

# Orthogonal Skip Connections

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## Abstract

ResNet architecture was a breakthrough in deep learning. Its success has been attributed to the use of skip connections, which in turn mitigated the problem of exploding gradients. It has been shown that ResNet overcame exploding gradients because its skip connections (identity matrices) are norm preserving. In this paper, we replace these identity matrices with orthogonal matrices, which are by definition norm preserving. First, we interestingly show that as the number of layers grows, the orthogonal matrices need to converge to the identity matrix, following the previous formulation of ResNet. Then, we explore the performance of orthogonal skip connections multiple regression tasks, using the recent efficient algorithm for gradient descent on orthogonal matrices [2]

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# 1 Introduction

## 2 Theoretical considerations

This part wouldn't have been possible if not the work of [1], which came up with a construction of the decomposition of a function into near-identity functions. Their proof has been adapted to orthogonal matrices.

### 2.1 Notation and definitions

### 2.2 Decomposing a function into near-orthogonal functions

**Theorem 1.** Fix  $R > 0$ , denote  $\mathcal{X} = B_R(\mathbb{R}^d)$ . Let  $h : \mathbb{R}^d \rightarrow \mathbb{R}^d$  be a differentiable, invertible map satisfying the following properties:

1. **Smoothness:** for some  $\alpha > 0$  and all  $x, y, u \in \mathcal{X}$ ,

$$\|(Dh(y) - Dh(x))u\| \leq \alpha \|y - x\| \|u\|; \quad (1)$$

2. **Lipschitz inverse:** for some  $M > 0$ ,  $\|h^{-1}\|_L \leq M$ ;

3. **Positive orientation:** For some  $x_0 \in \mathcal{X}$ ,  $\det(Dh(x_0)) > 0$ .

4. **Zero at origin:**  $h(0) = 0$

Then for all  $m$ , there exist  $m$  functions  $h_1, \dots, h_m : \mathbb{R}^d \rightarrow \mathbb{R}^d$  and  $m$  orthogonal matrices  $W_1, \dots, W_m \in \mathbb{R}^{n \times n}$  satisfying, for all  $x \in \mathcal{X}$ ,

$$h_m \circ h_{m-1} \circ \dots \circ h_1(x) = h(x),$$

and, on  $h_{i-1} \circ \dots \circ h_1(\mathcal{X})$ , the following terms decrease in  $O\left(\frac{\log m}{m}\right)$  rate:  $\|h_i - W_i\|_L$ ,  $\|I - W_i\|$  for  $i = 1, \dots, m$ .

**TODO:** We can probably replace the  $\log m/m$  term by choosing any sequence in  $(0, 1)$  that converges to 0

To help prove the theorem, we will note the following:

**Lemma 1.** For  $h$  satisfying the conditions of Theorem 1 and any  $x, y \in \mathcal{X}$ ,

$$\|h(y) - h(x) - Dh(x)(y - x)\| \leq \frac{\alpha}{2} \|y - x\|^2,$$

and moreover,

$$\|h\|_L \leq 1 + \alpha R.$$

Now we can proceed to prove Theorem 1.

*Proof.* To organize the proof, we will first set up our notation and then prove two main bounds (Case 1 and Case 2) that together imply the final estimate.

### 2.2.1 Proof setup

For  $i = 1, 2, \dots, m$ , define

$$g_i(x) := \frac{1}{a_i} W_i^\top h(a_i W_i x), \quad g_i : \mathcal{X} \longrightarrow \mathbb{R}^d.$$

Each  $a_i > 0$  is a scalar parameter with

$$0 < a_1 < a_2 < \dots < a_m = 1, \quad a_i = (1 - c)^{m-i} \text{ for some } c \in (0, 1).$$

The orthogonal matrices  $W_i \in \mathbb{R}^{d \times d}$  satisfy  $\|I - W_i\| \leq C\|a_i - a_{i-1}\|$  for some constant  $C > 0$  and all  $i = 1, \dots, m$ . Note that from this property we obtain bounds on closeness of consecutive  $W_i$ 's:

$$\|W_i - W_{i-1}\| \leq \|I - W_i\| + \|I - W_{i-1}\| \tag{2}$$

$$\leq C\|a_i - a_{i-1}\| + C\|a_{i-1} - a_{i-2}\| \tag{3}$$

$$\leq C\|a_i - a_{i-2}\| < C\|a_i - a_{i-1}\| \tag{4}$$

and

$$\|a_i W_i - a_{i-1} W_{i-1}\| \leq \|a_i W_i - a_i W_{i-1}\| + \|a_i W_{i-1} - a_{i-1} W_{i-1}\| \tag{5}$$

$$\leq a_i \|W_i - W_{i-1}\| + \|a_i - a_{i-1}\| \tag{6}$$

$$< a_i C \|a_i - a_{i-1}\| + \|a_i - a_{i-1}\| = \|a_i - a_{i-1}\| (Ca_i + 1) \tag{7}$$

Then we set

$$h_i := g_i \circ g_{i-1}^{-1} \quad (i = 1, \dots, m),$$

with the convention  $g_0 = \text{Id}$  (the identity map). Observe that

$$h = h_m \circ \dots \circ h_1 = g_m \circ g_{m-1}^{-1} \circ \dots \circ g_1 \circ g_0^{-1} = g_m \circ g_{m-1} \circ \dots \circ g_1,$$

so indeed the composition of  $h_1, \dots, h_m$  yields  $h$ .

We aim to show

$$\|h_i - W_i\|_L := \sup_{x \neq y} \frac{\|(h_i(x) - W_i x) - (h_i(y) - W_i y)\|}{\|x - y\|} \text{ is } O\left(\frac{\log m}{m}\right).$$

### 2.2.2 Bounding the first term $\|h_1 - W_1\|_L$

We have

$$h_1(x) = g_1(x) = \frac{1}{a_1} W_1^\top h(a_1 W_1 x).$$

Hence

$$h_1(x) - W_1 x = \frac{1}{a_1} W_1^\top h(a_1 W_1 x) - W_1 x.$$

Consider two inputs  $x, y \in \mathcal{X}$ . We want to bound

$$\|(h_1(x) - W_1 x) - (h_1(y) - W_1 y)\|.$$

Using Lemma 1, expand

$$h(a_1 W_1 x) = h(a_1 W_1 y) + Dh(a_1 W_1 y) (a_1 W_1 (x - y)) + r,$$

where  $\|r\| \leq (\alpha/2) \|a_1 W_1 (x - y)\|^2$ . Hence

$$\begin{aligned} & \| (h_1(x) - W_1 x) - (h_1(y) - W_1 y) \| = \\ & \left\| \frac{1}{a_1} W_1^\top [h(a_1 W_1 x) - h(a_1 W_1 y)] - W_1 (x - y) \right\| \leq \\ & \left\| \frac{1}{a_1} W_1^\top Dh(a_1 W_1 y) (a_1 W_1 (x - y)) - W_1 (x - y) \right\| + \left\| \frac{1}{a_1} W_1^\top r \right\| \leq \\ & \left\| Dh(W_1 y) - I \right\| a_1 \|x - y\| + \frac{\alpha a_1}{2} \|x - y\|^2 = \\ & a_1 \|x - y\| \left[ \left\| Dh(W_1 y) - I \right\| - \frac{\alpha}{2} \|x - y\| \right] \end{aligned}$$

### 2.2.3 Bounding the general term $\|h_i - W_i\|_L$

For  $i > 1$ , recall

$$h_i = g_i \circ g_{i-1}^{-1},$$

so

$$h_i(x) - W_i x = g_i(g_{i-1}^{-1}(x)) - W_i x.$$

Given  $x, y \in \mathcal{X}$ , define

$$u := g_{i-1}^{-1}(x), \quad v := g_{i-1}^{-1}(y).$$

Then

$$x = g_{i-1}(u), \quad y = g_{i-1}(v).$$

Note that since  $\|h^{-1}\|_L \leq M$ , we have

$$\begin{aligned} \|x - y\| &= \frac{1}{a_{i-1}} \|a_{i-1} W_{i-1} g_{i-1}(u) - a_{i-1} W_{i-1} g_{i-1}(v)\| \geq \\ & \frac{1}{M a_{i-1}} \|h^{-1}(a_{i-1} W_{i-1} g_{i-1}(u)) - h^{-1}(a_{i-1} W_{i-1} g_{i-1}(v))\| = \\ & \frac{1}{M a_{i-1}} \|h^{-1}(h(a_{i-1} W_{i-1} u)) - h^{-1}(h(a_{i-1} W_{i-1} v))\| = \\ & \frac{1}{M a_{i-1}} \|a_{i-1} W_{i-1} u - a_{i-1} W_{i-1} v\| = \\ & \frac{1}{M} \|u - v\| \end{aligned}$$

and also  $\|v\| \leq MR$  and  $\|u\| \leq MR$ . **TODO: Update the following to use this**  
The difference we need to bound is

$$\|(h_i(x) - W_i x) - (h_i(y) - W_i y)\| = \|g_i(u) - g_i(v) - W_i[g_{i-1}(u) - g_{i-1}(v)]\|.$$

Recall

$$g_i(u) = \frac{1}{a_i} W_i^\top h(a_i W_i u), \quad g_{i-1}(u) = \frac{1}{a_{i-1}} W_{i-1}^\top h(a_{i-1} W_{i-1} u).$$

Hence we can rewrite

$$\begin{aligned} & g_i(u) - g_i(v) - W_i [g_{i-1}(u) - g_{i-1}(v)] \\ &= \frac{1}{a_i} W_i^\top [h(a_i W_i u) - h(a_i W_i v)] - \frac{1}{a_{i-1}} W_i W_{i-1}^\top [h(a_{i-1} W_{i-1} u) - h(a_{i-1} W_{i-1} v)]. \end{aligned}$$

To shorten notation, let

$$A := a_i W_i u, \quad B := a_i W_i v, \quad X := a_{i-1} W_{i-1} u, \quad Y := a_{i-1} W_{i-1} v.$$

By Lemma 1, we can write

$$\begin{aligned} h(A) - h(B) &= Dh(B) (A - B) + r_1, \quad \text{where } \|r_1\| \leq \frac{\alpha}{2} \|A - B\|^2, \\ h(X) - h(Y) &= Dh(Y) (X - Y) + r_2, \quad \text{where } \|r_2\| \leq \frac{\alpha}{2} \|X - Y\|^2. \end{aligned}$$

and expanding further:

$$\begin{aligned} \|r_1\| &\leq \frac{\alpha}{2} \|A - B\|^2 \leq \frac{\alpha}{2} a_i^2 \|u - v\|^2 \\ \|r_2\| &\leq \frac{\alpha}{2} \|X - Y\|^2 \leq \frac{\alpha}{2} a_{i-1}^2 \|u - v\|^2 \end{aligned}$$

Thus

$$\begin{aligned} & \left\| \frac{1}{a_i} W_i^\top [h(A) - h(B)] - \frac{1}{a_{i-1}} W_i W_{i-1}^\top [h(X) - h(Y)] \right\| \\ &= \left\| \frac{1}{a_i} W_i^\top [Dh(B) (A - B) + r_1] - \frac{1}{a_{i-1}} W_i W_{i-1}^\top [Dh(Y) (X - Y) + r_2] \right\| \\ &\leq \left\| \frac{1}{a_i} W_i^\top Dh(B) (A - B) - \frac{1}{a_{i-1}} W_i W_{i-1}^\top Dh(Y) (X - Y) \right\| + \underbrace{\left\| \frac{1}{a_i} W_i^\top r_1 - \frac{1}{a_{i-1}} W_i W_{i-1}^\top r_2 \right\|}_{r :=} \\ &\leq \left\| \underbrace{\frac{1}{a_i} W_i^\top Dh(B) a_i W_i - \frac{1}{a_{i-1}} W_i W_{i-1}^\top Dh(Y) a_{i-1} W_{i-1}}_{J :=} \right\| \|u - v\| + r. \end{aligned}$$

We can split and bound the term  $J$  in the following way:

$$\begin{aligned} \|J\| &= \left\| \frac{1}{a_i} W_i^\top Dh(B) a_i W_i - \frac{1}{a_{i-1}} W_i W_{i-1}^\top Dh(Y) a_{i-1} W_{i-1} \right\| = \\ &= \left\| W_i^\top Dh(B) W_i - W_i W_{i-1}^\top Dh(Y) W_{i-1} \right\| = \\ &= \left\| \left[ W_i^\top Dh(B) W_i - W_i^\top Dh(Y) W_i \right] + \left[ W_i^\top Dh(Y) W_i - W_i W_{i-1}^\top Dh(Y) W_{i-1} \right] \right\| \leq \\ &\leq \alpha \|B - Y\|^2 + \underbrace{\left\| W_i^\top Dh(Y) W_i - W_i W_{i-1}^\top Dh(Y) W_{i-1} \right\|}_{J_2 :=} \end{aligned}$$

Then, abusing notation and writing  $Dh(Y)$  as  $D$

$$\begin{aligned}
\|J_2\| &= \left\| \left[ W_i^\top D W_i - W_i^\top D W_{i-1} \right] + \left[ W_i^\top D W_{i-1} - W_i W_{i-1}^\top D W_{i-1} \right] \right\| \leq \\
&\leq \|D\| \|W_i - W_{i-1}\| + \left\| W_i^\top - W_i W_{i-1}^\top \right\| \|D\| = \\
&= \|D\| \left( \|W_i - W_{i-1}\| + \left\| W_i^\top - W_i W_{i-1}^\top + W_i W_i^\top - W_i W_{i-1}^\top \right\| \right) \leq \\
&\leq \|D\| \left( \|W_i - W_{i-1}\| + \left\| W_i^\top - W_i W_{i-1}^\top \right\| + \left\| W_i W_i^\top - W_i W_{i-1}^\top \right\| \right) = \\
&= \|D\| \left( \|W_i - W_{i-1}\| + \|I - W_i\| + \left\| W_i^\top - W_{i-1}^\top \right\| \right) = \\
&= \|D\| (\|W_i - W_{i-1}\| + \|I - W_i\| + \|W_i - W_{i-1}\|).
\end{aligned}$$

Note that we can bound  $D$  by:

$$\|Dh(a_{i-1}W_{i-1}v)\| \leq \alpha \|a_{i-1}W_{i-1}v\| \leq \alpha a_{i-1}MR \quad (8)$$

Combining, we obtain:

$$\begin{aligned}
&\| (h_i(x) - W_i x) - (h_i(y) - W_i y) \| \leq r + \|u - v\| \left( \alpha \|B - Y\|^2 + J_2 \right) \leq \\
&\leq \frac{\alpha}{2} (a_i^2 \|u - v\|^2 + a_{i-1}^2 \|x - y\|^2) + \\
&\|u - v\| \left( \alpha \|a_i W_i v - a_{i-1} W_{i-1} v\|^2 + \|a_{i-1} MR\| (2\|W_i - W_{i-1}\| + \|I - W_i\|) \right) \\
&\leq \frac{\alpha}{2} ((a_i^2 M^2 + a_{i-1}^2) \|x - y\|^2) + \\
&M \|x - y\| \left( \alpha \|a_i W_i - a_{i-1} W_{i-1}\| R^2 + \|a_{i-1} MR\| (2\|W_i - W_{i-1}\| + \|I - W_i\|) \right) \\
&\leq \|x - y\| \left[ \frac{\alpha}{2} M^2 \|x - y\| + \alpha \|a_i W_i - a_{i-1} W_{i-1}\| R^2 + \|a_{i-1} MR\| (2\|W_i - W_{i-1}\| + \|I - W_i\|) \right] \\
&\quad \text{using the equations (4) and (7), we can write:} \\
&< \|x - y\| \left[ \frac{\alpha}{2} M^2 \|x - y\| + \alpha (Ca_i + 1)(a_i - a_{i-1})R^2 + \|a_{i-1} MR\| (2C(a_i - a_{i-1}) + C(a_i - a_{i-1})) \right] \\
&\leq \|x - y\| \left[ \frac{\alpha}{2} M^2 \|x - y\| + \alpha (Ca_i + 1)(a_i - a_{i-1})R^2 + 3C \|a_{i-1} MR\| (a_i - a_{i-1}) \right].
\end{aligned}$$

**Case 1: Arguments are close.** If  $\|x - y\| \leq \|a_i - a_{i-1}\|$ , then we can bound the above expression by

$$\|h_i - W_i\|_L < \left[ \frac{\alpha}{2} M^2 + \alpha (Ca_i + 1)R^2 + 3C \|a_{i-1} MR\| \right] \|a_i - a_{i-1}\|$$

**Case 2: Arguments are far.** If  $\|x - y\| \geq a_i - a_{i-1}$ , we can again use the fact that the increments  $a_i - a_{i-1}$ , as well as the orthogonal matrix differences  $\|W_i - W_{i-1}\|$  and  $\|I - W_i\|$ , are all  $O(a_i - a_{i-1})$ , but this time also use the global Lipschitz properties of  $h$ .

We can rewrite the main term, substituting  $S_k(z) = g_k(z) - g_{k-1}(z)$ :

$$\begin{aligned}
(h_i(x) - W_i x) - (h_i(y) - W_i y) &= [g_i(u) - g_{i-1}(u) - (g_i(v) - g_{i-1}(v))] + (I - W_i)[g_{i-1}(u) - g_{i-1}(v)] \\
&= S_i(u) + S_i(v) + (I - W_i)[g_{i-1}(u) - g_{i-1}(v)] = \\
&= S_i(u) - S_i(v) + (I - W_i)[x - y]
\end{aligned}$$

We have already shown the term  $I - W_i = O(a_i - a_{i-1})$ . Now we will show the function  $S_i(z)$  is Lipschitz with constant  $O(a_i - a_{i-1})$ .

Since  $Dg_k(z) = W_k^\top Dh(a_k W_k z) W_k$ , we have

$$\begin{aligned} DS_i(z) &= W_i^\top Dh(a_i W_i z) W_i - W_{i-1}^\top Dh(a_{i-1} W_{i-1} z) W_{i-1}, \\ &= W_i^\top [Dh(a_i W_i z) - Dh(a_{i-1} W_{i-1} z)] W_i + \\ &\quad + (W_i^\top - W_{i-1}^\top) Dh(a_{i-1} W_{i-1} z) W_{i-1} \\ &\quad + W_i^\top Dh(a_{i-1} W_{i-1} z) (W_i - W_{i-1}). \end{aligned}$$

Smoothness (1) and  $\|z\| \leq R$  give

$$\|Dh(a_i W_i z) - Dh(a_{i-1} W_{i-1} z)\| \leq \alpha \|a_i W_i z - a_{i-1} W_{i-1} z\| < \alpha R \|a_i - a_{i-1}\| (Ca_i + 1).$$

Therefore, combining the bounds for the terms of  $DS_i(z)$  and using the triangle inequality, we obtain

$$\begin{aligned} \|DS_i(z)\| &\leq \|Dh(a_i W_i z) - Dh(a_{i-1} W_{i-1} z)\| + \|W_i^\top - W_{i-1}^\top\| \|Dh(a_{i-1} W_{i-1} z)\| + \\ &\quad + \|Dh(a_{i-1} W_{i-1} z)\| \|W_i - W_{i-1}\| \\ &\leq \alpha R \|a_i - a_{i-1}\| (Ca_i + 1) + 2C \|a_i - a_{i-1}\| \|Dh(a_{i-1} W_{i-1} z)\| \\ &\leq \|a_i - a_{i-1}\| (\alpha R (Ca_i + 1) + 2C \alpha a_{i-1} R) = \\ &\leq \alpha R \|a_i - a_{i-1}\| (Ca_i + 2Ca_{i-1} + 1). \end{aligned}$$

Now we can bound the Lipschitz constant of  $S_i$ :

$$\begin{aligned} \|S_i(v) - S_i(u)\| &\leq \|DS_i(z)\| \cdot \|v - u\| \\ &\leq \alpha R \|a_i - a_{i-1}\| (Ca_i + 2Ca_{i-1} + 1) \cdot \|v - u\| \\ &= \alpha R M^{-1} \|a_i - a_{i-1}\| (Ca_i + 2Ca_{i-1} + 1) \cdot \|x - y\| \end{aligned}$$

Going back to the difference we need to bound, we have

$$\begin{aligned} \|(h_i(x) - W_i x) - (h_i(y) - W_i y)\| &\leq \|S_i(u) - S_i(v)\| + \|I - W_i\| \cdot \|x - y\| \\ &< \|x - y\| \|a_i - a_{i-1}\| \cdot \left[ \alpha R M^{-1} (Ca_i + 2Ca_{i-1} + 1) + C \right] \end{aligned}$$

#### 2.2.4 Combining the estimates

We have shown that for all  $i = 1, \dots, m$ :

$$\begin{aligned} \|h_i - W_i\|_L &\leq \|a_i - a_{i-1}\| \cdot \max\left\{ \frac{\alpha}{2} M^2 + \alpha (Ca_i + 1) R^2 + 3C \|a_{i-1} M R\|, \right. \\ &\quad \left. \alpha R M^{-1} (Ca_i + 2Ca_{i-1} + 1) + C \right\} \\ &\leq \|a_i - a_{i-1}\| \cdot \max\left\{ \frac{\alpha}{2} M^2 + \alpha (C + 1) R^2 + 3C M R, \right. \\ &\quad \left. \alpha R M^{-1} (3C + 1) + C \right\}. \end{aligned}$$

The choice of  $a_i = (1-c)^{m-i}$  guarantees  $a_i - a_{i-1} = O\left(\frac{\log m}{m}\right)$ , which implies that  $\|h_i - W_i\|_L = O\left(\frac{\log m}{m}\right)$  for all  $i = 1, \dots, m$ .

Finally, we can conclude that the composition of  $h_m \circ h_{m-1} \circ \dots \circ h_1$  converges to  $h$  in the sense of the theorem. □

## 2.3 Optimality Conditions via Zero Fréchet Derivatives

**NOTE:** Again reference to [1]

## 2.4 Analyzing the convergence of orthogonal connections during training

**TODO:** Refer to the papers where authors show singular vectors of consecutive layers converge to each other.

## 3 Empirical results

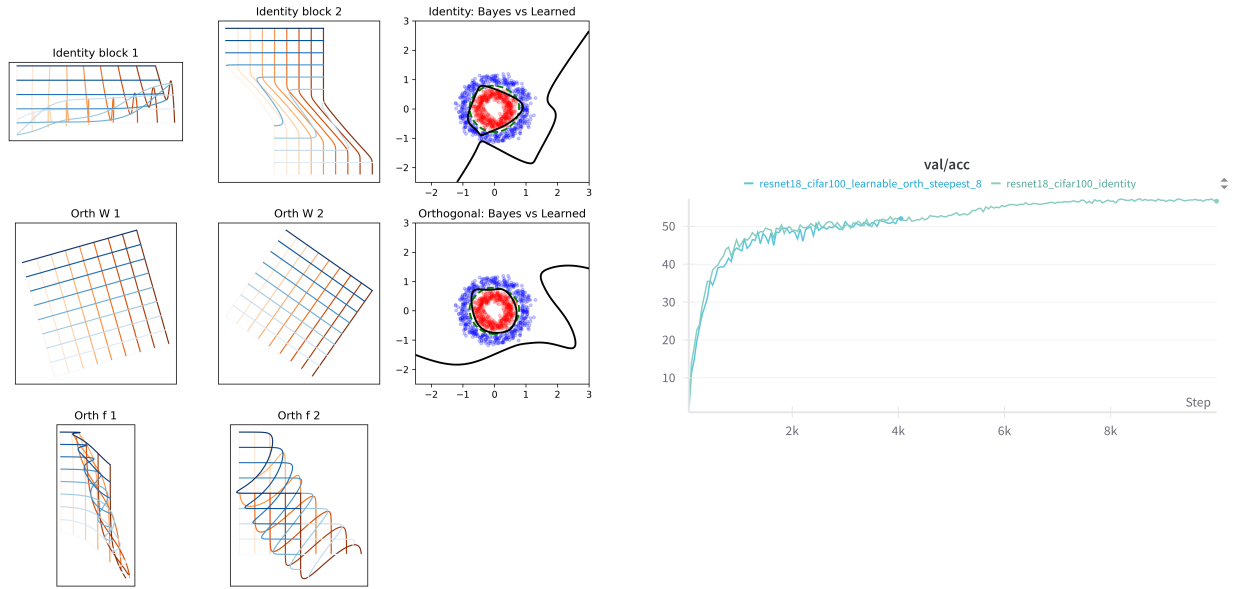


Figure 1: Left: Comparison of residual blocks on synthetic data. Right: Comparison of ResNet-18 variants on CIFAR-100.

Training Cifar10, Cifar100 doesn't show any difference, as seen on Figure 1. However, training on synthetic data shows that orthogonal skip connections are better than residual blocks, as seen on the left plot of Figure 1.



## References

- [1] Peter L. Bartlett, Steven N. Evans, and Philip M. Long. Representing smooth functions as compositions of near-identity functions with implications for deep network optimization, 2018.
- [2] Jeremy Bernstein. The modula docs, 2025.