# Analysis of the Generalization Properties and the Function Spaces Associated with Two-Layer Neural Network Model

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2023 Apr 11

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# Why neural networks (NN) excel across domains

- Image and video processing, segmentation
- Time series methods, NLP
- Generative models

Even simplest one are very capable! Two-layer neural network (2NN)

#### These are not new problems in computational mathematics

- Image classification: approximating function
- Generative models: approximating and sampling distribution with finite samples
- Go game: solving differential and difference equations

The major difference is **dimensionality** d!

d for a RGB image  $(512 \times 512) = 3 \times 512 \times 512 = 786,432$ 

#### These are not new problems in computational mathematics

Given observed data x, y, often with noise in practical cases.

Find the target function  $f_{True}: x \rightarrow y$ 

- y: labels in classification task
- y: response in most prediction tasks.

# Curse of dimensionality

#### Definition

For a specified accuracy  $\epsilon>0$ , the number of parameters to satisfy is growing exponentially.

To reduce the error by a factor of 10, we need to increase m by a factor of  $10^d$ . Holds for all classical algorithms, e.g. approximating functions using polynomials, trigonometric polynomials or wavelets.

#### 2NN: a special class of functions

$$f(x) = \sum_{j=1}^{n} a_j \sigma(b_j \cdot x + c_j)$$

where  $a_j, c_j \in \mathbb{R}, b_j \in \mathbb{R}^d$  and  $\sigma$  is the activation function.

#### Common activation functions:

- sigmoid:  $\sigma(z) = \frac{1}{1+e^{-z}}$ 
  - ReLU,  $\sigma(z) = \max\{z, 0\}$
  - ...

# Two main problems in approximation by NN (2NN)

- $\bullet$  density: the conditions where  $f_{target}$  can be approximated arbitrarily well
- $\bullet$  complexity: how "large" are necessary to give a prescribed degree of approximation  $\epsilon$

# Cybenko's Theorem: density

Any continuous functions on  $\mathbb{R}^d$  can be approximated uniformly well with 2NN.

#### Theorem

If  $\sigma$  is sigmoidal as  $\sigma(t) = 1$  as  $t \to \infty$  and  $\sigma(t) = 0$  as  $t \to -\infty$ , then any continuous functions over  $[0,1]^d$  be approximated uniformly well by 2NN.

Necessary and sufficient condition condition for "density" The activation must not be a polynomials (Leshno, Lin, Pinkus, and Schocken, 1993)

#### Finding the correct function spaces associated with 2NN

Find the functions that are well approximated by 2NN

### Fourier-analytic Barron spaces: construction

Let U be a nonempty bounded set on  $\mathbb{R}^d$ , functions  $f:U\to\mathbb{R}$  is said to be in

$$\mathcal{B}_{\mathcal{F},s}(U) := \left\{ f : U \to \mathbb{R} : v'_{f,s} < \infty \text{ and} 
ight.$$

$$\forall x \in U, f(x) = \int_{\mathbb{R}^d} e^{i\omega^\mathsf{T} x} \mathcal{F}(f)(\omega) \, d\omega \right\}$$

where  $v'_{f,s} = \int_{\mathbb{R}^d} (1 + |\omega|)^s |\mathcal{F}(f)(\omega)| d\omega$ .  $f \in \mathcal{B}_{\mathcal{F},1}(U)$ : functions with finite Fourier first moment.

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### Fourier-analytic Barron spaces: Approximation error rate

#### **Theorem**

For any  $f \in \mathcal{B}_{\mathcal{F},s}(U)$ , there exists a n > 0 such that

$$\left\|f - f_n\right\|_2 \lesssim n^{-1/2} \tag{1}$$

and the implied constant does depend upon the dimension.

- $\mathcal{B}_{\mathcal{F},1}(U)$  in  $L^2(U)$ :  $||f f_n||_2 \lesssim n^{-1/2}$
- $\mathcal{B}_{\mathcal{F},1}(U)$  in  $L^{\infty}(U)$ :  $||f f_n||_{\infty} \lesssim n^{-1/2}$



#### Infinite-width Barron spaces: construction

Let U be a nonempty bounded set on  $\mathbb{R}^d$ 

$$\mathcal{B}(U) := \left\{ f: U o \mathbb{R} : r(f, \mu, p) < \infty \text{ and} 
ight.$$
 $orall x \in U, f(x) = \int_{\Omega} a\sigma(b^{\intercal}x + c)\mu(da, db, dc) 
ight\}$ 

where  $r(f,\mu,p) = \mathbf{E}_{\mu} \left[ |a| \left( |b| + |c| \right) \right]$ 



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# Infinite-width Barron spaces: Approximation error rate

- in  $L^2(U)$ :  $||f f_n||_2 \lesssim n^{-1/2}$
- in  $L^{\infty}(U)$ :  $||f f_n||_{\infty} \lesssim n^{-1/2}$

# relationship between Fourier-analytic and Infinite-width Barron spaces

- ullet  $\mathcal{B}(U)$  depends on the choice of activation function  $\sigma$
- ReLU 2NN,  $\mathcal{B}(U)$  is sandwiched between  $\mathcal{B}_{\mathcal{F},1}(U)$  and  $\mathcal{B}_{\mathcal{F},2}(U)$

#### Varitaion space and variation norm

#### Definition (Varitaion norm)

The variation norm,  $\|f\|_{\mathcal{K}(\mathbb{D})}$ , of a subset  $\mathbb{D}$  of a linear space X is defined for all  $f \in X$  as

$$||f||_{\mathcal{K}(\mathbb{D})} := \inf\{c > 0 : f/c \in \mathsf{closed} \ \mathsf{convex} \ \mathsf{hull} \ \mathsf{of} \ \mathbb{D}\}$$

#### Definition (Varitaion space)

$$\mathcal{K}(\mathbb{D}) := \{ f \in \mathcal{H} : \|f\|_{\mathcal{K}(\mathbb{D})} < \infty \}$$

#### Connection to variation space

One can find a dictionary  $\mathbb D$  and the variation space  $\mathcal K(\mathbb D)$  for both  $\mathcal B_{\mathcal F,s}(U)$   $\mathcal B(U)$ 

$$ullet \; \mathbb{F}_{s} := \left\{ (1 + |\omega|)^{-s} \cdot e^{2\pi i \omega^\intercal imes} : \omega \in \mathbb{R}^d 
ight\}$$

•  $\mathbb{D}_k = \left\{ \sigma_k(b^\intercal x + c), \quad b \in S^{d-1}, c \in [c_1, c_2] \right\}$ ,  $S^{d-1}$  is the unit sphere, c is chosen to ensure  $\mathbb{D}_k$ 's compactness

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#### Improved rates

Improved rate with higher s

• in 
$$L^{\infty}(U)$$
:  $||f - f_n||_{\infty} \lesssim n^{-1/2 - s/d} \sqrt{\log n}$ 

If  $\sigma$  is Heaviside function, improved rate

• in 
$$L^{\infty}(U)$$
:  $||f - f_n||_{\infty} \lesssim n^{-1/2 - 1/2d}$ 

# Bibliography I

Leshno, M., V. Y. Lin, A. Pinkus, and S. Schocken (1993, January). Multilayer Feedforward Networks with Non-Polynomial Activation Function Can Approximate Any Function. *Neural Networks* 6(6), 861–867.