Intro to Data Science

What R we doing?

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Welcome to Data Science!

In this homework, we'll be working on getting you set up with the tools you will need for this class. Once you are set up, we'll do what we're here to do: analyze data!

Here's what we will accomplish by the end of the assignment:

1. Getting started with R
2. Getting started with RStudio
3. Analyze Data
4. <….>
5. Profit! (*profitability may vary by user*)

Introductions

We need two basic sets of tools for this class. We will need `R` to analyze data. We will need `RStudio` to help us interface with R and to produce documentation of our results.

Installing R

R is going to be the only programming language we will use. R is an extensible statistical programming environment that can handle all of the main tasks that we'll need to cover this semester: getting data, analyzing data and communicating data analysis.

If you haven't already, you need to download R here: https://cran.r-project.org/ (https://cran.r-project.org/).

Installing RStudio

When we work with R, we communicate via the command line. To help automate this process, we can write scripts, which contain all of the commands to be executed. These scripts generate various kinds of output, like numbers on the screen, graphics or reports in common formats (pdf, word). Most programming languages have several **I** ntegrated **D** evelopment **E** nvironments (IDEs) that encompass all of these elements (scripts, command line interface, output). The primary IDE for R is RStudio.

If you haven't already, you need to download RStudio here: https://rstudio.com/products/rstudio/download/ (https://rstudio.com/products/rstudio/download/). You need the free RStudio desktop version.

Accessing Files and Using Directories

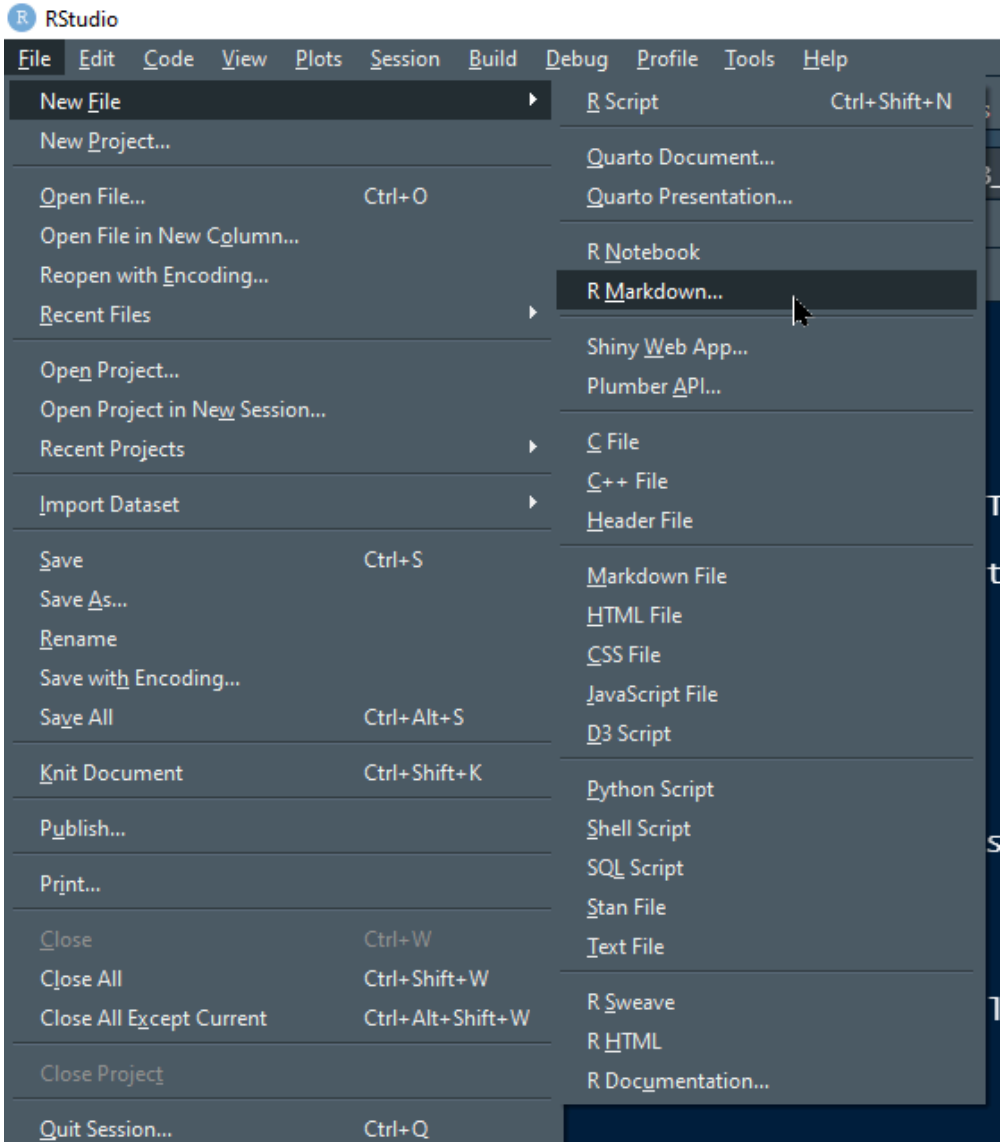
In each class, we're going to include some code and text in one file, and data in another file. You'll need to download both of these files to your computer. You need to have a particular place to put these files. Computers are organized using named directories (sometimes called folders). Don't just put the files in your Downloads directory. One common solution is to created a directory on your computer named after the class: `ds_1000`. Each time you access the files, you'll want to place them in that directory.

Yes We Code! Running R Code

We're going to grab some data that's part of the college scorecard (https://collegescorecard.ed.gov/data/documentation/) and do a bit of analysis on it.

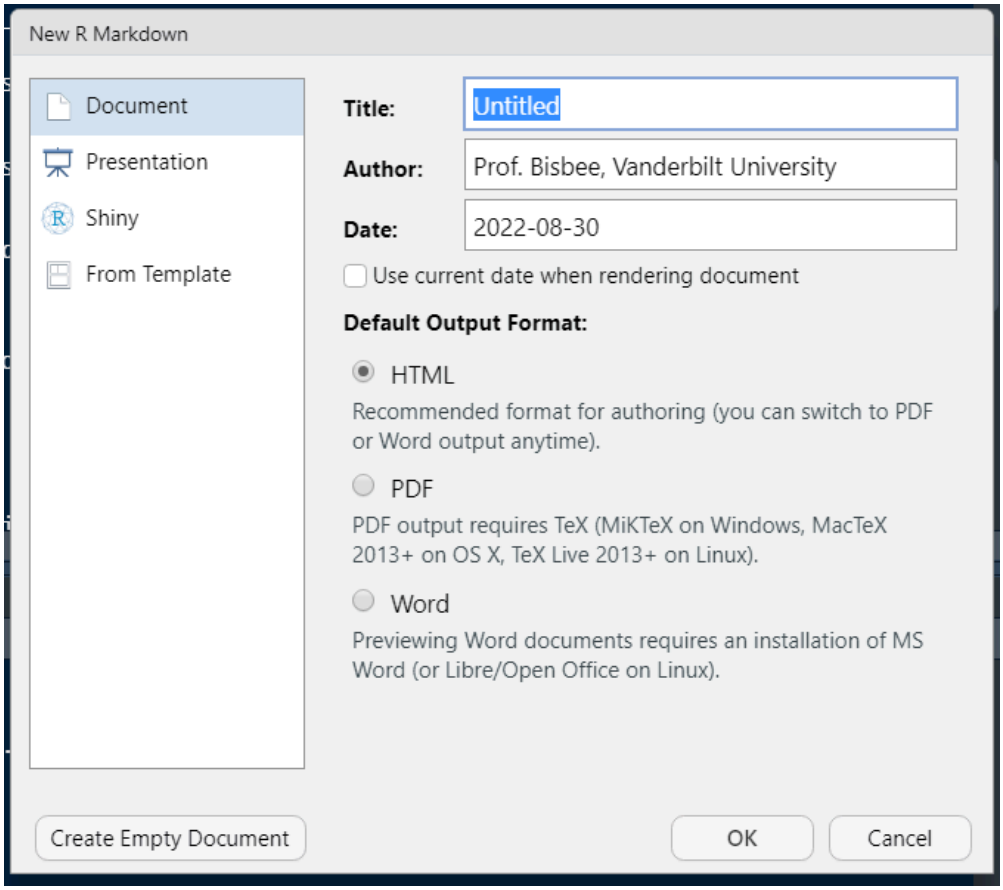
.Rmd Set Up

Open `RStudio`, then create a new `.Rmd` file. To do this, click on `File` → `New File` → `R Markdown...`.

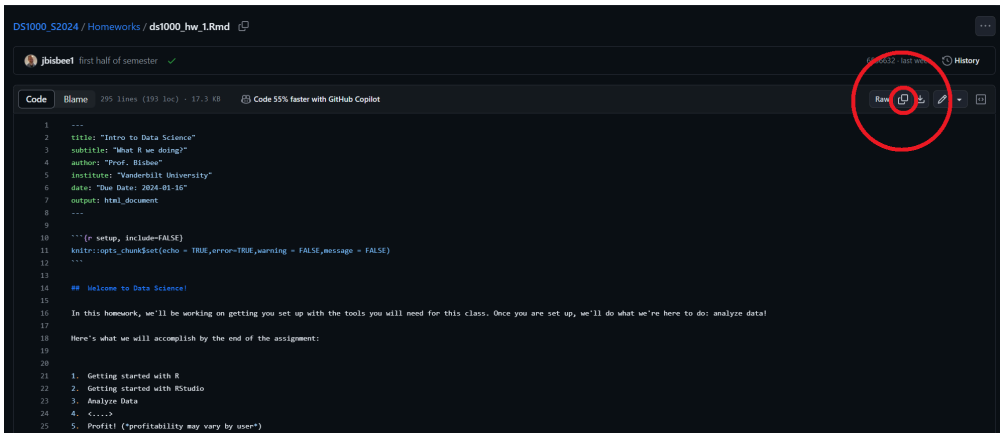


You will then be asked to determine a bunch of settings for this `.Rmd` document. For example, you can choose whether you want to create a "Document", "Presentation", "Shiny", or "From Template" on the left. You can set the "Title:" "Author:" and "Date:" on the top-right. And you can choose the "Default Output Format:" to be either "HTML",

“PDF”, or “Word”. You should **not change any of these settings**. Their defaults (“Document”, “Untitled”, “[Your name]”, “[Today’s Date]”, and “HTML”) are sufficient. Just click “OK”.

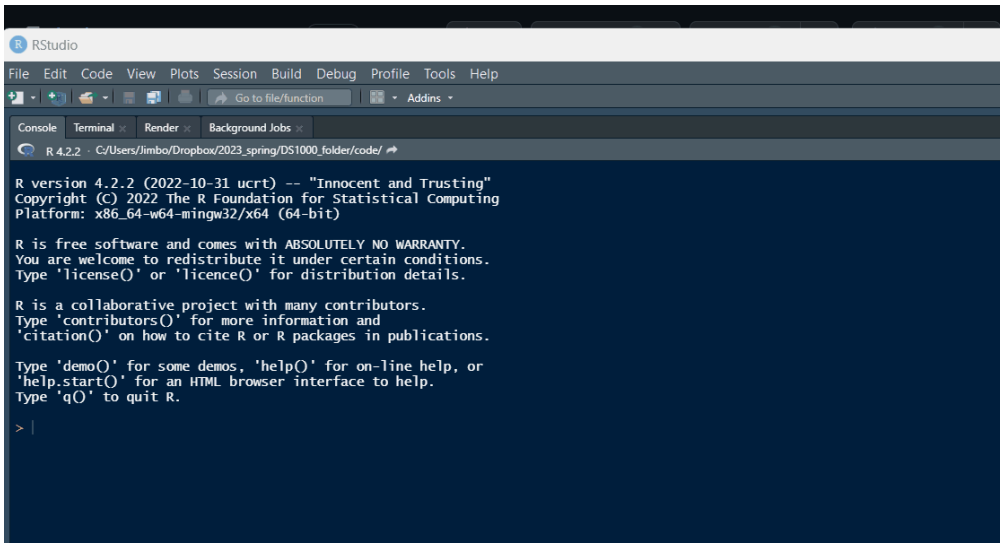


Copy the raw code from the `ISP_hw_1.Rmd` (https://github.com/jbisbee1/ISP_Data_Science_2024/blob/main/Homeworks/ISP_hw_1.Rmd) file by clicking on the copy button as shown in the image below.



Finally, replace the default code in your R Markdown file with the copied code from the GitHub!

If viewing this as an html file, you can view this gif for more help!



.Rmd Files

.Rmd files will be the only file format we work in this class. .Rmd files contain three basic elements:

1. Script that can be interpreted by R.
2. Output generated by R, including tables and figures.
3. Text that can be read by humans.

From a .Rmd file you can generate html documents, pdf documents, word documents, slides . . . lots of stuff. All class notes will be in .Rmd. Most assignments will be turned in as .Rmd files, and the guided exercise we'll have you do? You guessed it, .Rmd.

In the `.Rmd` file you'll notice that there are three open single quotes in a row, like so: ``` ``` This indicates the start of a "code chunk" in our file. The first code chunk that we load will include a set of programs that we will need all semester long.

Outputting results

I like to see results in the Console. By default Rstudio will output results from an Rmd file inline– meaning in the document itself. To change this, go to Tools–>global Options–>R Markdown, and uncheck the box for "show output inline for all Rmarkdown documents."

Using R Libraries

When we say that R is extensible, we mean that people in the community can write programs that everyone else can use. These are called "packages." In these first few lines of code, I load a set of packages using the library command in R. The set of packages, called `tidyverse` were written by Hadley Wickham and others and play a key role in his book. To install this set of packages, simply type in `install.packages("tidyverse")` at the R command prompt. Alternatively, you can use the "Packages" pane in the lower right hand corner of your Rstudio screen. Click on Packages, then click on install, then type in "tidyverse."

To run the code below in R, you can:

- Press the "play" button next to the code chunk
- In OS X, place the cursor in the code chunk and hit `CMD+RETURN`
- In Windows, place the cursor in the code chunk and hit `CTRL+RETURN`

```
## Get necessary libraries-- won't work the first time, because you need to install the
m!
# install.packages("tidyverse")  # Uncomment this to install
library(tidyverse)
```

Here's the thing about packages. There's a difference between *installing* a package and *calling* a package. *Installing* means that the package is on your computer and available to use. *Calling* a package means that the commands in the package will be used in this session. A "session" is basically when R has been opened up on your computer. As long as R/Rstudio are open and running, the session is active.

It's a good practice to shutdown R/Rstudio once you're no longer working on it, and then to restart it when you begin working again. Otherwise, the working environment can get pretty crowded with data and packages.

Loading Datasets

Now we're ready to load in data. The data frame will be our basic way of interacting with everything in this class. The `sc_debt.Rds` (found here: https://github.com/jbisbee1/ISP_Data_Science_2024/blob/main/data/sc_debt.Rds (https://github.com/jbisbee1/ISP_Data_Science_2024/blob/main/data/sc_debt.Rds)) data frame contains information from the college scorecard on different colleges and universities.

`tidyverse` includes a `read_rds()` function that can read data directly from the internet.

```
df <- read_rds('https://github.com/jbisbee1/ISP_Data_Science_2024/raw/main/data/sc_debt.
Rds')
```

You'll notice that the code above starts with `df`. This is just an arbitrary name for an object. You could name it `dat` or `raw` or `debt` or whatever you want. Then there's an arrow `<-`. This is an assignment operator. Then there's a function, `readRDS`, with parentheses, and an argument "sc_debt.Rds". Here's how to think about this.

- Functions in R always have arguments within parentheses. This function. `readRDS` opens a type of data–rds data. This function has one argument which is the name of the file I want to open.
- Assignment operators take the result of a function and assign it to an object name.
- Objects in R store information locall so that it can be accessed again.

So the command above says "use `readRDS` to open the file"sc_debt.Rds" and assign the result to the object `df`.

Let's take a quick look at the object `df`

```
df
```

```
## # A tibble: 2,546 × 16
##    unitid instnm   stabbr grad_debt_mdn control region preddeg openadmp adm_rate
##     <int> <chr>    <chr>          <int> <chr>   <chr>  <chr>      <int>    <dbl>
##  1 100654 Alabama… AL             33375 Public  South… Bachel…        2    0.918
##  2 100663 Univers… AL             22500 Public  South… Bachel…        2    0.737
##  3 100690 Amridge… AL             27334 Private South… Associ…        1   NA
##  4 100706 Univers… AL             21607 Public  South… Bachel…        2    0.826
##  5 100724 Alabama… AL             32000 Public  South… Bachel…        2    0.969
##  6 100751 The Uni… AL             23250 Public  South… Bachel…        2    0.827
##  7 100760 Central… AL             12500 Public  South… Associ…        1   NA
##  8 100812 Athens … AL             19500 Public  South… Bachel…       NA   NA
##  9 100830 Auburn … AL             24826 Public  South… Bachel…        2    0.904
## 10 100858 Auburn … AL             21281 Public  South… Bachel…        2    0.807
## # ℹ 2,536 more rows
## # ℹ 7 more variables: ccbasic <int>, sat_avg <int>, md_earn_wne_p6 <int>,
## #   ugds <int>, costt4_a <int>, selective <dbl>, research_u <dbl>
```

This is just the first part of the data frame. All data frames have the exact same structure. Each row is a case. In this example, each row is a college. Each column is a characteristics of the case, what we call a variable. Let's use the `names` command to see what variables are in the dataset.

```
names(df)
```

```
##  [1] "unitid"         "instnm"         "stabbr"         "grad_debt_mdn"
##  [5] "control"        "region"         "preddeg"        "openadmp"
##  [9] "adm_rate"       "ccbasic"        "sat_avg"        "md_earn_wne_p6"
## [13] "ugds"           "costt4_a"       "selective"      "research_u"
```

It's hard to know what these mean without some more information. We usually use a codebook to get more information about a dataset. Because we use very short names for variables, it's useful to have some more information (fancy name: metadata) that tells us about those variables. Below you'll see the `R` name for each variable next to a description of each variable.

Name	Definition
unitid	Unit ID
instnm	Institution Name
stabbr	State Abbreviation
grad_debt_mdn	Median Debt of Graduates
control	Control Public or Private
region	Census Region
preddeg	Predominant Degree Offered: Associates or Bachelors
openadmp	Open Admissions Policy: 1= Yes, 2=No,3=No 1st time students
adm_rate	Admissions Rate: proportion of applications accepted

Name	Definition
ccbasic	Type of institution– see here (https://data.ed.gov/dataset/9dc70e6b-8426-4d71-b9d5-70ce6094a3f4/resource/658b5b83-ac9f-4e41-913e-9ba9411d7967/download/collegescorecarddatadictionary_01192021.xlsx)
selective	Institution admits fewer than 10 % of applicants, 1=Yes, 0=No
research_u	Institution is a research university 1=Yes, 0=No
sat_avg	Average Sat Scores
md_earn_wne_p6	Average Earnings of Recent Graduates
ugds	Number of undergraduates
costt4a	Average cost of attendance (tuition-grants)

Looking at datasets

We can also look at the whole dataset using View. Just delete the `#` sign below to make the code work. That `#` sign is a comment in R code, which indicates to the computer that everything on that line should be ignored. To get it to run, we need to drop the `#`.

```
View(df)
```

You'll notice that this data is arranged in a rectangular format, with each row showing a different college, and each column representing a different characteristic of that college. Datasets are always structured this way— cases (or units) will form the rows, and the characteristics of those cases– or variables— will form the columns. Unlike working with spreadsheets, this structure is always assumed for datasets.

Filter, Select, Arrange

In exploring data, many times we want to look at smaller parts of the dataset. There are three commands we'll use today that help with this.

- `filter` selects only those cases or rows that meet some logical criteria.

- `select` selects only those variables or columns that meet some criteria

- `arrange` arranges the rows of a dataset in the way we want.

For more on these, please see this vignette (https://cran.rstudio.com/web/packages/dplyr/vignettes/introduction.html).

Let's grab just the data for Vanderbilt, then look only at the average test scores and admit rate. We can use filter to look at all of the variables for Vanderbilt:

```
df%>%
  filter(instnm=="Vanderbilt University")
```

```
## # A tibble: 1 × 16
##   unitid instnm    stabbr grad_debt_mdn control region preddeg openadmp adm_rate
##    <int> <chr>     <chr>          <int> <chr>   <chr>  <chr>      <int>    <dbl>
## 1 221999 Vanderbi… TN             14962 Private South… Bachel…        2   0.0912
## # ℹ 7 more variables: ccbasic <int>, sat_avg <int>, md_earn_wne_p6 <int>,
## #   ugds <int>, costt4_a <int>, selective <dbl>, research_u <dbl>
```

What's that weird looking `%>%` thing? That's called a pipe. This is how we chain commands together in R. Think of it as saying "and then" to R. In the above case, we said, take the data *and then* filter it to be just the data where the institution name is Vanderbilt University.

The command above says the following:

Take the dataframe `df` *and then* filter it to just those cases where `instnm` is equal to "Vanderbilt University." Notice the "double equals" sign, that's a logical operator asking if `instnm` is equal to "Vanderbilt University."

Many times, though we don't want to see everything, we just want to choose a few variables. `select` allows us to select only the variables we want. In this case, the institution name, its admit rate, and the average SAT scores of entering students.

```
df%>%
  filter(instnm=="Vanderbilt University")%>%
  select(instnm,adm_rate,sat_avg)
```

```
## # A tibble: 1 × 3
##   instnm                adm_rate sat_avg
##   <chr>                    <dbl>   <int>
## 1 Vanderbilt University   0.0912    1515
```

`filter` takes logical tests as its argument. The code `insntnm=="Vanderbilt University"` is a logical statement that will be true of just one case in the dataset– when institution name is Vanderbilt University. The `==` is a logical test, asking if this is equal to that. Other common logical and relational operators for R include

- `>` , `<` : greater than, less than
- `>=` , `<=` : greater than or equal to, less than or equal to
- `!` :not, as in `!=` not equal to
- `&` AND
- `|` OR

Next, we can use `filter` to look at colleges with low admissions rates, say less than 10% (or .1 in the proportion scale used in the dataset).

```
df%>%
  filter(adm_rate<.1)%>%
  select(instnm,adm_rate,sat_avg)%>%
  arrange(sat_avg,adm_rate)%>%
  print(n=20)
```

```
## # A tibble: 25 × 3
##    instnm                                    adm_rate sat_avg
##    <chr>                                        <dbl>   <int>
##  1 Colby College                               0.0967    1456
##  2 Swarthmore College                          0.0893    1469
##  3 Pomona College                              0.074     1480
##  4 Dartmouth College                           0.0793    1500
##  5 Stanford University                         0.0434    1503
##  6 Northwestern University                     0.0905    1506
##  7 Columbia University in the City of New York 0.0545    1511
##  8 Brown University                            0.0707    1511
##  9 University of Pennsylvania                  0.0766    1511
## 10 Vanderbilt University                       0.0912    1515
## 11 Harvard University                          0.0464    1517
## 12 Princeton University                        0.0578    1517
## 13 Yale University                             0.0608    1517
## 14 Rice University                             0.0872    1520
## 15 Duke University                             0.076     1522
## 16 University of Chicago                       0.0617    1528
## 17 Massachusetts Institute of Technology       0.067     1547
## 18 California Institute of Technology          0.0642    1557
## 19 Saint Elizabeth College of Nursing          0           NA
## 20 Yeshivat Hechal Shemuel                     0           NA
## # ℹ 5 more rows
```

Now let's look at colleges with low admit rates, and order them using `arrange` by SAT scores (`-sat_avg` gives descending order).

```
df%>%
  filter(adm_rate<.1)%>%
  select(instnm,adm_rate,sat_avg)%>%
  arrange(-sat_avg)
```

```
## # A tibble: 25 × 3
##    instnm                                    adm_rate sat_avg
##    <chr>                                        <dbl>   <int>
##  1 California Institute of Technology          0.0642    1557
##  2 Massachusetts Institute of Technology       0.067     1547
##  3 University of Chicago                       0.0617    1528
##  4 Duke University                             0.076     1522
##  5 Rice University                             0.0872    1520
##  6 Yale University                             0.0608    1517
##  7 Harvard University                          0.0464    1517
##  8 Princeton University                        0.0578    1517
##  9 Vanderbilt University                       0.0912    1515
## 10 Columbia University in the City of New York 0.0545    1511
## # ℹ 15 more rows
```

And one last operation: all colleges that admit between 20 and 30 percent of students, looking at their SAT scores, earnings of attendees six years letter, and what state they are in, then arranging by state, and then SAT score.

```
df%>%
  filter(adm_rate>.2&adm_rate<.3)%>%
  select(instnm,sat_avg,grad_debt_mdn,stabbr)%>%
  arrange(stabbr,-sat_avg)%>%
  print(n=20)
```

```
## # A tibble: 37 × 4
##    instnm                                          sat_avg grad_debt_mdn stabbr
##    <chr>                                             <int>         <int> <chr>
##  1 Heritage Christian University                        NA            NA AL
##  2 University of California-Santa Barbara             1370         15000 CA
##  3 California Polytechnic State University-San Lui…   1342         19501 CA
##  4 University of California-Irvine                    1306         15488 CA
##  5 California Institute of the Arts                     NA         27000 CA
##  6 University of Miami                                1371         17125 FL
##  7 Georgia Institute of Technology-Main Campus        1418         23000 GA
##  8 Point University                                    986         26000 GA
##  9 Grinnell College                                   1457         17500 IA
## 10 St Luke's College                                    NA         17750 IA
## 11 Purdue University Northwest                       1074         22250 IN
## 12 Alice Lloyd College                               1040         15838 KY
## 13 Wellesley College                                 1452         11000 MA
## 14 Boston College                                    1437         17500 MA
## 15 Brandeis University                               1434         26150 MA
## 16 Babson College                                    1362         22985 MA
## 17 Laboure College                                     NA         25229 MA
## 18 Coppin State University                            903         24076 MD
## 19 University of Michigan-Ann Arbor                  1448         17500 MI
## 20 University of North Carolina at Chapel Hill       1402         15400 NC
## # ℹ 17 more rows
```

Quick Exercise Choose a different college and two different things about that college. Have R print the output.

```
# INSERT CODE HERE
```

Summarizing Data

To summarize data, we use the `summarize` command. Inside that command, we tell R two things: what to call the new variable that we're creating, and what numerical summary we would like. The code below summarizes median debt for the colleges in the dataset by calculating the average of median debt for all institutions.

```
df%>%
  summarize(mean_debt=mean(grad_debt_mdn,na.rm=TRUE))
```

```
## # A tibble: 1 × 1
##   mean_debt
##       <dbl>
## 1    19646.
```

```
df%>%
  summarize(median_debt=median(grad_debt_mdn,na.rm=TRUE))
```

```
## # A tibble: 1 × 1
##   median_debt
##         <int>
## 1       21500
```

Quick Exercise Summarize the average entering SAT scores in this dataset.

```
# INSERT CODE HERE
```

Combining Commands

We can also combine commands, so that summaries are done on only a part of the dataset. Below, we summarize median debt for selective schools, and not very selective schools.

```
df%>%
  filter(adm_rate<.1)%>%
  summarize(mean_debt=mean(grad_debt_mdn,na.rm=TRUE))
```

```
## # A tibble: 1 × 1
##   mean_debt
##       <dbl>
## 1    16178.
```

What about for not very selective schools?

```
df%>%
  filter(adm_rate>.3)%>%
  summarize(mean_debt=mean(grad_debt_mdn,na.rm=TRUE))
```

```
## # A tibble: 1 × 1
##   mean_debt
##       <dbl>
## 1    23230.
```

Quick Exercise Calculate average earnings for schools where SAT>1200

```
# INSERT CODE HERE
```

Quick Exercise Calculate the average debt for schools that admit over 50% of the students who apply.

```
# INSERT CODE HERE
```

Looking at datasets

We can use “glimpse” to see what’s in a dataset. This gives a very quick rundown of the variables and the first few observations.

```
glimpse(df)
```

```
## Rows: 2,546
## Columns: 16
## $ unitid         <int> 100654, 100663, 100690, 100706, 100724, 100751, 100760,…
## $ instnm         <chr> "Alabama A & M University", "University of Alabama at B…
## $ stabbr         <chr> "AL", "AL", "AL", "AL", "AL", "AL", "AL", "AL", "AL", "…
## $ grad_debt_mdn  <int> 33375, 22500, 27334, 21607, 32000, 23250, 12500, 19500,…
## $ control        <chr> "Public", "Public", "Private", "Public", "Public", "Pub…
## $ region         <chr> "Southeast", "Southeast", "Southeast", "Southeast", "So…
## $ preddeg        <chr> "Bachelor's", "Bachelor's", "Associate", "Bachelor's", …
## $ openadmp       <int> 2, 2, 1, 2, 2, 2, 1, NA, 2, 2, 2, 1, 1, 2, 1, 1, 2, 2, …
## $ adm_rate       <dbl> 0.9175, 0.7366, NA, 0.8257, 0.9690, 0.8268, NA, NA, 0.9…
## $ ccbasic        <int> 18, 15, 20, 16, 19, 15, 2, 22, 18, 15, 21, 1, 5, 19, 7,…
## $ sat_avg        <int> 939, 1234, NA, 1319, 946, 1261, NA, NA, 1082, 1300, 123…
## $ md_earn_wne_p6 <int> 25200, 35100, 30700, 36200, 22600, 37400, 23100, 33400,…
## $ ugds           <int> 5271, 13328, 365, 7785, 3750, 31900, 1201, 2677, 4407, …
## $ costt4_a       <int> 23053, 24495, 14800, 23917, 21866, 29872, 10493, NA, 19…
## $ selective      <dbl> 0, 0, NA, 0, 0, 0, NA, NA, 0, 0, 0, NA, NA, 0, NA, NA, …
## $ research_u     <dbl> 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0…
```

Types of Variables

Notice that for each variable, it shows a different type, in angle brackets `<>`. So for instance, `instnm` has a type of `<chr>`. This is short for character– it’s also called a string variable.

Here are the types of data in this dataset

- `<int>` Integer data
- `<chr>` Character or string data
- `<dbl>` Double, (double-precision floating point) or just numeric data– can be measured down to an arbitrary number of data points.

This information is useful, because we wouldn’t want to try to run some kind of numeric analysis on string data. The average of institution names wouldn’t make a lot of sense (but it would probably be Southeast North State University College).

We’ll talk more about data types later, but we should also quickly note that there are some variables in this dataset where the numbers represent a characteristic, rather and a measurement. For instance, the variable `research_u` is set up—coded— such that a “1” indicates that the college is a research university and a “0” indicates that it is not a research university. The 1 and 0 don’t measure anything, they just indicate a characteristic.

Filter, Select, Arrange

Today, we’ll pick up where we left off– with the key commands of filter, select, and arrange.

In exploring data, many times we want to look at smaller parts of the dataset. There are three commands we'll use today that help with this.

- `filter` selects only those cases or rows that meet some logical criteria.

- `select` selects only those variables or columns that meet some criteria

- `arrange` arranges the rows of a dataset in the way we want.

For more on these, please see this vignette (https://cran.rstudio.com/web/packages/dplyr/vignettes/introduction.html).

We can look at the first 5 rows:

```
head(df)
```

```
## # A tibble: 6 × 16
##   unitid instnm    stabbr grad_debt_mdn control region preddeg openadmp adm_rate
##    <int> <chr>     <chr>          <int> <chr>   <chr>  <chr>      <int>    <dbl>
## 1 100654 Alabama … AL             33375 Public  South… Bachel…        2    0.918
## 2 100663 Universi… AL             22500 Public  South… Bachel…        2    0.737
## 3 100690 Amridge … AL             27334 Private South… Associ…        1   NA
## 4 100706 Universi… AL             21607 Public  South… Bachel…        2    0.826
## 5 100724 Alabama … AL             32000 Public  South… Bachel…        2    0.969
## 6 100751 The Univ… AL             23250 Public  South… Bachel…        2    0.827
## # ℹ 7 more variables: ccbasic <int>, sat_avg <int>, md_earn_wne_p6 <int>,
## #   ugds <int>, costt4_a <int>, selective <dbl>, research_u <dbl>
```

Or the last 5 rows:

```
tail(df)
```

```
## # A tibble: 6 × 16
##   unitid instnm    stabbr grad_debt_mdn control region preddeg openadmp adm_rate
##    <int> <chr>     <chr>          <int> <chr>   <chr>  <chr>      <int>    <dbl>
## 1 493716 Yeshiva … NJ                NA Private North… Associ…        2    0.477
## 2 493725 Universi… AR                NA Public  South… Bachel…        1   NA
## 3 493822 College … RI                NA Private New E… Bachel…        1   NA
## 4 494630 Christ M… TX                NA Private South… Bachel…        1   NA
## 5 494685 Urshan C… MO                NA Private Plains Bachel…        2    0.836
## 6 494737 Yeshiva … NY                NA Private North… Bachel…        1   NA
## # ℹ 7 more variables: ccbasic <int>, sat_avg <int>, md_earn_wne_p6 <int>,
## #   ugds <int>, costt4_a <int>, selective <dbl>, research_u <dbl>
```

Using filter in combination with other commands

`filter` can be used with any command that retruns true or false. This can be really powerful, for instance the command `str_detect` "detects" the relevant string in the data, so we can look for any college with the word "Colorado" in its name.

```
df%>%
  filter(str_detect(instnm,"Colorado"))%>%
  select(instnm,adm_rate,sat_avg)
```

```
## # A tibble: 12 × 3
##    instnm                                                adm_rate sat_avg
##    <chr>                                                    <dbl>   <int>
##  1 University of Colorado Denver/Anschutz Medical Campus    0.673    1124
##  2 University of Colorado Colorado Springs                  0.872    1136
##  3 University of Colorado Boulder                           0.784    1276
##  4 Colorado Christian University                           NA          NA
##  5 Colorado College                                         0.135      NA
##  6 Colorado School of Mines                                 0.531    1342
##  7 Colorado State University-Fort Collins                   0.814    1204
##  8 Colorado Mesa University                                 0.782    1063
##  9 University of Northern Colorado                          0.908    1096
## 10 Colorado State University Pueblo                         0.930    1047
## 11 Western Colorado University                              0.842    1114
## 12 Colorado State University-Global Campus                  0.986    1048
```

We can combine this with the | operator, which remember stands for “or.” Let’s say we want all the institutions in Colorado OR California.

```
df%>%
  filter(str_detect(instnm,"Colorado") | str_detect(instnm,"California"))%>%
  select(instnm,adm_rate,sat_avg)
```

```
## # A tibble: 57 × 3
##    instnm                                                adm_rate sat_avg
##    <chr>                                                    <dbl>   <int>
##  1 California Institute of Integral Studies                NA          NA
##  2 California Baptist University                           0.783     1096
##  3 California College of the Arts                          0.850       NA
##  4 California Institute of Technology                      0.0642    1557
##  5 California Lutheran University                          0.714     1168
##  6 California Polytechnic State University-San Luis Obispo 0.284     1342
##  7 California State University-Bakersfield                 0.807       NA
##  8 California State University-Stanislaus                  0.893       NA
##  9 California State University-San Bernardino              0.686      985
## 10 California State Polytechnic University-Pomona          0.546     1143
## # ℹ 47 more rows
```

We can also put this together in one (notice that everything goes inside the quotes)

```
df%>%
  filter(str_detect(instnm,"Colorado|California"))%>%
  select(instnm,adm_rate,sat_avg)
```

```
## # A tibble: 57 × 3
##    instnm                                                adm_rate sat_avg
##    <chr>                                                    <dbl>   <int>
##  1 California Institute of Integral Studies                NA           NA
##  2 California Baptist University                            0.783     1096
##  3 California College of the Arts                           0.850       NA
##  4 California Institute of Technology                       0.0642    1557
##  5 California Lutheran University                           0.714     1168
##  6 California Polytechnic State University-San Luis Obispo  0.284     1342
##  7 California State University-Bakersfield                  0.807       NA
##  8 California State University-Stanislaus                   0.893       NA
##  9 California State University-San Bernardino               0.686      985
## 10 California State Polytechnic University-Pomona           0.546     1143
## # ℹ 47 more rows
```

Reminder: logical operators

Here are (many of) the logical operators that we use in R:

- `>` , `<` : greater than, less than
- `>=` , `<=` : greater than or equal to, less than or equal to
- `!` :not, as in `!=` not equal to
- `&` AND
- `|` OR

Quick Exercise Select colleges that are from Texas AND have the word “community” in their name (the name variable is `instnm`).

```
# INSERT CODE HERE
```

Extending Select

Select can also be used with other characteristics.

For quick guide on this: https://dplyr.tidyverse.org/reference/select.html (https://dplyr.tidyverse.org/reference/select.html)

For example, we can select just variables that contain the word “region”

```
df%>%
  select(contains("region"))
```

```
## # A tibble: 2,546 × 1
##    region
##    <chr>
##  1 Southeast
##  2 Southeast
##  3 Southeast
##  4 Southeast
##  5 Southeast
##  6 Southeast
##  7 Southeast
##  8 Southeast
##  9 Southeast
## 10 Southeast
## # ℹ 2,536 more rows
```

`contains()` and `matches()` are equivalent functions

```
df %>%
  select(matches('region'))
```

```
## # A tibble: 2,546 × 1
##    region
##    <chr>
##  1 Southeast
##  2 Southeast
##  3 Southeast
##  4 Southeast
##  5 Southeast
##  6 Southeast
##  7 Southeast
##  8 Southeast
##  9 Southeast
## 10 Southeast
## # ℹ 2,536 more rows
```

We can augment these with the logical operators listed above

```
# Removes columns with "inst" in their names
df %>%
  select(!matches('inst'))
```

```
## # A tibble: 2,546 × 15
##    unitid stabbr grad_debt_mdn control region  preddeg openadmp adm_rate ccbasic
##     <int> <chr>          <int> <chr>   <chr>   <chr>      <int>    <dbl>   <int>
##  1 100654 AL             33375 Public  Southe… Bachel…        2    0.918      18
##  2 100663 AL             22500 Public  Southe… Bachel…        2    0.737      15
##  3 100690 AL             27334 Private Southe… Associ…        1   NA          20
##  4 100706 AL             21607 Public  Southe… Bachel…        2    0.826      16
##  5 100724 AL             32000 Public  Southe… Bachel…        2    0.969      19
##  6 100751 AL             23250 Public  Southe… Bachel…        2    0.827      15
##  7 100760 AL             12500 Public  Southe… Associ…        1   NA           2
##  8 100812 AL             19500 Public  Southe… Bachel…       NA   NA          22
##  9 100830 AL             24826 Public  Southe… Bachel…        2    0.904      18
## 10 100858 AL             21281 Public  Southe… Bachel…        2    0.807      15
## # ℹ 2,536 more rows
## # ℹ 6 more variables: sat_avg <int>, md_earn_wne_p6 <int>, ugds <int>,
## #   costt4_a <int>, selective <dbl>, research_u <dbl>
```

```
# Selects columns with either "inst" or an underline in their names
df %>%
  select(matches('inst|_'))
```

```
## # A tibble: 2,546 × 7
##    instnm      grad_debt_mdn adm_rate sat_avg md_earn_wne_p6 costt4_a research_u
##    <chr>               <int>    <dbl>   <int>          <int>    <int>      <dbl>
##  1 Alabama A …         33375    0.918     939          25200    23053          0
##  2 University…         22500    0.737    1234          35100    24495          0
##  3 Amridge Un…         27334   NA          NA          30700    14800          0
##  4 University…         21607    0.826    1319          36200    23917          1
##  5 Alabama St…         32000    0.969     946          22600    21866          0
##  6 The Univer…         23250    0.827    1261          37400    29872          0
##  7 Central Al…         12500   NA          NA          23100    10493          0
##  8 Athens Sta…         19500   NA          NA          33400       NA          0
##  9 Auburn Uni…         24826    0.904    1082          30100    19849          0
## 10 Auburn Uni…         21281    0.807    1300          39500    31590          0
## # ℹ 2,536 more rows
```

We can also select just variables by their type using `where()`

```
# Select only numeric variables
df%>%
  select(where(is.numeric))
```

```
## # A tibble: 2,546 × 11
##    unitid grad_debt_mdn openadmp adm_rate ccbasic sat_avg md_earn_wne_p6  ugds
##     <int>         <int>    <int>    <dbl>   <int>   <int>          <int> <int>
##  1 100654         33375        2    0.918      18     939          25200  5271
##  2 100663         22500        2    0.737      15    1234          35100 13328
##  3 100690         27334        1   NA          20      NA          30700   365
##  4 100706         21607        2    0.826      16    1319          36200  7785
##  5 100724         32000        2    0.969      19     946          22600  3750
##  6 100751         23250        2    0.827      15    1261          37400 31900
##  7 100760         12500        1   NA           2      NA          23100  1201
##  8 100812         19500       NA   NA          22      NA          33400  2677
##  9 100830         24826        2    0.904      18    1082          30100  4407
## 10 100858         21281        2    0.807      15    1300          39500 24209
## # ℹ 2,536 more rows
## # ℹ 3 more variables: costt4_a <int>, selective <dbl>, research_u <dbl>
```

Quick Exercise Use the same setup to select only character variables (`is.character`)

```
# INSERT CODE HERE
```

Summarizing Data

To summarize data, we use the `summarize` command. Inside that command, we tell R two things: what to call the new object (a data frame, really) that we're creating, and what numerical summary we would like. The code below summarizes median debt for the colleges in the dataset by calculating the average of median debt for all institutions.

Notice that inside the `mean` command

```
df%>%
  summarize(mean_debt=mean(grad_debt_mdn,na.rm=TRUE))
```

```
## # A tibble: 1 × 1
##   mean_debt
##       <dbl>
## 1    19646.
```

Quick Exercise Summarize the average entering SAT scores in this dataset.

```
# INSERT CODE HERE
```

Combining Commands

We can also combine commands, so that summaries are done on only a part of the dataset. Below, we summarize median debt for selective schools, and not very selective schools.

```
df%>%
  filter(stabbr=="CA")%>%
  summarize(mean_adm_rate=mean(adm_rate,na.rm=TRUE))
```

```
## # A tibble: 1 × 1
##   mean_adm_rate
##           <dbl>
## 1         0.592
```

Quick Exercise Calculate average earnings for schools where SAT>1200 & the admissions rate is between 10 and 20 percent.

```
# INSERT CODE HERE
```

Mutate

`mutate` is the verb for changing variables in R. Let's say we want to create a variable that's set to 1 if the college admits less than 10 percent of the students who apply.

```
df<-df%>%
  mutate(selective=ifelse(adm_rate<=.1,1,0))
```

The `ifelse()` function is powerful. It allows us to create one value if a logical expression is `TRUE`, and another value if the logical expression is `FALSE`. The inputs are: `ifelse([LOGIC],[VALUE IF TRUE],[VALUE IF FALSE])`. In this example, the "logical expression" is `adm_rate <= 0.1`. For every row where this is `TRUE`, we get the value `1`. For every row where this is `FALSE`, we get the value `0`.

Quick Exercise Create a new variable that's set to 1 if the college has more than 10,000 undergraduate students

```
# INSERT CODE HERE
```

Or what if we want to create another new variable that changes the admissions rate from its current proportion to a percent?

```
df<-df%>%
  mutate(adm_rate_pct=adm_rate*100)
```

To figure out if that worked we can use `summarize`

```
df%>%
  summarize(mean_adm_rate_pct=mean(adm_rate_pct,na.rm=TRUE))
```

```
## # A tibble: 1 × 1
##   mean_adm_rate_pct
##               <dbl>
## 1              67.9
```

Grouping

Above, we calculated the `mean_adm_rate` for schools in California by combining a `filter()` command with a `summarise()` command. Let's use the same approach to calculate the average SAT score for schools that are selective and for those that aren't.

```
# Mean SAT for selective schools
df %>%
  filter(selective == 1) %>%
  summarise(SATavg = mean(sat_avg,na.rm=T))
```

```
## # A tibble: 1 × 1
##   SATavg
##    <dbl>
## 1  1510.
```

```
# Mean SAT for non-selective schools
df %>%
  filter(selective == 0) %>%
  summarise(SATavg = mean(sat_avg,na.rm=T))
```

```
## # A tibble: 1 × 1
##   SATavg
##    <dbl>
## 1  1135.
```

This works, but requires two separate chunks of code. We can streamline this analysis with the `group_by()` function, which tells `R` to run a command on each group separately. Thus:

```
df %>%
  group_by(selective) %>%
  summarise(SATavg = mean(sat_avg,na.rm=T))
```

```
## # A tibble: 3 × 2
##   selective SATavg
##       <dbl>  <dbl>
## 1         0  1135.
## 2         1  1510.
## 3        NA   NaN
```

Quick Exercise Do the same, but calculate the average SAT score for each state, using `group_by()` .

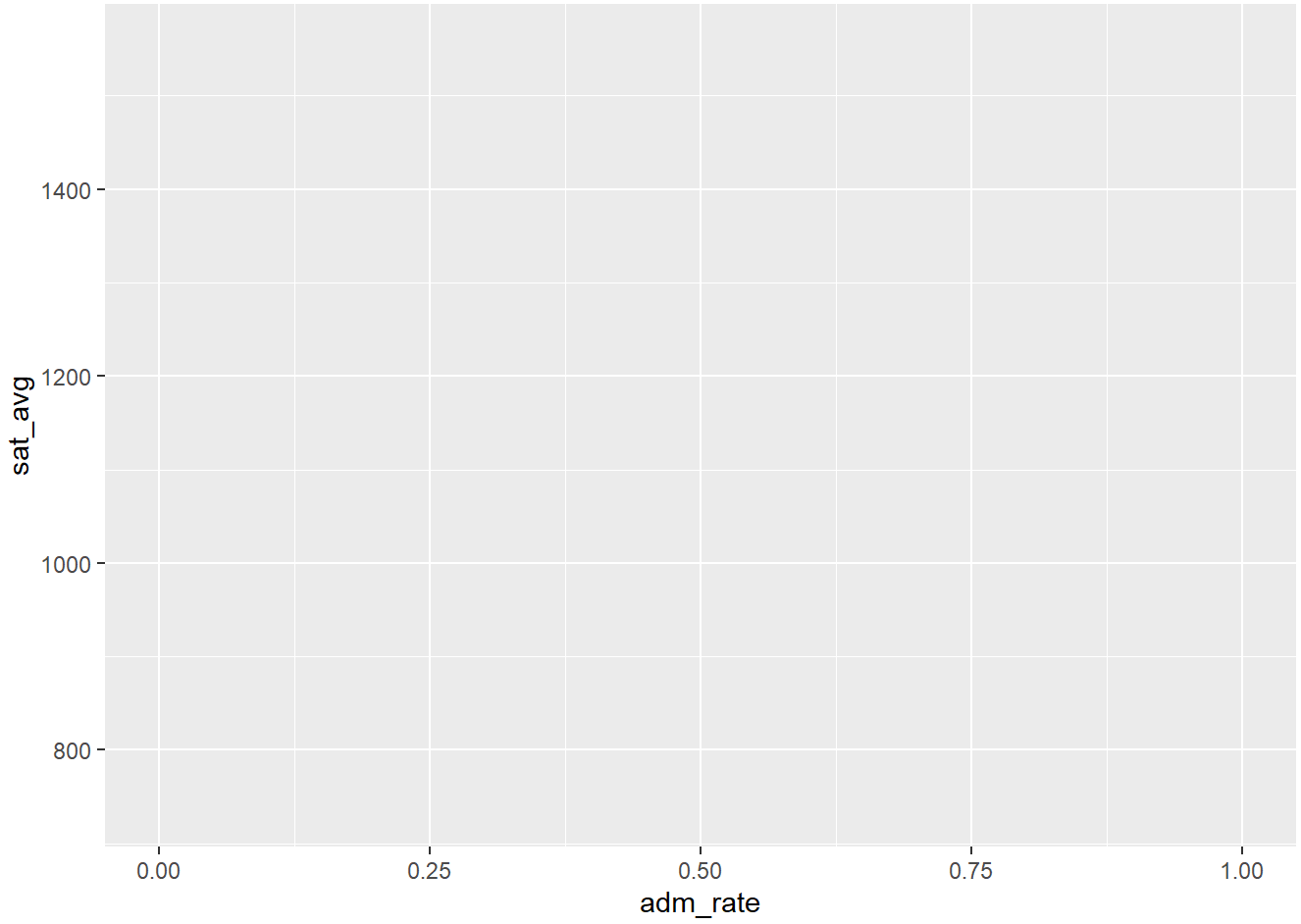
```
# INSERT CODE HERE
```

ggplot

`ggplot` works in layers, where the most simple layer is contained in the `ggplot()` function itself. Here, you set the x and y axes with a function called `aes()`. The primary inputs to `aes()` are `x` and `y`, although you can also set things like `color` and `fill` here.

Let's create the first layer of our plot by using the `%>%` function to link our data with the `ggplot()` function.

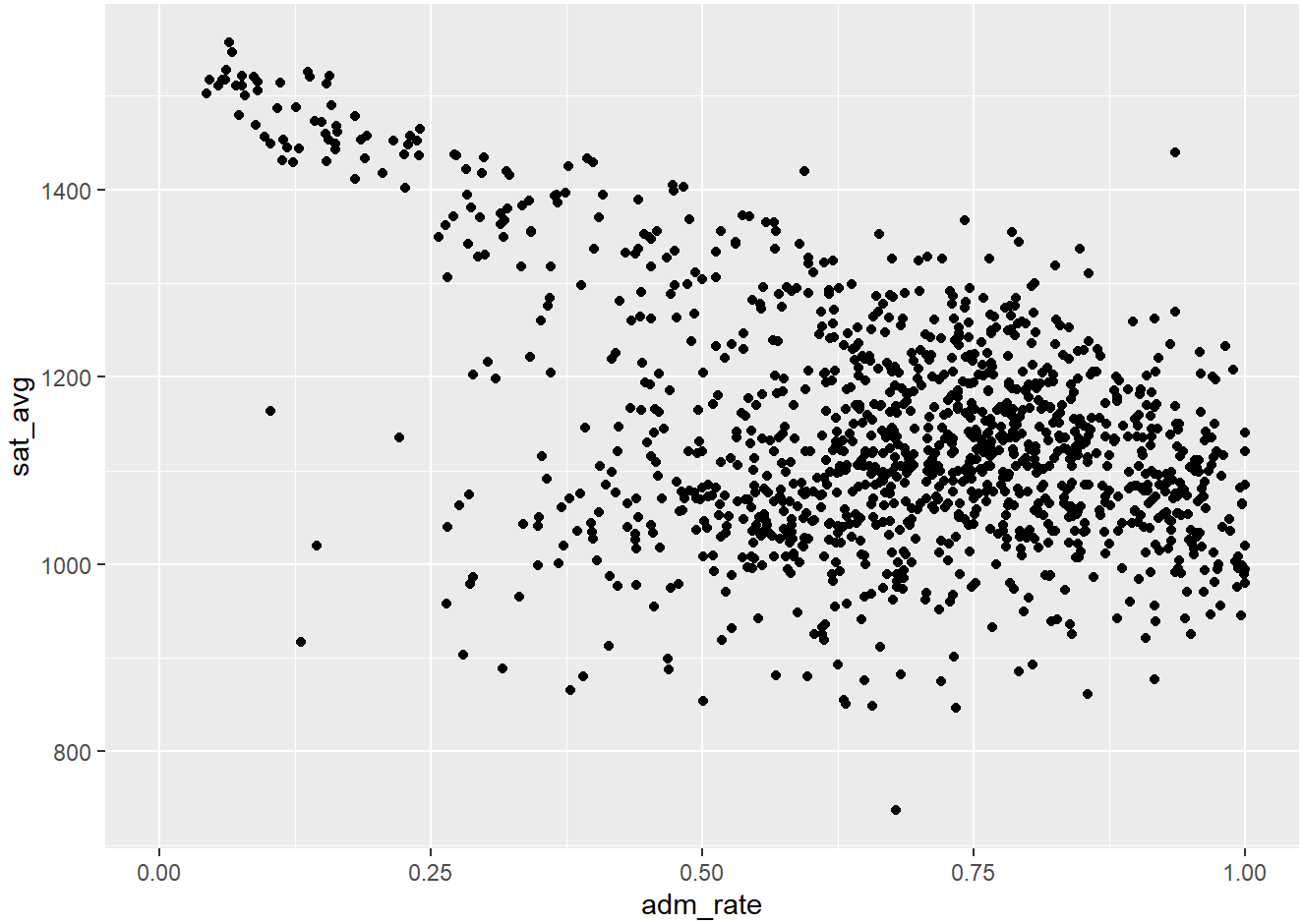
```
df %>%
  ggplot(aes(x = adm_rate,y = sat_avg))
```



This gives us a rather ugly looking graph box, where we see the admissions rate on the x-axis (the horizontal axis) and the SAT scores on the y-axis (the vertical axis). However, there are no visuals like lines or bars or points to help us actually SEE the data. We know that ggplot has them on the axes we specified, but we haven't drawn anything yet.

The next step is to add a "layer" to this plot that contains the visuals we want. To add a layer, we use the `+` sign to link our blank canvas to the function to draw the graph. In this situation, we are going to create a scatterplot using the function named `geom_point()`. (There are **many** other functions that are included with ggplot which will draw different plots… `geom_line()` and `geom_bar()` for example.)

```
df %>%
  ggplot(aes(x = adm_rate,y = sat_avg)) +
  geom_point()
```

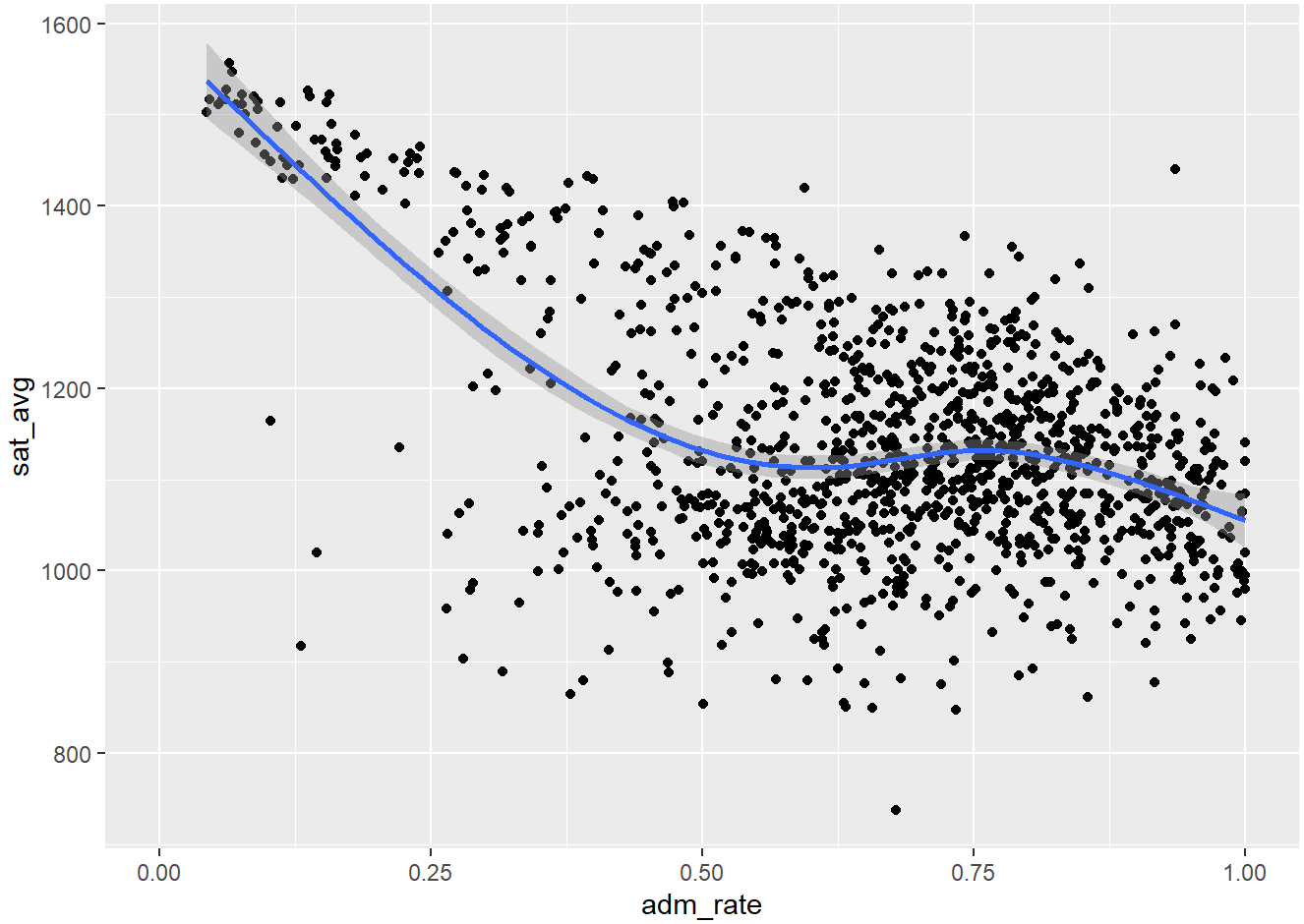


Tweaking Visuals

We have a visualization of our data! It suggests that there is a negative relationship between the admissions rate and SAT scores. When the admissions rate is very low (i.e., when schools are very selective), the average SAT scores of their students is above 1500 (top left part of the graph). When the admissions rate is very high, the average SAT scores is around 1000 (bottom right of the graph). Why might this be?

We can easily see this pattern just by looking at the data. However, we can make it even more clear by overlaying a “line of best fit” using a different function called `geom_smooth()` . This is going to be our **second** layer, meaning we need another `+` sign to link the function.

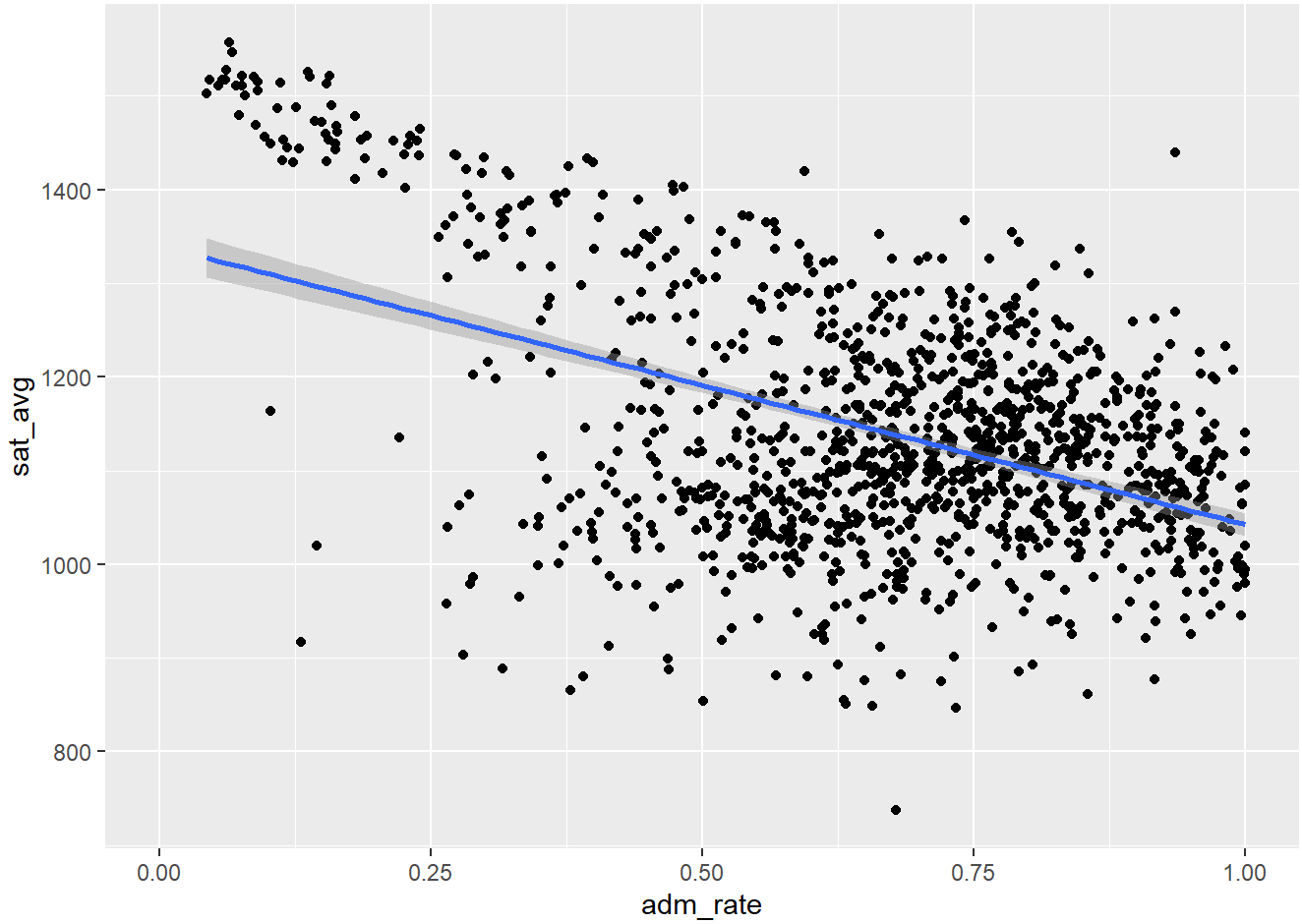
```
df %>%
  ggplot(aes(x = adm_rate,y = sat_avg)) +
  geom_point() +
  geom_smooth()
```



The default behavior of `geom_smooth()` is to draw a slightly curvy line that bends. This is potentially useful, since it reveals that the negative relationship between the admissions rate and the SAT scores is stronger among more selective schools (i.e., those with an admissions rate less than 0.50 or 50%), but almost flat among less selective schools.

However, if all we want is the **overall** relationship drawn with a straight line, we need to tell `geom_smooth()` to draw a straight line with the input `method = "lm"` . ("lm" stands for "linear model", a topic we will come back to later in the semester.)

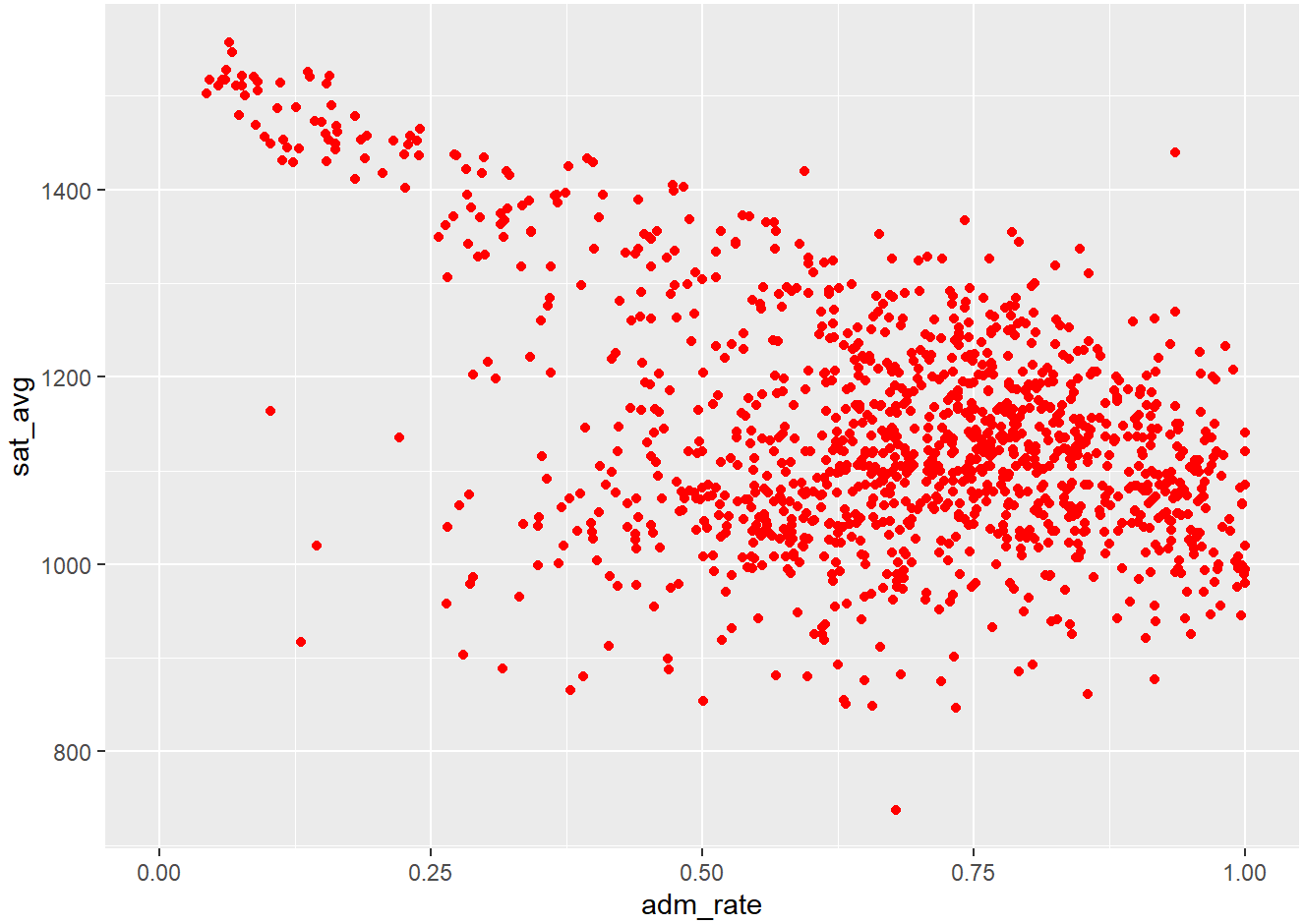
```
df %>%
  ggplot(aes(x = adm_rate,y = sat_avg)) +
  geom_point() +
  geom_smooth(method = 'lm')
```



Colors

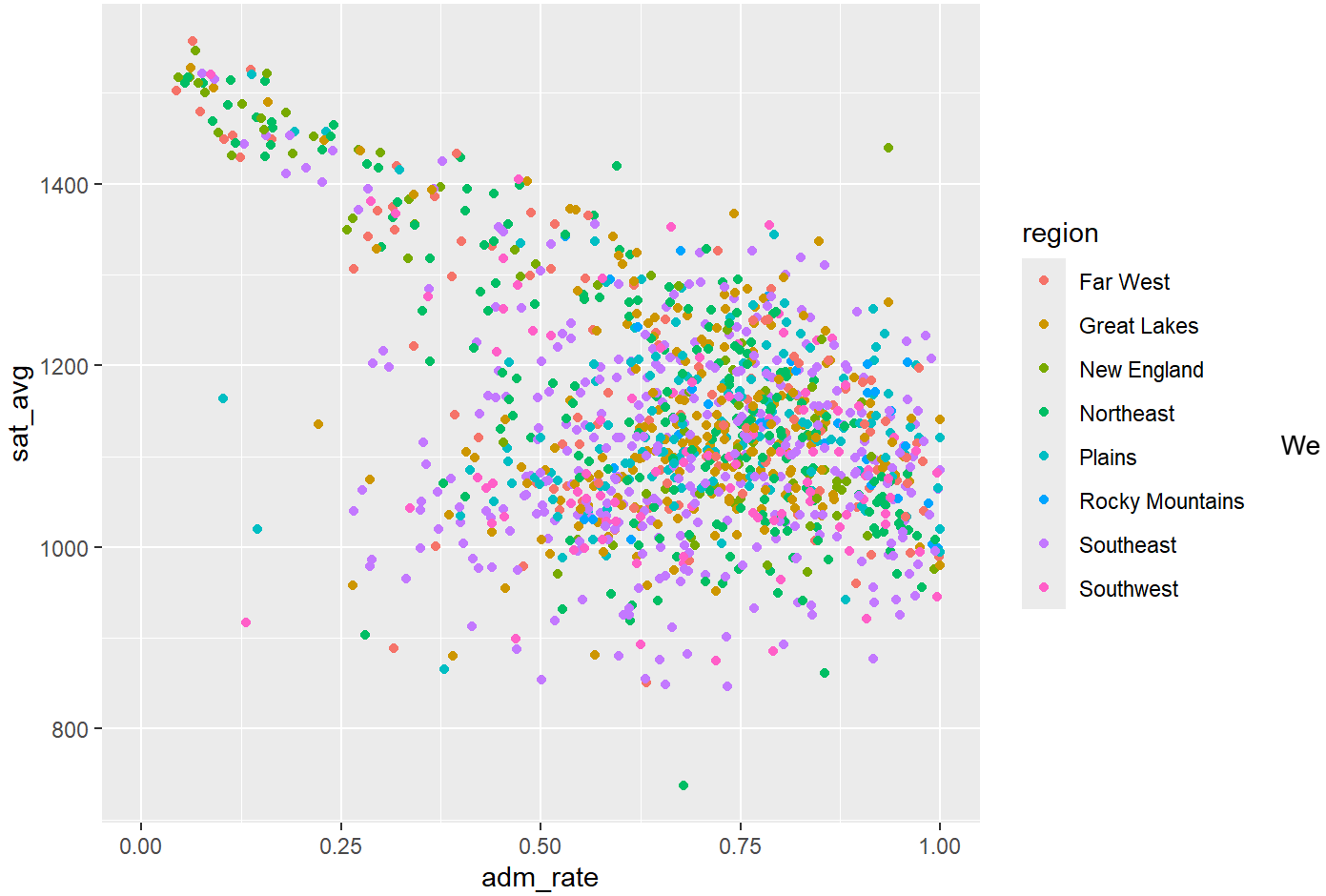
We can continue to tweak this plot by changing the colors of the points. For example, we could color EVERY point red as follows

```
df %>%
  ggplot(aes(x = adm_rate,y = sat_avg)) +
  geom_point(color = 'red')
```



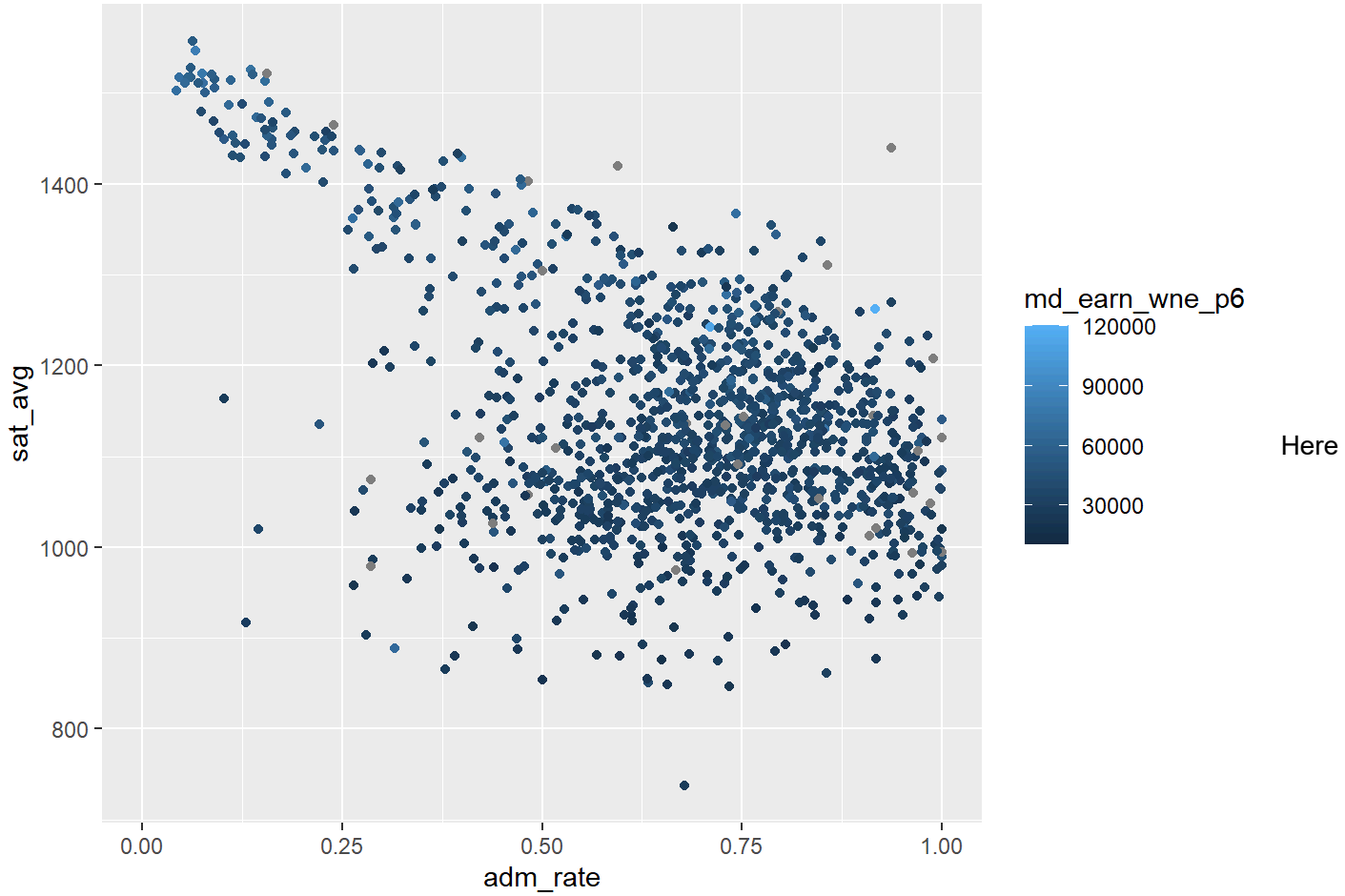
However, we could instead color points *based on their value*. To do so, we want to move the `color` input **inside** the `aes()` function, and set it equal to the variable we want to visualize with color.

```
df %>%
  ggplot(aes(x = adm_rate,y = sat_avg,
             color = region)) +
  geom_point()
```



now have a legend added to the plot that tells us what each color refers to. In this example, we set the color equal to a categorical variable. We could instead set it equal to a continuous variable, which would give us a gradient.

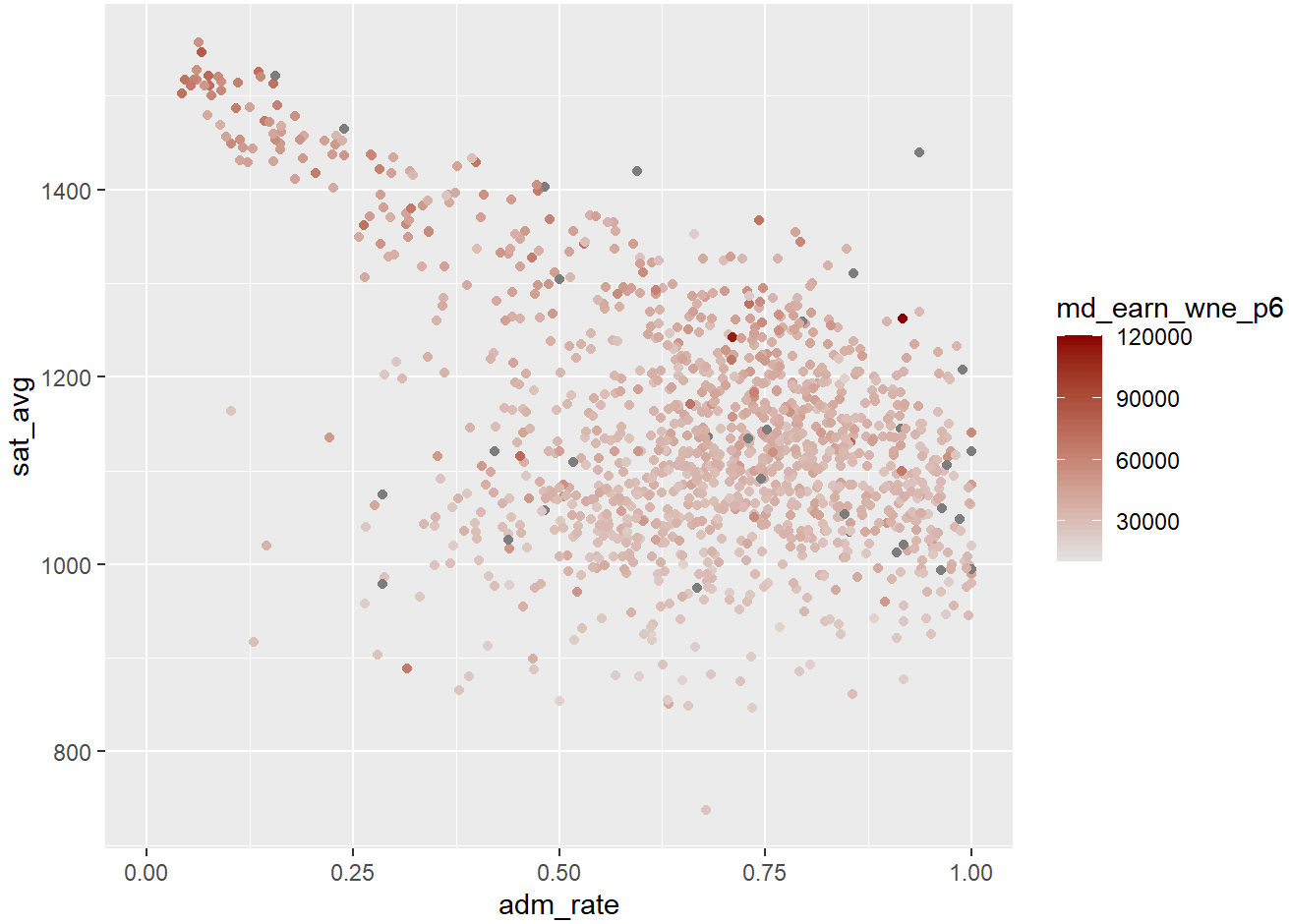
```
df %>%
  ggplot(aes(x = adm_rate,y = sat_avg,
             color = md_earn_wne_p6)) +
  geom_point()
```



we see two patterns. First, we continue to see the negative relationship between the admissions rate and the SAT scores. Second, we can *kinda* see a relationship between future wages of graduates and their SAT scores.

If we don't like the default choice of dark to light blue, we can modify this with `scale_color_gradient()`. As always, add another `+` to add the layer to the plot!

```
df %>%
  ggplot(aes(x = adm_rate,y = sat_avg,
             color = md_earn_wne_p6)) +
  geom_point() +
  scale_color_gradient(low = 'grey90',high = 'darkred')
```



Note that some of the points are dark gray. These are schools that don't report the median earnings of their recent graduates. These missing data default to a dark gray color.

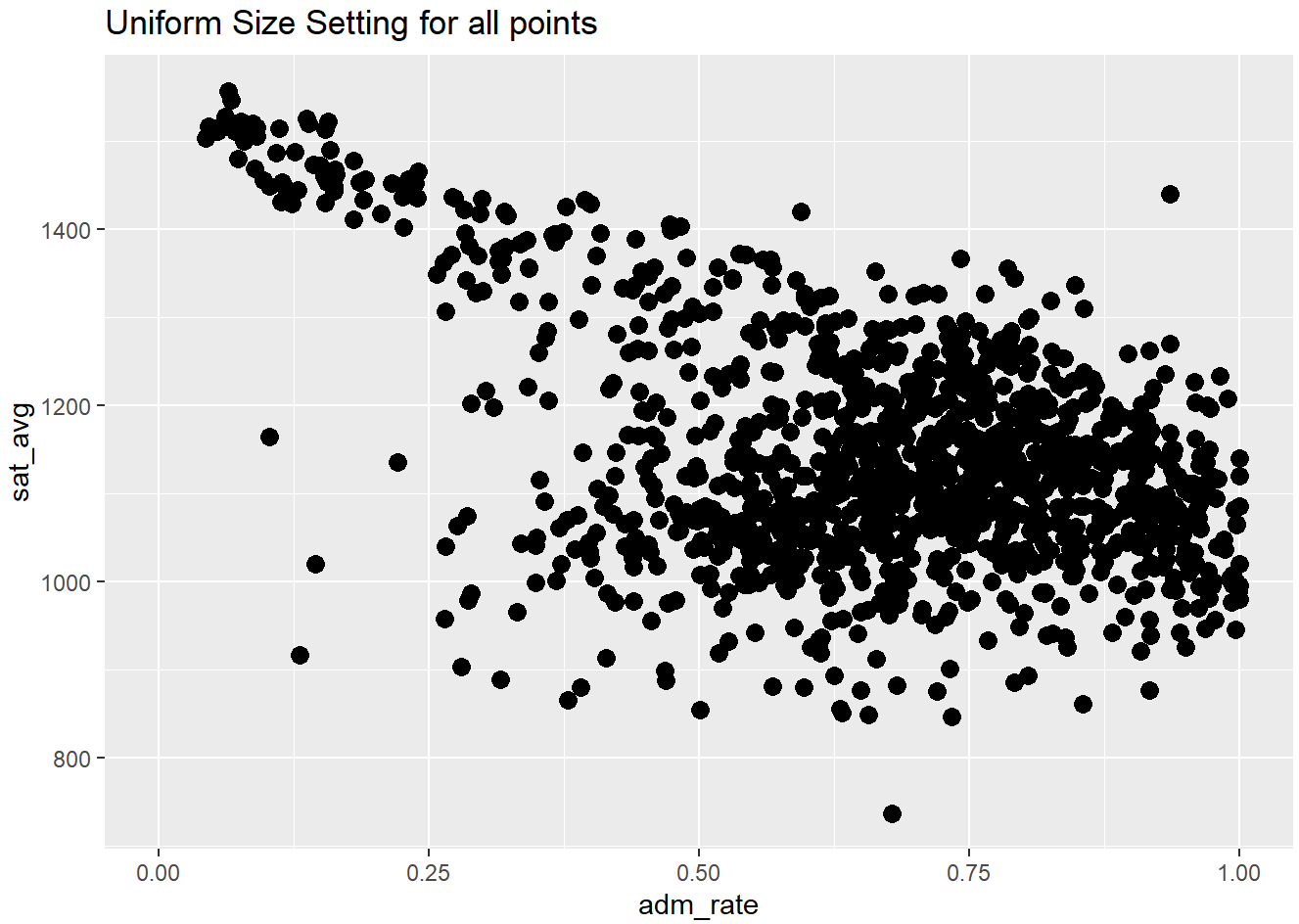
Quick Exercise Re-do this plot but put `md_earn_wne_p6` on the y-axis, and `sat_avg` on the x-axis. Is there a relationship between SAT scores and earnings? Why might this be the case?

```
# INSERT CODE HERE
```

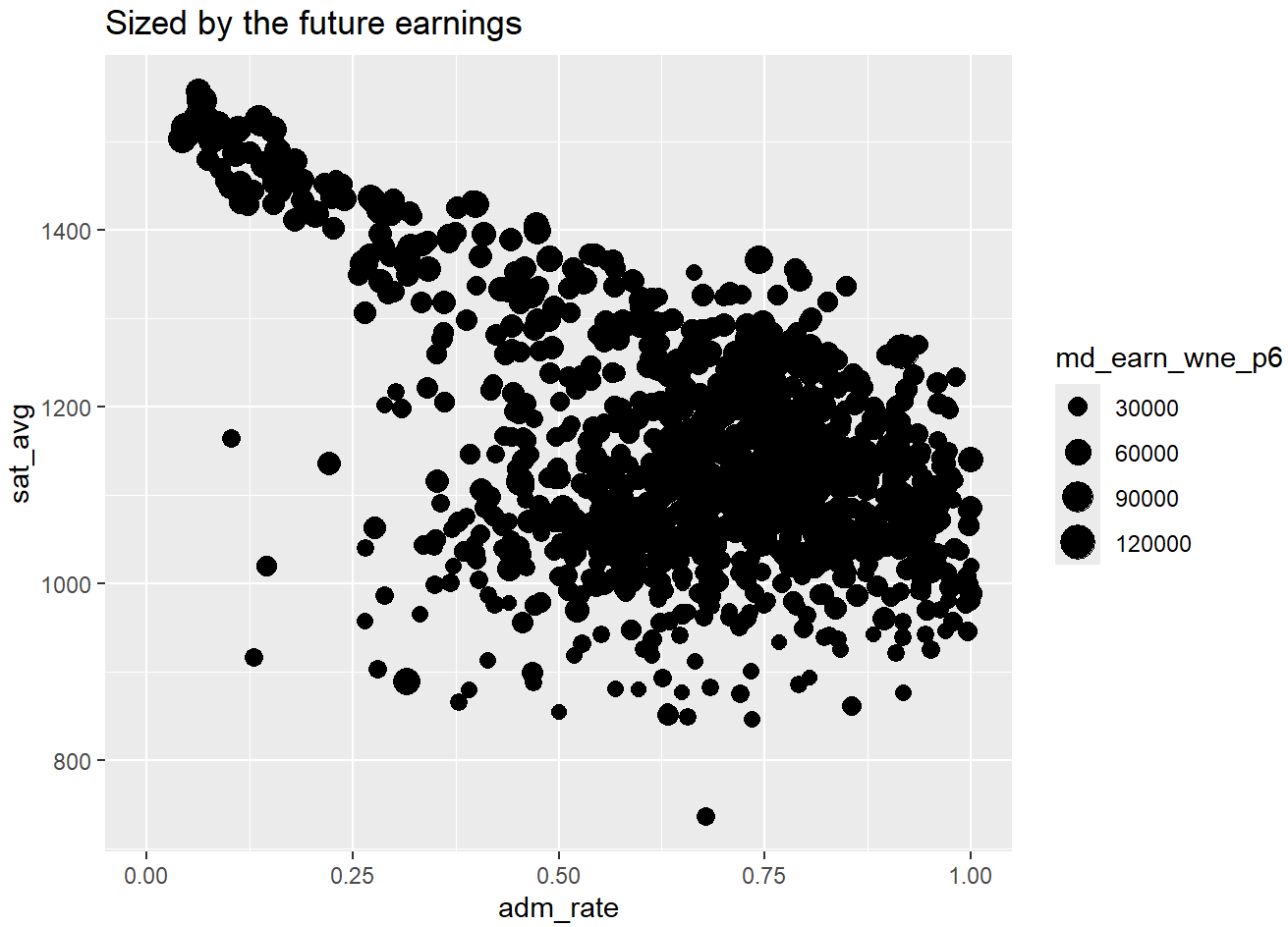
Other Aesthetics

We can also change the size of the points with the `size` input. As with `color`, this can either be set uniformly for all points, or we can make the size a function of another variable.

```
df %>%
  ggplot(aes(x = adm_rate,y = sat_avg)) +
  geom_point(size = 3) +
  labs(title = 'Uniform Size Setting for all points')
```



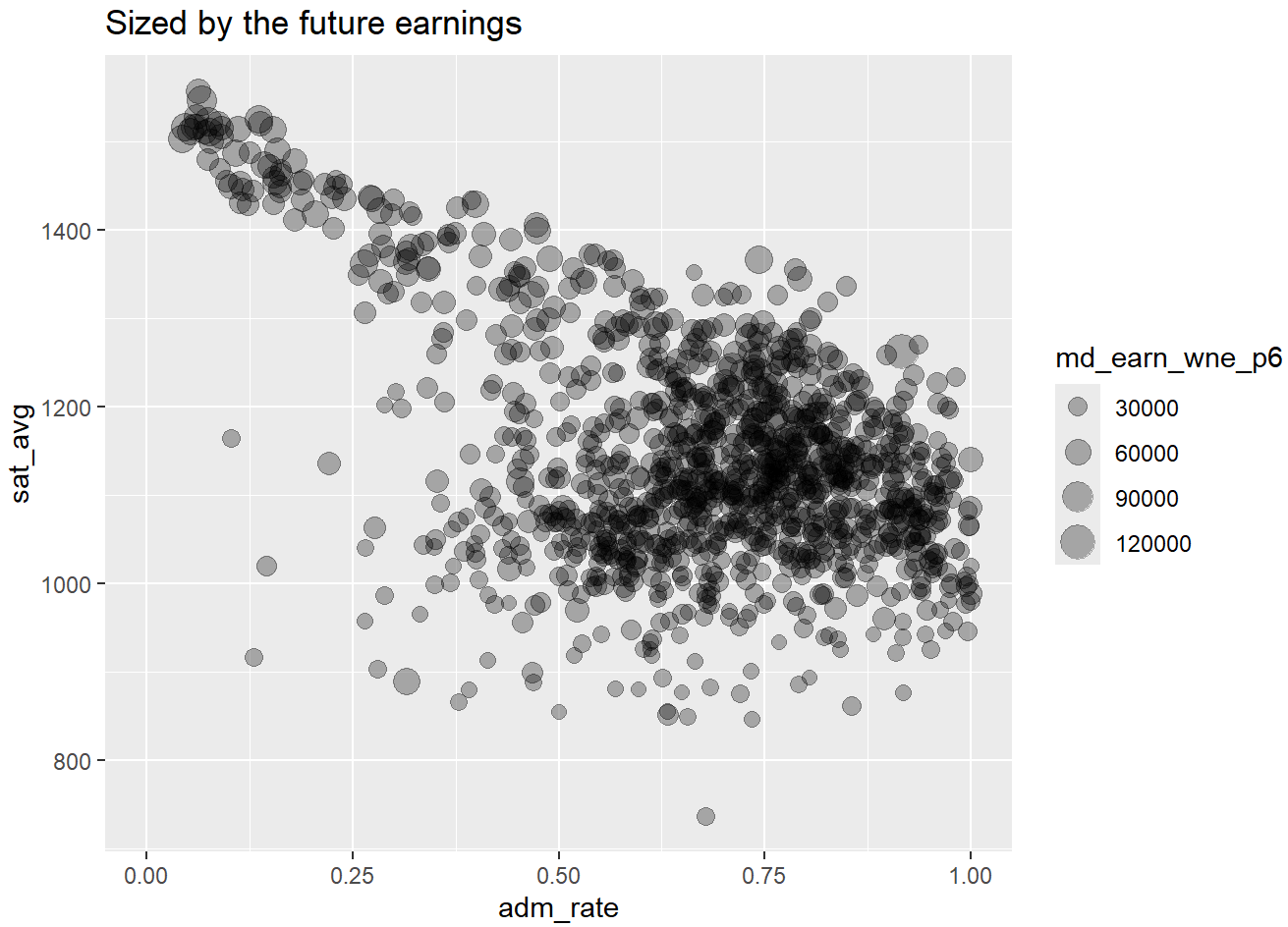

```
df %>%
  ggplot(aes(x = adm_rate,y = sat_avg,
             size = md_earn_wne_p6)) +
  geom_point() +
  labs(title = 'Sized by the future earnings')
```



Transparency

With so many points overlapping, especially with larger points, it becomes harder for the reader to see details. We can therefore adjust the transparency of these points with the `alpha` parameter, which can be a value between 0 and 1. Values closer to zero make the points more transparent, while values closer to 1 make them more opaque.

```
df %>%
  ggplot(aes(x = adm_rate,y = sat_avg,
             size = md_earn_wne_p6)) +
  geom_point(alpha = .3) +
  labs(title = 'Sized by the future earnings')
```



Other Types of Plots

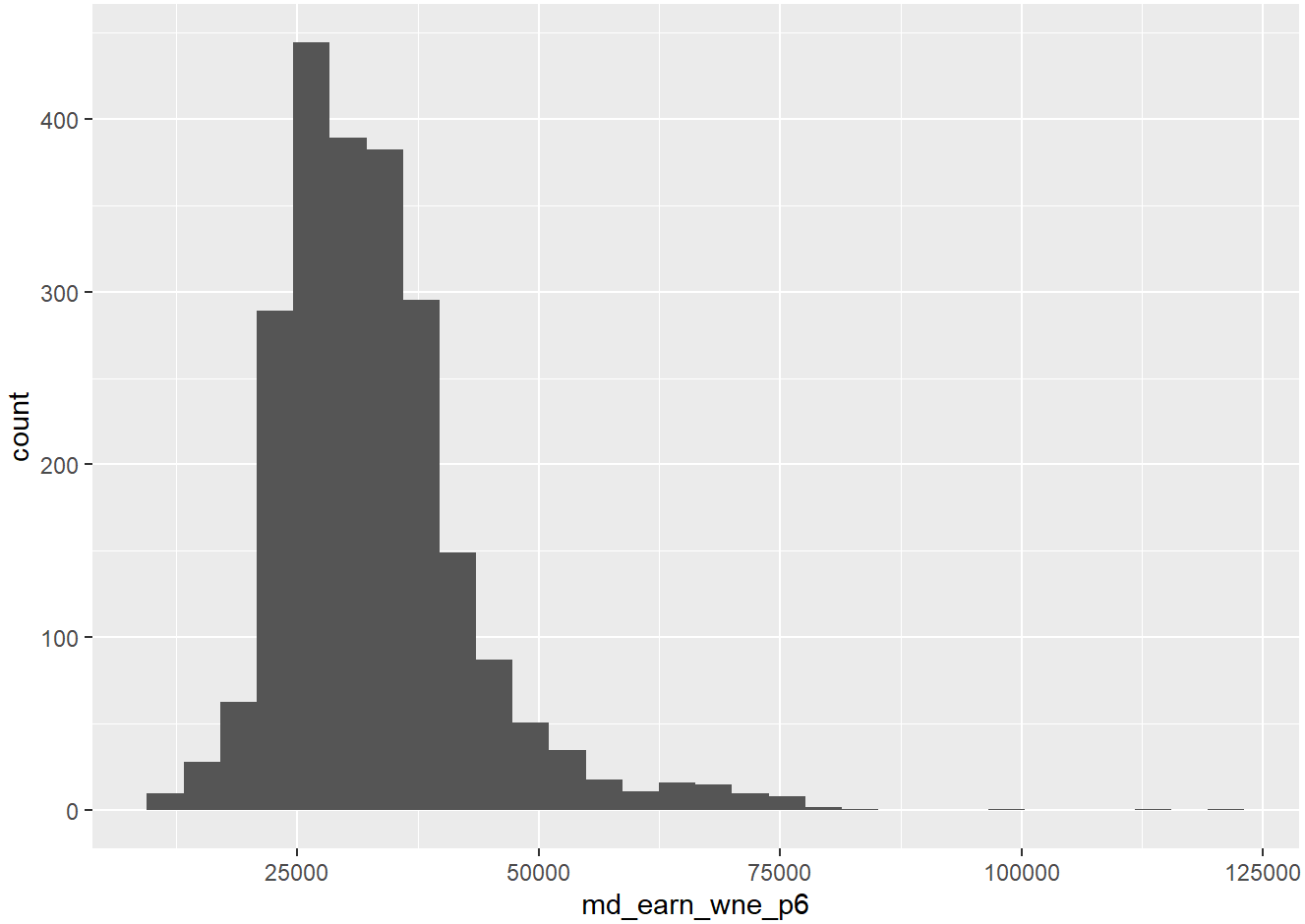
This topic is very **deep** and you can spend years becoming an `R` expert and still find new ways of visualizing things. I encourage you to keep this link bookmarked: http://r-statistics.co/Complete-Ggplot2-Tutorial-Part1-With-R-Code.html (http://r-statistics.co/Complete-Ggplot2-Tutorial-Part1-With-R-Code.html)

For now though, a few other types of plots:

Histograms & Densities

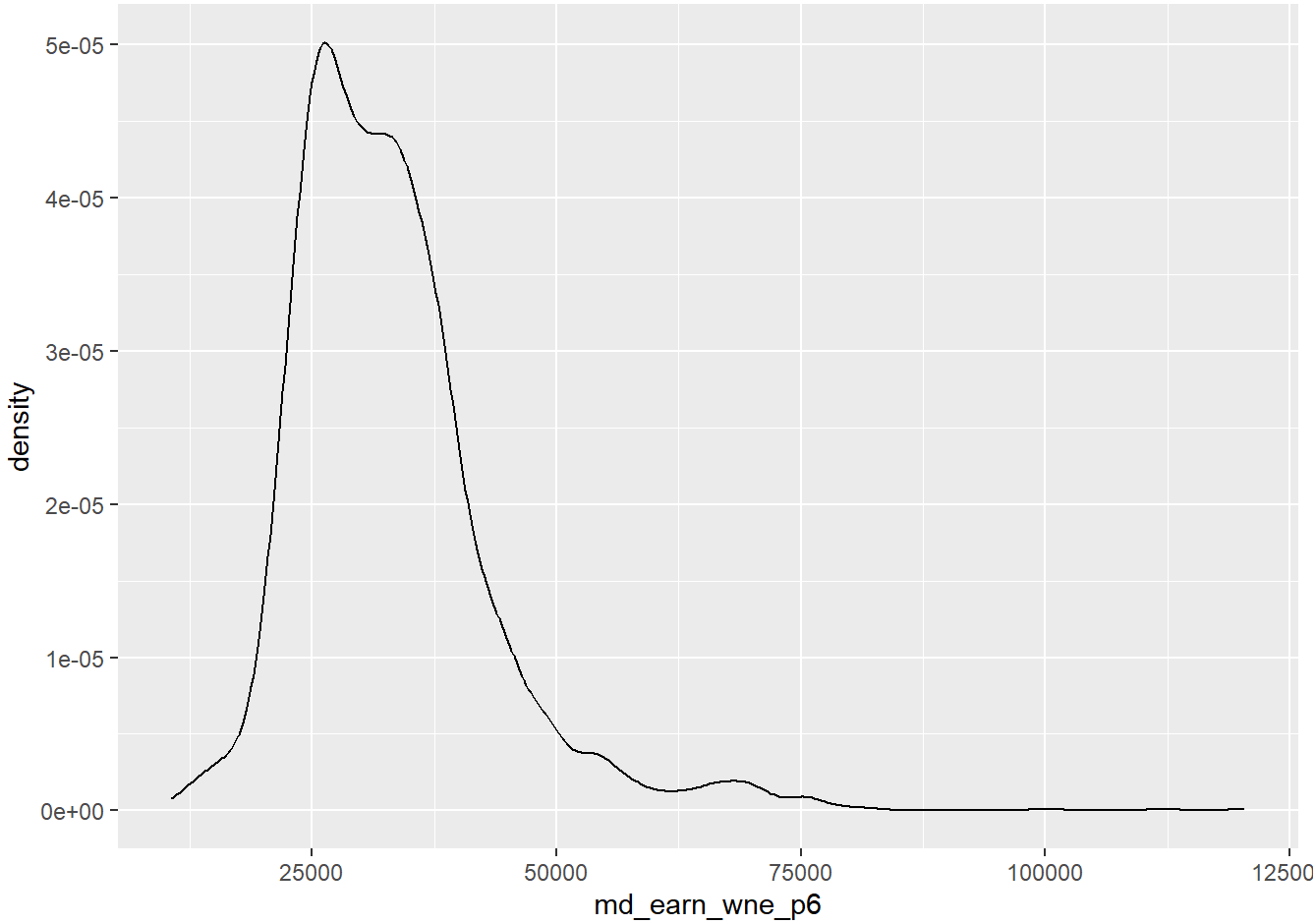
For visualization of a single measure, a histogram is often useful. Here, we only need to set the x-axis variable. The `geom_histogram()` function will calculate the y-axis values for us, which is the number of schools falling into each bin. If we add all the bins together, we get the total number of schools in the data.

```
df %>%
  ggplot(aes(md_earn_wne_p6)) +
  geom_histogram()
```



We can also get the same result with a density plot, which replaces the histogram with a line. The y-axis becomes the fraction of schools at each point on the x-axis, and adds up to 1.

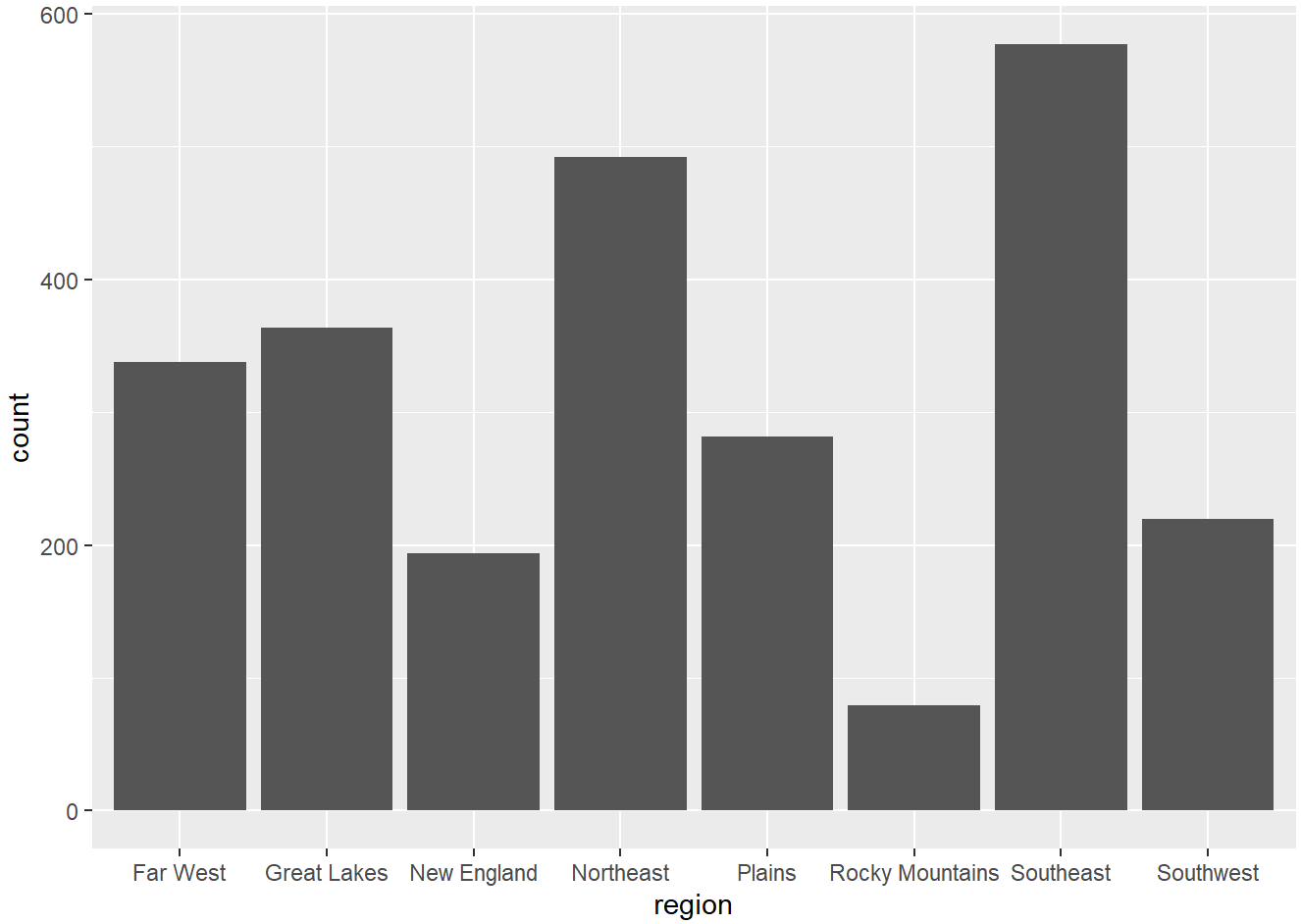
```
df %>%
  ggplot(aes(x = md_earn_wne_p6)) +
  geom_density()
```



Barplots

Barplots are another common type of data visualization. These are more appropriate for categorical data, or for types of continuous data where there are only a handful of distinct values.

```
df %>%
  ggplot(aes(x = region)) +
  geom_bar()
```


600
400
200
0
count
Far West
Great Lakes
New England
Northeast
Plains
Rocky Mountains
Southeast
Southwest
region