

Probabilistic Embedding through the Wasserstein Tangent Space

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NANMAT 24

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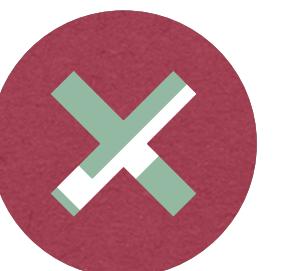
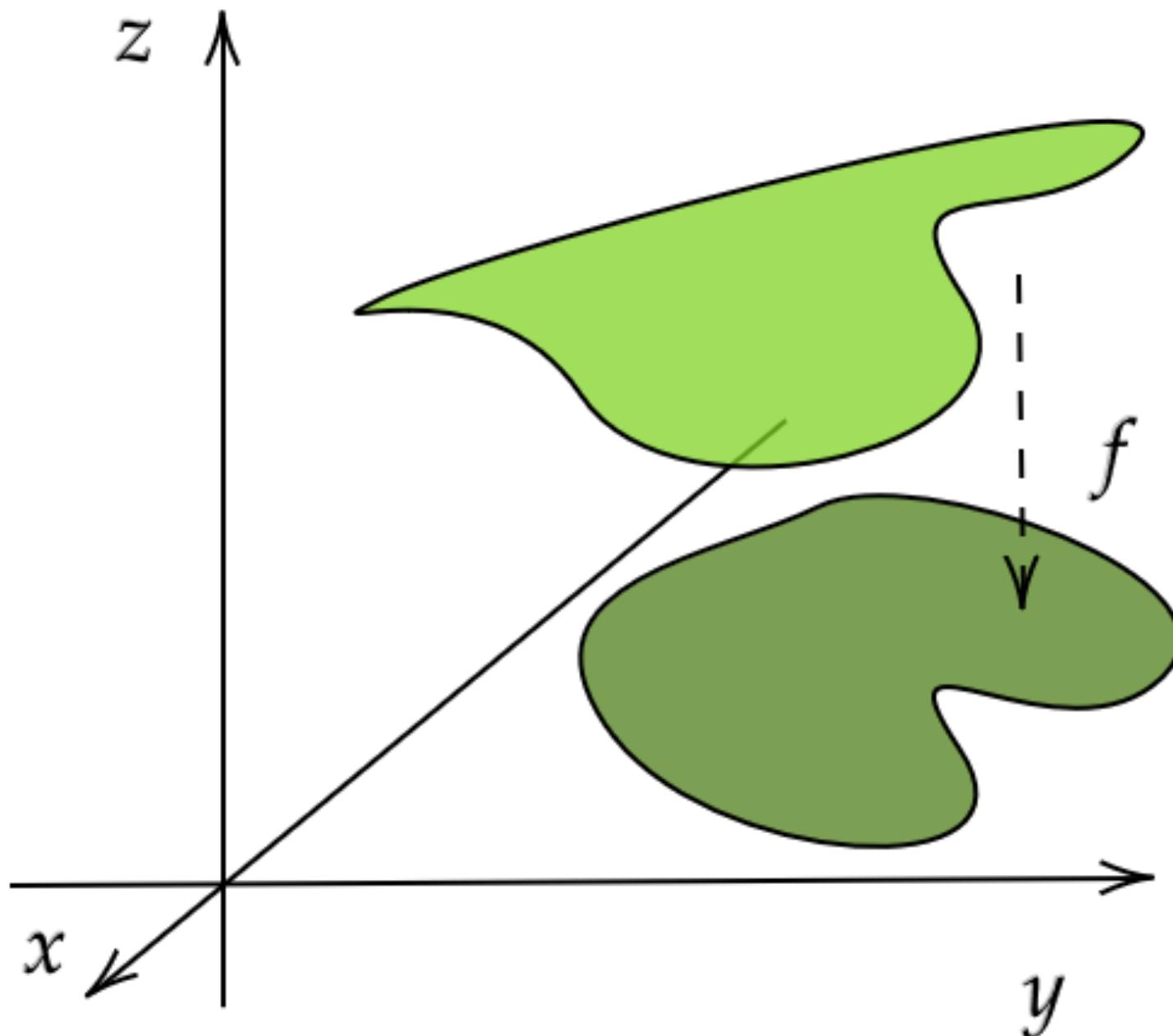
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Embeddings

- Notion of „sameness”
- Diffeomorphism that preserves the differential structure

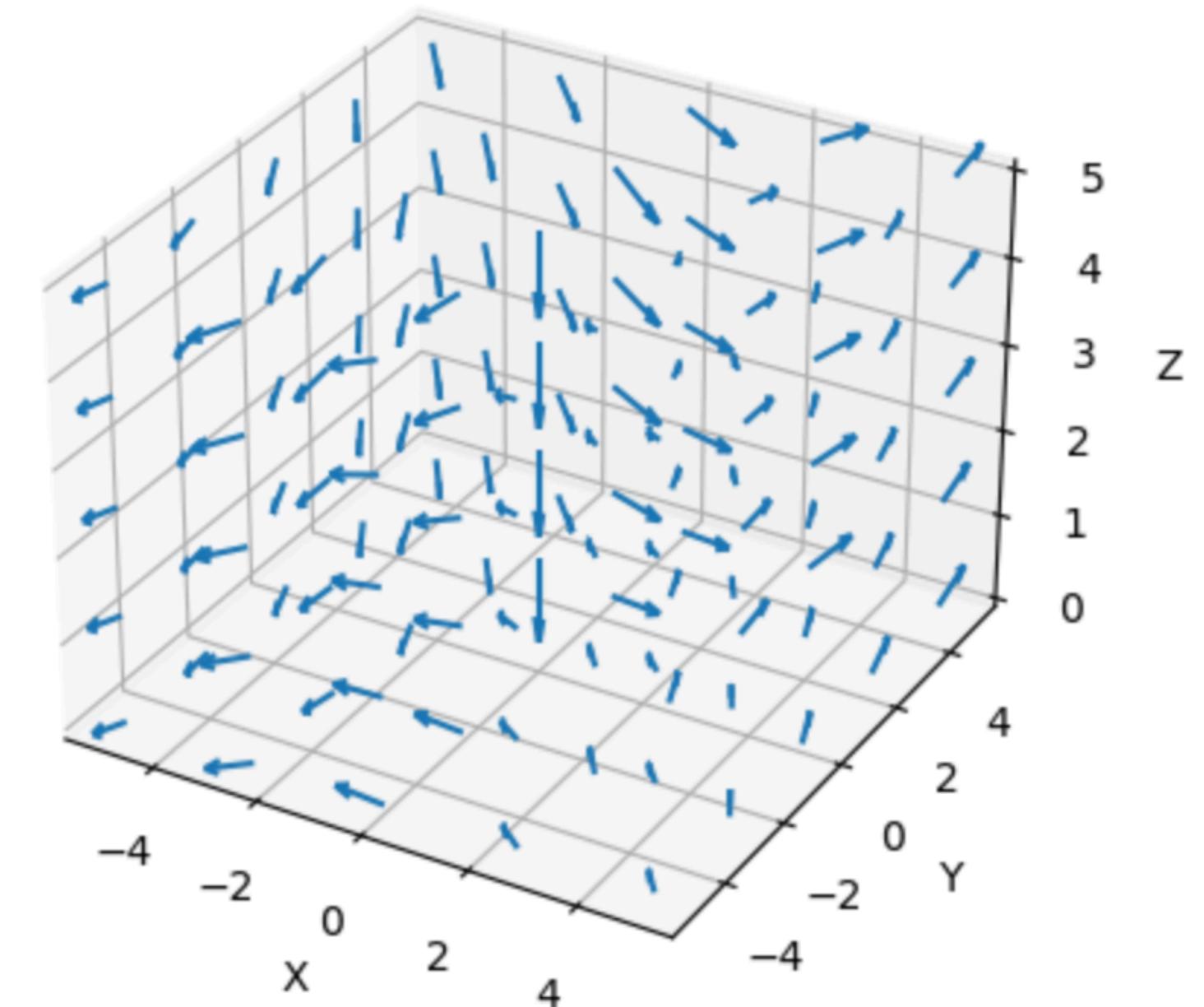
Definition: $f: M \rightarrow N$ is an embedding if:

- f is bijective onto $f(M)$
- f is differentiable
- Df_x is injective $\forall x \in M$



Takens' embedding

- Can we reconstruct the full state given partial information?
- Dynamical system $\dot{x} = f(x)$ with flow $\phi_t : M \rightarrow M, x(t) = \phi_t(x_0)$
- An observation: $h : M \rightarrow \mathbb{R}$



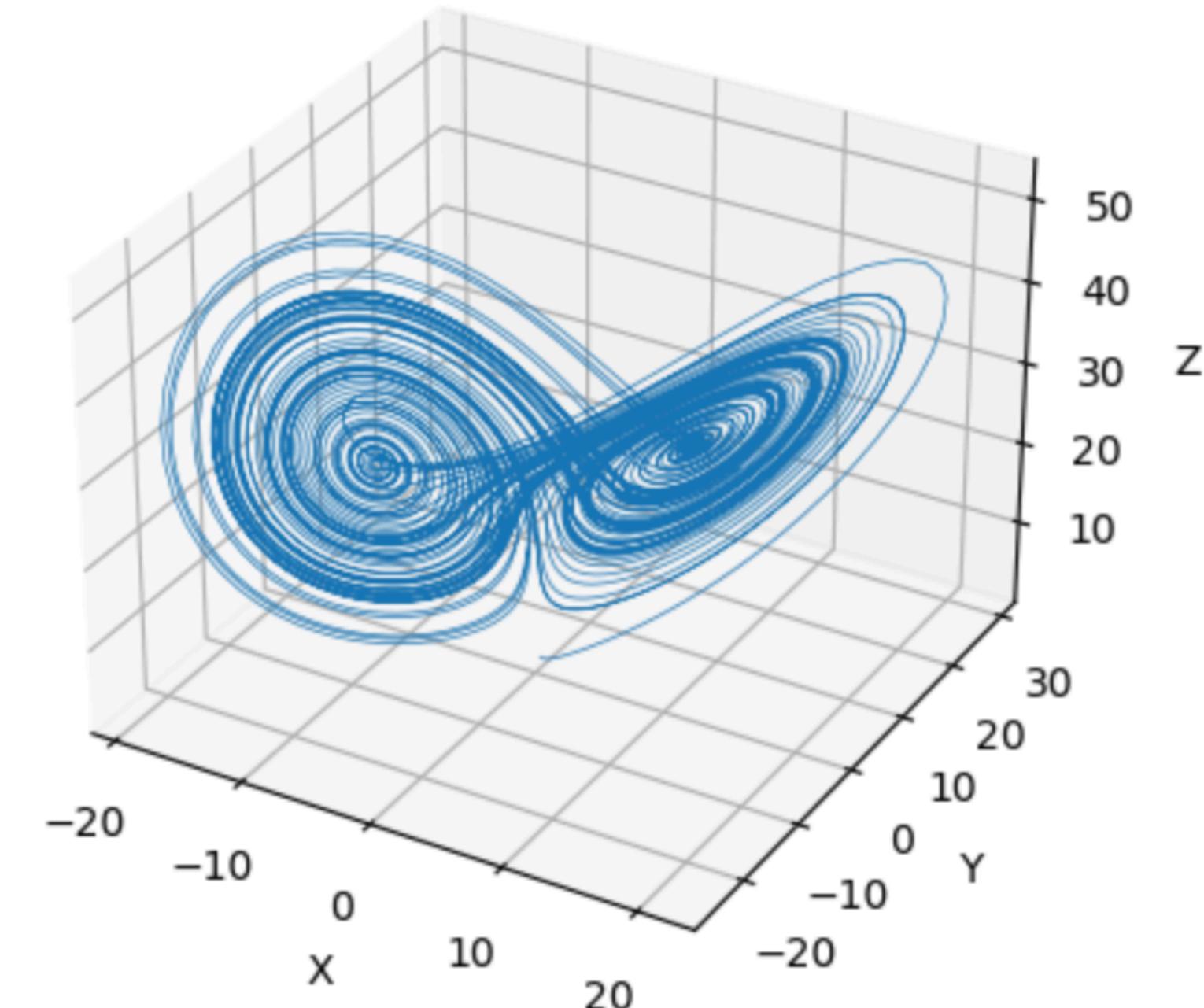
Theorem 1 If f satisfies:

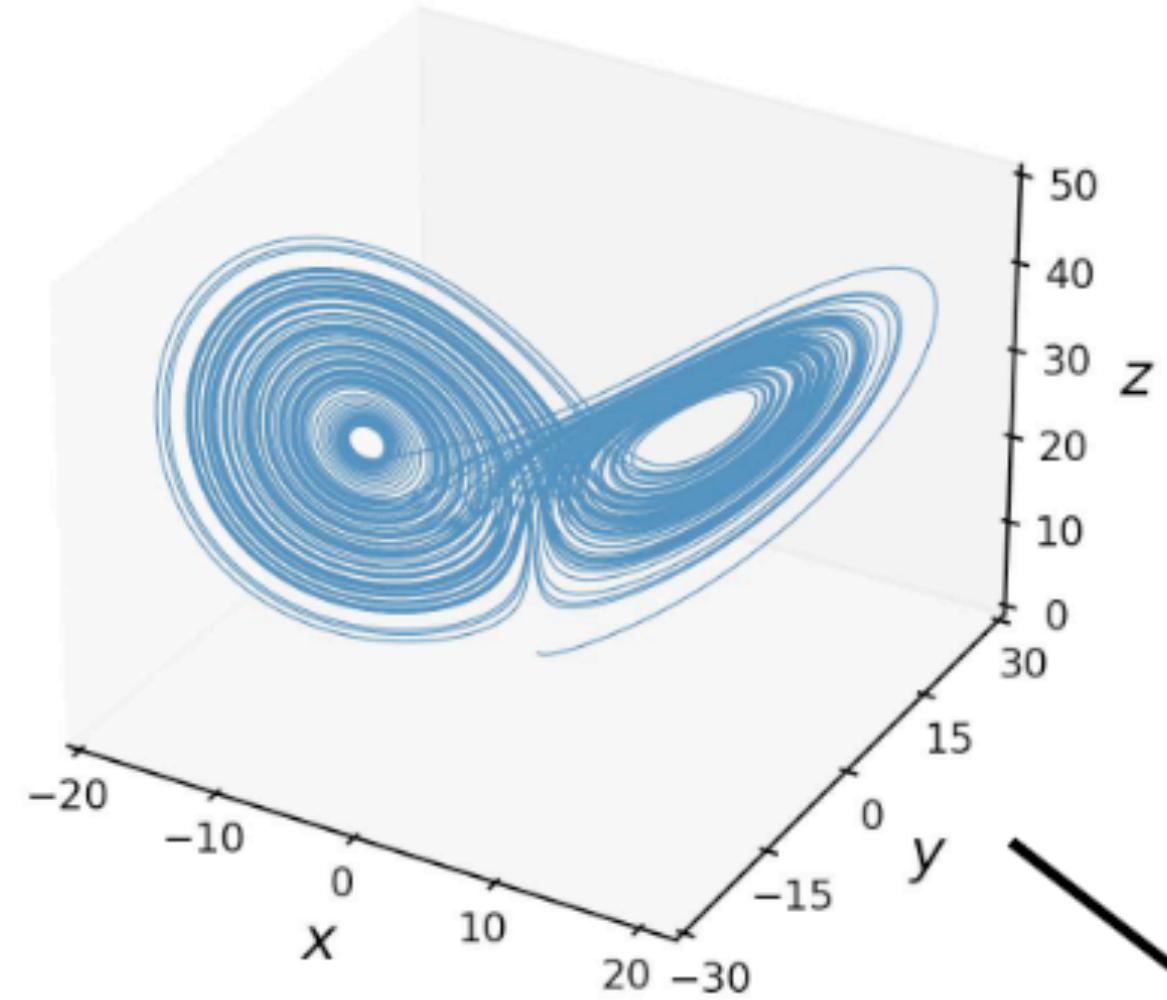
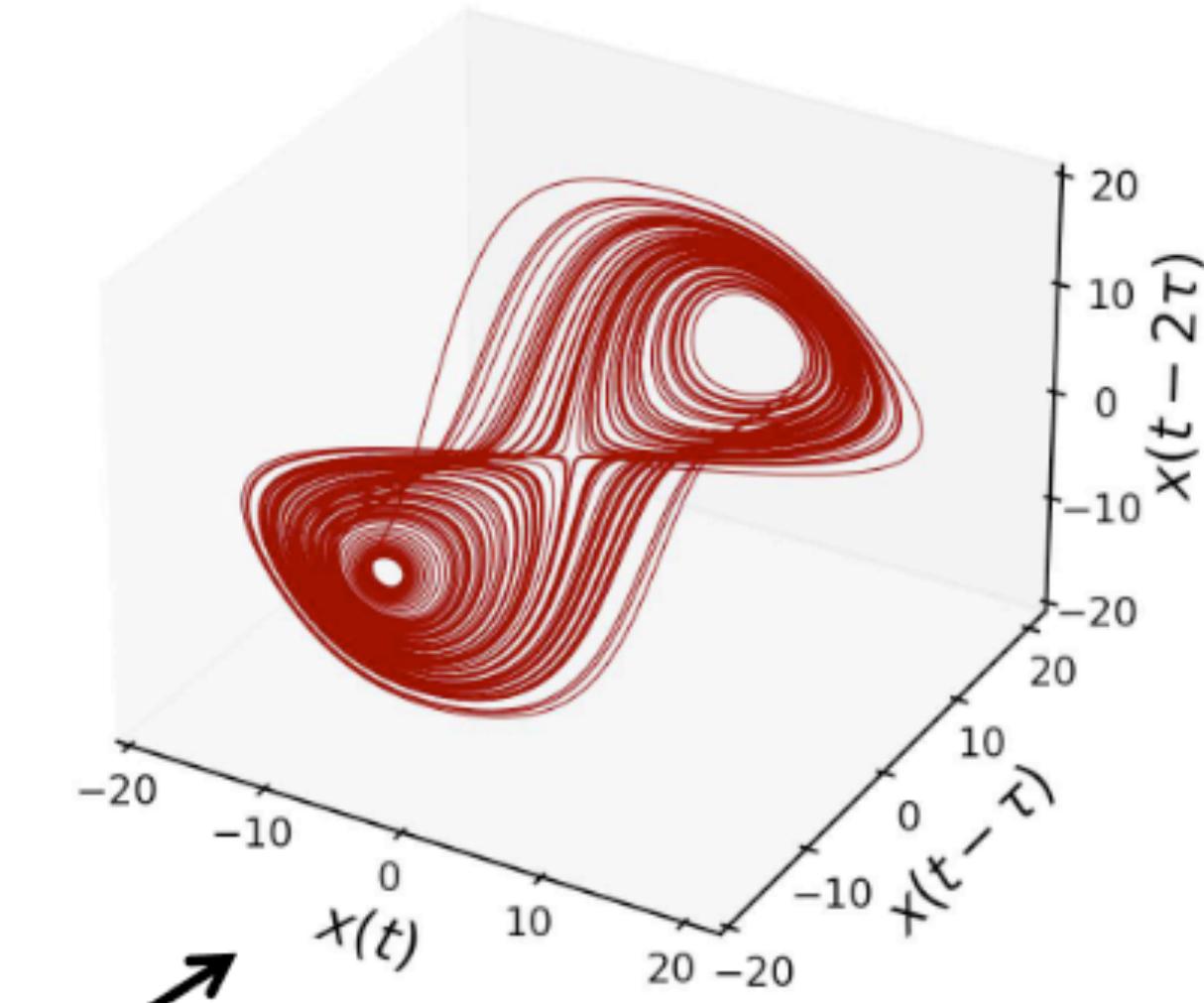
1. If $f(x) = 0$ then the eigenvalues of $d\phi_\tau|_x$ are all different and different to from 1,
2. No periodic integral curve of f has period less than $2d + 1$,

then it is a **generic property** that the **delay coordinate map** given by

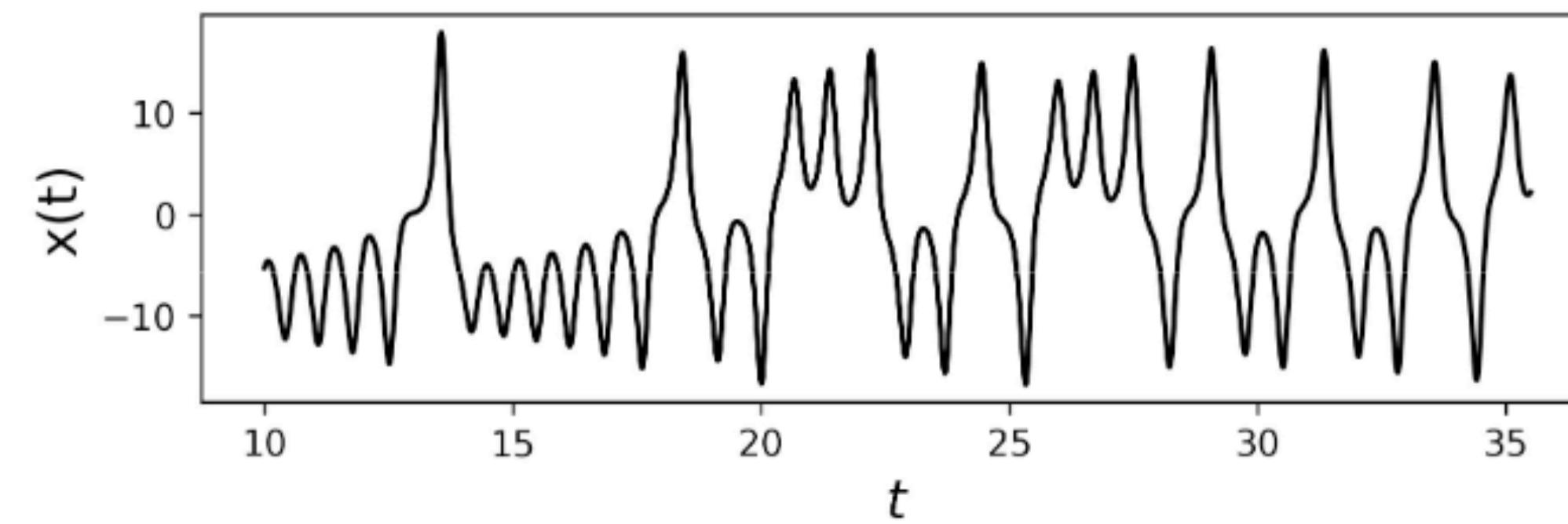
$$\Phi_{h,\phi_t}(x) := (h(x), h(\phi_\tau(x)), \dots, h(\phi_{(d-1)\tau}(x))) \in \mathbb{R}^d$$

an **embedding** of M into \mathbb{R}^d provided that $d \geq 2n + 1$.



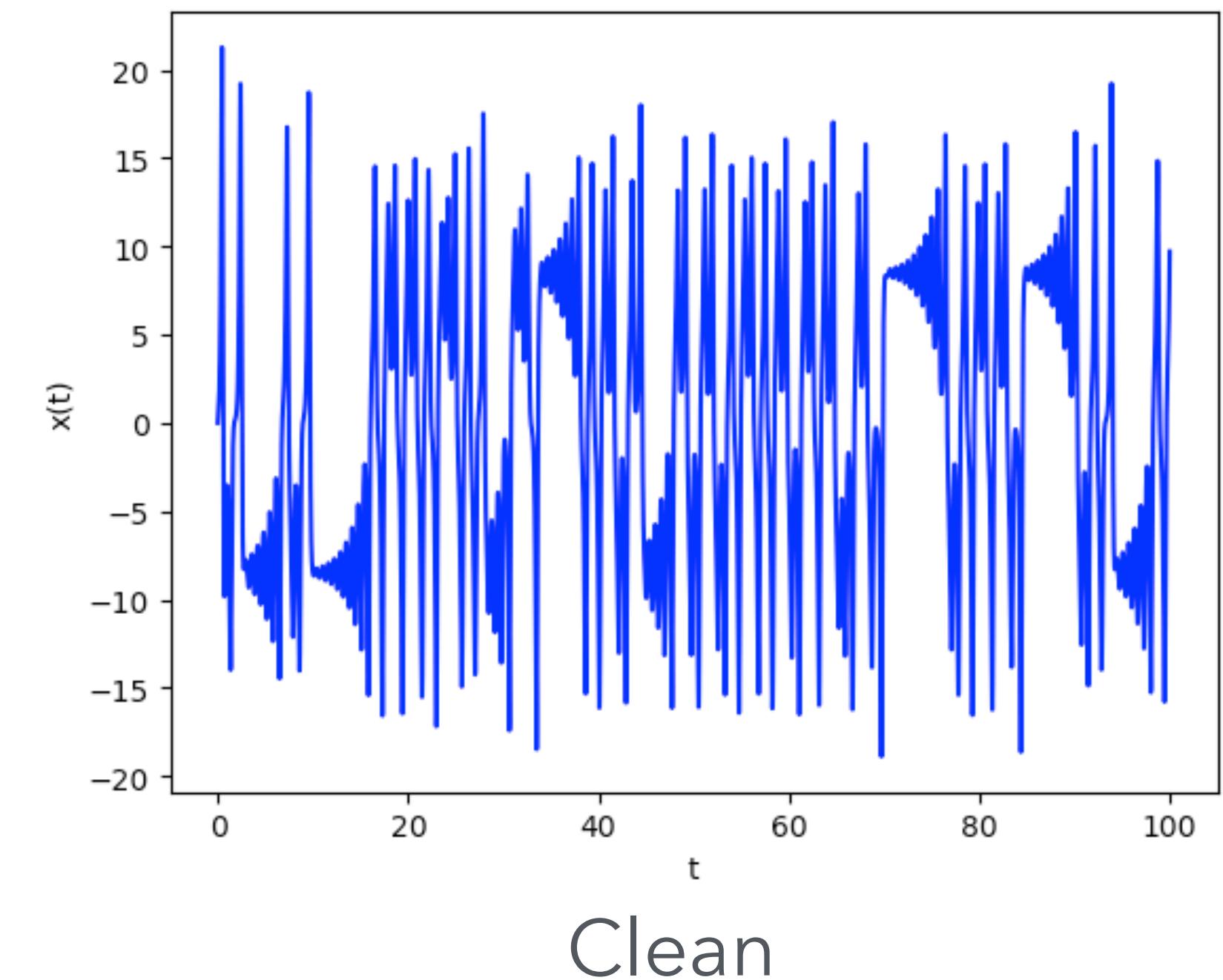
M  N  Φ Φ^{-1} $x(t)$

delay

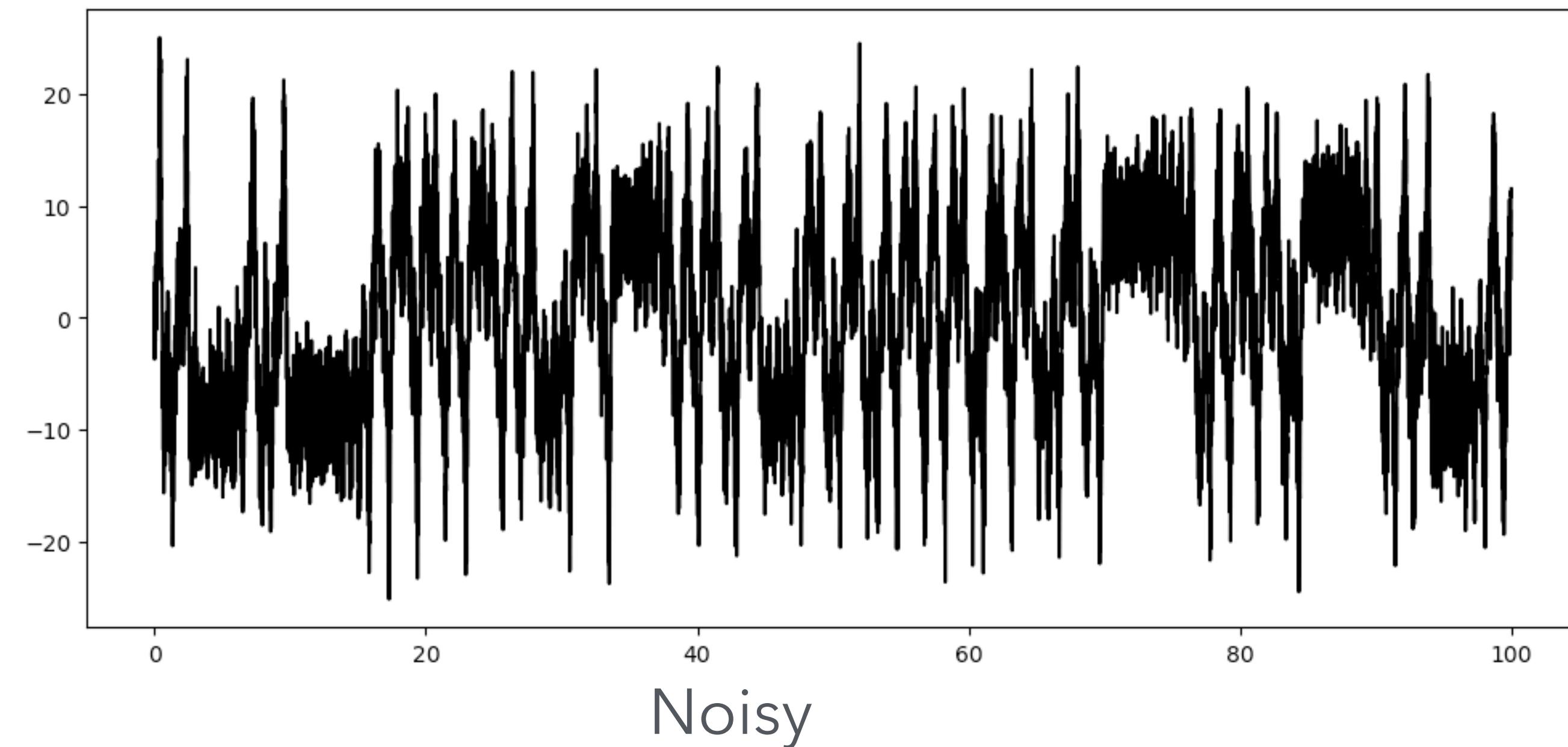


Limitations

- Takens requires clean data, deterministic setup.
- Chaos + Uncertainty in the initial position $\rho_0 \implies \phi_t \# \rho_0$
- Stochastic dynamics $\rho_t = \text{law}(X_t)$
- Noisy data $\tilde{x}_t = x_t + \mathcal{N}(0,1)$, $\rho_t = \delta_{x_t} * \mathcal{N}(0,1)$



Clean

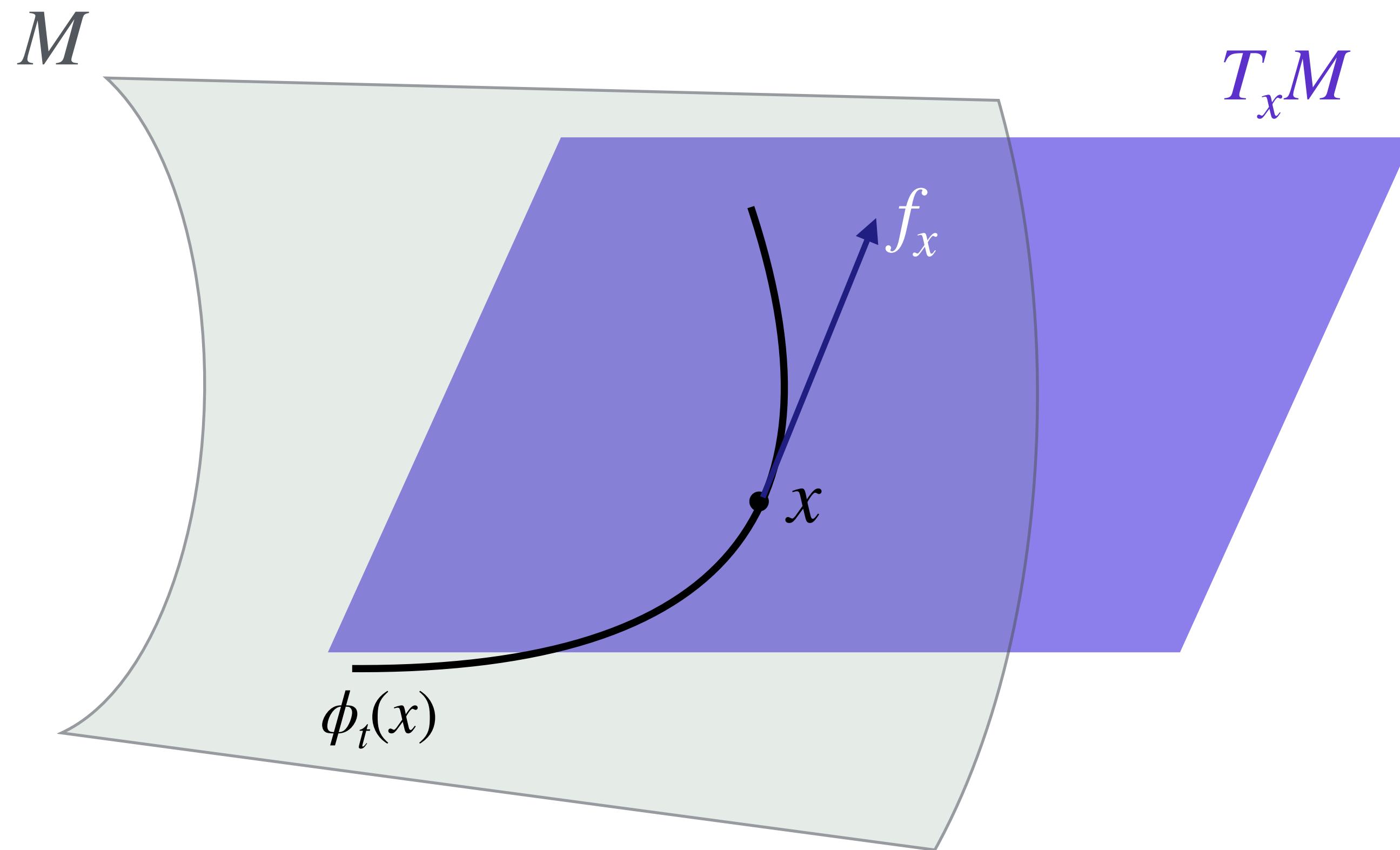


Noisy

Change of paradigm

Lagrangian	Eulerian
Manifold M	$\mathcal{P}_2(M) = \left\{ \rho, \int_M \rho = 1, \int_M x ^2 \rho < \infty \right\}$
Distance $d(x, y)$	Wasserstein metric $W_2(\rho_x, \rho_y)$
Vector field $f_x \in T_x M$	Modulo divergence free square integrable functions $v(\rho) \in L^2(TM, \rho) / \sim v \sim w \iff \nabla \cdot ((v - w)\rho) = 0$
Integral curve $\frac{d}{dt} \phi_t(x) := \dot{x} = f(x)$	Distributions solving the continuity equation $\partial_t \rho_t + \nabla \cdot (\rho_t v_t) = 0$

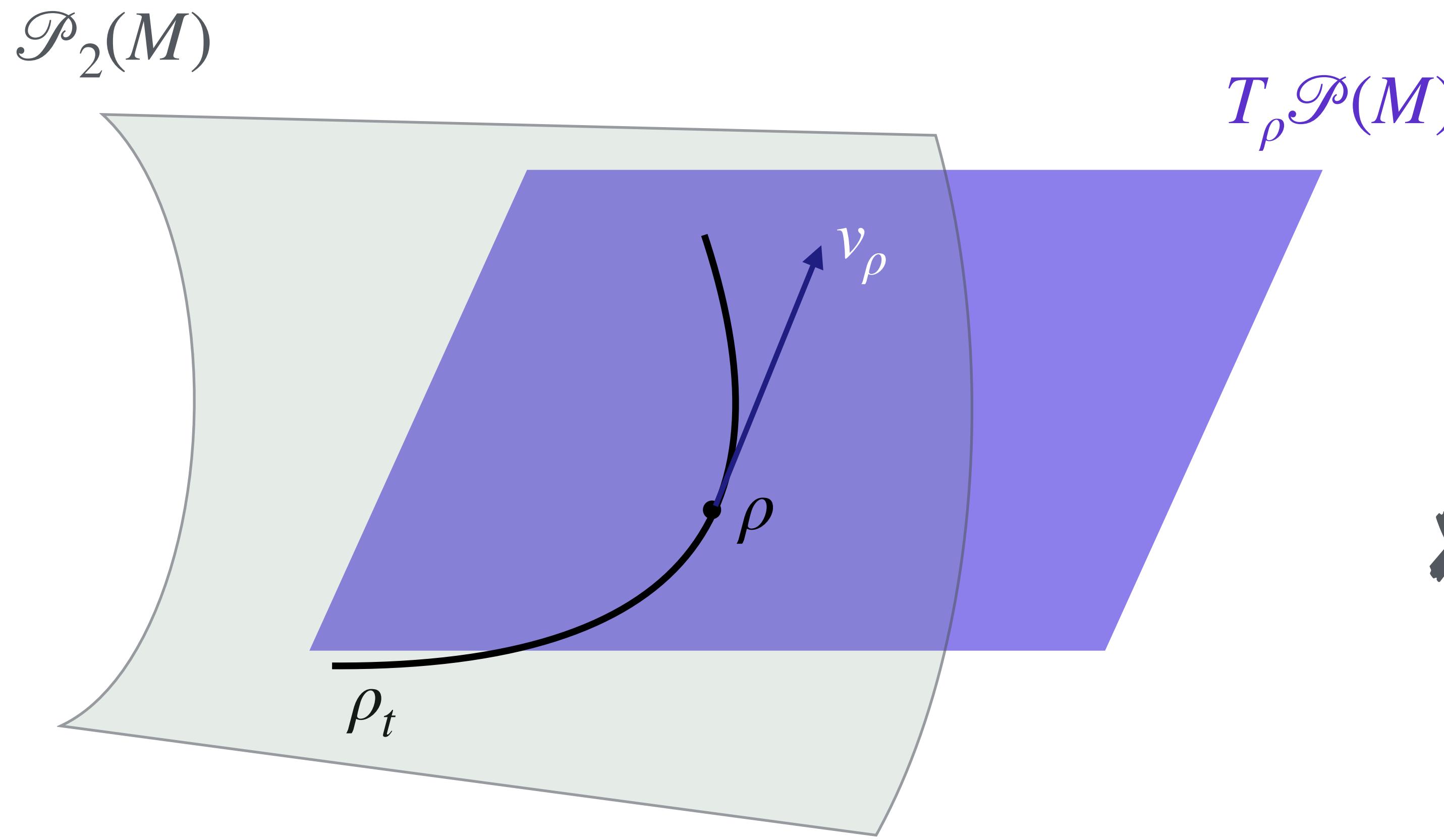
Schematic drawing



$$\frac{d}{dt} \phi_t(x) = \dot{x} = f_x$$

Schematic drawing

- If $X \sim \rho_0$ then $\Phi_t(X) = X_t \sim \rho_t$



$$\partial_t \rho_t + \nabla \cdot (\rho_t v_t) = 0 \text{ In the weak sense!!}$$

✗ Infinite dimensional
 v_ρ is a **function** for every ρ

- Many v_t satisfy the continuity equation. Project out the divergence free component!²

$$P_\rho : L^2(TM, \rho) \rightarrow T_\rho \mathcal{P}(M)$$

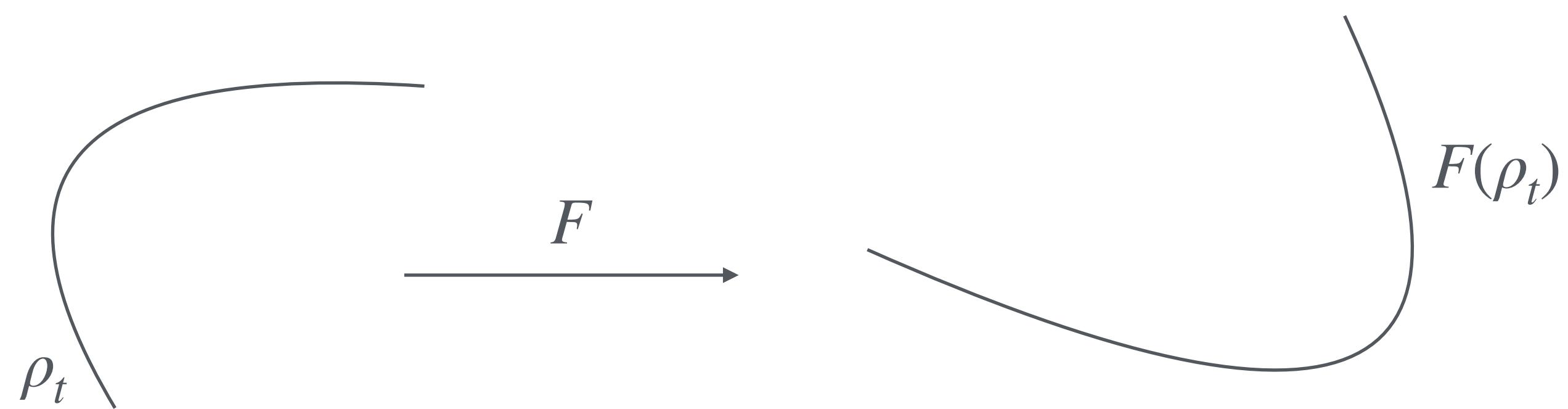
Embeddings in $\mathcal{P}_2(M)$

Definition: A map $F : \mathcal{P}(M) \rightarrow \mathcal{P}(N)$ is an embedding if

1. F is a bijection onto its image
2. F is differentiable
3. The derivative operator DF is injective i.e.

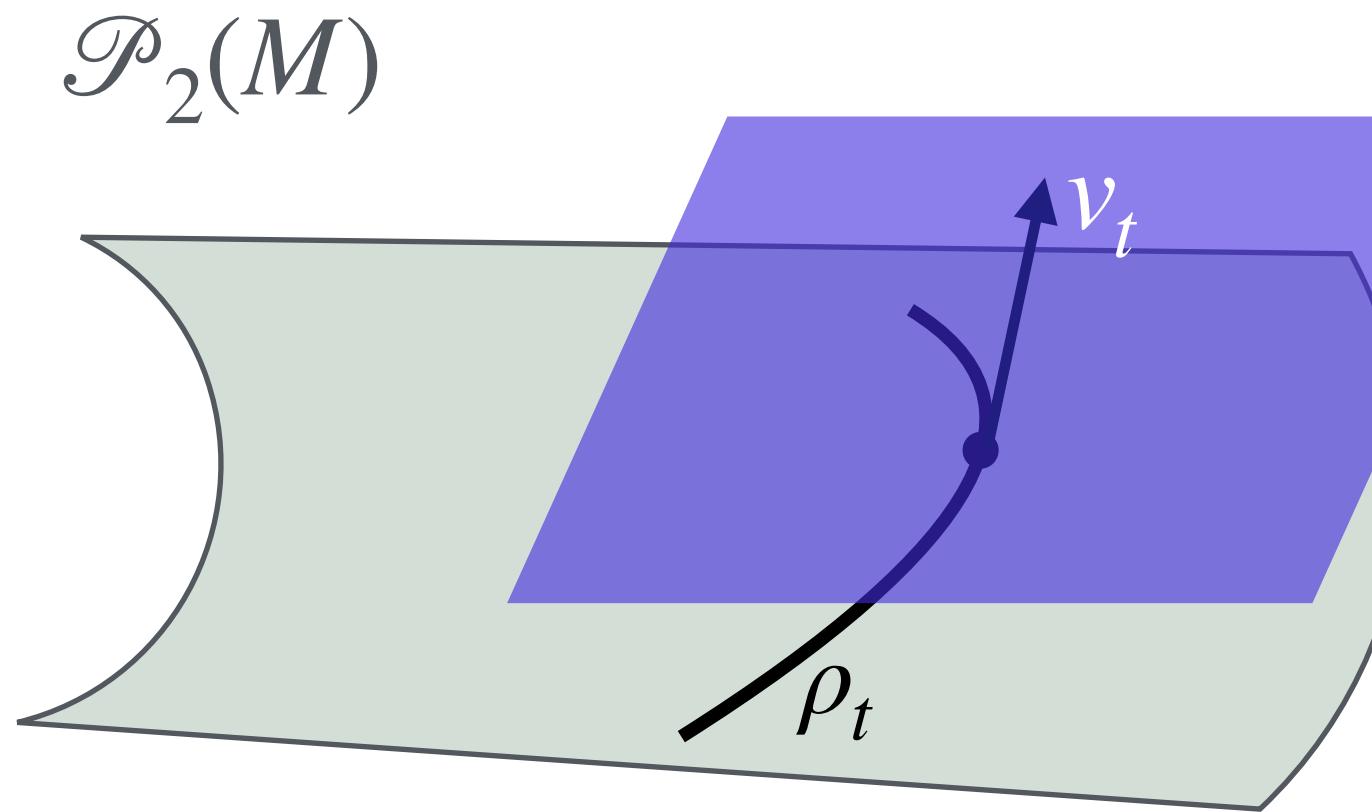
$$\forall v \neq w \in T_\rho \mathcal{P}(M), DF_\rho(v) \neq DF_\rho(w) \in T_{F(\rho)} \mathcal{P}(N)$$

- A map is differentiable if it takes differentiable curves to differentiable curves
- Differentiable \iff absolutely continuous²[Ambrogio, Gigli, Savare, Thm 8.3.1]

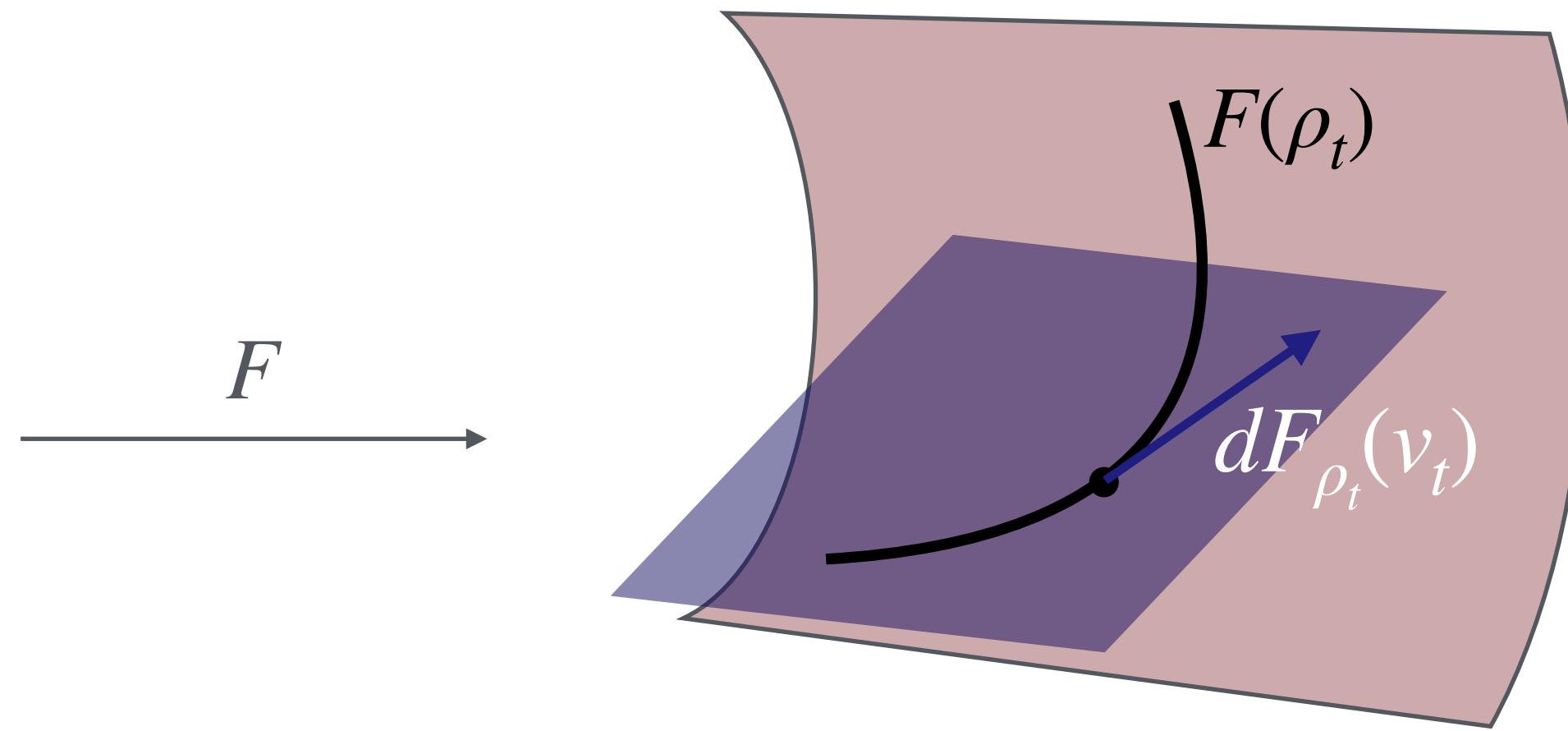


Derivative operator in $\mathcal{P}_2(M)$

$\mathcal{P}_2(N)$



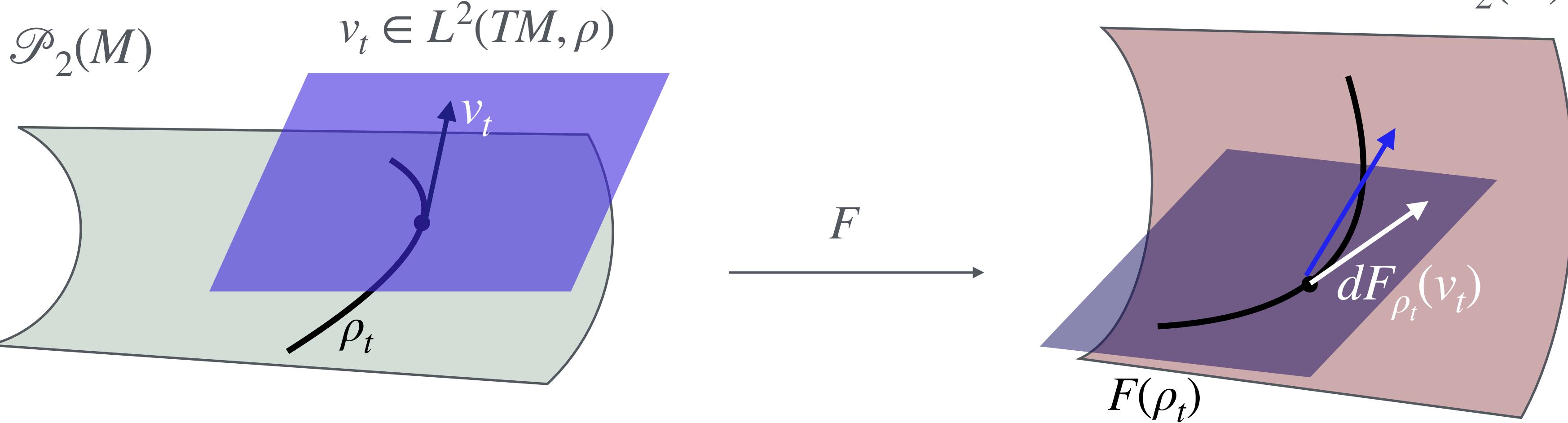
$$\partial_t \rho_t + \nabla \cdot (\rho_t v_t) = 0$$



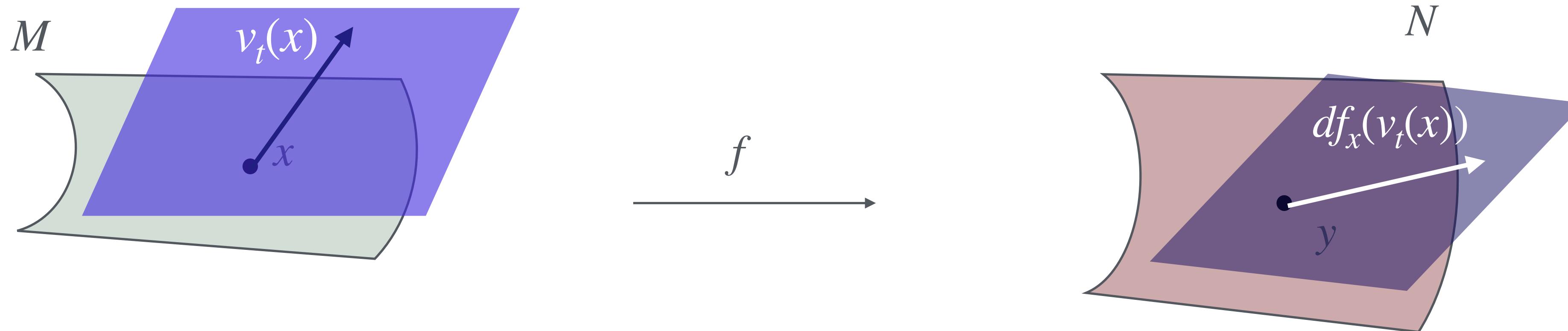
$$\partial_t F(\rho_t) + \nabla \cdot (F(\rho_t) dF_{\rho_t}(v_t)) = 0$$

- If $F = f\#$ then $y \rightarrow df_{f^{-1}(y)}v_t(f^{-1}(y))$ satisfies the continuity equation!
- Project to obtain a vector field in the tangent space $P_{F(\rho_t)}df_xv_x(x)$
- Define the derivative operator $dF_{\rho_t}(v_t)(y) = P_{F(\rho_t)}df_{f^{-1}(y)}v_t(f^{-1}(y))$

Derivative operator in $\mathcal{P}_2(M)$



$$dF_{\rho_t}(v_t) = P_{F(\rho_t)} df_{f^{-1}(\cdot)}(v_t(f^{-1}(\cdot)))$$



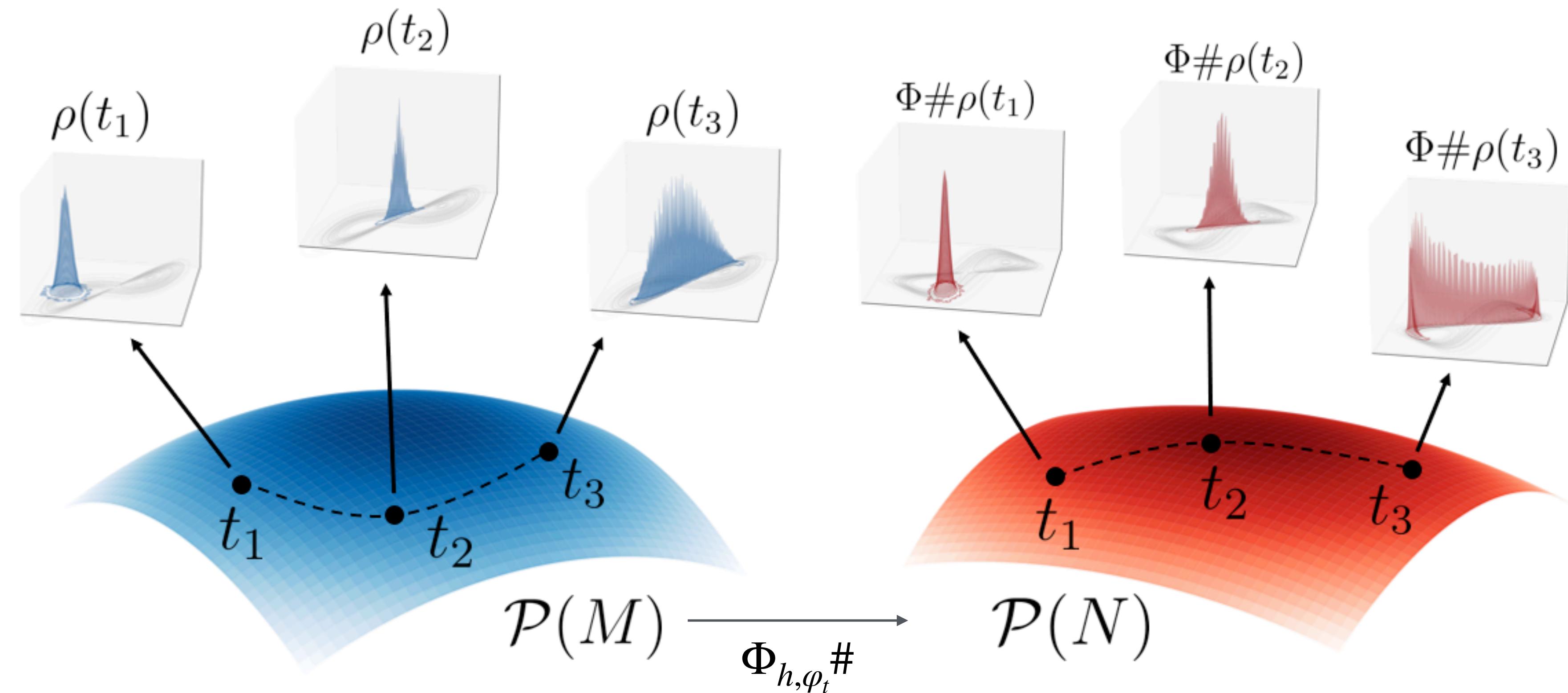
Main result

Theorem Let $f: M \rightarrow N$ be an embedding and denote by $F = f\# : \mathcal{P}_2(M) \rightarrow \mathcal{P}_2(N)$ its push-forward. Then F is an embedding with respect to the Wasserstein geometry.

- Explicit formula between df and $dF \implies$ Properties of f can be lifted to F

Lifted Takens Embedding

Corrolary: Let $\phi_t : M \rightarrow M$ be a dynamical system satisfying Takens conditions. Let $\Psi_{h,\phi_t} := \Phi_{h,\phi_t} \#$. Then if $d \geq n + 1$ it is a generic property that Ψ_{h,ϕ_t} is an embedding of $\mathcal{P}(M)$ to $\mathcal{P}(\mathbb{R}^d)$.



Numerical implementation

- Goal: Learn the reconstruction map i.e. Φ^{-1} from samples $\{x_i, \Phi(x_i)\}_{i=1}^N$
- Parametrize Φ^{-1} by a neural network R_θ
- Method 1: Point-wise matching $\arg \min_{\theta} \sum_{i=1}^N \|x_i - R_\theta(\Phi(x_i))\|_2^2$
- Method 2: Measure based reconstruction $\arg \min_{\theta} \sum_{i=1}^M \mathcal{D}(\mu_i, R_\theta \# \Phi \# \mu_i)$

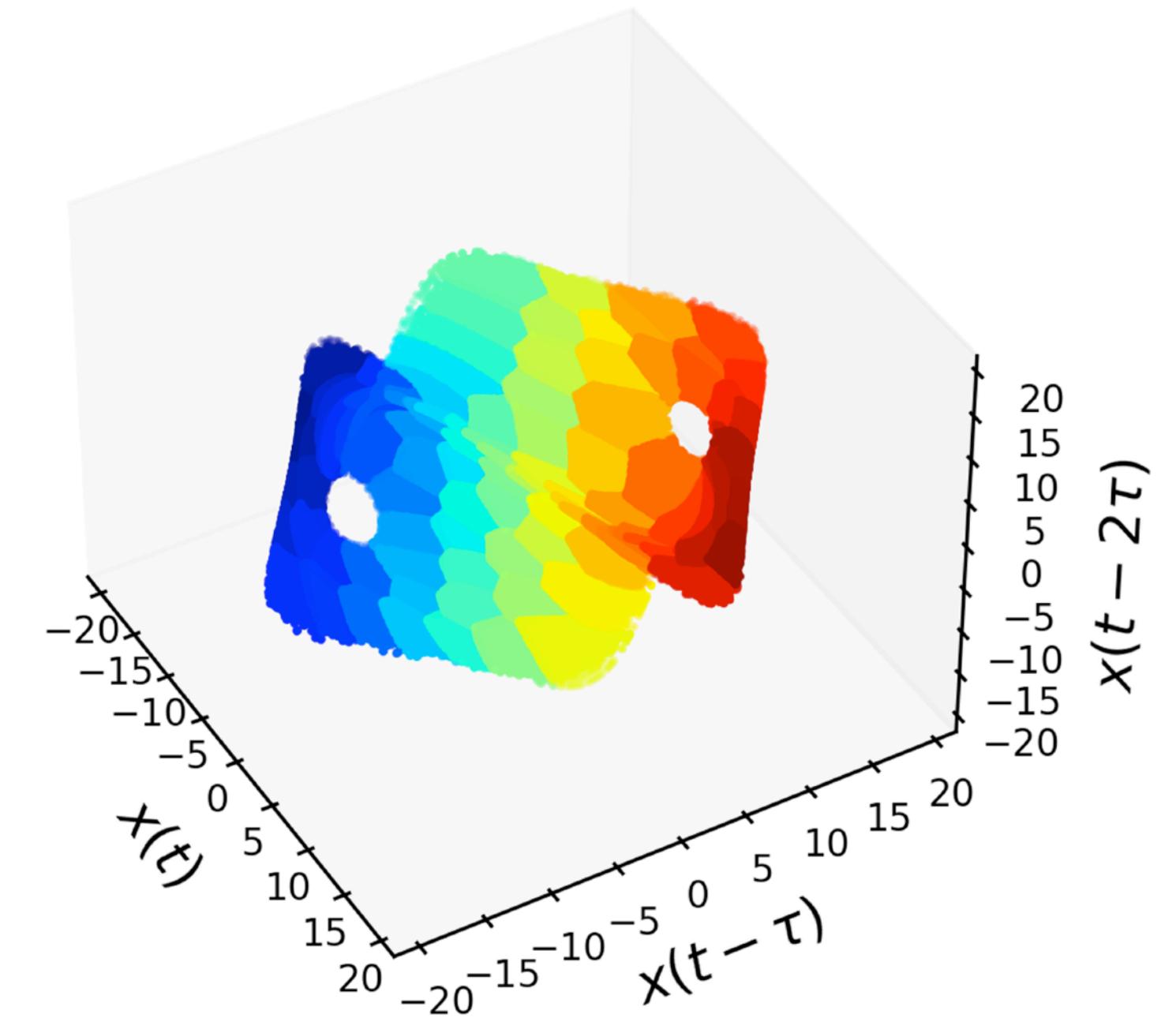
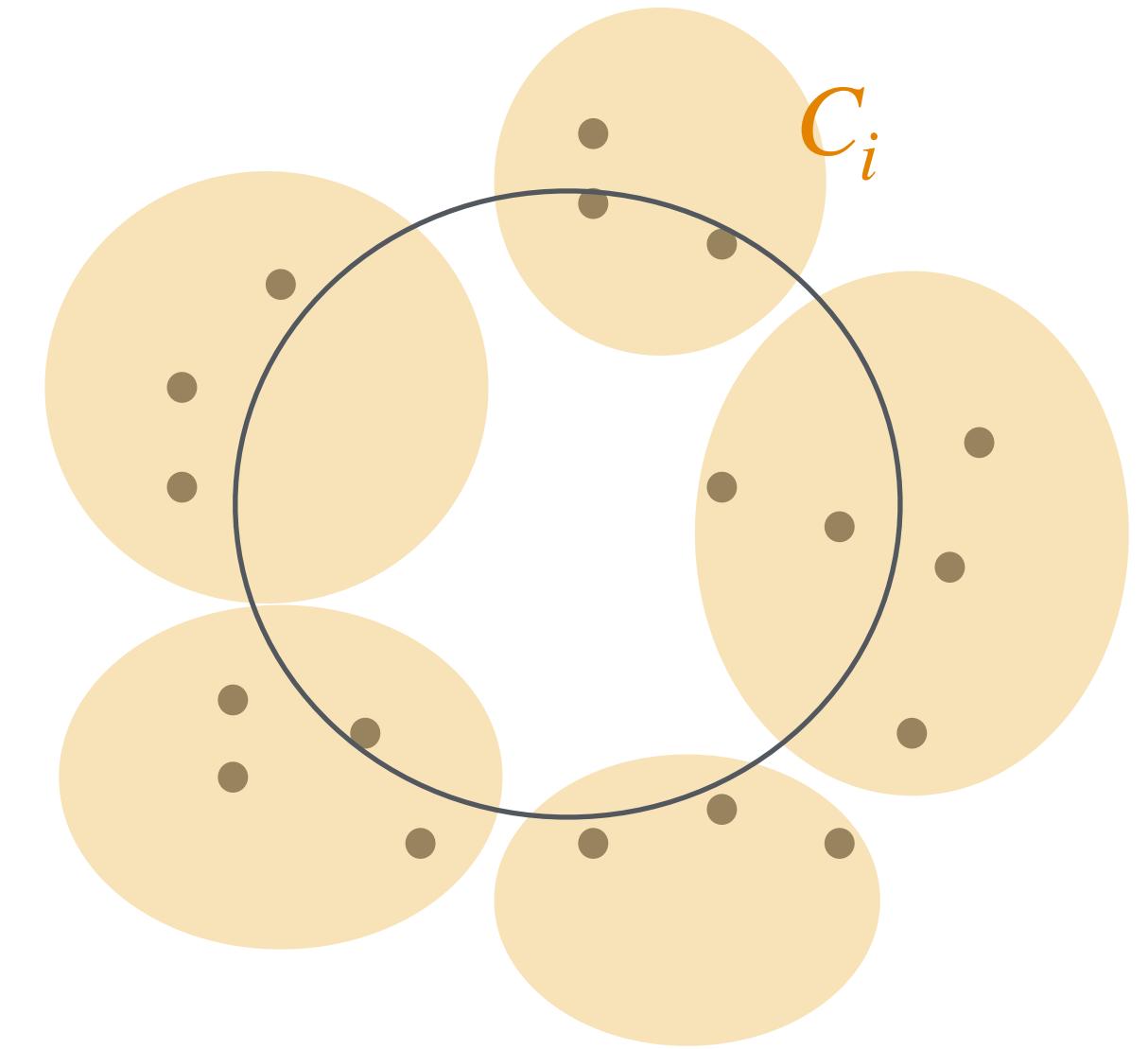
\mathcal{D} = maximum mean discrepancy

The measures μ_i are obtained from a long trajectory by partitioning into Voronoi cells $\implies \mu_i = \mu | C_i$

Numerical implementation

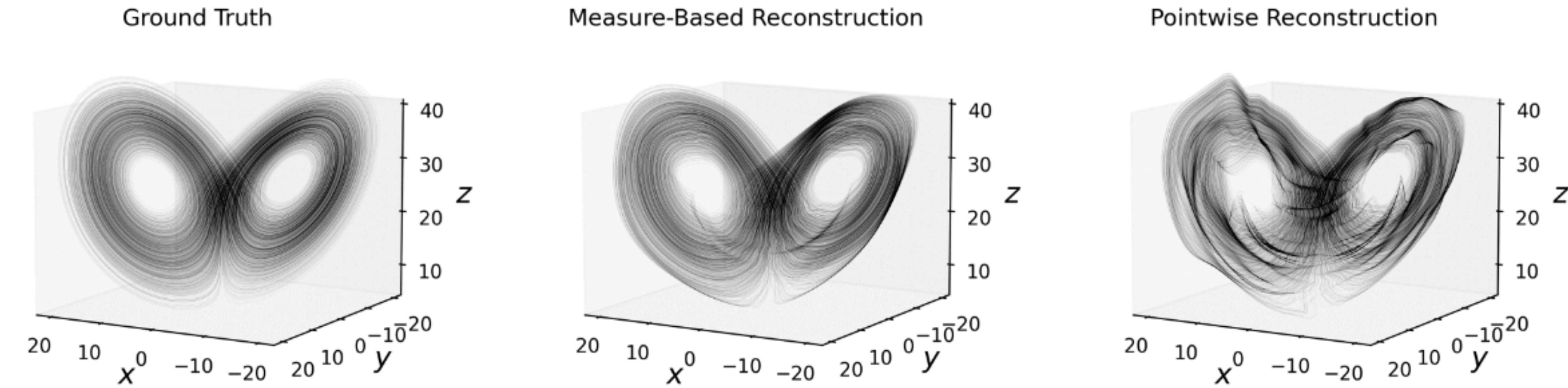
Method 2: Measure based reconstruction $\arg \min_{\theta} \sum_{i=1}^M \mathcal{D}(\mu_i, R_\theta \# \Phi \# \mu_i)$

- Partition domain into $\{C_i\}_{i=1}^M$
- Empirical distribution conditioned on the cell $\mu_i \sim \sum_{x_j \in C_i} \delta_{x_j}$
- As diameter of $C_i \rightarrow 0$ we obtain Method 1
- Works with different data assumptions

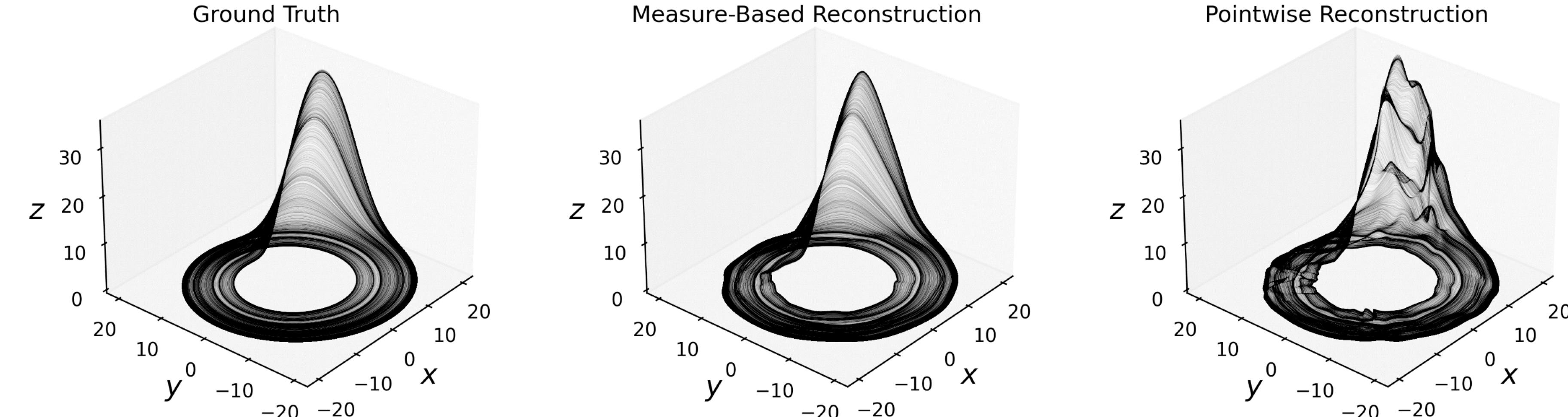


Numerical Results

Lorentz system



Roessler system



Thank you for your attention!

Contact me: mao237@cornell.edu

References: ¹ Floris Takens. Detecting strange attractors in turbulence. In *Dynamical Systems and Turbulence*, Warwick 1980, pages 366-381. Springer, 1981

²Luigi Ambrosio, Nicola Gigli, and Giuseppe Savare. *Gradient Flows in Metric Spaces and in the Space of Probability Measures*. Birkhaeuser Verlag, 2005.

³Jonah Botvinick-Greenhouse, Maria Oprea, Yunan Yang and Romit Maulik, *Measure-Theoretic Takens' Time-Delay Embedding:Analysis and Application*, preprint, 2024

Supplimental slides/figures

- Error in the attractor reconstruction

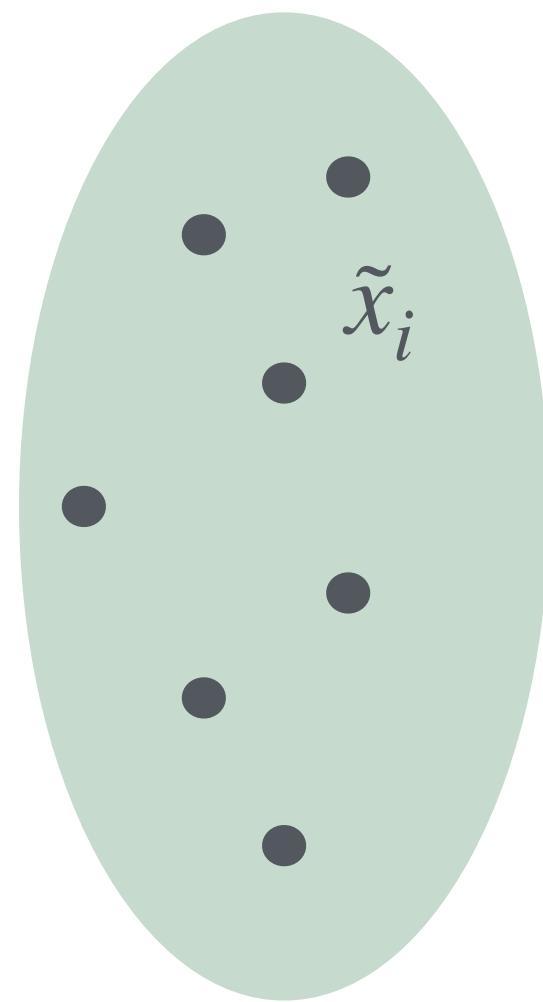
System	Pointwise MSE	Measure MSE
Lorenz	7.15×10^{-1}	2.84×10^{-1}
Rössler	3.99×10^{-1}	8.34×10^{-2}
Lotka–Volterra	2.10×10^{-4}	9.45×10^{-5}

- Steps of the proof:
 - Show that $F(\rho_t)$ is absolutely continuous if ρ_t is
 - Show that $F(\rho_t)$ satisfies the continuity equation if ρ_t also satisfies I, with velocity field given by $DF(v_t)(y) = w_t(y) := df_{f^{-1}(y)}v_t(f^{-1}(y))$ projected onto the tangent space
 - Show that the derivative is injective i.e. $\exists \varphi$ s.t. $\int_M \langle \nabla \varphi(x), DF(v_t)(x) - DF(v'_t)(x) \rangle d\rho(x) \neq 0.$

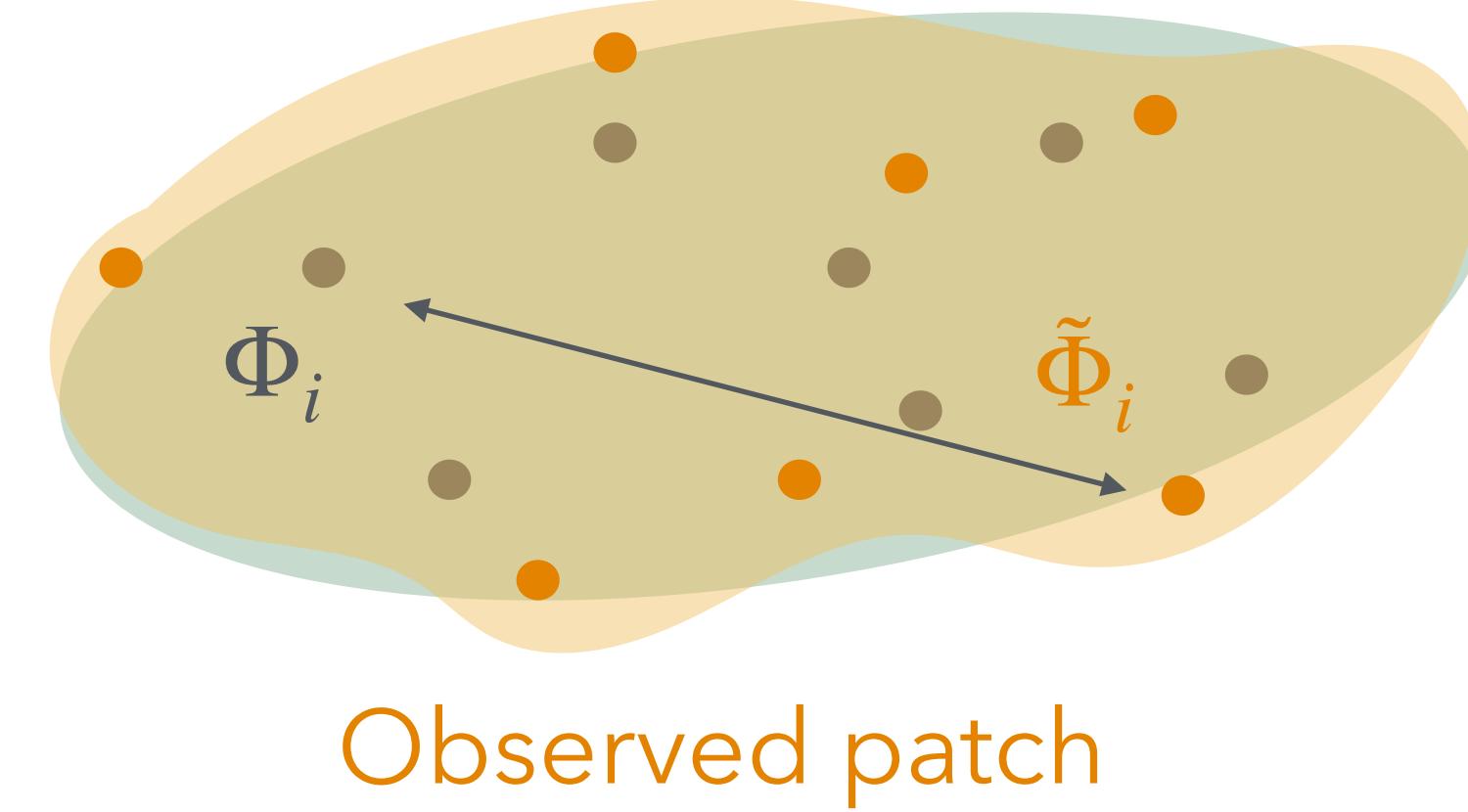
(They can only differ by a divergence free component)

- Observe $\tilde{x}_i = x_i + \epsilon_i$ then $\tilde{x}_i \sim \rho_i$
- Noisy data $\{\tilde{x}_i\} \implies$ smooth curve in $\rho_t \in \mathcal{P}_2(M)$

Patch in M



Corresponding patch in \mathbb{R}^d



- Want to minimize the distance $\mathcal{D}(\mu_C, R\#\Phi\#\mu_C)$. Instead we minimize $\mathcal{D}(\mu_C, R\#\tilde{\Phi}_C)$.
But the error is smaller than when minimizing the point wise distance