

end of W5 lectures.

But then  $E(X) \geq E(\delta Z) = \delta E(Z)$

since  $E(Z) = 1 \times P(Z=1) + 0 \times P(Z=0)$

$= 1 \times P(X \geq \delta) = P(X \geq \delta)$

so  $E(X) \geq \delta P(X \geq \delta)$  and

$P(X \geq \delta) \leq \frac{E(X)}{\delta}$   $\square$

Week 6

Example. A person wants to pass a driving test. On average, one needs 2.5 attempts. Prove that the event that one will need 10 or more attempt is at most  $\frac{1}{4}$ .

Solution.  $X$  = the number of attempts.

We know that  $E(X) = 2.5$ . Hence

$P(X \geq 10) \leq \frac{E(X)}{10} = \frac{2.5}{10} = \frac{1}{4}$   $\square$

# The Chebyshev inequality

Theorem. Let  $X$  be a r.v. with  $E(X) = \mu$ ,  $Var(X) = \sigma^2$ . Then for any  $\epsilon > 0$

$$P(|X - \mu| \geq \epsilon) \leq \frac{Var(X)}{\epsilon^2} = \frac{\sigma^2}{\epsilon^2}.$$

Proof. Set  $Y = (X - \mu)^2$ . Then

$$\begin{aligned} P(|X - \mu| \geq \epsilon) &= P((X - \mu)^2 \geq \epsilon^2) \\ &= P(Y \geq \epsilon^2). \end{aligned}$$

Since  $Y \geq 0$ , we can use the Markov inequality:

$$P(Y \geq \epsilon^2) \leq \frac{E(Y)}{\epsilon^2} = \frac{E((X - \mu)^2)}{\epsilon^2} = \frac{Var(X)}{\epsilon^2}.$$

Remark. We use one of the equivalent definitions of variance:  $Var(X) = E((X - \mu)^2)$ , where  $\mu = E(X)$ .

Example. Consider a sequence of 150 independent trials. The pr-ty of success in each trial is  $p = 0.4$ .

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Estimate the pr-ty of 80 successes in 150 trials.

Solution.  $X$  = the number of successes  
Then  $X \sim \text{Binomial}(150, 0.4)$ .

We know that  $E(X) = np = 150 \cdot 0.4 = 60$ ,

$$\text{Var}(X) = npq = 150 \cdot 0.4 \cdot 0.6 = 60 \cdot 0.6 = 36.$$

$$\text{Then } P(X \geq 80) = P(\underbrace{X - 60}_{X - \mu} \geq 20) \leq$$

$$P(|X - 60| \geq 20) \leq \frac{\text{Var}(X)}{20^2} = \frac{36}{20^2} = \frac{9}{5 \cdot 20} = 0.09.$$

The Law of Large Numbers (LLN)

We need the following

Lemma. If  $X_1, X_2, \dots, X_n$  are independent r.v.'s, then

$$\text{Var}\left(\sum_{i=1}^n X_i\right) = \sum_{i=1}^n \text{Var}(X_i)$$

Remark.  $E\left(\sum_{i=1}^n X_i\right) = \sum_{i=1}^n E(X_i)$  - this

does not require the  $X_i$ 's to be independent.

Theorem [The LLN], let  $x_1, x_2, \dots, x_n$  be a sequence of independent r.v.'s with  $E(x_i) = \mu, \text{Var}(x_i) = \sigma^2$ . Let

$$Y_n = \frac{1}{n} \sum_{i=1}^n x_i$$

Then for any  $\epsilon > 0$

$$P(|Y_n - \mu| \leq \epsilon) \rightarrow 1 \text{ as } n \rightarrow \infty,$$

Proof,  $E(Y_n) = E\left(\frac{1}{n} \sum_{i=1}^n x_i\right) = \frac{1}{n} E\left(\sum_{i=1}^n x_i\right)$   
 $= \frac{1}{n} \sum_{i=1}^n E(x_i) = \frac{1}{n} \sum_{i=1}^n \mu = \mu.$

$$\text{Var}(Y_n) = \text{Var}\left(\frac{1}{n} \sum_{i=1}^n x_i\right) = \frac{1}{n^2} \text{Var}\left(\sum_{i=1}^n x_i\right)$$

By the above Lemma,

$$\text{Var}\left(\sum_{i=1}^n x_i\right) = \sum_{i=1}^n \text{Var}(x_i) = n \sigma^2$$

Hence

$$\text{Var}(Y_n) = \frac{1}{n^2} \times n \sigma^2 = \frac{\sigma^2}{n}.$$

Now,

$$P(|Y_n - \mu| \geq \epsilon) = P(|Y_n - E(Y_n)| \geq \epsilon) \leq \frac{\text{Var}(Y_n)}{\epsilon^2} \text{ (by the Chebyshev inequality).}$$

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$$\text{So } P(|Y_n - \mu| > \varepsilon) \leq \frac{\sigma^2}{n\varepsilon^2} \xrightarrow{n \rightarrow \infty} 0$$

$$\text{Hence } P(|Y_n - \mu| \leq \varepsilon) = 1 - P(|Y_n - \mu| > \varepsilon) \rightarrow 1 \text{ as } n \rightarrow \infty$$

$\underbrace{\hspace{10em}}_{\rightarrow 0} \quad \square$

### The Central Limit Theorem (CLT)

Theorem. Let  $X_1, X_2, \dots, X_n$  be independent identically distributed r.v.s

with  $E(X_i) = \mu$ ,  $\text{Var}(X_i) = \sigma^2$ . Then

$$P\left(\frac{\sum_{i=1}^n X_i - n\mu}{\sqrt{n}\sigma} < x\right) \xrightarrow{n \rightarrow \infty} \frac{1}{\sqrt{2\pi}} \int_{-\infty}^x e^{-\frac{t^2}{2}} dt$$

Remarks) Denote  $Z_n = \frac{\sum_{i=1}^n X_i - n\mu}{\sqrt{n}\sigma}$ .

The CLT tells us that  $Z_n$  is approximately normal  $(0, 1)$ :

$$Z_n \approx \sim N(0, 1).$$

In applications, we suppose that  $Z_n \sim N(0, 1)$

$$2) \quad Y_n = \frac{1}{n} \sum_{i=1}^n X_i - \mu = \frac{1}{n} \left( \sum_{i=1}^n X_i - n\mu \right)$$

$$\text{So } Z_n = \frac{\sqrt{n}}{\sigma} Y_n$$

$$\begin{cases} Y_1 = X_1/X_2 \\ Y_2 = X_2 \end{cases} \Rightarrow \begin{cases} X_1 = Y_1 Y_2 \\ X_2 = Y_2 \end{cases} \quad x_1$$

$$J = \begin{vmatrix} y_2 & y_1 \\ 0 & 1 \end{vmatrix} = y_2.$$

$$f_{Y_1, Y_2}(y_1, y_2) = f_{X_1, X_2}(y_1 y_2, y_2) \cdot y_2 = 8 y_1 y_2^3.$$

$$0 < x_1 < x_2 < 1 \iff$$

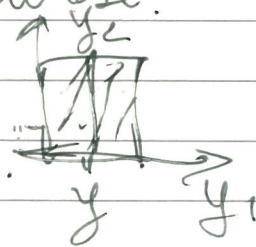
$$0 < y_1 y_2 < y_2 < 1.$$

$$\text{so } y_1 > 0, y_2 > 0; \quad y_2 < 1.$$

$$y_1 y_2 < y_2 \Rightarrow y_1 < 1.$$

so:

$$f_{Y_1, Y_2}(y_1, y_2) = \begin{cases} 8 y_1 y_2^3 & \text{if } 0 < y_1 < 1 \\ & 0 < y_2 < 1. \\ 0 & \text{otherwise.} \end{cases}$$

$$f_{Y_1}(y_1) = \int_0^1 f_{Y_1, Y_2}(y_1, y_2) dy_2 = 2y_1.$$


$$f_{Y_1}(y_1) = c y_1 = 2 y_1.$$

For other problems, see typeset solutions.

# Tutorial 6. CW6.

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facts used in CW5,6.

$$X \geq 0, \quad P(X \geq \delta) \leq \frac{E(X)}{\delta}$$

Markov's,

$$P(|X - \mu| \geq \varepsilon) \leq \frac{\text{Var}(X)}{\varepsilon^2}$$

Chebyshev's  
inequalities.

$$\frac{1}{n} \sum_{i=1}^n X_i \rightarrow \mu$$

LLN

$$\text{CLT} \quad S_n \stackrel{\text{def}}{=} \sum_{i=1}^n X_i \Rightarrow P\left(\frac{\sum_{i=1}^n X_i - n\mu}{\sqrt{n}\sigma} < x\right) \approx \frac{1}{\sqrt{2\pi}} \int_{-\infty}^x e^{-\frac{t^2}{2}} dt = \Phi(x)$$

## CW6.

$$\begin{aligned} 1) \quad \text{Var}\left(\sum_{i=1}^n X_i\right) &= E\left(\sum_{i=1}^n X_i - \sum_{i=1}^n \mu_i\right)^2 \\ &= E\left(\sum_{i=1}^n (X_i - \mu_i)\right)^2 \\ &= E\left(\sum_{i=1}^n (X_i - \mu_i)^2 + 2 \sum_{\substack{i < j \\ i, j \leq n}} (X_i - \mu_i)(X_j - \mu_j)\right) \\ &= \sum_{i=1}^n \underbrace{E(X_i - \mu_i)^2}_{\text{Var}(X_i)} + 2 \sum_{\substack{i < j \\ i, j \leq n}} \underbrace{E(X_i - \mu_i)(X_j - \mu_j)}_{\text{Cov}(X_i, X_j) = 0} \\ &= \sum_{i=1}^n \text{Var}(X_i). \end{aligned}$$

$$\begin{aligned} 3) \quad P\left(\left|\frac{1}{n} \sum_{i=1}^n X_i - \mu\right| < 0.15\right) &\geq 0.95 \Leftrightarrow \\ P\left(\left|\bar{X}_n - \mu\right| \geq 0.15\right) &\leq \frac{\sigma^2}{n(0.15)^2} = \frac{100}{n} \leq 0.05 \end{aligned}$$

$$\text{Var}(\bar{X}_n) = \frac{\sigma^2}{n}$$

$$\Rightarrow n \geq \frac{100}{0.05} = 2000.$$

4)  $X_i$  = the height of  $i$ -th person.

$$\frac{1}{100} \sum_{i=1}^{100} X_i \geq 163. \quad E(X_i) = 160, \text{Var}(X_i) = 15^2$$

$$\sum_{i=1}^{100} X_i \geq 100 \times 163$$

$$Z = \frac{\sum_{i=1}^{100} X_i - 100 \times 160}{\sqrt{10 \times 15}} \geq \frac{100 \times 163 - 100 \times 160}{10 \times 15} = \frac{300}{150} = 2$$

$\sim N(0, 1)$

$$P(Z \geq 2) = 1 - \Phi(2) = 0.023,$$

5)  $U = X_1 + \dots + X_{1000}$        $E(X_i) = 0.45 - 0.55 = -0.1$

$$\text{Var}(X_i) = 1 - 0.1^2 = 0.99$$

$E(X_i^2)$

$$P(U < -20) =$$

$$P\left(\frac{U + 1000 \times 0.1}{\sqrt{1000 \times 0.99}} < \frac{-20 + 100}{\sqrt{990}}\right)$$

$$= P\left(\frac{U + 100}{\sqrt{990}} < 2.54\right) = \Phi(2.54) = 0.9943$$

$$P(\text{Go bankrupt}) \geq 0.9943$$



# Comments concerning exam

(3)

Understand that:

$$1) \text{ Example } P(Y^2 > X > 0) = \int_0^{\infty} \left( \int_{\sqrt{x}}^{\infty} f_{X,Y}(x,y) dy \right) dx \\ = \int_0^{\infty} \left( \int_0^{y^2} f_{X,Y}(x,y) dx \right) dy$$

Know what it is  $f_{X|Y=y}$ ,  $f_{Y|X=x}$ .

$$2) \text{ Understand: } E(g(X)|Y=y) = \int_{-\infty}^{\infty} g(x) f_{X|Y=y}(x) dx$$

Be able to prove all statements we proved in lectures. Examples:

$$a) f_X(x) = \int_{-\infty}^{\infty} f_{X,Y}(x,y) dy, f_Y(y) = \int_{-\infty}^{\infty} f_{X,Y}(x,y) dx$$

$$(b) X, Y \text{ are independent} \Leftrightarrow f_{X,Y}(x,y) = h(x)g(y).$$

$$(c) X_1, \dots, X_n \text{ are normal r.v.'s, } X_i \sim N(\mu_i, \sigma_i^2).$$

$$\text{Then } \sum_{i=1}^n X_i \sim N\left(\sum_{i=1}^n \mu_i, \sum_{i=1}^n \sigma_i^2\right).$$

$$(d) X_i \sim \text{Exp}(\lambda), \text{ what is the pdf of } \sum_{i=1}^n X_i$$

(e) Inequalities: Markov, Chebyshev.

(f) LLN. Etc.

In other words: Know all proofs!