

## Problem Set 6

### Problem 1: Inequalities

a) Let  $X$  be a square-integrable random variable such that  $\mathbb{E}(X) = 0$  and  $\text{Var}(X) = \sigma^2$ . Show that

$$\mathbb{P}(\{X \geq t\}) \leq \frac{\sigma^2}{\sigma^2 + t^2} \quad \text{for } t > 0$$

*Hint:* You may try various versions of Chebyshev's inequality here, but not all of them work. A possibility is to use the function  $\psi(x) = (x + b)^2$ , where  $b$  is a free parameter to optimize (but watch out that only some values of  $b \in \mathbb{R}$  lead to a function  $\psi$  that satisfies the required hypotheses).

b) Deduce from a) that for any square-integrable random variable  $X$  with expectation  $\mu$  and variance  $\sigma^2$ , the following inequality holds:

$$\mathbb{P}(\{X \geq \mu + \sigma\}) \leq \frac{1}{2}$$

c) *Numerical application:* Check the inequality in b) for  $X \sim \text{Bern}(\frac{1}{2})$ .

d) Let  $X$  be a square-integrable random variable such that  $\mathbb{E}(X) > 0$ . Show that

$$\mathbb{P}(\{X > t\}) \geq \frac{(\mathbb{E}(X) - t)^2}{\mathbb{E}(X^2)} \quad \forall 0 \leq t \leq \mathbb{E}(X)$$

*Hint:* Use first Cauchy-Schwarz' inequality with the random variables  $X$  and  $Y = 1_{\{X > t\}}$ .

e) Deduce from d) that for any square-integrable random variable  $X$  with expectation  $\mu > 0$  and variance  $\sigma^2$  satisfying  $0 \leq \sigma \leq \mu$ , the following inequality holds:

$$\mathbb{P}(\{X > \mu - \sigma\}) \geq \frac{\sigma^2}{\sigma^2 + \mu^2}$$

f) *Numerical application:* Check the inequality in e) for  $X \sim \text{Bern}(\frac{1}{2})$ .

### Solution

a) Using  $\psi(x) = x^2$  or  $\psi(x) = \sigma^2 + x^2$  in Chebyshev's inequality leads to respectively

$$\mathbb{P}(\{X \geq t\}) \leq \frac{\sigma^2}{t^2} \quad \text{and} \quad \mathbb{P}(\{X \geq t\}) \leq \frac{2\sigma^2}{\sigma^2 + t^2}$$

which is not what we want. Using the hint (with  $b \geq 0$  in order to satisfy the hypotheses), we obtain

$$\mathbb{P}(\{X \geq t\}) \leq \frac{\mathbb{E}((X + b)^2)}{(t + b)^2} = \frac{\sigma^2 + b^2}{(t + b)^2}$$

Optimizing over the parameter  $b$ , we find that best possible bound is obtained by setting  $b^* = \frac{\sigma^2}{t}$  (which is non-negative), leading to

$$\mathbb{P}(\{X \geq t\}) \leq \frac{\sigma^2}{\sigma^2 + t^2}$$

b) Applying the inequality in a) to the random variable  $X - \mu$  (with the same variance  $\sigma^2$ ), we obtain

$$\mathbb{P}(\{X - \mu \geq \sigma\}) \leq \frac{\sigma^2}{\sigma^2 + \sigma^2} = \frac{1}{2}$$

c) For  $X \sim \text{Bern}(\frac{1}{2})$ , we have  $\mu = \sigma = \frac{1}{2}$ , so indeed  $\mathbb{P}(\{X \geq 1\}) = \frac{1}{2}$ : the above inequality is an equality in this case.

d) Using Cauchy-Schwarz's inequality with the random variables  $X$  and  $Y = 1_{\{X > t\}}$ , we obtain

$$\mathbb{E}(X 1_{\{X > t\}})^2 \leq \mathbb{E}(X^2) \mathbb{P}(\{X > t\})$$

On the other hand, we have  $\mathbb{E}(X 1_{\{X > t\}}) = \mathbb{E}(X) - \mathbb{E}(X 1_{\{X \leq t\}}) \geq \mathbb{E}(X) - t$ , therefore the result.

e) The inequality follows directly from d).

f) For  $X \sim \text{Bern}(\frac{1}{2})$ , we have  $\mu = \sigma = \frac{1}{2}$ , so indeed  $\mathbb{P}(\{X > 0\}) = \frac{1}{2}$ : the above inequality is (also) an equality in this case.