Data Science Workshops

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Contents

Materials for the software workshops held at the Institute for Quantitative Social Science and Harvard Business School at Harvard University.

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Contributors

The contents of these workshops are the result of a collaborative effort from members of the Data Science Services team at IQSS and the Research Computing Services team at HBS. The main contributors are: Ista Zahn, Steve Worthington, Bob Freeman, Jinjie Liu, Yihan Wang, and Victoria Liublinska.

These workshops are a work-in-progress, please provide feedback! Email: `help@iq.harvard.edu`

Part I

General

Chapter 1

Data Science Tools

Topics

- Data science tool selection
- Data analysis pipelines
- Programming languages comparison
- Text editor and IDE comparison
- Tools for creating reports

1.1 Tools for working with data

Working with data effectively requires learning at least one programming or scripting language. You can get by without this, but it would be like trying to cook with only a butter knife; not recommended! Compared to using a menu-driven interface (e.g., SPSS or SAS) or a spreadsheet (e.g., Excel), using a programming language allows you to:

- reproduce results,
- correct errors and update output,
- reuse code,
- collaborate with others,
- automate repetitive tasks, and
- generate manuscripts, reports, and other documents from your code.

So, you need to learn a programming language for working with data, but which one should you learn? Since you'll be writing code you'll want to set up a comfortable environment for writing and editing that code. Which text editors are good for this? You'll probably also want to learn at least one markup language (e.g., LaTeX, Markdown) so that you can create reproducible manuscripts. What tools are good for this? These questions will guide our discussion, the goal of which is to help you decide which tools you should invest time in learning.

1.2 The puzzle pieces

As we've noted, working effectively with data requires using a number of tools.

1.2.1 Data analysis building blocks

The basic pieces are:

- a data storage and retrieval system,
- an editor for writing code,
- an interpreter or compiler for executing that code,
- a system for presenting results, and
- some "glue" to make all the pieces work together.

1.3 Examples

Before looking in detail at each of these building blocks we'll look at a few examples to get an intuitive feel for the basic elements.

1.3.1 Old-school example

In this example we're going to process data in a text file in a way that would be familiar to a statistician working forty years ago. Surprisingly, it's not much different from the way we would do it today. Programs come and go, but the basic ideas remain pretty much the same!

Specifically, we'll process the data in `1980_census.txt` by writing **fortran** code in the **vi** text editor and running it through the **fortran** compiler. Then we'll take the results and put them in to a **TeX** file, again using the **vi** editor to create the report. For "glue" we will use a terminal emulator running the bash shell. All of these tools were available in 1980, though some features have been added since that time.

OLD SCHOOL DEMO:

example	data storage	editor	program	report tool	glue
old school	ASCII text file	vi	fortran	TeX	Bourne (compatible) shell

1.3.2 Something old & something new

Next we're going to do the same basic process, this time using a modern text editor (**Atom**), a different programming language (**Python**), and a modern report generation system (**LaTeX** processed via **XeLaTeX**). For the glue we're still going to use a shell.

OLD AND NEW DEMO:

example	data storage	editor	program	report tool	glue
old school	ASCII text file	vi	fortran	TeX	Bourne (compatible) shell
old and new	ASCII text file	Atom	python	LaTeX	Bash shell

1.3.3 A modern version

Finally, we'll produce the same report using modern tools. Remember, the process is basically the same: we're just using different tools.

MODERN DEMO:

example	data storage	editor	program	report tool	glue
old school	ASCII text file	vi	fortran	TeX	Bourne (compatable) shell
old and new	ASCII text file	Atom	python	LaTeX	Bash shell
modern	SQLite database	Rstudio	R	R Markdown	Rstudio

1.4 Data storage & retrieval

Data storage and retrieval is a fairly dry topic, so we won't spend too much time on it. There are roughly four types of technology for storing and retrieving data.

1.4.1 Text files

Storing data in text files (e.g., comma separated values, other delimited text formats) is simple and makes the data easy to access from just about any program. It is also good for archiving data since no specialized software is needed to read it. The main downsides are that retrieval is slow and often all-or-nothing, and the fact that storing metadata in plain text files is cumbersome.

1.4.2 Binary files

Many statistics packages and programming languages have a "native" binary data storage format. For example, Stata stores data in `.dta` files, and R stores data in `.rds` or `.Rdata` files. These storage formats usually more efficient than text files, and usually provide faster read/write access. They usually include a mechanism for storing metadata. The down side is that specialized software is required to read them (will Stata exist in 50 years? Are you sure?) and the ability to read them using other programs may be limited.

1.4.3 Databases

Storing data in a database requires more up-front planning and set up, but has several advantages. Databases provide fast selective retrieval and facilitate efficient storage and flexible retrieval.

1.4.4 Distributed file storage

Data that is too large to fit on a single hard drive may be stored and analyzed on a distributed file system or database such as the *Hadoop Distributed File System* or *Cassandra*. When working with data on this scale considerable infrastructure and specialized tools will be required.

1.5 Programming languages & statistics packages

There are tens of programs for statistics and data science available. Here we will focus only on the more popular programs that offer a wide range of features. Note that for specific applications a specialized program may be better, e.g., many people use Mplus for structural equation models and another program for everything else.

1.5.1 Programming language features

Things we want a statistics program to do include:

- read/write data from/to a variety of data storage systems,
- manipulate data,
- perform statistical methods,
- visualize data and results,
- export results in a variety of formats,
- be easy to use,
- be well documented,
- have a large user community.

Note that this list is deceptively simple; each item may include a diversity of complicated features. For example,"read/write data from/to a variety of data storage systems" may include reading from databases, image files, .pdf files, .html and .xml files from a website, and any number of proprietary data storage formats.

1.5.2 Program comparison

Program	Statistics	Visualization	Machine learning	Ease of use	Power/flexibility	Fun
Stata	Excellent	Servicable	Limited	Very easy	Low	Some
SPSS	OK	Servicable	Limited	Easy	Low	None
SAS	Good	Not great	Good	Moderate	Moderate	None
Matlab	Good	Good	Good	Moderate	Good	Some

Program	Statistics	Visualization	Machine learning	Ease of use	Power/flexibility	Fun
R	Excellent	Excellent	Good	Moderate	Excellent	Yes
Python	Good	Good	Excellent	Moderate	Excellent	Yes
Julia	OK	Excellent	Good	Hard	Excellent	Yes

1.5.3 Examples: Read data from a file & summarize

In this example we will compare the syntax for reading and summarizing data stored in a file.

- Stata

```
import delimited using "https://github.com/IQSS/dss-workshops/raw/master/General/DataScienceTools
sum
```

```
set more off
 "EconomistData.csv"
Picked up _JAVA_OPTIONS: -Dawt.useSystemAAFontSettings=gasp -Dswing.aatext=true -Dsun.java2d.open
(6 vars, 173 obs)
sum

    Variable |        Obs        Mean    Std. Dev.       Min        Max
-------------+---------------------------------------------------------
          v1 |        173          87    50.08493          1        173
     country |          0
     hdirank |        173    95.28324    55.00767          1        187
         hdi |        173    .6580867    .1755888       .286       .943
         cpi |        173    4.052023    2.116782        1.5        9.5
-------------+---------------------------------------------------------
      region |          0
```

- R

```
cpi <- read.csv("https://github.com/IQSS/dss-workshops/raw/master/General/DataScienceTools/dataSe
summary(cpi)
```

```
      X                Country       HDI.Rank           HDI
Min.   :  1   Afghanistan:  1   Min.   :  1.00   Min.   :0.2860
1st Qu.: 44   Albania    :  1   1st Qu.: 47.00   1st Qu.:0.5090
Median : 87   Algeria    :  1   Median : 96.00   Median :0.6980
Mean   : 87   Angola     :  1   Mean   : 95.28   Mean   :0.6581
3rd Qu.:130   Argentina  :  1   3rd Qu.:143.00   3rd Qu.:0.7930
Max.   :173   Armenia    :  1   Max.   :187.00   Max.   :0.9430
```

```
               (Other)    :167
     CPI                        Region
Min.   :1.500   Americas         :31
1st Qu.:2.500   Asia Pacific     :30
Median :3.200   East EU Cemt Asia:18
Mean   :4.052   EU W. Europe     :30
3rd Qu.:5.100   MENA             :18
Max.   :9.500   SSA              :46
```

- Matlab

```
tmpfile = websave(tempname(), 'https://github.com/IQSS/dss-workshops/raw/master/General/DataScien
cpi = readtable(tmpfile);
summary(cpi)
```

```
tmpfile = websave(tempname(), 'https://github.com/IQSS/dss-workshops/raw/master/General/DataScien
cpi = readtable(tmpfile);
summary(cpi)

Variables:

    Var1: 173×1 cell array of character vectors

    Country: 173×1 cell array of character vectors

    HDI_Rank: 173×1 double

        Description:  Original column heading: 'HDI.Rank'
        Values:

            Min          1
            Median      96
            Max        187

    HDI: 173×1 double

        Values:

            Min       0.286
            Median    0.698
            Max       0.943

    CPI: 173×1 double

        Values:

            Min       1.5
```

```
            Median    3.2
            Max       9.5

    Region: 173×1 cell array of character vectors
'org_babel_eoe'

ans =

    'org_babel_eoe'
```

- Python

```
import pandas as pd
cpi = pd.read_csv('https://github.com/IQSS/dss-workshops/raw/master/General/DataScienceTools/data
cpi.describe(include = 'all')
```

```
Python 3.6.2 (default, Jul 20 2017, 03:52:27)
[GCC 7.1.1 20170630] on linux
Type "help", "copyright", "credits" or "license" for more information.
        Unnamed: 0 Country    HDI.Rank         HDI         CPI Region
count   173.000000     173  173.000000  173.000000  173.000000    173
unique         NaN     173         NaN         NaN         NaN      6
top            NaN    Oman         NaN         NaN         NaN    SSA
freq           NaN       1         NaN         NaN         NaN     46
mean     87.000000     NaN   95.283237    0.658087    4.052023    NaN
std      50.084928     NaN   55.007670    0.175589    2.116782    NaN
min       1.000000     NaN    1.000000    0.286000    1.500000    NaN
25%      44.000000     NaN   47.000000    0.509000    2.500000    NaN
50%      87.000000     NaN   96.000000    0.698000    3.200000    NaN
75%     130.000000     NaN  143.000000    0.793000    5.100000    NaN
max     173.000000     NaN  187.000000    0.943000    9.500000    NaN
```

1.5.4 Examples: Fit a linear regression

Fitting statistical models is pretty straight-forward in all popular programs.

- Stata

```
regress hdi cpi
```

```
regress hdi cpi

      Source |       SS           df       MS      Number of obs   =       173
-------------+----------------------------------   F(1, 171)       =    168.85
       Model |  2.63475703         1  2.63475703   Prob > F        =    0.0000
```

```
    Residual |   2.6682467       171  .015603782   R-squared       =    0.4968
-------------+----------------------------------   Adj R-squared   =    0.4939
       Total |  5.30300372       172  .030831417   Root MSE        =    .12492

------------------------------------------------------------------------------
         hdi |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
         cpi |   .0584696   .0044996    12.99   0.000     .0495876    .0673515
       _cons |   .4211666   .0205577    20.49   0.000     .3805871    .4617462
------------------------------------------------------------------------------
```

- R

```r
summary(lm(HDI ~ CPI, data = cpi))
```

```

Call:
lm(formula = HDI ~ CPI, data = cpi)

Residuals:
     Min       1Q   Median       3Q      Max
-0.28452 -0.08380  0.01372  0.09157  0.24104

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)  0.42117    0.02056   20.49   <2e-16 ***
CPI          0.05847    0.00450   12.99   <2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.1249 on 171 degrees of freedom
Multiple R-squared:  0.4968,    Adjusted R-squared:  0.4939
F-statistic: 168.9 on 1 and 171 DF,  p-value: < 2.2e-16
```

- Matlab

```matlab
fitlm(cpi, 'HDI~CPI')
```

```

fitlm(cpi, 'HDI~CPI')

ans =


Linear regression model:
    HDI ~ 1 + CPI

Estimated Coefficients:
```

```
                   Estimate       SE        tStat       pValue
                   --------    ---------    ------    ----------

    (Intercept)    0.42117      0.020558    20.487    6.7008e-48
    CPI            0.05847     0.0044996    12.994    2.6908e-27


Number of observations: 173, Error degrees of freedom: 171
Root Mean Squared Error: 0.125
R-squared: 0.497,  Adjusted R-Squared 0.494
F-statistic vs. constant model: 169, p-value = 2.69e-27
'org_babel_eoe'

ans =

    'org_babel_eoe'
```

- Python

```
import statsmodels.formula.api as model
X = cpi[['CPI']]
Y = cpi[['HDI']]
model.OLS(Y, X).fit().summary()
```

```
<class 'statsmodels.iolib.summary.Summary'>
"""
                            OLS Regression Results
==============================================================================
Dep. Variable:                    HDI   R-squared:                       0.885
Model:                            OLS   Adj. R-squared:                  0.884
Method:                 Least Squares   F-statistic:                     1325.
Date:                Thu, 31 Aug 2017   Prob (F-statistic):           9.89e-83
Time:                        23:16:45   Log-Likelihood:                 8.1584
No. Observations:                 173   AIC:                            -14.32
Df Residuals:                     172   BIC:                            -11.16
Df Model:                           1
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
CPI            0.1402      0.004     36.401      0.000       0.133       0.148
==============================================================================
Omnibus:                       10.423   Durbin-Watson:                   1.616
Prob(Omnibus):                  0.005   Jarque-Bera (JB):               11.099
Skew:                          -0.599   Prob(JB):                      0.00389
Kurtosis:                       2.674   Cond. No.                         1.00
==============================================================================
```

```
Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
"""
```

1.5.5 Examples: Extract links for .html file

Retrieving data from a website is a common task. Here we parse a simple web page containing links to files we wish to download.

- Stata

```
disp "Ha ha ha! No, you do not want to use Stata for this!"
```

```
disp "Ha ha ha! No, you do not want to use Stata for this!"
Ha ha ha! No, you do not want to use Stata for this!
```

- R

```
library(xml2)
index_page <- read_html("http://tutorials.iq.harvard.edu/example_data/baby_names/EW/")
all_anchors <- xml_find_all(index_page, "//a")
all_hrefs <- xml_attr(all_anchors, "href")
data_hrefs <- grep("\\.csv$", all_hrefs, value = TRUE)
data_links <- paste0("http://tutorials.iq.harvard.edu/example_data/baby_names/EW/", data_hrefs)
data_links
```

```
 [1] "http://tutorials.iq.harvard.edu/example_data/baby_names/EW/boys_1996.csv"
 [2] "http://tutorials.iq.harvard.edu/example_data/baby_names/EW/boys_1997.csv"
 [3] "http://tutorials.iq.harvard.edu/example_data/baby_names/EW/boys_1998.csv"
 [4] "http://tutorials.iq.harvard.edu/example_data/baby_names/EW/boys_1999.csv"
 [5] "http://tutorials.iq.harvard.edu/example_data/baby_names/EW/boys_2000.csv"
 [6] "http://tutorials.iq.harvard.edu/example_data/baby_names/EW/boys_2001.csv"
 [7] "http://tutorials.iq.harvard.edu/example_data/baby_names/EW/boys_2002.csv"
 [8] "http://tutorials.iq.harvard.edu/example_data/baby_names/EW/boys_2003.csv"
 [9] "http://tutorials.iq.harvard.edu/example_data/baby_names/EW/boys_2004.csv"
[10] "http://tutorials.iq.harvard.edu/example_data/baby_names/EW/boys_2005.csv"
[11] "http://tutorials.iq.harvard.edu/example_data/baby_names/EW/boys_2006.csv"
[12] "http://tutorials.iq.harvard.edu/example_data/baby_names/EW/boys_2007.csv"
[13] "http://tutorials.iq.harvard.edu/example_data/baby_names/EW/boys_2008.csv"
[14] "http://tutorials.iq.harvard.edu/example_data/baby_names/EW/boys_2009.csv"
[15] "http://tutorials.iq.harvard.edu/example_data/baby_names/EW/boys_2010.csv"
[16] "http://tutorials.iq.harvard.edu/example_data/baby_names/EW/boys_2011.csv"
[17] "http://tutorials.iq.harvard.edu/example_data/baby_names/EW/boys_2012.csv"
[18] "http://tutorials.iq.harvard.edu/example_data/baby_names/EW/boys_2013.csv"
```

```
[19] "http://tutorials.iq.harvard.edu/example_data/baby_names/EW/boys_2014.csv"
[20] "http://tutorials.iq.harvard.edu/example_data/baby_names/EW/boys_2015.csv"
[21] "http://tutorials.iq.harvard.edu/example_data/baby_names/EW/girls_1996.csv"
[22] "http://tutorials.iq.harvard.edu/example_data/baby_names/EW/girls_1997.csv"
[23] "http://tutorials.iq.harvard.edu/example_data/baby_names/EW/girls_1998.csv"
[24] "http://tutorials.iq.harvard.edu/example_data/baby_names/EW/girls_1999.csv"
[25] "http://tutorials.iq.harvard.edu/example_data/baby_names/EW/girls_2000.csv"
[26] "http://tutorials.iq.harvard.edu/example_data/baby_names/EW/girls_2001.csv"
[27] "http://tutorials.iq.harvard.edu/example_data/baby_names/EW/girls_2002.csv"
[28] "http://tutorials.iq.harvard.edu/example_data/baby_names/EW/girls_2003.csv"
[29] "http://tutorials.iq.harvard.edu/example_data/baby_names/EW/girls_2004.csv"
[30] "http://tutorials.iq.harvard.edu/example_data/baby_names/EW/girls_2005.csv"
[31] "http://tutorials.iq.harvard.edu/example_data/baby_names/EW/girls_2006.csv"
[32] "http://tutorials.iq.harvard.edu/example_data/baby_names/EW/girls_2007.csv"
[33] "http://tutorials.iq.harvard.edu/example_data/baby_names/EW/girls_2008.csv"
[34] "http://tutorials.iq.harvard.edu/example_data/baby_names/EW/girls_2009.csv"
[35] "http://tutorials.iq.harvard.edu/example_data/baby_names/EW/girls_2010.csv"
[36] "http://tutorials.iq.harvard.edu/example_data/baby_names/EW/girls_2011.csv"
[37] "http://tutorials.iq.harvard.edu/example_data/baby_names/EW/girls_2012.csv"
[38] "http://tutorials.iq.harvard.edu/example_data/baby_names/EW/girls_2013.csv"
[39] "http://tutorials.iq.harvard.edu/example_data/baby_names/EW/girls_2014.csv"
[40] "http://tutorials.iq.harvard.edu/example_data/baby_names/EW/girls_2015.csv"
```

- Matlab

```
index_page = urlread('http://tutorials.iq.harvard.edu/example_data/baby_names/EW/');
all_hrefs = regexp(index_page, '<a href="([^"]*\.csv)">', 'tokens')';
all_hrefs = [all_hrefs{:}]';
all_links = strcat('http://tutorials.iq.harvard.edu/example_data/baby_names/EW/', all_hrefs)
```


```
index_page = urlread('http://tutorials.iq.harvard.edu/example_data/baby_names/EW/');
all_hrefs = regexp(index_page, '<a href="([^"]*\.csv)">', 'tokens')';
all_hrefs = [all_hrefs{:}]';
all_links = strcat('http://tutorials.iq.harvard.edu/example_data/baby_names/EW/', all_hrefs)
```


```
all_links =

  40×1 cell array

    'http://tutorials.iq.harvard.edu/example_data/baby_names/EW/boys_1996.csv'
    'http://tutorials.iq.harvard.edu/example_data/baby_names/EW/boys_1997.csv'
    'http://tutorials.iq.harvard.edu/example_data/baby_names/EW/boys_1998.csv'
    'http://tutorials.iq.harvard.edu/example_data/baby_names/EW/boys_1999.csv'
    'http://tutorials.iq.harvard.edu/example_data/baby_names/EW/boys_2000.csv'
    'http://tutorials.iq.harvard.edu/example_data/baby_names/EW/boys_2001.csv'
    'http://tutorials.iq.harvard.edu/example_data/baby_names/EW/boys_2002.csv'
    'http://tutorials.iq.harvard.edu/example_data/baby_names/EW/boys_2003.csv'
```

```
    'http://tutorials.iq.harvard.edu/example_data/baby_names/EW/boys_2004.csv'
    'http://tutorials.iq.harvard.edu/example_data/baby_names/EW/boys_2005.csv'
    'http://tutorials.iq.harvard.edu/example_data/baby_names/EW/boys_2006.csv'
    'http://tutorials.iq.harvard.edu/example_data/baby_names/EW/boys_2007.csv'
    'http://tutorials.iq.harvard.edu/example_data/baby_names/EW/boys_2008.csv'
    'http://tutorials.iq.harvard.edu/example_data/baby_names/EW/boys_2009.csv'
    'http://tutorials.iq.harvard.edu/example_data/baby_names/EW/boys_2010.csv'
    'http://tutorials.iq.harvard.edu/example_data/baby_names/EW/boys_2011.csv'
    'http://tutorials.iq.harvard.edu/example_data/baby_names/EW/boys_2012.csv'
    'http://tutorials.iq.harvard.edu/example_data/baby_names/EW/boys_2013.csv'
    'http://tutorials.iq.harvard.edu/example_data/baby_names/EW/boys_2014.csv'
    'http://tutorials.iq.harvard.edu/example_data/baby_names/EW/boys_2015.csv'
    'http://tutorials.iq.harvard.edu/example_data/baby_names/EW/girls_1996.csv'
    'http://tutorials.iq.harvard.edu/example_data/baby_names/EW/girls_1997.csv'
    'http://tutorials.iq.harvard.edu/example_data/baby_names/EW/girls_1998.csv'
    'http://tutorials.iq.harvard.edu/example_data/baby_names/EW/girls_1999.csv'
    'http://tutorials.iq.harvard.edu/example_data/baby_names/EW/girls_2000.csv'
    'http://tutorials.iq.harvard.edu/example_data/baby_names/EW/girls_2001.csv'
    'http://tutorials.iq.harvard.edu/example_data/baby_names/EW/girls_2002.csv'
    'http://tutorials.iq.harvard.edu/example_data/baby_names/EW/girls_2003.csv'
    'http://tutorials.iq.harvard.edu/example_data/baby_names/EW/girls_2004.csv'
    'http://tutorials.iq.harvard.edu/example_data/baby_names/EW/girls_2005.csv'
    'http://tutorials.iq.harvard.edu/example_data/baby_names/EW/girls_2006.csv'
    'http://tutorials.iq.harvard.edu/example_data/baby_names/EW/girls_2007.csv'
    'http://tutorials.iq.harvard.edu/example_data/baby_names/EW/girls_2008.csv'
    'http://tutorials.iq.harvard.edu/example_data/baby_names/EW/girls_2009.csv'
    'http://tutorials.iq.harvard.edu/example_data/baby_names/EW/girls_2010.csv'
    'http://tutorials.iq.harvard.edu/example_data/baby_names/EW/girls_2011.csv'
    'http://tutorials.iq.harvard.edu/example_data/baby_names/EW/girls_2012.csv'
    'http://tutorials.iq.harvard.edu/example_data/baby_names/EW/girls_2013.csv'
    'http://tutorials.iq.harvard.edu/example_data/baby_names/EW/girls_2014.csv'
    'http://tutorials.iq.harvard.edu/example_data/baby_names/EW/girls_2015.csv'
'org_babel_eoe'

ans =

    'org_babel_eoe'
```

- Python

```python
from lxml import etree
import requests

index_text = requests.get('http://tutorials.iq.harvard.edu/example_data/baby_names/EW/').text
index_page = etree.HTML(index_text)
all_hrefs = [a.values() for a in index_page.findall(".//a")]
data_links = ['http://tutorials.iq.harvard.edu/example_data/baby_names/EW/' +
              href[0] for href in all_hrefs if 'csv' in href[0]]
```

```python
for link in data_links:
    print(link)
```

```
http://tutorials.iq.harvard.edu/example_data/baby_names/EW/boys_1996.csv
http://tutorials.iq.harvard.edu/example_data/baby_names/EW/boys_1997.csv
http://tutorials.iq.harvard.edu/example_data/baby_names/EW/boys_1998.csv
http://tutorials.iq.harvard.edu/example_data/baby_names/EW/boys_1999.csv
http://tutorials.iq.harvard.edu/example_data/baby_names/EW/boys_2000.csv
http://tutorials.iq.harvard.edu/example_data/baby_names/EW/boys_2001.csv
http://tutorials.iq.harvard.edu/example_data/baby_names/EW/boys_2002.csv
http://tutorials.iq.harvard.edu/example_data/baby_names/EW/boys_2003.csv
http://tutorials.iq.harvard.edu/example_data/baby_names/EW/boys_2004.csv
http://tutorials.iq.harvard.edu/example_data/baby_names/EW/boys_2005.csv
http://tutorials.iq.harvard.edu/example_data/baby_names/EW/boys_2006.csv
http://tutorials.iq.harvard.edu/example_data/baby_names/EW/boys_2007.csv
http://tutorials.iq.harvard.edu/example_data/baby_names/EW/boys_2008.csv
http://tutorials.iq.harvard.edu/example_data/baby_names/EW/boys_2009.csv
http://tutorials.iq.harvard.edu/example_data/baby_names/EW/boys_2010.csv
http://tutorials.iq.harvard.edu/example_data/baby_names/EW/boys_2011.csv
http://tutorials.iq.harvard.edu/example_data/baby_names/EW/boys_2012.csv
http://tutorials.iq.harvard.edu/example_data/baby_names/EW/boys_2013.csv
http://tutorials.iq.harvard.edu/example_data/baby_names/EW/boys_2014.csv
http://tutorials.iq.harvard.edu/example_data/baby_names/EW/boys_2015.csv
http://tutorials.iq.harvard.edu/example_data/baby_names/EW/girls_1996.csv
http://tutorials.iq.harvard.edu/example_data/baby_names/EW/girls_1997.csv
http://tutorials.iq.harvard.edu/example_data/baby_names/EW/girls_1998.csv
http://tutorials.iq.harvard.edu/example_data/baby_names/EW/girls_1999.csv
http://tutorials.iq.harvard.edu/example_data/baby_names/EW/girls_2000.csv
http://tutorials.iq.harvard.edu/example_data/baby_names/EW/girls_2001.csv
http://tutorials.iq.harvard.edu/example_data/baby_names/EW/girls_2002.csv
http://tutorials.iq.harvard.edu/example_data/baby_names/EW/girls_2003.csv
http://tutorials.iq.harvard.edu/example_data/baby_names/EW/girls_2004.csv
http://tutorials.iq.harvard.edu/example_data/baby_names/EW/girls_2005.csv
http://tutorials.iq.harvard.edu/example_data/baby_names/EW/girls_2006.csv
http://tutorials.iq.harvard.edu/example_data/baby_names/EW/girls_2007.csv
http://tutorials.iq.harvard.edu/example_data/baby_names/EW/girls_2008.csv
http://tutorials.iq.harvard.edu/example_data/baby_names/EW/girls_2009.csv
http://tutorials.iq.harvard.edu/example_data/baby_names/EW/girls_2010.csv
http://tutorials.iq.harvard.edu/example_data/baby_names/EW/girls_2011.csv
http://tutorials.iq.harvard.edu/example_data/baby_names/EW/girls_2012.csv
http://tutorials.iq.harvard.edu/example_data/baby_names/EW/girls_2013.csv
http://tutorials.iq.harvard.edu/example_data/baby_names/EW/girls_2014.csv
http://tutorials.iq.harvard.edu/example_data/baby_names/EW/girls_2015.csv
```

1.6 Creating reports

Once you've analyzed your data you'll most likely want to communicate your results. For short informal projects this might take the form of a blog post or an email to your colleagues. For larger more formal projects you'll likely want to prepare a substantial report or manuscript for disseminating your findings via a journal publication or other means. Other common means of reporting research findings include posters or slides for a conference talk.

Regardless of the type of report, you may choose to use either a *markup language* or a WYSIWYG application like Microsoft Word/Powerpoint of a desktop publishing application such as Adobe InDesign.

1.6.1 Markup languages

A markup language is a system for producing a formatted document from a text file using information by the markup. A major advantage of markup languages is that the formatting instructions can be easily generated by the program you use for analyzing your data.

Markup languages include *HTML*, *LaTeX*, *Markdown* and many others. *LaTeX* and *Markdown* are currently popular among data scientists, although others are used as well.

Markdown is easy to write and designed to be human-readable. It is newer and somewhat less feature-full compared to LaTeX. It's main advantage is simplicity. *LaTeX* is more verbose but provides for just about any feature you'll ever need.

MARKDOWN DEMO LATEX DEMO

1.6.2 Word processors

Modern word processors are largely just graphical user interfaces that write a markup language (usually XML) for you. They are commonly used for creating reports, but care must be taken when doing so.

If you use a word processor to produce your reports you should

- use the structured outline feature,
- link rather than embed external resources (figures, tables, etc.),
- use cross-referencing features, and
- use a bibliography management system.

WORD PROCESSOR DEMO

1.7 Text editors & Integrated Development Environments

A text editor edits text obviously. But that is not all! At a minimum, a text editor will also have a mechanism for reading and writing text files. Most text editors do much more than this.

An IDE provides tools for working with code, such as syntax highlighting, code completion, jump-to-definition, execute/compile, package management, refactoring, etc. Of course an IDE includes a text editor.

Editors and IDE's are not really separate categories; as you add features to a text editor it becomes more like an IDE, and a simple IDE may provide little more than a text editor. For example, Emacs is commonly referred to as a text editor, but it provides nearly every feature you would expect an IDE to have.

A more useful distinction is between language-specific editors/IDEs and general purpose editors/IDEs. The former are typically easier to set up since they come pre-configured for use with a specific language. General purpose editors/IDEs typically provide language support via *plugins* and may require extensive configuration for each language.

1.7.1 Language specific editors & IDEs

Editor	Features	Ease of use	Language
RStudio	Excellent	Easy	R
Spyder	Excellent	Easy	Python
Stata do file editor	OK	Easy	Stata
SPSS syntax editor	OK	Easy	SPSS

LANGUAGE SPECIFIC IDE DEMO

1.7.2 General purpose editors & IDEs

Editor	Features	Ease of use	Language support
Vim	Excellent	Hard	Good
Emacs	Excellent	Hard	Excellent
VS code	Excellent	Easy	Very good
Atom	Good	Moderate	Good
Eclipse	Excellent	Easy	Good
Sublime Text	Good	Easy	Good
Notepad++	OK	Easy	OK
Textmate	Good	Moderate	Good
Kate	OK	Easy	Good

GENERAL PURPOSE EDITOR DEMO

1.8 Literate programming & notebooks

In one of the Early demos we say an example of embedding R code in a markdown document. A closely related approach is to create a *notebook* that includes the prose of the report, the code used for the analysis, and the results produced by that code.

1.8.1 Literate programming

Literate programming is the practice of embedding computer code in a natural language document. For example, using *RMarkdown* we can embed R code in a report authored using Markdown. Python and Stata have their own versions of literate programming using Markdown.

1.8.2 Notebooks

Notebooks go one step farther, and include the output produced by the original program directly in the notebook. Examples include *Jupyter*, *Appache Zeppelin*, and *Emacs Org Mode*.

NOTEBOOKS DEMO

1.9 Big data, annoying data, & computationally intensive methods

Thus far we've discussed popular programming languages, data storage and retrieval options, text editors, and reporting technology. These are the basic building blocks I recommend using just about any time you find yourself working with data. There are times however when more is needed. For example, you may wish to use distributed computing for large or resource intensive computations.

1.9.1 Computing clusters at Harvard

Harvard provides a number of computing clusters, including Odyssey and the Research Computing Environment. Using these systems will be much easier if you know the basic tools well. After all, you're still going to need data storage/retrieval, you'll still need a text editor write code, and a programming language to write it in. My advice is to master these basics, and learn the rest as you need it.

1.10 Wrap up

1.10.1 Feedback

These workshops are a work-in-progress, please provide any feedback to: `help@iq.harvard.edu`

1.10.2 Resources

- IQSS
  - Workshops: `https://dss.iq.harvard.edu/workshop-materials`
  - Data Science Services: `https://dss.iq.harvard.edu/`
  - Research Computing Environment: `https://iqss.github.io/dss-rce/`
- HBS
  - Research Computing Services workshops: `https://training.rcs.hbs.org/workshops`
  - Other HBS RCS resources: `https://training.rcs.hbs.org/workshop-materials`
  - RCS consulting email: `mailto:research@hbs.edu`

Part II

R

Chapter 2

R Installation

Your professional conduct is greatly appreciated. Out of respect to your fellow workshop attendees and instructors, please arrive at your workshop on time, having pre-installed all necessary software and materials. This will likely take 15-20 minutes.

Before starting any of our R workshops, it is necessary to complete 4 tasks. Please make sure all these tasks are completed **before** you attend your workshop, as, depending on your internet speed, they may take a long time.

1. download and unzip **class materials**
2. download and install **R**
3. download and install **RStudio**
4. install the `tidyverse` suite of **R packages**

2.1 Troubleshooting session

We will hold a troubleshooting session to help with setup during the 20 minutes prior to the start of the workshop. **If you are unable to complete all four tasks by yourself, please join us at the workshop location for this session.** Once the workshop starts we will **NOT** be able to give you one-to-one assistance with troubleshooting installation problems. Likewise, if you arrive late, please do **NOT** expect one-to-one assistance for anything covered at the beginning of the workshop.

2.2 Materials

Download class materials for your workshop:

- R Introduction: `https://github.com/IQSS/dss-workshops/raw/master/R/Rintro.zip`
- R Regression Models: `https://github.com/IQSS/dss-workshops/raw/master/R/Rmodels.zip`
- R Graphics: `https://github.com/IQSS/dss-workshops/raw/master/R/Rgraphics.zip`
- R Data Wrangling: `https://github.com/IQSS/dss-workshops/raw/master/R/RDataWrangling.zip`

Extract materials from the zipped directory (Right-click -> Extract All on Windows, double-click on Mac) and move them to your desktop.

It will be useful when you view the above materials for you to see the different file extensions on your computer. Here are instructions for enabling this:

- Mac OS
- Windows OS

2.3 Software

You must install **both R and RStudio**; it is essential that you have these pre-installed so that we can start the workshop on time. It is also important that you have the **latest versions** of each software, which currently are:

- R version **4.0.3**
- RStudio version **1.3.1093**

Mac OS X:

1. Install R by downloading and running this .pkg file from CRAN.
2. Install the RStudio Desktop IDE by downloading and running this .dmg file.

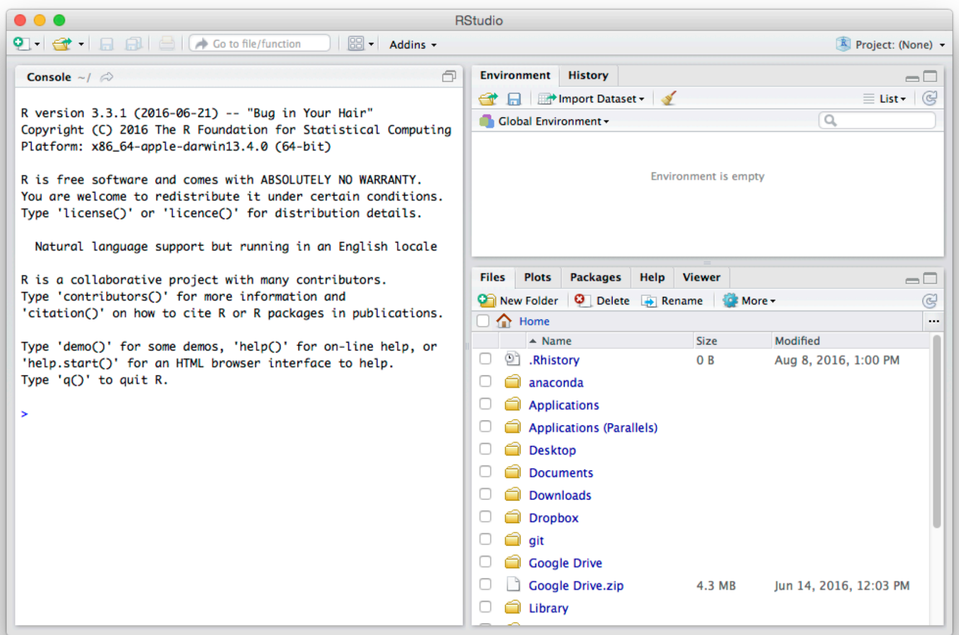
Windows:

1. Install R by downloading and running this .exe file from CRAN.
2. Install the RStudio Desktop IDE by downloading and running this .exe file.

Linux:

1. Install R by downloading the binary files for your distribution from CRAN. Or you can use your package manager (e.g., for Debian/Ubuntu run `sudo apt-get install r-base` and for Fedora run `sudo yum install R`).
2. Install the RStudio Desktop IDE for your distribution.

Success? After both installations, please launch RStudio. If you were successful with the installations, you should see a window similar to this (note that the R version reported may be newer):



If you are having any difficulties with the installations or your RStudio screen does not look like this one, please stop by the training room 20 minutes prior to the start of the workshop.

2.4 Installing the `tidyverse`

We will use the `tidyverse` suite of packages throughout these R workshops. Here are the steps for installation:

1. **Launch an R session within RStudio**

   On Windows, click the start button and search for RStudio then click on it. On Mac, RStudio will be in your applications folder — double click on it.

2. **Install `tidyverse`**

   In the left-hand side window (called the `console`), at the command prompt (`>`) type the following and press enter:

   `install.packages("tidyverse")`

   - If a choice appears that says something like:
     `Do you want to install from sources the package which needs compilation?`
     type `No` in the console.
   - If you are running Windows OS, you may see a message that says:
     `WARNING: Rtools is required to build R packages, but is not currently installed.`
     You can safely ignore this warning.

   A number of messages will scroll by, and there will be a long minute or two pause where nothing appears to happen (but the installation is actually occurring). At last, the output parade should end with a message like:

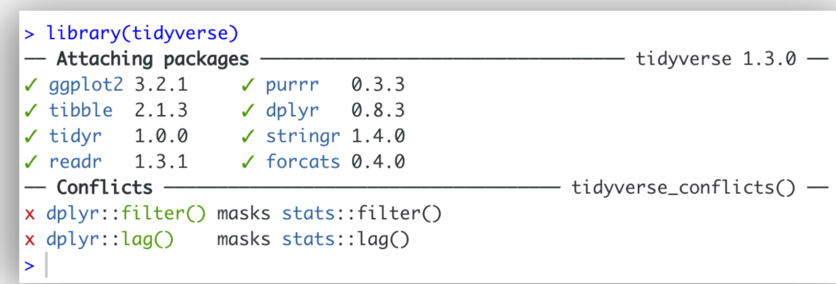
   `The downloaded source/binary packages are in....`

3. **Check that installation was successful**

   We can check that `tidyverse` has installed correctly by connecting it to our current R session. Type the following in the console at the command prompt (`>`) and press enter:

   `library(tidyverse)`

   Success? If so, you should see the following message in the console (note that the version numbers reported may be newer):



   If you do not see this message and encounter an error — try troubleshooting this in the next section.

2.4.1 Troubleshooting `tidyverse` installation

Sometimes, you may run into problems installing the `tidyverse` suite of packages. Here are some commonly encountered errors and suggestions for how to fix them:

1. **`tidyverse` is not available for R version...**
    - Solution: make sure you have the latest versions of both R (4.0.2) and RStudio (1.3.1073).
2. **there is no package `rlang`...**
    - Solution: run this command in the console at the command prompt (`>`):
    - `install.packages("dplyr")`
    - If a choice appears that says something like `Do you want to install from sources the package which needs compilation?`, type `No` in the console.
3. **there is no package `broom`...**
    - Solution: run these commands in the console at the command prompt (`>`), **in this order**:
    - `install.packages("backports")`
    - `install.packages("zeallot")`
    - `install.packages("broom")`
    - `install.packages("tidyverse")`
    - If a choice appears at any point that says something like `Do you want to install from sources the package which needs compilation?`, type `No` in the console.
4. **rlang and/or broom still do not work**
    - Solution: load individual packages that we need from the `tidyverse` suite, by running the following commands in the console at the command prompt (`>`):
    - `library("dplyr")` for the pipe function `%>%` and other SQL commands
    - `library("ggplot2")` modern data visualization
    - `library("readr")` to load CSV data files
    - `library("tidyr")` to reshape data frames

If you have still not successfully installed `tidyverse` (or at least `dplyr`, `ggplot2`, `readr`, and `tidyr`) after troubleshooting, please stop by the training room 20 minutes before the start of your workshop so we can help you. Without these packages, you will not be able to follow along with the workshop materials.

2.5 Installing `rmarkdown` (optional)

We can also install the `rmarkdown` package, which will allow us to combine our text and code into a formatted document at the end of the workshops. Installing this package is optional and will not affect your ability to follow along with the workshop.

1. **Install `rmarkdown`**

    At the command prompt in the console (`>`), please run the following command and press enter:

    `install.packages("rmarkdown")`

    then wait for the stream of messages to end with:

    `The downloaded source/binary packages are in....`

2. **Check that installation was successful**

   We can check that `rmarkdown` has installed correctly by connecting it to our R session. Type the following in the console at the command prompt (`>`) and press enter:

   ```
   library(rmarkdown)
   ```

   Success? If so, in the console you should see just a command prompt (`>`) with no messages to the right of it.

   If you see error or warning messages after the command prompt, the installation was not successful.

If all the above steps have been completed successfully, you should now be ready to start your workshop. **If you ran into any problems, please stop by the training room 20 minutes before the start of your workshop.**

2.6 Resources

- IQSS
  - Workshops: `https://www.iq.harvard.edu/data-science-services/workshop-materials`
  - Data Science Services: `https://www.iq.harvard.edu/data-science-services`
  - Research Computing Environment: `https://iqss.github.io/dss-rce/`
- HBS
  - Research Computing Services workshops: `https://training.rcs.hbs.org/workshops`
  - Other HBS RCS resources: `https://training.rcs.hbs.org/workshop-materials`
  - RCS consulting email: `mailto:research@hbs.edu`

Chapter 3

R Introduction

Topics

- Objects
- Assignment
- Functions
- Finding help
- Importing packages
- Basic data manipulation
- Operations within groups of data
- Saving data

3.1 Setup

3.1.1 Software and Materials

Follow the R Installation instructions and ensure that you can successfully start RStudio.

A handy base R cheat-sheet is available to help you look up and remember basic syntax. In addition, a data transformation cheat-sheet provides a convenient summary of data manipulation syntax.

3.1.2 Class Structure

Informal - Ask questions at any time. Really!

Collaboration is encouraged - please spend a minute introducing yourself to your neighbors!

3.1.3 Prerequisites

This is an introductory R course:

- Assumes no prior knowledge of **how to use** R
- We do assume you know **why** you want to learn R. If you don't, and want a comparison of R to other statistical software, see our Data Science Tools workshop
- Relatively slow-paced

3.1.4 Goals

We will learn about the R language by analyzing a dataset of baby names. In particular, our goals are to learn about:

1. What R is and how it works
2. How we can interact with R
3. Foundations of the language (objects, assignment, functions)
4. The `tidyverse` package ecosystem for data science
5. Basic data manipulation useful for cleaning datasets
6. Working with grouped data
7. Aggregating data to create summaries
8. Saving objects, data, and scripts

This workshop will not cover how to iterate over collections of data, create your own functions, produce publication quality graphics, or fit models to data. These topics are covered in our R Data Wrangling, R Graphics, and R Regression Models workshops.

3.2 R basics

GOAL: To learn about the foundations of the R language. In particular:

1. What R is and how it works
2. R interfaces
3. Objects
4. Assignment
5. Functions
6. Getting help
7. `tidyverse` package ecosystem for data science

3.2.1 What is R?

- R is a free language and environment for statistical computing and graphics

- R is an interpreted language, not a compiled one, meaning that all commands typed on the keyboard are directly executed without requiring to build a complete program (this is like Python and unlike C, Fortran, Pascal, etc.)
- R has existed for over 25 years
- R is modular — most functionality is from add-on packages. So the language can be thought of as a *platform* for creating and running a large number of useful packages.

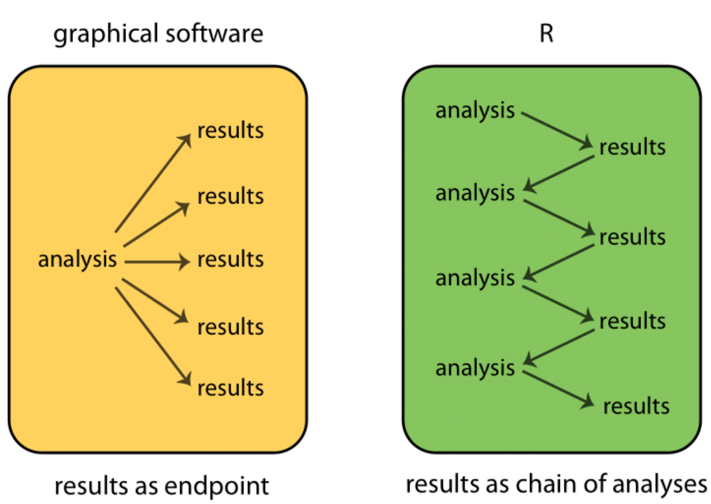
3.2.2 Why use R?

- The most popular software for data analysis
- Extremely flexible: can be used to manipulate, analyze, and visualize any kind of data
- Cutting edge statistical tools
- Publication quality graphics
- 16,000+ add on packages covering all aspects of statistics and machine learning
- Active community of users

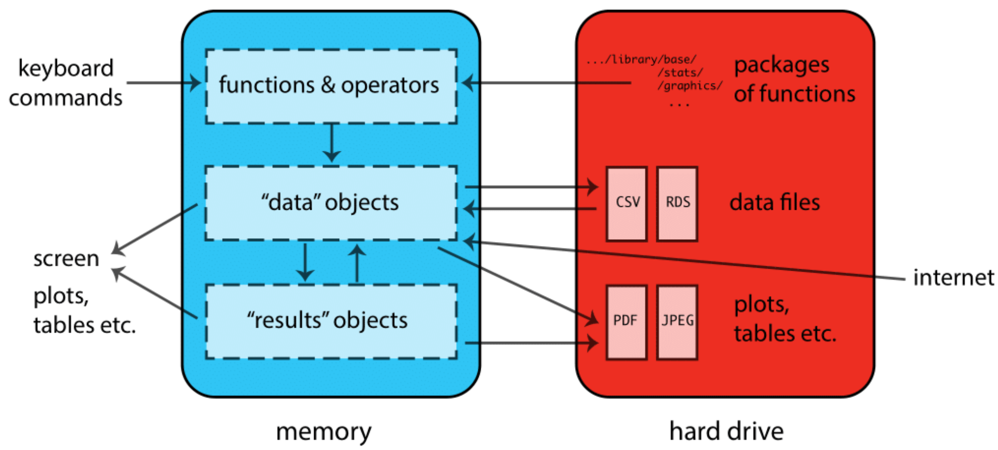
3.2.3 How does R work?

While graphical-based statistical software (e.g., SPSS, GraphPad) immediately display the results of an analysis, **R stores results in an `object` (a data structure)**, so that an analysis can be done with no result displayed. Such a feature is very useful, since a user can extract only that part of the results that is of interest and can pass results into further analyses.

For example, if you run a series of 20 regressions and want to compare the different regression coefficients, R can display only the estimated coefficients: thus the results may take a single line, whereas graphical-based software could open 20 results windows. In addition, these regression coefficients can be passed directly into further analyses — such as generating predictions.



When R is running, variables, data, functions, results, etc., are **stored in memory** on the computer in the form of `objects` that have a name. The user can **perform actions** on these objects with `operators` (arithmetic, logical, comparison, etc.) and `functions` (which are themselves objects). Here's a schematic of how this all fits together:



3.2.4 Interfaces

3.2.4.1 Text editors, IDEs, & Notebooks

There are different ways of interacting with R. The two main ways are through:

1. **text editors** or **Integrated Development Environments (IDEs):** Text editors and IDEs are not really separate categories; as you add features to a text editor it becomes more like an IDE. Some editors/IDEs are language-specific while others are general purpose — typically providing language support via plugins. For these workshops we will use RStudio; it is a good R-specific IDE with many useful features. Here are a few popular editors/IDEs that can be used with R:

Editor / IDE	Features	Ease of use	Language support
RStudio	Excellent	Easy	R only
Jupyter Lab	Good	Easy	Excellent
VS code	Excellent	Easy	Very good
Atom	Good	Moderate	Good
Vim	Excellent	Hard	Good
Emacs	Excellent	Hard	Excellent

2. **Notebooks:** Web-based applications that allow you to create and share documents that contain live code, equations, visualizations, and narrative text. A popular note-

book is the open source Jupyter Notebook that has support for 40+ languages.

3.2.4.2 Source code & literate programming

There are also several different **formats** available for writing code in R. These basically boil down to a choice between:

1. **Source code:** the practice of writing code, and possibly comments, in a plain text document. In R this is done by writing code in a text file with a `.R` or `.r` extension. Writing source code has the great advantage of being simple. Source code is the format of choice if you intend to run your code as a complete script - for example, from the command line.
2. **Literate programming:** the practice of embedding computer code in a natural language document. In R this is often done using **Rmarkdown**, which involves embedding R code in a document that is authored using *Markdown* and which has a `.Rmd` extension. *Markdown* is easy to write and designed to be human-readable. Markdown is the format of choice if you intend to run your code interactively, by running small pieces of code and looking at each output. Many researchers use Markdown to write their journal papers, dissertations, and statistics/math class notes, since it is easy to convert into other formats later, such as HTML (for a webpage), MS Word, or PDF (via LaTeX).

Here are some resources for learning more about RStudio and RMarkdown:

- `https://rmarkdown.rstudio.com/authoring_quick_tour.html`
- `https://cran.r-project.org/web/packages/rmarkdown/vignettes/rmarkdown.html`
- `https://rstudio.com/wp-content/uploads/2019/01/Cheatsheets_2019.pdf`

3.2.5 Launch a session

Start RStudio and create a new project:

- On Windows click the start button and search for RStudio. On Mac RStudio will be in your applications folder.
- In RStudio go to `File -> New Project`.
- Choose `Existing Directory` and browse to the workshop materials directory on your desktop.
- Choose `File -> Open File` and select the file with the word "BLANK" in the name.

3.2.6 Exercise 0

The purpose of this exercise is to give you an opportunity to explore the interface provided by RStudio. You may not know how to do these things; that's fine! This is an opportunity to figure it out.

Also keep in mind that we are living in a golden age of tab completion. If you don't know the name of an R function, try guessing the first two or three letters and pressing TAB. If you guessed correctly the function you are looking for should appear in a pop up!

1. Try to get R to add 2 plus 2.

```
##
```

2. Try to calculate the square root of 10.

```
##
```

3. R includes extensive documentation, including a manual named "An introduction to R". Use the RStudio help pane to locate this manual.

Click for Exercise 0 Solution

1. Try to get R to add 2 plus 2.

```
2 + 2
```

```
## [1] 4
```

```
# or
sum(2, 2)
```

```
## [1] 4
```

2. Try to calculate the square root of 10.

```
sqrt(10)
```

```
## [1] 3.162278
```

```
# or
10^(1/2)
```

```
## [1] 3.162278
```

3. R includes extensive documentation, including a manual named "An introduction to R". Use the RStudio help pane to locate this manual.

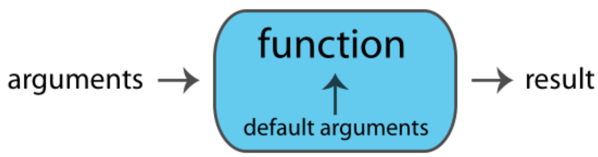
```
# Go to the main help page by running 'help.start() or using the GUI
# menu, find and click on the link to "An Introduction to R".
```

3.2.7 Syntax rules

- R is case sensitive
- R ignores white space
- Variable names should start with a letter (A-Z and a-z) and can include letters, digits (0-9), dots (.), and underscores (_)
- Comments can be inserted using a hash `#` symbol
- Functions must be written with parentheses, even if there is nothing within them; for example: `ls()`

3.2.8 Function calls

Functions perform actions — they take some input, called `arguments` and return some output (i.e., a result). Here's a schematic of how a function works:



The general form for calling R functions is

```
# FunctionName(arg.1 = value.1, arg.2 = value.2, ..., arg.n = value.n)
```

The arguments in a function can be objects (data, formulae, expressions, etc.), some of which could be defined by default in the function; these default values may be modified by the user by specifying options.

Arguments can be **matched by name**; unnamed arguments will be **matched by position**.

```
round(x = 2.34, digits = 1) # match by name
```

```
## [1] 2.3
```

```
round(2.34, 1) # match by position
```

```
## [1] 2.3
```

```
round(1, 2.34) # be careful when matching by position!
```

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

```r
round(digits = 1, x = 2.34) # matching by name is safer!
```

```
## [1] 2.3
```

3.2.9 Assignment

Objects (data structures) can be assigned names and used in subsequent operations:

- The **gets** `<-` operator (less than followed by a dash) is used to save objects
- The name on the left **gets** the object on the right

```r
sqrt(10) # calculate square root of 10; result is not stored anywhere
```

```
## [1] 3.162278
```

```r
x <- sqrt(10) # assign result to a variable named x
```

As mentioned in **Syntax rules** above, names should start with a letter, and contain only letters, numbers, underscores, and periods.

3.2.10 Asking for help

1. You can ask R for help using the `help` function, or the `?` shortcut.

   ```r
   help(help)
   ?help
   ?sqrt
   ```

   The `help` function can be used to look up the documentation for a function, or to look up the documentation to a package. We can learn how to use the `stats` package by reading its documentation like this:

   ```r
   help(package = "stats")
   ```

2. If you know the name of the package you want to use, then Googling "R *package-name*" will often get you to the documentation. Packages are hosted on several different repositories, including:

   - CRAN: `https://cran.r-project.org/web/packages/available_packages_by_name.html`
   - Bioconductor: `https://www.bioconductor.org/packages/release/bioc/`
   - Github: `http://rpkg.gepuro.net/`
   - R-Forge: `https://r-forge.r-project.org/R/?group_id=1326`

3. If you know the type of analysis you want to perform, you can Google "CRAN Task Views", where there are curated lists of packages `https://cran.r-project.org/web/views/`. If you want to know which packages are popular, you can look at `https://r-pkg.org`.

3.2.11 Reading data

R has data reading functionality built-in – see e.g., `help(read.table)`. However, faster and more robust tools are available, and so to make things easier on ourselves we will use a *contributed package* instead. This requires that we learn a little bit about packages in R.

3.2.12 Installing & using packages

R is a modular environment that is extended by the use of **packages**. Packages are collections of functions or commands that are designed to perform specific tasks (e.g., fit a type of regression model). A large number of contributed packages are available (> 16,000).

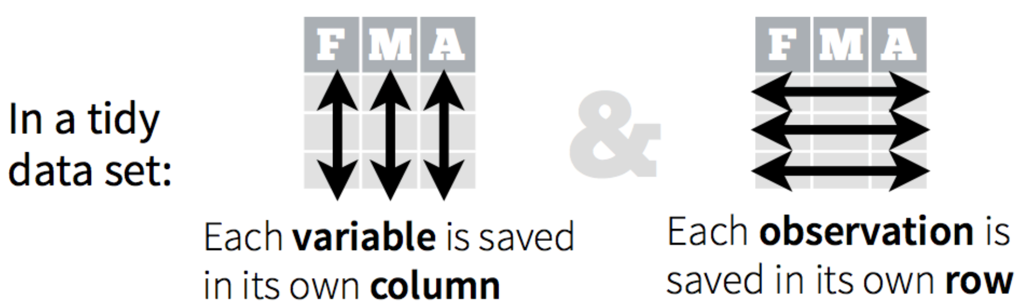
Using an R package is a **two step process**:

1. Install the package onto your computer using the `install.packages()` function. This only needs to be done the **first time** you use the package.

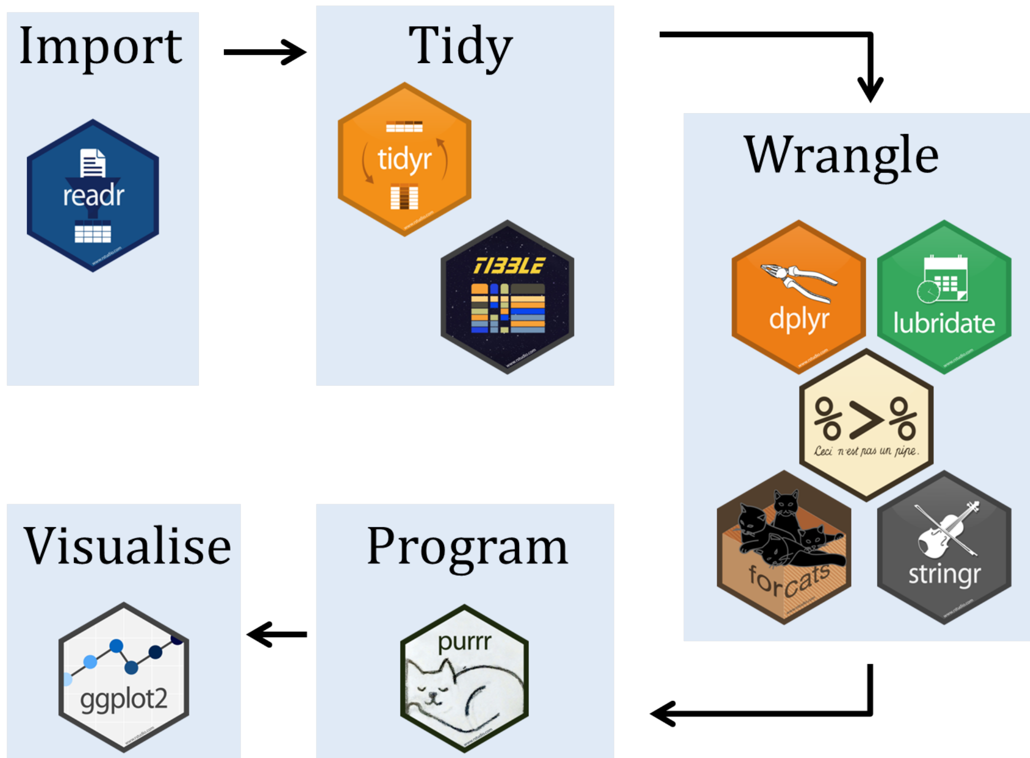
2. Load the package into your R session's search path using the `library()` function. This needs to be done **each time** you use the package.

3.2.13 The `tidyverse`

While R's built-in packages are powerful, in recent years there has been a big surge in well-designed *contributed packages* for R. In particular, a collection of R packages called `tidyverse` have been designed specifically for data science. All packages included in `tidyverse` share an underlying design philosophy, grammar, and data structures. This philosophy is rooted in the idea of "tidy data":



A typical workflow for using `tidyverse` packages looks like this:



You should have already installed the `tidyverse` and `rmarkdown` packages onto your computer before the workshop — see R Installation. Now let's load these packages into the search path of our R session.

```
# Load packages tidyverse and rmarkdown using library() function
library(tidyverse)
library(rmarkdown)
```

3.2.14 Readers for common file types

To read data from a file, you have to know what kind of file it is. The table below lists functions from the `readr` package, which is part of `tidyverse`, that can import data from common plain-text formats.

Data Type	Function
comma separated	`read_csv()`
tab separated	`read_delim()`
other delimited formats	`read_table()`
fixed width	`read_fwf()`

Note You may notice that there exist similar functions in one of the built-in packages in

R called `utils`, e.g., `read.csv` and `read.delim`. These are legacy functions that tend to be slower and less robust than the `readr` functions. One way to tell them apart is that the faster more robust versions use underscores in their names (e.g., `read_csv`) while the older functions use dots (e.g., `read.csv`). Our advice is to use the more robust newer versions, i.e., the ones with underscores.

3.2.15 Baby names data

As an example project we will analyze the popularity of baby names in the US from 1960 through 2017. The data were retrieved from `https://catalog.data.gov/dataset/baby-names-from-social-security-card-applications-national-level-data`.

Here are the questions we will use R to answer:

1. In which year did your name (or another name) occur most frequently by **count**?
2. Which names have the highest popularity by **proportion** for each sex and year?
3. How does the percentage of babies given one of the top 10 names of the year change over time?

3.2.16 Exercise 1

Reading the baby names data

Make sure you have installed the `tidyverse` suite of packages and attached them with `library(tidyverse)`.

1. Open the `read_csv()` help page to determine how to use it to read in data.

```
##
```

2. Read the baby names data using the `read_csv()` function and assign the result with the name `baby_names`.

```
##
```

3. BONUS (optional): Save the `baby_names` data as a Stata data set `babynames.dta` and as an R data set `babynames.rds`.

```
##
```

Click for Exercise 1 Solution

1. Open the `read_csv()` help page to determine how to use it to read in data.

```
?read_csv
```

2. Read the baby names data using the `read_csv()` function and assign the result with the name `baby_names`.

```
baby_names <- read_csv("babyNames.csv")
```

3. BONUS (optional): Save the `baby_names` data as a Stata data set `babynames.dta` and as an R data set `babynames.rds`.

```
write_dta(baby_names, version = 15, path = "babynames.dta")

write_rds(baby_names, file = "babynames.rds")
```

3.3 Manipulating data

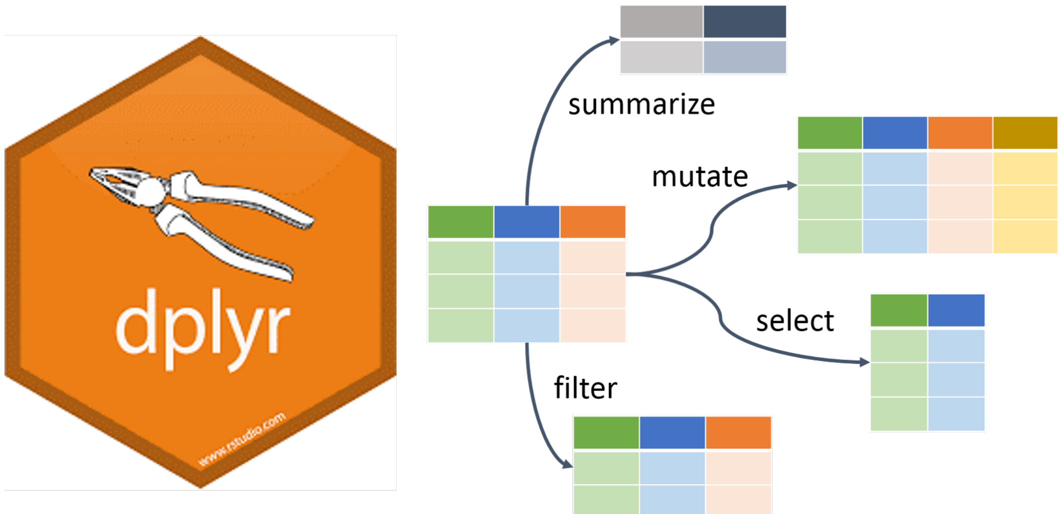
GOAL: To learn about basic data manipulation used to clean datasets. In particular:

1. Filtering data by choosing rows — using the `filter()` function
2. Selecting data by choosing columns — using the `select()` function
3. Arranging data by reordering rows — using the `arrange()` function
4. Using the pipe `%>%` operator to simplify sequential operations

In this section we will pull out specific names from the baby names data and examine changes in their popularity over time.

The `baby_names` object we created in the last exercise is a `data.frame`. There are many other data structures in R, but for now we'll focus on working with `data.frames`. Think of a `data.frame` as a spreadsheet. If you want to know more about R data structures, you can see a summary in our R Data Wrangling workshop.

R has decent data manipulation tools built-in – see e.g., `help(Extract)`. But, `tidyverse` packages often provide more intuitive syntax for accomplishing the same task. In particular, we will use the `dplyr` package from `tidyverse` to filter, select, and arrange data, as well as create new variables.



3.3.1 Filter, select, & arrange

One way to find the year in which your name was the most popular is to filter out just the rows corresponding to your name, and then arrange (sort) by `Count`.

To demonstrate these techniques we'll try to determine whether "Alex"" or "Mark" was more popular in 1992. We start by filtering the data so that we keep only rows where Year is equal to 1992 and Name is either "Alex" or "Mark".

```
# Read in the baby names data if you haven't already
baby_names <- read_csv("babyNames.csv")
```

```
# Filter data, keeping "Alex" and "Mark" in year 1992, and
# assign to a new object "baby_names_alexmark"
# Use logical operators to specify the filtering condition
baby_names_alexmark <- filter(baby_names,
             Year == 1992 & (Name == "Alex" | Name == "Mark"))

print(baby_names_alexmark) # explicit printing
```

```
## # A tibble: 4 x 4
##   Name  Sex   Count  Year
##   <chr> <chr> <dbl> <dbl>
## 1 Alex  Girls   366  1992
## 2 Mark  Girls    20  1992
## 3 Mark  Boys   8743  1992
## 4 Alex  Boys   7348  1992
```

```r
baby_names_alexmark # implicit printing
```

```
## # A tibble: 4 x 4
##   Name  Sex   Count  Year
##   <chr> <chr> <dbl> <dbl>
## 1 Alex  Girls   366  1992
## 2 Mark  Girls    20  1992
## 3 Mark  Boys   8743  1992
## 4 Alex  Boys   7348  1992
```

Notice that we can combine conditions using `&` (AND) and `|` (OR).

In this case it's pretty easy to see that "Mark" is more popular, but to make it even easier we can arrange the data so that the most popular name is listed first.

```r
# Arrange the data by Count to see the most popular name first
arrange(baby_names_alexmark, Count)
```

```
## # A tibble: 4 x 4
##   Name  Sex   Count  Year
##   <chr> <chr> <dbl> <dbl>
## 1 Mark  Girls    20  1992
## 2 Alex  Girls   366  1992
## 3 Alex  Boys   7348  1992
## 4 Mark  Boys   8743  1992
```

```r
# Arrange the data in descending order instead
arrange(baby_names_alexmark, desc(Count))
```

```
## # A tibble: 4 x 4
##   Name  Sex   Count  Year
##   <chr> <chr> <dbl> <dbl>
## 1 Mark  Boys   8743  1992
## 2 Alex  Boys   7348  1992
## 3 Alex  Girls   366  1992
## 4 Mark  Girls    20  1992
```

We can also use the `select()` function to subset the `data.frame` by columns. We can then assign the output to a new object. If we would just like to glance at the first few lines we can use the `head()` function:

```r
# Select columns Name and Count and assign to a new object "baby_names_subset"
baby_names_subset <- select(baby_names, Name, Count)

# Use head() to glance at the first few lines
head(baby_names_subset)
```

```
## # A tibble: 6 x 2
##   Name  Count
##   <chr> <dbl>
## 1 Mary  51474
## 2 Susan 39200
## 3 Linda 37314
## 4 Karen 36376
## 5 Donna 34133
## 6 Lisa  33702
```

```
head(baby_names_subset, n = 6) # default is n = 6
```

```
## # A tibble: 6 x 2
##   Name  Count
##   <chr> <dbl>
## 1 Mary  51474
## 2 Susan 39200
## 3 Linda 37314
## 4 Karen 36376
## 5 Donna 34133
## 6 Lisa  33702
```

3.3.2 Logical & relational operators

In a previous example we used `==` to filter rows. Here's a table of other commonly used relational operators:

Operator	Meaning
`==`	equal to
`!=`	not equal to
`>`	greater than
`>=`	greater than or equal to
`<`	less than
`<=`	less than or equal to
`%in%`	contained in

These relational operators may be combined with logical operators, such as `&` (and) or `|` (or). For example, we can create a **vector** (a **container for a collection of values**) and demonstrate some ways to combine operators:

```
# Create a vector of consecutive values between 1 and 10
x <- 1:10 # a vector
x
```

```
##  [1]  1  2  3  4  5  6  7  8  9 10
```

```
# Which elements of x are above 7
x > 7 # a simple condition
```

```
##  [1] FALSE FALSE FALSE FALSE FALSE FALSE FALSE  TRUE  TRUE  TRUE
```

```
# Which elements of x are above 7 or below 3
x > 7 | x < 3 # two conditions combined
```

```
##  [1]  TRUE  TRUE FALSE FALSE FALSE FALSE FALSE  TRUE  TRUE  TRUE
```

If we want to match multiple elements from two vectors we can use the `%in%` operator:

```
# x %in% vector
# elements of x matching numbers 1, 5, or 10
x %in% c(1, 5, 10)
```

```
##  [1]  TRUE FALSE FALSE FALSE  TRUE FALSE FALSE FALSE FALSE  TRUE
```

Notice that logical and relational operators return **logical vectors** of `TRUE` and `FALSE` values. The logical vectors returned by these operators can themselves be operated on by functions:

```
# Count the number of elements of x above 7
x > 7
```

```
##  [1] FALSE FALSE FALSE FALSE FALSE FALSE FALSE  TRUE  TRUE  TRUE
```

```
sum(x > 7)
```

```
## [1] 3
```

3.3.3 Exercise 2.1

Peak popularity of your name

In this exercise you will discover the year your name reached its maximum popularity.

Read in the "babyNames.csv" file if you have not already done so, assigning the result to `baby_names`. Make sure you have installed the `tidyverse` suite of packages and attached them with `library(tidyverse)`.

1. Use `filter` to extract data for your name (or another name of your choice).

```
##
```

2. Arrange the data you produced in step 1 above by `Count`. In which year was the name most popular?

```
##
```

3. BONUS (optional): Filter the data to extract *only* the row containing the most popular boys name in 1999.

```
##
```

Click for Exercise 2.1 Solution

1. Use `filter` to extract data for your name (or another name of your choice).

```
baby_names_george <- filter(baby_names, Name == "George")
```

2. Arrange the data you produced in step 1 above by `Count`. In which year was the name most popular?

```
arrange(baby_names_george, desc(Count))
```

```
## # A tibble: 97 x 4
##    Name   Sex   Count  Year
##    <chr>  <chr> <dbl> <dbl>
##  1 George Boys  14063  1960
##  2 George Boys  13638  1961
##  3 George Boys  12553  1962
##  4 George Boys  12084  1963
##  5 George Boys  11793  1964
##  6 George Boys  10683  1965
##  7 George Boys   9942  1966
##  8 George Boys   9702  1967
##  9 George Boys   9388  1968
## 10 George Boys   9203  1969
## # ... with 87 more rows
```

3. BONUS (optional): Filter the data to extract *only* the row containing the most popular boys name in 1999.

```
baby_names_boys_1999 <- filter(baby_names,
                               Year == 1999 & Sex == "Boys")
```

```r
filter(baby_names_boys_1999, Count == max(Count))
```

```
## # A tibble: 1 x 4
##   Name  Sex   Count  Year
##   <chr> <chr> <dbl> <dbl>
## 1 Jacob Boys  35361  1999
```

3.3.4 Pipe operator

There is one very special operator in R called a **pipe** operator that looks like this: `%>%`. It allows us to "chain" several function calls and, as each function returns an object, feed it into the next call in a single statement, without needing extra variables to store the intermediate results. The point of the pipe is to help you write code in a way that is easier to read and understand as we will see below.

There is no need to load any additional packages as the operator is made available via the `magrittr` package installed as part of `tidyverse`. Let's rewrite the sequence of commands to output ordered counts for names "Alex" or "Mark".

```r
# Filter data, keeping "Alex" and "Mark" in year 1992, and
# assign to a new object "baby_names_alexmark"
# Arrange the result in a descending order by Count

# unpiped version
baby_names_alexmark <- filter(baby_names, Year == 1992 & (Name == "Alex" | Name == "Mark"))
arrange(baby_names_alexmark, desc(Count))
```

```
## # A tibble: 4 x 4
##   Name  Sex   Count  Year
##   <chr> <chr> <dbl> <dbl>
## 1 Mark  Boys   8743  1992
## 2 Alex  Boys   7348  1992
## 3 Alex  Girls   366  1992
## 4 Mark  Girls    20  1992
```

```r
# piped version
baby_names %>%
  filter(Year == 1992 & (Name == "Alex" | Name == "Mark")) %>%
  arrange(desc(Count))
```

```
## # A tibble: 4 x 4
##   Name  Sex   Count  Year
##   <chr> <chr> <dbl> <dbl>
## 1 Mark  Boys   8743  1992
## 2 Alex  Boys   7348  1992
## 3 Alex  Girls   366  1992
## 4 Mark  Girls    20  1992
```

Hint: try pronouncing "then" whenever you see `%>%`. Using pseudocode, we can see what the pipe is doing:

```
# unpiped version
filter(dataset, condition)

# piped version
dataset %>% filter(condition)

# what the pipe is doing
output_of_thing_on_left %>% becomes_input_of_thing_on_right
```

Advantages of using the pipe:

1. We can avoid creating intermediate variables, such as `baby_names_alexmark`
2. Less to type
3. Easier to read and follow the logic (especially avoiding using nested functions)

3.3.5 Exercise 2.2

Rewrite the solution to Exercise 2.1 using pipes. Remember that we were looking for the year your name reached its maximum popularity. For that, we filtered the data and then arranged by `Count`.

```
# Use filter to extract data for your name (or another name of your choice)
# Arrange the data by Count
```

Click for Exercise 2.2 Solution

Rewrite the solution to Exercise 2.1 using pipes.

```
# Use filter to extract data for your name (or another name of your choice)
# Arrange the data by Count
baby_names %>%
    filter(Name == "George") %>%
    arrange(desc(Count))
```

```
## # A tibble: 97 x 4
##    Name   Sex   Count  Year
##    <chr>  <chr> <dbl> <dbl>
##  1 George Boys  14063  1960
##  2 George Boys  13638  1961
##  3 George Boys  12553  1962
##  4 George Boys  12084  1963
##  5 George Boys  11793  1964
##  6 George Boys  10683  1965
##  7 George Boys   9942  1966
##  8 George Boys   9702  1967
##  9 George Boys   9388  1968
## 10 George Boys   9203  1969
## # ... with 87 more rows
```

3.4 Plotting data

GOAL: Plot baby name trends over time – using the `qplot()` function

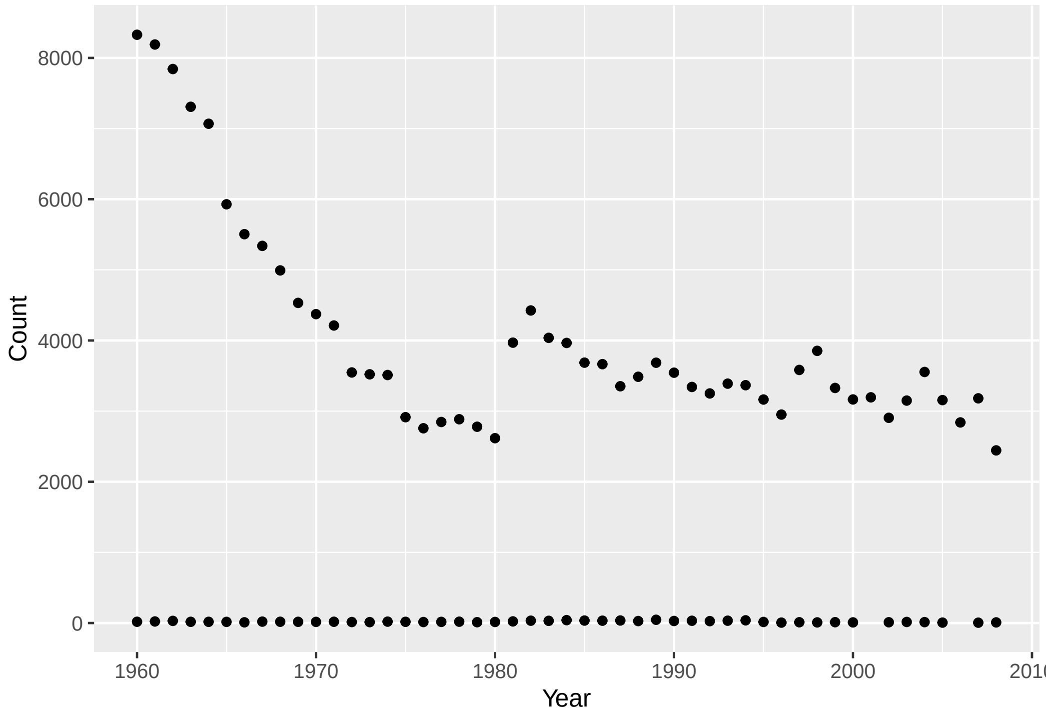
It can be difficult to spot trends when looking at summary tables. Plotting the data makes it easier to identify interesting patterns.

R has decent plotting tools built-in – see e.g., `help(plot)`. However, again, we will make use of a *contributed package* from `tidyverse` called `ggplot2`.

For quick and simple plots we can use the `qplot()` function from `ggplot2`. For example, we can plot the number of babies given the name "Diana" over time like this:

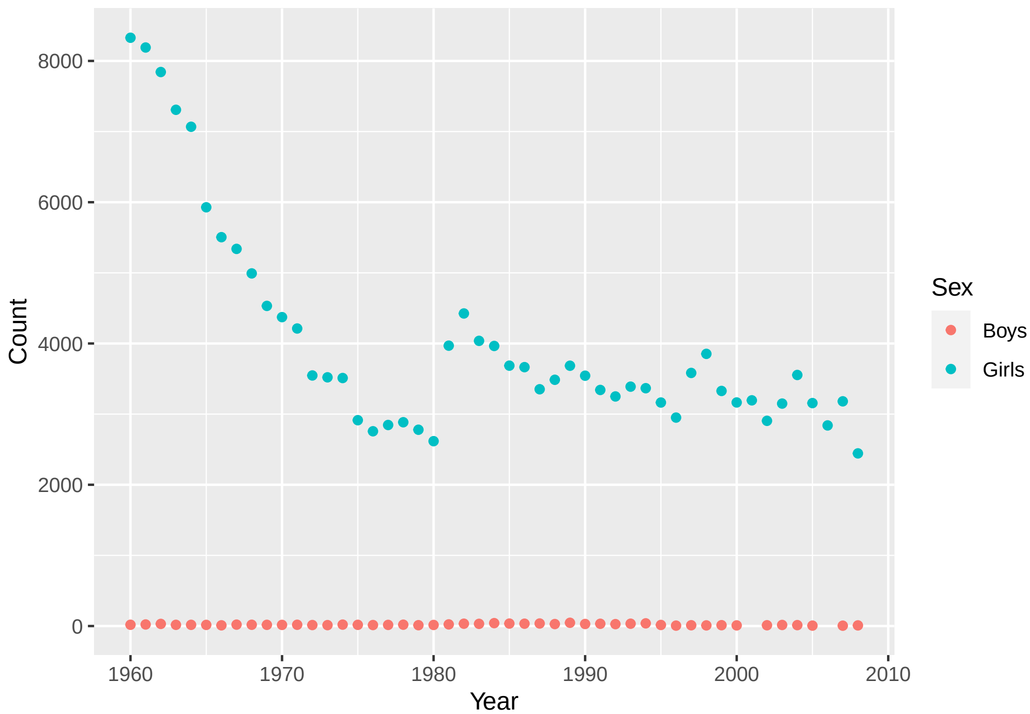
```
# Filter data keeping rows for name "Diana" and
# assign to a new object called "baby_names_diana"
baby_names_diana <- filter(baby_names, Name == "Diana")
```

```
# Use qplot() function to plot Counts (y) by Year (x)
qplot(x = Year, y = Count,
     data = baby_names_diana)
```



Interestingly, there are usually some gender-atypical names, even for very strongly gendered names like "Diana". Splitting these trends out by `Sex` is very easy:

```
# Use qplot() function to plot Counts (y) by Year (x).
# Split trends by Sex using color.
qplot(x = Year, y = Count, color = Sex,
      data = baby_names_diana)
```



3.4.1 Exercise 3

Plot peak popularity of your name

1. Use `filter` to extract data for your name (same as previous exercise)

```
##
```

2. Plot the data you produced in step 1 above, with `Year` on the x-axis and `Count` on the y-axis.

```
##
```

3. Adjust the plot so that is shows boys and girls in different colors.

```
##
```

4. BONUS (Optional): Adjust the plot to use lines instead of points.

```
##
```

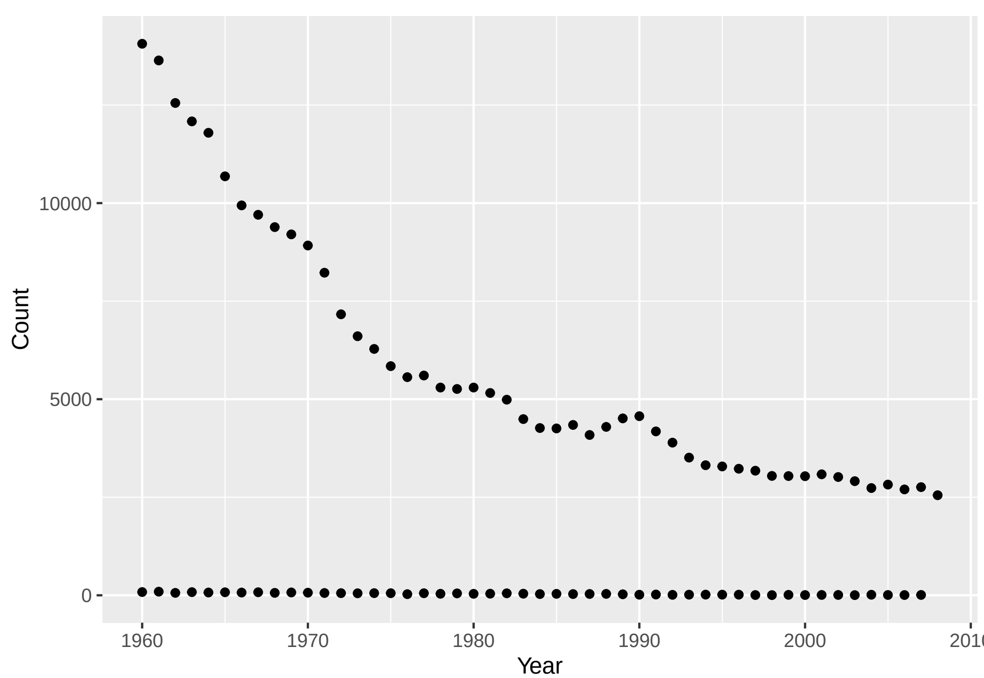
Click for Exercise 3 Solution

1. Use `filter()` to extract data for your name (same as previous exercise).

```
baby_names_george <- filter(baby_names, Name == "George")
```

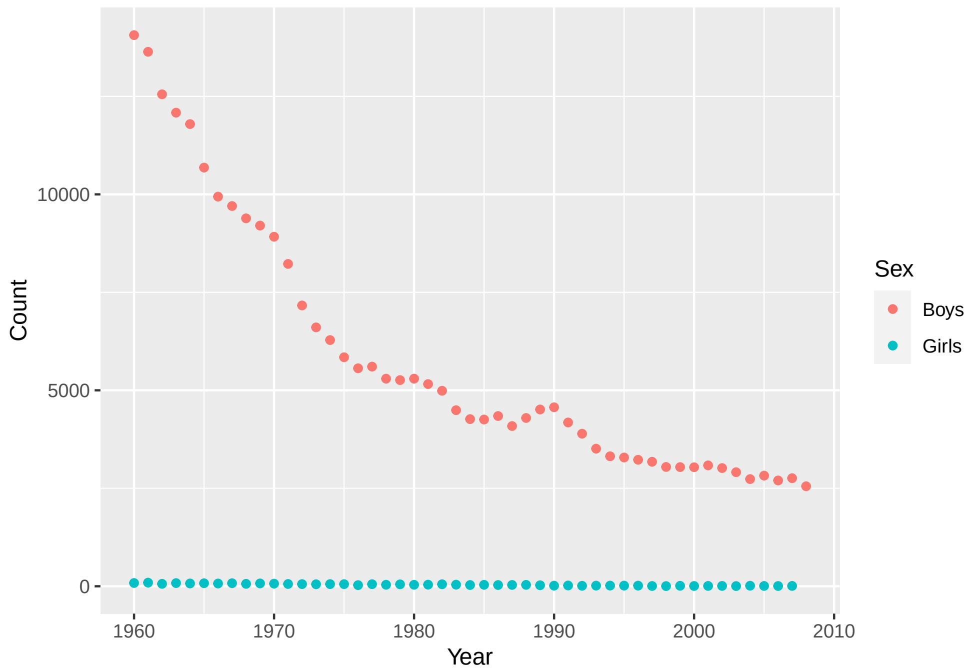
2. Plot the data you produced in step 1 above, with `Year` on the x-axis and `Count` on the y-axis.

```
qplot(x = Year, y = Count, data = baby_names_george)
```



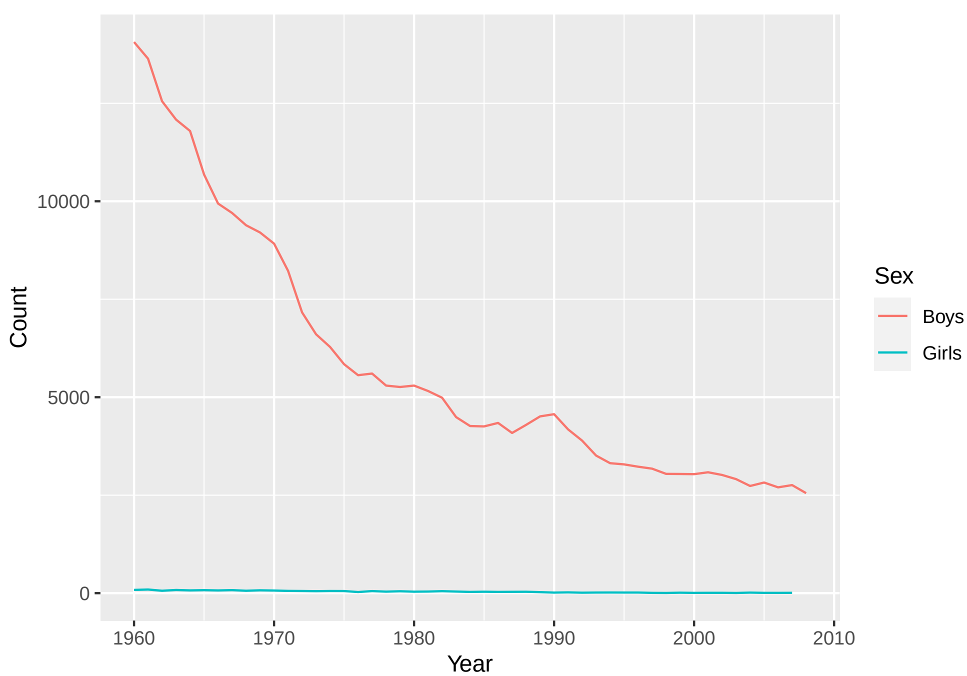
3. Adjust the plot so that is shows boys and girls in different colors.

```
qplot(x = Year, y = Count, color = Sex, data = baby_names_george)
```



4. BONUS (Optional): Adjust the plot to use lines instead of points.

```
qplot(x = Year, y = Count, color = Sex, data = baby_names_george, geom = "line")
```



3.5 Creating variables

GOAL: To learn how to create new variables with and without grouped data. In particular:

1. Creating new variables (columns) — using the `mutate()` function
2. Creating new variables within groups — by combining the `mutate()` and `group_by()` functions
3. Recode existing variables — by combining the `mutate()` and `case_when()` functions

We want to use these skills to find out which names have been the most popular.

3.5.1 Create or modify columns

So far we've used `Count` as a measure of popularity. A better approach is to use proportion to avoid confounding popularity with the number of babies born in a given year.

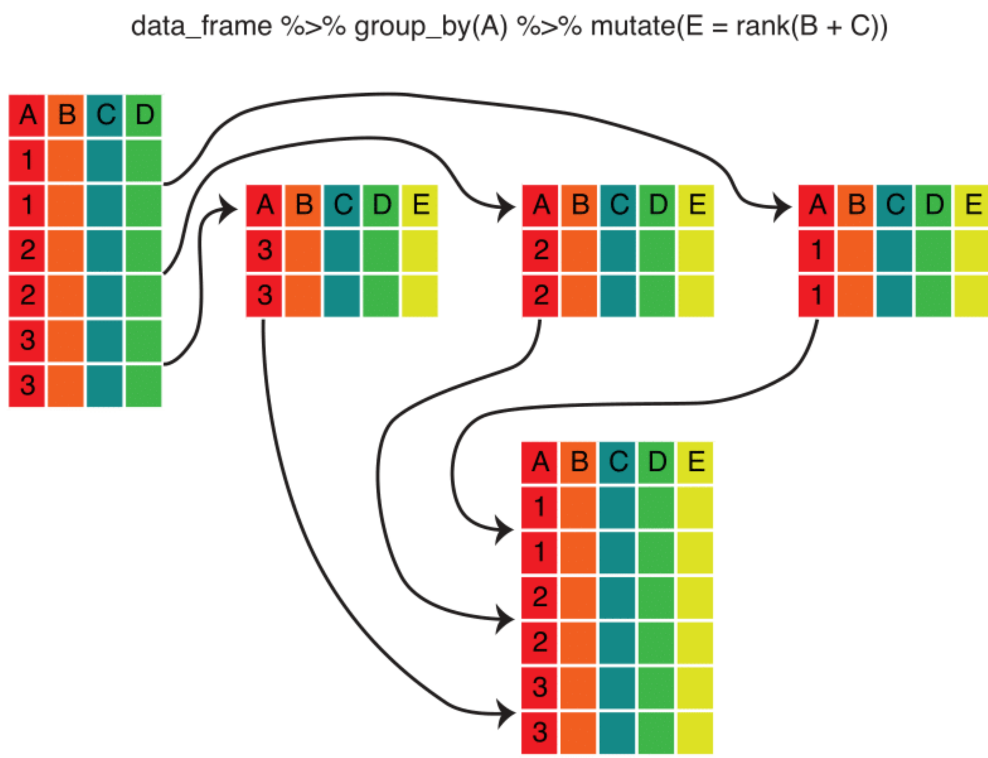
The `mutate()` function makes it easy to add or modify the columns of a `data.frame`. For example, we can use it to rescale the count of each name in each year:

```
# Use piping to add a new column to the data, called Count_1k,
# which rescales counts to thousands
baby_names <- baby_names %>% mutate(Count_1k = Count/1000)
head(baby_names)
```

```
## # A tibble: 6 x 5
##   Name  Sex   Count  Year Count_1k
##   <chr> <chr> <dbl> <dbl>    <dbl>
## 1 Mary  Girls 51474  1960     51.5
## 2 Susan Girls 39200  1960     39.2
## 3 Linda Girls 37314  1960     37.3
## 4 Karen Girls 36376  1960     36.4
## 5 Donna Girls 34133  1960     34.1
## 6 Lisa  Girls 33702  1960     33.7
```

3.5.2 Operating by group

Because of the nested nature of our data, we want to compute proportion or rank **within** each `Sex` by `Year` group. The `dplyr` package has a `group_by()` function that makes this relatively straightforward. Here's the logic behind this process:



Note that the group_by() function converts a **data frame** into a **grouped data frame** — that is, a data frame with metadata identifying the groups. The data remain grouped until you change the groups by running group_by() again or remove the grouping metadata using ungroup().

Here's the code that implements the calculation:

```
# Group baby_names by Year and Sex and rank Count_1k,
# within each group (calling the resulting new column "Rank").
# Remember to ungroup at the end!
baby_names <-
  baby_names %>%
  group_by(Year, Sex) %>%
  mutate(Rank = rank(Count_1k)) %>%
  ungroup()

head(baby_names)
```

```
## # A tibble: 6 x 6
##   Name  Sex   Count  Year Count_1k  Rank
##   <chr> <chr> <dbl> <dbl>    <dbl> <dbl>
```

```
## 1 Mary  Girls 51474  1960     51.5  7331
## 2 Susan Girls 39200  1960     39.2  7330
## 3 Linda Girls 37314  1960     37.3  7329
## 4 Karen Girls 36376  1960     36.4  7328
## 5 Donna Girls 34133  1960     34.1  7327
## 6 Lisa  Girls 33702  1960     33.7  7326
```

3.5.3 Recoding variables

It's often necessary to create a new variable that is a recoded version of an existing variable. For example, we might want to take our `Count_1k` variable and create a new variable that divides it into `low`, `medium`, and `high` categories. To do this, we can use the `case_when()` function within the `mutate()` function:

```
# Use case_when() to recode the newly created Rank column into:
# low (<=10), high (>40), and medium (all others).
# Call the resulting column "Count_levels".
baby_names <-
  baby_names %>%
  mutate(Count_levels = case_when(
                          Count_1k <= 10                ~ "low",
                          Count_1k  > 10 & Count_1k <= 40 ~ "medium",
                          Count_1k  > 40                ~ "high"
                          ))

head(baby_names)
```

```
## # A tibble: 6 x 7
##   Name  Sex   Count  Year Count_1k  Rank Count_levels
##   <chr> <chr> <dbl> <dbl>    <dbl> <dbl> <chr>
## 1 Mary  Girls 51474  1960     51.5  7331 high
## 2 Susan Girls 39200  1960     39.2  7330 medium
## 3 Linda Girls 37314  1960     37.3  7329 medium
## 4 Karen Girls 36376  1960     36.4  7328 medium
## 5 Donna Girls 34133  1960     34.1  7327 medium
## 6 Lisa  Girls 33702  1960     33.7  7326 medium
```

3.5.4 Exercise 4

Most popular names

In this exercise your goal is to identify the most popular names for each year.

1. Use `mutate()` and `group_by()` to create a column named `Proportion` where `Proportion = Count/sum(Count)` for each `Year X Sex` group. Use pipes wherever it makes sense.

```
##
```

2. Use `mutate()` and `group_by()` to create a column named `Rank` where `Rank = rank(desc(Count))` for each `Year X Sex` group.

```
##
```

3. Filter the baby names data to display only the most popular name for each `Year X Sex` group. Keep only the columns: `Year`, `Name`, `Sex`, and `Proportion`.

```
##
```

4. Plot the data produced in step 3, putting `Year` on the x-axis and `Proportion` on the y-axis. How has the proportion of babies given the most popular name changed over time?

```
##
```

5. BONUS (optional): Which names are the most popular for both boys and girls?

```
##
```

Click for Exercise 4 Solution

1. Use `mutate()` and `group_by()` to create a column named `Proportion` where `Proportion = Count/sum(Count)` for each `Year X Sex` group.

```
baby_names <-
  baby_names %>%
  group_by(Year, Sex) %>%
  mutate(Proportion = Count/sum(Count)) %>%
  ungroup()

head(baby_names)
```

```
## # A tibble: 6 x 8
##   Name  Sex   Count  Year Count_1k  Rank Count_levels Proportion
##   <chr> <chr> <dbl> <dbl>    <dbl> <dbl> <chr>             <dbl>
## 1 Mary  Girls 51474  1960     51.5  7331 high             0.0255
## 2 Susan Girls 39200  1960     39.2  7330 medium           0.0194
## 3 Linda Girls 37314  1960     37.3  7329 medium           0.0185
## 4 Karen Girls 36376  1960     36.4  7328 medium           0.0180
## 5 Donna Girls 34133  1960     34.1  7327 medium           0.0169
## 6 Lisa  Girls 33702  1960     33.7  7326 medium           0.0167
```

2. Use `mutate()` and `group_by()` to create a column named `Rank` where `Rank = rank(desc(Count))` for each `Year X Sex` group.

```
baby_names <-
  baby_names %>%
  group_by(Year, Sex) %>%
  mutate(Rank = rank(desc(Count))) %>%
  ungroup()

head(baby_names)
```

```
## # A tibble: 6 x 8
##   Name  Sex   Count  Year Count_1k  Rank Count_levels Proportion
##   <chr> <chr> <dbl> <dbl>    <dbl> <dbl> <chr>             <dbl>
## 1 Mary  Girls 51474  1960     51.5     1 high             0.0255
## 2 Susan Girls 39200  1960     39.2     2 medium           0.0194
## 3 Linda Girls 37314  1960     37.3     3 medium           0.0185
## 4 Karen Girls 36376  1960     36.4     4 medium           0.0180
## 5 Donna Girls 34133  1960     34.1     5 medium           0.0169
## 6 Lisa  Girls 33702  1960     33.7     6 medium           0.0167
```

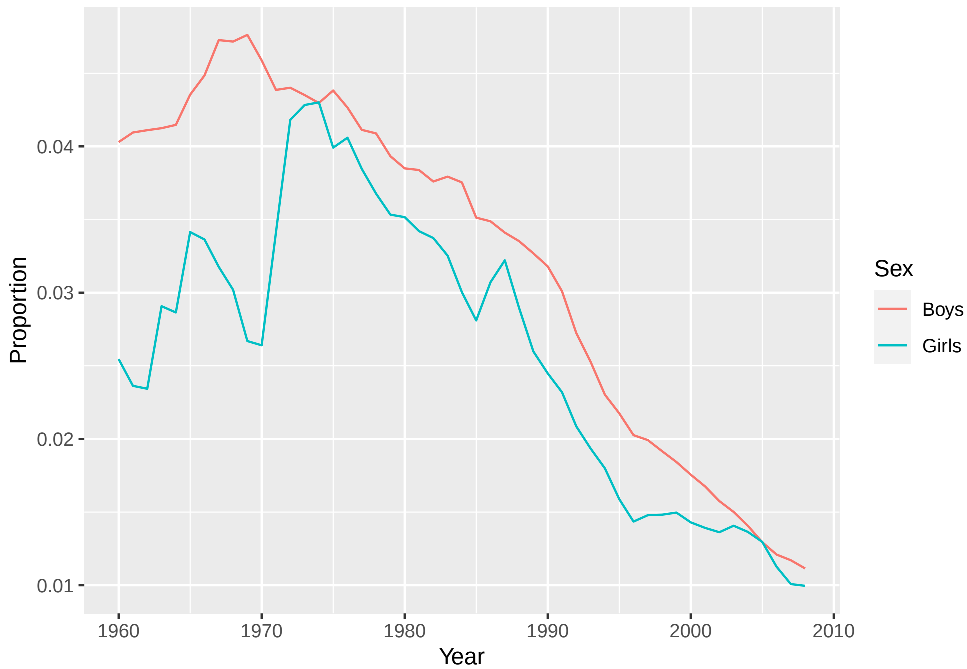
3. Filter the baby names data to display only the most popular name for each `Year X Sex` group.

```
top1 <-
  baby_names %>%
  filter(Rank == 1) %>%
  select(Year, Name, Sex, Proportion)

head(top1)
```

```
## # A tibble: 6 x 4
##    Year Name    Sex   Proportion
##   <dbl> <chr>   <chr>      <dbl>
## 1  1960 Mary    Girls     0.0255
## 2  1960 David   Boys      0.0403
## 3  1961 Mary    Girls     0.0236
## 4  1961 Michael Boys      0.0409
## 5  1962 Lisa    Girls     0.0234
## 6  1962 Michael Boys      0.0411
```

4. Plot the data produced in step 3, putting `Year` on the x-axis and `Proportion` on the y-axis. How has the proportion of babies given the most popular name changed over time?

```
qplot(x = Year,
      y = Proportion,
      color = Sex,
      data = top1,
      geom = "line")
```



5. BONUS (optional): Which names are the most popular for both boys and girls?

```
girls_and_boys <- inner_join(filter(baby_names, Sex == "Boys"),
                             filter(baby_names, Sex == "Girls"),
                             by = c("Year", "Name"))

girls_and_boys <- mutate(girls_and_boys,
                         Product = Count.x * Count.y,
                         Rank = rank(desc(Product)))

filter(girls_and_boys, Rank == 1)
```

```
## # A tibble: 1 x 16
##   Name  Sex.x Count.x  Year Count_1k.x Rank.x Count_levels.x Proportion.x Sex.y
##   <chr> <chr>   <dbl> <dbl>      <dbl>  <dbl> <chr>                 <dbl> <chr>
## 1 Tayl~ Boys     7688  1993       7.69     51 low                 0.00392 Girls
## # ... with 7 more variables: Count.y <dbl>, Count_1k.y <dbl>, Rank.y <dbl>,
## #   Count_levels.y <chr>, Proportion.y <dbl>, Product <dbl>, Rank <dbl>
```

3.6 Aggregating variables

GOAL: To learn how to aggregate data to create summaries with and without grouped data. In particular:

1. Collapsing data into summaries — using the `summarize()` function
2. Creating summaries within groups — by combining the `summarize()` and `group_by()` functions

You may have noticed that the percentage of babies given the most popular name of the year appears to have decreased over time. We can compute a more robust measure of the popularity of the most popular names by calculating the number of babies given one of the top 10 girl or boy names of the year.

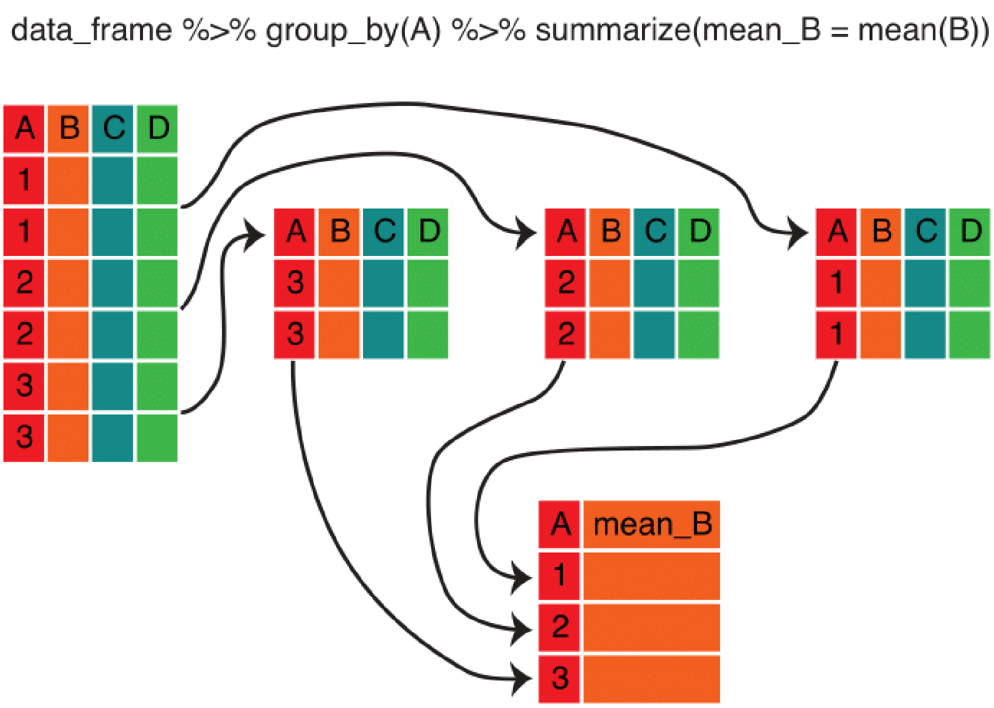
To compute this measure we need to operate within groups, as we did using `mutate()` above, but this time we need to collapse each group into a single summary statistic. We can achieve this using the `summarize()` function.

First, let's see how this function works without grouping. The following code outputs the total number of girls and boys in the data:

```r
# Use summarize() to output the total number of boys and girls in the sample
baby_names %>%
  summarize(Girls_n = sum(Sex=="Girls"),
            Boys_n = sum(Sex=="Boys"))
```

```
## # A tibble: 1 x 2
##   Girls_n Boys_n
##     <int>  <int>
## 1  641084 407491
```

Next, using `group_by()` and `summarize()` together, we can calculate the number of babies born each year. Here's the logic behind this process:



Note that, unlike with the `mutate()` function, the `summarize()` function returns a data frame with fewer rows than the original, because of aggregation.

Here's the code that implements the calculation:

```
# Group baby_names by Year and calculate the sum of Count
# Call the resulting column "Total"
# Assign the result to an object called "bn_by_year" and remember to ungroup!
bn_by_year <-
  baby_names %>%
  group_by(Year) %>%
  summarize(Total = sum(Count)) %>%
  ungroup()

head(bn_by_year)
```

```
## # A tibble: 6 x 2
##    Year   Total
##   <dbl>   <dbl>
## 1  1960 4154377
## 2  1961 4140244
## 3  1962 4035234
## 4  1963 3958791
```

```
## 5  1964 3887800
## 6  1965 3626029
```

3.6.1 Exercise 5

Popularity of the most popular names

In this exercise we will plot trends in the proportion of boys and girls given one of the 10 most popular names each year.

1. Filter the `baby_names` data, retaining only the 10 most popular girl and boy names for each year.

```
##
```

2. Summarize the data produced in step one to calculate the `Total Proportion` of boys and girls given one of the top 10 names each year.

```
##
```

3. Plot the data produced in step 2, with `Year` on the x-axis and `Total Proportion` on the y axis. Color by `Sex` and notice the trend.

```
##
```

Click for Exercise 5 Solution

1. Filter the `baby_names` data, retaining only the 10 most popular girl and boy names for each year.

```
most_popular <-
  baby_names %>%
  group_by(Year, Sex) %>%
  filter(Rank <= 10)

head(most_popular, n = 10)
```

```
## # A tibble: 10 x 8
## # Groups:   Year, Sex [1]
##    Name      Sex   Count  Year Count_1k  Rank Count_levels Proportion
##    <chr>     <chr> <dbl> <dbl>    <dbl> <dbl> <chr>             <dbl>
##  1 Mary      Girls 51474  1960     51.5     1 high             0.0255
##  2 Susan     Girls 39200  1960     39.2     2 medium           0.0194
##  3 Linda     Girls 37314  1960     37.3     3 medium           0.0185
##  4 Karen     Girls 36376  1960     36.4     4 medium           0.0180
##  5 Donna     Girls 34133  1960     34.1     5 medium           0.0169
```

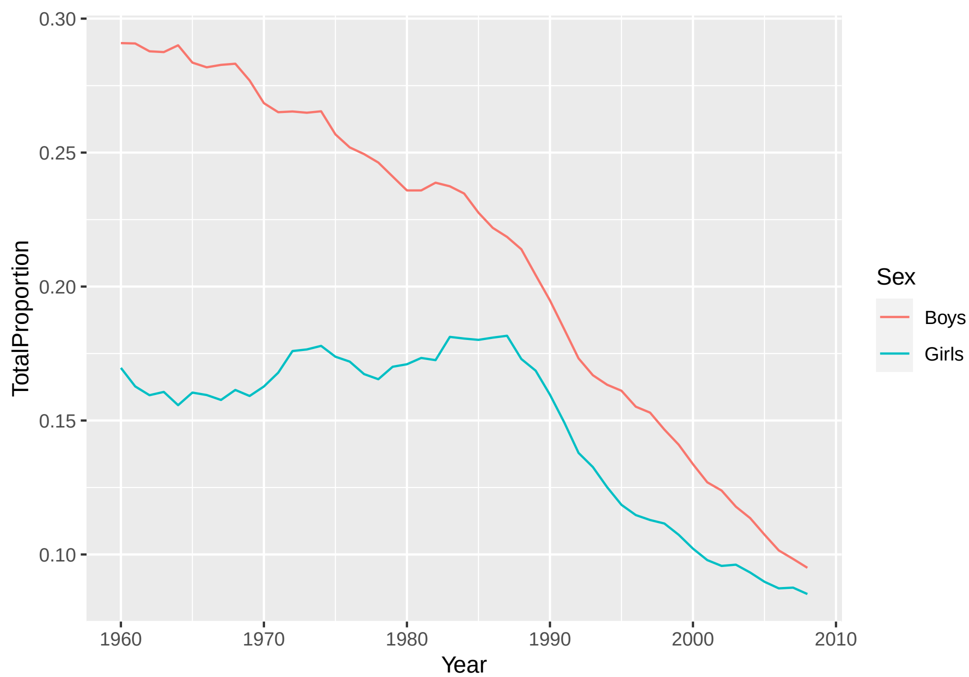
```
##  6 Lisa     Girls 33702  1960      33.7      6 medium            0.0167
##  7 Patricia Girls 32102  1960      32.1      7 medium            0.0159
##  8 Debra    Girls 26737  1960      26.7      8 medium            0.0132
##  9 Cynthia  Girls 26725  1960      26.7      9 medium            0.0132
## 10 Deborah  Girls 25264  1960      25.3     10 medium            0.0125
```

2. Summarize the data produced in step one to calculate the `Total Proportion` of boys and girls given one of the top 10 names each year.

```
top10 <-
  most_popular %>% # it is already grouped by Year and Sex
  summarize(TotalProportion = sum(Proportion))
```

3. Plot the data produced in step 2, with `Year` on the x-axis and `Total Proportion` on the y axis. Color by `Sex` and notice the trend.

```
qplot(x = Year,
      y = TotalProportion,
      color = Sex,
      data = top10,
      geom = "line")
```



3.7 Saving work

GOAL: To learn how to save objects, data, and scripts for later use.

Now that we have made some changes to our data set, we might want to save those changes to a file.

3.7.1 Saving individual datasets

You might find functions `write_csv()` and `write_rds()` from package `readr` handy!

```
# write baby_names to a .csv file
write_csv(baby_names, "babyNames.csv")
```

```
# write baby_names to an R file
write_rds(baby_names, "babyNames.rds")
```

3.7.2 Saving multiple datasets

```
ls() # list objects in our workspace
# Use save() function from the `base` R package to record some objects
# into a file named "myDataFiles.RData"
save(baby_names_diana, bn_by_year, baby_names_subset, file="myDataFiles.RData")
```

```
# Load the "myDataFiles.RData"
# load("myDataFiles.RData")
```

3.8 Wrap-up

3.8.1 Feedback

These workshops are a work-in-progress, please provide any feedback to: `help@iq.harvard.edu`

3.8.2 Resources

- IQSS
  - Workshops: `https://www.iq.harvard.edu/data-science-services/workshop-materials`
  - Data Science Services: `https://www.iq.harvard.edu/data-science-services`
  - Research Computing Environment: `https://iqss.github.io/dss-rce/`
- HBS

    - Research Computing Services workshops: `https://training.rcs.hbs.org/workshops`
    - Other HBS RCS resources: `https://training.rcs.hbs.org/workshop-materials`
    - RCS consulting email: `mailto:research@hbs.edu`

- Software (all free!):

    - R and R package download: `http://cran.r-project.org`
    - RStudio download: `http://rstudio.org`
    - ESS (Emacs R package): `http://ess.r-project.org/`

- Cheatsheets

    - `https://rstudio.com/wp-content/uploads/2019/01/Cheatsheets_2019.pdf`

- Online tutorials

    - `https://swirlstats.com/`
    - `https://r4ds.had.co.nz/`
    - `https://hbs-rcs.github.io/R_Intro-gapminder/base-r/`
    - `https://www.pluralsight.com/search?q=R`
    - `https://www.datacamp.com/`
    - `https://rmarkdown.rstudio.com/lesson-1.html`

- Getting help:

    - Documentation and tutorials: `http://cran.r-project.org/other-docs.html`
    - Recommended R packages by topic: `http://cran.r-project.org/web/views/`
    - Mailing list: `https://stat.ethz.ch/mailman/listinfo/r-help`
    - StackOverflow: `http://stackoverflow.com/questions/tagged/r`
    - R-Bloggers: `https://www.r-bloggers.com/`

- Coming from …

    - Stata: `http://www.princeton.edu/~otorres/RStata.pdf`
    - SAS/SPSS: `http://r4stats.com/books/free-version/`
    - Matlab: `http://www.math.umaine.edu/~hiebeler/comp/matlabR.pdf`
    - Python: `http://mathesaurus.sourceforge.net/matlab-python-xref.pdf`

Chapter 4

R Regression Models

Topics

- Formula interface for model specification
- Function methods for extracting quantities of interest from models
- Contrasts to test specific hypotheses
- Model comparisons
- Predicted marginal effects
- Modeling continuous and binary outcomes
- Modeling clustered data

4.1 Setup

4.1.1 Software and Materials

Follow the R Installation instructions and ensure that you can successfully start RStudio.

4.1.2 Class Structure

Informal - Ask questions at any time. Really!

Collaboration is encouraged - please spend a minute introducing yourself to your neighbors!

4.1.3 Prerequisites

This is an intermediate R course:

- Assumes working knowledge of R
- Relatively fast-paced
- This is not a statistics course! We will teach you *how* to fit models in R, but we assume you know the theory behind the models.

4.1.4 Goals

We will learn about the R modeling ecosystem by fitting a variety of statistical models to different datasets. In particular, our goals are to learn about:

1. Modeling workflow
2. Visualizing and summarizing data before modeling
3. Modeling continuous outcomes
4. Modeling binary outcomes
5. Modeling clustered data

We will not spend much time *interpreting* the models we fit, since this is not a statistics workshop. But, we will walk you through how model results are organized and orientate you to where you can find typical quantities of interest.

4.1.5 Launch an R session

Start RStudio and create a new project:

- On Windows click the start button and search for RStudio. On Mac RStudio will be in your applications folder.
- In Rstudio go to `File -> New Project`.
- Choose `Existing Directory` and browse to the workshop materials directory on your desktop.
- Choose `File -> Open File` and select the file with the word "BLANK" in the name.

4.1.6 Packages

You should have already installed the `tidyverse` and `rmarkdown` packages onto your computer before the workshop — see R Installation. Now let's load these packages into the search path of our R session.

```r
library(tidyverse)
library(rmarkdown)
```

Finally, lets install some packages that will help with modeling:

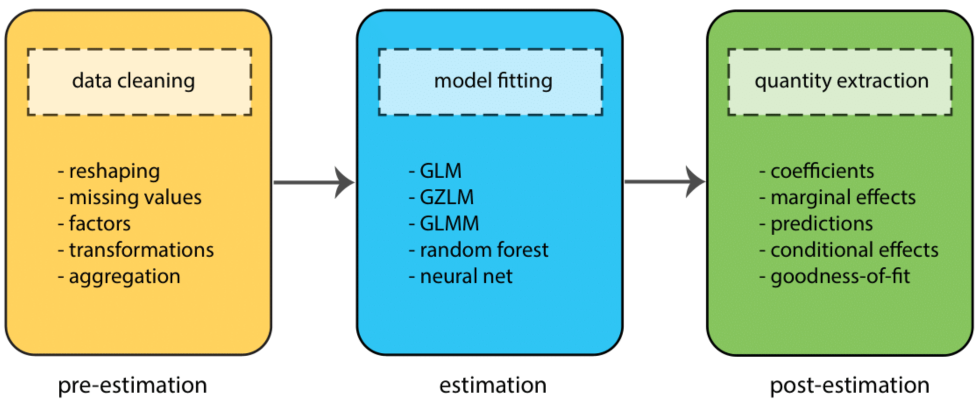
```r
# install.packages("lme4")
library(lme4)  # for mixed models

# install.packages("emmeans")
library(emmeans)  # for marginal effects

# install.packages("effects")
library(effects)  # for predicted marginal means
```

4.2 Modeling workflow

Before we delve into the details of how to fit models in R, it's worth taking a step back and thinking more broadly about the components of the modeling process. These can roughly be divided into 3 stages:

1. Pre-estimation
2. Estimation
3. Post-estimaton

At each stage, the goal is to complete a different task (e.g., to clean data, fit a model, test a hypothesis), but the process is sequential — we move through the stages in order (though often many times in one project!)



Throughout this workshop we will go through these stages several times as we fit different types of model.

4.3 R modeling ecosystem

There are literally hundreds of R packages that provide model fitting functionality. We're going to focus on just two during this workshop — `stats`, from Base R, and `lme4`. It's a good idea to look at CRAN Task Views when trying to find a modeling package for your needs, as they provide an extensive curated list. But, here's a more digestable table showing some of the most popular packages for particular types of model.

Models	Packages
Generalized linear	`stats`, `biglm`, `MASS`, `robustbase`
Mixed effects	`lme4`, `nlme`, `glmmTMB`, `MASS`
Econometric	`pglm`, `VGAM`, `pscl`, `survival`
Bayesian	`brms`, `blme`, `MCMCglmm`, `rstan`
Machine learning	`mlr`, `caret`, `h2o`, `tensorflow`

4.4 Before fitting a model

GOAL: To learn about the data by creating summaries and visualizations.

One important part of the pre-estimation stage of model fitting, is gaining an understanding of the data we wish to model by creating plots and summaries. Let's do this now.

4.4.1 Load the data

List the data files we're going to work with:

```
list.files("dataSets")
```

```
## [1] "Exam.rds"          "NatHealth2008MI"   "NatHealth2011.rds"
## [4] "states.rds"
```

We're going to use the `states` data first, which originally appeared in *Statistics with Stata* by Lawrence C. Hamilton.

```
# read the states data
states_data <- read_rds("dataSets/states.rds")

# look at the last few rows
tail(states_data)
```

```
##             state  region     pop  area density metro waste energy miles toxic
## 46        Vermont N. East  563000  9249   60.87  23.4  0.69    232  10.4  1.81
## 47       Virginia   South 6187000 39598  156.25  72.5  1.45    306   9.7 12.87
## 48     Washington    West 4867000 66582   73.10  81.7  1.05    389   9.2  8.51
## 49 West Virginia   South 1793000 24087   74.44  36.4  0.95    415   8.6 21.30
##    green house senate csat vsat msat percent expense income high college
## 46 15.17    85     94  890  424  466      68    6738 34.717 80.8    24.3
## 47 18.72    33     54  890  424  466      60    4836 38.838 75.2    24.5
## 48 16.51    52     64  913  433  480      49    5000 36.338 83.8    22.9
## 49 51.14    48     57  926  441  485      17    4911 24.233 66.0    12.3
##  [ reached 'max' / getOption("max.print") -- omitted 2 rows ]
```

Here's a table that describes what each variable in the dataset represents:

Variable	Description
csat	Mean composite SAT score
expense	Per pupil expenditures
percent	% HS graduates taking SAT
income	Median household income, $1,000
region	Geographic region: West, N. East, South, Midwest

Variable	Description
house	House '91 environ. voting, %
senate	Senate '91 environ. voting, %
energy	Per capita energy consumed, Btu
metro	Metropolitan area population, %
waste	Per capita solid waste, tons

4.4.2 Examine the data

Start by examining the data to check for problems.

```
# summary of expense and csat columns, all rows
sts_ex_sat <-
    states_data %>%
    select(expense, csat)

summary(sts_ex_sat)
```

```
##     expense          csat
##  Min.   :2960   Min.   : 832.0
##  1st Qu.:4352   1st Qu.: 888.0
##  Median :5000   Median : 926.0
##  Mean   :5236   Mean   : 944.1
##  3rd Qu.:5794   3rd Qu.: 997.0
##  Max.   :9259   Max.   :1093.0
```

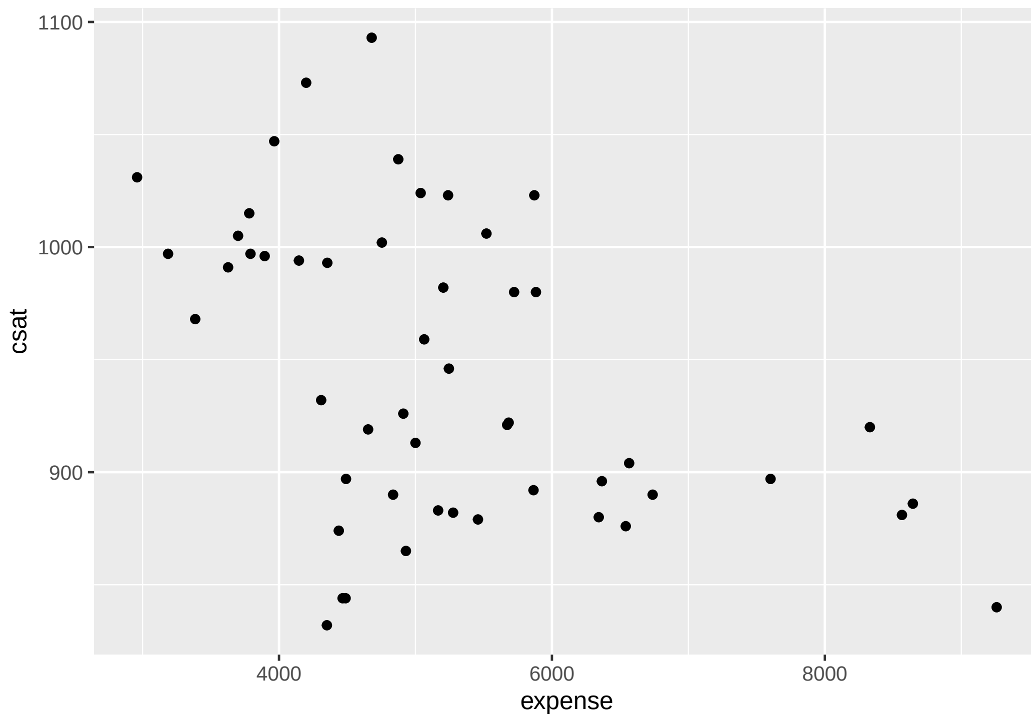
```
# correlation between expense and csat
cor(sts_ex_sat, use = "pairwise")
```

```
##            expense       csat
## expense  1.0000000 -0.4662978
## csat    -0.4662978  1.0000000
```

4.4.3 Plot the data

Plot the data to look for multivariate outliers, non-linear relationships etc.

```
# scatter plot of expense vs csat
qplot(x = expense, y = csat, geom = "point", data = sts_ex_sat)
```



Obviously, in a real project, you would want to spend more time investigating the data, but we'll now move on to modeling.

4.5 Models with continuous outcomes

GOAL: To learn about the R modeling ecosystem by fitting ordinary least squares (OLS) models. In particular:

1. Formula representation of model specification
2. Model classes
3. Function methods
4. Model comparison

Once the data have been inspected and cleaned, we can start estimating models. The simplest models (but those with the most assumptions) are those for continuous and unbounded outcomes. Typically, for these outcomes, we'd use a model estimated using Ordinary Least Lquares (OLS), which in R can be fit with the `lm()` (linear model) function.

To fit a model in R, we first have to convert our theoretical model into a `formula` — a symbolic representation of the model in R syntax:

```r
# formula for model specification
outcome ~ pred1 + pred2 + pred3

# NOTE the ~ is a tilde
```

For example, the following theoretical model predicts SAT scores based on per-pupil expenditures:

$$SATscores_i = \beta_0 1 + \beta_1 expenditures_i + \epsilon_i$$

We can use `lm()` to fit this model:

```r
# fit our regression model
sat_mod <- lm(csat ~ 1 + expense, # regression formula
              data = states_data) # data

# look at the basic printed output
sat_mod
```

```
##
## Call:
## lm(formula = csat ~ 1 + expense, data = states_data)
##
## Coefficients:
## (Intercept)      expense
##  1060.73244     -0.02228
```

The default printed output from the fitted model is very austere — just point estimates of the coefficients. We can get more information by passing the fitted model object to the `summary()` function, which provides standard errors, test statistics, and p-values for individual coefficients, as well as goodness-of-fit measures for the overall model.

```r
# get more informative summary information
summary(sat_mod)
```

```
##
## Call:
## lm(formula = csat ~ 1 + expense, data = states_data)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -131.811  -38.085    5.607   37.852  136.495
##
## Coefficients:
##                Estimate Std. Error t value Pr(>|t|)
```

```
## (Intercept)  1.061e+03  3.270e+01   32.44  < 2e-16 ***
## expense     -2.228e-02  6.037e-03   -3.69 0.000563 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 59.81 on 49 degrees of freedom
## Multiple R-squared:  0.2174, Adjusted R-squared:  0.2015
## F-statistic: 13.61 on 1 and 49 DF,  p-value: 0.0005631
```

If we just want to inspect the coefficients, we can further pipe the summary output into the function `coef()` to obtain just the table of coefficients.

```r
# show only the regression coefficients table
summary(sat_mod) %>% coef()
```

```
##                  Estimate   Std. Error   t value     Pr(>|t|)
## (Intercept) 1060.73244395 32.700896736 32.437412 8.878411e-35
## expense       -0.02227565  0.006037115 -3.689783 5.630902e-04
```

4.5.1 Why is the association between expense & SAT scores *negative*?

Many people find it surprising that the per-capita expenditure on students is negatively related to SAT scores. The beauty of multiple regression is that we can try to pull these apart. What would the association between expense and SAT scores be if there were no difference among the states in the percentage of students taking the SAT?

```r
lm(csat ~ 1 + expense + percent, data = states_data) %>%
summary()
```

```
##
## Call:
## lm(formula = csat ~ 1 + expense + percent, data = states_data)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -62.921 -24.318   1.741  15.502  75.623
##
## Coefficients:
##               Estimate Std. Error t value Pr(>|t|)
## (Intercept) 989.807403  18.395770  53.806  < 2e-16 ***
## expense       0.008604   0.004204   2.046   0.0462 *
## percent      -2.537700   0.224912 -11.283 4.21e-15 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
```

```
## Residual standard error: 31.62 on 48 degrees of freedom
## Multiple R-squared:  0.7857, Adjusted R-squared:  0.7768
## F-statistic: 88.01 on 2 and 48 DF,  p-value: < 2.2e-16
```

4.5.2 The `lm` class & methods

Okay, we fitted our model. Now what? Typically, the main goal in the **post-estimation stage** of analysis is to extract **quantities of interest** from our fitted model. These quantities could be things like:

1. Testing whether one group is different on average from another group
2. Generating average response values from the model for interesting combinations of predictor values
3. Calculating interval estimates for particular coefficients

But before we can do any of that, we need to know more about **what a fitted model actually is, what information it contains, and how we can extract from it information that we want to report**.

To understand what a fitted model object is and what information we can extract from it, we need to know about the concepts of **class** and **method**. A class defines a type of object, describing what properties it possesses, how it behaves, and how it relates to other types of objects. Every object must be an instance of some class. A method is a function associated with a particular type of object.

Let's start by examining the class of the model object:

```
# what class of object is the fitted model?
class(sat_mod)
```

```
## [1] "lm"
```

We can see that the fitted model object is of class `lm`, which stands for linear model. What quantities are stored within this model object?

```
# what are the elements stored within the fitted model object?
names(sat_mod)
```

```
##  [1] "coefficients"  "residuals"     "effects"       "rank"
##  [5] "fitted.values" "assign"        "qr"            "df.residual"
##  [9] "xlevels"       "call"          "terms"         "model"
```

We can see that 12 different things are stored within a fitted model of class `lm`. In what structure are these quantities organized?

```r
# what is the structure of the fitted model object?
str(sat_mod)
```

```
## List of 12
##  $ coefficients : Named num [1:2] 1060.7324 -0.0223
##   ..- attr(*, "names")= chr [1:2] "(Intercept)" "expense"
##  $ residuals    : Named num [1:51] 11.1 44.8 -32.7 26.7 -63.7 ...
##   ..- attr(*, "names")= chr [1:51] "1" "2" "3" "4" ...
##  $ effects      : Named num [1:51] -6742.2 220.7 -31.7 29.7 -63.2 ...
##   ..- attr(*, "names")= chr [1:51] "(Intercept)" "expense" "" "" ...
##  $ rank         : int 2
##  $ fitted.values: Named num [1:51] 980 875 965 978 961 ...
##   ..- attr(*, "names")= chr [1:51] "1" "2" "3" "4" ...
##  $ assign       : int [1:2] 0 1
##  $ qr           :List of 5
##   ..$ qr   : num [1:51, 1:2] -7.14 0.14 0.14 0.14 0.14 ...
##   .. ..- attr(*, "dimnames")=List of 2
##   .. .. ..$ : chr [1:51] "1" "2" "3" "4" ...
##   .. .. ..$ : chr [1:2] "(Intercept)" "expense"
##   .. ..- attr(*, "assign")= int [1:2] 0 1
##   ..$ qraux: num [1:2] 1.14 1.33
##   ..$ pivot: int [1:2] 1 2
##   ..$ tol  : num 1e-07
##   ..$ rank : int 2
##   ..- attr(*, "class")= chr "qr"
##  $ df.residual  : int 49
##  $ xlevels      : Named list()
##  $ call         : language lm(formula = csat ~ 1 + expense, data = states_data)
##  $ terms        :Classes 'terms', 'formula'  language csat ~ 1 + expense
##   .. ..- attr(*, "variables")= language list(csat, expense)
##   .. ..- attr(*, "factors")= int [1:2, 1] 0 1
##   .. .. ..- attr(*, "dimnames")=List of 2
##   .. .. .. ..$ : chr [1:2] "csat" "expense"
##   .. .. .. ..$ : chr "expense"
##   .. ..- attr(*, "term.labels")= chr "expense"
##   .. ..- attr(*, "order")= int 1
##   .. ..- attr(*, "intercept")= int 1
##   .. ..- attr(*, "response")= int 1
##   .. ..- attr(*, ".Environment")=<environment: R_GlobalEnv>
##   .. ..- attr(*, "predvars")= language list(csat, expense)
##   .. ..- attr(*, "dataClasses")= Named chr [1:2] "numeric" "numeric"
##   .. .. ..- attr(*, "names")= chr [1:2] "csat" "expense"
##  $ model        :'data.frame':   51 obs. of  2 variables:
##   ..$ csat   : int [1:51] 991 920 932 1005 897 959 897 892 840 882 ...
##   ..$ expense: int [1:51] 3627 8330 4309 3700 4491 5064 7602 5865 9259 5276 ...
##   ..- attr(*, "terms")=Classes 'terms', 'formula'  language csat ~ 1 + expense
##   .. .. ..- attr(*, "variables")= language list(csat, expense)
```

```
##   .. .. ..- attr(*, "factors")= int [1:2, 1] 0 1
##   .. .. .. ..- attr(*, "dimnames")=List of 2
##   .. .. .. .. ..$ : chr [1:2] "csat" "expense"
##   .. .. .. .. ..$ : chr "expense"
##   .. .. ..- attr(*, "term.labels")= chr "expense"
##   .. .. ..- attr(*, "order")= int 1
##   .. .. ..- attr(*, "intercept")= int 1
##   .. .. ..- attr(*, "response")= int 1
##   .. .. ..- attr(*, ".Environment")=<environment: R_GlobalEnv>
##   .. .. ..- attr(*, "predvars")= language list(csat, expense)
##   .. .. ..- attr(*, "dataClasses")= Named chr [1:2] "numeric" "numeric"
##   .. .. .. ..- attr(*, "names")= chr [1:2] "csat" "expense"
##  - attr(*, "class")= chr "lm"
```

We can see that the fitted model object is a `list` structure (a container that can hold different types of objects). What have we learned by examining the fitted model object? We can see that the default output we get when printing a fitted model of class `lm` is only a small subset of the information stored within the model object. How can we access other quantities of interest from the model?

We can use **methods** (functions designed to work with specific classes of object) to extract various quantities from a fitted model object (sometimes these are referred to as **extractor functions**). A list of all the available methods for a given class of object can be shown by using the `methods()` function with the `class` argument set to the class of the model object:

```
# methods for class `lm`
methods(class = class(sat_mod))
```

```
##  [1] add1           alias          anova          case.names     coerce
##  [6] confint        cooks.distance deviance       dfbeta         dfbetas
## [11] drop1          dummy.coef     Effect         effects        emm_basis
## [16] extractAIC     family         formula        fortify        hatvalues
## [21] influence      initialize     kappa          labels         logLik
## [26] model.frame    model.matrix   nobs           plot           predict
## [31] print          proj           qqnorm         qr             recover_data
## [36] residuals      rstandard      rstudent       show           simulate
## [41] slotsFromS3    summary        variable.names vcov
## see '?methods' for accessing help and source code
```

There are 44 methods available for the `lm` class. We've already seen the `summary()` method for `lm`, which is always a good place to start after fitting a model:

```
# summary table
summary(sat_mod)
```

```
##
## Call:
```

```
## lm(formula = csat ~ 1 + expense, data = states_data)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -131.811  -38.085    5.607   37.852  136.495
##
## Coefficients:
##               Estimate Std. Error t value Pr(>|t|)
## (Intercept)  1.061e+03  3.270e+01   32.44  < 2e-16 ***
## expense     -2.228e-02  6.037e-03   -3.69 0.000563 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 59.81 on 49 degrees of freedom
## Multiple R-squared:  0.2174, Adjusted R-squared:  0.2015
## F-statistic: 13.61 on 1 and 49 DF,  p-value: 0.0005631
```

We can use the `confint()` method to get interval estimates for our coefficients:

```
# confidence intervals
confint(sat_mod)
```

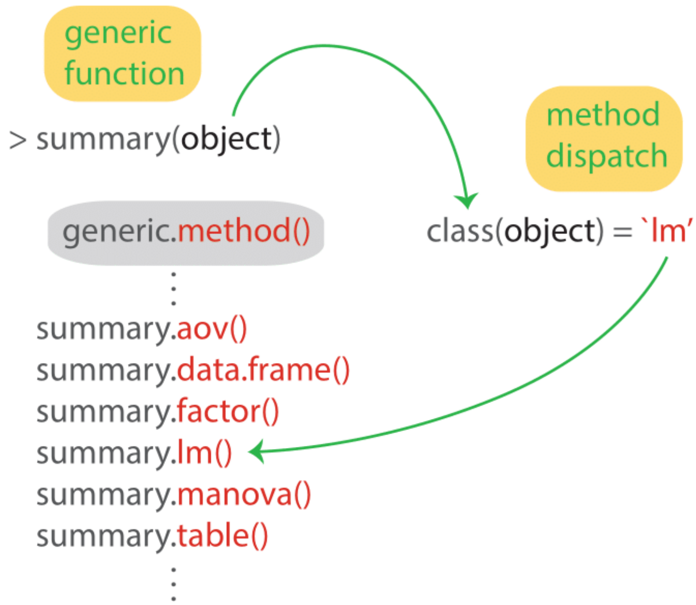
```
##                    2.5 %        97.5 %
## (Intercept) 995.01753164 1126.44735626
## expense      -0.03440768   -0.01014361
```

And we can use the `anova()` method to get an ANOVA-style table of the model:

```
# ANOVA table
anova(sat_mod)
```

```
## Analysis of Variance Table
##
## Response: csat
##           Df Sum Sq Mean Sq F value    Pr(>F)
## expense    1  48708   48708  13.614 0.0005631 ***
## Residuals 49 175306    3578
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

How does R know which method to call for a given object? R uses **generic functions**, which provide access to the methods. **Method dispatch** takes place based on the class of the first argument to the generic function. For example, for the generic function `summary()` and an object of class `lm`, the method dispatched will be `summary.lm()`. Here's a schematic that shows the process of method dispatch in action:



Function methods always take the form `generic.method()`. Let's look at all the methods for the generic `summary()` function:

```
# methods for generic `summary()` function
methods("summary")
```

```
##   [1] summary,ANY-method             summary,DBIObject-method
##   [3] summary,diagonalMatrix-method  summary,sparseMatrix-method
##   [5] summary.aareg*                 summary.allFit*
##   [7] summary.aov                    summary.aovlist*
##   [9] summary.aspell*                summary.cch*
##  [11] summary.check_packages_in_dir* summary.connection
##  [13] summary.corAR1*                summary.corARMA*
##  [15] summary.corCAR1*               summary.corCompSymm*
##  [17] summary.corExp*                summary.corGaus*
##  [19] summary.corIdent*              summary.corLin*
##  [21] summary.corNatural*            summary.corRatio*
##  [23] summary.corSpher*              summary.corStruct*
##  [25] summary.corSymm*               summary.coxph*
##  [27] summary.coxph.penal*           summary.data.frame
##  [29] summary.Date                   summary.DBIrepdesign*
##  [31] summary.DBIsvydesign*          summary.default
##  [33] summary.Duration*              summary.ecdf*
##  [35] summary.eff*                   summary.efflatent*
##  [37] summary.efflist*               summary.effpoly*
##  [39] summary.emm_list*              summary.emmGrid*
##  [41] summary.factor                 summary.ggplot*
```

```
## [43] summary.glht*                  summary.glht_list*
## [45] summary.glm                    summary.gls*
## [47] summary.haven_labelled*        summary.hcl_palettes*
## [49] summary.infl*                  summary.Interval*
## [51] summary.lm                     summary.lme*
## [53] summary.lmList*                summary.lmList4*
## [55] summary.loess*                 summary.loglm*
## [57] summary.manova                 summary.matrix
## [59] summary.mcmc*                  summary.mcmc.list*
## [61] summary.merMod*                summary.MIresult*
## [63] summary.mlm*                   summary.mlm.efflist*
## [65] summary.modelStruct*           summary.multinom*
## [67] summary.negbin*                summary.nls*
## [69] summary.nlsList*               summary.nnet*
## [71] summary.packageStatus*         summary.pdBlocked*
## [73] summary.pdCompSymm*            summary.pdDiag*
## [75] summary.pdIdent*               summary.pdLogChol*
## [77] summary.pdMat*                 summary.pdNatural*
## [79] summary.pdSymm*                summary.Period*
## [81] summary.polr*                  summary.POSIXct
## [83] summary.POSIXlt                summary.ppr*
## [85] summary.pps*                   summary.prcomp*
## [87] summary.prcomplist*            summary.predictorefflist*
## [89] summary.princomp*              summary.proc_time
## [91] summary.pyears*                summary.ratetable*
## [93] summary.reStruct*              summary.rlang_error*
## [95] summary.rlang_trace*           summary.rlm*
## [97] summary.shingle*               summary.srcfile
## [99] summary.srcref                 summary.stepfun
## [ reached getOption("max.print") -- omitted 37 entries ]
## see '?methods' for accessing help and source code
```

There are 137 `summary()` methods and counting!

It's always worth examining whether the class of model you've fitted has a method for a particular generic extractor function. Here's a summary table of some of the most often used extractor functions, which have methods for a wide range of model classes. These are post-estimation tools you will want in your toolbox:

Function	Package	Output
`summary()`	`stats`	standard errors, test statistics, p-values, GOF stats
`confint()`	`stats`	confidence intervals
`anova()`	`stats`	anova table (one model), model comparison (> one model)
`coef()`	`stats`	point estimates
`drop1()`	`stats`	model comparison
`predict()`	`stats`	predicted response values (for observed or new data)
`fitted()`	`stats`	predicted response values (for observed data only)
`residuals()`	`stats`	residuals

Function	Package	Output
`rstandard()`	`stats`	standardized residuals
`fixef()`	`lme4`	fixed effect point estimates (mixed models only)
`ranef()`	`lme4`	random effect point estimates (mixed models only)
`coef()`	`lme4`	empirical Bayes estimates (mixed models only)
`allEffects()`	`effects`	predicted marginal means
`emmeans()`	`emmeans`	predicted marginal means & marginal effects
`margins()`	`margins`	predicted marginal means & marginal effects

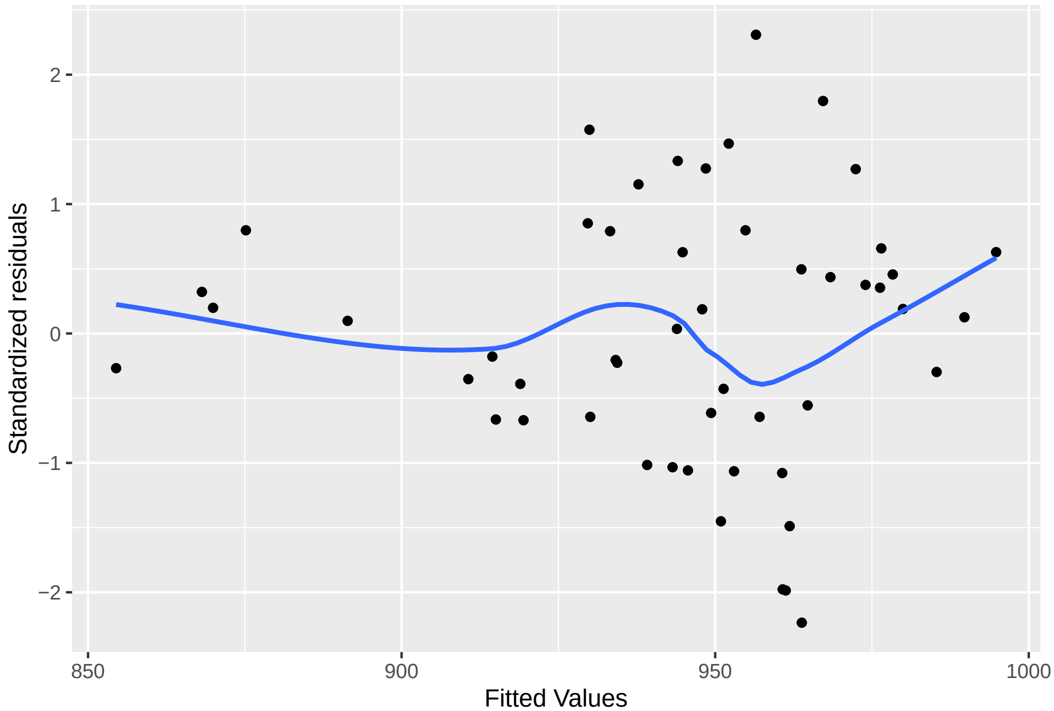
4.5.3 OLS regression assumptions

OLS regression relies on several assumptions, including:

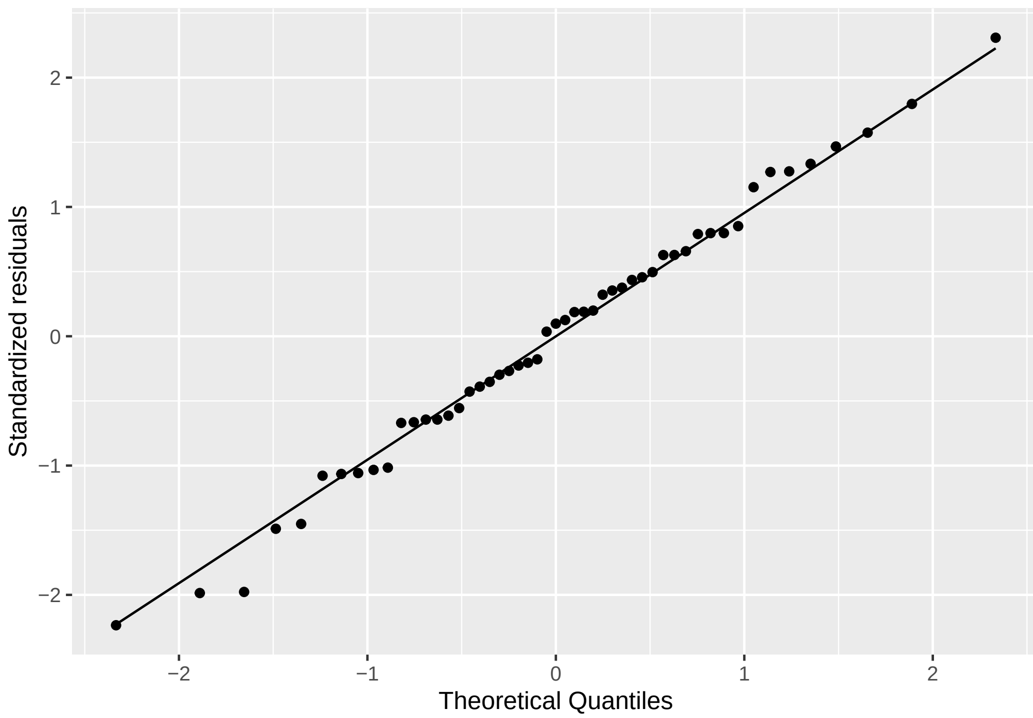
1. The model includes all relevant variables (i.e., no omitted variable bias).
2. The model is linear in the parameters (i.e., the coefficients and error term).
3. The error term has an expected value of zero.
4. All right-hand-side variables are uncorrelated with the error term.
5. No right-hand-side variables are a perfect linear function of other RHS variables.
6. Observations of the error term are uncorrelated with each other.
7. The error term has constant variance (i.e., homoscedasticity).
8. (Optional - only needed for inference). The error term is normally distributed.

Investigate assumptions #7 and #8 visually by plotting your model:

```r
# standardized residuals versus fitted values plot
qplot(x = fitted(sat_mod), y = rstandard(sat_mod), geom = "point") +
    geom_smooth(se = FALSE) +
    labs(x = "Fitted Values", y = "Standardized residuals")
```




```
# Quantile-quantile plot of standardized residuals
qplot(sample = rstandard(sat_mod), geom = c("qq", "qq_line")) +
    labs(x = "Theoretical Quantiles", y = "Standardized residuals")
```



4.5.4 Comparing models

Do congressional voting patterns predict SAT scores over and above expense? Fit two models and compare them:

```
# fit another model, adding house and senate as predictors
sat_voting_mod <- lm(csat ~ 1 + expense + house + senate,
                     data = na.omit(states_data))

summary(sat_voting_mod) %>% coef()
```

```
##                  Estimate   Std. Error    t value     Pr(>|t|)
## (Intercept) 1082.93438041 38.633812740 28.0307405 1.067795e-29
## expense       -0.01870832  0.009691494 -1.9303852 6.001998e-02
## house         -1.44243754  0.600478382 -2.4021473 2.058666e-02
## senate         0.49817861  0.513561356  0.9700469 3.373256e-01
```

Why are we using `na.omit()`? Let's see what `na.omit()` does by creating some fake data:

```
# fake data
dat <- data.frame(
  x = 1:5,
```

```
    y = c(3, 2, 1, NA, 5),
    z = c(6, NA, 2, 7, 3))
  dat
```

```
##   x  y  z
## 1 1  3  6
## 2 2  2 NA
## 3 3  1  2
## 4 4 NA  7
## 5 5  5  3
```

We can see that there are missing values on rows 2 and 4. Now let's use `na.omit()` on these data:

```
# listwise deletion of observations
na.omit(dat)
```

```
##   x y z
## 1 1 3 6
## 3 3 1 2
## 5 5 5 3
```

Here, the rows with missing values have been omitted — so, `na.omit()` performs *listwise deletion* of observations. For more flexibility, for example if we only want to exclude rows that have missing data for some subset of variables, we can use the `complete.cases()` function:

```
# ?complete.cases
dat[with(dat, complete.cases(x, y, z)), ]
```

```
##   x y z
## 1 1 3 6
## 3 3 1 2
## 5 5 5 3
```

To compare models, we must fit them to the same data. This is why we need `na.omit()`. Now let's update our first model using `na.omit()`:

```
# update model using `na.omit()`
sat_mod <-
    sat_mod %>%
    update(data = na.omit(states_data))

# compare using an F-test with the anova() function
anova(sat_mod, sat_voting_mod)
```

```
## Analysis of Variance Table
##
## Model 1: csat ~ 1 + expense
## Model 2: csat ~ 1 + expense + house + senate
##   Res.Df    RSS Df Sum of Sq      F  Pr(>F)
## 1     46 169050
## 2     44 149284  2     19766 2.9128 0.06486 .
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

4.5.5 Exercise 0

Ordinary least squares regression

Use the `states.rds` data set. Fit a model predicting energy consumed per capita (`energy`) from the percentage of residents living in metropolitan areas (`metro`). Be sure to

1. Examine/plot the data before fitting the model.

```
##
```

2. Print and interpret the model `summary()`.

```
##
```

3. Plot the model using `qplot()` to look for deviations from modeling assumptions.

```
##
```

4. Select one or more additional predictors to add to your model and repeat steps 1-3. Is this model significantly better than the model with `metro` as the only predictor?

```
##
```

Click for Exercise 0 Solution

Use the `states.rds` data set.

```
states <- read_rds("dataSets/states.rds")
```

Fit a model predicting energy consumed per capita (`energy`) from the percentage of residents living in metropolitan areas (`metro`). Be sure to:

1. Examine/plot the data before fitting the model.

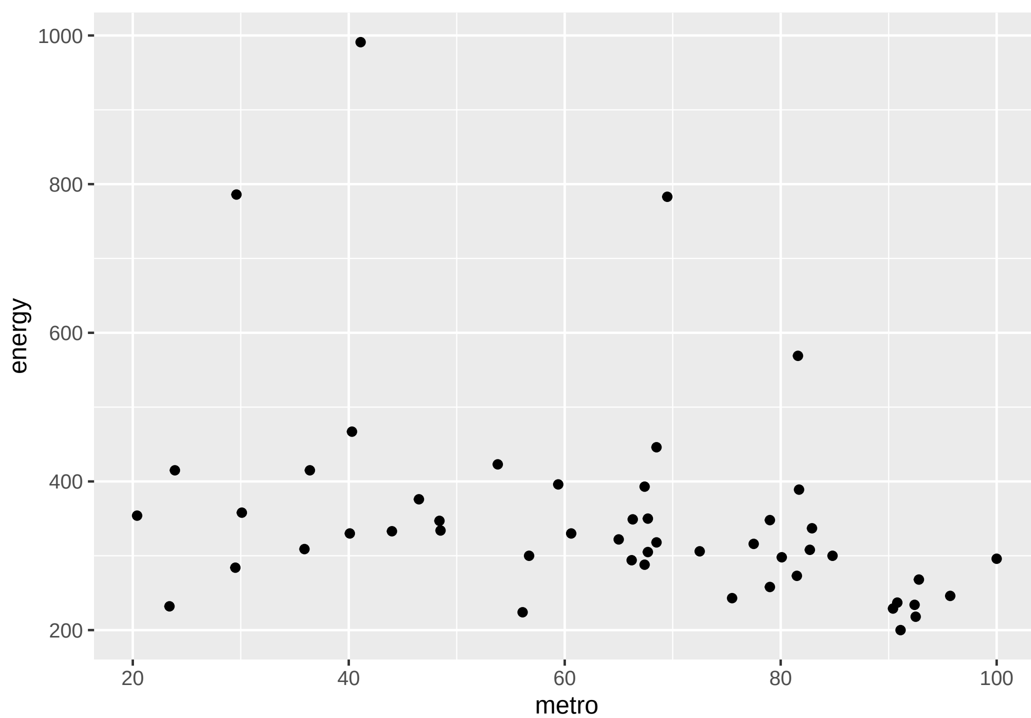
```r
states_en_met <-
    states %>%
    select(metro, energy)

summary(states_en_met)
```

```
##      metro            energy
##  Min.   : 20.40   Min.   :200.0
##  1st Qu.: 46.98   1st Qu.:285.0
##  Median : 67.55   Median :320.0
##  Mean   : 64.07   Mean   :354.5
##  3rd Qu.: 81.58   3rd Qu.:371.5
##  Max.   :100.00   Max.   :991.0
##  NA's   :1        NA's   :1
```

```r
cor(states_en_met, use = "pairwise")
```

```
##             metro     energy
## metro   1.0000000 -0.3397445
## energy -0.3397445  1.0000000
```

```r
qplot(x = metro, y = energy, geom = "point", data = states_en_met)
```



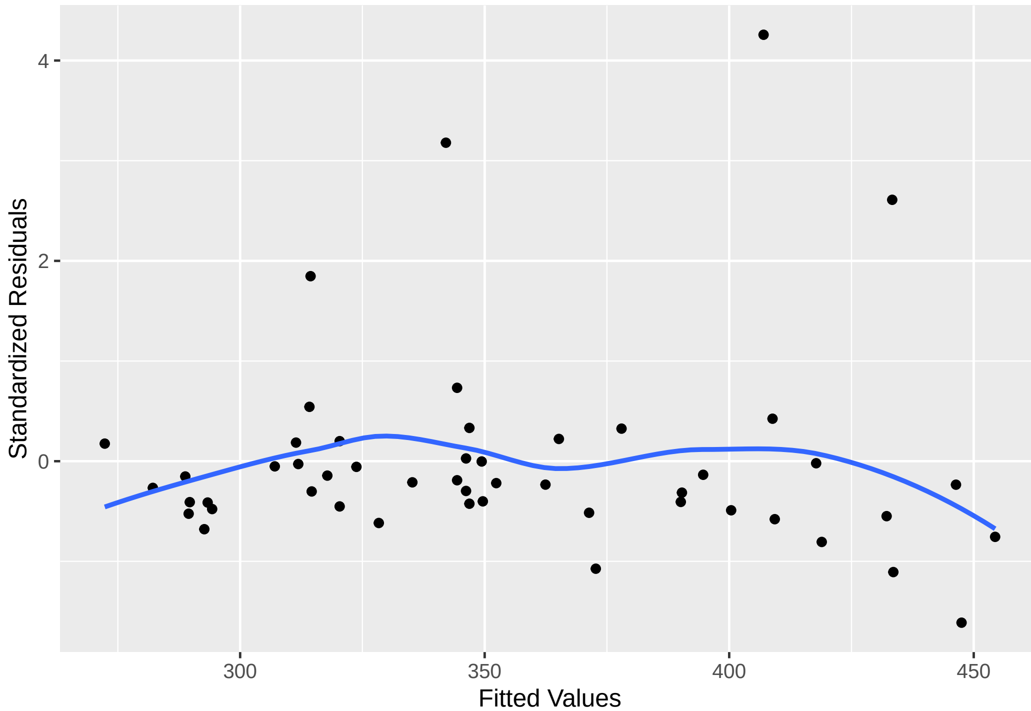
2. Print and interpret the model `summary()`.

```
mod_en_met <- lm(energy ~ metro, data = states)
summary(mod_en_met)
```

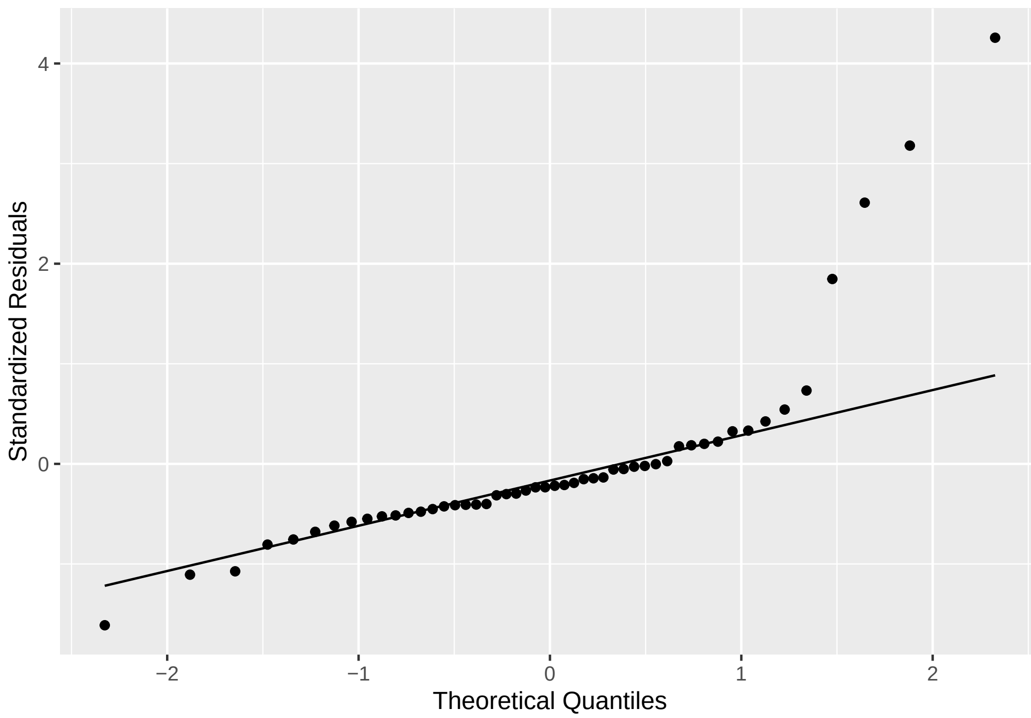
```
##
## Call:
## lm(formula = energy ~ metro, data = states)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -215.51  -64.54  -30.87   18.71  583.97
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept) 501.0292    61.8136   8.105 1.53e-10 ***
## metro        -2.2871     0.9139  -2.503   0.0158 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 140.2 on 48 degrees of freedom
##   (1 observation deleted due to missingness)
## Multiple R-squared:  0.1154, Adjusted R-squared:  0.097
## F-statistic: 6.263 on 1 and 48 DF,  p-value: 0.01578
```

3. Plot the model using `qplot()` to look for deviations from modeling assumptions.

```
  # standardized residuals versus fitted values plot
qplot(x = fitted(mod_en_met), y = rstandard(mod_en_met), geom = "point") +
    geom_smooth(se = FALSE) +
    labs(x = "Fitted Values", y = "Standardized Residuals")
```




```
# Quantile-quantile plot of standardized residuals
qplot(sample = rstandard(mod_en_met), geom = c("qq", "qq_line")) +
    labs(x = "Theoretical Quantiles", y = "Standardized Residuals")
```



4. Select one or more additional predictors to add to your model and repeat steps 1-3. Is this model significantly better than the model with `metro` as the only predictor?

```
states_en_met_pop_wst <-
    states %>%
    select(energy, metro, pop, waste)

summary(states_en_met_pop_wst)
```

```
##      energy          metro             pop                waste
##  Min.   :200.0   Min.   : 20.40   Min.   :  454000   Min.   :0.5400
##  1st Qu.:285.0   1st Qu.: 46.98   1st Qu.: 1299750   1st Qu.:0.8225
##  Median :320.0   Median : 67.55   Median : 3390500   Median :0.9600
##  Mean   :354.5   Mean   : 64.07   Mean   : 4962040   Mean   :0.9888
##  3rd Qu.:371.5   3rd Qu.: 81.58   3rd Qu.: 5898000   3rd Qu.:1.1450
##  Max.   :991.0   Max.   :100.00   Max.   :29760000   Max.   :1.5100
##  NA's   :1       NA's   :1        NA's   :1          NA's   :1
```

```
cor(states_en_met_pop_wst, use = "pairwise")
```

```
##             energy      metro         pop      waste
## energy  1.0000000 -0.3397445 -0.1840357 -0.2526499
```

```
## metro  -0.3397445  1.0000000  0.5653562  0.4877881
## pop    -0.1840357  0.5653562  1.0000000  0.5255713
## waste  -0.2526499  0.4877881  0.5255713  1.0000000
```

```
mod_en_met_pop_waste <- lm(energy ~ 1 + metro + pop + waste, data = states)
summary(mod_en_met_pop_waste)
```

```
##
## Call:
## lm(formula = energy ~ 1 + metro + pop + waste, data = states)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -224.62  -67.48  -31.76   12.65  589.48
##
## Coefficients:
##               Estimate Std. Error t value Pr(>|t|)
## (Intercept)  5.617e+02  9.905e+01   5.671    9e-07 ***
## metro       -2.079e+00  1.168e+00  -1.780   0.0816 .
## pop          1.649e-06  4.809e-06   0.343   0.7332
## waste       -8.307e+01  1.042e+02  -0.797   0.4295
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 142.2 on 46 degrees of freedom
##   (1 observation deleted due to missingness)
## Multiple R-squared:  0.1276, Adjusted R-squared:  0.07067
## F-statistic: 2.242 on 3 and 46 DF,  p-value: 0.09599
```

```
anova(mod_en_met, mod_en_met_pop_waste)
```

```
## Analysis of Variance Table
##
## Model 1: energy ~ metro
## Model 2: energy ~ 1 + metro + pop + waste
##   Res.Df    RSS Df Sum of Sq      F Pr(>F)
## 1     48 943103
## 2     46 930153  2     12949 0.3202 0.7276
```

4.6 Interactions & factors

GOAL: To learn how to specify interaction effects and fit models with categorical predictors. In particular:

1. Formula syntax for interaction effects
2. Factor levels and labels
3. Contrasts and pairwise comparisons

4.6.1 Modeling interactions

Interactions allow us assess the extent to which the association between one predictor and the outcome depends on a second predictor. For example: does the association between expense and SAT scores depend on the median income in the state?

```
# add the interaction to the model
sat_expense_by_percent <- lm(csat ~ 1 + expense + income + expense : income, data = states_data

# same as above, but shorter syntax
sat_expense_by_percent <- lm(csat ~ 1 + expense * income, data = states_data)

# show the regression coefficients table
summary(sat_expense_by_percent) %>% coef()
```

```
##                     Estimate   Std. Error   t value     Pr(>|t|)
## (Intercept)     1.380364e+03 1.720863e+02  8.021351 2.367069e-10
## expense        -6.384067e-02 3.270087e-02 -1.952262 5.687837e-02
## income         -1.049785e+01 4.991463e+00 -2.103161 4.083253e-02
## expense:income  1.384647e-03 8.635529e-04  1.603431 1.155395e-01
```

4.6.2 Regression with categorical predictors

Let's try to predict SAT scores (`csat`) from geographical region (`region`), a categorical variable. Note that you must make sure R does not think your categorical variable is numeric.

```
# make sure R knows region is categorical
str(states_data$region)
```

```
##  Factor w/ 4 levels "West","N. East",..: 3 1 1 3 1 1 2 3 NA 3 ...
```

Here, R is already treating `region` as categorical — that is, in R parlance, a "factor" variable. If `region` were not already a factor, we could make it so like this:

```
# convert `region` to a factor
states_data <- states_data %>%
    mutate(region = factor(region))

# arguments to the factor() function:
# factor(x, levels, labels)

# examine factor levels
levels(states_data$region)
```

```
## [1] "West"    "N. East" "South"   "Midwest"
```

Now let's add `region` to the model:

```
# add region to the model
sat_region <- lm(csat ~ 1 + region, data = states_data)

# show the results
summary(sat_region) %>% coef() # show only the regression coefficients table
```

```
##                  Estimate Std. Error    t value     Pr(>|t|)
## (Intercept)   946.30769   14.79582 63.9577807 1.352577e-46
## regionN. East -56.75214   23.13285 -2.4533141 1.800383e-02
## regionSouth   -16.30769   19.91948 -0.8186806 4.171898e-01
## regionMidwest  63.77564   21.35592  2.9863209 4.514152e-03
```

We can get an omnibus F-test for `region` by using the `anova()` method:

```
anova(sat_region) # show ANOVA table
```

```
## Analysis of Variance Table
##
## Response: csat
##           Df Sum Sq Mean Sq F value    Pr(>F)
## region     3  82049 27349.8  9.6102 4.859e-05 ***
## Residuals 46 130912  2845.9
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

So, make sure to tell R which variables are categorical by converting them to factors!

4.6.3 Setting factor reference groups & contrasts

Contrasts is the umbrella term used to describe the process of testing linear combinations of parameters from regression models. All statistical sofware use contrasts, but each software has different defaults and their own way of overriding these.

The default contrasts in R are "treatment" contrasts (aka "dummy coding"), where each level within a factor is identified within a matrix of binary `0` / `1` variables, with the first level chosen as the reference category. They're called "treatment" contrasts, because of the typical use case where there is one control group (the reference group) and one or more treatment groups that are to be compared to the controls. It is easy to change the default contrasts to something other than treatment contrasts, though this is rarely needed. More often, we may want to change the reference group in treatment contrasts or get all sets of pairwise contrasts between factor levels.

First, let's examine the default contrasts for `region`:

```
# default treatment (dummy) contrasts
contrasts(states_data$region)
```

```
##         N. East South Midwest
## West          0     0       0
## N. East       1     0       0
## South         0     1       0
## Midwest       0     0       1
```

We can see that the reference level is `West`. How can we change this? Let's use the `relevel()` function:

```
# change the reference group
states_data <- states_data %>%
    mutate(region = relevel(region, ref = "Midwest"))

# check the reference group has changed
contrasts(states_data$region)
```

```
##         West N. East South
## Midwest    0       0     0
## West       1       0     0
## N. East    0       1     0
## South      0       0     1
```

Now the reference level has changed to `Midwest`. Let's refit the model with the releveled `region` variable:

```
# refit the model
mod_region <- lm(csat ~ 1 + region, data = states_data)

# print summary coefficients table
summary(mod_region) %>% coef()
```

```
##                  Estimate Std. Error   t value     Pr(>|t|)
## (Intercept)    1010.08333   15.39998 65.589930 4.296307e-47
## regionWest      -63.77564   21.35592 -2.986321 4.514152e-03
## regionN. East -120.52778   23.52385 -5.123641 5.798399e-06
## regionSouth     -80.08333   20.37225 -3.931000 2.826007e-04
```

Often, we may want to get all possible pairwise comparisons among the various levels of a factor variable, rather than just compare particular levels to a single reference level. We could of course just keep changing the reference level and refitting the model, but this would be tedious. Instead, we can use the `emmeans()` post-estimation function from the `emmeans` package to do the calculations for us:

```r
# get all pairwise contrasts between means
mod_region %>%
    emmeans(specs = pairwise ~ region)
```

```
## $emmeans
##  region  emmean   SE df lower.CL upper.CL
##  Midwest   1010 15.4 46      979     1041
##  West       946 14.8 46      917      976
##  N. East    890 17.8 46      854      925
##  South      930 13.3 46      903      957
##
## Confidence level used: 0.95
##
## $contrasts
##  contrast          estimate   SE df t.ratio p.value
##  Midwest - West        63.8 21.4 46  2.986  0.0226
##  Midwest - N. East    120.5 23.5 46  5.124  <.0001
##  Midwest - South       80.1 20.4 46  3.931  0.0016
##  West - N. East        56.8 23.1 46  2.453  0.0812
##  West - South          16.3 19.9 46  0.819  0.8453
##  N. East - South      -40.4 22.2 46 -1.820  0.2774
##
## P value adjustment: tukey method for comparing a family of 4 estimates
```

4.6.4 Exercise 1

Interactions & factors

Use the `states` data set.

1. Add on to the regression equation that you created in Exercise 1 by generating an interaction term and testing the interaction.

```r
##
```

2. Try adding `region` to the model. Are there significant differences across the four regions?

```r
##
```

Click for Exercise 1 Solution

Use the `states` data set.

1. Add on to the regression equation that you created in exercise 1 by generating an interaction term and testing the interaction.

```
mod_en_metro_by_waste <- lm(energy ~ 1 + metro * waste, data = states)
```

2. Try adding `region` to the model. Are there significant differences across the four regions?

```
mod_en_region <- lm(energy ~ 1 + metro * waste + region, data = states)
anova(mod_en_metro_by_waste, mod_en_region)
```

```
## Analysis of Variance Table
##
## Model 1: energy ~ 1 + metro * waste
## Model 2: energy ~ 1 + metro * waste + region
##   Res.Df    RSS Df Sum of Sq    F Pr(>F)
## 1     46 930683
## 2     43 821247  3    109436 1.91 0.1422
```

4.7 Models with binary outcomes

GOAL: To learn how to use the `glm()` function to model binary outcomes. In particular:

1. The `family` and `link` components of the `glm()` function call
2. Transforming model coefficients into odds ratios
3. Transforming model coefficients into predicted marginal means

4.7.1 Logistic regression

Thus far we have used the `lm()` function to fit our regression models. `lm()` is great, but limited — in particular it only fits models for continuous dependent variables. For categorical dependent variables we can use the `glm()` function.

For these models we will use a different dataset, drawn from the National Health Interview Survey. From the CDC website:

> The National Health Interview Survey (NHIS) has monitored the health of the nation since 1957. NHIS data on a broad range of health topics are collected through personal household interviews. For over 50 years, the U.S. Census Bureau has been the data collection agent for the National Health Interview Survey. Survey results have been instrumental in providing data to track health status, health care access, and progress toward achieving national health objectives.

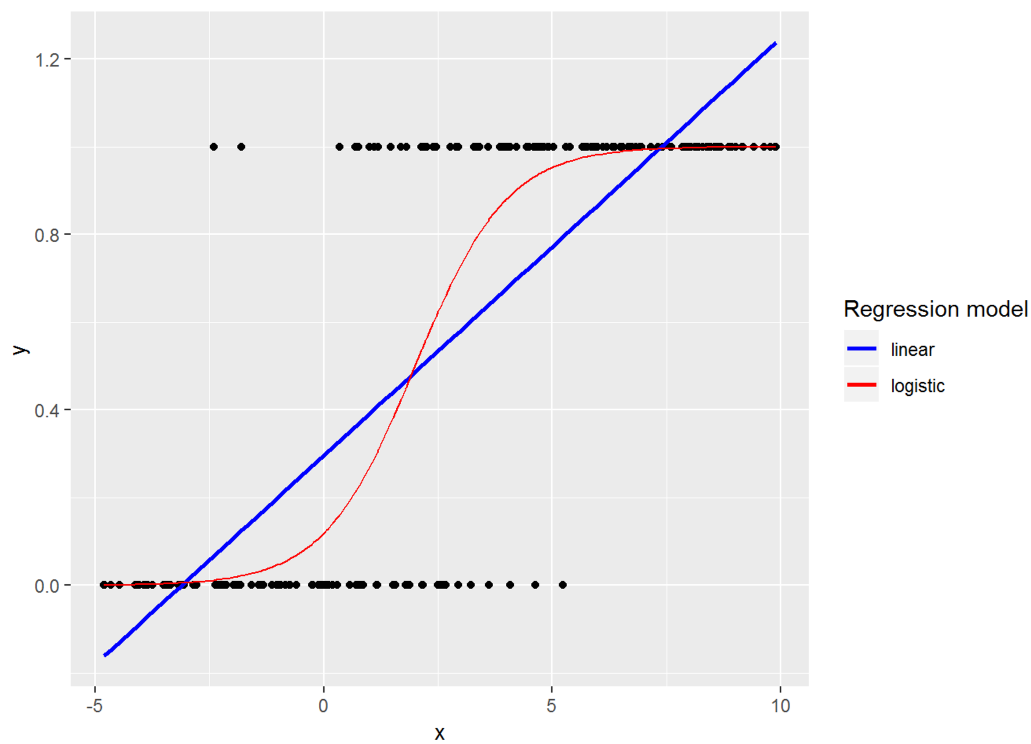
Load the National Health Interview Survey data:

```
NH11 <- read_rds("dataSets/NatHealth2011.rds")
```

4.7.2 Logistic regression example

Some motivations for using a logistic regression model, rather than a linear model, when we have a binary response:

1. Errors will not be normally distributed
2. Variance will not be homoskedastic
3. Predictions should be constrained to be on the interval [0, 1]



Anatomy of a generalized linear model:

```
# OLS model using lm()
lm(outcome ~ 1 + pred1 + pred2,
   data = mydata)

# OLS model using glm()
glm(outcome ~ 1 + pred1 + pred2,
    data = mydata,
    family = gaussian(link = "identity"))
```

```r
# logistic model using glm()
glm(outcome ~ 1 + pred1 + pred2,
    data = mydata,
    family = binomial(link = "logit"))
```

The `family` argument sets the error distribution for the model, while the `link` function argument relates the predictors to the expected value of the outcome.

Let's predict the probability of being diagnosed with hypertension based on age, sex, sleep, and bmi. Here's the theoretical model:

$$logit(p(hypertension_i = 1)) = \beta_0 1 + \beta_1 age_i + \beta_2 sex_i + \beta_3 sleep_i + \beta_4 bmi_i$$

where $logit(\cdot)$ is the non-linear link function that relates a linear expression of the predictors to the expectation of the binary response:

$$logit(p(hypertension_i = 1)) = ln\left(\frac{p(hypertension_i = 1)}{1 - p(hypertension_i = 1)}\right) = ln\left(\frac{p(hypertension_i = 1)}{p(hypertension_i = 0)}\right)$$

And here's how we fit this model in R. First, let's clean up the hypertension outcome by making it binary:

```r
str(NH11$hypev) # check stucture of hypev
```

```
##  Factor w/ 5 levels "1 Yes","2 No",..: 2 2 1 2 2 1 2 2 1 2 ...
```

```r
levels(NH11$hypev) # check levels of hypev
```

```
## [1] "1 Yes"             "2 No"              "7 Refused"
## [4] "8 Not ascertained" "9 Don't know"
```

```r
# collapse all missing values to NA
NH11 <- NH11 %>%
    mutate(hypev = factor(hypev, levels=c("2 No", "1 Yes")))
```

Now let's use `glm()` to estimate the model:

```r
# run our regression model
hyp_out <- glm(hypev ~ 1 + age_p + sex + sleep + bmi,
               data = NH11,
               family = binomial(link = "logit"))

# summary model coefficients table
summary(hyp_out) %>% coef()
```

```
##                 Estimate   Std. Error    z value     Pr(>|z|)
## (Intercept) -4.269466028 0.0564947294 -75.572820 0.000000e+00
## age_p        0.060699303 0.0008227207  73.778743 0.000000e+00
## sex2 Female -0.144025092 0.0267976605  -5.374540 7.677854e-08
## sleep       -0.007035776 0.0016397197  -4.290841 1.779981e-05
## bmi          0.018571704 0.0009510828  19.526906 6.485172e-85
```

4.7.3 Odds ratios

Generalized linear models use link functions to relate the average value of the response to the predictors, so raw coefficients are difficult to interpret. For example, the `age` coefficient of 0.06 in the previous model tells us that for every one unit increase in `age`, the log odds of hypertension diagnosis increases by 0.06. Since most of us are not used to thinking in log odds this is not too helpful!

One solution is to transform the coefficients to make them easier to interpret. Here we transform them into odds ratios by exponentiating:

```
# point estimates
coef(hyp_out) %>% exp()
```

```
## (Intercept)       age_p sex2 Female       sleep         bmi
##  0.01398925  1.06257935  0.86586602  0.99298892  1.01874523
```

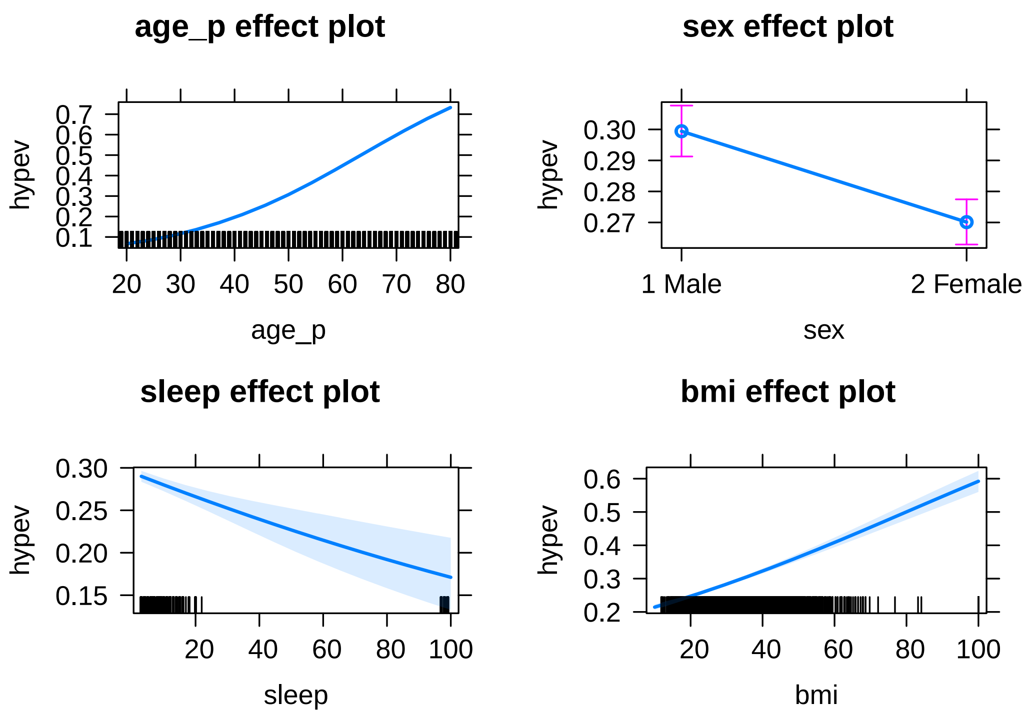
```
# confidence intervals
confint(hyp_out) %>% exp()
```

```
##                  2.5 %     97.5 %
## (Intercept) 0.01251677 0.01561971
## age_p       1.06087385 1.06430082
## sex2 Female 0.82155196 0.91255008
## sleep       0.98978755 0.99617465
## bmi         1.01685145 1.02065009
```

4.7.4 Predicted marginal means

Instead of reporting odds ratios, we may want to calculate predicted marginal means (sometimes called “least-squares means” or “estimated marginal means”). These are average values of the outcome at particular levels of the predictors. For ease of interpretation, we want these marginal means to be on the response scale (i.e., the probability scale). We can use the `effects` package to compute these quantities of interest for us (by default, the numerical output will be on the response scale).

```
# get predicted marginal means
hyp_out %>%
    allEffects() %>%
    plot(type = "response") # "response" refers to the probability scale
```



By default, `allEffects()` will produce predictions for all levels of factor variables, while for continuous variables it will chose 5 representative values based on quantiles. We can easily override this behavior using the `xlevels` argument and get predictions at any values of a continuous variable.

```
# generate a sequence of ages at which to get predictions of the outcome
age_years <- seq(20, 80, by = 5)
age_years
```

```
##  [1] 20 25 30 35 40 45 50 55 60 65 70 75 80
```

```
# get predicted marginal means
eff_df <-
    hyp_out %>%
    allEffects(xlevels = list(age_p = age_years)) %>% # override defaults for age
    as.data.frame() # get confidence intervals

eff_df
```

```
## $age_p
##    age_p        fit          se      lower      upper
## 1     20 0.06690384 0.001915704 0.06324553 0.07075778
## 2     25 0.08852692 0.002181618 0.08434323 0.09289708
```

```
## 3      30 0.11626770 0.002418813 0.11161020 0.12109307
## 4      35 0.15125876 0.002603243 0.14622690 0.15643204
## 5      40 0.19446321 0.002722428 0.18918282 0.19985467
## 6      45 0.24642528 0.002796260 0.24098582 0.25194677
## 7      50 0.30698073 0.002895857 0.30133437 0.31268554
## 8      55 0.37501156 0.003124112 0.36890868 0.38115441
## 9      60 0.44836479 0.003531792 0.44145305 0.45529654
## 10     65 0.52403564 0.004052454 0.51608756 0.53197156
## 11     70 0.59861876 0.004545531 0.58967801 0.60749436
## 12     75 0.66889903 0.004880732 0.65926418 0.67839434
## 13     80 0.73237506 0.004986539 0.72248912 0.74203457
##
## $sex
##        sex       fit          se     lower     upper
## 1   1 Male 0.2994186 0.004188707 0.2912739 0.3076922
## 2 2 Female 0.2701044 0.003715028 0.2628852 0.2774472
##
## $sleep
##   sleep       fit          se     lower     upper
## 1     3 0.2899941 0.003276427 0.2836147 0.2964575
## 2    30 0.2524895 0.007427001 0.2382124 0.2673219
## 3    50 0.2268657 0.012446183 0.2034008 0.2521806
## 4    80 0.1919843 0.018549461 0.1582199 0.2309771
## 5   100 0.1710955 0.021584286 0.1328287 0.2176200
##
## $bmi
##   bmi       fit          se     lower     upper
## 1  10 0.2144084 0.004121590 0.2064409 0.2225972
## 2  30 0.2835093 0.002849407 0.2779580 0.2891272
## 3  60 0.4085485 0.007450161 0.3940311 0.4232272
## 4  80 0.5003663 0.012139141 0.4765911 0.5241398
## 5 100 0.5921593 0.016180071 0.5601051 0.6234481
```

4.7.5 Exercise 2

Logistic regression

Use the `NH11` data set that we loaded earlier. Note that the data are not perfectly clean and ready to be modeled. You will need to clean up at least some of the variables before fitting the model.

1. Use `glm()` to conduct a logistic regression to predict ever worked (`everwrk`) using age (`age_p`) and marital status (`r_maritl`). Make sure you only keep the following two levels for `everwrk` (`1 Yes` and `2 No`). Hint: use the `factor()` function. Also, make sure to drop any `r_maritl` levels that do not contain observations. Hint: see `?droplevels`.

```
##
```

2. Predict the probability of working for each level of marital status. Hint: use `allEffects()`

```
##
```

Note that the data are not perfectly clean and ready to be modeled. You will need to clean up at least some of the variables before fitting the model.

Click for Exercise 2 Solution

Use the `NH11` data set that we loaded earlier. Note that the data are not perfectly clean and ready to be modeled. You will need to clean up at least some of the variables before fitting the model.

1. Use `glm()` to conduct a logistic regression to predict ever worked (`everwrk`) using age (`age_p`) and marital status (`r_maritl`). Make sure you only keep the following two levels for `everwrk` (`1 Yes` and `2 No`). Hint: use the `factor()` function. Also, make sure to drop any `r_maritl` levels that do not contain observations. Hint: see `?droplevels`.

```
NH11 <-
    NH11 %>%
    mutate(everwrk = factor(everwrk, levels = c("1 Yes", "2 No")),
           r_maritl = droplevels(r_maritl)
           )

mod_wk_age_mar <- glm(everwrk ~ 1 + age_p + r_maritl,
                      data = NH11,
                      family = binomial(link = "logit"))

summary(mod_wk_age_mar)
```

```
##
## Call:
## glm(formula = everwrk ~ 1 + age_p + r_maritl, family = binomial(link = "logit"),
##     data = NH11)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -1.0436  -0.5650  -0.4391  -0.3370   2.7308
##
## Coefficients:
##                                              Estimate Std. Error z value
## (Intercept)                                 -0.440248   0.093538  -4.707
## age_p                                       -0.029812   0.001645 -18.118
```

```
## r_marital2 Married - spouse not in household  0.049675   0.217310   0.229
## r_marital4 Widowed                             0.683618   0.084335   8.106
## r_marital5 Divorced                           -0.730115   0.111681  -6.538
## r_marital6 Separated                          -0.128091   0.151366  -0.846
## r_marital7 Never married                       0.343611   0.069222   4.964
## r_marital8 Living with partner                -0.443583   0.137770  -3.220
## r_marital9 Unknown marital status              0.395480   0.492967   0.802
##                                               Pr(>|z|)
## (Intercept)                                   2.52e-06 ***
## age_p                                          < 2e-16 ***
## r_marital2 Married - spouse not in household   0.81919
## r_marital4 Widowed                            5.23e-16 ***
## r_marital5 Divorced                           6.25e-11 ***
## r_marital6 Separated                           0.39742
## r_marital7 Never married                      6.91e-07 ***
## r_marital8 Living with partner                 0.00128 **
## r_marital9 Unknown marital status              0.42241
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 11082  on 14039  degrees of freedom
## Residual deviance: 10309  on 14031  degrees of freedom
##   (18974 observations deleted due to missingness)
## AIC: 10327
##
## Number of Fisher Scoring iterations: 5
```

2. Predict the probability of working for each level of marital status. Hint: use `allEffects()`.

```r
mod_wk_age_mar %>%
    allEffects() %>%
    as.data.frame()
```

```
## $age_p
##   age_p        fit          se      lower      upper
## 1    20 0.27587439 0.011448539 0.25400910 0.29886780
## 2    30 0.22043363 0.007483648 0.20611629 0.23545053
## 3    50 0.13477473 0.003183752 0.12865574 0.14113761
## 4    70 0.07902788 0.003053617 0.07324630 0.08522385
## 5    80 0.05987515 0.003123927 0.05403759 0.06629914
##
## $r_maritl
##                              r_maritl        fit          se      lower
## 1     1 Married - spouse in household 0.10822000 0.004259644 0.10014980
```

```
## 2 2 Married - spouse not in household 0.11310823 0.021393167 0.07746061
## 3                            4 Widowed 0.19381087 0.010634762 0.17381358
## 4                           5 Divorced 0.05524394 0.005361664 0.04562877
## 5                          6 Separated 0.09646417 0.012707502 0.07426824
## 6                      7 Never married 0.14611000 0.007459212 0.13208775
## 7               8 Living with partner 0.07224958 0.008904955 0.05662466
## 8            9 Unknown marital status 0.15270076 0.063528455 0.06440837
##        upper
## 1 0.11685606
## 2 0.16227532
## 3 0.21550873
## 4 0.06674358
## 5 0.12440219
## 6 0.16134411
## 7 0.09176661
## 8 0.32055728
```

4.8 Multilevel modeling

GOAL: To learn about how to use the `lmer()` function to model clustered data. In particular:

1. The formula syntax for incorporating random effects into a model
2. Calculating the intraclass correlation (ICC)
3. Model comparison for fixed and random effects

4.8.1 Multilevel modeling overview

- Multi-level (AKA hierarchical) models are a type of **mixed-effects** model
- They are used to model data that are clustered (i.e., non-independent)
- Mixed-effects models include two types of predictors: **fixed-effects** and **random effects**
  - **Fixed-effects** – observed levels are of direct interest (.e.g, sex, political party…)
  - **Random-effects** – observed levels not of direct interest: goal is to make inferences to a population represented by observed levels
  - In R, the `lme4` package is the most popular for mixed effects models
  - Use the `lmer()` function for linear mixed models, `glmer()` for generalized linear mixed models

4.8.2 The Exam data

The `Exam.rds` data set contains exam scores of 4,059 students from 65 schools in Inner London. The variable names are as follows:

Variable	Description
school	School ID - a factor.
normexam	Normalized exam score.
standLRT	Standardized LR test score.
student	Student id (within school) - a factor

Let's read in the data:

```
exam <- read_rds("dataSets/Exam.rds")
```

4.8.3 The null model & ICC

Before we fit our first model, let's take a look at the R syntax for multilevel models:

```
# anatomy of lmer() function
lmer(outcome ~ 1 + pred1 + pred2 + (1 | grouping_variable),
     data = mydata)
```

Notice the formula section within the brackets: `(1 | grouping_variable)`. This part of the formula tells R about the hierarchical structure of the model. In this case, it says we have a model with random intercepts (`1`) grouped by (`|`) a `grouping_variable`.

As a preliminary modeling step, it is often useful to partition the variance in the dependent variable into the various levels. This can be accomplished by running a null model (i.e., a model with a random effects grouping structure, but no fixed-effects predictors) and then calculating the intra-class correlation (ICC).

```
# null model, grouping by school but not fixed effects.
Norm1 <-lmer(normexam ~ 1 + (1 | school),
             data = na.omit(exam))
summary(Norm1)
```

```
## Linear mixed model fit by REML ['lmerMod']
## Formula: normexam ~ 1 + (1 | school)
##    Data: na.omit(exam)
##
## REML criterion at convergence: 9962.9
##
## Scaled residuals:
##     Min      1Q  Median      3Q     Max
## -3.8749 -0.6452  0.0045  0.6888  3.6836
##
## Random effects:
##  Groups   Name        Variance Std.Dev.
##  school   (Intercept) 0.1634   0.4042
```

```
##  Residual             0.8520   0.9231
## Number of obs: 3662, groups:  school, 65
##
## Fixed effects:
##             Estimate Std. Error t value
## (Intercept) -0.01310    0.05312  -0.247
```

The ICC is calculated as .163/(.163 + .852) = .161, which means that ~16% of the variance is at the school level.

There is no consensus on how to calculate p-values for MLMs; hence why they are omitted from the `lme4` output. But, if you really need p-values, the `lmerTest` package will calculate p-values for you (using the Satterthwaite approximation).

4.8.4 Adding fixed-effects predictors

Here's a theoretical model that predicts exam scores from student's standardized tests scores:

$$examscores_{ij} = \mu 1 + \beta_1 testscores_{ij} + U_{0j} + \epsilon_{ij}$$

where U_{0j} is the random intercept for the jth `school`. Let's implement this in R using `lmer()`:

```
# model with exam scores regressed on student's standardized tests scores
Norm2 <-lmer(normexam ~ 1 + standLRT + (1 | school),
             data = na.omit(exam))
summary(Norm2)
```

```
## Linear mixed model fit by REML ['lmerMod']
## Formula: normexam ~ 1 + standLRT + (1 | school)
##    Data: na.omit(exam)
##
## REML criterion at convergence: 8483.5
##
## Scaled residuals:
##     Min      1Q  Median      3Q     Max
## -3.6725 -0.6300  0.0234  0.6777  3.3340
##
## Random effects:
##  Groups   Name        Variance Std.Dev.
##  school   (Intercept) 0.09369  0.3061
##  Residual             0.56924  0.7545
## Number of obs: 3662, groups:  school, 65
##
## Fixed effects:
##               Estimate Std. Error t value
```

```
## (Intercept) -4.313e-05  4.055e-02  -0.001
## standLRT     5.669e-01  1.324e-02  42.821
##
## Correlation of Fixed Effects:
##          (Intr)
## standLRT 0.007
```

4.8.5 Multiple degree of freedom comparisons

As with `lm()` and `glm()` models, you can compare the two `lmer()` models using the `anova()` function. With mixed effects models, this will produce a likelihood ratio test.

```
# likelihood ratio test of two nested models
anova(Norm1, Norm2)
```

```
## Data: na.omit(exam)
## Models:
## Norm1: normexam ~ 1 + (1 | school)
## Norm2: normexam ~ 1 + standLRT + (1 | school)
##       npar    AIC    BIC  logLik deviance  Chisq Df Pr(>Chisq)
## Norm1    3 9964.9 9983.5 -4979.4   9958.9
## Norm2    4 8480.1 8505.0 -4236.1   8472.1 1486.8  1  < 2.2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

4.8.6 Random slopes

We can add a random effect of students' standardized test scores as well. Now in addition to estimating the distribution of intercepts across schools, we also estimate the distribution of the slope of exam on standardized test.

```
# add random effect of students' standardized test scores to model
Norm3 <- lmer(normexam ~ 1 + standLRT + (1 + standLRT | school),
              data = na.omit(exam))
summary(Norm3)
```

```
## Linear mixed model fit by REML ['lmerMod']
## Formula: normexam ~ 1 + standLRT + (1 + standLRT | school)
##    Data: na.omit(exam)
##
## REML criterion at convergence: 8442.8
##
## Scaled residuals:
##     Min      1Q  Median      3Q     Max
## -3.7904 -0.6246  0.0245  0.6734  3.4376
```

```
##
## Random effects:
##  Groups   Name        Variance Std.Dev. Corr
##  school   (Intercept) 0.09092  0.3015
##           standLRT    0.01639  0.1280   0.49
##  Residual             0.55589  0.7456
## Number of obs: 3662, groups:  school, 65
##
## Fixed effects:
##              Estimate Std. Error t value
## (Intercept) -0.01250    0.04011  -0.312
## standLRT     0.56094    0.02119  26.474
##
## Correlation of Fixed Effects:
##          (Intr)
## standLRT 0.360
```

4.8.7 Test the significance of the random slope

To test the significance of a random slope just compare models with and without the random slope term using a likelihood ratio test:

```r
# likelihood ratio test for random slope term
anova(Norm2, Norm3)
```

```
## Data: na.omit(exam)
## Models:
## Norm2: normexam ~ 1 + standLRT + (1 | school)
## Norm3: normexam ~ 1 + standLRT + (1 + standLRT | school)
##       npar    AIC    BIC  logLik deviance Chisq Df Pr(>Chisq)
## Norm2    4 8480.1 8505.0 -4236.1   8472.1
## Norm3    6 8444.1 8481.4 -4216.1   8432.1 40.01  2  2.051e-09 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

4.8.8 Exercise 3

Multilevel modeling

Use the `bh1996` dataset:

```r
## install.packages("multilevel")
data(bh1996, package = "multilevel")
```

From the data documentation:

> Variables are Leadership Climate (`LEAD`), Well-Being (`WBEING`), and Work Hours (`HRS`). The group identifier is named `GRP`.

1. Create a null model predicting wellbeing (`WBEING`)

```
##
```

2. Calculate the ICC for your null model

```
##
```

3. Run a second multi-level model that adds two individual-level predictors, average number of hours worked (`HRS`) and leadership skills (`LEAD`) to the model and interpret your output.

```
##
```

4. Now, add a random effect of average number of hours worked (`HRS`) to the model and interpret your output. Test the significance of this random term.

```
##
```

Click for Exercise 3 Solution

Use the dataset `bh1996`:

```
# install.packages("multilevel")
data(bh1996, package="multilevel")
```

From the data documentation:

> Variables are Leadership Climate (`LEAD`), Well-Being (`WBEING`), and Work Hours (`HRS`). The group identifier is named `GRP`.

1. Create a null model predicting wellbeing (`WBEING`).

```
mod_grp0 <- lmer(WBEING ~ 1 + (1 | GRP), data = na.omit(bh1996))
summary(mod_grp0)
```

```
## Linear mixed model fit by REML ['lmerMod']
## Formula: WBEING ~ 1 + (1 | GRP)
##    Data: na.omit(bh1996)
##
## REML criterion at convergence: 19347.3
```

```
##
## Scaled residuals:
##     Min      1Q  Median      3Q     Max
## -3.3217 -0.6475  0.0311  0.7182  2.6674
##
## Random effects:
##  Groups   Name        Variance Std.Dev.
##  GRP      (Intercept) 0.0358   0.1892
##  Residual             0.7895   0.8885
## Number of obs: 7382, groups:  GRP, 99
##
## Fixed effects:
##             Estimate Std. Error t value
## (Intercept)   2.7743     0.0222   124.9
```

2. Calculate the ICC for your null model

```r
0.0358 / (0.0358 + 0.7895)
```

```
## [1] 0.04337817
```

3. Run a second multi-level model that adds two individual-level predictors, average number of hours worked (`HRS`) and leadership skills (`LEAD`) to the model and interpret your output.

```r
mod_grp1 <- lmer(WBEING ~ 1 + HRS + LEAD + (1 | GRP), data = na.omit(bh1996))
summary(mod_grp1)
```

```
## Linear mixed model fit by REML ['lmerMod']
## Formula: WBEING ~ 1 + HRS + LEAD + (1 | GRP)
##    Data: na.omit(bh1996)
##
## REML criterion at convergence: 17860
##
## Scaled residuals:
##     Min      1Q  Median      3Q     Max
## -3.9188 -0.6588  0.0382  0.7040  3.6440
##
## Random effects:
##  Groups   Name        Variance Std.Dev.
##  GRP      (Intercept) 0.01929  0.1389
##  Residual             0.64668  0.8042
## Number of obs: 7382, groups:  GRP, 99
##
## Fixed effects:
##              Estimate Std. Error t value
```

```
## (Intercept)  1.686160   0.067702  24.906
## HRS         -0.031617   0.004378  -7.221
## LEAD         0.500743   0.012811  39.087
##
## Correlation of Fixed Effects:
##      (Intr) HRS
## HRS  -0.800
## LEAD -0.635  0.121
```

4. Now, add a random effect of average number of hours worked (`HRS`) to the model and interpret your output. Test the significance of this random term.

```
mod_grp2 <- lmer(WBEING ~ 1 + HRS + LEAD + (1 + HRS | GRP), data = na.omit(bh1996))
anova(mod_grp1, mod_grp2)
```

```
## Data: na.omit(bh1996)
## Models:
## mod_grp1: WBEING ~ 1 + HRS + LEAD + (1 | GRP)
## mod_grp2: WBEING ~ 1 + HRS + LEAD + (1 + HRS | GRP)
##          npar   AIC   BIC  logLik deviance  Chisq Df Pr(>Chisq)
## mod_grp1    5 17848 17882 -8918.9    17838
## mod_grp2    7 17851 17899 -8918.3    17837 1.2202  2     0.5433
```

4.9 Wrap-up

4.9.1 Feedback

These workshops are a work in progress, please provide any feedback to: `help@iq.harvard.edu`

4.9.2 Resources

- IQSS
  - Workshops: `https://www.iq.harvard.edu/data-science-services/workshop-materials`
  - Data Science Services: `https://www.iq.harvard.edu/data-science-services`
  - Research Computing Environment: `https://iqss.github.io/dss-rce/`
- HBS
  - Research Computing Services workshops: `https://training.rcs.hbs.org/workshops`
  - Other HBS RCS resources: `https://training.rcs.hbs.org/workshop-materials`
  - RCS consulting email: `mailto:research@hbs.edu`

Chapter 5

R Graphics

Topics

- R `ggplot2` package basics
- Geometric objects and aesthetics
- Aesthetic inheritance
- Aesthetic mapping versus assignment
- Statistical transformations
- Add and modify scales and legends
- Statify plots using facets
- Manipulate plot labels
- Change and create plot themes

5.1 Setup

5.1.1 Software and Materials

Follow the R Installation instructions and ensure that you can successfully start RStudio.

5.1.2 Class Structure

Informal - Ask questions at any time. Really!

Collaboration is encouraged - please spend a minute introducing yourself to your neighbors!

5.1.3 Prerequisites

This is an intermediate R course:

- Assumes working knowledge of R
- Relatively fast-paced

5.1.4 Launch an R session

Start RStudio and create a new project:

- On Windows click the start button and search for RStudio. On Mac RStudio will be in your applications folder.
- In Rstudio go to `File -> New Project`.
- Choose `Existing Directory` and browse to the workshop materials directory on your desktop.
- Choose `File -> Open File` and select the file with the word "BLANK" in the name.

5.1.5 Packages

You should have already installed the `tidyverse` and `rmarkdown` packages onto your computer before the workshop — see R Installation. Now let's load these packages into the search path of our R session.

```r
library(tidyverse)
library(rmarkdown)
```

The `ggplot2` package is contained within `tidyverse`, but we also want to install two additional packages, `scales` and `ggrepel`, which provide additional functionality.

```r
# install.packages("scales")
library(scales)

# install.packages("ggrepel")
library(ggrepel)
```

5.1.6 Goals

We will learn about the `grammar of graphics` — a system for understanding the building blocks of a graph — using the `ggplot2` package. In particular, we'll learn about:

1. Basic plots, **aesthetic mapping and inheritance**
2. Tailoring **statistical transformations** to particular plots
3. **Modifying scales** to change axes and add labels
4. **Faceting** to create many small plots
5. Changing plot **themes**

5.2 Why `ggplot2`?

`ggplot2` is a package within in the `tidyverse` suite of packages. Advantages of `ggplot2` include:

- consistent underlying `grammar of graphics` (Wilkinson, 2005)
- very flexible — plot specification at a high level of abstraction
- theme system for polishing plot appearance
- many users, active mailing list

That said, there are some things you cannot do with `ggplot2`:

- 3-dimensional graphics (see `rayshader` or the `rgl` package)
- Graph-theory type graphs (see `ggraph` or the `igraph` package)
- Interactive graphics (see the `ggvis` package)

5.2.1 `ggplot2` ecosystem

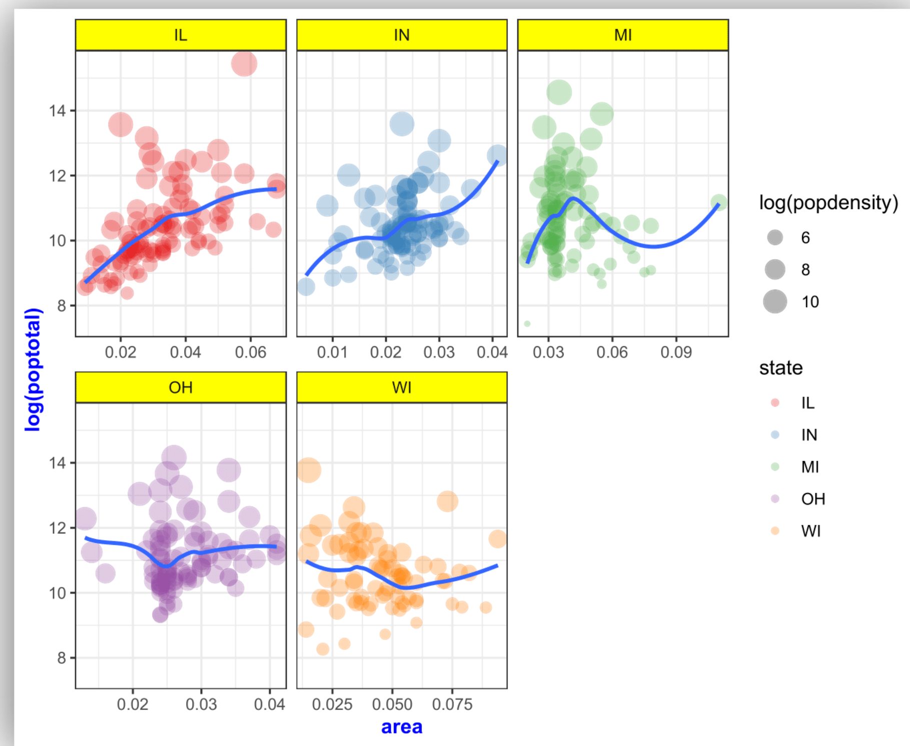
The `ggplot2` package has spawned a whole ecosystem of packages that extend the functionality of the base package. There are currently 80+ packages that offer many different options, including animated graphs (`gganimate`), interactive graphs (`ggvis`), network graphs (`ggraph`), 3D graphs (`rayshader`), adding results from statistical tests (`ggstatsplot`), and additional themes (`ggthemes`). A gallery of some of the available extensions can be found here: `https://exts.ggplot2.tidyverse.org/gallery/`.

5.2.2 What is the Grammar Of Graphics?

The basic idea: independently specify plot building blocks and combine them to create just about any kind of graphical display you want. Building blocks of a graph include the following (**bold denotes essential elements**):

- **data**
- **aesthetic mapping**
- **geometric object**
- statistical transformations
- scales
- coordinate system
- position adjustments
- faceting
- themes

By the end of this workshop, you should understand what these building blocks do and how to use them to create the following plot:



5.2.3 `ggplot2` VS base graphics

Compared to base graphics, `ggplot2`

- is more verbose for simple / canned graphics
- is less verbose for complex / custom graphics
- does not have methods (data should always be in a `data.frame`)
- has sensible defaults for generating legends

5.3 Geometric objects & aesthetics

5.3.1 Aesthetic mapping

In ggplot land *aesthetic* means "something you can see". Examples include:

- position (i.e., on the x and y axes)

- color (“outside” color)
- fill (“inside” color)
- shape (of points)
- linetype
- size

Each type of geom accepts only a subset of all aesthetics; refer to the geom help pages to see what mappings each geom accepts. Aesthetic mappings are set with the `aes()` function.

5.3.2 Geometric objects (`geom`)

Geometric objects are the actual marks we put on a plot. Examples include:

- points (`geom_point()`, for scatter plots, dot plots, etc.)
- lines (`geom_line()`, for time series, trend lines, etc.)
- boxplot (`geom_boxplot()`, for boxplots!)

A plot **must have at least one geom**; there is no upper limit. You can add a geom to a plot using the `+` operator.

Each `geom_` has a particular set of aesthetic mappings associated with it. Some examples are provided below, with required aesthetics in **bold** and optional aesthetics in plain text:

`geom_`	Usage	Aesthetics
`geom_point()`	Scatter plot	**`x`**,**`y`**,`alpha`,`color`,`fill`,`group`,`shape`,`size`,`stroke`
`geom_line()`	Line plot	**`x`**,**`y`**,`alpha`,`color`,`linetype`,`size`
`geom_bar()`	Bar chart	**`x`**,**`y`**,`alpha`,`color`,`fill`,`group`,`linetype`,`size`
`geom_boxplot()`	Boxplot	**`x`**,**`lower`**,**`upper`**,**`middle`**,**`ymin`**,**`ymax`**,`alpha`,`color`,`fill`
`geom_density()`	Density plot	**`x`**,**`y`**,`alpha`,`color`,`fill`,`group`,`linetype`,`size`,`weight`
`geom_smooth()`	Conditional means	**`x`**,**`y`**,`alpha`,`color`,`fill`,`group`,`linetype`,`size`,`weight`
`geom_label()`	Text	**`x`**,**`y`**,**`label`**,`alpha`,`angle`,`color`,`family`,`fontface`,`size`

You can get a list of all available geometric objects and their associated aesthetics at `https://ggplot2.tidyverse.org/reference/`. Or, simply type `geom_<tab>` in any good R IDE (such as Rstudio) to see a list of functions starting with `geom_`.

5.3.2.1 Points (scatterplot)

Now that we know about geometric objects and aesthetic mapping, we can make a ggplot. To add points to a plot, `geom_point()` requires mappings for x and y, all others are optional.

Example data: housing prices

Let’s look at data on housing prices.

```r
housing <- read_csv("dataSets/landdata-states.csv")
head(housing[1:5]) # view first 5 columns
```

```
## # A tibble: 6 x 5
##   State Region  Date Home_Value Structure_Cost
##   <chr> <chr>  <dbl>      <dbl>          <dbl>
## 1 AK    West   2010.     224952         160599
## 2 AK    West   2010.     225511         160252
## 3 AK    West   2010.     225820         163791
## 4 AK    West   2010      224994         161787
## 5 AK    West   2008      234590         155400
## 6 AK    West   2008.     233714         157458
```

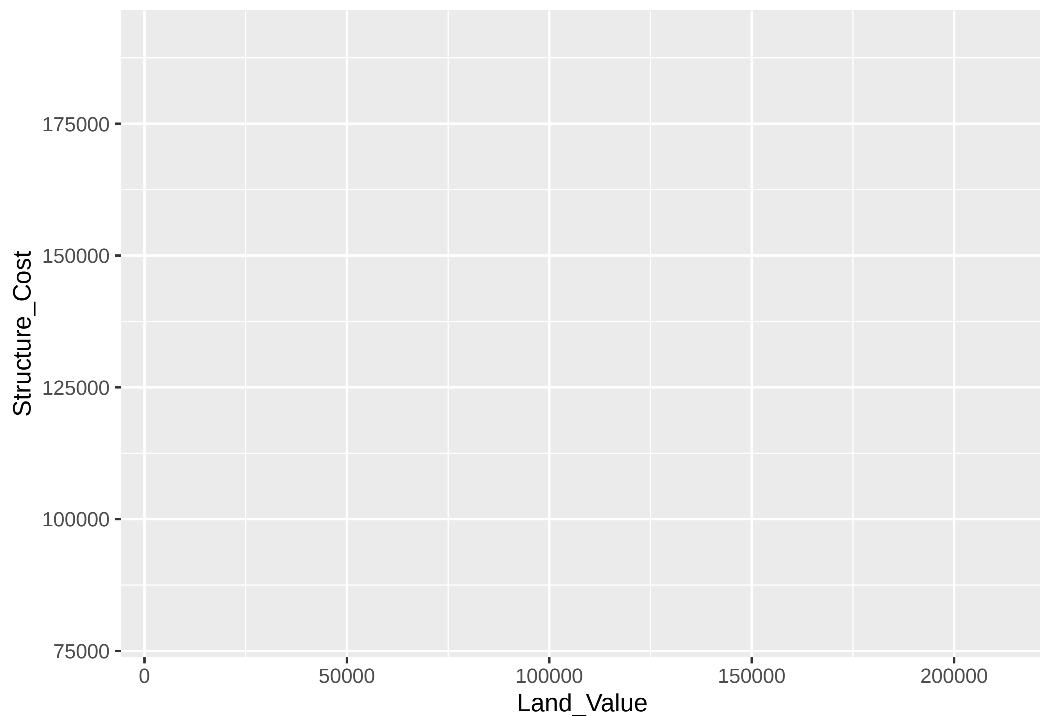
```r
# create a subset for 1st quarter 2001
hp2001Q1 <- housing %>% filter(Date == 2001.25)
```

Step 1: create a blank canvas by specifying data:

```r
ggplot(data = hp2001Q1)
```

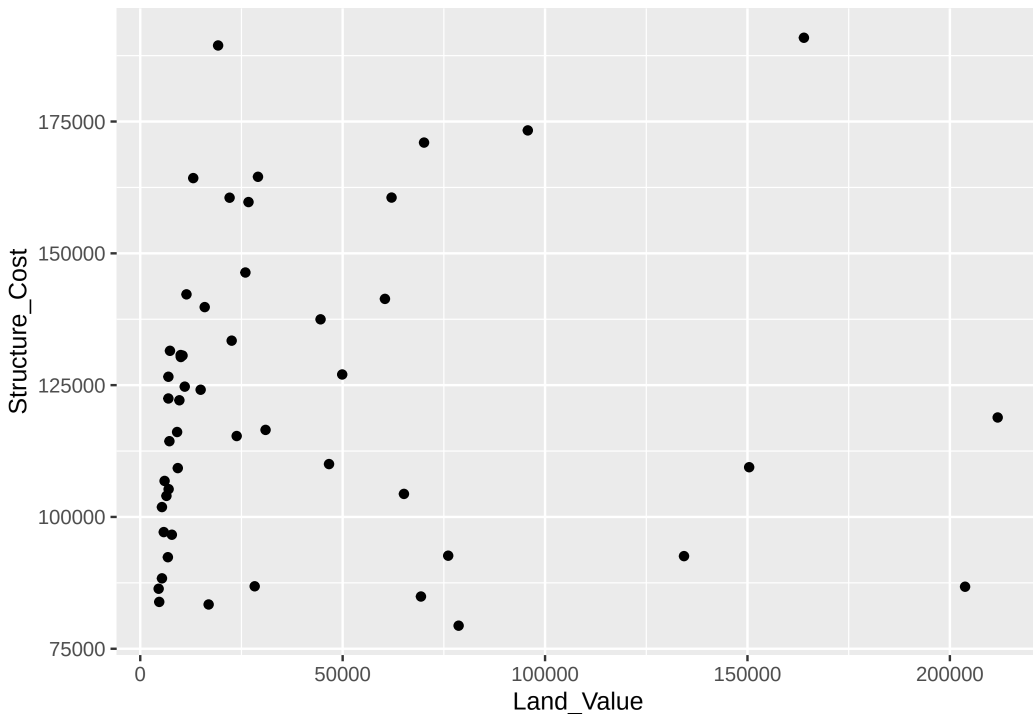

Step 2: specify aesthetic mappings (how you want to map variables to visual aspects):

```
# here we map "Land_Value" and "Structure_Cost" to the x- and y-axes.
ggplot(data = hp2001Q1, mapping = aes(x = Land_Value, y = Structure_Cost))
```



Step 3: add new layers of geometric objects that will show up on the plot:

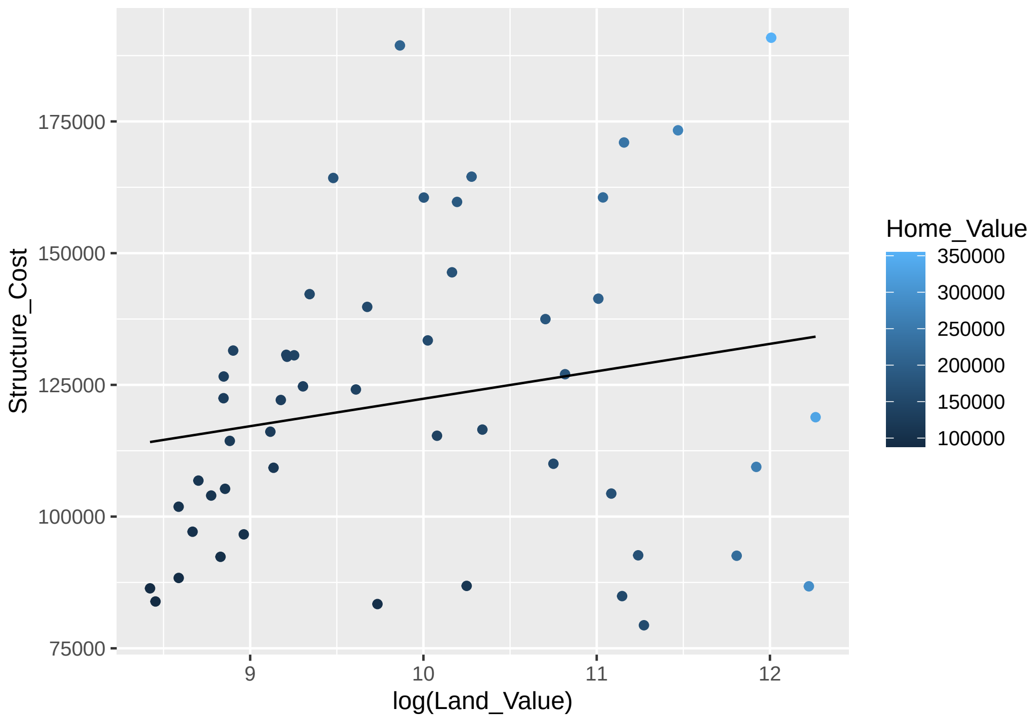
```
# here we use geom_point() to add a layer with point (dot) elements
# as the geometric shapes to represent the data.
ggplot(data = hp2001Q1, mapping = aes(x = Land_Value, y = Structure_Cost)) +
  geom_point()
```



5.3.2.2 Lines (prediction line)

A plot constructed with `ggplot()` can have more than one geom. In that case the mappings established in the `ggplot()` call are plot defaults that can be added to or overridden — this is referred to as **aesthetic inheritance**. Our plot could use a regression line:

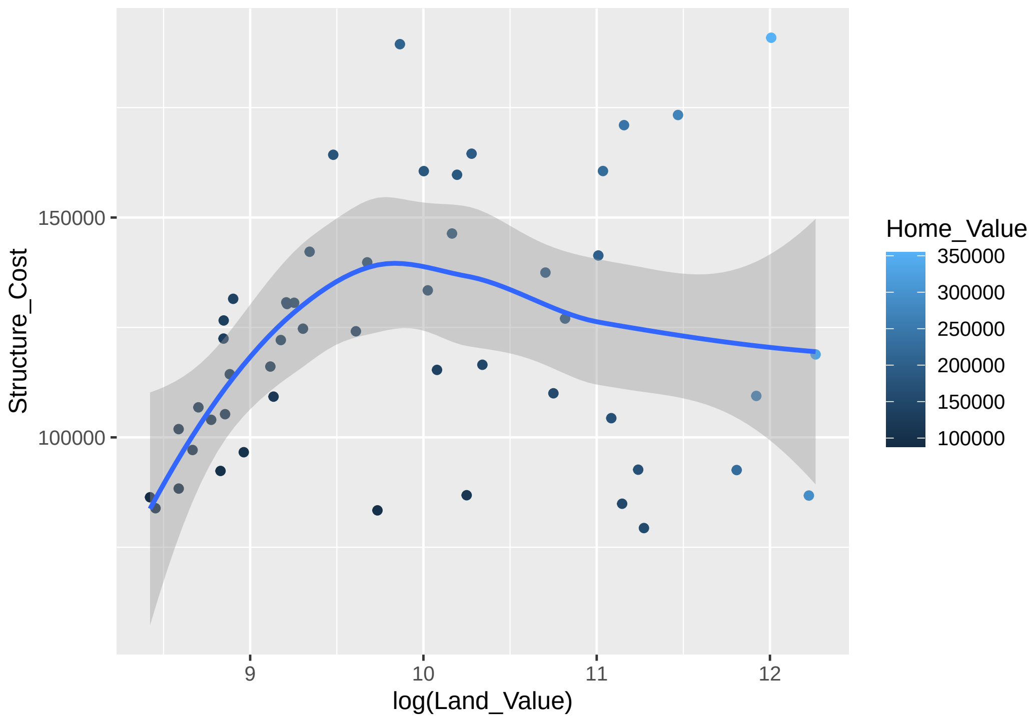
```
# get predicted values from a linear regression
hp2001Q1$pred_SC <- lm(Structure_Cost ~ log(Land_Value), data = hp2001Q1) %>%
  predict()

# here we store the 'base plot' - without geometric objects - in the object 'p1'
p1 <- ggplot(hp2001Q1, aes(x = log(Land_Value), y = Structure_Cost))

# we can then add geometric objects to our base plot 'p1'
p1 + geom_point(aes(color = Home_Value)) + # values for x and y are inherited from the ggplot() c
     geom_line(aes(y = pred_SC)) # add predicted values to the plot overriding the y values from
```



5.3.2.3 Smoothers

Not all geometric objects are simple shapes; the smooth geom includes a line and a ribbon.

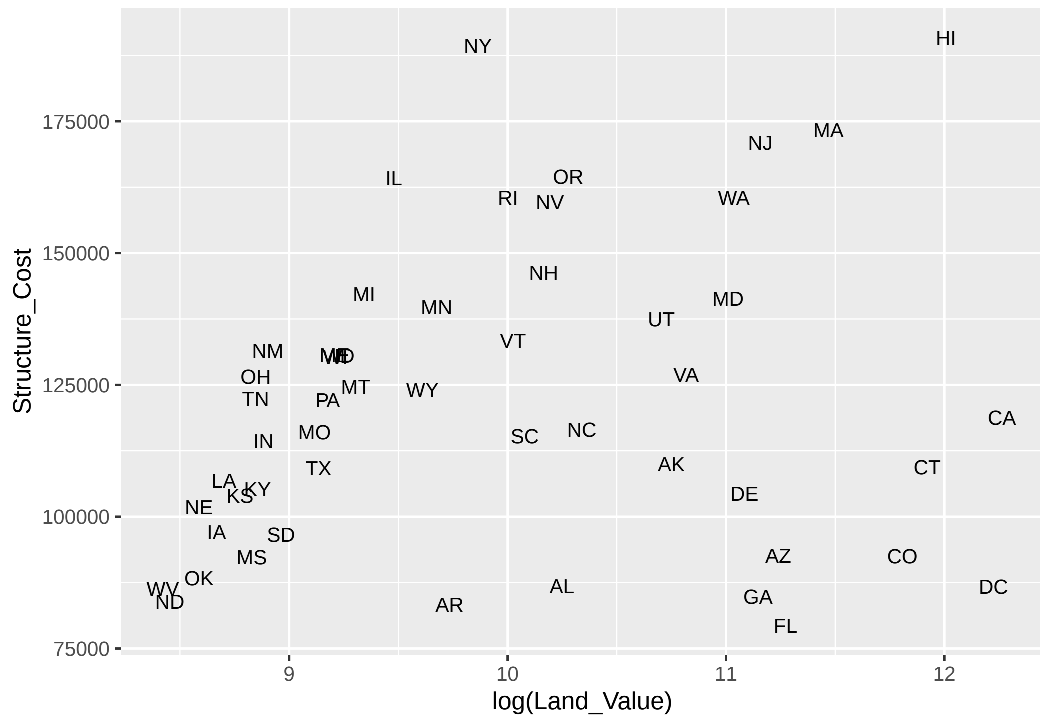
```
# add smooth geom to base plot
p1 +
  geom_point(aes(color = Home_Value)) +
  geom_smooth()
```



5.3.2.4 Text (label points)

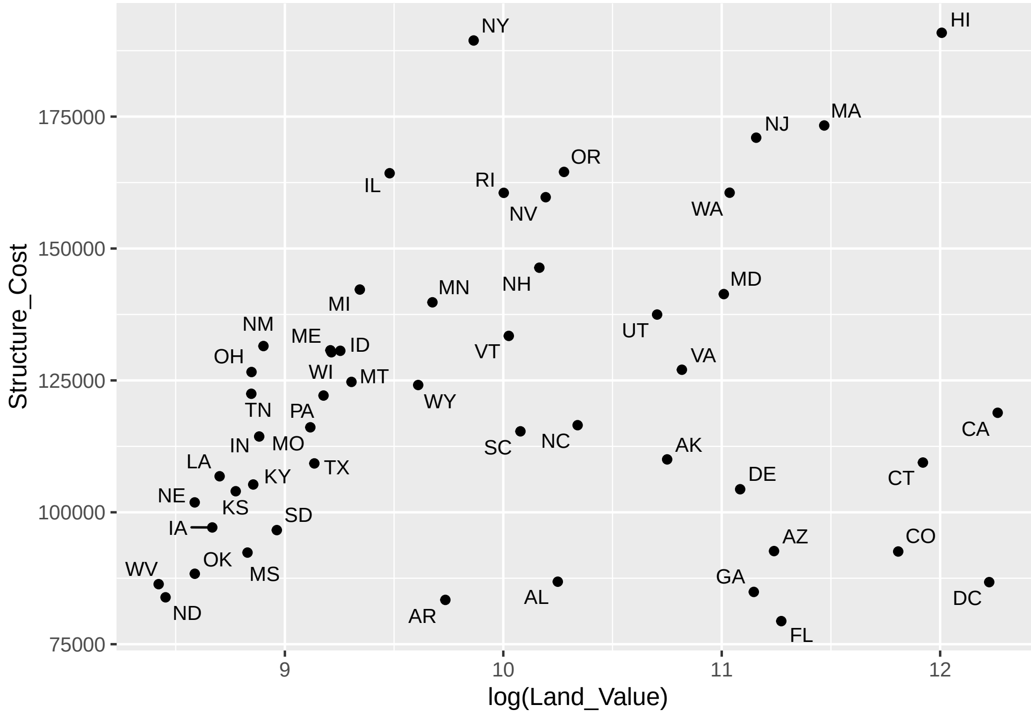
Each geom accepts a particular set of mappings; for example `geom_text()` accepts a `label` mapping.

```
# add text geom to base plot
p1 +
  geom_text(aes(label = State), size = 3)
```



But what if we want to include points and labels? We can use `geom_text_repel()` to keep labels from overlapping the points and each other.

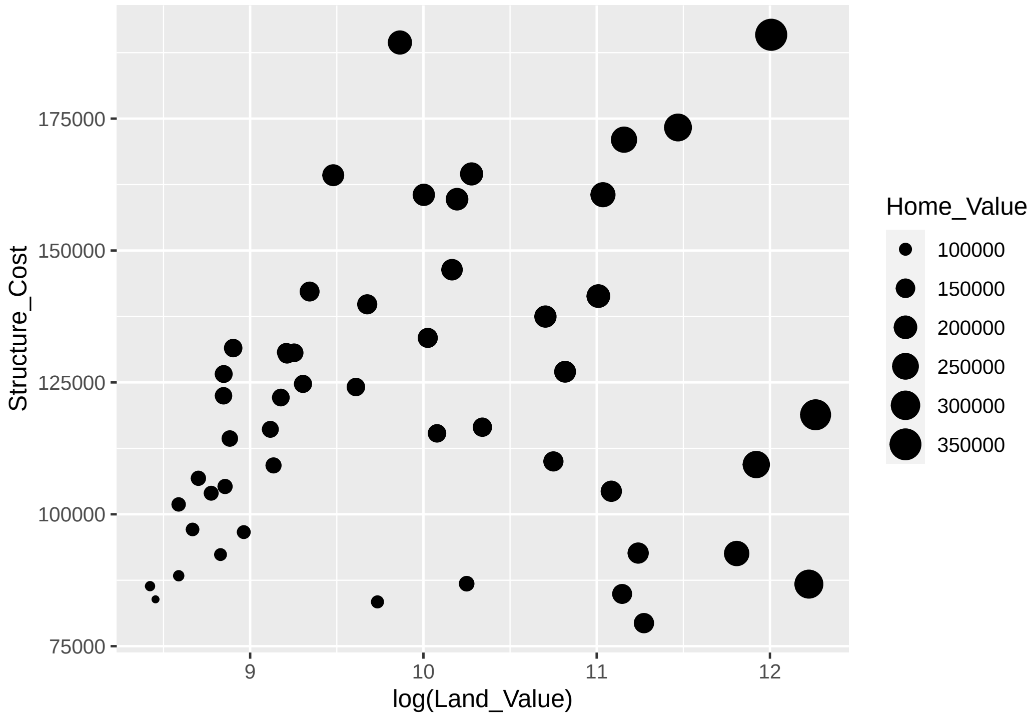
```
# add points and text geoms to base plot
p1 +
  geom_point() +
  geom_text_repel(aes(label = State), size = 3)
```



5.3.3 Aesthetic mapping VS assignment

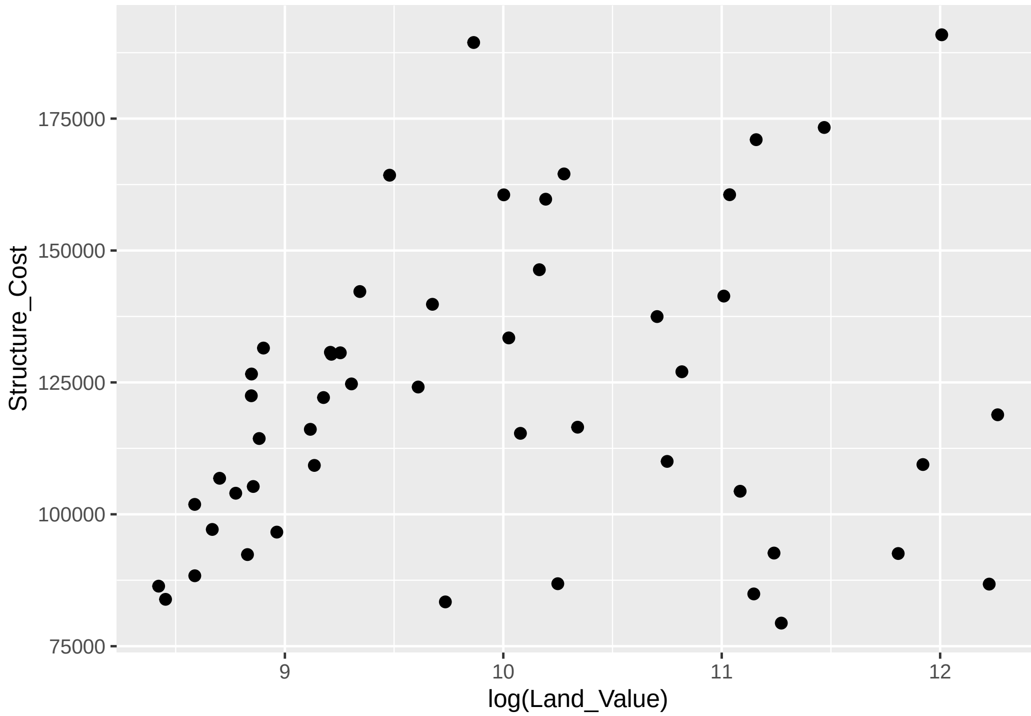
1. Variables are **mapped** to aesthetics inside the `aes()` function:

```
# map `Home_Value` to point size
p1 +
  geom_point(aes(size = Home_Value))
```



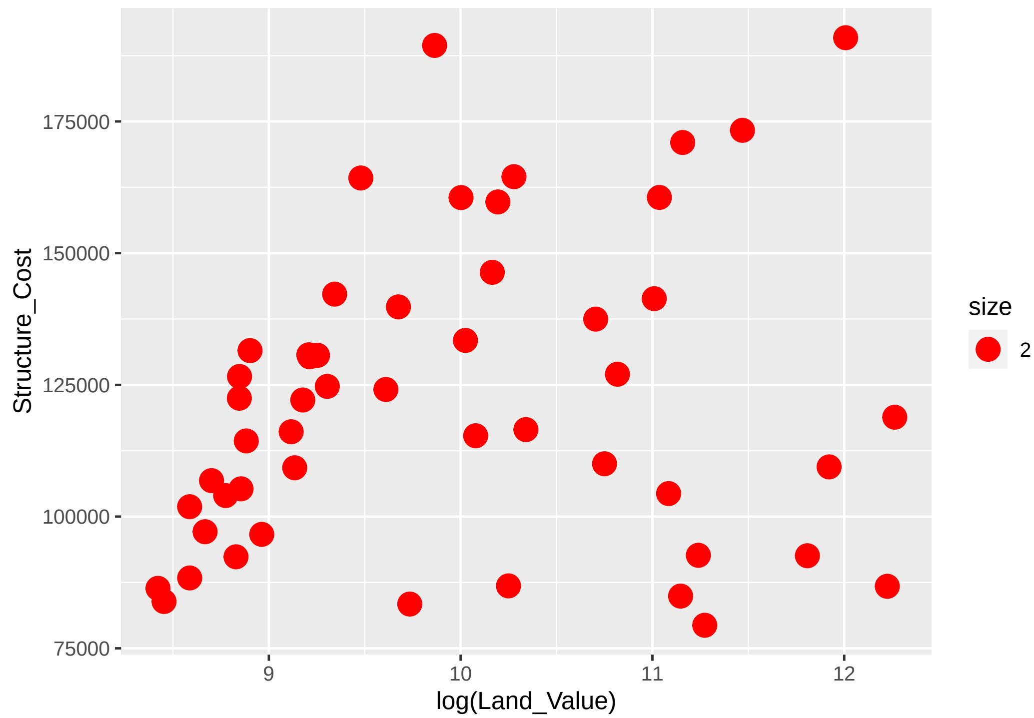
2. Constants are **assigned** to aesthetics outside the `aes()` call:

```
# assign all points a size of 2
p1 +
  geom_point(size = 2)
```



This sometimes leads to confusion, as in this example:

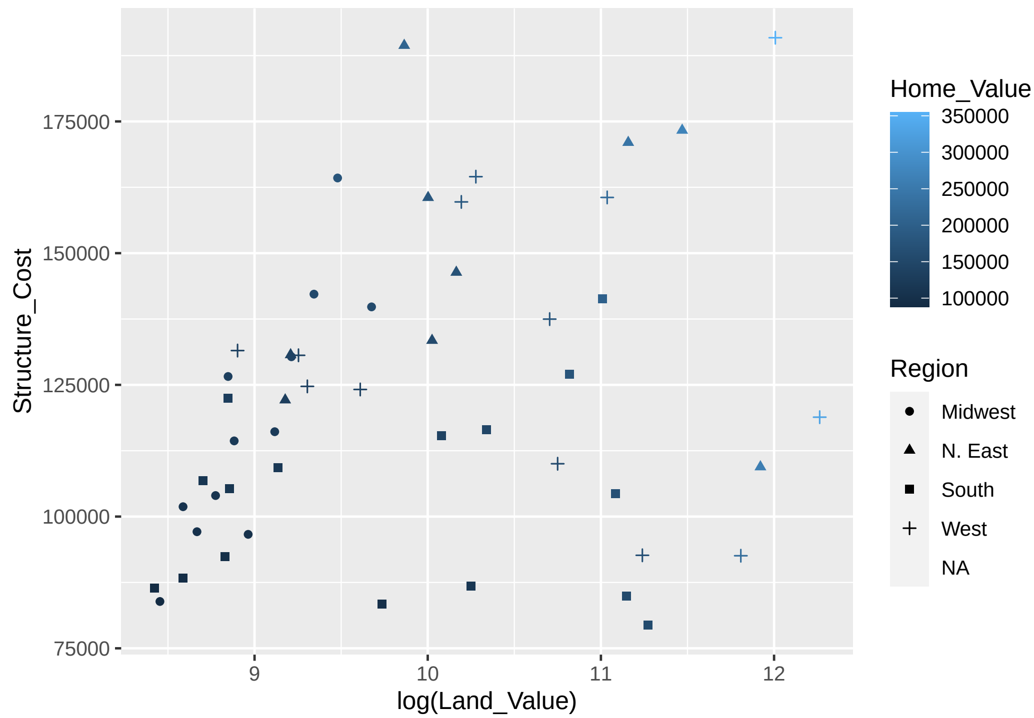
```
p1 +
  geom_point(aes(size = 2),# incorrect! 2 is not a variable
             color = "red") # this is fine -- all points red
```



5.3.4 Mapping variables to other aesthetics

Other aesthetics are mapped in the same way as x and y in the previous example.

```
# map `Home_Value` to color and `Region` to shape
p1 +
  geom_point(aes(color = Home_Value, shape = Region))
```



5.3.5 Exercise 0

The data for the next few exercises is available in the `dataSets/EconomistData.csv` file. Read it in with:

```
dat <- read_csv("dataSets/EconomistData.csv")
```

Original sources for these data are `http://www.transparency.org/content/download/64476/1031428` and `http://hdrstats.undp.org/en/indicators/display_cf_xls_indicator.cfm?indicator_id=103106&lang=en`

These data consist of *Human Development Index* and *Corruption Perception Index* scores for several countries.

1. Create a scatter plot with `CPI` on the x axis and `HDI` on the y axis.

```
##
```

2. Color the points in the previous plot blue.

```
##
```

3. Map the color of the the points to `Region`.

```
##
```

4. Keeping color mapped to `Region`, make the points bigger by setting size to 2

```
##
```

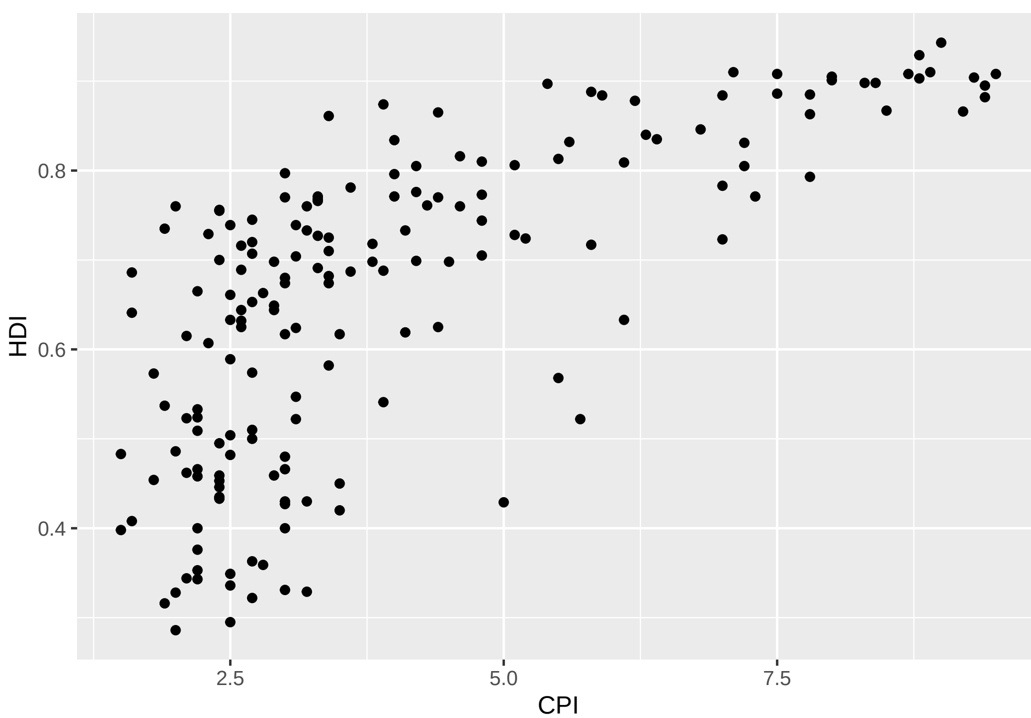
5. Keeping color mapped to `Region`, map the size of the points to `HDI_Rank`

```
##
```

Click for Exercise 0 Solution

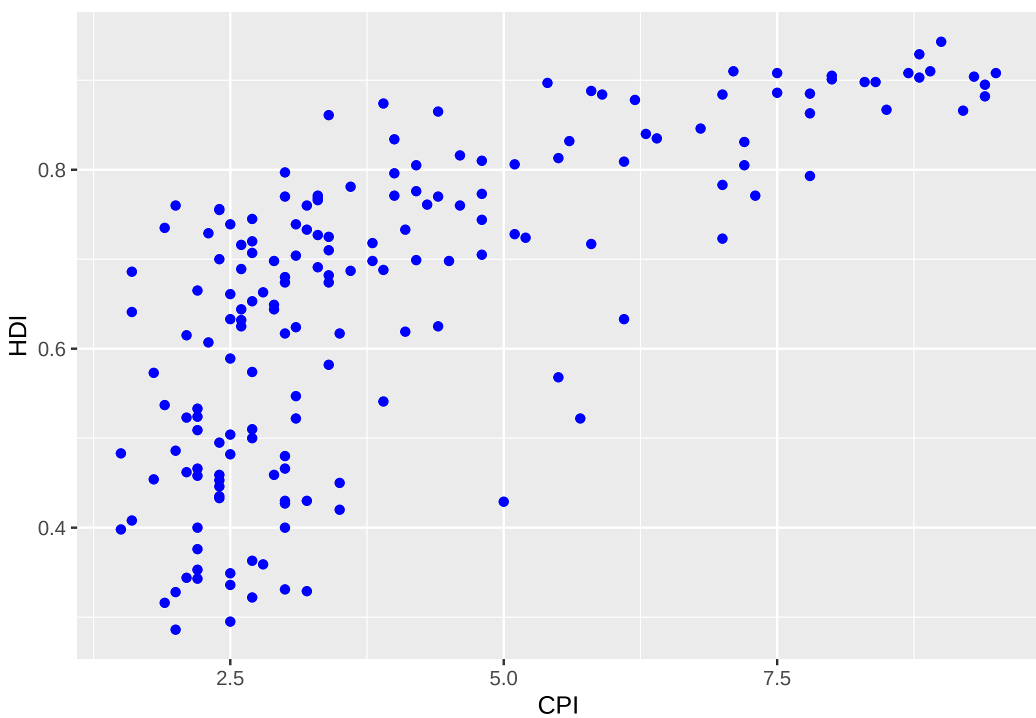
1. Create a scatter plot with `CPI` on the x axis and `HDI` on the y axis.

```
ggplot(dat, aes(x = CPI, y = HDI)) +
  geom_point()
```



2. Color the points in the previous plot blue.

```r
ggplot(dat, aes(x = CPI, y = HDI)) +
  geom_point(color = "blue")
```

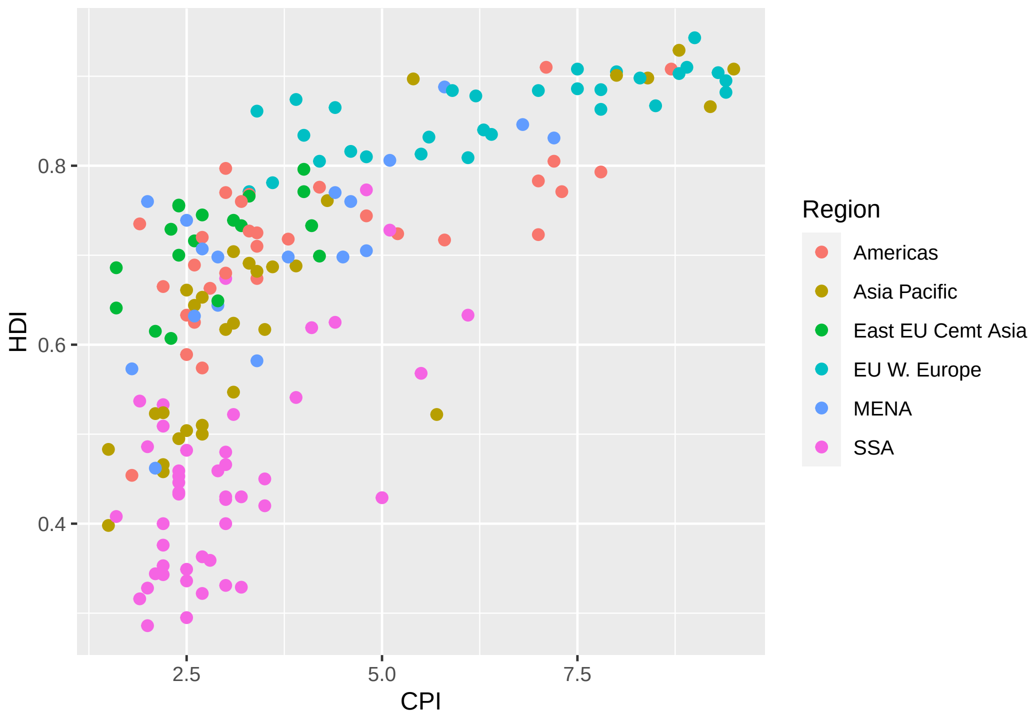


3. Map the color of the the points to `Region`.

```r
ggplot(dat, aes(x = CPI, y = HDI)) +
  geom_point(aes(color = Region))
```

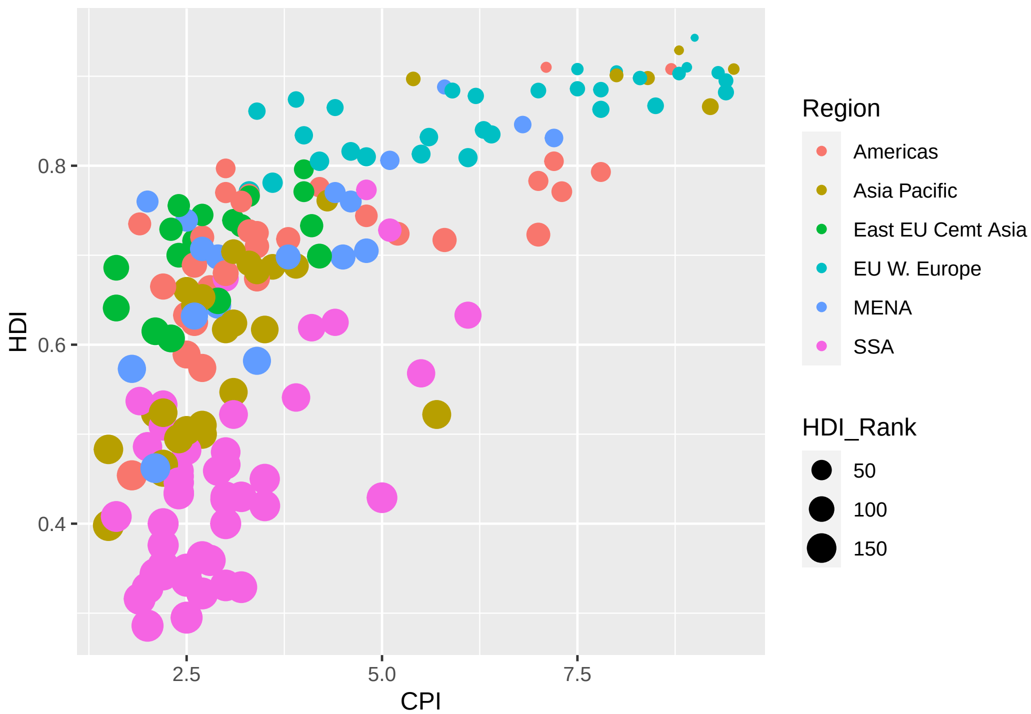
4. Keeping color mapped to `Region`, make the points bigger by setting size to 2.

```
ggplot(dat, aes(x = CPI, y = HDI)) +
  geom_point(aes(color = Region), size = 2)
```



5. Keeping color mapped to `Region`, map the size of the points to `HDI_Rank`.

```
ggplot(dat, aes(x = CPI, y = HDI)) +
geom_point(aes(color = Region, size =  HDI_Rank))
```



5.4 Statistical transformations

5.4.1 Why transform data?

Some plot types (such as scatterplots) do not require transformations; each point is plotted at x and y coordinates equal to the original value. Other plots, such as boxplots, histograms, prediction lines etc. require statistical transformations:

- For a boxplot, the y values must be transformed to the median, quartiles, and 1.5 times the interquartile range.
- For a smoother, the y values must be transformed into predicted mean values

5.4.2 Setting arguments

Each `geom_` function has a default statistic that it is paired with and, likewise, each `stat_` function has a default geometic object that it is paired with. For example, the default statistic for `geom_histogram()` is "bin" (called by the `stat_bin()` function), while the default geometric object for `stat_bin()` is "bar" (called by the `geom_bar()` function). These defaults can be changed.

Arguments to `stat_` functions can be passed through `geom_` functions and vice versa. This can be slightly annoying, because if you are using a `geom_` function, in order to specify some arguments you may have to first determine which statistic the geometric object uses, then determine the arguments to that `stat_` function.

Let's look at the arguments for the histogram geometric object (`geom_histogram()`):

```
args(geom_histogram)
```

```
## function (mapping = NULL, data = NULL, stat = "bin", position = "stack",
##     ..., binwidth = NULL, bins = NULL, na.rm = FALSE, orientation = NA,
##     show.legend = NA, inherit.aes = TRUE)
## NULL
```

Notice that the third argument is `stat = "bin"`, which calls the `stat_bin()` function. This is how the histogram geom is, by default, paired with the bin statistic. The fifth argument is `...`, which allows us to pass certain arguments to `stat_bin()` through our call to `geom_histogram()`. Now let's look at the arguments available through `stat_bin()`:

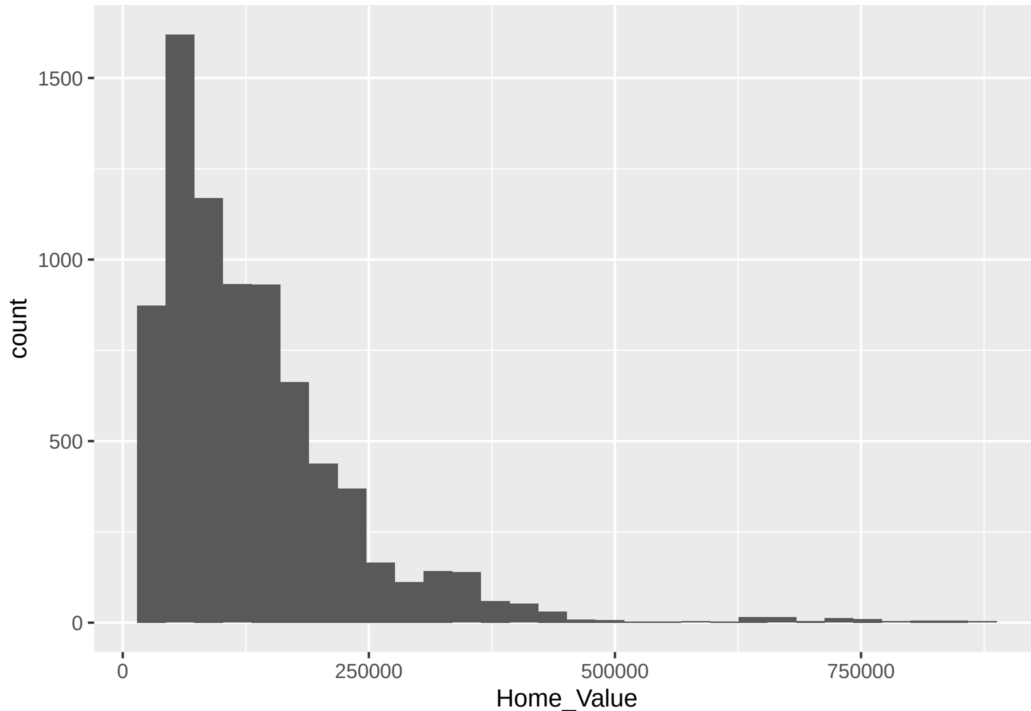
```
args(stat_bin)
```

```
## function (mapping = NULL, data = NULL, geom = "bar", position = "stack",
##     ..., binwidth = NULL, bins = NULL, center = NULL, boundary = NULL,
##     breaks = NULL, closed = c("right", "left"), pad = FALSE,
##     na.rm = FALSE, orientation = NA, show.legend = NA, inherit.aes = TRUE)
## NULL
```

The tenth argument is `breaks`, which allows us to supply a numeric vector of bin boundaries. Notice that this argument is *not* available in `geom_histogram()`, but we can still supply the argument and it will be passed to `stat_bin()` through the `...` argument.

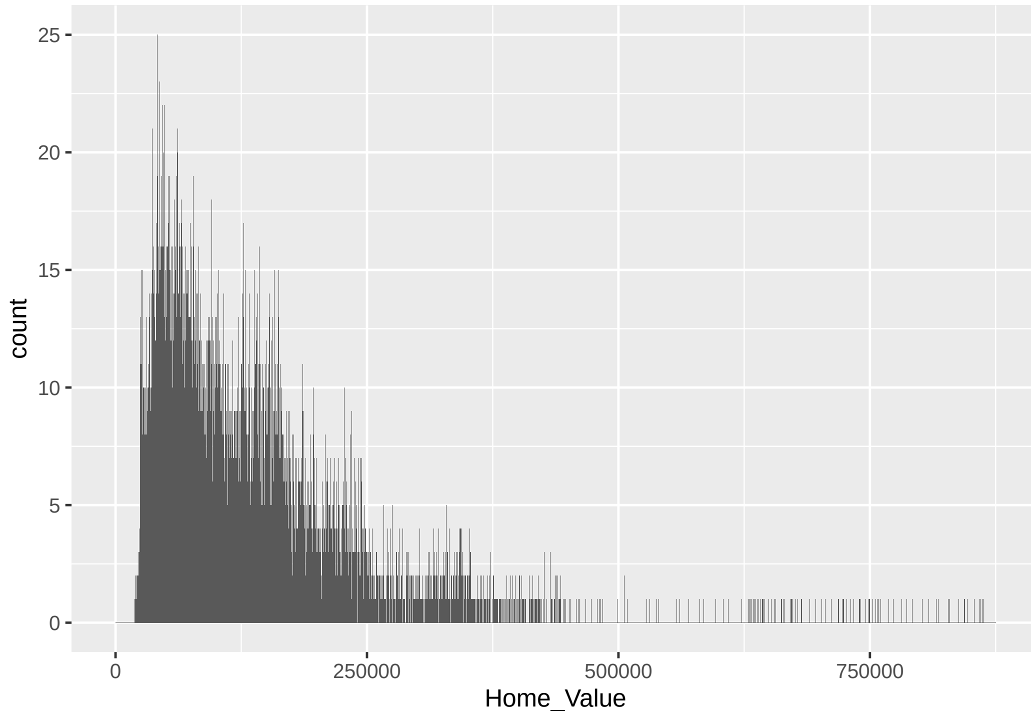
For example, here is the default histogram of `Home_Value`:

```
# histogram of `Home_Value`
p2 <- ggplot(housing, aes(x = Home_Value))
p2 + geom_histogram()
```



We can change the boundaries for the bins by passing the **breaks** argument through **geom_histogram()** to the **stat_bin()** function:

```
# change bin boundaries for histogram
p2 + geom_histogram(breaks = seq(0, 875000, by = 250))
```



For reference, here is a list of geometric objects and their default statistics `https://ggplot2.tidyverse.org/reference/`.

5.4.3 Changing the transformation

Sometimes the default statistical transformation is not what you need. This is often the case with pre-summarized data. Let's create a new variable `Home_Value_Mean` that is the mean of `Home_Value` for each `State`:

```
# create new variable that is the mean of 'Home Value' for each 'State'
housing_sum <-
  housing %>%
  group_by(State) %>%
  summarize(Home_Value_Mean = mean(Home_Value)) %>%
  ungroup()

head(housing_sum)
```

```
## # A tibble: 6 x 2
##   State Home_Value_Mean
##   <chr>           <dbl>
## 1 AK            147385.
## 2 AL             92545.
```

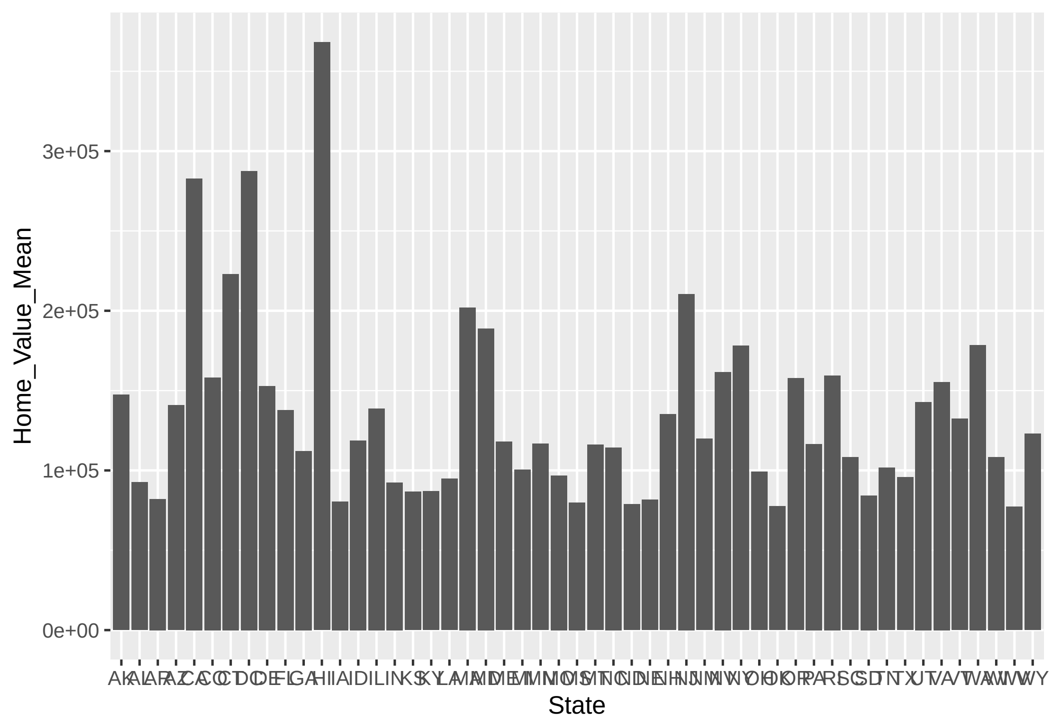
```
## 3 AR               82077.
## 4 AZ              140756.
## 5 CA              282808.
## 6 CO              158176.
```

Now let's try to create a bar chart using this pre-summarized data:

```
# barchart using pre-summarized data
ggplot(housing_sum, aes(x = State, y = Home_Value_Mean)) +
  geom_bar()

## Error: stat_count() must not be used with a y aesthetic.
```

What is the problem with the previous plot? Basically, we take binned and summarized data and ask `ggplot()` to bin and summarize it again (`geom_bar()` defaults to `stat = stat_count`). Obviously this will not work. We can fix it by telling `geom_bar()` to use a different statistical transformation function. The `identity` function returns the same output as the input.

```
# change the statistical transformation function
ggplot(housing_sum, aes(x = State, y = Home_Value_Mean)) +
  geom_bar(stat = "identity")
```



5.4.4 Exercise 1

1. Re-create a scatter plot with `CPI` on the x axis and `HDI` on the y axis (as you did in the previous exercise).

```
##
```

2. Overlay a smoothing line on top of the scatter plot using `geom_smooth()`.

```
##
```

3. Make the smoothing line in `geom_smooth()` less smooth. Hint: see `?loess`.

```
##
```

4. Change the smoothing line in `geom_smooth()` to use a linear model for the predictions. Hint: see `?stat_smooth`.

```
##
```

5. BONUS 1: Allow the smoothing line created in the last plot to vary across the levels of `Region`. Hint: map `Region` to the color and fill aesthetics.

```
##
```

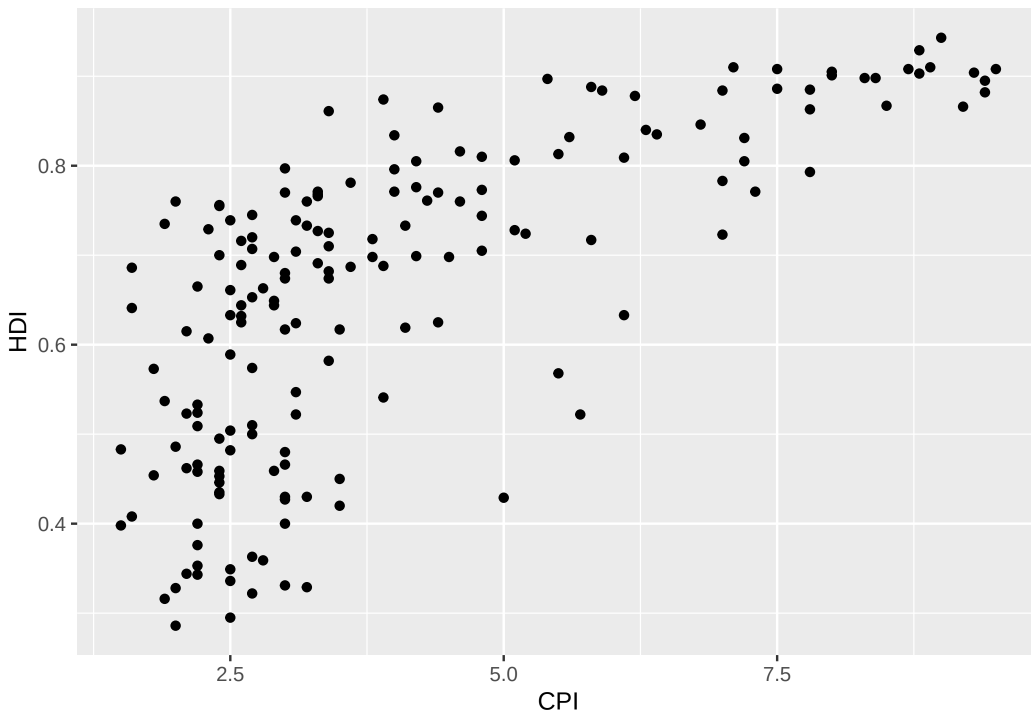
6. BONUS 2: Overlay a loess `(method = "loess")` smoothing line on top of the scatter plot using `geom_line()`. Hint: change the statistical transformation.

```
##
```

Click for Exercise 1 Solution

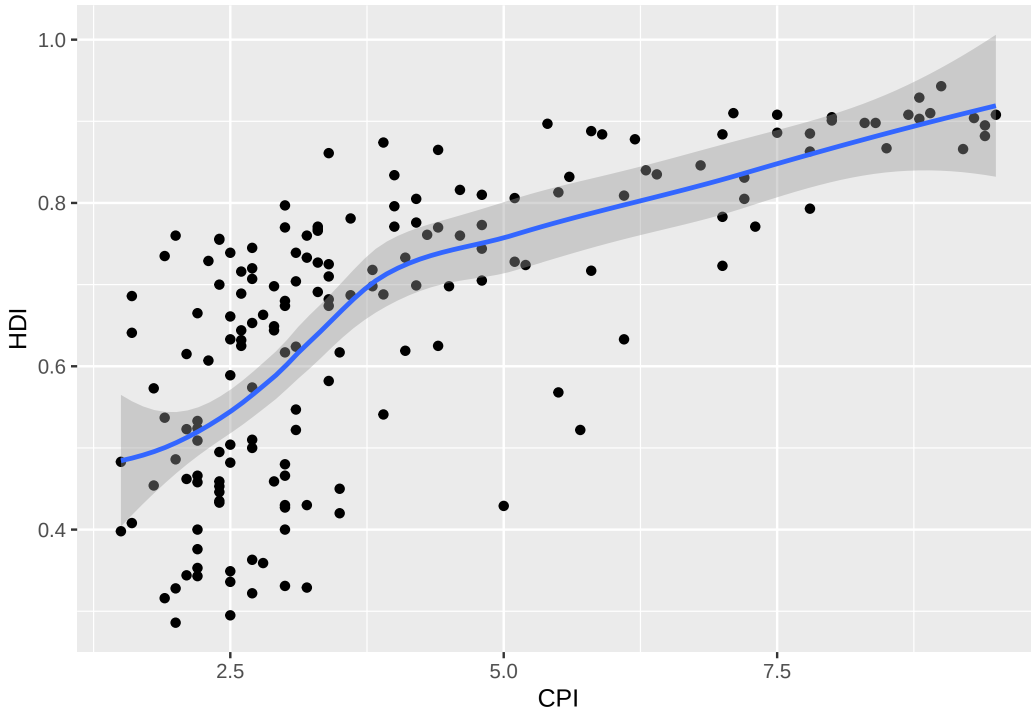
1. Re-create a scatter plot with `CPI` on the x axis and `HDI` on the y axis (as you did in the previous exercise).

```
ggplot(dat, aes(x = CPI, y = HDI)) +
  geom_point()
```



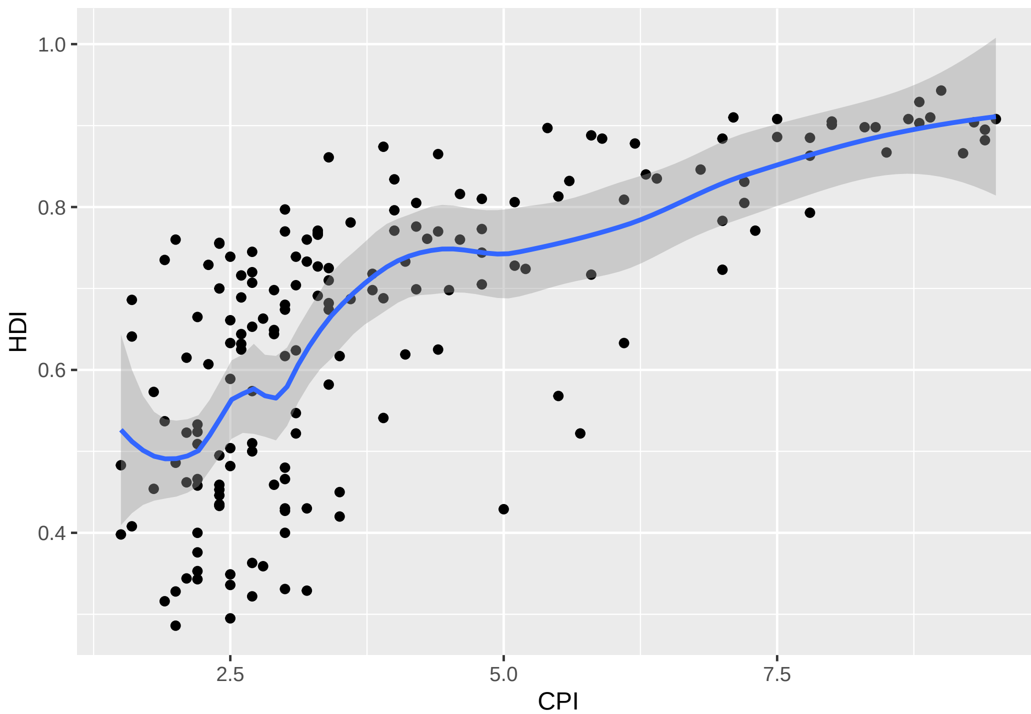
2. Overlay a smoothing line on top of the scatter plot using `geom_smooth()`.

```
ggplot(dat, aes(x = CPI, y = HDI)) +
  geom_point() +
  geom_smooth()
```



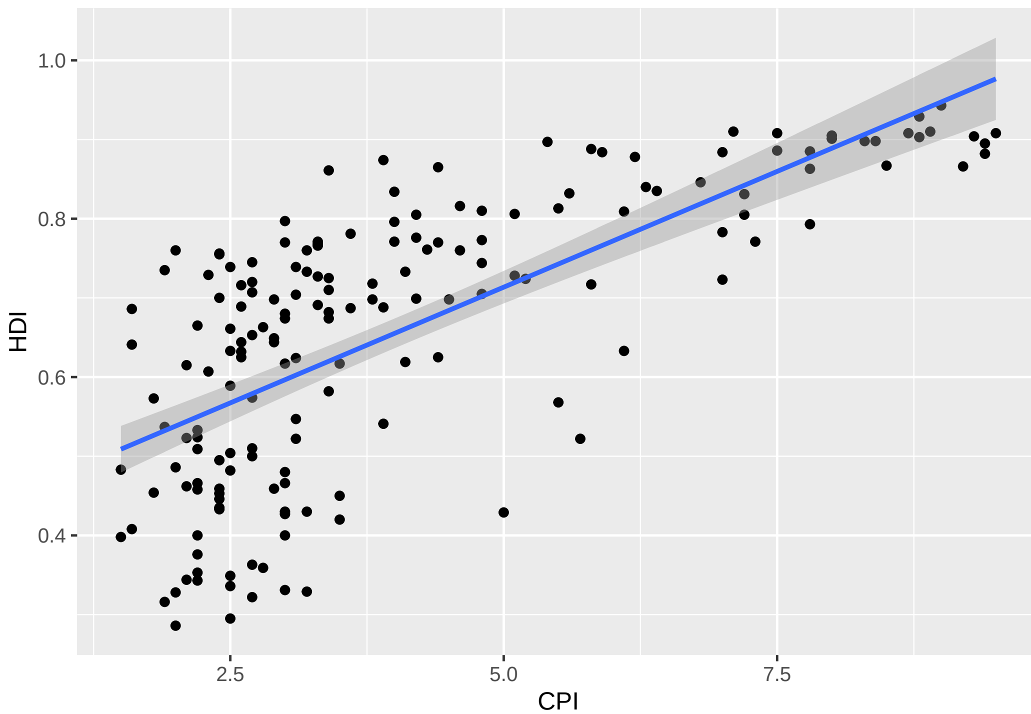
3. Make the smoothing line in `geom_smooth()` less smooth. Hint: see `?loess`.

```
ggplot(dat, aes(x = CPI, y = HDI)) +
  geom_point() +
  geom_smooth(span = .4)
```



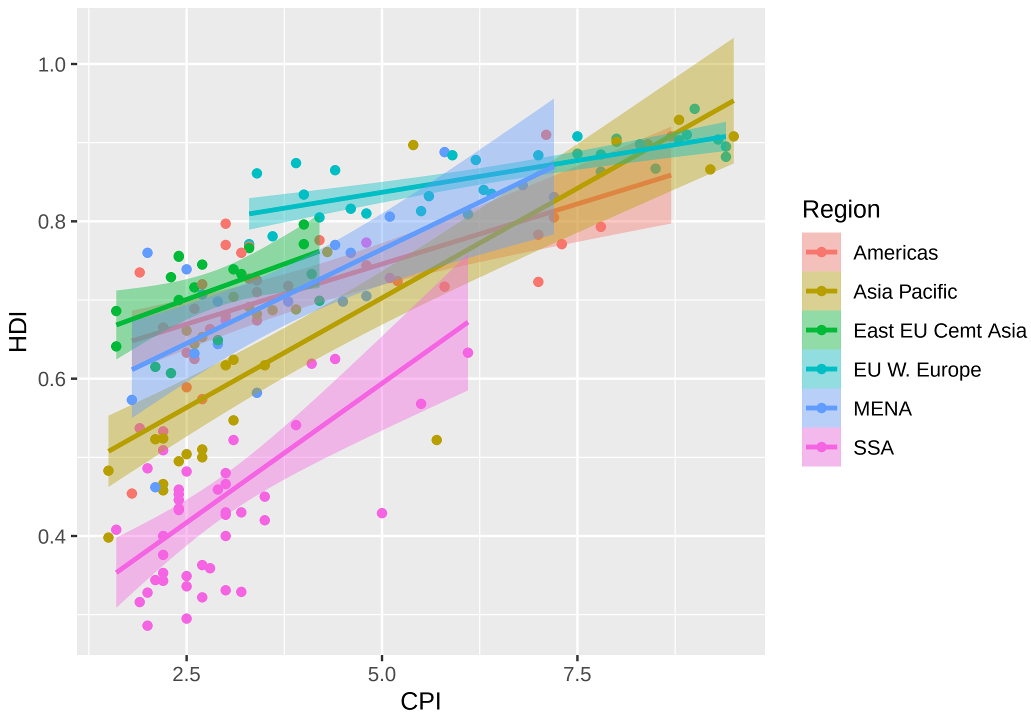
4. Change the smoothing line in `geom_smooth()` to use a linear model for the predictions. Hint: see `?stat_smooth`.

```
ggplot(dat, aes(x = CPI, y = HDI)) +
  geom_point() +
  geom_smooth(method = "lm")
```



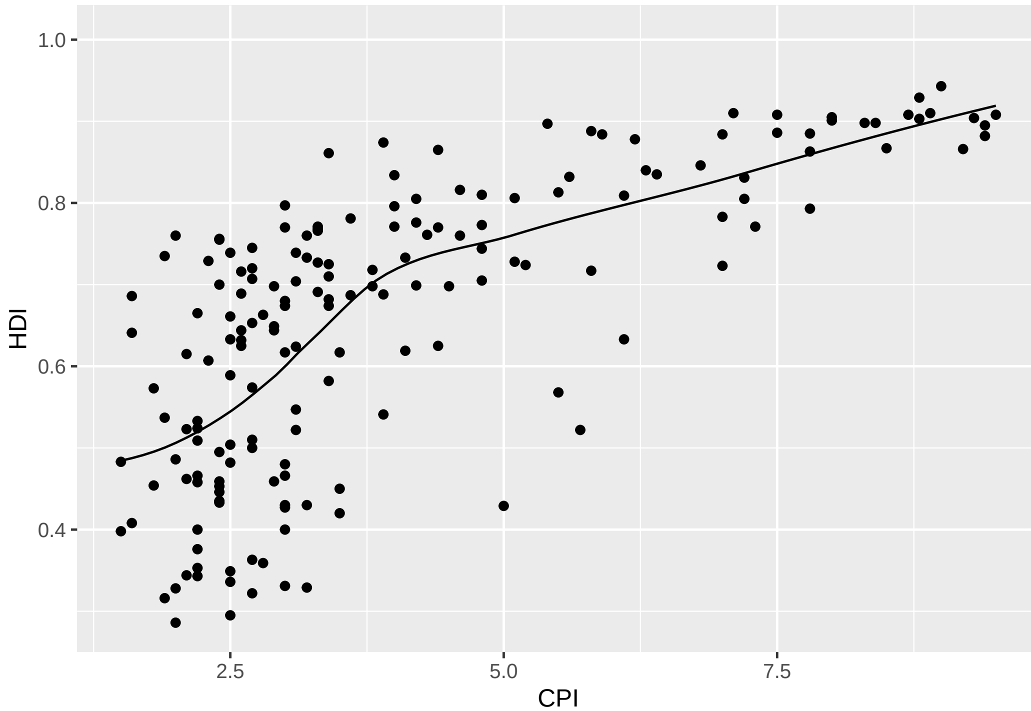
5. BONUS 1: Allow the smoothing line created in the last plot to vary across the levels of `Region`. Hint: map `Region` to the color and fill aesthetics.

```
ggplot(dat, aes(x = CPI, y = HDI, color = Region, fill = Region)) +
  geom_point() +
  geom_smooth(method = "lm")
```



6. BONUS 2: Overlay a loess (`method = "loess"`) smoothing line on top of the scatter plot using `geom_line()`. Hint: change the statistical transformation.

```
ggplot(dat, aes(x = CPI, y = HDI)) +
  geom_point() +
  geom_line(stat = "smooth", method = "loess")
```



5.5 Scales

5.5.1 Controlling aesthetic mapping

Aesthetic mapping (i.e., with `aes()`) only says that a variable should be mapped to an aesthetic. It doesn't say *how* that should happen. For example, when mapping a variable to *shape* with `aes(shape = x)` you don't say *what* shapes should be used. Similarly, `aes(color = y)` doesn't say *what* colors should be used. Also, `aes(size = z)` doesn't say *what* sizes should be used. Describing what colors/shapes/sizes etc. to use is done by modifying the corresponding *scale*. In `ggplot2` scales include:

- position
- color and fill
- size
- shape
- line type

Scales are modified with a series of functions using a `scale_<aesthetic>_<type>` naming scheme. Try typing `scale_<tab>` to see a list of scale modification functions.

5.5.2 Common scale arguments

The following arguments are common to most scales in `ggplot2`:

- **name:** the axis or legend title
- **limits:** the minimum and maximum of the scale
- **breaks:** the points along the scale where labels should appear
- **labels:** the labels that appear at each break

Specific scale functions may have additional arguments; for example, the `scale_color_continuous()` function has arguments `low` and `high` for setting the colors at the low and high end of the scale.

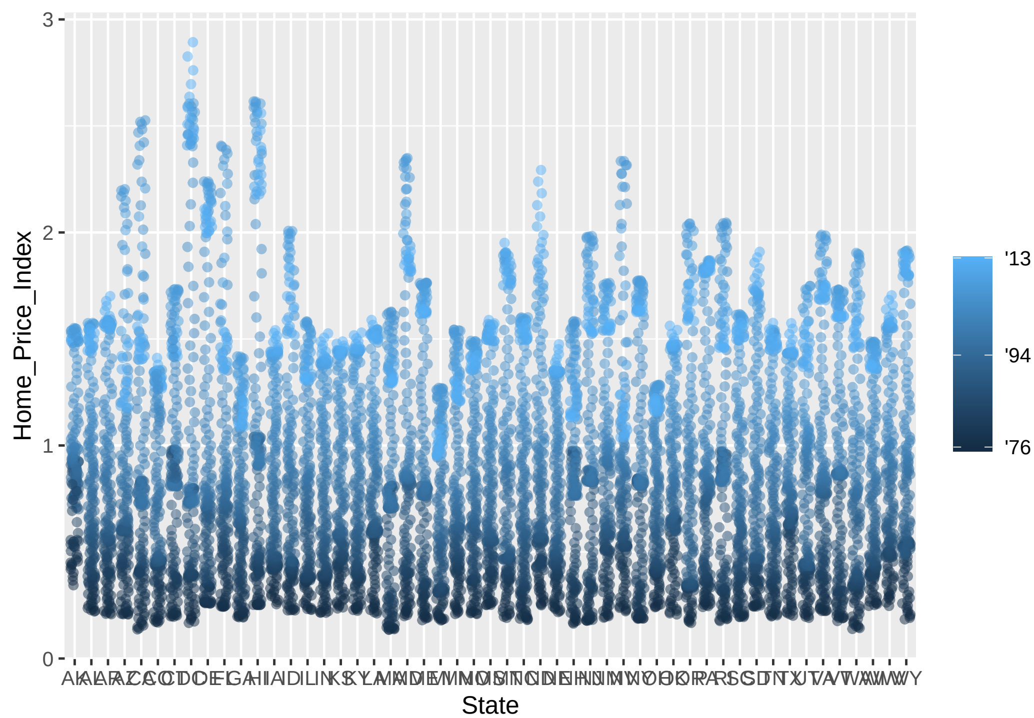
5.5.3 Scale modification examples

Start by constructing a dotplot showing the distribution of home values by `Date` and `State`.

```
# base dotplot
p3 <- ggplot(housing, aes(x = State, y = Home_Price_Index)) +
    geom_point(aes(color = Date), alpha = 0.5, size = 1.5,
               position = position_jitter(width = 0.25, height = 0))
```

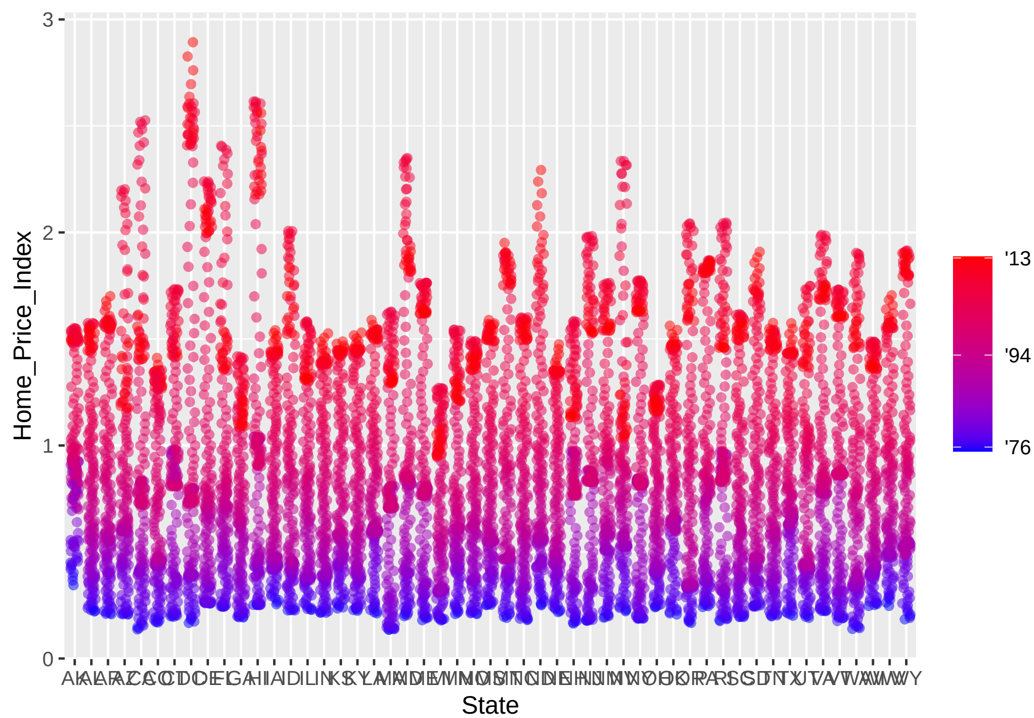
Now modify the breaks and shorten the labels for the color scales:

```
# modify color scale breaks and labels
p3 +
  scale_color_continuous(name="",
                         breaks = c(1976, 1994, 2013),
                         labels = c("'76", "'94", "'13"))
```



Next change the low and high values to blue and red:

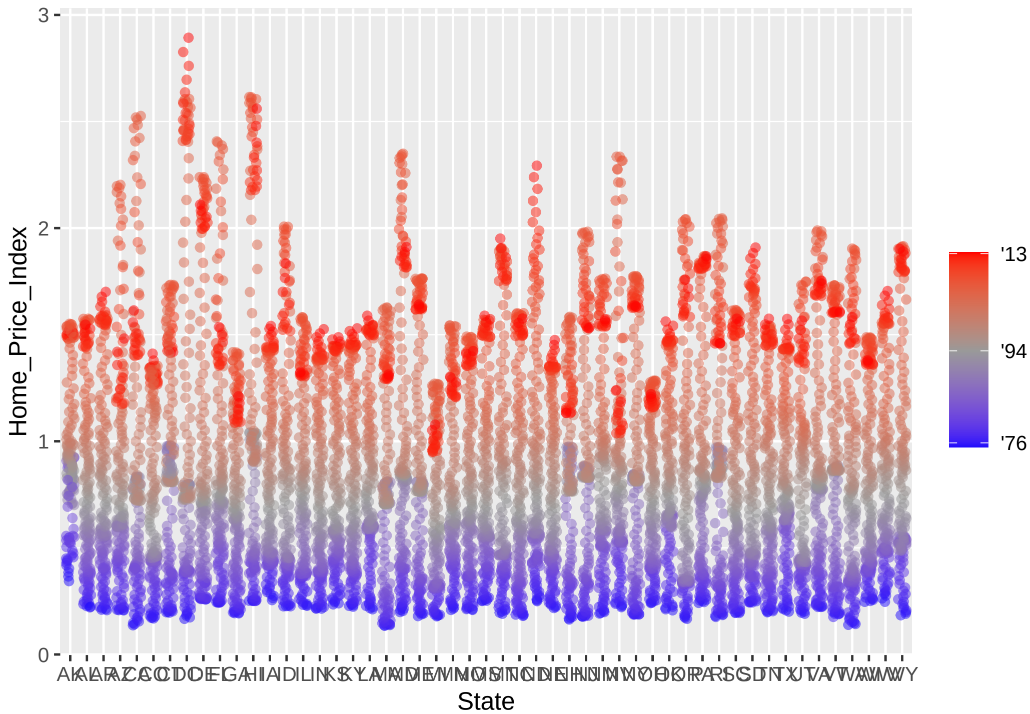
```
# modify color scale low and high values
p3 +
  scale_color_continuous(name="",
                         breaks = c(1976, 1994, 2013),
                         labels = c("'76", "'94", "'13"),
                         low = "blue", high = "red")
```



5.5.4 Using different color scales

`ggplot2` has a wide variety of color scales; here is an example using `scale_color_gradient2()` to interpolate between three different colors.

```
# modify color scale to interpolate between three different colors
p3 +
  scale_color_gradient2(name="",
                        breaks = c(1976, 1994, 2013),
                        labels = c("'76", "'94", "'13"),
                        low = "blue",
                        high = "red",
                        mid = "gray60",
                        midpoint = 1994)
```



5.5.5 Available scales

Here's a partial combination matrix of available scales:

`scale_`	Types	Examples
`scale_color_`	`identity`	`scale_fill_continuous()`
`scale_fill_`	`manual`	`scale_color_discrete()`
`scale_size_`	`continuous`	`scale_size_manual()`
	`discrete`	`scale_size_discrete()`
`scale_shape_`	`discrete`	`scale_shape_discrete()`
`scale_linetype_`	`identity`	`scale_shape_manual()`
	`manual`	`scale_linetype_discrete()`
`scale_x_`	`continuous`	`scale_x_continuous()`
`scale_y_`	`discrete`	`scale_y_discrete()`
	`reverse`	`scale_x_log()`
	`log`	`scale_y_reverse()`
	`date`	`scale_x_date()`
	`datetime`	`scale_y_datetime()`

Note that in RStudio you can type `scale_` followed by `tab` to get the whole list of available scales. For a complete list of available scales see `https://ggplot2.tidyverse.org/reference/`.

5.5.6 Exercise 2

1. Create a scatter plot with `CPI` on the x axis and `HDI` on the y axis. Color the points to indicate `Region`.

```
##
```

2. Modify the x, y, and color scales so that they have more easily-understood names (e.g., spell out "Human development Index" instead of `HDI`). Hint: see `?scale_x_continous`, `?scale_y_continuous`, and `?scale_color_discrete`.

```
##
```

3. Modify the color scale to use specific values of your choosing. Hint: see `?scale_color_manual`. NOTE: you can specify color by name (e.g., "blue") or by "Hex value" — see `https://www.color-hex.com/`.

```
##
```

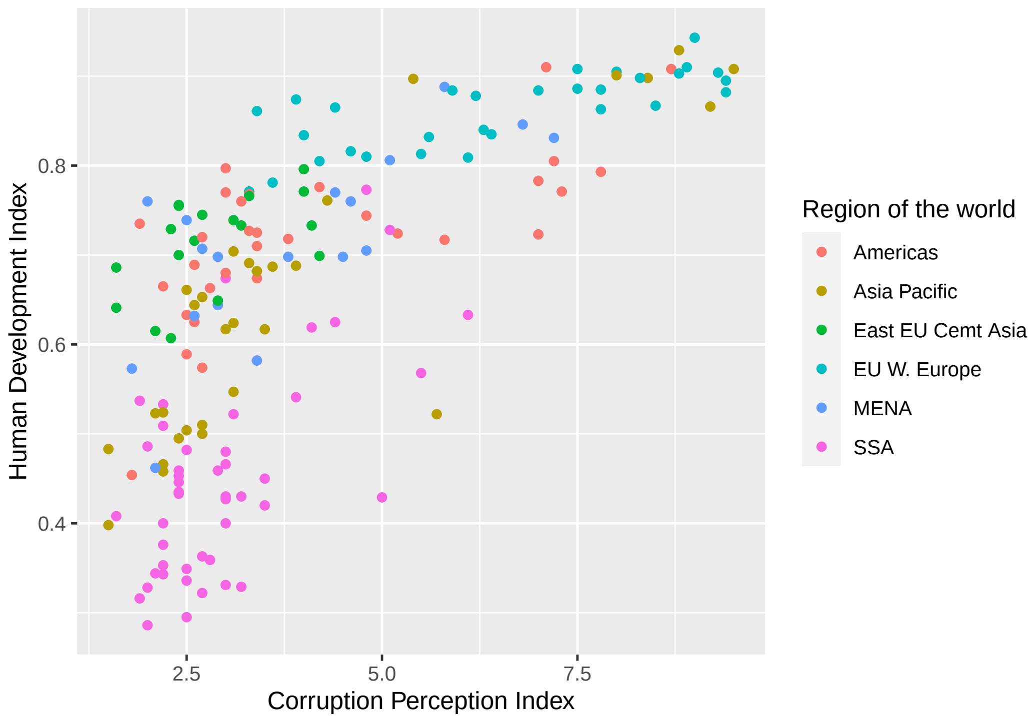
Click for Exercise 2 Solution

1. Create a scatter plot with `CPI` on the x axis and `HDI` on the y axis. Color the points to indicate `Region`.

```
ggplot(dat, aes(x = CPI, y = HDI, color = Region)) +
  geom_point()
```

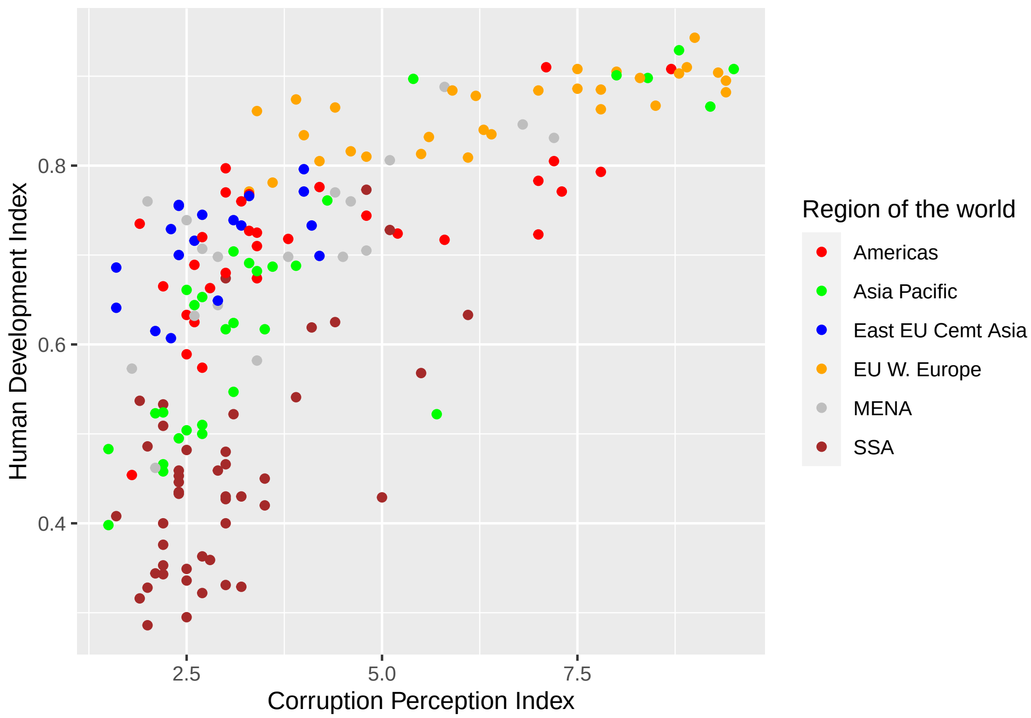
2. Modify the x, y, and color scales so that they have more easily-understood names (e.g., spell out "Human development Index" instead of `HDI`). Hint: see `?scale_x_continous`, `?scale_y_continuous`, and `?scale_color_discrete`.

```
ggplot(dat, aes(x = CPI, y = HDI, color = Region)) +
  geom_point() +
  scale_x_continuous(name = "Corruption Perception Index") +
  scale_y_continuous(name = "Human Development Index") +
  scale_color_discrete(name = "Region of the world")
```



3. Modify the color scale to use specific values of your choosing. Hint: see `?scale_color_manual`. NOTE: you can specify color by name (e.g., "blue") or by "Hex value" — see `https://www.color-hex.com/`.

```
ggplot(dat, aes(x = CPI, y = HDI, color = Region)) +
  geom_point() +
  scale_x_continuous(name = "Corruption Perception Index") +
  scale_y_continuous(name = "Human Development Index") +
  scale_color_manual(name = "Region of the world",
                     values = c("red", "green", "blue", "orange", "grey", "brown"))
```



5.6 Faceting

5.6.1 What is faceting?

- Faceting is `ggplot2` parlance for **creating individual graphs for subsets of data**
- `ggplot2` offers two functions for creating facets:

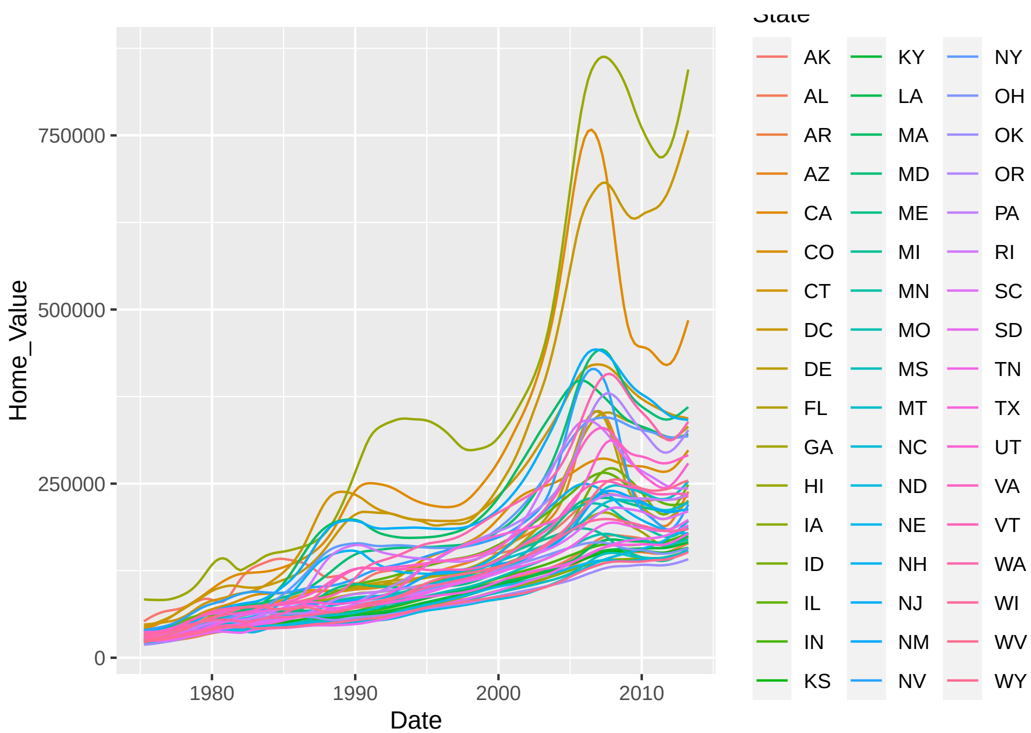
  1. `facet_wrap()`: define subsets as the levels of a single grouping variable
  2. `facet_grid()`: define subsets as the crossing of two grouping variables

- Facets facilitate comparison among plots, not just of geoms within a plot

5.6.2 What is the trend in housing prices in each state?

Start by using a technique we already know; map `State` to color:

```
# map `State` to color
p4 <- ggplot(housing, aes(x = Date, y = Home_Value))
p4 + geom_line(aes(color = State))
```

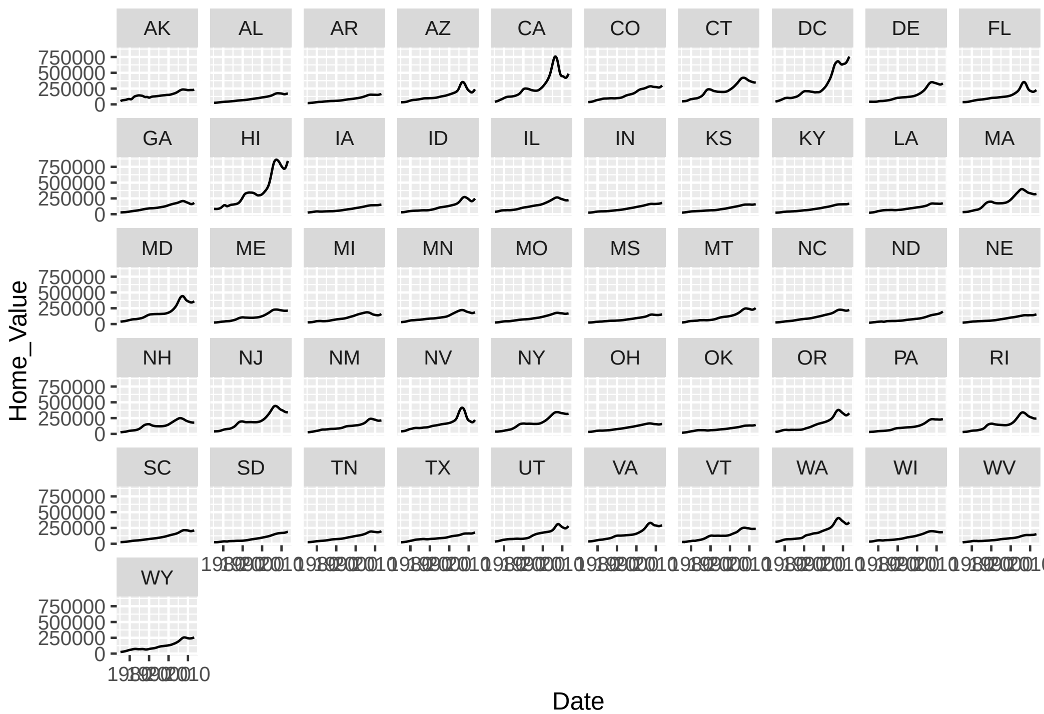


There are two problems here; there are too many states to distinguish each one by color, and the lines obscure one another.

5.6.3 Faceting to the rescue

We can remedy the deficiencies of the previous plot by faceting by `State` rather than mapping `State` to color.

```
# facet by `State`
p4 <- p4 + geom_line() +
  facet_wrap(~ State, ncol = 10)
p4
```



5.7 Themes

5.7.1 What are themes?

The `ggplot2` theme system handles non-data plot elements such as:

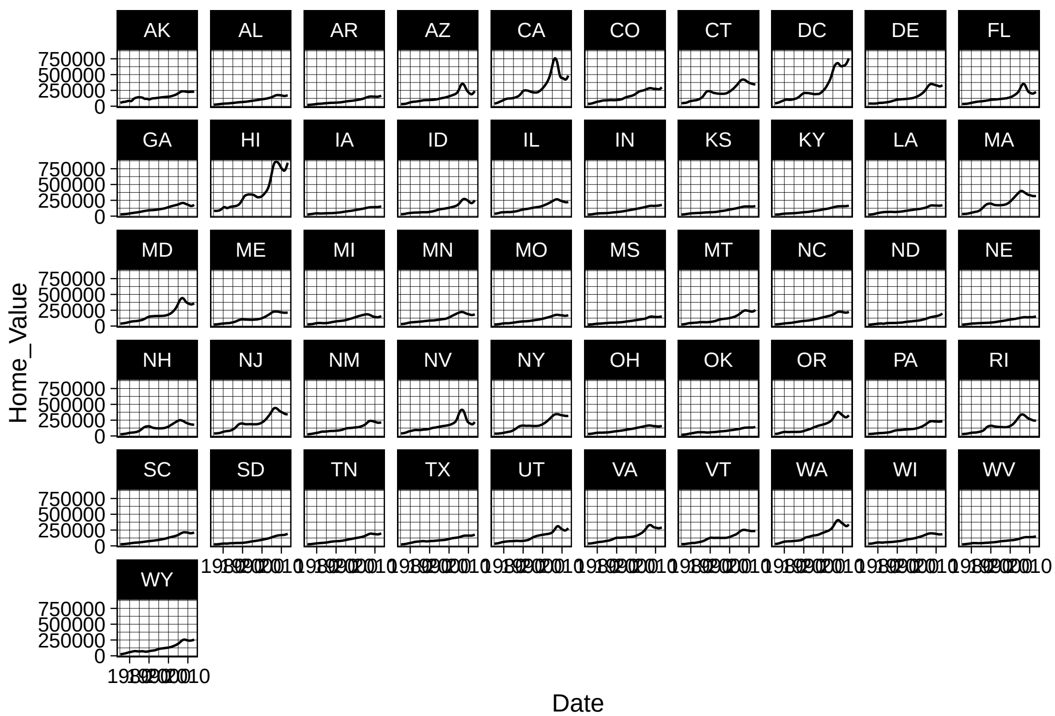
- Axis label properties (e.g., font, size, color, etc.)
- Plot background
- Facet label background
- Legend appearance

Built-in themes include:

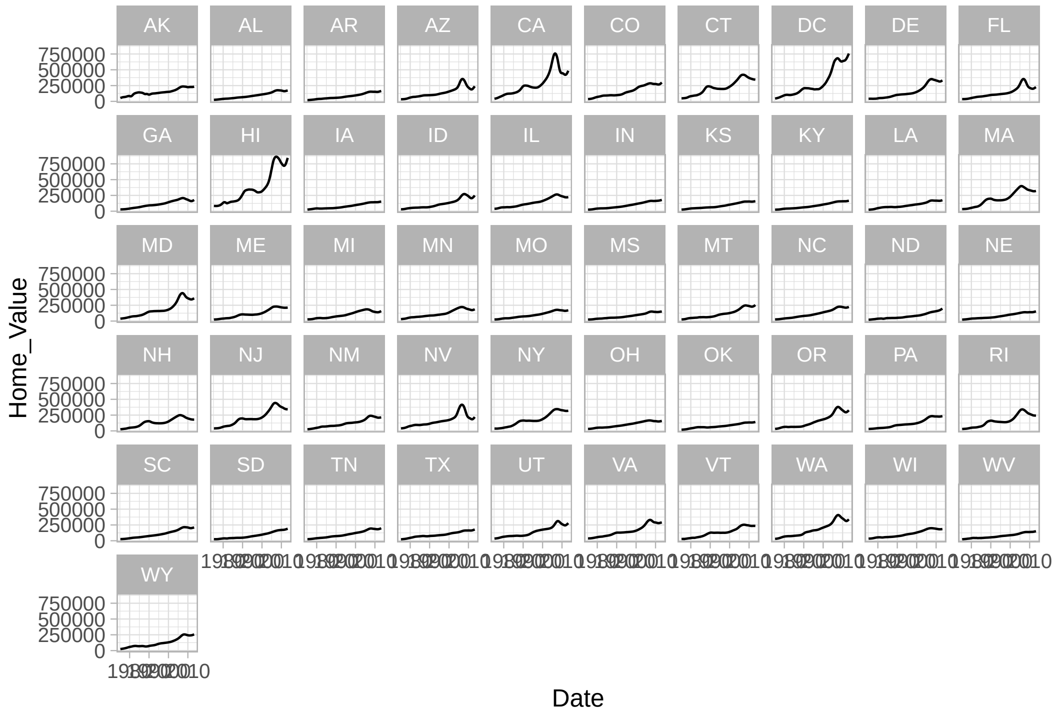
- `theme_gray()` (default)
- `theme_bw()`
- `theme_classic()`

Here are a couple of examples:

```
# theme linedraw
p4 + theme_linedraw()
```




```
# theme light
p4 + theme_light()
```

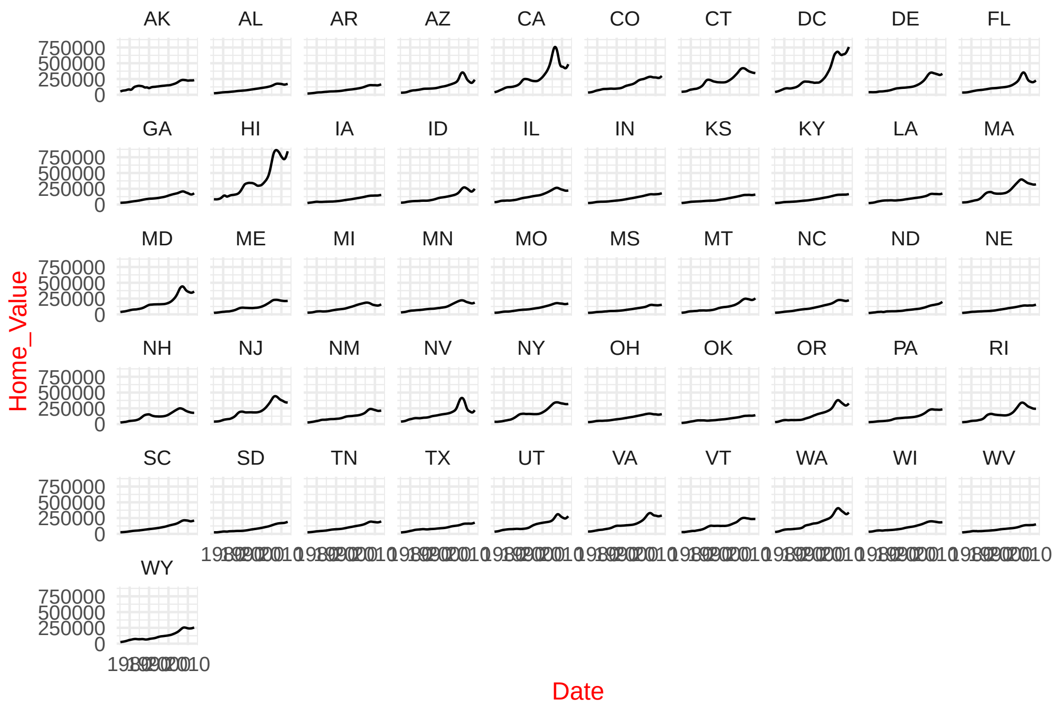


You can see a list of available built-in themes here: `https://ggplot2.tidyverse.org/reference/`.

5.7.2 Overriding theme defaults

Specific theme elements can be overridden using `theme()`. For example:

```
# theme(thing_to_modify = modifying_function(arg1, arg2))

p4 + theme_minimal() +
  theme(text = element_text(color = "red"))
```



All theme options are documented in `?theme`. We can also see the existing default values using:

```
theme_get()
```

5.7.3 Creating & saving new themes

You can create new themes, as in the following example:

```
theme_new <- theme_bw() +
  theme(plot.background = element_rect(size = 1, color = "blue", fill = "black"),
        text = element_text(size = 12, color = "ivory"),
        axis.text.y = element_text(colour = "purple"),
        axis.text.x = element_text(colour = "red"),
        panel.background = element_rect(fill = "pink"),
        strip.background = element_rect(fill = muted("orange")))

p4 + theme_new
```

5.8 Saving plots

We can save a plot to either a vector (e.g., pdf, eps, ps, svg) or raster (e.g., jpg, png, tiff, bmp, wmf) graphics file using the `ggsave()` function:

```
# save plot output to a file
ggsave(filename = "myplot.pdf", plot = p5, device = "pdf",
       height = 6, width = 6, units = "in")
```

5.9 The #1 FAQ

5.9.1 Map aesthetic to different columns

The most frequently asked question goes something like this: *"I have two variables in my data.frame, and I'd like to plot them as separate points, with different color depending on which variable it is. How do I do that?"*

Wrong way

Assigning, rather than mapping, the color aesthetic:

1. Produces verbose code when using many colors

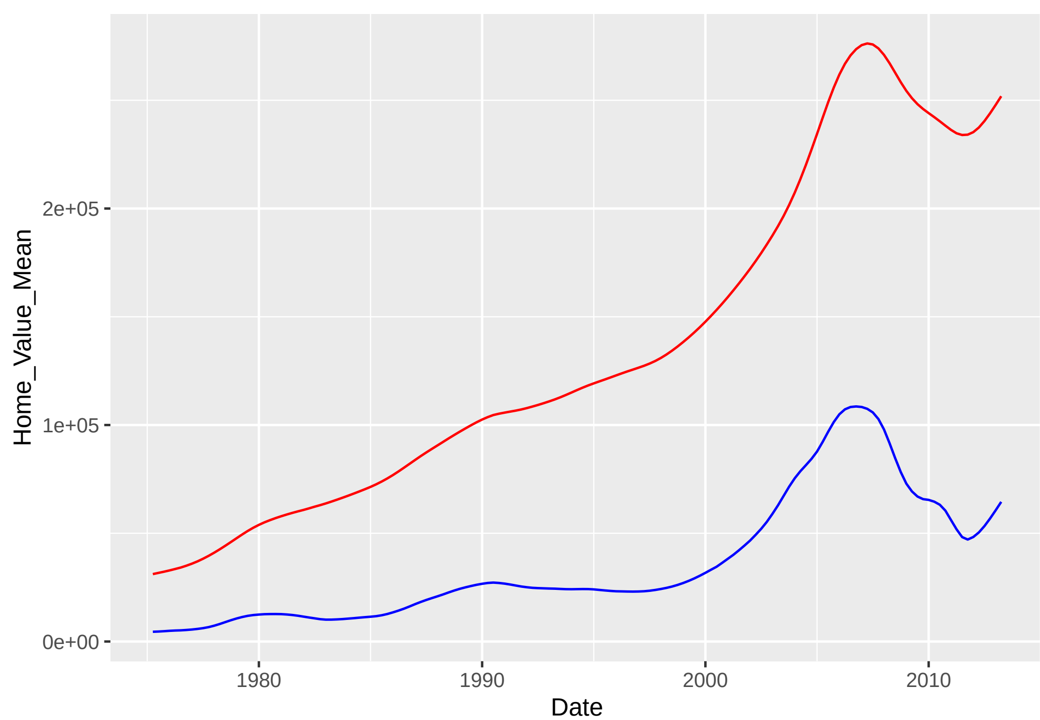
2. Results in no legend being produced
3. Means you cannot change color scales

To see this, let's first calculate summary home and land value data:

```
# get summary home and land value data
housing_byyear <-
  housing %>%
  group_by(Date) %>%
  summarize(Home_Value_Mean = mean(Home_Value),
            Land_Value_Mean = mean(Land_Value)) %>%
  ungroup()
```

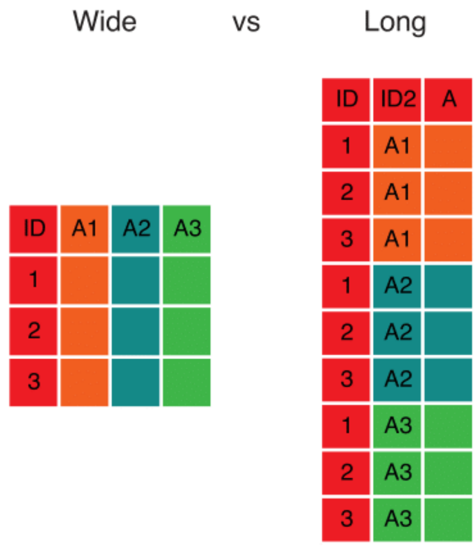
Now let's assign the color aesthetic to the line geom for each variable:

```
# assigning the color aesthetic to constants
ggplot(housing_byyear, aes(x=Date)) +
  geom_line(aes(y=Home_Value_Mean), color="red") +
  geom_line(aes(y=Land_Value_Mean), color="blue")
```



Right way

To avoid these pitfalls, we need to **map** our data to the color aesthetic. We can do this by **reshaping** our data from **wide format** to **long format**. Here is the logic behind this process:

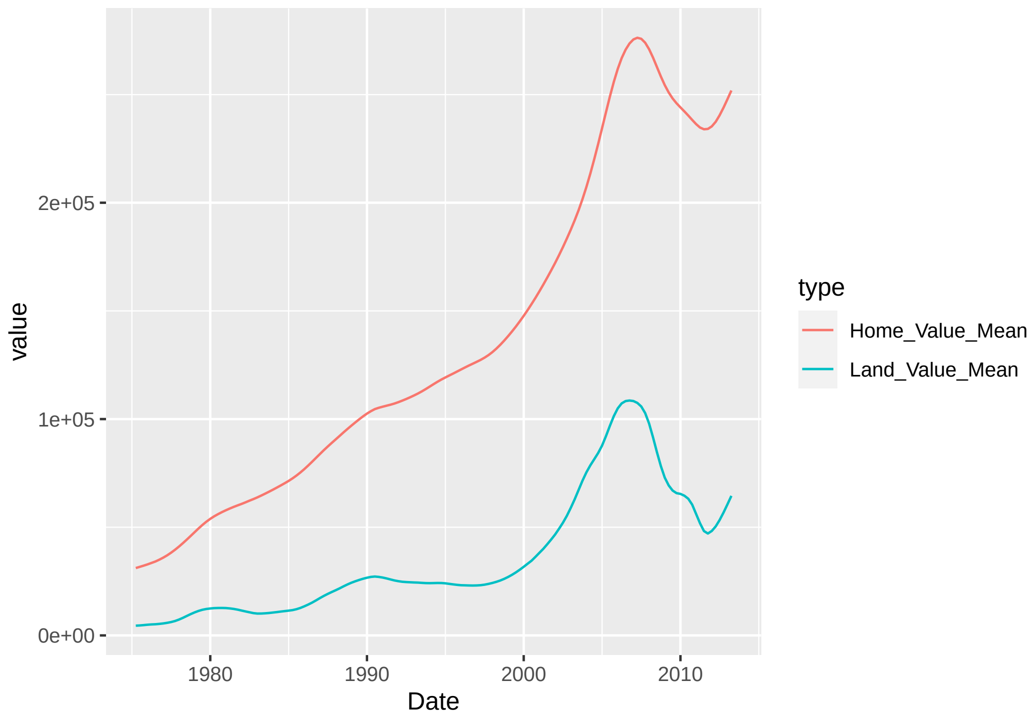


Here's the code that implements this transformation using `pivot_longer()`:

```
# reshape data from wide to long
home_land_byyear <-
    housing_byyear %>%
    pivot_longer(cols = c(Home_Value_Mean, Land_Value_Mean),
                 names_to = "type",
                 values_to = "value")
```

Now we can map all our variables to the color aesthetic simultaneously, and `ggplot()` will automatically create a legend for us:

```
# map data to the color aesthetic
ggplot(home_land_byyear, aes(x = Date, y = value, color = type)) +
  geom_line()
```



5.9.2 Exercise 3

For this exercise, we're going to use the built-in `midwest` dataset:

```
data("midwest", package = "ggplot2")
head(midwest)
```

```
## # A tibble: 6 x 28
##     PID county state  area poptotal popdensity popwhite popblack popamerindian
##   <int> <chr>  <chr> <dbl>    <int>      <dbl>    <int>    <int>         <int>
## 1   561 ADAMS  IL    0.052    66090      1271.    63917     1702            98
## 2   562 ALEXA~ IL    0.014    10626       759      7054     3496            19
## 3   563 BOND   IL    0.022    14991       681.    14477      429            35
## 4   564 BOONE  IL    0.017    30806      1812.    29344      127            46
## 5   565 BROWN  IL    0.018     5836       324.     5264      547            14
## 6   566 BUREAU IL    0.05     35688       714.    35157       50            65
## # ... with 19 more variables: popasian <int>, popother <int>, percwhite <dbl>,
## #   percblack <dbl>, percamerindan <dbl>, percasian <dbl>, percother <dbl>,
## #   popadults <int>, perchsd <dbl>, percollege <dbl>, percprof <dbl>,
## #   poppovertyknown <int>, percpovertyknown <dbl>, percbelowpoverty <dbl>,
## #   percchildbelowpovert <dbl>, percadultpoverty <dbl>,
## #   percelderlypoverty <dbl>, inmetro <int>, category <chr>
```

1. Create a scatter plot with `area` on the x axis and the log of `poptotal` on the y axis.

```
##
```

2. Within the `geom_point()` call, map color to `state`, map size to the log of `popdensity`, and fix transparency (`alpha`) to 0.3.

```
##
```

3. Add a smoother and turn off plotting the confidence interval. Hint: see the `se` argument to `geom_smooth()`.

```
##
```

4. Facet the plot by `state`. Set the `scales` argument to `facet_wrap()` to allow separate ranges for the x-axis.

```
##
```

5. Change the default color scale to use the discrete `RColorBrewer` palette called `Set1`. Hint: see `?scale_color_brewer`.

```
##
```

6. BONUS: Change the default theme to `theme_bw()` and modify it so that the axis title is colored blue in bold font face and the facet label background is filled in yellow. Hint: see `?theme` and especially `axis.title` and `strip.background`.

```
##
```

Click for Exercise 3 Solution

For this exercise, we're going to use the built-in `midwest` dataset:

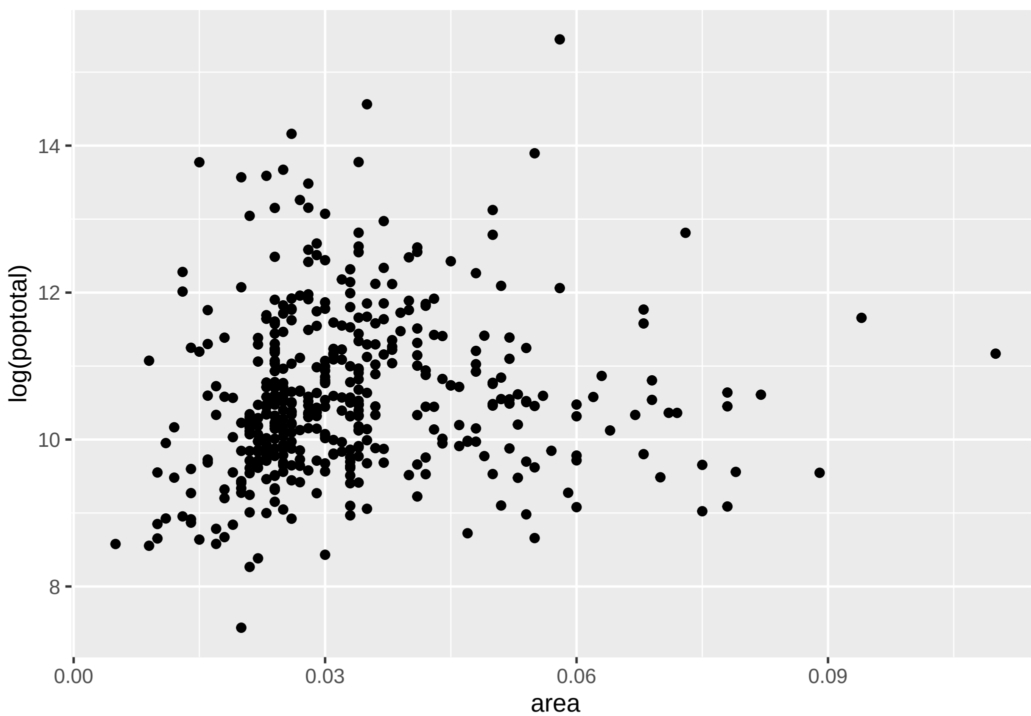
```
data("midwest", package = "ggplot2")
head(midwest)
```

```
## # A tibble: 6 x 28
##     PID county state  area poptotal popdensity popwhite popblack popamerindian
##   <int> <chr>  <chr> <dbl>    <int>      <dbl>    <int>    <int>         <int>
## 1   561 ADAMS  IL    0.052    66090      1271.    63917     1702            98
## 2   562 ALEXA~ IL    0.014    10626       759      7054     3496            19
## 3   563 BOND   IL    0.022    14991       681.    14477      429            35
## 4   564 BOONE  IL    0.017    30806      1812.    29344      127            46
## 5   565 BROWN  IL    0.018     5836       324.     5264      547            14
```

```
## 6   566 BUREAU IL    0.05     35688       714.    35157       50            65
## # ... with 19 more variables: popasian <int>, popother <int>, percwhite <dbl>,
## #   percblack <dbl>, percamerindan <dbl>, percasian <dbl>, percother <dbl>,
## #   popadults <int>, perchsd <dbl>, percollege <dbl>, percprof <dbl>,
## #   poppovertyknown <int>, percpovertyknown <dbl>, percbelowpoverty <dbl>,
## #   percchildbelowpovert <dbl>, percadultpoverty <dbl>,
## #   percelderlypoverty <dbl>, inmetro <int>, category <chr>
```

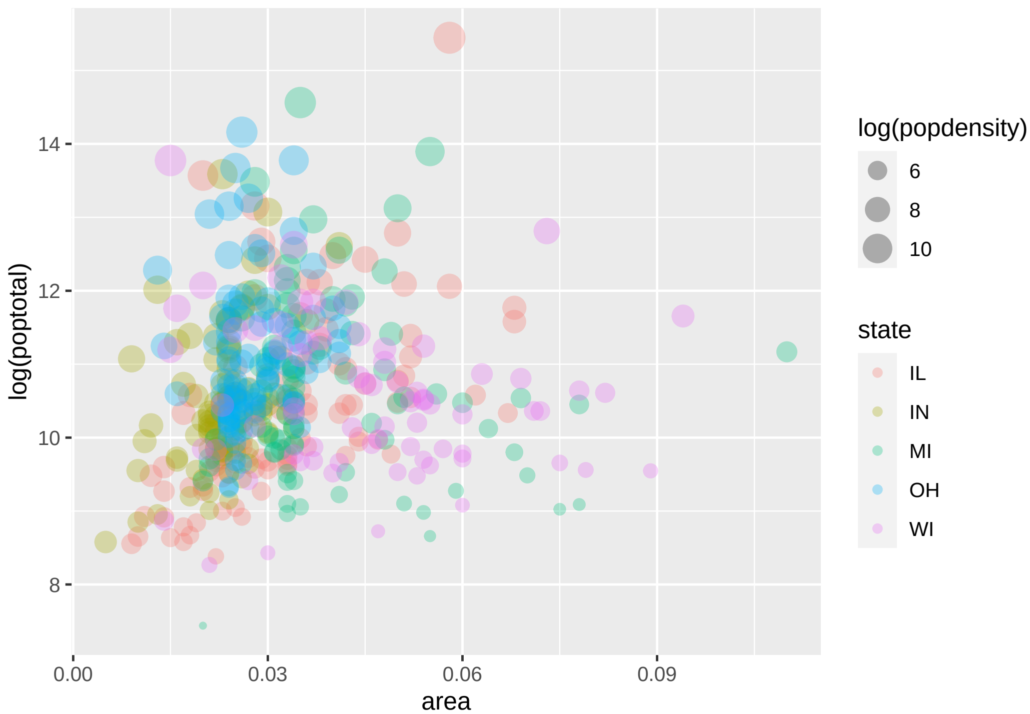
1. Create a scatter plot with `area` on the x axis and the log of `poptotal` on the y axis.

```r
p5 <- ggplot(midwest, aes(x = area, y = log(poptotal)))
p5 + geom_point()
```



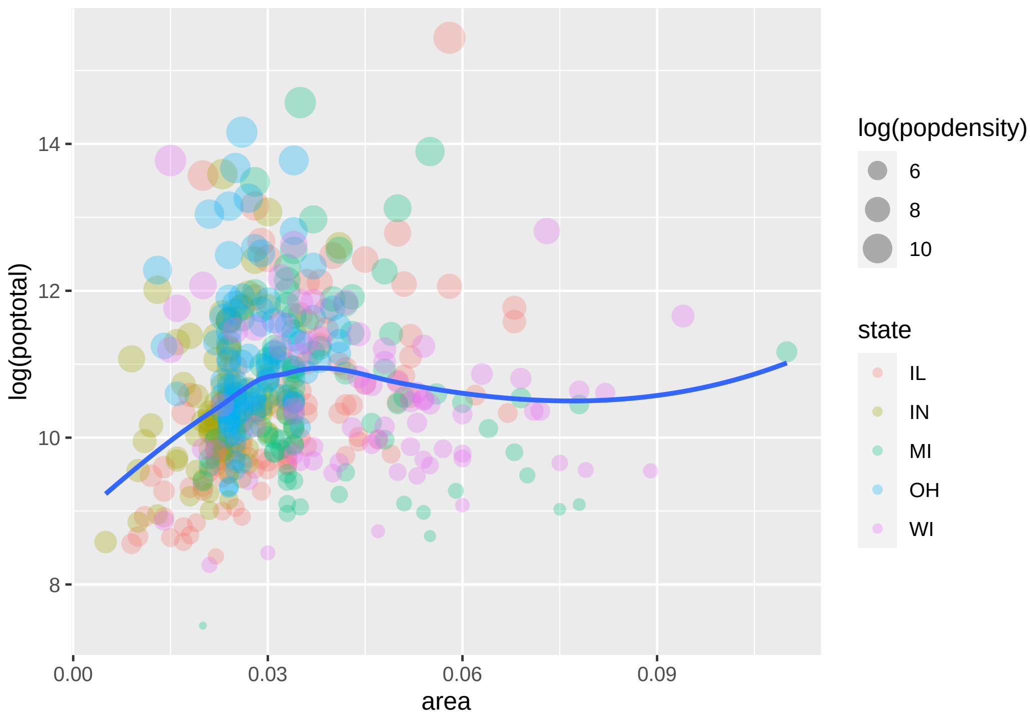
2. Within the `geom_point()` call, map color to `state`, map size to the log of `popdensity`, and fix transparency (`alpha`) to 0.3.

```r
p5 <- p5 + geom_point(aes(color = state, size = log(popdensity)), alpha = 0.3)
p5
```



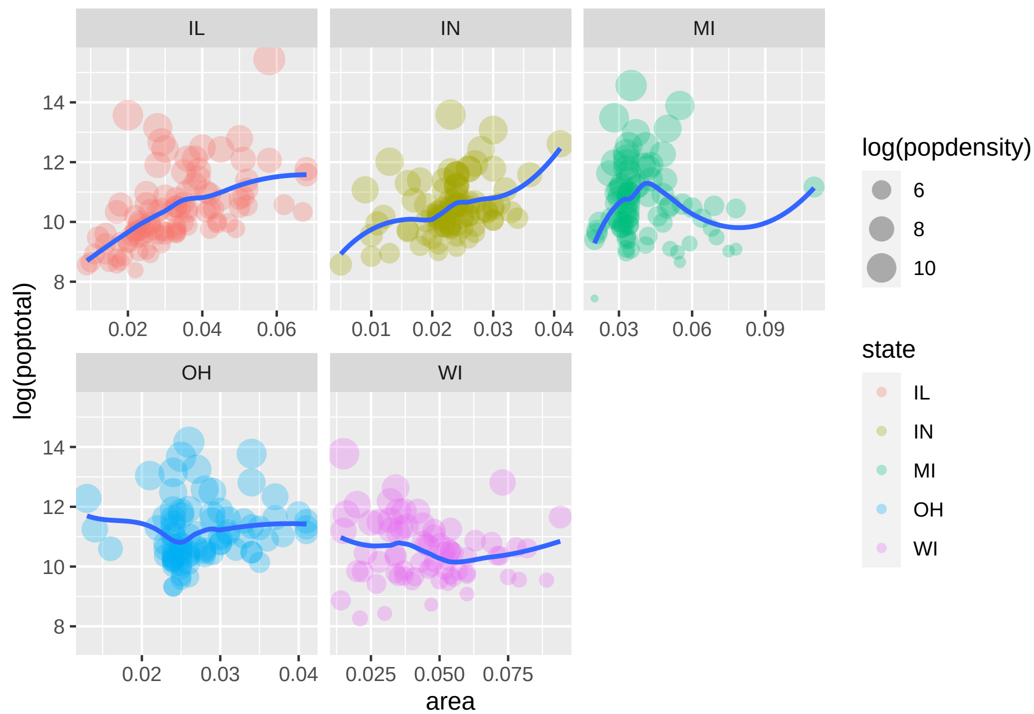
3. Add a smoother and turn off plotting the confidence interval. Hint: see the `se` argument to `geom_smooth()`.

```
p5 <- p5 + geom_smooth(method = "loess", se = FALSE)
p5
```



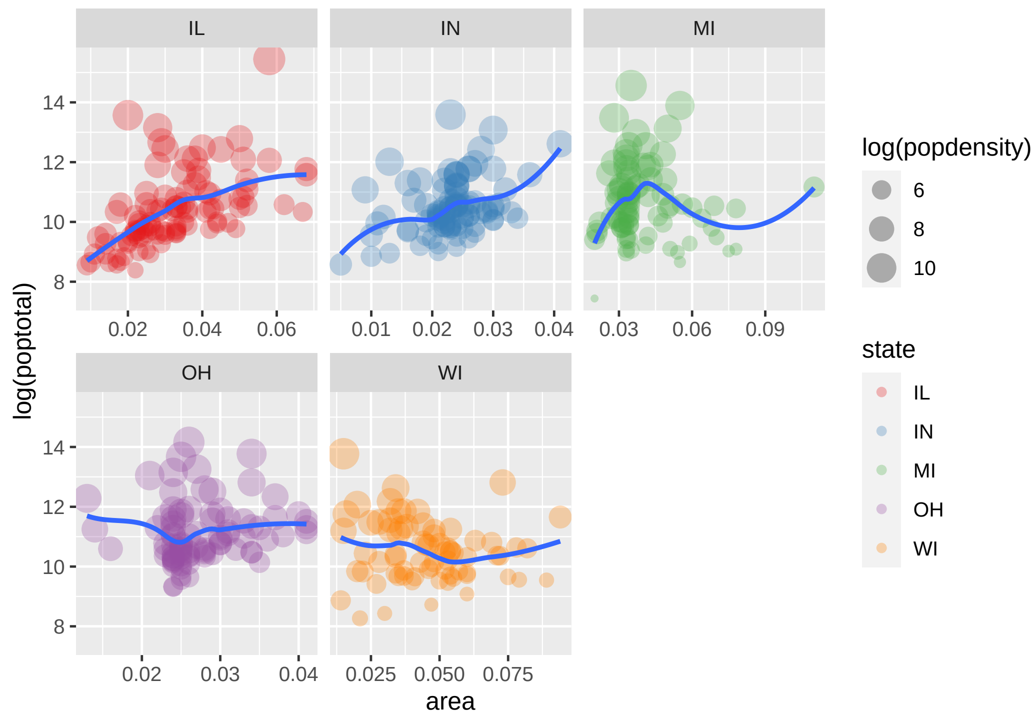
4. Facet the plot by `state`. Set the `scales` argument to `facet_wrap()` to allow separate ranges for the x-axis.

```
p5 <- p5 + facet_wrap(~ state, scales = "free_x")
p5
```



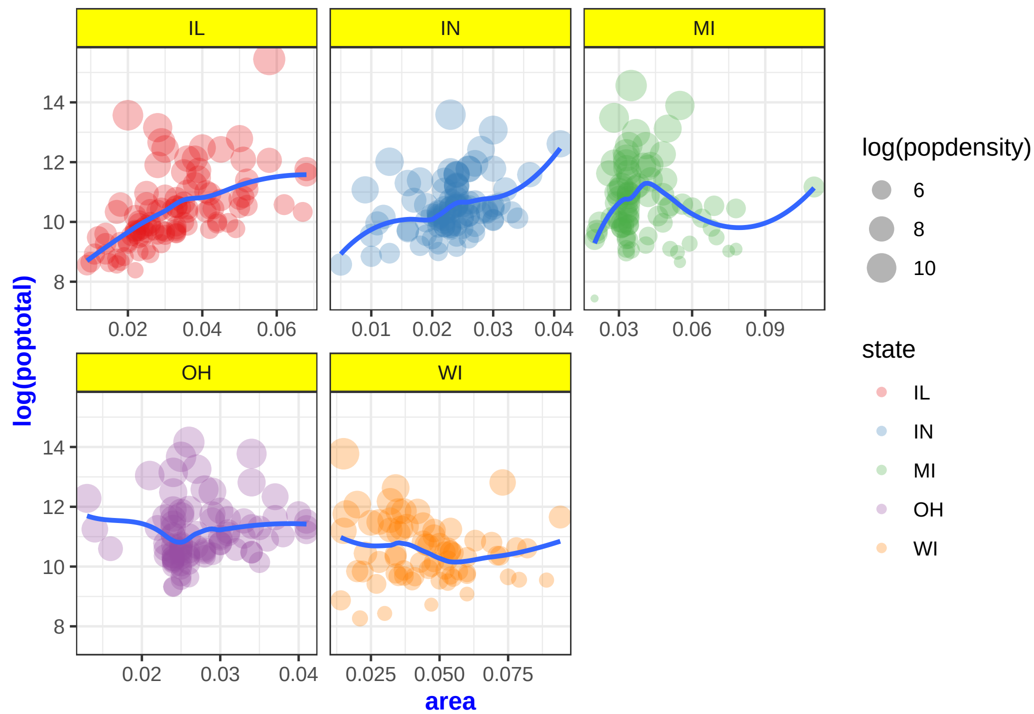
5. Change the default color scale to use the discrete `RColorBrewer` palette called `Set1`. Hint: see `?scale_color_brewer`.

```
p5 <- p5 + scale_color_brewer(palette = "Set1")
p5
```



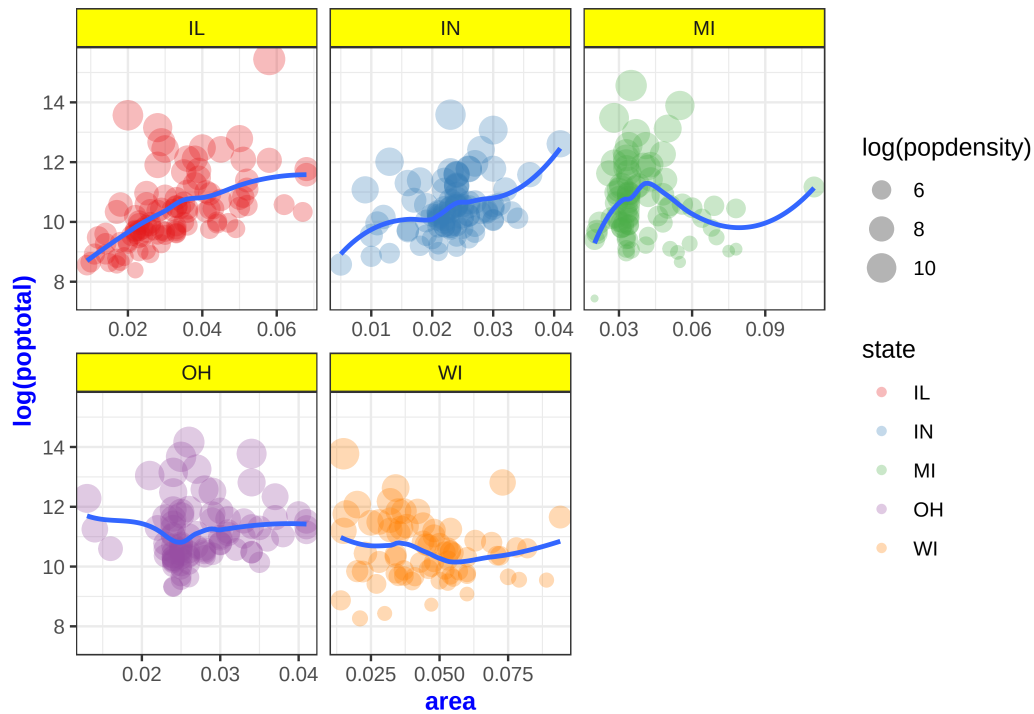
6. BONUS: Change the default theme to `theme_bw()` and modify it so that the axis title is colored blue in bold font face and the facet label background is filled in yellow. Hint: see `?theme` and especially `axis.title` and `strip.background`.

```
p5 <- p5 + theme_bw() +
    theme(axis.title = element_text(color = "blue", face = "bold"),
          strip.background = element_rect(fill = "yellow"))
p5
```



Here's the complete code for the Exercise 3 plot:

```
ggplot(midwest, aes(x = area, y = log(poptotal))) +
    geom_point(aes(color = state, size = log(popdensity)), alpha = 0.3) +
    geom_smooth(method = "loess", se = FALSE) +
    facet_wrap(~ state, scales = "free_x") +
    scale_color_brewer(palette = "Set1") +
    theme_bw() +
    theme(axis.title = element_text(color = "blue", face = "bold"),
          strip.background = element_rect(fill = "yellow"))
```



5.10 Wrap-up

5.10.1 Feedback

These workshops are a work in progress, please provide any feedback to: `help@iq.harvard.edu`

5.10.2 Resources

- IQSS
  - Workshops: `https://www.iq.harvard.edu/data-science-services/workshop-materials`
  - Data Science Services: `https://www.iq.harvard.edu/data-science-services`
  - Research Computing Environment: `https://iqss.github.io/dss-rce/`
- HBS
  - Research Computing Services workshops: `https://training.rcs.hbs.org/workshops`
  - Other HBS RCS resources: `https://training.rcs.hbs.org/workshop-materials`

- RCS consulting email: `mailto:research@hbs.edu`

- ggplot2
  - Reference: `https://ggplot2.tidyverse.org/reference/`
  - Cheatsheets: `https://rstudio.com/wp-content/uploads/2019/01/Cheatsheets_2019.pdf`
  - Examples: `http://r-statistics.co/Top50-Ggplot2-Visualizations-MasterList-R-Code.html`
  - Tutorial: `https://uc-r.github.io/ggplot_intro`
  - Mailing list: `http://groups.google.com/group/ggplot2`
  - Wiki: `https://github.com/hadley/ggplot2/wiki`
  - Website: `http://had.co.nz/ggplot2/`
  - StackOverflow: `http://stackoverflow.com/questions/tagged/ggplot`

Chapter 6

R Data Wrangling

Topics

- Loading Excel worksheets
- Iterating over files
- Writing your own functions
- Filtering with regular expressions (regex)
- Reshaping data

6.1 Setup

6.1.1 Software and Materials

Follow the R Installation instructions and ensure that you can successfully start RStudio.

6.1.2 Class Structure

Informal - Ask questions at any time. Really!

Collaboration is encouraged - please spend a minute introducing yourself to your neighbors!

6.1.3 Prerequisites

This is an intermediate / advanced R course:

- Assumes intermediate knowledge of R
- Relatively fast-paced

6.1.4 Launch an R session

Start RStudio and create a new project:

- On Windows click the start button and search for RStudio. On Mac RStudio will be in your applications folder.
- In Rstudio go to `File -> New Project`.
- Choose `Existing Directory` and browse to the workshop materials directory on your desktop.
- Choose `File -> Open File` and select the file with the word "BLANK" in the name.

6.1.5 Packages

You should have already installed the `tidyverse` and `rmarkdown` packages onto your computer before the workshop — see R Installation. Now let's load these packages into the search path of our R session.

```
library(tidyverse)
library(rmarkdown)
library(readxl) # installed with tidyverse, but not loaded into R session
```

6.1.6 Workshop Outline

Example data

The UK Office for National Statistics provides yearly data on the most popular boys names going back to 1996. The data is provided separately for boys and girls and is stored in Excel spreadsheets.

Overall Goal

Our mission is to extract and graph the **top 100** boys names in England and Wales for every year since 1996.

Name	Count	Year
JACK	10779	1996
DANIEL	10338	1996
THOMAS	9603	1996
JAMES	9385	1996
JOSHUA	7887	1996
MATTHEW	7426	1996
RYAN	6496	1996
JOSEPH	6193	1996
SAMUEL	6161	1996
LIAM	5802	1996
JORDAN	5750	1996
LUKE	5664	1996
CONNOR	5009	1996
ALEXANDER	4840	1996
BENJAMIN	4805	1996
ADAM	4538	1996
HARRY	4434	1996
JAKE	4331	1996
GEORGE	4287	1996
CALLUM	4281	1996
WILLIAM	4269	1996
MICHAEL	4187	1996
OLIVER	3655	1996
LEWIS	3569	1996
CHRISTOPHER	3483	1996

Exercise 0: Problems with the data

There are several things that make our goal challenging. Let's take a look at the data:

1. Locate the files named `1996boys_tcm77-254026.xlsx` and `2015boysnamesfinal.xlsx` and open them separately in a spreadsheet program.

(If you don't have a spreadsheet program installed on your computer you can download one from `https://www.libreoffice.org/download/download/`).

What issues can you identify that might make working with these data difficult?

In what ways is the format different between the two files?

Click for Exercise 0 Solution

1. Multiple Excel sheets in each file, each with a different name, but each file contains a `Table 1`.
2. The data does not start on row one. Headers are on row 7, followed by a blank line, followed by the actual data.
3. The data is stored in an inconvenient way, with ranks 1-50 in the first set of columns and ranks 51-100 in a second set of columns.
4. The second worksheet `2015boysnamesfinal.xlsx` contains extra columns between the data of interest, resulting in the second set of columns (ranks 51-100) being placed in a different position.
5. The year from which the data comes is only reported in the Excel file name, not within the data itself.
6. There are notes below the data.

These differences will make it more difficult to automate re-arranging the data since we have to write code that can handle different input formats.

Steps to accomplish the goal of extracting and graphing the *top 100* boys names in England and Wales for every year since 1996:

0. **Explore example data to highlight problems (already done!)**

1. **Reading data from multiple Excel worksheets into R data frames**

    - list Excel file names in a character vector
    - read Excel sheetnames into a list of character vectors
    - read Excel data for "Table 1" only into a list of data frames

2. **Clean up data within each R data frame**

    - sort and merge columns within each data frame inside the list
    - drop missing values from each data frame
    - reshape data format from wide to long

3. **Organize the data into one large data frame and store it**

    - create a year column within each data frame within the list
    - append all the data frames in the list into one large data frame

NOTE: please make sure you close the Excel files before continuing with the workshop, otherwise you may encounter issues with file paths when reading the data into R.

6.2 Working with Excel worksheets

GOAL: To learn how to read data from multiple Excel worksheets into R data frames. In particular:

1. List Excel file names in a character vector

2. Read Excel sheetnames into a list of character vectors
3. Read Excel data for "Table 1" only into a list of data frames

As you can see, the data is in quite a messy state. Note that this is not a contrived example; this is exactly the way the data came to us from the UK government website! Let's start cleaning and organizing it.

Each Excel file contains a worksheet with the boy names data we want. Each file also contains additional supplemental worksheets that we are not currently interested in. As noted above, the worksheet of interest differs from year to year, but always has "Table 1" in the sheet name.

The first step is to get a character vector of file names.

```
# read file names into a character vector
boy_file_names <- list.files("dataSets/boys", full.names = TRUE)
```

Now that we've told R the names of the data files, we can start working with them. For example, the first file is:

```
# view path of first file
boy_file_names[1]
```

```
## [1] "dataSets/boys/1996boys_tcm77-254026.xlsx"
```

and we can use the `excel_sheets()` function from the `readxl` package within `tidyverse` to list the worksheet names from this file.

```
# list worksheet names from first file
excel_sheets(boy_file_names[1])
```

```
## [1] "Contents"                     "Table 1 - Top 100 boys, E&W"
## [3] "Table 2-Top 10 boys by month" "Table 3 - Boys names - E&W"
```

6.2.1 Iterating with `map()`

Now that we know how to retrieve the names of the worksheets in an Excel file, we could start writing code to extract the sheet names from each file, e.g.,

```
# extract sheet names from each file
excel_sheets(boy_file_names[1])
```

```
## [1] "Contents"                     "Table 1 - Top 100 boys, E&W"
## [3] "Table 2-Top 10 boys by month" "Table 3 - Boys names - E&W"
```

```r
excel_sheets(boy_file_names[2])
```

```
## [1] "Contents"                         "Table 1 - Top 100 boys, E&W"
## [3] "Table 2 - Top 100 boys, England" "Table 3 - Top 100 boys, Wales"
## [5] "Table 4 - Top 10 boys by region" "Table 5 - Top 10 boys by month"
## [7] "Table 6 - Boys names - E&W"
```

```r
## ...
excel_sheets(boy_file_names[20])
```

```
##  [1] "Contents"             "Metadata"             "Terms and Conditions"
##  [4] "Table 1"              "Table 2"              "Table 3"
##  [7] "Table 4"              "Table 5"              "Table 6"
## [10] "Related Publications"
```

This is not a terrible idea for a small number of files, but it is more convenient to let R do the iteration for us. We could use a `for loop`, or `sapply()`, but the `map()` family of functions from the `purrr` package within `tidyverse` gives us a more consistent alternative, so we'll use that.

```r
# map(object to iterate over, function that does task within each iteration)

map(boy_file_names, excel_sheets)
```

```
## [[1]]
## [1] "Contents"                      "Table 1 - Top 100 boys, E&W"
## [3] "Table 2-Top 10 boys by month" "Table 3 - Boys names - E&W"
##
## [[2]]
## [1] "Contents"                         "Table 1 - Top 100 boys, E&W"
## [3] "Table 2 - Top 100 boys, England" "Table 3 - Top 100 boys, Wales"
## [5] "Table 4 - Top 10 boys by region" "Table 5 - Top 10 boys by month"
## [7] "Table 6 - Boys names - E&W"
##
## [[3]]
## [1] "Contents"                         "Table 1 - Top 100 boys' names"
## [3] "Table 2 - Top 100 boys, England" "Table 3 - Top 100 boys, Wales"
## [5] "Table 4 - Top 10 boys by region" "Table 5 - Top 10 boys by month"
## [7] "Table 6 - Boys names - E&W"
##
## [[4]]
## [1] "Contents"                         "Table 1 - Top 100 boys' names"
## [3] "Table 2 - Top 100 boys, England" "Table 3 - Top 100 boys, Wales"
## [5] "Table 4 - Top 10 boys by region" "Table 5 - Top 10 boys by month"
## [7] "Table 6 - Boys names - E&W"
```

```
##
## [[5]]
## [1] "Contents"                         "Table 1 - Top 100 boys, E&W"
## [3] "Table 2 - Top 100 boys, England" "Table 3 - Top 100 boys, Wales"
## [5] "Table 4 - Top 10 boys by region" "Table 5 - Top 10 boys by month"
## [7] "Table 6 - Boys names - E&W"
##
## [[6]]
## [1] "Contents"                         "Table 1 - Top 100 boys, E&W"
## [3] "Table 2 - Top 100 boys, England" "Table 3 - Top 100 boys, Wales"
## [5] "Table 4 - Top 10 boys by region" "Table 5 - Top 10 boys by month"
## [7] "Table 6 - Boys names - E&W"
##
## [[7]]
## [1] "Contents"                         "Table 1 - Top 100 boys, E&W"
## [3] "Table 2 - Top 100 boys, England" "Table 3 - Top 100 boys, Wales"
## [5] "Table 4 - Top 10 boys by region" "Table 5 - Top 10 boys by month"
## [7] "Table 6 - Boys names - E&W"
##
## [[8]]
## [1] "Contents"                         "Table 1 - Top 100 boys, E&W"
## [3] "Table 2 - Top 100 boys, England" "Table 3 - Top 100 boys, Wales"
## [5] "Table 4 - Top 10 boys by region" "Table 5 - Top 10 boys by month"
## [7] "Table 6 - Boys names - E&W"
##
## [[9]]
## [1] "Contents"                         "Table 1 - Top 100 boys, E&W"
## [3] "Table 2 - Top 100 boys, England" "Table 3 - Top 100 boys, Wales"
## [5] "Table 4 - Top 10 boys by region" "Table 5 - Top 10 boys by month"
## [7] "Table 6 - Boys names - E&W"
##
## [[10]]
## [1] "Contents"                         "Table 1 - Top 100 boys, E&W"
## [3] "Table 2 - Top 100 boys, England" "Table 3 - Top 100 boys, Wales"
## [5] "Table 4 - Top 10 boys by region" "Table 5 - Top 10 boys by month"
## [7] "Table 6 - Boys names - E&W"
##
## [[11]]
## [1] "Contents"                         "Table 1 - Top 100 boys, E&W"
## [3] "Table 2 - Top 100 boys, England" "Table 3 - Top 100 boys, Wales"
## [5] "Table 4 - Top 10 boys by region" "Table 5 - Top 10 boys by month"
## [7] "Table 6 - Boys names - E&W"
##
## [[12]]
## [1] "Contents"                         "Table 1 - Top 100 boys, E&W"
## [3] "Table 2 - Top 100 boys, England" "Table 3 - Top 100 boys, Wales"
## [5] "Table 4 - Top 10 boys by region" "Table 5 - Top 10 boys by month"
## [7] "Table 6 - Boys names - E&W"
```

```
##
## [[13]]
## [1] "Contents"                        "Table 1 - Top 100 boys' names"
## [3] "Table 2 - Top 100 boys, England" "Table 3 - Top 100 boys, Wales"
## [5] "Table 4 - Top 10 boys by region" "Table 5 - Top 10 boys by month"
## [7] "Table 6 - Boys names - E&W"
##
## [[14]]
## [1] "Contents"                        "Table 1 - Top 100 boys' names"
## [3] "Table 2 - Top 100 boys, England" "Table 3 - Top 100 boys, Wales"
## [5] "Table 4 - Top 10 boys by region" "Table 5 - Top 10 boys by month"
## [7] "Table 6 - Boys names - E&W"
##
## [[15]]
## [1] "Contents"                        "Table 1 - Top 100 boys, E&W"
## [3] "Table 2 - Top 100 boys, England" "Table 3 - Top 100 boys, Wales"
## [5] "Table 4 - Top 10 boys by region" "Table 5 - Top 10 boys by month"
## [7] "Table 6 - Boys names - E&W"
##
## [[16]]
##  [1] "Contents"                        "Metadata"
##  [3] "Terms and Conditions"            "Table 1 - Top 100 boys, E&W"
##  [5] "Table 2 - Top 100 boys, England" "Table 3 - Top 100 boys, Wales"
##  [7] "Table 4 - Top 10 boys by region" "Table 5 - Top 10 boys by month"
##  [9] "Table 6 - Boys names - E&W"      "Related Publications"
##
## [[17]]
##  [1] "Contents"                        "Metadata"
##  [3] "Terms and Conditions"            "Table 1 - Top 100 boys, E&W"
##  [5] "Table 2 - Top 100 boys, England" "Table 3 - Top 100 boys, Wales"
##  [7] "Table 4 - Top 10 boys by region" "Table 5 - Top 10 boys by month"
##  [9] "Table 6 - Boys names - E&W"      "Related Publications"
##
## [[18]]
##  [1] "Contents"                        "Metadata"
##  [3] "Terms and Conditions"            "Table 1 - Top 100 boys, E&W"
##  [5] "Table 2 - Top 100 boys, England" "Table 3 - Top 100 boys, Wales"
##  [7] "Table 4 - Top 10 boys by region" "Table 5 - Top 10 boys by month"
##  [9] "Table 6 - Boys names - E&W"      "Related Publications"
##
## [[19]]
##  [1] "Contents"                        "Metadata"
##  [3] "Terms and Conditions"            "Table 1 - Top 100 boys, E&W"
##  [5] "Table 2 - Top 100 boys, England" "Table 3 - Top 100 boys, Wales"
##  [7] "Table 4 - Top 10 boys by region" "Table 5 - Top 10 boys by month"
##  [9] "Table 6 - Boys names - E&W"      "Related Publications"
##
## [[20]]
```

```
##  [1] "Contents"              "Metadata"              "Terms and Conditions"
##  [4] "Table 1"               "Table 2"               "Table 3"
##  [7] "Table 4"               "Table 5"               "Table 6"
## [10] "Related Publications"
```

6.2.2 Filtering strings using regex

To extract the correct worksheet names we need a way to extract strings containing "Table 1".

Base R provides some string manipulation capabilities (see `?regex`, `?sub` and `?grep`), but we will use the `stringr` package within `tidyverse` because it is more user-friendly. `stringr` provides functions to:

1. detect
2. locate
3. extract
4. match
5. replace
6. combine
7. split

strings. Here we want to detect the pattern "Table 1", and only return elements with this pattern. We can do that using the `str_subset()` function:

1. The first argument to `str_subset()` is character vector we want to search in.
2. The second argument is a *regular expression* matching the pattern we want to retain.

```r
# example syntax
str_subset(character_vector, regex_pattern)
```

If you are not familiar with regular expressions (regex), `http://www.regexr.com/` is a good place to start. Regex is essentially just a programmatic way of doing operations like "find" or "find and replace" in MS Word or Excel.

Now that we know how to filter character vectors using `str_subset()` we can identify the correct sheet in a particular Excel file. For example,

```r
# we can do this by nesting functions
str_subset(excel_sheets(boy_file_names[1]), pattern = "Table 1")
```

```
## [1] "Table 1 - Top 100 boys, E&W"
```

```r
# or, we can do this by piping functions
excel_sheets(boy_file_names[1]) %>% str_subset(pattern = "Table 1")
```

```
## [1] "Table 1 - Top 100 boys, E&W"
```

6.2.3 Writing your own functions

The next step is to retrieve worksheet names and subset them.

The `map*` functions are useful when you want to apply a function to a vector of inputs and obtain the return values for each input. This is very convenient when a function already exists that does exactly what you want. In the examples above we mapped the `excel_sheets()` function to the elements of a character vector containing file names.

However, there is no function that both:

1. Retrieves worksheet names, and
2. Subsets the names

So, we will have to write one. Fortunately, writing functions in R is easy. Functions require 3 elements:

1. A **name**
2. One or more **arguments**
3. A **body** containing computations

Anatomy of a function:

```
# general function syntax
function_name <- function(arg1, arg2, ....) {

    body of function # where stuff happens

    return( results )
}
```

Simple examples:

```
# one argument
myfun <- function(x) {
  x^2
}

myfun(1:10)
```

```
##  [1]   1   4   9  16  25  36  49  64  81 100
```

```
# two arguments
myfun2 <- function(x, y) {
  z <- x^2 + y
  return(z)
}

myfun2(x=1:10, y=42)
```

```
##  [1]  43  46  51  58  67  78  91 106 123 142
```

Example using the Excel data:

```
# function to extract different sheet names using regex
get_data_sheet_name <- function(file, term){
  excel_sheets(file) %>% str_subset(pattern = term)
}
```

The goal is generalization — we can now extract any sheet name using this one function:

```
# extract different sheet names using regex
get_data_sheet_name(boy_file_names[1], term = "Table 1")
```

```
## [1] "Table 1 - Top 100 boys, E&W"
```

```
get_data_sheet_name(boy_file_names[1], term = "Table 2")
```

```
## [1] "Table 2-Top 10 boys by month"
```

Now we can map this new function over our vector of file names.

```
# map(object to iterate over,
#     function that does task within each iteration,
#     arguments to previous function)

map(boy_file_names,      # list object
    get_data_sheet_name, # our function
    term = "Table 1")    # argument to our function `get_data_sheet_name()`
```

```
## [[1]]
## [1] "Table 1 - Top 100 boys, E&W"
##
## [[2]]
## [1] "Table 1 - Top 100 boys, E&W"
##
## [[3]]
## [1] "Table 1 - Top 100 boys' names"
##
## [[4]]
## [1] "Table 1 - Top 100 boys' names"
##
## [[5]]
## [1] "Table 1 - Top 100 boys, E&W"
##
```

```
## [[6]]
## [1] "Table 1 - Top 100 boys, E&W"
##
## [[7]]
## [1] "Table 1 - Top 100 boys, E&W"
##
## [[8]]
## [1] "Table 1 - Top 100 boys, E&W"
##
## [[9]]
## [1] "Table 1 - Top 100 boys, E&W"
##
## [[10]]
## [1] "Table 1 - Top 100 boys, E&W"
##
## [[11]]
## [1] "Table 1 - Top 100 boys, E&W"
##
## [[12]]
## [1] "Table 1 - Top 100 boys, E&W"
##
## [[13]]
## [1] "Table 1 - Top 100 boys' names"
##
## [[14]]
## [1] "Table 1 - Top 100 boys' names"
##
## [[15]]
## [1] "Table 1 - Top 100 boys, E&W"
##
## [[16]]
## [1] "Table 1 - Top 100 boys, E&W"
##
## [[17]]
## [1] "Table 1 - Top 100 boys, E&W"
##
## [[18]]
## [1] "Table 1 - Top 100 boys, E&W"
##
## [[19]]
## [1] "Table 1 - Top 100 boys, E&W"
##
## [[20]]
## [1] "Table 1"
```

6.2.4 Reading Excel data files

Now that we know the correct worksheet from each file, we can actually read those data into R. We can do that using the `read_excel()` function.

We'll start by reading the data from the first file, just to check that it works. Recall that the actual data starts on row 7, so we want to skip the first 6 rows. We can use the `glimpse()` function from the `dplyr` package within `tidyverse` to view the output.

```
# read in data from the first file only
temp <- read_excel(
  path = boy_file_names[1],
  sheet = get_data_sheet_name(boy_file_names[1], term = "Table 1"),
  skip = 6
)

glimpse(temp)
```

```
## Rows: 59
## Columns: 7
## $ ...1      <chr> NA, "1", "2", "3", "4", "5", "6", "7", "8", "9", "10", "1...
## $ Name...2  <chr> NA, "JACK", "DANIEL", "THOMAS", "JAMES", "JOSHUA", "MATTH...
## $ Count...3 <dbl> NA, 10779, 10338, 9603, 9385, 7887, 7426, 6496, 6193, 616...
## $ ...4      <lgl> NA, NA, NA, NA, NA, NA, NA, NA, NA, NA, NA, NA, NA, NA, N...
## $ ...5      <dbl> NA, 51, 52, 53, 54, 55, 56, 57, 58, 59, 60, 61, 62, 63, 6...
## $ Name...6  <chr> NA, "DOMINIC", "NICHOLAS", "BRANDON", "RHYS", "MARK", "MA...
## $ Count...7 <dbl> NA, 1519, 1385, 1337, 1259, 1222, 1192, 1186, 1135, 1128,...
```

Note that R has added a suffix to each column name `...1`, `...2`, `...3`, etc. because duplicate names are not allowed, so the suffix serves to disambiguate. The trailing number represents the index of the column.

6.2.5 Exercise 1

1. Write a function called `read_boys_names` that takes a file name as an argument and reads the worksheet containing "Table 1" from that file. Don't forget to skip the first 6 rows.

```
##
```

2. Test your function by using it to read *one* of the boys names Excel files.

```
##
```

3. Use the `map()` function to create a list of data frames called `boysNames` from all the Excel files, using the function you wrote in step 1.

```
##
```

Click for Exercise 1 Solution

1. Write a function called `read_boys_names` that takes a file name as an argument and reads the worksheet containing "Table 1" from that file. Don't forget to skip the first 6 rows.

```
read_boys_names <- function(file, sheet_name) {
  read_excel(
    path = file,
    sheet = get_data_sheet_name(file, term = sheet_name),
    skip = 6
  )
}
```

2. Test your function by using it to read *one* of the boys names Excel files.

```
read_boys_names(boy_file_names[1], sheet_name = "Table 1") %>% glimpse()
```

```
## Rows: 59
## Columns: 7
## $ ...1      <chr> NA, "1", "2", "3", "4", "5", "6", "7", "8", "9", "10", "1...
## $ Name...2  <chr> NA, "JACK", "DANIEL", "THOMAS", "JAMES", "JOSHUA", "MATTH...
## $ Count...3 <dbl> NA, 10779, 10338, 9603, 9385, 7887, 7426, 6496, 6193, 616...
## $ ...4      <lgl> NA, NA, NA, NA, NA, NA, NA, NA, NA, NA, NA, NA, NA, NA, N...
## $ ...5      <dbl> NA, 51, 52, 53, 54, 55, 56, 57, 58, 59, 60, 61, 62, 63, 6...
## $ Name...6  <chr> NA, "DOMINIC", "NICHOLAS", "BRANDON", "RHYS", "MARK", "MA...
## $ Count...7 <dbl> NA, 1519, 1385, 1337, 1259, 1222, 1192, 1186, 1135, 1128,...
```

3. Use the `map()` function to create a list of data frames called `boysNames` from all the Excel files, using the function you wrote in step 1.

```
boysNames <- map(boy_file_names, read_boys_names, sheet_name = "Table 1")
```

6.3 Data cleanup

GOAL: To learn how to clean up data within each R data frame. In particular:

1. Sort and merge columns within each data frame inside the list
2. Drop missing values from each data frame
3. Reshape data format from wide to long

Now that we've read in the data, we can see that there are some problems we need to fix. Specifically, we need to:

1. fix column names
2. get rid of blank row at the top and the notes at the bottom
3. get rid of extraneous "changes in rank" columns if they exist
4. transform the side-by-side tables layout to a single table

```
# Rank 1:50 --- Names / Counts are in columns 2 and 3
# Rank 51:100 --- Names / Counts are in columns 6 and 7
glimpse(boysNames[[1]])
```

```
## Rows: 59
## Columns: 7
## $ ...1      <chr> NA, "1", "2", "3", "4", "5", "6", "7", "8", "9", "10", "1...
## $ Name...2  <chr> NA, "JACK", "DANIEL", "THOMAS", "JAMES", "JOSHUA", "MATTH...
## $ Count...3 <dbl> NA, 10779, 10338, 9603, 9385, 7887, 7426, 6496, 6193, 616...
## $ ...4      <lgl> NA, NA, NA, NA, NA, NA, NA, NA, NA, NA, NA, NA, NA, NA, N...
## $ ...5      <dbl> NA, 51, 52, 53, 54, 55, 56, 57, 58, 59, 60, 61, 62, 63, 6...
## $ Name...6  <chr> NA, "DOMINIC", "NICHOLAS", "BRANDON", "RHYS", "MARK", "MA...
## $ Count...7 <dbl> NA, 1519, 1385, 1337, 1259, 1222, 1192, 1186, 1135, 1128,...
```

```
# Rank 1:50 --- Names / Counts are in columns 2 and 3
# Rank 51:100 --- Names / Counts are in columns 7 and 8
glimpse(boysNames[[10]])
```

```
## Rows: 61
## Columns: 9
## $ ...1              <chr> NA, "1", "2", "3", "4", "5", "6", "7", "8", "9", "...
## $ Name...2          <chr> NA, "JACK", "JOSHUA", "THOMAS", "JAMES", "OLIVER",...
## $ Count...3         <dbl> NA, 7434, 7167, 6792, 5654, 5516, 5270, 5219, 5106...
## $ `since 2004...4` <chr> NA, "-", "-", "-", "-", "+2", "-1", "-1", "-", "+2...
## $ ...5              <lgl> NA, NA, NA, NA, NA, NA, NA, NA, NA, NA, NA, NA, NA...
## $ ...6              <dbl> NA, 51, 52, 53, 53, 55, 56, 57, 58, 59, 60, 61, 62...
## $ Name...7          <chr> NA, "NOAH", "MUHAMMAD", "ALEX", "ISAAC", "OSCAR", ...
## $ Count...8         <dbl> NA, 1346, 1318, 1302, 1302, 1262, 1256, 1172, 1126...
## $ `since 2004...9` <chr> NA, "+23", "-1", "-7", "+5", "+4", "-4", "+6", "+1...
```

```
# Rank 1:50 --- Names / Counts are in columns 2 and 3
# Rank 51:100 --- Names / Counts are in columns 8 and 9
glimpse(boysNames[[20]])
```

```
## Rows: 61
## Columns: 11
## $ Rank...1           <chr> NA, "1", "2", "3", "4", "5", "6", "7", "8", "9", ...
```

```
## $ Name...2          <chr> NA, "OLIVER", "JACK", "HARRY", "GEORGE", "JACOB",...
## $ Count...3         <dbl> NA, 6941, 5371, 5308, 4869, 4850, 4831, 4148, 408...
## $ `since 2014...4`  <chr> NA, " ", " ", " ", "+3 ", "-1 ", "-1 ", "+4 ",...
## $ `since 2005...5`  <chr> NA, "+4 ", "-1 ", "+6 ", "+13 ", "+16 ", "+6 ", "...
## $ ...6              <lgl> NA, NA, NA, NA, NA, NA, NA, NA, NA, NA, NA, NA, N...
## $ Rank...7          <chr> NA, "51", "52", "53", "54", "55", "56", "57", "58...
## $ Name...8          <chr> NA, "REUBEN", "HARLEY", "LUCA", "MICHAEL", "HUGO"...
## $ Count...9         <dbl> NA, 1188, 1175, 1167, 1165, 1153, 1148, 1112, 109...
## $ `since 2014...10` <chr> NA, " ", "-7 ", "+5 ", "-2 ", "+15 ", "-10 ", "+...
## $ `since 2005...11` <chr> NA, "+51* ", "+18 ", "+30 ", "-12 ", "+124* ", "-...
```

In short, we want to go from this:

Rank	Name	Count	since 2014	since 2005	Rank	Name	Count	since 2014	since 2005
6	CHARLIE	4,831	-1	+6	56	LEWIS	1,148	-10	-37
7	NOAH	4,148	+4	+44	57	FRANKIE	1,112	+7	+93*
8	WILLIAM	4,083	+2		58	LUKE	1,095	-14	-45
9	THOMAS	4,075	-3	-6	59	STANLEY	1,078	+1	+85*
10	OSCAR	4,066	-2	+45	60	TOMMY	1,075	-5	+63*
11	JAMES	3,912	-2	-7	61	JUDE	1,040	+4	+42*
12	MUHAMMAD	3,730	+2	+40	62	BLAKE	1,024	-5	+79*
13	HENRY	3,581	+2	+31	63	LOUIE	1,002	+4	+44*
14	ALFIE	3,540	-2	+9	64	NATHAN	997	-2	-29
15	LEO	3,468	+1	+22	65	GABRIEL	989	+13	+31
16	JOSHUA	3,394	-3	-14	66	CHARLES	985	-3	-17
17	FREDDIE	3,219	+3	+62	67	BOBBY	983	+4	+45*
18	ETHAN	2,940			68	MOHAMMAD	976	-12	
19	ARCHIE	2,912	-2	+19	69	RYAN	955		-44
20	ISAAC	2,829	+5	+33	70	TYLER	948	-23	-41
21	JOSEPH	2,786	-2	-11	71	ELLIOTT	938	+1	+54*
22	ALEXANDER	2,759			72	ALBERT	933	+12	+142*
23	SAMUEL	2,705	-2	-16	73	ELLIOT	926	+10	+9
24	DANIEL	2,622		-18	74	RORY	912	+13	+68*
25	LOGAN	2,610	-2	+52	75	ALEX	900		-22
26	EDWARD	2,593	+5	+20	76	FREDERICK	875	+5	+22
27	LUCAS	2,448	+3	+31	77	OLLIE	873	-3	+152*
28	MAX	2,407	-2	+3	78	LOUIS	854	-10	-35
29	MOHAMMED	2,332	-2	-9	79	DEXTER	850	-6	+216*
30	BENJAMIN	2,328	-2	-19	80	JAXON	837	+35*	+1055*
31	MASON	2,263	-2	+29	81	LIAM	836	-5	-53
32	HARRISON	2,241		+7	82	JACKSON	818	+18	+154*
33	THEO	2,103	+4	+85*	83	CALLUM	798	-1	-69
34	JAKE	2,013	-1	-18	83	RONNIE	798	+3	+77*
35	SEBASTIAN	1,988	+3	+54	85	LEON	795		-10
36	FINLEY	1,978		+28	86	KAI	775	-9	-20
37	ARTHUR	1,966	+4	+98*	87	AARON	773	-7	-42
38	ADAM	1,903	+1	-12	88	ROMAN	763	+22*	+105*
38	DYLAN	1,903	-4	-14	89	AUSTIN	751		+171*
40	RILEY	1,728	-5	+34	90	ELLIS	721	+4	-3
41	ZACHARY	1,644	-1	+54	91	JAMIE	708	-3	-58
42	TEDDY	1,430	+24	+226*	91	REGGIE	708	+18*	+201*
43	DAVID	1,394	+7	+18	93	SETH	703	-3	+88*
44	TOBY	1,363	-2	+4	94	CARTER	689	+24*	+182*
45	THEODORE	1,302	+14	+113*	95	FELIX	680	+3	+48*
46	ELIJAH	1,294	+7	+109*	96	IBRAHIM	674	-5	+32*
47	MATTHEW	1,279	+2	-32	97	SONNY	670	-2	+17*
48	JENSON	1,223	+13	+127*	98	KIAN	665	-44	-35
49	JAYDEN	1,219	-6	+35	99	CALEB	659	-6	+32*
50	HARVEY	1,190	-2	-23	100	CONNOR	642	-21	-70

Notes:
These rankings have been produced using the exact spelling of the name given at birth registration. Similar names with different spellings have been counted separately.
Births where the name was not stated have been excluded from these figures. Of the 358,136 baby boys in the 2015 dataset, 14 were excluded for this reason.
The sum of the counts for individual names appearing in Table 2 and Table 3 may not equal the count in Table 1. This is because births where the usual residence of mother was not stated at the time of registration have been excluded from the counts in Table 2 and Table 3.
* denotes new entry to top 100

to this:

Rank	Name	Count
1	OLIVER	6,941
2	JACK	5,371
3	HARRY	5,308
4	GEORGE	4,869
5	JACOB	4,850
6	CHARLIE	4,831
7	NOAH	4,148
8	WILLIAM	4,083
9	THOMAS	4,075
10	OSCAR	4,066
11	JAMES	3,912
12	MUHAMMAD	3,730
13	HENRY	3,581
14	ALFIE	3,540
15	LEO	3,468
16	JOSHUA	3,394
17	FREDDIE	3,219
18	ETHAN	2,940
19	ARCHIE	2,912
20	ISAAC	2,829
21	JOSEPH	2,786
22	ALEXANDER	2,759
23	SAMUEL	2,705
24	DANIEL	2,622
25	LOGAN	2,610
26	EDWARD	2,593
27	LUCAS	2,448
28	MAX	2,407
29	MOHAMMED	2,332
30	BENJAMIN	2,328
31	MASON	2,263
32	HARRISON	2,241
33	THEO	2,103
34	JAKE	2,013
35	SEBASTIAN	1,988
36	FINLEY	1,978
37	ARTHUR	1,966
38	ADAM	1,903
38	DYLAN	1,903
40	RILEY	1,728
41	ZACHARY	1,644
42	TEDDY	1,430
43	DAVID	1,394
44	TOBY	1,363
45	THEODORE	1,302
46	ELIJAH	1,294
47	MATTHEW	1,279
48	JENSON	1,223
49	JAYDEN	1,219
50	HARVEY	1,190
51	REUBEN	1,188
52	HARLEY	1,175
53	LUCA	1,167
54	MICHAEL	1,165
55	HUGO	1,153
56	LEWIS	1,148
57	FRANKIE	[illegible]

Sheet1

There are many ways to do this kind of data manipulation in R. We're going to use the `dplyr` and `tidyr` packages from within `tidyverse` to make our lives easier.

6.3.1 Selecting columns

Next we want to retain just the `Name...2`, `Name...6`, `Count...3` and `Count...7` columns. We can do that using the `select()` function:

```
boysNames[[1]]
```

```
## # A tibble: 59 x 7
##    ...1  Name...2 Count...3 ...4   ...5 Name...6 Count...7
##    <chr> <chr>        <dbl> <lgl> <dbl> <chr>        <dbl>
##  1 <NA>  <NA>            NA NA       NA <NA>            NA
##  2 1     JACK         10779 NA       51 DOMINIC       1519
##  3 2     DANIEL       10338 NA       52 NICHOLAS      1385
##  4 3     THOMAS        9603 NA       53 BRANDON       1337
##  5 4     JAMES         9385 NA       54 RHYS          1259
##  6 5     JOSHUA        7887 NA       55 MARK          1222
##  7 6     MATTHEW       7426 NA       56 MAX           1192
##  8 7     RYAN          6496 NA       57 DYLAN         1186
##  9 8     JOSEPH        6193 NA       58 HENRY         1135
## 10 9     SAMUEL        6161 NA       59 PETER         1128
## # ... with 49 more rows
```

```
# retain only columns of interest
boysNames[[1]] <- select(boysNames[[1]], Name...2, Name...6, Count...3, Count...7)
boysNames[[1]]
```

```
## # A tibble: 59 x 4
##    Name...2 Name...6 Count...3 Count...7
##    <chr>    <chr>        <dbl>     <dbl>
##  1 <NA>     <NA>            NA        NA
##  2 JACK     DOMINIC      10779      1519
##  3 DANIEL   NICHOLAS     10338      1385
##  4 THOMAS   BRANDON       9603      1337
##  5 JAMES    RHYS          9385      1259
##  6 JOSHUA   MARK          7887      1222
##  7 MATTHEW  MAX           7426      1192
##  8 RYAN     DYLAN         6496      1186
##  9 JOSEPH   HENRY         6193      1135
## 10 SAMUEL   PETER         6161      1128
## # ... with 49 more rows
```

6.3.2 Data types and structures

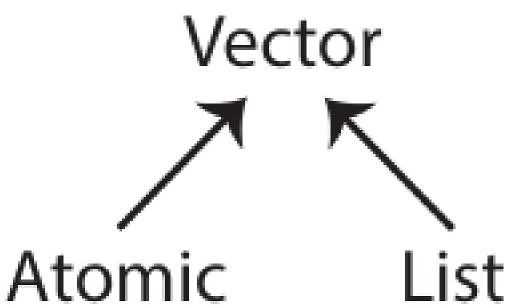
We've now encountered several different data types and data structures. Let's take a step back and survey the options available in R.

Data structures:

In R, the most foundational data structure is the **vector**. Vectors are *containers* that can hold a *collection* of values. Vectors come in two basic forms:

1. **atomic**: only hold elements of the same type; they are **homogeneous**. The `c()` function can be used to create atomic vectors.
2. **list**: can hold elements of different types; they are **heterogeneous**. The `list()` function can be used to create list vectors.

`NULL` is closely related to vectors and often serves the role of a zero length vector.



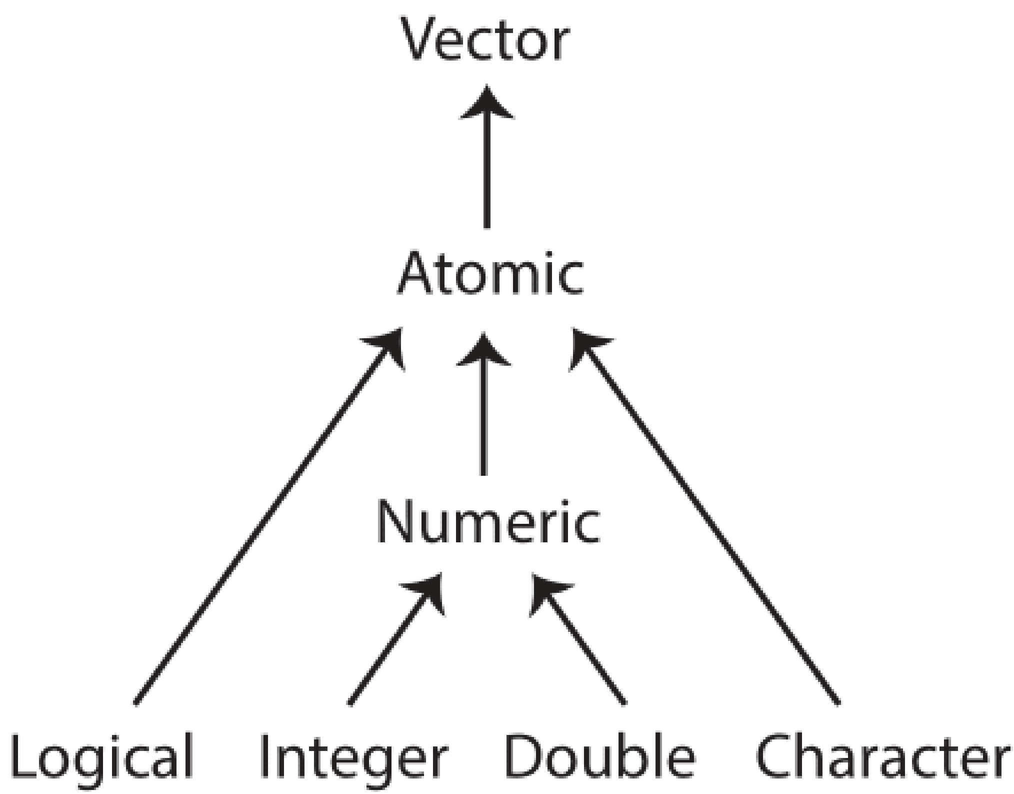
From these two basic forms, the following six structures are derived:

Type	Elements	Description
atomic vector	homogeneous	contains elements of the same **type**, one of: character, integer, double, logical
array	homogeneous	an atomic vector with attributes giving dimensions (1, 2, or >2)
matrix	homogeneous	an array with 2 dimensions
factor	homogeneous	an atomic integer vector containing only predefined values, storing categorical data
list	heterogeneous	a container whose elements can encompass any mixture of data types
data.frame	heterogeneous	a rectangular list with elements (columns) containing atomic vectors of equal length

Each vector can have **attributes**, which are a named list of metadata that can include the vector's **dimensions** and its **class**. The latter is a property assigned to an object that determines how **generic functions** operate with it, and thus which **methods** are available for it. The class of an object can be queried using the `class()` function. You can learn more details about R data structures here: `https://adv-r.hadley.nz/vectors-chap.html`.

Data types:

There are four primary types of atomic vectors. Collectively, integer and double vectors are known as numeric vectors. You can query the **type** of an object using the `typeof()` function.



Type	Description
character	"a", "swc"
integer	2L (the L tells R to store this as an integer)
double (floating point)	2, 15.5
logical	TRUE, FALSE

Coercion:

If heterogeneous elements are stored in an atomic vector, R will **coerce** the vector to the simplest type required to store all the information. The order of coercion is roughly: logical -> integer -> double -> character -> list. For example:

```
x <- c(1.5, 2.7, 3.9)
typeof(x) # the vector is numeric
```

```
## [1] "double"
```

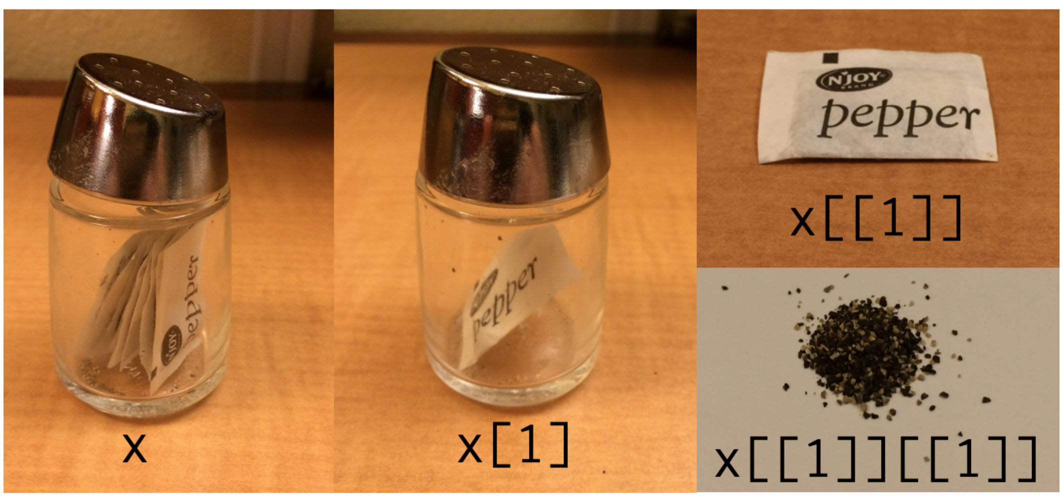
```
y <- c(1.5, 2.7, 3.9, "a")
typeof(y) # the vector has been coerced to character
```

```
## [1] "character"
```

6.3.3 List indexing

Now that we know about data structures more generally, let's focus on the *list* structure we created for `boysNames`. Why are we using **double brackets** `[[` to index this list object, instead of the single brackets `[` we used to index atomic vectors?

Here's a symbolic representation using pepper! The pepper pot represents a list, while each pepper sachet denotes a list element. On the left, we see a list structure with multiple elements `x`, while in the middle we extract the first list element `x[1]` using single brackets, which keeps the list structure. On the upper right, we use double brackets to extract the first list element `x[[1]]` and *remove the list structure*. On the lower right, we extract the first item within the first list element `x[[1]][[1]]` (e.g., the first column within a data frame stored inside the list).



Let's illustrate how this works with a practical example. Here's a list containing various data structures:

```
# various data structures
numbers <- 1:10
characters <- LETTERS[1:4]
```

```r
dataframe <- head(mtcars)
integer <- 237L

# combine in a list
mylist <- list(numbers, characters, dataframe, integer)
mylist
```

```
## [[1]]
##  [1]  1  2  3  4  5  6  7  8  9 10
##
## [[2]]
## [1] "A" "B" "C" "D"
##
## [[3]]
##                    mpg cyl disp  hp drat    wt  qsec vs am gear carb
## Mazda RX4         21.0   6  160 110 3.90 2.620 16.46  0  1    4    4
## Mazda RX4 Wag     21.0   6  160 110 3.90 2.875 17.02  0  1    4    4
## Datsun 710        22.8   4  108  93 3.85 2.320 18.61  1  1    4    1
## Hornet 4 Drive    21.4   6  258 110 3.08 3.215 19.44  1  0    3    1
## Hornet Sportabout 18.7   8  360 175 3.15 3.440 17.02  0  0    3    2
## Valiant           18.1   6  225 105 2.76 3.460 20.22  1  0    3    1
##
## [[4]]
## [1] 237
```

Using single brackets for extraction, we maintain the list structure. Here we extract a character vector stored within a list with only one element:

```r
# indexing the list
mylist[2]
```

```
## [[1]]
## [1] "A" "B" "C" "D"
```

```r
class(mylist[2]) # a list
```

```
## [1] "list"
```

While using double brackets for extraction, we remove the list structure. Here we extract the same character vector, but now without any surrounding list structure:

```r
mylist[[2]]
```

```
## [1] "A" "B" "C" "D"
```

```
class(mylist[[2]]) # a character vector
```

```
## [1] "character"
```

6.3.4 Dropping missing values

Next we want to remove blank rows and rows used for notes. An easy way to do that is to use `drop_na()` from the `tidyr` package within `tidyverse` to remove rows with missing values.

```
boysNames[[1]]
```

```
## # A tibble: 59 x 4
##    Name...2 Name...6 Count...3 Count...7
##    <chr>    <chr>        <dbl>     <dbl>
##  1 <NA>     <NA>            NA        NA
##  2 JACK     DOMINIC      10779      1519
##  3 DANIEL   NICHOLAS     10338      1385
##  4 THOMAS   BRANDON       9603      1337
##  5 JAMES    RHYS          9385      1259
##  6 JOSHUA   MARK          7887      1222
##  7 MATTHEW  MAX           7426      1192
##  8 RYAN     DYLAN         6496      1186
##  9 JOSEPH   HENRY         6193      1135
## 10 SAMUEL   PETER         6161      1128
## # ... with 49 more rows
```

```
# remove rows with missing values
boysNames[[1]] <- boysNames[[1]] %>% drop_na()

boysNames[[1]]
```

```
## # A tibble: 50 x 4
##    Name...2 Name...6 Count...3 Count...7
##    <chr>    <chr>        <dbl>     <dbl>
##  1 JACK     DOMINIC      10779      1519
##  2 DANIEL   NICHOLAS     10338      1385
##  3 THOMAS   BRANDON       9603      1337
##  4 JAMES    RHYS          9385      1259
##  5 JOSHUA   MARK          7887      1222
##  6 MATTHEW  MAX           7426      1192
##  7 RYAN     DYLAN         6496      1186
##  8 JOSEPH   HENRY         6193      1135
##  9 SAMUEL   PETER         6161      1128
## 10 LIAM     STEPHEN       5802      1122
## # ... with 40 more rows
```

6.3.5 Exercise 2

1. Write a function called `namecount` that takes a data frame as an argument and returns a modified version, which keeps only columns that include the strings `Name` and `Count` in the column names. HINT: see the `?matches` function.

```
##
```

2. Test your function on the first data frame in the list of `boysNames` data.

```
##
```

3. Use the `map()` function to call your `namecount()` function on each data frame in the list called `boysNames`.Save the results back to the list called `boysNames`.

```
##
```

Click for Exercise 2 Solution

1. Write a function called `namecount` that takes a data frame as an argument and returns a modified version, which keeps only columns that include the strings `Name` and `Count` in the column names. HINT: see the `?matches` function.

```
namecount <- function(data) {
    select(data, matches("Name|Count"))
}
```

2. Test your function on the first data frame in the list of `boysNames` data.

```
namecount(boysNames[[1]])
```

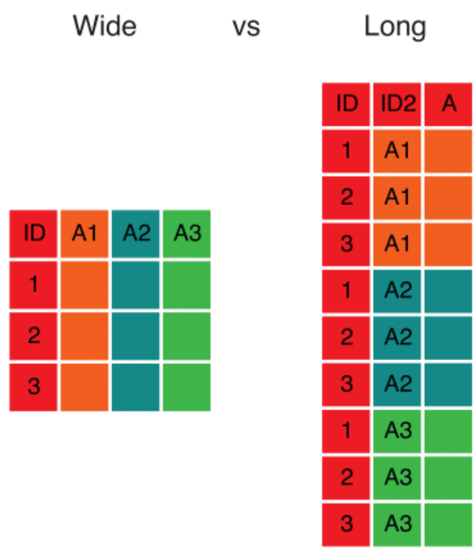
```
## # A tibble: 50 x 4
##    Name...2 Name...6 Count...3 Count...7
##    <chr>    <chr>        <dbl>     <dbl>
##  1 JACK     DOMINIC      10779      1519
##  2 DANIEL   NICHOLAS     10338      1385
##  3 THOMAS   BRANDON       9603      1337
##  4 JAMES    RHYS          9385      1259
##  5 JOSHUA   MARK          7887      1222
##  6 MATTHEW  MAX           7426      1192
##  7 RYAN     DYLAN         6496      1186
##  8 JOSEPH   HENRY         6193      1135
##  9 SAMUEL   PETER         6161      1128
## 10 LIAM     STEPHEN       5802      1122
## # ... with 40 more rows
```

3. Use the `map()` function to call your `namecount()` function on each data frame in the list called `boysNames`.Save the results back to the list called `boysNames`.

```
boysNames <- map(boysNames, namecount)
```

6.3.6 Reshaping from wide to long

Our final task is to re-arrange the data so that it is all in a single table instead of in two side-by-side tables. For many similar tasks the `pivot_longer()` function in the `tidyr` package is useful, but in this case we will be better off using a combination of `select()` and `bind_rows()`. Here is the logic behind this step:



Here is the code that implements the transformation:

```
boysNames[[1]]
```

```
## # A tibble: 50 x 4
##    Name...2 Name...6 Count...3 Count...7
##    <chr>    <chr>        <dbl>     <dbl>
##  1 JACK     DOMINIC      10779      1519
##  2 DANIEL   NICHOLAS     10338      1385
##  3 THOMAS   BRANDON       9603      1337
##  4 JAMES    RHYS          9385      1259
##  5 JOSHUA   MARK          7887      1222
##  6 MATTHEW  MAX           7426      1192
##  7 RYAN     DYLAN         6496      1186
##  8 JOSEPH   HENRY         6193      1135
```

```
##  9 SAMUEL   PETER         6161      1128
## 10 LIAM     STEPHEN       5802      1122
## # ... with 40 more rows
```

```
# select the two separate sets of columns and standardize the column names
first_columns <- select(boysNames[[1]], Name = Name...2, Count = Count...3)
second_columns <- select(boysNames[[1]], Name = Name...6, Count = Count...7)

# glue the rows together to form one long data frame
bind_rows(first_columns, second_columns)
```

```
## # A tibble: 100 x 2
##    Name    Count
##    <chr>   <dbl>
##  1 JACK    10779
##  2 DANIEL  10338
##  3 THOMAS   9603
##  4 JAMES    9385
##  5 JOSHUA   7887
##  6 MATTHEW  7426
##  7 RYAN     6496
##  8 JOSEPH   6193
##  9 SAMUEL   6161
## 10 LIAM     5802
## # ... with 90 more rows
```

6.3.7 Exercise 3

Cleanup all the data

In the previous examples we learned how to drop empty rows with `drop_na()`, select only relevant columns with `select()`, and re-arrange our data with `select()` and `bind_rows()`. In each case we applied the changes only to the first element of our `boysNames` list.

NOTE: some Excel files include extra blank columns between the first and second set of `Name` and `Count` columns, resulting in different numeric suffixes for the second set of columns. You will need to use a regular expression (regex) to match each of these different column names. HINT: see the `?matches` function.

1. Create a new function called `cleanupNamesData` that:

```
# A) subsets data to include only those columns that include the term `Name` and `Count` and app

# B) subsets two separate data frames, with first and second set of `Name` and `Count` columns

# C) appends the two datasets

# D) once you've written the function, test it out on *one* of the data frames in the list
```

2. Your task now is to use the `map()` function to apply each of these transformations to all the elements in `boysNames`.

```
##
```

Click for Exercise 3 Solution

1. Create a new function called `cleanupNamesData` that:

```
cleanupNamesData <- function(file){

  # A) subsets data to include only those columns that include the term `Name` and `Count` and a
  subsetted_file <- file %>%
    select(matches("Name|Count")) %>%
    drop_na()

  # B) subsets two separate data frames, with first and second set of `Name` and `Count` columns
  first_columns <- select(subsetted_file, Name = Name...2, Count = Count...3)

  second_columns <- select(subsetted_file, Name = matches("Name...6|Name...7|Name...8"),
                                           Count = matches("Count...7|Count...8|Count...9"))

  # C) appends the two datasets
  bind_rows(first_columns, second_columns)
}


# D) once you've written the function, test it out on *one* of the data frames in the list
boysNames[[2]] %>% glimpse() # before cleanup
```

```
## Rows: 61
## Columns: 4
## $ Name...2  <chr> NA, "JACK", "JAMES", "THOMAS", "DANIEL", "JOSHUA", "MATTH...
## $ Count...3 <dbl> NA, 10145, 9853, 9479, 9047, 7698, 7443, 6367, 5809, 5631...
## $ Name...7  <chr> NA, "SEAN", "DYLAN", "DOMINIC", "LOUIS", "RHYS", "NICHOLA...
## $ Count...8 <dbl> NA, 1388, 1380, 1359, 1325, 1291, 1274, 1244, 1241, 1158,...
```

```
boysNames[[2]] %>% cleanupNamesData() %>% glimpse() # after cleanup
```

```
## Rows: 100
## Columns: 2
## $ Name  <chr> "JACK", "JAMES", "THOMAS", "DANIEL", "JOSHUA", "MATTHEW", "SA...
## $ Count <dbl> 10145, 9853, 9479, 9047, 7698, 7443, 6367, 5809, 5631, 5404, ...
```

2. Your task now is to use the `map()` function to apply each of these transformations to all the elements in `boysNames`.

```
# apply your function to elements in `boysNames` using `map()`
boysNames <- map(boysNames, cleanupNamesData)
```

6.4 Data organization & storage

GOAL: To learn how to organize the data into one large data frame and store it. In particular:

1. Create a `Year` column within each data frame within the list
2. Append all the data frames in the list into one large data frame

Now that we have the data cleaned up and augmented, we can turn our attention to organizing and storing the data.

6.4.1 A list of data frames

Right now we have a list of data frames; one for each year. This is not a bad way to go. It has the advantage of making it easy to work with individual years; it has the disadvantage of making it more difficult to examine questions that require data from multiple years. To make the arrangement of the data clearer it helps to name each element of the list with the year it corresponds to.

```
# our unnamed list of data frames
head(boysNames) %>% glimpse()
```

```
## List of 6
##  $ : tibble [100 x 2] (S3: tbl_df/tbl/data.frame)
##   ..$ Name : chr [1:100] "JACK" "DANIEL" "THOMAS" "JAMES" ...
##   ..$ Count: num [1:100] 10779 10338 9603 9385 7887 ...
##  $ : tibble [100 x 2] (S3: tbl_df/tbl/data.frame)
##   ..$ Name : chr [1:100] "JACK" "JAMES" "THOMAS" "DANIEL" ...
##   ..$ Count: num [1:100] 10145 9853 9479 9047 7698 ...
##  $ : tibble [100 x 2] (S3: tbl_df/tbl/data.frame)
##   ..$ Name : chr [1:100] "JACK" "THOMAS" "JAMES" "DANIEL" ...
##   ..$ Count: num [1:100] 9845 9468 9197 7732 7672 ...
##  $ : tibble [100 x 2] (S3: tbl_df/tbl/data.frame)
##   ..$ Name : chr [1:100] "JACK" "THOMAS" "JAMES" "JOSHUA" ...
##   ..$ Count: num [1:100] 9785 9454 8748 7275 6935 ...
##  $ : tibble [100 x 2] (S3: tbl_df/tbl/data.frame)
##   ..$ Name : chr [1:100] "JACK" "THOMAS" "JAMES" "JOSHUA" ...
##   ..$ Count: num [1:100] 9079 8672 7489 7097 6229 ...
##  $ : tibble [100 x 2] (S3: tbl_df/tbl/data.frame)
##   ..$ Name : chr [1:100] "JACK" "THOMAS" "JOSHUA" "JAMES" ...
##   ..$ Count: num [1:100] 9000 8337 7182 7026 5759 ...
```

```r
# the file names containing the 'year' information
head(boy_file_names)
```

```
## [1] "dataSets/boys/1996boys_tcm77-254026.xlsx"
## [2] "dataSets/boys/1997boys_tcm77-254022.xlsx"
## [3] "dataSets/boys/1998boys_tcm77-254018.xlsx"
## [4] "dataSets/boys/1999boys_tcm77-254014.xlsx"
## [5] "dataSets/boys/2000boys_tcm77-254008.xlsx"
## [6] "dataSets/boys/2001boys_tcm77-254000.xlsx"
```

We can use regular expresssions (regex) to extract the year information from the file names and store it in a character vector:

```r
# use regex to extract years from file names
Years <- str_extract(boy_file_names, pattern = "[0-9]{4}")
Years
```

```
##  [1] "1996" "1997" "1998" "1999" "2000" "2001" "2002" "2003" "2004" "2005"
## [11] "2006" "2007" "2008" "2009" "2010" "2011" "2012" "2013" "2014" "2015"
```

Then we can assign the year vector to be the names of the list elements:

```r
names(boysNames) # returns NULL - since no names are currently in the list
```

```
## NULL
```

```r
# assign years to list names
names(boysNames) <- Years

names(boysNames) # check assignment by returning the years as list names
```

```
##  [1] "1996" "1997" "1998" "1999" "2000" "2001" "2002" "2003" "2004" "2005"
## [11] "2006" "2007" "2008" "2009" "2010" "2011" "2012" "2013" "2014" "2015"
```

Now when we view our list of data frames again we can see that year information has been added to each element as a name just after the $ extractor:

```r
# view named list of data frames
head(boysNames) %>% glimpse()
```

```
## List of 6
##  $ 1996: tibble [100 x 2] (S3: tbl_df/tbl/data.frame)
##   ..$ Name : chr [1:100] "JACK" "DANIEL" "THOMAS" "JAMES" ...
##   ..$ Count: num [1:100] 10779 10338 9603 9385 7887 ...
```

```
##  $ 1997: tibble [100 x 2] (S3: tbl_df/tbl/data.frame)
##   ..$ Name : chr [1:100] "JACK" "JAMES" "THOMAS" "DANIEL" ...
##   ..$ Count: num [1:100] 10145 9853 9479 9047 7698 ...
##  $ 1998: tibble [100 x 2] (S3: tbl_df/tbl/data.frame)
##   ..$ Name : chr [1:100] "JACK" "THOMAS" "JAMES" "DANIEL" ...
##   ..$ Count: num [1:100] 9845 9468 9197 7732 7672 ...
##  $ 1999: tibble [100 x 2] (S3: tbl_df/tbl/data.frame)
##   ..$ Name : chr [1:100] "JACK" "THOMAS" "JAMES" "JOSHUA" ...
##   ..$ Count: num [1:100] 9785 9454 8748 7275 6935 ...
##  $ 2000: tibble [100 x 2] (S3: tbl_df/tbl/data.frame)
##   ..$ Name : chr [1:100] "JACK" "THOMAS" "JAMES" "JOSHUA" ...
##   ..$ Count: num [1:100] 9079 8672 7489 7097 6229 ...
##  $ 2001: tibble [100 x 2] (S3: tbl_df/tbl/data.frame)
##   ..$ Name : chr [1:100] "JACK" "THOMAS" "JOSHUA" "JAMES" ...
##   ..$ Count: num [1:100] 9000 8337 7182 7026 5759 ...
```

6.4.2 One big data frame

While storing the data in separate data frames by year makes some sense, many operations will be easier if the data is simply stored in one big data frame. We have already seen how to turn a list of data frames into a single data frame using `bind_rows()`, but there is a problem; The year information is stored in the names of the list elements, and so flattening the data frames into one will result in losing the year information! Fortunately it is not too much trouble to add the year information to each data frame before flattening.

We can use the `imap()` function — which stands for 'index' mapping — to do this operation. We know that the `mutate()` function can create a new column within a data frame. Here, we create a column called `Year` within each data frame (indexed by `.x`) that takes the name of each list element (indexed by `.y`), converts it from character (i.e., `"1996"`) to integer (i.e., `1996`), and repeats it along the rows of the data frame.

```
# apply name of the list element (.y) as a new column in the data.frame (.x)
boysNames <- imap(boysNames, ~ mutate(.x, Year = as.integer(.y)))

# examine the first data frame within the list
boysNames[1]
```

```
## $`1996`
## # A tibble: 100 x 3
##    Name    Count  Year
##    <chr>   <dbl> <int>
##  1 JACK    10779  1996
##  2 DANIEL  10338  1996
##  3 THOMAS   9603  1996
##  4 JAMES    9385  1996
##  5 JOSHUA   7887  1996
##  6 MATTHEW  7426  1996
```

```
## 7 RYAN     6496  1996
## 8 JOSEPH   6193  1996
## 9 SAMUEL   6161  1996
## 10 LIAM    5802  1996
## # ... with 90 more rows
```

6.4.3 Exercise 4

Make one big `data.frame`

1. Turn the list of boys names data frames into a single data frame. HINT: see `?bind_rows`.

```
##
```

2. Create a new directory called `all` within `dataSets` and write the data to a `.csv` file. HINT: see the `?dir.create` and `?write_csv` functions.

```
##
```

3. What were the five most popular names in 2013?

```
##
```

4. How has the popularity of the name "ANDREW" changed over time?

```
##
```

Click for Exercise 4 Solution

1. Turn the list of boys names data frames into a single data frame.

```
# convert list of data frames into single data frame
boysNames <- bind_rows(boysNames)
glimpse(boysNames)
```

```
## Rows: 2,000
## Columns: 3
## $ Name  <chr> "JACK", "DANIEL", "THOMAS", "JAMES", "JOSHUA", "MATTHEW", "RY...
## $ Count <dbl> 10779, 10338, 9603, 9385, 7887, 7426, 6496, 6193, 6161, 5802,...
## $ Year  <int> 1996, 1996, 1996, 1996, 1996, 1996, 1996, 1996, 1996, 1996, 1...
```

2. Create a new directory called `all` within `dataSets` and write the data to a `.csv` file. HINT: see the `?dir.create` and `?write_csv` functions.

```r
dir.create("dataSets/all")

write_csv(boysNames, "dataSets/all/boys_names.csv")
```

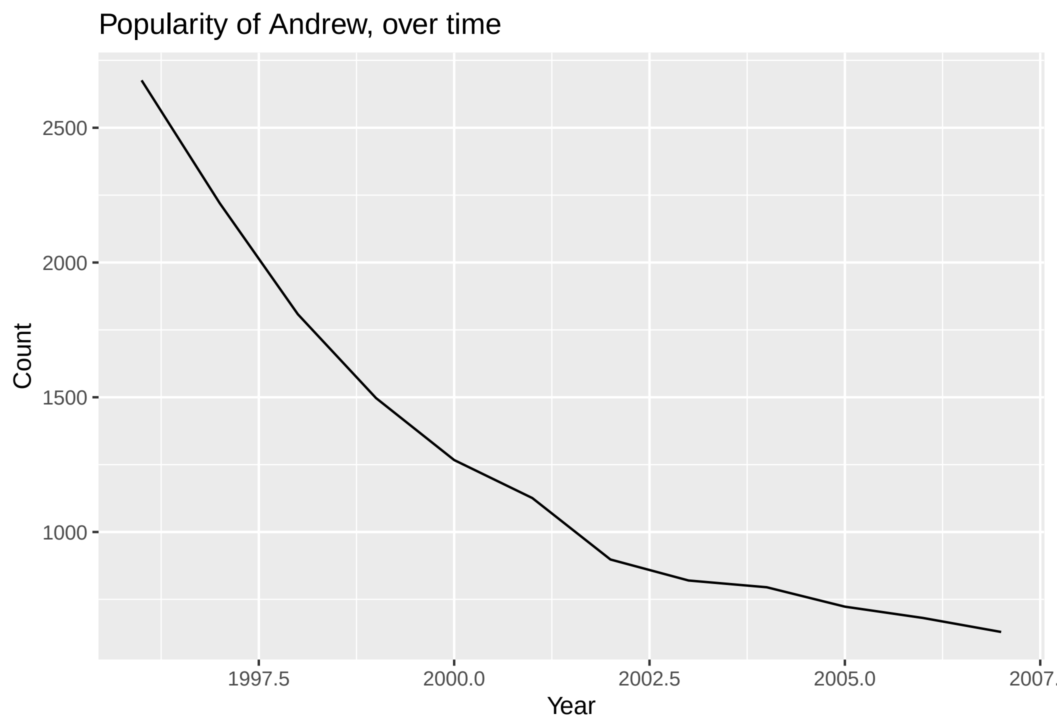
3. What were the five most popular names in 2013?

```r
boysNames %>%
  filter(Year == 2013) %>%
  arrange(desc(Count)) %>%
  head()
```

```
## # A tibble: 6 x 3
##   Name    Count  Year
##   <chr>   <dbl> <int>
## 1 OLIVER   6949  2013
## 2 JACK     6212  2013
## 3 HARRY    5888  2013
## 4 JACOB    5126  2013
## 5 CHARLIE  5039  2013
## 6 THOMAS   4591  2013
```

4. How has the popularity of the name “ANDREW” changed over time?

```r
andrew <- filter(boysNames, Name == "ANDREW")

ggplot(andrew, aes(x = Year, y = Count)) +
    geom_line() +
    ggtitle("Popularity of Andrew, over time")
```



6.5 Complete code

1. Code for Section 1: Reading data from multiple Excel worksheets into R data frames:

```
# read file names into a character vector
boy_file_names <- list.files("dataSets/boys", full.names = TRUE)

# function to extract sheet names from an Excel file
get_data_sheet_name <- function(file, term){
  excel_sheets(file) %>% str_subset(pattern = term)
}

# function to read in arbirary sheets from an Excel file
read_boys_names <- function(file, sheet_name) {
  read_excel(
    path = file,
    sheet = get_data_sheet_name(file, term = sheet_name),
    skip = 6
  )
}

# apply your function to elements in `boy_file_names` using `map()`
```

```
boysNames <- map(boy_file_names, read_boys_names, sheet_name = "Table 1")
```

2. Code for Section 2: Clean up data within each R data frame:

```
# function to clean up the data
cleanupNamesData <- function(file){

  # A) subset data to include only those columns that include the term `Name` and `Count`
  subsetted_file <- file %>%
    select(matches("Name|Count")) %>%
    drop_na()

  # B) subsets two separate data frames, with first and second set of `Name` and `Count` columns
  first_columns <- select(subsetted_file, Name = Name...2, Count = Count...3)
  second_columns <- select(subsetted_file, Name = matches("Name...6|Name...7|Name...8"),
                                            Count = matches("Count...7|Count...8|Count...9"))

  # C) appends the two datasets
  bind_rows(first_columns, second_columns)
}

# apply your function to elements in `boysNames` using `map()`
boysNames <- map(boysNames, cleanupNamesData)
```

3. Code for Section 3: Organize the data into one large data frame and store it:

```
# use regex to extract years from file names
Years <- str_extract(boy_file_names, pattern = "[0-9]{4}")

# assign years to list names
names(boysNames) <- Years

# apply name of the list element (.y) as a new column in the data.frame (.x)
boysNames <- imap(boysNames, ~ mutate(.x, Year = as.integer(.y)))

# convert list of data frames into single data frame
boysNames <- bind_rows(boysNames)
```

6.6 Wrap-up

6.6.1 Feedback

These workshops are a work in progress, please provide any feedback to: `help@iq.harvard.edu`

6.6.2 Resources

- IQSS
  - Workshops: `https://www.iq.harvard.edu/data-science-services/workshop-materials`
  - Data Science Services: `https://www.iq.harvard.edu/data-science-services`
  - Research Computing Environment: `https://iqss.github.io/dss-rce/`
- HBS
  - Research Computing Services workshops: `https://training.rcs.hbs.org/workshops`
  - Other HBS RCS resources: `https://training.rcs.hbs.org/workshop-materials`
  - RCS consulting email: `mailto:research@hbs.edu`
- R
  - Learn from the best: `http://adv-r.had.co.nz/`; `http://r4ds.had.co.nz/`
  - R documentation: `http://cran.r-project.org/manuals.html`
  - Collection of R tutorials: `http://cran.r-project.org/other-docs.html`
  - R for Programmers (by Norman Matloff, UC–Davis) `http://heather.cs.ucdavis.edu/~matloff/R/RProg.pdf`
  - Calling C and Fortran from R (by Charles Geyer, UMinn) `http://www.stat.umn.edu/~charlie/rc/`
  - State of the Art in Parallel Computing with R (Schmidberger et al.) `http://www.jstatso`|.org/v31/i01/paper

Part III

Python

Chapter 7

Python Installation

Your professional conduct is greatly appreciated. Out of respect to your fellow workshop attendees and instructors, please arrive at your workshop on time, having pre-installed all necessary software and materials. This will likely take 15-20 minutes.

Before starting any of our Python workshops, it is necessary to complete 2 tasks. Please make sure both of these tasks are completed **before** you attend your workshop, as, depending on your internet speed, they may take a long time.

1. download and unzip **class materials**
2. download and install **Anaconda Python 3 distribution**

7.1 Troubleshooting session

We will hold a troubleshooting session to help with setup during the 20 minutes prior to the start of the workshop. **If you are unable to complete all four tasks by yourself, please join us at the workshop location for this session.** Once the workshop starts we will **NOT** be able to give you one-to-one assistance with troubleshooting installation problems. Likewise, if you arrive late, please do **NOT** expect one-to-one assistance for anything covered at the beginning of the workshop.

7.2 Materials

Download class materials for your workshop:

- Python Introduction: `https://github.com/IQSS/dss-workshops/raw/master/Python/PythonIntro.zip`
- Python Webscraping: `https://github.com/IQSS/dss-workshops/raw/master/Python/PythonWebScrape.zip`

Extract materials from the zipped directory (Right-click => Extract All on Windows, double-click on Mac) and move them to your desktop.

It will be useful when you view the above materials for you to see the different file extensions on your computer. Here are instructions for enabling this:

- Mac OS
- Windows OS

7.3 Software

The **Anaconda Python distribution** is designed with data science in mind and contains a curated set of 270+ pre-installed Python packages. It is essential that you have the Anaconda Python distribution pre-installed so that we can start the workshop on time. It is also important that you have the **latest version** of the distribution, which currently is:

- Anaconda Python distribution version **2020.11**, which contains Python version **3.8.5**.

Mac OS X:

- Install Anaconda Python 3 by downloading and running this .pkg file. Accept the defaults proposed by the Anaconda installer.

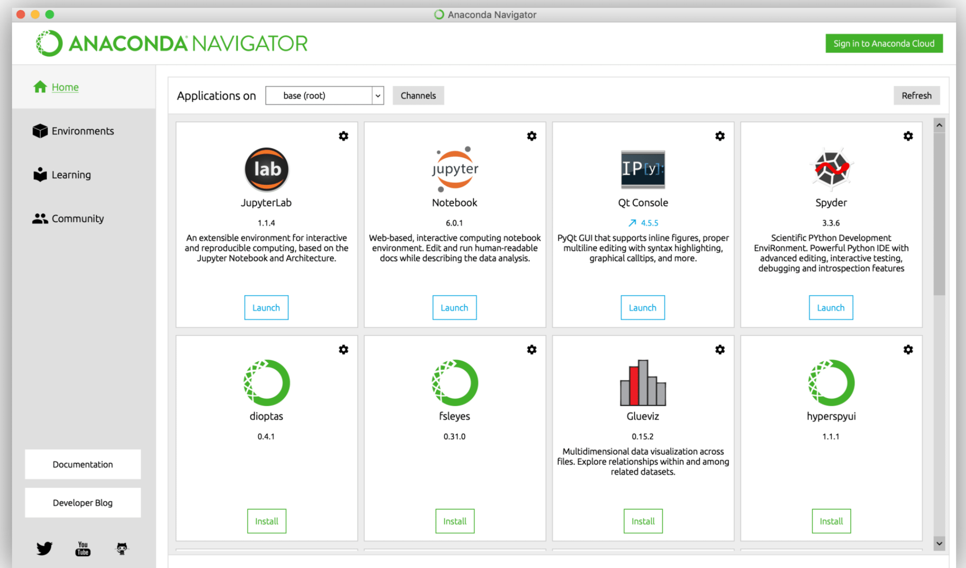
Windows:

- Install Anaconda Python 3 by downloading and running this .exe file. Accept the defaults proposed by the Anaconda installer.

Linux:

- Install Anaconda Python 3 by downloading and running this .sh file. Accept the defaults proposed by the Anaconda installer.

Success? After installing, please start the `Anaconda Navigator` program. If you were successful with the installation, you should see a window similar to this:



To check that the installation is working correctly, click the `Launch` button under `JupyterLab`. A JupyterLab window should open in your web browser.

If you are having any difficulties with the installation, please stop by the training room 20 minutes prior to the start of the workshop.

7.4 Jupyter notebook interfaces

We will be using Jupyter Notebooks to run our Python code. Jupyter Notebooks are documents that combine text, code, images, math, and rich media and can be viewed in a browser. There are two main ways to interact with Jupyter Notebooks:

1. using **JupyterLab**, a modern "extensible environment for interactive and reproducible computing" that runs in your web browser.
2. using **Jupyter Notebook**, an older browser-based application.

Compared to Jupyter Notebook, JupyterLab provides a more modern, richer and more robust coding environment. For this reason, **we strongly recommend that you use JupyterLab to interact with notebooks**.

7.4.1 Launch JupyterLab

Here's how to start JupyterLab and open a notebook within this interface (**recommended**):

1. Start the `Anaconda Navigator` program
2. Click the `Launch` button under `JupyterLab`
3. A browser window will open with your computer's files listed on the left hand side of the page. Navigate to the folder with the workshop materials that you downloaded to your desktop and double-click on the folder
4. Within the workshop materials folder, double-click on the file with the word "BLANK" in the name (`*_BLANK.ipynb`). (If a pop-up window asks you to `Select Kernel` choose `Python 3` kernel.) The Jupyter Notebook should now open on the right hand side of the page.

If you have technical difficulty with JupyterLab you can try the older Jupyter Notebook as a fallback by clicking the `Launch` button under `Jupyter Notebook` in step 2.

7.5 Resources

- IQSS
  - Workshops: `https://www.iq.harvard.edu/data-science-services/workshop-materials`
  - Data Science Services: `https://www.iq.harvard.edu/data-science-services`
  - Research Computing Environment: `https://iqss.github.io/dss-rce/`
- HBS
  - Research Computing Services workshops: `https://training.rcs.hbs.org/workshops`
  - Other HBS RCS resources: `https://training.rcs.hbs.org/workshop-materials`
  - RCS consulting email: `mailto:research@hbs.edu`

Chapter 8

Python Introduction

Topics

- Functions
- Objects
- Assignment
- Finding help
- List and dictionary structures
- Indexing data structures
- Iterating over collections of data
- Importing packages

8.1 Setup

8.1.1 Software and Materials

Follow the Python Installation instructions and ensure that you can successfully start JupyterLab.

A handy cheat-sheet is available to help you look up and remember basic syntax.

8.1.2 Class Structure

Informal - Ask questions at any time. Really!

Collaboration is encouraged - please spend a minute introducing yourself to your neighbors!

8.1.3 Prerequisites

This is an introductory Python course:

- Assumes no prior knowledge of **how to use** Python
- We do assume you know **why** you want to learn Python. If you don't, and want a comparison of Python to other statistical software, see our Data Science Tools workshop
- Relatively slow-paced

8.1.4 Goals

We will learn about the Python language by analyzing the text of Lewis Carroll's *Alice's Adventures in Wonderland*. In particular, our goals are to learn about:

1. What Python is and how it works
2. How we can interact with Python
3. Foundations of the language (functions, objects, assignment, methods)
4. Using methods and lists to analyze data
5. Iterating over collections of data to automate repetitive tasks
6. Storing related data in dictionaries (as key - value pairs)
7. Importing packages to add functionality

8.2 Python basics

GOAL: To learn about the foundations of the Python language.

1. What Python is and how it works
2. Python interfaces
3. Functions
4. Objects
5. Assignment
6. Methods

8.2.1 What is Python?

- Python is a free general purpose programming language
- Python is an interpreted language, not a compiled one, meaning that all commands typed on the keyboard are directly executed without requiring to build a complete program (this is like R and unlike C, Fortran, Pascal, etc.)
- Python has existed for about 30 years
- Python is modular — most functionality is from add-on packages. So the language can be thought of as a *platform* for creating and running a large number of useful packages.

8.2.2 Why use Python?

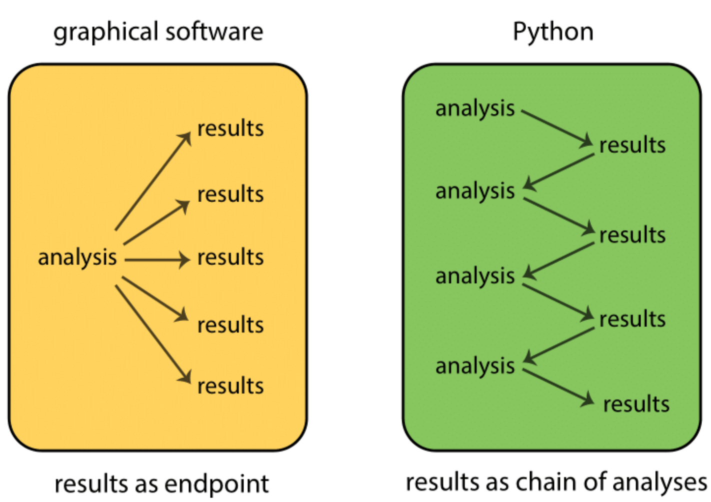
- Relatively easy to learn

- Extremely flexible: can be used to manipulate, analyze, and visualize data, make web sites, write games, and much more (Youtube and DropBox were written in Python)
- Cutting edge machine learning tools
- Publication quality graphics
- 150,000+ add on packages covering all aspects of statistics and machine learning
- Active community of users

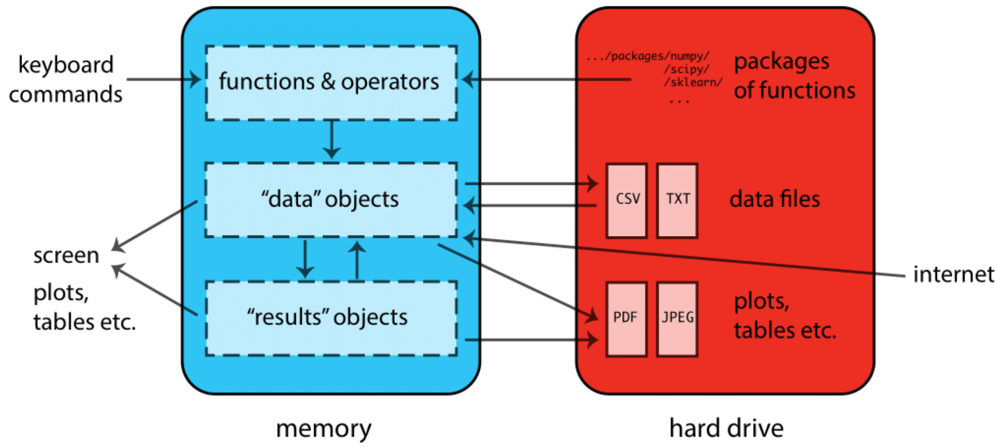
8.2.3 How does Python work?

While graphical-based statistical software (e.g., SPSS, GraphPad) immediately display the results of an analysis, **Python stores results in an `object` (a data structure)**, so that an analysis can be done with no result displayed. Such a feature is very useful, since a user can extract only that part of the results that is of interest and can pass results into further analyses.

For example, if you run a series of 20 regressions and want to compare the different regression coefficients, Python can display only the estimated coefficients: thus the results may take a single line, whereas graphical-based software could open 20 results windows. In addition, these regression coefficients can be passed directly into further analyses — such as generating predictions.



When Python is running, variables, data, functions, results, etc., are **stored in memory** on the computer in the form of `objects` that have a name. The user can **perform actions** on these objects with `operators` (arithmetic, logical, comparison, etc.) and `functions` (which are themselves objects). Here's a schematic of how this all fits together:



8.2.4 Interfaces

8.2.4.1 Text editors, IDEs, & Notebooks

There are different ways of interacting with Python. The two main ways are through:

1. **text editors** or **Integrated Development Environments (IDEs):** Text editors and IDEs are not really separate categories; as you add features to a text editor it becomes more like an IDE. Some editors/IDEs are language-specific while others are general purpose — typically providing language support via plugins. The following table lists a few popular editors/IDEs that can be used with Python. In this workshop, we will use JupyterLab, a modern "extensible environment for interactive and reproducible computing" that runs in your web browser.

Editor / IDE	Features	Ease of use	Language support
Spyder	Excellent	Easy	Python only
PyCharm	Excellent	Moderate	Python only
JupyterLab	Good	Easy	Excellent
VS code	Excellent	Easy	Very good
Atom	Good	Moderate	Good
Vim	Excellent	Hard	Good
Emacs	Excellent	Hard	Excellent

2. **Notebooks:** Browser-based applications that allow you to create and share documents that contain live code, equations, visualizations, and narrative text. One popular choice is Jupyter Notebook; an open source notebook that has support for 40+ languages, but has limited features compared with the JupyterLab IDE.

8.2.4.2 Source code & literate programming

There are also several different **formats** available for writing code in Python. These basically boil down to a choice between:

1. **Source code:** the practice of writing code, and possibly comments, in a plain text document. In Python this is done by writing code in a text file with a `.py` extension. Writing source code has the great advantage of being simple. Souce code is the format of choice if you intend to run your code as a complete script - for example, from the command line.

2. **Literate programming:** the practice of embedding computer code in a natural language document. In Python this is often done using the aformentioned Jupyter Notebook, which is a JSON document containing an ordered list of input/output cells which can contain code, text (using *Markdown*), mathematics, plots, and rich media, usually ending with the `.ipynb` extension. Jupyter Notebooks are easy to write, human-readable, and the format of choice if you intend to run your code interactively, by running small pieces of code and looking at each output. Researchers can use Notebooks to write their journal papers, dissertations, and statistics/math class notes, since it is easy to convert into other formats later, such as HTML (for a webpage), MS Word, or PDF (via LaTeX).

Here are some resources for learning more about Jupyter Notebooks:

- `https://www.dataquest.io/blog/jupyter-notebook-tutorial/`
- `https://www.datacamp.com/community/tutorials/tutorial-jupyter-notebook`
- `https://realpython.com/jupyter-notebook-introduction/`

8.2.5 Launch JupyterLab

1. Start the `Anaconda Navigator` program
2. Click the `Launch` button under `JupyterLab`
3. A browser window will open with your computer's files listed on the left hand side of the page. Navigate to the folder called `PythonIntro` that you downloaded to your desktop and double-click on the folder
4. Within the `PythonIntro` folder, double-click on the file with the word "BLANK" in the name (`PythonIntro_BLANK.ipynb`). A pop-up window will ask you to `Select Kernal` — you should select the Python 3 kernal. The Jupyter Notebook should now open on the right hand side of the page

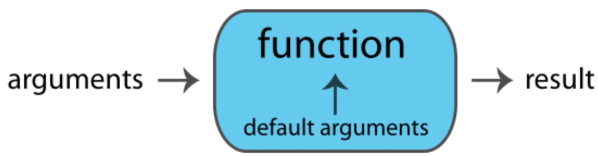
A Jupyter Notebook contains one or more *cells* containing notes or code. To insert a new cell click the `+` button in the upper left. To execute a cell, select it and press `Control+Enter` or click the `Run` button at the top.

8.2.6 Syntax rules

- Python is case sensitive
- Python uses white space as part of the syntax (it's important!)
- Variable names should start with a letter (A-Z and a-z) and can include letters, digits (0-9), and underscores (_)
- Comments can be inserted using a hash `#` symbol
- Functions must be written with parentheses, even if there is nothing within them; for example: `len()`

8.2.7 Function calls

Functions perform actions — they take some input, called `arguments` and return some output (i.e., a result). Here's a schematic of how a function works:



The general form for calling Python functions is

```
# function_name(arg1, arg2, arg3, ... argn)
```

The arguments in a function can be objects (data, formulae, expressions, etc.), some of which could be defined by default in the function; these default values may be modified by the user by specifying options.

8.2.8 Assignment

In Python we can assign an object (data structure) to an name using the `=` operator.

```
# name = thing_to_assign
x = 10
```

The name on the left of the equals sign is one that we chose. When choosing names, they must:

1. start with a *letter*
2. use only *letters*, *numbers* and *underscores*

8.2.9 Reading data

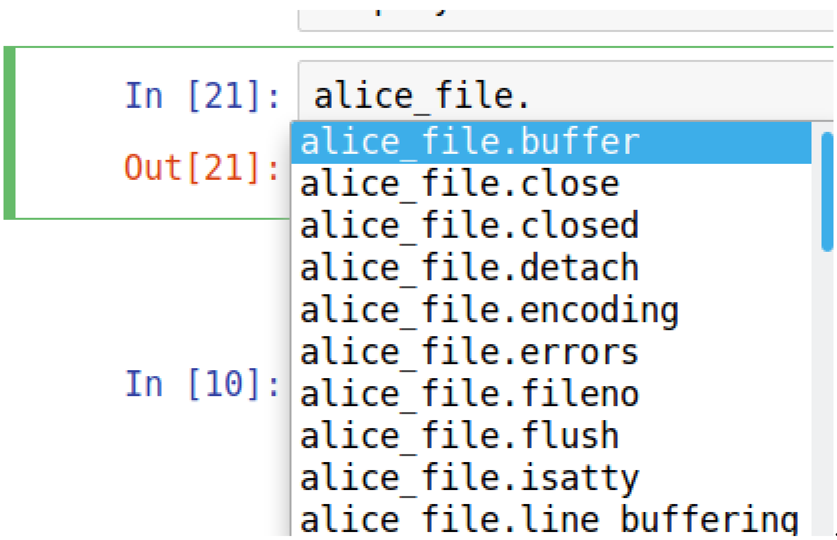
Reading information from a file is the first step in many projects, so we'll use functions to read data into Python and assign them to a named object. The workshop materials you downloaded earlier include a file named `Alice_in_wonderland.txt` which contains the text of Lewis Carroll's *Alice's Adventures in Wonderland*. We can use the `open()` function to create a file **object** that makes a **connection** to the file:

```
alice_file = open("Alice_in_wonderland.txt")
```

The `alice_file` object name we just created does *not* contain the contents of `Alice_in_wonderland.txt`. It is a representation in Python of the *file itself* rather than the *contents* of the file.

8.2.10 Object methods

The `alice_file` object provides *methods* that we can use to do things with it. Methods are invoked using syntax that looks like `ObjectName.method()`. You can see the methods available for acting on an object by typing the object's name followed by a `.` and pressing the `tab` key. For example, typing `alice_file.` and pressing `tab` will display a list of methods as shown below.



Among the methods we have for doing things with our `alice_file` object is one named `read`. We can use the `help` function to learn more about it.

```
help(alice_file.read)
```

```
## Help on built-in function read:
##
## read(size=-1, /) method of _io.TextIOWrapper instance
```

```
##     Read at most n characters from stream.
##
##     Read from underlying buffer until we have n characters or we hit EOF.
##     If n is negative or omitted, read until EOF.
```

Since `alice_file.read` looks promising, we will invoke this method and see what it does:

```
alice_txt = alice_file.read()
```

Now let's print the first 500 characters:

```
print(alice_txt[:500]) # the [:500] gets the first 500 characters -- more on this later.
```

```
## ALICE'S ADVENTURES IN WONDERLAND
##
## by
##
## Lewis Carroll
##
## CHAPTER I. Down the Rabbit-Hole
##
## Alice was beginning to get very tired of sitting by her sister on the
## bank, and of having nothing to do: once or twice she had peeped into the
## book her sister was reading, but it had no pictures or conversations in
## it, 'and what is the use of a book,' thought Alice 'without pictures or
## conversations?'
##
## So she was considering in her own mind (as well as she could, for the
## hot day made her feel very sleepy and s
```

That's all there is to it! We've read the contents of `Alice_in_wonderland.txt` and stored this text in a Python object we named `alice_txt`. Now let's start to explore this object, and learn some more things about Python along the way.

8.3 Using object methods & lists

GOAL: To learn how to use methods and lists to analyze data. We will do this using the Alice text to count:

1. Words
2. Chapters
3. Paragraphs

How many words does the text contain? To answer this question, we can split the text up so there is one element per word, and then count the number of words.

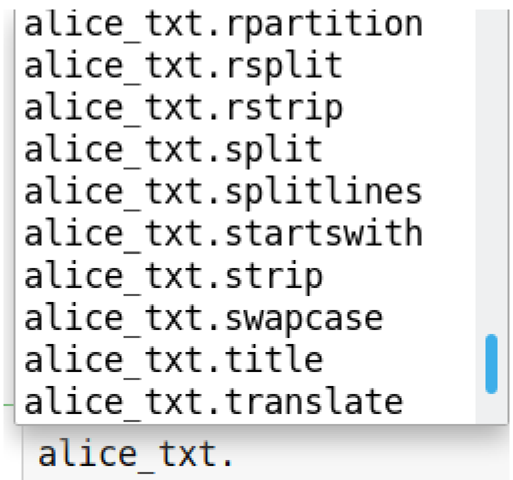
8.3.1 Splitting a string into a list of words

How do we figure out how to split strings in Python? We can ask Python what our `alice_txt` object is and what methods it provides. We can ask Python what things are using the `type()` function, like this:

```
type(alice_txt)
```

```
## <class 'str'>
```

Python tells us that `alice_txt` is of type `str` (i.e., it is a string). We can find out what methods are available for working with strings by typing `alice_txt.` and pressing `tab`. We'll see that among the methods is one named `split`, as shown below.



To learn how to use this method we can check the documentation.

```
help(alice_txt.split)
```

```
## Help on built-in function split:
##
## split(...) method of builtins.str instance
##     S.split(sep=None, maxsplit=-1) -> list of strings
##
##     Return a list of the words in S, using sep as the
##     delimiter string.  If maxsplit is given, at most maxsplit
##     splits are done. If sep is not specified or is None, any
##     whitespace string is a separator and empty strings are
##     removed from the result.
```

Since the default is to split on whitespace (spaces, newlines, tabs) we can get a reasonable word count simply by calling the `split` method and counting the number of elements in the result. But, before we do that, we should learn more about the type of object the `split` method has returned.

```
alice_words = alice_txt.split() # returns a list
type(alice_words)
```

```
## <class 'list'>
```

8.3.2 Working with lists

The `split` method we used to break up the text of *Alice in Wonderland* into words produced a *list*. A lot of the techniques we'll use later to analyze this text also produce lists, so its worth taking a few minutes to learn more about them.

Note that the displayed representation of lists and other data structures in Python often closely matches the syntax used to create them. For example, we can create a list using square brackets, just as we see when we print a list.

A *list* in Python is used to store a collection of items:

```
# create a list
y = [1, "b", 3, "D", 5, 6]
```

As with other types in Python, you can get a list of methods by typing the name of the object followed by a `.` and pressing `tab`.

8.3.3 Extracting subsets from lists

Among the things you can do with a list is extract subsets of items using **bracket indexing notation**. This is useful in many situations, including the current one where we want to inspect a long list without printing out the whole thing.

The examples below show how indexing works in Python. First using pseudocode:

```
# syntax
# object[ start : end : by ]

# defaults
# object[ 0 : end : 1 ]
```

Then using a real list:

```
# create a list
y = [1, "b", 3, "D", 5, 6]

y[0] # returns first element - the number 1 (yes, the index counts from zero!)
```

```
## 1
```

```
y[1] # returns second element - the letter "b"
```

```
## 'b'
```

```
y[ :3] # returns a list with only the first 3 elements, but index is of length 4 (0 to 3) becaus
```

```
## [1, 'b', 3]
```

```
y[2:5] # returns a list with elements 3, "D", 5
```

```
## [3, 'D', 5]
```

```
y[-1] # returns last element - the number 6
```

```
## 6
```

```
y[-4: ] # returns a list with last 4 elements
```

```
## [3, 'D', 5, 6]
```

```
alice_words[10:18] # returns a list with words 11 through 19
```

```
## ['the', 'Rabbit-Hole', 'Alice', 'was', 'beginning', 'to', 'get', 'very']
```

```
alice_words[-10: ] # returns a list with the last 10 words
```

```
## ['her', 'own', 'child-life,', 'and', 'the', 'happy', 'summer', 'days.', 'THE', 'END']
```

8.3.4 Using sets to count unique items

Now that we have a list containing the individual words from *Alice's Adventures in Wonderland*, we can calculate how many words there are in total using the `len()` (length) function:

```
len(alice_words) # counts elements in a data structure
```

```
## 26445
```

According to our above computation, there are about 26 thousand total words in the Alice text. But how many *unique* words are there? Python has a special data structure called a *set* that makes it easy to find out. A *set* drops all duplicates, giving a collection of the unique elements. Here's a simple example:

```
# set example
mylist = {1, 5, 9, 9, 4, 5}
set(mylist)
```

```
## {1, 4, 5, 9}
```

Now we can count the number of unique elements in the list by getting the length `len()` of the set `set()`:

```
len(set(mylist))
```

```
## 4
```

We can now use the `set()` function to convert the list of all words (`alice_words`) into a set of *unique* words and then count them:

```
len(set(alice_words)) # counts unique elements in a data structure
```

```
## 5295
```

There are 5295 unique words in the text.

8.3.5 Exercise 0

Reading text from a file & splitting

Alice's Adventures in Wonderland is full of memorable characters. The main characters from the story are listed, one-per-line, in the file named `Characters.txt`.

NOTE: we will not always explicitly demonstrate everything you need to know in order to complete an exercise. Instead we focus on teaching you how to discover available methods and how use the help function to learn how to use them. It is expected that you will spend some time during the exercises looking for appropriate methods and perhaps reading documentation.

1. Open the `Characters.txt` file and read its contents.

```
##
```

2. Split text on newlines to produce a list with one element per line. Store the result as `alice_characters`. HINT: you can split on newlines using the `\n` separator.

```
##
```

Click for Exercise 0 Solution

1. Open the Characters.txt file and read its contents.

```python
characters_file = open("Characters.txt")
characters_txt = characters_file.read()
```

2. Split text on newlines to produce a list with one element per line. Store the result as "alice_characters".

```python
alice_characters = characters_txt.split(sep="\n")
alice_characters
```

```
## ['Alice', 'White Rabbit', 'Mouse', 'Dodo', 'Lory', 'Eaglet', 'Duck', 'Pat', 'Bill the Lizard'
```

8.3.6 Control flow

Sometimes we may want to control the flow of code in an analysis using **choices**, such as `if` and `else` statements, which allow you to run different code depending on the input. The basic form is:

````
```python
if (condition) true_action else false_action
```

If `condition` is `TRUE`, `true_action` is evaluated; if `condition` is `FALSE`,
the optional `false_action` is evaluated.
````

The conditions that are evaluated use **logical and relational operators** to determine equivalence or make some other relational comparisons.

8.3.7 Logical & relational operators

Here's a table of commonly used relational operators:

Operator	Meaning
`==`	equal to
`!=`	not equal to
`>`	greater than
`>=`	greater than or equal to
`<`	less than
`<=`	less than or equal to

These relational operators may be combined with logical operators, such as `and` or `or`, as we'll see below.

8.3.8 Counting list elements

Now that we know how to split a string and how to work with the resulting list, we can split on chapter markers to count the number of chapters. All we need to do is specify the string to split on. Since each chapter is marked with the string `'CHAPTER '` followed by the chapter number, we can split the text up into chapters using this as the separator.

```
alice_chapters = alice_txt.split("CHAPTER ")
len(alice_chapters)
```

```
## 13
```

Since the first element contains the material *before* the first chapter, this tells us there are twelve chapters in the book.

We can also count the number of times the "Mouse" and "Duck" characters appear in a given Chapter, say Chapter 2:

```
mouse_count_ch2 = alice_chapters[2].count("Mouse")
print(mouse_count_ch2)
```

```
## 11
```

```
duck_count_ch2 = alice_chapters[2].count("Duck")
print(duck_count_ch2)
```

```
## 1
```

By combining choice statements with logical and/or relational operators, we can then determine which of these two characters appears more often in Chapter 2:

```
if mouse_count_ch2 < duck_count_ch2:
    print("Mouse count is less than Duck count in Chapter II.")
elif mouse_count_ch2 > duck_count_ch2:
    print("Mouse count is larger than Duck count in Chapter II.")
else:
    print("Mouse count is equal to Duck count in Chapter II.")
```

```
## Mouse count is larger than Duck count in Chapter II.
```

We can count paragraphs in a similar way to chapters. Paragraphs are indicated by a blank line, i.e., two newlines in a row. When working with strings we can represent newlines with `\n`. Paragraphs are indicated by two new lines, and so our basic paragraph separator is `\n\n`. We can see this separator by looking at the content.

```
print(alice_txt[:500]) # explicit printing --- formats text nicely
```

```
## ALICE'S ADVENTURES IN WONDERLAND
##
## by
##
## Lewis Carroll
##
## CHAPTER I. Down the Rabbit-Hole
##
## Alice was beginning to get very tired of sitting by her sister on the
## bank, and of having nothing to do: once or twice she had peeped into the
## book her sister was reading, but it had no pictures or conversations in
## it, 'and what is the use of a book,' thought Alice 'without pictures or
## conversations?'
##
## So she was considering in her own mind (as well as she could, for the
## hot day made her feel very sleepy and s
```

```
alice_txt[:500] # returns content without printing it
```

```
## "\ufeffALICE'S ADVENTURES IN WONDERLAND\n\nby\n\nLewis Carroll\n\nCHAPTER I. Down the Rabbit-H
```

```
alice_paragraphs = alice_txt.split("\n\n")
```

Before counting the number of paragraphs, I want to inspect the result to see if it looks correct:

```
print(alice_paragraphs[0], "\n==========")
```

```
## ALICE'S ADVENTURES IN WONDERLAND
## ==========
```

```
print(alice_paragraphs[1], "\n==========")
```

```
## by
## ==========
```

```
print(alice_paragraphs[2], "\n==========")
```

```
## Lewis Carroll
## ==========
```

We're counting the title, author, and chapter lines as paragraphs, but this will do for a rough count.

```
len(alice_paragraphs)
```

```
## 830
```

Now let's use a logical operator to find out if "Alice" or "Eaglet" appear in paragraph 11:

```
alice_eaglet_exist = "Alice" in alice_paragraphs[10] or "Eaglet" in alice_paragraphs[10]
alice_eaglet_exist
```

```
## True
```

8.3.9 Exercise 1

Count the number of main characters

So far we've learned that there are 12 chapters, around 830 paragraphs, and about 26 thousand words in *Alice's Adventures in Wonderland*. Along the way we've also learned how to open a file and read its contents, split strings, calculate the length of objects, discover methods for string and list objects, and index/subset lists in Python. Now it is time for you to put these skills to use to learn something about the main characters in the story.

1. Count the number of main characters in the story (i.e., get the length of the list you created in previous exercise).

```
##
```

2. Extract and print just the first character from the list you created in the previous exercise.

```
##
```

3. Test whether the length of the 3rd and 8th character's names are equal. Test whether the length of the 3rd character's name is greater than or equal to the length of the 6th character's name. Now test whether EITHER of the above conditions are true. HINT: use the `len()` function.

```
##
```

4. (BONUS, optional): Sort the list you created in step 2 alphabetically, and then extract the last element.

```
##
```

Click for Exercise 1 Solution

1. Count the number of main characters in the story (i.e., get the length of the list you created in previous exercise).

```
len(alice_characters)
```

```
## 22
```

2. Extract and print just the first character from the list you created in the previous exercise.

```
print(alice_characters[0])
```

```
## Alice
```

3. Test whether the length of the 3rd and 8th character's names are equal. Test whether the length of the 3rd character's name is greater than or equal to the length of the 6th character's name. Now test whether EITHER of the above conditions are true. HINT: use the `len()` function.

```
len(alice_characters[2]) == len(alice_characters[7]) or len(alice_characters[2]) >= len(alice_cha
```

```
## False
```

4. (BONUS, optional): Sort the list you created in step 2 alphabetically, and then extract the last element.

```
alice_characters.sort()
alice_characters[-1]
```

```
## 'White Rabbit'
```

8.4 Iterating over collections of data

GOAL: To learn how to automate repetitive tasks by iterating over collections of data. We will do this using the Alice text to count:

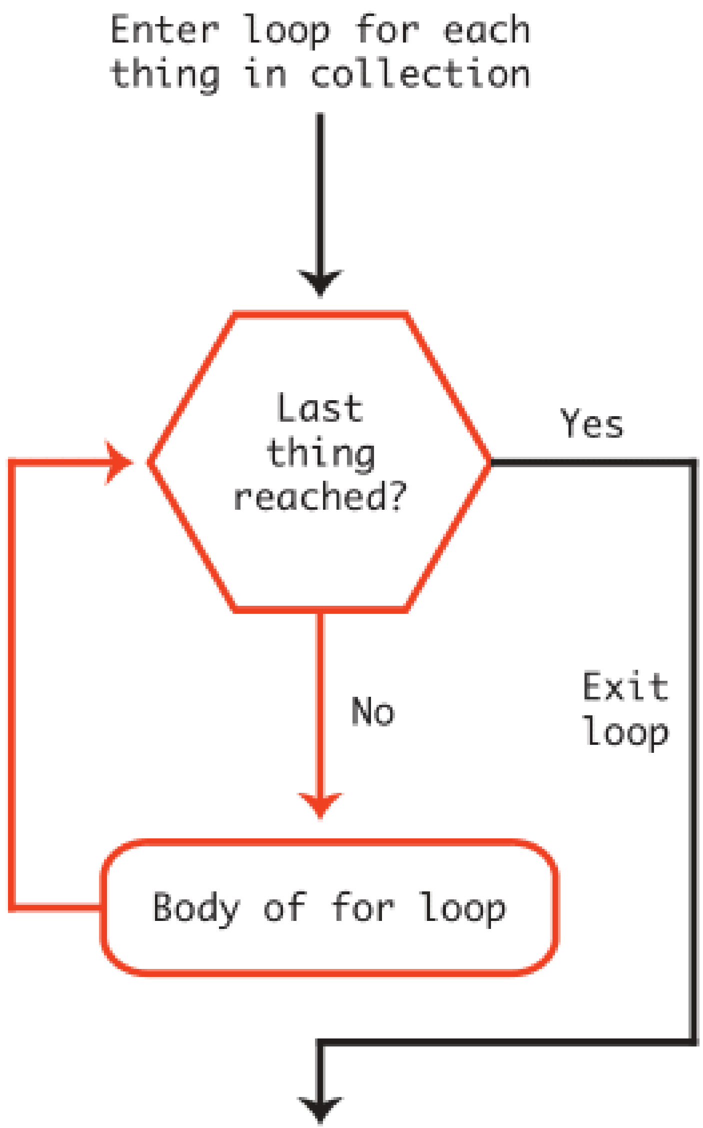
1. Words nested within paragraphs
2. Paragraphs nested within chapters

This far our analysis has treated the text as a "flat" data structure. For example, when we counted words we just counted words in the whole document, rather than counting the number of words in each chapter. If we want to treat our document as a nested structure, with words forming sentences, sentences forming paragraphs, paragraphs forming chapters, and chapters forming the book, we need to learn some additional tools. Specifically, we need to learn how to iterate over lists (or other collections) and do things with each element in a collection.

There are several ways to iterate in Python, of which we will focus on *for loops*.

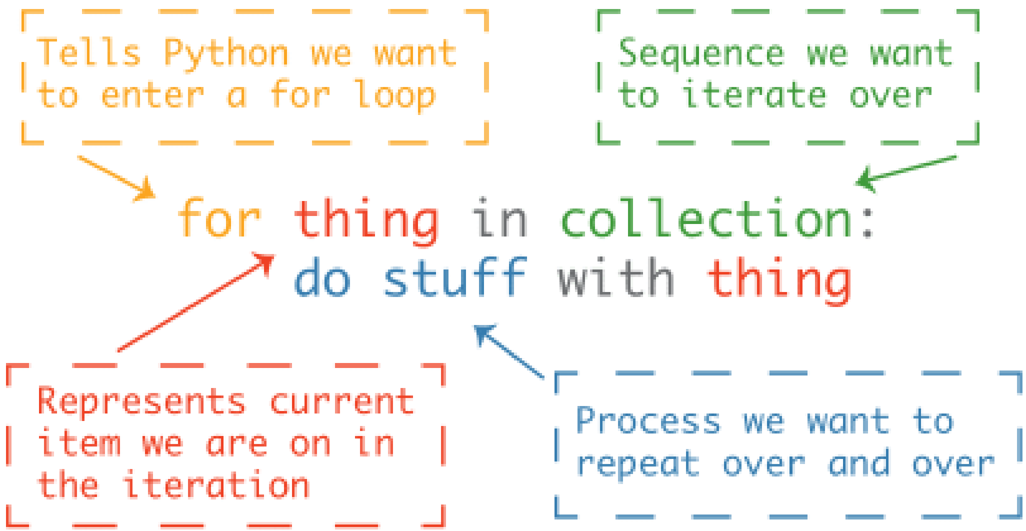
8.4.1 Iterating over lists using for-loops

A *for loop* is a way of cycling through the elements of a collection and doing something with each one. The for loop logic is:



The for loop syntax is:

```
for <thing> in <collection>:
    do stuff with <thing>
```



Notice that:

1. **the body of the for-loop is indented**. This is important, because it is this indentation that defines the *body* of the loop — the place where things are done.
2. **White space matters in Python!**

A simple example:

```
for i in range(10):
    print(i)
```

```
## 0
## 1
## 2
## 3
## 4
## 5
## 6
## 7
## 8
## 9
```

```
print('DONE.')
```

```
## DONE.
```

Notice that "DONE." is only printed once, since `print('DONE.')` is not indented and is therefore outside of the body of the loop.

As a simple example using the Alice text, we can cycle through the first 6 paragraphs and print each one. Cycling through with a loop makes it easy to insert a separator between the paragraphs, making it much clearer to read the output:

```
for paragraph in alice_paragraphs[:6]:
    print(paragraph)
    print('==================================')
```

```
## ALICE'S ADVENTURES IN WONDERLAND
## ==================================
## by
## ==================================
## Lewis Carroll
## ==================================
## CHAPTER I. Down the Rabbit-Hole
## ==================================
## Alice was beginning to get very tired of sitting by her sister on the
## bank, and of having nothing to do: once or twice she had peeped into the
## book her sister was reading, but it had no pictures or conversations in
## it, 'and what is the use of a book,' thought Alice 'without pictures or
## conversations?'
## ==================================
## So she was considering in her own mind (as well as she could, for the
## hot day made her feel very sleepy and stupid), whether the pleasure
## of making a daisy-chain would be worth the trouble of getting up and
## picking the daisies, when suddenly a White Rabbit with pink eyes ran
## close by her.
## ==================================
```

```
print('DONE.')
```

```
## DONE.
```

Loops in Python are great because the syntax is relatively simple, and because they are very powerful. Inside of the body of a loop you can use all the tools you use elsewhere in Python.

Here is one more example of a loop, this time iterating over all the chapters and calculating the number of paragraphs in each chapter.

```
for chapter in alice_chapters[1:]:
    paragraphs = chapter.split("\n\n")
    print(len(paragraphs))
```

```
## 33
## 29
```

```
## 51
## 45
## 81
## 84
## 108
## 74
## 95
## 88
## 77
## 73
```

8.4.2 Organizing results in dictionaries

It's often useful to store separate pieces of data that are related to one another in a `dict` (i.e., "dictionary"), which is designed to store key-value pairs. For example, we can calculate the number of times "Alice" is mentioned per chapter and associate each count with the chapter title it corresponds to.

The dictionary structure looks like:

```
# mydict = {key1:value1, key2:value2, key3:value3}
```

A simple example:

```
mydict = {"apple":5, "pear":6, "grape":10}
print(mydict)
```

```
## {'apple': 5, 'pear': 6, 'grape': 10}
```

```
# compare the above dict to a list
mylist =[5, 6, 10]
print(mylist)
```

```
## [5, 6, 10]
```

To associate chapter titles with "Alice" counts, we will first need to learn how to **append** elements to a list:

```
container = [] # a list

for i in range(10):
    container.append(i) # append elements to the list

print(container)
```

```
## [0, 1, 2, 3, 4, 5, 6, 7, 8, 9]
```

Now, with the Alice text, first we can iterate over each chapter and grab just the first line (that is, the chapter titles). These will become our **keys**.

```
chapter_titles = []

for chapter in alice_chapters[1:]:
    chapter_titles.append(chapter.split(sep="\n")[0])

print(chapter_titles)
```

```
## ['I. Down the Rabbit-Hole', 'II. The Pool of Tears', 'III. A Caucus-Race and a Long Tale', 'IV
```

Next, we can iterate over each chapter and count the number of times "Alice" was mentioned. These will become our **values**.

```
chapter_Alice = []

for chapter in alice_chapters[1:]:
    chapter_Alice.append(chapter.count("Alice"))

print(chapter_Alice)
```

```
## [28, 24, 23, 31, 35, 43, 51, 39, 52, 30, 16, 23]
```

Finally we can combine the chapter titles (**keys**) and "Alice" counts (**values**) and convert them to a dictionary.

```
# combine titles and counts
mydict = dict(zip(chapter_titles, chapter_Alice))

print(mydict)

# help(zip)
```

```
## {'I. Down the Rabbit-Hole': 28, 'II. The Pool of Tears': 24, 'III. A Caucus-Race and a Long Ta
```

8.4.3 Exercise 2

Iterating & counting things

Now that we know how to iterate using for-loops, the possibilities really start to open up. For example, we can use these techniques to count the number of times each character appears in the story.

1. Make sure you have both the text and the list of characters.

Open and read both “Alice_in_wonderland.txt” and “Characters.txt” if you have not already done so.

```
##
```

2. Which chapter has the most words?

Split the text into chapters (i.e., split on “CHAPTER”) and use a for-loop to iterate over the chapters. For each chapter, split it into words and calculate the length.

```
##
```

3. How many times is each character mentioned in the text?

Iterate over the list of characters using a for-loop. For each character, call the count method with that character as the argument.

```
##
```

4. (BONUS, optional): Put the character counts computed above in a dictionary with character names as the keys and counts as the values.

```
##
```

Click for Exercise 2 Solution

1. Make sure you have both the text and the list of characters. Open and read both “Alice_in_wonderland.txt” and “Characters.txt” if you have not already done so.

```
characters_txt = open("Characters.txt").read()
alice_txt = open("Alice_in_wonderland.txt").read()
```

2. Which chapter has the most words? Split the text into chapters (i.e., split on “CHAPTER”) and use a for-loop to iterate over the chapters. For each chapter, split it into words and calculate the length.

```
words_per_chapter = []

for chapter in alice_chapters:
    words_per_chapter.append(len(chapter.split()))

print(words_per_chapter)
```

```
## [7, 2184, 2098, 1701, 2614, 2185, 2592, 2286, 2486, 2271, 2028, 1877, 2104]
```

3. How many times is each character mentioned in the text? Iterate over the list of characters using a for-loop. For each character, call the count method with that character as the argument.

```
num_per_character = []

for character in characters_txt.split(sep="\n"):
    num_per_character.append(alice_txt.count(character))

print(num_per_character)
```

```
## [395, 20, 30, 13, 7, 3, 3, 3, 0, 0, 27, 42, 4, 30, 55, 40, 3, 3, 0, 55, 53, 144403]
```

4. (BONUS, optional): Put the character counts computed above in a dictionary with character names as the keys and counts as the values.

```
characters = characters_txt.split(sep="\n")
dict(zip(characters, num_per_character))
```

```
## {'Alice': 395, 'White Rabbit': 20, 'Mouse': 30, 'Dodo': 13, 'Lory': 7, 'Eaglet': 3, 'Duck': 3
```

8.5 Importing packages

GOAL: To learn how to expand Python's functionality by importing packages.

1. Import `numpy`
2. Calculate simple statistics

Now that we know how to iterate over lists and calculate numbers for each element, we may wish to do some simple math using these numbers. For example, we may want to calculate the mean and standard deviation of the distribution of the number of paragraphs in each chapter. Python has a handful of math functions built-in (e.g., `min()` and `max()`) but built-in math support is pretty limited.

When you find that something isn't available in Python itself, its time to look for a package that does it. Although it is somewhat overkill for simply calculating a mean we're going to use a popular package called `numpy` for this. The `numpy` package is included in the Anaconda Python distribution we are using, so we don't need to install it separately.

To use `numpy` or other packages, you must first import them.

```
# import <package-name>
```

We can import `numpy` as follows:

```
import numpy
```

To use functions from a package, we can prefix the function with the package name, separated by a period:

```
# <package-name>.<function_name>()
```

The `numpy` package is very popular and includes a lot of useful functions. For example, we can use it to calculate means and standard deviations:

```
print(numpy.mean(chapter_Alice))
```

```
## 32.916666666666664
```

```
print(numpy.std(chapter_Alice))
```

```
## 10.92747556493366
```

8.6 Wrap-up

8.6.1 Feedback

These workshops are a work in progress, please provide any feedback to: `help@iq.harvard.edu`

8.6.2 Resources

- IQSS
  - Workshops: `https://www.iq.harvard.edu/data-science-services/workshop-materials`
  - Data Science Services: `https://www.iq.harvard.edu/data-science-services`
  - Research Computing Environment: `https://iqss.github.io/dss-rce/`
- HBS
  - Research Computing Services workshops: `https://training.rcs.hbs.org/workshops`
  - Other HBS RCS resources: `https://training.rcs.hbs.org/workshop-materials`
  - RCS consulting email: `mailto:research@hbs.edu`
- Graphics

  - matplotlib: `https://matplotlib.org/`
  - seaborn: `https://seaborn.pydata.org/`
  - plotly: `https://plot.ly/python/`
- Quantitative Data Analysis
  - numpy: `http://www.numpy.org/`
  - scipy: `https://www.scipy.org/`
  - pandas: `https://pandas.pydata.org/`
  - scikit-learn: `http://scikit-learn.org/stable/`
  - statsmodels: `http://www.statsmodels.org/stable/`
- Text analysis
  - textblob: `https://textblob.readthedocs.io/en/dev/`
  - nltk: `http://www.nltk.org/`
  - Gensim: `https://radimrehurek.com/gensim/`
- Webscraping
  - scrapy: `https://scrapy.org/`
  - requests: `http://docs.python-requests.org/en/master/`
  - lxml: `https://lxml.de/`
  - BeautifulSoup: `https://www.crummy.com/software/BeautifulSoup/`
- Social Network Analysis
  - networkx: `https://networkx.github.io/`
  - graph-tool: `https://graph-tool.skewed.de/`

Chapter 9

Python Web-Scraping

Topics

- Web basics
- Making web requests
- Inspecting web sites
- Retrieving JSON data
- Using Xpaths to retrieve `html` content
- Parsing `html` content
- Cleaning and storing text from `html`

9.1 Setup

9.1.1 Software and Materials

Follow the Python Installation instructions and ensure that you can successfully start JupyterLab.

9.1.2 Class Structure

Informal - Ask questions at any time. Really!

Collaboration is encouraged - please spend a minute introducing yourself to your neighbors!

9.1.3 Prerequisites

This is an intermediate / advanced Python course:

- Assumes knowledge of Python, including:

  - lists
  - dictionaries
  - logical indexing
  - iteration with for-loops

- Assumes basic knowledge of web page structure
- Relatively fast-paced

If you need an introduction to Python or a refresher, we recommend our Python Introduction.

9.1.4 Goals

This workshop is organized into two main parts:

1. Retrive information in JSON format
2. Parse HTML files

Note that this workshop will not teach you everything you need to know in order to retrieve data from any web service you might wish to scrape.

9.2 Web scraping background

9.2.1 What is web scraping?

Web scraping is the activity of automating retrieval of information from a web service designed for human interaction.

9.2.2 Is web scraping legal? Is it ethical?

It depends. If you have legal questions seek legal counsel. You can mitigate some ethical issues by building delays and restrictions into your web scraping program so as to avoid impacting the availability of the web service for other users or the cost of hosting the service for the service provider.

9.2.3 Web scraping approaches

No two websites are identical — websites are built for different purposes by different people and so have different underlying structures. Because they are heterogeneous, there is no single way to scrape a website. **The scraping approach therefore has to be tailored to each individual site.** Here are some commonly used approaches:

1. Use requests to extract information from structured JSON / XML files

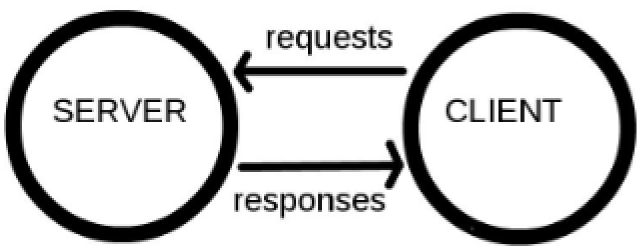
2. Use requests to extract information from HTML
3. Automate a browser to retrieve information from HTML

Bear in mind that even once you've decided upon the best approach for a particular site, it will be necessary to modify that approach to suit your particular use-case.

9.2.4 How does the web work?

9.2.4.1 Components

Computers connected to the web are called **clients** and **servers**. A simplified diagram of how they interact might look like this:



- **Clients** are the typical web user's internet-connected devices (for example, your computer connected to your Wi-Fi) and web-accessing software available on those devices (usually a web browser like Firefox or Chrome).
- **Servers** are computers that store webpages, sites, or apps. When a client device wants to access a webpage, a copy of the webpage is downloaded from the server onto the client machine to be displayed in the user's web browser.
- **HTTP** is a language for clients and servers to speak to each other.

9.2.4.2 So what happens?

When you type a web address into your browser:

1. The browser finds the address of the server that the website lives on.
2. The browser sends an **HTTP request message** to the server, asking it to send a copy of the website to the client.
3. If the server approves the client's request, the server sends the client a `200 OK` message, and then starts displaying the website in the browser.

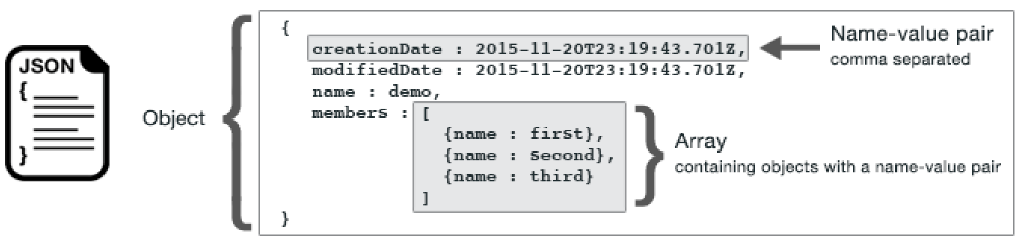
9.3 Retrieve data in JSON format if you can

GOAL: To retrieve information in JSON format and organize it into a spreadsheet.

1. Inspect the website to check if the content is stored in JSON format
2. Make a request to the website server to retrieve the JSON file
3. Convert from JSON format into a Python dictionary
4. Extract the data from the dictionary and store in a .csv file

We wish to extract information from `https://www.harvardartmuseums.org/collections`. Like most modern web pages, a lot goes on behind the scenes to produce the page we see in our browser. Our goal is to pull back the curtain to see what the website does when we interact with it. Once we see how the website works we can start retrieving data from it.

If we are lucky we'll find a resource that returns the data we're looking for in a structured format like JSON or XML.

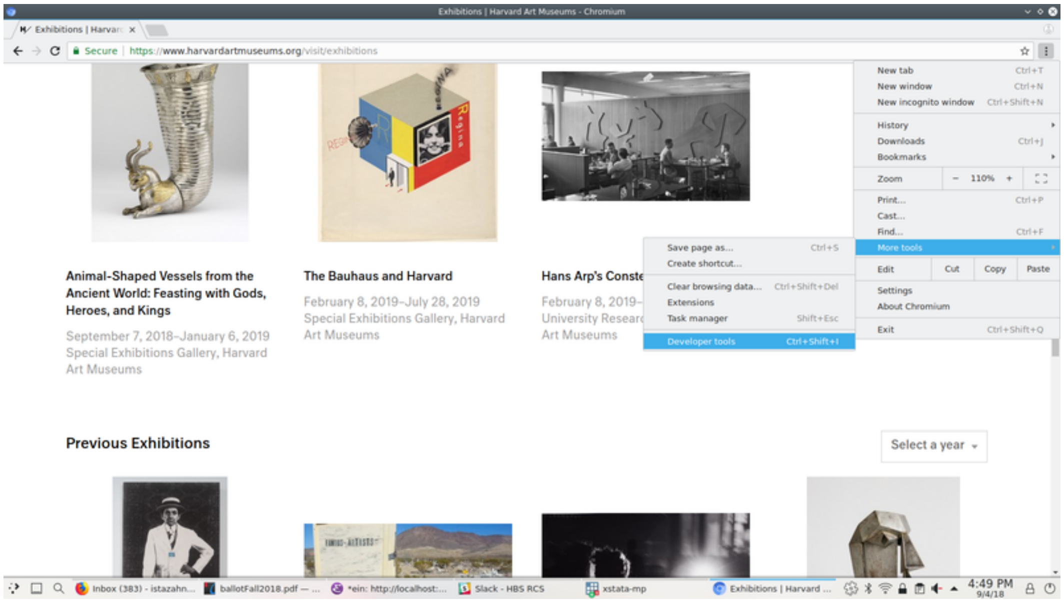


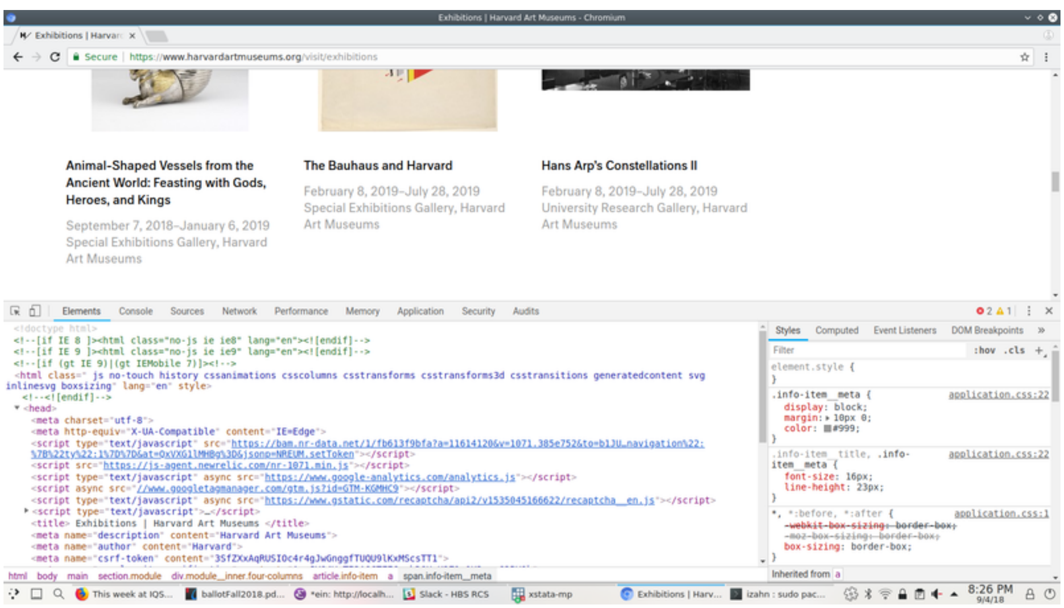
This is useful because it is very easy to convert data from JSON or XML into a spreadsheet type format — like a csv or Excel file.

9.3.1 Examine the website's structure

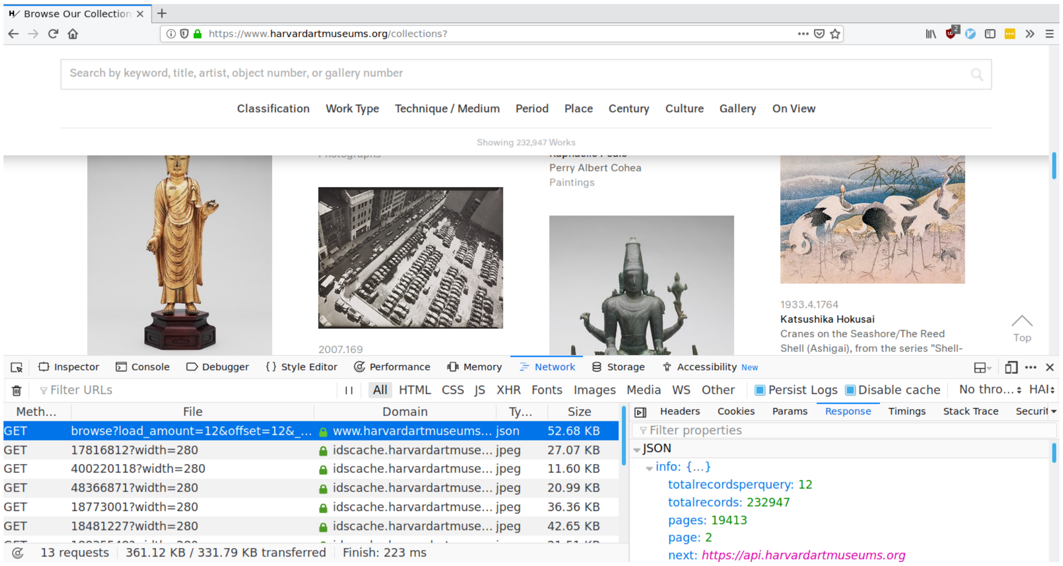
The basic strategy is pretty much the same for most scraping projects. We will use our web browser (Chrome or Firefox recommended) to examine the page you wish to retrieve data from, and copy/paste information from your web browser into your scraping program.

We start by opening the collections web page in a web browser and inspecting it.





If we scroll down to the bottom of the Collections page, we'll see a button that says "Load More". Let's see what happens when we click on that button. To do so, click on "Network" in the developer tools window, then click the "Load More Collections" button. You should see a list of requests that were made as a result of clicking that button, as shown below.



If we look at that second request, the one to a script named `browse`, we'll see that it returns all the information we need, in a convenient format called `JSON`. All we need to retrieve collection data is to make `GET` requests to `https://www.harvardartmuseums.org/browse` with the correct parameters.

9.3.2 Launch JupyterLab

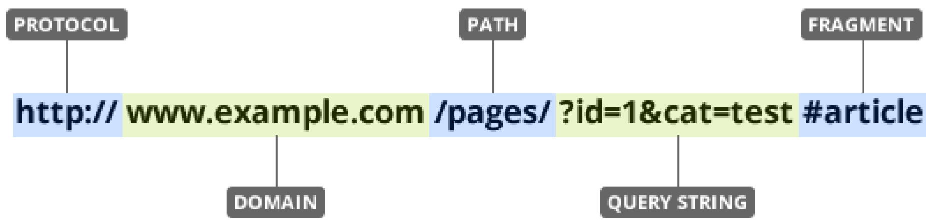
1. Start the `Anaconda Navigator` program
2. Click the `Launch` button under `Jupyter Lab`
3. A browser window will open with your computer's files listed on the left hand side of the page. Navigate to the folder called `PythonWebScrape` that you downloaded to your desktop and double-click on the folder
4. Within the `PythonWebScrape` folder, double-click on the file with the word "BLANK" in the name (`PythonWebScrape_BLANK.ipynb`). A pop-up window will ask you to `Select Kernal` — you should select the Python 3 kernal. The Jupyter Notebook should now open on the right hand side of the page

A Jupyter Notebook contains one or more *cells* containing notes or code. To insert a new cell click the `+` button in the upper left. To execute a cell, select it and press `Control+Enter` or click the `Run` button at the top.

9.3.3 Making requests

To retrieve information from the website (i.e., make a request), we need to know the location of the information we want to collect. The Uniform Resource Locator (URL) — commonly know as a "web address", specifies the location of a resource (such as a web page) on the internet.

A URL is usually composed of 5 parts:



The 4th part, the "query string", contains one or more **parameters**. The 5th part, the "fragment", is an internal page reference and may not be present.

For example, the URL we want to retrieve data from has the following structure:

```
protocol                    domain    path   parameters
   https www.harvardartmuseums.org  browse   load_amount=10&offset=0
```

It is often convenient to create variables containing the domain(s) and path(s) you'll be working with, as this allows you to swap out paths and parameters as needed. Note that the path is separated from the domain with `/` and the parameters are separated from the path with `?`. If there are multiple parameters they are separated from each other with a `&`.

For example, we can define the domain and path of the collections URL as follows:

```python
museum_domain = 'https://www.harvardartmuseums.org'
collection_path = 'browse'

collection_url = (museum_domain
                  + "/"
                  + collection_path)

print(collection_url)
```

```
## 'https://www.harvardartmuseums.org/browse'
```

Note that we omit the parameters here because it is usually easier to pass them as a `dict` when using the `requests` library in Python. This will become clearer shortly.

Now that we've constructed the URL we wish to interact with, we're ready to make our first request in Python.

```python
import requests

collections1 = requests.get(
    collection_url,
    params = {'load_amount': 10,
              'offset': 0}
)
```

Note that the parameters `load_amount` and `offset` are essentially another way of setting page numbers — they refer to the amount of information retrieved at one time and the starting position, respectively.

9.3.4 Parsing JSON data

We already know from inspecting network traffic in our web browser that this URL returns JSON, but we can use Python to verify this assumption.

```
collections1.headers['Content-Type']
```

```
## 'application/json'
```

Since JSON is a structured data format, parsing it into Python data structures is easy. In fact, there's a method for that!

```
collections1 = collections1.json()
# print(collections1)
```

That's it. Really, we are done here. Everyone go home!

OK not really, there is still more we can learn. But you have to admit that was pretty easy. If you can identify a service that returns the data you want in structured from, web scraping becomes a pretty trivial enterprise. We'll discuss several other scenarios and topics, but for some web scraping tasks this is really all you need to know.

9.3.5 Organizing & saving the data

The records we retrieved from `https://www.harvardartmuseums.org/browse` are arranged as a list of dictionaries. We can easily select the fields of arrange these data into a pandas `DataFrame` to facilitate subsequent analysis.

```
import pandas as pd
```

```
records1 = pd.DataFrame.from_records(collections1['records'])
```

```
print(records1)
```

```
##                         copyright  contextualtextcount  ...                                colors
## 0                            None                    0  ...                                   NaN
## 1                            None                    0  ...  [{'color': '#c8c8c8', 'spe...
## 2                            None                    0  ...  [{'color': '#323232', 'spe...
## 3                            None                    0  ...  [{'color': '#c8c8af', 'spe...   [{
## 4  © Berenice Abbott/Commerce...                    0  ...  [{'color': '#4b4b4b', 'spe...   [{
```

```
## 5                              None                       0  ...  [{'color': '#e1e1e1', 'spe...
## 6                              None                       0  ...  [{'color': '#fafafa', 'spe...
## 7                              None                       1  ...                         NaN  [{
## 8                              None                       0  ...  [{'color': '#e1e1e1', 'spe...  [{
## 9                              None                       0  ...  [{'color': '#af7d4b', 'spe...  [{
##
## [10 rows x 62 columns]
```

and write the data to a file.

```
records1.to_csv("records1.csv")
```

9.3.6 Iterating to retrieve all the data

Of course we don't want just the first page of collections. How can we retrieve all of them?

Now that we know the web service works, and how to make requests in Python, we can iterate in the usual way.

```
records = []
for offset in range(0, 50, 10):
    param_values = {'load_amount': 10, 'offset': offset}
    current_request = requests.get(collection_url, params = param_values)
    records.extend(current_request.json()['records'])
```

```
## convert list of dicts to a `DataFrame`
records_final = pd.DataFrame.from_records(records)
```

```
# write the data to a file.
records_final.to_csv("records_final.csv")
```

```
print(records_final)
```

```
##                          copyright  contextualtextcount  ...                        people
## 0                             None                    0  ...                           NaN
## 1                             None                    0  ...                           NaN
## 2                             None                    0  ...                           NaN
## 3                             None                    0  ...  [{'role': 'Artist', 'birth...
## 4    © Berenice Abbott/Commerce...                    0  ...  [{'role': 'Artist', 'birth...
## 5                             None                    0  ...                           NaN
## 6                             None                    0  ...                           NaN
## 7                             None                    1  ...  [{'role': 'Artist', 'birth...
## 8                             None                    0  ...  [{'role': 'Artist', 'birth...
## 9                             None                    0  ...  [{'role': 'Artist', 'birth...
## 10                            None                    0  ...                           NaN
```

```
## 11                          None                         0  ...  [{'role': 'Artist', 'birth...
## 12                          None                         0  ...  [{'role': 'Artist', 'birth...
## 13                          None                         0  ...                         NaN
## 14  © Succession H. Matisse / ...                         0  ...  [{'role': 'Artist', 'birth...
## 15                          None                         0  ...  [{'role': 'Artist', 'birth...
## 16                          None                         0  ...  [{'role': 'Artist', 'birth...
## 17  © Aperture Foundation Inc....                         0  ...  [{'role': 'Artist', 'birth...
## 18                          None                         0  ...                         NaN
## 19                          None                         0  ...  [{'role': 'Artist', 'birth...
## 20                          None                         0  ...                         NaN
## 21  © Succession H. Matisse / ...                         0  ...  [{'role': 'Artist', 'birth...
## 22  © Estate of Harry Callahan...                         0  ...  [{'role': 'Artist', 'birth...
## 23                          None                         0  ...                         NaN
## 24                          None                         0  ...  [{'role': 'Artist', 'birth...
## 25                          None                         1  ...                         NaN  {
## 26  © The Estate of Eva Hesse ...                         0  ...  [{'role': 'Artist', 'birth...
## 27            © 2004 Glenn Ligon                         0  ...  [{'role': 'Artist', 'birth...
## 28                          None                         0  ...  [{'role': 'Artist', 'birth...
## 29                          None                         0  ...  [{'role': 'Artist', 'birth...
## 30  © Artists Rights Society (...                         0  ...  [{'role': 'Artist', 'birth...
## 31                          None                         1  ...                         NaN  {
## 32  © Estate of Alfred Stiegli...                         0  ...  [{'role': 'Artist', 'birth...
## 33        © 2020 Allan McCollum                         0  ...  [{'role': 'Artist', 'birth...
## 34                          None                         0  ...  [{'role': 'Artist', 'birth...
## 35                          None                         0  ...  [{'role': 'Artist', 'birth...
## 36                          None                         0  ...  [{'role': 'Artist', 'birth...
## 37                          None                         0  ...  [{'role': 'Coin Constituen...  {
## 38                          None                         0  ...  [{'role': 'Artist', 'birth...
## 39                  © Roni Horn                         0  ...  [{'role': 'Artist', 'birth...
## 40                          None                         0  ...                         NaN
## 41                          None                         0  ...  [{'role': 'Artist', 'birth...
## 42                          None                         0  ...  [{'role': 'Artist', 'birth...
## 43                          None                         0  ...  [{'role': 'Artist', 'birth...
## 44                          None                         0  ...  [{'role': 'Artist', 'birth...
## 45                          None                         0  ...  [{'role': 'Artist', 'birth...
## 46                          None                         0  ...                         NaN  {
## 47                          None                         0  ...  [{'role': 'Coin Constituen...  {
## 48                          None                         0  ...  [{'role': 'Artist', 'birth...
## 49                          None                         0  ...  [{'role': 'Artist', 'birth...
##
## [50 rows x 63 columns]
```

9.3.7 Exercise 0

Retrieve exhibits data

In this exercise you will retrieve information about the art exhibitions at Harvard Art Museums from `https://www.harvardartmuseums.org/exhibitions`

1. Using a web browser (Firefox or Chrome recommended) inspect the page at `https://www.harvardartmuseums.org/exhibitions`. Examine the network traffic as you interact with the page. Try to find where the data displayed on that page comes from.

```
##
```

2. Make a `get` request in Python to retrieve the data from the URL identified in step1.

```
##
```

3. Write a *loop* or *list comprehension* in Python to retrieve data for the first 5 pages of exhibitions data.

```
##
```

4. Bonus (optional): Convert the data you retrieved into a pandas `DataFrame` and save it to a `.csv` file.

```
##
```

Click for Exercise 0 Solution

Question #1:

```
museum_domain = "https://www.harvardartmuseums.org"
exhibit_path = "search/load_next"
exhibit_url = museum_domain + "/" + exhibit_path
print(exhibit_url)
```

```
## 'https://www.harvardartmuseums.org/search/load_next'
```

Question #2:

```
import requests
from pprint import pprint as print
exhibit1 = requests.get(exhibit_url, params = {'type': 'past-exhibition', 'page': 1})
print(exhibit1.headers["Content-Type"])
```

```
## 'application/json'
```

```
exhibit1 = exhibit1.json()
# print(exhibit1)
```

Questions #3+4 (loop solution):

```
firstFivePages = []
for page in range(1, 6):
    records_per_page = requests.get(exhibit_url, params = {'type': 'past-exhibition', 'page': pag
    firstFivePages.extend(records_per_page)
firstFivePages_records = pd.DataFrame.from_records(firstFivePages)
print(firstFivePages_records)
```

```
##                     shortdescription                         images  ...                   public
## 0                               None  [{'date': '2018-11-09', 'c...  ...
## 1                               None  [{'date': '2018-06-04', 'c...  ...  [{'publicationplace':
## 2                               None  [{'date': '2001-03-01', 'c...  ...
## 3                               None  [{'date': '2005-04-18', 'c...  ...
## 4                               None  [{'date': '2018-06-29', 'c...  ...
## 5                               None  [{'date': '2018-03-15', 'c...  ...
## 6                               None  [{'date': '2016-10-17', 'c...  ...  [{'publicationplace':
## 7                               None  [{'date': '2017-02-16', 'c...  ...  [{'publicationplace':
## 8                               None  [{'date': '2018-01-23', 'c...  ...
## 9                               None  [{'date': '2001-04-01', 'c...  ...
## 10                              None  [{'date': '2016-06-10', 'c...  ...
## 11                              None  [{'date': '2008-10-27', 'c...  ...
## 12                              None  [{'date': '2017-10-05', 'c...  ...
## 13                              None  [{'date': '2002-05-01', 'c...  ...
## 14                              None  [{'date': '2007-08-01', 'c...  ...
## 15                              None  [{'date': '2003-03-21', 'c...  ...
## 16                              None  [{'date': '2017-05-08', 'c...  ...  [{'publicationplace':
## 17                              None  [{'date': '2002-08-01', 'c...  ...
## 18                              None  [{'date': '2016-07-05', 'c...  ...
## 19                              None  [{'date': '2017-03-29', 'c...  ...
## 20                              None  [{'date': '2015-03-22', 'c...  ...  [{'publicationplace':
## 21                              None  [{'date': '2017-03-07', 'c...  ...
## 22  Harvard professor Ewa Laje...  [{'date': '2001-03-01', 'c...  ...  [{'publicationplace':
## 23  This exhibition features w...  [{'date': '2016-07-12', 'c...  ...  [{'publicationplace':
## 24                              None  [{'date': '2017-02-08', 'c...  ...
## 25                              None  [{'date': '2001-06-01', 'c...  ...
## 26                              None  [{'date': '2005-11-03', 'c...  ...
## 27                              None  [{'date': '2015-04-06', 'c...  ...
## 28                       In progress  [{'date': '2016-07-28', 'c...  ...
## 29                              None  [{'date': None, 'copyright...  ...
## 30                              None  [{'date': '2016-03-21', 'c...  ...
## 31                              None  [{'date': '2007-04-18', 'c...  ...  [{'publicationplace':
## 32                              None  [{'date': '2015-04-01', 'c...  ...  [{'publicationplace':
## 33                              None  [{'date': '2016-01-12', 'c...  ...
## 34                              None  [{'date': '2002-07-01', 'c...  ...
## 35                              None  [{'date': '2007-02-27', 'c...  ...
## 36                              None  [{'date': '2006-01-18', 'c...  ...
## 37                              None  [{'date': '2015-10-29', 'c...  ...
## 38                              None  [{'date': '2014-08-12', 'c...  ...  [{'publicationplace':
```

```
## 39                          None  [{'date': '2005-11-03', 'c...  ...
## 40                          None  [{'date': '1989-08-01', 'c...  ...
## 41  This multi-component insta...  [{'date': '2014-03-31', 'c...  ...
## 42                          None  [{'date': '2009-11-30', 'c...  ...
## 43  Harvard Art Museums' new p...  [{'date': '2012-06-29', 'c...  ...
## 44                          None  [{'date': '2014-11-10', 'c...  ...
## 45  In the Japanese context, a...  [{'date': '2012-07-17', 'c...  ...
## 46  World's Fairs were created...  [{'date': '2005-12-21', 'c...  ...
## 47                          None  [{'date': '2005-11-09', 'c...  ...
## 48  Teaching Galleries\r\n\r\n...  [{'date': '2003-03-18', 'c...  ...
## 49  Teaching Galleries\r\n\r\n...  [{'date': '2005-11-02', 'c...  ...
##
## [50 rows x 19 columns]
```

Questions #3+4 (list comprehension solution):

```
first5Pages = [requests.get(exhibit_url, params = {'type': 'past-exhibition', 'page': page}).json
from itertools import chain
first5Pages = list(chain.from_iterable(first5Pages))
import pandas as pd
first5Pages_records = pd.DataFrame.from_records(first5Pages)
print(first5Pages_records)
```

```
##                 shortdescription                         images  ...                 public
## 0                          None  [{'date': '2018-11-09', 'c...  ...
## 1                          None  [{'date': '2018-06-04', 'c...  ...  [{'publicationplace':
## 2                          None  [{'date': '2001-03-01', 'c...  ...
## 3                          None  [{'date': '2005-04-18', 'c...  ...
## 4                          None  [{'date': '2018-06-29', 'c...  ...
## 5                          None  [{'date': '2018-03-15', 'c...  ...
## 6                          None  [{'date': '2016-10-17', 'c...  ...  [{'publicationplace':
## 7                          None  [{'date': '2017-02-16', 'c...  ...  [{'publicationplace':
## 8                          None  [{'date': '2018-01-23', 'c...  ...
## 9                          None  [{'date': '2001-04-01', 'c...  ...
## 10                         None  [{'date': '2016-06-10', 'c...  ...
## 11                         None  [{'date': '2008-10-27', 'c...  ...
## 12                         None  [{'date': '2017-10-05', 'c...  ...
## 13                         None  [{'date': '2002-05-01', 'c...  ...
## 14                         None  [{'date': '2007-08-01', 'c...  ...
## 15                         None  [{'date': '2003-03-21', 'c...  ...
## 16                         None  [{'date': '2017-05-08', 'c...  ...  [{'publicationplace':
## 17                         None  [{'date': '2002-08-01', 'c...  ...
## 18                         None  [{'date': '2016-07-05', 'c...  ...
## 19                         None  [{'date': '2017-03-29', 'c...  ...
## 20                         None  [{'date': '2015-03-22', 'c...  ...  [{'publicationplace':
## 21                         None  [{'date': '2017-03-07', 'c...  ...
## 22  Harvard professor Ewa Laje...  [{'date': '2001-03-01', 'c...  ...  [{'publicationplace':
```

```
## 23  This exhibition features w...  [{'date': '2016-07-12', 'c...  ...  [{'publicationplace':
## 24                          None  [{'date': '2017-02-08', 'c...  ...
## 25                          None  [{'date': '2001-06-01', 'c...  ...
## 26                          None  [{'date': '2005-11-03', 'c...  ...
## 27                          None  [{'date': '2015-04-06', 'c...  ...
## 28                   In progress  [{'date': '2016-07-28', 'c...  ...
## 29                          None  [{'date': None, 'copyright...  ...
## 30                          None  [{'date': '2016-03-21', 'c...  ...
## 31                          None  [{'date': '2007-04-18', 'c...  ...  [{'publicationplace':
## 32                          None  [{'date': '2015-04-01', 'c...  ...  [{'publicationplace':
## 33                          None  [{'date': '2016-01-12', 'c...  ...
## 34                          None  [{'date': '2002-07-01', 'c...  ...
## 35                          None  [{'date': '2007-02-27', 'c...  ...
## 36                          None  [{'date': '2006-01-18', 'c...  ...
## 37                          None  [{'date': '2015-10-29', 'c...  ...
## 38                          None  [{'date': '2014-08-12', 'c...  ...  [{'publicationplace':
## 39                          None  [{'date': '2005-11-03', 'c...  ...
## 40                          None  [{'date': '1989-08-01', 'c...  ...
## 41  This multi-component insta...  [{'date': '2014-03-31', 'c...  ...
## 42                          None  [{'date': '2009-11-30', 'c...  ...
## 43  Harvard Art Museums' new p...  [{'date': '2012-06-29', 'c...  ...
## 44                          None  [{'date': '2014-11-10', 'c...  ...
## 45  In the Japanese context, a...  [{'date': '2012-07-17', 'c...  ...
## 46  World's Fairs were created...  [{'date': '2005-12-21', 'c...  ...
## 47                          None  [{'date': '2005-11-09', 'c...  ...
## 48  Teaching Galleries\r\n\r\n...  [{'date': '2003-03-18', 'c...  ...
## 49  Teaching Galleries\r\n\r\n...  [{'date': '2005-11-02', 'c...  ...
##
## [50 rows x 19 columns]
```

9.4 Parsing HTML if you have to

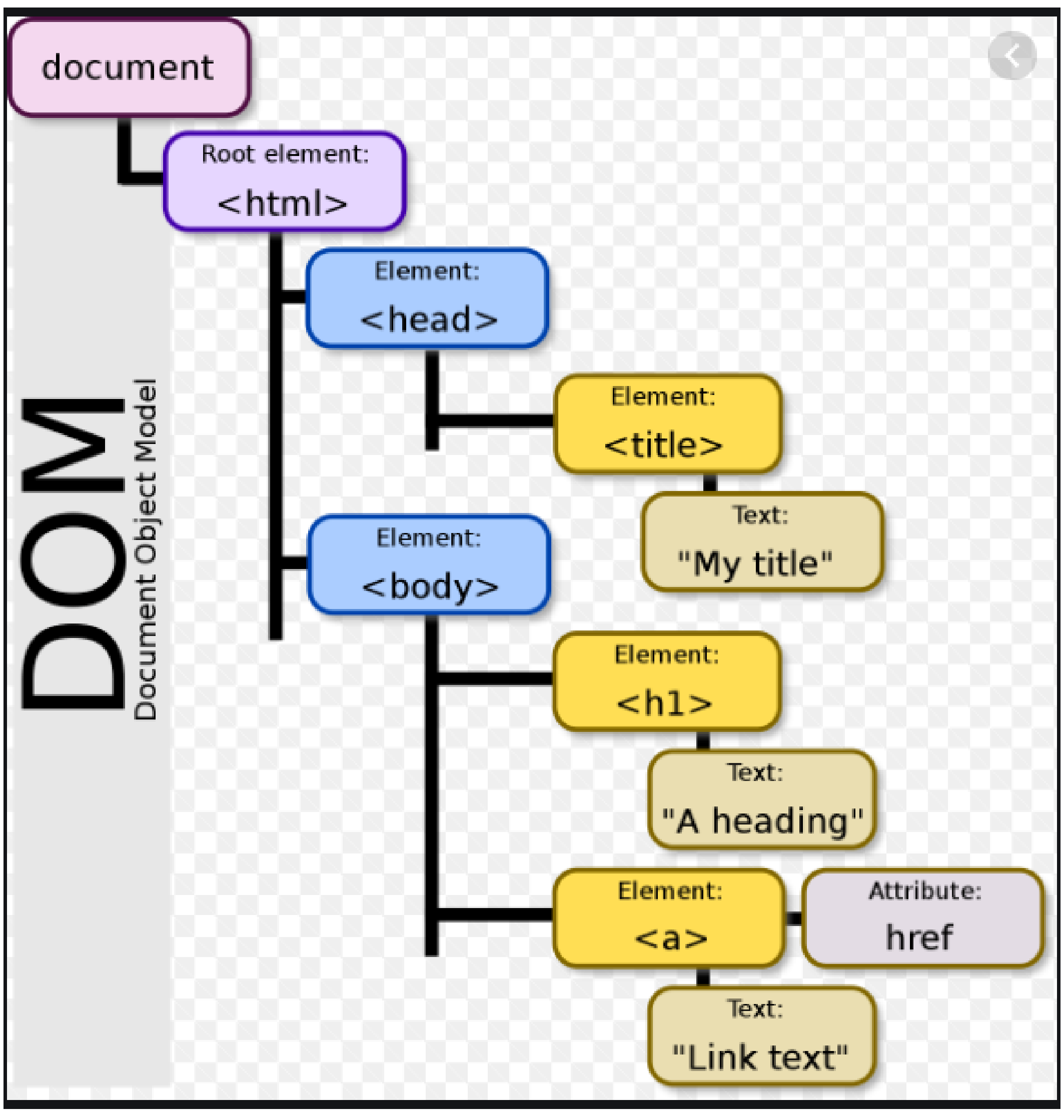
GOAL: To retrieve information in HTML format and organize it into a spreadsheet.

1. Make a request to the website server to retrieve the HTML
2. Inspect the HTML to determine the XPATHs that point to the data we want
3. Extract the information from the location the XPATHs point to and store in a dictionary
4. Convert from a dictionary to a .csv file

As we've seen, you can often inspect network traffic or other sources to locate the source of the data you are interested in and the API used to retrieve it. You should always start by looking for these shortcuts and using them where possible. If you are really lucky, you'll find a shortcut that returns the data as JSON or XML. If you are not quite so lucky, you will have to parse HTML to retrieve the information you need.

9.4.1 Document Object Model (DOM)

To parse HTML, we need to have a nice tree structure that contains the whole HTML file through which we can locate the information. This tree-like structure is the **Document Object Model (DOM)**. DOM is a cross-platform and language-independent interface that treats an XML or HTML document as a tree structure wherein each node is an object representing a part of the document. The DOM represents a document with a logical tree. *Each branch of the tree ends in a node, and each node contains objects.* DOM methods allow programmatic access to the tree; with them one can change the structure, style or content of a document. The following is an example of DOM hierarchy in an HTML document:



9.4.2 Retrieving HTML

When I inspect the network traffic while interacting with `https://www.harvardartmuseums.org/calendar` I don't see any requests that return JSON data. The best we can do appears to be to return HTML.

To retrieve data on the events listed in the calender, the first step is the same as before: we make a `get` request.

```
calendar_path = 'calendar'

calendar_url = (museum_domain # recall that we defined museum_domain earlier
                + "/"
                + calendar_path)

print(calendar_url)
```

```
## 'https://www.harvardartmuseums.org/calendar'
```

```
events = requests.get(calendar_url)
```

As before, we can check the headers to see what type of content we received in response to our request.

```
events.headers['Content-Type']
```

```
## 'text/html; charset=UTF-8'
```

9.4.3 Parsing HTML using the lxml library

Like JSON, HTML is structured; unlike JSON, it is designed to be rendered into a human-readable page rather than simply to store and exchange data in a computer-readable format. Consequently, parsing HTML and extracting information from it is somewhat more difficult than parsing JSON.

While JSON parsing is built into the Python `requests` library, parsing HTML requires a separate library. I recommend using the HTML parser from the `lxml` library; others prefer an alternative called `beautifulsoup4`.

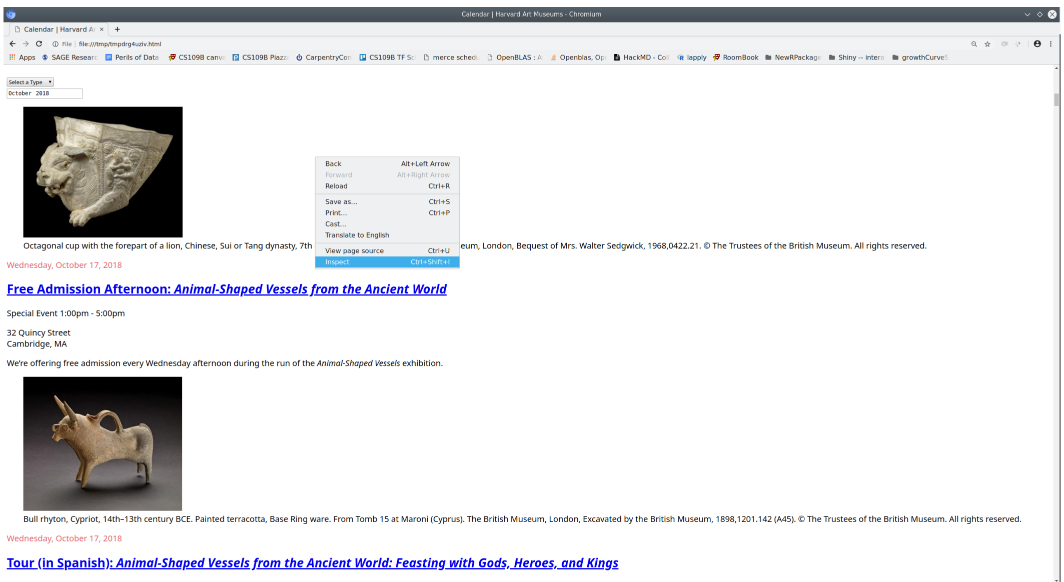
```
from lxml import html

# convert a html text representation (`events.text`) into
# a tree-structure (DOM) html representation (`events_html`)
events_html = html.fromstring(events.text)
```

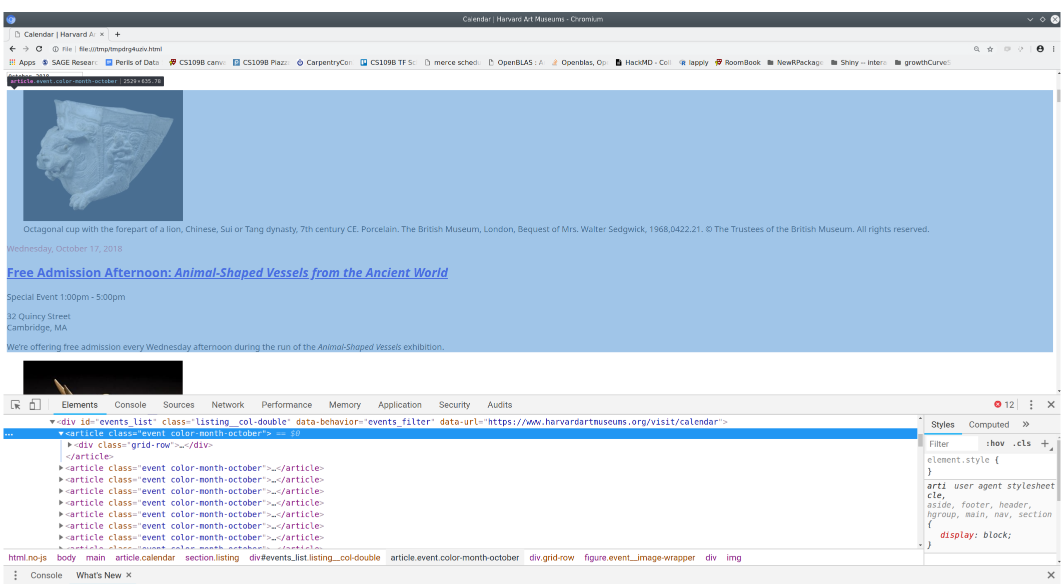
9.4.4 Using XPath to extract content from HTML

`XPath` is a tool for identifying particular elements within a HTML document. The developer tools built into modern web browsers make it easy to generate `XPath`s that can be used to identify the elements of a web page that we wish to extract.

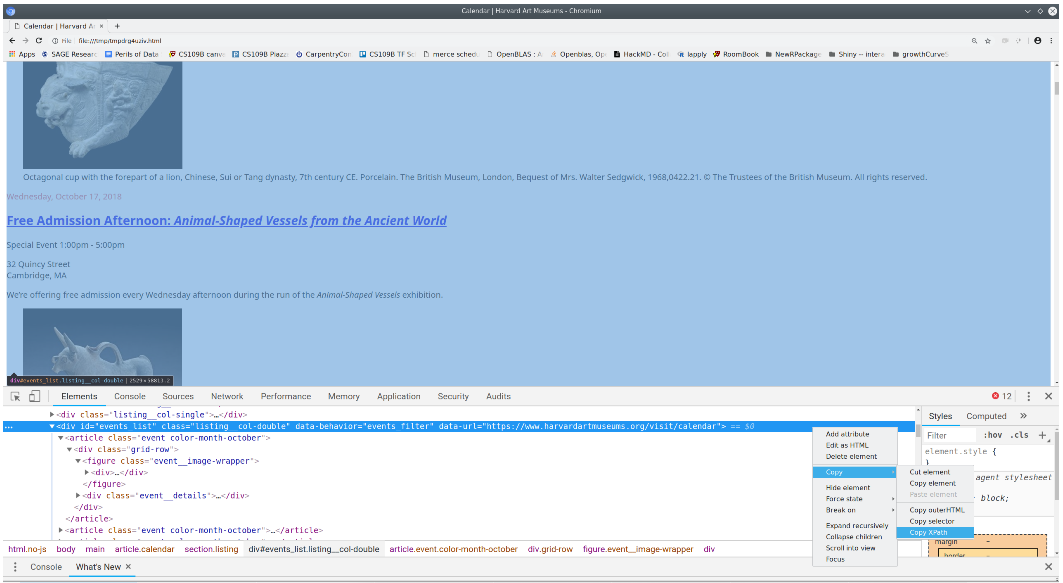
We can open the HTML document we retrieved and inspect it using our web browser.

```
html.open_in_browser(events_html, encoding = 'UTF-8')
```





Once we identify the element containing the information of interest we can use our web browser to copy the XPath that uniquely identifies that element.



Next we can use Python to extract the element of interest:

```python
events_list_html = events_html.xpath('//*[@id="events_list"]/article')
```

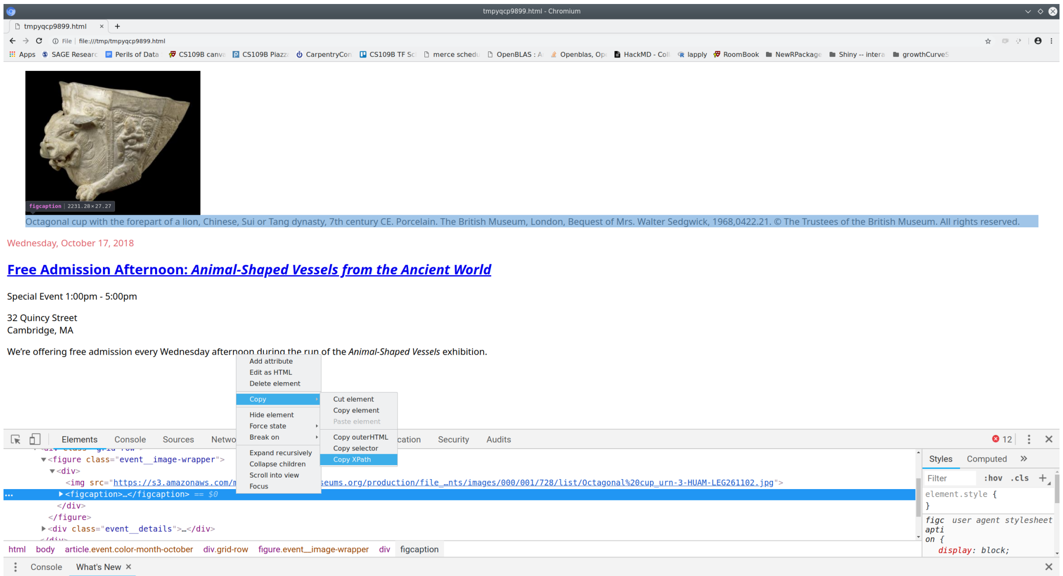
Let's just extract the second element in our events list.

```python
second_event_html = events_list_html[1]
```

Once again, we can use a web browser to inspect the HTML we're currently working with - from the second event - and to figure out what we want to extract from it.

```python
html.open_in_browser(second_event_html, encoding = 'UTF-8')
```

As before, we can use our browser to find the xpath of the elements we want.



(Note that the `html.open_in_browser` function adds enclosing `html` and `body` tags in order to create a complete web page for viewing. This requires that we adjust the `xpath` accordingly.)

By repeating this process for each element we want, we can build a list of the xpaths to those elements.

```
elements_we_want = {'figcaption': 'div/figure/div/figcaption',
                    'date': 'div/div/header/time',
                    'title': 'div/div/header/h2/a',
                    'time': 'div/div/div/p[1]/time',
                    'description': 'div/div/div/p[3]'
                    }
```

Finally, we can iterate over the elements we want and extract them.

```
second_event_values = {}
for key in elements_we_want.keys():
    element = second_event_html.xpath(elements_we_want[key])[0]
    second_event_values[key] = element.text_content().strip()

print(second_event_values)
```

```
## {'date': 'Thursday, January 14, 2021',
##  'description': 'Join curatorial fellow Kappy Mintie to examine Ben Shahn’s '
##                 'interest in photographing folk musicians during the Great '
##                 'Depression.',
##  'figcaption': 'Ben Shahn, American, Practicing for the Westmoreland Fair, '
##                'Pennsylvania, 1937. Gelatin silver print. Harvard Art '
```

```
##                  'Museums/Fogg Museum, Transfer from the Carpenter Center for '
##                  'the Visual Arts, 2.2002.3117.',
##  'time': '2:00pm - 2:30pm',
##  'title': 'Art Talk Live: Ben Shahn and Folk Music [CANCELED]'}
```

9.4.5 Iterating to retrieve content from a list of HTML elements

So far we've retrieved information only for the second event. To retrieve data for all the events listed on the page we need to iterate over the events. If we are very lucky, each event will have exactly the same information structured in exactly the same way and we can simply extend the code we wrote above to iterate over the events list.

Unfortunately, not all these elements are available for every event, so we need to take care to handle the case where one or more of these elements is not available. We can do that by **defining a function** that tries to retrieve a value and returns an empty string if it fails.

If you're not familiar with Python functions, here's the basic syntax:

```python
# anatomy of a function

def name_of_function(arg1, arg2, ...argn):  # define the function name and arguments
    <body of function>   # specify calculations
    return <result>      # output result of calculations
```

Here's an example of a simple function:

```python
def square_fun(x):
    y = x**2 # exponentiation
    return y

square_fun(4)
```

```
## 16
```

Here's a function to perform our actual task:

```python
def get_event_info(event, path):
    try:
        info = event.xpath(path)[0].text_content().strip()
    except:
        info = ''
    return info
```

Armed with this function, we can iterate over the list of events and extract the available information for each one.

```
all_event_values = {}
for key in elements_we_want.keys():
    key_values = []
    for event in events_list_html:
        key_values.append(get_event_info(event, elements_we_want[key]))
    all_event_values[key] = key_values
```

For convenience we can arrange these values in a pandas `DataFrame` and save them as .csv files, just as we did with our exhibitions data earlier.

```
all_event_values = pd.DataFrame.from_dict(all_event_values)

all_event_values.to_csv("all_event_values.csv")

print(all_event_values)
```

9.4.6 Exercise 1

parsing HTML

In this exercise you will retrieve information about the physical layout of the Harvard Art Museums. The web page at `https://www.harvardartmuseums.org/visit/floor-plan` contains this information in HTML from.

1. Using a web browser (Firefox or Chrome recommended) inspect the page at `https://www.harvardartmuseums.org/visit/floor-plan`. Copy the `XPath` to the element containing the list of level information. (HINT: the element if interest is a `ul`, i.e., `unordered list`.)

2. Make a `get` request in Python to retrieve the web page at `https://www.harvardartmuseums.org/visit/floor-plan`. Extract the content from your request object and parse it using `html.fromstring` from the `lxml` library.

```
##
```

3. Use your web browser to find the `XPath`s to the facilities housed on level one. Use Python to extract the text from those `Xpath`s.

```
##
```

4. Bonus (optional): Write a *for loop* or *list comprehension* in Python to retrieve data for all the levels.

```
##
```

Click for Exercise 1 Solution

Question #2:

```
from lxml import html
floor_plan = requests.get('https://www.harvardartmuseums.org/visit/floor-plan')
floor_plan_html = html.fromstring(floor_plan.text)
```

Question #3:

```
level_one = floor_plan_html.xpath('/html/body/main/section/ul/li[5]/div[2]/ul')[0]
print(type(level_one))
```

```
## <class 'lxml.html.HtmlElement'>
```

```
print(len(level_one))
```

```
## 6
```

```
level_one_facilities = floor_plan_html.xpath('/html/body/main/section/ul/li[5]/div[2]/ul/li')
print(len(level_one_facilities))
```

```
## 6
```

```
print([facility.text_content() for facility in level_one_facilities])
```

```
## ['Admissions', 'Collection Galleries', 'Courtyard', 'Shop', 'Café', 'Coatroom']
```

Question #4:

```
all_levels = floor_plan_html.xpath('/html/body/main/section/ul/li')
print(len(all_levels))
```

```
## 6
```

```
all_levels_facilities = []
for level in all_levels:
    level_facilities = []
    level_facilities_collection = level.xpath('div[2]/ul/li')
    for level_facility in level_facilities_collection:
        level_facilities.append(level_facility.text_content())
    all_levels_facilities.append(level_facilities)
print(all_levels_facilities)
```

```
## [['Conservation Center / Lightbox Gallery'],
##  ['Art Study Center'],
##  ['Collection Galleries',
##   'Special Exhibitions Gallery',
##   'University Galleries'],
##  ['Collections Galleries'],
##  ['Admissions',
##   'Collection Galleries',
##   'Courtyard',
##   'Shop',
##   'Café',
##   'Coatroom'],
##  ['Lower Lobby',
##   'Lecture Halls',
##   'Seminar Room',
##   'Materials Lab',
##   'Coatroom',
##   'Offices']]
```

9.5 Scrapy: for large / complex projects

Scraping websites using the `requests` library to make GET and POST requests, and the `lxml` library to process HTML is a good way to learn basic web scraping techniques. It is a good choice for small to medium size projects. For very large or complicated scraping tasks the `scrapy` library offers a number of conveniences, including asynchronous retrieval, session management, convenient methods for extracting and storing values, and more. More information about `scrapy` can be found at `https://doc.scrapy.org`.

9.6 Browser drivers: a last resort

It is sometimes necessary (or sometimes just easier) to use a web browser as an intermediary rather than communicate directly with a web service. This method of using a "browser driver" has the advantage of being able to use the javascript engine and session management features of a web browser; the main disadvantage is that it is slower and tends to be more fragile than using `requests` or `scrapy` to make requests directly from Python. For small scraping projects involving complicated sites with CAPTHAs or lots of complicated javascript using a browser driver can be a good option. More information is available at `https://www.seleniumhq.org/docs/03_webdriver.jsp`.

9.7 Wrap-up

9.7.1 Feedback

These workshops are a work in progress, please provide any feedback to: `help@iq.harvard.edu`

9.7.2 Resources

- IQSS
  - Workshops: `https://www.iq.harvard.edu/data-science-services/workshop-materials`
  - Data Science Services: `https://www.iq.harvard.edu/data-science-services`
  - Research Computing Environment: `https://iqss.github.io/dss-rce/`
- HBS
  - Research Computing Services workshops: `https://training.rcs.hbs.org/workshops`
  - Other HBS RCS resources: `https://training.rcs.hbs.org/workshop-materials`
  - RCS consulting email: `mailto:research@hbs.edu`

Part IV

Stata

Chapter 10

Stata Installation

Your professional conduct is greatly appreciated. Out of respect to your fellow workshop attendees and instructors, please arrive at your workshop on time, having pre-installed all necessary software and materials. This will likely take 10-15 minutes.

10.1 Troubleshooting

Unfortunately, we are not able to help with any Stata download or installation problems you may encounter. **If you are unable to download or install Stata SE or MP, please contact your vendor (e.g., HUIT or Stata Corp.) prior to the start of the workshop.** Once the workshop starts we will **NOT** be able to give you one-to-one assistance with setting up Stata. Likewise, if you arrive late, please do **NOT** expect one-to-one assistance for anything covered at the beginning of the workshop.

10.2 Materials

Download class materials for your workshop:

- Stata Introduction: `https://github.com/IQSS/dss-workshops/raw/master/Stata/StataIntro.zip`
- Stata Data Management: `https://github.com/IQSS/dss-workshops/raw/master/Stata/StataDataManage.zip`
- Stata Regression Models: `https://github.com/IQSS/dss-workshops/raw/master/Stata/StataModels.zip`
- Stata Graphics: `https://github.com/IQSS/dss-workshops/raw/master/Stata/StataGraphics.zip`

Extract materials from the zipped directory (Right-click -> Extract All on Windows, double-click on Mac) and move them to your desktop.

It will be useful when you view the above materials for you to see the different file extensions on your computer. Here are instructions for enabling this:

- Mac OS
- Windows OS

10.3 Software

It is important that you have the **latest numeric version** of Stata installed, which currently is:

- Stata version **16.1**

It does not matter whether you use Stata version MP, SE, or IC in this workshop, since we will not be performing computational intensive analyses.

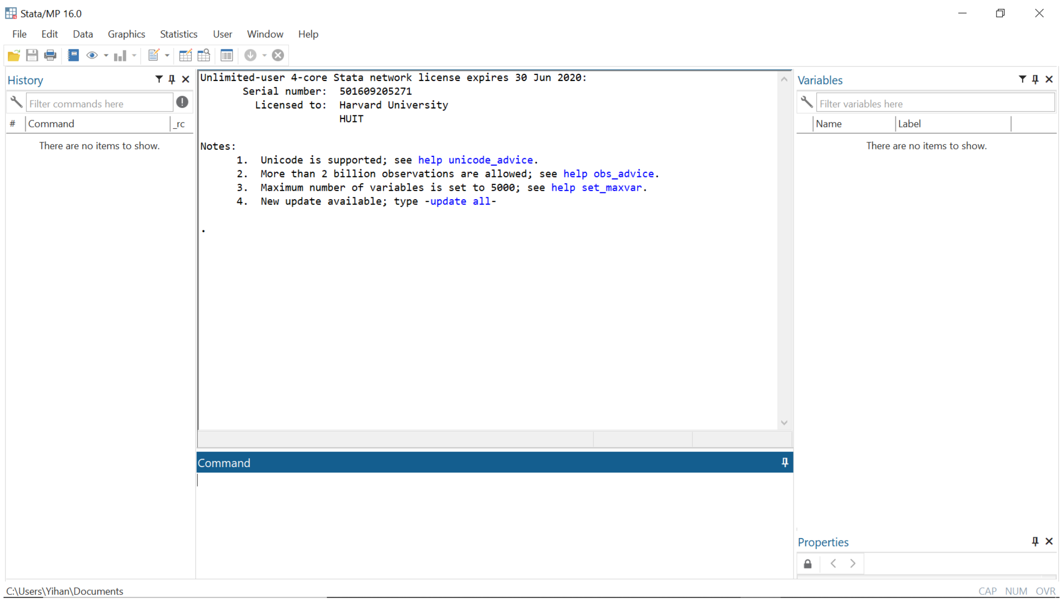
If you are affiliated with Harvard FAS:

You have access to the licensed Stata MP program. Go to the software download page: `https://downloads.fas.harvard.edu/download`, log in using your Harvard key and download Stata MP.

If you are affiliated with other Harvard schools or MIT:

- First check with your school or department whether they provide you free access to Stata MP, SE, or IC.
- If not, you can download the program directly from Stata Corporation with a single user annual license fee starting at $94 for Stata/IC for students or $125 for Stata/IC for education. Stata Corp.'s website is `https://www.stata.com/`.

After you successfully installed Stata, you should be able to open the program and see the following start page (note that the Stata version reported may be newer):



If you are having any difficulties with the installation or your Stata screen does not look like this one, please contact your Stata vendor for technical support prior to the start of the workshop.

10.4 Resources

- IQSS
  - Workshops: `https://www.iq.harvard.edu/data-science-services/workshop-materials`
  - Data Science Services: `https://www.iq.harvard.edu/data-science-services`
  - Research Computing Environment: `https://iqss.github.io/dss-rce/`
- HBS
  - Research Computing Services workshops: `https://training.rcs.hbs.org/workshops`
  - Other HBS RCS resources: `https://training.rcs.hbs.org/workshop-materials`
  - RCS consulting email: `mailto:research@hbs.edu`

Chapter 11

Stata Introduction

Topics

- Stata interface and Do-files
- Reading and writing data
- Basic summary statistics
- Basic graphs
- Basic data management
- Bivariate analyses

11.1 Setup

11.1.1 Software and Materials

Follow the Stata Installation instructions and ensure that you can successfully start Stata.

A handy set of Stata cheat-sheets is available to help you look up and remember command syntax.

11.1.2 Class Structure and organization

- Informal — Ask questions at any time. Really!
- Collaboration is encouraged - please spend a minute introducing yourself to your neighbors!
- If you are using a laptop, you will need to adjust file paths accordingly
- Make comments in your Do-file - save on flash drive or email to yourself

11.1.3 Prerequisites

This is an introductory Stata course:

- Assumes no prior knowledge of **how to use** Stata
- We do assume you know **why** you want to learn Stata. If you don't, and want a comparison of Stata to other statistical software, see our Data Science Tools workshop
- Relatively slow-paced

11.1.4 Goals

We will learn about the Stata language by analyzing data from the general social survey (gss). In particular, our goals are to:

1. Familiarize yourself with the Stata interface
2. Get data in and out of Stata
3. Compute statistics and construct graphical displays
4. Compute new variables and transformations
5. Perform univariate and bivariate data analyses

11.2 Stata basics

GOAL: To learn the basics about Stata, how to interact with Stata, and how to read in and save data. In particular:

1. What is Stata, why use Stata, and advantages of using Stata
2. Three ways of interacing with Stata
3. Set the working directory
4. Read, save, and write data

11.2.1 What is Stata?

- Stata is a statistical software package that you can use to perform data analysis and management, as well as create graphics
- Stata is commonly used among health, sociology, and economics researchers, particularly those working with large data sets

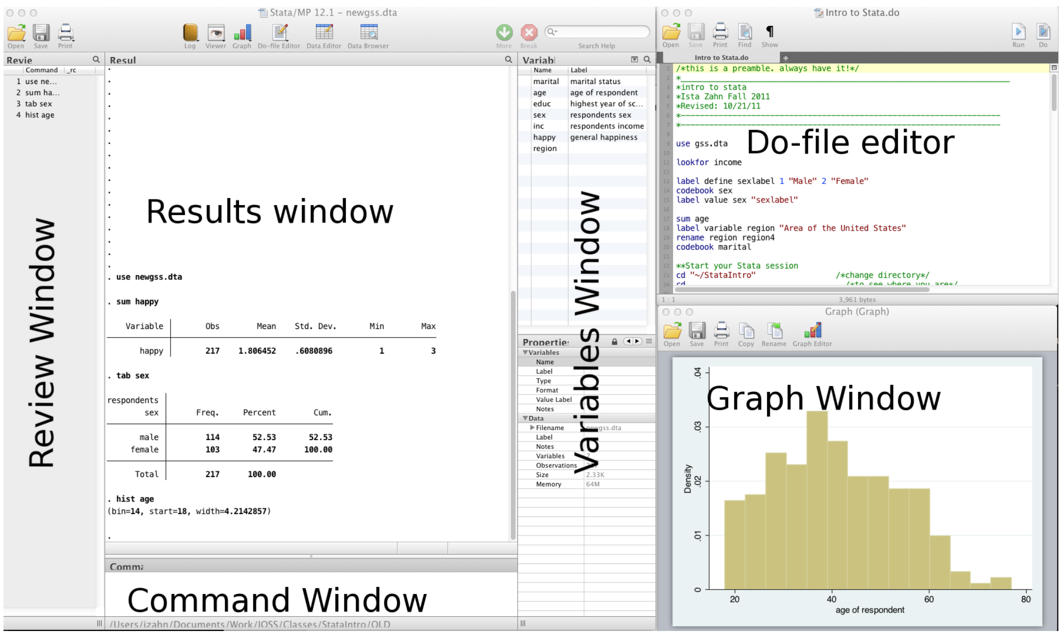
11.2.2 Why use Stata?

- It is easy to learn and is supported by a wide range of introductory textbooks
- It offers a wide range of statistical models in a consistent interface
- It presents results in a clear format
- It has very good built-in help documentation and a broad user community where you can seek help
- Student and other discount packages are available at reasonable cost

11.2.3 How does Stata work?

When Stata is running, variables, data, etc., are **stored in memory**. The user can use `clear` command to clear up memory before running further commands, unless they want to `save` their changes in the original dataset or a new dataset.

11.2.4 Interfaces



- Review and Variable windows can be closed (user preference)
- Command window can be shortened (recommended)

11.2.4.1 GUI and command window

There are two ways of interacting with Stata that will not result in a saveable record of what you have done:

1. **GUI**. The Graphical User Interface (GUI) allows you to perform analyses using drop-down menus, rather than writing code. This can be easier for first time users and Stata will helpfully display the command and proper syntax for the operation that you have selected. However, we strongly recommend not using the GUI, since it does not produce a script — a record of what you have done — and thus leads to analyses that are unreproducible.

2. **Command window**. From the command window you can type commands to manage and analyze your data.

- The advantage is that you can quickly produce output of a single command.
- The disadvantage is that you cannot store your syntax in a script to reproduce in the future.

11.2.4.2 Do-file

The third way of interacting with Stata does provide you with a saveable record of your work:

3. **Do-file**. A do-file is a plain text file within which you can write and save commands for later use. There are several advantages to using a do-file and we strongly recommend that you always interact with Stata in this way:

    - Allows you to submit more than one command to Stata at once.
    - Has specialized features for programmers such as syntax highlighting, code folding, autocompletion, and bookmarks to important lines in your code, brace matching, and more.
    - With a do-file, it is easy to **save, review, change, and share** your code with others — including your future self!

Here are some resources for learning more about Stata and do-files:

- `https://www.stata.com/`
- `https://www.stata.com/manuals13/gsw13.pdf`
- `https://sociology.fas.harvard.edu/files/sociology/files/creating_a_do_file.pdf`

11.2.5 Stata help

To get help in Stata type `help` followed by topic or command, e.g., `help codebook`.

11.2.6 Syntax rules

- Most Stata commands follow the same basic syntax: `Command varlist, options`.

- Use comments liberally — start with a comment describing your do-file and use comments throughout

    - Use `*` to comment a line and `//` for in-line comments
    - Use `///` to break varlists over multiple lines

11.2.7 Exercise 0

Launch the Stata program (MP or SE, does not matter unless doing computationally intensive work) * Open up a new do-file * Run our first Stata code!

1. Try to get Stata to say "Hello World!". Search `help display`.

```
##
```

2. Try to get Stata to break "Hello World!" over two lines:

```
##
```

Click for Exercise 0 Solution

1. Try to get Stata to say "Hello World!". Search `help display`.

```
disp "Hello " "World!" // 'disp' is short for 'display'
```

2. Try to get Stata to break "Hello World!" over two lines:

```
disp "Hello" ///
     " World!"
```

11.2.8 Working directory

1. print current working directory

```
pwd
```

2. change working directory

```
cd C:\Users\yiw640\Desktop\StataIntro\
```

11.2.8.1 A note about file path names

- If your file path has no spaces in the name (that means all directories, folders, file names, etc. can have no spaces), you can write the file path as it is
- If there are spaces, you need to put your file path name in quotes
- Best to get in the habit of quoting file paths

11.2.9 Reading data

11.2.9.1 Data file commands

- Next, we want to open our data file
- Open / save data sets with `use` and `save`:

```
// open the gss.dta data set
use gss.dta, clear

// save data file
save newgss.dta, replace // `replace` option means OK to overwrite existing file
```

11.2.9.2 Where's my data?

- Data editor (**browse**)
- Data editor (**edit**)
  - Using the data editor is discouraged (why?)
- Always keep any changes to your data in your do-file
- Avoid temptation of making manual changes by viewing data via the browser rather than editor

11.2.9.3 Reading non-Stata data

- Import / export delimited text files

```
// import data from a .csv file
import delimited gss.csv, clear

// save data to a .csv file
export delimited gss_new.csv, replace
```

- Import / export Excel files

```
// import/export Excel files
clear
import excel gss.xlsx
export excel gss_new, replace
```

What if my data is from another statistical software program?

- SPSS/PASW will allow you to save your data as a Stata file
  - Go to: file -> save as -> Stata (use most recent version available)
  - Then you can just go into Stata and open it
- Another option is `StatTransfer`, a program that converts data from/to many common formats, including SAS, SPSS, Stata, and many more.

11.3 Statistics & graphs

GOAL: To learn the basic commands to review, inspect, and plot data in Stata. In particular:

1. Learn more about the variables in our dataset — using the `describe`, `codebook`, and `browse` commands
2. Produce univariate distributions using `histogram`, and bivariate distribution using `scatterplot`
3. Tabulate or summarize your data within certain groups using `bysort`

The most frequently used commands for reviewing and inspecting data are summarized below:

Command	Description
`describe`	labels, storage type etc.
`sum`	statistical summary (mean, sd, min/max etc.)
`codebook`	storage type, unique values, labels
`list`	print actual values
`tab`	(cross) tabulate variables
`browse`	view the data in a spreadsheet-like window

First, let's ask Stata for help about these commands:

```
help sum
```

```
use gss.dta, clear

sum educ // statistical summary of education
```

```
codebook region // information about how region is coded
```

```
tab sex // numbers of male and female participants
```

Note — if you run these commands without specifying variables, Stata will produce output for every variable.

11.3.1 Basic graphing commands

Univariate distribution(s) using `hist`:

```
// Histograms
hist educ
```

```
// histogram with normal curve; see `help hist` for other options
hist age, normal
```

View bivariate distributions with scatterplots:

```
// scatterplots
twoway (scatter educ age)
```

```
graph matrix educ age inc
```

11.3.2 The `by` command

Sometimes, you'd like to generate output based on different categories of a grouping variable, for example:

1. you want to know the distribution of happiness seperately for men and women: tabulate `happy` by `sex`:

```
bysort sex: tab happy
```

2. you want to know the mean level of education for different marital status: summarize `education` by marital status (`marital`):

```
bysort marital: sum educ
```

Save your changes to the original `gss.dta` dataset.

11.3.3 Exercise 1

We are using The Generations of Talent Study (`talent.dta`) to practice reading in data, plotting data, and calculating descriptive statistics. The dataset includes information on quality of employment as experienced by today's multigenerational workforces. Here is a codebook of a subset of variables:

Variable name	Label
job	type of main job
workload	how long hours do you work per week
otherjob	do you have other paid jobs beside main job
schedule	which best describes your work schedule
fulltime	Does your employer consider you a full-time or part-time employee
B3A	How important are the following to you? Your work
B3B	How important are the following to you? Your family
B3C	How important are the following to you? Your friends
marital	Which of the following best describes your current marital status
I3	Sex/gender
income	What was your total household income during last year

Create a new do-file for the following exercise prompts. After the exercise save the do-file to your working directory.

1. Read in the dataset `talent.dta`:

```
##
```

2. Examine a few selected variables using the `describe`, `sum` and `codebook` commands:

```
##
```

3. Produce a histogram of hours worked (`workload`) and add a normal curve:

```
##
```

4. Summarize the total household income last year (`income`) by marital status (`marital`):

```
##
```

5. Cross-tabulate marital status (`marital`) with respondents' type of main job (`job`):

```
##
```

Click for Exercise 1 Solution

1. Read in the dataset `talent.dta`:

```
use talent.dta, clear
```

2. Examine a few selected variables using the `describe`, `sum` and `codebook` commands:

```
describe workperweek
tab I3
sum income
codebook job
```

3. Produce a histogram of hours worked (`workload`) and add a normal curve:

```
hist workload, normal
```

4. Summarize the total household income last year (`income`) by marital status (`marital`):

```
bysort marital: sum income
```

5. Cross-tabulate marital status (`marital`) with respondents' type of main job (`job`):

```
bysort job: tab marital
```

11.4 Basic data management

GOAL: To learn how to add *variable labels* and *value labels*, as well as create *new variables* in Stata. In particular:

1. Use `label` and `rename` to set / modify variable and value labels
2. Use `generate` and `replace` to create a new variables based on values of existing variables/recode a variable

11.4.1 Variable & value labels

11.4.1.1 Variable labels

It's good practice to ALWAYS label every variable, no matter how insignificant it may seem.

```
// Labelling and renaming
// Label variable inc "household income"
label var inc "household income"

// change the name "educ" to "education"
rename educ education

// you can search names and labels with `lookfor`
lookfor household
```

11.4.1.2 Value labels

Value labels are a little more complicated, with a two step process: define a value label, then assign defined label to variable(s)

```
// define a value label for sex
label define mySexLabel 1 "Male" 2 "Female"

// assign our label set to the sex variable
label values sex mySexLabel
```

11.4.2 Working on subsets

It is often useful to select just those rows of your data where some condition holds — for example select only rows where sex is 1 (male). The following operators allow you to do this:

Operator	Meaning
==	equal to
!=	not equal to
>	greater than
>=	greater than or equal to
<	less than
<=	less than or equal to
&	and
|	or

Note the double equals signs for testing equality.

11.4.3 Generating & replacing variables

Often, it can be useful to start with a new variable composed of blank values and fill values in based on the values of existing variables:

```
// generate a column of missings
gen age_wealth = .

// Next, start adding your qualifications
replace age_wealth=1 if age < 30 & inc < 10
replace age_wealth=2 if age < 30 & inc > 10
replace age_wealth=3 if age > 30 & inc < 10
replace age_wealth=4 if age > 30 & inc > 10
```

11.4.4 Exercise 2

Open the `talent.dta` data, use the basic data management tools we have learned to add labels and generate new variables:

1. Tabulate the variable, marital status (`marital`), with and without labels:

```
##
```

2. Summarize the total household income last year (`income`) for married individuals only:

```
##
```

3. Generate a new `overwork` dummy variable from the original variable `workperweek` that will take on a value of 1 if a person works more than 40 hours per week, and 0 if a person works equal to or less than 40 hours per week:

```
##
```

4. Generate a new `marital_dummy` dummy variable from the original variable `marital` that will take on a value of 1 if a person is either married or partnered and 0 otherwise:

```
##
```

5. Rename the `Sex` variable and give it a more intuitive name:

```
##
```

6. Give a variable label and value labels for the variable `overwork`:

```
##
```

7. Generate a new variable called `work_family` and code it as 2 if a respondent perceived work to be more important than family, 1 if a respondent perceived family to be more important than work, and 0 if the two are of equal importance:

```
##
```

8. Save the changes to `newtalent.dta`:

```
##
```

Click for Exercise 2 Solution

Open the `talent.dta` data, use the basic data management tools we have learned to add labels and generate new variables:

1. Tabulate the variable, marital status (`marital`), with and without labels:

```
use talent.dta, clear

tab marital
tab marital, nol
```

2. Summarize the total household income last year (`income`) for married individuals only:

```
summarize income if marital == 1
```

3. Generate a new `overwork` dummy variable from the original variable `workperweek` that will take on a value of 1 if a person works more than 40 hours per week, and 0 if a person works equal to or less than 40 hours per week:

```
gen overwork = .
replace overwork = 1 if workperweek > 40
replace overwork = 0 if workperweek <= 40
tab overwork
```

4. Generate a new `marital_dummy` dummy variable from the original variable `marital` that will take on a value of 1 if a person is either married or partnered and 0 otherwise:

```
gen marital_dummy = .
replace marital_dummy = 1 if marital == 1 | marital == 2
replace marital_dummy = 0 if marital != 1 & marital != 2
tab marital_dummy
```

5. Rename the `Sex` variable and give it a more intuitive name:

```
rename I3 Sex
```

6. Give a variable label and value labels for the variable `overwork`:

```
label variable overwork "whether someone works more than 40 hours per week"
label define overworklabel 1 "Yes" 0 "No"
label values overwork overworklabel
```

7. Generate a new variable called `work_family` and code it as 2 if a respondent perceived work to be more important than family, 1 if a respondent perceived family to be more important than work, and 0 if the two are of equal importance:

```
gen work_family = .
replace work_family = 2 if B3A > B3B
replace work_family = 1 if B3A < B3B
replace work_family = 0 if B3A == B3B
```

8. Save the changes to `newtalent.dta`:

```
save newtalent.dta, replace
```

11.5 Bivariate analyses

GOAL: To learn the basic commands for performing the following bivariate analyses.

1. Chi-squared test
2. Independent group t-test
3. One-way ANOVA

11.5.1 Chi-squared test

The Chi-squared statistic is commonly used for testing relationships between categorical variables.

In Stata, both the `tabulate` and `tabi` commands conduct the Pearson's Chi-square test.

- The `tabulate` (may be abbreviated as `tab`) command produces one- or two-way frequency tables given one or two raw variables
- The `tabi` command is used to re-analyze a published table without access to the raw data
- These commands also can run a Chi-square test using the `chi2` option:

```
tab sex happy, chi2
```

The first command below conducts a Chi-square test for a 2x2 table, while the second and third commands run the test for 3x2 and 2x3 tables, respectively.

```
tabi 33 48 \ 37 52, chi2
tabi 33 48 \ 37 52 \ 36 42, chi2
tabi 33 48 26 \ 37 52 38, chi2
```

11.5.2 t-test

The t-test is a type of inferential statistic that can be used to determine if a sample mean differs from a postulated population mean, or if two sample means came from the same population.

Types of t-test:

- Independent group t-test: designed to compare means of same variable between two groups. For example, test GRE scores between students from two countries
- Other t-tests: single sample t-test; paired t-test. More details see: `https://www.stata.com/manuals13/rttest.pdf`

In our example, we conduct an independent group t-test to compare mean income (`inc`) between males and females (`sex`):

```
ttest inc, by(sex)
```

11.5.3 One-way ANOVA

One-way ANOVA allows us to test the equality of more than two sample means (i.e., whether they could plausibly have come from the same population). For example, our dataset contains income (`inc`) and four regions of the country (`region`). Using one-way ANOVA, we can simultaneously test the equality of the income means across all regions.

```
oneway inc region
```

Now we find evidence that the means are different, but perhaps we are interested only in testing whether the means for the North (region==1) and South (region==4) are different. We also use one-way ANOVA, which in this case would be equivelant to the independent group t-test:

```
oneway inc region if region==1 | region==4
```

11.5.4 Exercise 3

Open the `newtalent.dta` data, use the basic data management tools we have learned to conduct bivariate analysis.

1. Test the relationship between two variables `sex` and type of main job (`job`):

```
##
```

2. Test if there is a significant difference in hours worked per week (`workload`) and `sex`:

```
##
```

3. Test if there is a significant difference in hours worked per week (`workload`) and marital status (`marital`):

```
##
```

Click for Exercise 3 Solution

Open the `newtalent.dta` data, use the basic data management tools we have learned to conduct bivariate analysis.

1. Test the relationship between two variables `sex` and type of main job (`job`):

```
use newtalent.dta, clear

tab Sex job, chi2
```

2. Test if there is a significant difference in hours worked per week (`workload`) and `sex`:

```
ttest workload, by(Sex)
```

3. Test if there is a significant difference in hours worked per week (`workload`) and marital status (`marital`):

```
oneway workload marital
```

11.6 Wrap-up

11.6.1 Feedback

These workshops are a work in progress, please provide any feedback to: `help@iq.harvard.edu`

11.6.2 Resources

- IQSS
  - Workshops: `https://www.iq.harvard.edu/data-science-services/workshop-materials`
  - Data Science Services: `https://www.iq.harvard.edu/data-science-services`
  - Research Computing Environment: `https://iqss.github.io/dss-rce/`
- HBS
  - Research Computing Services workshops: `https://training.rcs.hbs.org/workshops`
  - Other HBS RCS resources: `https://training.rcs.hbs.org/workshop-materials`
  - RCS consulting email: `mailto:research@hbs.edu`
- Stata
  - UCLA website: `http://www.ats.ucla.edu/stat/Stata/`
  - Stata website: `http://www.stata.com/help.cgi?contents`
  - Email list: `http://www.stata.com/statalist/`

Chapter 12

Stata Data Management

Topics

- Generating and replacing variables
- Missing values
- Variable types and conversion
- Merging, appending, and joining
- Creating summarized data sets

12.1 Setup

12.1.1 Software and Materials

Follow the Stata Installation instructions and ensure that you can successfully start Stata.

12.1.2 Class structure and organization

- Please feel free to ask questions at any point if they are relevant to the current topic (or if you are lost!)
- Collaboration is encouraged - please introduce yourself to your neighbors!
- If you are using a laptop, you will need to adjust file paths accordingly
- Make comments in your do-file - save on flash drive or email to yourself

12.1.3 Prerequisites

- This is an introduction to data management in Stata
- Assumes basic knowledge of Stata
- Not appropriate for people already familiar with Stata
- If you are catching on before the rest of the class, experiment with command features described in help files

12.1.4 Goals

We will learn about the Stata language by analyzing data from the general social survey (gss). In particular, our goals are to learn:

1. Basic data manipulation commands
2. Dealing with missing values
3. Variable types and conversion
4. Merging and appending datasets

12.2 Opening Files

GOAL: To understand the working directory of Stata, how to change working directory, and open files from the working directory. In particular:

Look at bottom left hand corner of Stata screen, this is the directory Stata is currently reading from. Files are located in the `StataDatMan` folder in your user directory. Let's start by telling Stata where to look for these:

```
// change directory
cd "~/Desktop/dss-workshops/Stata/StataDatMan"

// Use dir to see what is in the directory:
dir
dir dataSets
```

Now we can read in the `gss.dta` dataset:

```
use dataSets/gss.dta
```

12.3 Generating & replacing variables

GOAL: You'll learn how to generate new variables or recode existing variables. In particular, we will learn to use:

1. `generate` (`gen`) to create new variables
2. `egenerate` (`egen`) to create new variables using more complicated calculations than `gen` allows
3. `replace` to replace existing variables
4. `recode` to change existing categorical variables

12.3.1 Generate & Replace

The `generate` command creates a new variables. Often, this is used in combination with the `replace` command and logic statements to create a new variable. Available logical operators include the following:

Operator	Meaning
==	equal to
!=	not equal to
>	greater than
>=	greater than or equal to
<	less than
<=	less than or equal to
&	and

For example:

```
//create "hapnew" variable
gen hapnew = .

//set to 0 if happy equals 1
replace hapnew=0 if happy==1

//set to 1 if happy both and hapmar are greater than 3
replace hapnew=1 if happy>3 & hapmar>3

// tabulate the new
tab hapnew
```

12.3.2 Recode

The `recode` command is basically `generate` and `replace` combined. You can `recode` an existing variable OR use `recode` to create a new variable (via the `gen` option).

```
// recode the wrkstat variable
recode wrkstat (1=8) (2=7) (3=6) (4=5) (5=4) (6=3) (7=2) (8=1)

// recode wrkstat into a new variable named wrkstat2
recode wrkstat (1=8), gen(wrkstat2)

// tabulate workstat
tab wrkstat
```

The table below illustrates common forms of recoding:

Rule	Example	Meaning
#=#	3=1	3 recoded to 1
##=#	2.=9	2 and . recoded to 9
#/#=#	1/5=4	1 through 5 recoded to 4
nonmissing=#	nonmiss=8	nonmissing recoded to 8
missing=#	miss=9	missing recoded to 9

12.3.3 egen

The `egen` command ("extensions" to the `gen` command) reaches beyond simple computations (var1 + var2, log(var1), etc.) to add descriptive stats, standardizations and more. For example, we can use `egen` to create a new variable that counts the number of "yes" responses on computer, email and internet use:

```
// count number of yes on use comp email and net
egen compuser = anycount(usecomp usemail usenet), values(1)
tab compuser
```

Here are some additional examples of `egen` in action:

```
// assess how much missing data each participant has:
egen countmiss = rowmiss(age-wifeft)
codebook countmiss

// compare values on multiple variables
egen ftdiff = diff(wkftwife wkfthusb)
codebook ftdiff
```

You will need to refer to the documentation to discover what else `egen` can do: type `help egen` in Stata to get a complete list of available functions.

12.3.4 Exercise 0

1. Open the `gss.dta` data, `generate` a new variable that represents the squared value of `age`.

```
##
```

2. `generate` a new variable equal to "1" if `income` is greater than "19".

```
##
```

3. Create a new variable that counts the number of missing responses for each respondent. What is the maximum number of missing variables?

```
##
```

Click for Exercise 0 Solution

1. Open the `gss.dta` data, `generate` a new variable that represents the squared value of `age`.

```
use dataSets/gss.dta, clear
gen age2 = age^2
```

2. `generate` a new variable equal to "1" if `income` is greater than "19".

```
describe income
label list income
recode income (99=.) (98=.)
gen highincome =0 if income != .
replace highincome=1 if income>19
sum highincome
```

3. Create a new variable that counts the number of missing responses for each respondent. What is the maximum number of missing variables?

```
egen nmissing = rowmiss(_all)
sum nmissing
```

12.4 Missing values

GOAL: Learn how missing values are coded and how to recode them.

Stata's symbol for a missing value is a period `.` and this value is coded and treated as **positive infinity** (i.e., the largest possible value), so it's easy to make mistakes when making logical and relational comparisons!

12.4.1 Making sure missingness is preserved

To identify highly educated women, we might use the command:

```
// generate and replace without considering missing values
gen hi_ed=0
replace hi_ed=1 if wifeduc>15
// What happens to our missing values?
tab hi_ed, mi nola
```

It looks like around 66% have higher education, but look closer:

```
// generate hi_ed2, but only set a value if wifeduc is not missing
gen hi_ed2 = 0 if wifeduc != .
// only replace non-missing values
replace hi_ed2=1 if wifeduc >15 & wifeduc !=.
//check to see that missingness is preserved
tab hi_ed2, mi
```

The correct value is 10%. Moral of the story? Be careful with missing values and remember that Stata considers missing values to be **positive infinity**!

12.4.2 Bulk Conversion to missing values

Often the data collection / generating procedure will have used some other value besides . to represent missing values. The `mvdecode` command will convert all these values to missing. For example:

```
mvdecode _all, mv(999)
```

The `_all` command tells Stata to perform this conversion for all variables. Use this command carefully! If you have any variables where “999” is a legitimate value, Stata is going to recode it to missing. As an alternative, you could list var names separately rather than using `_all`.

12.5 Variable types

GOAL: Learn about the two main types of variables that Stata uses: string and numeric.

To be able to perform any mathematical operations, your variables need to be in a numeric format. Stata can store numbers with differing levels of precision, as described in the table below:

type	Minimum	Maximum	being 0	bytes
byte	-127	100	+/-1	1
int	-32,767	32,740	+/-1	2
long	-2,147,483,647	2,147,483,620	+/-1	4
float	-1.70141173319*1038	1.70141173319*1038	+/-10-38	4
double	-8.9884656743*10307	8.9884656743*10307	+/-10-323	8

Precision for float is 3.795x10-8. Precision for double is 1.414x10-16.

12.5.1 Converting to & from Strings

Stata provides several ways to convert to and from strings. You can use `tostring` and `destring` to convert from one type to the other:

```
// convert degree to a string
tostring degree, gen(degree_s)
// and back to a number
destring degree_s, gen(degree_n)
```

Use `decode` and `encode` to convert to / from variable labels:

```
// convert degree to a descriptive string
decode degree, gen(degree_s2)
// and back to a number with labels
encode degree_s2, gen(degree_n2)
```

12.5.2 Converting strings to date / time

Often date / time variables start out as strings — you'll need to convert them to numbers using one of the conversion functions listed below:

Format	Meaning	String-to-numeric conversion function
%tc	milliseconds	clock(string, mask)
%td	days	date(string, mask)
%tw	weeks	weekly(string, mask)
%tm	months	monthly(string, mask)
%tq	quarters	quarterly(string, mask)
%ty	years	yearly(string, mask)

Date / time variables are stored as the number of units elapsed since 01 January 1960 00:00:00.000. For example, the `date` function returns the number of days since that time, and the `clock` function returns the number of milliseconds since that time.

```
// create string variable and convert to date
gen date = "November 9 2020"
gen date1 = date(date, "MDY")
list date1 in 1/5
```

12.5.3 Formatting numbers as dates

Once you have converted a string to a number you can format it for display. You can either accept the defaults used by your formatting string or provide details to customize it.

```
// format so humans can read the date
format date1 %d
list date1 in 1/5
// format with detail
format date1 %tdMonth_dd,_CCYY
list date1 in 1/5
```

12.5.4 Exercise 1

Missing values, string conversion, & by processing

1. Recode values "99" and "98" on the variable `hrs1` as missing.

```
##
```

2. Recode the `marital` variable into a string variable and then back into a numeric variable.

```
##
```

3. Create a new variable that associates each individual with the average number of hours worked among individuals with matching educational degrees (see the last `by` example for inspiration).

```
##
```

Click for Exercise 1 Solution

1. Recode values "99" and "98" on the variable `hrs1` as missing.

```
use dataSets/gss.dta, clear
sum hrs1
recode hrs1 (99=.) (98=.)
sum hrs1
```

2. Recode the `marital` variable into a string variable and then back into a numeric variable.

```
tostring marital, gen(marstring)
destring marstring, gen(mardstring)

//compare with
decode marital, gen(marital_s)
encode marital_s, gen(marital_n)

describe marital marstring mardstring marital_s marital_n
sum marital marstring mardstring marital_s marital_n
```

3. Create a new variable that associates each individual with the average number of hours worked among individuals with matching educational degrees (see the last `by` example for inspiration).

```
bysort degree: egen hrsdegree = mean(hrs1)
tab hrsdegree
tab hrsdegree degree
```

12.6 Merging, appending, & collapsing

GOAL: To learn the basic commands to merge, append, or join two dataset in Stata. In particular:

1. How to append datasets
2. How to merge datasets and types of merge
3. Collapse from master data and create a new dataset of summary statistics

12.6.1 Appending datasets

Sometimes you have observations in two different datasets, or you'd like to add observations to an existing dataset. In this case you can use the `append` command to add observations to the end of the observations in the master dataset. For example:

```
clear
// from the append help file
webuse even
list
webuse odd
list
// Append even data to the end of the odd data
append using "http://www.stata-press.com/data/r14/even"
list
clear
```

To keep track of where observations came from, use the `generate` option as shown below:

```
webuse odd
append using "http://www.stata-press.com/data/r14/even", generate(observesource)
list
clear
```

There is a `force` option will allow for data type mismatches, but this is not recommended. Remember, `append` is for adding observations (i.e., rows) from a second data set to your current dataset.

12.6.2 Merging datasets

You can `merge` variables from a second dataset to the dataset you're currently working with. There are different ways that you might be interested in merging data:

- Two datasets with same participant pool, one row per participant (1:1)
- A dataset with one participant per row with a dataset with multiple rows per participant (1:many or many:1)

Before you begin:

1. Identify the ID that you will use to merge your two datasets
2. Determine which variables you'd like to merge
3. Variable types must match across datasets (there is a force option to get around this, but it is not recommended)

Note — data do NOT have to be sorted prior to merging.

```
// Adapted from the merge help page
webuse autosize
list
webuse autoexpense
list

webuse autosize
merge 1:1 make using "http://www.stata-press.com/data/r14/autoexpense"
list
clear

// keep only the matches (AKA "inner join")
webuse autosize, clear
merge 1:1 make using "http://www.stata-press.com/data/r14/autoexpense", keep(match) nogen
list
clear
```

Remember, merge is for adding variables (i.e., columns) from a second data set.

12.6.3 Merge Options

There are several options that provide more fine-grain control over what happens to non-id columns contained in both data sets. If you've carefully cleaned and prepared the data prior to merging this shouldn't be an issue, but here are some details about how Stata handles this situation.

- In standard merge, the current active dataset is the authority and WON'T CHANGE
- If your current dataset has missing data and some of those values are not missing in your new dataset, specify update – this will fill in missing data in the current dataset
- If you want data from your new dataset to overwrite that in your current dataset, specify replace update — this will replace current data with new data UNLESS the value is missing in the new dataset

12.6.4 Many-to-many merges - joinby command

Stata allows you to specify merges like merge m:m id using newdata.dta, but it is difficult to imagine a situation where this would be useful. If you are thinking about using merge m:m chances are good that you actually need joinby. Please refer to the joinby help page for details.

12.6.5 Collapse

collapse will take your current active dataset and create a new dataset of summary statistics

- Useful in hierarchical linear modeling if you'd like to create aggregate, summary statistics
- Can generate group summary data for many descriptive stats
- Can also attach weights

Before you collapse:

- Save your current dataset and then save it again under a new name (this will prevent collapse from writing over your original data
- Consider issues of missing data. Do you want Stata to use all possible observations? If not, the cw (casewise) option will make casewise deletions

```
// Adapted from the collapse help page
clear
webuse college
list
// mean and sd by hospital
collapse (mean) mean_gpa = gpa mean_hour = hour (sd) sd_gpa = gpa sd_hour = hour, by(year)
list
clear
```

You could also generate different statistics for multiple variables.

12.6.6 Exercise 2

Append, merge, & collapse

Open the gss2.dta dataset. This dataset contains only half of the variables that are in the complete gss dataset.

1. Merge dataset gss1.dta with dataset gss2.dta. The identification variable is id.

```
##
```

2. Open the gss.dta dataset and merge in data from the marital.dta dataset, which includes income information grouped by individuals' marital status. The marital.dta dataset contains collapsed data regarding average statistics of individuals based on their marital status.

```
##
```

3. Open the `gssAppend.dta` dataset and create a new dataset that combines the observations in `gssAppend.dta` with those in `gssAddObserve.dta`.

```
##
```

4. Open the `gss.dta` dataset and create a new dataset that summarizes the mean and standard deviation of income based on individuals' degree status (`degree`). In the process of creating this new dataset, rename your three new variables.

```
##
```

Click for Exercise 2 Solution

Open the `gss2.dta` dataset. This dataset contains only half of the variables that are in the complete gss dataset.

1. Merge dataset `gss1.dta` with dataset `gss2.dta`. The identification variable is `id`.

```
use dataSets/gss2.dta, clear
merge 1:1 id using dataSets/gss1.dta
save gss3.dta, replace
```

2. Open the `gss.dta` dataset and merge in data from the `marital.dta` dataset, which includes income information grouped by individuals' marital status. The `marital.dta` dataset contains collapsed data regarding average statistics of individuals based on their marital status.

```
use dataSets/gss.dta, clear
merge m:1 marital using dataSets/marital.dta, nogenerate replace update
save gss4.dta, replace
```

3. Open the `gssAppend.dta` dataset and create a new dataset that combines the observations in `gssAppend.dta` with those in `gssAddObserve.dta`.

```
use dataSets/gssAppend.dta, clear
append using dataSets/gssAddObserve, generate(observe)
```

4. Open the `gss.dta` dataset and create a new dataset that summarizes the mean and standard deviation of income based on individuals' degree status (`degree`). In the process of creating this new dataset, rename your three new variables.

```
use dataSets/gss.dta, clear
save collapse2.dta, replace
use collapse2.dta, clear
collapse (mean) meaninc=income (sd) sdinc=income, by(marital)
```

12.7 Wrap-up

12.7.1 Feedback

These workshops are a work-in-progress, please provide any feedback to: `help@iq.harvard.edu`

12.7.2 Resources

- IQSS
  - Workshops: `https://www.iq.harvard.edu/data-science-services/workshop-materials`
  - Data Science Services: `https://www.iq.harvard.edu/data-science-services`
  - Research Computing Environment: `https://iqss.github.io/dss-rce/`
- HBS
  - Research Computing Services workshops: `https://training.rcs.hbs.org/workshops`
  - Other HBS RCS resources: `https://training.rcs.hbs.org/workshop-materials`
  - RCS consulting email: `mailto:research@hbs.edu`
- Stata
  - UCLA website: `http://www.ats.ucla.edu/stat/Stata/`
  - Stata website: `http://www.stata.com/help.cgi?contents`
  - Email list: `http://www.stata.com/statalist/`

Chapter 13

Stata Regression Models

Topics

- Models with continuous outcomes
  - OLS regression
  - OLS model assumptions and diagnostics
  - Including interaction terms
  - Including categorical predictors
- Models with binary outcomes
  - Logistic regression
  - Obtaining odds ratios
- Exporting & saving results
  - Regression tables
  - Model comparison
- Obtaining quantities of interest
  - Margins of responses
    - APM: Average Predictive Margins
    - PMM: Predictive Margins at the Means
    - PMR: Predictive Margins at Representative values
  - Margins of changes in responses
    - AME: Average Marginal Effects
    - MEM: Marginal Effects at the Means
    - MER: Marginal Effects at Representative values

13.1 Setup

13.1.1 Software and Materials

Follow the Stata Installation instructions and ensure that you can successfully start Stata.

13.1.2 Class structure and organization

- Informal — Ask questions at any time. Really!
- Collaboration is encouraged - please spend a minute introducing yourself to your neighbors!
- If you are using a laptop, you will need to adjust file paths accordingly
- Make comments in your do-file - save on flash drive or email to yourself

13.1.3 Prerequisites

This is an intermediate-level Stata modeling workshop

- Assumes basic knowledge of Stata
- Not appropriate for people already well familiar with modeling in Stata
- If you are catching on before the rest of the class, experiment with command features described in help files

13.1.4 Goals

We will learn about the Stata modeling ecosystem by analyzing data from three datasets. In particular, our goals are to learn about:

1. Modeling workflow
2. Modeling continuous outcomes

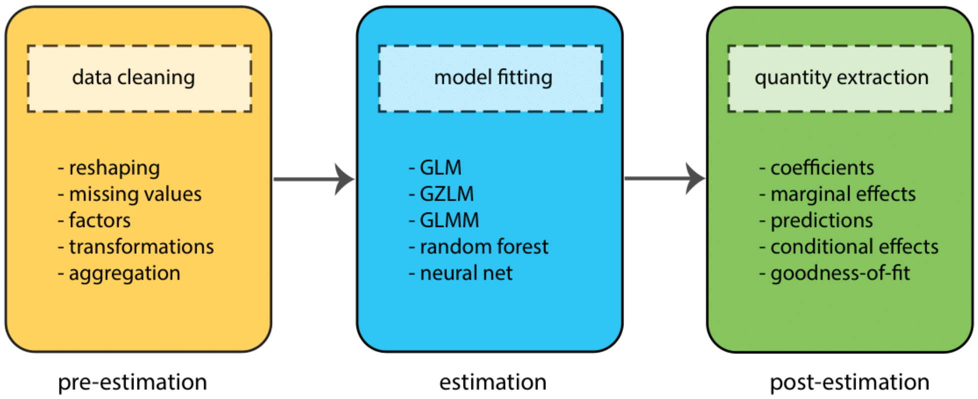
3. Modeling binary outcomes
4. Producing regression tables
5. Obtaining margins of responses
6. Obtaining margins of changes in responses

13.2 Modeling workflow

Before we delve into the details of how to fit models in Stata, it's worth taking a step back and thinking more broadly about the components of the modeling process. These can roughly be divided into 3 stages:

1. Pre-estimation
2. Estimation
3. Post-estimaton

At each stage, the goal is to complete a different task (e.g., to clean data, fit a model, test a hypothesis), but the process is sequential — we move through the stages in order (though often many times in one project!)



Throughout this workshop we will go through these stages several times as we fit different types of model.

13.3 Before fitting a model

GOAL: To learn about the data by creating summaries and visualizations.

13.3.1 The dataset

We have a dataset (`states.dta`) on a variety of variables for all 50 states. Variables include population, density, energy use, voting tendencies, graduation rates, income, etc.

We're going to ask the question: does the amount of money spent on education (`expense`), family income(`income`), and percentage of students taking SATs (`percent`) affect the mean SAT score (`csat`) in a state?

13.3.2 Set working directory

Files are located in the `dataSets` folder in `StataMod`. Start by telling Stata where to look for these:

```
// change directory
cd "~/Desktop/Stata/StataMod"
```

Use `dir` to see what is in the directory:

```
dir
cd dataSets
```

13.3.3 Load the data

```
// use the states data set
use dataSets/states.dta
```

13.3.4 Examine descriptive statistics

```
// descriptive statistics
sum expense income percent csat
```

13.3.5 Visualize the data

```
// visualize data
scatter expense income
scatter expense percent
```

13.4 Models with continuous outcomes

GOAL: To learn about the Stata modeling ecosystem by using the `regress` command to fit ordinary least squares (OLS) models. In particular:

1. Stata syntax for model specification
2. Model diagnostics for checking OLS assumptions
3. Including interaction terms
4. Including categorical predictors

13.4.1 Fit the model

To fit a model in Stata, we first have to convert our theoretical model into Stata syntax — a symbolic representation of the model:

```
// model specification
command outcome pred1 pred2 pred3
```

Note that immediately after the modeling command comes the outcome variable, followed by numerous predictors.

For example, the following model predicts SAT scores based on the amount of money spent on education (`expense`), family income(`income`), and percentage of students taking SATs (`percent`) in a state. Here's the theoretical model:

$$SATscores_i = \beta_0 1 + \beta_1 expenditures_i + \beta_2 income_i + \beta_3 SATpercent_i + \epsilon_i$$

And here's how we use the `regress` command to fit this model in Stata:

```
regress csat expense income percent
```

13.4.2 OLS assumptions

OLS regression relies on several assumptions, including:

1. The model includes all relevant variables (i.e., no omitted variable bias).
2. The model is linear in the parameters (i.e., the coefficients and error term).
3. The error term has an expected value of zero.
4. All right-hand-side variables are uncorrelated with the error term.
5. No right-hand-side variables are a perfect linear function of other RHS variables.
6. Observations of the error term are uncorrelated with each other.
7. The error term has constant variance (i.e., homoscedasticity).
8. (Optional - only needed for inference). The error term is normally distributed.

We can investigate assumptions #7 and #8 by plotting model diagnostics. A simple histogram of the residuals can be informative:

```
// graph the residual values of csat
predict resid, residual
histogram resid, normal
```

We can also examine homoscedasticity:

```
rvfplot, yline(0)
```

Type `-help regress postestimation` — for more information about model diagnostics. If assumptions are not met, alter the specification and refit the model.

13.4.3 Interactions

What if we wanted to test an interaction between `percent` and `high`?

Option 1: generate product terms by hand:

```
// generate product of percent and high
gen percenthigh = percent*high
regress csat expense income percent high percenthigh
```

Option 2: let Stata do your dirty work:

```
// use the # sign to represent interactions
regress csat percent high c.percent#c.high
// same as: regress csat c.percent##c.high
```

13.4.4 Categorical predictors

For categorical variables, we first need to dummy code. Let's use `region` as an example.

Option 1: create dummy codes before fitting regression model:

```
// create region dummy codes using tab
tab region, gen(region)

// regress csat on region
regress csat region1 region2 region3
```

Option 2: let Stata do it for you:

```
// regress csat on region using fvvarlist syntax
// see `help fvvarlist` for details
regress csat i.region
```

13.4.5 Exercise 0

Regression with continuous outcomes

Open the datafile, `gss.dta`.

Fit an OLS regression model to predict general happiness (`happy`) based on respondent's sex (`sex`), marital status (`marital`), highest year of school completed (`educ`), and respondent's income for last year (`rincome`).

1. Before running the regression, examine descriptive statistics of the variables and generate a few scatterplots.

```
##
```

2. Run your regression model.

```
##
```

3. Examine the plausibility of the assumptions of normality and homoscedasticity.

```
##
```

4. Add on to the regression equation by generating an interaction term between `sex` and `educ` and testing the interaction.

```
##
```

Click for Exercise 0 Solution

Open the datafile, `gss.dta`.

Fit an OLS regression model to predict general happiness (`happy`) based on respondent's sex (`sex`), marital status (`marital`), highest year of school completed (`educ`), and respondent's income for last year (`rincome`).

1. Before running the regression, examine descriptive statistics of the variables and generate a few scatterplots.

```
sum happy educ rincome
tab sex
tab marital

scatter happy rincome
```

2. Run your regression model.

```
regress happy i.sex educ i.marital rincome
```

3. Examine the plausibility of the assumptions of normality and homoscedasticity.

```
hist happy, normal
rvfplot,yline(0)
```

4. Add on to the regression equation by generating an interaction term between `sex` and `educ` and testing the interaction.

```
regress happy i.sex##c.educ i.marital rincome
```

13.5 Models with binary outcomes

GOAL: To learn how to use the `logit` command to model binary outcomes. In particular:

1. Run the model to obtain estimates on the log odds scale
2. Transform model coefficients into odds ratios

13.5.1 The Dataset

Using the `states.dta` data, we're going to ask the question: does people per square mile (`density`), percent HS graduates taking SAT (`percent`), and per pupil expenditures for primary and secondary school (`expense`) affect the probability of having an SAT score greater than or equal to 1000 (`sat_binary`)?

13.5.2 Load the dataset

```
// use the states data set
use dataSets/states.dta
```

13.5.3 Recode the outcome variable

Recode the composite SAT score (`csat`) into two categories: **whether a region's mean SAT score is greater than or equal to 1000, or less than 1000.**

```
gen sat_binary = .
replace sat_binary = 0 if csat < 1000
replace sat_binary = 1 if csat >= 1000
```

13.5.4 Run summary statistics

```
tab sat_binary
sum density percent expense
```

13.5.5 Run the logistic model

Let's predict the probability of having mean SAT score greater than or equal to 1000 based on `density`, `percent`, and `expense`.

Here's the theoretical model:

$$logit(p(SAT1000_i = 1)) = \beta_0 1 + \beta_1 density_i + \beta_2 SATpercent_i + \beta_3 expenditures_i$$

where $logit(\cdot)$ is the non-linear link function that relates a linear expression of the predictors to the expectation of the binary response:

$$logit(p(SAT1000_i = 1)) = ln\left(\frac{p(SAT1000_i = 1)}{1 - p(SAT1000_i = 1)}\right) = ln\left(\frac{p(SAT1000_i = 1)}{p(SAT1000_i = 0)}\right)$$

And here's how we use the `logit` command to fit this model in Stata:

```
// logit regression with estimates on the log odds scale
logit sat_binary density percent expense

// logit regression with estimates on the odds ratio scale
logit sat_binary density percent expense, or
```

13.5.6 Exercise 1

Regression with binary outcomes

Use the data file, `gss.dta`. Examine how age of a respondent (`age`), highest year of school completed (`degree`), hours per day watching TV (`tvhours`), and total family income for last year (`income`) relate to whether someone uses internet (`usenet`).

1. Load the dataset.

```
##
```

2. Run summary statistics, delete subjects who did not provide an answer to the `usenet` question.

```
##
```

Click for Exercise 1 Solution

Use the data file, `gss.dta`. Examine how age of a respondent (`age`), highest year of school completed (`degree`), hours per day watching TV (`tvhours`), and total family income for last year (`income`) relate to whether someone uses internet (`usenet`).

1. Load the dataset.

```
use gss.dta, clear
```

2. Run summary statistics, delete subjects who did not provide an answer to the `usenet` question.

```
tab usenet
drop if usenet == 9
tab degree
sum age tvhours income
```

13.6 Exporting & saving results

GOAL: To learn how to store and export Stata models. In particular:

1. How to store results from models
2. How to compare models
3. How to export Stata model output to Excel

13.6.1 Storing results

Stata offers several user-friendly options for storing and viewing regression output from multiple models. First, download the necessary packages:

```
// install outreg2 package
findit outreg2
```

Then store the results of some regression models using the `estimates` command and `store` option:

```
// fit two regression models and store the results
regress csat expense income percent high
estimates store Model1

regress csat expense income percent high i.region
estimates store Model2
```

The stored models can be recalled by name using the `estimates` command and `replay` option:

```
// display Model1
estimates replay Model1
```

13.6.2 Comparing models

The stored models can be compared by name using the `estimates` command and `table` option. For a more formal comparison, the `lrtest` command can be used to perform a likelihhod ratio test:

```
// compare Model1 and Model2 coefficients
estimates table Model1 Model2

// compare Model1 and Model2 fit
lrtest Model1 Model2
```

13.6.3 Exporting to Excel

To avoid human error when transferring coefficients into tables, Excel can be used to format publication-ready tables:

```
outreg2 [Model1 Model2] using csatprediction.xls, replace
```

13.6.4 Exercise 2

Exporting & saving results

1. Fit the logistic model and save it as `Model1`.

```
##
```

2. Add another predictor (`hrs1`) in the model and save the new model as `Model2` and compare between `Model1` and `Model2`.

```
##
```

3. Save the output of the better fitted model to a word document.

```
##
```

Click for Exercise 2 Solution

1. Fit the logistic model and save it as `Model1`.

```
logit usenet age i.degree tvhours income
est store Model1
```

2. Add another predictor (`hrs1`) in the model and save the new model as `Model2` and compare between `Model1` and `Model2`.

```
logit usenet age i.degree tvhours income hrs1
est store Model2

lrtest Model1 Model2
```

3. Save the better fitted model output to a word document.

```
logit usenet age i.degree tvhours income hrs1
outreg2 using Mymodel.doc
```

13.7 Obtaining quantities of interest

GOAL: To obtain easy to interpret output from regression models. In particular:

1. Margins of responses (a.k.a. predictive margins)
2. Margins of changes of responses (a.k.a. marginal effects)
3. Graphs of margins

The default summary model output that Stata produces is useful and intuitive for relatively simple models, especially if the outcome is continuous. For more complex models, especially non-linear models or those with interactions, the default output only reports a small subset of information from the model and/or presents results on an unintuitive scale. For such models, it is often easier to interpret **margins** — specifically, *margins of responses* or *margins of changes in responses*. Margins are statistics calculated from predictions of a previously fit model at fixed values of some covariates and averaging over the remaining covariates. Margins answers the question, **"What does my model have to say about such-and-such a group or such-and-such a person?"**. It answers this question:

1. Either conditionally —– based on fixed values of covariates (e.g., the mean) -—- or averaged over the observations in the data.
2. In terms of the response given covariate levels (**margins of responses**), or any other response you can calculate as a function of your estimated parameters -—- linear responses, probabilities, hazards, survival times, odds ratios, risk differences. (a.k.a. *predictive margins*, or *adjusted predictions*, or *estimated marginal means*, or *least-squares means*).
3. In terms of the *change* in the response for a *change* in covariate levels (**margins of changes in responses**). (a.k.a. *marginal effects* or *partial effects*).
4. Providing standard errors, test statistics, and confidence intervals and those statistics can take the covariates as given or adjust for sampling.

To calculate such effects in Stata, we need a flexible way of obtaining quantities of interest from the model. This is generally done using a post-estimation tool. The main post-estimation tool Stata has in its arsenal is the `margins` command. This is a very flexible tool for producing a variety of quantities of interest from almost all model types that Stata supports. In particular, `margins` can calculate:

1. Different types of *margins of responses*:
   - **APM: Average Predictive Margins** (average of the responses among actual people in the data)
   - **PMM: Predictive Margins at the Means** (expected response for a person with average characteristics)

- **PMR: Predictive Margins at Representative values** (expected response across a range of covariate values)

2. Difference types of *margins of changes in responses*:

   - **AME: Average Marginal Effects** (average of the changes in responses among actual people in the data)
   - **MEM: Marginal Effects at the Means** (expected change in response for a person with average characteristics)
   - **MER: Marginal Effects at Representative values** (expected change in response across a range of covariate values)

The `margins` command can only be used *after* you've run a regression and acts on the results of the most recent regression command. The `marginsplot` command can be used to graph any of these margins or comparisons of margins and acts on the results of the most recent `margins` command.

13.8 Margins of responses

GOAL: To learn how to produce margins of responses. In particular:

1. APM: Average Predictive Margins

2. PMM: Predictive Margins at the Means
3. PMR: Predictive Margins at Representative values
4. Graph margins of responses

13.8.1 The dataset

The case study examples use the `nhanesII` dataset (Second National Health and Nutrition Examination Survey), which was conducted in the mid to late 1970s. More on the study can be found at `https://wwwn.cdc.gov/nchs/nhanes/nhanes2/`. Let's load the data:

```
use dataSets/nhanesII.dta
```

13.8.2 Fit a model

We will examine a continuous measure of systolic blood pressure (`bpsystol`) as a function of a respondent's age (`age`), whether they have diabetes (`diabetes`), and what geographical region they come from (`region`), using OLS regression.

```
regress bpsystol age i.diabetes i.region
```

13.8.3 APM: Average Predictive Margins

If you just type `margins` by itself, Stata will calculate the predicted value of the model outcome (`bpsystol`) for each observation in the data, then report the mean value of those predictions.

```
margins
```

If `margins` is followed by a categorical variable, for example, `region`, Stata first identifies all the levels of the categorical variable. Then, it calculates what the mean predicted value of the model outcome (`bpsystol`) would be if all observations had that value for `region`. All other variables are left unchanged.

```
// margins for dummy variable
margins diabetes

// margins for multi-level categorical variable
margins region
```

13.8.4 PMM: Predictive Margins at the Means

By default, `margins` reports the average of the predictions for each person (i.e., observation) in the data. This is the average response among the actual people in the data. But we can also get `margins` to report the prediction at the average of the covariates by using the `atmeans` option. This represents the expected response of a person with average characteristics.

```
// margins for dummy variable
margins diabetes, atmeans
```

13.8.5 PMR: Predictive Margins at Representative values

For continuous variables, `margins` cannot look at all possible values, but we can specify which values we want to examine with the `at` option:

```
margins, at(age = (50 80))
```

The previous step calculates the mean predicted value of the model outcome (`bpsystol`) with `age` set to 50, and then again with `age` set to 80. We can also add more values by listing the numbers we want in a *numlist*:

```
// predicted values for ages 50 to 80 in 5 year increments
margins, at(age=(50(5)80))
```

13.8.6 Graph margins of responses

The previous step calculates the mean predicted value of `bpsystol` with age set to 50, 55, 60, 65, 70, 75, and 80. We can now use `marginsplot` to graph the results.

```
marginsplot
```

13.8.7 Exercise 3

Margins of responses

Open the datafile `gss.dta`.

1. Fit an OLS regression model to predict general happiness (`happy`) based on respondent's sex (`sex`), marital status (`marital`), highest year of school completed (`educ`), and respondent's income for last year (`rincome`). Obtain average predictive margins for `happy`.

```
##
```

2. Obtain predictive margins of `sex` and `marital`.

```
##
```

3. Obtain predictive margins of `rincome` from 10000 to 30000, with an interval of 5000.

```
##
```

4. Create a `marginsplot` and interpret the results.

```
##
```

Click for Exercise 3 Solution

Open the datafile `gss.dta`

1. Fit an OLS regression model to predict general happiness (`happy`) based on respondent's sex (`sex`), marital status (`marital`), highest year of school completed (`educ`), and respondent's income for last year (`rincome`). Obtain average predictive margins for `happy`.

```
regress happy i.sex educ i.marital rincome
margins
```

2. Obtain predictive margins of `sex` and `marital`.

```
margins, sex
margins, marital
```

3. Obtain predictive margins of `rincome` from 10000 to 30000, with an interval of 5000.

```
margins, at(rincome=(10000(5000)30000))
```

4. Create a `marginsplot` and interpret the results.

```
marginsplot
```

13.9 Margins of changes in responses

GOAL: To learn how to produce margins of changes in responses. In particular:

1. AME: Average Marginal Effects
2. MEM: Marginal Effects at the Means
3. MER: Marginal Effects at Representative values
4. Graph margins of changes in responses

13.9.1 The dataset

We will be using the same dataset as the previous example: the Second National Health and Nutrition Examination Survey (NHANES II). Let's load the data:

```
use dataSets/nhanesII.dta
```

13.9.2 Fit a model

We will predict the probability of someone having diabetes (`diabetes`), as a function of race (`black`), sex (`female`), and age (`age`), using logistic regression.

```
logit diabetes black female age, nolog
```

13.9.3 AME: Average Marginal Effects

We can first obtain the Average Predictive Margins of race (`black`) and sex (`female`). Then, we can use the `dydx` command to estimate changes in the response when the levels of race and sex change. Since, by default, these changes are averaged over each person in the dataset, we obtain Average Marginal Effects. As the current model is logistic, margins automatically back-transforms the APMs and AMEs from the estimation scale (i.e., the log odds scale) to the response scale (i.e., the probability scale).

```
// obtain Average Predictive Margins
margins black female

// calculate the average of all the marginal effects
margins, dydx(black female)
```

13.9.4 MEM: Marginal Effects at the Mean

By default, `margins` with the `dydx` command reports the average of the changes in the probability of the response among actual people in the data. But we can also get margins to report the expected change in the probability of the response for a person with average characteristics by using the `atmeans` option.

```
// obtain Predictive Margins at the Means
margins black female, atmeans

// calculate marginal effects with all other covariates fixed at their sample means
margins, dydx(black female) atmeans
```

13.9.5 MER: Marginal Effects at Representative values

For continuous variables, `margins` needs us to specify which values we want to examine using the `at` option. We can calculate the change in the probability of the model outcome (`diabetes`) when levels of race (`black`) and sex (`female`) change, across a range of values for `age` by supplying a list of numbers to a *numlist*:

```
// obtain Predictive Margins at Representative values
// choose range of values for one or more variables
// note: the `vsquish` option omits vertical white space between results
margins black, at(age=(20 30 40 50 60 70)) vsquish

// calculate marginal effects across that range
margins, dydx(black female) at(age=(20 30 40 50 60 70)) vsquish
```

13.9.6 Graph margins of changes in responses

The previous step calculates the average change in the predicted probability of `diabetes`, when levels of race (`black`) and sex (`female`) change, with age set to 20, 30, 40, 50, 60, and 70. We can now use `marginsplot` to graph the results.

```
marginsplot
```

13.9.7 Exercise 4

Margins of changes in responses

Open the datafile `gss.dta`.

1. Fit a logistic model to examine how whether someone uses internet (`usenet`) is related to age of the respondent (`age`), highest year of school completed (`degree`), hours per day watching TV (`tvhours`), and total family income for last year (`income`). Obtain Average Predictive Margins and Average Marginal Effects for `degree`.

```
##
```

2. Obtain Predictive Margins of `degree` at Representative values of `tvhours` from 0 to 10 hours, on a 1 hour interval. Examine how the marginal effect of `degree` differs across the range of `tvhours` (i.e., obtain Marginal Effects at Representative values).

```
##
```

3. Create a `marginsplot` for the marginal effects from #2.

```
##
```

Click for Exercise 4 Solution

Open the datafile `gss.dta`.

1. Fit a logistic model to examine how whether someone uses internet (`usenet`) is related to age of the respondent (`age`), highest year of school completed (`degree`), hours per day watching TV (`tvhours`), and total family income for last year (`income`). Obtain Average Predictive Margins and Average Marginal Effects for `degree`.

```
logit usenet age i.degree tvhours income

margins degree
margins, dydx(degree)
```

2. Obtain Predictive Margins of `degree` at Representative values of `tvhours` from 0 to 10 hours, on a 1 hour interval. Examine how the marginal effect of `degree` differs across the range of `tvhours` (i.e., obtain Marginal Effects at Representative values).

```
margins degree, at(tvhours=(0 1 2 3 4 5 6 7 8 9 10) vsquish
margins, dydx(degree) at(tvhours=(0 1 2 3 4 5 6 7 8 9 10)) vsquish
```

3. Create a `marginsplot` for the marginal effects from #2.

```
marginsplot
```

13.10 Wrap-up

13.10.1 Feedback

These workshops are a work in progress, please provide any feedback to: `help@iq.harvard.edu`

13.10.2 Resources

- IQSS
  - Workshops: `https://www.iq.harvard.edu/data-science-services/workshop-materials`
  - Data Science Services: `https://www.iq.harvard.edu/data-science-services`
  - Research Computing Environment: `https://iqss.github.io/dss-rce/`
- HBS
  - Research Computing Services workshops: `https://training.rcs.hbs.org/workshops`
  - Other HBS RCS resources: `https://training.rcs.hbs.org/workshop-materials`
  - RCS consulting email: `mailto:research@hbs.edu`
- Stata
  - UCLA website: `http://www.ats.ucla.edu/stat/Stata/`
  - Stata website: `http://www.stata.com/help.cgi?contents`
  - Email list: `http://www.stata.com/statalist/`

Chapter 14

Stata Graphics

Topics

- Univariate graphs
- Bivariate graphs

14.1 Setup

14.1.1 Software and Materials

Follow the Stata Installation instructions and ensure that you can successfully start Stata.

14.1.2 Class structure and organization

- Please feel free to ask questions at any point if they are relevant to the current topic (or if you are lost!)
- Collaboration is encouraged - please introduce yourself to your neighbors!
- If you are using a laptop, you will need to adjust file paths accordingly
- Make comments in your Do-file - save on flash drive or email to yourself

14.1.3 Prerequisites

This is an intermediate-level Stata graphics workshop

- Assumes basic knowledge of Stata
- Not appropriate for people already well familiar with graphing in Stata
- If you are catching on before the rest of the class, experiment with command features described in help files

14.1.4 Goals

We will learn about Stata graphics by practicing graphing using two real datasets. In particular, our goals are to:

1. Plot basic graphs in Stata
2. Plot two-way graphs in Stata

14.2 Graphing in Stata

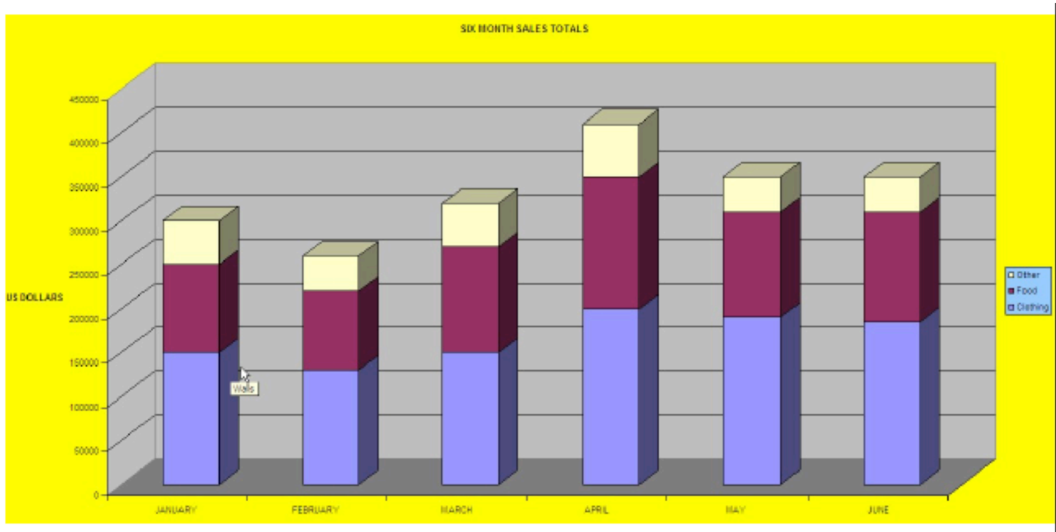
GOAL: To get familiar with how to produce graphs in Stata. In particular:

1. Learn about graphing strategies
2. Compare two examples of a bad graph and a good graph

14.2.1 Graphing strategies

- Keep it simple
- Labels, labels, labels!!
- Avoid cluttered graphs
- Every part of the graph should be meaningful
- Avoid:
    - Shading
    - Distracting colors
    - Decoration
- Always know what you are working with before you get started
    - Recognize scale of data
    - If you are using multiple variables, how do their scales align?
- Before any graphing procedure review variables with `codebook`, `sum`, `tab`, etc.
- HELPFUL STATA HINT: If you want your command to go on multiple lines use `///` at end of each line

14.2.2 Terrible graph



14.2.3 Much better graph

14.3 Univariate graphics

GOAL: To learn how to graph a single continuous and categorical variable. In particular:

1. Graph a continuous variable using a histogram
2. Graph a categorical variable using a bar graph

14.3.1 Our first dataset

- Time Magazine Public School Poll
  - Based on survey of 1,000 adults in U.S.
  - Conducted in August 2010
  - Questions regarding feelings about parental involvement, teachers union, current potential for reform
- Open Stata and call up the datafile for today

```
// Step 1: tell Stata where to find data:
cd "~/StataGraphics/dataSets"

// Step 2: call up our dataset:
use TimePollPubSchools.dta
```

14.3.2 Single continuous variable

Example: Histogram

- Stata assumes you are working with continuous data
- Very simple syntax:
  - `hist varname`
- Put a comma after your varname and start adding options
  - `bin(#)` : change the number of bars that the graph displays
  - `normal` : overlay normal curve
  - `addlabels` : add actual values to bars

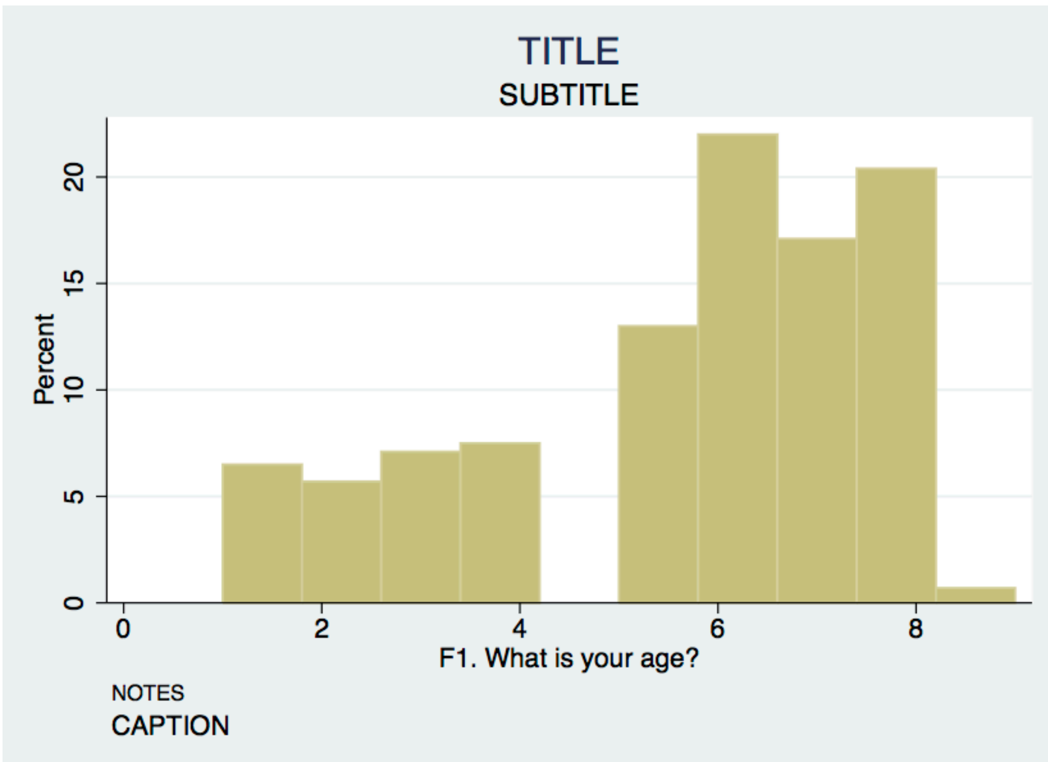
Histogram options

- To change the numeric depiction of your data add these options after the comma
  - Choose one: `density`, `fraction`, `frequency`, `percent`
- Be sure to properly describe your histogram:
  - `title("insert name of graph")`

- subtitle("insert subtitle of graph")
- note("insert note to appear at bottom of graph")
- caption("insert caption to appear below notes")

Histogram example

```
hist F1, bin(10) percent title("TITLE") ///
  subtitle("SUBTITLE") caption("CAPTION") note("NOTES")
```



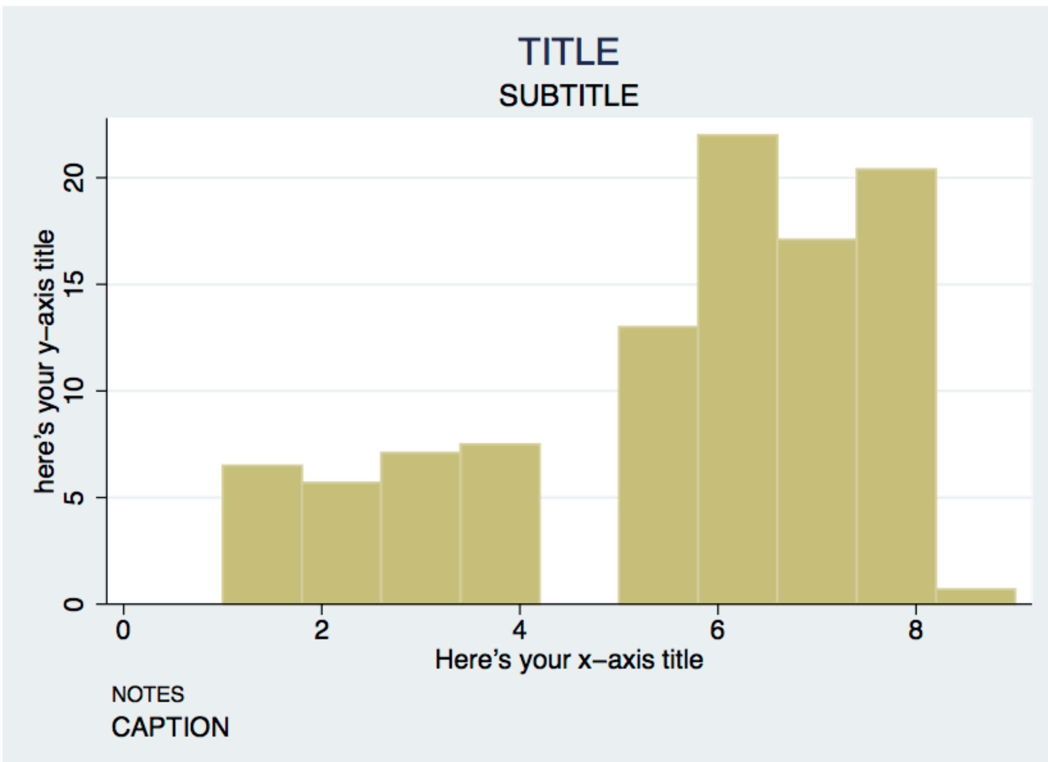
Axis titles & labels

- Axis title options (default is variable label):
  - xtitle("insert x axis name")
  - ytitle("insert y axis name")
- Don't want axis titles?
  - xtitle("")
  - ytitle("")
- Add labels to X or Y axis:
  - xlabel("insert x axis label")
  - ylabel("insert y axis label")

- Tell Stata how to scale each axis
  - `xlabel("start\#(increment)end\#")`
  - `xlabel(0(5)100)` This would label x-axis from 0-100 in increments of 5

Axis labels example

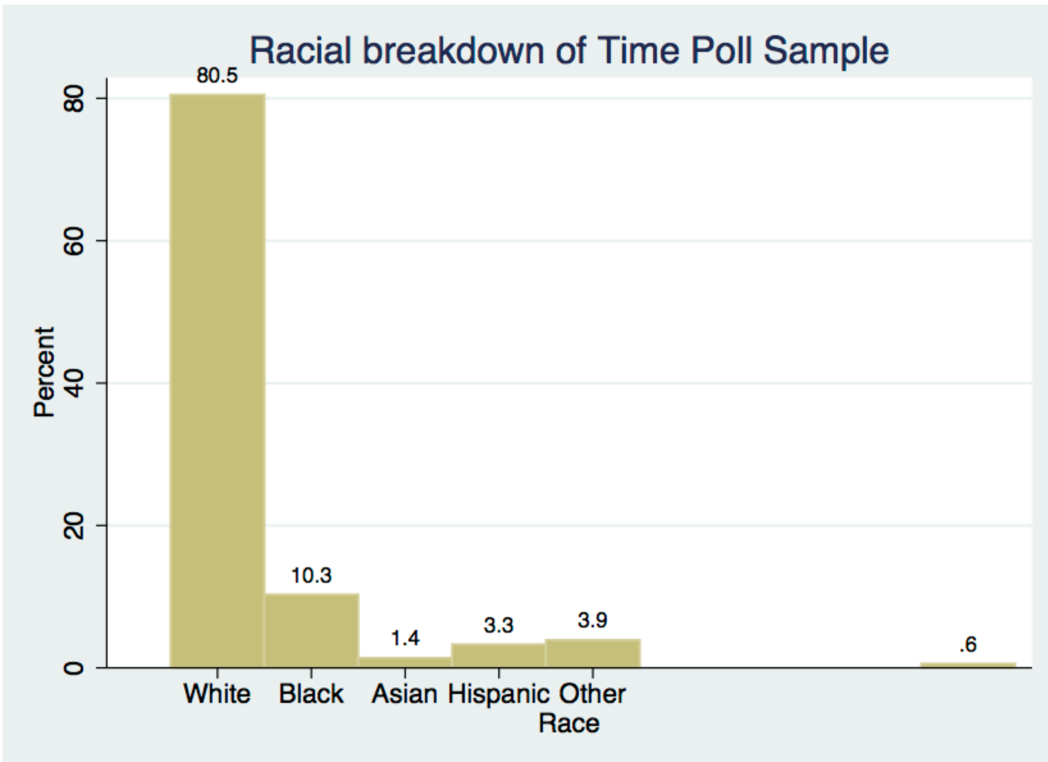
```
hist F1, bin(10) percent title("TITLE") subtitle("SUBTITLE") ///
    caption("CAPTION") note("NOTES") ///
    xtitle("Here's your x-axis title") ///
    ytitle("here's your y-axis title")
```



14.3.3 Single categorical variable

- We can also use the `hist` command for bar graphs
  - Simply specify the option `discrete`
- Stata will produce one bar for each level (i.e. category) of variable
- Use `xlabel` command to insert names of individual categories

```
hist F4, title("Racial breakdown of Time Poll Sample") xtitle("Race") ///
   ytitle("Percent") xlabel(1 "White" 2 "Black" 3 "Asian" 4 "Hispanic" ///
   5 "Other") discrete percent addlabels
```



14.3.4 Exercise 0

Histograms & bar graphs

1. Open the datafile, `NatNeighCrimeStudy.dta`.

```
##
```

2. Create a histogram of the tract-level poverty rate (`T_POVRTY`).

```
##
```

3. Insert the normal curve over the histogram.

```
##
```

4. Change the numeric representation on the Y-axis to `percent`.

```
##
```

5. Add appropriate titles to the overall graph and the x axis and y axis. Also, add a note that states the source of this data.

```
##
```

6. Open the datafile, `TimePollPubSchools.dta`.

```
##
```

7. Create a histogram of the question, "What grade would you give your child's school" (`Q11`). Be sure to tell Stata that this is a categorical variable.

```
##
```

8. Format this graph so that the axes have proper titles and labels. Also, add an appropriate title to the overall graph. Add a note stating the source of the data.

```
##
```

Click for Exercise 0 Solution

1. Open the datafile, `NatNeighCrimeStudy.dta`.

```
use NatNeighCrimeStudy.dta, clear
```

2. Create a histogram of the tract-level poverty rate (`T_POVRTY`).

```
hist T_POVRTY
```

3. Insert the normal curve over the histogram.

```
hist T_POVRTY, normal
```

4. Change the numeric representation on the Y-axis to `percent`.

```
hist T_POVRTY, normal percent
```

5. Add appropriate titles to the overall graph and the x axis and y axis. Also, add a note that states the source of this data.

```
hist T_POVRTY, normal percent title("Poverty Rate Distribution Among Study Participants") xtitle
```

6. Open the datafile, `TimePollPubSchools.dta`.

```
use TimePollPubSchools.dta, clear
```

7. Create a histogram of the question, "What grade would you give your child's school" (`Q11`). Be sure to tell Stata that this is a categorical variable.

```
hist Q11, discrete
```

8. Format this graph so that the axes have proper titles and labels. Also, add an appropriate title to the overall graph. Add a note stating the source of the data.

```
hist Q11, title("School grading breakdown of Time Poll Sample") xtitle("Grades") ytitle("Percent"
```

14.4 Bivariate graphics

GOAL: To learn how to produce two-way bivariate graphs. In particular, to learn:

1. The `twoway` command
2. The `twoway title` options
3. The `twoway symbol` options
4. How to overlay `twoway` graphs

14.4.1 Next dataset

- National Neighborhood Crime Study (NNCS)
  - N=9593 census tracts in 2000
  - Explore sources of variation in crime for communities in the United States
  - Tract-level data: crime, social disorganization, disadvantage, socioeconomic inequality
  - City-level data: labor market, socioeconomic inequality, population change

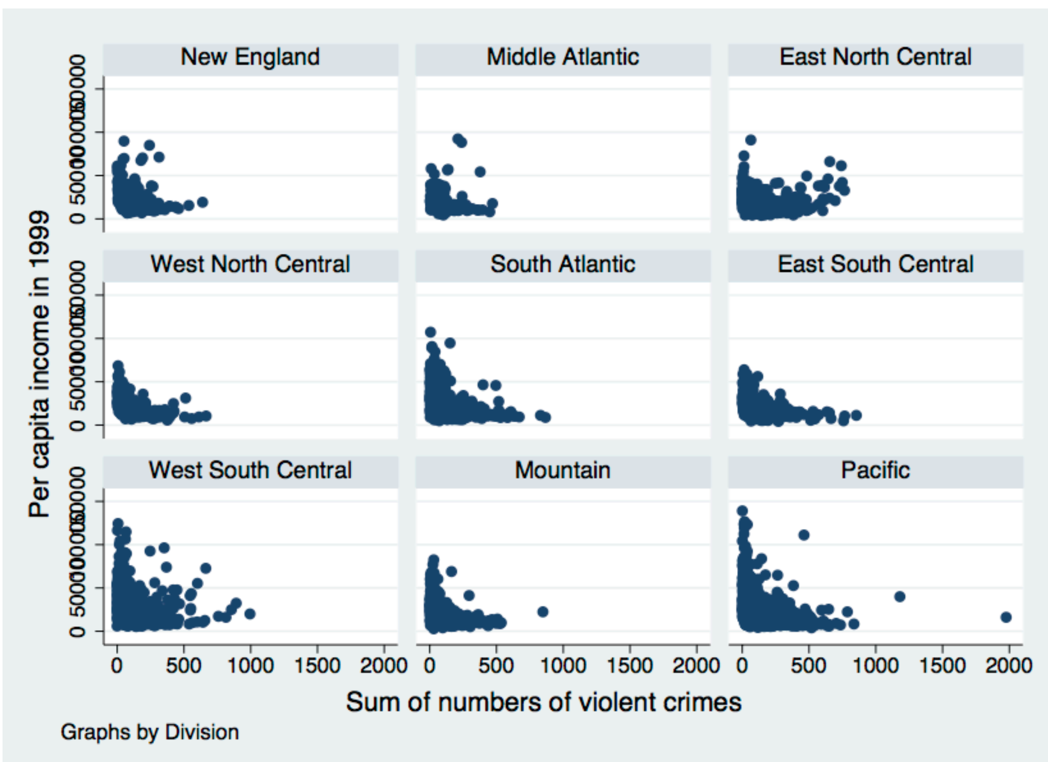
14.4.2 The twoway family

- `twoway` is basic Stata command for all two-way graphs
- Use `twoway` anytime you want to make comparisons among variables
- Can be used to combine graphs (i.e., overlay one graph with another)
  - e.g., insert line of best fit over a scatter plot
- Some basic examples:

```
use NatNeighCrimeStudy.dta, clear

twoway scatter T_PERCAP T_VIOLNT
twoway dropline T_PERCAP T_VIOLNT
twoway lfitci T_PERCAP T_VIOLNT
```

Twoway & the by statement

```
twoway scatter T_PERCAP T_VIOLNT, by(DIVISION)
```



Twoway title options

- Same title options as with histogram

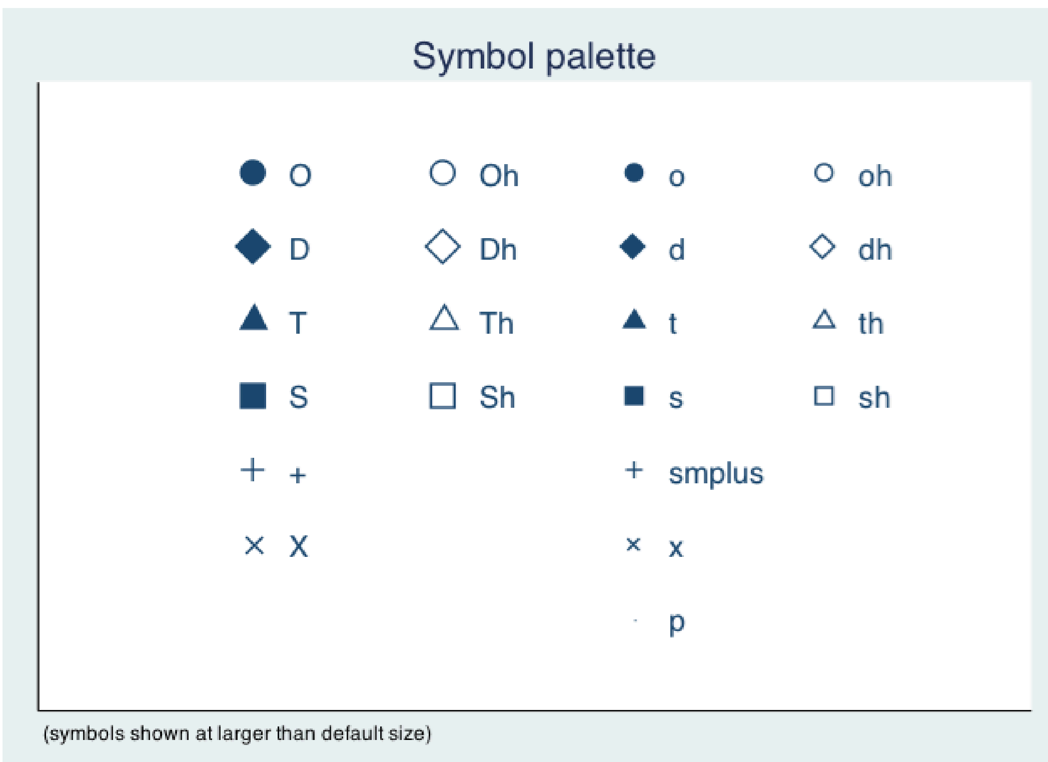
- title("insert name of graph")
- subtitle("insert subtitle of graph")
- note("insert note to appear at bottom of graph")
- caption("insert caption to appear below notes")

Twoway title options example

```
twoway scatter T_PERCAP T_VIOLNT, ///
    title("Comparison of Per Capita Income" ///
          "and Violent Crime Rate at Tract level") ///
    xtitle("Violent Crime Rate") ytitle("Per Capita Income") ///
    note("Source: National Neighborhood Crime Study 2000")
```

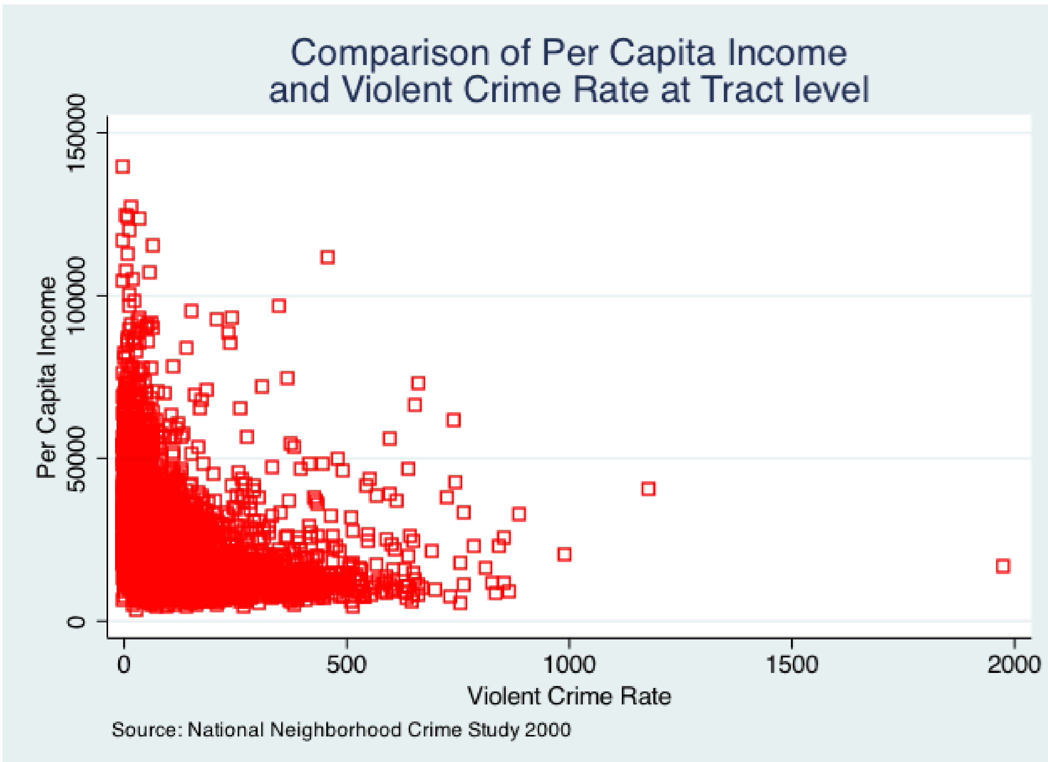
Twoway symbol options

- A variety of symbol shapes are available: use `palette symbolpalette` to see them and `msymbol()` to set them



Twoway symbol options example

```
twoway scatter T_PERCAP T_VIOLNT, ///
    title("Comparison of Per Capita Income" ///
          "and Violent Crime Rate at Tract level") ///
    xtitle("Violent Crime Rate") ytitle("Per Capita Income") ///
    note("Source: National Neighborhood Crime Study 2000") ///
    msymbol(Sh) mcolor("red")
```



14.4.3 Overlaying twoway graphs

- Very simple to combine multiple graphs by just putting each graph command in parentheses
  - `twoway (scatter var1 var2) (lfit var1 var2)`
- Add individual options to each graph within the parentheses
- Add overall graph options as usual following the comma
  - `twoway (scatter var1 var2) (lfit var1 var2), options`

Overlaying points & lines

```
twoway (scatter T_PERCAP T_VIOLNT) ///
    (lfit T_PERCAP T_VIOLNT), ///
    title("Comparison of Per Capita Income" ///
          "and Violent Crime Rate at Tract level") ///
    xtitle("Violent Crime Rate") ytitle("Per Capita Income") ///
    note("Source: National  Neighborhood Crime Study 2000")
```

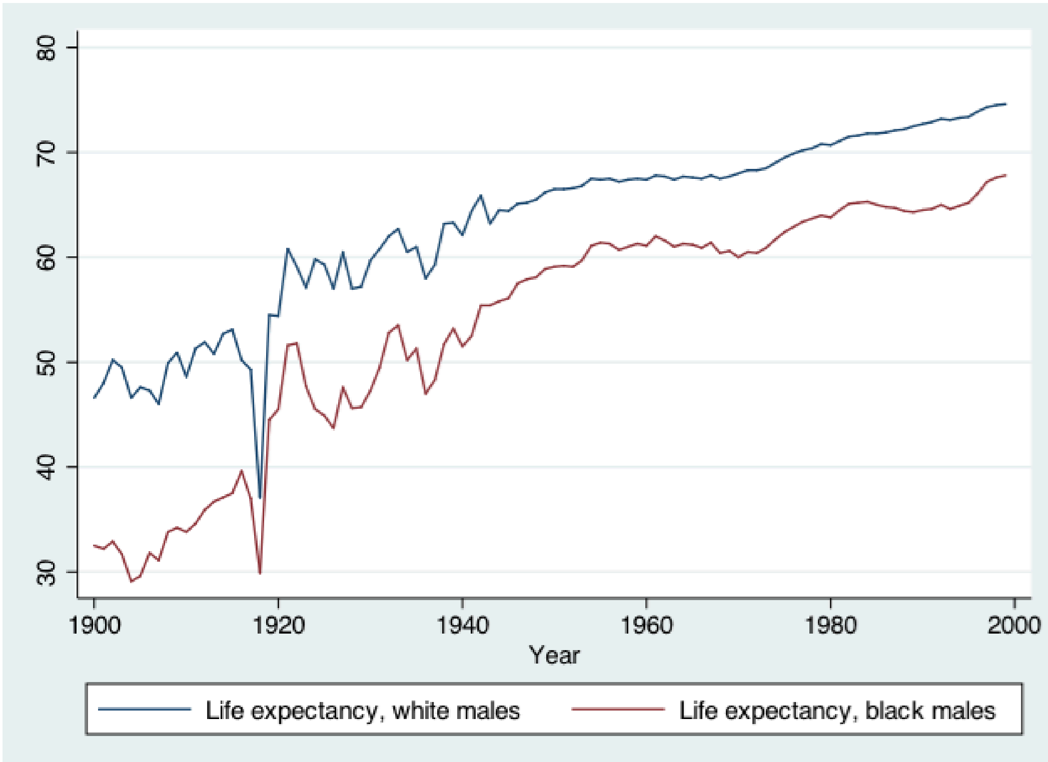
Overlaying points & labels

```
twoway (scatter T_PERCAP T_VIOLNT if T_VIOLNT==1976, ///
    mlabel("CITY")) (scatter T_PERCAP T_VIOLNT), ///
    title("Comparison of Per Capita Income" ///
          "and Violent Crime Rate at Tract level") ///
    xlabel(0(200)2400) note("Source: National Neighborhood" ///
                            "Crime Study 2000") legend(off)
```

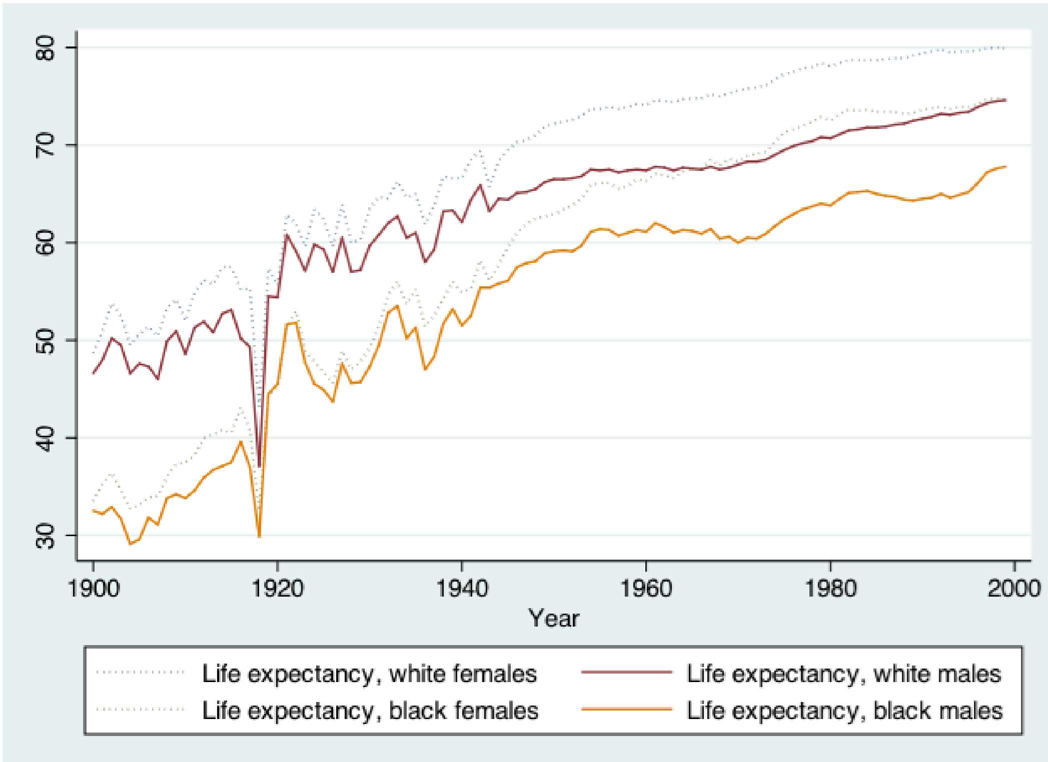
14.4.4 Twoway line graphs

- Line graphs helpful for a variety of data
  - Especially any type of time series data
- We will use data on US life expectancy from 1900-1999
  - `webuse uslifeexp, clear`

```
webuse uslifeexp, clear
twoway (line le_wm year, mcolor("red")) ///
       (line le_bm year, mcolor("green"))
```

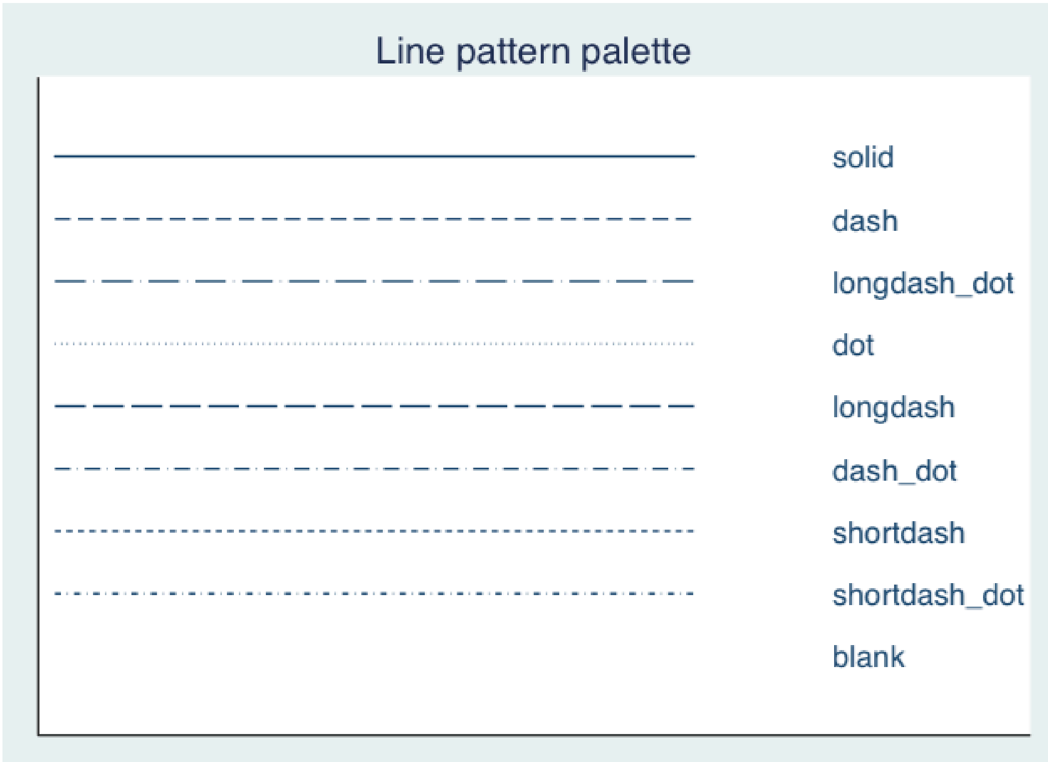



```
twoway (line (le_wfemale le_wmale le_bf le_bm) year, ///
       lpattern(dot solid dot solid))
```



14.4.5 Stata graphing lines

```
palette linepalette
```



14.4.6 Exercise 1

The `twoway` family

1. Open the datafile, `NatNeighCrimeStudy.dta`.

```
##
```

2. Create a basic twoway scatterplot that compares the city unemployment rate (`C_UNEMP`) to the percent secondary sector low-wage jobs (`C_SSLOW`).

```
##
```

3. Generate the same scatterplot, but this time, divide the plot by the dummy variable indicating whether the city is located in the south or not (`C_SOUTH`).

```
##
```

4. Change the color of the symbol that you use in this scatter plot.

```
##
```

5. Change the type of symbol you use to a marker of your choice.

```
##
```

6. Notice in your scatterplot that is broken down by `C_SOUTH` that there is an outlier in the upper right hand corner of the "Not South" graph. Add the city name label to this marker.

```
##
```

Click for Exercise 1 Solution

1. Open the datafile, `NatNeighCrimeStudy.dta`.

```
use NatNeighCrimeStudy.dta, clear
```

2. Create a basic twoway scatterplot that compares the city unemployment rate (`C_UNEMP`) to the percent secondary sector low-wage jobs (`C_SSLOW`).

```
twoway scatter C_UNEMP C_SSLOW
```

3. Generate the same scatterplot, but this time, divide the plot by the dummy variable indicating whether the city is located in the south or not (`C_SOUTH`).

```
twoway scatter C_UNEMP C_SSLOW, by(C_SOUTH)
```

4. Change the color of the symbol that you use in this scatter plot.

```
twoway scatter C_UNEMP C_SSLOW, by(C_SOUTH) mcolor("orange")
```

5. Change the type of symbol you use to a marker of your choice.

```
twoway scatter C_UNEMP C_SSLOW, by(C_SOUTH) mcolor("orange") msymbol(diamond)
```

6. Notice in your scatterplot that is broken down by `C_SOUTH` that there is an outlier in the upper right hand corner of the "Not South" graph. Add the city name label to this marker.

```
twoway scatter C_UNEMP C_SSLOW, by(C_SOUTH) if C_UNEMP>25 mcolor("orange") msymbol(diamond) mlabe
twoway (scatter C_UNEMP C_SSLOW if T_UNEMP>15 & C_SSLOW>25, mlabel(CITY) by(C_SOUTH)) (scatter C_
```

14.5 Exporting graphs

GOAL: To learn how to export graphs in Stata.

- From Stata, right click on image and select “save as” or try syntax:
  - `graph export myfig.esp, replace`
- In Microsoft Word: insert -> picture -> from file
  - Or, right click on graph in Stata and copy and paste into MS Word

14.6 Wrap-up

14.6.1 Feedback

These workshops are a work in progress, please provide any feedback to: `help@iq.harvard.edu`

14.6.2 Resources

- IQSS
  - Workshops: `https://www.iq.harvard.edu/data-science-services/workshop-materials`
  - Data Science Services: `https://www.iq.harvard.edu/data-science-services`
  - Research Computing Environment: `https://iqss.github.io/dss-rce/`
- HBS
  - Research Computing Services workshops: `https://training.rcs.hbs.org/workshops`
  - Other HBS RCS resources: `https://training.rcs.hbs.org/workshop-materials`
  - RCS consulting email: `mailto:research@hbs.edu`
- Stata
  - UCLA website: `http://www.ats.ucla.edu/stat/Stata/`
  - Stata website: `http://www.stata.com/help.cgi?contents`
  - Email list: `http://www.stata.com/statalist/`