IS5 in R: Inferences for Regression (Chapter 20)

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Table of contents

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.

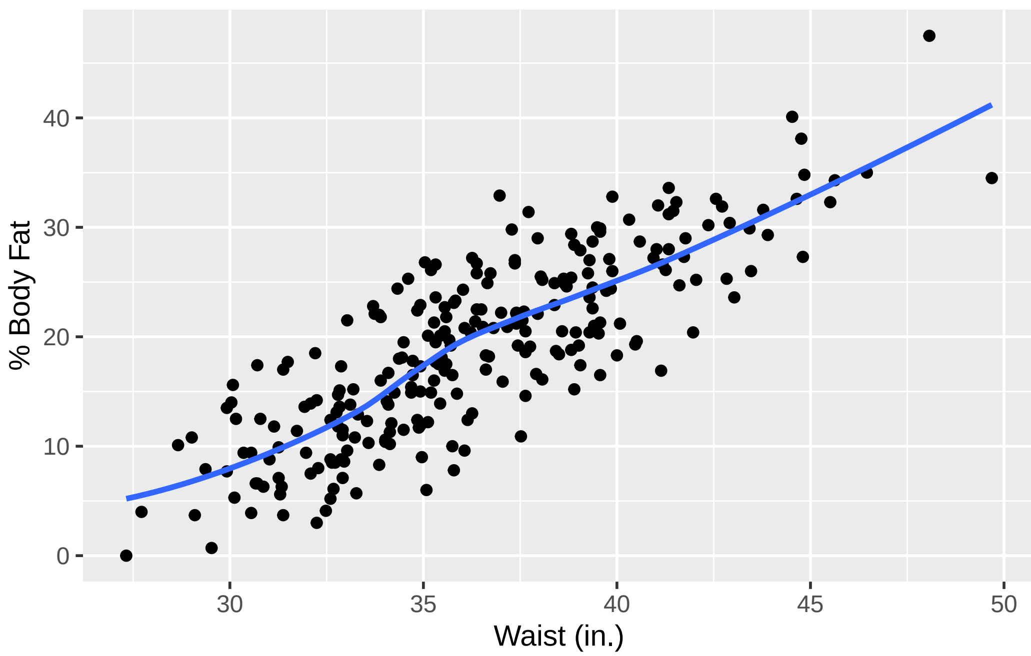
```r
library(mosaic)
library(tidyverse)
library(broom)
```

Chapter 20: Inferences for Regression

```r
BodyFat <- read_csv("http://nhorton.people.amherst.edu/is5/data/Bodyfat.csv") |>
  janitor::clean_names()
```

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

```r
# Figure 20.1, page 642
gf_point(pct_bf ~ waist, data = BodyFat) |>
  gf_smooth() |> # to show linear relationship
  gf_labs(x = "Waist (in.)", y = "% Body Fat")
```

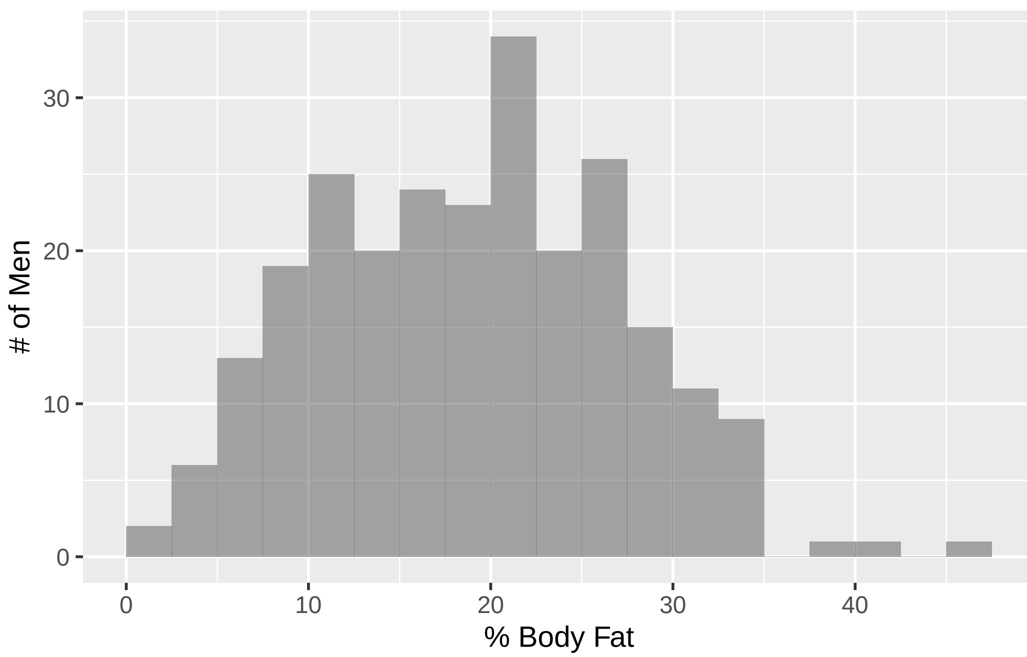


Section 20.1: The Regression Model

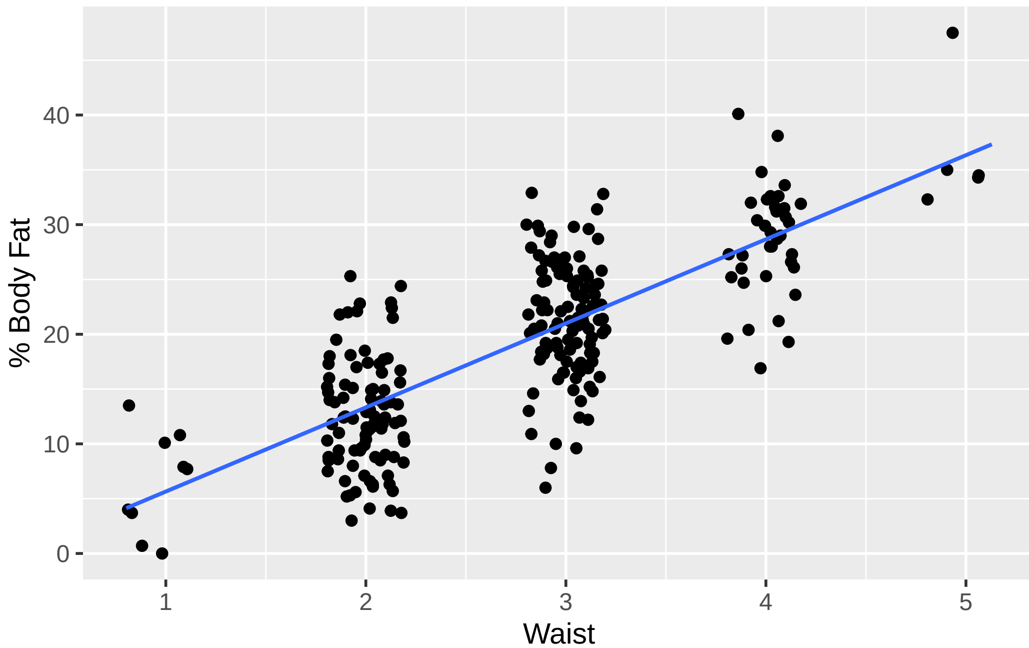
```
lm(pct_bf ~ waist, data = BodyFat)
```

```
Call:
lm(formula = pct_bf ~ waist, data = BodyFat)

Coefficients:
(Intercept)        waist
     -42.73         1.70
```

```
# Figure 20.2
gf_histogram(~ pct_bf, data = BodyFat, binwidth = 2.5, center = 1.25) |>
  gf_labs(x = "% Body Fat", y = "# of Men")
```




```
# Figure 20.3 (reinterpreted with points)
BodyFat <- BodyFat |>
  mutate(roundedwaist = cut(waist, breaks = c(0, 30, 35, 40, 45, Inf), labels = c(1:5)))
gf_point(pct_bf ~ jitter(as.numeric(roundedwaist)), data = BodyFat) |>
  gf_lm() |>
  gf_labs(y = "% Body Fat", x = "Waist")
```

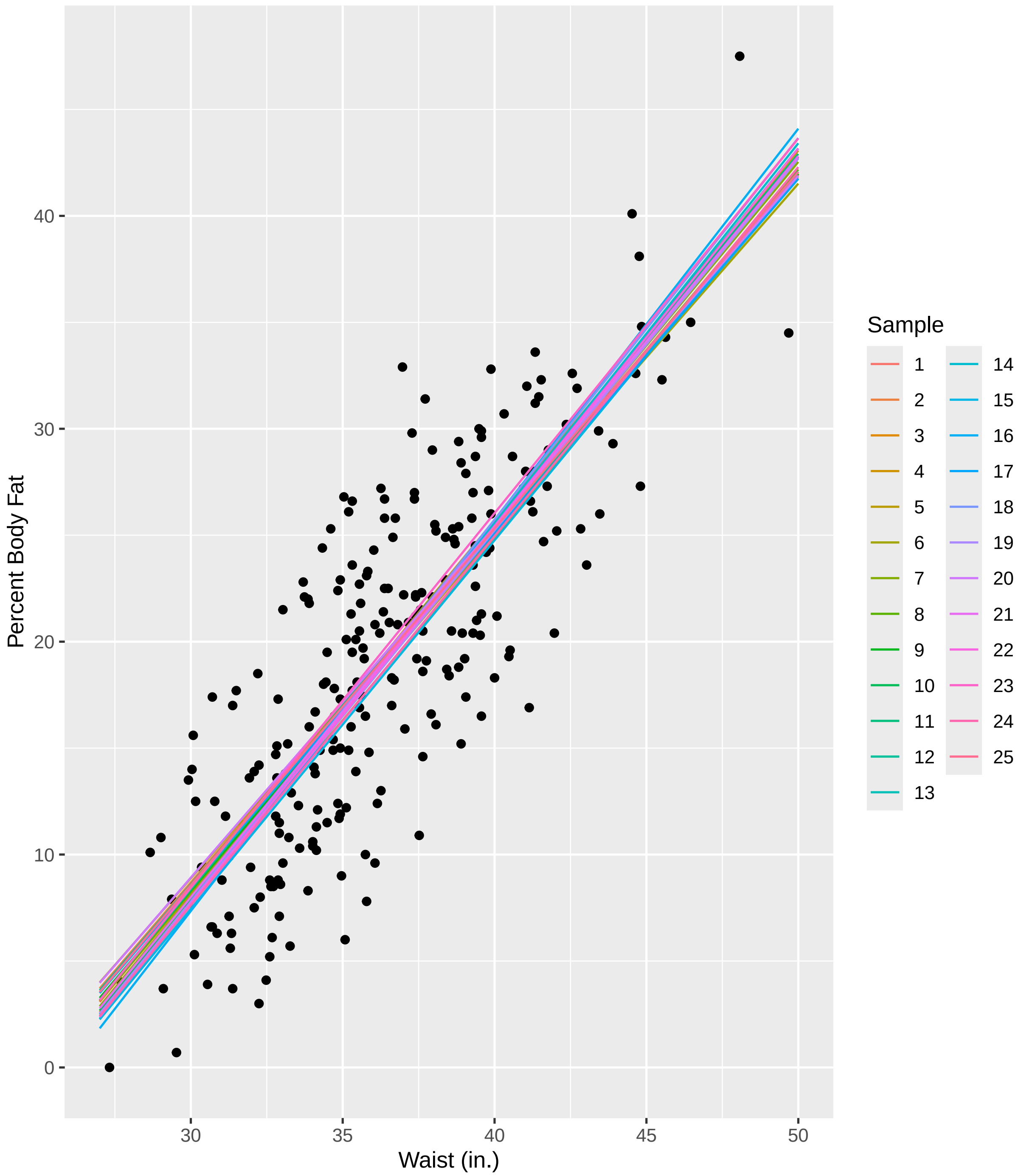


Random Matters: Slopes Vary

```
num_samp <- 25 # It's too messy to do any more than 25
slopesdata <- do(num_samp) * lm(pct_bf ~ waist, data = resample(BodyFat))
```

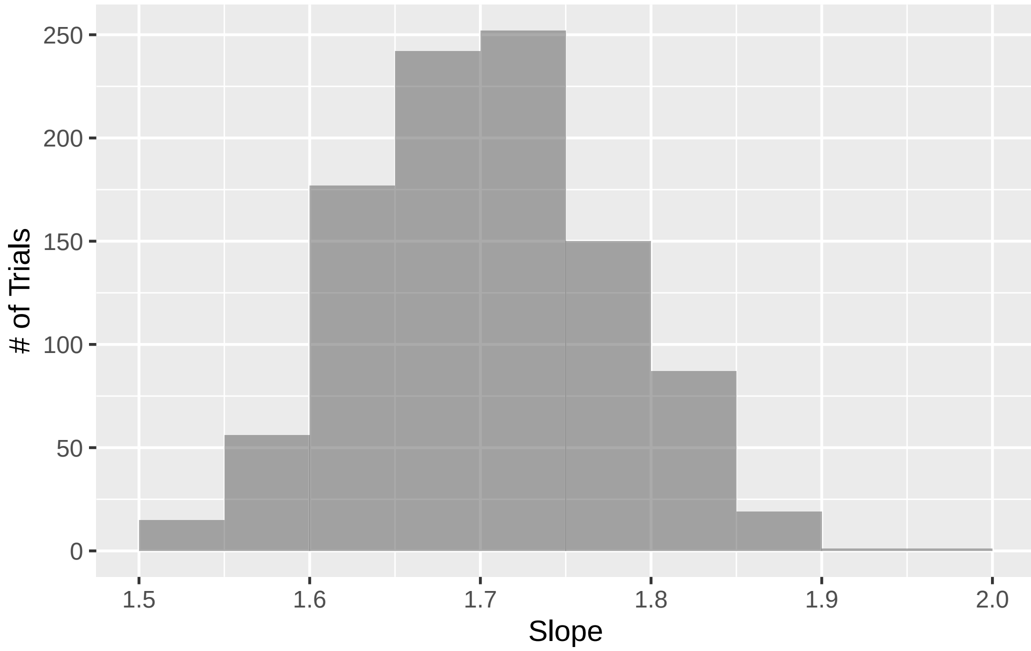
For more information about `resample()`, refer to the resampling vignette: https://cran.r-project.org/web/packages/mosaic/vignettes/Resampling.html

```
slopesdata <- slopesdata |>
  mutate(
    at27 = Intercept + waist * 27,
    at50 = Intercept + waist * 50,
    color = as.factor(1:num_samp)
  )
# Figure 20.4, page 644
gf_point(pct_bf ~ waist, data = BodyFat) |>
  gf_segment(at27 + at50 ~ 27 + 50, data = slopesdata, color = ~ color) |>
  gf_labs(color = "Sample", x = "Waist (in.)", y = "Percent Body Fat")
```




```
num_samp <- 1000 # To see the shape of the histogram
slopesdata <- do(num_samp) * lm(pct_bf ~ waist, data = resample(BodyFat))
# Figure 20.5
```

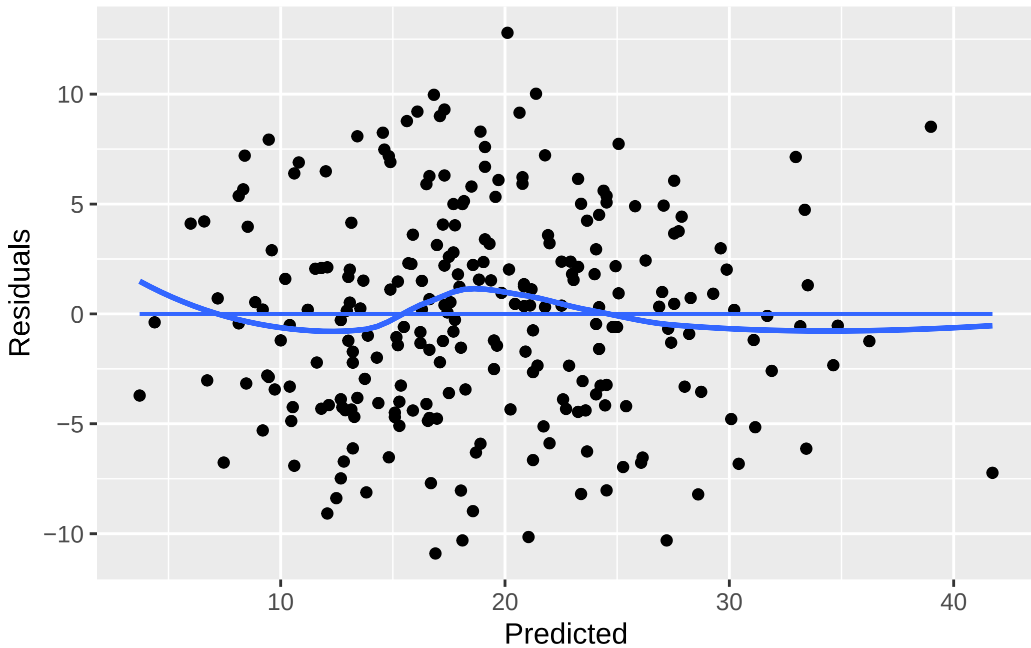
```r
gf_histogram(~ waist, data = slopesdata, binwidth = .05, center = .025) |>
  gf_labs(x = "Slope", y = "# of Trials")
```



For the histogram, we use 1,000 trials.

Section 20.2: Assumptions and Conditions

```r
# Figure 20.6 is the same as Figure 20.1
# Figure 20.7 (page 645)
bodyfatlm <- lm(pct_bf ~ waist, data = BodyFat)
gf_point(resid(bodyfatlm) ~ fitted(bodyfatlm)) |>
  gf_labs(x = "Predicted", y = "Residuals") |>
  gf_lm() |>
  gf_smooth()
```

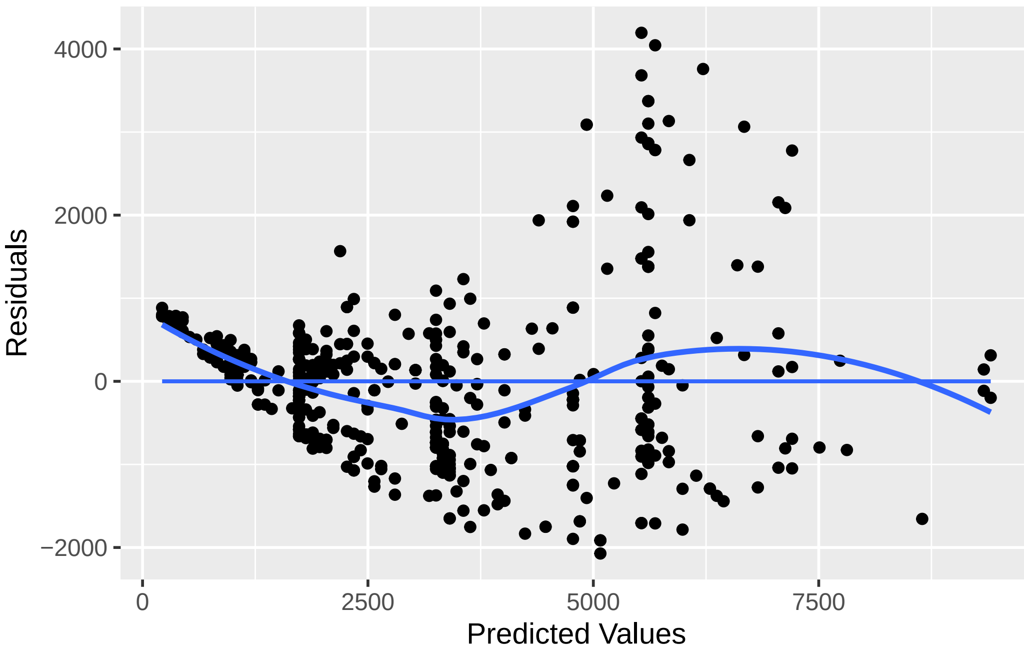


Here we've added a straight line and a smoother to help see any patterns.

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

Here we fit `price` by `carat_size` for diamonds with the color `E`.

```
diamondlm <- lm(price ~ carat_size, data = filter(Diamonds, color == "E"))
# Figure 20.8, page 646
gf_point(resid(diamondlm) ~ fitted(diamondlm)) |>
  gf_labs(x = "Predicted Values", y = "Residuals") |>
  gf_lm() |>
  gf_smooth()
```



Here we see some curvilinearity in the association between the predicted values and the residuals.

```
# Figure 20.9
gf_histogram(~ resid(bodyfatlm), binwidth = 2, center = 1) |>
  gf_labs(x = "Residuals", y = "Count")
```

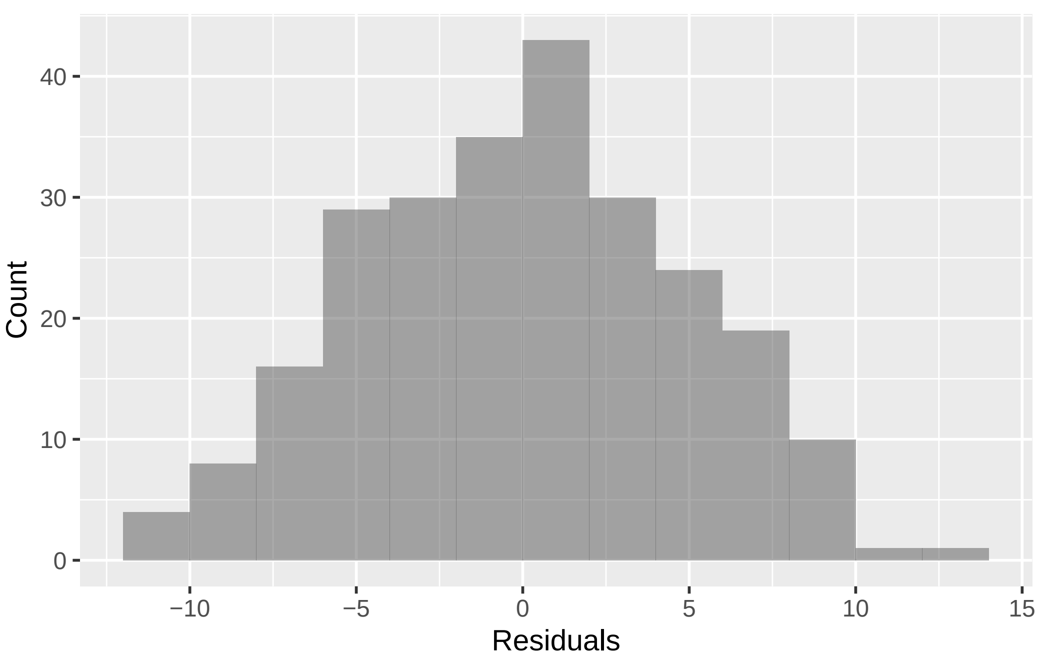


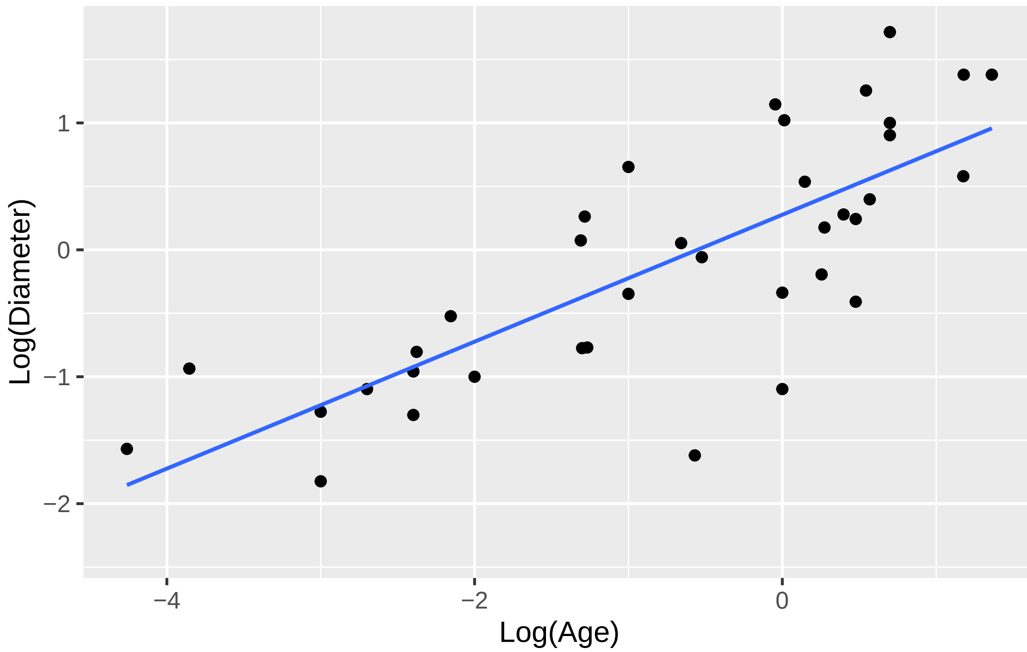
Figure 20.10 is intended to convey the same idea as Figure 20.3 (page 643).

Example 20.1: Checking Assumptions and Conditions

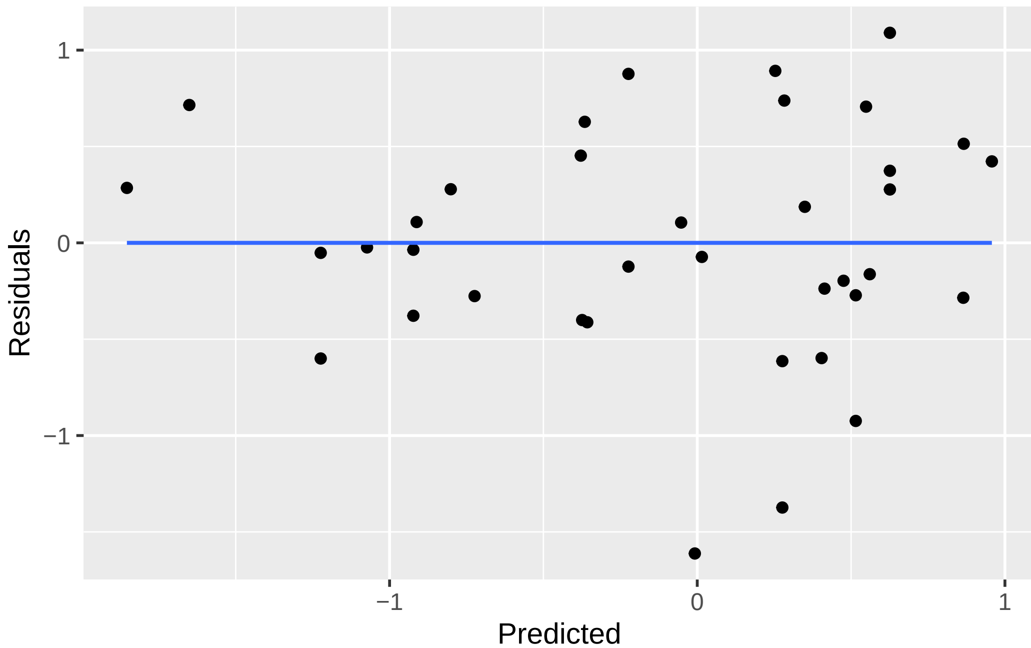
Note that points are removed to match the results in the textbook!

```
Craters <- read_csv("http://nhorton.people.amherst.edu/is5/data/Craters.csv") |>
  janitor::clean_names() |>
  filter(log_age <= 1.5) # Removed points to match the textbook
```

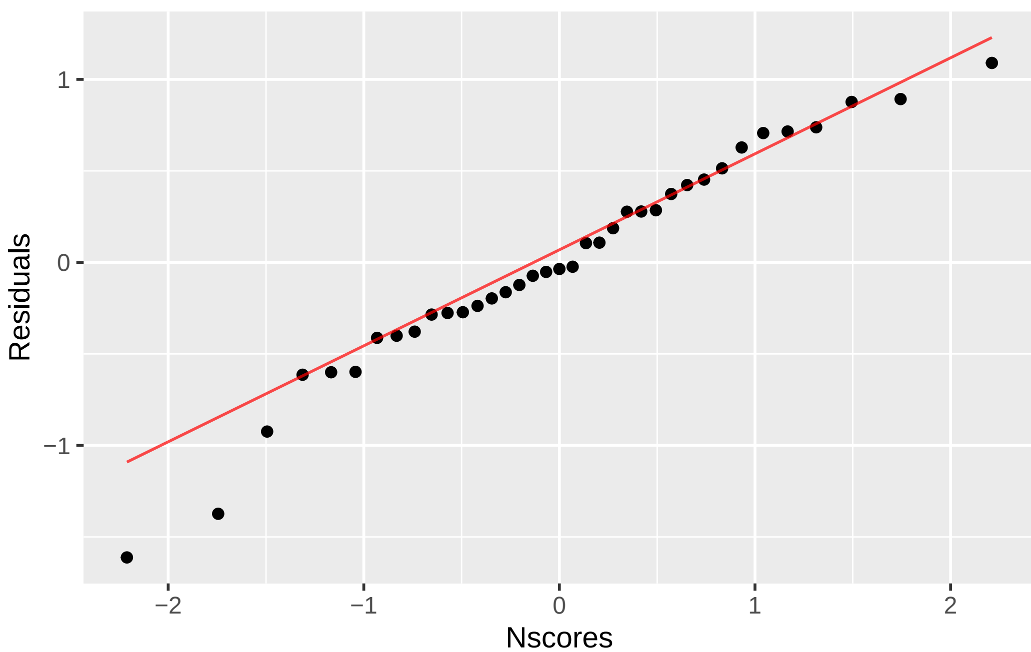
```
gf_point(log_diam ~ log_age, data = Craters) |>
  gf_lm() |>
  gf_labs(x = "Log(Age)", y = "Log(Diameter)")
```



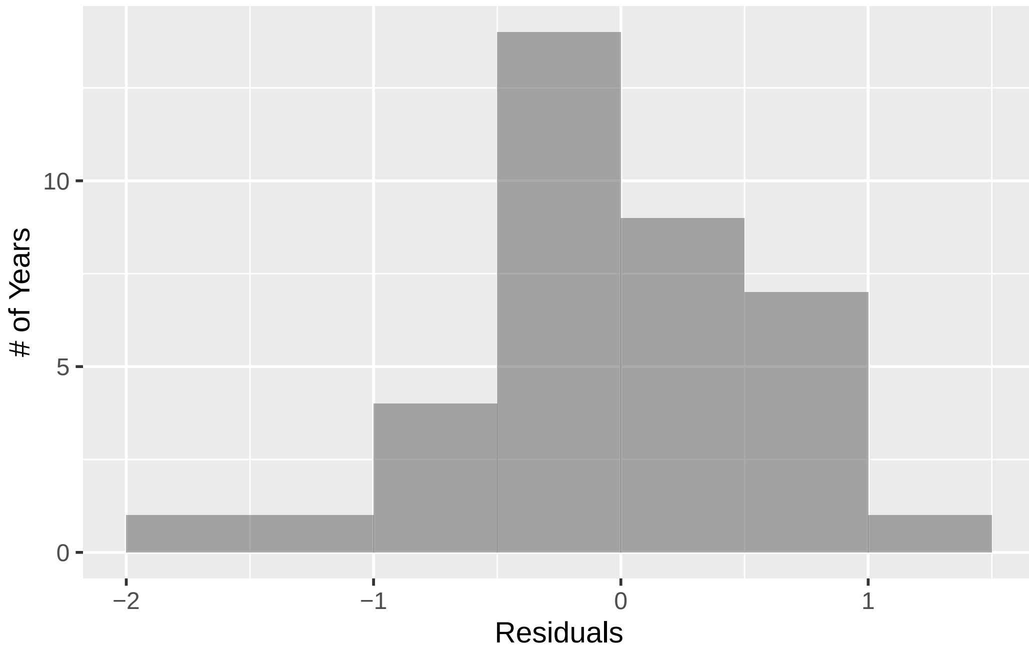

```
craterlm <- lm(log_diam ~ log_age, data = Craters)
gf_point(resid(craterlm) ~ fitted(craterlm)) |>
  gf_lm() |>
  gf_labs(x = "Predicted", y = "Residuals")
```




```
gf_qq(~ resid(craterlm)) |>
  gf_qqline(linetype = "solid", color = "red") |>
  gf_labs(x = "Nscores", y = "Residuals")
```



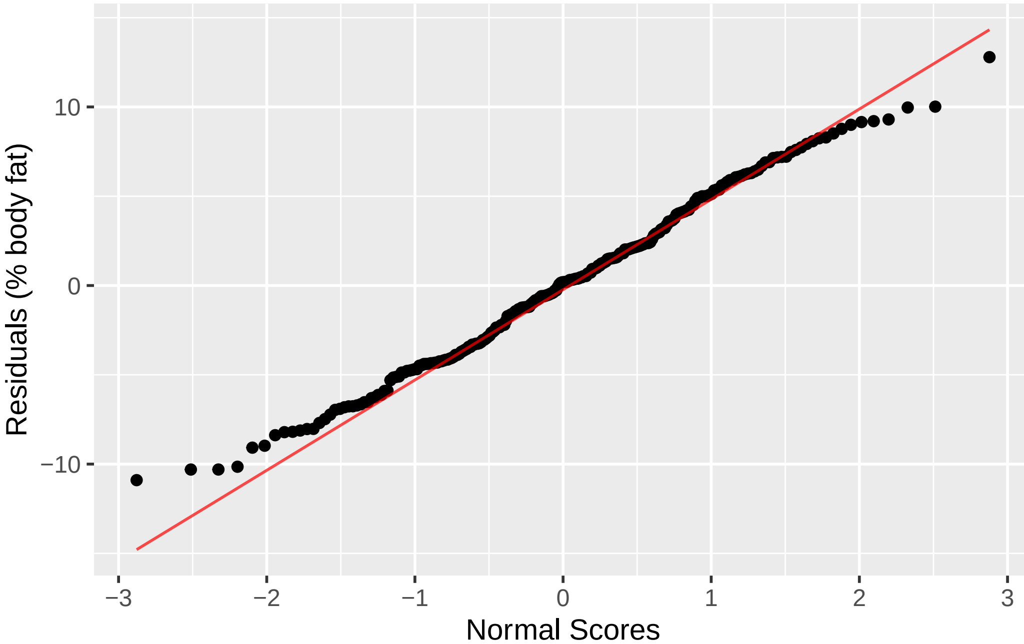
```
gf_histogram(~ resid(craterlm), binwidth = .5, center = 0.25) |>
  gf_labs(x = "Residuals", y = "# of Years")
```



Step-By-Step Example: Regression Inference

The following scatterplot matches Figure 20.1.

```
gf_qq(~ resid(bodyfatlm)) |>
  gf_qqline(linetype = "solid", color = "red") |>
  gf_labs(x = "Normal Scores", y = "Residuals (% body fat)")
```




```
msummary(bodyfatlm)
```

```
             Estimate Std. Error t value Pr(>|t|)
(Intercept) -42.73413    2.71651  -15.73   <2e-16 ***
waist         1.69997    0.07431   22.88   <2e-16 ***

Residual standard error: 4.713 on 248 degrees of freedom
Multiple R-squared:  0.6785,	Adjusted R-squared:  0.6772
F-statistic: 523.3 on 1 and 248 DF,  p-value: < 2.2e-16
```

```
confint(bodyfatlm)
```

```
                 2.5 %    97.5 %
(Intercept) -48.084497 -37.38377
waist         1.553603   1.84634
```

Section 20.3: Regression Inference and Intuition

See the displays on pages 650 and 651.

Example 20.2: Confidence Interval and Hypothesis Test for a Slope

```
mosaic::msummary(bodyfatlm)
```

```
             Estimate Std. Error t value Pr(>|t|)
(Intercept) -42.73413    2.71651  -15.73   <2e-16 ***
waist         1.69997    0.07431   22.88   <2e-16 ***

Residual standard error: 4.713 on 248 degrees of freedom
Multiple R-squared:  0.6785,    Adjusted R-squared:  0.6772
F-statistic: 523.3 on 1 and 248 DF,  p-value: < 2.2e-16
```

```
mean <- 1.70
se <- .074
tstats <- qt(p = c(.025, .975), df = 248)
tstats
```

```
[1] -1.969576  1.969576
```

```
mean + tstats * se
```

```
[1] 1.554251 1.845749
```

```
t <- (mean - 0.00) / se
t
```

```
[1] 22.97297
```

Section 20.4: The Regression Table

```
# Table 20.1, page 654
mosaic::msummary(bodyfatlm)
```

```
             Estimate Std. Error t value Pr(>|t|)
(Intercept) -42.73413    2.71651  -15.73   <2e-16 ***
waist         1.69997    0.07431   22.88   <2e-16 ***

Residual standard error: 4.713 on 248 degrees of freedom
Multiple R-squared:  0.6785,    Adjusted R-squared:  0.6772
F-statistic: 523.3 on 1 and 248 DF,  p-value: < 2.2e-16
```

```
broom::tidy(bodyfatlm) # an alternative way to display the model
```

```
# A tibble: 2 x 5
  term        estimate std.error statistic  p.value
  <chr>          <dbl>     <dbl>     <dbl>    <dbl>
1 (Intercept)   -42.7     2.72       -15.7 3.83e-39
2 waist           1.70    0.0743      22.9 4.85e-63
```

Section 20.5: Multiple Regression Inference

```
# Table 20.2, page 655
bodyfatmlm <- lm(pct_bf ~ waist + height, data = BodyFat)
msummary(bodyfatmlm)
```

```
            Estimate Std. Error t value Pr(>|t|)
(Intercept) -3.10088    7.68611  -0.403    0.687
waist        1.77309    0.07158  24.770  < 2e-16 ***
height      -0.60154    0.10994  -5.472 1.09e-07 ***

Residual standard error: 4.46 on 247 degrees of freedom
Multiple R-squared:  0.7132,    Adjusted R-squared:  0.7109
F-statistic: 307.1 on 2 and 247 DF,  p-value: < 2.2e-16
```

Just Checking

```
Mouth <- read_csv("http://nhorton.people.amherst.edu/is5/data/Mouth_volume.csv")
mouthlm <- lm(Mouth_Volume ~ Height, data = Mouth) # simple linear model
df_stats(~ Mouth_Volume, data = Mouth)
```

```
      response    min     Q1 median     Q3     max     mean      sd  n missing
1 Mouth_Volume 35.839 47.647  57.31 69.665 111.181 60.27038 16.8777 61       0
```

```
msummary(mouthlm)
```

```
            Estimate Std. Error t value Pr(>|t|)
(Intercept)   -44.71      32.16  -1.390  0.16966
Height         61.38      18.77   3.271  0.00179 **
```

```
Residual standard error: 15.66 on 59 degrees of freedom
Multiple R-squared:  0.1535,    Adjusted R-squared:  0.1391
F-statistic:  10.7 on 1 and 59 DF,  p-value: 0.001794
```

```r
mouthmlm <- lm(Mouth_Volume ~ Age + Height, data = Mouth) # multiple linear model
msummary(mouthmlm)
```

```
            Estimate Std. Error t value Pr(>|t|)
(Intercept) -51.0122    31.8843  -1.600  0.11505
Age           0.4373     0.2588   1.690  0.09646 .
Height       58.1009    18.5791   3.127  0.00276 **

Residual standard error: 15.42 on 58 degrees of freedom
Multiple R-squared:  0.1932,    Adjusted R-squared:  0.1654
F-statistic: 6.945 on 2 and 58 DF,  p-value: 0.001978
```

Collinearity

```r
Coasters <- read_csv("http://nhorton.people.amherst.edu/is5/data/Coasters_2015.csv")
nrow(Coasters)
```

```
[1] 241
```

```r
Coasters <- Coasters |>
  filter(Name != "Tower of Terror", Name != "Xcelerator") |>
  # Removed artificially accelerated coasters and Tower of Terror
  filter(Drop != "NA", Duration != "NA") |>
  mutate(Inversions = as.factor(Inversions))
nrow(Coasters)
```

```
[1] 89
```

```r
coasterlm <- lm(Duration ~ Drop, data = Coasters) # simple linear model
mosaic::msummary(coasterlm)
```

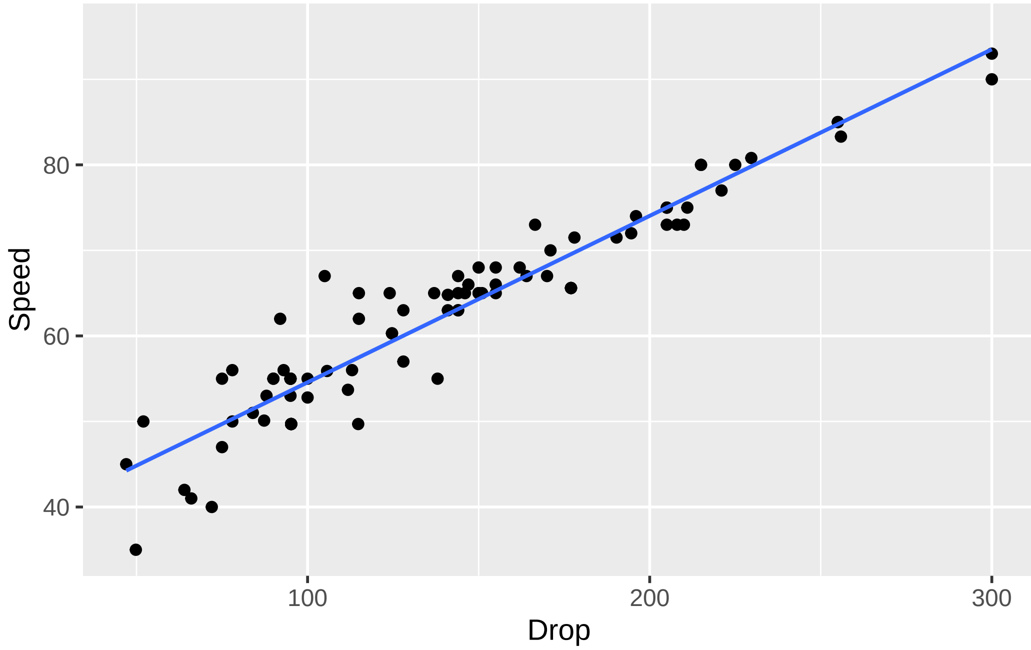
```
            Estimate Std. Error t value Pr(>|t|)
(Intercept) 88.48688    9.52406   9.291 1.14e-14 ***
Drop         0.38634    0.06279   6.153 2.26e-08 ***
```

```
Residual standard error: 33.27 on 87 degrees of freedom
Multiple R-squared:  0.3032,    Adjusted R-squared:  0.2952
F-statistic: 37.86 on 1 and 87 DF,  p-value: 2.264e-08
```

```
coastermlm <- lm(Duration ~ Drop + Speed, data = Coasters) # multiple linear regression model
mosaic::msummary(coastermlm)
```

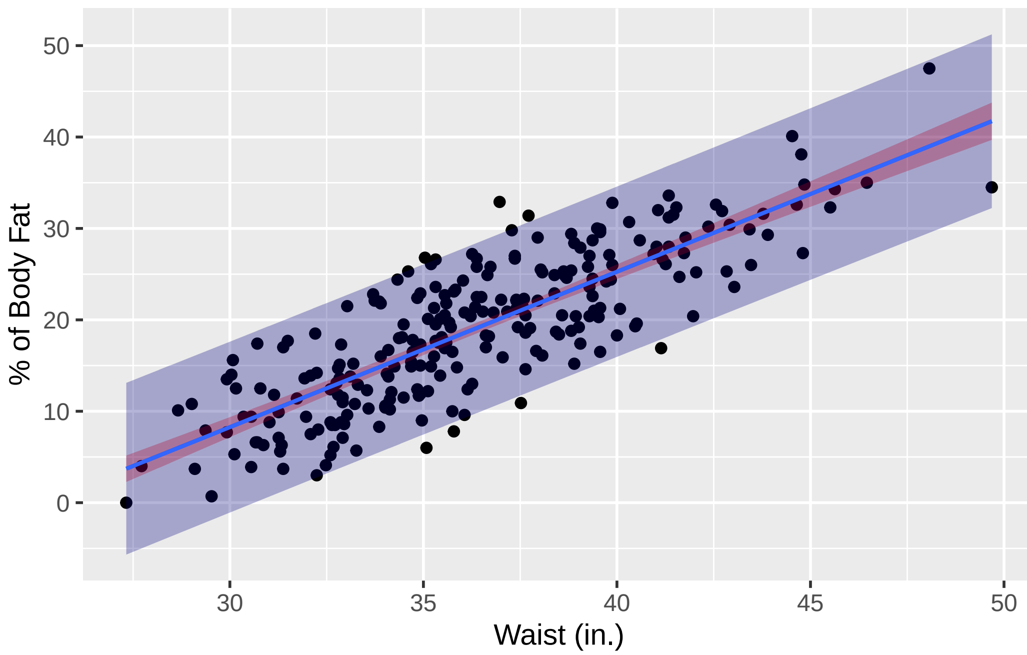
```
            Estimate Std. Error t value Pr(>|t|)
(Intercept)  -6.3932    34.0567  -0.188  0.85154
Drop         -0.1399     0.1917  -0.730  0.46754
Speed         2.7030     0.9346   2.892  0.00484 **

Residual standard error: 31.94 on 86 degrees of freedom
Multiple R-squared:  0.365, Adjusted R-squared:  0.3502
F-statistic: 24.71 on 2 and 86 DF,  p-value: 3.314e-09
```

```
gf_point(Speed ~ Drop, data = Coasters) |>
  gf_lm()
```



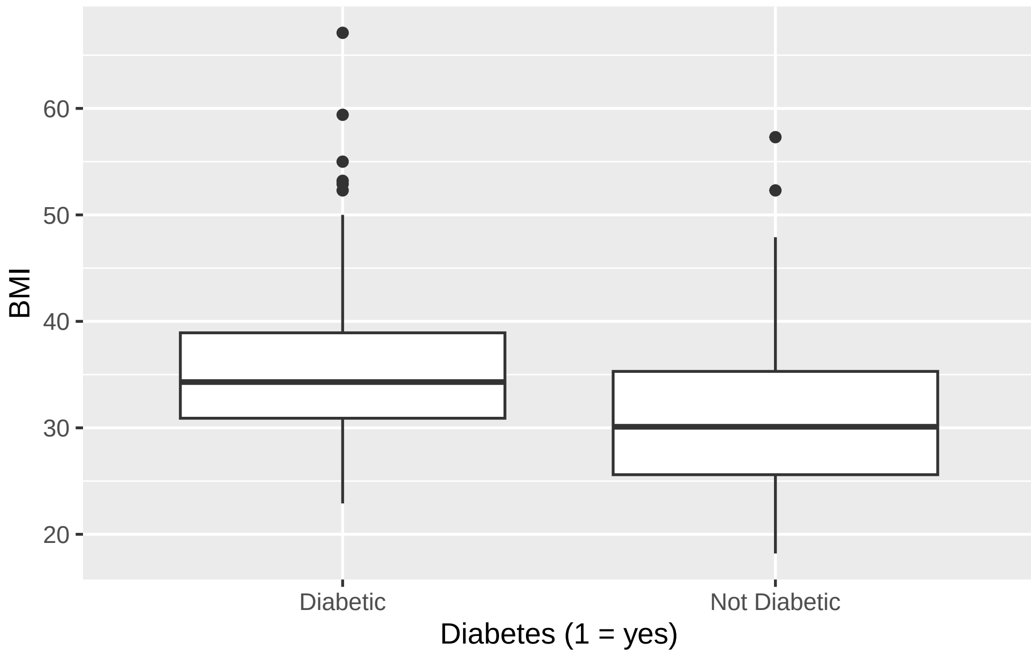
Section 20.6: Confidence and Prediction Intervals

```
# Figure 20.16, page 659
gf_point(pct_bf ~ waist, data = BodyFat) |>
  gf_lm(interval = "confidence", fill = "red") |>
  gf_lm(interval = "prediction", fill = "navy") |>
  gf_labs(x = "Waist (in.)", y = "% of Body Fat")
```

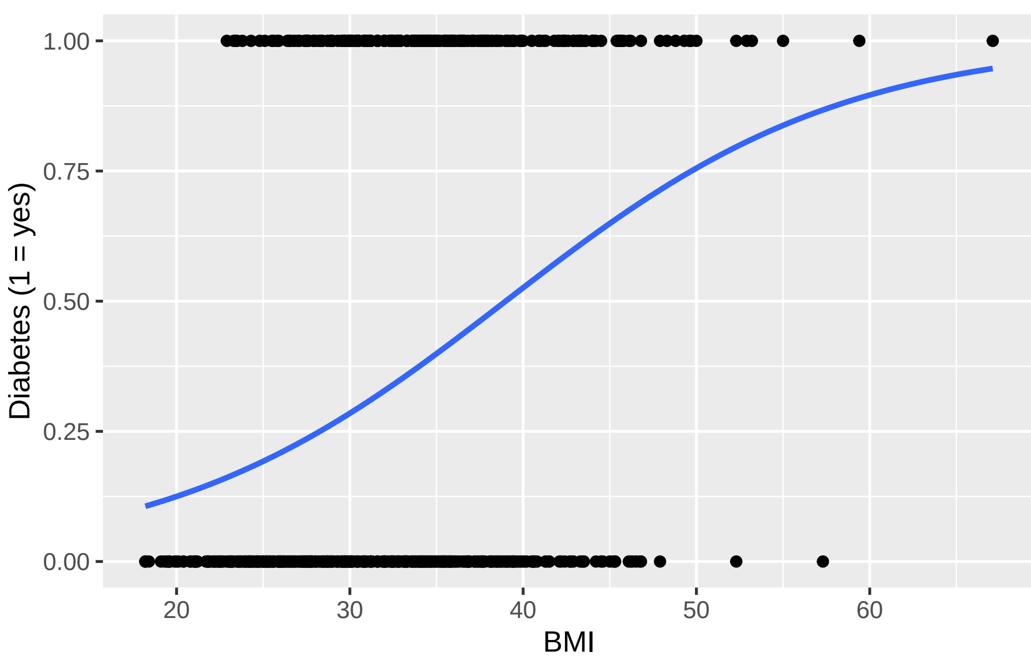


Section 20.7: Logistic Regression

```
PimaIndians <- read_csv("http://nhorton.people.amherst.edu/is5/data/Pima_indians.csv") |>
  filter(BMI != 0)
# Figure 20.17, page 661
PimaIndians |>
  mutate(Diabetes = ifelse(Diabetes == 1, "Diabetic", "Not Diabetic")) |>
  gf_boxplot(BMI ~ as.factor(Diabetes), xlab = "Diabetes (1 = yes)")
```




```
# Figure 20.21, page 663
gf_point(Diabetes ~ BMI, data = PimaIndians, ylab = "Diabetes (1 = yes)") |>
  gf_smooth(method = "glm", method.args = list(family = "binomial"))
```



Section 20.8: More About Regression