School of Informatics

Informatics Research Review
How the recent advance in Machine Learning can help to design and implement digital Game AI

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Abstract

The digital game market is pretty prosperous on 21 century, but the AI component usually is seen as a weak point on digital games. While with the great progress of machine learning in the last decade, someone believes it is also a panacea which can reshape this part of work in game industry through make a unified digital game AI framework by machine learning technology. In this article, we check the status quo of research on game AI area and evaluate whether some state of art technology could be practically used in actual game development, we focus on investigating and exploring the possibility of using advanced machine learning technology to contribute the AI design of the digital game industry. We found that the state of art machine learning technology approximately reaches the point to have the ability to create any kinds and level of AI agents in digital games, but some unsolved issues hinder the road to make them become a widely used practical product.

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Supervisor: [redacted]

1 Introduction

The digital game is a thriving market, which not only takes entertainment to people but also is used as an efficient education tool.[1] And over the whole history of digital games, computer-controlled agent, commonly called game AI, always play as a significant component of the game[2]. But traditional ways to design and implement game AI were not efficient and often inflexible in complex game system[3].

While as the machine learning technology made lots of progress in different areas in this century. Someone expect it may take a great change in digital AI or even take a general video game AI[4]. So in this review, I hope to investigate the state of art machine learning technology which related to digital game AI and explore how these technologies could contribute on digital game industry, and identifying possible further research direction.

In this article, we firstly introduce the background information of developing digital game AI and briefly talk about the progress of machine learning could take to digital game industry in Section 2. In Section 3, we review the legacy research of search-based game AI and state of art model-free and model-based deep learning game AI research. Section 4 lists two large-scale practical research in real complex game environment. Last Section gives a review of the whole literature review. Besides, we use the word of game AI to represent any types of computer-controlled agents in digital games.

2 Background

2.1 The difficult in traditional digital game AI design

As the quality and scope of commercial digital games increases very quickly and so too do the scope and ambitions of the AI systems within them. But at the same time, the development of game AI is not a trivial work. Instead, it is often a programmer intensive task and needs lots of effort. In modern digital game development, the AI component would normally cost a great part of the overall budget to development and time for debugging.

While although so much effort usually is take on those components, it still usually be seen that some good game concept designs be dragged by bad AI in real market, or some stillborn project which can not be done because of their complex AI system.

At that case, some researcher had tried to create some kind of commercialization general AI framework or middleware to support these developments, like the product of Kynapse and Xaitment[5]. An organization called Artificial Intelligence Interface Standards Committee(AIISC) also did some work to develop an interface standard for AI middleware for the whole digital game industry.[6]

But unluckily, these works did not make too much progress at that time, the two products listed above seems both failed, and the AIISC also dismissed without making the standard they wanted.

One of the major issues which hindered it I consider is the inner complexity of different games' requirement. Although different digital games often share certain degrees of similarities in their AI system. But it usually hard to find ways to efficiently exploit the similarities.

In general, different game developers often have different requirements on their AI design, while some may share certain similarities with other developers, and some may not. And in some rare cases (actually it is not so rare), developers may found they actually need some very special AI designs which only be used by themselves. And that is hard to be all included in a Standard framework.[7]

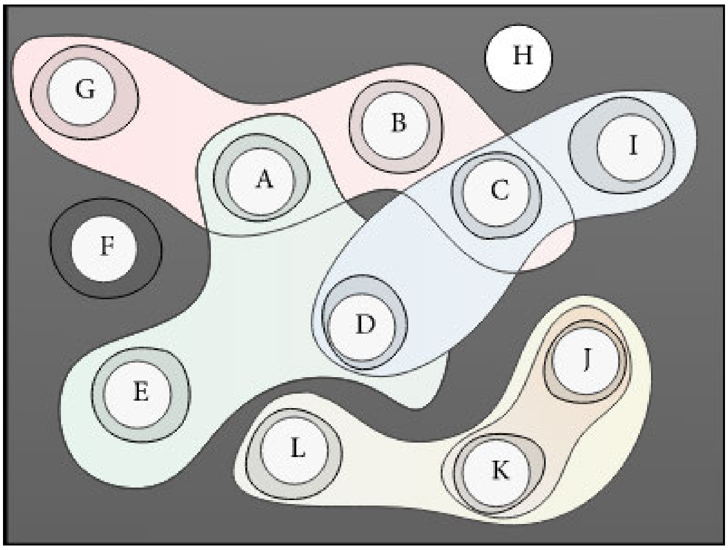

Figure 1: The messed conceptual problems (circles) and solutions (irregular forms) in digital game AI (original image from [7])

For example, like the fig.1 has shown, one game may meet problems AED but the other meet problems DCI. Meanwhile, another game meets problem G which is never met by others. The reason for that situation is that the digital game is often a metaphor of real world, which result that the problem they met are rough as the same hard as in the real world would meet, if not even harder.

And those issues and complexity together construct difficulties to abstractify digital game AI as a simple AI behaviour framework.

2.2 Great progress in machine learning

And as well-known that, in the last decade, with both the great progress in the theory of machine learning and the development of GPU takes to the hundreds of times speed up in training systems[8], which lead to a so-called "big bang" in machine learning research area, and make many potential usages of machine learning system come true.

This "big bang" also be considered could take some basic changes on the digital game industry(especially on game AI), and bring some hope to the prospective of a general video game AI[4]. If that become true, digital game programmers get freely create different kinds of AI character or system, rather than rely on complex hard code and predefined static game script. That can not only hugely reduce the digital game development cost but may also promote a certain number of new thoughts and designs on the digital game market.

Luckily, this problem is interesting and challenging enough to drawn extensive interest from the machine learning community.

3 Related research

3.1 Legacy search-based game AI

As far as the 1950s, the purpose of build powerful game-playing system attracts someone's interest in the domain of artificial intelligence. But at that period, their major interests focus on traditional board and card games, such as Chess or Poker. And mostly the system is traditional search-based, with detailed design and according to expert knowledge and game theory. [9]

A milestone of that period search-based game AI system happened in 1997. At that year, IBM showed their Deep Blue chess system and successfully defeat Garry Kasparov, World Chess Champion at that time[10], and another system called Logistello defeat the Othello Champion of that year[11].

The programs at those times are constructed by strong human players and programmers, they detailed handcraft features and tun weights of models try to evaluate different target positions, combined with high-performance search algorithms with a large number of clever heuristics and domain-specific adaptations to expands the search tree.[12]

Those explore at that time period give us a great fundamental for nowadays further study. And many concepts of that times' research has been accepted as the basic rule and widely used in the modern digital game industry like multi smart agent or behaviour search tree[9][13].

But later, researchers gradually found that the search-based methods have their inner limitations, the requirement of searching every possible possibility become extremely impossible in some tasks.

For example, the search space of traditional go game is even much higher than the most advanced supercomputer's computing ability, deeply traversal the whole possible behaviour tree becomes fully unrealistic in that case, which makes the search-based methods commonly work very bad on it, and make the go game considers as a grand challenge for artificial intelligence area. Which is also the case digital game AI would usually meet. Seemingly, the game AI research fell into a short trough.[14]

3.2 State of art deep learning research in game AI

3.2.1 Model-free deep reinforcement learning method

Even before recent great progress in the deep learning area, reinforcement learning is a popular method in game AI research. Unfortunately, researchers find this method does not work very well in high-dimensional state space as the efficient process and represent high-dimensional inputs still an unsolved issue.[15]

But more recently, the rise of multi-layer neural networks shows a better road to treat high-dimensional data from complex tasks. Which later takes to the idea of deep reinforcement learning.

This method firstly be introduced on 2013[16], and improved on 2015[17] by DeepMind. It designs a novel deep Q-network (DQN), which combines the reinforcement learning method with deep neural network. Be specified, they build a convolution neural network (CNN) which take the responsibility to take high-dimensional input data and estimate the optimal action-value function, and after the training is done, the DQN will be able to make the next decision among all valid actions. Then, they take their system on an Atari 2600 emulator platform to evaluate the performance and get a pretty good result.

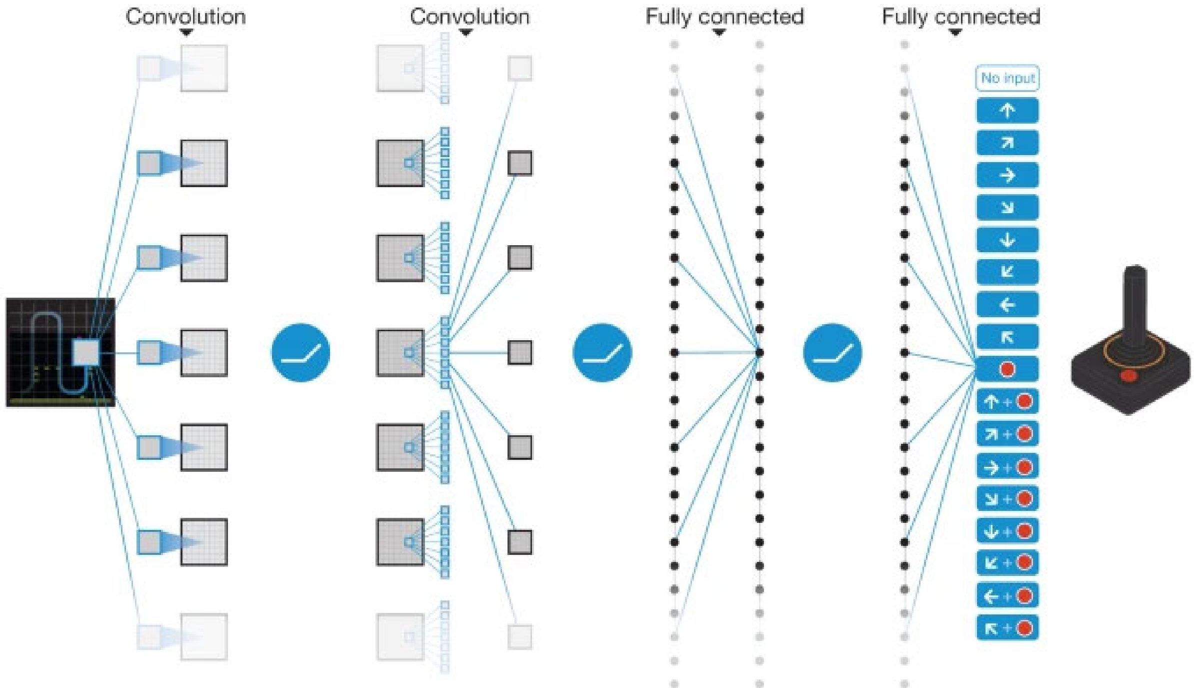

Figure 2: Schematic illustration of the convolutional neural network(original image from [17])

While as a model-free learning method, this agent could directly learning through interacting with the environment, but without constructing an environment model, that seems imply a huge generalization ability of this model, as there are nearly no special setup or magic parameter in this system. A simple consequent is that they can use this model for training and playing all games in Atari 2600 emulator with no modify.

But although with some benefits with the model-free learning method, an unavoidable issue is model-free learning method seems still can not make good logical reasoning and long-term strategy.

Actually most game in Atari 2600 emulator only with extremely simple play logic. And the performance of this DQN network also dramatically reduced in part of relative complex games in this emulator.

In fact, the newest research from DeepMind come back to model-based reinforcement learning again, they even commented that "Model-free algorithms are in turn far from the state of the art in domains that require precise and sophisticated look ahead, such as chess and Go." Instead, they construct an abstract Markov decision process(MDP) model and focused on predicting the value end to end. function.[18]

3.2.2 Model-based deep reinforcement learning method

Generally, although loss some generality, the state of art model-free learning algorithms normally could get much more learning potential than model-free algorithms especially in complex environments. [19]

Surprisingly (or saying unsurprisingly), the model-based deep reinforcement learning are also lead by Deepmind. The well-known AlphaGo[20] and subsequent AlphaGo Zero[21], are the two landmark research on the game AI area from DeepMind, they first time push the Go game AI to the human top level, which usually be considered still need few more decades to achieve.

The AlphaGo system combines advanced search tree with deep neural networks, and two neural networks have been created to support the system. The first one is the "policy network", which used for sampling actions and selects the next move for AI, another "value network", responsible for evaluating board positions. In each step, AlphaGo combines the policy and value networks in an MCTS algorithm and through look-ahead search to select further actions. While the "policy network" is pre-trained through supervised learning but later the two networks could Simultaneously be improved through continuous self-play reinforcement learning with itself.

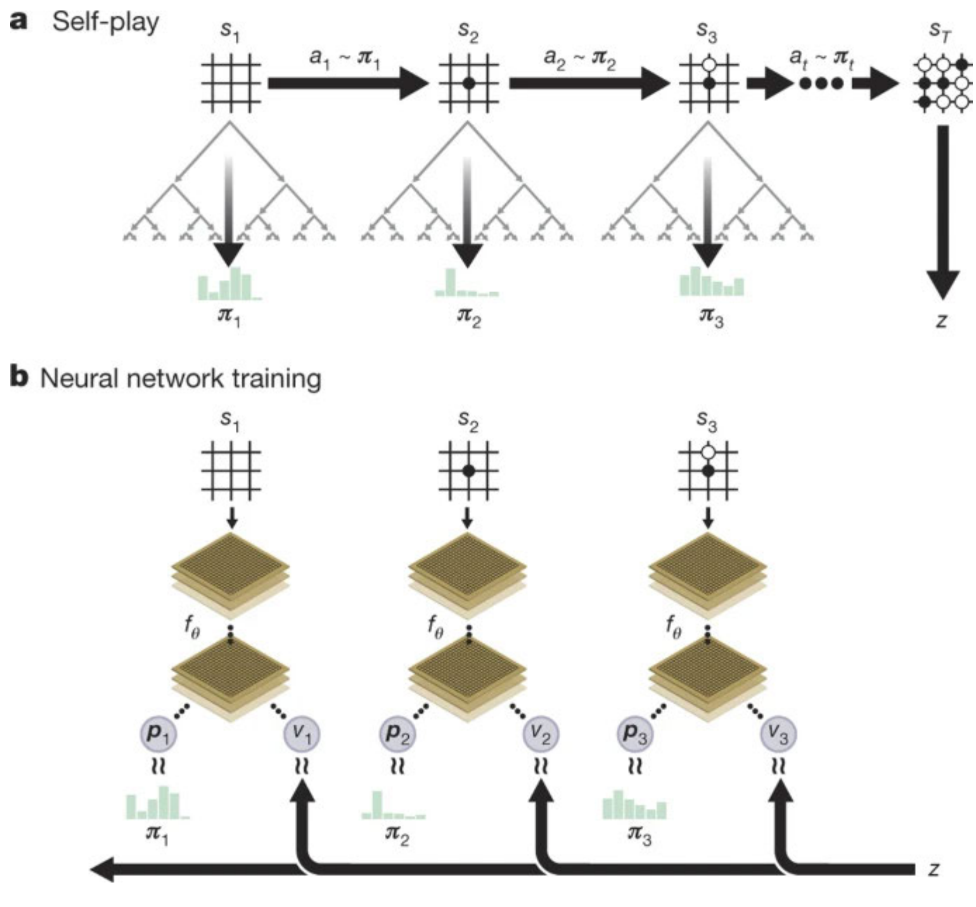

Figure 3: Self-play reinforcement learning in AlphaGo Zero(original image from [21])

The major contribution of this research is it used the way of neural networks to hugely reduce the search tree's depth and breadth, cut the unnecessary branches to an acceptable computing space.

And the subsequent improved AlphaGo zero, further merge the two policy and value network. It also drops the supervise learning process, which corresponds to the title "learning without human knowledge" which is another excellent display of the plasticity of the neural network.

More recently, the newest research from Deepmind called MuZero has been published in nature[18]. This research selective combined the few former studies. When MuZero receives some observation, it transforms the input to a hidden state, then the hidden state could update iteratively according to the previous state, input date and hypothetical action, then estimating policy, value function and reward. In other words, this method constructs an abstract MDP model, but there is no limitation for this hidden model to must match the state model of the real environment, instead, the hidden states have freedom to represent any thing that can help to estimate right output.

As a result, the special design gives the system both the benefits from model-free and model-based learning method. And so MuZero could play the go, chess and Atari game by a single learning model, and even gets better performance in Atari than former model-free method. I personally believe it symbolizes the "most" advanced research in game AI area.

4 Practical research of AI in digital game and critical analysis

As for practical, only a few research organizations try to apply state-of-art deep learning method and making some progress. One of them is OpenAI, another is still DeepMind.

4.1 OpenAI five

On April 13th, 2019, OpenAI announce its system called OpenAI Five became the first AI system which could match the world champions on a real e-sports game. It takes the popular Dota 2 video game as the playground, which is a 5v5 game, and each human player controls a unit in the normal human game.

OpenAI Five[22] is still a model-based learning system, it defines a policy function(π) which derived from the history observations of the different action distribution, which then parameterize as a recurrent neural network with about 159 million parameters(θ). And that neural network consists primarily of a single-layer 4096-unit LSTM. When the policy has been given, the neural network could participate in games by repeatedly evaluate the current observation and sampling actions from the output distribution on each timestep.

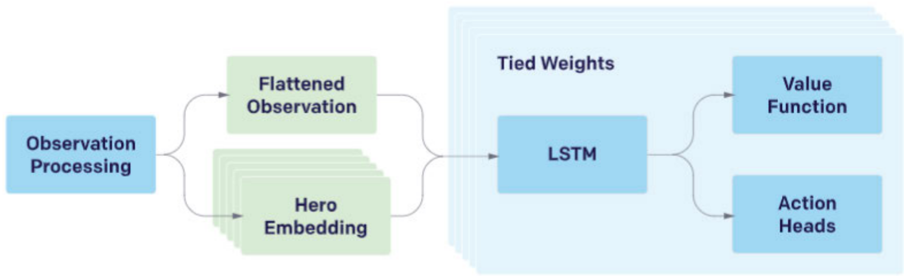

Figure 4: Simplified OpenAI Five Model Architecture(original image from [22])

Then, they training their system on their custom distributed training platform called Rapid, and use transfer learning to continual transfer their training model with different training hyper-parameter, model architecture and even different game version.

4.2 AlphaStar

A bit later than OpenAI five, Deepmind presented their Starcraft II AI agent AlphaStar[23], where that is a digital game with combinatorial action space, a planning horizon that extends over thousands of real-time decisions, and imperfect information.

AlphaStar generates its behaviour through a deep neural network which receives the game interface as input and outputs the operation to game. In detail, that network architecture applies a transformer torso to the units (just like relational deep reinforcement learning), combined with the concept of deep LSTM core, auto-regressive policy, and centralised value baseline.

The training process of AlphaStar is also pretty novel. Firstly they initially use supervised learning to train their neural network from real human games, then they use different seeds to create a league to process the multi-agent reinforcement learning process. With different agents playing games against others in this league, they also add new competitors into the league or kick old members dynamically, each agent in the league finally learns the games through the competition with others. (just like how human StarCraft Professional League would do).

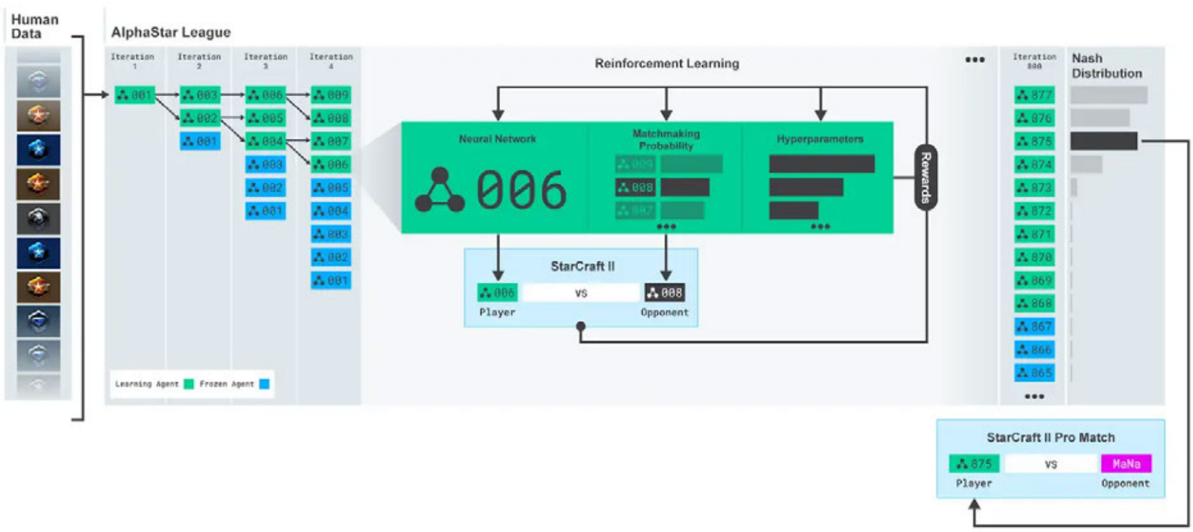

Figure 5: The AlphaStar League(original image from [7])

Through this multi-agent reinforcement learning process, they successfully make the AlphaStar get the ability to match the top-level human player.

4.3 Critical Analysis

But although the two research shows the great potential of deep learning AI in digital games if enough resource has been put, I consider we still have some distance to a general digital game AI framework.

In my view, the two projects are still kind of technology ability show-off. They do not want and without pushing power to further make it as a mature product. Be specified, the two projects both take some limitation on the game, which simplifies the game into a subset that can reduce the difficulty.

Beyond that, there are still some unsolved issues on the road to take these research into real game product. One of them is the huge demand for calculating power. Both the two project spends months of training on many high-end GPUs. OpenAI team even claim that the fundamental improvement they need for the OpenAI Five is the "scale". But that scale of calculating resource need is fully unacceptable on consumer or education market.

Another main issue is the two practicals still far from the dream of a generalization game AI. It is easy to see that these two projects are made by continuous observation and carefully adjusted training parameters, model structure and architecture.

And a notable point is, although the newest project of DeepMind's MuZero successfully uses a uniform model to solve go, chess and Atari problem, they did not try to include Starcraft game in it, and did not explain why. That probably imply the potential difficulty to generalize deep learning game model on complex tasks.

5 Summary & Conclusion

In this article, we firstly brief introduce the developing difficulty of digital game AI, and the great benefits if the advance in machine/deep learning could make contributions to the digital game industry. Then, we introduce history research of game AI, include legacy search-based game AI, where the main concepts of it have been accepted by game developers, and the state of art model-free deep Q-network, which be able to combine reinforcement learning method with deep neural network. Then the model-based deep reinforcement learning, which also leads by DeepMind, successfully reduce the search tree's depth and breadth, and make the greatest progress in this large scale game area.

At here, we found the model-based learning model shows some superiority in those sophisticated tasks like digital games and become the choice in few most successful practical research, OpenAI five and AlphaStar Also, we review the main design concept and the results of the two research, the OpenAI five use a 4096-unit single layer LSTM network, while AlphaStar uses an LSTM network with self-attention mechanism and scatter and through a novel league multi-agent learning algorithm to reinforce its system.

Finally, we analysed the two large-scale practical research from OpenAI and DeepMind on Dota 2 and starcraft II game AI, and point out that the huge requirement of computing resources in complex models and the need of detailed adjust and design of network structure on different complex tasks (the issue of generalization ability) still constraint the real wide usage of deep learning digital game AI, which is probably worthy for further research.

References

[1] JaeHwan Byun and Eunmi Joung. Digital game-based learning for k–12 mathematics education: A meta-analysis. *School Science and Mathematics*, 118(3-4):113–126, 2018.

[2] Steven Rabin. *Game AI pro: collected wisdom of game AI professionals*. CRC Press, 2013.

[3] Paradox Interactive. Creating complex ai behavior in 'stellaris' through data driven design. In *2017 Game Developers Conference*, 2017.

[4] Diego Perez-Liebana, Spyridon Samothrakis, Julian Togelius, Tom Schaul, and Simon Lucas. General video game ai: Competition, challenges and opportunities. In *Proceedings of the AAAI Conference on Artificial Intelligence*, volume 30, 2016.

[5] Audrey Christophory. Ai and the rise of gaming middleware: an interview with pierre pontevia of kynogon. *XRDS: Crossroads, The ACM Magazine for Students*, 13(2):7–7, 2006.

[6] Billy Yue and Penny de Byl. The state of the art in game ai standardisation. In *Proceedings of the 2006 International Conference on Game Research and Development*, pages 41–46. Murdoch University, 2006.

[7] Firas Safadi, Raphael Fonteneau, and Damien Ernst. Artificial intelligence in video games: Towards a unified framework. *International Journal of Computer Games Technology*, 2015, 2015.

[8] From not working to neural networking. In *The Economist*, 2016.

[9] Leo Galway, Darryl Charles, and Michaela Black. Machine learning in digital games: a survey. *Artificial Intelligence Review*, 29(2):123–161, 2008.

[10] Feng-Hsiung Hsu. *Behind Deep Blue: Building the computer that defeated the world chess champion*. Princeton University Press, 2002.

[11] Michael Buro. The othello match of the year: Takeshi murakami vs. logistello. *ICGA Journal*, 20(3):189–193, 1997.

[12] David Silver, Thomas Hubert, Julian Schrittwieser, Ioannis Antonoglou, Matthew Lai, Arthur Guez, Marc Lanctot, Laurent Sifre, Dharshan Kumaran, Thore Graepel, et al. A general reinforcement learning algorithm that masters chess, shogi, and go through self-play. *Science*, 362(6419):1140–1144, 2018.

[13] Ray Barrera, Aung Sithu Kyaw, Clifford Peters, and Thet Naing Swe. *Unity AI Game Programming*. Packt Publishing Ltd, 2015.

[14] Sylvain Gelly, Levente Kocsis, Marc Schoenauer, Michele Sebag, David Silver, Csaba Szepesvári, and Olivier Teytaud. The grand challenge of computer go: Monte carlo tree search and extensions. *Communications of the ACM*, 55(3):106–113, 2012.

[15] Aske Plaat, Walter Kosters, and Mike Preuss. Model-based deep reinforcement learning for high-dimensional problems, a survey. *arXiv preprint arXiv:2008.05598*, 2020.

[16] Volodymyr Mnih, Koray Kavukcuoglu, David Silver, Alex Graves, Ioannis Antonoglou, Daan Wierstra, and Martin Riedmiller. Playing atari with deep reinforcement learning. *arXiv preprint arXiv:1312.5602*, 2013.

[17] Volodymyr Mnih, Koray Kavukcuoglu, David Silver, Andrei A Rusu, Joel Veness, Marc G Bellemare, Alex Graves, Martin Riedmiller, Andreas K Fidjeland, Georg Ostrovski, et al. Human-level control through deep reinforcement learning. *nature*, 518(7540):529–533, 2015.

[18] Julian Schrittwieser, Ioannis Antonoglou, Thomas Hubert, Karen Simonyan, Laurent Sifre, Simon Schmitt, Arthur Guez, Edward Lockhart, Demis Hassabis, Thore Graepel, et al. Mastering atari, go, chess and shogi by planning with a learned model. *Nature*, 588(7839):604–609, 2020.

[19] Matteo Hessel, Joseph Modayil, Hado Van Hasselt, Tom Schaul, Georg Ostrovski, Will Dabney, Dan Horgan, Bilal Piot, Mohammad Azar, and David Silver. Rainbow: Combining improvements in deep reinforcement learning. In *Proceedings of the AAAI Conference on Artificial Intelligence*, volume 32, 2018.

[20] David Silver, Aja Huang, Chris J Maddison, Arthur Guez, Laurent Sifre, George Van Den Driessche, Julian Schrittwieser, Ioannis Antonoglou, Veda Panneershelvam, Marc Lanctot, et al. Mastering the game of go with deep neural networks and tree search. *nature*, 529(7587):484–489, 2016.

[21] David Silver, Julian Schrittwieser, Karen Simonyan, Ioannis Antonoglou, Aja Huang, Arthur Guez, Thomas Hubert, Lucas Baker, Matthew Lai, Adrian Bolton, et al. Mastering the game of go without human knowledge. *nature*, 550(7676):354–359, 2017.

[22] OpenAI, Christopher Berner, Greg Brockman, Brooke Chan, Vicki Cheung, Przemysław Debiak, Christy Dennison, David Farhi, Quirin Fischer, Shariq Hashme, Chris Hesse, Rafal Józefowicz, Scott Gray, Catherine Olsson, Jakub Pachocki, Michael Petrov, Henrique Pondé de Oliveira Pinto, Jonathan Raiman, Tim Salimans, Jeremy Schlatter, Jonas Schneider, Szymon Sidor, Ilya Sutskever, Jie Tang, Filip Wolski, and Susan Zhang. Dota 2 with large scale deep reinforcement learning. 2019.

[23] Oriol Vinyals, Igor Babuschkin, Wojciech M Czarnecki, Michaël Mathieu, Andrew Dudzik, Junyoung Chung, David H Choi, Richard Powell, Timo Ewalds, Petko Georgiev, et al. Grandmaster level in starcraft ii using multi-agent reinforcement learning. *Nature*, 575(7782):350–354, 2019.