On the Feasibility of Learning Human Biases for Reward Inference

Rohin Shah, Noah Gundotra, Pieter Abbeel, Anca Dragan

A conversation amongst IRL researchers

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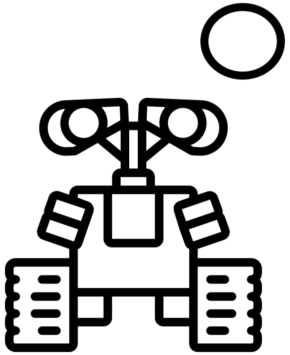
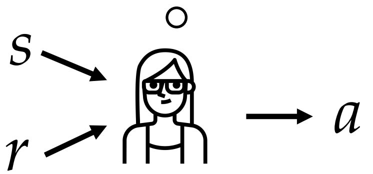


$$\pi(a|s) \propto e^{\beta Q(s,a;r)}$$



We can model human biases:
- Myopia
- Hyperbolic time discounting
- Sparse noise
- Risk sensitivity

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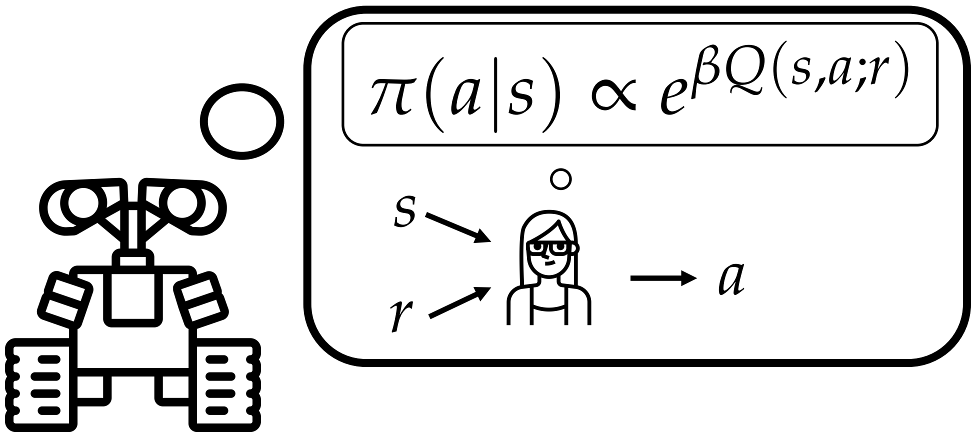

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[Steinhardt and Evans, 2017]

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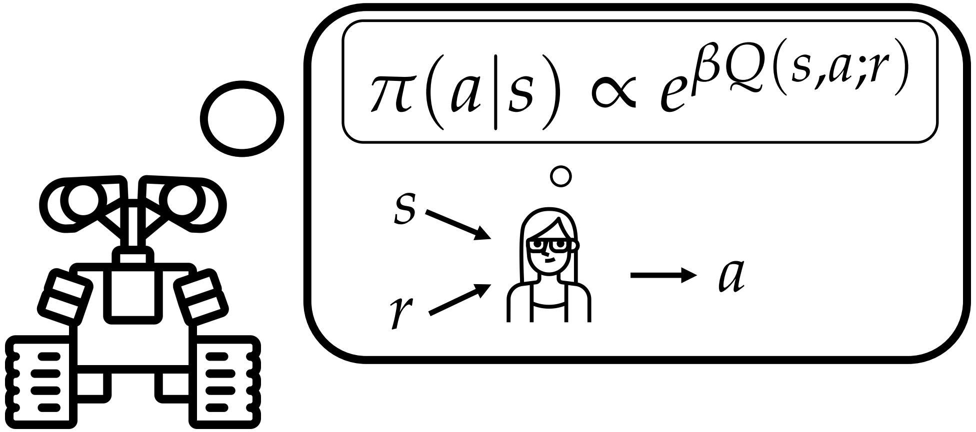

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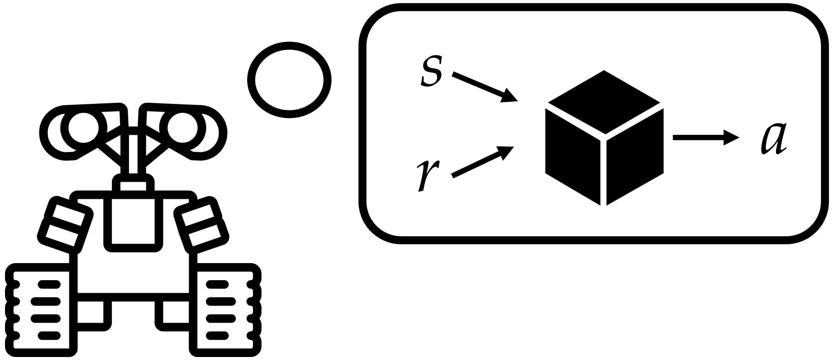

Hmm, maybe we can learn the *systematic* biases from data? Then we could correct for these biases during IRL

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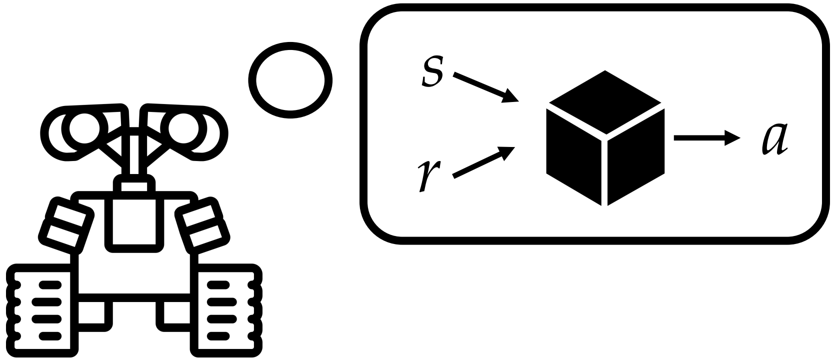

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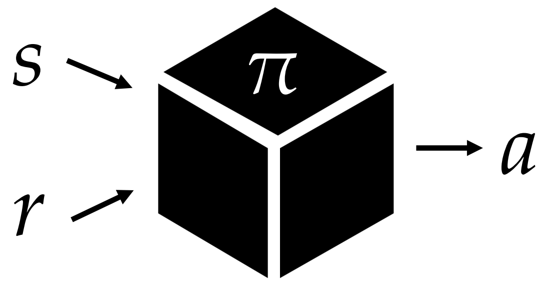
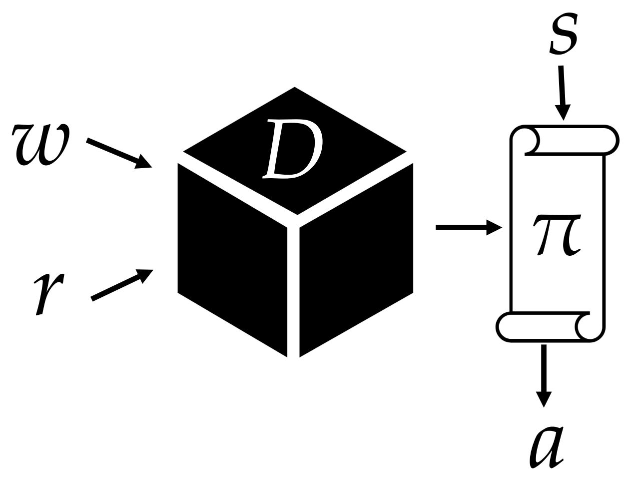
[Armstrong and Mindermann, 2017]

That's *impossible* without additional assumptions

Learning a policy isn't sufficient



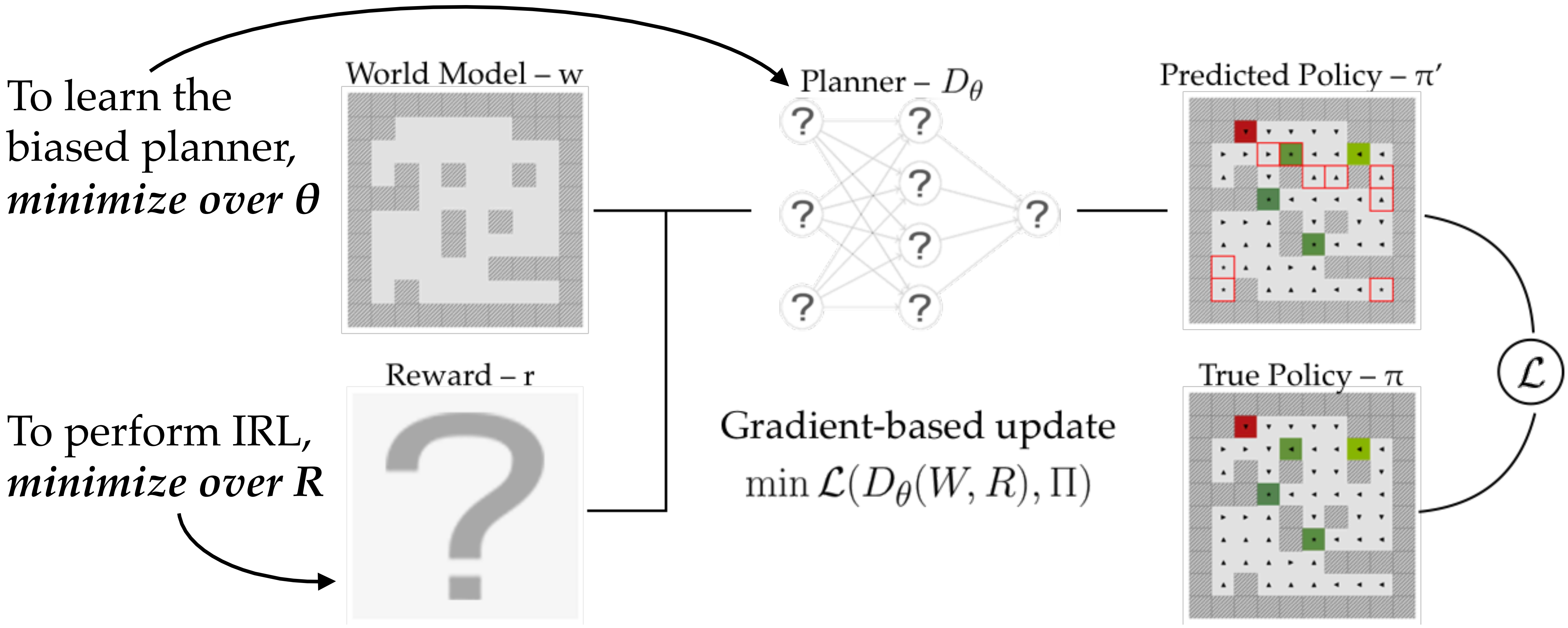


Biases are a part of cognition, and are not in the policy π

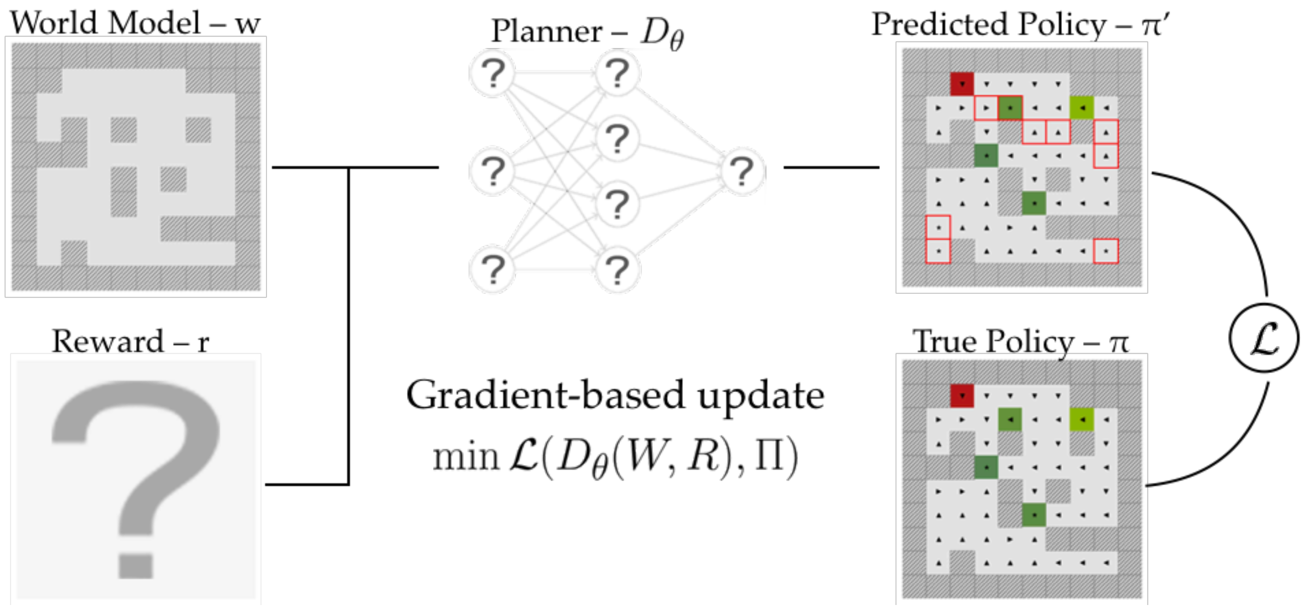
They are in the *planning algorithm* D that created the policy π

We consider a **multi-task setting** so that we can learn D from examples

Architecture



Algorithms



Algorithm 1: Some **known rewards**

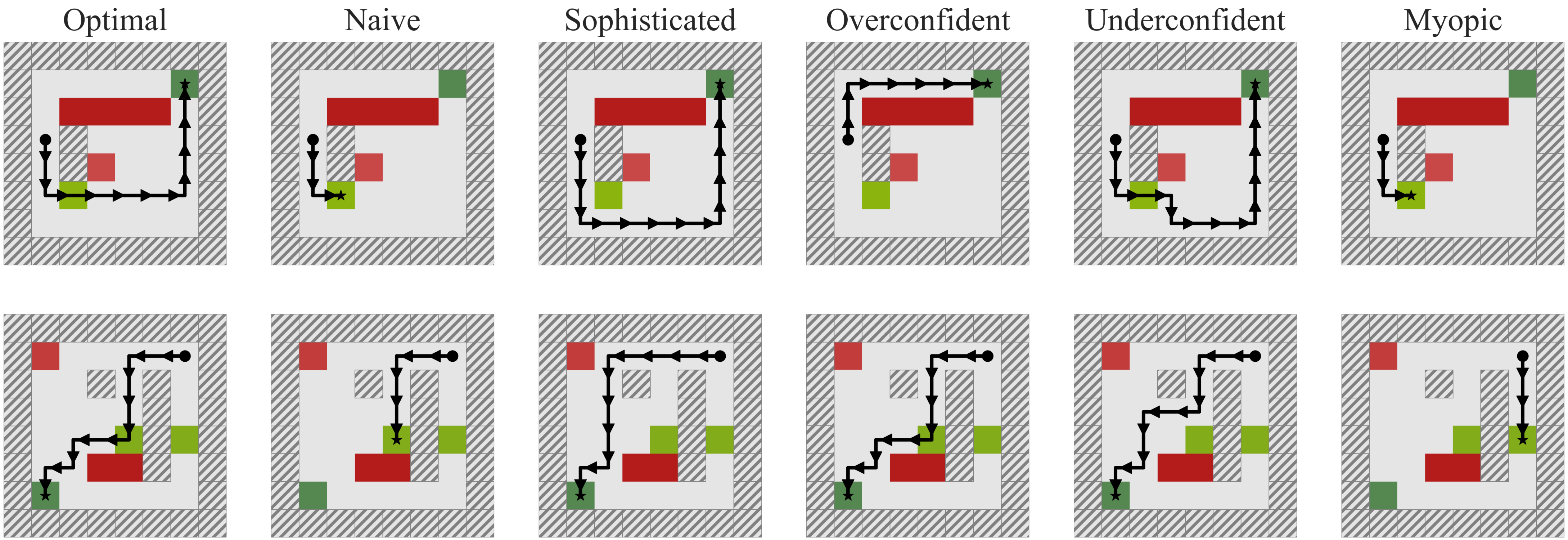
1. On tasks with known rewards, learn the planner
2. Freeze the planner and learn the reward on remaining tasks

Algorithm 2: **"Near" optimal**

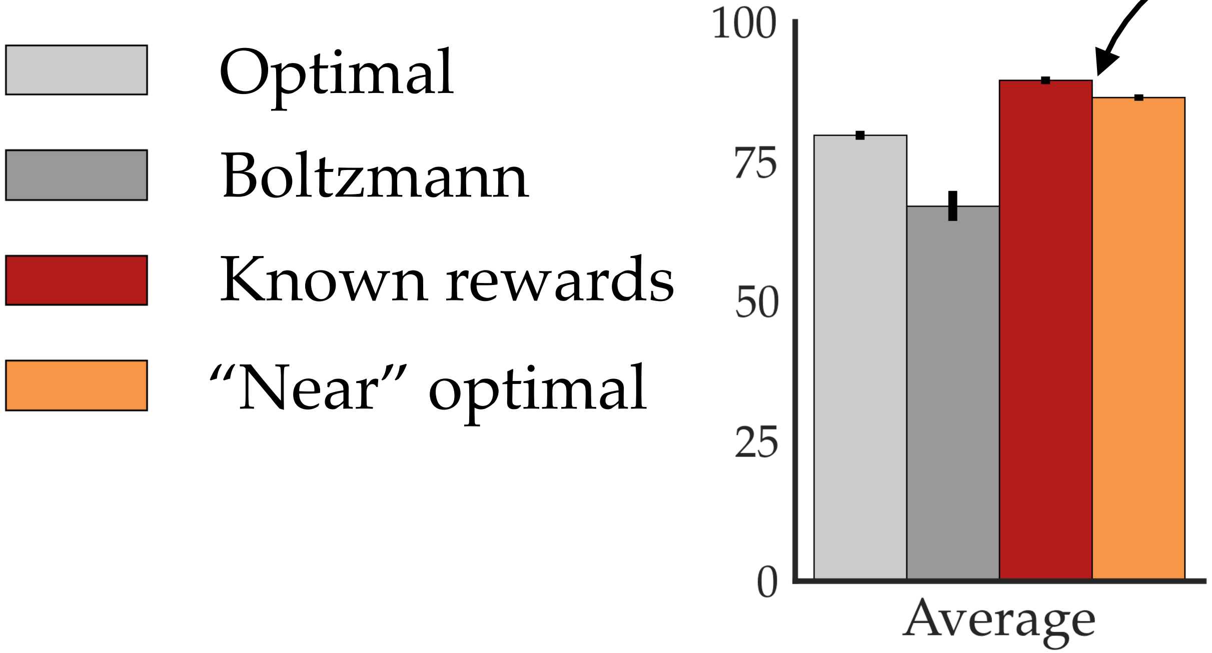
1. Use Algorithm 1 to mimic a simulated optimal agent
2. Finetune planner and reward jointly on human demonstrations

Experiments

We developed five simulated human biases to test our algorithms.



(Some) Results



Our algorithms perform better on average, compared to a learned Optimal or Boltzmann model

… But an exact model of the demonstrator does *much* better, hitting 98%.

Conclusion

*Learning systematic biases has the **potential to improve reward inference**, but differentiable planners need to **become significantly better** before this will be feasible.*