Towards new approaches to cluster detection for cosmology

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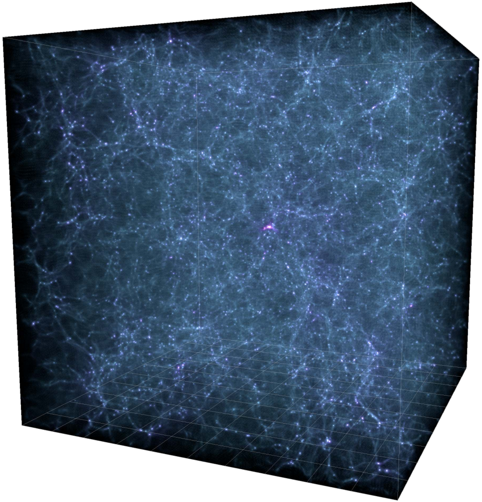
Halos in simulations



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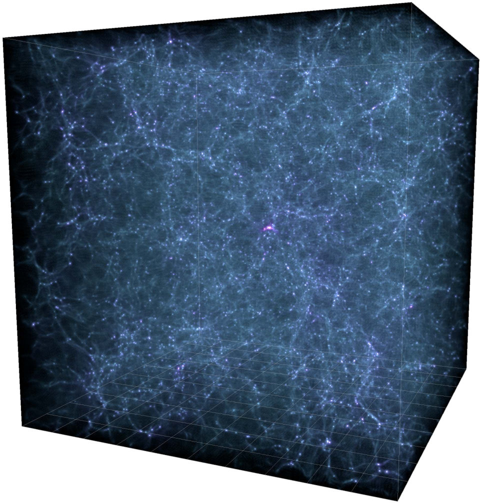

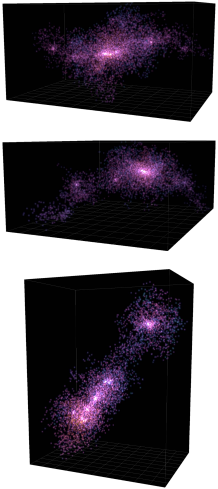

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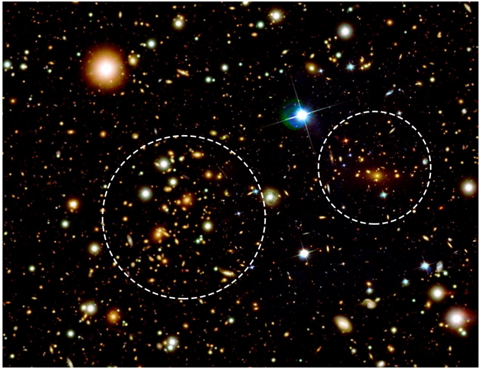

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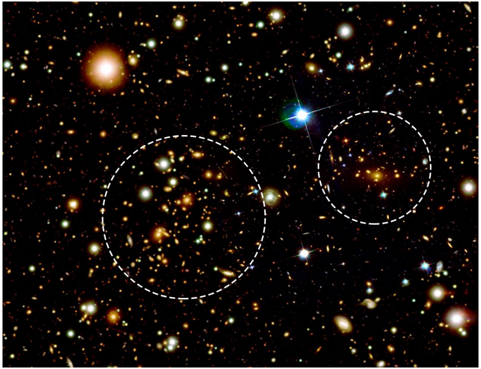
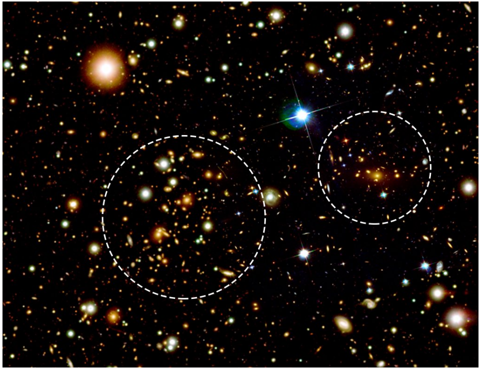


Observational cosmology using galaxy clusters

Galaxy clusters as building blocks of cosmological analyses.

Galaxy clusters in observations



Observational cosmology using galaxy clusters

Galaxy clusters as building blocks of cosmological analyses.

Main problem of this presentation in the context of LSST

How to detect galaxy clusters?

Galaxy cluster detection

Clusters in simulations

- Input: particles

Simulation cluster detectors

- Spherical Over Density (SOD)
- Friends-of-Friends (FoF)
- ...

Clusters in observations

- Input: sources/galaxies

Observational cluster detectors for LSST

- redMaPPer (Rykoff et al. 2013)
- WaZP (Benoist 2014)
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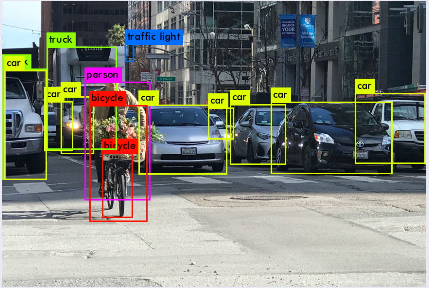
Improving cluster detection for observational cosmology

Can we use machine-learning to improve cluster detection for observational cosmology?

Clusters and computers

Using deep neural networks to detect galaxy clusters

Idea: try to adapt YOLO



You Only Look Once (Redmon et al. 2015)

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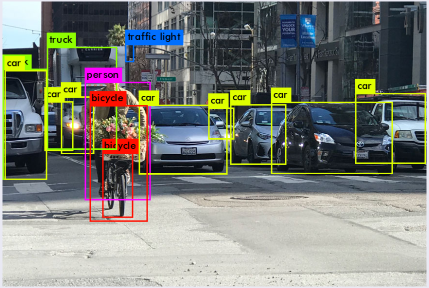

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- Ultra large images
- More than 3 colors

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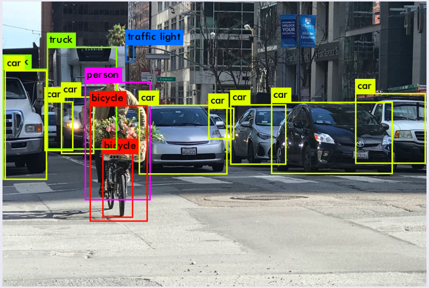

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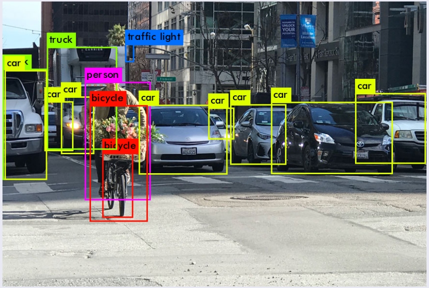

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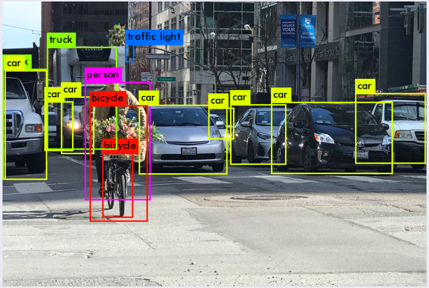

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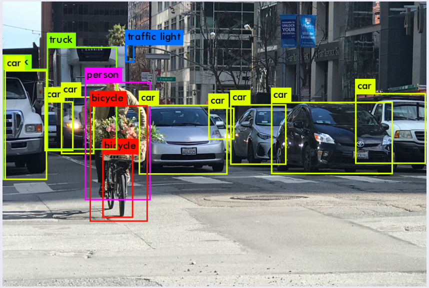

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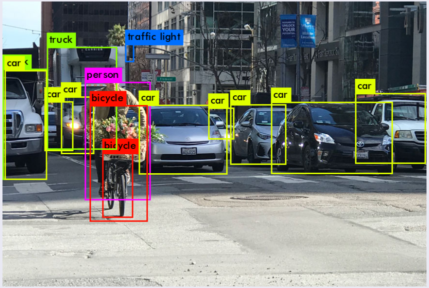

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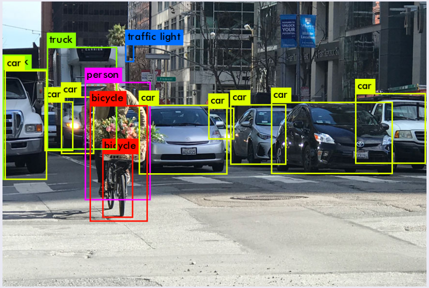

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Direction of investigation

Physics-guided machine-learning?

A problem of definition

The fundamental problem of clusters

- No universal definition: many definitions and parameterization accross simulations and observations
- Computers require definitions: implicit or explicit parameterization in algorithms
- Algorithms $\Leftrightarrow$ Definitions

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- Physical distance
- Gravitational potential
- Virialized structures
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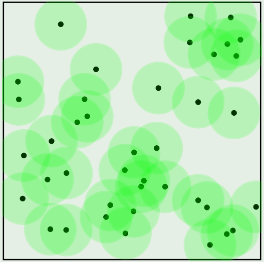
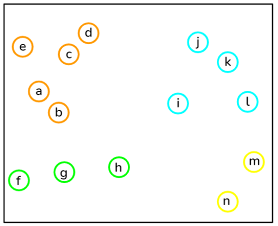
Example of FoF: linking-length

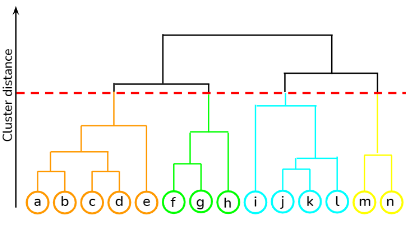


Trees as a universal representation for clustering results

Hierarchical clustering



Cluster dendrograms



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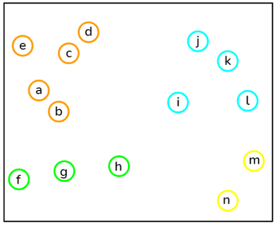

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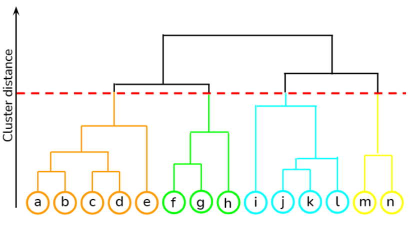
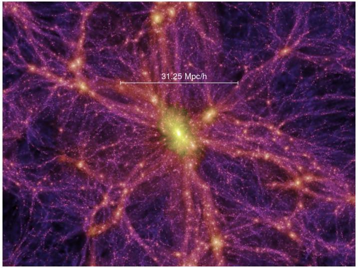
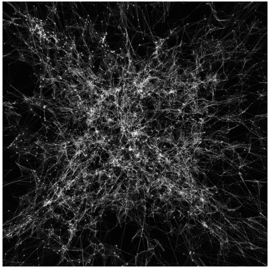


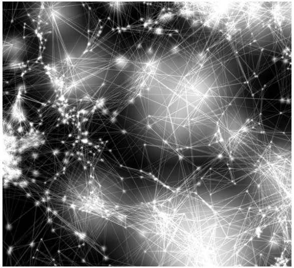
A universal representation

- Traditional galaxy cluster finders ⇒ 3-level trees (root/clusters/sources)
- With subhalo finders ⇒ 4-level trees (root/clusters/subclusters/sources)
- Hierarchical finders ⇒ N-level trees (root/supersuperclusters/superclusters/clusters/. . . /sources)

Graph as a numerical representation of the cosmic web







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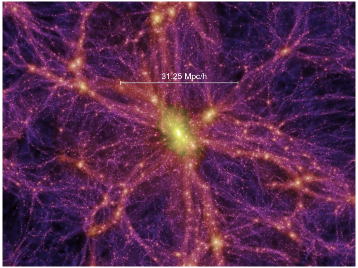

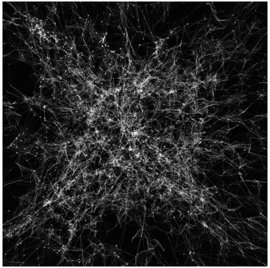

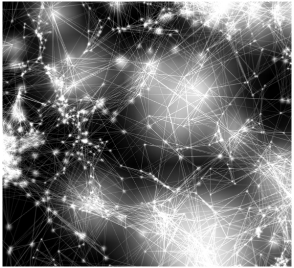

Representing the cosmic web as a graph

- Vertices: particles, sources
- Edges: physical parameterization (physical distance. . .)
- Going beyond: fuzzy graphs to take into account error bars

A computer science perspective on galaxy clustering: graphs and trees

Reframing of the galaxy clustering problem

- Cosmic web $\Leftrightarrow$ Graph
- Galaxy clustering $\Leftrightarrow$ Trees

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Computer science perspective

Galaxy clustering problem ⇔ Computing Trees on Graphs

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Galaxy clustering problem $\Leftrightarrow$ Computing Trees on Graphs

Discrete vs continuous mathematics

- Comparison of galaxy clustering algorithms $\Rightarrow$ comparison of trees
- Computer science related problem: tree metric and distances

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Research direction

Playing games on the cosmic web: computing galaxy clustering trees on the cosmic web graph

- Well-framed computer science problem
- Bridge between numerical cosmology, computer science, and discrete mathematics
- Computer science tools available

Game trees

Game trees: starting with Tic-Tac-Toe

Game trees

A universal way to represent sequential N-player(s) games with perfect information.

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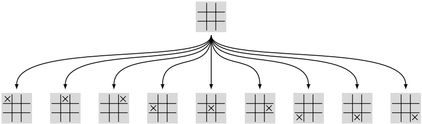

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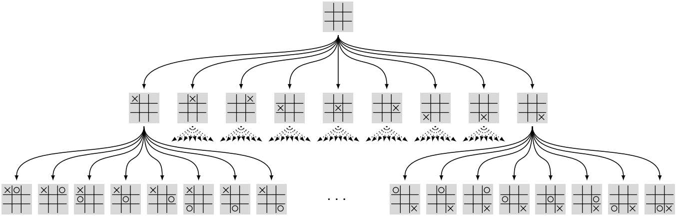

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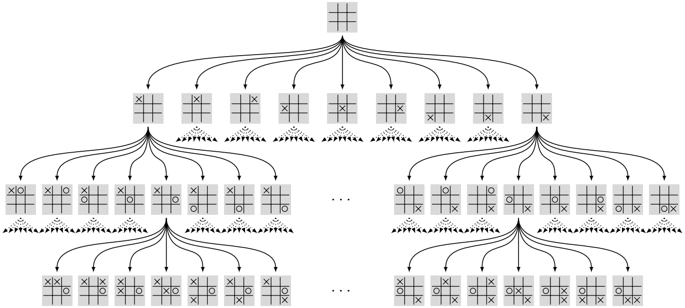

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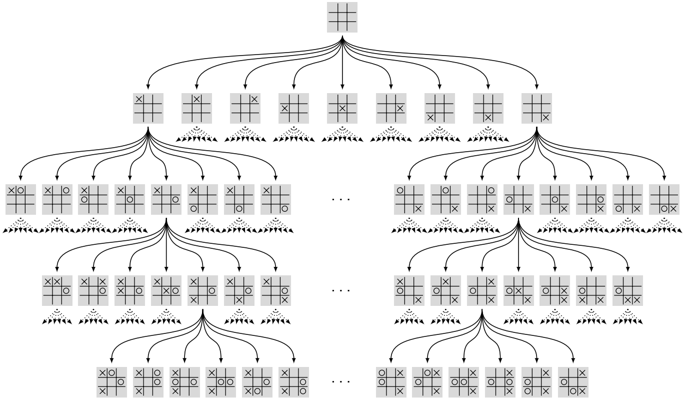

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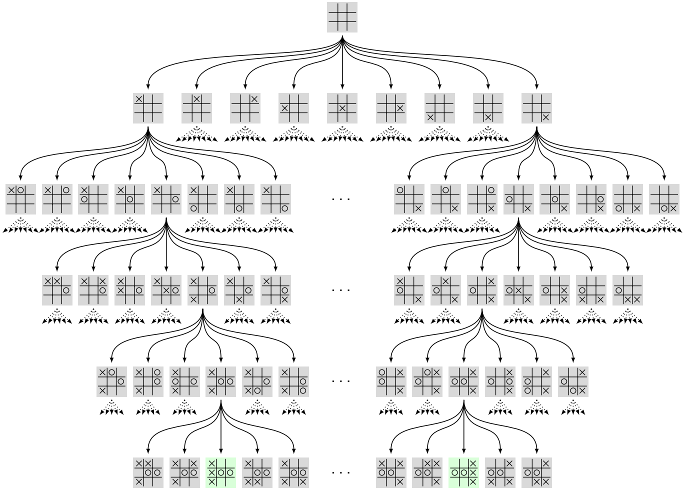

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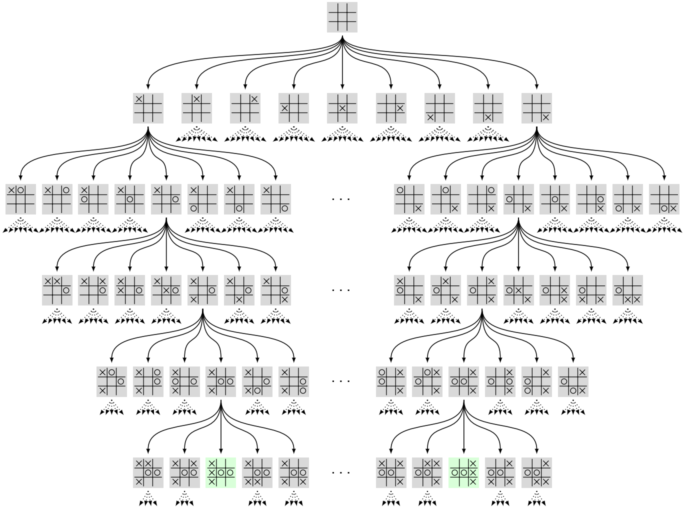

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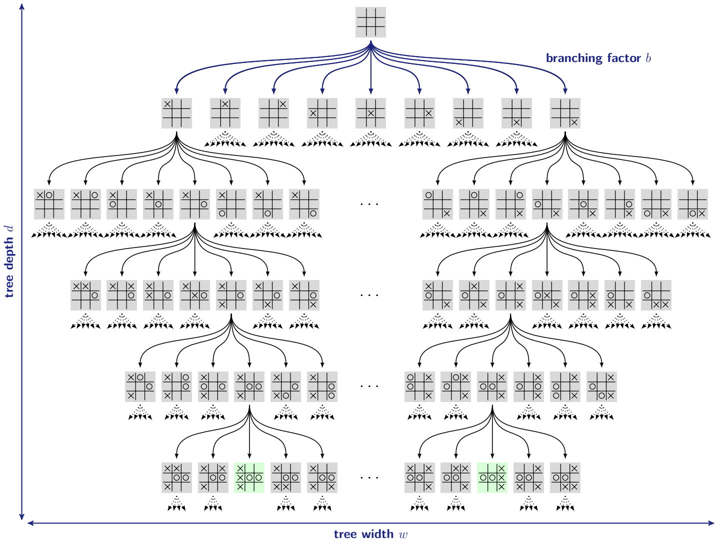

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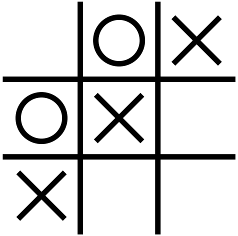
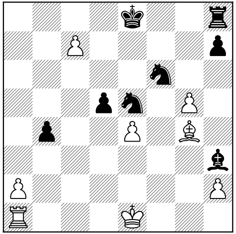
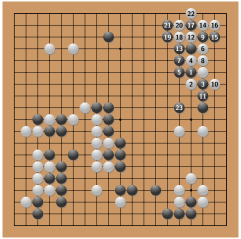
Game complexity







Tic-Tac-Toe

- Board size $\Rightarrow 3^2 = 9$
- Average game length $\Rightarrow 9$
- Average branching factor $\Rightarrow 4$
- Number of games $\Rightarrow 255\,168$

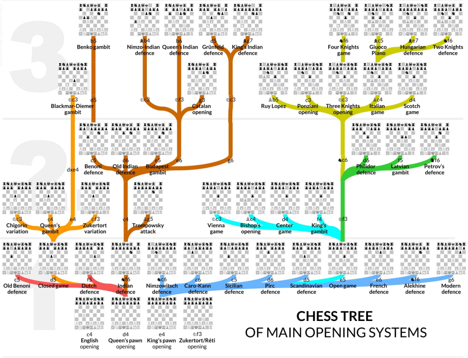
Chess

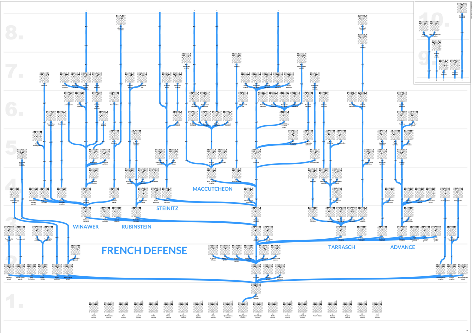
- Board size $\Rightarrow 8^2 = 64$
- Average game length $\Rightarrow 70$
- Average branching factor $\Rightarrow 35$
- Complexity $\Rightarrow 35^{70} \approx 10^{64}$

Go

- Board size $\Rightarrow 19^2 = 361$
- Average game length $\Rightarrow 150$
- Average branching factor $\Rightarrow 250$
- Complexity $\Rightarrow 250^{150} \approx 10^{360}$

Playing chess algorithmically





Brute-forcing

Game tree still tractable: average depth $d = 70$, average branching factor $b = 35$

The problem with the game of Go

Intractability

Go's game tree average depth $d = 150$, average branching factor $b = 250$

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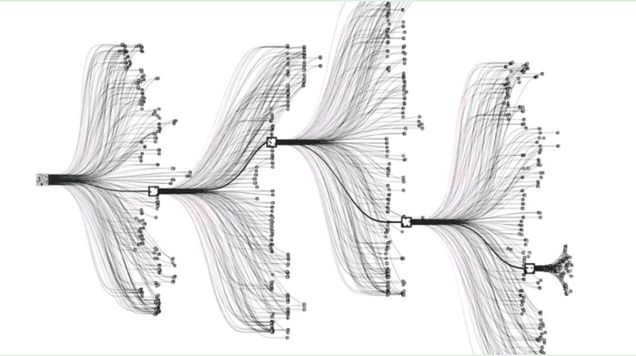
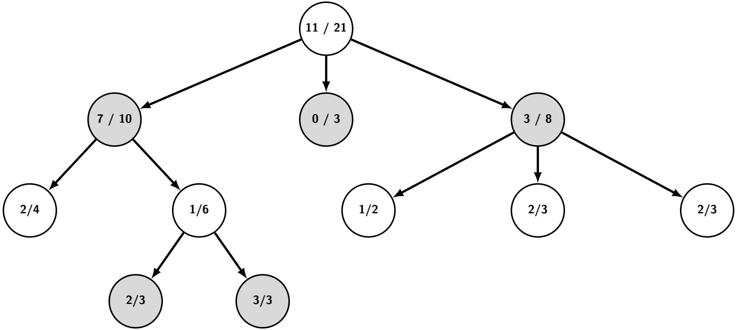
Deepmind's AlphaGo/AlphaZero



Breakthrough in 2017 (David Silver et al.)

MCTS and AlphaZero

Monte-Carlo-Tree-Search (MCTS) overview



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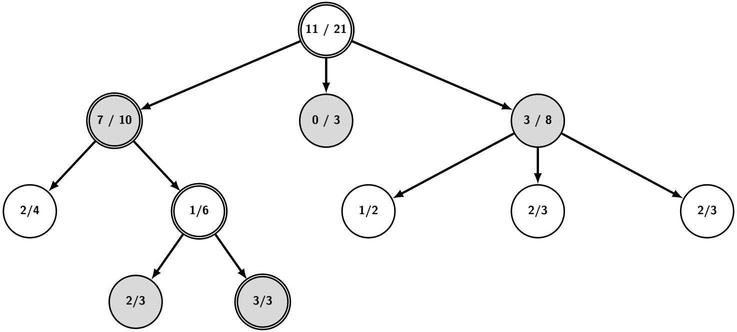

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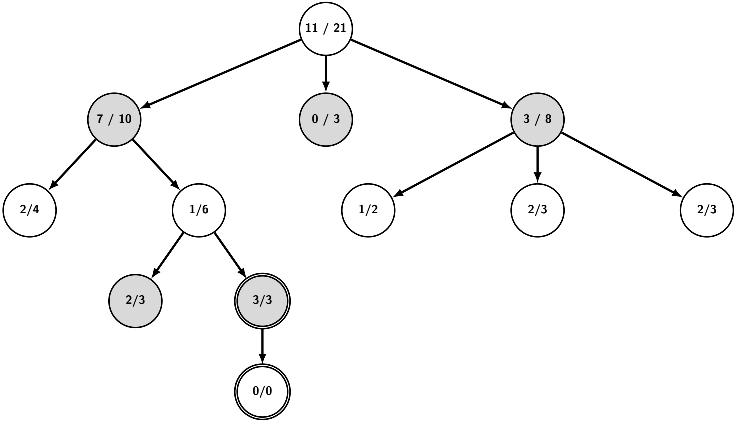

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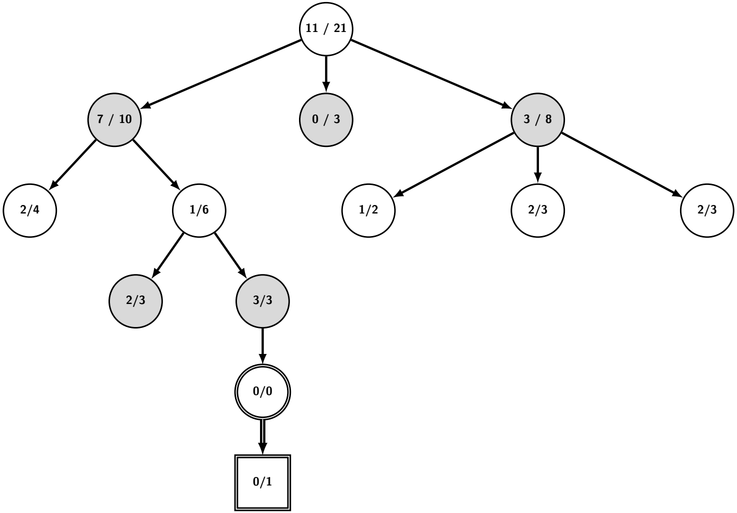

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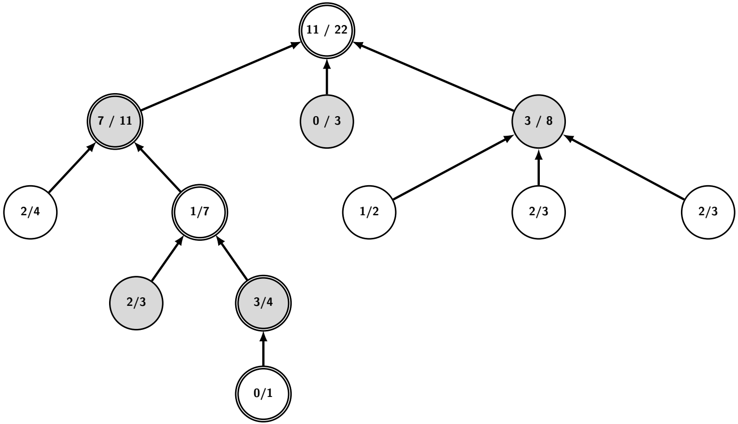

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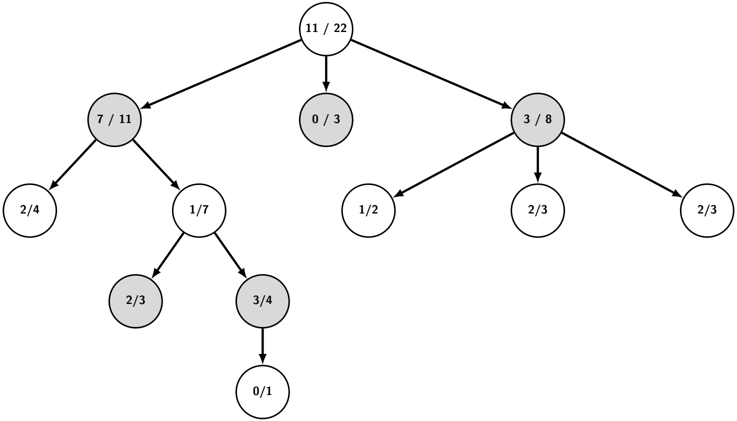

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Simulations

- To get a distribution of results, N_s simulations can be performed at each step
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Selection: exploitation vs exploration

Example of the UCT (Upper Confidence Bound 1 applied to Trees) policy:

$$\max_x \left(\frac{w_i(x)}{n_i(x)} + c\sqrt{\frac{\log(N_i(x))}{n_i(x)}} \right)$$

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- $N_i \Rightarrow$ total number of simulations for the parent node of x after the i-th move

Monte-Carlo-Tree-Search (MCTS) refinements

Simulations

- To get a distribution of results, N_s simulations can be performed at each step
- Simulated playouts can be done in a better way than using random moves

Selection: exploitation vs exploration

Example of the UCT (Upper Confidence Bound 1 applied to Trees) policy:

$$\max_x \left(\frac{w_i(x)}{n_i(x)} + c\sqrt{\frac{\log(N_i(x))}{n_i(x)}} \right)$$

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- $n_i \Rightarrow$ number of simulations for the node x after the i-th move
- $N_i \Rightarrow$ total number of simulations for the parent node of x after the i-th move
- $c \Rightarrow$ exploration coefficient ($c = \sqrt{2}$)

AlphaZero = Monte-Carlo-Tree-Search + Deep Neural Networks

Monte-Carlo-Tree-Search (MCTS)

- Selection
- Expansion
- Simulation
- Backpropagation

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Policy deep neural network

- Input: s, the current state of the board (+ optionally previous states)
- Output: p, to select the most probable/promising moves
- General idea: reduce the breadth of the tree search

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AlphaZero = MCTS + Policy Net + Value Net

Tree search guided by "intuition" and "expert-knowledge".

A clustering game

A clustering game

Game's board

The cosmic-web graph

A clustering game

Game's board

The cosmic-web graph

Game's goal

Extracting a clustering tree from the graph

A clustering game

Game's board

The cosmic-web graph

Game's goal

Extracting a clustering tree from the graph

Game's move

Create a link between a particle and its best neighbouring candidate

Using MCTS and Neural Nets to play the clustering game

Preparation using simulations

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- Compute the cosmic-web graph $\mathcal{G}$

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- Play the 1-player game using MCTS + Neural Nets on real observations using $\vec{x} = (x_0, x_1, x_2, \cdots, x_{n-1})$

Using MCTS and Neural Nets to play the clustering game

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- No need of observational data on ϕ

Combining the best of both worlds

Physics-guided machine-learning approach

- Works for any physics-based criteria ϕ and observational data $\vec{x}$ (including images and error bars)
- Builds an "intuition" on ϕ using simulations ($\phi \Leftrightarrow$ How does the game board looks like?)
- No black-box effect anymore

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Possible cluster definitions based on ϕ

- Physical distance
- Matter density
- Gravitational potential
- Virialization
- Linear combination of all of the above
- ...

Conclusions

Towards the ultimate definition?

Cluster definition collapse in $t = +\infty$

- In $t = +\infty \Rightarrow$ isolated clusters
- All definitions are equivalent

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Simulating the end of time

- Let simulations run far into the future
- Detect clusters

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- Let simulations run far into the future
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- Go back in time to $z = 0$ tracking particles

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Analysis

- Play the game using this criterion
- Use computer science and discrete mathematics to compare $\mathcal{T}_i = f(\phi_i)$

Conclusions

Limitations of machine-learning approaches

- Black-box approaches, hard to interpret and adjust in terms of physics
- Risk of circular definitions

Cluster detection as a computer science problem

- Cosmic-web $\Leftrightarrow$ Graph
- Clusters $\Leftrightarrow$ Trees
- Galaxy clustering problem $\Leftrightarrow$ Computing Trees on Graphs

The game of cluster detection

- MCTS + Deep Neural Networks = physics-guided machine-learning approach
- Work with arbitrary physics criterion ϕ and observational data $\vec{x}$

A starting project!

Reach out if you're interested: vincent.reverdy@lapp.in2p3.fr