Monte-Carlo Tree Search

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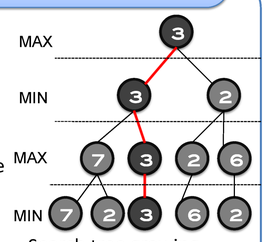
ABSTRACT HERE.....

Minimax Algorithm: the brute force solution

For the MAX player
1. Generate the game to terminal states
2. Apply the utility function to the terminal states
3. Back-up values
   - At MIN ply assign minimum payoff move
   - At MAX ply assign maximum payoff move
4. At root, MAX chooses the operator that led to the highest payoff



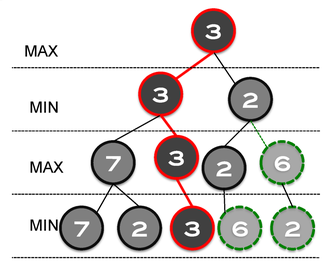
Search tree growing **exponentially** with the depth !

- Perfect play for deterministic, perfect-information games
- Assume that the opponent will select its best move choice and make no mistakes
- Totally impractical
  - Time complexity is $O(b^d)$
  - Space complexity is $O(b^d)$

AlphaBeta: an improvement of Minimax

- Algorithm : a MiniMax with **pruning**.

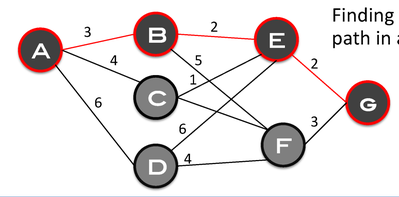
  ALPHABETA takes advantage of the calculated states when determining whether to continue searching a particular subtree or prune it.
- Pruning does not affect final result.
- Good move ordering improves effectiveness of pruning.
- Time complexity
  - **$O(b^{d/2})$**
  - means we go from an effective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



ALPHABETA twice faster

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.



Finding the shortest path in a graph

Monte-Carlo Tree Search: Algorithm sketch

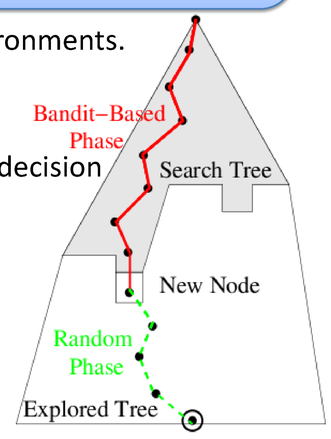
Input: a situation s
Output: a (hopefully good) move m for situation s
Memory = empty; statistics = empty mapping

```
While (time left > 0)                                   <- Restart games
  s'=s, game = ()

      While (s' in memory, not terminal)
            s'= reachable situation such that nbWins(s') / nbSims(s') max   <- Choose move to be explored Using statistics
      endwhile
      s''=s'

      While (s' not terminal)

            s'= random reachable situation from s'
      endwhile
      result = result(s')     memory = memory + s''     <- Choose move to be explored

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

endwhile
```

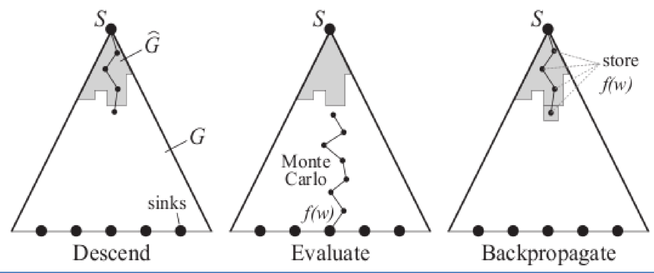
MCTS: how it works ?

- 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



K-armed bandit problem

- Problem Description :
  $p_1,...,p_N$ unknown probabilities $\in [0,1]$
  At each time step $t \in \{1,...,N\}$
  - Choose arm $a_t \in \{1,...,N\}$ (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: $R_N = N \max\{p_i\} - \sum r_t$ $(t<N)$

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

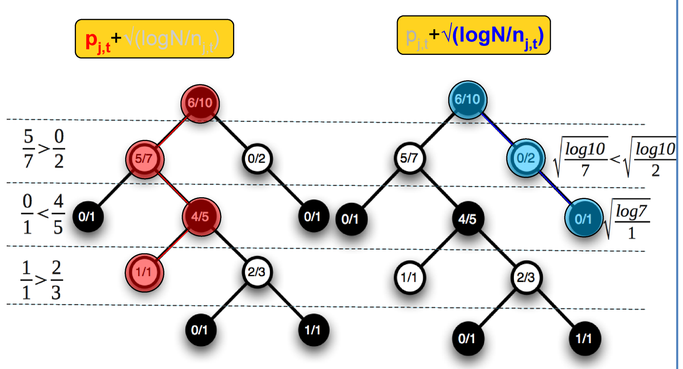
$$p_{j,t} + \sqrt{(\log N / n_{j,t})}$$

(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

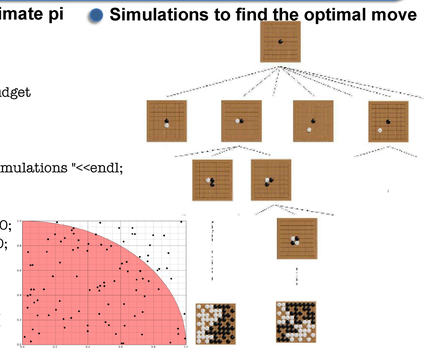


K-armed bandit problem

simulations to approximate pi

```
.....
double nbTotalPoints = 0;
double nbPointsInSquare = 0;
double PI;
int timeLeft = 10000; // time budget
double x, y;

srand(time(NULL));
cout << "Estimating PI by MC 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.

MoGo: record of achievement

2011 : First win against a pro (6D) H2 in 13x13	MoGoTW
2011 : First win against a pro (9P) H2.5 in 13x13	MoGoTW
2011 : First win against a pro in Blind-Go in 9x9	MoGoTW
2010 : Gold medalist in TAAI 2010 in three categories: 9x9 Go, 13x13 Go, 19x19 Go.	MoGoTW
2007: win against a pro (5p) in 9x9 (blitz)	MoGo
2008: win against a pro (5p) in 9x9 white	MoGo
2009: win against a pro (5p) in 9x9 black	MoGo
2009: win against a pro (9p) in 9x9 black	MoGoTW
2008: win against a pro (8p) 19x19, H9	MoGo
2009: win against a pro (9p) 19x19, H7	MoGo
2009: win against a pro (1p) 19x19, H6	MoGo

MCTS = an efficient approach for taking decisions under uncertainty

Application to energy

- MCTS in the continious domain
- Energy plant managment
- Financial market
- Application to partially observable problems