

## 5th Practice Class

### Concentration inequalities I

- 5.1** (a) Show that the Markov inequality is **sharp**. Namely, for every fixed real numbers  $0 < m \leq \lambda$  there exists a random variable  $X$  such that  $\mathbb{E}(X) = m$  and  $\mathbb{P}(X \geq \lambda) = m/\lambda$ .
- (b) Show that the Markov inequality is **not sharp**. Namely, for every fixed non-negative random variable  $X$  with finite expected value  $\lim_{\lambda \rightarrow \infty} \lambda \mathbb{P}(X \geq \lambda) / \mathbb{E}(X) = 0$ .

#### Solution

- (a) Let  $0 < m \leq \lambda$  and  $X$  such that

$$\mathbb{P}(X = \lambda) = 1 - \mathbb{P}(X = 0) = \frac{m}{\lambda}.$$

Then

$$\mathbb{E}(X) = 0 \cdot \left(1 - \frac{m}{\lambda}\right) + \lambda \cdot \frac{m}{\lambda} = m.$$

and

$$\mathbb{P}(X \geq \lambda) = \mathbb{P}(X = \lambda) = \frac{m}{\lambda} = \frac{\mathbb{E}(X)}{\lambda}.$$

- (b) First notice

$$\begin{aligned} \mathbb{E}(X) &= \mathbb{E}(X \mathbb{1}[X \geq \lambda]) + \mathbb{E}(X \mathbb{1}[X < \lambda]) \\ &\geq \lambda \mathbb{E}(\mathbb{1}[X \geq \lambda]) + \mathbb{E}(X \mathbb{1}[X < \lambda]) \\ &= \lambda \mathbb{P}(X \geq \lambda) + \mathbb{E}(X \mathbb{1}[X < \lambda]). \end{aligned}$$

Therefore,

$$0 \leq \lambda \mathbb{P}(X \geq \lambda) \leq \mathbb{E}(X) - \mathbb{E}(X \mathbb{1}[X < \lambda]).$$

Moreover, notice that

$$\lim_{\lambda \rightarrow \infty} \mathbb{E}(X \mathbb{1}[X < \lambda]) = \mathbb{E}(X).$$

It follows from monotone convergence since  $X \mathbb{1}[X < \lambda] \nearrow X$  almost surely as  $\lambda \rightarrow \infty$ . Thus,

$$\lim_{\lambda \rightarrow \infty} \lambda \mathbb{P}(X \geq \lambda) = 0.$$

Dividing by  $\mathbb{E}(X)$

$$\lim_{\lambda \rightarrow \infty} \lambda \mathbb{P}(X \geq \lambda) / \mathbb{E}(X) = 0.$$

- 5.4** Let  $X_1, X_2, \dots$  be random variables with finite variance, and 0 expected value (i.e. for every  $i \geq 1$ ,  $\mathbb{E}(X_i) = 0$ ,  $\sigma_i^2 := \mathbb{D}^2(X_i) = \mathbb{E}(X_i^2) < \infty$ ). Let  $r_n$  be a sequence such that  $\lim_{n \rightarrow \infty} r_n = 0$  and suppose that  $\mathbf{Cov}(X_i, X_j) = \mathbb{E}(X_i X_j) \leq r_{|i-j|}$  for every  $i, j \geq 1$  (In particular,  $\sigma_i^2 \leq r_0$ ). Let  $S_n := X_1 + X_2 + \dots + X_n$ . Show that  $\lim_{n \rightarrow \infty} \mathbb{P}(|S_n/n| > \delta) = 0$  for every  $\delta > 0$ .

#### Solution Notice

$$\mathbb{E}(S_n) = \mathbb{E}\left(\sum_{i=1}^n X_i\right) = \sum_{i=1}^n \underbrace{\mathbb{E}(X_i)}_{=0} = 0$$

and

$$\mathbb{D}^2(S_n) = \mathbf{Cov}(S_n, S_n) = \mathbf{Cov}\left(\sum_{i=1}^n X_i, \sum_{i=1}^n X_i\right) = \sum_{i=1}^n \sum_{j=1}^n \mathbf{Cov}(X_i, X_j) \leq \sum_{i=1}^n \sum_{j=1}^n r_{|i-j|}.$$

Now notice  $r_{|i-j|}$  only depends on the distance between  $i$  and  $j$ . The distance is zero in  $n$  cases ( $i = j$ ) and the distance is  $k$  ( $k = 1, \dots, n-1$ ) in  $2(n-k)$  cases ( $i = j+k$  or  $j = i+k$ ). Therefore,

$$\sum_{i=1}^n \sum_{j=1}^n r_{|i-j|} = nr_0 + 2 \sum_{k=1}^{n-1} (n-k)r_k \leq nr_0 + 2n \sum_{k=1}^{n-1} r_k.$$

We can use Chebyshev's inequality for  $\delta > 0$

$$\mathbb{P}(|S_n/n| > \delta) = \mathbb{P}(|S_n| > n\delta) = \mathbb{P}(|S_n - \mathbb{E}(S_n)| > n\delta) \leq \frac{1}{\delta^2 n^2} \mathbb{D}^2(S_n).$$

Using the previous bounds on  $\mathbb{D}^2(S_n)$  as  $n \rightarrow \infty$

$$\mathbb{P}(|S_n/n| > \delta) \leq \frac{r_0}{\delta^2} \cdot \frac{1}{n} + \frac{2}{\delta^2} \cdot \frac{1}{n} \sum_{k=1}^{n-1} r_k = \underbrace{\frac{r_0}{\delta^2}}_{\rightarrow 0} \cdot \frac{1}{n} + \frac{2}{\delta^2} \cdot \underbrace{\frac{n-1}{n}}_{\rightarrow 1} \cdot \underbrace{\frac{1}{n-1} \sum_{k=1}^{n-1} r_k}_{\rightarrow 0} \rightarrow 0.$$

The last convergence holds since  $\frac{1}{n-1} \sum_{k=1}^{n-1} r_k$  is the Césaro average of the sequence  $(r_n)$ . Therefore, it is convergent and has the same limit

$$\lim_{n \rightarrow \infty} \frac{1}{n-1} \sum_{k=1}^{n-1} r_k = \lim_{n \rightarrow \infty} r_n = 0.$$

**5.9** We toss a coin 60 times and denote the number of heads by  $X$ . Give an upper bound for the probability

$$\mathbb{P}(|X - 30| \geq 20)$$

by using Chebyshev's inequality. A better estimate can be given by using the turbo-Markov inequality:

- (a) Let  $Y_\beta = e^{\beta X}$ , where  $0 < \beta$ . Show that  $\mathbb{E}(Y_\beta) = 2^{-60}(1 + e^\beta)^{60}$ .
- (b) Give an upper estimate for  $\mathbb{P}(X \geq 50)$  by using Markov-inequality for the non-negative random variable  $Y_\beta$  for all  $\beta > 0$ .
- (c) Find the optimal  $\beta$ , that is, find the minimum of the estimate in (b). (This can be done by minimizing the convex function  $f(\beta) = \log(1 + e^\beta) - \frac{5}{6}\beta$ .)
- (d) Combining the previous points, show  $\mathbb{P}(|X - 30| \geq 20) \leq 2 \cdot 3^{60} \cdot 5^{-50} < 10^{-6}$ .

**Solution** We know that  $X \sim \text{Bin}(60, 1/2)$ . Therefore,

$$\mathbb{E}(X) = 60 \cdot \frac{1}{2} = 30 \quad \text{and} \quad \mathbb{D}^2(X) = 60 \cdot \frac{1}{2} \cdot \left(1 - \frac{1}{2}\right) = 15.$$

Chebyshev's inequality implies

$$\mathbb{P}(|X - 30| \geq 20) = \mathbb{P}(|X - \mathbb{E}(X)| \geq 20) \leq \frac{\mathbb{D}^2(X)}{20^2} = \frac{15}{400} = \frac{3}{80}.$$

(a)

$$\mathbb{E}(Y_\beta) = \mathbb{E}(e^{\beta X}) = \sum_{k=0}^n e^{\beta k} \binom{n}{k} \left(\frac{1}{2}\right)^k \left(1 - \frac{1}{2}\right)^{60-k} = 2^{-60} \sum_{k=0}^n \binom{n}{k} (e^\beta)^k = 2^{-60}(1 + e^\beta)^{60}.$$

(b) Applying the "Turbo" Markov inequality with the function  $x \mapsto e^{\beta x}$  (its range is in  $\mathbb{R}^+$  and it is non-decreasing)

$$\mathbb{P}(X \geq 50) \leq \frac{\mathbb{E}(e^{\beta X})}{e^{\beta 50}} = \mathbb{E}(Y_\beta) e^{-50\beta} = 2^{-60}(1 + e^\beta)^{60} e^{-50\beta}.$$

This bound holds for any  $\beta > 0$ .

(c) The optimal  $\beta > 0$  is the one which minimizes the right hand side of the inequality. Moreover, since log is strictly monotone increasing it is enough to minimize

$$\log(2^{-60}(1 + e^\beta)^{60} e^{-50\beta}) = -60 \log(2) + 60 \log(1 + e^\beta) - 50\beta.$$

Clearly, it attains its minimum at the same  $\beta$  as the function

$$f(\beta) = \log(1 + e^\beta) - \frac{5}{6}\beta.$$

The derivatives are

$$f'(\beta) = \frac{e^\beta}{1 + e^\beta} - \frac{5}{6}$$
$$f''(\beta) = \frac{e^\beta}{(1 + e^\beta)^2} > 0$$

Notice

$$0 = f'(\beta)$$
$$0 = e^\beta / (1 + e^\beta) - 5/6$$
$$e^\beta = 5$$
$$\beta = \log(5)$$

Therefore, the best bound using this method is

$$\mathbb{P}(X \geq 50) \leq 2^{-60} (1 + e^{\log(5)})^{60} e^{-50 \log(5)} = 2^{-60} \cdot 6^{60} \cdot 5^{-50} = 3^{60} \cdot 5^{-50}.$$

(d) Notice that

$$\mathbb{P}(|X - 30| \geq 20) = \mathbb{P}(X \leq 10) + \mathbb{P}(X \geq 50).$$

Moreover, since  $X \sim \text{Bin}(60, 1/2)$

$$\mathbb{P}(X \leq 10) = \mathbb{P}(X \geq 50).$$

It follows that

$$\mathbb{P}(|X - 30| \geq 20) \leq 2 \cdot \mathbb{P}(X \geq 50) = 2 \cdot 3^{60} \cdot 5^{-50} < 10^{-6}.$$