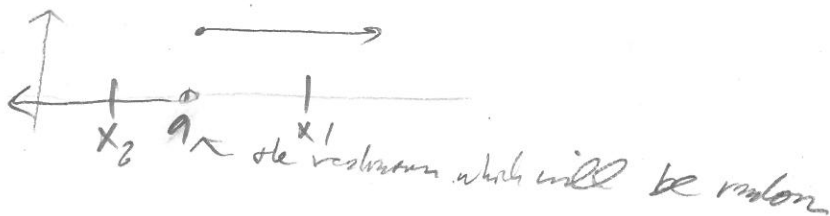


Lecture 21 12/2/19

New Bound

Let X be a r.v. with non- \neg support i.e. $\text{Supp}(X) \geq 0$ and finite expectation. Let $a \geq 0$, a constant. Consider:

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



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

If $X \geq a \Rightarrow a(1) \leq X \Rightarrow a \leq X \Rightarrow X \geq a$ i.e. same as restriction

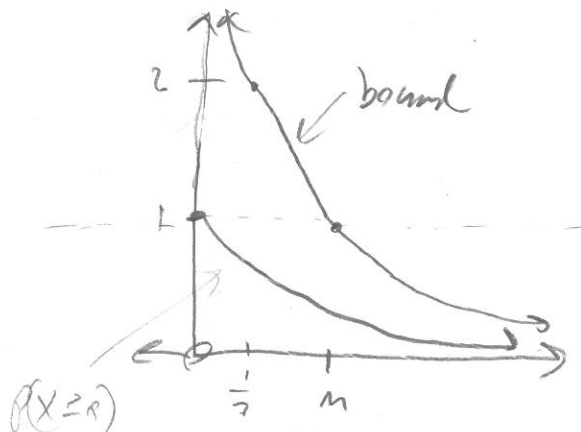
If $X < a \Rightarrow a(0) \leq X \Rightarrow 0 \leq X \Rightarrow X \geq 0$ the by premise

\Rightarrow Yes

Now let's take expectation of both sides

Markov's Inequality

$$E[a \mathbb{1}_{X \geq a}] \leq E[X] \Rightarrow a E[\mathbb{1}_{X \geq a}] \leq \mu \Rightarrow \overset{1 - F_X(a)}{P(X \geq a)} \leq \frac{\mu}{a}$$



this bound is "crude" means seldom informative

eg. $X \sim \text{Exp}(1) \Rightarrow P(X \geq 1) = e^{-1}$

a	$P(X \geq a)$	Markov Bound	Chebyshev's Bound	Clamp
2	0.1353	0.5	1	0.73526
5	0.0067	0.2	0.0635	0.09150
10	0.00004	0.1	0.0123	0.00123
\vdots				

Tons of Corollaries

* let $b = a\sigma$ $P(X \geq b) \leq \frac{\mu}{b} \Rightarrow P(X \geq a\sigma) \leq \frac{1}{a}$

* let $h(x)$ be a monotonically increasing function (thus 1:1)

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

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

X is
if, common

* let $a = Q_{\text{male}}(X, p) = F_X^{-1}(p)$

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

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

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

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

$\rightarrow \text{Med}(X) \leq 2\mu$

which exp.
is female!

* Let X be any r.v. (with possible infinite support)

$\Rightarrow |X|$ has ~~both-tail~~ support both tails have

$\Rightarrow P(|X| \geq a) \leq \frac{E(|X|)}{a}$ All above apply as well

Note $|X| = X1_{X \geq 0} - X1_{X < 0} \Rightarrow E(|X|) = E[X1_{X \geq 0}] - E[X1_{X < 0}]$

* Let X be any r.v. with finite mean and variance

let $Y = (X - \mu)^2$

$P(Y \geq a^2) \leq \frac{E(Y)}{a^2}$ by Markov's Inequality

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

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

difference between random and mean is bounded by its variance.

This is tighter! How to use this for one tail for a pos r.v.?

Assume $\text{Supp}(X) \geq 0$ def of abs. value addition for disjoint events

$P(|X - \mu| \geq a) = P(X - \mu \geq a \cup -(X - \mu) \geq a) = P(X - \mu \geq a) + P(X - \mu \leq -a)$
 $= P(X \geq \mu + a) + P(X \leq \mu - a)$
 $\Rightarrow P(X \geq \mu + a) \leq \frac{\sigma^2}{a^2} \Rightarrow P(X \geq b) \leq \frac{\sigma^2}{(b - \mu)^2}$

e.g. $X \sim \text{Exp}(1)$

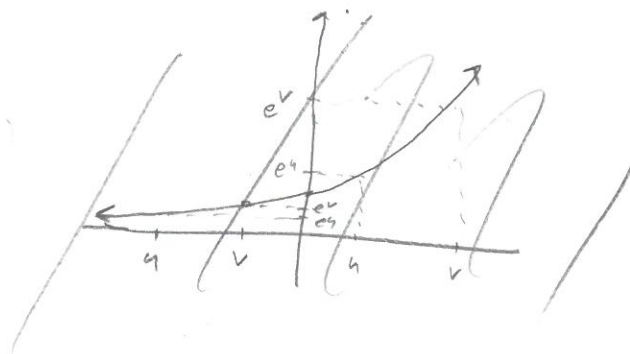
Markov $P(X \geq a) \leq \frac{1}{a}$

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

* Let X be any r.v. $Y = e^{tX}$ which is positive

Markov $\Rightarrow P(Y \geq c) \leq \frac{E(Y)}{c} \Rightarrow P(e^{tX} \geq c) \leq \frac{E(e^{tX})}{c} \Rightarrow P(e^{tX} \geq e^{ta}) \leq \frac{E(e^{tX})}{e^{ta}}$ $\frac{f_X(x)}{e^{ta}} \downarrow$

~~Properties~~
 ~~$e^v \geq e^u \Rightarrow v \geq u$~~
~~Let $u, v > 0$~~
 ~~$e^v \geq e^u \Rightarrow v \geq u$~~
~~Let $u, v < 0$~~



$\Rightarrow P(tX \geq ta) \leq e^{-ta} M_X(t)$

if $t > 0$

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

valid for all t

$\Rightarrow P(X \geq a) \leq \min_{t > 0} \{e^{-ta} M_X(t)\}$

if $t < 0$

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

$\Rightarrow P(X \leq a) \leq \min_{t < 0} \{e^{-ta} M_X(t)\}$

Chernoff's Inequality

For who λ does this work?

e.g. $X \sim \text{Exp}(\lambda)$

$M_X(t) = E(e^{tX}) = \int_0^\infty e^{tx} \lambda e^{-\lambda x} dx = \lambda \int_0^\infty e^{x(t-\lambda)} dx = \frac{\lambda}{t-\lambda} [e^{x(t-\lambda)}]_0^\infty$

$= \frac{\lambda}{t-\lambda} \left(\begin{cases} \infty & \text{if } t \geq \lambda \\ 0 & \text{if } t < \lambda \end{cases} - 1 \right) = \frac{\lambda}{\lambda-t}$ only defined if $t < \lambda$