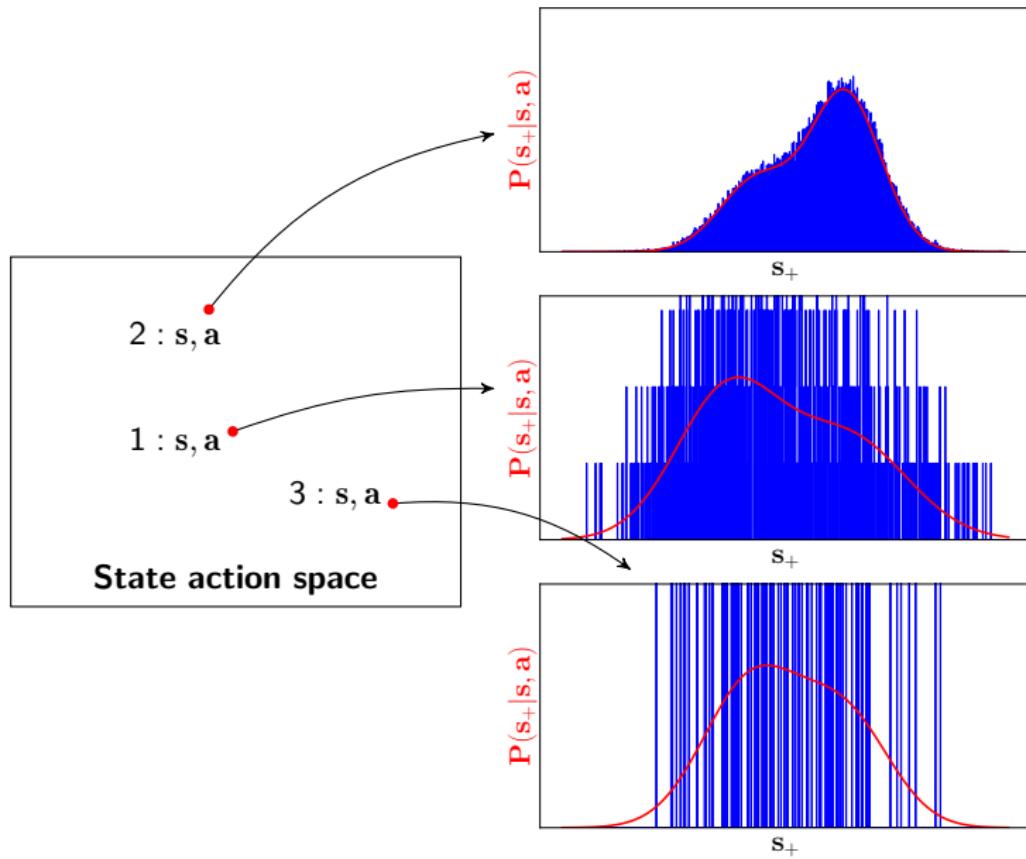


The Role of Probabilistic AI



Introduction to Theory of Safe Decision Making

Dr. Akhil Anand

1st AID Scientific Workshop, Trondheim

Forewords & Disclaimer

Objectives:

- Put in place some common concepts & language
- Identify some key points in safe decision making
- Connect to AI

Disclaimer: we are a broad group who needs to get to know each others scientifically.

Apologies if I don't "hit" the right level for all.

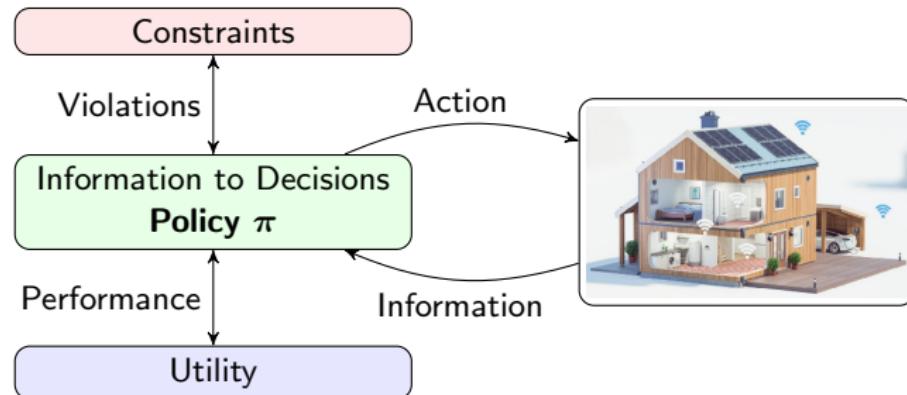
I have favored simplicity over "absolute" rigor.



Outline

- 1 Some Basics of Safe Decision Making
- 2 Methods
- 3 Safe Decisions from Data & AI
- 4 Epistemic Uncertainty and Safe Decisions

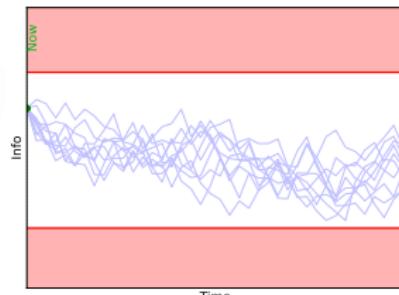
Formally Defining Safety?



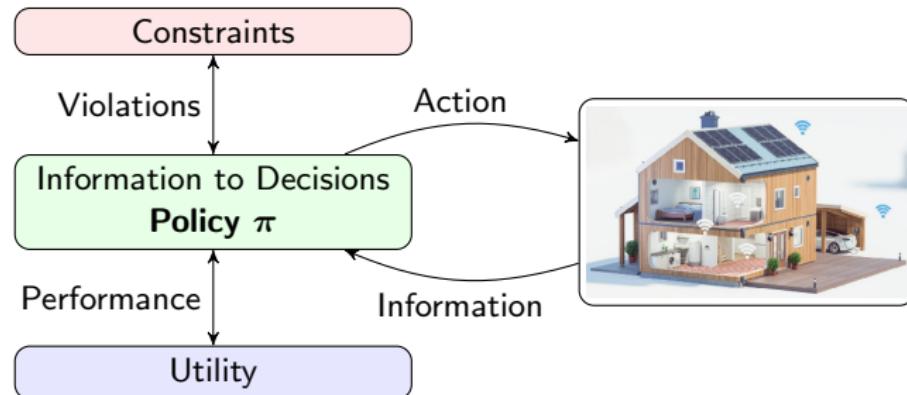
Safety in the real world



Safety in the math world



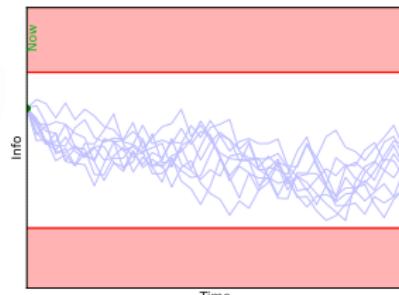
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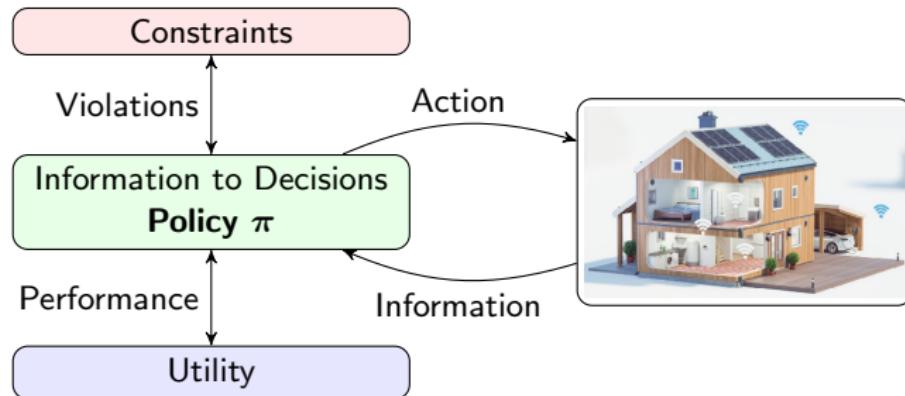
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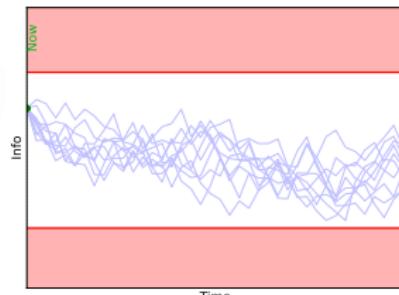
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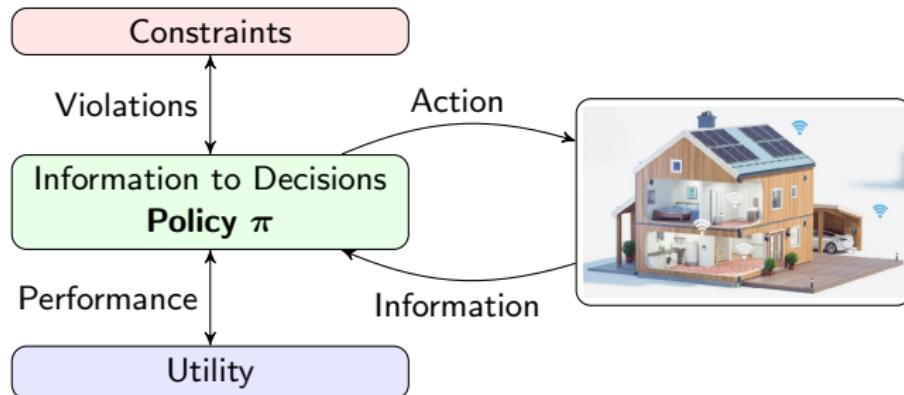
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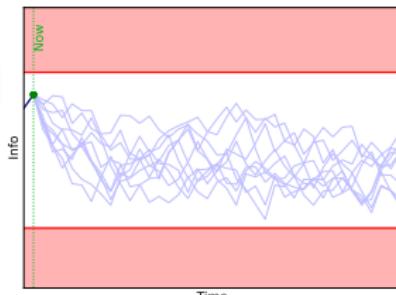
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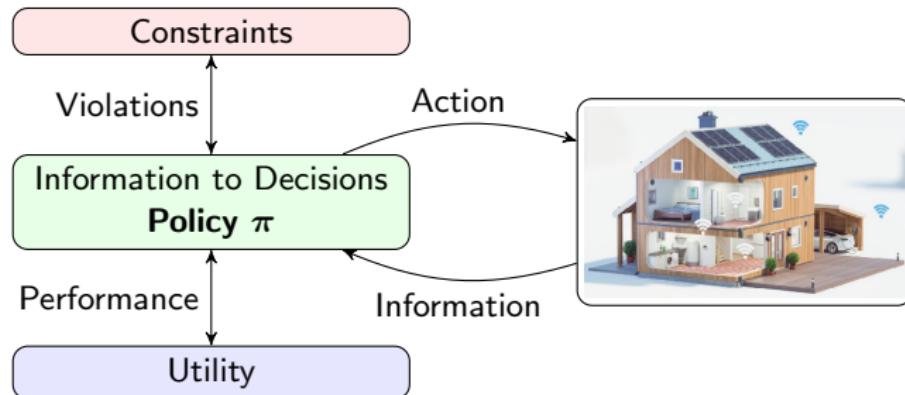
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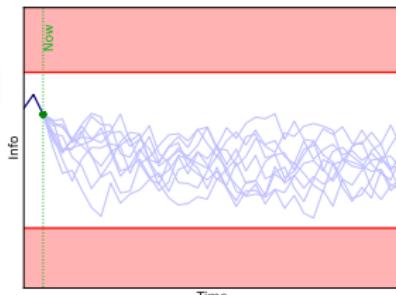
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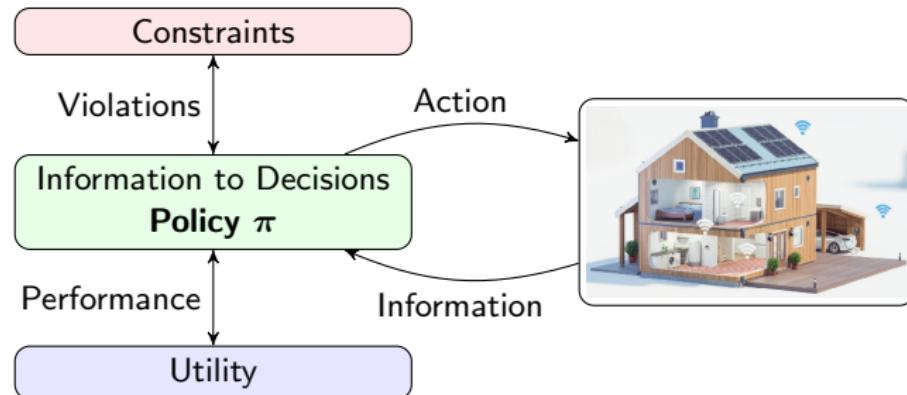
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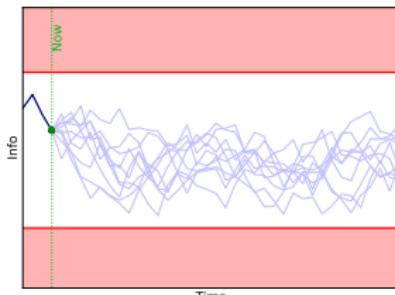
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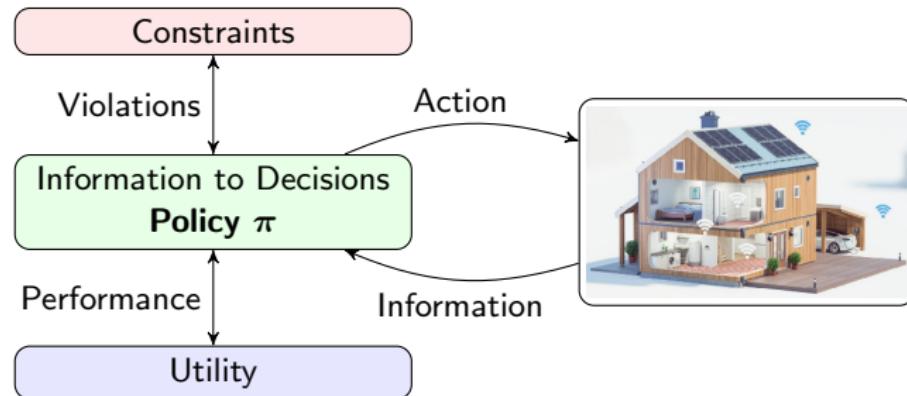
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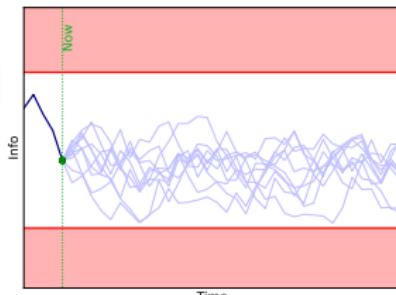
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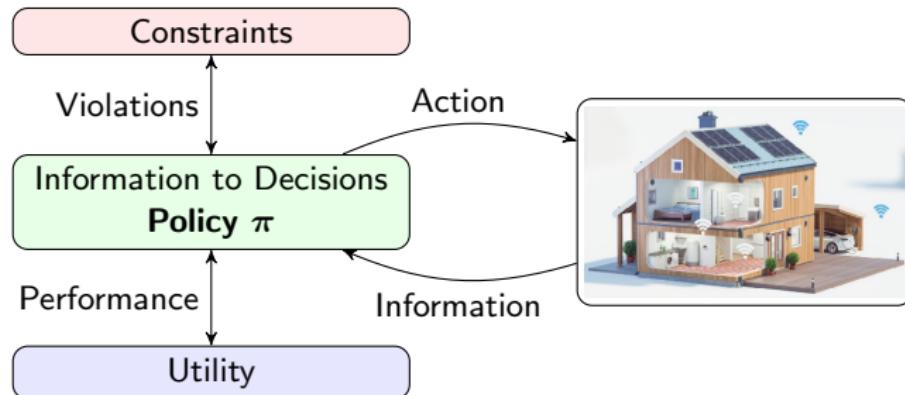
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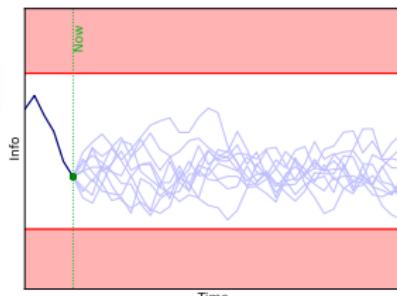
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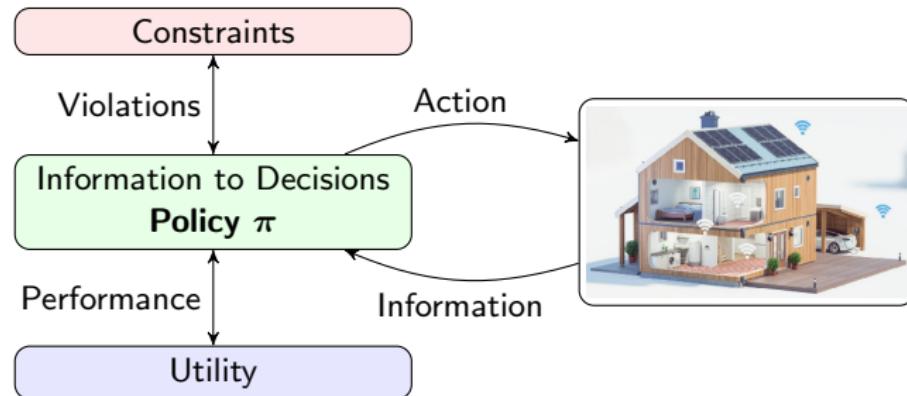
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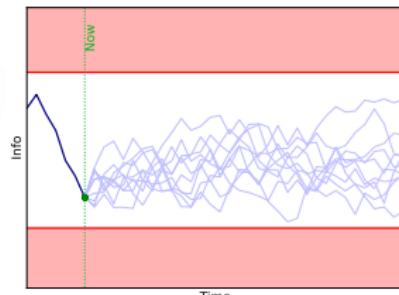
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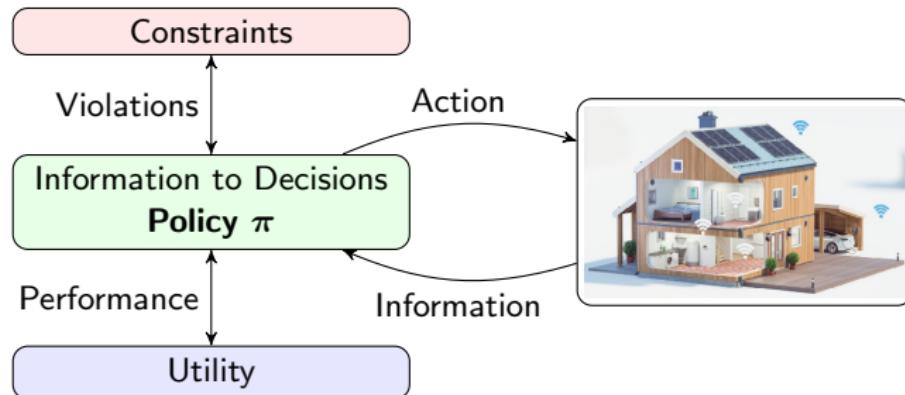
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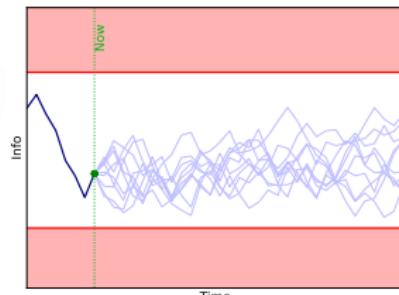
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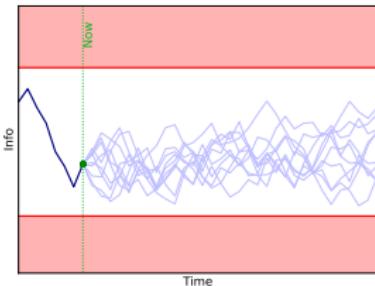


Constrained MDPs

In words

$$\pi^* = \arg \max_{\pi} E \left[\sum_{\text{time}} \text{Utility} \right]$$

s.t. Constraints ok at all time

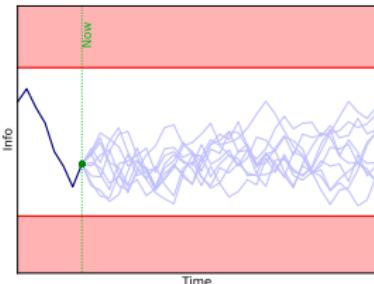


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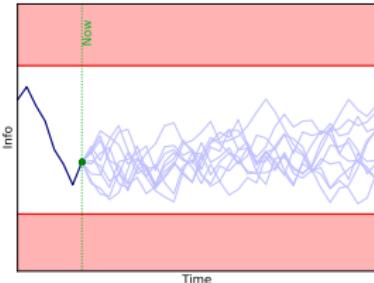
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Build policy using

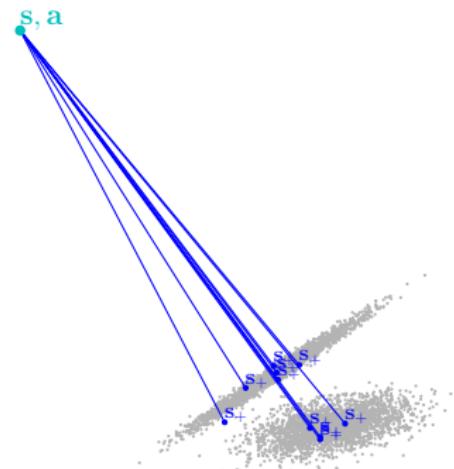
- Perfect model of the real world $\hat{P}[s_+|s, a] = P[s_+|s, a]$
- Model “pessimistic” about the uncertainties

... to evaluate “ $E[\cdot]$ ”

Pessimistic Models for Decision Making

- Model must “contain” the uncertainty
- “Container” (set) should be simple for computational reasons
- Trajectories predicted by pessimistic model will “cover” the real world
- Decision policy wants to be safe w.r.t. the “containers”

Distribution of one-step forward

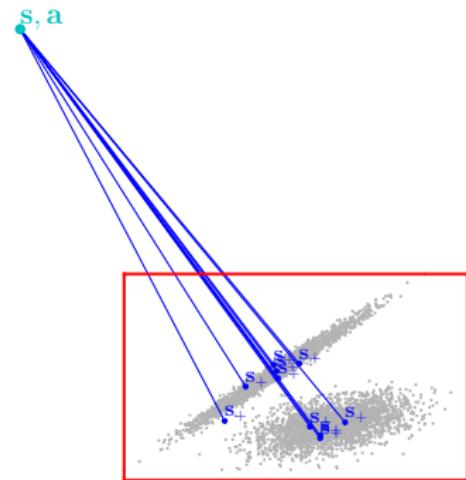


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Distribution of one-step forward with “container”

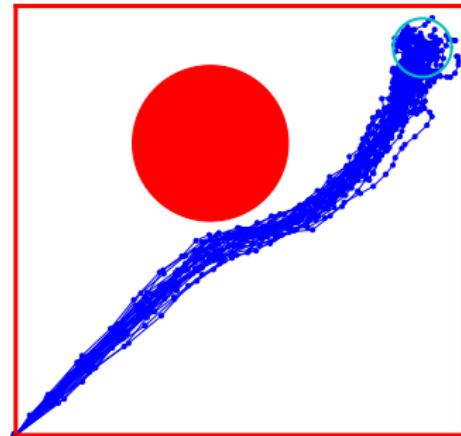


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Trajectories

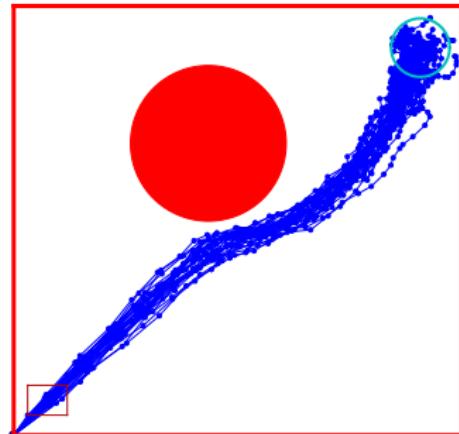


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Trajectories with “containers”

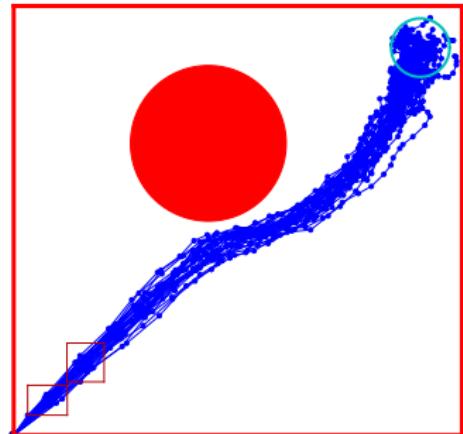


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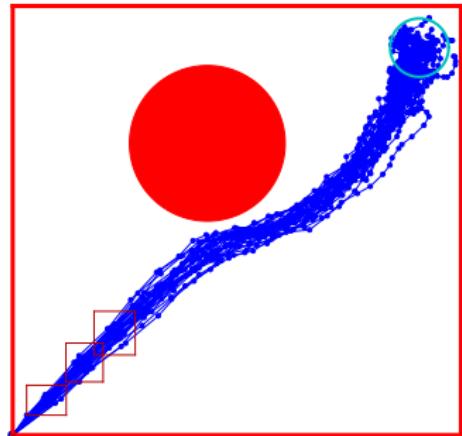


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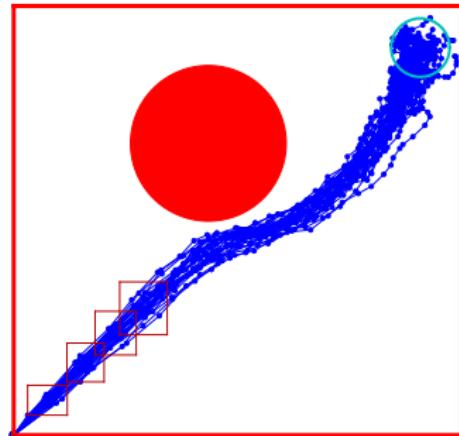


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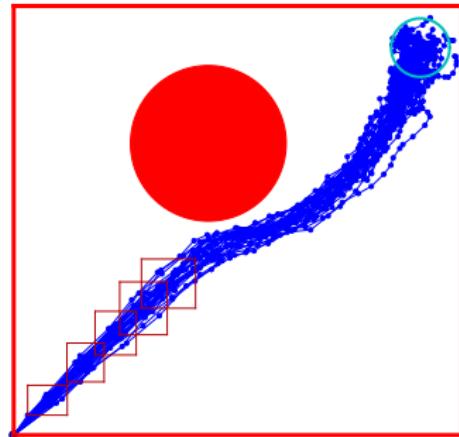


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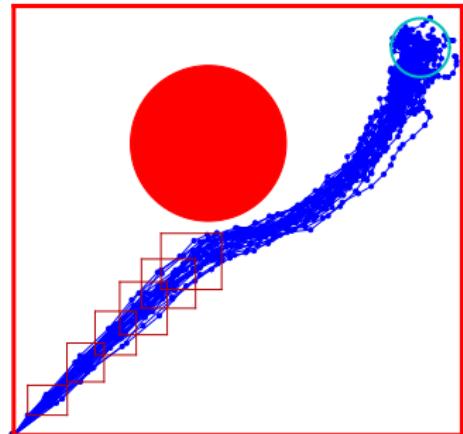


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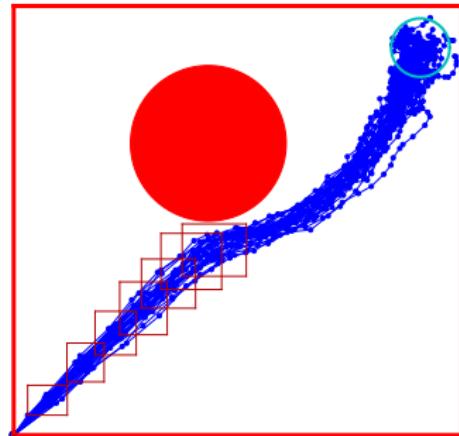


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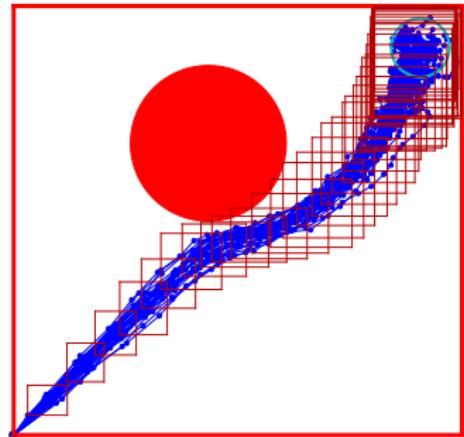


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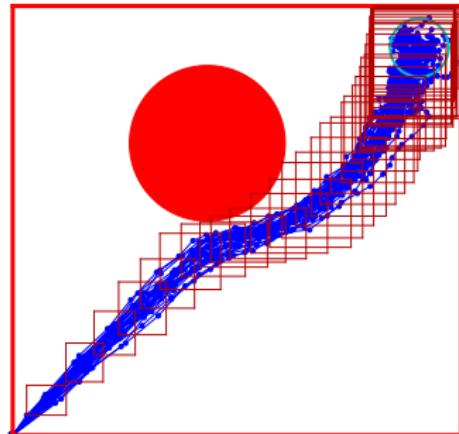
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Remarks

- The propagation of the “containers” in the model predictions can be expensive / difficult
- Pessimistic propagations are usually needed → pessimistic over pessimistic
- Policy based on worst-case perspective makes the decisions highly conservative
- Often labelled “Robust” decision making

Trajectories with “containers”



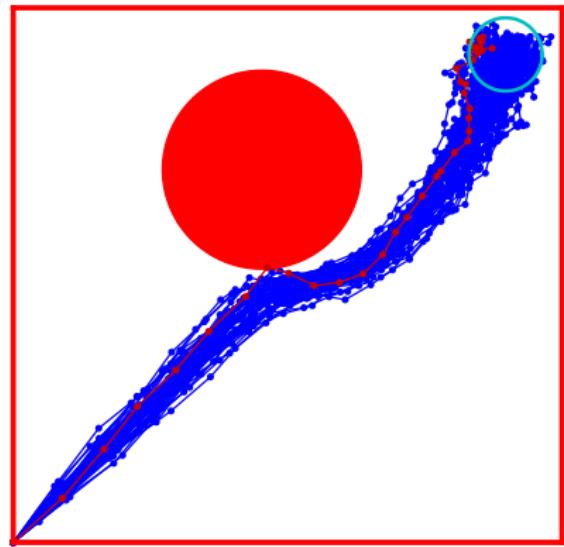
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MDPs with probabilistic safety

In words

$$\pi^* = \arg \max_{\pi} E \left[\sum_{\text{time}} \text{Utility} \right]$$

s.t. Probability of no violation $\geq c$



MDPs with probabilistic safety

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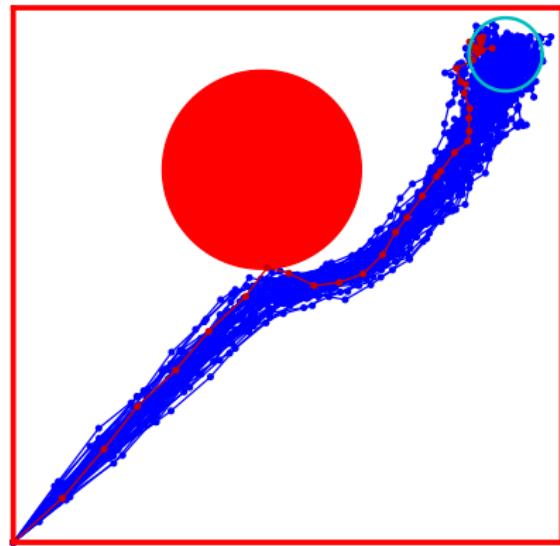
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Formally

$$\pi^* = \arg \max_{\pi} E \left[\sum_{k=0}^{\infty} \gamma^k L(s_k, a_k) \right]$$

s.t. $P[s_0, \dots, \infty \in \mathbb{S}] \geq c$



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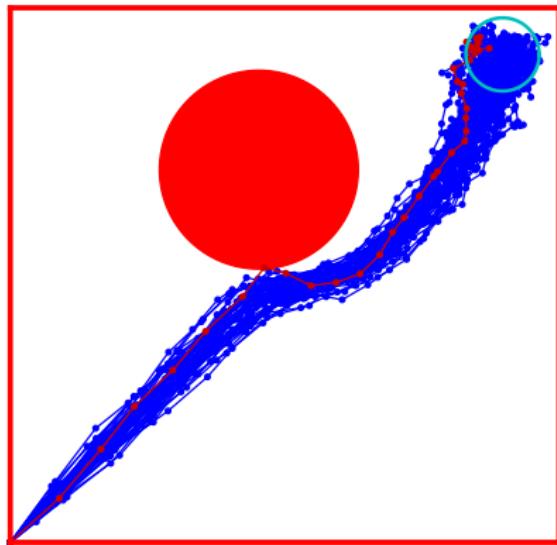
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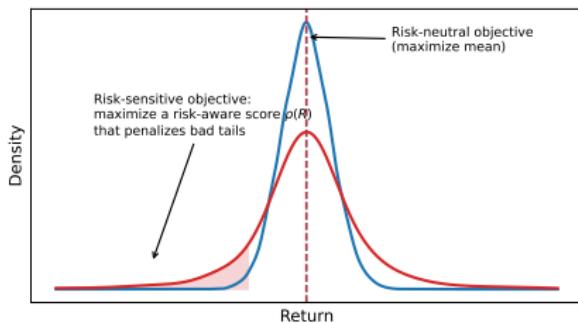
- If we can tolerate $c > 0$ (small) it can make a big gain in performance
- Aligned with industrial / practical standards on “large series”
- Problem needs a “termination” (time or goal reached)
- Building decisions can be difficult from a computational point of view



Risk-sensitive MDPs

In words

- Risk-sensitive MDPs optimizes a **risk measure** to account for the severity of rare outcomes.
- Intuition: a “tail-risk filter” even if outcomes are good most of the time, severe tails influence decisions.



Mean-optimal can ignore tails; risk-sensitive downweights heavy losses.

Risk-sensitive MDPs

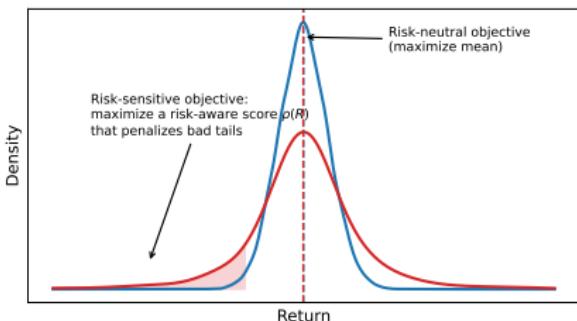
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$$\pi^* = \arg \max_{\pi} \rho \left(\sum_{t=0}^{\infty} \gamma^t r_t \right)$$

ρ is a risk measure (e.g., VaR, Entropic, CVaR).

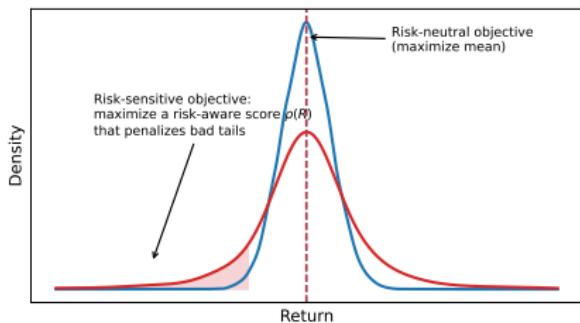


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Remarks:

- Often possible to solve using classical methods such as DP.
- Risk-sensitive criteria do *not* guarantee a bound on violation.
- Cares only about the average severity of bad outcomes in the tail and not about the rest.

Mean-optimal can ignore tails; risk-sensitive downweights heavy losses.

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Robust Repeated Planning

- Introduction: Robust MPC, Scenario Trees, MC, robust multi-stage stochastic programming, MPPI?
- Difficulties: guarantees for nonlinear systems, persistent safety (recursive feasibility)



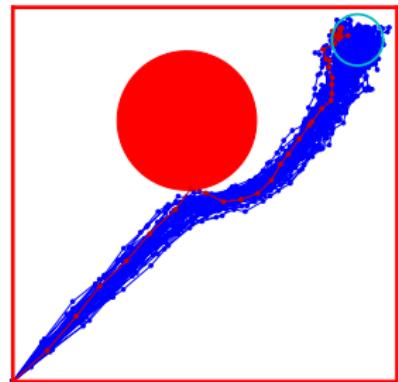
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Expected value form Illustrate??

$$\pi^* = \arg \max_{\pi} E \left[\sum_{k=0}^{\infty} \gamma^k L(s_k, a_k) \right]$$

s.t. $E \left[\begin{array}{ll} 1 & \text{if no violation occurred} \\ 0 & \text{otherwise} \end{array} \right] \geq c$



- Expected value form enables classical techniques (ref. 1st lecture), i.e. DP and RL
- Difficulties: estimate expected values (sample based) when $P[s_0, \dots, \infty \in S]$ is close to 1. **Illustrate??**

Safety Filters & Reinforcement Learning

- For any state s , an “oracle” tells you which actions will not jeopardize safety in the long run → “Safe set” $S(s)$

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that focuses only on utility

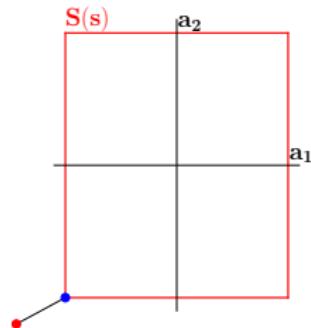
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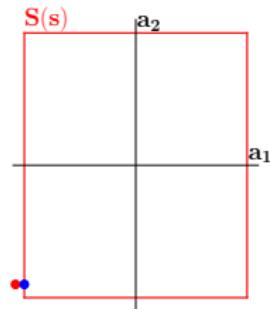
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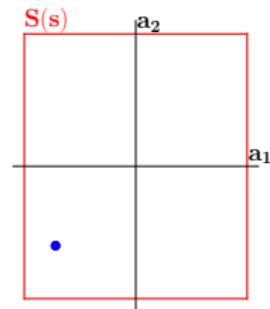
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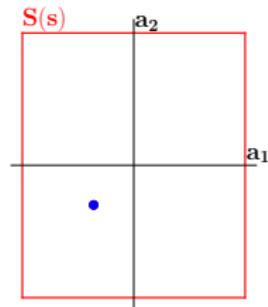
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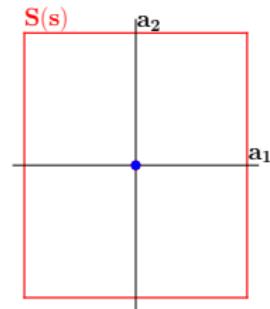
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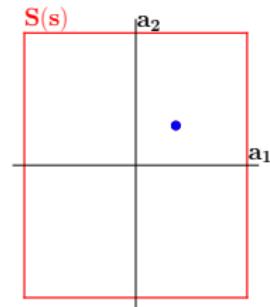
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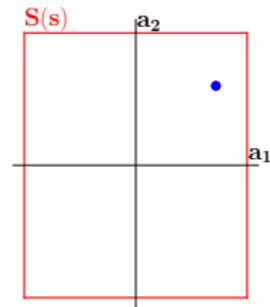
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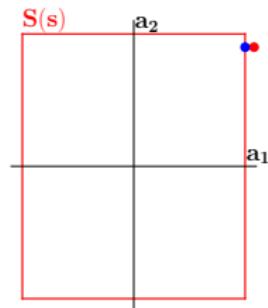
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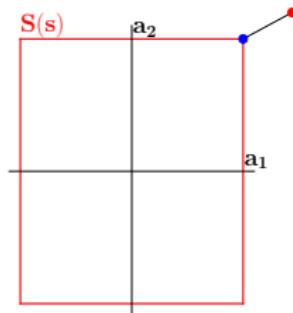
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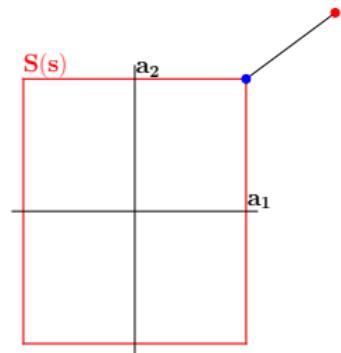
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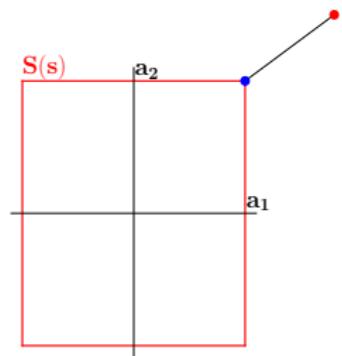
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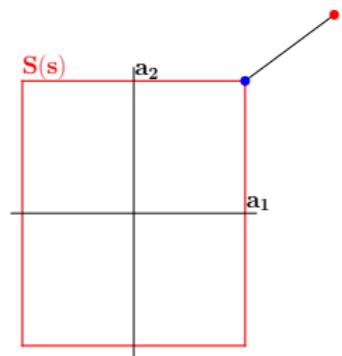
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Able to stop within the visible distance



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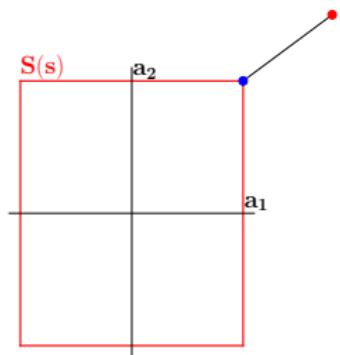
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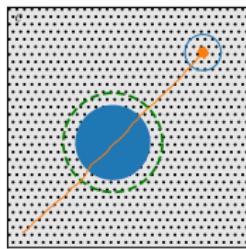
- Often close to practice, e.g., flight envelop protection in modern airplane, semi-autonomous driving in cars, etc
- Oracle \Rightarrow knowledge-based & conservative!



Control Barrier Functions (CBFs)

In words

- CBFs provide a formal, model-based way to build the “oracle” safe set.
- Use a barrier function $h(x)$ so that staying safe means $h(x) \geq 0$.
- At each step, if the proposed action would leave the safe set, a small QP minimally adjusts it to be safe.

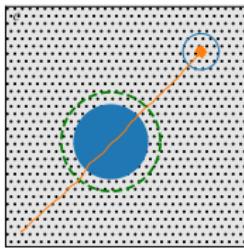


Unsafe trajectory: violates $h(x) \geq 0$.

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Formally

$$\dot{x} = f(x) + g(x)u, \quad \mathcal{C} = \{x : h(x) \geq 0\}$$

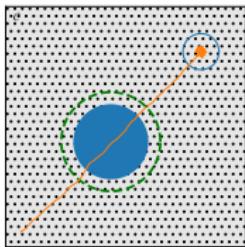
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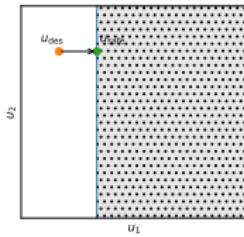
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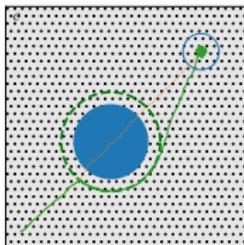


CBF filter: project u_{des} to feasible u_{safe} .

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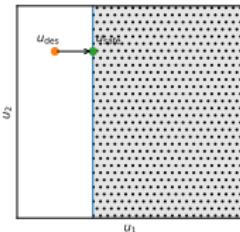
CBF-filtered trajectory.

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CBF filter: project u_{des} to feasible u_{safe} .

- The barrier function and safe set \mathcal{C} are typically **constructed from domain knowledge** (physics, rules, safety envelopes).
- Requires a (possibly simplified, conservative) **system model: robust approach**.

Outline

- 1 Some Basics of Safe Decision Making
- 2 Methods
- 3 Safe Decisions from Data & AI
- 4 Epistemic Uncertainty and Safe Decisions

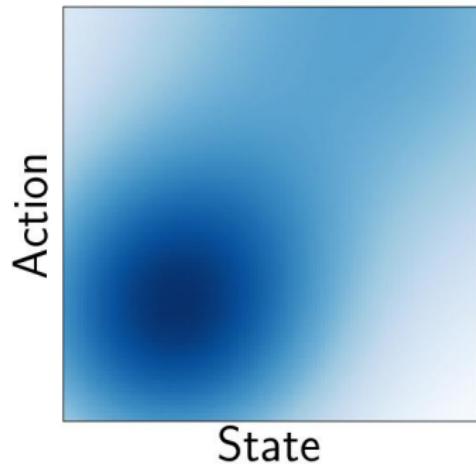
Epistemic Uncertainty in Decision Making

SG can do

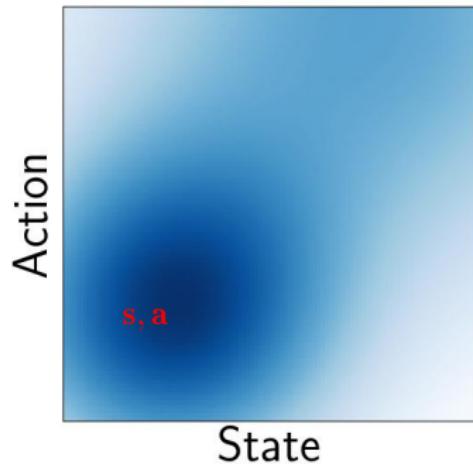
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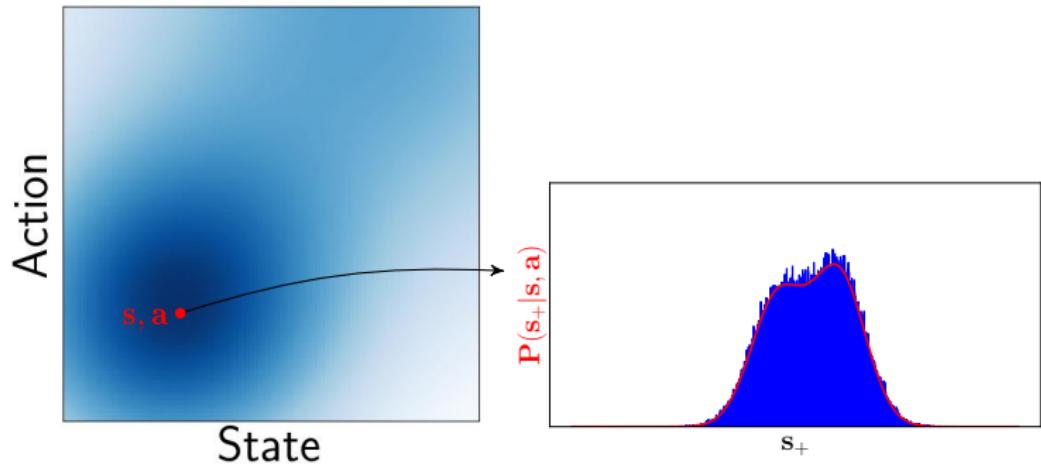
Data & Epistemic Uncertainty



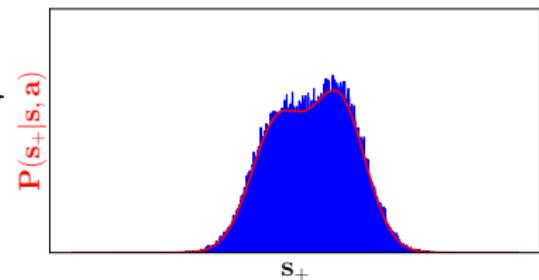
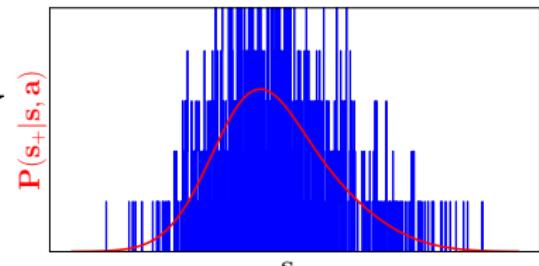
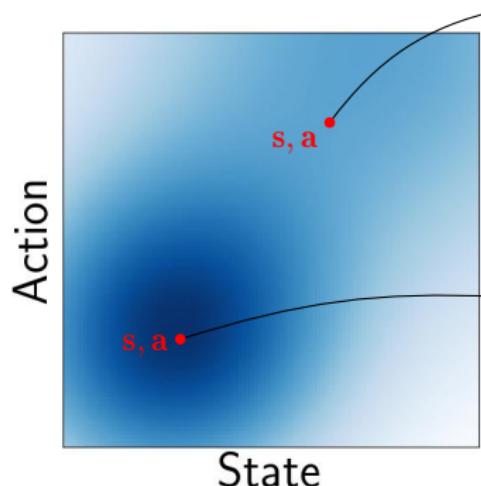
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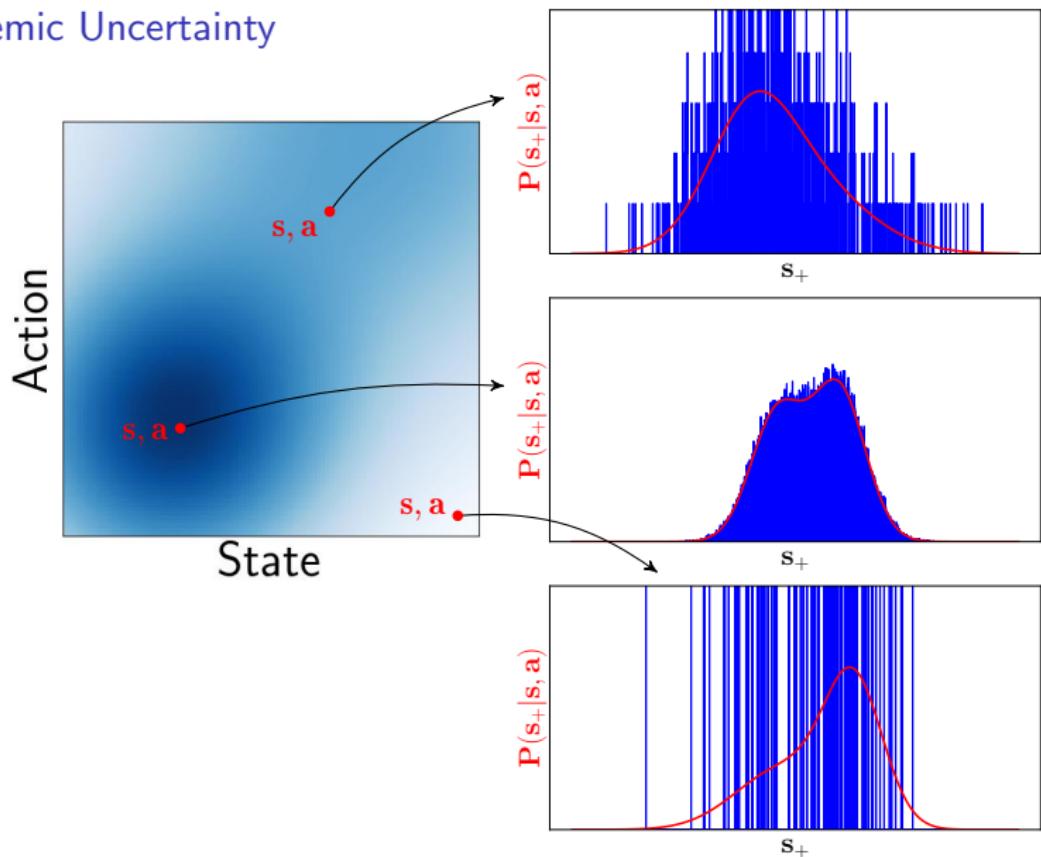
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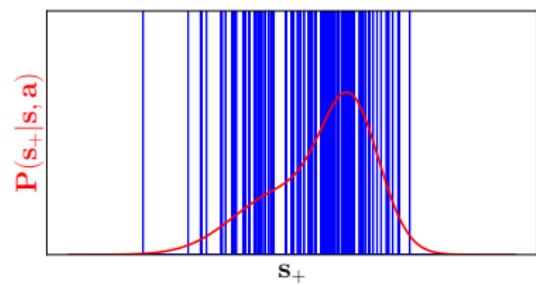
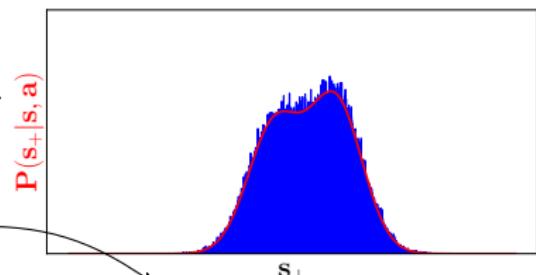
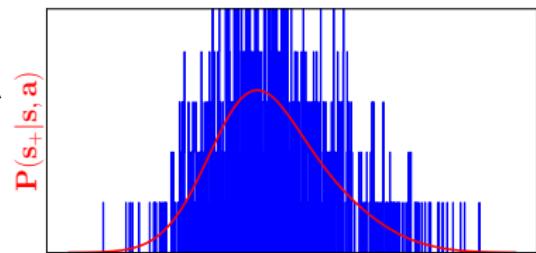
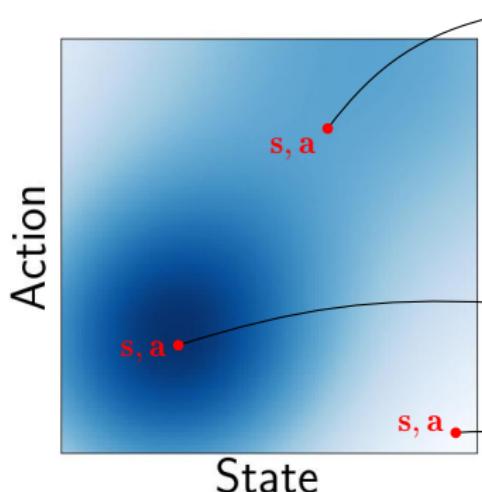
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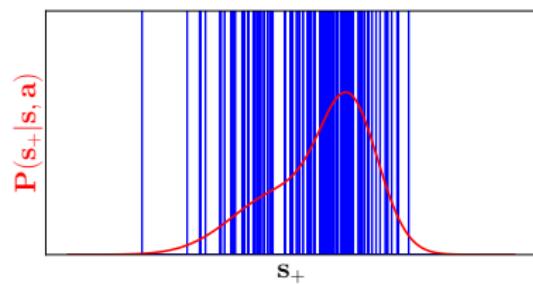
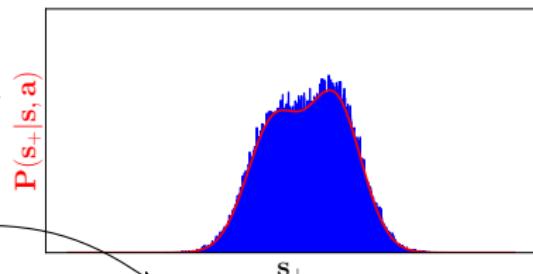
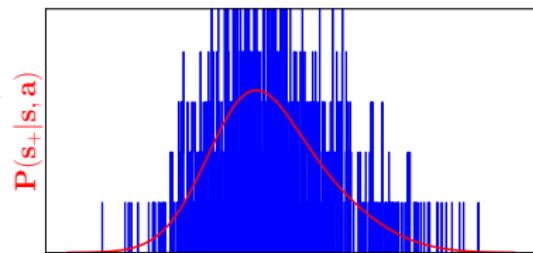
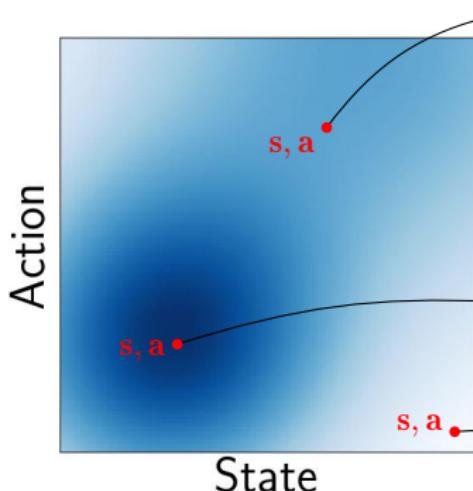
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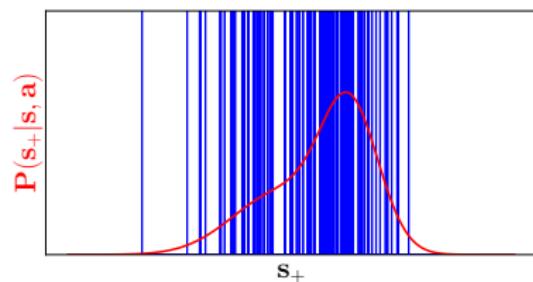
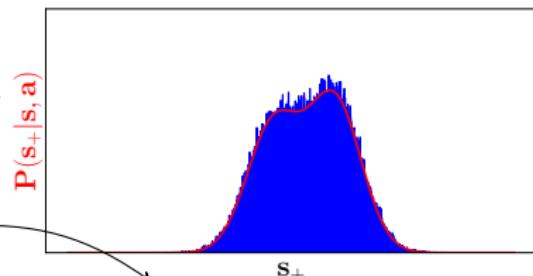
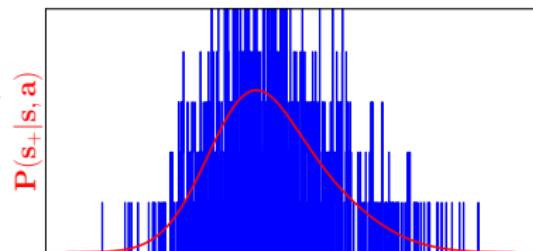
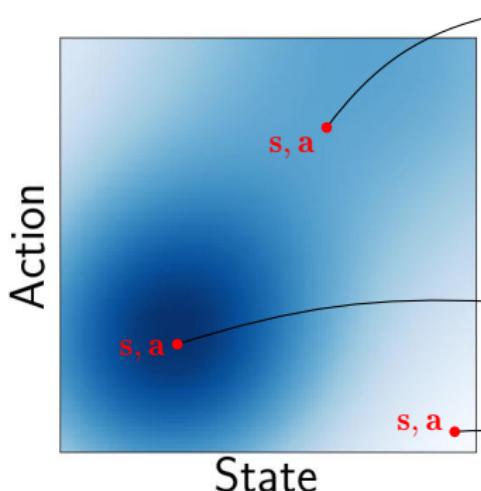
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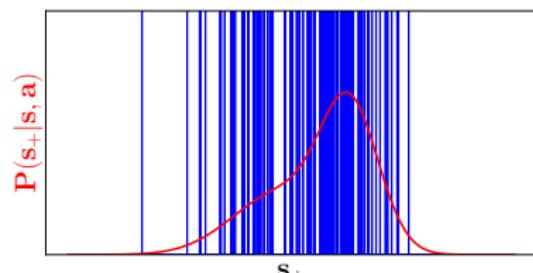
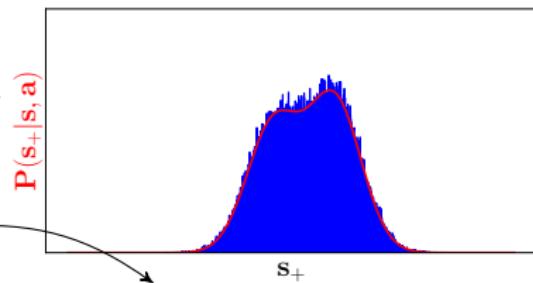
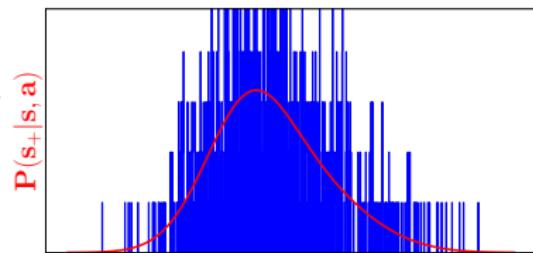
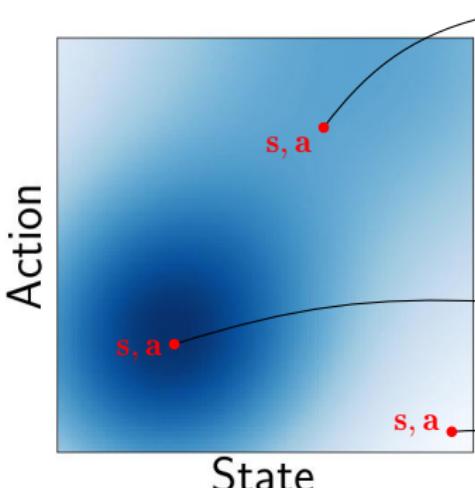
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