

1 Data separation implies eigenvalue bound on NTK

Data-separation is a reasonable assumption in deep learning theory. In this notes, we will show a connection between separation parameter δ and the smallest eigenvalue of NTK. Similar as previous lecture note, we will use one-hidden layer neural network with ReLU activation function as an example.

1.1 Neural Tangent Kernel

Definition 1 (Neural Tangent Kernel [JGH18]). *Given a set of points $\{(x_1, y_1), (x_2, y_2), \dots, (x_n, y_n)\} \subset \mathbb{R}^d \times \mathbb{R}$. We define Neural Tangent Kernel $H^{\text{cts}} \in \mathbb{R}^{n \times n}$*

$$H_{i,j}^{\text{cts}} = \mathbb{E}_{w \sim \mathcal{N}(0, I)} \left[x_i^\top x_j \phi'(w^\top x_i) \phi'(w^\top x_j) \right],$$

1.2 Main result

Lemma 2 (Lemma I.1 in [OS20]). *Let x_1, \dots, x_n be points in \mathbb{R}^d with $\|x_i\|_2 = 1, \forall i \in [n]$. Let $X = [x_1 \ \dots \ x_n]^\top \in \mathbb{R}^{n \times d}$. Let $\delta > 0$ be the parameter such that*

$$\min_{i \neq j} \{\|x_i - x_j\|_2, \|x_i + x_j\|_2\} \geq \delta$$

Then we have

$$\mathbb{E}_{w \sim \mathcal{N}(0, I_d)} [\phi'(Xw) \phi'(Xw)^\top] \succeq \delta / (100n^2)$$

Lemma 3 (Lemma I.1 in [OS20]). *Let x_1, \dots, x_n be points in \mathbb{R}^d with $\|x_i\|_2 = 1, \forall i \in [n]$. Let $X = [x_1 \ \dots \ x_n]^\top \in \mathbb{R}^{n \times d}$. Let $\delta > 0$ be the parameter such that*

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Then we have

$$\mathbb{E}_{w \sim \mathcal{N}(0, I_d)} [(\phi'(Xw) \phi'(Xw)^\top) \circ (XX^\top)] \succeq \delta / (100n^2)$$

1.3 Inequalities for PSD matrix

We state a key lemma about spectrum of the Hadamard product of matrices due to Shur [Sch11].

Lemma 4 (Shur [Sch11]). *Let $A, B \in \mathbb{R}^{n \times n}$ denote two PSD matrices. Then,*

$$\begin{aligned}\lambda_{\min}(A \circ B) &\geq (\min_{i \in [n]} B_{i,i}) \cdot \lambda_{\min}(A) \\ \lambda_{\max}(A \circ B) &\leq (\max_{i \in [n]} B_{i,i}) \cdot \lambda_{\max}(A)\end{aligned}$$

1.4 Probability tools

Lemma 5 (Hoeffding bound [Hoe63]). *Let X_1, \dots, X_n denote n independent bounded variables in $[a_i, b_i]$. Let $X = \sum_{i=1}^n X_i$, then we have*

$$\Pr[|X - \mathbb{E}[X]| \geq t] \leq 2 \exp\left(-\frac{2t^2}{\sum_{i=1}^n (b_i - a_i)^2}\right).$$

Lemma 6 (Bernstein inequality [Ber24]). *Let X_1, \dots, X_n be independent zero-mean random variables. Suppose that $|X_i| \leq M$ almost surely, for all i . Then, for all positive t ,*

$$\Pr\left[\sum_{i=1}^n X_i > t\right] \leq \exp\left(-\frac{t^2/2}{\sum_{j=1}^n \mathbb{E}[X_j^2] + Mt/3}\right).$$

Lemma 7 (Anti-concentration of Gaussian distribution). *Let $X \sim \mathcal{N}(0, \sigma^2)$, that is, the probability density function of X is given by $\phi(x) = \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{x^2}{2\sigma^2}}$. Then*

$$\Pr[|X| \leq t] \in \left(\frac{2}{3} \frac{t}{\sigma}, \frac{4}{5} \frac{t}{\sigma}\right).$$

References

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