IS5 in R: Multiple Regression (Chapter 9)

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2025-01-20

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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.

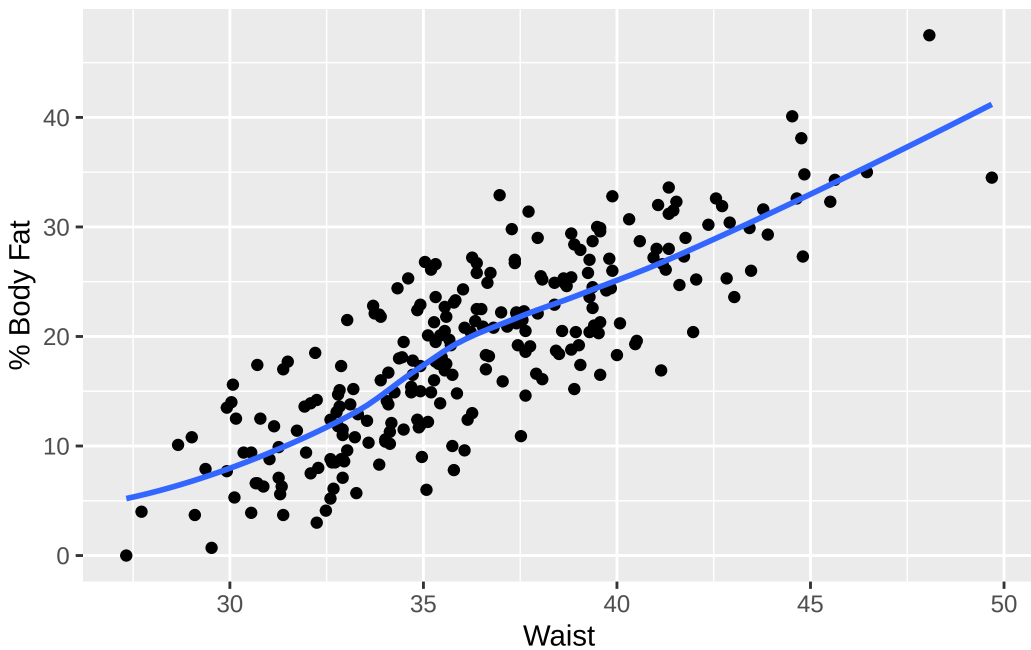
```
library(mosaic)
library(tidyverse)
library(broom) # We'll use this for augment() later
```

Chapter 9: Multiple Regression

```
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).

```
# Figure 9.1, page 276
gf_point(pct_bf ~ waist, data = BodyFat) |>
  gf_labs(x = "Waist", y = "% Body Fat") |>
  gf_smooth()
```



We've added `gf_smooth()` to demonstrate how to add a smoother.

Section 9.1: What is Multiple Regression?

```
# Table 9.1, page 277
multiplereg <- lm(pct_bf ~ waist + height, data = BodyFat)
summary(multiplereg)
```

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

Residuals:
     Min       1Q   Median       3Q      Max 
-11.1692  -3.4133  -0.0977   3.0995   9.9082 

Coefficients:
            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 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

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
```

The `summary()` function provides the multiple R-squared along with the regression coefficients.

```r
msummary(multiplereg)
```

```
            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
```

The `msummary()` function in the `mosaic` package provides a pruned version of the same output.

```r
broom::tidy(multiplereg)
```

```
# A tibble: 3 x 5
  term        estimate std.error statistic  p.value
```

```
  <chr>          <dbl>    <dbl>    <dbl>    <dbl>
1 (Intercept)   -3.10     7.69     -0.403 6.87e- 1
2 waist          1.77     0.0716   24.8   6.79e-69
3 height        -0.602    0.110    -5.47  1.09e- 7
```

The `tidy()` function in the `broom` package provides similar information as a tibble/dataframe.

Example 9.1: Modeling Home Prices

```r
RealEstate <- read_csv("http://nhorton.people.amherst.edu/is5/data/Real_Estate.csv") |>
  janitor::clean_names()
realestatelm <- lm(price ~ living_area + bedrooms, data = RealEstate)
summary(realestatelm)
```

```

Call:
lm(formula = price ~ living_area + bedrooms, data = RealEstate)

Residuals:
    Min      1Q  Median      3Q     Max 
-433211 -198136  -63249  137183 1054177 

Coefficients:
             Estimate Std. Error t value Pr(>|t|)    
(Intercept) 308100.44   41147.84   7.488 1.69e-13 ***
living_area    135.09      11.48  11.771  < 2e-16 ***
bedrooms    -43346.81   12844.14  -3.375 0.000771 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 266900 on 891 degrees of freedom
Multiple R-squared:  0.1463,	Adjusted R-squared:  0.1444 
F-statistic: 76.34 on 2 and 891 DF,  p-value: < 2.2e-16
```

Here we demonstrate how to create a function in R that can be used to calculate predicted values from a regression model.

```r
# Predicted Values
realestatefn <- makeFun(realestatelm) # Making a function to find predicted values
# Predicted price for a home with 2800 sq ft living area and 5 bedrooms
realestatefn(living_area = 2800, bedrooms = 5)
```

```
       1 
469614.9 
```

```r
# Predicted price for a home with 2801 sq ft living area and 5 bedrooms
realestatefn(living_area = 2801, bedrooms = 5)
```

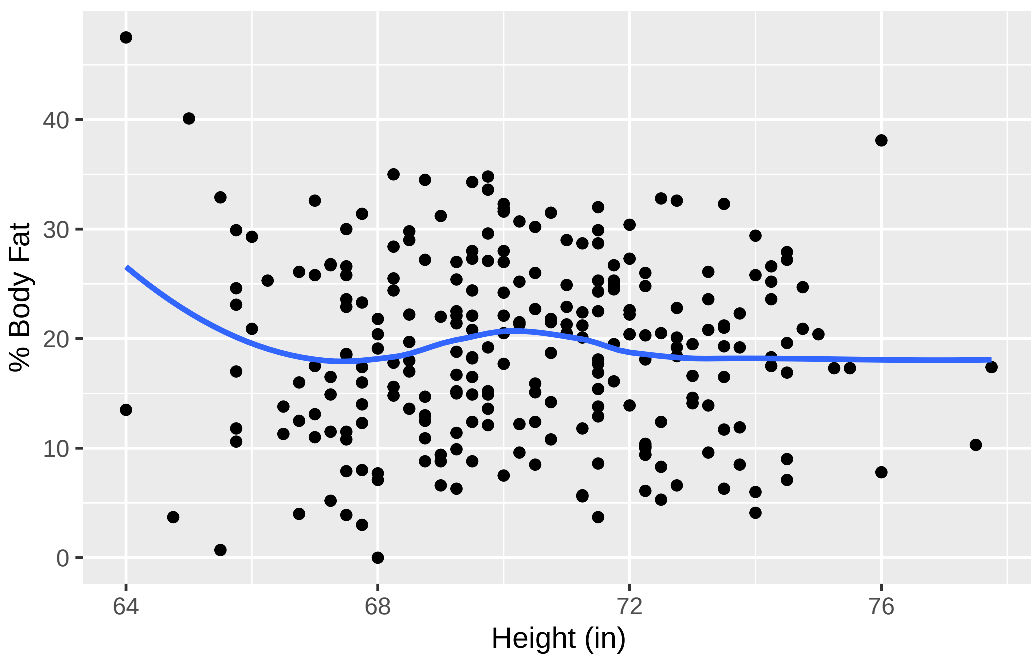
```
     1 
469750 
```

```r
# If we subtract predicted values one value apart, we get the slope
realestatefn(living_area = 2801, bedrooms = 5) -
  realestatefn(living_area = 2800, bedrooms = 5)
```

```
       1 
135.0887 
```

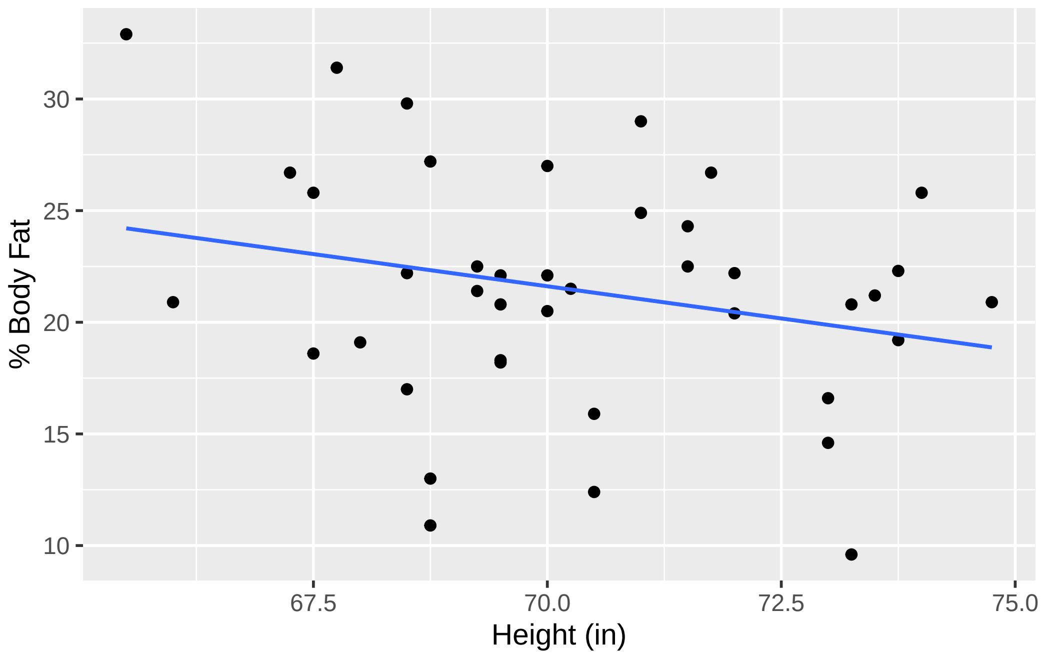
Section 9.2: Interpreting Multiple Regression Coefficients

```r
# Figure 9.2, page 279
gf_point(pct_bf ~ height, data = BodyFat) |>
  gf_smooth() |> # Added a smoother to assess linearity
  gf_labs(x = "Height (in)", y = "% Body Fat")
```

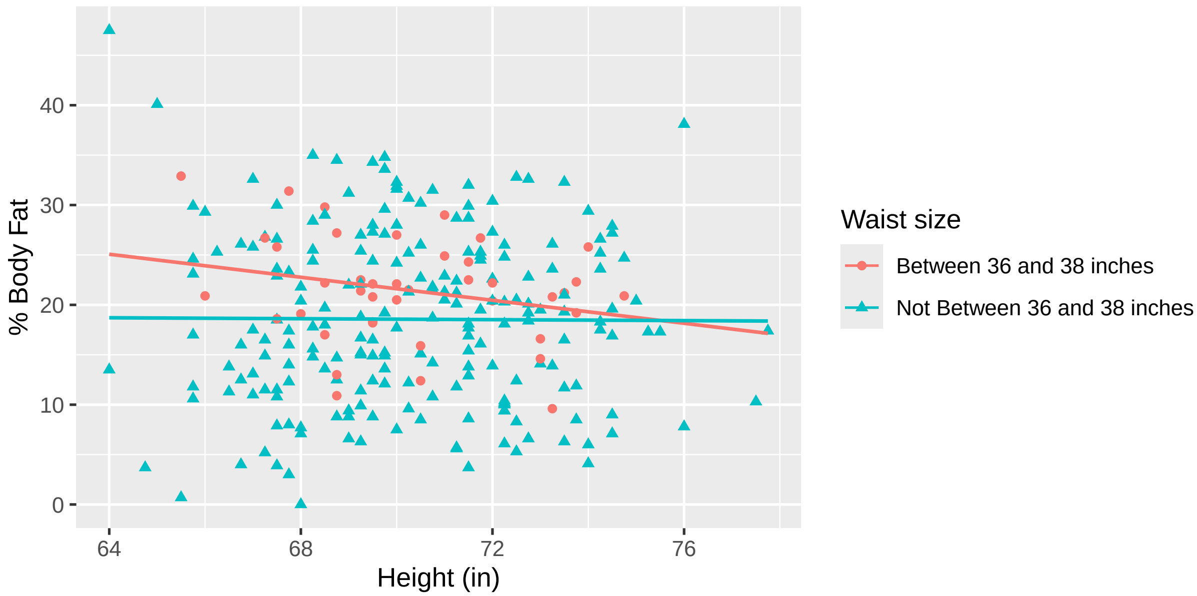


A message about the default smoother option was suppressed by adding `message: false` as a code chunk option.

```
# Figure 9.3
BodyFat |>
  filter(waist >= 36 & waist <= 38) |> # Just plotting waist sizes between 36 and 38 inches
  gf_point(pct_bf ~ height) |>
  gf_labs(x = "Height (in)", y = "% Body Fat") |>
  gf_lm()
```




```
# Plotting all points
BodyFat |>
  mutate(waistsize = ifelse(waist >= 36 & waist <= 38, "Between 36 and 38 inches",
    "Not Between 36 and 38 inches"
  )) |> # Subsetting
  gf_point(pct_bf ~ height, shape = ~ waistsize, color = ~ waistsize) |>
  gf_labs(
    x = "Height (in)",
    y = "% Body Fat",
    shape = "Waist size",
    color = "Waist size"
  ) |>
  gf_lm()
```



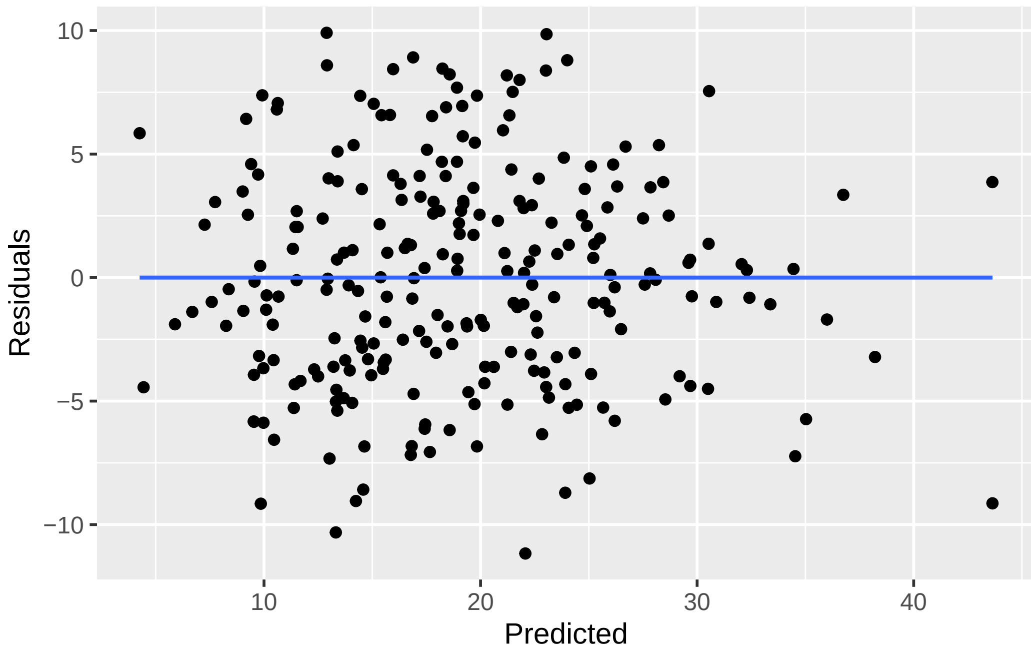
Section 9.3: The Multiple Regression Model–Assumptions and Conditions

Linearity Assumption

Equal Variance Assumption

We can assess the equal variance assumption in several ways. The simplest is through a scatterplot of residuals vs. fitted values.

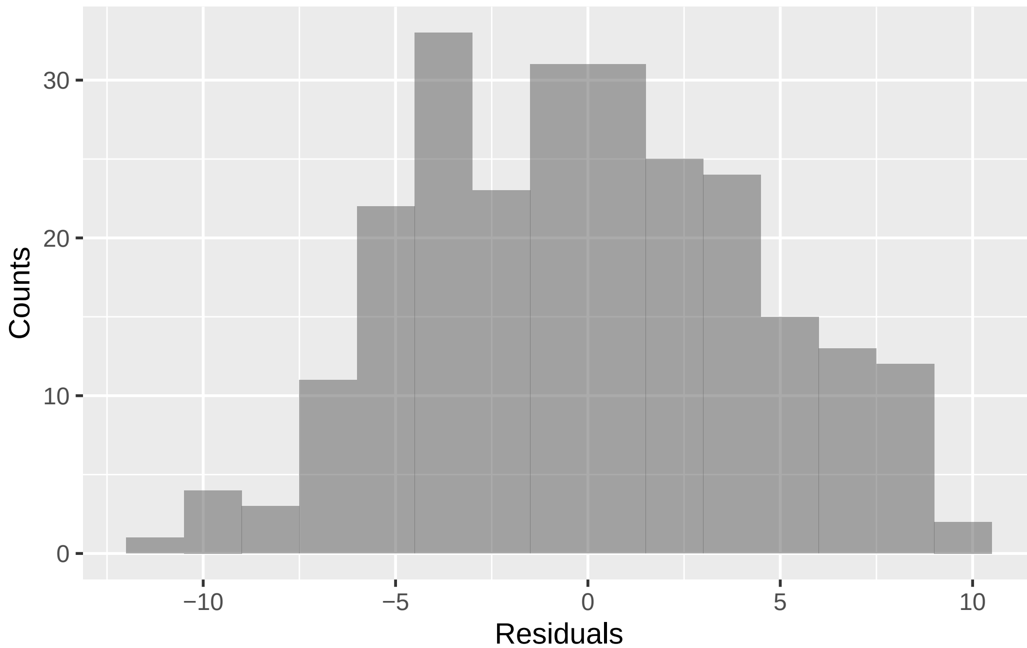
```
bodyfatlm <- lm(pct_bf ~ waist + height, data = BodyFat)
# Figure 9.4, page 282
gf_point(resid(bodyfatlm) ~ fitted(bodyfatlm)) |>
  gf_lm() |>
  gf_labs(x = "Predicted", y = "Residuals")
```



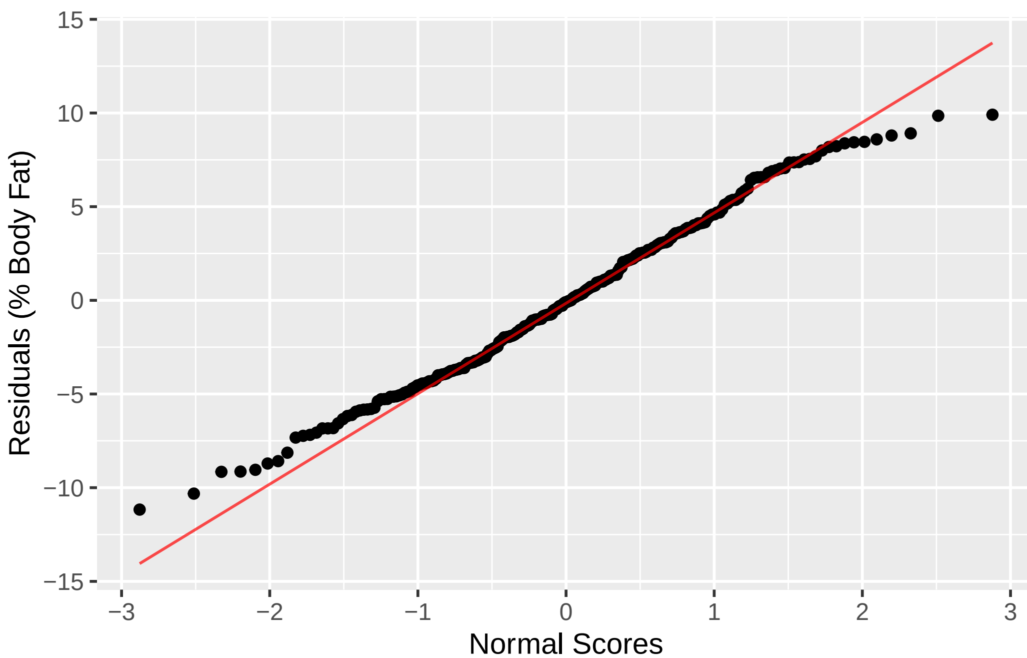
Check the Residuals

It's important to look at the residuals to see if the "Nearly Normal" condition is reasonable.

```
# Figure 9.5
gf_histogram(~ resid(bodyfatlm), binwidth = 1.5, center = 0.75) |>
  gf_labs(x = "Residuals", y = "Counts")
```



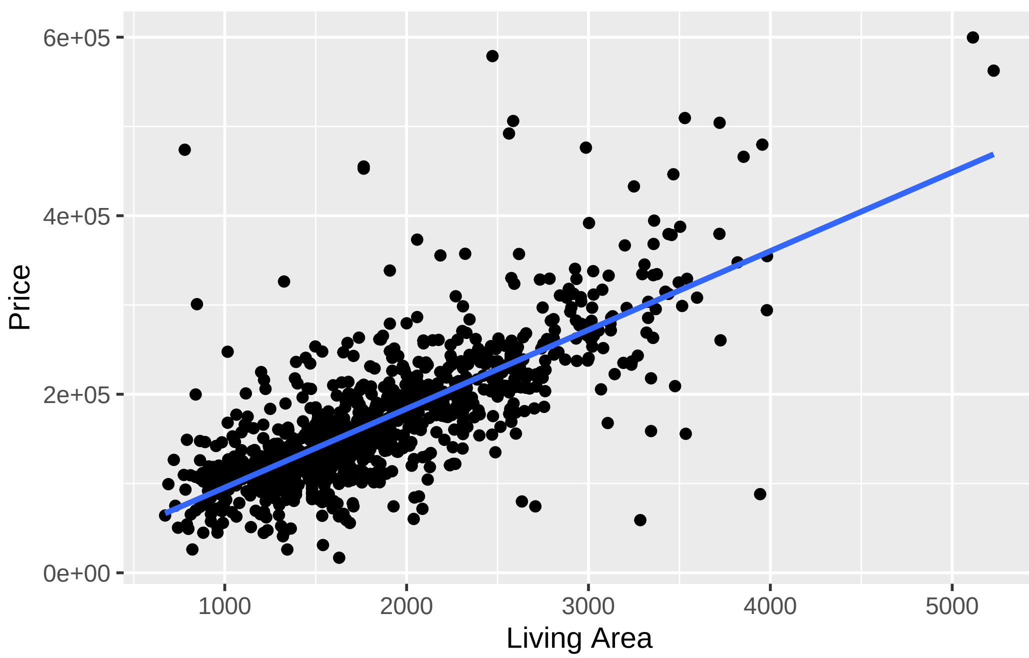

```
gf_qq(~ resid(bodyfatlm)) |>
  gf_qqline(linetype = "solid", color = "red") |>
  gf_labs(x = "Normal Scores", y = "Residuals (% Body Fat)")
```



Step-By-Step Example: Multiple Regression

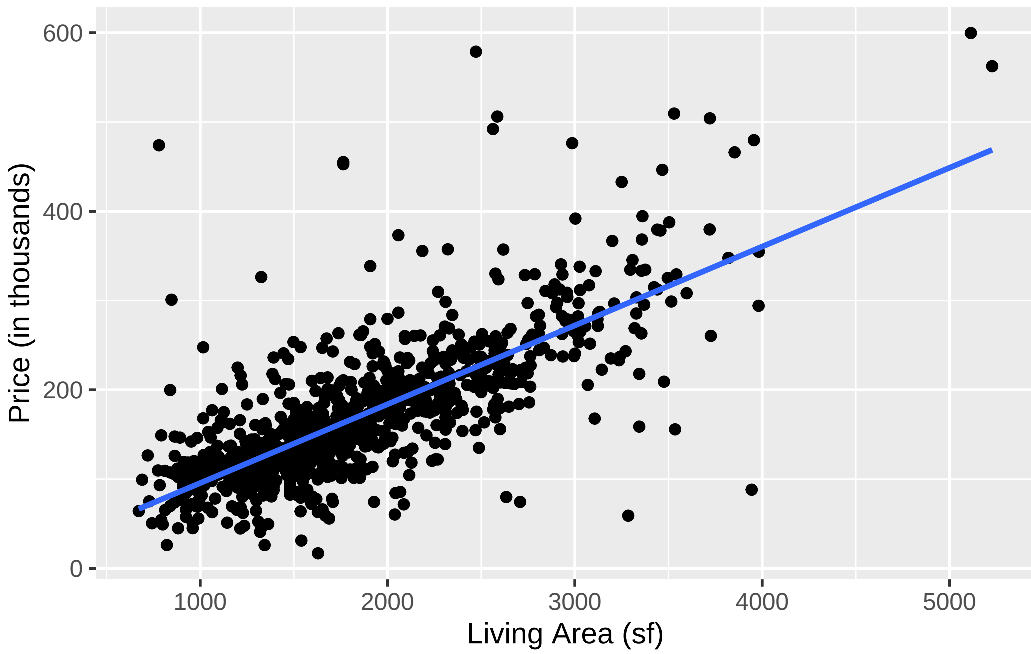
We begin by reading in the data for the step-by-step example.

```
HousingPrices <-
  read_csv("http://nhorton.people.amherst.edu/is5/data/Housing_prices.csv") |>
  janitor::clean_names()
gf_point(price ~ living_area, data = HousingPrices) |>
  gf_smooth() |>
  gf_labs(x = "Living Area", y = "Price")
```

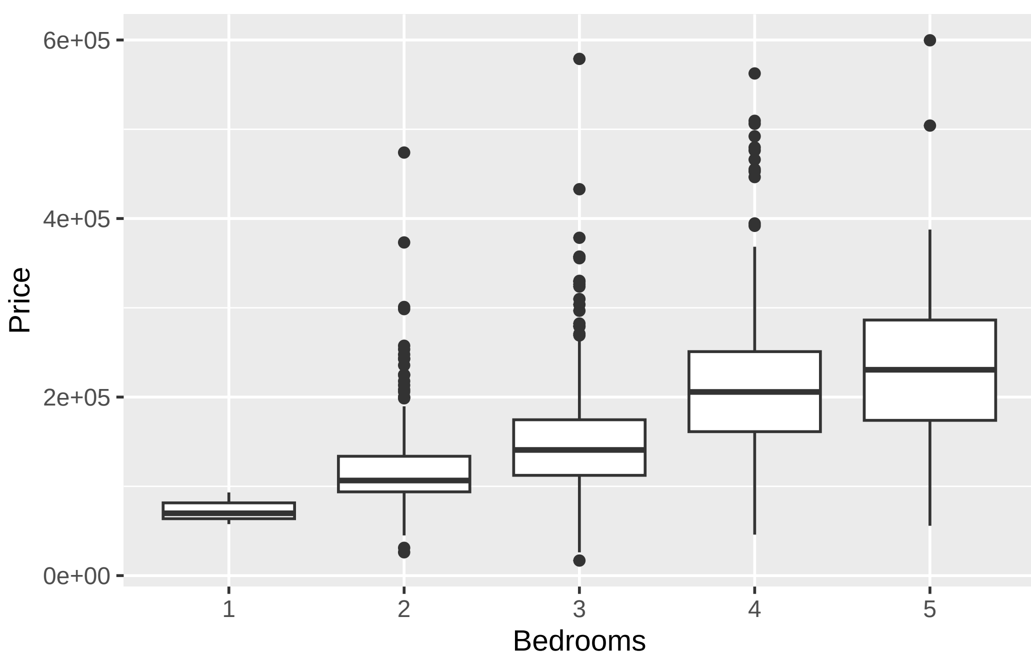


For this and other plots the y axis labels would be far easier to read if the values were rescaled. Here we demonstrate this but continue to mirror the book output for the other displays.

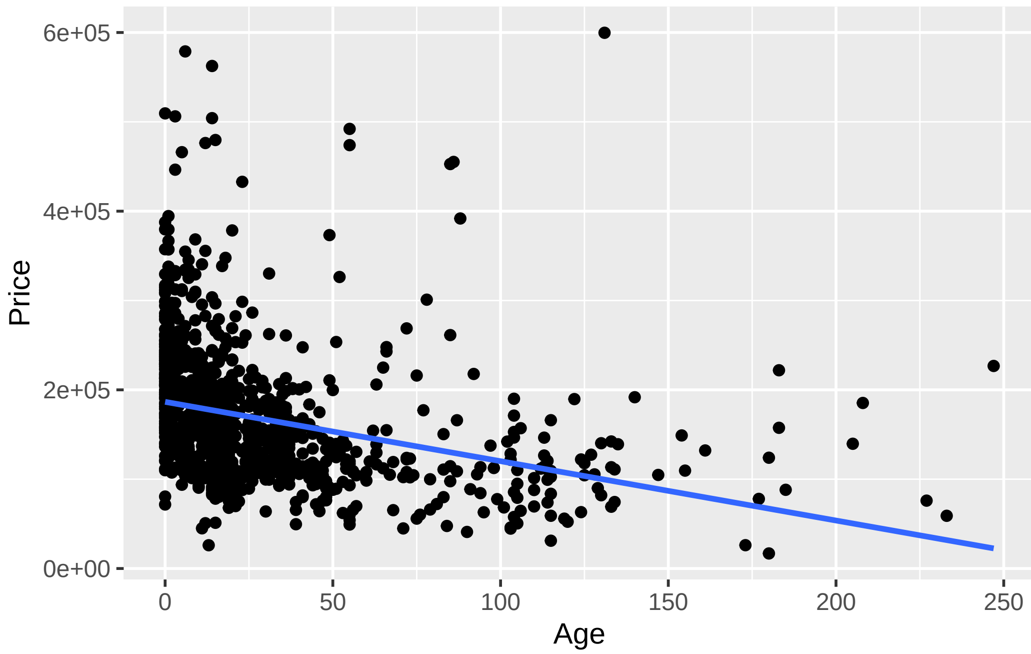
```
HousingRescaled <- HousingPrices |>
  mutate(price1000 = price / 1000)
gf_point(price1000 ~ living_area, data = HousingRescaled) |>
  gf_smooth() |>
  gf_labs(x = "Living Area (sf)", y = "Price (in thousands)")
```



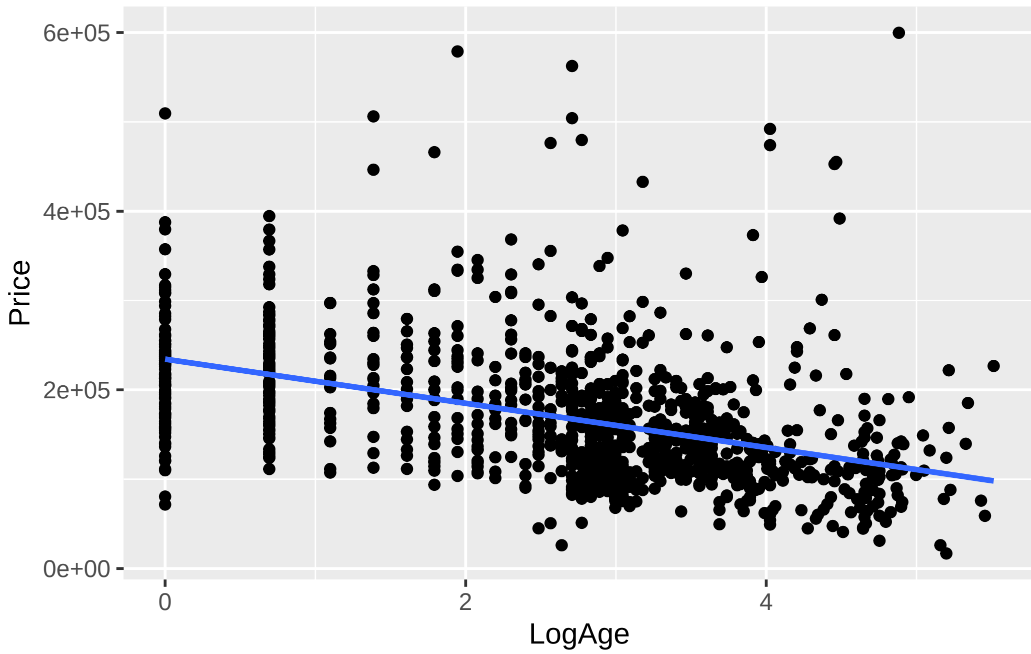

```
gf_boxplot(price ~ as.factor(bedrooms), data = HousingPrices) |>
  gf_labs(x = "Bedrooms", y = "Price")
```



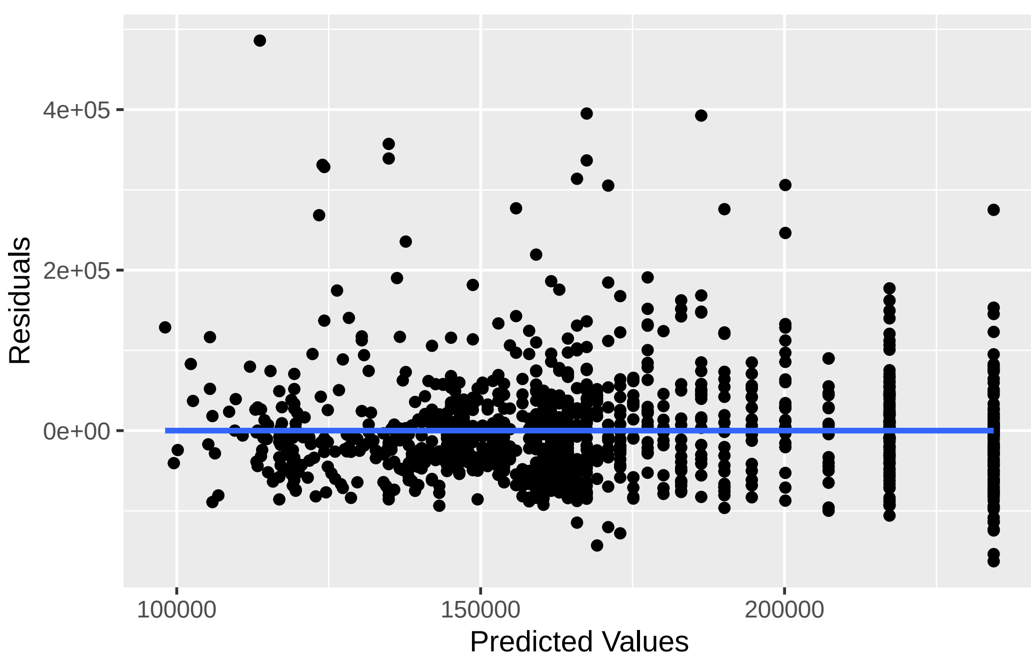
```r
gf_point(price ~ age, data = HousingPrices) |>
  gf_smooth() |>
  gf_labs(x = "Age", y = "Price")
```




```r
gf_point(price ~ log(age + 1), data = HousingPrices) |>
  gf_smooth() |>
  gf_labs(x = "LogAge", y = "Price")
```




```r
housinglm <- lm(price ~ log(age + 1), data = HousingPrices)
gf_point(resid(housinglm) ~ fitted(housinglm)) |>
  gf_smooth() |>
  gf_labs(x = "Predicted Values", y = "Residuals")
```

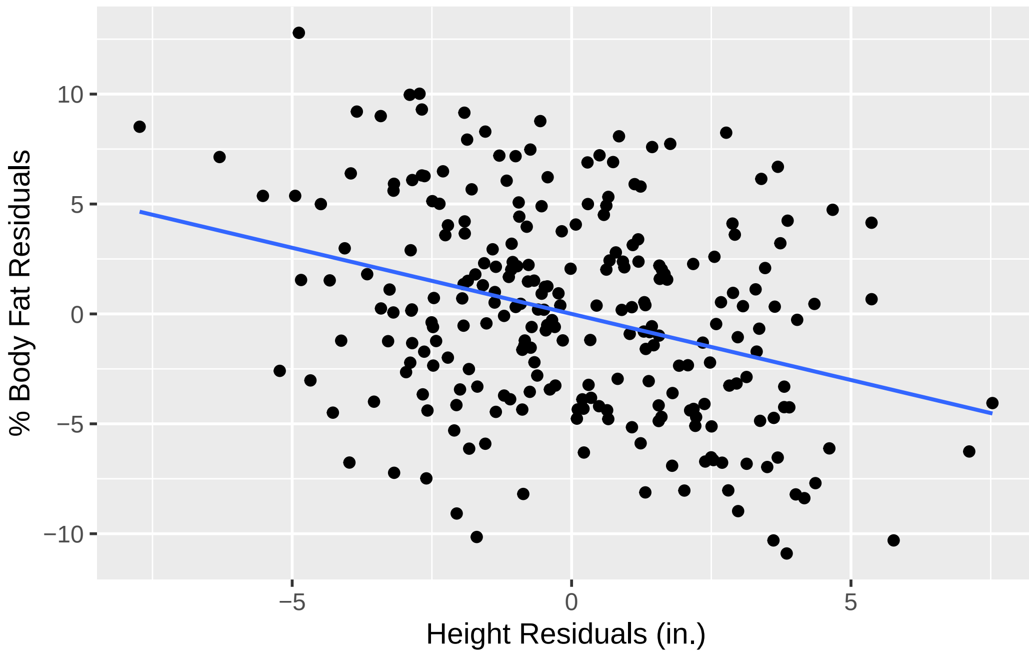


```r
housinglm2 <- lm(price ~ living_area + log(age + 1) + bedrooms, data = HousingPrices)
msummary(housinglm2)
```

```
              Estimate Std. Error t value Pr(>|t|)
(Intercept)  44797.165   8356.609   5.361 1.02e-07 ***
living_area     87.260      3.365  25.928  < 2e-16 ***
log(age + 1) -6270.813   1299.133  -4.827 1.59e-06 ***
bedrooms     -5902.756   2773.934  -2.128   0.0336 *

Residual standard error: 49620 on 1053 degrees of freedom
Multiple R-squared:  0.5876,    Adjusted R-squared:  0.5864
F-statistic: 500.1 on 3 and 1053 DF,  p-value: < 2.2e-16
```

Section 9.4: Partial Regression Plots

```r
# Figure 9.6 (instructions on 287)
# Step 1
otherthanheightlm <- lm(pct_bf ~ waist, data = BodyFat)
# Step 2
residualsoflm <- resid(otherthanheightlm)
# Step 3
yheightlm <- lm(height ~ waist, data = BodyFat)
# Step 4
residualsoflm2 <- resid(yheightlm)
# Step 5
gf_point(residualsoflm ~ residualsoflm2) |>
  gf_lm() |>
  gf_labs(x = "Height Residuals (in.)", y = "% Body Fat Residuals")
```



Just Checking

```
Hurricanes <- read_csv("http://nhorton.people.amherst.edu/is5/data/Hurricanes_2015.csv") |>
  janitor::clean_names()
hurricanelm <- lm(max_wind_speed_kts ~ year + central_pressure_mb, data = Hurricanes)
msummary(hurricanelm)
```

```
                      Estimate Std. Error t value Pr(>|t|)
(Intercept)          1.032e+03  3.852e+01  26.789   <2e-16 ***
year                -3.132e-04  9.075e-03  -0.035    0.973
central_pressure_mb -9.750e-01  3.287e-02 -29.666   <2e-16 ***

Residual standard error: 8.199 on 217 degrees of freedom
  (7 observations deleted due to missingness)
Multiple R-squared:  0.8056,    Adjusted R-squared:  0.8038
F-statistic: 449.6 on 2 and 217 DF,  p-value: < 2.2e-16
```

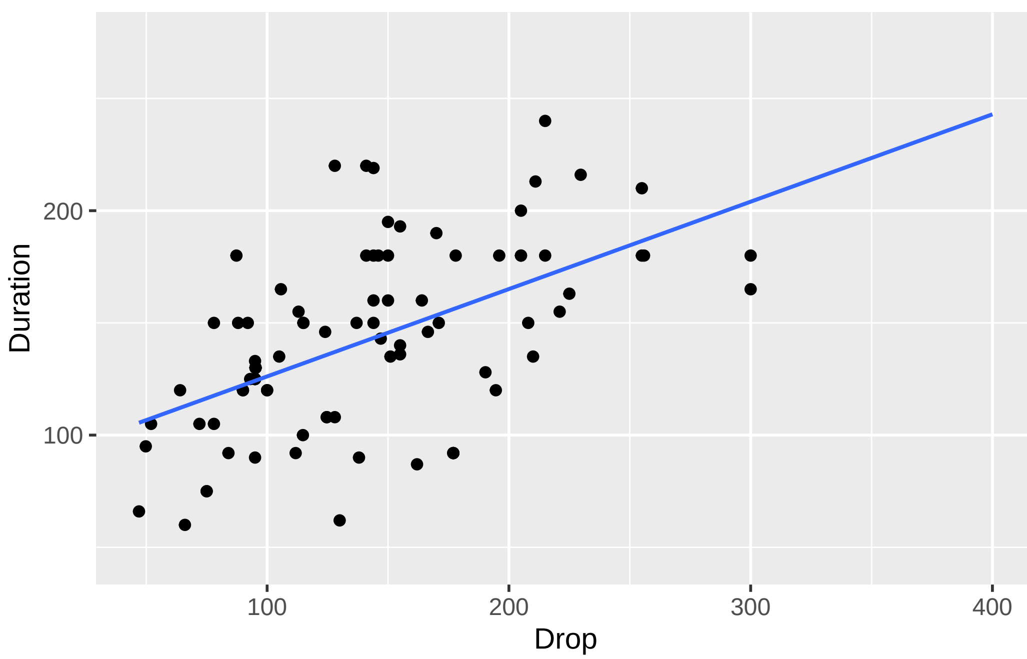
Section 9.5: Indicator Variables

```r
Coasters <- read_csv("http://nhorton.people.amherst.edu/is5/data/Coasters_2015.csv")
# Table 9.2, page 288
head(Coasters)
```

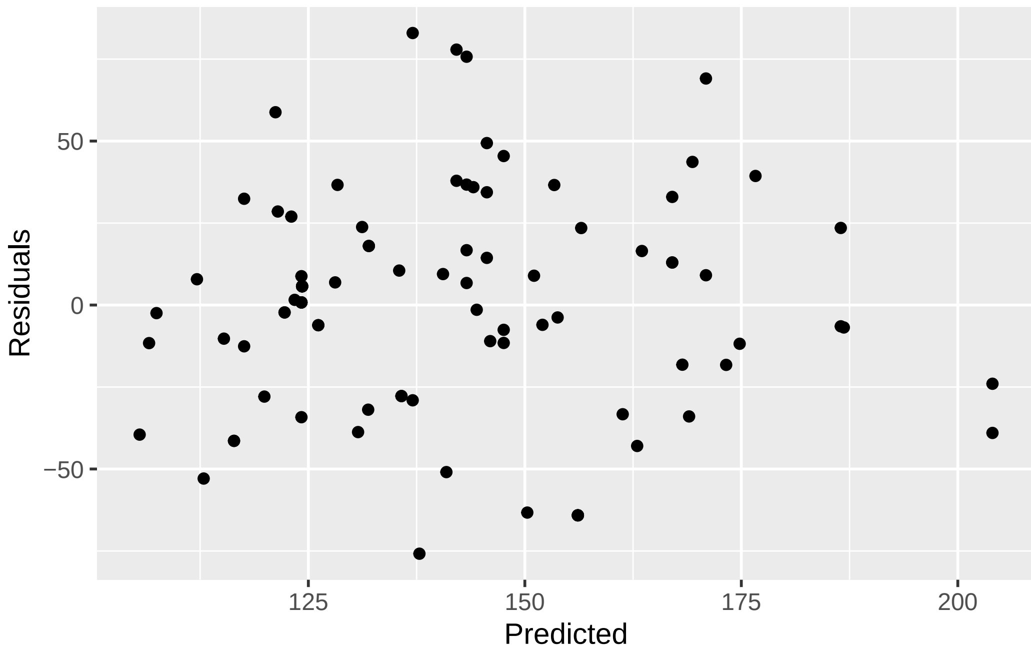
```
# A tibble: 6 x 9
  Name                Park   Track Speed Height  Drop Length Duration Inversions
  <chr>               <chr>  <chr> <dbl>  <dbl> <dbl>  <dbl>    <dbl>      <dbl>
1 Top Thrill Dragster Cedar~ Steel   120    420  400    2800       NA          0
2 Superman The Escap  Six F~ Steel   100    415  328.   1235       NA          0
3 Millennium Force    Cedar~ Steel    93    310  300    6595      165          0
4 Goliath             Six F~ Steel    85    235  255    4500      180          0
5 Titan               Six F~ Steel    85    245  255    5312      210          0
6 Phantom's Revenge   Kenny~ Steel    82    160  228    3200       NA          0
```

```r
# Figure 9.7
# Tower of Terror isn't included by the book, so we need to drop it
Coasters <- Coasters |>
  filter(Name != "Tower of Terror") |>
  mutate(Inversions = as.factor(Inversions)) # turn the variable into a factor
```

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



```r
coasterlm <- lm(Duration ~ Drop, data = Coasters)
gf_point(resid(coasterlm) ~ fitted(coasterlm)) |>
  gf_labs(x = "Predicted", y = "Residuals")
```



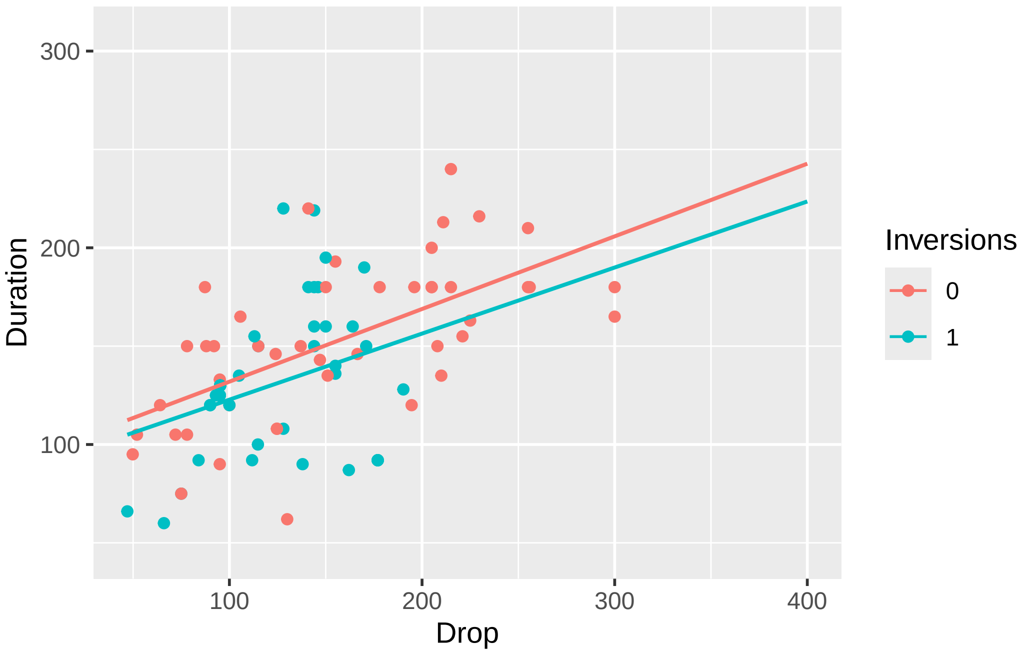

```r
msummary(coasterlm)
```

```
            Estimate Std. Error t value Pr(>|t|)
(Intercept) 87.22005    9.73524   8.959 4.98e-14 ***
Drop         0.38928    0.06428   6.056 3.36e-08 ***

Residual standard error: 34.06 on 88 degrees of freedom
  (150 observations deleted due to missingness)
Multiple R-squared:  0.2942,	Adjusted R-squared:  0.2862
F-statistic: 36.68 on 1 and 88 DF,  p-value: 3.356e-08
```

```r
# Figure 9.8
gf_point(Duration ~ Drop, color = ~Inversions, data = Coasters) |>
  gf_lm() |>
  gf_labs(color = "Inversions")
```

```
Warning: Removed 150 rows containing non-finite outside the scale range
(`stat_lm()`).
```

```
Warning: Removed 150 rows containing missing values or values outside the scale range
(`geom_point()`).
```



Here it would be appropriate to add `warning: false` as a code chunk option once we've verified that there are indeed 150 observations missing

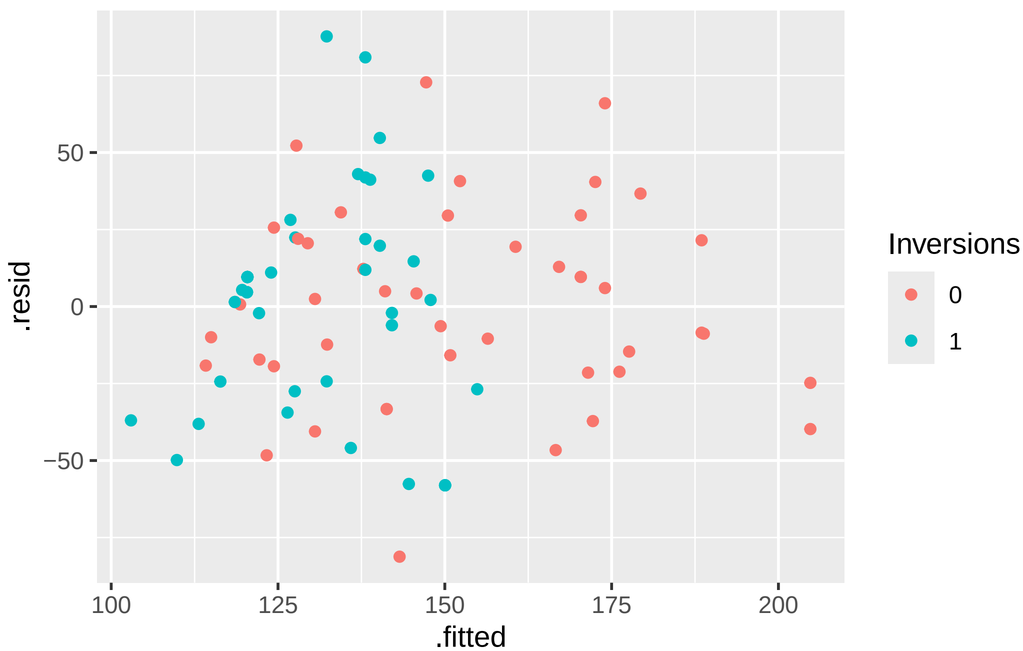
```
coasterlm2 <- lm(Duration ~ Drop + Inversions, data = Coasters)
msummary(coasterlm2)
```

```
             Estimate Std. Error t value Pr(>|t|)
(Intercept)  96.14026   11.69140   8.223 1.74e-12 ***
Drop          0.36215    0.06699   5.406 5.58e-07 ***
Inversions1 -10.20093    7.48401  -1.363    0.176

Residual standard error: 33.9 on 87 degrees of freedom
  (150 observations deleted due to missingness)
Multiple R-squared:  0.3089,    Adjusted R-squared:  0.293
F-statistic: 19.45 on 2 and 87 DF,  p-value: 1.045e-07
```

```
coasterlm2asdata <- broom::augment(coasterlm2) # another helpful function
broom::glance(coasterlm2) |> data.frame()
```

```
  r.squared adj.r.squared    sigma statistic     p.value df    logLik      AIC
1 0.3089346      0.293048 33.89636  19.44628 1.04492e-07  2 -443.2766 894.5532
       BIC deviance df.residual nobs
1 904.5524 99959.82          87   90
```

```
gf_point(.resid ~ .fitted, color = ~ Inversions, data = coasterlm2asdata)
```

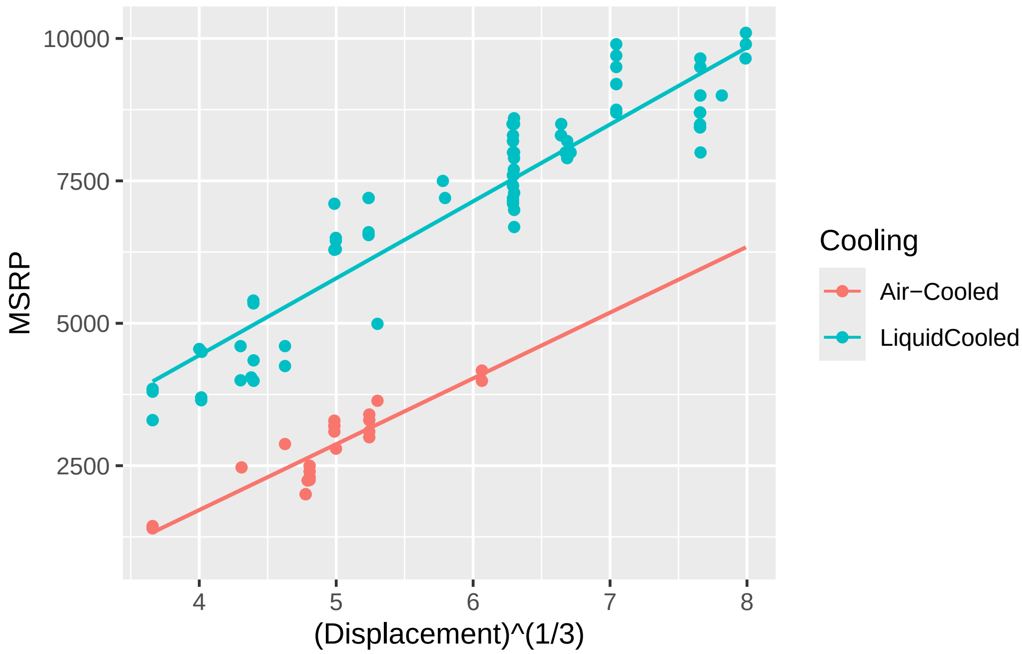


The `augment()` function from the `broom` package creates a data frame from a linear model that includes a column for residuals, fitted values, etc. Here we use `names()` to check out the column names and `glance()` to view the structure of the data set.

Example 9.3: Using Indicator Variables

We can explore the use of indicator variables to model categorical variables.

```
DirtBikes <- read_csv("http://nhorton.people.amherst.edu/is5/data/Dirt_bikes_2014.csv")
DirtBikes <- DirtBikes |>
  filter(Cooling != "NA") |>
  mutate(Cooling = ifelse(Cooling == "Air-Cooled", "Air-Cooled", "LiquidCooled"))
gf_point(MSRP ~ (Displacement)^(1 / 3), color = ~ Cooling, data = DirtBikes) |>
  gf_lm()
```




```r
bikeslm <- lm(MSRP ~ I(Displacement^(1 / 3)) + Cooling, data = DirtBikes)
msummary(bikeslm)
```

```
                        Estimate Std. Error t value Pr(>|t|)
(Intercept)              -3814.9      278.0  -13.72   <2e-16 ***
I(Displacement^(1/3))     1341.4       50.4   26.61   <2e-16 ***
CoolingLiquidCooled       2908.1      154.0   18.88   <2e-16 ***

Residual standard error: 602.7 on 106 degrees of freedom
Multiple R-squared:  0.9423,    Adjusted R-squared:  0.9413
F-statistic: 866.3 on 2 and 106 DF,  p-value: < 2.2e-16
```

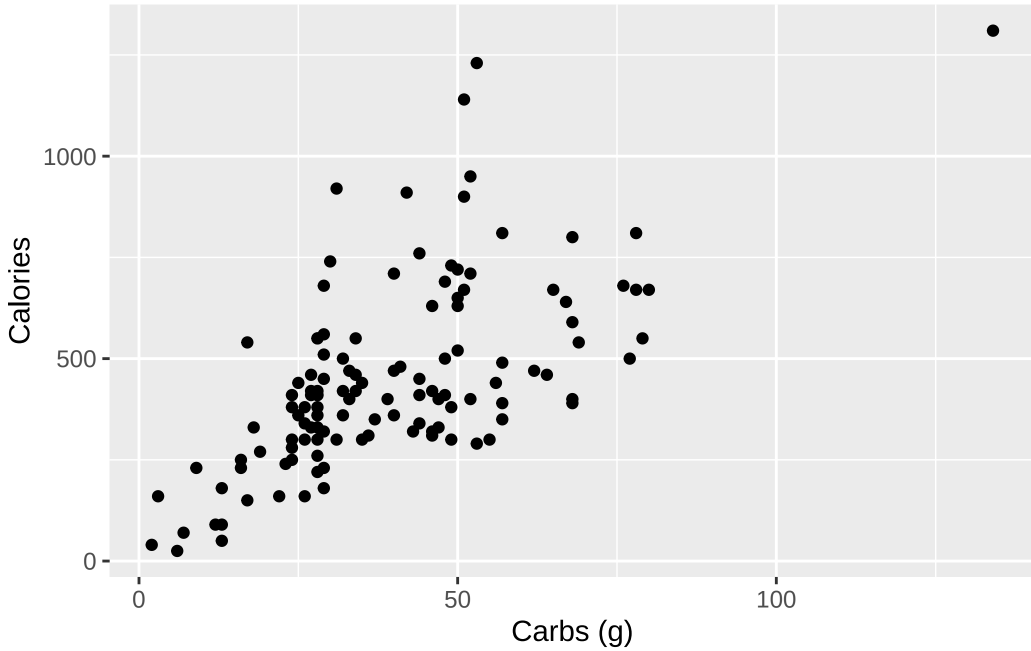
The `I()` function is used to keep the class of an object the same. Here we use it to keep the variable `Displacement` "as is" to prevent an error.

Adjusting for Different Slopes

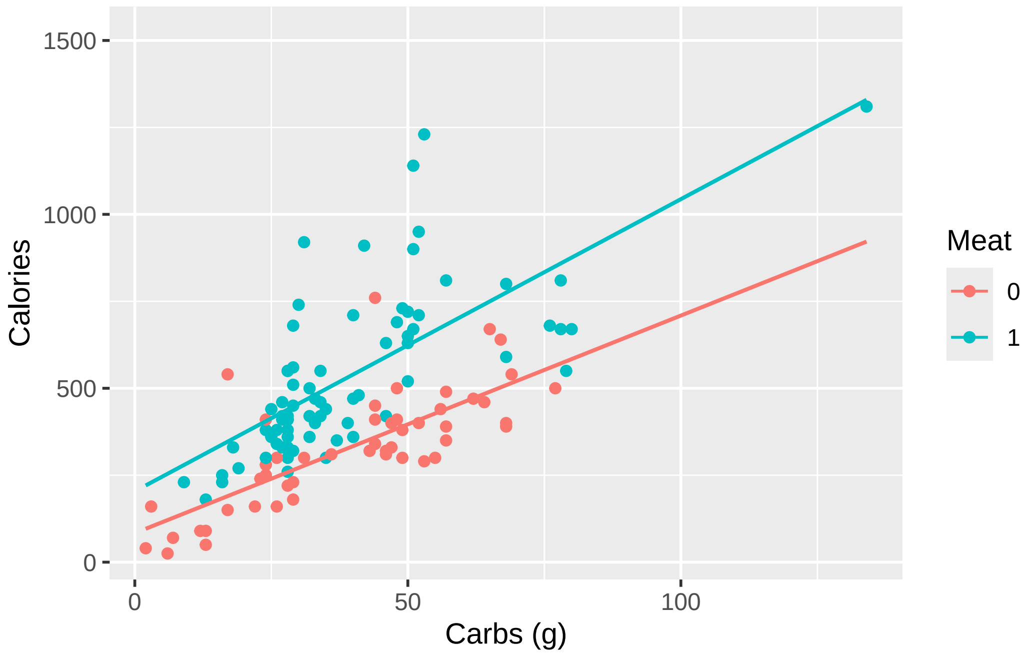
We can fit a model with different slopes.

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

```r
# Figure 9.9, page 292
gf_point(calories ~ carbs_g, data = BurgerKing) |>
  gf_labs(x = "Carbs (g)", y = "Calories")
```




```r
# Figure 9.10
gf_point(calories ~ carbs_g, color = ~ as.factor(meat), data = BurgerKing) |>
  gf_labs(x = "Carbs (g)", y = "Calories", color = "Meat") |>
  gf_lm()
```




```
msummary(lm(calories ~ carbs_g * as.factor(meat), data = BurgerKing))
```

```
                         Estimate Std. Error t value Pr(>|t|)    
(Intercept)                83.533     46.955   1.779   0.0778 .  
carbs_g                     6.255      1.063   5.885 3.81e-08 ***
as.factor(meat)1          120.220     60.694   1.981   0.0499 *  
carbs_g:as.factor(meat)1    2.145      1.378   1.557   0.1222    

Residual standard error: 146.5 on 118 degrees of freedom
Multiple R-squared:  0.6072,	Adjusted R-squared:  0.5972 
F-statistic:  60.8 on 3 and 118 DF,  p-value: < 2.2e-16
```

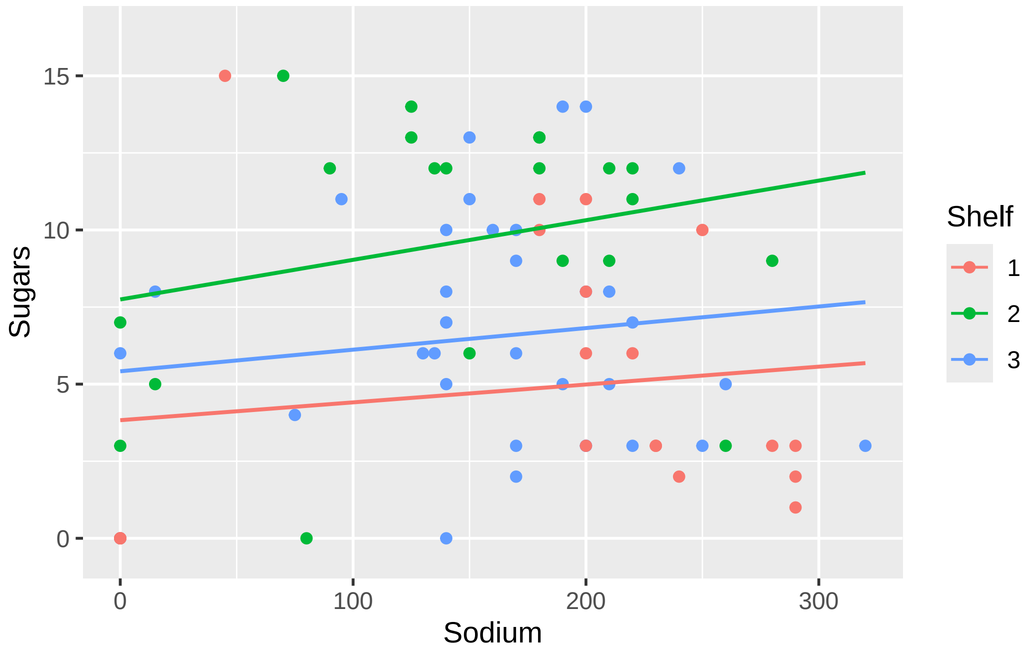
The output here is a bit ugly: it would be straightforward to create the new variables using `mutate()` to provide easier to read output.

One, Two, Many

We can also consider three level variables.

```
Cereal <- read_csv("http://nhorton.people.amherst.edu/is5/data/Cereals.csv")
cereallm <- lm(sugars ~ sodium + as.factor(shelf), data = Cereal)
gf_point(sugars ~ sodium, color = ~ as.factor(shelf), data = Cereal) |>
```

```
  gf_lm() |>
  gf_labs(x = "Sodium", y = "Sugars", color = "Shelf")
```




```
msummary(cereallm)
```

```
                   Estimate Std. Error t value Pr(>|t|)
(Intercept)        3.446740   1.345111   2.562 0.012457 *
sodium             0.007962   0.005620   1.417 0.160818
as.factor(shelf)2 5.012166   1.283154   3.906 0.000207 ***
as.factor(shelf)3 1.818214   1.139384   1.596 0.114857

Residual standard error: 4.07 on 73 degrees of freedom
Multiple R-squared:  0.1866,    Adjusted R-squared:  0.1532
F-statistic: 5.583 on 3 and 73 DF,  p-value: 0.001669
```

Example 9.4: Indicators for Variables with Several Levels

We will read in the diamonds data.

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

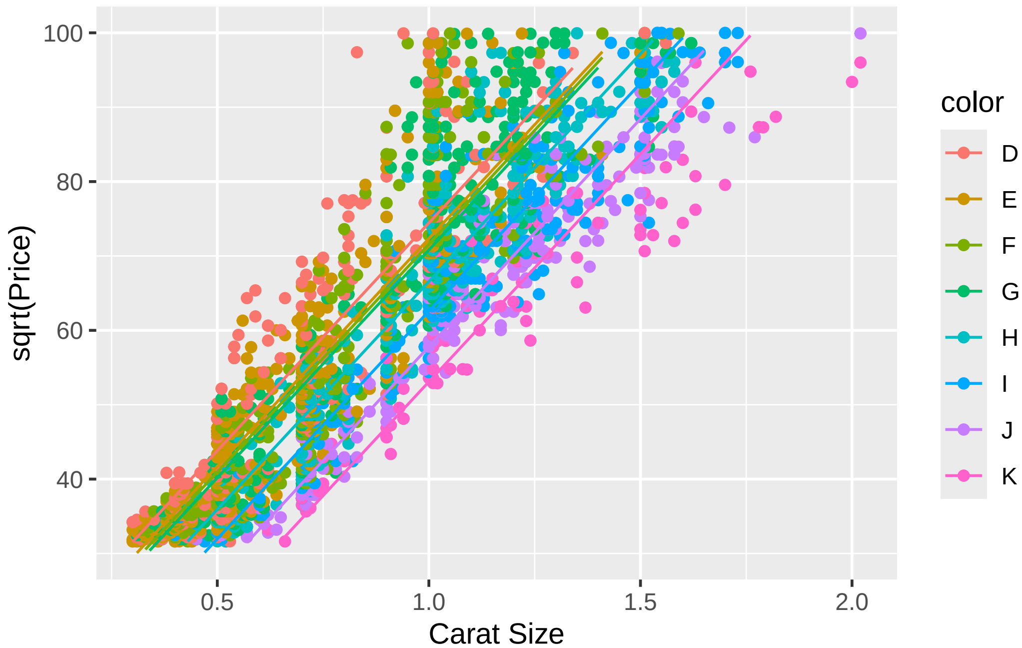
```r
# Parallel Slopes
diamondlm <- lm(sqrt(price) ~ carat_size + color, data = Diamonds)
msummary(diamondlm)
```

```
             Estimate Std. Error t value Pr(>|t|)
(Intercept)  13.1946     0.5488  24.043  < 2e-16 ***
carat_size   61.2491     0.5032 121.722  < 2e-16 ***
colorE       -2.1027     0.5399  -3.895 0.000101 ***
colorF       -2.8640     0.5576  -5.136 3.00e-07 ***
colorG       -3.6320     0.5769  -6.296 3.57e-10 ***
colorH       -7.8948     0.5858 -13.477  < 2e-16 ***
colorI      -11.8542     0.6261 -18.932  < 2e-16 ***
colorJ      -16.6404     0.6637 -25.071  < 2e-16 ***
colorK      -21.3577     0.8282 -25.787  < 2e-16 ***

Residual standard error: 7.218 on 2681 degrees of freedom
Multiple R-squared:  0.8583,    Adjusted R-squared:  0.8579
F-statistic:  2030 on 8 and 2681 DF,  p-value: < 2.2e-16
```

```r
diamondpredict <- makeFun(diamondlm)

diamonddata <- augment(diamondlm) |> # To get fitted values
  janitor::clean_names()
glimpse(diamonddata)
```

```
Rows: 2,690
Columns: 9
$ sqrt_price <dbl> 31.62278, 31.62278, 31.62278, 31.62278, 31.62278, 31.62278,~
$ carat_size <dbl> 0.30, 0.44, 0.31, 0.66, 0.47, 0.40, 0.36, 0.52, 0.53, 0.43,~
$ color      <chr> "E", "E", "E", "K", "H", "G", "D", "H", "D", "F", "F", "F",~
$ fitted     <dbl> 29.46659, 38.04146, 30.07908, 32.26133, 34.08682, 34.06221,~
$ resid      <dbl> 2.1561877, -6.4186795, 1.5436972, -0.6385503, -2.4640456, -~
$ hat        <dbl> 0.002687088, 0.002264823, 0.002650609, 0.009594672, 0.00374~
$ sigma      <dbl> 7.219488, 7.218542, 7.219547, 7.219598, 7.219451, 7.219454,~
$ cooksd     <dbl> 2.678455e-05, 1.998882e-04, 1.354152e-05, 8.505241e-06, 4.8~
$ std_resid  <dbl> 0.29911501, -0.89023651, 0.21414395, -0.08889063, -0.342003~
```

```r
gf_point(sqrt_price ~ carat_size, color = ~ color, data = diamonddata) |>
  gf_line(fitted ~ carat_size) |>
  gf_labs(x = "Carat Size", y = "sqrt(Price)") +
  ylim(30, 100)
```




```r
# With interaction
diamondlm2 <- lm(sqrt(price) ~ carat_size * color, data = Diamonds)
msummary(diamondlm2)
```

```
                   Estimate Std. Error t value Pr(>|t|)
(Intercept)          9.3239     1.2142   7.679 2.23e-14 ***
carat_size          67.0408     1.7025  39.379  < 2e-16 ***
colorE              -0.5392     1.5075  -0.358  0.72063
colorF              -2.3716     1.5627  -1.518  0.12922
colorG              -2.6709     1.6643  -1.605  0.10867
colorH              -3.9177     1.8248  -2.147  0.03189 *
colorI              -2.5481     1.9301  -1.320  0.18689
colorJ              -5.4176     2.0716  -2.615  0.00897 **
colorK               0.5976     2.7815   0.215  0.82991
carat_size:colorE   -2.4007     2.0999  -1.143  0.25305
carat_size:colorF   -1.3211     2.0954  -0.630  0.52843
carat_size:colorG   -2.5457     2.0868  -1.220  0.22260
carat_size:colorH   -5.9017     2.1774  -2.710  0.00676 **
carat_size:colorI  -10.9139     2.1812  -5.004 5.99e-07 ***
carat_size:colorJ  -12.4948     2.2531  -5.546 3.22e-08 ***
carat_size:colorK  -21.4477     2.6978  -7.950 2.72e-15 ***

Residual standard error: 7.058 on 2674 degrees of freedom
```

```
Multiple R-squared:  0.8649,	Adjusted R-squared:  0.8641 
F-statistic:  1141 on 15 and 2674 DF,  p-value: < 2.2e-16
```

```
gf_point(sqrt(price) ~ carat_size, color = ~ color, data = Diamonds) |>
  gf_lm() |>
  gf_labs(x = "Carat Size", y = "sqrt(Price)") +
  ylim(30, 100)
```