



# Wargaming with Monte-Carlo Tree Search

Presentation for the 14th NATO ORA Conference - Erik Kalmér and Christoffer Limér

# Project background

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- Started as our Bachelor's degree project at The Royal Institute of Technology (KTH) in collaboration with the Swedish Defence Research Agency (FOI)
- Within the context of artificial intelligence, there was an interest in applications within military strategy.
- Specifically, wargaming was chosen for exploration.



# Strategy games as training and evaluation of military strategies

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- Even the ancient Greeks played strategy board games in the fifth-century B.C
- The Germans (Prussians) further developed the game of Chess into more realistic strategy games that were used heavily during 19<sup>th</sup> century.
- *"It's not a game at all! It's training for war. I shall recommend it enthusiastically to the whole army."* - General Karl von Müffling of Prussia (1824)



Prussian officers playing Kriegsspiel (illustr. August 1872).

# Strategy games as training and evaluation of military strategies

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- Many aspects of wargaming have stayed the same.
- Wargaming is still relevant today, could modern AI techniques enhance this further?
- Could AI-agents be developed to give decision support for Course of Action (COA) within wargaming?

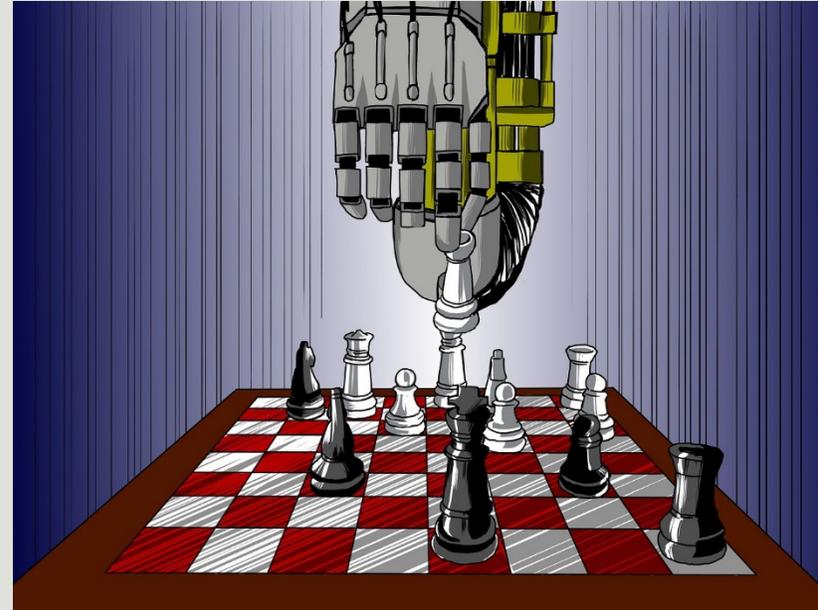


A wargame at the US Marine Corps War College (April 2019)

# Artificial intelligence for strategy games

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- In the early 50s when artificial intelligence was a somewhat new field, attempts were being made to get computers to play chess.
- In 1997 the Chess program Deep Blue officially beat the world champion, Garry Kasparov
- Since then, scientists have been looking for new challenges



# Artificial intelligence for strategy games

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- In March of 2016, the program AlphaGo defeats world champion Lee Sedol in the game of Go
- This was unexpected, some believed such a program would take at least another decade to develop
- A vital part of the AlphaGo and its successors is its use of an effective search algorithm called Monte Carlo Tree Search (MCTS)
- Could MCTS be used to play a less abstract strategic board game?

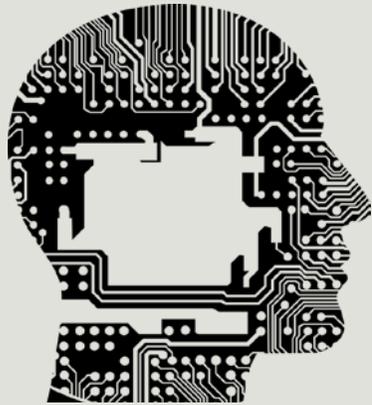


A Go game in progress

# Our research project in one sentence:

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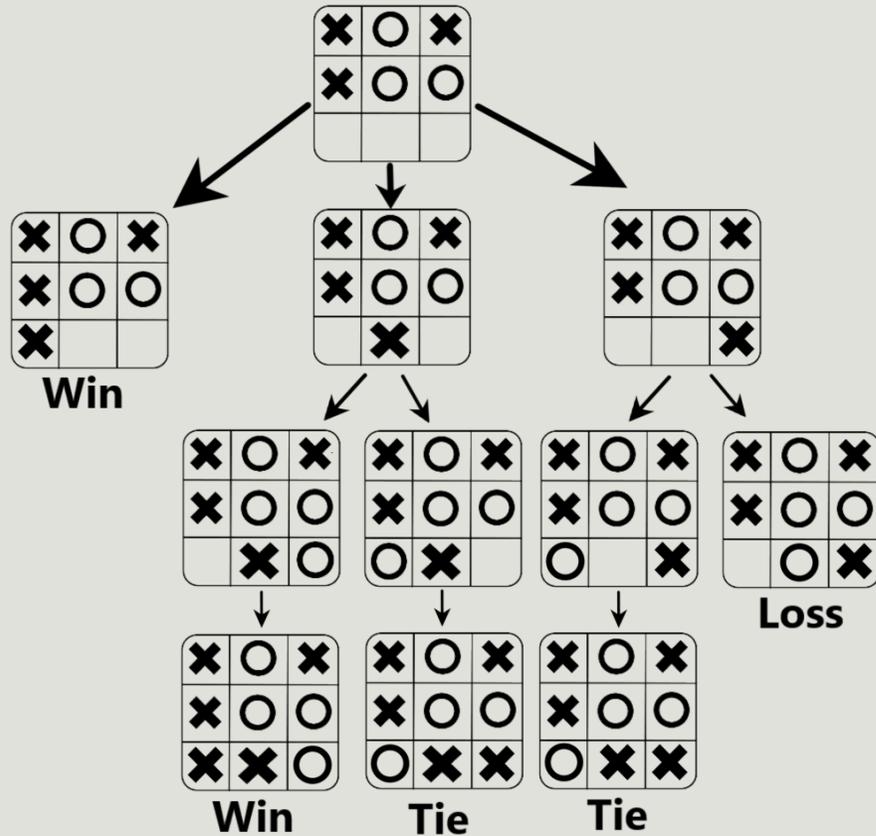
Can we create a program that can play the strategic board game Risk at a high skill level, using Monte Carlo Tree Search?



- A commercial strategic board game that is less abstract than Chess but with reasonable complexity
- Our first step towards more complex strategy environments

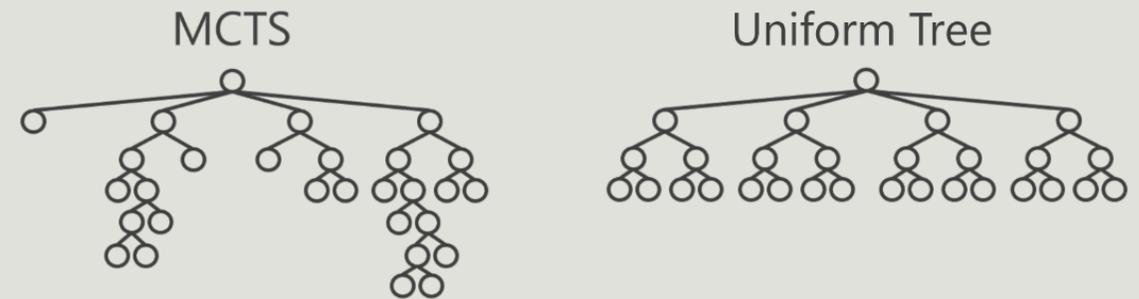
# What makes the Monte Carlo Tree Search effective?

- If we use an easy example, Tic-tac-toe



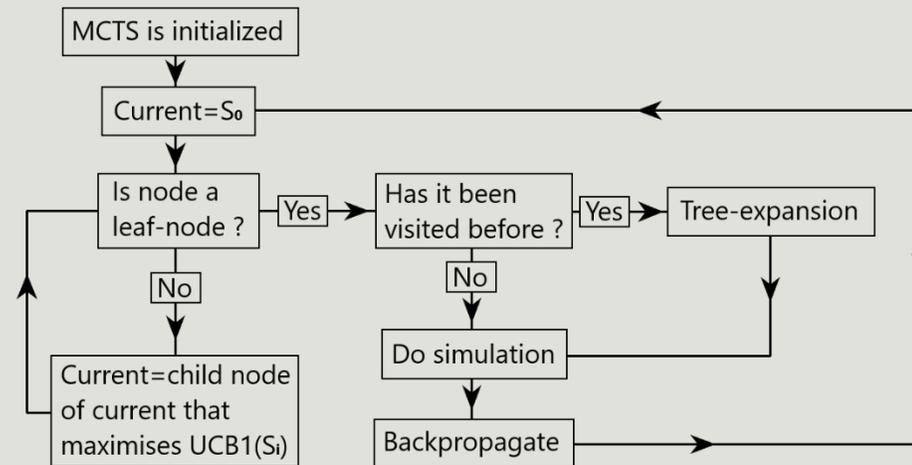
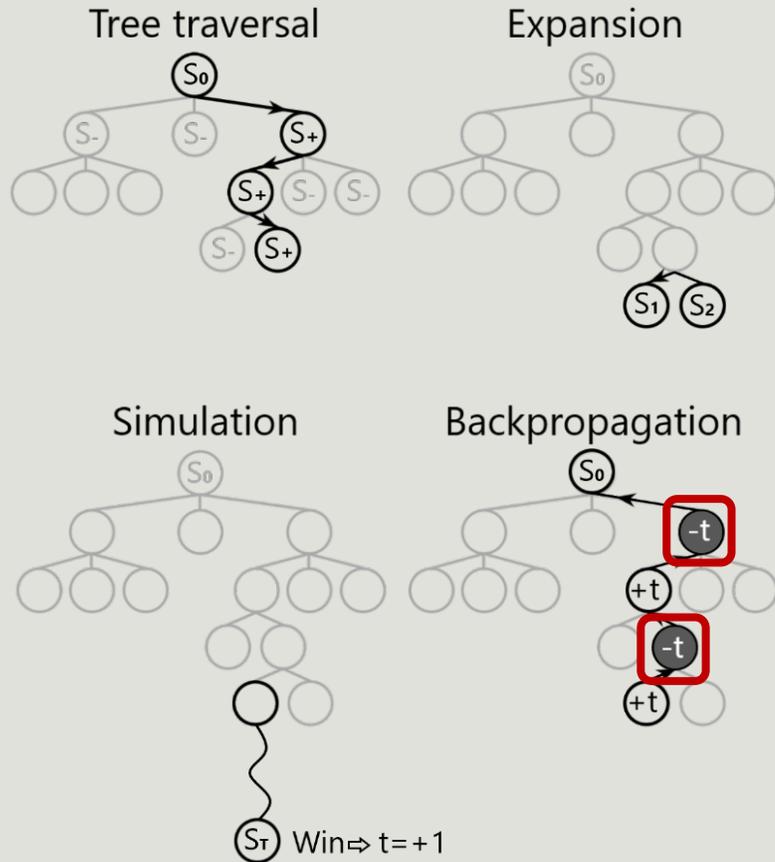
Example of a tree structure for Tic-tac-toe, played by X

- Monte Carlo Tree Search or Uniform Tree Search



# How the MCTS algorithm works at a glance

- The four phases of MCTS



Flowchart for MCTS

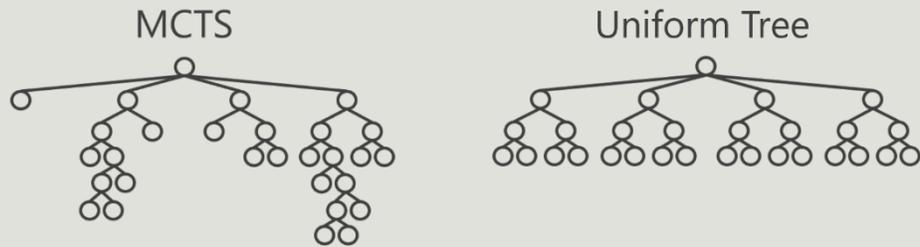
# Looking under the hood of MCTS using UCB1

- The UCB1 formula is used by MCTS to select the next move/node in the traversal phase

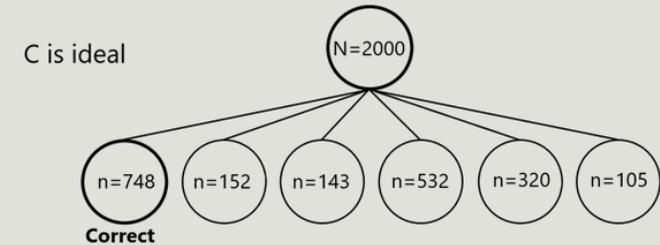
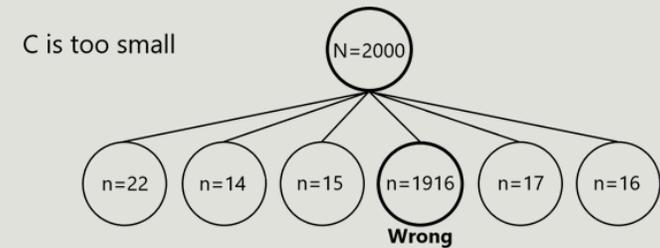
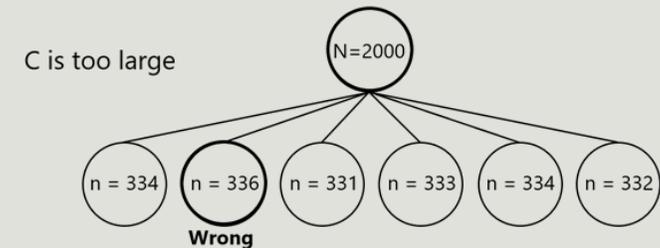
$$UCB1_i = \bar{V}_i + C * \sqrt{\frac{\ln N}{n_i}}$$

Where:

- $\bar{V}_i$  = Empirical mean-valuation ( $t_i/n_i$ )
- $n_i$  = Number of simulations for node  $i$
- $t_i$  = Sum of all valuations of node  $i$
- $N$  = Total number of simulations for parent-node
- $C$  = Constant (exploration parameter)

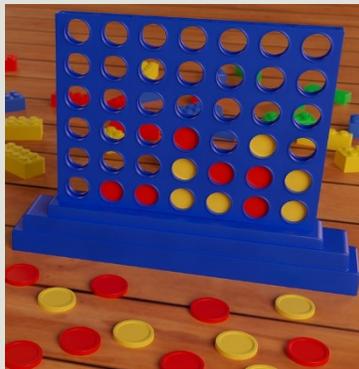


- The constant "C" is used to balance the exploration-exploitation trade-off, and it is essential to choose wisely



# Our first implementation with Connect 4

- We used the programming language Python to build our client from scratch
- An initial program was made to serve as a trial for our MCTS algorithm. The game of choice was Connect 4
- It was important to get a successful MCTS-agent on a simple game first, before moving on to a more complex game



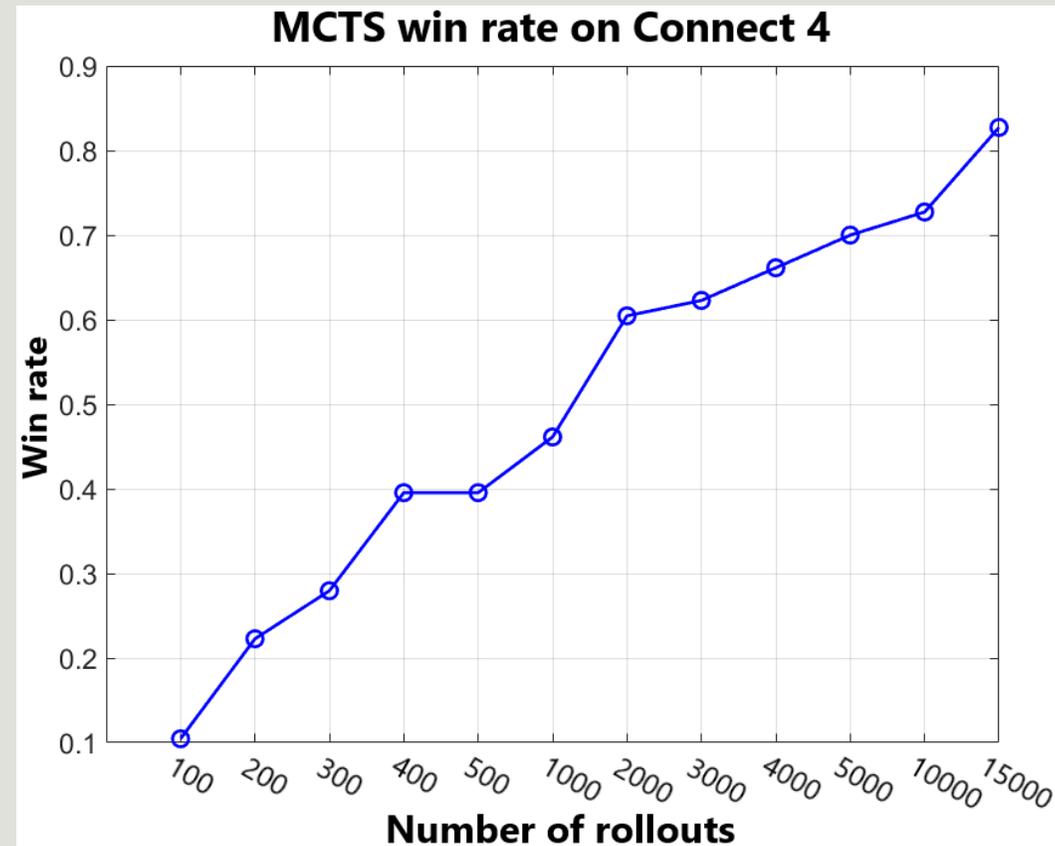
The game Connect 4

```
C:\Ubuntu\riskown\Tic_Tac.exe
 1 2 3 4 5 6 7
1 - - - - - -
2 - - - - - -
3 - - - 0 - - -
4 - - 0 X - - -
5 - 0 X 0 - - -
6 - X 0 X X - -
MOVES : [35, 22, 16, 10, 32, 40, 41]
 99%Yes!!!
number of children : 7
Node visits: [4937, 13, 9, 9, 9, 9, 13]
t-value: [-236. -11. -9. -9. -9. -9. -
11.]
UCB_choice_value [ -48. -846. -1000. -1000. -1000.
-1000. -846.]
Moves: [35, 22, 16, 10, 32, 40, 41]
 1 2 3 4 5 6 7
1 - - - - - -
2 - - - - - -
3 - - - 0 - - -
4 - - 0 X - - -
5 - 0 X 0 - - -
6 X X 0 X X - -
enter column: █
```

# Our first implementation with Connect 4

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- The term **Rollout** means the number of evaluated moves/nodes
- If the MCTS-agent works correctly, there should be a correlation between the number of rollouts and performance
- In the implementation of Connect 4, we see a distinct correlation between the win-rate and the number of rollouts
- The agent with 100 rollouts wins only about 10% of its matches, while the agent with 15000 wins almost 83%



# MCTS for Risk

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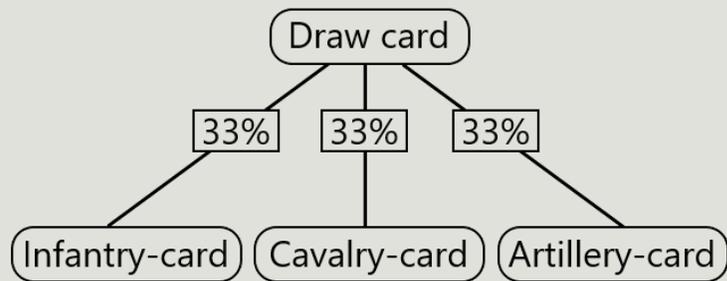
Risk has some challenges that must be solved when implementing it on the MCTS.

- For example, it is not a game with perfect information such as chess or connect-4 when army cards are kept secret by the opponent.
- There are some elements of uncertainty that our first MCTS-algorithm can't handle.
- To handle these and more, we have used various techniques to facilitate and improve our implementation.



# Chance-nodes

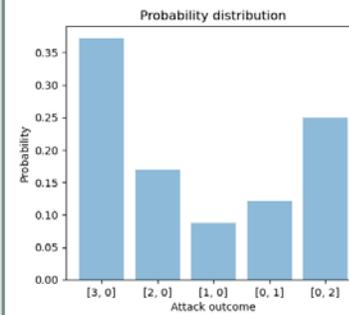
## Cards



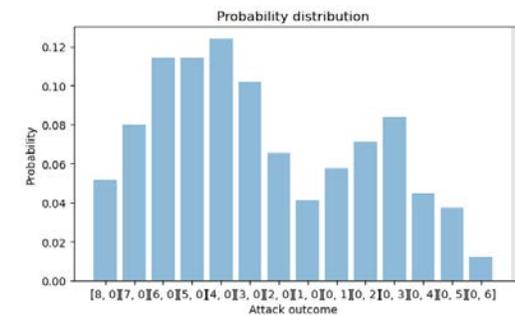
## Attack



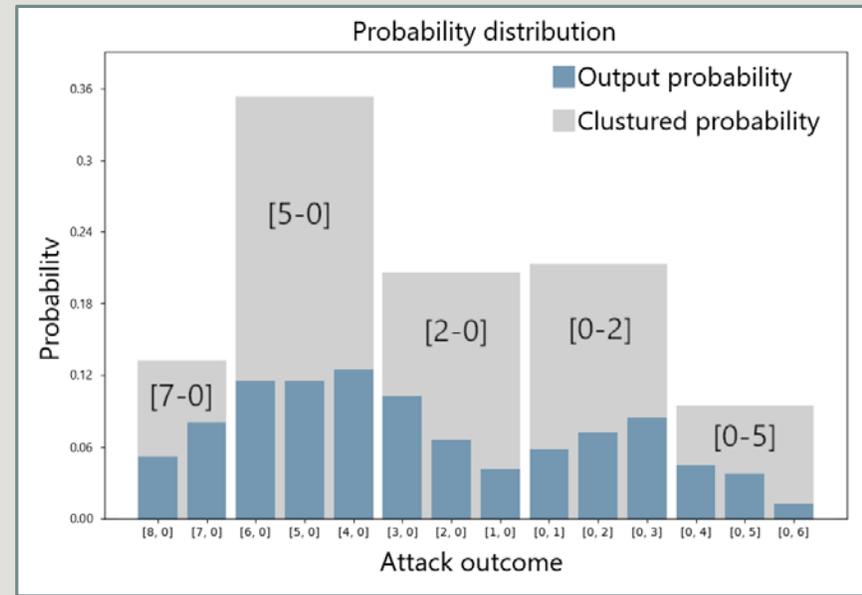
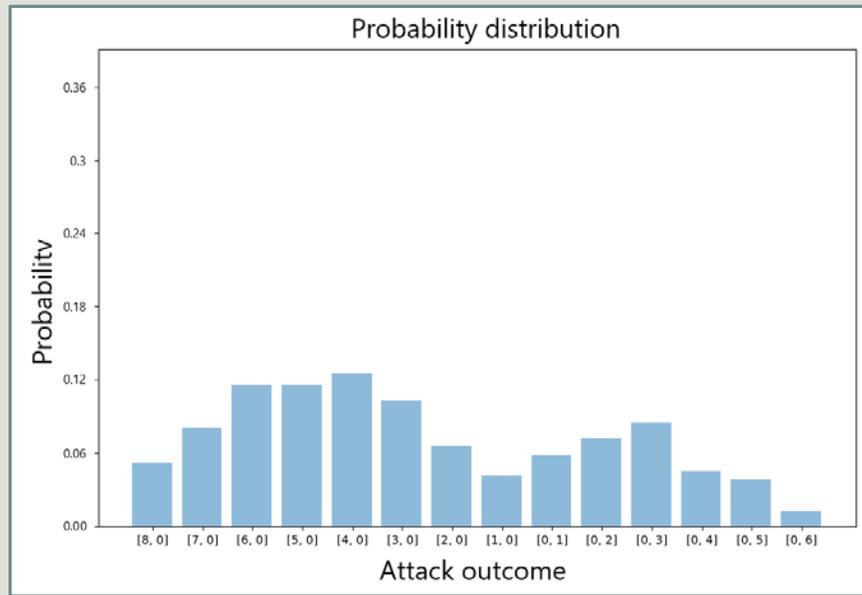
Small attack  
(3 vs 2)



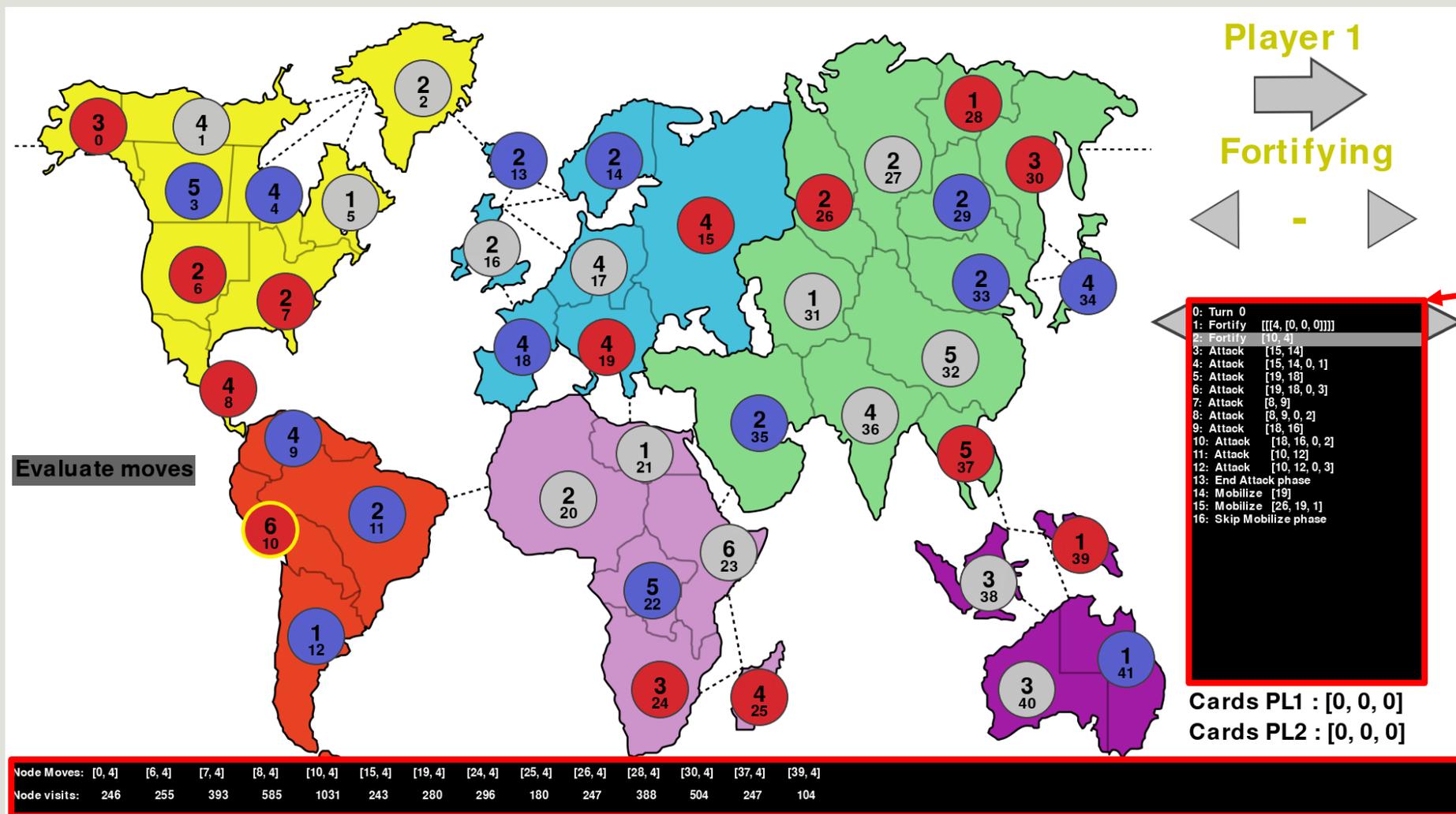
Large attack  
(8 vs 6)



# Chance-node Clustering



# User Interface (UI)

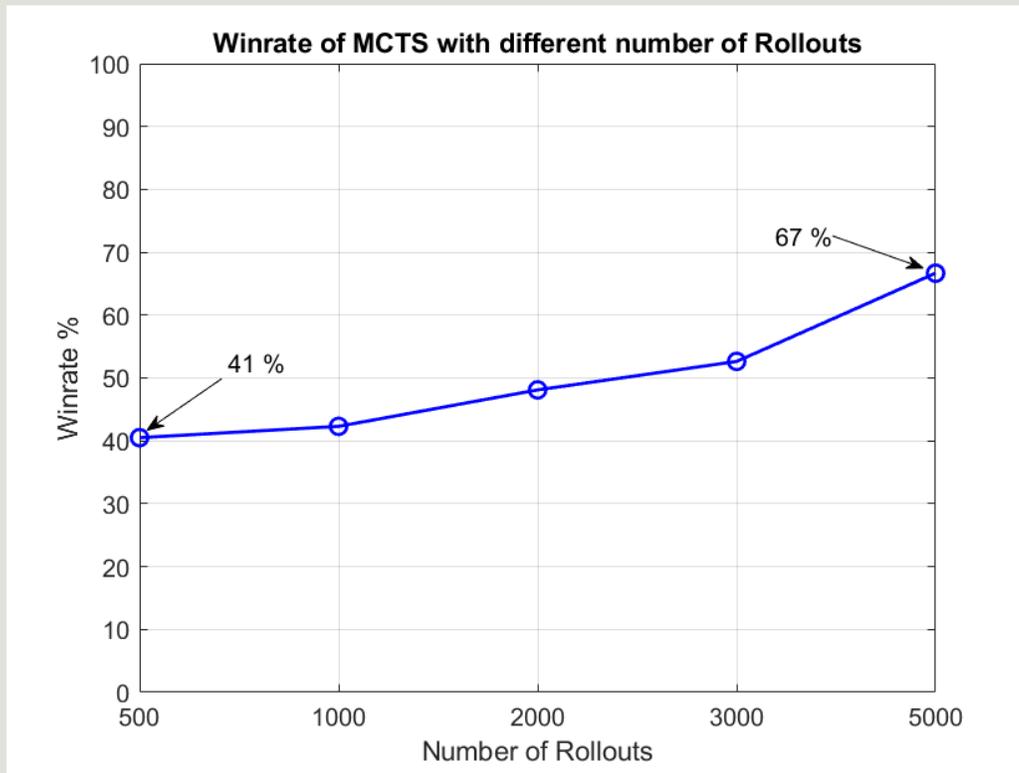


History list of previous Actions

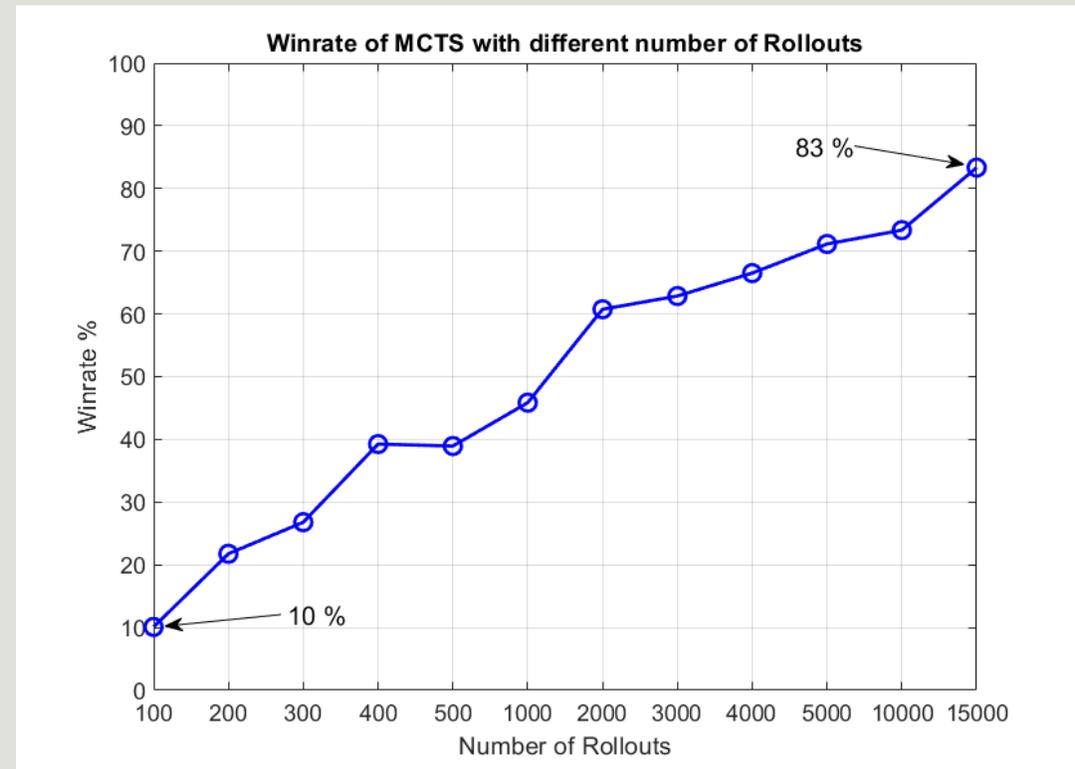
The MCTS evaluation of all other possible actions

# Testing the MCTS

## Risk

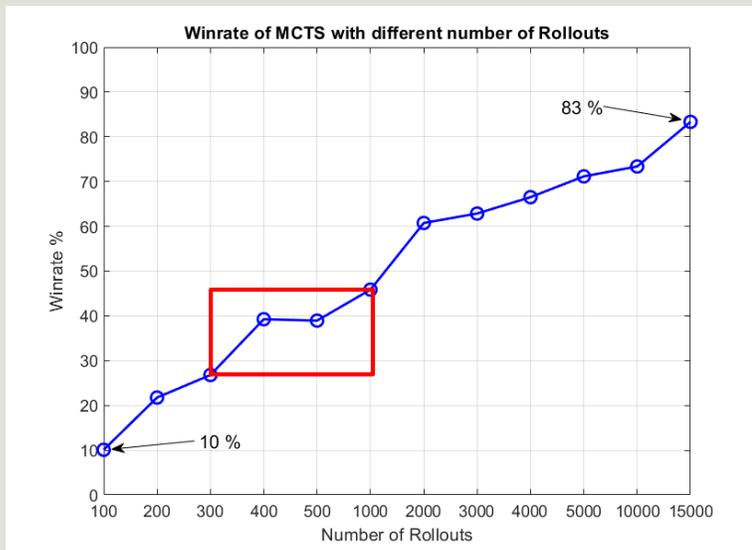


## Connect-4



# How does the MCTS stack up against human players?

## Connect-4



	Rollouts
Casual players	300-1000

## Risk

MCTS-agents with Cut-off 10	Win rate against human players	
500 Rollouts	10 %	Almost no wins
5 000 Rollouts	40 %	Under half
15 000 Rollouts	60 %	Just over half

Despite the game of Risk having a large amount of luck, which we first thought would disrupt the convergence, our MCTS has shown itself capable of playing at a human level, possibly even outperforming us.

# Applications in wargaming

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## Lessons learned when working with Risk

### What are the limitations?

- Large sets of possible actions may need "action pruning"
- Elements of chance/uncertainty prohibit the MCTS from converging

### How much work is needed for an implementation?

- Relatively little work and time required to implement on new environments

# Applications in wargaming

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## Possibilities for decision support

### Synthetic players in educational wargaming

- Relieve people from roles and tasks in wargaming scenarios. (Collaborator or/and Enemy) [Instead of a whole team of people playing different roles, the AI can play those roles with an equal skill/performance]
- Train people in different scenarios and learn from possible mistakes.

### Evaluations in analytical wargaming

- Evaluate action alternatives
- Scenario analysis

For further interest please read our paper or contact us: [limer@kth.se](mailto:limer@kth.se) or [ekalmer@kth.se](mailto:ekalmer@kth.se)

Thanks for listening!