

Lec 4: We want to develop easier criteria for $X <_{\text{var}} Y$

since it's hard to check

$$\int \phi dF_Y \leq \int \phi dF_X \quad * \text{ concave increasing } \phi$$

Ex: Karlin Novikoff (Criterion)

Let X and \tilde{X} have cdfs F and \tilde{F} . Then satisfy

the cut-criterion if

$$E[\tilde{X}] \leq E[X] \quad \leftarrow$$

$$\text{and } \exists z \text{ s.t. } F(x) \leq \tilde{F}(x) \quad x < z$$

$$F(x) \geq \tilde{F}(x) \quad x > z$$

Then we have $X <_{\text{var}} \tilde{X} \quad (\Rightarrow \mu_{\tilde{X}} \leq \mu_X)$ ($\text{if } F \neq \tilde{F}, F(0) < \tilde{F}(0)$)

The cut criterion implies

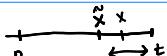
$$(2) \quad \int_{-\infty}^{\tilde{x}} F(x) \leq \int_{-\infty}^{\tilde{x}} \tilde{F}(x) \quad * x \quad (\text{when } X, \tilde{X} \text{ both integrable } E|X| < \infty)$$

Observations: lifetime of a lightbulb

Measured life: \tilde{X} is smaller than X in measured

life if $E(t - \tilde{X})^+ \geq E(t - X)^+ \quad \forall t \in \mathbb{R}$

X = "lifetime of a lightbulb" say.



We want to demonstrate X and Y

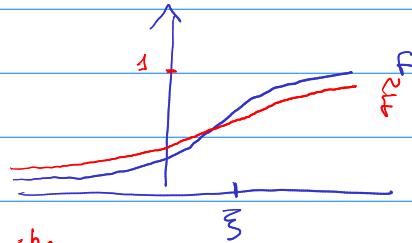
st $E[X] < E[Y]$ BUT $\mu_Y > \mu_X$

Compare X and Y .

If I knew this for all ϕ , then

$T = \text{passage}$ is one such fn. So

then of course $T(Y, x, y) < T(X, x, y)$



Then $\mu_{\tilde{X}} < \mu_X$

vander Berg Korten criterion.

Queueing theory, analyzing failure rates for lightbulbs.

and the life of the lightbulb that is used is $(t - \tilde{X})$.

If \tilde{X} is "smaller than" X stochastically, then it wears out less of its life.

So you require $E[(t - \tilde{X})^+] \geq E[(t - X)^+]$ (arrowed this)

Consider now $E[\min(t, \tilde{X})]$ and

$$E[\min(t, X)]$$

$$\hookrightarrow = E[1_{\{\tilde{X} > t\}}] + E[\tilde{X} 1_{\{\tilde{X} \leq t\}}]$$

$$= E[t(1_{\{\tilde{X} > t\}} + 1_{\{\tilde{X} \leq t\}})] + E[(\tilde{X} - t) 1_{\{\tilde{X} \leq t\}}]$$

$$= t - E[(t - \tilde{X})^+] \leq t - E[(t - X)^+] \quad \forall t$$

Relate this idea to Kullback-Leibler criterion.

$$t + E[(\tilde{X} - t) 1_{\{\tilde{X} \leq t\}}]$$

$$E[(t - \tilde{X})^+] \geq E[(t - X)^+] \quad \forall t$$

$$\Leftrightarrow E[\min(t, \tilde{X})] \leq E[\min(t, X)]$$

is equivalent to

$$E[(t - X)^+] \leq E[(t - \tilde{X})^+] \quad - \#1$$

Let \mathcal{L}_{cv} be the class of nondecreasing convex fns.

Recall: $\tilde{F} \leq_{var} F \quad \text{if}$

$$\int \psi(x) d\tilde{F} \leq \int \psi(x) dF \quad \forall \psi \in \mathcal{L}_{cv}$$

Theorem: $F \leq_{var} \tilde{F}$ iff $E[(t - X)^+] \leq E[(t - \tilde{X})^+]$ (indicated by "individual life of \tilde{X} is more, or 'stochastically' \tilde{X} is smaller than X ."

(for which the integrals make sense)

$$\text{Let's look at } E[(t - X)^+] = - \int_{-\infty}^t (t - u) dF(u)$$

$$= (t - u) F(u) \Big|_{-\infty}^t + \int_{-\infty}^t F(u) du = \int_{-\infty}^t F(u) du$$

Notice that we require $\lim_{u \rightarrow -\infty} (t - u) F(u)$ to be 0

Stoyan and Daley. (pretty elementary)



and we can only ensure that this is true when

$$\mathbb{E}[(J - X)^+] < \infty$$

One can show that this is true when $\mathbb{E}[X] < \infty$

When are $\mathbb{E}(J - X)^+$ and $\mathbb{E}(J - \tilde{X})^+$ finite. Just need X and \tilde{X} to be integrable.

Then $\mathbb{E}[X] = - \int_{-\infty}^0 u dF(u) = - \lim_{n \rightarrow \infty} \int_{-n}^0 u dF(u)$

$$= - \lim_{n \rightarrow \infty} n F(n) + \lim_{n \rightarrow \infty} \int_{-n}^0 F(u) du \quad (\text{by monotone convergence})$$

so this part must be 0.

$$\int f(u) dF(u) = - \int f(u) dT(u)$$

We will prove that the cut criterion implies

$$\mathbb{E}[(J - X)^+] \leq \mathbb{E}[(J - \tilde{X})^+]$$

Pf: (of cut criterion)

$$\text{Since } F(d) \leq \tilde{F}(t) \quad \text{for } t > \bar{x} \quad \Leftrightarrow \quad \tilde{T}(t) \leq T(t)$$

$$= \int_t^\infty \tilde{T}(u) du \leq \int_t^\infty T(u) du$$

$$\Rightarrow t + \int_t^\infty \tilde{T}(u) du \leq t + \int_t^\infty T(u) du$$

$$\Rightarrow t + \int_t^\infty u d\tilde{F}(u) \leq t + \int_t^\infty u dF(u) \quad (\text{using } EX^+ < \infty)$$

$$\Rightarrow \mathbb{E}[\min(t, X)] \leq \mathbb{E}[\min(t, \tilde{X})] \quad \forall t > \bar{x}$$

$$\begin{aligned} P(X \leq t) &= f(d), \quad 1 - F(d) = P(X > t) \\ &= T(d) \end{aligned}$$

tail

and we have

Similarly $\mathbb{E}[\max(t, \tilde{X})] \geq \mathbb{E}[\max(t, X)] \quad \forall t < \bar{x}$] using a similar computation.

However $\max(t, \tilde{X}) = (\tilde{X} - t)^+ + t = \tilde{X} + t - \min(t, \tilde{X})$

$$\mathbb{E}[\max(t, \tilde{X})] = \mathbb{E}[\tilde{X}] + t - \mathbb{E}[\min(t, \tilde{X})]$$

(when \tilde{X} integrable)

$$\Rightarrow \mathbb{E}[\min(t, \tilde{X})] \leq \mathbb{E}[\min(t, X)] \quad \forall t < \bar{x}$$

and thus we're done.

You can take a limit $\rightarrow t \uparrow \bar{t}$ and apply MCT to

get the $t = \bar{t}$ case.

Tensorization: What about concave functions of n variables.

$V = \mathbb{R}^n$ (a vector space in general). Let $F^{\otimes n}$ be the

n -fold product measure of a cdf F on \mathbb{R}^n .

$f: \mathbb{R}^n \rightarrow \mathbb{R}$ is concave if

$$f(\lambda x + (1-\lambda)y) \geq \lambda f(x) + (1-\lambda)f(y) \quad \forall x, y \in \mathbb{R}^n$$

f is nondecreasing requires ordering points in

\mathbb{R}^n : We say $x \leq y$ if $x_i \leq y_i$ $\forall i=1, \dots, n$

$$x \leq y \Rightarrow f(x) \leq f(y) \quad (\text{nondecreasing})$$

$F < \tilde{F}$ on \mathbb{R}
how about F and $\tilde{F}^{\otimes n}$ on \mathbb{R}^n ?

$$T(x_1, y_1, \dots, w_{N^2}) \text{ and}$$

$$\tilde{T}(x_1, y_1, \dots, w_{N^2})$$

Recall I needed concave AND
nondecreasing in my definition
of concave ordering.

Def: Let $X = (X_1, \dots, X_n)$ and $Y = (Y_1, \dots, Y_n)$ be

iid vectors with $F^{\otimes n}, G^{\otimes n}$ cdfs. We say $Y <_{\text{var}} X$ if

$$\int f(x) dF^{\otimes n} \leq \int f(y) dG^{\otimes n}$$

If f integrable, nondecreasing and concave.

generalization

Theorem: For any n $F^{\otimes n} <_{\text{var}} G^{\otimes n}$

$$\text{iff } F <_{\text{var}} G$$

(See Stoyan and Daley for proof)

One can prove this very easily for the dominance ordering

Ok. Back to the vBK Karsten Example

Consider $\left\{ \begin{array}{l} F_2 = \text{Unif} \{ \ell, \ell+1, \dots, m \} \quad \ell \geq 1 \\ F_1 = F_2 * \underbrace{\text{Unif} [-\frac{1}{2}, \frac{1}{2}]}_{\text{independent } \gamma} = \text{Unif} [\ell - \frac{1}{2}, m + \frac{1}{2}] \\ F_3 = \text{Unif} [\ell, m] \end{array} \right.$

Claim: $F_2 \leq_{\text{var}} F_1$

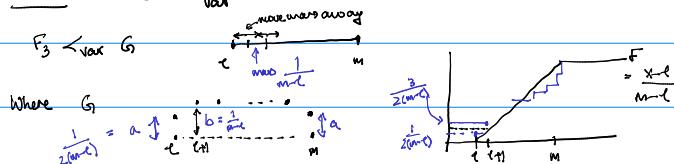
Pf: Fix ψ convex and non-decreasing.

$$\begin{aligned} \mathbb{E}[\psi(X_1)] &= \mathbb{E}[\psi(X_2 + \gamma)] = \mathbb{E}[\mathbb{E}[\psi(X_2 + \gamma) | X_2]] \\ &\leq \mathbb{E}[\psi(X_2 + \mathbb{E}[\gamma])] = \mathbb{E}[\psi(X_2)] \end{aligned}$$

Lesson: adding an bounded mean 0 rv to an rv makes it more variable

more variable

Claim: $F_3 \leq_{\text{var}} F_2$ Will show first that



So it's clear it satisfies the cut criterion and hence

$$F_3 \leq_{\text{var}} G$$

$$\begin{array}{c} \text{---} \\ \text{---} \end{array} \quad \begin{array}{c} 1 \\ 2 \end{array} \quad \left. \begin{array}{l} P(1) = \frac{1}{2} \\ P(2) = \frac{1}{2} \end{array} \right\} X_2$$

$$X_1 = X_2 + \gamma$$

$$\text{where } \gamma \sim \text{Unif} [-\frac{1}{2}, \frac{1}{2}]$$

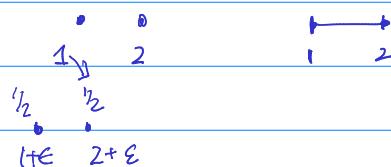
$$X_1 \sim \text{Unif} [-\frac{1}{2}, \frac{5}{2}]$$

$$X_3 \sim \text{Unif} [1, 2]$$

Repeatedly apply Karlin-Novikoff

$$F_3 \leq_{\text{var}} F_2 \leq_{\text{var}} F_1$$

$$M_{F_1} \leq M_{F_3} \text{ (vBk-Westen)}$$



$$M_{F_2}^{\epsilon} \rightarrow M_F^{\epsilon} \quad \text{But} \quad \mathbb{E}[M_{F_2}^{\epsilon}] = \frac{1+2+\epsilon}{2} > \frac{1+2}{2}$$

This theorem does extend to only many variables.

However it's easier to simply truncate $T(x,y)$ to $[-N,N]^d$

and apply the above theorem to it.

$$\text{Let } T^N(x,y) = \inf_{\substack{\gamma: x \rightarrow y \\ \gamma \subset [-N,N]^d}} T(\gamma)$$

$T^N(x,y)$ is obviously an increasing function of w^N (variables in the box) and it's also concave.

Thus if $G <_{var} F$ (both satisfying the condition for

$$\mathbb{E} T_F^N(x,y) \leq \mathbb{E} T_G^N(x,y) \quad \text{(the time constant)}$$

$$\rightarrow \mathbb{E} T_F(x,y) \leq \mathbb{E} T_G(x,y) \quad (\text{apply dominated convergence})$$

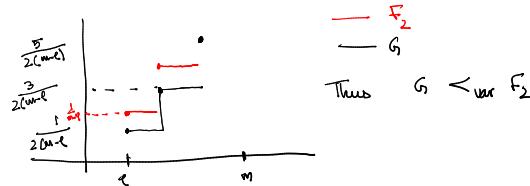
$$\Rightarrow M_F(x) \leq M_G(x) \quad \text{for } T_{(x,y)}^N \leq T(\Gamma_{x \rightarrow y}^{\text{path from}})$$

$$\text{any } x \in \mathbb{R}^d$$

Berg Kerkhoff says something stronger:

if F, G have finite means $G <_{var} F$ and

$$F \neq G \text{ Then } M_F(x) < M_G(x)$$



So by their theorem

$$M_{F_1}(e_i) \leq M_{F_2}(e_i) \leq M_{F_1}(e_i) \quad \text{--- 4}$$

$$F_2 = \text{Unif} \left\{ \left[l - \frac{1}{2}, m + \frac{1}{2} \right] \right\} \quad \mathbb{E}[X_2] = \frac{l+m}{2}$$

$$F_2^\epsilon = \text{Unif} \left\{ \left[l - \frac{1}{2} + \epsilon, m + \frac{1}{2} + \epsilon \right] \right\} \quad \mathbb{E}[X_2^\epsilon] = \frac{l+m+\epsilon}{2}$$

By Cox-Kesker continuity theorem

$$F_2^{\epsilon} \xrightarrow[\epsilon \downarrow 0]{\text{pointwise convergence at points of continuity}} F_2 \quad (\text{pointwise convergence at points of continuity})$$

$$\Rightarrow M_{F_2}^{\epsilon}(e_i) \rightarrow M_{F_2}(e_i)$$

Compare with 4 and discover $\exists \epsilon > 0$ st

$$M_{F_2}^{\epsilon}(e_i) < M_{F_1}(e_i)$$

$$\text{But } \mathbb{E}[X_2^\epsilon] = \frac{l+m+\epsilon}{2}, \quad \mathbb{E}[X_1] = \frac{l+m}{2}$$