When and how can inexact generative models still sample from the data manifold?

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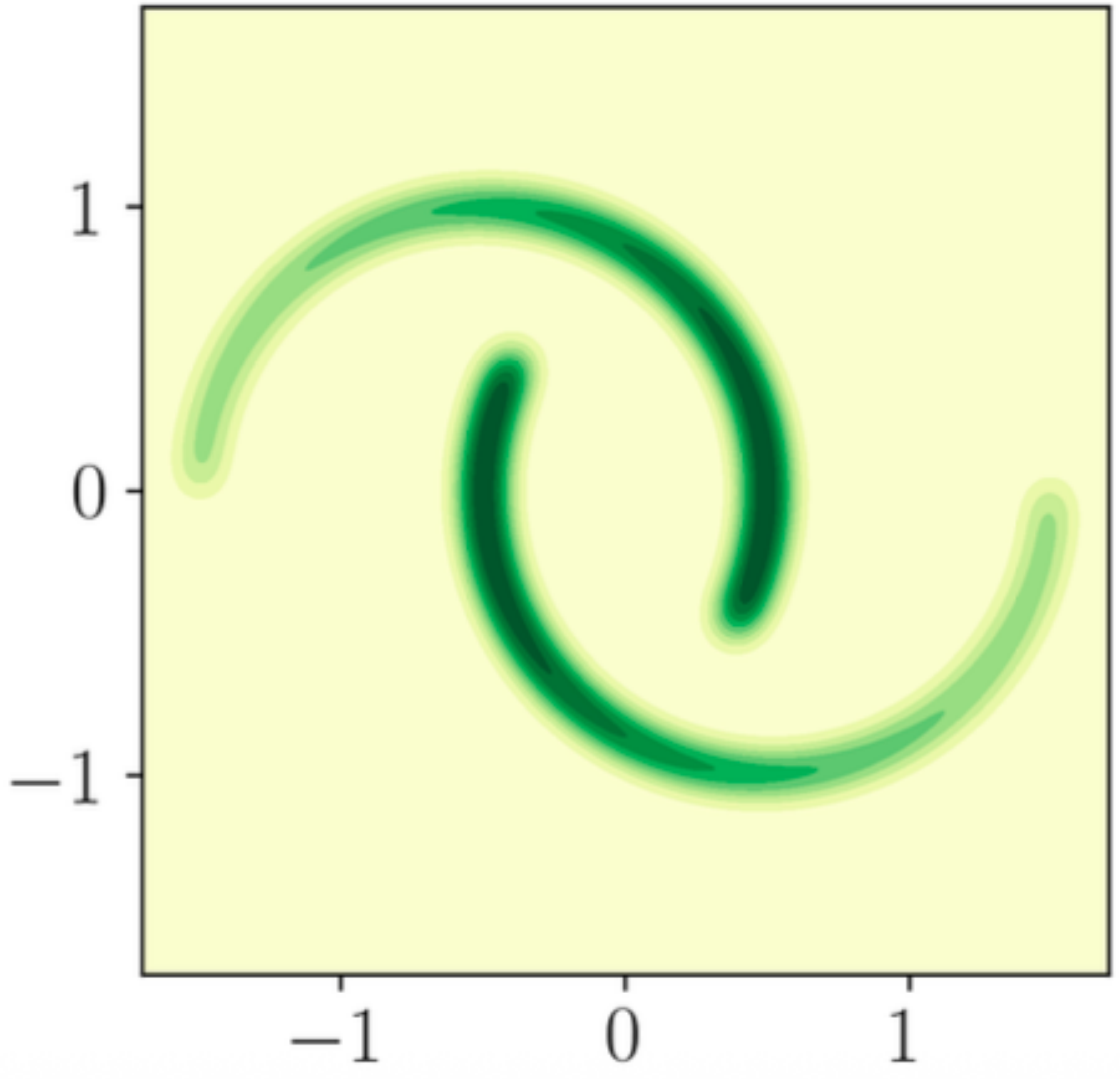
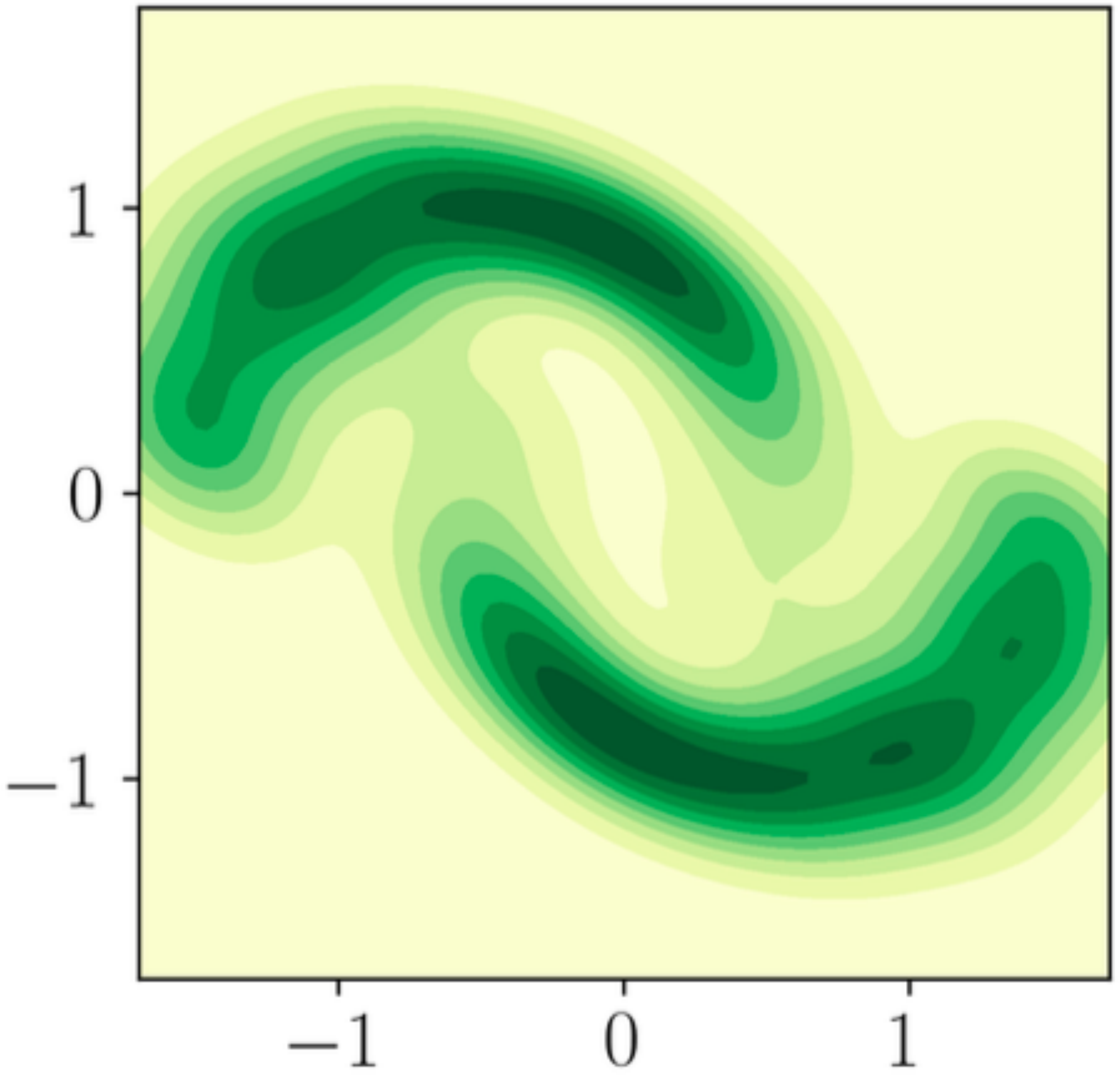
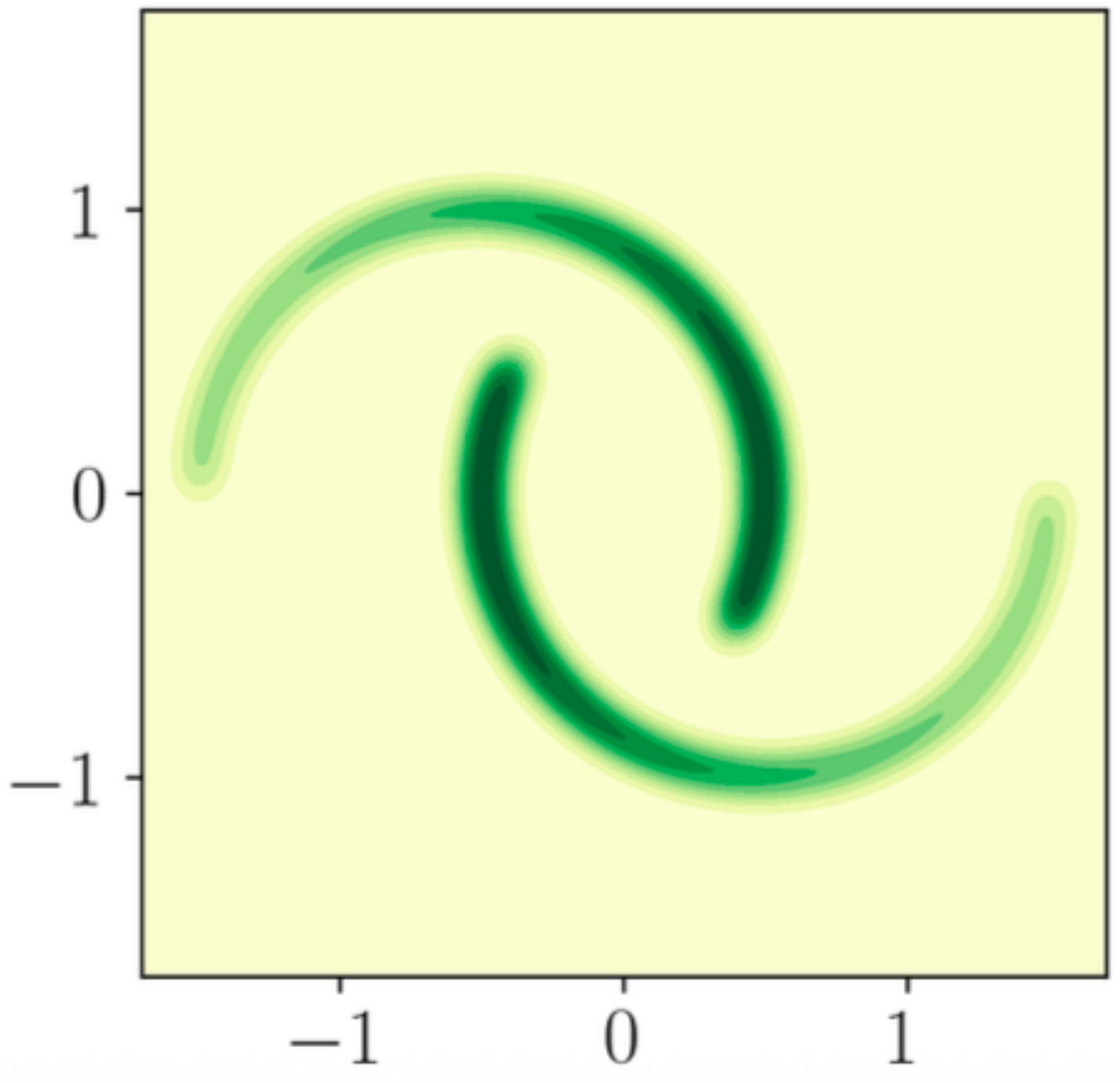


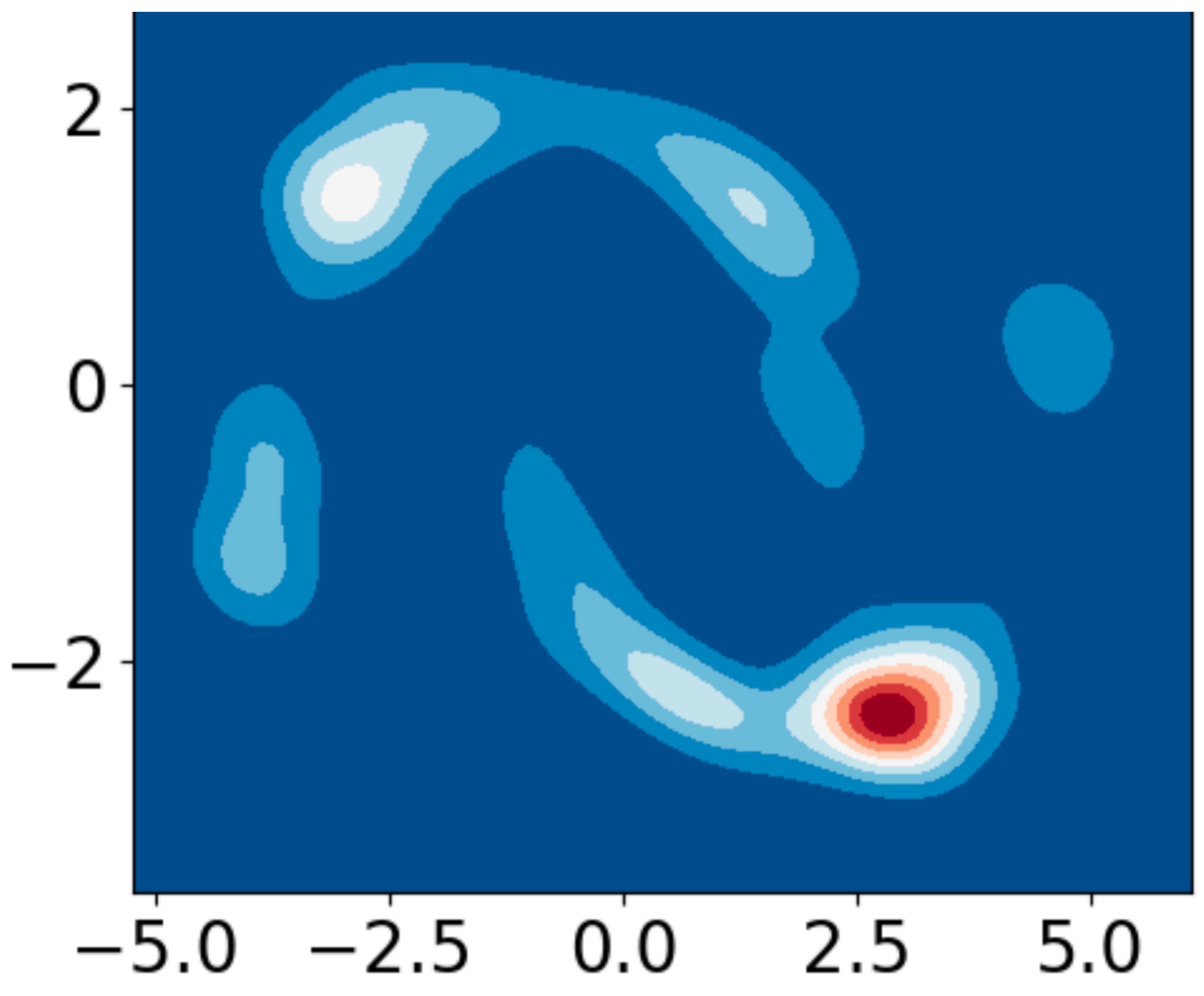


The support appears robust

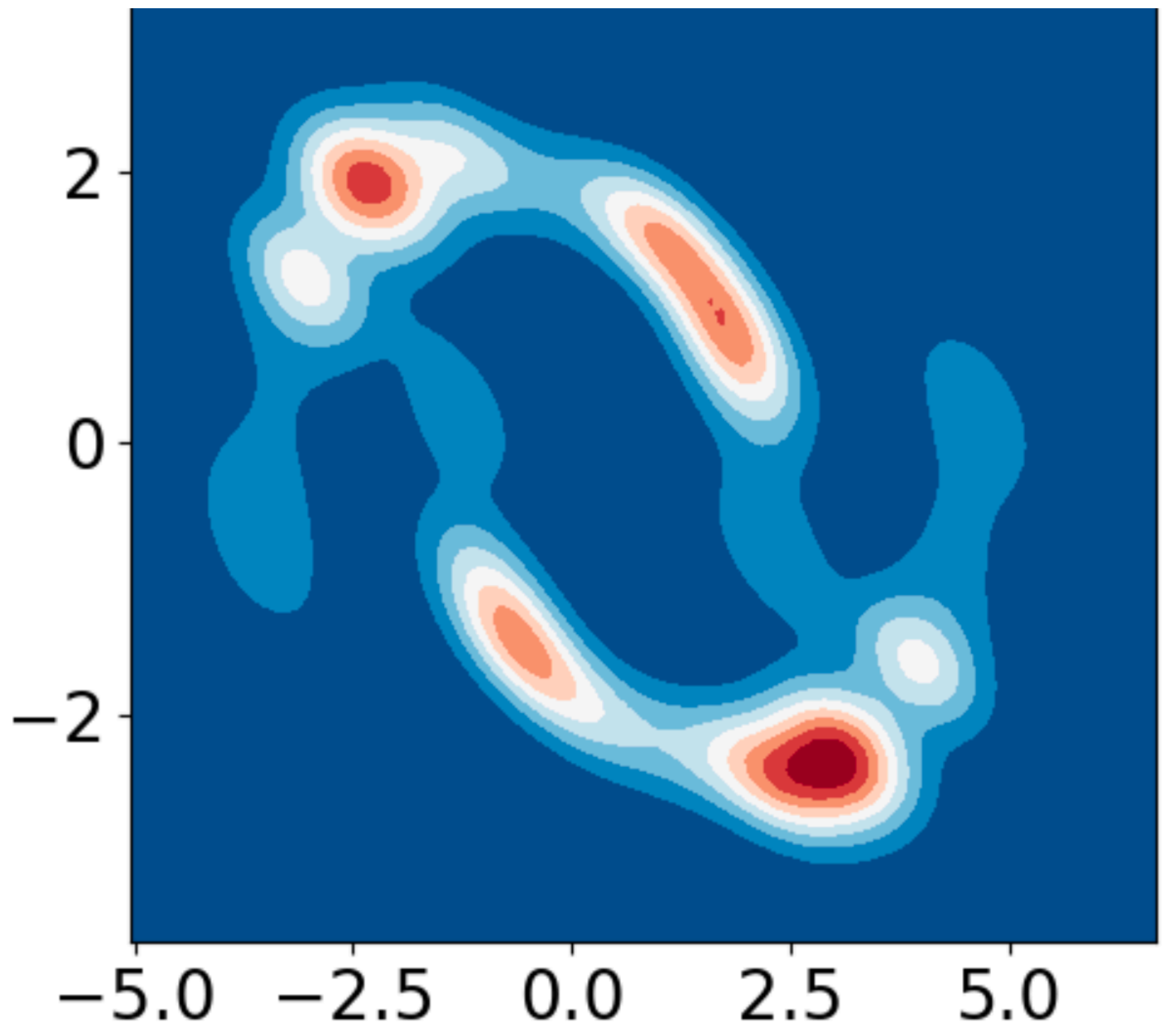
Robustness of the support



Target



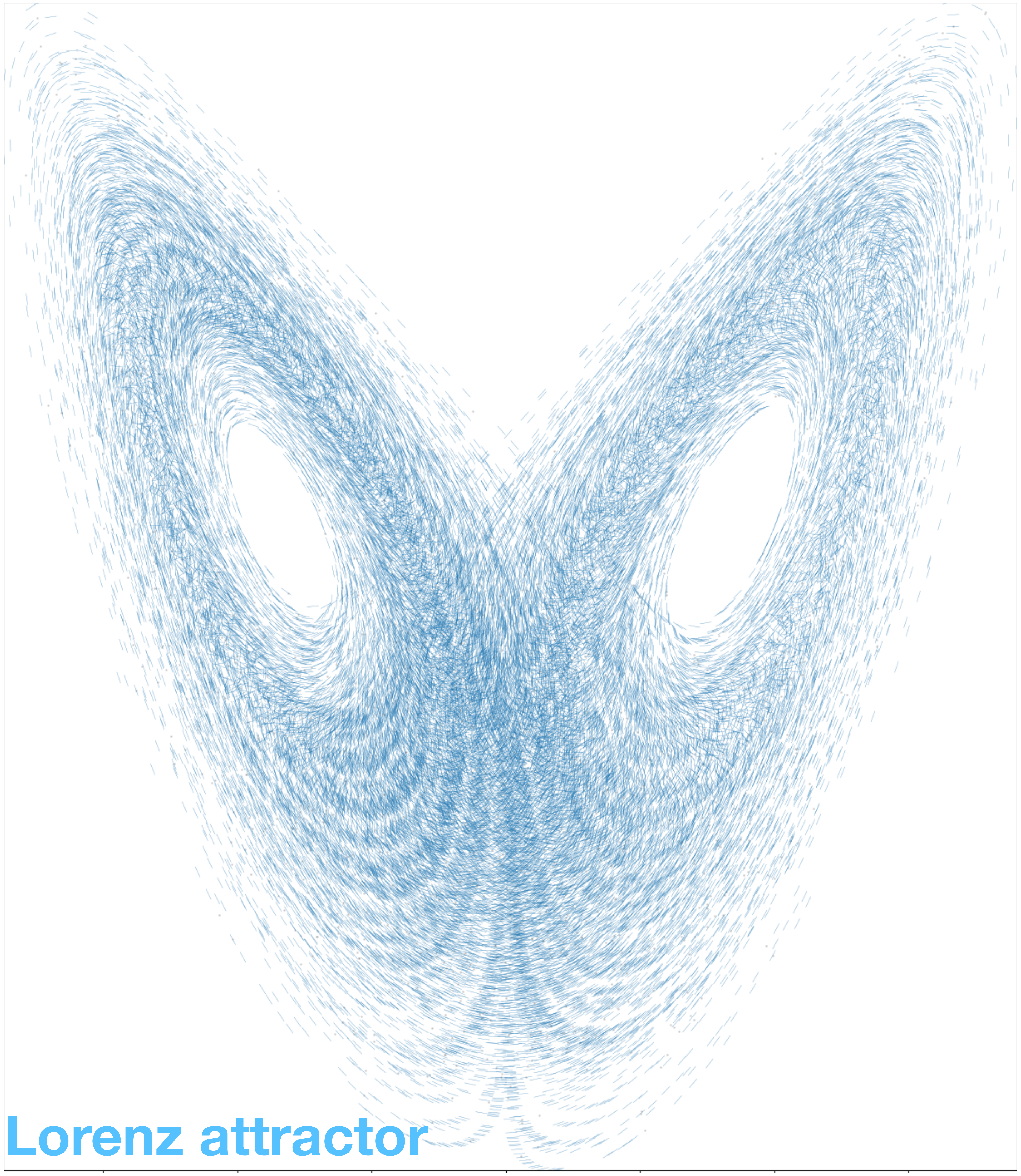
Conditional Flow matching



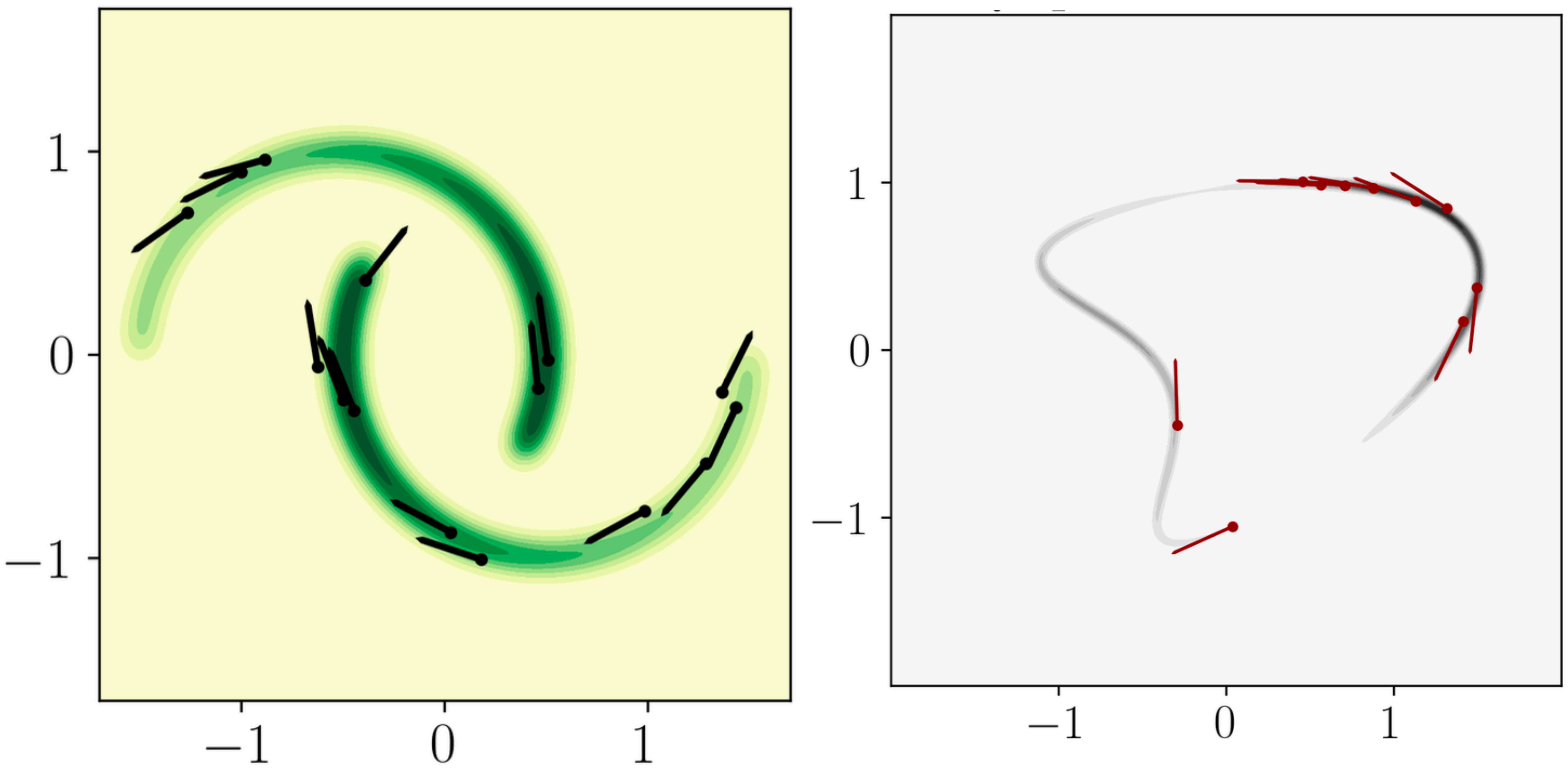
OT - Conditional Flow matching

All models are incorrect, but some are usefully incorrect

Low-dimensional absolutely continuous structure — in the physical sciences



The unstable subspaces on the Lorenz attractor

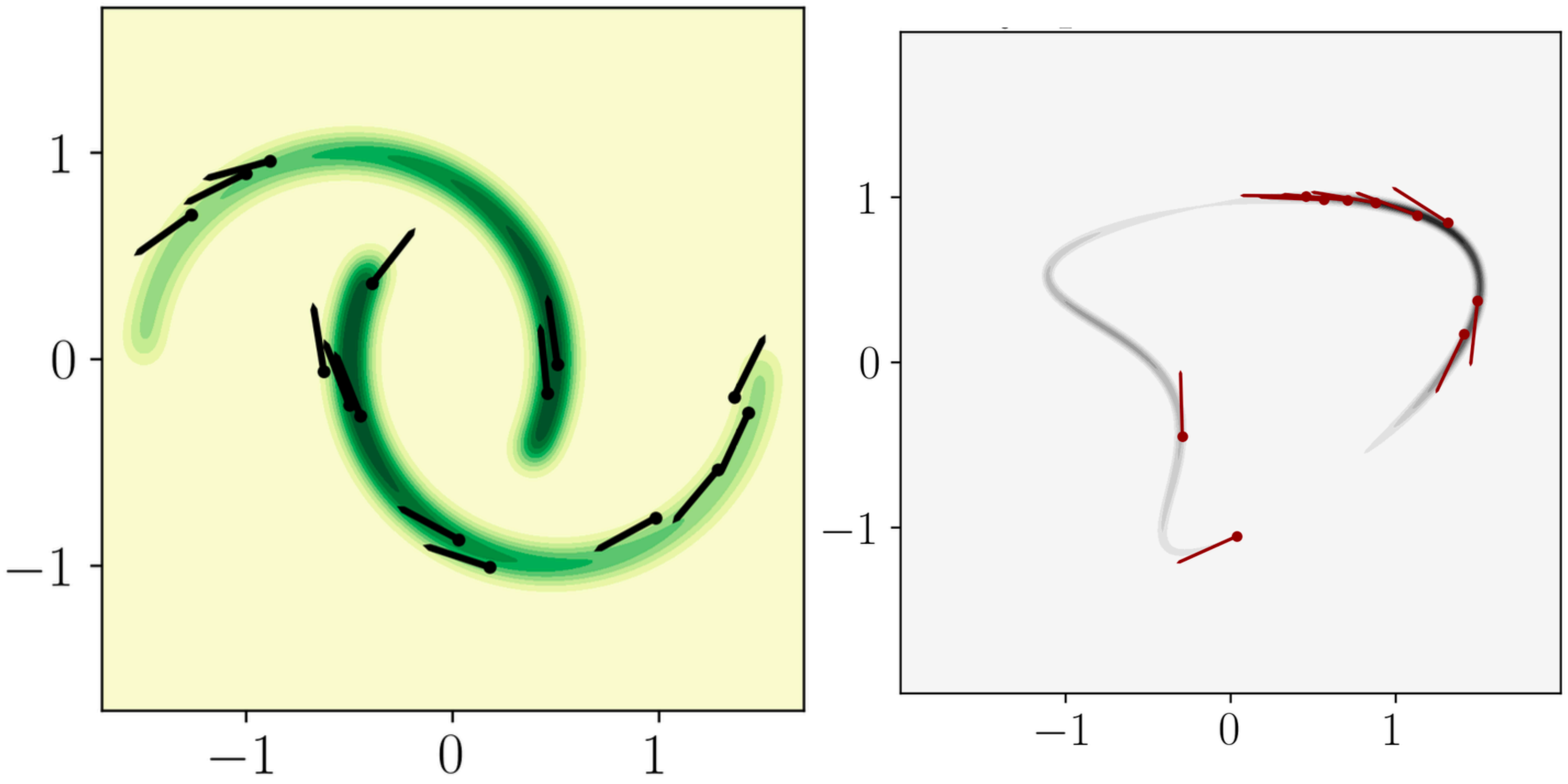


$E \approx$ top d Lyapunov Vectors of GM (F)

- d: intrinsic dimension.
- $\approx$ top d eigenvectors of $\nabla F(\nabla F)^\top$: where F takes noise samples to target samples

Alignment with support of p_{data}

- M: support of p_{data}
- A GM is ***aligned*** if TM is parallel to E



Learning the support

Informal: A convergent generative model learns the support of the target if **aligned**

- Convergent: optimal transport map of small norm exists between generated samples and the target samples; $||x_i - y_i|| \sim \mathcal{O}(\epsilon^c)$ (e.g., Lee, Lu, Tan 2023)

- Support estimation $\equiv$ Learning one-class classifier

- Margin does not change under alignment, hence has same generalization error

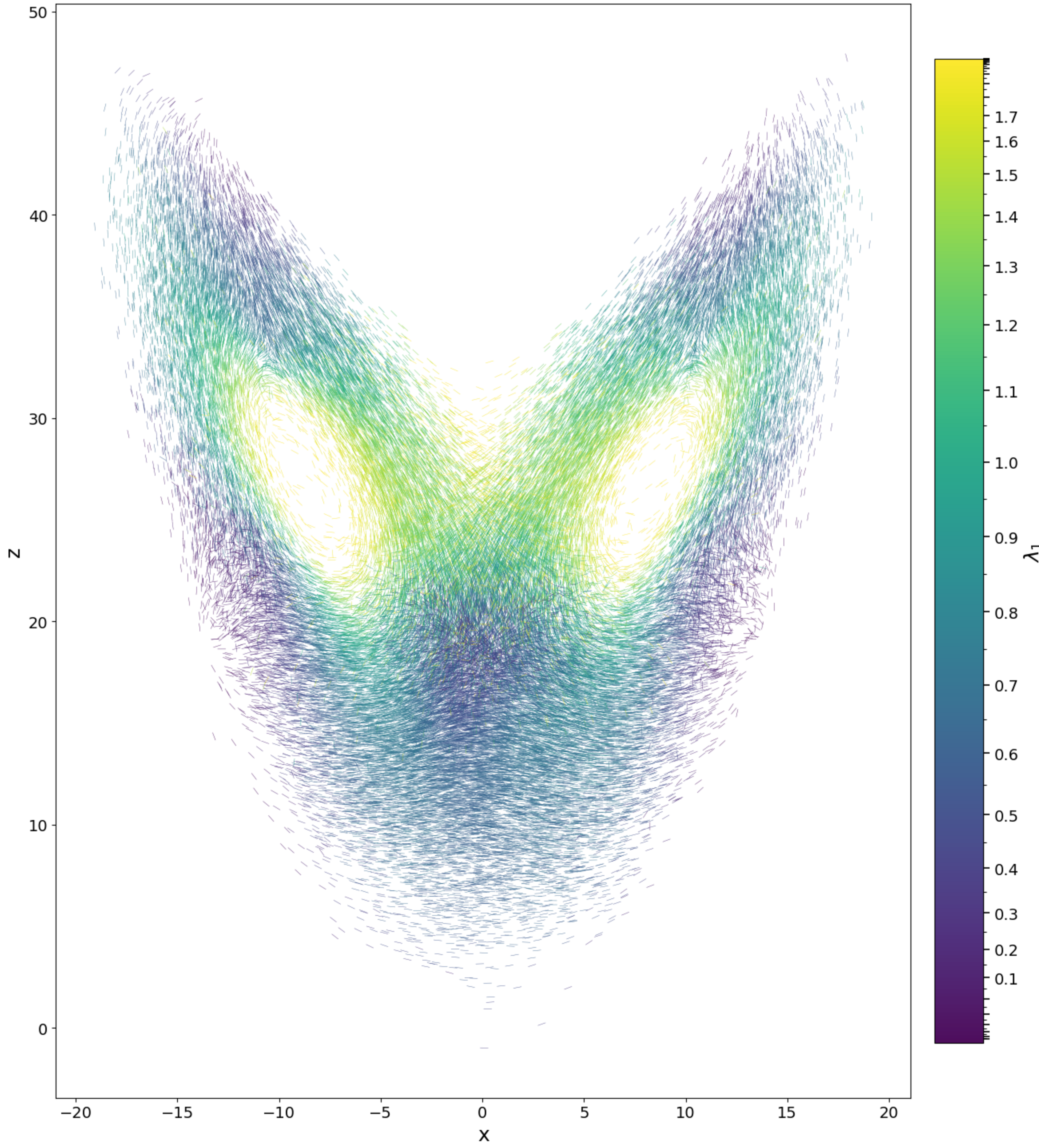
Alignment leads to learning the data manifold

- The most sensitive subspaces E_τ are constructively defined; scalable computation

- Is **alignment** preserved under perturbations? Yes, under smooth perturbations.

- What kind of dynamics leads to **alignment**?

- How to ensure **alignment**?



Summary

- GMs can be viewed as random dynamical systems
- This perspective explains their behavior under learning errors
- **Alignment** of the d most sensitive subspaces with the tangent space of the d-dimensional data manifold leads to robustness of the support
- Aligned generative models can learn the data manifold

C and de Clercq, NeuRIPS 2025, https://arxiv.org/abs/2508.07581