# Multiple Linear Regression

### Interactions & Transformations

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#### **Announcements**

- HW 02 due TODAY at 11:59p
- Team Feedback #1 due TODAY at 11:59p
  - Please provide honest and constructive feedback. This team feedback will be graded for completion.
- Reading 05 for Monday
- HW 03 due Wednesday, 10/1 at 11:59p



### Today's Agenda

- Categorical Predictors with K > 2 categories
- Interactions
- Log Transformations



# R packages

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



# **Categorical Predictors**



### Starting wages data

#### **Explanatory**

- Educ: years of Education
- **Exper:** months of previous work Experience (before hire at bank)
- Female: 1 if female, 0 if male
- **Senior**: months worked at bank since hire
- **Age:** Age in months

#### Response

■ **Bsal:** annual salary at time of hire



### Starting wages: Education categorical

term	estimate	std.error	statistic	p.value
(Intercept)	5637.224	183.730	30.682	0.000
SeniorCent	-21.710	5.320	-4.081	0.000
AgeCent	0.645	0.735	0.877	0.383
ExperCent	0.339	1.069	0.317	0.752
EducCat10	-665.340	535.844	-1.242	0.218
EducCat12	182.567	169.589	1.077	0.285
EducCat15	540.858	187.389	2.886	0.005
EducCat16	766.746	298.375	2.570	0.012
Female1	-756.105	129.586	-5.835	0.000



#### **EducCat Behind the scenes**

- The categorical variable EducCat has 5 levels, so there are 4 indicator variables for Education in the model.
- For a given observation, a value is assigned for each of thr 4 indicator variables based on the following scheme:

	Indicator Variables					
Observations	EducCat10	EducCat12	EducCat15	EducCat16		
Education = 8 (baseline)	0	0	0	0		
Education = 10	1	0	0	0		
Education = 12	0	1	0	0		
Education = 15	0	0	1	0		
Education = 16	0	0	0	1		



### **Application Exercise**

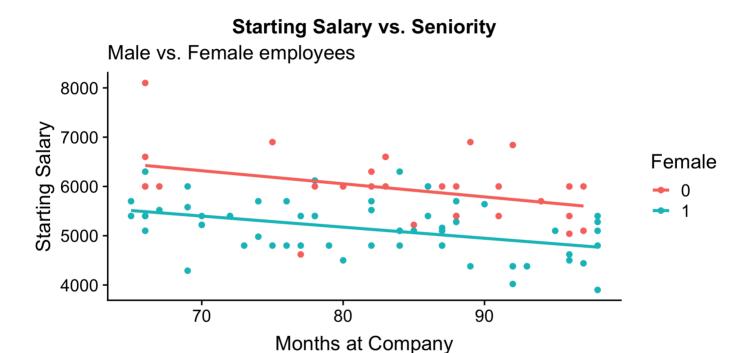
- Go to the **Wages** application exercise in RStudio Cloud.
- Fit a regression model with Education treated as a categorical variable.
  - What is the baseline for Education?
  - Interpret the coefficient for EducCat16.
  - What is your conclusion from the p-value of EducCat16?
  - Write the model equation for those with 8 years of education.
  - Write the model equation for those with 16 years of education.



## **Interactions**



### Checking for interactions



Do you think there is a significant interaction effect between Female and Senior? Why or why not?



### Checking for interactions

100



200

Months at Company

300

400

Do you think there is a significant interaction effect between Female and Exper? Why or why not?



#### Model with interactions

```
int_model <- lm(Bsal ~SeniorCent + AgeCent + ExperCent + EducCat +
kable(tidy(int_model), format = "markdown", digits = 3)</pre>
```

term	estimate	std.error	statistic	p.value
(Intercept)	5641.379	184.550	30.568	0.000
SeniorCent	-21.406	5.363	-3.991	0.000
AgeCent	0.583	0.745	0.783	0.436
ExperCent	-0.008	1.215	-0.007	0.995
EducCat10	-648.335	538.592	-1.204	0.232
EducCat12	180.877	170.251	1.062	0.291
EducCat15	531.351	188.744	2.815	0.006
EducCat16	738.594	303.058	2.437	0.017
Female1	-754.483	130.102	-5.799	0.000
ExperCent:Female1	0.741	1.219	0.608	0.545



# **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:

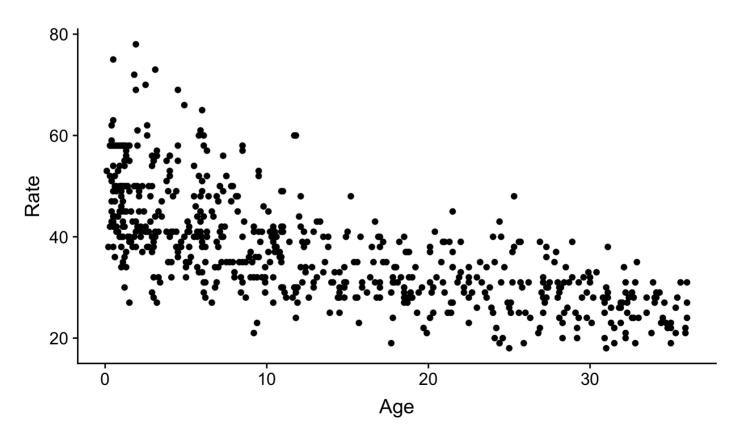
■ Age: age in months

Rate: respiratory rate (breaths per minute)



# Rate vs. Age

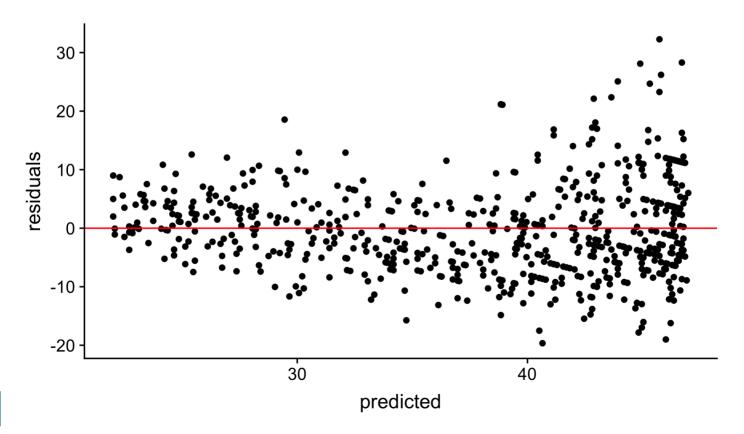
```
respiratory <- ex0824
ggplot(data=respiratory, aes(x=Age, y=Rate)) +
  geom_point() +
  labs("Respiratory Rate vs. Age")</pre>
```





# Rate vs. Age

term	estimate	std.error	statistic	p.value	conf.low	conf.high
(Intercept)	47.052	0.504	93.317	0	46.062	48.042
Age	-0.696	0.029	-23.684	0	-0.753	-0.638





# Log transformations



### Need to transform *y*

- Typically, a "fan-shaped" residual plot indicates the need for a transformation of the response variable y
  - log(y): Easiest to interpret
- When building a model:
  - Choose a transformation and build the model on the transformed data
  - Reassess the residual plots
  - If the residuals plots did not sufficiently improve, try a new transformation!



### Log transformation on *y*

- Use when the residual plot shows "fan-shaped" pattern
- If we apply a log transformation to the response variable, we want to estimate the parameters for the model...

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

• We want to interpret the model in terms of y not log(y), so we write all interpretations in terms of

$$y = \exp{\{\beta_0 + \beta_1 x\}} = \exp{\{\beta_0\}} \exp{\{\beta_1 x\}}$$



### Mean and median of log(y)

- Recall that  $y = \beta_0 + \beta_1 x_i$  is the **mean** value of y at the given value  $x_i$ . This doesn't hold when we log-transform y
- The mean of the logged values is **not** equal to the log of the mean value. Therefore at a given value of *x*

$$\exp\{Mean(\log(y))\} \neq Mean(y)$$

$$\Rightarrow \exp{\{\beta_0 + \beta_1 x\}} \neq \text{Mean}(y)$$



## Mean and median of log(y)

■ However, the median of the logged values **is** equal to the log of the median value. Therefore,

$$\exp{\text{Median}(\log(y))} = \text{Median}(y)$$

• If the distribution of log(y) is symmetric about the regression line, for a given value  $x_i$ ,

$$Median(log(y)) = Mean(log(y))$$



### Interpretation with log-transformed *y*

• Given the previous facts, if  $log(y) = \beta_0 + \beta_1 x$ , then

$$Median(y) = \exp{\{\beta_0\}} \exp{\{\beta_1 x\}}$$

- Intercept: When x = 0, the median of y is expected to be  $\exp\{\beta_0\}$
- Slope: For every one unit increase in x, the median of y is expected to multiply by a factor of  $\exp\{\beta_1\}$



### log(Rate) vs. Age

respiratory <- respiratory %>% mutate(log\_rate = log(Rate))

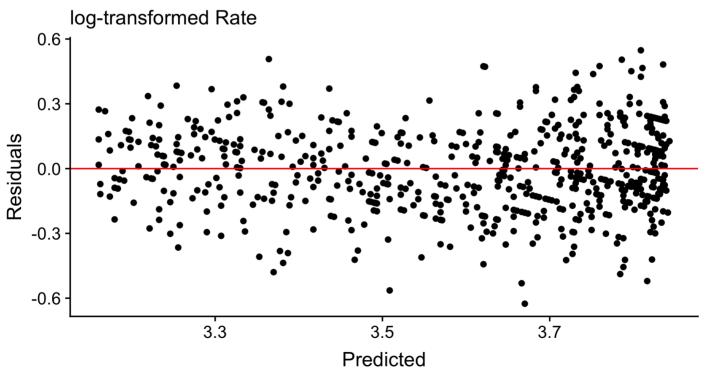




### log(Rate) vs. Age

log\_model <- lm(log\_rate ~ Age, data = respiratory)</pre>

#### Residuals vs. Predicted





### log(Rate) vs. Age

kable(tidy(log\_model, conf.int=TRUE),format="html", 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

- 1. Write the model in terms of log(rate).
- 2. Write the model in terms of *rate*. Interpret the slope and intercept.



## Confidence interval for $\beta_j$

■ 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

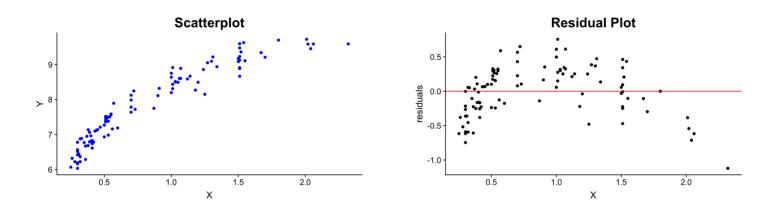
kable(tidy(log\_model, conf.int=TRUE),format="html", digits=3)

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

Interpret the 95% confidence interval for the coefficient of Age in terms of *rate*.



### Log Transformation on *x*



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



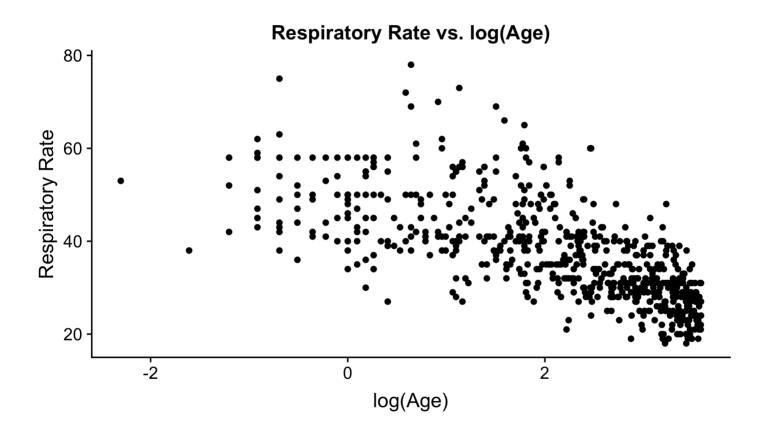
#### Model with Transformation on x

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

- Intercept: When  $\log(x) = 0$ , (x = 1), y is expected to be  $\beta_0$  (i.e. the mean of y is  $\beta_0$ )
- Slope: When x is multiplied by a factor of  $\mathbb{C}$ , y is expected to change by  $\beta_1 \log(\mathbb{C})$  units, i.e. the mean of y changes by  $\beta_1 \log(\mathbb{C})$ 
  - *Example*: when x is multiplied by a factor of 2, y is expected to change by  $\beta_1 \log(2)$  units



## Rate vs. log(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 <u>Log Transformations in Linear Regression</u> for more details about interpreting regression models with log-transformed variables.



### **Before Next Class**

■ Reading 05 for Monday

