

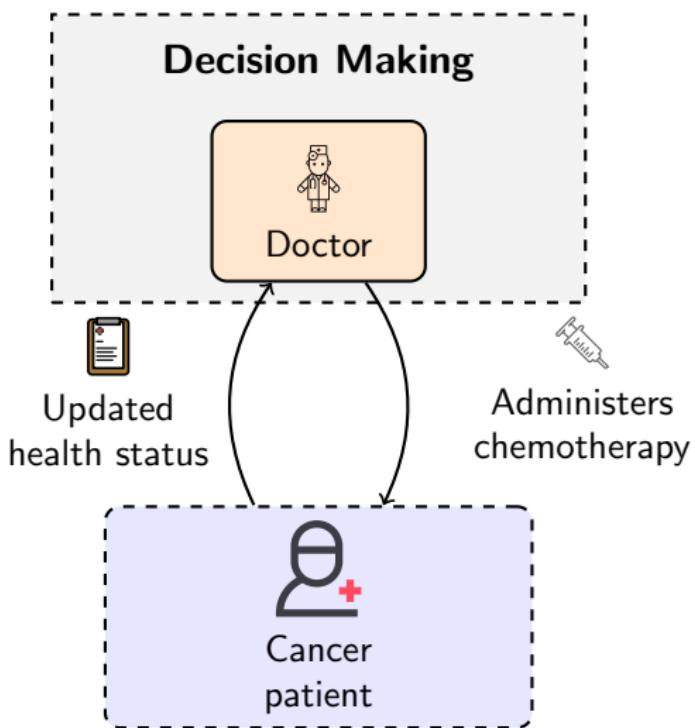
Interpretability, Decision Trees, and Sequential Decision Making

Hector Kohler

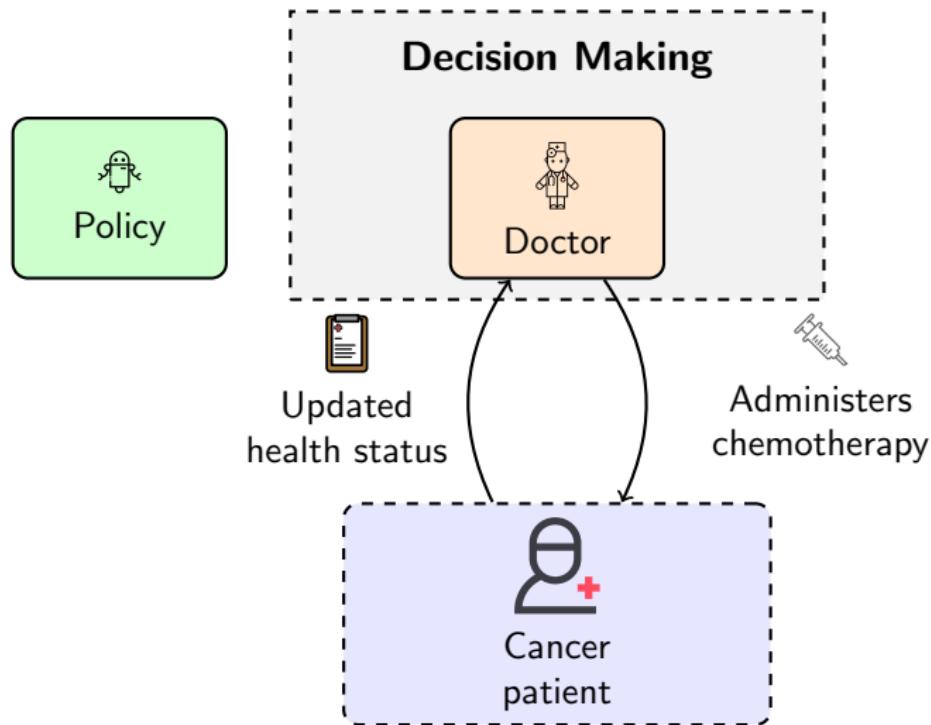
Supervised by Dr. Riad Akrou (HdR) and Prof. Philippe Preux (HdR)
Université de Lille, CNRS, Inria, UMR CRIStAL 9189, France

November 24, 2025

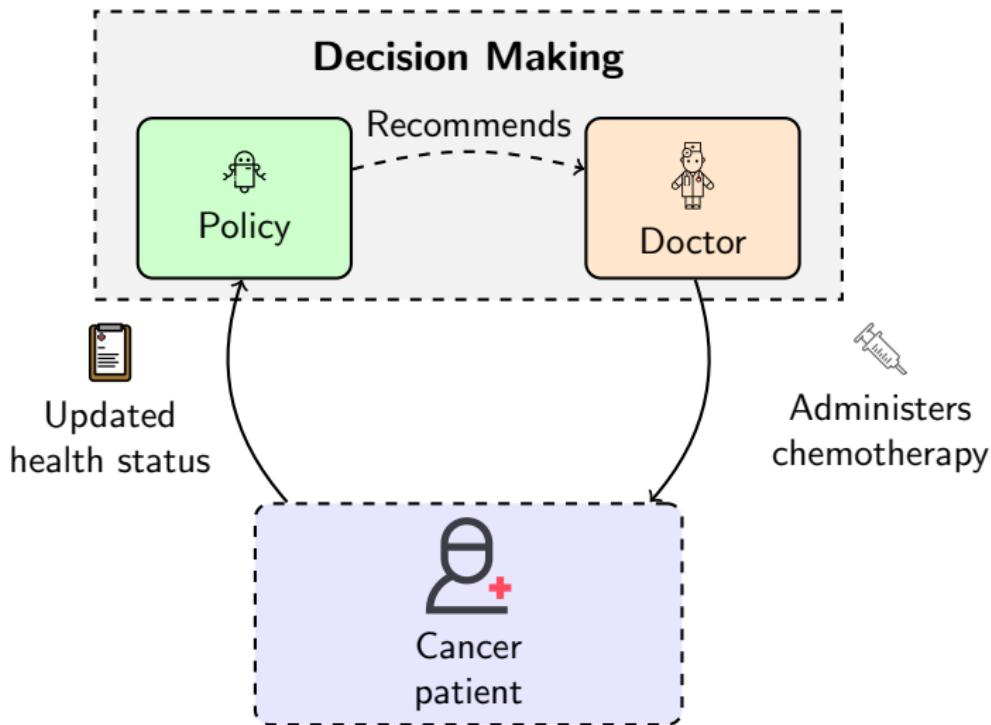
Sequential decision making (SDM) and machine learning (ML)



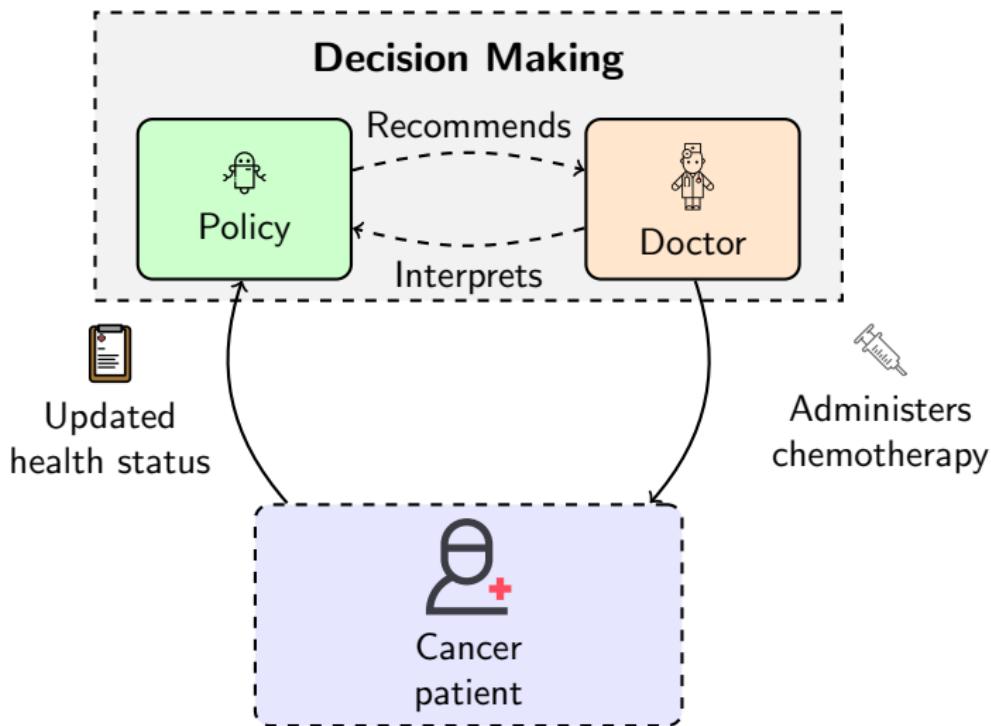
Sequential decision making (SDM) and machine learning (ML)



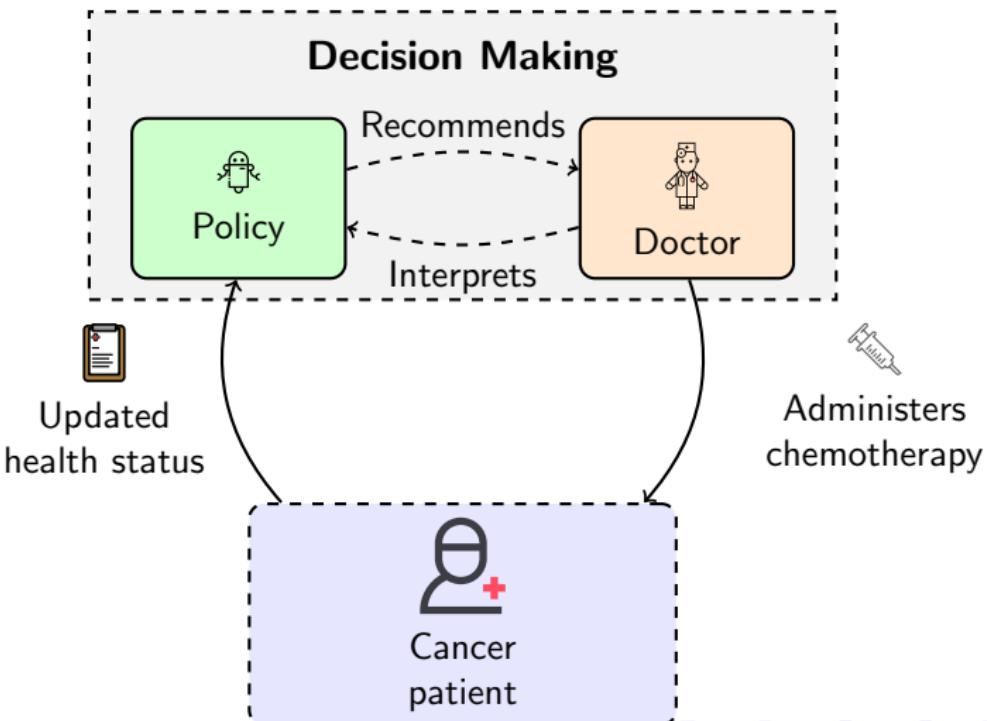
Sequential decision making (SDM) and machine learning (ML)



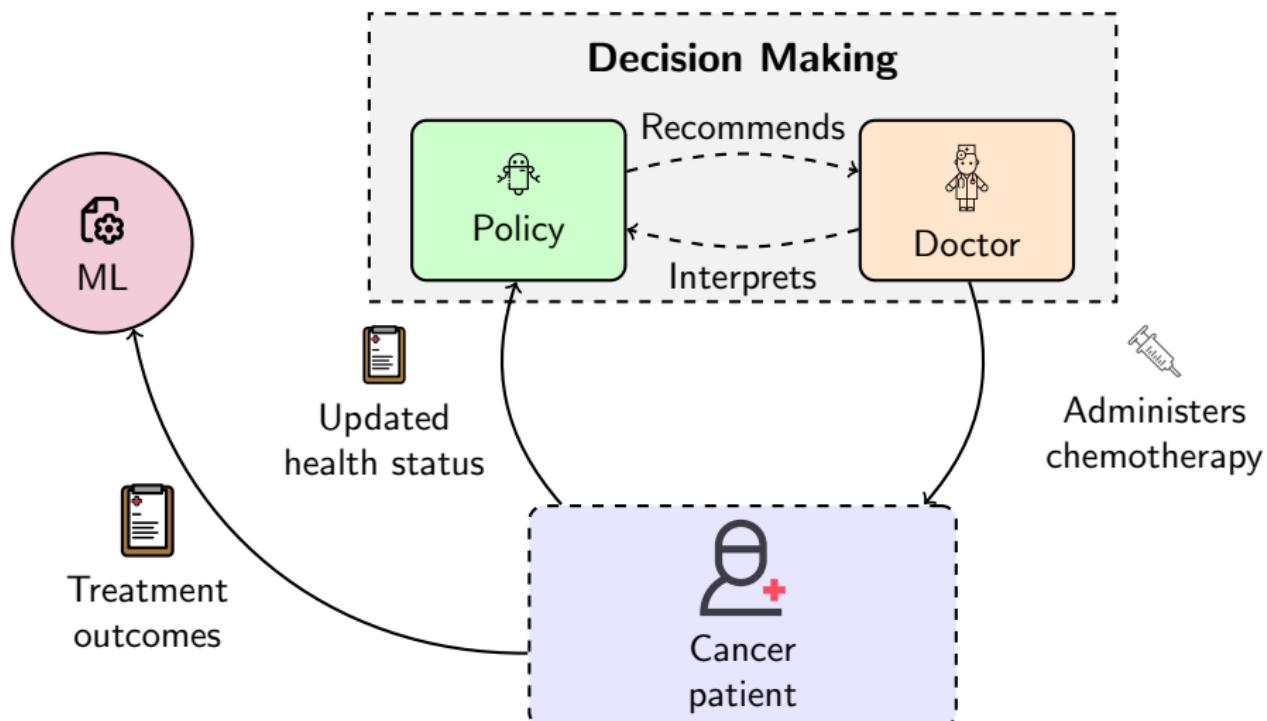
Sequential decision making (SDM) and machine learning (ML)



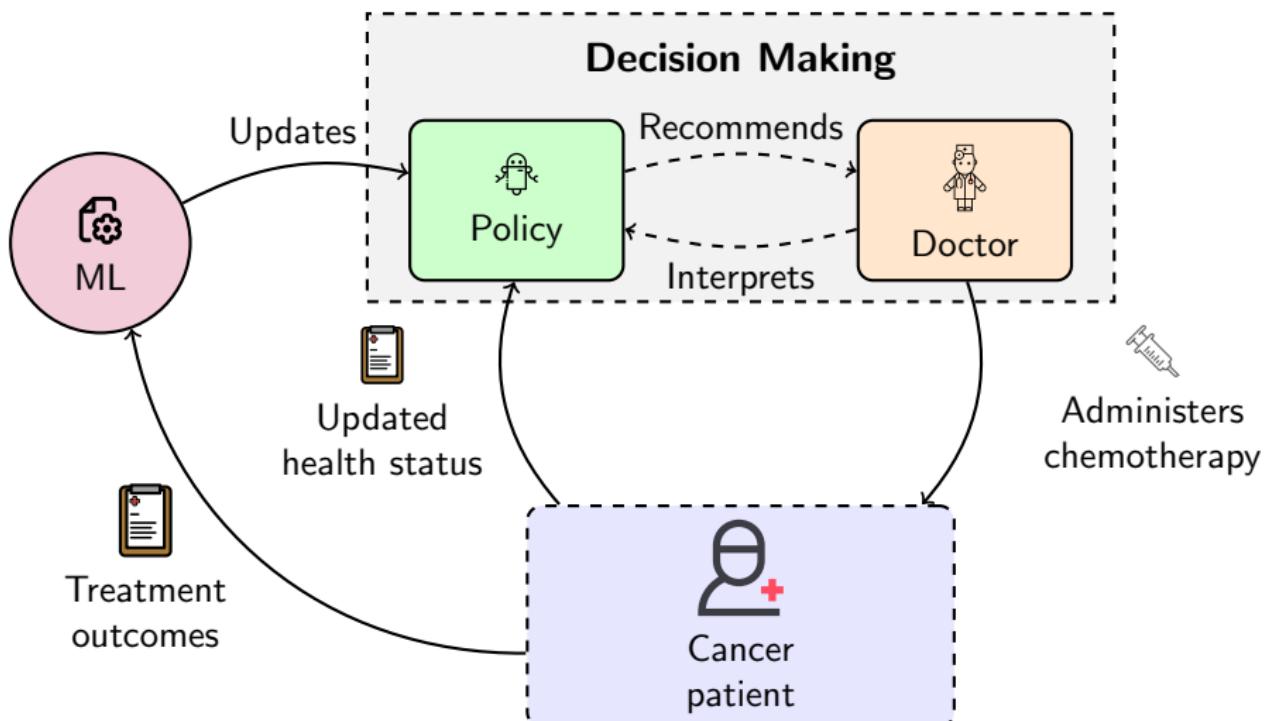
Sequential decision making (SDM) and machine learning (ML)



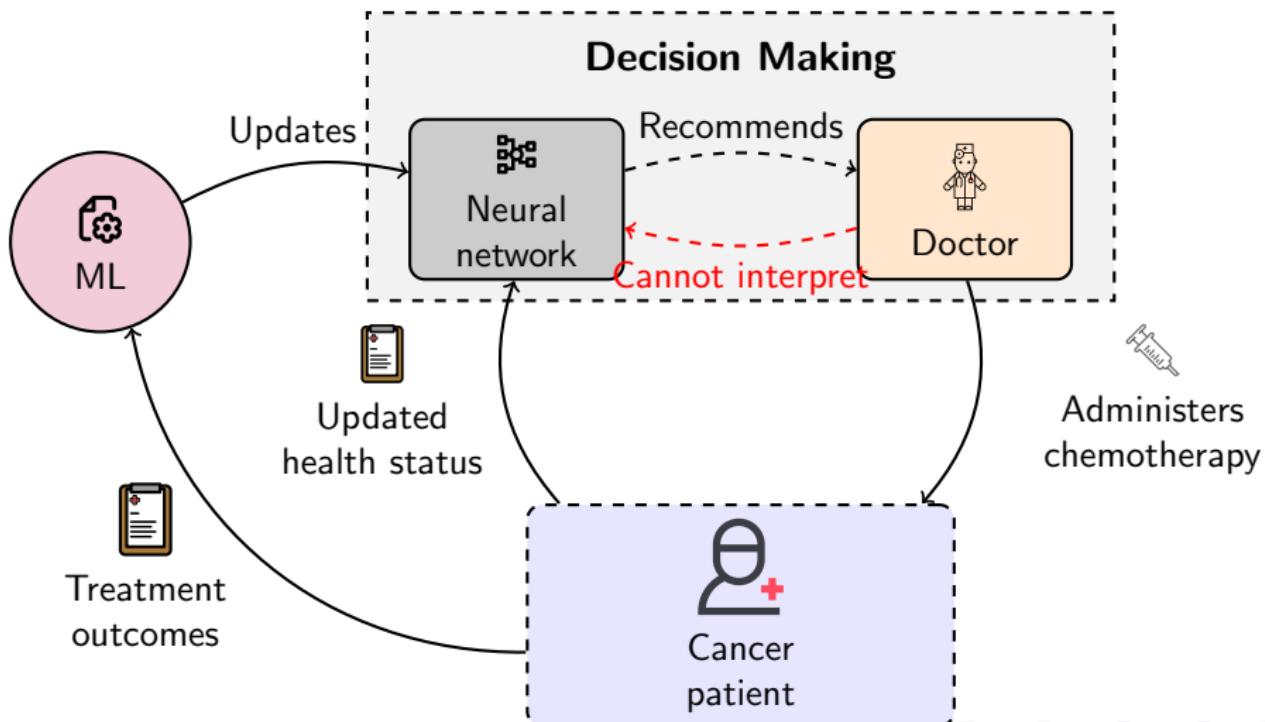
Sequential decision making (SDM) and machine learning (ML)



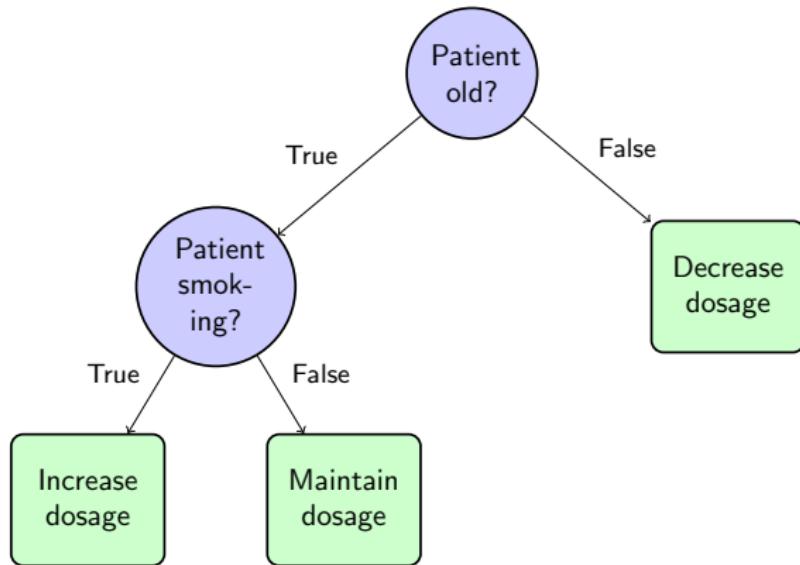
Sequential decision making (SDM) and machine learning (ML)



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

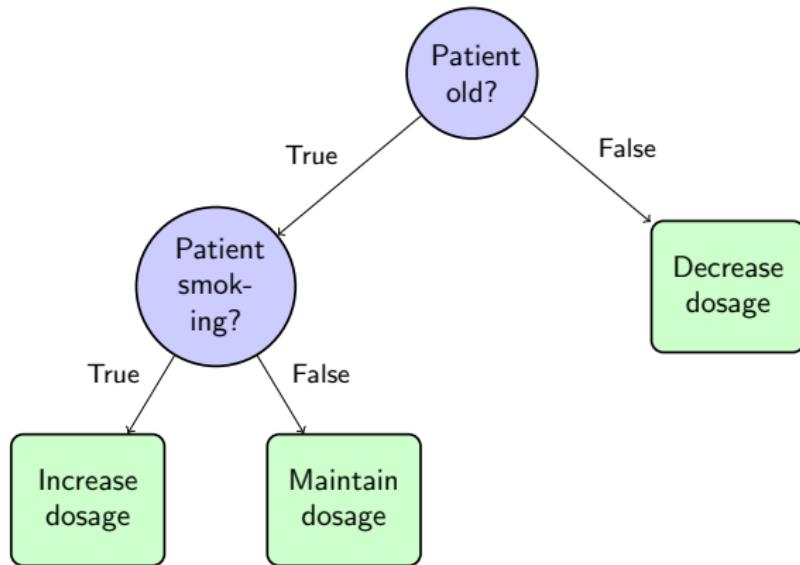


Decision trees



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

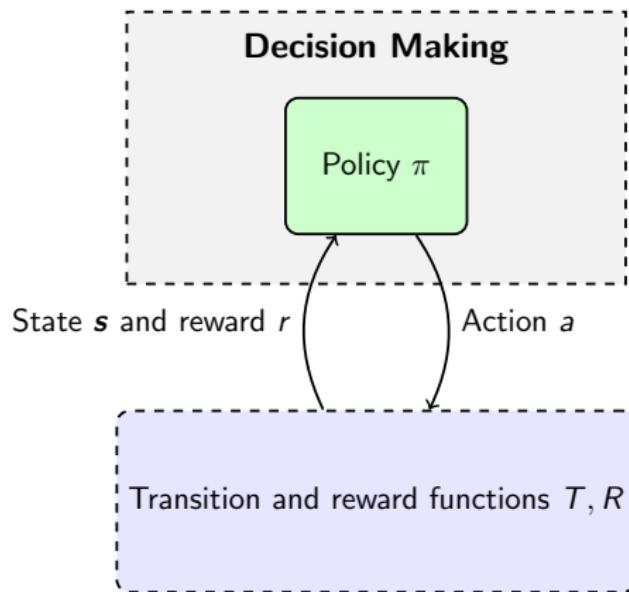
Decision trees



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

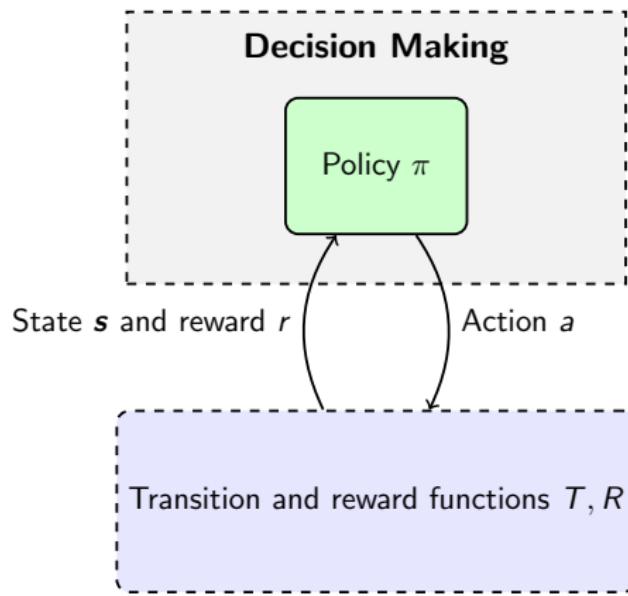
Successful algorithms for non-sequential learning: [Bre+84; BD17; Dem+22;
VZ19; MMW22] ... What about SDM?

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



Markov decision processes [Put94].

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

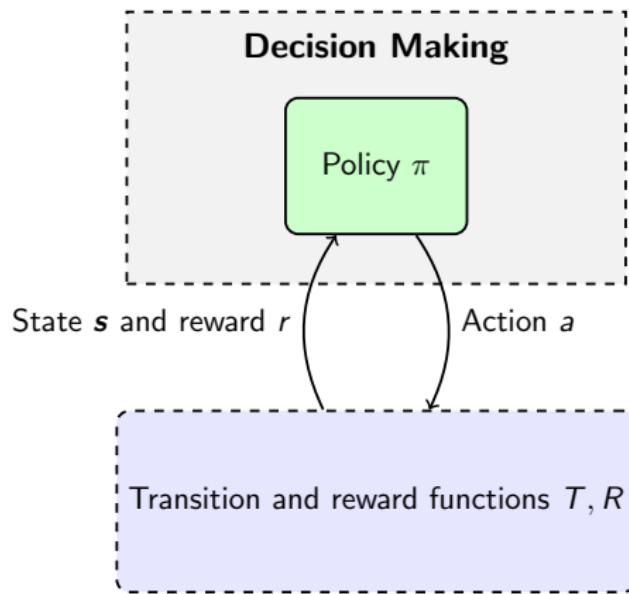


- RL [SB98] aims to find a policy, $\pi : S \rightarrow A$ that maximizes:

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

Markov decision processes [Put94].

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



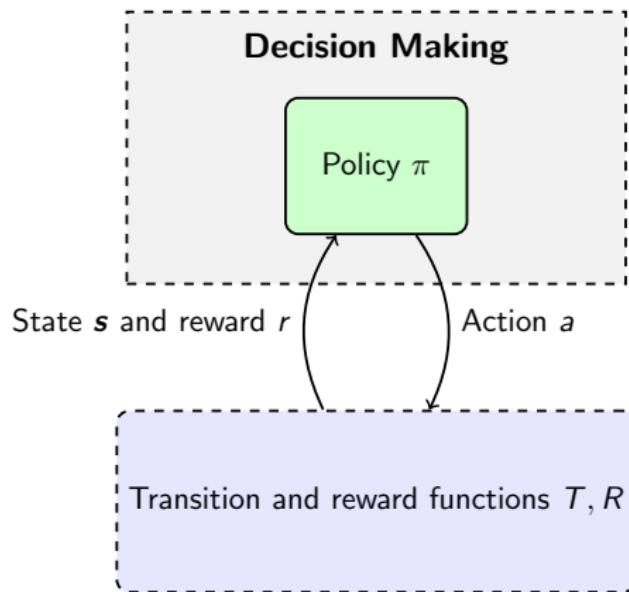
Markov decision processes [Put94].

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

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

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

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



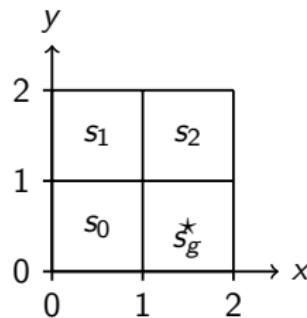
Markov decision processes [Put94].

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

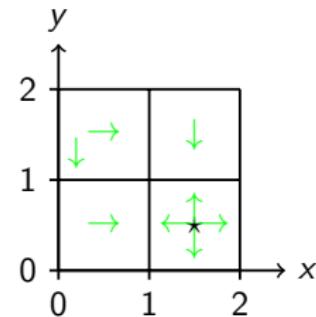
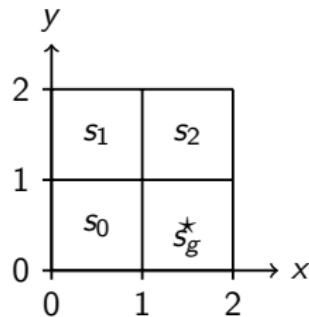
$$\mathbb{E}_{s_t \sim T} \left[\sum_{t=0}^{\infty} \gamma^t R(s_t, \pi(s_t)) \right]$$

- Lots of successful RL algorithms [SB98; Mni+15; Sch+17].
- No interpretability concerns.

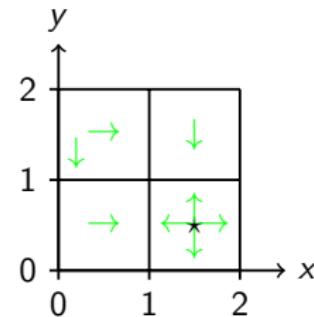
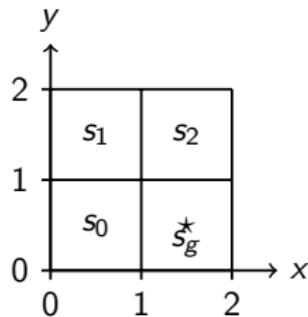
Grid world MDP



Grid world MDP

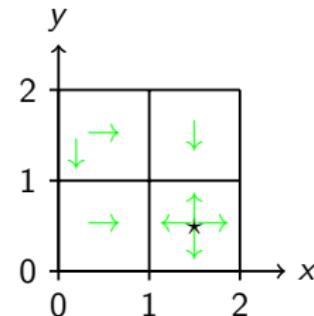
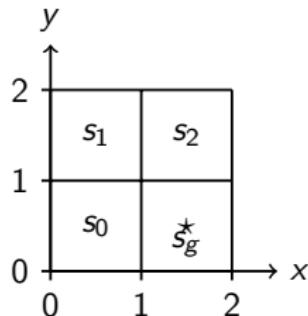


Grid world MDP

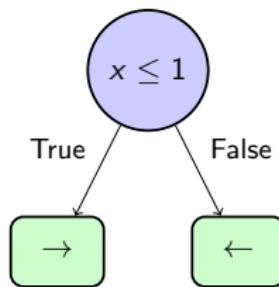


Grid world MDP and optimal actions.

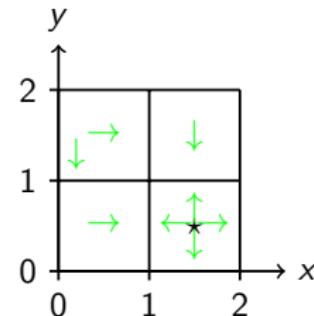
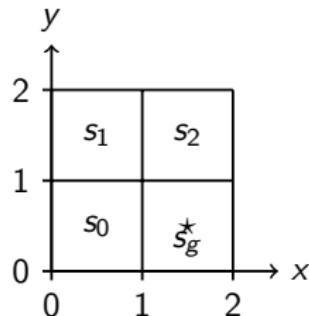
Grid world MDP



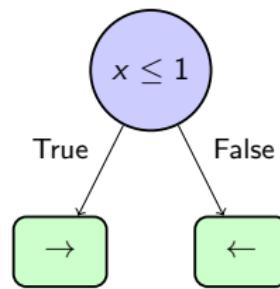
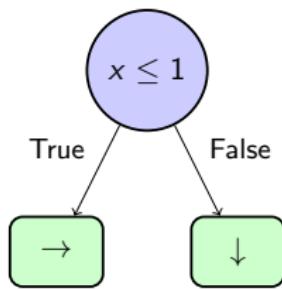
Grid world MDP and optimal actions.



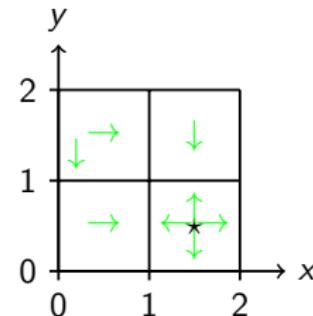
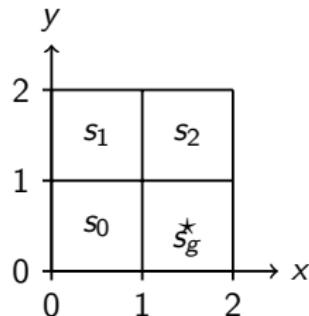
Grid world MDP



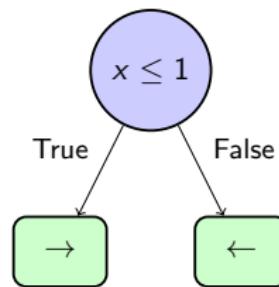
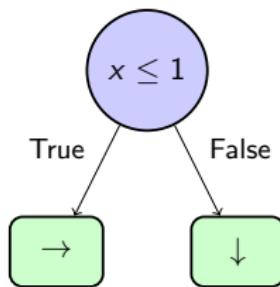
Grid world MDP and optimal actions.



Grid world MDP

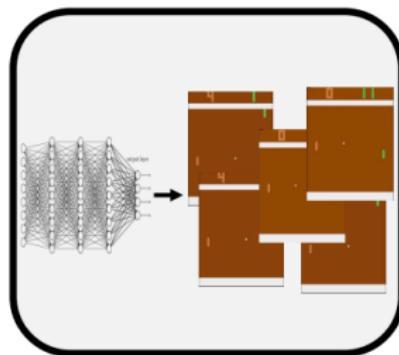


Grid world MDP and optimal actions.

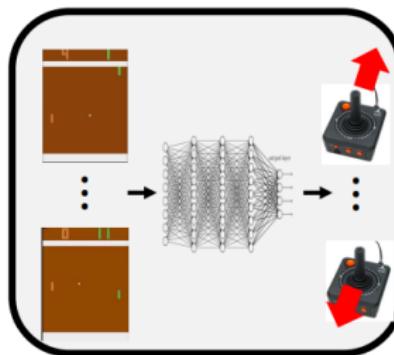


An optimal depth-1 decision tree policy and a sub-optimal depth-1 decision tree policy.

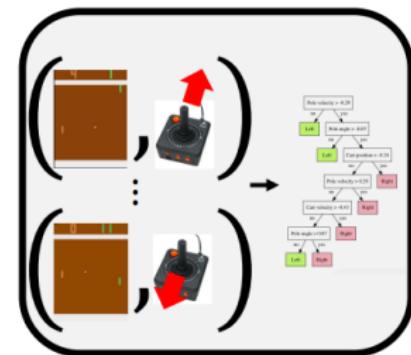
Indirect approach: imitation learning



Step 1: Use NN to generate states

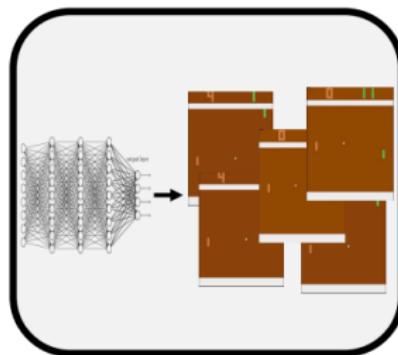


Step 2: Use NN to obtain actions

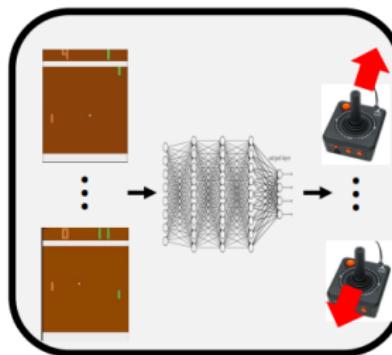


Step 3: Use supervised learning
to train a decision tree

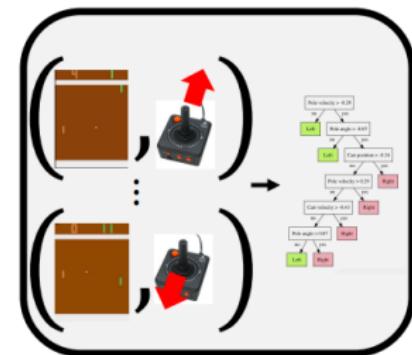
Indirect approach: imitation learning



Step 1: Use NN to generate states



Step 2: Use NN to obtain actions



Step 3: Use supervised learning to train a decision tree

Imitation learning works well in practice to get interpretable policies [Mil+24; BPS18; RGB10] but no optimality guarantees.

Contributions

- ① Why is learning optimal interpretable policies for sequential decision making difficult?
- ② How to leverage sequential decision making to learn interpretable classifiers for supervised learning?
- ③ How to measure policy interpretability in sequential decision making?

Contributions

- ① Why is learning optimal interpretable policies for sequential decision making difficult?
- ② How to leverage sequential decision making to learn interpretable classifiers for supervised learning?
- ③ How to measure policy interpretability in sequential decision making?

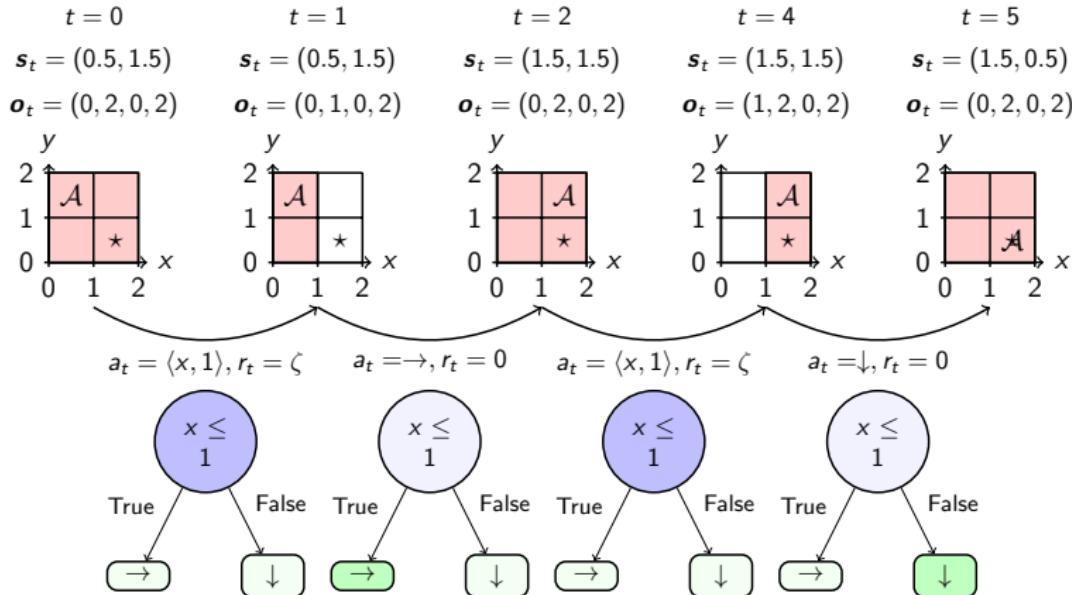
Contributions

- ① Why is learning optimal interpretable policies for sequential decision making difficult?
- ② How to leverage sequential decision making to learn interpretable classifiers for supervised learning?
- ③ How to measure policy interpretability in sequential decision making?

Contributions

- ① Why is learning optimal interpretable policies for sequential decision making difficult?
- ② How to leverage sequential decision making to learn interpretable classifiers for supervised learning?
- ③ How to measure policy interpretability in sequential decision making?

Iterative bounding Markov decision processes (IBMDP)



Trajectory in an IBMDP of the grid world MDP [Top+21]. Actions build a decision tree policy and rewards control the interpretability-performance trade-off.

Pros and cons of IBMDPs

Pros

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

Cons

- Only **deterministic** and **partially observable** (a.k.a. memoryless or reactive) policies are equivalent to decision tree policies.
- Finding the best **deterministic** and **partially observable** policy is NP-hard [Lit94]!

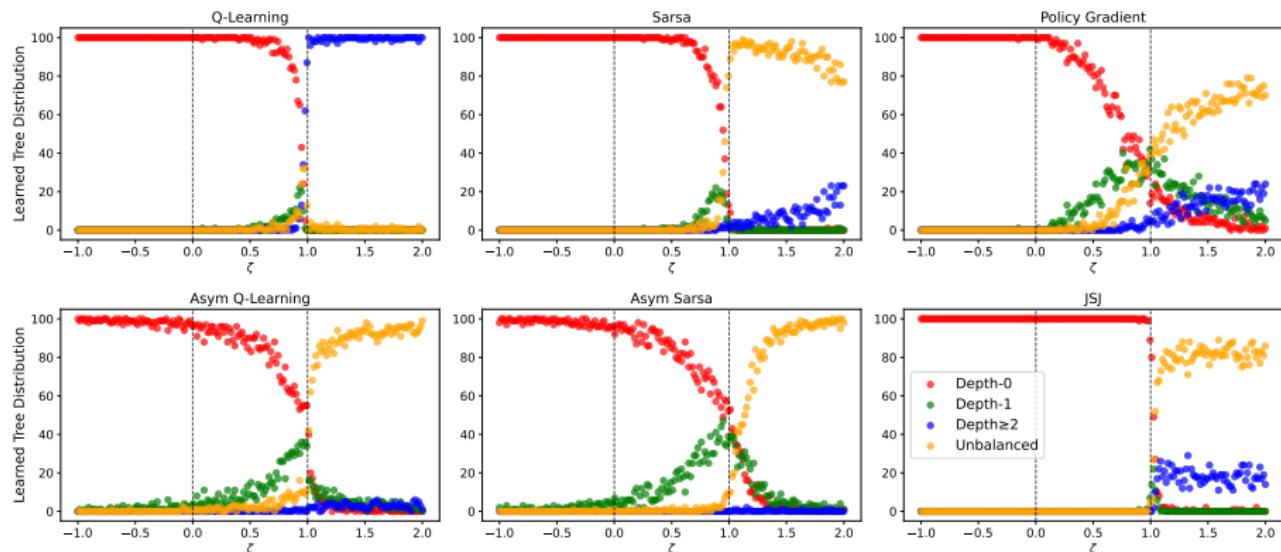
Re-formulation

Q: Can we use reinforcement learning to directly optimize trade-offs of performance and interpretability in SDM?



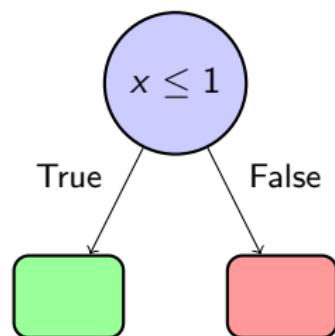
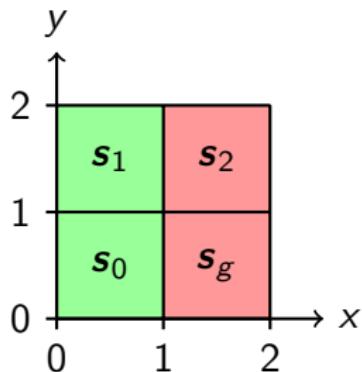
*Q: How does RL perform for optimizing **deterministic** and **partially observable** policies in IBMDPs?*

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



Distributions of final tree policies learned with various (asymmetric) RL algorithms [SB98; SJ94; LS98; BA22; BDA22] across 100 seeds. For each different performance-interpretability trade-off value ζ , each point represent the share of different trees.

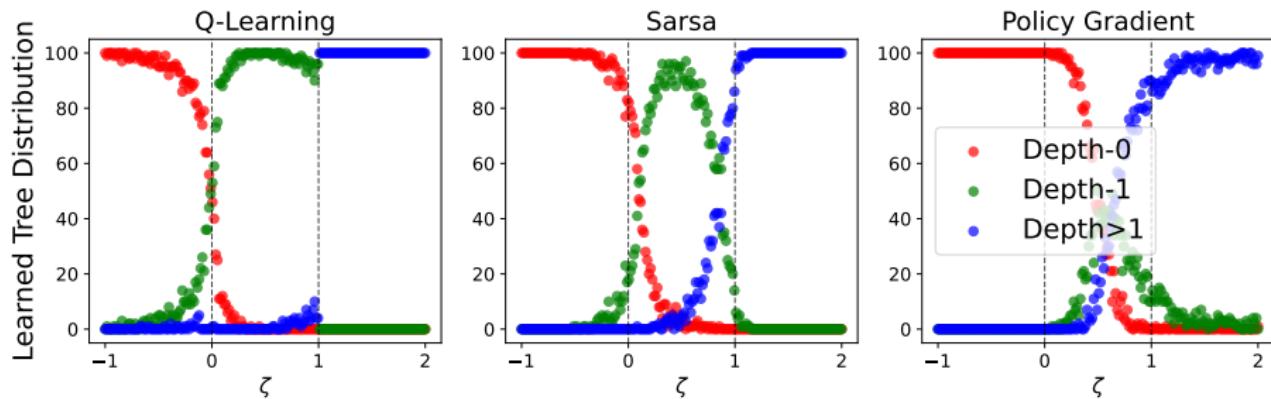
Interesting sub-class of MDPs: classification MDPs



Classification MDP and the unique optimal depth-1 tree.

We show that 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 MDPs



Distributions of final tree policies learned with various RL algorithms across 100 seeds. For each different performance-interpretability trade-off value ζ , each point represent the share of different trees.

Perspectives for direct RL of decision tree policies.

- Interpretability for SDM problems can be difficult 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])?
- Design algorithms that learn deterministic partially observable policies [LBE25; LEM25]?

RL works in classification MDPs

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

Decision trees in supervised learning

- N data points. Each x_i is described by p features and has a label $y_i \in \mathcal{Y}$.

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

- 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?

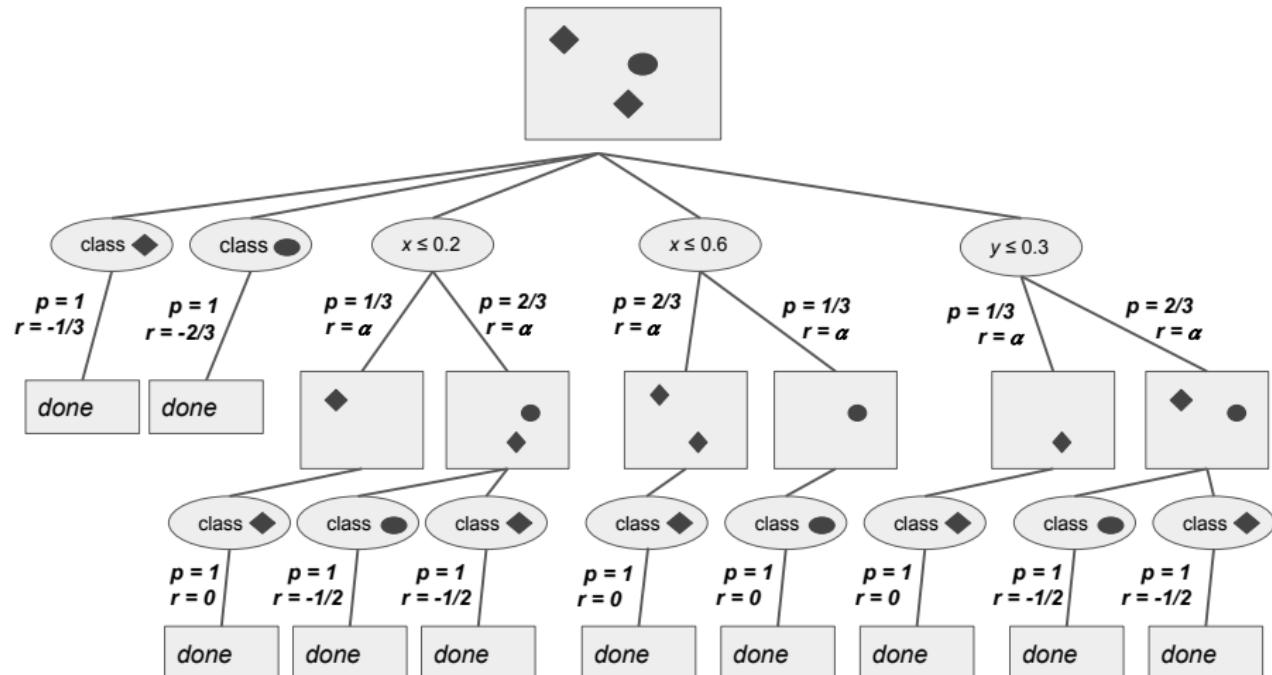
Decision tree induction as solving MDPs

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) \mathcal{E} , 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.

Decision tree induction as solving MDPs

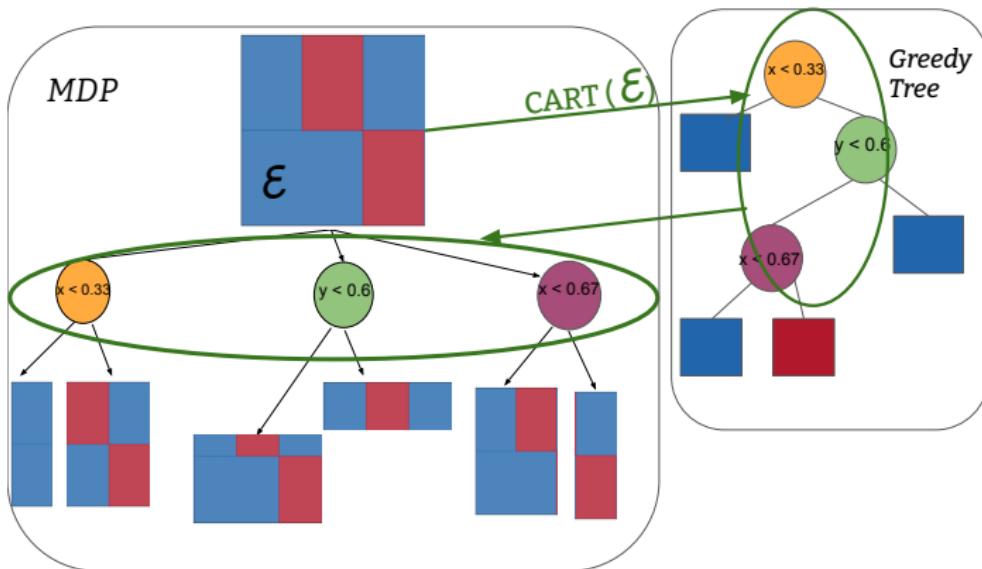


MDP formulation of a generic decision tree induction for a supervised learning task.

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

Dynamic Programming Decision Trees (DPDT)¹



Overview of our algorithm DPDT presented at the 31st ACM SIGKDD conference.

¹Because states are entire datasets, we implement DPDT with a depth-first search to limit the space complexity.

Theoretical motivation

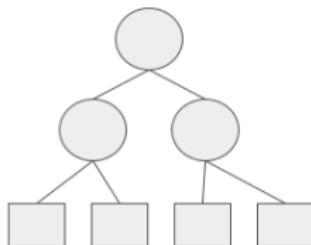
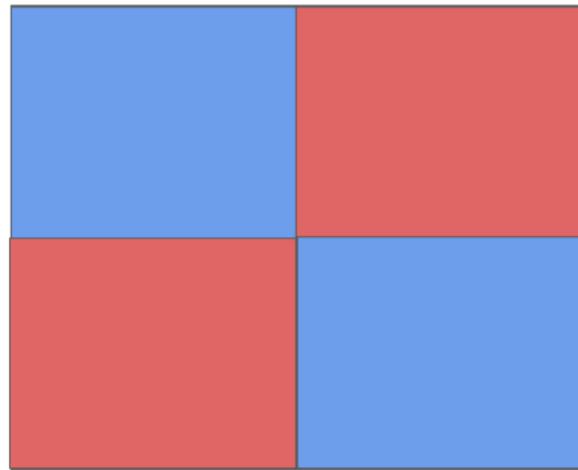
Theorem (DPDT trees are not worse than greedy trees)

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.

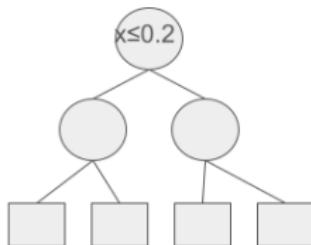
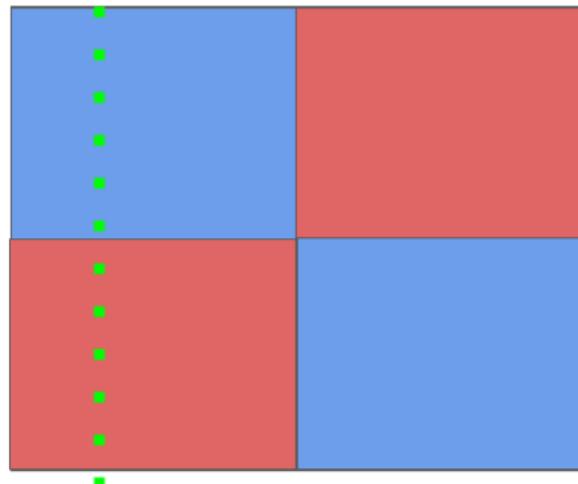
Theorem (DPDT trees can be strictly better than greedy trees)

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

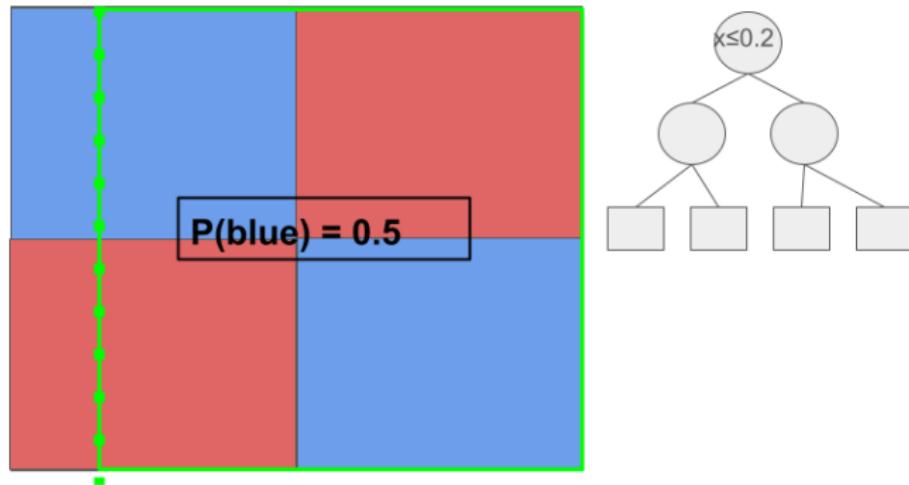
DPDT trees can be strictly better than greedy trees



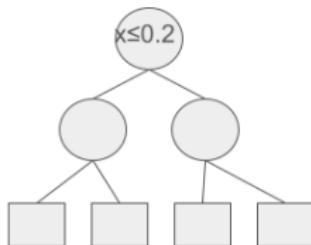
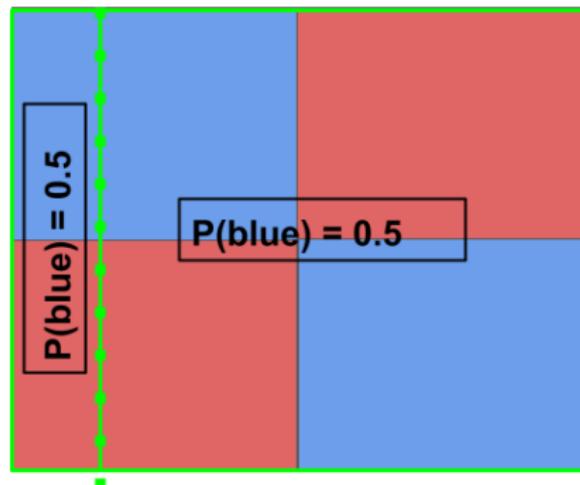
DPDT trees can be strictly better than greedy trees



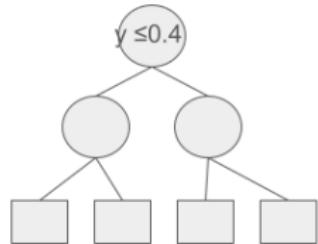
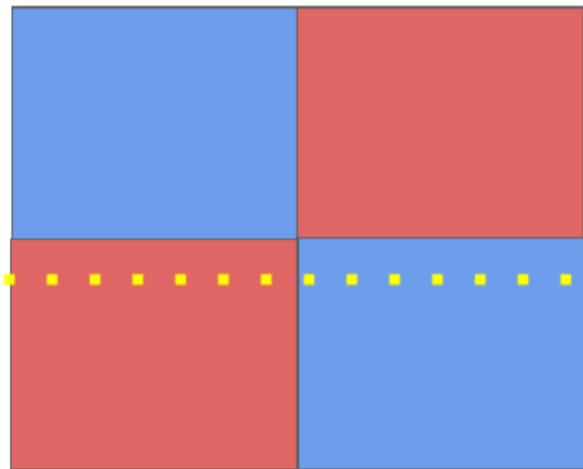
DPDT trees can be strictly better than greedy trees



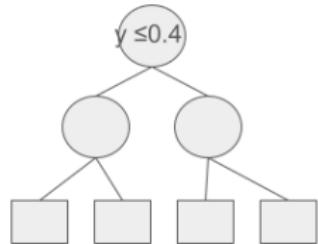
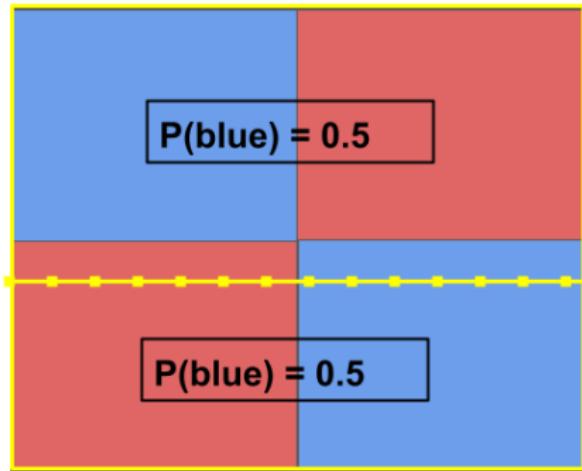
DPDT trees can be strictly better than greedy trees



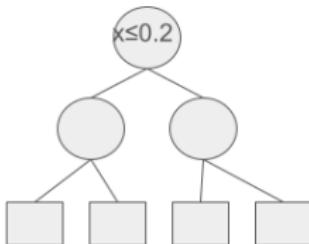
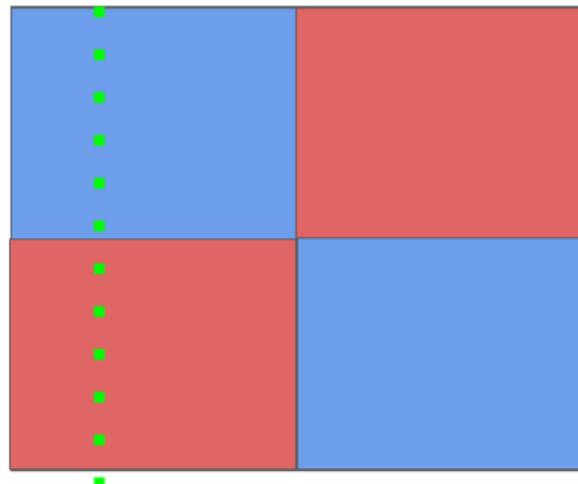
DPDT trees can be strictly better than greedy trees



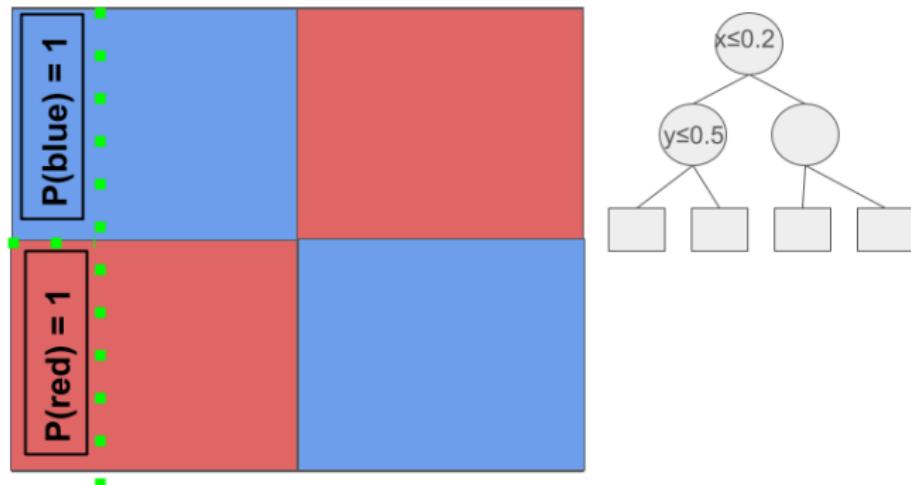
DPDT trees can be strictly better than greedy trees



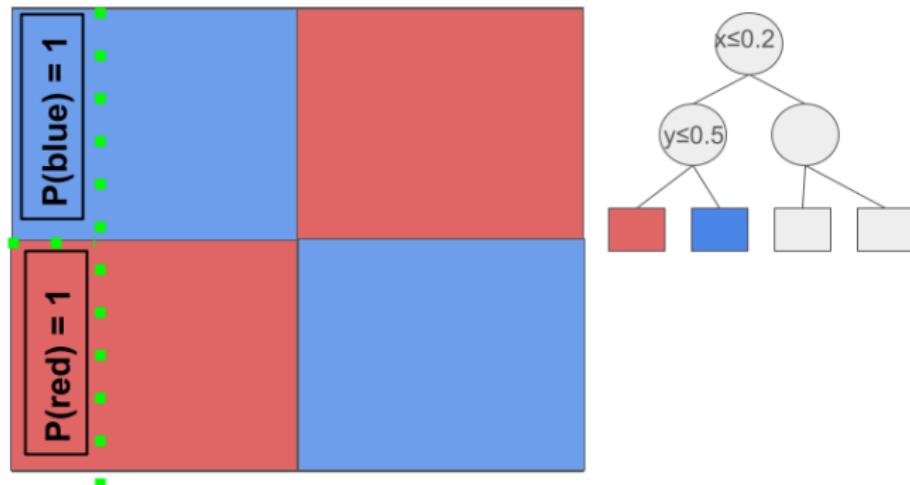
DPDT trees can be strictly better than greedy trees



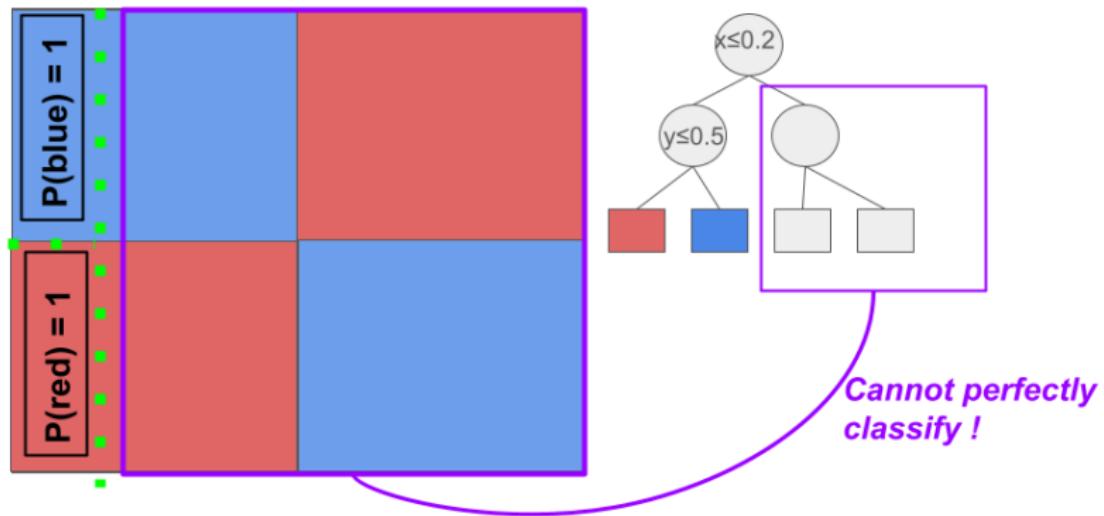
DPDT trees can be strictly better than greedy trees



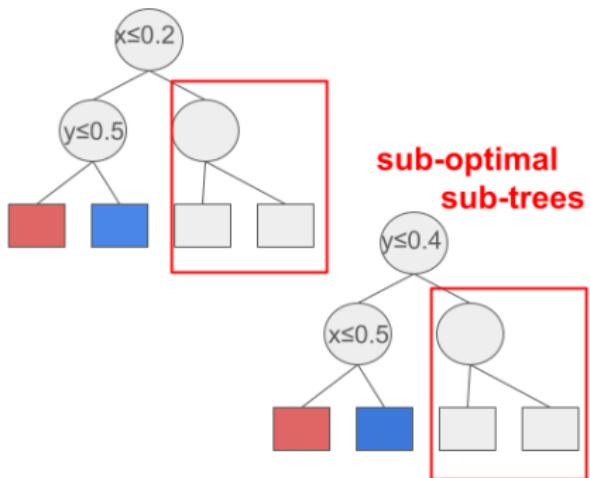
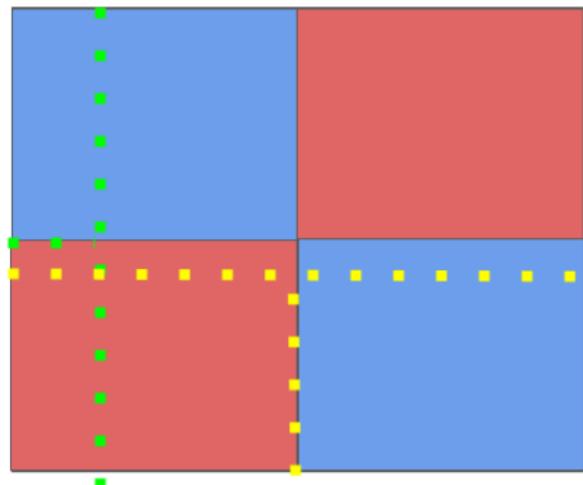
DPDT trees can be strictly better than greedy trees



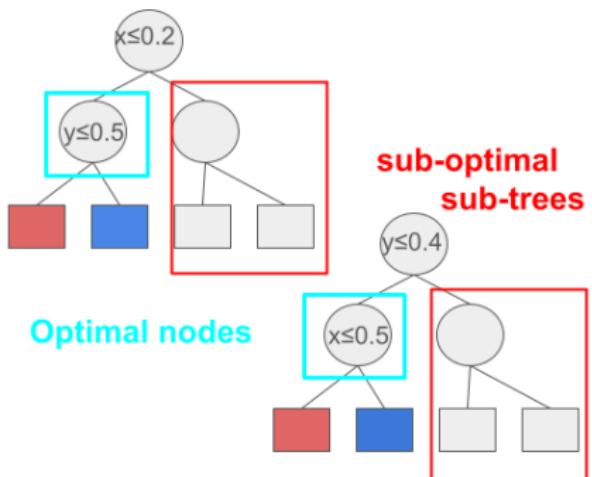
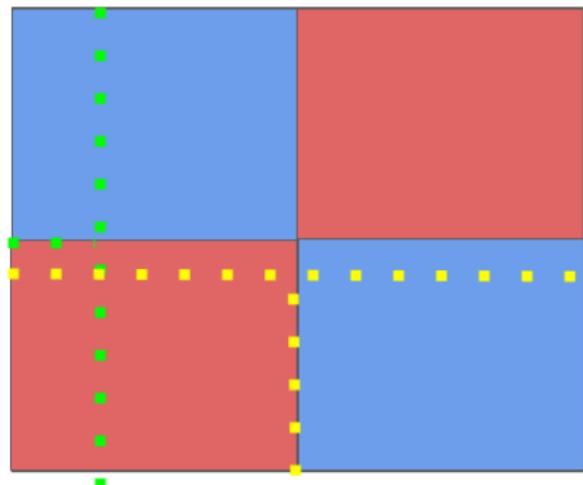
DPDT trees can be strictly better than greedy trees



DPDT trees can be strictly better than greedy trees



DPDT trees can be strictly better than greedy trees



Fast like greedy trees, accurate like optimal trees



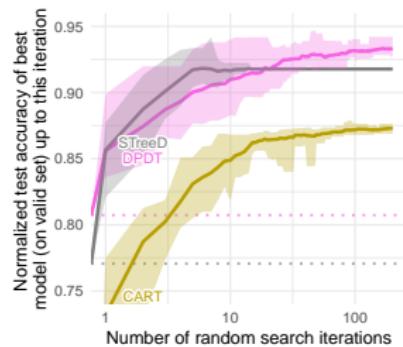
A checkers board data set highlights the limitations of existing works.

Comparing tree accuracy to complexity

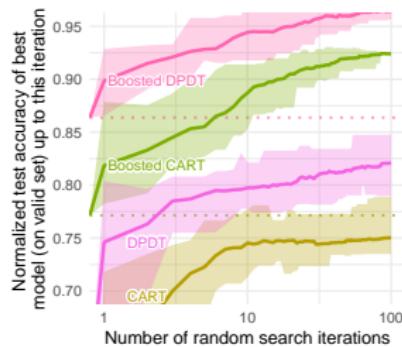
Train accuracy and operation count when learning depth-3 decision trees.

Dataset	N	p	Accuracy				Operations			
			Opt Quant-BnB	Greedy CART	DPDT light	DPDT full	Opt Quant-BnB	Greedy CART	DPDT light	DPDT full
room	8103	16	0.992	0.968	0.991	0.992	10^6	15	286	16100
bean	10888	16	0.871	0.777	0.812	0.853	$5 \cdot 10^6$	15	295	25900
eeg	11984	14	0.708	0.666	0.689	0.706	$2 \cdot 10^6$	13	289	26000
avila	10430	10	0.585	0.532	0.574	0.585	$3 \cdot 10^7$	9	268	24700
magic	15216	10	0.831	0.801	0.822	0.828	$6 \cdot 10^6$	15	298	28000
htru	14318	8	0.981	0.979	0.979	0.980	$6 \cdot 10^7$	15	295	25300
occup.	8143	5	0.994	0.989	0.991	0.994	$7 \cdot 10^5$	13	280	16300
skin	196045	3	0.969	0.966	0.966	0.966	$7 \cdot 10^4$	15	301	23300
fault	1552	27	0.682	0.553	0.672	0.674	$9 \cdot 10^8$	13	295	24200
segment	1848	18	0.887	0.574	0.812	0.879	$2 \cdot 10^6$	7	220	16300
page	4378	10	0.971	0.964	0.970	0.970	10^7	15	298	22400
bidding	5056	9	0.993	0.981	0.985	0.993	$3 \cdot 10^5$	13	256	9360
raisin	720	7	0.894	0.869	0.879	0.886	$4 \cdot 10^6$	15	295	20900
rice	3048	7	0.938	0.933	0.934	0.937	$2 \cdot 10^7$	15	298	25500
wilt	4339	5	0.996	0.993	0.994	0.995	$3 \cdot 10^5$	13	274	11300
bank	1097	4	0.983	0.933	0.971	0.980	$6 \cdot 10^4$	13	271	7990

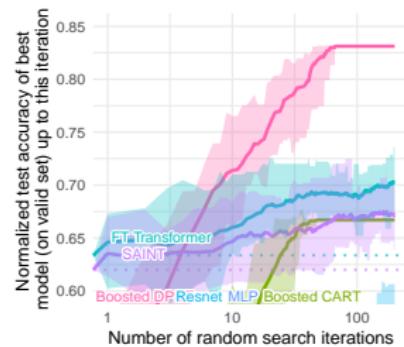
DPDT trees generalization



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



Boosted DPDT vs. Boosted
CART



Boosted DPDT vs. other
classifiers

Perspectives

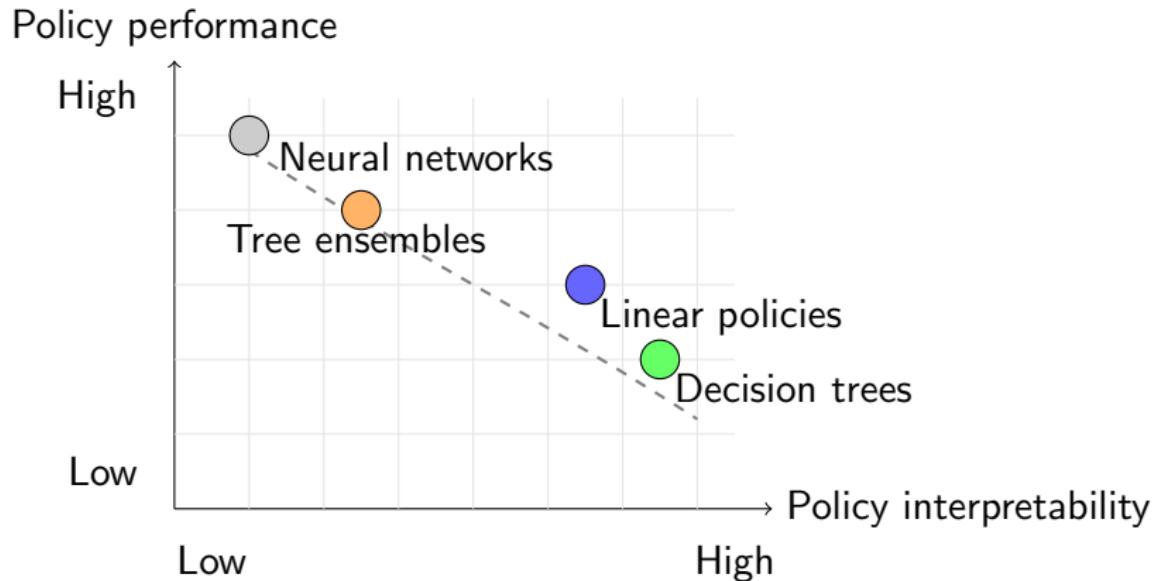
- New SOTA decision tree induction with dynamic programming in MDPs.
- What about using DPDT for indirect decision tree policy learning for SDM?
- What performances could we reach with an industry-grade implementation of XGboost+DPDT?

Let us take a step back

Q: Are decision trees really the most interpretable model?

A: It depends.

Policy interpretability



Heuristic interpretability-performance trade-offs of different policy classes.
Interpretability is often presented in opposition to performances.

How to measure policy interpretability?

Challenges [Gla+24; Lip18; DK17]

- No definition of interpretability.
- Measuring might require humans.

The notion of *simulability* [Lip18]

- Interpretability \simeq how long for human to make the same computations.
- Interpretability \simeq how much effort for a human to read through the entire policy.
- Less parameters mean more interpretability [Fre14; Lav99].
- Time to formally verify a policy decreases with interpretability [Bar+20].

A methodology to measure policy interpretability without humans

Simulability [Lip18]

- ➊ How long it takes for human to make the same computations given an input \simeq policy inference time.
- ➋ How much effort it would take a human to read through the entire policy once \simeq policy size in memory.

Not that simple in practice [Luo+24]

- Different hardwares (CPUs vs GPUs).
- Different implementations (matrix operations vs fully sequentially) ...

We propose policy unfolding

```
# 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:
                    if x[1] <=
-0.2156:
                        return 0
                    else:
                        return 2
            else:
                return 0
        else:
            return 2
```

```
# Small ReLU MLP for Pendulum
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
                           *x[1]-0.423*x[2]
                           +0.475
    h_layer_0_1 = max(0, h_layer_0_1
    )
    h_layer_1_0 = -0.109*h_layer_0_0
                           -0.377*h_layer_0_1
                           +1.694
    h_layer_1_0 = max(0, h_layer_1_0
    )
    h_layer_1_1 = -3.024*h_layer_0_0
                           -1.421*h_layer_0_1
                           +1.530
    h_layer_1_1 = max(0, h_layer_1_1
    )
    h_layer_2_0 = -1.790*h_layer_1_0
                           +2.840*h_layer_1_1
                           +0.658
    y_0 = h_layer_2_0
    return [y_0]
```

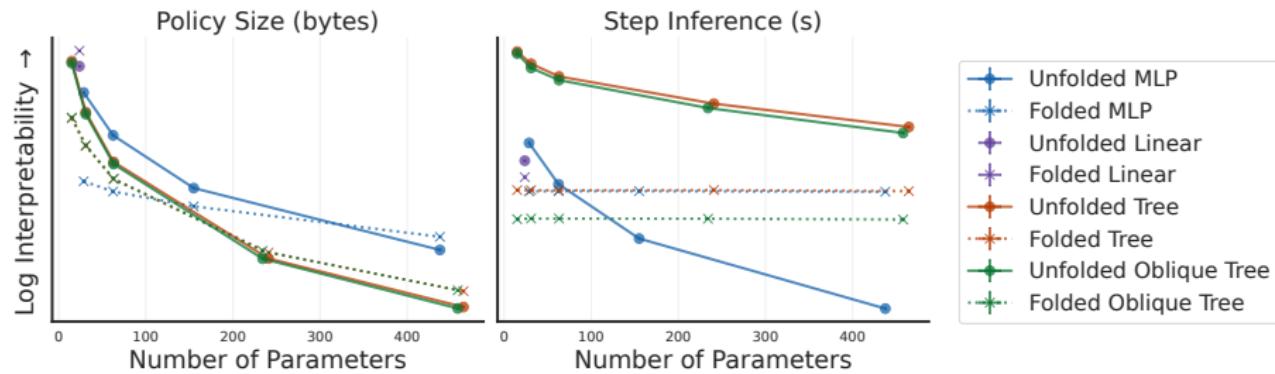
Empirical validation

- ① Does our methodology respect consensus on policy interpretability?
- ② Is policy unfolding necessary?
- ③ What kind of results we can obtain using our proposed methodology?

W

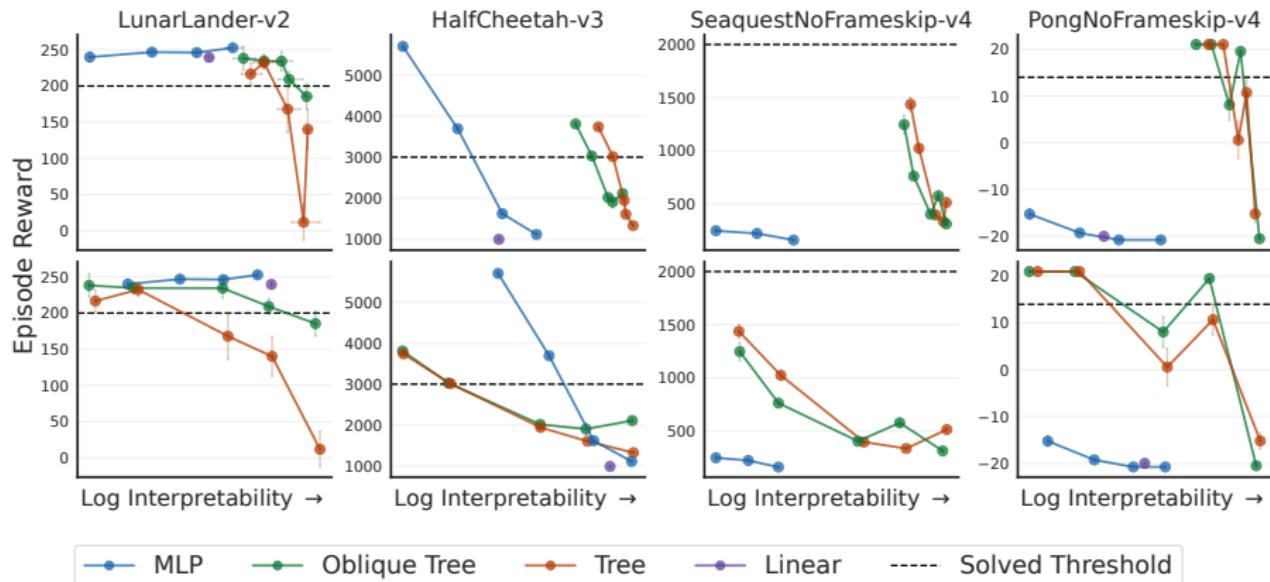
e imitate ~ 40000 expert policies from stable-baselines3 using various policy classes/nb parameters on various environments.

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.

Perspectives

- Beliefs such as "trees are more interpretable than neural networks" should be used with caution.
- Tree-like policy classes can have good inductive bias (e.g. Atari).
- Can a human study confirm our results?
- What about (very) big models?
- Can we use our policy programs as low level skills (hierarchical RL)?

Conclusion: interpretable machine learning is a difficult research topic

- Technical challenges: **partial observability in SDM, NP-hardness.**
→ Focus on indirect approaches and/or on POMDP research first.
- Fundamental challenges: **no definition.**
→ Discuss with the community (InterpPol workshop).
- **Decision trees offer good inductive bias for SDM in games or tabular data.**

My hope

Motivate interpretability by finding a real-world problem where interpretability is *really* necessary [Nag+24].

- [BA22] Andrea Baisero and Christopher Amato. "Unbiased Asymmetric Reinforcement Learning under Partial Observability". In: *Proceedings of the 21st International Conference on Autonomous Agents and Multiagent Systems*. AAMAS '22. Virtual Event, New Zealand: International Foundation for Autonomous Agents and Multiagent Systems, 2022, pp. 44–52. ISBN: 9781450392136.
- [Bar+20] Pablo Barceló et al. "Model interpretability through the lens of computational complexity". In: *Advances in neural information processing systems* (2020).
- [BD17] Dimitris Bertsimas and Jack Dunn. "Optimal classification trees". In: *Machine Learning* 106 (2017), pp. 1039–1082.
- [BDA22] Andrea Baisero, Brett Daley, and Christopher Amato. "Asymmetric DQN for partially observable reinforcement learning". In: *Proceedings of the Thirty-Eighth Conference on Uncertainty in Artificial Intelligence*. Ed. by James Cussens and Kun Zhang. Vol. 180. Proceedings of Machine Learning

- Research. PMLR, Jan. 2022, pp. 107–117. URL: <https://proceedings.mlr.press/v180/baisero22a.html>.
- [BPS18] Osbert Bastani, Yewen Pu, and Armando Solar-Lezama. “Verifiable Reinforcement Learning via Policy Extraction”. In: (2018).
- [Bre+84] L Breiman et al. *Classification and Regression Trees*. Wadsworth, 1984.
- [CRB24] Ayman Chaouki, Jesse Read, and Albert Bifet. “Branches: A Fast Dynamic Programming and Branch & Bound algorithm for Optimal Decision Trees”. In: (2024). arXiv: 2406.02175 [cs.LG]. URL: <https://arxiv.org/abs/2406.02175>.
- [Dem+22] Emir Demirovic et al. “MurTree: Optimal Decision Trees via Dynamic Programming and Search”. In: *Journal of Machine Learning Research* 23.26 (2022), pp. 1–47. URL: <http://jmlr.org/papers/v23/20-520.html>.
- [DK17] Finale Doshi-Velez and Been Kim. “Towards A Rigorous Science of Interpretable Machine Learning”. In: (2017). arXiv:

- 1702.08608 [stat.ML]. URL:
<https://arxiv.org/abs/1702.08608>.
- [Fre14] Alex A. Freitas. "Comprehensible classification models: a position paper". In: *SIGKDD Explor. Newslett.* 15.1 (Mar. 2014), pp. 1–10. ISSN: 1931-0145. DOI: 10.1145/2594473.2594475. URL: <https://doi.org/10.1145/2594473.2594475>.
- [Gla+24] Claire Ganois et al. "A survey on interpretable reinforcement learning". In: *Machine Learning* (2024), pp. 1–44.
- [GOV22] Léo Grinsztajn, Edouard Oyallon, and Gaël Varoquaux. "Why do tree-based models still outperform deep learning on typical tabular data?" In: *Advances in neural information processing systems* 35 (2022), pp. 507–520.
- [HR76] Laurent Hyafil and Ronald L. Rivest. "Constructing optimal binary decision trees is NP-complete". In: *Information Processing Letters* 5.1 (1976), pp. 15–17. ISSN: 0020-0190. DOI: [https://doi.org/10.1016/0020-0190\(76\)90095-8](https://doi.org/10.1016/0020-0190(76)90095-8).

URL: <https://www.sciencedirect.com/science/article/pii/0020019076900958>.

[Lav99] Nada Lavrač. "Selected techniques for data mining in medicine". In: *Artificial Intelligence in Medicine* 16.1 (1999). Data Mining Techniques and Applications in Medicine, pp. 3–23. ISSN: 0933-3657. DOI: [https://doi.org/10.1016/S0933-3657\(98\)00062-1](https://doi.org/10.1016/S0933-3657(98)00062-1). URL: <https://www.sciencedirect.com/science/article/pii/S0933365798000621>.

[LBE25] Gaspard Lambrechts, Adrien Bolland, and Damien Ernst. "Informed POMDP: Leveraging Additional Information in Model-Based RL". In: *Reinforcement Learning Journal* 2 (2025), pp. 763–784.

[LEM25] Gaspard Lambrechts, Damien Ernst, and Aditya Mahajan. "A Theoretical Justification for Asymmetric Actor-Critic algorithms". In: *Forty-second International Conference on Machine Learning*. 2025. URL: <https://openreview.net/forum?id=F1yANMCnAn>.

- [Lip18] **Zachary C. Lipton.** “The Mythos of Model Interpretability: In machine learning, the concept of interpretability is both important and slippery.”. In: *Queue* 16.3 (2018), pp. 31–57.
- [Lit94] **Michael L. Littman.** “Memoryless policies: theoretical limitations and practical results”. In: *Proceedings of the Third International Conference on Simulation of Adaptive Behavior: From Animals to Animats 3: From Animals to Animats 3*. SAB94. Brighton, United Kingdom: MIT Press, 1994, pp. 238–245. ISBN: 0262531224.
- [LS98] **John Loch and Satinder P. Singh.** “Using Eligibility Traces to Find the Best Memoryless Policy in Partially Observable Markov Decision Processes”. In: *Proceedings of the Fifteenth International Conference on Machine Learning*. ICML '98. San Francisco, CA, USA: Morgan Kaufmann Publishers Inc., 1998, pp. 323–331. ISBN: 1558605568.
- [Luo+24] **Lirui Luo et al.** “End-to-End Neuro-Symbolic Reinforcement Learning with Textual Explanations”. In: *International Conference on Machine Learning (ICML)* (2024).

- [LWD23] Jacobus van der Linden, Mathijs de Weerdt, and Emir Demirović. “Necessary and Sufficient Conditions for Optimal Decision Trees using Dynamic Programming”. In: *Advances in Neural Information Processing Systems 36* (2023). Ed. by A. Oh et al., pp. 9173–9212.
- [Mar+25] Sascha Marton et al. “Mitigating Information Loss in Tree-Based Reinforcement Learning via Direct Optimization”. In: (2025). URL: <https://openreview.net/forum?id=qpXctF2aLZ>.
- [Mil+24] Stephanie Milani et al. “Explainable Reinforcement Learning: A Survey and Comparative Review”. In: *ACM Comput. Surv.* 56.7 (Apr. 2024). ISSN: 0360-0300. DOI: 10.1145/3616864. URL: <https://doi.org/10.1145/3616864>.
- [MMW22] Rahul Mazumder, Xiang Meng, and Haoyue Wang. “Quant-BnB: A Scalable Branch-and-Bound Method for Optimal Decision Trees with Continuous Features”. In: *Proceedings of the 39th International Conference on Machine Learning*. Proceedings of Machine Learning Research 162

- (17–23 Jul 2022). Ed. by Kamalika Chaudhuri et al., pp. 15255–15277. URL: <https://proceedings.mlr.press/v162/mazumder22a.html>.
- [Mni+15] Volodymyr Mnih et al. “Human-level control through deep reinforcement learning”. In: *nature* 518.7540 (2015), pp. 529–533.
- [Nag+24] Myura Nagendran et al. “Eye tracking insights into physician behaviour with safe and unsafe explainable AI recommendations”. In: *NPJ Digital Medicine* 7.1 (2024), p. 202.
- [Put94] Martin L. Puterman. *Markov Decision Processes: Discrete Stochastic Dynamic Programming*. John Wiley & Sons, 1994.
- [Qui86] J. R. Quinlan. “Induction of Decision Trees”. In: *Mach. Learn.* 1.1 (1986), pp. 81–106.
- [Qui93] J Ross Quinlan. “C4. 5: Programs for machine learning”. In: *Morgan Kaufmann google schola* 2 (1993), pp. 203–228.

- [RGB10] Stéphane Ross, Geoffrey J. Gordon, and J. Andrew Bagnell.
“A Reduction of Imitation Learning and Structured Prediction
to No-Regret Online Learning”. In: (2010).
- [SB98] Richard S. Sutton and Andrew G. Barto. *Reinforcement
Learning: An Introduction*. Cambridge, MA: The MIT Press,
1998.
- [Sch+17] John Schulman et al. “Proximal policy optimization
algorithms”. In: *arXiv preprint arXiv:1707.06347* (2017).
- [SJJ94] Satinder P. Singh, Tommi S. Jaakkola, and Michael I. Jordan.
“Learning without state-estimation in partially observable
Markovian decision processes”. In: *Proceedings of the
Eleventh International Conference on International Conference
on Machine Learning*. ICML'94. New Brunswick, NJ, USA:
Morgan Kaufmann Publishers Inc., 1994, pp. 284–292. ISBN:
1558603352.
- [Top+21] Nicholay Topin et al. “Iterative bounding mdps: Learning
interpretable policies via non-interpretable methods”. In:

Proceedings of the AAAI Conference on Artificial Intelligence
35 (2021), pp. 9923–9931.

- [VZ19] Sicco Verwer and Yingqian Zhang. “Learning optimal classification trees using a binary linear program formulation”. In: *Proceedings of the AAAI conference on artificial intelligence* 33 (2019), pp. 1625–1632.
- [Wu+20] Mike Wu et al. “Regional Tree Regularization for Interpretability in Deep Neural Networks”. In: 34 (Apr. 2020), pp. 6413–6421. DOI: 10.1609/aaai.v34i04.6112. URL: <https://ojs.aaai.org/index.php/AAAI/article/view/6112>.