

Wednesday December 2<sup>nd</sup> 2020 - Lecture 22.

We'll continue with two more inequalities. Consider r.v's  $x$  and  $y$  with finite means and variances,  $\mu_x, \mu_y, \sigma_x^2, \sigma_y^2$  and let  $w = (x - cy)^2$  for some constant  $c$ . Note that  $w$  is non-negative by construction.

$$\Rightarrow E[w] \geq 0 \Rightarrow E[x^2 - 2cxy + c^2y^2] \geq 0$$

$$\Rightarrow E[x^2] - 2c E[xy] + c^2 E[y^2] \geq 0 \quad \text{let } c = \frac{E[xy]}{E[y^2]} \in \mathbb{R}$$

$$\Rightarrow E[x^2] - 2 \frac{E[xy]^2}{E[y^2]} + \frac{E[xy]^2}{E[y^2]} \geq 0$$

Multiply by

$$\frac{E[y^2]}{E[y^2]} \Rightarrow E[x^2]E[y^2] - 2E[xy]^2 + E[xy]^2 \geq 0$$

$$\Rightarrow E[x^2]E[y^2] - E[xy]^2 \geq 0$$

$$\Rightarrow E[xy]^2 \leq E[x^2]E[y^2] \Rightarrow |E[xy]| \leq \sqrt{E[x^2]E[y^2]}$$

if  $x, y$  non neg  $\Rightarrow E[xy] \leq \sqrt{E[x^2]E[y^2]}$  then called the Cauchy-Schwarz inequality and they're famous

Recall

$$\text{Cov}[x, y] = E[xy] - E[x]E[y]$$

$$\text{Corr}[x, y] = \frac{\text{Cov}[x, y]}{\text{SD}[x]\text{SD}[y]} \in [-1, 1]$$

Correlation of  $x$  and  $y$  a unitless metric. we now prove that its range is always  $-1$  to  $1$ :

$$\text{Let } Z_X = \frac{X - M_X}{\sigma_X} \text{ and } Z_Y = \frac{Y - M_Y}{\sigma_Y} \Rightarrow E[Z_X] = E[Z_Y] = 0$$

$$\text{SD}[Z_X] = \text{SD}[Z_Y] = 1 \Rightarrow E[Z_X^2] = E[Z_Y^2] = 1$$

$$|E[Z_X Z_Y]| \leq \sqrt{E[Z_X^2] E[Z_Y^2]} = \sqrt{1 \cdot 1} = 1 \Rightarrow E[Z_X Z_Y] \in [-1, 1]$$

$$\text{Corr}[X, Y] = \frac{E[XY] - M_X M_Y}{\sigma_X \sigma_Y} = \frac{E[(\sigma_X Z_X + M_X)(\sigma_Y Z_Y + M_Y)] - M_X M_Y}{\sigma_X \sigma_Y}$$

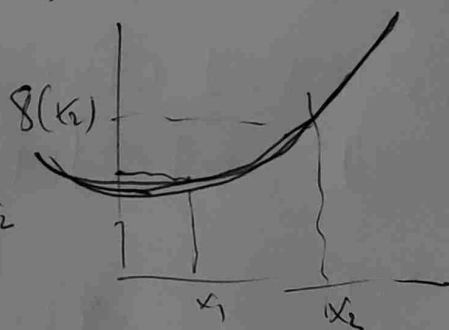
$$= \frac{\sigma_X \sigma_Y E[Z_X Z_Y] + M_X \sigma_Y E[Z_Y] + M_Y \sigma_X E[Z_X] + M_X M_Y - M_X M_Y}{\sigma_X \sigma_Y}$$

$$= E[Z_X Z_Y] \in [-1, 1]$$

Definition:  $g$  is a "convex function" on an interval,  $I$  a connected subset of the reals if for all  $\{x_1, x_2, \dots\} \subset I$  and for all  $w_1, w_2, \dots \in (0, 1)$  s.t. the sum of the  $w_i$ 's  $= 1$

$$g(w_1 x_1 + w_2 x_2 + \dots) \leq w_1 g(x_1) + w_2 g(x_2) + \dots$$

$$\Rightarrow g\left(\sum w_i x_i\right) \leq \sum w_i g(x_i)$$



Thm: if  $g$  is twice differentiable and  $g''(x) \geq 0$  for all  $x$  in  $I$ , then  $g$  is convex on  $I$ .

Consider a discrete r.v.  $X$  with pmf  $p$

$$E[X] = \sum_{x \in \text{supp}(X)} p(x)x \text{ and } \text{supp}(X) = \{x_1, x_2, \dots\} \text{ Let } w_i = p(x_i)$$

$$\Rightarrow \sum w_i = 1$$

and a convex function  $g$ . then just using the definition of convexity, we get the following inequality:

$$E[g(x)] = \sum p(x_i) g(x_i)$$

$$\Rightarrow g(E[x]) \leq E[g(x)]$$

Jensen's Inequality.

Types of convergence of random variables. we begin with reviewing convergence in distribution. Consider a sequence

$X_2, \dots, X_n$

$X_n \rightarrow X$  is defined as  $\lim_{n \rightarrow \infty} F_{X_n}(x) = F_X(x) \forall x$

$$\text{let } X_n \sim \begin{cases} \frac{1}{n+1} & \text{w.p. } \frac{1}{3} \\ 1 - \frac{1}{n+1} & \text{w.p. } \frac{2}{3} \end{cases} \quad \text{e.g. } X_2 \sim \begin{cases} \frac{1}{4} & \text{w.p. } \frac{1}{3} \\ \frac{3}{4} & \text{w.p. } \frac{2}{3} \end{cases}$$

It seems plausible that PMF convergence and CDF convergence are equivalent. then:  $\text{supp}[X_n] \subset \mathbb{Z}$  and  $\text{supp}[X] \subset \mathbb{Z}$  then they are equivalent.

If: CDF convergence  $\rightarrow$  PMF convergence (for discrete sequences).  $p_{X_n}(x) = F_{X_n}(x + \frac{1}{2}) - F_{X_n}(x - \frac{1}{2}) \forall x \in \mathbb{Z}$   
 $\lim_{n \rightarrow \infty} p_{X_n}(x) = \lim_{n \rightarrow \infty} F_{X_n}(x + \frac{1}{2}) - \lim_{n \rightarrow \infty} F_{X_n}(x - \frac{1}{2}) = F_X(x + \frac{1}{2}) - F_X(x - \frac{1}{2}) = p_X(x)$

Pf: PMF Convergence  $\Rightarrow$  CDF Convergence

$$F_{X_n}(x) = P(X_n \leq x) = \sum_{y=0}^x P_{X_n}(y)$$

$$\lim F_{X_n}(x) = \lim \sum_{y=0}^x P_{X_n}(y) = \sum_{y=0}^x \lim P_{X_n}(y) = \sum_{y=0}^x P_X(y) = P(X \leq x)$$

$X_n \sim \text{Binom}(n, \frac{\lambda}{n})$  show  $X_n \xrightarrow{d} X \sim \text{Poisson}(\lambda)$  How

Let  $c \in \mathbb{R}$  and let  $X_n \xrightarrow{d} c$  be defined as  $X_n \xrightarrow{d} c$  if  $X_n$  converges to  $c$

$$X_n \xrightarrow{d} X \sim \text{Deg}(c)$$

Which means by definition of conv. in distr.

$$\forall x \lim F_{X_n}(x) = \begin{cases} 1 & \text{if } x \geq c \\ 0 & \text{if } x < c \end{cases}$$

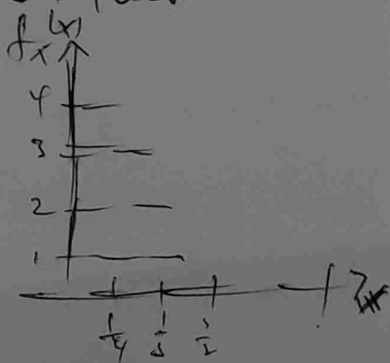
For Continuous rv's is PMF Convergence equivalent to CDF Convergence unconditionally? No. PMF Convergence  $\Rightarrow$  CDF

Convergence here is a counterexample to the other

direction:  $X_n \sim \text{Unif}(\frac{1}{n}, \frac{2}{n}) = n \mathbb{1}_{x \in [\frac{1}{n}, \frac{2}{n}]}$

$$\lim f_{X_n}(x) = \infty \text{ no PMF}$$

How. show  $\lim F_{X_n}(x) = \begin{cases} 1 & x \geq 0 \\ 0 & x < 0 \end{cases} X \sim \text{Deg}(0)$



Convergence in probability. But only to a constant  $c$ .

RV's can converge in probability to other RV's, but we just won't study it. A sequence of RV's  $X_1, X_2, \dots$  (denoted  $X_n$ )