IPS9 in R: Looking at Data – Relations (Chapter 2)

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Introduction and background

These documents are intended to help describe how to undertake analyses introduced as examples in the Ninth Edition of *Introduction to the Practice of Statistics* (2017) by Moore, McCabe, and Craig.

More information about the book can be found here. The data used in these documents can be found under Data Sets in the Student Site. This file as well as the associated R Markdown reproducible analysis source file used to create it can be found at https://nhorton.people.amherst.edu/ips9/.

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 (http://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.

Chapter 2: Looking at Data – Relationships

This file replicates the analyses from 2: Looking at Data – Relationships.

First, load the packages that will be needed for this document:

```
library(mosaic)
library(readr)
```

Section 2.1: Relationships

Section 2.2: Scatterplots

Example 2.8: Laundry detergents

```
Laundry <- read_csv("https://nhorton.people.amherst.edu/ips9/data/chapter02/EG02-008LAUNDRY.csv")
```

```
## Parsed with column specification:
## cols(
##   Price = col_integer(),
##   Rating = col_integer(),
##   Type = col_character()
## )
```

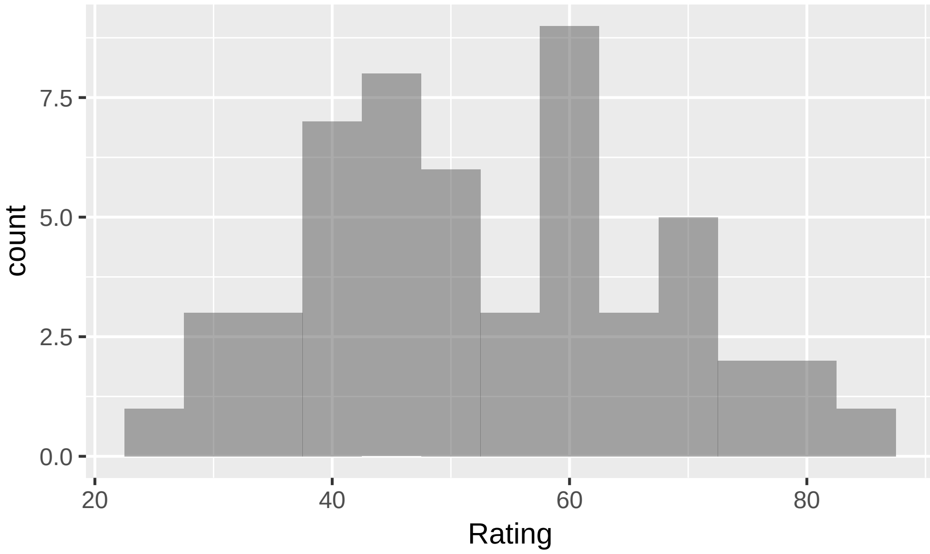
We use `read_csv()` from the `readr` package to import data into R.

```
# 2.10: Examine the spreadsheet
favstats(~ Rating, data = Laundry)
```

```
##  min Q1 median Q3 max     mean       sd  n missing
##   25 42     51 61  85 53.01887 14.25387 53       0
```

The `favstats()` function shows properties of variables.

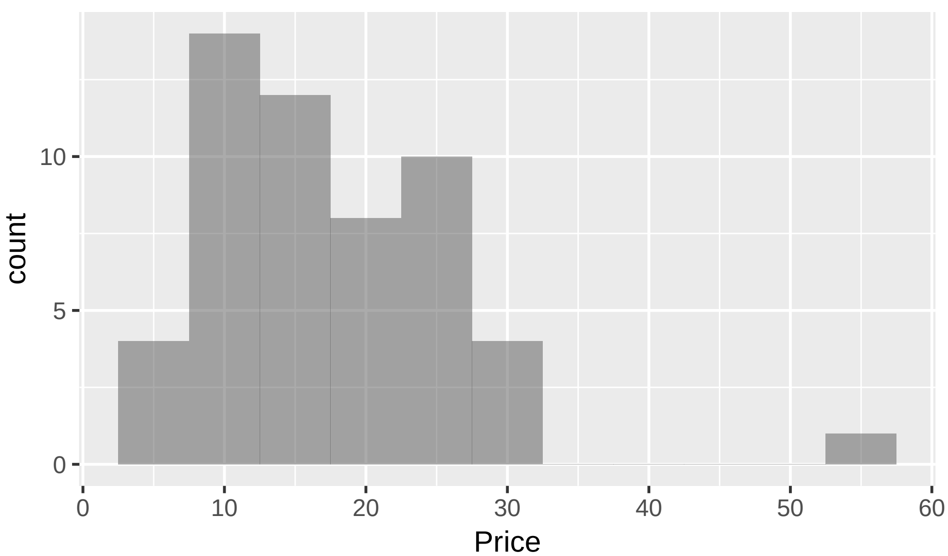
```r
gf_histogram(~ Rating, data = Laundry, binwidth = 5)
```




```r
favstats(~ Price, data = Laundry)
```

```
##  min Q1 median Q3 max     mean       sd  n missing
##    5 12     14 24  56 17.37736 8.838783 53       0
```

```r
gf_histogram(~ Price, data = Laundry, binwidth = 5)
```

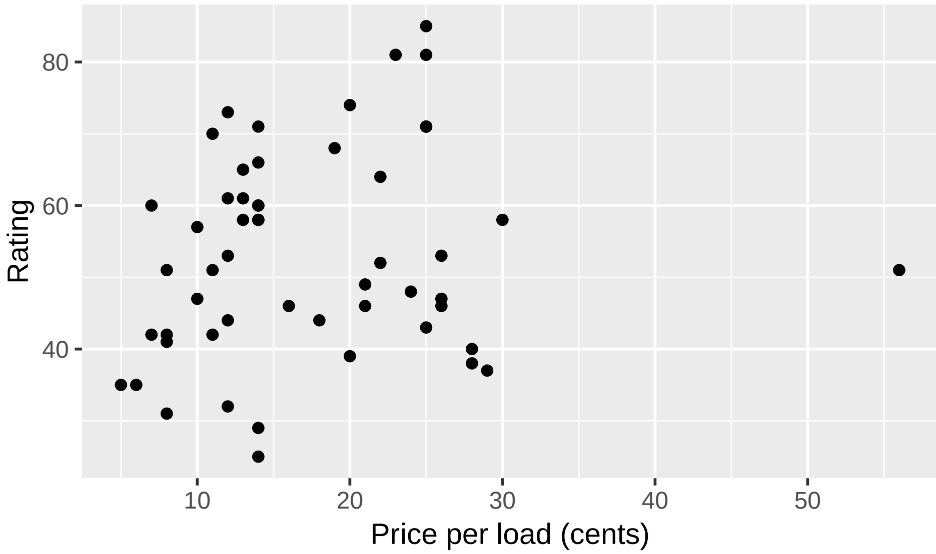


Example 2.9: Laundry detergents

```r
Laundry <- read_csv("https://nhorton.people.amherst.edu/ips9/data/chapter02/EG02-009LAUNDRY.csv")
```

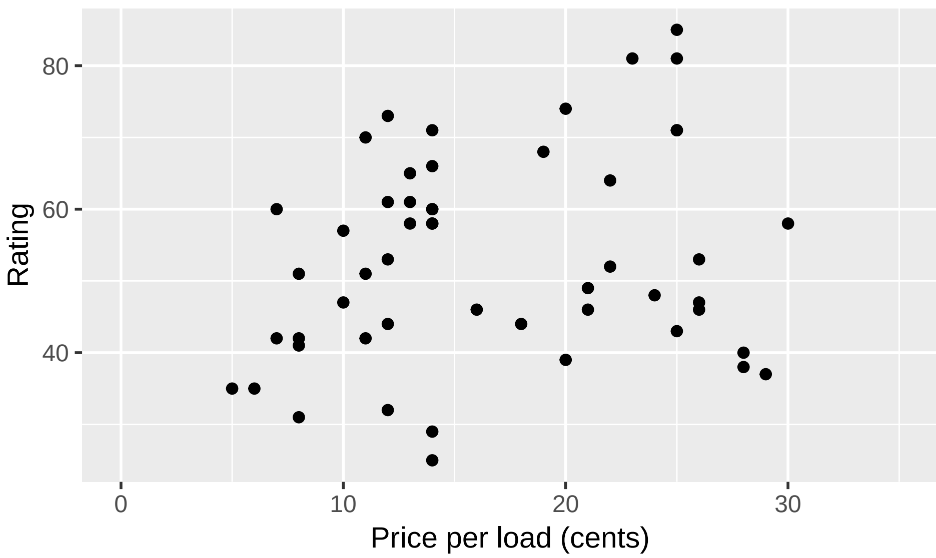
```
## Parsed with column specification:
## cols(
##   Price = col_integer(),
##   Rating = col_integer(),
##   Type = col_character()
## )
```

```r
# Figure 2.1, page 86
gf_point(Rating ~ Price, data = Laundry, xlab = "Price per load (cents)")
```



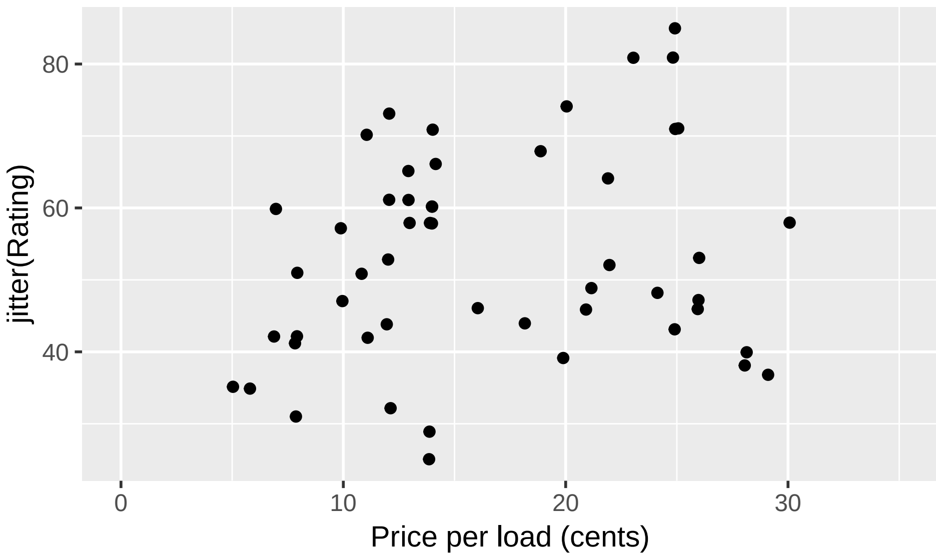

```r
# Figure 2.2
gf_point(Rating ~ Price, data = Laundry, xlab = "Price per load (cents)") %>%
  gf_lims(x = c(0, 35))
```

```
## Warning: Removed 1 rows containing missing values (geom_point).
```




```r
# 2.12: Make a scatterplot
gf_point(jitter(Rating) ~ jitter(Price), data = Laundry, xlab = "Price per load (cents)") %>%
  gf_lims(x = c(0, 35))
```

```
## Warning: Removed 1 rows containing missing values (geom_point).
```




```
  xlim(0, 35)
```

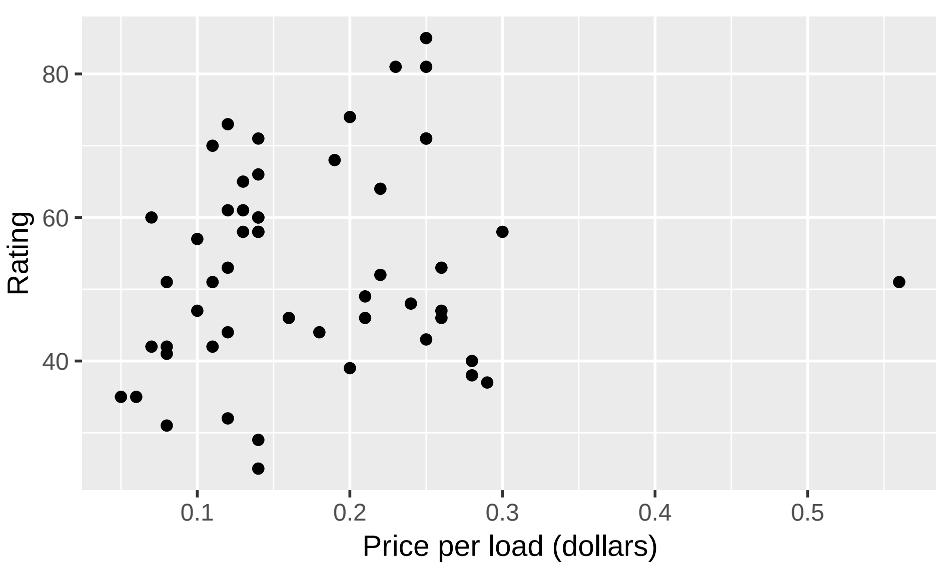
```
## <ScaleContinuousPosition>
##  Range:
##  Limits:    0 --   35
```

We can use `jitter()` to add some noise into the plot to show overlapped points.

```
# 2.13: Change the units
Laundry2 <- Laundry %>%
  mutate(Price = Price/100)
favstats(~ Price, data = Laundry2)
```

```
##   min   Q1 median   Q3  max      mean         sd  n missing
##  0.05 0.12   0.14 0.24 0.56 0.1737736 0.08838783 53       0
```

```
gf_point(Rating ~ Price, data = Laundry2, xlab = "Price per load (dollars)")
```

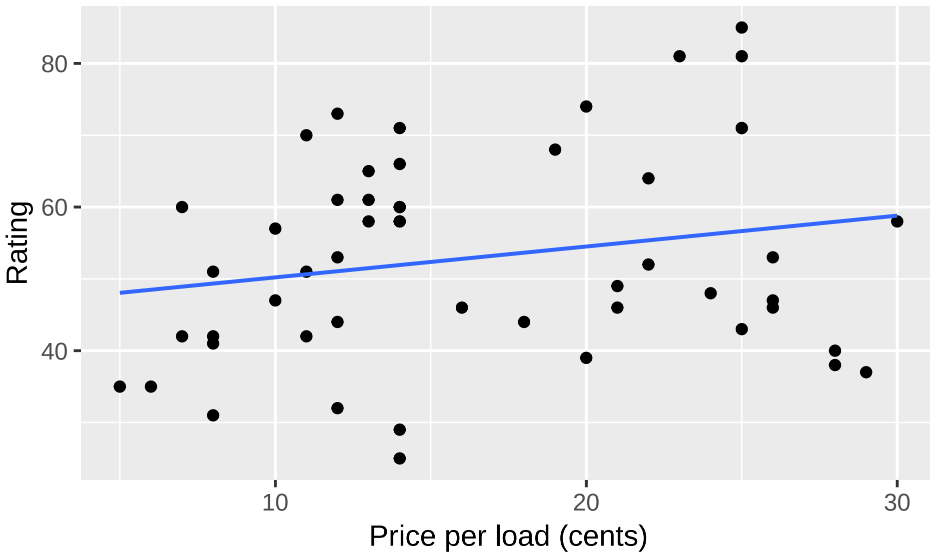


Example 2.10: Scatterplot with a straight line

```r
Laundry <- read_csv("https://nhorton.people.amherst.edu/ips9/data/chapter02/EG02-010LAUND.csv")
```

```
## Parsed with column specification:
## cols(
##   Price = col_integer(),
##   Rating = col_integer(),
##   Type = col_character()
## )
```

```r
gf_point(Rating ~ Price, data = Laundry, xlab = "Price per load (cents)") %>%
  gf_lm()
```



Example 2.11: Education spending and population: Benchmarking

```r
EduSpending <- read_csv("https://nhorton.people.amherst.edu/ips9/data/chapter02/EG02-011EDSPEND.csv")
```

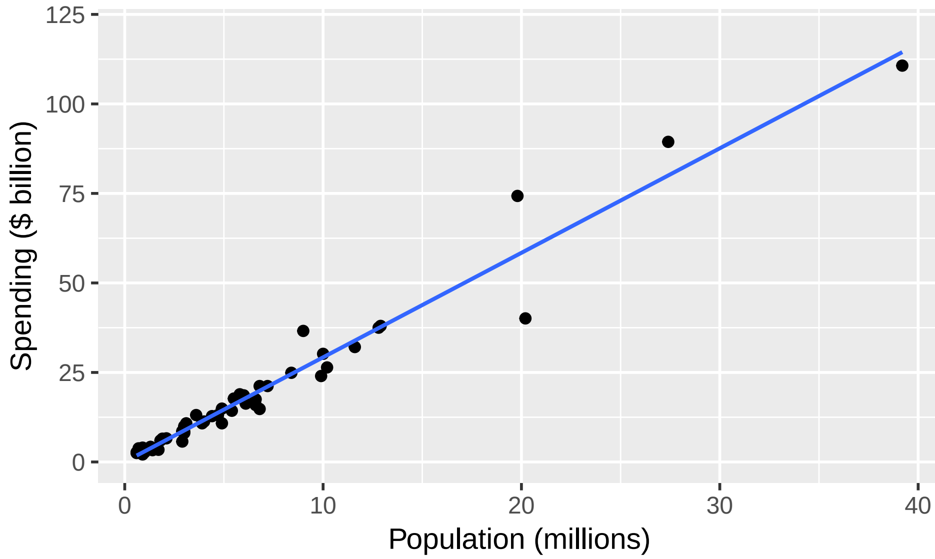
```
## Parsed with column specification:
## cols(
##   State = col_character(),
##   Spending = col_double(),
##   Population = col_double()
## )
```

```r
head(EduSpending)
```

```
## # A tibble: 6 x 3
##   State      Spending Population
##   <chr>         <dbl>      <dbl>
## 1 Alabama        14.9        4.9
## 2 Alaska          3.8        0.7
## 3 Arizona        14.8        6.8
## 4 Arkansas        8.5        3
## 5 California    111.        39.2
## 6 Colorado       14.3        5.4
```

We can use the `head()` function to look at the first rows of a data set.

```r
# Figure 2.5, page 90
gf_point(Spending ~ Population, data = EduSpending) %>%
  gf_lm() %>%
  gf_labs(x = "Population (millions)", y = "Spending ($ billion)")
```



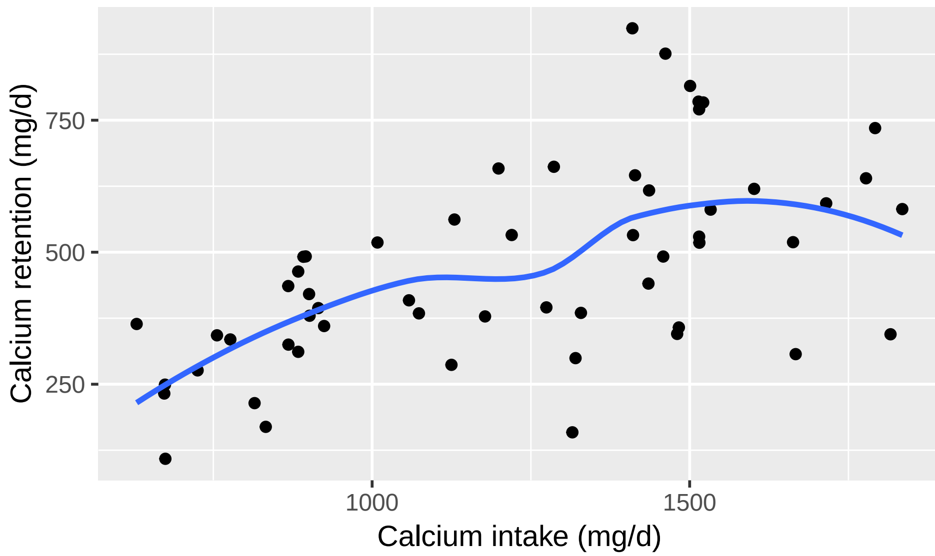
Example 2.12: Calcium retention

```r
Calcium <- read_csv("https://nhorton.people.amherst.edu/ips9/data/chapter02/EG02-012CALCIUM.csv")
```

```
## Parsed with column specification:
## cols(
##   CaIntake = col_double(),
##   CaRetention = col_double(),
##   LogRet = col_double()
## )
```

```r
# Figure 2.6
gf_point(CaRetention~ CaIntake, data = Calcium) %>%
  gf_smooth() %>%
  gf_labs(x = "Calcium intake (mg/d)", y = "Calcium retention (mg/d)")
```

```
## `geom_smooth()` using method = 'loess' and formula 'y ~ x'
```

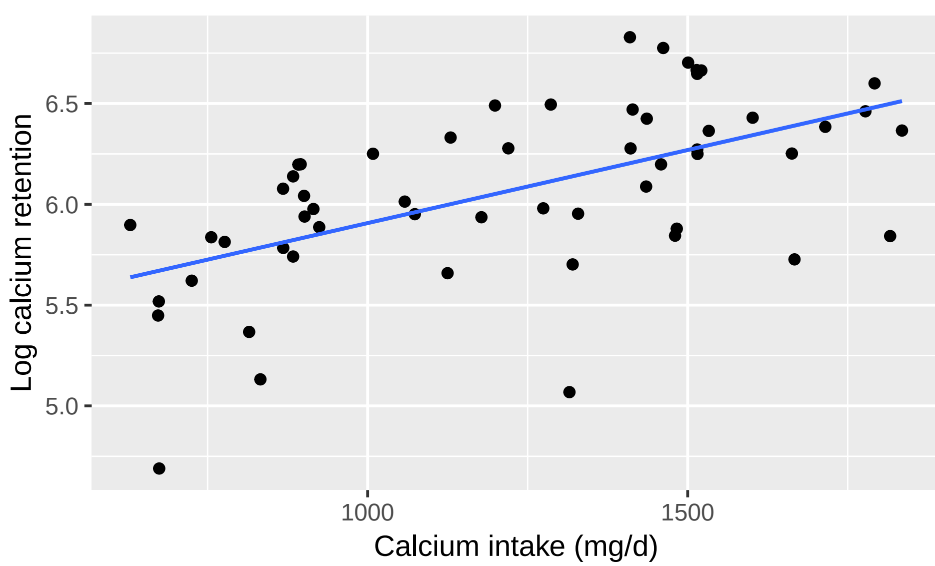


Example 2.13: Calcium retention with logarithms

```
Calcium <- read_csv("https://nhorton.people.amherst.edu/ips9/data/chapter02/EG02-013CALCIUM.csv")

## Parsed with column specification:
## cols(
##   CaIntake = col_double(),
##   CaRetention = col_double(),
##   LogRet = col_double()
## )

# Figure 2.7, page 91
gf_point(LogRet ~ CaIntake, data = Calcium) %>%
  gf_lm() %>%
  gf_labs(x = "Calcium intake (mg/d)", y = "Log calcium retention")
```

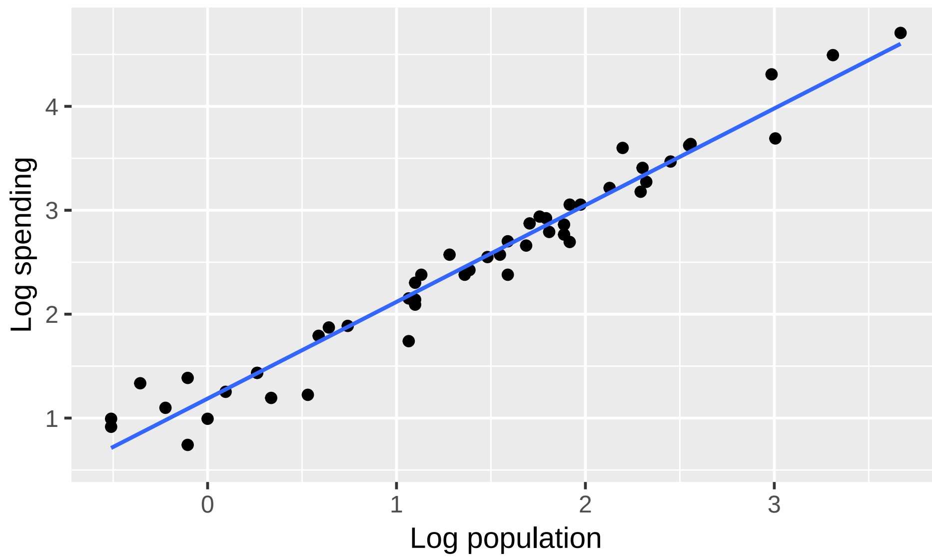


Example 2.14: Education spending and population with logarithms

```r
EduSpending <- read_csv("https://nhorton.people.amherst.edu/ips9/data/chapter02/EG02-014EDSPEND.csv")
```

```
## Parsed with column specification:
## cols(
##   State = col_character(),
##   Spending = col_double(),
##   Population = col_double()
## )
```

```r
# Figure 2.8, page 92
EduSpending %>%
  mutate(LogPop = log(Population), LogSpend = log(Spending)) %>%
  gf_point(LogSpend ~ LogPop) %>%
  gf_lm() %>%
  gf_labs(x = "Log population", y = "Log spending")
```



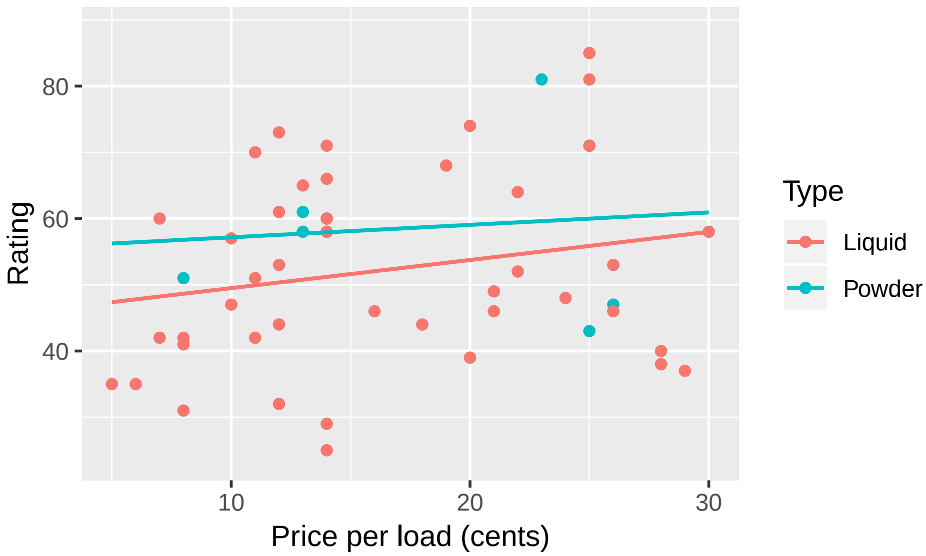
We use `mutate()` to create new variables in a dataset.

Example 2.15: Rating versus price and type of laundry detergent

```r
Laundry <- read_csv("https://nhorton.people.amherst.edu/ips9/data/chapter02/EG02-015LAUND.csv")
```

```
## Parsed with column specification:
## cols(
##   Price = col_integer(),
##   Rating = col_integer(),
##   Type = col_character()
## )
```

```r
# Figure 2.9, page 93
gf_point(Rating ~ Price, color = ~ Type, data = Laundry, xlab = "Price per load (cents)") %>%
  gf_lm()
```



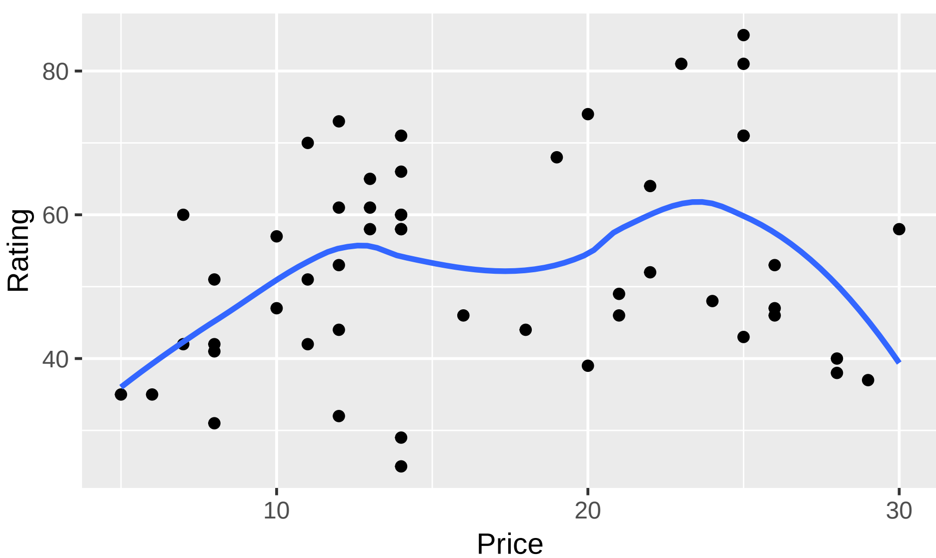
Example 2.16: Laundry rating versus price with a smooth fit

```
Laundry <- read_csv("https://nhorton.people.amherst.edu/ips9/data/chapter02/EG02-016LAUND.csv")
```

```
## Parsed with column specification:
## cols(
##   Price = col_integer(),
##   Rating = col_integer(),
##   Type = col_character()
## )
```

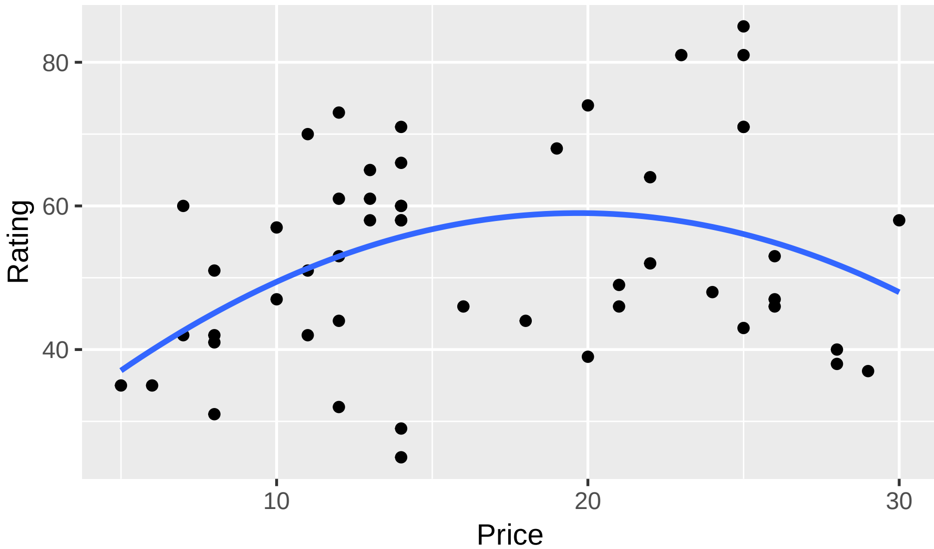
```
# Figure 2.10, page 94-95
gf_point(Rating ~ Price, data = Laundry) %>%
  gf_smooth(span = .5)
```

```
## `geom_smooth()` using method = 'loess' and formula 'y ~ x'
```




```
gf_point(Rating ~ Price, data = Laundry) %>%
  gf_smooth(span = 5)
```

```
## `geom_smooth()` using method = 'loess' and formula 'y ~ x'
```



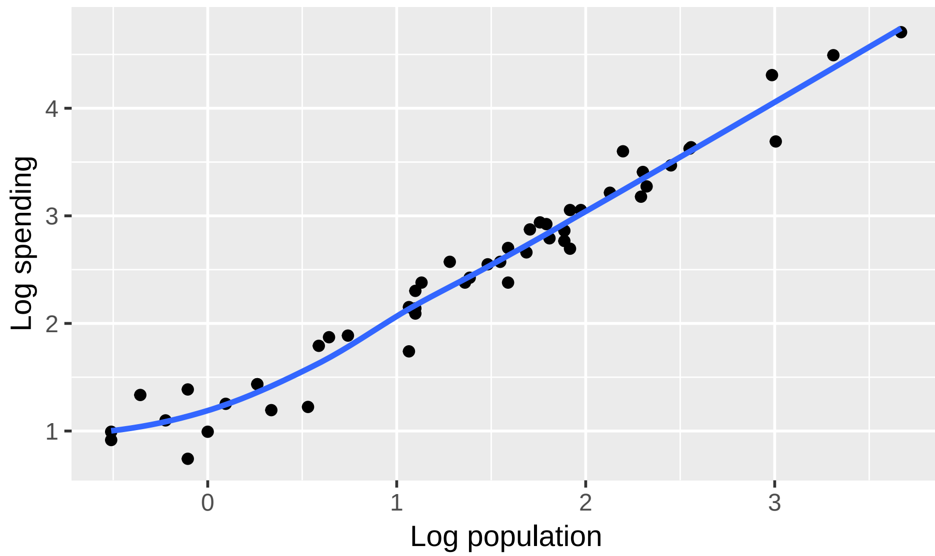
Example 2.17: A smooth fit for education spending and population with logs

```
EduSpending <- read_csv("https://nhorton.people.amherst.edu/ips9/data/chapter02/EG02-017EDSPEND.csv")
```

```
## Parsed with column specification:
## cols(
##   State = col_character(),
##   Spending = col_double(),
##   Population = col_double()
## )
```

```
# Figure 2.8, page 92
EduSpending %>%
  mutate(LogPop = log(Population), LogSpend = log(Spending)) %>%
  gf_point(LogSpend ~ LogPop) %>%
  gf_smooth() %>%
  gf_labs(x = "Log population", y = "Log spending")
```

```
## `geom_smooth()` using method = 'loess' and formula 'y ~ x'
```



Section 2.3: Correlation

Use Your Knowledge: Laundry detergents

```
# page 102
cor(Rating ~ Price, data = Laundry)
```

```
## [1] 0.2109681
```

The `cor()` function finds the correlation of two variables.

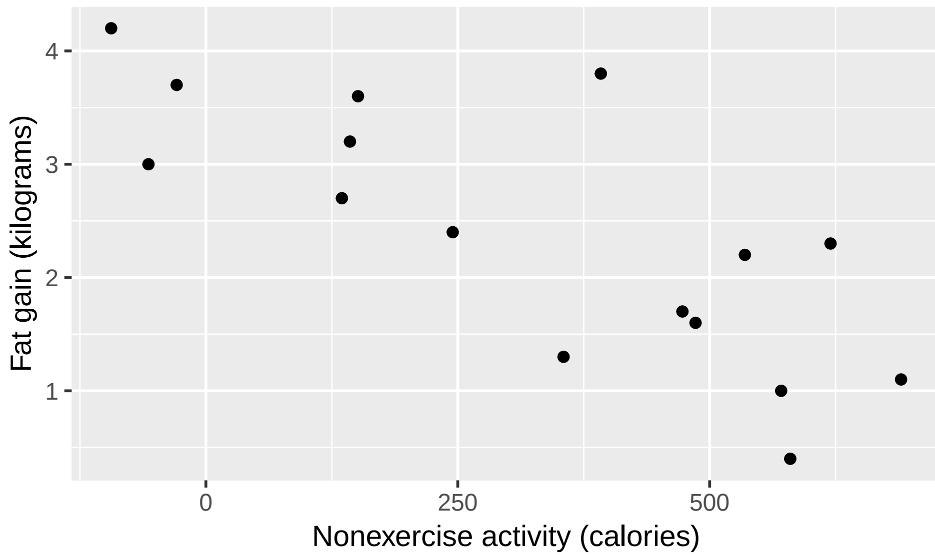
Section 2.4: Least Squares Regression

Example 2.19: Fidgeting and fat gain

```
Fidgeting <- read_csv("https://nhorton.people.amherst.edu/ips9/data/chapter02/EG02-019FIDGET.csv")
```

```
## Parsed with column specification:
## cols(
##   NEA = col_integer(),
##   Fat = col_double(),
##   Resid = col_double()
## )
```

```
# Figure 2.16, page 108
gf_point(Fat ~ NEA, data = Fidgeting) %>%
  gf_labs(x = "Nonexercise activity (calories)", y = "Fat gain (kilograms)")
```

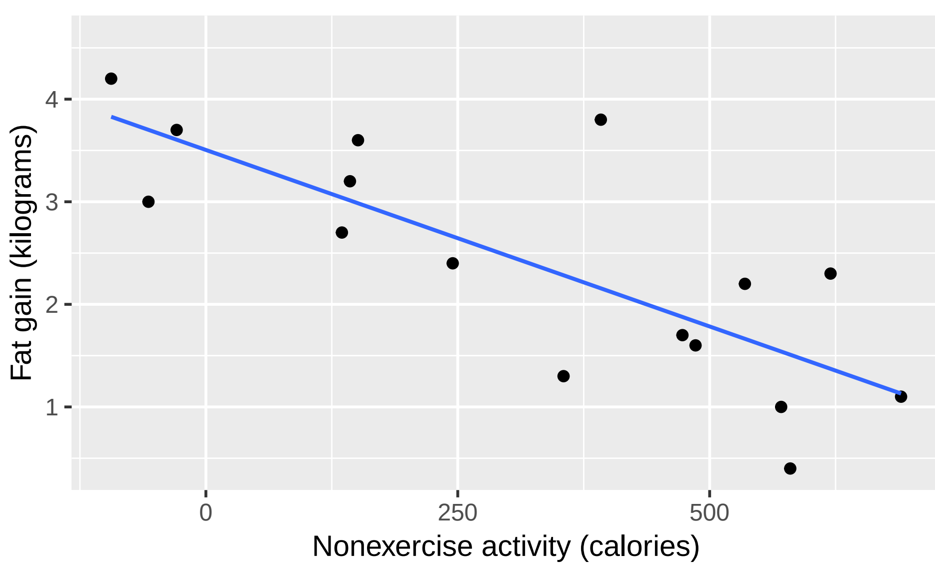


Example 2.20: Regression line for fat gain

```
Fidgeting <- read_csv("https://nhorton.people.amherst.edu/ips9/data/chapter02/EG02-020FIDGET.csv")
```

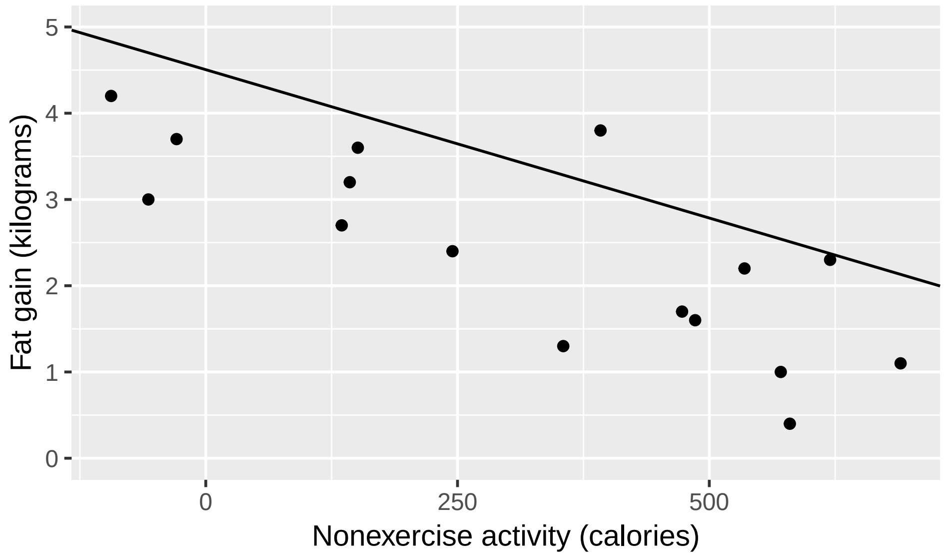
```
## Parsed with column specification:
## cols(
##   NEA = col_integer(),
##   Fat = col_double(),
##   Resid = col_double()
## )
```

```
# Figure 2.17, page 109
gf_point(Fat ~ NEA, data = Fidgeting) %>%
  gf_lm() %>%
  gf_labs(x = "Nonexercise activity (calories)", y = "Fat gain (kilograms)")
```




```
# Use Your Knowledge 2.61: Plot the line
gf_point(Fat ~ NEA, data = Fidgeting) %>%
```

```
  gf_abline(slope = -.00344, intercept = 4.505) %>%
  gf_labs(x = "Nonexercise activity (calories)", y = "Fat gain (kilograms)") +
  ylim(0, 5)
```



Example 2.21: Prediction for fat gain

```
fatlm <- lm(Fat ~ NEA, data = Fidgeting)
fatfun <- makeFun(fatlm)
fatfun(NEA = 400)
```

```
##        1
## 2.128528
```

We use `makeFun()` to create a function. Here, we make a function from our linear model, created from `lm()`, so we can find the output of a certain value of `NEA`.

Example 2.24: Regression

```
# page 113
msummary(fatlm)
```

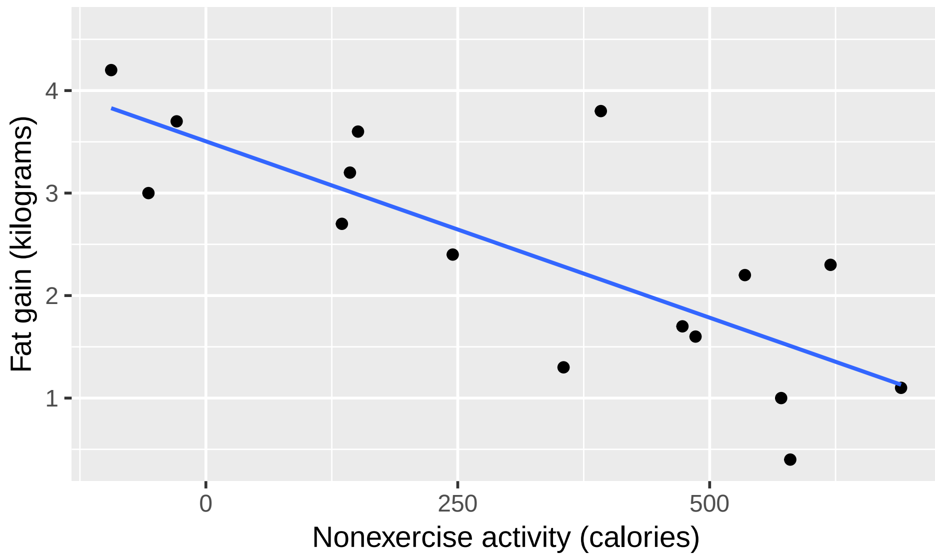
```
##                Estimate Std. Error t value Pr(>|t|)
## (Intercept)  3.5051229  0.3036164  11.545 1.53e-08 ***
## NEA         -0.0034415  0.0007414  -4.642 0.000381 ***
##
## Residual standard error: 0.7399 on 14 degrees of freedom
## Multiple R-squared:  0.6061, Adjusted R-squared:  0.578
## F-statistic: 21.55 on 1 and 14 DF,  p-value: 0.000381
```

The `msummary()` function shows the properties of the function.

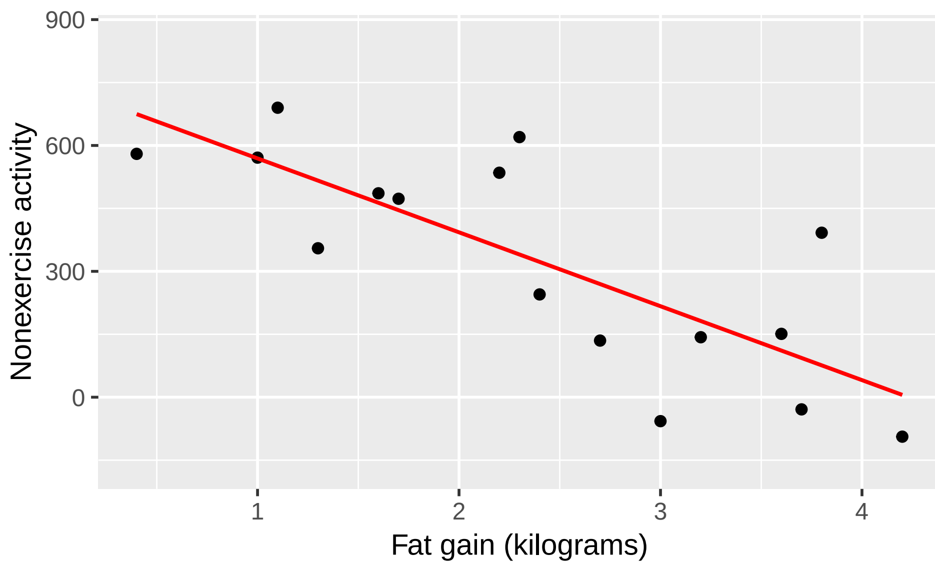
Example 2.25: Fidgeting and fat gain

```
# Figure 2.20, page 115 (split into two plots)
gf_point(Fat ~ NEA, data = Fidgeting) %>%
```

```
  gf_lm() %>%
  gf_labs(x = "Nonexercise activity (calories)", y = "Fat gain (kilograms)")
```




```
gf_point(NEA ~ Fat, data = Fidgeting) %>%
  gf_lm(color = "red") %>%
  gf_labs(x = "Fat gain (kilograms)", y = "Nonexercise activity")
```




```
# Models
fatlm
```

```
##
## Call:
## lm(formula = Fat ~ NEA, data = Fidgeting)
##
## Coefficients:
## (Intercept)          NEA
##    3.505123    -0.003441
```

```
NEAlm <- lm(NEA ~ Fat, data = Fidgeting)
NEAlm
```

```
##
## Call:
## lm(formula = NEA ~ Fat, data = Fidgeting)
##
## Coefficients:
## (Intercept)          Fat
##       745.3       -176.1
```

Section 2.5: Cautions about Correlation and Regression

Example 2.26: Residuals for fat gain

Here, we find the residual:

```
fatlm
```

```
##
## Call:
## lm(formula = Fat ~ NEA, data = Fidgeting)
##
## Coefficients:
## (Intercept)          NEA
##    3.505123    -0.003441
```

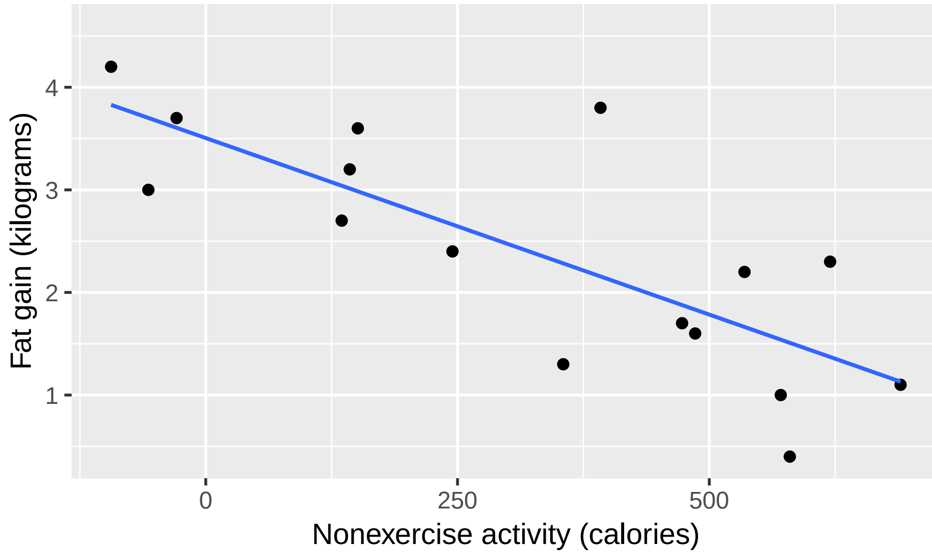
```
fatfun(NEA = 135)
```

```
##        1
## 3.040522
```

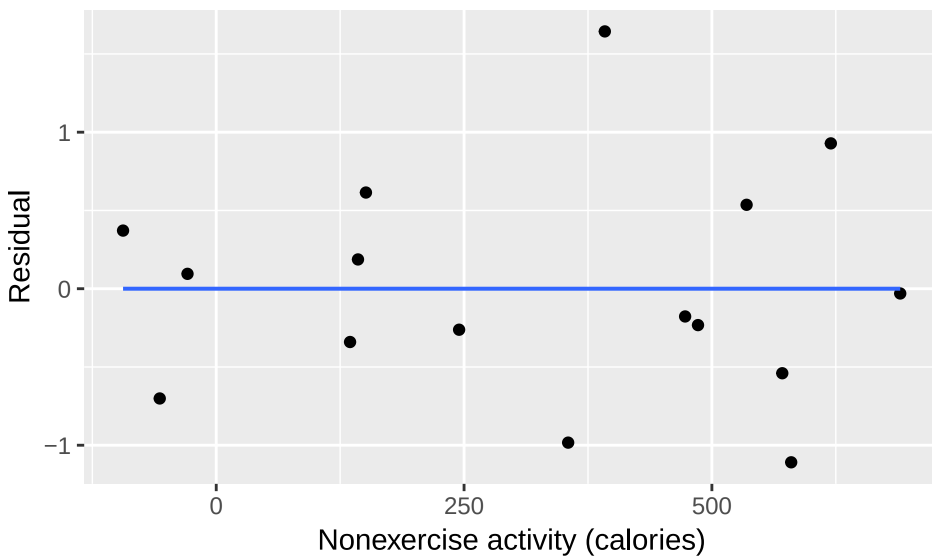
```
2.7 - fatfun(NEA = 135)
```

```
##          1
## -0.3405222
```

```
# Figure 2.23, page 124
gf_point(Fat ~ NEA, data = Fidgeting) %>%
  gf_lm() %>%
  gf_labs(x = "Nonexercise activity (calories)", y = "Fat gain (kilograms)")
```




```
gf_point(resid(fatlm) ~ NEA, data = Fidgeting) %>%
  gf_lm() %>%
  gf_labs(x = "Nonexercise activity (calories)", y = "Residual")
```

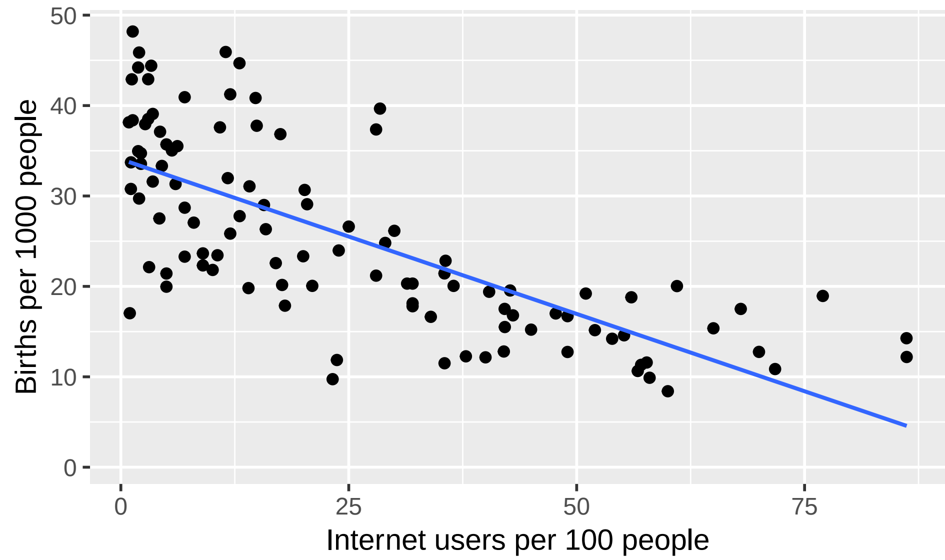


Example 2.27: Patterns in birthrate and Internet user residuals

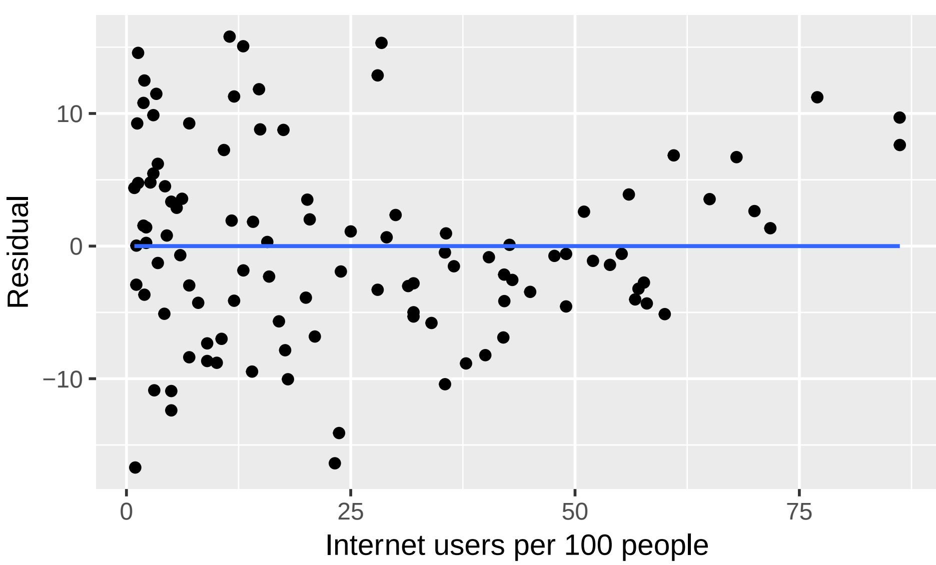
```
IntBirth <- read_csv("https://nhorton.people.amherst.edu/ips9/data/chapter02/EG02-027INBIRTH.csv")
```

```
## Parsed with column specification:
## cols(
##   Country_Name = col_character(),
##   CountryCode = col_character(),
##   BirthRate2011 = col_double(),
##   UsersPreviousYear = col_double(),
##   Users = col_double(),
##   LogBirth = col_double(),
##   LogUsers = col_double()
## )
```

```
intbirthlm <- lm(BirthRate2011 ~ Users, data = IntBirth)
# Figure 2.24, page 126
gf_point(BirthRate2011 ~ Users, data = IntBirth) %>%
  gf_lm() %>%
  gf_labs(x = "Internet users per 100 people", y = "Births per 1000 people")
```




```
gf_point(resid(intbirthlm) ~ Users, data = IntBirth) %>%
  gf_lm() %>%
  gf_labs(x = "Internet users per 100 people", y = "Residual")
```



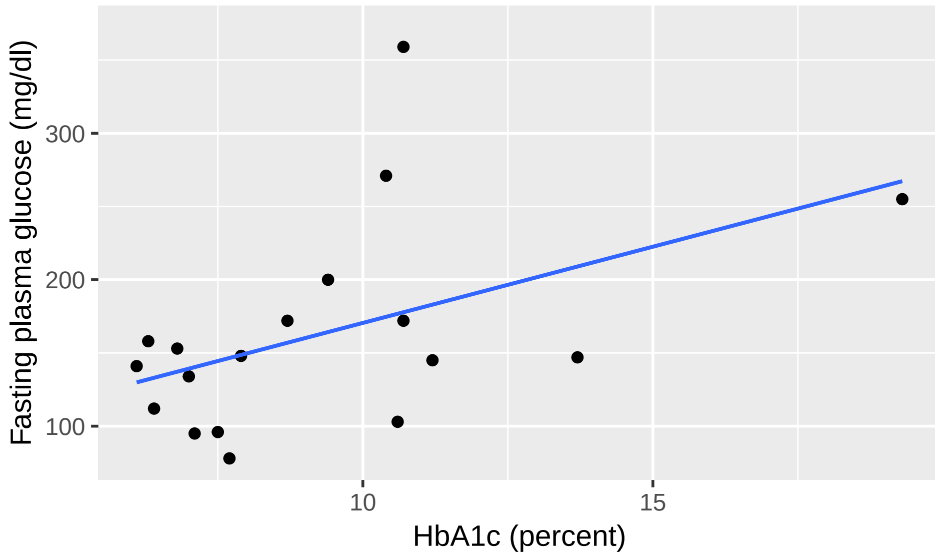
Example 2.28: Diabetes and blood sugar

```
Diabetes <- read_csv("https://nhorton.people.amherst.edu/ips9/data/chapter02/EG02-028HBA1C.csv")
```

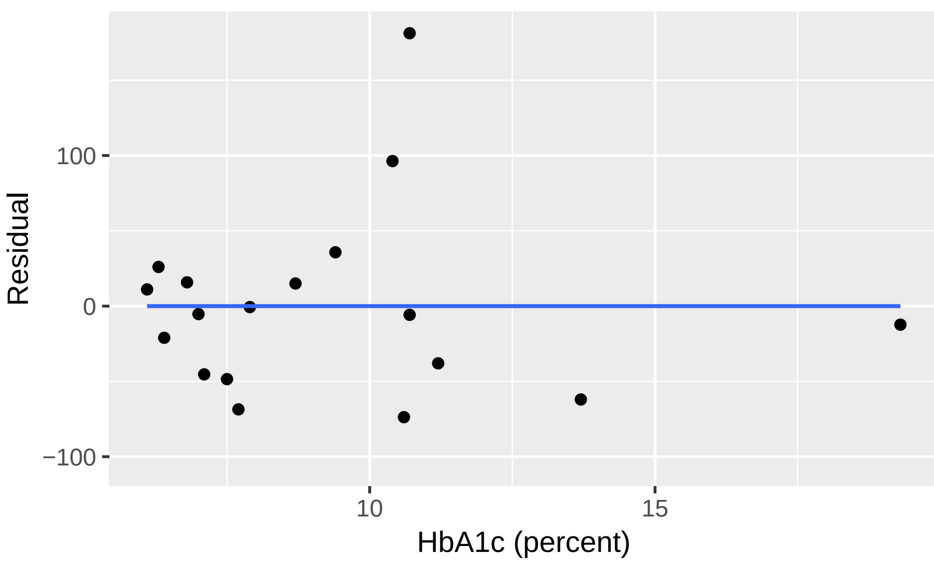
```
## Parsed with column specification:
## cols(
##   Subject = col_integer(),
##   HbA1c_percent = col_double(),
```

```
##   FPG_mg_ml = col_integer()
## )
```

```
diabeteslm <- lm(FPG_mg_ml ~ HbA1c_percent, data = Diabetes)
# Figure 2.25, page 127
gf_point(FPG_mg_ml ~ HbA1c_percent, data = Diabetes) %>%
  gf_lm() %>%
  gf_labs(x = "HbA1c (percent)", y = "Fasting plasma glucose (mg/dl)")
```




```
gf_point(resid(diabeteslm) ~ HbA1c_percent, data = Diabetes) %>%
  gf_lm() %>%
  gf_labs(x = "HbA1c (percent)", y = "Residual")
```

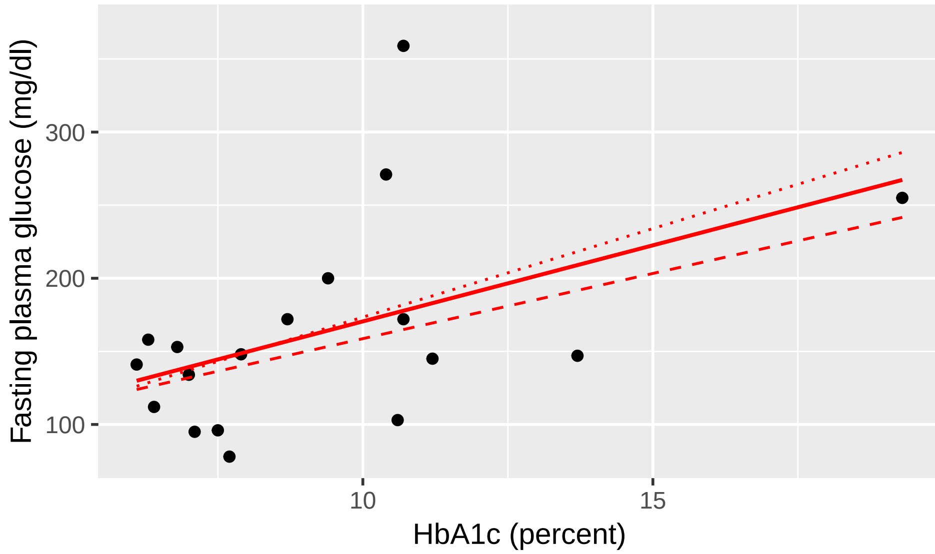


Example 2.29: Influential observations

We can use the `filter()` function to remove rows from a data set:

```
without15lm <- lm(FPG_mg_ml ~ HbA1c_percent, data = filter(Diabetes, FPG_mg_ml <= 300)) # model without
without18lm <- lm(FPG_mg_ml ~ HbA1c_percent, data = filter(Diabetes, HbA1c_percent <= 18)) # model with
```

```
# Figure 2.26, page 129
gf_point(FPG_mg_ml ~ HbA1c_percent, data = Diabetes) %>%
  gf_lm(color = "red") %>%
  gf_fun(without15lm, linetype = 2, color = "red") %>%
  gf_fun(without18lm, linetype = 3, color = "red") %>%
  gf_labs(x = "HbA1c (percent)", y = "Fasting plasma glucose (mg/dl)")
```



Section 2.6: Data Analysis from Two Way Tables

Example 2.33: Is the calcium intake adequate?

```
Calcium <- read_csv("https://nhorton.people.amherst.edu/ips9/data/chapter02/EG02-033IOM.csv")
```

```
## Parsed with column specification:
## cols(
##   Age = col_character(),
##   Met = col_character(),
##   Count = col_integer()
## )
```

```
Calcium
```

```
## # A tibble: 4 x 3
##   Age     Met   Count
##   <chr>   <chr> <int>
## 1 A05to10 No      194
## 2 A05to10 Yes     861
## 3 A11to13 No      557
## 4 A11to13 Yes     417
```

To create a data set with the structure we want (with each count as an observation), we can use `rbind()`.

```
# Creating data set from counts in the data table
CalciumC <- rbind(
 do(194) * data.frame(Age = "A05to10", Met = "No"),
 do(861) * data.frame(Age = "A05to10", Met = "Yes"),
 do(557) * data.frame(Age = "A11to13", Met = "No"),
```

```
 do(417) * data.frame(Age = "A11to13", Met = "Yes")
)

# Table
tally(Met ~ Age, data = CalciumC)
```

```
##      Age
## Met   A05to10 A11to13
##   No      194     557
##   Yes     861     417
```

Example 2.34: Add the margins to the table

```
tally(Met ~ Age, data = CalciumC, margins = TRUE)
```

```
##        Age
## Met     A05to10 A11to13
##   No        194     557
##   Yes       861     417
##   Total    1055     974
```

```
tally(Age ~ Met, data = CalciumC, margins = TRUE)
```

```
##          Met
## Age         No  Yes
##   A05to10  194  861
##   A11to13  557  417
##   Total    751 1278
```

Example 2.35: The joint distribution

```
tally(Met ~ Age, data = CalciumC, format = "proportion")
```

```
##      Age
## Met     A05to10   A11to13
##   No  0.1838863 0.5718686
##   Yes 0.8161137 0.4281314
```

```
# The tally differs from the book because they are by column
Calcium %>%
  mutate(proportion = Count/sum(Count)) %>%
  select(Age, Met, proportion)
```

```
## # A tibble: 4 x 3
##   Age     Met   proportion
##   <chr>   <chr>      <dbl>
## 1 A05to10 No        0.0956
## 2 A05to10 Yes       0.424
## 3 A11to13 No        0.275
## 4 A11to13 Yes       0.206
```

Example 2.36: The marginal distribution of age

```
tally(~ Age, data = CalciumC, format = "proportion")
```

```
## Age
##   A05to10   A11to13
## 0.5199606 0.4800394
```

Example 2.37: The marginal distribution of "met requirement"

```
tally(~ Met, data = CalciumC, format = "proportion")
```

```
## Met
##        No       Yes
## 0.3701331 0.6298669
```

Example 2.39: Conditional distribution of "met requirement" for children aged 5 to 10

```
# page 141
Calcium %>%
  filter(Age == "A05to10") %>%
  mutate(percent = Count/sum(Count)) %>%
  select(Met, percent)
```

```
## # A tibble: 2 x 2
##   Met   percent
##   <chr>   <dbl>
## 1 No      0.184
## 2 Yes     0.816
```

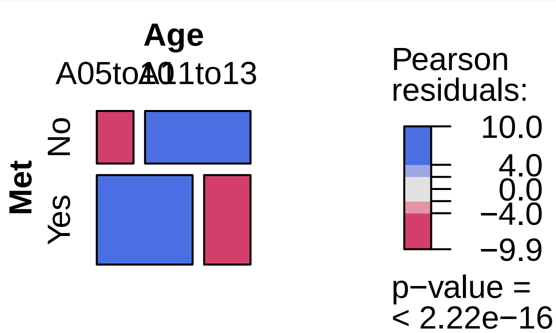
```
# use your knowledge 2.118: a conditional distribution
Calcium %>%
  filter(Age == "A11to13") %>%
  mutate(percent = Count/sum(Count)) %>%
  select(Met, percent)
```

```
## # A tibble: 2 x 2
##   Met   percent
##   <chr>   <dbl>
## 1 No      0.572
## 2 Yes     0.428
```

Example 2.40: Software output

We can use the `mosaic()` function from the `vcd` package to create mosaic plots with color.

```
# Figure 2.28 mosaic plot (page 143)
vcd::mosaic(~ Met + Age, data = CalciumC, shade = TRUE)
```



Example 2.41: Which customer service representative is better?

```
CustomerService <- read_csv("https://nhorton.people.amherst.edu/ips9/data/chapter02/EG02-041CUSTSER.csv
```

```
## Warning: Missing column names filled in: 'X4' [4], 'X9' [9]

## Warning: Duplicated column names deduplicated: 'Rep' => 'Rep_1' [5],
## 'GoalMet' => 'GoalMet_1' [6], 'Count' => 'Count_1' [8], 'Rep' =>
## 'Rep_2' [10], 'GoalMet' => 'GoalMet_2' [11], 'Week' => 'Week_1' [12],
## 'Count' => 'Count_2' [13]

## Parsed with column specification:
## cols(
##   Rep = col_character(),
##   GoalMet = col_character(),
##   Count = col_integer(),
##   X4 = col_character(),
##   Rep_1 = col_character(),
##   GoalMet_1 = col_character(),
##   Week = col_integer(),
##   Count_1 = col_integer(),
##   X9 = col_character(),
##   Rep_2 = col_character(),
##   GoalMet_2 = col_character(),
##   Week_1 = col_integer(),
##   Count_2 = col_integer()
## )
```

```
CustomerService %>%
  select(Rep, GoalMet, Count)
```

```
## # A tibble: 4 x 3
##   Rep    GoalMet Count
##   <chr>  <chr>   <int>
## 1 Alexis Yes       172
## 2 Alexis No         28
## 3 Peyton Yes       118
## 4 Peyton No         82
```

Example 2.42: Look at the data more carefully

```
CustomerService %>%
  select(Rep, GoalMet_1, Count_1, GoalMet_2, Count_2)
```

```
## # A tibble: 4 x 5
##   Rep    GoalMet_1 Count_1 GoalMet_2 Count_2
##   <chr>  <chr>       <int> <chr>       <int>
## 1 Alexis Yes           162 Yes            10
## 2 Alexis No             18 No             10
## 3 Peyton Yes            19 Yes            99
## 4 Peyton No              1 No             81
```

Section 2.7: The Question of Causation