# Missions d'exploration multirobots décentralisée garantie

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LIX - Cosynus

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# Table of contents

# Introduction

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- Find a robust solution under realistic assumptions (communication. . . ) to multi-agents exploration problems

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- Probabilistic solutions:
  - Monte Carlo Tree Search (MCTS)
  - Variations

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- Probabilistic solutions:
  - Monte Carlo Tree Search (MCTS)
  - Variations
- (Use knowledge:
  - Epistemic logic
  - Assumption on the map)

# Multi-agent exploration problem

Assumptions:

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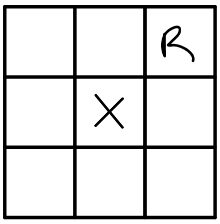
Possible directions:

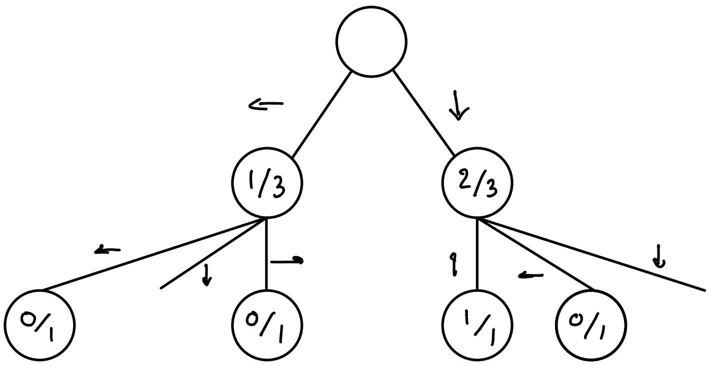
- Objectives
  - Auction methods
  - Allocation tasks
  - ...
- Planification
  - Heuristic methods (A*)
  - Frontier methods
  - ...
- Global
  - Learning methods
  - MCTS
  - ...

# MCTS - Example

Example:

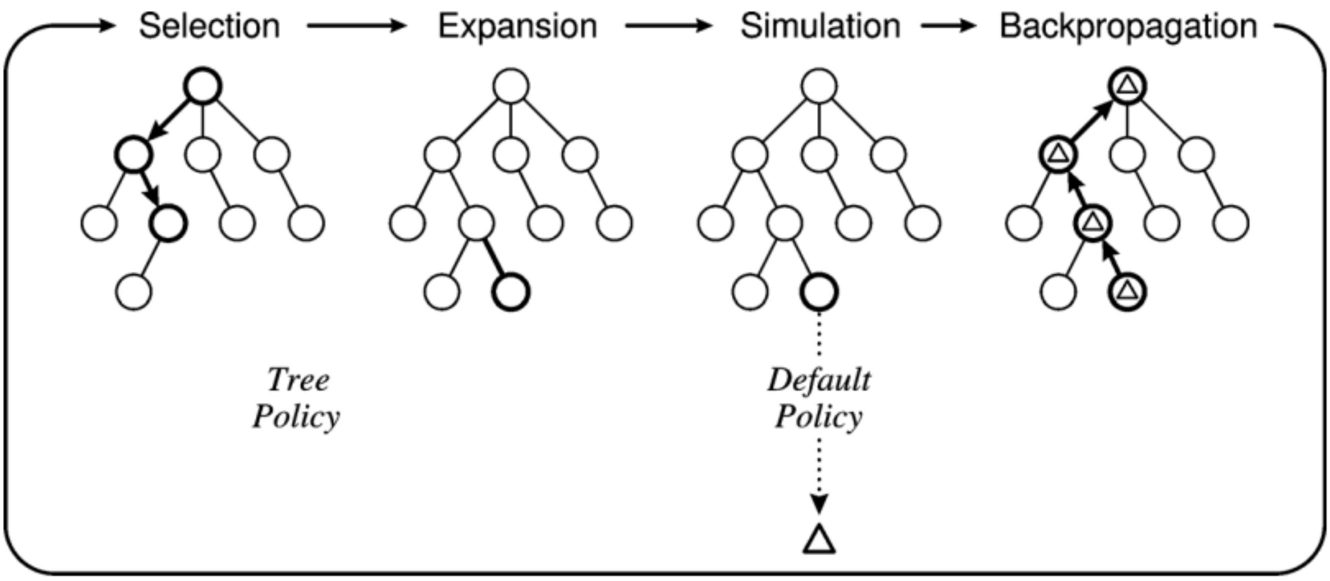
$$UCB = \bar{X} + \sqrt{\frac{2ln(n_{parent})}{n}}$$



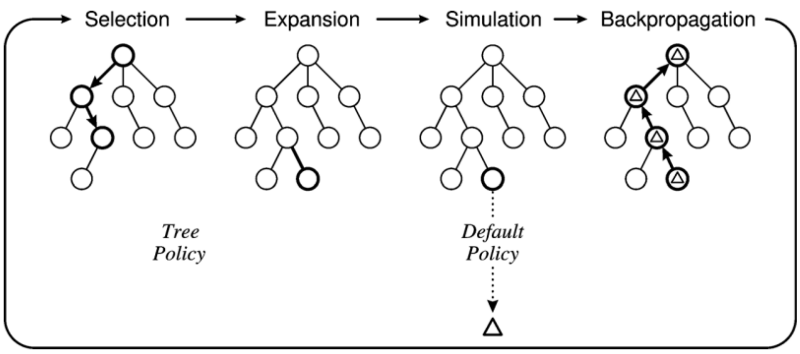
# MCTS

4 steps:



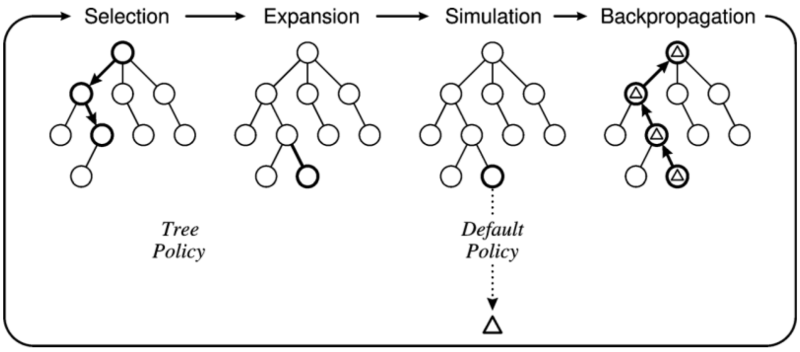

Browne et al. 2012

# MCTS




Usually:

# MCTS




Usually:

- Tree policy: Upper Confidence Bound $UCB = \bar{X} + \sqrt{\frac{2ln(n_{parent})}{n}}$

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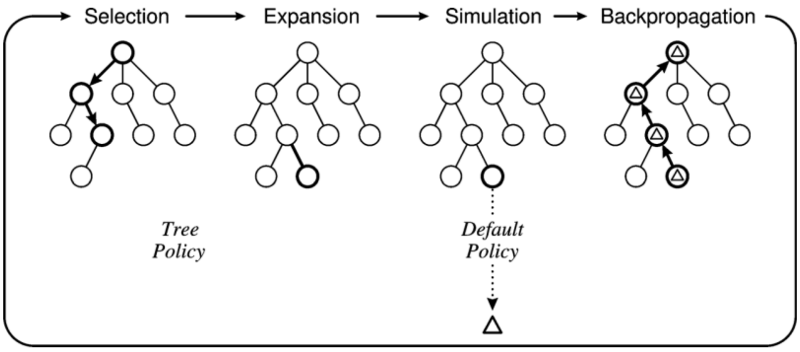


Usually:

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  $\rightarrow$ exploitation term + exploration term

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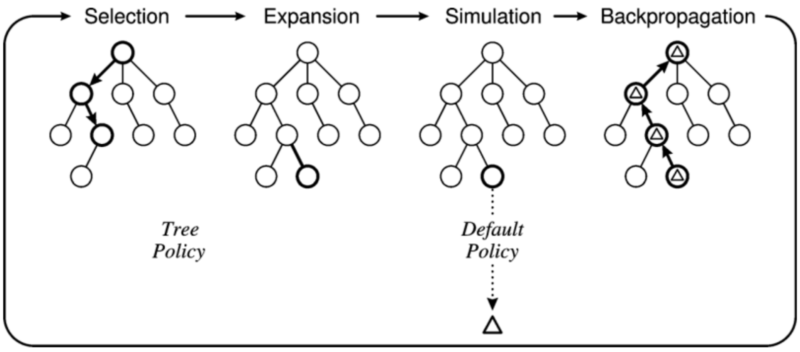


Usually:

- Tree policy: Upper Confidence Bound $UCB = \bar{X} + \sqrt{\frac{2ln(n_{parent})}{n}}$
  $\rightarrow$ exploitation term + exploration term
- Default policy: random choice

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$$UCB = \bar{X} + \sqrt{\frac{2 ln(n_{parent})}{n}}$$

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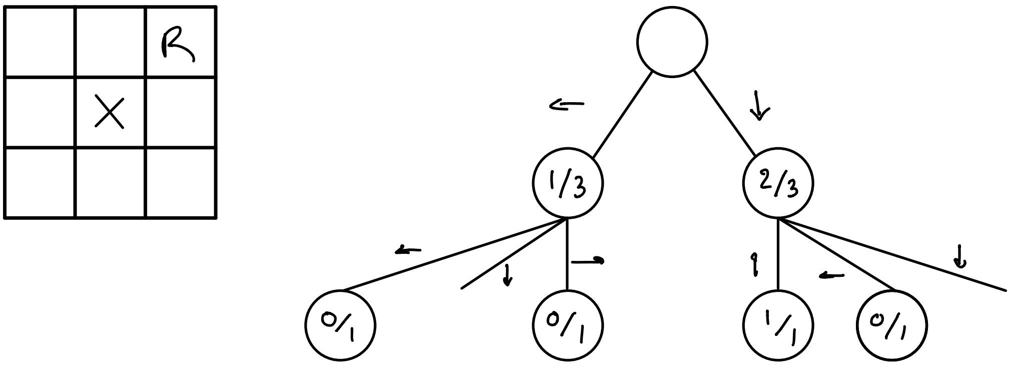
Selection



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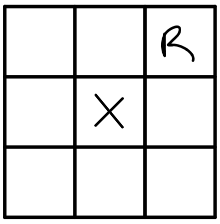
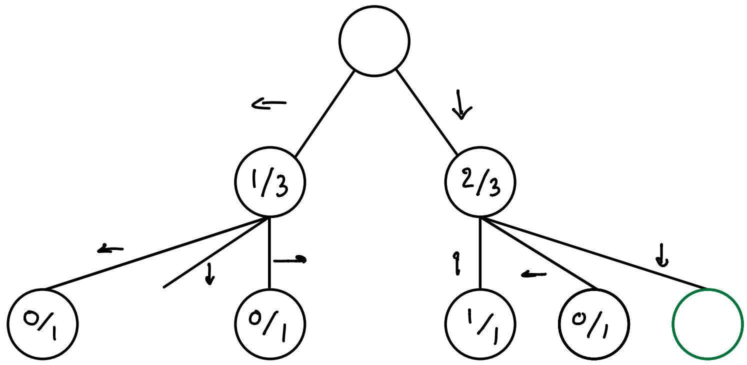
Example:

$$UCB = \bar{X} + \sqrt{\frac{2 ln(n_{parent})}{n}}$$

Expansion



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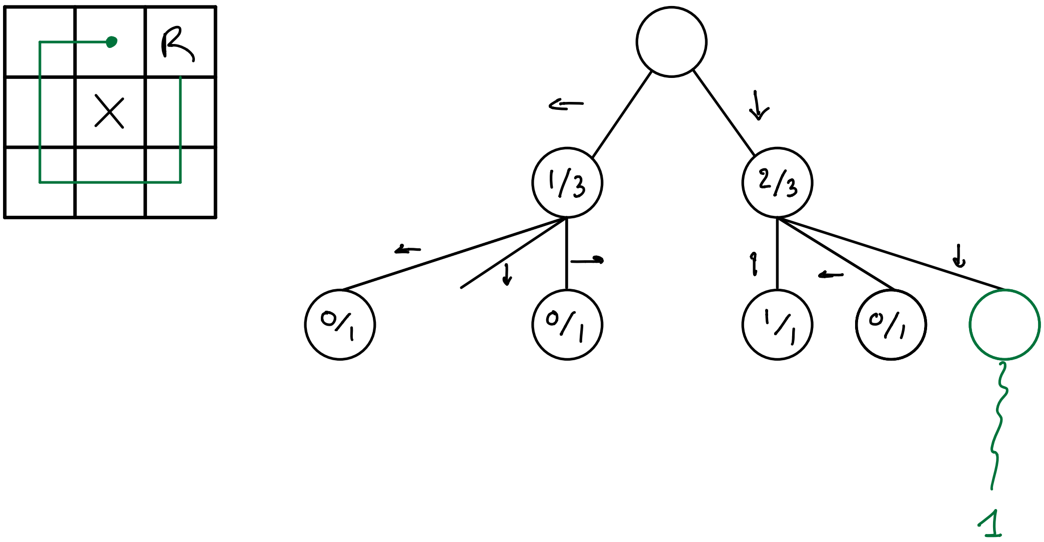
Example:

$UCB = \bar{X} + \sqrt{\frac{2 ln(n_{parent})}{n}}$

Simulation



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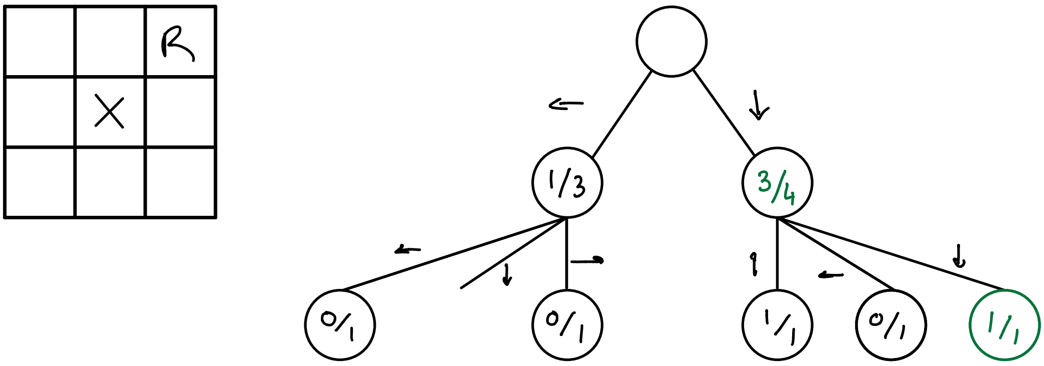
Example:

$UCB = \bar{X} + \sqrt{\frac{2ln(n_{parent})}{n}}$

Backpropagation + Selection



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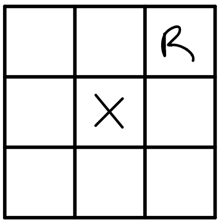


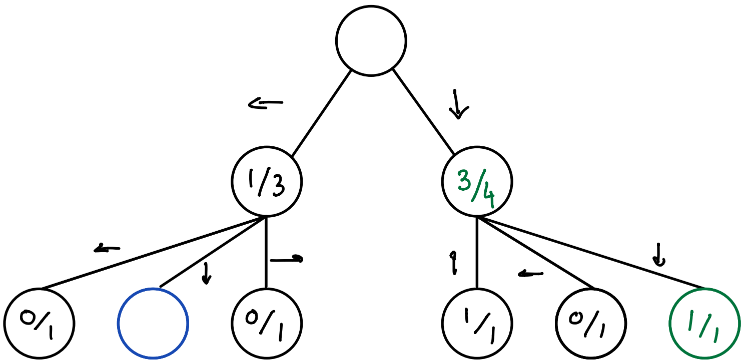

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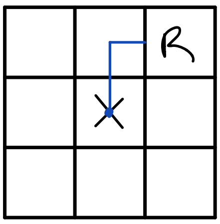


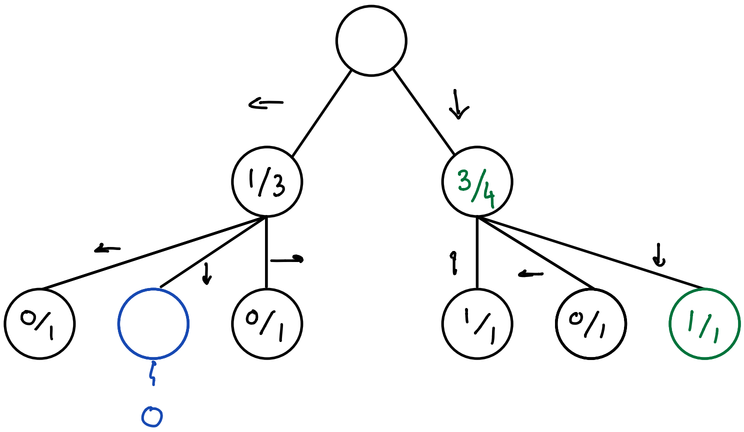

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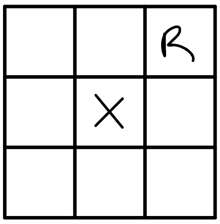
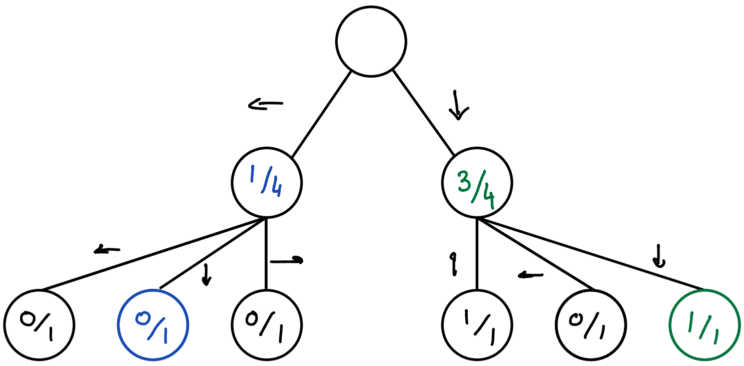
Backpropagation



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Example:

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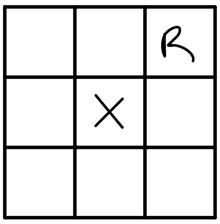
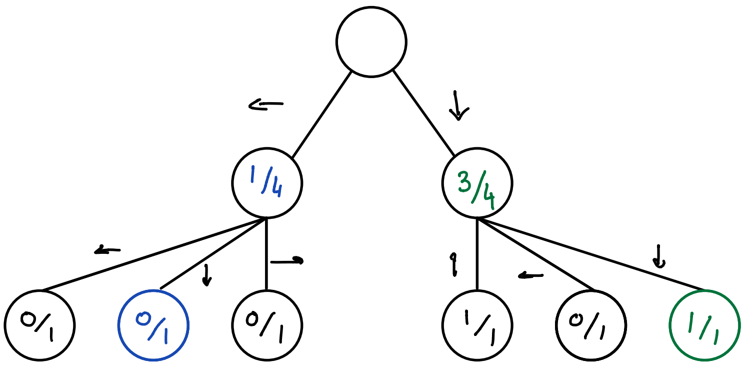
If end of rollout, choice of the real action $\rightarrow$ several criteria



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- Can usually demonstrate that UCB converges toward an optimal solution
- Easily parallelizable
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## Classic MCTS

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- Easily parallelizable
- Robust to the mission
- Online and offline solution

- Computing power
- UCB performs poorly in domains with many trap states

## Variations

- Decentralized MCTS : use communication to optimize its own tree and reduce computating
- Partially Observable environment : use the inherent properties (random) of MCTS and particle filter

# MCTS

## Decentralized MCTS

Problem: Multi-robot exploration mission + Decentralized

Best et al. 2019

# MCTS

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- 1 robot = 1 tree
- root = actual state
- 1 tree = sample of possible sequences of actions over a time horizon

Best et al. 2019

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Best et al. 2019

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$\rightarrow$

- if communication is possible, share their trees
- Optimization of the set of possibles actions = prune the tree

Best et al. 2019

# MCTS

## Partially Observable MCTS

Problem: Exploration mission + partially observable
$\rightarrow$ Particle filter = compute random posterior distributions of a partially observable state to find the most accurate.
$\rightarrow$ MCTS = compute random posterior actions to find the optimal one.
Idea :

Silver and Veness 2010

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- Mix MCTS and particle filter
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- 1 simulation = update 1 particle

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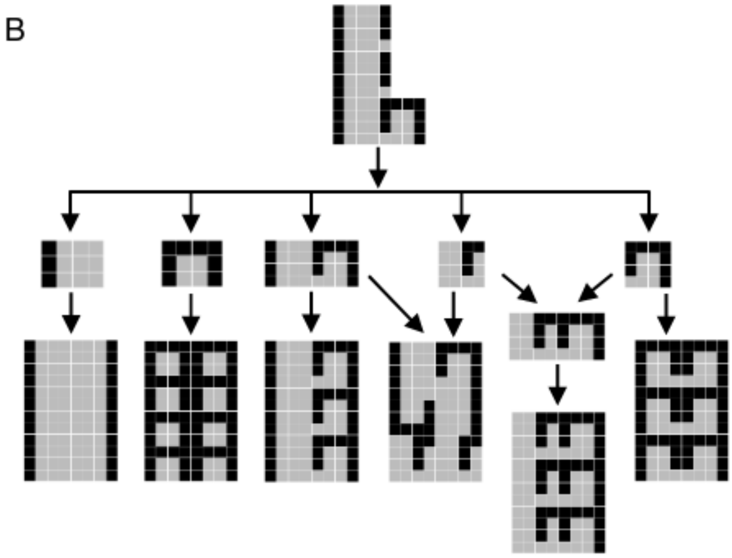
- 1 node = either an action or on observation
- 1 simulation = update 1 particle

→ Update belief state and find optimal action

Silver and Veness 2010

- How to use knowledge of the environment to make exploration more efficient ?
- Where are we according what we see ? Building ? Outdoor ?
- What we will probably see next ?




Sharma et al. 2022

# Current directions

## Temporal Logic

- Specify tasks :
  - Rendez-vous/ gathering
  - Communication
  - Get back the info to the operator
- If lots of robots :
  - Specify density of the swarm (Djeumou, Xu, and Topcu 2020; Djeumou, Xu, Cubuktepe, et al. 2021)
  - Control if that they are not too far from each other

## Epistemic Logic

- Task to do only when we know something
- Consensus over a leader, a task, an information, ...
- Way to modelize communication

Thank you !

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