Data Analytics
CS301
Plotting and Basic Data Transformations

Week 4
Fall 2018
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Ask the Mileage Data

Ask: *What classes of cars (i.e,. suv's, trucks, etc.) get the best city and highway mileage?*

I know! I will use some MPG data from the Tidyverse library and see what the data says!!

```
library(tidyverse)
   # check the data
View(mpg)
   # run simple plot
ggplot(data = mpg) +
  geom_point(mapping = aes(x = mpg$displ, y = mpg$hwy ))
```

From Last Time: Code for a Simple GGPlot

- **ggplot(data = mpg) + geom_point(mapping = aes(x = displ, y = hwy))**

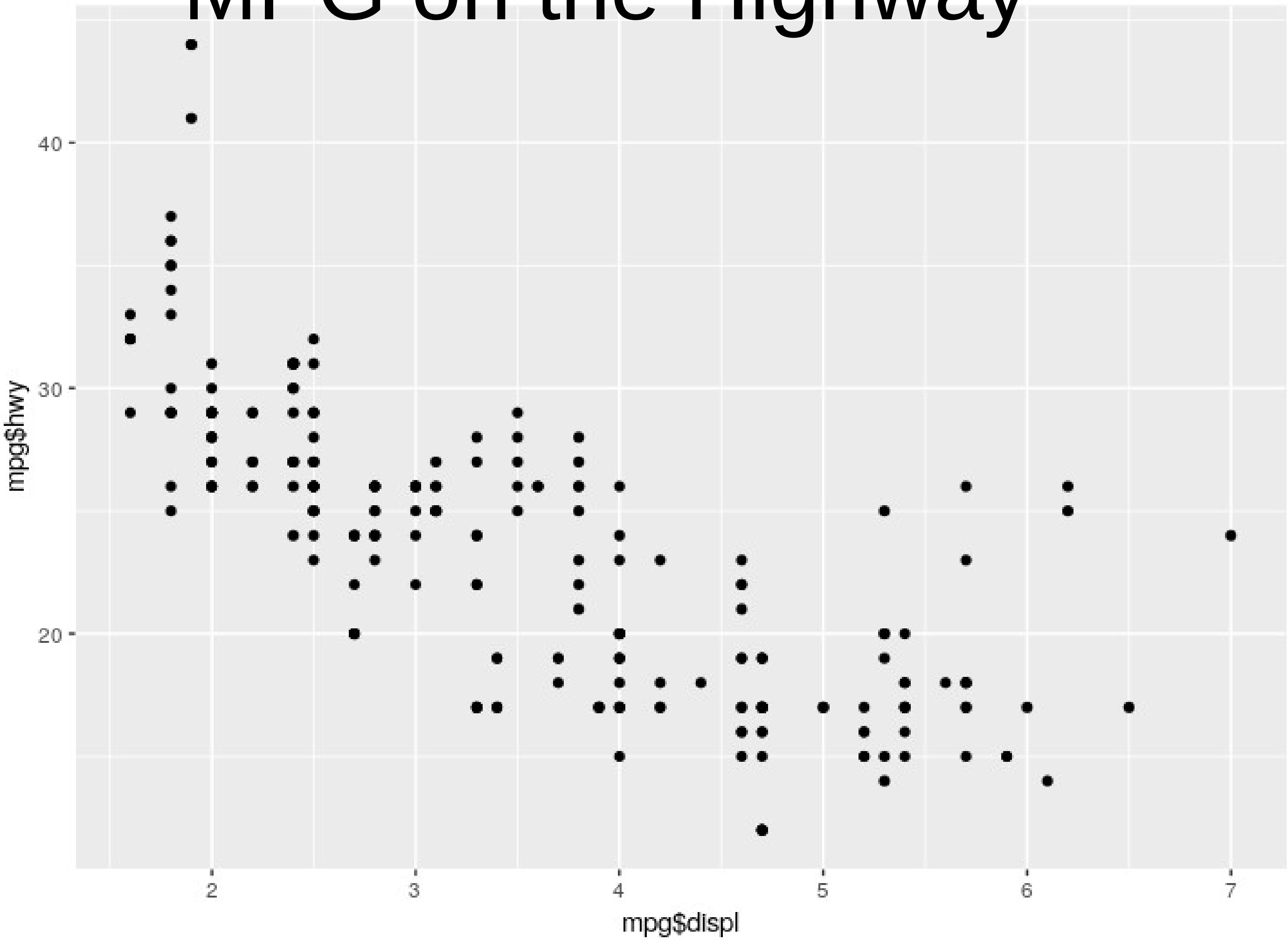
- Establish the *canvas* (where the plot is shown)
- **Ggplot()**

- Link to the data (set is called, ‘mpg’)
  - **ggplot(data = mpg)**

- Compute the geometery of point placement on canvas
  - **geom_point(mapping = …)**

- Compute the aesthetics of the plot (titles, color, point type, etc)
  - **aes(x = displ, y = hwy)**

Displacement (Car Weight) by MPG on the Highway

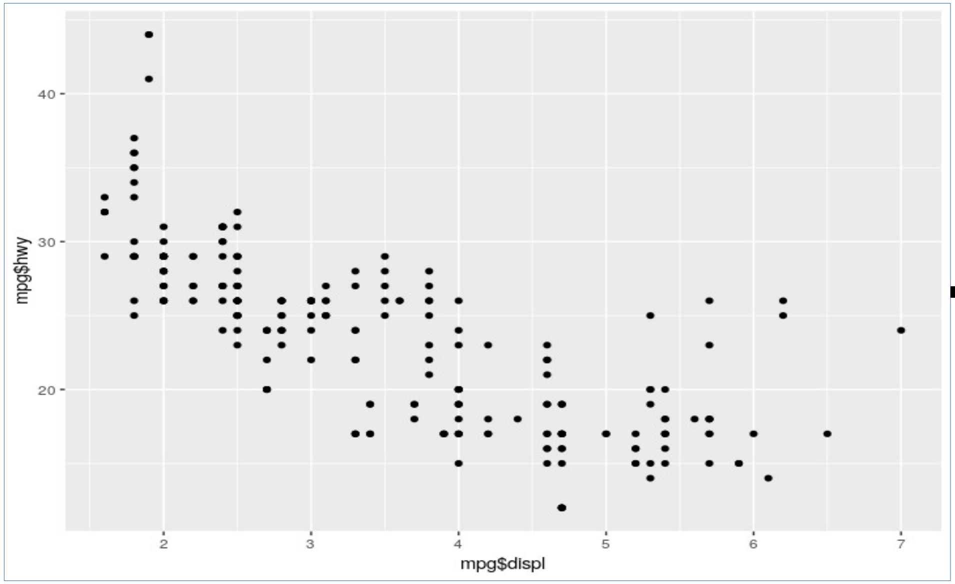



```
ggplot(data = mpg) +
  geom_point(mapping = aes(x = mpg$displ, y = mpg$hwy ))
```

Displacement (Car Weight) by MPG on the Highway

Is there more to learn from this data?

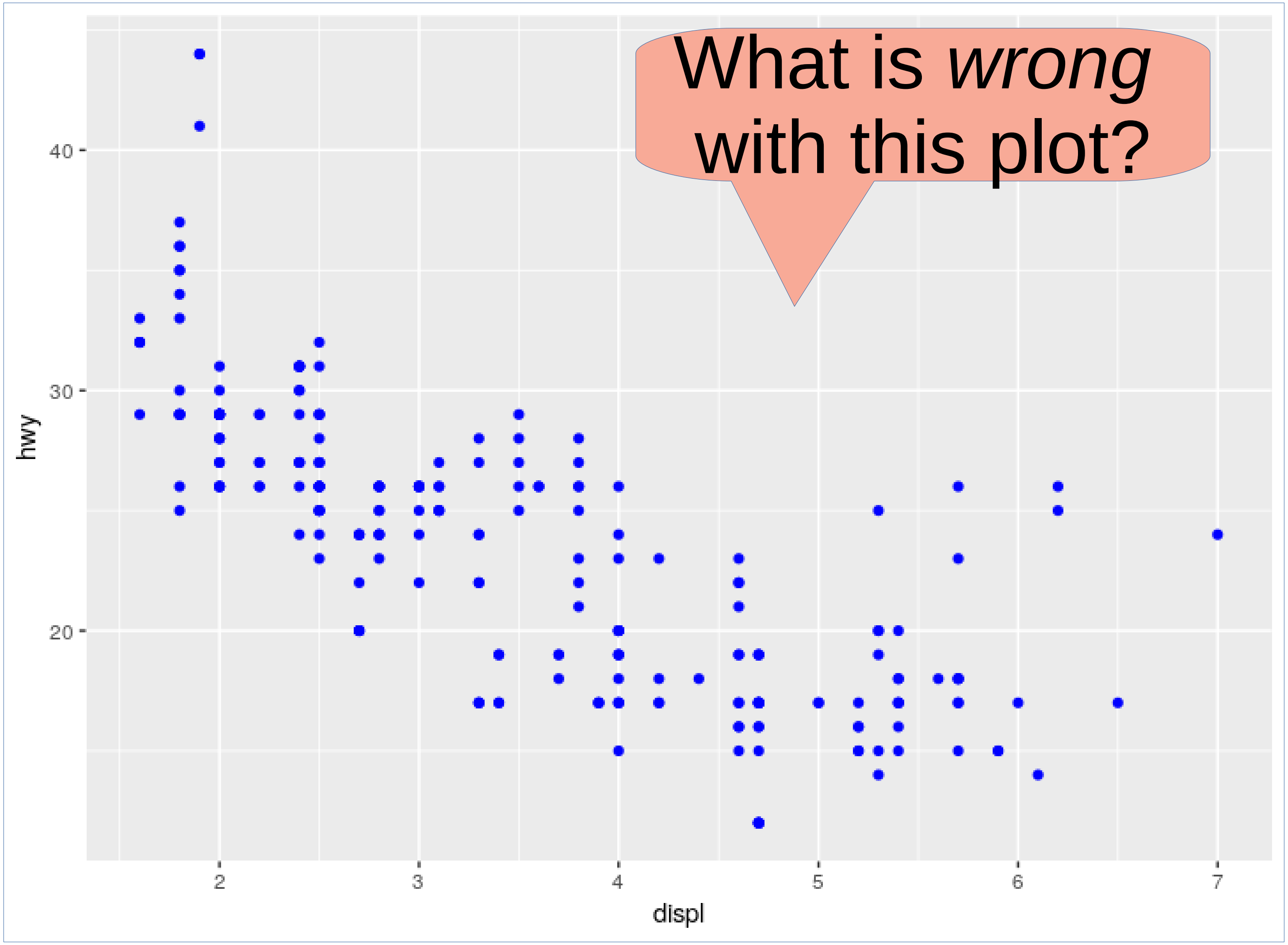
What is *wrong* with this the previous plot?



Yes!

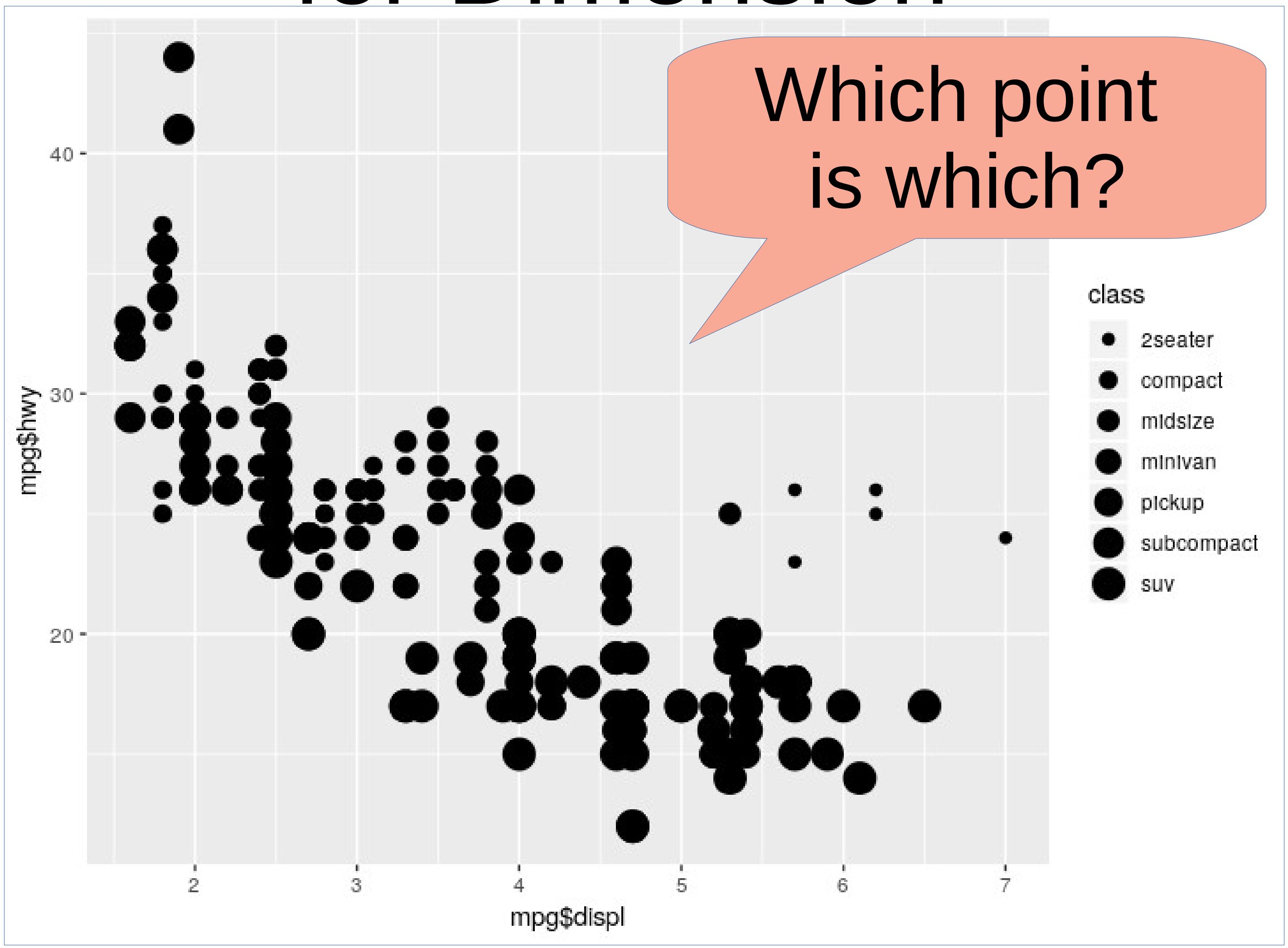
No??

New Blue Plot?



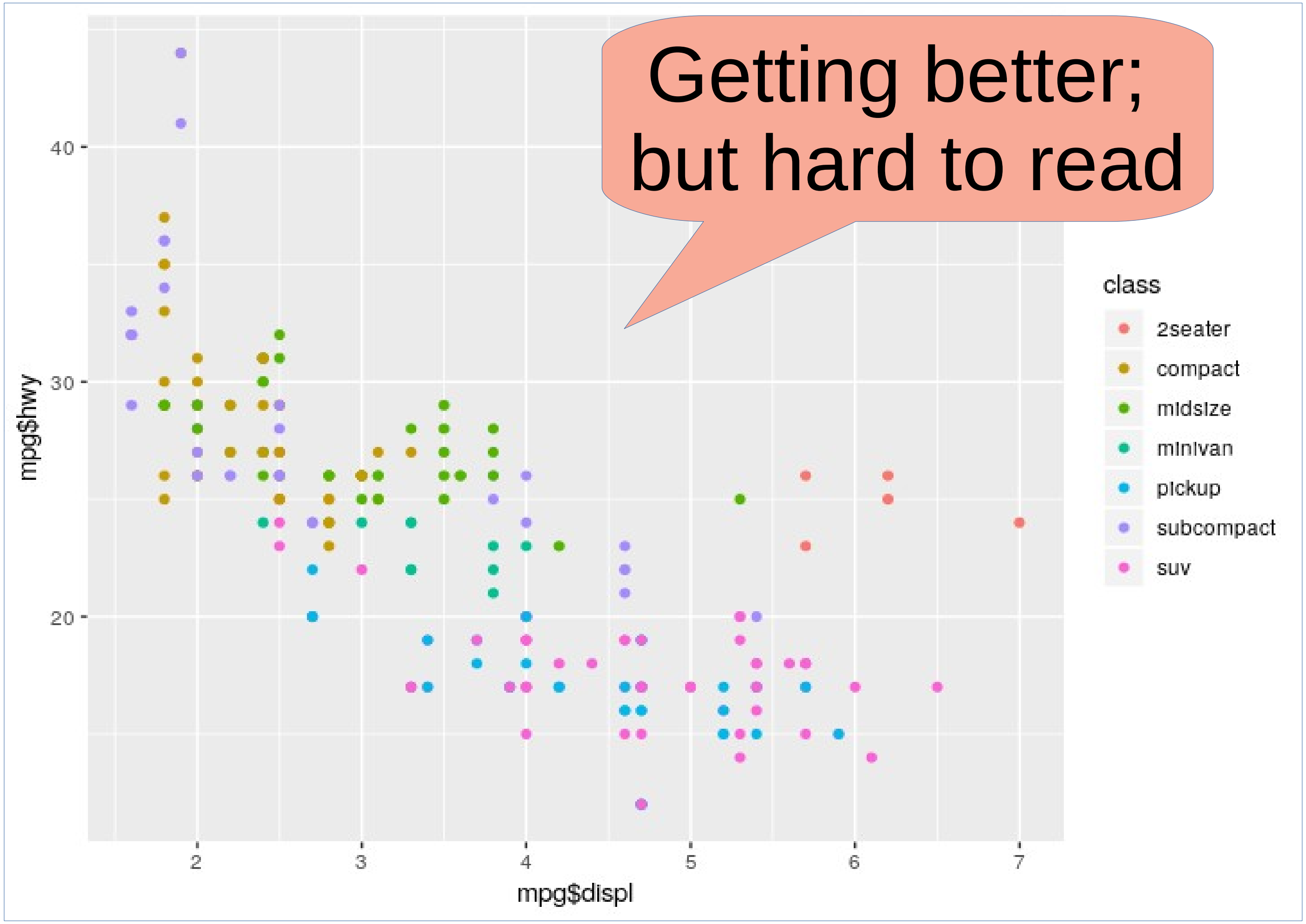

```
ggplot(data = mpg) + geom_point(mapping = aes(x = displ,
y = hwy), color = "blue")
```

Try Sizing the points for Dimension



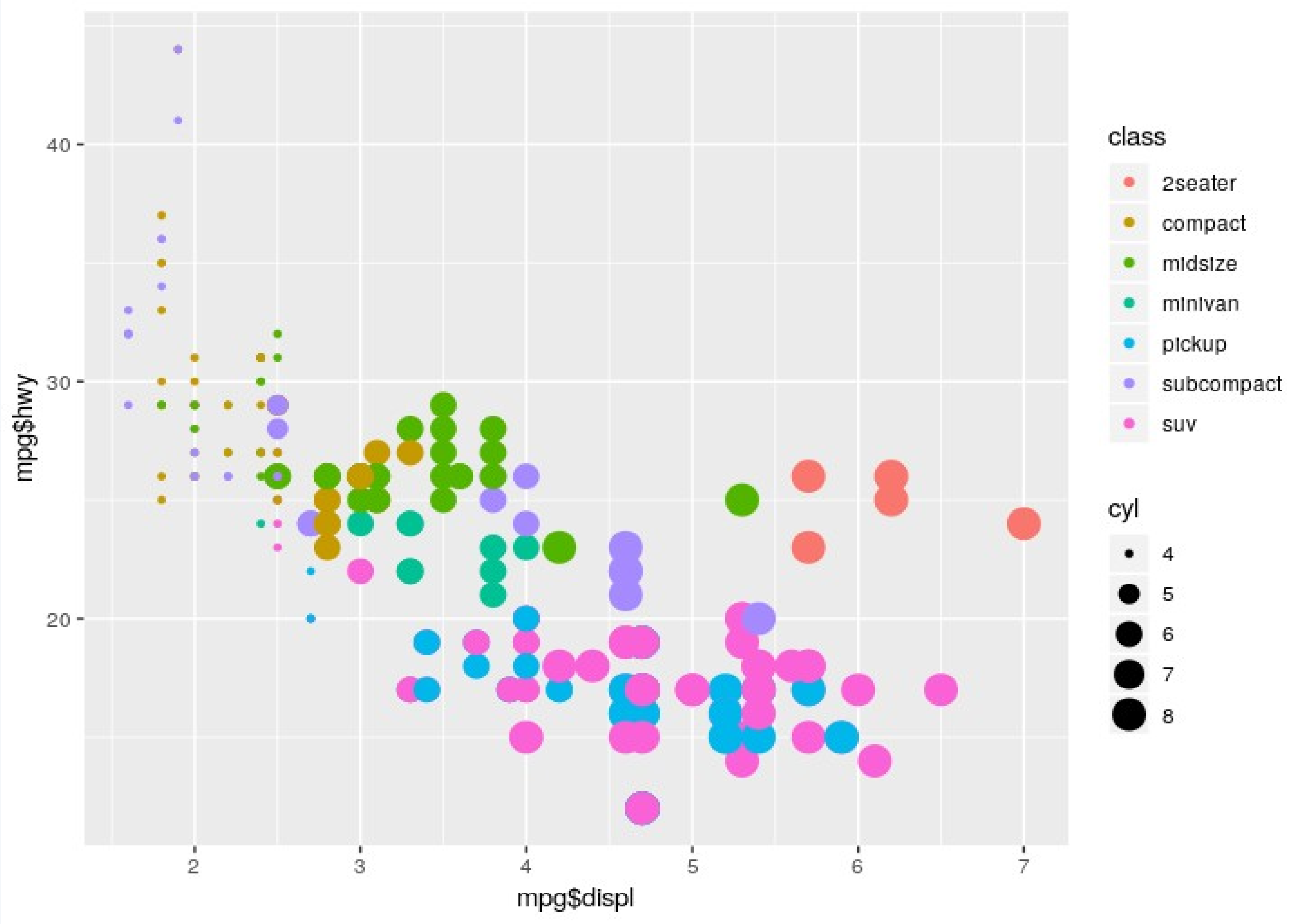

```
ggplot(data = mpg) + geom_point(mapping = aes(x = mpg$displ,
y = mpg$hwy, size = class))
```

Try Coloring for Dimension



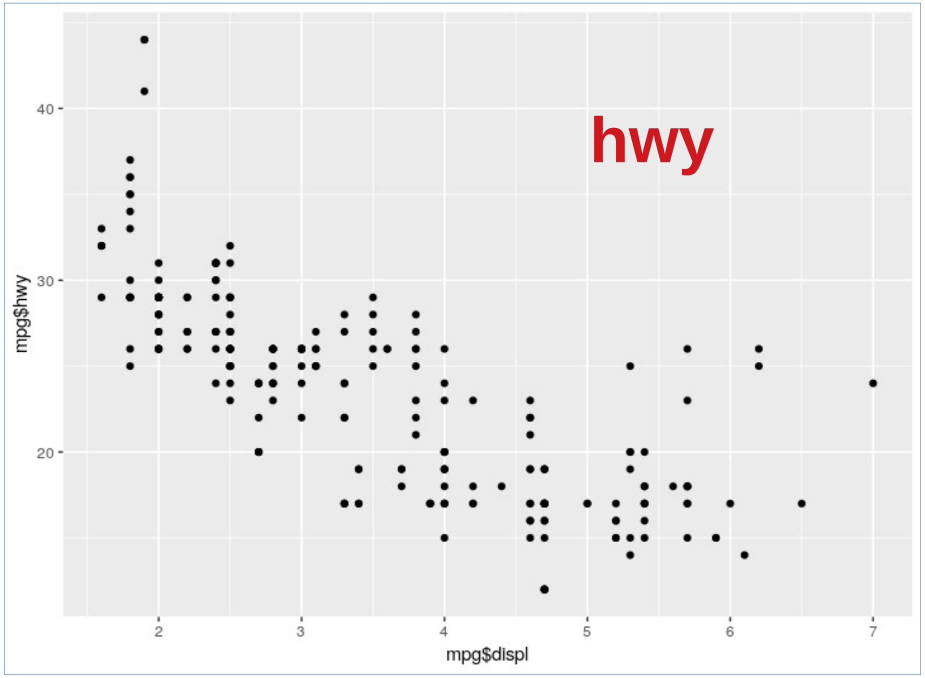

```
ggplot(data = mpg) + geom_point(mapping = aes(x = mpg$displ,
y = mpg$hwy, color = class))
```

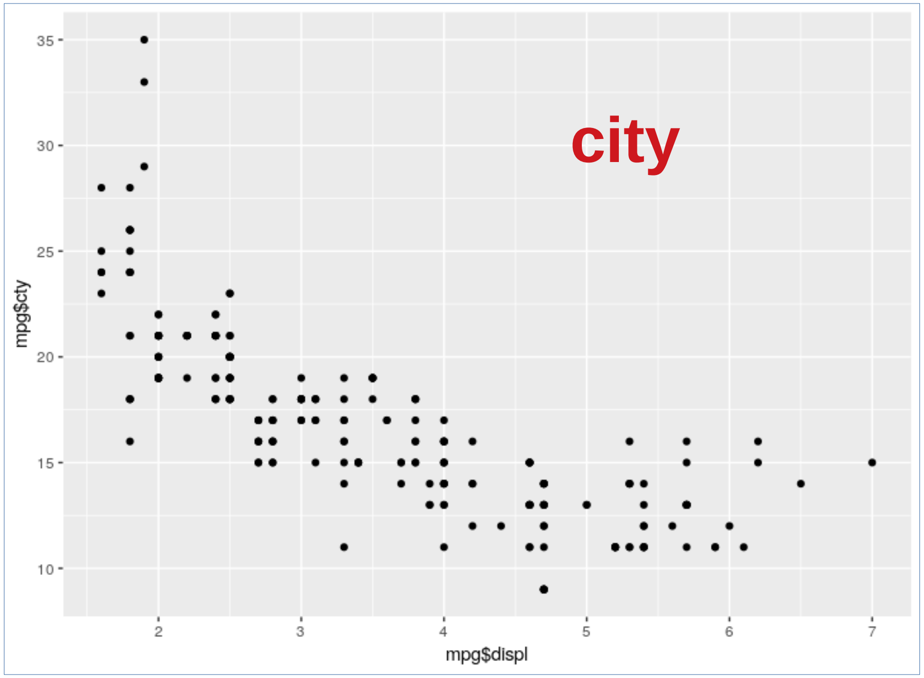
Combine Color, Sized Points and Cycle



ggplot(data = mpg) + geom_point(mapping = aes(x = mpg$displ, y = mpg$hwy, color = class, size = cyl))

Comparing Hwy and City Mileage

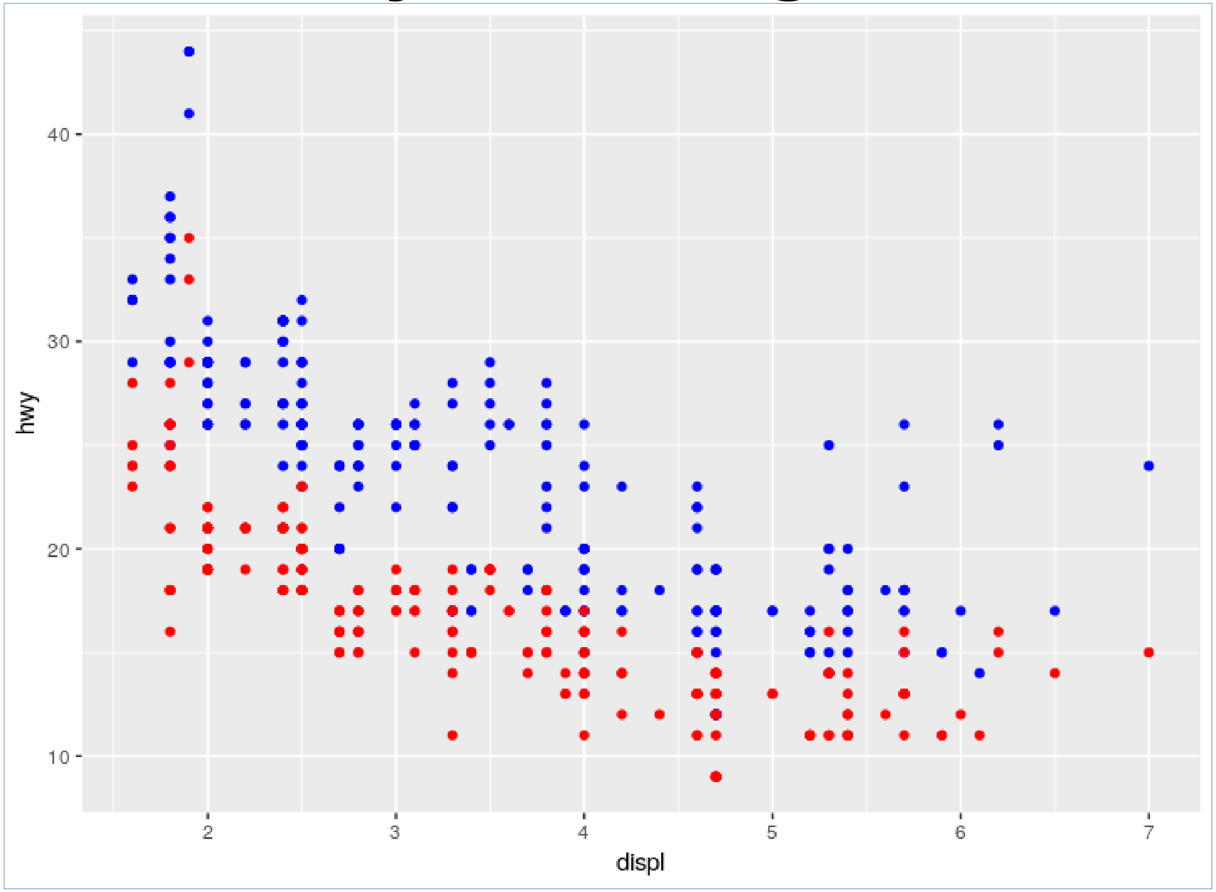





```
# hwy mileage
ggplot(data = mpg) + geom_point(mapping = aes(x = mpg$displ, y
= mpg$hwy ))

# city mileage
ggplot(data = mpg) + geom_point(mapping = aes(x = mpg$displ, y
= mpg$cty ))
```

Comparing Hwy and City Mileage

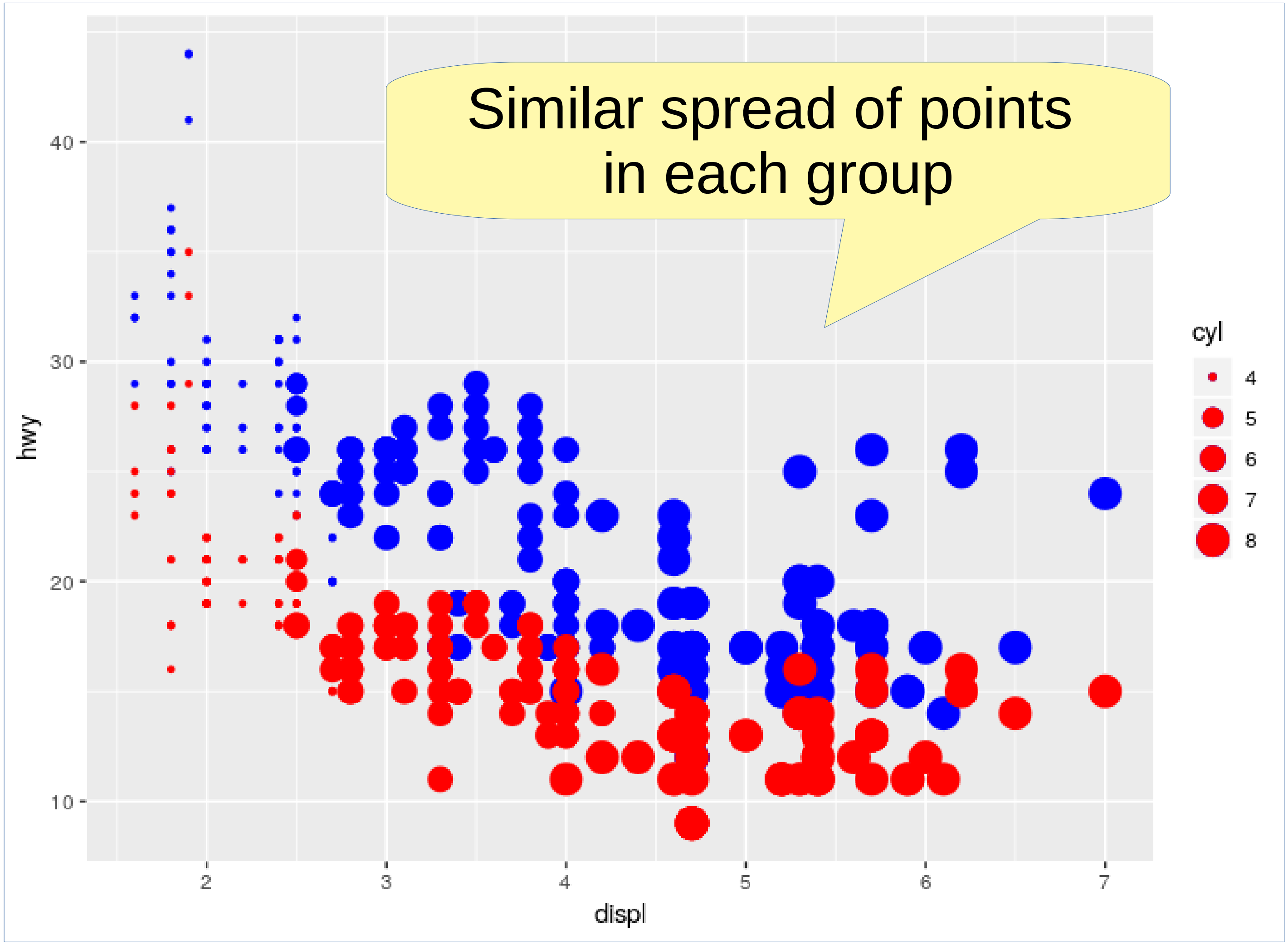


#incorporate **hwy and cty** mileage together in same plot
ggplot(data = mpg) + geom_point(mapping = aes(x = displ, y = hwy), color = "blue") + geom_point(mapping = aes(x = displ, y = cty), color="Red")

Add Sized Points

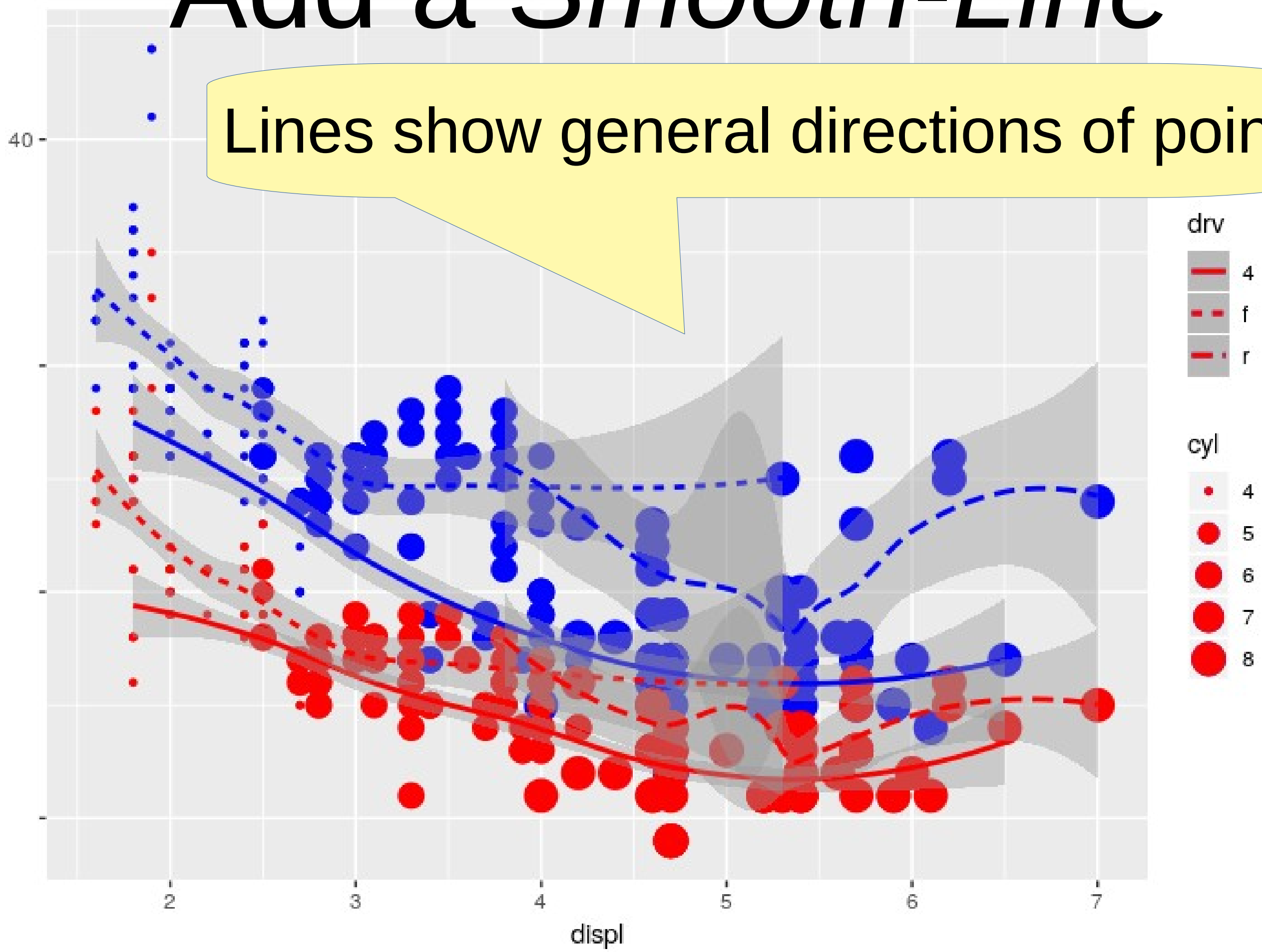
Hwy

City




```
ggplot(data = mpg) + geom_point(mapping = aes(x = displ, y = hwy,
size = cyl), color = "blue") + geom_point(mapping = aes(x = displ, y
= cty, size = cyl), color="Red")
```

Add a *Smooth-Line*



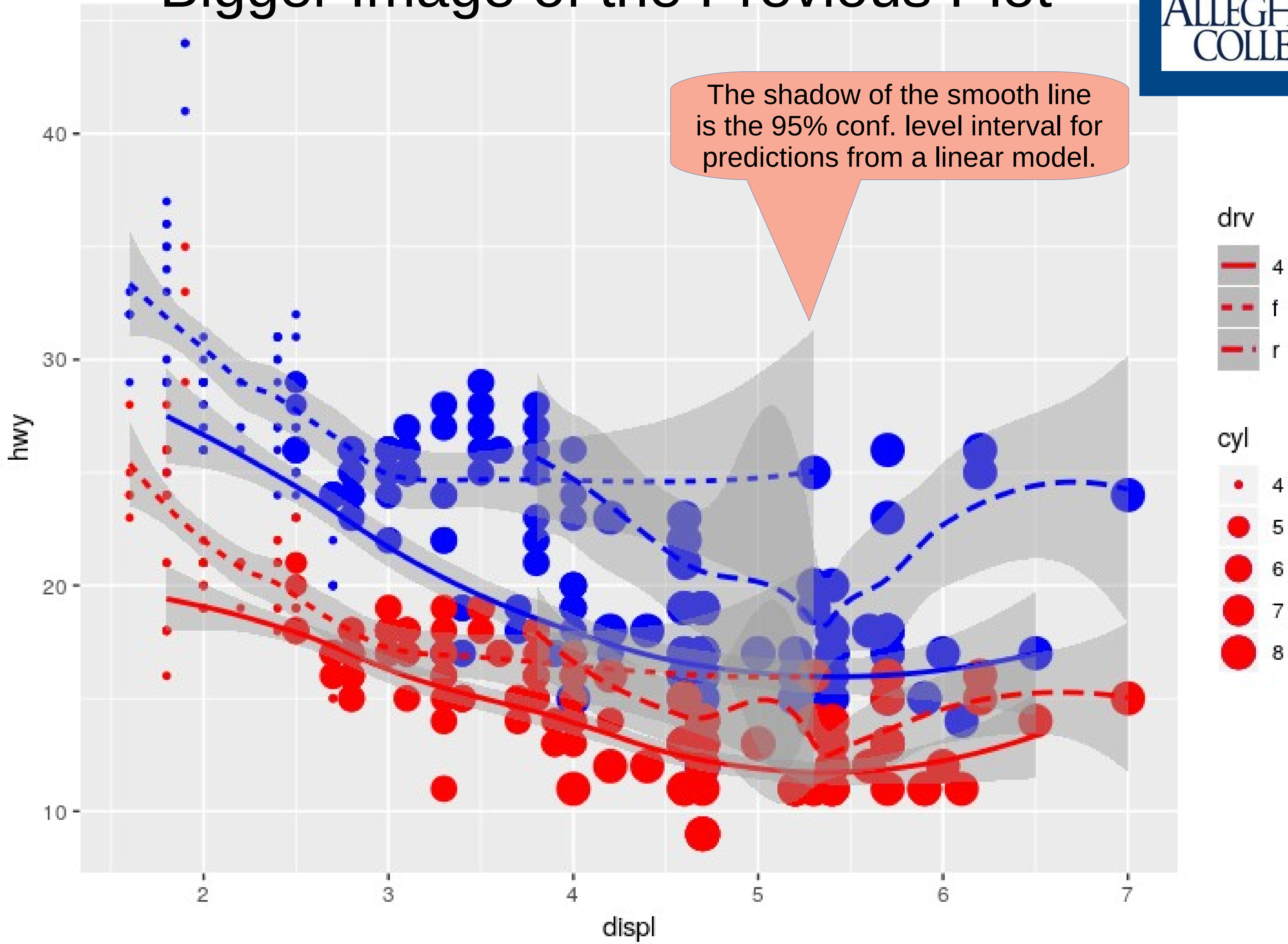
Lines show general directions of points

Hwy

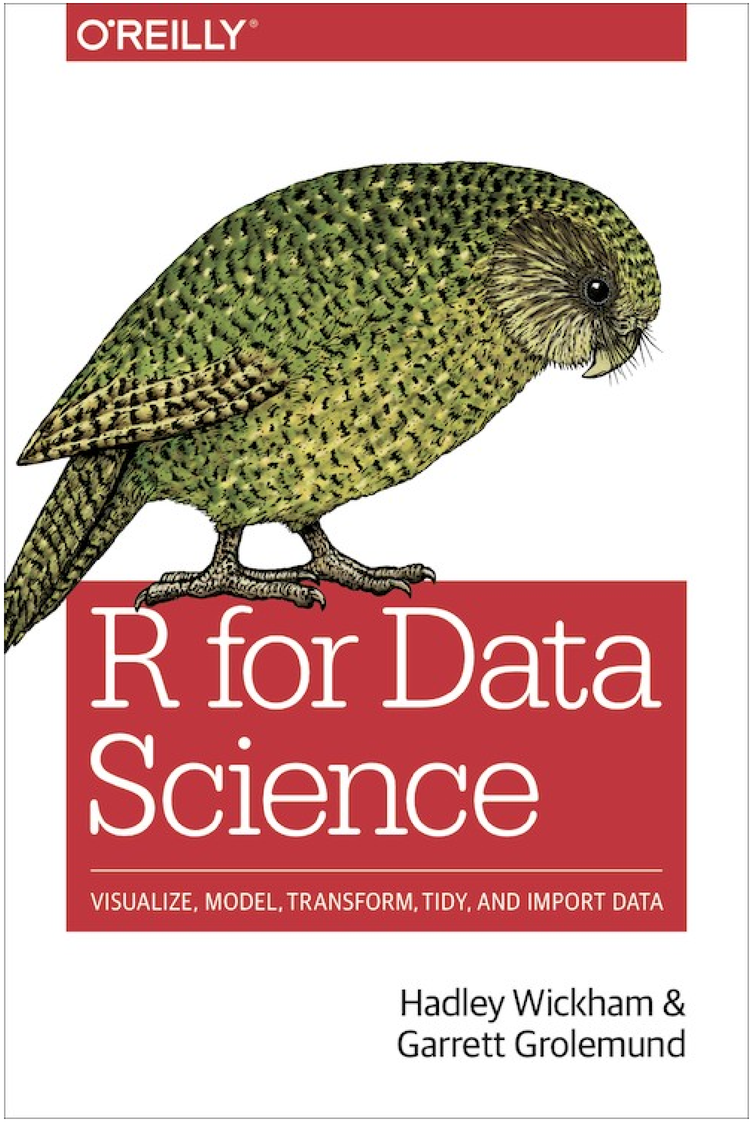
City

```
ggplot(data = mpg) + geom_point(mapping = aes(x = displ, y = hwy, size = cyl), color = "blue") + geom_point(mapping = aes(x = displ, y = cty, size = cyl), color="Red") + geom_smooth(mapping = aes(x = displ, y = hwy, linetype = drv), color = "blue") + geom_smooth(mapping = aes(x = displ, y = cty, linetype = drv), color = "red")
```

Bigger Image of the Previous Plot



Where in the Web?
Where in the Book?



- Note the chapter differences!
- Book:
  - Chap 3: Data Transformation with dplyr
  - Pages 43 - 73
- Web:
  - Chap 5: Data Transformation with dplyr
  - http://r4ds.had.co.nz/transform.html

Transformation?

- What you want to show is in the data
- Unfortunately: To begin to show this is complicated.
  - Too much noise
  - Clutter
  - Unrelated pieces of data in the way

Filters

- Filters allow us to keep part of the whole while removing what we do not want

Filters to Transform Data?

Dictionary

transformation

trans·for·ma·tion

/ˌtran(t)sfərˈmāSH(ə)n/

noun

a thorough or dramatic change in form or appearance.
"its landscape has undergone a radical transformation"
synonyms: change, alteration, mutation, conversion, metamorphosis, transfiguration, transmutation, sea change; More

- a metamorphosis during the life cycle of an animal.
- PHYSICS
  the induced or spontaneous change of one element into another by a nuclear process.

Data Transformation

- Filter out the unwanted stuff to leave the “good” stuff
- Easier to work with and visualize
- **Data transformation:** the process of converting data or information from one format to another,
- Usually from the format of a source system into the required format of a new destination system.

Let the Transformation Begin!!

- # Install the library containing the data (if necessary)

  install.packages("nycflights13")

  library(nycflights13)

  library(tidyverse)

- # check that the data is found in the library

  nycflights13::flights

What is the Data?

- # assign this data to an object.

  flights <- nycflights13::flights

- # View the table's columns

  names(nycflights13::flights)

- #Or, run,

  names(flights)

- What do you see?

Flight Data

flights

Filter

	year	month	day	dep_time	sched_dep_time	dep_delay	arr_time	sched_arr_time	arr_delay	carrier	flight	tailnum	origin	dest	air_time	distance	hour	minute	time_hour
1	2013	1	1	517	515	2	830	819	11	UA	1545	N14228	EWR	IAH	227	1400	5	15	2013-01-01 05:00
2	2013	1	1	533	529	4	850	830	20	UA	1714	N24211	LGA	IAH	227	1416	5	29	2013-01-01 05:00
3	2013	1	1	542	540	2	923	850	33	AA	1141	N619AA	JFK	MIA	160	1089	5	40	2013-01-01 05:00
4	2013	1	1	544	545	-1	1004	1022	-18	B6	725	N804JB	JFK	BQN	183	1576	5	45	2013-01-01 05:00
5	2013	1	1	554	600	-6	812	837	-25	DL	461	N668DN	LGA	ATL	116	762	6	0	2013-01-01 06:00
6	2013	1	1	554	558	-4	740	728	12	UA	1696	N39463	EWR	ORD	150	719	5	58	2013-01-01 05:00
7	2013	1	1	555	600	-5	913	854	19	B6	507	N516JB	EWR	FLL	158	1065	6	0	2013-01-01 06:00
8	2013	1	1	557	600	-3	709	723	-14	EV	5708	N829AS	LGA	IAD	53	229	6	0	2013-01-01 06:00
9	2013	1	1	557	600	-3	838	846	-8	B6	79	N593JB	JFK	MCO	140	944	6	0	2013-01-01 06:00
10	2013	1	1	558	600	-2	753	745	8	AA	301	N3ALAA	LGA	ORD	138	733	6	0	2013-01-01 06:00
11	2013	1	1	558	600	-2	849	851	-2	B6	49	N793JB	JFK	PBI	149	1028	6	0	2013-01-01 06:00
12	2013	1	1	558	600	-2	853	856	-3	B6	71	N657JB	JFK	TPA	158	1005	6	0	2013-01-01 06:00
13	2013	1	1	558	600	-2	924	917	7	UA	194	N29129	JFK	LAX	345	2475	6	0	2013-01-01 06:00

Showing 1 to 13 of 336,776 entries

```
> View(flights)
> names(nycflights13::flights)
 [1] "year"           "month"          "day"            "dep_time"       "sched_dep_time" "dep_delay"
 [7] "arr_time"       "sched_arr_time" "arr_delay"      "carrier"        "flight"         "tailnum"
[13] "origin"         "dest"           "air_time"       "distance"       "hour"           "minute"
[19] "time_hour"
```

Upon A Closer Inspection...

- This data frame contains all 336,776 flights that departed from New York City in 2013. The data comes from the US Bureau of Transportation Statistics, and is documented in ?flights.
- Flight numbers,
- Date, takeoff time and duration of flight
- Scheduled departure and arrival times
- Actual departure and arrival times (delays)
- Carrier
- Airports (origin and destination for a flight)
- Distance flown
- And more...

What are the Elements?

- #show whole dataset

  View(flights)

- # show first and second row of data table

  flights[1:2,]
- # show first and second cols
- flights[,1:2]
- # show cols 1 and 5 (using a vector)
- flights[,c(1,5)]

Data Types?

- #show the data types

  flights[1,]

```
> flights[1,]
# A tibble: 1 x 19
   year month   day dep_time sched_dep_time dep_delay arr_time sched_arr_time arr_delay
  <int> <int> <int>    <int>          <int>     <dbl>    <int>          <int>     <dbl>
1  2013     1     1      517            515         2      830            819        11
# ... with 10 more variables: carrier <chr>, flight <int>, tailnum <chr>, origin <chr>,
#   dest <chr>, air_time <dbl>, distance <dbl>, hour <dbl>, minute <dbl>, time_hour <dttm>
```

Why should we care about the data type?

Just My Type!

- **int** stands for integers.
- **dbl** stands for doubles, or real numbers.
- **chr** stands for character vectors, or strings.
- **dttm** stands for date-times (a date + a time).

- #others
- **lgl** stands for logical, vectors that contain only TRUE or FALSE.
- **fctr** stands for factors, which R uses to represent categorical variables with fixed possible values.
- **date** stands for dates.

dplyr Basics

- Five key dplyr functions
  - Pick observations by their values (**filter()**).
  - Reorder the rows (**arrange()**).
  - Pick variables by their names (**select()**).
  - Create new variables with functions of existing variables (**mutate()**).
  - Collapse many values down to a single summary (**summarise()**).
- Find help for each: ?keyword

Filter()

- #filter(object, column_header to consider)

  filter(flights, month == 1, day == 1)

  filter(flights, month == 1, dep_time == 554)

- #Assign a variable to this particular object

  dep_timeFlights554 <- filter(flights, month == 1, dep_time == 554)

- View(dep_timeFlights554)

Comparisons with Filter()

- R provides the standard suite: >, >=, <, <=, != (not equal), and == (equal).

- # select * from flights where month == 1;

  filter(flights, month == 1)
- #What happens here?

  filter(flights, month >=11)

  filter(flights, month <=11)

De Morgan’s Law with Filter()

- #De Morgan’s law: !(x & y) is the same as !x | !y, !(x | y) is the same as !x & !y.
- #For example, if you wanted to find flights that weren’t delayed (on arrival or departure) by more than two hours, you could use either of the following two filters:

```
filter(flights, !(arr_delay > 120 | dep_delay > 120))
filter(flights, arr_delay <= 120, dep_delay <= 120)
```

Arrange()

- arrange() works similarly to filter() except that instead of selecting rows, it changes their order.
- #Show rows and cols as ordered by a particular column.
- #arrange(object, column_header)
- #What happens here?

```
arrange(flights, minute)
filter(flights, day == 30, dep_time == 554)
```

Arrange()

- #If you provide more than one column name, each additional column will be used to break ties in the values of preceding columns.

  arrange(flights, year, month, day)

- #Use desc() to re-order by a column in **descending** order.

  arrange(flights, desc(arr_delay))

  arrange(flights, arr_delay)

Select()

- #select() allows you to rapidly zoom in on a useful subset using operations based on the names of the variables.

  select(flights, year, month, day)

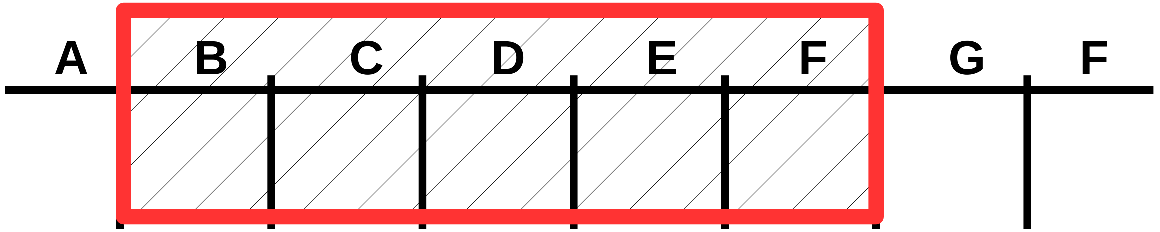
- # Select all columns going across the headers found between year and day (inclusive)

  select(flights, year:day)

- # Select all columns except those from year to day (inclusive)

  select(flights, -(year:day))

Selecting(data, A:F)



Mutate()

- #add new columns that are functions of existing columns
- #create a new object from flights having new cols.
- # xx and yy could be equations using existing data.
- xy <- mutate(flights,xx = day, yy = month)
- View(xy)

Summarise()

- Collapse your data into a single row
- Use with group_by() to organize data into groups to help you see results from that time.

```
# A tibble: 365 x 4
# Groups:   year, month [?]
   year month   day  mean
  <int> <int> <int> <dbl>
1  2013     1     1 11.5
2  2013     1     2 13.9
3  2013     1     3 11.0
4  2013     1     4  8.95
5  2013     1     5  5.73
6  2013     1     6  7.15
7  2013     1     7  5.42
8  2013     1     8  2.55
```

```
by_day <- group_by(flights, year, month, day)
summarise(by_day, delay = mean(dep_delay, na.rm = TRUE))

# or, another way to enter the command using pipes...

flights %>%
  group_by(year, month, day) %>%
  summarise(mean = mean(dep_delay, na.rm = TRUE))
```

Practice Datasets

- **iris** data set gives the measurements in centimeters of the variables sepal length, sepal width, petal length and petal width, respectively, for 50 flowers from each of 3 species of iris. The species are Iris setosa, versicolor, and virginica.
- **ToothGrowth** data set contains the result from an experiment studying the effect of vitamin C on tooth growth in 60 Guinea pigs. Each animal received one of three dose levels of vitamin C (0.5, 1, and 2 mg/day) by one of two delivery methods, (orange juice or ascorbic acid (a form of vitamin C and coded as VC).
- **PlantGrowth**: Results obtained from an experiment to compare yields (as measured by dried weight of plants) obtained under a control and two different treatment condition.
- **USArrests**: This data set contains statistics about violent crime rates by us state.
- *Data() # to see more sets in R*

Data Analytics

CS301

Exploratory Data Analysis

Let’s Make a Table of Data, *off the cuff*

- What if we want to *quickly* make a data set and work with it?
- This technique could be used to grow data tables from data from copied and pasted data.
- We will be using the “Tibble” package for R.
  - Provides a “tbl_df” class (the “tibble”) that provides stricter checking and better formatting than the traditional data frame (2-dim array of data or table).

**For example,
you could make a
data set to track rainfall!**

	A	B
1	Daily rainfall	Particulate
2	(centimeters)	(micrograms/cubic meter)
3	4.1	122
4	4.3	117
5	5.7	112
6	5.4	114
7	5.9	110
8	53	114
9	3.6	128
10	1.9	137
11	7.3	104

Installing and Loading the *Tibble* Package

- # Install the library containing the data.

  install.packages("tibble")

  library(tibble)

  library(tidyverse)

Use data_frame() to Create a Table

- # Create a new tibble by combining vectors using the *data_frame()* function.

```
data_frame(
   rowA = c("a1","b1","c1","d1"),
   rowB = c("a2","b2","c2","d2"),
   rowC = c("a3","b3","c3","d3"),
   rowD = c(14,24,34,44)
   )
```

- **What are the data types here? How do you know??**

Use data_frame() to Create a Table

- # Give your table a name.

```
SampleData <- data_frame(
   rowA = c("a1","b1","c1","d1"),
   rowB = c("a2","b2","c2","d2"),
   rowC = c("a3","b3","c3","d3"),
   rowD = c(14,24,34,44)
   )

SampleData[,1] #Cols

sampleData[1,] #Rows

# Element of first col, first row
sampleData[1,1]
```

Another Tibble Table Using data_frame()

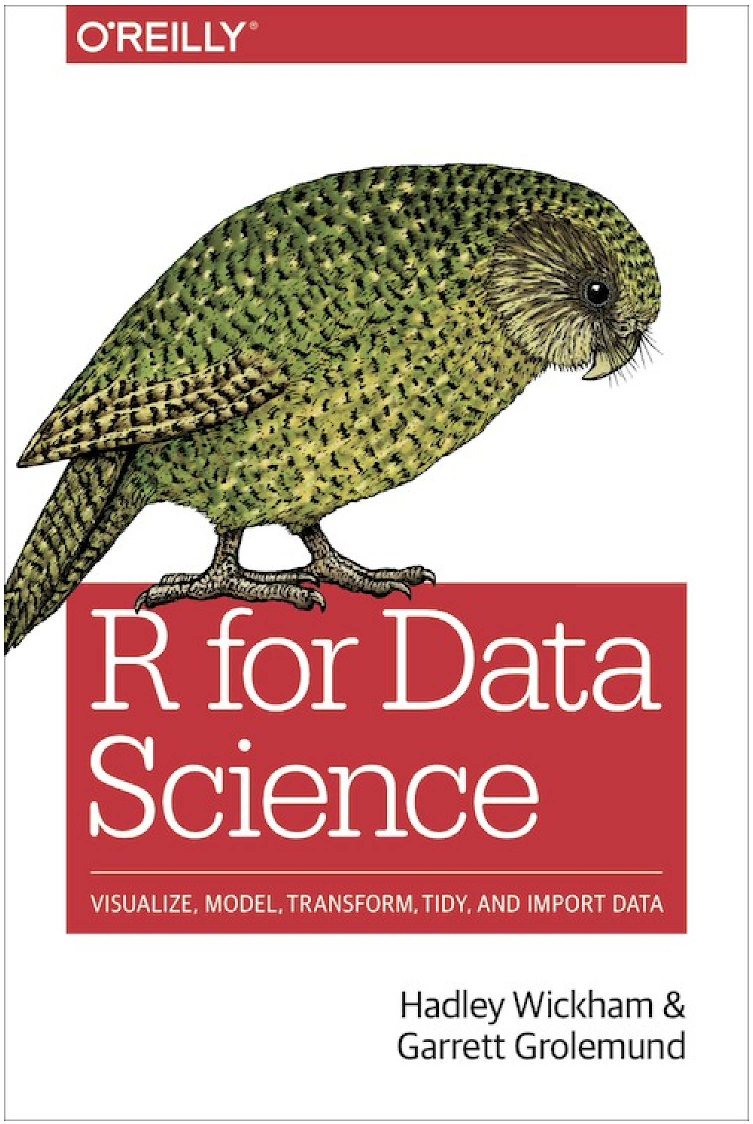
- # Create

  ```
  friends_data <- data_frame(
    name = c("Alexander", "Luke", "Freddy", "Sam"),
    age = c(27, 25, 29, 26),
    height = c(180, 170, 185, 169),
    married = c(TRUE, FALSE, TRUE, TRUE)
  )
  ```
- # Print

  ```
  friends_data
  ```
- #print first two lines

  ```
  head(friends_data, 2)
  ```

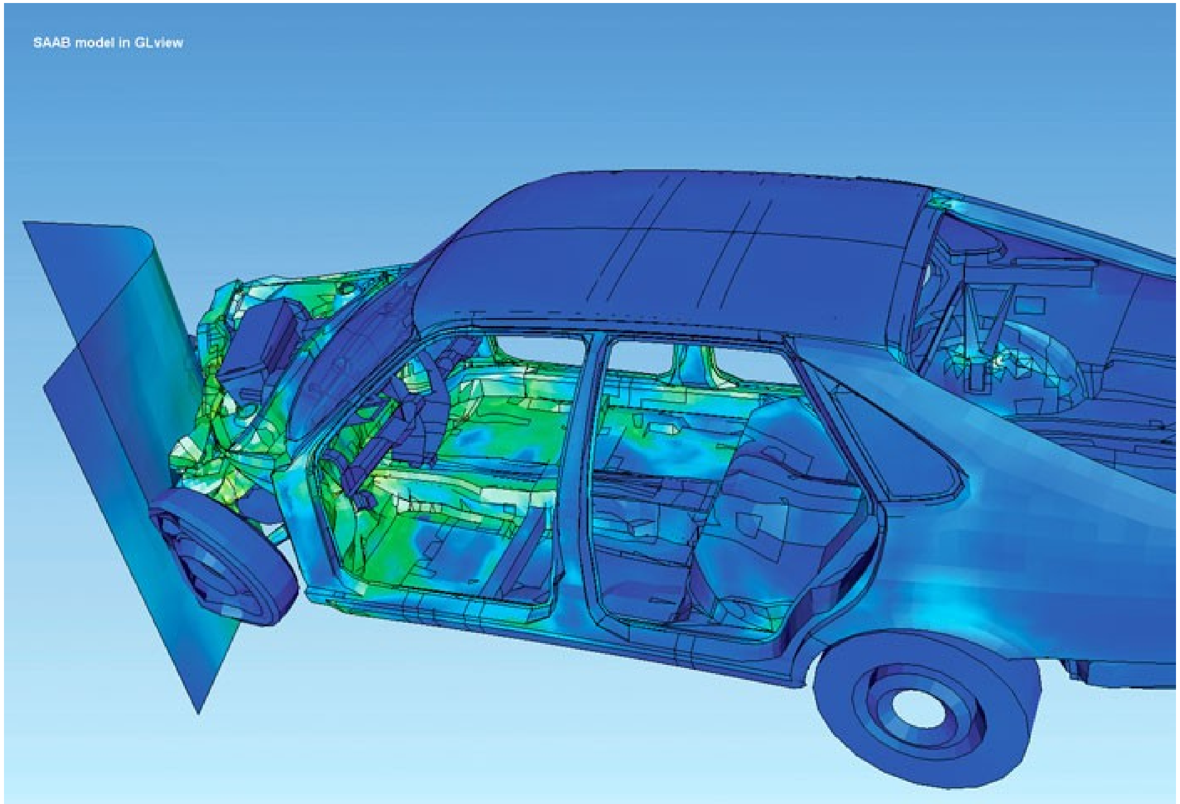
Where in the Web?
Where in the Book?



- Note the chapter differences!
- Book:
  - Chap 5: Exploratory Data Analysis
- Web:
  - http://r4ds.had.co.nz/exploratory-data-analysis.html
  - Chap 7: Exploratory Data Analysis

Exploratory Data Analysis

- The use of visualization and transformation to explore data systematically
- Learn more about data using graphical tools (easy to pot trends)
- Any technique for creating images, diagrams, or animations to communicate a message



Questions to Ask?

- No rules about which questions to ask to guide your research.
- Two types of general questions for making discoveries
  - What type of variation occurs within my variables?
  - What type of covariation occurs between my variables?

Terms To Know

- A **variable** is a quantity, quality, or property that you can measure.

- A **value** is the state of a variable when you measure it. The value of a variable may change from measurement to measurement.

- An **observation** is a set of measurements made under similar conditions (you usually make all of the measurements in an observation at the same time and on the same object). An observation will contain several values, each associated with a different variable. I'll sometimes refer to an observation as a data point.

- **Tabular data** is a set of values, each associated with a variable and an observation. Tabular data is tidy if each value is placed in its own "cell", each variable in its own column, and each observation in its own row.

Terms To Know

- **Categorical data** is the statistical data type consisting of categorical variables or of data that has been converted into that form, for example as grouped data.
- Categorical data can only take one of a small set of values.
  - "M" for male, "F" for female
  - January = "1" … December = "12"

Nationality	C1	C2	C3
French	0	0	1
Italian	1	0	0
German	0	1	0
Other	−1	−1	−1

What’s Ahead?

- We combine what you’ve learned about *dplyr* and *ggplot2* to interactively ask questions, answer them with data, and then ask new questions

- # **If is it not already installed, install *tidyverse*.**

  install.packages("tidyverse")
- #Otherwise just load the library.

  library(“tibble”)

Categorical Data in Diamonds

- # Is your data loaded?

  View(diamonds), names(diamonds), or diamonds

- **Where is the categorical data?**

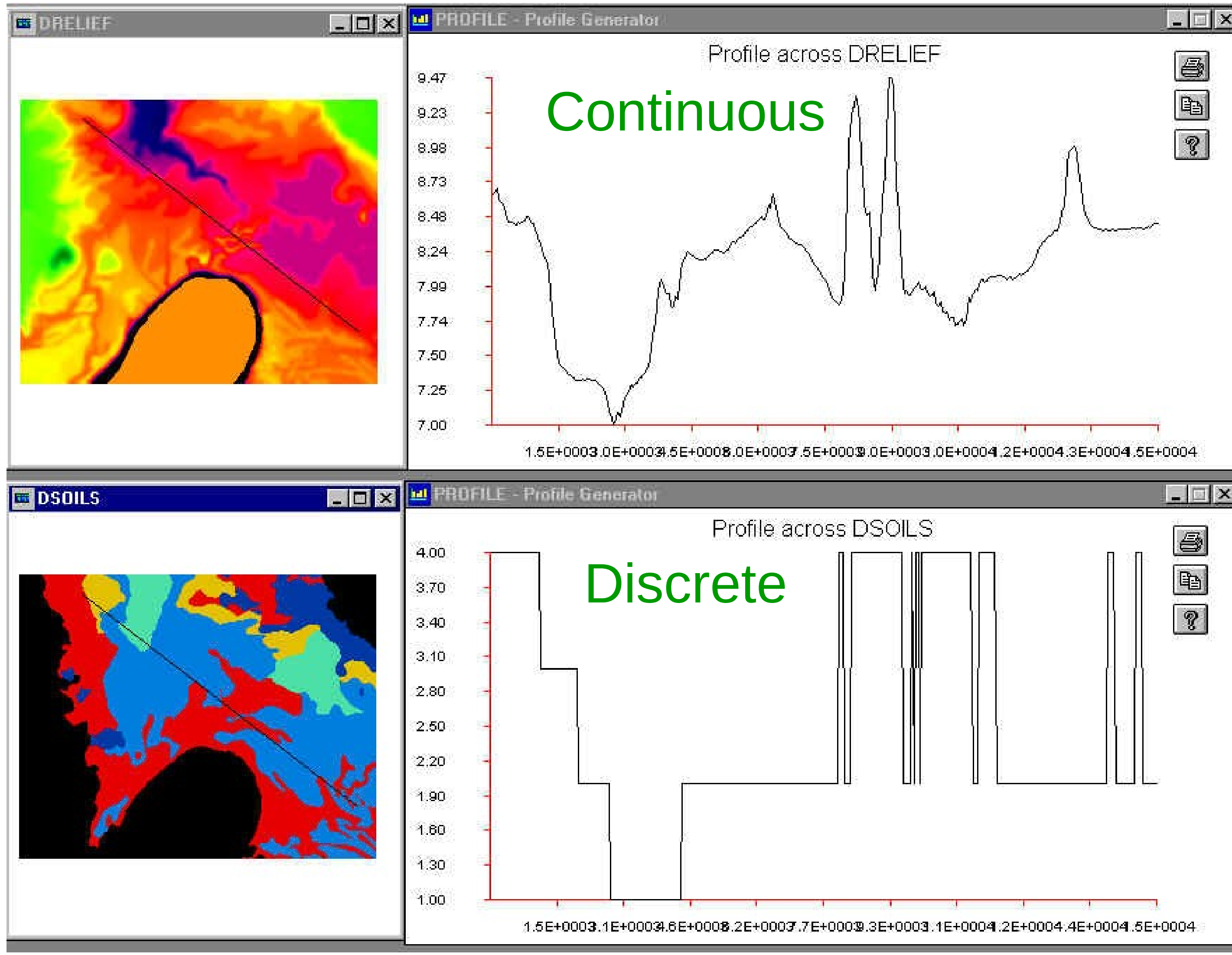
```
> diamonds
# A tibble: 53,940 x 10
   carat       cut color clarity depth table price     x     y     z
   <dbl>     <ord> <ord>   <ord> <dbl> <dbl> <int> <dbl> <dbl> <dbl>
 1  0.23     Ideal     E     SI2  61.5    55   326  3.95  3.98  2.43
 2  0.21   Premium     E     SI1  59.8    61   326  3.89  3.84  2.31
 3  0.23      Good     E     VS1  56.9    65   327  4.05  4.07  2.31
 4  0.29   Premium     I     VS2  62.4    58   334  4.20  4.23  2.63
 5  0.31      Good     J     SI2  63.3    58   335  4.34  4.35  2.75
 6  0.24 Very Good     J    VVS2  62.8    57   336  3.94  3.96  2.48
```

Plot the Categorical Cuts

- # generate a plot
  ggplot(data = diamonds) +
  geom_bar(mapping = aes(x = cut))
- # find “local” statistics about the “cut” column:
  diamonds %>% count(cut)
- **What did that last command return?!**
- **Count the numbers in output!**

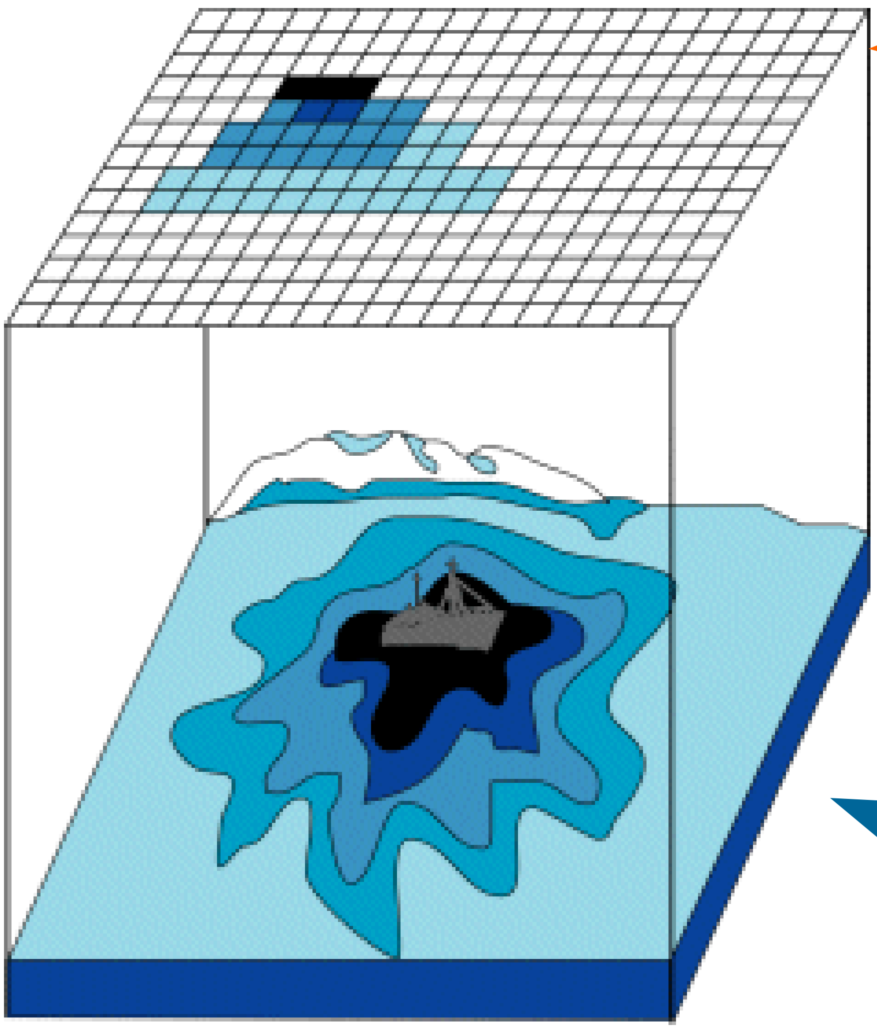
Continuous Data in Diamonds

- **Continuous data** is information that can be measured on a continuum or scale.
- Can have almost any numeric value and can be meaningfully subdivided into finer and finer increments, depending upon the precision of the measurement system.



Continuous Data in Diamonds

Discrete data



Note the discrete data as a function of the continuous data.

Continuous data

Continuous Data in Diamonds

Where is the continuous data in the table?

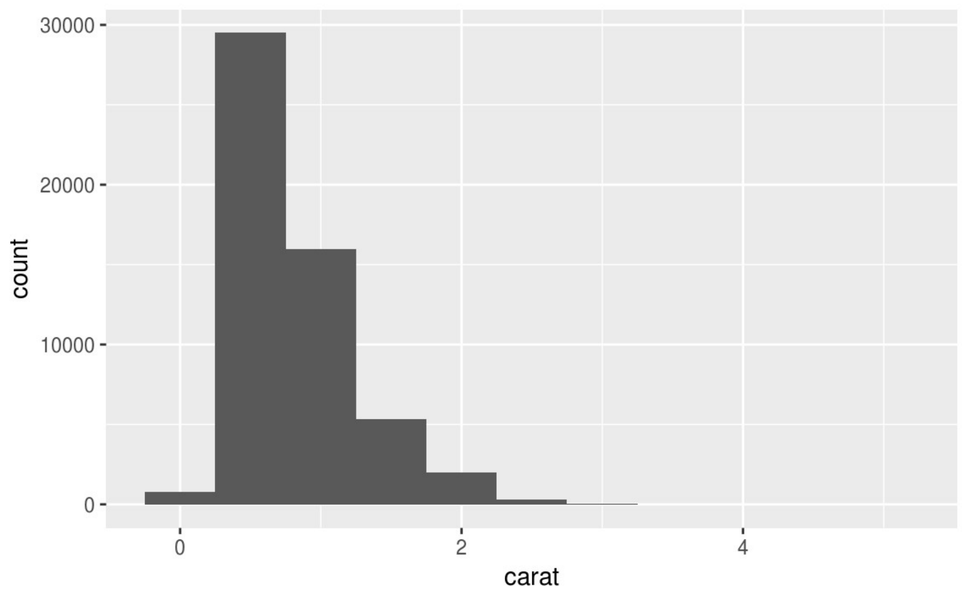
```
> diamonds
# A tibble: 53,940 x 10
  carat       cut color clarity depth table price     x     y     z
  <dbl>     <ord> <ord>   <ord> <dbl> <dbl> <int> <dbl> <dbl> <dbl>
1  0.23     Ideal     E     SI2  61.5    55   326  3.95  3.98  2.43
2  0.21   Premium     E     SI1  59.8    61   326  3.89  3.84  2.31
3  0.23      Good     E     VS1  56.9    65   327  4.05  4.07  2.31
4  0.29   Premium     I     VS2  62.4    58   334  4.20  4.23  2.63
5  0.31      Good     J     SI2  63.3    58   335  4.34  4.35  2.75
6  0.24 Very Good     J    VVS2  62.8    57   336  3.94  3.96  2.48
```

Plot the Continuous Carats

- # To examine the distribution of a continuous variable, use a histogram
- ggplot(data = diamonds) +

  geom_histogram(mapping = aes(x = carat),

  binwidth = 0.5)



Plot the Continuous Carats

- # Find “local” statistics about the “carat” column:

  diamonds %>% count(carat)
- # note, the syntax, “%>%” denotes the dataset to use
- # Discretise numeric data into categorical

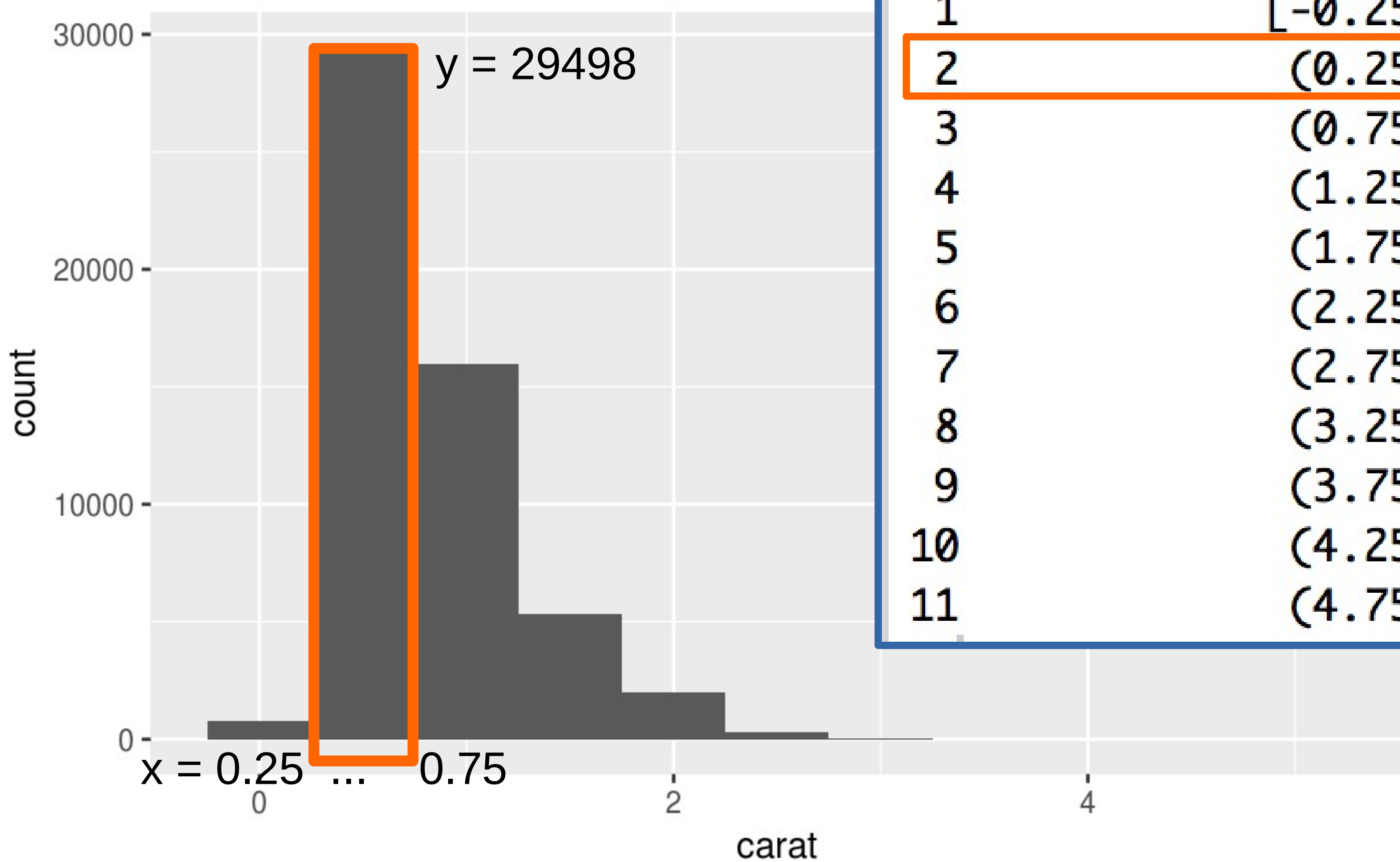
  ?cut_width()

What did that last command return?!

Histogram as Text

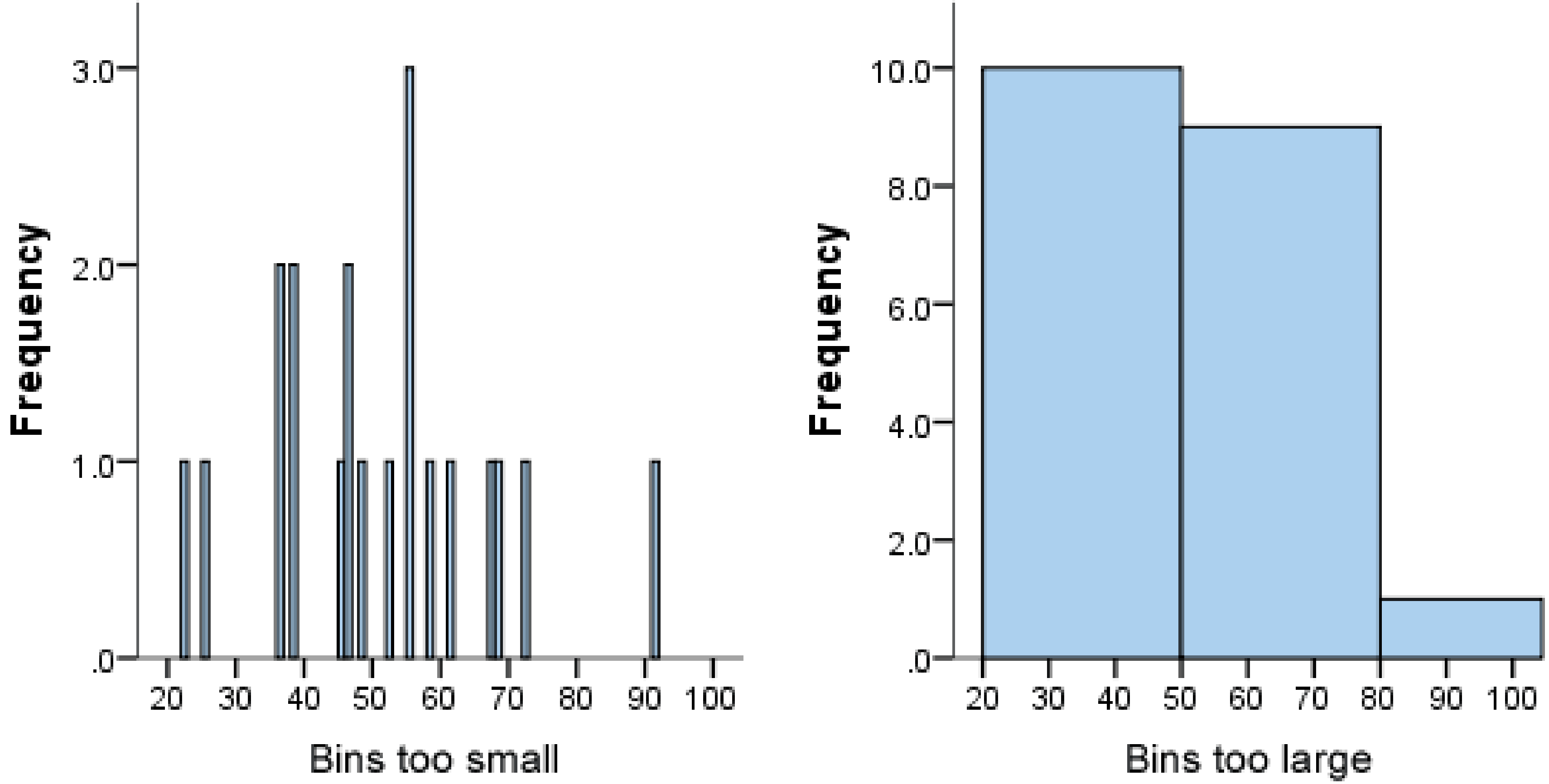
- The cut_width() gives a textual representation of the histogram.

```
> diamonds %>%
+     count(cut_width(carat, 0.5))
# A tibble: 11 x 2
  `cut_width(carat, 0.5)`     n
                   <fctr> <int>
1            [-0.25,0.25]   785
2             (0.25,0.75] 29498
3             (0.75,1.25] 15977
4             (1.25,1.75]  5313
5             (1.75,2.25]  2002
6             (2.25,2.75]   322
7             (2.75,3.25]    32
8             (3.25,3.75]     5
9             (3.75,4.25]     4
10            (4.25,4.75]     1
11            (4.75,5.25]     1
```



Different Bin Widths

- Set the width of the intervals in a histogram with the binwidth argument, which is measured in the units of the *x* variable.
- Left histogram: bins are too small, too much individual data and hides underlying pattern (frequency distribution).
- Right histogram: bins are too large, hard to spot trends in the data.



Different Bin Widths

```
• # New bin width,
• # Note: we zoom in on carats sizes < 3
  smaller <- diamonds %>% filter(carat < 3)
  ggplot(data = smaller, mapping = aes(x = carat)) +
  geom_histogram(binwidth = 0.1)
```

Which is the best bin width for this data??

Different Bin Widths

- # New bin width,
- # Note: **we zoom in on carats sizes < 3**

```
smaller <- diamonds %>% filter(carat < 3)
ggplot(data = smaller, mapping = aes(x = carat, colour = cut)) +
geom_histogram(binwidth = 0.1)
```

What does this graphic inform us?
Are the bin widths too small?

Different Bin Widths

- # New bin width

  smaller <- diamonds %>% filter(carat < 3)

  ggplot(data = smaller, mapping = aes(x = carat, colour = cut)) + geom_freqpoly(**binwidth = 0.1**)

  ggplot(data = smaller, mapping = aes(x = carat, colour = cut)) + geom_freqpoly(**binwidth = 0.2**)

  ggplot(data = smaller, mapping = aes(x = carat, colour = cut)) + geom_freqpoly(**binwidth = 0.3**)

  ggplot(data = smaller, mapping = aes(x = carat, colour = cut)) + geom_freqpoly(**binwidth = 0.4**)

Which is the best bin width for this data??