

STAT011 Statistical Methods I

Lecture 25 Multiple Linear Regression

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Conducting simple linear regression analysis

- 1. State the statistical model for simple linear regression $y = \mu_v + \epsilon = \beta_0 + \beta_1 x + \epsilon$, where $\epsilon \sim N(0, \sigma)$
- 2. Do exploratory data analysis: scatterplot and correlation
- 3. Obtain the least-squares regression line and add the line to the scatterplot
- 4. Check assumptions 1. SRS 2. Linearity 3. Constant SD 4. Normaility If assumptions are violated, try transformation
- 5. Assess the fitting of the model: r^2
- 6. Make inferences:

Confidence intervals for both intercept and slope $b_0 \pm t^* SE_{b_0}$ and $b_1 \pm t^* SE_{b_1}$ Significance test for the slope $t = \frac{b_1 - 0}{SE_{b_1}} \stackrel{approx.}{\sim} t(n-2)$

7. Predictions:

Mean response and its confidence interval $\hat{\mu}_y \pm t^* SE_{\hat{\mu}_y}$ Individual response and its prediction interval $\hat{y} \pm t^* SE_{\hat{y}}$

Outline

Multiple linear regression

- Statistical model
- Model interpretation
- ▶ Inference for the slopes
- Model assessment

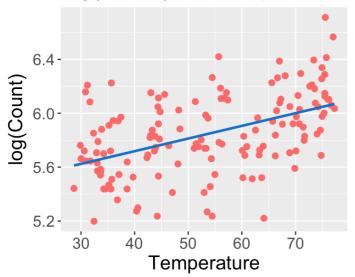
Data

head(UFO, 15)

##		Year	Month	Temperature	Precipitation	Count
##	1	2000	1	34.24	2.03	230
##	2	2000	2	40.59	2.01	200
##	3	2000	3	47.04	2.38	224
##	4	2000	4	53.51	2.27	194
##	5	2000	5	64.10	2.62	185
##	6	2000	6	69.87	3.49	268
##	7	2000	7	74.63	2.30	356
##	8	2000	8	74.78	1.92	295
##	9	2000	9	66.22	2.17	294
##	10	2000	10	55.73	2.21	325
##	11	2000	11	38.59	2.68	230
##	12	2000	12	28.68	1.65	231
##	13	2001	1	31.76	1.81	283
##	14	2001	2	34.62	2.14	230
##	15	2001	3	42.30	2.50	290

UFO and temperature

log(Count) vs. Temperature



- $\log(Count) = 5.34 + 0.01 \times Temperature$
- As *Temperature* increases one degree, *log(Count)* increases 0.01 unit.
- t test for the slope of *Temperature* has t = 6.55 and $P = 1.01 \times 10^{-9} << 0.05$. *Temperature* and log(Count) have a highly significant positive relationship.

```
m1 <- lm(log(Count) ~ Temperature, data=UFO)
summary(m1)</pre>
```

```
## Estimate Std. Error t value Pr(>|t|)
## (Intercept) 5.342374 0.080562 66.314 < 2e-16 ***
## Temperature 0.009403 0.001437 6.546 1.01e-09 ***
```

UFO and raining





We are all living in 2017 while this kid is living in 3017



5:40 AM - 3 Sep 2017

83,265 Retweets 204,588 Likes 🔞 🍨 🌑 🧗 🌑 🦠 🦫 🥐







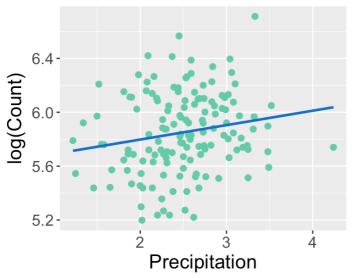






UFO and raining

log(Count) vs. Precipitation



- $\log(Count) = 5.58 + 0.11 \times Precipitation$
- As *Precipitation* increases 1 unit, *log(Count)* increases 0.11 unit.
- t test for the slope of *Precipitation* has t = 2.21 and P = 0.029 < 0.05. *Precipitation* and log(Count) have a significant positive relationship.

```
m2 <- lm(log(Count) ~ Precipitation, data=UFO)
summary(m2)</pre>
```

```
## Estimate Std. Error t value Pr(>|t|)
## (Intercept) 5.58322 0.12315 45.34 <2e-16 ***
## Precipitation 0.10709 0.04847 2.21 0.0287 *
```

UFO and raining

```
m1 <- lm(log(Count) ~ Temperature, data=UFO)</pre>
summary(m1)
##
             Estimate Std. Error t value Pr(>|t|)
## (Intercept) 5.342374 0.080562 66.314 < 2e-16 ***
## Temperature 0.009403 0.001437 6.546 1.01e-09 ***
                                                               r^2 = 0.2318
##
## Residual standard error: 0.2626 on 142 degrees of freedom
## Multiple R-squared: 0.2318, Adjusted R-squared: 0.2264
## F-statistic: 42.84 on 1 and 142 DF, p-value: 1.005e-09
m2 <- lm(log(Count) ~ Precipitation, data=UFO)</pre>
summary(m2)
##
                Estimate Std. Error t value Pr(>|t|)
## (Intercept) 5.58322
                           0.12315 45.34 <2e-16 ***
## Precipitation 0.10709 0.04847 2.21 0.0287 *
                                                               r^2 = 0.0332.
##
## Residual standard error: 0.2946 on 142 degrees of freedom
## Multiple R-squared: 0.03324, Adjusted R-squared: 0.02643
## F-statistic: 4.882 on 1 and 142 DF, p-value: 0.02874
```

Multiple Linear Regression Model

Denote log(Count) as y, Precipitation as x_1 and Temperature as x_2 .

$$y = \mu_y + \epsilon$$
Data = Fit + Residual

- $\mu_y = \beta_0 + \beta_1 x_1 + \beta_2 x_2$
- $\epsilon \sim N(0, \sigma)$

Statistical Model: $y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \epsilon$, where $\epsilon \sim N(0, \sigma)$

Parameters: β_0 , β_1 , β_2 , σ

Estimated regression line: $\hat{y} = b_0 + b_1 x_1 + b_2 x_2$

```
summary(m3 <- lm(log(Count) ~ Precipitation + Temperature, data=UFO))</pre>
## Call:
## lm(formula = log(Count) ~ Precipitation + Temperature, data = UFO)
##
                                                         b_0 = 5.43, b_1 = -0.05,
## Residuals:
##
           10 Median
                                                           b_2 = 0.01, \sigma = 0.26
       Min
                                   30
                                           Max
## -0.72722 -0.17891 -0.00509 0.19283 0.68442
                                                         Note: model estimates
##
                                                           and fitting stays the
## Coefficients:
##
                Estimate Std. Error t value Pr(>|t|)
                                                           same when
                            0.11260 48.199 < 2e-16 ***
## (Intercept) 5.42728
                                                           Temperature goes
## Precipitation -0.05451 0.05053 -1.079 0.283
                                                           before Precipitation in
## Temperature 0.01035 0.00168 6.157 7.29e-09 ***
## ---
                                                           the model.
## Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1
##
## Residual standard error: 0.2625 on 141 degrees of freedom
## Multiple R-squared: 0.2381, Adjusted R-squared: 0.2273
## F-statistic: 22.03 on 2 and 141 DF, p-value: 4.731e-09
```

summary(m3)

```
## Estimate Std. Error t value Pr(>|t|)
## (Intercept) 5.42728 0.11260 48.199 < 2e-16 ***
## Precipitation -0.05451 0.05053 -1.079 0.283
## Temperature 0.01035 0.00168 6.157 7.29e-09 ***
```

Estimated regression line:

```
log(Count) = 5.43 - 0.05 \times Precipitation + 0.01 \times Temperature
```

- As *Precipitation* increases one unit, log(*Count*) descreases 0.05 unit, given that *Temperature* is held constant.
 - When temperature stays the same: more rain \Rightarrow less UFO reports.
- As *Temperature* increases one unit, log(*Count*) increases 0.01 unit, given that *Precipitation* is held constant.
 - When precipitation stays the same: higher temperature \Rightarrow more UFO reports.

summary(m3)

```
## Estimate Std. Error t value Pr(>|t|)
## (Intercept) 5.42728 0.11260 48.199 < 2e-16 ***
## Precipitation -0.05451 0.05053 -1.079 0.283
## Temperature 0.01035 0.00168 6.157 7.29e-09 ***
```

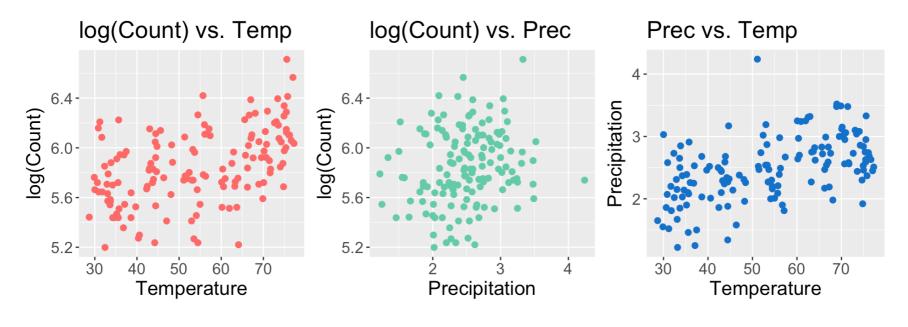
- ▶ Test the significance of *Precipitation* $H_0: \beta_1 = 0$ vs. $H_a: \beta_1 \neq 0$
 - t = -1.08, P = 0.28 > 0.05
 - Given that *Temperature* is held constant, the relationship between *Precipitation* and UFO count is negative but not significant.
- **Test the significance of** *Temperature* $H_0: \beta_2 = 0$ vs. $H_a: \beta_2 \neq 0$
 - $t = 6.16, P = 7.3 \times 10^{-9} < 0.05$
 - Given that *Precipitation* is held constant, the relationship between UFO count and *Temperature* is positive and highly significant.

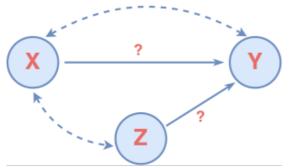
- Model 1: $log(Count) = 5.34 + 0.01 \times Temperature$
 - t = 6.55 and $P = 1.01 \times 10^{-9} << 0.05$
 - $r^2 = 0.2318$
- Model 2: $log(Count) = 5.58 + 0.11 \times Precipitation$
 - t = 2.21 and P = 0.029 < 0.05
 - $r^2 = 0.0332$
- Model 3: $log(Count) = 5.43 0.05 \times Precipitation + 0.01 \times Temperature$
 - t = -1.08, P = 0.28 > 0.05 for *Precipitation*
 - $t = 6.16, P = 7.3 \times 10^{-9} << 0.05 \text{ for Temperature}$
 - $r^2 = 0.2381$
- ▶ How do the relationships change when both *Precipitation* and *Temperature* are in the model?

Consider the t tests and r^2 values in Model 1 & 3, the relationship between *Temperature* and log(Count) stays similar with or without *Precipitation*.

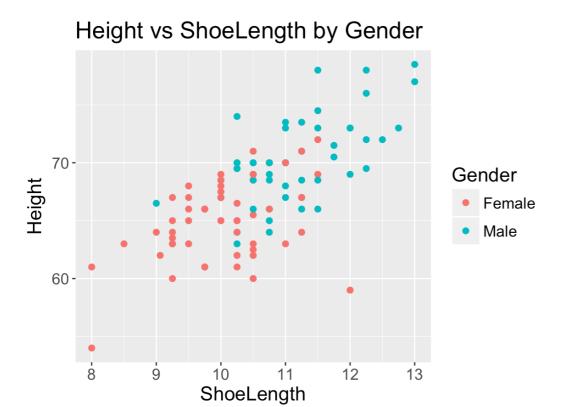
Consider the t tests and r^2 values in Model 2 & 3, the relationship between *Precipitation* and log(Count) changes dramatically when adding *Temperature* to the model, which

- reverses the direction of the relationship between *Precipitation* and *log(Count)* from positive to negative Simpson's paradox.
- explains 21% more variability in *log(Count)*.
- ▶ makes *Precipitation* no longer a significant predictor for *log(Count)*.





Temperature is a confounder in the relationship between *Precipitation* and log(Count). It affects the relationship so heavily because it is associated with *Precipitation* (r = 0.52).



Denote Height as y, ShoeLength as x_1 and Gender as x_2 .

Model: $y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \epsilon$, where $\epsilon \sim N(0, \sigma)$

Parameters: β_0 , β_1 , β_2 , σ

- λ_1 is quantitative
- x_2 is categorical, $x_2 = 1$ for male and 0 for female.

Height, shoe length

```
summary(m4 <- lm(Height ~ ShoeLength, data=Survey))</pre>
## Call:
## lm(formula = Height ~ ShoeLength, data = Survey)
##
## Residuals:
## Min 10 Median 30
                                         Max
## -12.7443 -1.8357 0.8686 1.9295 7.7253
##
## Coefficients:
##
              Estimate Std. Error t value Pr(>|t|)
## (Intercept) 36.4759 3.3775 10.800 < 2e-16 ***
## ShoeLength 2.9390 0.3182 9.236 3.69e-15 ***
## ---
## Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 3.251 on 103 degrees of freedom
## Multiple R-squared: 0.453, Adjusted R-squared: 0.4477
## F-statistic: 85.31 on 1 and 103 DF, p-value: 3.688e-15
```

```
summary(m5 <- lm(Height ~ ShoeLength + Gender, data=Survey))</pre>
## Call:
## lm(formula = Height ~ ShoeLength + Gender, data = Survey)
##
## Residuals:
## Min 10 Median 30
                                       Max
## -10.3595 -1.9134 0.2278 2.0169 7.0396
##
## Coefficients:
##
              Estimate Std. Error t value Pr(>|t|)
## (Intercept) 43.1009 3.6403 11.840 < 2e-16 ***
## ShoeLength 2.1882 0.3606 6.068 2.22e-08 ***
## GenderMale 2.6950 0.7192 3.747 0.000297 ***
## ---
## Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 3.062 on 102 degrees of freedom
## Multiple R-squared: 0.5192, Adjusted R-squared: 0.5098
## F-statistic: 55.08 on 2 and 102 DF, p-value: < 2.2e-16
```

summary(m5)

```
## Estimate Std. Error t value Pr(>|t|)
## (Intercept) 43.1009 3.6403 11.840 < 2e-16 ***
## ShoeLength 2.1882 0.3606 6.068 2.22e-08 ***
## GenderMale 2.6950 0.7192 3.747 0.000297 ***
```

$Height = 43.1 + 2.2 \times ShoeLength + 2.7 \times Gender$

- As *ShoeLength* increases 1 inch, *Height* increases 2.2 inches, given that *Gender* is held constant.
 - When *Gender* stays the same: longer shoe length \Rightarrow larger height value.
- As *Gender* increases one unit (from *Female* to *Male*), *Height* increases 2.7 inches, given that *ShoeLength* is held constant.
 - When *ShoeLength* stays the same: males are 2.7 inches taller than females on average.

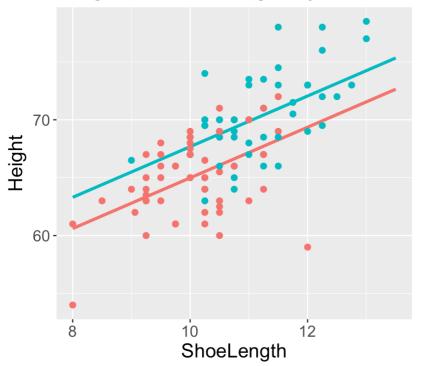
summary(m5)

```
## Estimate Std. Error t value Pr(>|t|)
## (Intercept) 43.1009 3.6403 11.840 < 2e-16 ***
## ShoeLength 2.1882 0.3606 6.068 2.22e-08 ***
## GenderMale 2.6950 0.7192 3.747 0.000297 ***
```

$\widehat{Height} = 43.1 + 2.2 \times ShoeLength + 2.7 \times Gender$

- For females, Gender = 0, $\widehat{Height} = 43.1 + 2.2 \times ShoeLength$
- For males, Gender = 1, $\widehat{Height} = 43.1 + 2.2 \times ShoeLength + 2.7 = 45.8 + 2.2 \times ShoeLength$

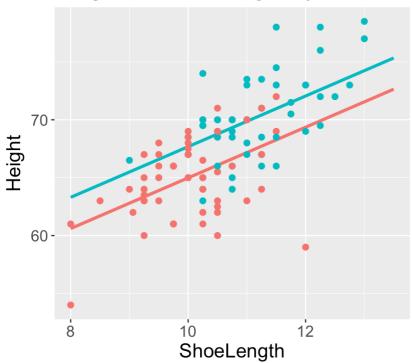
Height vs ShoeLength by Gender



$$\widehat{Height} = 43.1 + 2.2 \times ShoeLength + 2.7 \times Gender$$

- Gender
 Female
 Male
- $b_1 = 2.2$ measures the rate of change in *Height* as *ShoeLength* changes for both male and female students.
 - b₂ = 2.7 measures the difference in Height between Gender=1 (male) and Gender=0 (female) given the same ShoeLength.

Height vs ShoeLength by Gender



$$\widehat{Height} = 43.1 + 2.2 \times ShoeLength + 2.7 \times Gender$$

- Gender
 Female
 Male
- Model without *Gender: ShoeLength* and *Height* have a significant relationship; $r^2 = 0.453$.
- Model with *Gender*: Both *Gender* and *ShoeLength* have significant relationships with *Height*; $r^2 = 0.519$.
- Adding *Gender* to the model improves model fitting.

For multiple linear regression model with k explanatory variables,

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \dots + \beta_k x_k + \epsilon$$

where $\epsilon \sim N(0, \sigma)$, how do we know the significance/effectiveness of the whole model?

- F test with degrees of freedom k and n k 1.
 - $P \le 0.05$, **the model** is significant at level 0.05.
 - P > 0.05, **the model** is not significant at level 0.05 all explanatory variables are not statistically associated with the response variable.
- r^2 : fraction of variability in the response variable explained by **all the explanatory variables** together.

```
summary(m3)
```

```
## Call:
## lm(formula = log(Count) ~ Precipitation + Temperature, data = UFO)
##
## Residuals:
                                                          F = 22.03
## Min 10 Median 30
                                         Max
                                                            P = 4.7 \times 10^{-9}
## -0.72722 -0.17891 -0.00509 0.19283 0.68442
##
                                                          r^2 = 0.2381
## Coefficients:
##
                Estimate Std. Error t value Pr(>|t|)
## (Intercept) 5.42728 0.11260 48.199 < 2e-16 ***
## Precipitation -0.05451 0.05053 -1.079 0.283
## Temperature 0.01035 0.00168 6.157 7.29e-09 ***
## ---
## Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.2625 on 141 degrees of freedom
## Multiple R-squared: 0.2381, Adjusted R-squared: 0.2273
## F-statistic: 22.03 on 2 and 141 DF, p-value: 4.731e-09
```

```
summary(m5)
```

```
## Call:
## lm(formula = Height ~ ShoeLength + Gender, data = Survey)
##
## Residuals:
                                                         F = 55.8
## Min 10 Median 30
                                        Max
                                                           P < 2.2 \times 10^{-16}
## -10.3595 -1.9134 0.2278 2.0169
                                     7.0396
##
                                                         r^2 = 0.5192
## Coefficients:
##
             Estimate Std. Error t value Pr(>|t|)
## (Intercept) 43.1009
                         3.6403 11.840 < 2e-16 ***
## ShoeLength 2.1882 0.3606 6.068 2.22e-08 ***
## GenderMale 2.6950 0.7192 3.747 0.000297 ***
## ---
## Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 3.062 on 102 degrees of freedom
## Multiple R-squared: 0.5192, Adjusted R-squared: 0.5098
## F-statistic: 55.08 on 2 and 102 DF, p-value: < 2.2e-16
```

Summary

Multiple linear regression

- Statistical model $y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \dots + \beta_k x_k + \epsilon$ where $\epsilon \sim N(0, \sigma)$
- ▶ Model interpretation given that xxx is held constant
- ▶ Inference for the slopes
- Model assessment F test and r^2

Final Exam

Final Exam

- ▶ Tuesday 5/14 9am-12pm **SCI 101**
- ▶ Practice problems available on Thursday 5/2

Important dates

- Office hours
 - Tuesday 4/30 (today), 2:40 4:30pm
 - Thursday 5/9, 9:30 11:30am
- Muses sessions
 - Wednesday 5/1, 8 10pm
 - Monday 5/13, 7 9pm
- Stat Clinics
 - Friday 5/10 & Saturday 5/11, 3 6pm
 - Sunday 5/12, 6 9pm