# Expository Data Analysis in R

Regressions

Day 1



# When to use Regression Analysis in Economics

- Trying to identify causation
- Correlation vs. causation
  - ► Height vs. Weight
  - Get taller gain weight!
  - Spurious correlations

## Regression Analysis More Formally Defined

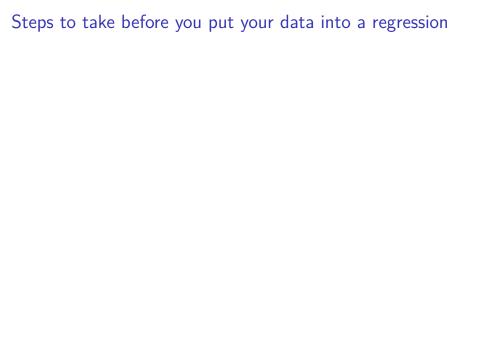
- ▶ Regression analysis is used to describe the relationship between:
  - ▶ A single response variable Y and
  - ▶ One or more predictor variables  $X_1$ ,  $X_2$ ,  $X_3$ , ...,  $X_n$
- ▶ What conditions must the response variable meet for OLS?

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- ▶ What conditions must the predictor variables meet?
  - None! These variables can be continuous, discrete, or categorical



## Steps to take before you put your data into a regression

- Check for:
  - Missing values
  - Outliers
  - Asymmetric distributions
  - Clustering of values
  - Unexpected patterns
- Numerical Summaries
  - Mean, min, max, variance, etc.
  - Correlations
- Graphical Summaries
  - Scatter plots
  - Histograms
  - Box plots

# ACS/Census Data from IPUMS

- ► IPUMS is a great resource!
- Let's check out how you can create a sample of data to download

## ACS/Census Data

- ▶ Please change the code in your regressions\_lecture. R file so that you can read in the IPUMS data file a with this lecture.
- ► Also be sure to load the appropriate packages (dplyr, ggplot2)
- ▶ What variables do we have in our data? What are the variable classes in the data?
- Run the summary function on the dataset. What do we learn?
- Check out the code book. What variables are we going to have to re-code?

## ACS/Census Data

The American Community Survey. . . is a survey!

# Survey Data

Why do we weight survey data?

### Survey Data

Why do we weight survey data? To make statistics computed from the data more representative of the population.

 Design Weight - compensate for over- or under-sampling of specific cases

### Example?

 Post-Stratification or Non-response Weight - compensate for that fact that persons with certain characteristics are not as likely to respond to the survey.

### Example?

### Survey Data

- Weights primarily adjust means and proportions.
- May adversely affect inferential data and standard errors.
- Weights almost always increase the standard errors of your estimates.
- Introduce instability into your data.
- Very large weights (or very small ones) can also introduce instabilities (fivethirtyeight).

### Recoding Variables

▶ How should we re-code the variable EDUC to transform the education variable from a categorical variable to a continuous variable?

## Recoding Variables

- ► NA N/A or no schooling
- 5 Nursery school to grade 4
- ▶ 9 Grade 5, 6, 7, or 8
- ▶ 10 Grade 9
- ▶ 11 Grade 10
- ▶ 12 Grade 11
- ▶ 13 Grade 12
- ▶ 14 1 year of college
- ▶ 15 2 years of college
- ► 16 3 years of college
- ▶ 17 4 years of college
- 17 4 years of college
- ▶ 18 5+ years of college

### Recoding Variables

- ▶ For ease of plotting let's also re-code the SEX, RACE, and HISPAN variables
- SEX
  - ▶ 1 Male
  - 2 Female
- RACE
  - ▶ 1 White
  - 2 Black
  - ▶ 3 American Indian or Alaska Native
  - ▶ (4,5,6) Asian or Pacific Islander
  - ▶ 7 Other
  - ▶ What is a problem with how I am handling this variable?
- HISPAN
  - ▶ 0 Not Hispanic
  - ► (1,2,3,4) Hispanic

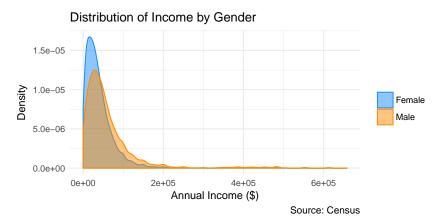
### Filtering Variables

#### Filter out all individuals:

- ► That are missing data for new\_educ
- Younger than 18 or older than 65
- Not in the workforce
- Missing data for OCC
- ► With a negative salary

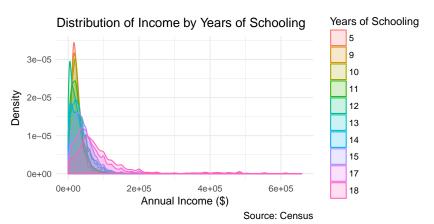
### Plotting the Data

▶ Please make a density plot of wages by gender. It should look something like:



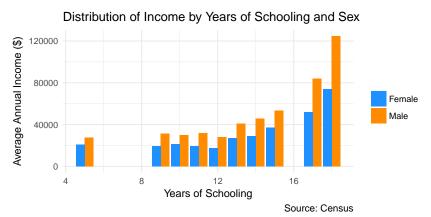
### Plotting the Data

▶ Please plot the distribution of wages by years of schooling. It should look something like:



### Plotting the Data

▶ Lets make a barchart of average income vs. years of schooling by gender:



▶ Let's write down a baseline model of an individual's Salary as a function of the years of education.

Salary<sub>i</sub> = 
$$\beta_0 + \beta_1$$
Years of Education

What do you think? What variables might be missing?

- ► How do we run a OLS regression in R? With the Im() function.
- ▶ What are the arguments to the Im() function?

Some example code:

```
# run a multiple linear regression
my_model <- lm(y ~ x1 + x2 + x3, data = mydata)

#show results
summary(my_model)</pre>
```

- Try it out! Run a simple regression of salary on years of education.
- What are the results?
- ► How do we add weights?
- ▶ How can we interpret the result?
- ▶ What is the structure of the model object?

## The Broom Package

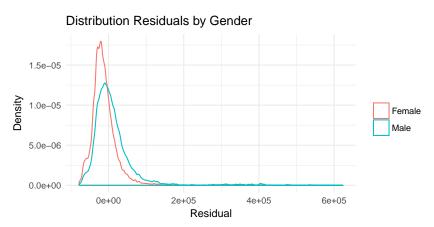
- Model results are messy and hard to work with by themselves in R
- The broom package is there to help!
- ► The broom package can turn these messy and unfamiliar model objects into good old data frames.
- ▶ The three main functions of the broom package are
  - tidy() for creating a data frame of component statistics
  - augment() for observation level statistics (like fitted values and residuals)
  - glance()- for model level statistics (like R-squared etc.)

## The Broom Package

- Let's try it out!
- tidy, augment, and glance at the results of the baseline model
- ► How can we use the augment function to keep all of our original columns?

### Improving our model

- Let's make a plot of the distribution of residuals by gender.
- ▶ What do we learn from this chart?



### Improving our model

▶ Let's run the regression described by

$$\mathsf{Salary}_i = \beta_0 + \beta_1 \mathsf{Years} \ \mathsf{of} \ \mathsf{Education}_i + \beta_2 \mathsf{Gender}_i$$

► How do the two models compare?

### Improving our model

- What if we think that the difference of an additional year of education on salary differs by gender?
- ▶ How does this change our model?
- ▶ How can we calculate interaction terms using lm()?

### Presenting Regression Results

- ► The stargazer package is designed to beautify the results of a regression in R.
- ▶ Let's install the package and run stargazer() on the baseline model.
- ► The output of the function is the code to create a beautiful latex table.
- ▶ We do not expect you to use latex for this class.
- You can plug the latex into http://quicklatex.com/ to create a nice image of the table.

## Put my models to shame

- Pair up!
- ➤ Take 15 20 mins to improve on the models we have done so far.
- ▶ I want to see plots that explain why you are adding in variables or interaction terms
- ▶ I want to see beautiful regression output tables
- I want you to spend 5 minutes writing up a post on piazza that includes a graph, a table, and a brief explanation of your model