ICML 2026 Tutorial

Diffusion and Flow Matching

From Memorization to Generalization & Beyond

Quentin Bertrand & Mathurin Massias

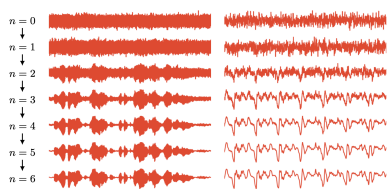
https://memorization-generalization.github.io

Inria | ENS Lyon | Laboratoire Hubert Curien | Mila Affiliated Member | CIFAR Global Scholar

Diffusion and Flow matching are everywhere

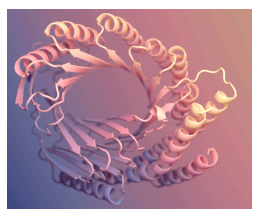
- Diffusion introduced in 2015[1], took off in 2020[2,3]
- Flow matching introduced in 2023[4,5,6]
- Current SOTA techniques for generation of images, audio, videos, proteins...

Stable Diffusion



WaveGrad

Sora



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- And even for text now

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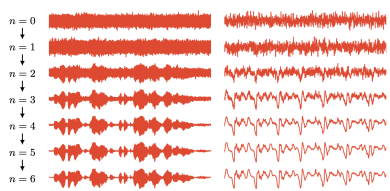

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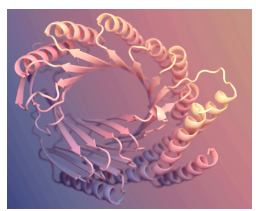

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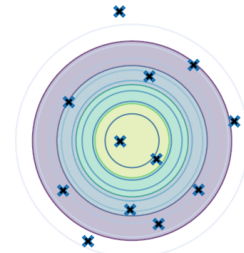

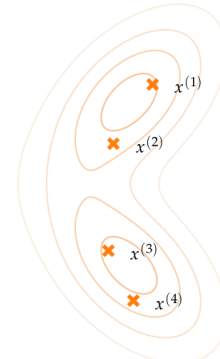

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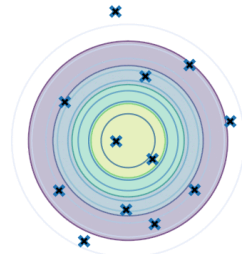

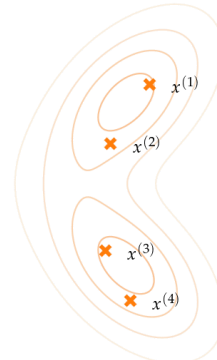

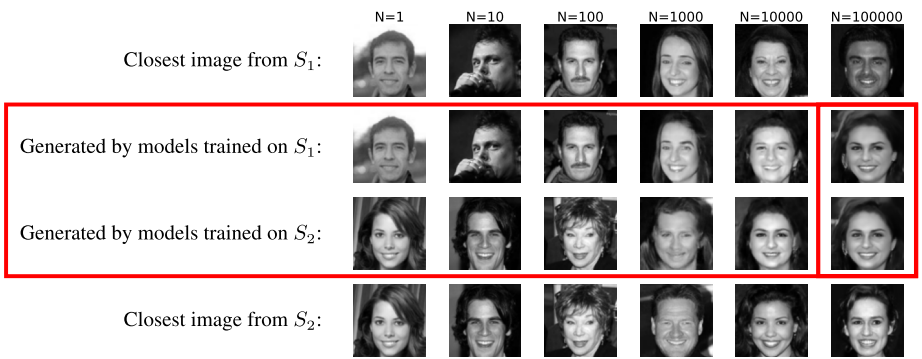

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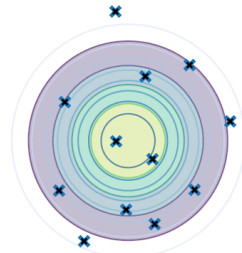
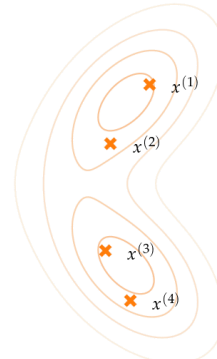
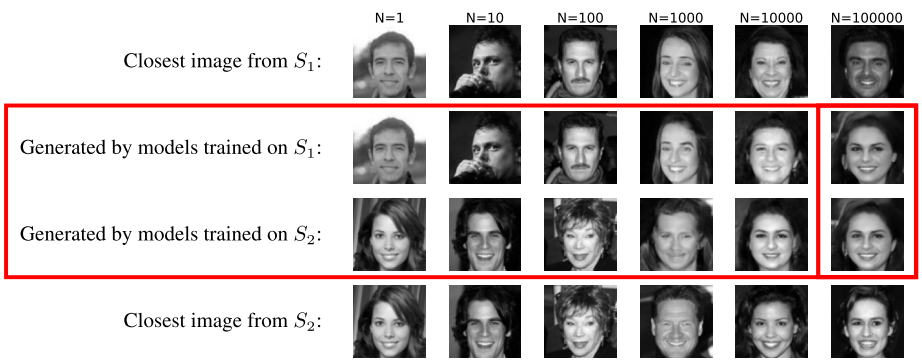
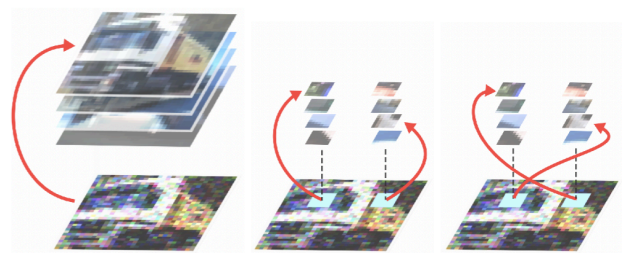
- Models trained on different datasets generate the same images?[8]
- Generated images are patchworks of training images?[9]









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Tutorial goal

When, how, and why do Diffusion & Flow matching create new data?

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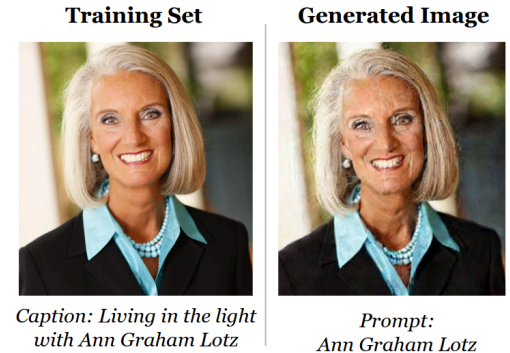
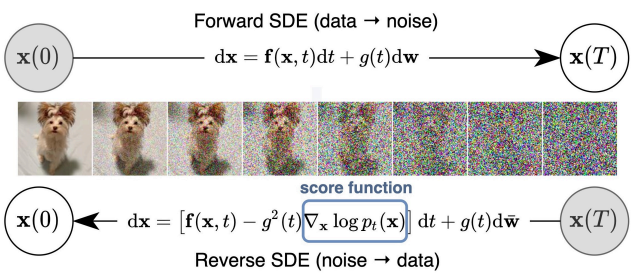
- Introduction to Flow matching and Diffusion: why should they memorize? (40 min)
- Discussion #1 (10 min)



Extracting Training Data from Diffusion Models Carlini et al. (2023)



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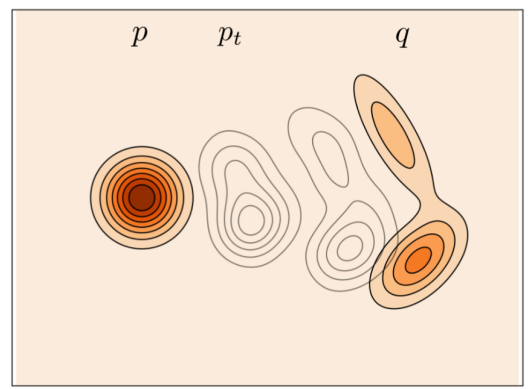

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- Toward understanding the generalization of Flow matching and Diffusion (30 min)
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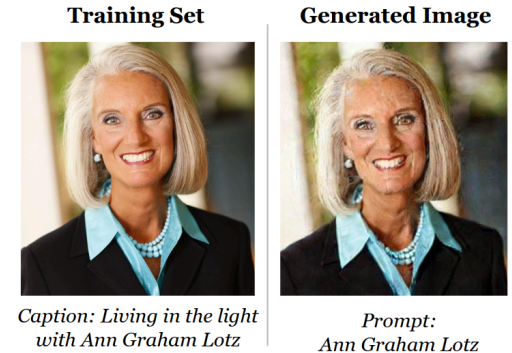

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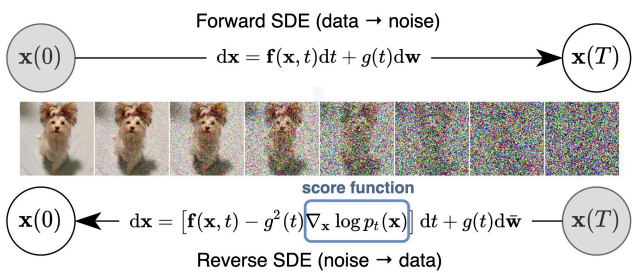

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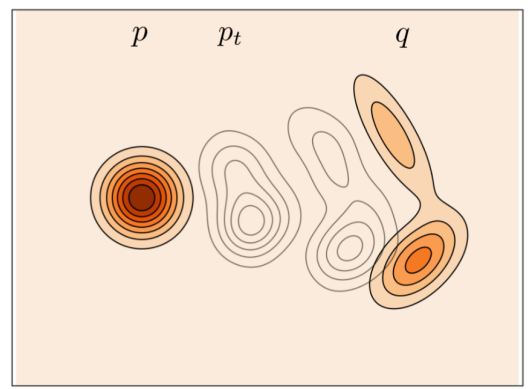

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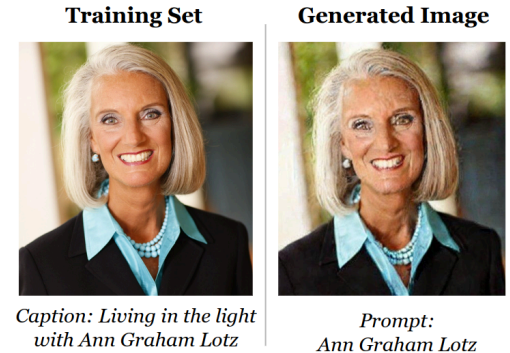
- Discussion #2 (10 min)
- Beyond generalization (30 min)
- Current open problems (15 min)
- Discussion #3 (15 min)



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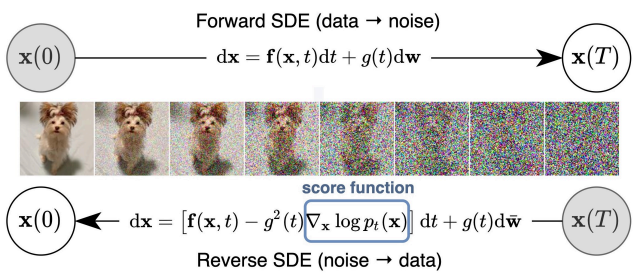

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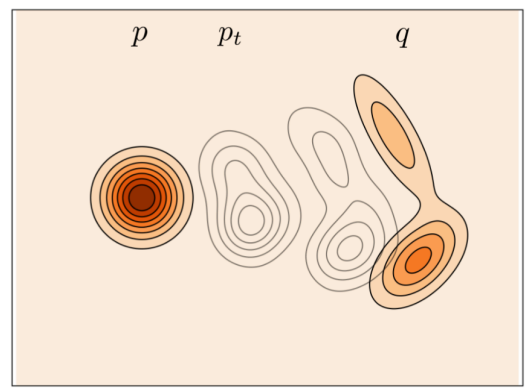

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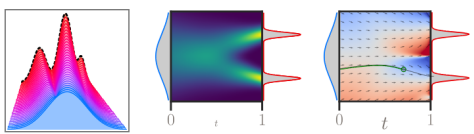
Who we are

- Researchers at Inria (France)
- Blog post[10] and contributions in memorization[11,12]

A Visual Dive into Conditional Flow Matching



On the Closed-Form of Flow Matching: Generalization Does Not Arise from Target Stochasticity

Quentin Bertrand[15]*; Anne Gagneux[2]*; Mathurin Massias[3]*; Rémi Emonet[14]*

TRAINING FLOW MATCHING: THE ROLE OF WEIGHTING AND PARAMETERIZATION

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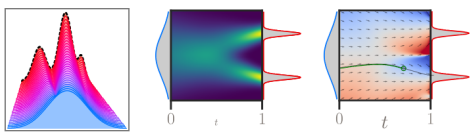

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- Many thanks to Rémi Emonet, Ségolène Martin, Anne Gagneux, Georges Le Bellier and Eloi Tanguy who contributed to the material





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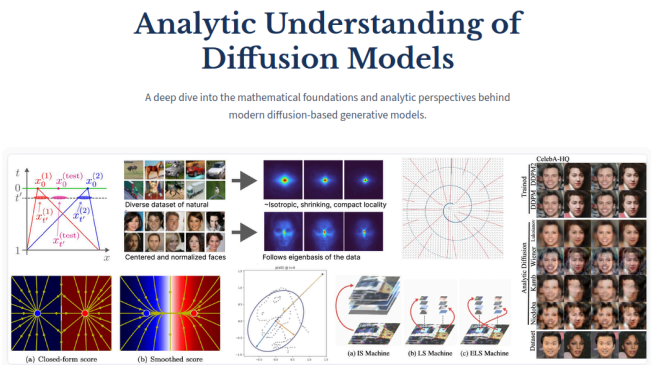

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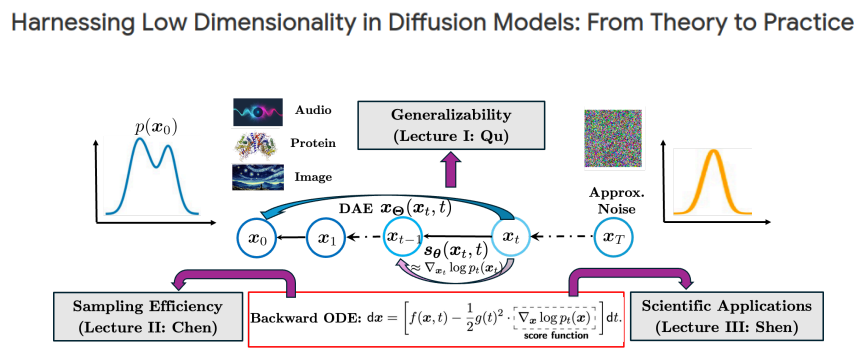

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Introduction to
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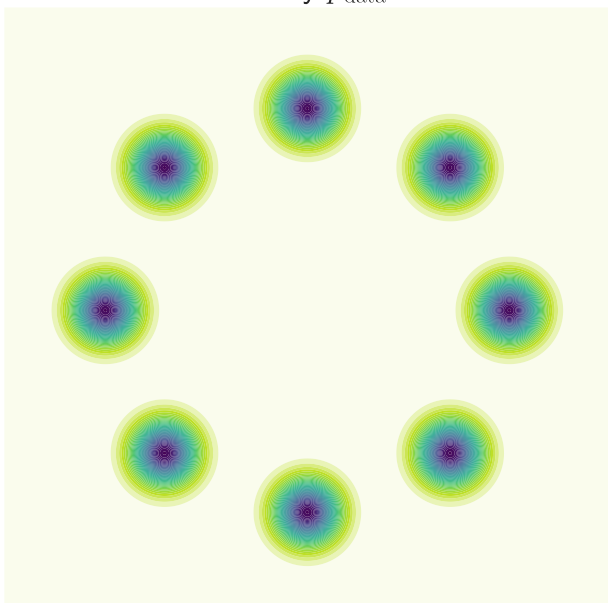
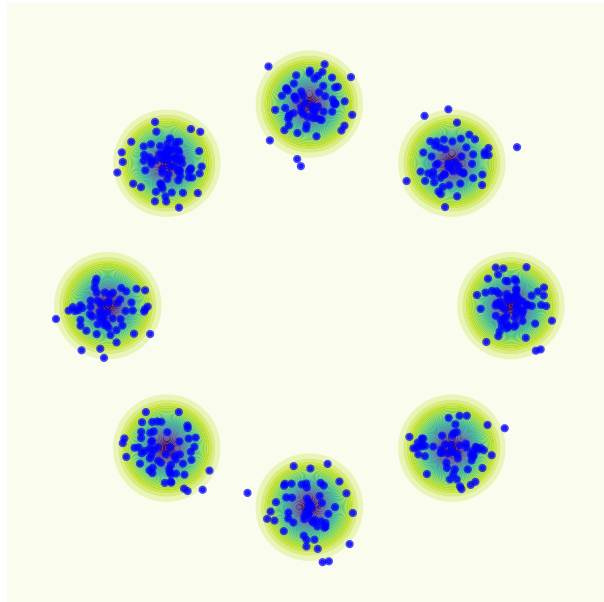


A step back: what is generative modeling?

density p_{data} + samples $x^{(1)}, \ldots, x^{(n)} \sim p_{\text{data}}$



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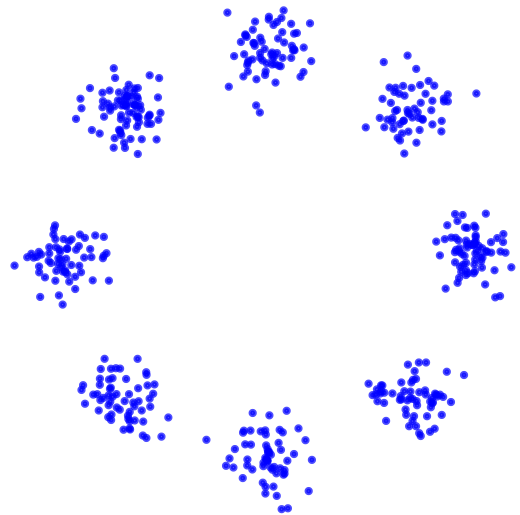

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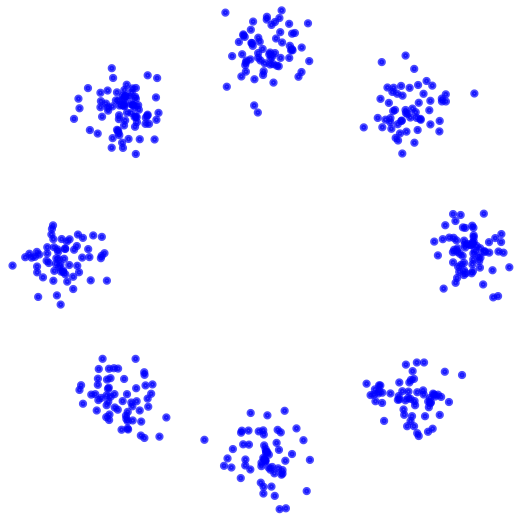

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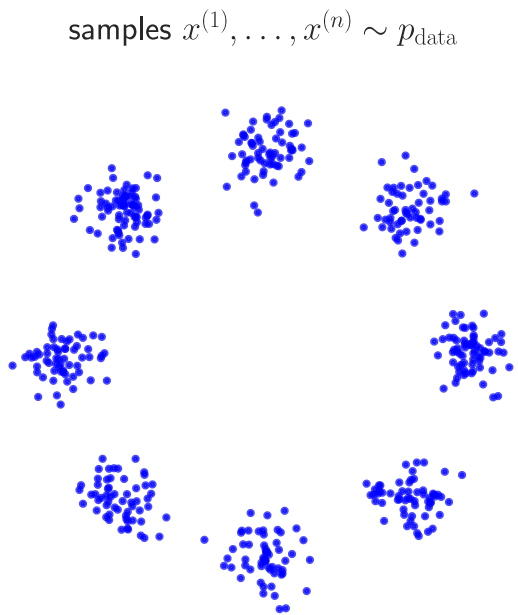

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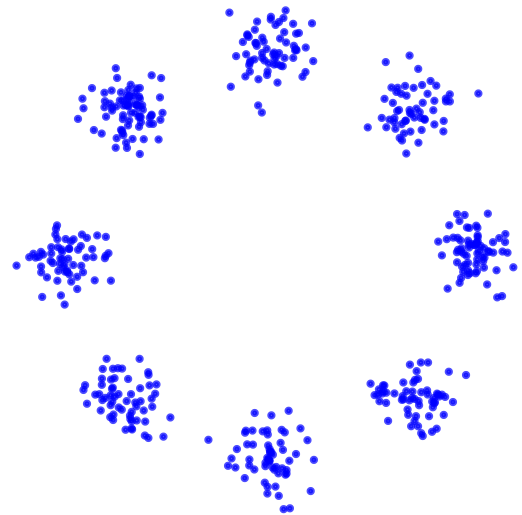

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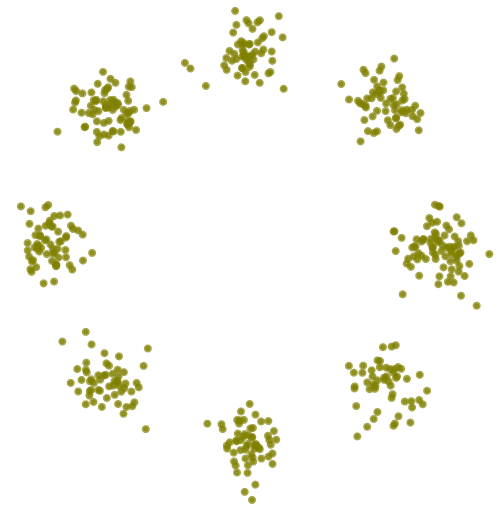

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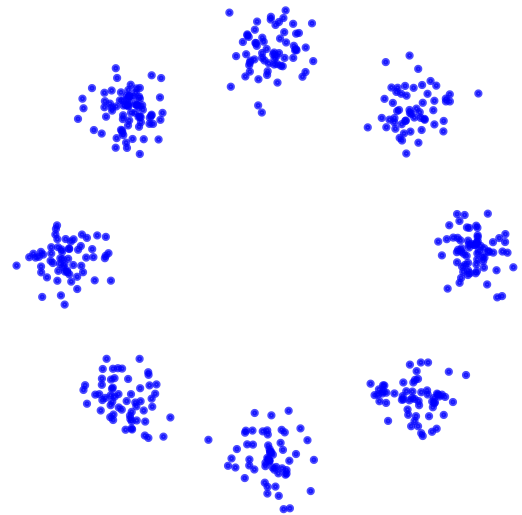

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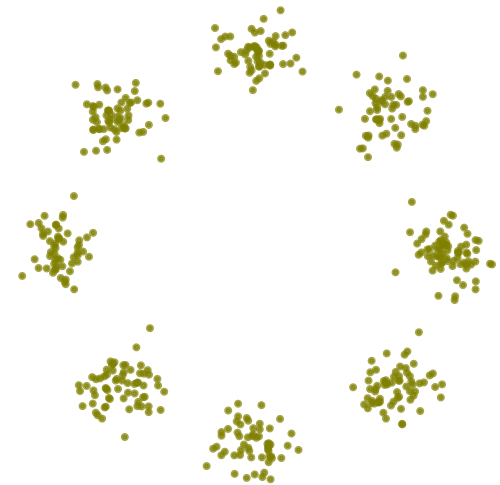

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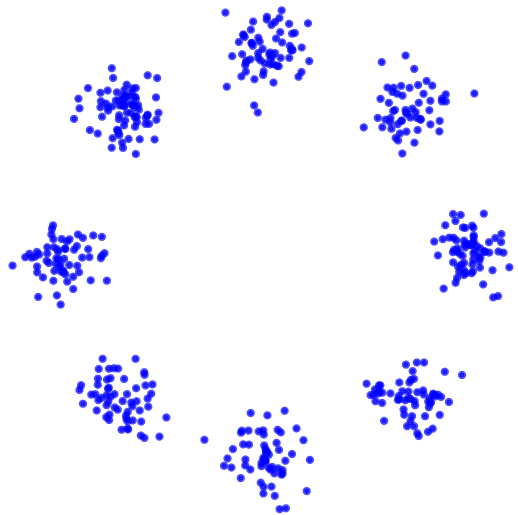

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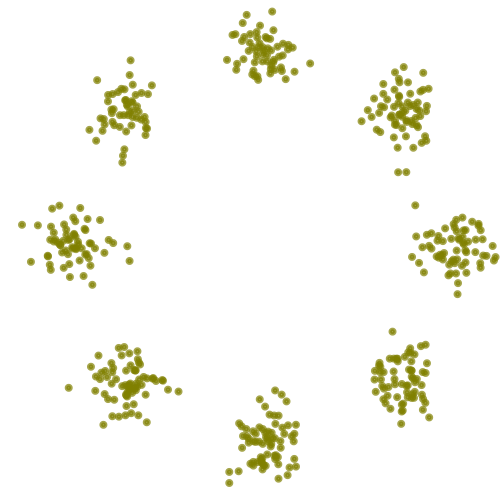

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A step back: what is generative modeling?

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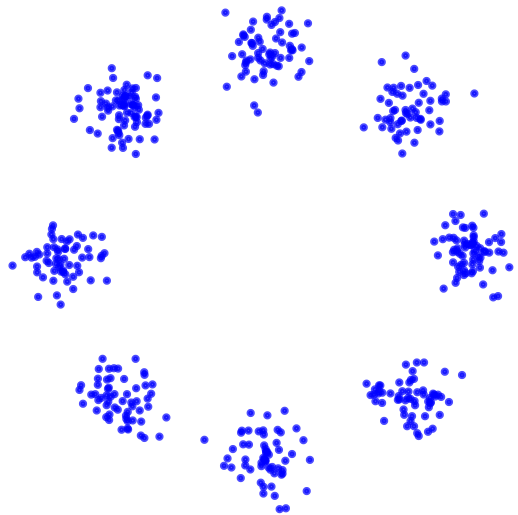

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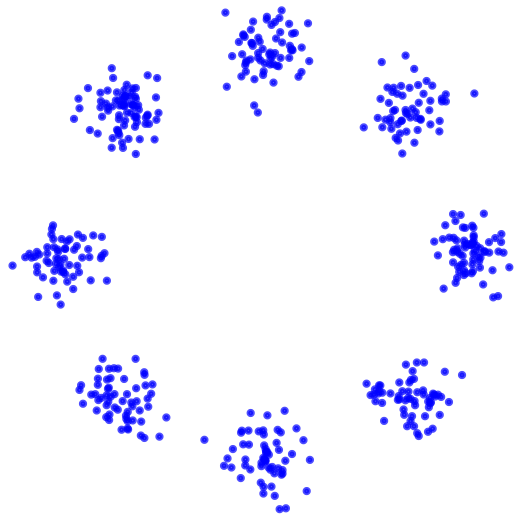

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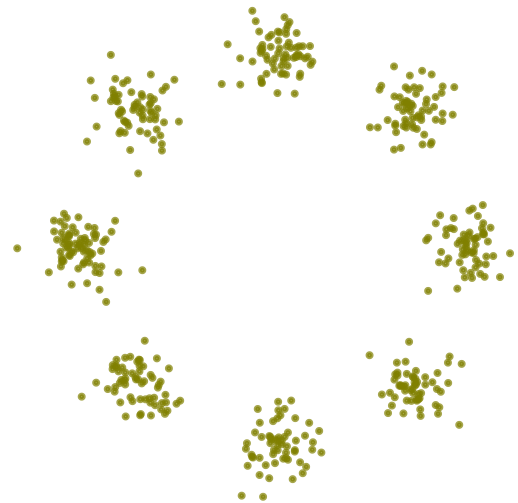

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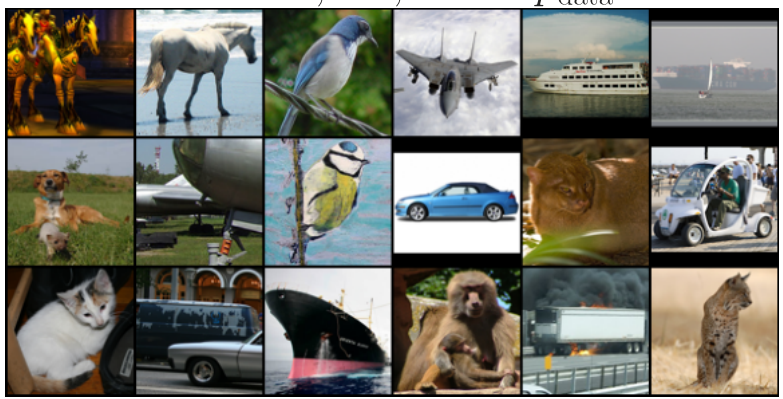

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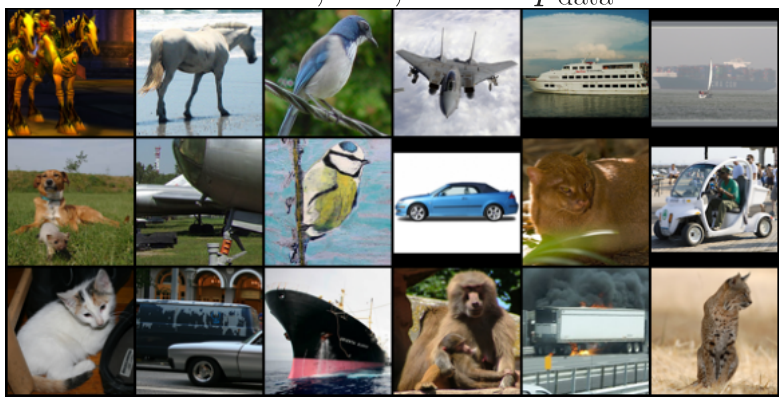

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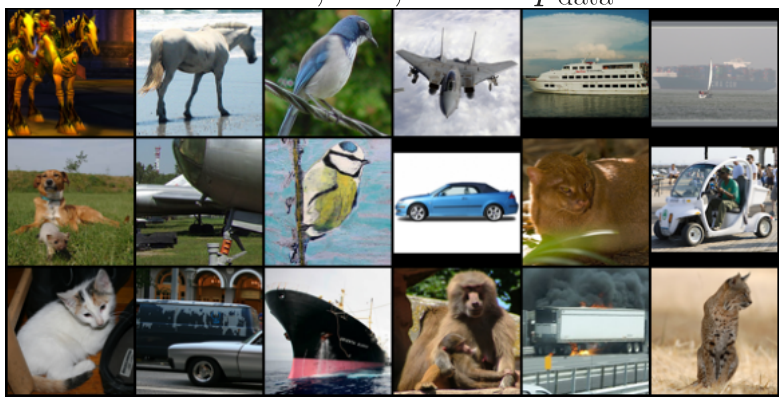

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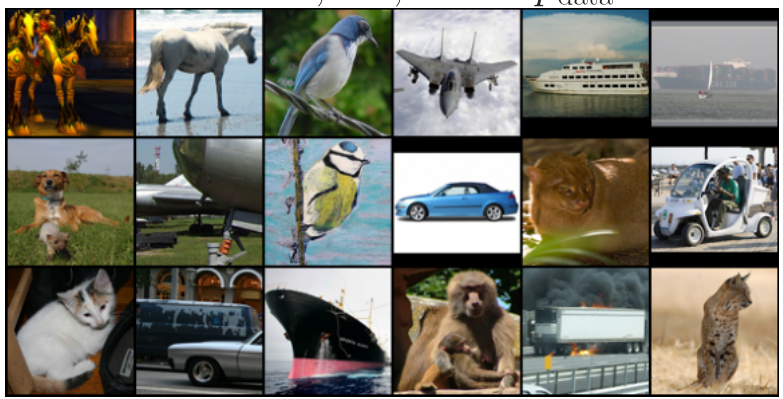

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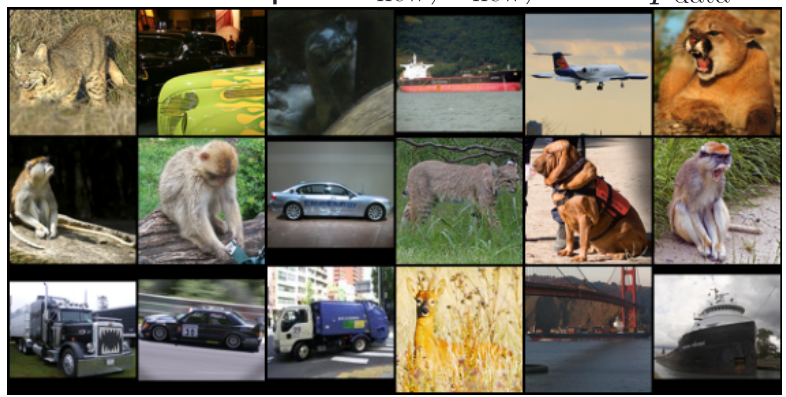

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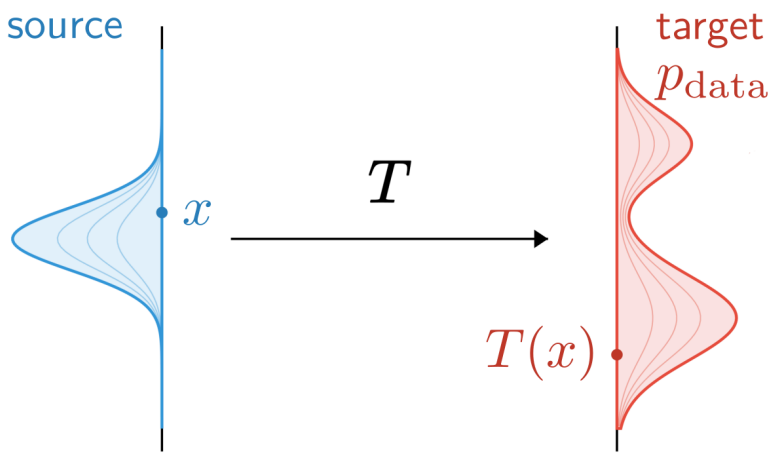
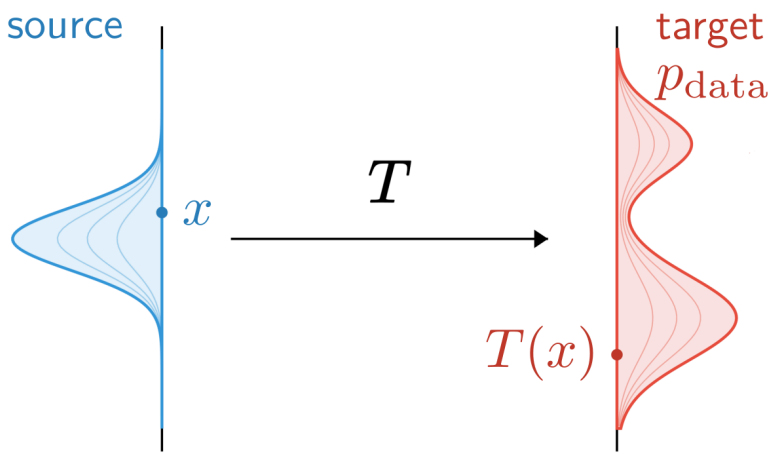
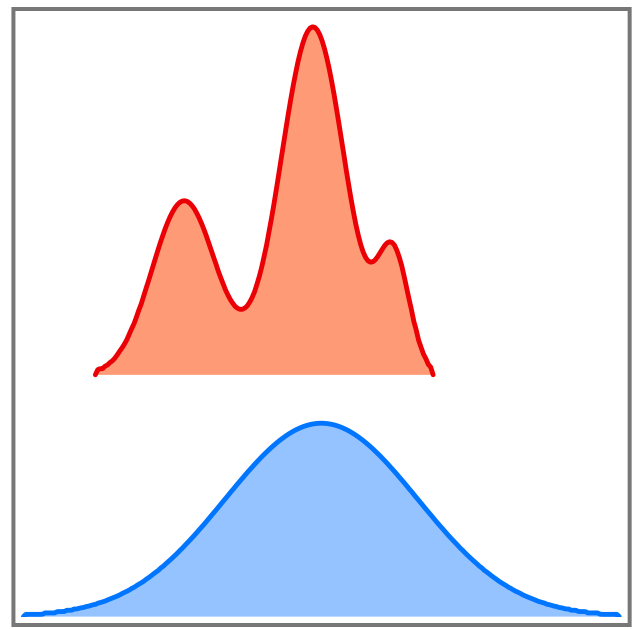


Diffusion and Flow matching: the big picture

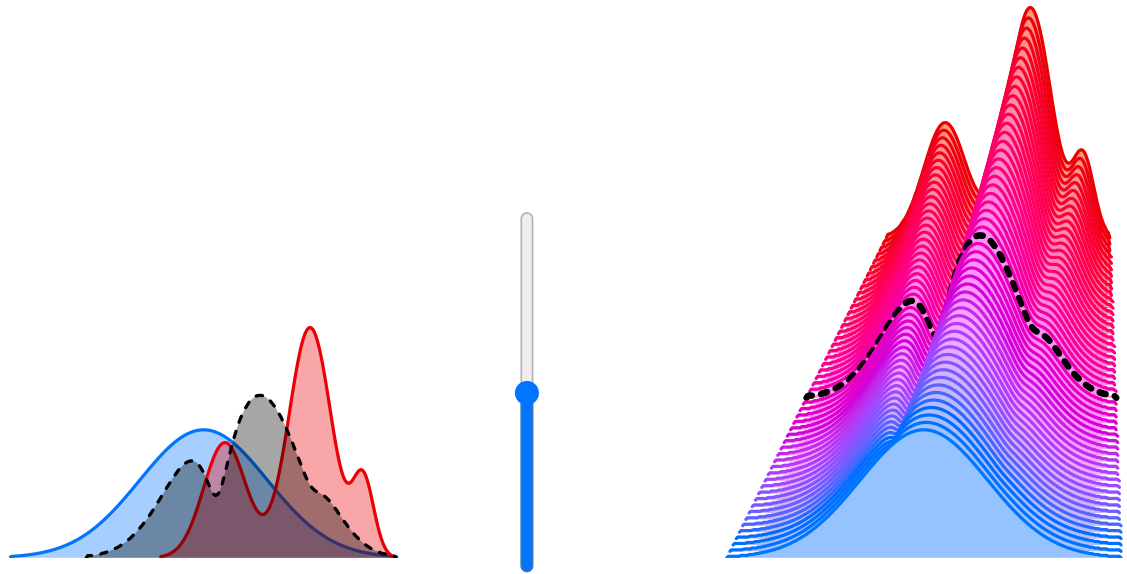
Common idea:

- Learn mapping T sending samples from source distribution to samples from target distribution p_{data}
- Rely on a continuous interpolation between the source and target distributions





Play with paths from to source and target distributions!



NB: Diffusion only supports Gaussian source distribution

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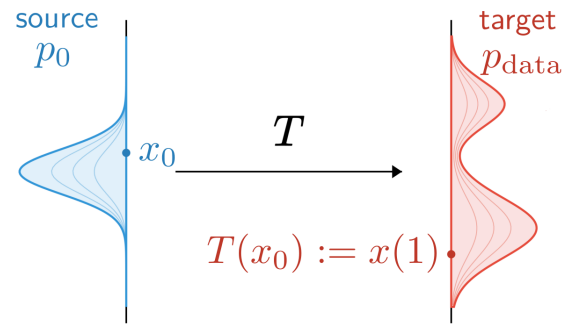

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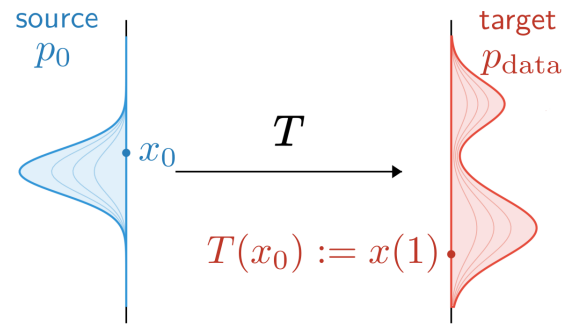

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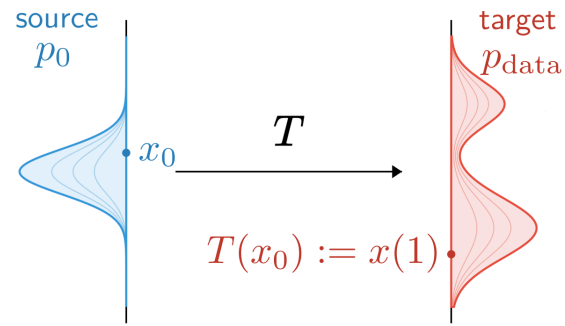

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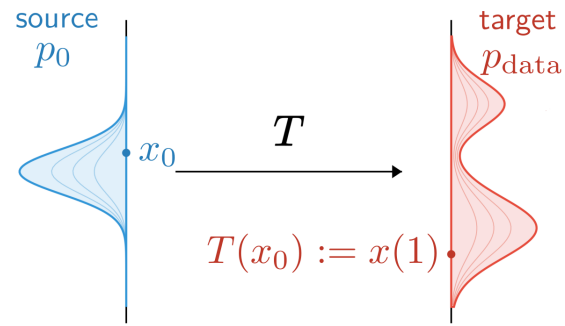

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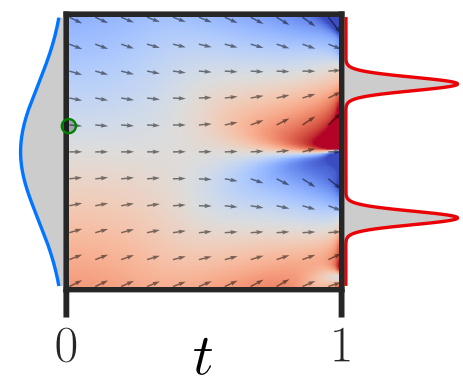

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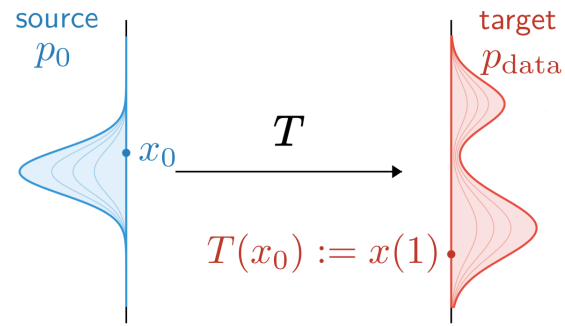

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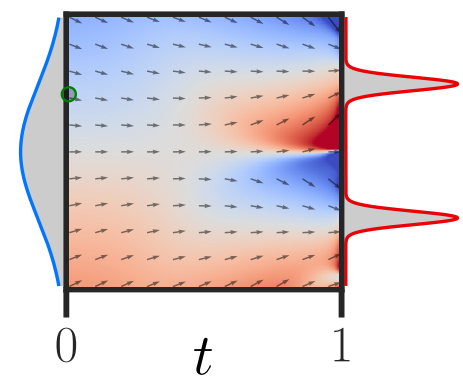
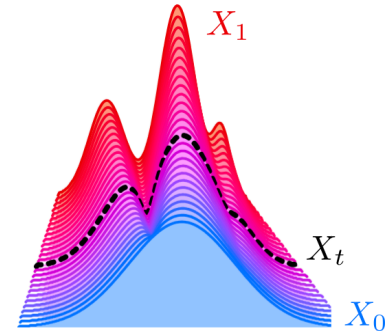


But how to find a *good* velocity $u(x, t)$?

How to find a good velocity?



Setup: define three random variables

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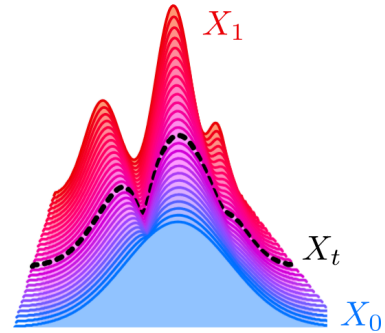

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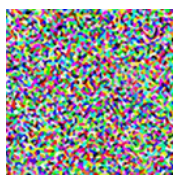
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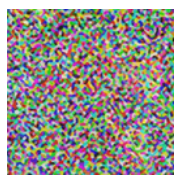
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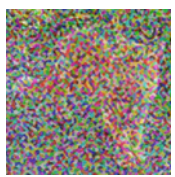
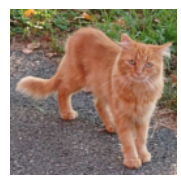

$X_{t=0.5}$


$X_{t=0.75}$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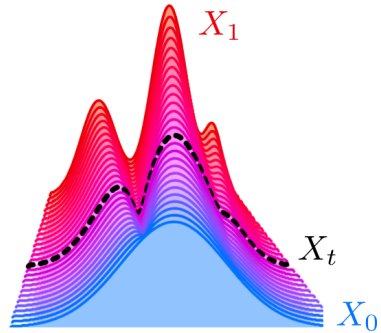

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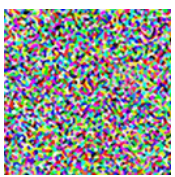
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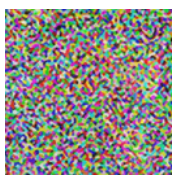
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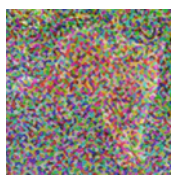
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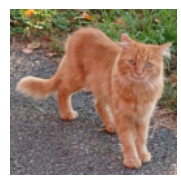
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The FM magic[5,13,14] : $u(x,t) := \mathbb{E}[X_1 - X_0 | X_t = x]$ is a *good* velocity:

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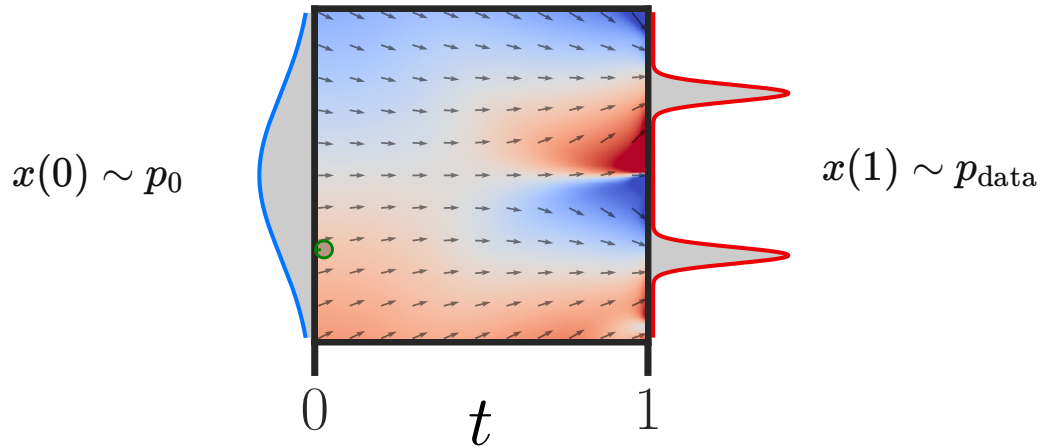
[5] M. Albergo et al., **Building Normalizing Flows with Stochastic Interpolants,** In: ICLR, 2023.

[13] Y. Lipman et al., **Flow Matching for Generative Modeling,** In: ICLR, 2023.

[14] X. Liu et al., **Flow Straight and Fast: Learning to Generate and Transfer Data with Rectified Flow,** In: ICLR, 2023.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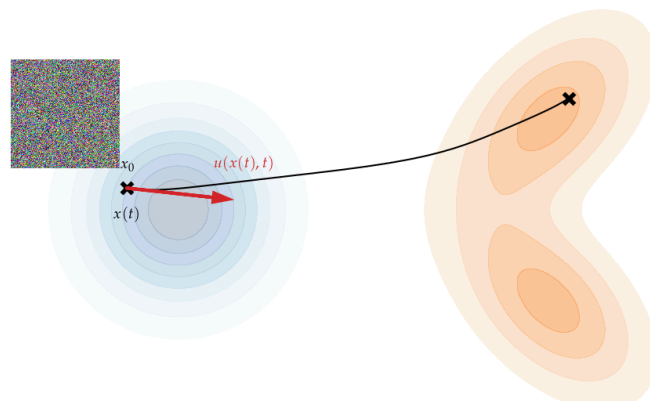
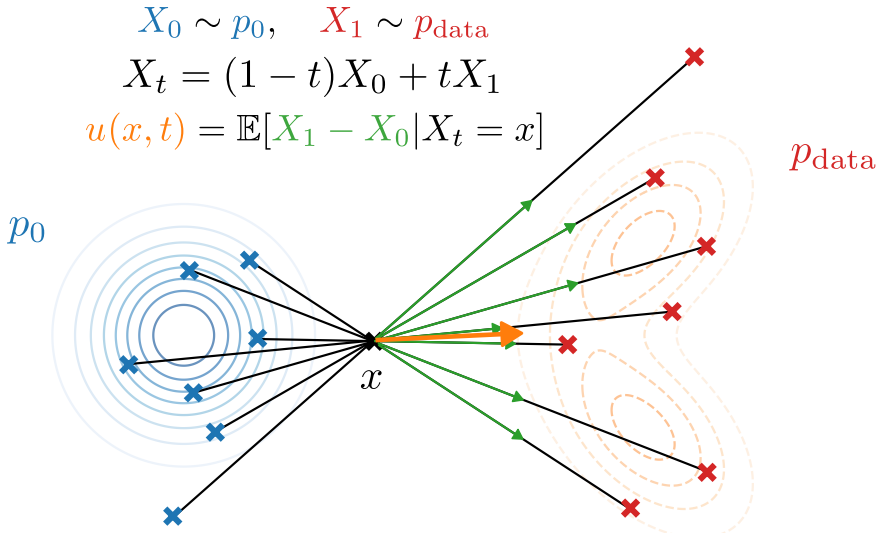
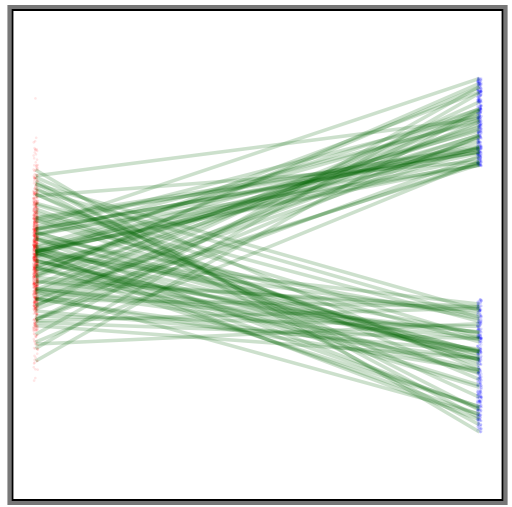
$x(1) \sim p_{\text{data}}$
0
t
1


x_0
$u(x(t), t)$
$x(t)$

Why the conditional expectation is "good"





More in our blog post: **A Visual dive into conditional flow matching**[10]: https://dl.heeere.com/cfm/

[10] A. Gagneux et al., **A Visual Dive into Conditional Flow Matching,** In: ICLR Blogposts, 2025.

How to train a Flow matching model?

$$\min_{u_\theta} \mathbb{E}_{\substack{x_0 \sim p_0 \\ x_1 \sim p_{\text{data}} \\ t \sim \text{unif}([0,1])}} \| u_\theta(\underbrace{(1-t)x_0 + t x_1}_{=x_t}, t) - (x_1 - x_0) \|^2$$

Train practically with:

$$\begin{aligned} x_0 &\sim p_0 = \mathcal{N}(0, \text{Id}_d) \\ x_1 &\sim p_{\text{data}} \\ t &\sim \text{Uniform}([0,1]) \\ x_t &= (1-t)x_0 + t x_1 \end{aligned}$$

SGD step on θ with loss $\| u_\theta(x_t, t) - (x_1 - x_0) \|^2$

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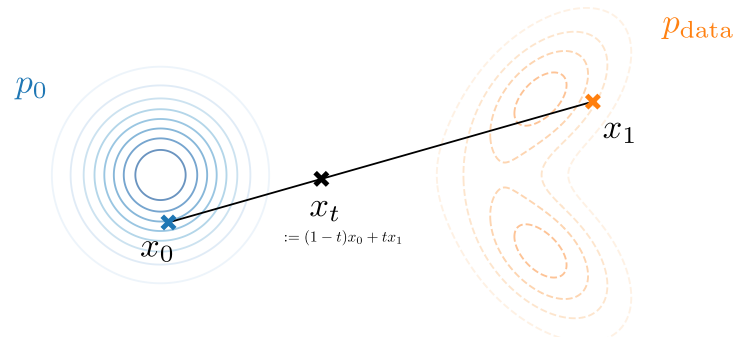

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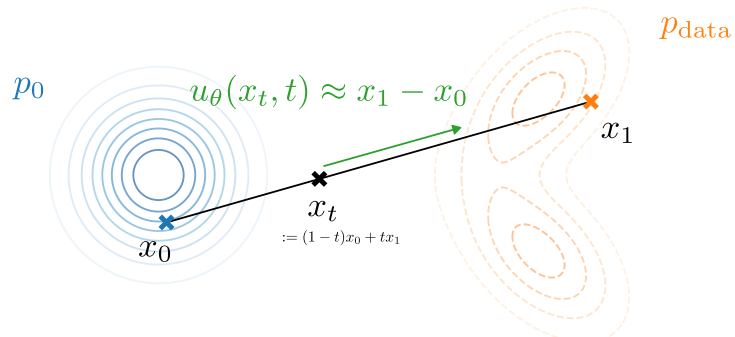

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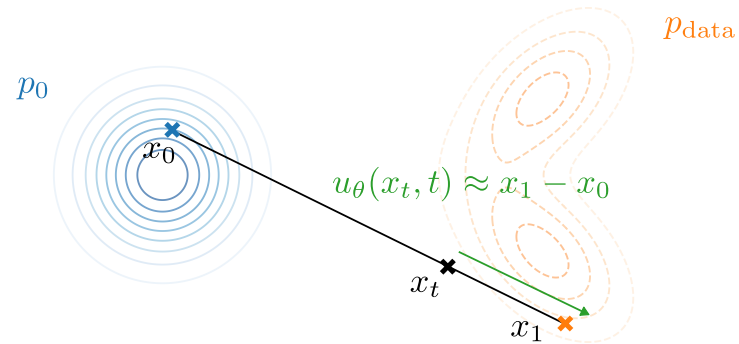

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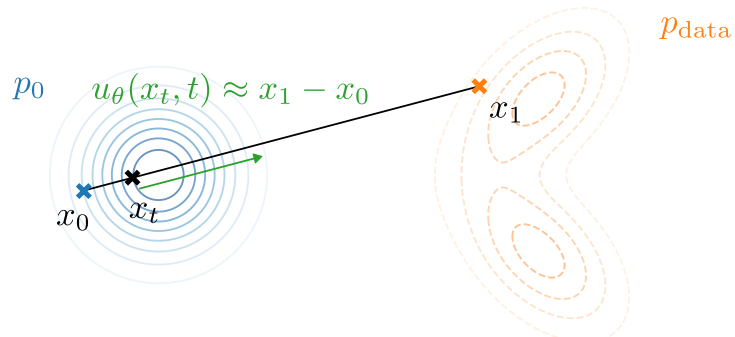

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the minimizer is $u(x,t) = \mathbb{E}[X_1 - X_0 | X_t = x]$

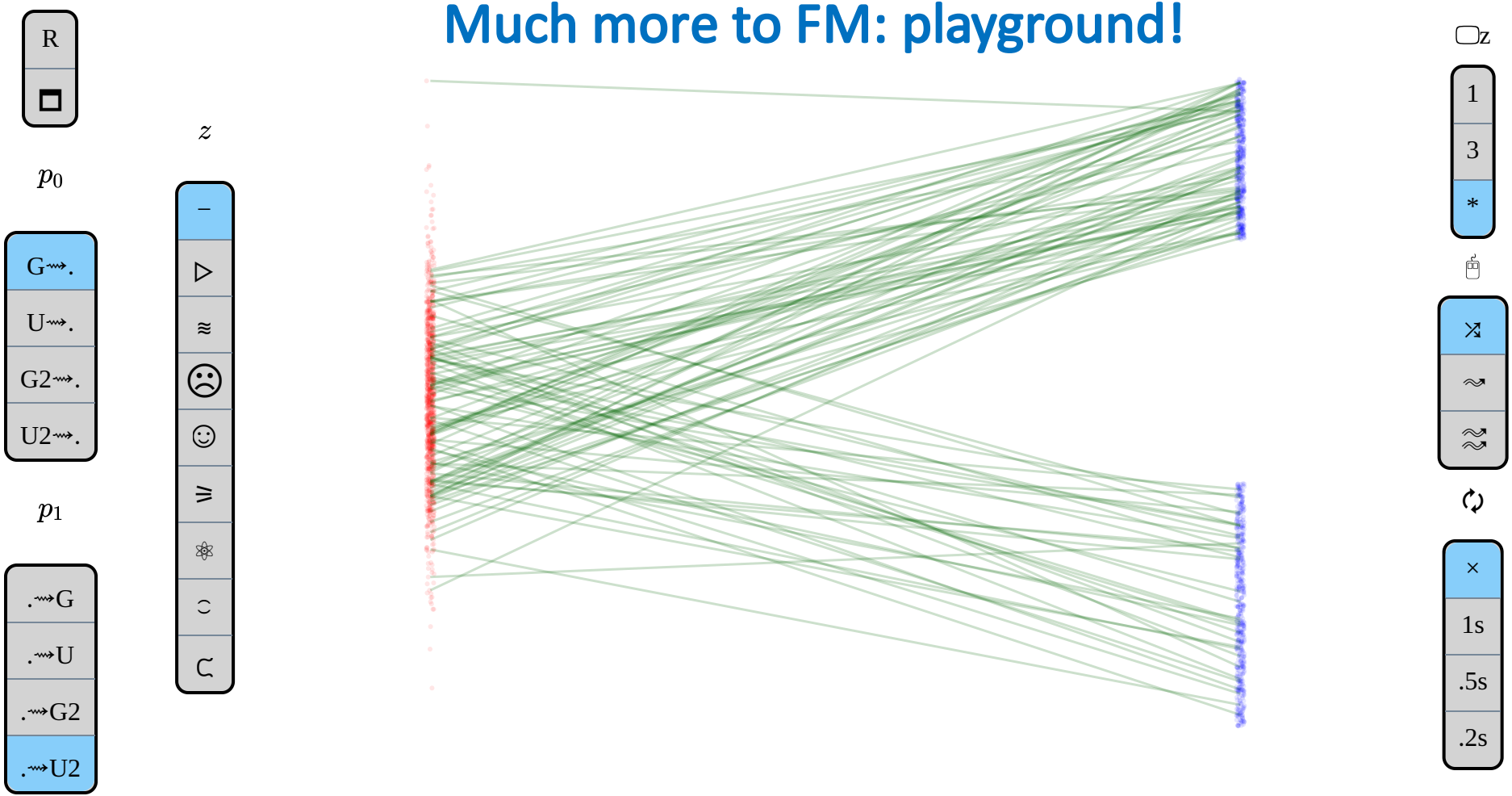
the minimizer (over all measurable functions)

Bonus: much more to FM[15,16]

- Source distribution p_0 can be arbitrary
- Time sampling need not be uniform
- In training, x_0 and x_1 need not be sampled independently[17,18]
- X_t need not equal $(1-t)X_0 + tX_1$
- In practice guidance/conditioning is used a lot

[15] E. Pierret et al., **Flow Matching for Applied Mathematicians,** In: , 2026.
[16] Y. Lipman et al., **Flow matching guide and code,** In: arXiv preprint arXiv:2412.06264, 2024.
[17] A. Pooladian et al., **Multisample flow matching: Straightening flows with minibatch couplings,** In: ICML, 2023.
[18] A. Tong et al., **Improving and generalizing flow-based generative models with minibatch optimal transport,** In: TMLR, 2023.

Much more to FM: playground!



Diffusion

Only thing to know: it's equivalent to Flow matching[19]!

Diffusion Meets Flow Matching: Two Sides of the Same Coin

https://diffusionflow.github.io/

[19] R. Gao et al., **Diffusion Meets Flow Matching: Two Sides of the Same Coin,** In: ICLR Blogposts, 2025.

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- Convention differs from Flow matching: $t = 0$ corresponds to clean data

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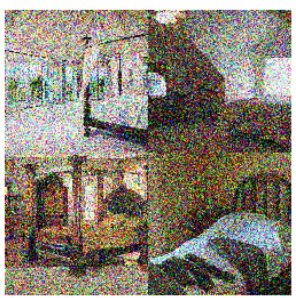

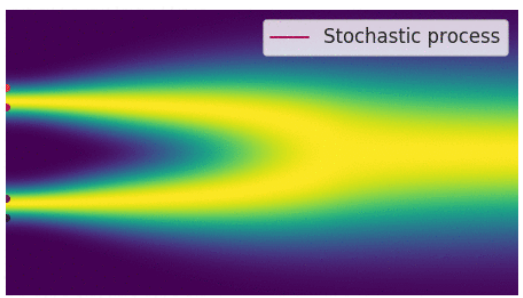

https://yang-song.net/blog/2021/score/

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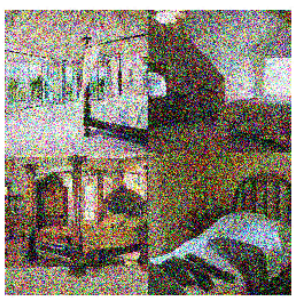
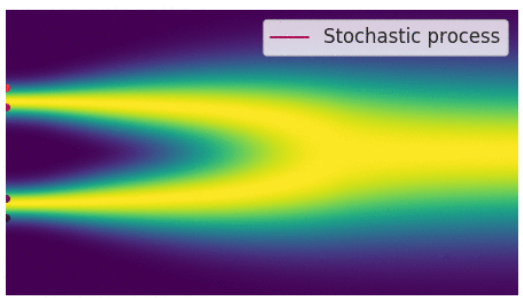
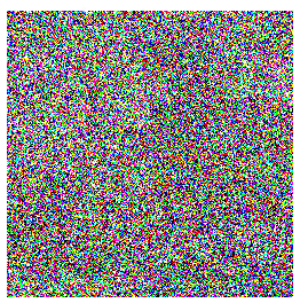
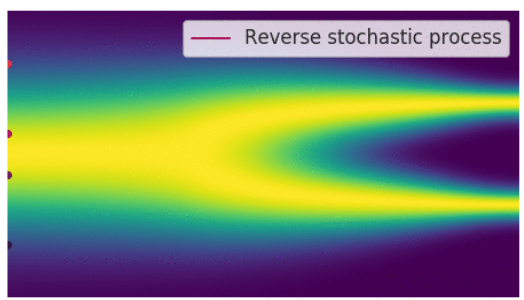
- Convention differs from Flow matching: $t = 0$ corresponds to clean data
- Similar idea: progressively corrupt image by adding Gaussian noise
- Trajectories are stochastic
- One learns to reverse the noising process









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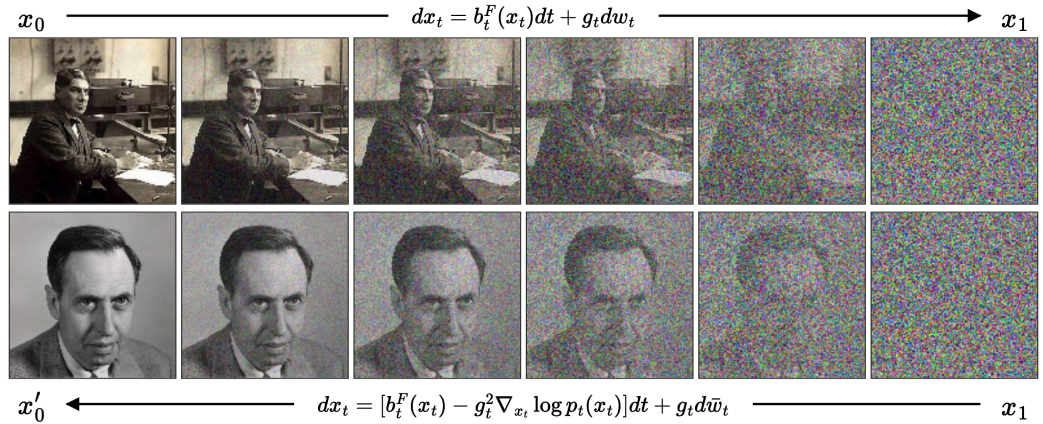
Learning Diffusion

- Instead of learning the velocity u, diffusion learns to reverse the corruption process
- It is driven by a Stochastic Differential Equation (SDE)



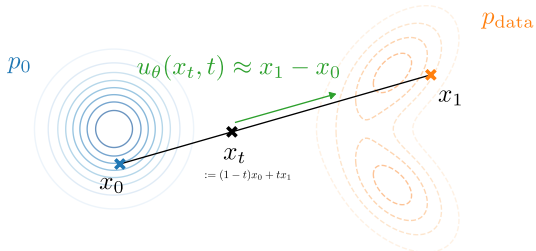
- A key quantity to learn is the *score* $\nabla \log p_t(x_t) \in \mathbb{R}^d$ (p_t is the density of X_t)

  It is theoretically equivalent to learn to predict the score, the added noise or the original image from the corrupted image x_t

- Training procedure is similar to Flow matching: sample clean image, noise it, learn to denoise it

Memorization in Diffusion & Flow Matching

A small caveat in training



Flow matching training:

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\begin{aligned}
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x_t &= (1-t)x_0 + tx_1
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$$

SGD step on θ with loss $\|u_\theta(x_t, t) - (x_1 - x_0)\|^2$

Flow matching code

Flow Matching

Yaron Lipman[1], Marton Havas
Ricky T. Q. Chen[1], David Lope
[1]FAIR at Meta, [2]MIT CSAI

```
24  # training
25  flow = Flow()
26  optimizer = torch.optim.Adam(flow.parameters(), 1e-2)
27  loss_fn = nn.MSELoss()
28
29  for _ in range(10000):
30    x_1  = Tensor(make_moons(256, noise=0.05)[0])
31    x_0  = torch.randn_like(x_1)
32    t    = torch.rand(len(x_1), 1)
33    x_t  = (1 - t) * x_0 + t * x_1
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35    optimizer.zero_grad()
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No si
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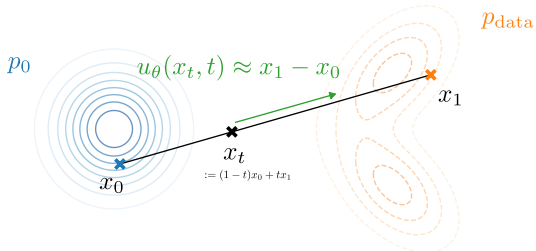

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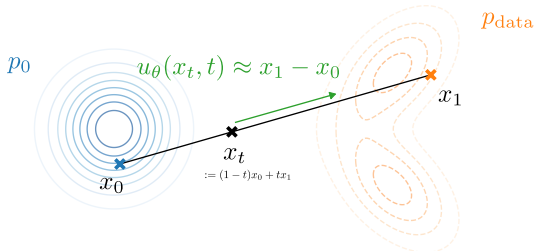

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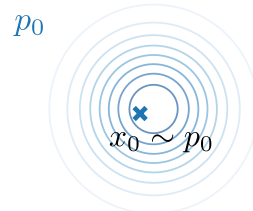

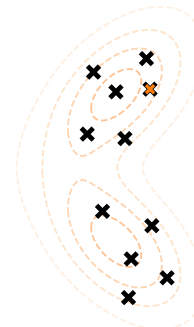

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$x_1 \in \{x^{(1)}, \ldots, x^{(n)}\}$

only usable loss: $\mathbb{E}_{\substack{x_0 \sim p_0 \\ x_1 \sim \hat{p}_{\text{data}} \\ t \sim \text{unif}([0,1])}} \|u_\theta((1-t)x_0 + tx_1, t) - (x_1 - x_0)\|^2$

Expectation vs reality

$$\text{only usable loss:} \quad \mathbb{E}_{\substack{x_0 \sim p_0 \\ x_1 \sim \hat{p}_{\text{data}} \\ t \sim \text{unif}([0,1])}} \left\| u_\theta((1-t)x_0 + t x_1, t) - (x_1 - x_0) \right\|^2$$

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$$\hat{u}^\star(x,t) := \sum_{i=1}^n \lambda_i(x,t) \frac{x^{(i)} - x}{1-t}$$

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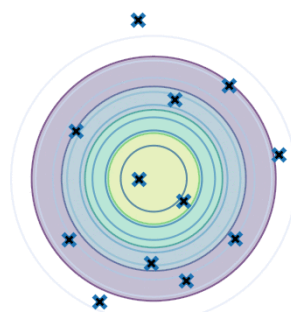

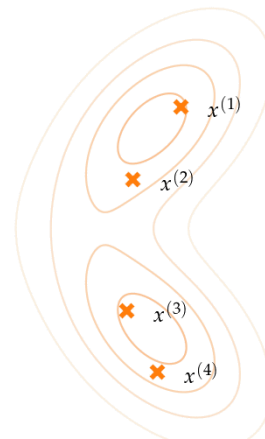

it only generates training points!

What about diffusion?

- Training diffusion is a particular instance of Flow matching parametrization
- The ideal diffusion score $s^\star(x,t) = \nabla \log p_t(x)$ is related to the ideal velocity by $s(x,t) = \frac{tu^\star(x,t)-x}{1-t}$
- Closed-form minimizer for velocity $\implies$ closed-form minimizer for score! (which also blows up)

Diffusion suffers from the same curse!

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- Simple training algorithms
- Closed-form for the ideal score/velocity
- Closed-form can only generate training samples
- Properly trained Flow matching and diffusion should only generate training data (like all unregularized generative models)
- So why do they generate new samples?