Minimum Width for Universal Approximation using RELU Networks on Compact Domain

TL;DR. We find the exact minimum width and the lower bound for universal approximation using RELU networks on compact domain.

Motivation

Universal Approximation (UA). For any continuous function f^* and error $\varepsilon > 0$, we want to find a neural network f such that

distance $(f^*, f) \leq \varepsilon$.

• Two popular choices for distance:

 L^p distance : $||f^* - f||_p$, Uniform distance : $\sup ||f^*(x) - f(x)||_{\infty}$.

Classical Results. Mainly focus on shallow and wide networks.

Theorem ([Hornik+89; Cybenko89; Leshno+93; Pinkus99]). Twolayer neural networks with a non-polynomial activation function are universal approximators in both L^p and uniform distance.

- Namely, the minimum depth for universal approximation is exactly two.
- The universal approximation property of deep and narrow networks has been studied as a dual problem.

Problem. The minimum width enabling universal approximation?

Summary of Bounds on Minimum Width

Ref.	Distance	Function class	s Activation σ	Exact n				
Park+21	L^p	$C(\mathbb{R}^{d_x},\mathbb{R}^{d_y})$	ReLU	$w_{\min} =$				
Cai23	L^p	$C([0,1]^{d_x}, \mathbb{R}^{d_y})$	Leaky-RELU	$w_{\min} =$				
Thm. 1.	L^p	$C([0,1]^{d_x}, \mathbb{R}^{d_y})$	ReLU	$w_{\min} =$				
Thm. 2.	L^p	$C([0,1]^{d_x},\mathbb{R}^{d_y})$	$\operatorname{ReLU-Like}^{\dagger}$	$ $ w_{\min} =				
[‡] is an activation function similar to RELU such as Leaky-RELU, (
Ref.	Distance	Function class	Activation σ	Lo				
Park+21	Uniform	$C([0,1],\mathbb{R}^2)$	ReLU	$w_{\min} > 2$				
Cai23	Uniform	$C([0,1],\mathbb{R}^2)$	Leaky-RELU	$w_{\min} > 2$				
Thm. 3.	Uniform	$C([0,1]^{d_x}, \mathbb{R}^{d_y})$	Conti. monotone	$w_{\min} \ge$				
• Theorem 1. For L^p distance and RELU networks domain, $w_{\min} = \max\{d_x, d_y, 2\}$ for UA. - This shows a dichotomy between bounded and un mains: $w_{\min} = \max\{d_x+1, d_y\}$ when the domain is								
• Theorem 2. $w_{\min} = \max\{d_x, d_y, 2\}$ for the networks RELU-LIKE activation functions, which generalizes result for Leaky-RELU networks.								
• Theorem 3. For uniform distance and networks usin monotone activation function (e.g., RELU, Leaky-R $d_y + 1$ if $d_x < d_y \le 2d_x$.								
- This generalizes the previous result: $w_{\min} \ge d_y$ networks if $d_x = 1$ and $d_y = 2$.								

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Proof Sketch: Achieving Exact Minimum Widths Idea. Given a partition $\{S_1, \ldots, S_k\}$ of the domain with diam (S_i) is small, map almost all of each S_i (i.e., T_i below) to an approximate target vector. $ightarrow \{u_1, u_2, u_3, u_4\} \subset \mathbb{R}$ $g(\mathcal{T}_4)$ **Encoder.** Our encoder iteratively maps $\mathcal{T}_1, \ldots, \mathcal{T}_k$ to distinct scalar values using width $\max\{d_x, 2\}$ RELU networks, using Lemma 1. **Lemma 1.** For any $d_x \in \mathbb{N}$, a compact set $\mathcal{K} \subset \mathbb{R}^{d_x}$, $a, c \in \mathbb{R}^{d_x}$ such that $a^{\top}c > 0$, and $b \in \mathbb{R}$, there exists a two-layer RELU network $f: \mathcal{K} \to \mathbb{R}^d_x$ of width d_x such that

$$f(x) = \begin{cases} x \\ x - \frac{a^{\top}x + b}{a^{\top}c} \times c \end{cases}$$

• Using a RELU network of width d_x , preserve the points in the halfspace $\mathcal{H}^+ = \{x \in \mathbb{R}^{d_x} : a^\top x + b \ge 0\}$ and project points not in \mathcal{H}^+ to the boundary along the direction c.





Decoder. Our decoder maps each scaler value generated by the encoder to an approximate target vector, which can be implemented by a RELU network of width $\max\{d_u, 2\}$.

• Overall, for L^p distance and RELU networks on compact domain, $w_{\min} \leq \max\{d_x, d_y, 2\}$ for UA.

Matching lower bound. $w_{min} \ge \max\{d_x, d_y, 2\}$ is rather straightforward.

- Width either $d_x 1$ or $d_y 1$: lose input/output information.
- Width 1: cannot approximate non-monotonic function.

RELU-LIKE activation functions. RELU can be approximated by a width 1 network using any of RELU-LIKE activation functions.

• Thus, our proof techniques can be generalized to networks using any of RELU-LIKE activation functions; $w_{\min} = \max\{d_x, d_y, 2\}$ for UA.









if $a^{\top}x + b \ge 0$ if $a^{\top}x + b < 0$

Proof Sketch: Lower Bound on Minimum Width

We assume our activation function σ is a continuous injection; this easily generalizes to continuous monotone functions. **Proof by Contradiction.** Our counterexample $f^* : [0,1]^{d_x} \to \mathbb{R}^{d_y}$ is defined as follows:

 $[2/3,1]^r \times \{1\}^{d_x-r},$

$$f^*(x) = \begin{cases} (1 - 6x_1, 1) \\ (0, \dots, 0, 6x_n) \\ g^*(x) \end{cases}$$

However, such f cannot be injective based on the topological argument.



Minimum Width for Recurrent Neural Networks

and bidirectional recurrent neural networks.

Networks	Distance	Function class	Activation σ	Upper / lower bounds			
RNN	L^p	$C([0,1]^{d_x \times T}, \mathbb{R}^{d_y \times T})^{\dagger,\ddagger}$	ReLU	$w_{\min} = \max\{d_x, d_y, 2\}$			
			ReLU-Like	$w_{\min} = \max\{d_x, d_y, 2\}$			
BRNN	L^p	$C([0,1]^{d_x \times T}, \mathbb{R}^{d_y \times T})^{\dagger}$	ReLU	$w_{\min} \le \max\{d_x, d_y, 2\}$			
			ReLU-Like	$w_{\min} \le \max\{d_x, d_y, 2\}$			
t consists of all continuous functions with length T from $[0, 1]^{d_x}$ to \mathbb{R}^{d_y}							

consists of all continuous functions with length T from $[0, 1]^{ax}$ to \mathbb{R}^{ay} . ‡ are *past-dependent*; the *t*-th output is a function of the first to *t*-th inputs.

•	RNNs. For L^p distance, $w_{\min} = \max\{d_x, d_y, 2\}$ for UA.	
	BRNNS. For L^p distance, $w_{\min} \leq \max\{d_x, d_y, 2\}$ for UA.	-



 $-6x_2, \ldots, 1 - 6x_{d_x}, 0, \ldots, 0)$ if $x \in \mathcal{D}_1$ $5x_1 - 5, 6x_2 - 5, \dots, 6x_r - 5)$ if $x \in \mathcal{D}_2$, otherwise

where g^* is some continuous function that makes f^* continuous.

Network f **Approximating** f^* . Suppose for a contradiction that there is a σ network f of width d_y such that $\|f^* - f\|_{\infty}$ is small enough. • Since φ is injective, f is also an injection, i.e., $f(\mathcal{D}_1) \cap f(\mathcal{D}_2) = \emptyset$.

Our encoder & decoder can also be applied to recurrent neural networks