

Multiple Linear Regression

Model Assessment

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Announcements

- Lab 05 due Tuesday at 11:59p
- HW 03 due Wednesday at 11:59p
- [Reading 06](#) for Wednesday

R packages

```
library(tidyverse)
library(knitr)
library(broom)
library(Sleuth3) # ex0824 data
library(cowplot) # use plot_grid function
```

Log Transformations

Respiratory Rate vs. Age

- A high respiratory rate can potentially indicate a respiratory infection in children. In order to determine what indicates a "high" rate, we first want to understand the relationship between a child's age and their respiratory rate.
- The data contain the respiratory rate for 618 children ages 15 days to 3 years.
- **Variables:**
 - **Age:** age in months
 - **Rate:** respiratory rate (breaths per minute)

Log transformation on y

```
log_model <- lm(log_rate ~ Age, data = respiratory)
kable(tidy(log_model, conf.int = TRUE), format = "markdown", digits = 3)
```

term	estimate	std.error	statistic	p.value	conf.low	conf.high
(Intercept)	3.845	0.013	304.500	0	3.82	3.870
Age	-0.019	0.001	-25.839	0	-0.02	-0.018

$$\log \hat{\text{rate}} = 3.845 - 0.019 \times \text{Age}$$

- **Slope:** For every one month increase in Age, we expect the median respiratory rate to be multiplied by a factor of $\exp\{-0.019\} = 1.019$ breaths per minute.
- **Intercept:** The expected respiratory rate for a child who is 0 months old (a newborn) is $\exp\{3.845\} = 46.76$ beats per minute.

Confidence interval for β_j

- The confidence interval for the coefficient of x describing its relationship with $\log(y)$ is

$$\hat{\beta}_j \pm t^* SE(\hat{\beta}_j)$$

- The confidence interval for the coefficient of x describing its relationship with y is

$$\exp \left\{ \hat{\beta}_j \pm t^* SE(\hat{\beta}_j) \right\}$$

Coefficient of Age

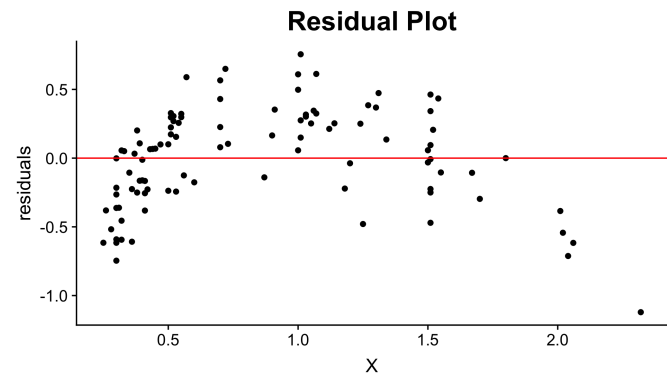
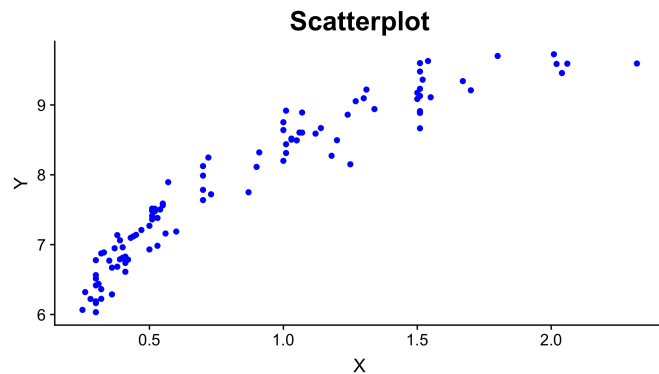
term	estimate	std.error	statistic	p.value	conf.low	conf.high
(Intercept)	3.845	0.013	304.500	0	3.82	3.870
Age	-0.019	0.001	-25.839	0	-0.02	-0.018

The 95% confidence interval for the coefficient of Age in terms of Rate:

$$[\exp\{-0.02\}, \exp\{-0.018\}] = [0.981, 0.982]$$

Interpretation: We are 95% confident that for each additional month in age, we can expect the median respiratory rate to be multiplied by a factor of 0.981 to 0.982.

Log Transformation on x



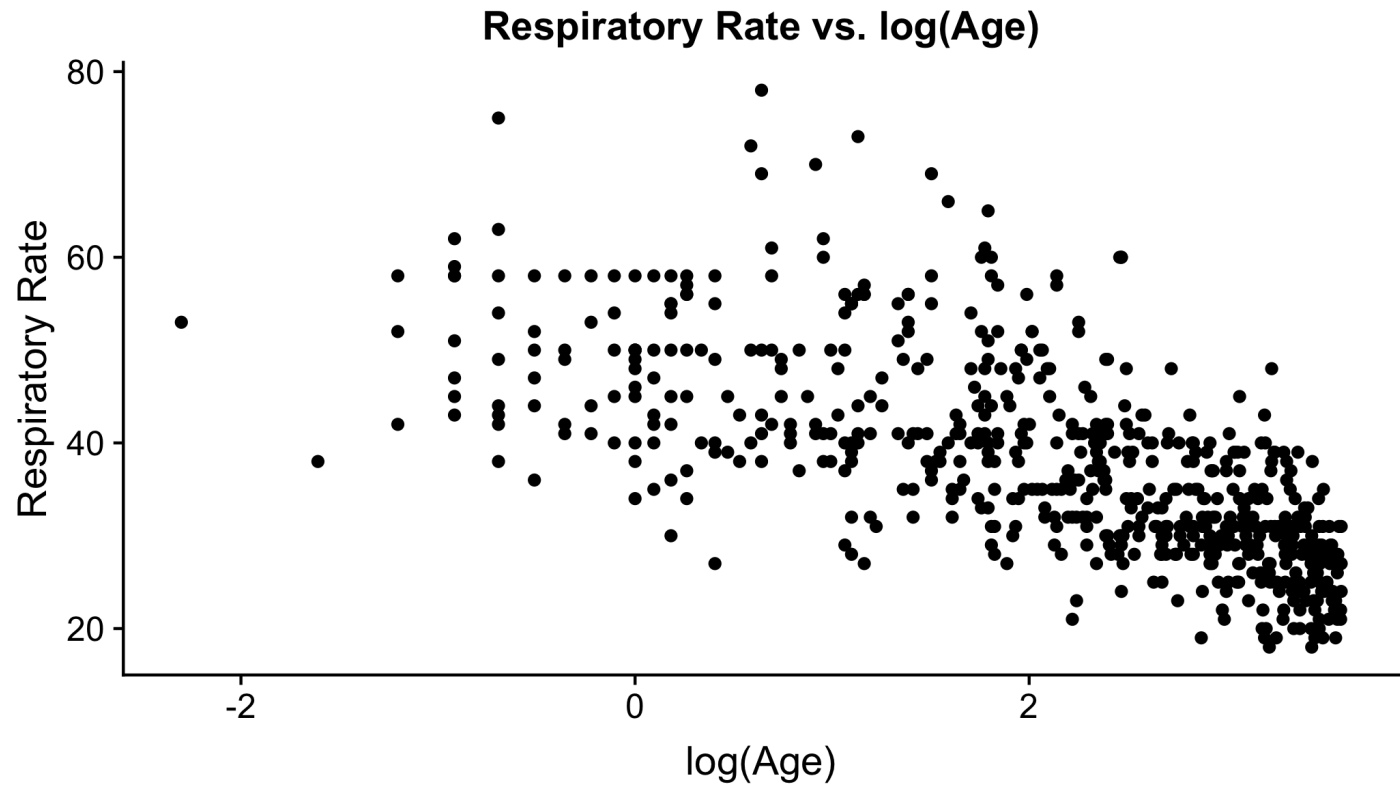
- Try a transformation on X if the scatterplot shows some curvature but the variance is constant for all values of X

Model with Transformation on x

$$y = \beta_0 + \beta_1 \log(x)$$

- **Intercept:** When $\log(x) = 0$, ($x = 1$), y is expected to be β_0 (i.e. the mean of y is β_0)
- **Slope:** When x is multiplied by a factor of \mathbf{C} , y is expected to change by $\beta_1 \log(\mathbf{C})$ units, i.e. the mean of y changes by $\beta_1 \log(\mathbf{C})$
 - *Example:* when x is multiplied by a factor of 2, y is expected to change by $\beta_1 \log(2)$ units

Rate vs. $\log(\text{Age})$



Rate vs. Age

term	estimate	std.error	statistic	p.value	conf.low	conf.high
(Intercept)	50.134533	0.6319775	79.32961	0	48.893441	51.375625
log.age	-5.982434	0.2626097	-22.78070	0	-6.498153	-5.466715

1. Write the equation for the model of y regressed on $\log(x)$.
2. Interpret the intercept in the context of the problem.
3. Interpret the slope in terms of how the mean respiratory rate changes when a child's age doubles.
4. Suppose a doctor has a patient who is currently 3 years old. Will this model provide a reliable prediction of the child's respiratory rate when her age doubles? Why or why not?

See [Log Transformations in Linear Regression](#) for more details about interpreting regression models with log-transformed variables.

Model Assessment & Selection

Restaurant tips

What affects the amount customers tip at a restaurant?

- Response:

- **Tip**: amount of the tip

- Predictors:

- **Party**: number of people in the party
 - **Meal**: time of day (Lunch, Dinner, Late Night)
 - **Age**: age category of person paying the bill (Yadult, Middle, SenCit)

```
tips <- read_csv("data/tip-data.csv") %>%  
  filter(!is.na(Party))
```


ANOVA table for regression

We can use the Analysis of Variance (ANOVA) table to decompose the variability in our response variable

	Sum of Squares	DF	Mean Square	F-Stat	p-value
Regression (Model)	$\sum_{i=1}^n (\hat{y}_i - \bar{y})^2$	p	$\frac{MSS}{p}$	$\frac{MMS}{RMS}$	$P(F > \text{F-Stat})$
Residual	$\sum_{i=1}^n (y_i - \hat{y}_i)^2$	$n - p - 1$	$\frac{RSS}{n - p - 1}$		
Total	$\sum_{i=1}^n (y_i - \bar{y})^2$	$n - 1$	$\frac{TSS}{n - 1}$		

The estimate of the regression variance, $\hat{\sigma}^2 = RMS$

R^2

- **Recall:** R^2 is the proportion of the variation in the response variable explained by the regression model
- R^2 will always increase as we add more variables to the model
 - If we add enough variables, we can always achieve $R^2 = 100\%$
- If we only use R^2 to choose a best fit model, we will be prone to choose the model with the most predictor variables

Adjusted R^2

- **Adjusted R^2** : a version of R^2 that penalizes for unnecessary predictor variables
- Similar to R^2 , it measures the proportion of variation in the response that is explained by the regression model
- Differs from R^2 by using the mean squares rather than sums of squares and therefore adjusting for the number of predictor variables

R^2 and Adjusted R^2

$$R^2 = \frac{\text{Total Sum of Squares} - \text{Residual Sum of Squares}}{\text{Total Sum of Squares}}$$

$$\text{Adj. } R^2 = \frac{\text{Total Mean Square} - \text{Residual Mean Square}}{\text{Total Mean Square}}$$

- $\text{Adj. } R^2$ can be used as a quick assessment to compare the fit of multiple models; however, it should not be the only assessment!
- Use R^2 when describing the relationship between the response and predictor variables

Restaurant tips: model

```
model1 <- lm(Tip ~ Party + Meal + Age , data = tips)
kable(tidy(model1),format="html",digits=3)
```

term	estimate	std.error	statistic	p.value
(Intercept)	1.254	0.394	3.182	0.002
Party	1.808	0.121	14.909	0.000
MealLate Night	-1.632	0.407	-4.013	0.000
MealLunch	-0.612	0.402	-1.523	0.130
AgeSenCit	0.390	0.394	0.990	0.324
AgeYadult	-0.505	0.412	-1.227	0.222

Restaurant tips: ANOVA

■ R output

	Df	Sum Sq	Mean Sq	F value	Pr(>F)
Party	1	1188.636	1188.636	311.002	0.000
Meal	2	88.460	44.230	11.573	0.000
Age	2	13.032	6.516	1.705	0.185
Residuals	163	622.979	3.822	NA	NA

■ ANOVA table

	Sum of Squares	DF	Mean Square	F-Stat	p-value
Regression (Model)	1290.12829	5	258.025658	67.5113618	0
Residual	622.97932	163	3.821959		
Total	1913.10761	168			

Calculating R^2 and Adj R^2

	Sum of Squares	DF	Mean Square	F-Stat	p-value
Regression (Model)	1290.12829	5	258.025658	67.5113618	0
Residual	622.97932	163	3.821959		
Total	1913.10761	168			

```
#r-squared
```

```
tss <- 1188.63588 + 88.46005 + 13.03236 + 622.97932
```

```
rss <- 622.97932
```

```
(r_sq <- (tss - rss)/tss)
```

```
## [1] 0.6743626
```

```
#adj r-squared
```

```
tms <- tss/(nrow(tips)-1)
```

```
rms <- 3.821959
```

```
(adj_r_sq <- (tms - rms)/tms)
```

```
## [1] 0.6643738
```

Restaurant tips: R^2 and Adj. R^2

```
glance(model1)
```

```
## # A tibble: 1 x 11
##   r.squared adj.r.squared sigma statistic  p.value    df logLik   AIC    <d
##   <dbl>      <dbl> <dbl>    <dbl>    <dbl> <int>  <dbl> <dbl> <d
## 1    0.674      0.664   1.95     67.5 6.14e-38     6  -350.  714.  7
## # ... with 2 more variables: deviance <dbl>, df.residual <int>
```

- Close values of R^2 and Adjusted R^2 indicate that the variables in the model are significant in understanding variation in tips

ANOVA F Test

- Using the ANOVA table, we can test whether any variable in the model is a significant predictor of the response. We conduct this test using the following hypotheses:

$$H_0 : \beta_1 = \beta_2 = \dots = \beta_p = 0$$

$$H_a : \text{at least one } \beta_j \text{ is not equal to } 0$$

- The statistic for this test is the F test statistic in the ANOVA table
- We calculate the p-value using an F distribution with p and $(n - p - 1)$ degrees of freedom

ANOVA F Test in R

```
model0 <- lm(Tip ~ 1, data=tips)
```

```
model1 <- lm(Tip ~ Party + Meal + Age , data = tips)
```

```
kable(anova(model0,model1),format="html")
```

Res.Df	RSS	Df	Sum of Sq	F	Pr(>F)
168	1913.1076	NA	NA	NA	NA
163	622.9793	5	1290.128	67.51136	0

At least one coefficient is non-zero, i.e. at least one predictor in the model is significant

Testing subset of coefficients

- Sometimes we want to test whether a subset of coefficients are all equal to 0
- This is often the case when we want test
 - whether a categorical variable with k levels is a significant predictor of the response
 - whether the interaction between a categorical and quantitative variable is significant
- To do so, we will use the **Nested F Test**

Nested F Test

- Suppose we have a full and reduced model:

$$\text{Full : } y = \beta_0 + \beta_1 x_1 + \cdots + \beta_q x_q + \beta_{q+1} x_{q+1} + \cdots + \beta_p x_p$$

$$\text{Red : } y = \beta_0 + \beta_1 x_1 + \cdots + \beta_q x_q$$

- We want to test whether any of the variables $x_{q+1}, x_{q+2}, \dots, x_p$ are significant predictors. To do so, we will test the hypothesis:

$$H_0 : \beta_{q+1} = \beta_{q+2} = \cdots = \beta_p = 0$$

$$H_a : \text{at least one } \beta_j \text{ is not equal to } 0$$

Nested F Test

- The test statistic for this test is

$$F = \frac{(RSS_{reduced} - RSS_{full}) / (p_{full} - p_{reduced})}{RSS_{full} / (n - p_{full} - 1)}$$

- Calculate the p-value using the F distribution with $(p_{full} - p_{reduced})$ and $(n - p_{full} - 1)$ degrees of freedom

Is Meal a significant predictor of tips?

term	estimate	std.error	statistic	p.value
(Intercept)	1.254	0.394	3.182	0.002
Party	1.808	0.121	14.909	0.000
AgeSenCit	0.390	0.394	0.990	0.324
AgeYadult	-0.505	0.412	-1.227	0.222
MealLate Night	-1.632	0.407	-4.013	0.000
MealLunch	-0.612	0.402	-1.523	0.130

Tips data: Nested F Test

$$H_0 : \beta_{latenight} = \beta_{lunch} = 0$$

$$H_a : \text{at least one } \beta_j \text{ is not equal to 0}$$

```
reduced <- lm(Tip ~ Party + Age, data = tips)
```

```
full <- lm(Tip ~ Party + Age + Meal, data = tips)
```

```
kable(anova(full,reduced),format="html")
```

Res.Df	RSS	Df	Sum of Sq	F	Pr(>F)
163	622.9793	NA	NA	NA	NA
165	686.4439	-2	-63.46457	8.302623	0.0003684

At least one coefficient associated with **Meal** is not zero. Therefore, **Meal** is a significant predictor of **Tips**.

Why is it not good practice to use the individual p-values to determine a categorical variable with $k > 2$ levels) is significant?
Hint: What does it actually mean if none of the $k - 1$ p-values are significant?

Practice with Interactions

term	estimate	std.error	statistic	p.value
(Intercept)	1.2764989	0.4910882	2.5993270	0.0102086
Party	1.7947980	0.1715003	10.4652753	0.0000000
AgeSenCit	0.4007889	0.3969295	1.0097230	0.3141431
AgeYadult	-0.4701634	0.4197146	-1.1201978	0.2642977
MealLate Night	-1.8454674	0.7089728	-2.6030159	0.0101039
MealLunch	-0.4608832	0.8651044	-0.5327487	0.5949421
Party:MealLate Night	0.1108600	0.2846584	0.3894491	0.6974586
Party:MealLunch	-0.0500822	0.2825586	-0.1772455	0.8595384

1. Write the general form of the model.
2. Write the model for `Meal == "Late Night"`.
3. How does the mean change when `Meal == "Late Night"`?
4. How does the slope of `Party` change when `Meal == "Late Night"`?

Nested F test for interactions

Is the interaction between **Party** and **Meal** significant?

```
reduced <- lm(Tip ~ Party + Age + Meal, data = tips)
```

```
full <- lm(Tip ~ Party + Age + Meal + Meal*Party, data = tips)
```

```
kable(anova(full, reduced), format="html")
```

Res.Df	RSS	Df	Sum of Sq	F	Pr(>F)
161	621.9651	NA	NA	NA	NA
163	622.9793	-2	-1.014261	0.1312743	0.877071