Interactively Learning Preference Constraints in Linear Bandits

International Conference on Machine Learning (ICML), 2022

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[1]ETH Zurich; [2]University of Vienna; [3]Microsoft Research Cambridge

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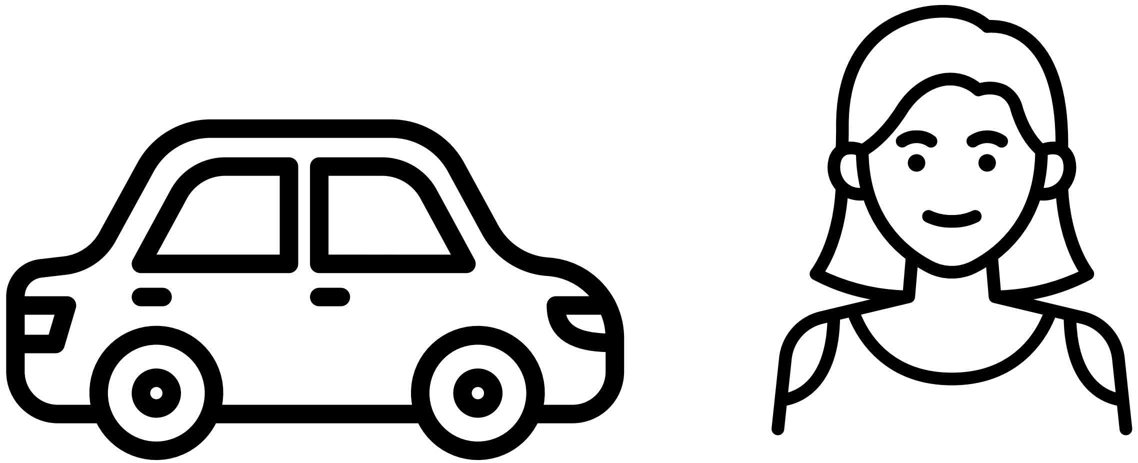

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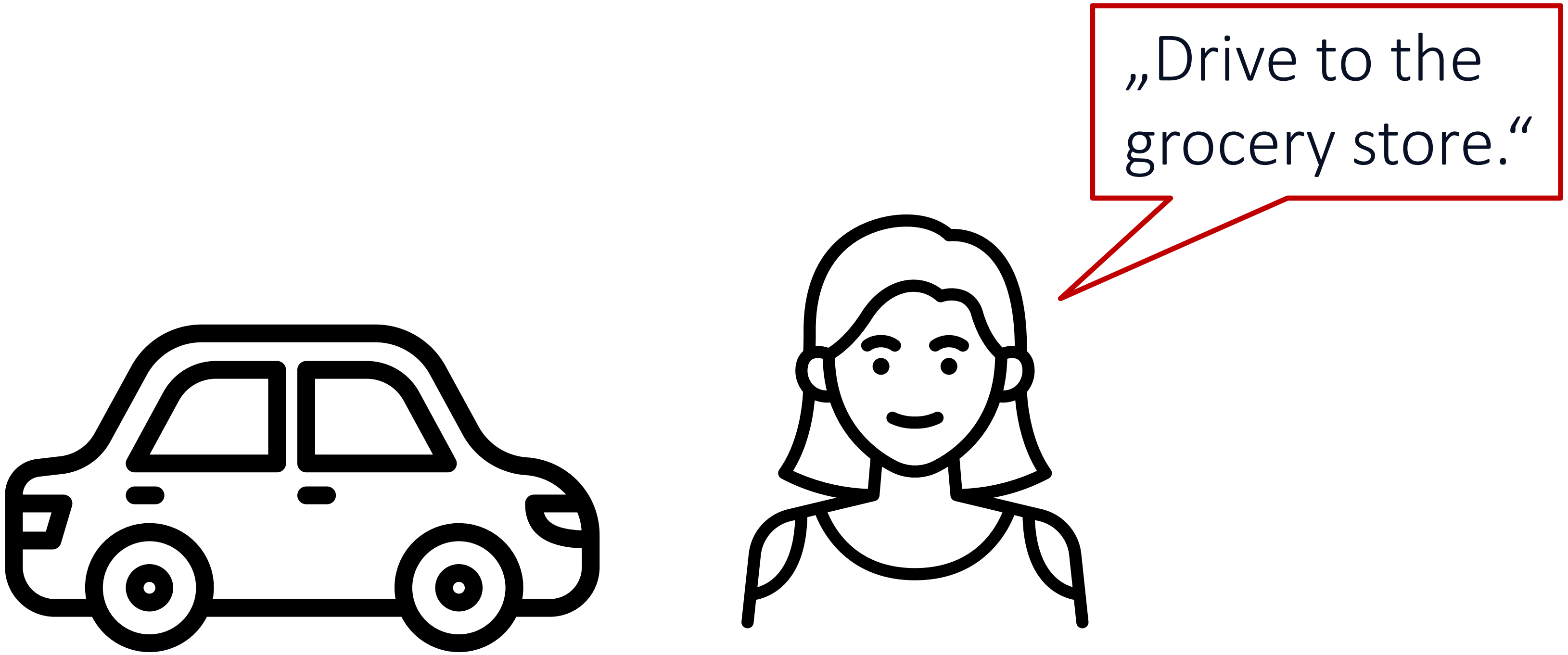

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Constraint can be more transferable and robust than rewards

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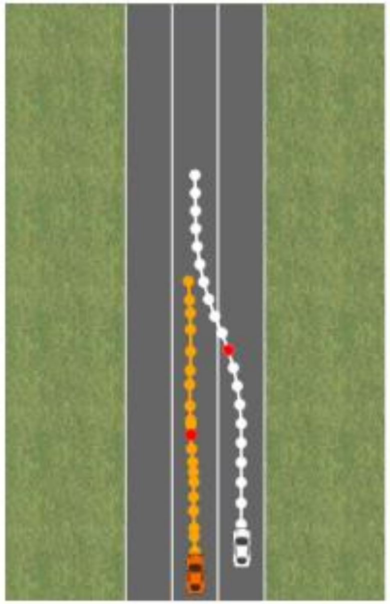
Encode task as reward + penalty



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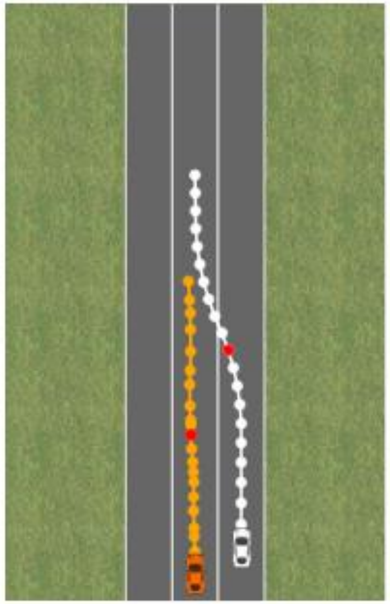

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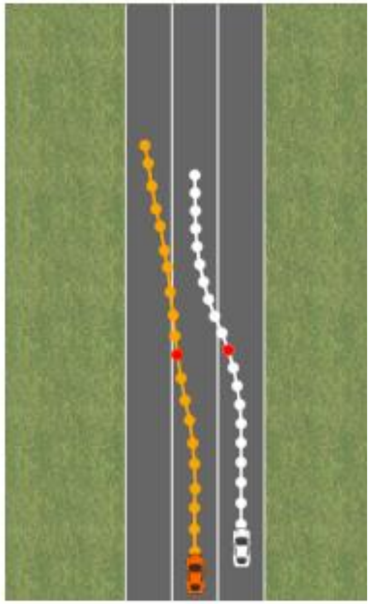

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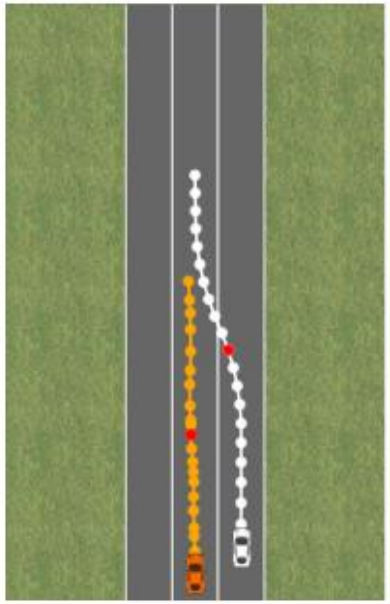

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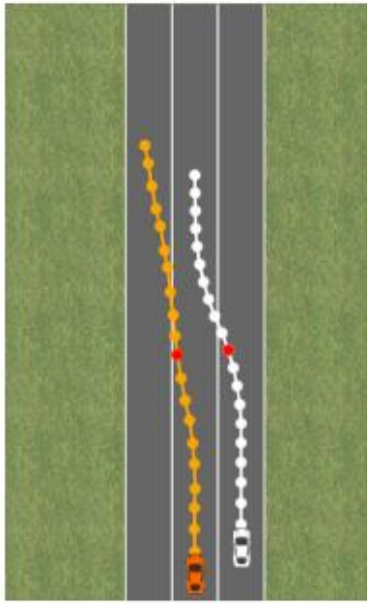

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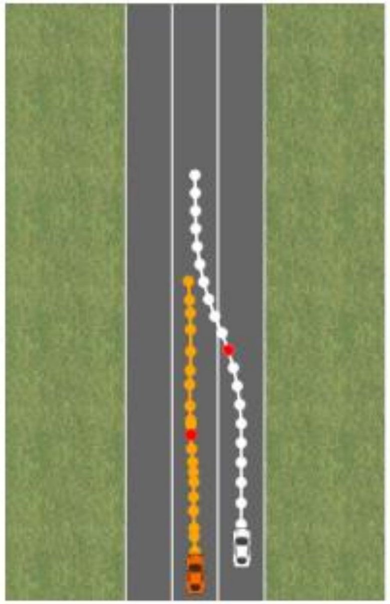
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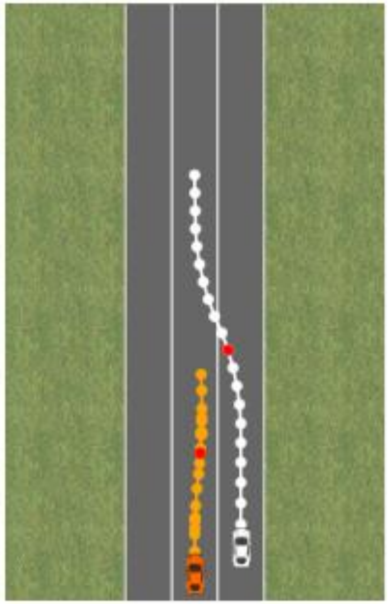
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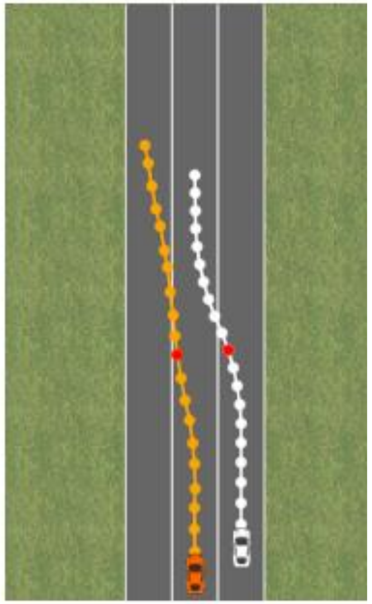
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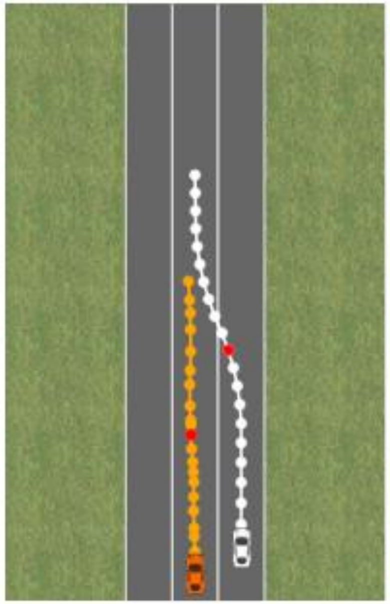

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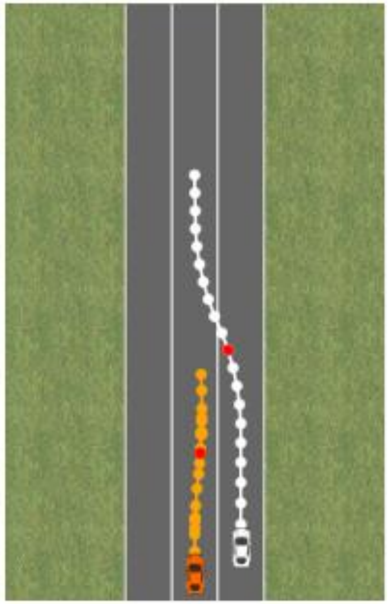

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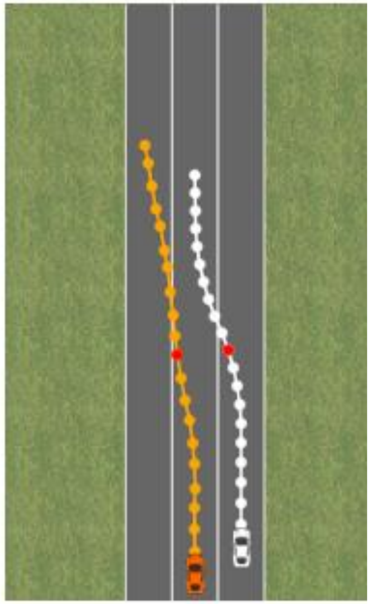

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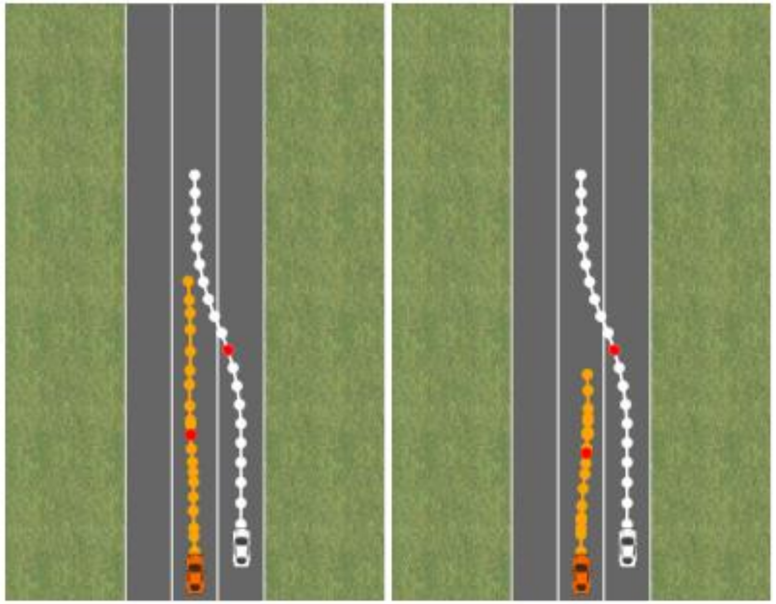

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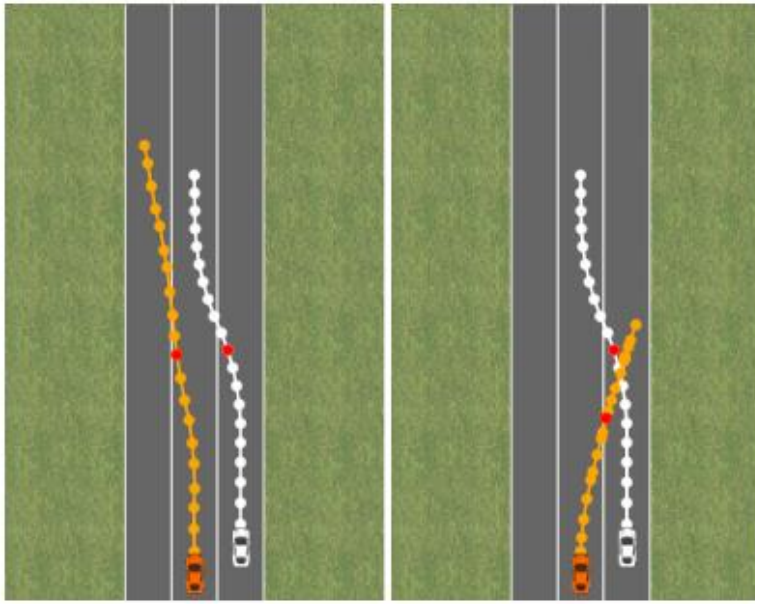

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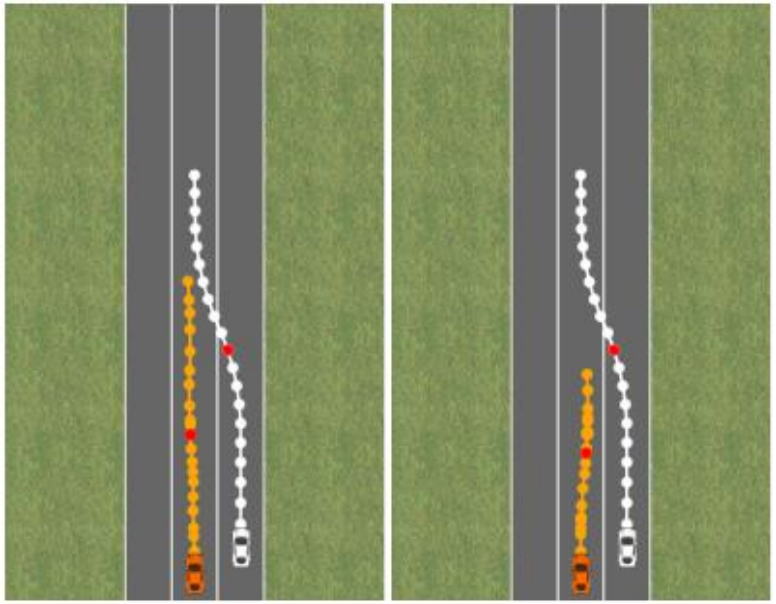

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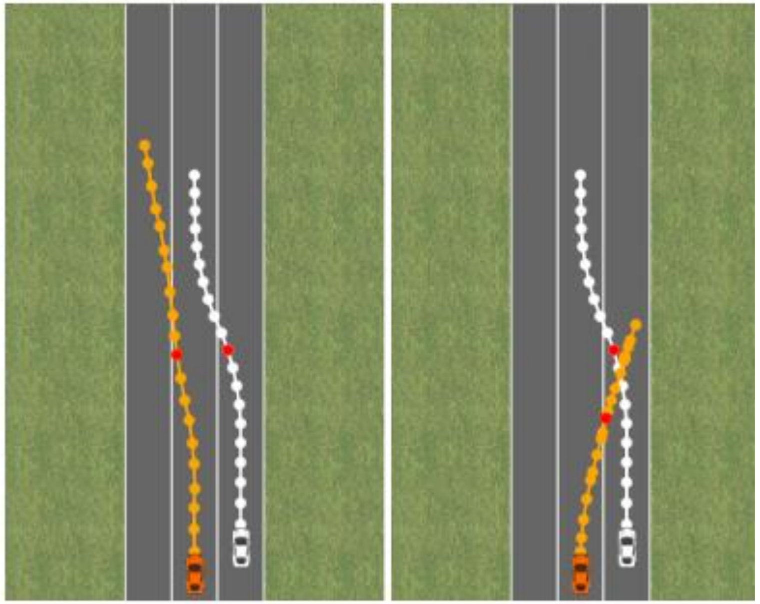

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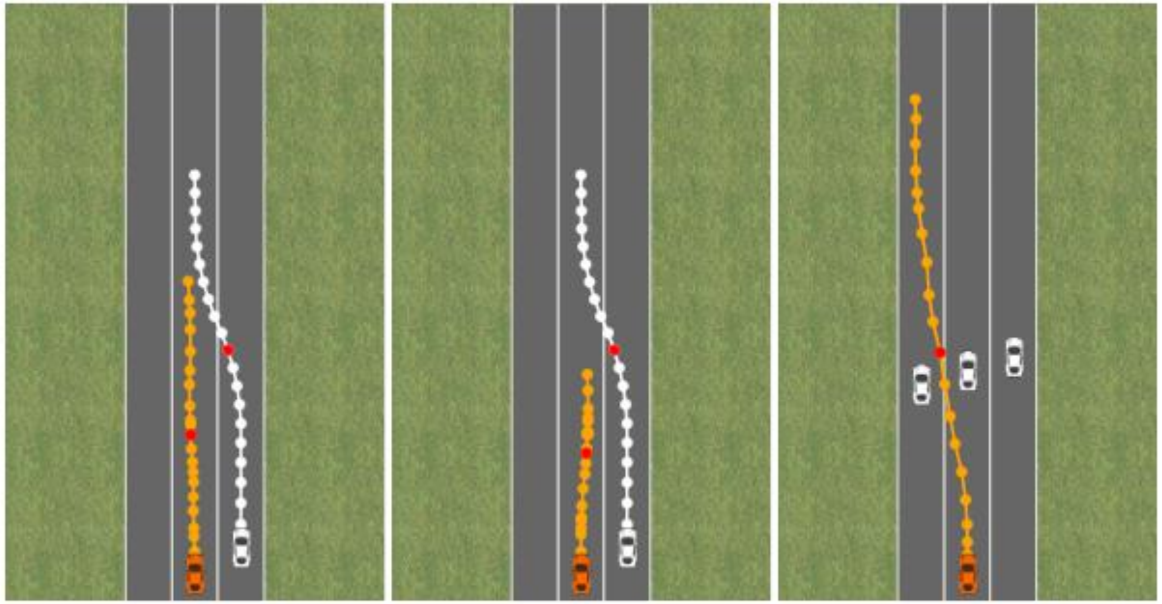

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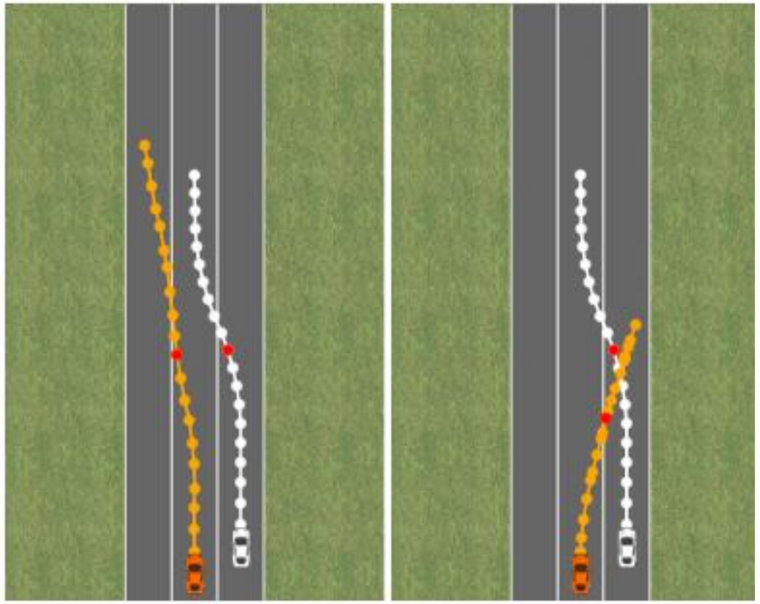

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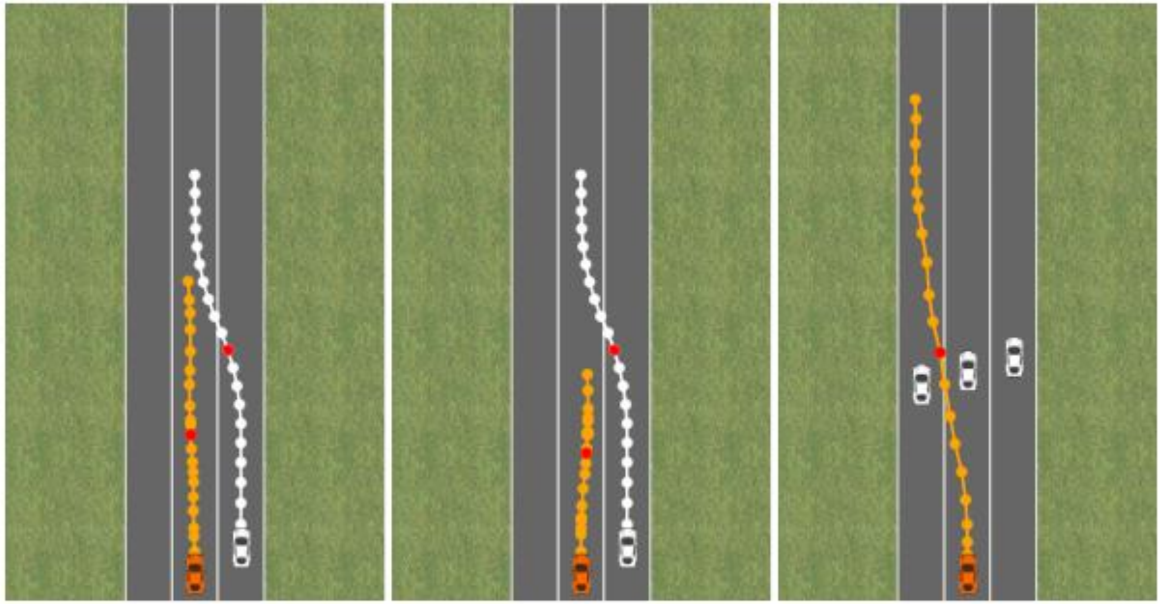

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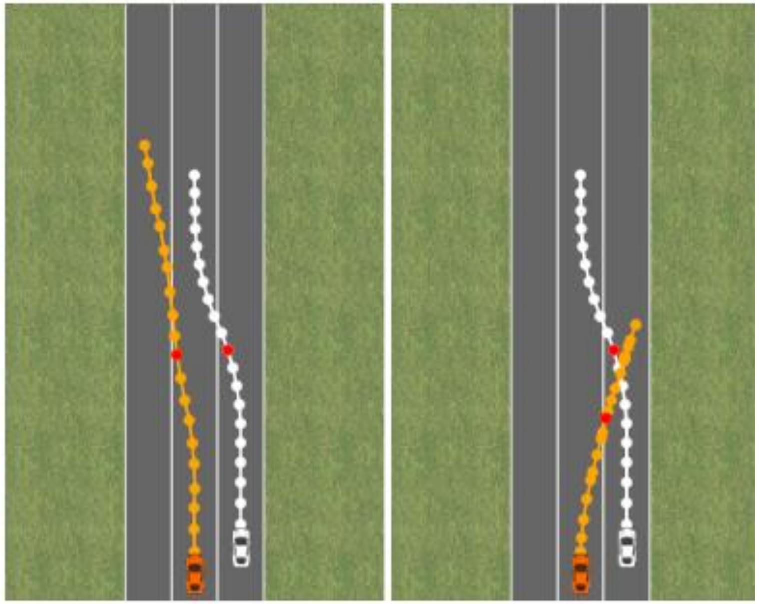

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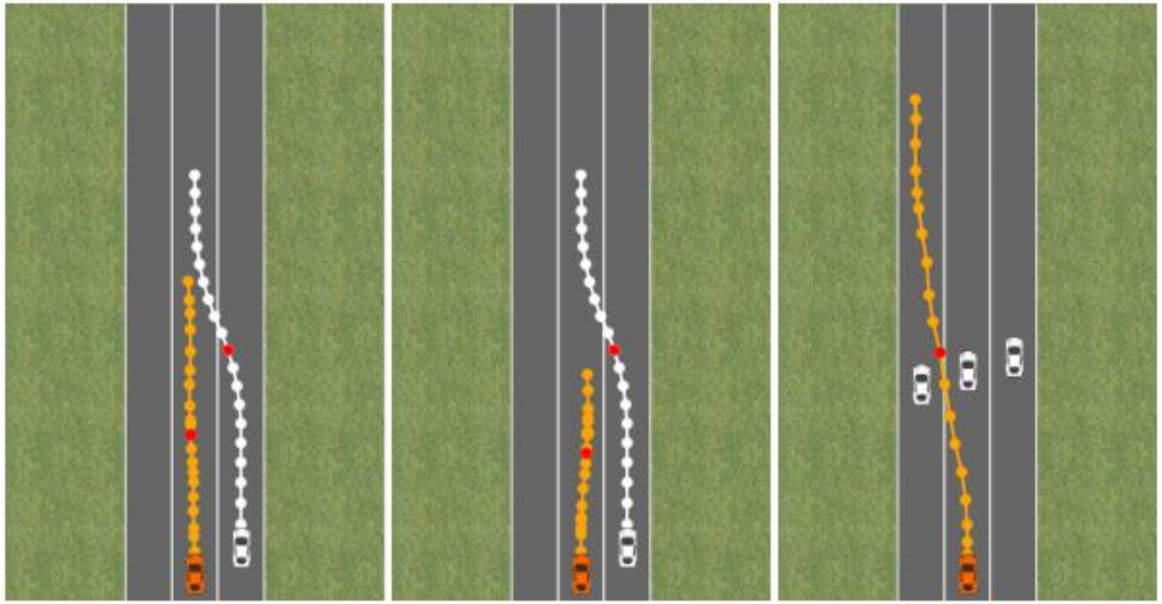

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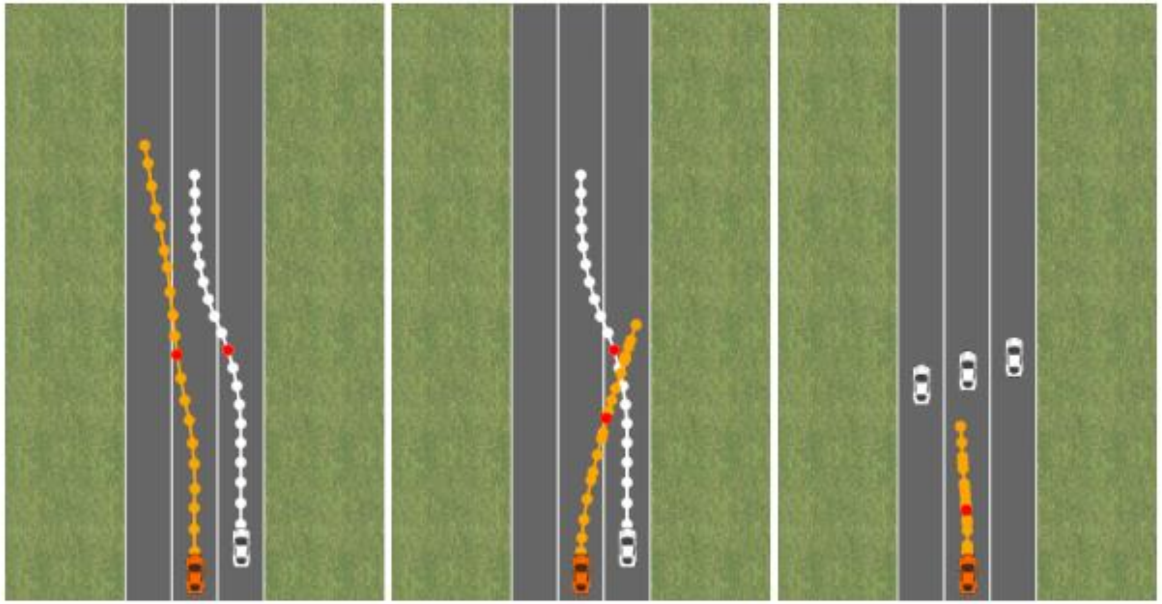

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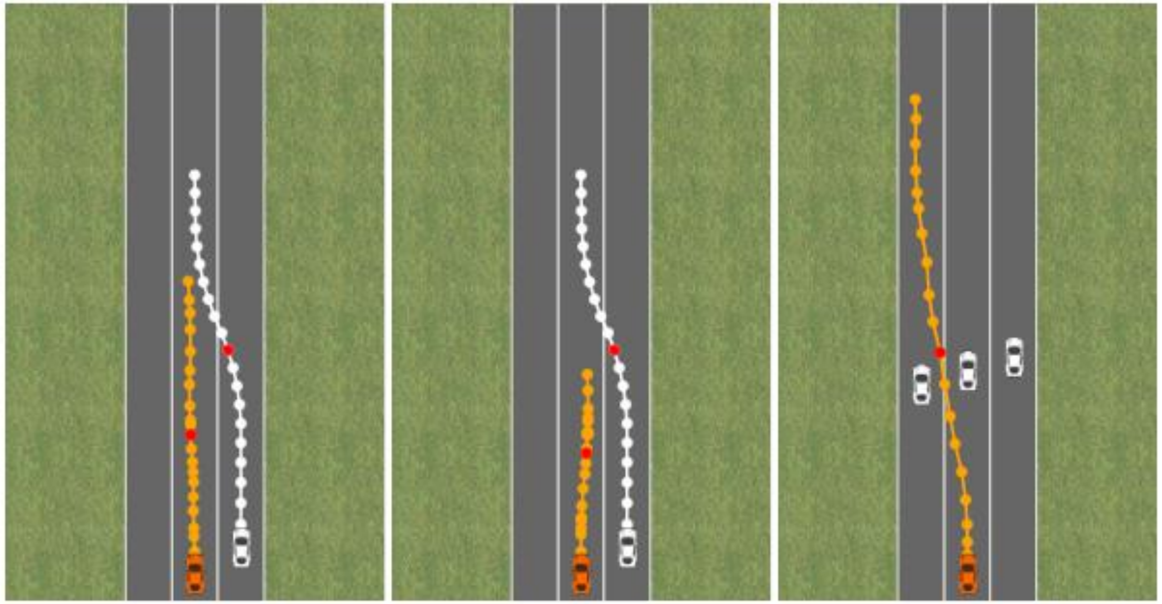

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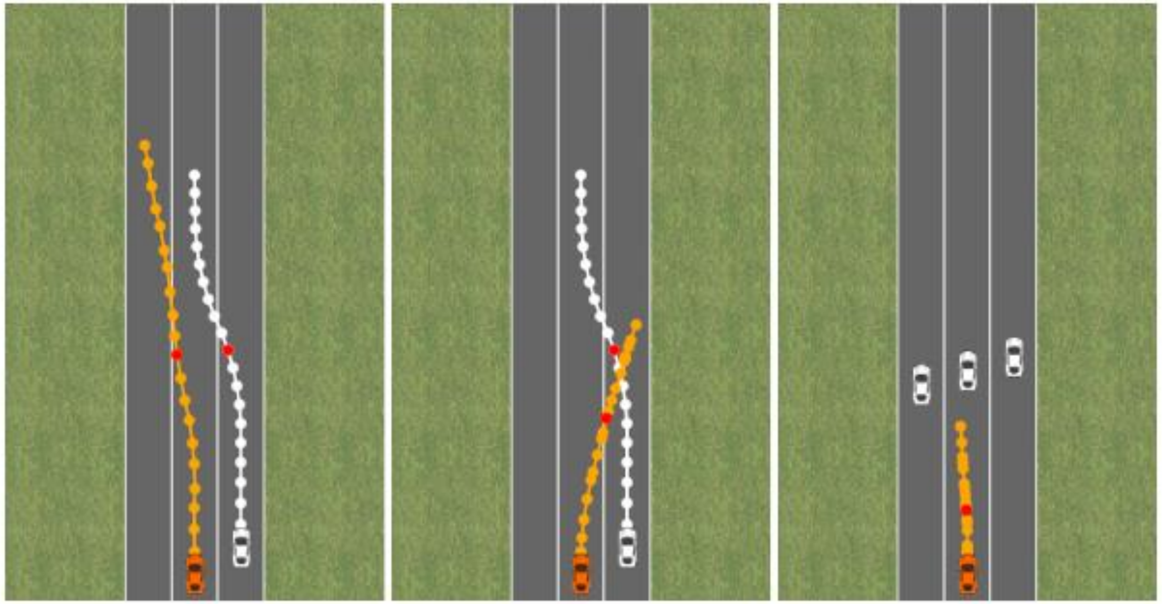

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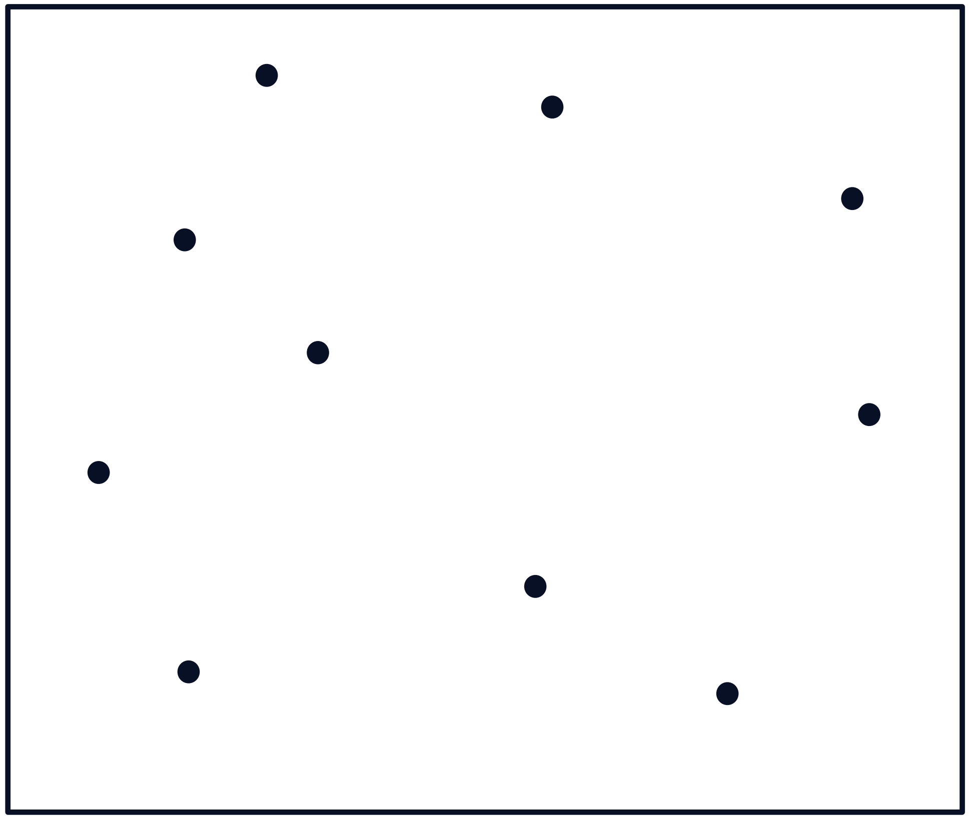
Known set of arms $\mathcal{X} \subset \mathbb{R}^d$



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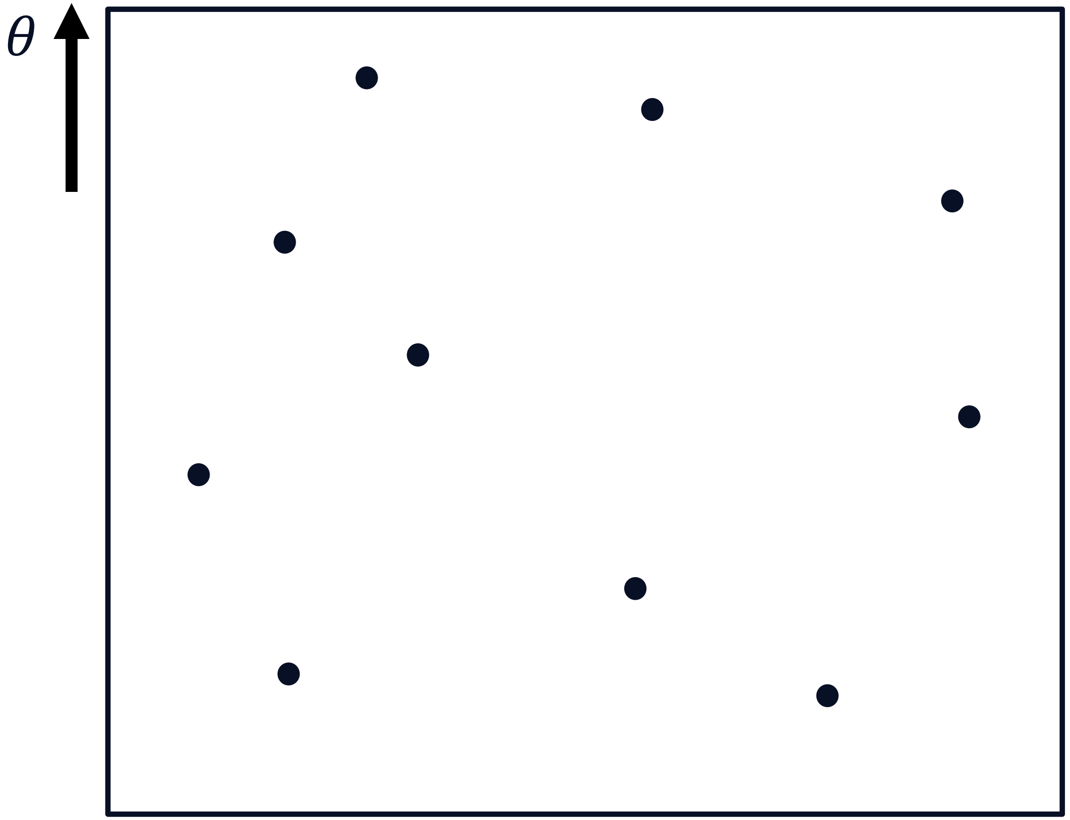

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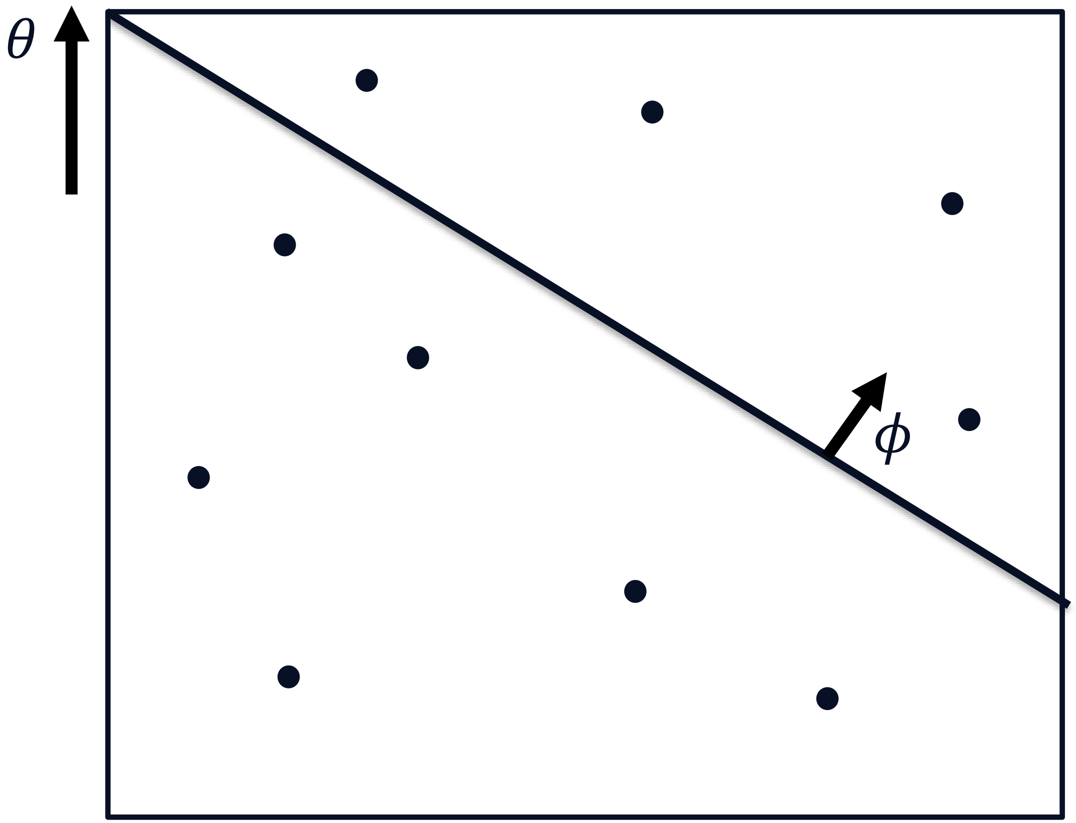

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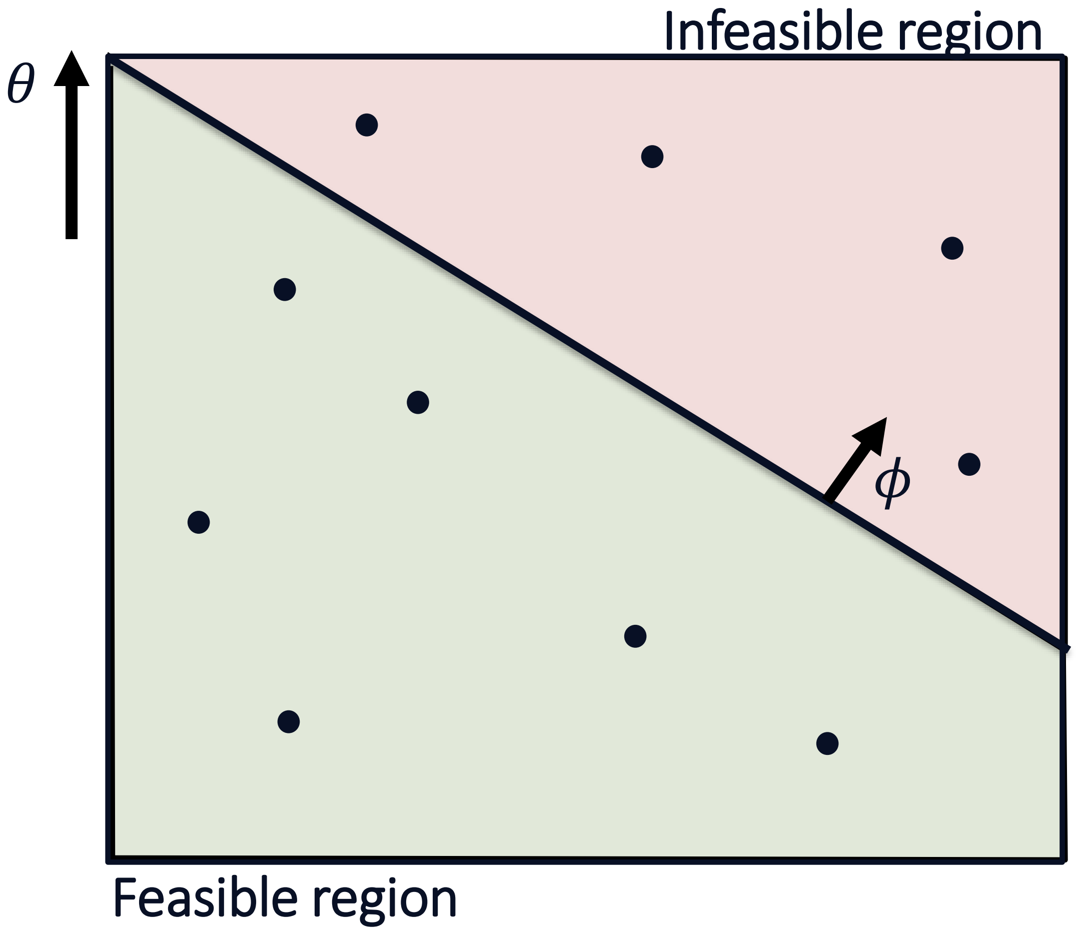

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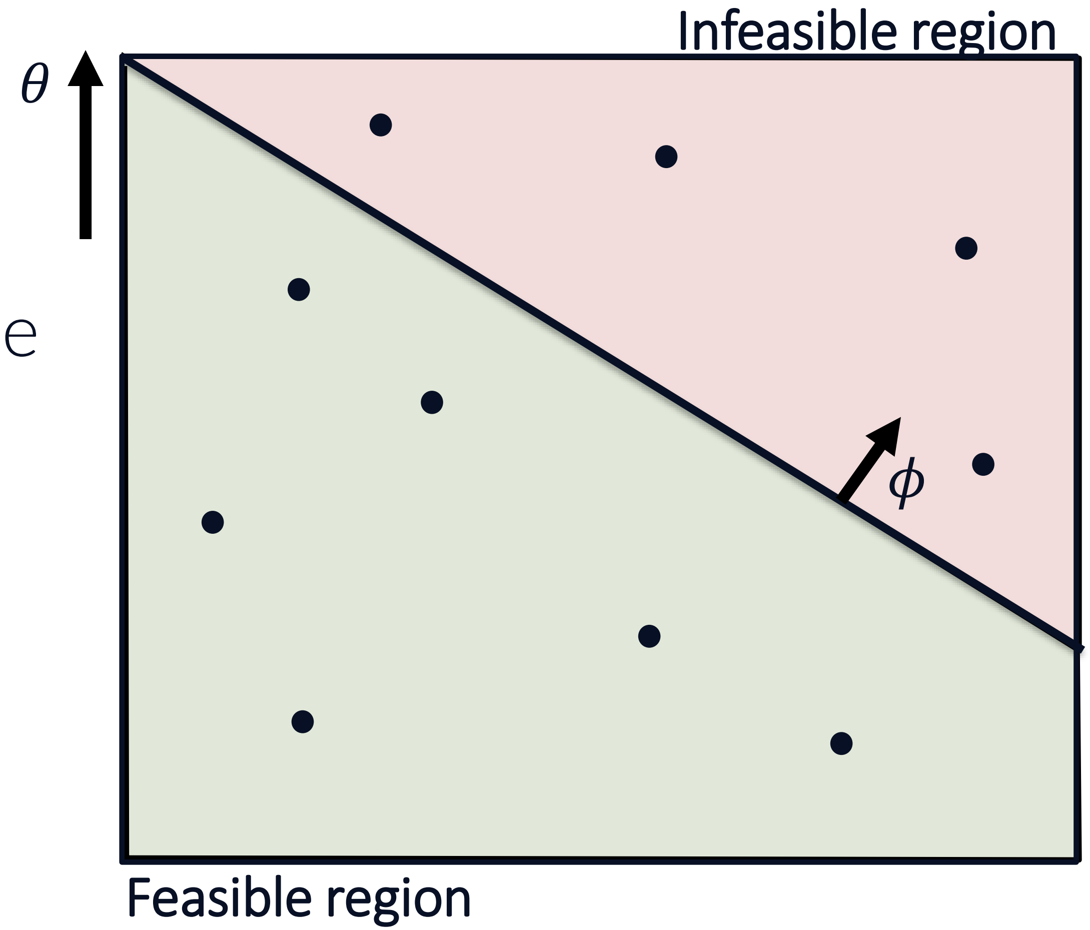

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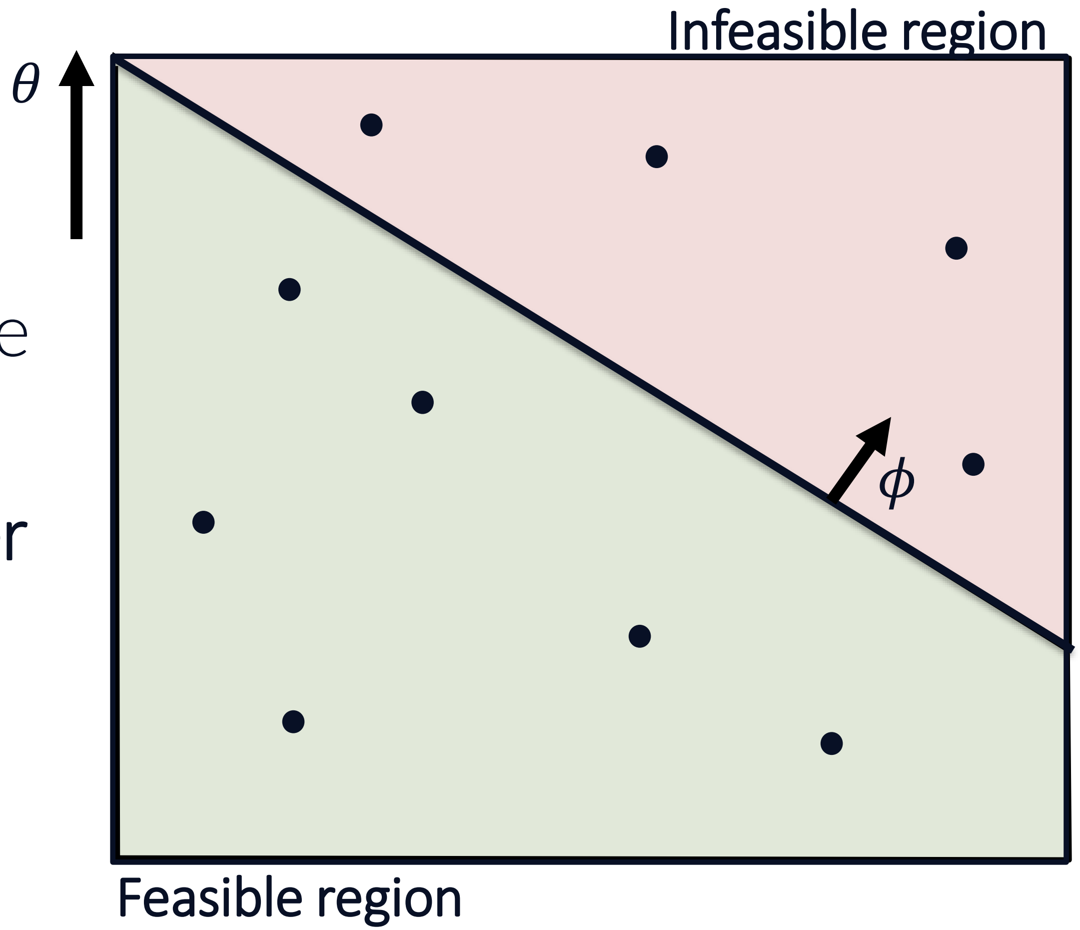

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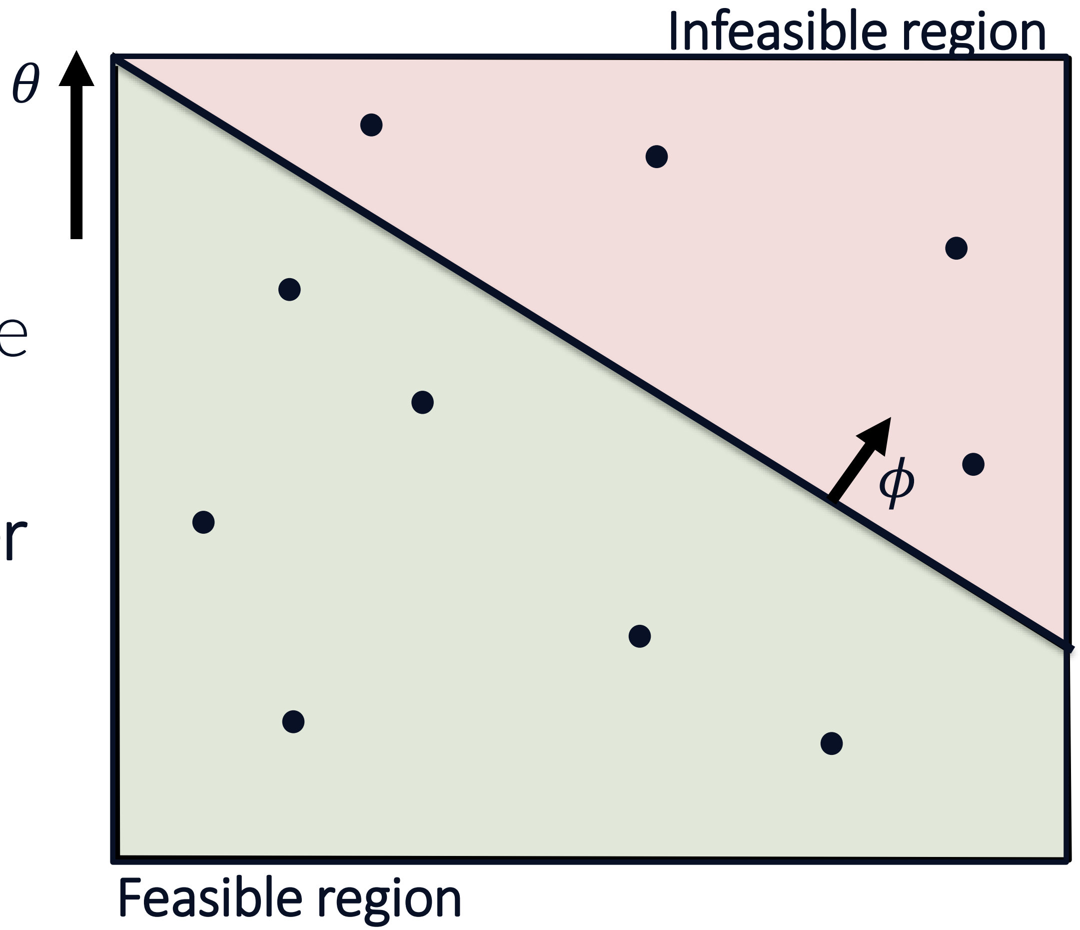
in as few iterations as possible



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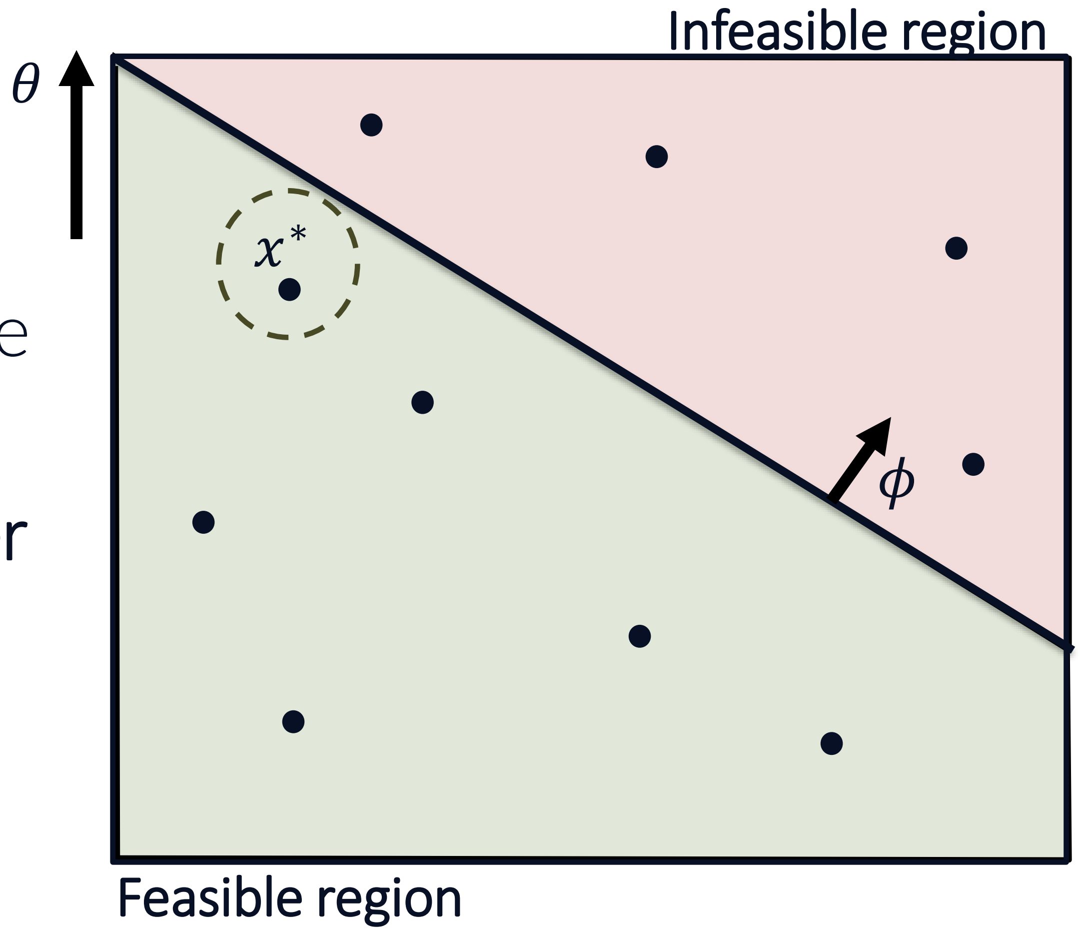

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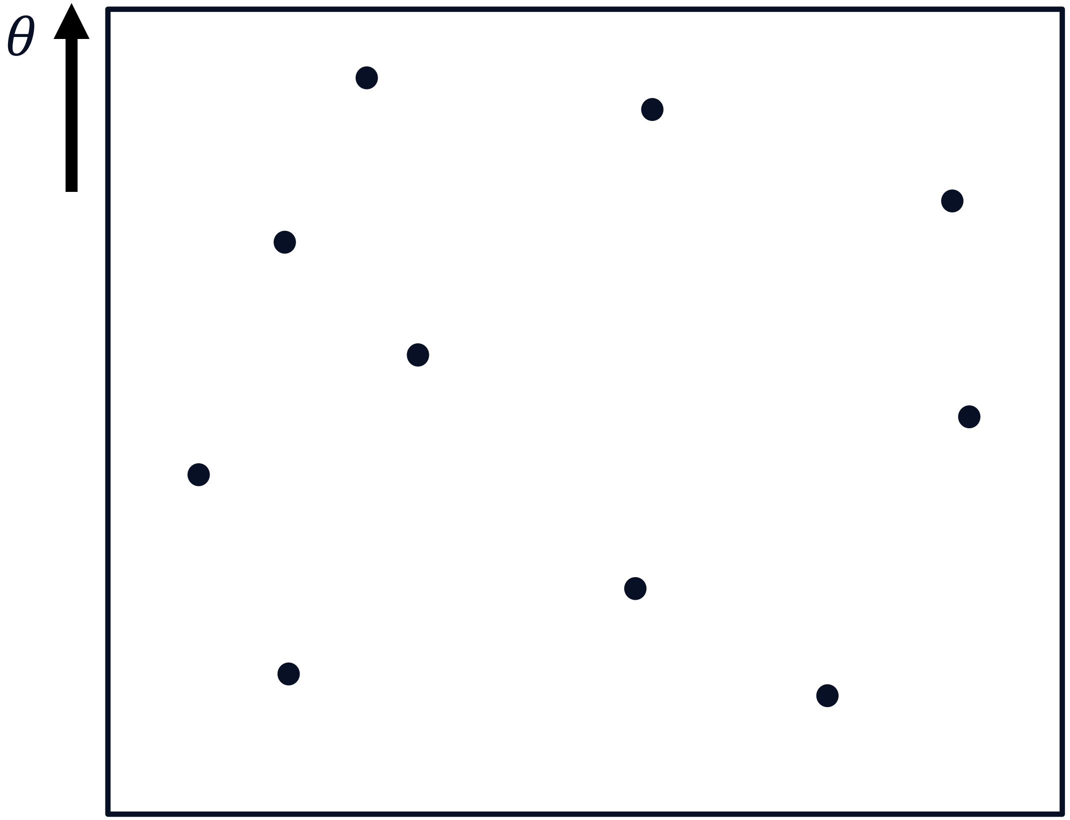

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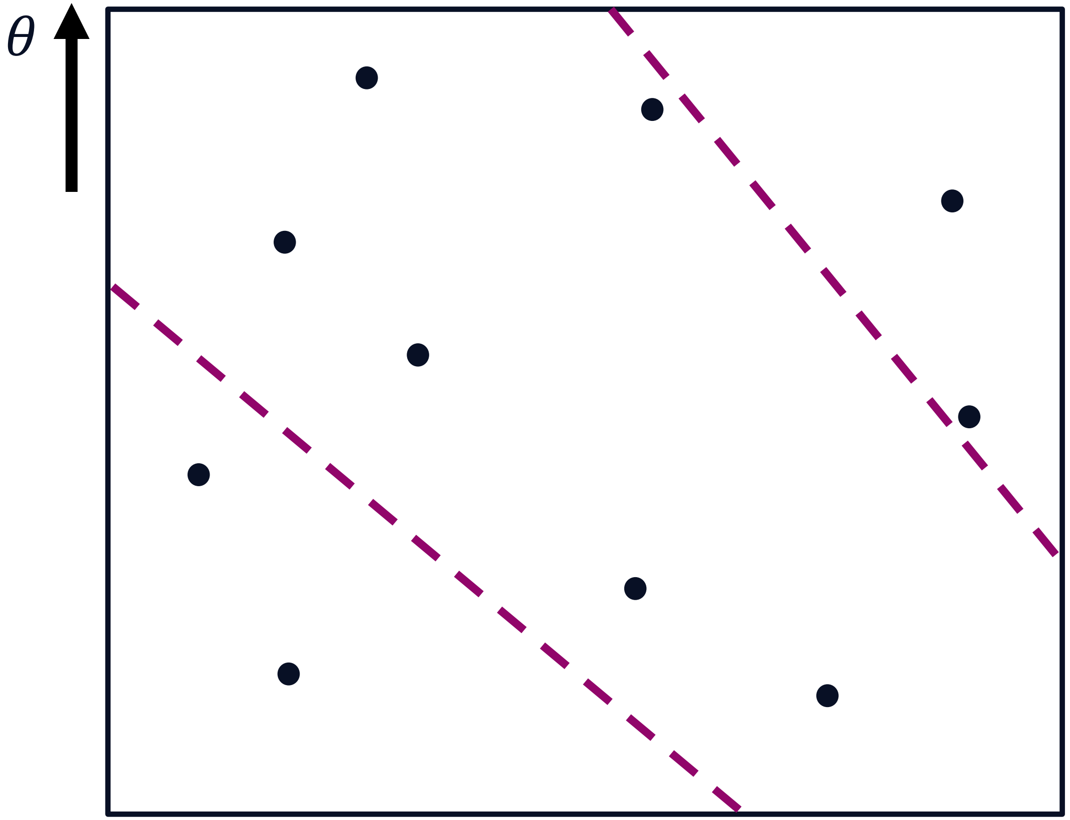

Adaptive constraint learning (ACOL)

1. Estimate confidence regions around the estimated constraint
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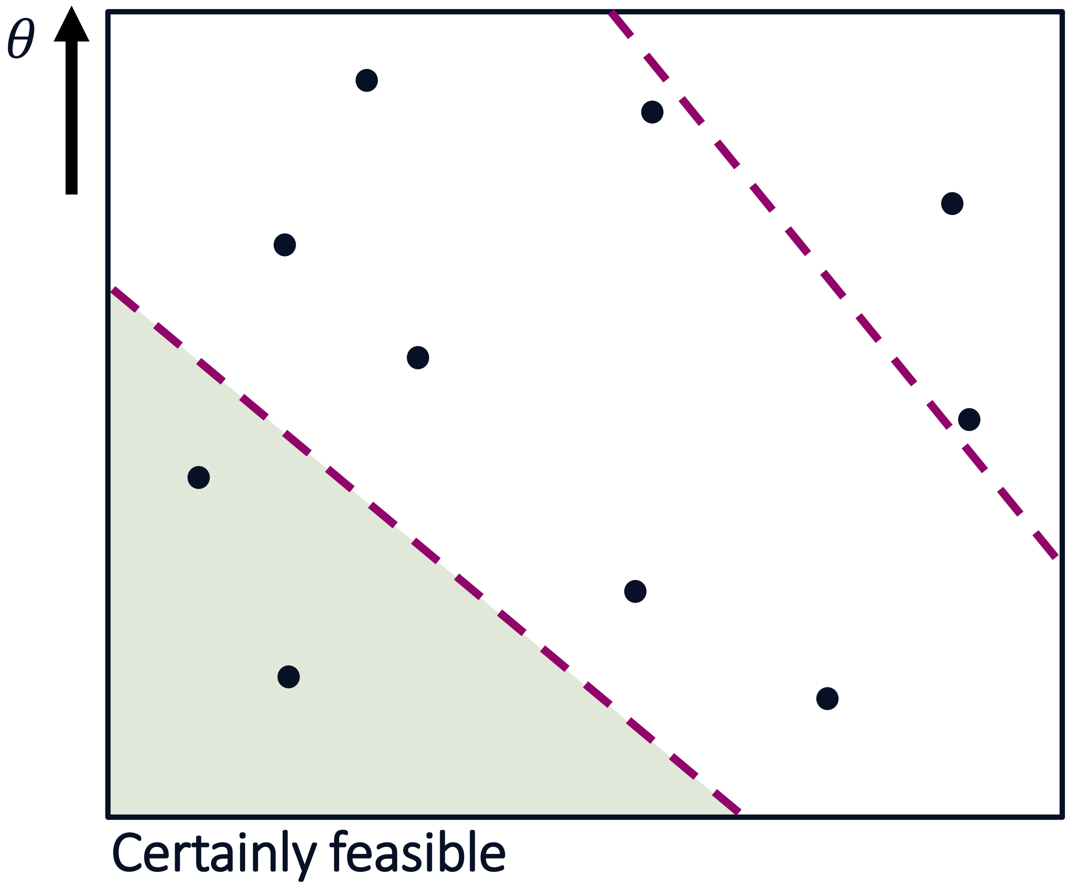

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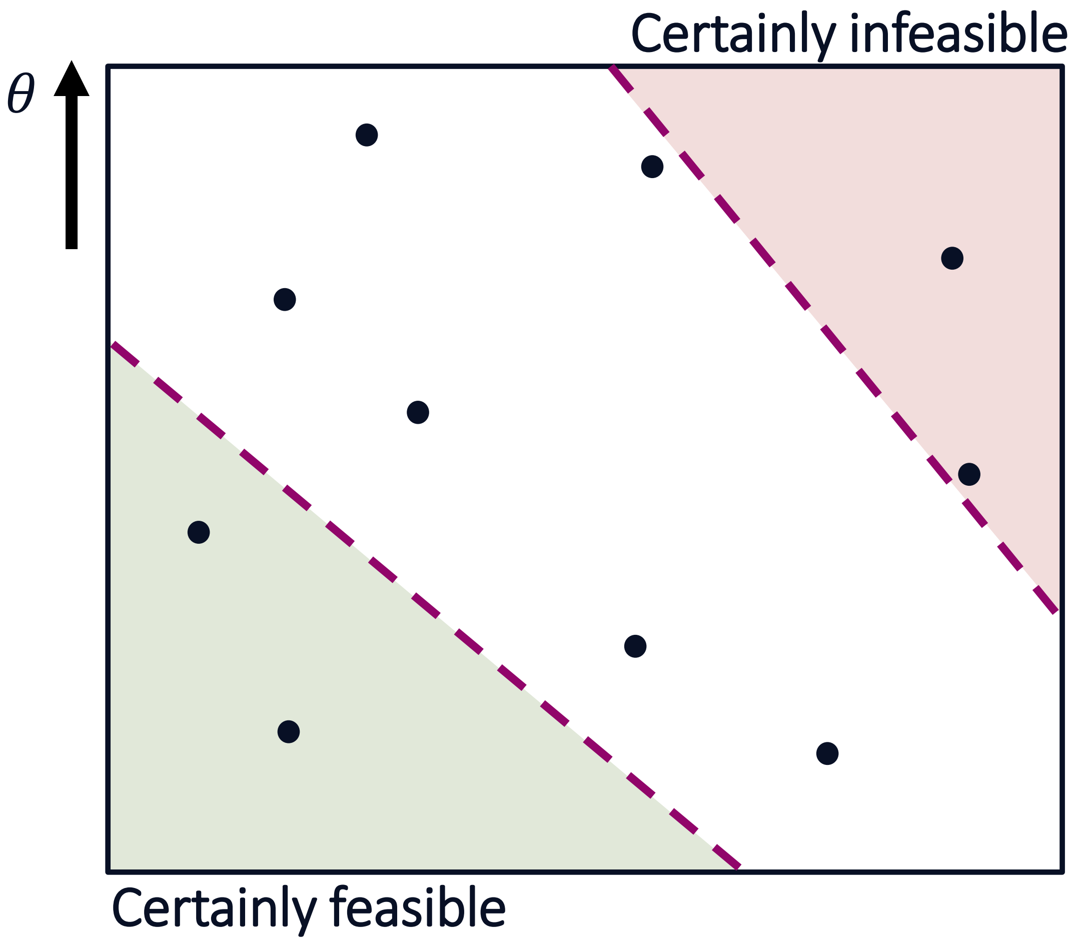

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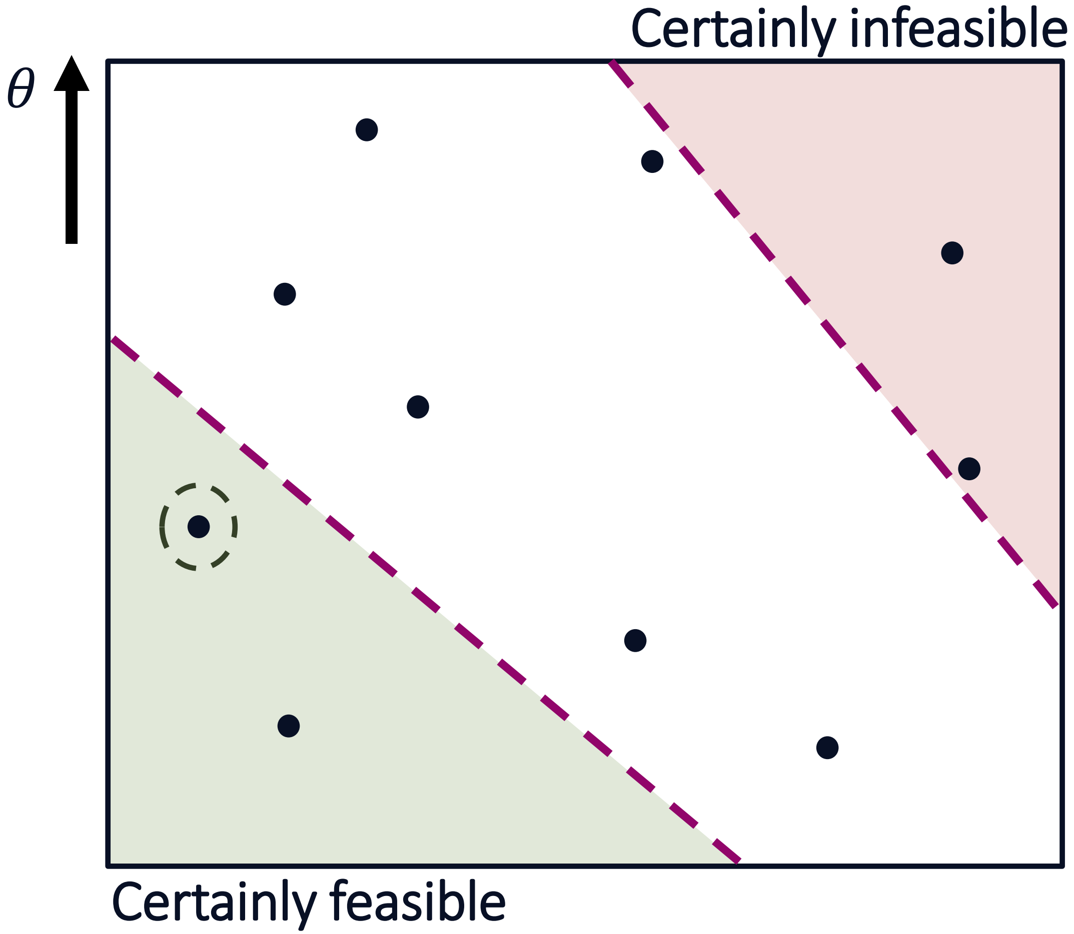

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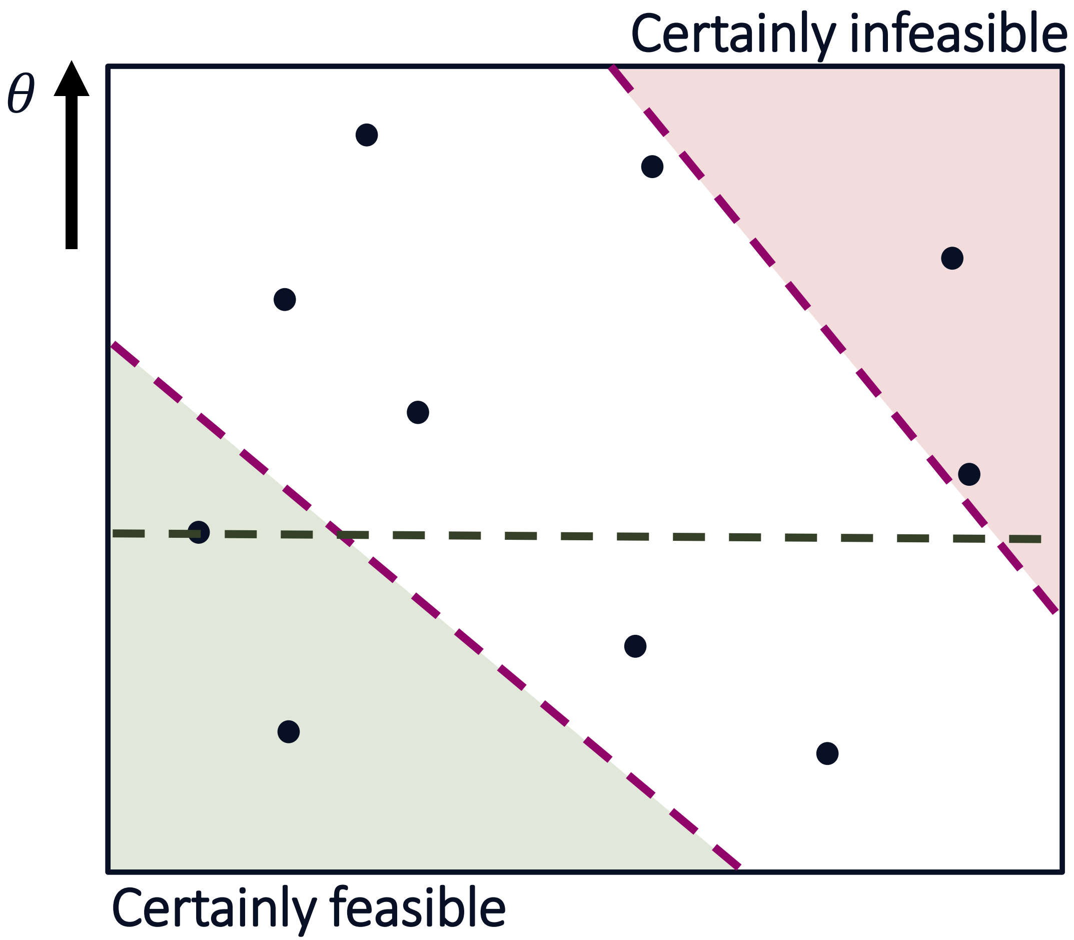

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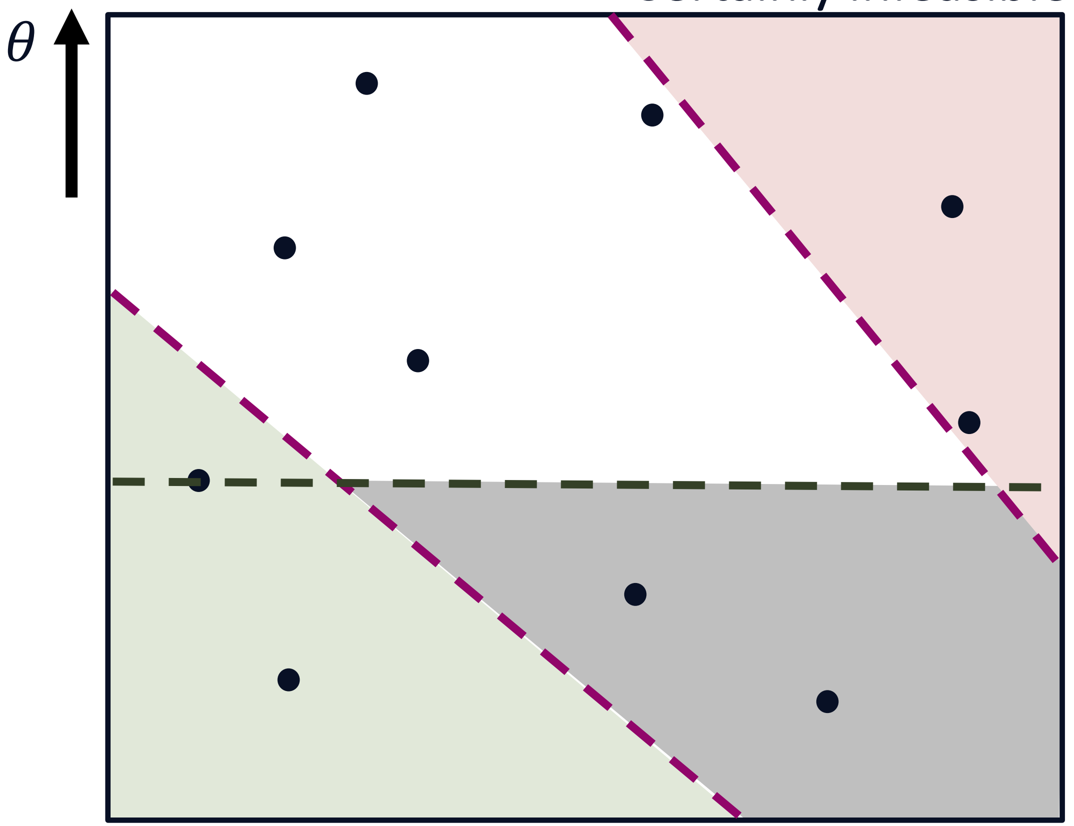

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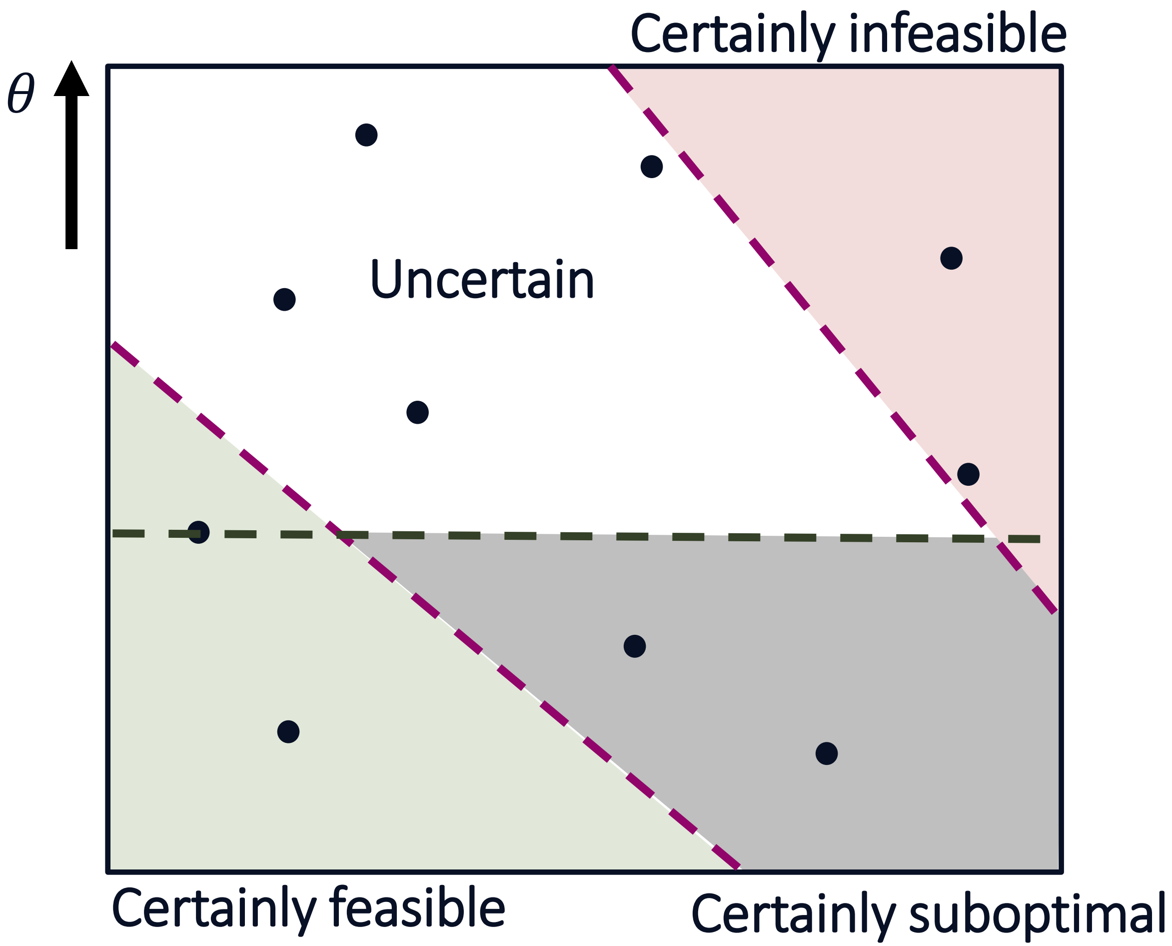

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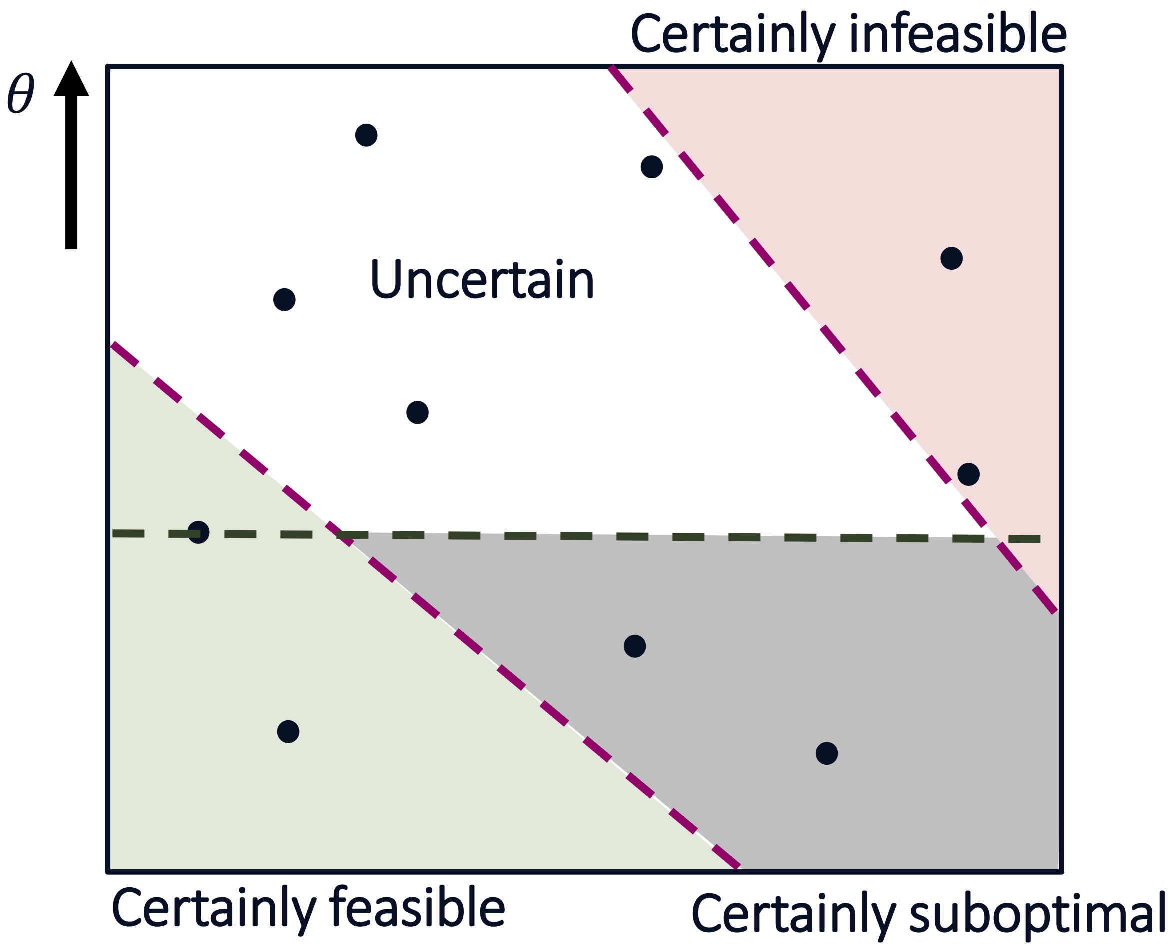

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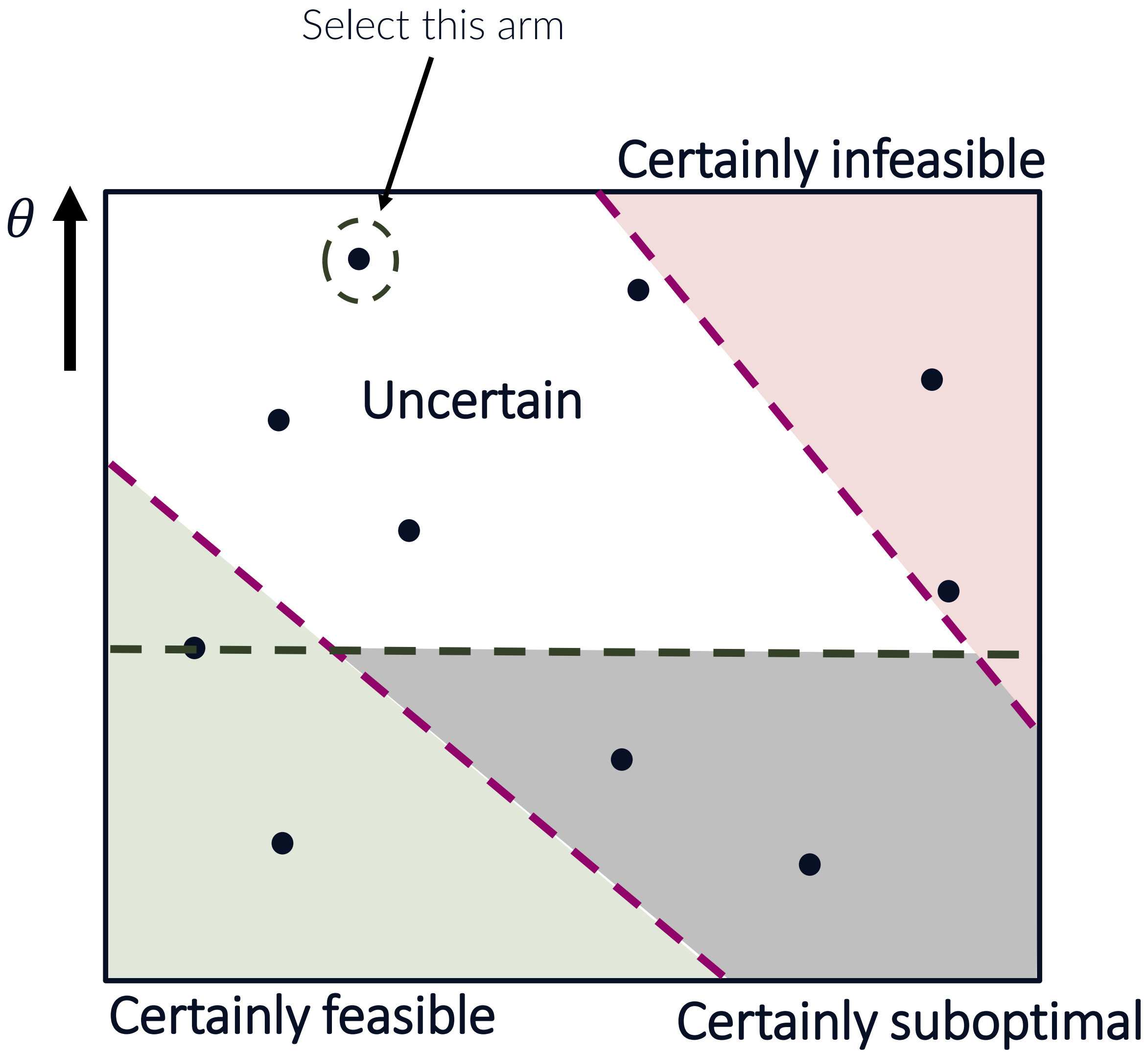

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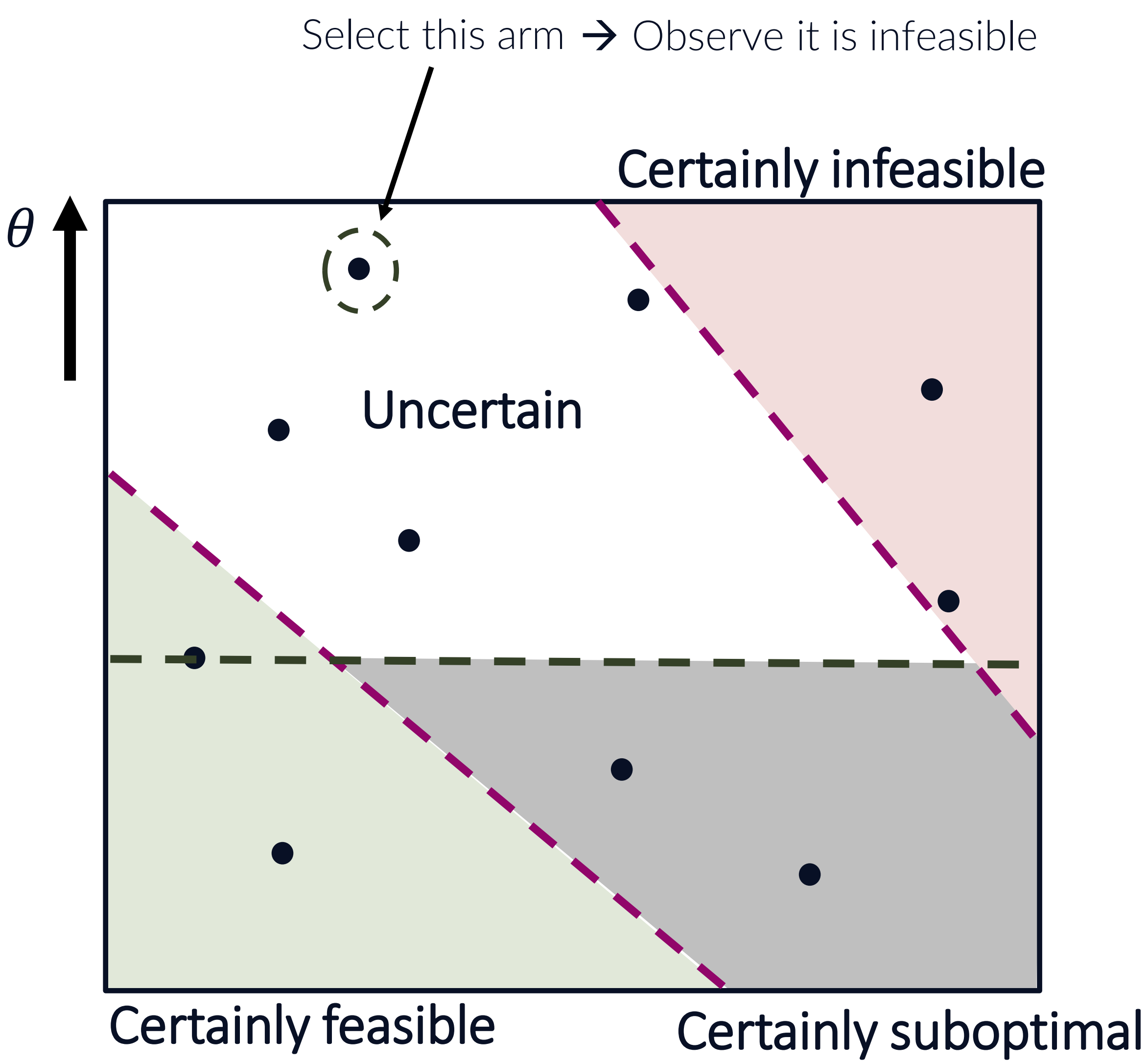

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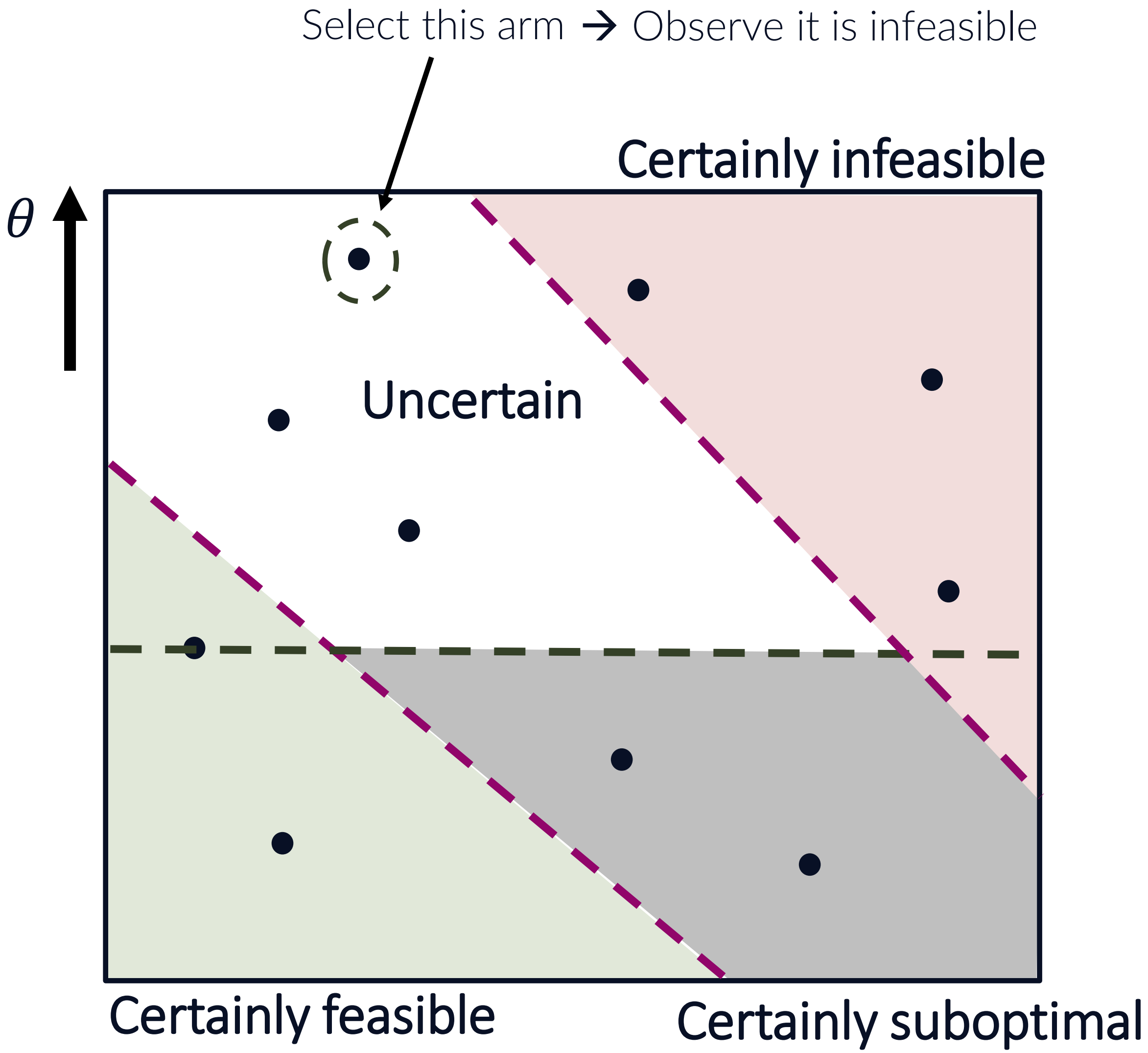

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We provide a tight sample complexity guarantee for ACOL

CBAI lower bound (informal)

The number of samples necessary to solve a CBAI problem is lower bounded by

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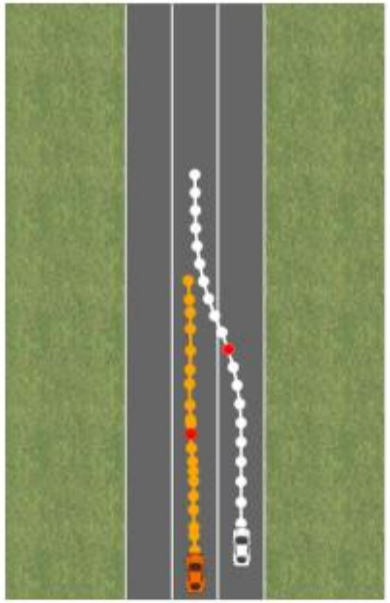

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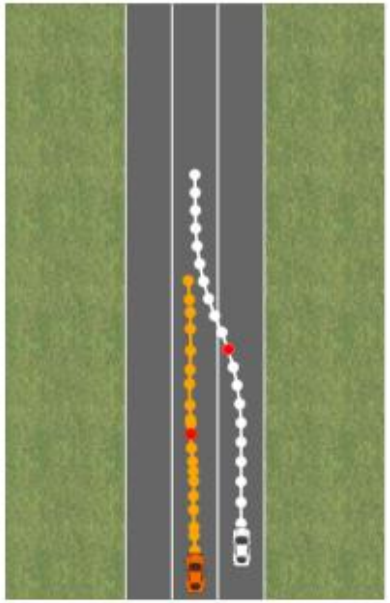
Adaptive constraint learning works well in simulations



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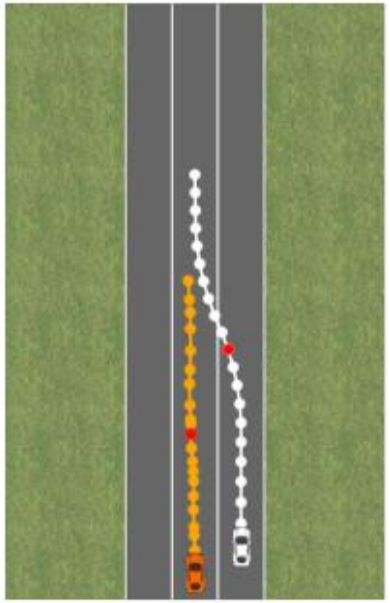

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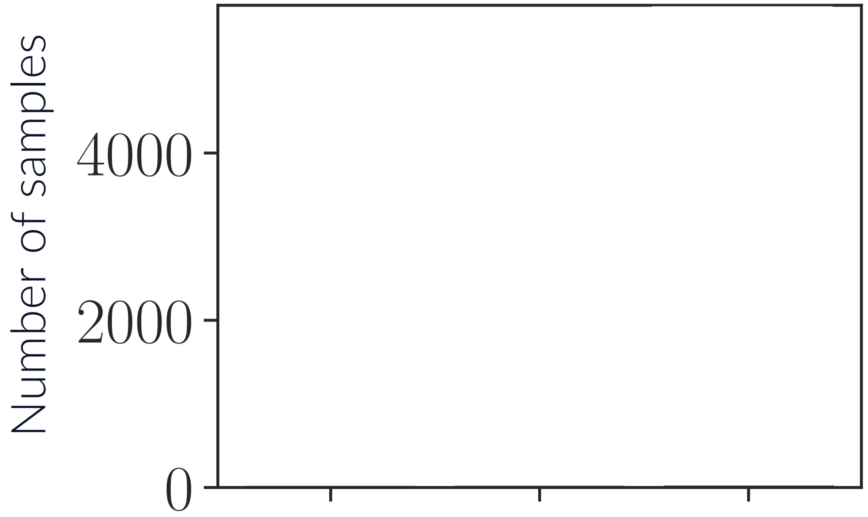

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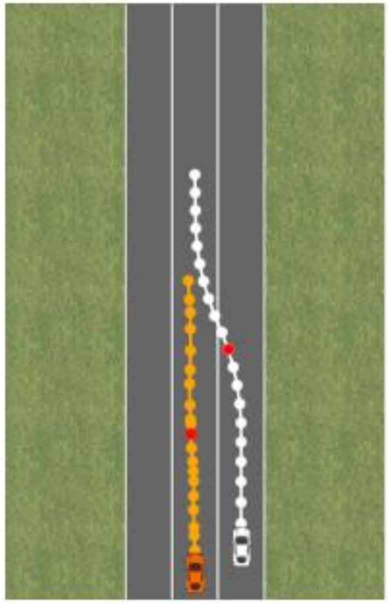

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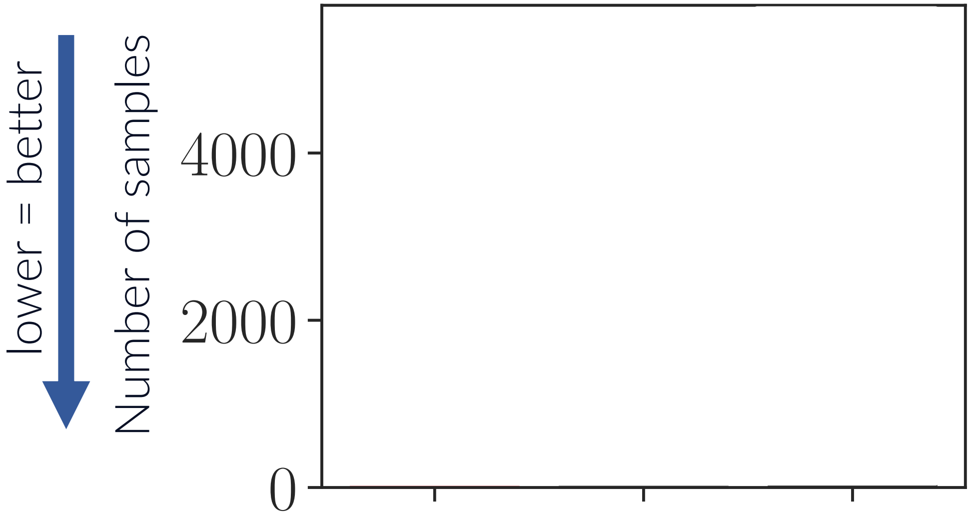

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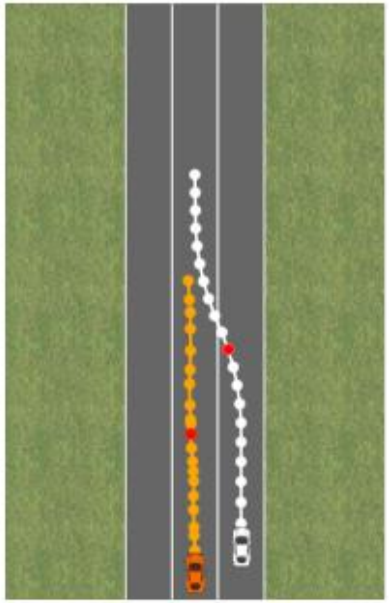

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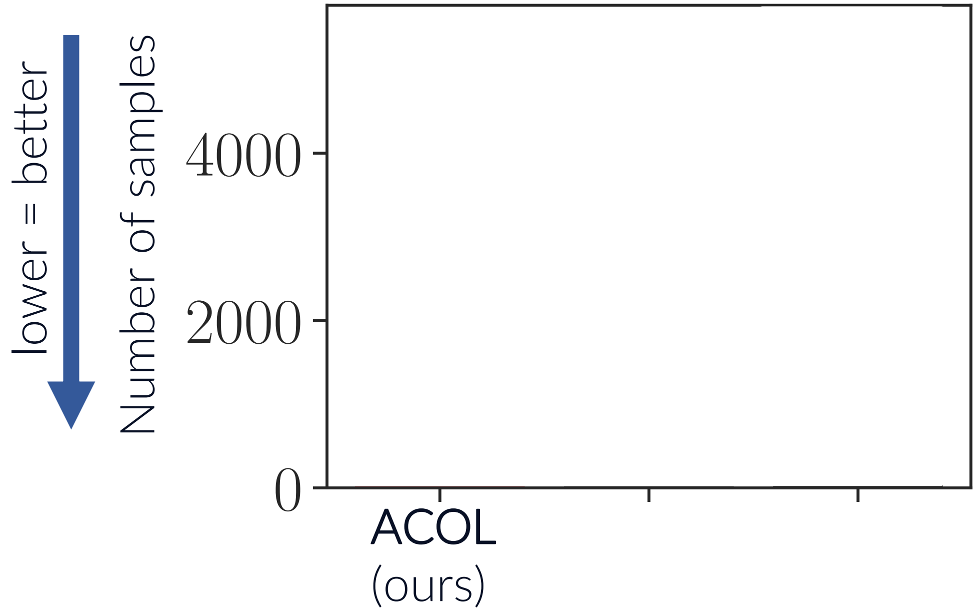
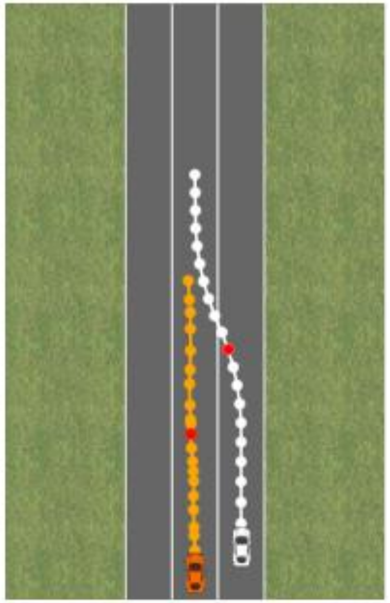


Adaptive constraint learning works well in simulations



- Driving simulation with known reward but unknown constraints
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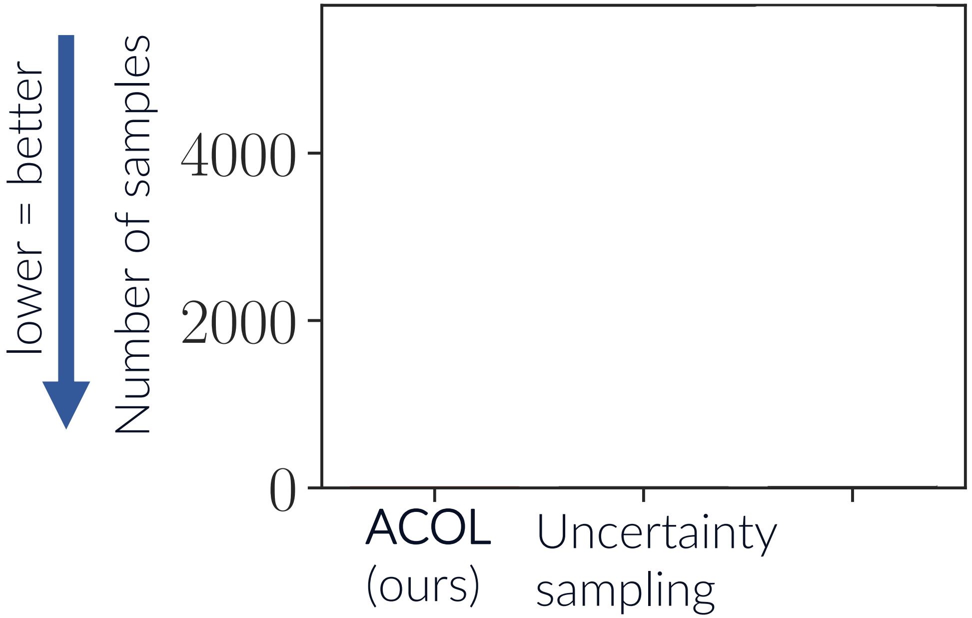

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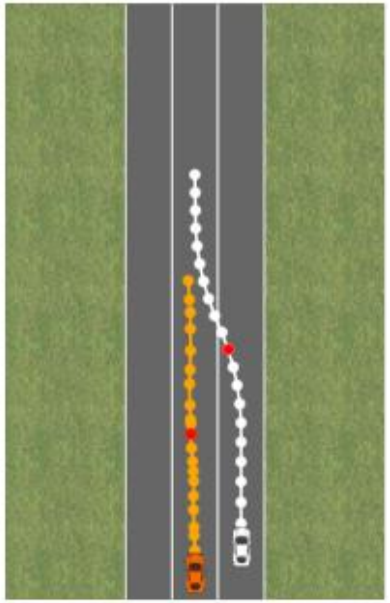

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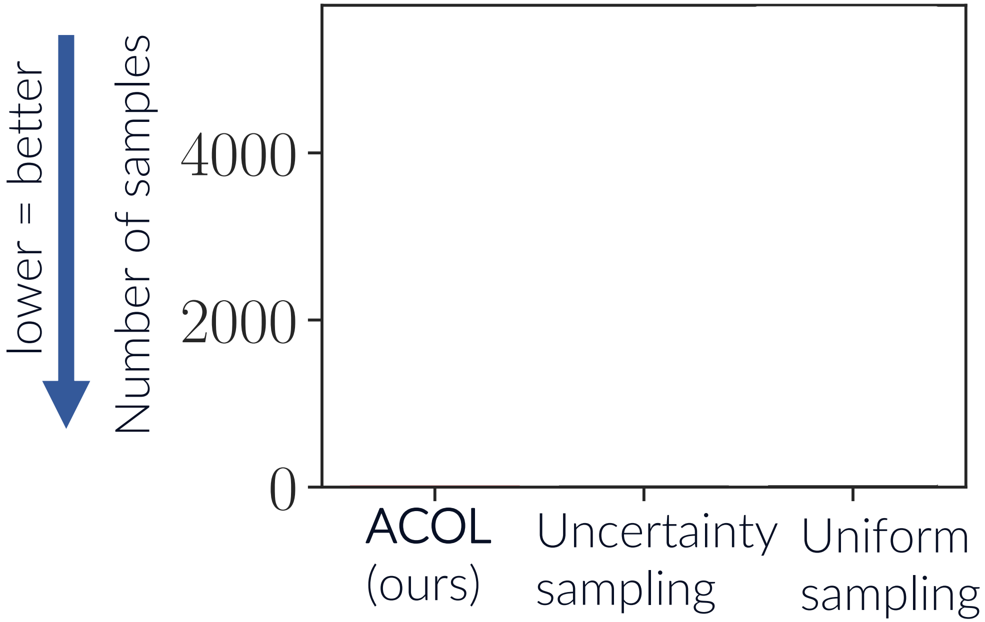

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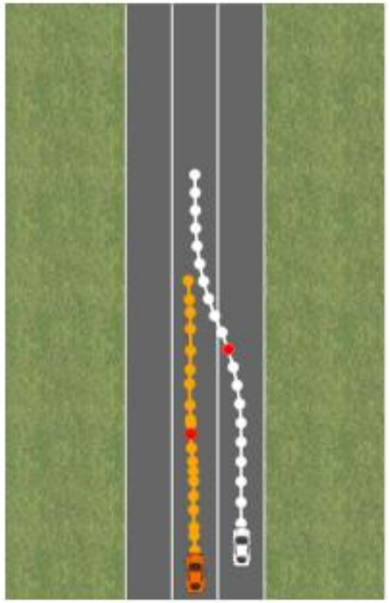

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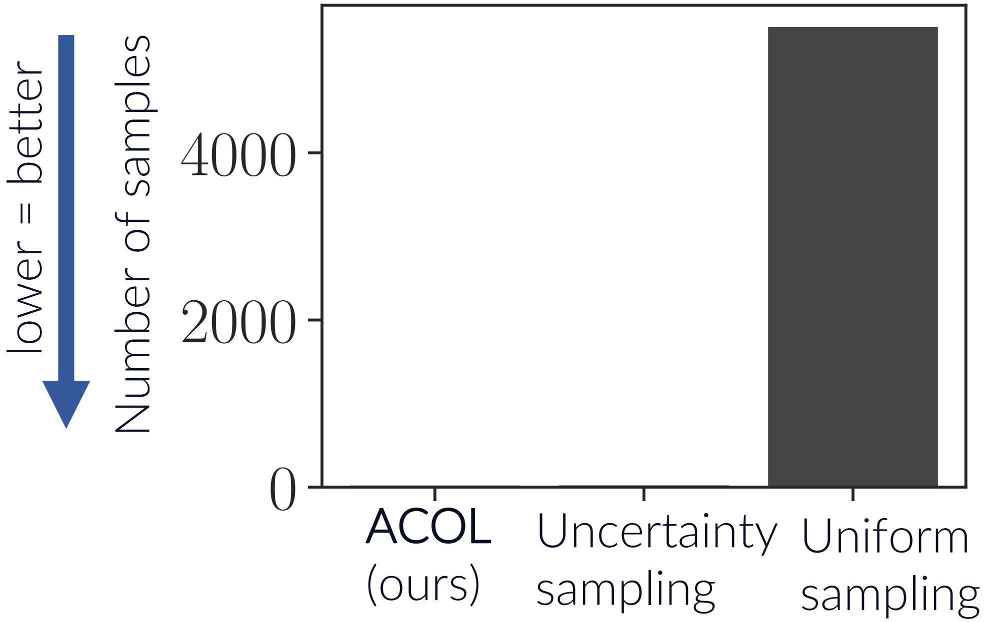

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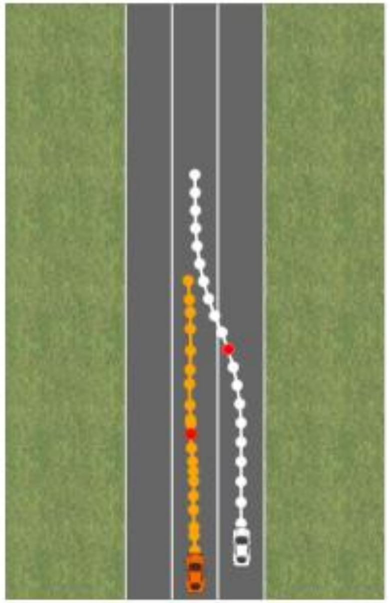

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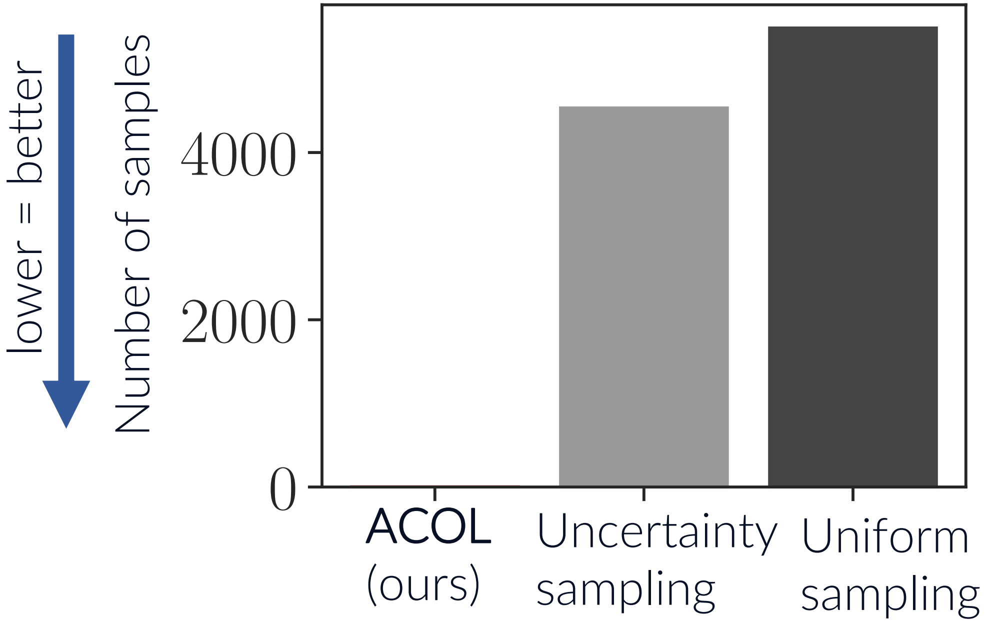

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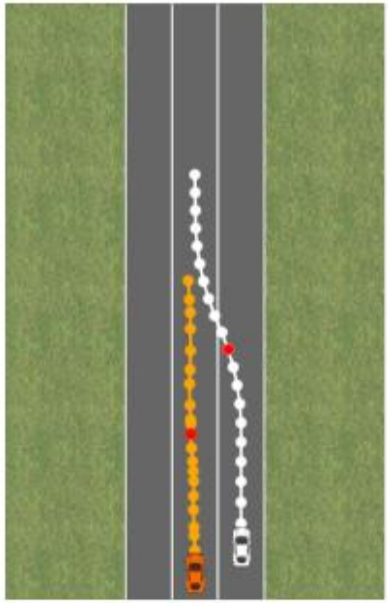

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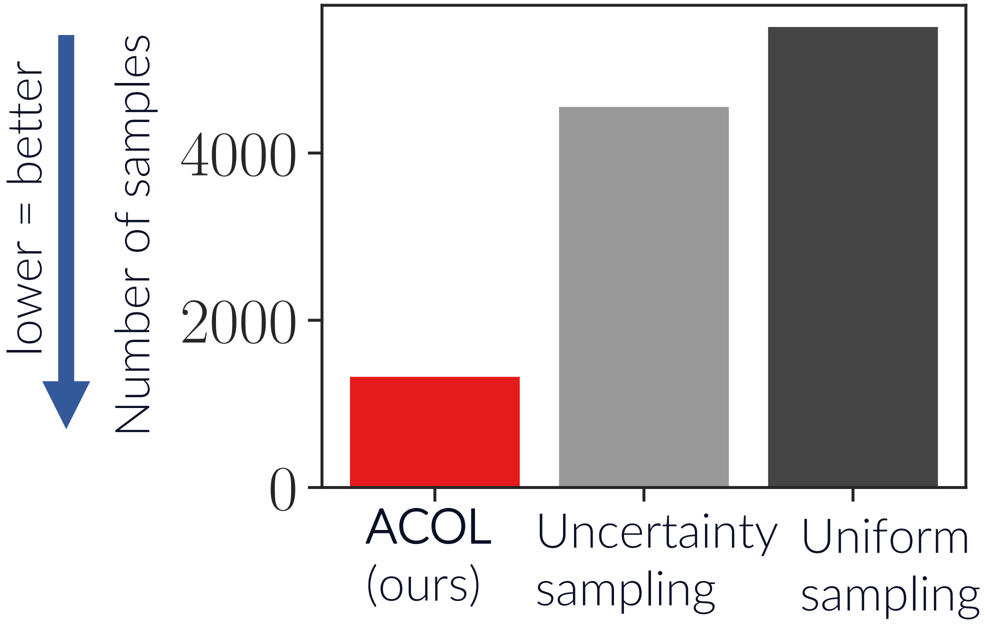

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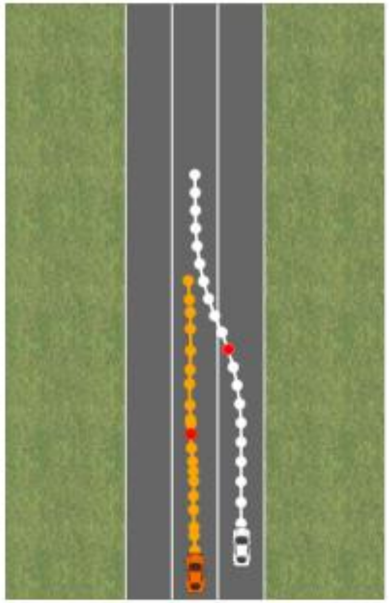

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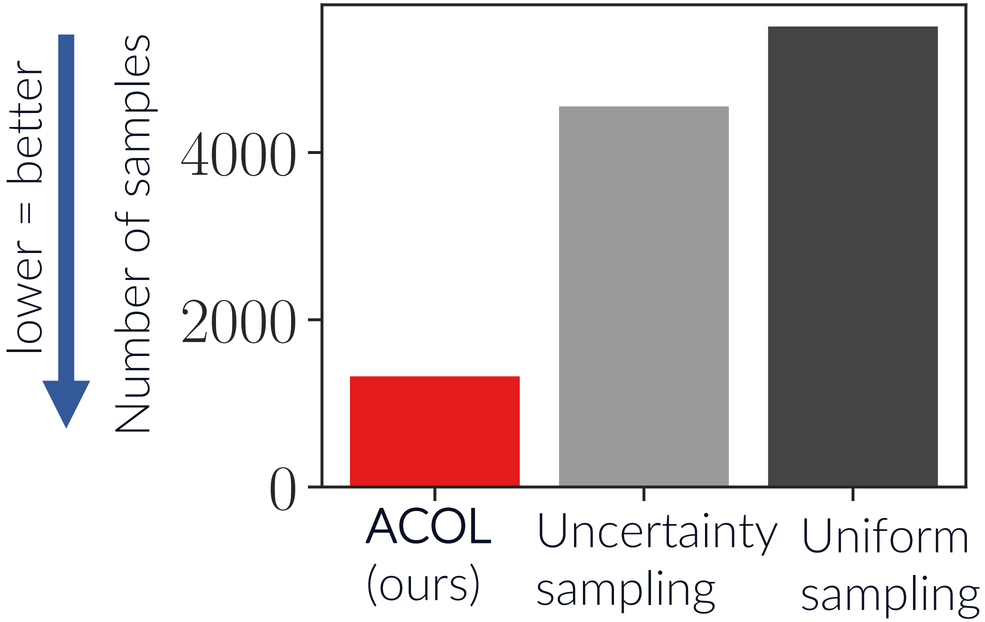
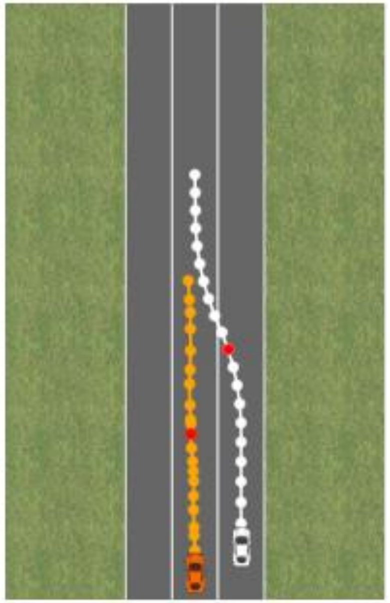


- Constraints are a natural and robust way to represent human preferences

Adaptive constraint learning works well in simulations



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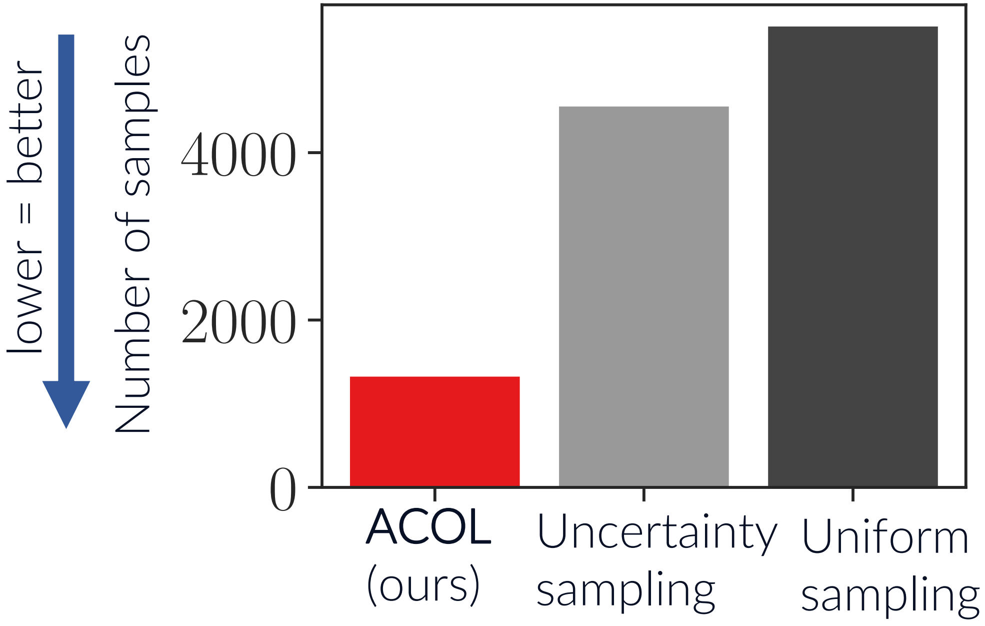
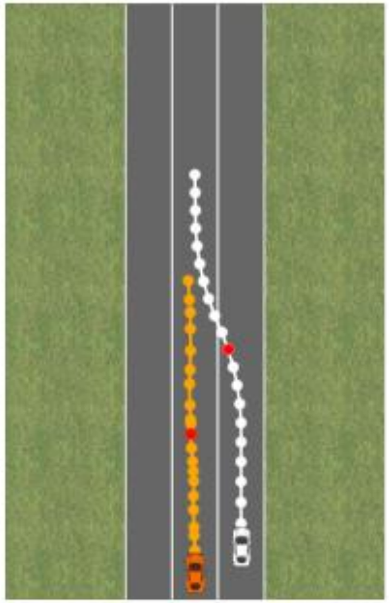


- Constraints are a natural and robust way to represent human preferences
- Adaptive Constraint Learning can efficiently learn constraints in linear bandits

Adaptive constraint learning works well in simulations



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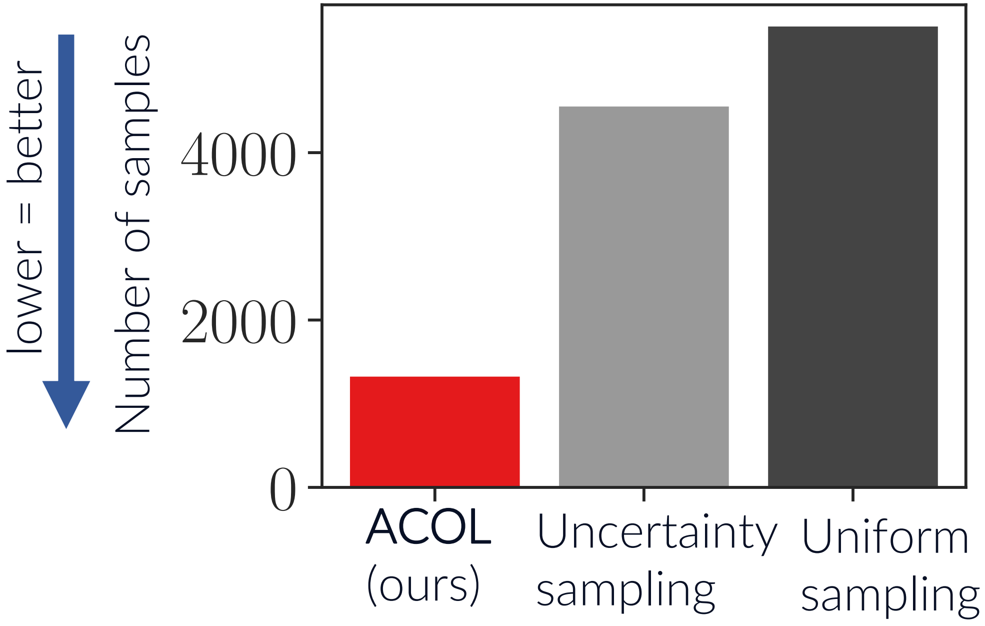

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https://arxiv.org/abs/2206.05255