

# Human Decision-Making in Artificial Intelligence

NC STATE UNIVERSITY

Maggie Lin (mclin@ncsu.edu) & Derek Martin (dmartin7@ncsu.edu)  
Department of Computer Science, NC State University

## Background

Monte Carlo Tree Search (MCTS) is a heuristic search technique in the field of artificial intelligence that is utilized to improve the action selection process.

While artificial intelligence has been used to mimic humans behaviors in various fields, current models mostly determine the degree of expertise of the decision-making process by how long the model is trained before being stopped instead of mimicking human decision-making behaviors.

## Methods

Examine psychological and economic behavior analysis research for popular concepts related to the human decision-making process (E.g. Delay Discounting & Fisher Information)

Combine the concepts with the MCTS heuristic into a model that adapts behavior due to the amount of risk that is present within an environment

Experiment with the combined model in games such as the Atari Learning Environment and see how well they match human decision making behaviors



Atari Space Invaders

## Experiments

Based on the paper *Adaptive Expert Decision Making: Skilled Chess Players Search More and Deeper*, it is observed that while expert chess players can carry out extensive searches, the strengths that differentiate them from lower-skilled chess players are their pattern recognition and selective search abilities.

This leads to an idea that we wanted to try out on the general MCTS method where instead of a fifty-fifty chance of exploring a new node each time we expand the tree, we decrease the percentage of exploration as the level of the tree increases to simulate selective search.

## Findings

A simple game that implemented the MCTS heuristic was used to experiment with the selective search simulation. The goal of the game is to get as close to zero as possible at the end of the total number of turns. The number of turns is indicated at the beginning of the game and during each turn, there are four different numbers to choose from.

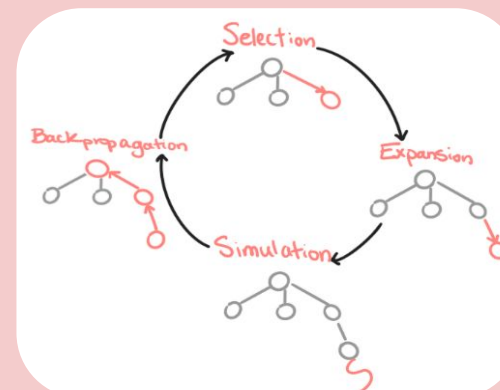
Despite the decrease in percentage of new node expansion as we move down the levels of the tree, the result stay relatively similar to the general MCTS implementation of the game.

Goal: Get as close to zero as possible in the number of turns given.  
Turns: 4 Turns

Turn	Choices
1	-8, 8, -12, 12
2	-6, 6, 9, -9
3	-4, 4, 6, -6
4	-2, 2, 3, -3

Possible Optimal Playout: -8, 9, -4, 3  
Resulting Sum:  $-8 + 9 - 4 + 3 = 0$

Example of game payout



MCTS Iteration

## Conclusions

Decrease in numbers of nodes explored in the MCTS heuristic may not be negatively impacted the result compared to the general MCTS heuristic.

While the aim of this research is not to make a modified search algorithm that is more efficient or accurate than the original, but instead to mimic human behavior, there may be ways to modify the algorithm that mimics human behavior such as pattern recognition and extensive search and result in more efficient search times.

## Future Work

Continue researching how modifying the MCTS search technique with concepts such as Delay Discounting and Fisher Information, which we did not get to this summer, can mimic human behavior on games such as the Atari Learning Environment.

## References

- [1] Campitelli, G., & Gobet, F. "Adaptive Expert Decision Making: Skilled Chess Players Search More and Deeper." ICGA Journal, 2004
- [2] Haroldsultan, "Haroldsultan/MCTS: Python implementations of Monte Carlo Tree Search," GitHub, <https://github.com/haroldsultan/MCTS> (accessed Jul. 20, 2023).

## Acknowledgements



This research experience was made possible due to funding provided by the Engineering Grand Challenges Scholars Program.