Interpretability, Decision Trees, and Sequential Decision Making

Hector Kohler

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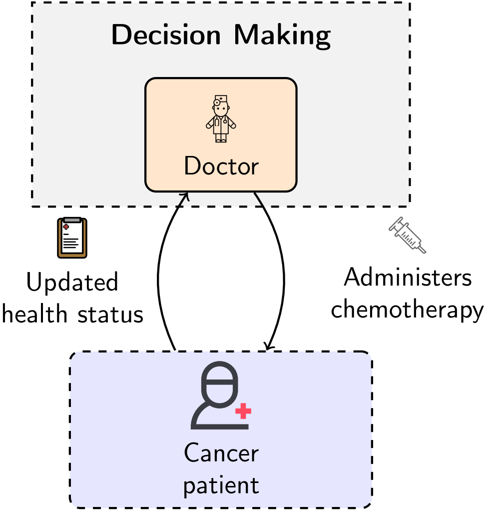
November 27, 2025

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



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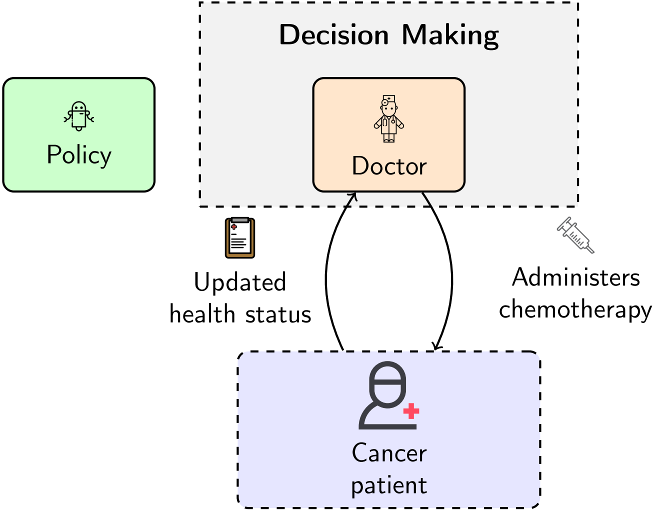

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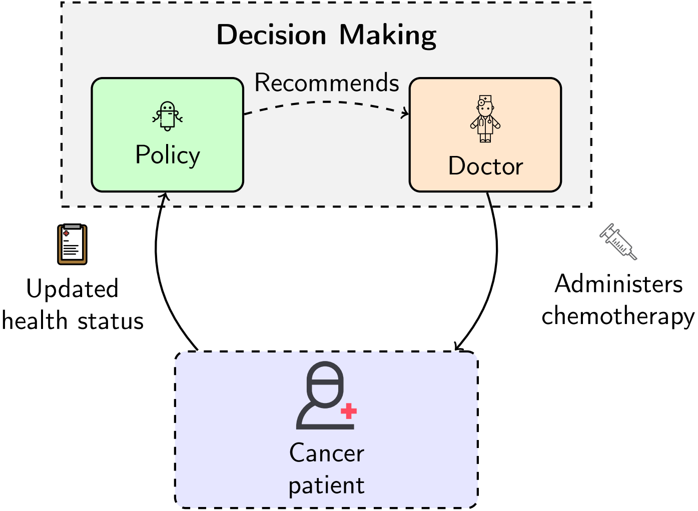

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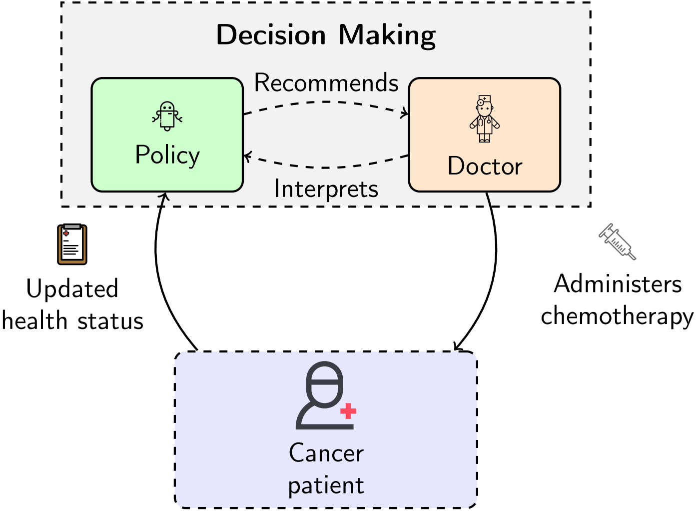

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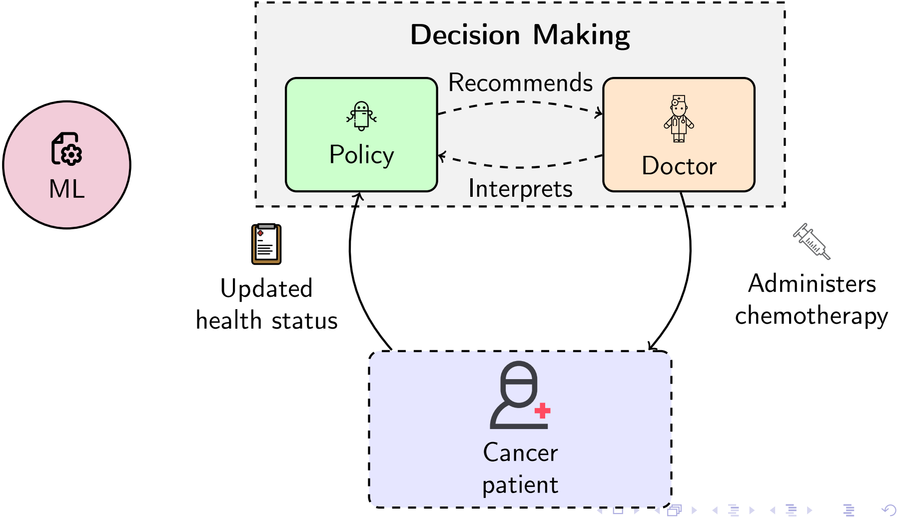

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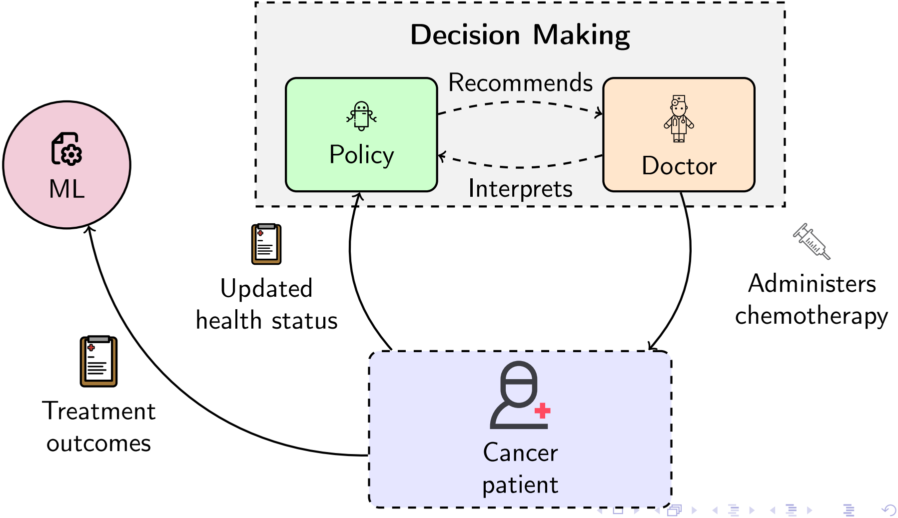

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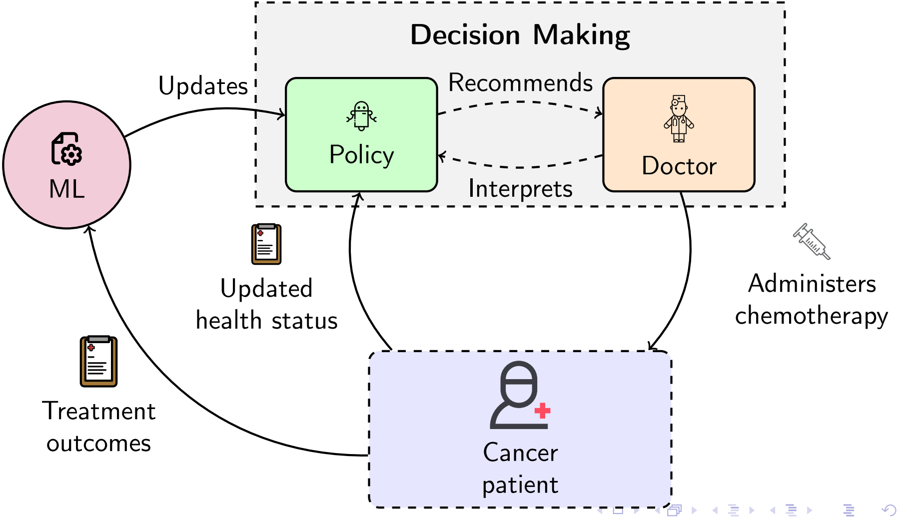

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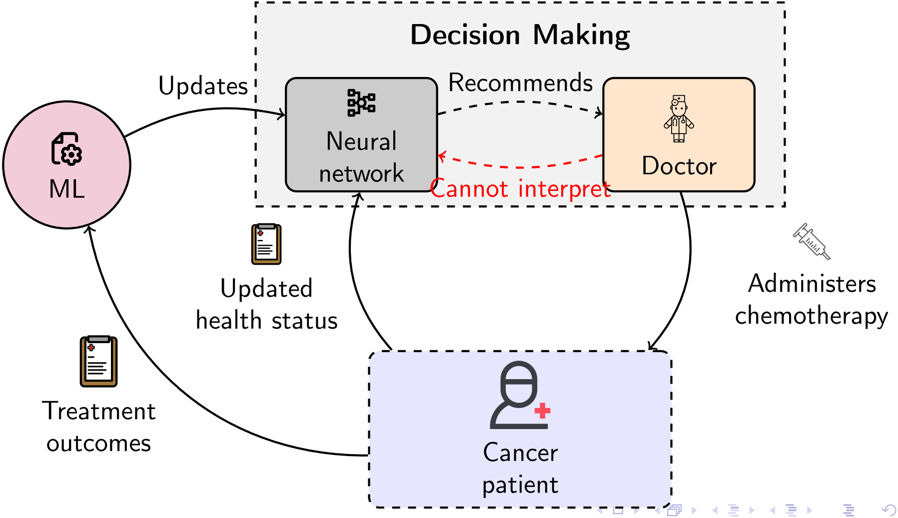
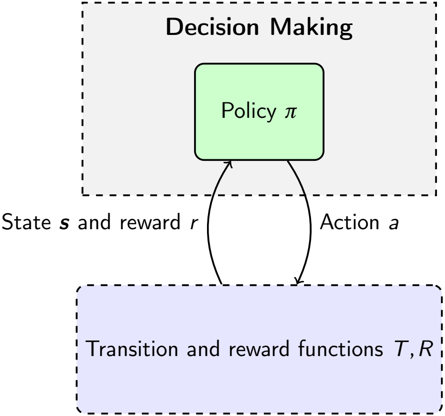


Markov decision processes (MDPs) and reinforcement learning (RL)



Markov decision processes [Put94].

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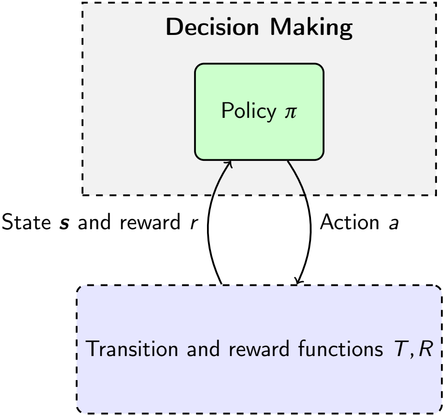

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- RL [SB98] aims to find a policy, $\pi : S \to A$ that maximizes:

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

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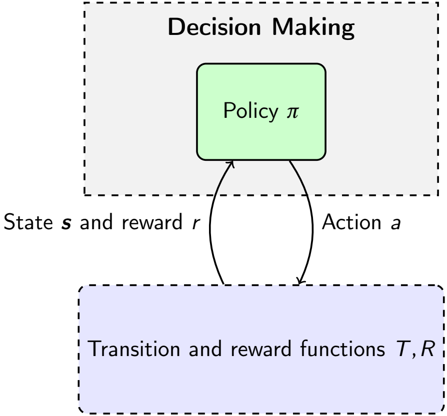

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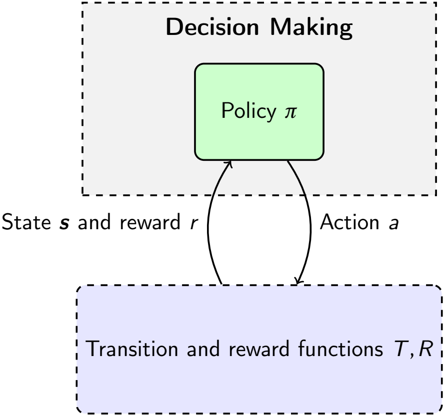

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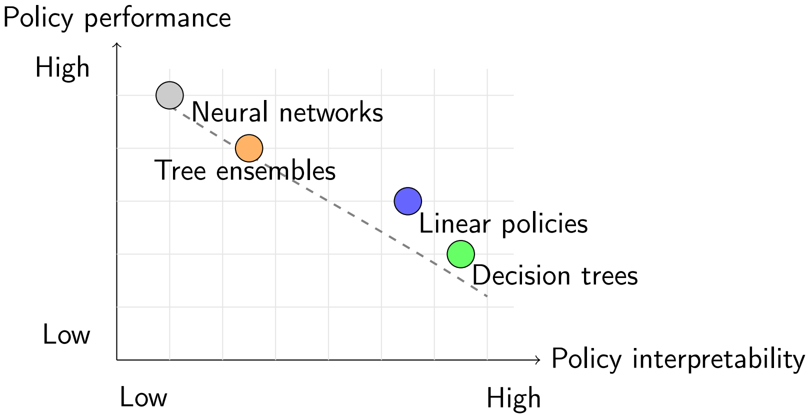
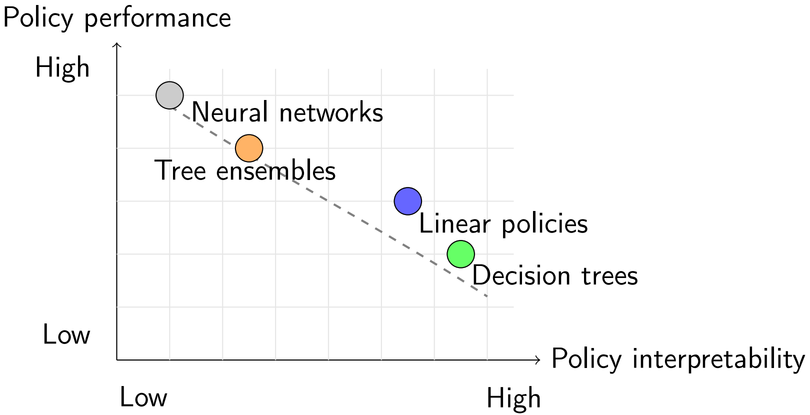
- Lots of succesful RL algorithms [SB98; Mni+15; Sch+17].
- Few interpretability concerns.

Policy interpretability



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

Policy interpretability



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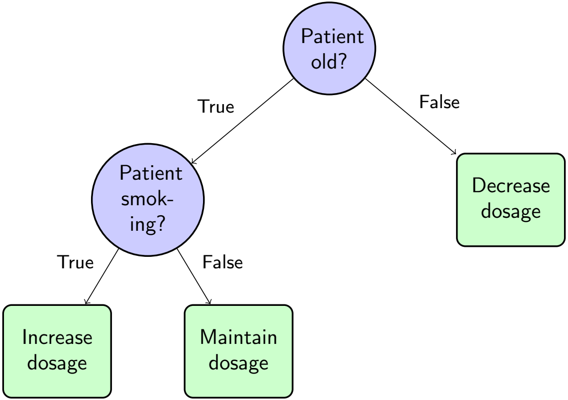
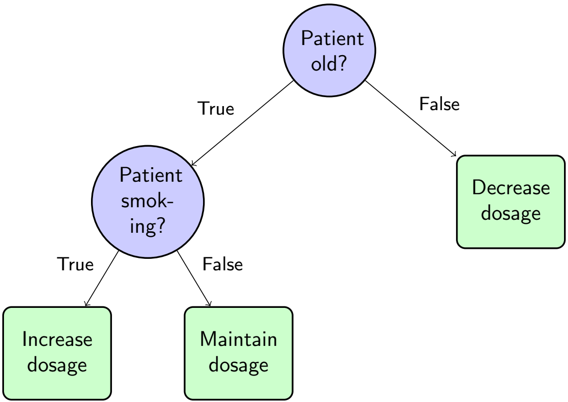
⚠ **No definition of interpretability for machine learning models!**

Decision trees



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

Decision trees



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Successful algorithms for classification/regression: [Bre+84; BD17; Dem+22; VZ19; MMW22] . . .

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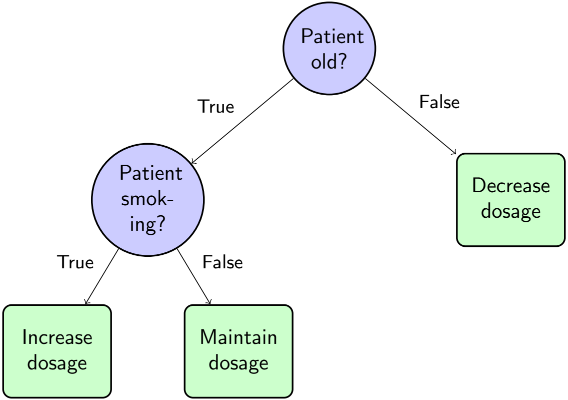

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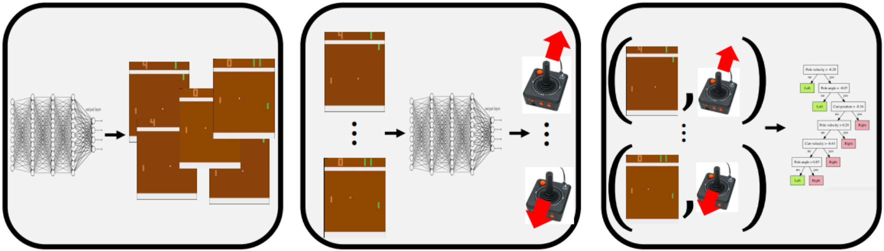
What about SDM?

Indirect approach: imitation learning

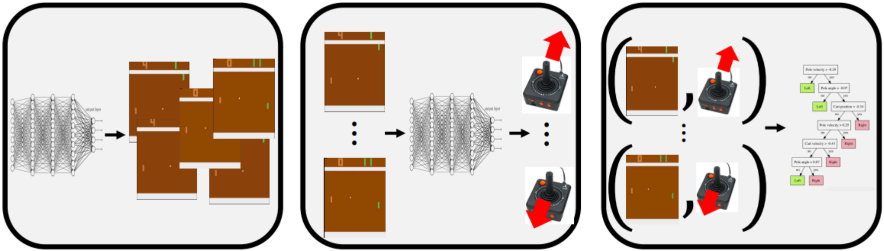


Step 1: Use NN to generate states

Step 2: Use NN to obtain actions

Step 3: Use supervised learning to train a decision tree

Indirect approach: imitation learning



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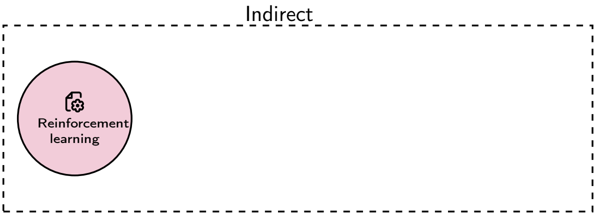
Most research focused on indirect learning of interpretable policies [RGB10; BPS18; Ver+18; Mil+24].

Two ways to get interpretable policies for SDM



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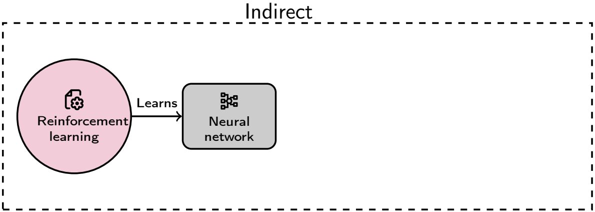

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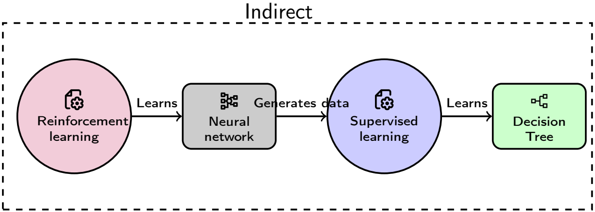

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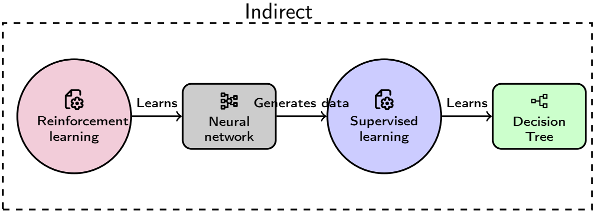

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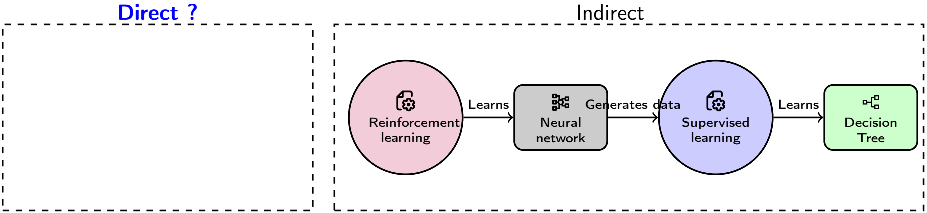

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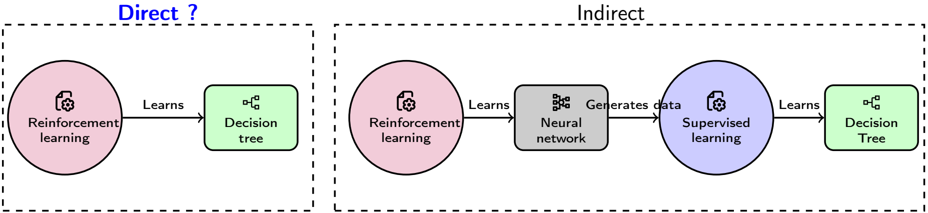

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Contributions

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2. Can we leverage SDM to learn interpretable classifiers for supervised learning?
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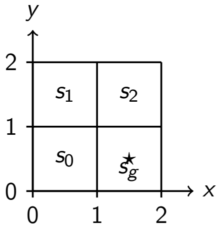
Grid world MDP and decision tree policies



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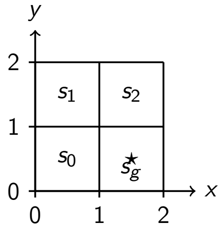

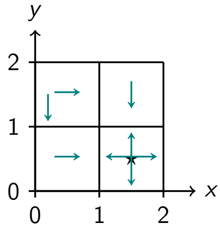

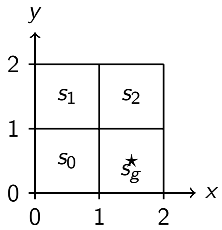

Grid world MDP and optimal actions.

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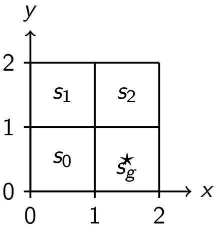

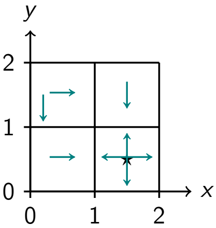

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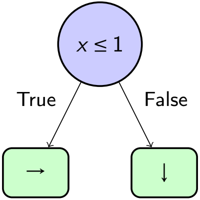

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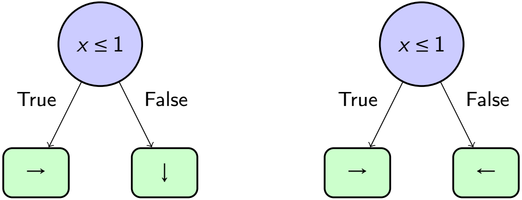

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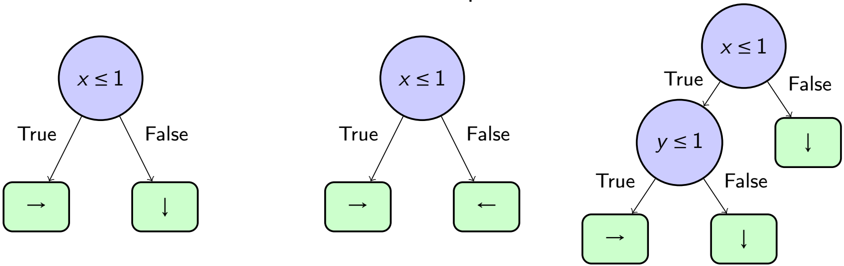

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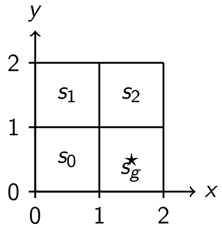

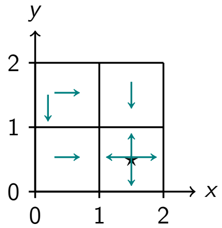

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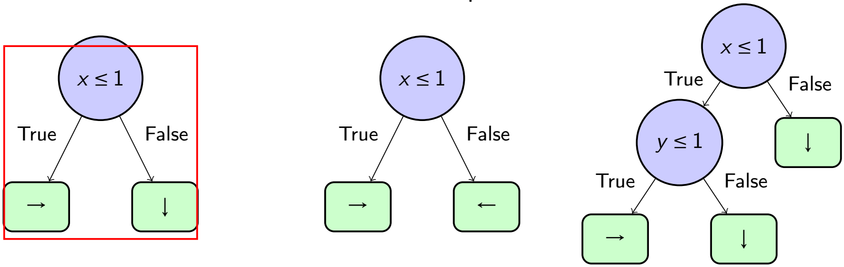

Decision tree policies with different interpretability-performance trade-offs.

Grid world MDP and decision tree policies: indirect approach

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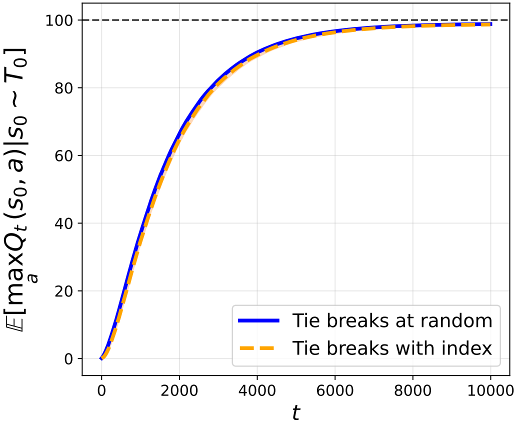

Sample complexity curve of Q-learning over 100 random seeds.

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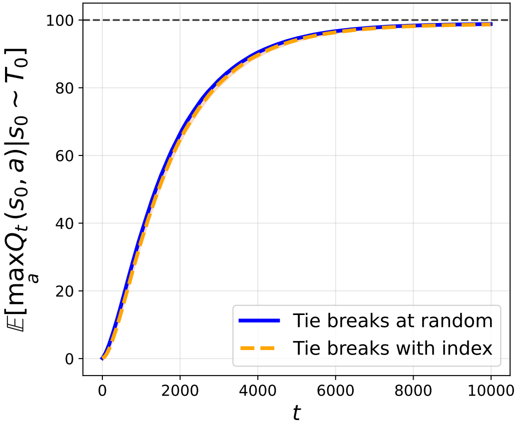

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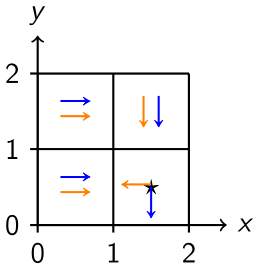
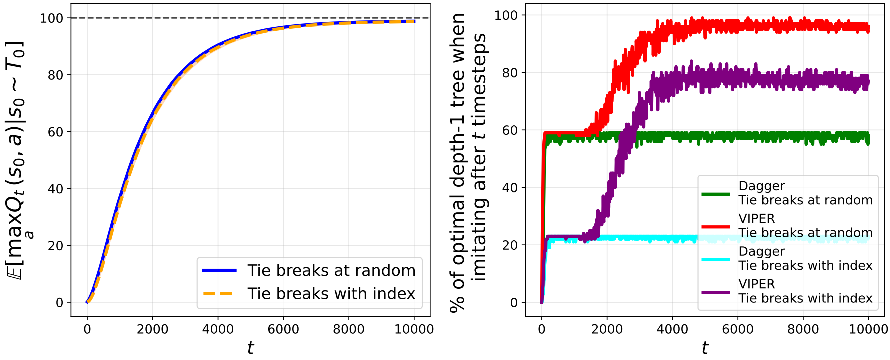


Expert policies.

Grid world MDP and decision tree policies: indirect approach



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.

Direct RL of decision tree policies with iterative bounding Markov decision processes

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IBMDPs promises

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- No need to design new algorithm: we can use RL.

Direct RL of decision tree policies with iterative bounding Markov decision processes

IBMDPs promises

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

Deterministic partially observable policies in IBMDPs

Deterministic

Otherwise

Partially observable

Otherwise

RL for POMDPs

Finding the best **deterministic** and **partially observable** policy is NP-hard [Lit94]!

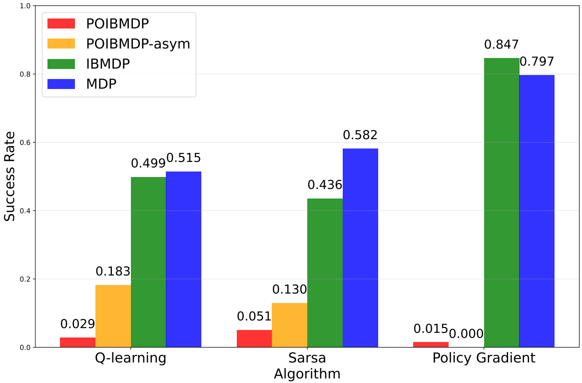
Asymmetric RL for POMDPs

Access the hidden state during training

- Value based →
- Actor-critic →[a]

[a] Although those return stochastic policies, we can be greedy.

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 IBMDP[1].

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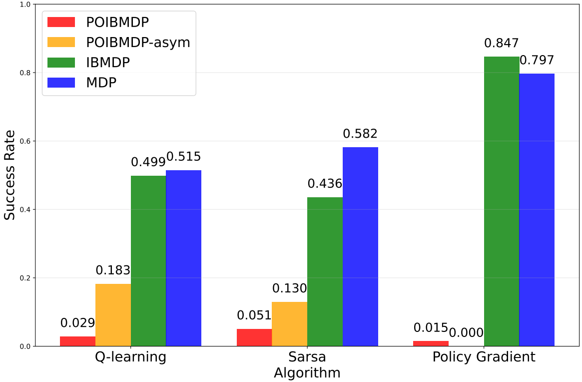

Success rates over thousands of RL runs with varying hyperparameters when learning different policies in the same IBMDP[1]. **Is it all for nothing?**

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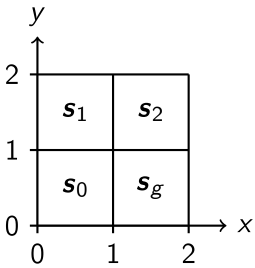
Result: decision tree policies for classification MDPs are standard Markovian policies in IBMDPs



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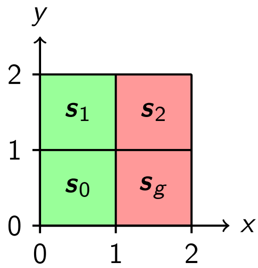

Classification MDP and the unique optimal depth-1 tree.

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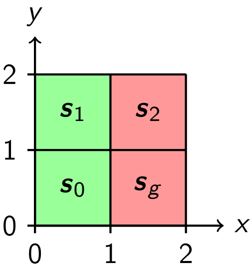

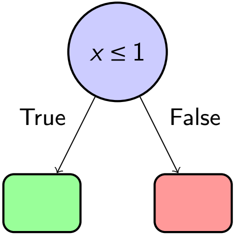

Classification MDP and the unique optimal depth-1 tree.

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

Perspectives for direct RL of decision tree policies.

- It seems that interpretability for SDM problems can be difficult to achieve because of **partial observability**.
- Should we focus on indirect approaches? Hybrid approaches [Wu+20]?
- Fixing the policy tree structure a priori (paramteric trees, [Mar+25])?
- Can other policies (programs, oblique trees, algebraic expressions. . .) be directly optimized with RL in IBMDPs?
- Design algorithms that learn deterministic partially observable policies [LBE25; LEM25]?

RL works in classification MDPs

Q: Can we leverage SDM to design new decision tree induction algorithms for the supervised learning setting? **A: Yes!**

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- It seems that interpretability for SDM problems can be difficult to achieve because of **partial observability**.
- Should we focus on indirect approaches? Hybrid approaches [Wu+20]?
- Fixing the policy tree structure a priori (paramteric trees, [Mar+25])?
- Can other policies (programs, oblique trees, algebraic expressions. . .) be directly optimized with RL in IBMDPs?
- Design algorithms that learn deterministic partially observable policies [LBE25; LEM25]?

RL works in classification MDPs

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Decision trees in supervised learning

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

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

- Trees **interpretable** and **competitive with neural nets** [GOV22].
- Greedy algorithms **sub-optimal accuracy**, but $\boldsymbol{O(2^D)}$ operations [Bre+84; Qui86; Qui93] .
- Optimal algorithms, **optimal accuracy**, but $\boldsymbol{O((2Np)^D)}$ 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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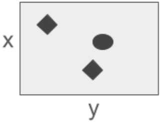

Example of decision tree induction as an MDP.

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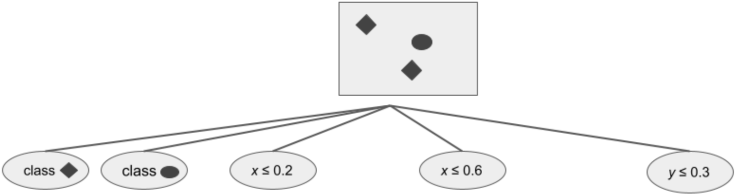

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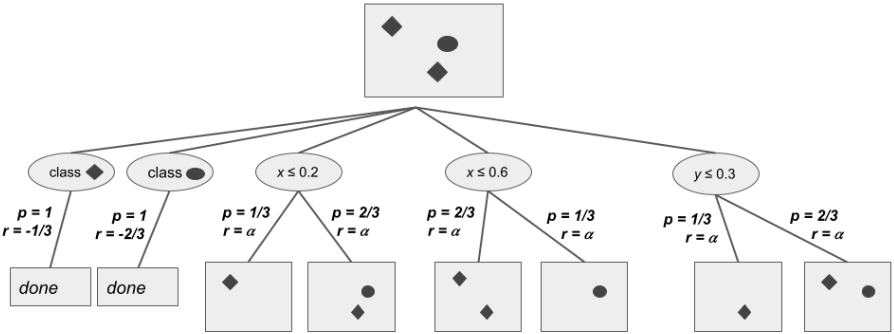

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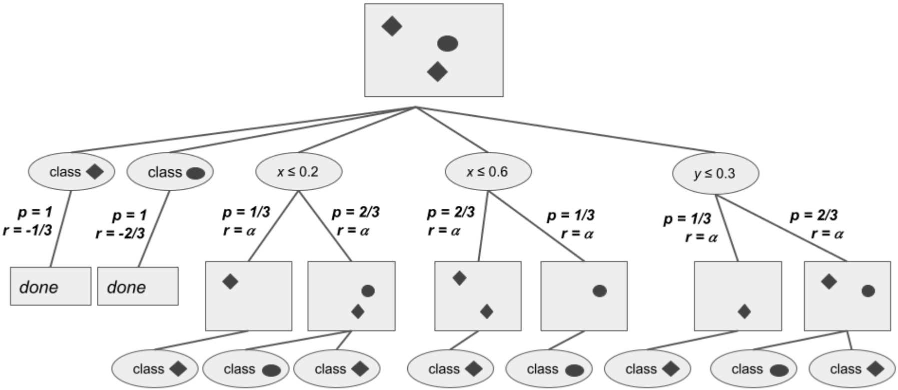

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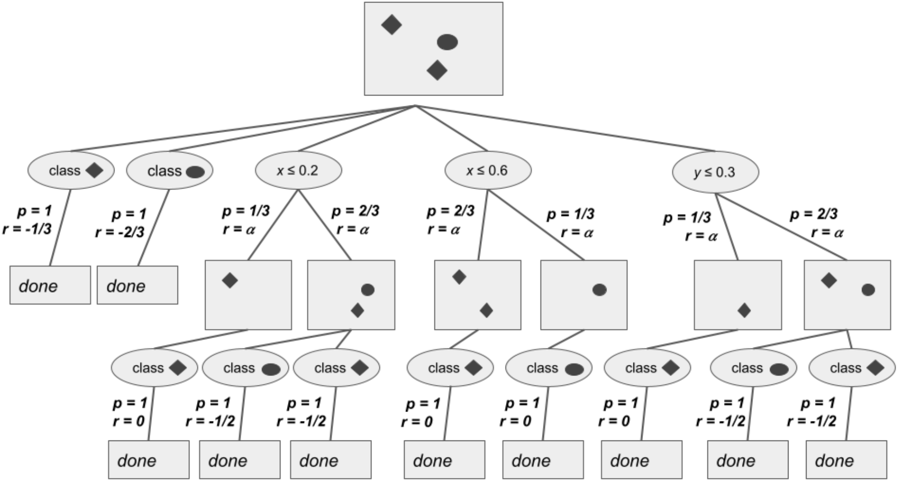

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Controlling the time complexity of decision tree induction

- 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
  → **MDP state space size is $O((2Np)^D)$**.
- **Dynamic Programming Decision Trees (DPDT)**: Let's choose candidate actions adaptively
  → for each MDP state consider B actions: **state space size is $O((2B)^D)$**.

How to choose the B candidate actions/splits?

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

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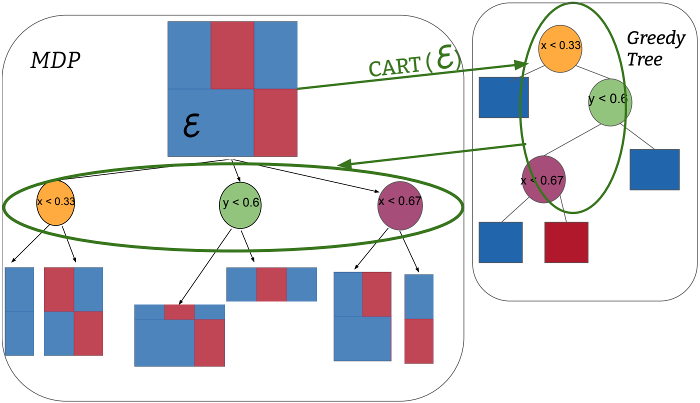
Practical implemenataion of DPDT



We can use greedy trees nodes as candidate actions.

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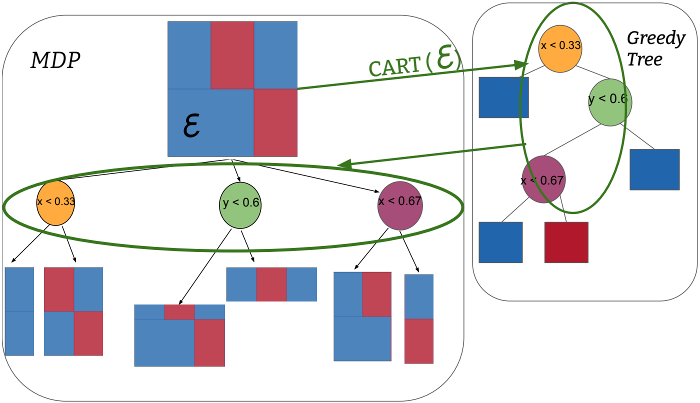

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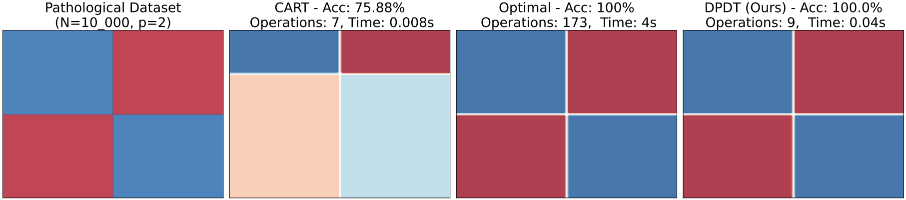
Fast like greedy trees, accurate like optimal trees



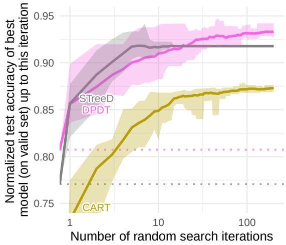
Comparison of greedy, optimal, and DPDT depth-2 trees on the checkersboard dataset.

Fast like greedy trees, accurate like optimal trees

Comparison of accuracies and operations for depth-3 trees.

Dataset	Accuracy: Opt	Accuracy: Greedy	Accuracy: DPDT CART$^-$	Accuracy: DPDT CART$^+$	Accuracy: DPDT TopB$^-$	Accuracy: DPDT TopB$^+$	Operations: Opt	Operations: Greedy	Operations: DPDT CART$^-$	Operations: DPDT CART$^+$	Operations: DPDT TopB$^-$	Operations: DPDT 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 detph-5 trees

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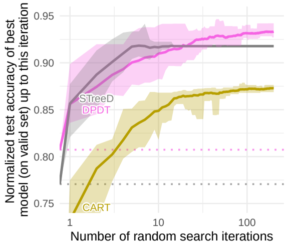

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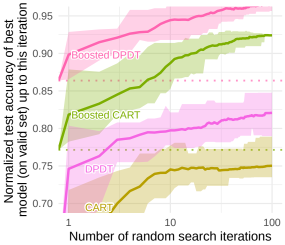

Boosted DPDT vs. Boosted CART

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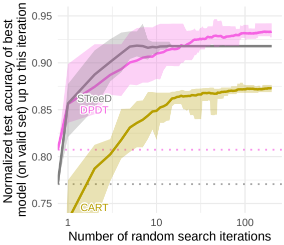

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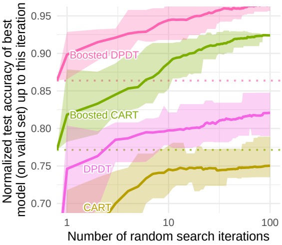

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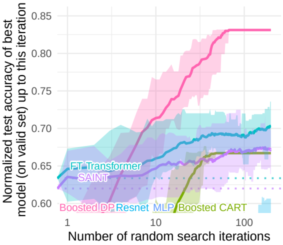

Boosted DPDT vs. other classifiers

Why generating candidate splits with CART?

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.

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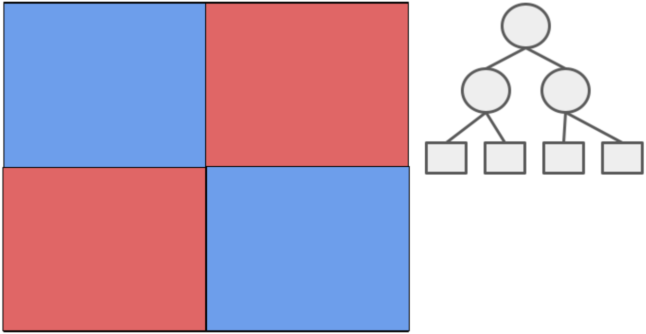

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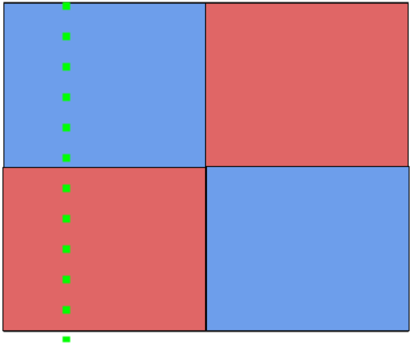

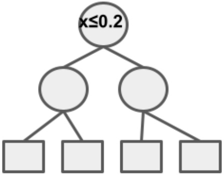

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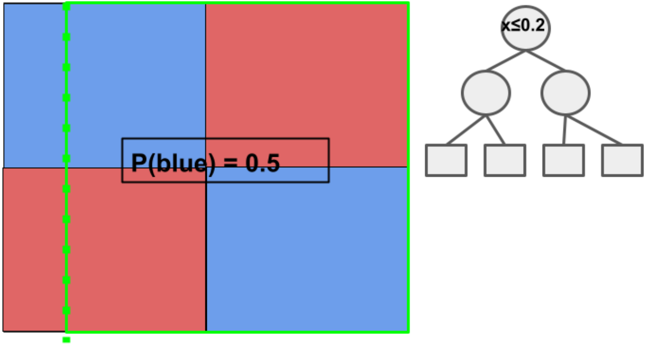

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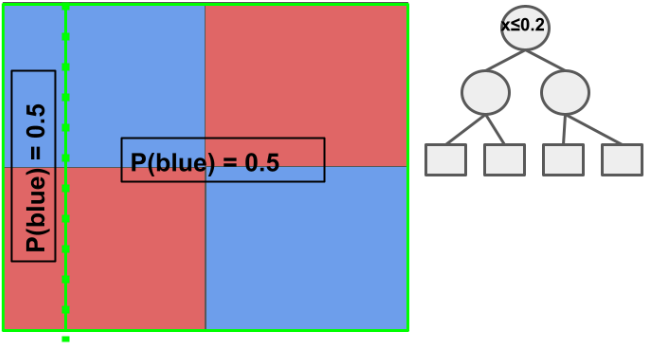

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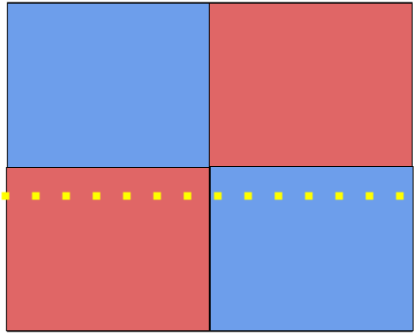

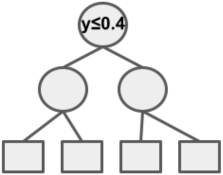

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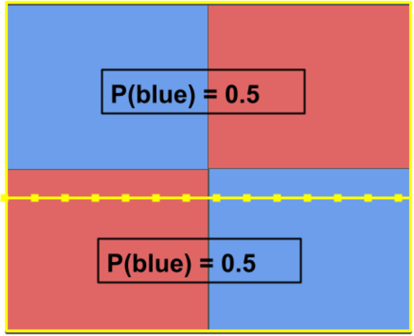

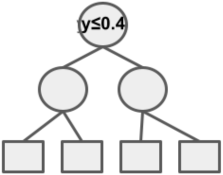

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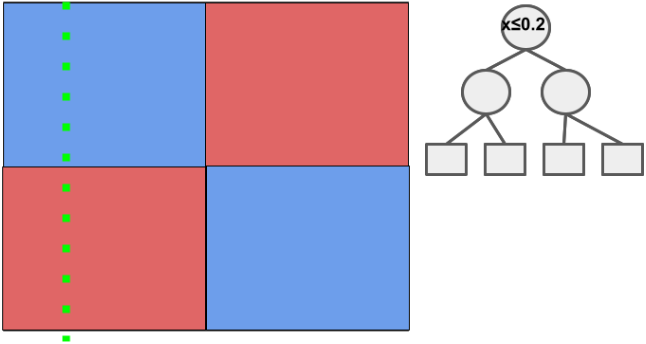

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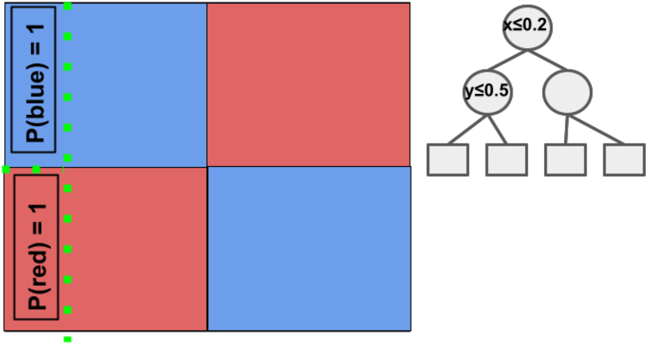

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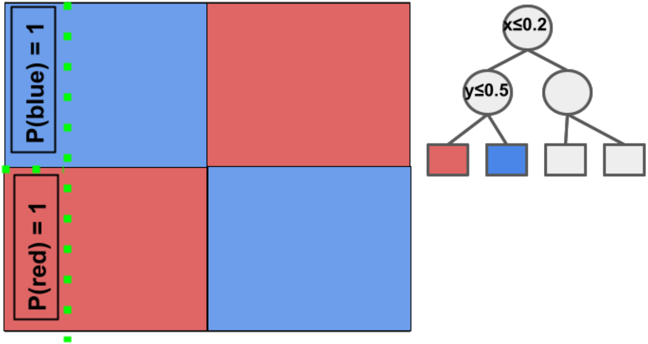

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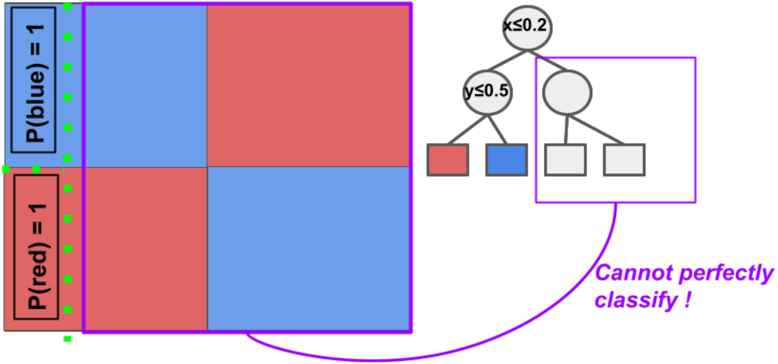

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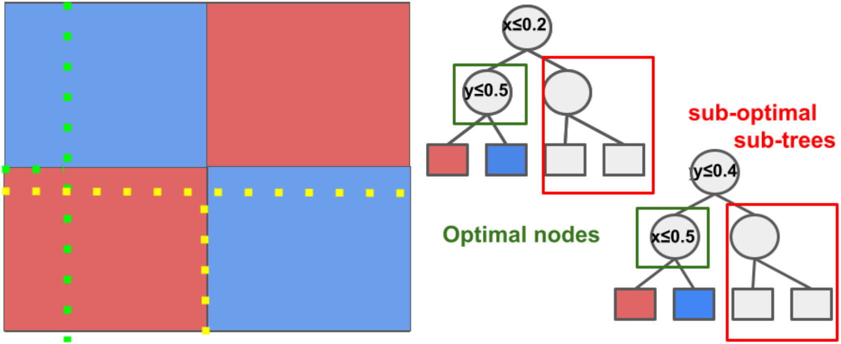

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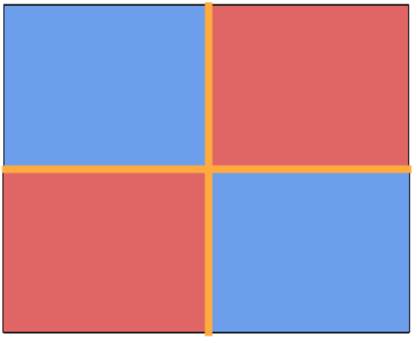

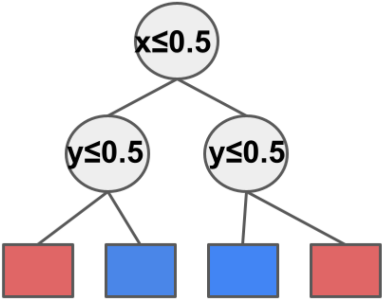

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We propose policy unfolding

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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:
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# Small ReLU MLP for Pendulum
def play(x):
    h_layer_0_0 = 1.238*x[0]+0.971*x
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    h_layer_0_0 = max(0, h_layer_0_0
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    h_layer_0_1 = -1.221*x[0]+1.001
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    h_layer_0_1 = max(0, h_layer_0_1
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    h_layer_1_0 = -0.109*h_layer_0_0
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    h_layer_1_0 = max(0, h_layer_1_0
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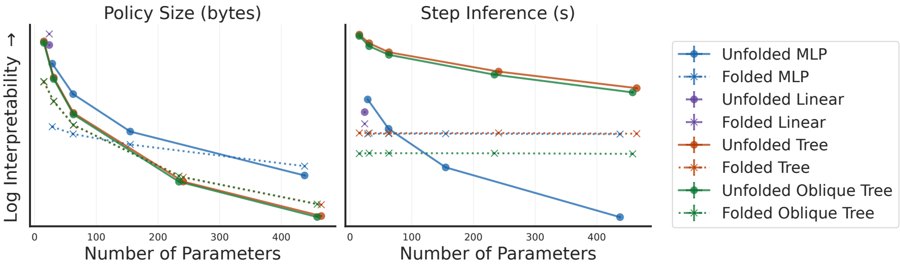
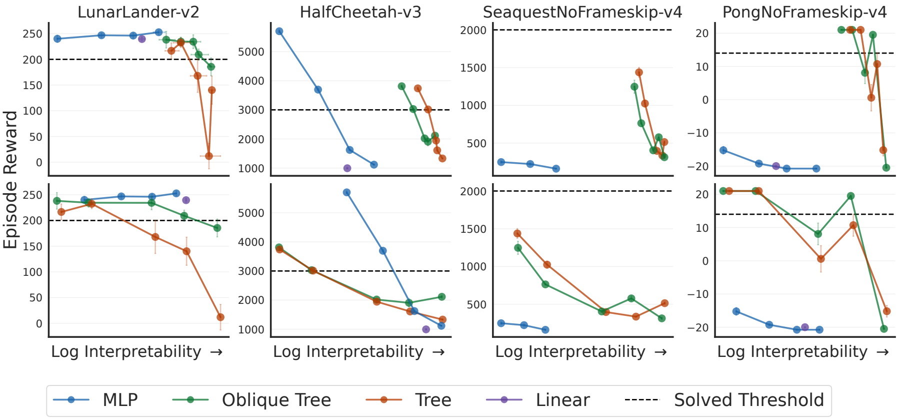
Result: unfolding policies is necessary to respect consensus



Aggregated policies interpretability on classic control environments

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.

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- Beliefs such as "trees are more interpretable than neural networks" should be used with caution.
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