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SDS 384 11: Theoretical Statistics

Lecture 6: Lipschitz continuous functions

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Recall-Lipschitz functions of Gaussian random variables

Definition

A function $f : \mathbb{R}^n \to \mathbb{R}$ is $L-$Lipschitz w.r.t the Euclidean norm if

$$|f(x) - f(y)| \leq L\|x - y\|_2 \qquad \forall x, y \in \mathbb{R}^n$$

Theorem (LG:Lipschtiz functions of Gaussians)

Let $(X_1, \ldots, X_n)$ be a vector of iid $N(0,1)$ random variables. Let $f : \mathbb{R}^n \to \mathbb{R}$ be $L-$Lipschitz w.r.t the Euclidean norm. Then $f(X) - E[f(X)]$ is sub-gaussian with parameter at most L, i.e. $\forall t \geq 0$,

$$P\left(|f(X) - E[f(X)]| \geq t\right) \leq e^{-\frac{t^2}{2L^2}}$$

- So a $L-$Lipschitz function of n gaussian random variables behave like a subgaussian with variance proxy L^2.

Proof – (Courtesy Tao, Maurey and Pisier)

Proof.

- WLOG assume $E[F(X)] = 0$ and $L = 1$. Assume for simplicity that F is smooth
- We will just prove the upper tail $P(F(X) \geq \lambda) \leq C \exp(-c\lambda^2)$.
- All we need is

$$E[e^{tF(X)}] \leq e^{C' t^2} \qquad \text{for } t > 0 \tag{1}$$

- Lipschitz property implies the gradient $|\nabla F(x)| \leq 1 \forall x \in \mathbb{R}^n$

Proof contd.

Proof contd.

- Consider an iid copy Y.
- Jensen's inequality implies $E[e^{-tF(Y)}] \geq e^{-tE[F(Y)]} = 1$
- $E[e^{tF(X)}] \leq E\left[e^{t(F(X)-F(Y))}\right]$

$$F(X) - F(Y) = \int_0^{\pi/2} \frac{d}{d\theta} F(\underbrace{X\sin\theta + Y\cos\theta}_{X_\theta}) d\theta$$

- $$= \frac{\pi}{2} E_\theta \left[F'(X_\theta) \cdot X'_\theta\right]$$

$$e^{t(F(X)-F(Y))} \leq E_\theta \left[e^{\frac{\pi}{2} tF'(X_\theta) \cdot X'_\theta}\right]$$

- $X'_\theta = X\cos\theta - Y\sin\theta$. Also note that $X_\theta, X'_\theta \overset{iid}{\sim} N(0,1)$

Proof contd.

Proof contd.

- $e^{t(F(X)-F(Y))} \leq \frac{2}{\pi}\int_0^{\pi/2} e^{\frac{\pi}{2}tF'(X_\theta)X'_\theta d\theta} d\theta$
- $X'_\theta = X\cos\theta - Y\sin\theta$. Also note that $X_\theta, X'_\theta \overset{iid}{\sim} N(0, I_n)$

  $$E[e^{t(F(X)-F(Y))}] \leq \frac{2}{\pi}\int_0^{\pi/2} E[e^{\frac{\pi}{2}tF'(X_\theta)\cdot X'_\theta}]d\theta$$
- $$= \frac{2}{\pi}\int_0^{\pi/2} E_{X_\theta}E_{X'_\theta}[e^{\frac{\pi}{2}tF'(X_\theta)\cdot X'_\theta}|X_\theta]d\theta$$
  $$\leq e^{\frac{\pi^2 t^2}{4}}$$
- The last step is true because conditioned on X_θ, $F'(X_\theta)\cdot X'_\theta \sim N(0,\sigma^2)$ where $\sigma \leq 1$.
- This proves Eq 1.

Example 1

- Remember our friend chi square r.v.s? Consider $\{X_i\}_{i=1}^n \overset{\text{iid}}{\sim} N(0,1)$.
- We proved that $Y = \sum_i X_i^2$ is subexponential and we got the bound $P(|Y/n - 1| \geq \epsilon) \leq 2e^{-n\epsilon^2/8}$.
- Lets try to prove a similar bound with the LG theorem.
- Let $\underline{x} = (x_1, \ldots, x_n)$ and $f(\underline{x}) = \|\underline{x}\|_2$.
- Note that Euclidian norm is 1-Lipschitz.
- So we have $P(f(X) - E[f(X)] \geq t) \leq e^{-t^2/2}$ for $t \geq 0$.
- Since $E[\sqrt{V}] \leq \sqrt{E[V]}$, we have $E[\sqrt{Y}] \leq \sqrt{E[Y]} = \sqrt{n}$.
- $P(f(X) \geq E[f(X)] + t) \geq P(\sqrt{Y} \geq \sqrt{n} + t) = P(Y/n \geq (1+\epsilon)^2)$
- Since $(1+\epsilon^2) \leq 1 + 3\epsilon$, $e^{-n\epsilon_0^2/18} \geq P(Y/n \geq (1+\epsilon_0/3)^2) \geq P(Y/n \geq 1 + \epsilon_0)$

Example 2: order statistics

Example

Consider a sequence of independent r.v.s $X = \{X_1, \ldots, X_n\}$. Let $X_{(1)} \geq X_{(2)} \geq \cdots \geq X_{(n)}$. $P(|X_{(k)} - E[X_{(k)}]| \geq \epsilon) \leq 2e^{-\epsilon^2/2}$

Proof.

- First note that $|X_{(k)} - Y_{(k)}| \leq \|X - Y\|_2$. (How?)
- So the order statistics are 1-Lipschitz.

$\square$