IS5 in R: Scatterplots, Association, and Correlation (Chapter 6)

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Introduction and background

This document is intended to help describe how to undertake analyses introduced as examples in the Fifth Edition of *Intro Stats* (2018) by De Veaux, Velleman, and Bock. This file as well as the associated Quarto reproducible analysis source file used to create it can be found at http://nhorton.people.amherst.edu/is5.

This work leverages initiatives undertaken by Project MOSAIC (http://www.mosaic-web.org), an NSF-funded effort to improve the teaching of statistics, calculus, science and computing in the undergraduate curriculum. In particular, we utilize the `mosaic` package, which was written to simplify the use of R for introductory statistics courses. A short summary of the R needed to teach introductory statistics can be found in the mosaic package vignettes (https://cran.r-project.org/web/packages/mosaic). A paper describing the mosaic approach was published in the *R Journal*: https://journal.r-project.org/archive/2017/RJ-2017-024.

We begin by loading packages that will be required for our analyses.

```
library(mosaic)
library(tidyverse)
```

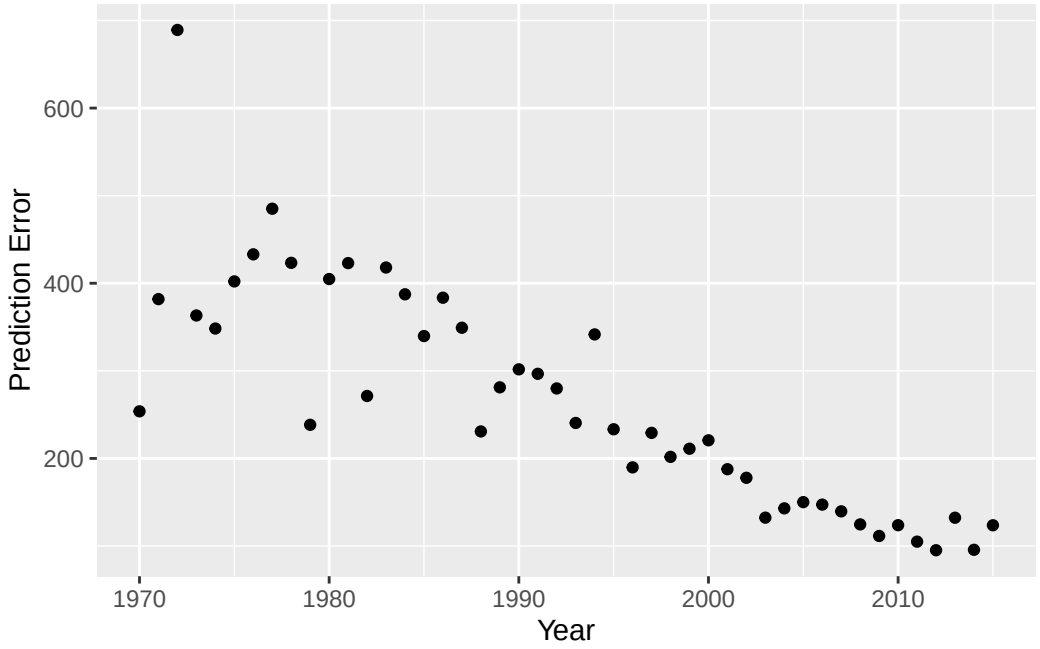
Chapter 6: Scatterplots, Association, and Correlation

We begin by reading in the data.

```
Hurricanes <-
  read_csv("http://nhorton.people.amherst.edu/is5/data/Tracking_hurricanes_2015.csv")
```

By default, `read_csv()` prints the variable names. These messages can (and should!) be suppressed using the `message: false` code chunk option to save space and improve readability.

```
# Figure 6.1, page 164
gf_point(Error_72h ~ Year, data = Hurricanes, ylab = "Prediction Error")
```



Section 6.1: Scatterplots

See dots on pages 164-165.

Example 6.1: Comparing Prices Worldwide

We begin by reading in the data.

```
Prices <- read_csv("http://nhorton.people.amherst.edu/is5/data/Prices_and_Earnings.csv") |>
  janitor::clean_names()
names(Prices)
```

```
 [1] "city"                    "food_costs"
 [3] "womens_clothing"         "mens_clothing"
 [5] "i_phone_4s_hr"           "clothing_index"
 [7] "hours_worked"            "wage_gross"
 [9] "wage_net"                "vacation_days"
[11] "col_excl_rent"           "col_incl_rent"
[13] "pur_power_gross"         "pur_power_net"
[15] "pur_power_annual"        "big_mac_min"
[17] "bread_kg_in_min"         "rice_kg_in_min"
[19] "goods_and_services"      "good_and_services_index"
[21] "food_index"
```

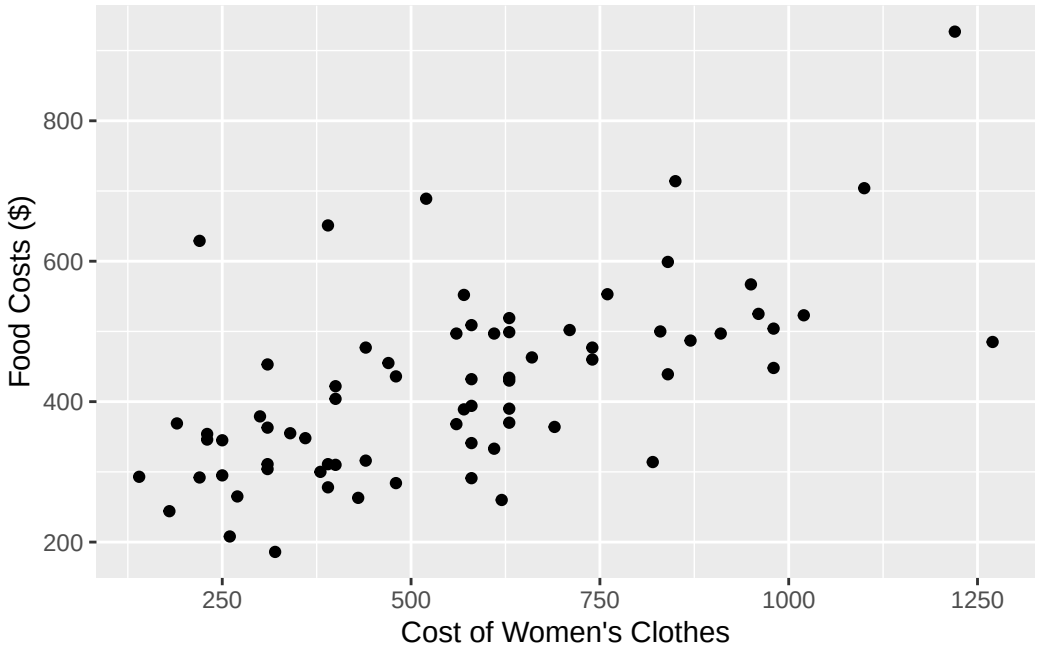
```
glimpse(Prices)
```

```
Rows: 72
Columns: 21
$ city                    <chr> "Amsterdam", "Athens", "Auckland", "Bangkok", ~
$ food_costs              <dbl> 364, 390, 497, 422, 394, 463, 389, 363, 345, 4~
$ womens_clothing         <dbl> 690, 630, 560, 400, 580, 660, 570, 310, 250, 6~
$ mens_clothing           <dbl> 1040, 1110, 670, 600, 1110, 700, 710, 440, 340~
$ i_phone_4s_hr           <dbl> 44.5, 86.0, 51.0, 165.0, 52.5, 184.0, 55.5, 14~
$ clothing_index          <dbl> 110.8, 112.5, 79.2, 64.2, 109.2, 87.5, 82.5, 4~
$ hours_worked            <dbl> 1755, 1822, 1852, 2312, 1761, 1979, 1742, 1981~
$ wage_gross              <dbl> 78.3, 41.4, 59.8, 14.6, 59.6, 17.0, 79.2, 22.3~
$ wage_net                <dbl> 69.4, 40.0, 63.5, 17.4, 58.7, 18.0, 70.1, 22.0~
$ vacation_days           <dbl> 24, 23, 20, 7, 29, 9, 29, 15, 24, 20, 26, 23, ~
$ col_excl_rent           <dbl> 77.0, 66.1, 76.7, 55.3, 74.7, 60.3, 72.3, 53.1~
$ col_incl_rent           <dbl> 69.0, 58.1, 67.7, 48.1, 65.6, 51.8, 64.1, 46.9~
$ pur_power_gross         <dbl> 101.6, 62.6, 78.0, 26.5, 79.7, 28.3, 109.6, 42~
$ pur_power_net           <dbl> 90.1, 60.5, 82.9, 31.4, 78.6, 29.9, 97.0, 41.4~
$ pur_power_annual        <dbl> 75.7, 52.1, 74.8, 33.7, 66.8, 28.2, 82.1, 38.5~
$ big_mac_min             <dbl> 16, 30, 16, 36, 19, 34, 16, 52, 32, 20, 57, 49~
$ bread_kg_in_min         <dbl> 7, 13, 17, 26, 12, 28, 11, 34, 21, 11, 21, 14,~
$ rice_kg_in_min          <dbl> 9, 26, 8, 20, 6, 16, 9, 17, 20, 12, 27, 27, 17~
$ goods_and_services      <dbl> 3034, 2605, 3019, 2178, 2941, 2375, 2847, 2089~
$ good_and_services_index <dbl> 77.0, 66.1, 76.7, 55.3, 74.7, 60.3, 72.3, 53.1~
$ food_index              <dbl> 66.0, 70.7, 90.0, 76.5, 71.3, 83.9, 70.5, 65.8~
```

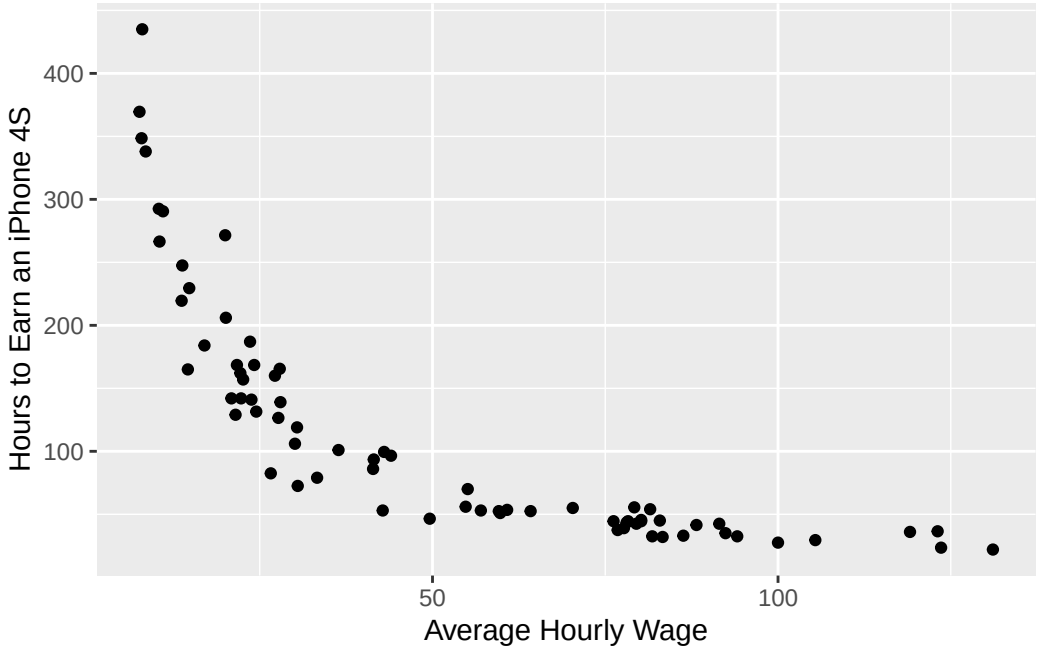
Here we use the `clean_names()` function from the `janitor` package to sanitize the names of the columns (which would otherwise contain special characters or whitespace).

The `names()` function displays the names while the `glimpse()` function provides more detail about the dataset.

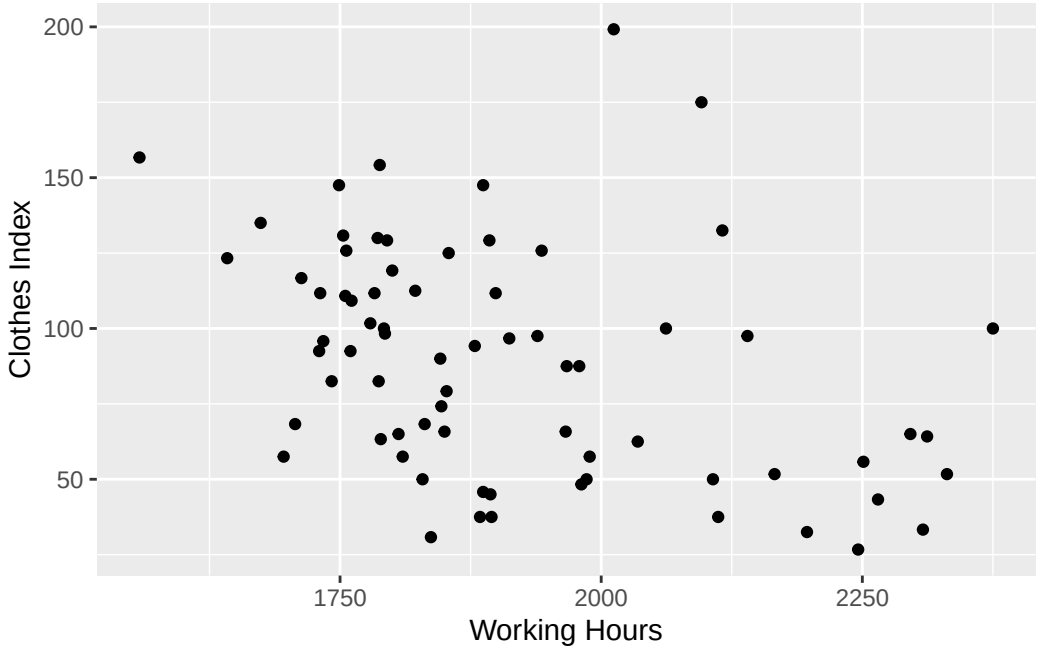
```
gf_point(food_costs ~ womens_clothing, data = Prices) |>
  gf_labs(x = "Cost of Women's Clothes", y = "Food Costs ($)")
```



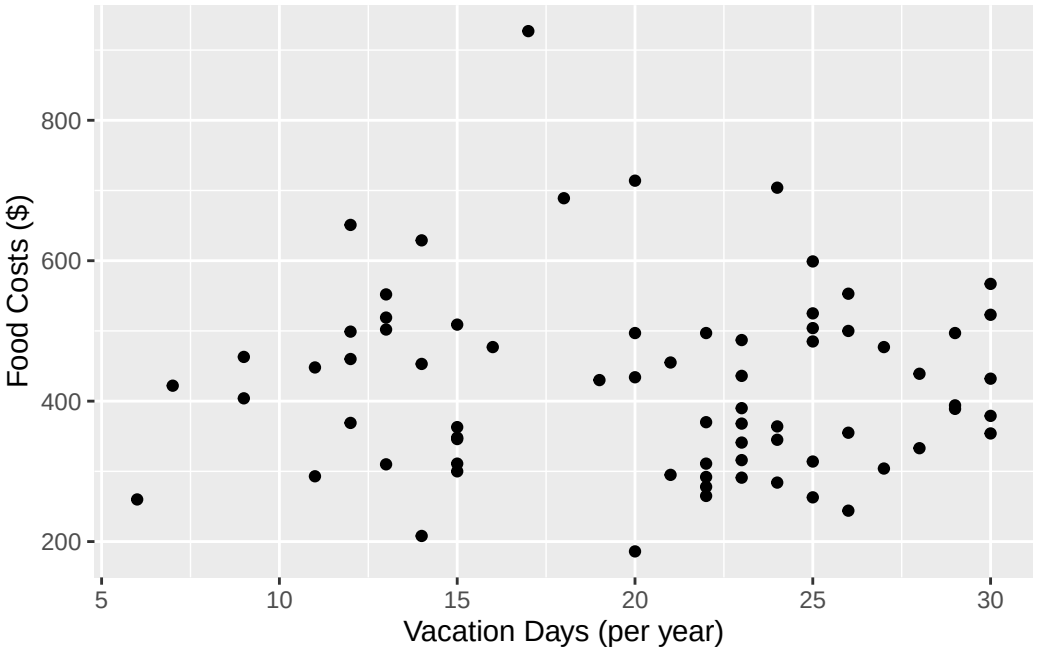

```
gf_point(i_phone_4s_hr ~ wage_gross, data = Prices) |>
  gf_labs(x = "Average Hourly Wage", y = "Hours to Earn an iPhone 4S")
```




```
gf_point(clothing_index ~ hours_worked, data = Prices) |>
  gf_labs(x = "Working Hours", y = "Clothes Index")
```



```
gf_point(food_costs ~ vacation_days, data = Prices) |>
  gf_labs(x = "Vacation Days (per year)", y = "Food Costs ($)")
```



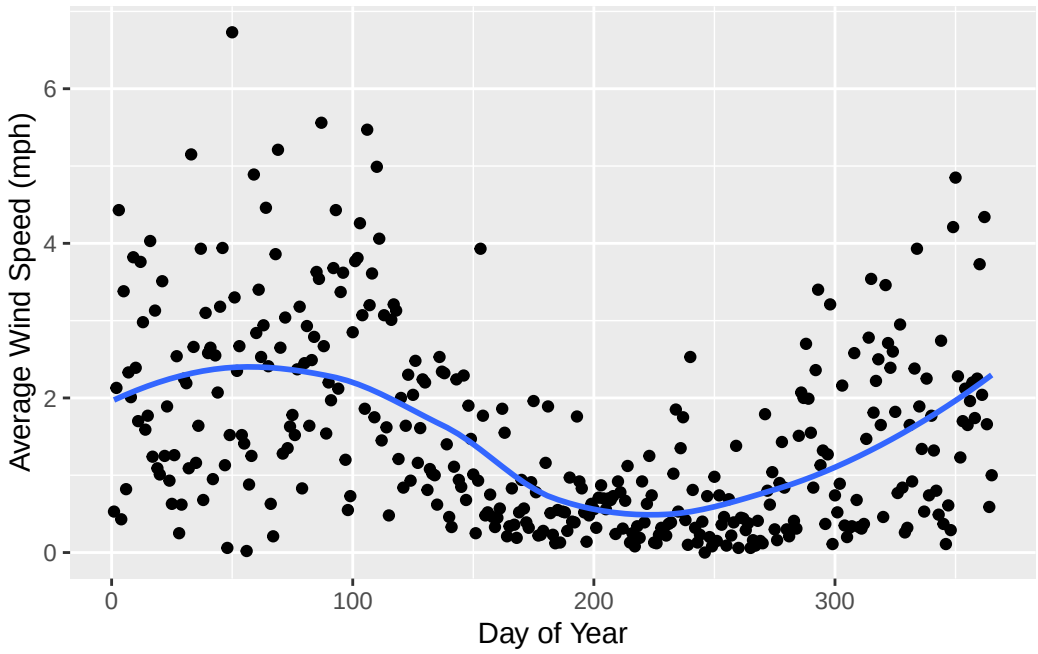
Roles for Variables

Smoothing Scatterplots

Many of the previous scatterplots would have benefited from adding a smoother (or smoothing spline).

We demonstate using the `HopkinsForest` data.

```
HopkinsForest <-
  read_csv("http://nhorton.people.amherst.edu/is5/data/Hopkins_Forest.csv") |>
  janitor::clean_names()
# Figure 6.2, page 168
gf_point(avg_wind_mph ~ day_of_year, data = HopkinsForest) |>
  gf_smooth(se = FALSE) |>
  gf_labs(x = "Day of Year", y = "Average Wind Speed (mph)")
```

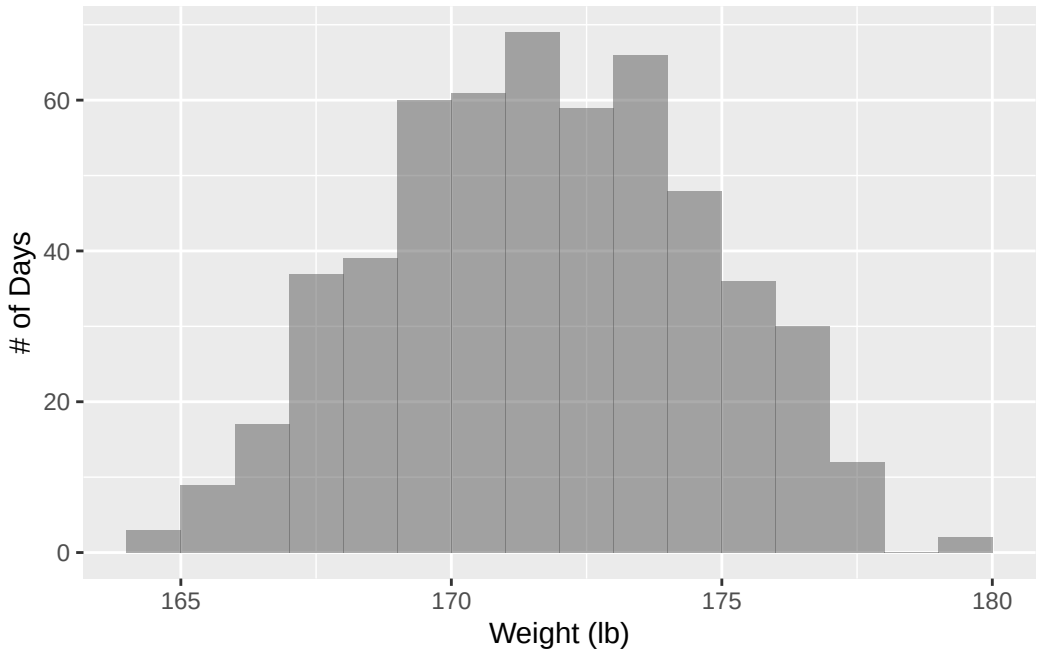


The smoother warning messages provided by `gf_smooth()` have been removed from this output using the `warning: false` code chunk option.

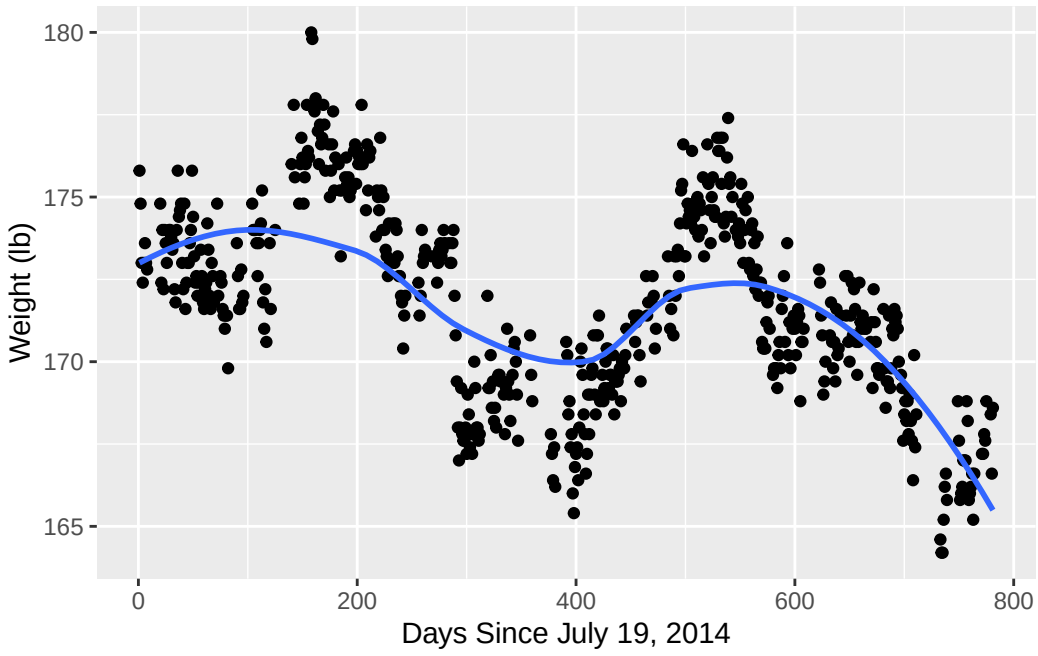
Example 6.2: Smoothing Timeplots

We will explore smoothing using the fitness data.

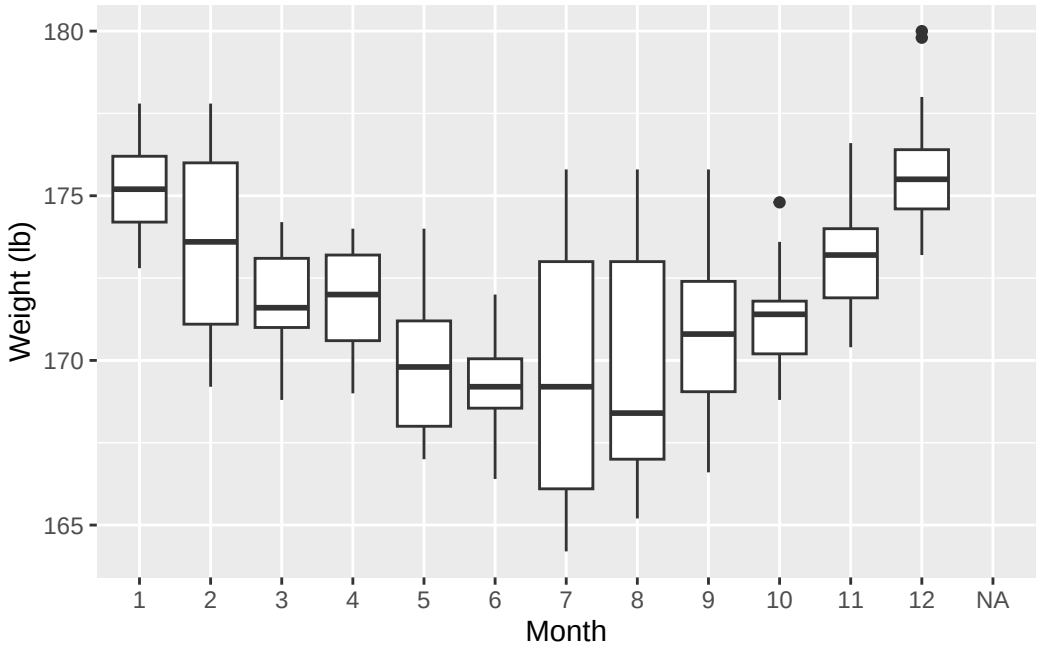
```
Fitness <- read_csv("http://nhorton.people.amherst.edu/is5/data/Fitness_data.csv") |>
  janitor::clean_names()
gf_histogram(~weight, data = Fitness, binwidth = 1, center = .5) |>
  gf_labs(x = "Weight (lb)", y = "# of Days")
```




```
gf_point(weight ~ days_since_july_19_2014, data = Fitness) |>
  gf_smooth(se = FALSE) |>
  gf_labs(x = "Days Since July 19, 2014", y = "Weight (lb)")
```



```
gf_boxplot(weight ~ as.factor(month), data = Fitness) |>
  gf_labs(x = "Month", y = "Weight (lb)")
```

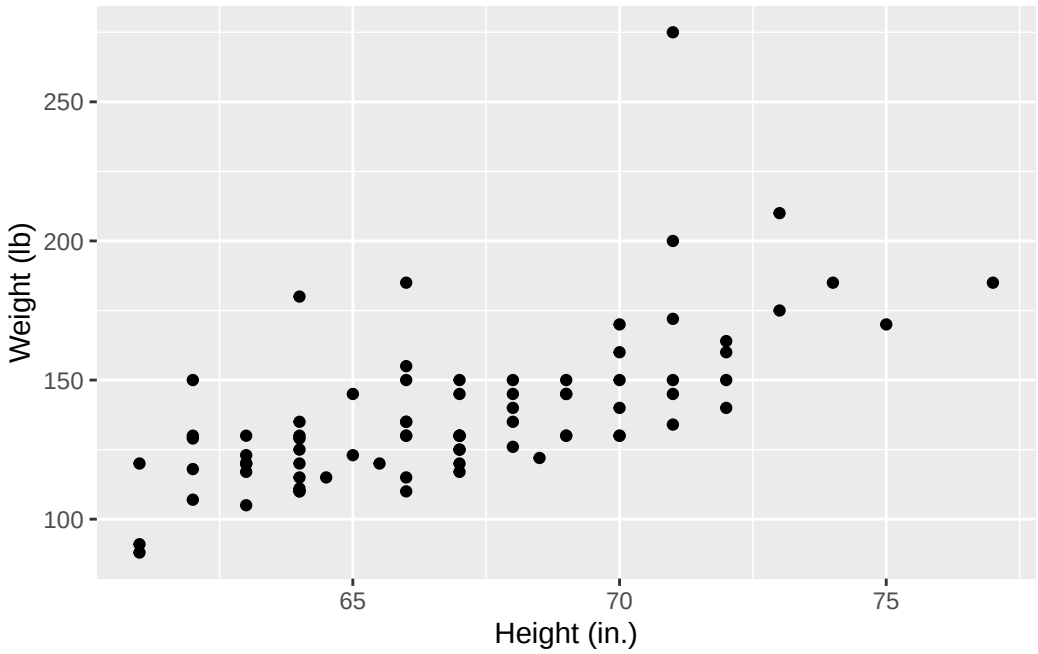


Warnings should be suppressed for your work but only when you have determined that they are innocuous.

Section 6.2: Correlation

We begin by reading in the data.

```
HeightsWeights <-
  read_csv("http://nhorton.people.amherst.edu/is5/data/Heights_and_weights.csv")

# Figure 6.3, page 170
gf_point(Weight ~ Height, data = HeightsWeights) |>
  gf_labs(x = "Height (in.)", y = "Weight (lb)")
```




```
cor(Weight ~ Height, data = HeightsWeights)
```

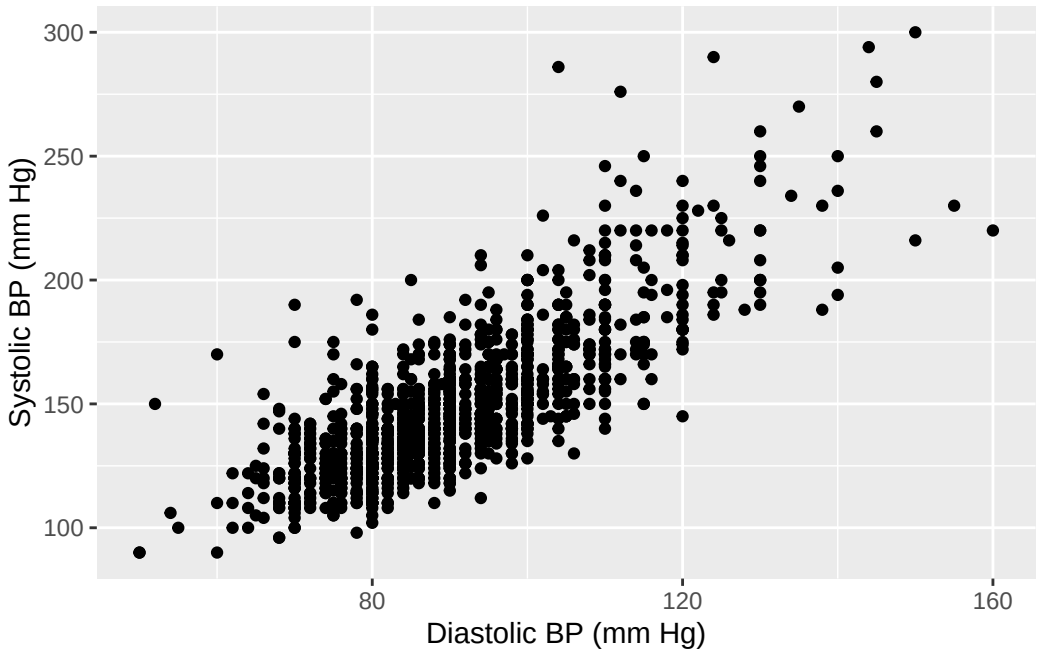
```
[1] 0.6440311
```

See displays on pages 170 - 171.

Step-by-Step Example: Looking at Association

We begin by loading the Framingham data.

```
Framingham <- read_csv("http://nhorton.people.amherst.edu/is5/data/Framingham.csv")
gf_point(SBP ~ DBP, data = Framingham) |>
  gf_labs(x = "Diastolic BP (mm Hg)", y = "Systolic BP (mm Hg)")
```



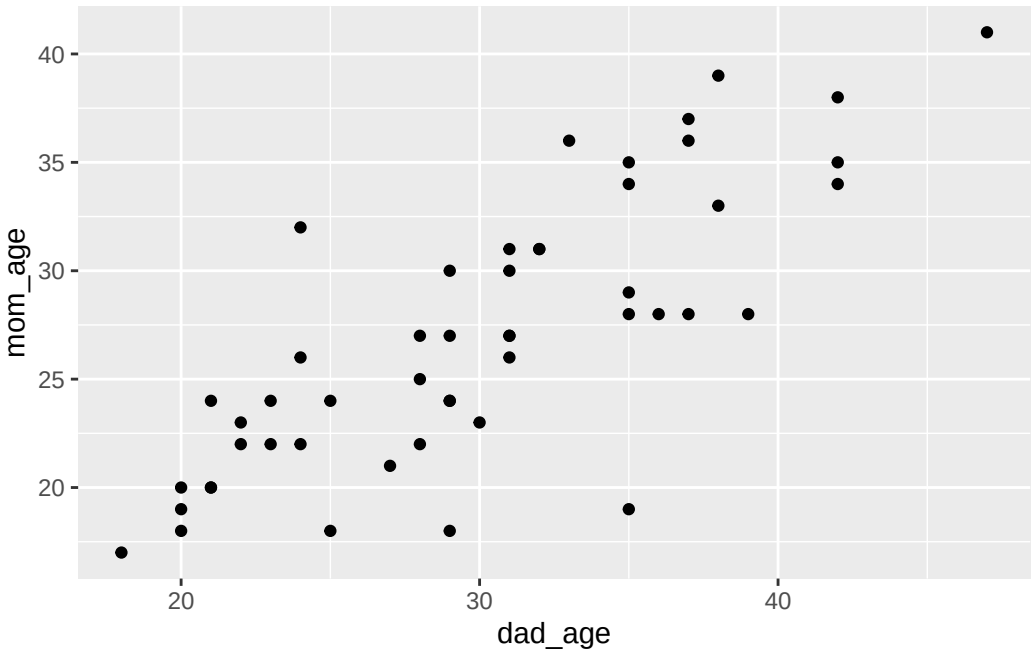

```
cor(SBP ~ DBP, data = Framingham)
```

```
[1] 0.7924792
```

Random Matters: Correlations Vary

A recurring theme in the course involves random sampling of various sorts.
Here we explore a sample of babies born in 1998.

```
LiveBirths <- read_csv("http://nhorton.people.amherst.edu/is5/data/Babysamp_98.csv") |>
  janitor::clean_names()
LiveBirths <- LiveBirths |>
  filter(dad_age != "NA")
set.seed(14513) # To ensure we get the same values when we run it multiple times
num_sim <- 10000 # Number of samples
samp_size <- 50
gf_point(mom_age ~ dad_age, data = sample(LiveBirths, size = samp_size))
```




```
# Graph will look different for different samples
cor(mom_age ~ dad_age, data = LiveBirths)
```

```
[1] 0.7516507
```

```
# What does mosaic::do() do?

cor(mom_age ~ dad_age, data = sample(LiveBirths, size = samp_size))
```

```
[1] 0.7596176
```

```
# Correlation of one random sample

cor(mom_age ~ dad_age, data = sample(LiveBirths, size = samp_size))
```

```
[1] 0.8087199
```

```
# Correlation of another random sample

do(2) * cor(mom_age ~ dad_age, data = sample(LiveBirths, size = samp_size))
```

```
        cor
1 0.7447461
2 0.7583890
```

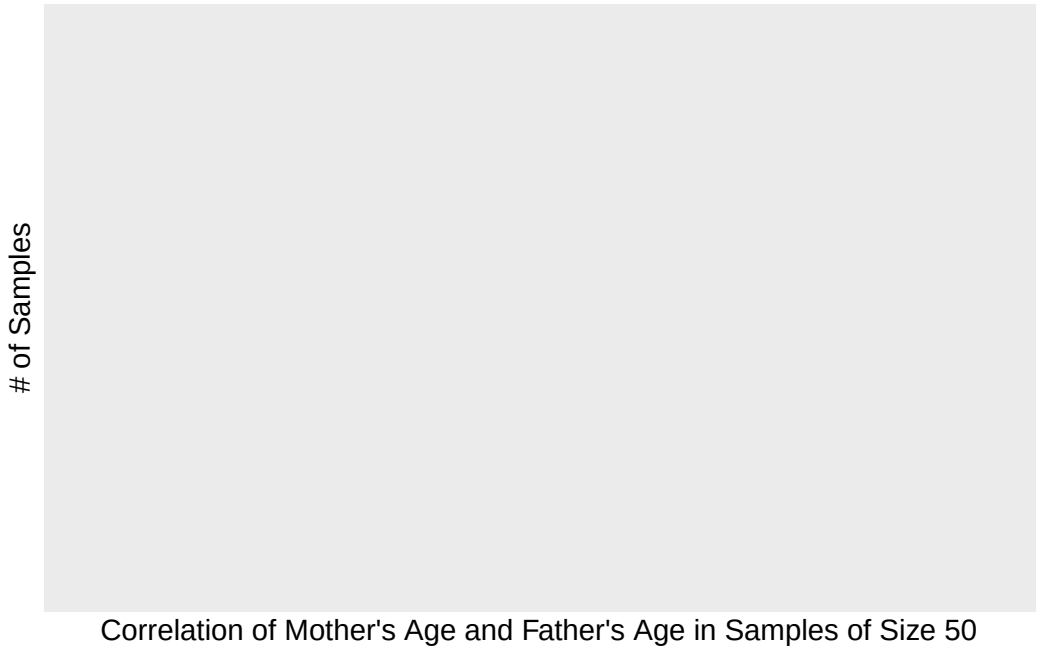
```
# Finds the correlation twice

# For the visualization, we need num_sim = 10,000 correlations
LiveCorr <- do(num_sim) * cor(mom_age ~ dad_age, data = sample(LiveBirths, size = samp_size))
```

The `do()` function runs, 10,000 times, the correlation and sampling functions each time on a random sample of `samp_size = 50`.

(We can use the chunk option `cache: true` to enable caching to save results for next time.)

```
# Figure 6.8, page 176
gf_histogram(~ cor, data = LiveCorr, binwidth = -0.05, center = 0.025) |>
  gf_labs(
    x = "Correlation of Mother's Age and Father's Age in Samples of Size 50",
    y = "# of Samples"
  )
```

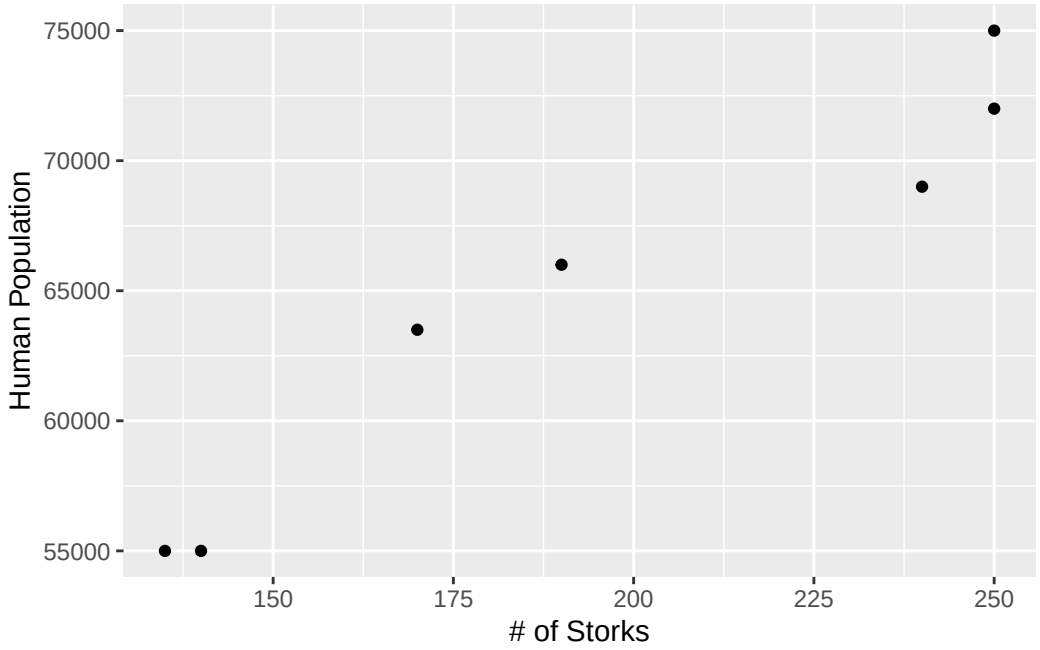
```
Warning: Computation failed in `stat_bin()`.
Caused by error in `bin_breaks_width()`:
! `binwidth` must be a number larger than or equal to 0, not the number -0.05.
```



Section 6.3: Warning: Correlation $\neq$ Causation

The storks data is a classic example of how correlation does not always imply causation.

```
Storks <- read_csv("http://nhorton.people.amherst.edu/is5/data/Storks.csv")
# Figure 6.9
gf_point(Population ~ Storks, data = Storks) |>
  gf_labs(x = "# of Storks", y = "Human Population")
```



Correlation Tables

We can display correlation tables as seen in Table 6.1 on page 178.

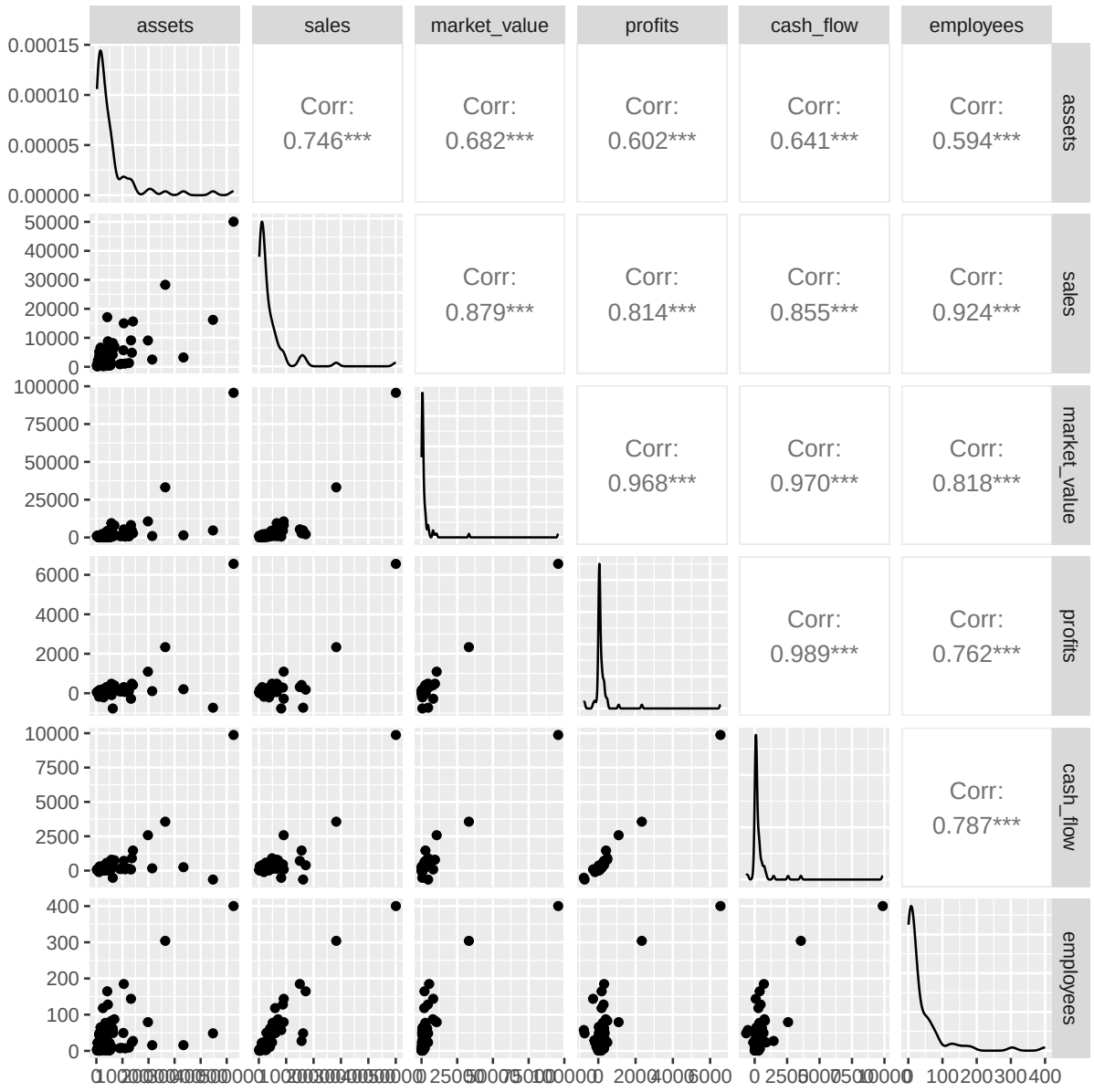
```
Companies <- read_csv("http://nhorton.people.amherst.edu/is5/data/Companies.csv") |>
  janitor::clean_names()
# Table 6.1, page 178
Companies |>
  select(assets, sales, market_value, profits, cash_flow, employees) |>
  cor()
```

```
              assets     sales market_value   profits cash_flow employees
assets       1.0000000 0.7464649    0.6822122 0.6016986 0.6409018 0.5943581
sales        0.7464649 1.0000000    0.8788920 0.8137758 0.8549172 0.9240429
```

```
market_value 0.6822122 0.8788920    1.0000000 0.9681987 0.9702851 0.8182161
profits      0.6016986 0.8137758    0.9681987 1.0000000 0.9887795 0.7621057
cash_flow    0.6409018 0.8549172    0.9702851 0.9887795 1.0000000 0.7866148
employees    0.5943581 0.9240429    0.8182161 0.7621057 0.7866148 1.0000000
```

```
Companies |>
  select(assets, sales, market_value, profits, cash_flow, employees) |>
  GGally::ggpairs()
```

```
Registered S3 method overwritten by 'GGally':
  method from
  +.gg   ggplot2
```

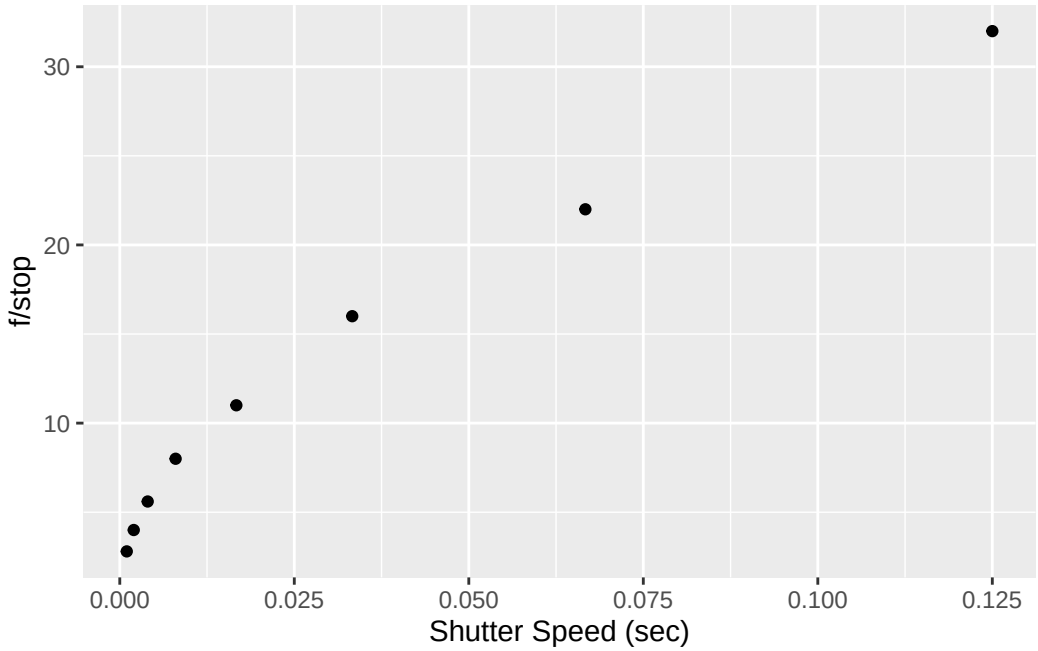


Section 6.4: Straightening Scatterplots

It's often possible to straighten scatterplots through use of a transformation.

```
FStops <- read_csv("http://nhorton.people.amherst.edu/is5/data/F-stops.csv") |>
  janitor::clean_names()
# Figure 6.10, page 179
```

```
gf_point(f_stop ~ shutter_speed, data = FStops) |>
  gf_labs(x = "Shutter Speed (sec)", y = "f/stop")
```




```
cor(f_stop ~ shutter_speed, data = FStops)
```

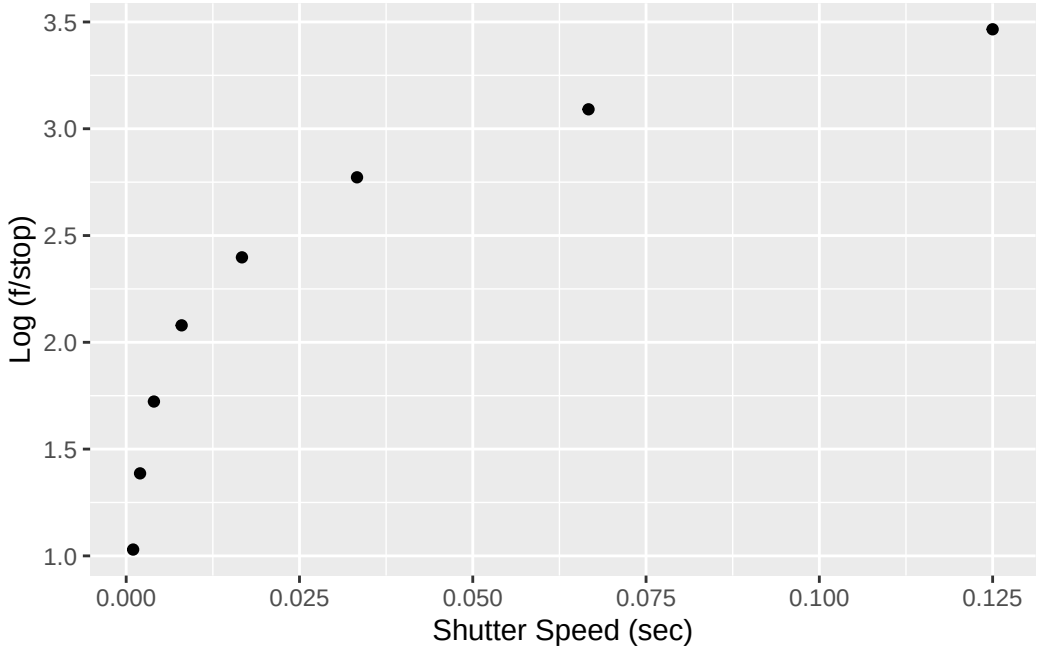
```
[1] 0.9786716
```

The Ladder of Powers

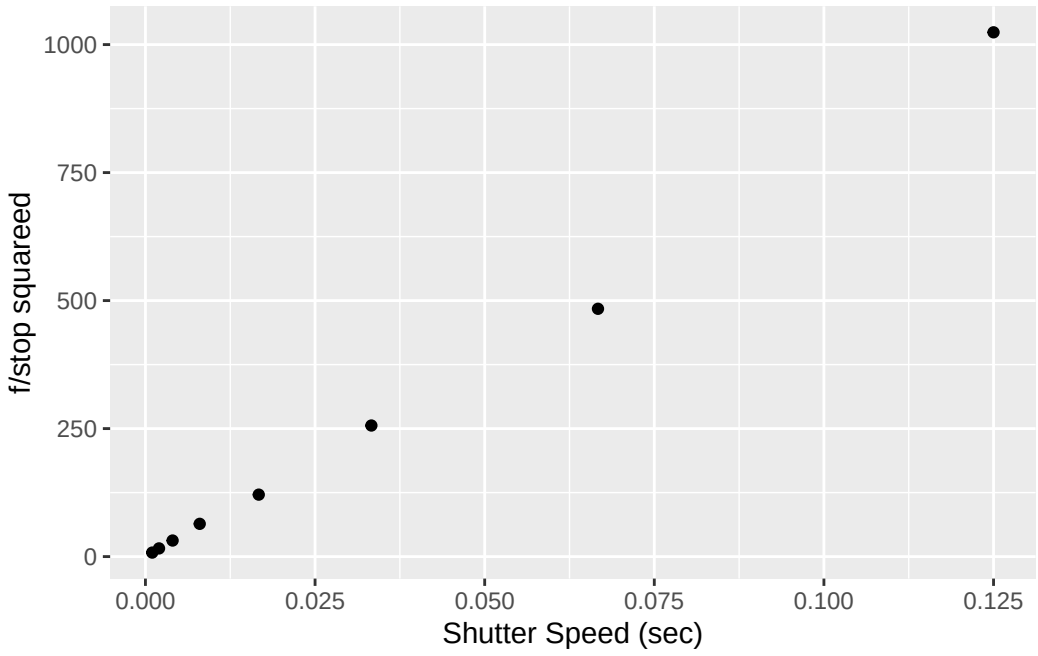
f/Stops Again

The f/Stops example is reviewed on page 181 (Figure 6.11)

```
gf_point(log(f_stop) ~ shutter_speed, data = FStops) |>
  gf_labs(x = "Shutter Speed (sec)", y = "Log (f/stop)")
```




```
# Figure 6.12
gf_point((f_stop)^2 ~ shutter_speed, data = FStops) |>
  gf_labs(x = "Shutter Speed (sec)", y = "f/stop squareed")
```



See the displays in "What Can Go Wrong?" on pages 181-183.