## SCIM122

AY24/25 SEM 2

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#### **Probability**

$$P(A \cup B) = P(A) + P(B) - P(A \cap B)$$

 $P(A \cap B) = P(A)P(B \mid A)$ 

$$P(A | B) = \frac{P(B | A)P(A)}{P(B | A)P(A) + P(B | A')P(A')}$$

#### Discrete distributions

For a discrete random variable X taking values x, with probabilities P(X = x)

Expectation (mean):  $E(X) = \mu = \sum x_i P(X = x_i)$ 

Variance: 
$$Var(X) = \sigma^2 = \sum_i (x_i - \mu)^2 P(X = x_i) = \sum_i x_i^2 P(X = x_i) - \mu^2$$

For a function g(X):  $E(g(X)) = \sum g(x_i) P(X = x_i)$ 

## Random Variables

Types of Random Variables Binomial: Random variable with parameters n and p

 $Y = X_1 + X_2 + \cdots + X_n$  are independent.

$$P(X = k) = \binom{n}{k} p^k (1 - p)^{n-k}$$

P(k successes from n independent trials each with probability of p

Example: number of red balls out of n balls drawn with replacement.

$$\mathbb{E}(Y) = np$$
,  $Var(Y) = np(1-p)$ 

**Negative Binomial:** X = number of trials until k successes are

$$P(X = x) = {x-1 \choose k-1} p^k (1-p)^{x-k}, \quad \text{for } x = k, k+1, \dots$$

**Geometric:** X = number of trials until a success is obtained.where k is the number of trials needed

$$P(X = k) = (1 - p)^{k-1}p$$

**Hypergeometric**: X = number of trials until success, without

$$P(X = x) = \frac{\binom{k}{x} \binom{N-k}{n-x}}{\binom{N}{x}}, \quad \text{for possible } x$$

Poisson distribution

$$P(X = x) = \frac{e^{-\mu}\mu^x}{x!}, \text{ for } x = 0, 1, 2, \dots$$

#### Variance

**Definition.** Let X be a random variable with probability distribution f(x) and mean  $\mu$ .

The **variance** of X is

$$\sigma_X^2 = E[(X-\mu_X)^2] = \sum_x (x-\mu_X)^2 f(x) (X \text{ is discrete}),$$

$$\sigma_X^2 = E[(X - \mu_X)^2] = \int_{-\infty}^{\infty} (x - \mu_X)^2 f(x) \, dx \\ (X = E[(X - \mu_X)^2] = \int_{-\infty}^{\infty} (x - \mu_X)^2 f(x) \, dx \\ (X = E[(X - \mu_X)^2] = \int_{-\infty}^{\infty} (x - \mu_X)^2 f(x) \, dx \\ (X = E[(X - \mu_X)^2] = \int_{-\infty}^{\infty} (x - \mu_X)^2 f(x) \, dx \\ (X = E[(X - \mu_X)^2] = \int_{-\infty}^{\infty} (x - \mu_X)^2 f(x) \, dx \\ (X = E[(X - \mu_X)^2] = \int_{-\infty}^{\infty} (x - \mu_X)^2 f(x) \, dx \\ (X = E[(X - \mu_X)^2] = \int_{-\infty}^{\infty} (x - \mu_X)^2 f(x) \, dx \\ (X = E[(X - \mu_X)^2] = \int_{-\infty}^{\infty} (x - \mu_X)^2 f(x) \, dx \\ (X = E[(X - \mu_X)^2] = \int_{-\infty}^{\infty} (x - \mu_X)^2 f(x) \, dx \\ (X = E[(X - \mu_X)^2] = \int_{-\infty}^{\infty} (x - \mu_X)^2 f(x) \, dx \\ (X = E[(X - \mu_X)^2] = \int_{-\infty}^{\infty} (x - \mu_X)^2 f(x) \, dx \\ (X = E[(X - \mu_X)^2] = \int_{-\infty}^{\infty} (x - \mu_X)^2 f(x) \, dx \\ (X = E[(X - \mu_X)^2] = \int_{-\infty}^{\infty} (x - \mu_X)^2 f(x) \, dx \\ (X = E[(X - \mu_X)^2] = \int_{-\infty}^{\infty} (x - \mu_X)^2 f(x) \, dx \\ (X = E[(X - \mu_X)^2] = \int_{-\infty}^{\infty} (x - \mu_X)^2 f(x) \, dx \\ (X = E[(X - \mu_X)^2] = \int_{-\infty}^{\infty} (x - \mu_X)^2 f(x) \, dx \\ (X = E[(X - \mu_X)^2] = \int_{-\infty}^{\infty} (x - \mu_X)^2 f(x) \, dx \\ (X = E[(X - \mu_X)^2] = \int_{-\infty}^{\infty} (x - \mu_X)^2 f(x) \, dx \\ (X = E[(X - \mu_X)^2] = \int_{-\infty}^{\infty} (x - \mu_X)^2 f(x) \, dx \\ (X = E[(X - \mu_X)^2] = \int_{-\infty}^{\infty} (x - \mu_X)^2 f(x) \, dx \\ (X = E[(X - \mu_X)^2] = \int_{-\infty}^{\infty} (x - \mu_X)^2 f(x) \, dx \\ (X = E[(X - \mu_X)^2] = \int_{-\infty}^{\infty} (x - \mu_X)^2 f(x) \, dx \\ (X = E[(X - \mu_X)^2] = \int_{-\infty}^{\infty} (x - \mu_X)^2 f(x) \, dx \\ (X = E[(X - \mu_X)^2] = \int_{-\infty}^{\infty} (x - \mu_X)^2 f(x) \, dx \\ (X = E[(X - \mu_X)^2] = \int_{-\infty}^{\infty} (x - \mu_X)^2 f(x) \, dx \\ (X = E[(X - \mu_X)^2] = \int_{-\infty}^{\infty} (x - \mu_X)^2 f(x) \, dx \\ (X = E[(X - \mu_X)^2] = \int_{-\infty}^{\infty} (x - \mu_X)^2 f(x) \, dx \\ (X = E[(X - \mu_X)^2] = \int_{-\infty}^{\infty} (x - \mu_X)^2 f(x) \, dx \\ (X = E[(X - \mu_X)^2] = \int_{-\infty}^{\infty} (x - \mu_X)^2 f(x) \, dx \\ (X = E[(X - \mu_X)^2] = \int_{-\infty}^{\infty} (x - \mu_X)^2 f(x) \, dx \\ (X = E[(X - \mu_X)^2] = \int_{-\infty}^{\infty} (x - \mu_X)^2 f(x) \, dx \\ (X = E[(X - \mu_X)^2] = \int_{-\infty}^{\infty} (x - \mu_X)^2 f(x) \, dx \\ (X = E[(X - \mu_X)^2] = \int_{-\infty}^{\infty} (x - \mu_X)^2 f(x) \, dx \\ (X = E[(X - \mu_X)^2] = \int_{-\infty}^{\infty} (x - \mu_X)^2 f(x) \, dx \\ (X = E[(X - \mu_X)^2] = \int_{-\infty}^{\infty} (x - \mu_X)^2 f(x) \, dx \\ (X = E[(X - \mu_X)^2] = \int_{-\infty}^{\infty} (x - \mu_X)^2 f$$

The **standard deviation** of X is the (non-negative) square root of the

$$\sigma_X^2 = E(X^2) - \mu_X^2$$

If X is a random variable, and are constants, then

$$\sigma_{aX+b}^2 = \sigma_{aX}^2 = a^2 \sigma_X^2$$

#### **Continuous Uniform Distribution**

Suppose that X is a continuous uniform random variable on the interval [A, B]. The density function of X is

$$f(x) = \begin{cases} \frac{1}{B-A}, & A \le X \le B, \\ 0, & \text{otherwise.} \end{cases}$$

## **Exponential Distribution**

Suppose that X follows an exponential distribution with the density

$$f(x) = \begin{cases} \frac{1}{\beta} e^{-x/\beta}, & x > 0, \\ 0, & \text{otherwise.} \end{cases}$$

where  $\beta$  is a positive constant.

## Joint Probability Distributions

**Definition.** The function f(x, y) is a joint probability distribution (or **probability mass function**) of discrete random variables X and

- 1.  $f(x,y) \geq 0$  for all (x,y),
- 2.  $\sum_{x} \sum_{y} f(x, y) = 1$ ,
- 3. P(X = x, Y = y) = f(x, y).

For any region A in the xy-plane.

$$P((X,Y) \in A) = \sum_{(x,y)\in A} f(x,y).$$

**Definition.** The function f(x, y) is a **joint density function** of continuous random variables X and Y if:

- 1.  $f(x,y) \geq 0$  for all (x,y),
- 2.  $\int_{-\infty}^{\infty} \int_{-\infty}^{\infty} f(x,y) dx dy = 1,$
- 3.  $P((X,Y) \in A) = \iint_A f(x,y) dx dy$ , for any region Ain the xy-plane.

# Estimating Proportion

## Estimating a proportion

An (approximate)  $100(1-\alpha)\%$  confidence interval for the proportion p is

$$\hat{p} - z_{\alpha/2} \sqrt{\frac{\hat{p}\hat{q}}{n}}$$

where  $\hat{p}$  = the proportion of successes in a random sample of size n, and  $\hat{q} = 1 - \hat{p}$ 

- sample of size n
- · number of successes X
- proportion of success  $\hat{p} = \frac{X}{2}$
- Standard Error, SE =  $\sqrt{\frac{\hat{p}(1-\hat{p})}{n}} = \sqrt{\frac{\hat{p}\hat{q}}{n}}$
- Confidence interval = α
- find  $z_{\alpha/2}$  value of  $\alpha/2$  in table

## Estimating the difference between two proportions

An (approximate)  $100(1-\alpha)\%$  confidence interval for the

$$(\hat{p}_1 - \hat{p}_2) - z_{\alpha/2} \sqrt{\frac{\hat{p}_1 \hat{q}_1}{n_1} + \frac{\hat{p}_2 \hat{q}_2}{n_2}} < p_1 - p_2 < (\hat{p}_1 - \hat{p}_2) + z_{\alpha/2} \sqrt{\frac{\hat{p}_1 \hat{q}_1}{n_1} + \frac{\hat{p}_2 \hat{q}_2}{n_2}}$$

# **Estimating variance**

$$S^2 = \frac{1}{n-1} \sum_{i=1}^n (X_i - \bar{X})^2 = \frac{n \sum_{i=1}^n X_i^2 - \left(\sum_{i=1}^n X_i\right)^2}{n(n-1)} \\ | \text{has the $F$-distribution with $\nu_1 = n_1 - 1$ and $\nu_2 = n_2$} \\ | \text{degrees of freedom. The critical region is $f_\alpha(\nu_1, \nu_2)$ in $F$-distribution table, $\alpha$ is critical value} \\ | \text{F-distribution table, $\alpha$$$

#### **Unbiased estimator**

The sample mean is

$$\bar{X} = \frac{1}{n} \sum_{i=1}^{n} X_i.$$

The sample variance is

$$S^{2} = \frac{1}{n-1} \sum_{i=1}^{n} (X_{i} - \bar{X})^{2}.$$

# Chi-square distribution

A chi-squared distribution is a continuous probability distribution whose density function is

$$f(x) = \begin{cases} \frac{1}{2^{\nu/2}\Gamma(\nu/2)} x^{\nu/2-1} e^{-x/2}, & x > 0 \\ 0, & \text{otherwise} \end{cases}$$

where the parameter  $\nu$  is called the degrees of freedom ( $\nu$  is a positive integer).

and  $\Gamma$  is the Gamma function, i.e.

$$\Gamma(\alpha) = \int_0^\infty x^{\alpha - 1} e^{-x} \, dx \quad \text{for } \alpha > 0.$$

#### Constructing a confidence interval for a variance

$$\chi^2 = \frac{(n-1)S^2}{\sigma^2}$$

has the chi-squared distribution with  $\nu=n-1$  degrees of freedom

$$P\left(\chi_{1-\alpha/2}^{2} < \chi^{2} < \chi_{\alpha/2}^{2}\right) = 1 - \alpha$$

If  $s_1^2$  and  $s_2^2$  are the variances of independent random samples of size  $n_1$  and  $n_2$ , respectively, from normal populations, then a  $100(1-\alpha)\%$  confidence interval for  $\frac{\sigma_1^2}{\sigma_2^2}$  is

$$\frac{s_1^2}{s_2^2} \cdot \frac{1}{f_{\alpha/2}(v_1, v_2)} < \frac{\sigma_1^2}{\sigma_2^2} < \frac{s_1^2}{s_2^2} \cdot f_{\alpha/2}(v_2, v_1)$$

where  $f_{\alpha/2}(v_1, v_2)$  is the critical value of the F-distribution with  $v_1 = n_1 - 1$  and  $v_2 = n_2 - 1$  degrees of freedom, with area on the right tail  $\alpha/2$ 

(and  $f_{\alpha/2}(v_2, v_1)$  is defined similarly).

## Maximum likelihood estimation





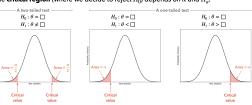




$$p \times p \times (1-p) = p^2 - p^3$$

The **level of significance** ( $\alpha$ ) = the probability of rejecting  $H_0$  when it is true.

The **critical region** (where we decide to reject  $H_0$ ) depends on  $\alpha$  and  $H_a$ .



= the probability of making a Type I error

## Hypothesis testing for two variances

$$F = \frac{s_1^2/\sigma_1^2}{s_2^2/\sigma_2^2}$$

has the F-distribution with  $u_1=n_1-1$  and  $u_2=n_2-1$ F-distribution table,  $\alpha$  is critical value

#### Test for independence

expected frequency,  $e_i = \frac{(\text{column total}) \times (\text{row total})}{\text{grand total}}$ 

Test statistic:  $\chi^2 = \sum_i \frac{(o_i - e_i)^2}{e^{-i}}$ 

Observed frequency, o<sub>i</sub>, from table in question

### Confidence Interval for Difference in Proportions

A marketing research is investigating customers' preferences between two brands of a particular product. In two independent samples, 180 out of 400 people have heard about brand A, while 210 out of 500 have heard about brand B. Construct a 95% confidence interval for the difference: $p_A - p_B$ , where  $p_A$  and  $p_B$  are the proportions of customers who have heard about brand A and brand B, respectively

$$\hat{p}_A = \frac{180}{400} = 0.45, \hat{p}_B = \frac{210}{500} = 0.42$$

$$z^* = 1.96$$
 
$$\text{CI} = (\hat{p}_A - \hat{p}_B) \pm z^* \cdot \sqrt{\frac{\hat{p}_A(1 - \hat{p}_A)}{n_A} + \frac{\hat{p}_B(1 - \hat{p}_B)}{n_B}}$$

$$=0.03\pm1.96\cdot\sqrt{\frac{0.45\cdot0.55}{400}+\frac{0.42\cdot0.58}{500}}$$

A manufacturing company wants to ensure consistency in the thickness of its glass panels. Let  $X_1, X_2, \ldots, X_{30}$  be the thickness of 30 panels in a random sample. Suppose that:

$$\sum_{i=1}^{30} X_i = 110.6 \text{ mm}, \quad \sum_{i=1}^{30} X_i^2 = 478.24 \text{ mm}^2$$

 $= 0.03 \pm 1.96(0.03326) \Rightarrow CI = (-0.0352, 0.0952)$ 

Calculate the variance of this sample.

$$s^{2} = \frac{1}{n-1} \left( \sum X_{i}^{2} - \frac{(\sum X_{i})^{2}}{n} \right)$$
$$= \frac{1}{29} \left( 478.24 - \frac{(110.6)^{2}}{30} \right)$$
$$= \frac{1}{29} \left( 478.24 - 407.75 \right) = 2.4309$$

In country A, each person has a 25% chance of having blood type O. In country B, each person has a 30% chance of having blood type O. 30 people from country A are randomly chosen, and let X be the number of people in this group who have blood type O. 25 people from country B are randomly chosen, and let Y be the number of people in this group who have blood type O. Which random variable has a greater variance, X or Y? Since both Xand Y follow Binomial distributions:

$$Var(X) = 30 \cdot 0.25 \cdot 0.75 = 5.625$$
  
 $Var(Y) = 25 \cdot 0.30 \cdot 0.70 = 5.25$ 

 $\Rightarrow$  So, X has a greater variance.