Assignment 1

Research Methods in CSE

Assignment 1 of Research Method Course
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1. Introduction

Recent developments in the field of artificial intelligence and machine learning have led to a paradigm shift in the way that machines perceive and adjust to their surroundings. With the use of cutting-edge algorithms and neural network architectures, artificial intelligence (AI) systems are growing more self-sufficient and able to improve over time without direct human intervention.

Driven by deep learning techniques, these self-learning systems demonstrate impressive capabilities in a variety of fields, including robotics, computer vision, and natural language processing. They can also identify patterns, anticipate problems, and even come up with new solutions. AI agents can also make decisions based on trial and error thanks to the integration of reinforcement learning algorithms, which increases their adaptability and problem-solving skills. In machine learning, Monte Carlo Tree Search (MCTS) has become a potent tool for making decisions in challenging situations. MCTS effectively traverses broad search spaces to find the best course of action by strategically exploring the decision tree and simulating a multitude of potential outcomes.

Applications of this technique can be found in a variety of fields, such as board games like AlphaGo, where it transformed the competition by outperforming human champions. The versatility and potential of MCTS to advance machine learning capabilities are demonstrated by its ability to balance exploration and exploitation, which makes it especially effective in scenarios with incomplete or uncertain information.

2. Assignment Requirements

The requirements are fairly straightforward: we want to learn more about MCTS's functionality and use cases, and we intend to write a master's thesis on the creation of an AI player for our favorite board game.

We need to find three excellent quality research articles on this subject in order to understand how MCTS functions and how it can be applied to board games so that we can acquire broader knowledge and add the knowledge to the thesis paper.

Also, we must include a bibliographical reference for each article that was found for this assignment, along with the DOI or website where the article was published. We must write a brief paragraph explaining why we selected those articles for consideration based on two factors: their high quality and relevance to the research project. Finding at least one article with a research survey or systematic literature review is another prerequisite.

3. Searching Process

3.1. Keywords

At first, Reading the requirements again and again, we fixed few keywords to search which are in below –

- Monte Carlo Tree Search for games
- Monte Carlo tree search methods
- Monte Carlo Tree Search
- Reinforcement learning
- Neural Network in AI Player Game

Reading the main article also helped us to choose these keywords. Bacause it talked about AlphaGo games and its upgraded versions using Reinforcement learning in AI.

3.2. Websites

There were few sites introduced during the lecture on Finding research paper in the class. So, after reviewing the class lecture we searched those keywords in these websites.

- https://scholar.google.fi/
- https://dl.acm.org/
- https://dblp.org/
- https://ieeexplore.ieee.org/
- https://www.sciencedirect.com/
- https://link.springer.com/

4. Three Top Quality Articles

4.1. Playing Atari with Deep Reinforcement Learning

4.1.1. Summary

The paper ("Playing Atari with deep reinforcement learning") demonstrates the amazing combination of reinforcement learning and deep neural networks. The model acquires knowledge straight from raw pixel inputs, eliminating the need for manual feature engineering, by utilizing a deep Q-network (DQN) and end-to-end learning. By implementing experience replay, temporal correlations are lessened, resulting in more effective learning. When compared to alternative techniques, the DQN produces cutting-edge results on Atari 2600 games, proving its efficacy and scalability. Moreover, the trained DQN's capacity to apply what it has learned to new games underscores the possibility of transfer learning in domains of reinforcement learning.

4.1.2. Meta Information

Abstract:

We present the first deep learning model to successfully learn control policies directly from high-dimensional sensory input using reinforcement learning. The model is a convolutional neural network, trained with a variant of Q-learning, whose input is raw pixels and whose output is a value function estimating future rewards. We apply our method to seven Atari 2600 games from the Arcade Learning Environment, with no adjustment of the architecture or learning algorithm. We find that it outperforms all previous approaches on six of the games and surpasses a human expert on three of them.

Table 1

Title	Information
Published	19 December 2013
Total Citations	14289
Total Versions	40
Published At	https://arxiv.org/
Authors	Volodymyr Mnih, Koray Kavukcuoglu, David Silver, Alex Graves, Ioannis Antonoglou, Daan Wierstra, Martin Riedmiller
DOI	https://doi.org/10.48550/arXiv.1312.5602

Meta information about the article ” Playing Atari with Deep Reinforcement Learning”

4.1.3. *Reason to choose*

For a number of reasons, this article is a great resource for learning reinforcement learning in games. First of all, it offers a thorough explanation of the deep Q-network (DQN) algorithm, a key idea in the area. Furthermore, it provides useful advice on how to apply reinforcement learning in a gaming context, making it understandable and useful even for novices.

Additionally, learners can comprehend how reinforcement learning techniques can be tailored to various scenarios by using the diverse set of challenges provided by Atari 2600 games as a testbed. Ultimately, the paper is an invaluable tool for learning about the theory and real-world applications of reinforcement learning in gaming environments because of its concise explanations and insightful experimental findings.

As this article has almost 14289 citations and it is there for a quite a long time, it reflects that the article is an excellent literature to read. Also, it is related with our thesis topic. The Go game used the reinforcement learning with the help of MCTS methods that is why it is important to learn reinforcement learning before we dive into MCTS method.

4.2. A Survey of Monte Carlo Tree Search Methods

4.2.1. *Summary*

The Monte Carlo Tree Search (MCTS) algorithm and its variations are thoroughly explained in ("A Survey of Monte Carlo Tree Search Methods"). The survey addresses many facets of MCTS, such as its historical evolution, essential ideas, and applications in diverse fields. It looks at the fundamental ideas behind MCTS, including simulation, backpropagation, expansion, and selection, and explains how each of these elements adds to the system's efficiency.

The evolution of MCTS variants is also covered in the paper, along with improvements and modifications made to fit particular problem domains. For researchers and practitioners looking for a deeper understanding of MCTS and its applications in artificial intelligence and decision-making, the survey is a useful tool overall.

4.2.2. *Meta Information*

Abstract:

Monte Carlo tree search (MCTS) is a recently proposed search method that combines the precision of tree search with the generality of random sampling. It has received considerable interest due to its spectacular *success in the difficult problem of computer Go, but has also proved beneficial in a range of other domains. This paper is a survey of the literature to date, intended to provide a snapshot of the state of the art after the first five years of MCTS research. We outline the core algorithm's derivation, impart some structure on the many variations and enhancements that have been proposed, and summarize the results from the key game and nongame domains to which MCTS methods have been applied. A number of open research questions indicate that the field is ripe for future work.*

Table 2

Title	Information
Published	03 February 2012
Total Citations	3635
Total Versions	54
Published At	IEEE
Authors	Cameron Browne, Edward Powley, Daniel Whitehouse, Simon Lucas, Peter I. Cowling, Philipp Rohlfshagen, Stephen Tavener, Diego Perez, and Spyridon Samothrakis
DOI	https://doi.org/10.1109/TCIAIG.2012.2186810

Meta information about the article "A Survey of Monte Carlo Tree Search Methods"

4.2.3. Reason to choose

For those who are interested in learning more about Monte Carlo Tree Search (MCTS) and how it is used in games, this article is a great resource. Its thorough coverage offers a strong basis for comprehending the theoretical foundations of MCTS, including its fundamental ideas and historical evolution.

The paper gives readers the tools necessary to implement and modify MCTS algorithms for diverse game environments by clarifying the various parts of MCTS and going over its variations and extensions. Furthermore, the large number of citations and acknowledgement from the academic community highlight the validity and significance of the data offered, making it a reliable resource for novices and experts alike who want to use MCTS in game AI development.

With almost 3700 citations, this article stands out with other articles written on MCTS. Also, it meets the requirement of finding at least one research survey or systematic literature review. Considering it's age of almost 12 years when it was published, keeping this ahead compared to other articles.

4.3. Monte-Carlo Tree Search: A New Framework for Game AI

4.3.1. Summary

The paper ("Monte-Carlo Tree Search: A New Framework for Game AI") presents a novel method for game AI called Monte-Carlo Tree Search (MCTS). The study, which was written by Cameron Browne, describes MCTS as an adaptable and powerful technique for gaming decision-making. It describes the fundamental ideas of MCTS, such as rollout policies, node selection, and tree traversal. The article showcases the versatility and scalability of MCTS by applying it to a variety of games through examples and case studies. All things considered, the paper is a seminal work in the field of game AI, offering practitioners and researchers interested in using MCTS for gaming advice and insights.

4.3.2. Meta Information

Abstract:

Classic approaches to game AI require either a high quality of domain knowledge, or a long time to generate effective AI behaviour. These two characteristics hamper the goal of establishing challenging game AI. In this paper, we put forward Monte-Carlo Tree Search as a novel, unified framework to game AI. In the framework, randomized explorations of the search space are used to predict the most promising game actions. We will demonstrate that Monte-Carlo Tree Search can be applied effectively to (1) classic board-games, (2) modern board-games, and (3) video games.

Table 3

Title	Information
Published	27 September 2021
Total Citations	580
Total Versions	21
Published At	ojs.aaai.org
Authors	Guillaume Chaslot, Sander Bakkes, Istvan Szita, Pieter Spronck
DOI	https://doi.org/10.1609/aiide.v4i1.18700

Meta information about the article ”Monte-Carlo Tree Search: A New Framework for Game AI”

4.3.3. Reason to choose

For multiple reasons, this article is a vital resource for anyone interested in learning how to use Monte-Carlo Tree Search (MCTS) for AI in games. First of all, it makes MCTS understandable to novices by giving a thorough summary of the subject, including its fundamental ideas and algorithms. Second, it provides useful information by means of case studies and examples, showing how MCTS can be successfully used in a range of gaming contexts.

Furthermore, the paper is credible and authoritative in the field because it was written by Cameron Browne, a well-known authority on game AI. Lastly, it is an invaluable learning resource for researchers and practitioners looking to use MCTS to improve game AI capabilities because of its concise explanations and helpful examples..

With almost 600 citations, this article may not look an excellent article but to related with our goal this article fits very well. As it is purely focused on MCTS and AI games, it can help us to understand the topic and develop an AI player game.

References

Volodymyr Mnih, Koray Kavukcuoglu, David Silver, Alex Graves, Ioannis Antonoglou, Daan Wierstra, Martin Riedmiller. 2013. “Playing Atari with deep reinforcement learning” arXiv preprint arXiv:1312.5602.

Browne, C., Powley, E., Whitehouse, D., Lucas, S., Cowling, P. I., Rohlfshagen, P., Stephen, T., Perez, D. & Samothrakis, S. (2012). A survey of Monte Carlo tree search methods. IEEE Transactions on Computational Intelligence and AI in Games, 4(1), 1-43.

Guillaume Chaslot, Sander Bakkes, Istvan Szita, Pieter Spronck. 2021. “Monte-Carlo Tree Search: A New Framework for Game AI.” https://doi.org/10.1609/aiide.v4i1.18700.