ICML 2026 Tutorial

Diffusion and Flow Matching

From Memorization to Generalization & Beyond

Quentin Bertrand & Mathurin Massias

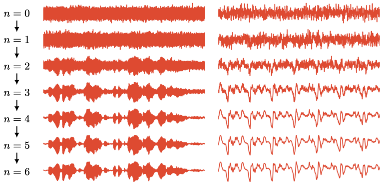
https://memorization-generalization.github.io

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

Diffusion and Flow matching are everywhere

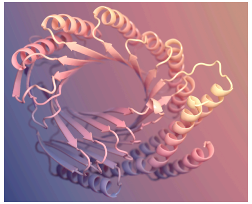
- Diffusion introduced in 2015[1], took off in 2020[2,3]
- Flow matching introduced in 2023[4,5,6]
- Current SOTA techniques for generation of images, audio, videos, proteins...

Stable Diffusion



WaveGrad

Sora



RF Diffusion

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- And even for text now

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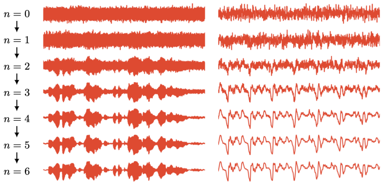

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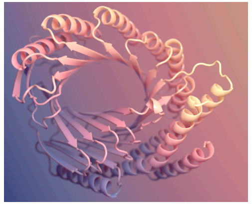

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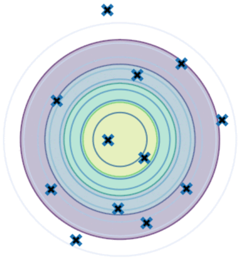

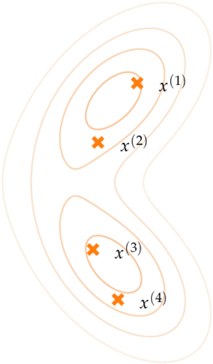

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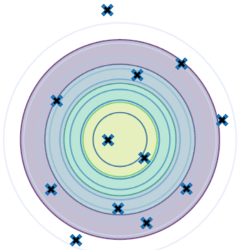

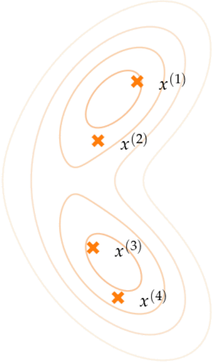

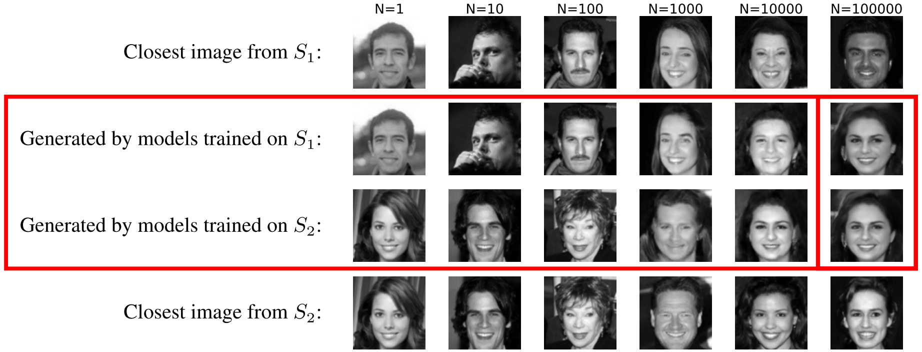

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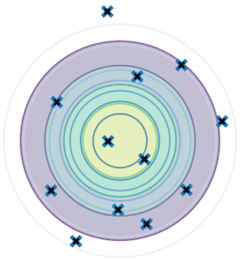
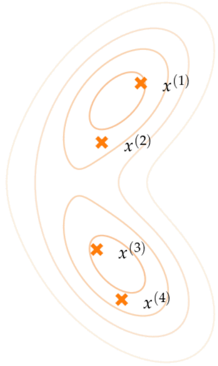
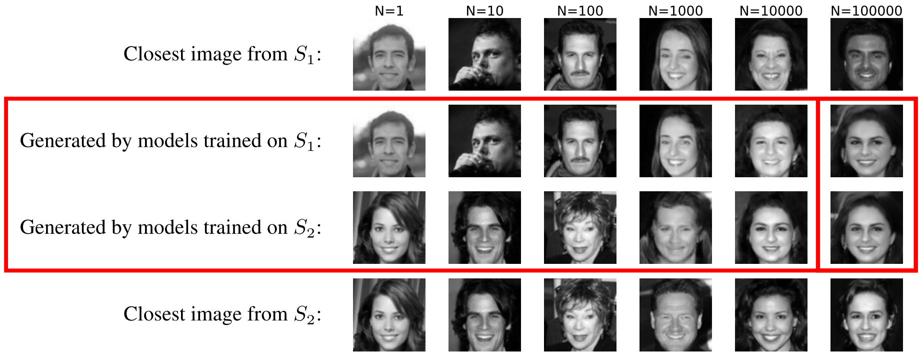
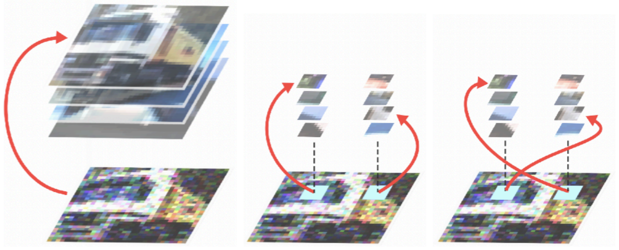
- Models trained on different datasets generate the same images?[8]
- Generated images are patchworks of training images?[9]









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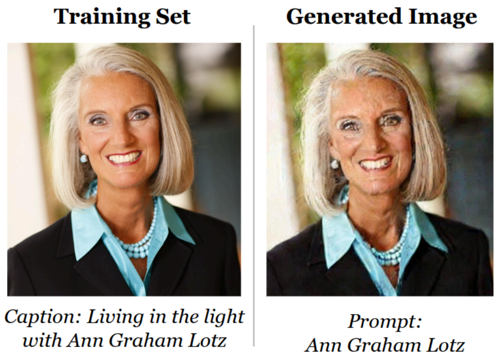
Tutorial goal

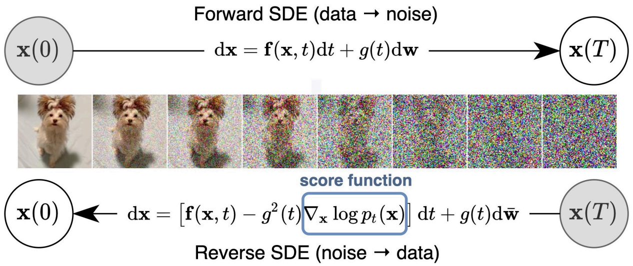
When, how, and why do Diffusion & Flow matching create new data?

Plan

- 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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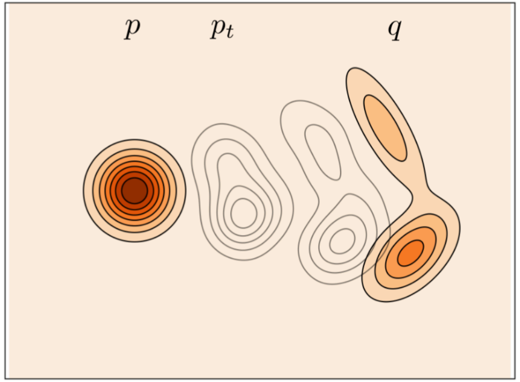

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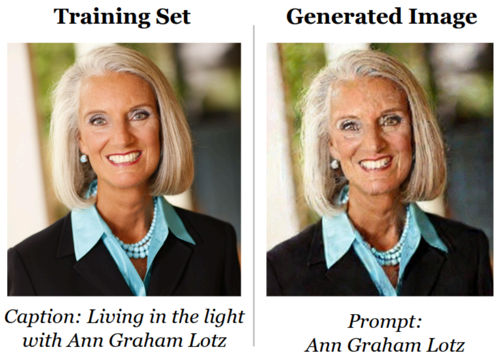

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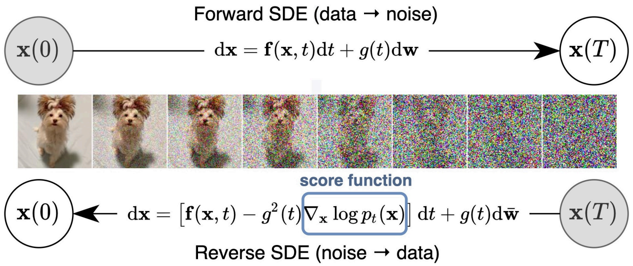

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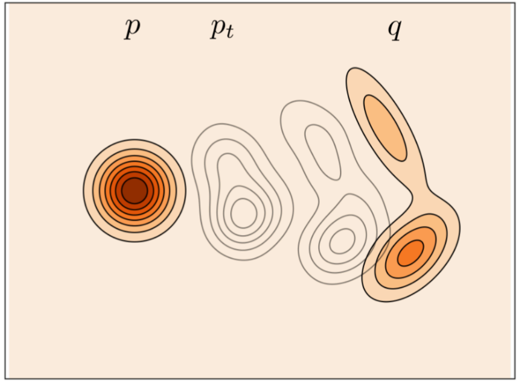

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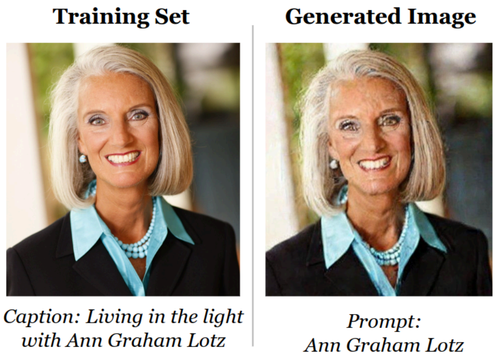
- Beyond generalization (30 min)
- Current open problems (15 min)
- Discussion #3 (15 min)



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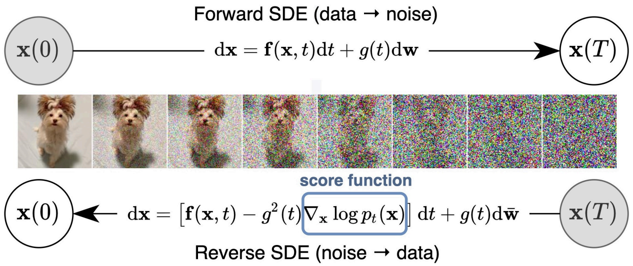

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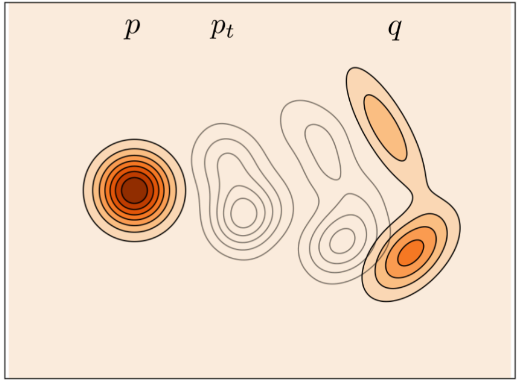

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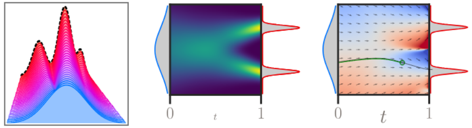
Who we are

RÉPUBLIQUE FRANÇAISE
Liberté
Égalité
Fraternité

Inria

- 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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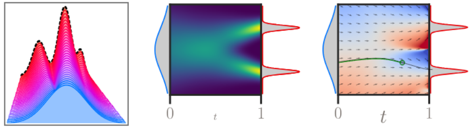

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- Many thanks to Rémi Emonet, Ségolène Martin, Anne Gagneux, Georges Le Bellier and Eloi Tanguy who contributed to the material





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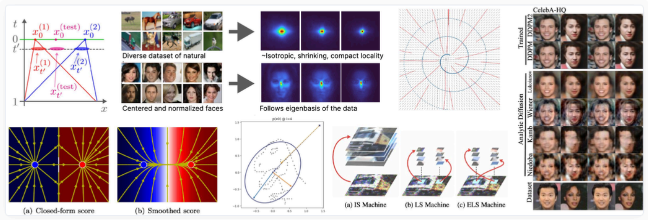
- Other tutorials!

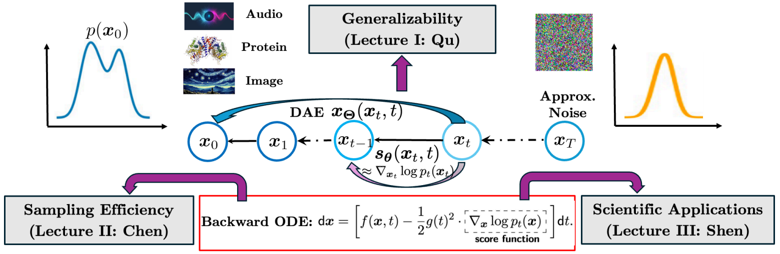
Analytic Understanding of Diffusion Models

A deep dive into the mathematical foundations and analytic perspectives behind modern diffusion-based generative models.



https://analytic-diffusion.github.io/ CVPR 2026

Harnessing Low Dimensionality in Diffusion Models: From Theory to Practice



https://icml-2025-tutorial.github.io/ ICML 2025

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Introduction to
Flow matching and Diffusion

A step back: what is generative modeling?

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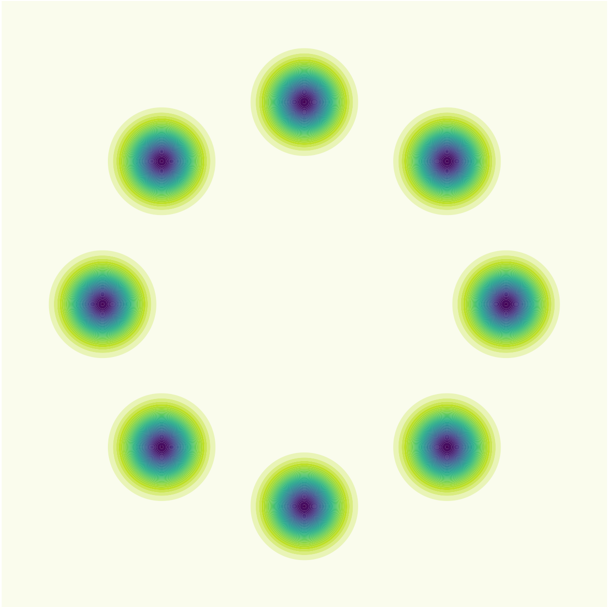
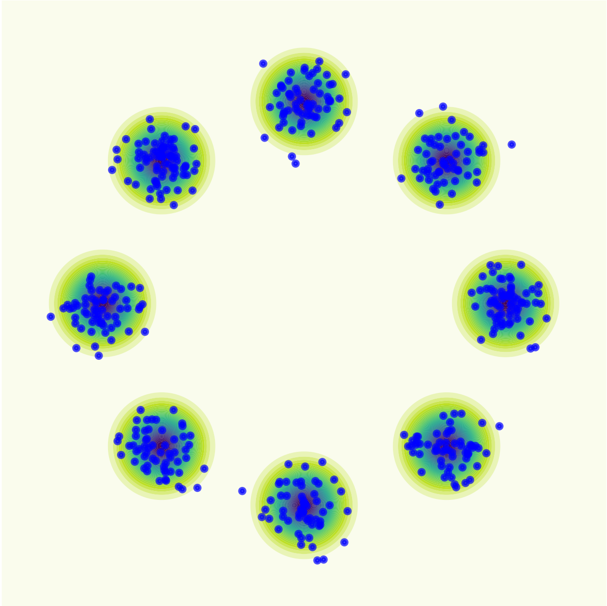


A step back: what is generative modeling?

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



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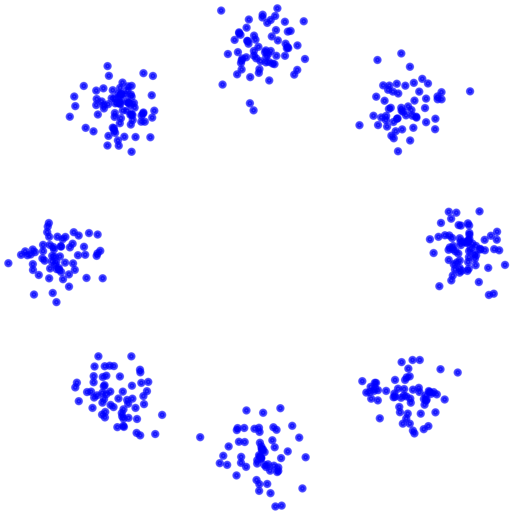

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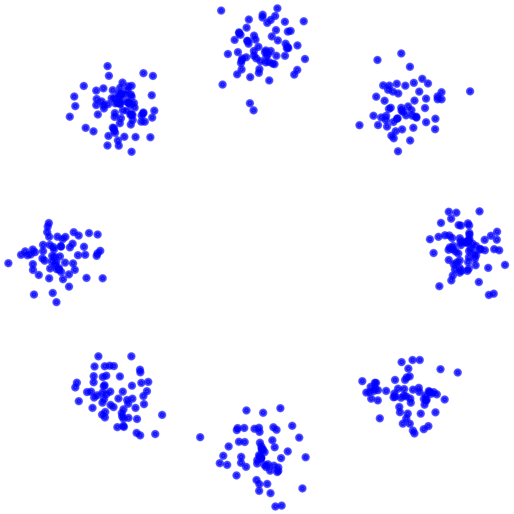

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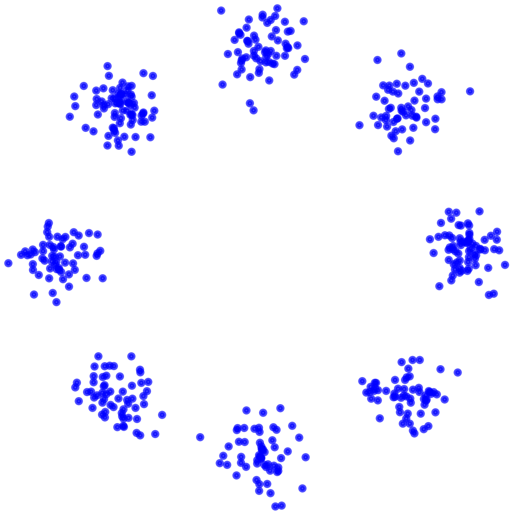

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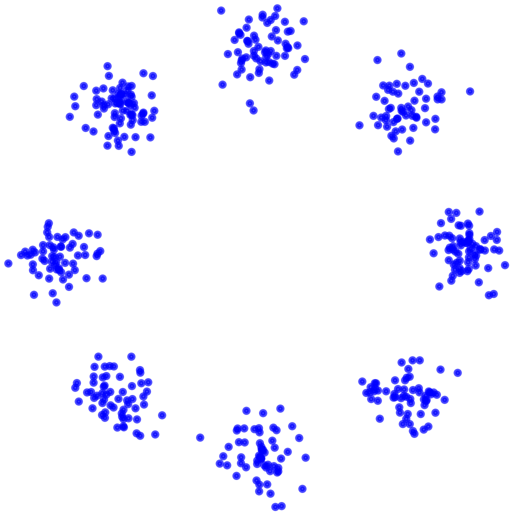

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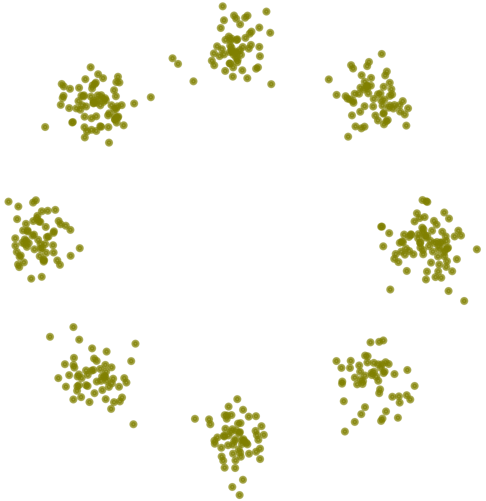

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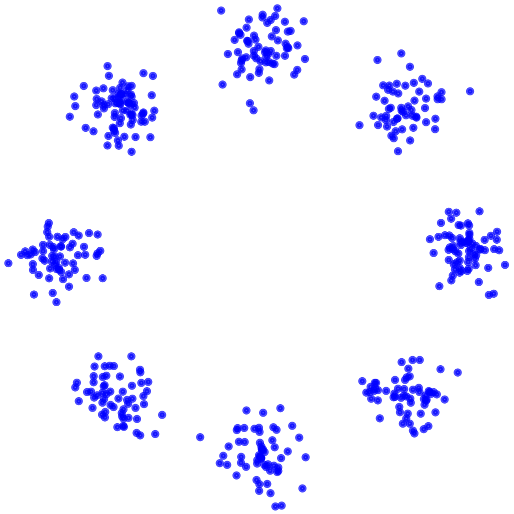

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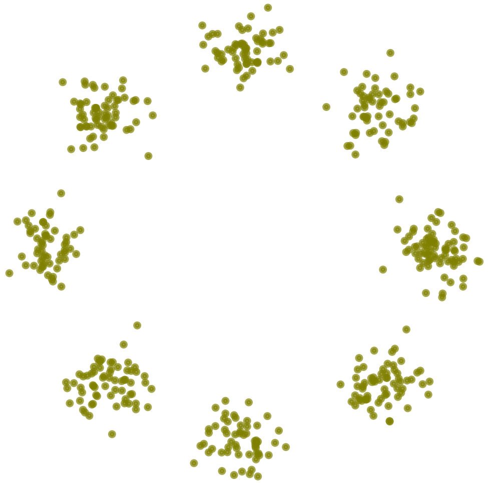

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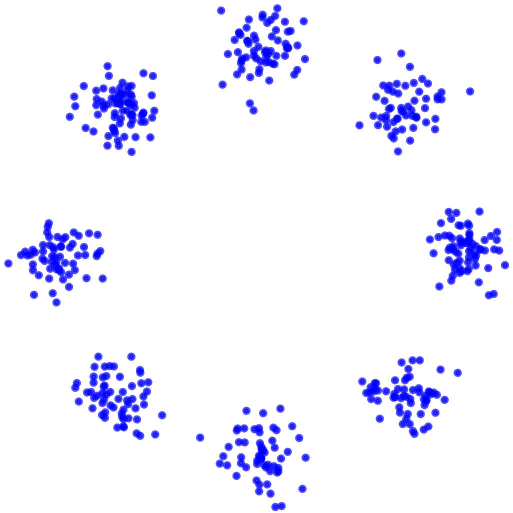

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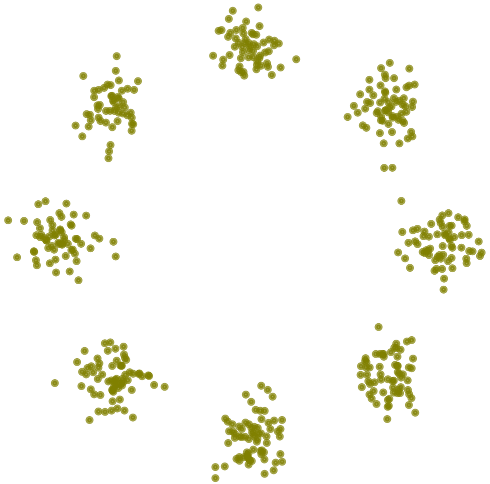

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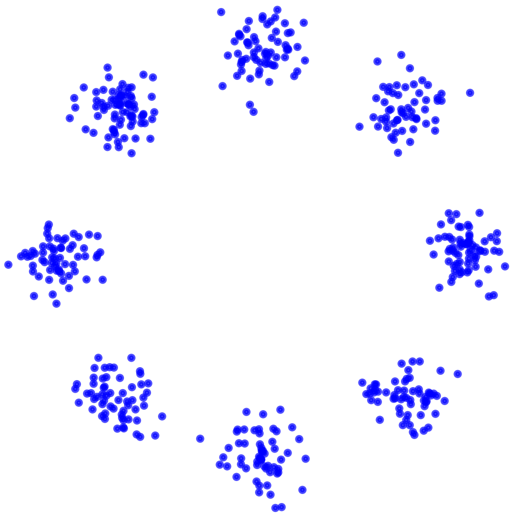

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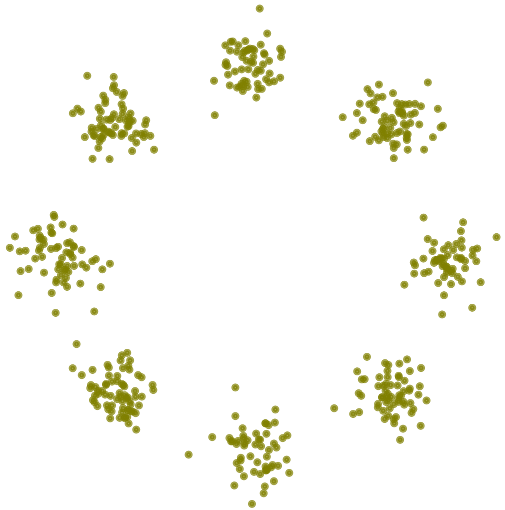

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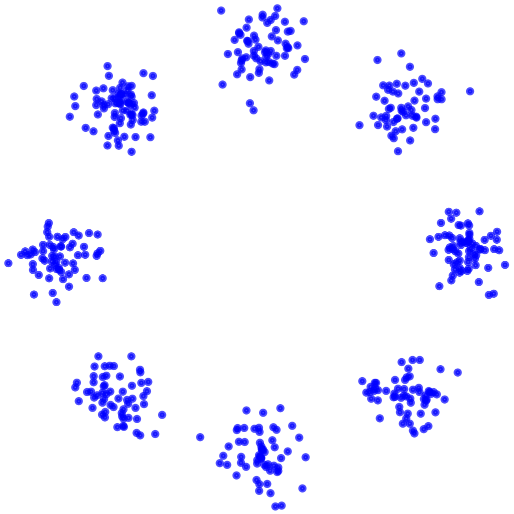

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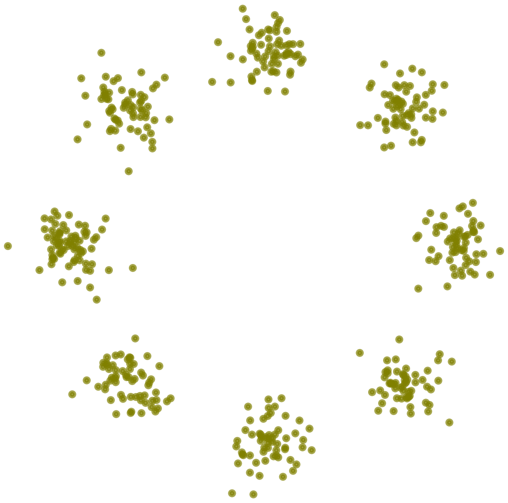

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Generative modeling: an image example

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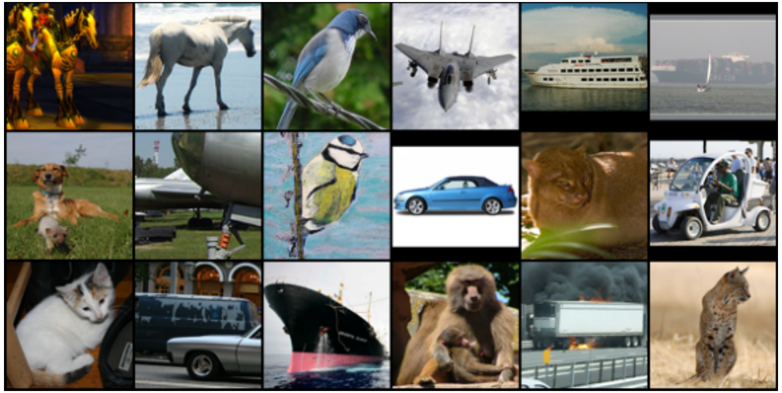

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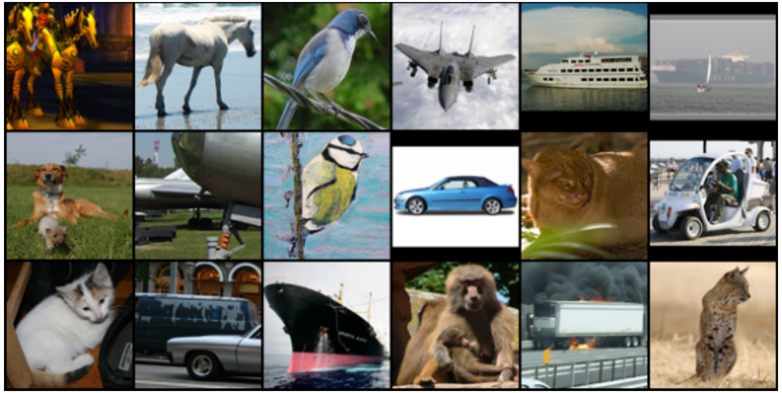

Data:

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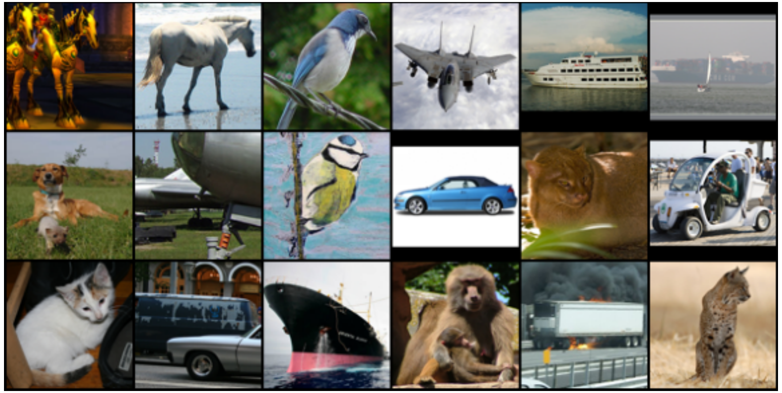

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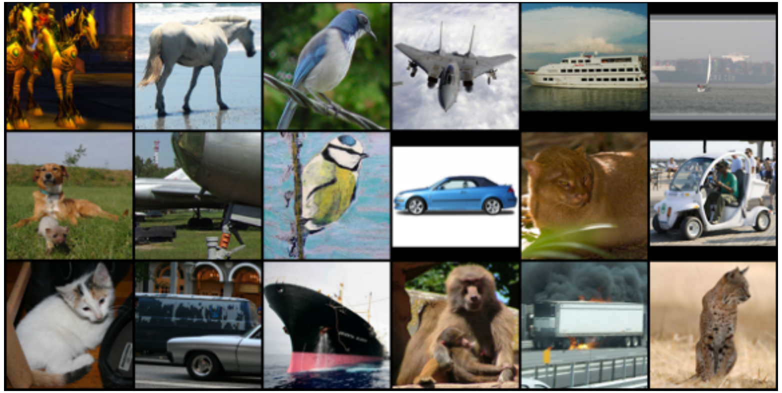

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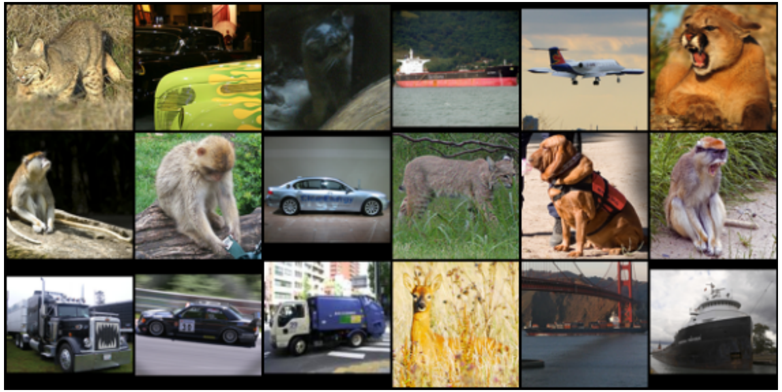

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Diffusion and Flow matching: the big picture

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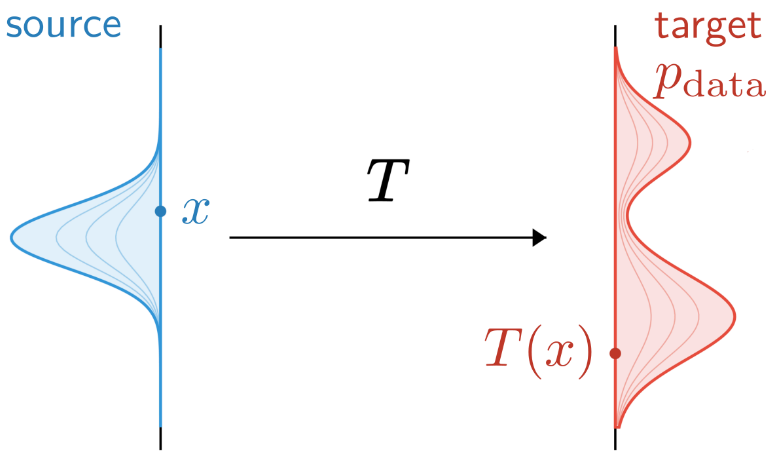
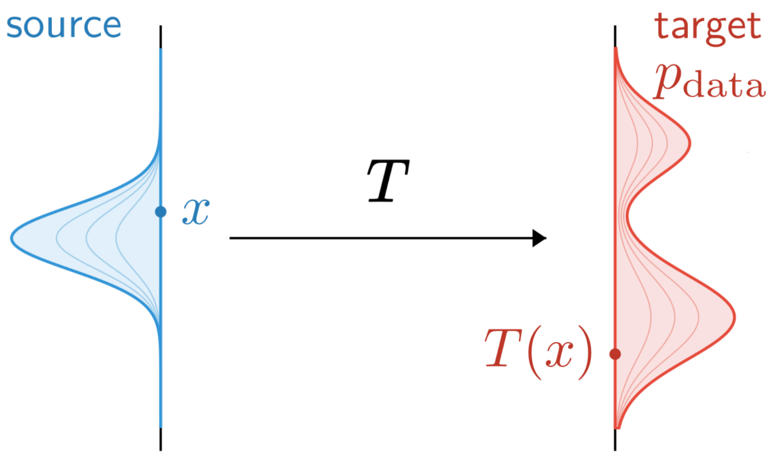
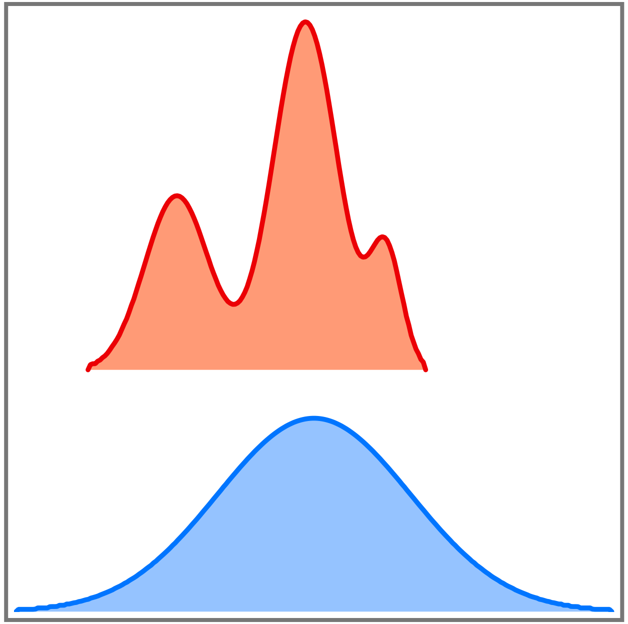


Diffusion and Flow matching: the big picture

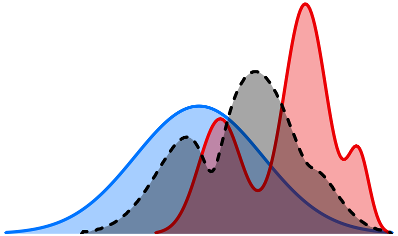
Common idea:

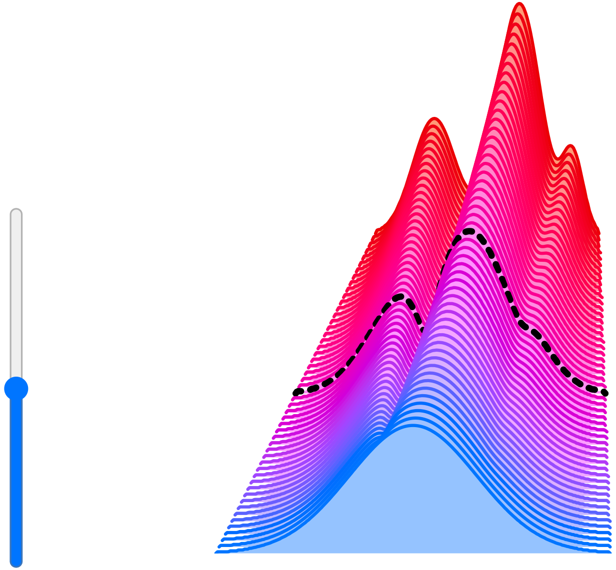
- Learn mapping T sending samples from source distribution to samples from target distribution p_{data}
- Rely on a continuous interpolation between the source and target distributions





Play with paths from to source and target distributions!





NB: Diffusion only supports Gaussian source distribution

Flow matching

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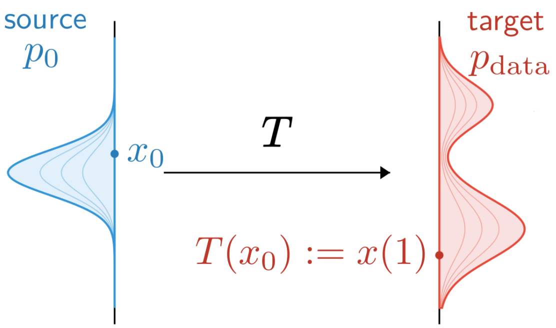

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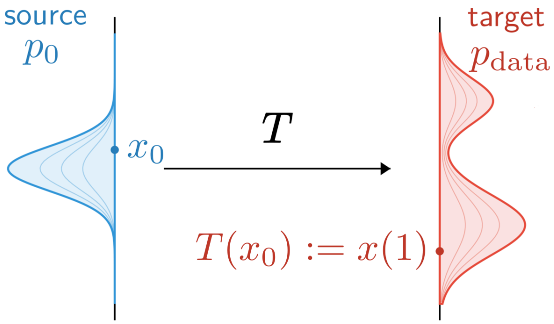

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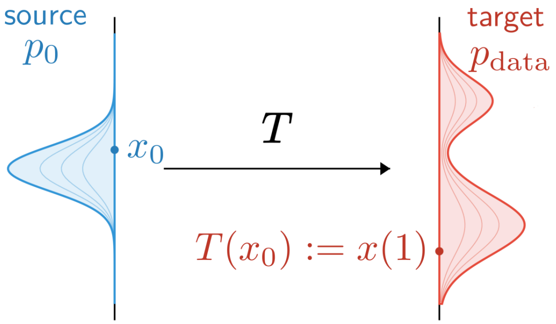

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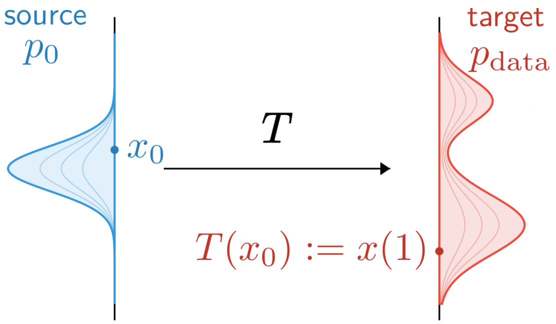

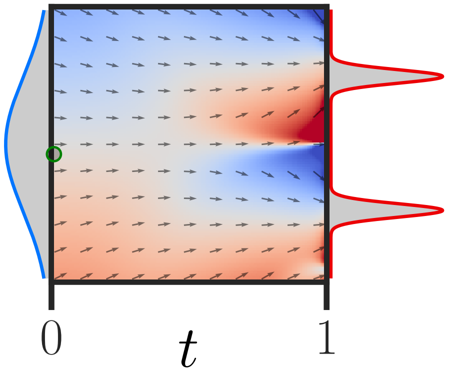

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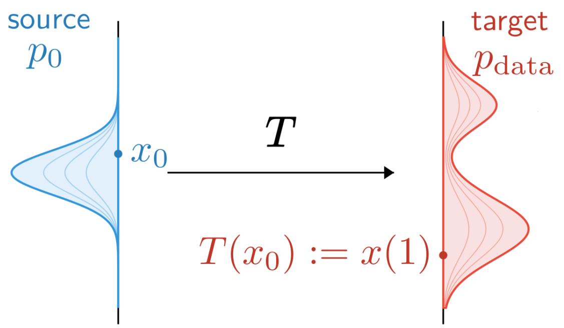
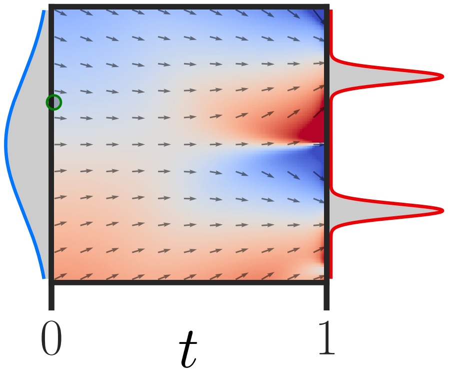


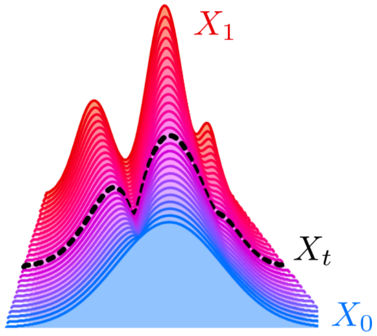


But how to find a *good* velocity $u(x,t)$?

How to find a good velocity?

Setup: define three random variables

- $X_0 \sim p_0$ source distribution: we will take $p_0 = \mathcal{N}(0, \mathrm{Id}_d)$
- $X_1 \sim p_{\mathrm{data}}$ target distribution: clean image
- $X_t := (1-t)X_0 + tX_1$ interpolation: noised image



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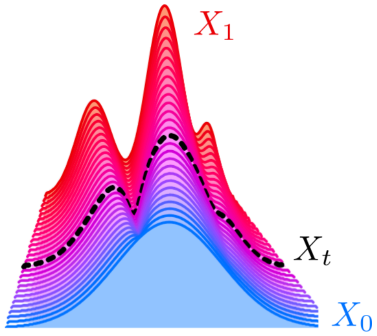

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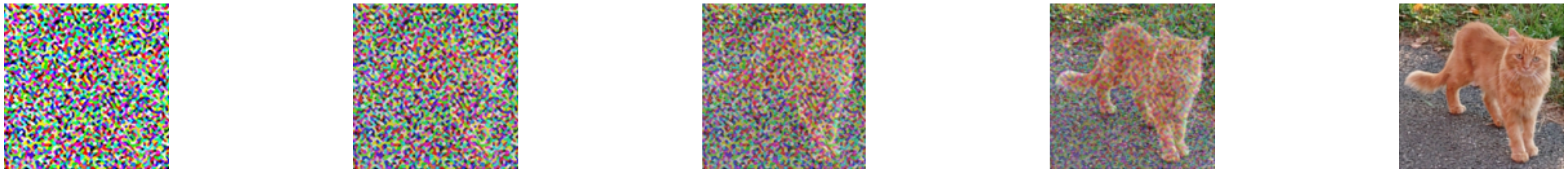

$X_{t=0}$ $X_{t=0.25}$ $X_{t=0.5}$ $X_{t=0.75}$ $X_{t=1}$

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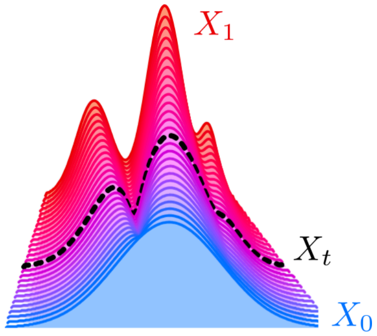

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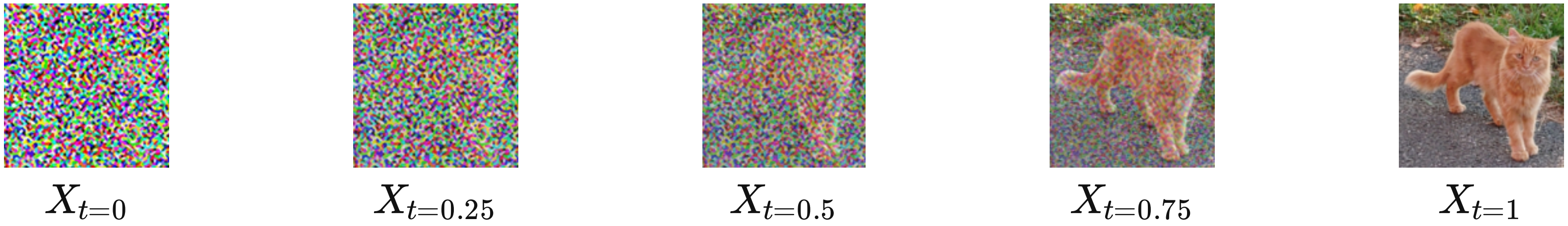

The FM magic[5,13,14] : $u(x,t) := \mathbb{E}[X_1 - X_0 | X_t = x]$ is a *good* velocity:

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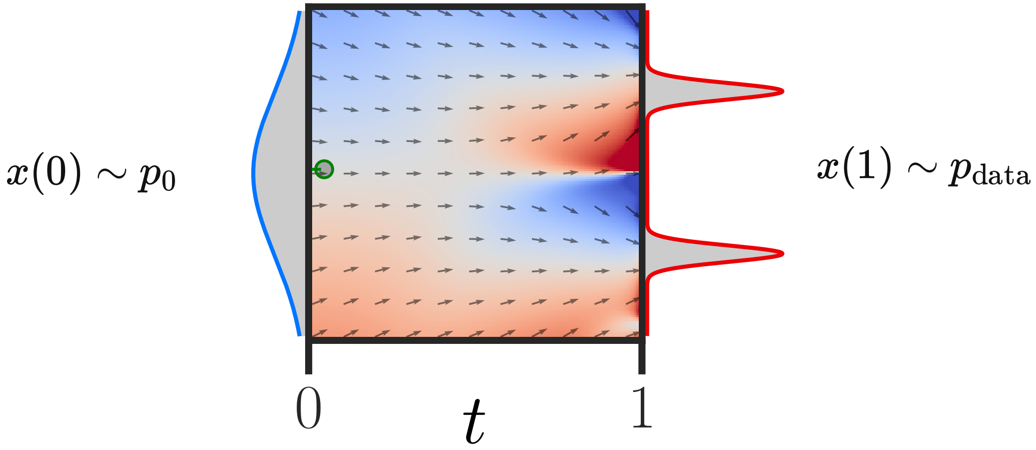
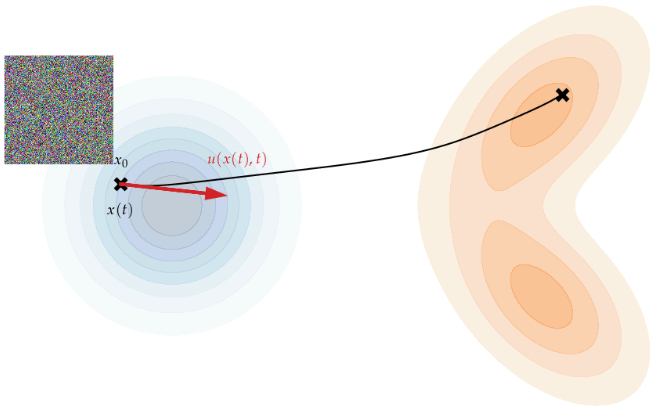
[5] M. Albergo et al., **Building Normalizing Flows with Stochastic Interpolants,** In: ICLR, 2023.

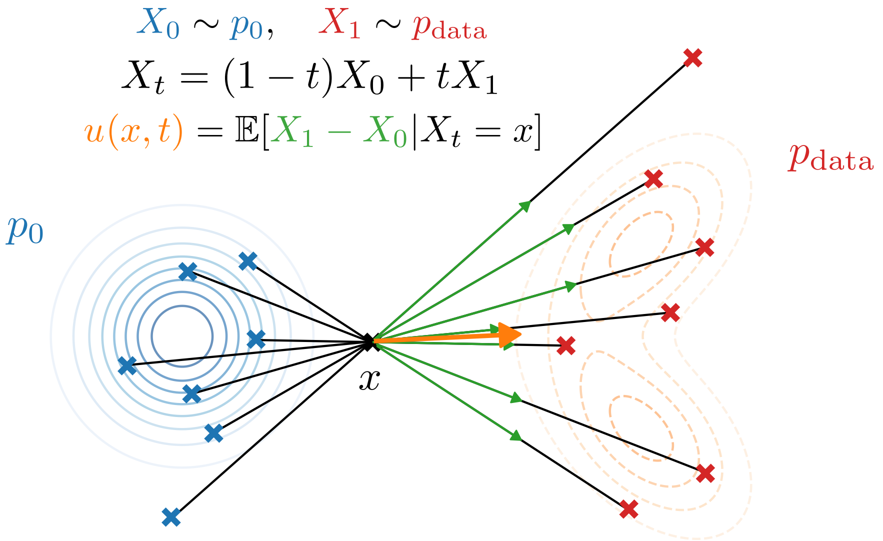
[13] Y. Lipman et al., **Flow Matching for Generative Modeling,** In: ICLR, 2023.

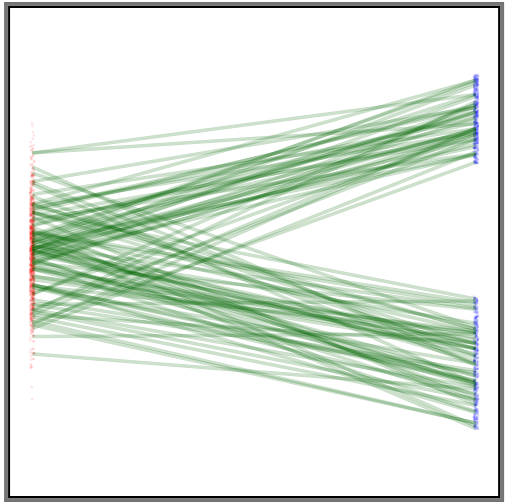
[14] X. Liu et al., **Flow Straight and Fast: Learning to Generate and Transfer Data with Rectified Flow,** In: ICLR, 2023.


$x(0) \sim p_0$
$x(1) \sim p_{\text{data}}$
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?

$$\min_{u_\theta} \mathbb{E}_{\substack{x_0 \sim p_0 \\ x_1 \sim p_{\text{data}} \\ t \sim \text{unif}([0,1])}} \left\| u_\theta(\underbrace{(1-t)x_0 + tx_1}_{=x_t}, t) - (x_1 - x_0) \right\|^2$$

Train practically with:

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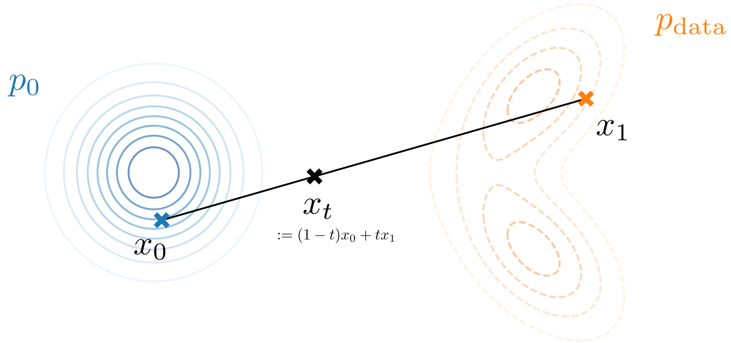

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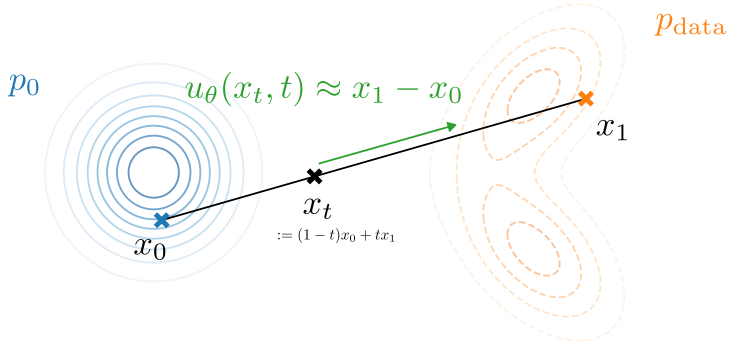

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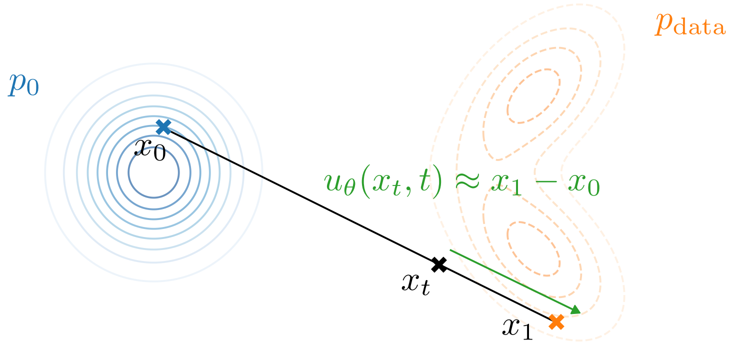

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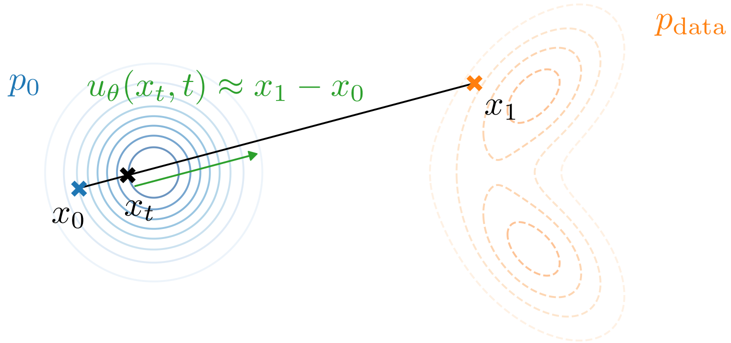

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the minimizer is $u(x,t) = \mathbb{E}[X_1 - X_0 | X_t = x]$

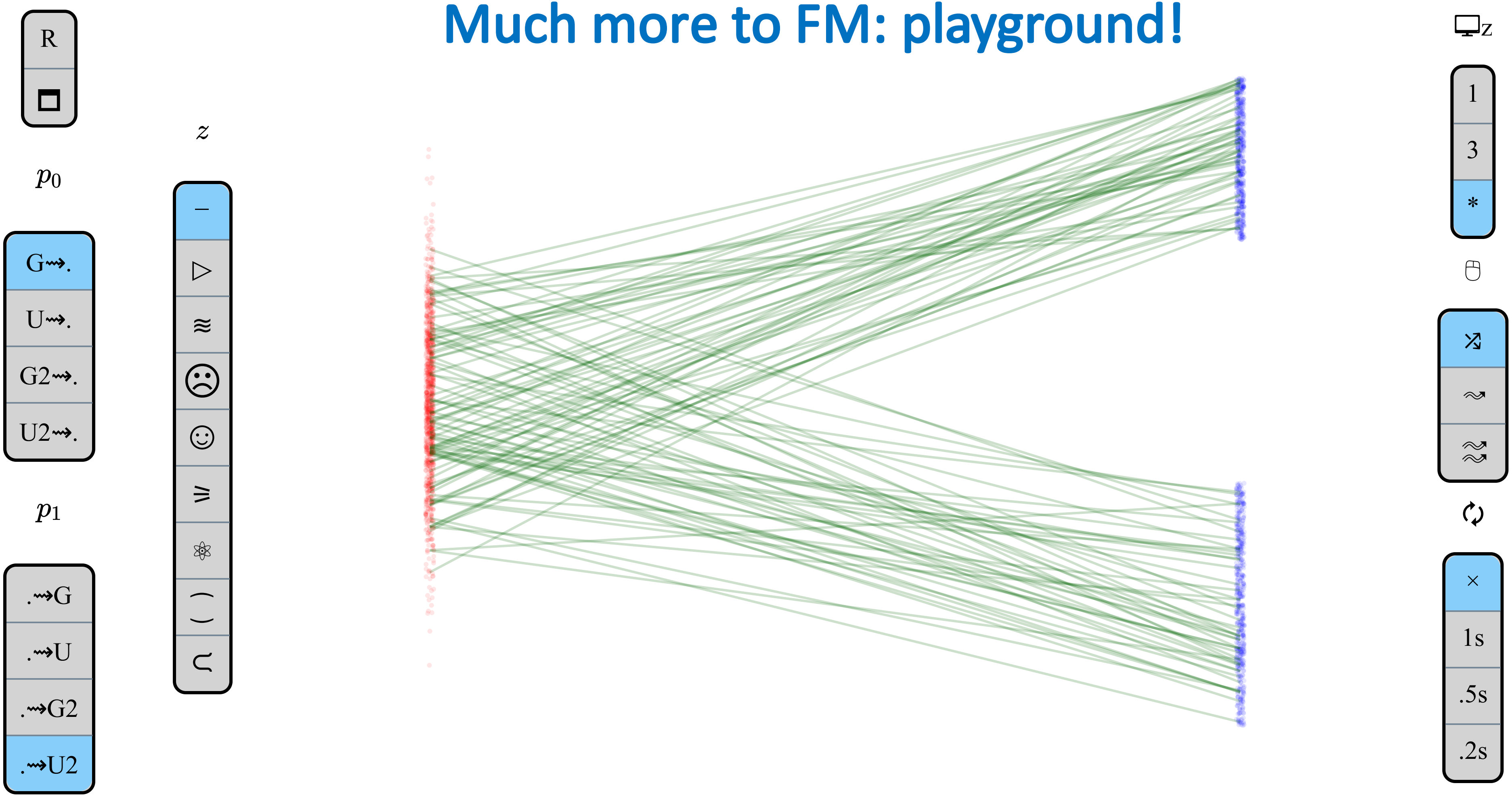
the minimizer (over all measurable functions)

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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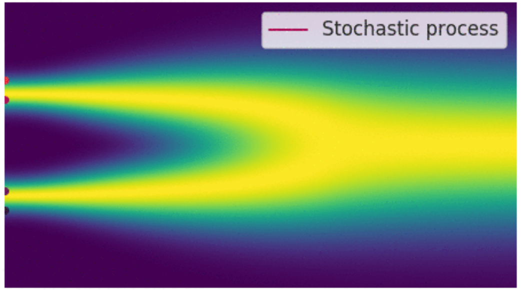

https://yang-song.net/blog/2021/score/

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- Convention differs from Flow matching: $t = 0$ corresponds to clean data
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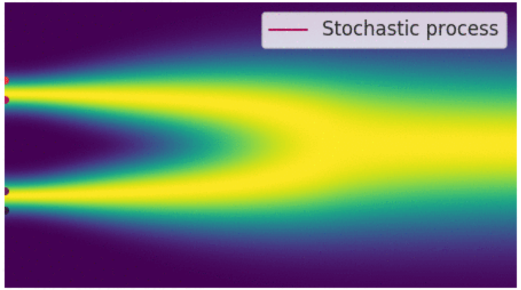
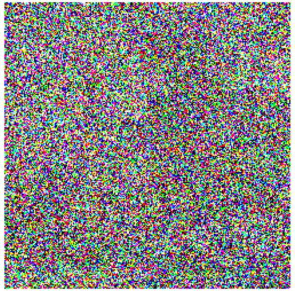
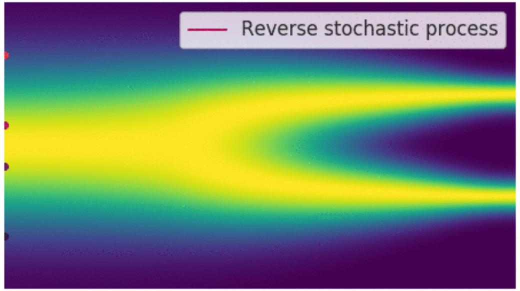
- Trajectories are stochastic
- One learns to reverse the noising process







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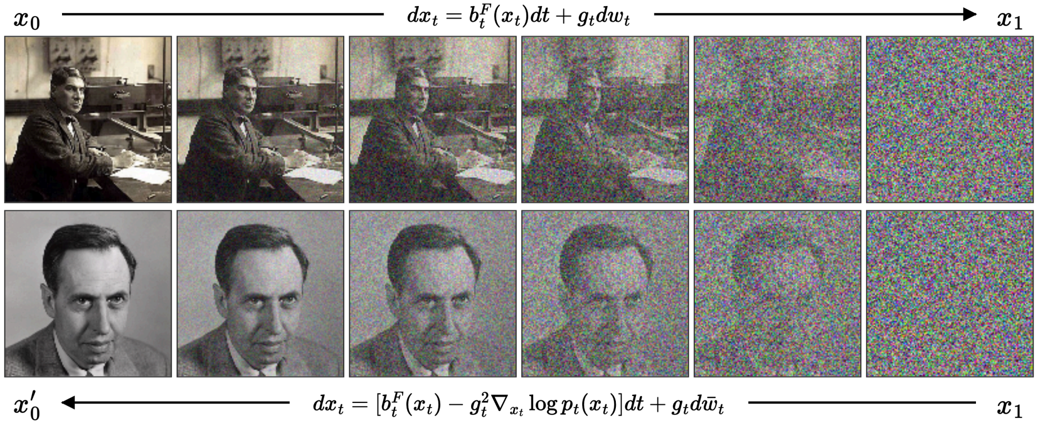
Learning Diffusion

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

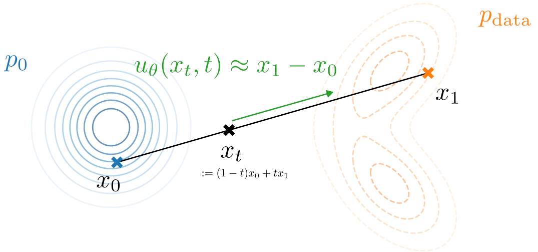


- A key quantity to learn is the *score* $\nabla \log p_t(x_t) \in \mathbb{R}^d$ (p_t is the density of X_t)

  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:

$$x_0 \sim p_0 = \mathcal{N}(0, \mathrm{Id}_d)$$
$$x_1 \sim p_{\mathrm{data}}$$
$$t \sim \mathrm{Uniform}([0,1])$$
$$x_t = (1-t)x_0 + tx_1$$

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

```
# training
flow = Flow()
optimizer = torch.optim.Adam(flow.parameters(), 1e-2)
loss_fn = nn.MSELoss()

for _ in range(10000):
  x_1  = Tensor(make_moons(256, noise=0.05)[0])
  x_0  = torch.randn_like(x_1)
  t    = torch.rand(len(x_1), 1)
  x_t  = (1 - t) * x_0 + t * x_1
  dx_t = x_1 - x_0
  optimizer.zero_grad()
  loss_fn(flow(x_t, t), dx_t).backward()
  optimizer.step()
```

No si
ODE

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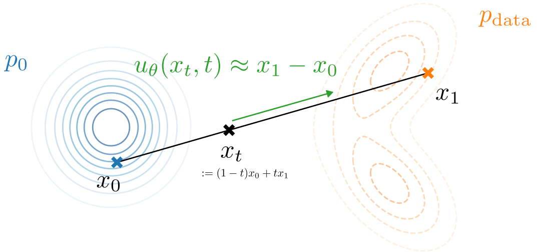

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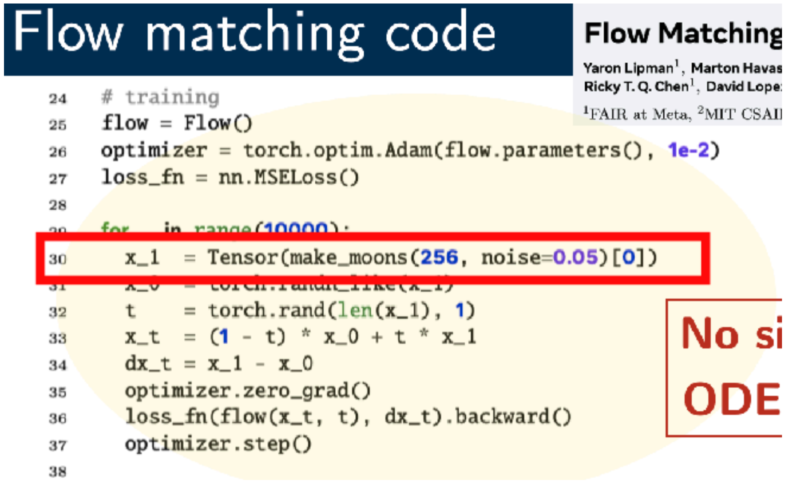


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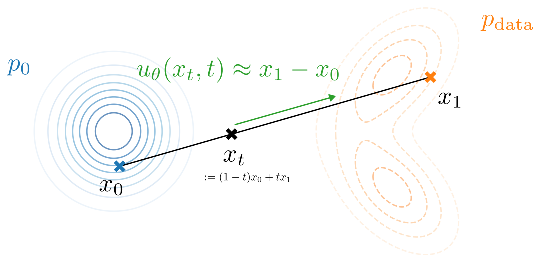

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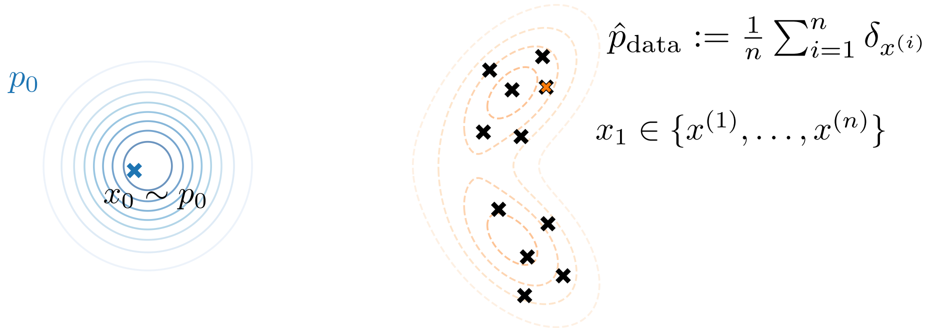

$$\text{only usable loss:} \quad \mathbb{E}_{\substack{x_0 \sim p_0 \\ x_1 \sim \hat{p}_{\text{data}} \\ t \sim \text{unif}([0,1])}} \|u_\theta((1-t)x_0 + tx_1, t) - (x_1 - x_0)\|^2$$

Expectation vs reality

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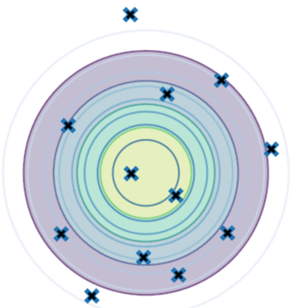
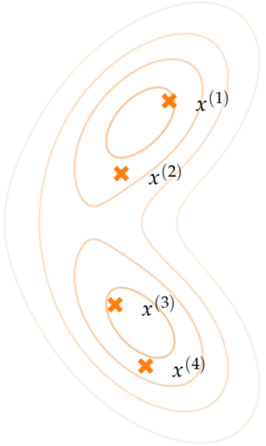
it only generates training points!





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!

Wrap-up of Part I

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Wrap-up of Part I

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- Properly trained Flow matching and diffusion should only generate training data (like all unregularized generative models)
- So why do they generate new samples?

ICML 2026 Tutorial

Diffusion and Flow Matching

Part II: From Memorization to Generalization

Quentin Bertrand & Mathurin Massias

https://memorization-generalization.github.io

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

Generative models: high dimensional density estimation

DALL·E, Ramesh et al.

Generative models: high dimensional density estimation

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Diffusion & Flow matching models sample from **high dimensional** densities

An unavoidable curse?

- Data in dimension d
  - e.g. moderate size images $d = 256 \times 256 \times 3$
- Estimation of the joint density $p(x_1, \ldots, x_d)$
- Number of samples needed to estimate a density for data in dimension d ?
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In theory: density estimation in such high dimension should fail!

From memorization to generalization

Memorization and closed-form minimizers observed since 2023[2,3]

Seminal experiment in 2024[4]:

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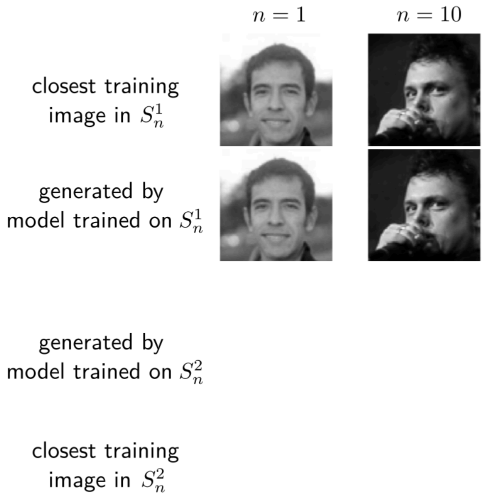

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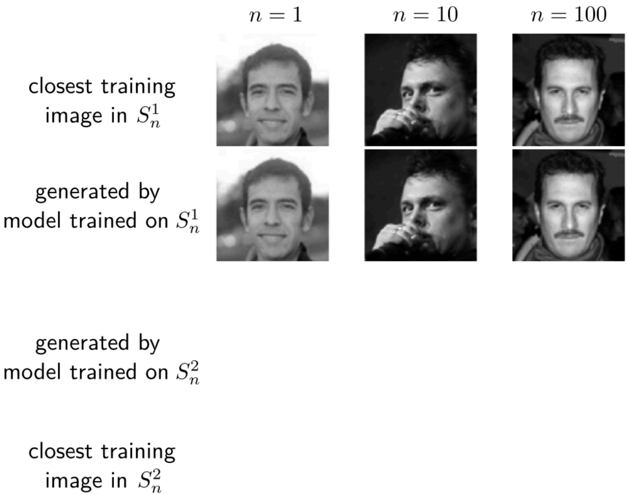

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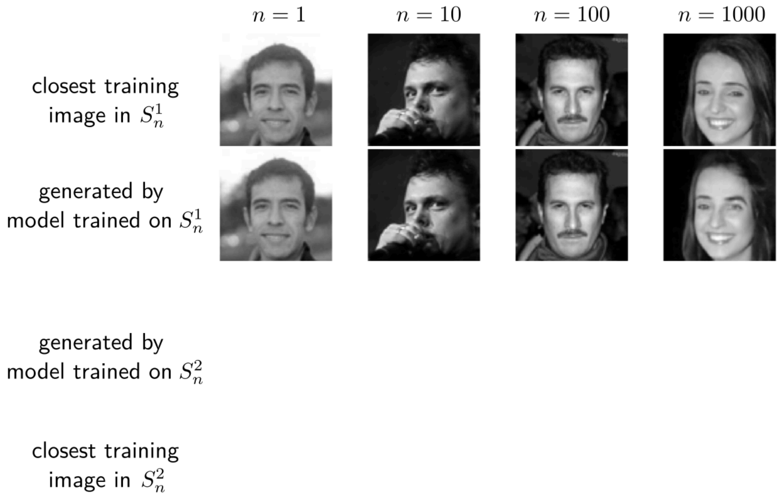

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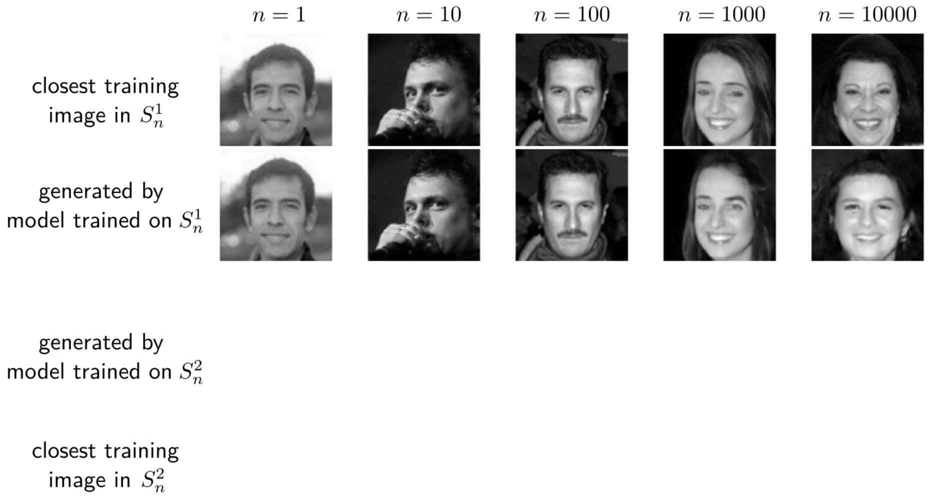

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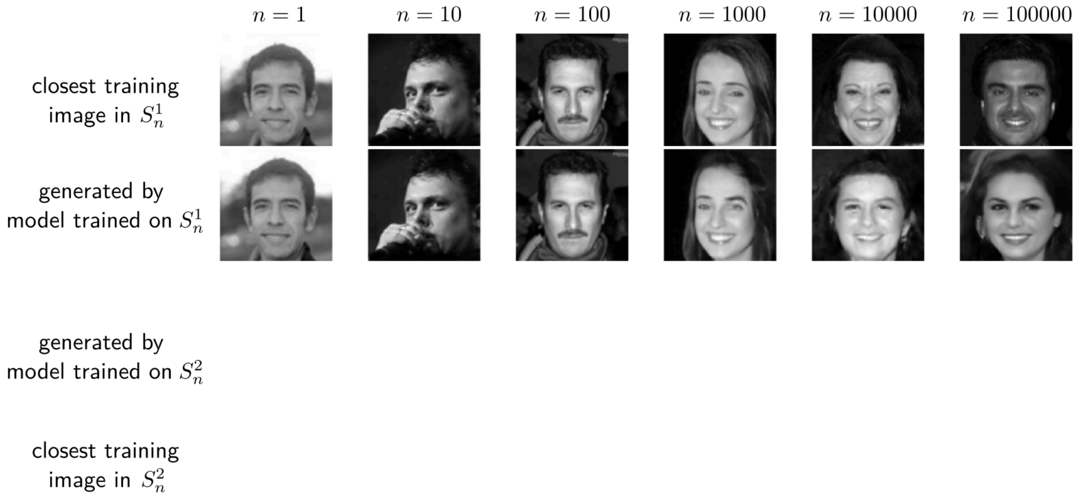

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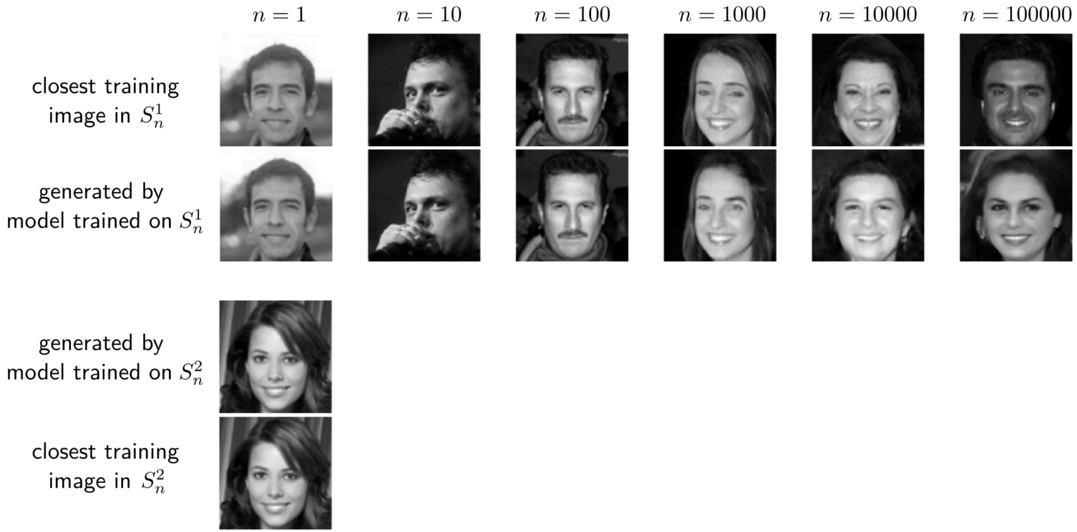

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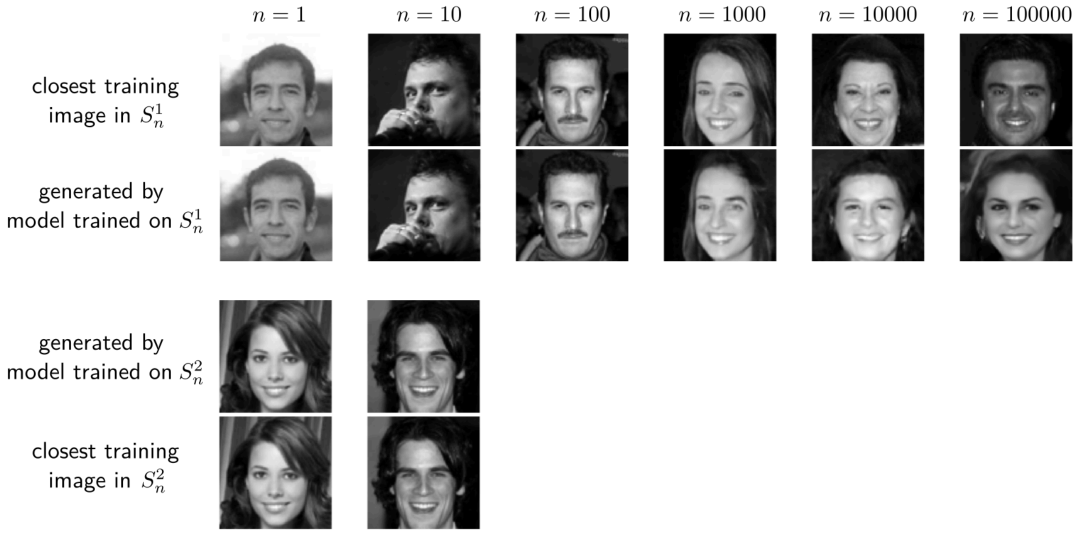

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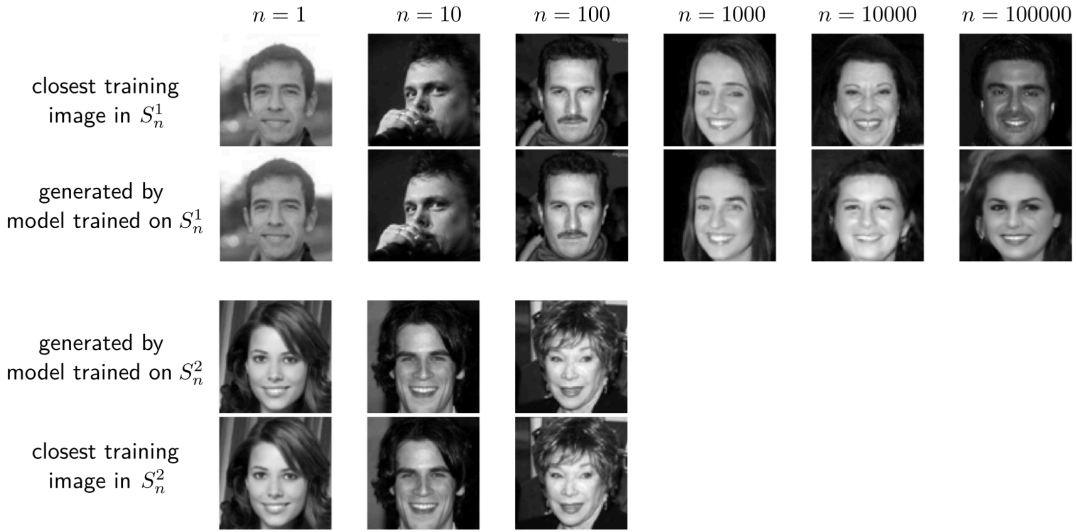

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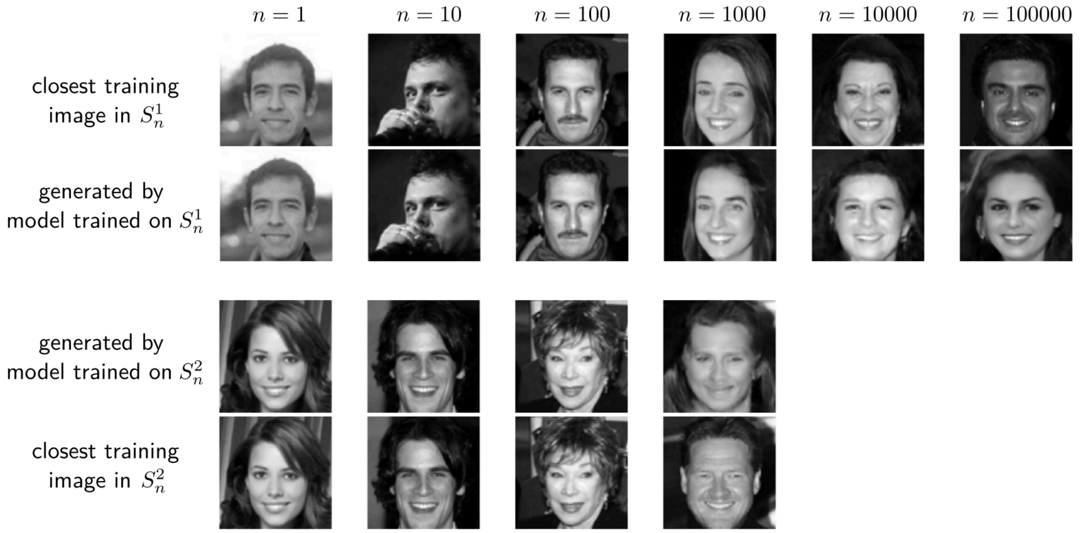

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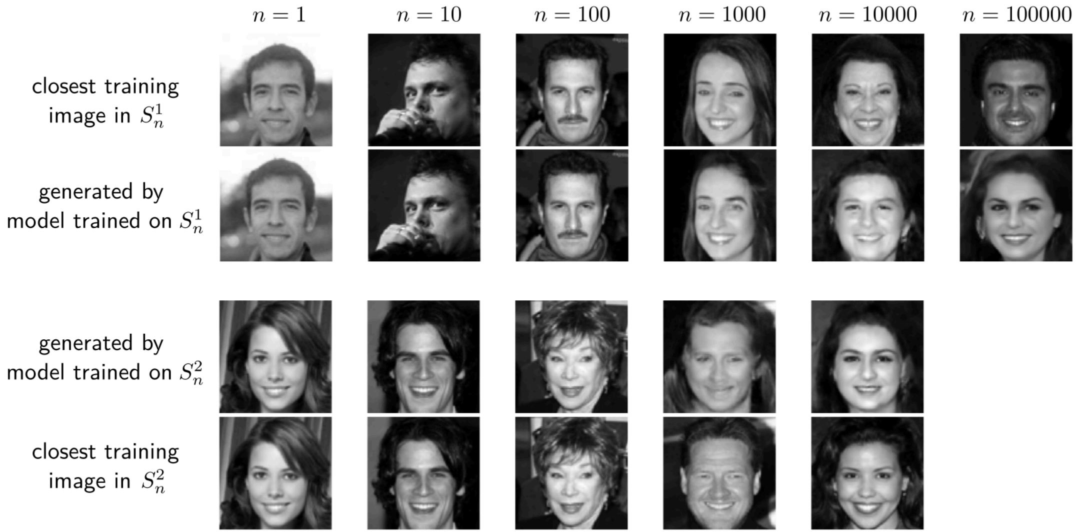

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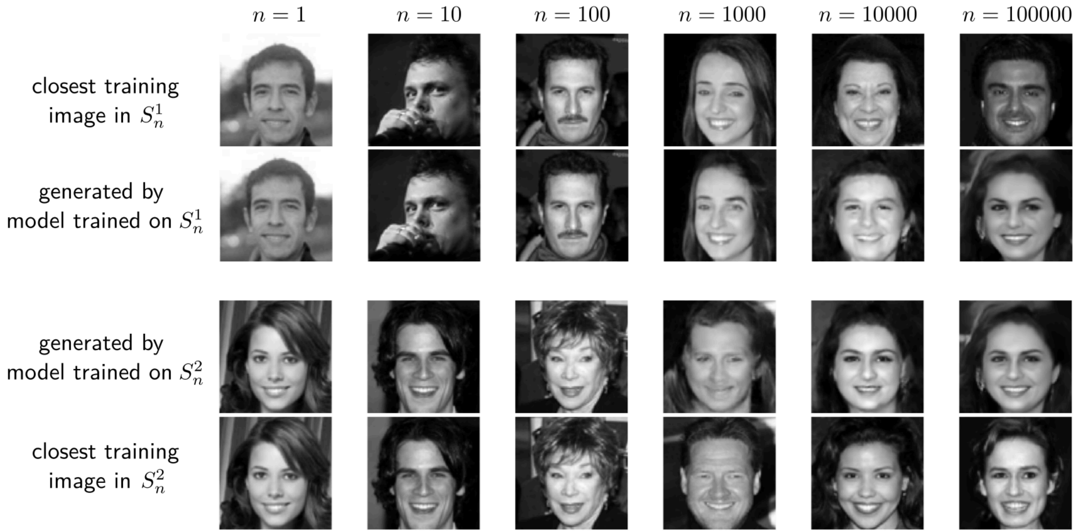

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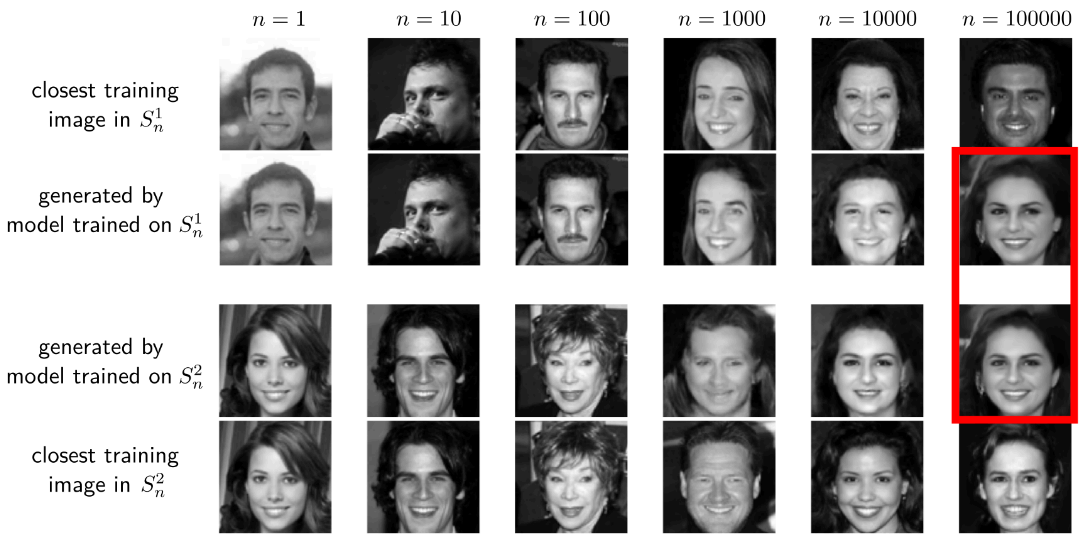

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Additional mystery: models generate the same data!

Memorization and generalization in Flow matching and Diffusion

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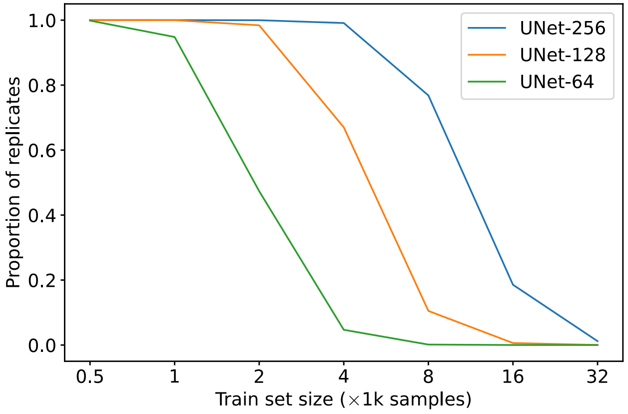

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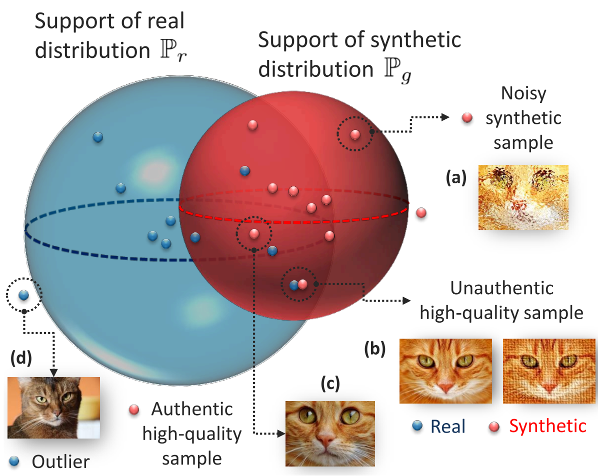

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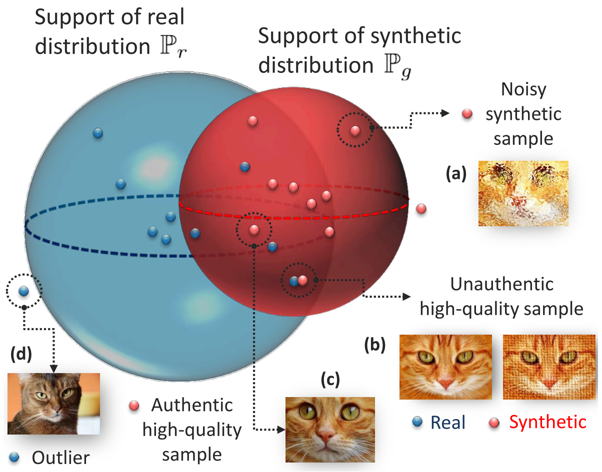

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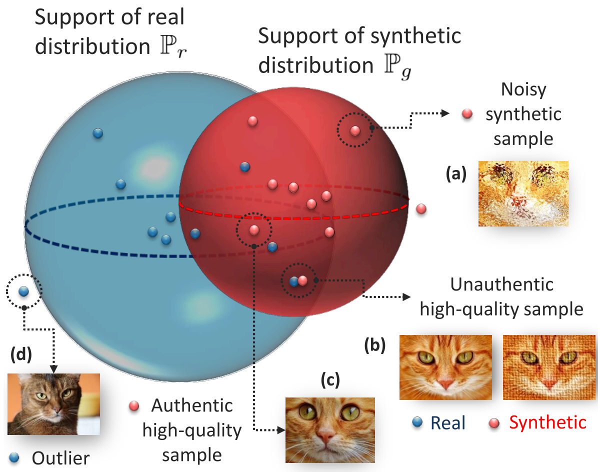

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Diffusion Probabilistic Models Generalize when They Fail to Memorize

TaeHo Yoon[1] Joo Young Choi[1] Sehyun Kwon[2] Ernest K. Ryu[1,2]

Abstract

In this work, we study the training of diffusion probabilistic models through a series of hypotheses and carefully designed experiments. We call our key finding the memorization-generalization dichotomy, and it asserts that generalization and memorization are mutually exclusive phenomena.

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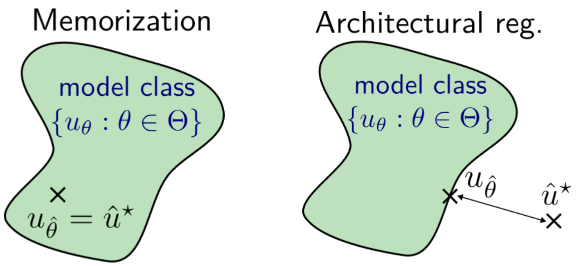

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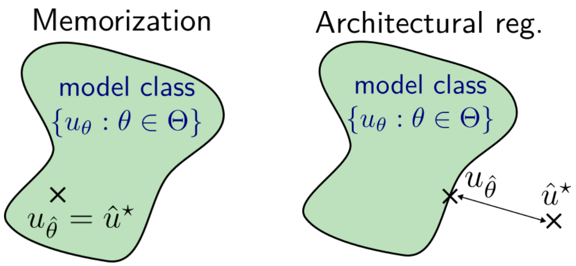

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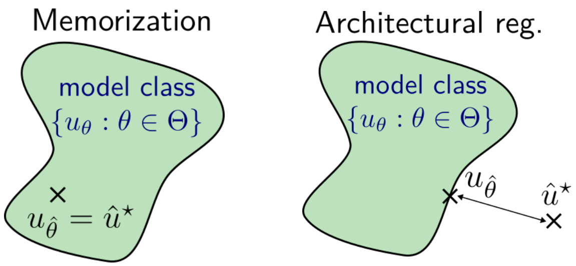

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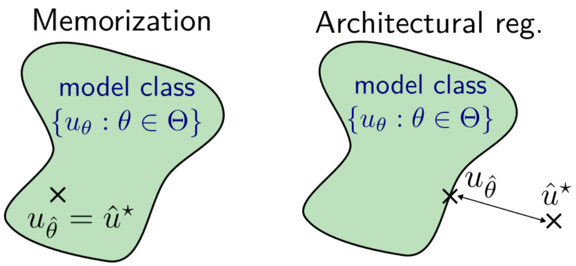

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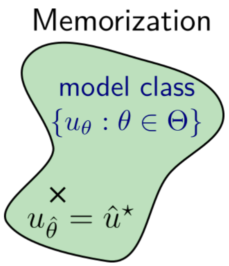
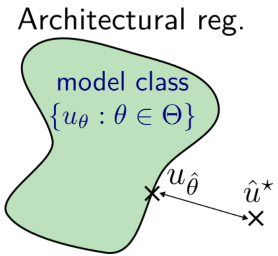
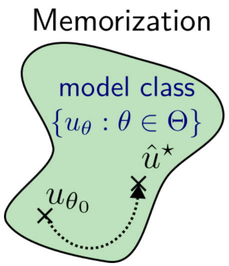
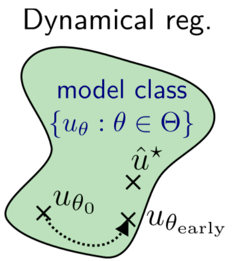




Conflicting points of view:

- Inductive bias:
  - The network explicitly regularizes the velocity with the architecture
  - Limits the capacity of the network to learn the ideal score/velocity
- Optimization dynamics:
  - The network has enough capacity to learn the ideal velocity
  - Would memorize the training samples
  - Works because of gradient descent + early stopping





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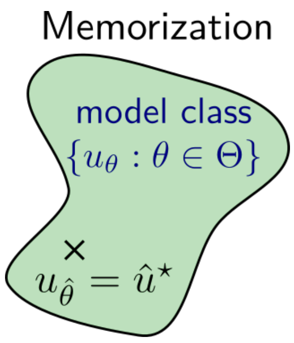
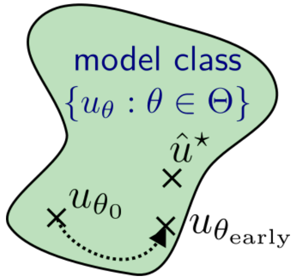
Dynamical and architectural regularization

Inductive bias and optimization

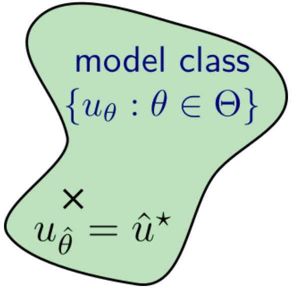


Inductive bias and optimization

Dynamical reg.

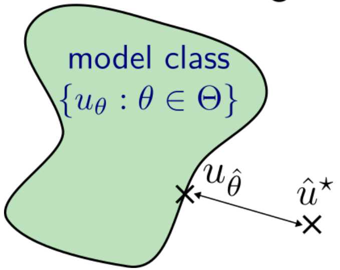


Memorization



Inductive bias and optimization

Architectural reg.



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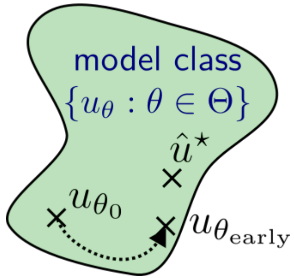

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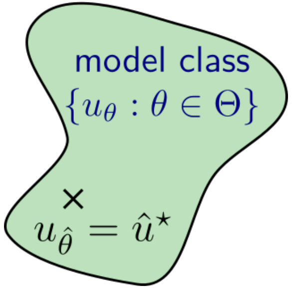

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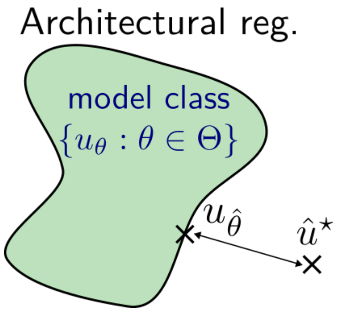
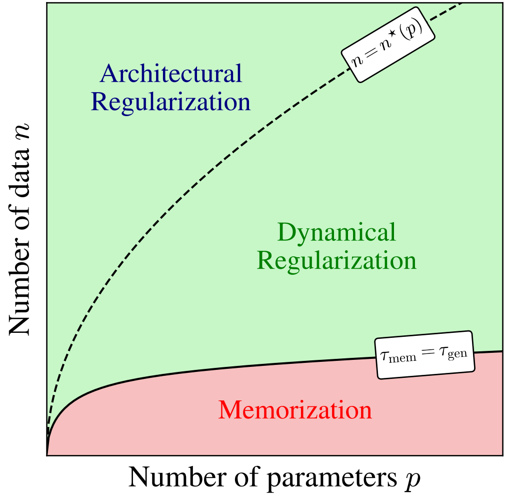
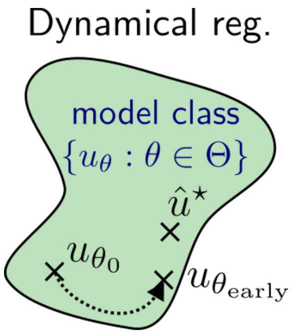
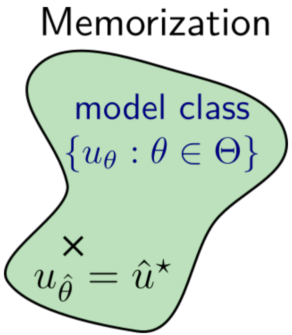




Bonnaire et al. (2026)





Dynamical[14,15] then Architectural[4,12,13]?

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Architectural regularization[16]

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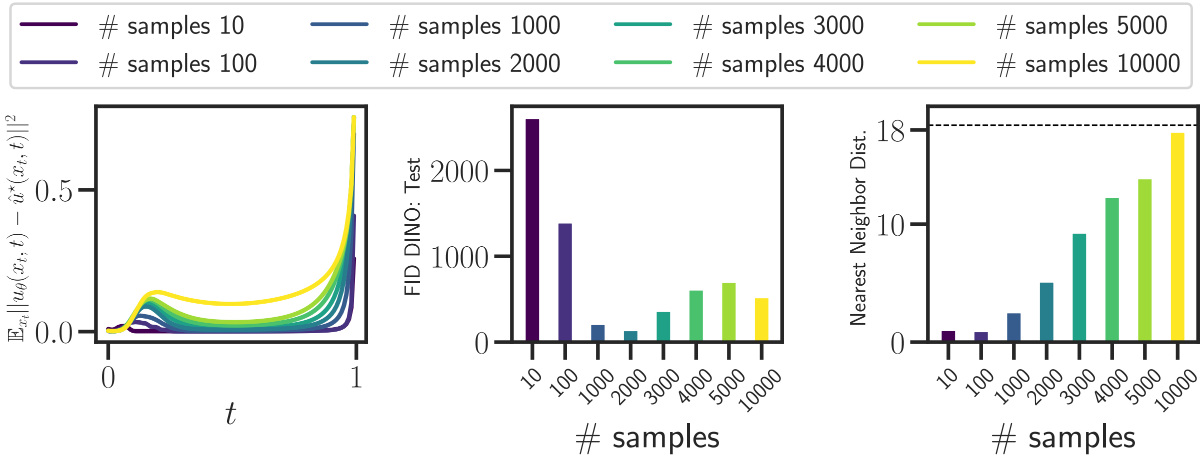

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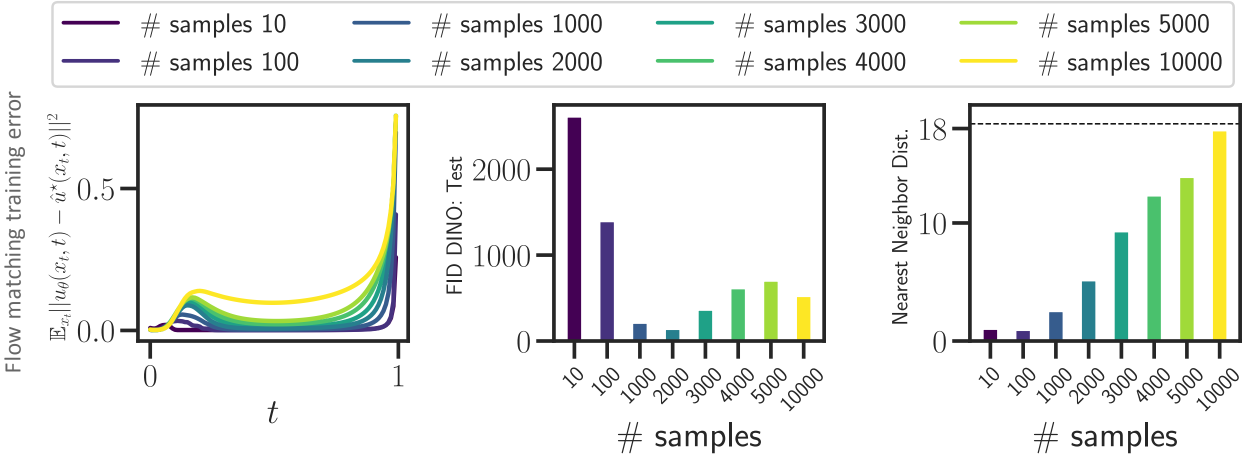

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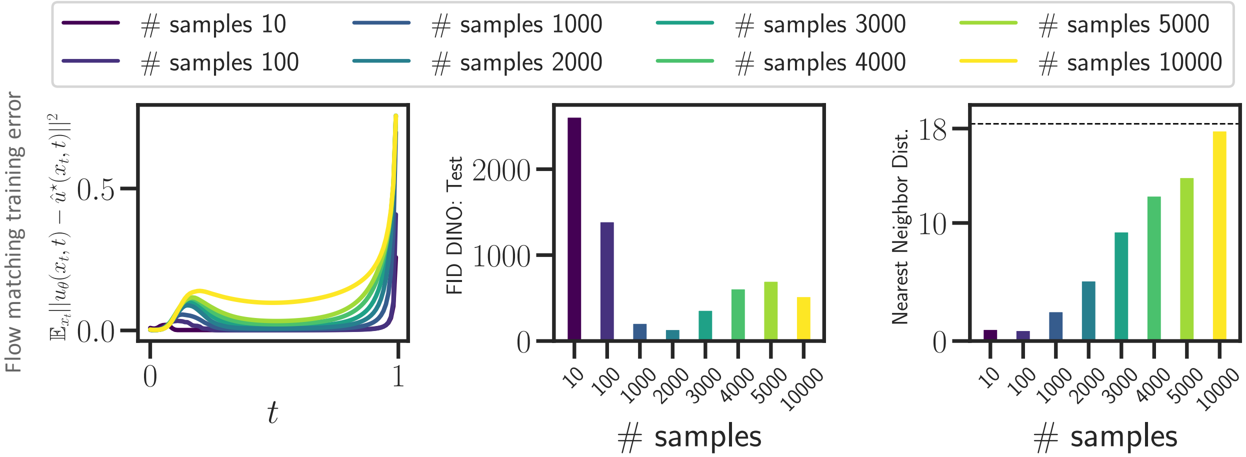

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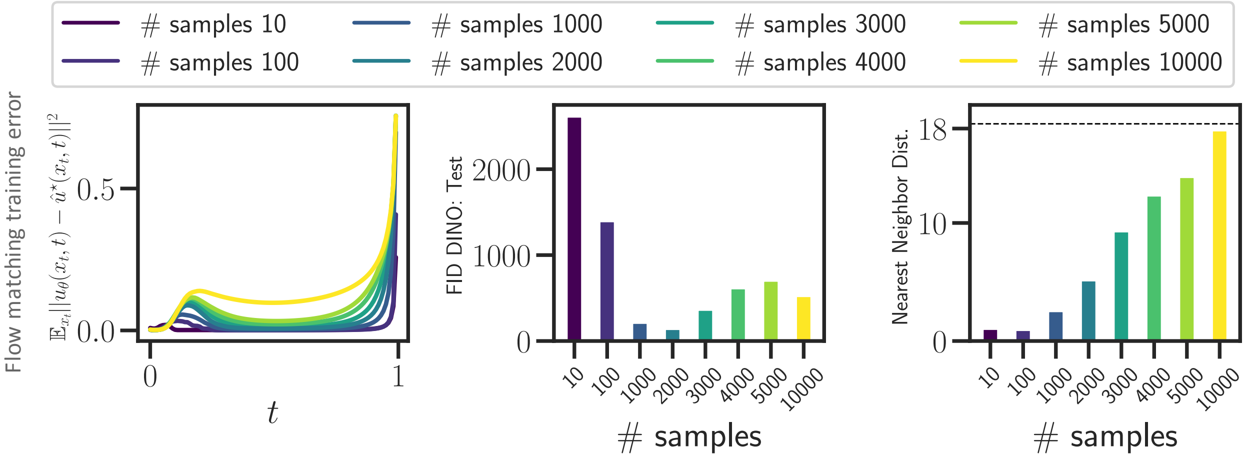

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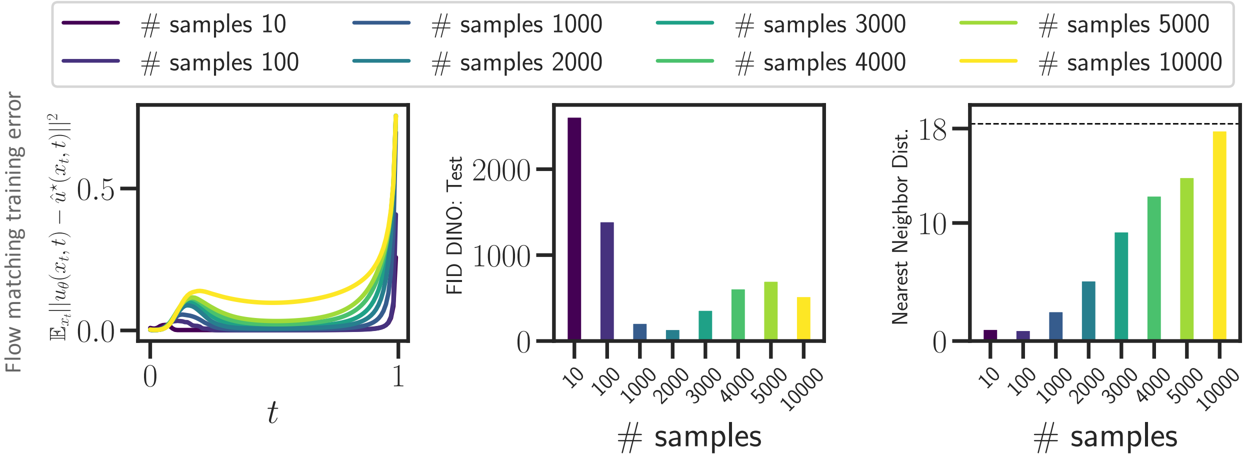

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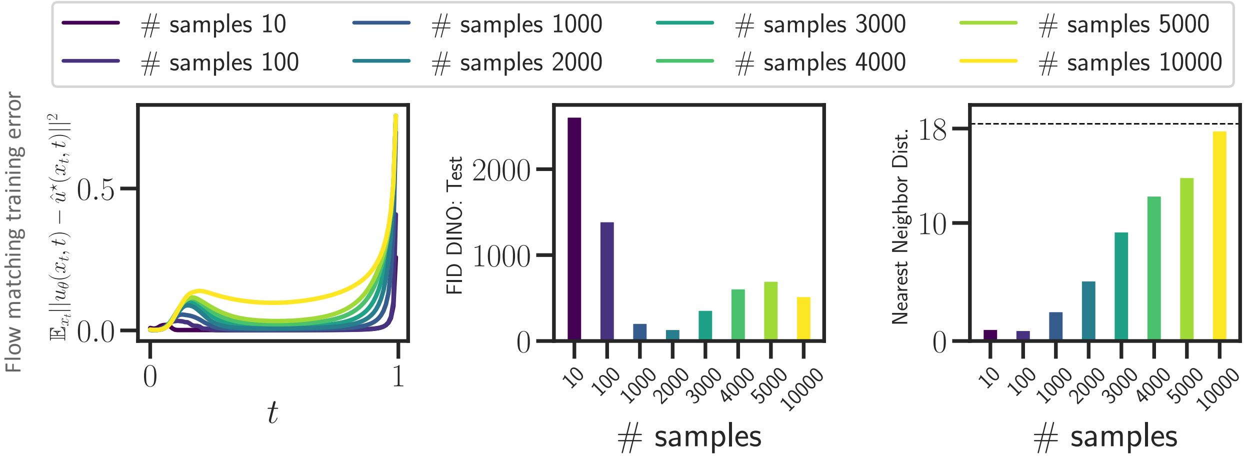

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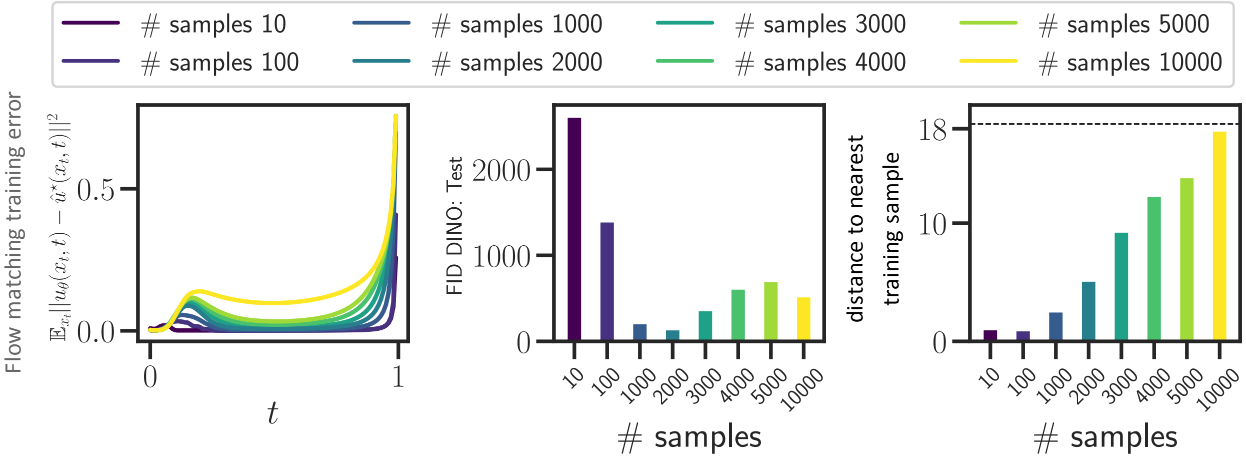

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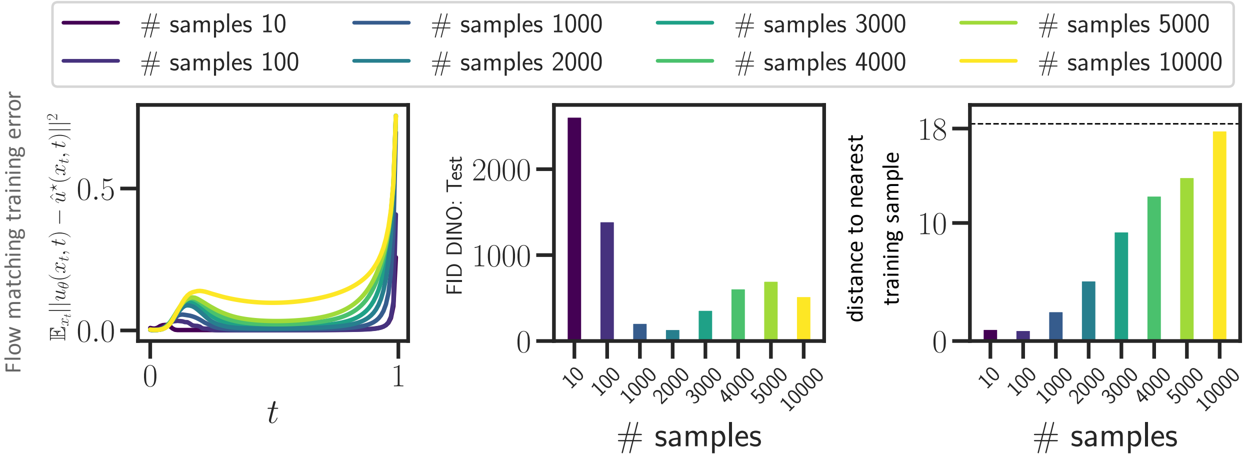

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Models stop memorizing when they can no longer fit $\hat{u}^\star$

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Importance of small times[16]

From a good trained u_θ , we build a **hybrid model** (fixed $\tau \in [0,1]$):

- on $[0,\tau]$: follow $\hat{u}^\star$
- on $[\tau,1]$: follow u_θ
- $\tau = 1$ means completely following $\hat{u}^\star$ (full memorization)
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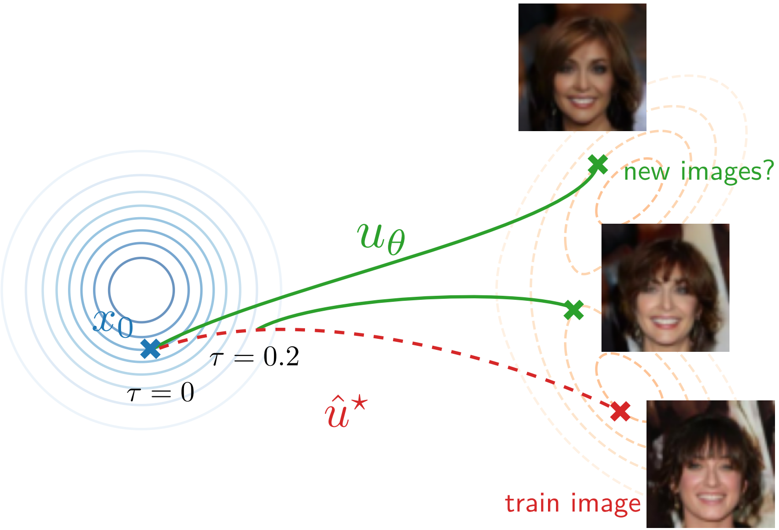

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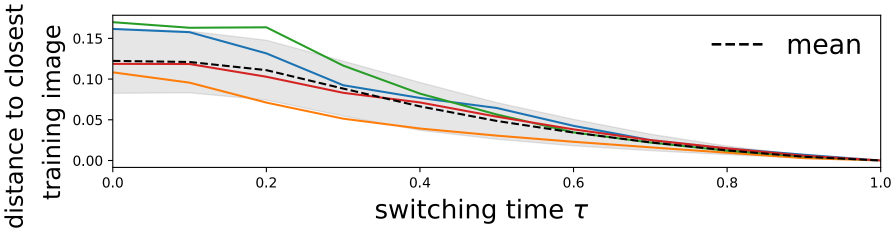

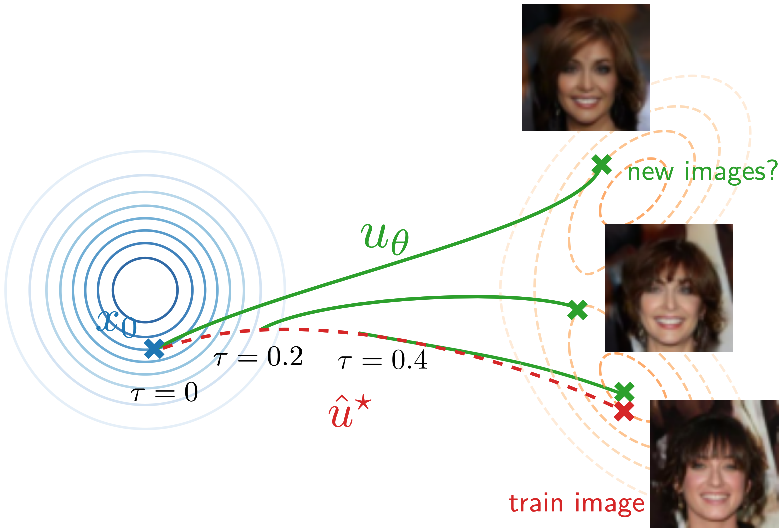

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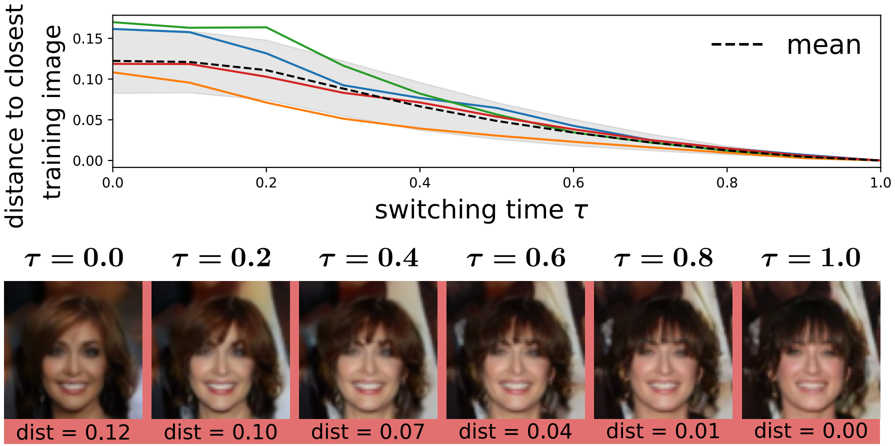

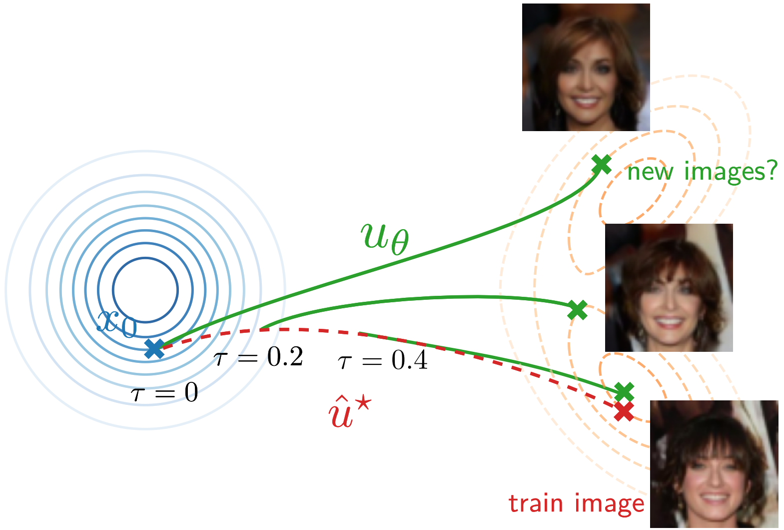

Not fitting small times is critical

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Dynamical regularization[14,15]

- Fixed architecture size, increase number of training samples n (CelebA 32×32)

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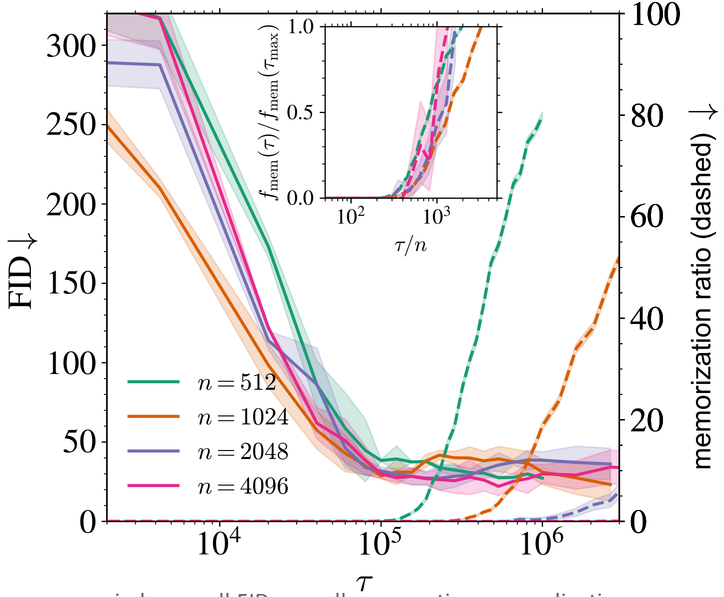

reminder: small FID + small mem. ratio = generalization

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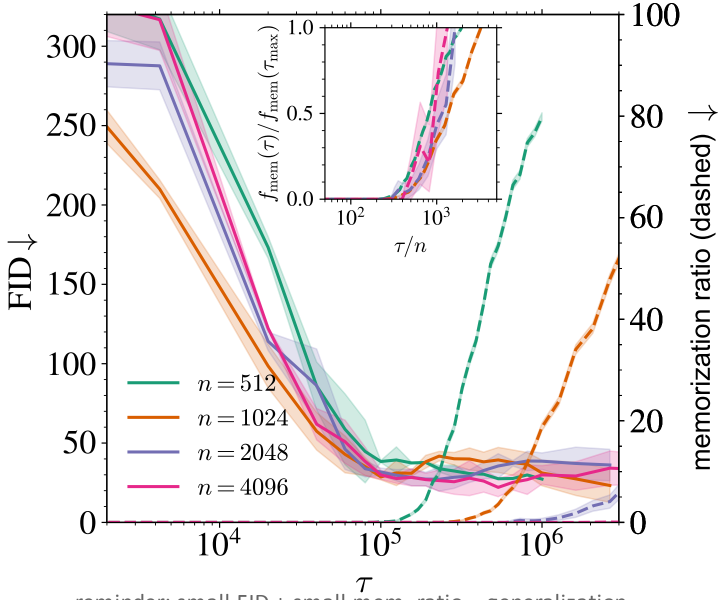

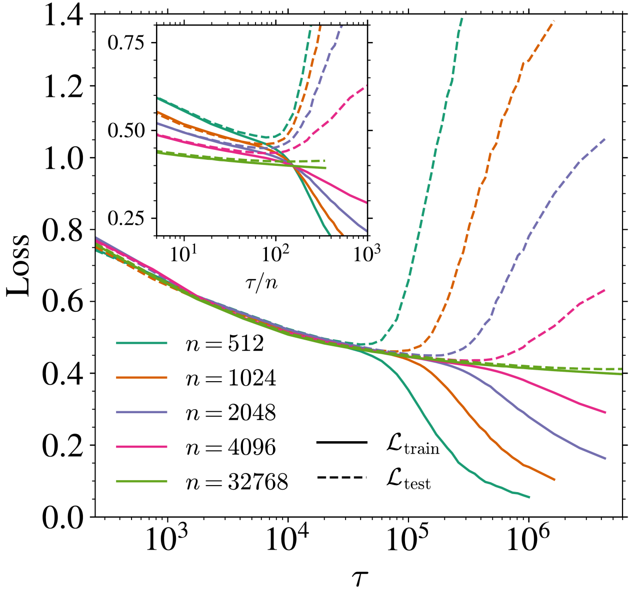

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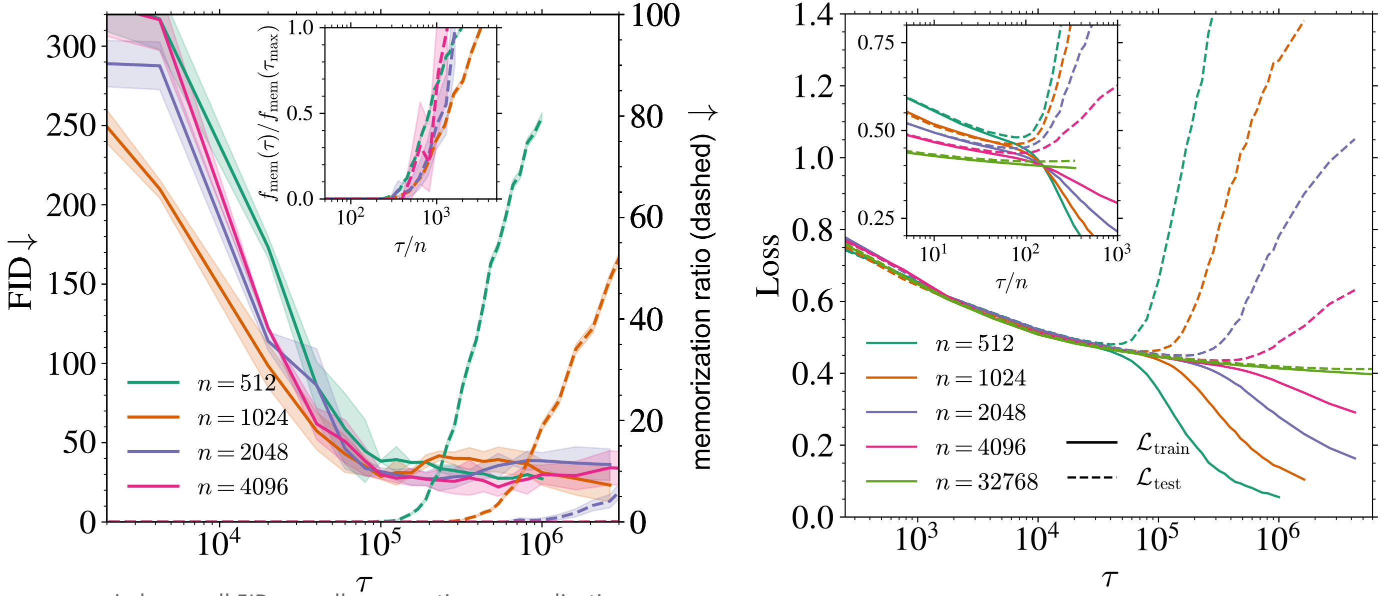

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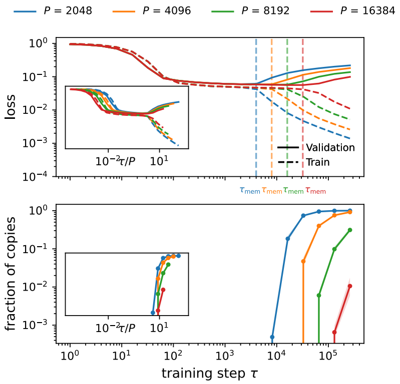

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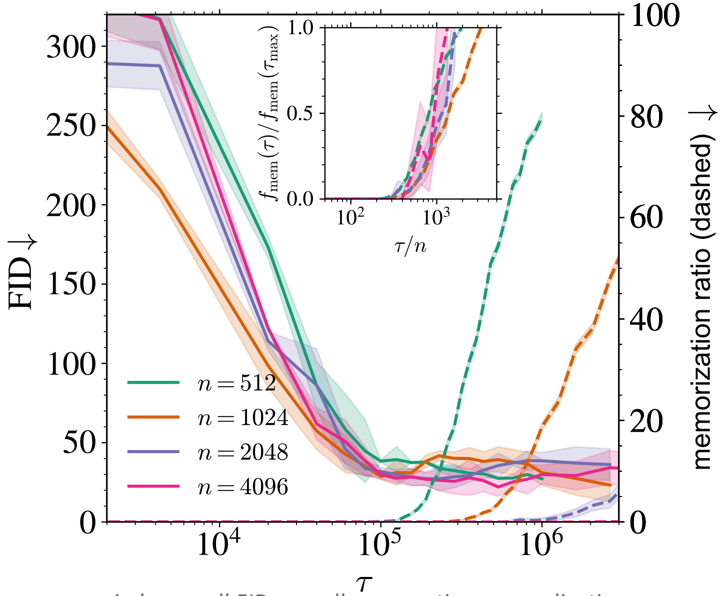

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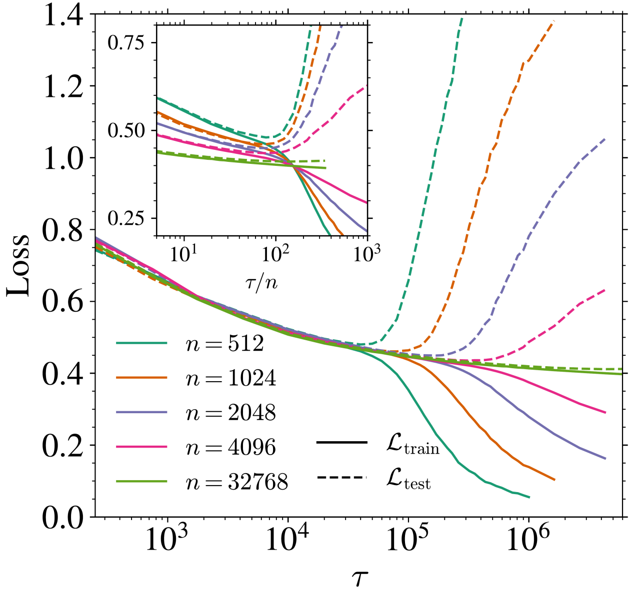

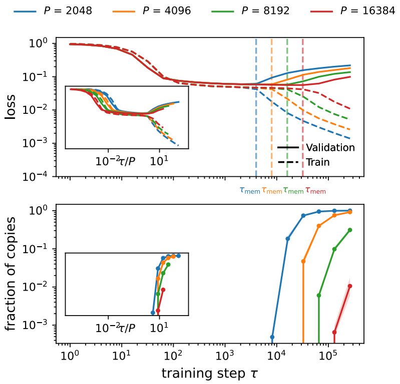

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Overparametrized models can still generalize if early stopped

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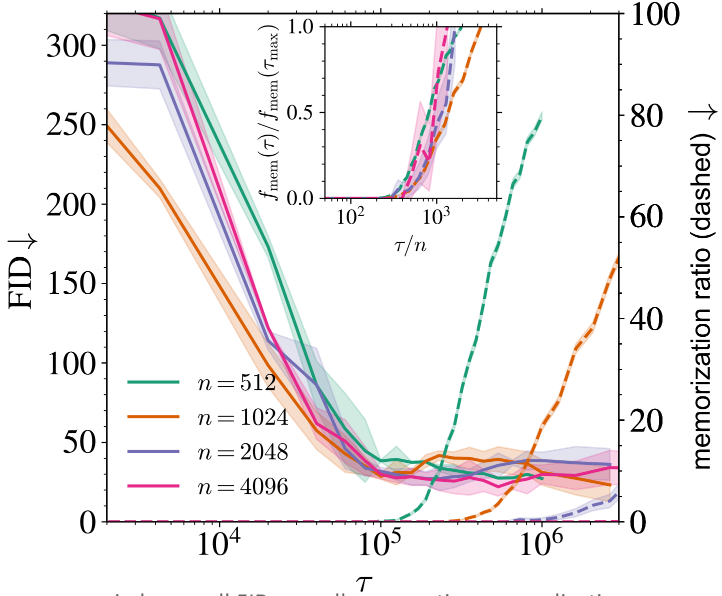

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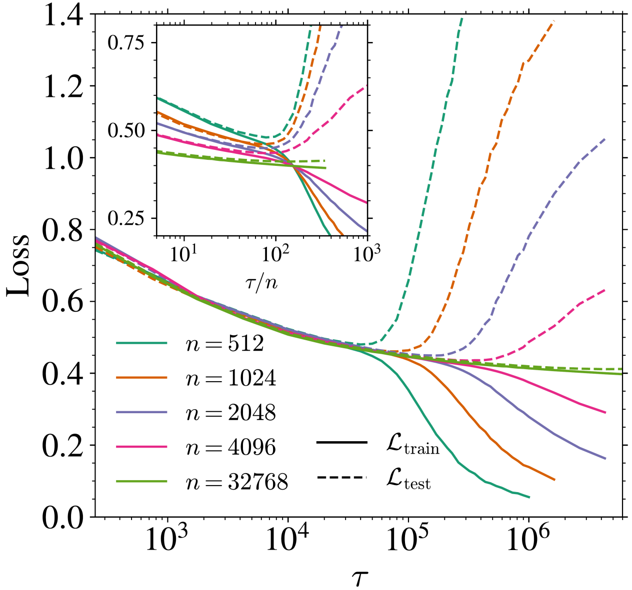

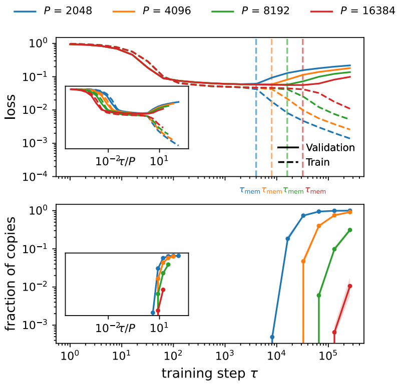

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Memorization starts at $\tau_{\text{mem}} = \mathcal{O}(\#\text{samples})$

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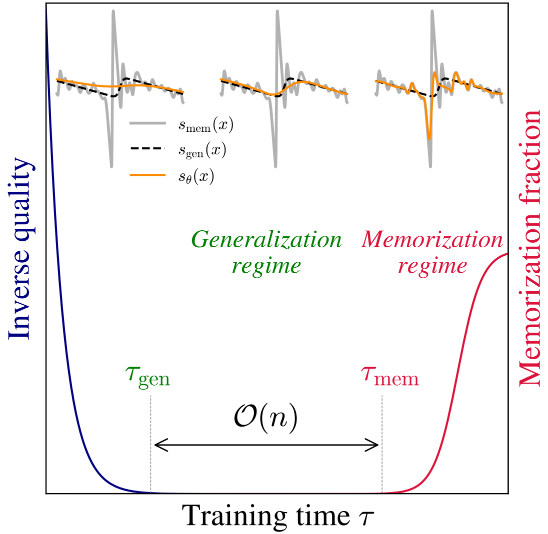

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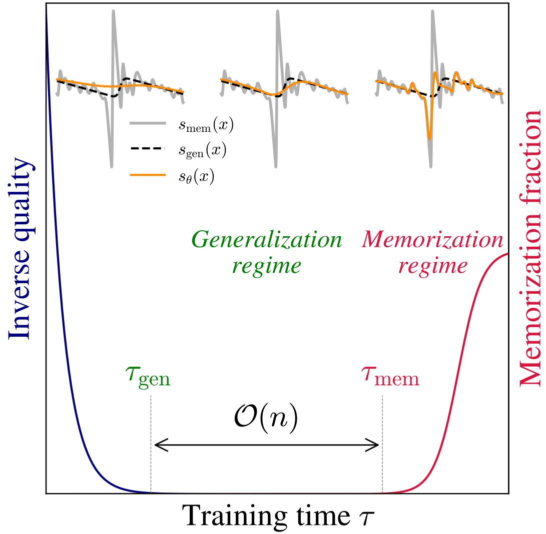

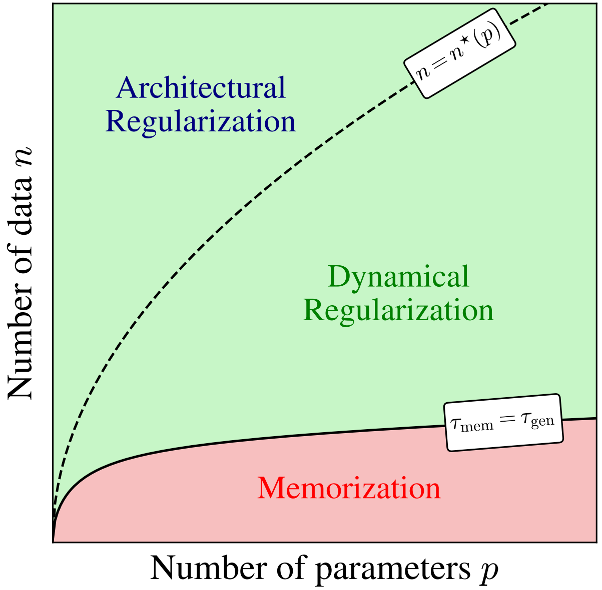

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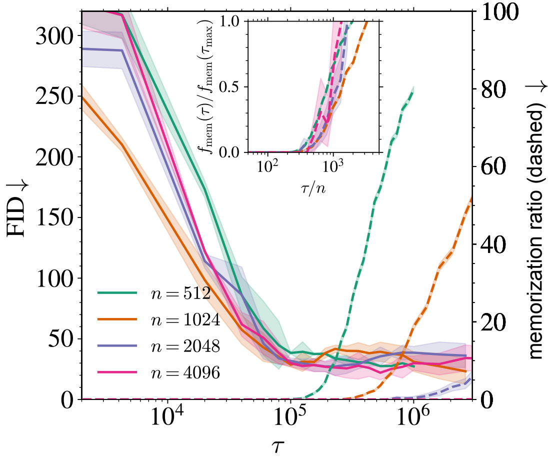
Caveats in overparametrization and early stopping[14]



Data & architecture. We conduct our experiments on the CelebA face dataset [26], which we convert to grayscale downsampled images of size $d = 32 \times 32$, and vary the training set size n from 128 up to 32768. Our score model has a U-Net architecture [35] with three resolution levels, and a base channel

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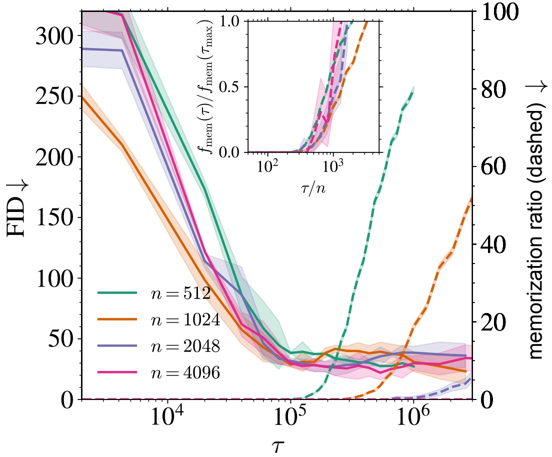

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- In this experiment the dataset size is very reduced (both through n and d)

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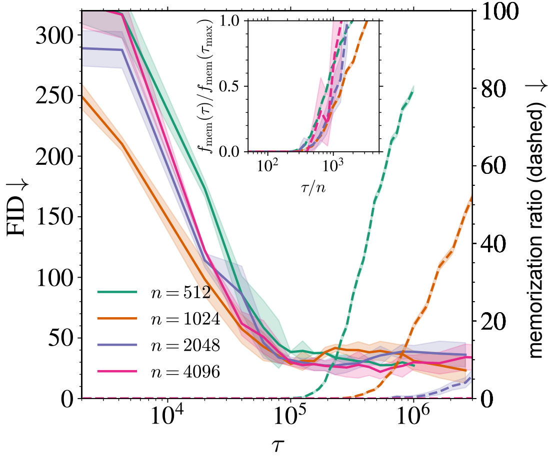

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- Real CelebA has $178 \times 218 \times 3 \times 200000 \approx 2.3 \times 10^{10}$ pixels

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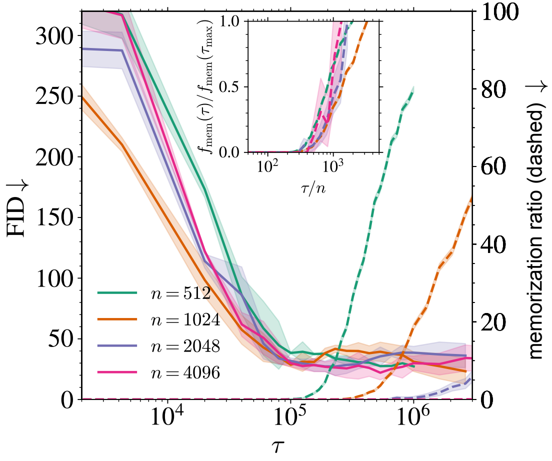
Caveats in overparametrization and early stopping[14]



Data & architecture. We conduct our experiments on the CelebA face dataset [26], which we convert to grayscale downsampled images of size $d = 32 \times 32$, and vary the training set size n from 128 up to 32768. Our score model has a U-Net architecture [35] with three resolution levels, and a base channel

- In this experiment the dataset size is very reduced (both through n and d)
- Real CelebA has $178 \times 218 \times 3 \times 200000 \approx 2.3 \times 10^{10}$ pixels
- Open question: do models have enough capacity to memorize their datasets?

[14] T. Bonnaire et al., **Why Diffusion Models Don't Memorize: The Role of Implicit Dynamical Regularization in Training,** In: NeurIPS, 2025.

Conclusion

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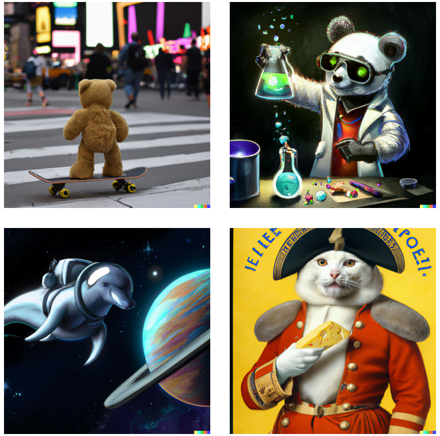

The generalization properties of flow matching/diffusion are poorly understood

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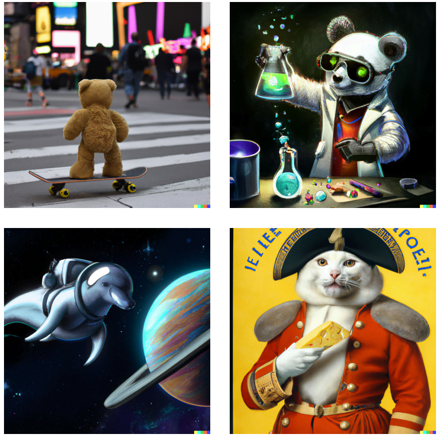

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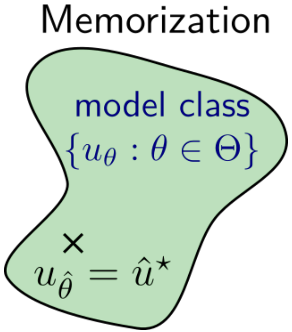

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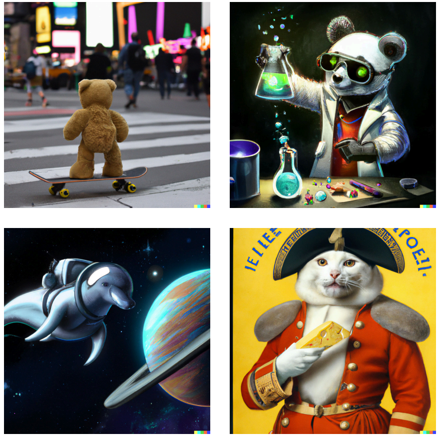
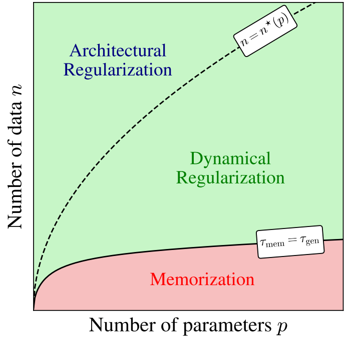
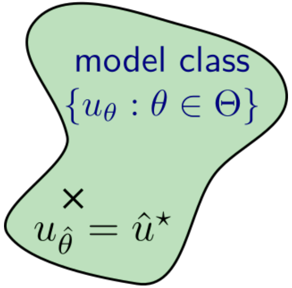




Bonnaire et al. (2026)

Memorization



The generalization properties of flow matching/diffusion are poorly understood

- Mainly two hypotheses:

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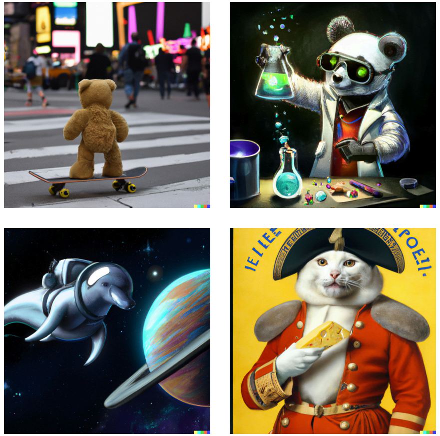

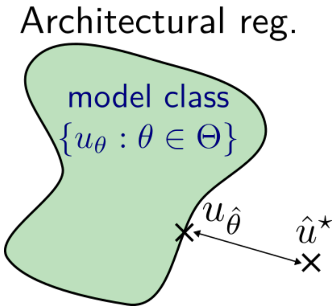

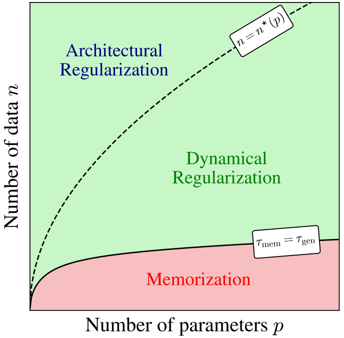

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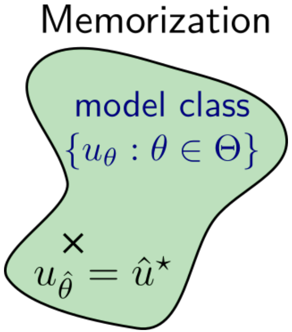

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- Mainly two hypotheses:
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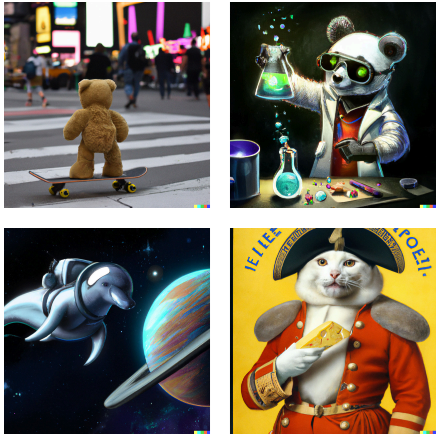

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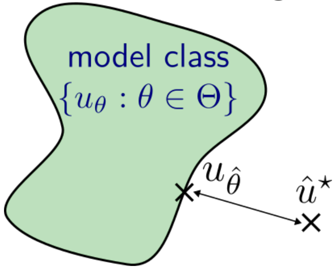

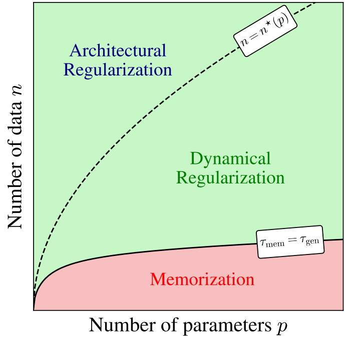

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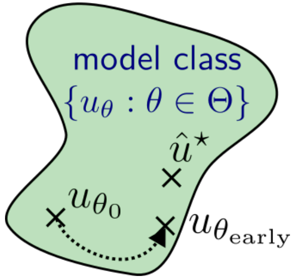
Dynamical reg.



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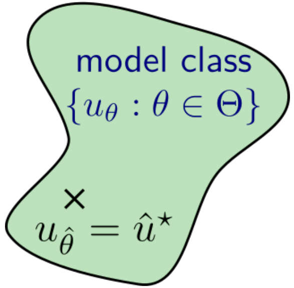

The generalization properties of flow matching/diffusion are poorly understood

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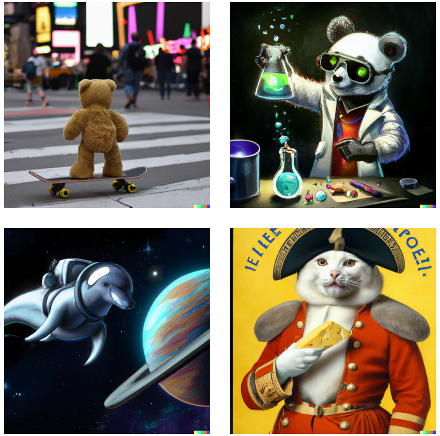
Conclusion



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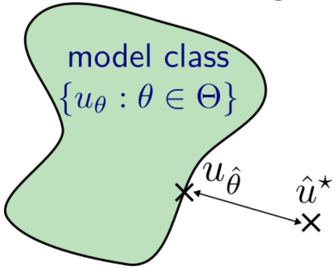

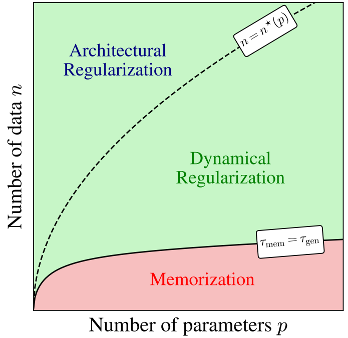

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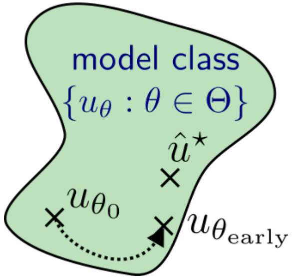

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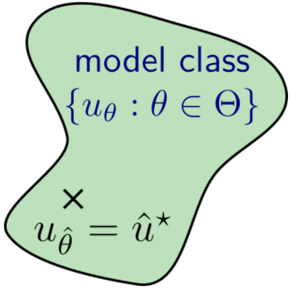

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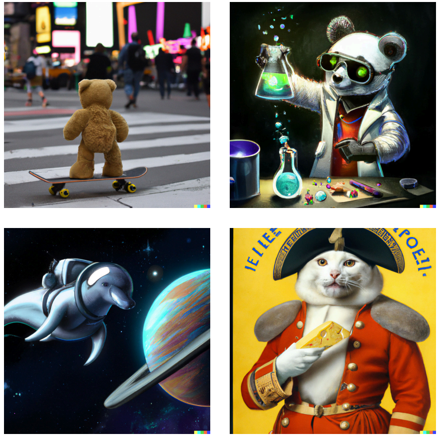
Conclusion



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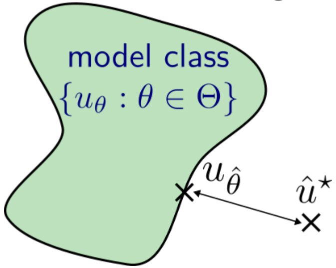

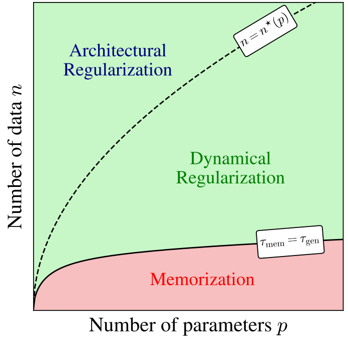

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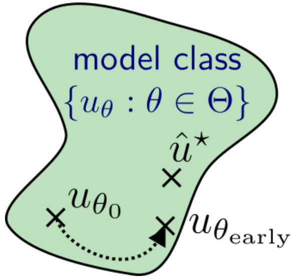

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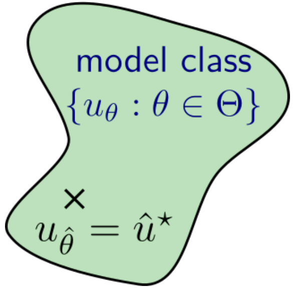

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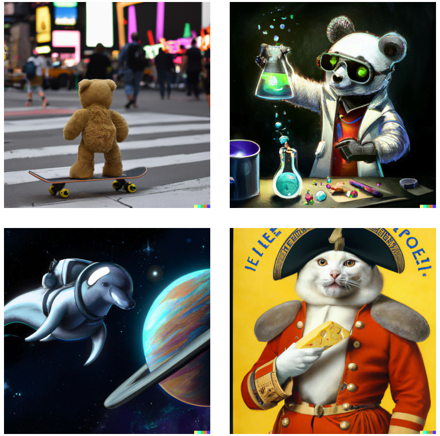

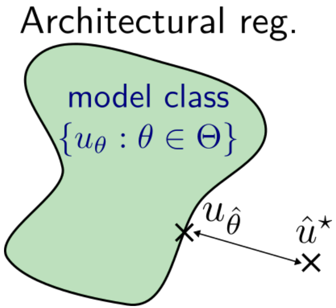

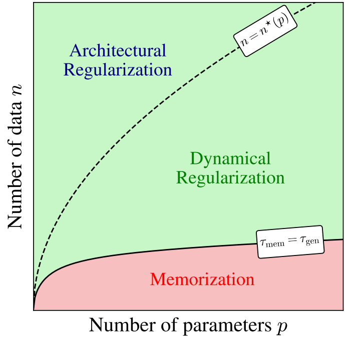

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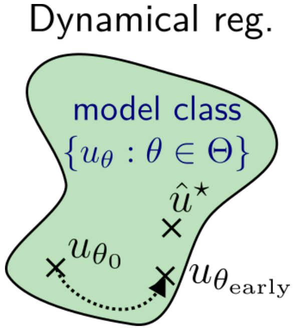

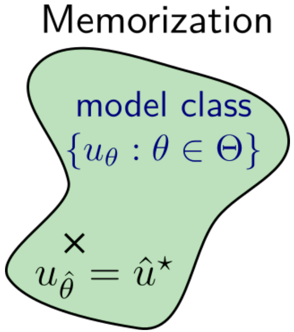

Thank you for your attention!

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ICML 2026 tutorial

Diffusion and Flow Matching

Part III: Beyond Generalization: Creativity

Quentin Bertrand & Mathurin Massias

https://memorization-generalization.github.io

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

Why do Diffusion & Flow matching work so well?

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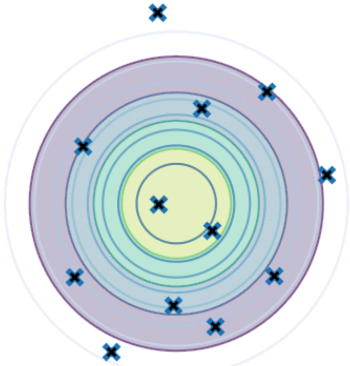

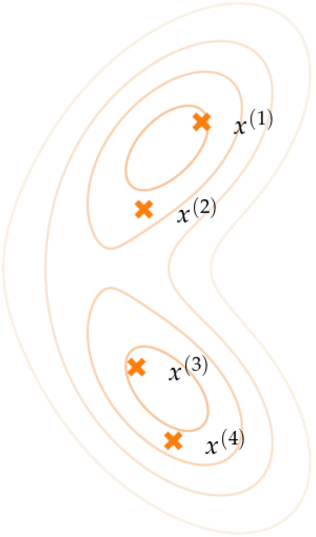

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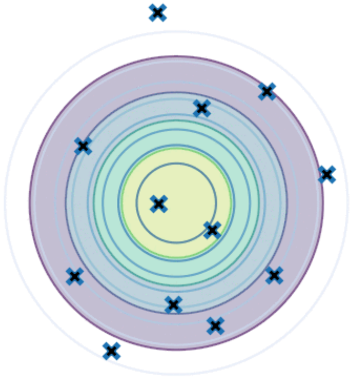

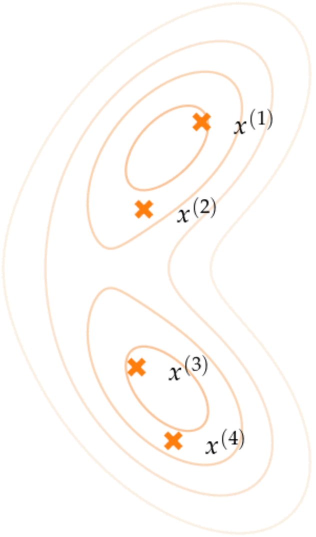

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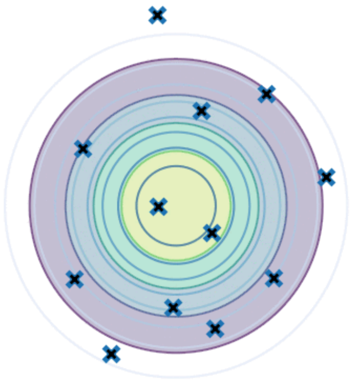

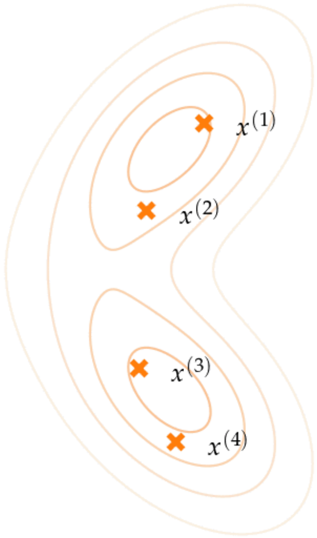

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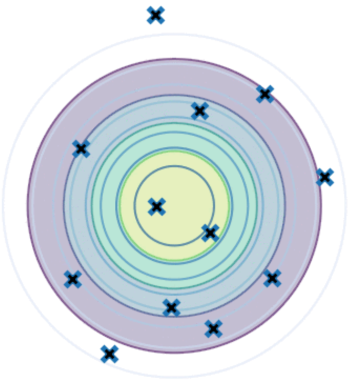

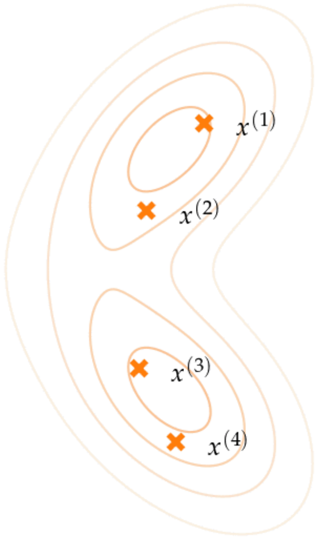

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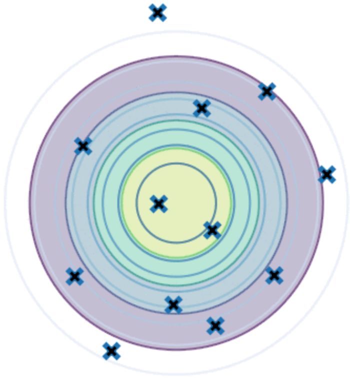

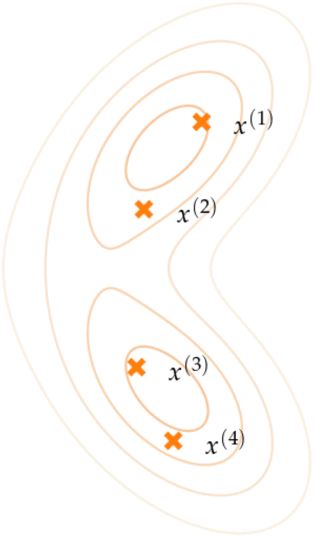

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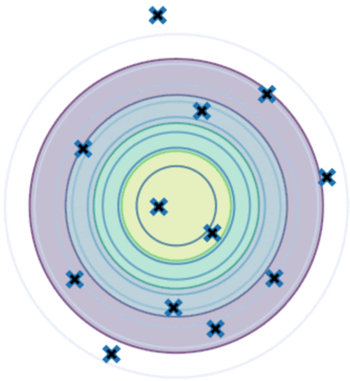

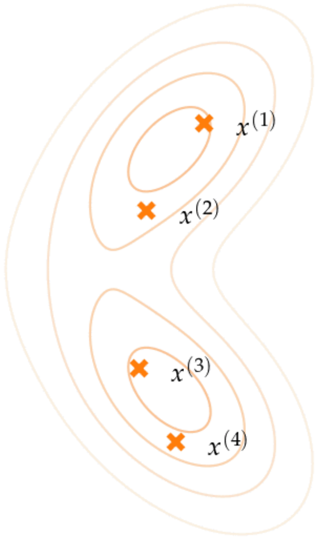

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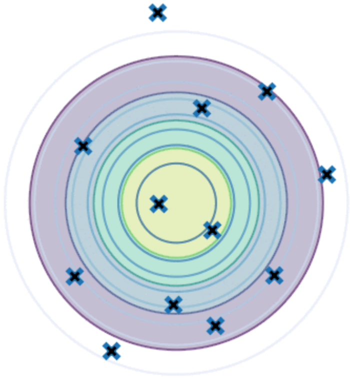

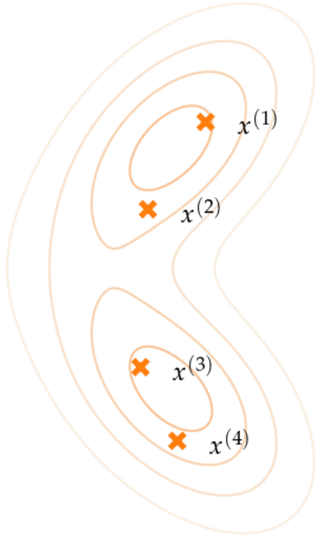

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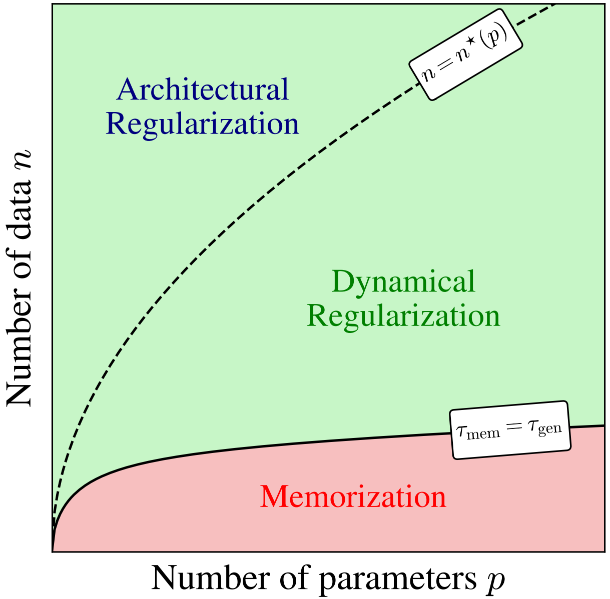

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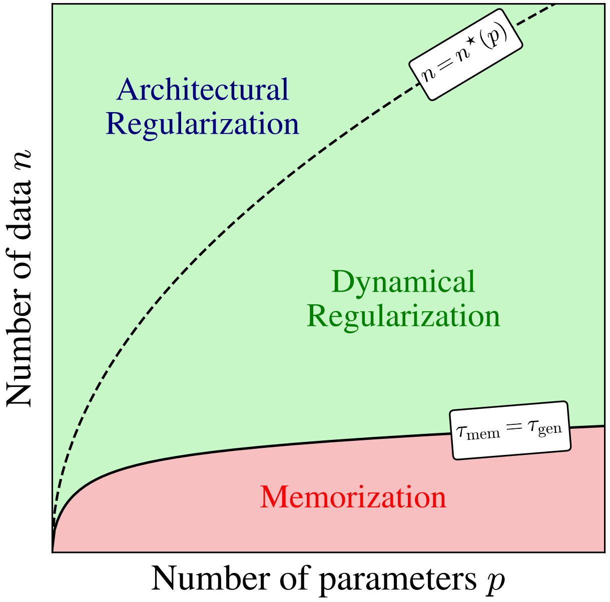

Bonnaire et al. (2025)

Rest of this part: architectural regularization

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Beyond memorization: Mix and Match capabilities[4]

DALL·E, Ramesh et al.

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How to understand diffusion mix and match capabilities in a minimalistic framework?

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Roadmap

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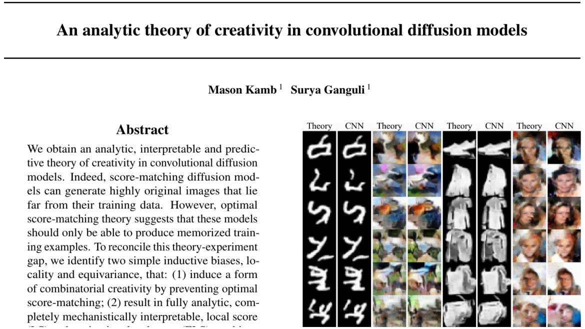

An analytic theory of creativity in convolutional diffusion models

Mason Kamb[1] Surya Ganguli[1]

Abstract

We obtain an analytic, interpretable and predictive theory of creativity in convolutional diffusion models. Indeed, score-matching diffusion models can generate highly original images that lie far from their training data. However, optimal score-matching theory suggests that these models should only be able to produce memorized training examples. To reconcile this theory-experiment gap, we identify two simple inductive biases, locality and equivariance, that: (1) induce a form of combinatorial creativity by preventing optimal score-matching; (2) result in fully analytic, completely mechanistically interpretable, local score

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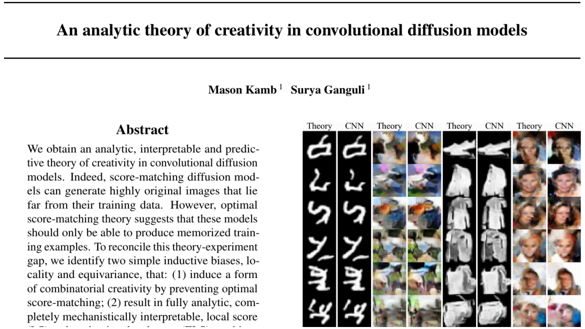

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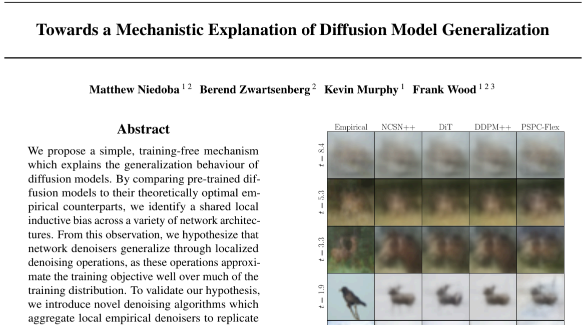

Towards a Mechanistic Explanation of Diffusion Model Generalization

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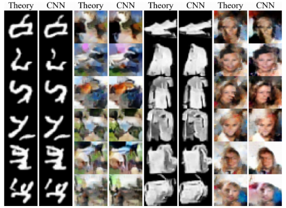

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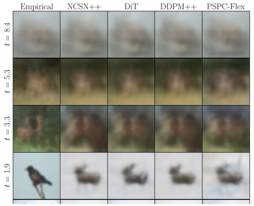

Locality in Image Diffusion Models Emerges from Data Statistics

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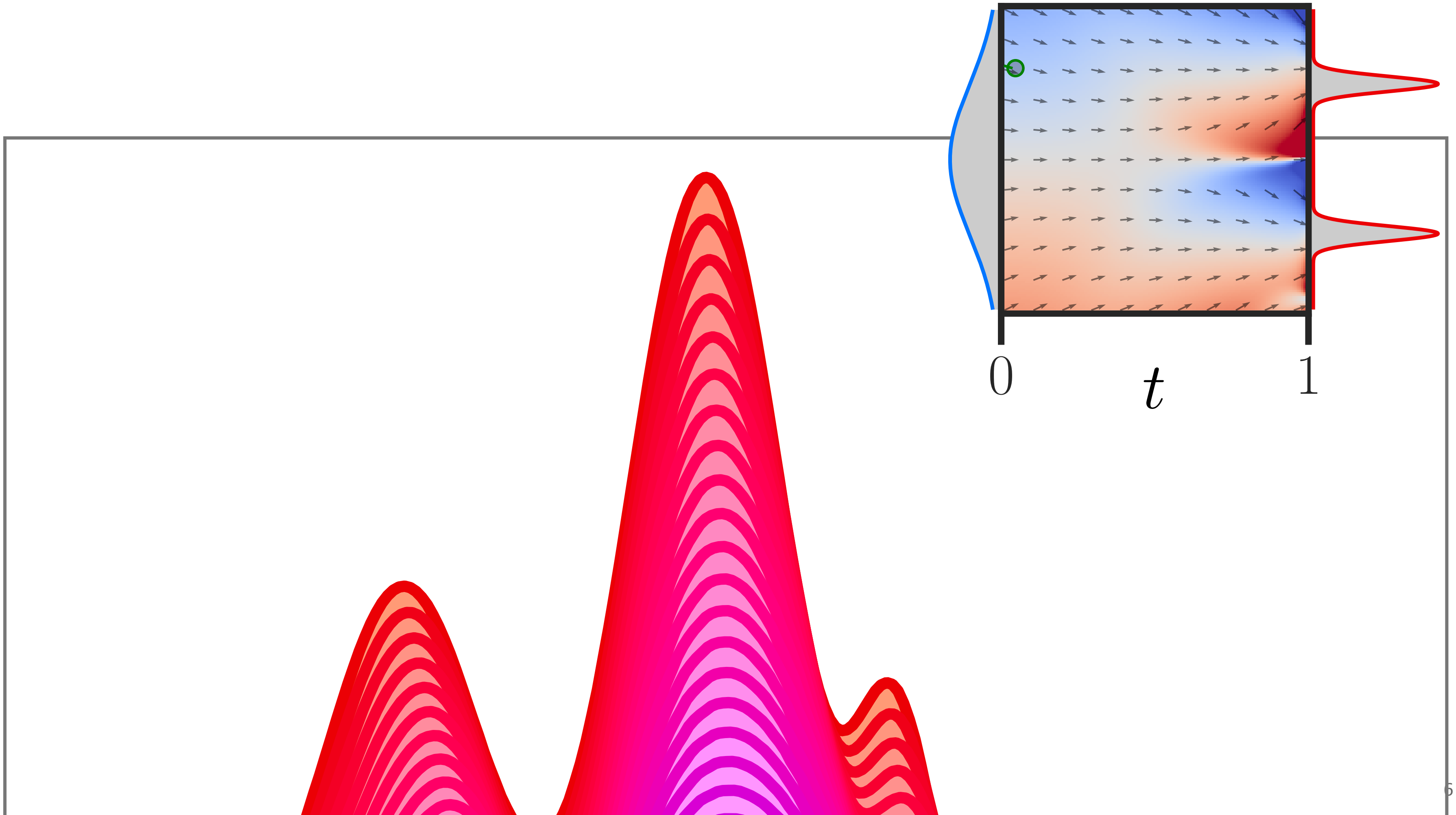

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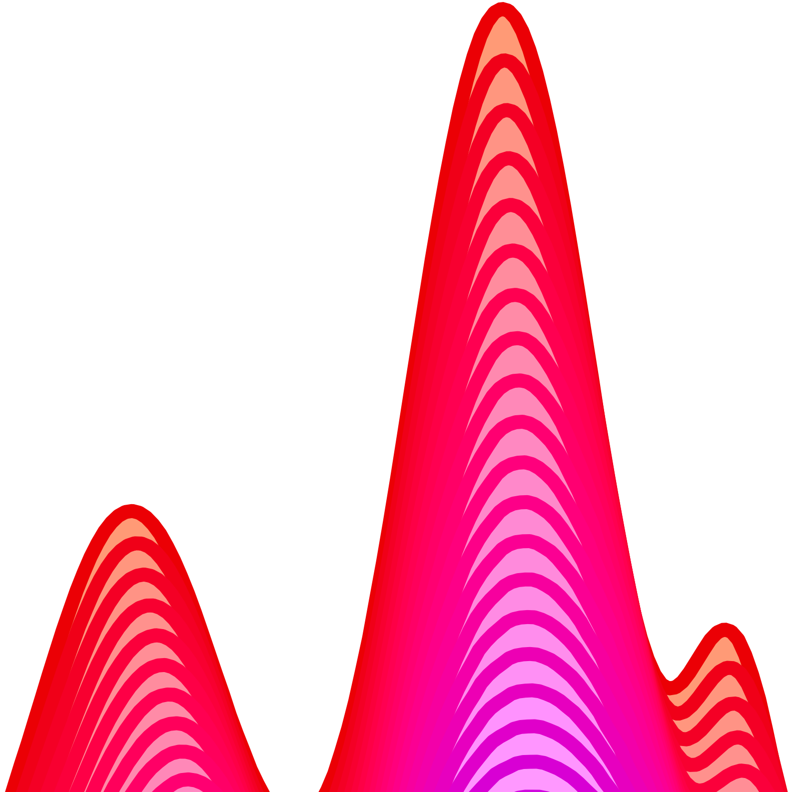

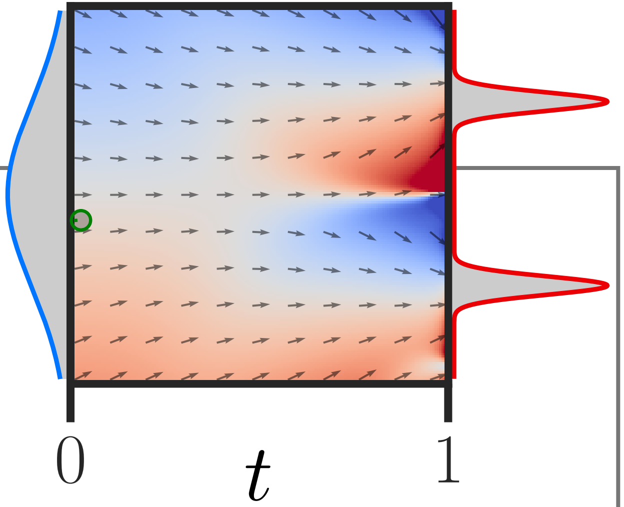

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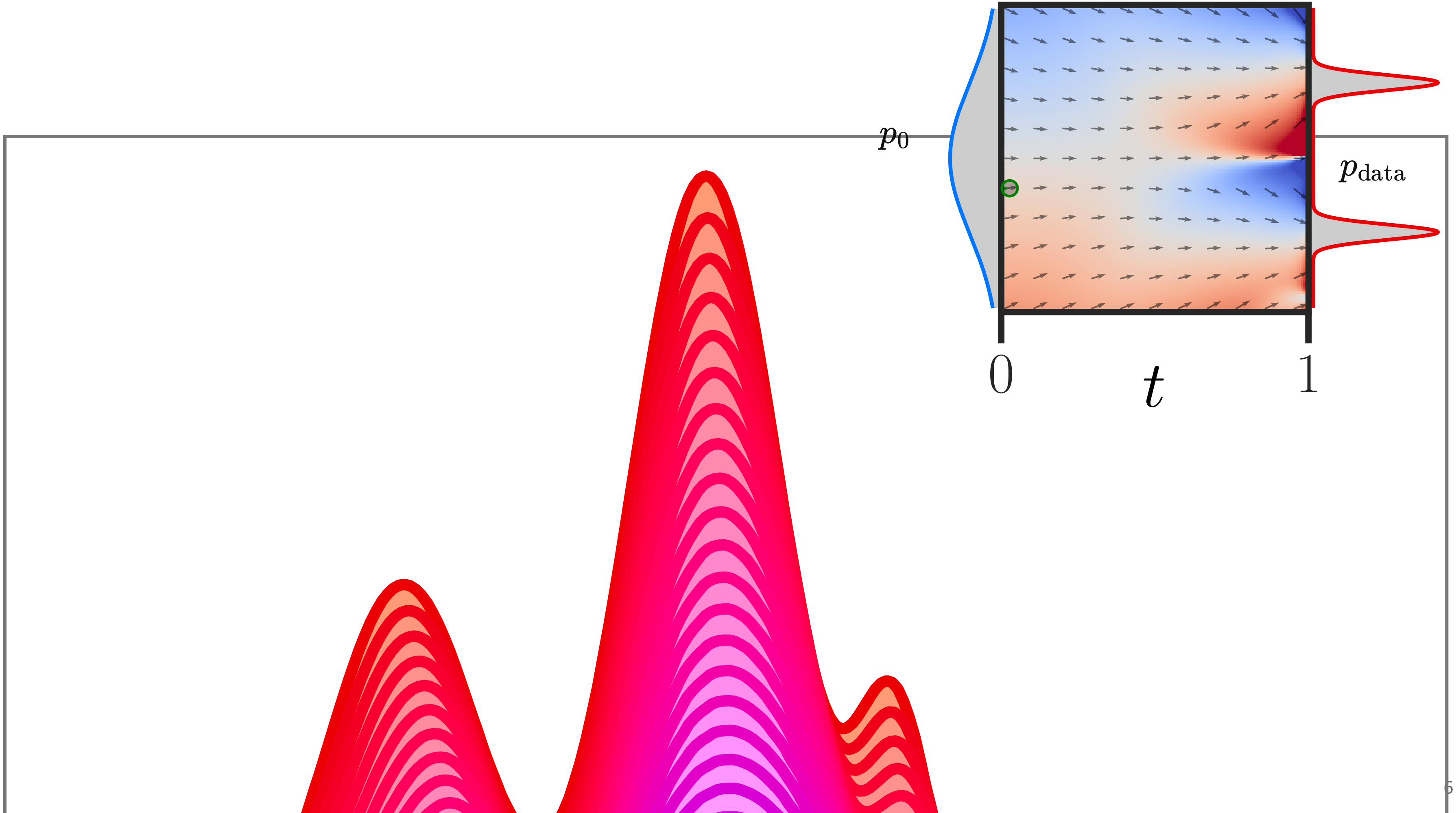

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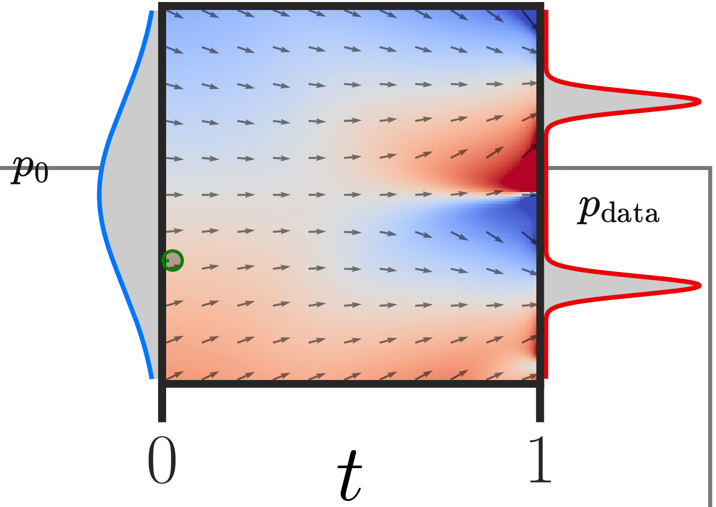

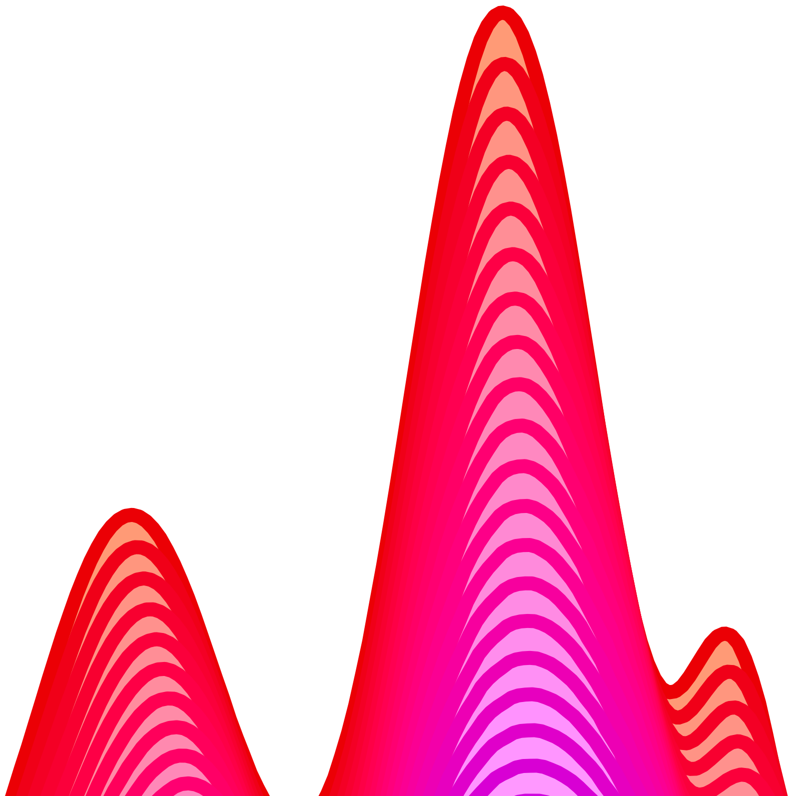

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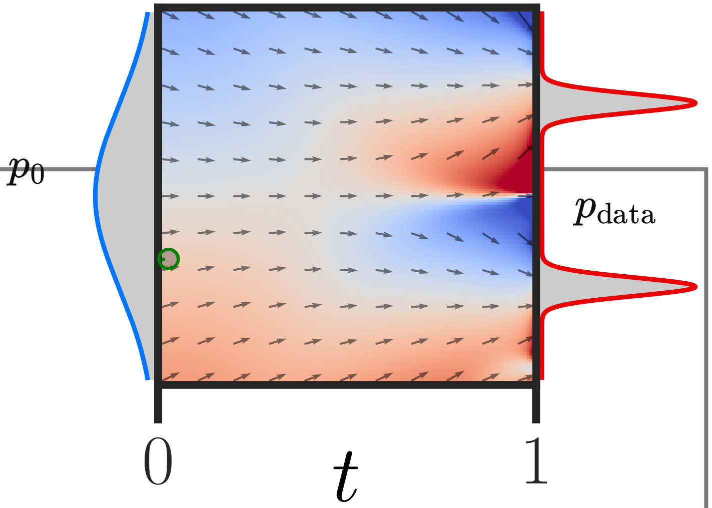

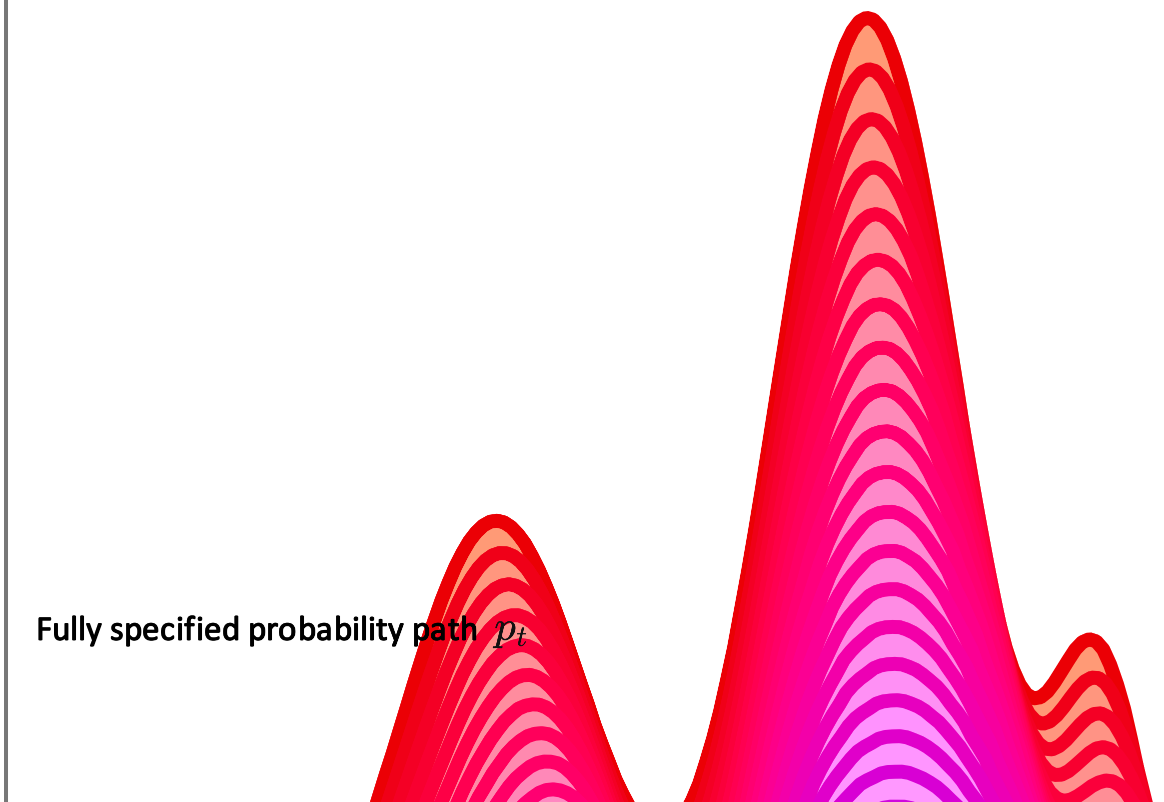

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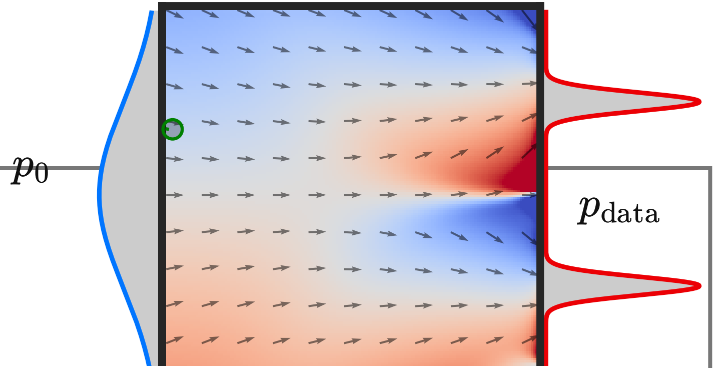
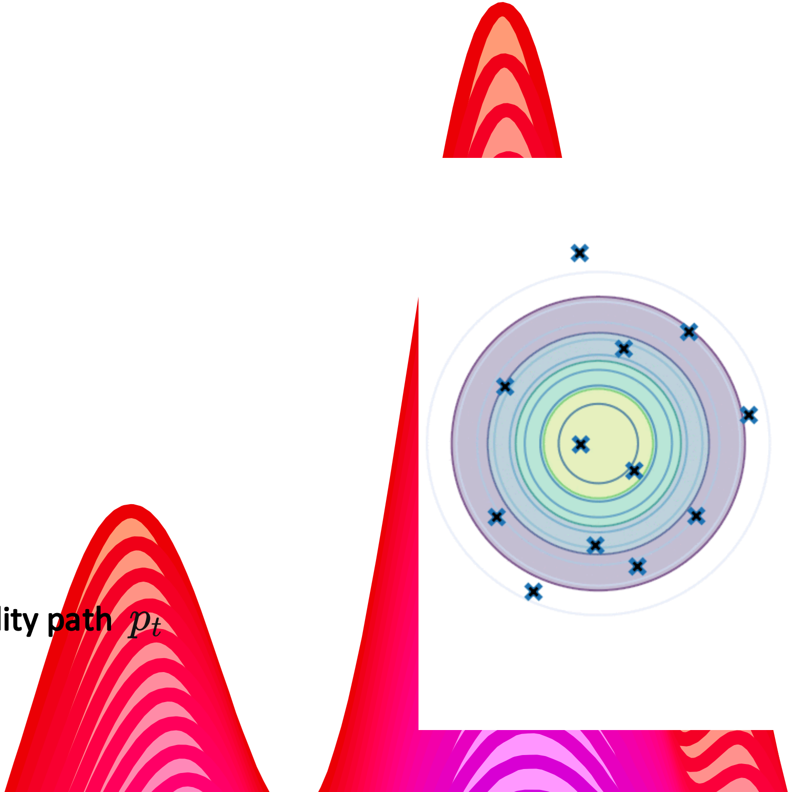
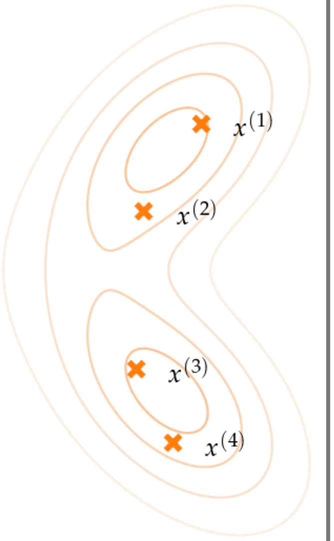


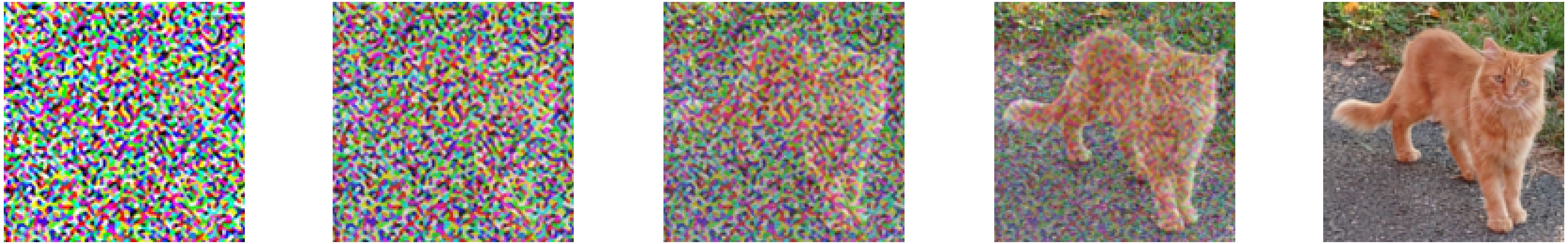




Fully specified probability path p_t

Flow matching reminder

Goal: learn a velocity field $u : \mathbb{R}^d \times [0, 1] \to \mathbb{R}^d$



$X_{t=0}$ $X_{t=0.25}$ $X_{t=0.5}$ $X_{t=0.75}$ $X_{t=1}$

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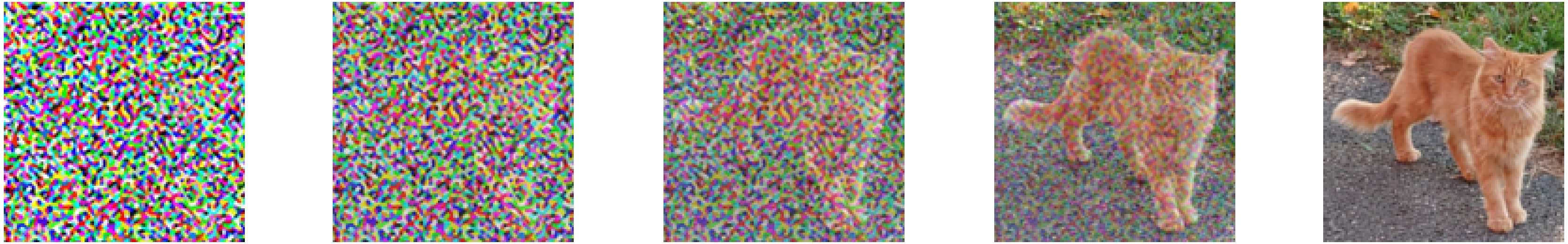

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Practical loss[9,10,11]:

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

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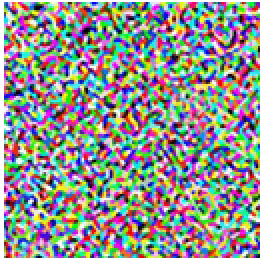
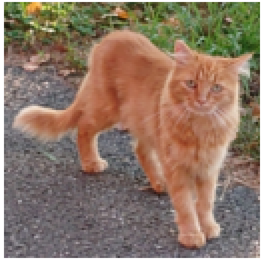


$X_{t=0}$

Closed-form solution for the minimizer $\hat{u}^\star$

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

(if infinite capacity/no constraints on u_θ)



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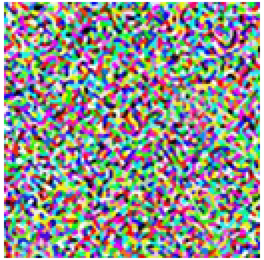

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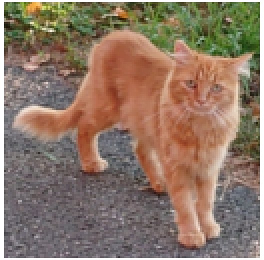

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Can only generate samples $x^{(1)}, \ldots, x^{(n)}$ from the training set

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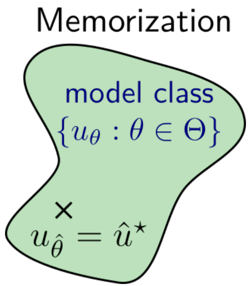

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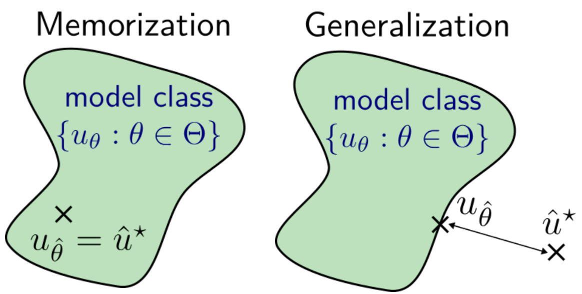

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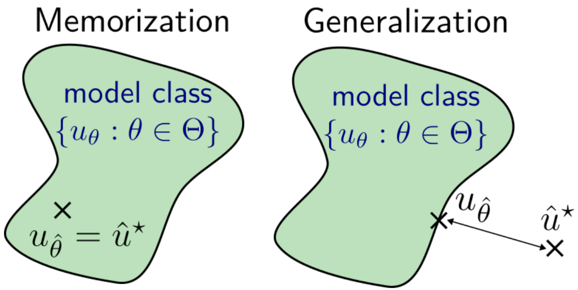
- **Minimalist model**: what about explicit constraints on the velocity field u ?[4,5]



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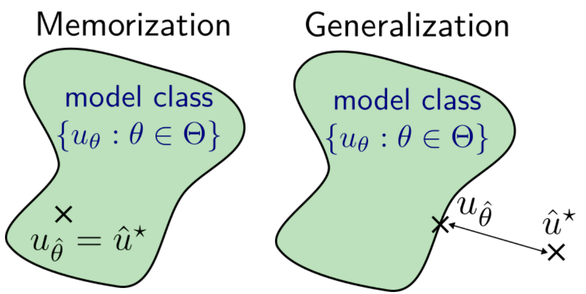

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Main idea: add explicit regularization on the score/velocity u

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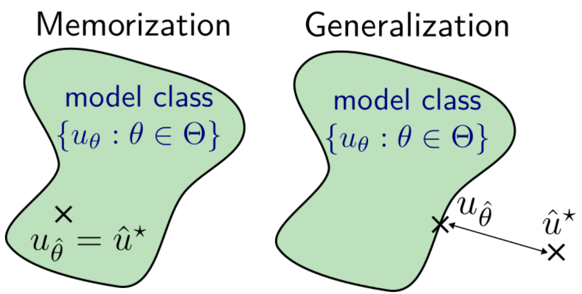

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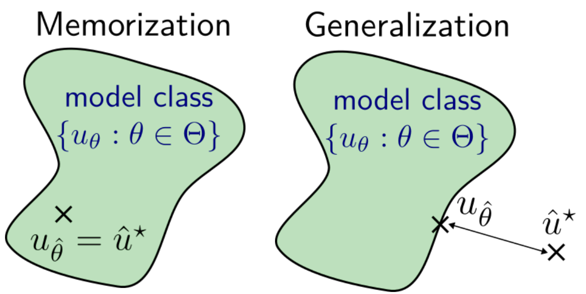

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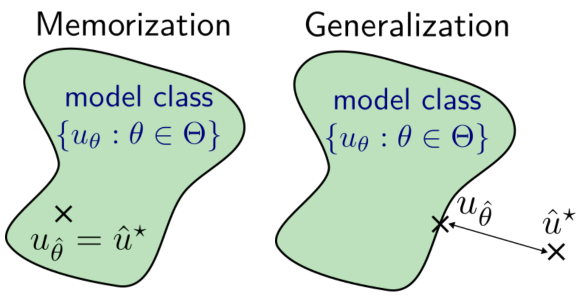

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Explicit architectural regularization: idea

Main results:

- Derive a closed-form formula for this constrained optimization problem
- Show that it matches images generated by a U-Net in practice

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Explicit architectural regularization #1: Equivariance[4]

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Closed-form solution for the minimizer $\hat{u}^\star_{\text{Eq.}}$ with equivariance constraints

$$\hat{u}^\star_{\text{Eq.}}(x,t) := \sum_{i=1}^{n} \sum_{T \in \mathcal{T}^{2D}} \lambda_{i,T}(x,t) \left(\frac{T(x^{(i)}) - x}{1-t} \right)$$

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Equivalent to data augmentation

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$$M_t^q : \text{binary mask centered on pixel } q$$

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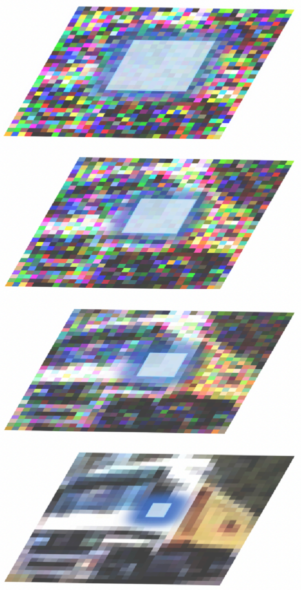

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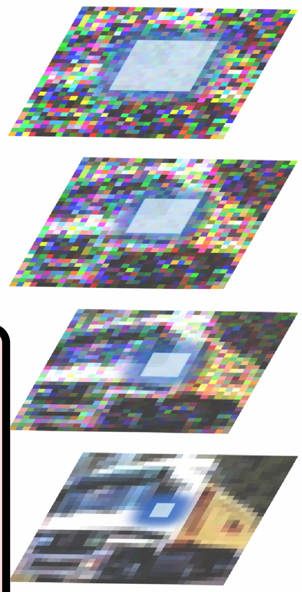

Closed-form solution for the minimizer $\hat{u}^\star_{\text{Loc.}}$ with locality constraints

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Constraint is on the denoiser. Not on the velocity field.

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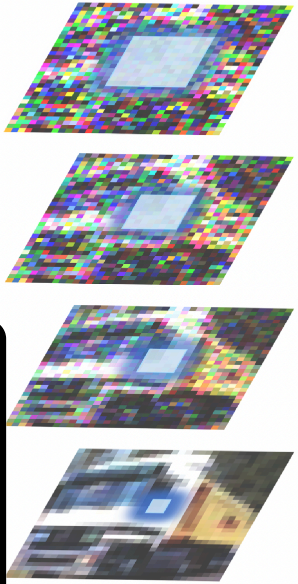

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Equivalence AND Locality[4]

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Illustration of the impact of locality & equiv. constraints

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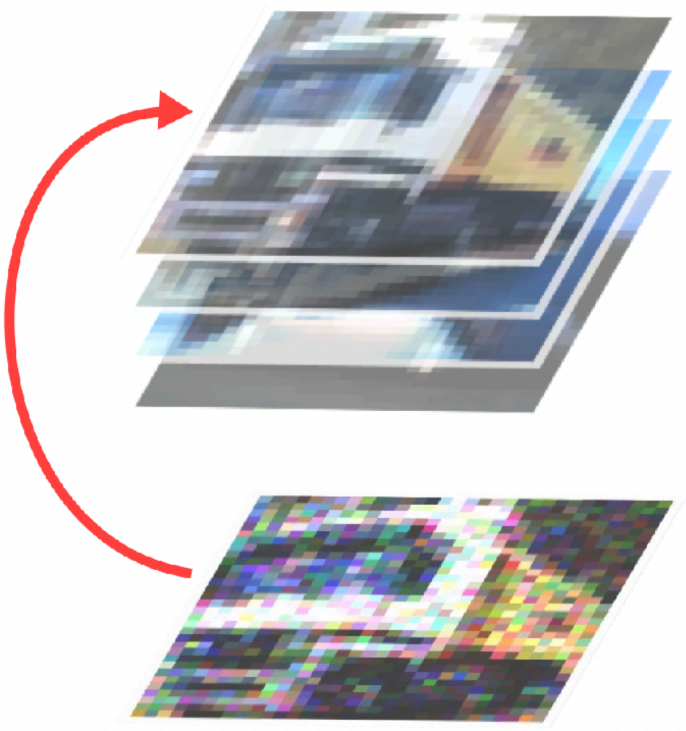
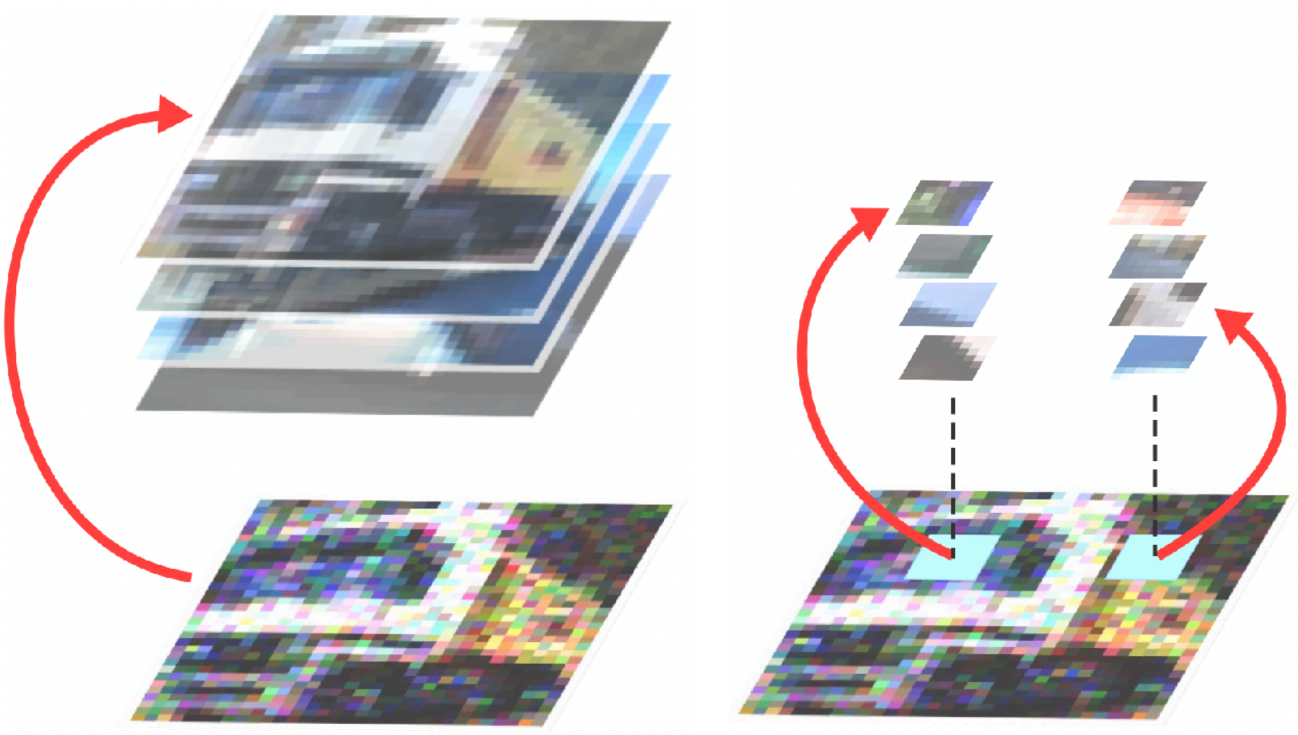


Vanilla closed-form

Illustration of the impact of locality & equiv. constraints



Vanilla closed-form

Closed-form for locality constraints

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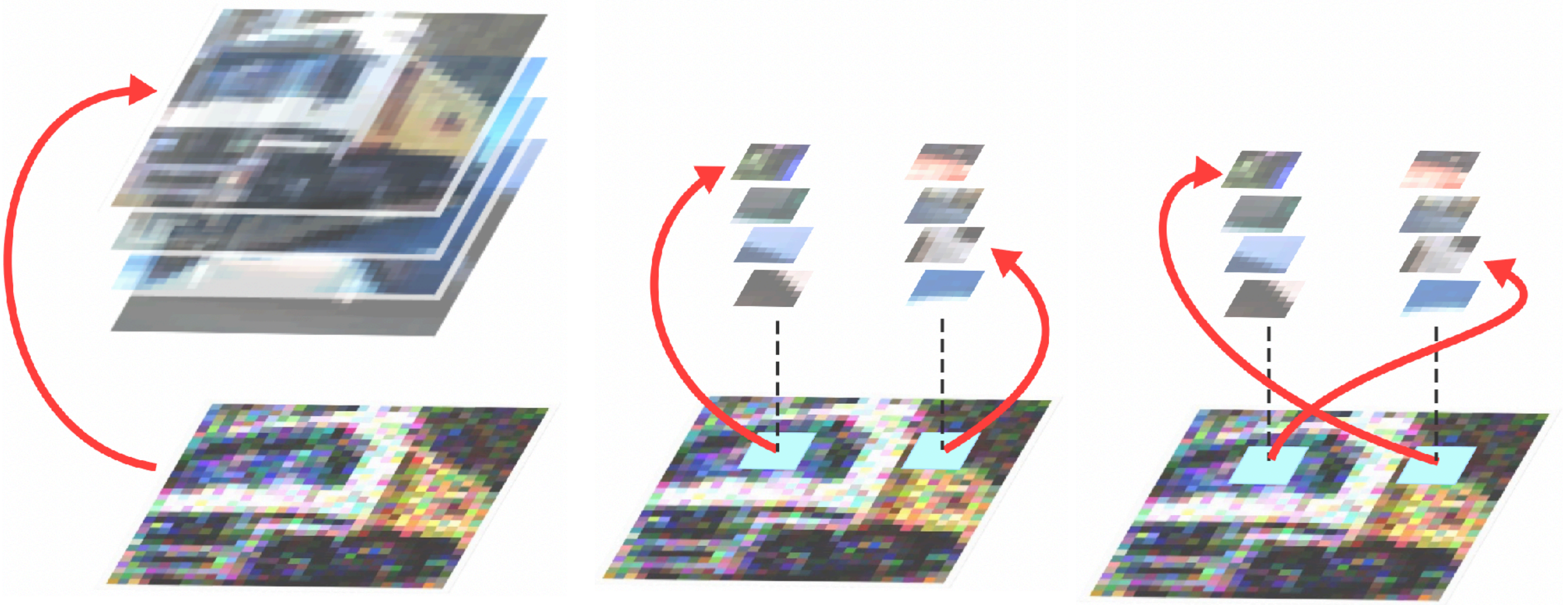

Vanilla closed-form

Closed-form for locality constraints

Closed-form for locality + equivariance constraints

Empirical validation: closed-form vs U-Net

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Left: Closed-Form with Locality and Equivariance Constraints
Right: Learned (small) U-Net

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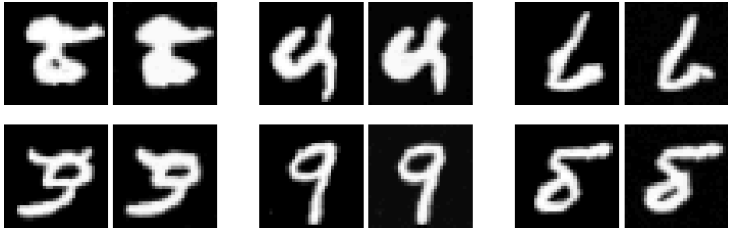
MNIST



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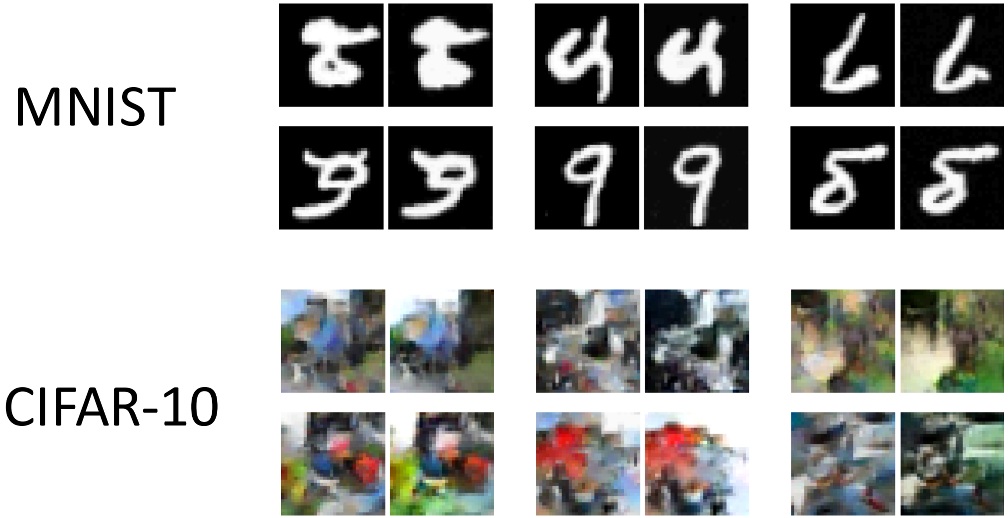

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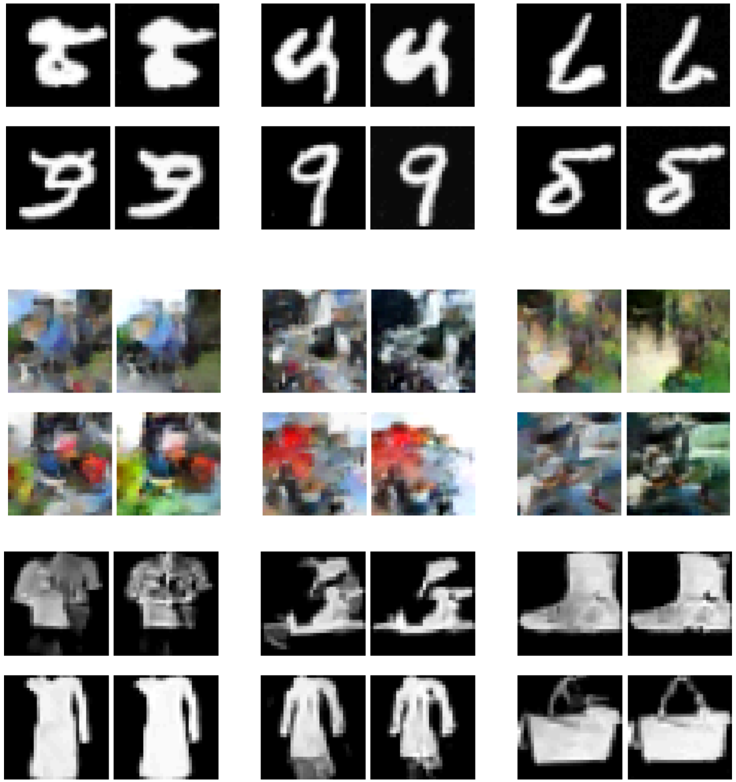

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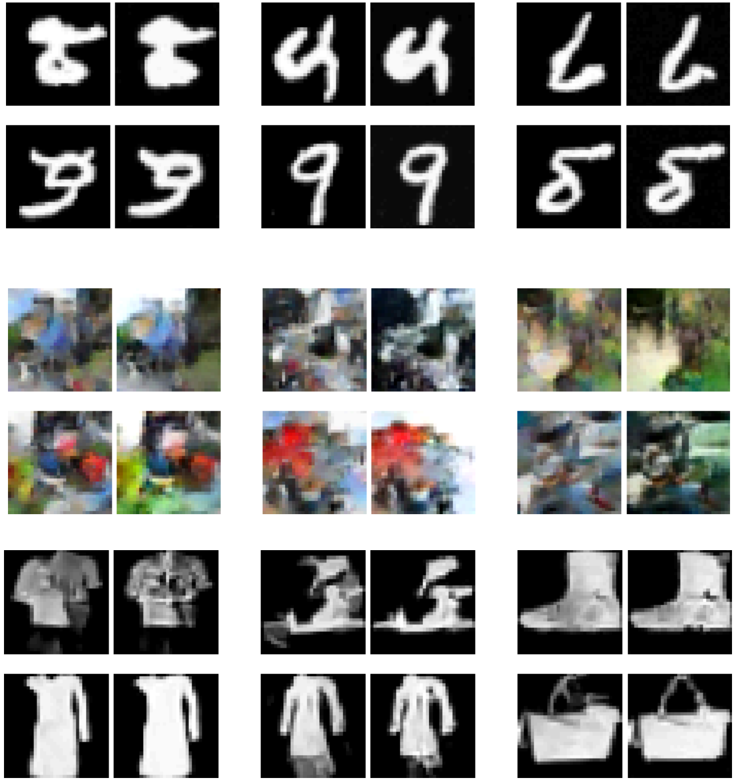

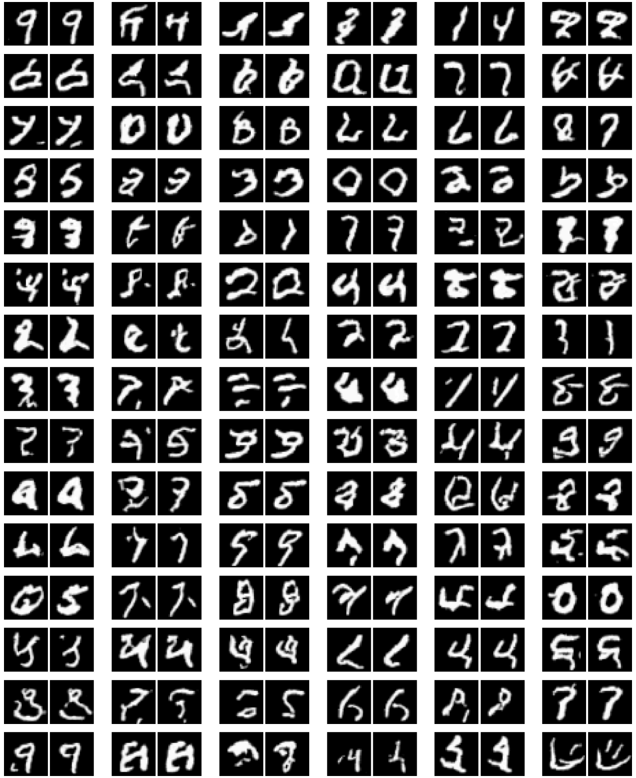

Empirical validation: receptive field comparison 1/2

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What is a receptive field?

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- Value of the velocity field at pixel q : $\underbrace{u_\theta^q(\overbrace{x}^{\text{image}}, t)}_{\in\mathbb{R},\ \text{real valued}}$

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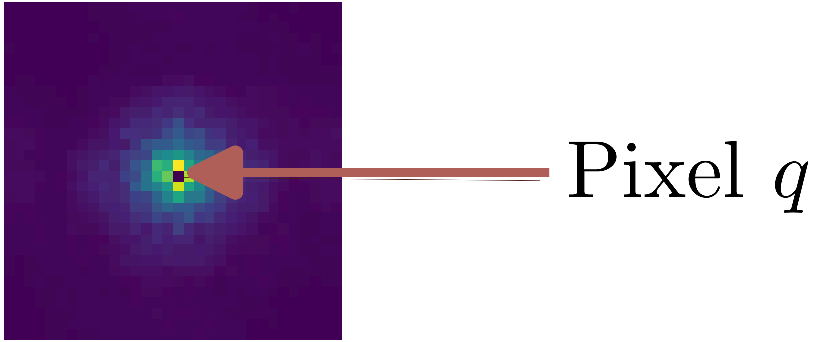
$$\underbrace{\nabla_x u_\theta^q(\overbrace{x}^{\text{image}},t)}_{\text{image; receptive field at pixel } q}$$



Empirical validation: receptive field comparison 2/2

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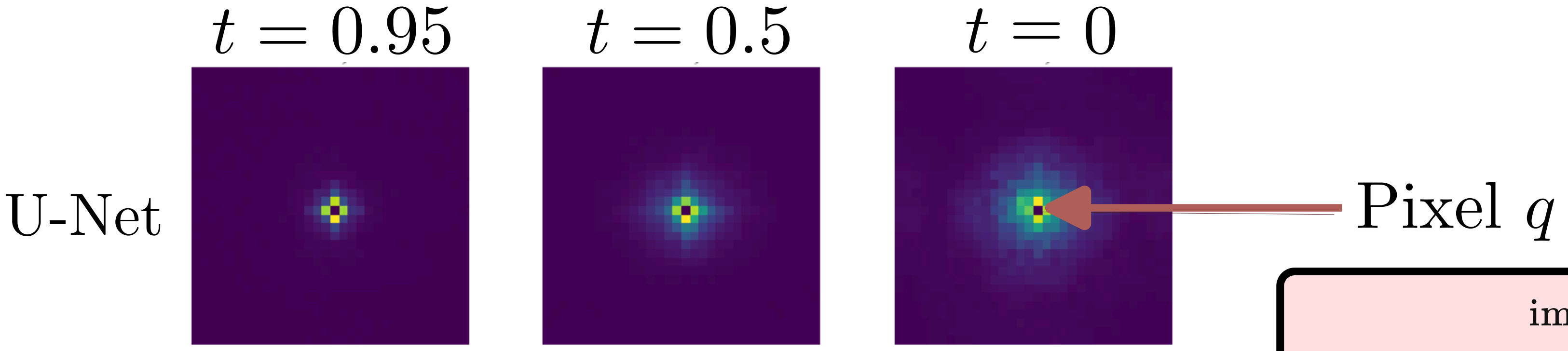

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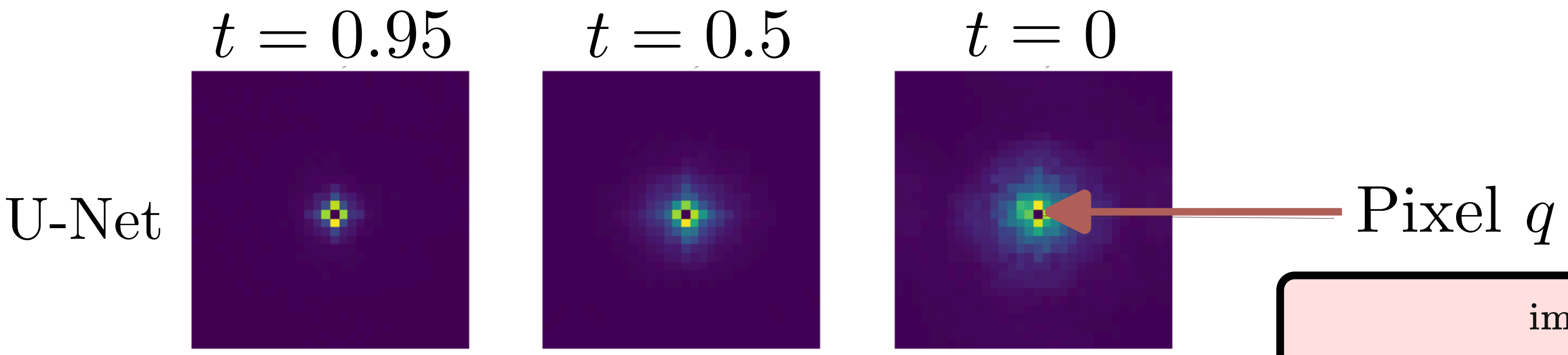

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Large receptive field at $t = 0$

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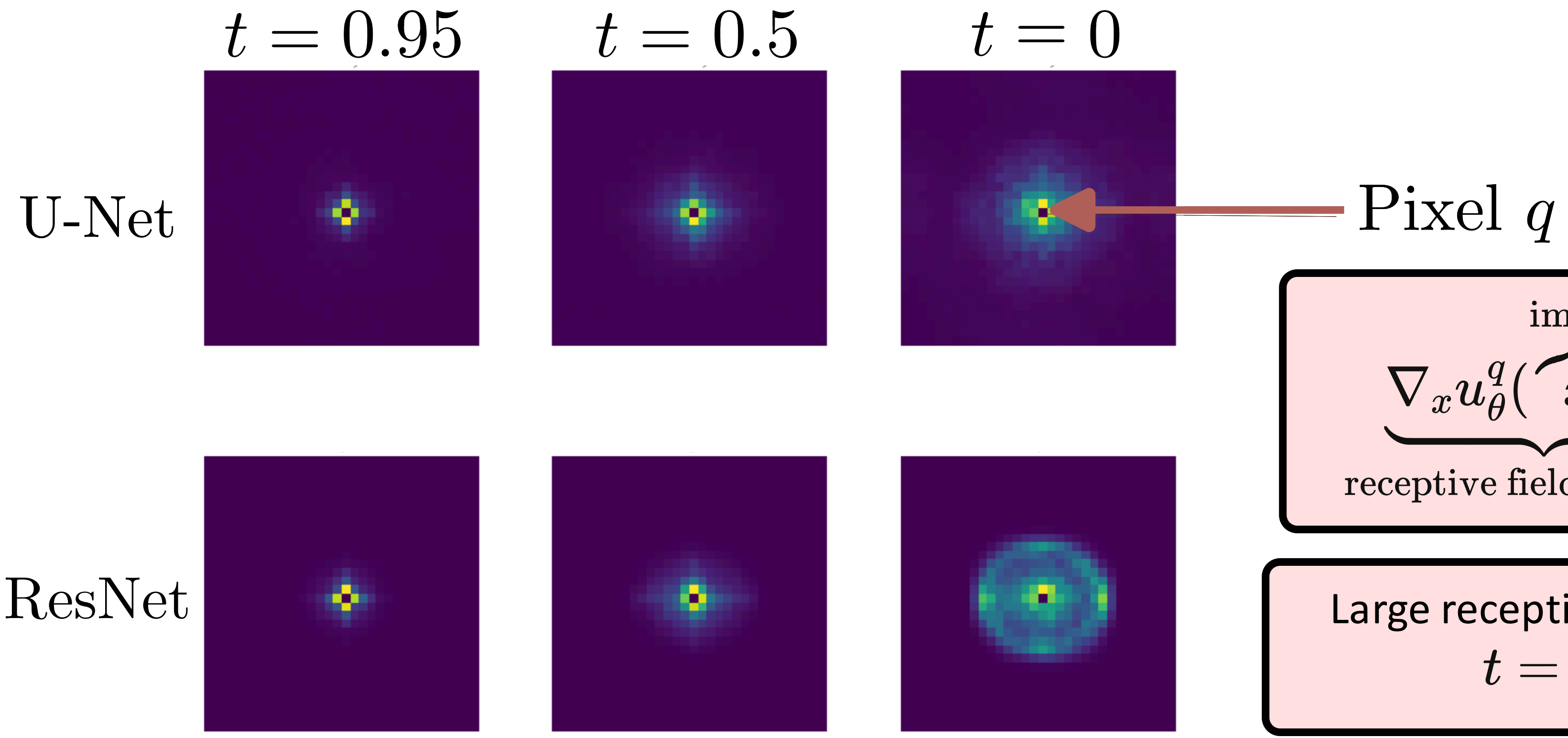

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Large receptive field at $t = 0$

Local mask constraint limitations[6]

Locality constraint reminder

$$\min_u \mathbb{E}_{\substack{x_0\sim p_0\\ x_1\sim p_{\text{data}}\\ t\sim\mathcal{U}([0,1])}} ||u(tx_1+(1-t)x_0,t)-(x_1-x_0)||^2$$

$$\text{s.t. } u^q(x,t)=u^q(M_t^q\odot x,t), \text{(Loc.)}$$

$$M_t^q : \text{Binary mask centered on pixel } q$$

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- And for each time t

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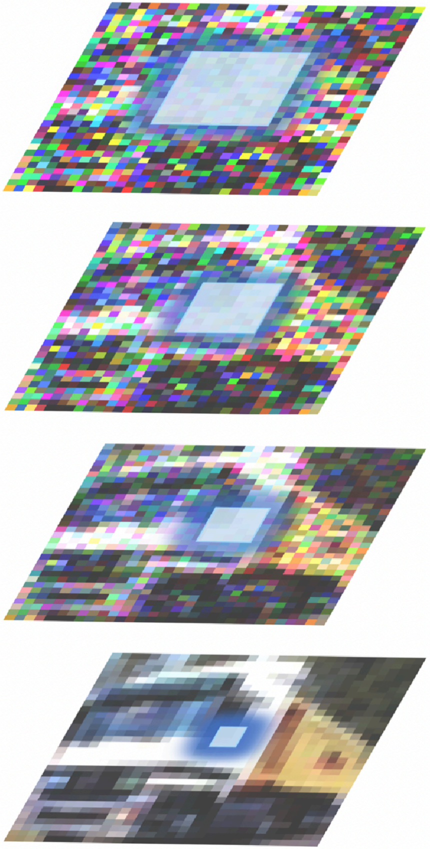

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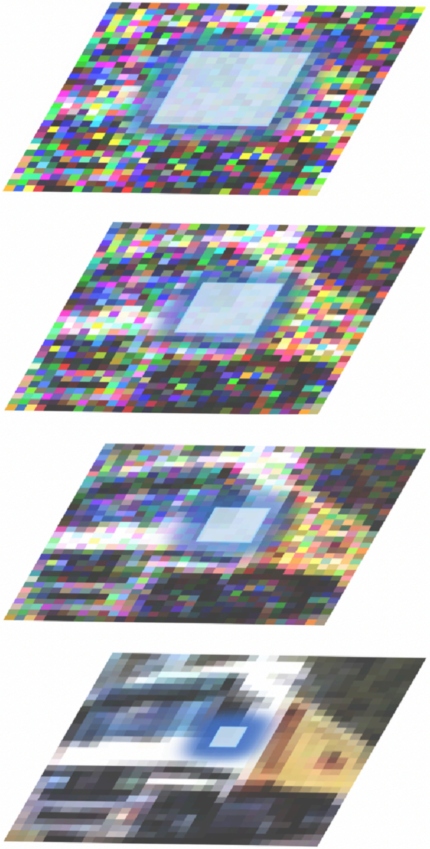

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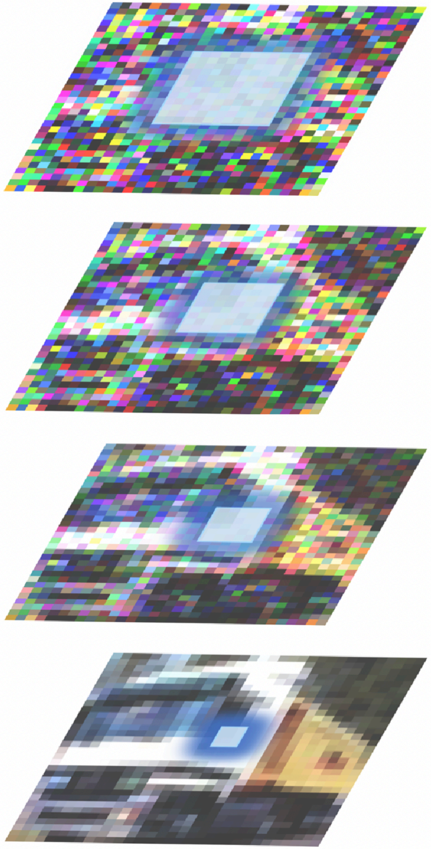

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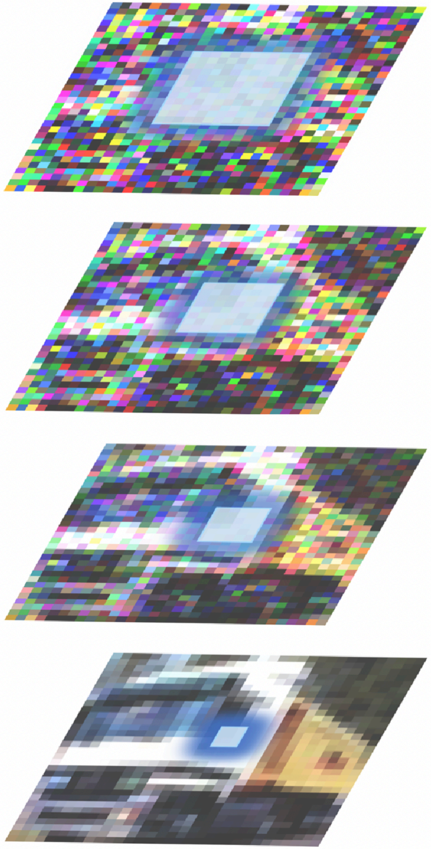
Local receptive field: too restrictive



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Example of non-local receptive field[6]

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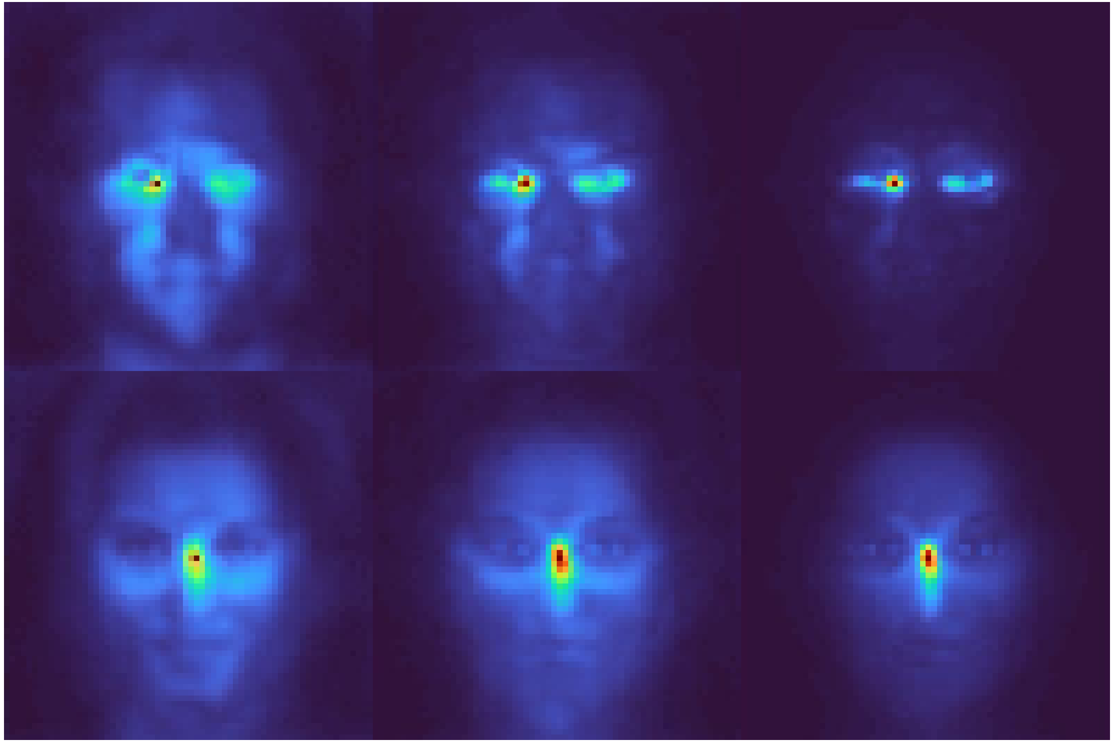

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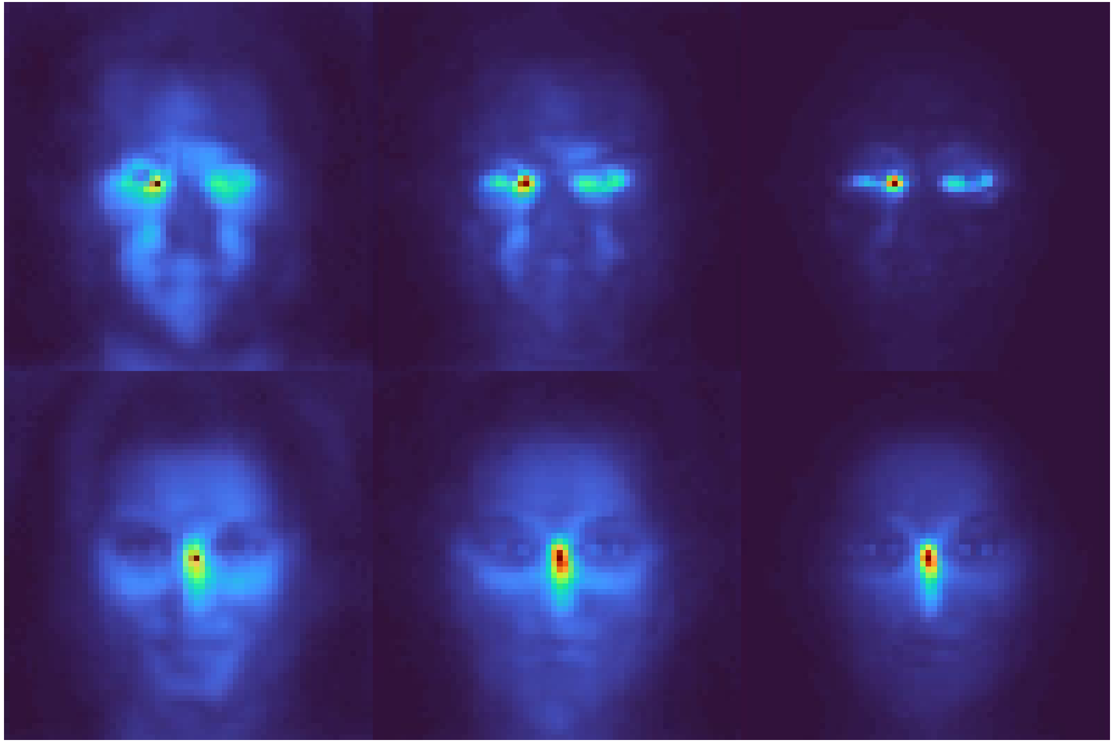
Example of non-local receptive field[6]

Receptive field for the pixel in the eye: non local



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Locality constraints: too restrictive?[6]

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Main Idea 1: generalize the locality constraints

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Main Idea 1: generalize the locality constraints

- Generalize the locality constraints M_t^q , to "correlation" constraints
- Learn these correlation constraints M_t^q using a simple linear denoiser/velocity

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$$\min_u \mathbb{E}_{\substack{x_0 \sim p_0 \\ x_1 \sim \hat{p}_{\text{data}} \\ t \sim \mathcal{U}([0,1])}} \| u(tx_1 + (1-t)x_0, t) - (x_1 - x_0) \|^2$$

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What about the simple linear velocity case $u(x,t) = W_t x$?

[6] A. Lukoianov et al., **Locality in Image Diffusion Models Emerges From Data Statistics,** In: NeurIPS, 2025.

Linear Score/Velocity[12]

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Well-known result: Wiener filter

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$$W_t = U \text{diag} \frac{(1-t) - t\lambda_i^2}{(1-t)^2 + t^2\lambda_i^2} U^\top \qquad \text{with } \text{Cov}(X) = U \text{diag}(\lambda_1^2, \ldots, \lambda_d^2) U^\top$$

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The masks M_t^q are then chosen as a binarization of the q-th row of the Wiener filter W_t

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Combining all the building blocks[6]

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$W_t = U\mathrm{diag}\frac{(1-t)-t\lambda_i^2}{\ldots}U^\top ; \mathrm{Cov}(X) = U\mathrm{diag}(\lambda^2 \ldots \lambda^2)U^\top$

Binary masks M_t^q : binarized q -th row of the Wiener filter W_t

Closed-form solution for the minimizer $u^\star_{\mathrm{Corr.}}$ with correlations

$$u^\star_{\mathrm{Corr.}}(x,t) = \sum_{i=1}^{n} \lambda_i(x,t)\left(\frac{x^{(i)} - x}{1-t}\right)$$

$$\lambda_i(x,t) = \mathrm{softmax}\left(-\frac{\|M_t^q \odot (tx^{(j)} - x)\|^2}{2(1-t)^2}\right)_i$$

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Empirical results[6]

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Summary and Conclusion[4,5,6,7,8]

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- Explicit regularization of the score/velocity

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Summary and Conclusion[4,5,6,7,8]

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- Explicit regularization of the score/velocity
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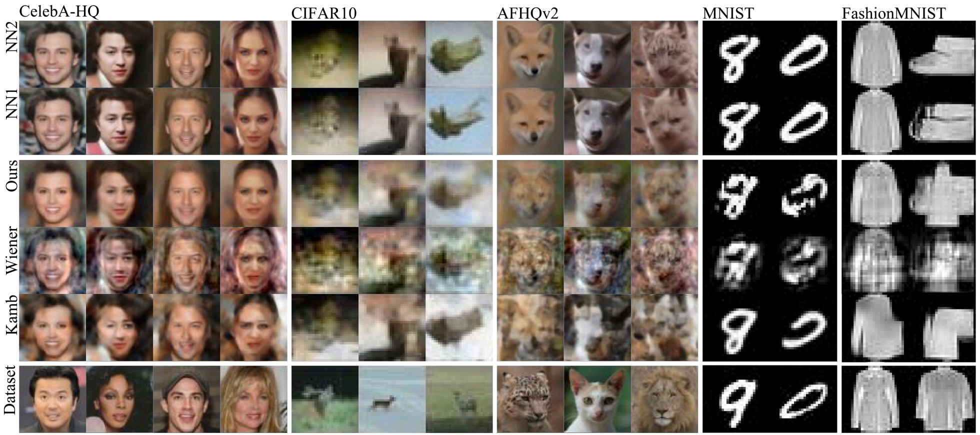
  - Generalization of locality to correlation constraints
- Closed-form formula for the constrained problem



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- Explicit regularization of the score/velocity
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- Closed-form formula for the constrained problem
  - Empirically "match well" small U-Nets

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Summary and Conclusion[4,5,6,7,8]

- Explicit regularization of the score/velocity
  - Equivariance
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- Closed-form formula for the constrained problem
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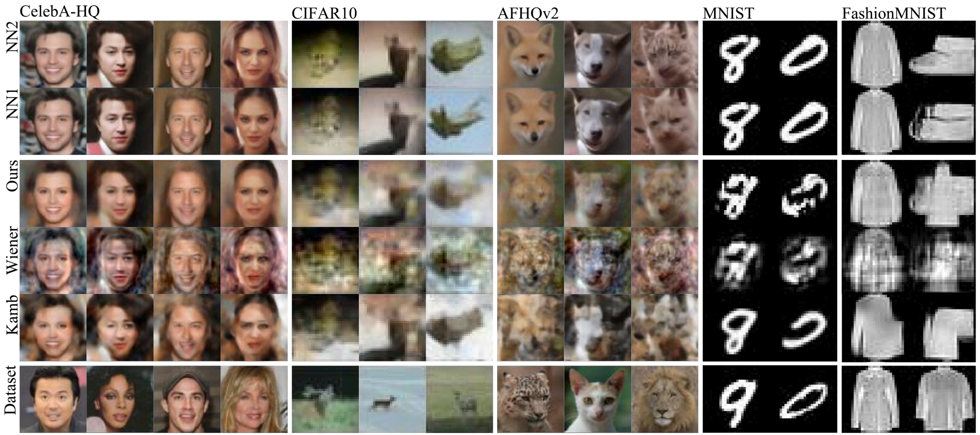

Thank you for your attention!

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ICML 2026 tutorial

Diffusion and Flow Matching

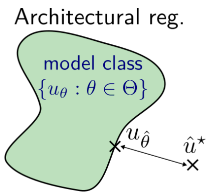
Part IV: Open Questions & Discussions

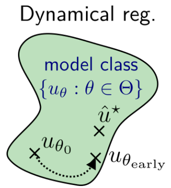
Quentin Bertrand & Mathurin Massias

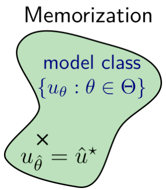
https://memorization-generalization.github.io

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

Over- vs under-parameterized models







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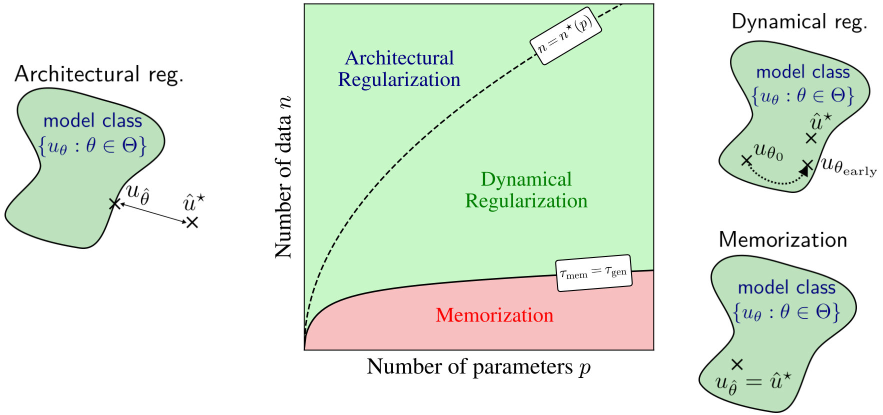

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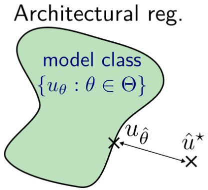

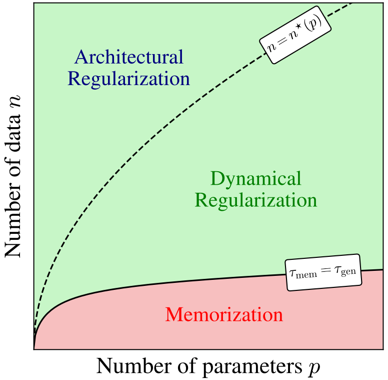

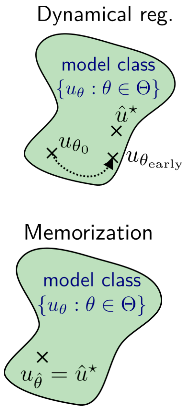

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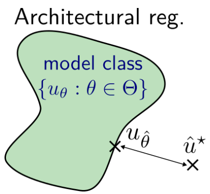

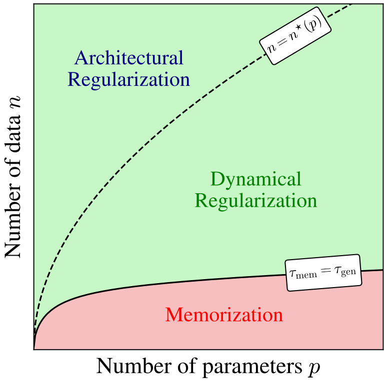

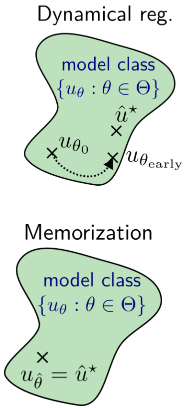

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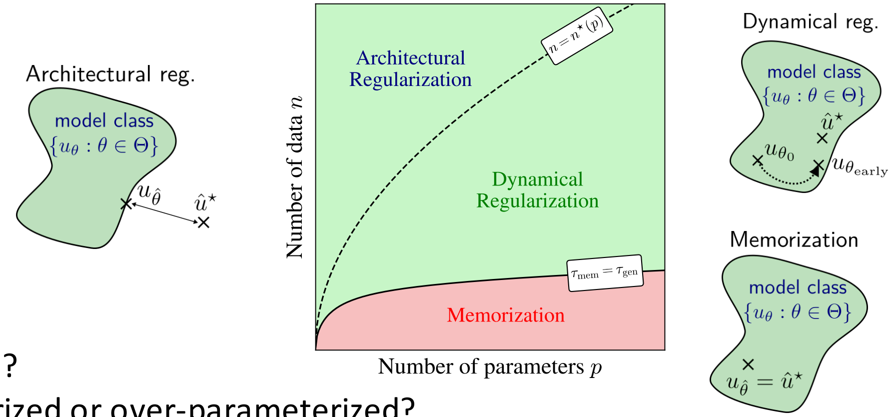

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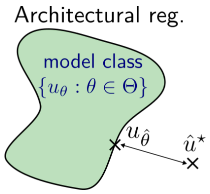

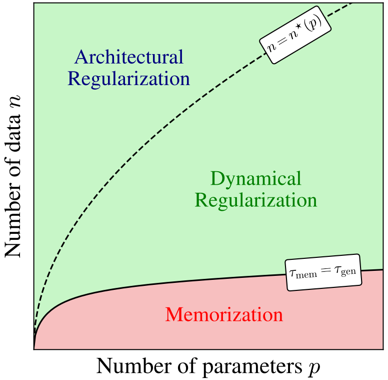

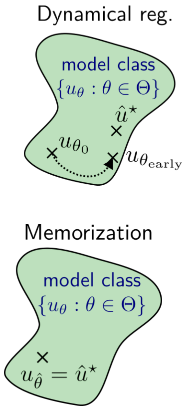

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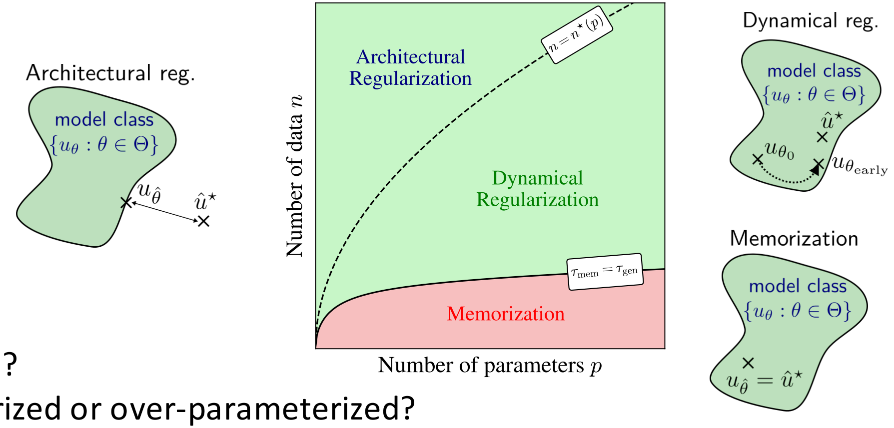

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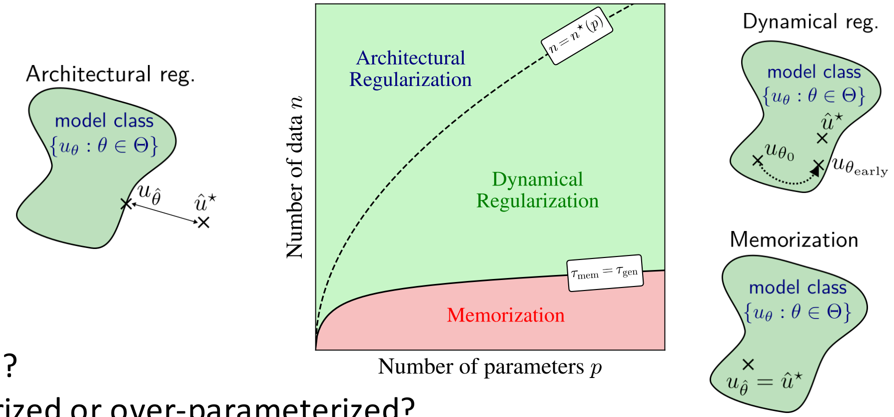

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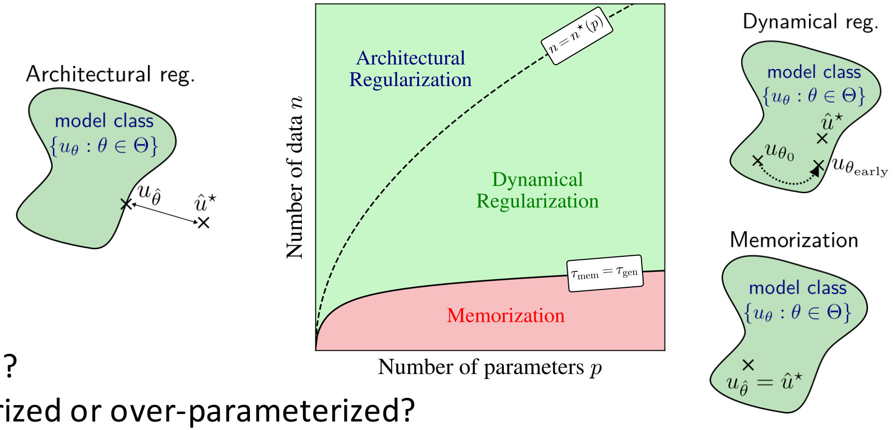

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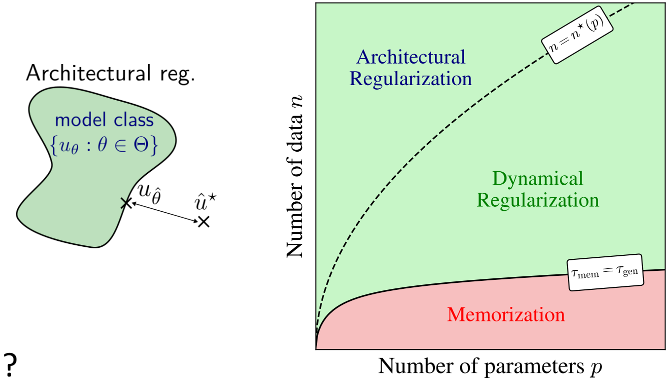

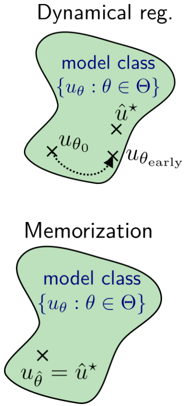

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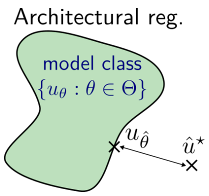

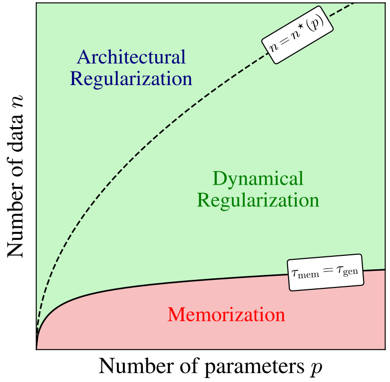

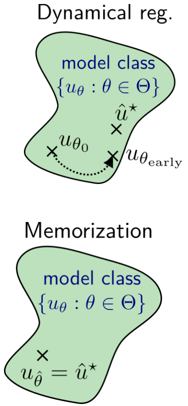

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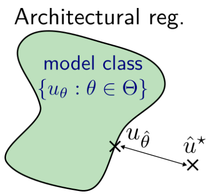

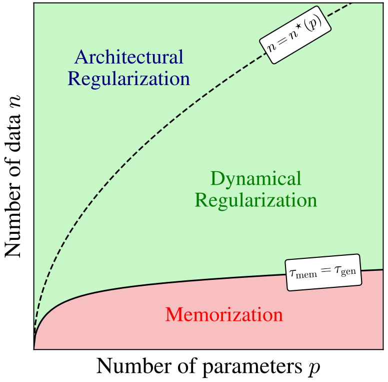

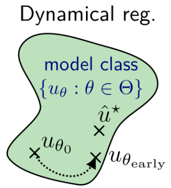

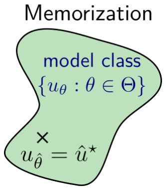

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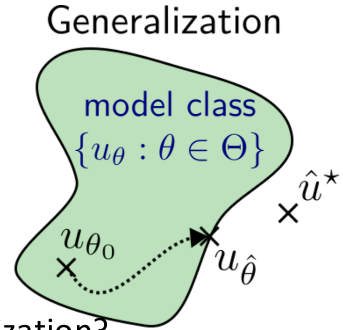
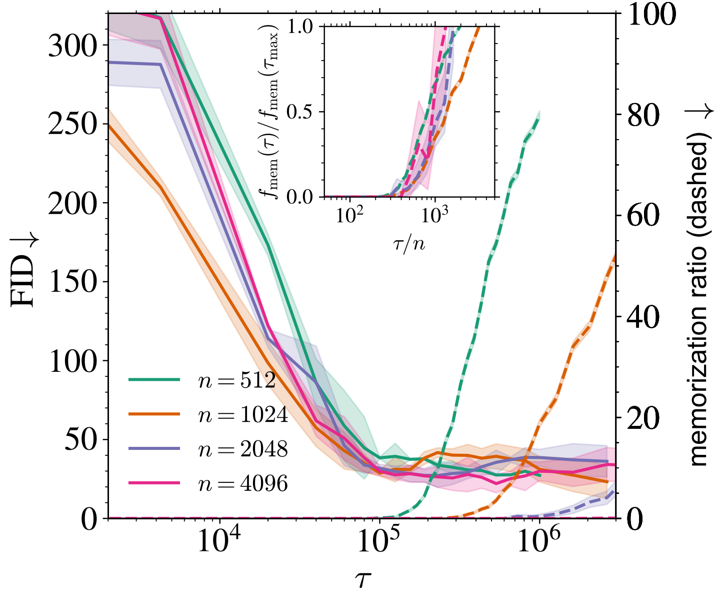


Memorization/Generalization dichotomy?



Bonnaire et al. (2025)

Memorization/Generalization dichotomy?

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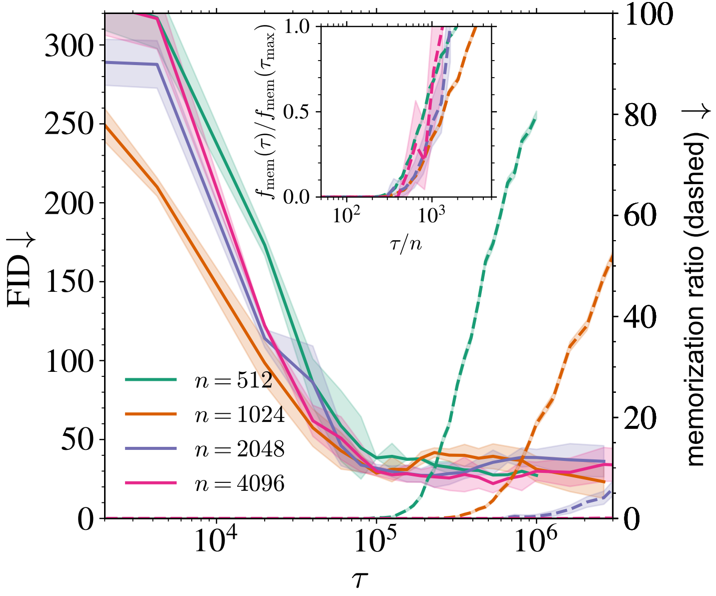

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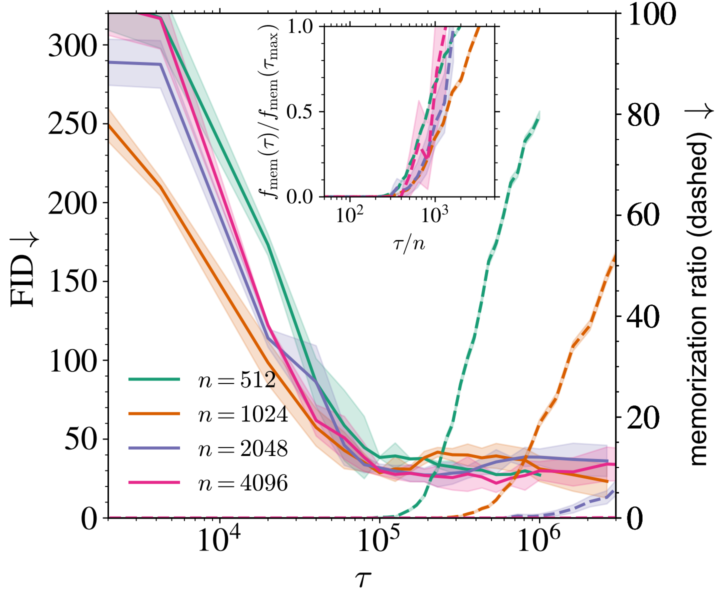

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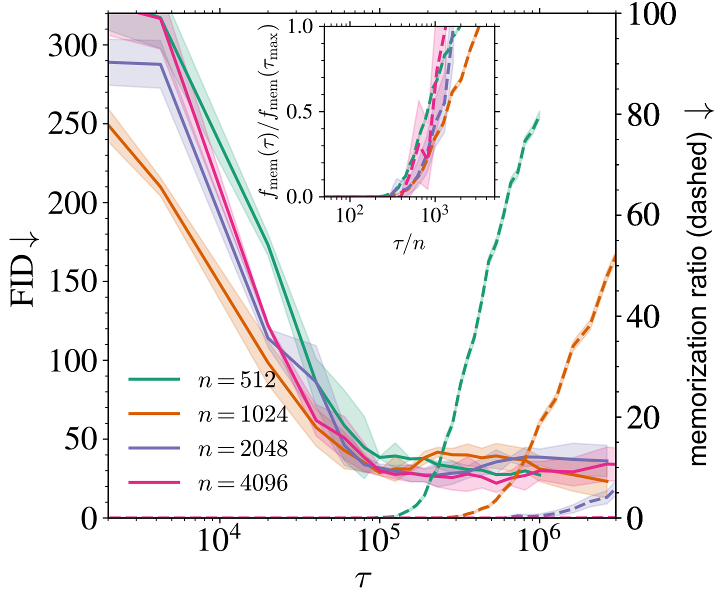

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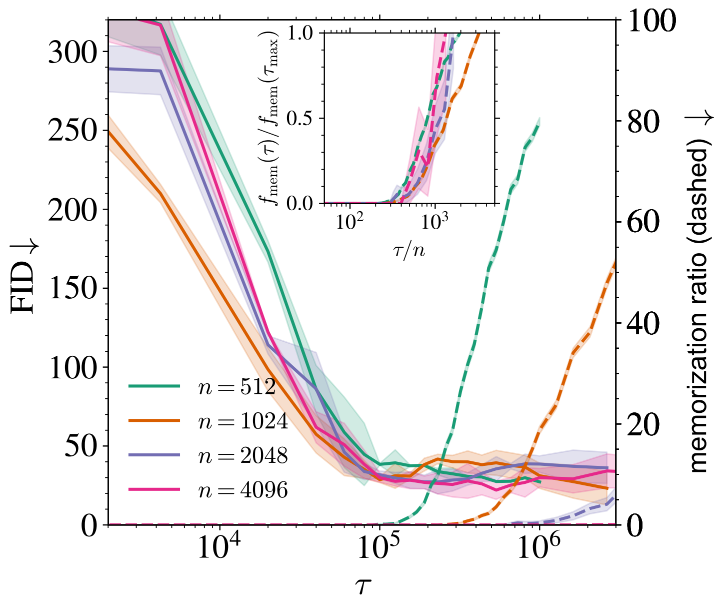

Bonnaire et al. (2025)

[1] C. Merger et al., **Local Coverage Governs Memorization in Diffusion Models,** In: arXiv preprint arXiv:2606.14390, 2026.

Beyond U-Nets?

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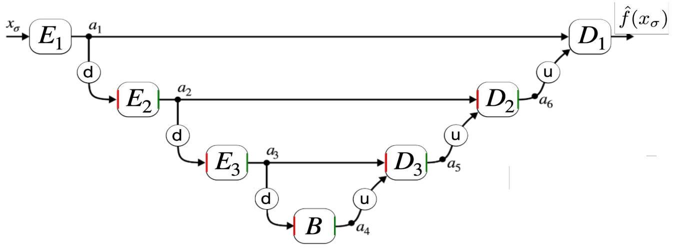

Kadkhodaie et al. (2026)

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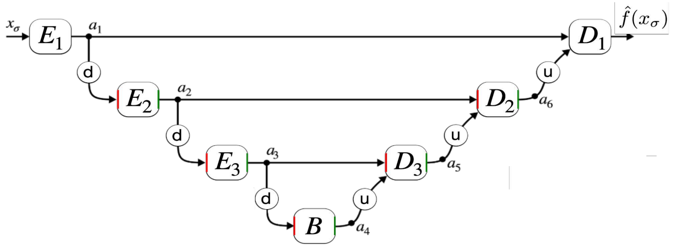

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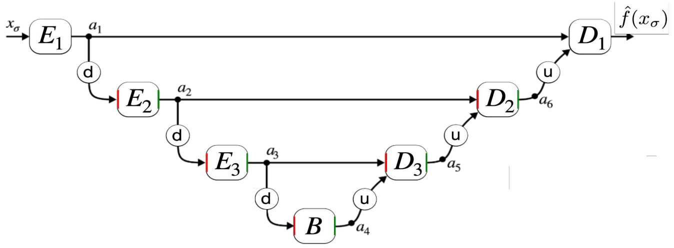

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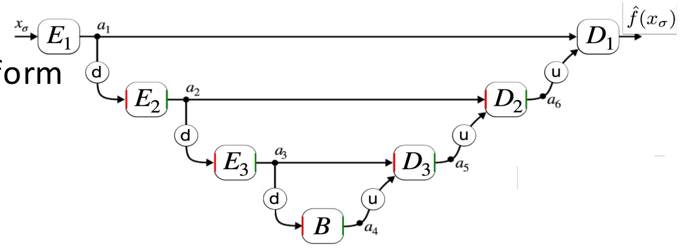

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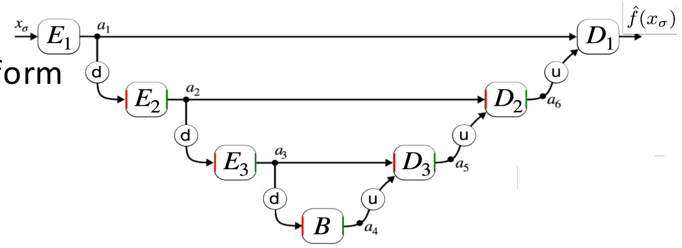

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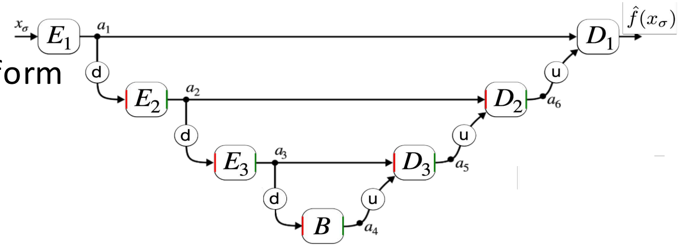

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Beyond unconditional image generation?

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- What about class/text-conditional generative models?[10]

[10] A. Ramesh et al., **Hierarchical text-conditional image generation with clip latents,** In: arXiv preprint arXiv:2204.06125, 2022.
[11] C. Schuhmann et al., **Laion-5b: An open large-scale dataset for training next generation image-text models,** In: NeurIPS, 2022.
[12] S. Dieleman, **The geometry of diffusion guidance,** In: , 2023.
[13] P. Dhariwal et al., **Diffusion Models Beat GANs on Image Synthesis,** In: Advances in Neural Information Processing Systems, 2021.
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Thank you for your attention!

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