

8. Approximation: Benefits of depth

Recap

- We have shown several universal approximation results
 - Three-layer: O
 - Two-layer: O
 - One-layer: X
 - Thus, two layer is the **minimum depth**

This lecture

- **Question.** Why are deeper nets often better than shallower ones?

This lecture

- **Question.** Why are deeper nets often better than shallower ones?
- **Answer.** In terms of the approximation, deeper nets are more **parameter-efficient**
 - In particular, certain **depth separation** holds:
 - Deep nets can express some function with N neurons
 - Shallow nets cannot, with N neurons
 - Key question. What function is difficult to be learned by shallow nets?
 - We count #neurons here, but anything can be used for separation
 - e.g., norm

Case 1: Wedges

Wedge

- We are interested in the **wedge function** 

$$\begin{aligned}\Delta(x) &= 2 \cdot \sigma\left(x\right) - 4 \cdot \sigma\left(x - \frac{1}{2}\right) + 2 \cdot \sigma\left(x - 1\right) \\ &= \begin{cases} 2x & \dots & x \in [0, 1/2], \\ 2 - 2x & \dots & x \in [1/2, 1] \\ 0 & \dots & \text{otherwise} \end{cases}\end{aligned}$$

- Expressible with a two-layer ReLU net with 3 neurons

Wedges and Wedges

- Think about the composition

$$\Delta^2(x) = \Delta \circ \Delta(x)$$

- **Question.** What would this function look like? 

Wedges and Wedges and Wedges

- Now, consider the L -time composition

$$\Delta^L(x)$$

- **Question.** What would this look like? 

Depths vs. Width

- For this Δ , we already have some ideas
 - **Deep.** For k wedges, we can express using $O(\log k)$ layers with constant width
 - **Shallow.** For k wedges, you need $O(k)$ neurons
- Can we formally show that this is “necessary”?

Depths vs. Width

- **Difficulty.** Giving a lower bound for shallow nets

- Upper bound (Achievability)

$$\min_{s \in S} \ell(s) \leq t$$

- Easy, find a good s

- Lower bound (Impossibility)

$$\min_{s \in S} \ell(s) \geq t$$

- Difficult; check all s ?

Main claim

- Here is what we'll prove today

Theorem 5.1.

Let $L \geq 2$. Let $f = \Delta^{L^2+2}$ be a ReLU net with $3L^2 + 6$ nodes and $2L^2 + 4$ layers.

Then, any ReLU net g with $\leq 2^L$ nodes and $\leq L$ layers cannot approximate f , i.e.,

$$\int_{[0,1]} |f(x) - g(x)| \, dx \geq \frac{1}{32}$$

- What tools can we use?

Tool: *Affine* Pieces

Tool: Counting Affine Pieces

- **Idea.** We show that shallow nets have small number of affine pieces

Definition (**Affine Pieces**).

For any univariate function $f : \mathbb{R} \rightarrow \mathbb{R}$, let $N_A(f)$ denote the number of affine pieces of f : the minimum cardinality of a partition of \mathbb{R} , so that f is affine when restricted to each piece.

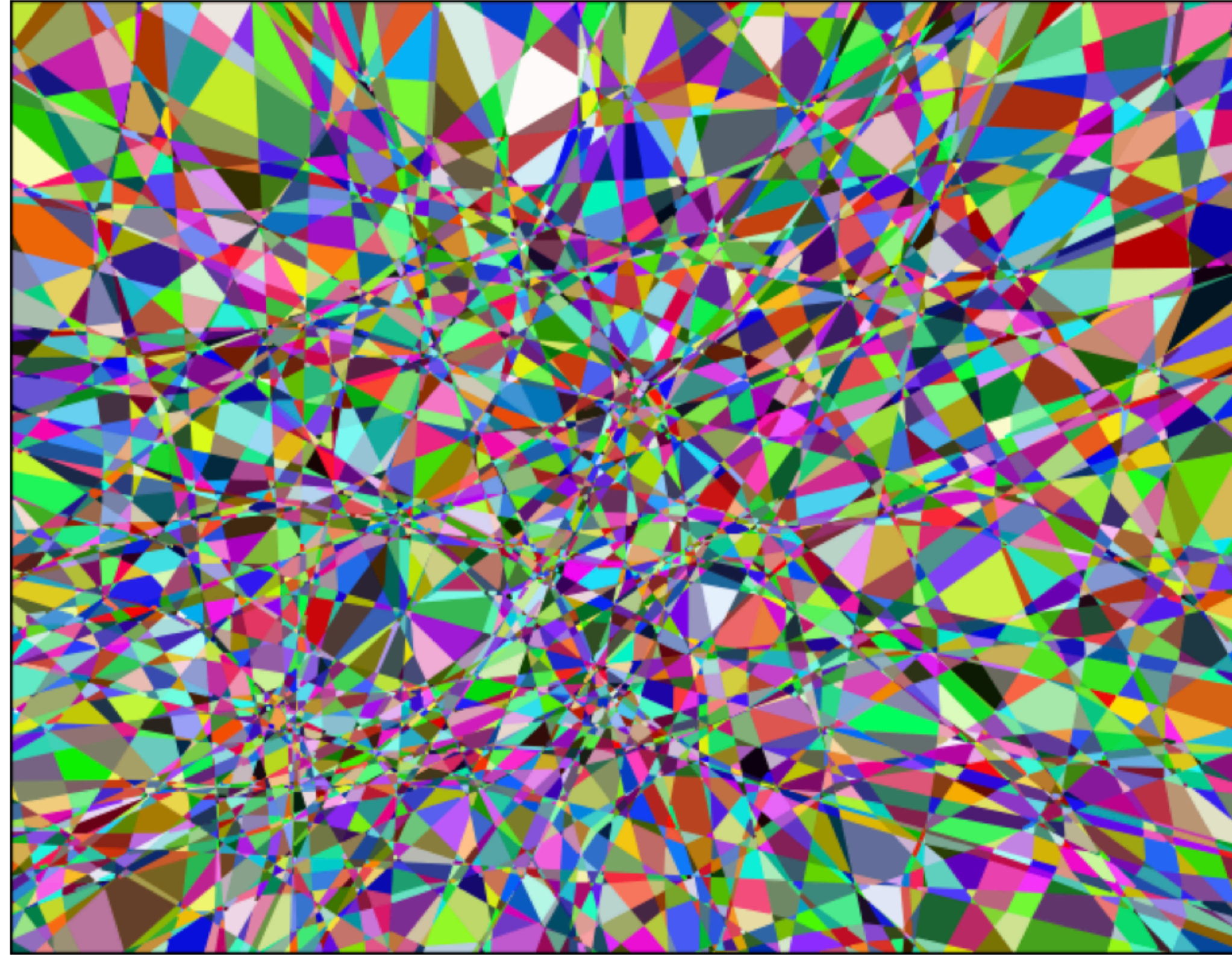


Figure 1. How many linear regions? This figure shows a two-dimensional slice through the 784-dimensional input space of vectorized MNIST, as represented by a fully-connected ReLU network with three hidden layers of width 64 each. Colors denote different linear regions of the piecewise linear network.

Basic properties

- We have the following lemma

Lemma 5.2.

Let functions f, g and a scalar c be given. Then, we have:

- $N_A(0) = 1$
- $N_A(c \cdot f) = N_A(f)$ when $c \neq 0$
- $N_A(f + c) = N_A(f)$
- $N_A(f + g) \leq N_A(f) + N_A(g)$
- $N_A(f \circ g) \leq N_A(f) \cdot N_A(g)$

- **Proof idea.** Utilize the partitions, and the definition of linearity

Bounding the number of affine regions

- Using the properties, we can show the following lemma.

Lemma 5.1.

Let $f : \mathbb{R} \rightarrow \mathbb{R}$ be a ReLU network with L layers, of widths m_1, \dots, m_L .

- Let $g : \mathbb{R} \rightarrow \mathbb{R}$ denote the output of some node at layer i . Then, we have

$$N_A(g) \leq 2^i \cdot \left(\prod_{j < i} m_j \right)$$

- Let $\bar{m} = (m_1 + m_2 + \dots + m_L)/L$. Then, we have

$$N_A(f) \leq 2^L \cdot \bar{m}^L$$

- Idea?

Bounding the number of affine regions

Let $f : \mathbb{R} \rightarrow \mathbb{R}$ be a ReLU network with L layers, of widths m_1, \dots, m_L .

- Let $g : \mathbb{R} \rightarrow \mathbb{R}$ denote the output of some node at layer i . Then, we have

$$N_A(g) \leq 2^i \cdot \left(\prod_{j < i} m_j \right)$$

- **Proof idea.** Prove by induction

Bounding the number of affine regions

Let $f : \mathbb{R} \rightarrow \mathbb{R}$ be a ReLU network with L layers, of widths m_1, \dots, m_L .

- Let $g : \mathbb{R} \rightarrow \mathbb{R}$ denote the output of some node at layer i . Then, we have

$$N_A(g) \leq 2^i \cdot \left(\prod_{j < i} m_j \right)$$

- Let $\bar{m} = (m_1 + m_2 + \dots + m_L)/L$. Then, we have

$$N_A(f) \leq 2^L \cdot \bar{m}^L$$

- **Proof idea.** With the first claim, suffices to show that

$$\prod m_j \leq \bar{m}^L$$

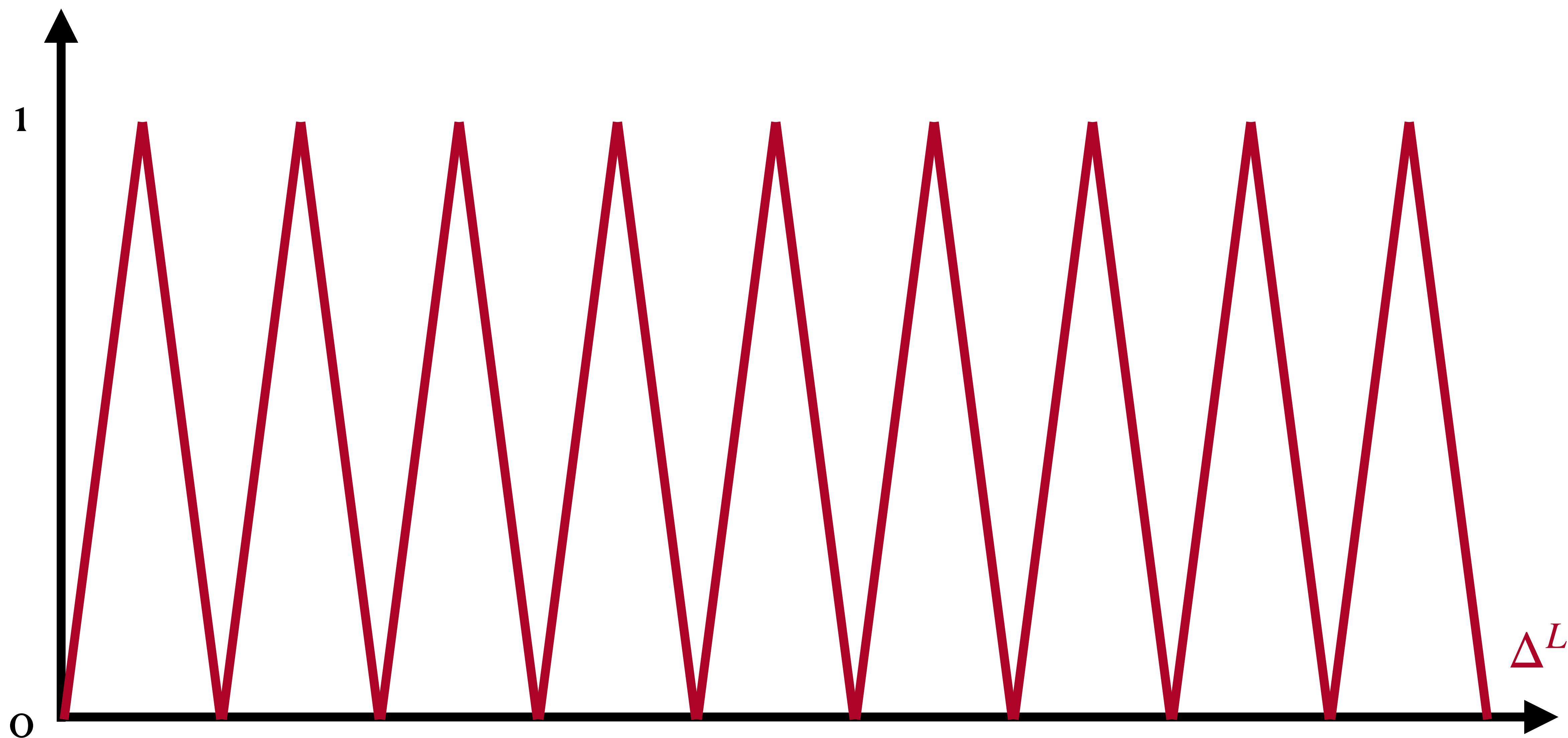
- Taking log, suffices to show that

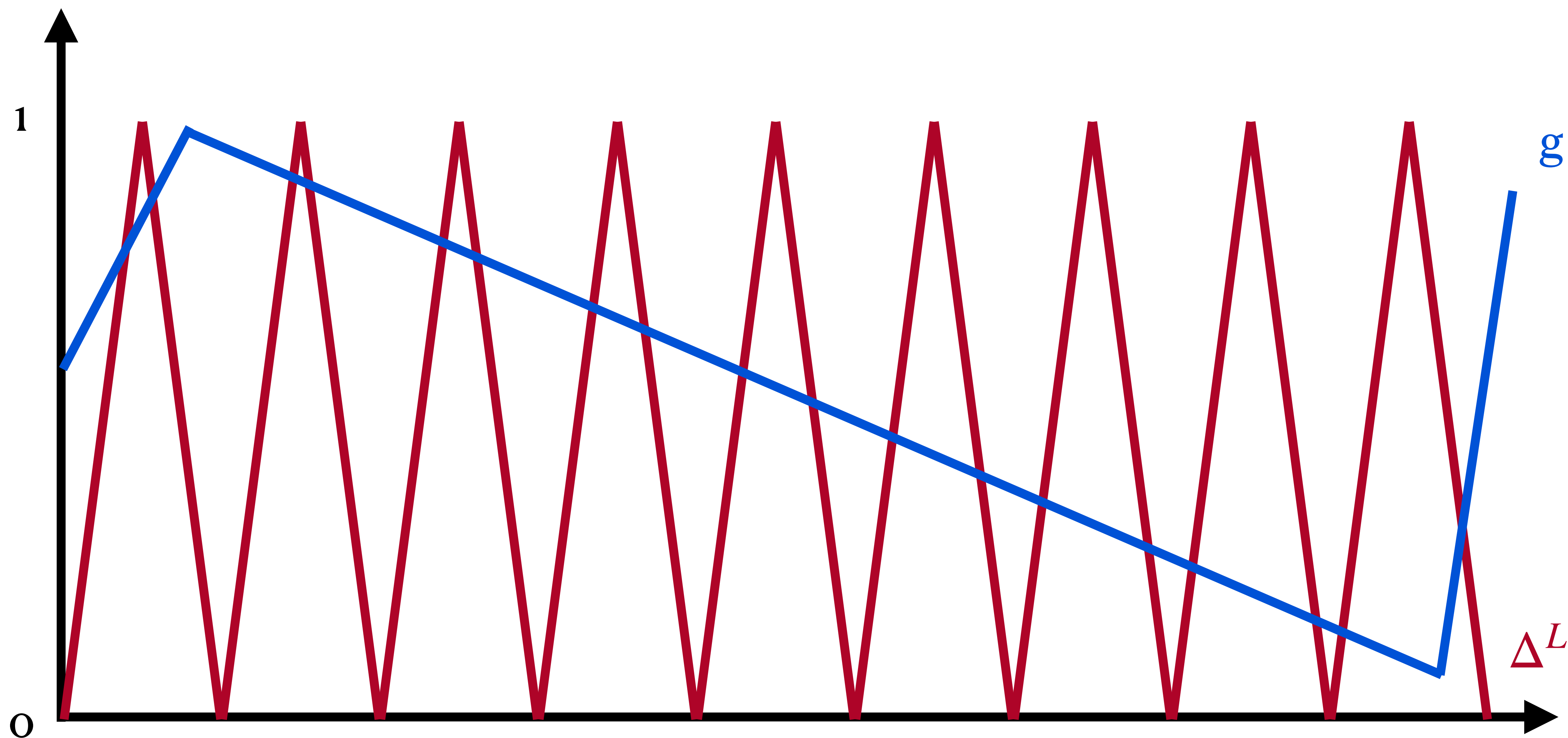
$$\frac{1}{L} \sum \log(m_j) \leq \log(\bar{m})$$

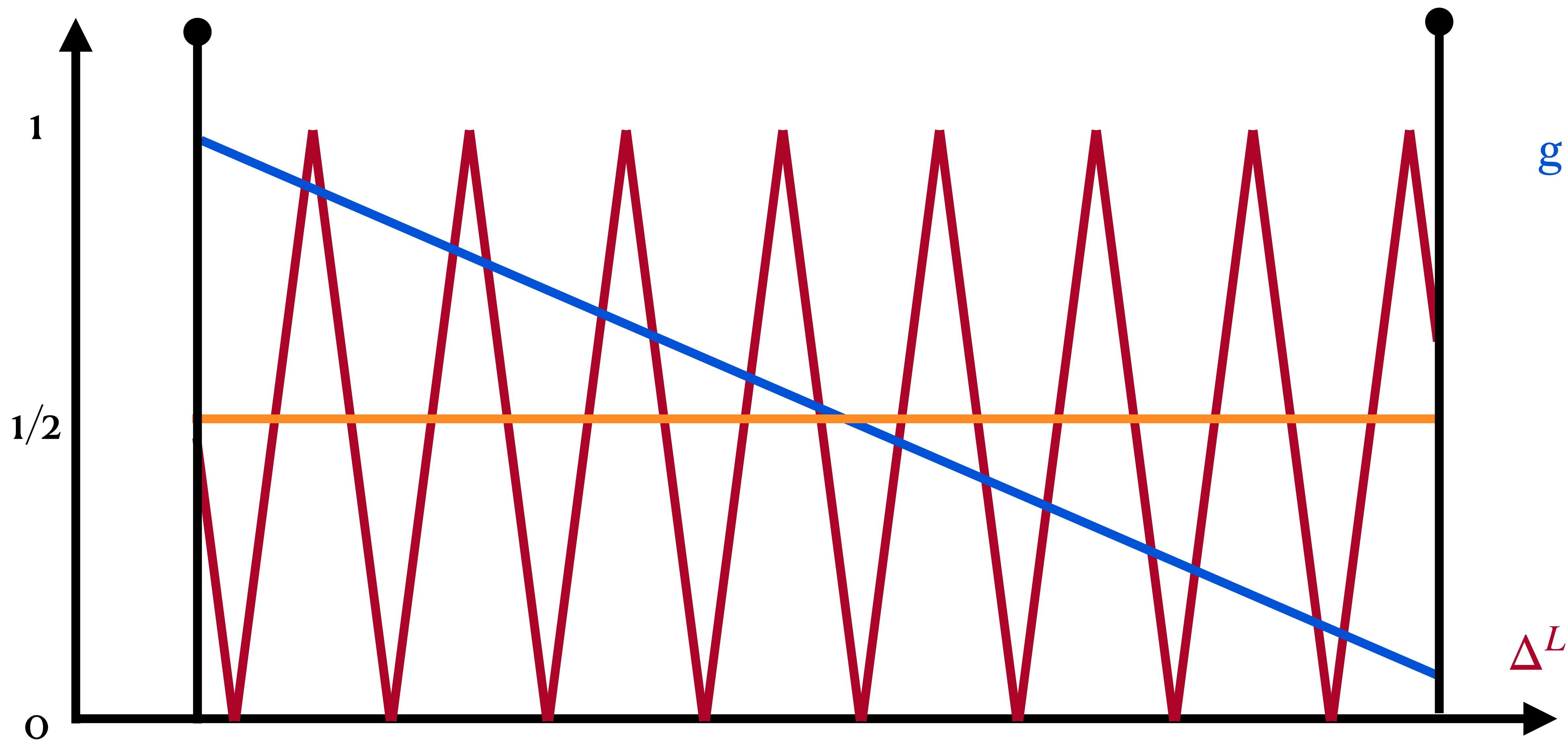
- Ring a bell?

Bounding the number of affine regions

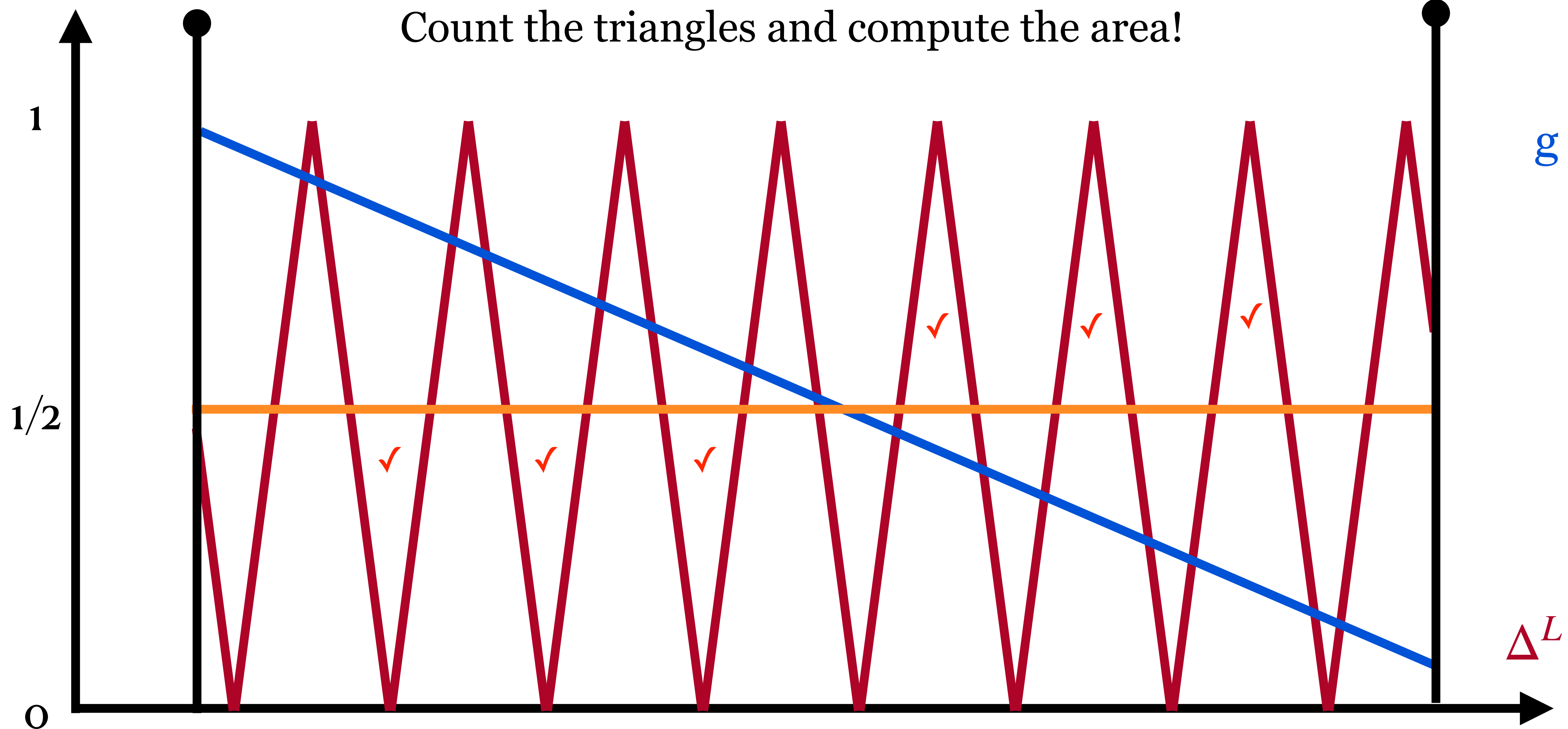
- Now we know that shallow nets have an **UB on #affine regions**
- **Question.** How do we translate it to a **LB on L_1 approximate error for Δ^L ?**
 - Very neat graphical argument







Count the triangles and compute the area!



Case 2: x^2

$$x^2$$

- Wedges were rather special functions
- **Question.** Do depth separation hold for simple functions as well?
- **Answer.** Yes—we'll look at the case of x^2
 - Note. A technique for expressing x^2 can be used to express xy

$$xy = \frac{1}{2} \left((x + y)^2 - x^2 - y^2 \right)$$

x^2 -approximating ReLU net

- We start from the fact that

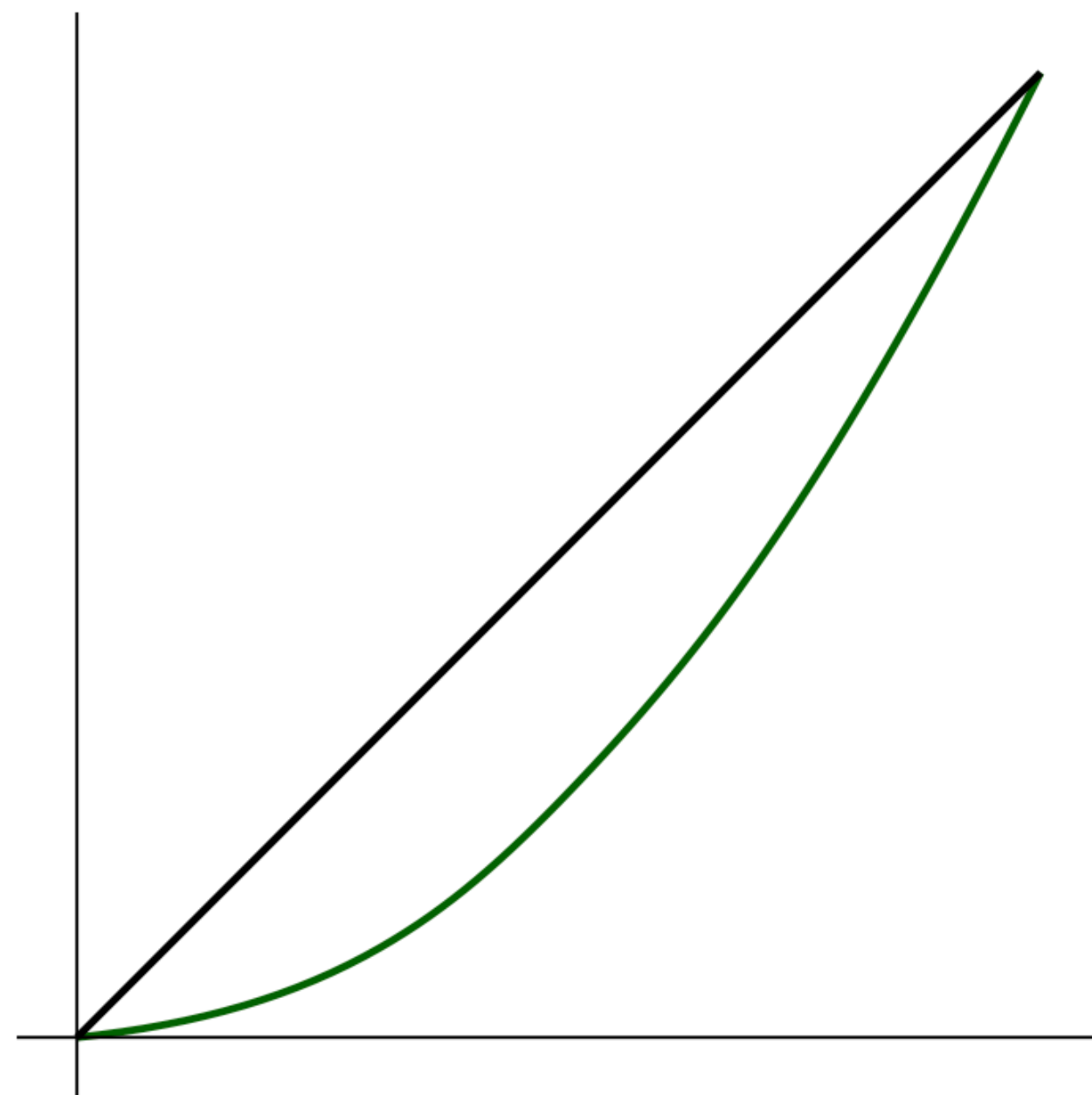
$$x^2 = \int_0^\infty 2 \cdot \sigma(x - b) \, db$$

- Recalling the sampling bounds, natural to assume a **uniform distribution** of neurons
 - Approximate this by piecewise linear approximation, with uniform interval
- Let $\{h_i\}_{i=1}^n$ be a sequence of piecewise linear approximations on uniform intervals
 - Here, $h_i(x)$ interpolates the partition into 2^i intervals:

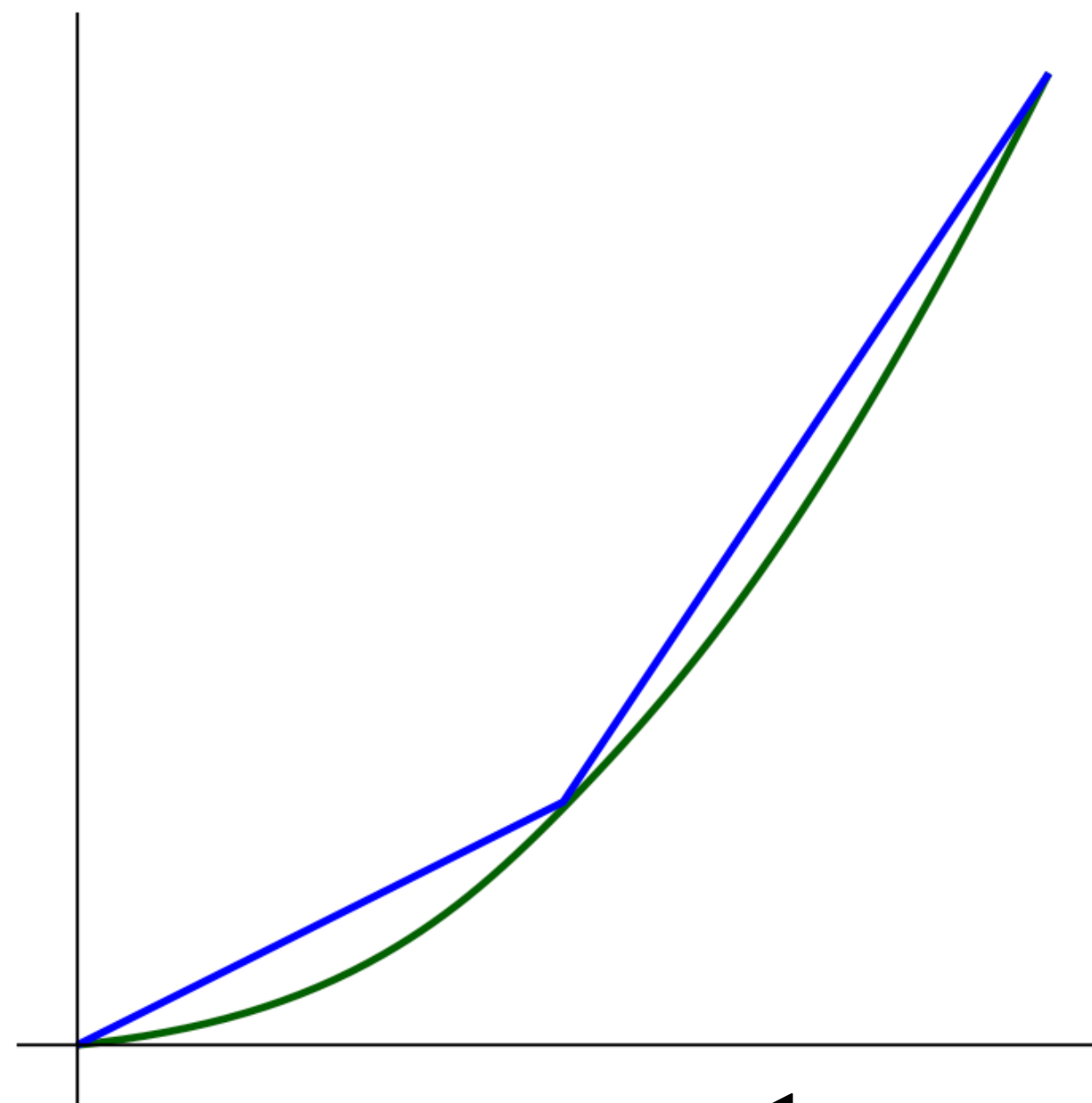
$$S_i := \left(0, \frac{1}{2^i}, \frac{2}{2^i}, \dots, \frac{2^i}{2^i} \right)$$

Δ -approximators

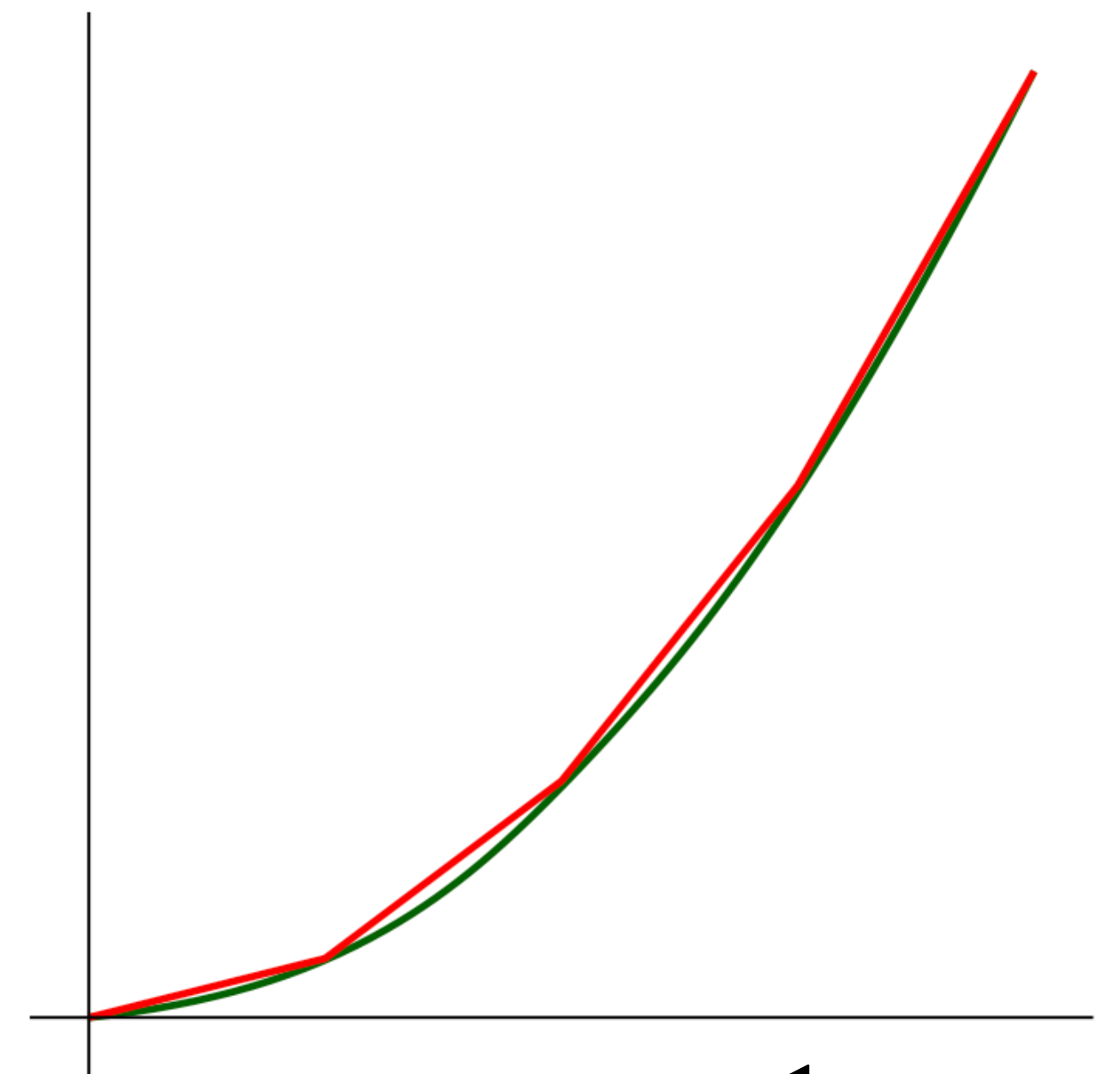
- **Observation.** The approximators h_i can be expressed in terms of **wedges**



$$h_0 = x$$



$$h_1 = h_0 - \frac{1}{4}\Delta$$



$$h_2 = h_1 - \frac{1}{4^2}\Delta^2$$

Δ -approximators

- **Observation.** The approximators h_i can be expressed in terms of wedges
 - More formally, for any $x \in S_i \setminus S_{i-1}$, we have, for $\epsilon = 1/2^i$:

$$\begin{aligned} h_i(x) - h_{i-1}(x) &= x^2 - \frac{(x - \epsilon)^2 + (x + \epsilon)^2}{2} \\ &= x^2 - (x^2 - \epsilon x + \epsilon x + \epsilon^2) \\ &= -\frac{1}{4^i} \end{aligned}$$

- This does not depend on “which x” (i.e., the same height)
 - Thus, making it Δ -like

$$h_i(x) = x - \sum_{j=1}^i \frac{\Delta^j}{4^j}$$

What we want

- We want to show three claims
 - **Claim 1.** Deep nets can construct $h_i(x)$ efficiently
 - **Claim 2.** $h_i(x)$ approximates x^2 well
 - **Claim 3.** Shallow nets cannot approximate x^2 well

What we want

- **Claim 1.** Deep nets can construct $h_i(x)$ efficiently

$$h_i(x) = x - \frac{1}{4}\Delta^1 - \frac{1}{4^2}\Delta^2 - \dots - \frac{\Delta^i}{4^i}$$

- Can be constructed as many parallel nets
 - Roughly $2i$ layers
 - Roughly $4i$ neurons

What we want

- **Claim 2.** $h_i(x)$ approximates x^2 well
 - More concretely, we claim that

$$\sup_{x \in [0,1]} |h_i(x) - x^2| \leq 4^{-i-1}$$

What we want

- **Claim 2.** $h_i(x)$ approximates x^2 well
 - More concretely, we claim that

$$\sup_{x \in [0,1]} |h_i(x) - x^2| \leq 4^{-i-1}$$

- **Proof idea.**

- Fix some $x \in [0,1]$
- We know that $x \in [j\tau, (j+1)\tau]$ for some j , where $\tau = 1/2^i$
- Then, we can write:

$$h_i(x) = (j\tau)^2 + \frac{((j+1)\tau)^2 - (j\tau)^2}{\tau} \cdot (x - j\tau)$$

What we want

- **Claim 3.** Shallow nets cannot approximate x^2 well

- More concretely, we claim that:

Any ReLU net with $\leq L$ layers and $\leq N$ nodes satisfy

$$\int_0^1 (g(x) - x^2)^2 \, dx \geq \frac{1}{5760 \cdot (2N/L)^{4L}}$$

What we want

- **Claim 3.** Shallow nets cannot approximate x^2 well

- More concretely, we claim that:

Any ReLU net with $\leq L$ layers and $\leq N$ nodes satisfy

$$\int_0^1 (g(x) - x^2)^2 dx \geq \frac{1}{5760 \cdot (2N/L)^{4L}}$$

- **Proof idea.** Use the fact that

$$\min_{(c,d)} \int_a^b (x^2 - (cx + d))^2 dx = \frac{(b-a)^5}{180}$$

Next up

- Near-initialization approximation and kernel regime