# Kalah Game

GROUP 36

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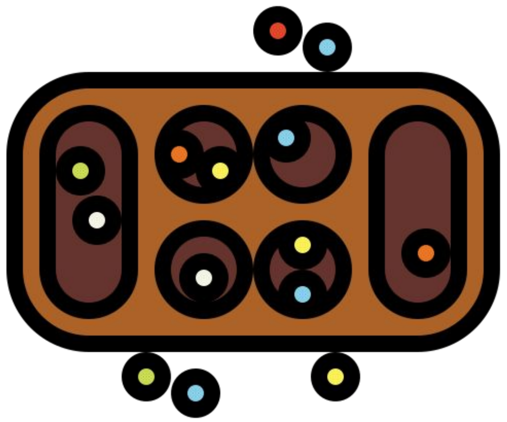
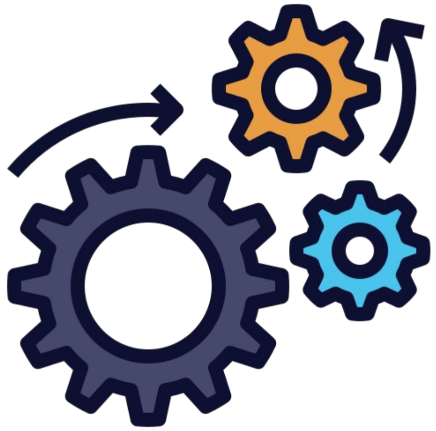
## Game and parser



Mancala Game in python

Used in
- Developing strategies
- Evaluation between agents

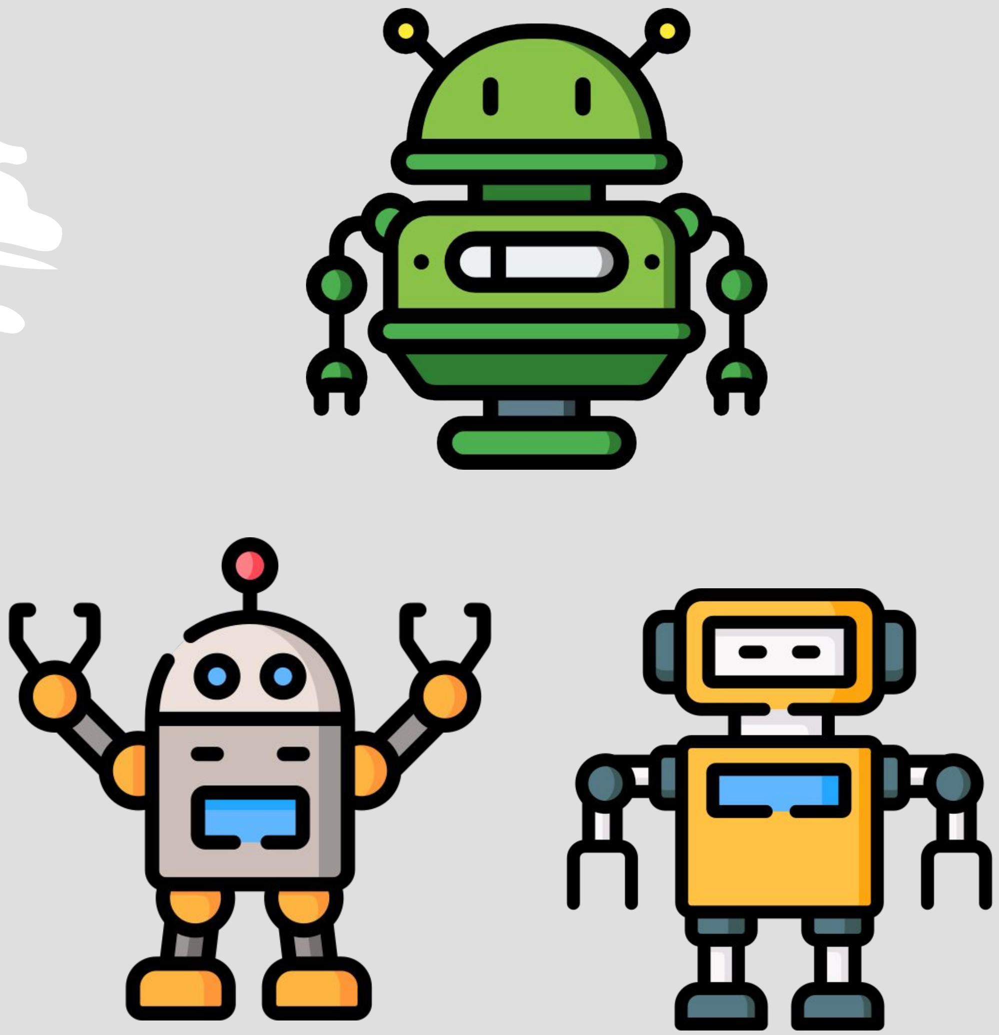


Parser

Protocol info -> information needed
Provide state/board info etc.
Basic communication with protocol

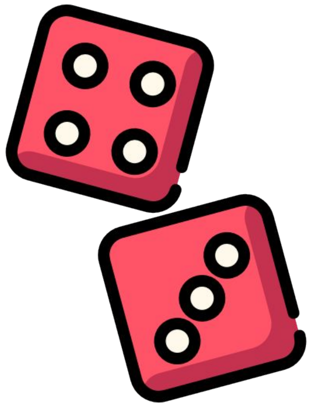
## Agents

- Random Agent
- Simple Agent
- Alpha-beta pruning Agent
- MCTS Agent
- Model Agent



## Random Agent

- Perform random move from available moves



## Simple Agent

Implemented using simple rules:

Go through available moves, do:

- Winning move

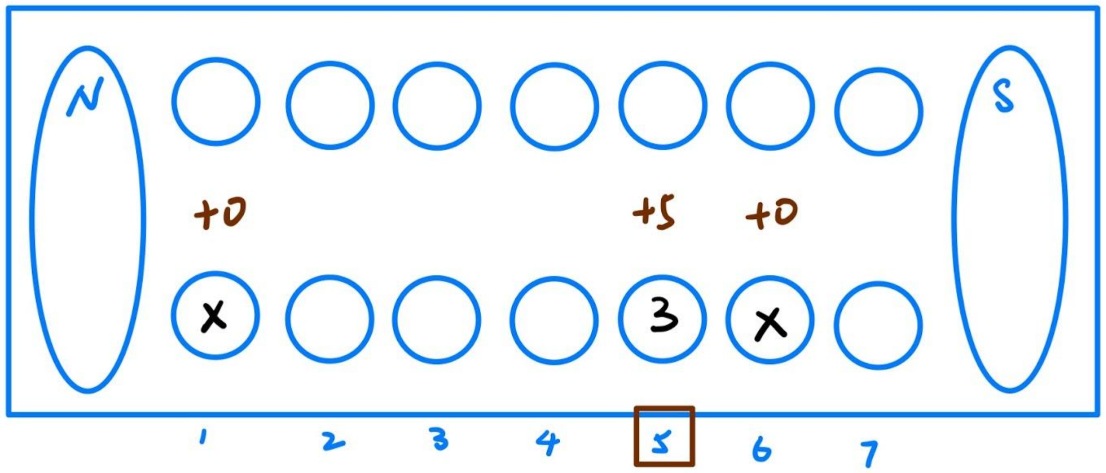
Else, consider:

- Extra move chance
- Maximise self-gain and Minimize opponent-gain

## Heuristics

⇒ avaliability of extra move

⇒ score increase



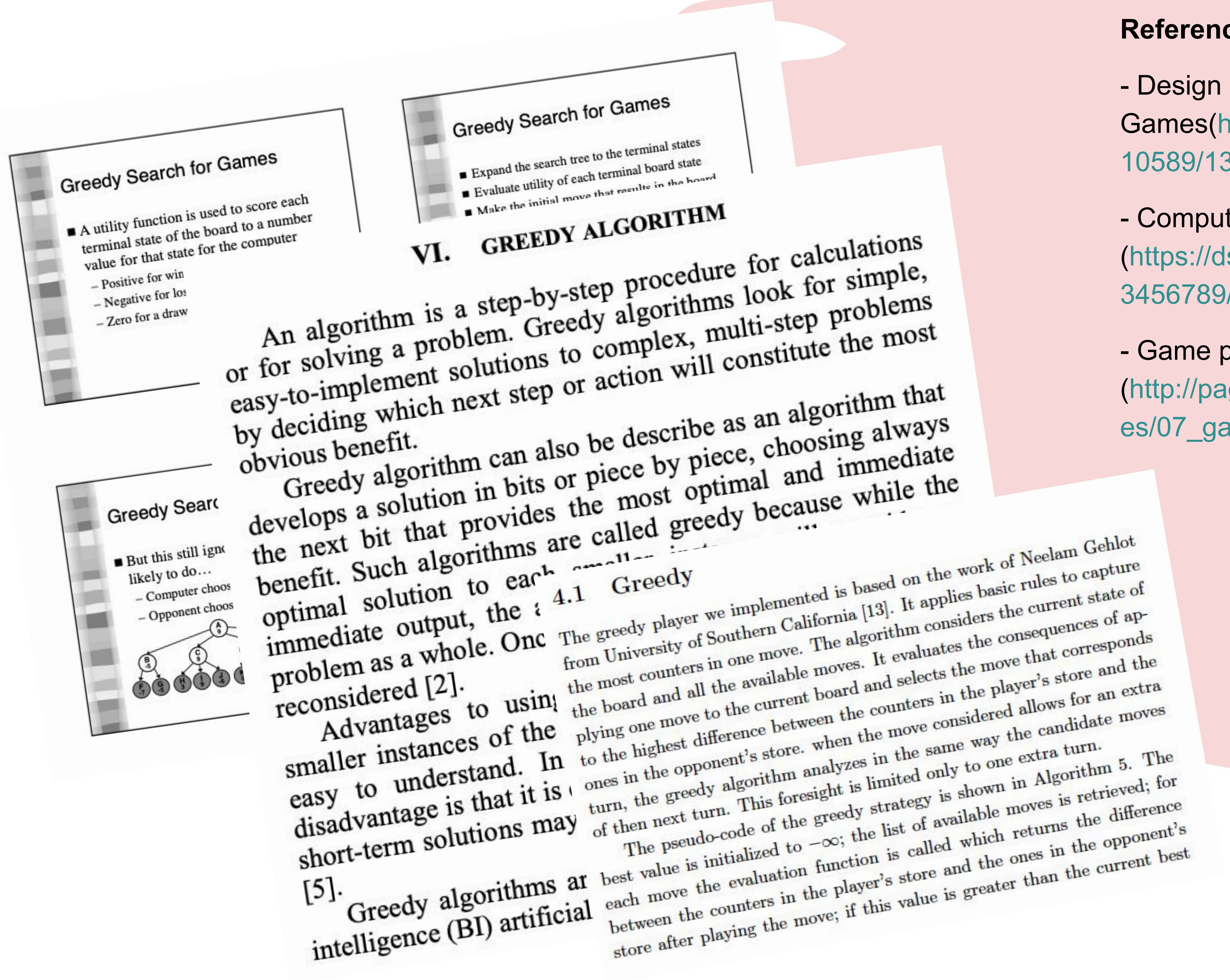
step 1

All avaliable moves for me — +12 — +1 — +6 — step 2

max of all avaliable moves of opponent — max oppo. +15 — +5 — +1 — step 3

suppose no extra moves

return move of max value — $12-15=-3$ — $5+1-5=1$ — $6-1=5$ — step 4



Greedy Search for Games

- A utility function is used to score each terminal state of the board to a number value for that state for the computer
  - Positive for win
  - Negative for los
  - Zero for a draw

Greedy Search for Games

- Expand the search tree to the terminal states
- Evaluate utility of each terminal board state
- Make the initial move that results in the board

Greedy Searc

- But this still igno likely to do…
  - Computer choos
  - Opponent choos

VI. GREEDY ALGORITHM

An algorithm is a step-by-step procedure for calculations or for solving a problem. Greedy algorithms look for simple, easy-to-implement solutions to complex, multi-step problems by deciding which next step or action will constitute the most obvious benefit.

Greedy algorithm can also be describe as an algorithm that develops a solution in bits or piece by piece, choosing always the next bit that provides the most optimal and immediate benefit. Such algorithms are called greedy because while the optimal solution to each smaller instance will … immediate output, the a problem as a whole. Onc reconsidered [2].

Advantages to using smaller instances of the easy to understand. In disadvantage is that it is short-term solutions may [5].

Greedy algorithms ar intelligence (BI) artificial

## 4.1 Greedy

The greedy player we implemented is based on the work of Neelam Gehlot from University of Southern California [13]. It applies basic rules to capture the most counters in one move. The algorithm considers the current state of the board and all the available moves. It evaluates the consequences of applying one move to the current board and selects the move that corresponds to the highest difference between the counters in the player's store and the ones in the opponent's store. when the move considered allows for an extra turn, the greedy algorithm analyzes in the same way the candidate moves of then next turn. This foresight is limited only to one extra turn.

The pseudo-code of the greedy strategy is shown in Algorithm 5. The best value is initialized to $-\infty$; the list of available moves is retrieved; for each move the evaluation function is called which returns the difference between the counters in the player's store and the ones in the opponent's store after playing the move; if this value is greater than the current best

**References:**

- Design of Artificial Intelligence for Mancala Games(https://www.politesi.polimi.it/bitstream/10589/134455/3/Thesis.pdf) page 31-32

- Computerized Board Game: Dara (https://dspace.unijos.edu.ng/jspui/bitstream/123456789/799/1/L_10853_11.6951.pdf) page 3

- Game playing (http://pages.cs.wisc.edu/~bsettles/cs540/lectures/07_game_playing.pdf) page 2

## Alpha beta pruning agent

Heuristics:

- Scores of our side - scores of opponent side
  - Straightforward and easy to implement
- Refined heuristics
  - A lot of variants bring a lot of uncertainties
  - Time consumed.
  - If time is enough, experiments will be made to find better heuristics.

Reference:

- Design of Artificial Intelligence for Mancala Games([https://www.politesi.polimi.it/bitstream/10589/134455/3/Thesis.pdf](https://www.politesi.polimi.it/bitstream/10589/134455/3/Thesis.pdf)) page 34

# MCTS Agent

Using Monte Carlo Tree Search to make the move

- Using RAVE(*Rapid Action Value Estimation*), with modified UCB1 formula to calculate the score of each move

$$(1-\beta(n_i,\tilde{n}_i))\frac{w_i}{n_i}+\beta(n_i,\tilde{n}_i)\frac{\tilde{w}_i}{\tilde{n}_i}+c\sqrt{\frac{\ln t}{n_i}}$$

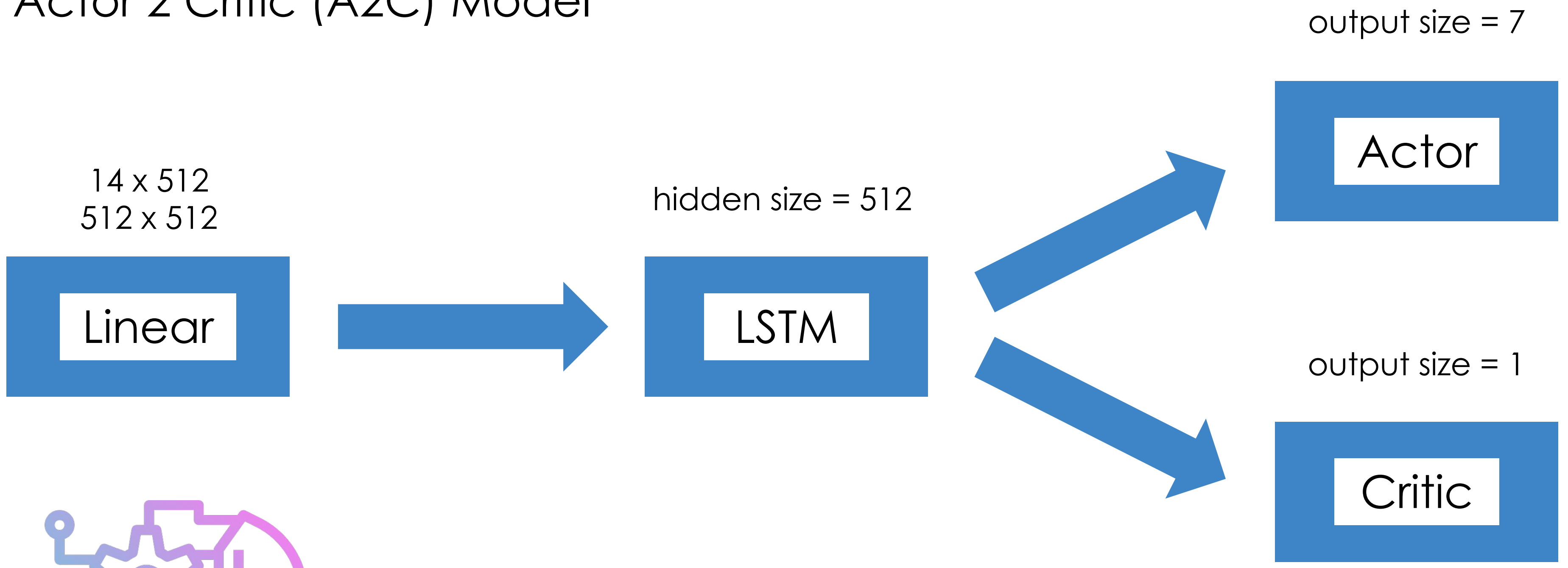
- with alpha-beta pruning agent to forward each move
- return if there exists one child node with score 1 OR the move of the child node with the most visits

References:

- Design of Artificial Intelligence for Mancala Games(https://www.politesi.polimi.it/bitstream/10589/134455/3/Thesis.pdf) page 37 - 38
- Chang, Hyeong Soo; Fu, Michael C.; Hu, Jiaqiao; Marcus, Steven I. (2005). "An Adaptive Sampling Algorithm for Solving Markov Decision Processes" (PDF). *Operations Research*. **53**: 126–139. doi:10.1287/opre.1040.0145. hdl:1903/6264
- David Silver (2009). *Reinforcement Learning and Simulation-Based Search in Computer Go* (PDF). PhD thesis, University of Alberta.

# Model Agent - Architecture

Actor 2 Critic (A2C) Model



https://arxiv.org/abs/1602.01783v2
https://arxiv.org/abs/1909.09586
https://github.com/pytorch/examples/blob/master/reinforcement_learning/actor_critic.py

# Model Agent - Loss

## Reward Loss

1. Calculate the reward for each move by according to discount factor.
2. Normalize the reward.
3. Multiply each move's reward by move's probability.

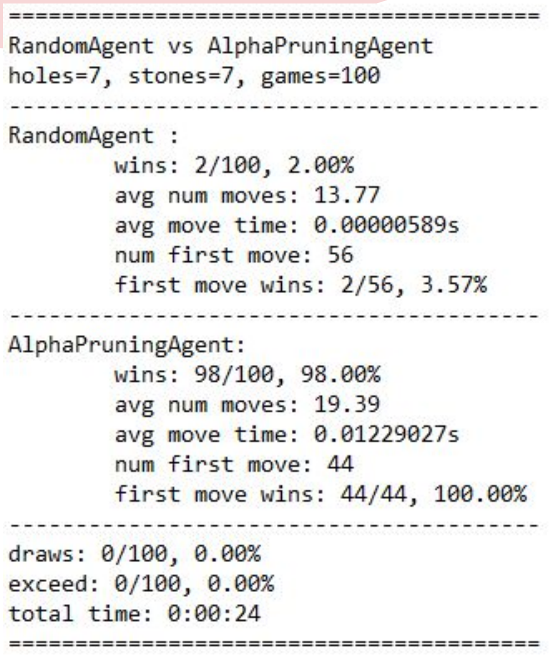
## Value Loss

1. L1 smooth loss of critic output and reward

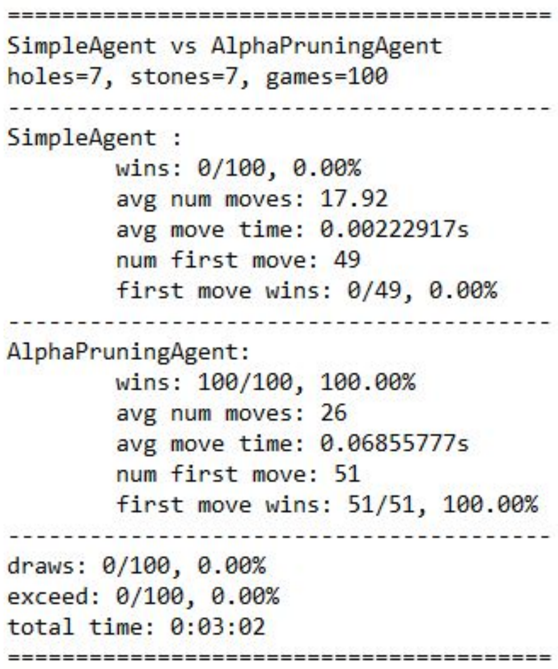
**Total Loss = reward loss + 0.5 * value loss**

https://pytorch.org/docs/stable/generated/torch.nn.SmoothL1Loss.html#torch.nn.SmoothL1Loss
https://github.com/pytorch/examples/blob/master/reinforcement_learning/reinforce.py#L62
http://rail.eecs.berkeley.edu/deeprlcourse/static/slides/lec-6.pdf

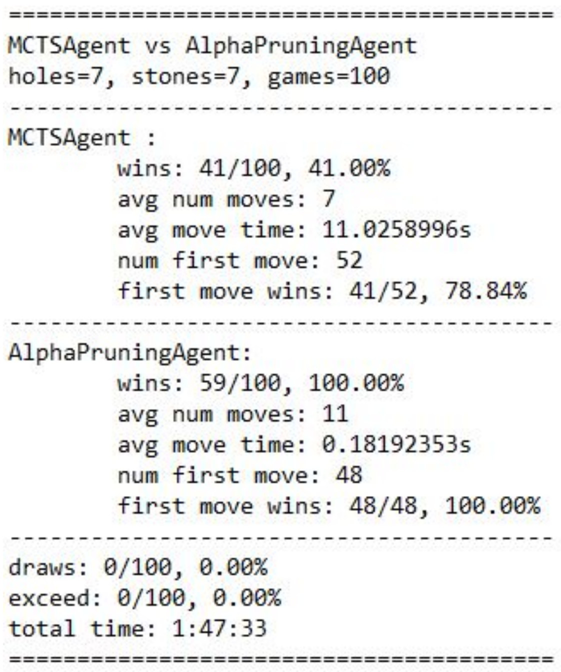
# Evaluation - each agent against each other



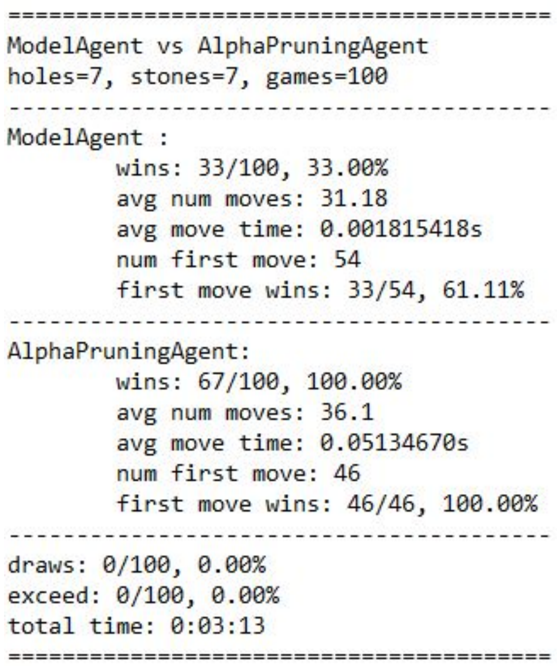
```
=========================================
RandomAgent vs AlphaPruningAgent
holes=7, stones=7, games=100
-----------------------------------------
RandomAgent :
        wins: 2/100, 2.00%
        avg num moves: 13.77
        avg move time: 0.00000589s
        num first move: 56
        first move wins: 2/56, 3.57%
-----------------------------------------
AlphaPruningAgent:
        wins: 98/100, 98.00%
        avg num moves: 19.39
        avg move time: 0.01229027s
        num first move: 44
        first move wins: 44/44, 100.00%
-----------------------------------------
draws: 0/100, 0.00%
exceed: 0/100, 0.00%
total time: 0:00:24
=========================================
```



```
=========================================
SimpleAgent vs AlphaPruningAgent
holes=7, stones=7, games=100
-----------------------------------------
SimpleAgent :
        wins: 0/100, 0.00%
        avg num moves: 17.92
        avg move time: 0.00222917s
        num first move: 49
        first move wins: 0/49, 0.00%
-----------------------------------------
AlphaPruningAgent:
        wins: 100/100, 100.00%
        avg num moves: 26
        avg move time: 0.06855777s
        num first move: 51
        first move wins: 51/51, 100.00%
-----------------------------------------
draws: 0/100, 0.00%
exceed: 0/100, 0.00%
total time: 0:03:02
=========================================
```



```
=========================================
MCTSAgent vs AlphaPruningAgent
holes=7, stones=7, games=100
-----------------------------------------
MCTSAgent :
        wins: 41/100, 41.00%
        avg num moves: 7
        avg move time: 11.0258996s
        num first move: 52
        first move wins: 41/52, 78.84%
-----------------------------------------
AlphaPruningAgent:
        wins: 59/100, 100.00%
        avg num moves: 11
        avg move time: 0.18192353s
        num first move: 48
        first move wins: 48/48, 100.00%
-----------------------------------------
draws: 0/100, 0.00%
exceed: 0/100, 0.00%
total time: 1:47:33
=========================================
```



```
=========================================
ModelAgent vs AlphaPruningAgent
holes=7, stones=7, games=100
-----------------------------------------
ModelAgent :
        wins: 33/100, 33.00%
        avg num moves: 31.18
        avg move time: 0.001815418s
        num first move: 54
        first move wins: 33/54, 61.11%
-----------------------------------------
AlphaPruningAgent:
        wins: 67/100, 100.00%
        avg num moves: 36.1
        avg move time: 0.05134670s
        num first move: 46
        first move wins: 46/46, 100.00%
-----------------------------------------
draws: 0/100, 0.00%
exceed: 0/100, 0.00%
total time: 0:03:13
=========================================
```

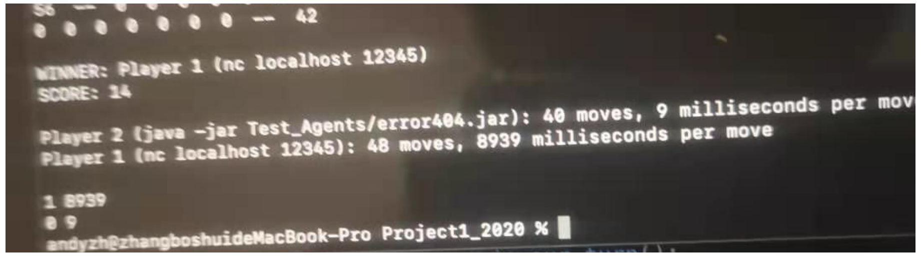
**Result shows that alpha beta pruning agent comes to the best**

**Random < Simple < MCTS < Model < Alpha Beta Pruning**

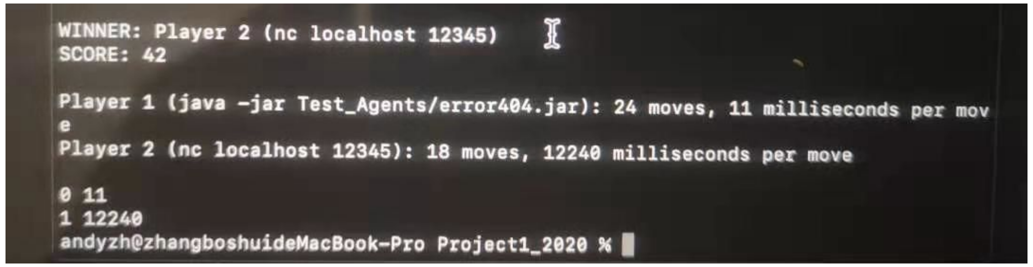
# Evaluation - final agent with test agents

- with alpha-beta pruning agent with depth 7

**error404.jar**

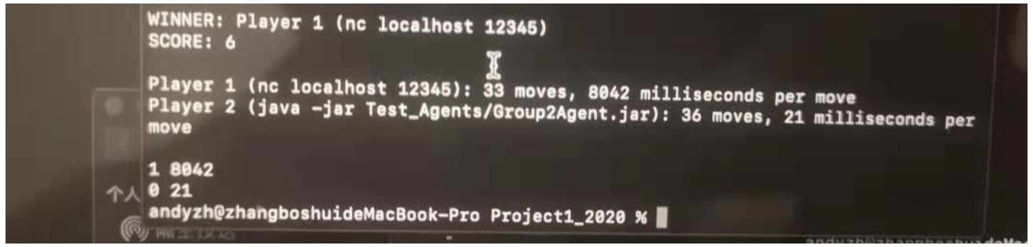


```
0  0  0  0  0  0  0  --  42

WINNER: Player 1 (nc localhost 12345)
SCORE: 14

Player 2 (java -jar Test_Agents/error404.jar): 40 moves, 9 milliseconds per mov
Player 1 (nc localhost 12345): 48 moves, 8939 milliseconds per move

1 8939
0 9
andyzh@zhangboshuideMacBook-Pro Project1_2020 %
```

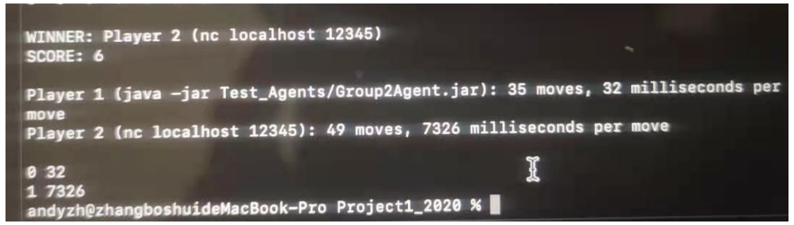


```
WINNER: Player 2 (nc localhost 12345)
SCORE: 42

Player 1 (java -jar Test_Agents/error404.jar): 24 moves, 11 milliseconds per mov
e
Player 2 (nc localhost 12345): 18 moves, 12240 milliseconds per move

0 11
1 12240
andyzh@zhangboshuideMacBook-Pro Project1_2020 %
```

**Group2Agent.jar**

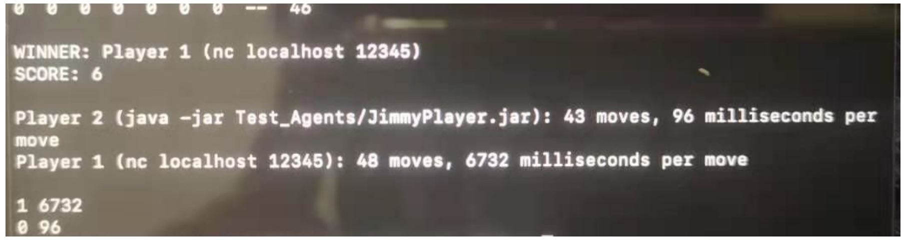


```
WINNER: Player 1 (nc localhost 12345)
SCORE: 6

Player 1 (nc localhost 12345): 33 moves, 8042 milliseconds per move
Player 2 (java -jar Test_Agents/Group2Agent.jar): 36 moves, 21 milliseconds per
move

1 8042
0 21
andyzh@zhangboshuideMacBook-Pro Project1_2020 %
```

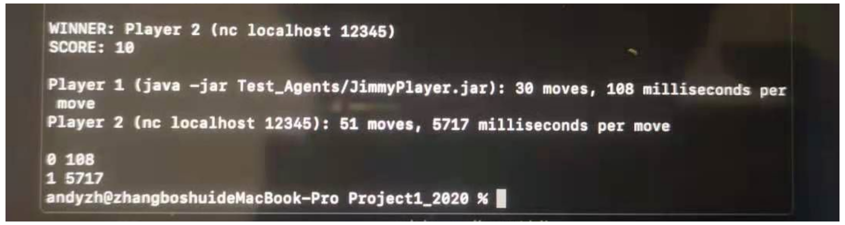


```
WINNER: Player 2 (nc localhost 12345)
SCORE: 6

Player 1 (java -jar Test_Agents/Group2Agent.jar): 35 moves, 32 milliseconds per
move
Player 2 (nc localhost 12345): 49 moves, 7326 milliseconds per move

0 32
1 7326
andyzh@zhangboshuideMacBook-Pro Project1_2020 %
```

**JimmyPlayer.jar**



```
0  0  0  0  0  0  0  --  46

WINNER: Player 1 (nc localhost 12345)
SCORE: 6

Player 2 (java -jar Test_Agents/JimmyPlayer.jar): 43 moves, 96 milliseconds per
move
Player 1 (nc localhost 12345): 48 moves, 6732 milliseconds per move

1 6732
0 96
```



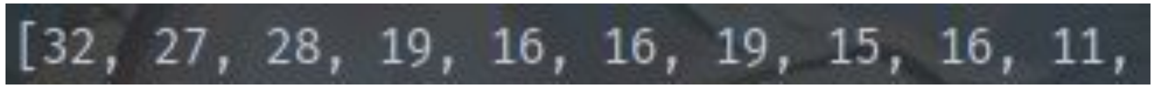
```
WINNER: Player 2 (nc localhost 12345)
SCORE: 10

Player 1 (java -jar Test_Agents/JimmyPlayer.jar): 30 moves, 108 milliseconds per
 move
Player 2 (nc localhost 12345): 51 moves, 5717 milliseconds per move

0 108
1 5717
andyzh@zhangboshuideMacBook-Pro Project1_2020 %
```

# Alpha Beta Pruning Optimization

Python - depth = 8

- More than 1 mins per move

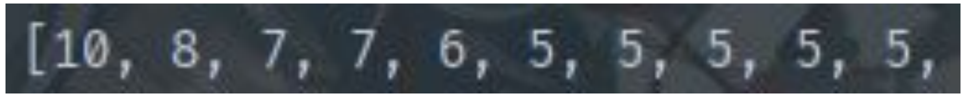
Java without Optimization depth = 10



```
[32, 27, 28, 19, 16, 16, 19, 15, 16, 11,
```

In seconds

Java with Optimization depth = 10
(multi-threading, etc...)



```
[10, 8, 7, 7, 6, 5, 5, 5, 5, 5,
```

In seconds

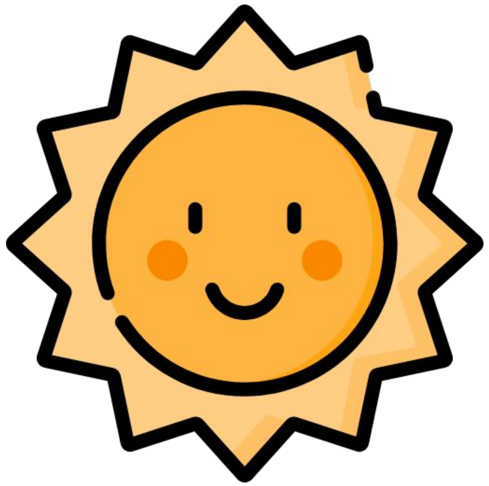
## Expected accomplishment

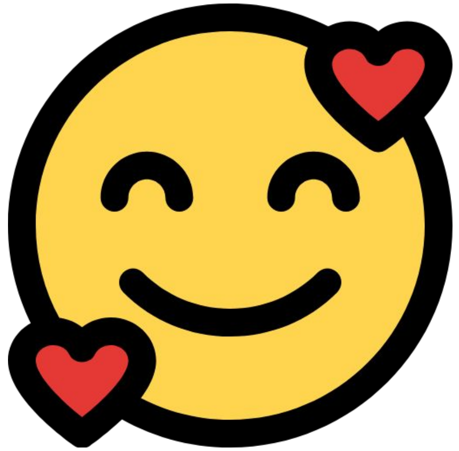
- We will submit the Java Implementation of Alpha Beta Pruning Agent.
- We will have tests to ensure correctness of our code
- Ensure runtime is within time limit
  - For the first several steps,  higher searching depth
  - With time elapsing, reduce searching depth
- To be Top 10 in the tournament.

## Thank You!

Group 36

- Bushui
- Weilue
- Yecheng
- Zhaoyu





https://github.com/Redcxx/KalahPlayer