

# Monte-Carlo Tree Search

## An introduction

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# Introduction

# Monte-Carlo Tree Search (MCTS)

- ▶ MCTS is a recent algorithm for *sequential decision making*
- ▶ It applies to *Markov Decision Processes* (MDP)
  - ▶ discrete-time  $t$  with finite horizon  $T$
  - ▶ state  $\mathbf{s}_t \in \mathcal{S}$
  - ▶ action  $\mathbf{a}_t \in \mathcal{A}$
  - ▶ transition function  $\mathbf{s}_{t+1} = \mathcal{P}(\mathbf{s}_t, \mathbf{a}_t)$
  - ▶ cost function  $r_t = \mathcal{R}_{\mathcal{P}}(\mathbf{s}_t)$
  - ▶ reward  $R = \sum_{t=0}^T r_t$
  - ▶ policy function  $\mathbf{a}_t = \pi_{\mathcal{P}}(\mathbf{s}_t)$
  - ▶ we look for the policy  $\pi^*$  that maximizes expected  $R$

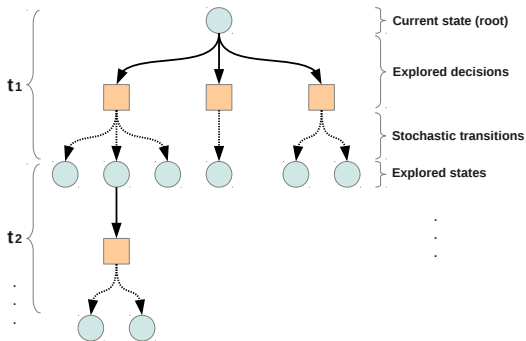
# MCTS strength

- ▶ Mcts is a versatile algorithm (it does not require knowledge about the problem)
- ▶ especially, does not require any knowledge about the Bellman value function
- ▶ stable on high dimensional problems
- ▶ it outperforms all other algorithms on some problems (difficult games like Go, general game playing, ...)

# MCTS

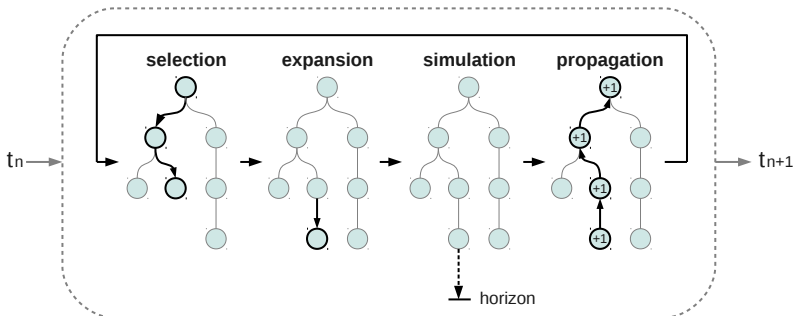
Problems are represented as a tree structure:

- ▶ blue circles = states
- ▶ plain edges + red squares = decisions
- ▶ dashed edges = stochastic transitions between two states



# Monte-Carlo Tree Search

# Main steps of MCTS



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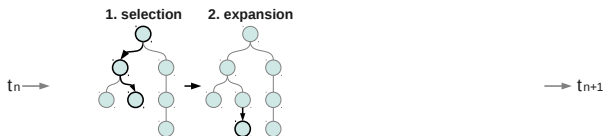


Starting from an initial state:

1. select the state we want to expand from



# Main steps of MCTS

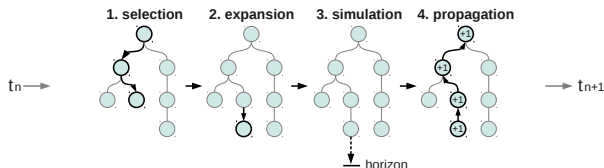


Starting from an initial state:

1. select the state we want to expand from
2. add the generated state in memory



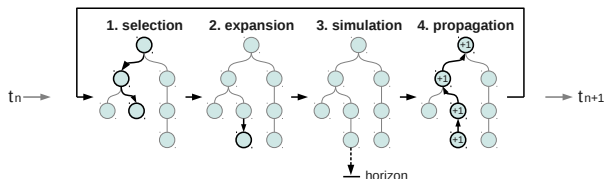
# Main steps of MCTS



Starting from an initial state:

1. select the state we want to expand from
2. add the generated state in memory
3. evaluate the new state with a default policy until horizon is reached
4. back-propagation of some information:
  - ▶  $n(\mathbf{s}, \mathbf{a})$  : number of times decision  $\mathbf{a}$  has been simulated in  $\mathbf{s}$
  - ▶  $n(\mathbf{s})$  : number of time  $\mathbf{s}$  has been visited in simulations
  - ▶  $\hat{Q}(\mathbf{s}, \mathbf{a})$  : mean reward of simulations where  $\mathbf{a}$  was chosen in  $\mathbf{s}$

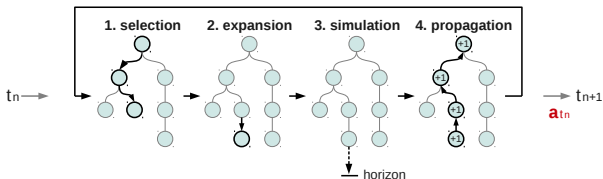
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# Main steps of MCTS



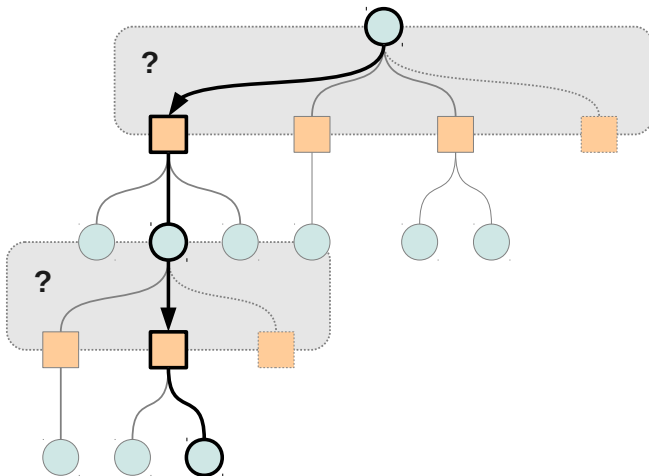
## The selected decision

$\mathbf{a}_{t_n}$  = the most visited decision form the current state (root node)

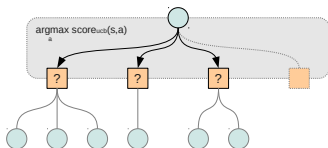
# Selection and expansion

## Selection step

How to select the state to expand ?



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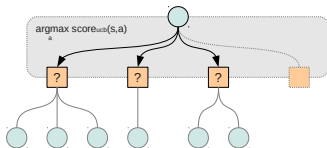
The *selection* phase is driven by *Upper Confidence Bound*

$$\text{score}_{\text{ucb}}(\mathbf{s}, \mathbf{a}) = \underbrace{\hat{Q}(\mathbf{s}, \mathbf{a})}_1 + \underbrace{\sqrt{\frac{\log(2 + n(\mathbf{s}))}{2 + n(\mathbf{s}, \mathbf{a})}}}_2$$

1. mean reward of simulations including action  $\mathbf{a}$  in state  $\mathbf{s}$
2. the uncertainty on this estimation of the action's value



## How to select the state to expand ?



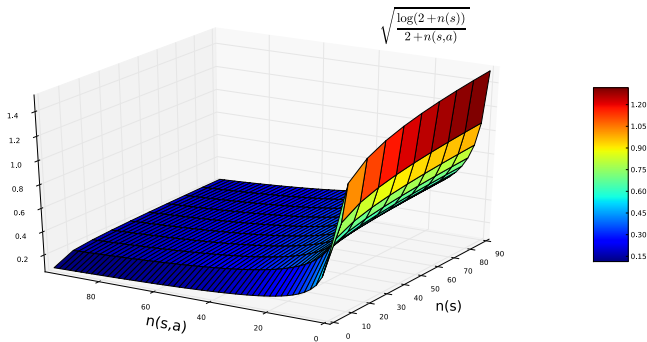
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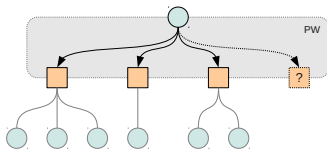
The selected action:

$$\mathbf{a}^* = \arg \max_{\mathbf{a}} \text{score}_{\text{ucb}}(\mathbf{s}, \mathbf{a})$$

# How to select the state to expand ?



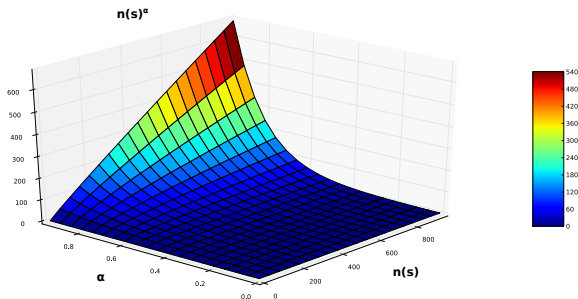
## When should we expand?



One standard way of tackling the exploration/exploitation dilemma is *Progressive Widening*.

A new parameter  $\alpha \in [0; 1]$  is introduced, to choose between exploration (add a decision to the tree) and exploitation (go to an existing node)

## How to select the state to expand ?

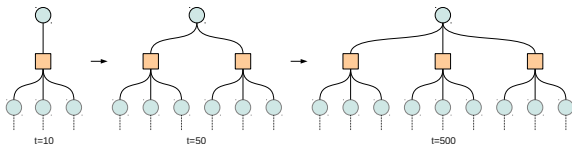


- ▶ if  $(|\mathcal{A}'_s| < n(s)^\alpha)$  then we explore a new decision
- ▶ else we simulate a known decision

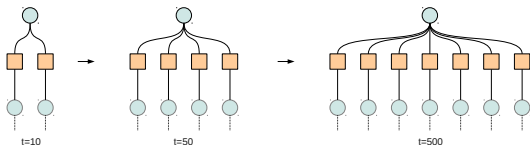
With  $|\mathcal{A}'_s|$  the number of legal actions in state  $s$

# When should we expand?

$$\alpha = 0.2$$



$$\alpha = 0.8$$



# References I