

# Lecture 8: signal-to-noise; kernels

Announcements:

- \* hwk 1 postponed
- \* lecture plan

Apk

\* near initialization / overparameterization

\* other topics

Optimization

\* starting 9/27, don't bother with old notes.

Theorem. Let "teacher"  $g(x) = \sum_{k=1}^r \alpha_k \sigma(\beta_k^T x)$  be given along with signal-to-noise parameter  $\sigma > 0$ , where  $\|\beta_k\| = 1$ ,  $\min_{i \neq j} \|\beta_i - \beta_j\| \geq \sigma$ , and define temperature  $e := \frac{\sigma^2}{2\alpha_1}$ . [σ ReLU]

If  $n \geq \frac{1}{e^2} \ln\left(\frac{1}{\delta}\right)$ , w/  $pr \geq 1 - \delta$ ,  $\exists V \in \mathbb{R}^{n \times d}$  with:

1.  $\|V - V_0\|_F \leq \frac{\|\alpha\|_2}{e}$  and  $\max_i \|v_i - v_{0,i}\| \leq \frac{\|\alpha\|_2}{e \sqrt{m}}$ .

2.  $\forall x, \|x\| \leq 1, F(x; V) = F_0(x; V)$ , and  $\left| \frac{e}{\sqrt{m}} F(x; V) - g(x) \right| \leq e \left( \ln d \ln\left(\frac{m}{\delta}\right) + \|\alpha\|_1 \right)$ .

Lemma. σ ReLU.

1. For any fixed  $x \in \mathbb{R}^d$ , w/  $pr \geq 1 - \delta$ ,

$$|F(x; V_0)| \leq \|x\| \sqrt{m} \ln\left(\frac{2m}{\delta}\right).$$

2. w/  $pr \geq 1 - 2\delta$ ,  $\forall x \in \mathbb{R}^d$  with  $\|x\| \leq 1$ ,

$$|F(x; V_0)| \leq 32d \sqrt{m} \ln\left(\frac{m}{\delta}\right).$$

overparameterization

"interpolation" & "benign overfitting"

Proof of "noise magnitude" lemma.

①  $\forall x$  w/  $\|v\| \leq \delta$   $|F(x; \omega_0)| \leq O(\sqrt{m} \ln \frac{m}{\delta})$   $g_i \sim \mathcal{D}$

$$F(x; \omega_0) = \sum_i a_j \sigma(v_j^T x) = \|x\| \sum_i a_j \sigma(g_j) = \|x\| \sum_i a_j |g_j| \mathbb{1}[g_j \geq 0].$$

w/  $\|v\| \leq \delta$   $|g_j| \leq (1 + \sqrt{2 \ln \frac{m}{\delta}}) \|x\|$

Define  $z_j := a_j \sigma(g_j) \rightarrow |z_i z_j| \leq \sqrt{\sum_i m (1 + \sqrt{2 \ln \frac{m}{\delta}})^2 \ln(\frac{2}{\delta})}$   
 $\geq O(\sqrt{m} \ln \frac{m}{\delta}).$

Remark. nearly wrong, should be  $(\sqrt{m} \ln \frac{m}{\delta})$ .

② w/  $\|v\| \leq \delta$ ,  $\forall x$ ,  $\|x\| \leq 1$ ,  $|F(x; \omega_0)| \leq O(d \sqrt{m} \ln \frac{m}{\delta})$ .

Fix  $\epsilon$ -cover  $S$  of  $\|x\| \leq 1$ ; i.e.,  $\forall x$   $\|x\| \leq 1$ ,  $\exists x' \in S$ ,  $\|x - x'\| \leq \epsilon$ .

By brute force,  $|S| \leq (\frac{2}{\epsilon})^d$ .

By previous part + union bound, w/  $\|v\| \leq \delta$   $\max_{x \in S} |F(x; \omega_0)| \leq O(\sqrt{m} \ln \frac{m |S|}{\delta})$

w/  $\|v\| \leq \delta$ ,  $\max_i \|v_i\| \leq 1 + \sqrt{2 \ln \frac{m}{\delta}}$ ,

$\Rightarrow \forall x$ ,  $\|x\| \leq 1$ , pick  $z \in S$  s.t.  $\|x - z\| \leq \epsilon$ , whereby

$$|F(x; \omega_0)| \leq \underbrace{|F(z; \omega_0)|}_{\leq O(\sqrt{m} \ln \frac{m}{\delta})} + \underbrace{|F(x; \omega_0) - F(z; \omega_0)|}_{\leq \sum_i a_j |\sigma(v_j^T x) - \sigma(v_j^T z)|}$$

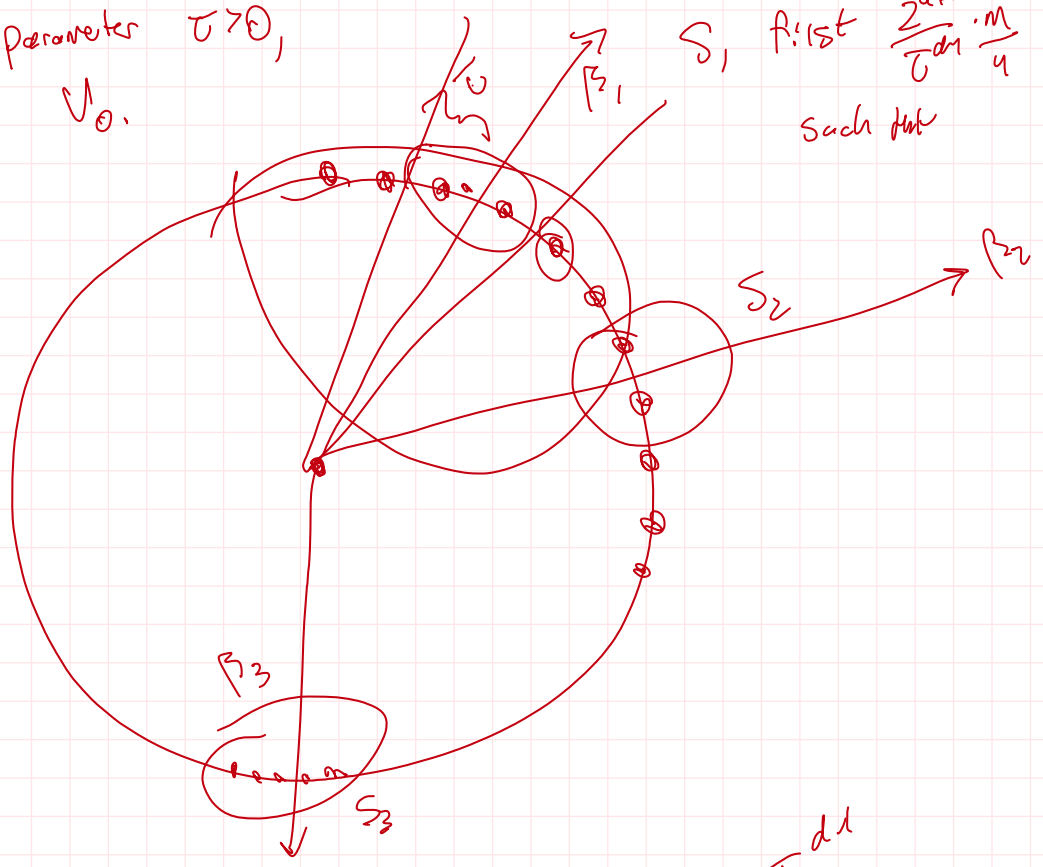
$$\leq \sum_i a_j \|v_i\| \cdot \|x - z\|$$

$$\leq \text{label } m \cdot (1 + \sqrt{2 \ln \frac{m}{\delta}}) \cdot \epsilon \quad //$$

Proof of theorem.

Given  $g(x) = \sum_{k=1}^r \alpha_k \sigma(\beta_k^T x)$ ,  $\|\beta_k\| = 1$ ,

Noise parameter  $\tau > 0$ ,  
random  $V_0$ .



$\# |S_i| = m \cdot \mathbb{P}[v_i \in S_i] \geq m \cdot \frac{\tau^{d-1}}{2^{d+1}}$

$\forall_j \quad v_j := \begin{cases} v_{0,j} & \text{if } j \in S_i \\ v_{0,j} + \frac{v_{0,j}}{\|v_{0,j}\|} \cdot \frac{2^{d+1} |x_i|}{\tau^{d-1} \cdot \tau \cdot m} & \text{if } j \in S_i \text{ \& } \text{sgn}(a_i) = \text{sgn}(a_j) \end{cases}$

clad

Note:  $\| \cdot \|_p$  &  $\| \cdot \|_{2,\infty}$  conditions satisfied

$\forall F(x; w_0) = F_0(x; w_0)$

$$a_j \sigma(v_j^T x) = a_j \sigma \left( \left( 1 + \frac{c \cdot |a_i|}{\|v_{0,j}\|} \right) v_{0,j}^T x \right)$$

$$= a_j \left( 1 + \frac{c \cdot |a_i|}{\|v_{0,j}\|} \right) \sigma(v_{0,j}^T x)$$

$\# \left| F(x; w_0) - \underbrace{\sum_{i=1}^r \alpha_i \sigma(\beta_i^T x)}_{\text{cardinality of } S_1, \dots, S_r} \right|$

$$\leq \left| \sum_{k=1}^r \alpha_k \sigma(\beta_k^T x) - \sum_{j \in S_i} a_j (\sigma(v_j^T x) - \sigma(v_{0,j}^T x)) \right|$$

also small  
by construction + Lipschitz.

$+ |F(x; V_0)|$   
 $= \partial(d \ln \frac{m}{r})$