36-788: Topics in High Dimensional Statistics I

Lecture 4: Sept. 10

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Fall 2015

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## 4.1 More on Hoeffding's Inequality

Last time, we went through Hoeffding's inequality:

**Theorem 4.1 (Hoeffding)** Let  $X_1, ..., X_n$  be independent r.v.'s such that  $\mathbb{E}X_i = 0$ ,  $a_i \leq X_i \leq b_i$  a.s.. Let  $S_n = \sum_{i=1}^n X_i$ , then for any t > 0,

$$\mathbb{P}(|S_n| > t) \le 2 \exp\left\{-\frac{2t^2}{\sum_{i=1}^n (b_i - a_i)^2}\right\}$$

Hoeffding's inequality is not always optimal. The proof uses the fact that

$$\Psi_{X_i - \mathbb{E}X_i}(\lambda) \le \frac{\lambda^2 (b_i - a_i)^2}{8} \, .$$

which depends on the extreme values of  $X_i$  and thus accounts for the "worst" case. The following theorem sharpens the bound by taking into account where  $\mathbb{E}X_i$  locates.

**Theorem 4.2 (Berend-Kontorovich)** [BK13] Under the same assumptions as in Theorem 4.1, let

$$\gamma_i = \frac{\mathbb{E}X_i - a_i}{b_i - a_i} \; ,$$

we have

$$\mathbb{P}(|S_n| > t) \le 2 \exp\left\{-\frac{t^2}{4\sum_{i=1}^n c_i(b_i - a_i)^2}\right\}$$

where

$$c_i = \begin{cases} 0, & \gamma_i = 0\\ \frac{1-2\gamma_i}{4\log\left(\frac{1-\gamma_i}{\gamma_i}\right)}, & 0 < \gamma_i < \frac{1}{2}\\ \frac{\gamma_i(1-\gamma_i)}{2}, & \frac{1}{2} \le \gamma_i \le 1 \end{cases}$$

Especially, when  $\gamma_i = \frac{1}{2}$  (that is,  $\mathbb{E}X_i = \frac{a_i + b_i}{2}$ ), it recovers Hoeffding's inequality. When  $X_i \sim \text{Bernoulli}(p)$ , the bound becomes  $2 \exp\left\{-\frac{t^2}{2np(1-p)}\right\}$ , which is much better than Hoeffding's when p is close to 0 or 1.

**Example 1 (Rademacher distribution)** Let  $X_i = \begin{cases} 1, & \text{with probability } \frac{1}{2} \\ -1, & \text{with probability } \frac{1}{2} \end{cases}$ , and  $X = \sum_{i=1}^n \alpha_i X_i$ , then  $V(X) = ||\alpha||^2$ , and by Hoeffding's inequality,

$$\mathbb{P}(X \ge t) \le \exp\left\{-\frac{t^2}{2||\alpha||^2}\right\}$$

This is exactly the Chernoff bound we would get if  $X \sim N(0, ||\alpha||^2)$ . Hoeffding's is optimal in this case.

For bounded r.v.  $a_i \leq X_i \leq b_i$ , we have  $V(X_i) \leq \frac{(b_i - a_i)^2}{4}$ . We have seen that when  $V(X_i)$  achieves this upper bound, Hoeffding's is optimal. But when  $V(X_i)$  is much smaller, we will see that Bernstein's inequality becomes better. Before coming to that, we first introduce another class of random variables that is more general than sub-gaussian.

## 4.2 Sub-Exponential Random Variables

**Definition 4.3** A r.v. X is sub-exponential with parameters  $\nu, c > 0$ , if

$$\Psi_{X-\mathbb{E}X}(\lambda) \leq \frac{\lambda^2 \nu^2}{2} \text{ for } \forall \ |\lambda| \in [0, \frac{1}{c})$$

and we write  $X \in S(\nu, c)$ .

By definition, sub-gaussian r.v.'s are always sub-exponential.

**Theorem 4.4** If  $X \in S(\nu, c)$  with  $\mathbb{E}X = 0$ , then for  $\forall \lambda \in [0, \frac{1}{c})$ ,

$$\mathbb{P}(X \ge t) \le \begin{cases} e^{-\frac{t^2}{2\nu^2}}, & 0 \le t \le \frac{\nu^2}{c} \\ e^{-\frac{t}{2c}}, & t > \frac{\nu^2}{c} \end{cases}$$

**Proof:** We know that

$$\mathbb{P}(X \ge t) \le \exp\{-\lambda t + \Psi_X(\lambda)\} \le \exp\left\{-\lambda t + \frac{\lambda^2 \nu^2}{2}\right\}$$

We want to minimize RHS over  $\lambda \in [0, \frac{1}{c})$ . Without this constraint, the minima is  $\lambda^* = \frac{t}{\nu^2}$ .

- (i) If  $\lambda^* \leq \frac{1}{c}$ , i.e.,  $t \leq \frac{\nu^2}{c}$ , then  $\min_{\lambda \in [0, 1/c)} \text{RHS} = e^{-\frac{t^2}{2\nu^2}}$ .
- (ii) If  $\lambda^* > \frac{1}{c}$ , i.e.,  $t < \frac{\nu^2}{c}$ , then RHS is monotonically decreasing when  $\lambda \in [0, \frac{1}{c})$ , so  $\min_{\lambda \in [0, 1/c)} \text{RHS} = \exp\left\{-\frac{t}{c} + \frac{\nu^2}{2c^2}\right\} \le \exp\left\{-\frac{t}{2c}\right\}$ .

**Example 2 (Chi-square distribution)** Let  $X \sim \mathcal{X}_1$ , then  $X \stackrel{d}{=} Z^2$  where  $Z \sim N(0,1)$ , and  $\mathbb{E}X = 1$ . We

can show that  $X \in S(2,4)$ :

$$\begin{split} \mathbb{E}\left[e^{\lambda(X-1)}\right] &= \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{+\infty} e^{\lambda(z^2-1)} e^{-z^2/2} dz \\ &= \frac{e^{-\lambda}}{\sqrt{2\pi}} \int_{-\infty}^{+\infty} \exp\left\{-\frac{z^2}{2}(1-2\lambda)\right\} dz \\ &= \frac{e^{-\lambda}}{\sqrt{1-2\lambda}} \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{+\infty} e^{-\frac{y^2}{2}} dy \quad \left(\text{Let } \mathbf{y} = \sqrt{1-2\lambda}\mathbf{z}, \text{ for } \lambda \in \left(0, \frac{1}{2}\right)\right) \\ &= \frac{e^{-\lambda}}{\sqrt{1-2\lambda}} \leq e^{2\lambda^2}, \text{ if } \lambda \in \left(0, \frac{1}{4}\right). \end{split}$$

Properties of  $S(\nu, c)$ :

1. If  $V(X) = \nu^2$  and  $|X - \mathbb{E}X| \le c$  a.e., then  $X \in S(\sqrt{2}\nu, 2c)$ . **Proof:** 

$$\begin{split} \mathbb{E}\left[e^{\lambda(X-\mathbb{E}X)}\right] &= 1 + \frac{\lambda^2\nu^2}{2} + \sum_{n=3}^{\infty} \frac{\lambda^n}{n!} \mathbb{E}\left[(X-\mathbb{E}X)^n\right] \\ &\leq 1 + \frac{\lambda^2\nu^2}{2} + \frac{\lambda^2\nu^2}{2} \sum_{n=3}^{\infty} (\lambda c)^{n-2} \quad \left(\text{ since } \mathbb{E}\left[(X-\mathbb{E}X)^n\right] \leq \mathbb{E}\left[(X-\mathbb{E}X)^2 c^{n-2}\right]\right) \\ &= 1 + \frac{\lambda^2\nu^2}{2} \sum_{n=0}^{\infty} (\lambda c)^n \\ &= 1 + \frac{\lambda^2\nu^2}{2} \frac{1}{1-\lambda c} \quad \left(\text{if } \lambda < \frac{1}{c}\right) \\ &\leq \exp\left\{\frac{\lambda^2\nu^2}{2(1-\lambda c)}\right\} \\ &\leq \exp\{\lambda^2\nu^2\} \quad \left(\text{if } \lambda < \frac{1}{2c}\right) \end{split}$$

2. If  $X_i \in S(\nu_i, c_i)$  independently,  $\mathbb{E}X_i = 0$ , then  $\sum_i X_i \in S\left(\sqrt{\sum_i \nu_i^2}, \max_i c_i\right)$ . **Proof:** 

$$\Psi_{\sum_{i} X_{i}}(\lambda) = \sum_{i} \Psi_{X_{i}}(\lambda) \le \frac{\lambda^{2} \sum_{i} \nu_{i}^{2}}{2}, \text{ if } |\lambda| < \min_{i} \frac{1}{c_{i}}$$

This implies that

$$\mathbb{P}\left(\frac{1}{n}\sum_{i}X_{i} \ge t\right) \le \begin{cases} e^{-\frac{nt^{2}}{2\nu^{2}}}, & 0 < t \le \frac{\nu^{2}}{c} \\ e^{-\frac{nt}{2c}}, & \frac{\nu^{2}}{c} < t \end{cases} \le \exp\left\{-n \cdot \min\left\{\frac{t^{2}}{2\nu^{2}}, \frac{t}{2\nu}\right\}\right\}$$

where  $\nu^2 = \frac{1}{n} \sum_i \nu_i^2$ ,  $c = \max_i c_i$ .

3. If  $X \in S(\nu, c)$ , then  $(\mathbb{E}[|X|^p])^{1/p} \le cp$  for  $p \ge 1$ .

# 4.3 Bernstein's Inequality

**Theorem 4.5 (Easy Bernstein)** Let X be such that  $V(X) = \nu^2$ ,  $|X - \mathbb{E}X| \le c$  a.e., then

$$\mathbb{P}(X - \mathbb{E}X \ge t) \le \exp\left\{-\frac{t^2}{2(\nu^2 + ct)}\right\}$$

Note that when  $\nu^2 \gg t$ , the bound behaves like  $\exp\left\{-\frac{t^2}{2\nu^2}\right\}$ ; when  $\nu^2 \ll t$ , it behaves like  $\exp\left\{-\frac{t}{2c}\right\}$ . **Proof:** We saw in previous section that  $X \in S(\sqrt{2\nu}, 2c)$ , and

$$\mathbb{E}\left[e^{\lambda(X-\mathbb{E}X)}\right] \le \exp\left\{\frac{\lambda^2\nu^2}{2(1-\lambda c)}\right\}, \quad \lambda \in [0,\frac{1}{c})$$

Picking  $\lambda = \frac{t}{ct+\nu^2} < \frac{1}{c}$  gives the desired result.

**Theorem 4.6 (Bernstein)** Let  $X_1, ..., X_n$  be independent r.v.'s such that for  $\nu, c > 0, q = 3, 4, ...,$ 

(1)  $\sum_{i=1}^{n} \mathbb{E}(X_{i}^{2}) \leq \nu^{2}$ (2)  $\sum_{i=1}^{n} \mathbb{E}(|X_{i}|^{q}) \leq \frac{q!}{2}\nu^{2}c^{q-2}$  (in fact, it is enough to assume  $\sum_{i=1}^{n} \mathbb{E}(|X_{i}|^{q}) \leq \frac{q!}{2}\nu^{2}c^{q-2}$ )

Then  $\forall t > 0$ ,

$$\mathbb{P}\left(\sum_{i=1}^{n} X_i \ge t\right) \le \exp\left\{-\frac{\nu^2}{c^2} h_1\left(\frac{ct}{\nu^2}\right)\right\} \le \exp\left\{-\frac{t^2}{2\nu^2 + ct}\right\}$$

where  $h_1(u) = 1 + u + \sqrt{1 + 2u}, \ u > 0.$ 

#### Remarks

- As a result, we have

$$\mathbb{P}\left(\sum_{i=1}^{n} X_i \ge \sqrt{2\nu^2 t} + ct\right) \le e^{-t}$$

- If we add additional assumptions such that  $|X_i - \mathbb{E}X_i| \leq B \ a.e., \sum_{i=1}^n \mathbb{E}(X_i^2) = \nu^2$ , then

$$\mathbb{P}\left(\sum_{i=1}^{n} X_i \ge t\right) \le \exp\left\{-\frac{t^2}{2\nu^2 + \frac{B}{3}t}\right\}$$

We defer the proof to next lecture.

## References

[BK13] D. BEREND and A. KONTOROVICH, "On the concentration of the missing mass", *Electron. Commun. Probab.*, 2013, 18 (3), 1-7.