

**tags:** Methods1

**NOTE:**

**field:** 100000

**field:** Epidemiology Definition of Causation

**field:** Factor/variable  $X$  **causes** result  $Y$  if some cases of  $Y$  would not have occurred if  $X$  had been absent.

**NOTE:**

**field:** 100001

**field:** Sample variance

**field:**  $s^2 = \frac{1}{n-1} \sum_{i=1}^n (x_i - \bar{x})^2$

**NOTE:**

**field:** 100002

**field:** Population(s) of interest

**field:** The group to which you would like your answer to apply

**NOTE:**

**field:** 100003

**field:** Variable of Interest

**field:** A measurement that can be made on each individual/member of the population

**NOTE:**

**field:** 100004

**field:** Facts about Normal Distributions

**field:**

- If  $Z$  has a Normal(0,1) distribution then  $X = \sigma Z + \mu$  has a Normal( $\mu, \sigma^2$ ) distribution
- If  $X$  has a Normal( $\mu, \sigma^2$ ) distribution, then  $Z = \frac{X - \mu}{\sigma}$  has a Normal(0,1) distribution.
- If  $X$  has a Normal( $\mu_x, \sigma_x^2$ ) distribution, and  $Y$  has a Normal( $\mu_y, \sigma_y^2$ ) distribution, and  $X$  and  $Y$  are independent of each other, then  $X + Y \sim \text{Normal}(\mu_x + \mu_y, \sigma_x^2 + \sigma_y^2)$

**NOTE:**

**field:** 100005

**field:** Sample mean

**field:**  $\bar{Y} = \frac{1}{n} \sum_{i=1}^n Y_i$

**NOTE:**

**field:** 100006

**field:** Sampling distribution for population  $Y \sim \text{Normal}(\mu, \sigma)$

**field:**  $N(\mu, \sigma^2/n)$

**NOTE:**

**field:** 100007

**field:** Variance (Expected value)

**field:**  $V(Y) = E[(X - E(X))^2] = E(X^2) - E[(X)]^2$

**NOTE:**

**field:** 100008

**field:** Covariance

**field:**  $Cov(X, Y) = E[(X - E(X))(Y - E(Y))]$

**NOTE:**

**field:** 100009

**field:** If  $X$  and  $Y$  are independent (covariance)

**field:** The covariance is 0

**NOTE:**

**field:** 100010

**field:** If  $Cov(X, Y) = 0$ , (independence)

**field:** Cannot say that  $X$  and  $Y$  are independent

**NOTE:**

**field:** 100011

**field:**  $Cov(X, X) =$

**field:**  $Var(X)$

**NOTE:**

**field:** 100012

**field:**  $X \sim N(\mu, \sigma^2)$

- $E(\bar{X}) =$
- $V(\bar{X}) =$

**field:**

- $E(\bar{X}) = \mu$
- $V(\bar{X}) = \sigma^2/n$

**NOTE:**

**field:** 100013

**field:** Central Limit Theorem (in words)

**field:** If the population distribution of a variable  $X$  has population mean  $\mu$  and finite population variance  $\sigma^2$ , then the sampling distribution of the sample mean becomes closer and closer to a Normal distribution as the sample size  $n$  increases:  $\bar{X} \sim N(\mu, \sigma^2/n)$

**NOTE:**

**field:** 100014

**field:** Central Limit Theorem (theoretical)

**field:** Let  $X_1, X_2, \dots, X_n$  be an iid sample from some population distribution  $F$  with mean  $\mu$  and variance  $\sigma^2 < \infty$ . Then as the sample size  $n \rightarrow \infty$ , we have

$$\frac{\sqrt{n}(\bar{X}_n - \mu)}{\sigma} \rightarrow N(0, 1)$$

**NOTE:**

**field:** 100015

**field:**  $X \sim (\mu, \sigma^2)$

- $E(\bar{X}) =$
- $V(\bar{X}) =$

**field:**

- $E(\bar{X}) = \mu$
- $V(\bar{X}) = \sigma^2/n$

**NOTE:**

**field:** 100016

**field:** Reject  $H_0$  when  $H_0$  True

**field:** Type I error (false positive)

**NOTE:**

**field:** 100017

**field:** Type I error (false positive)

**field:** Reject  $H_0$  when  $H_0$  True

**NOTE:**

**field:** 100018

**field:** Fail to Reject  $H_0$  when  $H_0$  false

**field:** Type II error

**NOTE:**

**field:** 100019

**field:** Type II error

**field:** Fail to Reject  $H_0$  when  $H_0$  false

**NOTE:**

**field:** 100020

**field:** Significance level

**field:**  $\alpha$  the probability of a Type I error

**NOTE:**

**field:** 100021

**field:** Power (at  $\theta_1$ )

**field:** Probability of rejecting the null hypothesis when  $\theta_1$  is the truth

**NOTE:**

**field:** 100022

**field:** Test for data setting:  $X_1, X_2, \dots, X_n$  iid with sample mean  $\bar{X}$ , and known population variance  $\sigma^2$ , Null hypothesis  $\mu = \mu_0$

- Test name
- Test Statistic
- Test Reference Distribution
- Critical Value
  - Lower
  - Upper
  - Two sided
- Confidence interval
- pvalue
  - upper:
  - lower:
  - two-sided
- Consistent/Finite Sample Exact/ Asymptotically Exact

**field:** z-test

- Test statistic:  $Z(\mu_0) = \frac{\bar{X} - \mu_0}{\sqrt{\sigma^2/n}}$
- Reference Distribution: Under  $H_0$ ,  $Z(\mu_0) \sim N(0, 1)$ 
  - Lower: Reject when  $Z(\mu_0) < z_\alpha = \text{qnorm}(\alpha)$
  - Upper: Reject when  $Z(\mu_0) > z_{1-\alpha} = \text{qnorm}(1-\alpha)$
  - Two sided: Reject when  $|Z(\mu_0)| > z_{1-\alpha/2} = \text{qnorm}(1 - \alpha/2)$
- Confidence interval:  $\bar{X} \pm z_{1-\alpha/2} \sqrt{\frac{\sigma^2}{n}}$
- pvalue:

- upper:  $1 - \Phi(z) = 1 - \text{pnorm}(z)$
- lower:  $\Phi(z) = \text{pnorm}(z)$
- two-sided:  $2(1 - \Phi(|z|)) = 2*(1 - \text{pnorm}(\text{abs}(z)))$
- Consistent: Yes / Finite Sample Exact: Yes if  $X_i \sim N$  / Asymptotically Exact: Yes

**NOTE:**

**field:** 100023

**field:** Exactness (finite/asymptotic)

**field:** Under any setting for which the null hypothesis is true, is the actual rejection probability equal to the desired level  $\alpha$ ?

- Finite Sample Exact: for sample size  $n$  is  $P(\text{Reject}H_0) = \alpha$  when  $H_0$  is true?
- Asymptotic Exactness: As  $n \rightarrow \infty$  does  $P(\text{Reject}H_0) \rightarrow \alpha$  when  $H_0$  is true?

**NOTE:**

**field:** 100024

**field:** When is a test exact?

**field:**

- A test is FSE if the reference distribution is the true distribution of the test statistic  $T$  when  $H_0$  is true
- A test is AE if the reference distribution is the asymptotic distribution of the test statistic when  $H_0$  is true.
- (Distribution of p-values should be  $\text{Unif}(0.1)$ )



**NOTE:**

**field:** 100025

**field:** Consistency

**field:** When  $H_0$  is false (the alternative hypothesis is true), does the rejection probability (probability reject the null) tend to 1 as  $n \rightarrow \infty$ ?

**NOTE:**

**field:** 100026

**field:** Interpretation of Confidence intervals

**field:**  $(1 - \alpha)100\%$  of the time, intervals constructed in this manner will include  $\mu$

**NOTE:**

**field:** 100027

**field:** Test for data setting:  $X_1, X_2, \dots, X_n$  iid with sample mean  $\bar{X}$ , and unknown population variance, Null hypothesis  $\mu = \mu_0$

- Test name
- Test Statistic
- Test Reference Distribution
- Critical Value/ Rejection region
  - upper:
  - lower:
  - two-sided
- Confidence interval

- pvalue
  - upper:
  - lower:
  - two-sided
- Consistent/Finite Sample Exact/ Asymptotically Exact

**field:**

- Test name: t-test
- Test Statistic:  $t(\mu_0) = \frac{\bar{X} - \mu_0}{\sqrt{s^2/n}}$
- Test Reference Distribution:  $t_{n-1}$
- Critical Value/ Rejection region
  - upper: Reject if  $t(\mu_0) > t_{(n-1), 1-\alpha} = \text{qt}(1 - \alpha, n-1)$
  - lower: Reject if  $t(\mu_0) < t_{n-1, \alpha}$
  - two sided: Reject if  $|t(\mu_0)| > t_{n-1, 1-\alpha/2}$
- Confidence interval:  $\bar{X} \pm t_{n-1, 1-\alpha/2} \sqrt{\frac{s^2}{n}}$
- pvalue, with  $t(\mu_0) = t$ , and pt representing the cdf of a t distribution
  - upper:  $1 - \text{pt}(t, n - 1)$
  - lower:  $\text{pt}(t, n-1)$
  - two-sided:  $2*(1 - \text{pt}(\text{abs}(t)), n-1)$
- Consistent Yes/Finite Sample Exact Yes if normal/ Asymptotically Exact Yes

**NOTE:**

**field:** 100028

**field:** Test for data setting  $Y_1, \dots, Y_n$  iid Bernoulli( $p$ ) (option 1), parameter of interest  $p$

- Test name
- Test Statistic
- Test Reference Distribution
- Critical Value/ Rejection region
  - upper:
  - lower:
  - two-sided
- Confidence interval
- pvalue
- Consistent/Finite Sample Exact/ Asymptotically Exact

**field:** Test for data setting  $Y_1, \dots, Y_n$  iid Bernoulli( $p$ ), parameter of interest  $p$

- Test name: Exact Binomial Test (uses the distribution of the sum of Bern( $p$ ) RVs)
- Test Statistic:  $X = \sum_{i=1}^n Y_i = n\bar{Y}$
- Test Reference Distribution: Under  $H_0$  Binomial( $n, p_0$ )
- Critical Value/ Rejection region: Sometimes use randomized test
  - upper: Reject  $H_0$  for  $X \geq c$  for  $c$  such that  $P(X \geq c) \leq \alpha$
  - lower: Reject  $H_0$  for  $X \leq c$  for  $c$  such that  $P(X \leq c) \leq \alpha$
  - two-sided: Reject  $H_0$  for  $p_0(X) \leq c$  for  $c$  such that  $P_{H_0}(p_0(X) \leq c) \leq \alpha$ , where  $p_0(X)$  is  $P(X = x)$  under  $H_0$
- Confidence interval: Values that are not rejected
- pvalue: Sum of the probabilities that are less than or equal to the observed value (under the null hypothesis)
- Consistent/Finite Sample Exact/ Asymptotically Exact

**NOTE:**

**field:** 100029

**field:** Test for data setting  $Y_1, \dots, Y_n$ , parameter of interest:  $p$  iid Bernoulli( $p$ ) (option 2)

- Test name
- Test Statistic
- Test Reference Distribution
- Critical Value/ Rejection region
  - upper:
  - lower:
  - two-sided
- Confidence interval
- pvalue
- Consistent/Finite Sample Exact/ Asymptotically Exact

**field:** Test for data setting  $Y_1, \dots, Y_n$ , parameter of interest:  $p$  iid Bernoulli( $p$ ) (option 2)

- Test name: Binomial  $z$ -test (Use when  $np_0 > 5$  and  $n(1 - p_0) > 5$ )
- Test Statistic:  $X = \sum_{i=1}^n Y_i = n\bar{Y}$ ,  $\hat{p} = X/n$ ,  $z(p_0) = \frac{\hat{p} - p_0}{\sqrt{p_0(1-p_0)/n}}$  (score)
- Test Reference Distribution: Under  $H_0$ , Approximately  $X \sim N(np_0, np_0(1-p_0))$  and  $z(p_0) \sim N(0, 1)$
- Critical Value/ Rejection region
  - upper:  $z(p_0) > z_{1-\alpha}$
  - lower:  $z(p_0) < z_\alpha$
  - two-sided:  $|z(p_0)| > z_{1-\alpha/2}$

- Confidence interval: Uses wald interval (derived from t-test) (with 
$$z_w(p_0) = \frac{\hat{p} - p_0}{\sqrt{\hat{p}(1-\hat{p})/n}} \hat{p} \pm z_{1-\alpha/2} \sqrt{\frac{\hat{p}(1-\hat{p})}{n}}$$
)
- pvalue
  - upper:  $1 - \Phi(z(p_0)) = 1 - \text{pnorm}(z(p_0))$
  - lower:  $\Phi(z(p_0)) = \text{pnorm}(z)$
  - two-sided:  $2(1 - \Phi(|z(p_0)|)) = 2*(1 - \text{pnorm}(\text{abs}(z)))$
- Consistent: Yes/Finite Sample Exact: No/ Asymptotically Exact: Yes

**NOTE:**

**field:** 100030

**field:** Continuity correction for Binomial z-test

**field:** With  $X \sim \text{Binom}(n, p)$ , instead of  $P(X \leq x)$ , use  $P(W \leq x + 1/2)$  where  $W \sim N(np, np(1 - p))$

**NOTE:**

**field:** 100031

**field:** Data Setting:  $X_1, \dots, X_n$ , iid parameter of interest:  $M$  - median  $H_0 : M = M_0$

- Test name:
- Test Statistic
- Test Reference Distribution
- Critical Value/ Rejection region
  - upper:
  - lower:

- two-sided
- Confidence interval
- pvalue
  - upper:
  - lower:
  - two-sided
- If ties?
- Consistent/Finite Sample Exact/ Asymptotically Exact

**field:**

- Test name: Sign Test
- Test Statistic:  $Y_i = I(X_i < M_0)$ ,  $\hat{p}_{M_0} = \frac{\sum Y_i}{n}$  (proportion of observations less than or equal to hypothesized median)
- Test Reference Distribution: Normal distribution: with  $p_0 = .5$
- Critical Value/ Rejection region:  $z = \frac{\hat{p}_{M_0} - p_0}{\sqrt{p_0(1-p_0)/n}}$ 
  - upper:  $z > z_{1-\alpha}$
  - lower:  $z < z_\alpha$
  - two-sided:  $|z| > z_{1-\alpha/2}$
- Confidence interval: cant use the binomial proportion CI Set of values of  $M_0$  that wouldn't be rejected at level  $\alpha$

$$\left(\frac{n - z_{1-\alpha/2}\sqrt{n}}{2}\right)^{th} \text{ Smallest Observation, } \left(\frac{n - z_{1-\alpha/2}\sqrt{n}}{2}\right)^{th} \text{ Smallest Observation}$$

- pvalue (binomial test on proportion)
  - upper:  $1 - \Phi(z(p_0)) = 1 - \text{pnorm}(z(p_0))$

- lower:  $\Phi(z(p_0)) = \text{pnorm}(z)$
- two-sided:  $2(1 - \Phi(|z(p_0)|)) = 2*(1 - \text{pnorm}(\text{abs}(z)))$
- If there are ties: remove all observations equal to  $M_0$ , then test prop of observations  $< M_0$  given not equal to  $M_0$  is .5
- Consistent: yes/Finite Sample Exact: No / Asymptotically Exact: yes

**NOTE:**

**field:** 100032

**field:** Data Setting:  $X_1, \dots, X_n$ , iid parameter of interest:  $M$  - median  
 $H_0 : M = M_0$  (option 2)

- Test name:
- Procedure:
- Test Statistic
- Test Reference Distribution
- Critical Value/ Rejection region
  - upper:
  - lower:
  - two-sided
- Confidence interval
- pvalue
- Consistent/Finite Sample Exact/ Asymptotically Exact

**field:** Data Setting:  $X_1, \dots, X_n$ , iid parameter of interest:  $M$  - median  
 $H_0 : M = M_0$  (option 1)

- Test name: Wilcoxon signed-rank test (require symmetry assumption)  
- equivalently a test of the mean - Tests the pseudo-median
- Procedure: testing  $c_0$  is the center (median)
  - Calculate distance of each observation from  $c_0$
  - Rank observations by the distance (abs value) from  $c_0$
- Test Statistic:  $S$  sum of the ranks that correspond to observations larger than  $c_0$ ,  $Z = \frac{S - \frac{n(n+1)}{4}}{\sqrt{\frac{n(n+1)(2n+1)}{24}}} \sim N(0, 1)$
- Test Reference Distribution:
  - Exact p-value - assume each rank has the same chance of being assigned to observations above or below  $c_0$  - all possible ways to assign the ranks
  - Normal approximation to the null distribution  $S \sim N\left(\frac{n(n+1)}{4}, \frac{n(n+1)(2n+1)}{24}\right)$
- Critical Value/ Rejection region
  - upper:
  - lower:
  - two-sided
- Confidence interval
- pvalue - Same as for Normal
- Consistent Yes under symmetry assumption /Finite Sample Exact No/  
Asymptotically Exact Yes (under symmetry assumption)

**NOTE:**

**field:** 100033

**field:** Pseudomedian



**field:** Median of the distribution of sample means from samples of size 2

**NOTE:**

**field:** 100034

**field:** Data Setting:  $X_1, \dots, X_n$ , iid  $N(\mu, \sigma^2)$  parameter of interest:  $\sigma^2 = \text{Var}(X)$ , sample variance:  $s^2 = \frac{1}{n-1} \sum_{i=1}^n (X_i - \bar{X})^2$ ,  $H_0 : \sigma^2 = \sigma_0^2$

- Test name:
- Test Statistic
- Test Reference Distribution
- Critical Value/ Rejection region
- Confidence interval
- pvalue
- Consistent/Finite Sample Exact/ Asymptotically Exact

**field:** Data Setting:  $X_1, \dots, X_n$ , iid  $N(\mu, \sigma^2)$  parameter of interest:  $\sigma^2 = \text{Var}(X)$ , sample variance:  $s^2 = \frac{1}{n-1} \sum_{i=1}^n (X_i - \bar{X})^2$ ,  $H_0 : \sigma^2 = \sigma_0^2$

- Test name:  $\chi^2$  for Population Variance
- Test Statistic  $X(\sigma_0) = \frac{(n-1)s^2}{\sigma_0^2}$
- Test Reference Distribution: Under  $H_0 : X(\sigma_0) = \frac{(n-1)s^2}{\sigma_0^2} \sim \chi_{n-1}^2$
- Critical Value/ Rejection region
  - $\sigma^2 > \sigma_0^2$  Reject  $H_0$  for  $X(\sigma_0^2) > \chi_{n-1}^2(1 - \alpha)$
  - $\sigma^2 < \sigma_0^2$  Reject  $H_0$  for  $X(\sigma_0^2) < \chi_{n-1}^2(\alpha)$
  - $\sigma^2 \neq \sigma_0^2$  Reject  $H_0$  for  $X(\sigma_0^2) > \chi_{n-1}^2(1 - \alpha/2)$  or  $X(\sigma_0) < \chi_{n-1}^2(\alpha/2)$

- Confidence interval

$$\left( \frac{(n-1)s^2}{\chi_{n-1}^2(1-\alpha/2)}, \frac{(n-1)s^2}{\chi_{n-1}^2(\alpha/2)} \right)$$

- pvalue

- $\sigma^2 > \sigma_0^2$ :  $p = 1 - pchisq(X(\sigma_0)^2, n-1)$
- $\sigma^2 < \sigma_0^2$ :  $p = pchisq(X(\sigma_0^2), n-1)$
- $\sigma^2 \neq \sigma_0^2$ :  $p = 2 \min(1 - pchisq(X(\sigma_0^2), n-1), pchisq(X(\sigma_0^2)), n-1)$

- Consistent/Finite Sample Exact/ Asymptotically Exact

**NOTE:**

**field:** 100035

**field:** Data Setting:  $X_1, \dots, X_n$ , iid  
 Parameter of interest:  $\sigma^2 = Var(X)$ ,  
 Sample variance:  $s^2 = \frac{1}{n-1} \sum_{i=1}^n (X_i - \bar{X})^2$ ,  
 $H_0 : \sigma^2 = \sigma_0^2$  (asymptotic)

- Test name:
- Test Statistic
- Test Reference Distribution
- Critical Value/ Rejection region
- Confidence interval
- pvalue

**field:** Data Setting:  $X_1, \dots, X_n$ , iid parameter of interest:  $\sigma^2 = \text{Var}(X)$ ,  
sample variance:  $s^2 = \frac{1}{n-1} \sum_{i=1}^n (X_i - \bar{X})^2$ ,  $H_0 : \sigma^2 = \sigma_0^2$

- Test name: Asymptotic  $t$ -test for population variance
- Test Statistic:  $Y = (X_i - \bar{X})^2$ ,

$$t(\sigma_0^2) = \frac{Y - \frac{n-1}{n} \sigma_0^2}{\sqrt{s_y^2/n}} \rightarrow N(0, 1)$$

Note  $\bar{Y} = \frac{n-1}{n} s^2$

- Tests that the population mean of the  $Y_i$  is  $\frac{n-1}{n} \sigma_0^2$
- Test Reference Distribution  $\frac{\frac{n-1}{n} s^2 - \frac{n-1}{n} \sigma^2}{\sqrt{\text{Var}(\frac{n-1}{n} s^2)}} = \frac{\bar{Y} - \frac{n-1}{n} \sigma^2}{\sqrt{\text{Var}(\bar{Y})}} \rightarrow N(0, 1)$ , so we can use t-test
- Critical Value/ Rejection region
  - upper: Reject if  $t(\sigma_0^2) > t_{(n-1), 1-\alpha} = \text{qt}(1 - \alpha, n-1)$
  - lower: Reject if  $t(\sigma_0^2) < t_{n-1, \alpha}$
  - two sided: Reject if  $|t(\sigma_0^2)| > t_{n-1, 1-\alpha/2}$
- Confidence interval:  $\bar{X} \pm t_{n-1, 1-\alpha/2} \sqrt{\frac{s^2}{n}}$
- pvalue, with  $t(\mu_0) = t$ , and pt representing the cdf of a t distribution
  - upper:  $1 - \text{pt}(t, n-1)$
  - lower:  $\text{pt}(t, n-1)$
  - two-sided:  $2*(1 - \text{pt}(\text{abs}(t)), n-1)$

**NOTE:**

**field:** 100036

**field:** Test for data setting  $X_1, \dots, X_n$  iid from population distribution  $F$ .  
Test  $H_0 : F = F_0$

- Test name:
- Process
- Test Statistic
- Test Reference Distribution
- Critical Value/ Rejection region

**field:** Test for data setting  $X_1, \dots, X_n$  iid from population distribution  $F$ .  
Test  $H_0 : F = F_0$

- Test name: Kolmogorov-Smirnov Test
- Process
- Test Statistic:  $D(F_0) = \sup_x |\hat{F}(x) - F_0(x)|$ , where  $\hat{F}(x) = \frac{1}{n} \sum_{i=1}^n 1(X_i \leq x)$  is the empirical cdf and  $F_0(x)$  is the null hypothesis cdf (maximum values of difference between empirical and null)
- Test Reference Distribution: Kolmogorov distribution
- Critical Value/ Rejection region: Reject for large values of  $\sqrt{n}D(F_0)$
- Note the one sided version does not have an easy interpretation

**NOTE:**

**field:** 100037

**field:** Data setting:  $X_1, \dots, X_n$  iid from discrete distribution. Test fit of distribution

- Test name:
- Process
- Test Statistic

- Test Reference Distribution
- Critical Value/ Rejection region
- If parameter values of discrete distribution are not known

**field:** Data setting:  $X_1, \dots, X_n$  iid from discrete distribution. Test fit of distribution

- Test name:  $\chi^2$  goodness of fit test, test for discrete distributions
- Process: Test the underlying population distribution is  $P(X = x) = p_0(x)$ , where  $\hat{p}(x) = \frac{1}{n} \sum_{i=1}^n 1(X_i = x)$ 
  - Let  $j = 1, \dots, k$  the different categories that  $X_i$  can take
  - Let  $O_j$  be the observed number of observations that belong to category  $j$
  - Let  $E_j = np_0(j)$  be the expected number of observations that would belong to category  $j$  if the null hypothesis were true
- Test Statistic:  $X(p_0) = \sum_x \frac{n(\hat{p}(x) - p_0(x))^2}{p_0(x)} = \sum_{j=1}^k \frac{(O_j - E_j)^2}{E_j}$
- Test Reference Distribution: Under  $H_0$ ,  $X(p_0) \rightarrow \chi_{k-1}^2$
- Critical Value/ Rejection region: Reject for large values of  $X(p_0)$  - Reject  $H_0$  for  $X(p_0) > \chi_{k-1}^2(1 - \alpha)$
- Note: Null hypothesis doesn't completely specify the distribution, just the family of distributions with perhaps unknown parameters
  - Estimate the parameters
  - Use null distribution with estimated parameter values for  $E_j$
  - Compute  $\chi^2$  test statistic
  - Compare to  $\chi_{k-d-1}^2$  distribution where  $k$  = number of categories,  $d$  = number of estimated parameters

**NOTE:**

**field:** 100038

**field:** Data setting  $X_1, \dots, X_n, Y_1, \dots, Y_m$  iid with known  $\sigma_x, \sigma_y$ . Estimate  $d = \mu_x - \mu_y$

- Test name:
- Test Statistic
- Test Reference Distribution
- Critical Value/ Rejection region
- Confidence interval
- p-value

**field:** Data setting  $X_1, \dots, X_m, Y_1, \dots, Y_n$  iid with known  $\sigma_x, \sigma_y$ . Estimate  $d$ ,

- Test name: 2 sample  $z$  test
- Test Statistic:  $z(d_0) = \frac{(\bar{X} - \bar{Y}) - d_0}{\sqrt{\frac{\sigma_x^2}{m} + \frac{\sigma_y^2}{n}}}$
- Test Reference Distribution: Under  $H_0$ ,  $z(d_0) \sim N(0, 1)$
- Critical Value/ Rejection region
  - Lower:  $d \leq d_0$  Reject when  $z(d_0) < z_\alpha = \text{qnorm}(\alpha)$
  - Upper:  $d \geq d_0$  Reject when  $z(d_0) > z_{1-\alpha} = \text{qnorm}(1-\alpha)$
  - Two sided:  $d \neq d_0$  Reject when  $|z(d_0)| > z_{1-\alpha/2} = \text{qnorm}(1 - \alpha/2)$
- Confidence interval:

$$(\bar{X} - \bar{Y}) \pm z(1 - \frac{\alpha}{2}) \sqrt{\frac{\sigma_x^2}{m} + \frac{\sigma_y^2}{n}}$$

**NOTE:**

**field:** 100039

**field:** Data setting  $X_1, \dots, X_n, Y_1, \dots, Y_m$  iid with unknown but equal  $\sigma_x, \sigma_y$  Estimate  $d$

- Test name:
- Estimate of  $\sigma_x^2 = \sigma_y^2$
- Test Statistic
- Test Reference Distribution
- Critical Value/ Rejection region
- Confidence interval
- When not equal

**field:** Data setting  $X_1, \dots, X_n, Y_1, \dots, Y_m$  iid with unknown  $\sigma_x, \sigma_y$ . Estimate  $d$

- Test name: Equal variance 2-sample t-test
- Note: Estimate of  $\sigma_x^2 = \sigma_y^2 = s_p^2 = \frac{\sum_{i=1}^m (X_i - \bar{X})^2 + \sum_{i=1}^n (Y_i - \bar{Y})^2}{(m-1) + (n-1)} = \frac{(m-1)s_x^2 + (n-1)s_y^2}{(m+n-2)}$   
(weighted average of the two sample variances )
- Test Statistic:  $t(d_0) = \frac{(\bar{X} - \bar{Y}) - d_0}{\sqrt{s_p^2(\frac{1}{m} + \frac{1}{n})}}$
- Test Reference Distribution: For Normal populations, under  $H_0$ :  $t(d_0) \sim t_{m+n-2}$
- Critical Value/ Rejection region
  - $d > d_0$  Reject  $H_0$  for  $t_e(d_0) > t_{m+n-2}(1 - \alpha)$
  - $d < d_0$  Reject  $H_0$  for  $t_e(d_0) < t_{m+n-2}(\alpha)$
  - $d \neq d_0$  Reject  $H_0$  for  $|t_e(d_0)| > t_{m+n-2}(1 - \alpha/2)$
- Confidence interval  $(\bar{X} - \bar{Y}) \pm t_{m+n-2}(1 - \frac{\alpha}{2}) \sqrt{s_p^2(\frac{1}{m} + \frac{1}{n})}$
- When not equal:

- Expected value of Estimated variance is larger than it should be when the smaller sample comes from the population with smaller variance - the test statistic will be closer to zero than it should be, and rejection rates will be smaller - Less power - more conservative
- Expected value of Estimated variance is smaller than it should be when smaller sample comes from the population with the larger variance - test statistic will have a larger absolute value than it should - rejection rates will be larger - more power - anti conservative

**NOTE:**

**field:** 100040

**field:** Data setting  $X_1, \dots, X_m, Y_1, \dots, Y_n$  iid with unknown not equal  $\sigma_x, \sigma_y$  Estimate  $d = \mu_x - \mu_y$

- Test name:
- Estimate of  $Var(\bar{X} - \bar{Y})$
- Test Statistic
- Test Reference Distribution
- Degrees of freedom
- Critical Value/ Rejection region
- Confidence interval
- Compare to equal variance

**field:** Data setting  $X_1, \dots, X_m, Y_1, \dots, Y_n$  iid with unknown not equal equal  $\sigma_x, \sigma_y$  Estimate  $d$

- Test name: Unequal variance 2 sample t-test
- Estimate of  $Var(\bar{X} - \bar{Y}) = \frac{s_x^2}{m} + \frac{s_y^2}{n}$



- Test Statistic:  $t_U(d_0) = \frac{(\bar{X} - \bar{Y}) - d_0}{\sqrt{\frac{s_x^2}{m} + \frac{s_y^2}{n}}}$
- Test Reference Distribution: If the two distributions are Normal, there is not an exact distribution for the test statistic - Use Welch-Satterthwaite approximation: Estimate degrees of freedom

$$v = \frac{\left(\frac{s_x^2}{m} + \frac{s_y^2}{n}\right)^2}{\frac{s_x^4}{m^2(m-1)} + \frac{s_y^4}{n^2(n-1)}}$$

$\min(m-1, n-1) \leq v \leq m+n-2$  Under  $H_0$   $t_u(d_0)$  approx  $\sim t_v$

- Critical Value/ Rejection region: same as t-test
- Confidence interval:  $(\bar{X} - \bar{Y}) \pm t_v(1 - \frac{\alpha}{2})\sqrt{\frac{s_x^2}{m} + \frac{s_y^2}{n}}$
- Compare to equal variance:
  - For unequal sample sizes with unequal population variances, equal variance t-test does not have correct calibration
  - When samples sizes are equal both test statistics are the same, but degrees of freedom differ
  - When equal variance assumption is true, equal variance has slightly better power, and very slightly better calibration (more exact)

## NOTE:

**field:** 100041

**field:** Data setting  $X_1, \dots, X_n$  iid  $F_x$ ,

$Y_1, \dots, Y_n$  iid  $F_y$ ,

$X_i$  not independent  $Y_i$ ,

$(X_1, Y_1), \dots, (X_n, Y_n)$  iid  $F_{XY}$   $Cov(X_i, Y_i) = \sigma_{XY}$ ,  $Cov(X_i, Y_j) = 0$ .

Estimate  $d = \mu_x - \mu_y$ , when  $\sigma_x^2, \sigma_y^2, \sigma_{XY}$  known

- Test name:
- Test Statistic

- Test Reference Distribution
- Critical Value/ Rejection region
- Confidence interval

**field:** Data setting  $X_1, \dots, X_n$  iid  $F_x$ ,  
 $Y_1, \dots, Y_n$  iid  $F_y$ ,  
 $X_i$  not independent  $Y_i$ ,  
 $(X_1, Y_1), \dots, (X_n, Y_n)$  iid  $F_{XY}$   $Cov(X_i, Y_i) = \sigma_{XY}$ ,  $Cov(X_i, Y_j) = 0$ .  
Estimate  $d = \mu_x - \mu_y$ , when  $\sigma_x^2, \sigma_y^2, \sigma_{XY}$  known

- Test name: Paired z-test
- Test Statistic:  $z(d_0) = \frac{(\bar{X} - \bar{Y}) - d_0}{\sqrt{\frac{\sigma_x^2}{n} + \frac{\sigma_y^2}{n} - 2\frac{\sigma_{XY}}{n}}} = \frac{\bar{D} - d_0}{\sqrt{\frac{\sigma_D^2}{n}}}$
- Test Reference Distribution: Under  $H_0$ ,  $z(d_0)$  approx  $\sim N(0, 1)$
- Critical Value/ Rejection region: Same as normal
- Confidence interval :

$$(\bar{X} - \bar{Y}) \pm z(1 - \frac{\alpha}{2}) \sqrt{\frac{\sigma_x^2}{n} + \frac{\sigma_y^2}{n} - 2\frac{\sigma_{XY}}{n}} = \bar{D} \pm z(1 - \alpha/2) \sqrt{\frac{\sigma_D^2}{n}}$$

**NOTE:**

**field:** 100042

**field:** Data setting  $X_1, \dots, X_n$  iid  $F_x$ ,  $Y_1, \dots, Y_n$  iid  $F_y$ ,  $X_i$  not independent  $Y_i$ ,  $(X_1, Y_1), \dots, (X_n, Y_n)$  iid  $F_{XY}$   $Cov(X_i, Y_i) = \sigma_{XY}$ ,  $Cov(X_i, Y_j) = 0$   
Estimate  $d = \mu_x - \mu_y$ ,  $\sigma_x^2, \sigma_y^2, \sigma_{XY}$  unknown

- Test name:
- Estimate of  $\sigma_{XY}$
- Estimate of  $Var(\bar{X} - \bar{Y})$
- Test Statistic

- Test Reference Distribution
- Critical Value/ Rejection region
- Confidence interval

**field:** Data setting  $X_1, \dots, X_n$  iid  $F_x$ ,  $Y_1, \dots, Y_n$  iid  $F_y$ ,  $X_i$  not independent  $Y_i$ ,  $(X_1, Y_1), \dots, (X_n, Y_n)$  iid  $F_{XY}$   $Cov(X_i, Y_i) = \sigma_{XY}$ ,  $Cov(X_i, Y_j) = 0$   
Estimate  $d = \mu_x - \mu_y$ ,  $\sigma_x^2, \sigma_y^2, \sigma_{XY}$  unknown

- Test name: Paired Data t-test
- Estimate of  $\sigma_{XY} = \frac{1}{n-1} \sum_{i=1}^n (X_i - \bar{X})(Y_i - \bar{Y})$
- Estimate of  $Var(\bar{X} - \bar{Y}) = \frac{s_d^2}{n} = \frac{s_x^2}{n} + \frac{s_y^2}{n} - 2\frac{s_{XY}}{n}$
- Test Statistic:  $t(d_0) = \frac{(\bar{X} - \bar{Y}) - d_0}{\sqrt{\frac{s_x^2}{n} + \frac{s_y^2}{n} - 2\frac{s_{XY}}{n}}} = \frac{\bar{D} - d_0}{\sqrt{\frac{s_D^2}{n}}}$
- Test Reference Distribution: If differences are Normal (note X,Y Normal does not imply Differences are normal unless X,Y are jointly multivariate-normal) Under  $H_0$ ,  $t(d_0) \sim t_{n-1}$  (exact distribution)
- Critical Value/ Rejection region Same as t
- Confidence interval

$$(\bar{X} - \bar{Y}) = t_{n-1} \left(1 - \frac{\alpha}{2}\right) \sqrt{\frac{s_x^2}{n} + \frac{s_y^2}{n} - 2\frac{s_{XY}}{n}} = \bar{D} \pm t_{n-1} \left(1 - \frac{\alpha}{2}\right) \sqrt{\frac{s_D^2}{n}}$$

- Equivalent to a one sample - t-test on the differences

**NOTE:**

**field:** 100043

**field:** Data setting  $X_1, \dots, X_m$  iid Bernoulli( $p_x$ ),  $Y_1, \dots, Y_n$  iid Bernoulli( $p_y$ ),  
 Test  $H_0 : p_x - p_y = 0$

- Test name:
- Test Statistic
- Test Reference Distribution
- Critical Value/ Rejection region
- Confidence interval

**field:** Data setting  $X_1, \dots, X_m$  iid Bernoulli( $p_x$ ),  $Y_1, \dots, Y_n$  iid Bernoulli( $p_y$ ),  
 Test  $H_0 : p_x - p_y = 0$

- Test name: Binomial proportions two-sample z-test
- Test Statistic:

$$z = \frac{\hat{p}_x - \hat{p}_y}{\sqrt{\hat{p}_c(1 - \hat{p}_c(\frac{1}{m} + \frac{1}{n}))}}$$

$$\text{Where } \hat{p}_c = \frac{m\hat{p}_x + n\hat{p}_y}{m+n} = \frac{b+d}{N}$$

- Test Reference Distribution: Under  $H_0 : z$  approx  $\sim N(0, 1)$
- Critical Value/ Rejection region: Same as regular 2-sample
- Confidence interval:

$$\hat{p}_x - \hat{p}_y \pm z_{1-\alpha/2} \sqrt{\left(\frac{\hat{p}_x(1 - \hat{p}_x)}{m} + \frac{\hat{p}_y(1 - \hat{p}_y)}{n}\right)}$$

**NOTE:**

**field:** 100044

**field:** Multinomial sampling

**field:** Collection of random samples, recording what group they are in: Can estimate  $P(X = x|G = g)$ , where  $G$  is the group

**NOTE:**

**field:** 100045

**field:** Two-Sample Binomial sampling

**field:** Sample  $m$  units from group 1 and  $n$  units from group 2

**NOTE:**

**field:** 100046

**field:** Can we estimate  $P(X = x|G = g)$  with binomial sampling

**field:** Cannot estimate

**NOTE:**

**field:** 100047

**field:**  $P(X = x|G = g)$  with multinomial sampling

**field:** Can estimate

**NOTE:**

**field:** 100048

**field:**  $E(g(T)) =$

**field:**  $E(g(T)) \neq g(E(T))$

**NOTE:**

**field:** 100049

**field:** Reason for performing transformations on data

**field:** Some tests are FSE only when population distribution is Normal (otherwise the methods are asymptotically exact), requiring a large  $n$ . Transformations that improve approximation of normality make Normal-based methods perform more exactly

**NOTE:**

**field:** 100050

**field:** Data setting  $X_1, \dots, X_m$  iid Bernoulli( $p_x$ ),  $Y_1, \dots, Y_n$  iid Bernoulli( $p_y$ ), Test  $H_0 : p_x - p_y = 0$  (Association/independent/relationship)

- Test name:
- Test Statistic
- Test Reference Distribution
- Critical Value/ Rejection region

**field:** Data setting  $X_1, \dots, X_m$  iid Bernoulli( $p_x$ ),  $Y_1, \dots, Y_n$  iid Bernoulli( $p_y$ ), Test  $H_0 : p_x - p_y = 0$  (Association/independent/relationship)

- Test name: Pearson's Chi-squared Test
- Test Statistic:  $X = \sum_{i,j \in \{1,2\}} \frac{(O_{ij} - E_{ij})^2}{E_{ij}}$  Where  $O_{ij} = n_{ij}$  and  $E_{ij} = \frac{R_i C_j}{N}$
- Test Reference Distribution: Under  $H_0$   $X \sim \chi_1^2$
- Critical Value/ Rejection region: Reject for  $X > \chi_1^2(1 - \alpha)$
- Note: Equal to to sided z-test for binomial proportions:  $X = z^2$

**NOTE:**

**field:** 100051

**field:** Data setting  $X_1, \dots, X_m$  iid Bernoulli( $p_x$ ),  $Y_1, \dots, Y_n$  iid Bernoulli( $p_y$ ),  
 Test  $H_0 : p_x = p_y$  (No association between response variable  $X$  and grouping variable  $G$ )

- Test name:
- Test Statistic:
- pvalue
- Test Reference Distribution
- Critical Value/ Rejection region
- Confidence interval

**field:** Data setting  $X_1, \dots, X_m$  iid Bernoulli( $p_x$ ),  $Y_1, \dots, Y_n$  iid Bernoulli( $p_y$ ),  
 Test  $H_0 : p_x = p_y$  (No association between response variable  $X$  and grouping variable  $G$ )

- Test name: Fisher's Exact Test (of homogeneity of proportions)
- Test Statistic: Probability of observed table conditioning on margins:  
 Compute all tables with the same margin totals:  $\frac{\binom{C_2}{O_{12}}\binom{C_1}{O_{11}}}{\binom{N}{R_1}}$
- pvalue: Sum of probability of all tables more extreme than observed table More Extreme:
  - $p_x > p_y$  More extreme = larger  $O_{12}$
  - $p_x < p_y$  More extreme = smaller  $O_{12}$
  - $p_x \neq p_y$  More extreme = less likely table

**NOTE:**

**field:** 100052

**field:** Data setting  $X_1, \dots, X_m$  iid Bernoulli( $p_x$ ),  $Y_1, \dots, Y_n$  iid Bernoulli( $p_y$ ),  
 Test  $H_0 : p_x = p_y$  Binomial sampling scheme

- Test name:
- Test Statistic:
- Test Reference Distribution
- Critical Value/ Rejection region
- Confidence interval

**field:** Data setting  $X_1, \dots, X_m$  iid Bernoulli( $p_x$ ),  $Y_1, \dots, Y_n$  iid Bernoulli( $p_y$ ),  
 Test  $H_0 : p_x = p_y$  Binomial sampling scheme

- Test name: Log Odds - test  $H_0 : \omega = 1$
- Test Statistic:  $\hat{\omega} = \frac{ad}{bc}$ ,  $z = \frac{\log(\hat{\omega})}{\sqrt{\frac{1}{a} + \frac{1}{b} + \frac{1}{c} + \frac{1}{d}}}$
- Test Reference Distribution  $\log(\hat{\omega})$  approx  $\sim N(\log(\omega), \frac{1}{a} + \frac{1}{b} + \frac{1}{c} + \frac{1}{d})$ ,  
 $z$  approx  $\sim N(0, 1)$
- Critical Value/ Rejection region
- Confidence interval  $(\hat{\omega} e^{-z(1-\frac{\alpha}{2})\sqrt{\frac{1}{a} + \frac{1}{b} + \frac{1}{c} + \frac{1}{d}}}, \hat{\omega} e^{z(1-\frac{\alpha}{2})\sqrt{\frac{1}{a} + \frac{1}{b} + \frac{1}{c} + \frac{1}{d}}})$
- :  $\omega > 1, p_1 > p_2$ ,  $\omega = 1, p_1 = p_2$ , small  $p_1, p_2$ ,  $\omega = p_1/p_2 =$  relative risk

**NOTE:**

**field:** 100053

**field:** Data setting  $X_1, \dots, X_n$  iid Bernoulli( $p_x$ ),  $Y_1, \dots, Y_n$  iid Bernoulli( $p_y$ ),  
 $X, Y$  not independent (paired) test proportions equal in groups (equally likely/probability)

- Test name:
- Test Statistic:
- Test Reference Distribution
- Critical Value/ Rejection region



**field:** Data setting  $X_1, \dots, X_n$  iid Bernoulli( $p_x$ ),  $Y_1, \dots, Y_n$  iid Bernoulli( $p_y$ ),  $X, Y$  not independent (paired), test proportions equal in groups (equally likely/probability)

<ul style="list-style-type: none"> <li>Note, requires a table that keeps track of the pairs</li> </ul>	Measurement 2	Measurement 1		
		No	Yes	T
	No Yes	a c	b d	
	Total	$C_1$	$C_2$	

- Test name: McNemar's Test
- Test Statistic:  $z = \frac{b-c}{\sqrt{b+c}}$
- Test Reference Distribution:  $z \sim N(0, 1)$ ,  $z^2 \sim \chi_1^2$
- Critical Value/ Rejection region: Two sided reject  $|z| > z(1 - \alpha/2)$
- Note equivalent to performing a paired t-test on the differences:

$$t = \frac{b - c}{\sqrt{\frac{n}{n-1} (b + c - \frac{(b-c)^2}{40})}}$$

compare to  $t_{n-1}$

**NOTE:**

**field:** 100054

**field:** Data setting:  $n$  observations, record Group 1 and Group 2, where each group takes on  $> 2$  values, Test if there is an association between the groups

- Test name:
- Test Statistic:
- Test Reference Distribution

**field:** Data setting:  $n$  observations, record Group 1 ( $r$  values) and Group 2 ( $c$ ) values, Test if there is an association between the groups

- Test name: Pearsons  $\chi^2$
- Test Statistic:  $X = \sum_{i=1}^r \sum_{j=1}^c \frac{(O_{ij}-E_{ij})^2}{E_{ij}}$ , where  $E_{ij} = \frac{n_i n_j}{N}$
- Test Reference Distribution: Under  $H_0$ ,  $X$  approx  $\sim \chi^2_{(r-1)(c-1)}$
- Note not FSE, but performance is good if  $E_{ij} > 5$

**NOTE:**

**field:** 100055

**field:** Data setting  $X_1, \dots, X_m$  iid  $F_x$ ,  $Y_1, \dots, Y_n$  iid  $F_y$ . Test  $m_x = m_y$  (medians )

- Test name:
- Assumptions
- Process
- pvalue
- Test Reference Distribution
- Test Statistic:
- Ties
- Continuity correction
- Consistency

**field:** Data setting  $X_1, \dots, X_n$  iid  $F_x$ ,  $Y_1, \dots, Y_n$  iid  $F_y$ . Test  $m_x = m_y$  (medians )

- Test name: Wilcoxon Rank-Sum (Mann-Whitney U-test)
- Note this is only a test of medians only if just additive effect -  $F_x$  is just a shift from  $F_y$  (shape and scale must be same ) (but then just the same as a test of mean, 10th percentile, min,  $F_x = F_y$  etc )
- If No additive assumption - test of  $H_0 : P(X > Y) = .5$
- Process:
  - Combine samples
  - Rank the observations in combined sample from smallest to largest (1 to  $n + m$ )
  - Add ranks of the smaller group (assume wlog that  $X$  is the smaller group)
- pvalue: Calculate using permutations: Count number of permutations that lead to a R value more extreme than observed out of total permutations  $\binom{n+m}{m}$
- Test Statistic:  $R$  sum of the ranks, or  $z = \frac{R - \frac{m(m+n+1)}{2}}{\sqrt{\frac{mn(m+n+1)}{12}}}$
- Test Reference Distribution: If there was no difference between two populations, then each rank has equal chance of being assigned to group 1 (belongs to  $X$ :  $p = \frac{m}{n+m}$ ) Normal approximation:  $R \sim N(\frac{m(m+n+1)}{2}, \frac{mn(m+n+1)}{12})$ ,  $z \sim N(0, 1)$
- Notes: If ties, assign ranks, and then average ranks of tied values
- Continuity correction to normal distribution: add .5 to R if lower probability, subtract .5 from R if upper probability (ie 1 - pnorm())
- Not consistent test unless under additive assumption. IS consistent test of  $H_0 : P(X > Y) = .5$

**NOTE:**

**field:** 100056

**field:** Data setting  $X_1, \dots, X_m$  iid  $F_x$ ,  $Y_1, \dots, Y_n$  iid  $F_y$ . Test  $m_x = m_y$  (medians )

- Test name:
- Process
- Test statistic:

**field:** Data setting  $X_1, \dots, X_m$  iid  $F_x$ ,  $Y_1, \dots, Y_n$  iid  $F_y$ . Test  $m_x = m_y$  (medians )

- Test name: Mood's Test for Equality of Population Medians
- Process:
  - Find combined sample median  $\hat{m}$
  - Calculate  $\hat{p}_x$  = proportion of  $X$ s greater than  $\hat{m}$ ,  $\hat{p}_y$ , proportion of  $Y$ s greater than  $\hat{m}$
  - Conduct two sample binomial z-test( Pearsons chi-squared test) or Fisher's exact test
  - Test statistic:

$$z = \frac{\hat{p}_x - \hat{p}_y}{\sqrt{\hat{p}_c(1 - \hat{p}_c(\frac{1}{m} + \frac{1}{n}))}}$$

$$\text{Where } \hat{p}_c = \frac{m\hat{p}_x + n\hat{p}_y}{m+n} = \frac{b+d}{N}$$

**NOTE:**

**field:** 100057

**field:** Data setting  $X_1, \dots, X_n$  iid  $F_x$ ,  $Y_1, \dots, Y_n$  iid  $F_y$ . Test some statistic  $W$

- Test name:
- Process

**field:** Data setting  $X_1, \dots, X_n$  iid  $F_x$ ,  $Y_1, \dots, Y_n$  iid  $F_y$ . Test some statistic  $W$

- Test name: Permutation test
- Process: Permute group labels across observations and recalculate statistic for each permutation to create permutation distribution - calculate p-values using the permutation distribution
- Performance: Many settings (like medians equal), will not reject correctly (even in large samples) if the medians are equal, but the distributions differ
- Permutation hypothesis is that the observations from the two populations are exchangeable (ie same population distributions, not just equal medians )

**NOTE:**

**field:** 100058

**field:** Data setting: Estimate value of nuisance parameter

**field:**

- Test name: Bootstrap
- Process: Since the empirical distribution function converges to the true distribution function, we can use samples from the empirical distribution to approximate how samples from the true distribution would behave.
- Confidence interval:  $100(\alpha/2)$  largest resampled statistic  $100(1 - (\alpha/2))$  largest resampled statistic

**NOTE:**

**field:** 100059

**field:** Data setting: Data setting  $X_1, \dots, X_m$  iid  $N$ ,  $Y_1, \dots, Y_n$  iid  $N$ .  $H_0 : \sigma_x^2 = \sigma_y^2$  or  $H_0 \sigma_x^2 / \sigma_y^2 = r$

**field:** Data setting: Data setting  $X_1, \dots, X_m$  iid  $F_x$ ,  $Y_1, \dots, Y_n$  iid  $F_y$ .  $H_0 : \sigma_x^2 = \sigma_y^2$  or  $H_0 \sigma_x^2 / \sigma_y^2 = r$

- Test name: F
- Recall  $s_x^2 = \frac{1}{n-1} \sum_{i=1}^m (X_i - \bar{X})^2$
- Note that  $\frac{(m-1)s_x^2}{\sigma_x^2} \sim \chi_{m-1}^2$ ,  $\frac{(n-1)s_y^2}{\sigma_y^2} \sim \chi_{n-1}^2$ ,
- Test Statistic:  $F(r) = \frac{s_x^2 / \sigma_x^2}{s_y^2 / \sigma_y^2} = \frac{s_x^2}{s_y^2} \frac{1}{r}$
- Test Reference Distribution: Under  $H_0 : F(r) \sim F_{m-1, n-1}$
- Critical Value/ Rejection region
  - $\sigma_x^2 / \sigma_y^2 > r$  Reject for  $F(r) > F_{m-1, n-1}(1 - \alpha)$
  - $\sigma_x^2 / \sigma_y^2 > r$  Reject for  $F(r) > F_{m-1, n-1}(\alpha)$
  - $\sigma_x^2 / \sigma_y^2 \neq r$  Reject for  $F(r) > F_{m-1, n-1}(1 - \alpha/2)$  or  $F(r) < F_{m-1, n-1}(\alpha/2)$
- Performance: Not Well if underlying population is not normal: Not FSE or AE (but is consistent ) - don't use if population is not normal

**NOTE:**

**field:** 100060

**field:** Data setting: Data setting  $X_1, \dots, X_m$  iid  $F_x$ ,  $Y_1, \dots, Y_n$  iid  $F_y$ .  $H_0 : \sigma_x^2 = \sigma_y^2$

- Test name:
- Process:
- Interpretation
- Assumptions

**field:** Data setting: Data setting  $X_1, \dots, X_m$  iid  $F_x$ ,  $Y_1, \dots, Y_n$  iid  $F_y$ .  $H_0 : \sigma_x^2 = \sigma_y^2$

- Test name: Levene's Test
- Process:
  - Construct new variables:
    - \*  $U_i = |X_i - \text{med}(X)|$  or  $(X_i - \text{med}(X))^2$  or  $|X_i - \bar{X}|$  or  $(X_i - \bar{X})^2$
    - \*  $V_i = |Y_i - \text{med}(Y)|$  or  $(Y_i - \text{med}(Y))^2$  or  $|Y_i - \bar{Y}|$  or  $(Y_i - \bar{Y})^2$
  - Perform two-sample  $t$  test on  $U_i$  and  $V_i$  (use Welch)
- Interpretation: If last option used, can be a test in difference in population variances
- Assumptions:
  - Independence
  - Large sample sizes, so t-test assumptions are met
- Note: dont use as a test to determine which t-test version to use

**NOTE:**

**field:** 100061

**field:** Data setting: Data setting  $X_1, \dots, X_m$  iid  $F_x$ ,  $Y_1, \dots, Y_n$  iid  $F_y$ . Test  $H_0 : F_x = F_y$

- Test name
- Test statistic

**field:** Data setting: Data setting  $X_1, \dots, X_m$  iid  $F_x$ ,  $Y_1, \dots, Y_n$  iid  $F_y$ . Test  $H_0 : F_x = F_y$

- Test name: Two-sample Kolmogorov-Smirnov Test
- Test statistic:  $D = \sup_x |\hat{F}_x(x) - \hat{F}_y(y)|$  ie the largest distance between the empirical CDF for  $X$  and  $Y$

- Reject for large values of  $\sqrt{\frac{mn}{m+n}}D$
- Only for continuous distributions, for discrete distributions, use Pearsons  $\chi^2$

**NOTE:**

**field:** 100062

**field:** Multiple 2x2 tables under  $k$  different conditions  $p_{xj} = P(X = 1 \text{ in Table } j), p_{yj} = P(Y = 1 \text{ in Table } j)$   $H_0 : p_{xj} = p_{yj}$  for all  $j$

**field:**

- Test name: Mantel-Haenszel Test
- Test statistic:  $\omega_j = \frac{p_{xj}(1-p_{xj})}{p_{yj}(1-p_{yj})}, H_0 : \omega_j = 1$  for all  $j$

$$E(n_{X1j}) = \mu_{X1j} = \frac{n_{X \cdot j} n_{\cdot 1j}}{n_{\cdot j}}, V(n_{X1j}) = \sigma_{X1j}^2 = \frac{n_{X \cdot j} n_{Y \cdot j} n_{\cdot 1j} n_{\cdot 0j}}{n_{\cdot j}^2 (n_{\cdot j} - 1)}$$

$$C = \frac{[\sum_j (n_{X1j} - \mu_{X1j})]^2}{\sum_j \sigma_{X1j}^2}$$

- Under  $H_0$   $C \sim \chi^2(1)$
- Assumes the odds-ratios are the same in all  $k$  tables

**NOTE:**

**field:** 100063

**field:** Test for data setting: Sample 1:  $X_{1,1}, \dots, X_{1n_1}$  from population 1 with mean  $\mu_1$ ,

Sample 2:  $X_{2,1}, \dots, X_{2n_2}$  from population 2 with mean  $\mu_2$ ,

... Sample M:  $X_{M,1}, \dots, X_{Mn_M}$  from population M with mean  $\mu_M$

- Independence within and between groups
- Populations (approximately ) normal
- Equal variances



**field:**

- Test name: ANOVA
- Estimate of common variance  $s_p = \frac{(n_1-1)s_1^2 + \dots + (n_M-1)s_M^2}{(n_1-1) + \dots + (n_M-1)}$
- Could use two-sample-t test on two population means
- Could test are population means 1 through M equal to each other?
- Compare the variability between groups to the variability within groups
- Sum of squares within groups:

$$SSW = (n - M)s_p^2 = \sum_{i=1}^{n_1} (X_{1i} - \bar{X}_1)^2 + \dots + \sum_{i=1}^{n_M} (X_{Mi} - \bar{X}_M)^2$$

degrees of freedom:  $n - M$

- Sum of squares total

$$SST = \sum_{i=1}^{n_1} (X_{1,i} - \bar{X})^2 + \dots + \sum_{i=1}^{n_M} (X_{M,i} - \bar{X})^2$$

degrees of freedom:  $n - 1$

- Sum of squares between groups:  $SSB = SST - SSW = \sum_{j=1}^M n_j (\bar{X}_j - \bar{X})^2$  df:  $(n - 1) - (n - M) = M - 1$
- Test statistic:

$$F = \frac{MSB}{MSW} = \frac{SSB/(M - 1)}{SSW/(n - M)}$$

- Reference distribution: Under  $H_0$ ,  $F \sim F_{M-1, n-M}$

**tags:** Methods2

**NOTE:**

**field:** 100064

**field:** Vectors  $\mathbf{x}$  and  $\mathbf{y}$  orthogonal

**field:** Vectors  $\mathbf{x}$  and  $\mathbf{y}$  orthogonal (perpendicular) if  $(\mathbf{x}, \mathbf{y}) = \mathbf{x}^t \mathbf{y} = 0$

**NOTE:**

**field:** 100065

**field:** A matrix  $\mathbf{A}$  is orthogonal if:

**field:** A matrix  $\mathbf{A}$  is orthogonal if  $\mathbf{A}^t \mathbf{A} = \mathbf{A} \mathbf{A}^t = \mathbf{I}_n$

**NOTE:**

**field:** 100066

**field:** A set of  $n$  vectors are linearly dependent

**field:** A set of  $n$  vectors are linearly dependent if there exist constants  $c_1, \dots, c_n$  not all 0 such that  $\sum_{j=1}^n c_j \mathbf{x}_j = 0$

**NOTE:**

**field:** 100067

**field:** Inverse of a square matrix:  $\mathbf{A}_{n \times n}$

**field:** The matrix that will satisfy  $\mathbf{A} \mathbf{A}^{-1} = \mathbf{I}$

**NOTE:**

**field:** 100068

**field:** Inverse of  $\mathbf{A}$ ,  $\mathbf{A}^{-1}$  where  $\mathbf{A}$  is  $2 \times 2$

**field:**  $\mathbf{A}^{-1} = \begin{pmatrix} a & b \\ c & d \end{pmatrix}^{-1} = \frac{1}{ad-bc} \begin{pmatrix} d & -b \\ -c & a \end{pmatrix}$

**NOTE:**

**field:** 100069

**field:** A square matrix is invertible if:

**field:** A square matrix is invertible if the columns (rows) are linearly independent. (If the columns are not independent, the matrix is called singular)

**NOTE:**

**field:** 100071

**field:** Square of matrix  $\mathbf{A}$

**field:**  $\mathbf{A}\mathbf{A}^t$

**NOTE:**

**field:** 100072

**field:** Norm of a vector  $|\mathbf{x}|$

**field:**  $|\mathbf{x}| = \sqrt{\sum_{j=1}^p x_j^2}$

**NOTE:**

**field:** 100073

**field:** Determinant of a  $2 \times 2$  matrix

**field:**  $\left| \begin{pmatrix} a & b \\ c & d \end{pmatrix} \right| = ad - bc$

**NOTE:**

**field:** 100074

**field:** Trace of a square matrix

**field:** Sum of the diagonal elements

**NOTE:**

**field:** 100075

**field:** Rank of a matrix

**field:** Number of linearly independent columns

**NOTE:**

**field:** 100076

**field:** Eigenvalue and eigenvector

**field:**  $\lambda$  is an eigen value and  $\mathbf{u}_{n \times 1}$  is the eigen vector of  $\mathbf{A}_{n \times n}$  if  $\mathbf{A}\mathbf{u} = \lambda\mathbf{u}$

- A real symmetric matrix has  $n$  eigen values and  $n$  eigen vectors, and each are orthogonal to each other
- Roots of  $\det(\mathbf{A} - \lambda\mathbf{I})$  determine the eigenvalues of  $A$

**NOTE:**

**field:** 100077

**field:** Matrix properties

- $(AB)^t =$
- $(A + B)^t =$
- $(AB)^{-1} =$
- $(\mathbf{A}^{-1})^t =$

**field:** Matrix properties

- $(AB)^t = B^t A^t$
- $(A + B)^t = A^t + B^t$
- For invertible matrices  $(AB)^{-1} = B^{-1} A^{-1}$
- For invertible matrices  $(\mathbf{A}^{-1})^t = (\mathbf{A}^t)^{-1}$

**NOTE:**

**field:** 100079

**field:**

$$E(Y_i | X_{i1}, \dots, X_{ip}) =$$

Where  $Y_i$  is the  $i$ th response and  $X_{ij}$  is the  $i$ th value of the  $j$ th predictor

**field:** Since the error terms  $\epsilon_i$  are independent and normally distributed with mean 0,

$$E(Y_i | X_{i1}, \dots, X_{ip}) = \beta_0 + \beta_1 X_{i1} + \beta_2 X_{i2} + \dots + \beta_p X_{ip}$$

**NOTE:**

**field:** 100080

**field:** Matrix form of linear Model and data

**field:**

$$\begin{pmatrix} Y_1 \\ Y_2 \\ \vdots \\ Y_n \end{pmatrix} = \begin{pmatrix} 1 & X_{11} & X_{12} & \cdots & X_{1p} \\ 1 & X_{21} & X_{22} & \cdots & X_{2p} \\ \vdots & \vdots & \vdots & & \vdots \\ 1 & X_{n1} & X_{n2} & \cdots & X_{np} \end{pmatrix} \begin{pmatrix} \beta_0 \\ \beta_1 \\ \vdots \\ \beta_p \end{pmatrix} + \begin{pmatrix} \epsilon_1 \\ \epsilon_2 \\ \vdots \\ \epsilon_n \end{pmatrix}$$

**NOTE:**

**field:** 100081

**field:** Assumptions of a linear model

**field:**

- Linearity:  $E(\epsilon_i) = 0$  or  $E(\epsilon) = \mathbf{0}$  or  $E(\mathbf{Y}) = \mathbf{X}\beta$
- Constant variance  $V(Y_i) = \sigma^2 = Var(\epsilon_i)$  or  $V(\epsilon) = \sigma^2 \mathbf{I}_n$
- Normality  $Y_i$  follows normal distribution, equivalently,  $\epsilon_i$  follows normal distribution
- Independence  $Y_i$  are independent equivalently under normality  $Cov(\epsilon_i, \epsilon_j) = 0$

**NOTE:**

**field:** 100082

**field:** Interpretation of intercept of linear model

**field:** Mean response when all explanatory variables are 0

**NOTE:**

**field:** 100083

**field:** Interpretation of slopes of linear model

**field:** Change in mean response for 1 unit change in the value of the explanatory, keeping all other variables constant. When  $p = 2$

$$E(Y|X_1 + 1, X_2) - E(Y|X_1, X_2) = \beta_1$$

**NOTE:**

**field:** 100084

**field:** Reason for  $g - 1$  indicator variables for a variable with  $g$  values

**field:** The model matrix  $X_{n \times (p+1)}$  needs to be full column rank -  $\mathbf{X}^t \mathbf{X}$  needs to be non-singular. If there is no intercept, we can include all groups, but interpretation will be different

**NOTE:**

**field:** 100085

**field:** Interpretation of slope coefficient for indicator variable  $\beta$

**field:** Difference in expected value of  $Y$  between group value  $a$  and  $b$  where  $a$  is the associated value for  $\beta_j$  and  $b$  is the base category

**NOTE:**

**field:** 100086

**field:**

- $E(\mathbf{AU} + \mathbf{b}) =$

- $V(\mathbf{AU} + \mathbf{b}) =$

**field:**

- $E(\mathbf{AU} + \mathbf{b}) = \mathbf{A}E(\mathbf{U}) + \mathbf{b}$

- $V(\mathbf{AU} + \mathbf{B}) = \mathbf{A}V(\mathbf{U})\mathbf{A}^t$

**NOTE:**

**field:** 100087

**field:** Least squares estimate of  $\beta$  (process to find )

**field:** Minimize the squared error loss ( $L(\beta)$ ) with respect to  $\beta$

$$L(\beta) = \sum_{i=1}^n Y_i - (\beta_0 + \beta_1 X_{i1} + \cdots + \beta_p X_{ip})^2 = (\mathbf{Y} - \mathbf{X}\beta)^t(\mathbf{Y} - \mathbf{X}\beta)$$

**NOTE:**

**field:** 100088

**field:**

$$\frac{\partial}{\partial \beta} L(\beta) =$$



**field:**

$$\begin{aligned}\frac{\partial}{\partial \beta} L(\beta) &= \frac{\partial}{\partial \beta} (\mathbf{Y} - \mathbf{X}\beta)^t (\mathbf{Y} - \mathbf{X}\beta) \\ &= \frac{\partial}{\partial \beta} \mathbf{Y}^t \mathbf{Y} - \beta^t \mathbf{X}^t \mathbf{Y} - \mathbf{Y}^t \mathbf{X} \beta - \beta^t \mathbf{X}^t \mathbf{X} \beta \\ &= 0 - \mathbf{X}^t \mathbf{Y} - \mathbf{X}^t \mathbf{Y} + 2\mathbf{X}^t \mathbf{X} \beta \\ \mathbf{X}^t \mathbf{X} \beta &= \mathbf{X}^t \mathbf{Y} \\ \beta &= (\mathbf{X}^t \mathbf{X})^{-1} \mathbf{X}^t \mathbf{Y}\end{aligned}$$

**NOTE:**

**field:** 100089

**field:** Least squares estimate of  $\hat{\beta}$

**field:**

$$\hat{\beta} = (\mathbf{X}^t \mathbf{X})^{-1} \mathbf{X}^t \mathbf{Y}$$

(if  $\mathbf{X}^t \mathbf{X}$  is invertible )

**NOTE:**

**field:** 100090

**field:** Residual

**field:**  $e_i = Y_i - \hat{Y}_i$ ,  $\mathbf{e}_{n \times 1} = \mathbf{Y} - \hat{\mathbf{Y}}$

**NOTE:**

**field:** 100091

**field:** Vector of fitted values (linear regression )

**field:**  $\hat{\mathbf{Y}} = \mathbf{X}\hat{\boldsymbol{\beta}} = \mathbf{X}(\mathbf{X}^t\mathbf{X})^{-1}\mathbf{X}^t\mathbf{Y}$

**NOTE:**

**field:** 100092

**field:** Projection matrix

**field:** Hat matrix

$$\mathbf{H}_{n \times n} = \mathbf{X}(\mathbf{X}^t\mathbf{X})^{-1}\mathbf{X}^t$$

$H_{ij}$  is the rate at which the  $i$ th fitted value changes as we vary the  $j$ th observation (influence )

**NOTE:**

**field:** 100093

**field:** Properties of projection matrix

**field:**

- $H$  and  $\mathbf{I} - \mathbf{H}$  are symmetric matrices
- $\mathbf{H}\mathbf{X} = \mathbf{X}$  item  $(\mathbf{I} - \mathbf{X})\mathbf{X} = \mathbf{0}$
- $\mathbf{H}^2 = \mathbf{H}$
- $(\mathbf{I} - \mathbf{H})\mathbf{H} = \mathbf{0}$
- $\mathbf{X}^t\mathbf{e} = 0$

**NOTE:**

**field:** 100094

**field:** Unbiased estimate of  $\sigma^2$

**field:**  $\hat{\sigma}^2 = \frac{1}{n-(p+1)} \sum_{i=1}^n e_i^2 = \frac{1}{n-(p+1)} \mathbf{e}^t \mathbf{e}$

**NOTE:**

**field:** 100095

**field:**  $\mathbf{e}^t \mathbf{e} =$

**field:**  $\mathbf{e}^t \mathbf{e} = \mathbf{Y}^t \mathbf{Y} - \mathbf{Y}^t \mathbf{H} \mathbf{Y}$

**NOTE:**

**field:** 100096

**field:**  $E(\hat{\beta}) =$

**field:**  $E(\hat{\beta}) = E((\mathbf{X}^t \mathbf{X})^{-1} \mathbf{X}^t \mathbf{Y}) = (\mathbf{X}^t \mathbf{X})^{-1} \mathbf{X}^t E(\mathbf{Y}) = (\mathbf{X}^t \mathbf{X})^{-1} \mathbf{X}^t \mathbf{X} \beta = \beta$   
So  $\hat{\beta}$  is an unbiased estimate

**NOTE:**

**field:** 100097

**field:** Gauss - Markov Theorem

**field:** If  $E(\mathbf{Y}) = \mathbf{X}\beta$  and  $V(\mathbf{Y}) = \sigma^2 \mathbf{I}$ , then the least squares estimate  $\hat{\beta}$  has the least variance among all linear unbiased estimators of  $\beta$ . (BLUE)  
Note that non-normal (or iid) residuals is not necessary, just must be uncorrelated.

**NOTE:**

**field:** 100098

**field:**  $V(\hat{\beta}) =$

**field:**  $V(\hat{\beta}) = \sigma^2(\mathbf{X}^t\mathbf{X})^{-1}$

**NOTE:**

**field:** 100099

**field:**  $E(\hat{\sigma}^2) =$

**field:**  $E(\hat{\sigma}^2) = \sigma^2$

**NOTE:**

**field:** 100100

**field:** If  $\mathbf{X}_{p \times 1}$  has a multivariate normal distribution  $N(\mu_{p \times 1}, \Sigma_{p \times p})$ , then  $\mathbf{AX} + b \sim$

**field:** If  $\mathbf{X}_{p \times 1}$  has a multivariate normal distribution  $N(\mu_{p \times 1}, \Sigma_{p \times p})$ , then  $\mathbf{AX} + \mathbf{b} \sim N(\mathbf{A}\mu + \mathbf{b}, \mathbf{A}\Sigma\mathbf{A}^t)$

**NOTE:**

**field:** 100101

**field:** Multivariate normal properties for  $\mathbf{X}_{p \times 1} \sim N(\mu_{p \times 1}, \Sigma_{p \times p})$

**field:**

- $Cov(X_j, X_k) = 0$  if and only if  $X_j, X_k$  are independent (two way due to multivariate normal )
- All subsets of elements of  $\mathbf{X}$  have a multivariate normal distribution
- All linear combinations of the components of  $X$  are normally distributed
- $\mathbf{a}^t\mathbf{X} \sim N(\mathbf{a}^t\mu, \mathbf{a}^t\Sigma\mathbf{a})$  for a vector  $\mathbf{a}$

**NOTE:**

**field:** 100102

**field:** Linear Hypothesis testing single parameter  $H_0 : \mathbf{c}^t \beta = d$

- $E(\mathbf{c}^t \beta), V(\mathbf{c}^t \beta) =$
- Test statistic and distribution
- Item of setting up hypothesis test
- Rejection Region

**field:** For a vector  $\mathbf{c}_{(p+1) \times 1}$ , we have that

- $E(\mathbf{c}^t \hat{\beta}) = \mathbf{c}^t \beta, V(\mathbf{c}^t \hat{\beta}) = \sigma^2 \mathbf{c}^t (\mathbf{X}^t \mathbf{X})^{-1} \mathbf{c}$
- Thus

$$\frac{\mathbf{c}^t \hat{\beta} - \mathbf{c}^t \beta}{\sigma \sqrt{\mathbf{c}^t (\mathbf{X}^t \mathbf{X})^{-1} \mathbf{c}}} \sim N(0, 1)$$

and under  $H_0$

$$T = \frac{\mathbf{c}^t \hat{\beta} - d}{\sqrt{\hat{\sigma}^2 \mathbf{c}^t (\mathbf{X}^t \mathbf{X})^{-1} \mathbf{c}}} \sim t_{n-(p+1)}$$

- Example: testing  $H_0 : \beta_1 = \beta_2, \mathbf{c} = (0, 1, -1)^t, d = 0$
- Reject  $H_a : \mathbf{c}^t \beta \neq d : |T| > t_{n-(p+1)}(1 - \alpha/2)$   
 $\mathbf{c}^t \beta > d, T > t_{n-(p+1)}(\alpha)$   
 $\mathbf{c}^t \beta < d : T < -t_{n-(p+1)}(\alpha)$

**NOTE:**

**field:** 100103

**field:** Confidence interval for a single parameter (linear regression slope estimate)

**field:**

$$\hat{\beta}_j \pm t_{n-(p-1)}(1 - \alpha/2)\sqrt{\hat{\sigma}^2((\mathbf{X}^t\mathbf{X})^{-1})_{j+1,j+1}}$$
$$\mathbf{c}^t\beta \pm t_{n-(p-1)}(1 - \alpha/2)\sqrt{\hat{\sigma}^2\mathbf{c}^t((\mathbf{X}^t\mathbf{X})^{-1})\mathbf{c}}$$

eg if we were testing  $\beta_1 - \beta_2$ ,  $c = (0, 1, -1)$

**NOTE:**

**field:** 100104

**field:** F statistic in matrix form

**field:**

- $\mathbf{K}$  is  $p \times k$ ,  $\mathbf{m}$  is  $k \times 1$
- Testing  $H_0 : \mathbf{K}^t\beta = \mathbf{m}$
- $F = \frac{((\mathbf{K}\hat{\beta}-\mathbf{m})^t(\mathbf{K}(\mathbf{X}^t\mathbf{X})^{-1}\mathbf{K}^{-1})(\mathbf{K}\hat{\beta}-\mathbf{m}))}{k\hat{\sigma}^2} \sim F_{k,n-p}$
- $\text{Eg } K = \begin{pmatrix} 0 \\ 1 \\ \vdots \\ 0 \end{pmatrix}, m = 0$
- Tests  $\beta_1 = 0$
- Note the  $\mathbf{K}^t$  matrix is the coefficients of the system of linear equations for the the null hypothesis, and  $m$  is what they are equal to

**NOTE:**

**field:** 100105

**field:** Overall regression F-test

**field:** Tests if any predictors are related to the response

- Full model:  $\mathbf{Y} = \mathbf{X}\beta + \epsilon$
- Reduced model a nested model with  $q$  estimated parameters
- eg: Reduced model:  $\mathbf{Y} = \beta_0 + \epsilon$ ,  $q = 1$
- $H_0 : \beta_1 = \dots = \beta_p = 0$
- $F = \frac{(RSS_{\omega} - RSS_{\Omega}) / (p - q)}{RSS_{\Omega} / (n - p)}$
- 

**NOTE:**

**field:** 100106

**field:** Analysis of Variance Table and calculated F stat

	Type	df	Sum of Squares	Mean SS
<b>field:</b>	Regression	$p$	SS(Reg)	SS(Reg)/p
	Residual	$n - p + 1$	SS(Res)	$\hat{\sigma}^2 = \text{SS(Res)} / n - p - 1$
	Total	$n - 1$	SS(Total) = SS(Reg) + SS(Res)	$\frac{1}{n-1} \sum_{i=1}^n (y_i - \bar{y})^2$

and  $F = \frac{\text{Mean}(SSREG)}{\text{Mean}(SSRES)}$

**NOTE:**

**field:** 100107

**field:** Distribution of  $\hat{\beta}$ , where  $\hat{\beta}$  are the estimated coefficients of linear regression.

**field:**  $\hat{\beta} \sim N(\beta, \sigma^2(\mathbf{X}^t \mathbf{X})^{-1})$

**NOTE:**

**field:** 100108

**field:** RSS (in terms of  $\Omega$  and  $\omega$ )

**field:**

$$RSS_{\Omega} = \sum_{i=1}^n e_i^2$$

$$RSS_{\omega} = \sum_{i=1}^n (Y_i - \bar{Y})^2$$

**NOTE:**

**field:** 100109

**field:**  $R^2$

**field:**  $R^2 = \frac{SS(Reg)}{SS(Tot)} = 1 - \frac{SS(Res)}{SS(Tot)}$

Where SS(Reg) is the regression sum of square:  $\sum_i (\hat{y}_i - \bar{y})^2$  (fitted minus mean) and SS(Tot) or TSS is the total sum of squares  $\sum_i (y_i - \bar{y})^2$  and SS(Res) (or error sum of squares)  $SS_E$  or RSS is the residual sum of squares  $\sum_i (y_i - \hat{y}_i)^2 = \sum_i e_i^2$

And SS(Tot) = SS(Res) + SS(Reg)

**NOTE:**

**field:** 100110

**field:** Properties of the estimate of  $\sigma^2$

**field:**

- $\hat{\sigma}^2 = \frac{|\mathbf{e}|^2}{n-(p+1)}$
- Under normality:  $\frac{(n-(p+1))\hat{\sigma}^2}{\sigma^2} \sim \chi_{n-(p+1)}^2$
- $\hat{\sigma}^2$  is independent from  $\hat{\beta}$



**NOTE:**

**field:** 100111

**field:** Prediction Interval

**field:** Predicting a future response  $\mathbf{x}_0^t \hat{\beta} \pm t_{n-p}(\alpha/2) \hat{\sigma} \sqrt{1 + x_0^t (X^t X)^{-1} x_0}$   
A 95% prediction interval for a response with (list values) is between and

**NOTE:**

**field:** 100112

**field:** Confidence interval

**field:** Confidence in mean response  $\mathbf{x}_0^t \hat{\beta} \pm t_{n-p}(\alpha/2) \hat{\sigma} \sqrt{x_0^t (X^t X)^{-1} x_0}$  With  
95% confidence, the expected mean response

**NOTE:**

**field:** 100113

**field:** Residual Plot

**field:**

- Plot residuals against fitted values (so there is only 1 plot vs against explanatory variables)
- Verifies linearity and constant variance

**NOTE:**

**field:** 100114

**field:** Leverage

**field:**

- An observation has high leverage if the explanatory variable values of the observation are different from general pattern
- $h_i = H_{ii} = (X(X^t X)^{-1} X^t)_{ii}$
- High leverage  $h_i > \frac{2(p+1)}{n}$

**NOTE:**

**field:** 100115

**field:** Standardized Residual

**field:**  $r_i = \frac{e_i}{\hat{\sigma}\sqrt{1-h_i}}$  Large if  $|r_i| > 2$  - indicates outlier

**NOTE:**

**field:** 100116

**field:** Influential

**field:** if fitted model depends highly on the value Measure using cook's distance

$$D_i = \frac{(\hat{Y} - \hat{Y}_{(i)})^t (\hat{Y} - \hat{Y}_{(i)})}{(p+1)\hat{\sigma}^2} = \frac{1}{p+1} r_i^2 \frac{h_i}{(1-h_i)}$$

Where  $Y_i$  is the vector of fitted values when the model is fitted to the data without the  $i$  ths observationl Moderate if  $> 1$  Large if  $> 6$

**NOTE:**

**field:** 100117

**field:** Multicollinearity

**field:**

- $X^t X$  is close to singular
- Some columns are highly correlated
- there is a relationship between predictors
- leads to large standard errors
- Not a violation of assumptions, but leads to issues in interpretations
- Calculate using Condition number if  $> 30$  than large, or Variance inflation factors  $VIF_j = \frac{1}{1-R_j^2}$  where  $R_j^2$  is  $R^2$  from regression of the  $j$ th explanatory variable on all the other explanatory variables
- Not a problem for prediction
- Fix using selection of explanatory variables, generalized inverse, ridge regression

**NOTE:**

**field:** 100118

**field:** Ridge Regression

**field:**  $\hat{\beta} = (X^t X + \lambda I)^{-1} X^t Y$ , where  $\lambda$  is chosen. Note these are biased estimators

**NOTE:**

**field:** 100119

**field:** Fix non-constant spread/variance

**field:**

- Transform response (box-cox)
- Use more complicated model (glm)

**NOTE:**

**field:** 100120

**field:** Fix non-linearity

**field:**

- Transform response
- Transform predictor
- allow for curvature: predictor squared, splines, gam
- use a non linear model

**NOTE:**

**field:** 100121

**field:** Fix Non-normality

**field:**

- Transform response
- more complicated models : glm

**NOTE:**

**field:** 100122

**field:** Missing data completely at random (MCAR)

**field:**

- Throwing out cases with missing data does not bias inferences
- There's no relationship between whether a data point is missing and any values in the data set, missing or observed.
- The missing data are just a random subset of the data.

**NOTE:**

**field:** 100123

**field:** Missing at random (MAR)

**field:**

- the propensity for a data point to be missing is not related to the missing data, but it is related to some of the observed data.
- Probability of missingness depends only on available information, like the explanatory variables and the response variables present in the regression - impute missing data
- A better name would actually be Missing Conditionally at Random, because the missingness is conditional on another variable.

**NOTE:**

**field:** 100124

**field:** Model Selection methods

**field:**

- Sequential Methods: Backward/Forward (eliminate until all values have p-value below critical value) Elimination
- Penalized Regression: Ridge and Lasso

**NOTE:**

**field:** 100125

**field:** AIC

**field:** Estimate the distance of a candidate model from the true model (small good)

$$n \log(RSS/n) + 2(p + 1)$$

**NOTE:**

**field:** 100126

**field:** BIC

**field:** Estimate the best parsimonious model, using a prior distribution on the parameters (small good)

$$n \log(RSS/n) + \log(n)(p + 1)$$

Where  $n$  is the number of observations,  $p$  is the number of predictors (not including intercept), and  $RSS = \sum(Y_i - \hat{Y})^2 = \sum e_i^2$

**NOTE:**

**field:** 100127

**field:** Adjusted  $R^2$

**field:** Adjusts for multiple parameters

$$1 - \frac{n-1}{n-p}(1 - R^2)$$

(large is good) (where  $p$  includes the intercept)

$$\frac{MS(Reg)}{MS(Total)} = 1 - \frac{SS(Reg)/(n-p-1)}{SS(Tot)/(n-1)}$$

**NOTE:**

**field:** 100128

**field:** Mallows's Cp

**field:**

$$RSS/\hat{\sigma}^2 + 2p - n$$

(small good)

**NOTE:**

**field:** 100129

**field:** Box-Cox Transformation

**field:** Transform so model is  $g(Y) = X\beta + \epsilon$  where  $g(y) = \frac{y^\lambda - 1}{\lambda}$  if  $\lambda \neq 0, 0$  otherwise

**tags:** Methods3

**NOTE:**

**field:** 100130

**field:** Components of an experiment

**field:** Experimental units, treatment, design (how eus are allocated to treatments)

**NOTE:**

**field:** 100130

**field:** Model and assumptions for CRD

**field:** Model and assumptions for Completely randomized design

$$y_{ij} = \mu_i + \epsilon_{ij}$$

Where

- $y_{ij}$  is the response on the  $j$ th eu in the  $i$ th group
- $\mu_i$  is the population mean in the  $i$ th group
- $\epsilon_{ij}$  is the random error for the  $j$ th eu in the  $i$ th group
- Assume  $\epsilon_{ij} \sim iidN(0, \sigma^2)$

**NOTE:**

**field:** 100131

**field:** Point estimate of  $\hat{\mu}_i$

**field:**  $\hat{\mu}_i = \bar{y}_i = \text{mean in the } i\text{th group}$

**NOTE:**

**field:** 100132

**field:** Point estimate of  $\hat{\sigma}^2$

**field:**

$$\hat{\sigma}^2 = MSE = \frac{\text{error sum of squares}}{df} = \frac{\text{residual SS}}{df} \quad (1)$$

$$= \frac{\sum_{i=1}^g \sum_{j=1}^{n_i} (y_{ij} - \bar{y}_{i.})^2}{N - g} \quad (2)$$

$$= s^2 \quad (3)$$

Where

- $g$  is the number of groups



- $N$  is the overall sample size
- $n_i$  the number of eus in the  $i$ th group
- $Df = \text{sample size} - \text{number of parameters} = N - g$
- $i$ th residual  $= y_{ij} - \hat{y}_{ij} = y_{ij} - \bar{y}_i$ .

**NOTE:**

**field:** 100133

**field:** Hypothesis test and interval estimates for  $\mu_i$  in CRD

**field:**  $\hat{\mu}_i = \bar{y}_i = \text{sample mean of } y_{i1}, \dots, y_{in_i} \sim iidN(\mu_i, \sigma^2)$

$$\bar{y}_i \sim N\left(\mu_i, \frac{\sigma^2}{n_i}\right)$$

$$SE(\bar{y}_i) = \sqrt{\frac{s^2}{n_i}}$$

$$CI: \bar{y}_i \pm t_{(a/2, N-g)} \sqrt{\frac{s^2}{n_i}}$$

$$H_0 : \mu_i = 0 \quad t = \frac{\bar{y}_i}{\sqrt{s^2/n_i}} \sim t_{(N-g)}$$

**NOTE:**

**field:** 100134

**field:** Cell Means Parametrization (eg  $g = 3, n_i = 2$ )

**field:**

$$\begin{pmatrix} y_{11} \\ y_{12} \\ y_{21} \\ y_{22} \\ y_{31} \\ y_{32} \end{pmatrix} = \begin{pmatrix} 1 & 0 & 0 \\ 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \\ 0 & 0 & 1 \end{pmatrix} \begin{pmatrix} \mu_1 \\ \mu_2 \\ \mu_3 \end{pmatrix} + \begin{pmatrix} \epsilon_{11} \\ \epsilon_{12} \\ \epsilon_{21} \\ \epsilon_{22} \\ \epsilon_{31} \\ \epsilon_{32} \end{pmatrix}$$

**NOTE:**

**field:** 100135

**field:** Regression parametrization (eg  $g = 3, n_i = 2$ )

**field:** Code categorical variables using indicators  $y_{ij} = \beta_0 + \beta_1 X_{1,ij} + \beta_2 X_{2,ij} + \epsilon_{ij}$

$$\begin{pmatrix} y_{11} \\ y_{12} \\ y_{21} \\ y_{22} \\ y_{31} \\ y_{32} \end{pmatrix} = \begin{pmatrix} 1 & 1 & 0 \\ 1 & 1 & 0 \\ 1 & 0 & 1 \\ 1 & 0 & 1 \\ 1 & 0 & 0 \\ 1 & 0 & 0 \end{pmatrix} \begin{pmatrix} \beta_0 \\ \beta_1 \\ \beta_2 \end{pmatrix} + \begin{pmatrix} \epsilon_{11} \\ \vdots \\ \epsilon_{32} \end{pmatrix}$$

**NOTE:**

**field:** 100136

**field:** Factor (Treatment) Effects Parametrization

**field:**

$$y_{ij} = \mu + \alpha_i + \epsilon_{ij}$$

Where

- $\mu$  = overall mean: average of  $\mu_i$
- $\alpha_i$  = effect of level  $i$  of the treatment factor, deviation away from  $\mu$  associated with the  $i$ th treatment

$$\begin{pmatrix} y_{11} \\ y_{12} \\ y_{21} \\ y_{22} \\ y_{31} \\ y_{32} \end{pmatrix} = \begin{pmatrix} 1 & 1 & 0 \\ 1 & 1 & 0 \\ 1 & 0 & 1 \\ 1 & 0 & 1 \\ 1 & -1 & -1 \\ 1 & -1 & -1 \end{pmatrix} \begin{pmatrix} \mu \\ \alpha_1 \\ \alpha_2 \end{pmatrix} + \begin{pmatrix} \epsilon_{11} \\ \vdots \\ \epsilon_{32} \end{pmatrix}$$

Note that  $\alpha_3 = -\alpha_1 - \alpha_2$

**NOTE:**

**field:** 100137

**field:** Extra Sum of Squares  $F$ - test

**field:**

- Compares full and reduced models

$$F = \frac{(SS_E(\text{red}) - SS_E(\text{full})) / (df(\text{red}) - df(\text{full}))}{SS_E(\text{full}) / df(\text{full})}$$

- Can use to test for differences across the group means

$$H_0 : \mu_1 = \dots = \mu_g = \mu$$

$$H_A : \mu_i \neq \mu_j \text{ for some } i \neq j$$

- Reduced model:  $y_{ij} = \mu + \epsilon_{ij}$
- Full model:  $y_{ij} = \mu_i + \epsilon_{ij}$
- $SS_E = \sum_j (y_j - \hat{y}_j)^2 = \text{residual SS}$
- $SS_E(\text{full}) = \sum_{i=1}^g \sum_{j=1}^{n_i} (y_{ij} - \bar{y}_{i.})^2$  Where  $\bar{y}_{i.}$  is the fitted value for obs in  $i$ th group
- $SS_E(\text{red}) = \sum_{i=1}^g \sum_{j=1}^{n_i} (y_{ij} - \bar{y}_{..})^2$  where  $\bar{y}_{..} = \sum_i \sum_j y_{ij} / N$  mean of all obs
- $df(\text{full}) = N - g$
- $df(\text{red}) = N - 1$
- $SSE(\text{red}) - SSE(\text{full}) = SSTreatment$  for CRD
- Reduced model will have more unexplained variation

**NOTE:**

**field:** 100138

**field:** CRD ANOVA Table

		DF	SS	MS	F
<b>field:</b>	Treatment	$g - 1$	SS(Trt)	$SS(\text{Trt})/(g - 1)$	$MS(\text{trt})/MS(E) \sim F_{g-1, N-g}$
	Error	$N - g$	SS(E)	$SS(E)/(N - g)$	
	Total	$N - 1$	SS(T)		

**NOTE:**

**field:** 100139

**field:** Distribution of  $SS(\text{Total})/\sigma^2$ ,  $SS(\text{Treatment})/\sigma^2$  and  $SS(E)/\sigma^2$

**field:**  $\chi^2_{N-1}$ ,  $\chi^2_{g-1}$ ,  $\chi^2_{N-g}$

**NOTE:**

**field:** 100140

**field:**  $E(MS_{\text{Trt}}) =$

**field:**

$$E(MS_{\text{Trt}}) =$$

- If  $H_0$  true, then  $E(MS_{\text{Trt}}) = \sigma^2$
- If  $H_A$  true, then  $E(MS_{\text{Trt}}) > E(MS_E)$

**NOTE:**

**field:** 100141

**field:**  $E(MS_E) =$

**field:**  $E(MS_E) = \sigma^2$

**NOTE:**

**field:** 100142

**field:** Contrast

**field:** A contrast is a linear combination of treatment means where the coefficients sum to 0  $C = \sum_{i=1}^g w_i \mu_i$  where  $\sum_{i=1}^g w_i = 0$  Examples:

- $\frac{\mu_1 + \mu_2 + \mu_3}{3} - \mu_4$ ,  $C = 1/3, 1/3, 1/3, -1$

**NOTE:**

**field:** 100143

**field:** Hypothesis test of contrast

**field:**

- $\hat{C} = \sum_{i=1}^g w_i \bar{y}_i$ .
- $V(\hat{C}) = V\left(\sum_{i=1}^g w_i \bar{y}_i\right) = \sum_{i=1}^g w_i^2 \frac{\sigma^2}{n_i}$
- $\hat{V}(\hat{C}) = \sum_{i=1}^g w_i^2 \frac{MS_E}{n_i} = \sum_{i=1}^g w_i^2 \frac{\hat{\sigma}^2}{n_i}$
- CI:  $\hat{C} \pm t_{(1-\alpha/2, N-g)} SE(\hat{C})$
- $t = \frac{\hat{C} - 0}{SE(\hat{C})} \sim t_{N-g}$
- Eg if  $C = \mu_1 - \mu_4$  a test of  $C = 0$  is testing  $\mu_1 = \mu_4$

**NOTE:**

**field:** 100144

**field:** Contrast sums of squares

**field:**  $SS_{\text{Contrast}} = SS_E(\text{reduced}) - SS_E(\text{full})$

- The full model is the separate means model  $y_{ij} = \mu_i + \epsilon_{ij}$
- The reduced model is the full model with the restriction  $H_0 : C = 0$  imposed on the  $\mu_i$
- Eg:  $C = \frac{\mu_1 + \mu_2 + \mu_3}{3} = \mu_4$  Full model parameter vector  $(\mu_1, \dots, \mu_4)^t$ , reduced model parameter vector:  $(\mu_1, \mu_2, \mu_3)$  with  $\mu_4 = \frac{\mu_1 + \mu_2 + \mu_3}{3}$
- $\text{df full} = N - 4$ ,  $\text{df reduced} = N - 3$ ,  $\text{df contrast} = 1 = (N - 3) - (N - 4)$

**NOTE:**

**field:** 100145

**field:** Orthogonal contrasts

**field:** Contrasts  $C_1$  and  $C_2$  are orthogonal if  $\sum_{i=1}^g \frac{w_i w_i^*}{n_i} = 0$   
We usually only consider orthogonal contrasts when  $n_i = n$  (balanced design)  
With  $g$  treatments, we can have at most  $g - 1$  orthogonal contrasts  
If contrasts are orthogonal  $SS(\text{trt}) = SS(C_1) + \dots + SS(C_{g-1})$

**NOTE:**

**field:** 100146

**field:** Orthogonal polynomial contrasts and polynomial regression

**field:**

- When data are balanced and treatments are incremental and equally spaced, we can use orthogonal polynomial contrasts
- With  $g$  treatments, fit a  $g - 1$  degree polynomial model. Fitted polynomial will fit each treatment mean exactly
- The  $g - 1$  degree polynomial is another parametrization of the separate means model
- The cell means model ignores the incremental nature of treatment - polynomial one doesn't
- Polynomial models imply something about interpolation
- ex:  $y_{ij} = \beta_0 + \beta_1 X_i + \beta_2 X_i^2 + \beta_3 X_i^3 + \epsilon_{ij}$   $X_i$  is the amount of treatment in the  $i$ th group.
- $SS(\text{trt}) = SS(\text{linear}) + SS(\text{quad}) + SS(\text{cubic})$

**NOTE:**

**field:** 100147

**field:** Design matrix for orthogonal polynomial contrasts

**field:**

$$X = \begin{pmatrix} 1 & 0 & 0^2 & 0^3 \\ \vdots & \vdots & \vdots & \vdots \\ 1 & 50 & 50^2 & 50^3 \\ \vdots & \vdots & \vdots & \vdots \\ 1 & 100 & 100^2 & 100^3 \\ \vdots & \vdots & \vdots & \vdots \\ 1 & 150 & 150^2 & 150^3 \\ \vdots & \vdots & \vdots & \vdots \end{pmatrix}$$

$$\beta = (\beta_0, \beta_1, \beta_2, \beta_3)^t$$

**NOTE:**

**field:** 100148

**field:** Per comparison error rate

**field:**

- $P(\text{reject } H_{0i})$  when  $H_{0i}$  is true
- Usual  $\alpha$
- No correction for multiple comparisons

**NOTE:**

**field:** 100149

**field:** Experimentwise error rate

**field:**  $\alpha_E = P(\text{reject at least one } H_{0i})$  when  $H_0$  is true (all  $H_{0i}$  true )

**NOTE:**

**field:** 100150

**field:** False Discovery rate (FDR)

**field:**  $FDR = \frac{\text{number false rejections}}{\text{total number rejections}}$ , or 0 when no rejections  
Allows more incorrect rejections as the number of true rejections increases

**NOTE:**

**field:** 100151

**field:** Strong familywise error rate



**field:**  $\alpha_F = P(\text{at least one false rejection}) = P(FDR > 0)$

**NOTE:**

**field:** 100152

**field:** Tradeoff of multiple comparisons

**field:** Stronger error control - less powerful test

**NOTE:**

**field:** 100153

**field:** Bonferroni correction

**field:**

- $K$  comparisons
- Fix  $\alpha_F = P(\text{at least one false rejection})$  and set per comparison error rate  $\alpha = \alpha_F / K$
- Reject  $H_{0i}$  if its p value is less than  $\alpha_F / K$
- Very strict, but easy test

**NOTE:**

**field:** 100154

**field:** Holm multiple comparison

**field:**

- $K$  comparisons
- Sort individual p-values from small to large  $p_1, \dots, p_k$
- Reject  $H_{0i}$  if  $p_i < \frac{\alpha_F}{K-i+1}$
- Note  $\frac{\alpha_F}{K-i+1} \geq \frac{\alpha_F}{K}$ , so Holm is more powerful than Bonferroni, but still conservative

**NOTE:**

**field:** 100155

**field:** Multiple comparison method: FDR (edit: define FDR)

**field:**

- $K$  comparisons
- Sort p-values
- Reject  $H_{0i}$  if  $p_i < \frac{i \cdot FDR}{K}$
- Controls the false discovery rate

**NOTE:**

**field:** 100156

**field:** Scheffes method

**field:**

- Only method that controls  $\alpha_F$  if we've snooped the data
- Tests all possible contrasts (all are 0 )
- very conservative
- Reject  $H_{0i} : C_i = 0$  if

$$\frac{SS_{C_i}(g-1)}{MS_E} > F_{\alpha_F, g-1, N-g}$$

- Confidence interval:

$$\hat{C}_i \pm \sqrt{(g-1)F_{\alpha_F, g-1, N-g}SE(\hat{C}_i)}$$

**NOTE:**

**field:** 100157

**field:** Multiple comparison for pairwise comparisons

**field:**

- Contrasts of the form  $\mu_i - \mu_j$
- For  $g$  treatment groups there are  $\binom{g}{2}$  possible pairwise comparisons
- Tukey's Honestly Significant Difference (balanced)
- Tukey-Kramer (not balanced )

**NOTE:**

**field:** 100157

**field:** Tukey's Honestly Significant Difference (HSD)

**field:**

- Pairwise comparisons
- Simultaneous tests and CIs of all  $C = \mu_i - \mu_j$
- Controls  $\alpha_F$
- CI:

$$\bar{y}_{i\cdot} - \bar{y}_{j\cdot} \pm q_{\alpha_F, g, N-g} \sqrt{\frac{MS_E}{n}}$$

- Assumes  $n$  observations in each group (balanced)
- Where  $q$  is the studentized range distribution - dividing a statistic by the estimate of its standard error

**NOTE:**

**field:** 100158

**field:** Tukey-Kramer

**field:**

- Pairwise comparison
- If the data are not balanced (but close)
- Replace  $\sqrt{\frac{MS_E}{n}}$  with  $\sqrt{MS_E \frac{n_i + n_j}{2n_i n_j}}$  in
- CI:

$$\bar{y}_{i\cdot} - \bar{y}_{j\cdot} \pm q_{\alpha_F, g, N-g} \sqrt{\frac{MS_E}{n}}$$

**NOTE:**

**field:** 100159

**field:** Ryan-Einot-Gabriel-Welsch Range (REGWR) test

**field:**

- Controls  $\alpha_F$
- Stepdown procedure
- Order sample means from small to large
- Test ranges, starting with largest range  $\mu_{(1)} = \mu_{(g)}$
- If fail to reject, stop, conclude that no means differ. Otherwise stop down and test next largest ranges. etc

**NOTE:**

**field:** 100160

**field:** Dunnett's Procedure

**field:**

- Compare all treatments to control
- 

**NOTE:**

**field:** 100161

**field:** Multiple Comparisons with the best *MCB*

**field:**

- Identifies either  $\max(\mu_i)$  or  $\min(\mu_i)$
- Intervals either contain 0 (not different from best) or have 0 as an endpoint, which implies they are different from the best.
- Usually done with ANOVA

**NOTE:**

**field:** 100162

**field:** Difference between Type I and Type III Sum of Squares

**field:**

- Type I is a nested model - variables are added
- Type III removes one variable

**NOTE:**

**field:** 100163

**field:** Effect of non-normality ("Robustness")

**field:**

- If tails are too long (compared to normal) estimate of variance will be too large, inference will be conservative (CI too wide, p-values too big, type I error smaller than  $\alpha$ , lower power)
- If tails are too short, reverse is true

**NOTE:**

**field:** 100164

**field:** Equal variance diagnostics

**field:**

- Levene's test
- Plot residuals vs fitted values

**NOTE:**

**field:** 100165

**field:** Effect of non-constant variance + Remedy

**field:**

- If data are balance and variances are not too unequal, standard procedures work pretty well
- If data are unbalanced and large  $n_i$  corresponds to larger variances, procedures too conservative
- Small  $n_i$  correspond to large variances, opposite
- Remedy using Welch's ANOVA/weighted least squares, larger balanced sample

**NOTE:**

**field:** 100166

**field:** RF Plot

**field:**

- Residual-Fit Spread plot
- Left plot has sorted centered fits  $\hat{y}_{ij} - \hat{\bar{y}}_{i\cdot}$
- Right plot has sorted residuals  $y_{ij} - \hat{y}_{ij}$
- Left plot shows variability explained by the model
- Right plot shows unexplained variability
- Want spread of left plot to be larger than right plot - indicates we have a good model

**NOTE:**

**field:** 100167

**field:** Sample size to perform a 2 sample z test

**field:** For a 2 sample  $z$  test  $H_0 : \mu_1 = \mu_2$  with  $\sigma^2$  known

$$n \geq 2(z_{\alpha/2} + z_{\beta})^2 \frac{\sigma^2}{\delta^2}$$

- $n$  sample size in each group
- $\alpha$  = Type I error rate
- $\beta$  = Type II error rate = 1-Power
- $z_{\alpha/2}$  = standard normal  $1 - \alpha/2$  quantile
- $z_{\beta}$  = standard normal  $1 - \beta$  quantile
- $\sigma^2$  = common variance
- $\delta = \mu_1 - \mu_2$

**NOTE:**

**field:** 100168

**field:** Sample size for one-way ANOVA

**field:** Depends on the distribution when  $H_A$  is the case - non central F distribution - to find sample size, simulate repeated sampling under  $H_A$  to calculate power for different  $N$

**NOTE:**

**field:** 100169



**field:**  $2 \times 2$  Factorial design difference from ANOVA

**field:** ANOVA fits a model like, for group 1 with treatments C,F and group2

	CH	CL	FH	FL
treatments HL				
(ignores the structure of treatments )				
			Liquid L	H
Factorial design:	Screen	C F		

Uses contrasts

**NOTE:**

**field:** 100170

**field:** Interaction plot

**field:**

- If the interaction contrast is 0, then the lines will be parallel
- If we see non parallel lines, it indicates there is an interaction
- Parallel lines associated with large p values of interaction term

**NOTE:**

**field:** 100171

**field:** Model for a  $2 \times 2$  factorial design

**field:**  $y_{ijk}$  is response from the  $k$ th replicate with  $i$ th level of factor A, and  $j$ th level of factor B  
eg:

		B	
		$j = 1$	$j = 2$
A	$i = 1$	$y_{11k}$	$y_{12k}$
	$i = 2$	$y_{21k}$	$y_{22k}$

**NOTE:**

**field:** 100172

**field:** Cell means parametrization for  $2 \times 2$  factorial design

**field:**

$$y_{ijk} = \mu_{ij} + \epsilon_{ijk}$$

$y_{ijk}$  is response from the  $k$ th replicate with  $i$ th level of factor A, and  $j$ th level of factor B  
 $\epsilon_{ijk} \sim N(0, \sigma^2)$

**NOTE:**

**field:** 100173

**field:** Factor effects parametrization for  $2 \times 2$  design

**field:**

$$y_{ijk} = \mu + \alpha_i + \beta_j + (\alpha\beta)_{ij} + \epsilon_{ijk}$$

Where

- $\mu$  is the overall mean
- $\alpha_i$  effect of  $i$ th level of factor A

- $\beta_j$  effect of  $j$ th level of factor B
- $(\alpha\beta)_{ij}$  interaction of  $i$ th level of A and  $j$ th level of B
- Where  $\epsilon_{ijk} \sim N(0, \sigma^2)$
- $0 = \sum_{i=1}^2 \alpha_i = \sum_{j=1}^2 \beta_j = \sum_{i=1}^2 (\alpha\beta)_{ij} = \sum_{i=1}^2 (\alpha\beta)_{ij}$

**NOTE:**

**field:** 100174

**field:** Equivalence of cell means and factor effects parametrizations

**field:**

	$j = 1$	$j = 2$
$i = 1$	$\mu_{11} = \mu + \alpha_1 + \beta_1 + (\alpha\beta)_{11}$	$\mu_{12} = \mu + \alpha_1 + \beta_2 + (\alpha\beta)_{12} = \mu + \alpha_1 + \beta_2 + (\alpha\beta)_{11} + \beta_1 - \beta_2$
$i = 2$	$\mu_{21} = \mu + \alpha_2 + \beta_1 + (\alpha\beta)_{21} = \mu - \alpha_1 + \beta_1 - (\alpha\beta)_{11}$	$\mu_{22} = \mu + \alpha_2 + \beta_2 + (\alpha\beta)_{22} = \mu - \alpha_1 + \beta_2 - (\alpha\beta)_{11} + \beta_1$

**NOTE:**

**field:** 100175

**field:** Design matrix for  $2 \times 2$  factorial design, where each group has 2 options

**field:**

$$\begin{pmatrix} y_{111} \\ \vdots \\ y_{11n} \\ y_{121} \\ \vdots \\ y_{12n} \\ y_{211} \\ \vdots \\ y_{21n} \\ y_{221} \\ \vdots \\ y_{22n} \end{pmatrix} = \begin{pmatrix} 1 & 1 & 1 & 1 \\ \vdots & \vdots & \vdots & \vdots \\ 1 & 1 & -1 & -1 \\ \vdots & \vdots & \vdots & \vdots \\ 1 & -1 & 1 & -1 \\ \vdots & \vdots & \vdots & \vdots \\ 1 & -1 & -1 & 1 \\ \vdots & \vdots & \vdots & \vdots \end{pmatrix} \begin{pmatrix} \mu \\ \alpha_1 \\ \beta_1 \\ (\alpha\beta)_{11} \end{pmatrix} + \epsilon$$

**NOTE:**

**field:** 100176

**field:** General model for a 2-factor design

**field:**  $y_{ijk} = \mu + \alpha_i + \beta_j + (\alpha\beta)_{ij} + \epsilon_{ijk}$

- A has levels  $1 \cdots a$
- B has levels  $1 \cdots b$
- $\epsilon_{ijk} \sim N(0, \sigma^2)$
- $0 = \sum_{i=1}^a \alpha_i = \sum_{j=1}^b \beta_j = \sum_{i=1}^a (\alpha\beta)_{ij} = \sum_{j=1}^b (\alpha\beta)_{ij}$
- There are  $a \times b$  parameters to estimate
- $a - 1 \alpha_i$ s ,  $b - 1 \beta_j$ s,  $(a - 1)(b - 1)(\alpha\beta)_{ij}$ s =  $ab$  total parameters

**NOTE:**

**field:** 100177

**field:** Parameter estimates for  $2 \times 2$  factorial design

**field:**

- $\hat{\mu} = \bar{y}_{...}$
- $\hat{\alpha}_i = \hat{\mu}_{i.} - \hat{\mu} = \bar{y}_{i.} - \bar{y}_{...}$
- $\hat{\beta}_j = \hat{\mu}_{.j} - \hat{\mu} = \bar{y}_{.j} - \bar{y}_{...}$
- $(\hat{\alpha}\hat{\beta})_{ij} = \hat{\mu}_{ij} - \hat{\alpha}_i - \hat{\beta}_j - \hat{\mu}$
- Where :
- $\mu_{i.}$  population mean for  $i$ th level of factor A
- $\mu_{.j}$  population mean for  $j$ th level of factor B
- $\alpha_i$  deviation from the overall mean associated with  $i$ th level of factor A
- $(\alpha\beta)_{ij}$  deviation of cell mean from the row column and overall mean

**NOTE:**

**field:** 100178

**field:** ANOVA for 2 factor design - Hypothesis test interpretation

**field:** Degrees of freedom:

- $A : a - 1$
- $B : b - 1$
- $AB : (a - 1)(b - 1)$
- Error  $N - ab$

- Total  $N - 1$

Each row in anova sum of squares table gives the F value for if that row was zero, ie test all  $\alpha_i = 0$  indicates that that factor has no effect

#### NOTE:

**field:** 100179

**field:** General factorial design (eg  $8 \times 2 \times 2$ )

**field:**

$$y_{ijkl} = \mu + \alpha_i + \beta_j + \gamma_k + (\alpha\beta)_{ij} + (\alpha\gamma)_{ik} + (\beta\gamma)_{jk} + (\alpha\beta\gamma)_{ijk} + \epsilon_{ijkl}$$

Where

- $y_{ijkl}$  response for  $l$ th replicate at  $i$ th level of A,  $j$ th level of B and  $k$ th level of C
- $\mu$  overall mean
- $\alpha_i$  effect of  $i$ th level of A
- $(\alpha\beta)_{ij}$  interaction of A and B
- $(\alpha\beta\gamma)$  interaction of A and B and C
- $\epsilon_{ijkl} iid \sim N(0, \sigma^2)$

#### NOTE:

**field:** 100180

**field:** Type I Type II Type III Sum of squares (unbalanced )

**field:**

- When data are unbalanced Type I and Type III SS are different
- I is sequential
- II is partial
- III is hierarchical

Type	SS	Effects in full model	Effects in reduced model
I	A	A	intercept only
III	A	A,B,C,AB,AC,BC,ABC	B,C,AB,AC,BC,ABC
II	A	A,B,C,BC	B,C,BC
III	AB	A,B,C,AB,AC,BC,ABC	A,B,C,AC,BC,ABC
II	AB	A,B,C,AB,AC,BC	A,B,C,AC,BC

**NOTE:**

**field:** 100181

**field:** Issues with Unbalanced Data for overall mean estimate and sum of squares

**field:**

- The fitted value for  $y_{ijk}$  is still the observed cell mean with unbalanced data
- Estimate of overall mean is not the average of all y values  $\hat{\mu} \neq \bar{y}_{...}$
- Issues with row and cell means
- $\bar{y}_{1..} \neq \frac{\bar{y}_{11} + \bar{y}_{12}}{2}$
- Type I still sums to Model Sum of Squares, but Type II and III does not (but it does for balanced data)
- Type II useful for model building
- Type III SS useful for hypothesis testing

**NOTE:**

**field:** 100182

**field:** Full and Reduced Type II Sum of squares, with factors  $A$ ,  $B$ ,  $C$

**field:**

- Reduced model for factor  $A$  is largest model not containing  $A$  in any terms (ie remove interactions with  $a$ ), full model adds  $A$ , but not interactions of  $A$
- Sum of Squares for  $A$
- Full:  $A, B, C, BC$
- Reduced:  $B, C, BC$
- Sum of Squares for  $AB$
- Full:  $A, B, C, AB, AC, BC$
- Reduced:  $A, B, C, AC, BC$

**NOTE:**

**field:** 100183

**field:** Type I sum of squares, full and reduced model, with factors  $A, B, C$

**field:**

- Note we could get different values depending on the order of the factors in the specified model (even p-values)
- Sequential
- Full model  $AB$ :  $A, B, C, AB$
- Reduced model:  $A, B, C$



- Full model: A:, A
- Reduced model: intercept only

**NOTE:**

**field:** 100184

**field:** Predicted values for different type of SS for factor A

		Reduced model	Full model
<b>field:</b>	Type I	$\hat{y}_{ijk} = \hat{\mu}$	$\hat{y}_{ijk} = \hat{\mu} + \hat{\alpha}_i$
	Type II	$\hat{y}_{ijk} = \hat{\mu} + \hat{\beta}_j$	$\hat{y}_{ijk} = \hat{\mu} + \hat{\alpha}_i + \hat{\beta}_j$
	Type III	$\hat{y}_{ijk} = \hat{\mu} + \hat{\beta}_j + (\hat{\alpha}\hat{\beta})_{ij}$	$\hat{y}_{ijk} = \hat{\mu} + \hat{\alpha}_i + \hat{\beta}_j + (\hat{\alpha}\hat{\beta})_{ij}$

**NOTE:**

**field:** 100185

**field:** Estimates for 2-factor means and interactions

**field:**

$$\hat{\mu} = \bar{y}_{...}$$

$$\hat{\alpha}_i = \bar{y}_{i..} - \bar{y}_{...} \quad \text{group mean - overall mean}$$

$$\hat{\beta}_j = \bar{y}_{.j.} - \bar{y}_{...}$$

$$(\hat{\alpha}\hat{\beta})_{ij} = \bar{y}_{ij.} - \bar{y}_{i..} - \bar{y}_{.j.} + \bar{y}_{...} \quad \text{cell mean - row and col means + overall mean}$$

**NOTE:**

**field:** 100186

**field:** Contrasts, balanced data and orthogonal

**field:**

- When data are balanced, a contrast for one main effect or interaction is orthogonal to a contrast for any other main effect
- Because of orthogonality, we can estimate effects and compute SS one term at a time, and the results for that term don't depend on what other terms are in the model.
- With unbalanced data, we don't have orthogonality

**NOTE:**

**field:** 100187

**field:** Example of converting a categorical variable into numeric

**field:**

- We should know at design stage if we want to treat variable as categorical or numeric
- Linear model will be less complicated than categorical - lower model degrees of freedom

**NOTE:**

**field:** 100188

**field:** Missing cell

**field:**

- Factorial structure is missing
- Can analyze using cell means model and look at contrasts

**NOTE:**

**field:** 100189

**field:** When to use random effects

**field:**

- Levels of a factor are sampled from a larger population
- Repeating experiment would use different factor levels (ie if the choice of levels are drawn using a random sample from larger population)
- Need to model dependence among observations from the same level of a factor
- key word - batch
- Not all observations independent (ie boxes from same machine are similar )

**NOTE:**

**field:** 100190

**field:** Random effects Dependence among observations in a single group-covariance

**field:**

$$\begin{aligned} Cov(y_{11}, y_{12}) &= Cov(\mu + \alpha_1 + \epsilon_{11}, \mu + \alpha_1 + \epsilon_{12}) \\ &= Cov(\alpha_1, \alpha_1) + Cov(\alpha_1, \epsilon_{12}) + Cov(\epsilon_{11}, \epsilon_{12}) \\ &= \sigma_{\alpha}^2 \end{aligned}$$

- Last three terms are 0 because independence assumptions within and between
- $\alpha_1$  and  $\epsilon_{ij}$  are random,  $\mu$  is fixed
- Note this model assumes positive covariance
- Note that covariance between observations in different groups is 0

**NOTE:**

**field:** 100191

**field:** Random Effects Model and Assumptions (1 factors)

**field:**

$$y_{ij} + \alpha_i + \epsilon_{ij}$$

Where

- $y_{ij}$  = strength of  $j$ th box made by  $i$ th machine
- $\mu$  = overall mean
- $\alpha_i$  = effect of  $i$ th machine (allows boxes made by two different machines to systematically differ)
- $\epsilon_{ij}$  = random error

Assumptions:

- $\epsilon_{ij} \sim iidN(0, \sigma^2)$
- $\alpha_i \sim iidN(0, \sigma_\alpha^2)$
- $\epsilon$  independent from  $\alpha$
- Different condition from fixed effects  $\sum_i \alpha = 0$

**NOTE:**

**field:** 100192

**field:** Estimates for  $\mu$  for random effects model (1 factor ) to make inference

**field:**

$$\begin{aligned}\hat{m}u &= \bar{y}_{..} \\ E(\hat{\mu}) &= \mu \\ Var(\hat{\mu}) &= \frac{n\sigma_{\alpha}^2 + \sigma^2}{N} \\ \hat{\mu} &\sim N\left(\mu, \frac{n\sigma_{\alpha}^2 + \sigma^2}{N}\right)\end{aligned}$$

**NOTE:**

**field:** 100193

**field:** Random effects model - how to test differences among levels of the factor

**field:**

- If  $\alpha_i$  were fixed, test  $H_0 : \alpha_i = 0$
- If random effect, cant use this  $H_0$  since the hypotheses must be about the parameters, and  $\alpha_i$  are random variables
- Instead test  $H_0 : \sigma_{\alpha}^2 = 0$  - no machine effect
- Estimated  $\sigma^2, \sigma_{\alpha}^2$  are called variance components

**NOTE:**

**field:** 100194

**field:** Anova for one random factor design (A)

	Source	df	SS	EMS
<b>field:</b>	A	$\alpha - 1$	$\sum_i \sum_j (\bar{y}_{i.} - \bar{y}_{..})^2$	$\sigma^2 + n\sigma_\alpha^2$
	Error	$N - \alpha$	$\sum_i \sum_j (\bar{y}_{ij} - \bar{y}_{i.})^2$	$\sigma^2$
	Total	$N - 1$	$\sum_i \sum_j (\bar{y}_{ij} - \bar{y}_{..})^2$	

$$\frac{SS_A/(\alpha - 1)}{SS_E/(N - \alpha)} \sim F_{\alpha-1, N-\alpha}$$

Where  $\alpha$  is the number of factors in A

**NOTE:**

**field:** 100195

**field:** Expected Mean Squares in one random factor ANOVA

**field:**

- $H_0 = \alpha_i$  is true, then  $E(MS_{trt}) = \sigma^2 = E(MS_E)$
- $H_0 = \alpha_i$  is false, then  $E(MS_{trt}) > E(MS_E)$
- F statistic is  $\frac{MS_{trt}}{MS_E}$ , and we reject  $H_0$  if the F statistic is large
- $E(MS_A) = \sigma^2 + n\sigma_\alpha^2$ . If  $H_0 : \sigma_\alpha^2 = 0$  true,  $E(MS_A) = \sigma^2$
- Expected mean squares tell us how to form the F statistic,
- The denominator is the MS whose expectation is equal to the numerator  $E(MS)$  under  $H_0$

**NOTE:**

**field:** 100196

**field:**  $MS_{trt}$  in factor design

**field:**  $MS_{trt}$  is  $MS_A$  for the A treatment. or  $MS_B$  if testing B treatment  
so  $F = \frac{MS_{trt}}{MS_E}$

**NOTE:**

**field:** 100197

**field:** Two random factors Model and assumptions

**field:**

$$y_{ijk} = \mu + \alpha_i + \beta_j + (\alpha\beta)_{ij} + \epsilon_{ijk}$$

Where

- $y_{ijk}$  = strength of  $k$ th box from the  $i$ th machine made by  $j$ th operator
- $\mu$  = overall mean (fixed)
- $\alpha_i$  = effect of  $i$ th machine
- $\beta_j$  = effect of  $j$ th operator
- $(\alpha\beta)_{ij}$  = interaction between  $i$ th machine and  $j$ th operator
- $\epsilon_{ijk}$  = random error

Assumptions:

- $\alpha_i \sim iidN(0, \sigma_\alpha^2)$
- $\beta_j \sim iidN(0, \sigma_\beta^2)$
- $(\alpha\beta) \sim iidN(0, \sigma_{\alpha\beta}^2)$
- $\epsilon_{ijk} \sim iidN(0, \sigma^2)$
- $\alpha, \beta, (\alpha\beta), \epsilon$  all independent

**NOTE:**

**field:** 100198

**field:** ANOVA for two random factor model

	Source	DF	EMS
<b>field:</b>	A	$a - 1$	$\sigma^2 + n\sigma_{\alpha\beta}^2 + nb\sigma_{\alpha}^2$
	B	$b - 1$	$\sigma^2 + n\sigma_{\alpha\beta}^2 + na\sigma_{\beta}^2$
	AB	$(a - 1)(b - 1)$	$\sigma^2 + n\sigma_{\alpha\beta}^2$
	Error	$N - ab = ab(n - 1)$	$\sigma^2$

- Balanced design  $N = abn$
- To construct test for treatment X, find  $MS_X$ , and find EMS under  $H_0$  for denominator in f test
- Interpretation: If we have significant pvalue, there is evidence that response varies due to random effect A (if testing A)

**NOTE:**

**field:** 100199

**field:** Estimate variance components

**field:**

- Can either use MoM or REML (restricted maximum likelihood)
- For MoM, set MS sample quantities equal to their expectation (EMS) from ANOVA table
- Solve system of equations
- Note MoM estimates may not be in parameter estimates (ie variances negative, can just set to 0 if case), although this may indicate that model is inadequate
- If data are (approximately) balanced, and model is good, MoM and REML estimates should be close

**NOTE:**

**field:** 100200



**field:** Model and assumptions for 3 random factors design

**field:**

$$y_{ijkl} = \mu + \alpha_i + \beta_j + \gamma_k + (\alpha\beta)_{ij} + (\alpha\gamma)_{ik} + (\beta\gamma)_{jk} + (\alpha\beta\gamma)_{ijk} + \epsilon_{ijkl}$$

Where

- $y_{ijkl}$ : strength of  $l$ th box from  $i$ th machine,  $j$ th operator and  $k$ th batch of glue
- $\mu$  = overall mean (fixed)
- $\alpha_i$ : effect of  $i$ th machine
- $\beta_j$ : effect of  $j$ th operator
- $\gamma_k$ : effect of  $k$ th batch of glue
- $(\alpha\beta)_{ij}$ : machine  $\times$  operator interaction
- $(\alpha\gamma)_{ik}$ : machine  $\times$  glue interaction
- $(\beta\gamma)_{jk}$ : operator  $\times$  glue interaction
- $(\alpha\beta\gamma)_{ijk}$ : three way interaction
- $\epsilon_{ijkl}$ : random error

Assumptions

- Each random quantity  $X$  is independent from others and distributed iid  $N(0, \sigma_X^2)$

**NOTE:**

**field:** 100201

**field:** Anova for 3 factor random effects

**field:**

- Needs approximate F test
- there is no MS with expectation of  $MS_X$  under  $H_0$ , so we must find a linear combination of the MS that has the right expectation:  $\sum_s g_s MS_s$
- Since the denominator of  $F$  statistic is a linear combination of the MSs, the F test is approximate, so we have to approximate the degrees of freedom too
- Denominator df:

$$v^* = \frac{(\sum_s g_s MS_s)^2}{\sum_s g_s^2 MS_s^2 / v_s}$$

where  $v_s$  = df for  $MS_s$  (same as Satterthwaite approximation for Welch t-test)

- Generally don't estimate variance components (ie for a confidence interval), since these tests are asymptotic (unlike F -test )

**NOTE:**

**field:** 100202

**field:** Crossed factors: model and assumptions  $A$  is fixed  $B$  is random

**field:**

- Mixed effects model
- All combos of factors are tested
- Each machine is used by all operators
- Each operator produces boxes using both machines

$$y_{ijk} = \mu + \alpha_i + \beta_j + (\alpha\beta)_{ij} + \epsilon_{ijk}$$

- $y_{ijk}$ : strength of  $k$ th box, made with  $i$ th machine and  $j$ th operator
- $\mu$ : overall mean (fixed)

- $\alpha_i$ : effect of  $i$ th machine (fixed)
- $\beta_j$ : effect of  $j$ th operator
- $(\alpha\beta)_{ij}$ : machine  $\times$  operator interaction
- $\epsilon_{ijk}$ : random error

#### Assumptions

- $\sum_{i=1}^2 \alpha_i = 0$
- $\beta_j \sim iid N(0, \sigma_\beta^2)$
- $(\alpha\beta)_{ij} \sim iid N(0, \sigma_{\alpha\beta}^2)$
- $\epsilon_{ijk} \sim N(0, \sigma^2)$
- $\beta, (\alpha, \beta), \epsilon$  all independent

#### NOTE:

**field:** 100203

**field:** Nested factors : Model and Assumptions

		B			
field:	A	1	2	3	4
	1	$A_1B_{1(1)}$	$A_1B_{2(1)}$	$A_1B_{3(1)}$	$A_1B_{4(1)}$
	2	$A_2B_{1(2)}$	$A_2B_{2(2)}$	$A_2B_{3(2)}$	$A_2B_{4(2)}$

- A is fixed, B is random
- Each operator uses only one machine
- Neither machine is used by all operators
- Can't compare machine effect among operations( because we dont know how boxes would vary if the operator had used the other machine), so we cant model the interaction
- Model does not include  $A \times B$

$$y_{ijk} = \mu + \alpha_i + \beta_{j(i)} + \epsilon_{ijk}$$

- $y_{ijk}$ : strength of  $k$ th box, made with  $i$ th machine, and  $j$ th operator
- $\mu$ : overall mean
- $\alpha_i$ : effect of  $i$ th machine
- $\beta_{j(i)}$ : effect of  $j$ th operator for the  $i$ th machine
- $\sum_{i=1}^a \alpha_i = 0$ ,  $\beta_{j(i)} \sim iidN(0, \sigma_\beta^2)$ ,  $\epsilon_{ijk} \sim iidN(0, \sigma^2)$ , both independent

**NOTE:**

**field:** 100204

**field:** Comparison between crossed factors and nested factors

**field:**

- Crossed factors: every level of A saw every level of B, and vice versa,
- Nested factors: if B is nested in A, levels of B only see one level of A

**NOTE:**

**field:** 100205

**field:** Reason for nesting

**field:**

- Feasibility, if machines are in different locations, we wouldn't want to transport operators around
- Subsampling: Multiple observations on the same experimental unit
  - Observation is nested in experimental unit
  - Experimental units are always nested in treatment (ie fish in temp fish tank), treatment tank, measurement fish
  - Usually nested effects are random, but not necessary

**NOTE:**

**field:** 100206

**field:** Multiple levels of nesting Model and assumption

**field:** A, factory (random), B, machine (random), C = operator (random )

- Operator is nested in machine version, nested in factory
- No crossed effects means no interaction term
- $y_{ijkl} = \mu + \alpha_i + \beta_{j(i)} + \gamma_{k(ij)} + \epsilon_{ijkl}$
- Assume each term iid Normal with associated variance, all independent.
- $Cov(y_{ijkl}, y_{ijkl'}) = \sigma_\alpha^2 + \sigma_\beta^2 + \sigma_\gamma^2$ , covariance within same levels of each factor

**NOTE:**

**field:** 100207

**field:** Crossed and nested factors

**field:**

- All random
- Operator nested in machine (operators make boxes using only one machine)
- Operator crossed with glue (operators make boxes using both batches of glue )
- So glue sees all operators and all machines
- $y_{ijkl} = \mu + \alpha_i + \beta_{j(i)} + \gamma_k + (\alpha\gamma)_{ik} + (\beta\gamma)_{j(i)k} + \epsilon_{ijkl}$
- All normality and independence assumptions
- No three way interaction or machine times operator interaction

**NOTE:**

**field:** 100208

**field:** Estimating means and contrasts for a mixed model

**field:**

- A (machine) fixed, B (operator) random
- $V(\bar{y}_{1..}) = V\left(\frac{\sum_{j=1}^b \sum_{k=1}^n y_{1jk}}{bn}\right) \frac{1}{bn}(n\sigma_\beta^2 + n\sigma_{\alpha\beta}^2 + \sigma^2)$
- Calculated using independence assumptions,  $\mu, \alpha_1$  fixed
- $\hat{C} = \sum_{i=1}^g w_i \bar{y}_i$ .
- To compare machine 1 and 2, let  $w_1 = 1, w_2 = -1$
- Compute point estimate  $\hat{C} - \bar{y}_{1..} - \bar{y}_{2..}$ .

**NOTE:**

**field:** 100209

**field:** Complete Block Designs (RCB,RCBD)

**field:**

- Grouping observations into groups that are homogeneous
- Generalized pair - observations in a group not independent,
- Example: litter of animals, locations
- Experimental units stratified into blocks
- Within each block, randomly assign experimental units to treatments
- At least one replicate of each combination in each block

- In a balanced design, each block will have the same number of replicates for each treatment combination
- Draw out experimental design to identify blocked designs

**NOTE:**

**field:** 100210

**field:** Why use blocking

**field:**

- Account for non-independence
- Explain some of the variability in the response (blocking as a nuisance parameter )
- If experimental units can be grouped into homogeneous blocks, then blocks explain some of the variability
- variance reduction design

**NOTE:**

**field:** 100211

**field:** Model and assumptions for RCBD (with  $n = 1$  observations per cell)

**field:**

- Resembles a factorial design
- $y_i = \mu + \alpha_i + \beta_j + \epsilon_{ij}$
- $y_{ij}$ : response for the  $i$ th level of the treatment in the  $j$ th block
- $\mu$ : overall mean
- $\alpha_i$ : treatment effect

- $\beta_j$ : block effect
- $\epsilon_{ij}$ ; random error
- Assume:  $\sum_i \alpha_i = \sum_j \beta_j = 0, \epsilon_{ij} \sim iidN(0, \sigma^2)$
- Note no interaction term - we don't want a blocking factor that interacts with treatments

**NOTE:**

**field:** 200212

**field:** ANOVA for RCBD ( $n = 1$  replicate )

	Source	DF	SS
<b>field:</b> With a treatment with $g$ groups, and $r$ blocks	Treatment	$g - 1$	
	Block	$r - 1$	
	Error	$(g - 1)(r - 1)$	
	Total	$gr - 1 = N - 1$	

Note usually don't test block effect (but can't infer causation since not randomly assigned to blocks )

**NOTE:**

**field:** 200213

**field:** Relative efficiency

**field:**

- Want to compare the amount of information captured from the data by two designs.
- Note a more complicated model (eg RCBD) would have a smaller  $SS_E$  but also a smaller  $df_{error}$
- For a single observation from a normal distribution  $I = \frac{1}{\sigma^2}$



- Information increases as variance decreases
- $RE = \frac{I_1}{I_2} = \frac{\sigma_2^2}{\sigma_1^2}$
- By convention:  $I_2$  is the simpler design.
- Where  $\sigma_i^2$  is the error variance in design  $i$  (which is assumed Normal)
- Since variances are not known, they must be estimated
- The variance of the design not performed will have to be calculated differently

**NOTE:**

**field:** 200214

**field:** Calculating and interpreting relative efficiency

**field:** EG for comparing CRD and RCBD

- $\widehat{RE} = \frac{\hat{\sigma}_{CRD}^2}{\hat{\sigma}_{RCBD}^2} \cdot \frac{(v_{RCBD}+1)(v_{CRD}+3)}{(v_{RCBD}+3)(v_{CRD}+1)}$
- Where  $v_{design}$  is the degrees of freedom for that design ( $v_{CRD} = N - g$ )
- $\hat{\sigma}_{CRD}^2 = \frac{(r-1)MS_{block} + ((g-1) + (r-1)(g-1)MS_E)}{(r-1) + (g-1) + (r-1)(g-1)}$  Weighted average of  $MS_{block}$  and  $MS_E$
- IF  $RE = 2$ , then the RCBD is twice as efficient as CRD, so we should only need half as many replicates in the blocked design.

**NOTE:**

**field:** 100215

**field:** Latin squares design

**field:**

- If we have multiple blocking factors, this requires many eus.
- For a RCBD need at least one experiment unit in each cell for each treatment
- LS design is incomplete block design
- A Latin square design has  $g$  levels of the treatment, and 2 blocking factors, each with  $g$  levels. Each treatment level occurs exactly once for each level of the blocking factor. (like sudoku )
- To randomize a LS experiment pick one LS at random from all possible LS designs of appropriate size. For  $g = 3$ , there are 12

**NOTE:**

**field:** 100216

**field:** Model and assumptions for Latin squares design

**field:**

$$y_{ijk} = \mu + \alpha_i + \beta_j + \gamma_k + \epsilon_{ijk}$$

- $y_{ijk}$  response for  $i$ th level of treatment,  $j$ th row(level of blocking factor 1),  $k$ th column (level of blocking factor 2)
- $\mu$  = overall mean
- $\alpha_i$  effect of level  $i$  of treatment
- $\beta_j$  effect of level  $j$  of blocking factor (row effect)
- $\gamma_k$  effect of level  $k$  of blocking factor 2 (column effect)
- Assumptions: Sum to zero constraints or normality/independence constraints if fixed/random.  $\epsilon_{ijk} \sim N(0, \sigma^2)$

**NOTE:**

**field:** 100217

**field:** ANOVA for Latin Squares design

	Source	DF	MS	F
	Treatment	(g-1)	MS(treat)	MS(treat)/MS(E)
	Row	(g-1)	MS(row)	
<b>field:</b>	Column	(g-1)	MS(col)	
	Error	(g-1)(g-2)	MS(E)	
	Total	$g^2 - 1 = N - 1$		

**NOTE:**

**field:** 100218

**field:** Relative efficiency of LS design compared to RCBD

**field:**

$$\widehat{RE}_{LS,RCBD} = \frac{\hat{\sigma}_{RCBD}^2 (v_{LS} + 1)(v_{RCBD} + 3)}{\hat{\sigma}_{LS}^2 (v_{LS} + 3)(v_{RCBD} + 1)}$$

- Where  $\hat{\sigma}_{RCBD} = \frac{(g-1)MS(row) + ((g-1) + (g-1)(g-2)MS(E))}{2(g-1) + (g-1)(g-2)}$

**NOTE:**

**field:** 100219

**field:** Split-plot design description

**field:**

- Choose a split-plot design when some factors are more difficult or expensive to vary than others
- Example A - irrigation (large plot) and B - variety (small subplot of each large plot )
- Randomize assignment of levels of A

- In each level of A, randomize the subplots and assign levels of factor B
- Whole plots are experimental units wrt A, subplots are eus wrt B
- $n$  - number of replicates for each level of A. If we want to replicate, we need an entire other set of levels of A.
- Assume whole plots are independent of each other
- Observations within a single whole plot are not assumed independent
- Whole plots nested in A, A and B are crossed

**NOTE:**

**field:** 100220

**field:** Model and assumptions for split plot design

**field:** example when fixed factors

$$y_{ijk} = \mu + \alpha_i \eta_{k(i)} + \beta_j + (\alpha\beta)_{ij} + \epsilon_{k(i)j}$$

- $\alpha_i$  effect of  $i$ th level of A
- $\eta_{k(i)}$  whole plot error , random effect for whole plot nested in A
- $\beta_j$  effect of  $j$ th level of B
- $(\alpha\beta)_{ij}$  interaction of irrigation and variety
- $\epsilon_{k(i)j}$  random subplot error
- $\alpha, \beta$ , interaction assumptions based on fixed/random
- $\epsilon_{k(i)j} \sim iidN(0, \sigma^2)$  independent from  $\eta_{k(i)} \sim N(0, \sigma_\eta^2)$
- Note that the first terms are a CRD model, which reflects we did a CRD at whole-plot level, if we did a more complicated design at whole-plot level, our model would reflect that.

**NOTE:**

**field:** 100221

**field:** Difference between split-plot design and complete factorial, blocking

**field:**

- Between complete factorial
  - Split plot has two stages of randomization
  - Complete factorial has one stage where combinations of factors are assigned to units
- Blocking
  - Randomization occurred at two stages, RDBD units are not randomly assigned to blocks
  - Dont care about inference for blocks, do care about inference for whole plot factor
- Nesting
  - Subplots are nested in whole plot, each level of A sees all level of B and each level of B sees all levels of A
  - Includes an interaction for A and B

**NOTE:**

**field:** 100222

**field:** ANOVA for split-plot design

	Source	DF	EMS
	A	a-1	$\sigma^2 + b\sigma_\eta^2 + nb\frac{\sum_i \alpha_i^2}{a-1}$
<b>field:</b>	Whole plot error	$a(n-1)$	$\sigma^2 + b\sigma_\eta^2$
	B	b-1	$\sigma^2 + na\frac{\sum_j \beta_j^2}{b-1}$
	AB	$(a-1)(b-1)$	$\sigma^2 + n\frac{\sum_i \sum_j (\alpha\beta)_{ij}^2}{(a-1)(b-1)}$
	Subplot error	$a(n-1)(b-1)$	$\sigma^2$

**NOTE:**

**field:** 100223

**field:** Hypothesis tests for a split-plot design

**field:**

- For fixed effects,
- A effect:  $H_0 : \alpha_i = 0: F = \frac{MS_A}{MS_{\text{whole plot}}}$
- B effect:  $H_0 : \beta_j = 0: F = \frac{MS_B}{MS_{\text{sub plot}}}$
- AB effect  $H_0 : (\alpha\beta)_{ij} = 0, F = \frac{MS_{AB}}{MS_{\text{subplot}}}$
- Under the null hypothesis, use the EMS for treatment factor to find the associated denominator EMS

**NOTE:**

**field:** 100224

**field:** Dependence between subplots of same whole plot - Cov and Corr

**field:**

$$\begin{aligned} Cov(y_{ijk}, y_{ij'k}) &= Cov(\eta_{k(i)} + \epsilon_{k(i)j}, \eta_{k(i)} + \epsilon_{k(i)j'}) \\ &= \sigma_\eta^2 \\ Corr(y_{ijk}, y_{ij'k}) &= \frac{Cov(y_{ijk}, y_{ij'k})}{\sqrt{Var(y_{ijk})Var(y_{ij'k})}} \\ &= \frac{\sigma_\eta^2}{\sigma_\eta^2 + \sigma^2} \end{aligned}$$

**NOTE:**

**field:** 100225

**field:** Split plot design, estimate difference and CI (example)

**field:**

- Eg, CI for difference in 2 factors of B :  $\beta_1 - \beta_2$ :  $\bar{y}_{\cdot 1} - \bar{y}_{\cdot 2}$ .
- Calculate variance by using model equation to find average, and use independence, and fixed variance rules.
- Replace  $MS_X$  as the estimate for  $\sigma_X^2$
- Use  $t$  as reference distribution with DF for MS that gives us the variance estimate.

**NOTE:**

**field:** 100226

**field:** Repeated measures

**field:**

- Multiple observations on the SAME experimental unit
- Often repeated measurements in time.
- Questions to ask to use repeated measure
  - Ignoring repeated measurements, what is experimental design?
  - Are observations on the same EU independent?
  - What are research objective? (ie does it want an interaction between time and treatment )
- Use split-plot design, but time is not randomized

**NOTE:**

**field:** 100227

**field:** Repeated measures model and assumptions

**field:** Example model (fixed effects):

$$y_{ijk} = \mu + \alpha_i + \epsilon_{k(i)} + \beta_j + (\alpha\beta)_{ij} + (\epsilon\beta)_{k(i)j}$$

- $\mu$ : overall mean
- $\alpha_i$ : formula effect (fixed)
- $\epsilon_{k(i)}$ : random baby effect
- $\beta_j$ : time effect
- $(\alpha\beta)_{ij}$ : formula times time interaction
- $(\epsilon\beta)_{k(i)j}$ : baby  $\times$  time interaction
- All assumptions for fixed/random factors (Here:  $0 = \sum_i \alpha_i = \sum_j \beta_j = \sum_i (\alpha\beta)_{ij} = \sum_j (\alpha\beta)_{ij}$ )
- $\epsilon_{k(i)} \sim iidN(0, \sigma^2)$  independent from  $(\epsilon\beta)_{k(i)j} \sim iidN(0, \sigma_{\alpha\beta}^2)$
- Note assumes constant correlation over time, Correlation matrix R of one EU is 1 on diagonal and  $\rho$  everywhere else Correlation matrix overall is blocks of R on diagonal, 0 everywhere else.

**NOTE:**

**field:** 100228

**field:** ANCOVA



field:

- Same as regression parametrization for interaction terms - separate intercepts equal slopes
- $y_{ij} = \mu + \alpha_i + \beta x_{ij} + \epsilon_{ij}$
- Assumes relationships between  $x_{ij}$  and  $y_{ij}$  is the same for all three groups (equal slopes ) Or we could have had  $\beta_i$  to have different slopes
- Cant compare  $\bar{y}_{1.}, \bar{y}_{2.}, \bar{y}_{3.}$  since  $\bar{x}_1 \neq \bar{x}_2 \neq \bar{x}_3$  (ie if we draw over mean y for mean  $x_i$ ) these arent comparable.
- Compare mean ys by having common x value (often  $\bar{x}$ )
- Covariate adusted means:  $y_{ij} = \tilde{\mu} + \alpha_i + \beta(x_{ij} - \bar{x}_{..}) + \epsilon_{ij}$
- $\tilde{\mu} - \beta\bar{x}_{..} = \mu$