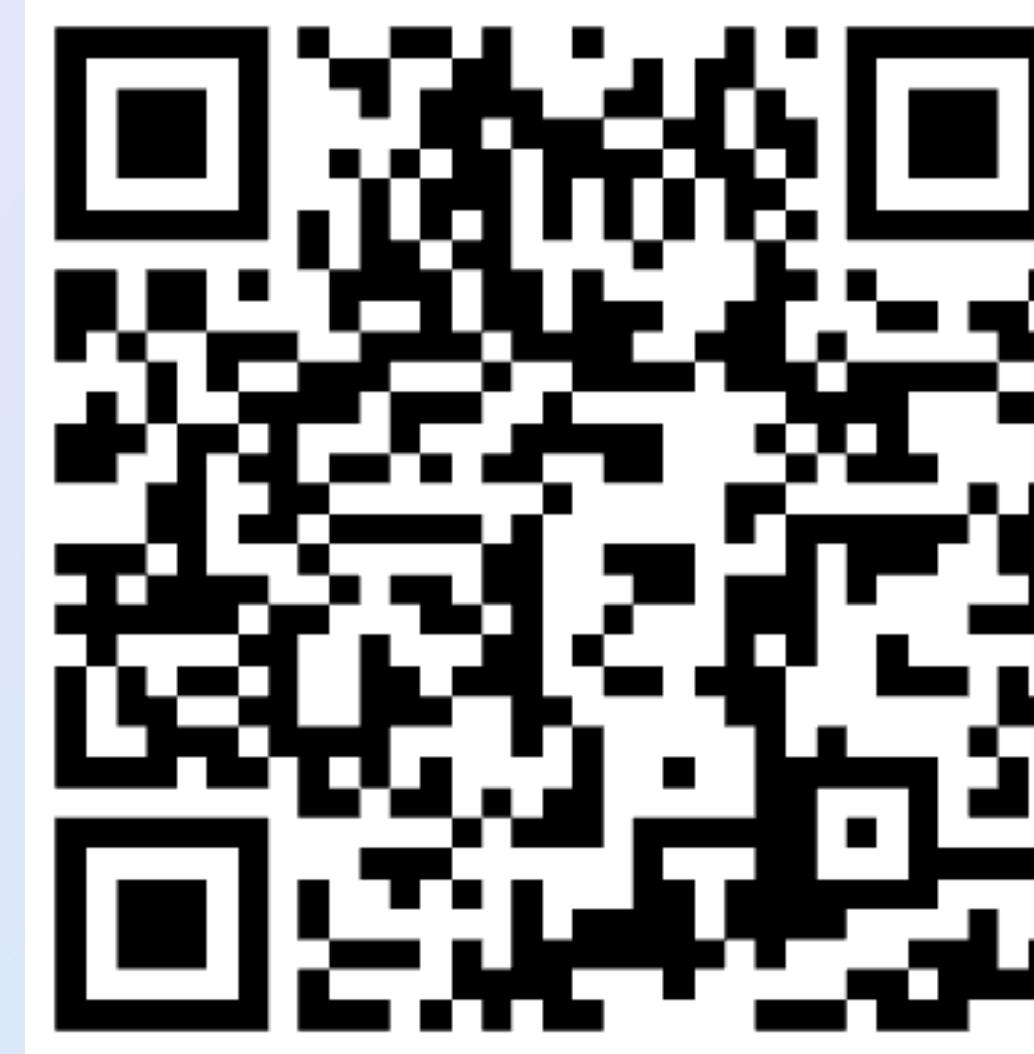


Stochastic Control for Large Scale

Reward-Driven Generative Modeling

Link to slides:



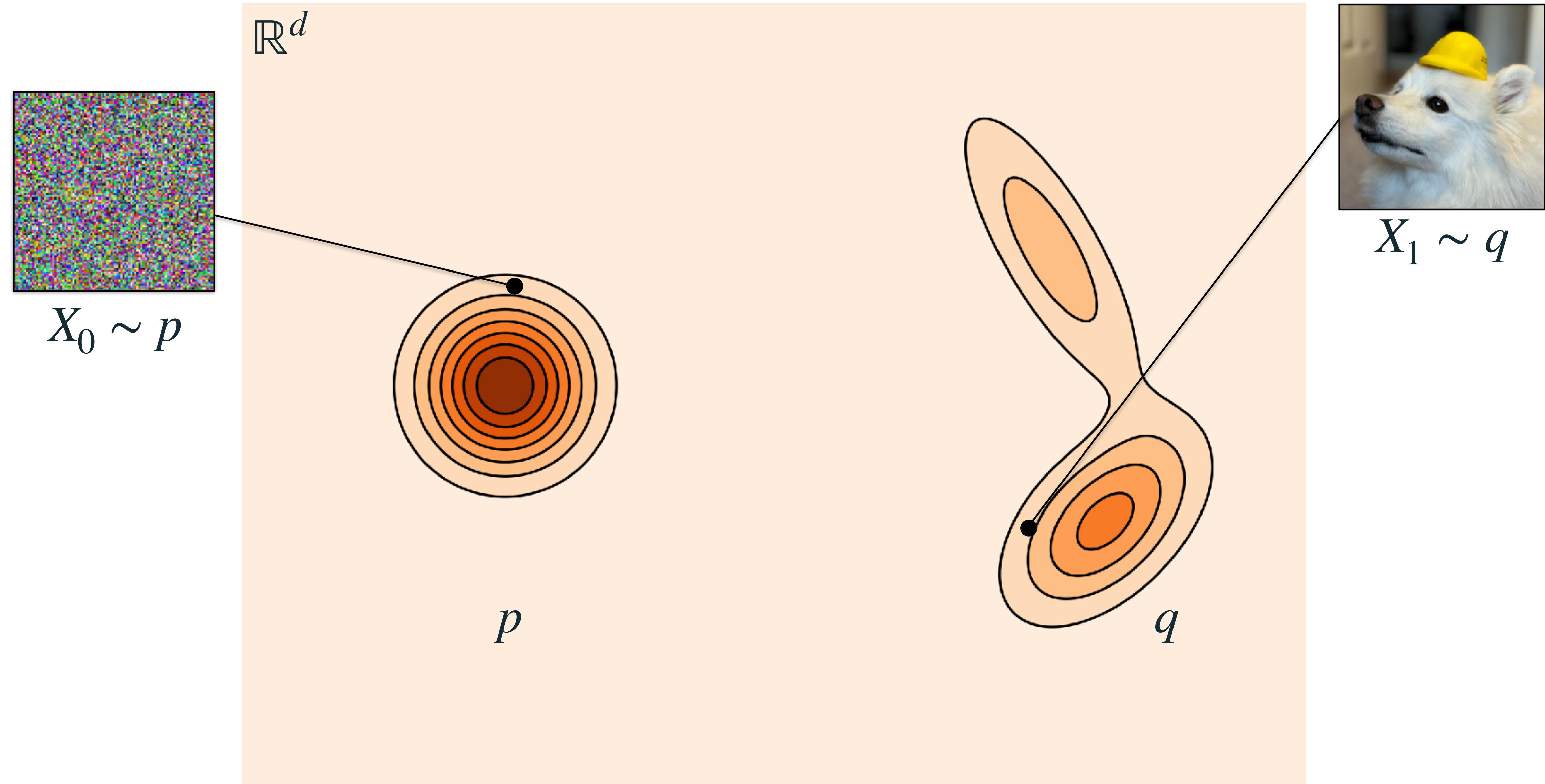
Ricky T. Q. Chen

The Generative Modeling problem

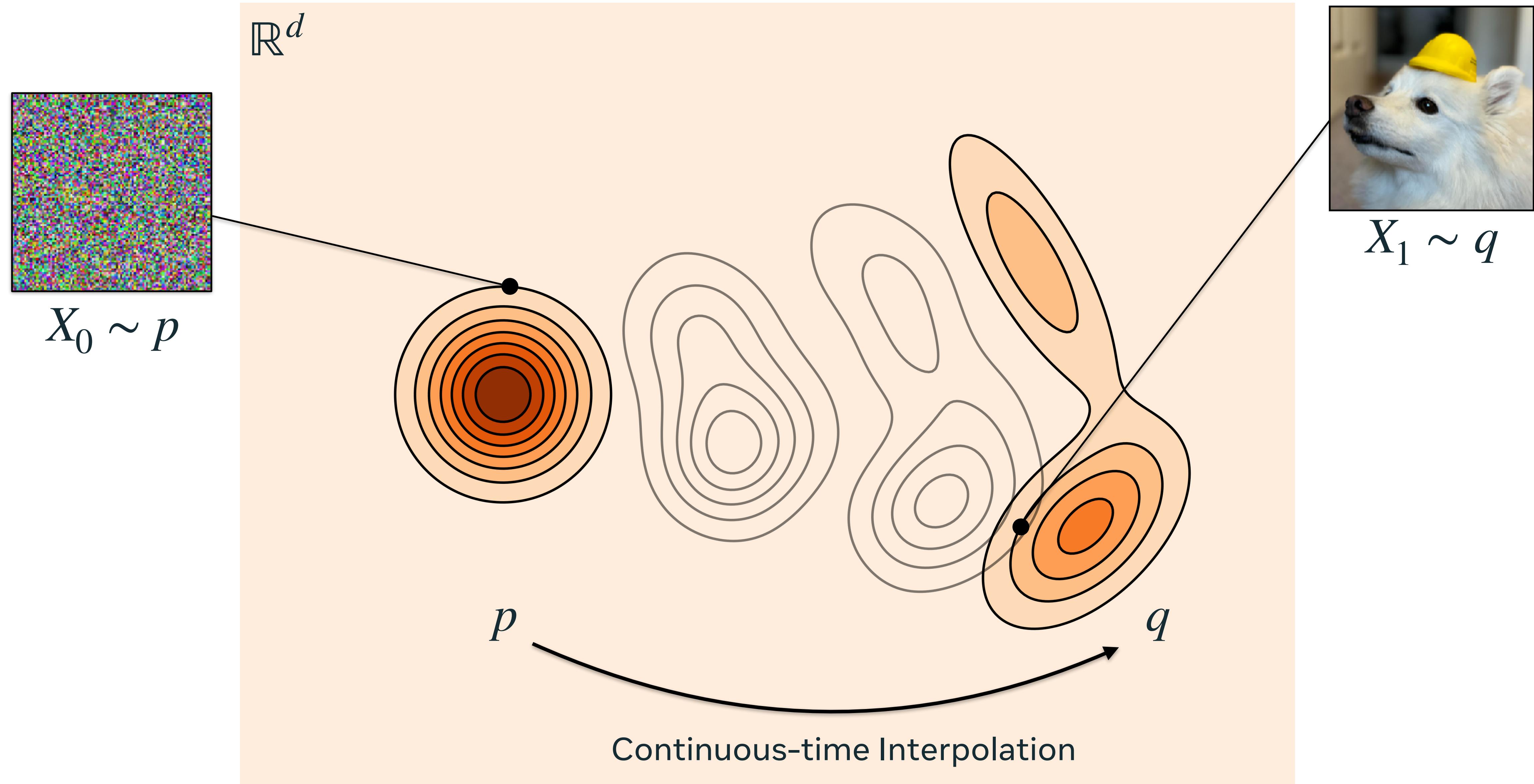
\mathbb{R}^d



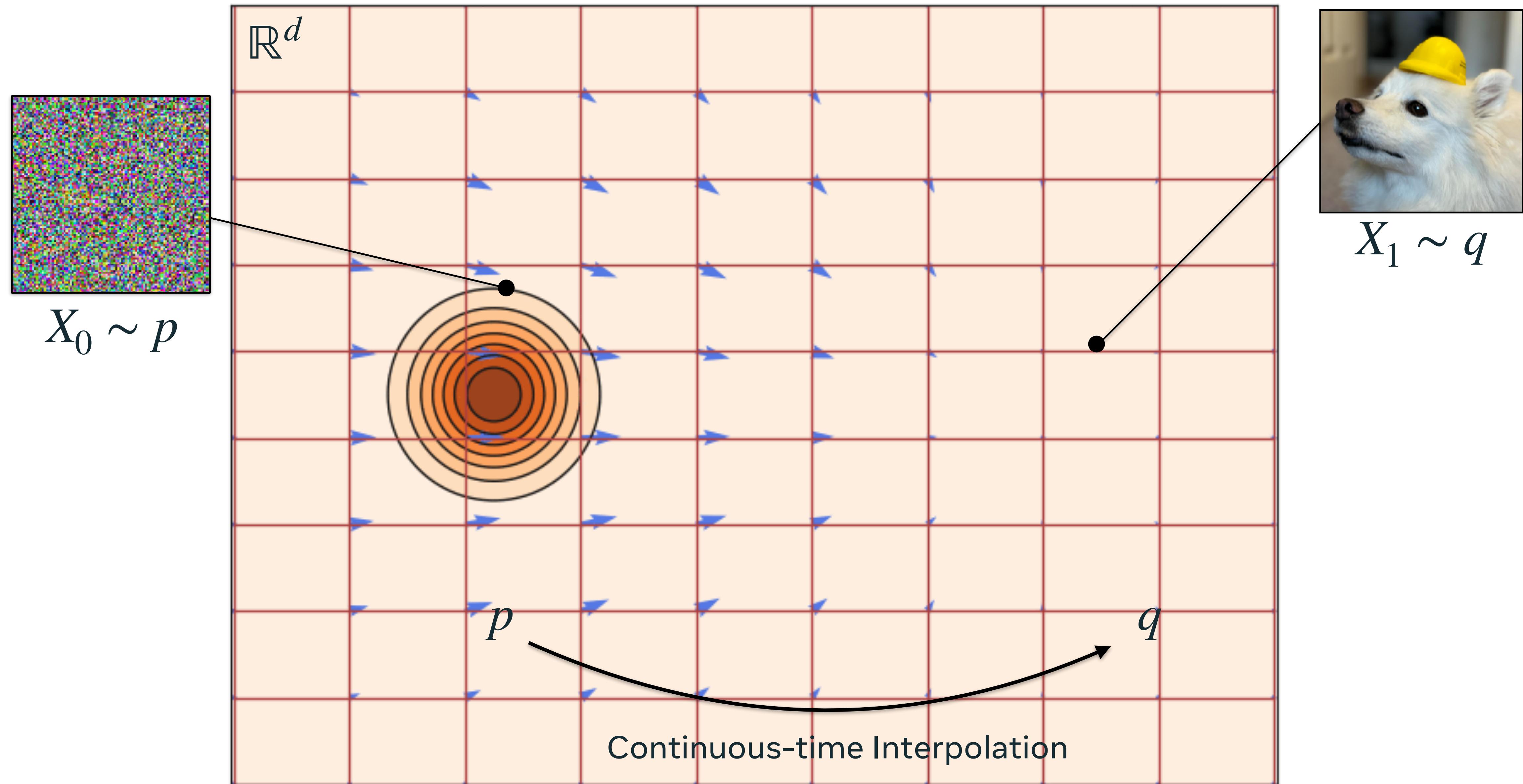
The Generative Modeling problem



The Generative Modeling problem



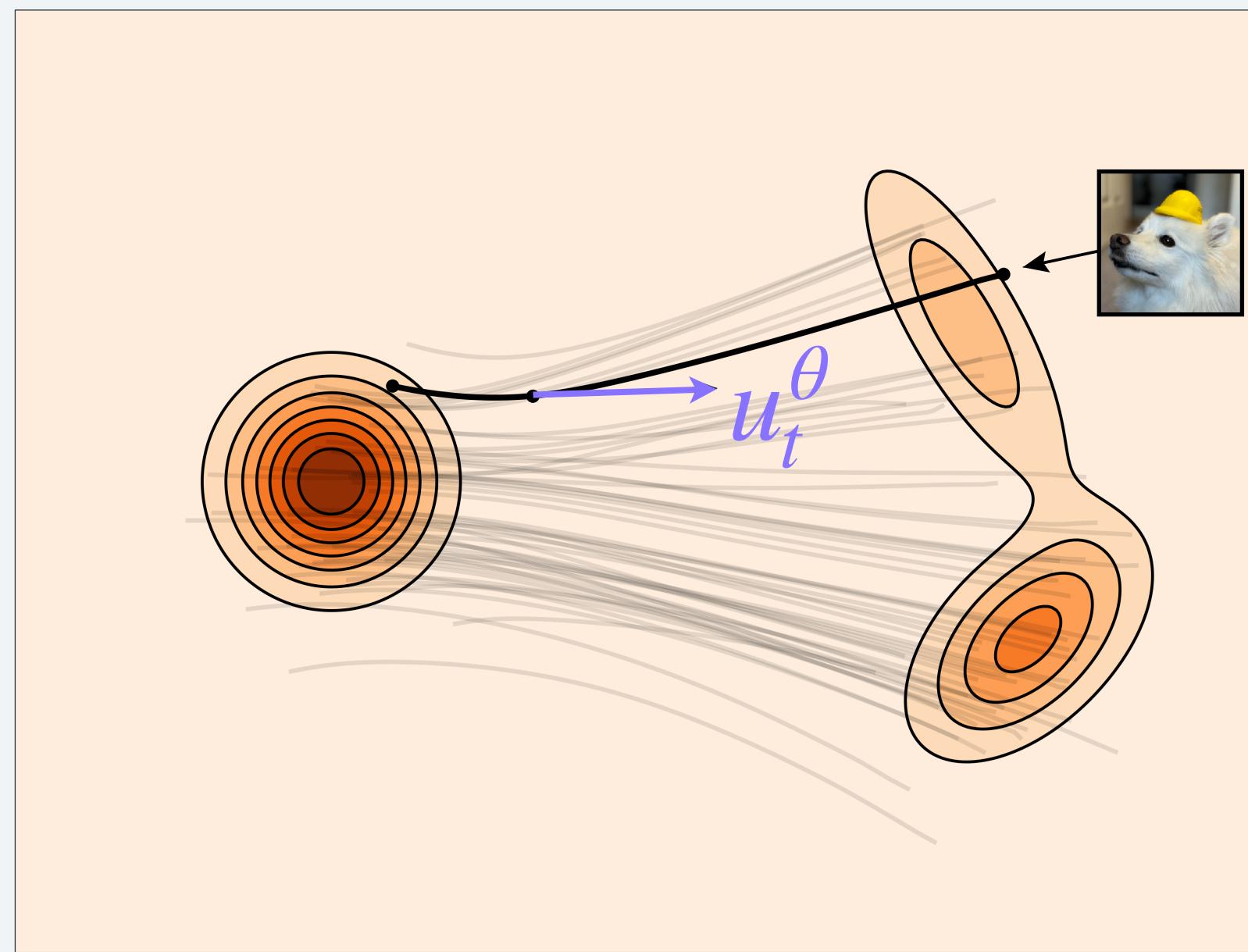
The Generative Modeling problem



A family of continuous-time generative models

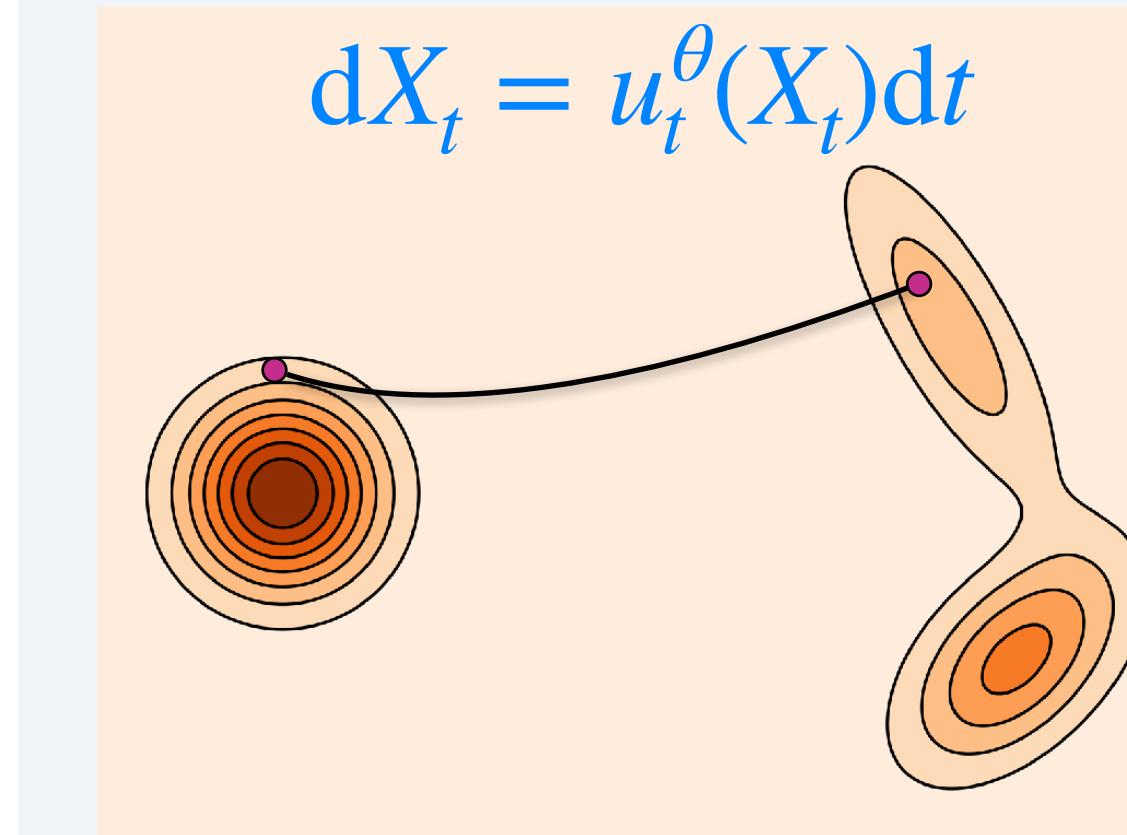
Parameterization

A **vector field** u_t^θ that points towards the data

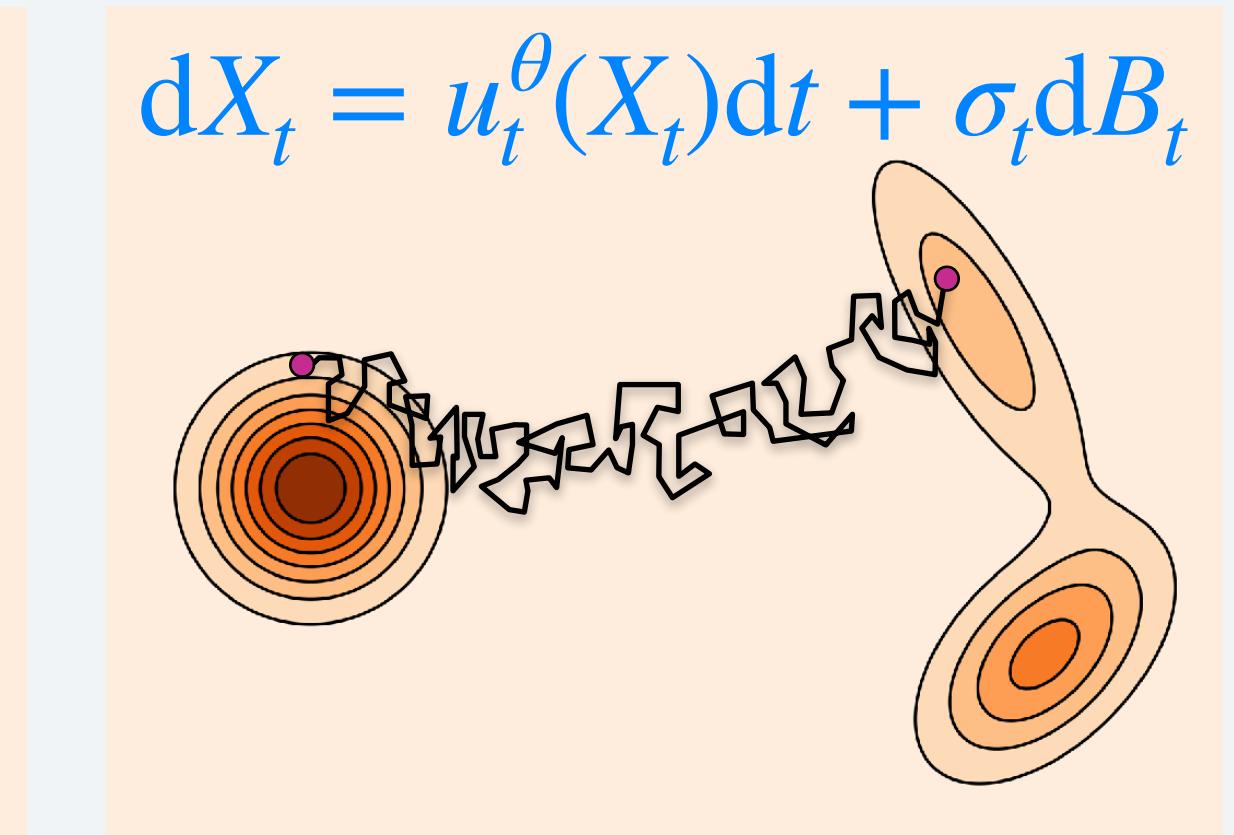


Sampling

A **diffusion process** X_t with (optional) diffusion coefficient σ_t



Ordinary Differential Equation



Stochastic Differential Equation

Data-driven vs. reward-driven learning problems

Data-driven

- fit to data
- simple & scalable

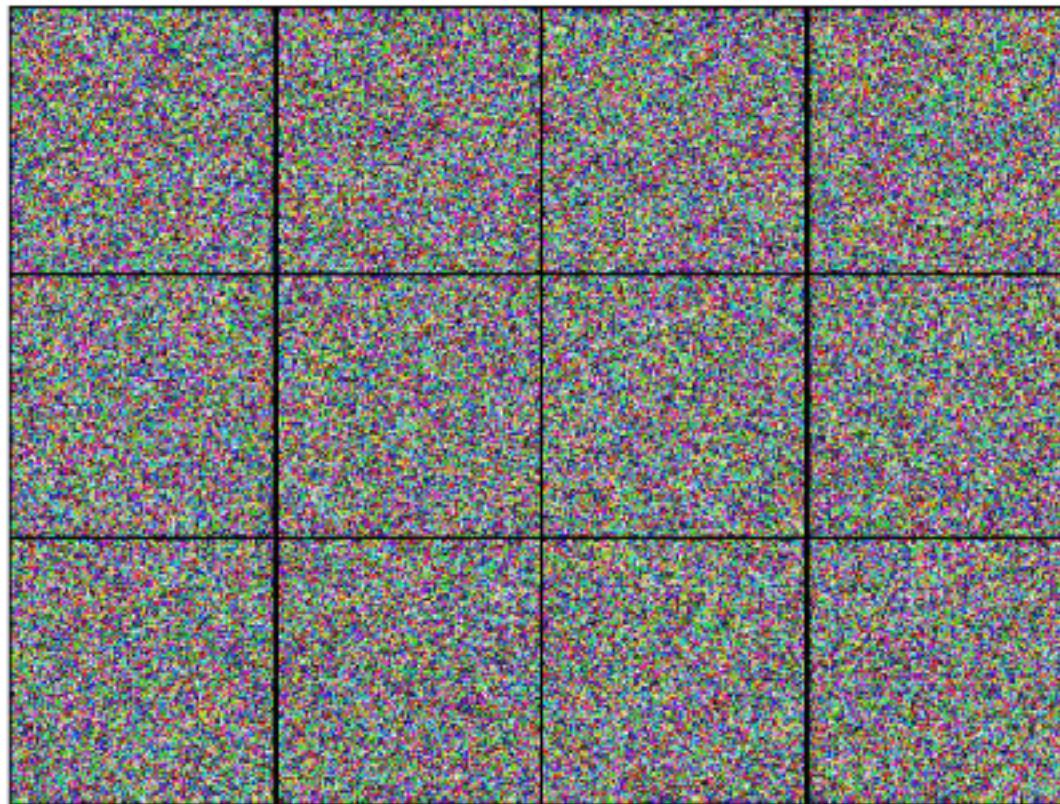


Image Generation



Meta MovieGen

Data-driven vs. reward-driven learning problems

Data-driven

- fit to data
- simple & scalable

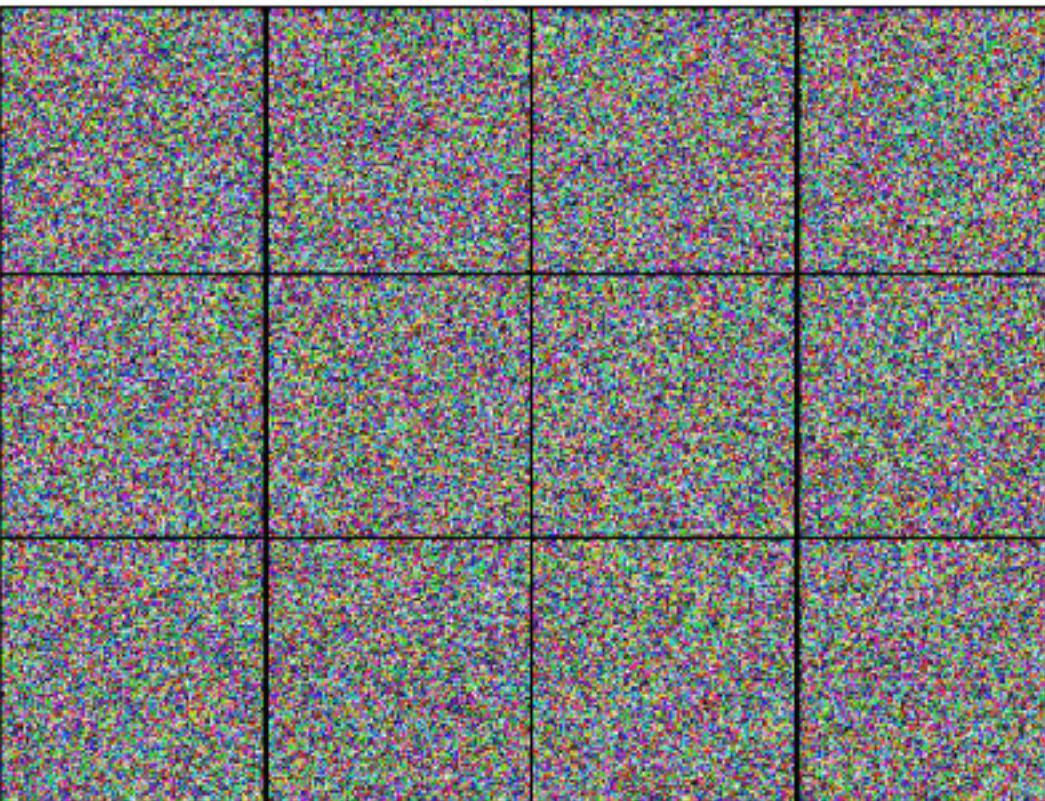


Image Generation



Meta MovieGen

Reward-driven

- maximize reward
- no data available



Reward Fine-tuning



Low Energy Generation

I. How to formulate the problem?

II. How to solve the problem?

III. How to scale the method?

I. How to formulate the problem?

Stochastic Optimal Control formulations
for reward-driven generative modeling

Reward-driven generative modeling

Basic setup

Sampling from unnormalized distribution

$$p^*(x) \propto \exp\{-E(x)\} = \exp\{r(x)\}$$

(differentiable) energy model

or

(differentiable) reward model

More generally,

Sampling from tilted distribution

$$p^*(x) \propto p^{\text{base}}(x) \exp\{r(x)\}$$

(sample-able) base generative model

(differentiable) reward model

SDEs as generative models

Target distribution

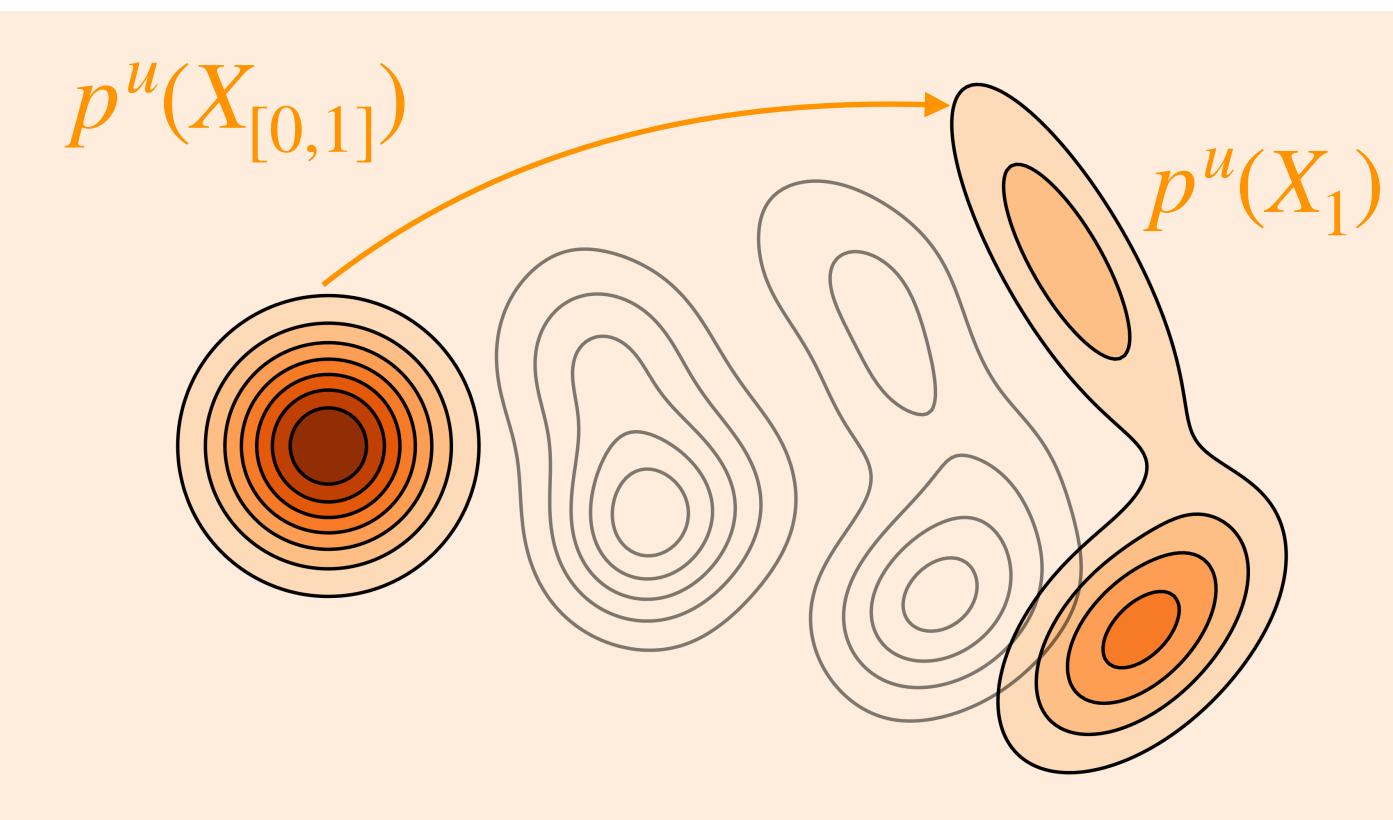
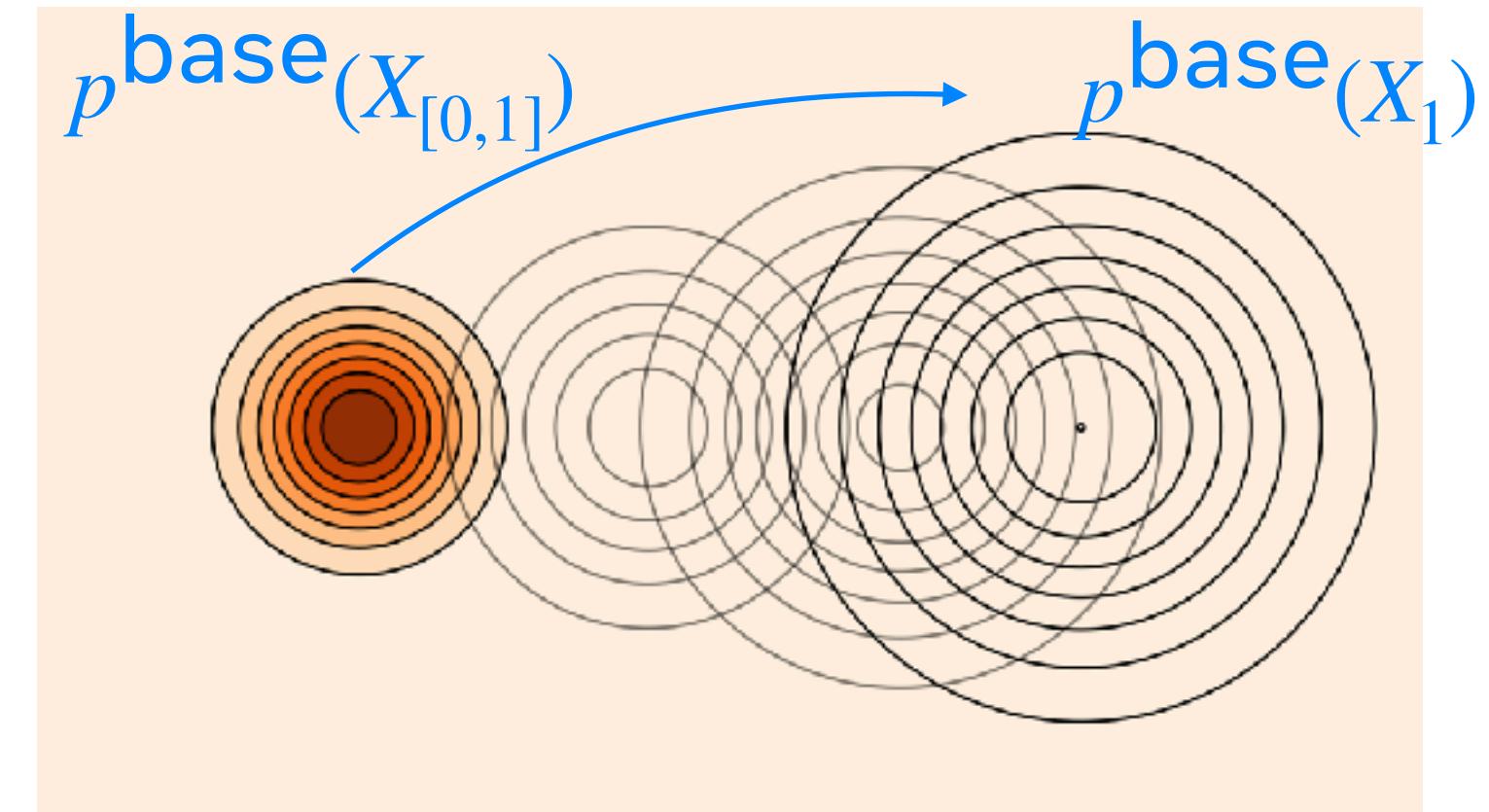
$$p^*(x) \propto p^{\text{base}}(x) \exp\{r(x)\}$$

Base generative process

$$dX_t = b_t(X_t)dt + \sigma_t dB_t \quad X_0 \sim p$$

Controlled generative process

$$dX_t = [b_t(X_t) + \sigma_t u_t^\theta(X_t)]dt + \sigma_t dB_t$$



KL divergence and path measures

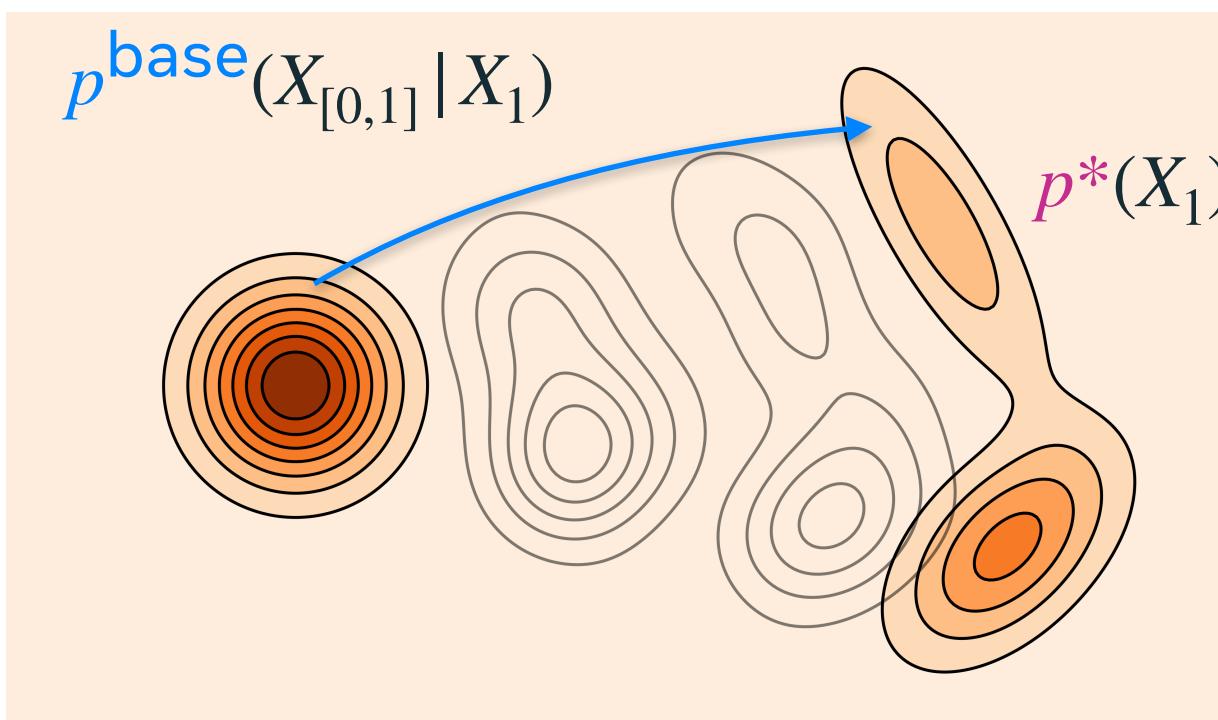
Target distribution

$$p^*(x) \propto p^{\text{base}}(x) \exp\{r(x)\}$$



Extend to stochastic process

$$p^*(X_{[0,1]}) \triangleq p^{\text{base}}(X_{[0,1]} | X_1) p^*(X_1)$$



Base generative process

$$dX_t = b_t(X_t)dt + \sigma_t dB_t \quad X_0 \sim p$$

Controlled generative process

$$dX_t = [b_t(X_t) + \sigma_t u_t^\theta(X_t)]dt + \sigma_t dB_t$$

KL divergence over stochastic process

$$\begin{aligned} & D_{\text{KL}}(p^u(X_1) \| p^*(X_1)) \\ & \leq \boxed{D_{\text{KL}}(p^u(X_{[0,1]}) \| p^*(X_{[0,1]}))} \end{aligned}$$

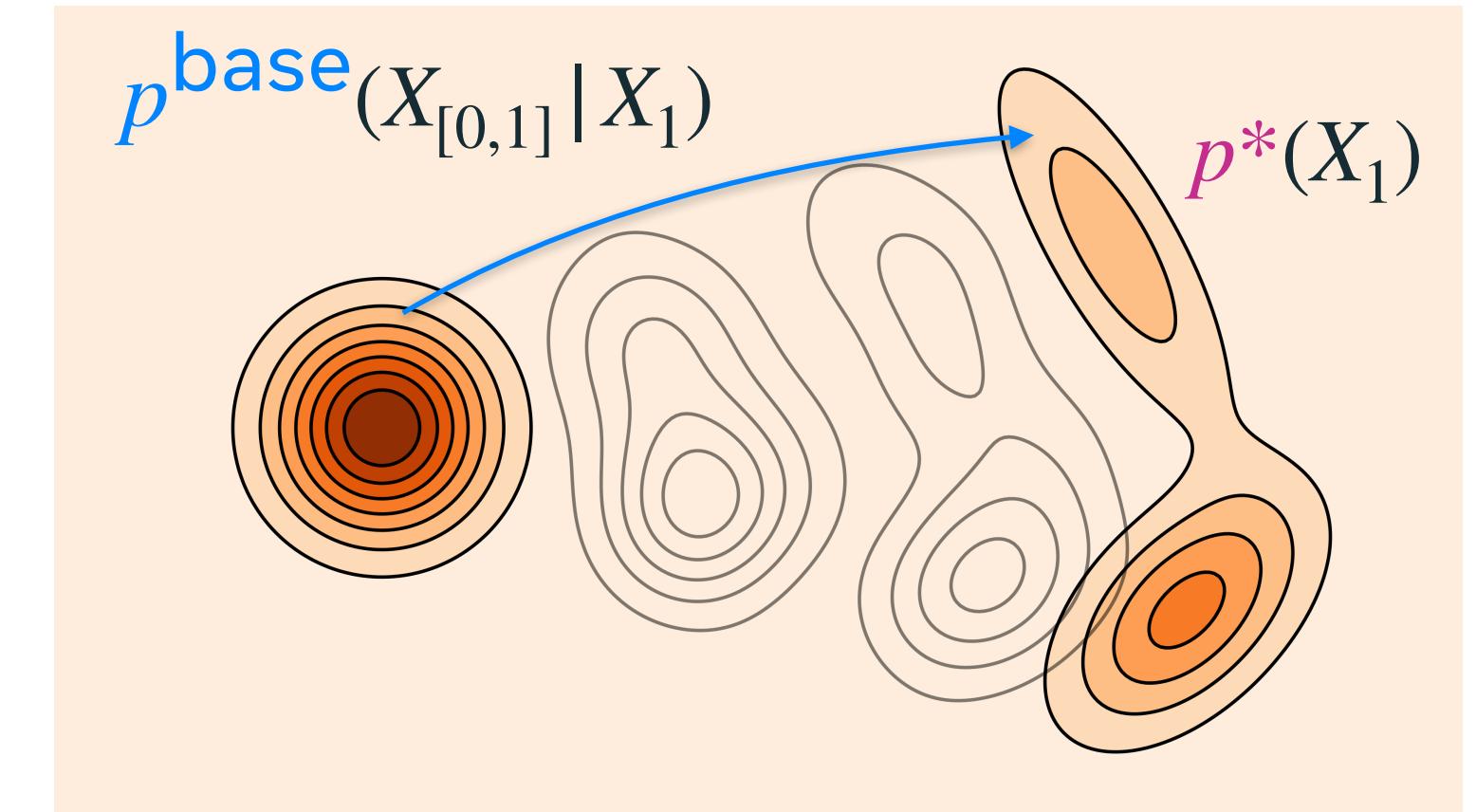
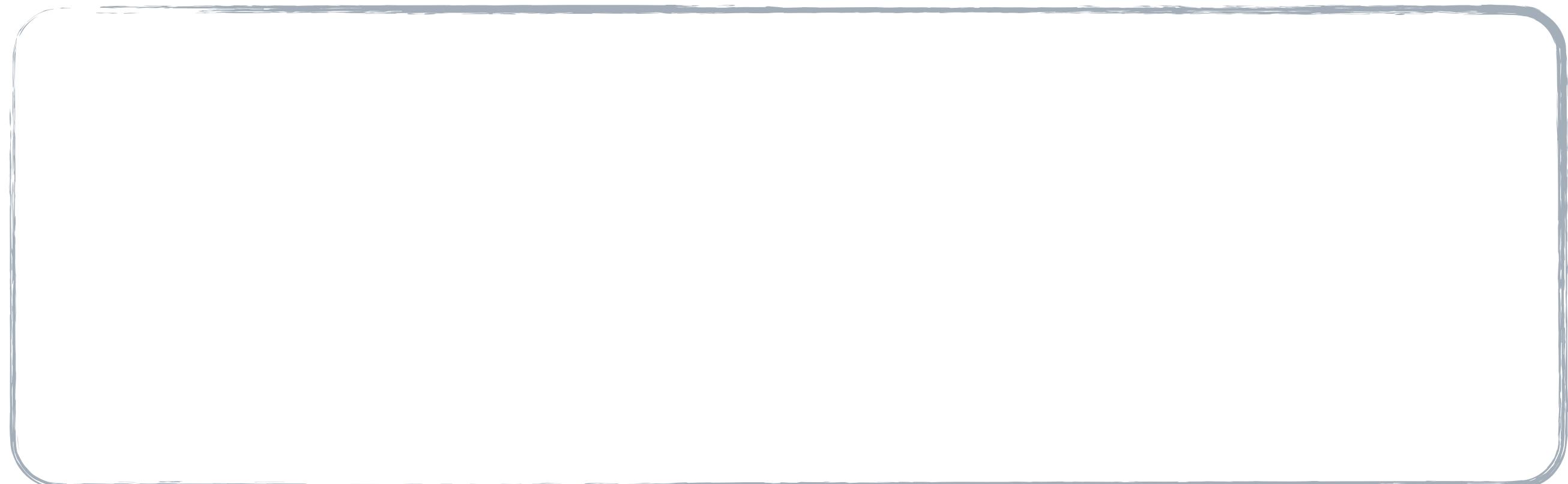
KL divergence and path measures

Target distribution

$$p^*(x) \propto p^{\text{base}}(x) \exp\{r(x)\}$$

KL objective

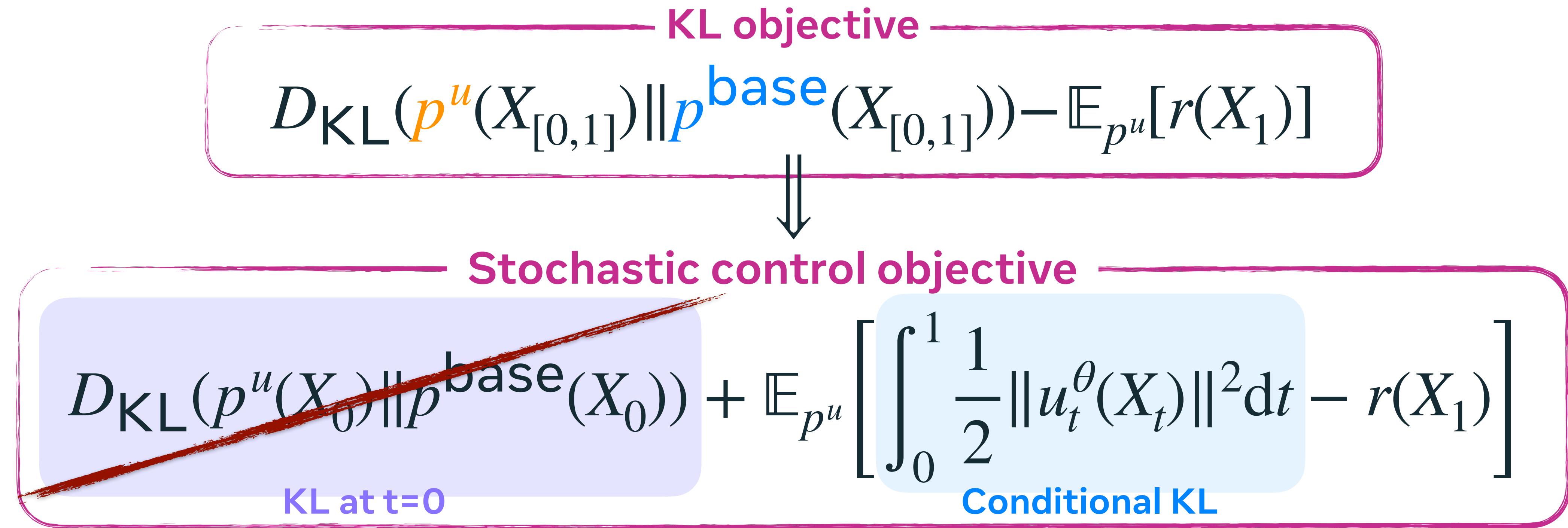
$$D_{\text{KL}}(p^u(X_{[0,1]}) \| p^*(X_{[0,1]}))$$



KL objective

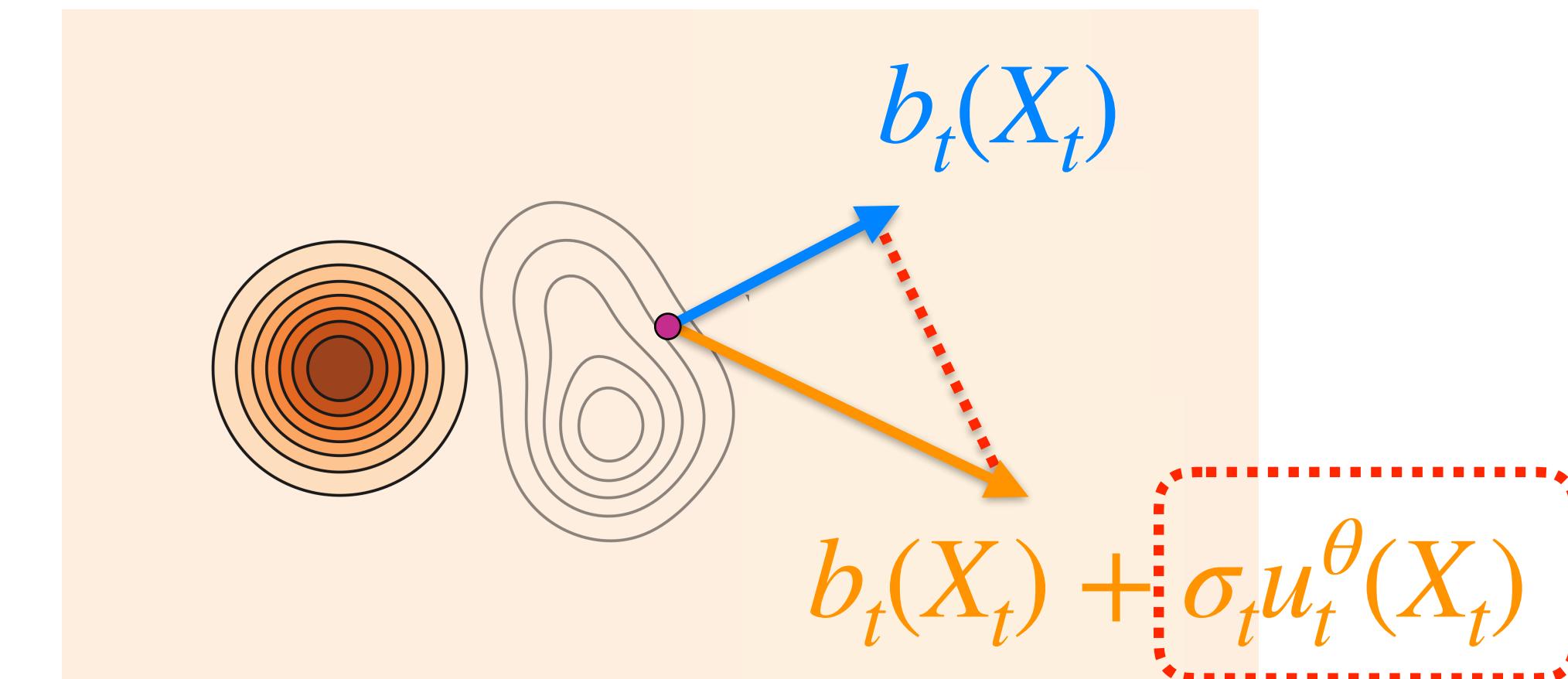
$$D_{\text{KL}}(p^u(X_{[0,1]}) \| p^{\text{base}}(X_{[0,1]})) - \mathbb{E}_{p^u}[r(X_1)]$$

Memoryless base processes



Don't need to optimize $p^u(X_0)$ if the base process is “**memoryless**”:

$$p^{\text{base}}(X_0, X_1) = p^{\text{base}}(X_0)p^{\text{base}}(X_1)$$



Summary of the SOC formulation

Target distribution

$$p^*(x) \propto p^{\text{base}}(x) \exp\{r(x)\}$$

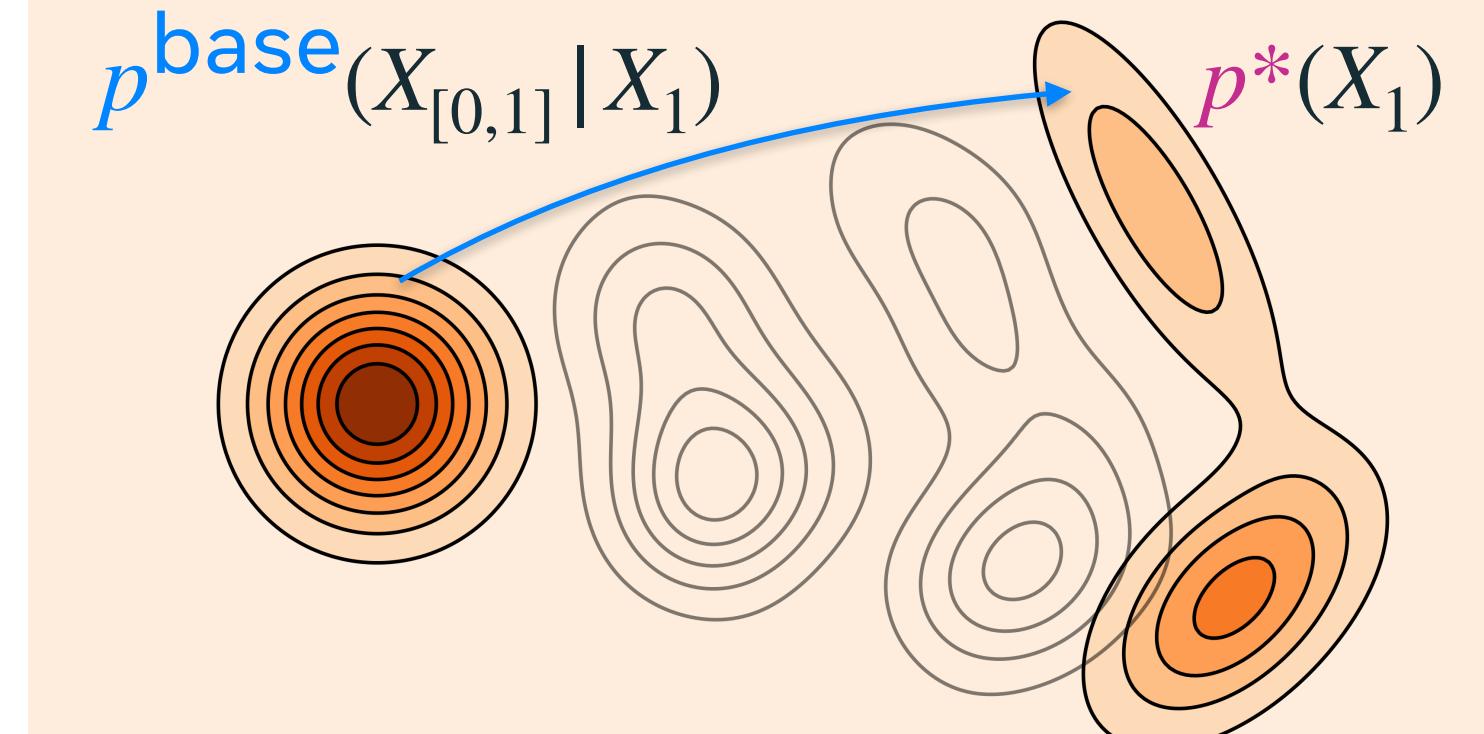
Base generative process

$$dX_t = b_t(X_t)dt + \sigma_t dB_t \quad X_0 \sim p$$

Controlled generative process

$$dX_t = [b_t(X_t) + \sigma_t u_t^\theta(X_t)]dt + \sigma_t dB_t$$

Minimize KL to



Summary of the SOC formulation

Target distribution

$$p^*(x) \propto p^{\text{base}}(x) \exp\{r(x)\}$$

Base generative process

$$dX_t = b_t(X_t)dt + \sigma_t dB_t \quad X_0 \sim p$$

Controlled generative process

$$dX_t = [b_t(X_t) + \sigma_t u_t^\theta(X_t)]dt + \sigma_t dB_t$$

If the base process is “memoryless”:

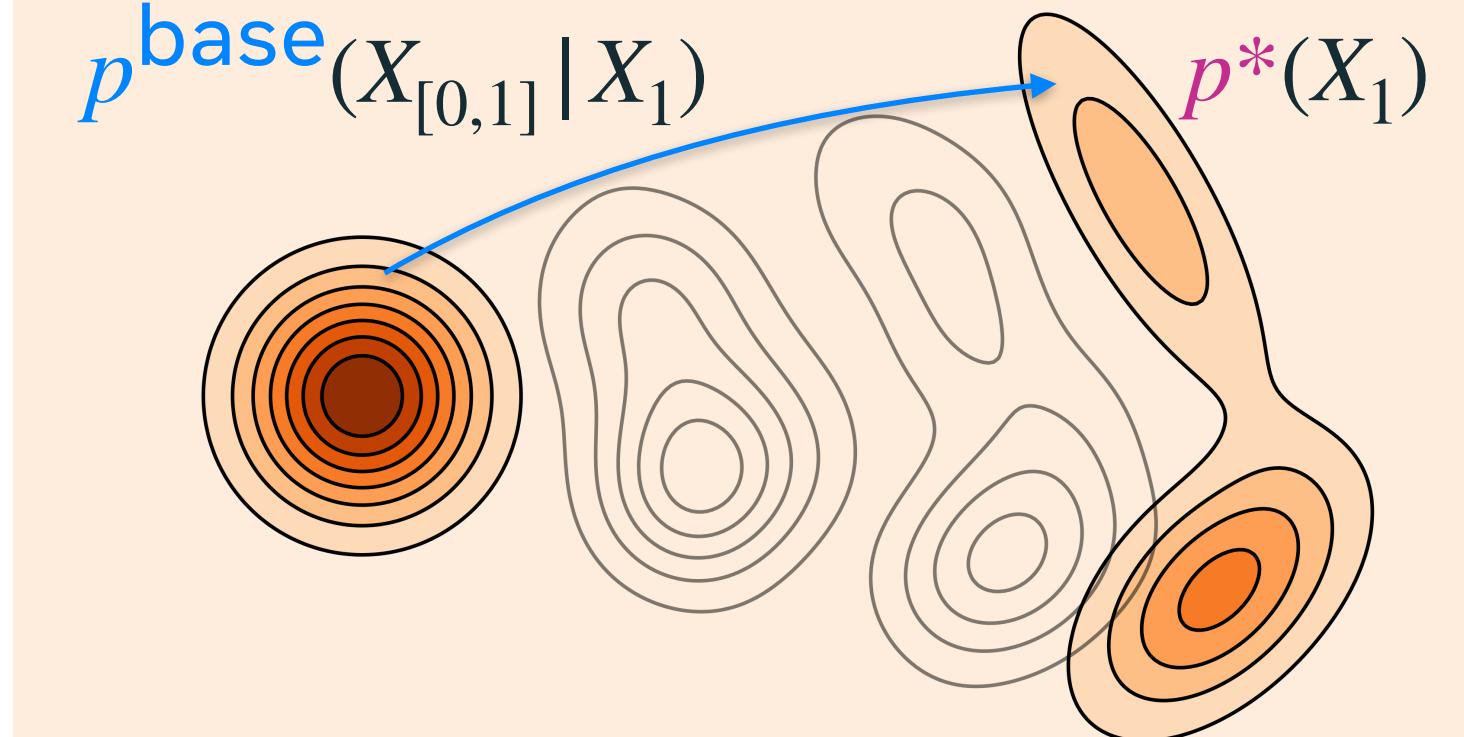
$$p^{\text{base}}(X_0, X_1) = p^{\text{base}}(X_0)p^{\text{base}}(X_1)$$

Minimizing KL is equivalent to optimizing:

Stochastic control objective

$$\mathbb{E}_{p^u} \left[\int_0^1 \frac{1}{2} \|u_t^\theta(X_t)\|^2 dt - r(X_1) \right]$$

Minimize KL to



A memoryless noise schedule for Flow Matching

If the base process is “memoryless”:

$$p^{\text{base}}(X_0, X_1) = p^{\text{base}}(X_0)p^{\text{base}}(X_1)$$

Flow Matching Base Model ?



Reward Fine-tuned Model



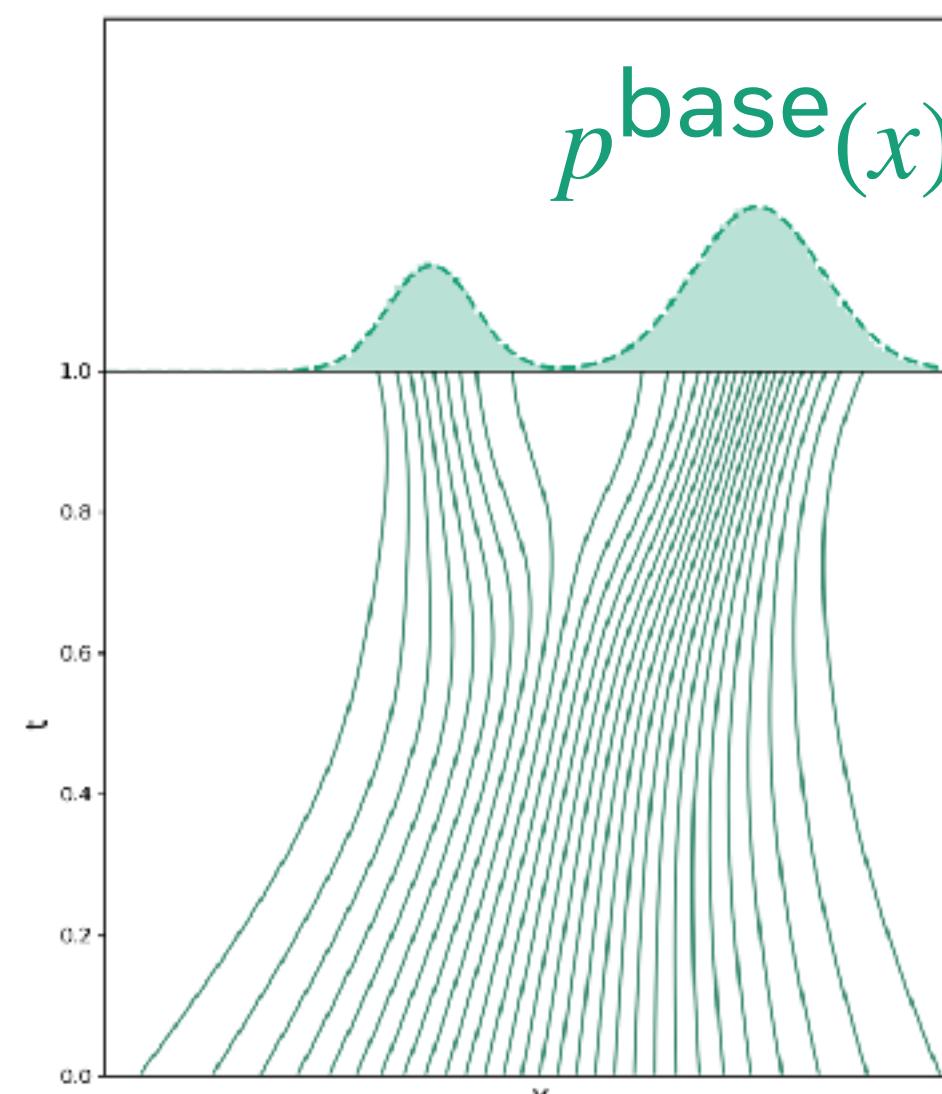
A memoryless noise schedule for Flow Matching

If the base process is “memoryless”:

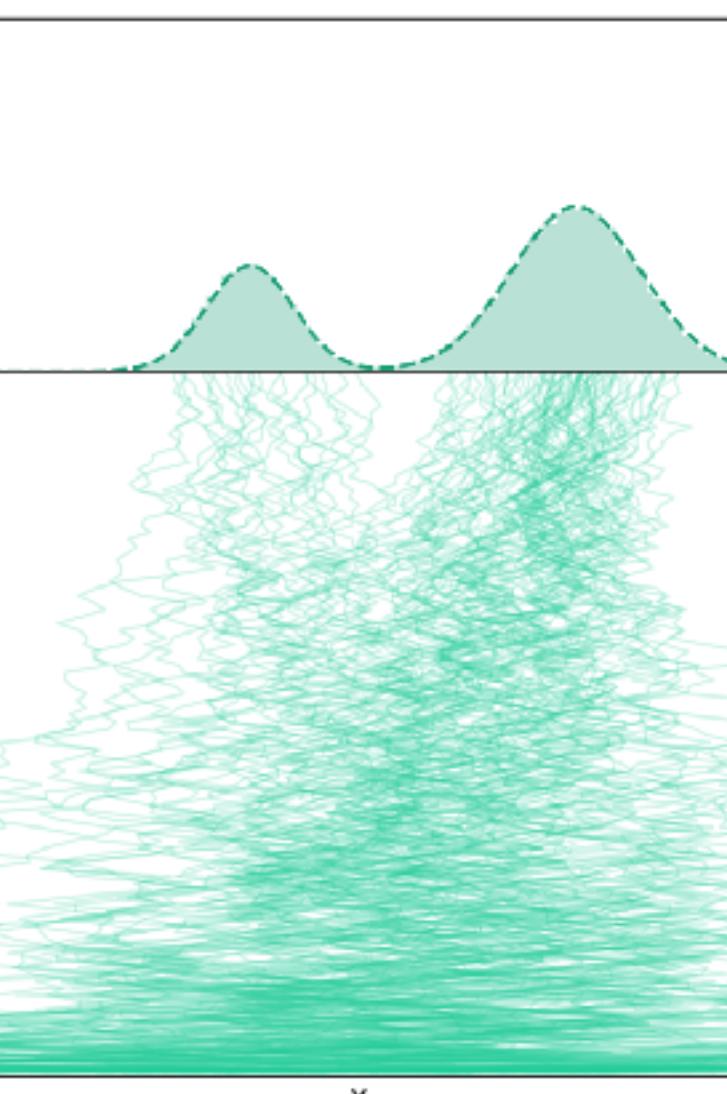
$$p^{\text{base}}(X_0, X_1) = p^{\text{base}}(X_0)p^{\text{base}}(X_1)$$

Pretrained Flow Matching model with linear scheduler $X_t = (1 - t)X_0 + tX_1$:

$$dX_t = v_t(X_t)dt$$



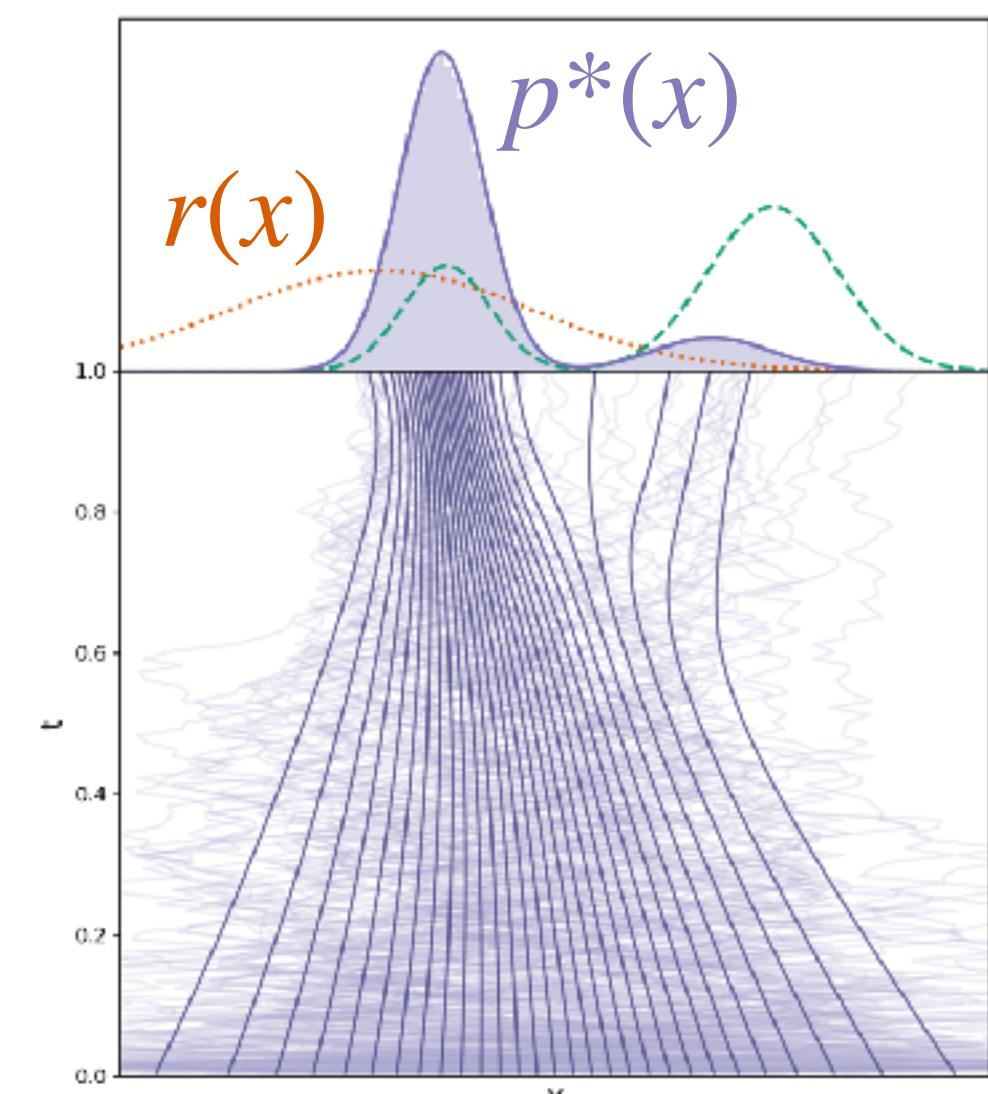
Convert to
Memoryless



The **Memoryless** Flow Matching conversion is:

$$\left\{ \begin{array}{l} b_t(X_t) = 2v_t(X_t) - \frac{1}{t}X_t \\ \sigma_t = \frac{1-t}{t} \end{array} \right.$$

Fine-tune
with SOC



A memoryless noise schedule for Flow Matching

If the base process is “memoryless”:

$$p^{\text{base}}(X_0, X_1) = p^{\text{base}}(X_0)p^{\text{base}}(X_1)$$

Pretrained Flow Matching model with

linear scheduler $X_t = (1 - t)X_0 + tX_1$:

$$dX_t = v_t(X_t)dt$$

The Memoryless Flow Matching conversion is:

$$dX_t = b_t(X_t)dt + \sigma_t dB_t \quad \begin{cases} b_t(X_t) = 2v_t(X_t) - \frac{1}{t}X_t \\ \sigma_t = \frac{1-t}{t} \end{cases}$$

[!] Related to minimizing KL to the (memoryless) process used as training signal.

Refs: DDPM (Ho et al. 2020), Scalable Interpolant Transformers (Ma et al. 2024).

II. How to solve the problem?

Adjoint Matching: a new approach for solving stochastic optimal control

The most classic approach: adjoint method

Stochastic control

$$\min_u \mathcal{L}(u) = \mathbb{E}_{p^u} \left[\int_0^1 \frac{1}{2} \|u_t^\theta(X_t)\|^2 dt - r(X_1) \right]$$

s.t. $dX_t = [b_t(X_t) + \sigma_t u_t^\theta(X_t)]dt + \sigma_t dB_t, \quad X_0 \sim p$

The most classic approach: adjoint method

Stochastic control

$$\begin{aligned} \min_u \mathcal{L}(u) = & \mathbb{E}_{p^u} \left[\int_0^1 \frac{1}{2} \|u_t^\theta(X_t)\|^2 dt - r(X_1) \right] \\ \text{s.t. } dX_t = & [b_t(X_t) + \sigma_t u_t^\theta(X_t)] dt + \sigma_t dB_t, \quad X_0 \sim p \end{aligned}$$

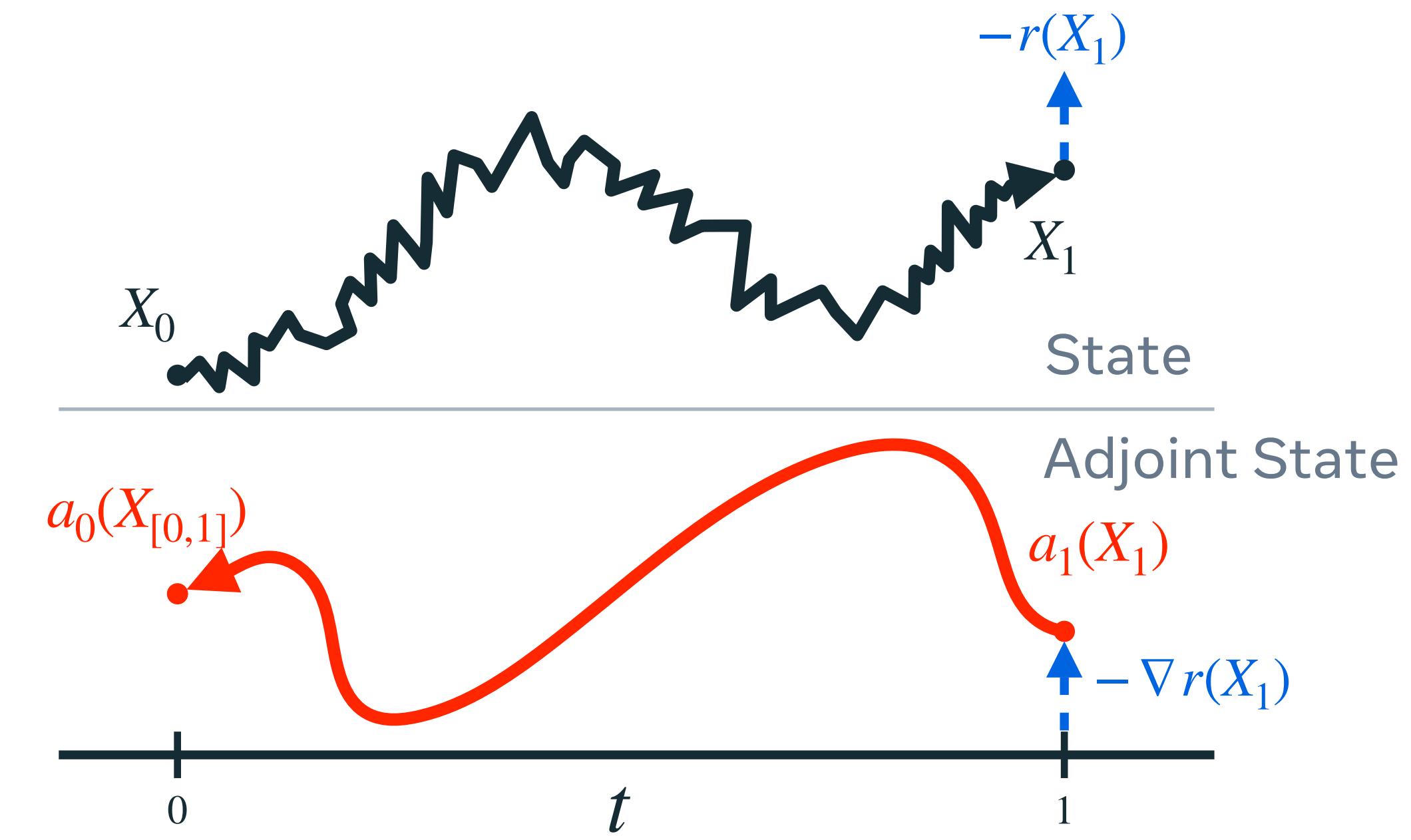
Adjoint state

(a.k.a. the gradient w.r.t. state)

$$a_t(X_{[0,1]}) := \nabla_{X_t} \left[\int_t^1 \frac{1}{2} \|u_t^\theta(X_t)\|^2 dt - r(X_1) \right]$$

Discretization

$$\begin{aligned} X_{t_{i+1}} &= X_{t_i} + h [b_{t_i}(X_{t_i}) + \sigma_{t_i} u_{t_i}^\theta(X_{t_i})] + \sqrt{h} \sigma_t \varepsilon \\ a_{t_i} &= a_{t_{i+1}}^\top \frac{\partial X_{t_{i+1}}}{\partial X_{t_i}} = a_{t_{i+1}}^\top + h a_{t_{i+1}}^\top \nabla_{X_{t_i}} [b_{t_i}(X_{t_i}) + \sigma_{t_i} u_{t_i}^\theta(X_{t_i})] \end{aligned}$$



The most classic approach: adjoint method

Stochastic control

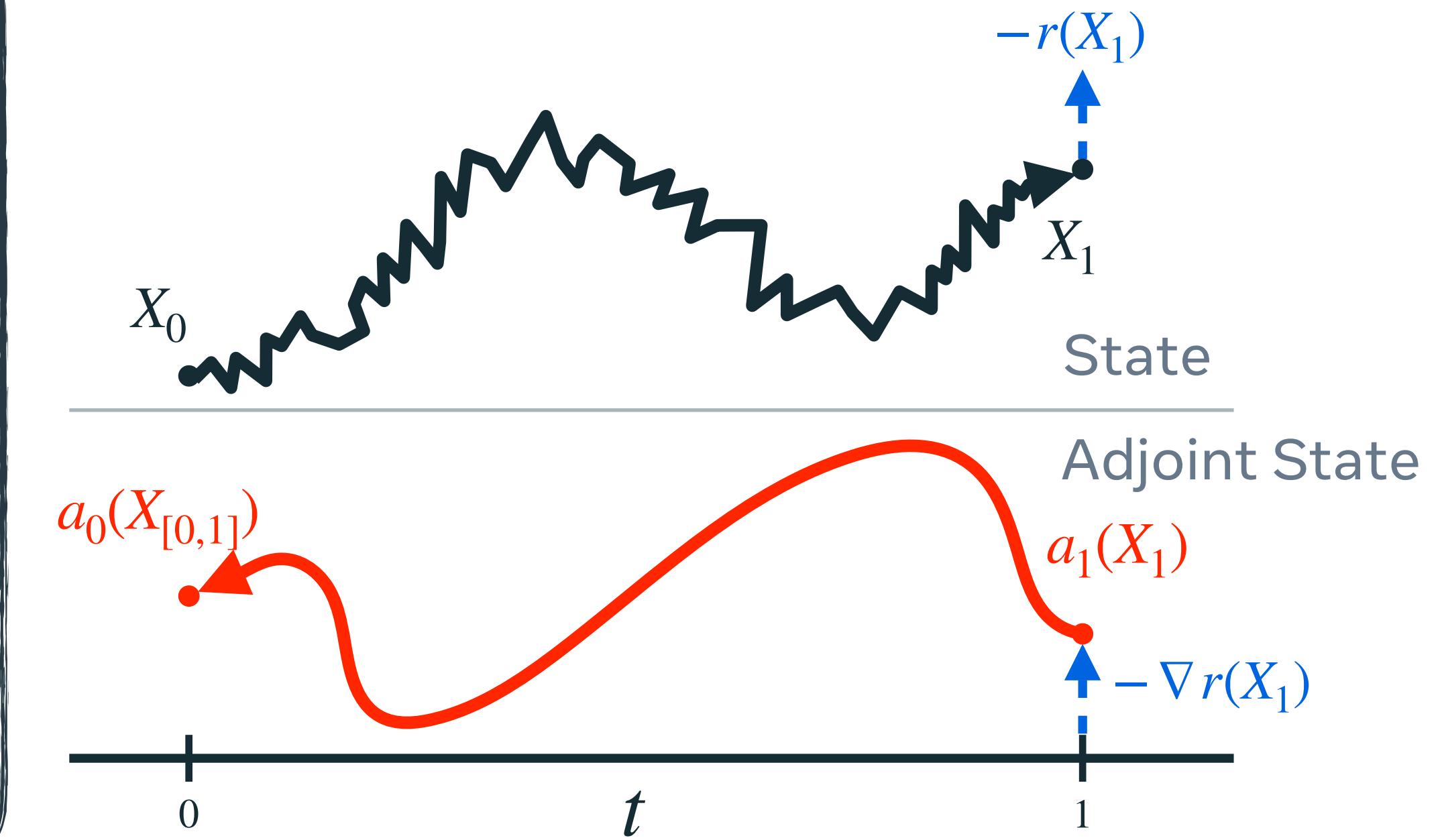
$$\begin{aligned} \min_u \mathcal{L}(u) = & \mathbb{E}_{p^u} \left[\int_0^1 \frac{1}{2} \|u_t^\theta(X_t)\|^2 dt - r(X_1) \right] \\ \text{s.t. } dX_t = & [b_t(X_t) + \sigma_t u_t^\theta(X_t)] dt + \sigma_t dB_t, \quad X_0 \sim p \end{aligned}$$

Adjoint state

(a.k.a. the gradient w.r.t. state)

$$\begin{aligned} a_t(X_{[0,1]}) &:= \nabla_{X_t} \left[\int_t^1 \frac{1}{2} \|u_t^\theta(X_t)\|^2 dt - r(X_1) \right] \\ \frac{d}{dt} a_t(X_{[0,1]}) &= -a_t(X_{[0,1]})^\top \nabla_{X_t} (b_t(X_t) + \sigma_t u_t^\theta(X_t)) \end{aligned}$$

$$a_1(X_{[0,1]}) = -\nabla r(X_1)$$



The most classic approach: adjoint method

Stochastic control

$$\begin{aligned} \min_u \mathcal{L}(u) = & \mathbb{E}_{p^u} \left[\int_0^1 \frac{1}{2} \|u_t^\theta(X_t)\|^2 dt - r(X_1) \right] \\ \text{s.t. } dX_t = & [b_t(X_t) + \sigma_t u_t^\theta(X_t)] dt + \sigma_t dB_t, \quad X_0 \sim p \end{aligned}$$

Adjoint state

(a.k.a. the gradient w.r.t. state)

$$a_t(X_{[0,1]}) := \nabla_{X_t} \left[\int_t^1 \frac{1}{2} \|u_t^\theta(X_t)\|^2 dt - r(X_1) \right]$$

$$\frac{d}{dt} a_t(X_{[0,1]}) = -a_t(X_{[0,1]})^\top \nabla_{X_t} (b_t(X_t) + \sigma_t u_t^\theta(X_t)) - \nabla_{X_t} \left(\frac{1}{2} \|u_t^\theta(X_t)\|^2 \right)$$

$$a_1(X_{[0,1]}) = -\nabla r(X_1)$$

$$\frac{d\mathcal{L}}{d\theta} = \int_0^1 \frac{\partial u_t^\theta(X_t)}{\partial \theta}^\top \sigma_t a_t(X_{[0,1]}) + \frac{\partial}{\partial \theta} \frac{1}{2} \|u_t^\theta(X_t)\|^2 dt$$

Aggregate ↴

An alternative perspective: fixed point iteration

Cost functional

(a.k.a. expected future cost)

$$J(u; t, x) := \mathbb{E}_{p^u} \left[\int_t^1 \frac{1}{2} \|u_t^\theta(X_t)\|^2 dt - r(X_1) \mid X_t = x \right]$$

Optimality criterion

(a.k.a. steepest descent)

$$u_t^*(x) = -\sigma_t \nabla_x J(u^*; t, x)$$

Relation to adjoint state

$$\nabla_x J(u^*; t, x) = \mathbb{E}_{p^u} [a_t(X_{[0,1]}) \mid X_t = x]$$

“Basic” Adjoint Matching

$$\min_u \mathcal{L}(u) = \int_0^1 \|u_t^\theta(X_t) + \sigma_t \nabla_x J(u^*; t, X_t)\|^2 dt$$

$$\begin{aligned} X_{[0,1]} &\sim p^{\bar{u}} \\ \bar{u} &= \text{stopgrad}(u) \end{aligned}$$

An alternative perspective: fixed point iteration

Cost functional

(a.k.a. expected future cost)

$$J(u; t, x) := \mathbb{E}_{p^u} \left[\int_t^1 \frac{1}{2} \|u_t^\theta(X_t)\|^2 dt - r(X_1) \mid X_t = x \right]$$

Optimality criterion

(a.k.a. steepest descent)

$$u_t^*(x) = -\sigma_t \nabla_x J(u^*; t, x)$$

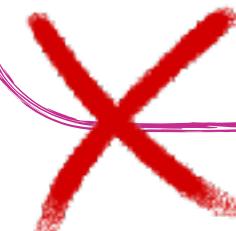
Relation to adjoint state

$$\nabla_x J(u^*; t, x) = \mathbb{E}_{p^u} [a_t(X_{[0,1]}) \mid X_t = x]$$

“Basic” Adjoint Matching

$$\min_u \mathcal{L}(u) = \int_0^1 \|u_t^\theta(X_t) + \sigma_t a_t(X_{[0,1]})\|^2 dt$$

$$X_{[0,1]} \sim p^{\bar{u}} \\ \bar{u} = \text{stopgrad}(u)$$



Exactly equivalent to adjoint method: $\frac{d\mathcal{L}}{d\theta} = \int_0^1 \frac{\partial u_t^\theta(X_t)}{\partial \theta}^\top \sigma_t a_t(X_{[0,1]}) + \frac{\partial}{\partial \theta} \frac{1}{2} \|u_t^\theta(X_t)\|^2 dt$

Adjoint Matching and the *lean* adjoint state

Adjoint state

$$\frac{d}{dt} \mathbf{a}_t(\mathbf{X}_{[0,1]}) = -\mathbf{a}_t(\mathbf{X}_{[0,1]})^\top \nabla_{\mathbf{X}_t} (\sigma_t u_t^\theta(\mathbf{X}_t) + b_t(\mathbf{X}_t)) - \nabla_{\mathbf{X}_t} \left(\frac{1}{2} \|u_t^\theta(\mathbf{X}_t)\|^2 \right)$$

At optimum

$$u_t^*(x) = -\sigma_t \nabla_x J(u^*; t, x)$$

$$u_t^*(x) = \mathbb{E}_{p^u} [-\sigma_t \mathbf{a}_t(\mathbf{X}_{[0,1]}) | X_t = x]$$

$$\mathbb{E}_{p^u} [u_t^*(X_t) + \sigma_t \mathbf{a}_t(\mathbf{X}_{[0,1]})] = 0$$

$$\mathbb{E}_{p^u} [u_t^*(X_t)^\top \nabla_{X_t} u_t^*(X_t) + \sigma_t \mathbf{a}_t(\mathbf{X}_{[0,1]})^\top \nabla_{X_t} u_t^*(X_t)] = 0$$

Adjoint Matching and the *lean* adjoint state

Adjoint state

$$\frac{d}{dt} \tilde{a}_t(X_{[0,1]}) = -\tilde{a}_t(X_{[0,1]})^\top \nabla_{X_t} (\sigma_t u_t^\theta(X_t) + b_t(X_t)) - \nabla_{X_t} \left(\frac{1}{2} \|u_t^\theta(X_t)\|^2 \right)$$

Adjoint Matching

“Lean” adjoint state

$$\frac{d}{dt} \tilde{a}_t(X_{[0,1]}) = -\tilde{a}_t(X_{[0,1]})^\top \nabla_{X_t} b_t(X_t)$$

$$\tilde{a}_1(X_{[0,1]}) = -\nabla r(X_1)$$

$$\min_u \mathcal{L}(u) = \int_0^1 \|u_t^\theta(X_t) + \sigma_t \tilde{a}_t(X_{[0,1]})\|^2 dt \quad X_{[0,1]} \sim p^{\bar{u}}$$

$\bar{u} = \text{stopgrad}(u)$



Fixed point \iff optimal control

$$\frac{\delta \mathcal{L}(u)}{\delta u} = 0 \iff u = u^*$$

Adjoint Matching for reward fine-tuning

Target distribution

$$p^*(x) \propto p^{\text{base}}(x) \exp\{r(x)\}$$



Flow
(Pre-trained)

Flow Matching

$$dX_t = v_t(X_t)dt$$

$$X_0 \sim p$$

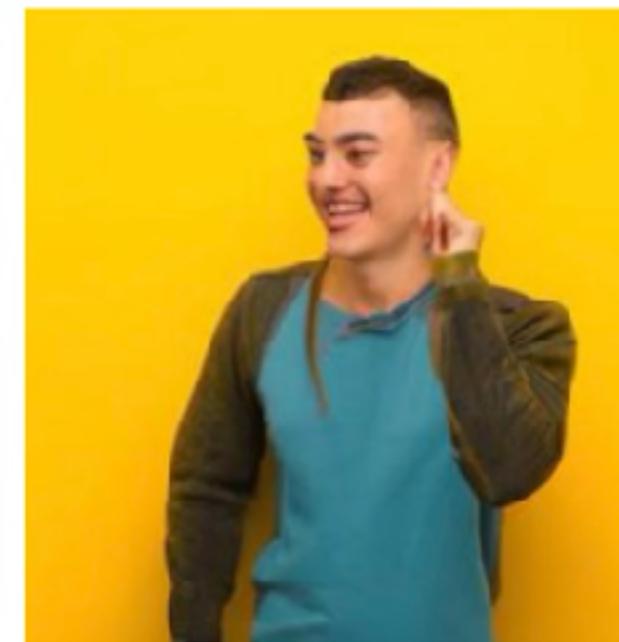
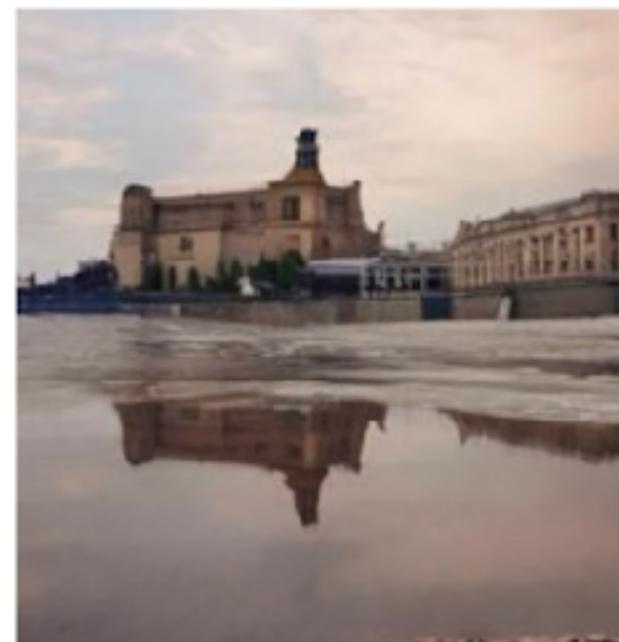
Adjoint Matching for reward fine-tuning

Target distribution

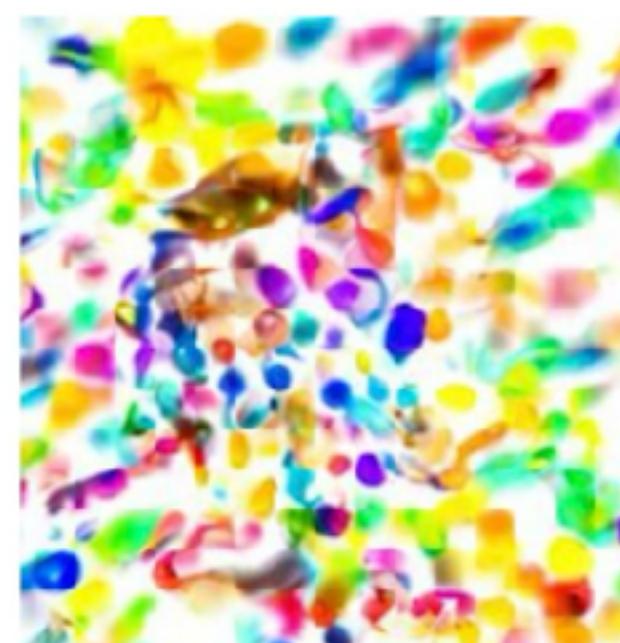
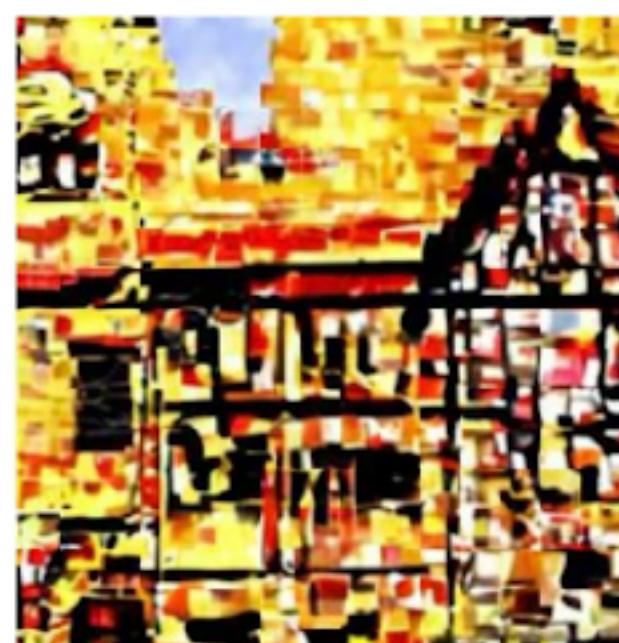
$$p^*(x) \propto p^{\text{base}}(x) \exp\{r(x)\}$$

Memoryless Flow Matching

$$dX_t = b_t(X_t)dt + \sigma_t dB_t \quad X_0 \sim p$$



Flow
(Pre-trained)



Memoryless
(Pre-trained)

Adjoint Matching for reward fine-tuning

Stochastic control

$$\begin{aligned} \min_u \mathcal{L}(u) = & \mathbb{E}_{p^u} \left[\int_0^1 \frac{1}{2} \|u_t^\theta(X_t)\|^2 dt - r(X_1) \right] \\ \text{s.t. } dX_t = & [b_t(X_t) + \sigma_t u_t^\theta(X_t)] dt + \sigma_t dB_t, \quad X_0 \sim p \end{aligned}$$



Memoryless
(Pre-trained)



Memoryless
(Fine-tuned)



Adjoint Matching for reward fine-tuning

Memoryless Flow Matching

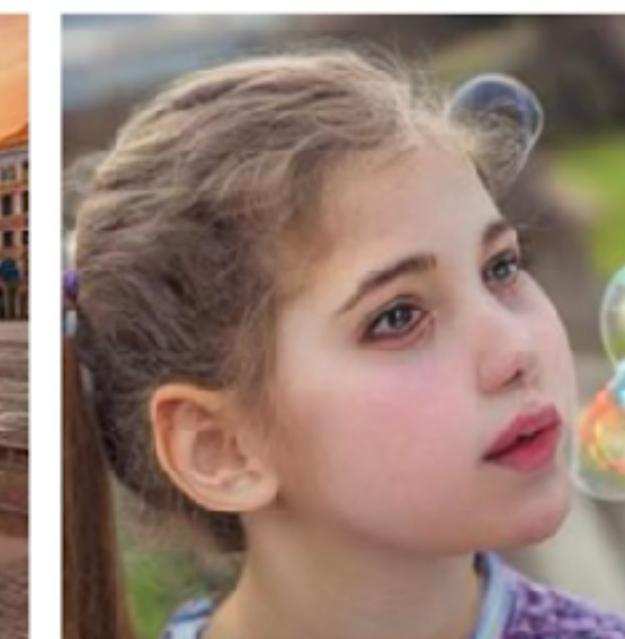
$$dX_t = b_t(X_t) + \sigma_t u_t^\theta(X_t) dt + \sigma_t dB_t$$

Fine-tuned Flow Matching

$$dX_t = v_t^\theta(X_t) dt$$



Memoryless
(Fine-tuned)



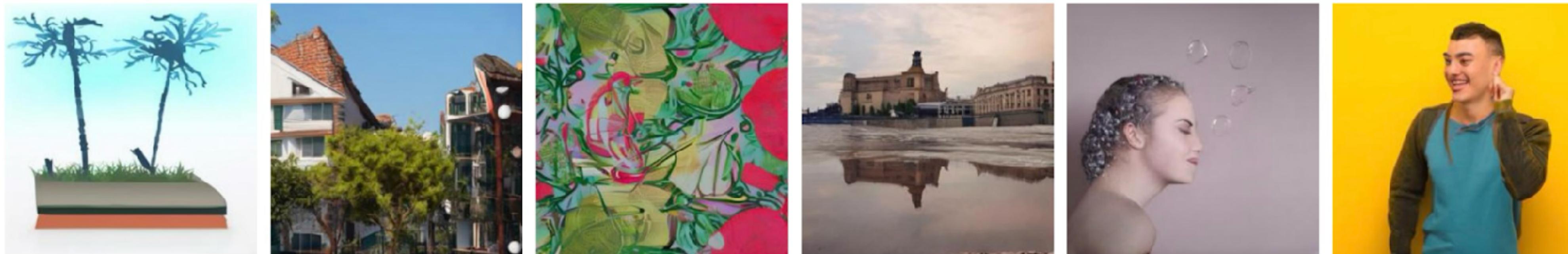
Flow
(Fine-tuned)

Adjoint Matching for reward fine-tuning

Memoryless Flow Matching

$$dX_t = b_t(X_t) + \sigma_t u_t^\theta(X_t) dt + \sigma_t dB_t \rightarrow dX_t = v_t^\theta(X_t) dt$$

Fine-tuned Flow Matching



Flow
(Pre-trained)



Flow
(Fine-tuned)

Reward fine-tuning for MovieGen Audio

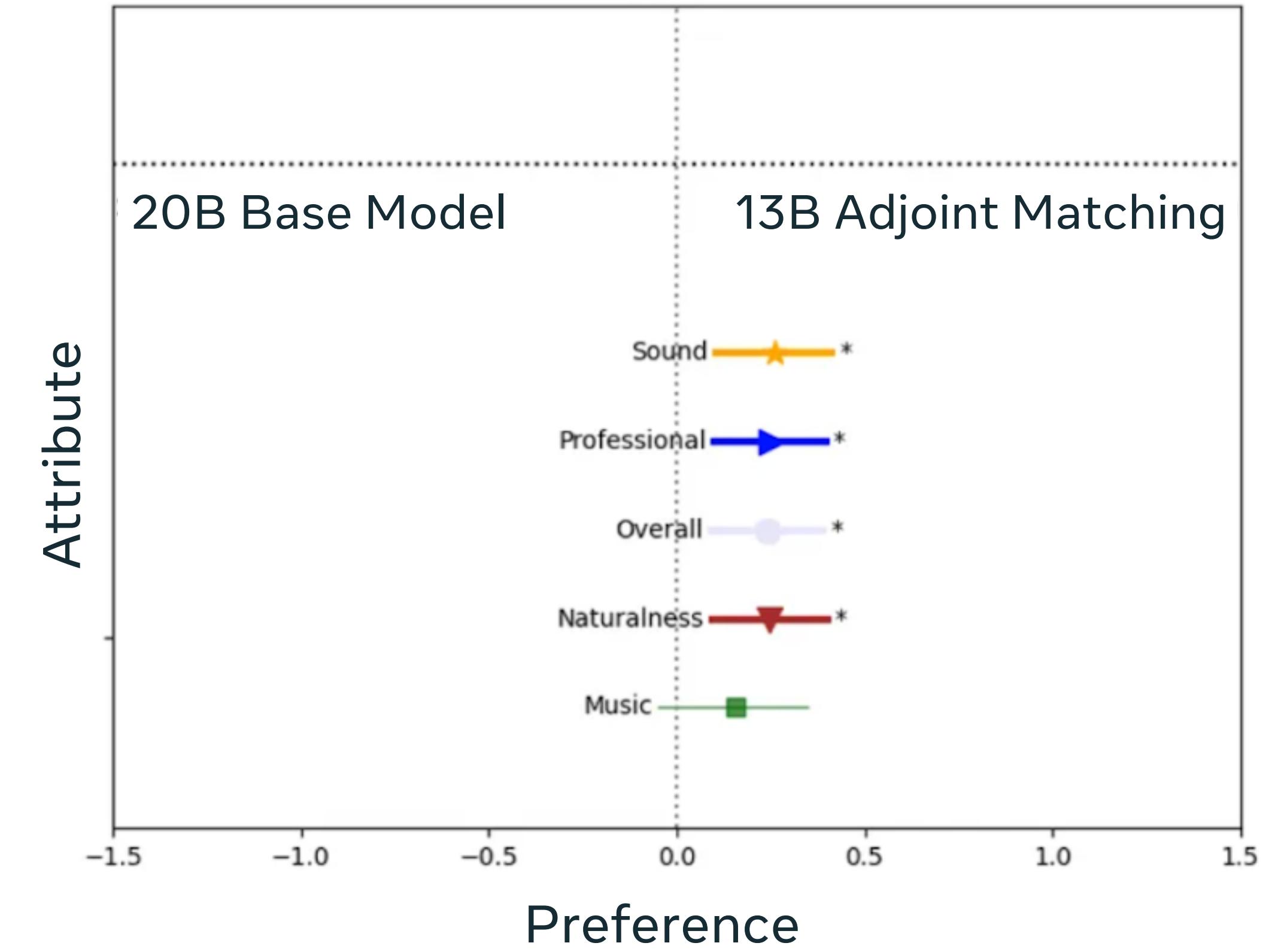
Meta MovieGen



Text & Video → Audio

Text input: “Whistling sounds, followed by a sharp explosion and loud crackling.”

Human Evaluation



(Statistically significant improvement)

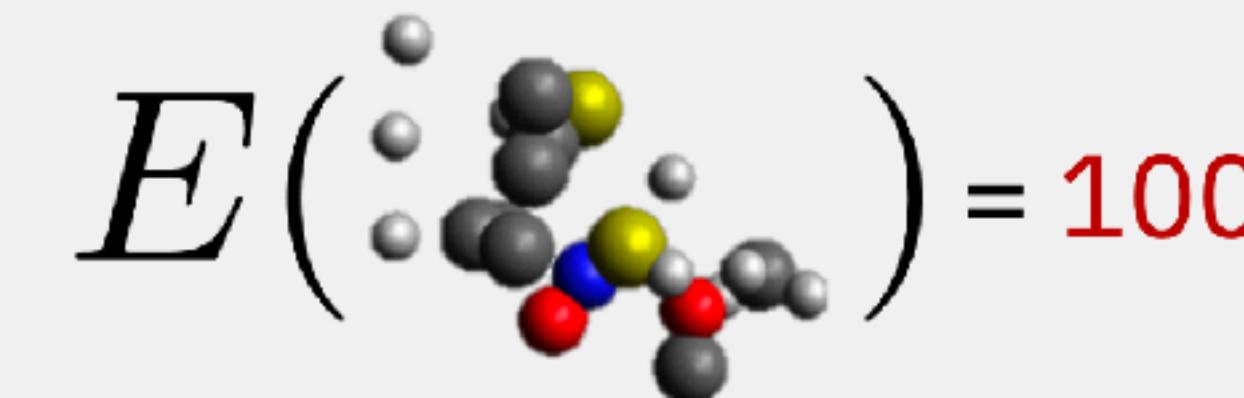
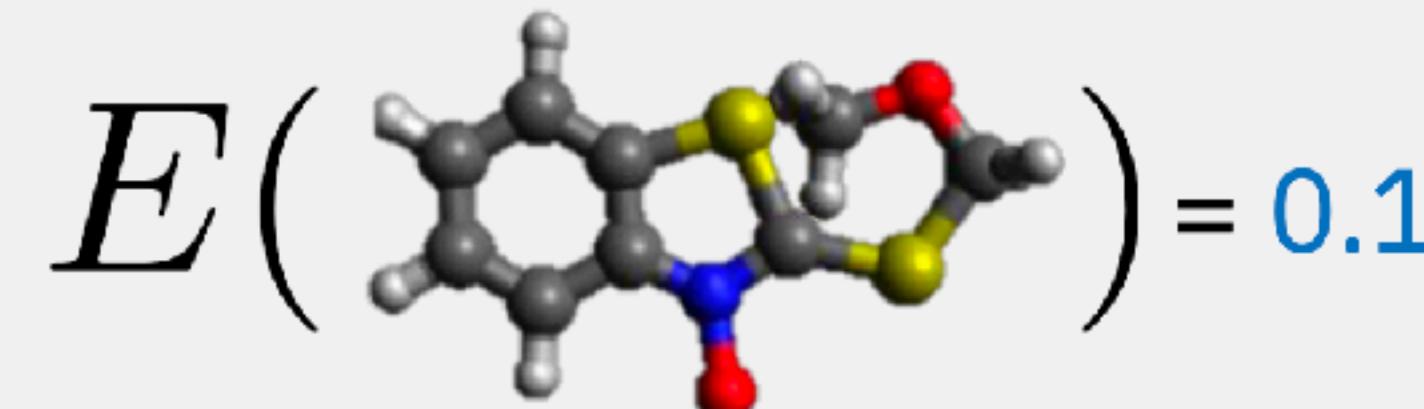
II. How to scale the method?

Adjoint Sampling: highly scalable method for amortized sampling at scale

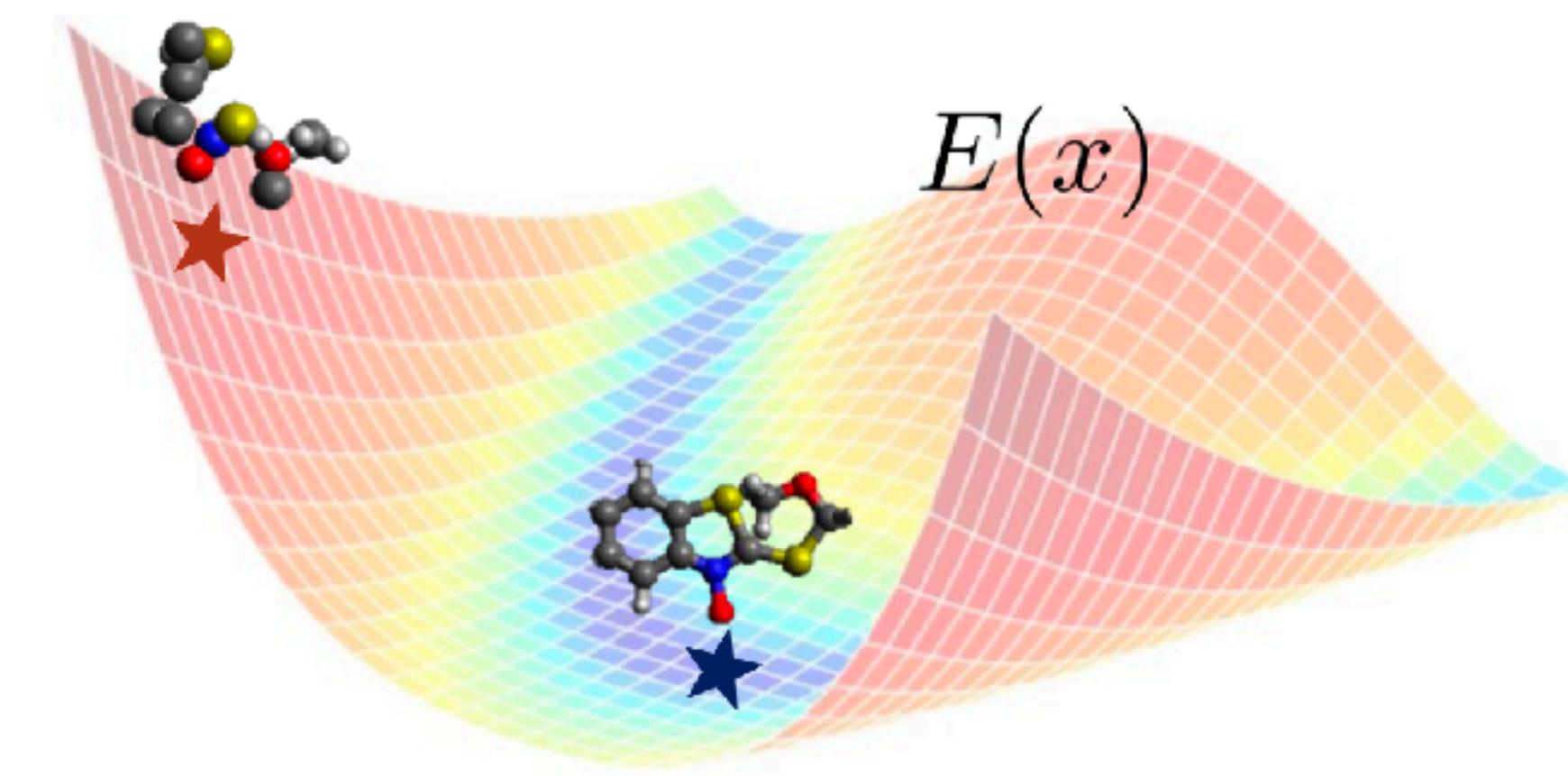
Stochastic control formulation for sampling

Sampling from unnormalized distribution

$$p^*(x) \propto \exp\{-E(x)\}$$



low energy → stable structure → likely to appear → high probability
high energy → unstable structure → unlikely to appear → low probability



[!] Estimating this energy
is also very expensive.

Stochastic control formulation for sampling

Sampling from unnormalized distribution

$$p^*(x) \propto \exp\{-E(x)\}$$

Know how to target this:

$$p_1^*(x) \propto p_1^{\text{base}}(x) \exp\{r(X_1)\}$$

Can define reward:

$$r(X_1) = -E(X_1) - \log p_1^{\text{base}}(X_1)$$

Stochastic control objective

$$\min_u \mathcal{L}(u) = \mathbb{E}_{p^u} \left[\int_0^1 \frac{1}{2} \|u_t^\theta(X_t)\|^2 dt + E(X_1) + \log p_1^{\text{base}}(X_1) \right]$$

$$\text{s.t. } dX_t = [b_t(X_t) + \sigma_t u_t^\theta(X_t)] dt + \sigma_t dB_t, \quad X_0 \sim p$$

Adjoint Matching simplified

Base generative process

$$dX_t = b_t(X_t)dt + \sigma_t dB_t \quad X_0 = 0$$

Adjoint Matching

“Lean” adjoint state

$$\frac{d}{dt} \tilde{a}_t(X_{[0,1]}) = -\tilde{a}_t(X_{[0,1]})^\top \nabla_{X_t} b_t(X_t)$$

$$\tilde{a}_1(X_{[0,1]}) = \nabla E(X_1) + \nabla \log p_1^{\text{base}}(X_1)$$

$$\int_0^1 \| u_t^\theta(X_t) + \sigma_t \tilde{a}_t(X_{[0,1]}) \|^2 dt$$

$$X_{[0,1]} \sim p^{\bar{u}}$$

$\bar{u} = \text{stopgrad}(u)$

Adjoint Matching simplified

Base process

$$dX_t = \sigma_t dB_t \quad X_0 = 0$$

Adjoint Matching

“Lean” adjoint state

$$\frac{d}{dt} \tilde{a}_t(X_{[0,1]}) = 0$$

$$\tilde{a}_1(X_{[0,1]}) = \nabla E(X_1) + \nabla \log p_1^{\text{base}}(X_1)$$

$$\int_0^1 \| u_t^\theta(X_t) + \sigma_t \tilde{a}_t(X_{[0,1]}) \|^2 dt$$

$$X_{[0,1]} \sim p^{\bar{u}}$$

$\bar{u} = \text{stopgrad}(u)$

Adjoint Matching simplified

Base process

$$dX_t = \sigma_t dB_t \quad X_0 = 0$$

Adjoint Matching

$$\int_0^1 \mathbb{E}_{(X_t, X_1) \sim p^u} \| u_t^\theta(X_t) + \sigma_t (\nabla E(X_1) + \nabla \log p_1^{\text{base}}(X_1)) \|^2 dt$$

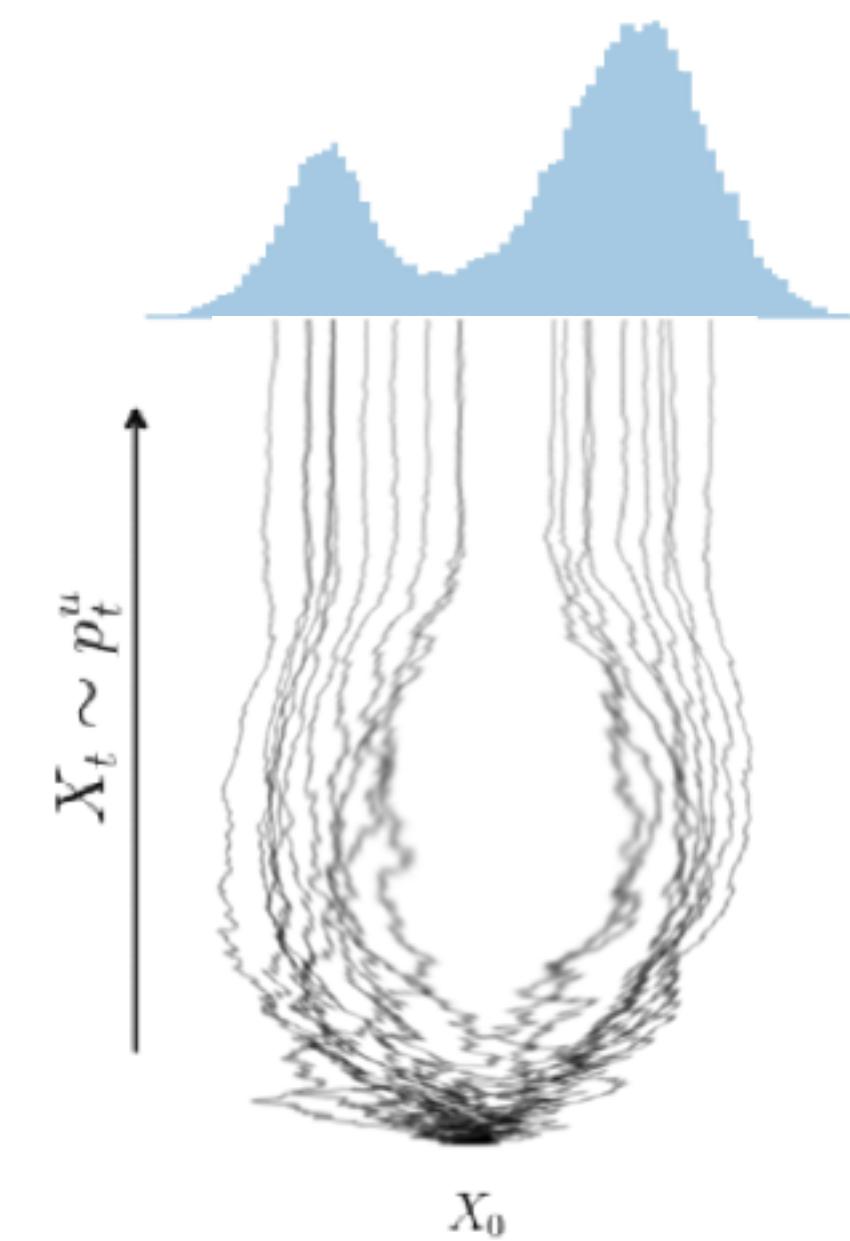
Improving optimality with a projection

Adjoint Matching

$$\int_0^1 \mathbb{E}_{(X_t, X_1) \sim p^u} \|u_t^\theta(X_t) + \sigma_t(\nabla E(X_1) + \nabla \log p_1^{\text{base}}(X_1))\|^2 dt$$

Recall optimal stochastic process

$$u^* = \arg \min_{\nu} D_{\text{KL}}(p^\nu(X_{[0,1]}) \| p^{\text{base}}(X_{[0,1]} | X_1) p^*(X_1))$$



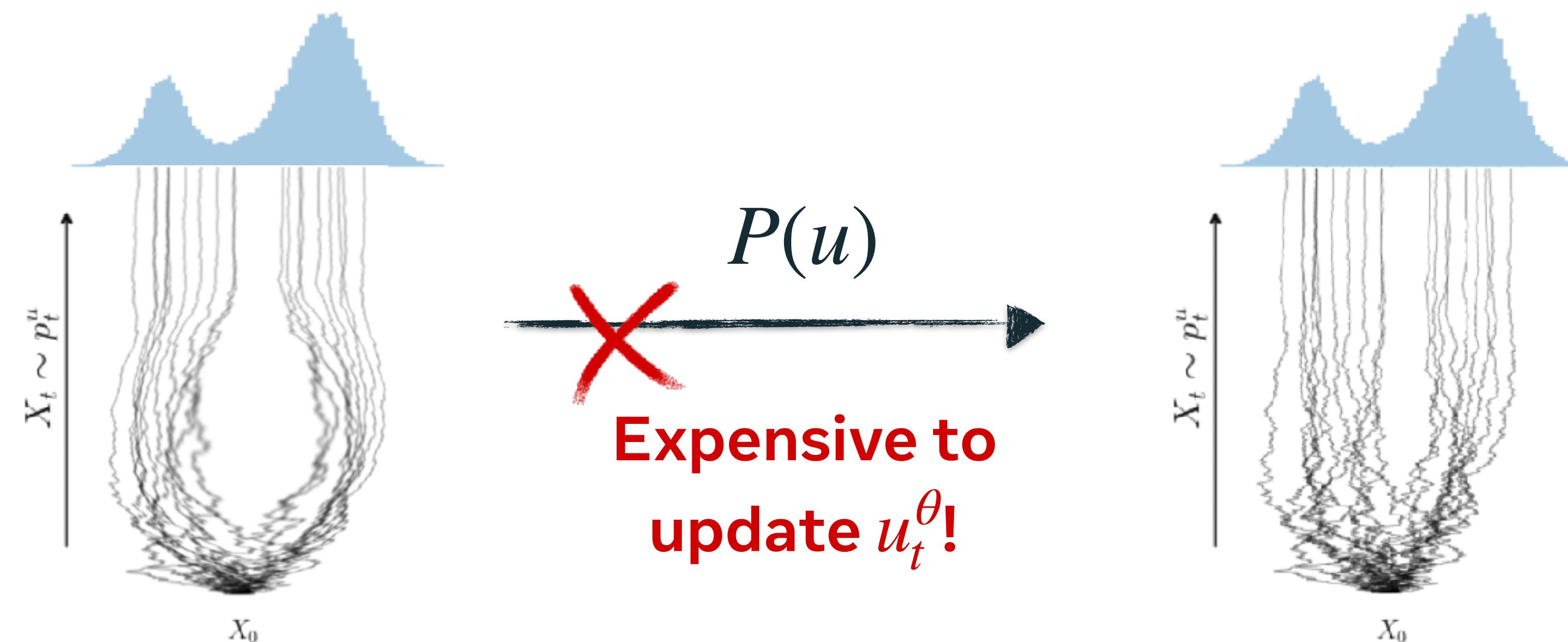
Improving optimality with a projection

Adjoint Matching

$$\int_0^1 \mathbb{E}_{(X_t, X_1) \sim p^u} \|u_t^\theta(X_t) + \sigma_t(\nabla E(X_1) + \nabla \log p_1^{\text{base}}(X_1))\|^2 dt$$

Projection of the current control

$$P(u) = \arg \min_{\nu} D_{\text{KL}}(p^{\nu}(X_{[0,1]}) \| p^{\text{base}}(X_{[0,1]} | X_1) p^u(X_1))$$



Improving optimality with a projection

Reciprocal Adjoint Matching

$$\int_0^1 \mathbb{E}_{X_1 \sim p_1^u, X_t \sim p^{\text{base}}(X_t | X_1)} \|u_t^\theta(X_t) + \sigma_t(\nabla E(X_1) + \nabla \log p_1^{\text{base}}(X_1))\|^2 dt$$

Sample $X_t | X_1$ optimally

Improving optimality with a projection

Reciprocal Adjoint Matching

$$\int_0^1 \mathbb{E}_{\substack{X_1 \sim p_1^u, X_t \sim p_{\text{base}}(X_t | X_1)}} \|\nu_t(X_t) + \sigma_t(\nabla E(X_1) + \nabla \log p_1^{\text{base}}(X_1))\|^2 dt$$

Leave Fixed

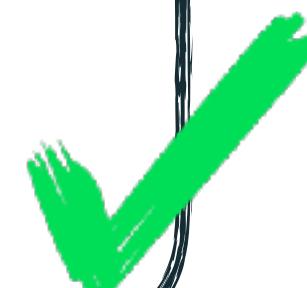
Sample $X_t | X_1$ optimally

$=: \mathcal{L}_{\text{RAM}}(\nu; u)$

Theory of RAM: project for free

$$u_{i+1} = \arg \min_{\nu} \mathcal{L}_{\text{RAM}}(\nu; u_i)$$

$$= P(u_i) - \frac{\delta \mathcal{L}_{\text{AM}}}{\delta u}(P(u_i))$$



i.e., Equivalent to projecting
the control then performing
Adjoint Matching

Fixed point \iff optimal control

Adjoint Sampling

Reciprocal Adjoint Matching

$$\int_0^1 \mathbb{E}_{\substack{X_1 \sim \mathcal{B}, X_t \sim p}} \text{base}_{(X_t|X_1)} \|u_t^\theta(X_t) + \sigma_t(\nabla E(X_1) + \nabla \log p_1^{\text{base}}(X_1))\|^2 dt$$

Replay Buffer

Adjoint Sampling Algorithm

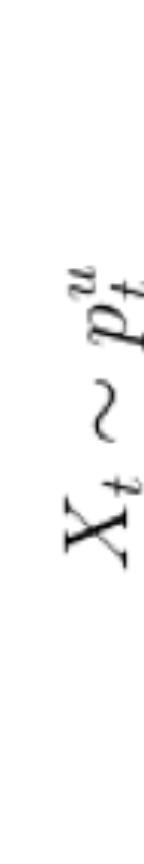
Alternate between:

1. $\mathcal{B} \leftarrow \{X_1^i, E^i\}$, $X_1^i \sim p_1^u$, $E^i = E(X_1)$

2. Optimize \mathcal{L}_{RAM} multiple iterations

Infrequent sample generation & energy evaluation.

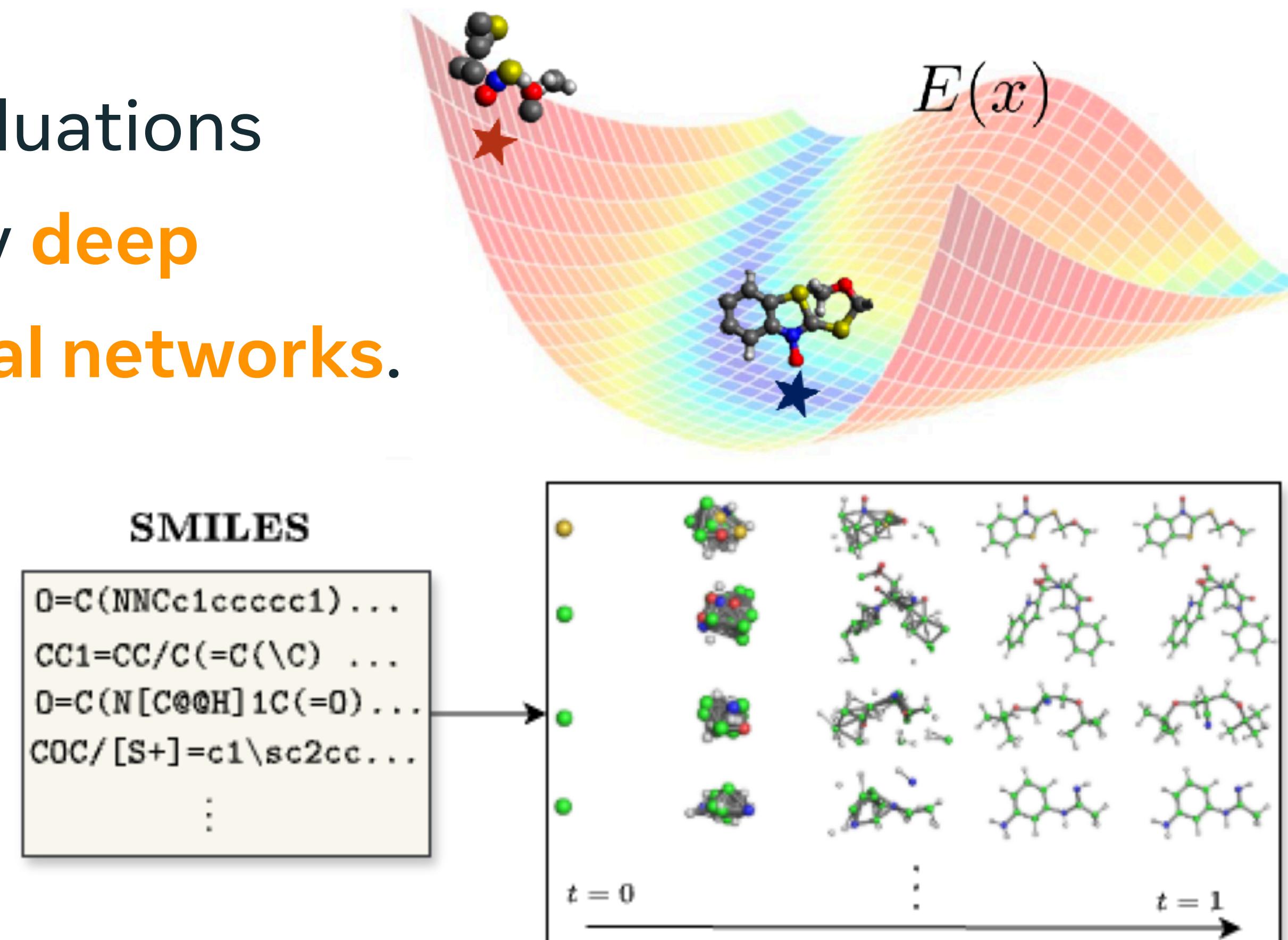
Very fast gradient updates.



A new benchmark for highly scalable sampling

Evaluates sampling methods on both **efficiency** and **generalization**.

Energy evaluations
modeled by **deep
graph neural networks**.

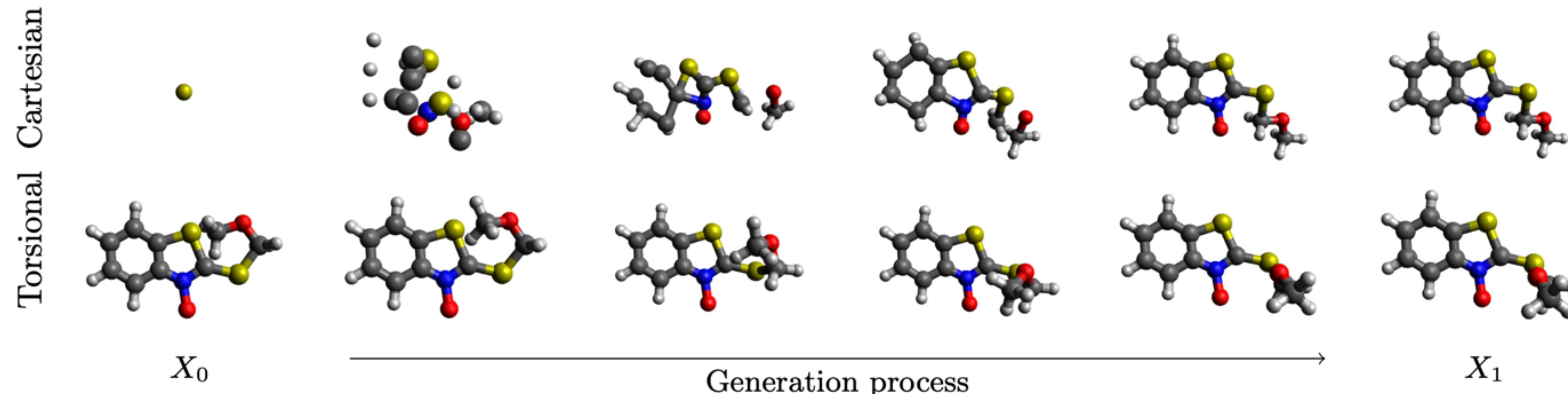


Train on **24,000**
molecules.

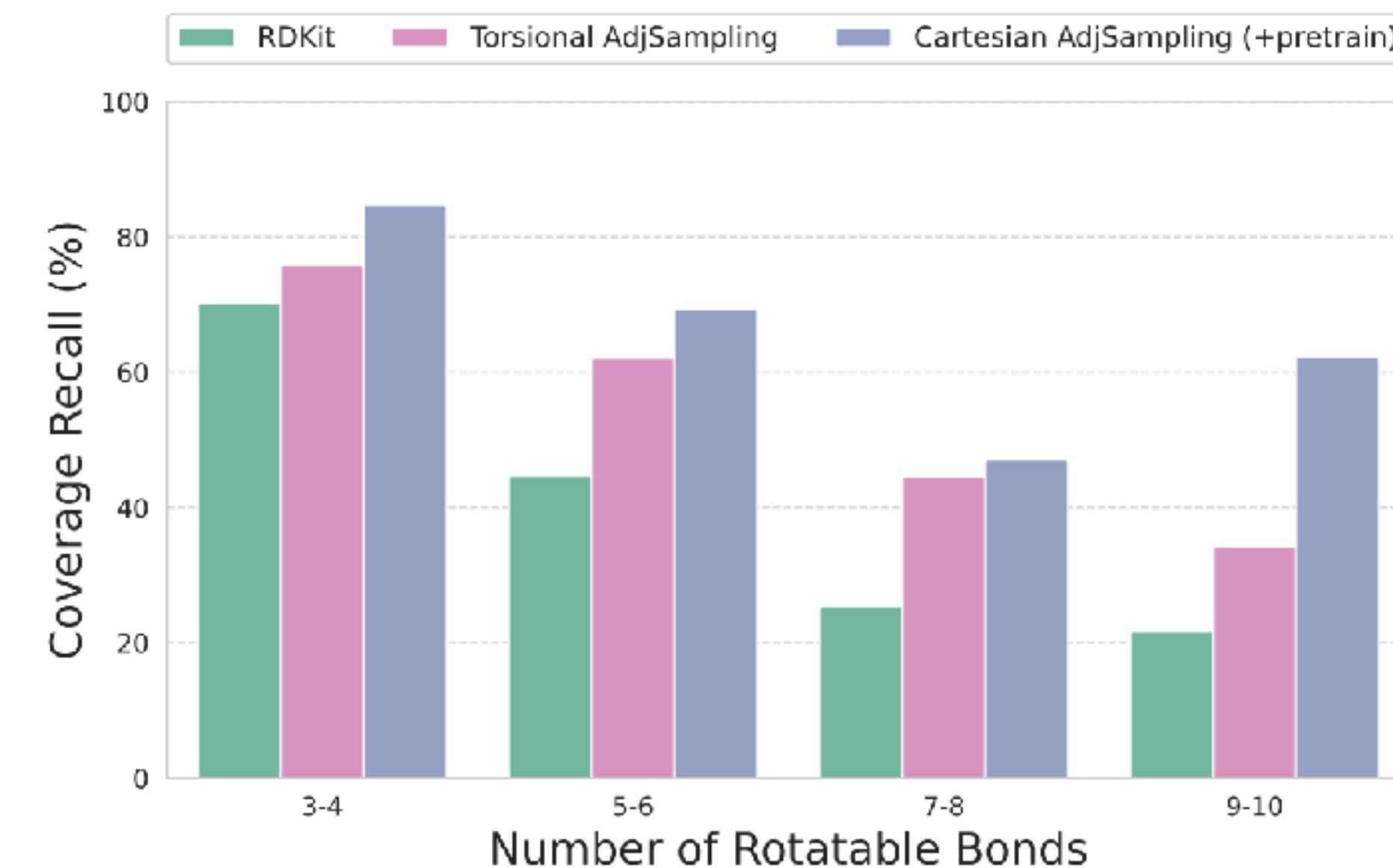
Tests generalization to
unseen molecules.

Each with $\mathcal{O}(100)$ of local
minima. **Need to find all**.

A new benchmark for highly scalable sampling



Larger improvement
over RD-KIT at
higher difficulties



More difficult / more local minima

Papers & Collaborators

Adjoint Matching: Fine-tuning Flow and Diffusion Generative Models with Memoryless Stochastic Optimal Control

Carles Domingo-Enrich¹, Michal Drozdzal¹, Brian Karrer¹, Ricky T. Q. Chen¹

¹FAIR, Meta

Adjoint Matching

implementation:



Adjoint Sampling: Highly Scalable Diffusion Samplers via Adjoint Matching

Aaron Havens^{2,†,*}, Benjamin Kurt Miller^{1,*}, Bing Yan^{1,3,*}, Carles Domingo-Enrich⁴, Anuroop Sriram¹, Brandon Wood¹, Daniel Levine¹, Bin Hu², Brandon Amos¹, Brian Karrer¹, Xiang Fu^{1,*}, Guan-Horng Liu^{1,*}, Ricky T. Q. Chen^{1,*}

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