Monte-Carlo Tree Search

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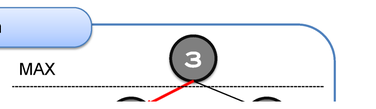
ABSTRACT HERE.....

Minimax Algorithm: the brute force solution

For the MAX player
1. Generate the game to terminal states
2. Apply the utility fun
   states
3. Back-up values
   - At MIN ply assign
   - At MAX ply assigr
4. At root, MAX choos
   led to the highest p

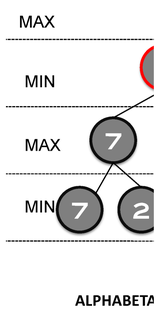
- Perfect play for deter
  information games
- The program must ass
  opponent will select it
  make no mistakes
- Totally impractical sinc
  whole tree
  - Time complexity is
  - Space complexity i



AlphaBeta: an improvement of Minimax

Algorithm : a MiniMax with pruning.

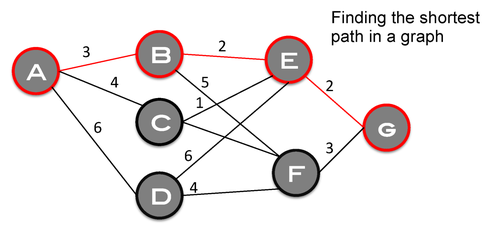
- ALPHABETA takes advantage of the calculated states when determining **whether** to continue searching a particular subtree or prune it.
- Pruning does not affect final result.
- Good move ordering improves effectiveness of pruning.
- Time complexity
  - $O(b^{d/2})$
  - means we go from an effective branching factor of b to sqrt(b) (e.g. 35 -> 6 for chess).



ALPHABETA

Dynamic programming:

- Dynamic Programming is a method used to optimize the objective function in a planning problem.
- Recursively **decompose** the problem into subproblems, solve subproblems and construct the global solution.
- However, the algorithm is **not anytime**; if stopped before then, there is no result.
- Can be seen as one player game against a **random** player.



Monte-Carlo Tree search: Algorithm sketch

Input: a situation s
Output: a (hopefully good) move m for situation s
Memory = empty; statistics = empty mapping

```
While (time left > 0)
   s'=s, game = ()

        While (s' in memory, not terminal)
                s'= reachable situation such that nbWins(s') / nbSims(s') max
        endwhile
        s''=s'

        While (s' not terminal)

                s'= random reachable situation from s'
        endwhile
        result = result(s')     memory = memory + s''

        for all states in the simulation
                statistics(s) = statistics(s) + statistics(game,result)
        endfor

endwhile
```

Restart games

Choose move to be explored Using statistics

Choose move to be explored

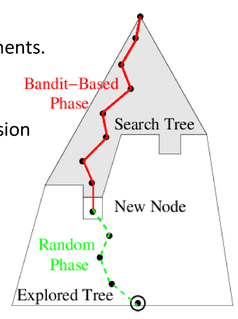
Update statistics

Monte-Carlo Tree search: how it works ?

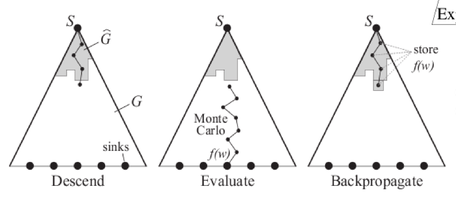
Algorithms for taking decisions in uncertain environments.

Principles:

- Iteratively growing **unbalanced** tree (choosing a decision is seen as bandit problems – UCT).
- Random simulations (Monte-Carlo simulations as an **evaluation** function).



3 steps loop while time budget > 0



G: Real tree
G^: Constructed tree

K-one armed bandit problem

- Problem Description :
  $p_1,\dots,p_N$ unknown probabilities $\in [0,1]$
  At each time step $t \in \{1,\dots,N\}$
  - Choose arm $a_t \in \{1,\dots,N\}$ (as a function of a_j and r_t $j<t$)
  - With probability $p_{j,t}$
    - win ($r_t = 1$)
    - loose ($r_t = 0$)
- Goal: minimize a Regret: $R_N = N \max\{p_i\} - \sum r_t \quad (t<N)$

Classical solution:
UCB: Choose arm j maximizing the compromise:

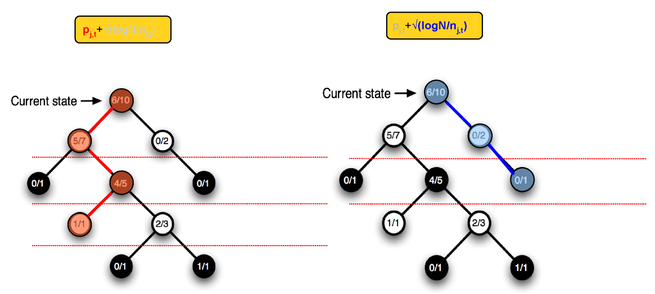
$$p_{j,t} + \sqrt{(\log N / n_{j,t})}$$

(Lai et al; Auer et al)

$p_{j,t}$:Empirical average for decision j
N :Total number of trials
$n_{j,t}$:number of trials with decision j

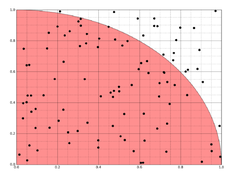
- Optimal regret O(log(n))

Exploitation vs Exploration dilema



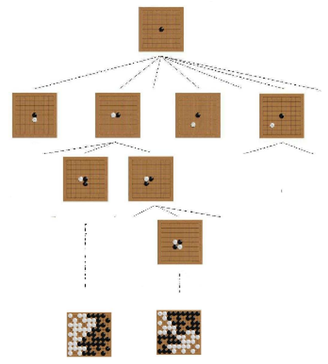
Monte-Carlo simulations

- **simulations to approximate pi**



```
double nbTotalPoints = 0;
double nbPointsInSquare = 0;
double PI;
int timeLeft = 10000;
double x, y;

srand(time(NULL));
cout <<"**** Estimating PI by Monte-Carlo Simulations ****"<<endl;

while (timeLeft > 0) {
  x = (double)(rand() % 10) / 10;
  y = (double)(rand() % 10) /10;

  nbTotalPoints ++;

  if ((sqrt (x * x + y * y)) < 1) {
    nbPointsInSquare ++;
  }
  timeLeft --;
}

PI = 4 * (nbPointsInSquare / nbTotalPoints);
```

- **Simulations to find the optimal move**



Monte-Carlo evaluation function consists in starting from the postion and playing with a *simulation policy* until the end of the game. Then the game is scored exactly simply using the rules.