Introduction to AI 2020 spring final project

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The Task

- As in the decription of the assignment
- A variant of orthello that the inner $6*6$ board can be placed at any time and the corners of the board are removed

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Agent Design

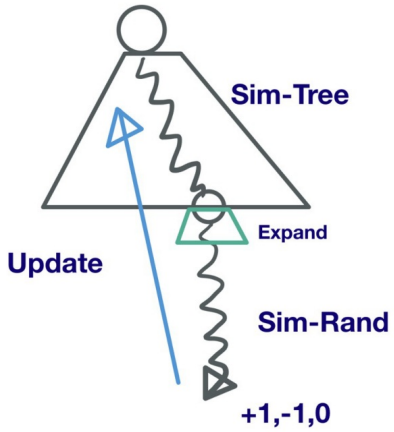
Our agent utilizes both MCTS and Min Max Search to play the designated variant of orthello. We use MCTS as the backbone of our algorithm, and include 3 main improvements to the Vanilla MCTS algorithm, listed as followed.

- Heuristic guided simulation (HS)
- Min Max Agent for closing Game (MC)
- Min Max Search for closing simulation (MS)

the details of MCTS algorithm and the features(HS/MC/HS) will be covered in the following sections.

Basic of Monte Carlo Tree Search

- For each step, MCTS agent do thousands of simulation of the game guided by UCB1 score
- The basic of MCTS can be visualize with the following figure



- we won't cover the very detail of the algorithm please refer to the wiki page
  - https://en.wikipedia.org/wiki/Monte_Carlo_tree_search
- UCB1 score is defined as follow
  - $vis(u)$:=# of visit to node u
  - c:= a constant of exploration
  - $UCB(u)=\frac{\#\text{ of win}}{vis(u)}+c\sqrt{\frac{\ln(\sum vis(u\text{'s parent}))}{vis(u)}}$
- For each simulation
  - step 0: game tree is clear, only root have been expanded
  - step 1: select (sim-tree)
    - start from root
    - recursively pick the node with highest UCB1 score
    - until reach an unexpanded node
  - step 2: expand (expand)
    - on reaching an unexpanded node
    - expand the node and init its children with default value
  - step 3: rollout (sim-rand)
    - simulate the game to the end by random
  - step 4: backpropagation (upgrade)
    - update the (expanded) nodes on the path with the simulate game result
- after the sumulations, the algorithm return the "most vistied child" of root as the move predicted by the agent

Heuristice Guided Simulation(HS)

- We use a heuristic to guide the roll out process of
- Instead of sampling from uniform distribution, we sample by a heuristic weighted distribution
- The heuristic is defined as follow
  - $H(pos)=1$, if pos is adjacent to the edges of board
  - $H(pos)=3$, if pos is on the edges of board
  - $H(pos)=2$, otherwise
- The implementation detail of HS is as follow
  - $moves$ = all possible moves in the current board
  - $sum=\sum moves[i]*H(moves[i])$
  - $pre[i]=$ prefix sum of $H[i]$

- sample d randomly with $\text{rand}()\text{mod}\text{sum}$
- find i such that $d \geq pre[i-1]$ and $d < pre[i]$
- use $move[i]$ as the sampled result

Min Max search Agent for closing Game(MC)

- An improvement is bound to be made if we use exhaustic search instead of probabilistic approximation method(like MCTS)
- But since the seach space is way too large, it's almost impossible to apply exhaustic search at the beginning.
- However, we can mix the two types of agent so that MCTS deals with the earlier stages of games and Min-Max Search deals with the end games.
- This is the MC improvement

A prunning strategy

- A well known prunning strategy called alpha-beta prunning is apllied

Min Max Search for closing simulation(MS)

- Another possible way to improve the MCTS agent is again trying to improve the simulation process
- Using exhaustic search at the end of each simulation should improve the performamce by lowering bias(more closed to the optimal strategy) and variance(since exhaustic search is deterministic)

Experiment

- There are some difficulties to do experiment:
  - since two games requires about $5 * 64 * 2$ seconds to run.
  - and I donnot have a good Win10 system computer at hand.
- So even with a python script, we are not able to conduct too many experiments on the constant c_{UCB1} and experiment on afferent H
- But still a couple of meanningful experiments show positive result on the features(HS/MC/MS) proposed
- In the statement
  - MS agent = Vanilla MCTS + MS improvement
  - MS+HS = Vanilla MCTS + MS improvement + HS improvement
  - MS/HS+HC = game between MS and HS+MC
- Discussions of the experimental result will be cover in detailed in the discussion sections

Time Limit and Agent Strength

- agent strength grows with time limit
- when changing 1.8 second time limit to 4.8 second (vanilla MCTS)
- 4.8 agent had 100% winrate on 1.8 second agent

Heuristice Guided Simulation(HS)

- HS wins 75% of games against Vanilla MCTS

- losing game was when HS took black stone

Min Max search Agent for closing Game(MC)

- HS+MC wins 100% of games against HS counterpart

Min Max Search for closing simulation(MS)

- At the beginning of experiment, MS agent kept exceeding time limit of 5 second since the last iteration can take a lot of time to complete
- by reducing the theshould (i.e. the empty cells count), we finally did successful experiments of MS/HS, MS/HS+HC
- the result shows that MS with time limit lost games to its counterparts

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Discussion

Reason of Algorithn designs

Why not deep learning

- I have heard from Dr. I-Chen Wu that Alpha Zero did not perform well on the original game of orthello
- CNN may fail to capture the key information required for the original game of orthello
- I have though of adding hand craft feature(parity…) to improve performance of neural models, but since the lack of time I chose not to risk it.
- There is no data for the variant of orthello, meanning that we can only use alpha zero(means a lot of computational resources is required), or hope fine-tuning can work
- The course is named “Introduction to AI”, study of classical AI algorithms are more to the topic of the course.

Why chose MCTS

- There are two main approaches to reinforcement learning - MC and TD
- MC stands for Monre Carlo
  - Samples from distribution to try to approximate real value
  - High Variance, Low Bias
- TD stands for Temperal difference
  - Use
  - Low Variance, High Bias
- MCTS belongs to the type of MC method
- Since the game of orthello tends to shift a lot between each steps, I do not think that TD method is suitable for the task

The reason for advicing the features

- Heuristic for MCTS roll out
  - Utilizing the domain knowledge that taking edges is usually better.
- Min max for MCTS roll out
  - Using exhaustic search at the end of each simulation should improve the performamce by lowering bias(more closed to the optimal strategy) and variance(since exhaustic search is deterministic)

    - However according to our experiments, when fixing the “thinking time”, the cost the search is not of more value than doing more simulation
- Min max for Closing game
    - Closing game with exhaustic search is better than closing game with MCTS when time limit allows.
    - Can be consider a aggregation of models with discrete flag

A noticible second-go advantage

- Most board games have first-move advantage that can be proven by swapping arguement
- However, orthello, and the variation of it, cannot use the swapping arguement, since redundant move can be shown to be harmful to a player
- It seems that reacting after opponent’s move is a good strategy in orthello.
- This reflects the fact that most match-ups in our experiment have second-go advantage.

Future Work

- More experiments can be conducted to search for optimal c_{UCB1}
- More experiments can be conducted to search for a better H function
- Can still try RL algorithms combined with function approximation strategy(ex: NN) like DQN, A2C, Alpha Zero, etc.
    - Learning to Play Othello with Deep Neural Networks
    - Application of reinforcement learning to the game of Othello
    - Mastering the Game of Go without Human Knowledge