

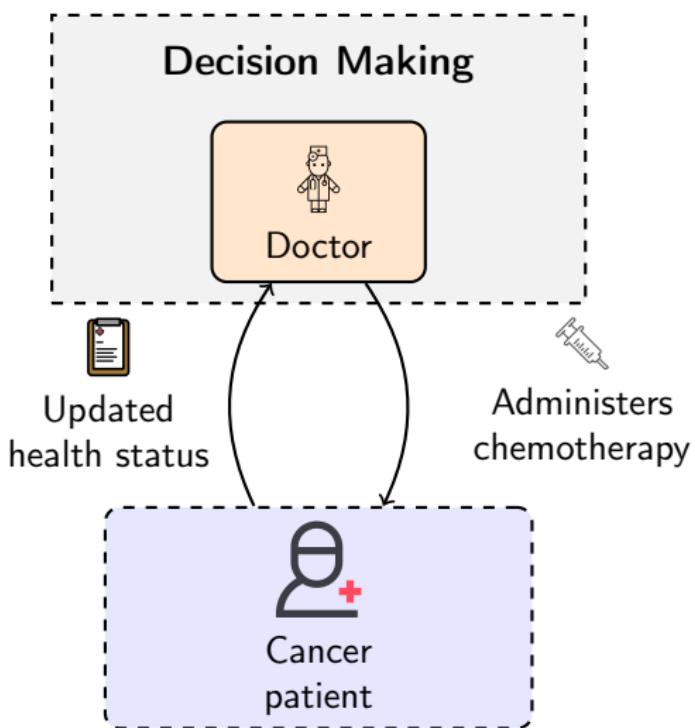
Interpretability, Decision Trees, and Sequential Decision Making

Hector Kohler

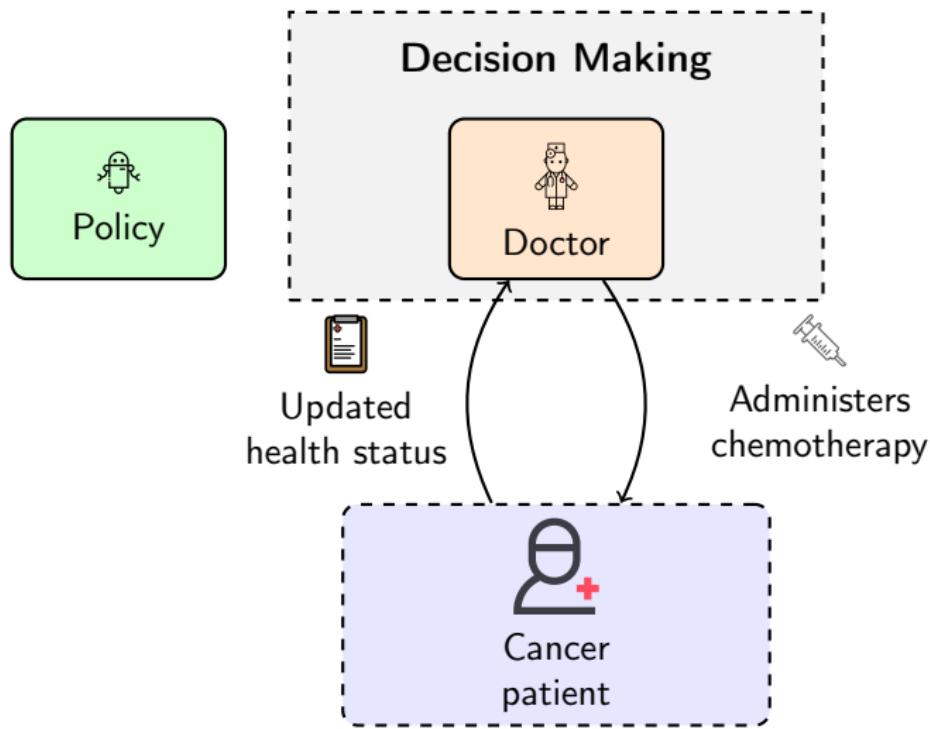
Supervised by Dr. Riad Akrour (HdR) and Prof. Philippe Preux (HdR)
Université de Lille, CNRS, Inria, UMR CRIStAL 9189, France

November 28, 2025

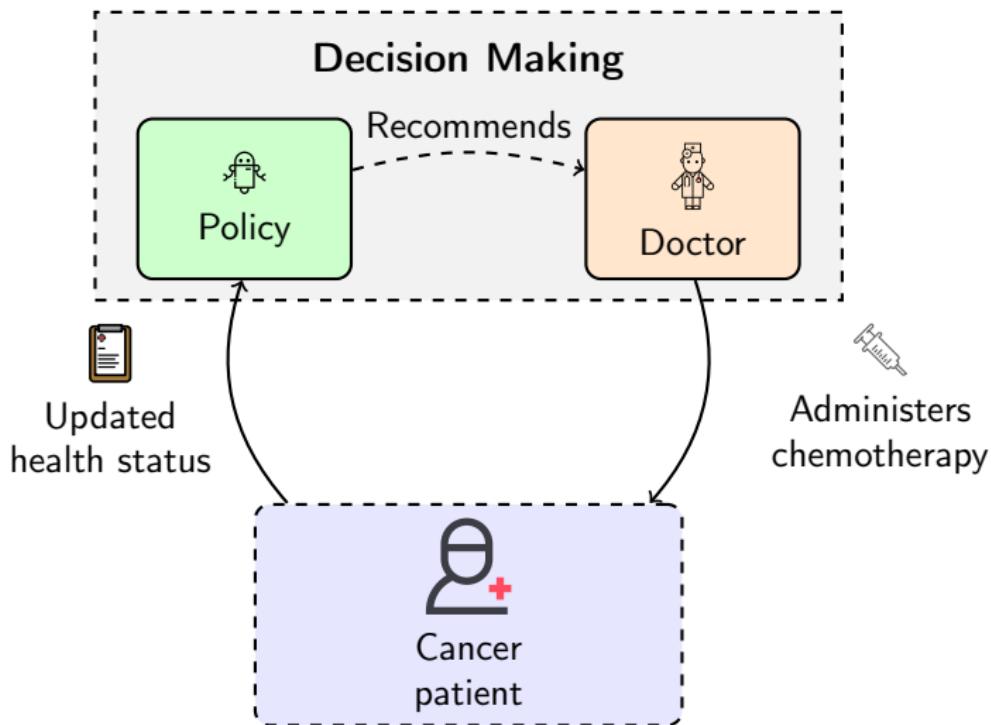
Sequential decision making (SDM) and machine learning (ML)



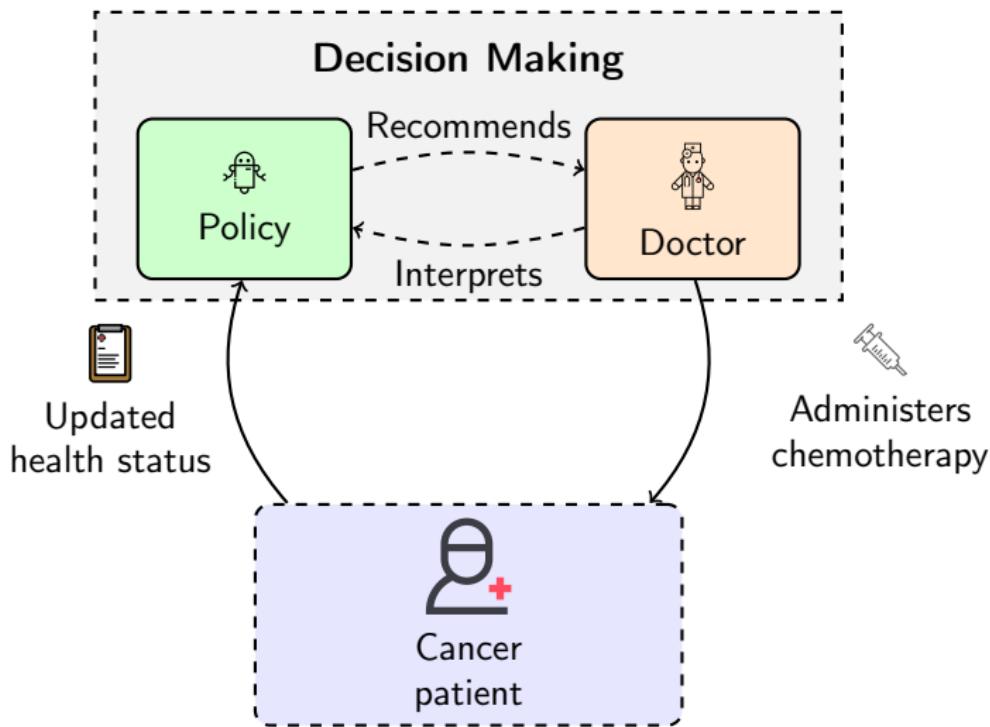
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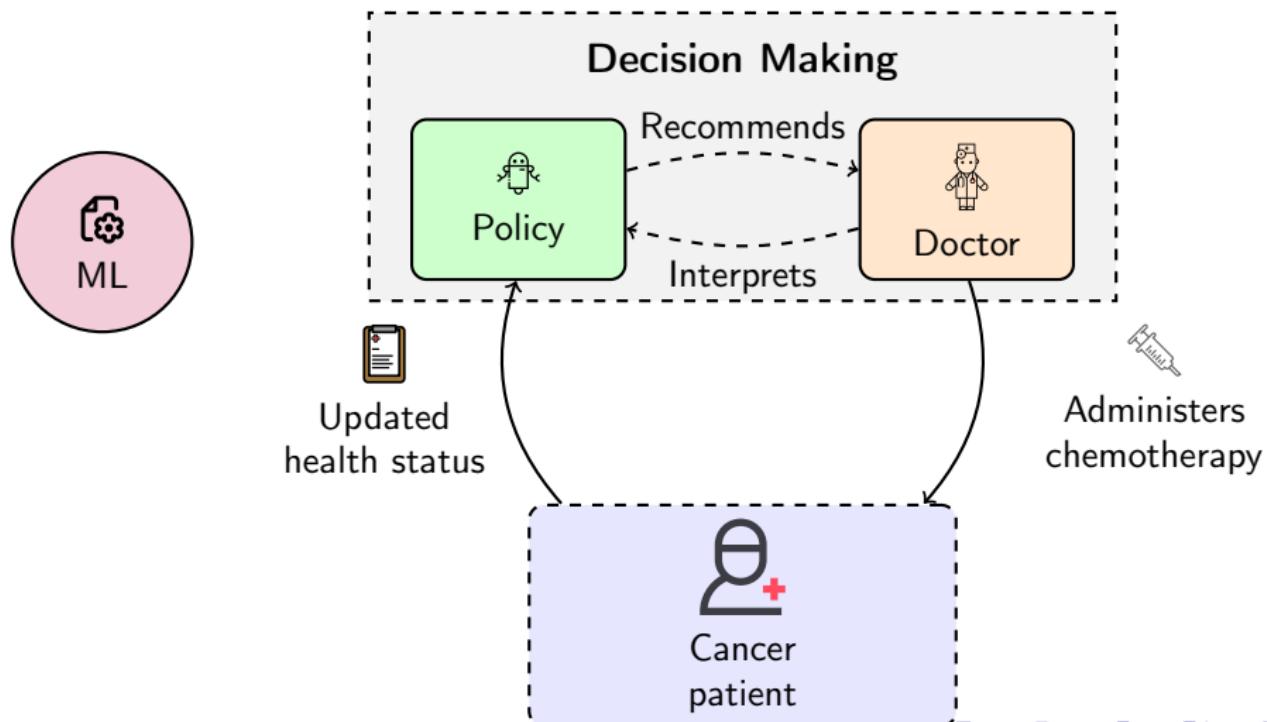
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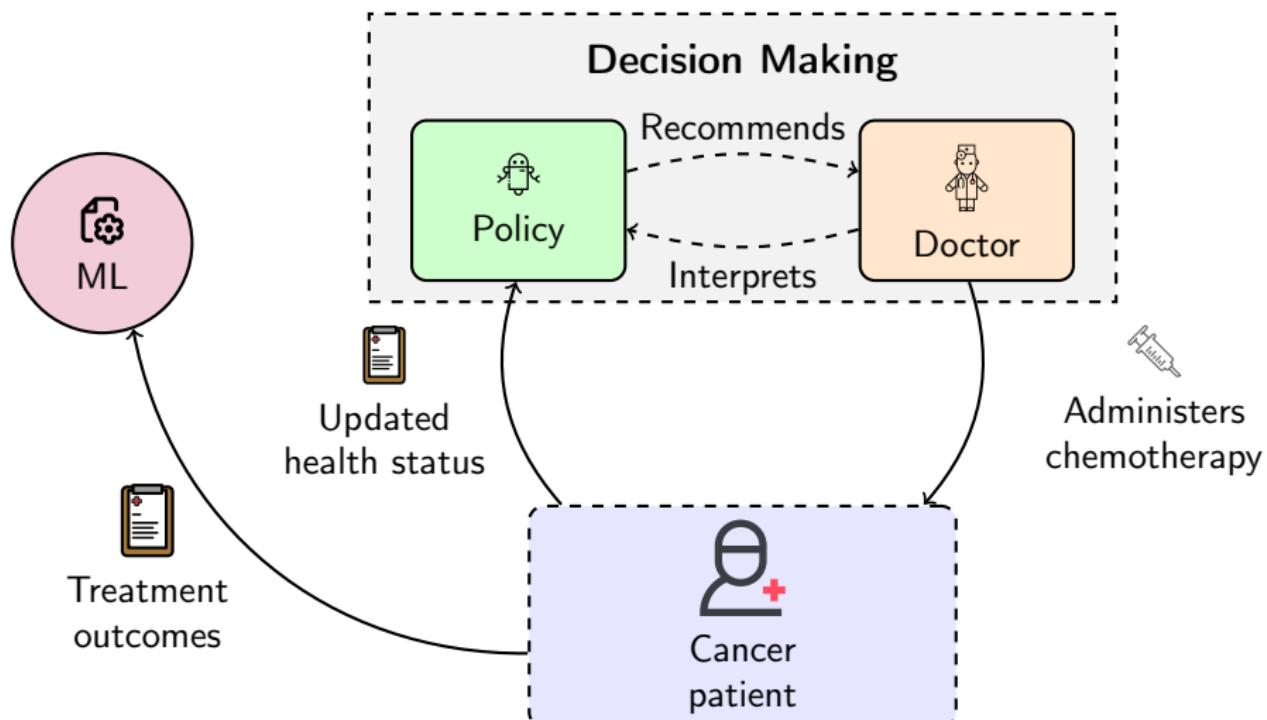
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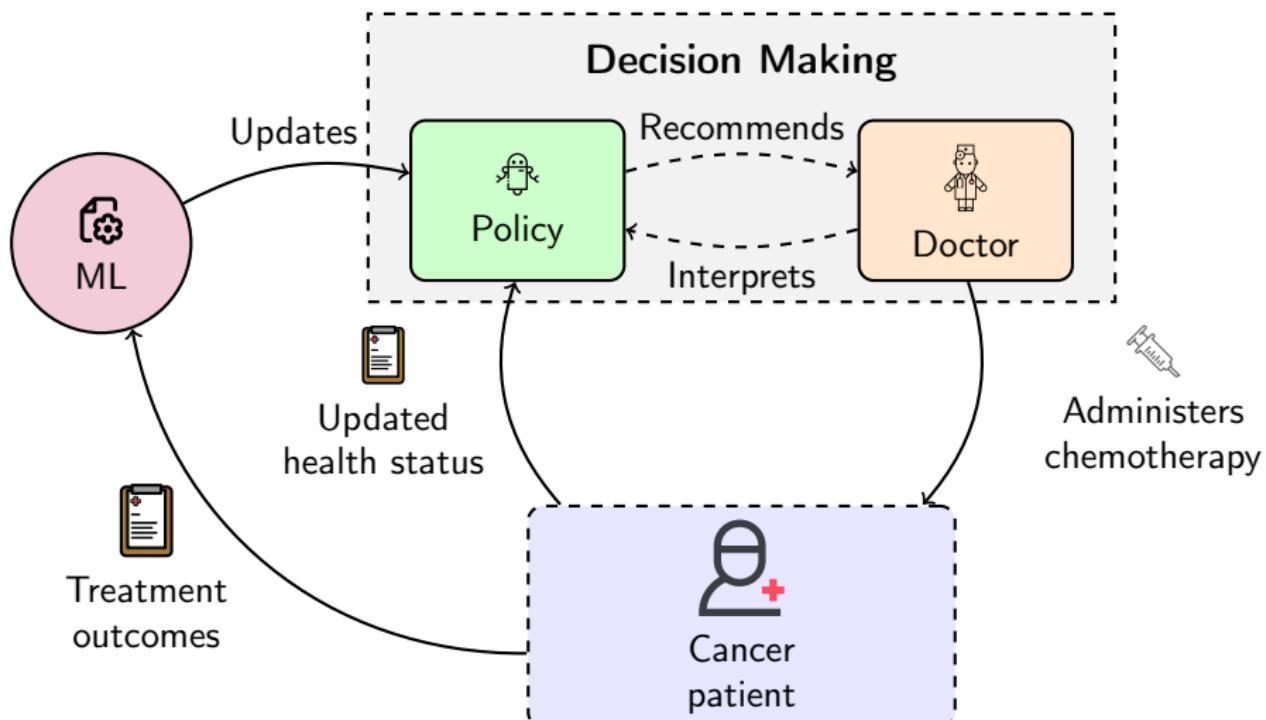
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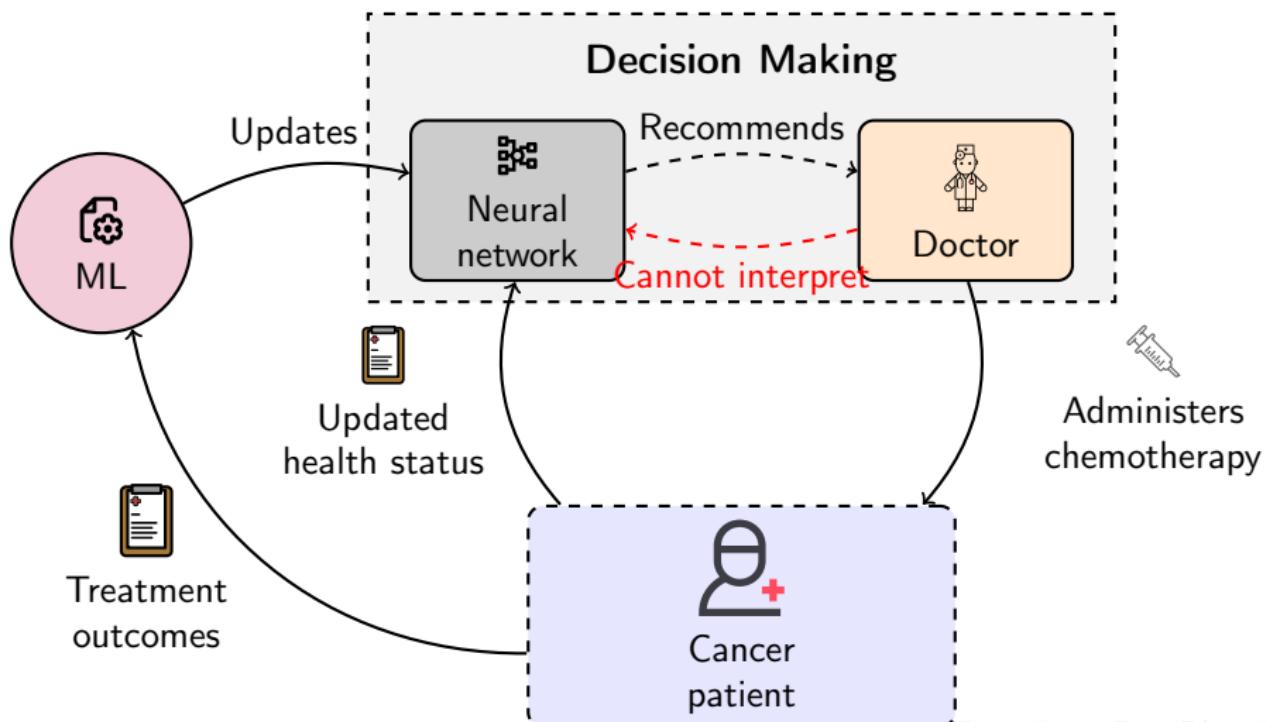
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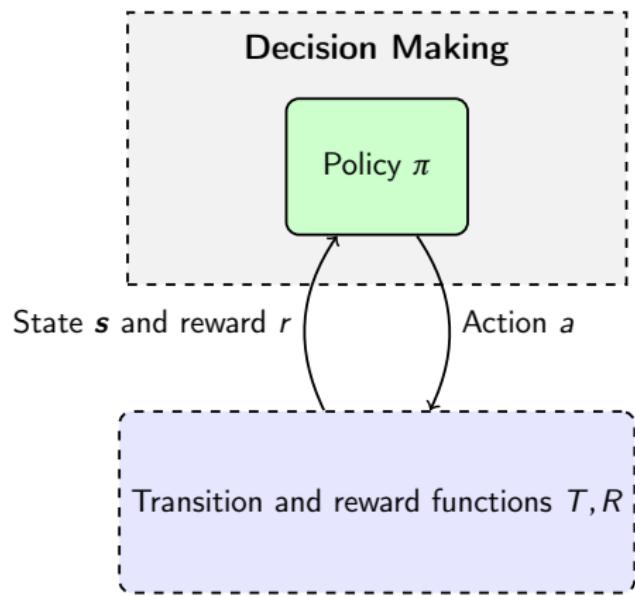
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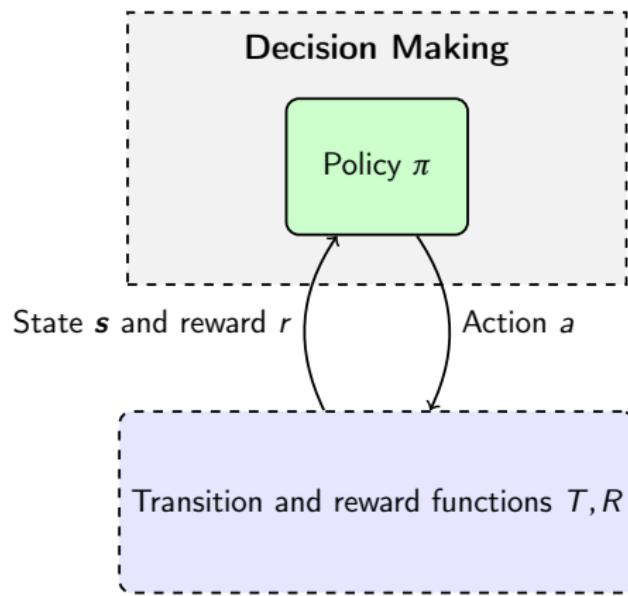


Markov decision processes (MDPs) and reinforcement learning (RL)



Markov decision processes [Put94].

Markov decision processes (MDPs) and reinforcement learning (RL)

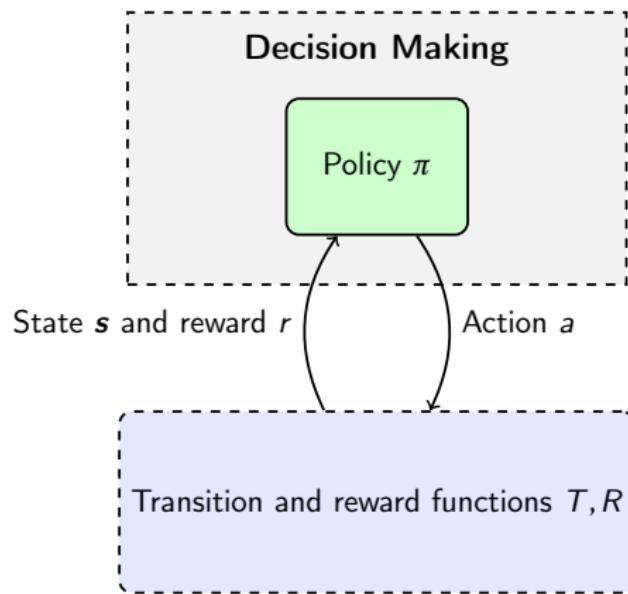


- RL [SB98] aims to find a policy, $\pi : S \rightarrow A$ that maximizes:

$$\mathbb{E}_{s_t \sim T} \left[\sum_{t=0}^{\infty} \gamma^t R(s_t, \pi(s_t)) \right]$$

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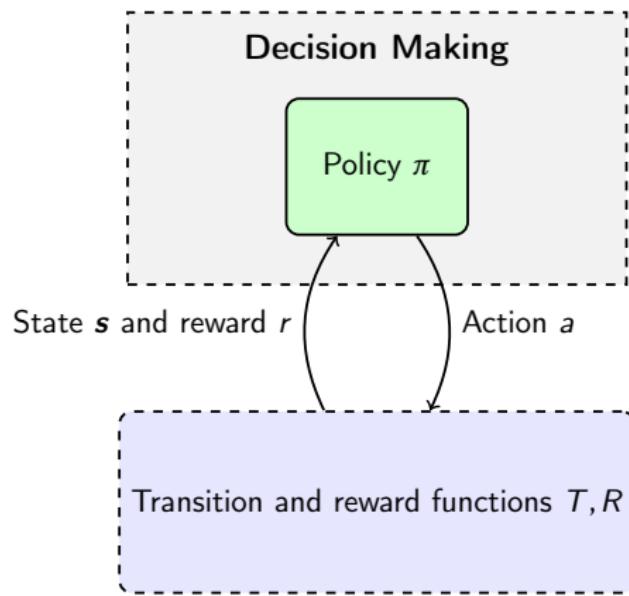
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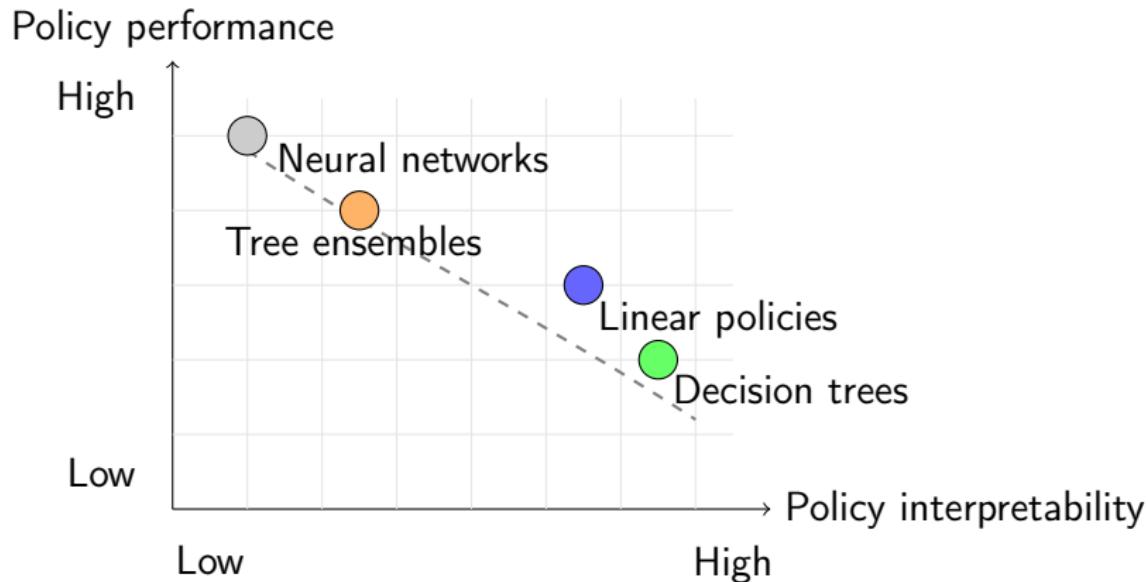
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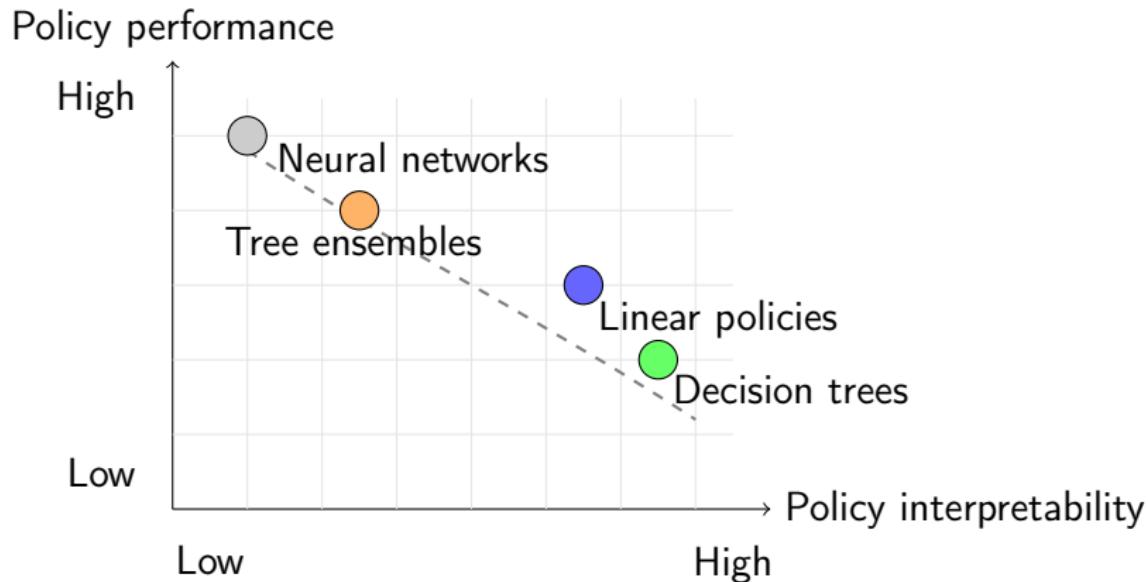
- Lots of successful RL algorithms [SB98; Mni+15; Sch+17].
- Few interpretability concerns.

Policy interpretability



Heuristic interpretability-performance trade-offs of different policy classes.

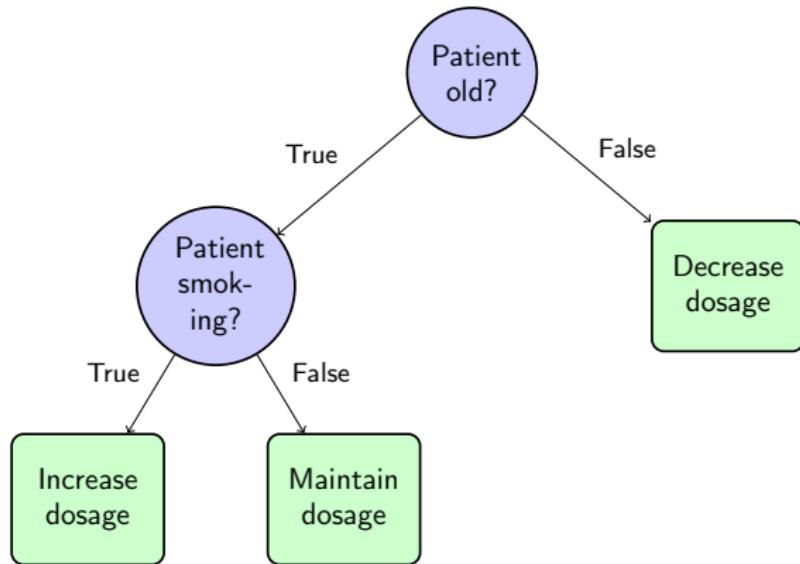
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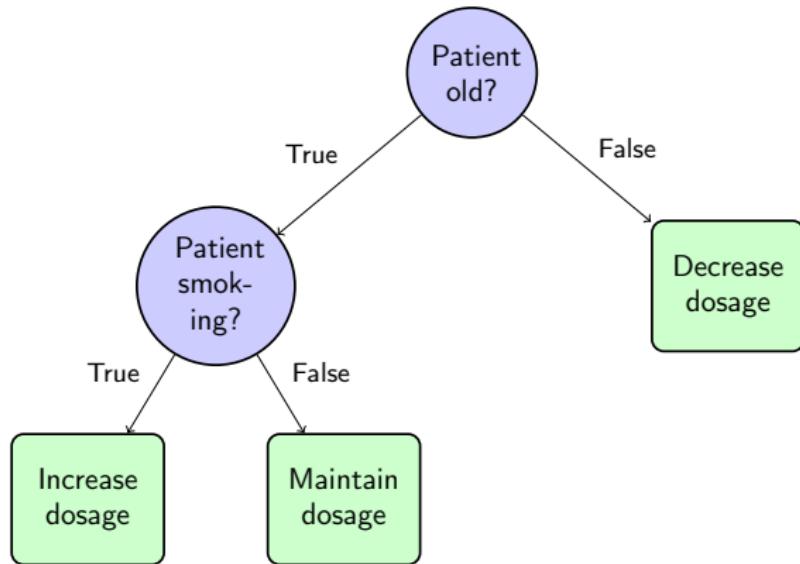
⚠ No definition of interpretability for machine learning models!

Decision trees



A generic decision tree of depth $D = 2$.

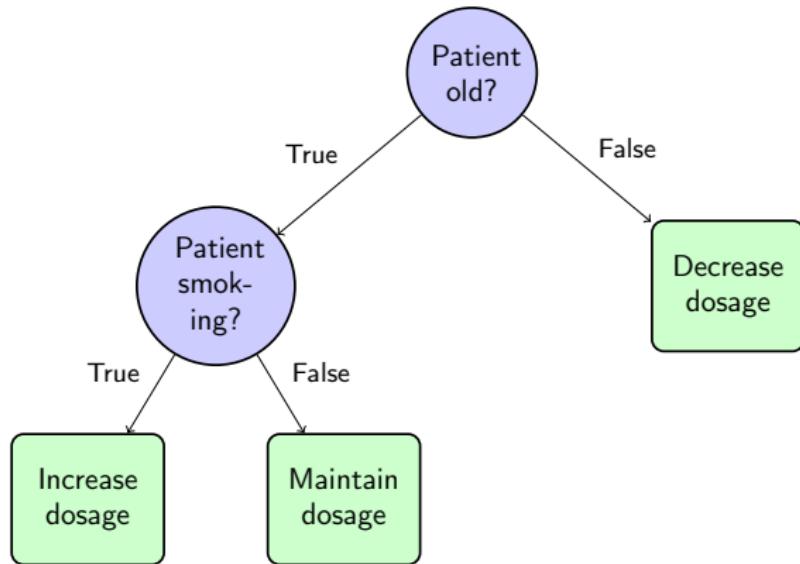
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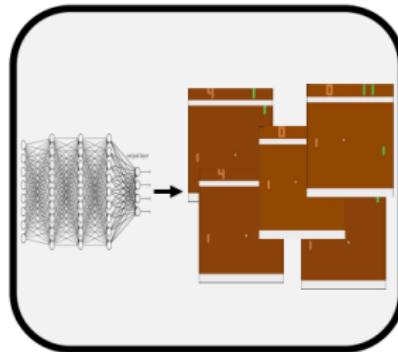


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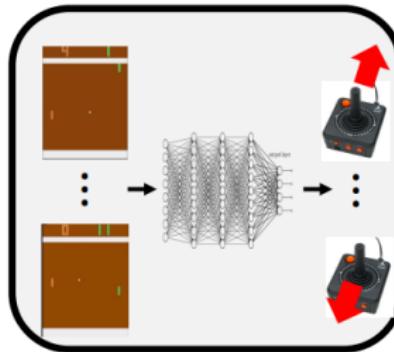
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What about SDM?

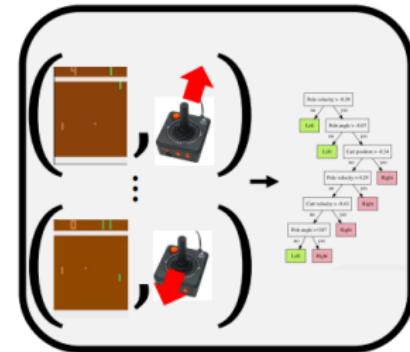
Imitation learning



Step 1: Use NN to generate states

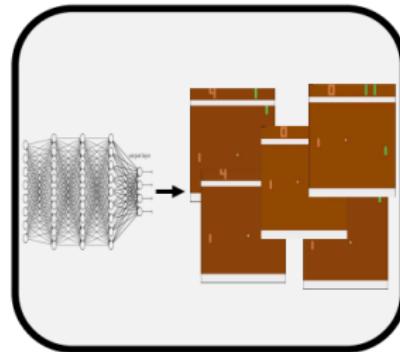


Step 2: Use NN to obtain actions

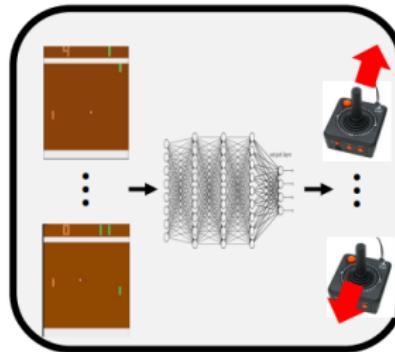


Step 3: Use supervised learning
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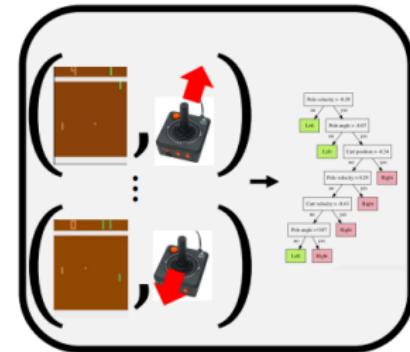
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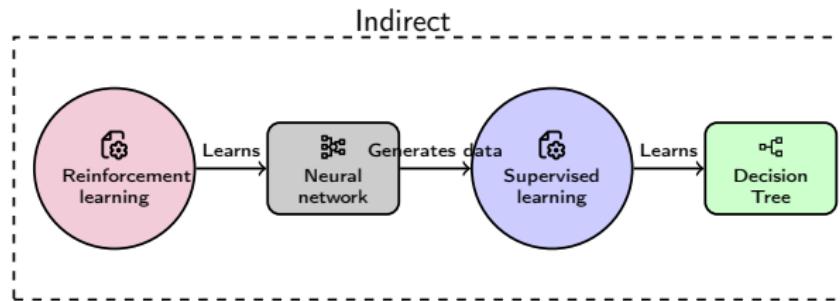
Most research focused on indirect learning of interpretable policies [RGB10;
BPS18; Ver+18; Mil+24].

Two ways to get interpretable policies for SDM

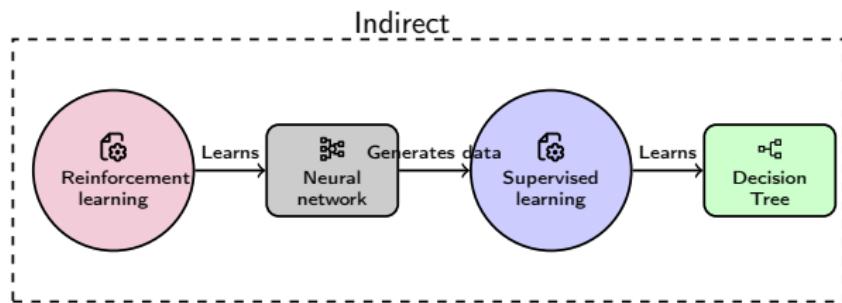
Indirect



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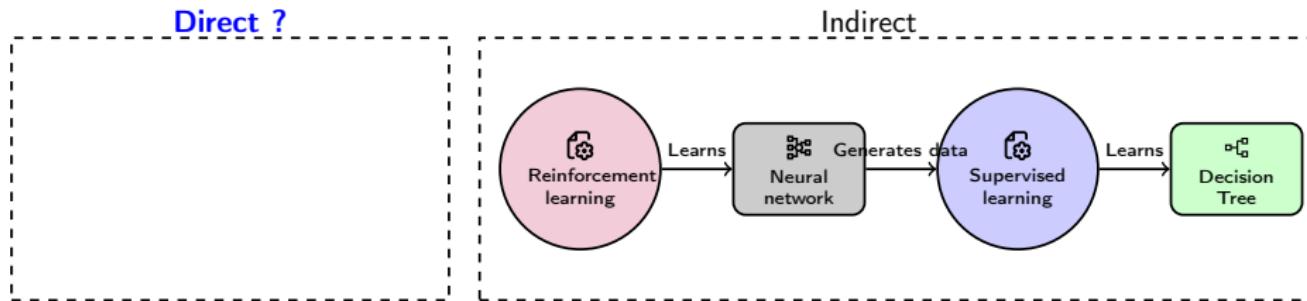


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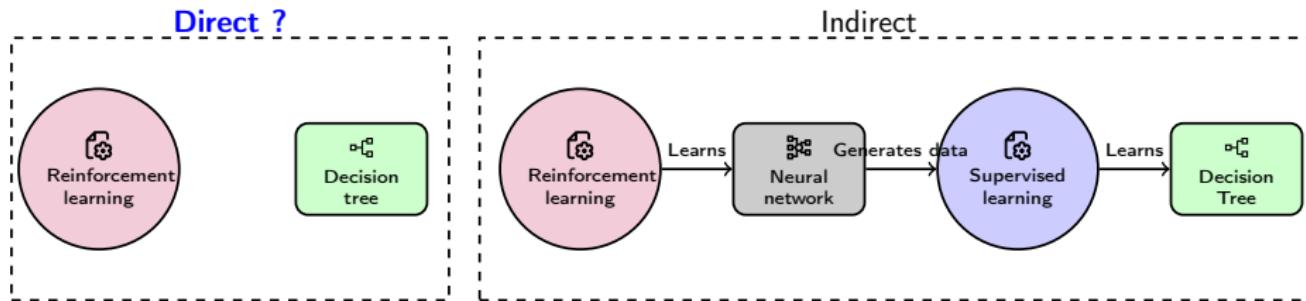
⚠ Policies obtained indirectly optimize a surrogate objective rather than an MDP cumulative rewards.

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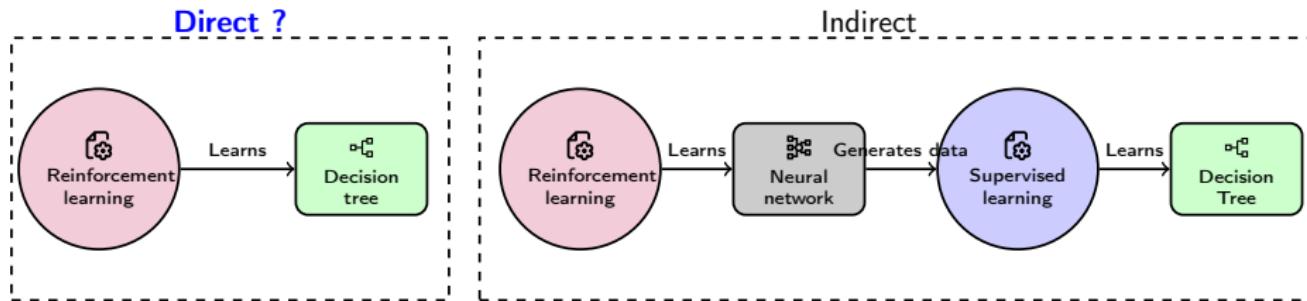
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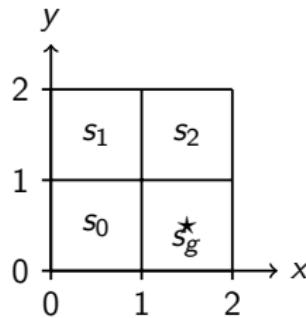
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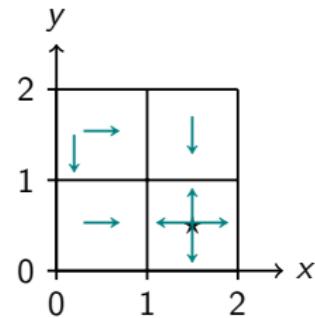
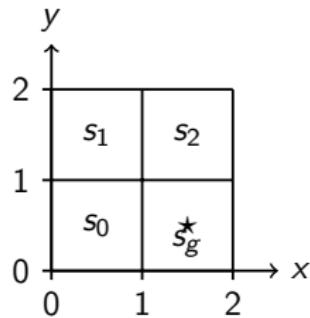
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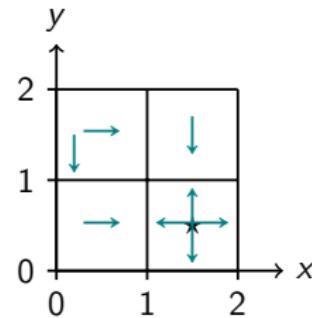
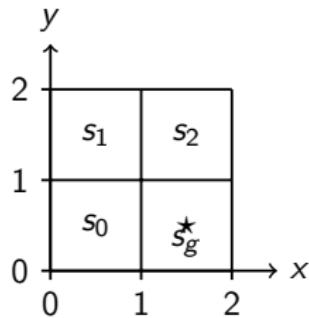
Grid world MDP and decision tree policies



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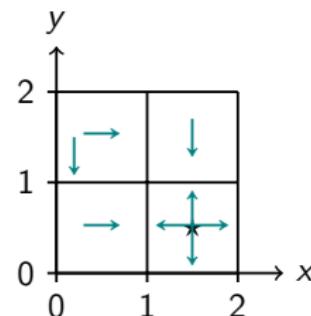
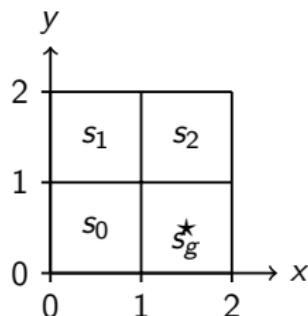


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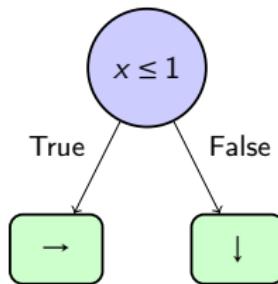


Grid world MDP and optimal actions.

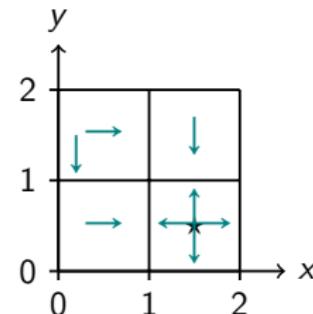
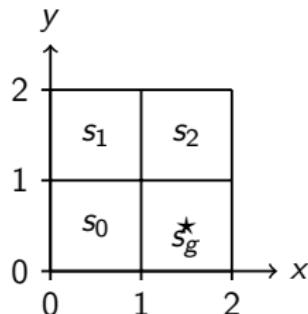
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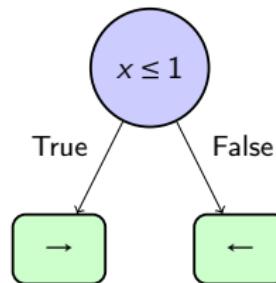
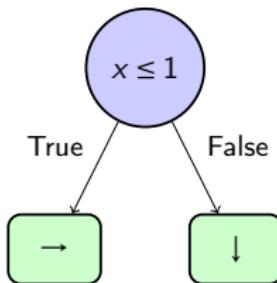
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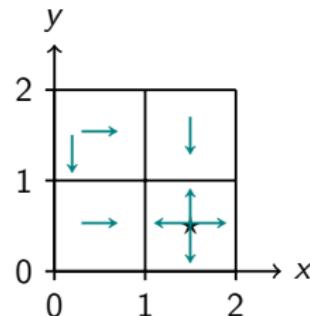
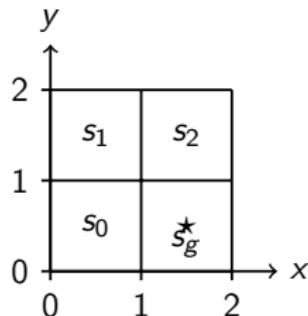
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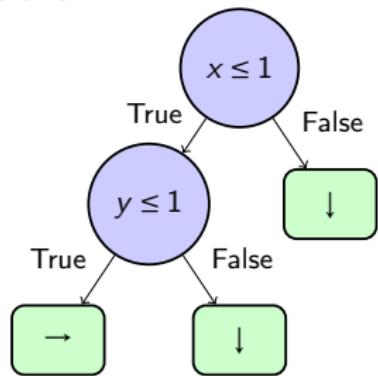
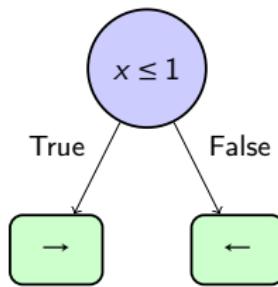
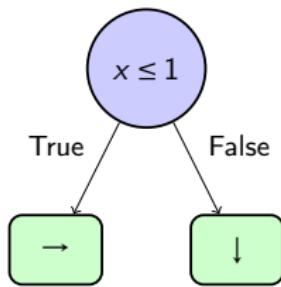
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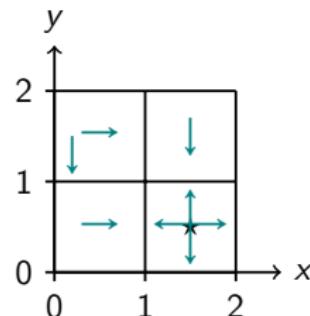
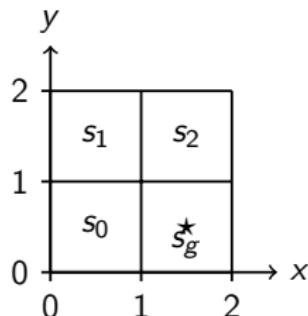
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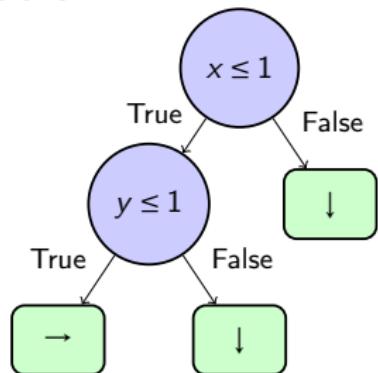
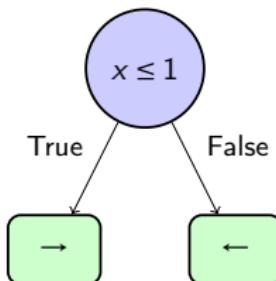
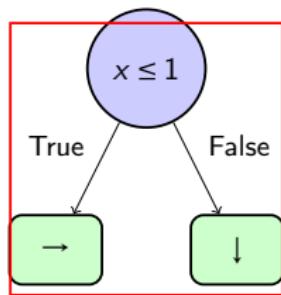
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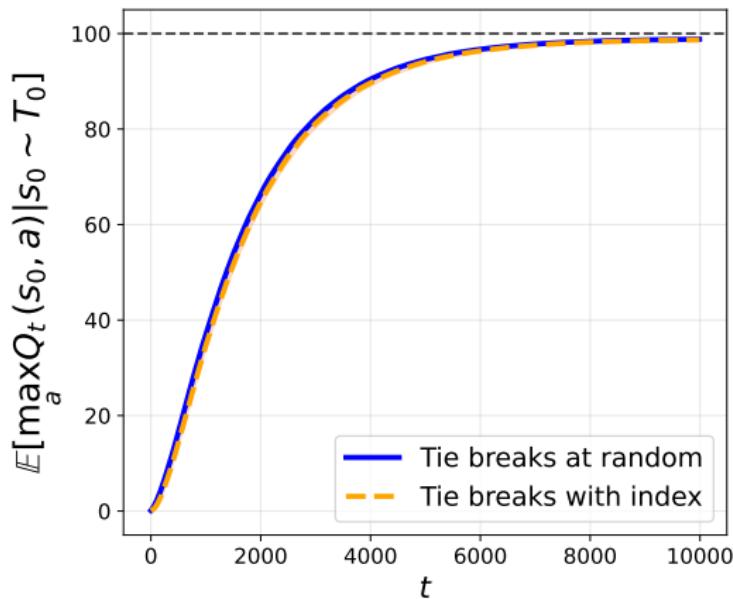
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Decision tree policies with different interpretability-performance trade-offs.

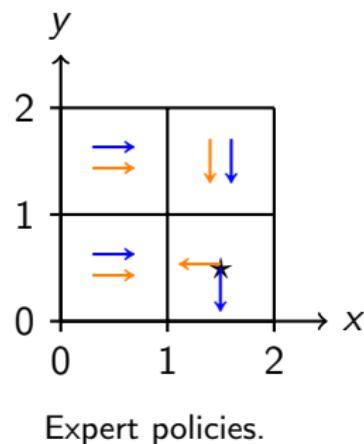
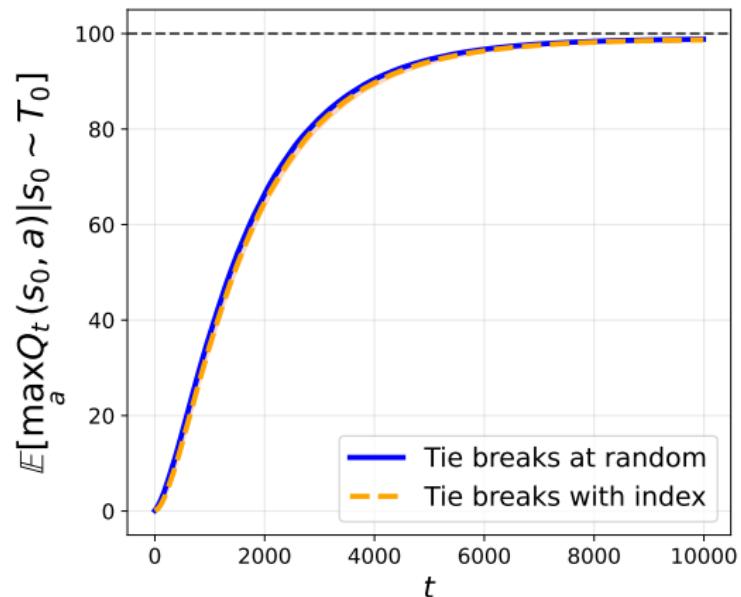
Grid world MDP and decision tree policies: indirect approach

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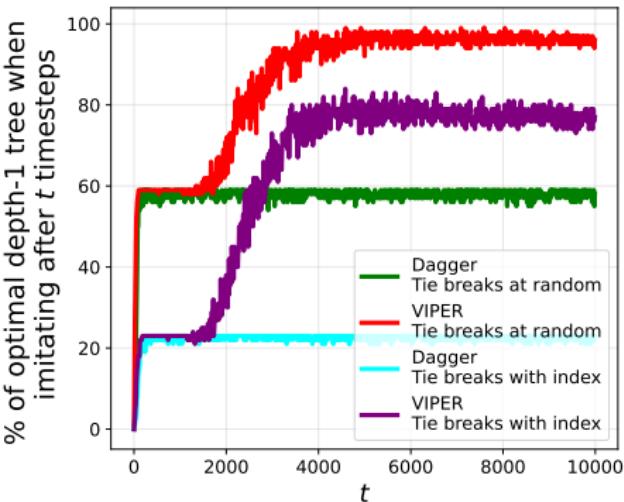
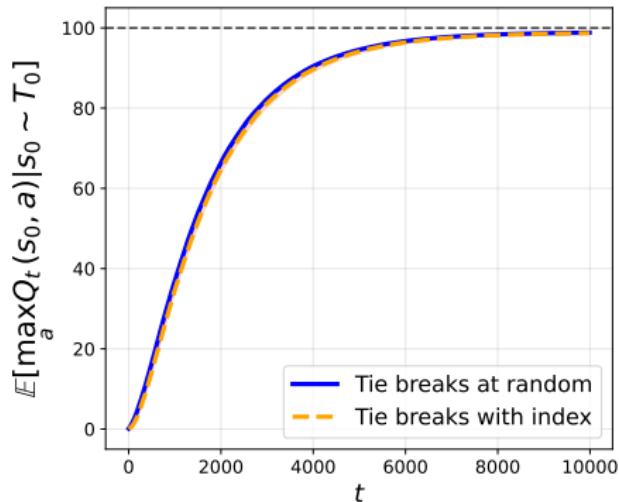


Sample complexity curve of Q-learning over 100 random seeds.

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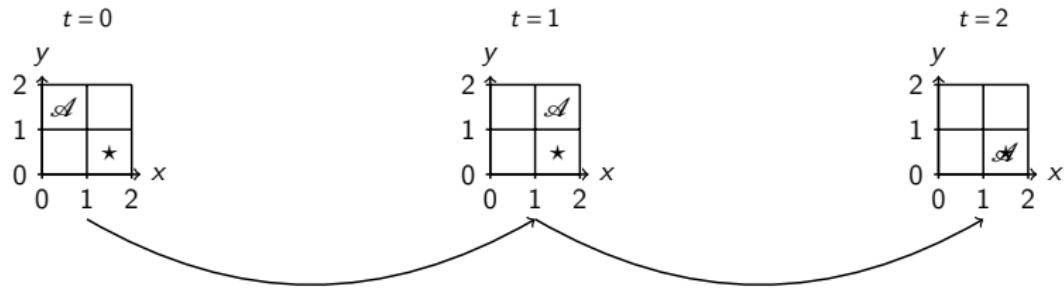


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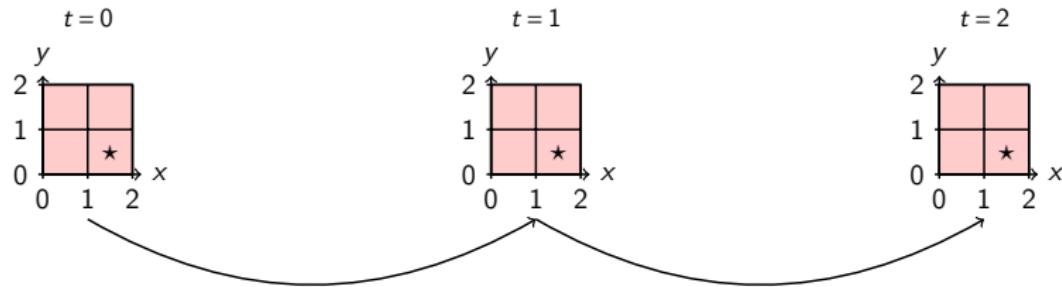


Sample complexity curve of Q-learning over 100 random seeds and performance of indirect interpretable methods when imitating the greedy policy with a tree at different Q-learning stages.

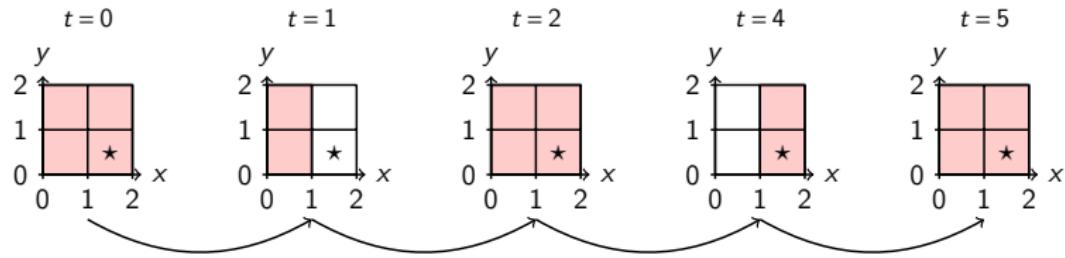
Iterative bounding Markov decision processes [Top+21]



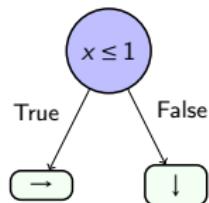
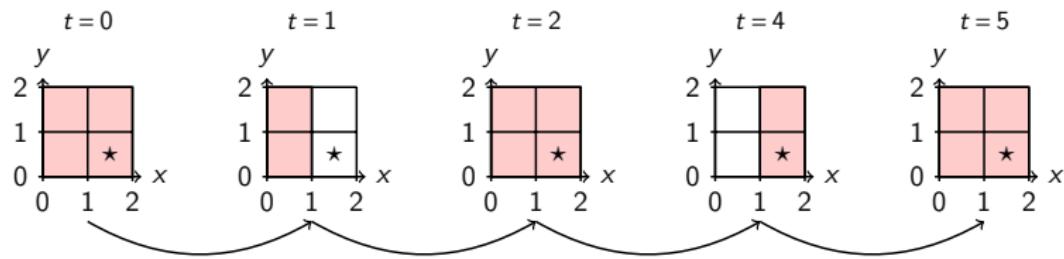
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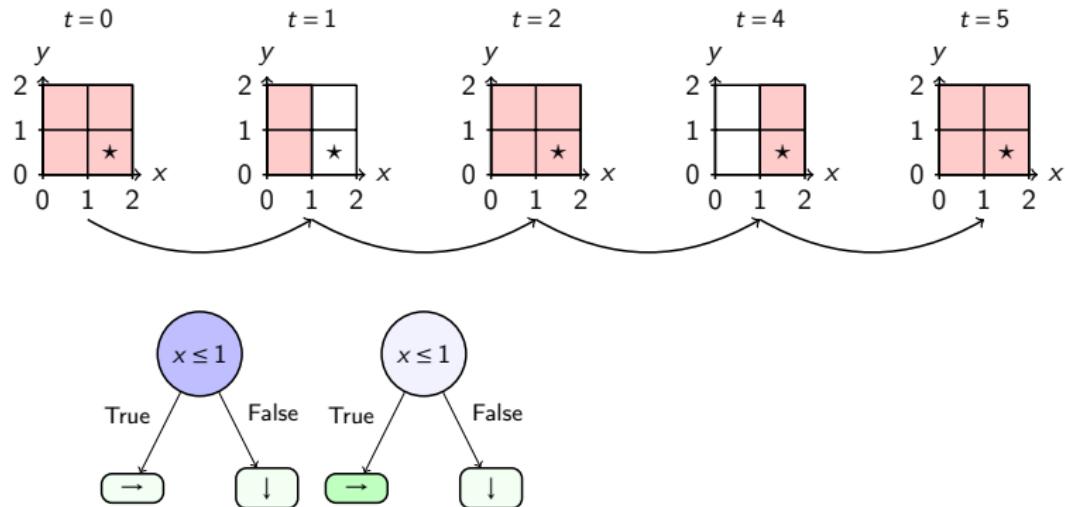
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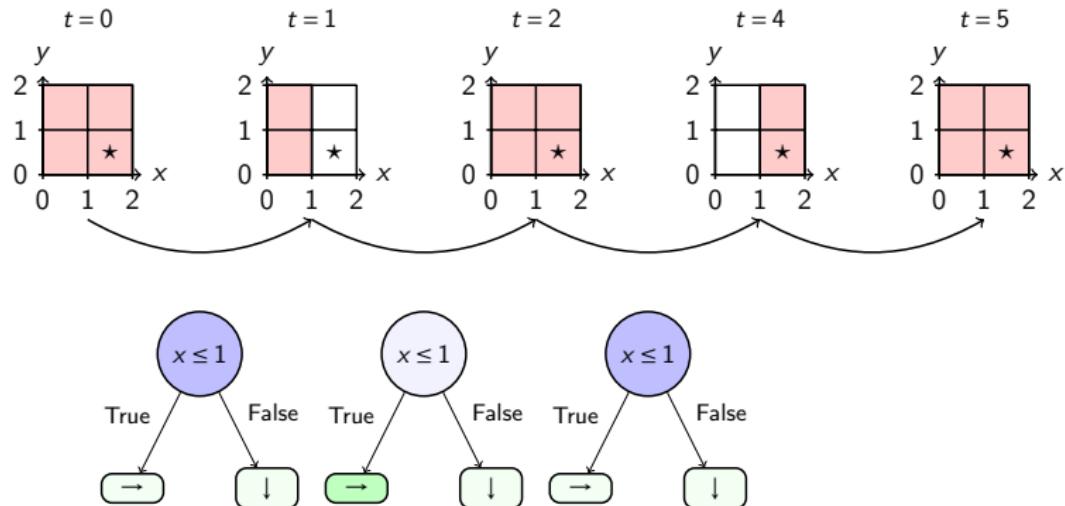
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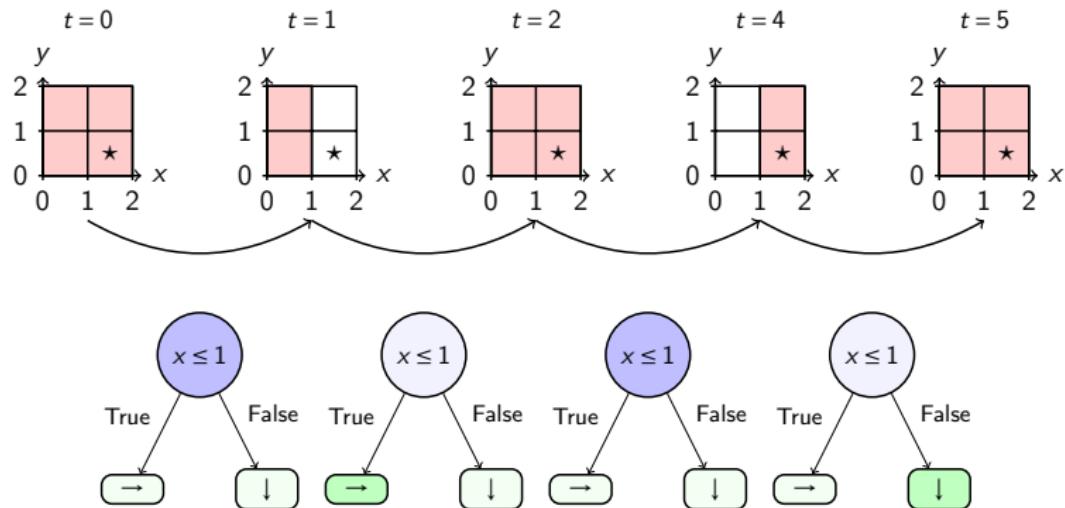
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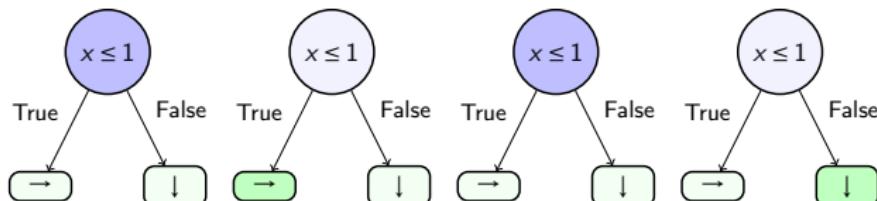
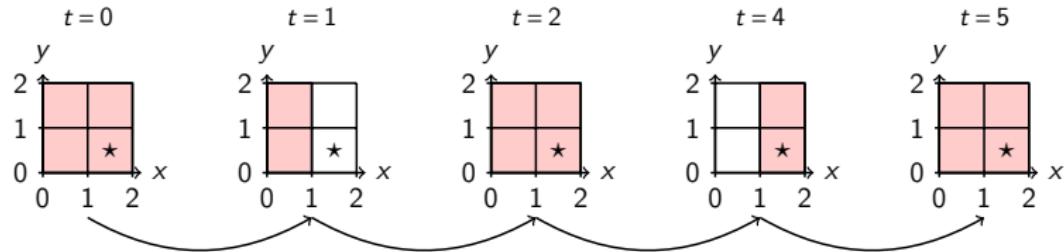
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⚠ To learn decision tree policies for an MDP we need to hide and allow agents to query information about state features.

Deterministic partially observable policies in IBMDPs

IBMDPs promises

- No need to design new algorithm: we can use RL.
- IBMDP rewards trade-off naturally interpretability and performances.

RL for partially observable policies

- Finding the best deterministic and partially observable policy is NP-hard [Lit94].
- The best partially observable policy can be stochastic [SJJ94].
- Value-based RL converges to sub-optimal solutions [SJJ94; LS98].

Asymmetric RL

- Access to hidden states during training but not at execution [Pin+17].
- Value-based \rightarrow learns $Q(o, a)$ with TD targets $Q(s, a)$ [BDA22].
- Actor-critic^a \rightarrow policy gradient on $\pi(o, a)$ using a critic $V(s)$ [BA22].
- Supposed to work better for our problem [EFM95].

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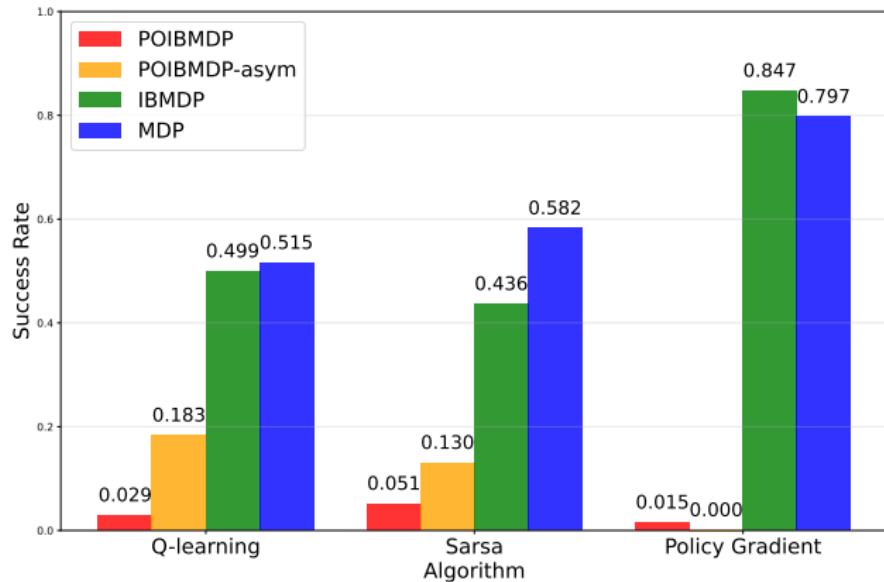
Result: for similar problems, RL struggles more when there is partial observability



Success rates over thousands of RL runs with varying hyperparameters when learning different policies in the same IBMDP¹.

¹We also observed similar results on classic controls and variants of the *grid world* MDP. A set of small, semi-transparent navigation icons typically used in Beamer presentations for navigating between slides.

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Decision trees in supervised learning

- N data points $\{x_i, y_i\}$. Each x_i is described by p features and has a label $y_i \in \mathcal{Y}$. We want to find a tree of depth at most D $T \in \mathcal{T}_D$ that minimizes:

$$\mathcal{L}_\alpha(T) = \frac{1}{N} \sum_{i=1}^N \ell(y_i, T(x_i)) + \alpha C(T)$$

- Trees interpretable and competitive with neural nets [GOV22].
- Greedy algorithms **sub-optimal accuracy**, but $O(2^D)$ operations [Bre+84; Qui86; Qui93] .
- Optimal algorithms, **optimal accuracy**, but $O((2Np)^D)$ operations (NP-hard) [BD17; Dem+22; LWD23; CRB24; HR76].
- In between optimal and greedy?

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Decision tree induction as solving MDPs

Intuition

The induction of a decision tree is made of a sequence of decisions: at each node, we must decide whether it is better to split (a subset of) the training data, or to create a leaf node.

- S: data subsets.
- A: test or leaf nodes that can be added to the tree.
- R: penalty or accuracies.
- T: node traversals.

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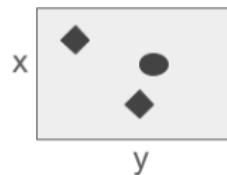
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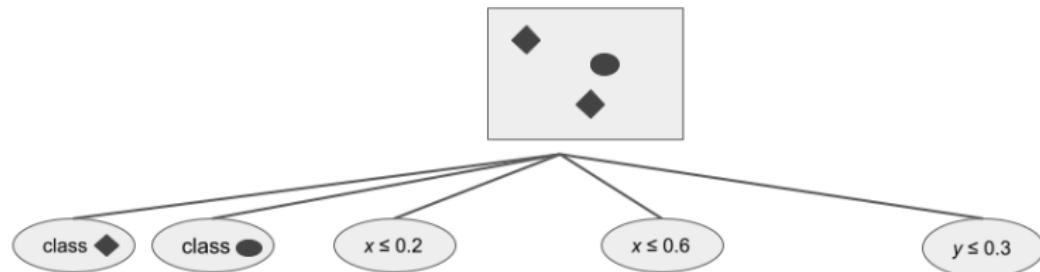
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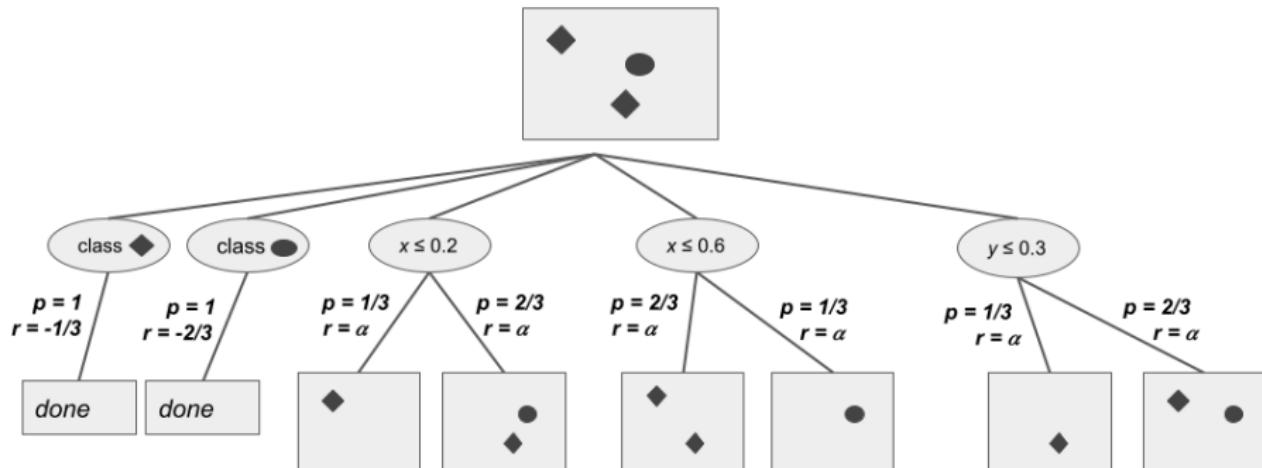
Example of decision tree induction as an MDP.

Decision tree induction as solving MDPs



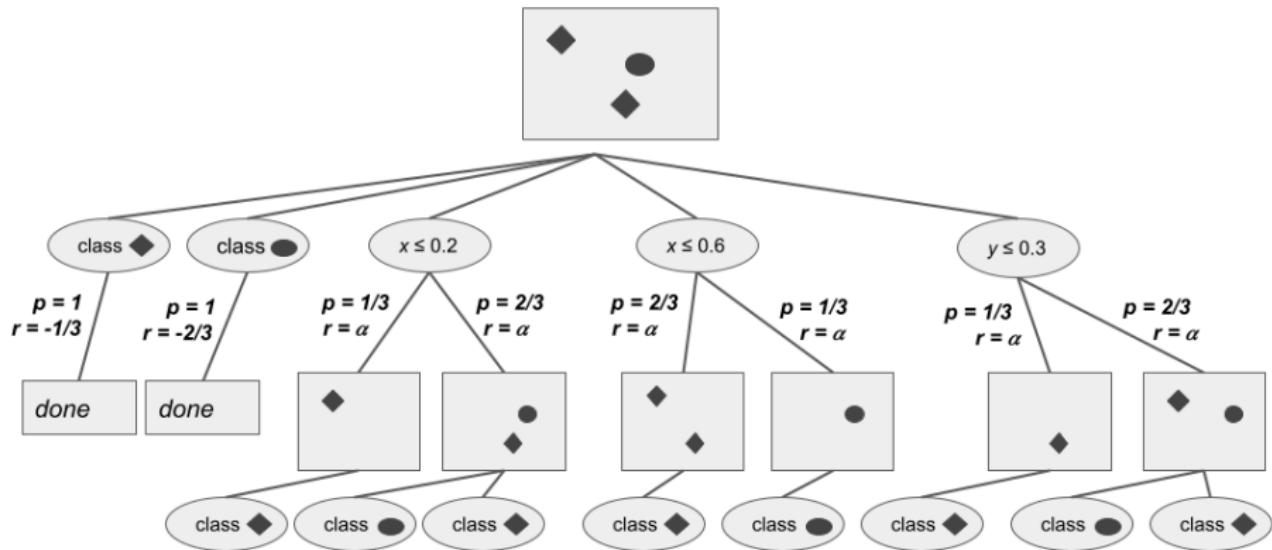
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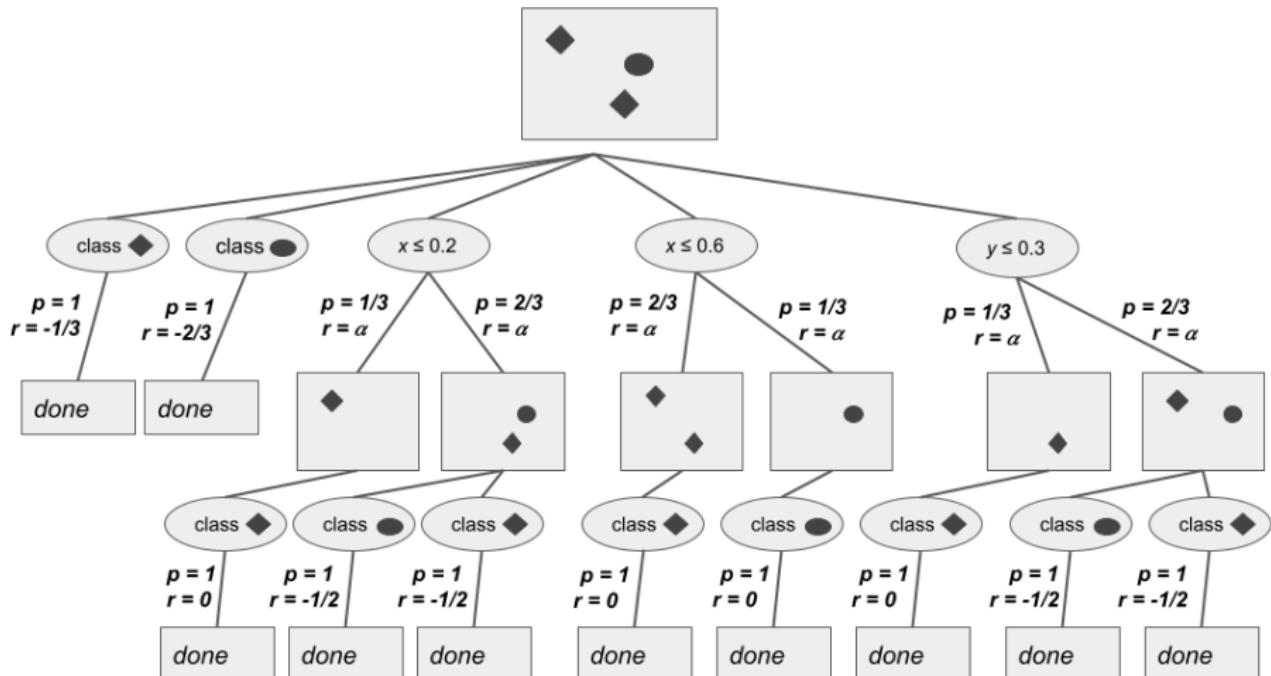
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Controlling the time complexity of decision tree induction

- Greedy algorithms consider only one candidate action in each state which is the test that minimizes some impurity criterion
→ MDP state space size is $O(2^D)$.
- Optimal algorithms consider all possible actions in each state
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- Dynamic Programming Decision Trees (DPDT): Let's choose candidate actions adaptively
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How to choose the B candidate actions/splits?

Top-B greedy splits [Bla+23], quantiles, random...

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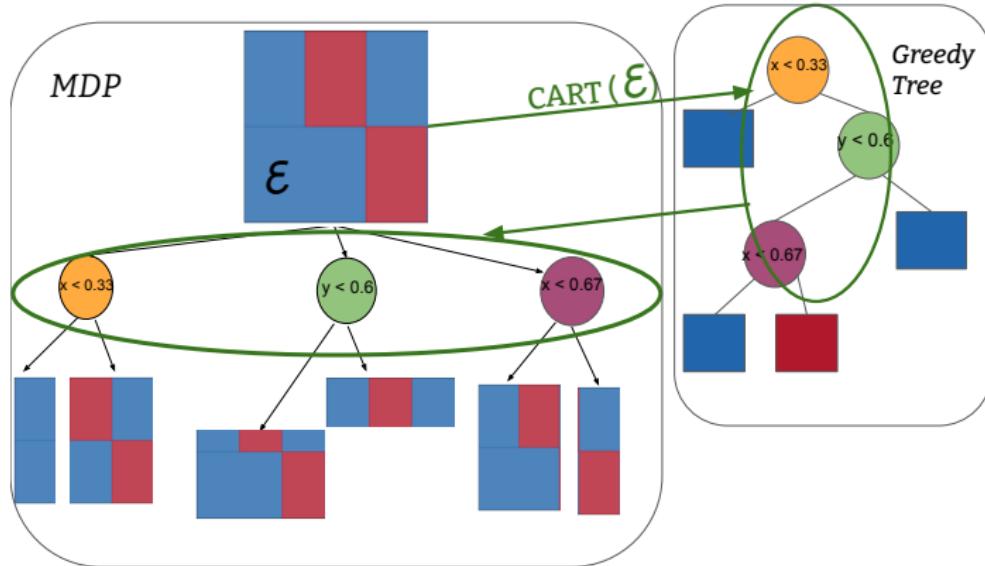
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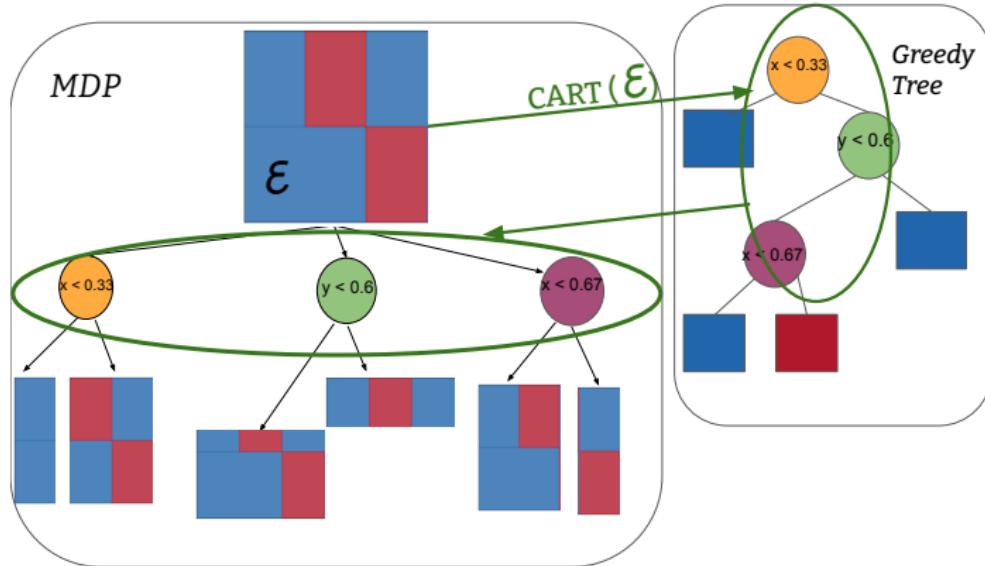
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Practical implemenataion of DPDT



We can use greedy trees nodes as candidate actions.

Practical implemenataion of DPDT



We can use greedy trees nodes as candidate actions.

Fast like greedy trees, accurate like optimal trees



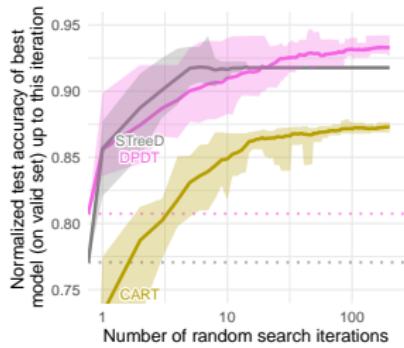
Comparison of greedy, optimal, and DPDT depth-2 trees on the checkersboard dataset.

Fast like greedy trees, accurate like optimal trees

Comparison of accuracies and operations for depth-3 trees.

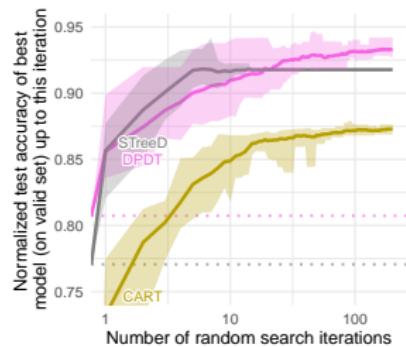
Dataset	Accuracy						Operations					
	Opt	Greedy	DPDT				Opt	Greedy	DPDT			
			CART ⁻	CART ⁺	TopB ⁻	TopB ⁺			CART ⁻	CART ⁺	TopB ⁻	TopB ⁺
room	0.992	0.968	0.991	0.992	0.990	0.992	10^6	15	286	16100	111	16100
bean	0.871	0.777	0.812	0.853	0.804	0.841	$5 \cdot 10^6$	15	295	25900	112	16800
eeg	0.708	0.666	0.689	0.706	0.684	0.699	$2 \cdot 10^6$	13	289	26000	95	11000
avila	0.585	0.532	0.574	0.585	0.563	0.572	$3 \cdot 10^7$	9	268	24700	60	38900
magic	0.831	0.801	0.822	0.828	0.807	0.816	$6 \cdot 10^6$	15	298	28000	70	4190
htru	0.981	0.979	0.979	0.980	0.979	0.980	$6 \cdot 10^7$	15	295	25300	55	2180
occup.	0.994	0.989	0.991	0.994	0.990	0.992	$7 \cdot 10^5$	13	280	16300	33	510
skin	0.969	0.966	0.966	0.966	0.966	0.966	$7 \cdot 10^4$	15	301	23300	20	126
fault	0.682	0.553	0.672	0.674	0.672	0.673	$9 \cdot 10^8$	13	295	24200	111	16800
segment	0.887	0.574	0.812	0.879	0.786	0.825	$2 \cdot 10^6$	7	220	16300	68	11400
page	0.971	0.964	0.970	0.970	0.964	0.965	10^7	15	298	22400	701	4050
bidding	0.993	0.981	0.985	0.993	0.985	0.993	$3 \cdot 10^5$	13	256	9360	58	2700
raisin	0.894	0.869	0.879	0.886	0.875	0.883	$4 \cdot 10^6$	15	295	20900	48	1440
rice	0.938	0.933	0.934	0.937	0.933	0.936	$2 \cdot 10^7$	15	298	25500	49	1470
wilt	0.996	0.993	0.994	0.995	0.994	0.994	$3 \cdot 10^5$	13	274	11300	33	465
bank	0.983	0.933	0.971	0.980	0.951	0.974	$6 \cdot 10^4$	13	271	7990	26	256

DPDT trees generalization



DPDT depth-5 trees vs.
other depth-5 trees

DPDT trees generalization

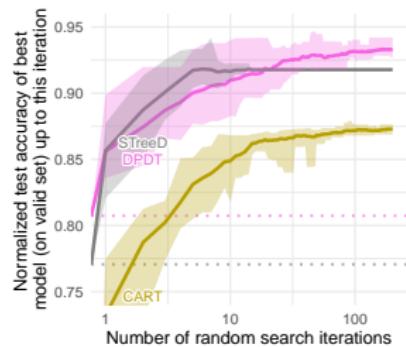


DPDT depth-5 trees vs.
other depth-5 trees

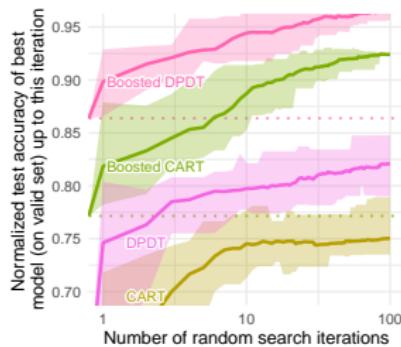


Boosted DPDT vs. Boosted
CART

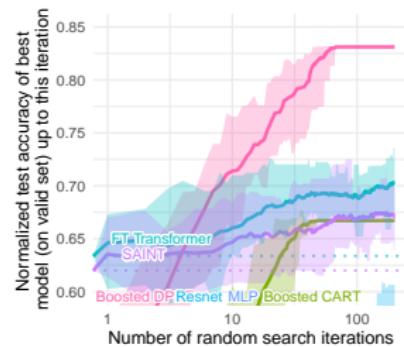
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Boosted DPDT vs. other
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Theorem (DPDT trees are not worse than greedy trees)

The greedy tree is always a solution of the MDPs we solve. Because we solve the MDPs exactly with DP, if the greedy tree is the best solution, DPDT will find it.

Theorem (DPDT trees can be strictly better than greedy trees)

There exist a depth budget D and a dataset for which DPDT trees are strictly better than greedy trees.^a

^acf. checkersboard dataset.

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CART generates more diverse splits than Top B

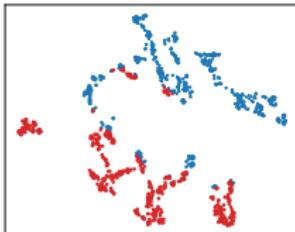
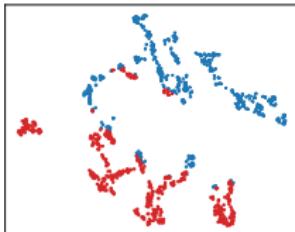
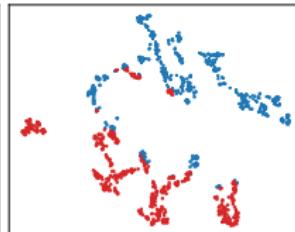
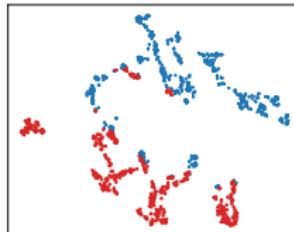
DPDT-Top B Naive-Heuristic Root node candidates for bank

$f_0 \leq 0.56265$

$f_0 \leq 0.56309$

$f_0 \leq 0.56227$

$f_0 \leq 0.56168$

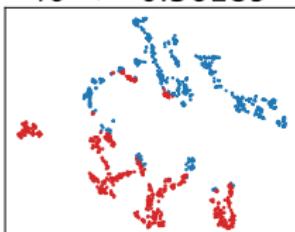
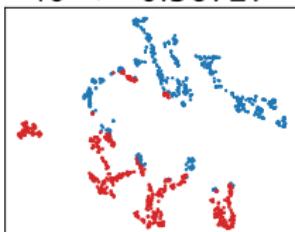
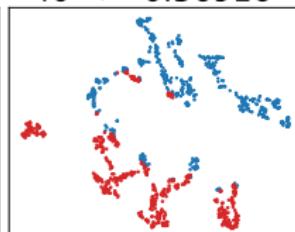
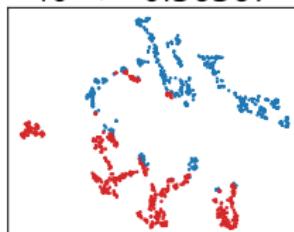


$f_0 \leq 0.56367$

$f_0 \leq 0.56916$

$f_0 \leq 0.56727$

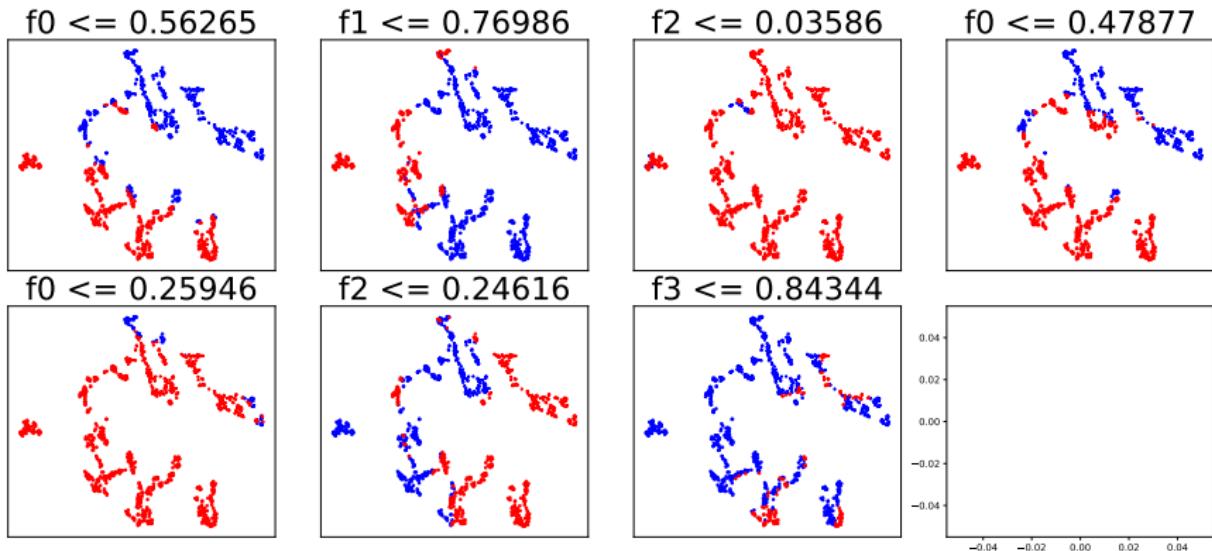
$f_0 \leq 0.56189$



- Left child ■ Right child ○ Class 0 * Class 1

CART generates more diverse splits than Top B

DPDT-CART-Heuristic Root node candidates for bank



- Left child
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- New SOTA decision tree induction with dynamic programming in MDPs.
- What about using DPDT for indirect decision tree policy learning for SDM?
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Challenges [Gla+24; Lip18; DK17]

- No definition of interpretability.
- Measuring might require humans.
- Different hardwares (CPUs vs GPUs).
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We propose policy unfolding

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# Decision tree for Mountain Car
def play(x):
    if x[1] <= -0.2597:
        if x[1] <= -0.6378:
            return 0
        else:
            if x[0] <= -1.0021:
                return 2
            else:
                return 0
    else:
        if x[1] <= -0.0508:
            if x[0] <= 0.2979:
                if x[0] <= 0.0453:
                    return 2
                else:
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def play(x):
    h_layer_0_0 = 1.238*x[0]+0.971*x
    [1]
                           +0.430*x[2]+0.933
    h_layer_0_0 = max(0, h_layer_0_0
    )
    h_layer_0_1 = -1.221*x[0]+1.001
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    h_layer_1_1 = max(0, h_layer_1_1
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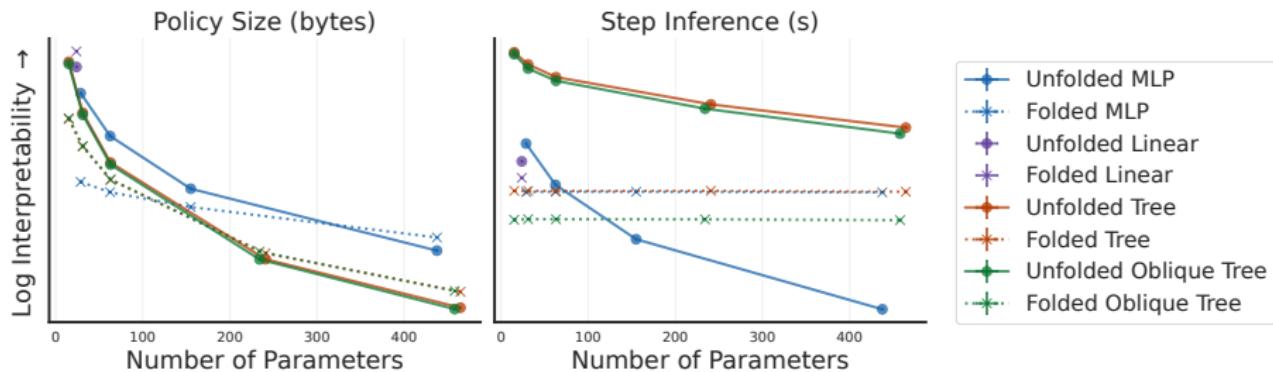
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Aggregated policies interpretability on classic control environments

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- Technical challenges: Learning interpretable policies for SDM involves partial observability.
 - Focus on indirect approaches and/or on POMDP research first?
 - Created opportunities for new decision tree algos for classif/regression
- Fundamental challenges: no definition.
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Motivate interpretability by finding a real-world problem where interpretability is *really* necessary [Nag+24].

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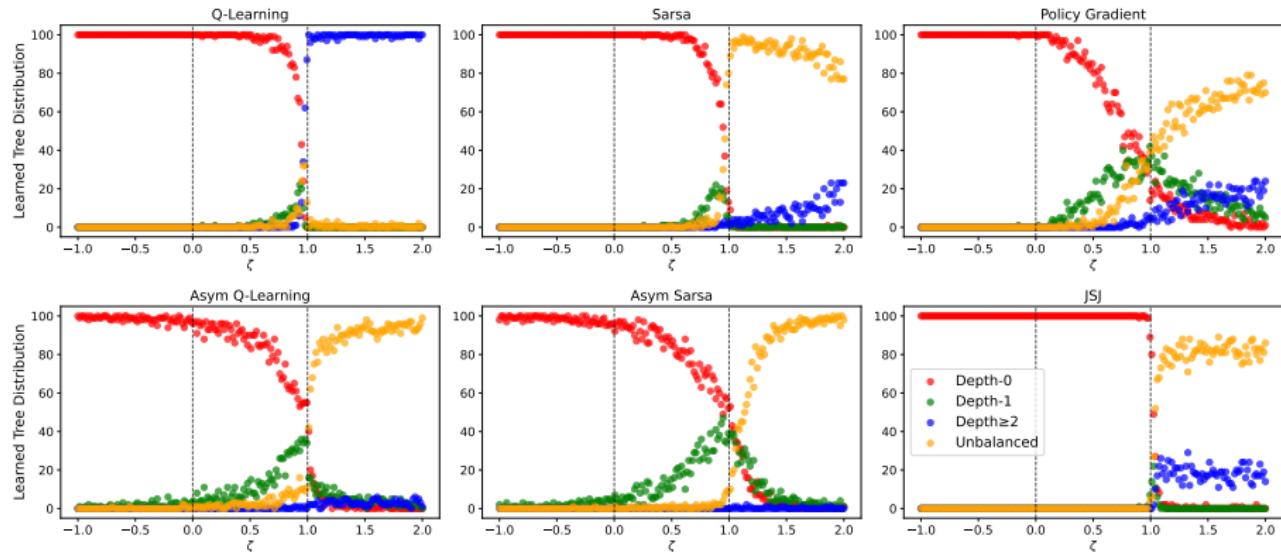
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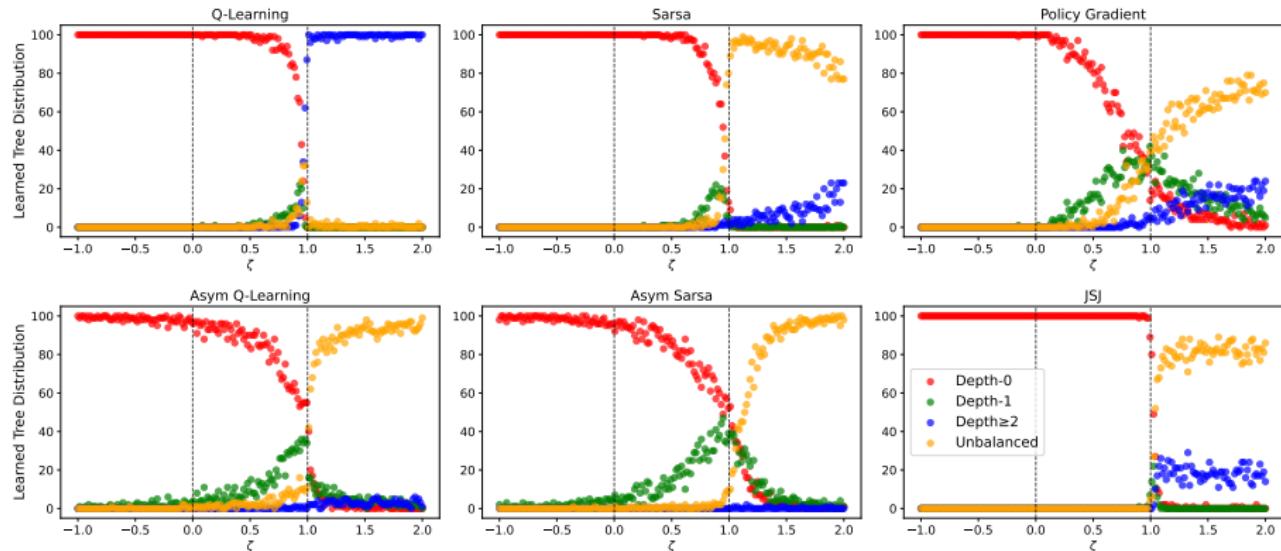
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Result: RL cannot retrieve optimal depth-1 trees for the grid world MDP

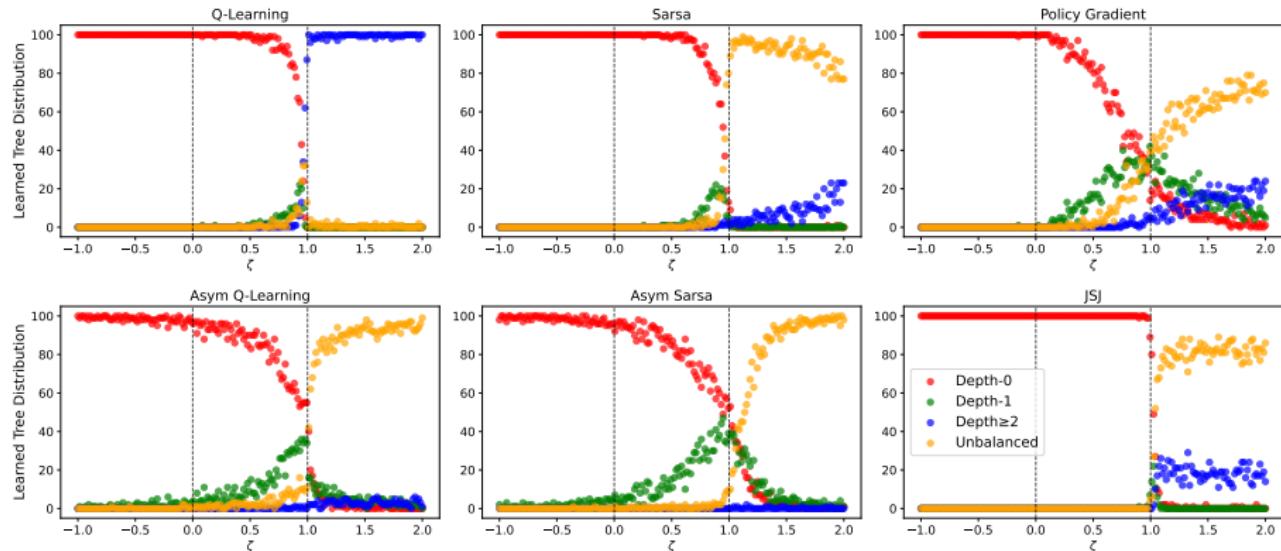


Result: RL cannot retrieve optimal depth-1 trees for the grid world MDP



Distributions of tree policies learned with (asymmetric) RL algorithms [SB98; SJ94; LS98; BA22; BDA22] as a function of the interpretability reward ζ .

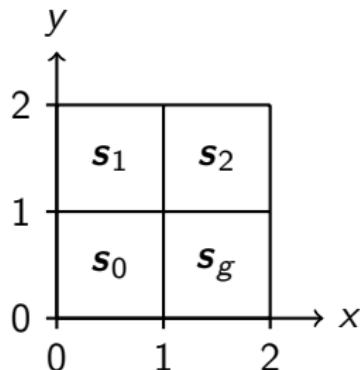
Result: RL cannot retrieve optimal depth-1 trees for the grid world MDP



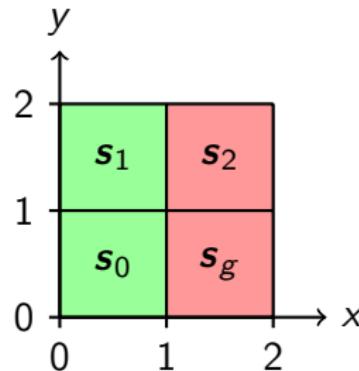
Distributions of tree policies learned with (asymmetric) RL algorithms [SB98; SJ94; LS98; BA22; BDA22] as a function of the interpretability reward ζ .

Are the poor performances due to partial observability?

Result: decision tree policies for classification MDPs are standard Markovian policies in IBMDPs

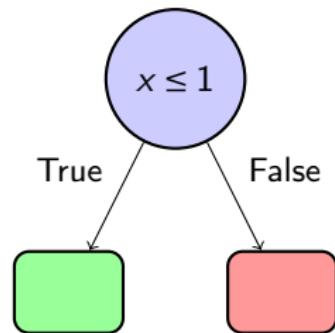
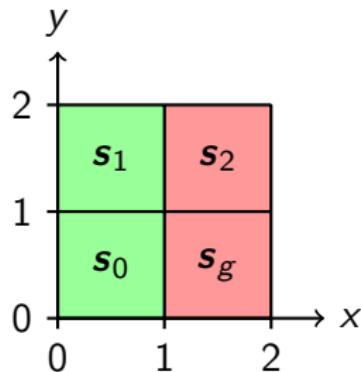


Result: decision tree policies for classification MDPs are standard Markovian policies in IBMDPs



Classification MDP and the unique optimal depth-1 tree.

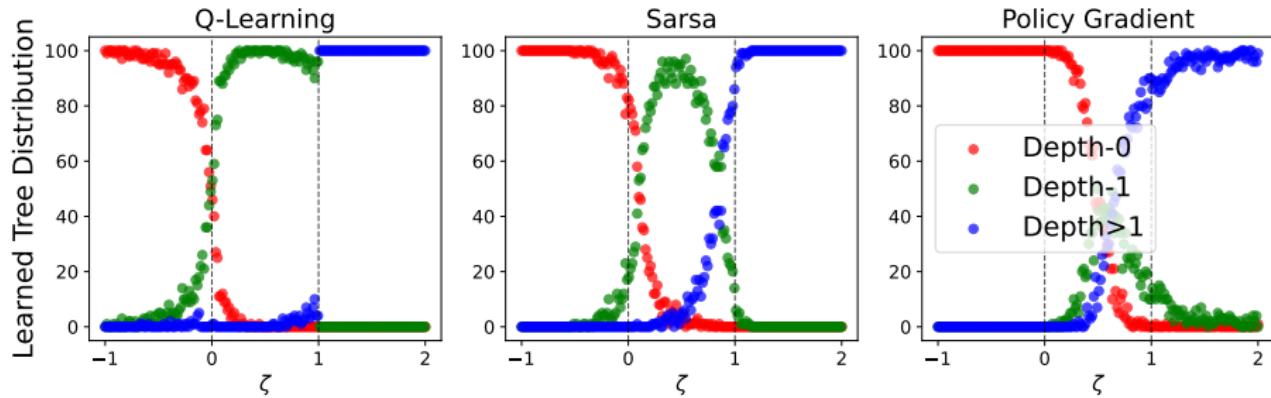
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Classification MDP and the unique optimal depth-1 tree.

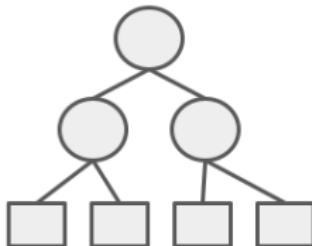
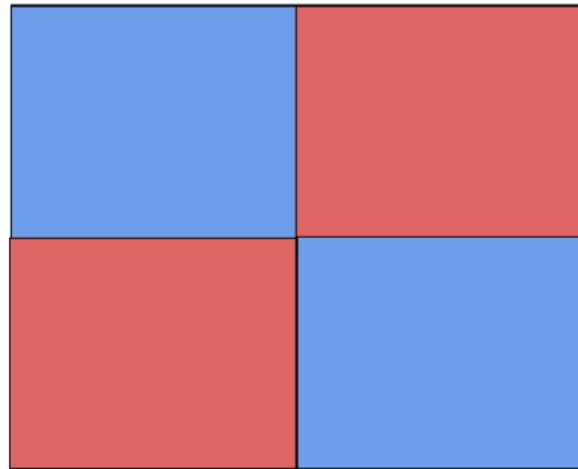
Deterministic partially observable policies for classification IBMDPs
(\Leftrightarrow decision tree policies) are in fact Markovian.

Result: RL can retrieve optimal depth-1 trees for the toy classification MDP

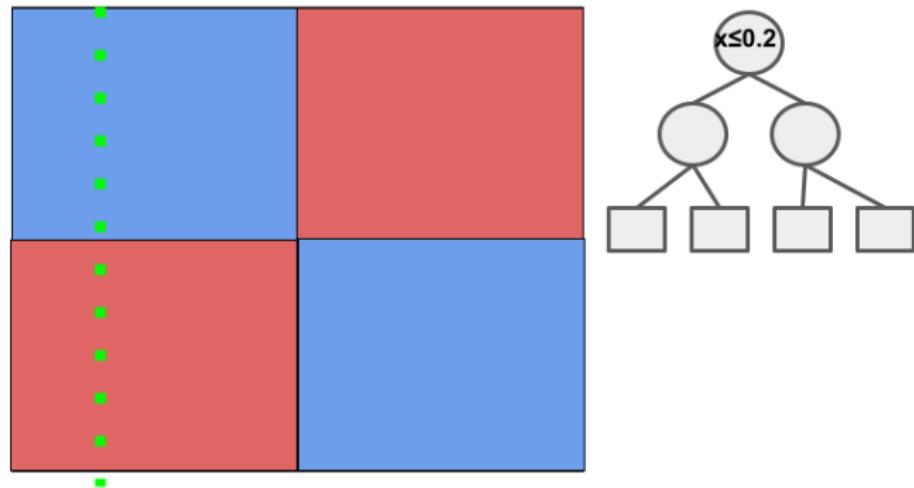


Distributions of tree policies learned with various RL algorithms.

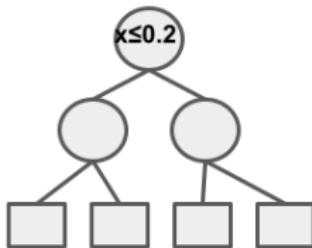
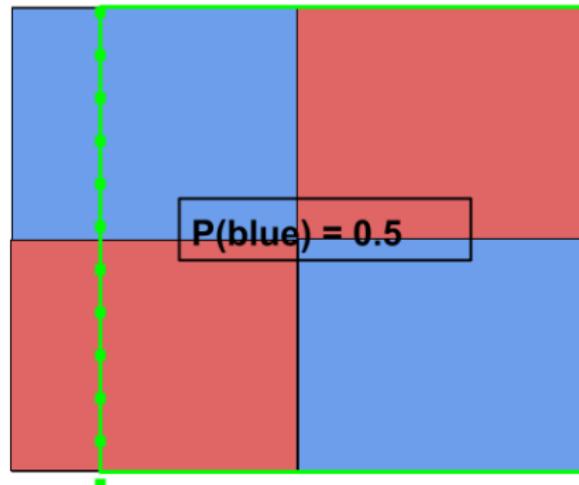
DPDT trees can be strictly better than greedy trees



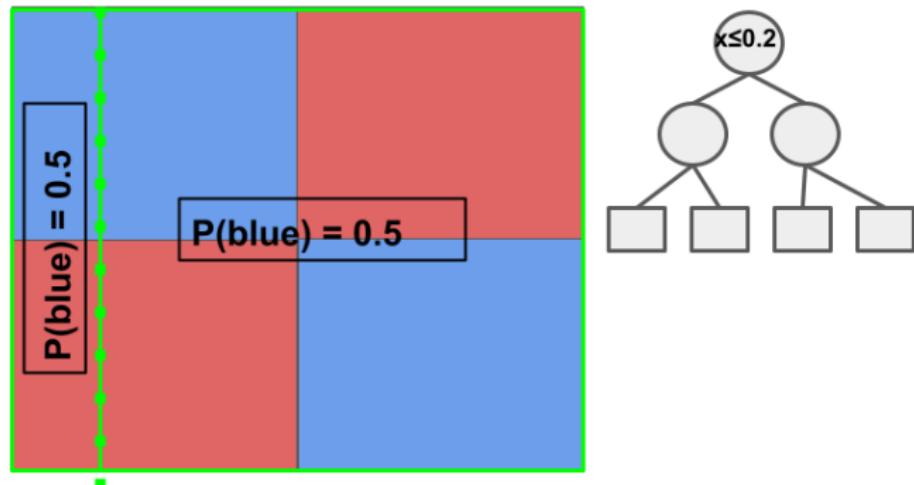
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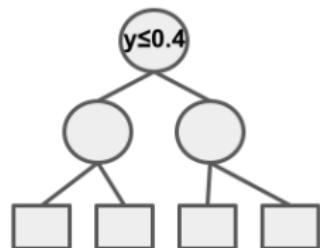
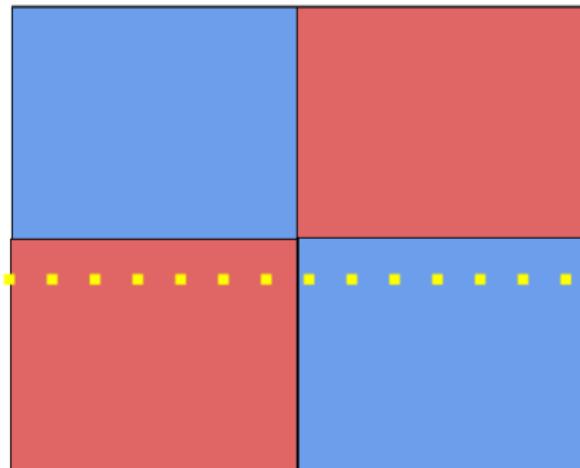
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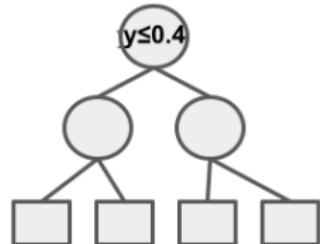
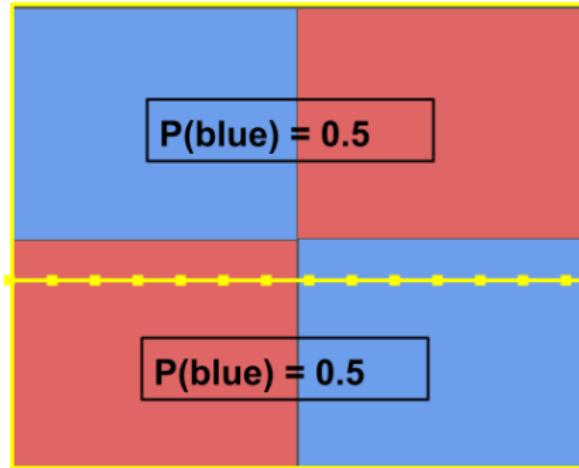
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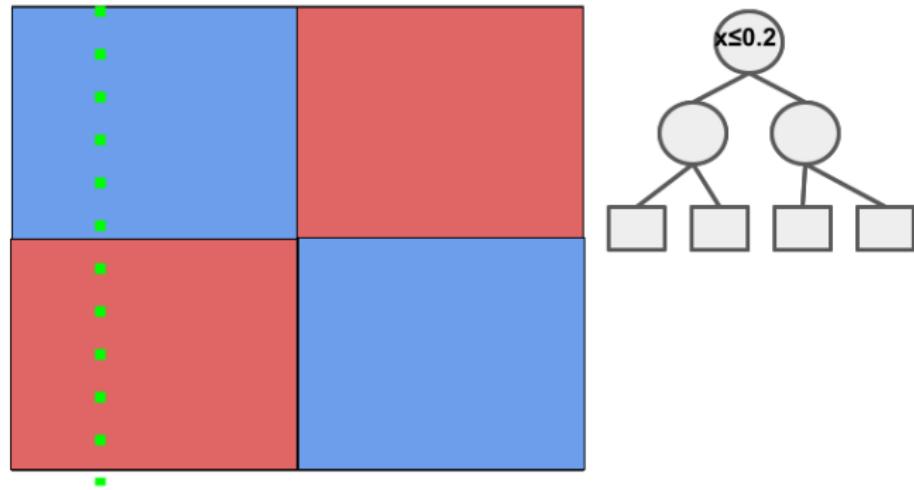
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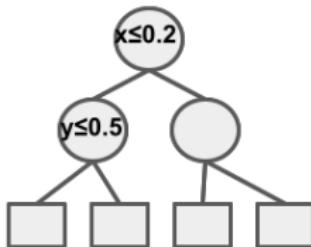
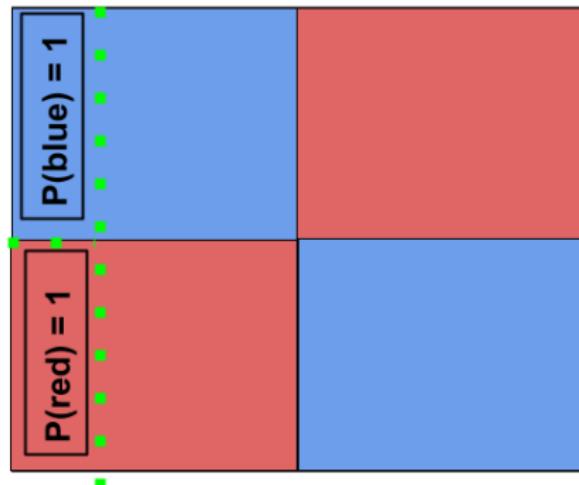
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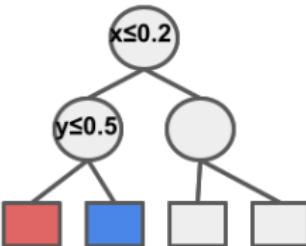
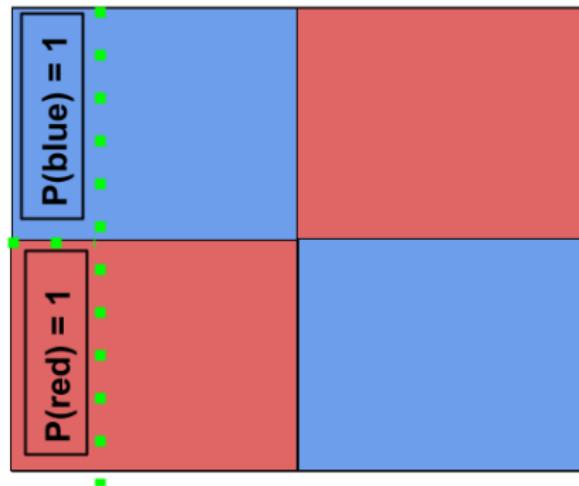
DPDT trees can be strictly better than greedy trees



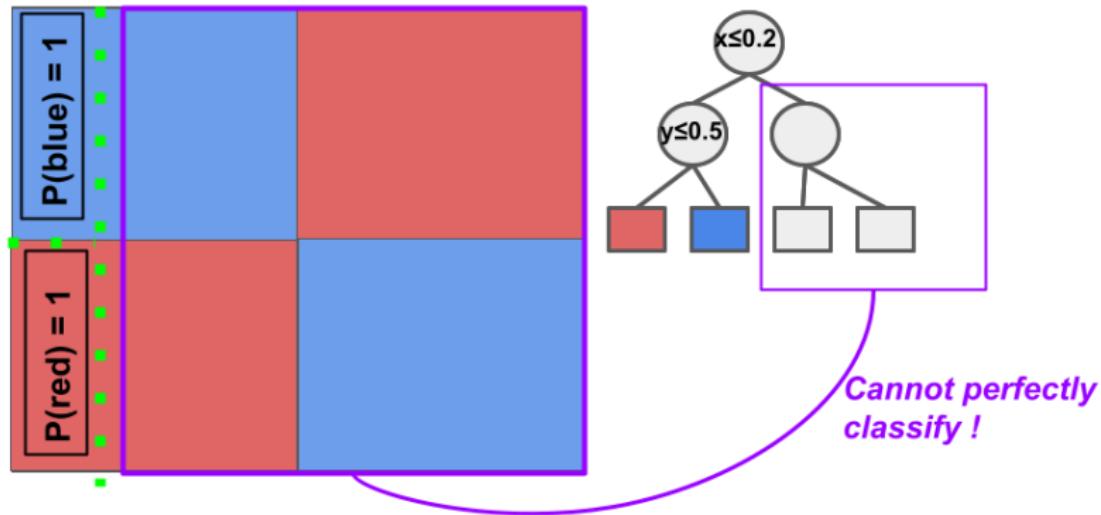
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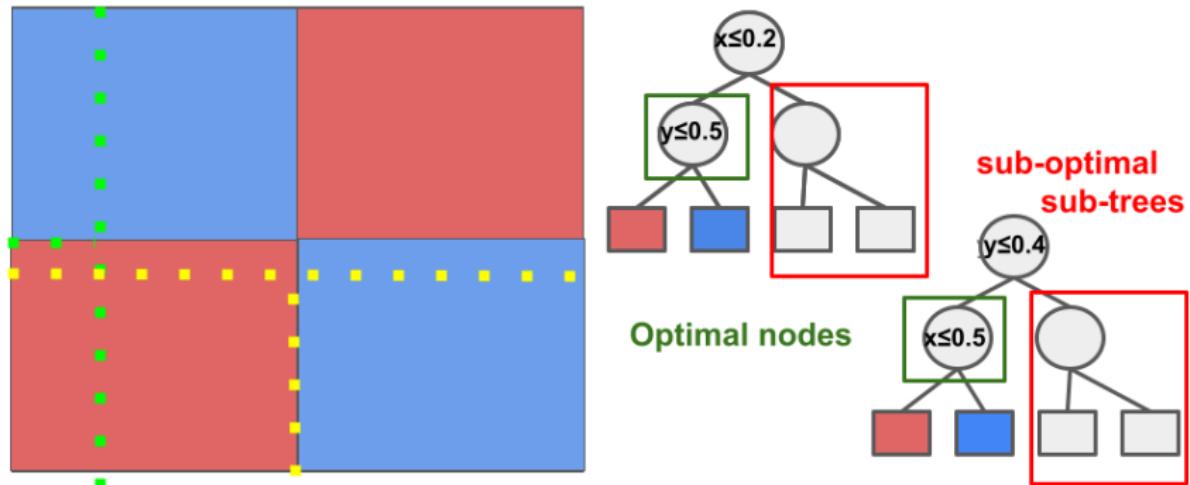
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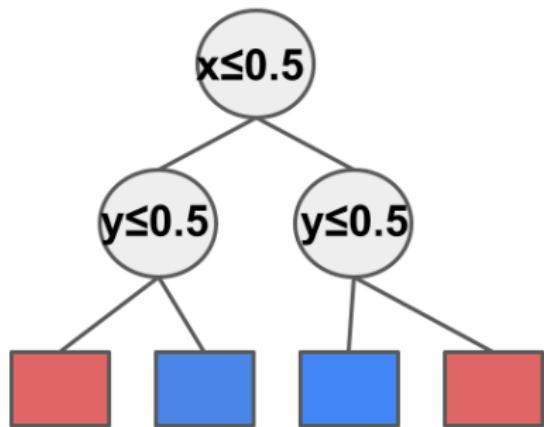
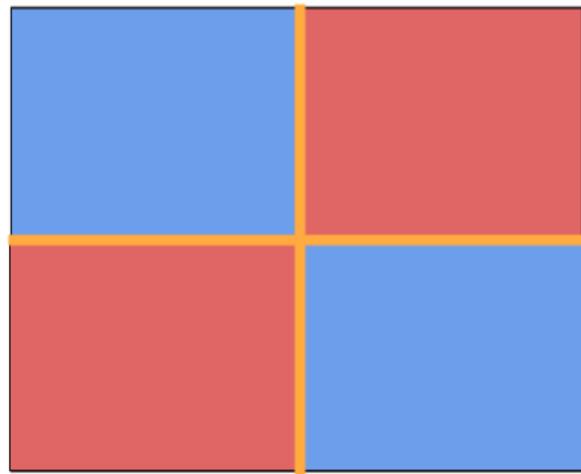
DPDT trees can be strictly better than greedy trees



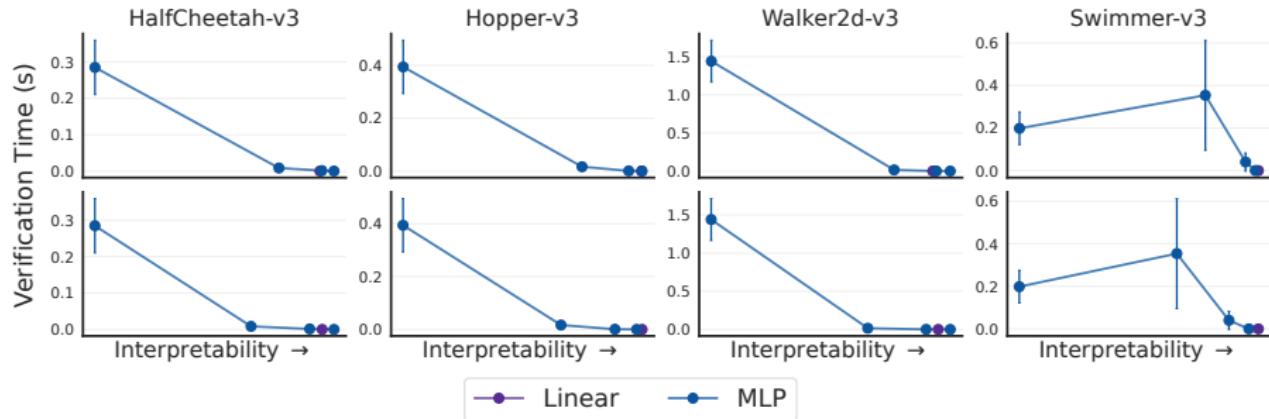
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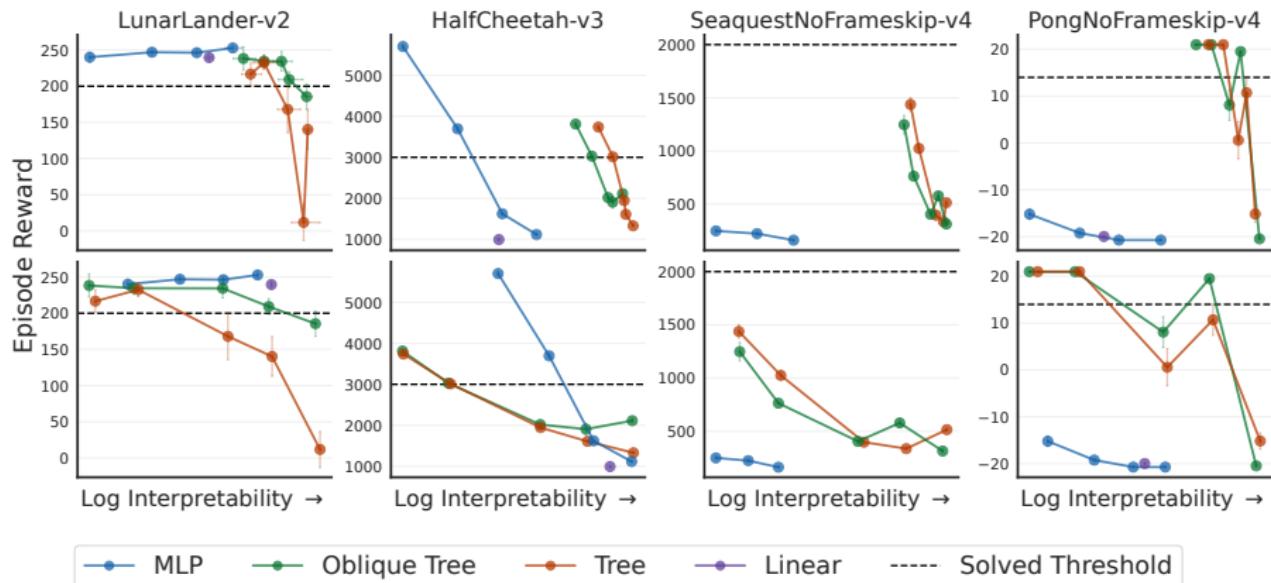


Result: verification time does scale with step inference time



Verification time as a function of policy interpretability. Top row, interpretability is measured with step inference times. Bottom row, the interpretability is measured with policy size.

Result: there is no dominating policy class for all environments



Interpretability-Performance trade-offs. Top row, interpretability is measured with step inference times. Bottom row, the interpretability is measured with policy size.