Statistical Modeling and Inference

UCLA Advanced NeuroImaging Summer School, 2010
Models help tell stories
Models help tell stories

P<0.01

RT=1.79+0.16*Age
Goal of next 2 hours

• Hour 1
  – Brush up on some stats lingo
  – Review the general linear model (GLM)

• Hour 2
  – Hypothesis testing
  – Building Models
Statistical Terms

• Probability: The expected relative frequency of a particular outcome.
  – If you flip a “fair” coin, 50% of the time you’ll get “heads”
    • P(heads)=0.5
  – You measure the heights of people and 30% of the time they are taller than 69 inches
    • P(height>69)=0.3
Statistical Terms

• Random variable
  – Variable determined by random experiment
  – $P(H > h) =$ Probability that height is larger than some observed height $h$
Statistical Terms

• Probability distribution, $f(h)$
  – Describes the distribution of a random variable
  – Area under pdf gives probability
Statistical Terms

• What distribution do we use?
  – Typically assume normal (Gaussian)
  – Functions of normals give other popular distributions
    • Chisquare is the square of a normal
    • T involves a normal and a chisquare
    • F is the ratio of two chisquares
Statistical Terms

• Statistical Independence
  – X and Y are independent if the occurrence of X tells us nothing about Y

• Expected Value
  – The mean of a random variable ($E[Y]$)
Statistical Terms

• Variance
  – How the values of the RV are dispersed about the mean

• Covariance
  – How much 2 RV’s vary together
  – \( \text{Cov}[X, Y] = E[(X - E[X])(Y - E[Y])] \)
  – If 2 RV’s are independent, \( \text{Cov}[X, Y] = 0 \) BUT the opposite is not true
Statistical Terms

• Bias and Variance can be used to assess an estimator
  – Bias: On average, the estimate is correct
  – Variance: The reliability of the estimate
  – Efficient: The most efficient estimate has the lowest variance among all unbiased estimators
Bias and Variance

- **High bias / low variance**
  - The model is underfitting.
  - The error on both training and validation sets is high.

- **Low bias / high variance**
  - The model is overfitting.
  - The error on the training set is low, but the error on the validation set is high.

- **High bias / high variance**
  - The model is underfitting.
  - The error on both training and validation sets is high.

- **Low bias / low variance**
  - The model is well-fitted.
  - The error on the training and validation sets is low.
The Model

• For the ith observational unit

\[ Y_i = \beta_0 + \beta_1 X_i + \epsilon_i \]

• \( Y_i \): The dependent (random) variable
• \( X_i \): Predictor variable (not random)
• \( \beta_0, \beta_1 \): Model parameters
• \( \epsilon_i \): Random error, how the observation deviates from the population mean
• Simple linear regression
• Simple: Only 1 regressor and intercept
• Linear: Linear in its parameters

\[ Y_i = \beta_0 + \beta_1 X_i + \epsilon_i \]
$Y_i = \beta_0 + \beta_1 X_i + \epsilon_i$

- **Fixed:** $\beta_0 + \beta_1 X_i$
  - Mean of $Y_i$, $(E[Y_i])$
- **Random:** $\epsilon_i$
  - Variability of $Y_i$
    - $E(\epsilon_i) = 0$, $\text{Var}(\epsilon_i) = \sigma^2$, $\text{Cov}(\epsilon_i, \epsilon_j) = 0$
    - It follows that the variance of $Y_i$ is $\sigma^2$
$E[Y] = 1 + 0.1 \times \text{Age}$

$Y_i = 3.8$

$e_i = 0.8$

$E[Y_i] = 3$
Fitting the Model

Q: Which line fits the data best?

Reaction Time (s) vs. Age
Minimize the distance between the data and the line (error).

Absolute distance? squared distance?

Error term:

\[ e_i = Y_i - (\hat{\beta}_0 + \hat{\beta}_1 X_i) \]
Least Squares

• Minimize squared differences

• Minimize \[ \sum_{i=1}^{N} e_i^2 = \sum_{i=1}^{N} (Y_i - \hat{Y}_i)^2 \]
  
  – Works out nicely distribution-wise
  – You can use calculus to get the estimates

\[ \hat{\beta}_1 = \frac{\sum (X_i - \bar{X})(Y_i - \bar{Y})}{\sum (X_i - \bar{X})^2} \]

\[ \hat{\beta}_0 = \bar{Y} - \hat{\beta}_1 \bar{X} \]
Property of Least Squares

- Gauss-Markov theorem
  - Under the assumptions we’ve made so far (error has mean 0, with constant variance and uncorrelated) the least squares estimators are unbiased and have minimum variance among all unbiased linear estimates.

- i.e. The logical way to estimate the model gives really great estimates!
What’s maximum likelihood?

- Maximize the likelihood: $P(Y|\beta)$

Mean = 110
- Small likelihood

Mean = 120
- Large likelihood
Maximum Likelihood

• Under normality assumption, same as least squares

• Why bring it up?
  – Studying $P(Y|\beta)$ is a **Frequentist** approach
  – There are also **Bayesian** methods, which focus on $P(\beta|Y)$
What about the variance?

• We also need an estimate for $\sigma^2$
  – Start with the sums of squared error
    $$SSE = \sum (Y_i - \hat{Y}_i)^2 = \sum e_i^2$$
  – Divide by the appropriate degrees of freedom
    • # of independent pieces of information - # parameters in model
    $$\hat{\sigma}^2 = \frac{\sum e_i^2}{N - 2}$$
Multiple Linear Regression

- Add more parameters to the model

\[ Y_i = \beta_0 + \beta_1 X_{1i} + \beta_2 X_{2i} + \beta_3 X_{3i} + \epsilon_i \]

- Time for linear algebra!
Matrices

- $A$ is a 2x3 matrix

$$A = [a_{ij}] \quad i = 1, 2; \quad j = 1, 2, 3$$
Matrices

- **Square matrix** - Same # of rows and columns

\[
\begin{pmatrix}
  a_{11} & a_{12} & a_{13} \\
  a_{21} & a_{22} & a_{23} \\
  a_{31} & a_{32} & a_{33}
\end{pmatrix}
\]

- **Vector** - column(row) vector has 1 column(row)

\[
\begin{pmatrix}
  a_{11} \\
  a_{21} \\
  a_{31}
\end{pmatrix}
\]

\[
\begin{pmatrix}
  a_{11} & a_{12} & a_{13}
\end{pmatrix}
\]
Matrices

• Special matrices
  – Diagonal Matrix

\[
\begin{pmatrix}
1 & 0 & 0 \\
0 & 9 & 0 \\
0 & 0 & 3
\end{pmatrix}
\]

– Identity - $I_N$

\[
I_3 = \begin{pmatrix}
1 & 0 & 0 \\
0 & 1 & 0 \\
0 & 0 & 1
\end{pmatrix}
\]
Matrices

• Transpose: $A^T$ or $A'$. Swap columns and rows.

$$A = \begin{pmatrix}
1 & 2 & 3 \\
5 & 6 & 7 \\
\end{pmatrix} \Rightarrow A' = \begin{pmatrix}
1 & 5 \\
2 & 6 \\
3 & 7 \\
\end{pmatrix}$$

• Element-wise addition and subtraction

$$\begin{pmatrix}
1 & 2 & 3 \\
5 & 6 & 7 \\
\end{pmatrix} + \begin{pmatrix}
4 & 7 & 3 \\
1 & 8 & 1 \\
\end{pmatrix} = \begin{pmatrix}
5 & 9 & 6 \\
6 & 14 & 8 \\
\end{pmatrix}$$
Matrices

• Multiplication: Trickier
  – Number of columns of first matrix must match number of rows of second matrix
Matrices

- Multiplication

\[ AB = C \rightarrow c_{ij} = \sum_{n=1}^{\text{cols}_A} a_{im} b_{mj} \]

\[
\begin{pmatrix}
1 & 2 \\
4 & 9 \\
3 & 2
\end{pmatrix}
\times
\begin{pmatrix}
4 & \quad \quad 2 \\
1 & \quad \quad 4
\end{pmatrix}
= 
\begin{pmatrix}
\quad \\
\quad \\
\quad
\end{pmatrix}
\]
Matrices

- Multiplication

\[
AB = C \rightarrow c_{ij} = \sum_{n=1}^{\text{cols}_A} a_{im} b_{mj}
\]

\[
\begin{pmatrix}
1 & 2 \\
4 & 9 \\
3 & 2
\end{pmatrix}
\times
\begin{pmatrix}
4 \\
1 \\
2 \\
4
\end{pmatrix}
=
\begin{pmatrix}
\text{？} \\
\text{？}
\end{pmatrix}
\]

1x4+
Matrices

• Multiplication

\[
AB = C \rightarrow c_{ij} = \sum_{n=1}^{\text{cols}_A} a_{im}b_{mj}
\]

\[
\begin{pmatrix}
1 & 2 \\
4 & 9 \\
3 & 2
\end{pmatrix}
\times
\begin{pmatrix}
4 \\
1 \\
2 \\
4
\end{pmatrix}
= \begin{pmatrix}
6
\end{pmatrix}
\]

1\times4 + 2\times1 = 6
Matrices

• Multiplication

\[ AB = C \rightarrow c_{ij} = \sum_{n=1}^{\text{cols}_A} a_{im} b_{mj} \]

\[
\begin{pmatrix}
1 & 2 \\
4 & 9 \\
3 & 2
\end{pmatrix}
\times
\begin{pmatrix}
4 & 2 \\
1 & 4
\end{pmatrix}
= 
\begin{pmatrix}
6 & 10
\end{pmatrix}
\]

\[1 \times 2 + 2 \times 4 = 10\]
Matrices

- Multiplication

\[ AB = C \rightarrow c_{ij} = \sum_{n=1}^{\text{cols}_A} a_{im} b_{mj} \]

\[
\begin{pmatrix}
1 & 2 \\
4 & 9 \\
3 & 2
\end{pmatrix} \times \begin{pmatrix}
4 & 2 \\
1 & 4
\end{pmatrix} = \begin{pmatrix}
6 & 10 \\
25 & 44 \\
14 & 14
\end{pmatrix}
\]
Matrix Inverse

- Denoted $A^{-1}$
- $A^{-1}A = AA^{-1} = I$
- Only for square matrices
- Only exists if matrix is full rank
  - All columns (rows) are linearly independent

- $A^{-1} \neq \begin{bmatrix} 1 \\ a_{ij} \end{bmatrix}$, but I’ll spare the details
Rank Deficient Matrices

\[
\begin{pmatrix}
1 & 0 & 2 \\
2 & 1 & 4 \\
3 & 3 & 6
\end{pmatrix}
\quad \quad
\begin{pmatrix}
1 & 0 & 1 \\
3 & 1 & 4 \\
2 & 1 & 3
\end{pmatrix}
\]

2*column1=column3 \quad \quad \text{column1+column2=column3}
Pseudoinverse

- If the columns *only* are linearly independent, then \( A'A \) is invertible
- Pseudoinverse: \((A'A)^{-1}A'\)
- \((A'A)^{-1}A'A = I\)
Expectation and Variance

• $E[Y] = \begin{pmatrix} E[y_1] \\ E[y_2] \\ E[y_3] \end{pmatrix}$

• $\text{Var}[Y] = \begin{pmatrix} \text{Var}[y_1] & \text{Cov}[y_1, y_2] & \text{Cov}[y_1, y_3] \\ \text{Cov}[y_1, y_2] & \text{Var}[y_2] & \text{Cov}[y_2, y_3] \\ \text{Cov}[y_1, y_3] & \text{Cov}[y_2, y_3] & \text{Var}[y_3] \end{pmatrix}$
Matrix Operations

- A few final properties
  \[(AB)' = B' A'\]
  \[(A')' = A\]
  \[(A^{-1})^{-1} = A\] (when \(A\) is invertible)
  \[(AB)^{-1} = B^{-1} A^{-1}\] (when \(A\) and \(B\) are invertible)
Back to linear regression

\[ Y_1 = \beta_0 + \beta_1 X_{11} + \beta_2 X_{21} + \beta_3 X_{31} + \epsilon_1 \]
\[ Y_2 = \beta_0 + \beta_1 X_{12} + \beta_2 X_{22} + \beta_3 X_{32} + \epsilon_2 \]
\[ \vdots \]
\[ Y_n = \beta_0 + \beta_1 X_{1n} + \beta_2 X_{2n} + \beta_3 X_{3n} + \epsilon_n \]

\[
\begin{pmatrix}
Y_1 \\
Y_2 \\
\vdots \\
Y_n \\
\end{pmatrix}
= 
\begin{pmatrix}
1 & X_{11} & X_{21} & X_{31} \\
1 & X_{12} & X_{22} & X_{32} \\
\vdots & \vdots & \vdots & \vdots \\
1 & X_{1n} & X_{2n} & X_{3n} \\
\end{pmatrix}
\begin{pmatrix}
\beta_0 \\
\beta_1 \\
\beta_2 \\
\beta_3 \\
\end{pmatrix}
+ 
\begin{pmatrix}
\epsilon_1 \\
\epsilon_1 \\
\vdots \\
\epsilon_n \\
\end{pmatrix}
\]
Back to linear regression

\[ Y_1 = \beta_0 + \beta_1 X_{11} + \beta_2 X_{21} + \beta_3 X_{31} + \epsilon_1 \]
\[ Y_2 = \beta_0 + \beta_1 X_{12} + \beta_2 X_{22} + \beta_3 X_{32} + \epsilon_2 \]
\[ \vdots \]
\[ Y_n = \beta_0 + \beta_1 X_{1n} + \beta_2 X_{2n} + \beta_3 X_{3n} + \epsilon_n \]

\[ Y = X \beta + \epsilon \]
Viewing the Design Matrix

- Look at the actual numbers

\[
\begin{pmatrix}
M & F & \text{age} \\
1 & 0 & 29 \\
1 & 0 & 33 \\
1 & 0 & 26 \\
1 & 0 & 22 \\
1 & 0 & 23 \\
0 & 1 & 28 \\
0 & 1 & 21 \\
0 & 1 & 27 \\
0 & 1 & 30 \\
0 & 1 & 32 \\
\end{pmatrix}
\]
Viewing the Design Matrix

- Look at in image representation
  - Darker = smaller #
Viewing the Design Matrix

- Look at in image representation
  - Darker = smaller #
  - Useful for large fMRI designs

fMRI example (FSL)
Multiple Linear Regression

• The distribution of $Y$ is a multivariate Normal

\[
Y \sim N (X\beta, \sigma^2 I_n)
\]

\[
\sigma^2 \begin{pmatrix}
1 & 1 & \cdots & 0 \\
0 & 1 & \cdots & 1
\end{pmatrix} = \begin{pmatrix}
\sigma^2 & \sigma^2 & \cdots & 0 \\
0 & \sigma^2 & \cdots & \sigma^2
\end{pmatrix}
\]
Multiple Linear Regression

- $\hat{\beta}$ is really easy to derive

\[
\begin{align*}
Y &= X\hat{\beta} \\
X'Y &= (X'X)\hat{\beta} \\
(X'X)^{-1}X'Y &= \hat{\beta}
\end{align*}
\]
Multiple Linear Regression

• $\hat{\beta}$ is really easy to derive

\[
\begin{align*}
Y &= X \hat{\beta} \\
X'Y &= (X'X)\hat{\beta} \\
(X'X)^{-1}X'Y &= \hat{\beta}
\end{align*}
\]

Same as least squares, but much easier to understand and write code for...thanks linear algebra!
Multiple Linear Regression

\[ \hat{\sigma}^2 = \frac{e' e}{N - p} \]

where \( e = Y - X\hat{\beta} = Y - \hat{Y} \)

- N=length(\(Y\))
- \(p=\text{length}(\beta)\)
Statistical Properties

- \( E[\hat{\beta}] = E[(X'X)^{-1}X'Y] \)
  \[ = \beta \]  
  So the estimate is unbiased

- \( \text{Var}[\hat{\beta}] = \text{Var}[(X'X)^{-1}X'Y] \)
  \[ = \sigma^2 (X'X)^{-1} \]  
  But we don’t know \( \sigma^2 \)

- \( \text{Var}[\hat{\beta}] = \hat{\sigma}^2 (X'X)^{-1} \)
Linear regression is flexible!

• One sample t-test
• Two sample t-test
• Paired t-test
• ANOVA
• ANCOVA
• Correlation analysis (careful with interpretation!)
• So, we call it the general linear model (GLM)
Hypothesis Testing

• How we evaluate the estimates
• Fitted model B matches the data better than fitted model A
5 Parts of Hypothesis Tests

- The null hypothesis, $H_0$
- The alternative hypothesis, $H_A$
- The test statistic and p-value
- The rejection region
- The conclusion about the hypothesis
$H_0$ and $H_A$

- **Null Hypothesis, $H_0$**
  - Typically what you want to disprove
  - $H_0$: My boyfriend is cheating on me

- **Alternative Hypothesis, $H_A$**
  - Typically what you want to be true
  - $H_A$: My boyfriend isn’t cheating on me
How to use $H_0$ and $H_A$

- Assuming the null is true (my boyfriend is cheating on me), how likely are my data?
  - Case 1: He buys me gifts, emails me throughout the day, cooks me dinner, tells everybody how awesome it is that he’s dating a biostatistician
    - If he were cheating on me, these things wouldn’t be very likely… so reject $H_0$ in favor of $H_A$
How to use $H_0$ and $H_A$

• Assuming the null is true (my boyfriend is cheating on me), how likely are my data?

  – Case 1: He buys me gifts, emails me throughout the day, cooks me dinner, tells everybody how awesome it is that he’s dating a biostatistician
    • If he were cheating on me, these things wouldn’t be very likely….so reject $H_0$ in favor of $H_A$

  – Case 2: He stays out late, never says anything nice to me, keeps talking about his fun female coworker, has lipstick on his collar
    • If he were cheating on me, these things would be very likely….so do not reject $H_0$. 
H₀ and Hₐ in GLM

• Your study
  – How is reaction time associated with age?
  – \( RT = \beta_0 + \text{AGE}\beta_{\text{age}} + \epsilon \)

• Two-sided hypothesis
  – As age increases, reaction time changes
  – \( H_0 : \beta_{\text{age}} = 0 \quad \text{versus} \quad H_A : \beta_{\text{age}} \neq 0 \)
  – Rejection of null means slope is positive or negative
H₀ and Hₐ in GLM

• One-sided hypothesis test
  – As age increases reaction time increases
  – \( H₀ : \beta_{age} \leq 0 \) versus \( Hₐ : \beta_{age} > 0 \)
  – Rejecting null only concludes a positive slope
  – Typically the type of hypothesis test for fMRI
Test Statistic

• Decision about $H_0$ is based on our data
• We need a statistic with a known distribution!
  – $\hat{\beta}_{age} \sim N(\beta_{age}, \text{Var}(\hat{\beta}_{age}))$
  – Ugh! We don’t know $\text{Var}(\hat{\beta}_{age})$
Test Statistic

- We do know

\[
t = \frac{\hat{\beta}_{age}}{\sqrt{\text{Var}(\hat{\beta}_{age})}} \sim T_{N-p}
\]
Contrasts

• Sometimes we’re interested in the sums or differences of 2 parameters
  – Compare G1 to G2

\[ X\beta = \begin{pmatrix} G1 \\ G2 \\ G3 \end{pmatrix} \begin{pmatrix} \beta_1 \\ \beta_2 \\ \beta_3 \end{pmatrix} \]
Contrasts

- Sometimes we’re interested in the sums or differences of 2 parameters
  - Compare G1 to G2
    - $H_0 : \beta_1 - \beta_2 = 0$

\[ X\beta = \begin{pmatrix} \beta_1 \\ \beta_2 \\ \beta_3 \end{pmatrix} \]
Contrasts

- Sometimes we’re interested in the sums or differences of 2 parameters
  - Compare G1 to G2
    - $H_0 : \beta_1 - \beta_2 = 0$
    - $H_0 : c\beta = 0$
      - $c = [1 \ -1 \ 0]$
      - $c$ is a contrast

\[
X\beta = \begin{pmatrix}
\beta_1 \\
\beta_2 \\
\beta_3 
\end{pmatrix}
\]
Test Statistic

• Of course we can test contrasts of parameters as well

\[ H_0 : c\beta = 0 \]

\[ t = \frac{c\hat{\beta}}{\sqrt{c\text{Cov}({\hat{\beta}})c'}} \sim T_{N-p} \]
P Values 1-Sided Hypothesis

• Given the null is true, how likely is it to obtain a value more extreme than our statistic?
  – What is meant by ‘more extreme’?
\[ H_0 : \beta_{age} \leq 0 \quad versus \quad H_A : \beta_{age} > 0 \]

- Start with the distribution under the null
  - There were 22 observations (N=22)
  - Simple linear regression (p=2)
  - Null is a central T distribution with 20 df
\[ H_0 : \beta_{age} < 0 \quad versus \quad H_A : \beta_{age} \geq 0 \]
$H_0 : \beta_{age} < 0 \quad versus \quad H_A : \beta_{age} \geq 0$

Observed test statistic $= 2$
\[ H_0 : \beta_{age} < 0 \quad \text{versus} \quad H_A : \beta_{age} \geq 0 \]
$H_0 : \beta_1 = 0$ versus $H_A : \beta_1 \neq 0$
$H_0 : \beta_1 = 0$ versus $H_A : \beta_1 \neq 0$

Sum = P value
Assessing a P Value

- 0.1 < p
  - Data support the null
- 0.05 < p < 0.1
  - Weak evidence against the null
- 0.01 < p < 0.05
  - Some evidence against the null
- 0.001 < p < 0.01
  - Good evidence against the null
- p < 0.001
  - Really good evidence against the null
Notes About P Values

• The P value is **not** the probability that the null is true $p \neq P(H_0)$
  
  - $P(T_{N-p} > t|H_0)$ (one sided)

• 1-p is **not** the probability that the alternative is true
Rejection Region

• We need to choose a threshold
• A p value is significant if it falls below the threshold
• Denoted by \( \alpha \), typically set at 0.05 or 0.01
  – The probability that the null is rejected when it is true
  – For \( \alpha = 0.05 \) if 100 independent tests were conducted and the null was true, 5 times we’d reject the null
<table>
<thead>
<tr>
<th>Decision</th>
<th>TRUE</th>
<th>FALSE</th>
</tr>
</thead>
<tbody>
<tr>
<td>Reject null</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Accept null</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
Types of Error

Null Hypothesis

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Types of Error

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<tbody>
<tr>
<td>Reject null</td>
<td>Type I Error</td>
<td>Correct!</td>
</tr>
<tr>
<td></td>
<td>$\alpha$</td>
<td></td>
</tr>
<tr>
<td>Accept null</td>
<td>Correct!</td>
<td>Type II Error</td>
</tr>
<tr>
<td></td>
<td></td>
<td>$\beta$</td>
</tr>
</tbody>
</table>
Power

• Probability of rejecting the null, when the alternative is true
  – \( \text{Power} = 1 - \beta \)

• Ideal situation has low \( \alpha \) and high power
  – Power is a function of \( \alpha \)
  – Increasing \( \alpha \) increases power
Testing Multiple Contrasts

- You can test multiple contrasts simultaneously
  - Are any of my beta’s 0?
  - $H_0: \beta_1 = \beta_2 = \beta_3 = 0$
  - Use a contrast matrix
    \[
    \begin{pmatrix}
    1 & 0 & 0 \\
    0 & 1 & 0 \\
    0 & 0 & 1 \\
    \end{pmatrix}
    \]
  - Turns into an F test
    - $f = (c\hat{\beta})'[r \ast c(\widehat{\text{Cov}}(\hat{\beta})c')]^{-1}(c\hat{\beta}) \sim F_{r,N-p}$
    - $r=\text{rank}(c)$
F tests are great!

• If the F test isn’t significant, then none of the individual t tests will be significant.
• I’ve heard of reviewers getting angry when two insignificant t tests were reported as opposed to 1 F test.
• Why does it matter how many tests we run?
Multiple Testing Problems

• What if we perform many hypothesis tests?
• ‘Confidence coefficient’ $= 1 - \alpha = 0.95$
• Joint confidence coefficient for 5 independent tests
  - $(1 - \alpha)^5 = 0.95^5 = 0.77$
  - Much smaller than we’d like
Multiple Testing Problems

• Bonferroni method
  – Use $\alpha^* = \alpha/n = 0.05/5 = 0.01$
  – $(1 - \alpha^*)^n = 0.99^5 = 0.951$
  – With fMRI data multiple testing is a big problem and Bonferroni is too conservative…stay tuned
Let’s talk about models!

- Focus on residuals and degrees of freedom
- Goal…make our t stat as big as we can without using too many DF

\[ t = \frac{c\beta}{\hat{\sigma}^2 c(X'X)^{-1} c'} \sim T_{N-p} \]
Let’s talk about models!

- Focus on residuals and degrees of freedom
- Goal…make our t stat as big as we can without using too many DF

\[ t = \frac{c\hat{\beta}}{\hat{\sigma}^2 c (X'X)^{-1}c'} \sim T_{N-p} \]

Can’t do much about these pieces
Let’s talk about models!

- Focus on residuals and degrees of freedom
- Goal…make our t stat as big as we can without using too many DF

\[ t = \frac{c\hat{\beta}}{\hat{\sigma}^2 c (X'X)^{-1} c'} \sim T_{N-p} \]

Try to decrease this estimate
Variance Estimate

• Recall \( \hat{\sigma}^2 = \frac{\sum(Y_i - \hat{Y}_i)^2}{N - p} \)

• If we make our model fit better, the estimate will decrease
  – Add in regressors to model confounding factors (age, gender, etc)
  – Make sure the regressors you do have capture the trends you are modeling
Linear regressor is not significant (p=0.5)
Quadratic regressor is significant (p<0.0001)
Watch degrees of freedom!

$T_{16}$

$P=0.05$
Watch degrees of freedom!

Add 13 regressors, increasing statistic
Watch degrees of freedom!

Both have $p=0.05$
Recall

• GLM is flexible
  – One Sample T Test
  – ANOVA
  – Two sample T Test
  – Paired T test

• What do the models look like?
1-Sample T Test

\[ X\beta = \begin{pmatrix}
1 \\
1 \\
1 \\
1 \\
1 \\
1 \\
1 \\
1 \\
1
\end{pmatrix} \beta \]

Overall mean

\[ H_0 : c\beta = 0 \quad \text{where} \quad c = [1] \]
2-Sample T Test

\[
\begin{pmatrix}
A_1 \\
A_1 \\
A_1 \\
A_1 \\
A_1 \\
A_2 \\
A_2 \\
A_2 \\
A_2 \\
A_2
\end{pmatrix}
= 
\begin{pmatrix}
1 & 0 \\
1 & 0 \\
1 & 0 \\
1 & 0 \\
1 & 0 \\
0 & 1 \\
0 & 1 \\
0 & 1 \\
0 & 1 \\
0 & 1
\end{pmatrix}
\begin{pmatrix}
\beta_1 \\
\beta_2
\end{pmatrix}
\]

\[H_0 : c\beta = 0 \text{ where } c = [1 \quad -1]\]
2-Sample T Test

\[
\begin{pmatrix}
A_1 \\
A_1 \\
A_1 \\
A_1 \\
A_1 \\
A_2 \\
A_2 \\
A_2 \\
A_2
\end{pmatrix}
= 
\begin{pmatrix}
1 & 1 \\
1 & 1 \\
1 & 1 \\
1 & 1 \\
1 & 1 \\
1 & 0 \\
1 & 0 \\
1 & 0 \\
1 & 0
\end{pmatrix}
\begin{pmatrix}
\beta_1 \\
\beta_2
\end{pmatrix}
\]
Understanding a model

• If you’re unsure about a model or the contrasts
  – Plug in numbers
  – Look at graphs (fMRI data)
• Always ask yourself if your model is doing what you want it to
For example...

• For the 2 sample T test
  – Set $\beta_1 = 3$  $\beta_2 = 5$
  – Then G1=8 and G2=3
  – So $\beta_1$ is the mean of group 2 and $\beta_2$ is the difference between the groups
  – What are the contrasts to test
    • Mean of G2 $c = [1 \ 0]$
    • Mean of G1
    • G1-G2

$$x\beta = \begin{pmatrix}
1 & 1 \\
1 & 1 \\
1 & 1 \\
1 & 1 \\
1 & 0 \\
1 & 0 \\
1 & 0 \\
\end{pmatrix} \begin{pmatrix}
\beta_1 \\
\beta_2 \\
\end{pmatrix}$$
For example...

- For the 2 sample T test
  - Set $\beta_1 = 3$, $\beta_2 = 5$
  - Then $G1=8$ and $G2=3$
  - So $\beta_1$ is the mean of group 2 and $\beta_2$ is the difference between the groups
  - What are the contrasts to test
    - Mean of G2 $c = [1 \ 0]$
    - Mean of G1 $c = [1 \ 1]$
    - G1-G2

\[
x \beta = \begin{pmatrix}
1 & 1 \\
1 & 1 \\
1 & 1 \\
1 & 1 \\
1 & 0 \\
1 & 0 \\
1 & 0
\end{pmatrix} \begin{pmatrix}
\beta_1 \\
\beta_2
\end{pmatrix}
\]
For example...

• For the 2 sample T test
  – Set $\beta_1 = 3$  $\beta_2 = 5$
  – Then G1=8 and G2=3
  – So $\beta_1$ is the mean of group 2 and $\beta_2$ is the difference between the groups
  – What are the contrasts to test
    • Mean of G2 $c = [1 \ 0]$
    • Mean of G1 $c = [1 \ 1]$
    • G1-G2 $c = [0 \ 1]$

$X\beta = \begin{pmatrix}
1 & 1 \\
1 & 1 \\
1 & 1 \\
1 & 1 \\
1 & 0 \\
1 & 0 \\
1 & 0 \\
1 & 0
\end{pmatrix} \begin{pmatrix}
\beta_1 \\
\beta_2
\end{pmatrix}$
Paired T Test

- A common mistake is to use a 2-sample t test instead of a paired test
- Tire example

<table>
<thead>
<tr>
<th>Automobile</th>
<th>Tire A</th>
<th>Tire B</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>10.6</td>
<td>10.2</td>
</tr>
<tr>
<td>2</td>
<td>9.8</td>
<td>9.4</td>
</tr>
<tr>
<td>3</td>
<td>12.3</td>
<td>11.8</td>
</tr>
<tr>
<td>4</td>
<td>9.7</td>
<td>9.1</td>
</tr>
<tr>
<td>5</td>
<td>8.8</td>
<td>8.3</td>
</tr>
</tbody>
</table>

- 2-sample T test p=0.58
- Paired T test p<0.001
Why so different?
Why so different?
Why so different?

Difference is OK
Why so different?

Residuals are HUGE!
Paired T Test

Adjust for the mean of each pair
Paired T Test

Mean A

Mean B
Paired T Test

Difference is same
Residual variance much smaller
Paired T Test GLM

\[
\begin{pmatrix}
A_1 \\
B_1 \\
A_2 \\
B_2 \\
A_3 \\
B_3 \\
A_4 \\
B_4 \\
A_5 \\
B_5 \\
\end{pmatrix}
= 
\begin{pmatrix}
1 & 1 & 0 & 0 & 0 & 0 \\
-1 & 1 & 0 & 0 & 0 & 0 \\
1 & 0 & 1 & 0 & 0 & 0 \\
-1 & 0 & 1 & 0 & 0 & 0 \\
1 & 0 & 0 & 1 & 0 & 0 \\
-1 & 0 & 0 & 1 & 0 & 0 \\
1 & 0 & 0 & 0 & 1 & 0 \\
-1 & 0 & 0 & 0 & 1 & 0 \\
1 & 0 & 0 & 0 & 0 & 1 \\
-1 & 0 & 0 & 0 & 0 & 1 \\
\end{pmatrix}
\begin{pmatrix}
\beta_1 \\
\beta_2 \\
\beta_3 \\
\beta_4 \\
\beta_5 \\
\beta_6 \\
\end{pmatrix}
\]

\(H_0 : \text{Paired difference} = 0\)
\(H_0 : c\beta = 0, \quad c = [1 \ 0 \ 0 \ 0 \ 0 \ 0]\)
ANOVA

1-way ANOVA

\[
\begin{align*}
\mu_1 \\
\mu_2 \\
\vdots \\
\mu_N
\end{align*}
\]

2-way ANOVA

\[
\begin{array}{ccc}
\mu_{11} & \mu_{12} \\
\mu_{21} & \mu_{22} \\
\mu_{31} & \mu_{32}
\end{array}
\]

Graphs showing measures and levels of A and B.
Modeling ANOVA with GLM

• Cell means model
  – 1-way ANOVA \( Y_{in} = \mu_i + \epsilon_{in} \)
  – 2-way ANOVA \( Y_{ijn} = \mu_{ij} + \epsilon_{ijn} \)
  – EVs are easy, but contrasts are trickier
Modeling ANOVA with GLM

• Cell means model
  – 1-way ANOVA \( Y_{in} = \mu_i + \epsilon_{in} \)
  – 2-way ANOVA \( Y_{ijn} = \mu_{ij} + \epsilon_{ijn} \)
  – EVs are easy, but contrasts are trickier

• Factor effects
  – 1-way \( Y_{in} = \mu + \alpha_i + \epsilon_{in} \)
  – 2-way \( Y_{ijn} = \mu + \alpha_i + \beta_j + (\alpha\beta)_{ij} + \epsilon_{ijn} \)
  – EVs take more thought, but contrasts are easier

• ANOVA = F tests!
1 Way ANOVA - Cell Means

\[
\begin{pmatrix}
A_1 \\
A_1 \\
A_2 \\
A_2 \\
A_3 \\
A_3 \\
A_4 \\
A_4
\end{pmatrix}
= 
\begin{pmatrix}
1 & 0 & 0 & 0 \\
1 & 0 & 0 & 0 \\
0 & 1 & 0 & 0 \\
0 & 1 & 0 & 0 \\
0 & 0 & 1 & 0 \\
0 & 0 & 1 & 0 \\
0 & 0 & 0 & 1 \\
0 & 0 & 0 & 1
\end{pmatrix}
\begin{pmatrix}
\beta_1 \\
\beta_2 \\
\beta_3 \\
\beta_4
\end{pmatrix}
\]

\[H_0 : G2 - G3 = 0\]
1 Way ANOVA - Cell Means

\[
\begin{pmatrix}
A_1 \\
A_1 \\
A_2 \\
A_2 \\
A_3 \\
A_3 \\
A_4 \\
A_4 \\
\end{pmatrix}
= 
\begin{pmatrix}
1 & 0 & 0 & 0 \\
1 & 0 & 0 & 0 \\
0 & 1 & 0 & 0 \\
0 & 1 & 0 & 0 \\
0 & 0 & 1 & 0 \\
0 & 0 & 1 & 0 \\
0 & 0 & 0 & 1 \\
0 & 0 & 0 & 1 \\
\end{pmatrix}
\begin{pmatrix}
\beta_1 \\
\beta_2 \\
\beta_3 \\
\beta_4 \\
\end{pmatrix}
\]

\(H_0 : G2 - G3 = 0\)

\(H_0 : c\beta = 0\) where \(c = [0 \ 1 \ -1 \ 0]\)
1 Way ANOVA - Cell Means

\[
\begin{pmatrix}
A_1 \\
A_1 \\
A_2 \\
A_2 \\
A_3 \\
A_3 \\
A_4 \\
A_4 \\
\end{pmatrix}
= 
\begin{pmatrix}
1 & 0 & 0 & 0 \\
1 & 0 & 0 & 0 \\
0 & 1 & 0 & 0 \\
0 & 1 & 0 & 0 \\
0 & 0 & 1 & 0 \\
0 & 0 & 1 & 0 \\
0 & 0 & 0 & 1 \\
0 & 0 & 0 & 1 \\
\end{pmatrix}
\begin{pmatrix}
\beta_1 \\
\beta_2 \\
\beta_3 \\
\beta_4 \\
\end{pmatrix}
\]

\[H_0 : G_1 = G_2 = G_3 = G_4 = 0\]
1 Way ANOVA - Cell Means

\[
\begin{pmatrix}
A_1 \\
A_1 \\
A_2 \\
A_2 \\
A_3 \\
A_3 \\
A_4 \\
A_4
\end{pmatrix}
= 
\begin{pmatrix}
1 & 0 & 0 & 0 \\
1 & 0 & 0 & 0 \\
0 & 1 & 0 & 0 \\
0 & 1 & 0 & 0 \\
0 & 0 & 1 & 0 \\
0 & 0 & 1 & 0 \\
0 & 0 & 0 & 1 \\
0 & 0 & 0 & 1
\end{pmatrix}
\begin{pmatrix}
\beta_1 \\
\beta_2 \\
\beta_3 \\
\beta_4
\end{pmatrix}
\]

\[H_0 : G1 = G2 = G3 = G4 = 0\]

\[H_0 : c\beta = 0 \text{ where } c = 
\begin{pmatrix}
1 & 0 & 0 & 0 \\
0 & 1 & 0 & 0 \\
0 & 0 & 1 & 0 \\
0 & 0 & 0 & 1
\end{pmatrix}
\]
1 Way ANOVA - Factor Effects

• In general
  – # of regressors for a factor = # levels - 1
  – Factor with 4 levels

\[
X_i = \begin{cases} 
1 & \text{if case from level } i \\
-1 & \text{if case from level 4} \\
0 & \text{otherwise}
\end{cases}
\]
1 Way ANOVA - Factor Effects

\[
\begin{pmatrix}
A_1 \\
A_1 \\
A_2 \\
A_2 \\
A_3 \\
A_3 \\
A_4 \\
A_4 \\
\end{pmatrix}
= 
\begin{pmatrix}
1 & 1 & 0 & 0 \\
1 & 1 & 0 & 0 \\
1 & 0 & 1 & 0 \\
1 & 0 & 1 & 0 \\
1 & 0 & 0 & 1 \\
1 & 0 & 0 & 1 \\
1 & -1 & -1 & -1 \\
1 & -1 & -1 & -1 \\
\end{pmatrix}
\begin{pmatrix}
\beta_1 \\
\beta_2 \\
\beta_3 \\
\beta_4 \\
\end{pmatrix}
\]

\[
G_1 = \beta_1 + \beta_2 \\
G_2 = \beta_1 + \beta_3 \\
G_3 = \beta_1 + \beta_4 \\
G_4 = \beta_1 - \beta_2 - \beta_3 - \beta_4
\]
1 Way ANOVA - Factor Effects

\[ \beta_1, \beta_2, \beta_3, \beta_4 \]

measure

\[ -\beta_2 - \beta_3 - \beta_4 \]
1 Way ANOVA - Factor Effects

\[
\begin{pmatrix}
A_1 \\
A_1 \\
A_2 \\
A_2 \\
A_3 \\
A_3 \\
A_4 \\
A_4 \\
\end{pmatrix}
= 
\begin{pmatrix}
1 & 1 & 0 & 0 \\
1 & 1 & 0 & 0 \\
1 & 0 & 0 & 1 \\
1 & 0 & 0 & 1 \\
1 & 0 & 1 & 0 \\
1 & 0 & 1 & 0 \\
1 & -1 & -1 & -1 \\
1 & -1 & -1 & -1 \\
\end{pmatrix}
\begin{pmatrix}
\beta_1 \\
\beta_2 \\
\beta_3 \\
\beta_4 \\
\end{pmatrix}

H_0 : \text{mean of G1} = 0
1 Way ANOVA - Factor Effects

\[
\begin{pmatrix}
A_1 \\
A_1 \\
A_2 \\
A_2 \\
A_3 \\
A_3 \\
A_4 \\
A_4 \\
\end{pmatrix} = \begin{pmatrix}
1 & 1 & 0 & 0 \\
1 & 1 & 0 & 0 \\
1 & 0 & 0 & 1 \\
1 & 0 & 1 & 0 \\
1 & 0 & 0 & 1 \\
1 & 1 & 1 & -1 \\
1 & 1 & 1 & -1 \\
\end{pmatrix} \begin{pmatrix}
\beta_1 \\
\beta_2 \\
\beta_3 \\
\beta_4 \\
\end{pmatrix}
\]

\[H_0: \text{mean of } G1 = 0\]

\[H_0: c\beta = 0 \text{ where } c = [1 \ 1 \ 0 \ 0]\]
1 Way ANOVA - Factor Effects

\[
\begin{pmatrix}
A_1 \\
A_1 \\
A_2 \\
A_2 \\
A_3 \\
A_3 \\
A_4 \\
A_4
\end{pmatrix}
= 
\begin{pmatrix}
1 & 1 & 0 & 0 \\
1 & 1 & 0 & 0 \\
1 & 0 & 0 & 1 \\
1 & 0 & 1 & 0 \\
1 & 0 & 1 & 0 \\
1 & -1 & -1 & -1 \\
1 & -1 & -1 & -1
\end{pmatrix}
\begin{pmatrix}
\beta_1 \\
\beta_2 \\
\beta_3 \\
\beta_4
\end{pmatrix}

H_0 : G1 - G4 = 0
1 Way ANOVA - Factor Effects

$$
\begin{pmatrix}
A_1 \\
A_1 \\
A_2 \\
A_2 \\
A_3 \\
A_3 \\
A_4 \\
A_4 \\
\end{pmatrix}
= 
\begin{pmatrix}
1 & 1 & 0 & 0 \\
1 & 1 & 0 & 0 \\
1 & 0 & 0 & 1 \\
1 & 0 & 1 & 0 \\
1 & 0 & 1 & 0 \\
1 & -1 & -1 & -1 \\
1 & -1 & -1 & -1 \\
\end{pmatrix}
\begin{pmatrix}
\beta_1 \\
\beta_2 \\
\beta_3 \\
\beta_4 \\
\end{pmatrix}
$$

$$H_0 : G_1 - G_4 = 0$$

$$c = (1 \ 1 \ 0 \ 0) - (1 \ -1 \ -1 \ -1 \ -1) = (0 \ 2 \ 1 \ 1)$$
2 Way ANOVA (3x2)

\[
\begin{pmatrix}
A_1 B_1 \\
A_1 B_1 \\
A_1 B_2 \\
A_1 B_2 \\
A_2 B_1 \\
A_2 B_1 \\
A_2 B_2 \\
A_2 B_2 \\
A_3 B_1 \\
A_3 B_1 \\
A_3 B_2 \\
A_3 B_2
\end{pmatrix}
= 
\begin{pmatrix}
1 & 0 & 0 & 0 & 0 & 0 \\
1 & 0 & 0 & 0 & 0 & 0 \\
0 & 1 & 0 & 0 & 0 & 0 \\
0 & 1 & 0 & 0 & 0 & 0 \\
0 & 0 & 1 & 0 & 0 & 0 \\
0 & 0 & 1 & 0 & 0 & 0 \\
0 & 0 & 0 & 1 & 0 & 0 \\
0 & 0 & 0 & 1 & 0 & 0 \\
0 & 0 & 0 & 0 & 1 & 0 \\
0 & 0 & 0 & 0 & 1 & 0 \\
0 & 0 & 0 & 0 & 0 & 1 \\
0 & 0 & 0 & 0 & 0 & 1
\end{pmatrix}
\begin{pmatrix}
\beta_1 \\
\beta_2 \\
\beta_3 \\
\beta_4 \\
\beta_5 \\
\beta_6
\end{pmatrix}
\]

\(H_0: \text{main factor A effect} = 0\)
2 Way ANOVA (3x2)

$H_0 : \text{main factor } A \text{ effect} = 0$

<table>
<thead>
<tr>
<th></th>
<th>B1</th>
<th>B2</th>
</tr>
</thead>
<tbody>
<tr>
<td>A1</td>
<td>5</td>
<td>3</td>
</tr>
<tr>
<td>A2</td>
<td>2</td>
<td>3</td>
</tr>
<tr>
<td>A3</td>
<td>-1</td>
<td>7</td>
</tr>
<tr>
<td></td>
<td>6</td>
<td>13</td>
</tr>
</tbody>
</table>

No effect means the marginals would be the same
Null: $A1 = A2 = A3$  equivalently $A1 - A3 = 0$ and $A2 - A3 = 0$
2 Way ANOVA (3x2)

\[
\begin{pmatrix}
A_1 B_1 \\
A_1 B_1 \\
A_1 B_2 \\
A_1 B_2 \\
A_2 B_1 \\
A_2 B_1 \\
A_2 B_2 \\
A_2 B_2 \\
A_3 B_1 \\
A_3 B_1 \\
A_3 B_2 \\
A_3 B_2 \\
\end{pmatrix}
= 
\begin{pmatrix}
1 & 0 & 0 & 0 & 0 & 0 \\
1 & 0 & 0 & 0 & 0 & 0 \\
0 & 1 & 0 & 0 & 0 & 0 \\
0 & 1 & 0 & 0 & 0 & 0 \\
0 & 0 & 1 & 0 & 0 & 0 \\
0 & 0 & 1 & 0 & 0 & 0 \\
0 & 0 & 0 & 1 & 0 & 0 \\
0 & 0 & 0 & 1 & 0 & 0 \\
0 & 0 & 0 & 0 & 1 & 0 \\
0 & 0 & 0 & 0 & 1 & 0 \\
0 & 0 & 0 & 0 & 0 & 1 \\
0 & 0 & 0 & 0 & 0 & 1 \\
\end{pmatrix}
\begin{pmatrix}
\beta_1 \\
\beta_2 \\
\beta_3 \\
\beta_4 \\
\beta_5 \\
\beta_6 \\
\end{pmatrix}
\]

\[H_0 : \text{main factor A effect} = 0\]
2 Way ANOVA (3x2)

\[
\begin{pmatrix}
A_1 B_1 \\
A_1 B_1 \\
A_1 B_2 \\
A_1 B_2 \\
A_2 B_1 \\
A_2 B_1 \\
A_2 B_2 \\
A_2 B_2 \\
A_3 B_1 \\
A_3 B_1 \\
A_3 B_2 \\
A_3 B_2
\end{pmatrix} =
\begin{pmatrix}
1 & 0 & 0 & 0 & 0 & 0 & 0 \\
1 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 1 & 0 & 0 & 0 & 0 & 0 \\
0 & 1 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 1 & 0 & 0 & 0 & 0 \\
0 & 0 & 1 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 1 & 0 & 0 & 0 \\
0 & 0 & 0 & 1 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 1 & 0 & 0 \\
0 & 0 & 0 & 0 & 1 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 1 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 1 
\end{pmatrix}
\begin{pmatrix}
\beta_1 \\
\beta_2 \\
\beta_3 \\
\beta_4 \\
\beta_5 \\
\beta_6
\end{pmatrix}
\]

\(H_0 : \text{main factor A effect} = 0\)

\(H_0 : c\beta = 0\) where \(c = \begin{pmatrix} 1 & 1 & 0 & 0 & -1 & -1 \\
0 & 0 & 1 & 1 & -1 & -1 \end{pmatrix}\)
2 Way ANOVA (3x2)

\[
\begin{pmatrix}
A_1B_1 \\
A_1B_1 \\
A_1B_2 \\
A_1B_2 \\
A_2B_1 \\
A_2B_1 \\
A_2B_2 \\
A_2B_2 \\
A_3B_1 \\
A_3B_1 \\
A_3B_2 \\
A_3B_2 \\
\end{pmatrix}
\begin{pmatrix}
1 & 0 & 0 & 0 & 0 & 0 \\
1 & 0 & 0 & 0 & 0 & 0 \\
0 & 1 & 0 & 0 & 0 & 0 \\
0 & 1 & 0 & 0 & 0 & 0 \\
0 & 0 & 1 & 0 & 0 & 0 \\
0 & 0 & 1 & 0 & 0 & 0 \\
0 & 0 & 0 & 1 & 0 & 0 \\
0 & 0 & 0 & 1 & 0 & 0 \\
0 & 0 & 0 & 0 & 1 & 0 \\
0 & 0 & 0 & 0 & 1 & 0 \\
0 & 0 & 0 & 0 & 0 & 1 \\
0 & 0 & 0 & 0 & 0 & 1 \\
\end{pmatrix}
\begin{pmatrix}
\beta_1 \\
\beta_2 \\
\beta_3 \\
\beta_4 \\
\beta_5 \\
\beta_6 \\
\end{pmatrix}
\]

\(H_0: \text{interaction effect} = 0\)
2 Way ANOVA (3x2)

\[ H_0 : \text{interaction effect} = 0 \]

<table>
<thead>
<tr>
<th></th>
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<td>3</td>
</tr>
<tr>
<td>A3</td>
<td>-1</td>
<td>7</td>
</tr>
<tr>
<td></td>
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<td>13</td>
</tr>
</tbody>
</table>

No effect means the lines would be parallel
2 Way ANOVA (3x2)

\[ H_0 : \text{interaction effect} = 0 \]

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<td>2</td>
<td>3</td>
</tr>
<tr>
<td>A3</td>
<td>-1</td>
<td>7</td>
</tr>
<tr>
<td></td>
<td>6</td>
<td>13</td>
</tr>
</tbody>
</table>

No effect means the lines would be parallel

2 Way ANOVA (3x2)

\[
\begin{pmatrix}
A_1B_1 \\
A_1B_1 \\
A_1B_2 \\
A_1B_2 \\
A_2B_1 \\
A_2B_1 \\
A_2B_2 \\
A_2B_2 \\
A_3B_1 \\
A_3B_1 \\
A_3B_2 \\
A_3B_2 \\
\end{pmatrix}
= 
\begin{pmatrix}
1 & 0 & 0 & 0 & 0 & 0 \\
1 & 0 & 0 & 0 & 0 & 0 \\
0 & 1 & 0 & 0 & 0 & 0 \\
0 & 1 & 0 & 0 & 0 & 0 \\
0 & 0 & 1 & 0 & 0 & 0 \\
0 & 0 & 1 & 0 & 0 & 0 \\
0 & 0 & 0 & 1 & 0 & 0 \\
0 & 0 & 0 & 1 & 0 & 0 \\
0 & 0 & 0 & 0 & 1 & 0 \\
0 & 0 & 0 & 0 & 1 & 0 \\
0 & 0 & 0 & 0 & 0 & 1 \\
0 & 0 & 0 & 0 & 0 & 1 \\
\end{pmatrix}
\begin{pmatrix}
\beta_1 \\
\beta_2 \\
\beta_3 \\
\beta_4 \\
\beta_5 \\
\beta_6 \\
\end{pmatrix}
\]

\(H_0: \text{interaction effect} = 0\)

\(H_0: c\beta = 0\) where \(c = \begin{pmatrix}
1 & -1 & 0 & 0 & -1 & 1 \\
0 & 0 & 1 & -1 & -1 & 1 \\
\end{pmatrix}\)
2 Way ANOVA - Factor Effects

- Recall for factor effects, a factor with n levels has regressors set up like:

\[
X_i = \begin{cases} 
1 & \text{if case from level } i \\
-1 & \text{if case from level } n \\
0 & \text{otherwise} 
\end{cases}
\]

- A has 3 levels, so 2 regressors
- B has 2 levels, so 1 regressor
2 Way ANOVA - Factor Effects

\[ \begin{pmatrix} A_1 B_1 \\ A_1 B_1 \\ A_1 B_2 \\ A_1 B_2 \\ A_2 B_1 \\ A_2 B_1 \\ A_2 B_2 \\ A_2 B_2 \\ A_3 B_1 \\ A_3 B_1 \\ A_3 B_2 \\ A_3 B_2 \end{pmatrix} = \begin{pmatrix} 1 & 1 & 0 & 1 & 1 & 0 \\ 1 & 1 & 0 & 1 & 1 & 0 \\ 1 & 1 & 0 & -1 & -1 & 0 \\ 1 & 1 & 0 & -1 & -1 & 0 \\ 1 & 0 & 1 & 1 & 0 & 1 \\ 1 & 0 & 1 & 1 & 0 & 1 \\ 1 & 0 & 1 & -1 & 0 & -1 \\ 1 & 0 & 1 & -1 & 0 & -1 \\ 1 & -1 & -1 & 1 & -1 & -1 \\ 1 & -1 & -1 & 1 & -1 & -1 \\ 1 & -1 & -1 & -1 & 1 & 1 \\ 1 & -1 & -1 & -1 & 1 & 1 \end{pmatrix} \begin{pmatrix} \beta_1 \\ \beta_2 \\ \beta_3 \\ \beta_4 \\ \beta_5 \\ \beta_6 \end{pmatrix} \]
2 Way ANOVA - Factor Effects

\[
\begin{pmatrix}
A_1B_1 \\
A_1B_1 \\
A_1B_2 \\
A_1B_2 \\
A_2B_1 \\
A_2B_1 \\
A_2B_2 \\
A_2B_2 \\
A_3B_1 \\
A_3B_1 \\
A_3B_2 \\
A_3B_2
\end{pmatrix}
= 
\begin{pmatrix}
1 & 1 & 0 & 1 & 1 & 0 \\
1 & 1 & 0 & 1 & 1 & 0 \\
1 & 1 & 0 & -1 & -1 & 0 \\
1 & 1 & 0 & -1 & -1 & 0 \\
1 & 0 & 1 & 1 & 0 & 1 \\
1 & 0 & 1 & 1 & 0 & 1 \\
1 & 0 & 1 & -1 & 0 & -1 \\
1 & 0 & 1 & -1 & 0 & -1 \\
1 & -1 & -1 & 1 & -1 & -1 \\
1 & -1 & -1 & 1 & -1 & -1 \\
1 & -1 & -1 & -1 & 1 & 1 \\
1 & -1 & -1 & -1 & 1 & 1
\end{pmatrix}
\begin{pmatrix}
\beta_1 \\
\beta_2 \\
\beta_3 \\
\beta_4 \\
\beta_5 \\
\beta_6
\end{pmatrix}

H_0: \text{main factor A effect} = 0
2 Way ANOVA - Factor Effects

\[
\begin{pmatrix}
A_1 B_1 \\
A_1 B_1 \\
A_1 B_2 \\
A_1 B_2 \\
A_2 B_1 \\
A_2 B_1 \\
A_2 B_2 \\
A_2 B_2 \\
A_3 B_1 \\
A_3 B_1 \\
A_3 B_2 \\
A_3 B_2 \\
\end{pmatrix}
= 
\begin{pmatrix}
1 & 1 & 0 & 1 & 1 & 1 & 0 \\
1 & 1 & 0 & 1 & 1 & 1 & 0 \\
1 & 1 & 0 & -1 & -1 & 0 & 0 \\
1 & 1 & 0 & -1 & -1 & 0 & 0 \\
1 & 0 & 1 & 1 & 0 & 1 & 1 \\
1 & 0 & 1 & 1 & 0 & 1 & 1 \\
1 & 0 & 1 & -1 & 0 & -1 & 1 \\
1 & 0 & 1 & -1 & 0 & -1 & 1 \\
1 & -1 & -1 & 1 & -1 & -1 & 1 \\
1 & -1 & -1 & 1 & -1 & -1 & 1 \\
1 & -1 & -1 & -1 & 1 & 1 & 1 \\
1 & -1 & -1 & -1 & 1 & 1 & 1 \\
\end{pmatrix}
\begin{pmatrix}
\beta_1 \\
\beta_2 \\
\beta_3 \\
\beta_4 \\
\beta_5 \\
\beta_6 \\
\end{pmatrix}
\]

\(H_0: \text{main factor A effect} = 0\)

\(H_0: c\beta = 0\) where \(c = \begin{pmatrix} 0 & 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 & 0 \end{pmatrix}\)
2 Way ANOVA - Factor Effects

\[
\begin{pmatrix}
A_1B_1 \\
A_1B_1 \\
A_1B_2 \\
A_1B_2 \\
A_2B_1 \\
A_2B_1 \\
A_2B_2 \\
A_2B_2 \\
A_3B_1 \\
A_3B_1 \\
A_3B_2 \\
A_3B_2
\end{pmatrix}
\begin{pmatrix}
1 & 1 & 0 & 1 & 1 & 0 \\
1 & 1 & 0 & 1 & 1 & 0 \\
1 & 1 & 0 & -1 & -1 & 0 \\
1 & 1 & 0 & -1 & -1 & 0 \\
1 & 0 & 1 & 1 & 0 & 1 \\
1 & 0 & 1 & 1 & 0 & 1 \\
1 & 0 & 1 & -1 & 0 & -1 \\
1 & 0 & 1 & -1 & 0 & -1 \\
1 & -1 & -1 & 1 & -1 & -1 \\
1 & -1 & -1 & 1 & -1 & -1 \\
1 & -1 & -1 & -1 & 1 & 1 \\
1 & -1 & -1 & -1 & 1 & 1
\end{pmatrix}
\begin{pmatrix}
\beta_1 \\
\beta_2 \\
\beta_3 \\
\beta_4 \\
\beta_5 \\
\beta_6
\end{pmatrix}
\]

\(H_0: \text{interaction effect} = 0\)
2 Way ANOVA - Factor Effects

\[
\begin{pmatrix}
A_1B_1 \\
A_1B_1 \\
A_1B_2 \\
A_1B_2 \\
A_2B_1 \\
A_2B_1 \\
A_2B_2 \\
A_2B_2 \\
A_3B_1 \\
A_3B_1 \\
A_3B_2 \\
A_3B_2 \\
\end{pmatrix}
= 
\begin{pmatrix}
1 & 1 & 0 & 1 & 1 & 0 \\
1 & 1 & 0 & 1 & 1 & 0 \\
1 & 1 & 0 & -1 & -1 & 0 \\
1 & 1 & 0 & -1 & -1 & 0 \\
1 & 0 & 1 & 1 & 0 & 1 \\
1 & 0 & 1 & 1 & 0 & 1 \\
1 & 0 & 1 & -1 & 0 & -1 \\
1 & 0 & 1 & -1 & 0 & -1 \\
1 & -1 & -1 & 1 & -1 & -1 \\
1 & -1 & -1 & 1 & -1 & -1 \\
1 & -1 & -1 & -1 & 1 & 1 \\
1 & -1 & -1 & -1 & 1 & 1 \\
\end{pmatrix}
\begin{pmatrix}
\beta_1 \\
\beta_2 \\
\beta_3 \\
\beta_4 \\
\beta_5 \\
\beta_6 \\
\end{pmatrix}
\]

\[H_0: \text{interaction effect} = 0\]

\[H_0: c\beta = 0 \quad \text{where} \quad c = 
\begin{pmatrix}
0 & 0 & 0 & 0 & 0 & 1 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 1 \\
\end{pmatrix}
\]
2 Way ANOVA - Factor Effects

\[
\begin{pmatrix}
A_1B_1 \\
A_1B_1 \\
A_1B_2 \\
A_1B_2 \\
A_2B_1 \\
A_2B_1 \\
A_2B_2 \\
A_2B_2 \\
A_3B_1 \\
A_3B_1 \\
A_3B_2 \\
A_3B_2
\end{pmatrix}
\begin{pmatrix}
1 & 1 & 0 & 1 & 1 & 1 & 0 \\
1 & 1 & 0 & 1 & 1 & 0 & 0 \\
1 & 1 & 0 & -1 & -1 & 0 & 0 \\
1 & 1 & 0 & -1 & -1 & 0 & 0 \\
1 & 0 & 1 & 1 & 1 & 0 & 1 \\
1 & 0 & 1 & 1 & 0 & 1 & 1 \\
1 & 0 & 1 & -1 & 0 & -1 & 1 \\
1 & 0 & 1 & -1 & 0 & -1 & 1 \\
1 & -1 & -1 & 1 & -1 & -1 & 1 \\
1 & -1 & -1 & 1 & -1 & -1 & 1 \\
1 & -1 & -1 & -1 & 1 & 1 & 1 \\
1 & -1 & -1 & -1 & 1 & 1 & 1
\end{pmatrix}
\begin{pmatrix}
\beta_1 \\
\beta_2 \\
\beta_3 \\
\beta_4 \\
\beta_5 \\
\beta_6
\end{pmatrix}
\]

\[H_0 : \text{mean cell } A_1B_1 = 0\]
2 Way ANOVA - Factor Effects

\[
\begin{pmatrix}
A_1B_1 \\
A_1B_1 \\
A_1B_2 \\
A_1B_2 \\
A_2B_1 \\
A_2B_1 \\
A_2B_2 \\
A_2B_2 \\
A_3B_1 \\
A_3B_1 \\
A_3B_2 \\
A_3B_2
\end{pmatrix}
\begin{pmatrix}
1 & 1 & 0 & 1 & 1 & 0 \\
1 & 1 & 0 & 1 & 1 & 0 \\
1 & 1 & 0 & -1 & -1 & 0 \\
1 & 1 & 0 & -1 & -1 & 0 \\
1 & 0 & 1 & 1 & 0 & 1 \\
1 & 0 & 1 & 1 & 0 & 1 \\
1 & 0 & 1 & -1 & 0 & -1 \\
1 & 0 & 1 & -1 & 0 & -1 \\
1 & -1 & -1 & 1 & -1 & -1 \\
1 & -1 & -1 & 1 & -1 & -1 \\
1 & -1 & -1 & -1 & 1 & 1 \\
1 & -1 & -1 & -1 & 1 & 1
\end{pmatrix}
\begin{pmatrix}
\beta_1 \\
\beta_2 \\
\beta_3 \\
\beta_4 \\
\beta_5 \\
\beta_6
\end{pmatrix}

H_0 : \text{mean cell } A_1B_1 = 0

H_0 : c\beta = 0 \text{ where } c = (1, 1, 0, 1, 1, 0)
For more examples

- The FSL folks have a bunch of great examples
  - http://www.fmrib.ox.ac.uk/fsl/feat5/detail.html

- Check the FSL help list regularly
  - Subscribe at jiscmail
  - Often others have already asked your questions!
Why did I just tell you all of this?

- The GLM is a flexible model that allows for a variety of analyses
- Focusing on residuals and degrees of freedom will help you build good models
- Use an F test when appropriate
- A lot of the stats lingo and linear algebra stuff comes up in methods papers
Why did I just tell you all of this?

• The Gauss-Markov theorem tells us our least squares estimates are best if
  – Errors are mean zero, uncorrelated, constant variance
  – fMRI data tend to violate these assumptions

• Multiple comparisons is a huge problem with fMRI data and Bonferroni doesn’t work well