## New Predictors From Old

READING: 3.4

EXERCISES: NONE

ASSIGNED: HW 9

PRODUCER: DR. MARIO



#### Motivation

- The Set of Possible Predictors in a Model May Be Larger Than the Number of Variables in Our Data
- We May Want to Consider Interactions (Example: Plant Growth)
- We May Want to Consider Polynomial Terms to Capture Nonlinearity
- We May Want to Create Metrics Off Our Variables
  - Ratios, Differences, Lags, etc.

#### Regression Model With Interaction

Model:

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_1 X_2 + \epsilon$$

- Interaction Variable is a **Product** of Two Other Variables
- Interaction Variable Allows the Slope of Each of the Individual Variables to be Dependent on the Value of the Other Variable

$$Y = \beta_0 + (\beta_1 + \beta_3 X_2) X_1 + \beta_2 X_2 + \epsilon$$

$$Y = \beta_0 + \beta_1 X_1 + (\beta_2 + \beta_3 X_1) X_2 + \epsilon$$

#### Example: Predicting Weight of Perch

- Data Perch in Stat2Data Package
- Response: Weight
- Predictors: Length & Width
- Interaction: Length X Width

```
library (Stat2Data)
data ("Perch")
head (Perch)
```

```
## 1 104 5.9 8.8 1.4
## 2 105 32.0 14.7 2.0
## 3 106 40.0 16.0 2.4
## 4 107 51.5 17.2 2.6
## 5 108 70.0 18.5 2.9
## 6 109 100.0 19.2 3.3
```

#### Example: Predicting Weight of Perch

#### Model:

 $Weight = \beta_0 + \beta_1 Length + \beta_2 Width + \beta_3 (Length \times Width) + \epsilon$ 

• Code:

mod.interact = lm(Weight ~ Length \* Width, data=Perch)
summary(mod.interact)

• Output:

```
Coefficients:

Estimate Std. Error t value Pr(>|t|)

(Intercept) 113.9349 58.7844 1.938 0.058.

Length -3.4827 3.1521 -1.105 0.274

Width -94.6309 22.2954 -4.244 9.06e-05 ***

Length:Width 5.2412 0.4131 12.687 < 2e-16 ***

---

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1

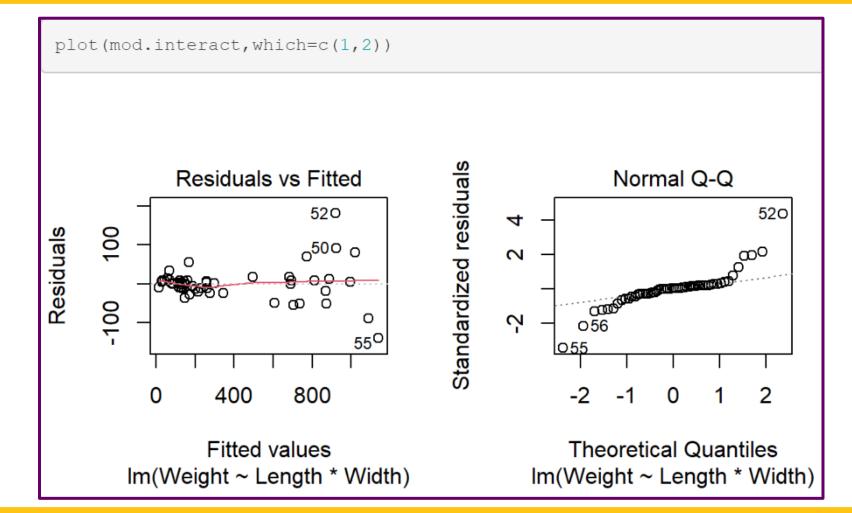
Residual standard error: 44.24 on 52 degrees of freedom

Multiple R-squared: 0.9847, Adjusted R-squared: 0.9838

F-statistic: 1115 on 3 and 52 DF, p-value: < 2.2e-16
```

### Example: Predicting Weight of Perch

Residuals:



#### Polynomial Regression Model

• Model: 
$$Y = \beta_0 + \beta_1 X^1 + \dots + \beta_k X^k + \epsilon$$

- We Need to Choose the Degree of the Polynomial k
- Polynomial Regression Models are More Difficult to Explain
- This Model Can Be Used to Estimate Nonlinear Relationships but It is Still a Linear Regression Model

#### Example: Predicting CO2

- Data CO2Germany in Stat2Data Package
- Predict CO2 Based Off Day
- Clear Relationship Seen

```
data("CO2Germany")
head(CO2Germany)

## CO2 Day
## 1 377.04 91
## 2 375.52 92
## 3 380.69 93
## 4 379.21 94
## 5 377.12 95
## 6 378.38 96
```

```
library (mosaic)
plot(CO2~Day, data = CO2Germany)
    380
         100
                  200
                          300
                   Day
```

#### Example: Predicting CO2

Model:

$$CO2 = \beta_0 + \beta_1 Day + \beta_2 Day^2 + \epsilon$$

• Code:

poly2 = lm(CO2~Day + I(Day^2), data=CO2Germany)
summary(poly2)

Output:

```
Coefficients:

Estimate Std. Error t value Pr(>|t|)

(Intercept) 4.150e+02 2.856e+00 145.28 <2e-16 ***

Day -4.760e-01 2.874e-02 -16.57 <2e-16 ***

I(Day^2) 1.158e-03 6.684e-05 17.32 <2e-16 ***

---

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1

Residual standard error: 4.619 on 234 degrees of freedom Multiple R-squared: 0.5734, Adjusted R-squared: 0.5698

F-statistic: 157.3 on 2 and 234 DF, p-value: < 2.2e-16
```

#### Example: Predicting CO2

- Fitted Model:  $\widehat{CO2} = 414.97 0.476Day + 0.00116Day^2 + \epsilon$
- Visualization of Model:

# Thank You

Make Reasonable Decisions

