Diffusion Models 2

Practicals

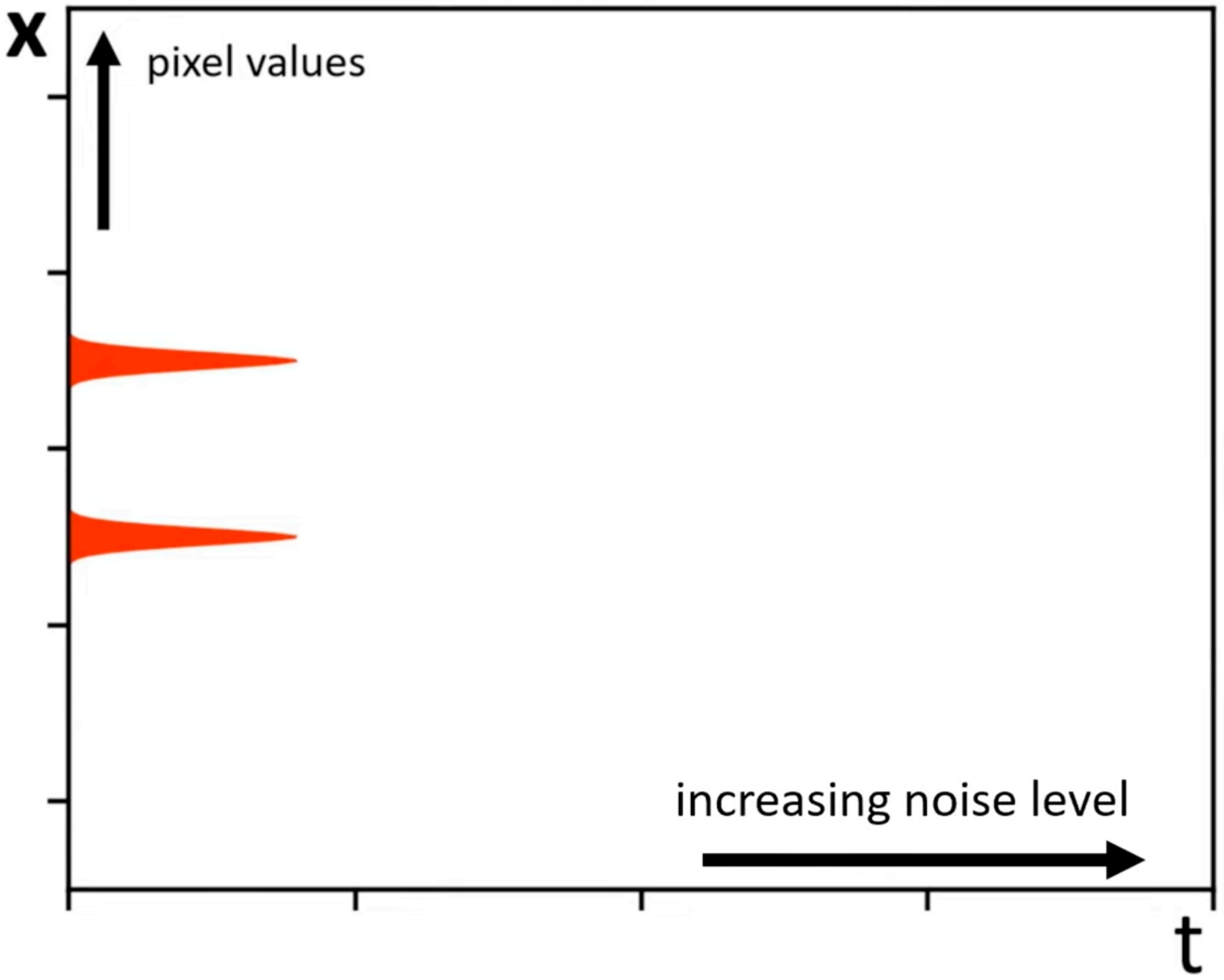
CS280

Songwei Ge & David McAllister

Outline

- Flow matching model samplers
- Inversion/Distillation
- Guidance
- Application

Revisit diffusion models with a 1D example



Credit: Miika Aittala

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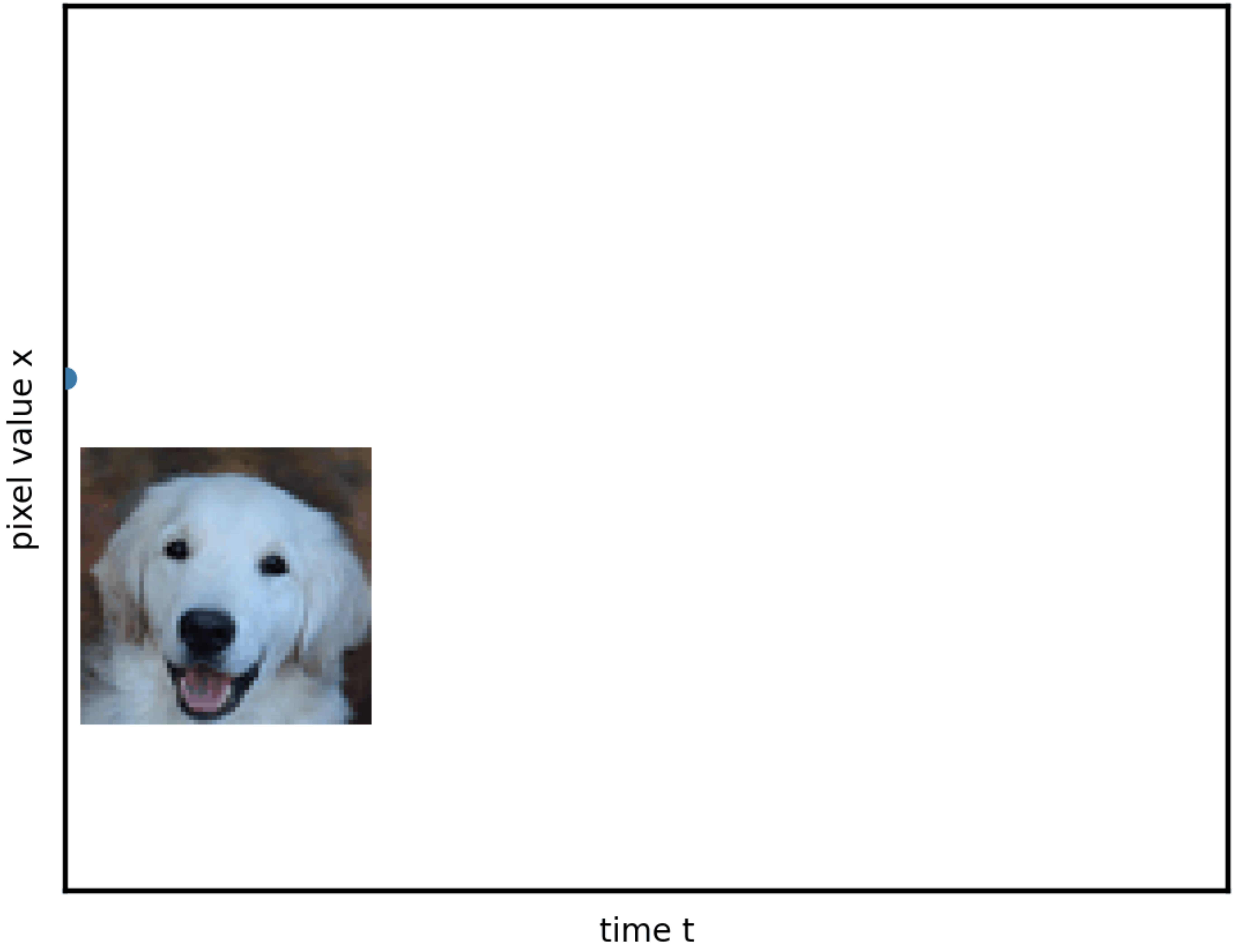

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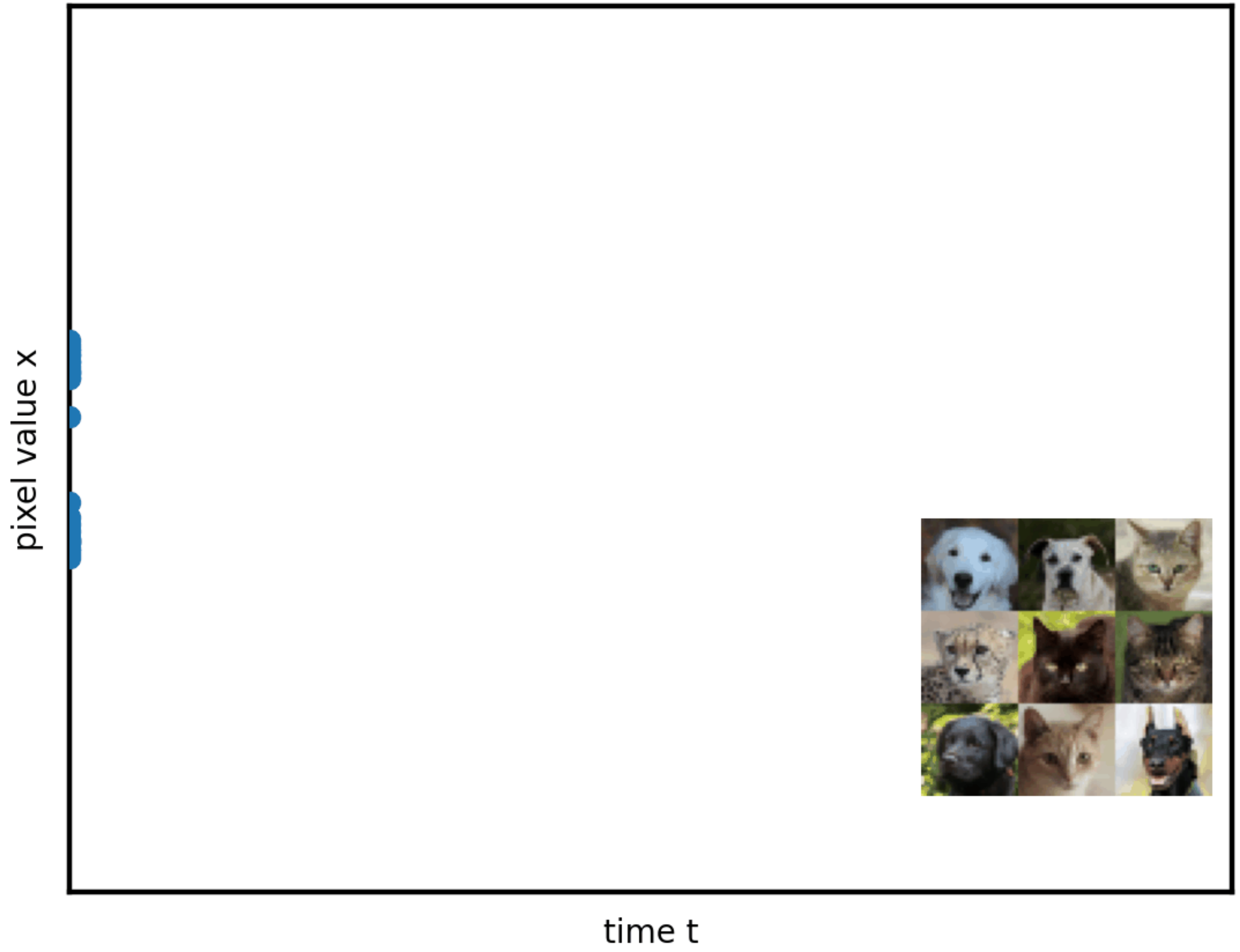

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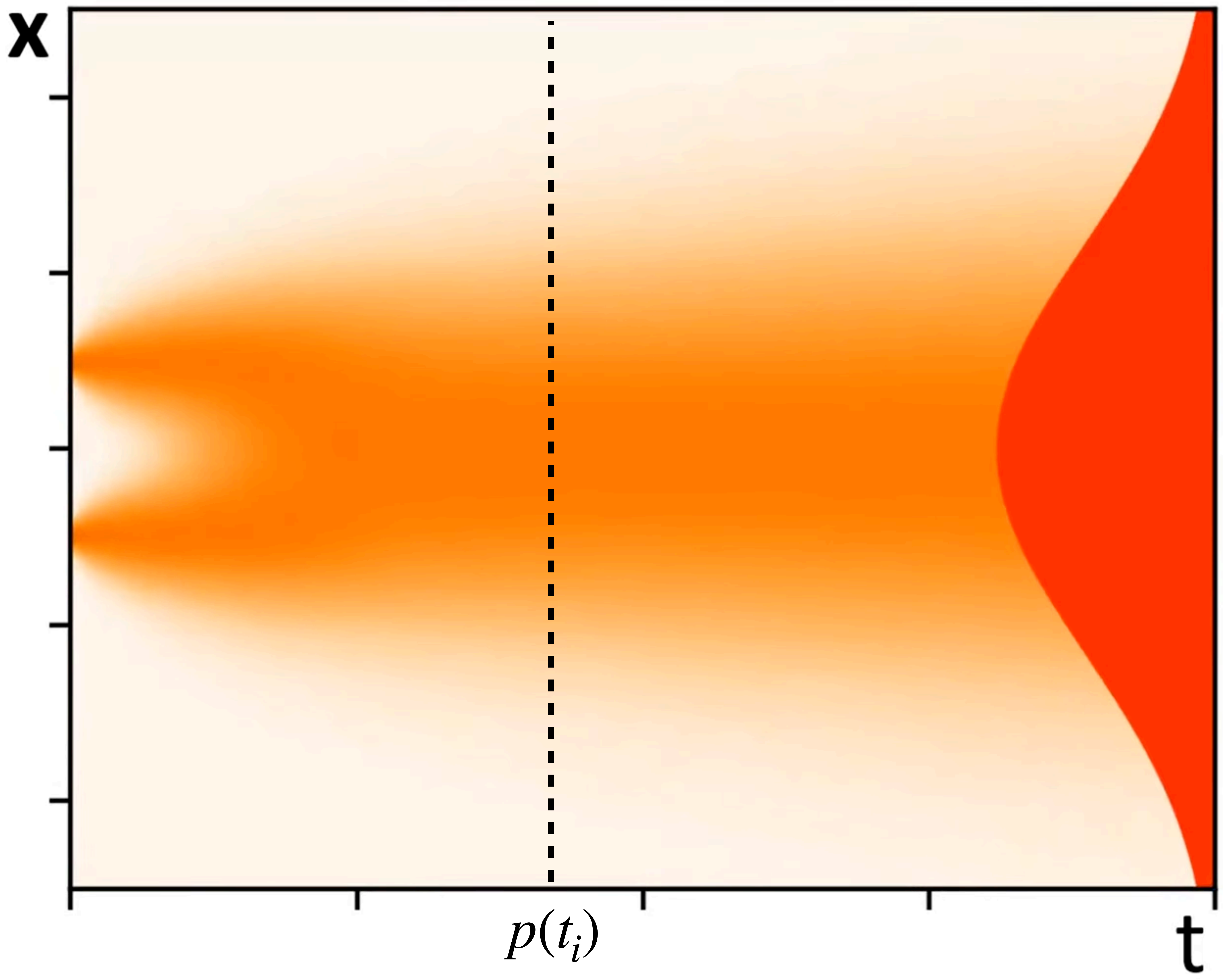
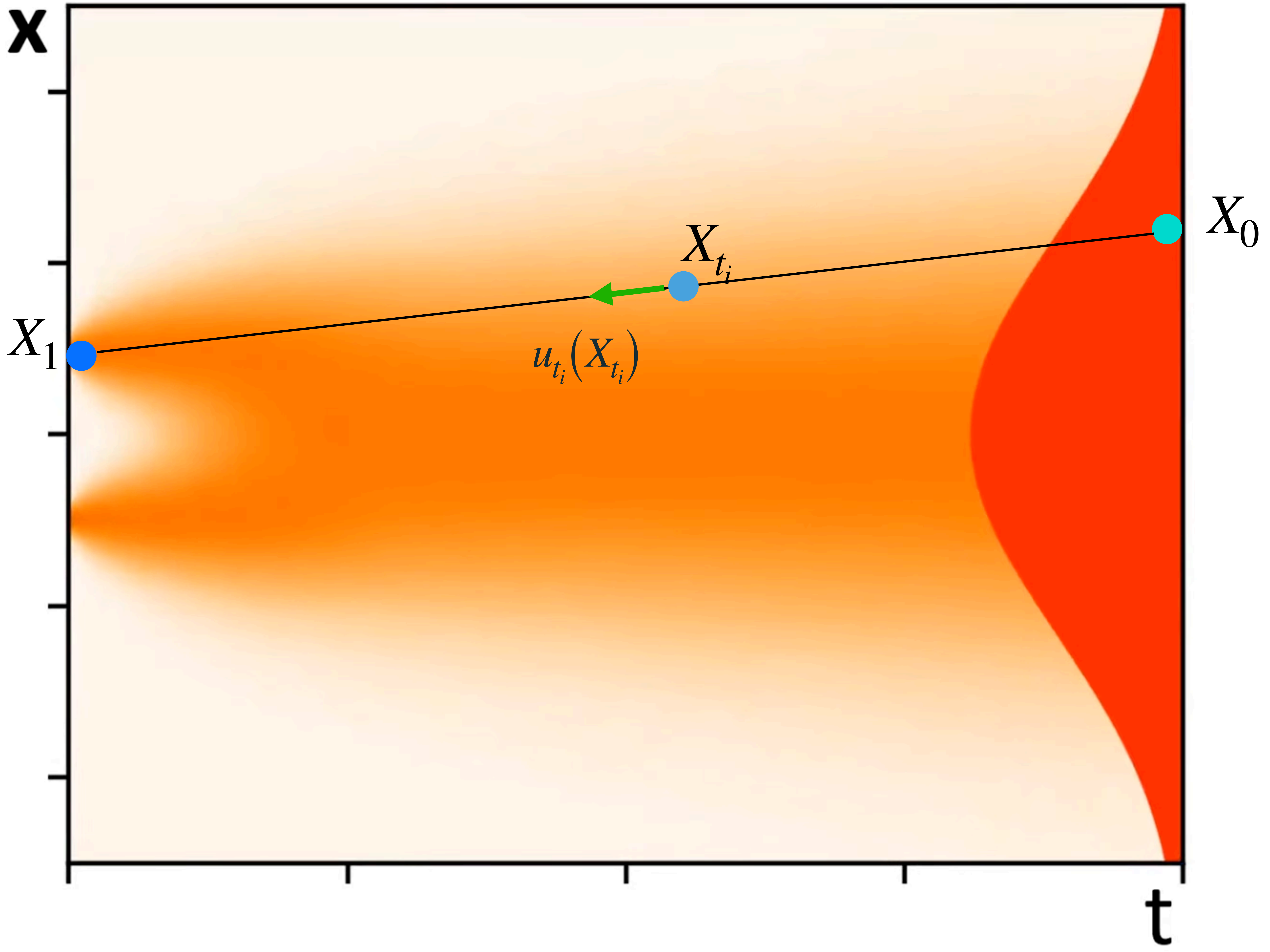


Credit: Miika Aittala

Flow matching model training

Training Objective:

$$\mathbb{E}_{t,X_0,X_1}\left\| u^{\theta}_{t_i}(X_{t_i}) - u_{t_i}(X_{t_i}) \right\|^2$$

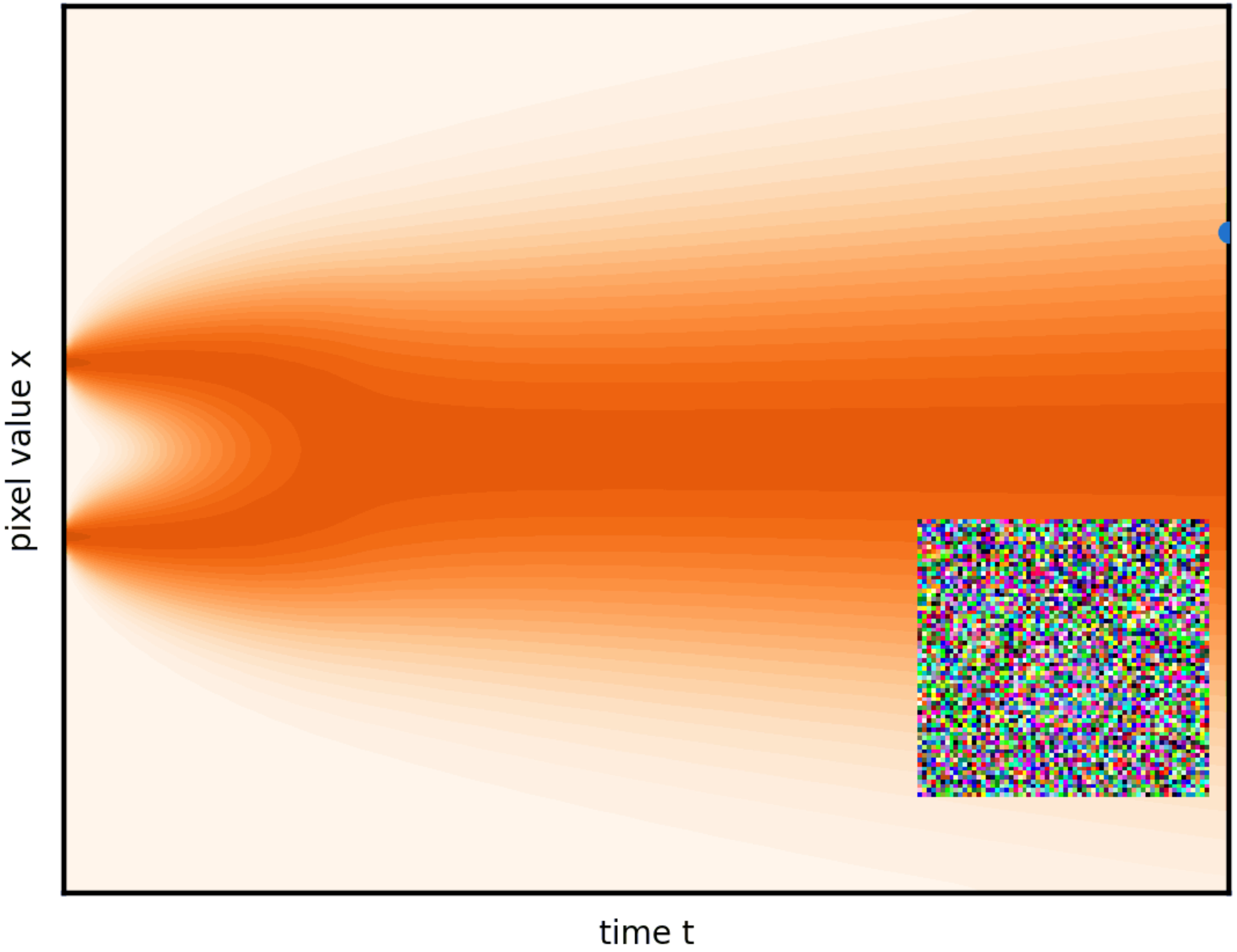


Credit: Miika Aittala

Sampling by solving the flow ODE

Flow ODE

$$\frac{\mathrm{d}x_t}{\mathrm{d}t} = u_t^\theta(x_t)$$

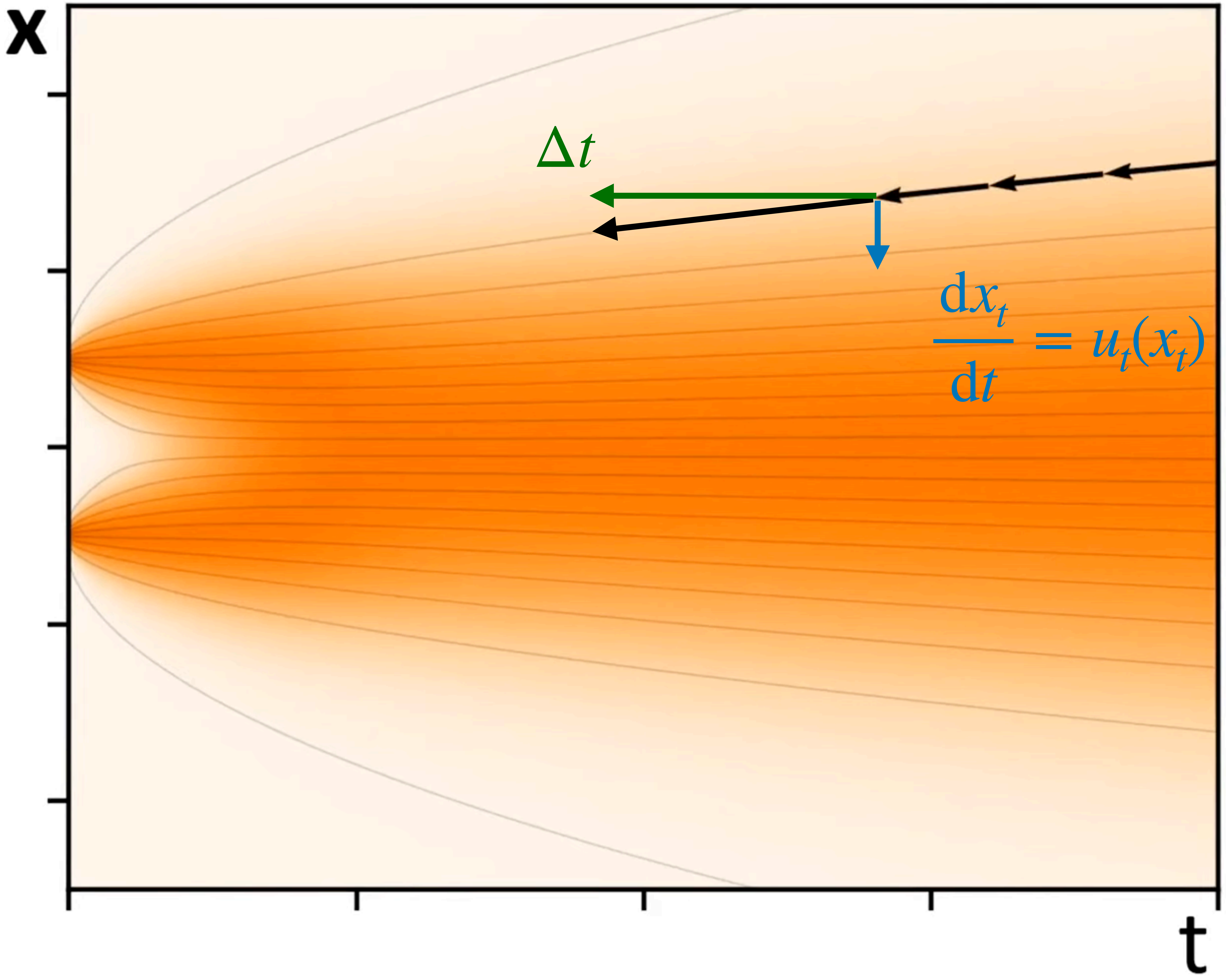


Credit: Miika Aittala

Solving the flow ODE with discretization

Euler step:

$$x_{t+\Delta t} = x_t + \Delta t \cdot \left.\frac{dx}{dt}\right|_{x_t,t}$$



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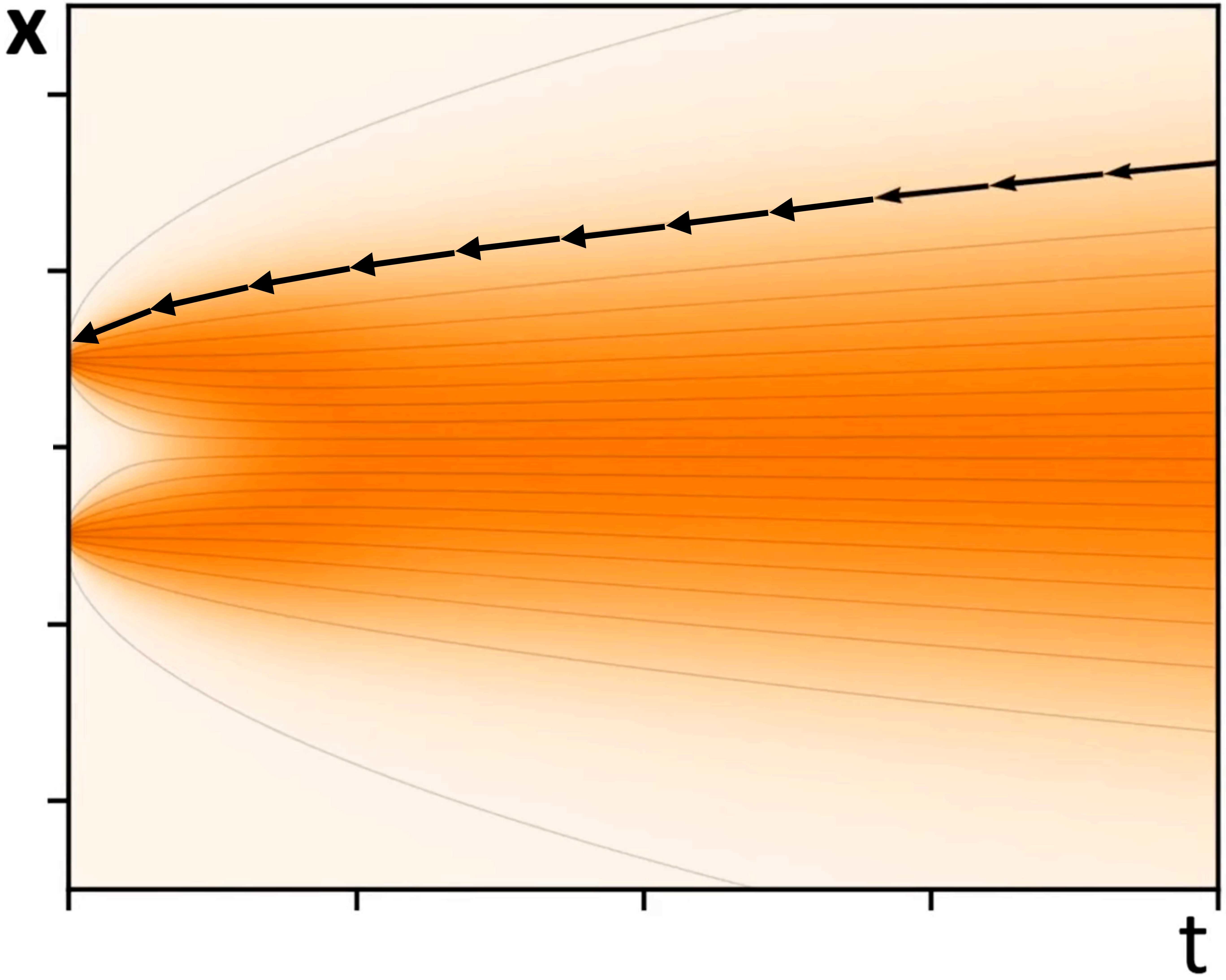

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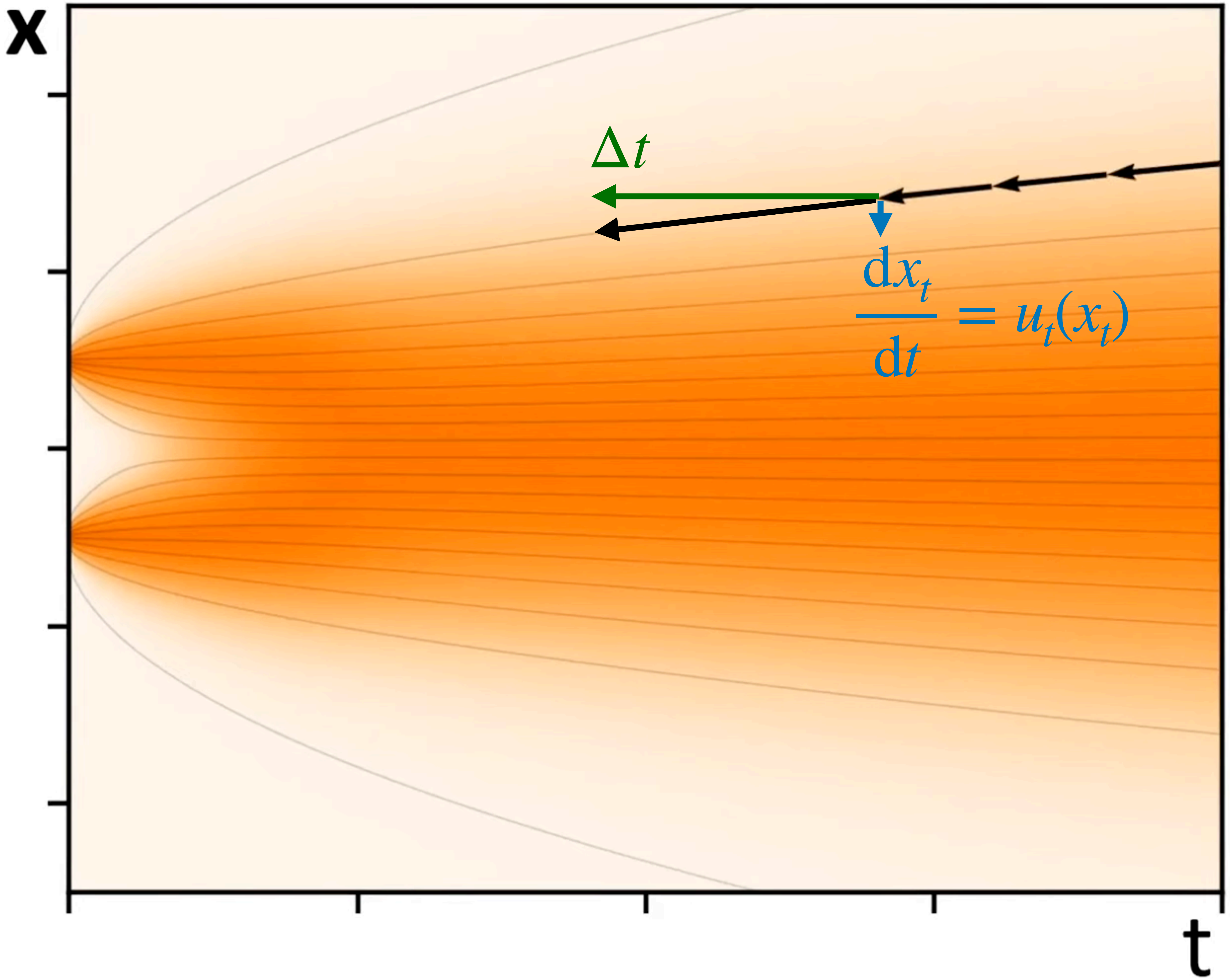
What can go wrong with this sampling process



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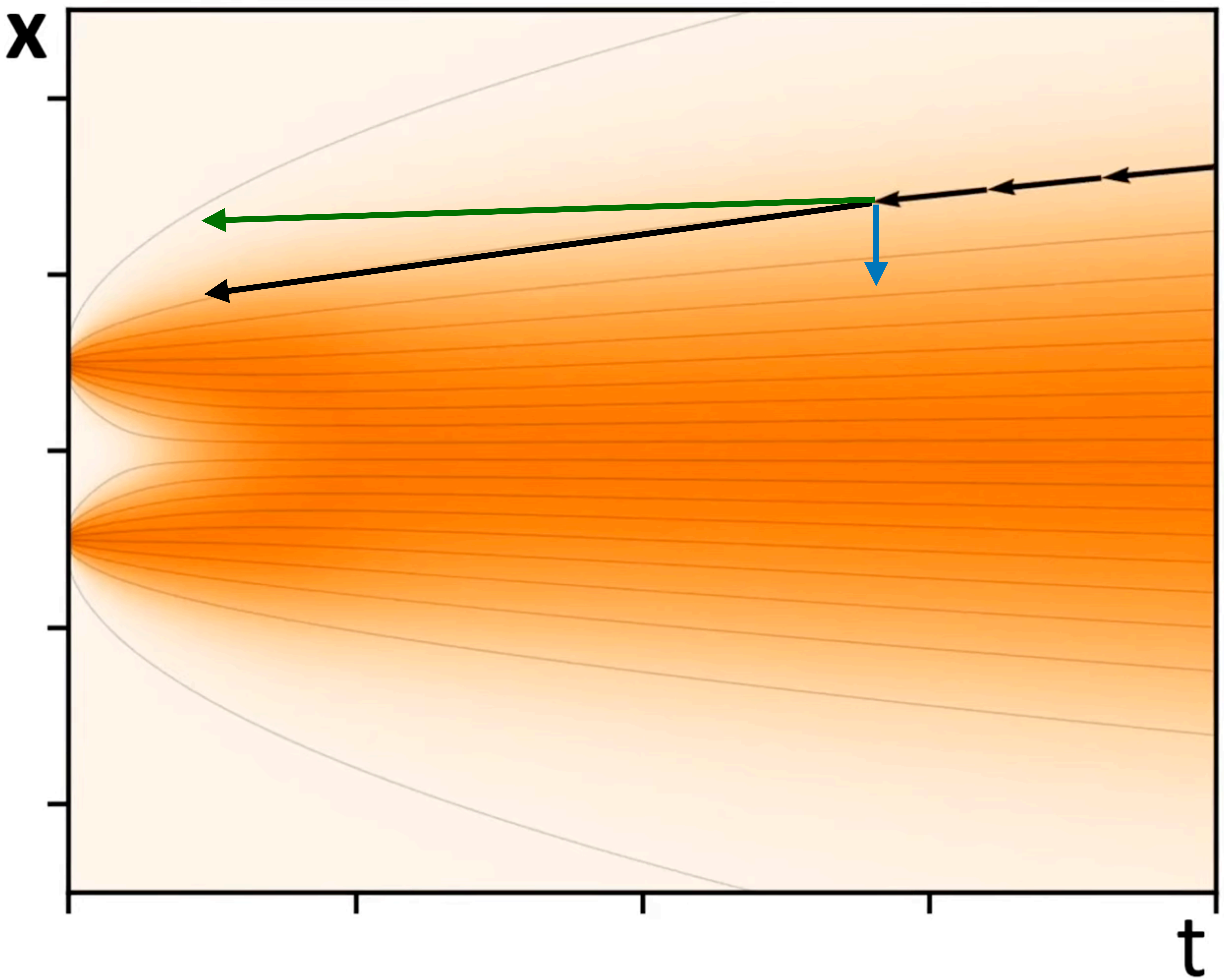

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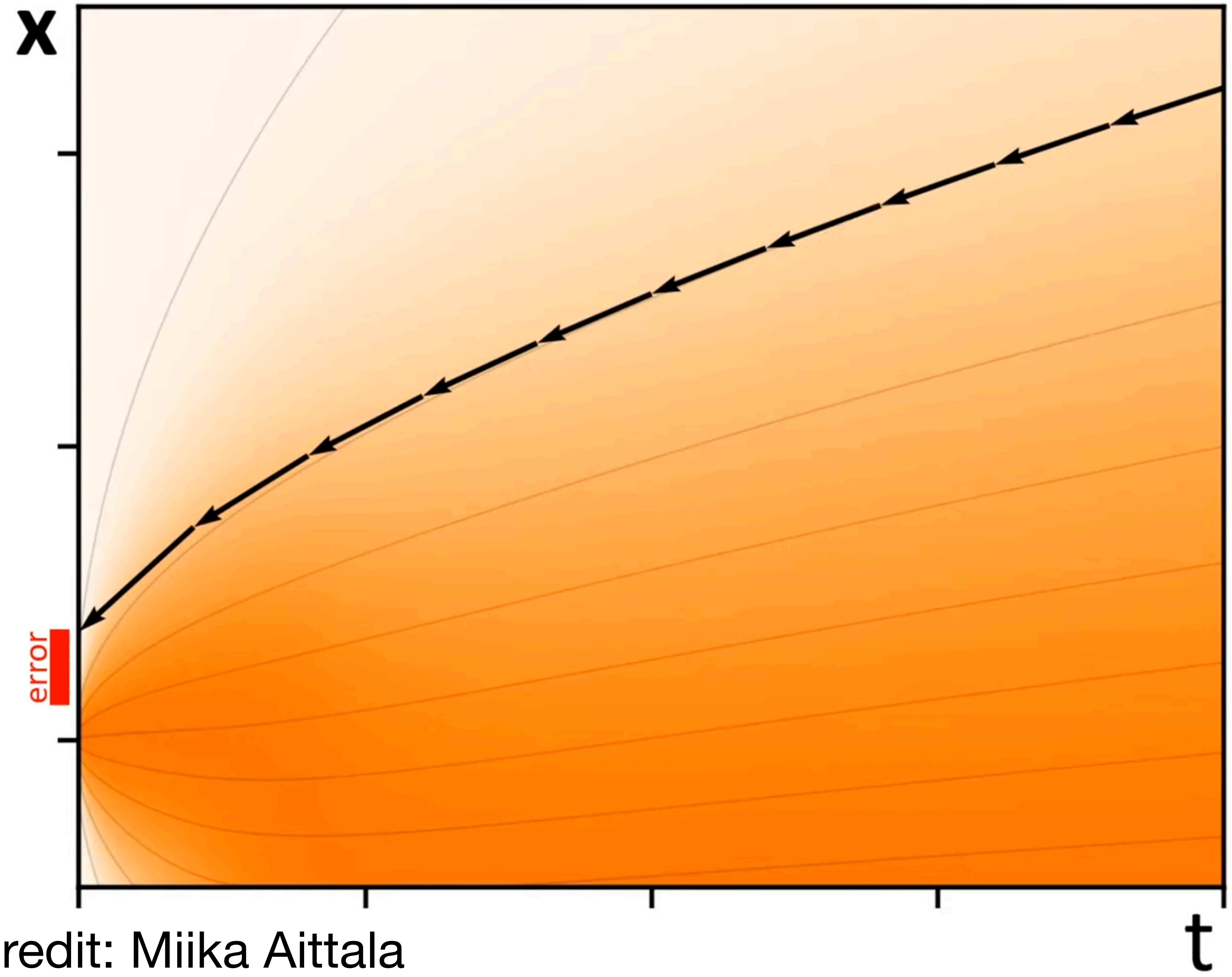
Error Sources when Solving the flow ODE

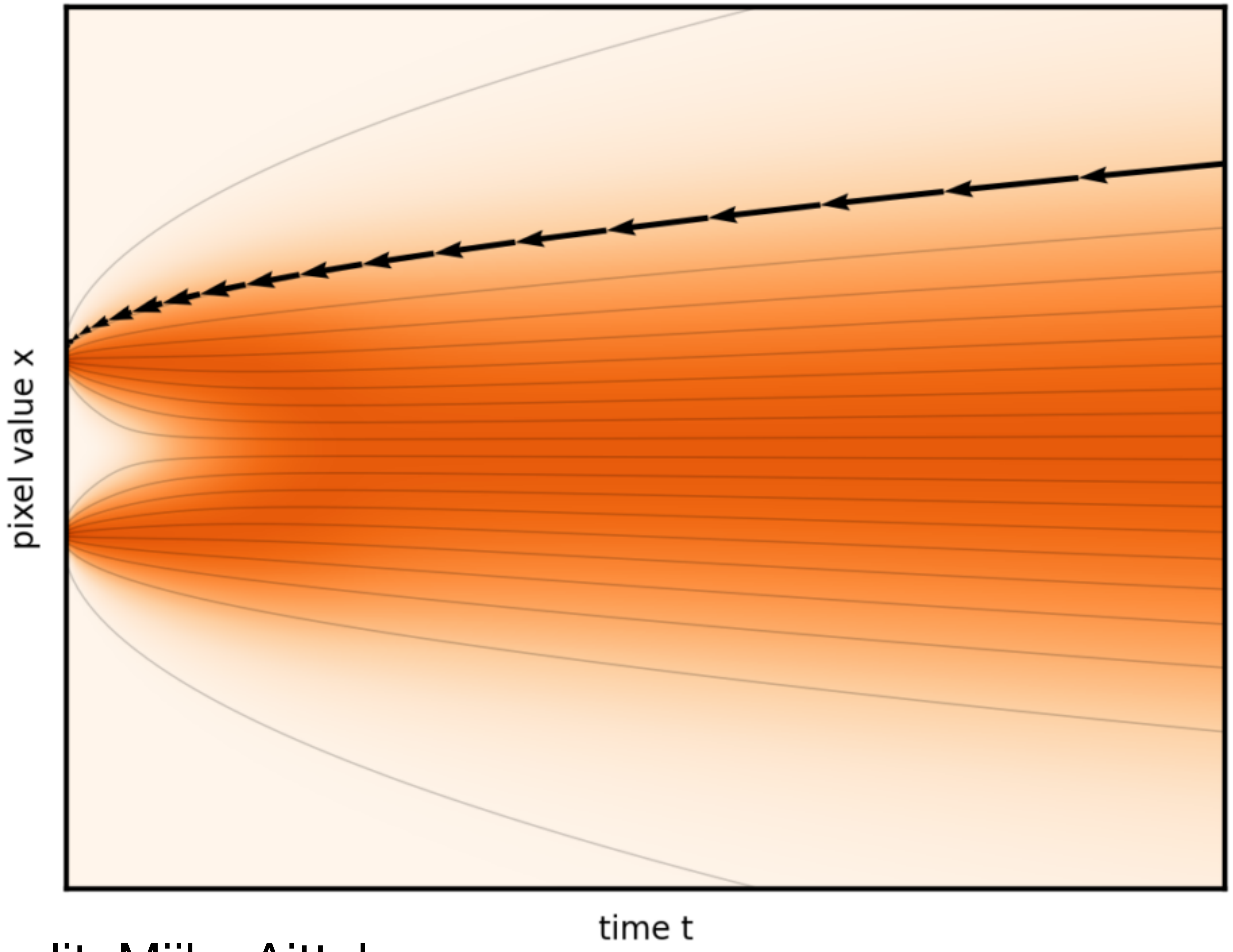


Credit: Miika Aittala

1. Truncation error: fails to approximate ideal trajectory by finite steps.

    1. Naive solution: sampling with more steps.

Smart Time Step Schedule



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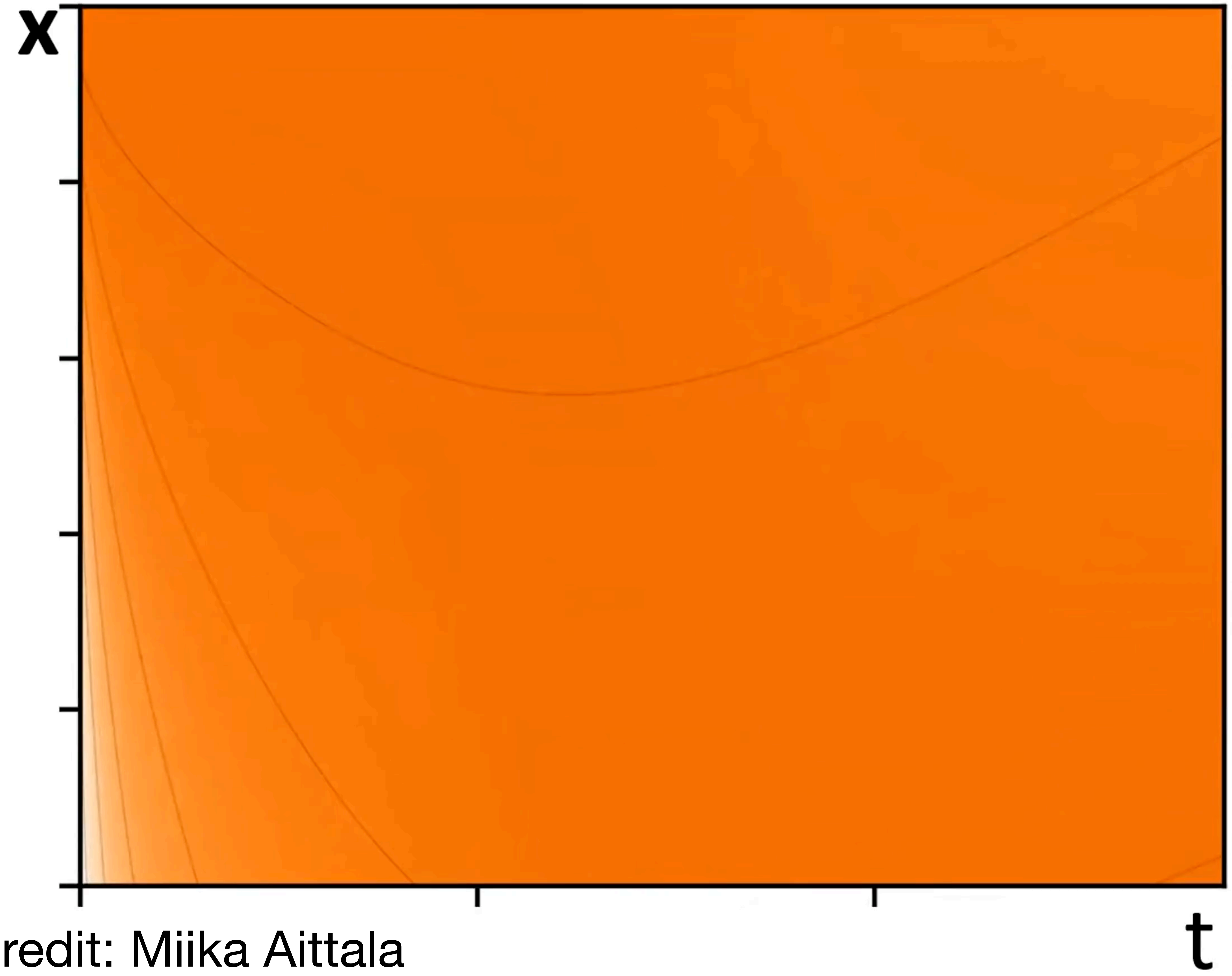
   2. Time steps are long at high noise levels and short at low noise levels

Advanced ODE Solvers



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1. Truncation error: fails to approximate ideal trajectory by finite steps.

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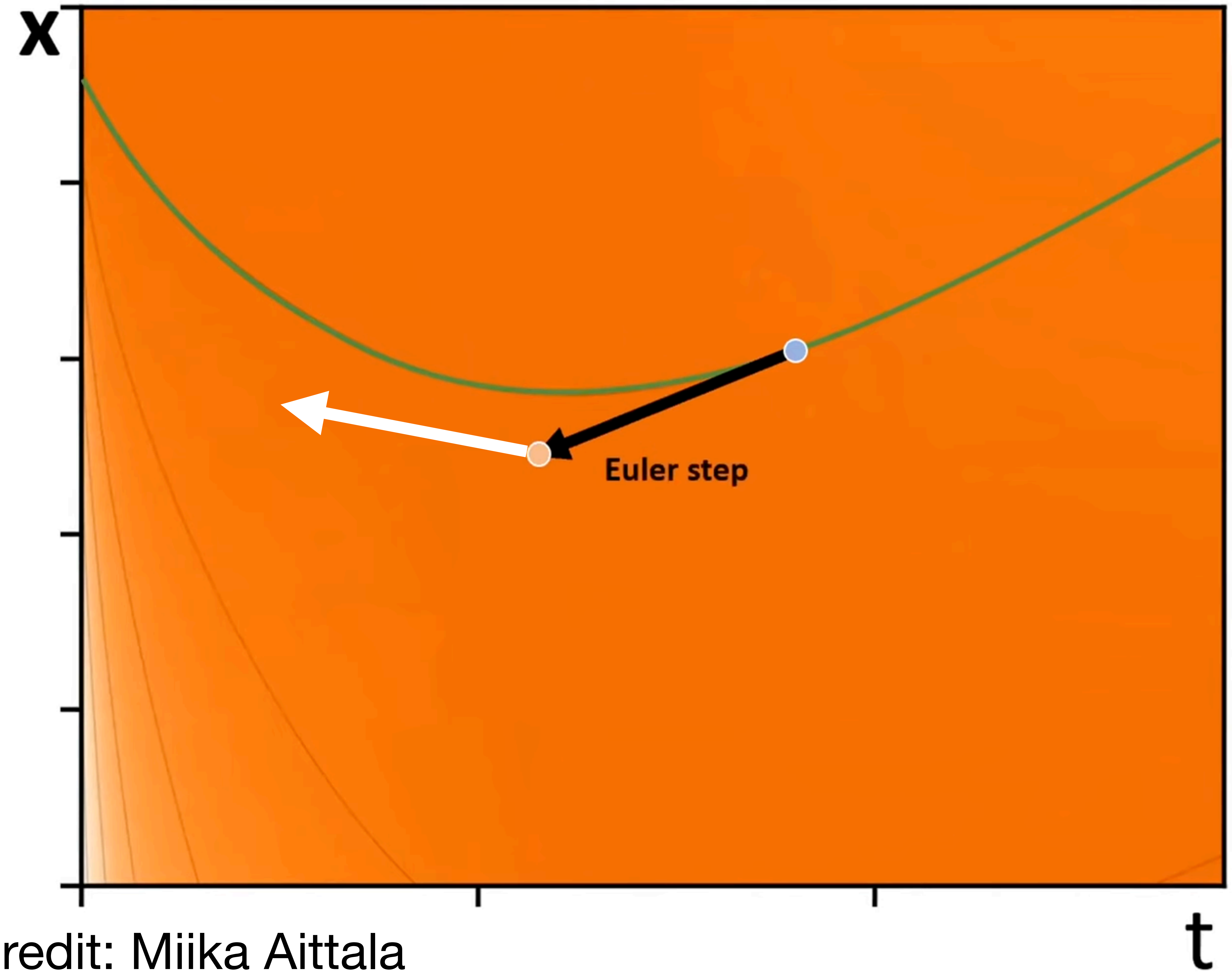
    3. Higher-order ODE solver

Higher-order solvers



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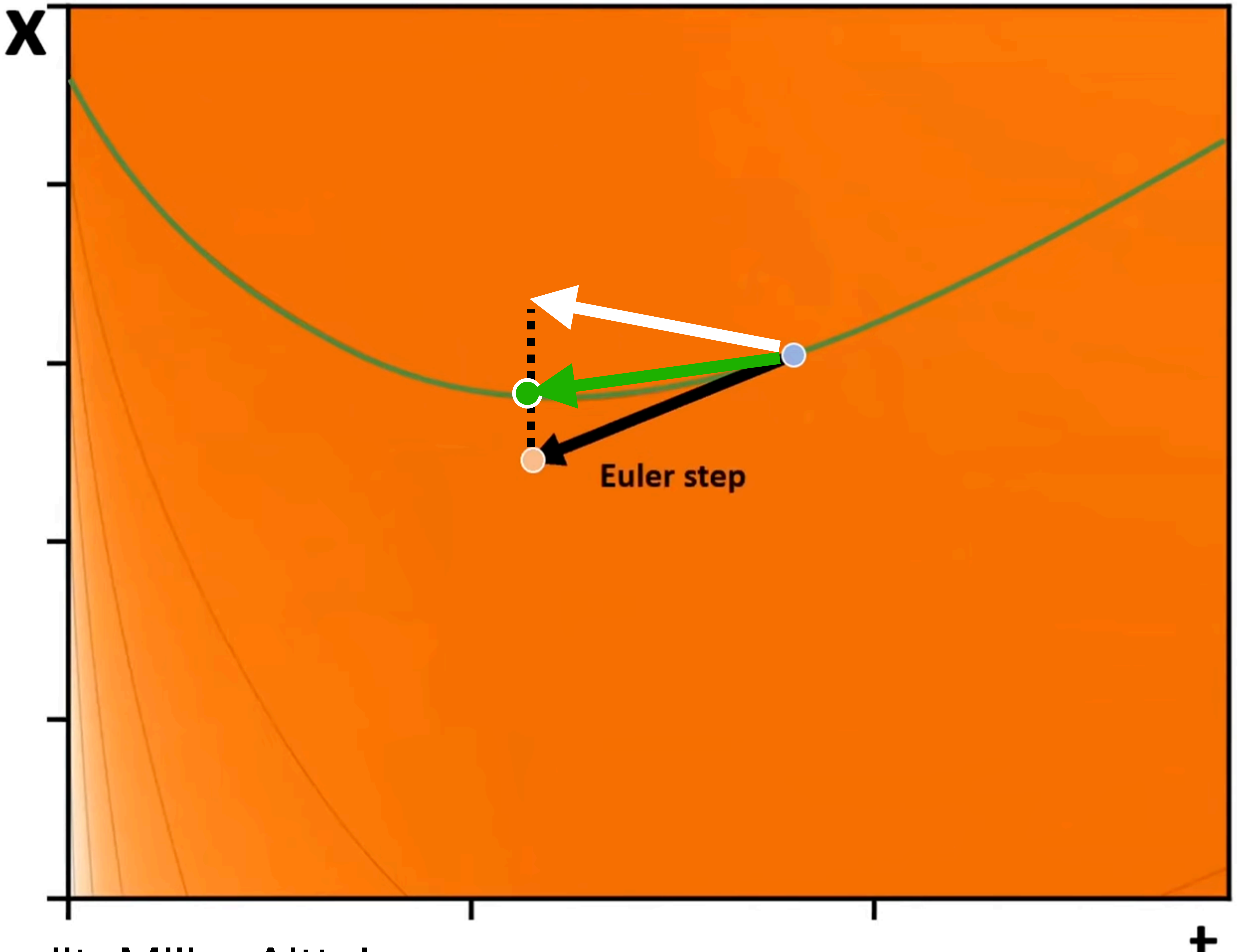
- Clever sub-steps -> higher accuracy though more cost
- 2nd order Heun method as an example

Higher-order solvers



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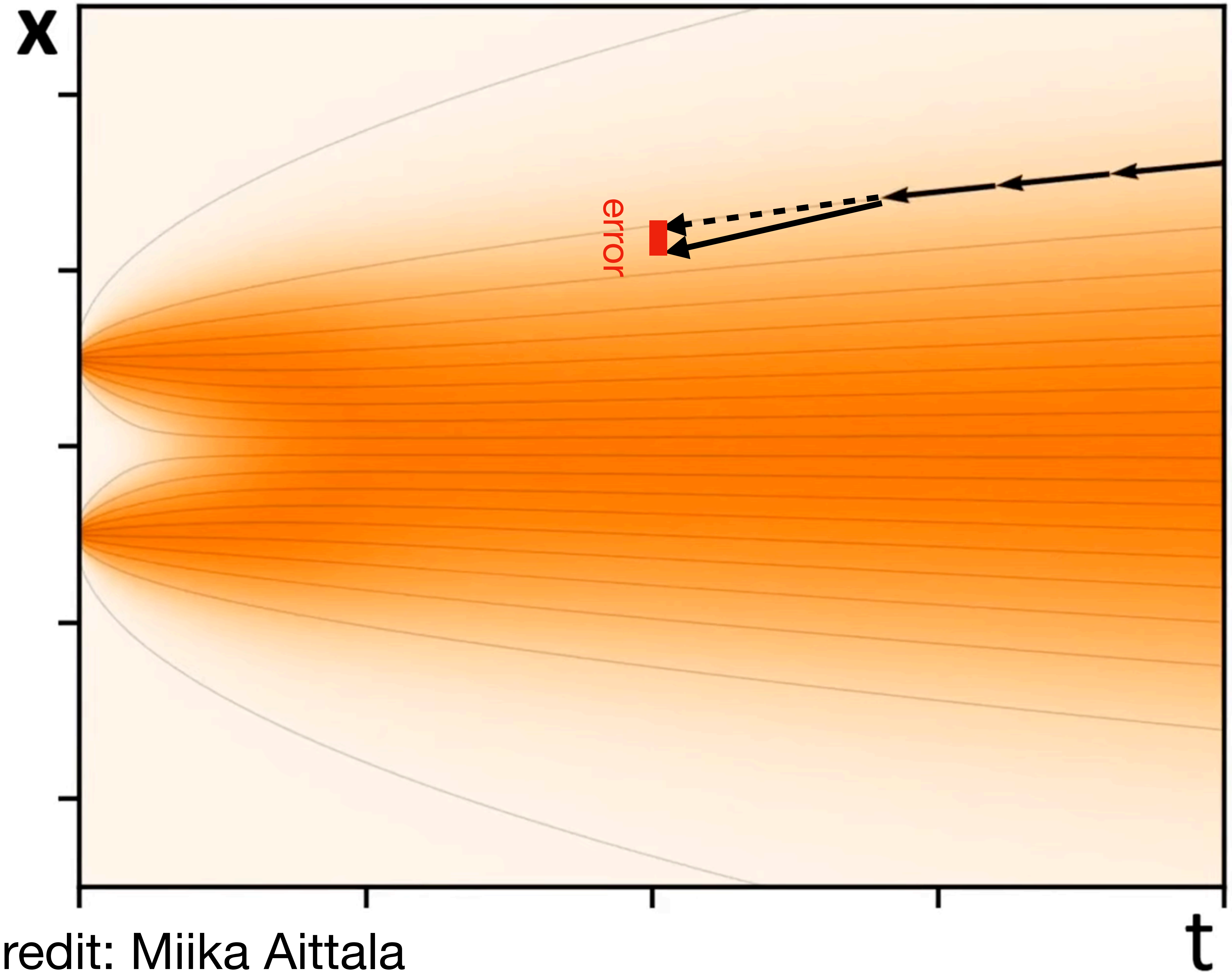

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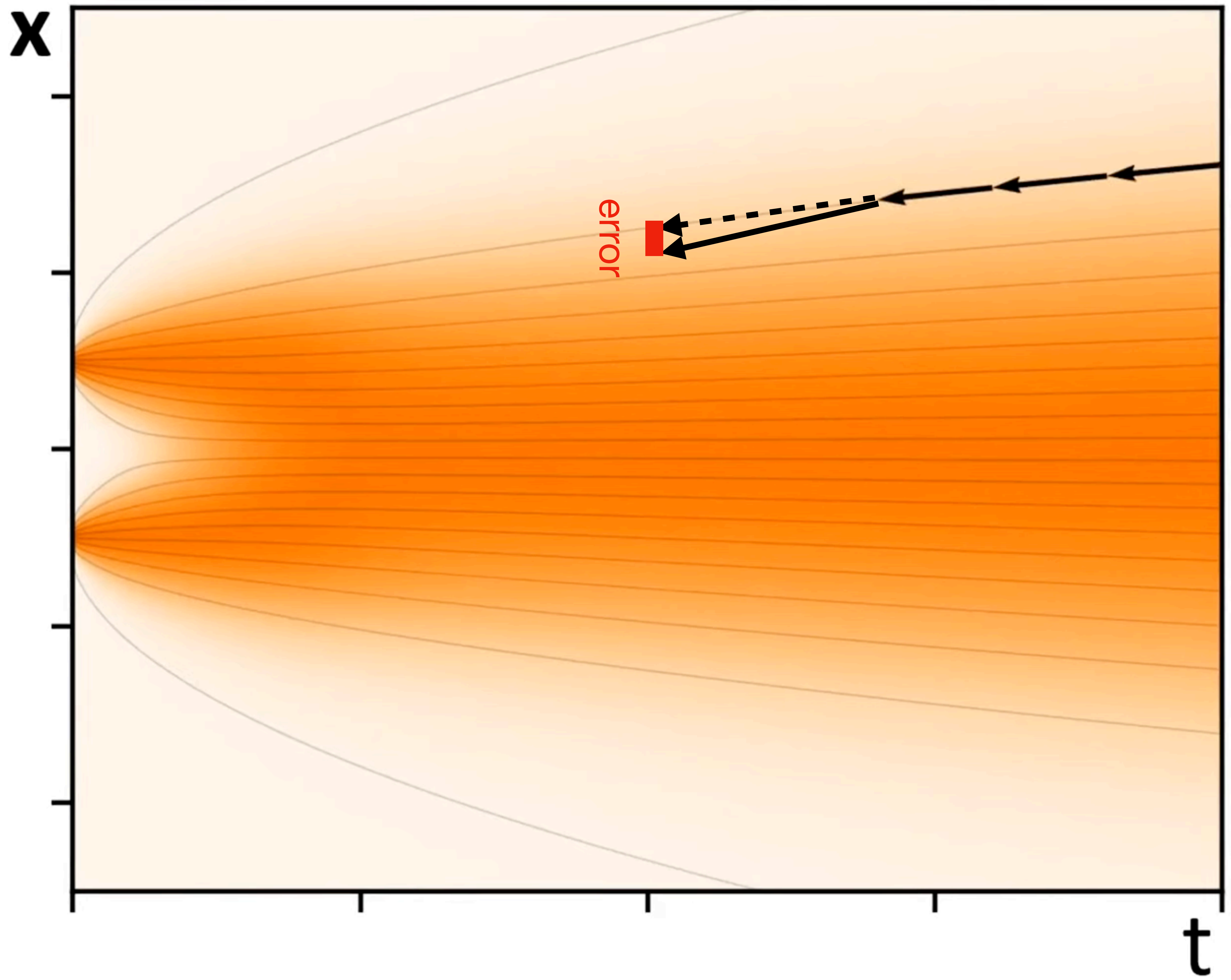
1. Truncation error: fails to approximate ideal trajectory by finite steps.

2. Model fails to approximate the marginal flow.

Stochastic Sampler



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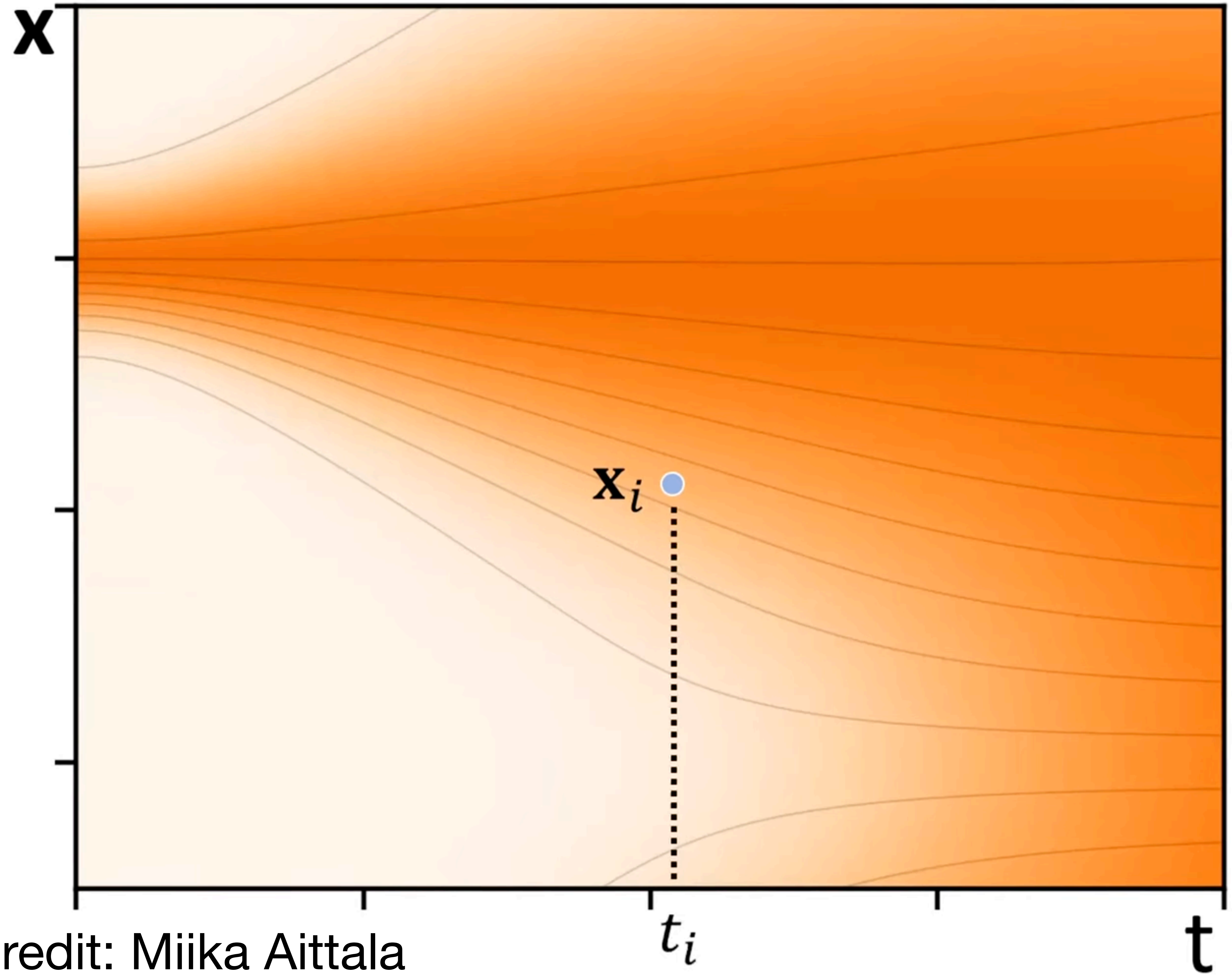
    1. Stochastic sampler (SDE) injects fresh noise throughout the evolution in addition to reducing the noise.

Stochastic Sampler: why does it improve quality



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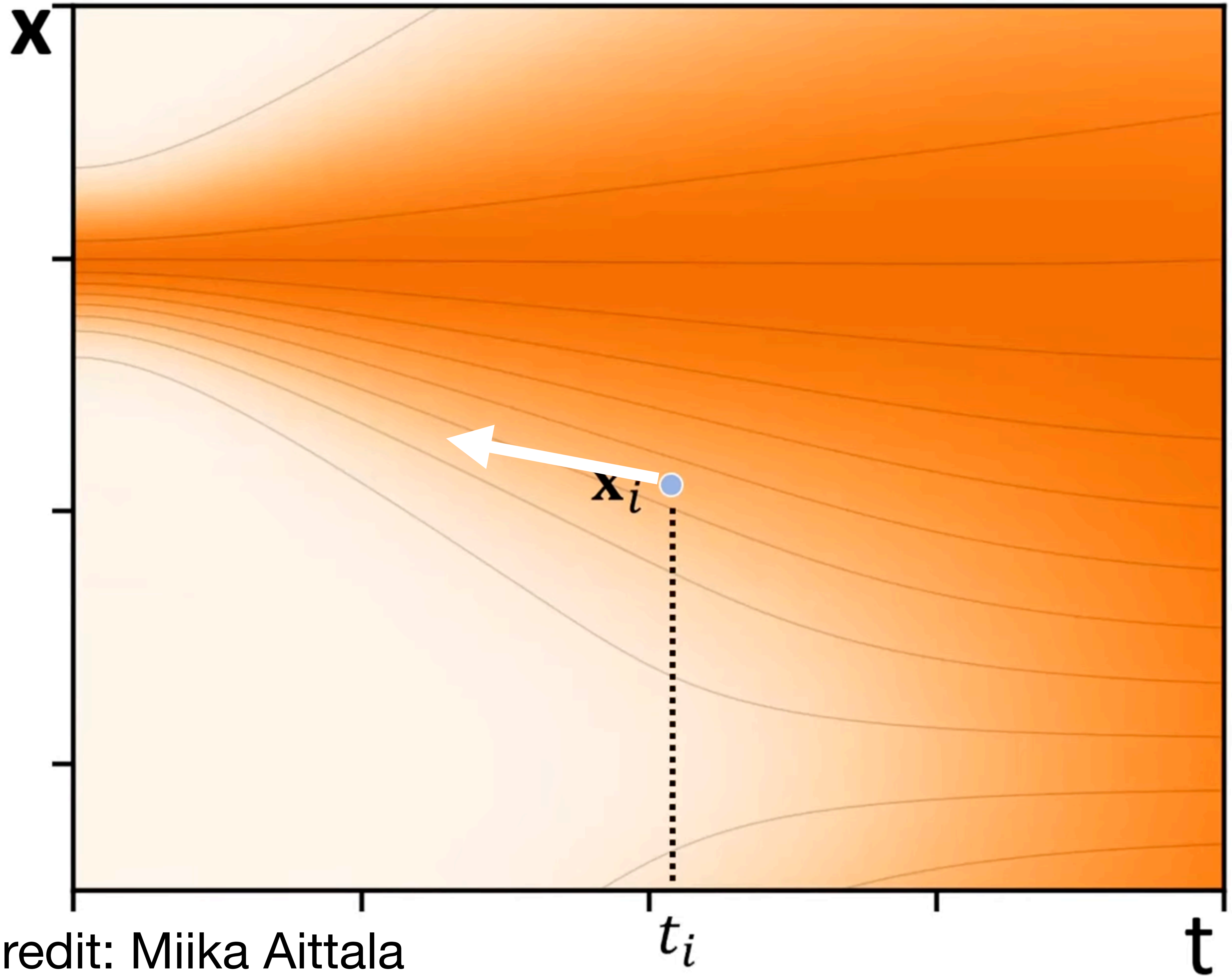

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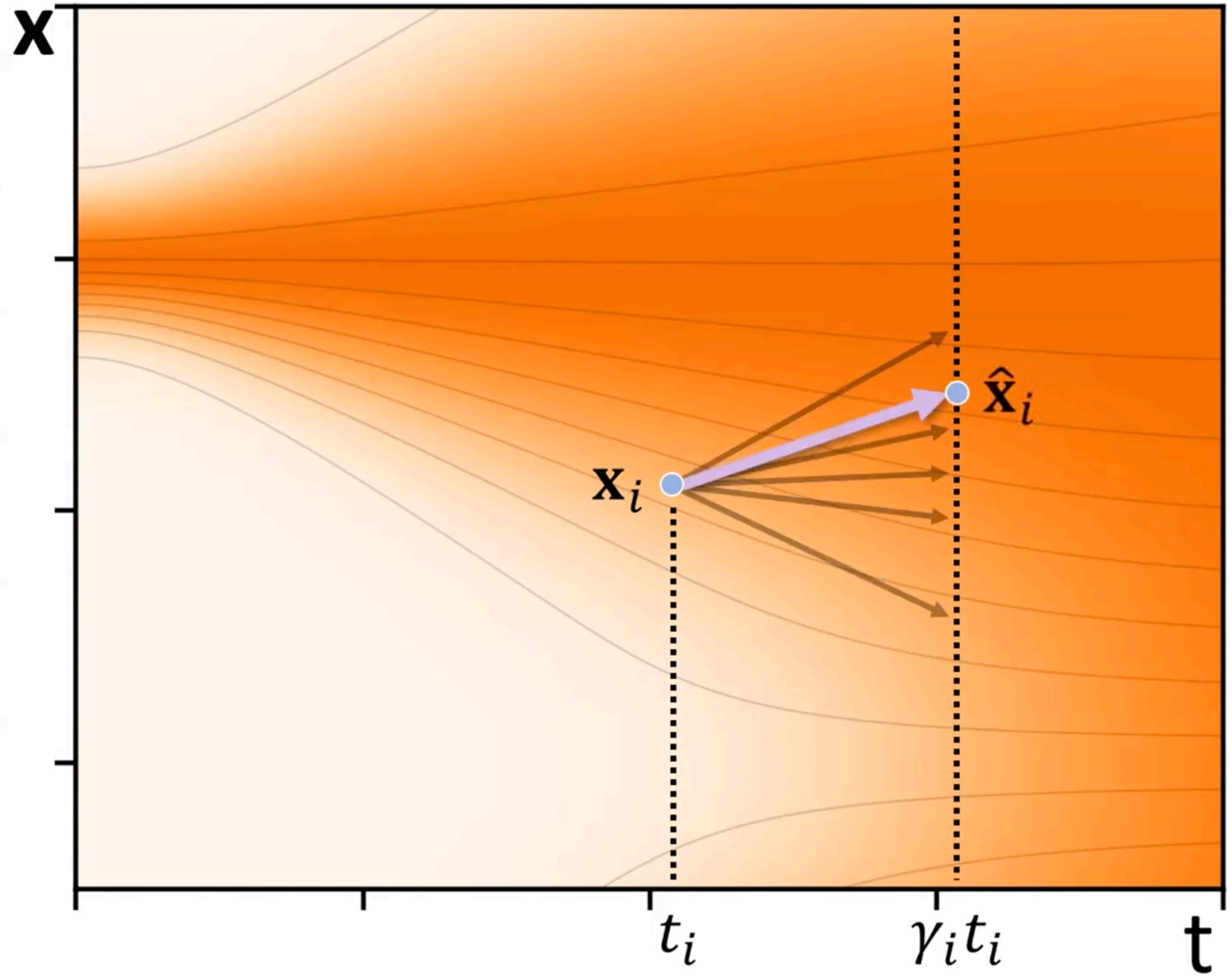

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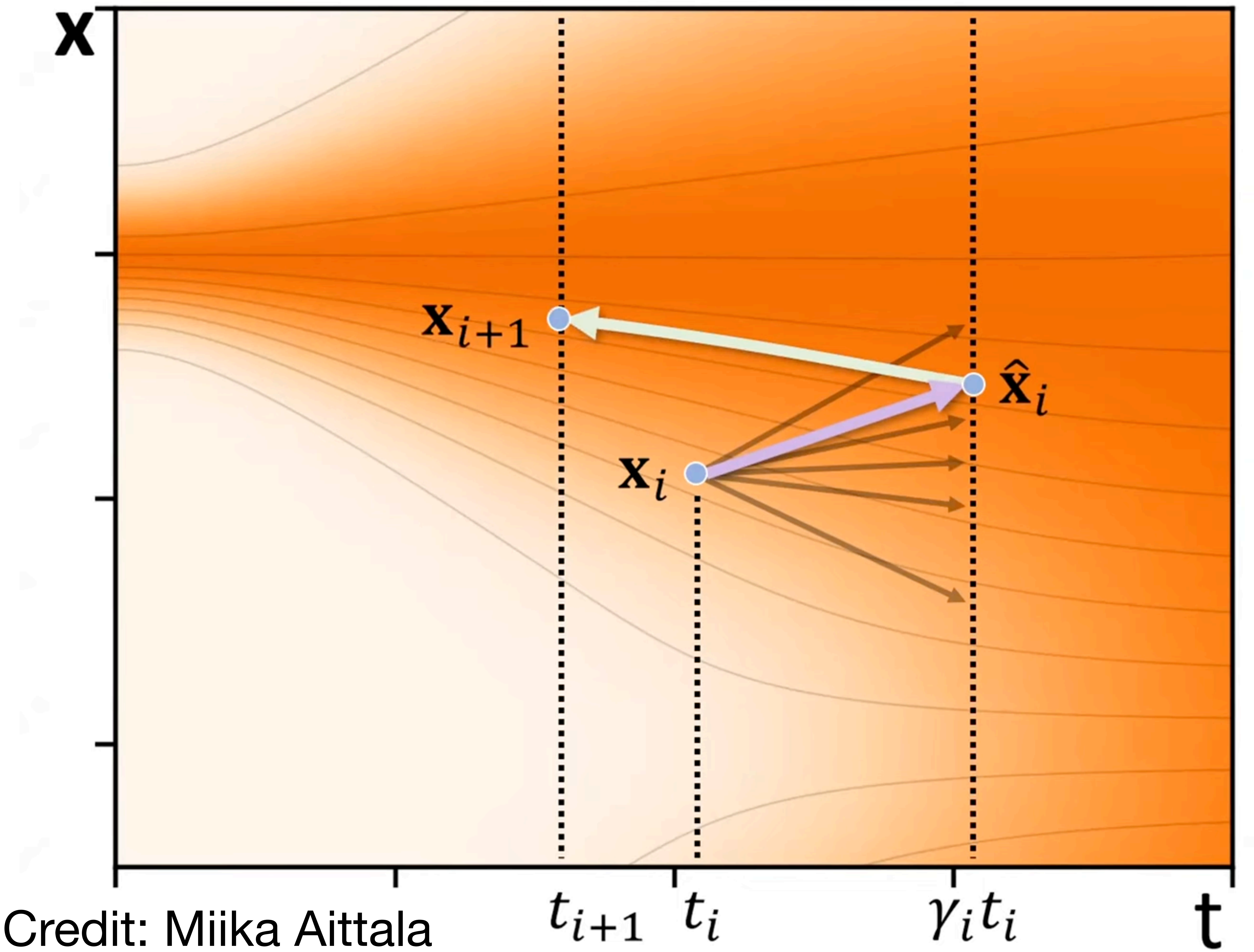

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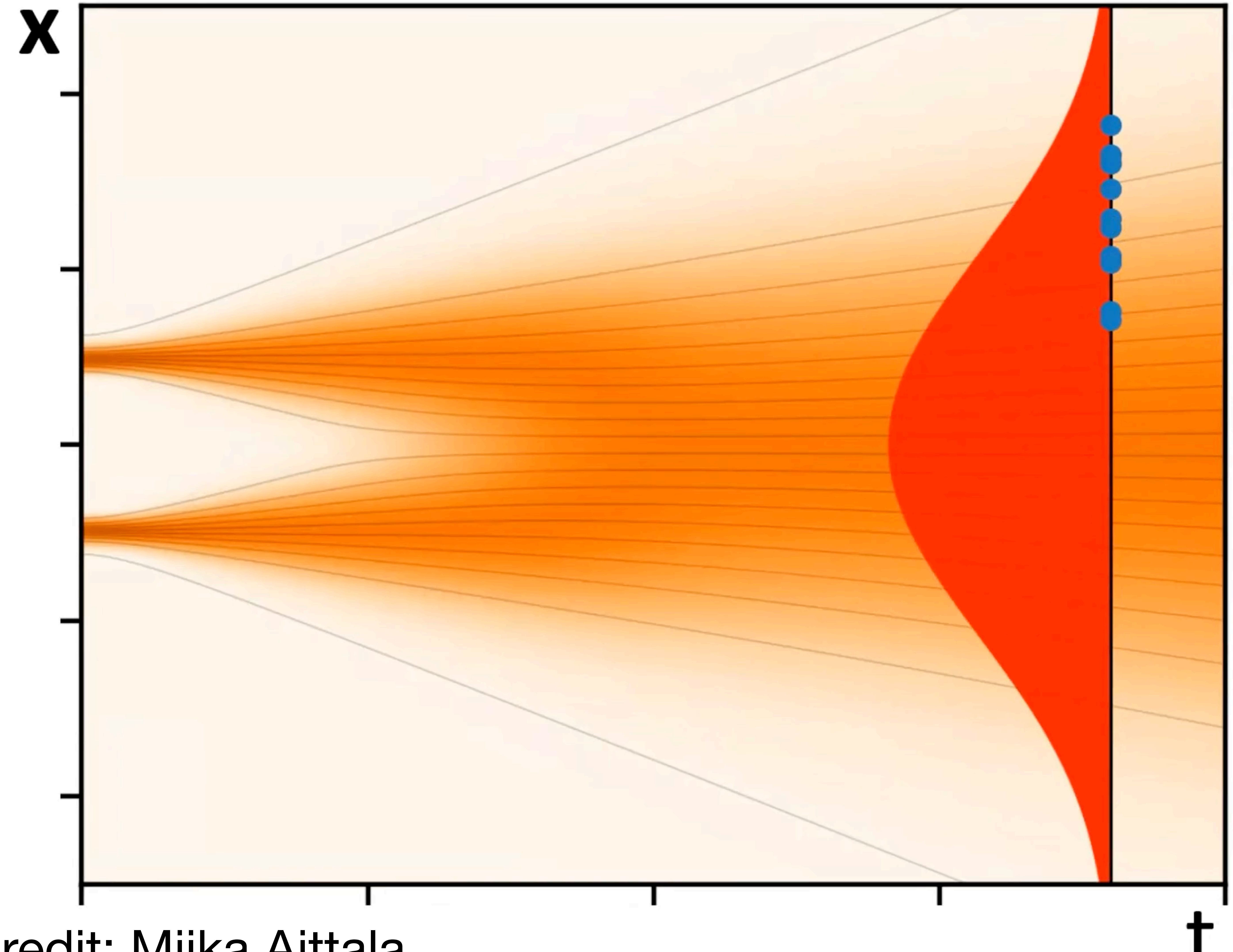
Stochastic Sampler Helps Explore the Distribution



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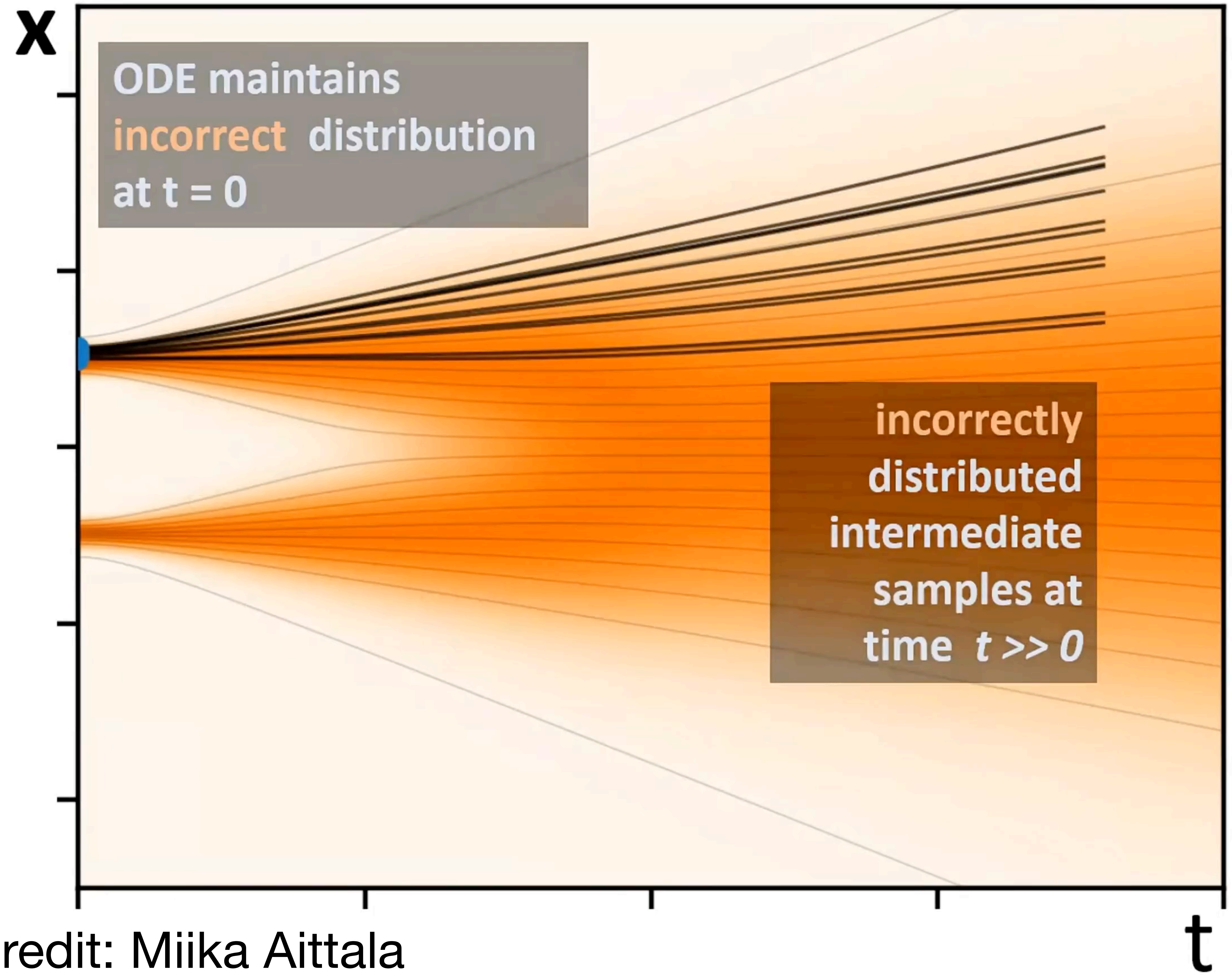

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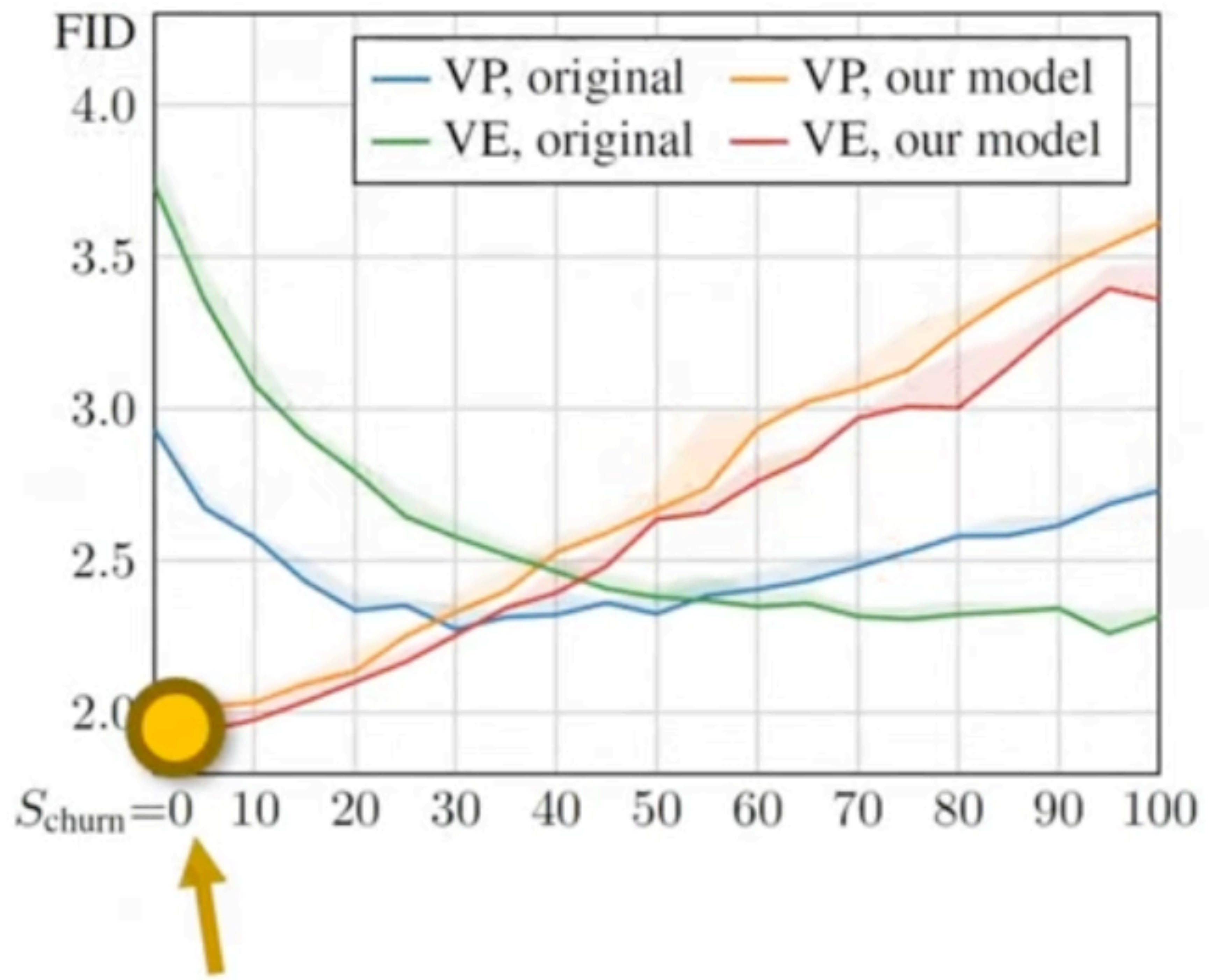
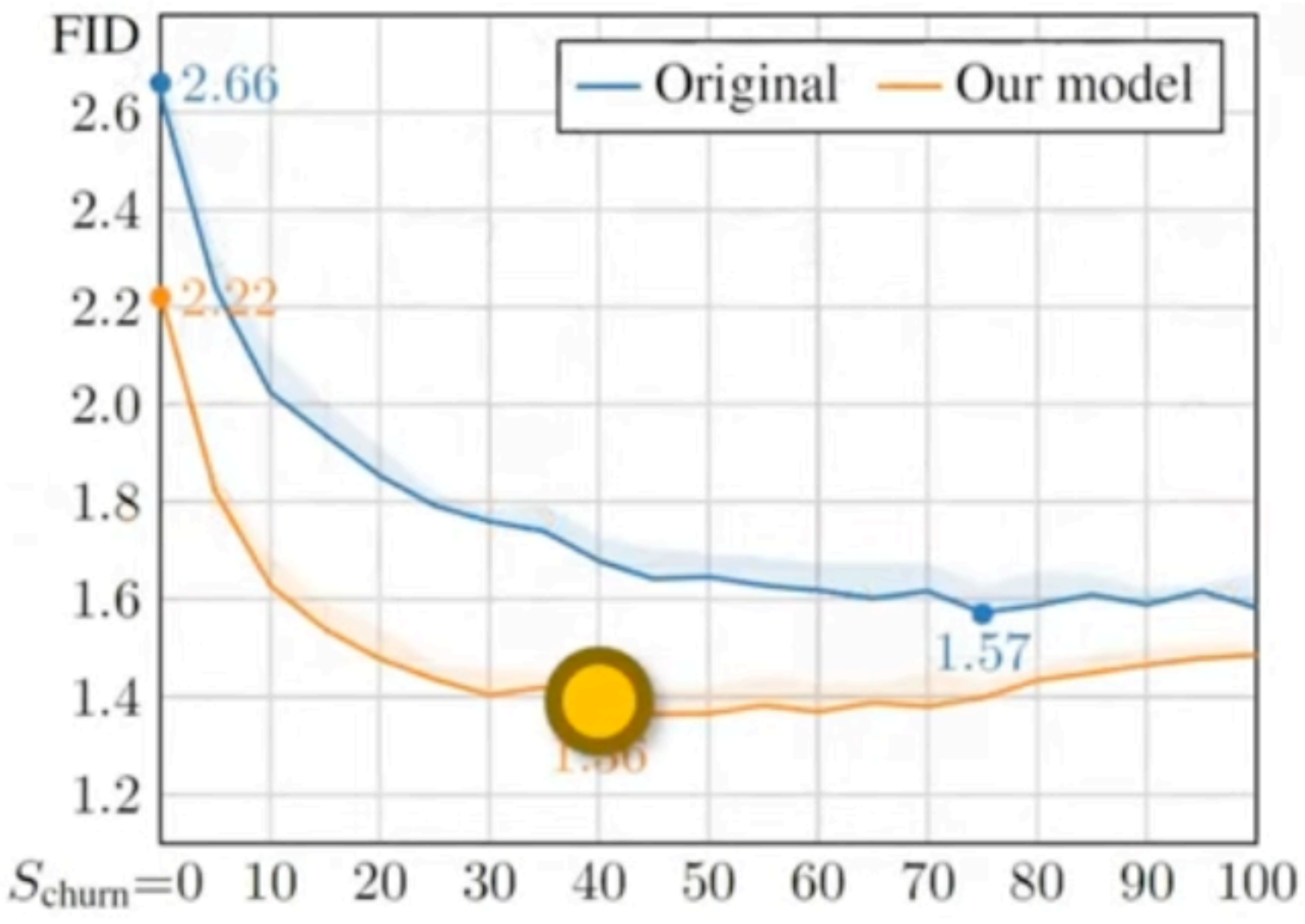
Is stochasticity always helpful?

CIFAR-10: no



best FID at *zero* stochasticity

Imagenet: yes



Credit: Miika Aittala

Image Generation by Solving the Flow ODE

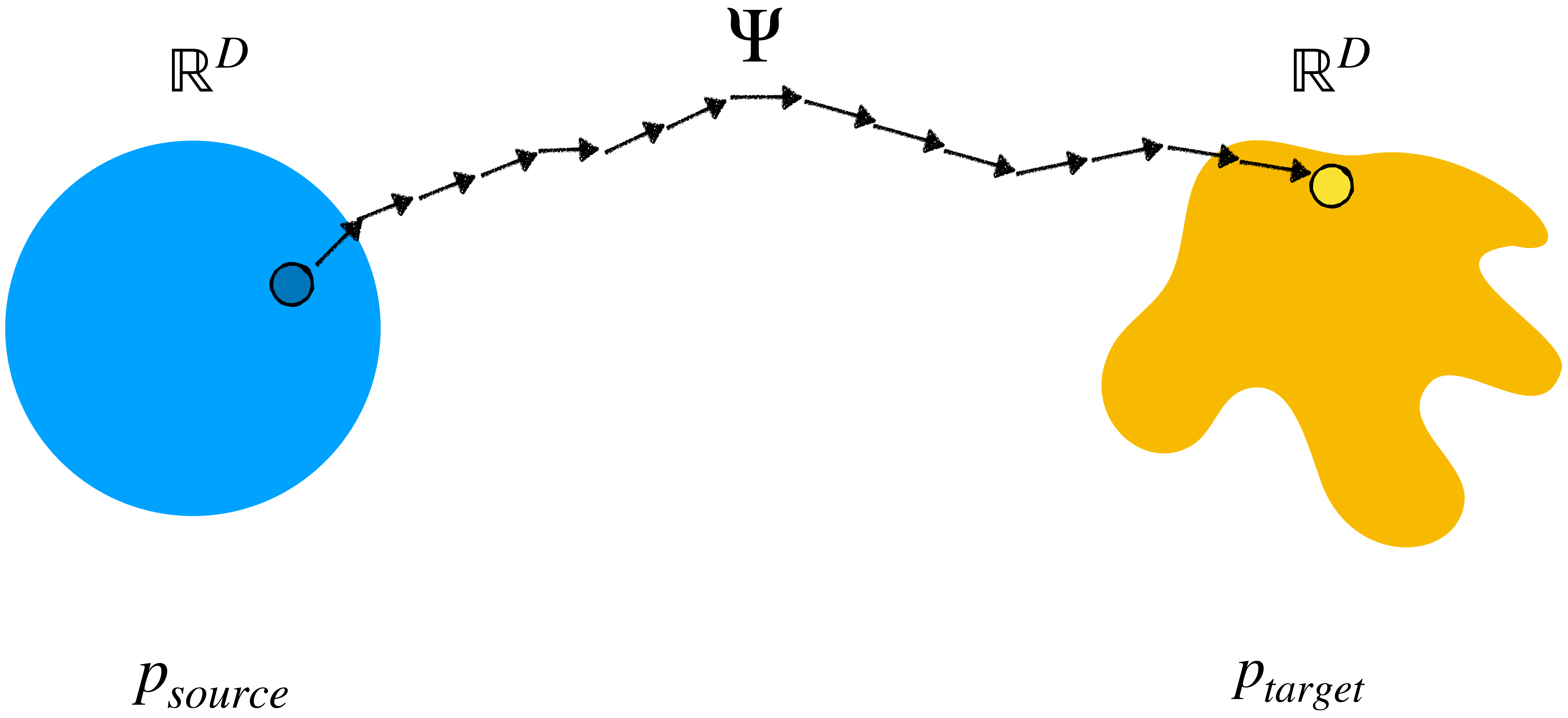
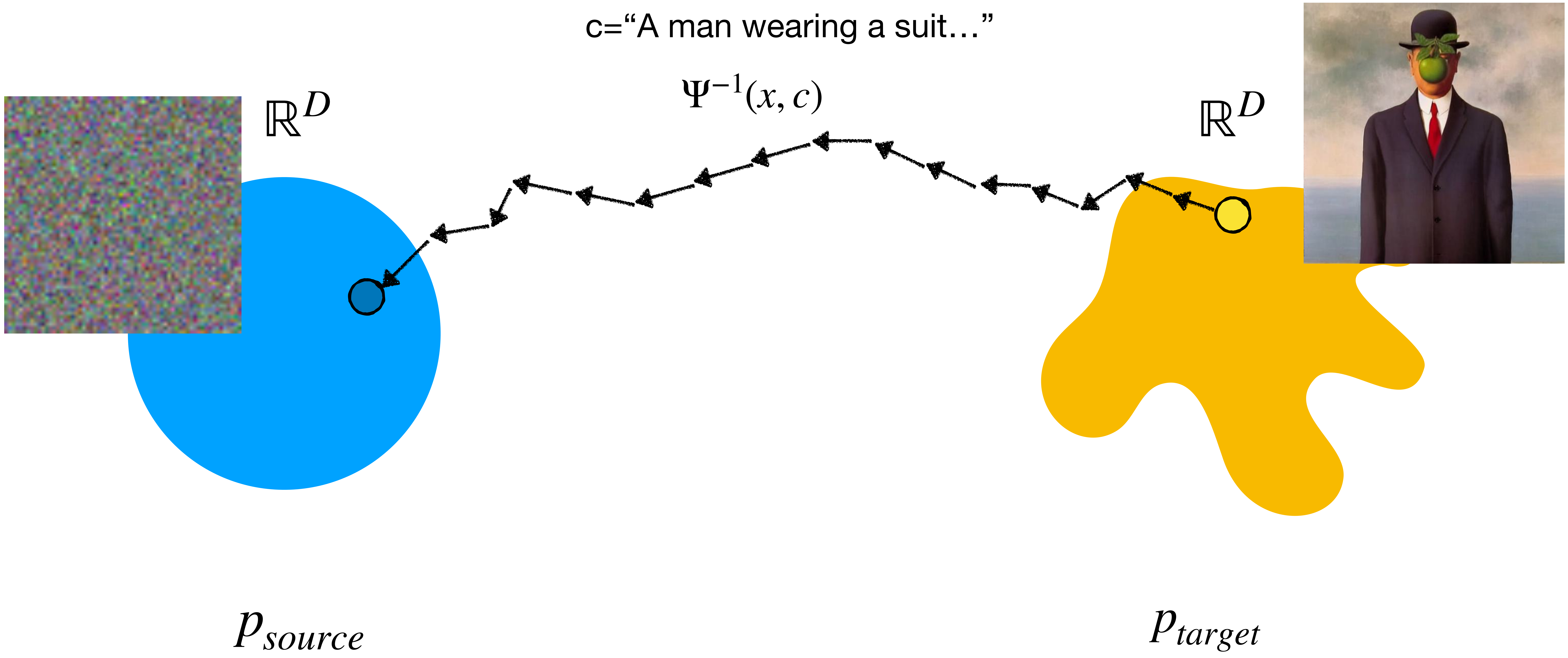


Image Editing with Diffusion Inversion



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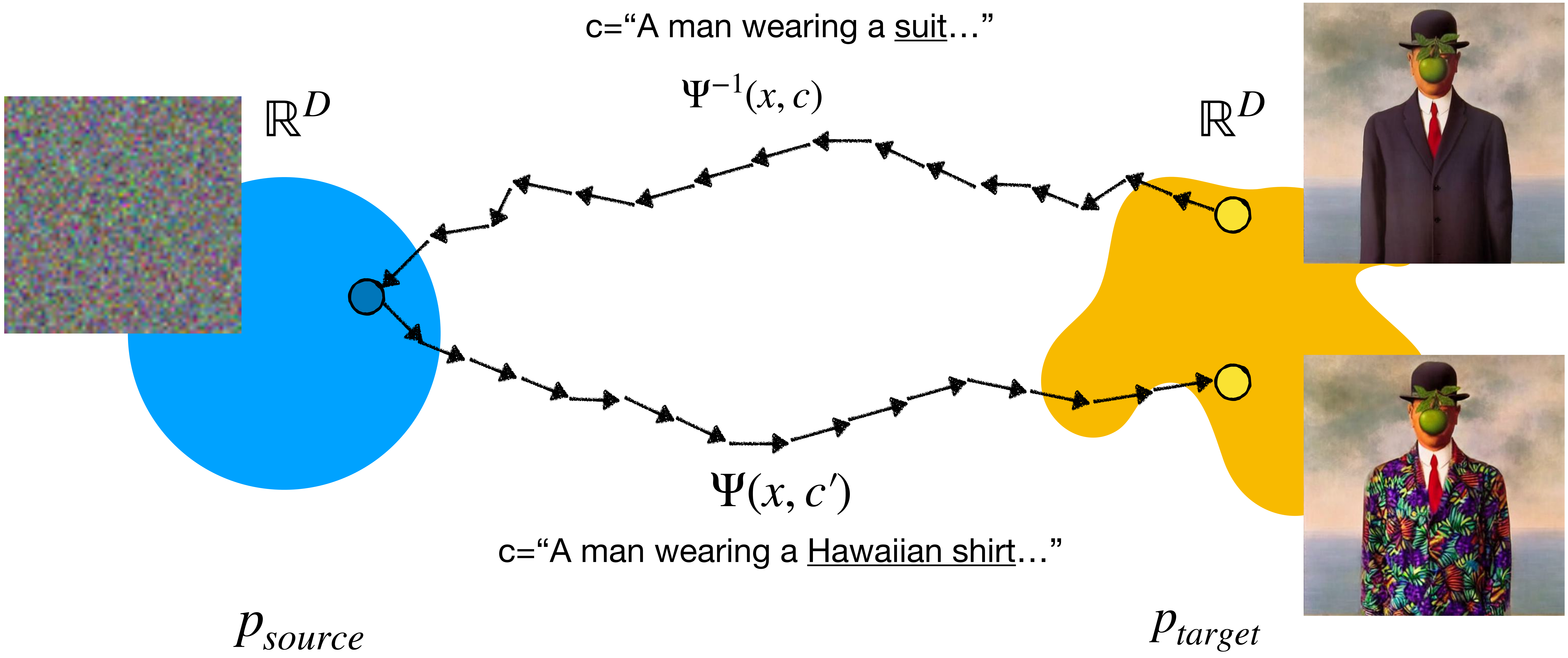
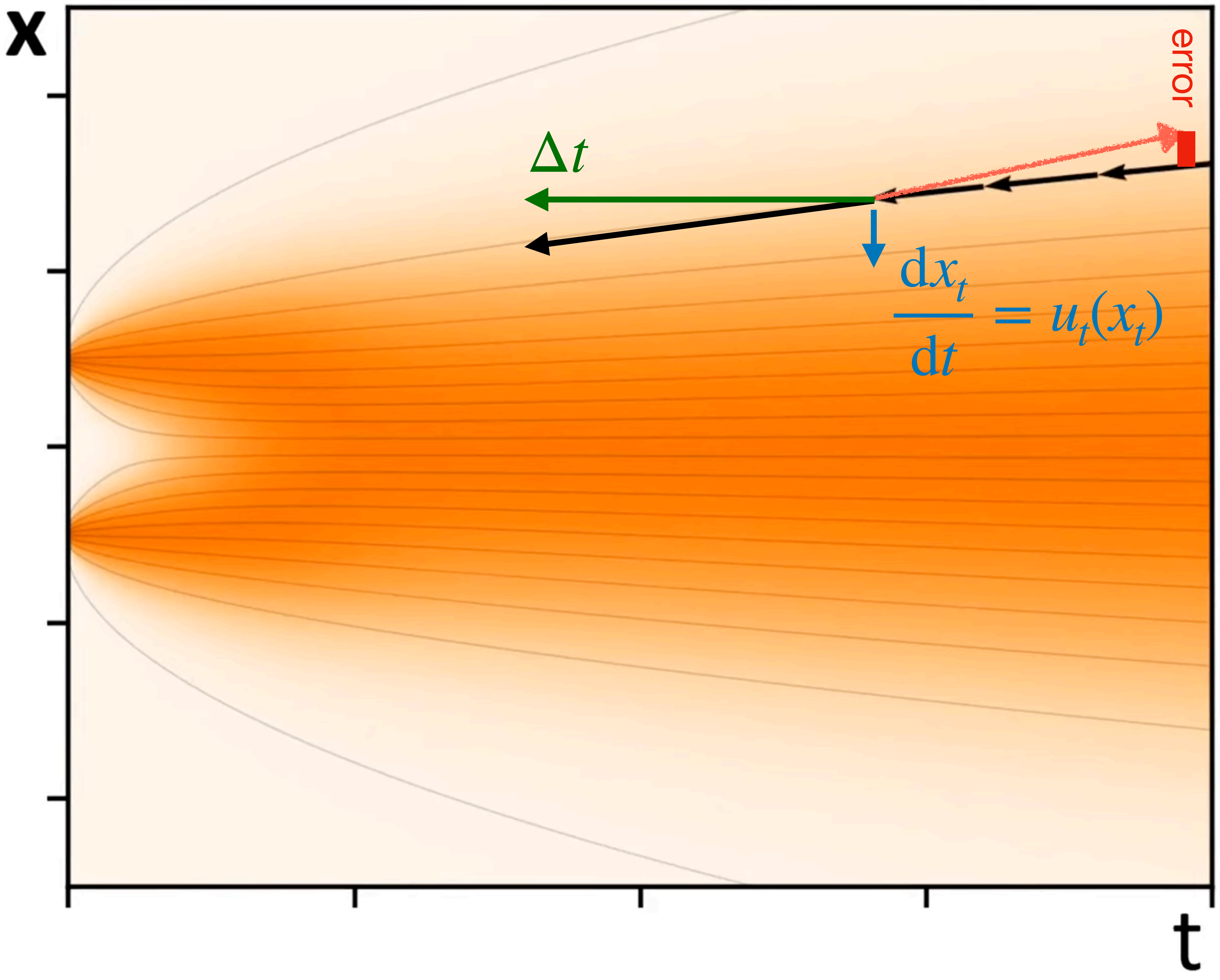


Inverting a diffusion model is not easy



$$x_{t-\Delta t} = x_t - \Delta t \cdot \left.\frac{dx}{dt}\right|_{x_t,t}$$

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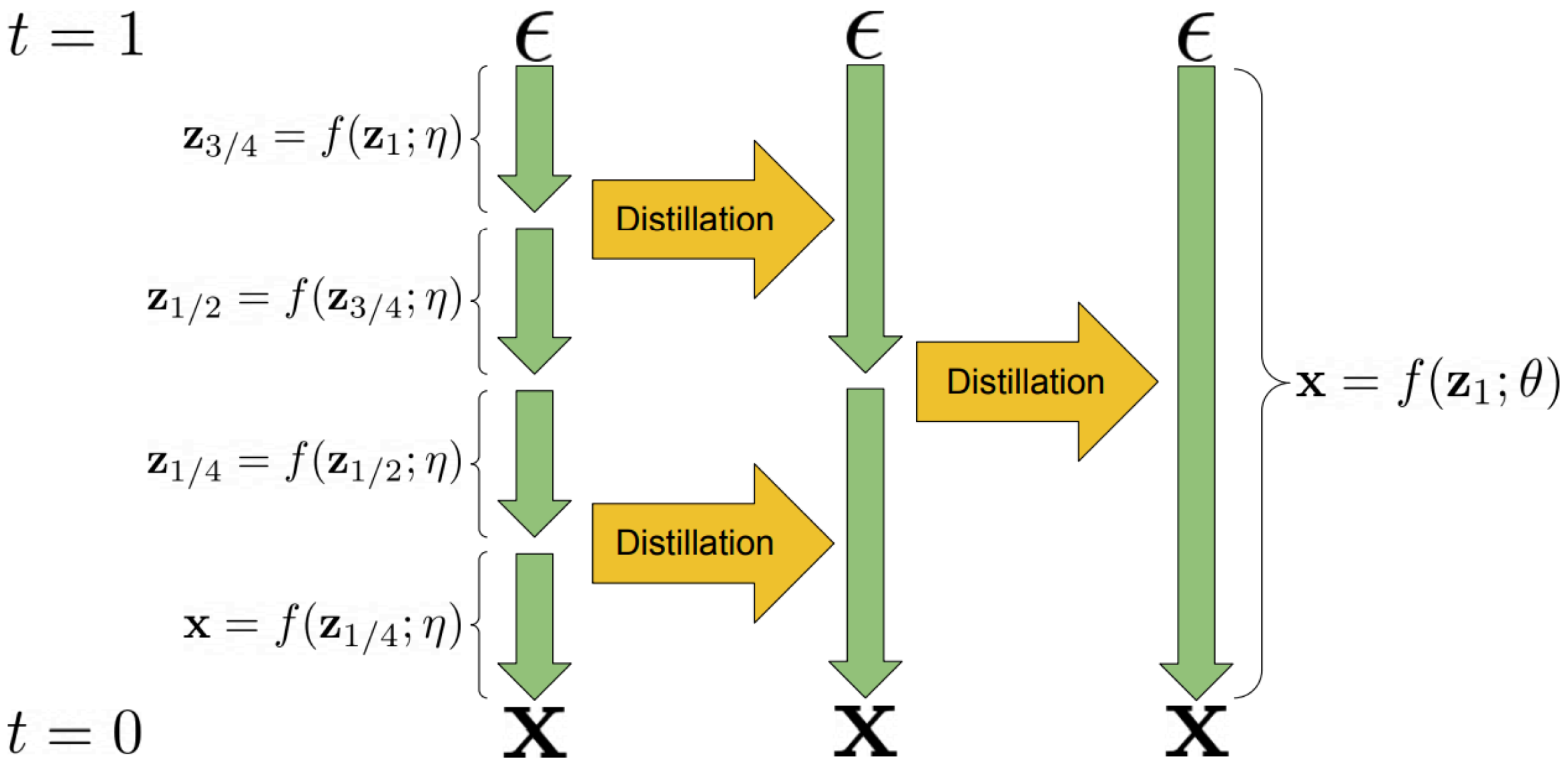
Sampling is slow!

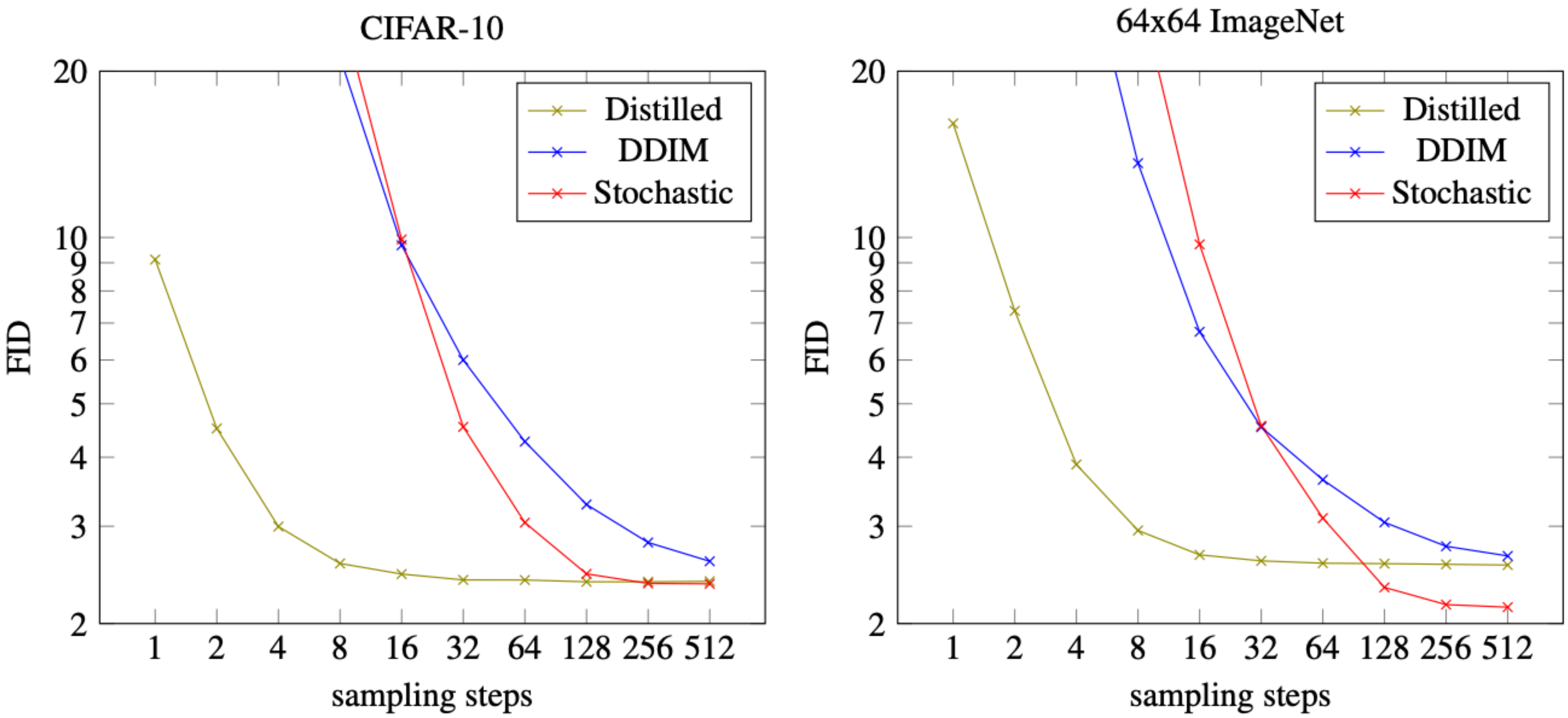
Generating a 3s HD video could take 15 minutes!

Progressive Distillation



Salimans, Tim, and Jonathan Ho. "Progressive distillation for fast sampling of diffusion models.

Progressive Distillation



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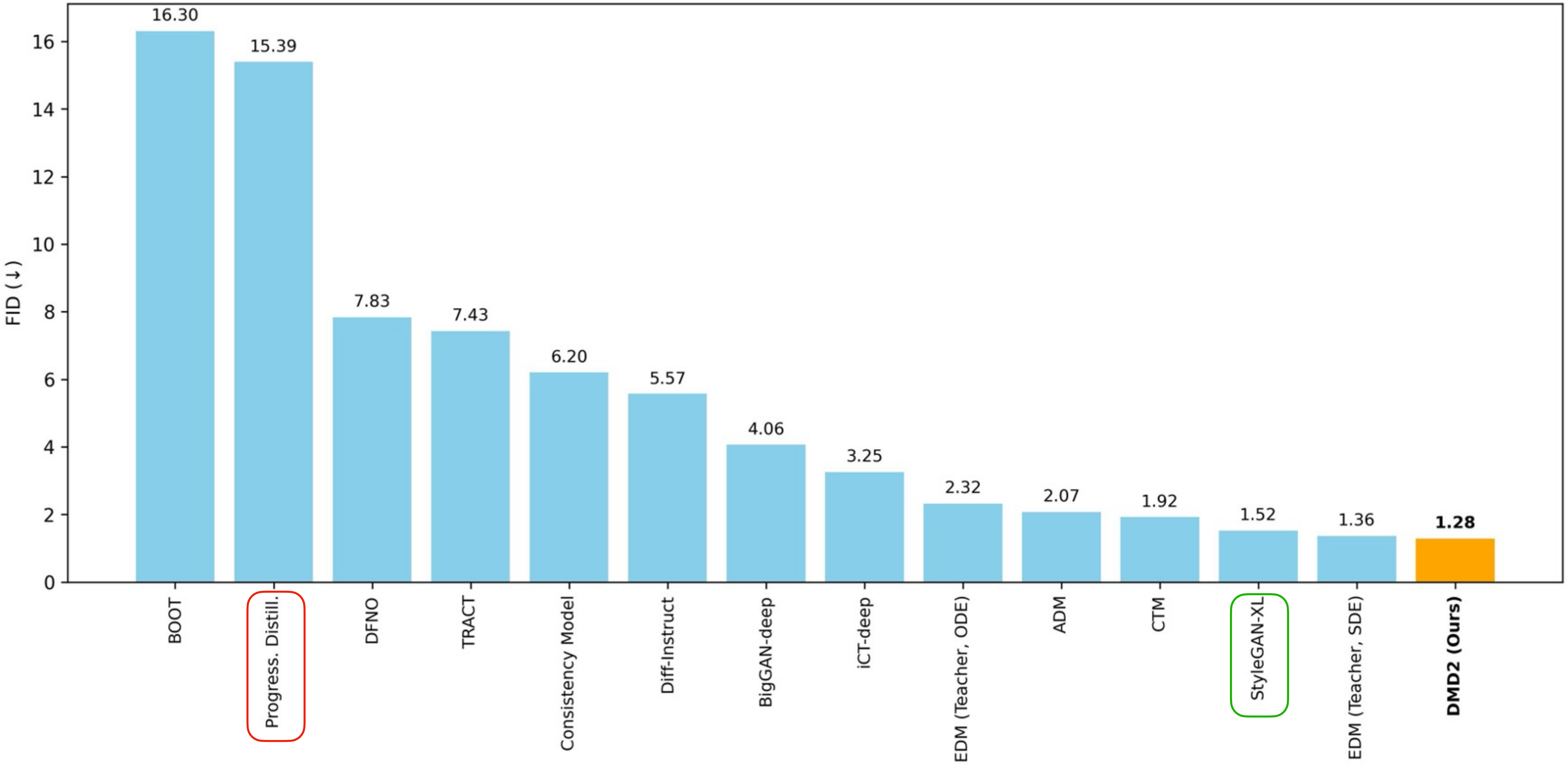
Distribution Matching Distillation

Yin, Tianwei, et al. "One-step diffusion with distribution matching distillation."

Distribution Matching Distillation



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"beret of raspberries"

Conditioning & Guidance

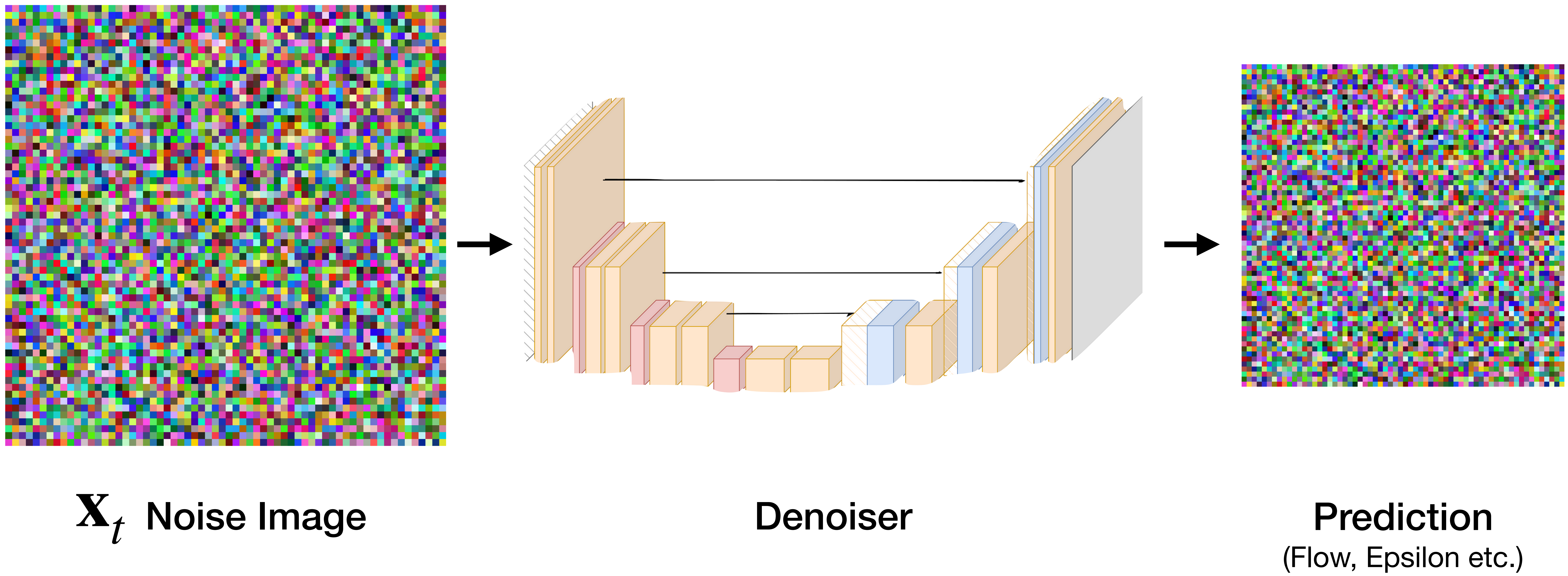
slide from Steve Seitz's [video]

raspberry beret

slide from Steve Seitz's video

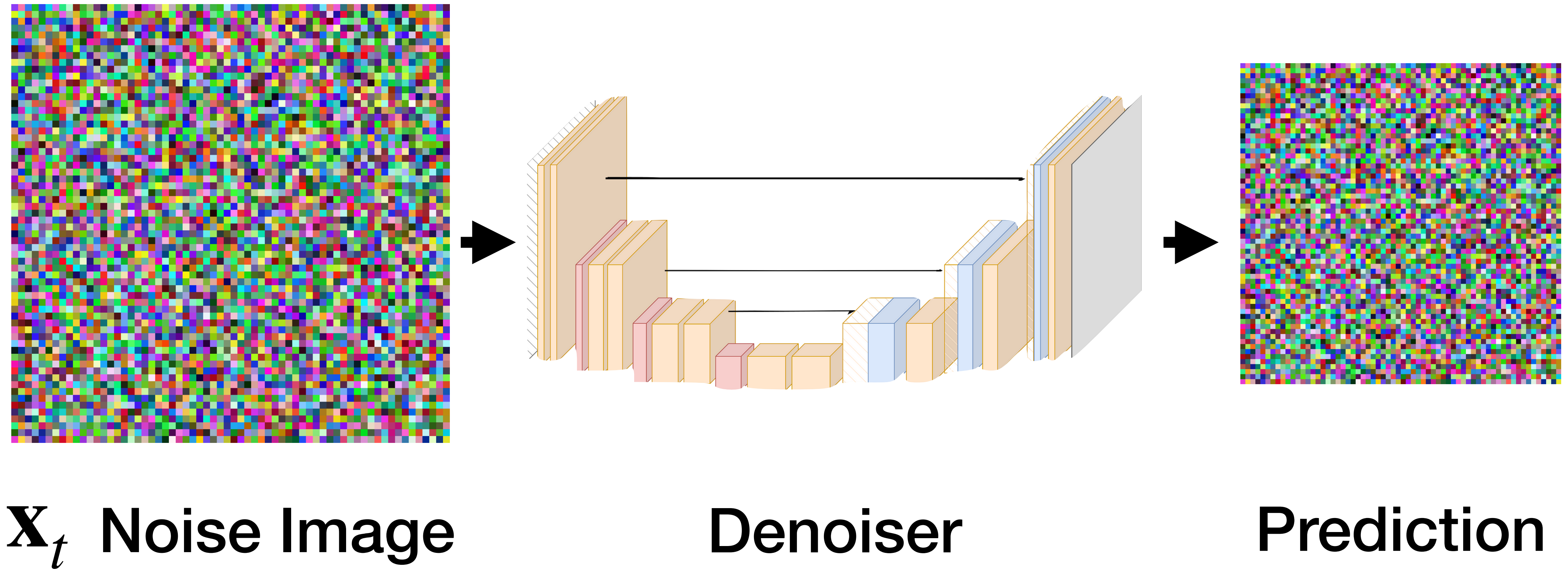
Diffusion Guidance

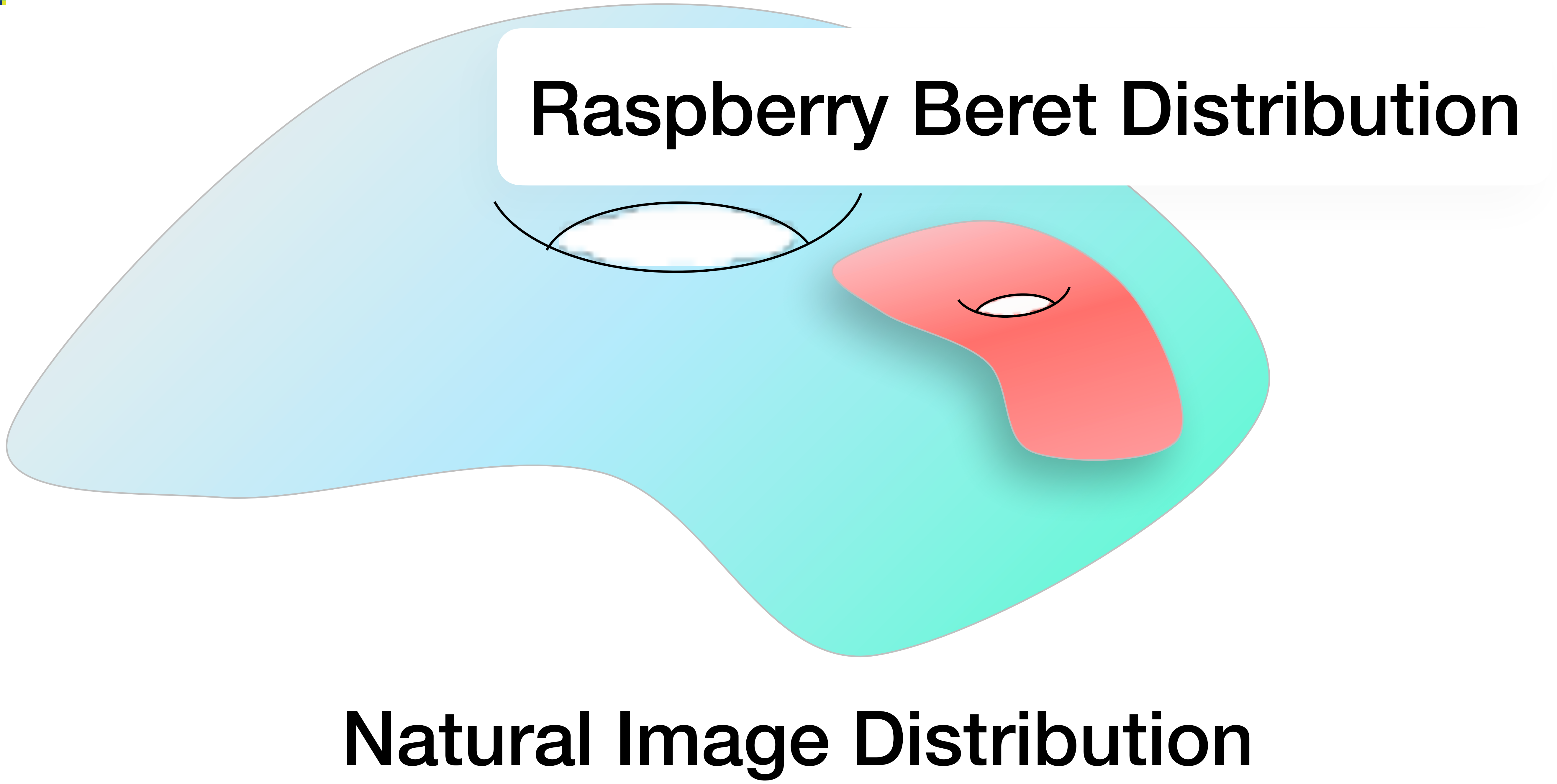
Motivation



Diffusion Guidance

Motivation





Diffusion Guidance

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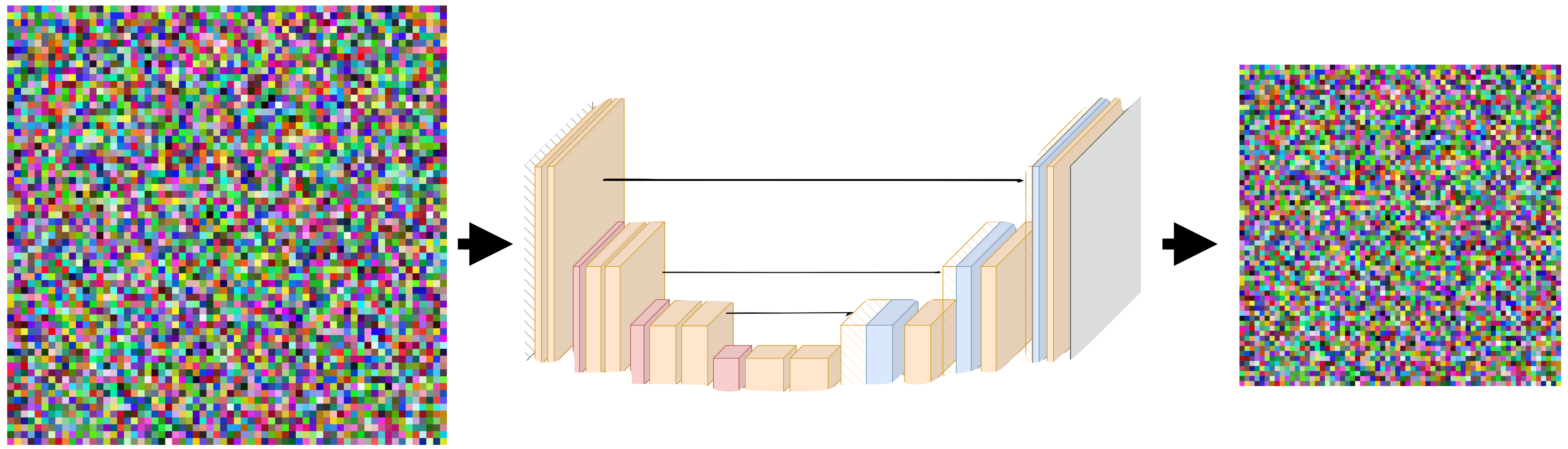

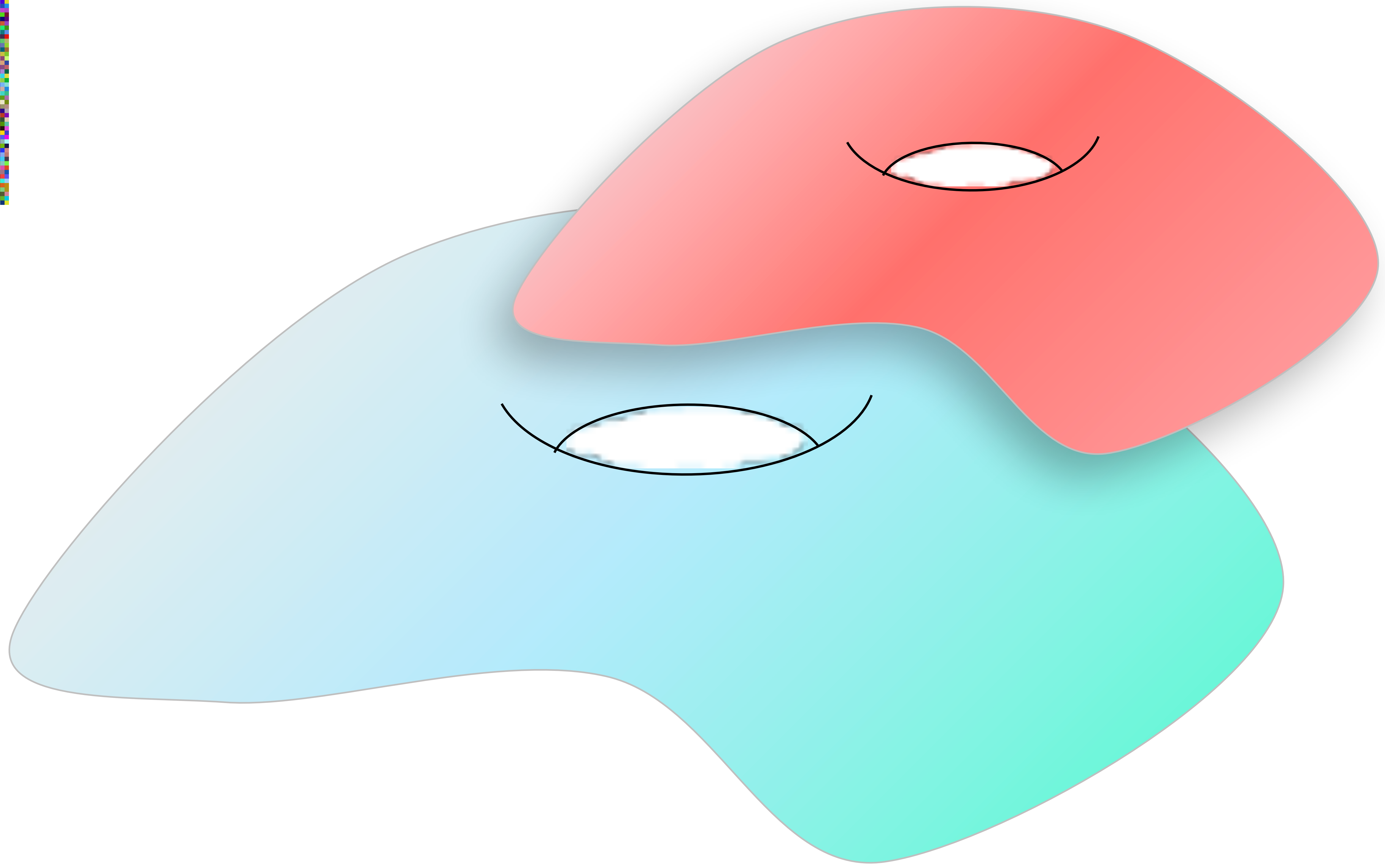

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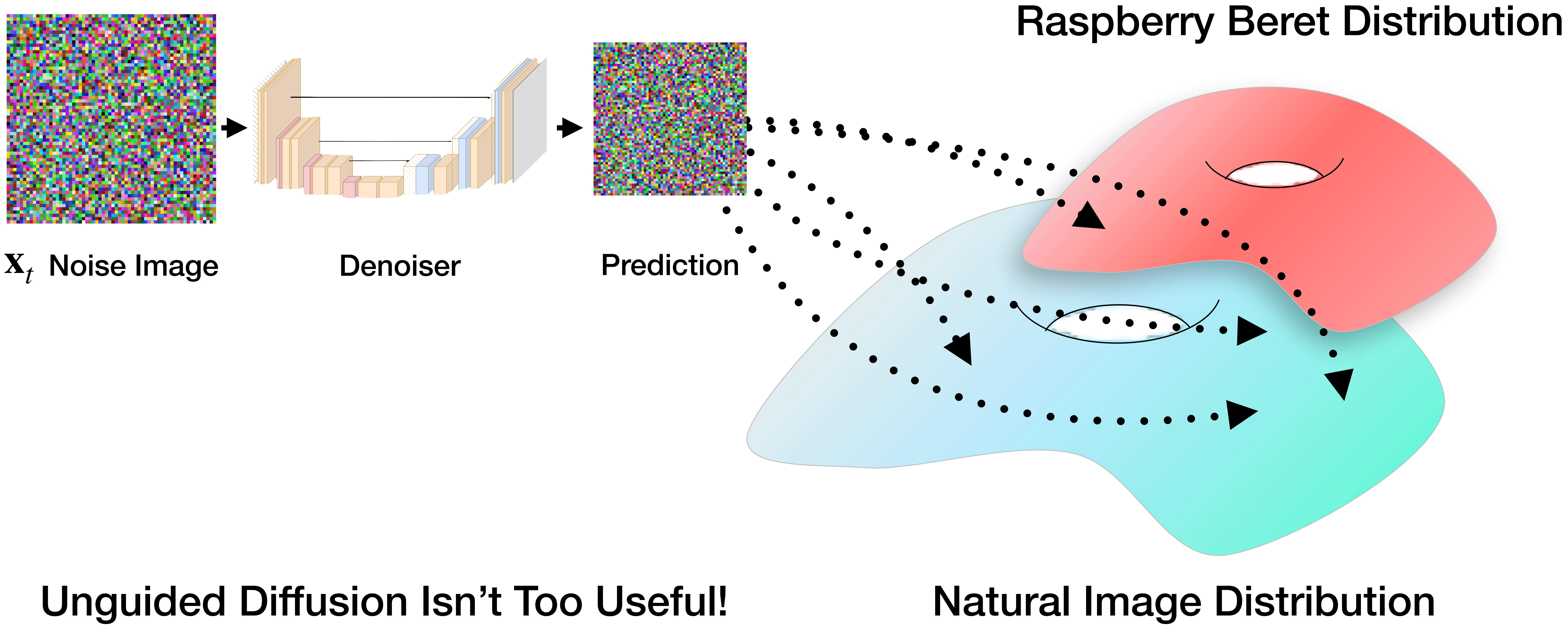
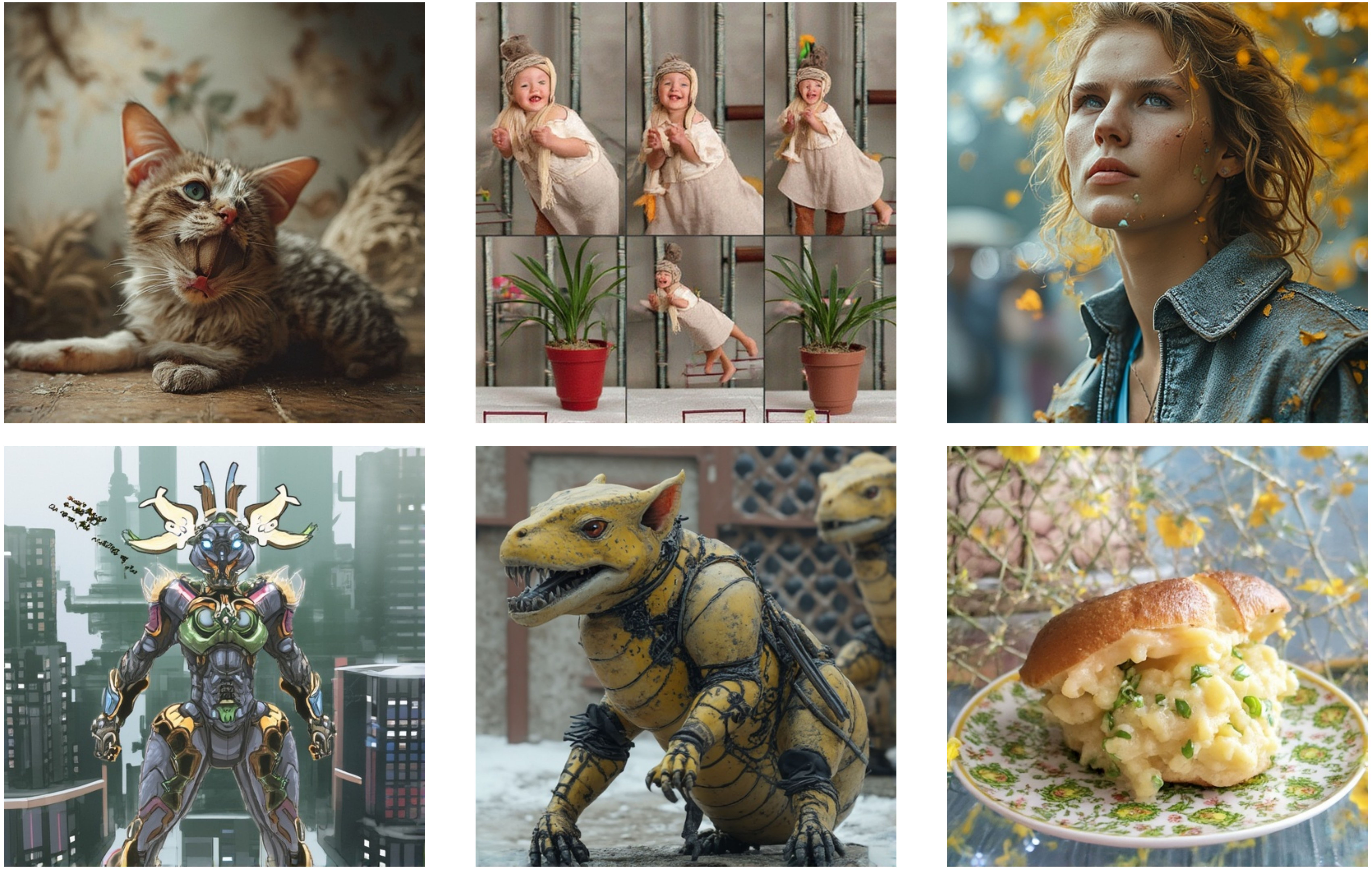


Unguided Diffusion Isn't Too Useful!

Flux Pro Unguided Samples

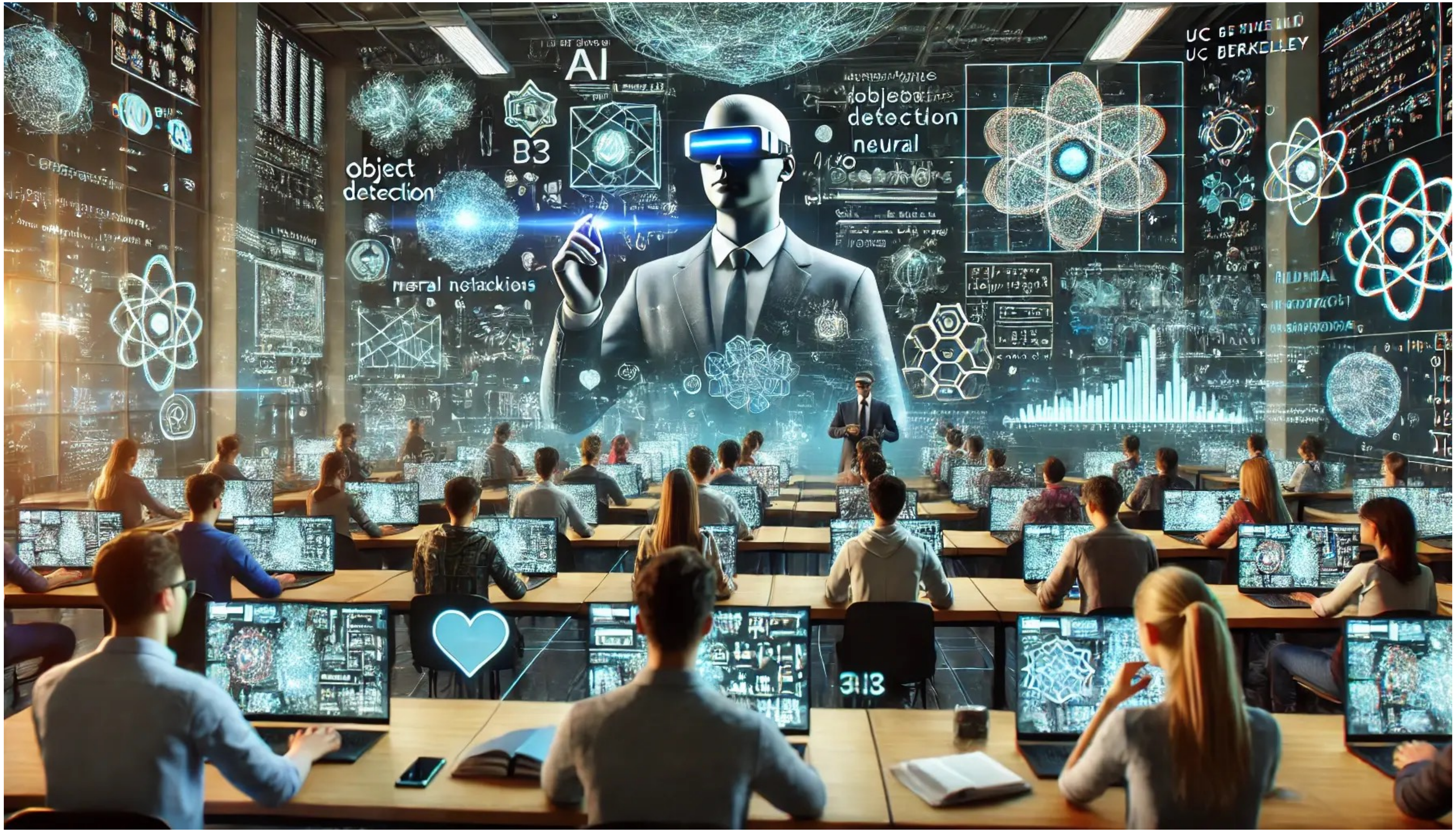
Imitates Distribution of Internet Training Data



Flux Pro Guided Samples

“beret of raspberries”

Generate a photo of a Berkeley computer vision class

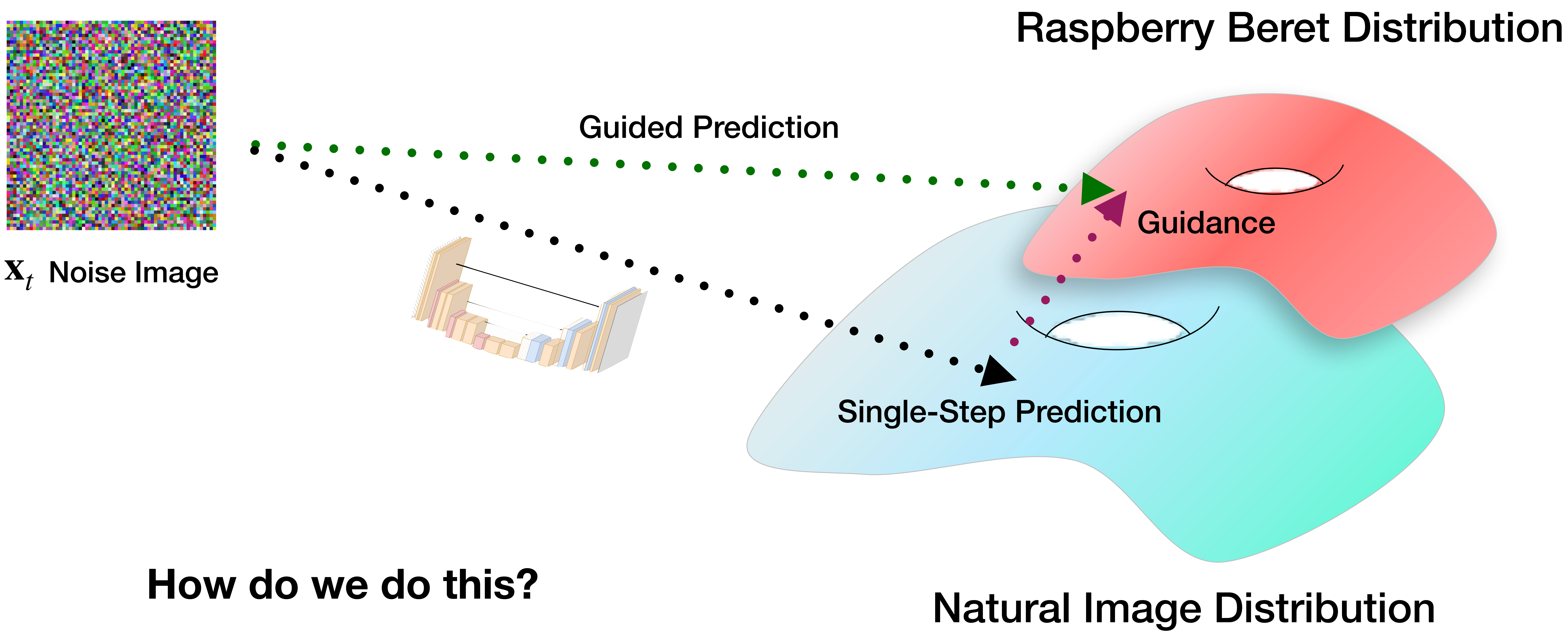


Make it more epic

Make it THE MOST EPIC computer vision class that you can ever think of

Diffusion Guidance

Push Toward a Conditional Mode



How do we do this?

Two Approaches

Original

Classifier Guidance

Guide with a pretrained classifier.

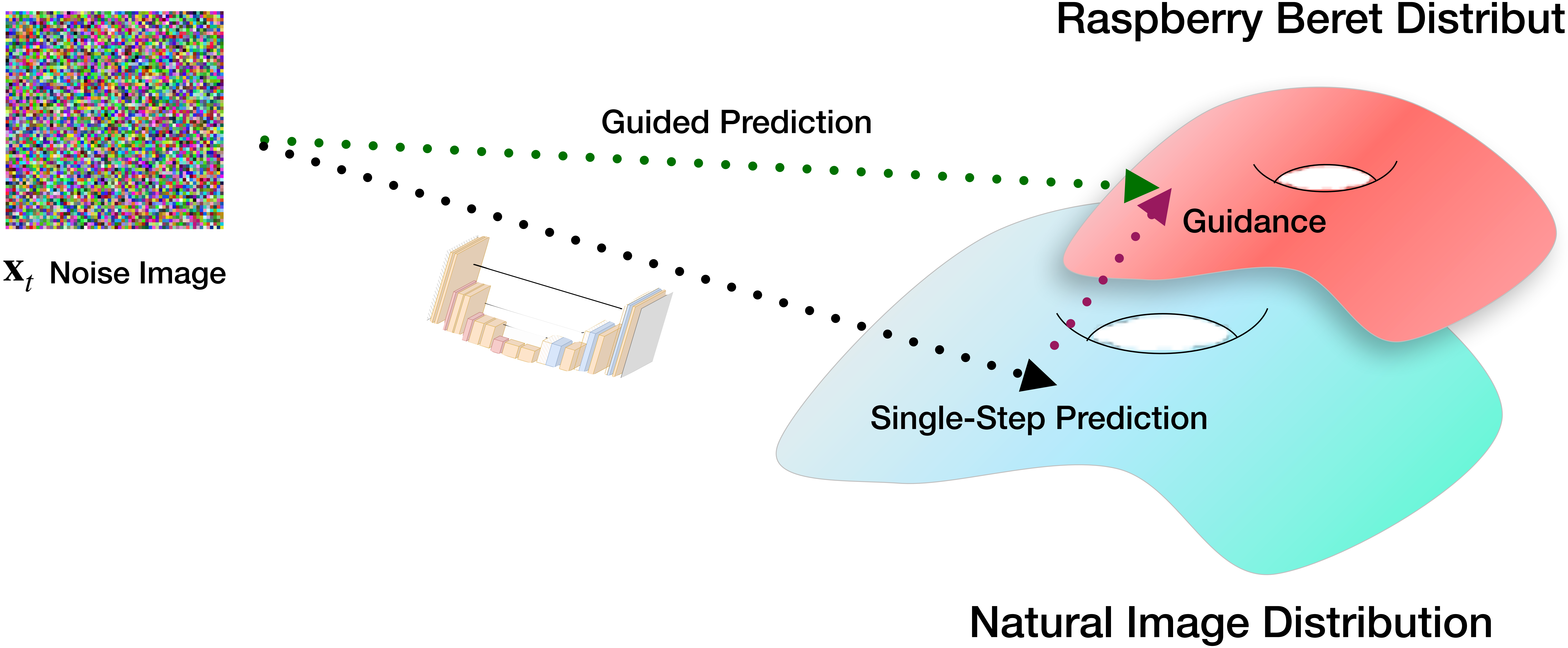
Current

Classifier-Free Guidance

Guide a diffusion model with itself.

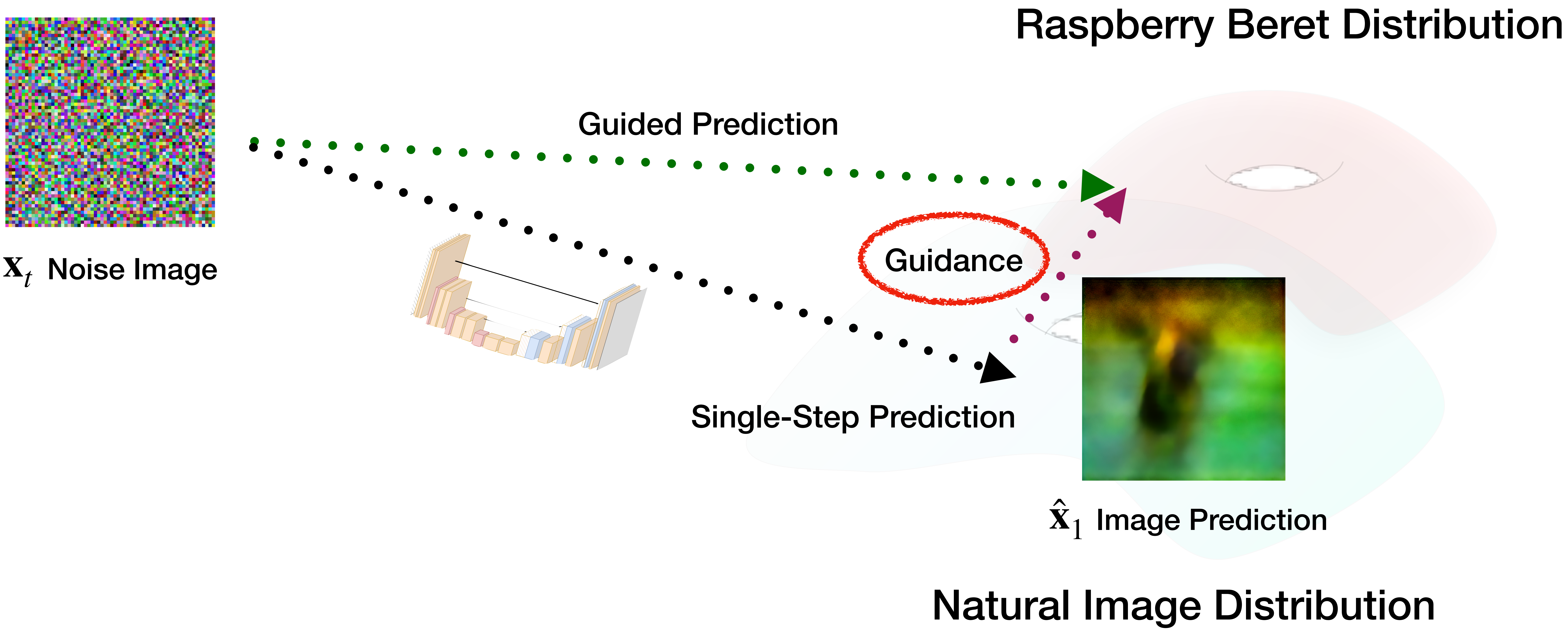
Diffusion Guidance

Push Toward a Conditional Mode



Classifier Guidance

Using a Pretrained Classifier



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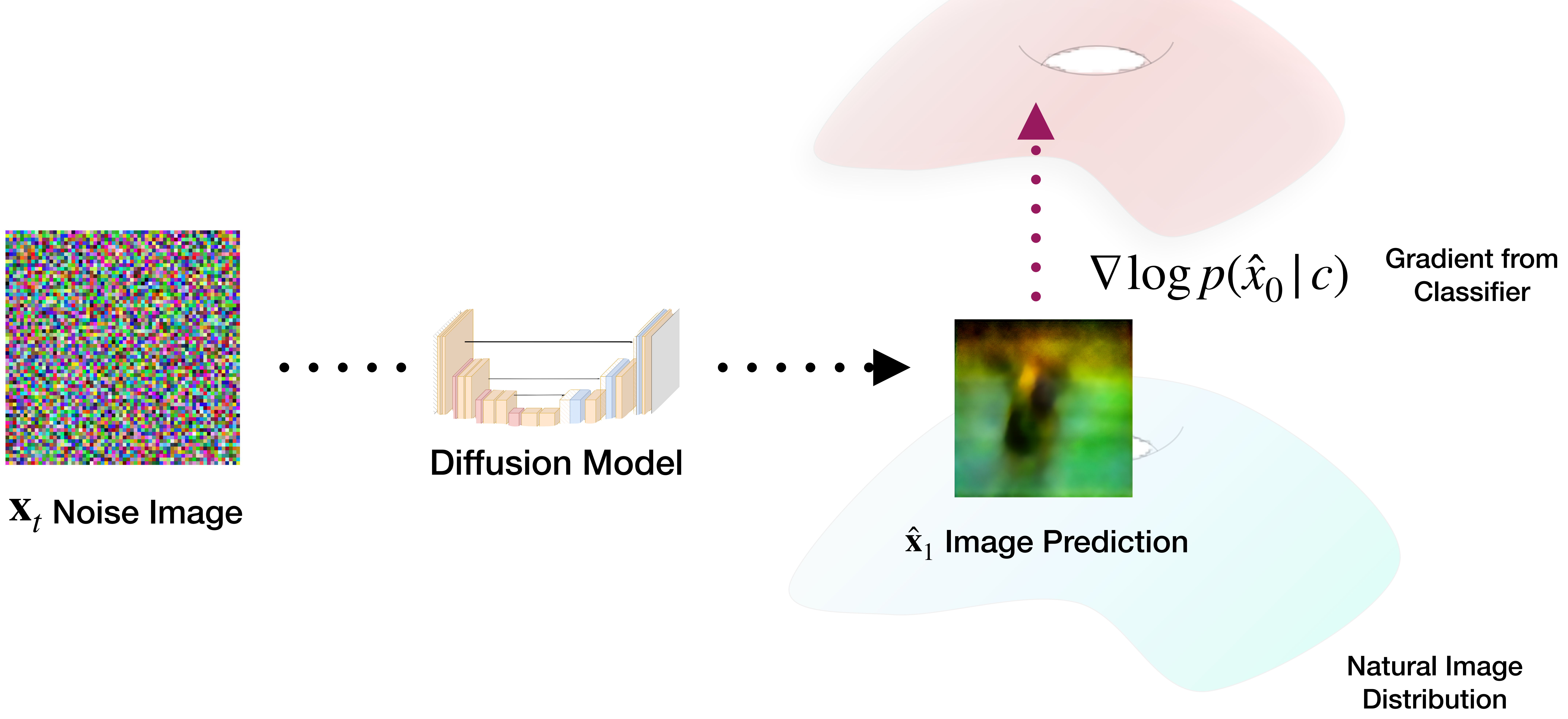
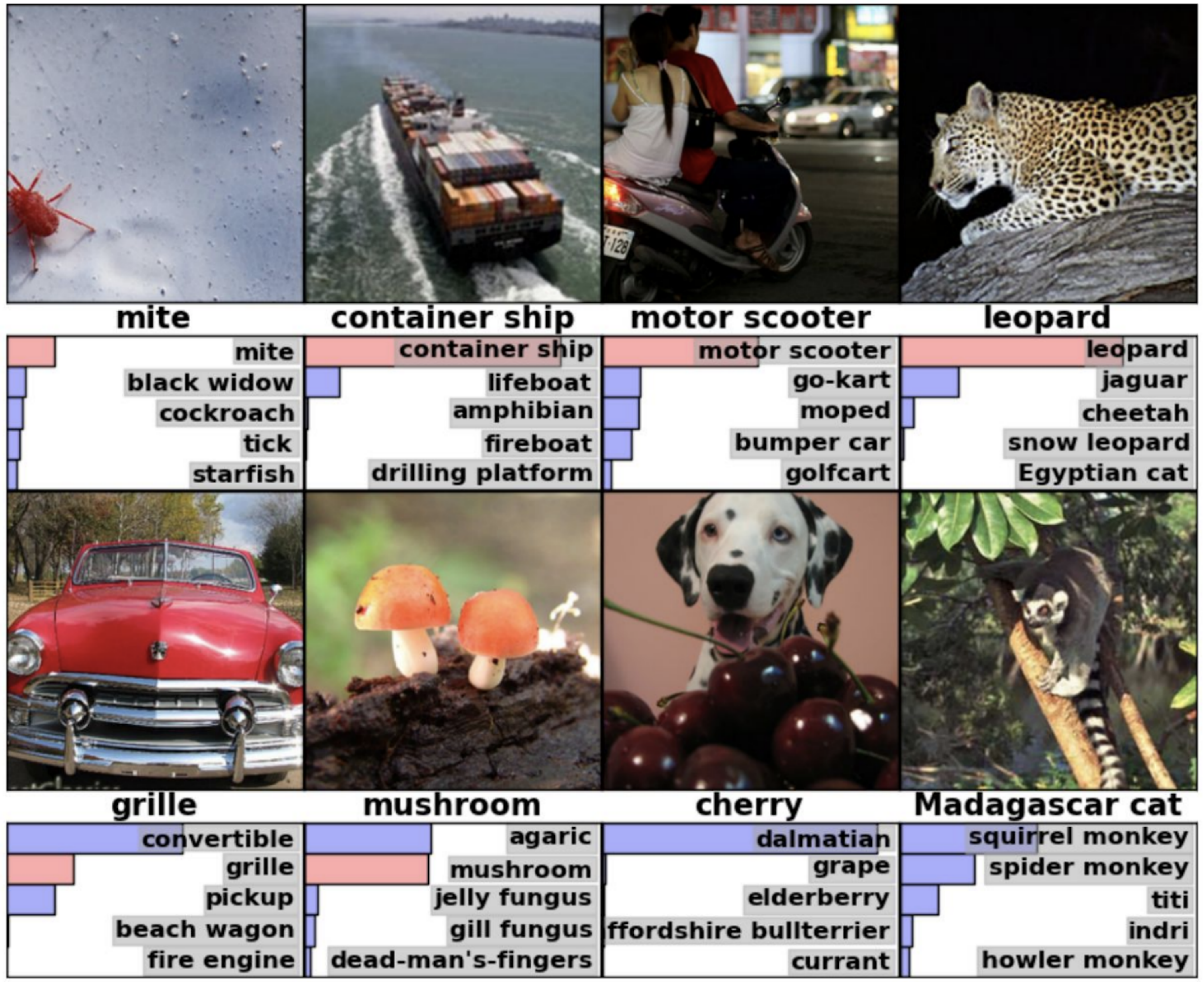


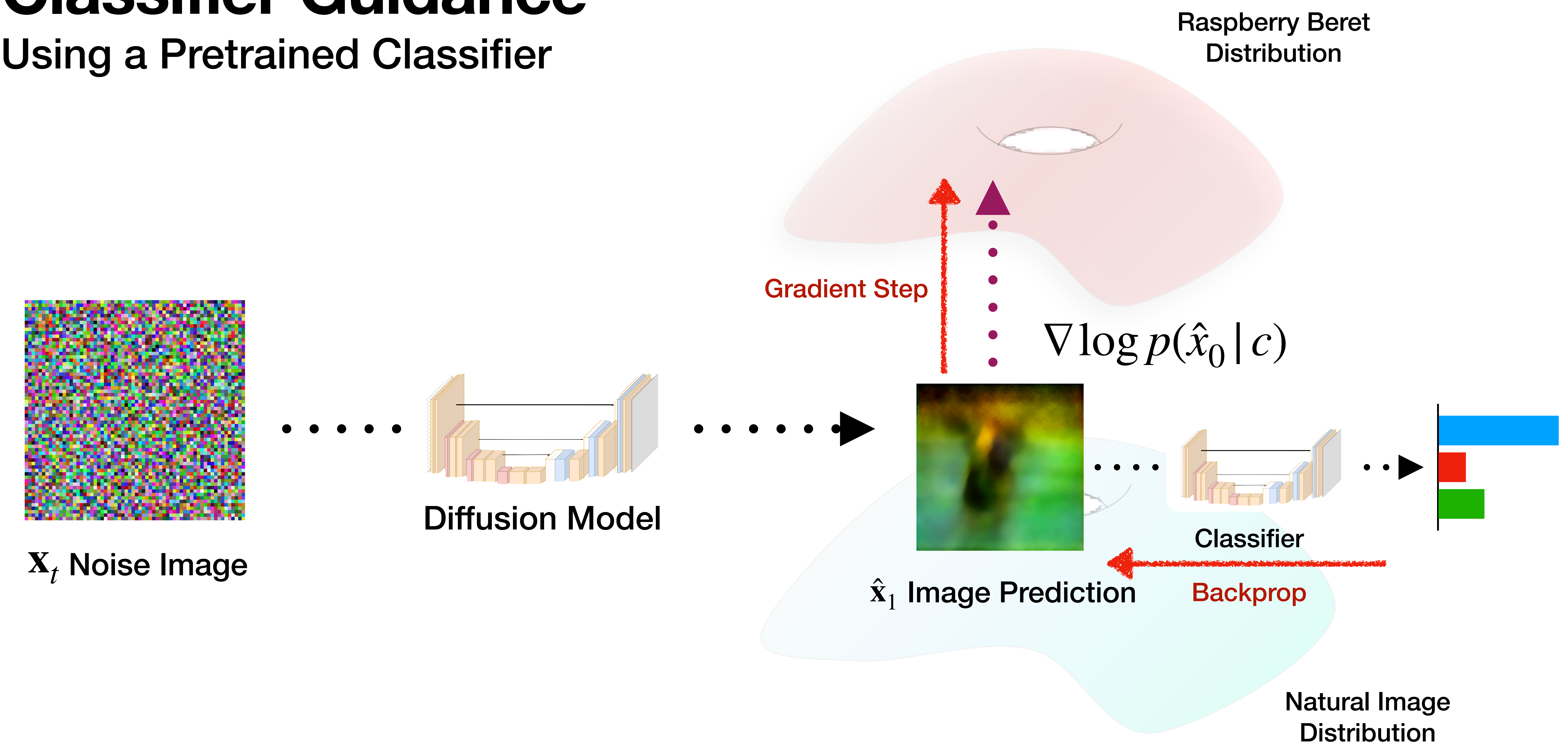
For Example…



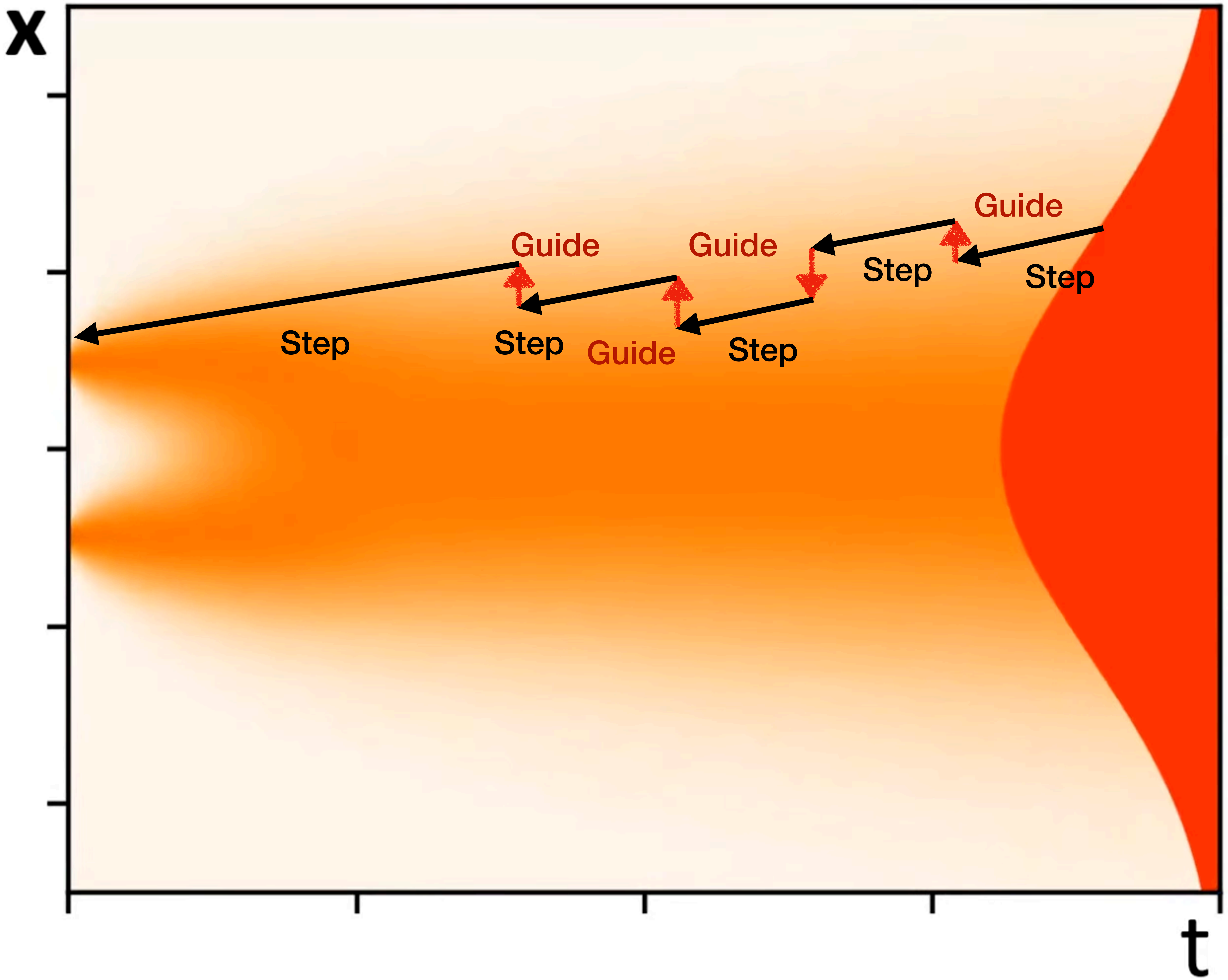
IMAGENET

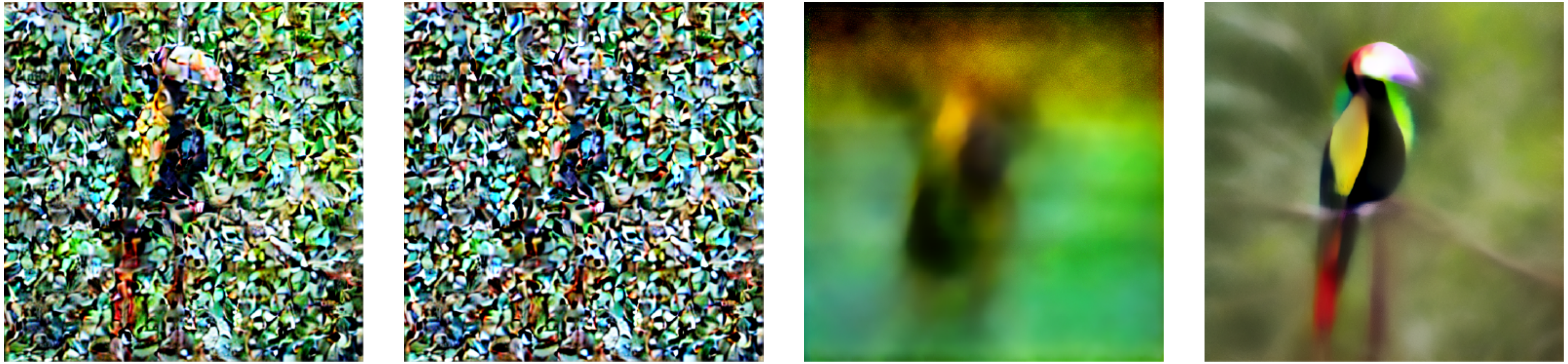
Classifier Guidance

Using a Pretrained Classifier



Sampling ODE View





Classify These Images!

Classifier Guidance Pathologies

Intermediate Diffusion Steps are O.O.D. for Classifier

ImageNet Training Data

$\mathbf{x}_t$ Noise Image $\hat{\mathbf{x}}_1$ Image Prediction

Two Approaches

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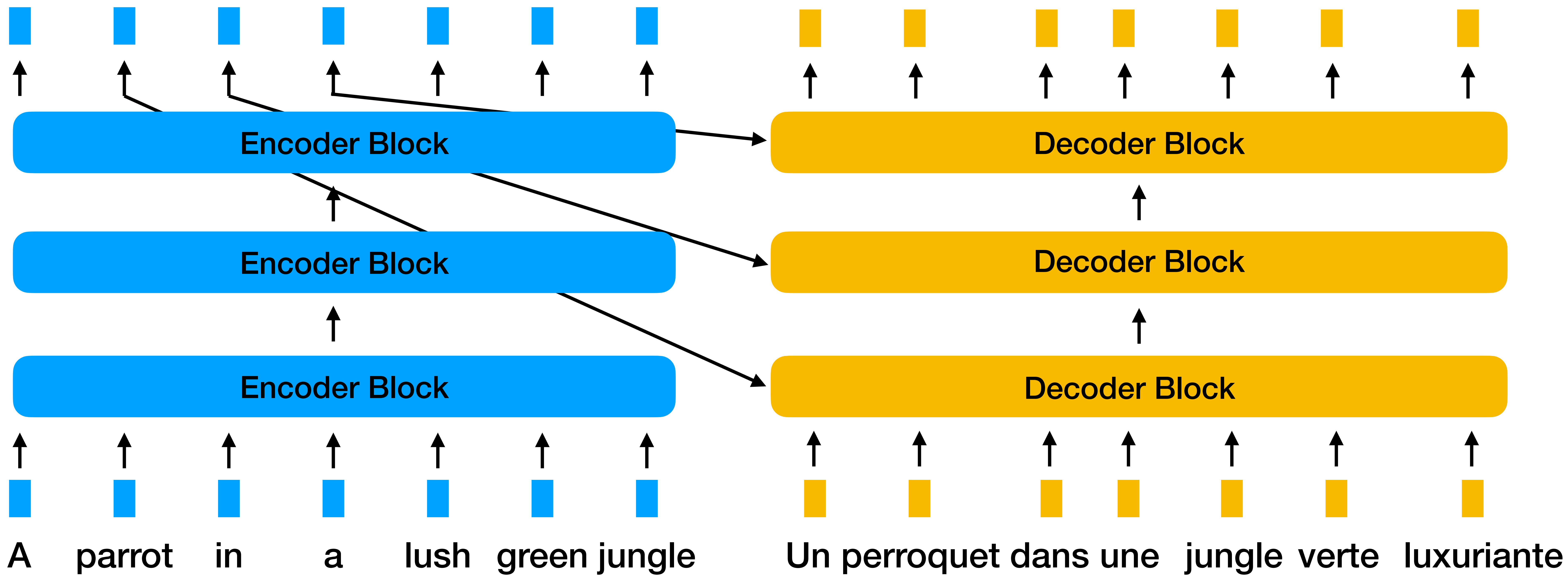
Classifier-Free Guidance

Guide a diffusion model with itself.

Encoder-Decoder Architecture

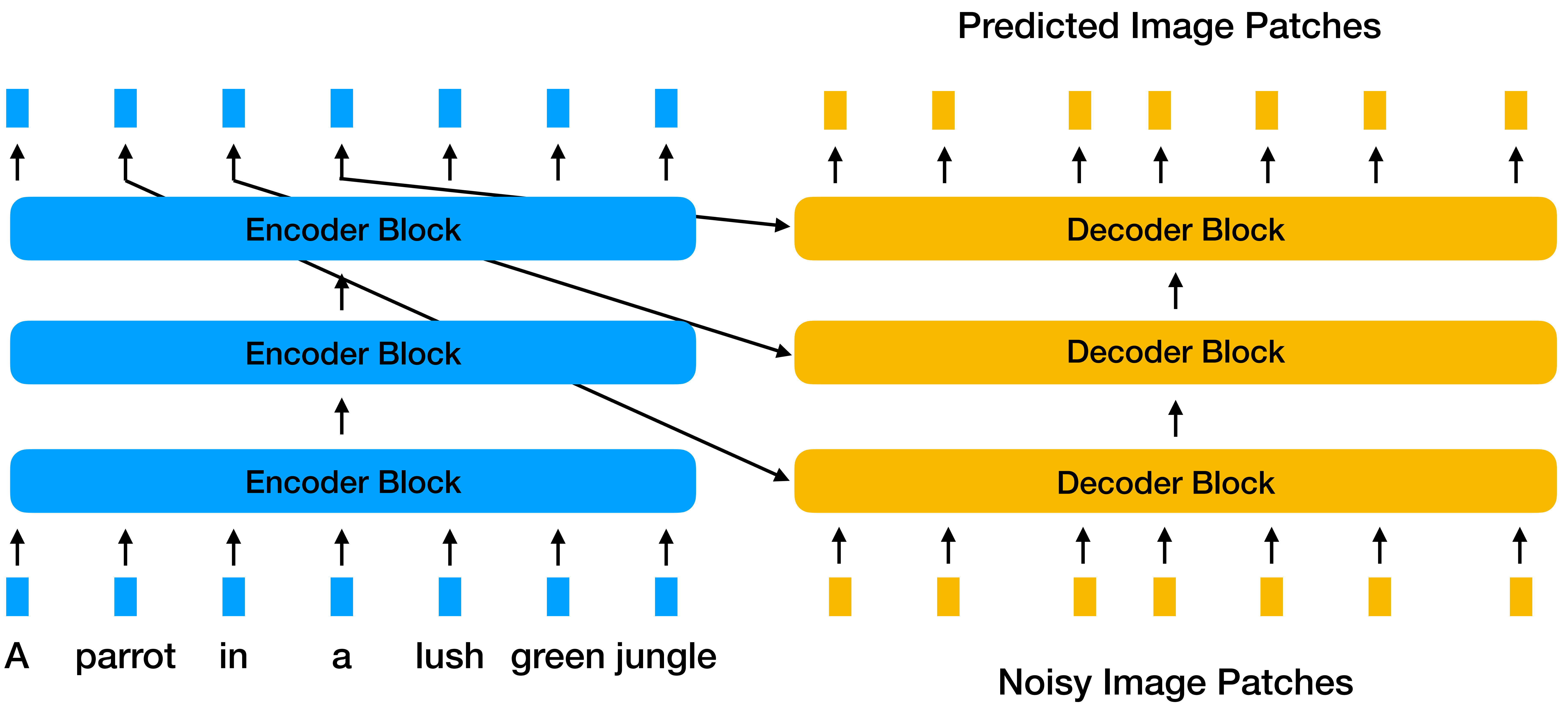
Attention is All You Need

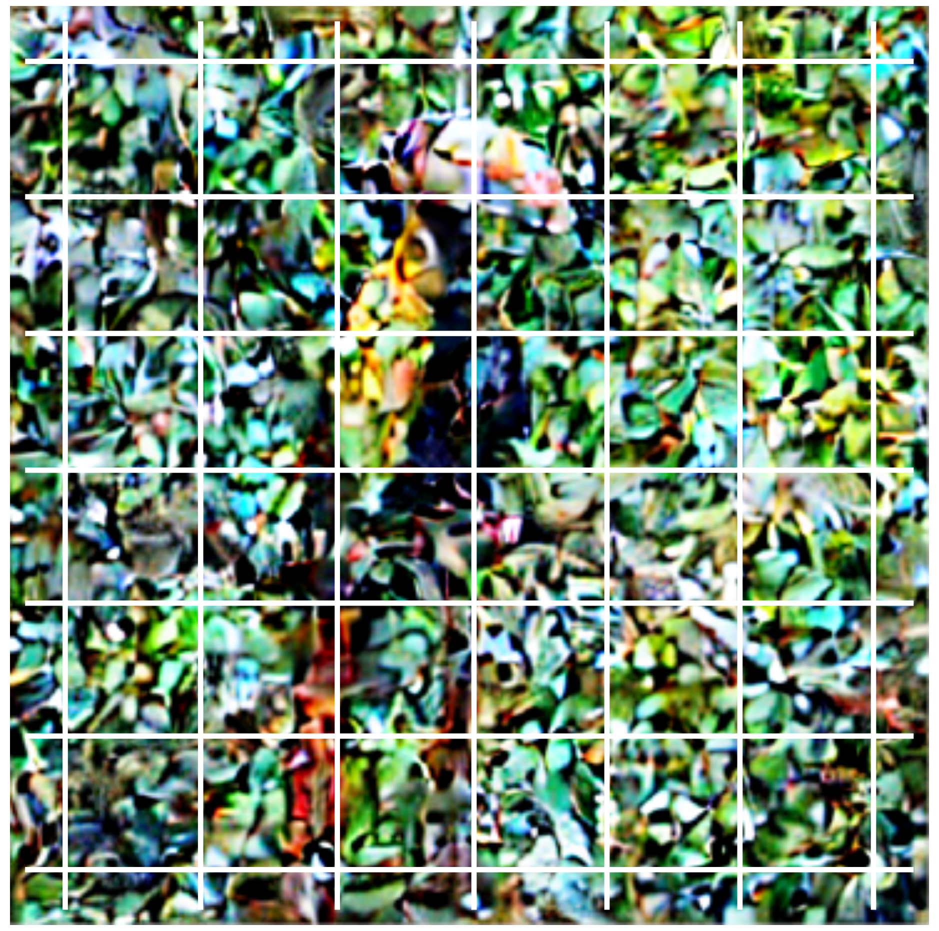


Adapted from HuggingFace Transformers-based Encoder-Decoder Models

Diffusion Transformer Architecture

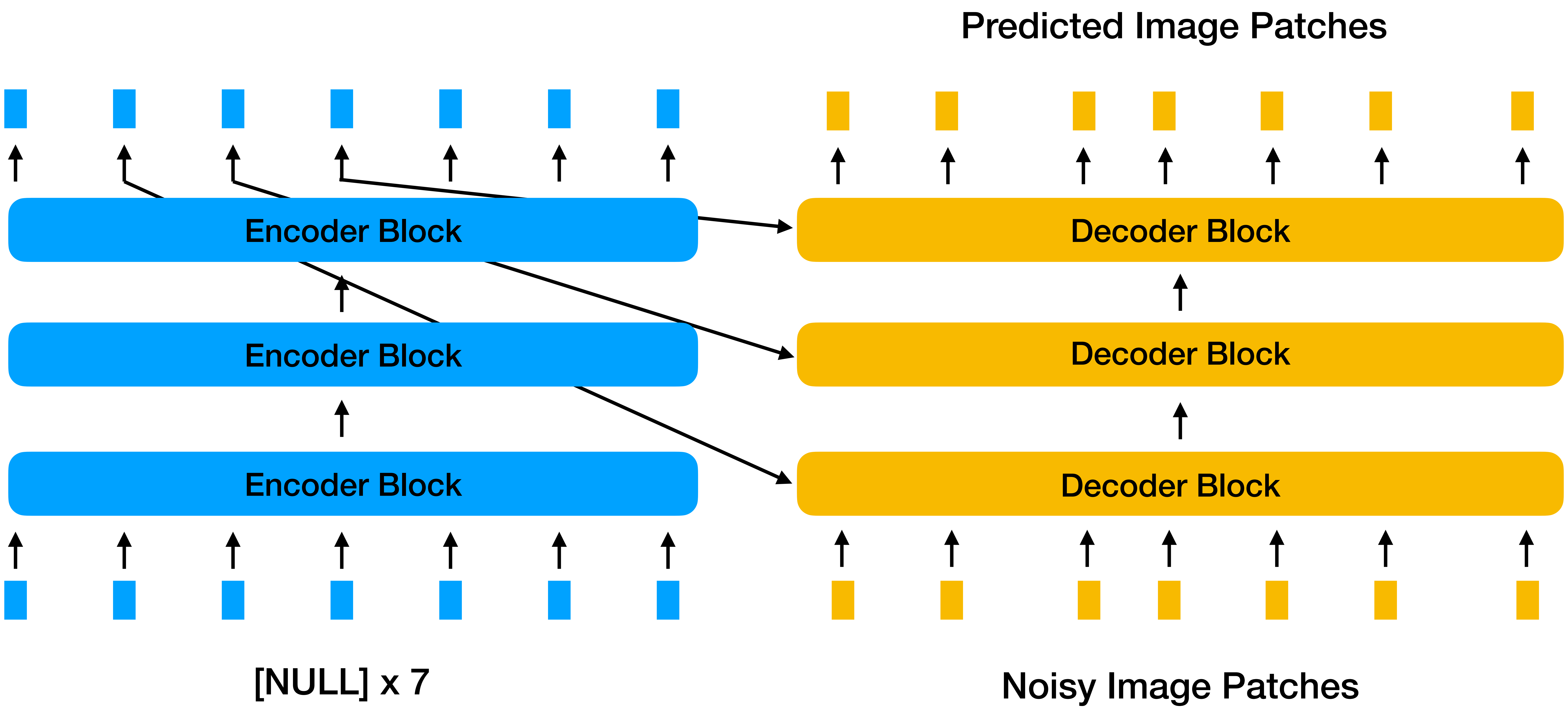
DiT, PixArt Alpha, MMDiT, etc.

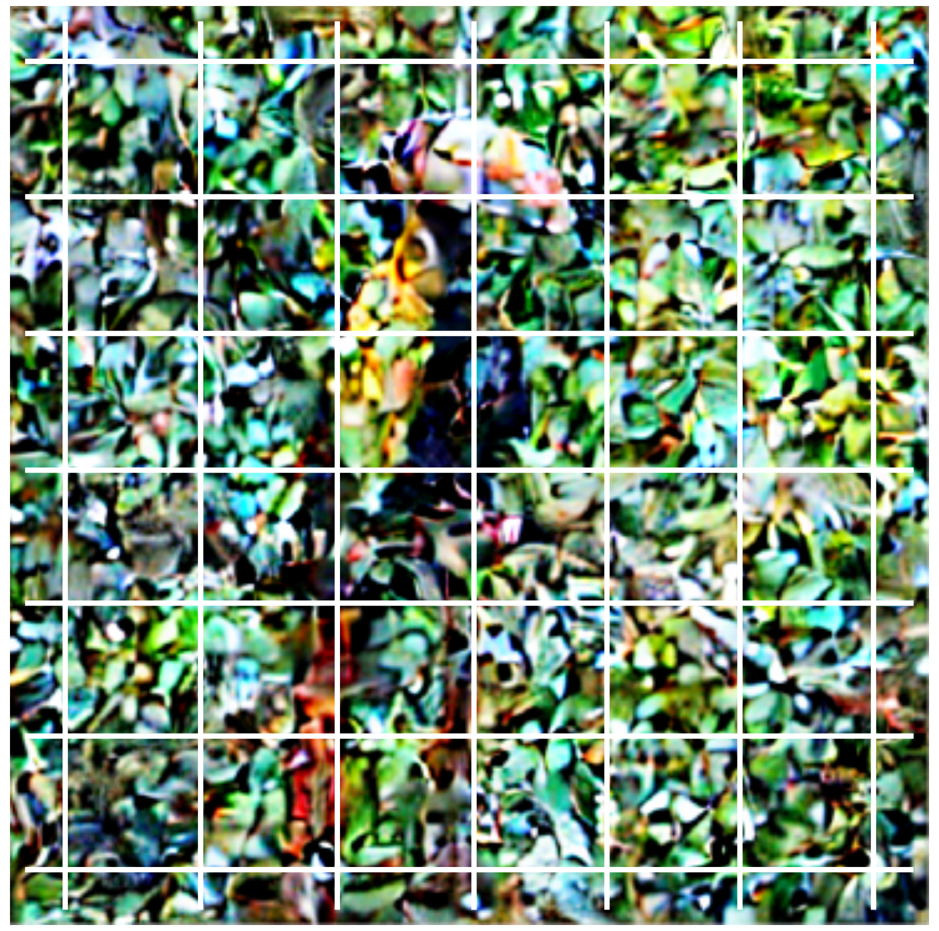




Dropout Conditioning

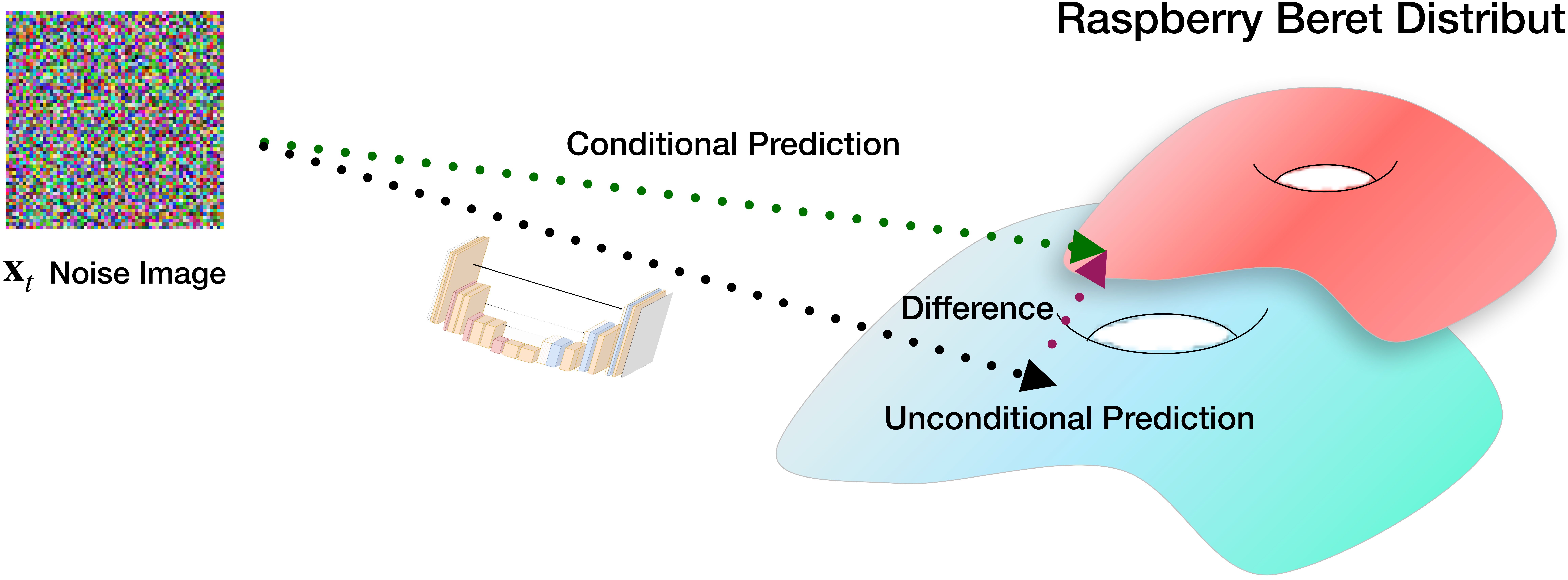
Maybe 30% of Training Samples





Conditional Diffusion

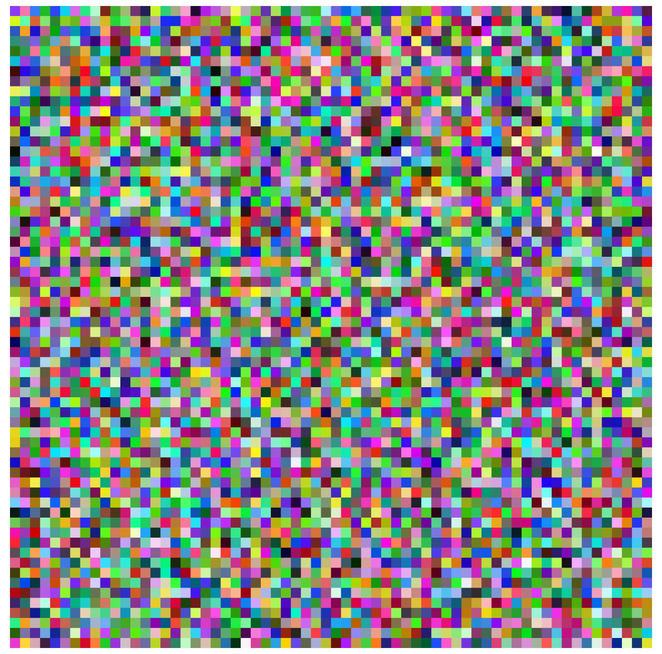
Model Knows Unconditional, Text-Conditioned Distributions



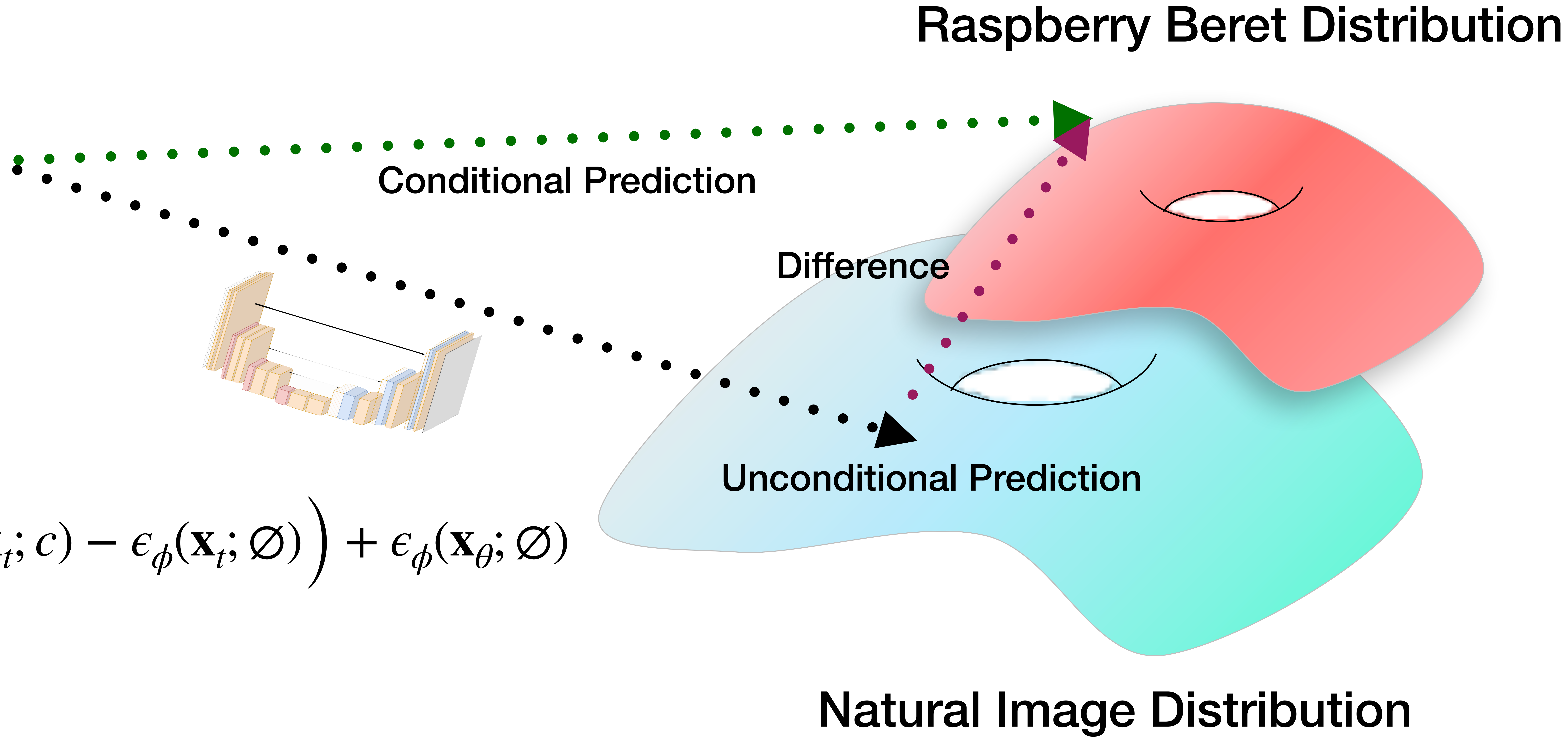
Natural Image Distribution

Classifier-Free Guidance

Model Knows Unconditional, Text-Conditioned Distributions



$\mathbf{x}_t$ Noise Image



$$\epsilon_{CFG} = s \cdot \Big(\epsilon_\phi(\mathbf{x}_t; c) - \epsilon_\phi(\mathbf{x}_t; \varnothing)\Big) + \epsilon_\phi(\mathbf{x}_\theta; \varnothing)$$

ϵ_ϕ Predicted Noise

$\varnothing$ Null Prompt

c Target Prompt

s CFG Scale

Classifier-Free Guidance

TLDR: Amplify Delta Between Conditional, Unconditional Predictions

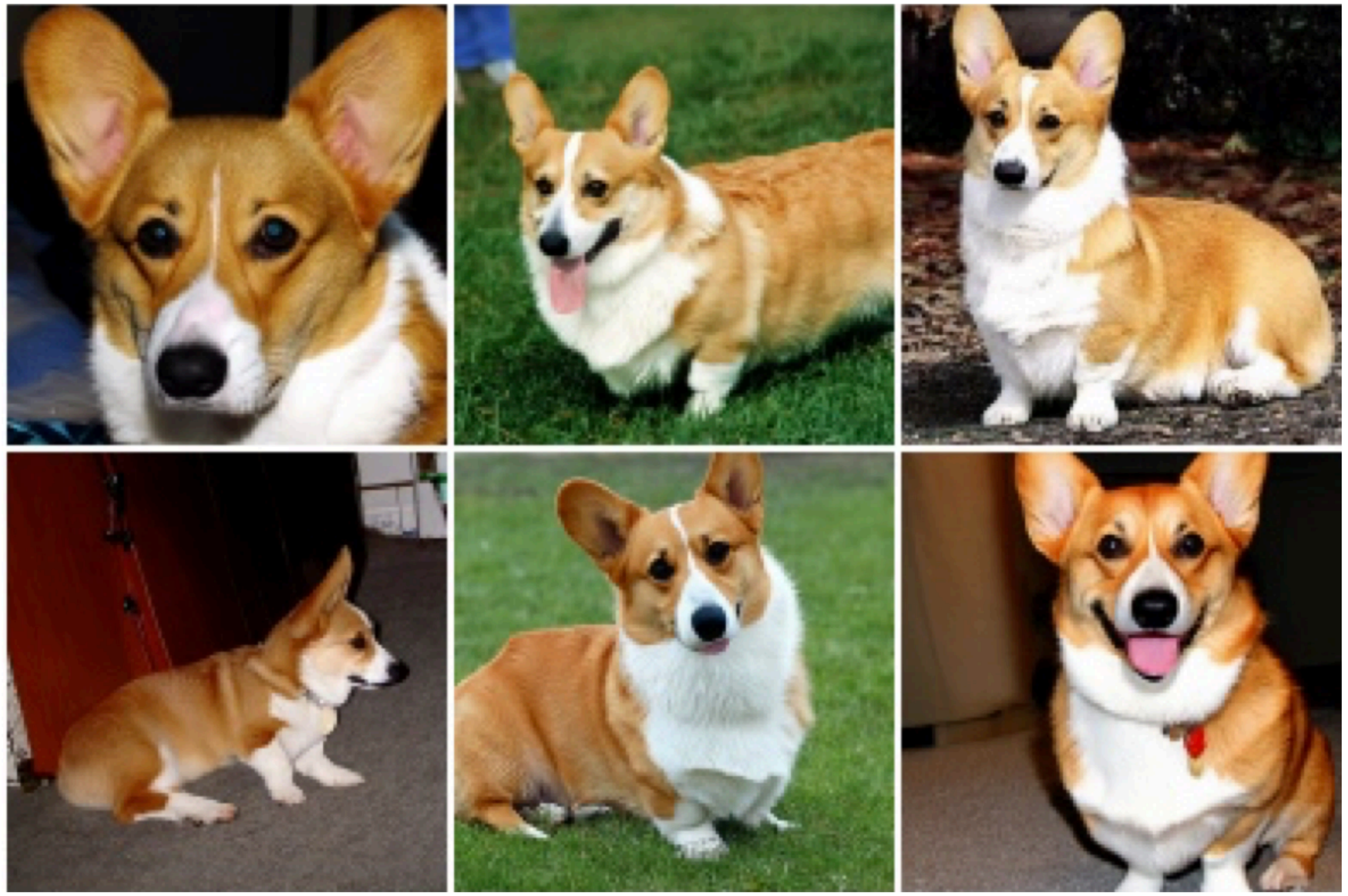
$$\epsilon_{\phi,CFG} = s \cdot \Big(\epsilon_\phi(\mathbf{x}_t; c) - \epsilon_\phi(\mathbf{x}_t; \varnothing)\Big) + \epsilon_\phi(\mathbf{x}_\theta; \varnothing)$$

ϵ_ϕ	Predicted Noise
$\varnothing$	Null Prompt
c	Target Prompt
s	CFG Scale

Classifier-Free Guidance

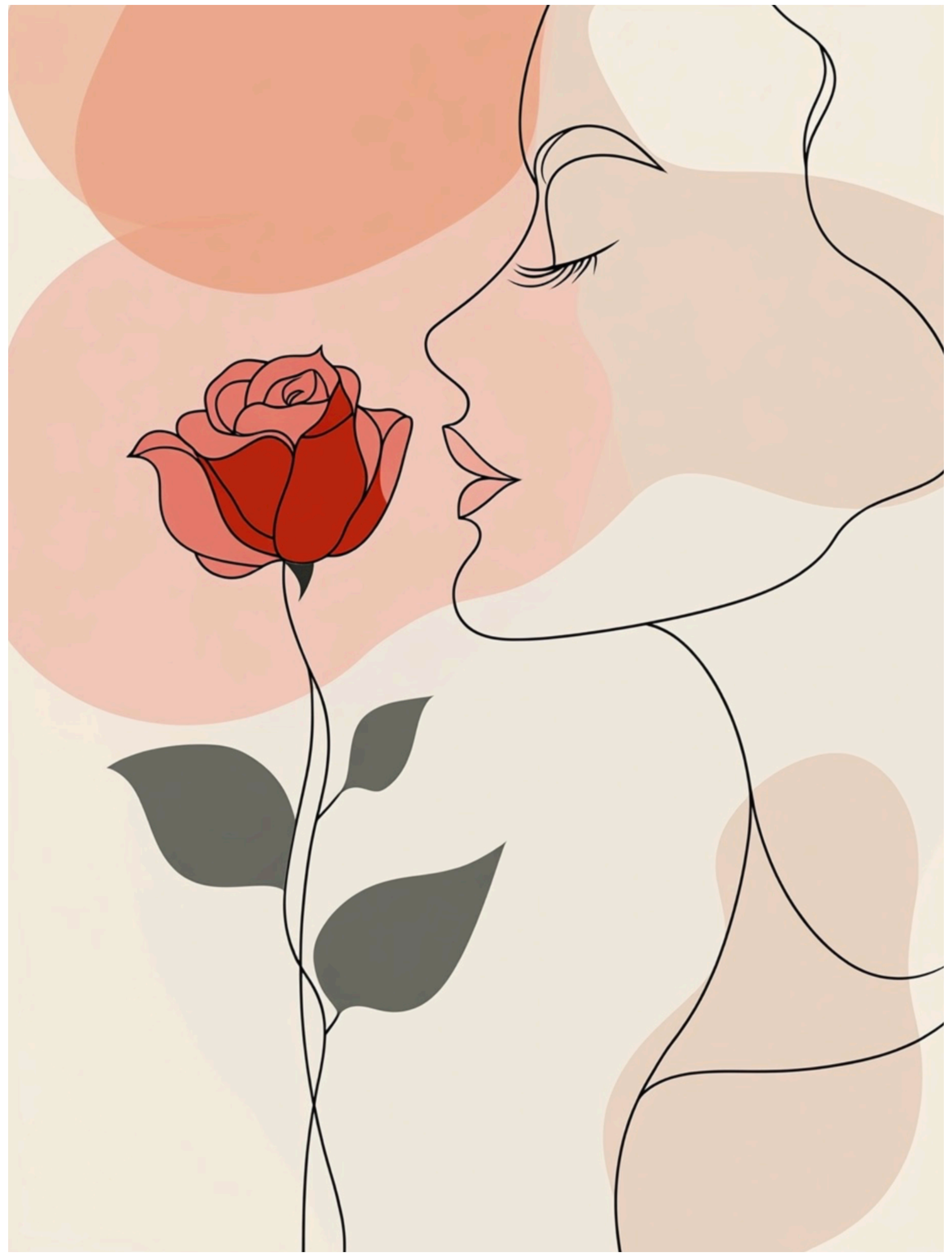
Drives Generations Toward Conditional Mode

s = 1 (Conditional Generation)



s = 3 (Conditional Generation)

"Classifier-Free Diffusion Guidance" Ho et al. (2022)



Text-Conditioned Diffusion Samples

(Midjourney)

Text-Conditioned Diffusion Sample

(Veo 2)

$$p(x \mid c)$$

Guidance Lets Us Sample a Conditional Distribution

$$p(x \mid c)$$

Guidance Lets Us Sample a Conditional Distribution

What if we're creative about the conditioning?

Condition on the First frame and Audio, Generate the Video

OmniHuman-1: Rethinking the Scaling-Up of One-Stage Conditioned Human Animation Models. Lin et al. (2025)

Condition on the First Frame and Actions, Generate an Interactive Environment

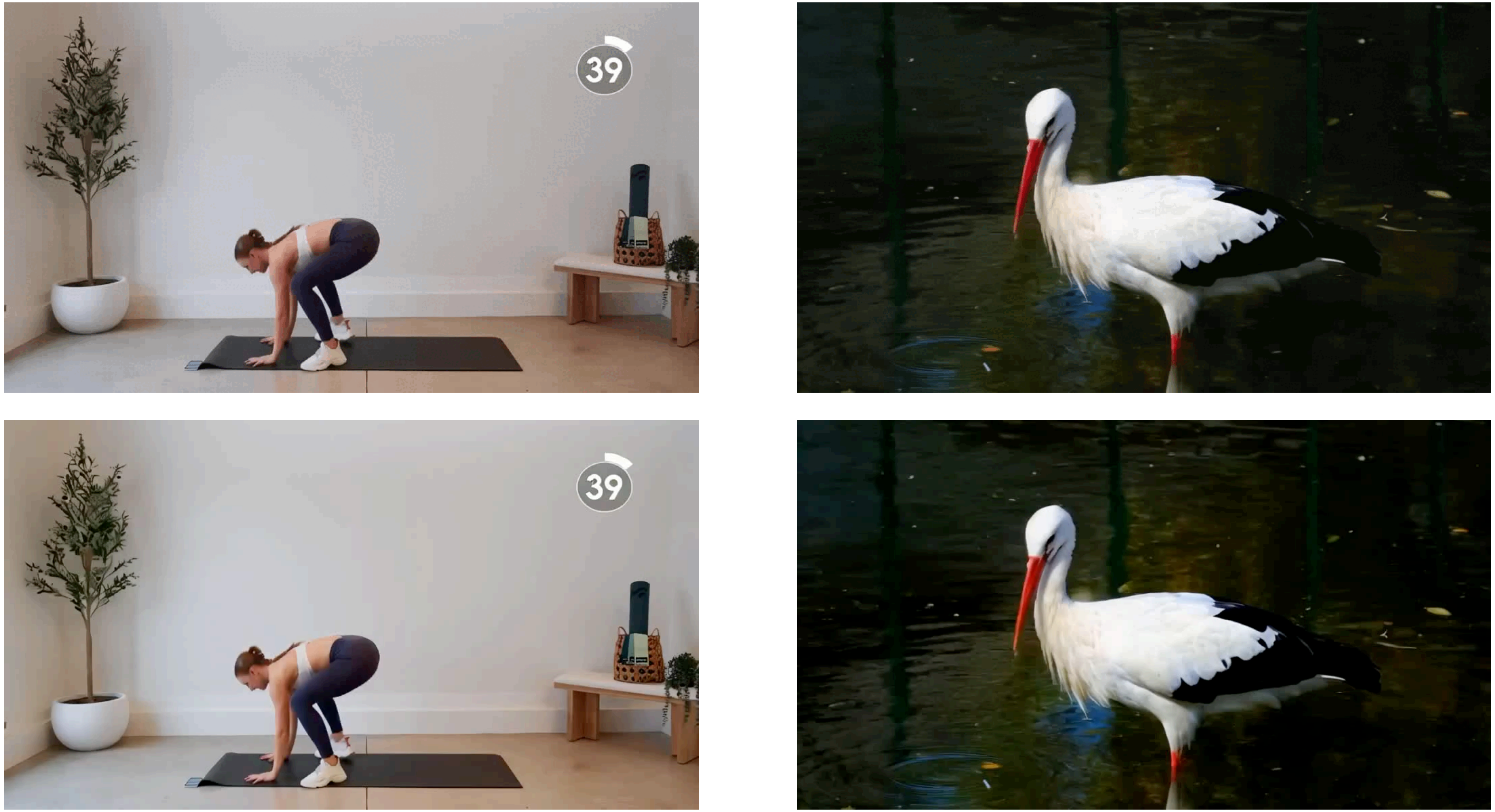
Genie: Generative Interactive Environments. Jake et al. (2024)

Condition on Video Pixels, Generate Depth Map

"Generating Consistent Long Depth Sequences for Open-world Videos" Hu et al. (2025)

Conditioning

Samples

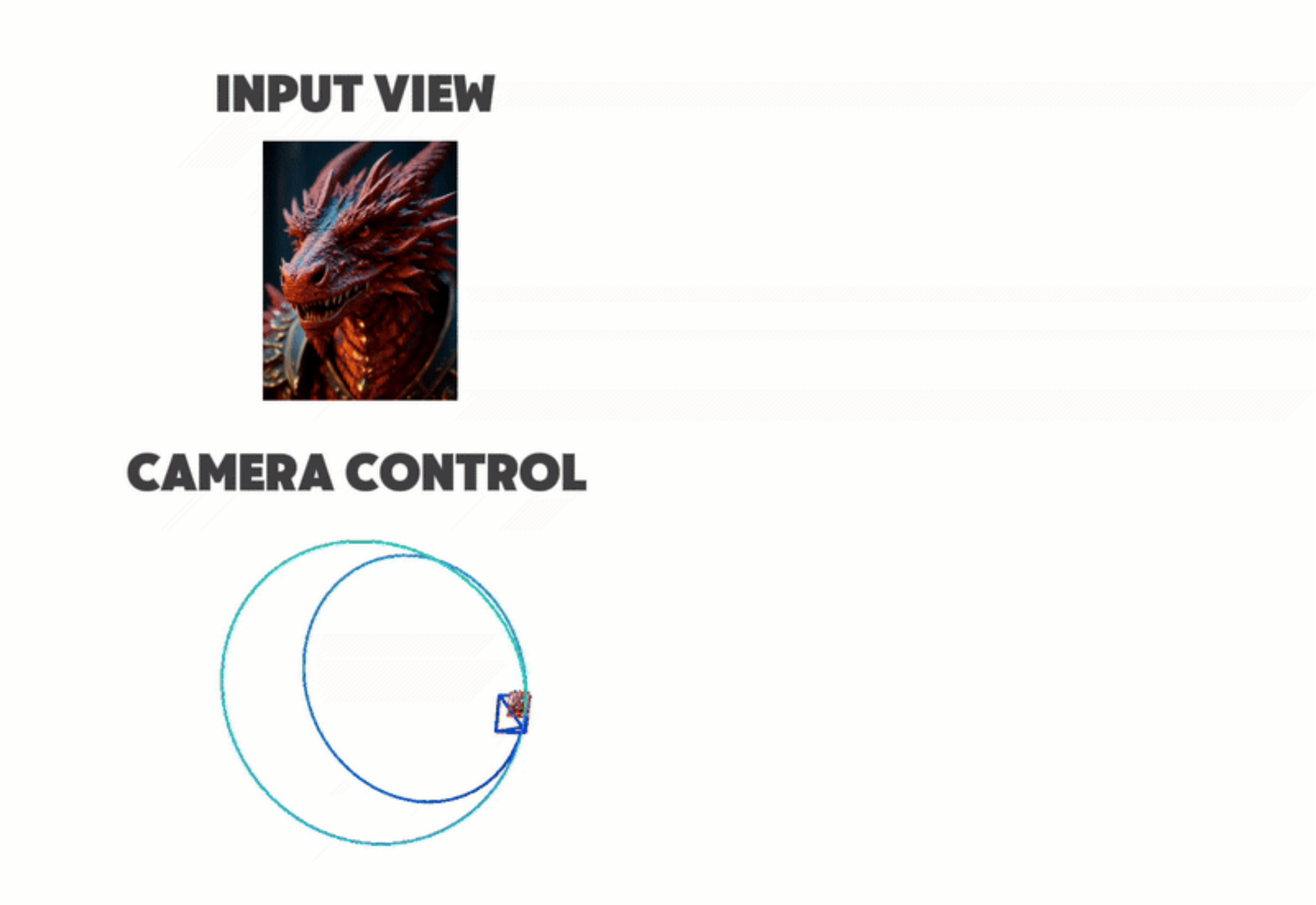


Condition on Start and End Frame, Generate Intermediate Frames

"Explorative Inbetweening of Time and Space" Feng et al. (2024)

Condition on Image + Camera, Generate Novel Views

"CAT3D: Create Anything in 3D with Multi-View Diffusion Models" Gao et al. (2024)



Condition on Image + Camera, Generate Novel Views

Stable Virtual Camera: Generative View Synthesis with Diffusion Models (Zhou*, Gao* et al.)

Condition on Ego View, Generate Human Poses

"EgoAllo" Yi et al. (2025)