05/2021  11:01    <DIR>          Werewolf
17/02/2021  19:01             2,590 Werewolf.sln
15/02/2021  19:36               563 Werewolf.sln.startup.json
               9 File(s)         10,948 bytes
              10 Dir(s)  121,979,322,368 bytes free

C:\University\Diss\Werewolf>py -3.7 BuildClient.py
```

Figure B.2: Building the *Client* executable



```
C:\Windows\System32\cmd.exe
53378 INFO: Building EXE from EXE-00.toc
53841 INFO: Copying icons from ['C:\\Users\\georgi.velikov\\AppData\\Roaming\\Python\\Python37\\site-
53914 INFO: Writing RT_GROUP_ICON 0 resource with 104 bytes
53914 INFO: Writing RT_ICON 1 resource with 3752 bytes
53915 INFO: Writing RT_ICON 2 resource with 2216 bytes
53916 INFO: Writing RT_ICON 3 resource with 1384 bytes
53917 INFO: Writing RT_ICON 4 resource with 37019 bytes
53917 INFO: Writing RT_ICON 5 resource with 9640 bytes
53918 INFO: Writing RT_ICON 6 resource with 4264 bytes
53918 INFO: Writing RT_ICON 7 resource with 1128 bytes
53930 INFO: Updating manifest in C:\University\Diss\Werewolf\build\ClientInstance\run.exe.3x4vv7nj
54533 INFO: Updating resource type 24 name 1 language 0
54545 INFO: Appending archive to EXE C:\University\Diss\Werewolf\dist\ClientInstance.exe
55101 INFO: Building EXE from EXE-00.toc completed successfully.

C:\University\Diss\Werewolf>
```

Figure B.3: Successful build of the *Client* executable

B.2 Client

The *Client* Python Project consists of the GUI implementation (see Section 4.2 for information on functionality). The *Client* project holds references to the *Shared* project, and contains usage of Pygubu and a bespoke .ui rendering framework, whose purpose is to abstract away the GUI creation and abide by the *Rapid Application Development* methodology (Beynon-Davies et al., 1999). The basic GUI development pipeline is as follows:

1. Create a *View*:

    - Through writing XML in a .ui file; or
    - Through the Pygubu GUI editor.

2. Use the *ScreenBase* class, contained in **Client.screens.ScreenBase.py**, which is the formal "renderer" of the .ui file. An example of *ScreenBase*'s usage can be seen in **Client.screens.GameListScreen.py** and **Client.screens.GameLobbyScreen.py**.

3. Define any handler methods, i.e. Click, Drag, Scroll events, within the new renderer class, which inherits *ScreenBase*.

The descriptions of the code files contained in the *Client* Project, can be seen in Table B.1.

Client source code listings	
Filename	**Description**
ClientInstance.py	The entry point for the *Client* GUI
MainWindow.py	The root Tkinter Window, used by all screens of the *Client*
constants/ClientConstants.py	A configuration file, containing global constants to be used by all *Clients*
context/ServiceContext.py	The set of all service calls to the *Server*, which can be made by the *Client*
context/UIContext.py	The set of all navigation manipulating calls, which can be made on the *Client*, e.g. showing a specific screen or showing a dialog
context/ViewModelContext.py	The collection of all "contexts", supported by the *Client*, "contexts" are defined as logic units which have some common greater purpose, e.g. UIContext is concerned with UI elements, ServiceContext is concerned with service calls
models/TalkMessage.py	The abstraction of a message, seen in the *Game*. It can be sent by the *Server* or other *Clients*
screens/GameListScreen.py	The code-behind file for the Game List Screen. A list of games a *Client* can join, with the relevant *join* and *create Game* functionalities
screens/GameLobbyScreen.py	The de facto *Game* screen. This can be referred as a game lobby which has a single *Game* running in it, at any given point of time. Once a *Game* has finished, it is reset
screens/MainMenuScreen.py	The landing screen of the *Client*, this is the main menu where users can set their username and connect to the binded *Server*
screens/ScreenBase.py	The base class for all screens, this is responsible for rendering the .ui files
utility/PacketUtility.py	A utility class which provides short-hand methods for creating all necessary *Packets* to send to the *Server* with the *ServiceContext*
utility/TalkMessageUtility.py	The class responsible for classifying all of the communication preset messages to their respective *roles*, which can be sent through a *Client*

views/GameListScreen.ui	The XML definition of the game list screen, created with Pygubu
views/GameLobbyScreen.ui	The XML definition of the de facto *Game* screen, created with Pygubu
views/MainMenuScreen.ui	The XML definition of the mainmenu screen, created with Pygubu

Table B.1: *Client* Project code listings

B.3 Server

The *Server* project contains the implementation of the *Game* host, which multiple *Clients* can connect to. The *Server* is also responsible for logging requests, both to the *Server* itself and any *Games* hosted onto it.

Server source code listings	
Filename	**Description**
HandlerContext.py	The handler "context" contains a reference to all handlers the *Server* has access to. Handlers are the logic units of the server, which are split by general functionality – similarly to the *Client* "contexts"
ServerInstance.py	The *Server* entry-point
handlers/GameActionHandler.py	The handler containing all logic concerned with *Game* actions, i.e. *Vote*, *Whisper*, *Attack* etc.
handlers/GameLobbyHandler.py	The handler containing all logic concerned with the game lobby list, that is – the ability to get the list of available *Games*, joining a *Game* etc.
handlers/HandlerBase.py	The base class for all handlers. Contains boilerplate code and helper references
utility/ConversionHelper.py	A utility class to convert specific models to DTOs which can be passed to the *Client*. Currently used to translate a *Game* to a *GameDto*

Table B.2: *Server* Project code listings

B.4 Shared

The *Shared* Project contains code files which are used in more than one Project, from the set of currently existing Projects – *Client*, *Server*, and *Werewolf*. The most prominent usage for the *Shared* Project is for the data transmission files and common data files that both the *Client* and *Server* use, in order to communicate with each other.

Shared source code listings	
Filename	**Description**

Packet.py	The base communication "unit" that the *Client* and *Server* use to communicate to each other. A *Packet* has data and a type
constants/CommunicationPresetConstants.py	Contains the definitions of all preset communications that can be sent from the *Client*
constants/GameConstants.py	The configuration for each *Game* – min/max *Player* count and the role distribution ratios
constants/LogConstants.py	Tags used for logging, used to classify messages which are stored in the logs
constants/NetConstants.py	The *Server* configuration for the host IP, port, and formats for logging. Contains constants used in the socket connection established between a *Client* and the *Server*
dtos/AddAgentGameDto.py	The DTO sent by the *Client* whenever they want to join a *Game*
dtos/ConnectDto.py	The DTO sent by the *Client* whenever they want to connect to the binded *Server*
dtos/CreateGameDto.py	The DTO sent by the *Client* whenever they want to create a *Game* on the *Server* they are connected to
dtos/GameActionDto.py	The DTO sent by the *Client* whenever they are doing a specific *Game* action within a *Game* they are in, e.g. *Whisper*, *Attack*, *Vote*
dtos/GameDto.py	The DTO which represents a minimal version of the current *Game* state for some *Player*. Not all *GameDtos* given by the *Server* are the same
dtos/GameListDto.py	The DTO which contains all of the *Games* which a *Client* can see in the game list screen
dtos/MessageDto.py	A DTO which represents a minimal version of the *Messages* within a *Game*, *Clients* do not get all *Messages*
dtos/MessageMetaDataDto.py	The DTO which contains various meta data for some *Message* with details to who the *Message* is targeted to and what the message type is. Used as a means to defer the need of *Natural Language Processing*
dtos/PlayerGameDto.py	The DTO which contains the *Player* identifier and the *Game* state they have requested. This is used by the *Server* to pass back the *Game* state to the *Client*
dtos/PlayerGameIdentifierDto.py	The DTO which a *Player* passes to a *Server*, in order to get the latest *Game* state

dtos/UpdatedEntityDto.py	A DTO which is used as a wrapper over some other DTO, providing a datetime, created by the *Server*, which provides the “birthdate” of that child DTO. This is used as a minor version control for *Messages* and *Game* states
enums/AgentTypeEnum.py	An enum class containing all *Agent* types
enums/FactionTypeEnum.py	An enum class containing all “factions” supported by the *Game*
enums/MessageTypeEnum.py	An enum class containing all types of *Messages* that can be created
enums/PacketTypeEnum.py	An enum class containing all types of *Packets*
enums/PlayerTypeEnum.py	An enum class containing all of the roles, supported by the *Game*
enums/TimeOfDayEnum.py	An enum class containing all of the times of day, which can be played through in a turn of the *Game*
enums/TurnPhaseTypeEnum.py	An enum class which contains all game turn phases – *Introduction*, *Discussion*, *Event*, *Accusation*, and *Voting*
enums/VoteResultTypeEnum.py	An enum class containing all possible results from some *Game* action
exceptions/GameException.py	A specific type of exception that is handled by both *Server* and *Client*
utility/DateTimeUtility.py	A utility class which deals with the conversion of date time’s from UTC to Local and Local to UTC
utility/Helpers.py	A generic helpers method container – contains references to third-party packages who have useful utility methods, i.e. *Faker’s* name generation, and *varname’s* **nameof** utility
utility/KillableThread.py	A custom thread which can *gracefully* be awaited/killed off on a secondary thread with minor exception handling. Used extensively in the *Client* to clean off any recursive polling threads
utility/LogUtility.py	Utility methods for logging *Messages*, *Actions* or some string. Used primarily in the *Werewolf* and *Server* Projects. The logging functionality creates logs on the host machine the utility methods are called on

Table B.3: *Shared* Project code listings

B.5 Werewolf

The author’s recommendation is that logging is disabled whenever using the “auto-play service” (*TrainableEnvironmentWrapper*) or training as it will decrease the average game time by 2.5-3 times. All metrics provided by the *Environment* will be stored in “Statistics.csv”, stored within the root *Werewolf* Project folder (see Section 4.4 for more information on metrics).

Werewolf source code listings	
Filename	**Description**
Environment.py	The entry-point for the training process, doubles as the configuration file for what the training *Game* will have in terms of *Agents* and how many games the *Environment* & auto-play service must go through
TrainableEnvironmentWrapper.py	A bridge class between the *Environment* & the *TrainablePlayer*
agents/AgentPlayer.py	The base *Agent* class which is used by all subsequent *Agent* definitions. Used as an abstract class to make sure the APIs RLereWolf expects are there
agents/DummyPlayer.py	The most basic built-in *Agent*, does stochastic, valid *Actions*
agents/RuleBasedPlayer.py	An intermediate built-in *Agent*, has a basic understanding of *honesty* and *trust*. Does mostly stochastic actions with minor reasoning, all actions are valid
agents/TrainablePlayer.py	The built-in *Reinforcement Learning Agent*. Has no understanding of the *Game* and can do invalid actions. Learns how to play Werewolf by playing multiple *Games* with an *Environment* around it
environment/Observation.py	All information about the *Game* state an *Agent* can "see"
environment/Statistics.py	The metrics recorded by the *Environment* for the *Game* in it. The metrics recorded are local and global.
environment/TrainingRewards.py	The definition of all rewards/penalties, given to *Agents*
environment/WerewolfEnvironment.py	The actual *Environment* which wraps over the *Game* which "listens" for results from the *Game* for some *Agent* action. Has the auto-play service integrated which just makes sure the *Game* within the *Environment* is never stuck

Table B.4: *Werewolf* Project code listings

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