

Module 1

Day 4: Introduction to Regression Analysis in R

Recap last week

- ▶ `facet_wrap()`
- ▶ `wtd.mean()`, `wtd.median()`
- ▶ `stargazer()`
- ▶ `scale_color_manual()`, `theme()`, `theme_`
- ▶ `unique()`
- ▶ `as.Date()`, `scale_x_date()`

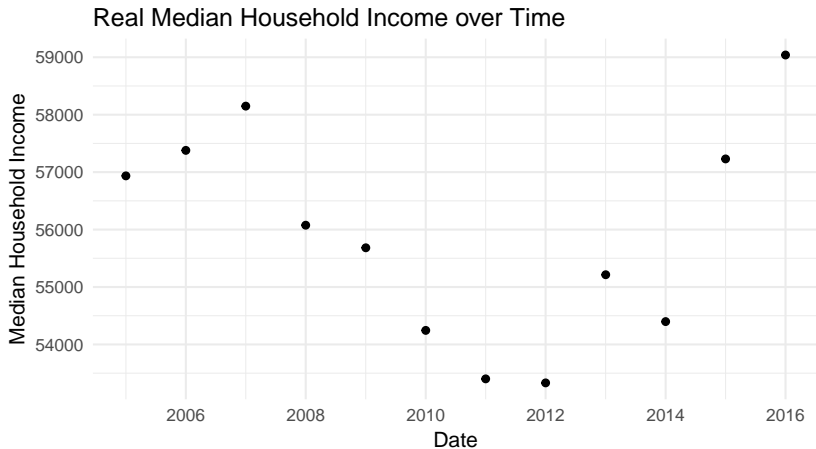
Organize your folders

- ▶ You should have one folder for this class
- ▶ Inside that folder there should be one folder for each lecture
- ▶ Make a folder for your project with sub folders - data, plots, literature

Recap last week

- ▶ Read in the data file “fred_median_income.csv”
- ▶ Convert the data column from a character to a Date
- ▶ Filter to data post 2005
- ▶ Make a scatter plot with the date on the x axis and median_hh_income on the y axis
- ▶ Be sure to label your chart appropriately
- ▶ Use the scale_x_dates() function to label every 2 years

Recap last week



Source: FRED

What do we mean when we say “real” income?

lag() and lead()

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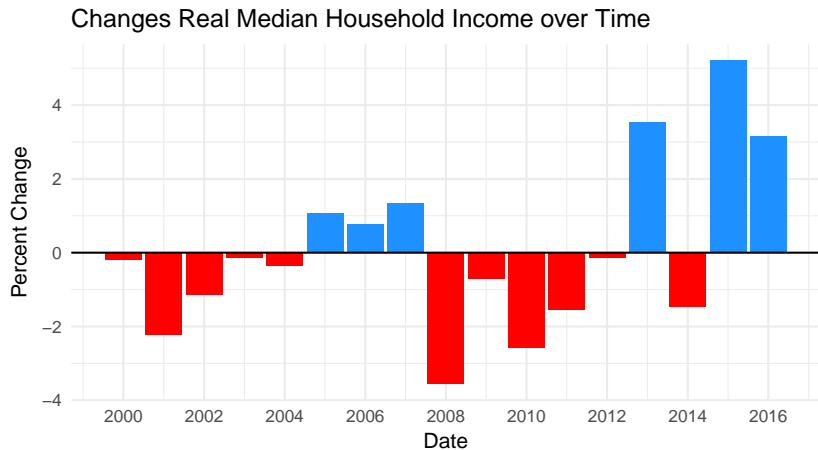
- ▶ Find the “next” or “previous” values in a vector.
- ▶ Useful for comparing values ahead of or behind the current values.

How could we use this function to calculate the percent change in median household income?

Shrinking Real Incomes

- ▶ Use the `lag()` function to calculate the percent change in household income
- ▶ Add a new column called `shrunk` that “Yes” if the percent change is less than zero and “No” otherwise
- ▶ Make a column chart (`geom_col`) of the percent change in median household income since 2000
- ▶ Use the variable `shrunk` as the color axis
- ▶ Use `geom_hline()` to add a horizontal line at $y = 0$ to highlight years where real income shrunk
- ▶ Turn off the color axis by using `guides(color = FALSE)`
- ▶ Use `scale_color_manual()` so that when income shrinks the point is red and if it grows it's blue

Shrinking Real Incomes



Source: FRED

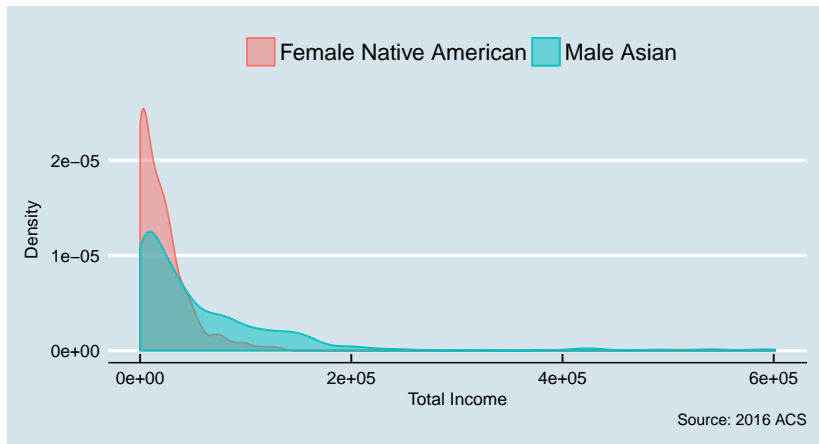
Recap last week

- ▶ Read in the data file “acs_2016_sample.csv”
- ▶ Apply our standard transformations
- ▶ Create a new data frame called acs_mean_median that is the weighted mean and median income by race and sex
- ▶ Add a column that is the difference between the mean and median income
- ▶ Which group has the biggest difference? Which the smallest?

Recap last week

- ▶ Going back to the whole sample filter to only Native American Females and Asian Males
- ▶ Use the paste function to create a new variable called group that is `paste(sex, race)`
- ▶ Make a density plot of the income of the two groups
- ▶ Set the alpha parameter to 0.5

Recap last week



What does it mean for the distribution if there is a big difference between the mean and median?

Regression Analysis

We have spent the past few weeks

- ▶ Learning some R
- ▶ Uncovering relationships between characteristics and income

Time to formalize our understanding

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 $X_1, X_2, X_3, \dots, X_n$
- ▶ What conditions must the response variable meet for OLS?

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 - ▶ Continuous! but ... (sometimes economists cheat)
- ▶ 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
 - ▶ Line charts
 - ▶ Density charts

What relationships have we already uncovered in the data?

Prepping the data

Create a new data frame `acs_2016_cleaned` which is `acs_2016_transformed` filtered to people:

- ▶ Between 18 and 65
- ▶ In the workforce
- ▶ With a total wage $\leq 1,000,000$
- ▶ Worked more than 0 hours a week
- ▶ Worked more than 0 weeks
- ▶ Add a column for hourly wage

What fraction of the original observations do we have?

Preping the data

Select the columns

- ▶ wage_income, age, hrs_worked , weeks_worked, and hourly_wage

Make a stargazer summary table

Table 1: Summary Statistics

Statistic	Mean	St. Dev.	Min	Max
wage_income	46,831.870	60,970.610	0	665,000
age	41.660	13.588	18	65
hrs_worked	38.843	12.626	1	99
weeks_worked	47.403	10.510	13	52
hourly_wage	23.988	83.714	0.000	9,246.154

OLS Regression

- ▶ Let's write down a baseline model of an individual's hourly wage as a function of their age.

$$\text{Hourly Wage}_i = \beta_0 + \beta_1 \text{Age}_i$$

- ▶ What do you think? What variables might be missing?

OLS Regression

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

OLS Regression

- Some example code:

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

OLS Regression

- ▶ Try it out! Run a simple regression of salary on ages

```
baseline_model <- lm(hourly_wage ~ age, acs_2016_cleaned)
```

- ▶ What are the results?
- ▶ How can we interpret the result?
- ▶ How much more per hour is a 40 year old expected to earn than a 20 year old?
- ▶ What is the structure of the model object?

OLS Regression

How do we add weights?

```
baseline_model <- lm(hourly_wage ~ age, weights = weight,  
                      acs_2016_cleaned)
```

stargazer()

- Once again, we can use stargazer to look at the results

```
stargazer(baseline_model, title = "Baseline Model",  
          header = F, dep.var.caption = "",  
          omit.stat = c("ser", "f"),  
          no.space = T)
```

- Lots of options to customize your stargazer table — read more [here](#)

Simple regression results

Table 2: Baseline Model

	hourly_wage
age	0.39*** (0.04)
Constant	7.02*** (1.79)
Observations	19,929
R ²	0.004
Adjusted R ²	0.004

Note: *p<0.1; **p<0.05; ***p<0.01

Interpreting the results

- ▶ Is the effect of age on income per hour significant
 - ▶ Statistically?
 - ▶ Economically?
- ▶ What is the marginal effect that one year of age has on how much you earn per hour?
- ▶ Is this a good model? Why or why not

The Broom Package

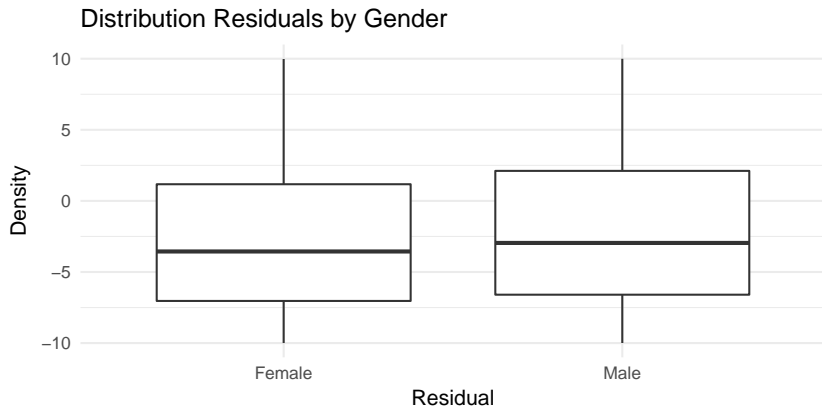
- ▶ Model results are messy and hard to work with by themselves in R
- ▶ The broom package is there to help!
- ▶ The broom package can turn these messy and unfamiliar model objects into good old data frames.
- ▶ The three main functions of the broom package are
 - ▶ `tidy()` - for creating a data frame 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?



Dummy Variables

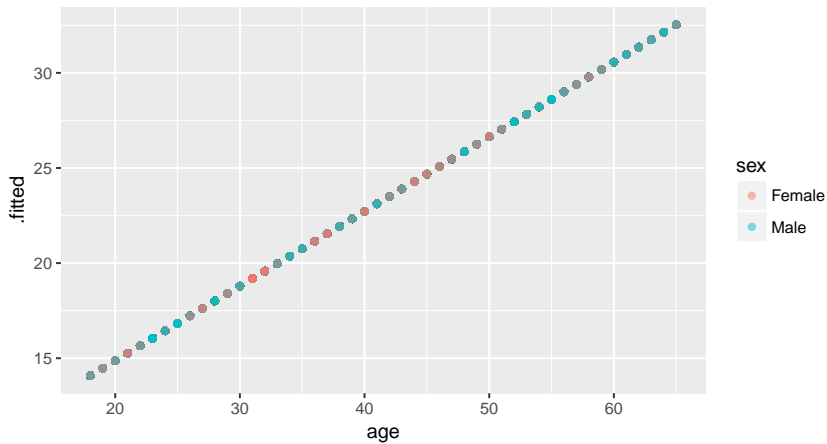
- ▶ Use categorical variables in regressions — but first must be transformed to dummy variables
- ▶ Dummy variable — any variable that takes on a value of 0 or 1 to indicate whether an observation fits into a particular category.
- ▶ For example, in our data:

$$sexMale = \begin{cases} 1 & \text{for male} \\ 0 & \text{for female} \end{cases}$$

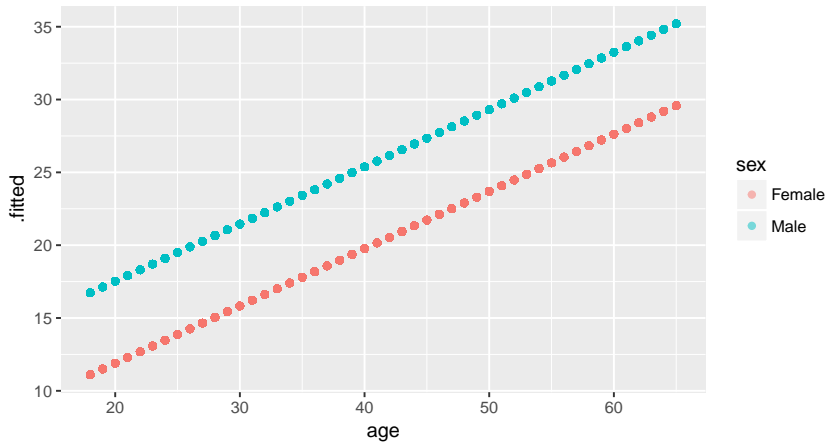
Dummy Variables

- ▶ But why do we use dummy variables?
- ▶ Recall from your econometrics class that dummy variables allow effects of different levels of a category to vary
 - ▶ The difference between no high school diploma and a high school diploma is different than a bachelor's degree and a PhD
- ▶ WE NEED TO EXCLUDE ONE DUMMY VARIABLE FROM THE REGRESSION
 - ▶ Called the base group
 - ▶ Cannot run a regression with all of the dummy variables in the model
- ▶ including dummy variables changes the interpretation of our β_0 coefficient

Dummy Variables



Dummy Variables



Improving our model

- ▶ Let's run the regression described by

$$\text{Salary}_i = \beta_0 + \beta_1 \text{Age}_i + \beta_2 \text{Sex}_i$$

- ▶ How do the two models compare?

Improving our model

- ▶ Let's update the code for our model:

```
improved_model <- lm(hourly_wage ~ age + sex,  
                     weights = weight,  
                     acs_2016_cleaned)
```

- ▶ It's real easy to compare multiple models with stargazer()

```
stargazer(baseline_model, improved_model,  
          title = "Model Comparison",  
          header = F, dep.var.caption = "",  
          omit.stat = c("ser", "f"),  
          no.space = T)
```

Regression Results

Table 3: Model Comparison

	hourly_wage	
	(1)	(2)
age	0.392*** (0.042)	0.393*** (0.042)
sexMale		5.623*** (1.132)
Constant	7.019*** (1.792)	4.036** (1.889)
Observations	19,929	19,929
R ²	0.004	0.006
Adjusted R ²	0.004	0.005

Note: *p<0.1; **p<0.05; ***p<0.01

Interpreting the results

- ▶ Luckily, our interpretation of age is unchanged!
- ▶ What is the omitted group?
- ▶ β_0 = wage of a worker that is 0 years old
- ▶ β_2 = “bonus” for being a man

R^2

- What is R^2

R^2

- ▶ A statistical measure of how close the data are to the regression line.

$$R^2 = \frac{\text{Explained variation}}{\text{Total variation}}$$

What is the range of values R^2 can have?

Adjusted R^2

- ▶ Important for models with multiple variables
- ▶ Similar to R^2 , except there is an *adjustment* for adding additional terms
- ▶ A way of testing whether the added variables are actually helping your model

Some more ways of understanding R Squared

Comparing the two models

- ▶ Are these coefficients significant:
 - ▶ Statistically?
 - ▶ Economically?
- ▶ Are the coefficients different?
- ▶ Now that we know about adjusted R^2 , which of the two models is better (marginally)?

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
- ▶ 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