



# Universal Joint Approximation of Manifolds and Densities by Simple Injective Flows

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If for  $\ell = 1, \dots, L$ ,  $n_\ell \in \mathbb{N}$ ,

1.  $\mathcal{T}_\ell^{n_\ell} \subset C(\mathbb{R}^{n_\ell}, \mathbb{R}^{n_\ell})$  is a flow network,
2.  $\mathcal{R}_\ell^{n_{\ell-1}, n_\ell} \subset C(\mathbb{R}^{n_{\ell-1}}, \mathbb{R}^{n_\ell})$  is an injective ReLU layer,

then

$$\mathcal{E} = \mathcal{T}_L^{n_L} \circ \mathcal{R}_L^{n_{L-1}, n_L} \circ \dots \circ \mathcal{T}_1^{n_1} \circ \mathcal{R}_1^{n_0, n_1} \circ \mathcal{T}_0^{n_0}$$

is always a family of injective mappings, where

$$\mathcal{H} \circ \mathcal{G} := \{h \circ g : h \in \mathcal{H}, g \in \mathcal{G}\}.$$



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When are these networks universal approximators?

# Embedding Gap



We call a function  $f$  an embedding and denote it by  $f \in \text{emb}(X, Y)$  if  $f : X \rightarrow Y$  is continuous, injective, and  $f^{-1} : f(X) \rightarrow X$  is continuous.

## Definition (Embedding Gap)

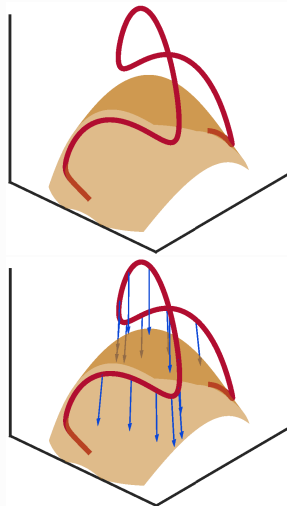
If,

- ▶  $K \subset \mathbb{R}^n$  and  $W \subset \mathbb{R}^o$ , both compact,
- ▶  $f \in \text{emb}(K, \mathbb{R}^m)$ , and  $g \in \text{emb}(W, \mathbb{R}^m)$

then we define

$$B_{K,W}(f, g) = \inf_{r \in \text{emb}(f(K), g(W))} \|I - r\|_{L^\infty(f(K))}$$

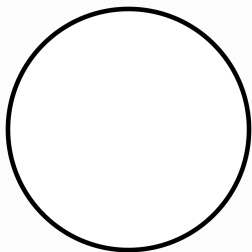
where  $I : f(K) \rightarrow f(K)$  is the identity function.



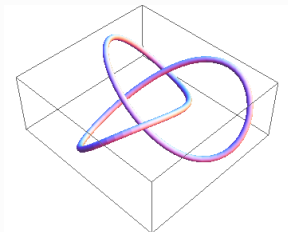
# Non-approximable single-chart manifold



Let  $K = S^1$  be a circle, and  $f \in \text{emb}(K, \mathbb{R}^3)$  an embedding of a trefoil knot into  $\mathbb{R}^3$ . There are no  $E \in \mathcal{E} := \mathcal{T} \circ \mathcal{R}$  so that  $E(K) = f(K)$ .



(a)  $K = S^1$



(b) Trefoil knot embedded in  $\mathbb{R}^3$ .

The trivial and trefoil knots are not equivalent.



## Definition (Extendable Embedding)

With the above topological difficulty in mind, we define the set of extendable embeddings as

$$\mathcal{I}(\mathbb{R}^n, \mathbb{R}^m) := \{\Phi \circ R \in C(\mathbb{R}^n, \mathbb{R}^m) : R \in C(\mathbb{R}^n, \mathbb{R}^m), \Phi \in \mathbb{R}^m \rightarrow \mathbb{R}^m\}.$$

where  $R$  is linear full-rank, and  $\phi$  is a  $C^1$ -smooth diffeomorphism.

## Theorem (P. et al. 2022)

*When  $m \geq 3n + 1$  and  $k \geq 1$ , for any  $C^k$  embedding  $f \in \text{emb}^k(\mathbb{R}^n, \mathbb{R}^m)$  and compact set  $K \subset \mathbb{R}^n$ , there is a map in the closures of the flow type neural network  $E \in \mathcal{I}^k(\mathbb{R}^n, \mathbb{R}^m)$  such that  $E(K) = f(K)$ . Moreover,*

$$\mathcal{I}^k(K, \mathbb{R}^m) = \text{emb}^k(K, \mathbb{R}^m)$$



Let  $\mathcal{F} = \text{emb}(K, \mathbb{R}^m)$ , or  $\mathcal{F} = \mathcal{I}(K, \mathbb{R}^m)$ .

## Theorem (P. et al. 2022)

Let  $\mu \in \mathcal{P}(K)$  be an absolutely continuous measure w.r.t. Lebesgue measure and

1.  $\mathcal{R}_\ell^{n_\ell-1, n_\ell}$  is injective,
2.  $\mathcal{T}_\ell^{n_\ell}$  is injective, universal approximator of diffeomorphisms,
3.  $\mathcal{T}_0^n$  is distributionally universal and injective

Then, there is a sequence of

$\{E_i\}_{i=1, \dots, \infty} \subset \mathcal{E} := \mathcal{T}_L^{n_L} \circ \mathcal{R}_L^{n_L-1, n_L} \circ \dots \circ \mathcal{R}_1^{n_0, n_1} \circ \mathcal{T}_0^{n_0}$  such that

$$\lim_{i \rightarrow \infty} W_2(F_{\#}\mu, E_i\#\mu) = 0.$$

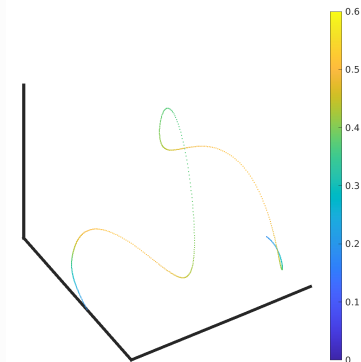


Optimality of layers of these deep neural networks can be established layer-by-layer.



Consider the problem of learning  $\nu = f_{\#}\mu$  the following 1 dimensional distribution embedded in  $\mathbb{R}^3$  with a network of the form

$$F_{\theta}(x) = T_2 \circ R_2 \circ T_1 \circ R_1 \circ T_0(x)$$



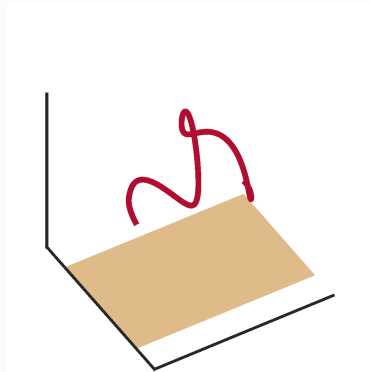
# Decoupling: Step one



First, we can update  $T_2 \circ R_2$  to decrease

$$B_{K,W}(f, T_2 \circ R_2)$$

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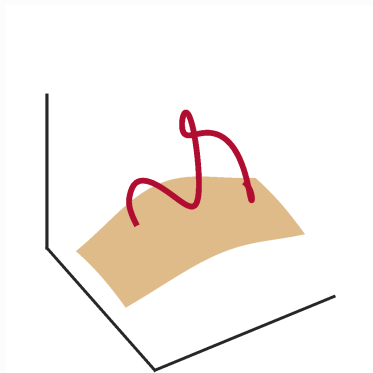
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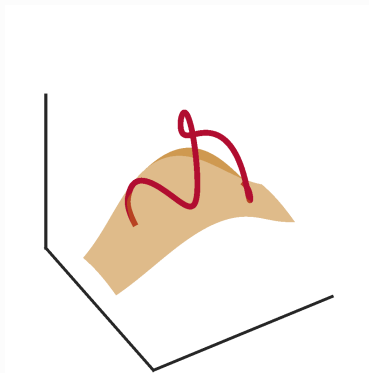
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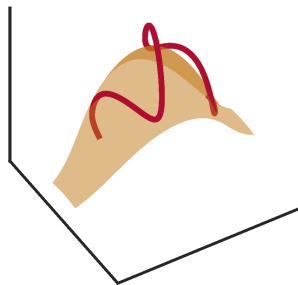
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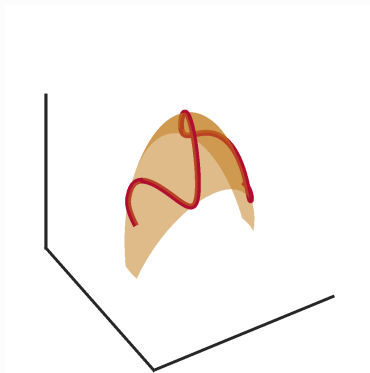
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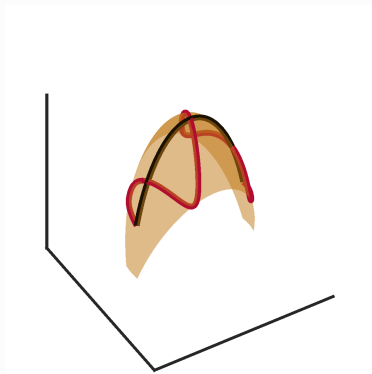
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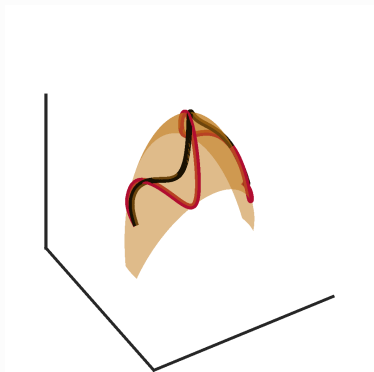
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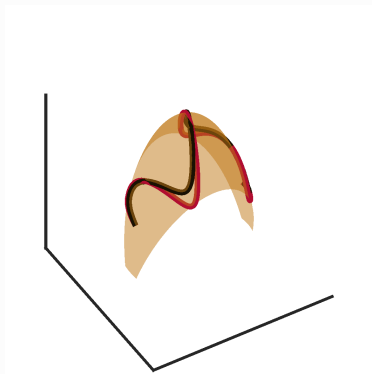
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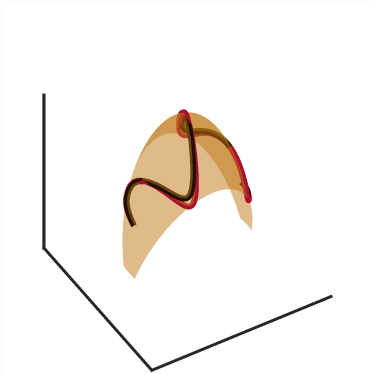
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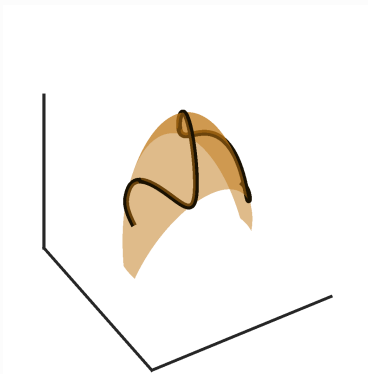
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