

Size-Noise Tradeoffs in Generative Networks

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Generative networks

Easy distribution $X \in \mathbb{R}^n$.

Hard distribution $Y \in \mathbb{R}^d$.

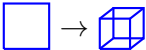
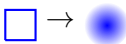
Generator Network $g : X \rightarrow Y$.

What can Y be?

Previous Work

- ▶ Universal approximation theorem:
Shallow networks approximate continuous functions.
- ▶ “On the ability of neural nets to express distributions”:
Upper bounds for representability & shallow depth separation.

Our Contribution: Wasserstein Error Bounds

- ▶ ($n < d$) Tight error bounds $\approx (\text{Width})^{\text{Depth}}$ 
This is a *deep* lower bound.
- ▶ ($n = d$) Switching distributions $\approx \text{polylog}(1/\text{Error})$. 
- ▶ ($n > d$) Trivial networks approximate normal by addition.

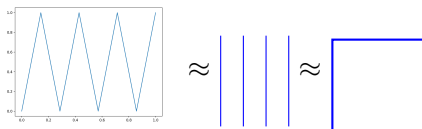
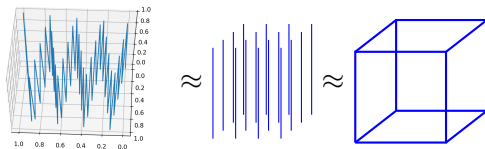
Increasing Uniform Noise ($n < d = kn$)

Networks going from Uniform $[0, 1]^n$ to $[0, 1]^{kn}$:

$$\text{Optimal Error} \approx (\text{Width})^{-\left(\frac{\text{Depth}}{k-1}\right)}.$$

Upper Bound Proof: Space filling curve.

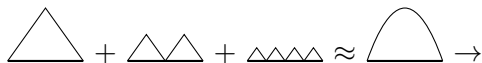
Lower Bound Proof: Affine piece counting.



Normal \leftrightarrow Uniform ($n = d = 1$)

Normal \rightarrow Uniform: Upper Bound

Approximate the normal CDF with Taylor series.

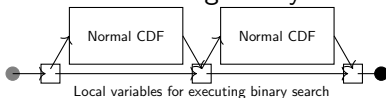


Size = $\text{polylog}(1/\text{Error})$.



Uniform \rightarrow Normal: Upper Bound

Approximate the inverse CDF using binary search.



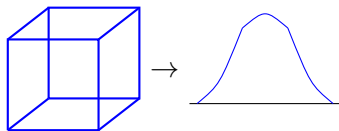
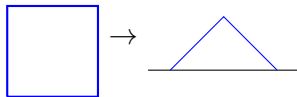
Size = $\text{polylog}(1/\text{Error})$.

Lower bounds

Size $> \log(1/\text{Error})$ with more affine piece counting.

High Dimensional Uniform to Normal ($n > d$)

Summing independent uniform distributions approximates a normal.



With a version of Berry-Esseen, we have:

$$\text{Error} \approx 1/\sqrt{\text{Number of inputs.}}$$

Poster 10:45 AM - 12:45 PM Room 210 & 230 AB #141