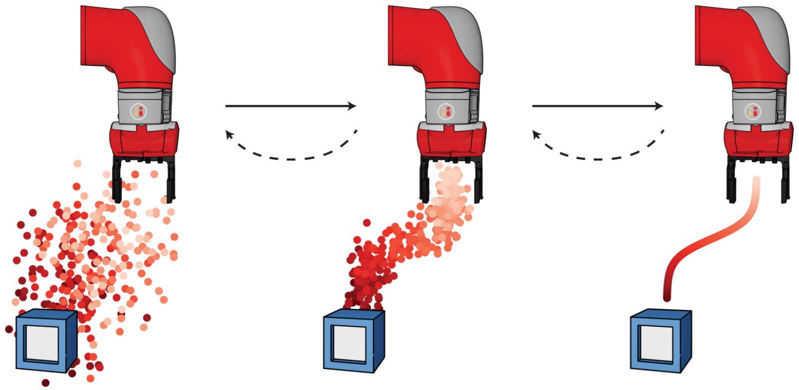
Planning with Diffusion for Flexible Behavior Synthesis

Michael Janner* Yilun Du* Joshua B. Tenenbaum Sergey Levine

*equal contribution

`diffusion-planning.github.io`



ICML 2022

A simple recipe for RL and data-driven control:

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planning "in the now": Kaelbling & Lozano-Pérez. AAAI 2010.
van Hasselt, Hessel, & Aslanides. NeurIPS 2019.

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supervised learning $\boxed{\min_{\boldsymbol{f}} \text{imize } \mathbb{E}_{\mathbf{s}_t, \mathbf{a}_t, \mathbf{s}_{t+1} \sim \mathcal{D}} \left[\|\mathbf{s}_{t+1} - \boldsymbol{f}(\mathbf{s}_t, \mathbf{a}_t)\| \right]}$

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trajectory optimization

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Neural nets + trajectory optimization

Great in principle, a headache in practice.

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- It does sometimes work [Chua et al. 2018; Argenson & Dulac-Arnold 2021]

- But most contemporary model-based RL algorithms pull more from the model-free RL toolbox than from trajectory optimization

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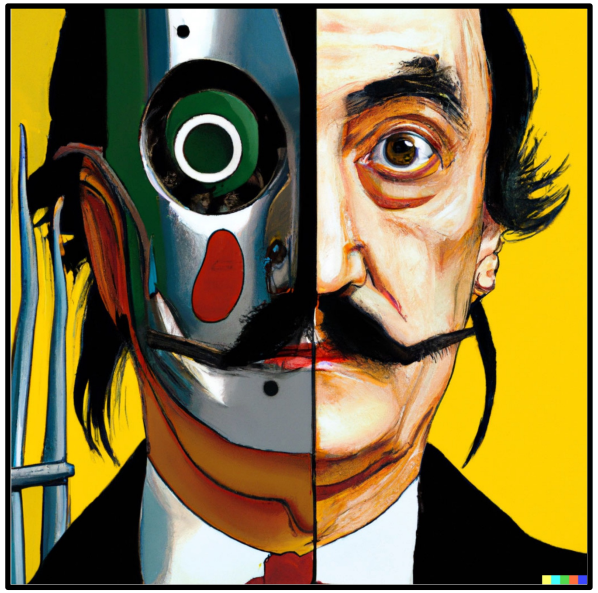
Why?

- Long-horizon predictions are unreliable
- Optimizing for reward with neural net models produces adversarial examples in trajectory space
- **Neural net models aren't good enough?**

Is the model the bottleneck?

- This reasoning should sound suspicious
- Generative modeling (on images) is really working!

- What can RL learn from these successes?

DALL-E 2: Ramesh et al, 2022. Imagen: Saharia et al, 2022.

Planning as generative modeling

- Offload as much of MBRL into contemporary generative modeling as possible

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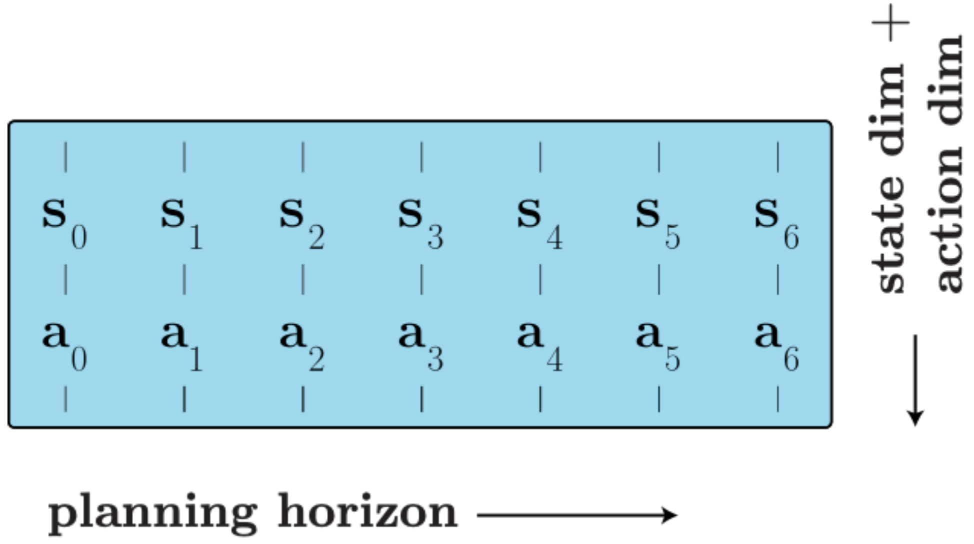
A generative model of trajectories

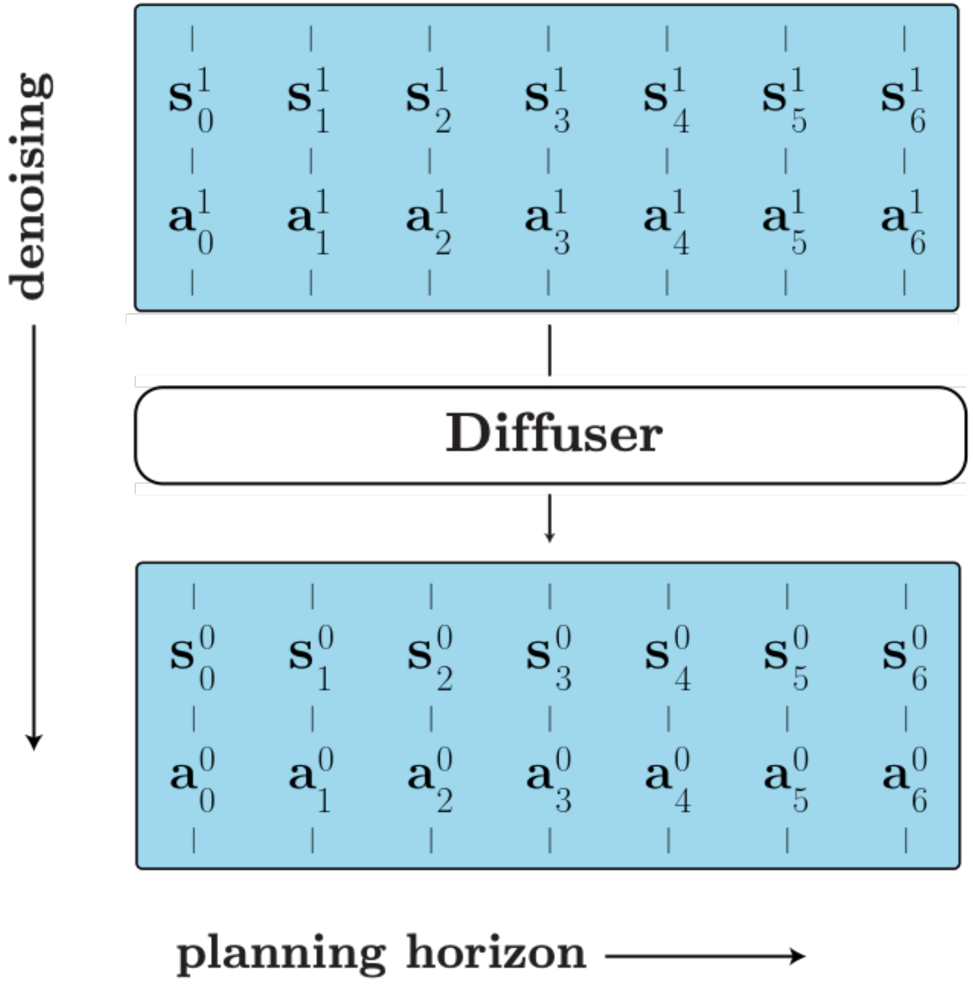
- Represent trajectories as single-channel images

$\tau =$



A generative model of trajectories

- Represent trajectories as single-channel images
- Train a diffusion model to iteratively denoise entire trajectory



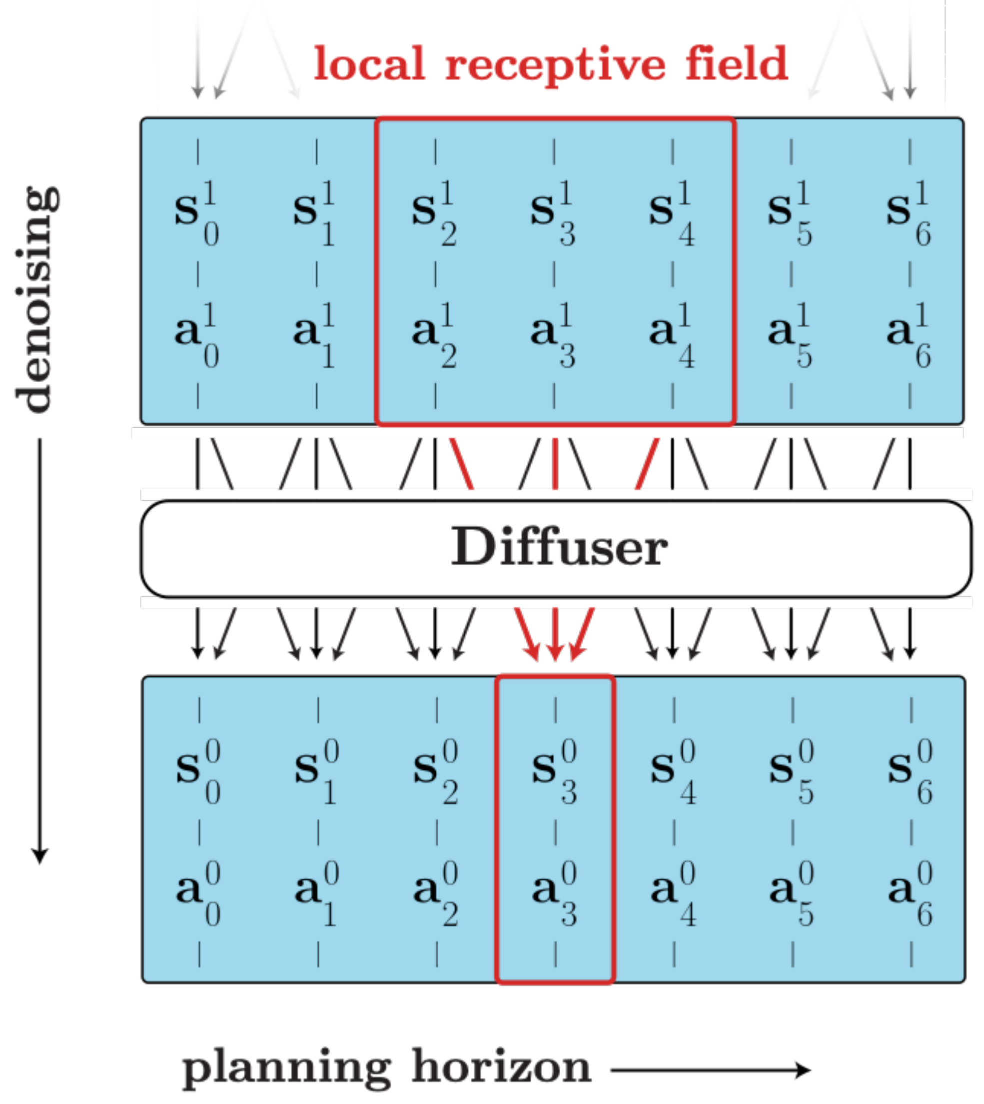
diffusion models: Sohl-Dickstein et al. ICML 2015 & Ho et al. NeurIPS 2020.

A generative model of trajectories

- Represent trajectories as single-channel images

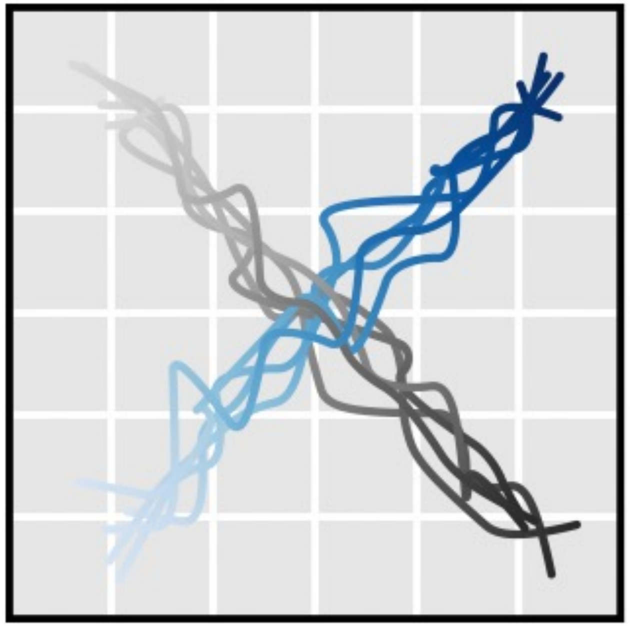
- Train a diffusion model to iteratively denoise entire trajectory

- Use (one-dimensional) convolutions for temporal equivariance and horizon-independence



Compositionality via local consistency

- Diffuser is non-Markovian, but still compositional due to temporal convolutions



data

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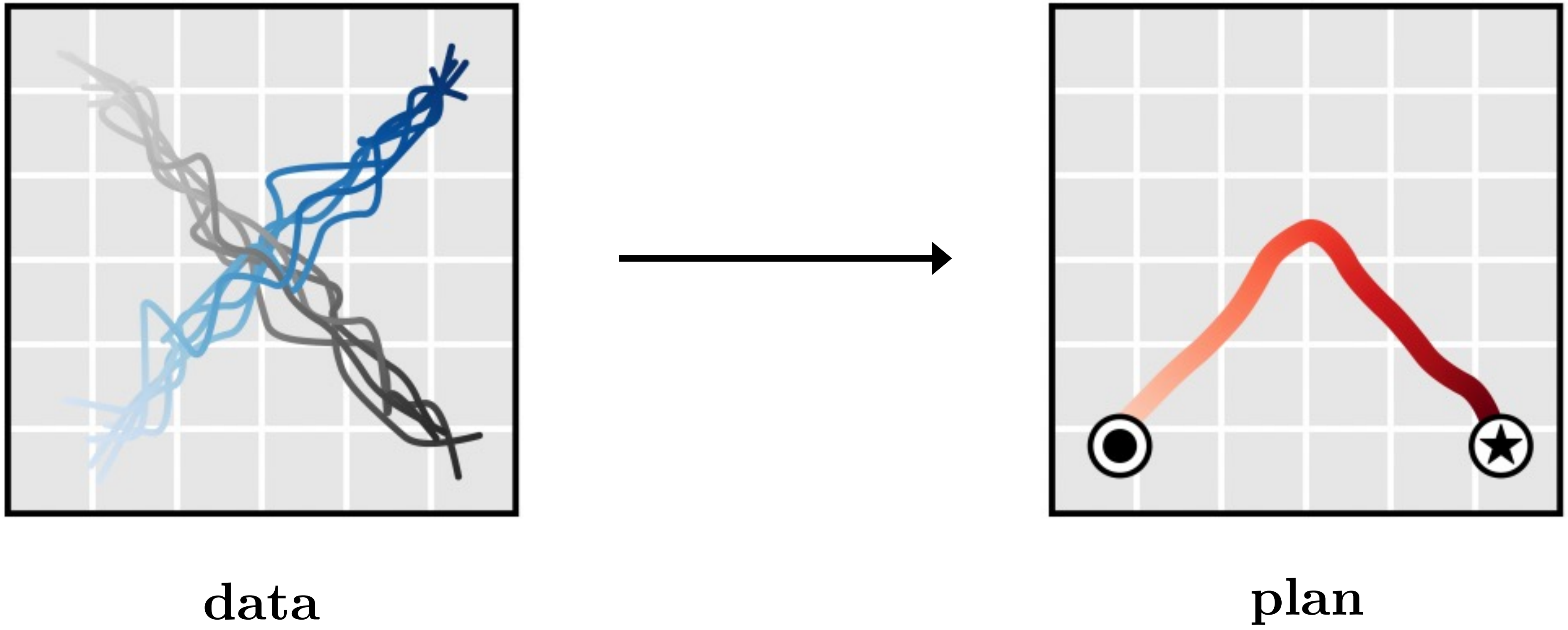

Variable-length predictions

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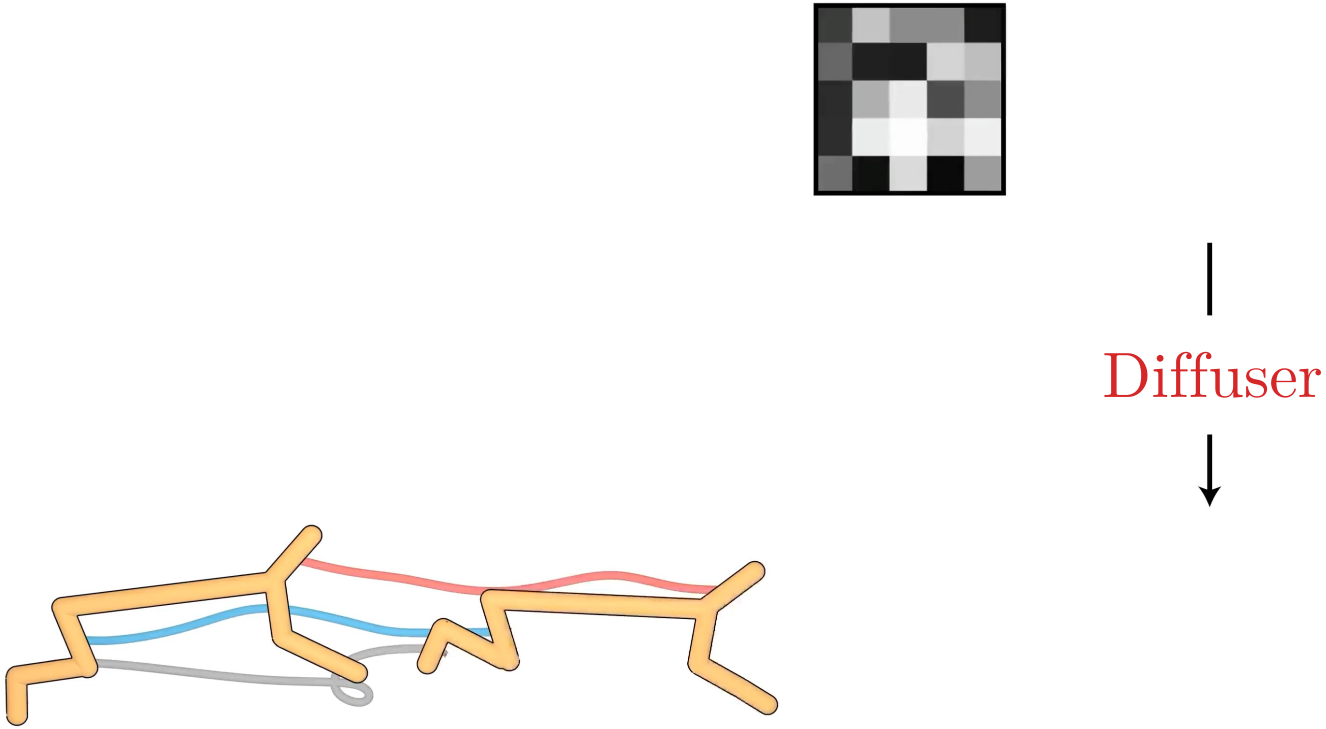

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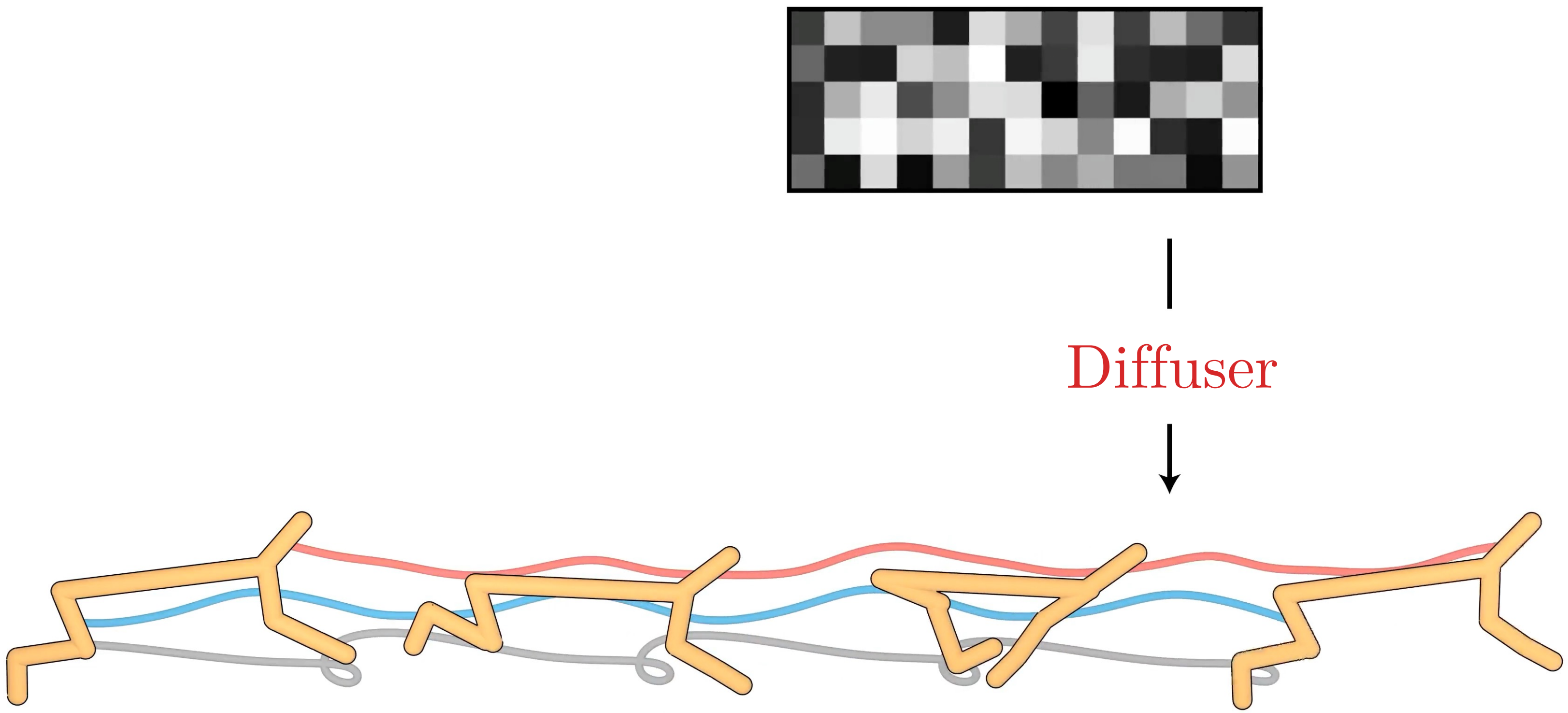

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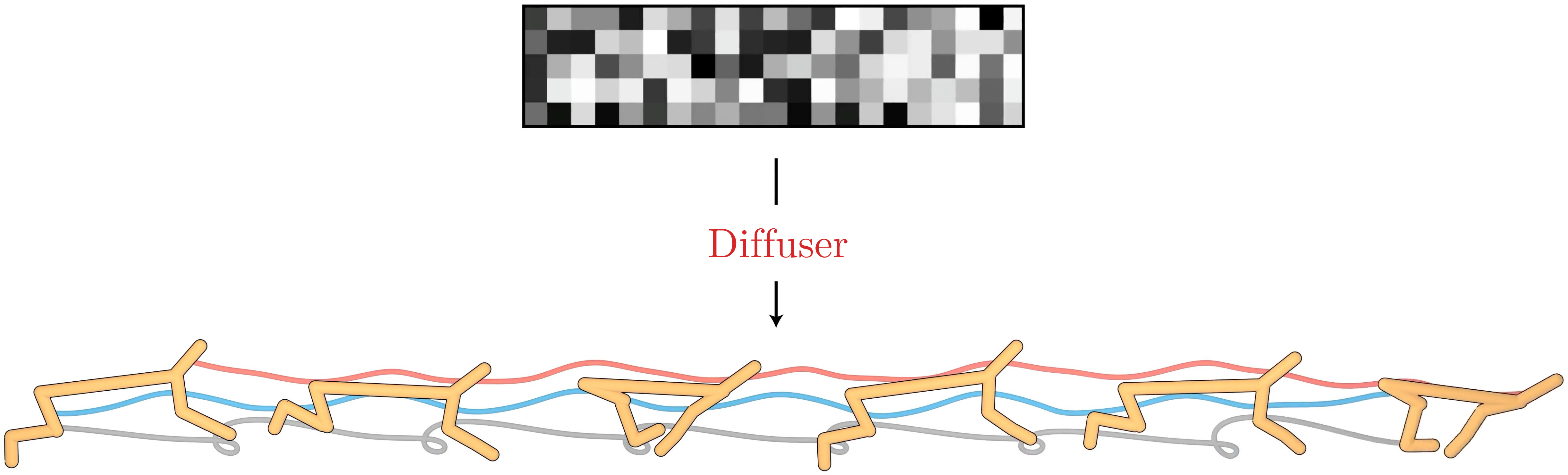

Non-autoregressive prediction

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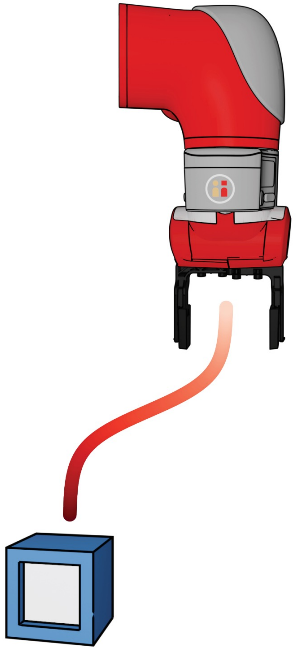

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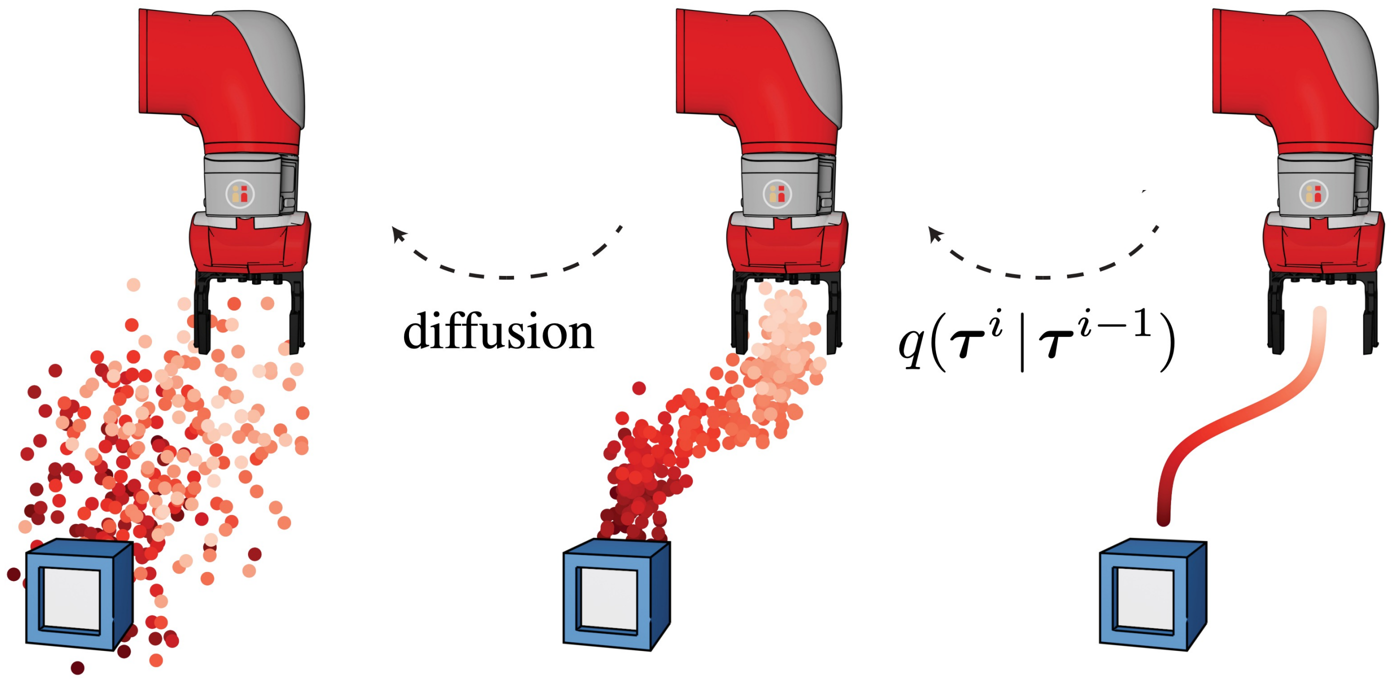

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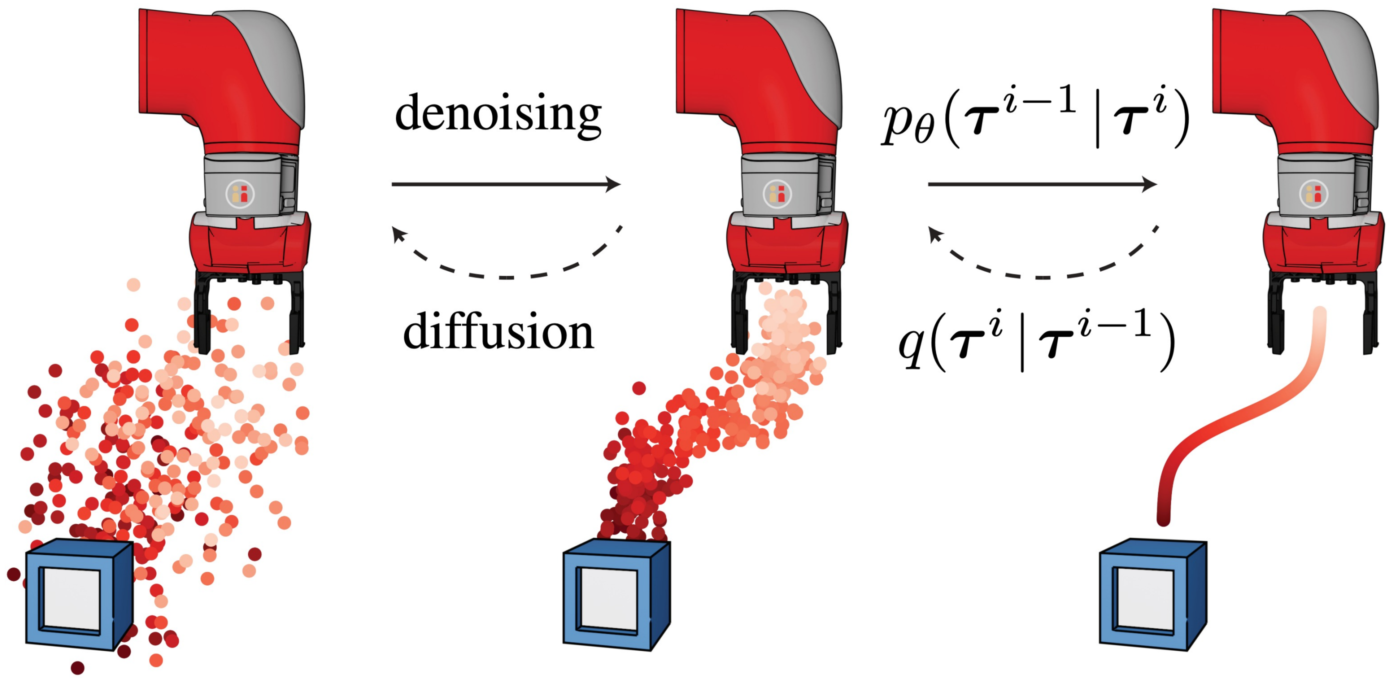
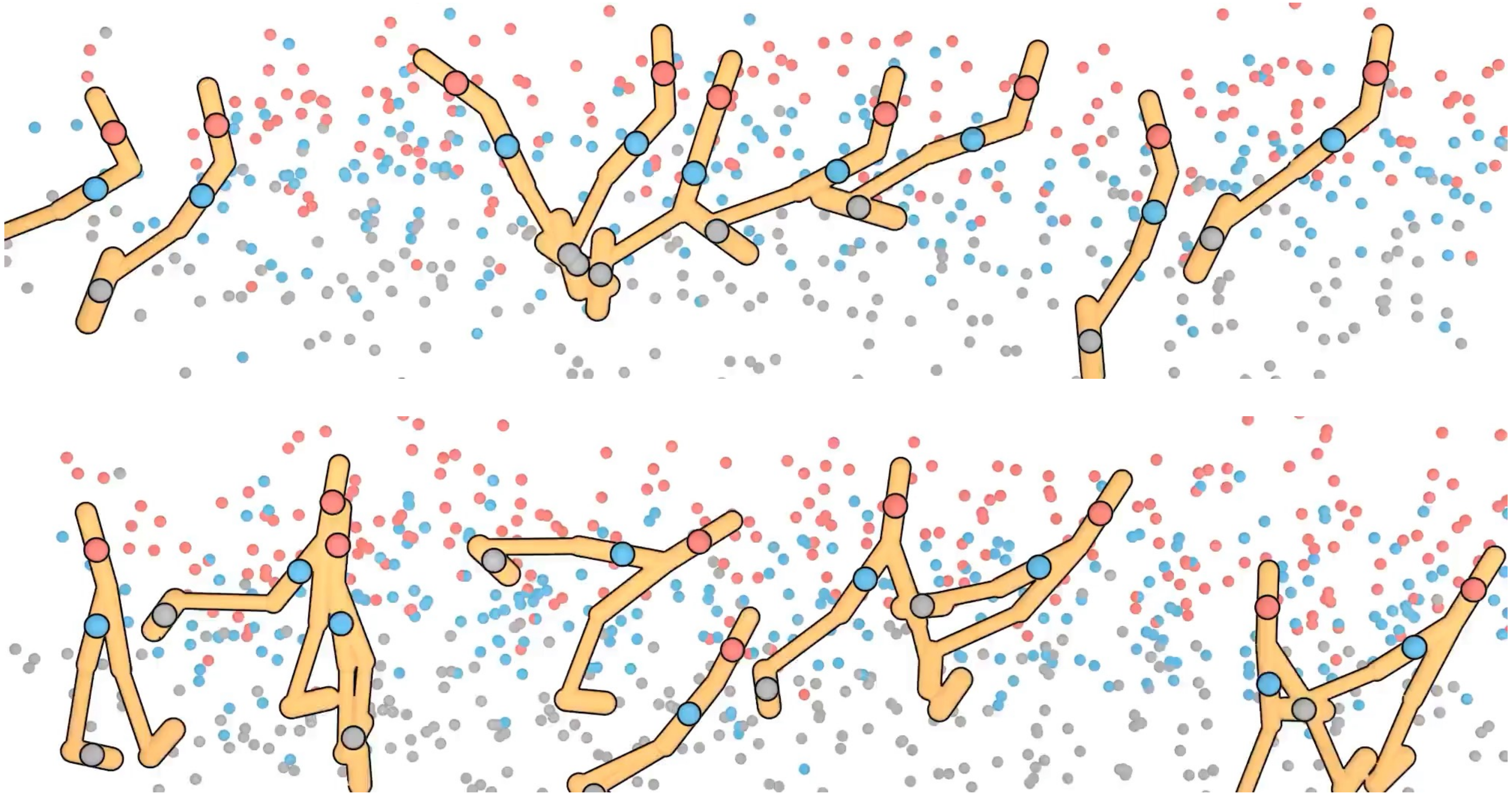


Sampling from Diffuser

- Sampling occurs by iteratively refining randomly-initialized trajectories



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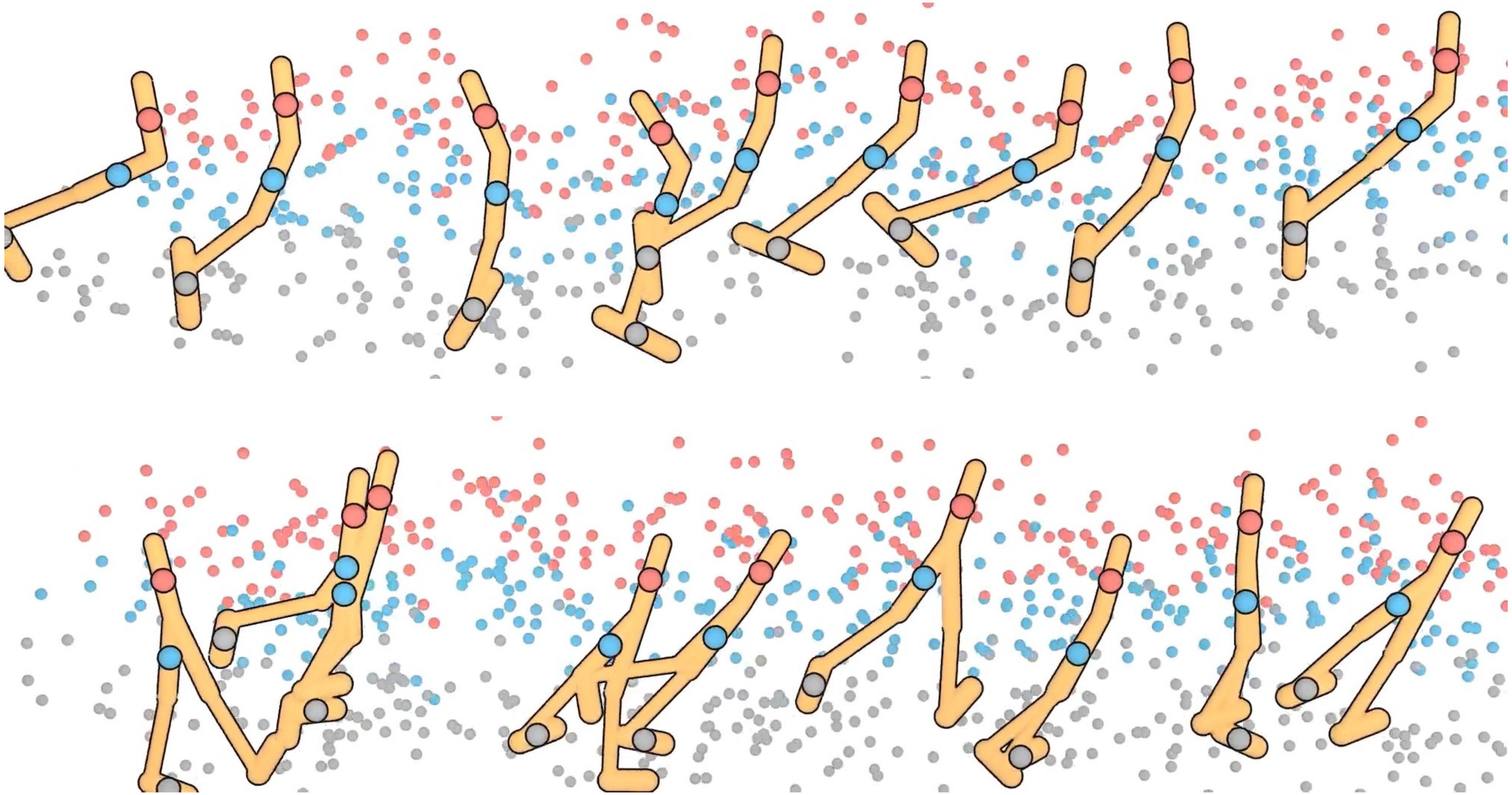

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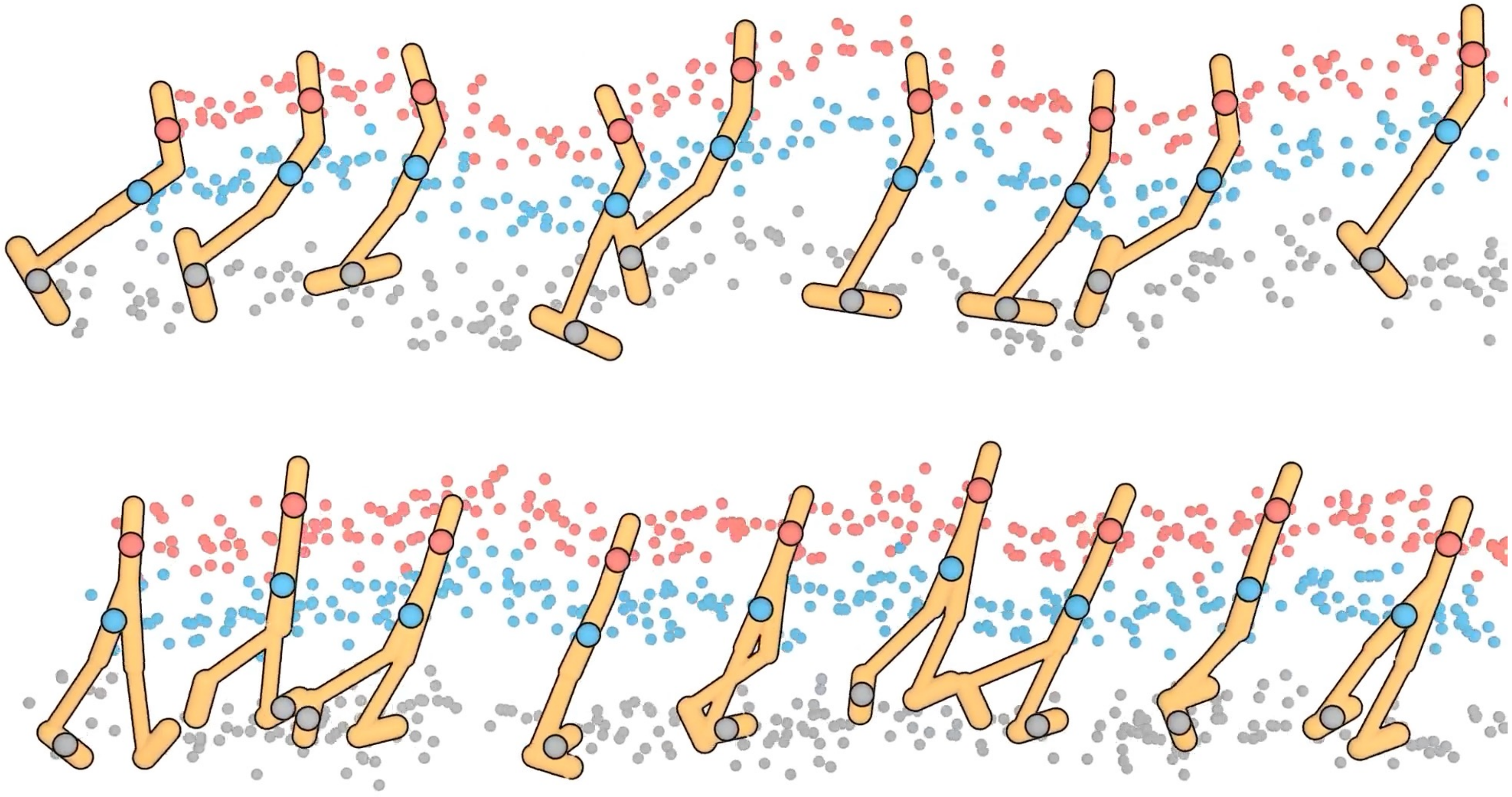

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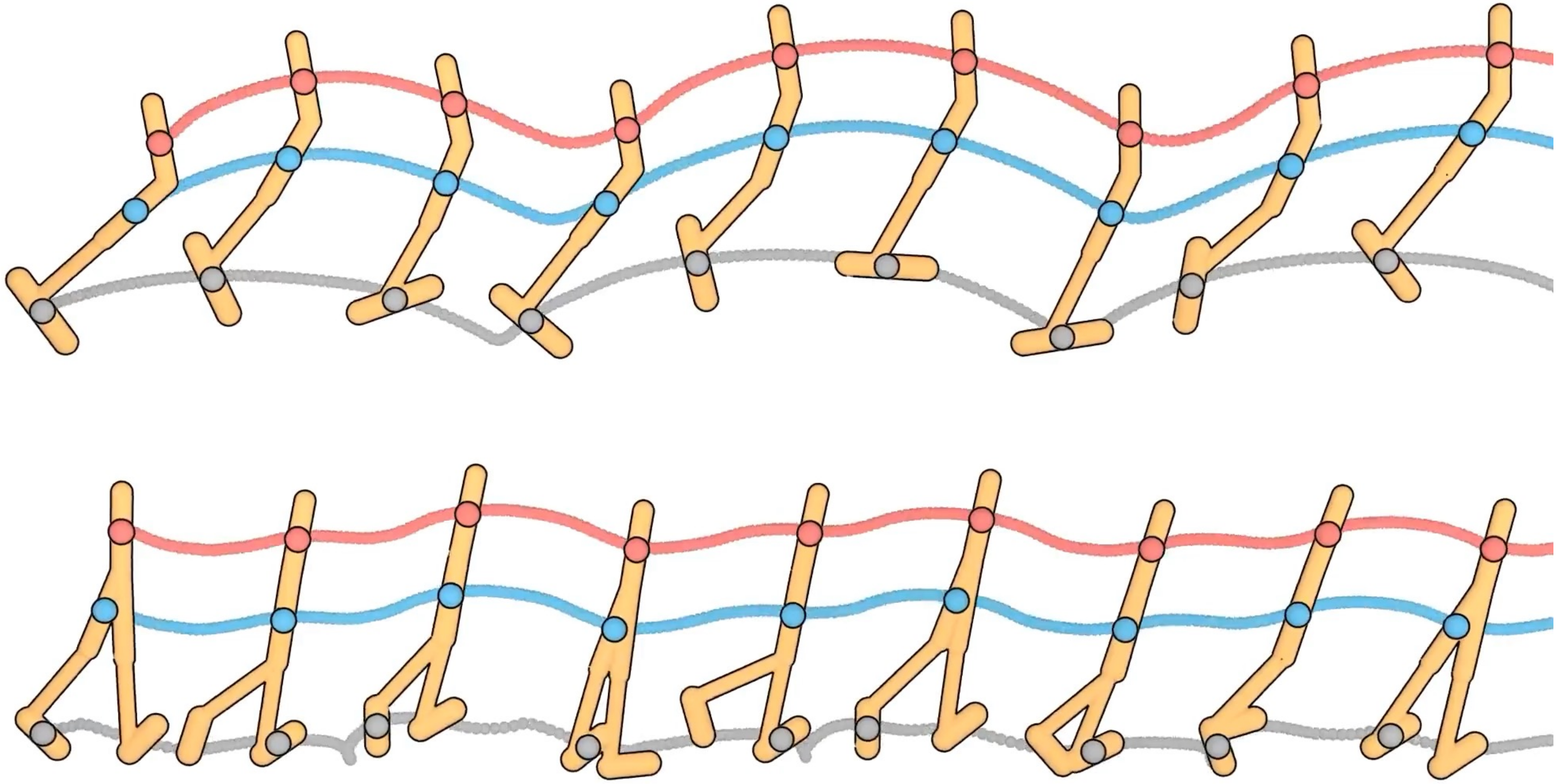

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See also: Model Based Planning with Energy Based Models: Du at al, CoRL 2019.

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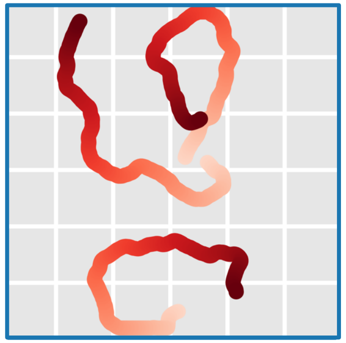

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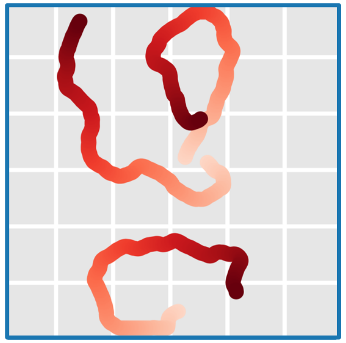

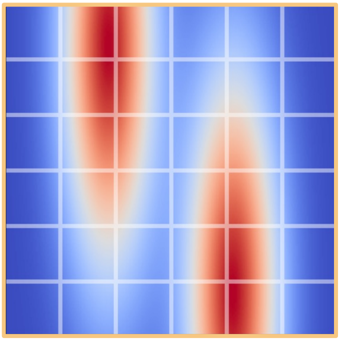

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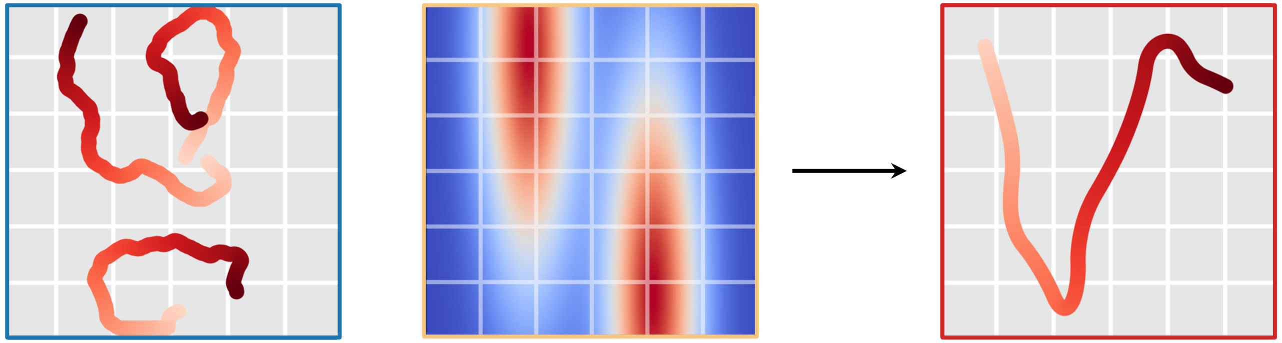

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- Guidance functions transforms an unconditional trajectory model into a conditional policy for diverse tasks.

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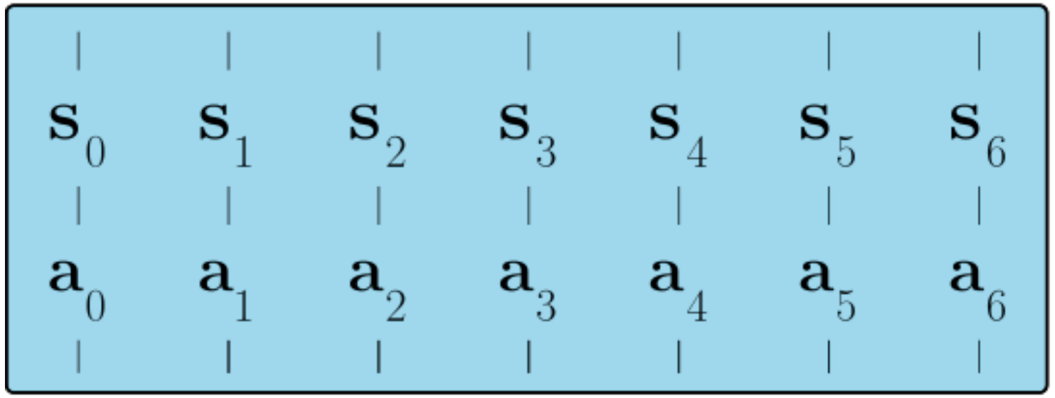
Offline Reinforcement Learning through Value Guidance

- Can use a value function to bias trajectory model to particular task

$p_\theta(\boldsymbol{\tau})$



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$$p_\theta(\boldsymbol{\tau}) \quad \begin{bmatrix} | & | & | & | & | & | & | \\ \mathbf{s}_0 & \mathbf{s}_1 & \mathbf{s}_2 & \mathbf{s}_3 & \mathbf{s}_4 & \mathbf{s}_5 & \mathbf{s}_6 \\ | & | & | & | & | & | & | \\ \mathbf{a}_0 & \mathbf{a}_1 & \mathbf{a}_2 & \mathbf{a}_3 & \mathbf{a}_4 & \mathbf{a}_5 & \mathbf{a}_6 \\ | & | & | & | & | & | & | \end{bmatrix}$$

$$h(\boldsymbol{\tau}) \quad r(\mathbf{s}_0) + \gamma r(\mathbf{s}_1) + \gamma^2 r(\mathbf{s}_2) + \gamma^3 r(\mathbf{s}_3) + \gamma^4 r(\mathbf{s}_4) + \gamma^5 V(\mathbf{s}_5)$$

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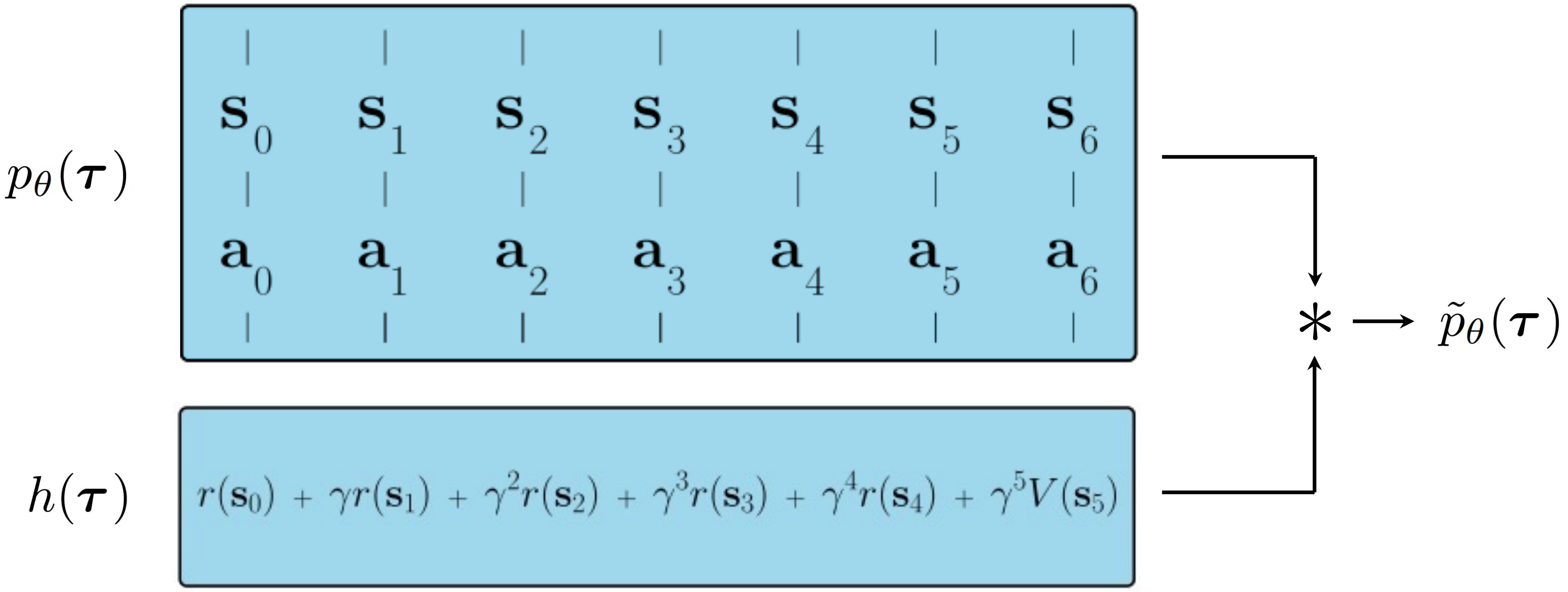
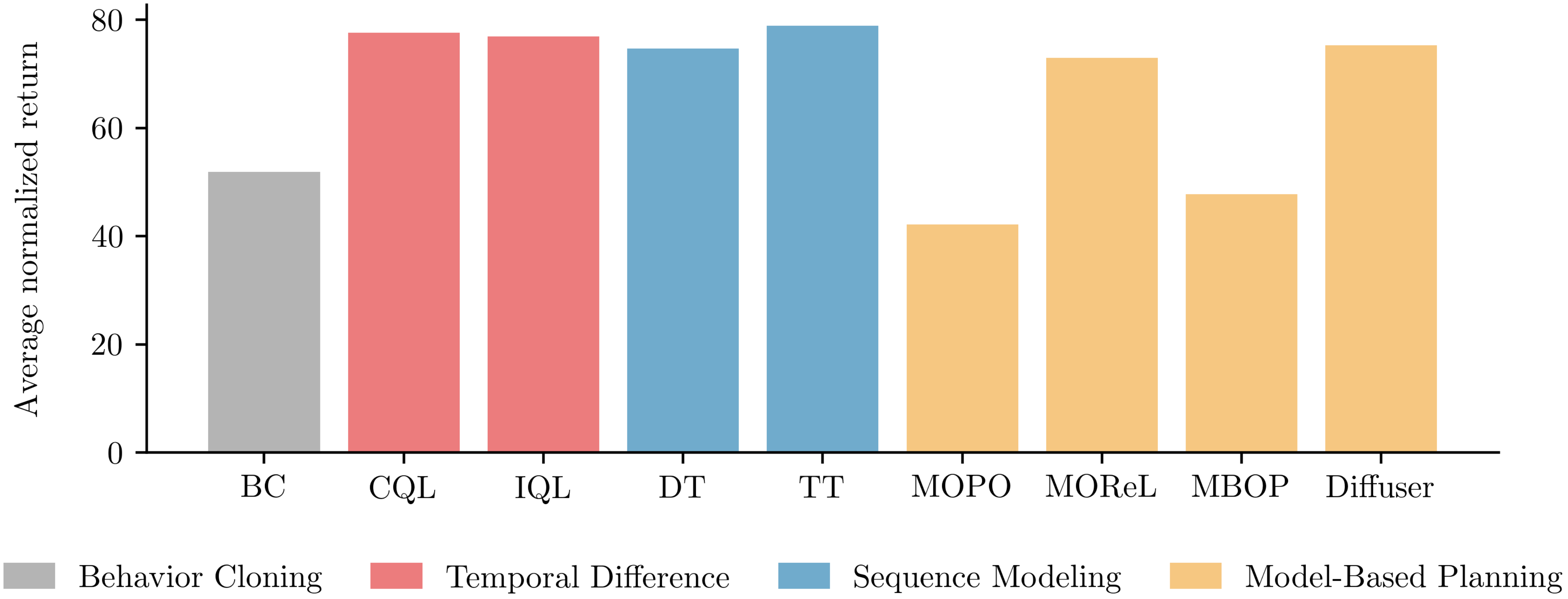


- Can use a single Diffuser model for multiple different tasks

Offline Reinforcement Learning through Value Guidance



Goal Planning through Inpainting

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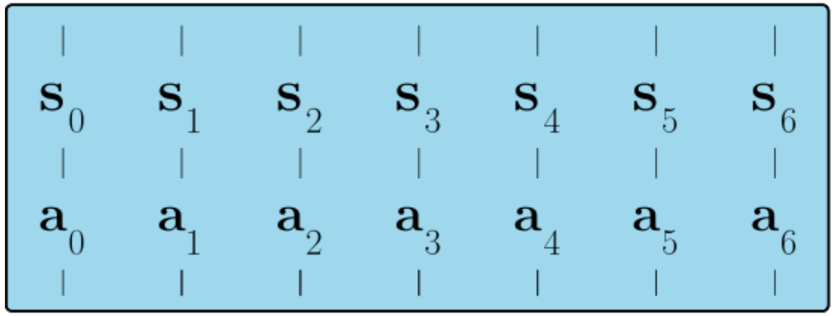

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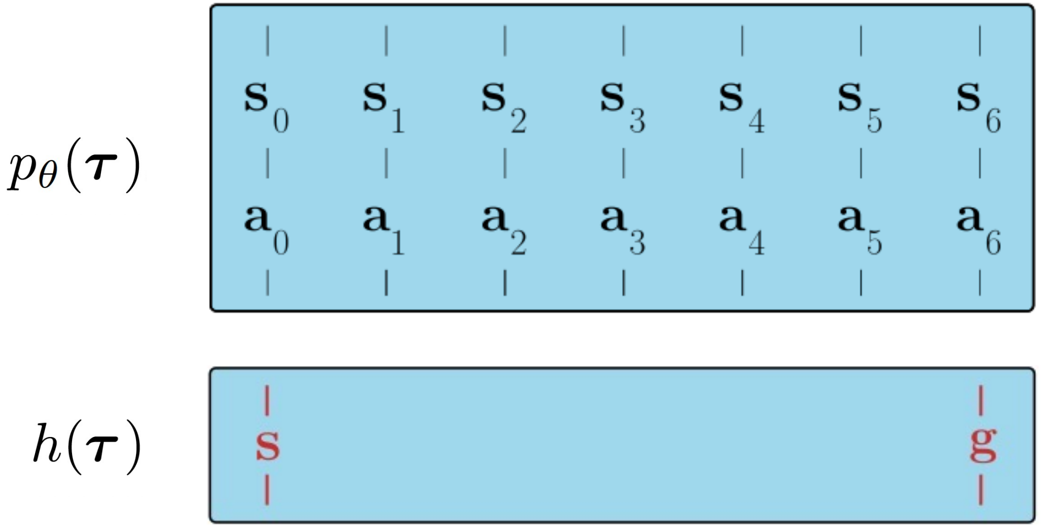

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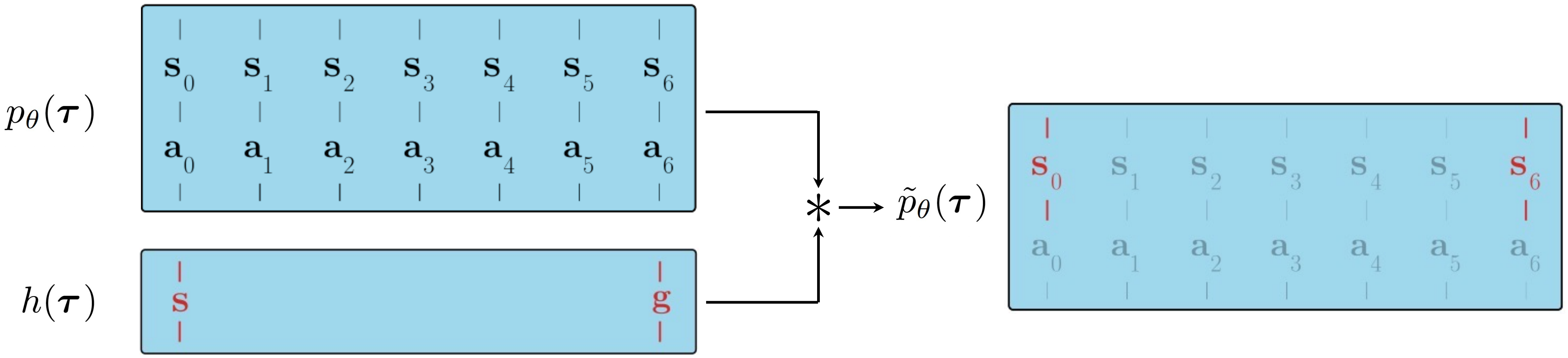

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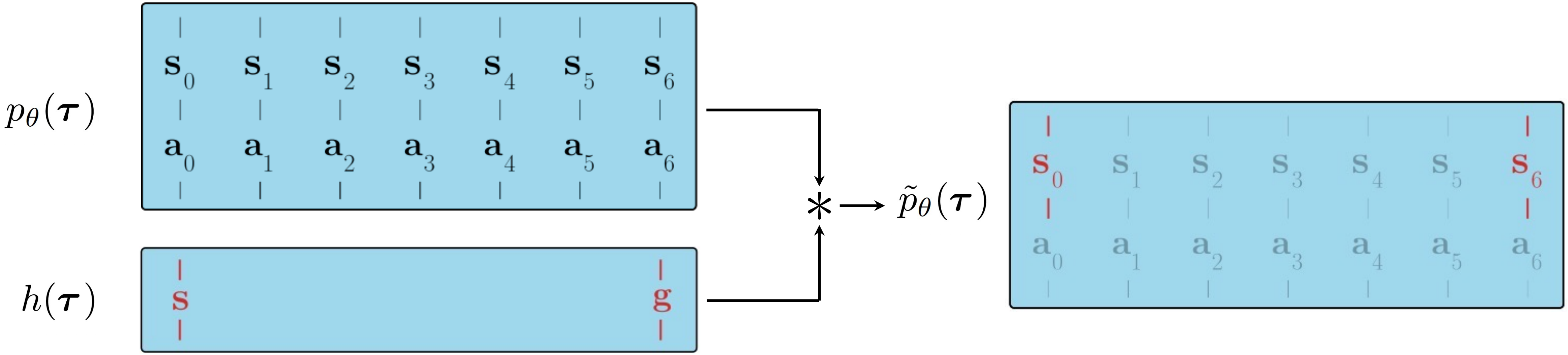

- Construct a goal seeking policy through guidance

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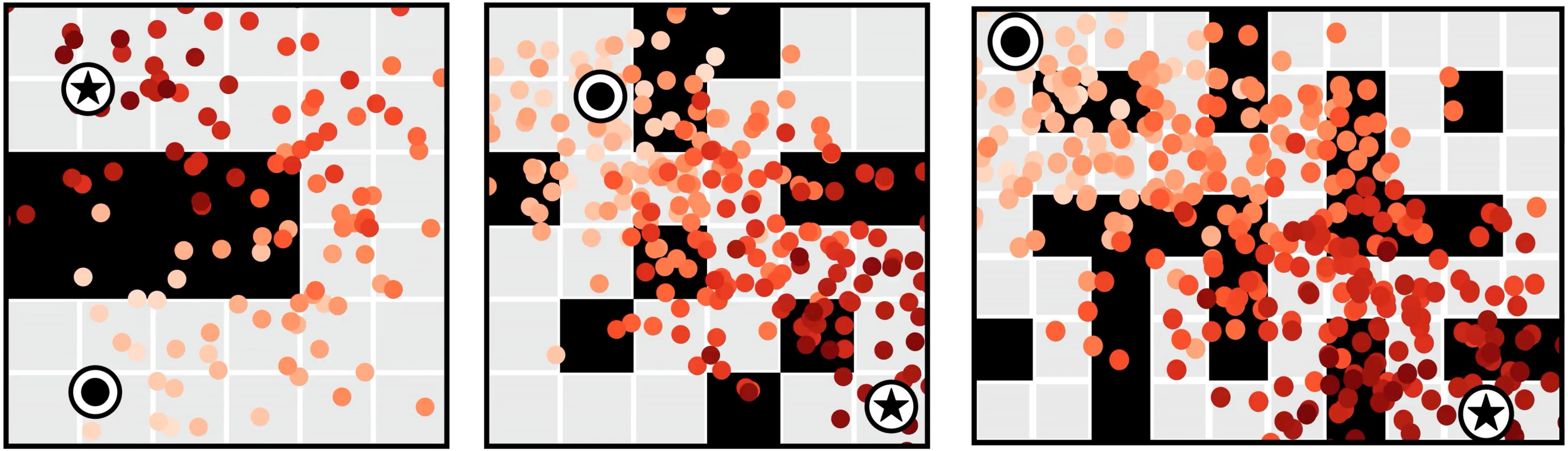

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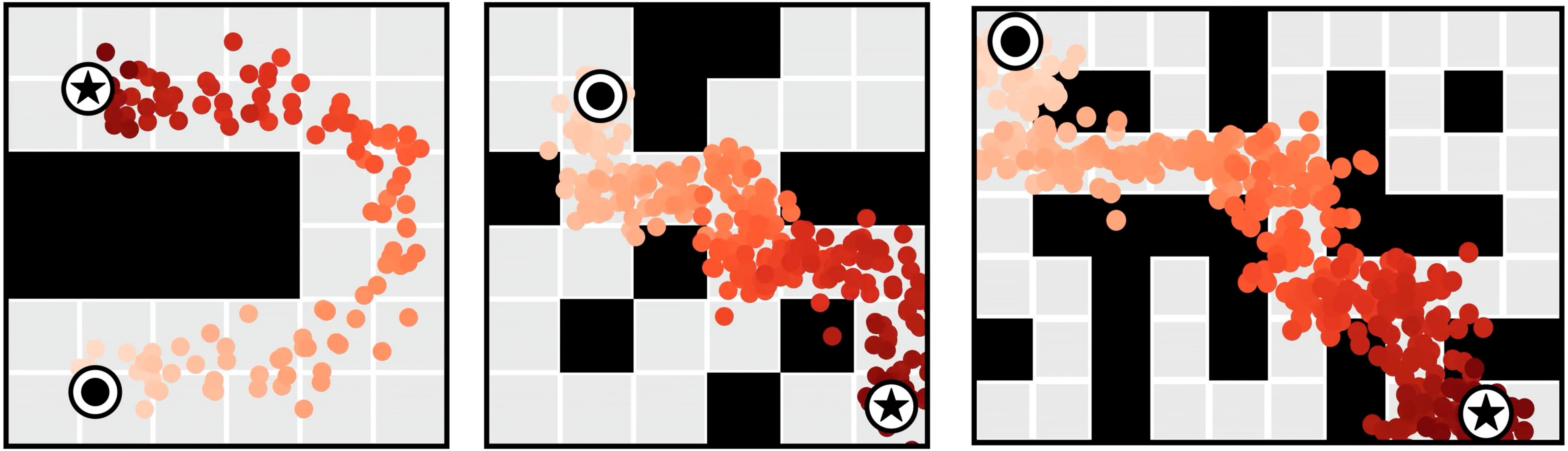
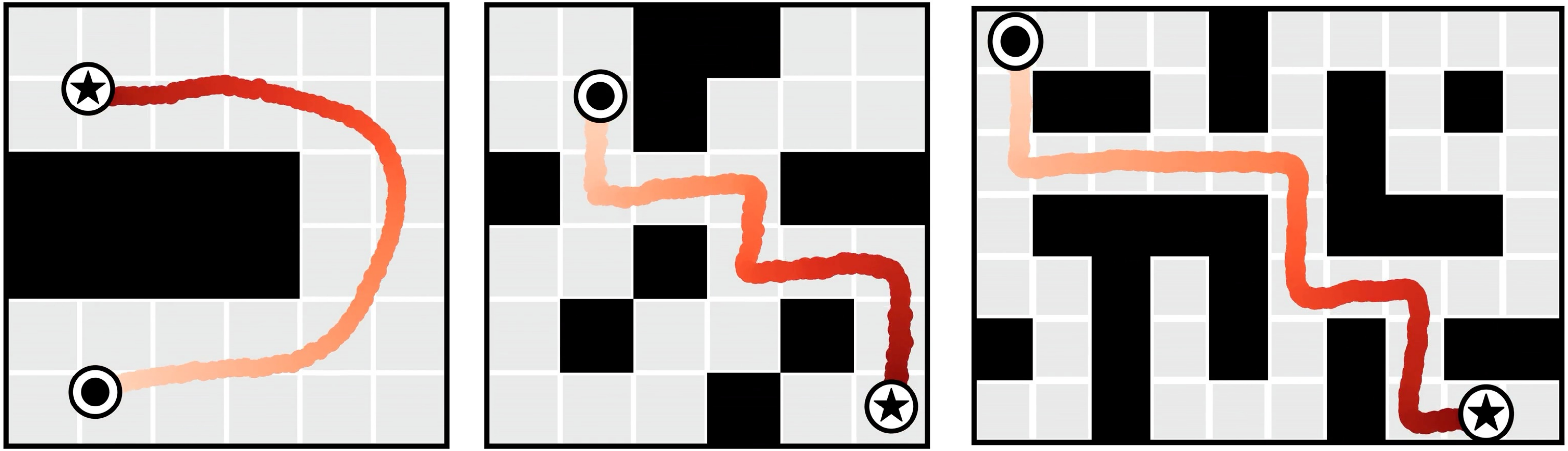
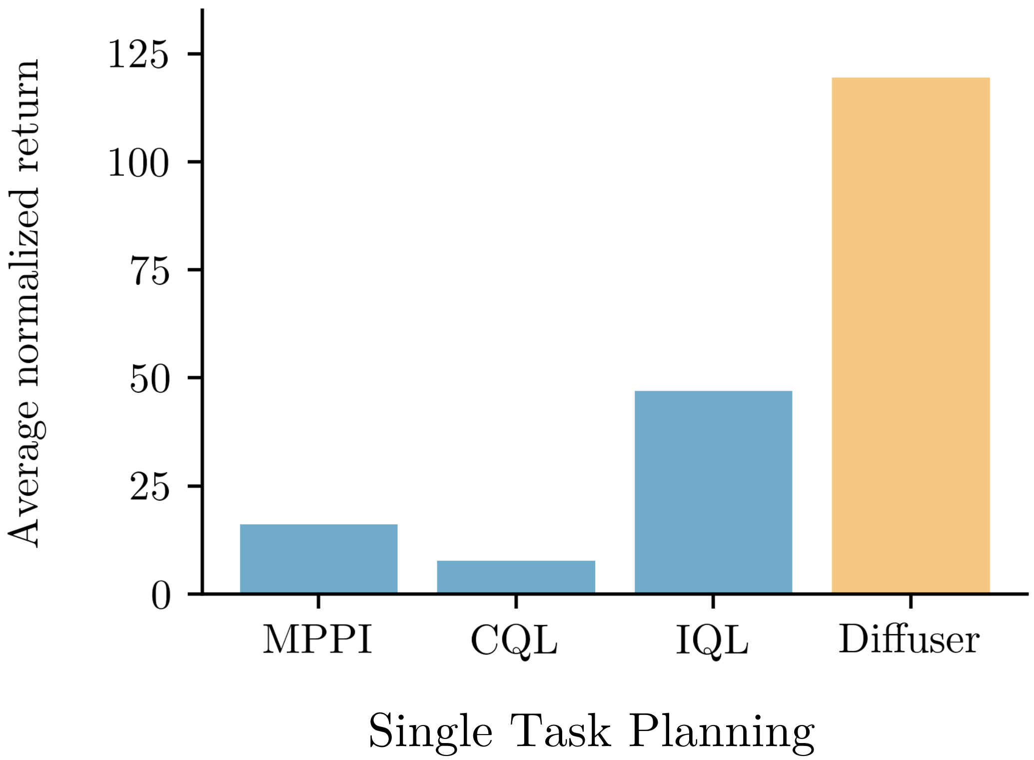


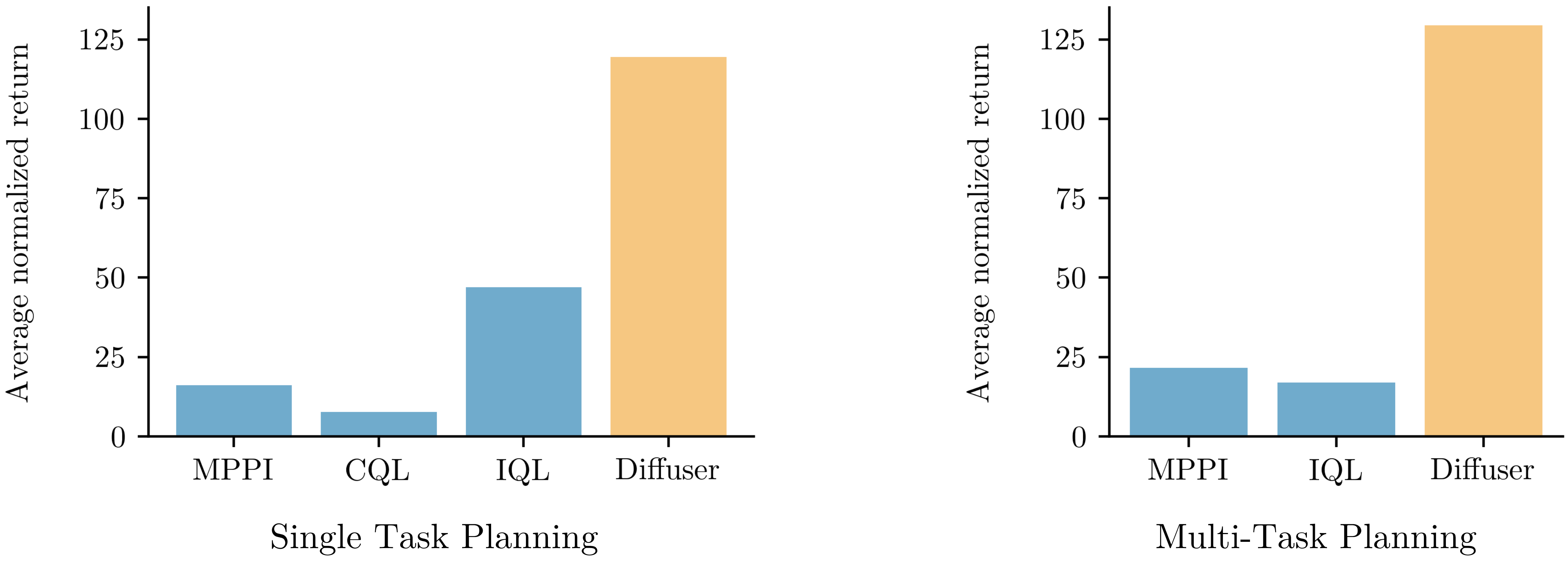
Goal Planning through Inpainting



Goal Planning through Inpainting



Goal Planning through Inpainting



Test-Time Cost Functions

- Can use guidance function to specify arbitrary costs on a trajectory

Test-Time Cost Functions

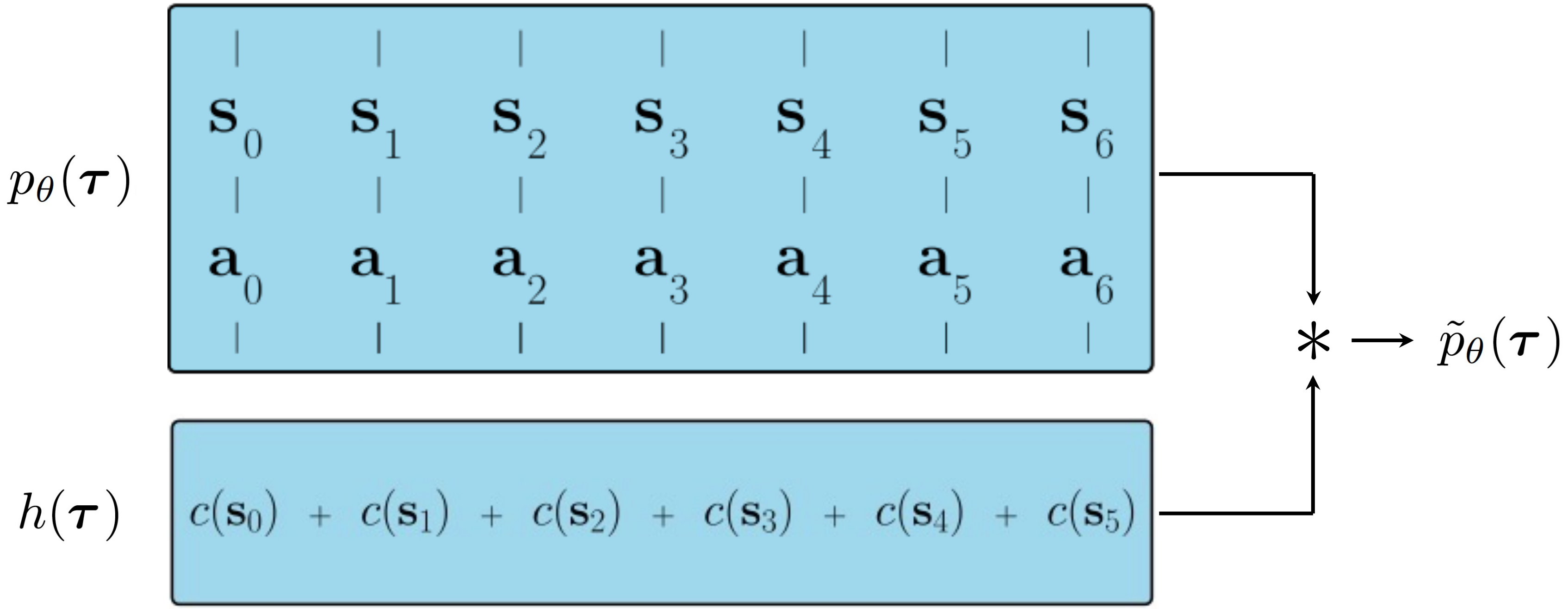
- Can use guidance function to specify arbitrary costs on a trajectory

$$p_\theta(\boldsymbol{\tau}) \quad \begin{bmatrix} \mathbf{s}_0 & \mathbf{s}_1 & \mathbf{s}_2 & \mathbf{s}_3 & \mathbf{s}_4 & \mathbf{s}_5 & \mathbf{s}_6 \\ \mathbf{a}_0 & \mathbf{a}_1 & \mathbf{a}_2 & \mathbf{a}_3 & \mathbf{a}_4 & \mathbf{a}_5 & \mathbf{a}_6 \end{bmatrix}$$

$$h(\boldsymbol{\tau}) \quad \boxed{c(\mathbf{s}_0) + c(\mathbf{s}_1) + c(\mathbf{s}_2) + c(\mathbf{s}_3) + c(\mathbf{s}_4) + c(\mathbf{s}_5)}$$

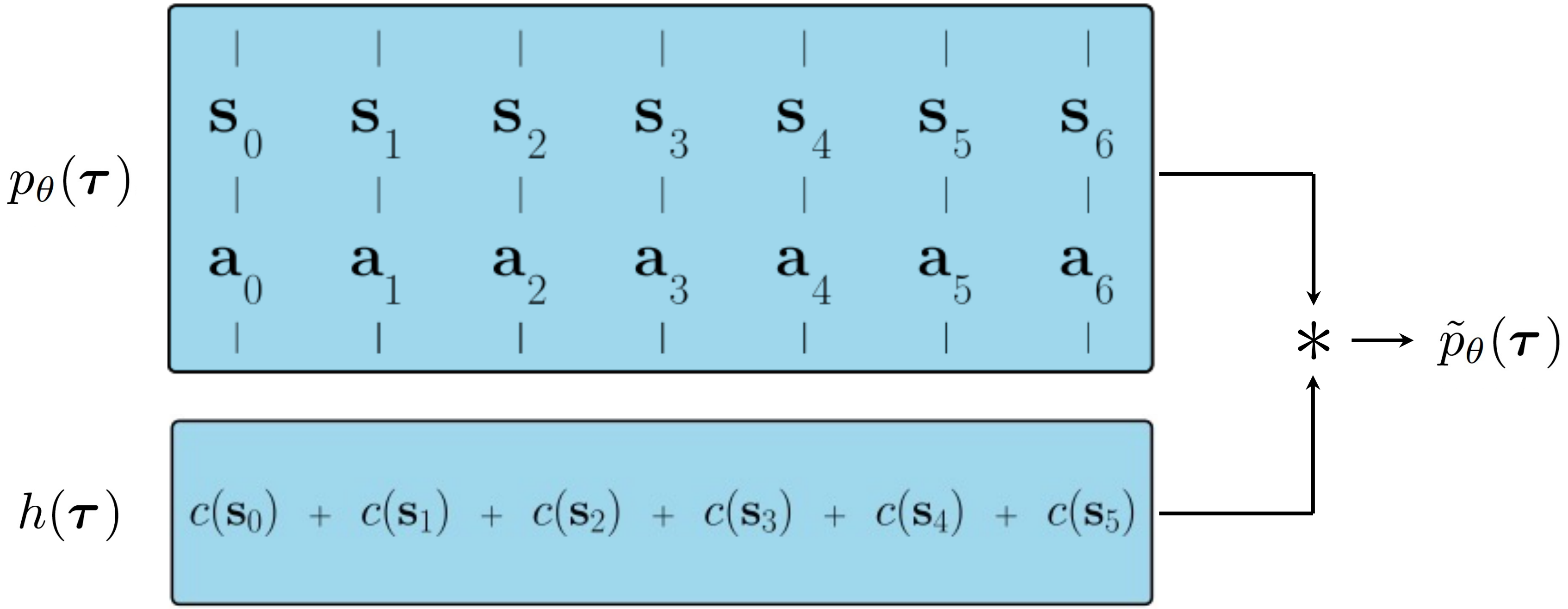
Test-Time Cost Specification

- Can use guidance function to specify arbitrary costs on a trajectory



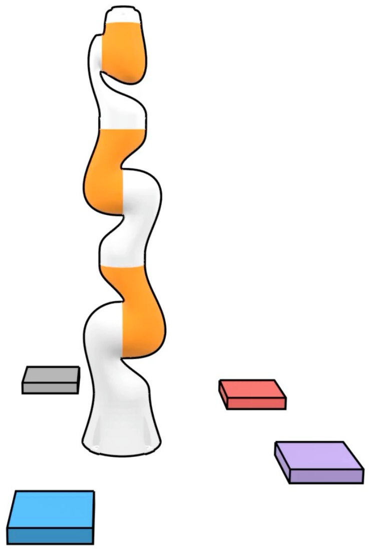
Test-Time Cost Specification

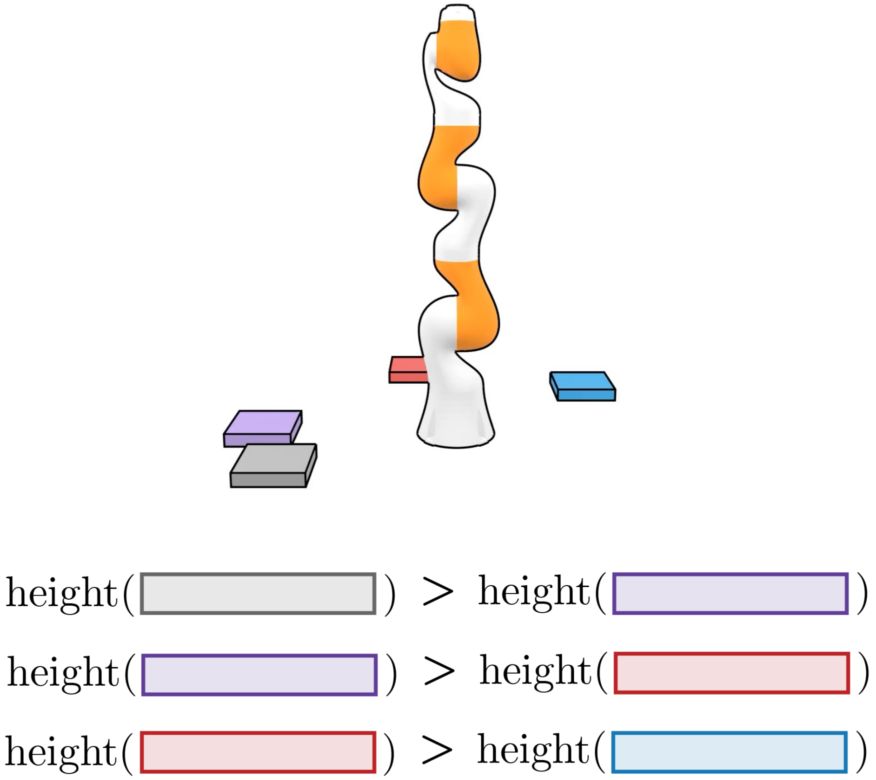
- Can use guidance function to specify arbitrary costs on a trajectory



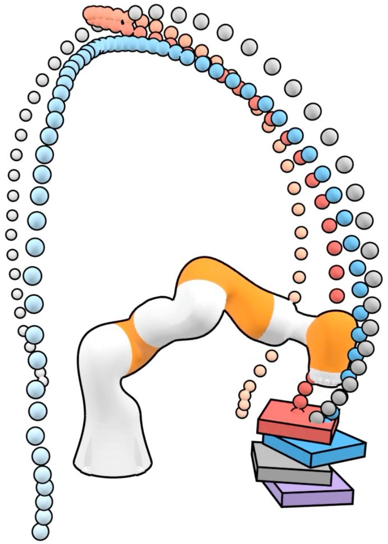
- Can be seen as a learned analogue of trajectory optimization

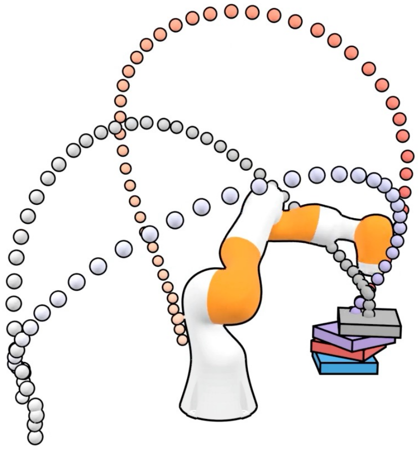
Test-Time Cost Specification





Test-Time Cost Specification





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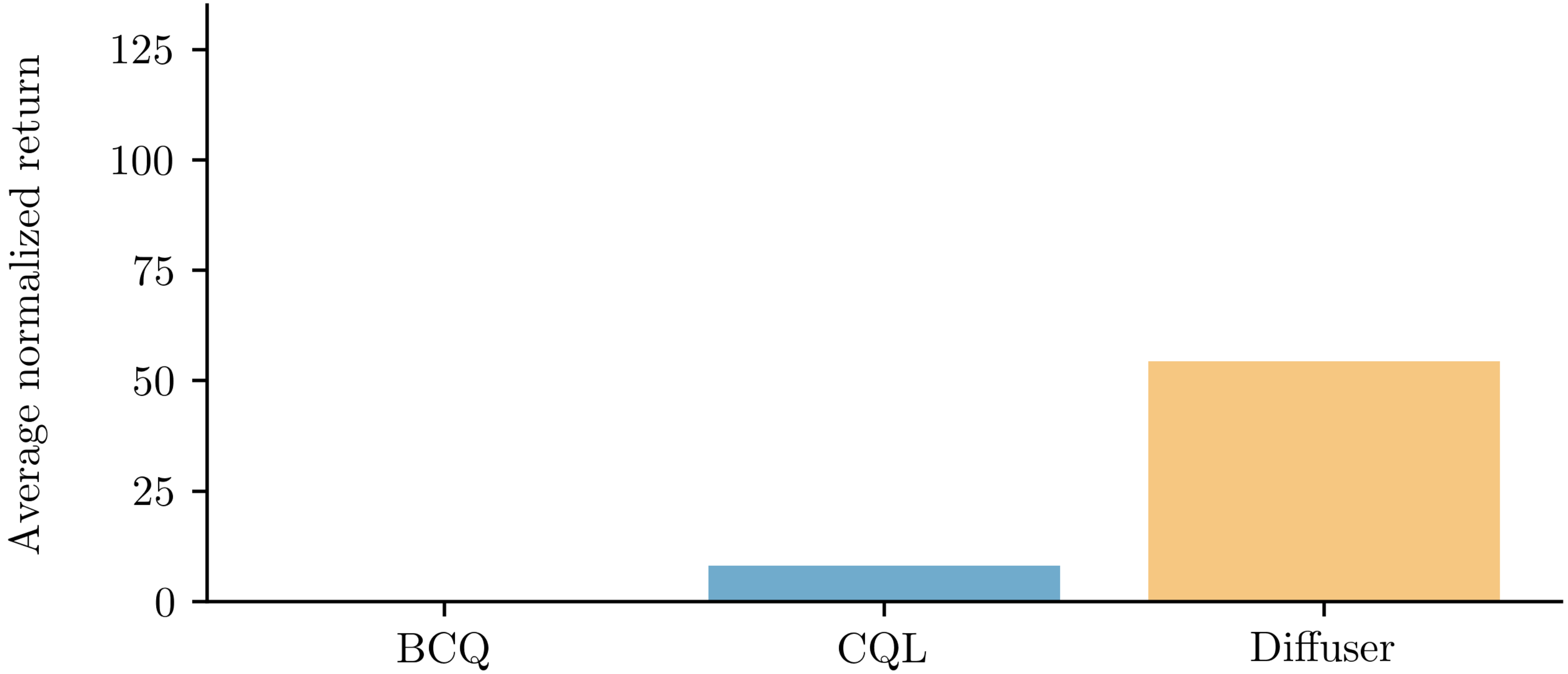
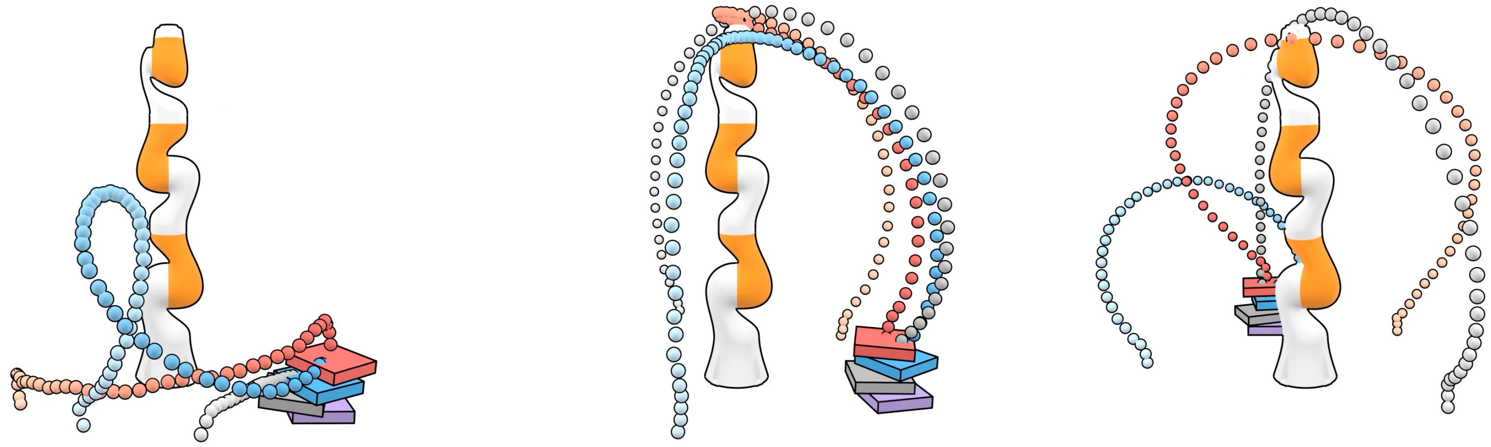
Test-Time Cost Specification



Thanks!



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