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Orthogonal Matrix \Rightarrow square mat w/ A' = A^{-1}
 If sym mat \Rightarrow \exists orth mat V st A = V\Lambda V'
 E(AY + B) = AE(Y) + b = A\mu + b
 Cov(AY + b) = ACov(Y)A' = A\Sigma A'
 Z^2 = \chi^2(1) If Z_1, ..., Z_n ind:
 W = \sum_{i=1}^{\infty} Z_{i}^{2} \sim \chi^{2}(n)
\Rightarrow \mu = n\sigma^{2} = 2n
Z/\sqrt{W/n} \sim T(n) symmetric about 0
 X_1 \sim \chi^2(n_1) \perp X_2 \sim \chi^2(n_2):
 (X_1/n_1)/(X_2/n_2) \sim F(n_1, n_2)
 T \sim T(v) T^2 \sim F(1, v), F is asymmetric, +
(X_{n\times p})'(X_{n\times p})\hat{\beta} = (X_{n\times p})'y_{n\times 1}
 (AB)' = B'A' \quad A^{-1}A = AA^{-1} = I
(AB)^{-1} = B^{-1}A^{-1} (A')^{-1} = (A^{-1})'
|A^{-1}| = \frac{1}{|A|} \quad \frac{1}{|A|} \begin{vmatrix} a_{22} & -a_{12} \\ -a_{21} & a_{11} \end{vmatrix}
 \det(\text{inv}) = \text{inv}(\det) evector Ax = \lambda x e val=\lambda
\begin{array}{l} \text{char eqn } (|A-\lambda I|=0) = \det \left| \begin{smallmatrix} a_{11}-\lambda & a_{12} \\ a_{21} & a_{22}-\lambda \end{smallmatrix} \right. \\ \text{full rank} \Leftrightarrow \text{no } \lambda = 0 \quad \det = 0 \Leftrightarrow \geq 1 \ \lambda = 0 \end{array}
 X full rank for \hat{\beta} unique
 E(rand mat)=mat of E
 Cov(Y) = E[(Y - \mu)(Y - \mu)'] = \Sigma
 \sigma_{ij} = Cov(Y_i, Y_j) = E[(Y_i - \mu_i)(Y_j - \mu_j)']
 1) lin trans of mvn yields mvn.
 If X \sim N_n(\mu, \Sigma) and Y = AX + b
 with A_{r\times n} matrix of constants and b_{r\times 1} vector
 of constants. Then Y \sim N_r(A\mu + b, A\Sigma A')
 2) lin combin of ind mvns is mvn
 X_1, \ldots, X_k iid X_i \sim N_n(\mu_i, \Sigma_i)
 Let Y = a_1 X_1 + \cdots + a_k X_k
Then Y \sim N(\mu^*, \Sigma^*) where \mu^* = \sum_{i=1}^k a_i \mu_i and \Sigma^* = \sum_{i=1}^k a_i^2 \Sigma_i
3) Marginals of mvn are mvn
If X \sim N_n(\mu, \Sigma)
Partition: X = \begin{pmatrix} X_1 \\ X_2 \end{pmatrix} where X_1 is r \times 1 and X_2
 is (n-r) \times 1
\mu = \begin{pmatrix} \mu_1 \\ \mu_2 \end{pmatrix} where \mu_1 is r \times 1 and \mu_2 is (n-r) \times 1
 \Sigma = \begin{bmatrix} \Sigma_{11} & \Sigma_{12} \\ \Sigma_{21} & \Sigma_{22} \end{bmatrix}
 where \Sigma_{11} is r \times r, \Sigma_{21} is (n-r) \times r and \Sigma_{22}
 is (n-r) \times (n-r)
 Marginals: X_1 \sim N_r(\mu_1, \Sigma_{11})
 X_2 \sim N_{(n-r)}(\mu_2, \Sigma_{22})
 4) Conditionals of mvn are mvn.
 Suppose X \sim N_n(\mu, \Sigma)
 Partition same way
X_1|X_2 = x_2 \sim N_r(\mu_1 + \Sigma_{12}\Sigma_{22}^{-1}(x_2 - \mu_2), \Sigma^*)
where \Sigma^* = \Sigma_{11} - \Sigma_{12} \Sigma_{22}^{-1} \Sigma_{21}
 Topic 3, 4 y = X\beta + \epsilon  \hat{\beta} = (X'X)^{-1}X'y
 \hat{y} = X\hat{\beta} = Hy H = X(X'X)^{-1}X'
 M = C(X'X)^{-1}C'
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\hat{\epsilon} = y - \hat{y} = y - Hy = (1 - Hy)
\hat{\theta} = C\hat{\beta} \hat{Var}(\hat{\theta}) = \hat{\sigma^2}(C(X'X)^{-1}C')
\hat{Var}(\hat{\beta}) = \hat{\sigma^2}(X'X)^{-1}
SSH = (\hat{\theta} - \theta_0)' M^{-1} (\hat{\theta} - \theta_0)
SSE = (y - \hat{y})'(y - \hat{y}) = y'[I - H]y = \epsilon' \epsilon
Use MSE for \hat{\sigma}^2, use diag df_{total} = n - 1
se = \sqrt{\hat{V}ar} \quad MS* = SS*/DF*
t-value= \hat{\beta}/se p-value= F(df_{model}, df_{error})
95% CI \hat{\theta} \pm 1.96 \sqrt{MSE(M)}
95% PI \hat{y_h} \pm t(\alpha/2, n-r)se(\hat{y_h})
F_{obs} = \frac{(\hat{\theta} - \theta_0)' M^{-1} (\hat{\theta} - \theta_0)/a}{\hat{\sigma}^2} \ a = rank(C)
F_{obs}(1, n-r) = tval^2(n-r)
One-sided t-Test (only for scalar hypothesis)
H_A: \theta < \theta_0 \text{ Uses } \alpha H_A: \theta > \theta_0 \text{ uses } (1-\alpha)
Two-sided t H_A: \theta \neq \theta_0 uses \alpha/2 and (1-\alpha/2)
In all cases reject H_0 if |\text{test stat}| > |\text{crit value}|
Two-sided F uses \alpha crit value
One-sided F \theta < \theta_0 uses 2\alpha and requires
appropriate sign of difference
H_0: \beta_i = 0 if \beta_i is estimable
t = \frac{\hat{\beta}_j - 0}{\sqrt{var(\hat{\beta}_j)}}
Obtain estimate \hat{\sigma}^2 = MSE
if know \sigma^2 then t \sim N(0, 1)
if estimate \sigma^2 from data then t \sim t_{dfE}
Topic 5: Distributional Results for GLM
X full rank \hat{\beta} \sim N_p(\beta, \sigma^2(X'X)^{-1})
\hat{\theta} \sim N_a(\theta, \sigma^2 C(X'X)^{-1}C')
\hat{y} = X\hat{\beta} = [X(X'X)^{-1}X']y = Hy
E(\hat{y}) = X\beta
Cov(\hat{y}) = \sigma^2 X (X'X)^{-1} X'
Resid Var \Rightarrow \hat{\sigma^2} = \frac{SSE}{n-p} = \frac{\hat{\epsilon}\hat{\epsilon}'}{n-p} = \frac{y'(I-H)y}{n-p}
Topic 6: MR General Considerations
Topic of Mrk General Considerations R_{adj}^2 = 1 - \frac{SSE/(n-r)}{CSS(Total)/(n-1)} 2 ANOVA tables based on full, reduced: F_{obs} = \frac{MSH}{MSE} = \frac{SSH/dfH}{SSE/dfE} = \frac{SSE(reduced) - SSE(full)/dfE(reduced) - dfE(full)}{SSE(full)/dfE(full)}
                       SSE(full)/dfE(full)
 SSE(full)/c \\ \_ CSS(Regression)/(p-1) 
         SSE(full)/(n-p)
Reject hypothesis if:
F_{obs} \ge F_F^{-1}(1-\alpha, p-1, n-p) = f_{crit} Usual overall regression test assumes model
spans an intercept and excludes it from test
R_c^2 = \frac{CSS(reg)}{CSS(reg) + SSE(full)} = \frac{CSS(reg)}{CSS(total)}
R_c^2 estimates \rho_c^2, pop ratio of mod to total var
Corrected test for overall regression:
H_0: \beta_1 = \cdots = \beta_{n-1} = 0 holds iff H_0: \rho_c^2 = 0
Topic 7: Testing Hypotheses in MR
All tests compare 2 models:full,reduced (LRT)
Overall test: F_{obs} = \frac{CSS(\beta_1, \dots, B_{p-1})/(p-1)}{SSE(\beta_0, \dots, \beta_{p-1})/(n-p)}
added-last test(Type III): assess the usefulness
of one predictor over all others
df always 1 for num b/c testing 1 parameter
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F_{obs} = \text{Topic } 6 = \frac{(\hat{\theta} - \theta_0)' M^{-1} (\hat{\theta} - \theta_0) / df H}{y'(I - H)y / df E}
where C = [0...010...0]
Added in order test(Type I): assess the
contribution of predictor j over all preceding j-1
predictors without j + 1, \ldots in model. pval
changes based on order of putting things in
model unlike Type III
 Topic 8: Correlations
\rho = Corr(X, Y) = \frac{Cov(X, Y)}{\sqrt{Var(X)Var(Y)}}
R = \frac{\sum (X_i - \bar{X})(Y_i - \bar{Y})}{\sqrt{\sum (X_i - \bar{X})^2 (\sum (Y_i - \bar{y})^2)}}
 Topic 9: GLM assumption Diagnostics
H.L: violations seen in pattern of residuals
I: assessed through logic of sampling scheme
E: finite sample
Gauss: box plot, histogram of resid, test of
gauss dist of resid
Discrepancy between T and N vars somewhat
 inflates prob of reject H_0
 Outliers: leverage, Influence \Rightarrow Cook's D
Collinearity: cond ind for kth eigval= \sqrt{\frac{\lambda_1}{\lambda_L}}
Condit num: max condit ind
R_j^2 = R^2(X_j, \{X_1, \dots, X_{j-1}, X_{j+1}, \dots, X_{p-1}\})

VIF_j = \frac{1}{1 - R_j^2} = \frac{1}{\text{tolerance}}
 • One-way ANOVA coding schemes:
     Classic ANOVA:
     Reference cell: y = \mu + \beta_1 I_A + \beta_2 I_B + \epsilon group
     C is the reference
 • Two-way ANOVA coding schemes:
     Classic ANOVA:
     y = \mu + \beta_1 I_A + \beta_2 I_B + \beta_3 I_C + \alpha_1 + \alpha_2 + \epsilon
     Cell means (fit only when they want
     interaction terms in the model):
     y = \gamma_{A1} + \gamma_{A2} + \gamma_{A3} + \gamma_{B1} + \gamma_{B2} + \gamma_{B3} + \gamma_{B4} + \epsilon
     Reference cell: y = \mu + \beta_1 I_A + \beta_2 I_B + \alpha_1 + \epsilon
Ref cell: Group 1 is reference \mu (grand mean)
Cell mean: all of the \beta's equal group means
 Topic 14: Logistic Regression
E(y) = p = \frac{\exp(\beta_0 + \beta_1 x)}{1 + \exp(\beta_0 + \beta_1 x)} = \frac{1}{1 + \exp(-\beta_0 - \beta_1 x)}
 \frac{p}{1-p} = exp(\beta_0 + \beta_1 x)
logit(p_i) = log\left(\frac{p_i}{1-p_i}\right) = \beta_0 + \beta_1 x + \dots
=\beta_0+\beta_1x_{i1}+\beta_2x_{i2}+\cdots+\beta_{p-1}x_{i,p-1}\ (x\in 0,1) OR = \frac{p_1/(1-p_1)}{p_2/(1-p_2)} = \frac{\exp(\beta_0+\beta_1(1))}{\exp(\beta_0+\beta_1(0))} =
 \exp(\beta_0 + \beta_1(1) - \beta_0 - \beta_1(0)) = \exp(\beta_1)
\log(OR) = \beta_1
95% CI OR (\log(OR) = \hat{\beta_1}) \exp(\hat{\beta_1} \pm 1.96se)
 y_i \sim Bern(p_i) i = 1, ..., n ys ind of each other
LRT whether k_{th} covariate affects P(success)
H_0: \beta_k = 0
Interaction \Rightarrow LRT of full vs reduced
 H_0: interaction not significant
LRT comparing nested models:
 -2\log(L(smaller)) - (-2\log(L(larger)))
 H_0 \sim \chi_k^2  k = df_{larger} - df_{smaller}
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H_0: \beta_j = B_{jk(interaction)} = 0
Var = p(1-p)
Topic 15: Mixed Effect Model
everything is the same as for regression models
only difference is covariates
Y=fixed effects + random effects + error
Y_i + X_i\beta + Z_ib_i + \epsilon_i
Z_i indicator vars for cluster(family)membership
    \begin{bmatrix} \sigma_{11} & \sigma_{12} & \dots & \sigma_{1k} \end{bmatrix}
     \sigma_{12} \sigma_{22} ... \sigma_{2k}
   the following matrix is diagonal (if off-diagonal
   elements are zero) with some \sigma_w^2. H_0: \sigma_b^2 = 0, \sigma_w^2's
  elements are zero) with some \sigma_w. H_0 . \sigma_b = \sigma_s, \sigma_w s are the same \begin{bmatrix} \sigma_b^2 + \sigma_w^2 & \sigma_b^2 & \dots & \sigma_b^2 \\ \sigma_b^2 & \sigma_b^2 + \sigma_w^2 & \dots & \sigma_b^2 \\ \dots & \dots & \dots & \dots \\ \sigma_b^2 & \sigma_b^2 & \dots & \sigma_b^2 + \sigma_w^2 \end{bmatrix}
Autoregressive: Used for time-series/longitudinal
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$$b_i \text{ q-dim vector of random effects} \\ \textbf{Blocking:} \text{ group homogeneous exper units} \\ \textbf{together to form block, assign treats at random} \\ \textbf{to exper units within block} \\ \underline{\textbf{Mixed Effect Models}} \text{ 3 types of covariance matrices.} \\ \textbf{Unstructured: Contains} \frac{k(k+1)}{2} \text{ unique} \\ \textbf{parameters. LRT tests whether off-diagonals are zero} \\ \textbf{and diagonals are the same. k*(k-1)/2 total} \\ \textbf{parameters, but testing that the diagonal elements} \\ \textbf{are the same. That's why you have } (k*(k-1)/2) - 1 \\ \textbf{degrees of freedom. Null Model Likelihood Ratio Test} \\ \textbf{in SAS.} \\ \begin{bmatrix} \sigma_{11} & \sigma_{12} & \dots & \sigma_{1k} \\ \sigma_{12} & \sigma_{22} & \dots & \sigma_{2k} \\ \dots & \dots & \dots & \dots \\ \sigma_{1k} & \sigma_{2k} & \dots & \sigma_{kk} \end{bmatrix} \\ \textbf{Compound Symmetry: Model with subject effect} \\ \textbf{(b) and within-subject error } \textbf{(w):} \\ Y_{ij} = \mathbf{X}_{ij}\beta + b_i + w_{ij} \text{ with } b_i \sim N(0, \sigma_b^2) \text{ and} \\ w_{ij} \sim N(0, \sigma_w^2). \text{ Contains 2 unique parameters. The LRT SAS outputs for the model is testing whether the followis-partitive diagonal of the filter of the state of$$

data and contains 2 unique parameters.

$$\sigma^{2} \begin{bmatrix} 1 & \rho & \rho^{2} & \dots & \rho^{k-1} \\ \rho & 1 & \rho & \dots & \rho^{k-2} \\ \dots & \dots & \dots & \dots & \dots \\ \rho^{k-1} & \rho^{k-2} & \dots & \rho & 1 \end{bmatrix}$$

• The test to compare two nested mixed effect models is an LRT with test statistic -2log(red) - -2log(full) and follows a χ^2_{df}

with df =
$$\frac{k(k+1)}{2} - 2$$
.

- · For testing CS vs UN, if you reject the null then you have to use UN.
- AR(1) and CS are nested in UN.

Miscellaneous

- · ANOVA has only categorical predictors. ANCOVA has categorical and continuous, and FMiEC has interactions between categorical and continuous, making ANCOVA a special type of FMiEC.
- Cluster design-say 40 mice and 3 measures per mice. The covariance matrix will be block diagonal with each mouse being one block. Everything off-diagonal is zero, but those 40 3x3 matrices are non-zero. So the total number of non-zero elements is 9*40 and number of zero is 120*120 - 360.