Research Design 2

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Abstract*—This paper offers some additional guidelines for MCAST IICT 2nd year B.Sc. students on research paper writing. The abstract is the first paragraph that any researcher reads and thus you need to capture the essence of your research. Dedicate 1 sentence for the theme (subject matter), another for your project aim, one for the proposed solution, then for the general outcome of this project (positive/negative result/outcome), another for the technology used (Windows/Linux, Android/iOS, C#/Java, Unity/Unreal), finally for any technique used (Neural Networks, Pearl Noise, Market Basket Analysis, K-Means, HMM, Augmented Reality). Following is an example: *In this research we are tackling the automatic annotation of cast members and use of key props within movies. Movies tend to gather a huge fan gathering who dedicate a lot of time and resources for documenting the content, thus tools to automate processes such as the timeline when cast members appear, presents of props such as weapons and other forms of annotations are desired. In this research we propose the use of image processing techniques, namely Principal Component Analysis (PCA) and Convolutional Neural Networks (CNN) for the automatic annotation of actors' timeline and presence of weapons in the popular Tv series Game of Thrones (GoT). Our proposed solution managed to detect the targets in 85% of the cases and we identify situations where this is challenging and recommend future research directions.

***Index Terms*—MCAST, IICT, LaTeX, Project, Paper**

I. Chosen Research

A balanced difficulty plays a crucial part in shaping an enjoyable player experience in a video game. Many have tried to address this problem using popular emerging technologies. This research, therefore, aims to study the creation of in-game opponents via the use of Reinforcement Learning (RL) and Deep Reinforcement Learning (DRL) techniques for generating difficulty settings in a casual strategy game. It is hoped that this research will provide developers with a set of recommendations for the creation of effective difficulty settings that may be expanded upon in future works, such as with the use of Dynamic Difficulty Adjustment (DDA) to provide an improved player experience.

This research is positioned in the following manner on the Research Onion as described by [1].

- **Research Philosophy** - Pragmatism
- **Research Approach** - Deductive
- **Research Strategy** - Experimental Research
- **Choices** - Mixed-methods
- **Time Horizon** - Cross-sectional
- **Techniques and Procedures** - Prototype game extracting quantitative metrics and a qualitative focus group

This research was inspired by the pursuit of enjoyable player experience in video games. Artificial Intelligence (AI) has been used prominently in games to enhance player experience, sometimes in the role of an opponent to the player. Many technologies have been used in the development of these AI opponents, or "agents" as they may be referred to. In recent years, usage of RL and DRL has been popular for developing these agents, seeing usage in all types of games. Difficulty also tends to be a major factor in forming an enjoyable game experience. Players will want to select a difficulty setting that caters to their skills, or this would be done for them automatically through the use of DDA. Therefore, there has been thought to combine RL and DRL technologies to develop difficulty settings enjoyable for several types of players.

This research presents the following hypothesis: By using versions of an RL agent trained at varying lengths, effective difficulty settings can be created in a strategy game.

The intent of this sequential mixed-methods study is to test the effectiveness of an RL agent to create an opponent with multiple difficulty settings, In the first phase, a prototype game played by a sample of participants will be used to measure the relationship between an agent set to a particular difficulty setting and the difference between final player and opponent scores. This will be followed by a qualitative focus group with the participants to better understand how players perceived the difficulty between difficulty settings.

II. Review of Research Methodology

The use of Deep Reinforcement Learning (DRL) agents in games has seen a steady increase in recent years. An influential study showing the potential of DRL agents is [2]. In this study, a DRL agent was trained to play several classic Atari 2600 games. This was achieved by supplying the agent with a high-dimensional visual input at a steady rate as an observation [2]. After the completion of training, evaluation was carried out by having the agent play multiple rounds of every game, then comparing its average performance to agents using other learning methods as well as an expert human player [2].

[2] did not study, however, games in which a computer opponent directly competes with a player. Other studies have tackled this scenario. One notable study was conducted in 2017 on the use of a DRL agent in the fighting game *Super Smash Bros. Melee* [3]. Instead of raw visual input, this agent was trained on a simpler setup of directly observing in-game

variables concerning itself and its opponent, such as position, velocity, and action state [3]. This AI was trained using the "self-play" technique, in which it learnt by playing against past versions of itself. Evaluation on this agent was carried out having it play against professional players in two major tournaments [3].

In a competitive strategy setting, DRL has also seen success. One of the most notable examples of this in recent years is OpenAI Five in *Dota 2* [4]. This agent was also trained using self-play, similar to [3]. Training was significantly more complex however, as the agent needed to observe around 16,000 variables, and therefore took 180 days of training [4]. Also similar to [3], this agent was evaluated by examining its performance in a professional competitive setting, playing against the world champion team in an Esports game [4].

It may be observed that the previous studies all based their research on existing games. Despite this, DRL and RL technologies can be implemented by developers in their own games. For developers using the *Unity* game engine, this is readily available through the Unity ML-Agents package. This has been used successfully in the methodologies of studies using DRL in fighting games [5], as well as board games [6].

The studies mentioned thus far, however, do not study DRL agents developed for multiple difficulty settings, focusing instead on the development of a single optimal agent. Studying this requires different approaches in methodology. A 2019 study attempted this on the first-person shooter game, *Unreal Tournament 2004* [7]. Training saw the agent duel against a native bot set on the hardest difficulty, throughout which, versions of the agent were periodically saved. Outside of training, this agent was set to dynamically switch between versions, attempting to find the ideal difficulty for its opponent [7]. Evaluation was performed by pitting the agent against native bots of every difficulty, but was not tested on human players, which the study recommended for future work [7].

When testing difficulty on human players, it is best to use a sample size of multiple participants to have better chances of obtaining people with differing skills. A study testing DDA in the game *Dota 2*, for instance, made use of eleven participants [8]. After agreeing to participate in the study, the participants were given a quick tutorial on how to play the game. Participants later played two rounds of the game, one of which using a DDA system, the other with a static difficulty setting [8]. Following the gameplay, participants were interviewed to gather qualitative data on how they perceived the game's difficulty [8].

III. Reflection on the Chosen Methodology

The following research questions were formulated when undertaking this research:

- On what data can a reinforcement learning agent be trained?
- How can difficulty levels be created based on a reinforcement learning agent?
- How can the effectiveness of difficulty levels be evaluated?

Therefore, to address these research questions, the following objectives were to be accomplished:

- Find an optimal learning setup for the agent.
- Extract models during the agent's training process.
- Evaluate and select optimal models for difficulty settings.
- Create metric and log saving system in prototype to use for evaluation.

Multiple research philosophies had to be analysed to settle on the best one for this research. The major ones include:

- **Positivism**; viewing the world as objective and can be understood with direct analysis and measurement. If knowledge cannot be confirmed as true or false, it is dismissed as meaningless.
- **Interpretivism**; viewing the world as subjective, analysing people's opinions and ideas in a social and cultural context. The aim of interpretivist study is to understand the meanings of social phenomena from people's unique points-of-view.
- **Pragmatism**; focusing on the use of multiple methods, using the most appropriate method to address each research question. Pragmatism lends itself to complex, multi-faceted research issues.

This research, therefore, gears towards a pragmatic approach, as it aims to understand both the technical quantitative data of player and agent performance, as well the subjective qualitative opinions of how difficulty is perceived from player to player.

Elements were taken from the methodologies of several of the reviewed studies to form this research's methodology. For this research, the decision was made to develop an AI opponent using DRL, considering its success in competitive strategy, as seen in [4]. It was decided to make use of Unity ML-Agents, as seen in [6] and [5], to implement DRL in a custom game. To create difficulty levels with a DRL agent, a system similar to the one used by [7] was adopted to create an agent corresponding to different difficulty levels. For evaluating our results, a qualitative angle was pursued by gathering participant opinions on the difficulty following testing, similar to [8].

The first step in this research's methodology was the development of a prototype competitive strategy game, in which a player competes against an AI opponent to gain as many points as possible by gathering resources of different types. This game was developed using the Unity game engine, and used the Unity ML-Agents package to develop the opponent based on DRL. Different learning setups of the agent were trained and tested before settling on a final version, from which three models were extracted and used for each difficulty setting.

The testing setup consisted of nine participants who were asked to view an in-game tutorial and play each difficulty setting, during which the game automatically saved quantitative metrics regarding player and agent performance. Following the gaming session, the participants were gathered for a focus group, during which participants could discuss their experience playing the game and their thoughts on the game's difficulty.

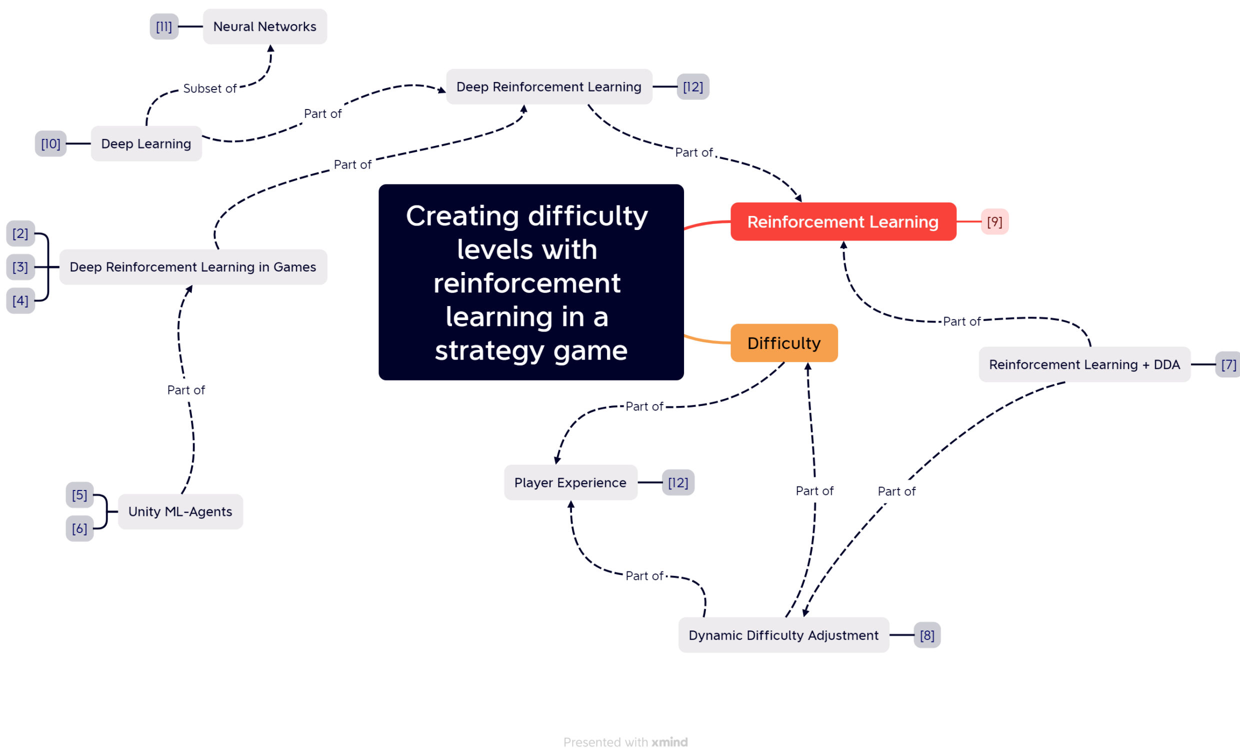

Fig. 1. Literature Map, citing additional sources: [9] [10] [11] [12] [13]

The discussion was recorded and transcribed to be used as qualitative data in the analysis.

There were some ethical considerations that needed addressing. Data from participants was to be collected during testing, including images taken by the researcher during gameplay, along with a recording containing their voice that was to be transcribed. This data was handled in the most ethical way possible, limiting its use exclusively to this research, as well as keeping all participants anonymous. A participant's data was also not to be used at all if the participant decided to drop from the study, which they could do at any time. It was crucial that the participants understood all of this before agreeing, and therefore they were given a letter of information detailing what would be expected of them and how their data would be used before signing a consent form. If something wasn't clear to them, they were allowed to ask questions at any time.

IV. Findings & Discussion of Results

This section is a delicate section and you are encouraged to be as honest and open as possible. The aim is not to show that you got a perfect solution to a long existing problem. Trying to state that in a few months you developed a perfect solution with 100% is not convincing and raises doubts. It is recommended that you document your findings in every step of your research pipeline, highlighting your observations and decisions taken. Present your results and very importantly compare with existing research which you documented in Section II.

The focus of the Project module is for you to delve into an area that exposes you to new technologies and offers you an opportunity to be critical of your work. So you are expected to document where your solution/research worked and where it did not. Reflect and document reasons why the solution/research did not perform as expected and propose ways of addressing this. From these observations you will produce new research questions in the next section. Consider the research in "Brand usage detection within audio streams", where certain key terms were searched within videos, the results of which are documented in Table I. You will notice that the terms "Peppa" and "Sushi" were the least recognised terms even by the best transcribers. Upon investigation we determined that "Peppa" was not recognised cause of voice morphing to create childish voices in the cartoon video, whilst "Sushi" was pronounced by a Japanese person speaking English. So the research student decided to focus his dissertation research on how to create a system that is able to recognise heavy accents to automate the configuration of a transcriber, in this case to cater for English spoken by a Japanese person, which accent is very different from an Indian accent, British accent or Italian accent, just to name a few.

TABLE I
RECALL RESULTS

#	Term	Google Cloud	Google Speech	Sphinx CMU
1	Peppa	27%	33%	0%
2	Peppa	33%	22%	0%
3	Apple	96%	92%	79%
4	Galaxy	100%	100%	100%
5	Galaxy	95%	95%	80%
6	Sushi	75%	35%	0%
	Average	71%	62%	43%

V. CONCLUSION

So the conclusion is most probably the second section that a reader would use to consider reading in full your research. Thus it is important to highlight the essence of your research. The recommended approach is to answer your research methodology. Start by answering your research questions, then stating to what degree did this research achieve its aim and objectives, highlighting potential causes for not being able to do so at a desired level, such as time, or other circumstances. Consider the following: *A student was due to research the use of MCAST computers during out-of-office hours to offer a private cloud computing service for research, similar to Google Cloud but free for MCAST students. Due to the lock-down by COVID-19 pandemic we could not continue on the original planned research objective and had to adapt.*

The final and most important part of the conclusion are your recommendations for future research, not necessarily for yourself (referring to what you plan to do in your dissertation or beyond), but also to other future researchers who might consider doing similar work to yours. The recommendations you provide here will set such prospective researchers on a better track/direction thanks to your experience.

APPENDIX A
SUPPORTING MATERIAL

You can add screen shots and statistics. Stick to essential information.

ACKNOWLEDGEMENT

You can dedicate this section for special assistance that you were given by a 3rd party. Not your mentor, relatives or questionnaire participants.

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