

One Factor Experiments

$$H_0 = \mu_1 = \dots = \mu_I$$

$$H_1 = \text{two or more of the } \mu_i \text{ are different}$$

$$\begin{aligned} SSTr &= \sum_{i=1}^I J_i (\bar{X}_{i.} - \bar{X}_{..})^2 \\ &= \sum_{i=1}^I J_i \bar{X}_{i.}^2 - N \bar{X}_{..}^2 \end{aligned}$$

$$\begin{aligned} SSE &= \sum_{i=1}^I \sum_{j=1}^{J_i} (X_{ij} - \bar{X}_i)^2 \\ &= \sum_{i=1}^I \sum_{j=1}^{J_i} X_{ij}^2 - \sum_{i=1}^I J_i \bar{X}_i^2 \end{aligned}$$

$$MSTr = \frac{SSTr}{I-1} \quad MSE = \frac{SSE}{N-I}$$

$$F = \frac{MSTr}{MSE}$$

$$SST = SSTr + SSE$$

$$\begin{aligned} SST &= \sum_{i=1}^I \sum_{j=1}^{J_i} (X_{ij} - \bar{X}_{..})^2 \\ &= \sum_{i=1}^I \sum_{j=1}^{J_i} X_{ij}^2 - N \bar{X}_{..}^2 \end{aligned}$$

$$p\text{-value} < \alpha \implies \text{reject } H_0$$

$$p\text{-value} \geq \alpha \implies \text{fail to reject } H_0$$

Two Factor Experiments

$$X_{ijk} = \mu + \alpha_i + \beta_j + \gamma_{ij} + \epsilon_{ijk}$$

$$\alpha_i = \bar{\mu}_{i.} - \mu$$

$$\beta_j = \bar{\mu}_{.j} - \mu$$

$$\gamma_{ij} = \mu_{ij} - \bar{\mu}_{i.} - \bar{\mu}_{.j} + \mu$$

$$\epsilon_{ijk} = X_{ijk} - \mu_{ij}$$

$$H_{0,AB} : \gamma_{11} = \gamma_{12} = \dots = \gamma_{IJ} = 0$$

$$H_{H,AB} : \text{at least one of the } \gamma_{ij} \text{ is nonzero}$$

$$H_{0,A} : \alpha_1 = \alpha_2 = \dots = \alpha_I = 0$$

$$H_{1,A} : \text{at least one of the } \alpha_i \text{ is nonzero}$$

Sum of Squares for Two-Way ANOVA

- Treatment sum of squares: $SSTr$ (d.f. = I*J - 1)
- Row sum of squares: $SSA = JK \sum_{i=1}^I \hat{\alpha}_i^2$ (d.f. = I - 1)
- Column sum of squares: $SSB = IK \sum_{j=1}^J \hat{\beta}_j^2$ (d.f. = J - 1)
- Interaction sum of squares: $SSAB = K \sum_{i=1}^I \sum_{j=1}^J \hat{\gamma}_{ij}^2$ (d.f. = (I-1)(J-1))
- Error sum of squares: SSE (d.f. = I*J(K-1))
- Total sum of squares: SST (d.f. = I*J*K - 1)

$$F_{AB}^* = \frac{MSAB}{MSE} \quad F_A^* = \frac{MSA}{MSE} \quad \frac{MSB}{MSE}$$

$$MSA = \frac{SSA}{I-1} \quad MSB = \frac{SSB}{J-1} \quad MSAB + \frac{SSAB}{(I-1)(J-1)}$$

Bernoulli Distribution

$$\mu_x = p$$

$$\sigma_x^2 = p(1-p)$$

Binomial Distribution

$$p(x) = P(X = x) = \begin{cases} \binom{n}{x} p^x (1-p)^{n-x} & x = 0, 1, \dots, n \\ 0 & \text{otherwise} \end{cases}$$

$$\text{where } \binom{n}{k} = \frac{n!}{k!(n-k)!}$$

$$\mu_x = np$$

$$\sigma_x^2 = np(1-p)$$

$$\bar{p} = \frac{\text{number of successes}}{\text{number of trials}} = \frac{X}{n}$$

$$\sigma_{\bar{p}} = \sqrt{\text{Var}(\bar{p})} \approx \sqrt{\frac{\bar{p}(1-\bar{p})}{n}}$$

Poisson Distribution

$$p(x) = P(X = x) = \begin{cases} \frac{e^{-\lambda} \lambda^x}{x!} & x = 0, 1, \dots, n \\ 0 & \text{otherwise} \end{cases}$$

$$\mu_x = \lambda \quad \sigma_x^2 = \lambda$$

The Normal Distribution

If a continuous random variable x with mean μ and variance σ^2 has the following probability density function

$$f(x) = \frac{1}{\sigma \sqrt{2\pi}} e^{-\frac{(x-\mu)^2}{2\sigma^2}}$$

$$Z = \frac{X - \mu}{\sigma}$$

The Exponential Distribution

The notation is as follows $X \sim \text{Exp}(\lambda)$

$$f(x) = \begin{cases} \lambda e^{-\lambda x} & x = 0, 1, \dots, n \\ 0 & \text{otherwise} \end{cases}$$

$$F(x) = \begin{cases} 0 & x \leq 0 \\ 1 - e^{-\lambda x} & x > 0 \end{cases}$$

$$P(T > t + s | T > s) = P(T > t)$$

$$s_i^2 = \sigma_i^2 = \frac{1}{J_i - 1} \sum_{j=1}^{J_i} (X_{ij} - \bar{X}_{i.})^2$$