

PSTAT 120B - Outline [Shravan Shenoy]

1) - A random sample is a collection of independent and identically distributed (iid) random variables

- $Y_1, Y_2, Y_3, \dots, Y_n$ are a random sample if they have properties that allow them to be written as:

$$Y_1, \dots, Y_n \stackrel{\text{iid}}{\sim} F(y)$$

2) - A statistic is a function of the observable random variables in a sample and known constants

- any function $h(\mathbf{Y})$

3) - The term "sampling distribution" refers to the probability distributions of statistics.

- The sampling distribution of a statistic provides a theoretical model for the relative frequency histogram of the possible values of the statistic that would be observed through repeated sampling

4) Central Limit Theorem - The sample average of n random variables converges to a Gaussian distribution, which can be stated in several equivalent ways:

$$\bullet \sqrt{n}(\bar{Y}_n - \mu) \xrightarrow{d} N(0, \sigma^2) \quad \bullet \frac{\sqrt{n}(\bar{Y}_n - \mu)}{\sigma} \xrightarrow{d} N(0, 1)$$

$$\bullet \frac{\bar{Y}_n - \mu}{\sigma/\sqrt{n}} \xrightarrow{d} N(0, 1)$$

5) When $Y_1, \dots, Y_n \stackrel{\text{iid}}{\sim} N(\mu, \sigma^2)$, the sampling distribution of $\bar{Y} = n^{-1} \sum_{i=1}^n Y_i$ is normal with mean $\mu_{\bar{Y}} = \mu$ and variance $\sigma_{\bar{Y}}^2 = \sigma^2/n$

b) When Y_1, \dots, Y_n i.i.d $f(y)$ with common mean μ and var σ^2 ,

- The mean and variance of sample mean \bar{Y} is:

• mean of $\bar{Y} = \mu$ • variance(Y_i) = $\frac{\sigma^2}{n}$

- The approximate sampling distribution of $\bar{Y} = \frac{1}{n} \sum_{i=1}^n Y_i$ is:

• $\frac{\bar{Y} - \mu}{\sigma/\sqrt{n}} \sim N(0,1)$ or $\bar{Y} \sim N(\mu, \sigma^2/n)$

PSTAT 120B HW 2

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$$1) E\left(\sum_{i=1}^n a_i Y_i\right)$$

$$= E(a_1 Y_1 + a_2 Y_2 + \dots + a_n Y_n)$$

$$= \iiint (a_1 Y_1 + a_2 Y_2 + \dots + a_n Y_n) f(Y_1, \dots, Y_n) dY_1 \dots dY_n$$

$$= \iint a_1 Y_1 f(Y_1, \dots, Y_n) dY_1 \dots dY_n +$$

$$\iint a_2 Y_2 f(Y_1, \dots, Y_n) dY_1 \dots dY_n +$$

$$\iint a_n Y_n f(Y_1, \dots, Y_n) dY_1 \dots dY_n$$

$$= a_1 \int Y_1 f(Y_1) dY_1 + a_2 \int Y_2 f(Y_2) dY_2 +$$

$$+ a_n \int Y_n f(Y_n) dY_n$$

$$= \sum_{i=1}^n a_i EY_i$$

$$2) \text{Var}\left[\sum_{i=1}^n a_i Y_i\right]$$

$$\text{Use } \text{Var}(X) = E[(X - E(X))^2]$$

$$\Rightarrow E\left[\left(\sum_{i=1}^n a_i Y_i - \sum_{i=1}^n a_i Y_i E[Y_i]\right)^2\right]$$

$$\Rightarrow E\left[\sum_{i=1}^n a_i^2 (Y_i - E[Y_i])^2 + \sum_{i=1}^n \sum_{j=1}^n a_i a_j (Y_i - E[Y_i])(Y_j - E[Y_j])\right]$$

$$\Rightarrow E\left[\sum_{i=1}^n a_i^2 (Y_i - E[Y_i])^2 + \sum_{i=1}^n \sum_{j=1}^n a_i a_j (Y_i - E[Y_i])(Y_j - E[Y_j])\right]$$

$$= \sum_{i=1}^n a_i^2 E[(Y_i - E[Y_i])^2] + \sum_{i=1}^n \sum_{j=1}^n a_i a_j E[(Y_i - E[Y_i])(Y_j - E[Y_j])]$$

$$= \sum_{i=1}^n a_i^2 \text{Var}(Y_i) + 2 \sum_{i < j} a_i a_j \text{cov}(Y_i, Y_j)$$

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$$= \sum_{i=1}^n a_i^2 \text{Var}(Y_i) + 2 \sum_{i < j} a_i a_j \text{cov}(Y_i, Y_j)$$

$$3) Y_1, Y_2, Y_3, \dots, Y_n \stackrel{\text{iid}}{\sim} N(\mu, \sigma^2)$$

$$\bar{Y} = n^{-1} \sum_{i=1}^n Y_i$$

$$E\left(\frac{X-a}{b}\right) = e^{-\frac{a^2}{b^2}} E\left(\frac{X}{b}\right)$$

$$\Rightarrow \bar{Y} \sim N(\mu, \sigma^2/n)$$

The MGF for the normal dist. with parameters μ and σ is $m(t) = e^{\mu t + \sigma^2 t^2/2}$

Since the Y_i 's are independent, the mgf of

$$Z = \frac{\bar{Y} - \mu}{\sigma/\sqrt{n}} \text{ is: } M_Z(t) = E(e^{tZ})$$

$$\Rightarrow \prod_{i=1}^n E(e^{t \frac{Y_i - \mu}{\sigma}}) = e^{\mu t \sum_{i=1}^n \frac{1}{\sigma} + (t^2 \sigma^2/2) \sum_{i=1}^n \frac{1}{\sigma^2}}$$

$$\sim \text{Dist}(\text{mean } \mu \sum_{i=1}^n \frac{1}{\sigma}, \text{var } \sigma^2 \sum_{i=1}^n \frac{1}{\sigma^2})$$

$$4) Y_1, \dots, Y_n \text{ (random sample)}$$

Common mean μ , common var σ^2

$$P(\bar{Y} \leq x) = P((Y_1 + Y_2 + \dots + Y_n)/n \leq x)$$

$$= P(Y_1 + Y_2 + \dots + Y_n \leq nx)$$

$$E[Y_i] = \mu; E[\bar{Y}] = n\mu$$

$$\text{Var}[Y_i] = \sigma^2; \text{Var}(\bar{Y}) = n\sigma^2$$

$$P\left(\frac{(Y_1, \dots, Y_n) - n\mu}{n\sigma^2} \leq \frac{nx - n\mu}{\sqrt{n}\sigma}\right) = P(Z \leq \frac{nx - n\mu}{\sqrt{n}\sigma})$$

$$\Rightarrow P\left(\frac{(Y_1, \dots, Y_n) - n\mu}{n\sigma^2} \leq \frac{nx - n\mu}{\sqrt{n}\sigma}\right)$$

$$\lim_{n \rightarrow \infty} \frac{(Y_1, \dots, Y_n) - n\mu}{n\sigma^2} \rightarrow N(0, 1)$$

$$\Rightarrow P(\bar{Y} \leq x) = P(Z \leq \frac{\sqrt{n}(x - \mu)}{\sigma})$$

$$= \Phi\left(\frac{\sqrt{n}(x - \mu)}{\sigma}\right)$$

5) $\mu = 7$ $\sigma = .5$ 64 workers

$$\sigma_x = \frac{\sigma}{\sqrt{n}} = \frac{.5}{\sqrt{64}}$$

$$z = \frac{\bar{x} - \mu}{\sigma/\sqrt{n}}$$

$$P(\bar{x} \leq 6.90) = P\left(\frac{\bar{x} - \mu}{\sigma/\sqrt{n}} \leq \frac{6.90 - 7}{.5/8}\right)$$

$$= P\left(\frac{\bar{x} - \mu}{\sigma/\sqrt{n}} \leq \frac{-.10}{.0625}\right)$$

$$= P(z \leq -1.6)$$

$$= \Phi(-1.6)$$

$$= 1 - \Phi(1.6)$$

$$= \boxed{.0548}$$