

Project 2-1

Backgammon
Group 19

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Tossaint

Randomness AI

- Chooses a move from set of possible moves
- Fully random
- No learning/ analyzing
- Tool for comparison
- $O(n)$

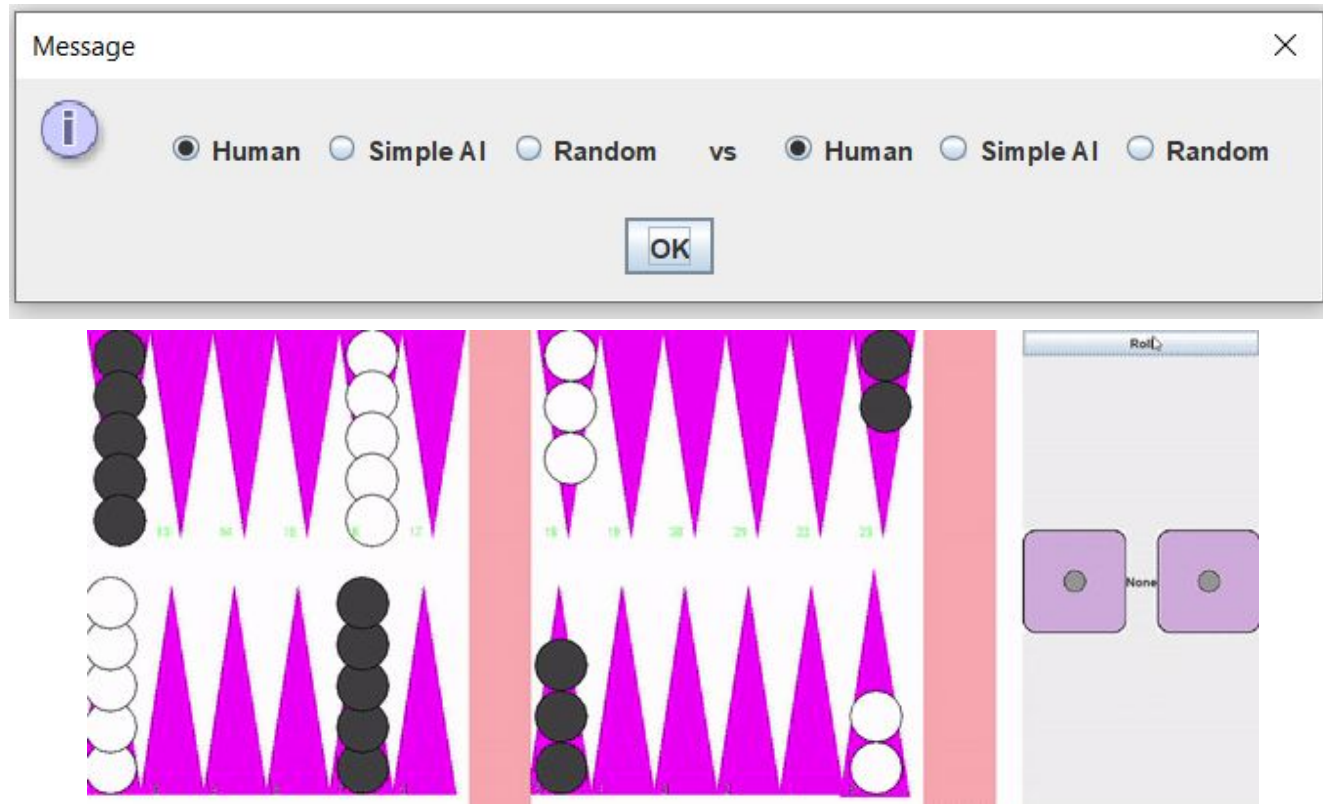
Simple AI

- Evaluates moves using Evaluation Function
- Chooses move with the highest value
- Basic analysis
- $O(n)$

Evaluation Function

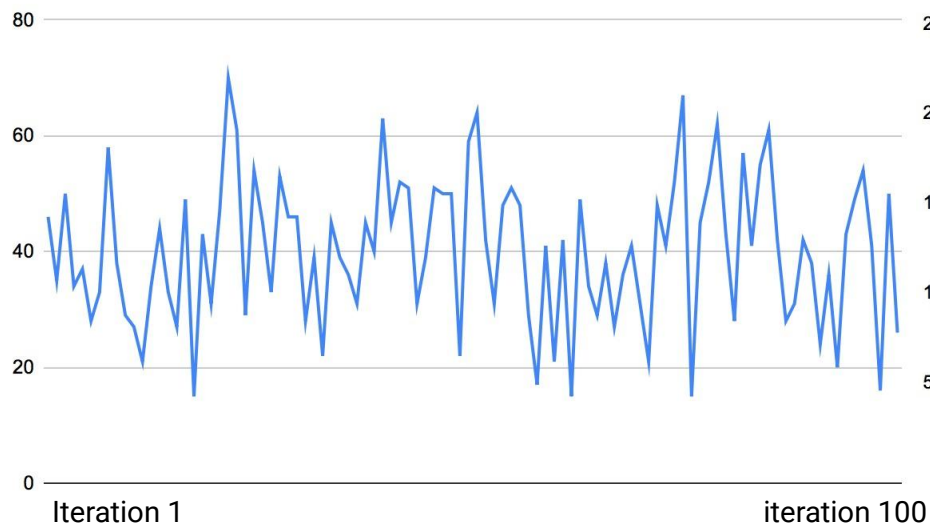
$$\frac{|distance|}{6} - soloStones \times probability + \frac{gates}{3} + hitStone + takenStones$$

Integration with UI

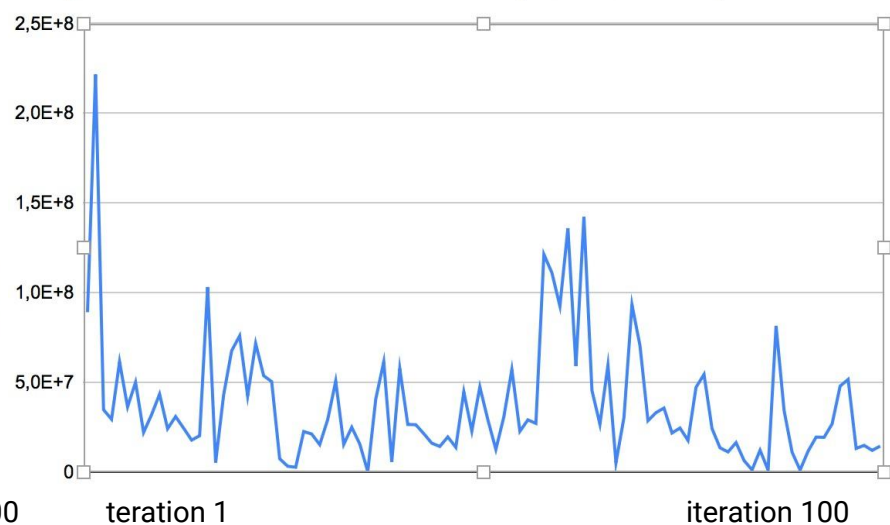


Comparison

Simple AI vs Random, Rounds per iteration

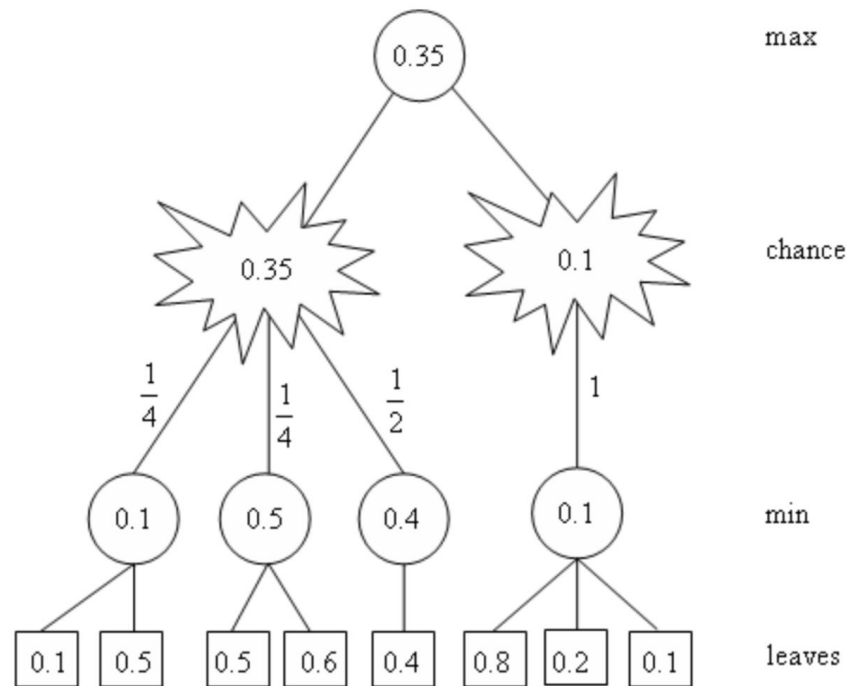


Simple AI vs Random AI Run times (nano seconds)



Expectimax AI

- Chooses move depending on opponent's optimal move
- Root in max \rightarrow optimal value of children
- Root in min \rightarrow worst value of children
- Chance layer \rightarrow Add value \times probability
- Depth first search
- $O(n^2)$



Monte Carlo Search Tree

- Tree of nodes
- Each node contains:
 - Boardstate
 - Win ratio
- Evaluation by Playouts
- Weight that relies on the long-term effect of moves

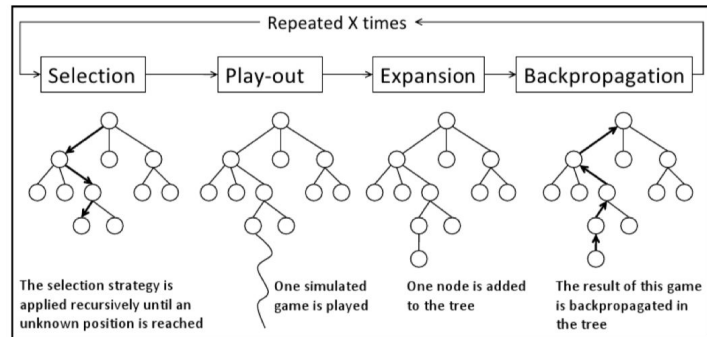


Figure 2: Outline of the Monte-Carlo Tree Search [19].

- Four phases
 - Selection
 - Play-out
 - Expansion
 - Backpropagation

Time complexity of monte carlo tree search

It does four steps of n iterations

$O(n * (\text{selection} + \text{expansion} + \text{simulation} + \text{backpropagation}))$

Expansion add a node which we can do in constant time
so

$O(n * (\text{selection} + \text{simulation} + \text{backpropagation}))$

Given the branching factor b , and d as the depth of our tree, the selection phase runs in $O(b * d)$, so

$O(n * (b * d + \text{simulation} + \text{backpropagation}))$

Backpropagation and simulation takes time proportional to the depth of the tree as well, so that becomes:

$O(n * (b * d + d + d))$

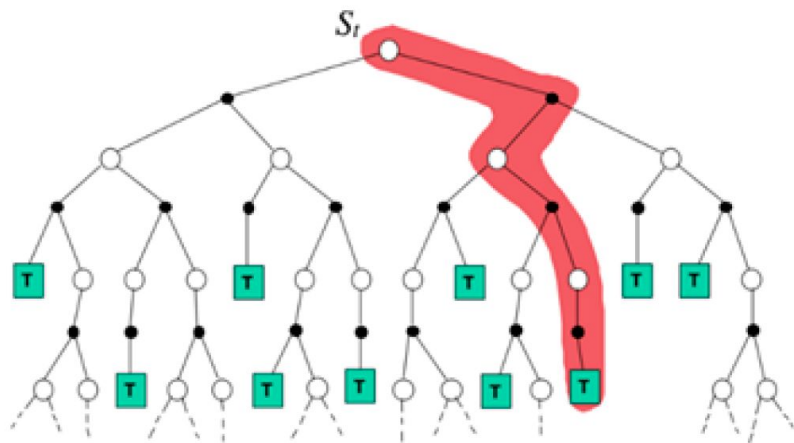
TD-Gammon

- Trains a 3 layer feed-forward network to compute utility of a given board configuration
- Backpropagate expected utility from next step as “expected”/ground truth output from current step
- At end of game send 1 as reward for a win, -1 for a loss

TD-Gammon

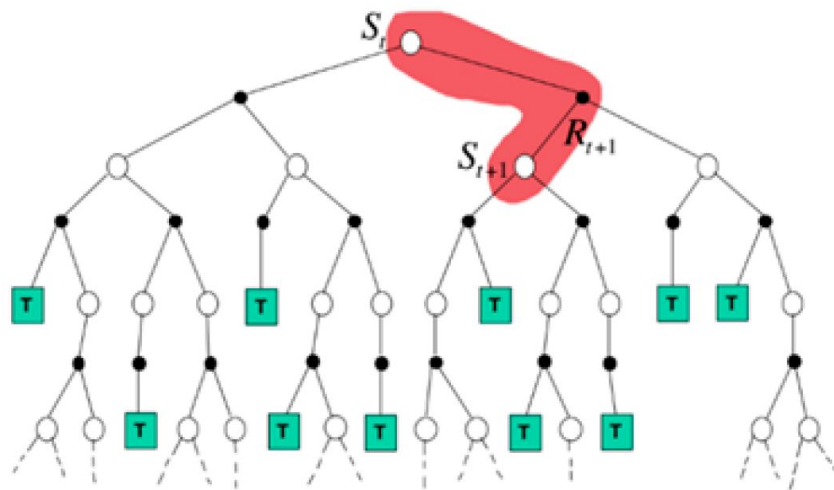
Monte Carlo

$$V(S_t) \leftarrow V(S_t) + \alpha [G_t - V(S_t)]$$



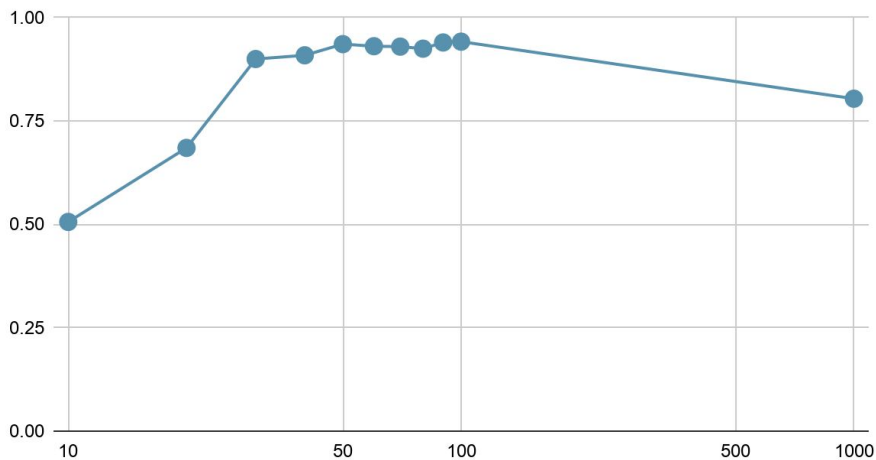
Simplest TD Method

$$V(S_t) \leftarrow V(S_t) + \alpha [R_{t+1} + \gamma V(S_{t+1}) - V(S_t)]$$

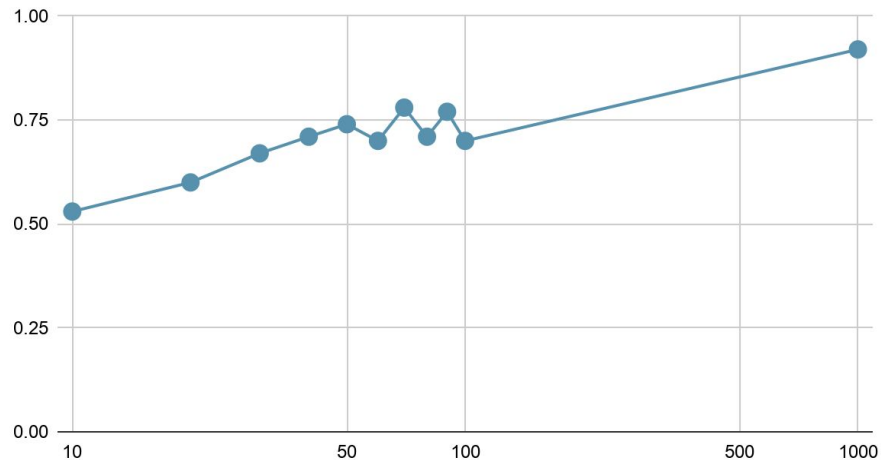


TD-Gammon

Games won against random agent



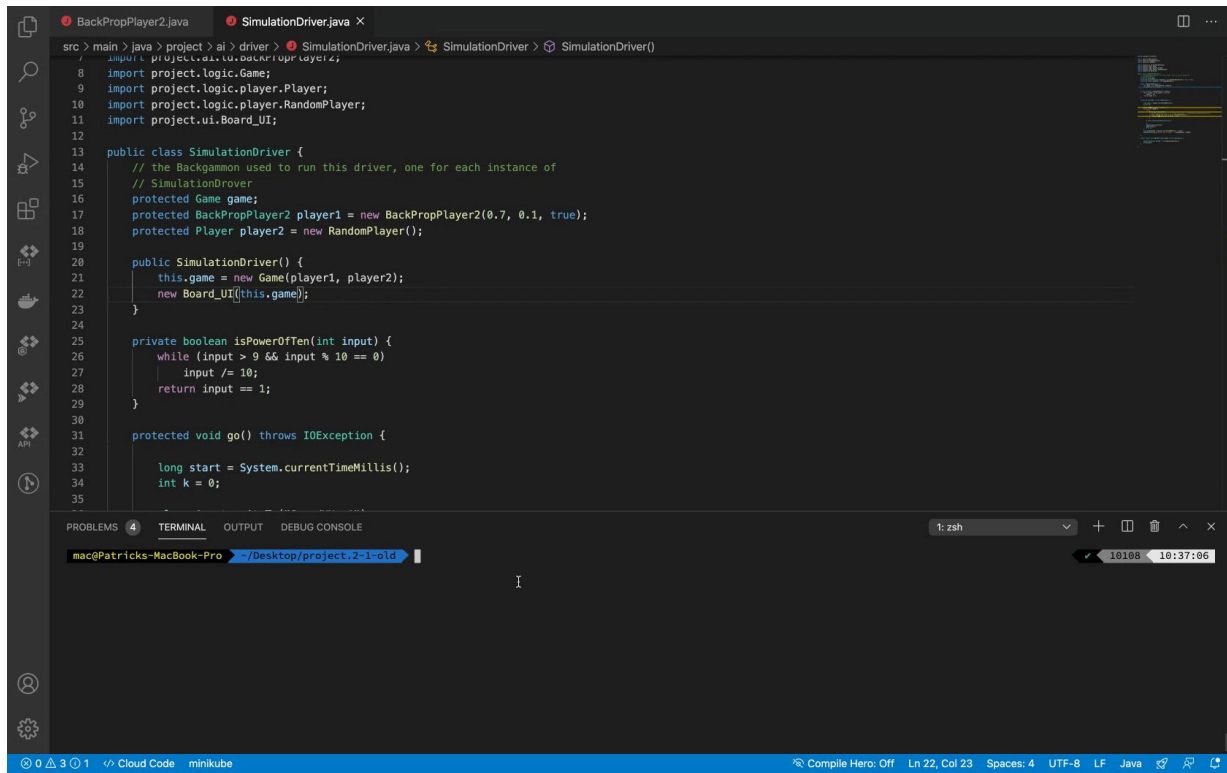
Games won against random agent w/ randomized weights



TD-Gammon Improvements

- Plateau at ~93% win-rate against random agent
- Train for longer
- Alter depth of network

Time per move: 1.17ms
Regardless of “search depth”



```
BackPropPlayer2.java SimulationDriver.java X
src > main > java > project > ai > driver > SimulationDriver.java > SimulationDriver > SimulationDriver()
7 import project.ai.to.board.uprayer;
8 import project.logic.Game;
9 import project.logic.player.Player;
10 import project.logic.player.RandomPlayer;
11 import project.ui.Board_UI;
12
13 public class SimulationDriver {
14     // the Backgammon used to run this driver, one for each instance of
15     // SimulationDriver
16     protected Game game;
17     protected BackPropPlayer2 player1 = new BackPropPlayer2(0.7, 0.1, true);
18     protected Player player2 = new RandomPlayer();
19
20     public SimulationDriver() {
21         this.game = new Game(player1, player2);
22         new Board_UI(this.game);
23     }
24
25     private boolean isPowerOfTen(int input) {
26         while (input > 9 && input % 10 == 0)
27             input /= 10;
28         return input == 1;
29     }
30
31     protected void go() throws IOException {
32         long start = System.currentTimeMillis();
33         int k = 0;
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Python TD-Gammon



- TD gammon in python
- Neural network did not have time to train (acting randomly).
- 198 input vector, 50 hidden units, 4 output vector.
- All sigmoid functions (hidden/output)
- Output: white win or black win, gammon or normal win

TD-gammon vs human

Conclusion

- Monte Carlo Tree Search outperforms TD-Gammon in skill
- TD-Gammon requires training, but in-game execution is faster than multi-level search algorithms
- TD gammon implementation shows 93% win-rate against random agents.
- ExpectiMax algorithm including chance nodes
- Backgammon implemented both in Java and Python