

University of Nottingham

Computer Science with Artificial Intelligence MSci

G54IRP/COMP4027 — Individual Research Project

AI for General Video Game Playing

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Contents

1	Introduction	1
1.1	Introduction	1
1.2	Planning VS learning	1
1.3	Motivation	1
1.4	Aims and Objectives	1
2	Related Work	1
2.1	AI and Game Playing	1
2.1.1	Early Artificial Intelligence	1
2.1.2	Chess	2
2.1.3	AlphaGo and Successors	2
2.1.4	Conclusions	2
2.2	GVGAI and VGD L	2
2.3	OPEN AI GYM and GVGAI GYM	3
2.4	Subsection to end all subsections	3
3	Appendix	4
3.1	Meeting Minutes	4
3.2	Work Plan	5
3.3	References	5

1 Introduction

1.1 Introduction

- Popularity of Video Games
- Variety of Video games being played
- Video Games as a testing ground for AI

1.2 Planning VS learning

- As the title says, just to get some definitions out of the way

1.3 Motivation

- Individual desire to get better at deep reinforcement learning
- Learning more Methods
- Applying Methods
- Learning to use more robust and real world frameworks for DRL
-
- Seeing the state of the art in DRL and AI game playing

1.4 Aims and Objectives

- Look at the project plan aims and objectives

2 Related Work

2.1 AI and Game Playing

- AI approaches have specialised heuristics or only been developed for a single game
-
- Go — previous interim report / PP
- Chess — previous interim report / PP
- ALE — Learning works for games
- OpenAIFive — Learning works on big games too, and MP
- GET MORE THINGS FROM PP
- Conclusion for this section
-
- Dartmouth Workshop

2.1.1 Early Artificial Intelligence

The history of AI game playing begins near the start of artificial intelligence as a field, in the 1950s. Strachey created a draughts player for one of the first general computing machines (Manchester Ferranti Mark I) which by 1952 could “play a complete game of draughts at a reasonable speed”[2]. Prinz wrote a simplified chess player for the Manchester Machine as well which could solve the mate-in-two problem. This meant that if there was a checkmate solution in 2 turns it could successfully find it[2]. Prinz simply used an exhaustive search technique to find the correct moves, and even though computing power was limited at the time it was clear that this wouldn’t scale to full games. This led to Turing starting to program ‘Turbochamp’ a chess program that would be able to play a full game of chess using heuristics[2]

These simple games were made before the term artificial intelligence was being used even in an academic setting showing how natural AI and game playing go together.

2.1.2 Chess

Chess was an early and significant example in the history of AI game playing. In 1997 IBM managed to beat the reigning world champion, Garry Kasparov, using their custom developed machine, Deep Blue[1]. This was significant as, at the time, creating a winning chess AI was seen to be the next big milestone at the time in AI.

To achieve this Deep Blue used a combination of techniques with the main underlying AI technique being a search method. As Chess is a deterministic game and both players have complete information of the board state it was possible for Deep Blue to generate future board states. With this forward model its possible to generate a search tree of possible moves and their resulting game states. The tree was efficiently generated by a combination of a massively parallel architecture over 30 nodes and the fact that each node has special purpose chess chips, generating around 6–8 moves ahead on average. Alpha-beta pruning was used in a MinMax algorithm to help efficiently search the tree while using the custom hardware to evaluate each node quickly.

IBM had proven that search methods could achieve strong results against human opponents but this was mostly due to brute force computing power and a heavy reliance on expert knowledge. The expert knowledge came from other grandmasters and was used in the form of an opening/closing move database and the special purpose hardware to evaluate board states. While higher computing power will always benefit AI techniques, later techniques have been developed to reduce the need of expert knowledge and to make more efficient use of hardware available.

2.1.3 AlphaGo and Successors

- Concept
- AlphaGo Fan, Lee and Master
- AlphaGo Zero
- AlphaZero (Chess and Shogi? too)

Although Deep Blue had proven that AI systems could beat an expert in games, the methods used wouldn't scale to more complex games such as Go, new methods would be needed to tackle more complex games and to further the field of AI. Go was set as the next milestone in AI game playing by the community as it proved vastly more complex than chess while still having few rules and a simple goal, like chess. To compare the difficulty between the 2 games, chess uses a 8×8 board while Go uses a 19×19 board. What is a better indicator of the AI performance is the branching factor of the games for each move, as this more accurately shows how large the search tree grows for each possible move. On average, Chess has a branching factor of 35 and Go has a branching factor of 250[3]. In 2016 DeepMind reached this milestone with AlphaGo claiming its victory against a 9th dan professional Go player, Lee Sedol, in March 2016[4].

This achievement was accomplished with a combination of Monte Carlo Tree Search (MCTS) and 2 Deep Neural Networks trained with reinforcement learning, one was a value network to assess the board predicting the winner and the other a policy network to predict which move would be played next by an expert. By augmenting MCTS with the policy network, the problem of the large branching factor was greatly reduced, the value network made the addition that it was quicker and more accurate at determining who would win than conventional methods and didn't require an ending game state to be reached. Initially these networks were trained on a large number of human played games as a labeled dataset, after this 'boot strapping' phase they were trained through instance of self play.

2.1.4 Conclusions

- Deep Blue proves that games can effectively use forward planning to beat human experts, early techniques require a lot of power so intelligent methods are needed to speed up results/improve search depth
- AlphaGo Fan, Lee and Master show planning is still effective but by using more advanced techniques we can generate search trees better (ANNs). Also shows how learning can benefit AI techniques and boost the powerful planning techniques.
- AlphaGo Zero shows how learning doesn't need to require expert knowledge and can just learn from lots of experience in the environment
- AlphaZero shows how more generic systems can still perform well allowing for techniques that could be transplanted into many environments and still perform well.

2.2 GVGAI and VGD L

- TODO Make some notes up here

2.3 OPEN AI GYM and GVGAI GYM

- What is OPEN AI GYM
- Why is OPEN AI GYM helpful for RL
- GVGAI GYM
- Initial results from GVG AI GYM paper
- Maybe some more here

[5]

2.4 Subsection to end all subsections

- Maybe something about the open AI baselines
- Depends what technique I would be using but I should look into that
- Where does reinforcement learning come into this bad buoy

3 Appendix

3.1 Meeting Minutes

3.2 Work Plan

3.3 References

References

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