

Markov's Inequality

Let X be a non-negative random variable
(i.e. $\text{Supp}(X) = (0, \infty)$)
with finite expectation μ .

Let $a > 0$ (a is a constant)
and consider the following inequality

$$a \mathbb{1}_{X \geq a} \leq X$$

Verify the inequality:

if $x \geq a$ then $a(1) \leq X \Rightarrow x \geq a \checkmark$

if $x < a$ then $a(0) \leq X \Rightarrow x \geq 0$ (this because X is non-neg.)

Let's take $E[\cdot]$ on both sides

$$E[a \mathbb{1}_{X \geq a}] \leq E[X]$$

$$\Rightarrow a E[\mathbb{1}_{X \geq a}] \leq \mu$$

$$E[\mathbb{1}_{X \geq a}] = 1P(X \geq a) + 0P(X < a) = P(X \geq a)$$

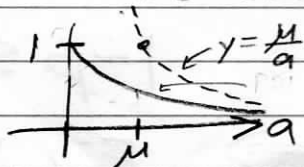
$$\Rightarrow E[\mathbb{1}_{X \geq a}] \leq \frac{\mu}{a}$$

$$\Rightarrow P(X \geq a) \leq \frac{\mu}{a}$$

← Markov's Inequality

$$\Rightarrow 1 - \overset{\text{CDF}}{F}(a) \leq \frac{\mu}{a}$$

"Markov's Tail bound"
"crude bound is $\frac{\mu}{a}$ "



only useful if $a > \mu$

$$X \sim \text{Exp}(1) \Rightarrow \mu = 1, \sigma^2 = 1$$

$$\Rightarrow P(X \geq a) = e^{-a}$$

a	$P(X \geq a)$	Markov $\frac{\mu}{a}$
2	0.1353	0.5
5	0.0067	0.2
10	0.00004	0.1

← shows how crude this bound is

Corollaries of Markov's Inequality

① $b = a\mu$ where $b > 0$

$$P(X \geq b) \leq \frac{\mu}{b} \quad \leftarrow \frac{\mu}{a\mu} = \frac{1}{a}$$

$$\Rightarrow P(X \geq a\mu) \leq \frac{1}{a}$$

② Let $h(x)$ be one-to-one

$$P(h(X) \geq h(a)) \leq \frac{E[h(X)]}{h(a)}$$

$$\Rightarrow P(X \geq a) \leq \frac{E[h(X)]}{h(a)} \quad \text{for one-to-one function } h$$

③ Let $a = \text{Quantile}[X, p]$ (this means $P(X \leq a) = p$)
if X is continuous with connected support $\left. \begin{array}{l} F(a) = p \end{array} \right\}$

$$a = \text{Quantile}[X, p] = F_X^{-1}(p) \quad \rightarrow a = F_X^{-1}(p)$$

$$P(X \geq a) \leq \frac{\mu}{a}$$

$$1 - F_X(a) \leq \frac{\mu}{a}$$

$$1 - F_X(F_X^{-1}(p)) \leq \frac{\mu}{F_X^{-1}(p)}$$

$$1 - p \leq \frac{\mu}{F_X^{-1}(p)}$$

$$\Rightarrow F_X^{-1}(p) \leq \frac{\mu}{1-p}$$

notice

if $p = \frac{1}{2}$

$$F_X^{-1}\left(\frac{1}{2}\right) \leq \frac{\mu}{\frac{1}{2}}$$

$$\text{Med}[X] \leq 2\mu$$

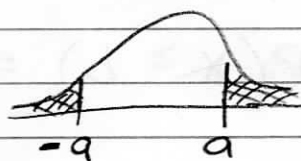
more Corrolaries of Markov's Inequality

④ Let X be any r.v., and $E[X]$ is finite

Note $|X|$ is non-negative

$$P(|X| \geq a) \leq \frac{E[X]}{a} \quad \text{Note: } E[|X|] < \infty$$

↑
right and
left tail



⑤ Let X be a random variable with mean μ , variance σ^2
Let $Y = (X - \mu)^2$. Note Y is non-negative

$$P(Y \geq a^2) \leq \frac{E(Y)}{a^2}$$

$$P((X - \mu)^2 \geq a^2) \leq \frac{E[(X - \mu)^2]}{a^2}$$

$$P(|X - \mu| \geq a) \leq \frac{\sigma^2}{a^2} \quad \text{Chebyshev's Inequality}$$

$$P(-a \leq X - \mu < a) = \frac{\sigma^2}{a^2} \quad \text{or } P(|X - \mu| < a) = 1 - \frac{\sigma^2}{a^2}$$

Assume X is non-negative

$$P(X - \mu \geq a \text{ OR } X - \mu \leq -a)$$

$$= P(X - \mu \geq a) + P(X - \mu \leq -a)$$

$$= P(X \geq \mu + a) + P(X \leq \mu - a)$$

$$= P(X \geq \mu + a) + P(X < 0)$$

$$\begin{aligned}
 &= P(X \geq \mu + a) + P(X < 0) \\
 &= P(X \geq \mu + a) + 0 \leftarrow \text{since } X \text{ is non-neg.} \\
 &= P(X \geq \mu + a)
 \end{aligned}$$

$$\begin{aligned}
 \text{let } b &= \mu + a \Rightarrow b > 2\mu \\
 a &= b - \mu
 \end{aligned}$$

$$= P(X \geq b) \leq \frac{\sigma^2}{(b - \mu)^2} \quad \leftarrow \begin{array}{l} \text{so chebychev} \\ \text{better} \\ \text{than} \\ \text{Markov} \end{array}$$

$$\begin{aligned}
 \text{If } X \sim \text{Exp}(1) &\Rightarrow \mu = 1, \sigma^2 = 1 \\
 &\Rightarrow P(X \geq a) = e^{-a}
 \end{aligned}$$

$$= P(X \geq b) \leq \frac{1}{(b - 1)^2}$$

a	$P(X \geq x)$	Markov	Chebychev
2	0.1353	0.5	1
5	0.0067	0.2	0.0635
10	0.00004	0.1	0.0125

Markov's Inequality

$$P(X \geq a) \leq \frac{\mu}{a}$$

X is non-neg. r.v.

a is constant, $a > 0$

$$\mu = E(X)$$

Chebychev's Inequality

$$P(|X - \mu| \geq a) \leq \frac{\sigma^2}{a^2}$$

X is any r.v.

a is a constant, $a > 0$

$$\mu = E(X), \sigma^2 = \text{Var}[X]$$

Chebyshev's Inequality:

$$P(|X - \mu| \geq a) \leq \frac{\sigma^2}{a^2} \quad \left(\begin{array}{l} \text{can also be written} \\ P(|X - \mu| \geq k\sigma) \leq \frac{1}{k^2} \end{array} \right)$$

\uparrow $k = \# \text{ of standard deviation}$

Corollaries of Markov's Inequality

⑥ Let X be any r.v.

$$Y = e^{tx} \text{ where } t \neq 0$$

note Y is nonnegative for all t

$$\Rightarrow P(Y \geq c) \leq \frac{E[Y]}{c} \quad \text{let } c = e^{at} > 0$$

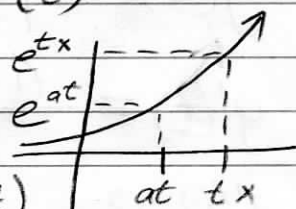
$$\Rightarrow P(e^{tx} \geq e^{at}) \leq \frac{E[e^{tx}]}{e^{at}} = e^{-at} M_X(t)$$

$$P(e^{tx} \geq e^{at}) \leq M_X(t)$$

\uparrow moment generating function

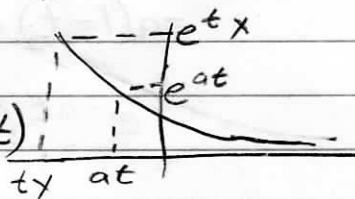
if $t > 0$

$$P(X \geq a) \leq e^{-at} M_X(t)$$



if $t < 0$

$$P(X \leq a) \leq e^{-at} M_X(t)$$



Negative for both left and right tails

$$\Rightarrow \begin{array}{l} \text{if } t > 0: P(X \geq a) \leq \min_{t > 0} \{ e^{-at} M_X(t) \} \\ \text{if } t < 0: P(X \leq a) \leq \min_{t < 0} \{ e^{-at} M_X(t) \} \end{array} \quad \begin{array}{l} \text{Chernoff's} \\ \text{Inequality} \end{array}$$

Chernoff's Inequality

$$P(X \geq a) \leq \min_{\text{for } t > 0} (e^{-at} M_X(t))$$

Chernoff's
Bounds

$$P(X \leq a) \geq \max_{\text{for } t < 0} (e^{-at} M_X(t))$$

$$X \sim \text{Exp}(\lambda)$$

$$\begin{aligned} M_X(t) &= \int_0^{\infty} e^{tx} \lambda e^{-\lambda x} dx = \lambda \int_0^{\infty} e^{(t-\lambda)x} dx \\ &= \frac{\lambda}{t-\lambda} \left[e^{-(t-\lambda)x} \right]_0^{\infty} = \frac{\lambda}{t-\lambda} (0-1) = \frac{\lambda}{\lambda-t} \end{aligned}$$

if $t-\lambda < 0$
same as $t < \lambda$

if $\lambda = 1$ (i.e. $X \sim \text{Exp}(1)$)

get $M_X(t) = \frac{1}{1-t}$

$$\text{let } g(t) = \frac{e^{-at}}{1-t}$$

$$g'(t) = \frac{(1-t)(-a)e^{-at} - e^{-at}(-1)}{(1-t)^2}$$

$$\text{set } g'(t) = 0$$

$$-a(1-t)e^{-at} + e^{-at} = 0$$

$$e^{-at}(a(t-1) + 1) = 0$$

$$at - a + 1 = 0$$

$$at = a - 1$$

$$t = \frac{a-1}{a}$$

$$t = 1 - \frac{1}{a} \in (0,1) \text{ if } a > 1$$

$$P(X \leq a) = e^{-a(1-\frac{1}{a})} \frac{1}{1-(1-\frac{1}{a})}$$

Chernoff's
inequality

$$P(X \leq a) \leq e^{-a(1-\frac{1}{a})} \frac{1}{1-(1-\frac{1}{a})}$$

$$P(X \leq a) \leq e^{-a+1} \frac{1}{\frac{1}{a}}$$

$$P(X \leq a) \leq a e^{-a+1} = \frac{ea}{e^a}$$

↑ Chernoff's Inequality application to Exp(1)

$$X \sim \text{Exp}(1) \Rightarrow \mu=1, \sigma^2=1 \Rightarrow P(X \geq a) = e^{-a}$$

$$Z = \frac{X-1}{1}$$

a	P(X ≥ a)	Markov	Chebyshev	Chernoff
2	0.1353	0.5	1	0.73536
5	0.0067	0.2	0.0635	0.09158
10	0.00004	0.1	0.0123	0.00123

X, Y are r.v.'s with means μ_X, μ_Y
variances σ_X^2, σ_Y^2

$\text{Cov}[X, Y]$
denoted \rightarrow
 σ_{XY}

$$\text{Cov}[X, Y] = E[XY] - \mu_X \mu_Y$$

this is a measure of linear dependence
in terms of X and Y

$\text{Corr}[X, Y]$
denoted \rightarrow
 ρ_{XY}

$$\text{Corr}[X, Y] = \frac{\text{Cov}[X, Y]}{SE[X] SE[Y]}$$

also written

$$\rho_{XY} = \frac{\sigma_{XY}}{\sigma_X \sigma_Y}$$

"Correlation"

which is unitless

and bounded $\text{Corr}[X, Y] \in [-1, 1]$

let $Y = cX$

$$\text{Corr}[X, Y] = \frac{\text{Cov}[X, cX]}{SE[X] SE[cX]} = \frac{c \text{Cov}[X, X]}{SE[X] SE[cX]}$$

$$= \frac{c \text{Var}[X]}{SE[X] |c| SE[X]} = \frac{c \text{Var}[X]}{|c| \text{Var}[X]} = \frac{c}{|c|}$$

$$\text{Corr}[X, Y] = \frac{c}{|c|} = \begin{cases} 1 & \text{if } c > 0 \\ -1 & \text{if } c < 0 \end{cases}$$

$$(SE[X])^2 = \text{Var}[X]$$

So if Y is a multiple of X ,
 $\text{Corr}[X, Y]$ is 1 or -1