Analysis of Variance

BIOE 498/598 PJ

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Our analysis is based on the *sum of squares*, or SS. In particular, the total SS is the combination of the SS explained by our model and the SS that is residual (or unexplained).

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 $SS_{ ext{residual}} = \sum_{i} (y_i - \text{predicted}(y_i))^2$
 $SS_{ ext{explained}} = SS_{ ext{total}} - SS_{ ext{residual}}$

Does our model do anything?

Let's analyze the data from the stuffed monkey throwing experiment.

```
##
## Call:
## lm(formula = distance ~ hand + hat + boots)
##
## Residuals:
##
        2 3 4 5
## -0.375 -1.125 0.625 0.875 1.125 0.375 -1.375 -0.125
##
## Coefficients:
             Estimate Std. Error t value Pr(>|t|)
##
## (Intercept) 5.375
                         0.857 6.272 0.0033 **
## handright 2.250 0.857 2.626 0.0585.
## hatyes -1.500 0.857 -1.750 0.1549
## bootsyes 1.000 0.857 1.167 0.3081
## ---
## Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 1.212 on 4 degrees of freedom
## Multiple R-squared: 0.7389, Adjusted R-squared: 0.5431
## F-statistic: 3.773 on 3 and 4 DF, p-value: 0.1161
```

For our throwing data

[1] 22.500 5.875 16.625

```
ss <- function(x) sum(x^2)
sst <- ss(distance - mean(distance))
ssr <- ss(residuals(model))
ssx <- sst - ssr
c(sst, ssr, ssx)</pre>
```

Degrees of freedom

The amount of variation we expect to see depends on the number of independent parameters in the model. These are the *degrees of freedom*, and we need to normalize the SS by them.

For analyzing variation, the number of parameters does not include the intercept.

- ▶ For SS_{total} , DF = (# data points) 1
- ▶ For $SS_{\text{explained}}$, DF = # of parameters
- lacksquare For $SS_{
 m residual}$, DF = (# data points) (# parameters) 1

The *F*-statistic

The value of our model is explained by the ratio between the explained variance and the residual (unexplained) variance after adjusting for the DF.

$$F = \frac{SS_{\text{explained}}/\text{DF}(SS_{\text{explained}})}{SS_{\text{residual}}/\text{DF}(SS_{\text{residual}})}$$

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For our throwing example

$$F = \frac{16.625/3}{5.875/(8-3-1)} = 3.773$$

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How big should the F**-statistic be?** The F-statistic follows the F-distribution. We can use this distribution to convert the F-statistic into a p-value.

```
summary(model)
##
## Call:
## lm(formula = distance ~ hand + hat + boots)
##
## Residuals:
## 1 2 3 4 5 6
## -0.375 -1.125 0.625 0.875 1.125 0.375 -1.375 -0.125
##
## Coefficients:
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##
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Testing single factors

We previously compared the entire model against the residuals to see if the model added value. We can apply the same procedure to a single variable.

This is called the *analysis of variance*, or ANOVA.

ANOVA on handedness

Let's find the explained variance for a model with only handedness:

```
model_hand <- lm(distance ~ hand)
sst - ss(residuals(model_hand))</pre>
```

[1] 10.125

Now let's compare this to the residuals of the entire model:

ANOVA on handedness

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model_hand <- lm(distance ~ hand)
sst - ss(residuals(model_hand))</pre>
```

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Now let's compare this to the residuals of the entire model:

$$F = \frac{10.125/1}{5.875/(8-3-1)} = 6.894$$

ANOVA on a linear model

We can repeat this procedure for every variable, or we can use R's built-in ANOVA command.

```
anova(model)
## Analysis of Variance Table
##
## Response: distance
##
           Df Sum Sq Mean Sq F value Pr(>F)
## hand 1 10.125 10.1250 6.8936 0.05846 .
## hat 1 4.500 4.5000 3.0638 0.15495
## boots 1 2.000 2.0000 1.3617 0.30807
## Residuals 4 5.875 1.4688
## ---
## Signif. codes: 0 '***' 0.001 '**' 0.05 '.' 0.1 ' '
```

Conclusions

- p-values on effect sizes tell us if the effect size in nonzero.
- ▶ A significant effect size does not mean the effect matters.
- ANOVA can tell us which variables explain a significant fraction of the variance in our data.
- Significance is realtive to the unexplained variance in the model.