R Code for **Teaching Statistics Using Baseball**, 2nd Ed.

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This document contains R code to reproduce the plots, tables, and statistics presented in Jim Albert's *Teaching Statistics Using Baseball*, 2nd Ed. Some of the data is taken from sources other than the author's web site or his **tsub** package for **R**.

The following code is usually put in the ***setup*** of the **.RMD** file. It is included here so that you can read it if you don't have access to the ***.RMD*** for this file.

```
### Install or load the pacman library
if (!require(pacman)){
  install.packages("pacman", dependencies = TRUE)
  require(pacman)
}

p_load(dplyr)   ### Used by Albert's tsub package

### Install or load the tsub package that ontains a few of Albert's functions and all of the book data
if (!require(tsub)){
    p_load(devtools)                    ### Install or load the devtools package
    install_github("bayesball/tsub")    ### Install tsub from github
    p_load(tsub)                        ### Load tsub
}

p_load(Lahman)     ### Contains the Lahman data
p_load(lattice)    ### Load the lattice graphics package
p_load(ggplot2)    ### Load Hadley's ggplot graphics package
p_load(lubridate)  ### Used to modify dates.  Things like getting the year from mm-dd-yyyy, etc.
p_load(aplpack)    ### Pretty stemplots
```

Chapter One

Lahman has a site at https://www.seanlahman.com/baseball-archive/statistics that has his data in various formats and describes the tables that make up the data. Documentation for the data can be found at https://www.seanlahman.com/files/database/readme2021.txt. The data are also available in the **Lahman** package for **R**.

Rickey Henderson using Lahman's data

The first step is to install and load the **Lahman** package.

```
# p_load is in the pacman package which is installed above
p_load(Lahman)
```

The Lahman package contains a number of tables and a few functions that help subset the data. For now we will work with Henderson's batting data.

```
### Get the Batting data.frame ###
data(Batting)
### Figure out what it looks like ###
head(Batting)
```

```
##    playerID yearID stint teamID lgID  G  AB  R  H X2B X3B HR RBI SB CS BB SO
## 1 abercda01   1871     1    TRO   NA  1   4  0  0   0   0  0   0  0  0  0  0
## 2  addybo01   1871     1    RC1   NA 25 118 30 32   6   0  0  13  8  1  4  0
## 3 allisar01   1871     1    CL1   NA 29 137 28 40   4   5  0  19  3  1  2  5
## 4 allisdo01   1871     1    WS3   NA 27 133 28 44  10   2  2  27  1  1  0  2
## 5 ansonca01   1871     1    RC1   NA 25 120 29 39  11   3  0  16  6  2  2  1
## 6 armstbo01   1871     1    FW1   NA 12  49  9 11   2   1  0   5  0  1  0  1
##   IBB HBP SH SF GIDP
## 1  NA  NA NA NA    0
## 2  NA  NA NA NA    0
## 3  NA  NA NA NA    1
## 4  NA  NA NA NA    0
## 5  NA  NA NA NA    0
## 6  NA  NA NA NA    0
```

```
### Some of the Lahman functions require dplyr ###
p_load(dplyr)
```

Albert's text works on Rickey Henderson's 25 seasons. It would be nice if we could pull this information out of the Lahman data to confirm the values and compute a few statistics.

As a first step, we need to find Henderson's player information.

```
data(Master)
```

```
## Warning in data(Master): data set 'Master' not found
```

```
playerInfo(nameLast = "Henderson")
```

```
##       playerID nameFirst  nameLast
## 7931 hendebe01    Bernie Henderson
## 7932 hendebi01      Bill Henderson
## 7933 hendebi99      Bill Henderson
## 7934 hendeda01      Dave Henderson
## 7935 hendeed01        Ed Henderson
## 7936 hendeha01    Hardie Henderson
## 7937 hendeji01       Jim Henderson
## 7938 hendejo01       Joe Henderson
## 7939 hendeke01       Ken Henderson
## 7940 henderi01    Rickey Henderson
## 7941 hendero01       Rod Henderson
## 7942 hendest01     Steve Henderson
```

```
playerInfo(nameFirst = "Rickey")
```

```
##       playerID nameFirst  nameLast
## 3298 clarkri01    Rickey     Clark
## 3846 cradlri01    Rickey    Cradle
## 7940 henderi01    Rickey Henderson
## 9487 keetori01    Rickey    Keeton
```

```
playerInfo("henderi01")
```

```
##       playerID nameFirst  nameLast
## 7940 henderi01    Rickey Henderson
```

Knowing that Rickey Henderson is "henderi01" means that we can subset his information.

```
  batting = battingStats()
  Henderson = batting[Batting$playerID=="henderi01",]
  head(Henderson)
```

```
##        playerID yearID stint teamID lgID   G  AB   R   H X2B X3B HR RBI  SB CS
## 56777 henderi01   1979     1    OAK   AL  89 351  49  96  13   3  1  26  33 11
## 57733 henderi01   1980     1    OAK   AL 158 591 111 179  22   4  9  53 100 26
## 58676 henderi01   1981     1    OAK   AL 108 423  89 135  18   7  6  35  56 22
## 59632 henderi01   1982     1    OAK   AL 149 536 119 143  24   4 10  51 130 42
## 60637 henderi01   1983     1    OAK   AL 145 513 105 150  25   7  9  48 108 19
## 61632 henderi01   1984     1    OAK   AL 142 502 113 147  27   4 16  58  66 18
##        BB SO IBB HBP SH SF GIDP    BA  PA  TB SlugPct   OBP   OPS BABIP
## 56777  34 39   0   2  8  3    4 0.274 398 118   0.336 0.338 0.674 0.303
## 57733 117 54   7   5  6  3    6 0.303 722 236   0.399 0.420 0.819 0.320
## 58676  64 68   4   2  0  4    7 0.319 493 185   0.437 0.408 0.845 0.365
## 59632 116 94   1   2  0  2    5 0.267 656 205   0.382 0.398 0.780 0.306
## 60637 103 80   8   4  1  1   11 0.292 622 216   0.421 0.414 0.835 0.332
## 61632  86 81   1   5  1  3    7 0.293 597 230   0.458 0.399 0.857 0.321
```

```
  dim(Henderson)
```

```
## [1] 29 29
```

```
  table(Henderson$yearID)
```

```
##
## 1979 1980 1981 1982 1983 1984 1985 1986 1987 1988 1989 1990 1991 1992 1993 1994
##    1    1    1    1    1    1    1    1    1    1    2    1    1    1    2    1
## 1995 1996 1997 1998 1999 2000 2001 2002 2003
##    1    1    2    1    1    2    1    1    1
```

These values do *not* correspond to the yearly values in Table 1.1 of Albert's book. The years 1989, 1993, 1997, and 2000 include information for two teams. Albert's table has combined the information.

At this point, we will just import Albert's Table 1.1 data. Later we will see how to use R to compute yearly information. The first method is to import Albert's comma seperated value (CSV) file. These files can either be local (I have mine stored in a folder CSV within the same folder as this RMD file) or we can find the file on the web. Both methods are shown below.

```
  ### Read the local file
  Henderson.local <- read.csv("CSV/case_1_1.csv")
  head(Henderson.local, 13)
```

```
##    Year Age  Tm   G  AB   R   H X2B X3B HR RBI  SB CS  BB SO    BA   OBP   SLG
## 1  1979  20 OAK  89 351  49  96  13   3  1  26  33 11  34 39 0.274 0.338 0.336
## 2  1980  21 OAK 158 591 111 179  22   4  9  53 100 26 117 54 0.303 0.420 0.399
## 3  1981  22 OAK 108 423  89 135  18   7  6  35  56 22  64 68 0.319 0.408 0.437
## 4  1982  23 OAK 149 536 119 143  24   4 10  51 130 42 116 94 0.267 0.398 0.382
## 5  1983  24 OAK 145 513 105 150  25   7  9  48 108 19 103 80 0.292 0.414 0.421
## 6  1984  25 OAK 142 502 113 147  27   4 16  58  66 18  86 81 0.293 0.399 0.458
## 7  1985  26 NYY 143 547 146 172  28   5 24  72  80 10  99 65 0.314 0.419 0.516
## 8  1986  27 NYY 153 608 130 160  31   5 28  74  87 18  89 81 0.263 0.358 0.469
## 9  1987  28 NYY  95 358  78 104  17   3 17  37  41  8  80 52 0.291 0.423 0.497
## 10 1988  29 NYY 140 554 118 169  30   2  6  50  93 13  82 54 0.305 0.394 0.399
```

```
## 11 1989  30 TOT 150 541 113 148  26   3 12  57  77 14 126 68 0.274 0.411 0.399
## 12 1990  31 OAK 136 489 119 159  33   3 28  61  65 10  97 60 0.325 0.439 0.577
## 13 1991  32 OAK 134 470 105 126  17   1 18  57  58 18  98 73 0.268 0.400 0.423
##      OPS
## 1  0.675
## 2  0.820
## 3  0.845
## 4  0.780
## 5  0.835
## 6  0.857
## 7  0.934
## 8  0.827
## 9  0.920
## 10 0.793
## 11 0.810
## 12 1.016
## 13 0.823
```

```
  tail(Henderson.local, 13)
```

```
##    Year Age  Tm   G  AB   R   H X2B X3B HR RBI SB CS  BB  SO    BA   OBP   SLG
## 13 1991  32 OAK 134 470 105 126  17   1 18  57 58 18  98  73 0.268 0.400 0.423
## 14 1992  33 OAK 117 396  77 112  18   3 15  46 48 11  95  56 0.283 0.426 0.457
## 15 1993  34 TOT 134 481 114 139  22   2 21  59 53  8 120  65 0.289 0.432 0.474
## 16 1994  35 OAK  87 296  66  77  13   0  6  20 22  7  72  45 0.260 0.411 0.365
## 17 1995  36 OAK 112 407  67 122  31   1  9  54 32 10  72  66 0.300 0.407 0.447
## 18 1996  37 SDP 148 465 110 112  17   2  9  29 37 15 125  90 0.241 0.410 0.344
## 19 1997  38 TOT 120 403  84 100  14   0  8  34 45  8  97  85 0.248 0.400 0.342
## 20 1998  39 OAK 152 542 101 128  16   1 14  57 66 13 118 114 0.236 0.376 0.347
## 21 1999  40 NYM 121 438  89 138  30   0 12  42 37 14  82  82 0.315 0.423 0.466
## 22 2000  41 TOT 123 420  75  98  14   2  4  32 36 11  88  75 0.233 0.368 0.305
## 23 2001  42 SDP 123 379  70  86  17   3  8  42 25  7  81  84 0.227 0.366 0.351
## 24 2002  43 BOS  72 179  40  40   6   1  5  16  8  2  38  47 0.223 0.369 0.352
## 25 2003  44 LAD  30  72   7  15   1   0  2   5  3  0  11  16 0.208 0.321 0.306
##      OPS
## 13 0.823
## 14 0.883
## 15 0.906
## 16 0.776
## 17 0.855
## 18 0.754
## 19 0.742
## 20 0.723
## 21 0.889
## 22 0.673
## 23 0.717
## 24 0.721
## 25 0.627
```

```
  dim(Henderson.local)
```

```
## [1] 25 19
```

```
  ### Read from the web
  Henderson.web <- read.csv("http://facweb1.redlands.edu/fac/jim_bentley/Data/FYS28/TSUB2/CSV/case_1_1.
  head(Henderson.web)
```

```
##   Year Age  Tm   G  AB   R   H X2B X3B HR RBI  SB CS  BB SO    BA   OBP   SLG
## 1 1979  20 OAK  89 351  49  96  13   3  1  26  33 11  34 39 0.274 0.338 0.336
## 2 1980  21 OAK 158 591 111 179  22   4  9  53 100 26 117 54 0.303 0.420 0.399
## 3 1981  22 OAK 108 423  89 135  18   7  6  35  56 22  64 68 0.319 0.408 0.437
## 4 1982  23 OAK 149 536 119 143  24   4 10  51 130 42 116 94 0.267 0.398 0.382
## 5 1983  24 OAK 145 513 105 150  25   7  9  48 108 19 103 80 0.292 0.414 0.421
## 6 1984  25 OAK 142 502 113 147  27   4 16  58  66 18  86 81 0.293 0.399 0.458
##     OPS
## 1 0.675
## 2 0.820
## 3 0.845
## 4 0.780
## 5 0.835
## 6 0.857
```

```
dim(Henderson.web)
```

```
## [1] 25 19
```

Albert has made it easy to load all the data that is used in TSUB2. By loading his **TSUB** package, all of the case and exercise data are made available.

```
p_load(devtools)                  ### Install or load the devtools package
install_github("bayesball/tsub")  ### Install tsub from github
```

```
## Skipping install of 'tsub' from a github remote, the SHA1 (563eded6) has not changed since last insta
##   Use `force = TRUE` to force installation
```

```
p_load(tsub)                      ### Load tsub
```

Now that the **tsub** package is installed, we can call the different datasets.

```
Henderson.tsub <- case_1_1
head(Henderson.tsub)
```

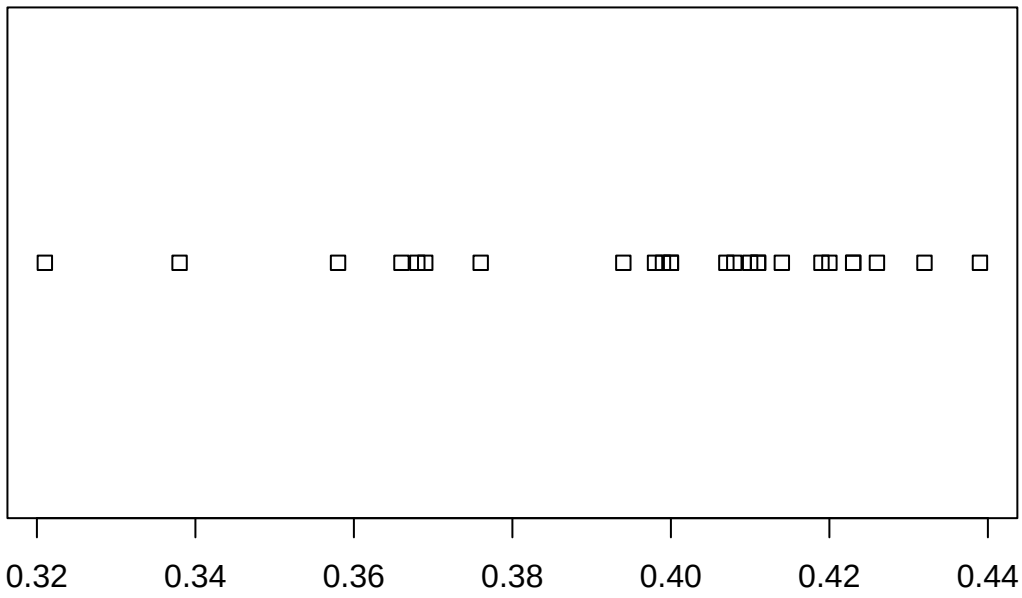
```
##   Year Age  Tm   G  AB   R   H X2B X3B HR RBI  SB CS  BB SO    BA   OBP   SLG
## 1 1979  20 OAK  89 351  49  96  13   3  1  26  33 11  34 39 0.274 0.338 0.336
## 2 1980  21 OAK 158 591 111 179  22   4  9  53 100 26 117 54 0.303 0.420 0.399
## 3 1981  22 OAK 108 423  89 135  18   7  6  35  56 22  64 68 0.319 0.408 0.437
## 4 1982  23 OAK 149 536 119 143  24   4 10  51 130 42 116 94 0.267 0.398 0.382
## 5 1983  24 OAK 145 513 105 150  25   7  9  48 108 19 103 80 0.292 0.414 0.421
## 6 1984  25 OAK 142 502 113 147  27   4 16  58  66 18  86 81 0.293 0.399 0.458
##     OPS
## 1 0.675
## 2 0.820
## 3 0.845
## 4 0.780
## 5 0.835
## 6 0.857
```

These values compare well with those presented in Table 1.1 of the text and the data as imported above.

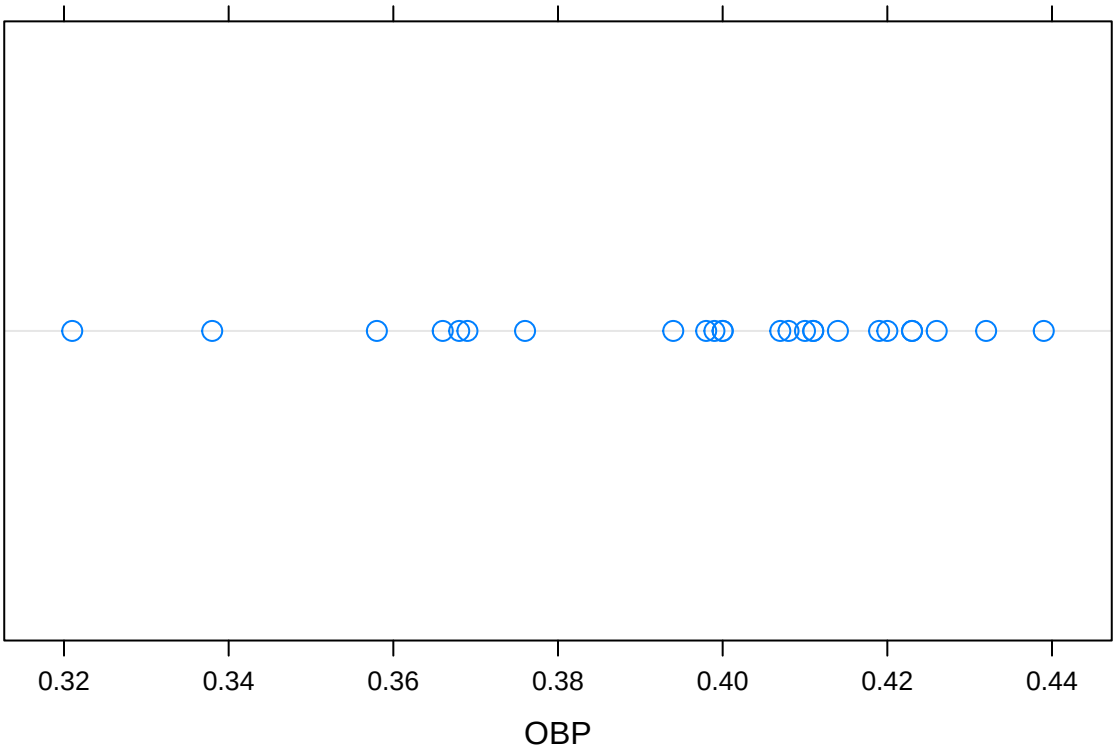
Henderson's On Base Percentage

TSUB2 provides a dotplot of Henderson's ***OBP*** during his first 23 years. We can create this plot in a few ways.

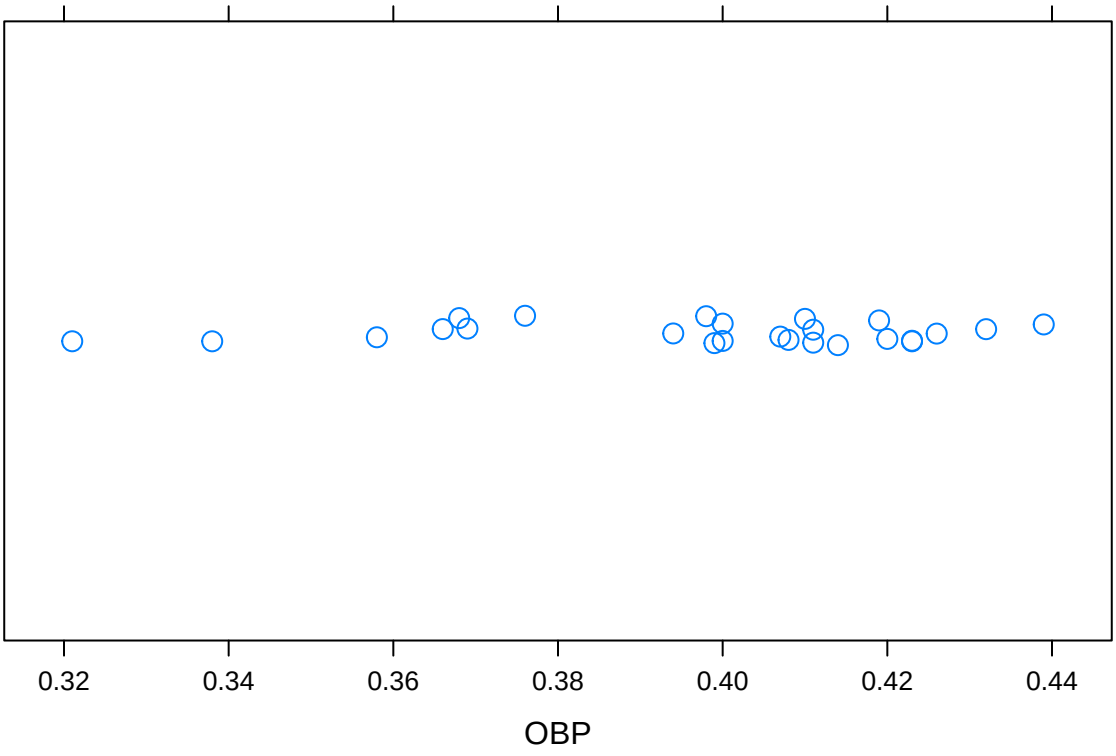
```
### First use base graphics
stripchart(case_1_1$OBP)
```



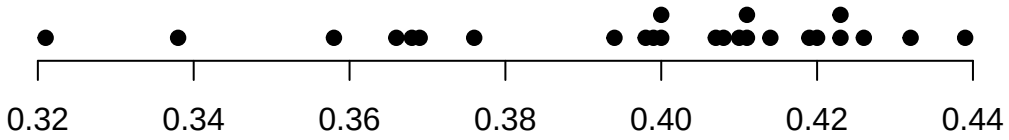

```
### Use the lattice library.  cex is the character size multiplier
### Using pch=1 chooses open circles which better show overlapped data.
p_load(lattice)
dotplot(~OBP, data=case_1_1, cex=1.25, pch=1)
```




```
stripplot(~OBP, data=case_1_1, cex=1.25, pch=1, jitter=TRUE, factor=1.5)
```




```
### Albert likes the minitab version of the plotrix dotplot
p_load(plotrix)
dotplot.mtb(case_1_1$OBP)
```

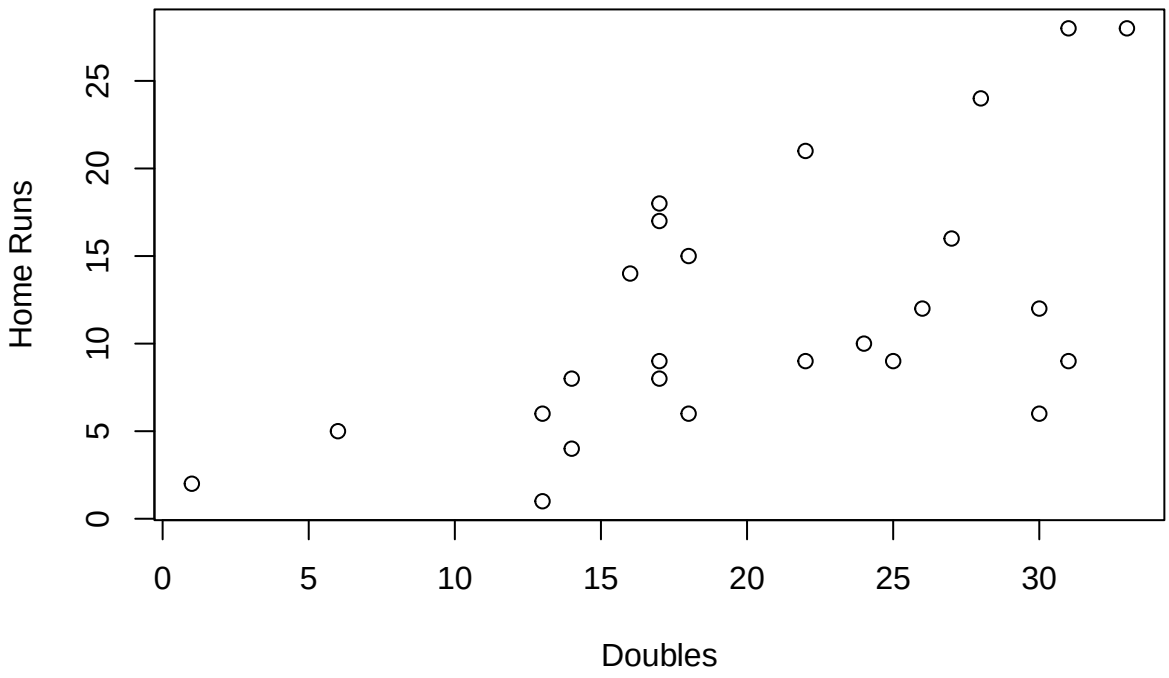


These plots are similar to Figure 1.1 in the text.

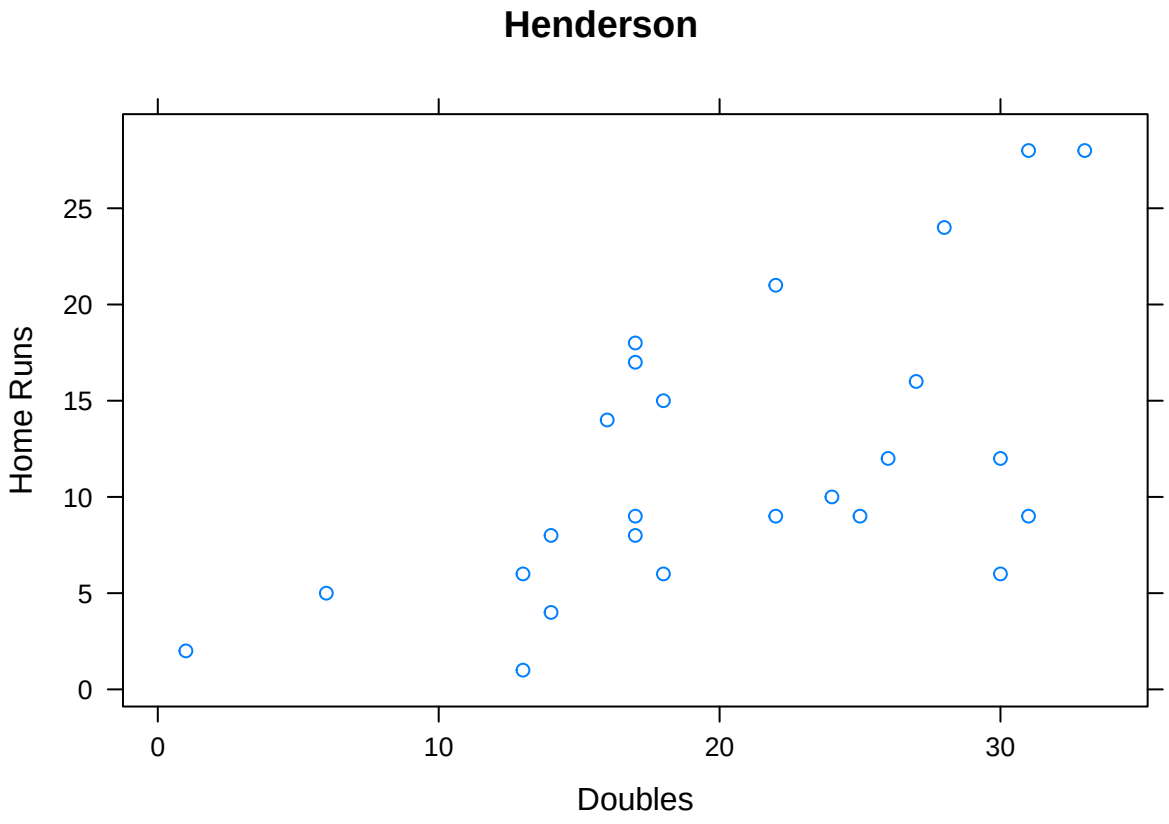
Henderson's Doubles versus Home Runs

The text compares Henderson's home run production (***HR***) against his doubles (***X2B***) using a scatterplot. There are multiple methods for generating scatterplots in R. We will look at three.

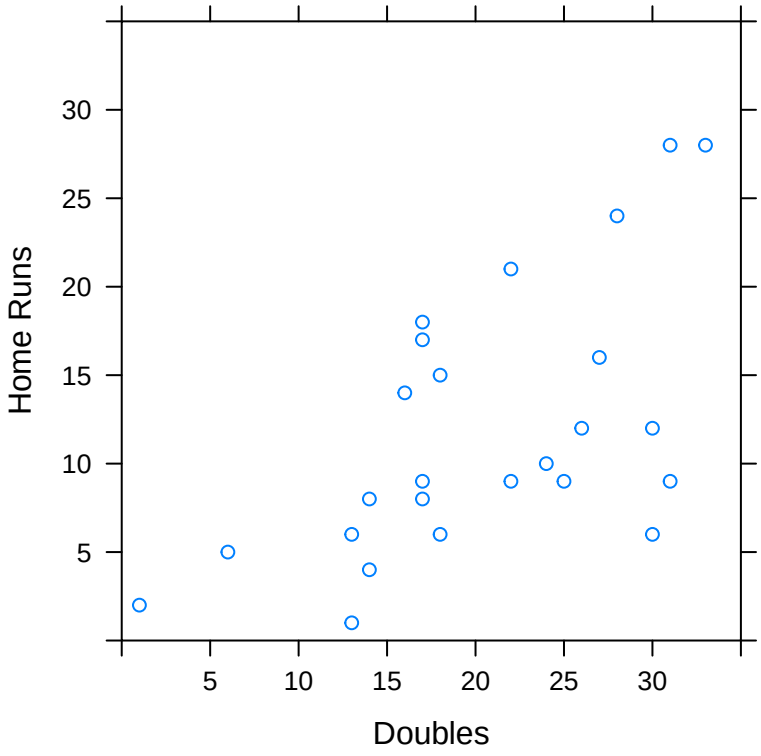
```
### Using base R we get ###
plot(case_1_1$X2B, case_1_1$HR, xlab="Doubles", ylab="Home Runs")
```



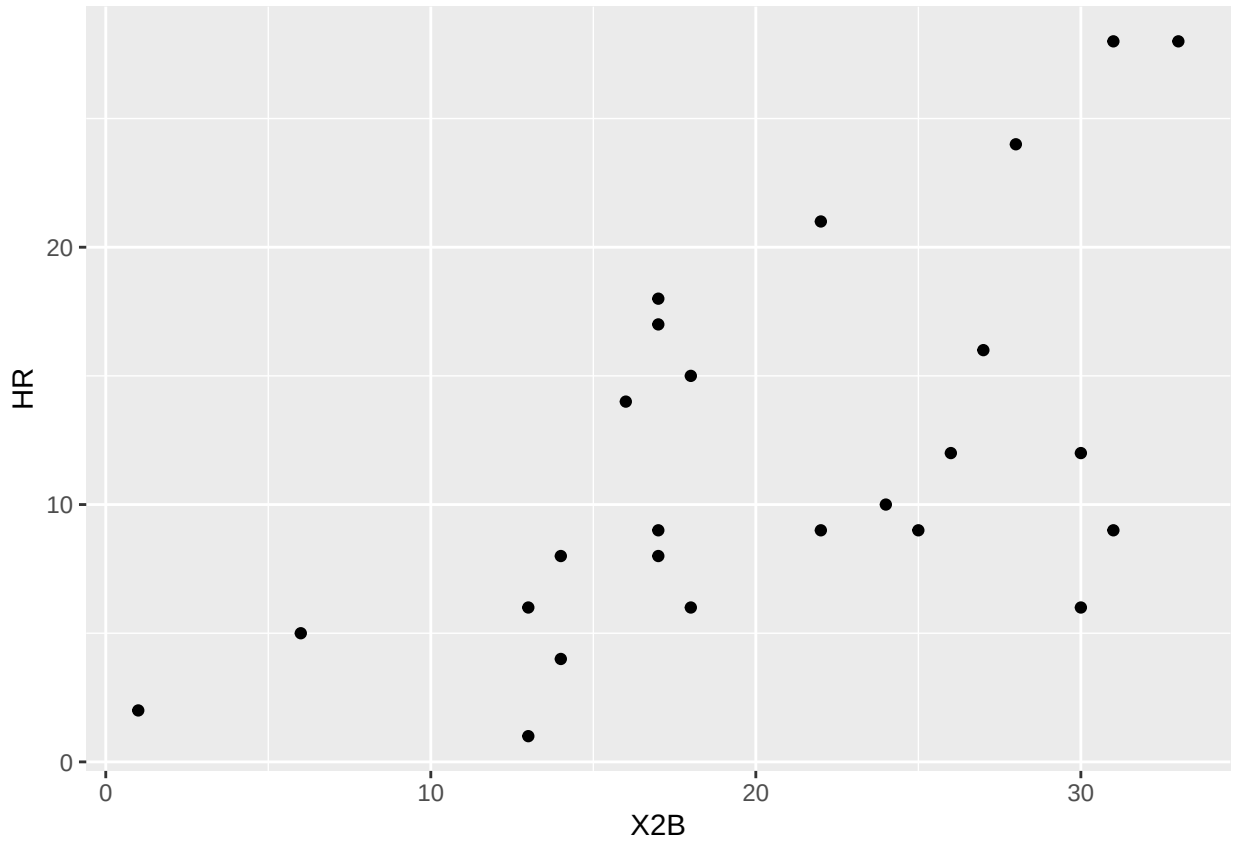

```
### Using lattice graphics
p_load(lattice)
xyplot(HR~X2B, data=case_1_1, xlab="Doubles", ylab="Home Runs", main="Henderson")
```



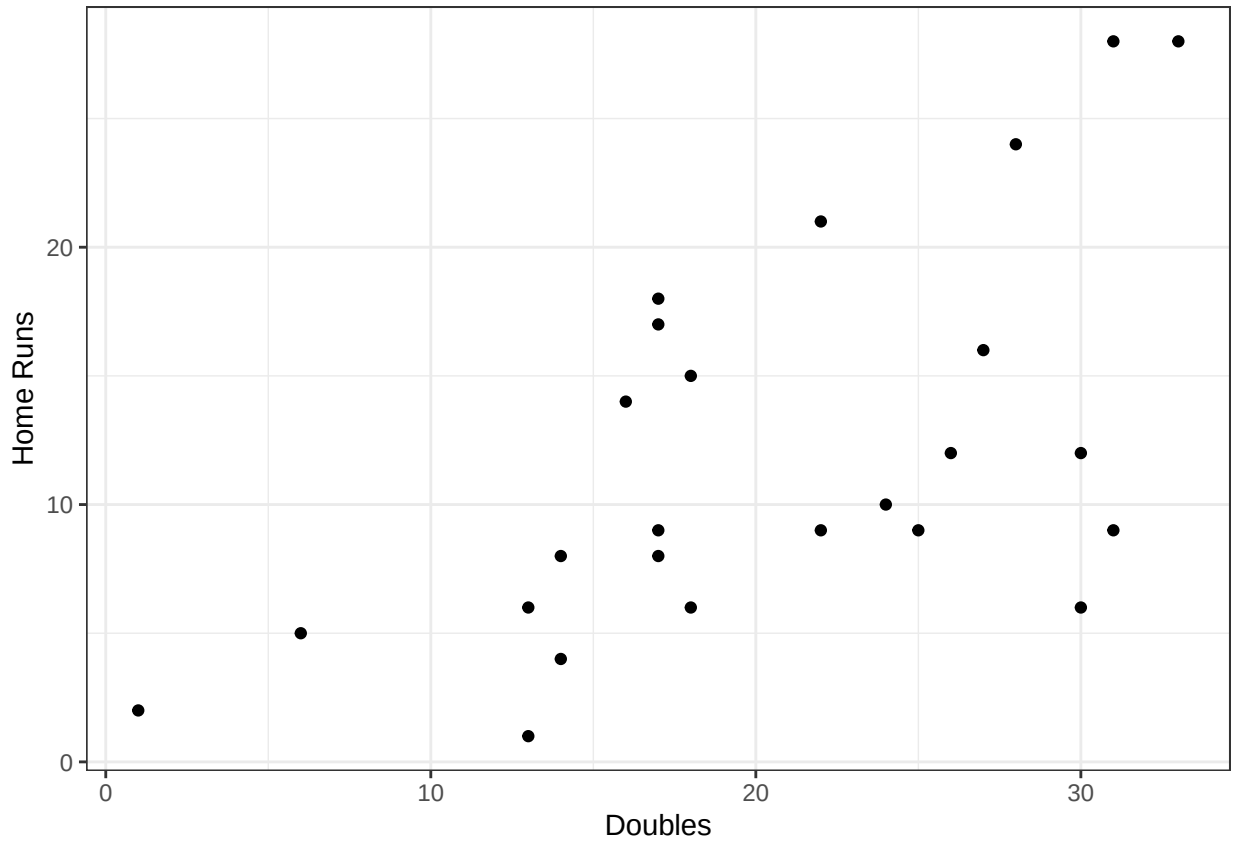

```
xyplot(HR~X2B, data=case_1_1, xlab="Doubles", ylab="Home Runs", xlim=c(0:35), ylim=c(0:35), aspect=1)
```




```
### Use ggplot ###
p_load(ggplot2)
p = ggplot(case_1_1, aes(X2B, HR))  ### Define data.frame and variables
p + geom_point()  ### Request a point plot
```




```
p + geom_point() + theme_bw() + xlab("Doubles") + ylab("Home Runs")
```



Simulating Henderson's Spinner Using R

Hendersons hitting statistics for 1990 were

```
### Grab Henderon's batting data and get totals by year using dplyr and piping to make it easy
p_load(dplyr)
Henderson.total <- Batting %>%                              ### Get all of the batting data
                   filter(playerID == "henderi01") %>%      ### Subset for Henderson
                   group_by(yearID) %>%                     ### Work on year subsets from here on out
                   summarize(
                     teams = n(),
                     G = sum(G),
                     AB = sum(AB),
                     R = sum(R),
                     H = sum(H),
                     X2B = sum(X2B),
                     X3B = sum(X3B),
                     HR = sum(HR),
                     RBI = sum(RBI),
                     SB = sum(SB),
                     CS = sum(CS),
                     BB = sum(BB),
                     SO = sum(SO),
                     IBB = sum(IBB),
                     HBP = sum(HBP),
                     SH = sum(SH),
```

```
                        SF = sum(SF),
                        GIDP = sum(GIDP)
                      )

  names(Henderson.total)
```

```
##  [1] "yearID" "teams"  "G"      "AB"     "R"      "H"      "X2B"    "X3B"
##  [9] "HR"     "RBI"    "SB"     "CS"     "BB"     "SO"     "IBB"    "HBP"
## [17] "SH"     "SF"     "GIDP"
```

```
  ### Now add computed performance statistics for each year... e.g. BA, OBP, etc.
  Henderson.total <- battingStats(Henderson.total)

  ### Check the data against Albert's Table 1.1
  Henderson.total %>%
    filter(teams == 2)
```

```
##   yearID teams   G  AB   R   H X2B X3B HR RBI SB CS  BB SO IBB HBP SH SF GIDP
## 1   1989     2 150 541 113 148  26   3 12  57 77 14 126 68   5   3  0  4    8
## 2   1993     2 134 481 114 139  22   2 21  59 53  8 120 65   7   4  1  4    9
## 3   1997     2 120 403  84 100  14   0  8  34 45  8  97 85   2   6  1  2   10
## 4   2000     2 123 420  75  98  14   2  4  32 36 11  88 75   1   4  3  4   11
##      BA  PA  TB SlugPct   OBP   OPS BABIP
## 1 0.274 674 216   0.399 0.411 0.810 0.292
## 2 0.289 610 228   0.474 0.432 0.906 0.296
## 3 0.248 509 138   0.342 0.400 0.742 0.295
## 4 0.233 519 128   0.305 0.368 0.673 0.272
```

The values for the four years when Henderson played for two teams match those in Table 1.1.

Albert uses only the 1990 season when creating Henderson's spinner. We can do the same.

```
  spinner <- Henderson.total %>%                ### Grab the total batting data from above
              filter(yearID == 1990) %>%        ### Keep only the 1990 season
              mutate(                           ### Create a few variables
                X1B = H - (X2B + X3B + HR),     ###    Singles are hits minus doubles, trips, and homers
                Out = AB - (H + BB),            ###    Outs are at bats that aren't hits or walks
                Walk = BB                       ###    Walks are base on balls
              )

  ### Check the counts
  spinner
```

```
##   yearID teams   G  AB   R   H X2B X3B HR RBI SB CS BB SO IBB HBP SH SF GIDP
## 1   1990     1 136 489 119 159  33   3 28  61 65 10 97 60   2   4  2  2   13
##      BA  PA  TB SlugPct   OBP   OPS BABIP X1B Out Walk
## 1 0.325 594 282   0.577 0.439 1.016 0.325  95 233   97
```

```
  ### Probabilities are counts divided by at bats... sort of.  We ignore HBP, interference, etc.
  spinner.prob = spinner[c("X1B","X2B","X3B","HR","Walk","Out")]  ### Keep only those outcomes we care
  spinner.prob = spinner.prob/sum(spinner.prob)
  spinner.prob
```

```
##        X1B        X2B         X3B         HR     Walk       Out
## 1 0.194274 0.06748466 0.006134969 0.05725971 0.198364 0.4764826
```

```
  sum(spinner.prob)
```

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

```
  ### Turn the data frame into a vector so that we can plot it
  dim(spinner.prob)
```

```
## [1] 1 6
```

```
  spinner.prob = as.vector(t(spinner.prob))
  dim(spinner.prob)
```

```
## NULL
```

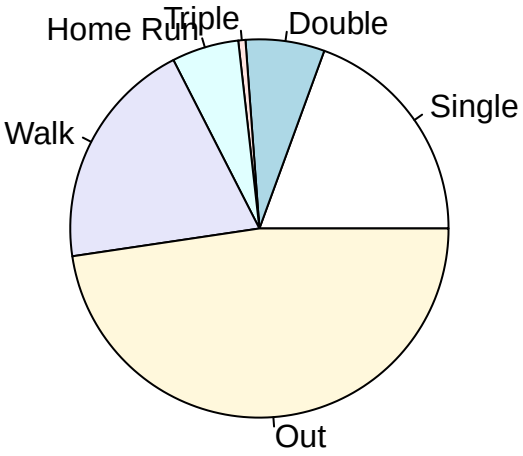
```
  length(spinner.prob)
```

```
## [1] 6
```

```
  spinner.prob
```

```
## [1] 0.194274029 0.067484663 0.006134969 0.057259714 0.198364008 0.476482618
```

```
  ### Create Figure 1.3
  pie(spinner.prob,labels=c("Single", "Double","Triple","Home Run","Walk","Out"))
```



Now, Albert has created a nice spinner, but he hasn't used it. Let's see what we get for Henderson if we let him bat (randomly) 179 times — the number of at bats that he had in 2002).

```
  outcomes = c("X1B","X2B","X3B","HR","Walk","Out")   ### Create a list of outcomes with probs in spinn
  spin2002 = sample(outcomes, 179, replace=TRUE, prob=spinner.prob) ### Sample from outcomes using spin
  spin2002 = factor(spin2002,levels=c("X1B","X2B","X3B","HR","Walk","Out"))  ### Make the data categori
  table(spin2002)  ### Compute the number of each type of outcome
```

```
## spin2002
##  X1B  X2B  X3B   HR Walk  Out
##   34   14    1   10   40   80
```

```
  ### List the stats for 2002 and 2003
  Henderson.total %>%
                filter(yearID >= 2002) %>%
                mutate(
                  Walk = BB + IBB + HBP,
                  X1B = H - (X2B + X3B + HR),
                  Out = AB - (H + Walk)
                ) %>%
                select(yearID, AB, H, X1B, X2B, X3B, HR, Walk, Out)
```

```
##   yearID  AB  H X1B X2B X3B HR Walk Out
## 1   2002 179 40  28   6   1  5   42  97
## 2   2003  72 15  12   1   0  2   12  45
```

Computing Basic Measures of Performance

We have already computed a few measures of a batter's performance using functions defined by others. In the previous section, we computed a few of these by hand. We can confirm that the functions and raw code provide the same results.

```
  ### Slugging percentage
  Hend7983 = Henderson.total %>%
                filter(yearID <= 1983) %>%   ### Grab Henderson's 1979 to 1983 years
                mutate(                      ### Create a few batting stats
                  x1b = H - (X2B + X3B + HR),
                  tb = 1*x1b + 2*X2B + 3*X3B + 4*HR,
                  slg = round(tb/AB,3)
                )

  temp <- Henderson.total %>%
            filter(yearID <= 1983) %>%
            select(yearID, SlugPct)

  cbind(head(Hend7983[,c(1,6:9,27:29)]), temp$SlugPct)
```

```
##   yearID   H X2B X3B HR x1b  tb   slg temp$SlugPct
## 1   1979  96  13   3  1  79 118 0.336        0.336
## 2   1980 179  22   4  9 144 236 0.399        0.399
## 3   1981 135  18   7  6 104 185 0.437        0.437
## 4   1982 143  24   4 10 105 205 0.382        0.382
## 5   1983 150  25   7  9 109 216 0.421        0.421
```

Similar computations can be used to compute pitching statistics. We look at Orel Hershiser's AL years.

```
  ### Start a search for Hershier's player ID
  playerInfo("hers")
```

```
##       playerID nameFirst    nameLast
## 5420 etherse01      Seth    Etherton
## 8110 hershea01      Earl       Hersh
## 8111 hershfr01     Frank     Hershey
## 8112 hershmi01      Mike Hershberger
## 8113 hershor01      Orel   Hershiser
```

```
## 8114 hershwi01   Willard Hershberger
```

```
  ### Figure out what's in the pitching data.frame
  names(Pitching)
```

```
##  [1] "playerID" "yearID"   "stint"    "teamID"   "lgID"     "W"
##  [7] "L"        "G"        "GS"       "CG"       "SHO"      "SV"
## [13] "IPouts"   "H"        "ER"       "HR"       "BB"       "SO"
## [19] "BAOpp"    "ERA"      "IBB"      "WP"       "HBP"      "BK"
## [25] "BFP"      "GF"       "R"        "SH"       "SF"       "GIDP"
```

```
  ### Subset out Hershiser's AL years
  HershAL = Pitching %>%                                        ### Grab all the pitching data
              filter(playerID == "hershor01" & lgID == "AL")    ### subset hor Orel and AL
  head(HershAL)
```

```
##    playerID yearID stint teamID lgID  W L  G GS CG SHO SV IPouts   H ER HR BB
## 1 hershor01   1995     1    CLE   AL 16 6 26 26  1   1  0    502 151 72 21 51
## 2 hershor01   1996     1    CLE   AL 15 9 33 33  1   0  0    618 238 97 21 58
## 3 hershor01   1997     1    CLE   AL 14 6 32 32  1   0  0    586 199 97 26 69
##    SO BAOpp  ERA IBB WP HBP BK BFP GF   R SH SF GIDP
## 1 111 0.244 3.87   1  3   5  0 683  0  76  3  4   26
## 2 125 0.287 4.24   4 11  12  1 908  0 115  5  4   24
## 3 107 0.272 4.47   2 11  11  0 826  0 105  6  8   31
```

```
  ### Compute his effective "complete"" innings pitched based upon total outs
  HershAL$ip = HershAL$IPouts/3
  ### Convert innings to games
  HershAL$gp = HershAL$ip/9
  ### As is indicated in TSUB, ERA is earned runs over total games pitched
  HershAL$era = round(HershAL$ER/HershAL$gp, 4)
  ### Now compare
  HershAL[,c("yearID","teamID","IPouts","ER","ip","gp","ERA","era")]
```

```
##   yearID teamID IPouts ER       ip       gp  ERA    era
## 1   1995    CLE    502 72 167.3333 18.59259 3.87 3.8725
## 2   1996    CLE    618 97 206.0000 22.88889 4.24 4.2379
## 3   1997    CLE    586 97 195.3333 21.70370 4.47 4.4693
```

Not so amazingly, the internal value, **ERA**, is equal to our computed value, **era**.

Chapter Two

The generation of the graphs and statistics that are presented in the discussion of Case 2.1 is simplified by the use of R. The data from the 2014 MLB season is obtainable from Lahman.

```
  p_load(Lahman, dplyr)

  MLB2014 = Teams %>%                                                ### Grab the Teams dataframe
              filter(yearID==2014 & lgID %in% c("AL","NL")) %>%      ### Subset 2014 and AL or NL
              arrange(name)                                          ### Sort by league and wins withing le
                                                                     ### Note: %in% checks if a value is in


  head(MLB2014)
```

```
##   yearID lgID teamID franchID divID Rank   G Ghome  W  L DivWin WCWin LgWin
## 1   2014   NL    ARI      ARI     W    5 162    81 64 98      N     N     N
## 2   2014   NL    ATL      ATL     E    2 162    81 79 83      N     N     N
```

```
## 3   2014   AL    BAL      BAL     E    1 162    81 96 66      Y     N     N
## 4   2014   AL    BOS      BOS     E    5 162    81 71 91      N     N     N
## 5   2014   NL    CHN      CHC     C    5 162    81 73 89      N     N     N
## 6   2014   AL    CHA      CHW     C    4 162    81 73 89      N     N     N
##   WSWin   R   AB    H X2B X3B  HR  BB   SO SB CS HBP SF  RA  ER  ERA CG SHO SV
## 1     N 615 5552 1379 259  47 118 398 1165 86 33  43 36 742 683 4.26  2   4 35
## 2     N 573 5468 1316 240  22 123 472 1369 95 33  43 27 597 547 3.38  5  13 54
## 3     N 705 5596 1434 264  16 211 401 1285 44 20  62 36 593 557 3.43  3  13 53
## 4     N 634 5551 1355 282  20 123 535 1337 63 25  68 52 715 653 4.01  3   7 36
## 5     N 614 5508 1315 270  31 157 442 1477 65 40  54 41 707 636 3.91  1  11 37
## 6     N 660 5543 1400 279  32 155 417 1362 85 36  60 38 758 687 4.29  3   6 36
##   IPouts   HA HRA BBA  SOA   E  DP    FP                name
## 1   4333 1467 154 469 1278 101 147 0.983 Arizona Diamondbacks
## 2   4365 1369 121 472 1301  85 143 0.986       Atlanta Braves
## 3   4384 1342 151 472 1174  87 156 0.986    Baltimore Orioles
## 4   4397 1458 154 482 1213  92 155 0.985       Boston Red Sox
## 5   4390 1398 115 504 1311 103 137 0.983         Chicago Cubs
## 6   4323 1468 140 557 1152 107 170 0.982    Chicago White Sox
##                         park attendance BPF PPF teamIDBR teamIDlahman45
## 1                Chase Field    2073730 102 102      ARI            ARI
## 2               Turner Field    2354305  99  99      ATL            ATL
## 3 Oriole Park at Camden Yards    2464473 100 100      BAL            BAL
## 4              Fenway Park II    2956089 102 101      BOS            BOS
## 5               Wrigley Field    2652113 103 104      CHC            CHN
## 6         U.S. Cellular Field    1650821 100 101      CHW            CHA
##   teamIDretro
## 1         ARI
## 2         ATL
## 3         BAL
## 4         BOS
## 5         CHN
## 6         CHA
```

```
names(MLB2014)
```

```
##  [1] "yearID"         "lgID"           "teamID"         "franchID"
##  [5] "divID"          "Rank"           "G"              "Ghome"
##  [9] "W"              "L"              "DivWin"         "WCWin"
## [13] "LgWin"          "WSWin"          "R"              "AB"
## [17] "H"              "X2B"            "X3B"            "HR"
## [21] "BB"             "SO"             "SB"             "CS"
## [25] "HBP"            "SF"             "RA"             "ER"
## [29] "ERA"            "CG"             "SHO"            "SV"
## [33] "IPouts"         "HA"             "HRA"            "BBA"
## [37] "SOA"            "E"              "DP"             "FP"
## [41] "name"           "park"           "attendance"     "BPF"
## [45] "PPF"            "teamIDBR"       "teamIDlahman45" "teamIDretro"
```

Case 2.1

While we could compute statistics like team batting average from hits and at bats, we can also import the data from the text. In this case we pull it off of the class website.

```
### Read the CSV file from the web
case.2.1 = read.csv("http://facweb1.redlands.edu/fac/jim_bentley/Data/FYS28/TSUB2/CSV/case_2_1.csv")
names(case.2.1)                                ### Get the dataframe column names
```

```
##  [1] "Team" "G"    "AB"   "PA"   "H"    "X1B"  "X2B"  "X3B"  "HR"   "R"
## [11] "RBI"  "BB"   "IBB"  "SO"   "HBP"  "SF"   "SH"   "GDP"  "SB"   "CS"
## [21] "AVG"
```

```
case.2.1                                    ### Look at the dataframe
```

```
##            Team    G   AB   PA    H  X1B X2B X3B  HR   R RBI  BB IBB   SO HBP
## 1        Tigers 1961 5630 6202 1557 1051 325  26 155 757 731 443  51 1144  44
## 2       Rockies 2120 5612 6164 1551 1017 307  41 186 755 721 397  39 1281  48
## 3       Dodgers 2163 5560 6231 1476 1002 302  38 134 718 686 519  30 1246  61
## 4        Royals 1788 5545 6058 1456 1046 286  29  95 651 604 380  22  985  53
## 5       Pirates 2220 5536 6224 1436  975 275  30 156 682 659 520  46 1244  78
## 6        Angels 1929 5652 6284 1464  974 304  31 155 773 729 492  42 1266  60
## 7     Blue Jays 2060 5549 6167 1435  952 282  24 177 723 690 502  27 1151  41
## 8       Rangers 1801 5460 6026 1400 1001 260  28 111 637 597 417  37 1162  61
## 9       Orioles 1901 5596 6130 1434  943 264  16 211 705 681 401  29 1285  62
## 10       Giants 2140 5523 6087 1407  976 257  42 132 665 636 427  37 1245  43
## 11        Twins 1785 5567 6233 1412  941 316  27 128 715 675 544  29 1329  53
## 12    Nationals 1913 5542 6216 1403  959 265  27 152 686 635 517  29 1304  56
## 13      Indians 1860 5575 6222 1411  962 284  23 142 669 644 504  24 1189  42
## 14    Cardinals 2069 5426 6086 1371  970 275  21 105 619 585 471  28 1133  86
## 15      Marlins 1963 5538 6185 1399  987 254  36 122 645 614 501  49 1419  35
## 16    White Sox 1817 5543 6077 1400  934 279  32 155 660 625 417  33 1362  60
## 17      Brewers 2008 5462 6065 1366  891 297  28 150 650 617 423  32 1197  73
## 18 Diamondbacks 1958 5552 6089 1379  955 259  47 118 615 573 398  31 1165  43
## 19         Rays 1915 5516 6205 1361  957 263  24 117 612 586 527  31 1124  66
## 20      Yankees 1786 5497 6082 1349  929 247  26 147 633 591 452  16 1133  56
## 21    Athletics 2003 5545 6245 1354  922 253  33 146 729 686 586  34 1104  49
## 22      Red Sox 1733 5551 6226 1355  930 282  20 123 634 601 535  36 1337  68
## 23     Mariners 1928 5450 5977 1328  913 247  32 136 634 600 396  33 1232  60
## 24     Phillies 1987 5603 6198 1356  953 251  27 125 619 584 443  42 1306  55
## 25       Astros 1865 5447 6055 1317  895 240  19 163 629 596 495  27 1442  55
## 26       Braves 1928 5468 6064 1316  931 240  22 123 573 545 472  31 1369  43
## 27         Cubs 2009 5508 6102 1315  857 270  31 157 614 590 442  29 1477  54
## 28         Mets 2135 5472 6145 1306  887 275  19 125 629 602 516  42 1264  54
## 29         Reds 1926 5395 5978 1282  877 254  20 131 595 562 415  22 1252  52
## 30       Padres 2148 5294 5905 1199  836 224  30 109 535 500 468  27 1294  41
##    SF SH GDP  SB CS   AVG
## 1  61 24 137 106 41 0.277
## 2  48 59 121  85 48 0.276
## 3  43 47 120 138 50 0.265
## 4  47 33 131 153 36 0.263
## 5  35 54 127 104 47 0.259
## 6  54 26 112  81 39 0.259
## 7  40 35 128  78 21 0.259
## 8  45 41 148 105 59 0.256
## 9  36 35 112  44 20 0.256
## 10 49 45 113  56 27 0.255
## 11 44 25  97  99 36 0.254
## 12 41 60 115 101 23 0.253
## 13 49 51 126 104 27 0.253
## 14 39 64 140  57 32 0.253
## 15 39 71 143  58 21 0.253
## 16 38 19 127  85 36 0.253
## 17 37 70 137 102 43 0.250
```

```
## 18 36 56 115  86 33 0.248
## 19 53 43 135  63 27 0.247
## 20 47 29 111 112 26 0.245
## 21 43 19 118  83 20 0.244
## 22 52 20 138  63 25 0.244
## 23 34 35 113  96 42 0.244
## 24 37 59  95 109 26 0.242
## 25 36 22 122 122 37 0.242
## 26 27 53 121  95 33 0.241
## 27 41 57  94  65 40 0.239
## 28 44 59 112 101 34 0.239
## 29 37 76  88 122 52 0.238
## 30 45 56 118  91 34 0.226
```

```
  case.2.1[order(case.2.1$AVG),c("Team","AVG")]  ### Rows are sorted by AVG, columns are only Team and
```

```
##            Team   AVG
## 30       Padres 0.226
## 29         Reds 0.238
## 27         Cubs 0.239
## 28         Mets 0.239
## 26       Braves 0.241
## 24     Phillies 0.242
## 25       Astros 0.242
## 21    Athletics 0.244
## 22      Red Sox 0.244
## 23     Mariners 0.244
## 20      Yankees 0.245
## 19         Rays 0.247
## 18 Diamondbacks 0.248
## 17      Brewers 0.250
## 12    Nationals 0.253
## 13      Indians 0.253
## 14    Cardinals 0.253
## 15      Marlins 0.253
## 16    White Sox 0.253
## 11        Twins 0.254
## 10       Giants 0.255
## 8       Rangers 0.256
## 9       Orioles 0.256
## 5       Pirates 0.259
## 6        Angels 0.259
## 7     Blue Jays 0.259
## 4        Royals 0.263
## 3       Dodgers 0.265
## 2       Rockies 0.276
## 1        Tigers 0.277
```

```
  ### Or, use the MLB2014 data taken from the Lahman Teams data
  case_2.1 = MLB2014                              ### Make a copy of MLB2014
  case_2.1$avg = case_2.1$H/case_2.1$AB           ### Create a new variable/column avg using H and AB
  case_2.1[order(case_2.1$avg),c("name","avg")]  ### Rows are sorted by avg, columns are only name and
```

```
##                            name       avg
## 23              San Diego Padres 0.2264828
```

```
## 7                Cincinnati Reds 0.2376274
## 18                 New York Mets 0.2386696
## 5                   Chicago Cubs 0.2387436
## 2                  Atlanta Braves 0.2406730
## 11                 Houston Astros 0.2417845
## 21         Philadelphia Phillies 0.2420132
## 25              Seattle Mariners 0.2436697
## 4                  Boston Red Sox 0.2441002
## 20             Oakland Athletics 0.2441839
## 19              New York Yankees 0.2454066
## 27                 Tampa Bay Rays 0.2467368
## 1           Arizona Diamondbacks 0.2483790
## 16             Milwaukee Brewers 0.2500915
## 6              Chicago White Sox 0.2525708
## 15                 Miami Marlins 0.2526183
## 26           St. Louis Cardinals 0.2526723
## 8              Cleveland Indians 0.2530942
## 30          Washington Nationals 0.2531577
## 17              Minnesota Twins 0.2536375
## 24          San Francisco Giants 0.2547529
## 3              Baltimore Orioles 0.2562545
## 28                 Texas Rangers 0.2564103
## 29             Toronto Blue Jays 0.2586052
## 13 Los Angeles Angels of Anaheim 0.2590234
## 22            Pittsburgh Pirates 0.2593931
## 12            Kansas City Royals 0.2625789
## 14           Los Angeles Dodgers 0.2654676
## 9               Colorado Rockies 0.2763721
## 10                Detroit Tigers 0.2765542
```

```
### Or, we can use dplyr to do the same thing
case_2.1 = MLB2014 %>%                          ### Copy the MLB2014 data
             mutate(avg = H/AB) %>%             ### Create a new variable avg using H and AB
             arrange(avg)                       ### Sort by avg

case_2.1 %>% select(name, avg)                ### Display only name and avg
```

```
##                            name       avg
## 1              San Diego Padres 0.2264828
## 2               Cincinnati Reds 0.2376274
## 3                 New York Mets 0.2386696
## 4                  Chicago Cubs 0.2387436
## 5                 Atlanta Braves 0.2406730
## 6                 Houston Astros 0.2417845
## 7          Philadelphia Phillies 0.2420132
## 8               Seattle Mariners 0.2436697
## 9                 Boston Red Sox 0.2441002
## 10             Oakland Athletics 0.2441839
## 11              New York Yankees 0.2454066
## 12                Tampa Bay Rays 0.2467368
## 13          Arizona Diamondbacks 0.2483790
## 14             Milwaukee Brewers 0.2500915
## 15             Chicago White Sox 0.2525708
## 16                Miami Marlins 0.2526183
## 17          St. Louis Cardinals 0.2526723
```

```
## 18             Cleveland Indians 0.2530942
## 19          Washington Nationals 0.2531577
## 20               Minnesota Twins 0.2536375
## 21          San Francisco Giants 0.2547529
## 22             Baltimore Orioles 0.2562545
## 23                 Texas Rangers 0.2564103
## 24             Toronto Blue Jays 0.2586052
## 25 Los Angeles Angels of Anaheim 0.2590234
## 26            Pittsburgh Pirates 0.2593931
## 27            Kansas City Royals 0.2625789
## 28           Los Angeles Dodgers 0.2654676
## 29              Colorado Rockies 0.2763721
## 30                Detroit Tigers 0.2765542
```

R makes it very easy to create a stemplot. A few options also make it easy to modify the stemplot so that it is easily interpretable.

```
  ### The default stem has too few stems
  stem(case.2.1$HR)
```

```
##
##   The decimal point is 1 digit(s) to the right of the |
##
##    8 | 5
##   10 | 59178
##   12 | 2335581246
##   14 | 2670255567
##   16 | 37
##   18 | 6
##   20 | 1
```

```
  ### We can split the stems in half to match the text
  stem(case.2.1$HR, 2)
```

```
##
##   The decimal point is 1 digit(s) to the right of the |
##
##    9 | 5
##   10 | 59
##   11 | 178
##   12 | 233558
##   13 | 1246
##   14 | 267
##   15 | 0255567
##   16 | 3
##   17 | 7
##   18 | 6
##   19 |
##   20 |
##   21 | 1
```

```
  ### Further division of stems is overkill
  stem(case.2.1$HR, 5)
```

```
##
##   The decimal point is at the |
##
```

```
##    94 | 0
##    96 |
##    98 |
##   100 |
##   102 |
##   104 | 0
##   106 |
##   108 | 0
##   110 | 0
##   112 |
##   114 |
##   116 | 0
##   118 | 0
##   120 |
##   122 | 000
##   124 | 00
##   126 |
##   128 | 0
##   130 | 0
##   132 | 0
##   134 | 0
##   136 | 0
##   138 |
##   140 |
##   142 | 0
##   144 |
##   146 | 00
##   148 |
##   150 | 0
##   152 | 0
##   154 | 000
##   156 | 00
##   158 |
##   160 |
##   162 | 0
##   164 |
##   166 |
##   168 |
##   170 |
##   172 |
##   174 |
##   176 | 0
##   178 |
##   180 |
##   182 |
##   184 |
##   186 | 0
##   188 |
##   190 |
##   192 |
##   194 |
##   196 |
##   198 |
##   200 |
```

```
##   202 |
##   204 |
##   206 |
##   208 |
##   210 | 0
```

If we need a back-to-back stemplot we need to use the ***aplpack*** package.

```
p_load(aplpack)
### Create vectors that contain HR for either NL or AL using base R
nlhr2014 = MLB2014$HR[MLB2014$lgID=="NL"]    ### Use the HR variable and subset only NL
alhr2014 = MLB2014$HR[MLB2014$lgID=="AL"]    ### Use the HR variable and subset only AL
stem.leaf.backback(nlhr2014, alhr2014)
```

```
## ----------------------------
##   1 | 2: represents 12, leaf unit: 1
##     nlhr2014      alhr2014
## ----------------------------
##            |  9 |5      1
##    2     95| 10 |
##    3      8| 11 |17     3
##    7   5532| 12 |38     5
##   (3)   421| 13 |6      6
##           | 14 |267   (3)
##    5   7620| 15 |555    6
##           | 16 |3      3
##           | 17 |7      2
##    1      6| 18 |
##           | 19 |
## ----------------------------
##                  HI: 211
## n:       15      15
## ----------------------------
```

```
### Or, use dplyr to do the same thing
nlhr2014 = MLB2014 %>% filter(lgID == "NL") %>% select(HR)
alhr2014 = MLB2014 %>% filter(lgID == "AL") %>% select(HR)
stem.leaf.backback(as.vector(t(alhr2014)), as.vector(t(nlhr2014))) ### Force the dataframes to col ve
```

```
## ----------------------------
##   1 | 2: represents 12, leaf unit: 1
## as.vector(t(alhr2014))
##                  as.vector(t(nlhr2014))
## ----------------------------
##    1      5|  9 |
##           | 10 |59     2
##    3     71| 11 |8      3
##    5     83| 12 |2355   7
##    6      6| 13 |124   (3)
##   (3)   762| 14 |
##    6    555| 15 |0267   5
##    3      3| 16 |
##    2      7| 17 |
##           | 18 |6      1
##           | 19 |
## ----------------------------
```

```
## HI: 211
## n:       15      15
## ----------------------------
```

Team on base percentage (OBP) is easily graphed. Computing statistics on the statistic is also simple.

```
  ### Add the OBP to the dataframe using dplyr
  case.2.1 = case.2.1 %>% mutate(OBP = round((H + BB + HBP)/(AB + BB + HBP + SF), 3))

  ### Stem plot sing base R
  stem(case.2.1$OBP)
```

```
##
##   The decimal point is 2 digit(s) to the left of the |
##
##   29 | 2
##   29 | 6
##   30 | 0022
##   30 | 5789
##   31 | 011144
##   31 | 6777
##   32 | 001234
##   32 | 7
##   33 | 013
```

```
  ### Using aplpack
  stem.leaf(case.2.1$OBP)
```

```
## 1 | 2: represents 0.012
##  leaf unit: 0.001
##             n: 30
##    1    29* | 2
##    2    29. | 6
##    6    30* | 0022
##   10    30. | 5789
##   (6)   31* | 011144
##   14    31. | 6777
##   10    32* | 001234
##    4    32. | 7
##    3    33* | 013
```

```
  ### While we can read the sorted data from the stem plot, sort the data to check
  sort(case.2.1$OBP)
```

```
##  [1] 0.292 0.296 0.300 0.300 0.302 0.302 0.305 0.307 0.308 0.309 0.310 0.311
## [13] 0.311 0.311 0.314 0.314 0.316 0.317 0.317 0.317 0.320 0.320 0.321 0.322
## [25] 0.323 0.324 0.327 0.330 0.331 0.333
```

```
  ### How many observations
  length(case.2.1$OBP)
```

```
## [1] 30
```

```
  ### What are the OBPs for the 15th and 16th obs?
  case.2.1$OBP[15:16]            ### Oops, not sorted
```

```
## [1] 0.317 0.310
```

```
  sort(case.2.1$OBP)[15:16]      ### That's better
```

```
## [1] 0.314 0.314
```

```
  ### Find the median
  median(case.2.1$OBP)
```

```
## [1] 0.314
```

```
  ### What are the OBPs for the 8th and 23rd sorted obs?
  sort(case.2.1$OBP)[c(8,23)]
```

```
## [1] 0.307 0.321
```

```
  ### Find the quartiles
  quantile(case.2.1$OBP)[c(2,4)]
```

```
##     25%     75%
## 0.30725 0.32075
```

```
  ### Or...
  summary(case.2.1$OBP)
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##  0.2920  0.3073  0.3140  0.3137  0.3207  0.3330
```

Case 2.2

The plots and statistics for Derek Jeter that are presented in Case 2.2 are variations on those already presented above. For this case we download the data Albert's GitHub repository.

```
  ### Get the data.  Be careful about getting the "raw" CSV file from GitHub
  case.2.2 <- read.csv("https://raw.githubusercontent.com/bayesball/Teaching-Statistics-Using-Baseball/m

  ### See what's in it
  head(case.2.2)
```

```
##   Year Age   G  PA  AB   R   H X2B X3B HR RBI BB  SO    BA   OBP   SLG   OPS
## 1 1995  21  15  51  48   5  12   4   1  0   7  3  11 0.250 0.294 0.375 0.669
## 2 1996  22 157 654 582 104 183  25   6 10  78 48 102 0.314 0.370 0.430 0.800
## 3 1997  23 159 748 654 116 190  31   7 10  70 74 125 0.291 0.370 0.405 0.775
## 4 1998  24 149 694 626 127 203  25   8 19  84 57 119 0.324 0.384 0.481 0.864
## 5 1999  25 158 739 627 134 219  37   9 24 102 91 116 0.349 0.438 0.552 0.989
## 6 2000  26 148 679 593 119 201  31   4 15  73 68  99 0.339 0.416 0.481 0.896
```

```
  ### Albert's Table 2.2 contains fewer variables
  table.2.2 = case.2.2 %>%
                select(Year, AB:HR, BB:OPS) %>%   ### Use ":" to get all variables between those indica
                rename(AVG = BA)                  ### Rename batting average from BA to AVG
  head(table.2.2)
```

```
##   Year  AB   R   H X2B X3B HR BB  SO   AVG   OBP   SLG   OPS
## 1 1995  48   5  12   4   1  0  3  11 0.250 0.294 0.375 0.669
## 2 1996 582 104 183  25   6 10 48 102 0.314 0.370 0.430 0.800
## 3 1997 654 116 190  31   7 10 74 125 0.291 0.370 0.405 0.775
## 4 1998 626 127 203  25   8 19 57 119 0.324 0.384 0.481 0.864
## 5 1999 627 134 219  37   9 24 91 116 0.349 0.438 0.552 0.989
## 6 2000 593 119 201  31   4 15 68  99 0.339 0.416 0.481 0.896
```

Albert removed Jeter's rookie year (1995) and his injury year(2013).

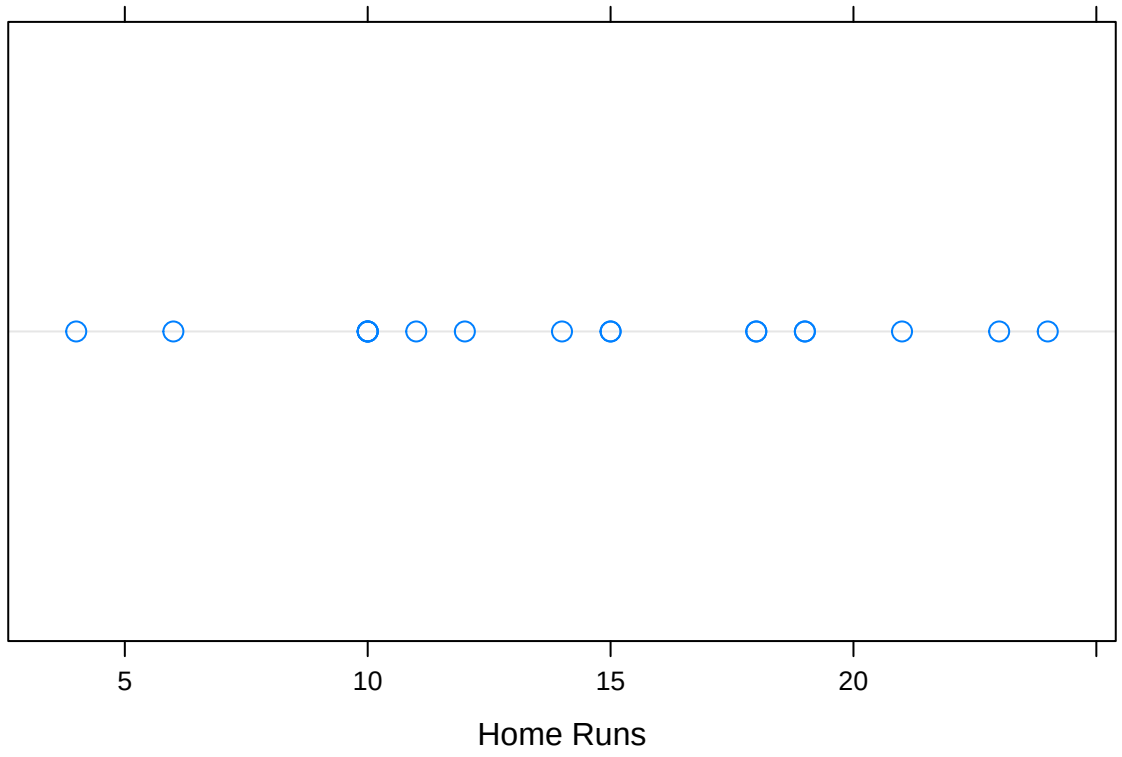
```
  case.2.2$Year                       ### Look at Jeter's years
```

```
##  [1] 1995 1996 1997 1998 1999 2000 2001 2002 2003 2004 2005 2006 2007 2008 2009
## [16] 2010 2011 2012 2013 2014
```

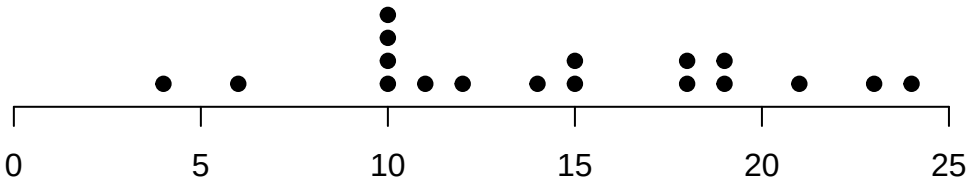
```
  albert.2.2 = case.2.2[-c(1,19), ]   ### Remove rows 1 and 19 (negative index), but keep all columns (b
  albert.2.2$Year                     ### 1995 and 2013 are not listed
```

```
##  [1] 1996 1997 1998 1999 2000 2001 2002 2003 2004 2005 2006 2007 2008 2009 2010
## [16] 2011 2012 2014
```

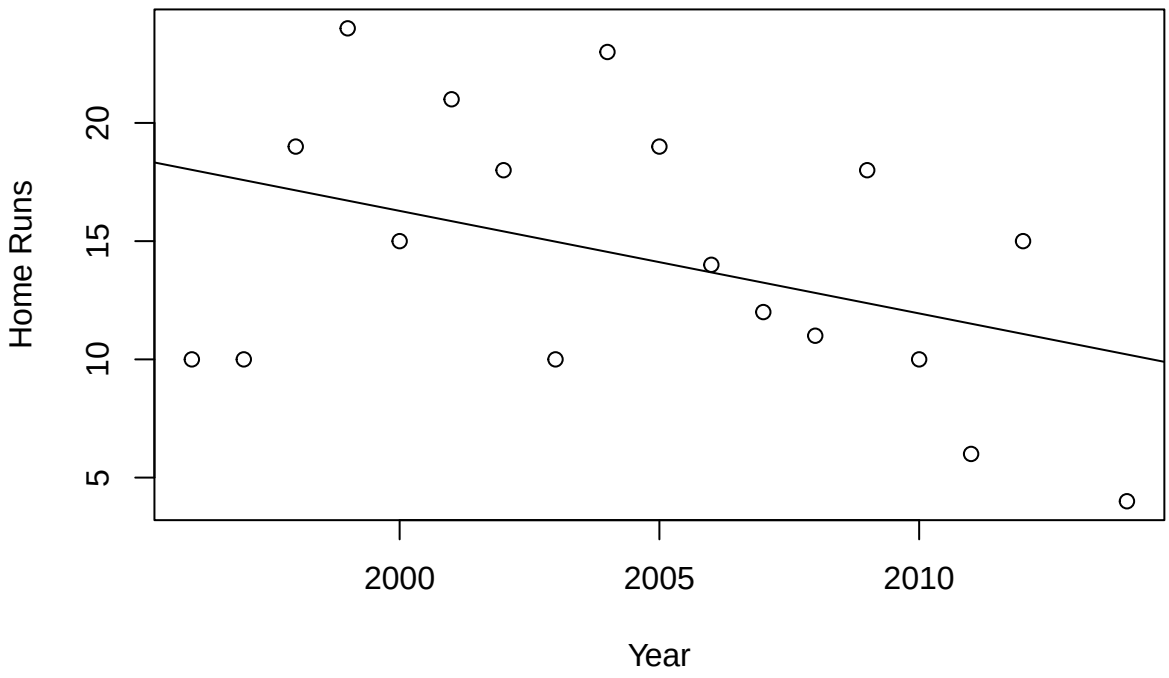
```
  case.2.2 = albert.2.2               ### Update case.2.2

  ### Create Figure 2.5
  dotplot(~HR, data=case.2.2, cex=1.25, pch=1, xlab="Home Runs")
```



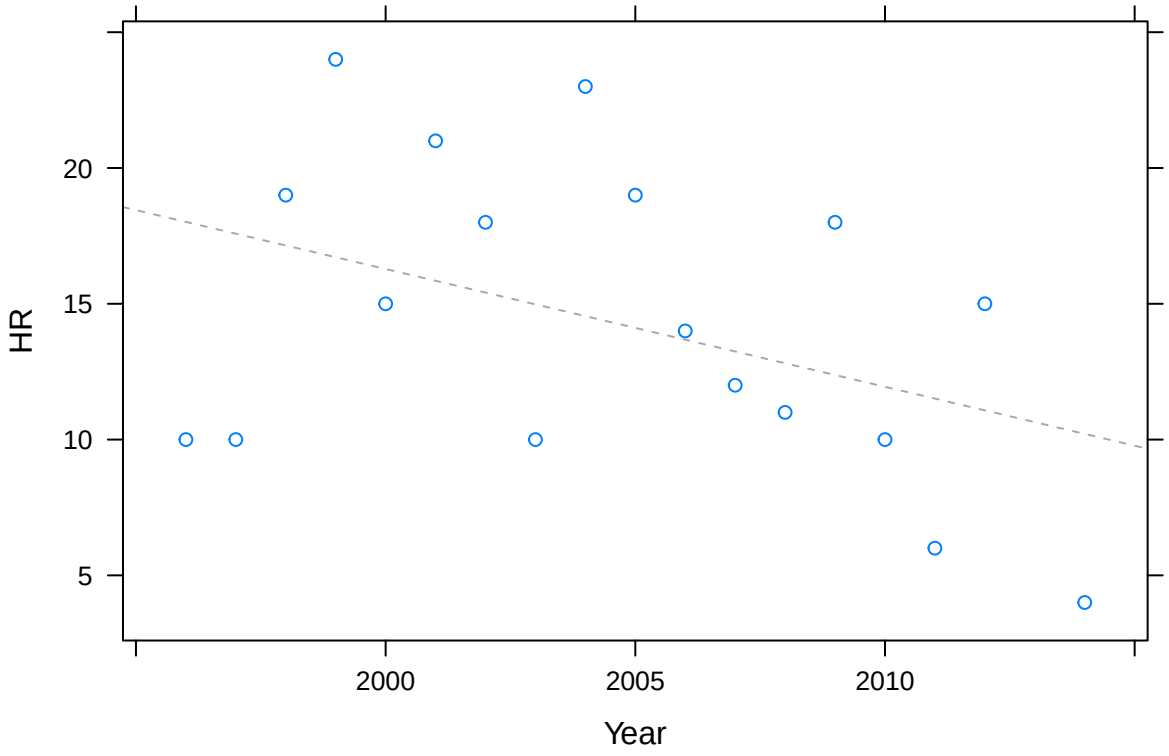

```
  dotplot.mtb(case.2.2$HR)
```




```
### Create Figure 2.6
plot(case.2.2$Year, case.2.2$HR, xlab="Year", ylab="Home Runs")

### Create Figure 2.7
plot(case.2.2$Year, case.2.2$HR, xlab="Year", ylab="Home Runs")
abline(a=883.68, b=-0.4337)                                    ### Doesn't show in RStudio.  Knit t
```

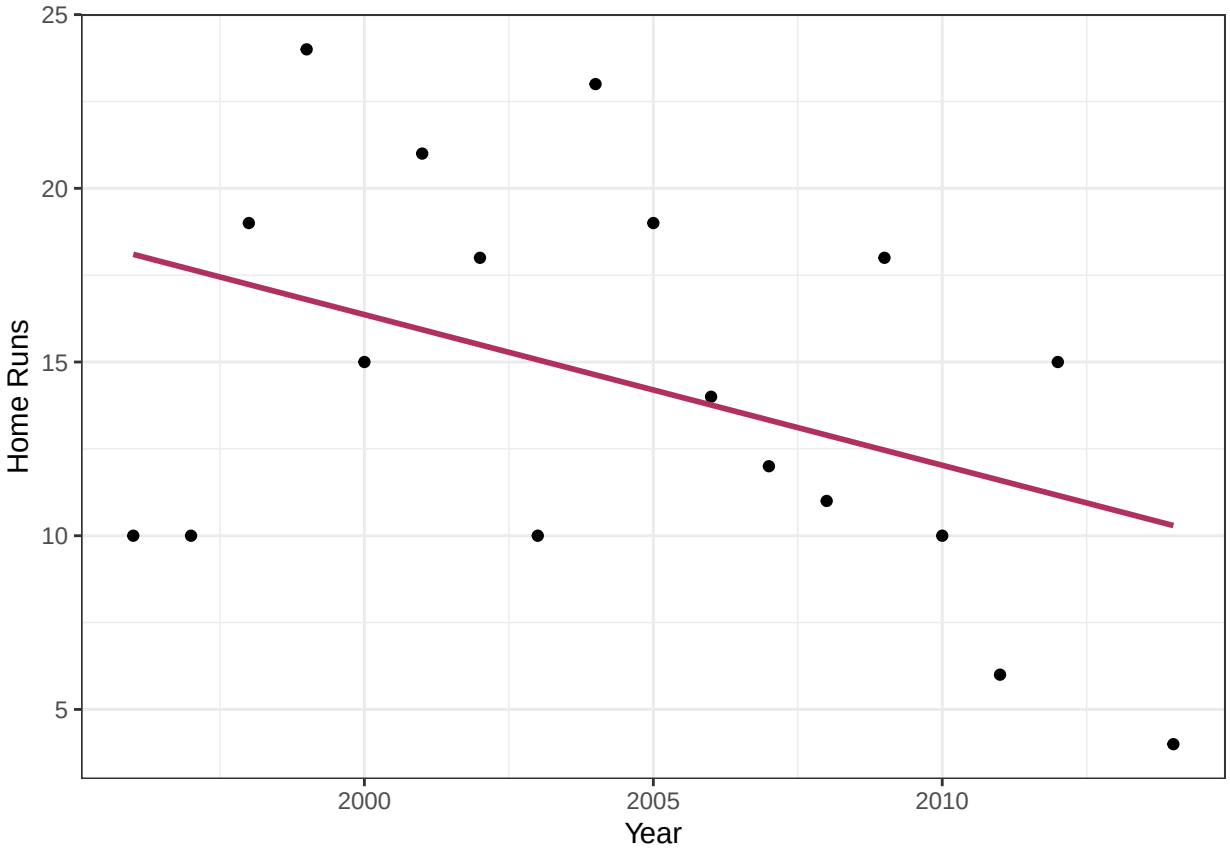



```
# Lattice approach
p_load(lattice)
xyplot(HR~Year, data=case.2.2, pch=1,
       panel=function(x, y, ...){
         panel.xyplot(x, y, ...)
         panel.abline(a=883.68, b=-0.4337, col="darkgray", lty=2)
       }
)
```




```
  # ggplot2 approach
  p_load(ggplot2)
  ggplot(case.2.2, aes(Year, HR)) + geom_point() + theme_bw() + xlab("Year") + ylab("Home Runs") + stat_
```

```
## `geom_smooth()` using formula 'y ~ x'
```




```
  ### Create Figure 2.8
  stem(case.2.2$OPS, 2)
```

```
##
##   The decimal point is 1 digit(s) to the left of the |
##
##   6 | 2
##   6 |
##   7 | 14
##   7 | 7899
##   8 | 02444
##   8 | 667
##   9 | 00
##   9 | 9
```

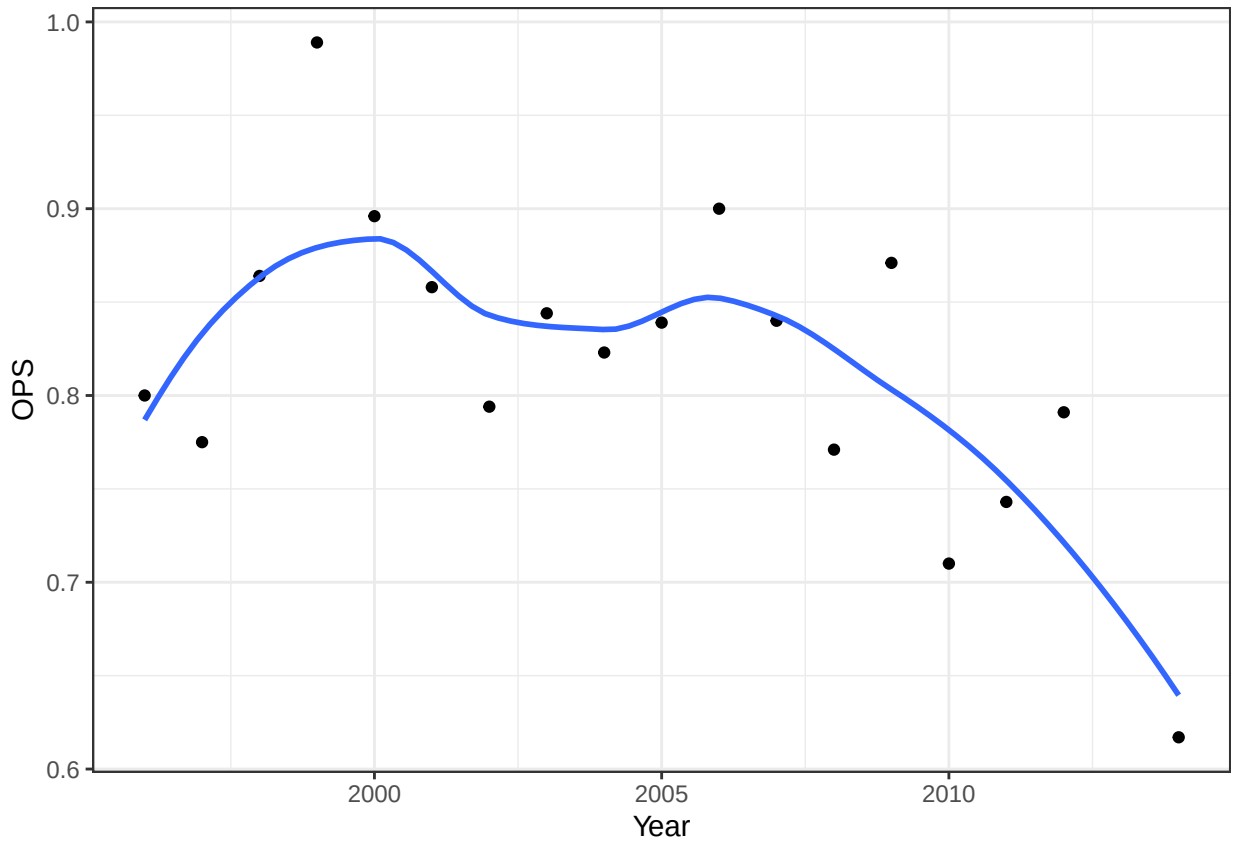
```
  ### Oops, Albert's software truncated to two decimals rather than rounded
  stem(trunc(100*case.2.2$OPS)/100, 2)
```

```
##
##   The decimal point is 1 digit(s) to the left of the |
##
##   6 | 1
##   6 |
##   7 | 14
##   7 | 7799
##   8 | 02344
##   8 | 5679
```

```
##   9 | 0
##   9 | 8
```

```
### Create Figure 2.9
# ggplot2 approach
ggplot(case.2.2, aes(Year, OPS)) + geom_point() + theme_bw() + xlab("Year") +
  geom_smooth(method = "loess", span = 2/3, se = FALSE)
```

```
## `geom_smooth()` using formula 'y ~ x'
```



Case 2.3

This case provides an opportunity to create a new statistic and to use some new graphical features. We will use Randy Johnson's data from the **tsub** package.

```
### Get the data
case.2.3 = case_2_3
head(case.2.3)
```

```
##   yearID  W  L  G     IP   H   R  SO  BB  ERA
## 1   1988  3  0  4  26.00  23   8  25   7 2.42
## 2   1989  7 13 29 160.67 147 100 130  96 4.82
## 3   1990 14 11 33 219.67 174 103 194 120 3.65
## 4   1991 13 10 33 201.33 151  96 228 152 3.98
## 5   1992 12 14 31 210.33 154 104 241 144 3.77
## 6   1993 19  8 35 255.33 185  97 308  99 3.24
```

```
### Compute the magic strikeout rate, SOR
case.2.3$sor = (case.2.3$SO/case.2.3$IP) * 9
```

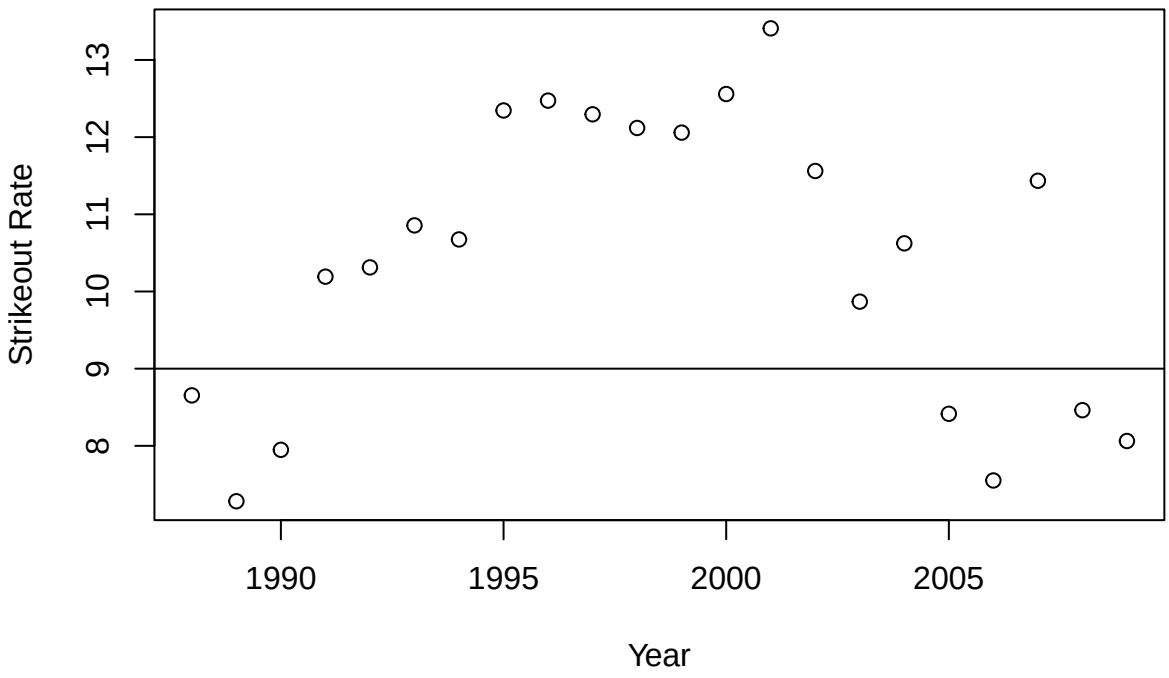
```
  case.2.3[, c("yearID","sor")]
```

```
##    yearID       sor
## 1    1988  8.653846
## 2    1989  7.282007
## 3    1990  7.948286
## 4    1991 10.192222
## 5    1992 10.312366
## 6    1993 10.856539
## 7    1994 10.674419
## 8    1995 12.345449
## 9    1996 12.473504
## 10   1997 12.295775
## 11   1998 12.118856
## 12   1999 12.058748
## 13   2000 12.558813
## 14   2001 13.409701
## 15   2002 11.561538
## 16   2003  9.868421
## 17   2004 10.624008
## 18   2005  8.414942
## 19   2006  7.551220
## 20   2007 11.434621
## 21   2008  8.461957
## 22   2009  8.062500
```

```
  ### Create Figure 2.10
  stem(case.2.3$sor,5)
```

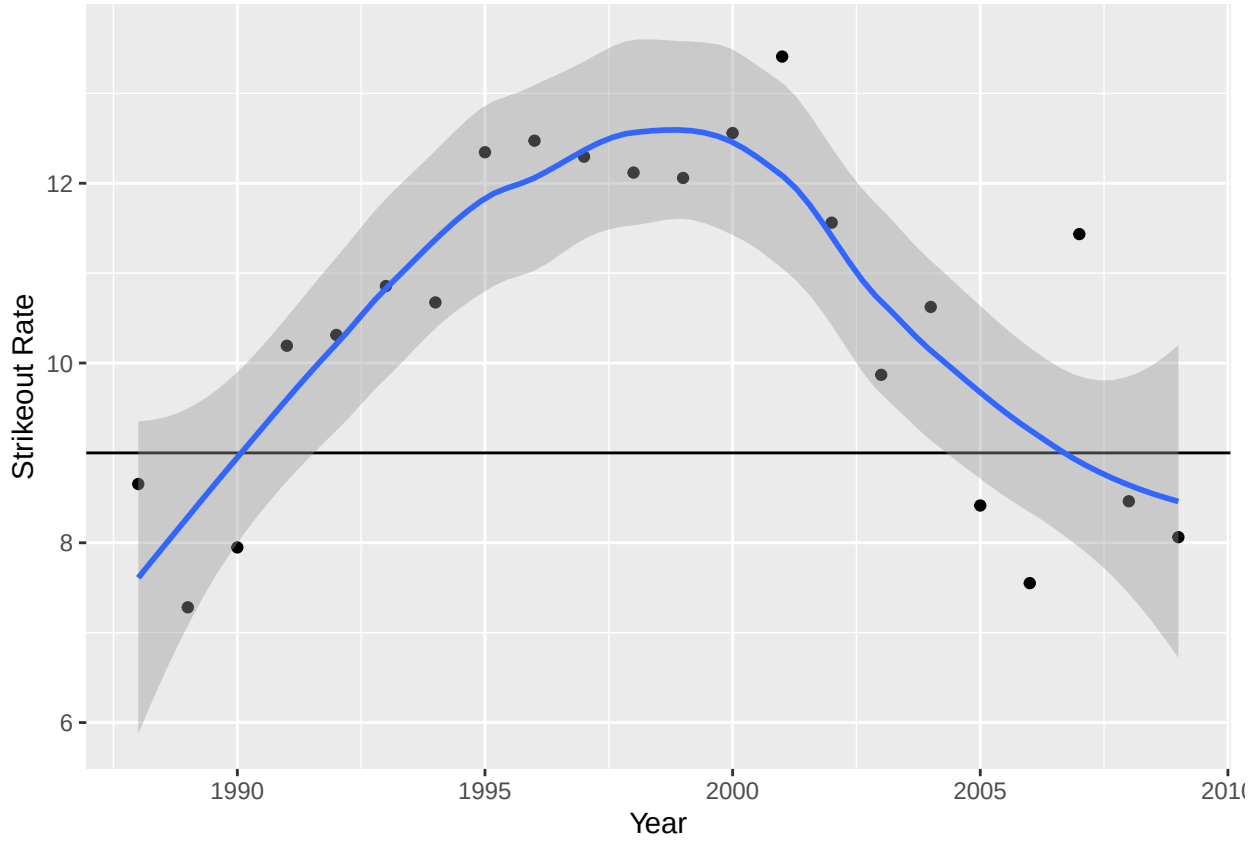
```
##
##   The decimal point is at the |
##
##    7 | 3
##    7 | 69
##    8 | 14
##    8 | 57
##    9 |
##    9 | 9
##   10 | 23
##   10 | 679
##   11 | 4
##   11 | 6
##   12 | 1133
##   12 | 56
##   13 | 4
```

```
  ### Again, the figures differ by rounding versus truncating

  ### Generate Figure 2.11
  plot(case.2.3$yearID, case.2.3$sor, xlab="Year", ylab="Strikeout Rate")
  abline(h=9)
```




```
  # ggplot2 approach
  p_load(ggplot2)
  ggplot(case.2.3, aes(yearID, sor)) + geom_point() + xlab("Year") + ylab("Strikeout Rate") +
    geom_hline(aes(yintercept=9)) + geom_smooth(method="loess", span = 2/3)
```

```
## `geom_smooth()` using formula 'y ~ x'
```



Of course, the data for Figures 2.12 and 2.13 are not in case_2_3.csv. So, we need to get a little creative.

```
### We'll use dplyr to pull Johnson's ID from Lahman's People table
p_load(Lahman, dplyr)
johnson.id = People %>%                                          ### Grab the People dataframe
               filter(nameFirst=="Randy" & nameLast=="Johnson") # %>%  ### Get Randy Johnson
### There are three Randy Johnson's
head(johnson.id)
```

```
##    playerID birthYear birthMonth birthDay birthCountry birthState    birthCity
## 1 johnsra03      1958          8       15          USA         FL        Miami
## 2 johnsra04      1956          6       10          USA         CA    Escondido
## 3 johnsra05      1963          9       10          USA         CA Walnut Creek
##   deathYear deathMonth deathDay deathCountry deathState deathCity nameFirst
## 1        NA         NA       NA         <NA>       <NA>      <NA>     Randy
## 2        NA         NA       NA         <NA>       <NA>      <NA>     Randy
## 3        NA         NA       NA         <NA>       <NA>      <NA>     Randy
##   nameLast      nameGiven weight height bats throws      debut  finalGame
## 1  Johnson Randall Stuart    195     74    L      L 1980-07-05 1982-10-03
## 2  Johnson  Randall Glenn    190     73    R      R 1982-04-27 1984-09-30
## 3  Johnson  Randall David    225     82    R      L 1988-09-15 2009-10-04
##    retroID   bbrefID deathDate  birthDate
## 1 johnr101 johnsra03      <NA> 1958-08-15
## 2 johnr001 johnsra04      <NA> 1956-06-10
## 3 johnr005 johnsra05      <NA> 1963-09-10
```

```
  ### We want the one whose first game was in 1988
  johnson.id = johnson.id %>%
                  filter(year(debut) == 1988) %>%  ### Make sure debut year was 1988
                  select(retroID)                  ### We need only his ID
  head(johnson.id)
```

```
##    retroID
## 1 johnr005
```

```
  johnson.id = as.character(johnson.id)  ### Make it a value not a dataframe

  ### Starting pitchers and runs can be found in RetroSheet
  ###    RetroSheet can sometimes be hard to install.  If p_load fails,
  ###    uncomment the two lines that follow and run once.
  ## p_load(devtools)
  ## devtools::install_github("rmscriven/retrosheet")
  p_load(retrosheet)
  game1995 = getRetrosheet("game", 1995)

  ### Use SQL to subset the SEA games and order them by date
  p_load(sqldf)
  sqlsea1995 = sqldf("SELECT * FROM game1995 WHERE (HmTm='SEA' OR VisTm='SEA') ORDER BY Date")
  ### Or, use dplyr to get SEA games and order by Date
  sea1995 = game1995 %>%
              filter(HmTm=="SEA" | VisTm=="SEA") %>% ### Get home and away games for SEA
              arrange(Date)
  ### Check to see if the two dataframes are the same
  all_equal(sea1995, sqlsea1995) ### Good news, they are the same
```

```
## [1] TRUE
```

```
  ### Now figure out which ones Johnson started in and which were home
  sea1995$RJstart = sea1995$VisStPchID==johnson.id | sea1995$HmStPchID==johnson.id  ### RJ started TRUE
  sea1995$AtHome = sea1995$HmTm=="SEA"                                 ### Home team SEA TRUE/FALSE
  sea1995[sea1995$AtHome, "runs"] = sea1995[sea1995$AtHome, "HmRuns"] ### Rows: AtHome==TRUE; runs=HmRu
  sea1995[!sea1995$AtHome,"runs"] = sea1995[!sea1995$AtHome, "VisRuns"] ### Rows: AtHome==FALSE; runs=V
  ### Subset the data for Johnson starts
  runs.rj.start = sea1995$runs[sea1995$RJstart]

  ### Text "table" of runs when RJ started.
  runs.rj.start
```

```
##  [1]  3 15  3  6  4  5  8 11  2  3  1  9  3  5  4  5  3  4  8  2  2  6  6  7  4
## [26]  7  8  7  6  9
```

```
  ### Create Figure 2.12
  stem(runs.rj.start, 2)
```

```
##
##   The decimal point is at the |
##
##    1 | 0
##    2 | 000
##    3 | 00000
##    4 | 0000
##    5 | 000
```

```
##    6 | 0000
##    7 | 000
##    8 | 000
##    9 | 00
##   10 |
##   11 | 0
##   12 |
##   13 |
##   14 |
##   15 | 0
```

```
  ### While the shape is right, the leaves and stems aren't pretty. Try aplpack.
  p_load(aplpack)
  stem.leaf(runs.rj.start)
```

```
## 1 | 2: represents 1.2
##  leaf unit: 0.1
##             n: 30
##    1     1 | 0
##    4     2 | 000
##    9     3 | 00000
##   13     4 | 0000
##   (3)    5 | 000
##   14     6 | 0000
##   10     7 | 000
##    7     8 | 000
##    4     9 | 00
##         10 |
##    2    11 | 0
## HI: 15
```

```
  ### Create Figure 2.13
  runs.rj.nostart = sea1995$runs[!sea1995$RJstart]
  stem.leaf.backback(runs.rj.start,runs.rj.nostart)
```

```
## ------------------------------------------------------
##   1 | 2: represents 1.2, leaf unit: 0.1
##           runs.rj.start      runs.rj.nostart
## ------------------------------------------------------
##                         |  0 |00                   2
##    1                  0|  1 |000000000000        14
##    4                000|  2 |00000000000000      28
##    9              00000|  3 |00000000000         39
##   13               0000|  4 |000000000000        51
##   (3)               000|  5 |000000000000       (12)
##   14               0000|  6 |0000000000000000    52
##   10                000|  7 |00000               36
##    7                000|  8 |00000               31
##    4                 00|  9 |0000000             26
##                        | 10 |000000000           19
##    2                  0| 11 |000000              10
##                        | 12 |
##                        | 13 |
##                        | 14 |0                    4
##    1                  0| 15 |000                  3
```

```
## ------------------------------------------------------
## n:                    30      115
## ------------------------------------------------------
```

```
  ### Means and medians
  mean(runs.rj.start)
```

```
## [1] 5.533333
```

```
  median(runs.rj.start)
```

```
## [1] 5
```

```
  mean(runs.rj.nostart)
```

```
## [1] 5.478261
```

```
  median(runs.rj.nostart)
```

```
## [1] 5
```

Case 2.4

TSUB2 now looks at attendance. As seen above, this information is included in Lahman's data. However, we will use Albert's data for convenience.

```
  ### Make a local copy of the tsub dataframe
  case.2.4 = case_2_4
  head(case.2.4)
```

```
##   HomeTeam  Mean
## 1      ANA 38221
## 2      ARI 25602
## 3      ATL 29065
## 4      BAL 30426
## 5      BOS 36495
## 6      CHA 20381
```

```
  ### The variable names are messed up.  We fix them.
  names(case.2.4)                              ### Ask for the column names
```

```
## [1] "HomeTeam" "Mean"
```

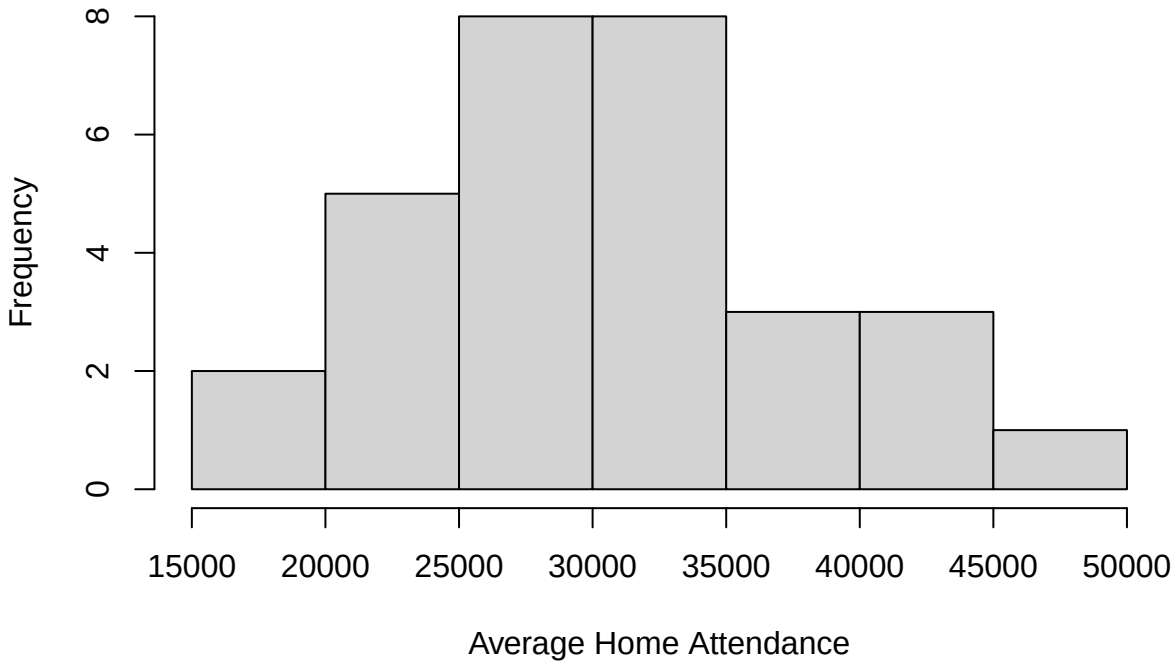
```
  names(case.2.4) <- c("Team","Attendance")   ### Set the column names with the new names
  names(case.2.4)                              ### Ask for the column names
```

```
## [1] "Team"       "Attendance"
```

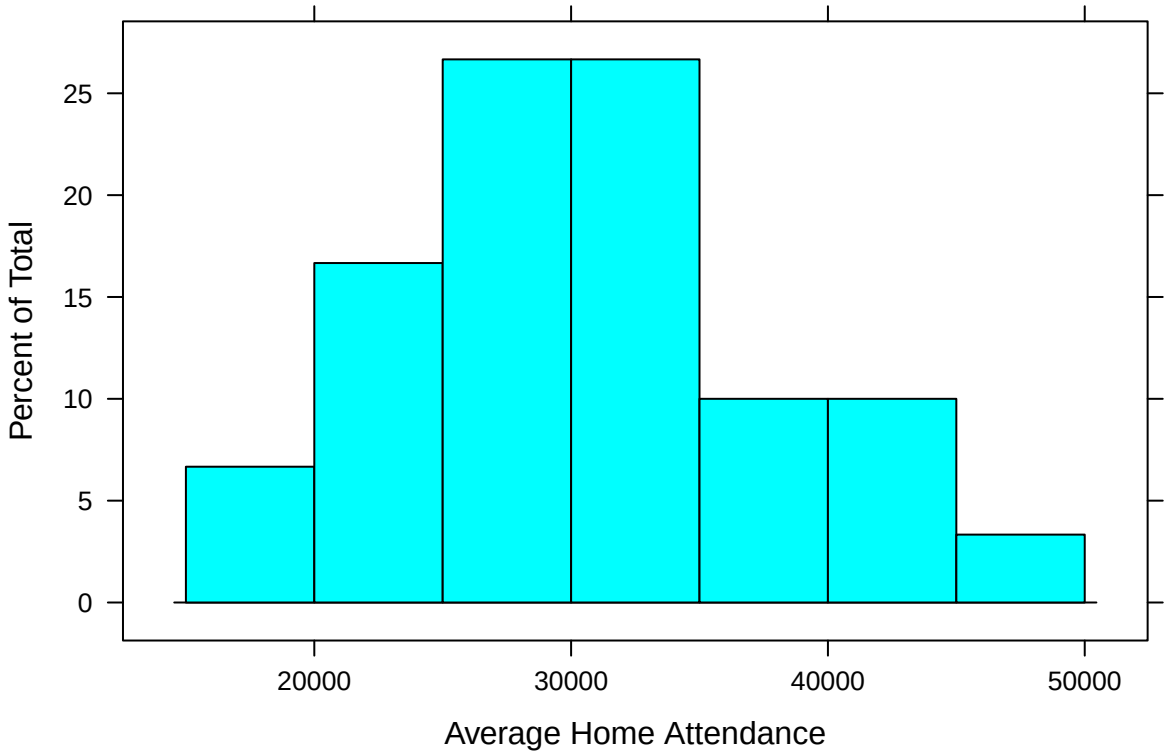
```
  head(case.2.4)                               ### Look at the dataframe
```

```
##   Team Attendance
## 1  ANA      38221
## 2  ARI      25602
## 3  ATL      29065
## 4  BAL      30426
## 5  BOS      36495
## 6  CHA      20381
```

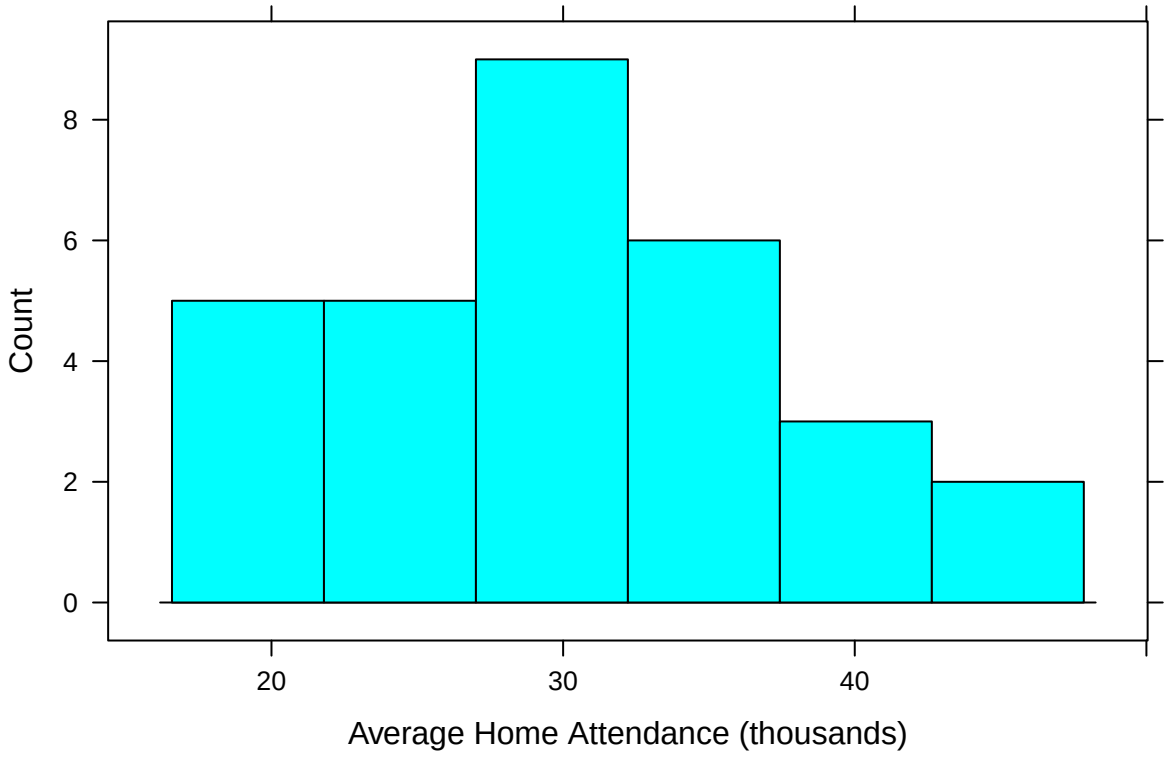
```
  ### Plot Figure 2.14 using base R
  hist(case.2.4$Attendance, xlab="Average Home Attendance", main="")
```




```
### and the lattice package
histogram(~Attendance, data=case.2.4, xlab="Average Home Attendance", breaks=15000+5000*(0:7))
```

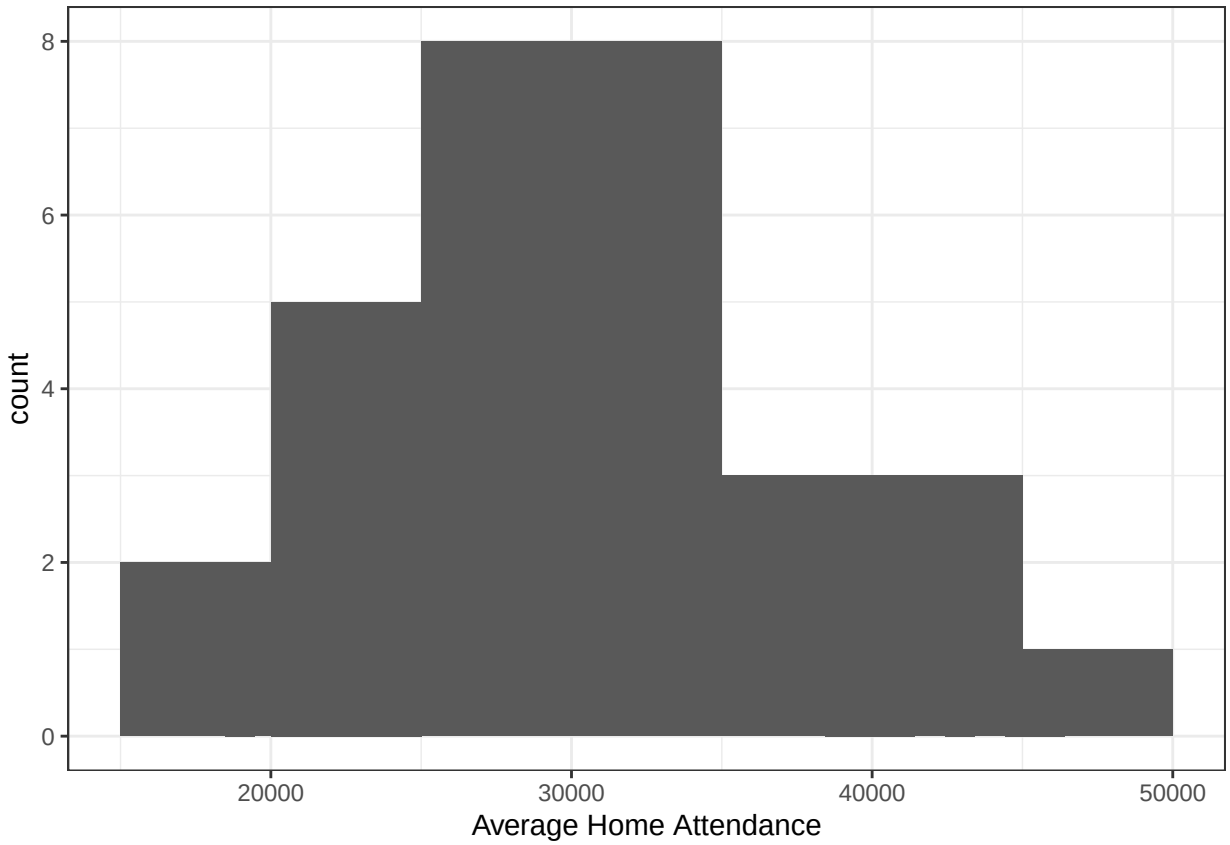



```
histogram(~Attendance/1000, data=case.2.4, xlab="Average Home Attendance (thousands)", type="count")
```



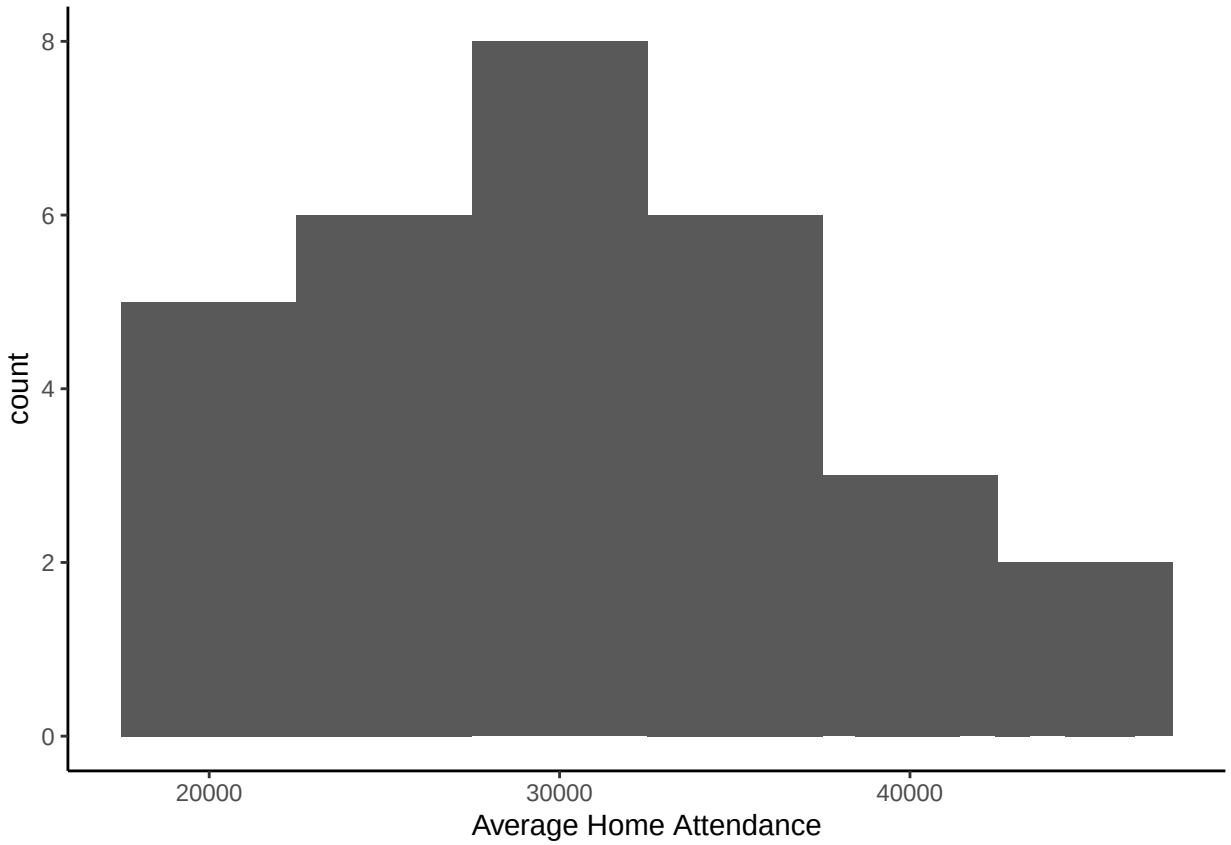

```
  ### and using ggplot
  p_load(ggplot2)
  ggplot(case.2.4,aes(Attendance)) + geom_histogram() + xlab("Average Home Attendance") + stat_bin(breal
```

```
## `stat_bin()` using `bins = 30`. Pick better value with `binwidth`.
```




```
  ggplot(case.2.4,aes(Attendance)) + geom_histogram() + xlab("Average Home Attendance") + stat_bin(binw
```

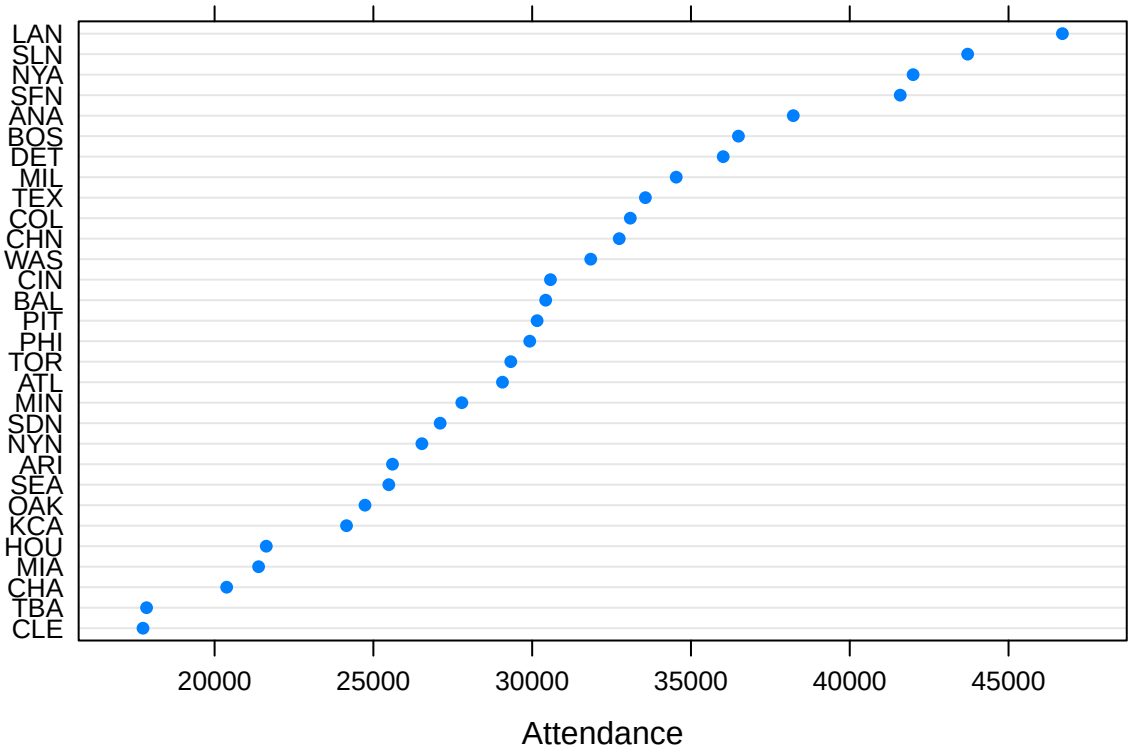
```
## `stat_bin()` using `bins = 30`. Pick better value with `binwidth`.
```




```
  ### Create Figure 2.15
  p_load(aplpack)
  stem.leaf(case.2.4$Attendance)
```

```
## 1 | 2: represents 12000
##  leaf unit: 1000
##             n: 30
##    2    1. | 77
##    7    2* | 01144
##   (8)   2. | 55677999
##   (8)   3* | 00012334
##    7    3. | 668
##    4    4* | 113
##    1    4. | 6
```

```
  ### Create Figure 2.16
  ### We can use the lattice package to create the Bill Cleveland style dotplot of average attendance
  p_load(lattice)
  dotplot(reorder(Team, Attendance)~Attendance, data=case.2.4)  ### We order the teams by their mean at
```



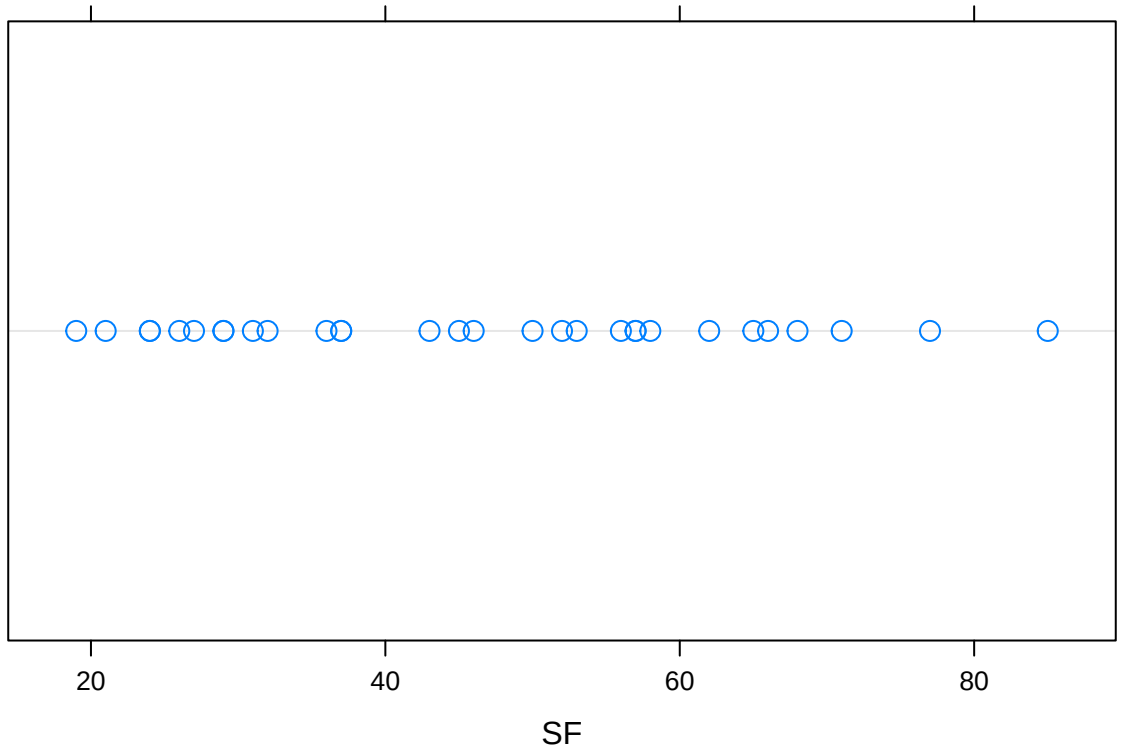
Case 2.5

Finally, we look at the use of the sacrifice bunt during the 2013 season. The data list ***SF*** which appears to be sac FLIES not bunts. The values are the same as those of Table 2.6. The **tsub** package data do not include ***League***.

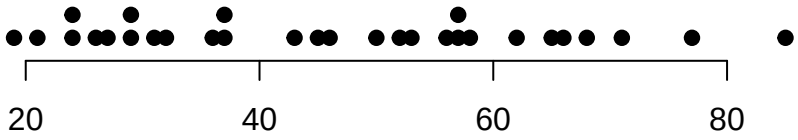
```
  ### Get the case_2_5 data
  case.2.5 = read.csv("http://facweb1.redlands.edu/fac/jim_bentley/Data/FYS28/TSUB2/CSV/case_2_5.csv")
  head(case.2.5)
```

```
##   BAT_TEAM SF League
## 1      ANA 37     AL
## 2      ARI 50     NL
## 3      ATL 58     NL
## 4      BAL 27     AL
## 5      BOS 24     AL
## 6      CHA 19     AL
```

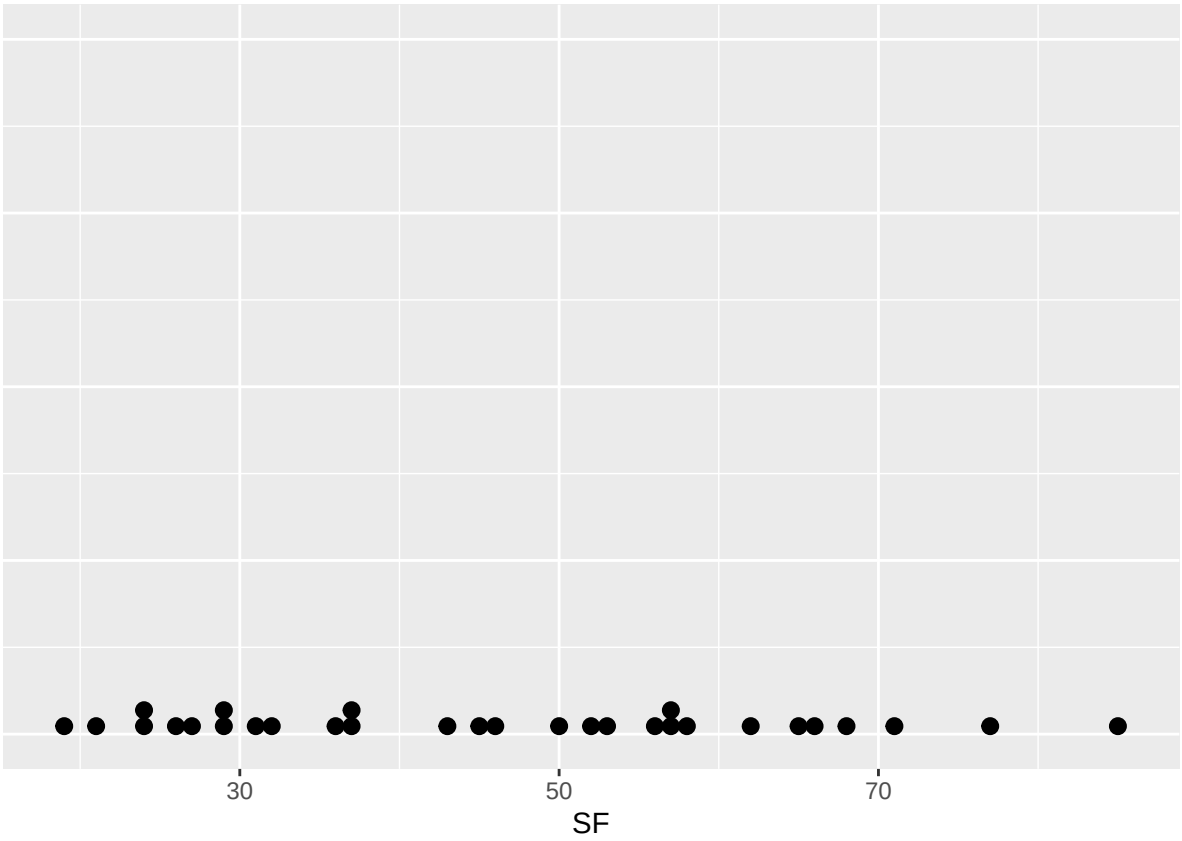
```
  names(case.2.5)[1] <- "Team"  ### Replace BAT_TEAM with Team.  Is SH sac bunts?

  ### Figure 2.17
  p_load(lattice)
  dotplot(~SF, data=case.2.5, cex=1.25, pch=1)
```




```
dotplot.mtb(case.2.5$SF)
```



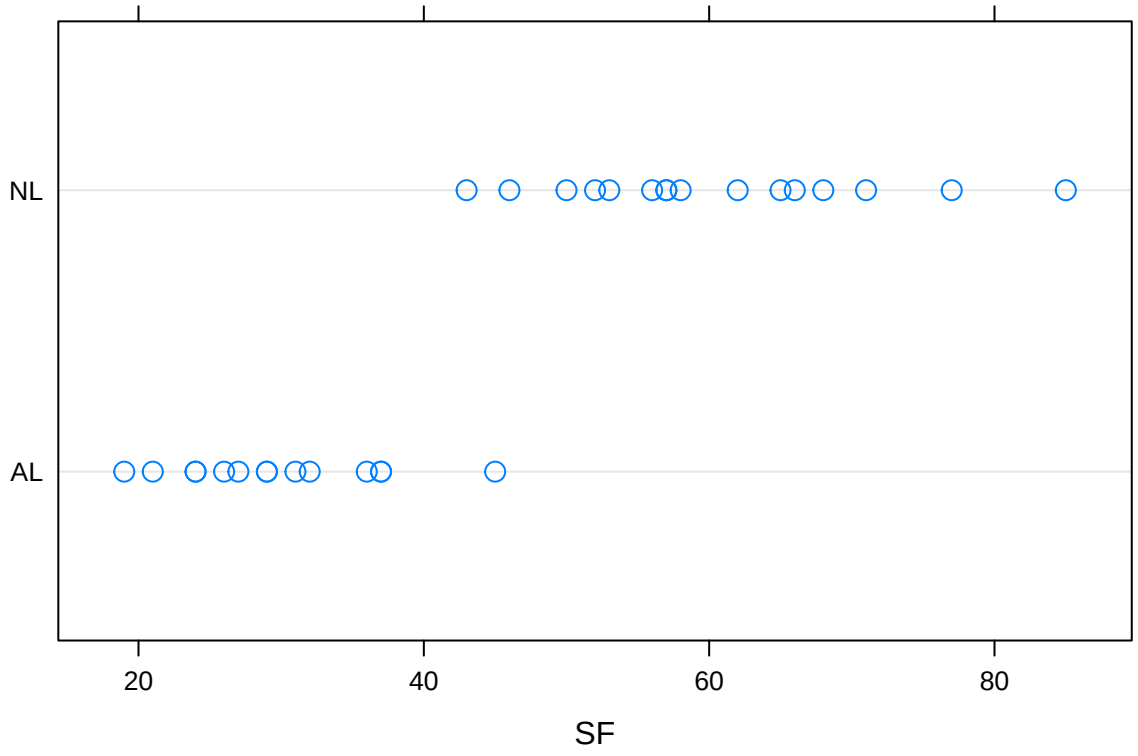

```
plt = case.2.5 %>%
      ggplot(aes(x = SF)) +
         geom_dotplot(binwidth = 1)
plt + theme(axis.text.y=element_blank(),
            axis.ticks.y=element_blank()
      ) + labs(y="")
```



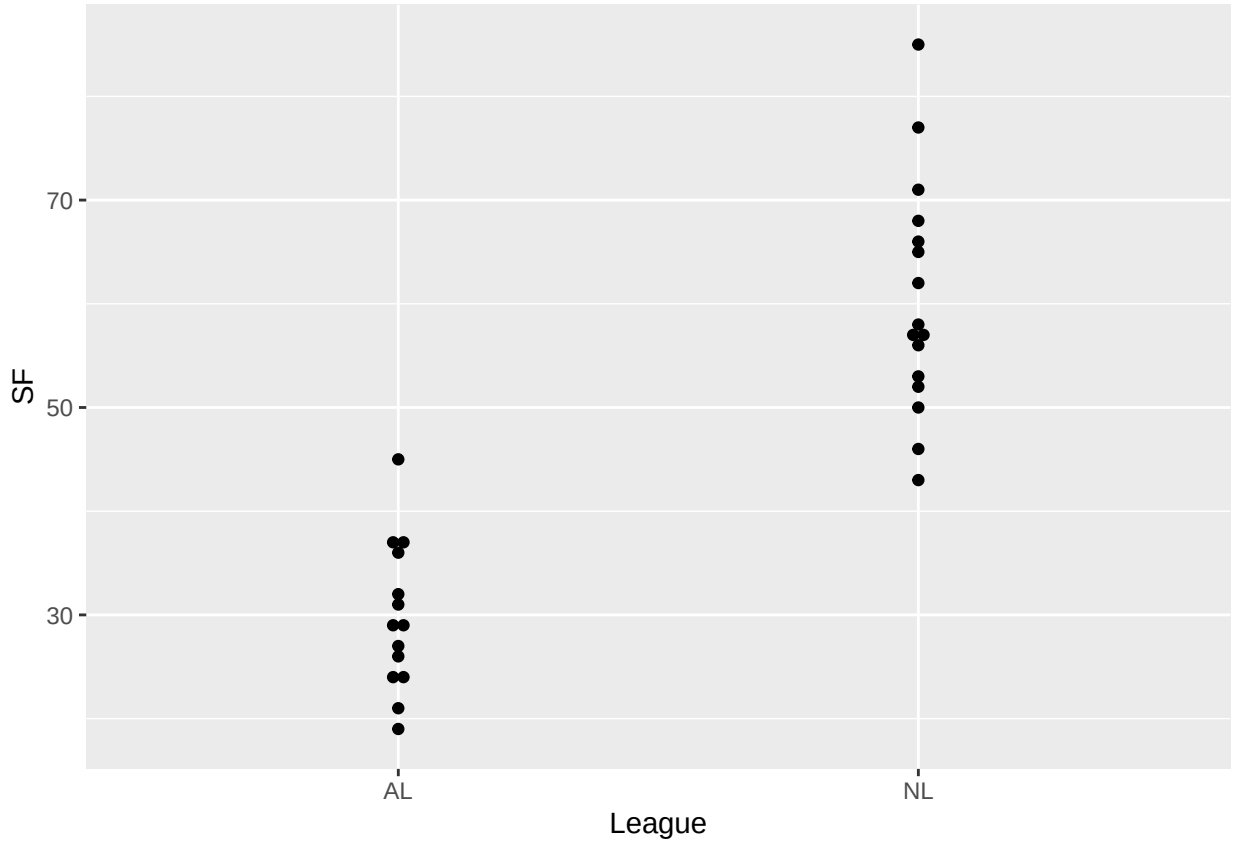

```
  ### Compute simple statistics
  summary(case.2.5$SF)
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##   19.00   29.50   45.50   46.10   57.75   85.00
```

```
  ### Since we are using the lattice package, Figure 2.18 is an easy fix
  dotplot(League ~ SF, data=case.2.5, cex=1.25, pch=1)
```




```
plt = case.2.5 %>%
      ggplot(aes(x = League, y = SF)) +
         geom_dotplot(binaxis = "y", stackdir = "center", binwidth = 1)
plt
```




```
  ### Compute associated statistics
  by(case.2.5$SF,case.2.5$League,summary)
```

```
## case.2.5$League: AL
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##   19.00   24.50   29.00   29.79   35.00   45.00
## ------------------------------------------------------------
## case.2.5$League: NL
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##   43.00   52.75   57.50   60.38   66.50   85.00
```

Chapter Three

Chapter 3 moves from describing one characteristic to comparing a couple. R's developers have made this transition easy.

Case 3.1

The plots and statistics for comparing Albert Pujols and Manny Ramirez that are presented in Case 3.1 are, for the most part, variations on those already presented above. For this case we download the data from my web site.

```
  ### Get the data
  case.3.1 = read.csv("http://facweb1.redlands.edu/fac/jim_bentley/Data/FYS28/TSUB2/CSV/case_3_1.csv")

  ### Table 3.1 is just the data.frame
  case.3.1 %>% select(Player, Age, SLG, OBP, OPS)
```

```
##     Player Age       SLG       OBP   OPS
## 1  Rameriz  22 0.5206897 0.3571429 0.878
## 2  Rameriz  23 0.5578512 0.4024605 0.960
## 3  Rameriz  24 0.5818182 0.3987635 0.981
## 4  Rameriz  25 0.5383244 0.4147465 0.953
## 5  Rameriz  26 0.5989492 0.3770739 0.976
## 6  Rameriz  27 0.6628352 0.4421875 1.105
## 7  Rameriz  28 0.6970387 0.4567669 1.154
## 8  Rameriz  29 0.6086957 0.4048387 1.014
## 9  Rameriz  30 0.6467890 0.4498069 1.097
## 10 Rameriz  31 0.5869947 0.4270987 1.014
## 11 Rameriz  32 0.6126761 0.3966817 1.009
## 12 Rameriz  33 0.5938628 0.3876923 0.982
## 13 Rameriz  34 0.6191537 0.4390681 1.058
## 14 Rameriz  35 0.4927536 0.3884007 0.881
## 15 Rameriz  36 0.6014493 0.4296636 1.031
## 16 Rameriz  37 0.5312500 0.4176334 0.949
## 17 Rameriz  38 0.4603774 0.4093750 0.870
## 18  Pujols  21 0.6101695 0.4029630 1.013
## 19  Pujols  22 0.5610169 0.3940741 0.955
## 20  Pujols  23 0.6666667 0.4394161 1.106
## 21  Pujols  24 0.6570946 0.4147399 1.072
## 22  Pujols  25 0.6091371 0.4300000 1.039
## 23  Pujols  26 0.6710280 0.4305994 1.102
## 24  Pujols  27 0.5681416 0.4285714 0.997
## 25  Pujols  28 0.6526718 0.4617785 1.114
## 26  Pujols  29 0.6584507 0.4428571 1.101
## 27  Pujols  30 0.5962521 0.4142857 1.011
## 28  Pujols  31 0.5405872 0.3655914 0.906
## 29  Pujols  32 0.5156507 0.3432836 0.859
## 30  Pujols  33 0.4373402 0.3295711 0.767
## 31  Pujols  34 0.4660348 0.3237410 0.790
## 32  Pujols  35 0.4800664 0.3071104 0.787
```

```
  names(case.3.1)
```

```
##  [1] "Player" "yearID" "AB"     "BB"     "HBP"    "H"      "X2B"    "X3B"
##  [9] "HR"     "SF"     "Age"    "SLG"    "OBP"    "OPS"
```

```
  ### Albert next creates Figure 3.1, a back-to-back stemplot
  p_load(aplpack)
  (pujols = case.3.1 %>% filter(Player=="Pujols"))
```

```
##    Player yearID  AB  BB HBP   H X2B X3B HR SF Age       SLG       OBP   OPS
## 1  Pujols   2001 590  69   9 194  47   4 37  7  21 0.6101695 0.4029630 1.013
## 2  Pujols   2002 590  72   9 185  40   2 34  4  22 0.5610169 0.3940741 0.955
## 3  Pujols   2003 591  79  10 212  51   1 43  5  23 0.6666667 0.4394161 1.106
## 4  Pujols   2004 592  84   7 196  51   2 46  9  24 0.6570946 0.4147399 1.072
## 5  Pujols   2005 591  97   9 195  38   2 41  3  25 0.6091371 0.4300000 1.039
## 6  Pujols   2006 535  92   4 177  33   1 49  3  26 0.6710280 0.4305994 1.102
## 7  Pujols   2007 565  99   7 185  38   1 32  8  27 0.5681416 0.4285714 0.997
## 8  Pujols   2008 524 104   5 187  44   0 37  8  28 0.6526718 0.4617785 1.114
## 9  Pujols   2009 568 115   9 186  45   1 47  8  29 0.6584507 0.4428571 1.101
## 10 Pujols   2010 587 103   4 183  39   1 42  6  30 0.5962521 0.4142857 1.011
## 11 Pujols   2011 579  61   4 173  29   0 37  7  31 0.5405872 0.3655914 0.906
## 12 Pujols   2012 607  52   5 173  50   0 30  6  32 0.5156507 0.3432836 0.859
```

```
## 13 Pujols   2013 391  40   5 101  19   0 17  7  33 0.4373402 0.3295711 0.767
## 14 Pujols   2014 633  48   5 172  37   1 28  9  34 0.4660348 0.3237410 0.790
## 15 Pujols   2015 602  50   6 147  22   0 40  3  35 0.4800664 0.3071104 0.787
```

```
  (ramirez = case.3.1 %>% filter(Player=="Ramirez"))
```

```
##  [1] Player yearID AB     BB     HBP    H      X2B    X3B    HR     SF
## [11] Age    SLG    OBP    OPS
## <0 rows> (or 0-length row.names)
```

Wait. There aren't any Ramirez observations? What's going on?

```
  table(case.3.1$Player)
```

```
##
##  Pujols Rameriz
##      15      17
```

It looks like Albert typoed. Let's fix it and move on.

```
  ### Select only those rows with Player == "Rameriz" and replace the Player column value with "Ramirez
  case.3.1[case.3.1$Player == "Rameriz", "Player" ] <- "Ramirez"
  (ramirez = case.3.1 %>% filter(Player=="Ramirez"))
```

```
##     Player yearID  AB  BB HBP   H X2B X3B HR SF Age       SLG       OBP   OPS
## 1  Ramirez   1994 290  42   0  78  22   0 17  4  22 0.5206897 0.3571429 0.878
## 2  Ramirez   1995 484  75   5 149  26   1 31  5  23 0.5578512 0.4024605 0.960
## 3  Ramirez   1996 550  85   3 170  45   3 33  9  24 0.5818182 0.3987635 0.981
## 4  Ramirez   1997 561  79   7 184  40   0 26  4  25 0.5383244 0.4147465 0.953
## 5  Ramirez   1998 571  76   6 168  35   2 45 10  26 0.5989492 0.3770739 0.976
## 6  Ramirez   1999 522  96  13 174  34   3 44  9  27 0.6628352 0.4421875 1.105
## 7  Ramirez   2000 439  86   3 154  34   2 38  4  28 0.6970387 0.4567669 1.154
## 8  Ramirez   2001 529  81   8 162  33   2 41  2  29 0.6086957 0.4048387 1.014
## 9  Ramirez   2002 436  73   8 152  31   0 33  1  30 0.6467890 0.4498069 1.097
## 10 Ramirez   2003 569  97   8 185  36   1 37  5  31 0.5869947 0.4270987 1.014
## 11 Ramirez   2004 568  82   6 175  44   0 43  7  32 0.6126761 0.3966817 1.009
## 12 Ramirez   2005 554  80  10 162  30   1 45  6  33 0.5938628 0.3876923 0.982
## 13 Ramirez   2006 449 100   1 144  27   1 35  8  34 0.6191537 0.4390681 1.058
## 14 Ramirez   2007 483  71   7 143  33   1 20  8  35 0.4927536 0.3884007 0.881
## 15 Ramirez   2008 552  87  11 183  36   1 37  4  36 0.6014493 0.4296636 1.031
## 16 Ramirez   2009 352  71   7 102  24   2 19  1  37 0.5312500 0.4176334 0.949
## 17 Ramirez   2010 265  46   6  79  16   0  9  3  38 0.4603774 0.4093750 0.870
```

```
  stem.leaf.backback(pujols$OPS, ramirez$OPS)
```

```
## ------------------------------
##   1 | 2: represents 0.12, leaf unit: 0.01
##     pujols$OPS       ramirez$OPS
## ------------------------------
##              |  7* |
##    3     986|  7. |
##              |  8* |
##    4       5|  8. |778     3
##    5       0|  9* |4       4
##    7      95|  9. |56788  (5)
##   (3)    311| 10* |0113    8
##    5       7| 10. |59      4
##    4    1000| 11* |0       2
```

```
##             | 11. |5       1
##             | 12* |
## ------------------------------
## n:        15       17
## ------------------------------
```

That's better, but where did Pujols' 78 come from? How many observations should he have? The online data contains an extra season for Pujols — when he was 35.

```
  ### Five number summaries can be computed in a number of ways
  ### Median
  (n = nrow(pujols))
```

```
## [1] 15
```

```
  (n+1)/2
```

```
## [1] 8
```

```
  m = sort(pujols$OPS)[(n+1)/2]
  m
```

```
## [1] 1.011
```

```
  median(pujols$OPS)
```

```
## [1] 1.011
```

```
  ### Quartiles
  sort(pujols$OPS[pujols$OPS < m])
```

```
## [1] 0.767 0.787 0.790 0.859 0.906 0.955 0.997
```

```
  ql = median(pujols$OPS[pujols$OPS < m])
  ql
```

```
## [1] 0.859
```

```
  qu = median(pujols$OPS[pujols$OPS > m])
  qu
```

```
## [1] 1.101
```

```
  quantile(pujols$OPS)[c(2,4)]
```

```
##    25%    75%
## 0.8825 1.0865
```

```
  sort(pujols$OPS)
```

```
##  [1] 0.767 0.787 0.790 0.859 0.906 0.955 0.997 1.011 1.013 1.039 1.072 1.101
## [13] 1.102 1.106 1.114
```

```
  ### Min and max are easy
  min(pujols$OPS)
```

```
## [1] 0.767
```

```
  max(pujols$OPS)
```

```
## [1] 1.114
```

```
  range(pujols$OPS)
```

```
## [1] 0.767 1.114
```

```
  ### Together, the statistics from above are the five-number-summary
  quantile(pujols$OPS)
```

```
##     0%    25%    50%    75%   100%
## 0.7670 0.8825 1.0110 1.0865 1.1140
```

```
  summary(pujols$OPS) # Ignore the mean for now.
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##  0.7670  0.8825  1.0110  0.9746  1.0865  1.1140
```

```
  quantile(ramirez$OPS)
```

```
##    0%   25%   50%   75%  100%
## 0.870 0.953 0.982 1.031 1.154
```

```
  summary(ramirez$OPS)
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##  0.8700  0.9530  0.9820  0.9948  1.0310  1.1540
```

```
  ### Albert computes a "step" that is then used to compute the u/l fences
  ### Note that the difference between steps found using Albert's method and
  ### the internal function is minimal.  We'll use Albert's value.
  (qu = quantile(ramirez$OPS)[4])
```

```
##   75%
## 1.031
```

```
  (ql = quantile(ramirez$OPS)[2])
```

```
##   25%
## 0.953
```

```
  step = 1.5*(qu-ql)
  step
```

```
##   75%
## 0.117
```

```
  1.5 * c(-1,1) %*% quantile(ramirez$OPS)[c(2,4)]  ### A little different due to different quantiles
```

```
##       [,1]
## [1,] 0.117
```

```
  fu = qu + step
  fu
```

```
##   75%
## 1.148
```

```
  fl = ql - step
  fl
```

```
##   25%
## 0.836
```

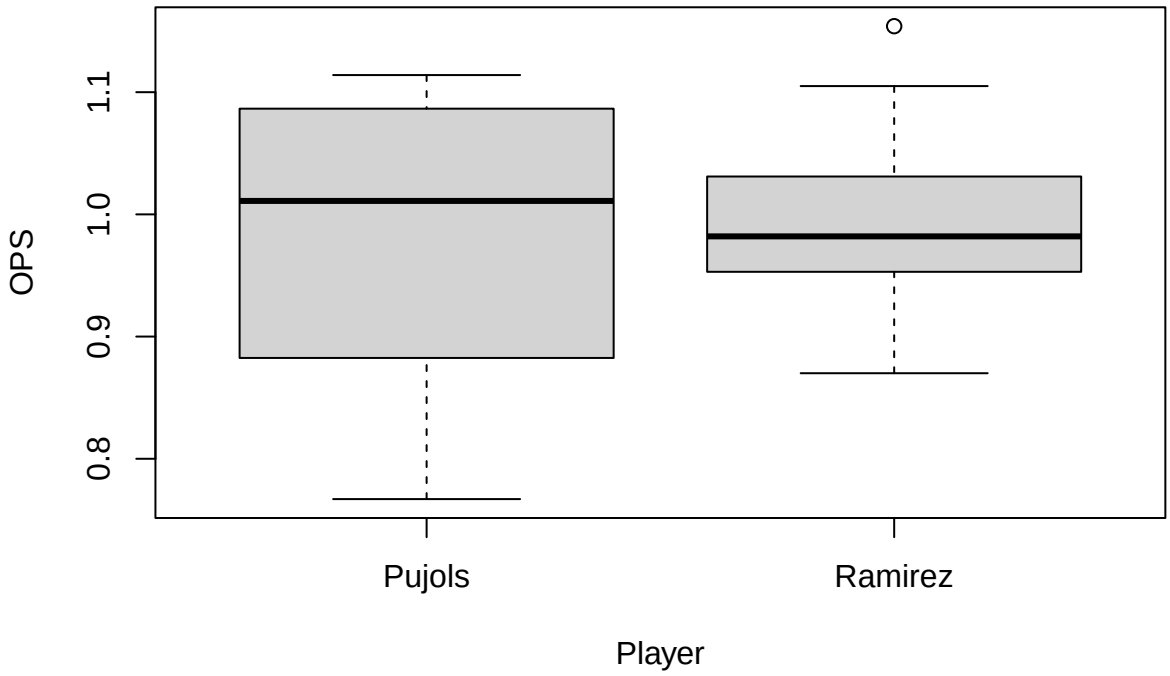
```
  ### So values greater than fu and less than fl are possible outliers
  ramirez$OPS[ramirez$OPS > fu | ramirez$OPS < fl]
```

```
## [1] 1.154
```

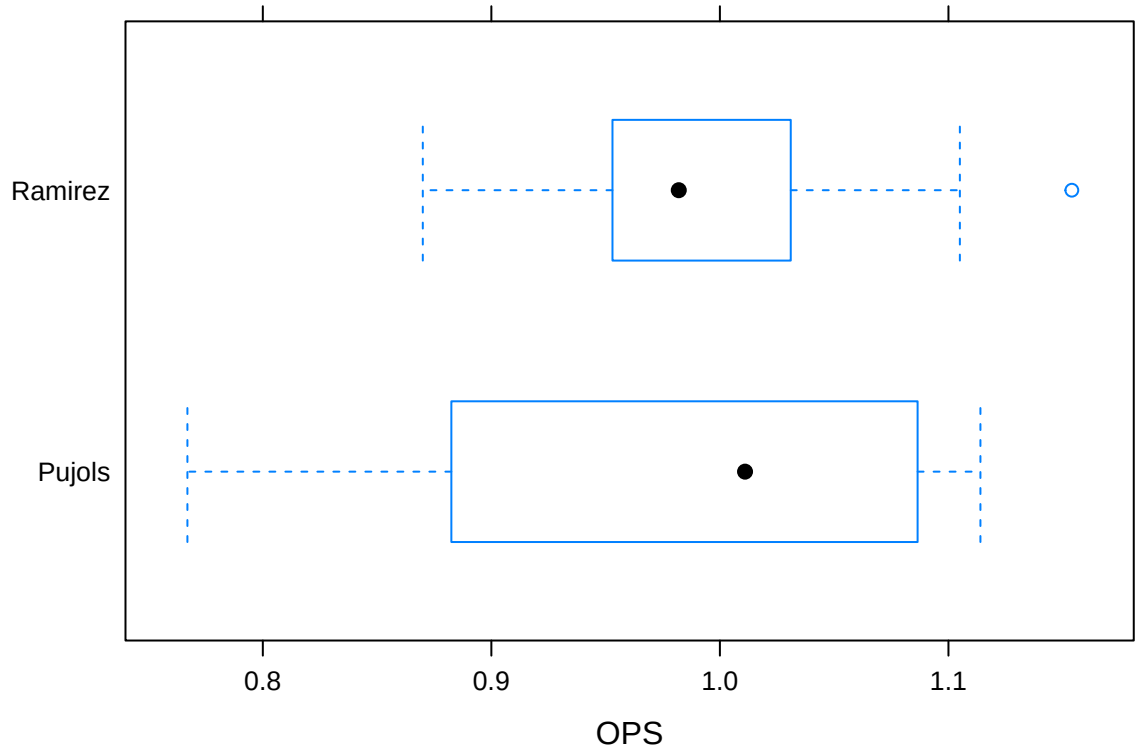
```
  sort(ramirez$OPS)
```

```
##  [1] 0.870 0.878 0.881 0.949 0.953 0.960 0.976 0.981 0.982 1.009 1.014 1.014
## [13] 1.031 1.058 1.097 1.105 1.154
```

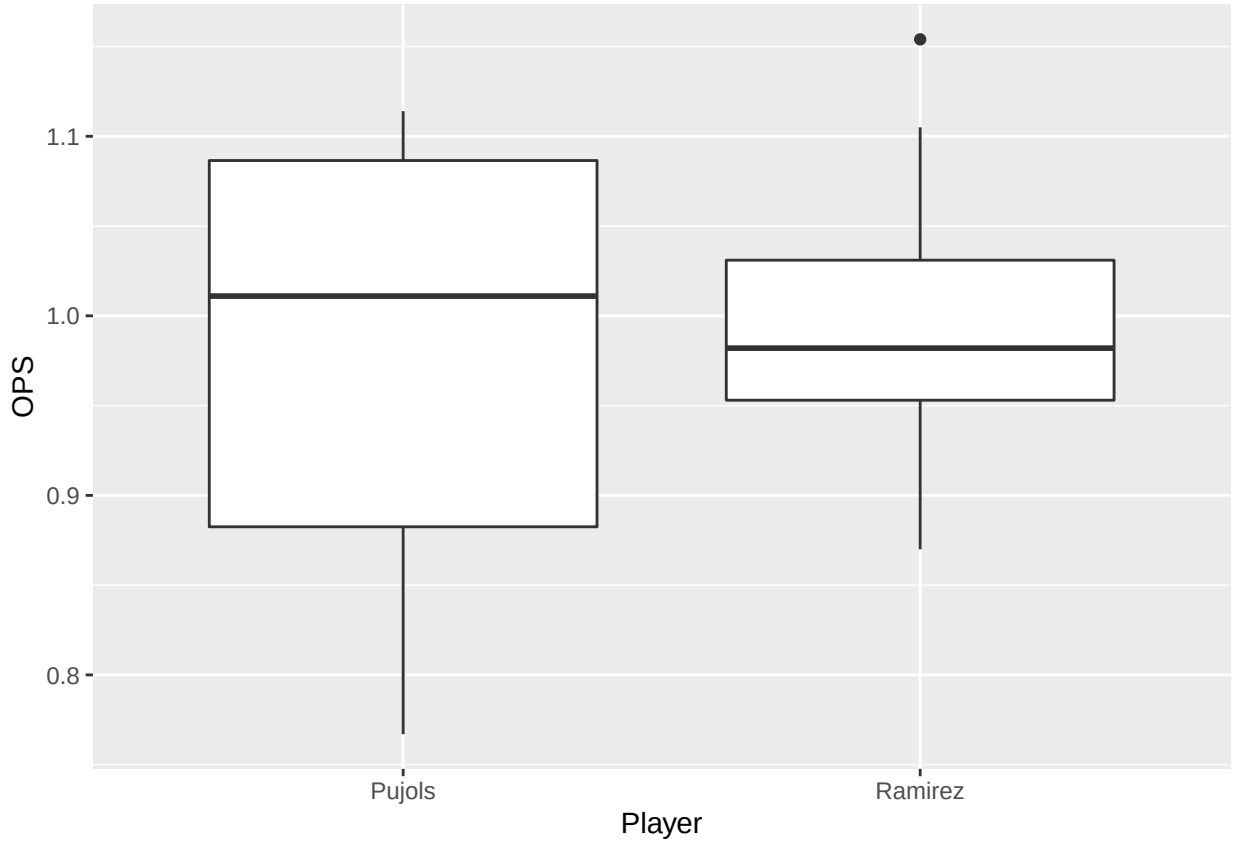
```
  ### Now we generate boxplots
  boxplot(OPS~Player, data=case.3.1, ylab="OPS")
```



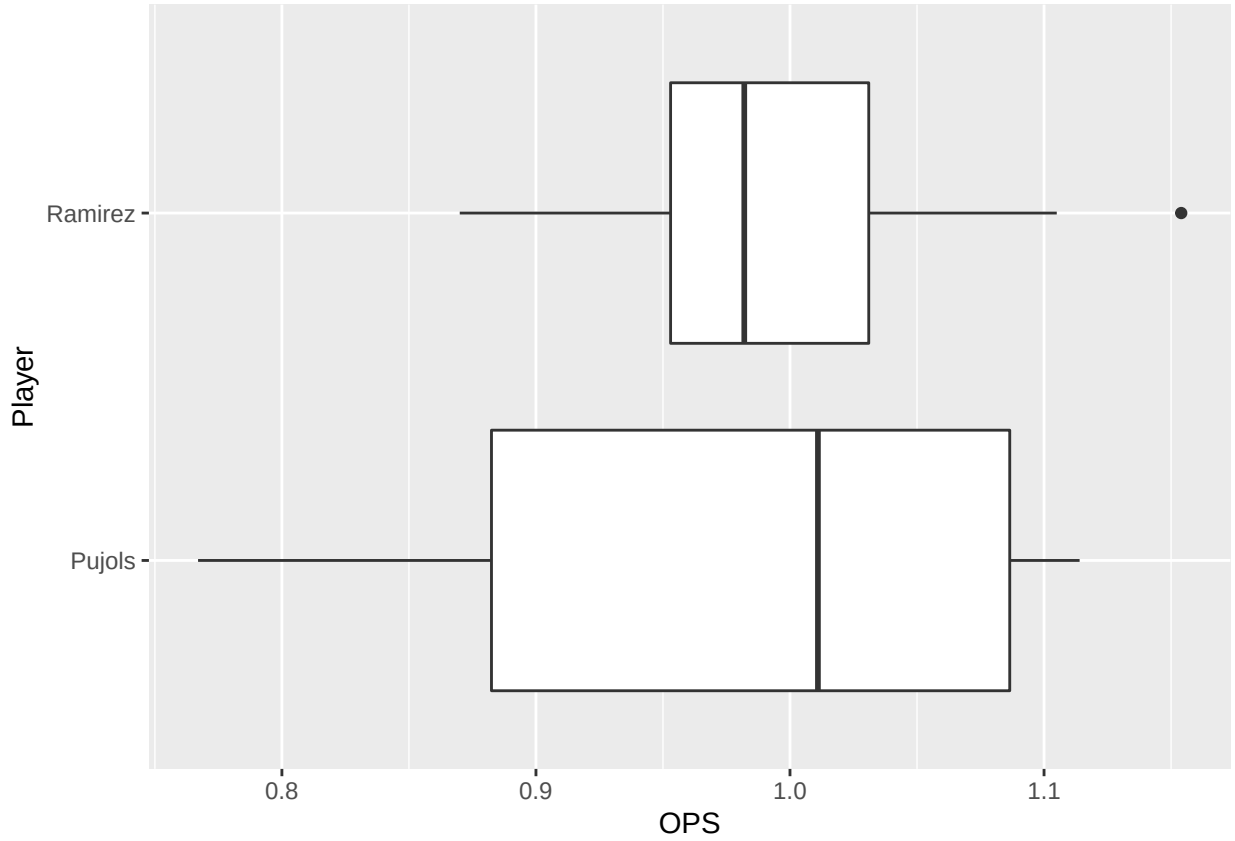

```
  p_load(lattice)
  bwplot(Player~OPS, data=case.3.1)
```




```
p_load(ggplot2)
ggplot(case.3.1,aes(Player, OPS)) + geom_boxplot()
```



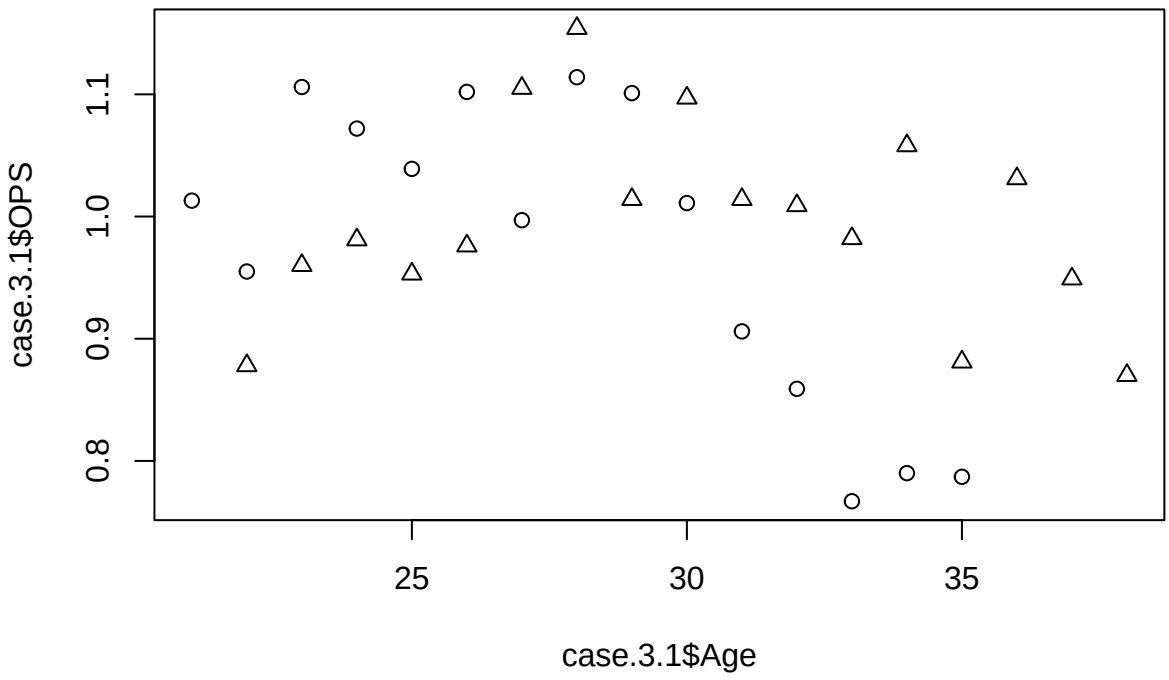

```
ggplot(case.3.1,aes(Player, OPS)) + geom_boxplot() + coord_flip()
```



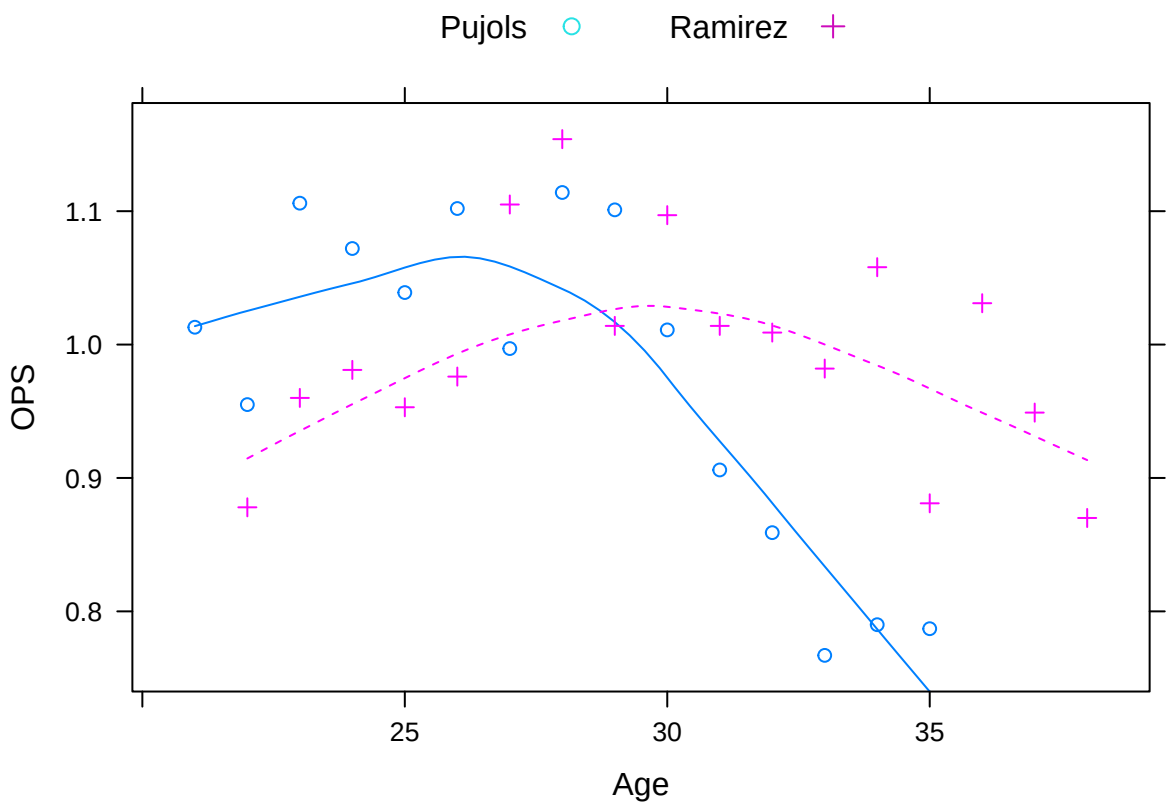

```
  ### Compare means
  median(pujols$OPS)-median(ramirez$OPS)
```

```
## [1] 0.029
```

```
  ### Create Figure 3.4
  plot(case.3.1$Age, case.3.1$OPS, pch=as.numeric(factor(case.3.1$Player)))
```

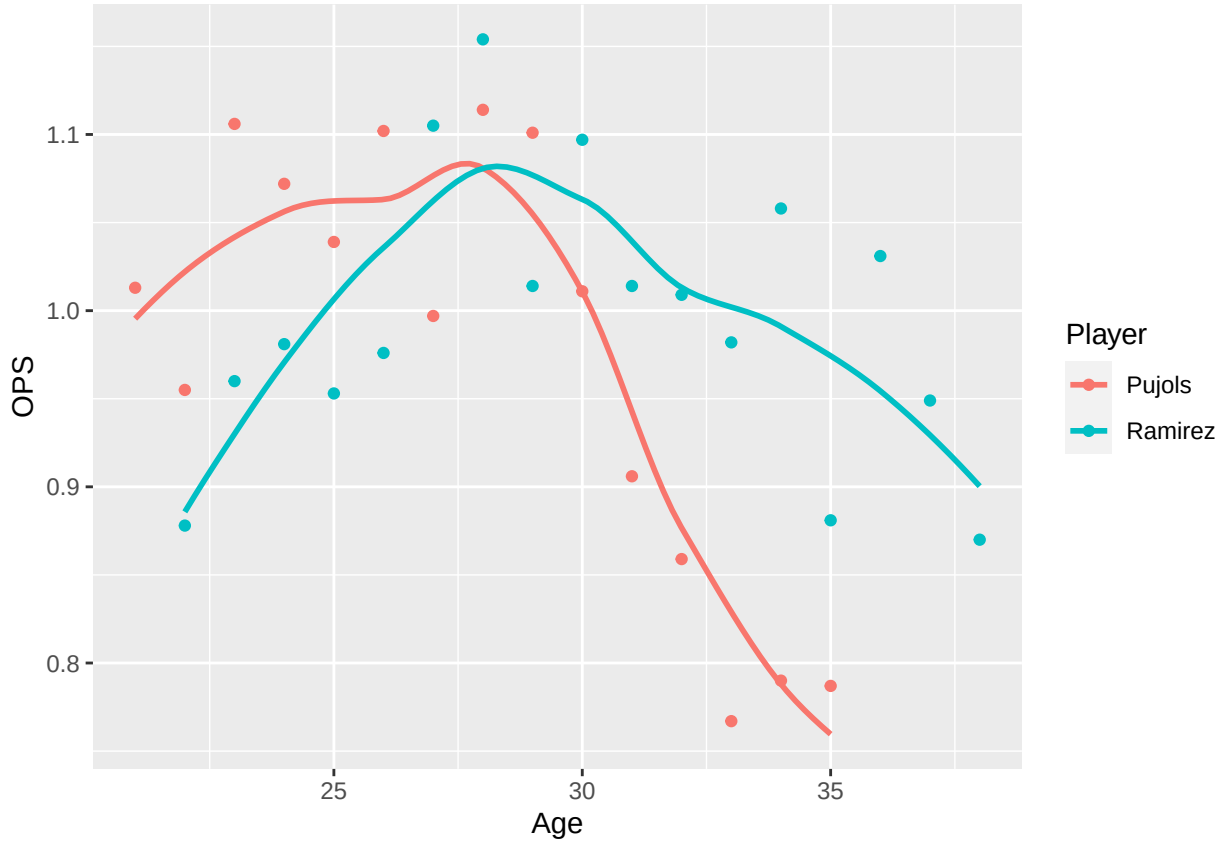



```
xyplot(OPS~Age, data=case.3.1, group=Player,
       type=c("p","smooth"), span=0.75, pch=c(1,3), lty=c(1,2),
       key=list(text=list(c("Pujols", "Ramirez")),
                points=list(pch=c(1,3), col=c(13,14)),
                columns=2)
       )
```




```
  ggplot(case.3.1, aes(x=Age, y=OPS, color=Player)) +
      geom_point() + geom_smooth(span=0.75, se=FALSE)
```

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



Case 3.2

The plots and statistics for comparing the pitchers Robin Roberts and Whitey Ford that are presented in Case 3.2 are, for the most part, variations on those already presented above. For this case we again download the data from my web site.

```
### Get the data
case.3.2 = read.csv("http://facweb1.redlands.edu/fac/jim_bentley/Data/FYS28/TSUB2/CSV/case_3_2.csv")
### Albert next creates Figure 3.5, a back-to-back stemplot
p_load(aplpack)
roberts = subset(case.3.2, Player=="Roberts")
roberts
```

```
##    Year  Player Age      Tm  W  L  G    IP   H  ER HR BB  SO  ERA X.lgERA
## 1  1948 Roberts  21     PHI  7  9 20 146.7 148  52 10 61  84 3.19    3.96
## 2  1949 Roberts  22     PHI 15 15 43 226.7 229  93 15 75  95 3.69    3.96
## 3  1950 Roberts  23     PHI 20 11 40 304.3 282 102 29 77 146 3.02    4.06
## 4  1951 Roberts  24     PHI 21 15 44 315.0 284 106 20 64 127 3.03    3.84
## 5  1952 Roberts  25     PHI 28  7 39 330.0 292  95 22 45 148 2.59    3.66
## 6  1953 Roberts  26     PHI 23 16 44 346.7 324 106 30 61 198 2.75    4.20
## 7  1954 Roberts  27     PHI 23 15 45 336.7 289 111 35 56 185 2.97    4.03
## 8  1955 Roberts  28     PHI 23 14 41 305.0 292 111 41 53 160 3.28    3.96
## 9  1956 Roberts  29     PHI 19 18 43 297.3 328 147 46 40 157 4.45    3.73
## 10 1957 Roberts  30     PHI 10 22 39 249.7 246 113 40 43 128 4.07    3.80
## 11 1958 Roberts  31     PHI 17 14 35 269.7 270  97 30 51 130 3.24    3.95
## 12 1959 Roberts  32     PHI 15 17 35 257.3 267 122 34 35 137 4.27    4.11
## 13 1960 Roberts  33     PHI 12 16 35 237.3 256 106 31 34 122 4.02    3.88
```

```
## 14 1961 Roberts  34     PHI  1 10 26 117.0 154  76 19 23  54 5.85    4.07
## 15 1962 Roberts  35     BAL 10  9 27 191.3 176  59 17 41 102 2.78    3.77
## 16 1963 Roberts  36     BAL 14 13 35 251.3 230  93 35 40 124 3.33    3.52
## 17 1964 Roberts  37     BAL 13  7 31 204.0 203  66 18 52 109 2.91    3.59
## 18 1965 Roberts  38 BAL/HOU 10  9 30 190.7 171  59 18 30  97 2.78    3.42
## 19 1966 Roberts  39 CHC/HOU  5  8 24 112.0 141  60 15 21  54 4.82    3.54
##    X.ERA.
## 1     124
## 2     107
## 3     135
## 4     127
## 5     141
## 6     152
## 7     136
## 8     121
## 9      84
## 10     93
## 11    122
## 12     96
## 13     96
## 14     70
## 15    136
## 16    106
## 17    123
## 18    123
## 19     73
```

```
  ford = subset(case.3.2, Player=="Ford")
  ford
```

```
##    Year Player Age  Tm  W  L  G    IP   H  ER HR  BB  SO  ERA X.lgERA X.ERA.
## 20 1950   Ford  21 NYY  9  1 20 112.0  87  35  7  52  59 2.81    4.30    153
## 21 1953   Ford  24 NYY 18  6 32 207.0 187  69 13 110 110 3.00    3.68    123
## 22 1954   Ford  25 NYY 16  8 34 210.7 170  66 10 101 125 2.82    3.42    121
## 23 1955   Ford  26 NYY 18  7 39 253.7 188  74 20 113 137 2.63    3.76    143
## 24 1956   Ford  27 NYY 19  6 31 225.7 187  62 13  84 141 2.47    3.87    156
## 25 1957   Ford  28 NYY 11  5 24 129.3 114  37 10  53  84 2.57    3.60    140
## 26 1958   Ford  29 NYY 14  7 30 219.3 174  49 14  62 145 2.01    3.54    176
## 27 1959   Ford  30 NYY 16 10 35 204.0 194  69 13  89 114 3.04    3.63    119
## 28 1960   Ford  31 NYY 12  9 33 192.7 168  66 15  65  85 3.08    3.60    117
## 29 1961   Ford  32 NYY 25  4 39 283.0 242 101 23  92 209 3.21    3.70    115
## 30 1962   Ford  33 NYY 17  8 38 257.7 243  83 22  69 160 2.90    3.73    129
## 31 1963   Ford  34 NYY 24  7 38 269.3 240  82 26  56 189 2.74    3.52    128
## 32 1964   Ford  35 NYY 17  6 39 244.7 212  58 10  57 172 2.13    3.62    170
## 33 1965   Ford  36 NYY 16 13 37 244.3 241  88 22  50 162 3.24    3.39    105
## 34 1966   Ford  37 NYY  2  5 22  73.0  79  20  8  24  43 2.47    3.33    135
## 35 1967   Ford  38 NYY  2  4  7  44.0  40   8  2   9  21 1.64    3.13    191
```

```
  stem.leaf.backback(ford$ERA, roberts$ERA, m=2, Min=1.5, Max=6)
```

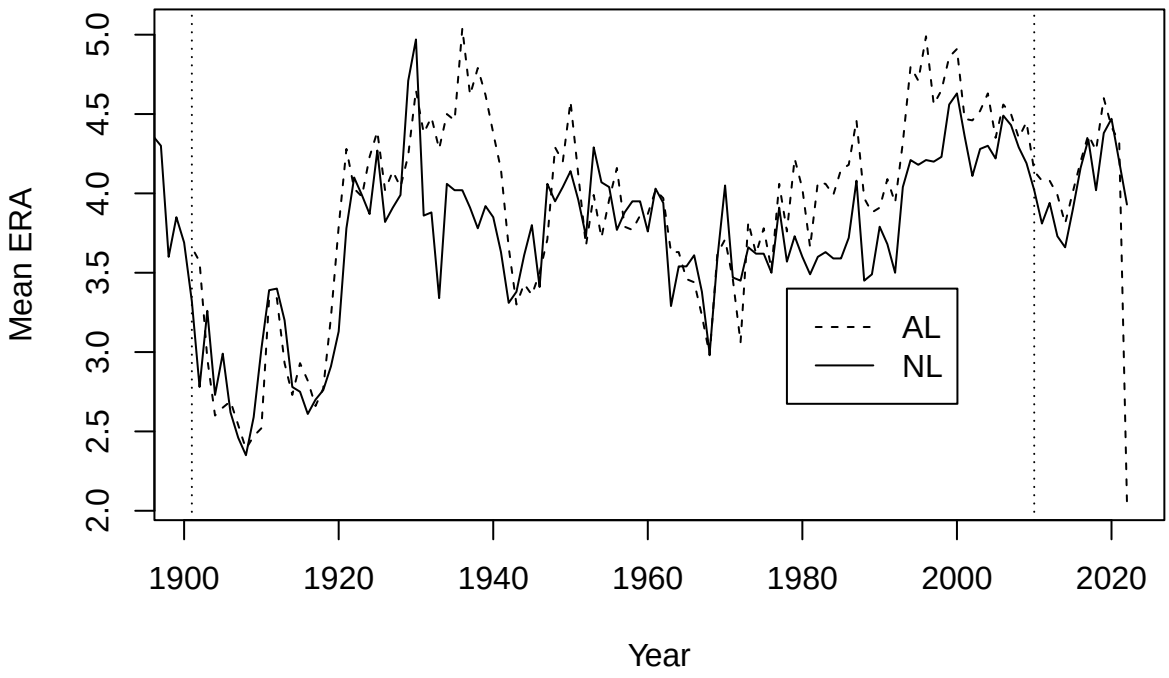
```
## ------------------------------
##   1 | 2: represents 1.2, leaf unit: 0.1
##      ford$ERA      roberts$ERA
## ------------------------------
##              | 1* |
##    1        6| 1. |
```

```
##    5     4410| 2* |
##   (6)  988765| 2. |577799   6
##    5    22000| 3* |001223  (6)
##              | 3. |6        7
##              | 4* |0024     6
##              | 4. |8        2
##              | 5* |
##              | 5. |8        1
##              | 6* |
## --------------------------------
## n:         16      19
## --------------------------------
```

The back-to-back stemplot seems to be the same as Figure 3.5.

In the first edition of TSUB, Albert forgot to include league average information. **case__3__2.csv** contains this information for ERA which is what we need. However, it might be useful to be able to get this, or similar, information in the future. Code for generating more complete league average data is presented below.

```
### Make Figure 3.6
### To get league average pitcher information...
### The data can be found at
###   http://www.baseball-reference.com/leagues/NL/pitch.shtml#teams_standard_pitching::none
###   and http://www.baseball-reference.com/leagues/AL/pitch.shtml#teams_standard_pitching::none
### Click on CSV and then EXPORT to save them to your machine.
### The files are also available at the URLs given below.
  nlpitch = read.csv("http://facweb1.redlands.edu/fac/jim_bentley/Data/FYS04/nlpitchingaverages.csv")
  alpitch = read.csv("http://facweb1.redlands.edu/fac/jim_bentley/Data/FYS04/alpitchingaverages.csv")
  nlpitch$lgID = "NL" ### Identify the data as NL
  alpitch$lgID = "AL" ### Identify the data as AL

  pitch = rbind(alpitch, nlpitch)  ### Stack the data into a single dataframe
  pitch = pitch %>% filter(Year < 2022) ### Get rid of the incomplete 2022 season
  plot(alpitch$Year,alpitch$ERA,type="l", lty=2, xlab="Year", ylab="Mean ERA")
  lines(nlpitch$Year,nlpitch$ERA, lty=1)

### Note that Albert only used years where both the AL and NL had data -- 1901 on.
### Albert didn't have data beyond about 2010 but we have through 2021.
  abline(v=2010,lty=3)
  abline(v=1901, lty=3)
### Add a legend.
  legend(1978,3.4,legend=c("AL","NL"),lty=c(2,1))
```



We can recreate the plot using actual data scraping rather than downloading.

```
  ### Install and load a few support packages.
    p_load(rvest)    # Scrapes
    p_load(stringr)  # String tools
    p_load(tidyr)    # Data frame manipulation
  ### Get the NL pitching page
    url = 'http://www.baseball-reference.com/leagues/NL/pitch.shtml#teams_standard_pitching::none'
    webpage = read_html(url)
  ### Use the rvest functions html_nodes and html_table to extract what we want
    ### Grab the tables on the page
    nl_table = html_nodes(webpage, 'table')
    nl_table
```

```
## {xml_nodeset (2)}
## [1] <table class="sortable stats_table" id="teams_standard_pitching" data-col ...
## [2] <table class="sortable stats_table" id="teams_standard_pitching_totals" d ...
```

```
  ### Two tables are read.  Assign the tables to separate data frames
    nl1 = html_table(nl_table)[[1]]
    nl2 = html_table(nl_table)[[2]]
    head(nl1)
```

```
## # A tibble: 6 x 32
##   Year  Tms   `#P`  PAge  `R/G` ERA   G     GF    CG    SHO   tSho  SV    IP
##   <chr> <chr> <chr> <chr> <chr> <chr> <chr> <chr> <chr> <chr> <chr> <chr> <chr>
## 1 2022  15    377   29.1  4.47  4.14  1292  0.99  0.01  0.00  0.06  0.26  8.86
## 2 2021  15    497   28.9  4.48  4.20  2428  0.99  0.01  0.01  0.07  0.25  8.76
```

```
## 3 2020  15    383   28.4  4.66  4.47  898   0.98  0.02  0.01  0.06  0.21  8.56
## 4 2019  15    426   28.3  4.71  4.38  2430  0.99  0.01  0.00  0.06  0.25  8.94
## 5 2018  15    431   28.2  4.34  4.02  2432  0.99  0.01  0.00  0.07  0.26  8.98
## 6 2017  15    381   28.4  4.63  4.34  2430  0.99  0.01  0.01  0.06  0.25  8.90
## # ... with 19 more variables: H <chr>, R <chr>, ER <chr>, HR <chr>, BB <chr>,
## #   IBB <chr>, SO <chr>, HBP <chr>, BK <chr>, WP <chr>, BF <chr>, WHIP <chr>,
## #   BAbip <chr>, H9 <chr>, HR9 <chr>, BB9 <chr>, SO9 <chr>, `SO/W` <chr>,
## #   E <chr>
```

```
    head(nl2)
```

```
## # A tibble: 6 x 32
##   Year  Tms   `#P`  PAge  `R/G` ERA   G     GF    CG    SHO   tSho  SV    IP
##   <chr> <chr> <chr> <chr> <chr> <chr> <chr> <chr> <chr> <chr> <chr> <chr> <chr>
## 1 2022  15    377   29.1  4.47  4.14  1292  1283  9     3     83    331   11451~
## 2 2021  15    497   28.9  4.48  4.20  2428  2399  29    18    166   596   21265~
## 3 2020  15    383   28.4  4.66  4.47  898   880   18    7     57    193   7689.1
## 4 2019  15    426   28.3  4.71  4.38  2430  2412  18    11    143   607   21732~
## 5 2018  15    431   28.2  4.34  4.02  2432  2415  17    8     169   621   21828~
## 6 2017  15    381   28.4  4.63  4.34  2430  2403  27    13    135   605   21626~
## # ... with 19 more variables: H <chr>, R <chr>, ER <chr>, HR <chr>, BB <chr>,
## #   IBB <chr>, SO <chr>, HBP <chr>, BK <chr>, WP <chr>, BF <chr>, WHIP <chr>,
## #   BAbip <chr>, H9 <chr>, HR9 <chr>, BB9 <chr>, SO9 <chr>, `SO/W` <chr>,
## #   E <chr>
```

```
    ### Since the first table is averages and the second is totals, get rid of the second
    nl = nl1
    rm(nl1, nl2)
    head(nl)
```

```
## # A tibble: 6 x 32
##   Year  Tms   `#P`  PAge  `R/G` ERA   G     GF    CG    SHO   tSho  SV    IP
##   <chr> <chr> <chr> <chr> <chr> <chr> <chr> <chr> <chr> <chr> <chr> <chr> <chr>
## 1 2022  15    377   29.1  4.47  4.14  1292  0.99  0.01  0.00  0.06  0.26  8.86
## 2 2021  15    497   28.9  4.48  4.20  2428  0.99  0.01  0.01  0.07  0.25  8.76
## 3 2020  15    383   28.4  4.66  4.47  898   0.98  0.02  0.01  0.06  0.21  8.56
## 4 2019  15    426   28.3  4.71  4.38  2430  0.99  0.01  0.00  0.06  0.25  8.94
## 5 2018  15    431   28.2  4.34  4.02  2432  0.99  0.01  0.00  0.07  0.26  8.98
## 6 2017  15    381   28.4  4.63  4.34  2430  0.99  0.01  0.01  0.06  0.25  8.90
## # ... with 19 more variables: H <chr>, R <chr>, ER <chr>, HR <chr>, BB <chr>,
## #   IBB <chr>, SO <chr>, HBP <chr>, BK <chr>, WP <chr>, BF <chr>, WHIP <chr>,
## #   BAbip <chr>, H9 <chr>, HR9 <chr>, BB9 <chr>, SO9 <chr>, `SO/W` <chr>,
## #   E <chr>
```

```
  ### Repeat the above for the AL
    ### Get the AL pitching page
    url = 'http://www.baseball-reference.com/leagues/AL/pitch.shtml#teams_standard_pitching::none'
    webpage = read_html(url)
  ### Use the rvest functions html_nodes and html_table to extract what we want
    ### Grab the tables on the page
    al_table = html_nodes(webpage, 'table')
    al_table
```

```
## {xml_nodeset (2)}
## [1] <table class="sortable stats_table" id="teams_standard_pitching" data-col ...
## [2] <table class="sortable stats_table" id="teams_standard_pitching_totals" d ...
```

```
    ### Assign the first table to the data frame
    al = html_table(al_table)[[1]]
    head(al)
```

```
## # A tibble: 6 x 32
##   Year  Tms   `#P`  PAge  `R/G` ERA   G     GF    CG    SHO   tSho  SV    IP
##   <chr> <chr> <chr> <chr> <chr> <chr> <chr> <chr> <chr> <chr> <chr> <chr> <chr>
## 1 2022  15    374   28.6  4.19  3.86  1284  0.99  0.01  0.00  0.08  0.25  8.86
## 2 2021  15    471   28.5  4.58  4.32  2430  0.99  0.01  0.00  0.05  0.24  8.79
## 3 2020  15    375   28.2  4.63  4.42  898   0.99  0.01  0.01  0.05  0.26  8.66
## 4 2019  15    456   28.4  4.95  4.60  2428  0.99  0.01  0.01  0.05  0.24  8.93
## 5 2018  15    420   28.6  4.56  4.27  2430  0.99  0.01  0.00  0.06  0.26  8.91
## 6 2017  15    417   28.6  4.67  4.37  2430  0.99  0.01  0.01  0.05  0.24  8.90
## # ... with 19 more variables: H <chr>, R <chr>, ER <chr>, HR <chr>, BB <chr>,
## #   IBB <chr>, SO <chr>, HBP <chr>, BK <chr>, WP <chr>, BF <chr>, WHIP <chr>,
## #   BAbip <chr>, H9 <chr>, HR9 <chr>, BB9 <chr>, SO9 <chr>, `SO/W` <chr>,
## #   E <chr>
```

```
  ### Did we get the right years for the leagues?
    range(al$Year)
```

```
## [1] "1901" "Year"
```

```
    table(al$Year)
```

```
##
## 1901 1902 1903 1904 1905 1906 1907 1908 1909 1910 1911 1912 1913 1914 1915 1916
##    1    1    1    1    1    1    1    1    1    1    1    1    1    1    1    1
## 1917 1918 1919 1920 1921 1922 1923 1924 1925 1926 1927 1928 1929 1930 1931 1932
##    1    1    1    1    1    1    1    1    1    1    1    1    1    1    1    1
## 1933 1934 1935 1936 1937 1938 1939 1940 1941 1942 1943 1944 1945 1946 1947 1948
##    1    1    1    1    1    1    1    1    1    1    1    1    1    1    1    1
## 1949 1950 1951 1952 1953 1954 1955 1956 1957 1958 1959 1960 1961 1962 1963 1964
##    1    1    1    1    1    1    1    1    1    1    1    1    1    1    1    1
## 1965 1966 1967 1968 1969 1970 1971 1972 1973 1974 1975 1976 1977 1978 1979 1980
##    1    1    1    1    1    1    1    1    1    1    1    1    1    1    1    1
## 1981 1982 1983 1984 1985 1986 1987 1988 1989 1990 1991 1992 1993 1994 1995 1996
##    1    1    1    1    1    1    1    1    1    1    1    1    1    1    1    1
## 1997 1998 1999 2000 2001 2002 2003 2004 2005 2006 2007 2008 2009 2010 2011 2012
##    1    1    1    1    1    1    1    1    1    1    1    1    1    1    1    1
## 2013 2014 2015 2016 2017 2018 2019 2020 2021 2022 Year
##    1    1    1    1    1    1    1    1    1    1    4
```

```
  ### Oops, al seems to have multiple headers in the data and "Year" appears within Year.  We fix that
  ### by filtering out (!= is not equal) the bad obs and then convert Year to a numeric.
    al = al %>%
             filter(Year != "Year") %>%
             mutate(Year = as.numeric(Year)) %>%
             filter(Year < 2022) ### As before, we drop 2022 because it's not complete
    range(al$Year)
```

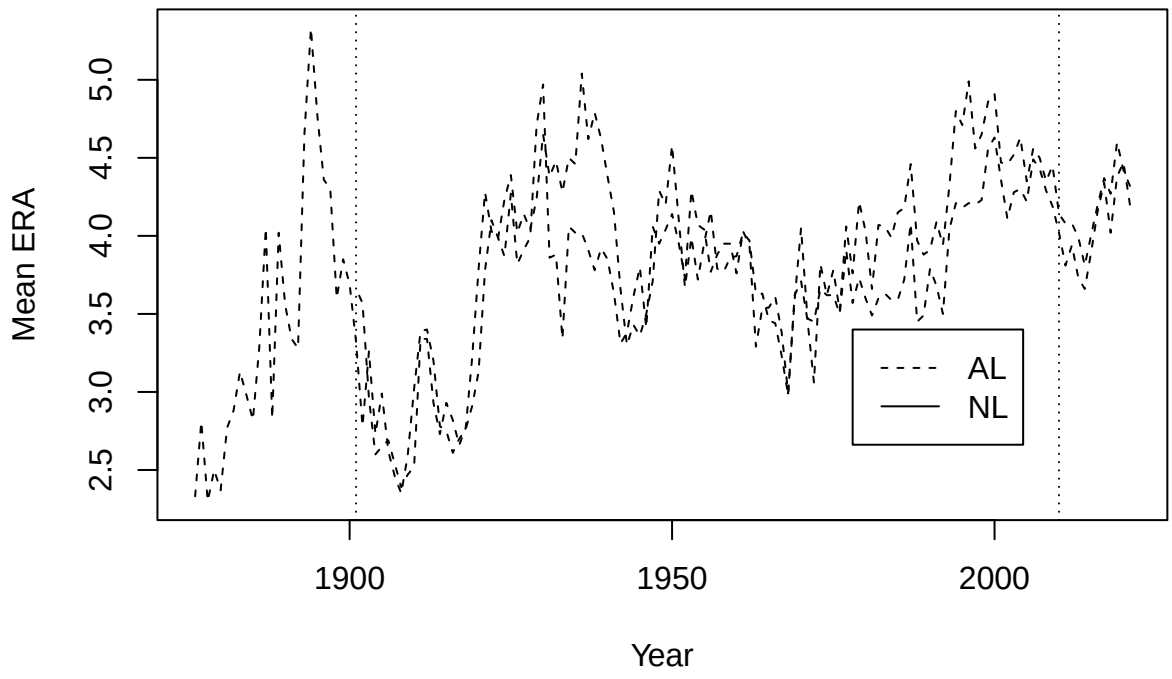
```
## [1] 1901 2021
```

```
    nl = nl %>%
             filter(Year != "Year") %>%
             mutate(Year = as.numeric(Year)) %>%
             filter(Year < 2022) ### As before, we drop 2022 because it's not complete
```

```
    range(nl$Year)
```

```
## [1] 1876 2021
```

```
    # That's better. Now compare ERAs.
    plot(nl$Year,nl$ERA,type="l", lty=2, xlab="Year", ylab="Mean ERA")
    lines(al$Year,al$ERA, lty=2)
    abline(v=2010,lty=3)
    abline(v=1901, lty=3)
    legend(1978,3.4,legend=c("AL","NL"),lty=c(2,1))
```



A bit of work, but it's nice to know that we can get up to date data.

We move on to Figure 3.7.

```
###
### Create Figure 3.7
### We can use the data already imported for Figure 3.5
head(roberts)
```

```
##   Year  Player Age  Tm  W  L  G    IP   H  ER HR BB  SO  ERA X.lgERA X.ERA.
## 1 1948 Roberts  21 PHI  7  9 20 146.7 148  52 10 61  84 3.19    3.96    124
## 2 1949 Roberts  22 PHI 15 15 43 226.7 229  93 15 75  95 3.69    3.96    107
## 3 1950 Roberts  23 PHI 20 11 40 304.3 282 102 29 77 146 3.02    4.06    135
## 4 1951 Roberts  24 PHI 21 15 44 315.0 284 106 20 64 127 3.03    3.84    127
## 5 1952 Roberts  25 PHI 28  7 39 330.0 292  95 22 45 148 2.59    3.66    141
## 6 1953 Roberts  26 PHI 23 16 44 346.7 324 106 30 61 198 2.75    4.20    152
```

```
### Note that x.ERA. (*ERA) is equal to the formula in the book (within rounding)
  cbind(roberts$X.lgERA/roberts$ERA*100, roberts$X.ERA.)[1:5,]
```

```
##          [,1] [,2]
## [1,] 124.1379  124
## [2,] 107.3171  107
## [3,] 134.4371  135
## [4,] 126.7327  127
## [5,] 141.3127  141
```

```
  stem.leaf.backback(ford$X.ERA.,roberts$X.ERA., Max=190)
```

```
## ------------------------------
##   1 | 2: represents 12, leaf unit: 1
##     ford$X.ERA.      roberts$X.ERA.
## ------------------------------
##                |  7 |03       2
##                |  8 |4        3
##                |  9 |366      6
##    1         5| 10 |67       8
##    4       975| 11 |
##   (4)     9831| 12 |123347  (6)
##   (1)        5| 13 |566      5
##    7        30| 14 |1        2
##    5        63| 15 |2        1
##                | 16 |
##    3        60| 17 |
##                | 18 |
##    1         1| 19 |
## ------------------------------
## n:          16      19
## ------------------------------
```

This back-to-back stemplot is similar (within truncation/rounding) to Figure 3.7 in **TSUB2**.

Case 3.3

Albert now looks at home runs and the rate at which they occur. For this case we download the data from Albert's GitHub site.

```
  ### Get the data.  Be careful about getting the "raw" CSV file from GitHub
  case.3.3 <- read.csv("https://raw.githubusercontent.com/bayesball/Teaching-Statistics-Using-Baseball/

  ### See what's in it
  head(case.3.3)
```

```
##   YEAR  HR   G RATE
## 1 1927  54 156 0.35
## 2 1927  84 153 0.55
## 3 1927 109 155 0.70
## 4 1927  74 153 0.48
## 5 1927  29 153 0.19
## 6 1927  39 154 0.25
```

```
  ### Get the number of teams in each year to compare to Table 3.4
  case.3.3 %>%
```

```
    group_by(YEAR) %>%
    summarize(nTeams = n())
```

```
## # A tibble: 4 x 2
##    YEAR nTeams
##   <int>  <int>
## 1  1927     16
## 2  1961     18
## 3  1998     30
## 4  2001     30
```

```
   ### Or
   table(case.3.3$YEAR)
```

```
##
## 1927 1961 1998 2001
##   16   18   30   30
```

It looks like the data are okay.

R doesn't generate parallel stemplots, so for Figure 3.8 we create multiple back-to-back stemplots

```
    homers.1927 = case.3.3[case.3.3$YEAR==1927,]  ### Subset those rows/obs that are YEAR == 1927
    homers.1961 = case.3.3[case.3.3$YEAR==1961,]  ### Blank after the comma means keep all columns
    homers.1998 = case.3.3[case.3.3$YEAR==1998,]
    homers.2001 = case.3.3[case.3.3$YEAR==2001,]

    p_load(aplpack)
    stem.leaf.backback(homers.1927$RATE,homers.1961$RATE, Min=.1, Max=1.6)
```

```
## ------------------------------
##   1 | 2: represents 0.12, leaf unit: 0.01
## homers.1927$RATE
##                  homers.1961$RATE
## ------------------------------
##    4    9887|  1 |
##    7     544|  2 |
##   (5)  76553|  3 |
##    4       8|  4 |
##    3       5|  5 |6       1
##             |  6 |669     4
##    2       0|  7 |4       5
##             |  8 |35      7
##             |  9 |13     (2)
##    1       2| 10 |234    (3)
##             | 11 |0378    6
##             | 12 |1       2
##             | 13 |
##             | 14 |7       1
##             | 15 |
##             | 16 |
## ------------------------------
## n:        16      18
## ------------------------------
```

```
    stem.leaf.backback(homers.1927$RATE,homers.1998$RATE, Min=.1, Max=1.6)
```

```
## ---------------------------------
##   1 | 2: represents 0.12, leaf unit: 0.01
## homers.1927$RATE
##                     homers.1998$RATE
## ---------------------------------
##    4      9887|  1 |
##    7       544|  2 |
##   (5)    76553|  3 |
##    4         8|  4 |
##    3         5|  5 |
##                |  6 |68        2
##    2         0|  7 |017       5
##                |  8 |245       8
##                |  9 |1124889  (7)
##    1         2| 10 |223      (3)
##                | 11 |3        12
##                | 12 |12478    11
##                | 13 |02367     6
##                | 14 |5         1
##                | 15 |
##                | 16 |
## ---------------------------------
## n:          16      30
## ---------------------------------
```

```
stem.leaf.backback(homers.1927$RATE,homers.2001$RATE, Min=.1, Max=1.6)
```

```
## ----------------------------------------
##   1 | 2: represents 0.12, leaf unit: 0.01
##     homers.1927$RATE      homers.2001$RATE
## ----------------------------------------
##    4         9887|  1 |
##    7          544|  2 |
##   (5)       76553|  3 |
##    4            8|  4 |
##    3            5|  5 |
##                  |  6 |
##    2            0|  7 |5             1
##                  |  8 |146           4
##                  |  9 |14899         9
##    1            2| 10 |112479       (6)
##                  | 11 |
##                  | 12 |0033367889  (10)
##                  | 13 |112           5
##                  | 14 |5             2
##                  | 15 |2             1
##                  | 16 |
## ----------------------------------------
## n:             16      30
## ----------------------------------------
```

```
stem.leaf.backback(homers.1961$RATE,homers.1998$RATE, Min=.1, Max=1.6)
```

```
## ---------------------------------
##   1 | 2: represents 0.12, leaf unit: 0.01
```

```
## homers.1961$RATE
##                     homers.1998$RATE
## ----------------------------------
##               |  1 |
##               |  2 |
##               |  3 |
##               |  4 |
##    1         6|  5 |
##    4       966|  6 |68        2
##    5         4|  7 |017       5
##    7        53|  8 |245       8
##   (2)       31|  9 |1124889  (7)
##   (3)      432| 10 |223      (3)
##    6      8730| 11 |3        12
##    2         1| 12 |12478    11
##              | 13 |02367     6
##    1         7| 14 |5         1
##              | 15 |
##              | 16 |
## ----------------------------------
## n:          18      30
## ----------------------------------
```

```
    stem.leaf.backback(homers.1961$RATE,homers.2001$RATE, Min=.1, Max=1.6)
```

```
## ----------------------------------------
##   1 | 2: represents 0.12, leaf unit: 0.01
##     homers.1961$RATE      homers.2001$RATE
## ----------------------------------------
##                  |  1 |
##                  |  2 |
##                  |  3 |
##                  |  4 |
##    1            6|  5 |
##    4          966|  6 |
##    5            4|  7 |5             1
##    7           53|  8 |146           4
##   (2)          31|  9 |14899         9
##   (3)         432| 10 |112479       (6)
##    6         8730| 11 |
##    2            1| 12 |0033367889  (10)
##                  | 13 |112           5
##    1            7| 14 |5             2
##                  | 15 |2             1
##                  | 16 |
## ----------------------------------------
## n:             18      30
## ----------------------------------------
```

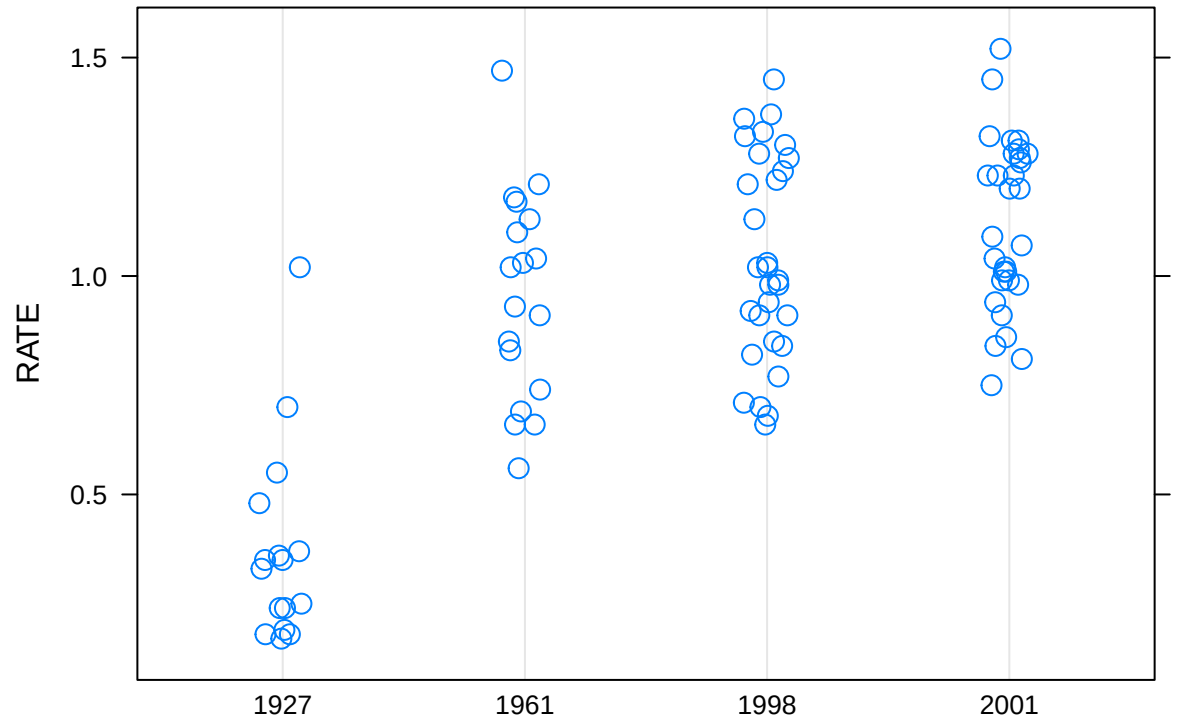
```
    stem.leaf.backback(homers.1998$RATE,homers.2001$RATE, Min=.1, Max=1.6)
```

```
## ----------------------------------------
##   1 | 2: represents 0.12, leaf unit: 0.01
##     homers.1998$RATE      homers.2001$RATE
## ----------------------------------------
```

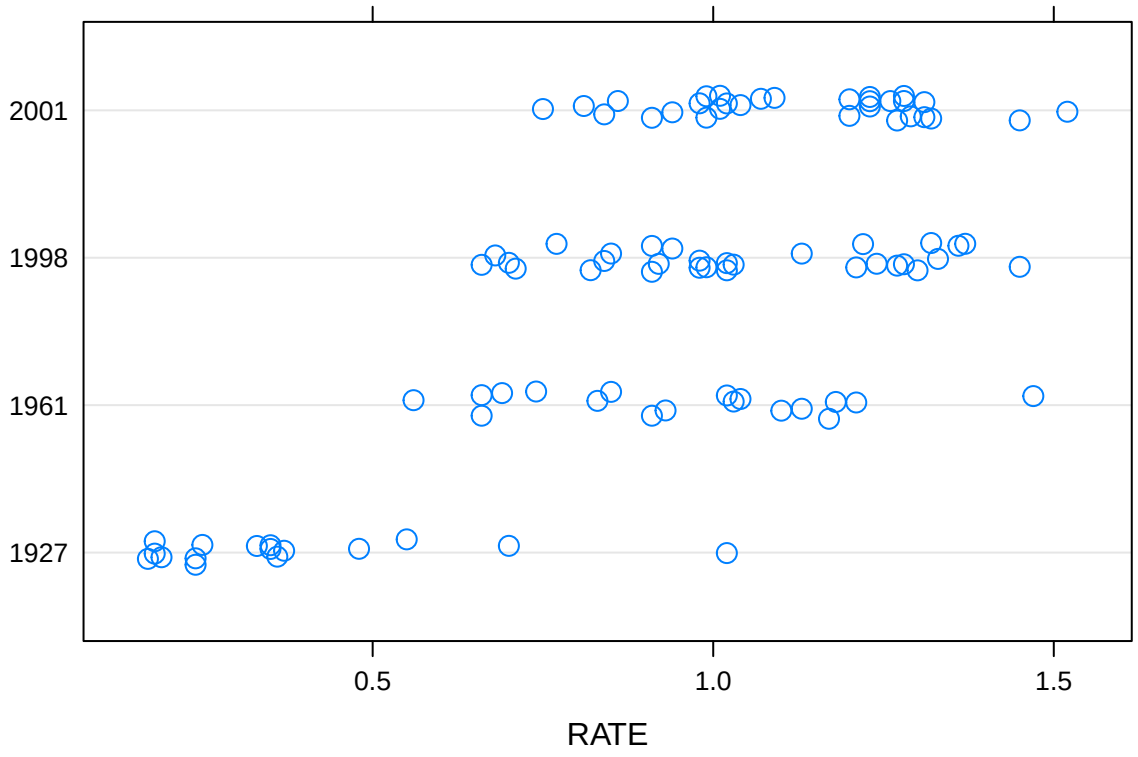
```
##                  |  1 |
##                  |  2 |
##                  |  3 |
##                  |  4 |
##                  |  5 |
##    2           86|  6 |
##    5          710|  7 |5             1
##    8          542|  8 |146           4
##   (7)     9884211|  9 |14899         9
##   (3)         322| 10 |112479       (6)
##   12            3| 11 |
##   11        87421| 12 |0033367889   (10)
##    6        76320| 13 |112           5
##    1            5| 14 |5             2
##                  | 15 |2             1
##                  | 16 |
## ---------------------------------------
## n:             30      30
## ---------------------------------------
```

A quick dotplot might help here.

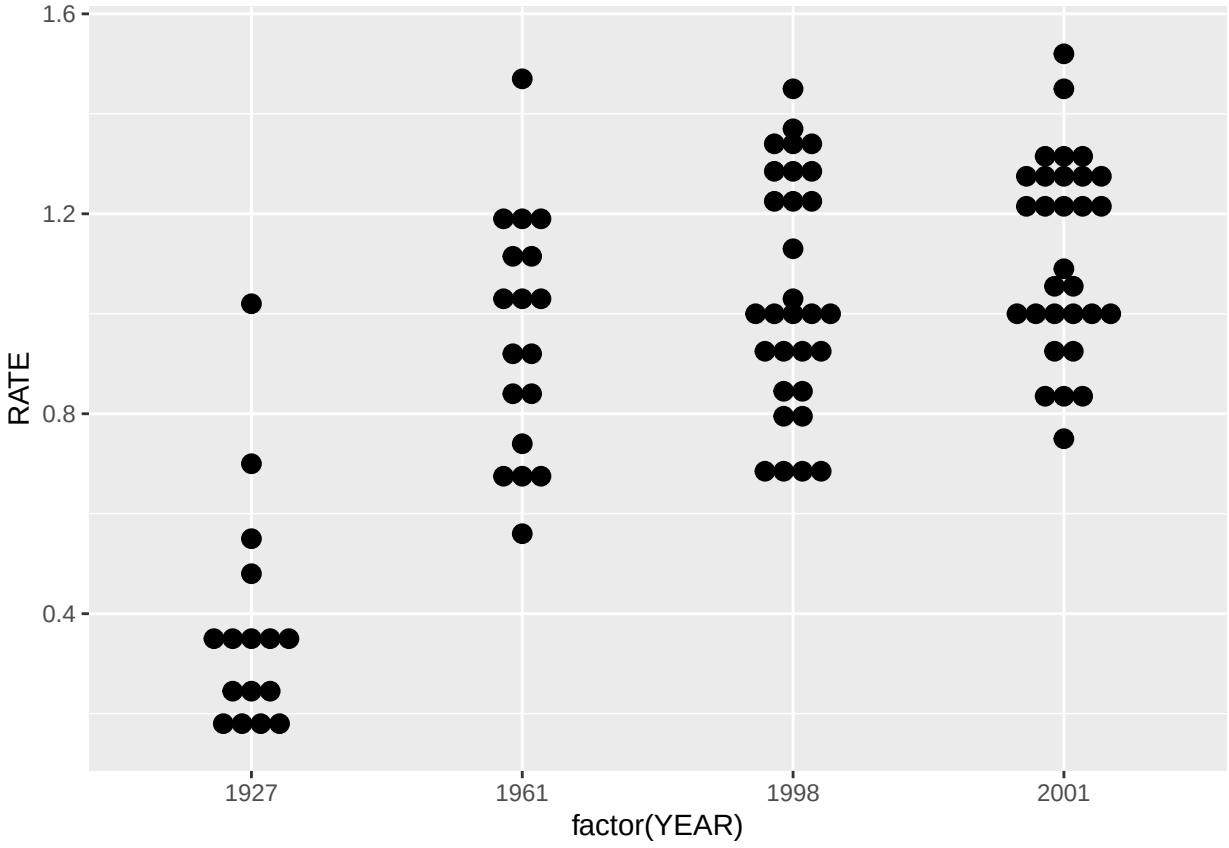
```
### Figure 3.8 can be generated using the lattice package
p_load(lattice)
dotplot(RATE ~ factor(YEAR), data=case.3.3, cex=1.25, pch=1, jitter.x=TRUE)
```



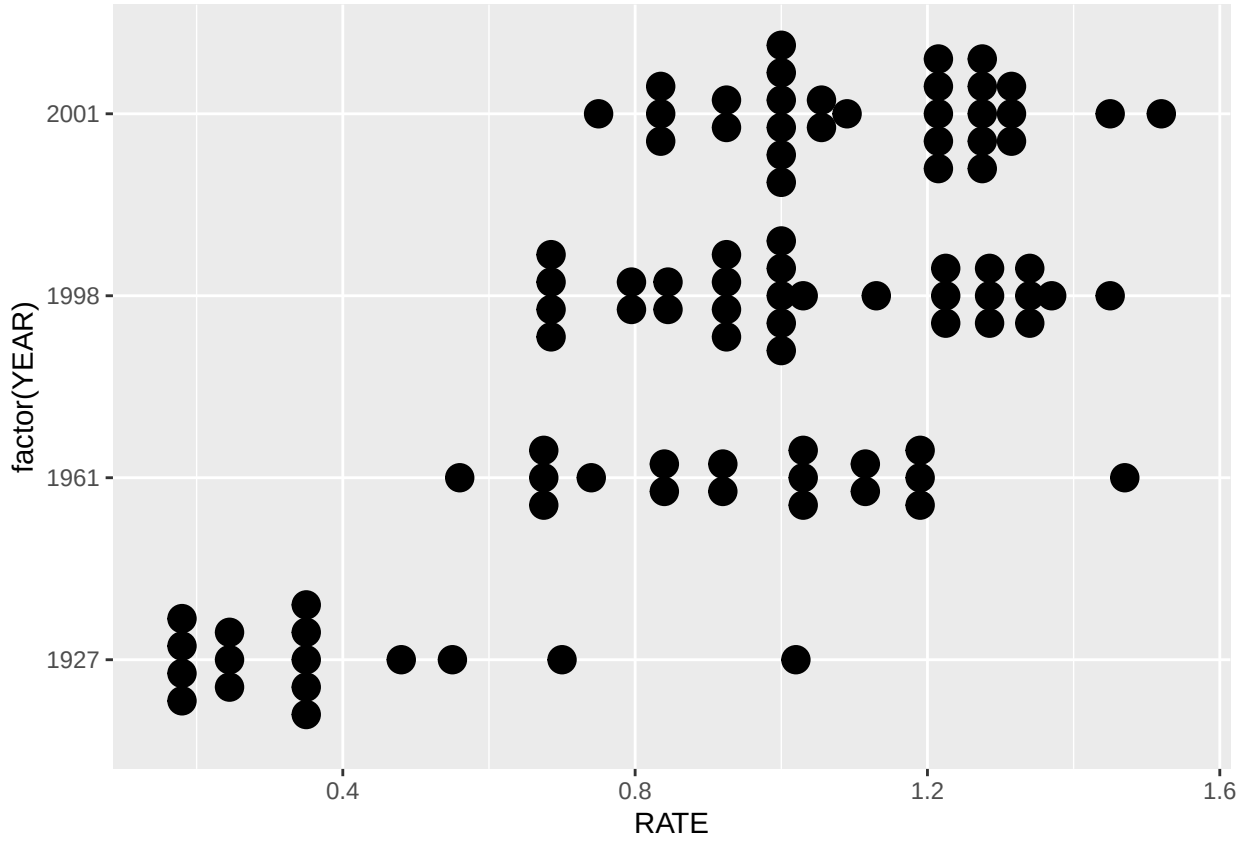
```
dotplot(factor(YEAR) ~ RATE, data=case.3.3, cex=1.25, pch=1, jitter.y=TRUE)
```




```
### or ggplot2
plt = case.3.3 %>%
      ggplot(aes(x = factor(YEAR), y = RATE)) +
         geom_dotplot(binaxis = "y", stackdir = "center", binwidth=0.05, dotsize=0.75)
plt
```




```
plt + coord_flip()
```



Tough to interpret? Yep. Maybe a boxplot would be better.

```
    ### Create 5-number summaries
    by(case.3.3[,"RATE"],case.3.3[,"YEAR"], summary)
```

```
## case.3.3[, "YEAR"]: 1927
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##  0.1700  0.2275  0.3400  0.3725  0.3975  1.0200
## ------------------------------------------------------------
## case.3.3[, "YEAR"]: 1961
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##  0.5600  0.7625  0.9750  0.9544  1.1225  1.4700
## ------------------------------------------------------------
## case.3.3[, "YEAR"]: 1998
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##   0.660   0.865   1.005   1.040   1.262   1.450
## ------------------------------------------------------------
## case.3.3[, "YEAR"]: 2001
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##   0.750   0.990   1.145   1.123   1.278   1.520
```

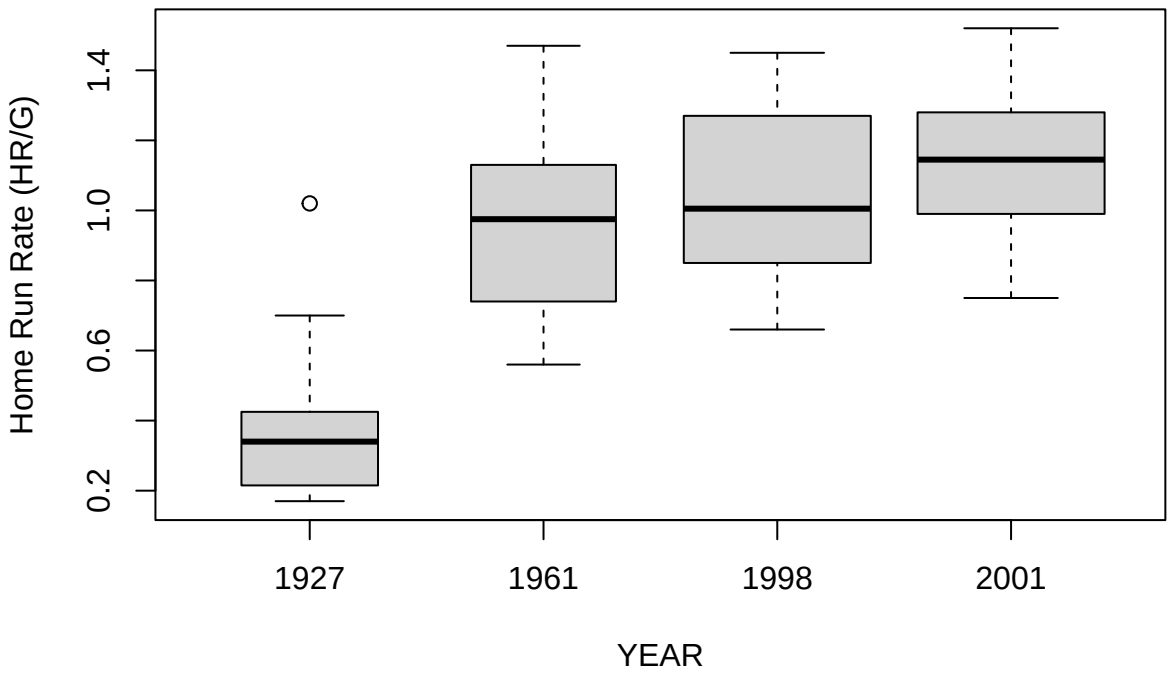
```
    ### and figure out how many teams there were in each year
    cnts = table(case.3.3$YEAR)
    cnts
```

```
##
## 1927 1961 1998 2001
##   16   18   30   30
```

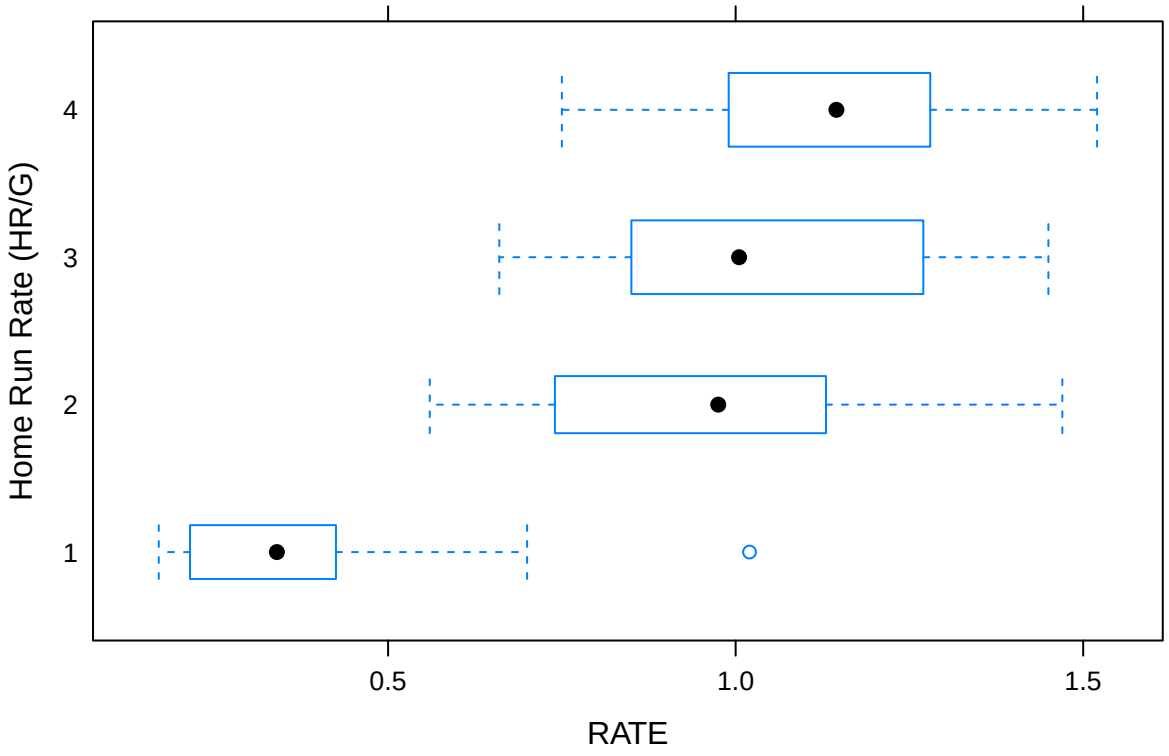
```r
### or
case.3.3 %>%
  group_by(YEAR) %>%
  summarise(n = n(),
       min = fivenum(RATE)[1],
       Q1 = fivenum(RATE)[2],
       median = fivenum(RATE)[3],
       Q3 = fivenum(RATE)[4],
       max = fivenum(RATE)[5]
  )
```

```
## # A tibble: 4 x 7
##    YEAR     n   min    Q1 median    Q3   max
##   <int> <int> <dbl> <dbl>  <dbl> <dbl> <dbl>
## 1  1927    16  0.17 0.215  0.34  0.425  1.02
## 2  1961    18  0.56 0.74   0.975 1.13   1.47
## 3  1998    30  0.66 0.85   1.00  1.27   1.45
## 4  2001    30  0.75 0.99   1.14  1.28   1.52
```

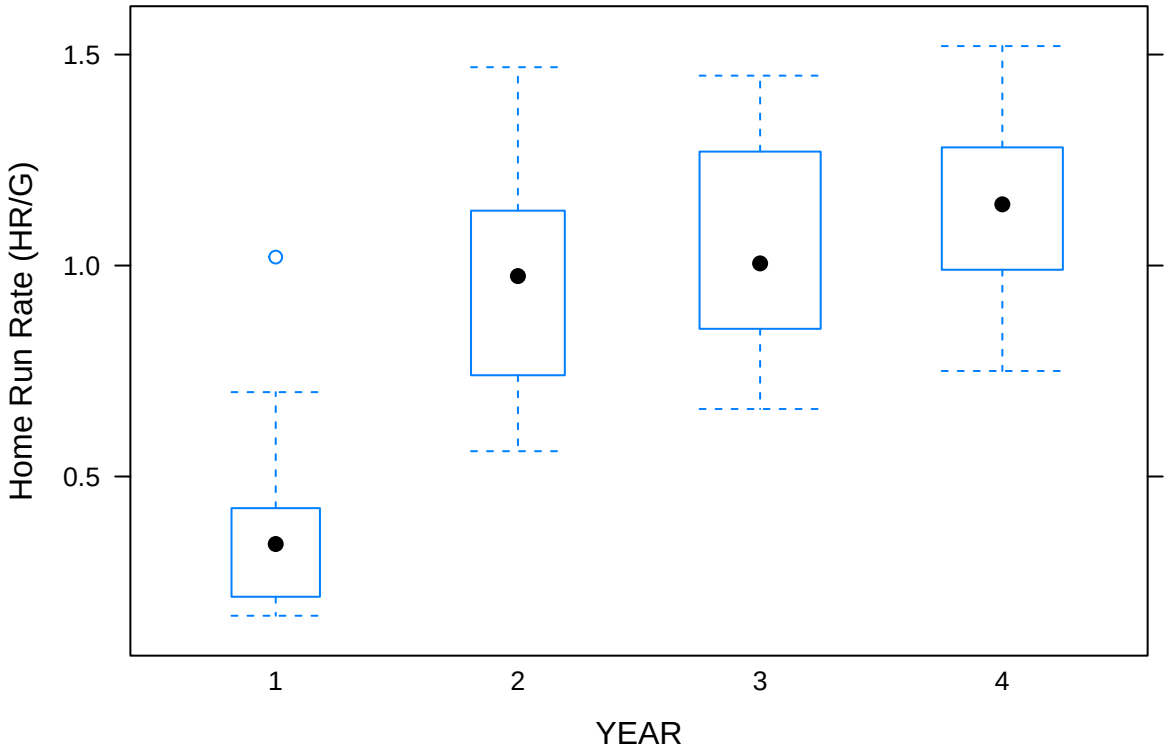
```r
### The Figure 3.9 boxplots look like
boxplot(RATE~YEAR, data=case.3.3, ylab="Home Run Rate (HR/G)", varwidth=TRUE)
```



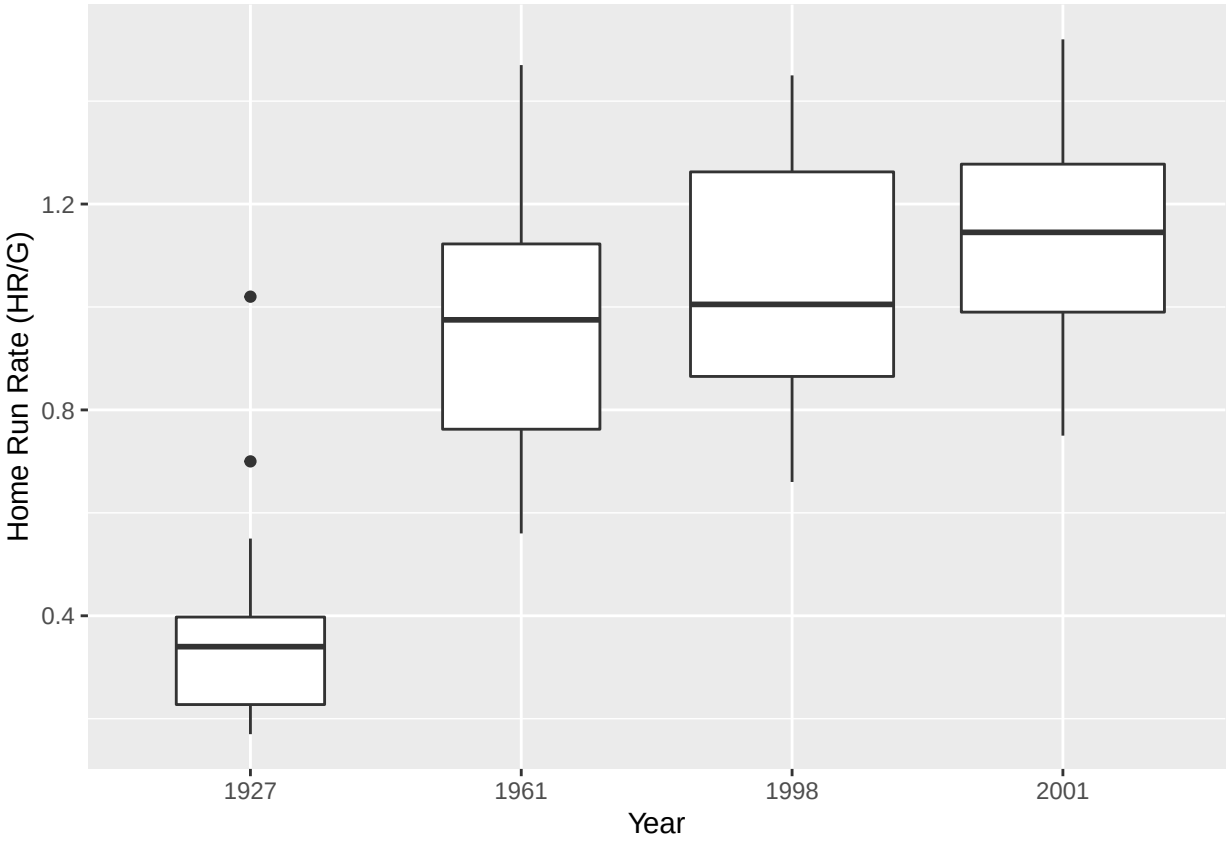

```r
p_load(lattice)
bwplot(YEAR~RATE, data=case.3.3, ylab="Home Run Rate (HR/G)", varwidth=TRUE)
```



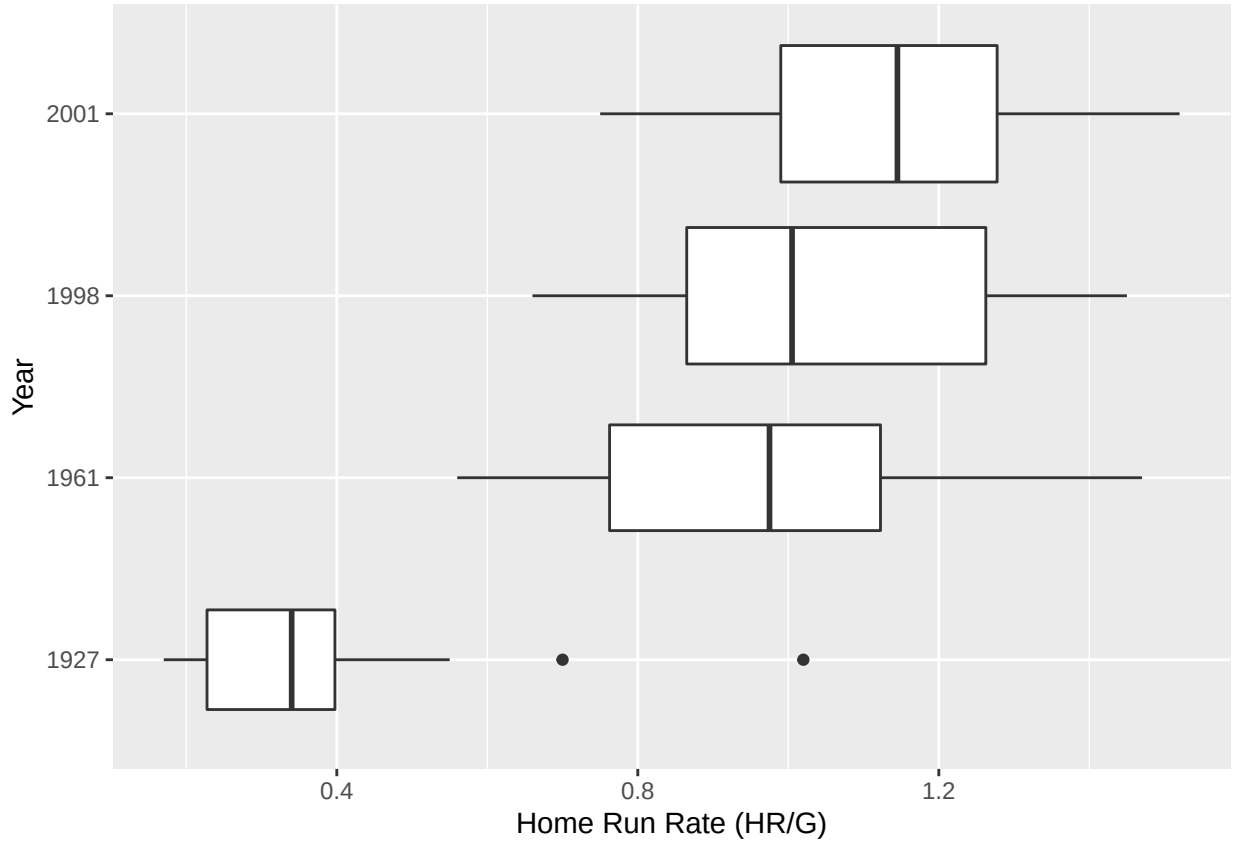

```
bwplot(RATE~YEAR, data=case.3.3, ylab="Home Run Rate (HR/G)", varwidth=TRUE, horizontal = FALSE)
```




```
    p_load(ggplot2)
    ggplot(case.3.3, aes(factor(YEAR), RATE)) + geom_boxplot(varwidth=TRUE) + xlab("Year") + ylab("Hom
```




```
ggplot(case.3.3,aes(factor(YEAR), RATE)) + geom_boxplot(varwidth=TRUE) + coord_flip() + xlab("Year
```



Case 3.4

The text now discusses the idea of the normal distribution. We will suplement the discussion with a couple of "modern" techniques. For this case we download the data from the author's site. Note that many of the values disagree with those in the text. Please let me know if you figure out why.

```
### Get the data.  Be careful about getting the "raw" CSV file from GitHub
case.3.4 <- read.csv("https://raw.githubusercontent.com/bayesball/Teaching-Statistics-Using-Baseball/
  head(case.3.4)
```

```
##    playerID       SLG
## 1 abreujo02 0.5809353
## 2 ackledu01 0.3984064
## 3 adamsma01 0.4573055
## 4 altuvjo01 0.4530303
## 5 amarial01 0.3144208
## 6 andruel01 0.3327948
```

```
  case.3.4$SLG
```

```
##   [1] 0.5809353 0.3984064 0.4573055 0.4530303 0.3144208 0.3327948 0.3604888
##   [8] 0.5000000 0.3786078 0.5244123 0.3475336 0.4918033 0.4019851 0.4401349
##  [15] 0.3624535 0.3603604 0.5057283 0.4528302 0.3488372 0.3732252 0.3788707
##  [22] 0.4450085 0.3869801 0.4577465 0.5237316 0.4118896 0.4503043 0.2896040
##  [29] 0.4537815 0.3747899 0.4911243 0.3939962 0.3655914 0.4375000 0.4500000
##  [36] 0.4267782 0.3736264 0.3003953 0.3145336 0.3890020 0.3628510 0.5252855
##  [43] 0.4044444 0.4570858 0.4013015 0.3857442 0.4300169 0.5665138 0.3297872
##  [50] 0.4555921 0.4163880 0.4805447 0.4149184 0.4012346 0.4191304 0.5471698
```

```
##  [57] 0.3765112 0.4064665 0.3403361 0.3955774 0.3986175 0.4589615 0.4612850
##  [64] 0.3831169 0.4216216 0.4340909 0.4159483 0.5418719 0.4721649 0.4773519
##  [71] 0.4822335 0.4316163 0.3776683 0.3882979 0.3325000 0.3552398 0.3724008
##  [78] 0.4903846 0.3723404 0.3563433 0.3839442 0.3672655 0.4407666 0.3808463
##  [85] 0.3976143 0.3796134 0.4462659 0.3588517 0.3371212 0.3467337 0.3777240
##  [92] 0.3778706 0.3132530 0.3608247 0.4689441 0.4112903 0.3827751 0.5064695
##  [99] 0.3970827 0.4195906 0.3300000 0.3822115 0.4554656 0.3481781 0.3800000
## [106] 0.4038462 0.3545817 0.4649573 0.3862928 0.4525253 0.5532880 0.3639775
## [113] 0.5650624 0.3714286 0.4060606 0.5419708 0.3571429 0.3873518 0.3861386
## [120] 0.3701431 0.4960159 0.4748858 0.4380000 0.3610503 0.3846154 0.4026846
## [127] 0.4192771 0.3950104 0.5173745 0.4548673 0.3686200 0.3756806 0.4446154
## [134] 0.4428571 0.4031142 0.3722944 0.4230769 0.4899452 0.4123134 0.4802867
## [141] 0.4660348 0.4083601 0.4271255 0.4476615 0.4730832 0.3610649 0.3983607
## [148] 0.3983740 0.5267176 0.3940520 0.4149660 0.4269871 0.4716049 0.3538462
## [155] 0.4542373 0.3255361 0.3314815 0.4401806 0.3688699 0.4163934 0.5547310
## [162] 0.3827434 0.3977273 0.5614618 0.3333333 0.4911661 0.4074703 0.4351464
## [169] 0.3251232 0.4053537 0.4667969 0.4550562 0.3880597 0.3738318 0.4020619
## [176] 0.3947368 0.4041096
```

We can create Figure 3.10. Again, rounding creates some minor differences.

```
### Create Figure 3.10
stem(case.3.4$SLG)
```

```
##
##   The decimal point is 2 digit(s) to the left of the |
##
##   28 | 0
##   30 | 0345
##   32 | 560013337
##   34 | 07889455679
##   36 | 00111234679901222344567888899
##   38 | 00123334566677889445567888889
##   40 | 112233444566781225566699
##   42 | 023777024588
##   44 | 00135568003334455567789
##   46 | 1567922357
##   48 | 012001126
##   50 | 0667
##   52 | 4457
##   54 | 22735
##   56 | 157
##   58 | 1
```

```
### or
p_load(aplpack)
stem.leaf(case.3.4$SLG)
```

```
## 1 | 2: represents 0.12
##  leaf unit: 0.01
##             n: 177
##     1    2. | 8
##     5    3* | 0111
##    14     t | 222333333
##    25     f | 44444555555
##    54     s | 66666666666677777777777777777
```

```
##    82    3. | 88888888888888888999999999999
##   (25)   4* | 0000000000000011111111111
##    70     t | 22222333333
##    59     f | 44444444555555555555555
##    36     s | 6666677777
##    26    4. | 888899999
##    17    5* | 0001
##    13     t | 2222
##     9     f | 44455
##     4     s | 666
##     1    5. | 8
```

The values that Albert presents can be computed fairly easily.

```
  ### Compute the statistics that Albert presents
     n = length(case.3.4$SLG)
     n                              # The number of observations
```

```
## [1] 177
```

```
     xbar = mean(case.3.4$SLG)
     xbar                           # The sample mean
```

```
## [1] 0.4158045
```

```
     median(case.3.4$SLG)
```

```
## [1] 0.4038462
```

```
     mean(case.3.4$SLG, trim=0.05) # A 10% trimmed mean
```

```
## [1] 0.4137492
```

```
     variance = var(case.3.4$SLG)
     sd = sqrt(variance)
     sd                             # Standard deviation
```

```
## [1] 0.05955793
```

```
     sqrt(variance/n)               # Standard error of the mean
```

```
## [1] 0.004476648
```

```
     summary(case.3.4$SLG)
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##  0.2896  0.3738  0.4038  0.4158  0.4542  0.5809
```

```
  ### Computing the mean plus/minus k standard deviations is "easy".  Use rounded values to match Alber
     xbar = .416
     sd = 0.060
     xbar + c(-1,1)%*%t(1:3)*sd  # Compute values for k=1,2,3 at the same time
```

```
##       [,1]  [,2]  [,3]
## [1,] 0.356 0.296 0.236
## [2,] 0.476 0.536 0.596
```

```
     # Compare with actual values
     length(case.3.4$SLG[.356 < case.3.4$SLG & case.3.4$SLG < .476])
```

```
## [1] 128
```

```
    length(case.3.4$SLG[.296 < case.3.4$SLG & case.3.4$SLG < .536])
```

```
## [1] 167
```

```
    length(case.3.4$SLG[.236 < case.3.4$SLG & case.3.4$SLG < .596])
```

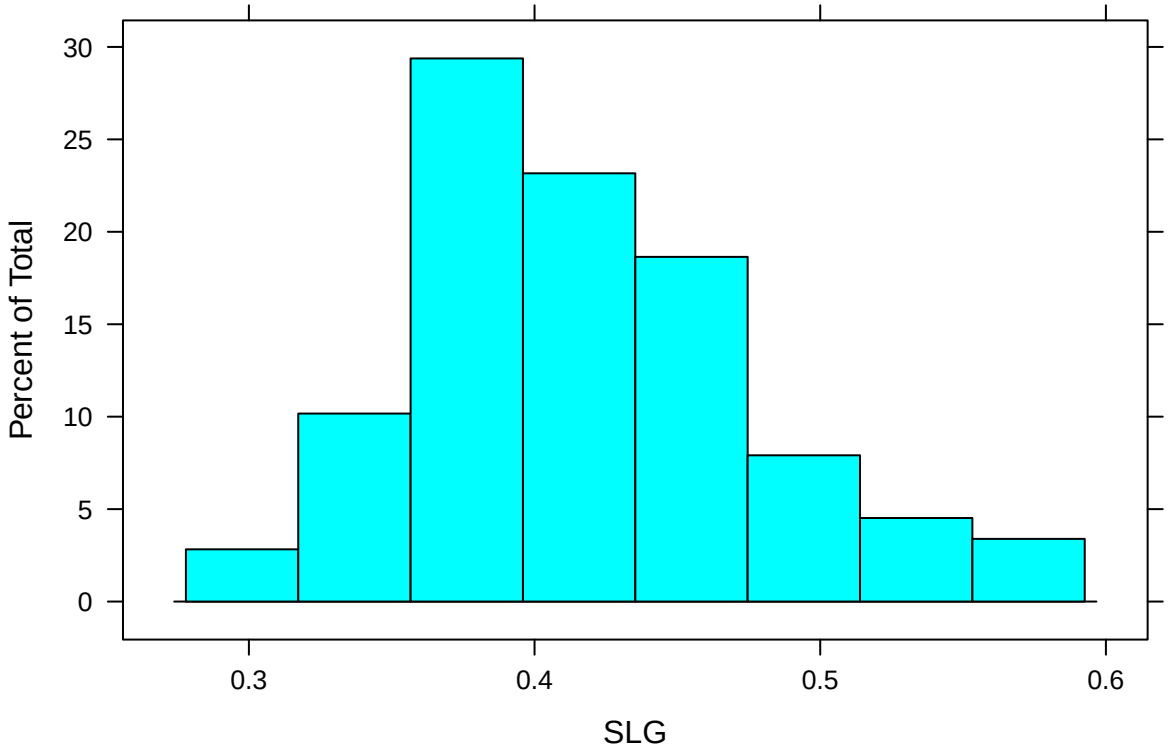
```
## [1] 177
```

```
    c(126,167,177)/178 * 100
```

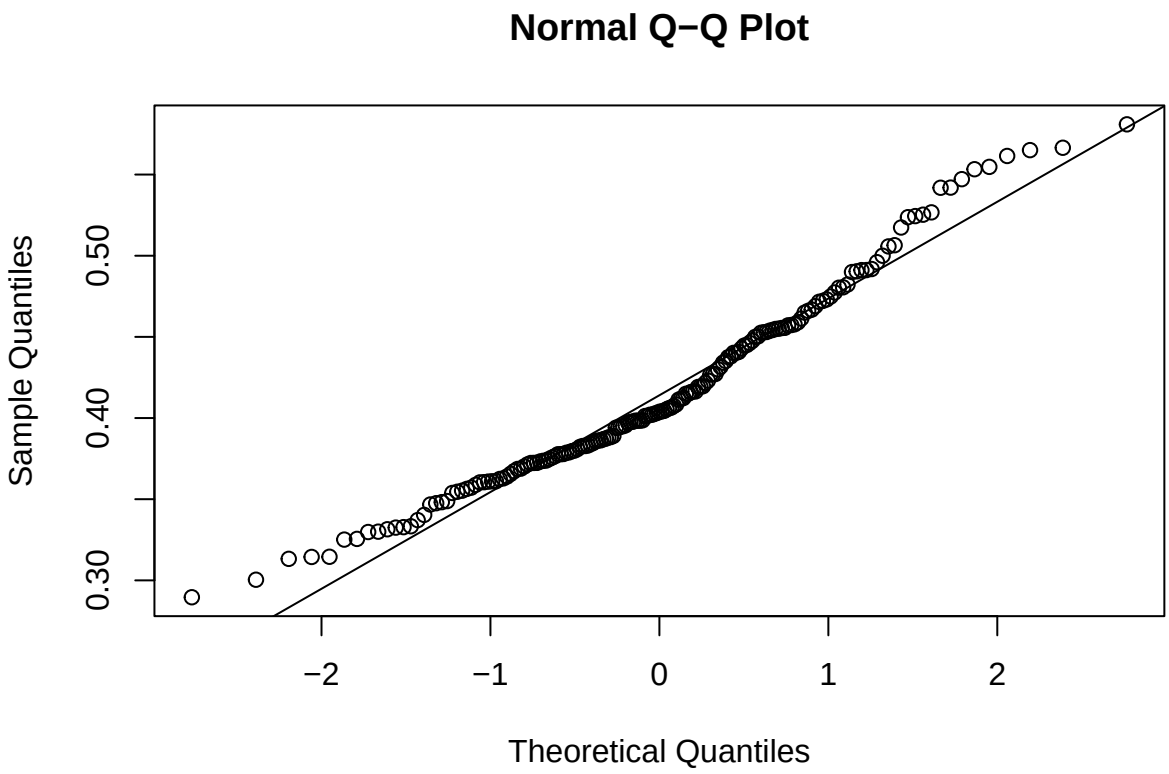
```
## [1] 70.78652 93.82022 99.43820
```

Graphical methods are sometimes helpful. A graphical method for checking normality is the normal probability or normal quantile plot. If the data are normally distributed, what we observe and what we expect to see should be the same. Hence, the plotted values should fall on the diagonal line.

```
    histogram(~SLG, data=case.3.4)
```




```
    qqnorm(case.3.4$SLG)
    qqline(case.3.4$SLG)
```



There are also some "tests" for normality.

```
  p_load(nortest)
  ad.test(case.3.4$SLG)
```

```
##
##  Anderson-Darling normality test
##
## data:  case.3.4$SLG
## A = 1.6986, p-value = 0.0002268
```

```
  cvm.test(case.3.4$SLG)
```

```
##
##  Cramer-von Mises normality test
##
## data:  case.3.4$SLG
## W = 0.29369, p-value = 0.0003855
```

```
  lillie.test(case.3.4$SLG)
```

```
##
##  Lilliefors (Kolmogorov-Smirnov) normality test
##
## data:  case.3.4$SLG
## D = 0.093368, p-value = 0.0007091
```

```
  pearson.test(case.3.4$SLG)
```

```
##
```

```
##  Pearson chi-square normality test
##
## data:  case.3.4$SLG
## P = 24.492, p-value = 0.0269
```

```
  sf.test(case.3.4$SLG)
```

```
##
##  Shapiro-Francia normality test
##
## data:  case.3.4$SLG
## W = 0.97109, p-value = 0.001516
```

```
  shapiro.test(case.3.4$SLG)
```

```
##
##  Shapiro-Wilk normality test
##
## data:  case.3.4$SLG
## W = 0.96939, p-value = 0.0006182
```

Since all of the p-values are "small" it appears that it is unlikely that the data are truly normal. How different from normal they are is debatable.

Case 3.5

The last case in this chapter discusses battting averages. For this case we download the data from the author's site.

```
   ### Get the data.  Be careful about getting the "raw" CSV file from GitHub
   case.3.5 <- read.csv("https://raw.githubusercontent.com/bayesball/Teaching-Statistics-Using-Baseball/
     head(case.3.5)
```

```
##     Lastname Firstname Year  AB   H X2B X3B HR
## 1    Appling      Luke 1941 592 186  26   8  1
## 2   Benjamin      Stan 1941 480 113  20   7  3
## 3  Berardino    Johnny 1941 469 127  30   4  5
## 4 Bloodworth     Jimmy 1941 506 124  24   3  7
## 5   Boudreau       Lou 1941 579 149  45   8 10
## 6     Bragan     Bobby 1941 557 140  19   3  4
```

```
     dim(case.3.5)
```

```
## [1] 98  8
```

```
     table(case.3.5$Year)
```

```
##
## 1941
##   98
```

It appears that the data on GitHub aren't quite right. We can pull the data from the **TSUB** package.

```
     case.3.5 <- case_3_5
     table(case.3.5$Year)
```

```
##
## 1941 1977 1980 1994
##   98  168  148   63
```

```
    head(case.3.5)
```

```
##     Lastname Firstname Year  AB   H X2B X3B HR
## 1    Appling      Luke 1941 592 186  26   8  1
## 2   Benjamin      Stan 1941 480 113  20   7  3
## 3  Berardino    Johnny 1941 469 127  30   4  5
## 4 Bloodworth     Jimmy 1941 506 124  24   3  7
## 5   Boudreau       Lou 1941 579 149  45   8 10
## 6     Bragan     Bobby 1941 557 140  19   3  4
```

Or, we can go the source... Mr. Lahman.

```
  ### Unfortunately, the online dataset is for 1941 and not 1977.  We go to
  ### Lahman to get the 1977 data.
    p_load(Lahman)
    data(Batting)
    head(Batting)
```

```
##    playerID yearID stint teamID lgID  G  AB  R  H X2B X3B HR RBI SB CS BB SO
## 1 abercda01   1871     1    TRO   NA  1   4  0  0   0   0  0   0  0  0  0  0
## 2  addybo01   1871     1    RC1   NA 25 118 30 32   6   0  0  13  8  1  4  0
## 3 allisar01   1871     1    CL1   NA 29 137 28 40   4   5  0  19  3  1  2  5
## 4 allisdo01   1871     1    WS3   NA 27 133 28 44  10   2  2  27  1  1  0  2
## 5 ansonca01   1871     1    RC1   NA 25 120 29 39  11   3  0  16  6  2  2  1
## 6 armstbo01   1871     1    FW1   NA 12  49  9 11   2   1  0   5  0  1  0  1
##   IBB HBP SH SF GIDP
## 1  NA  NA NA NA    0
## 2  NA  NA NA NA    0
## 3  NA  NA NA NA    1
## 4  NA  NA NA NA    0
## 5  NA  NA NA NA    0
## 6  NA  NA NA NA    0
```

```
    batting = battingStats()
    dim(batting)
```

```
## [1] 110495     29
```

```
    batting = batting[batting$yearID %in% c(1941, 1977, 1980, 1994),]
    dim(batting)
```

```
## [1] 3546   29
```

```
    batting = batting[batting$lgID %in% c("AL","NL"),]
    dim(batting)
```

```
## [1] 3546   29
```

```
    batting = batting[batting$AB >= 400, ]
    dim(batting)
```

```
## [1] 477  29
```

```
    table(batting$yearID)
```

```
##
## 1941 1977 1980 1994
##   98  168  148   63
```

```
  ### Or, the tidyverse approach
     p_load(tidyverse)
     batting = battingStats() %>%     ### Get the supplemented batting data
                 filter(yearID %in% c(1941, 1977, 1980, 1994)) %>%  ### Keep the right years
                 filter(lgID %in% c("AL", "NL")) %>%                ### Keep only the major leagues
                 filter(AB >= 400)                                  ### Keep people who actually batted
    table(batting$yearID)
```

```
##
## 1941 1977 1980 1994
##   98  168  148   63
```

```
  ### Or, the shorter tidyverse approach
     p_load(tidyverse)
     batting = battingStats() %>%     ### Get the supplemented batting data
                 filter(yearID %in% c(1941, 1977, 1980, 1994)       ### Keep the right years
                          & lgID %in% c("AL", "NL")                 ### Keep only the major leagues
                          & AB >= 400                               ### Keep people who actually batted
                        )
    table(batting$yearID)
```

```
##
## 1941 1977 1980 1994
##   98  168  148   63
```

It's nice to know that the **TSUB** package data are the same as Lahman's.

So, onward with the great batters. Albert looks at 1977 and there appear to have been 168 MLB batters with at least 400 appearances in 1977. We can analyze them as Albert did to see if our conclusions are the same.

```
    ### Get the 1977 data
    batting.1977 <- batting %>% filter(yearID == 1977)

     ### Figure 3.11
     stem(batting.1977$BA)
```

```
##
##   The decimal point is 2 digit(s) to the left of the |
##
##   20 | 06
##   21 | 6
##   22 | 9
##   23 | 0133559
##   24 | 001135566778
##   25 | 00111222344567799
##   26 | 001111223334444556677899
##   27 | 00112223344555557788999
##   28 | 000001222233334444467777889999
##   29 | 000111122336778899
##   30 | 00022445778899
##   31 | 011225788
##   32 | 002568
##   33 | 668
##   34 |
##   35 |
##   36 |
```

```
##   37 |
##   38 | 8
```

```
    p_load(aplpack)
    stem.leaf(batting.1977$BA)
```

```
## 1 | 2: represents 0.012
##  leaf unit: 0.001
##             n: 168
## LO: 0.2 0.206
##     3    21 | 6
##     4    22 | 9
##    11    23 | 0133559
##    23    24 | 001135566778
##    40    25 | 00111222344567799
##    64    26 | 001111223334444556677899
##   (24)   27 | 001122233445555557788999
##    80    28 | 000001222233334444446777788999
##    51    29 | 000111122336778899
##    33    30 | 00022445778899
##    19    31 | 011225788
##    10    32 | 002568
##     4    33 | 668
## HI: 0.388
```

Note that Albert says 168 in the text but the plot shows 173. This is strange. We'll continue computing statistics and see if they differ from the text.

```
    summary(batting.1977$BA)
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##  0.2000  0.2607  0.2780  0.2774  0.2923  0.3880
```

```
    xbar = mean(batting.1977$BA)
    xbar
```

```
## [1] 0.2774226
```

```
    sd = sqrt(var(batting.1977$BA))
    sd
```

```
## [1] 0.02717155
```

```
    batting.1977$BA.z = (batting.1977$BA - xbar)/sd
    stem(batting.1977$BA.z)
```

```
##
##   The decimal point is at the |
##
##   -2 | 86
##   -2 | 3
##   -1 | 8776666
##   -1 | 444333222211100000
##   -0 | 99999988887766666666555555555
##   -0 | 444433333222222211111111100
##    0 | 00111111111222222222223444444444
##    0 | 55555555566777888888899
##    1 | 000111122222334
```

```
##    1 | 555666889
##    2 | 222
##    2 |
##    3 |
##    3 |
##    4 | 1
```

```
summary(batting.1977$BA.z)
```

```
##     Min.  1st Qu.   Median     Mean  3rd Qu.     Max.
## -2.84940 -0.61361  0.02125  0.00000  0.54570  4.06960
```

Table 3.6 includes the 1900 season, so we can throw it in too. We compute the means and standard deivations.

```
p_load(tidyverse)
table.3.6 = battingStats() %>%     ### Get the supplemented batting data
              filter(yearID %in% c(1900, 1941, 1977, 1980, 1994) ### Keep the right years
                       & lgID %in% c("AL", "NL")                 ### Keep only the major leagues
                       & AB >= 400                               ### Keep people who actually batt
                     ) %>%
              group_by(yearID) %>%                               ### Group by year
              summarize(BA.mean = mean(BA),                      ### Compute mean BA by year
                        BA.sd   = sqrt(var(BA)),                 ### Compute the sd of BA by year
                        n       = n()                            ### Confirm the number of batters
                        )
table.3.6
```

```
## # A tibble: 5 x 4
##   yearID BA.mean  BA.sd     n
##    <int>   <dbl>  <dbl> <int>
## 1   1900   0.296 0.0374    45
## 2   1941   0.281 0.0328    98
## 3   1977   0.277 0.0272   168
## 4   1980   0.279 0.0275   148
## 5   1994   0.293 0.0320    63
```

Chapter Four

Chapter 4 moves from looking at a single variable in isolation to looking at how variables behave together. Changing one may cause the other to change, or they may just change together. We discuss both causality and association.

Case 4.1

In this section, Albert looks at team offensive stats. We will use the data from Albert's site.

```
### Get the data.  Be careful about getting the "raw" CSV file from GitHub
case.4.1 <- read.csv("https://raw.githubusercontent.com/bayesball/Teaching-Statistics-Using-Baseball/
  head(case.4.1)
```

```
##    Tm NBat BatAge  R.G   G   PA   AB   R    H X2B X3B  HR RBI SB CS  BB   SO
## 1 ARI   52   27.6 3.80 162 6089 5552 615 1379 259  47 118 573 86 33 398 1165
## 2 ATL   39   26.8 3.54 162 6064 5468 573 1316 240  22 123 545 95 33 472 1369
## 3 BAL   44   28.3 4.35 162 6130 5596 705 1434 264  16 211 681 44 20 401 1285
## 4 BOS   55   29.2 3.91 162 6226 5551 634 1355 282  20 123 601 63 25 535 1337
## 5 CHC   48   26.8 3.79 162 6102 5508 614 1315 270  31 157 590 65 40 442 1477
## 6 CHW   44   27.7 4.07 162 6077 5543 660 1400 279  32 155 625 85 36 417 1362
```

```
##      BA   OBP   SLG   OPS OPS.   TB GDP HBP SH SF IBB  LOB
## 1 0.248 0.302 0.376 0.678   88 2086 115  43 56 36  31 1092
## 2 0.241 0.305 0.360 0.665   87 1969 121  43 53 27  31 1128
## 3 0.256 0.311 0.422 0.734  106 2363 112  62 35 36  29 1088
## 4 0.244 0.316 0.369 0.684   92 2046 138  68 20 52  36 1168
## 5 0.239 0.300 0.385 0.684   88 2118  94  54 57 41  29 1069
## 6 0.253 0.310 0.398 0.708  100 2208 127  60 19 38  33 1071
```

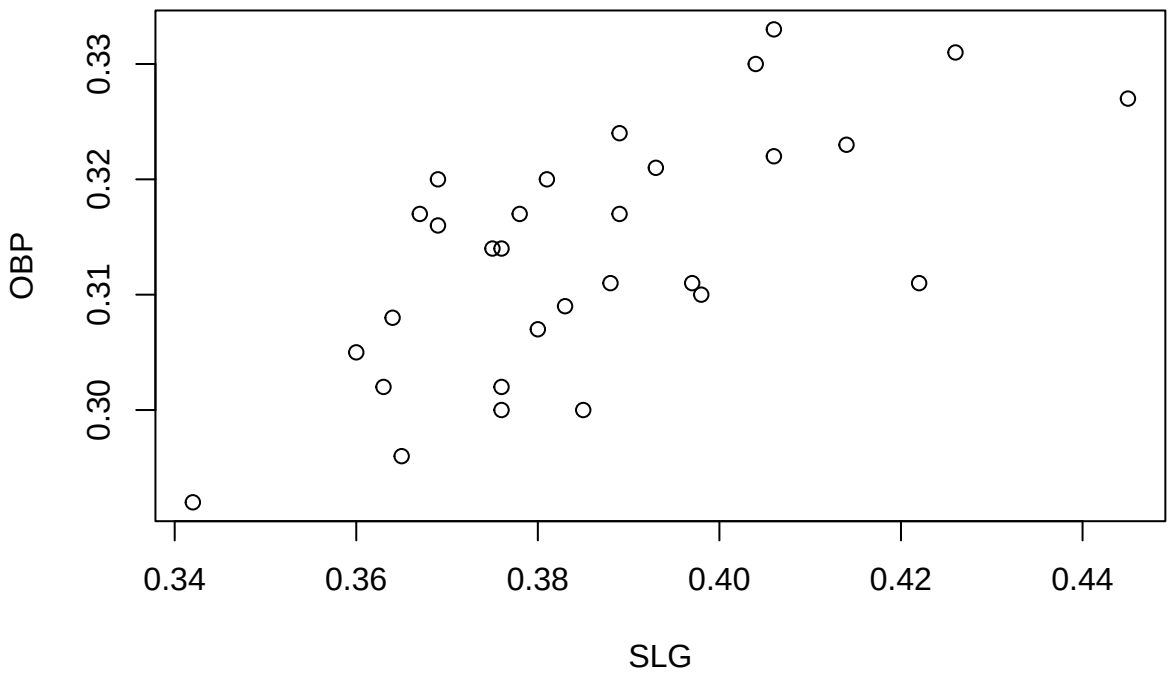
```
dim(case.4.1)
```

```
## [1] 30 29
```

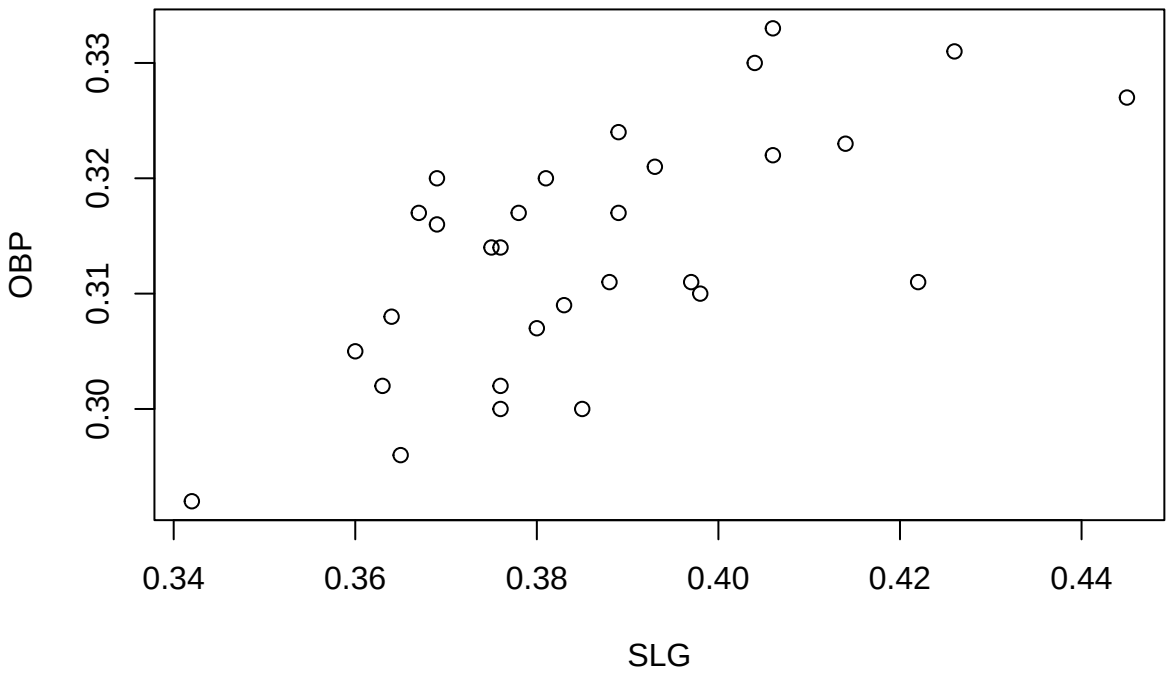
The data appear to be similar to Table 4.1.

Albert now looks at the relationships that exist between these variables using scatter plots.

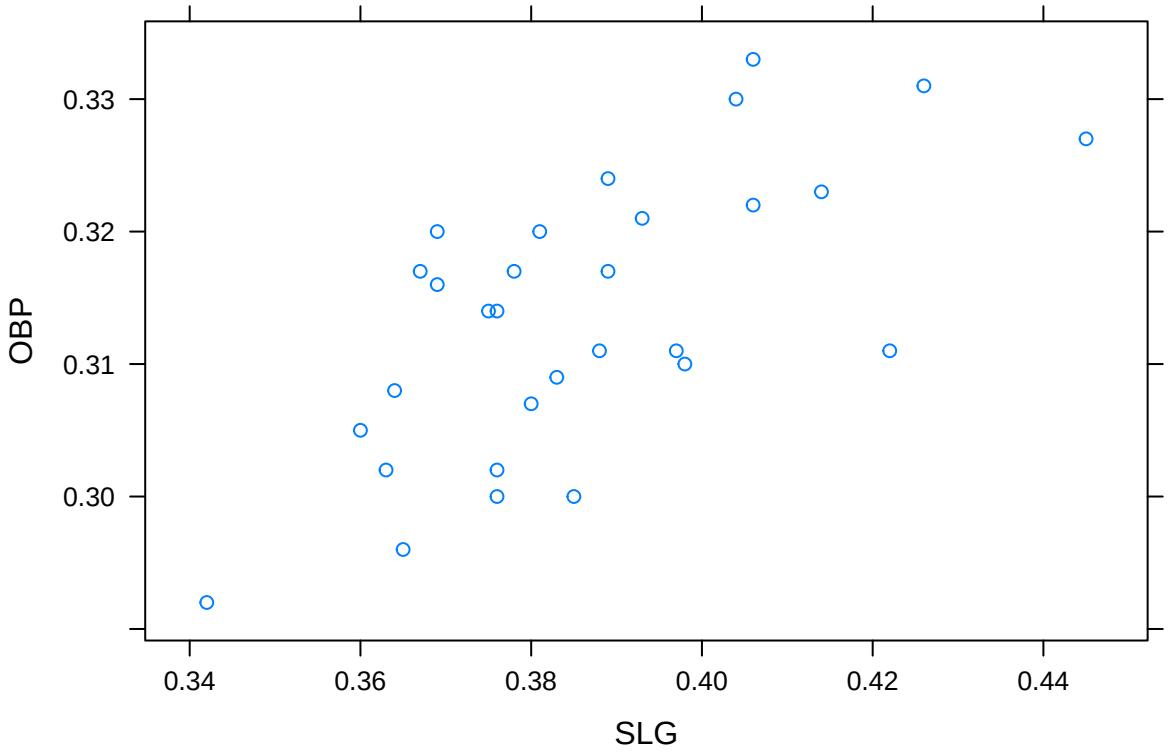
```
### Figure 4.1 is just a scatter plot
plot(case.4.1$SLG, case.4.1$OBP, xlab="SLG", ylab="OBP")
```



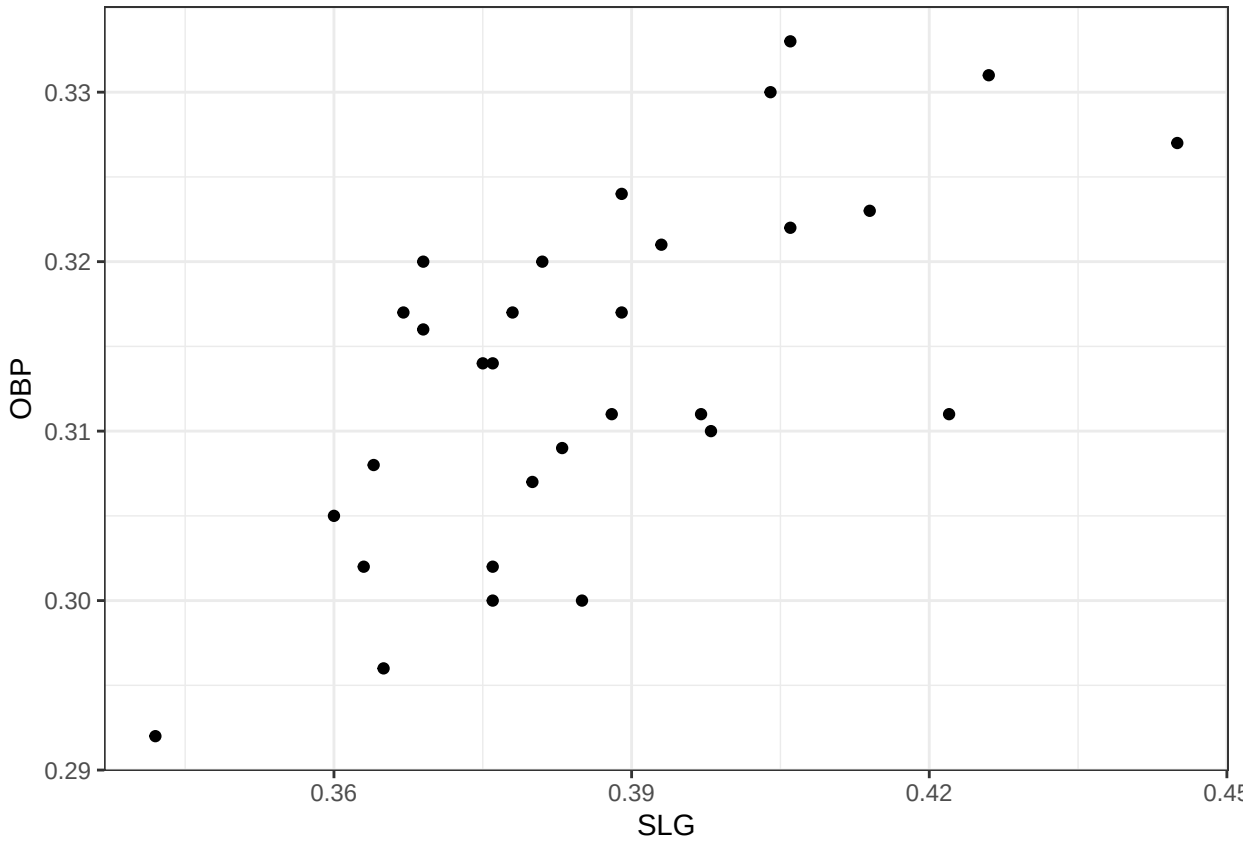

```
plot(OBP~SLG, data=case.4.1, xlab="SLG", ylab="OBP")
```



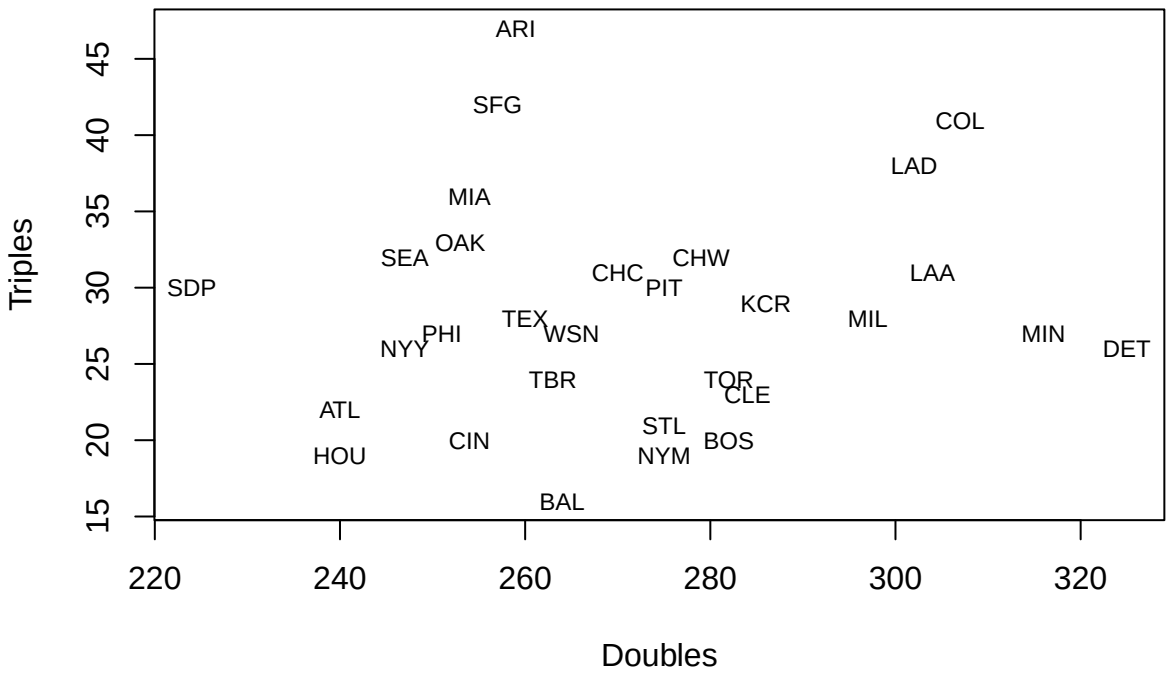

```
p_load(lattice)
xyplot(OBP~SLG, data=case.4.1, xlab="SLG", ylab="OBP")
```




```
    p_load(ggplot2)
    ggplot(case.4.1, aes(SLG, OBP)) + geom_point() + xlab("SLG") + ylab("OBP") + theme_bw()
```




```
### Figure 4.2 uses three letter team designators
   plot(case.4.1$X2B, case.4.1$X3B, ylab="Triples", xlab="Doubles", type="n")  ### plot nothing to le
   text(case.4.1$X2B, case.4.1$X3B, case.4.1$Tm, cex=0.75)                     ### add the text
```




```
  ### Analysis of Table 4.2 data
    ### The data are somewhat hidden
    search()              ### Look to see which paths are available
```

```
##  [1] ".GlobalEnv"         "package:forcats"    "package:purrr"
##  [4] "package:readr"      "package:tibble"     "package:tidyverse"
##  [7] "package:nortest"    "package:tidyr"      "package:stringr"
## [10] "package:rvest"      "package:sqldf"      "package:RSQLite"
## [13] "package:gsubfn"     "package:proto"      "package:retrosheet"
## [16] "package:devtools"   "package:usethis"    "package:plotrix"
## [19] "package:aplpack"    "package:lubridate"  "package:ggplot2"
## [22] "package:lattice"    "package:Lahman"     "package:tsub"
## [25] "package:dplyr"      "package:pacman"     "package:stats"
## [28] "package:graphics"   "package:grDevices"  "package:utils"
## [31] "package:datasets"   "package:methods"    "Autoloads"
## [34] "package:base"
```

```
    ls(pos=23)            ### On my machine, the tsub package is the 23rd object in the path.  We can lo
```

```
##  [1] "AllstarFull"         "Appearances"         "AwardsManagers"
##  [4] "AwardsPlayers"       "AwardsShareManagers" "AwardsSharePlayers"
##  [7] "Batting"             "battingLabels"       "BattingPost"
## [10] "battingStats"        "CollegePlaying"      "Fielding"
## [13] "fieldingLabels"      "FieldingOF"          "FieldingOFsplit"
## [16] "FieldingPost"        "HallOfFame"          "HomeGames"
## [19] "Label"               "LahmanData"          "Managers"
## [22] "ManagersHalf"        "Parks"               "People"
```

```
## [25] "Pitching"            "pitchingLabels"      "PitchingPost"
## [28] "playerInfo"          "Salaries"            "Schools"
## [31] "SeriesPost"          "teamInfo"            "Teams"
## [34] "TeamsFranchises"     "TeamsHalf"
```

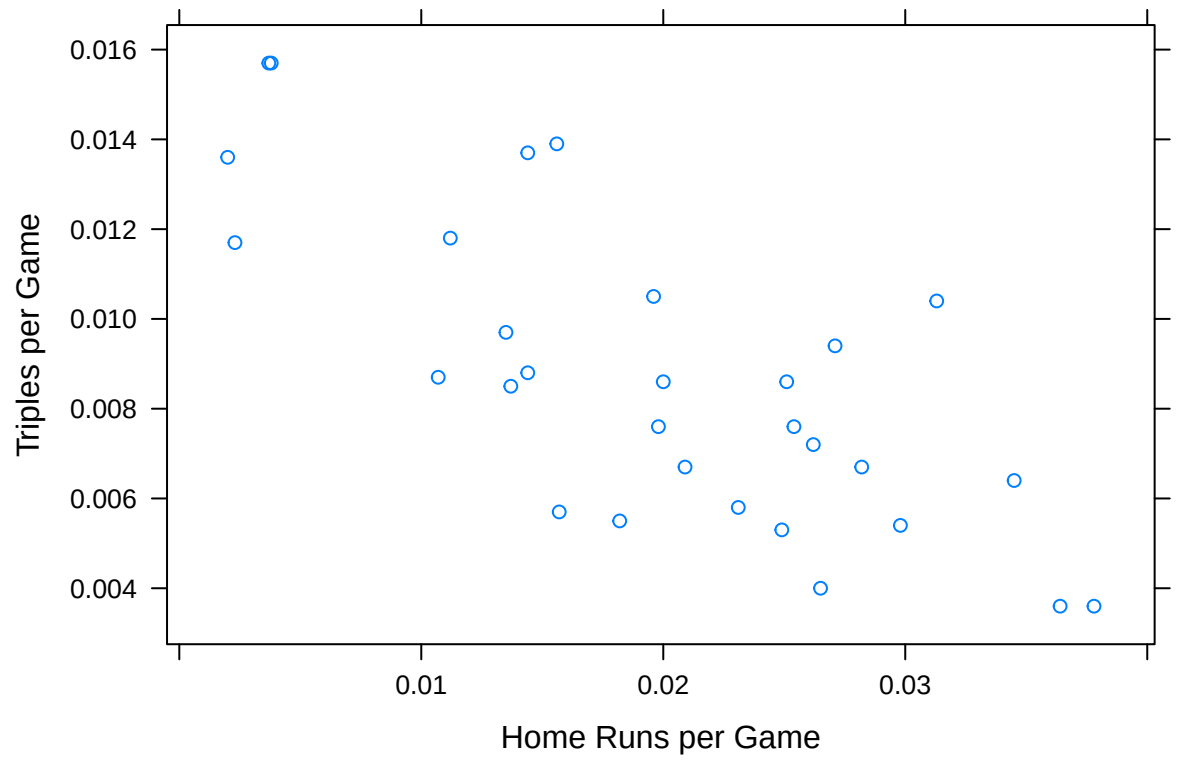
```
    head(case_4_1b)      ### The case_4_1b object contains the proper data.
```

```
##   teamID yearID HomeRun.Rate Triples.Rate
## 1    WS1   1916       0.0023       0.0117
## 2    CHN   1983       0.0254       0.0076
## 3    ATL   1982       0.0265       0.0040
## 4    CLE   1983       0.0157       0.0057
## 5    SDN   2003       0.0231       0.0058
## 6    SDN   1984       0.0198       0.0076
```

```
    table.4.2 = tsub::case_4_1b  ### Make a local copy of the case_4_1b data
    names(table.4.2)
```

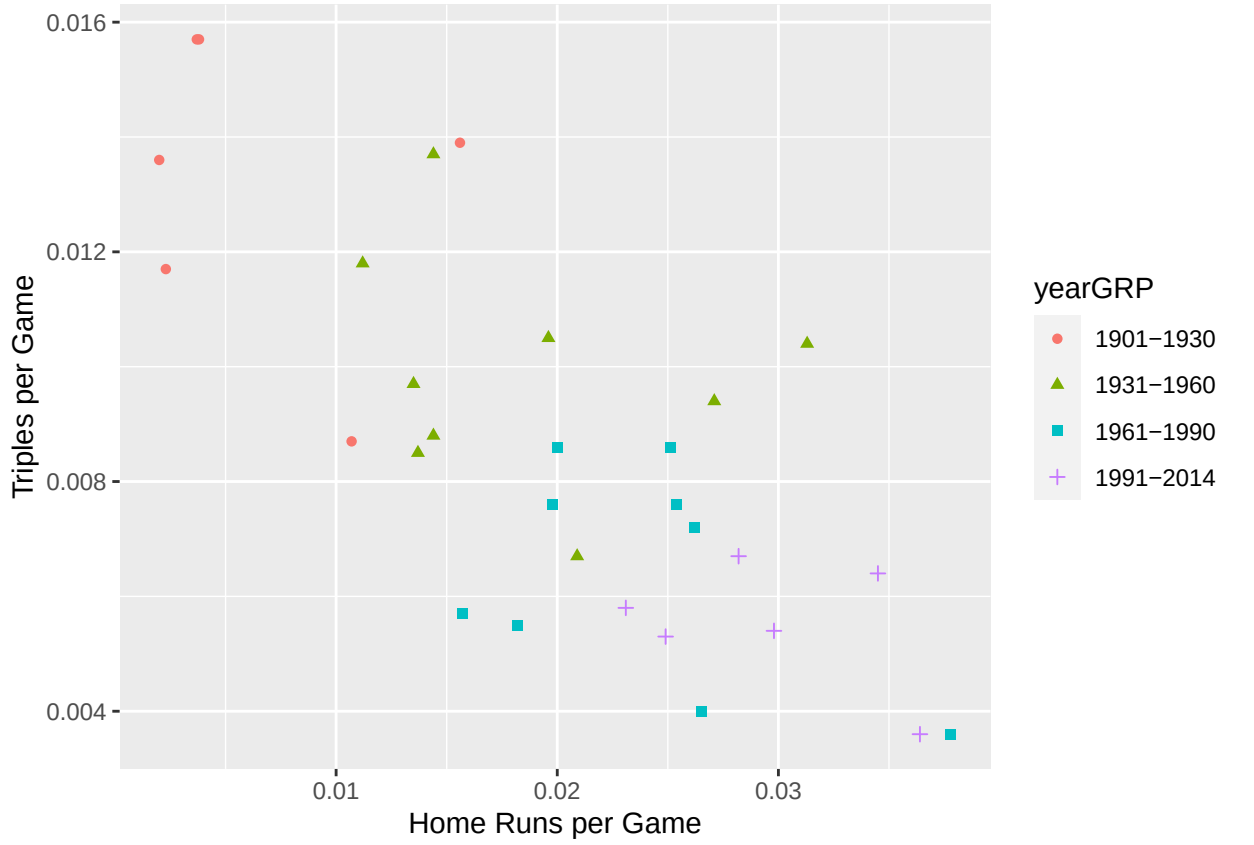
```
## [1] "teamID"       "yearID"       "HomeRun.Rate" "Triples.Rate"
```

```
    # It's time to make Figure 4.3
      p_load(lattice)
      xyplot(Triples.Rate~HomeRun.Rate, data=table.4.2, xlab="Home Runs per Game", ylab="Triples per Ga
```




```
  ### Create Figure 4.4
    # To create the factor variable that contains the year groups we use "cut"
      table.4.2$yearGRP = cut(table.4.2$yearID,
                              breaks=c(1901,1931,1961,1991,2014),
                              include.lowest=TRUE,
```

```
                              labels=c("1901-1930","1931-1960","1961-1990","1991-2014")
                              )
p_load(ggplot2)
ggplot(table.4.2, aes(x=HomeRun.Rate, y=Triples.Rate, shape=yearGRP, col=yearGRP)) +
   geom_point() +  xlab("Home Runs per Game") + ylab("Triples per Game")
```



Case 4.2

Albert now turns to looking at offensive statistics that are associated with scoring runs. We will use the data from Albert's **tsub** package.

```
case.4.2 = case_4_2     ### Make a local copy
head(case.4.2)
```

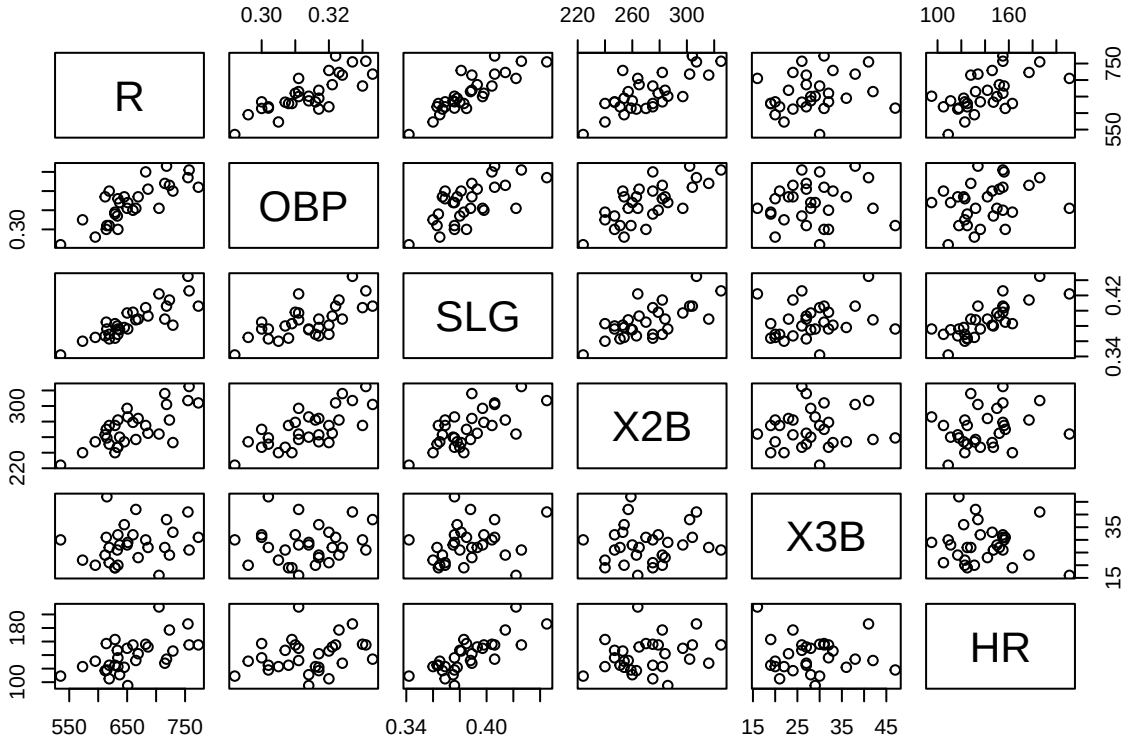
```
##    Tm NBat BatAge  R.G   G   PA   AB   R    H X2B X3B  HR RBI SB CS  BB   SO
## 1 ARI   52   27.6 3.80 162 6089 5552 615 1379 259  47 118 573 86 33 398 1165
## 2 ATL   39   26.8 3.54 162 6064 5468 573 1316 240  22 123 545 95 33 472 1369
## 3 BAL   44   28.3 4.35 162 6130 5596 705 1434 264  16 211 681 44 20 401 1285
## 4 BOS   55   29.2 3.91 162 6226 5551 634 1355 282  20 123 601 63 25 535 1337
## 5 CHC   48   26.8 3.79 162 6102 5508 614 1315 270  31 157 590 65 40 442 1477
## 6 CHW   44   27.7 4.07 162 6077 5543 660 1400 279  32 155 625 85 36 417 1362
##      BA   OBP   SLG   OPS OPS.   TB GDP HBP SH SF IBB  LOB
## 1 0.248 0.302 0.376 0.678   88 2086 115  43 56 36  31 1092
## 2 0.241 0.305 0.360 0.665   87 1969 121  43 53 27  31 1128
## 3 0.256 0.311 0.422 0.734  106 2363 112  62 35 36  29 1088
## 4 0.244 0.316 0.369 0.684   92 2046 138  68 20 52  36 1168
## 5 0.239 0.300 0.385 0.684   88 2118  94  54 57 41  29 1069
```

```
## 6 0.253 0.310 0.398 0.708  100 2208 127  60 19 38  33 1071
```

```
    names(case.4.2)
```

```
##  [1] "Tm"     "NBat"   "BatAge" "R.G"    "G"      "PA"     "AB"     "R"
##  [9] "H"      "X2B"    "X3B"    "HR"     "RBI"    "SB"     "CS"     "BB"
## [17] "SO"     "BA"     "OBP"    "SLG"    "OPS"    "OPS."   "TB"     "GDP"
## [25] "HBP"    "SH"     "SF"     "IBB"    "LOB"
```

```
  ### Make the pairs plot
    pairs(case.4.2[,c("R","OBP","SLG","X2B","X3B","HR")])
```




```
  ### The correlations presented in Table 4.3 are easily computed
    case.4.2$TB = case.4.2$AB * case.4.2$SLG
    table.4.3 = round(cor(case.4.2[,c("R", "OBP", "SLG", "X2B", "X3B", "HR")]),3)  ### The values are
    table.4.3
```

```
##         R   OBP   SLG   X2B    X3B     HR
## R   1.000 0.797 0.857 0.737  0.202  0.578
## OBP 0.797 1.000 0.668 0.724  0.104  0.260
## SLG 0.857 0.668 1.000 0.676  0.209  0.788
## X2B 0.737 0.724 0.676 1.000  0.090  0.238
## X3B 0.202 0.104 0.209 0.090  1.000 -0.094
## HR  0.578 0.260 0.788 0.238 -0.094  1.000
```

```
    ### Table 4.4 can be constructed by rearranging the rows of the first column ot Table 4.4
    as.matrix(table.4.3[c(3,2,4,6,5), 1], ncol=1)
```

```
##      [,1]
```

```
## SLG 0.857
## OBP 0.797
## X2B 0.737
## HR  0.578
## X3B 0.202
```

Case 4.3

We now look at the most valuable hitting statistics. In this section we get to play with linear regression and prediction. We will use the data from Albert's package.

```
  ### We get the Table 4.4 data from ALbert's tsub package.
     p_load(tsub)
     case.4.3 = case_4_3   ### make a local copy of the dataframe
     names(case.4.3)
```

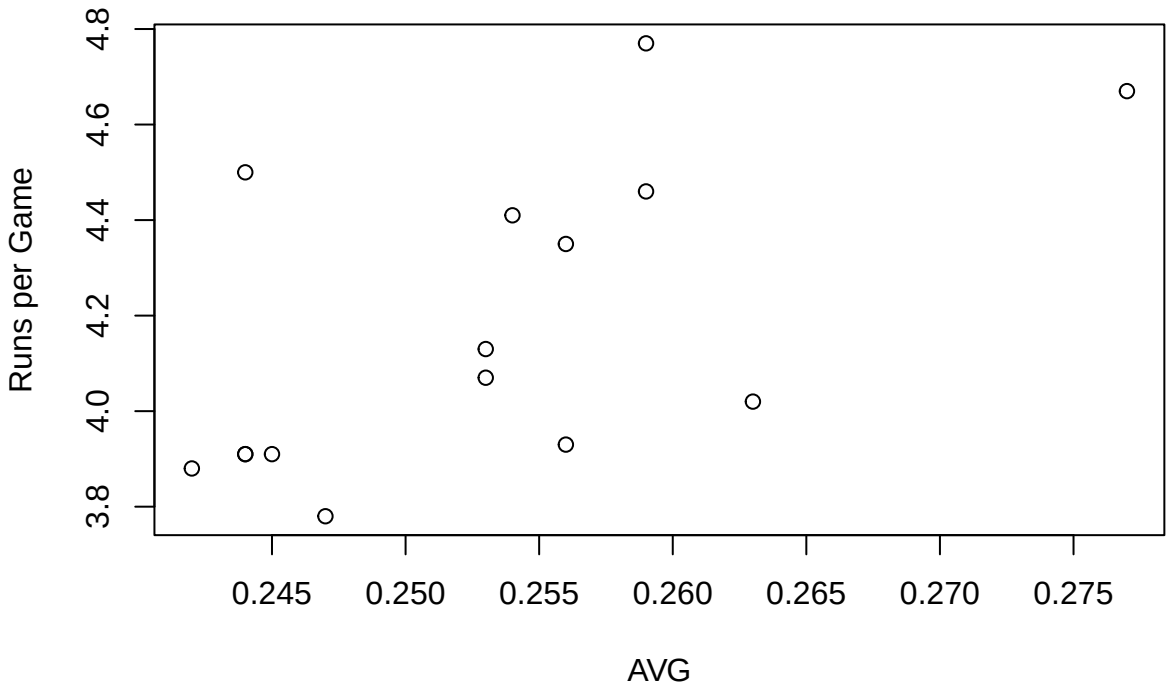
```
##  [1] "teamID" "R"      "G"      "R.G"    "AVG"    "OBP"    "SLG"    "OPS"
##  [9] "RC"     "TA"     "BRA"
```

```
     head(case.4.3)  ### Table 4.5 similar data
```

```
##   teamID   R   G  R.G   AVG   OBP   SLG   OPS  RC    TA   BRA
## 1    BAL 705 162 4.35 0.256 0.311 0.422 0.733 723 0.664 0.131
## 2    BOS 634 162 3.91 0.244 0.316 0.369 0.685 635 0.615 0.117
## 3    CHA 660 162 4.07 0.253 0.310 0.398 0.708 673 0.634 0.123
## 4    CLE 669 162 4.13 0.253 0.317 0.389 0.706 683 0.641 0.123
## 5    DET 757 162 4.67 0.277 0.331 0.426 0.757 790 0.698 0.141
## 6    HOU 629 162 3.88 0.242 0.309 0.383 0.692 636 0.624 0.118
```

Figure 4.6 is a plot that is then made into 4.7 by adding a regression line and the residuals.

```
    # Figure 4.6 looks like
     plot(R.G~AVG, data=case.4.3, ylab="Runs per Game")
```



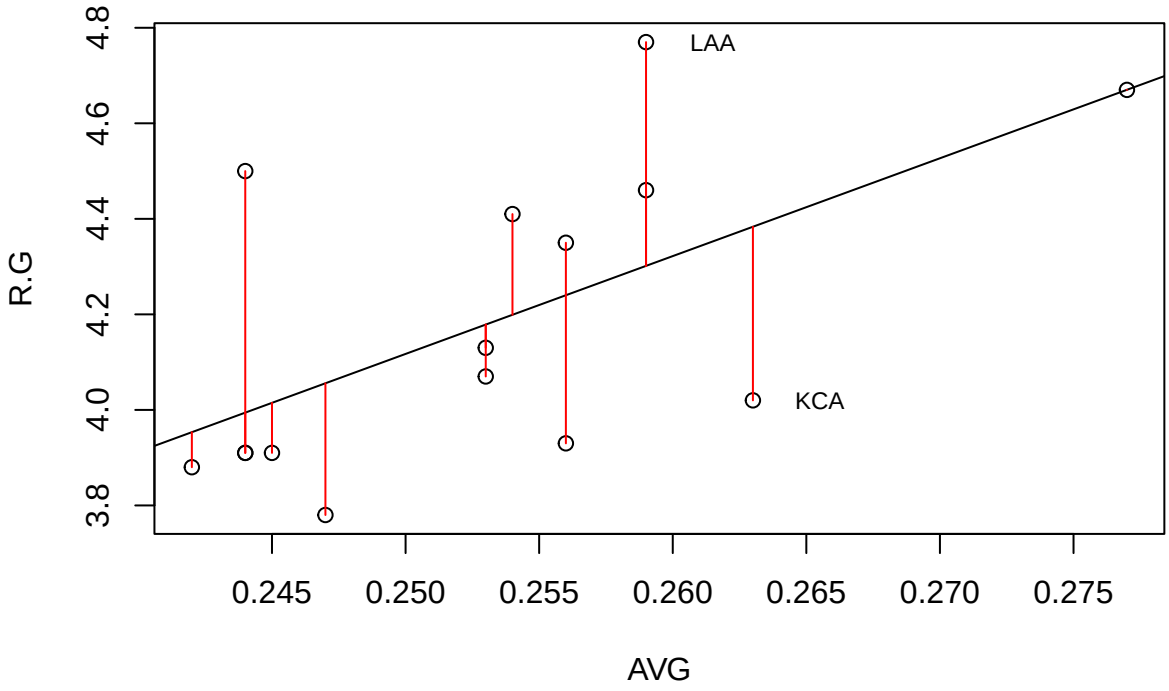

```
    # We compute a linear regression line
     summary(lm(R.G~AVG, data=case.4.3))
```

```
##
## Call:
## lm(formula = R.G ~ AVG, data = case.4.3)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -0.36344 -0.10671 -0.07335  0.13420  0.50569
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept)   -1.003      1.905  -0.526   0.6075
## AVG           20.480      7.524   2.722   0.0174 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.264 on 13 degrees of freedom
## Multiple R-squared:  0.363,  Adjusted R-squared:  0.314
## F-statistic: 7.409 on 1 and 13 DF,  p-value: 0.01745
```

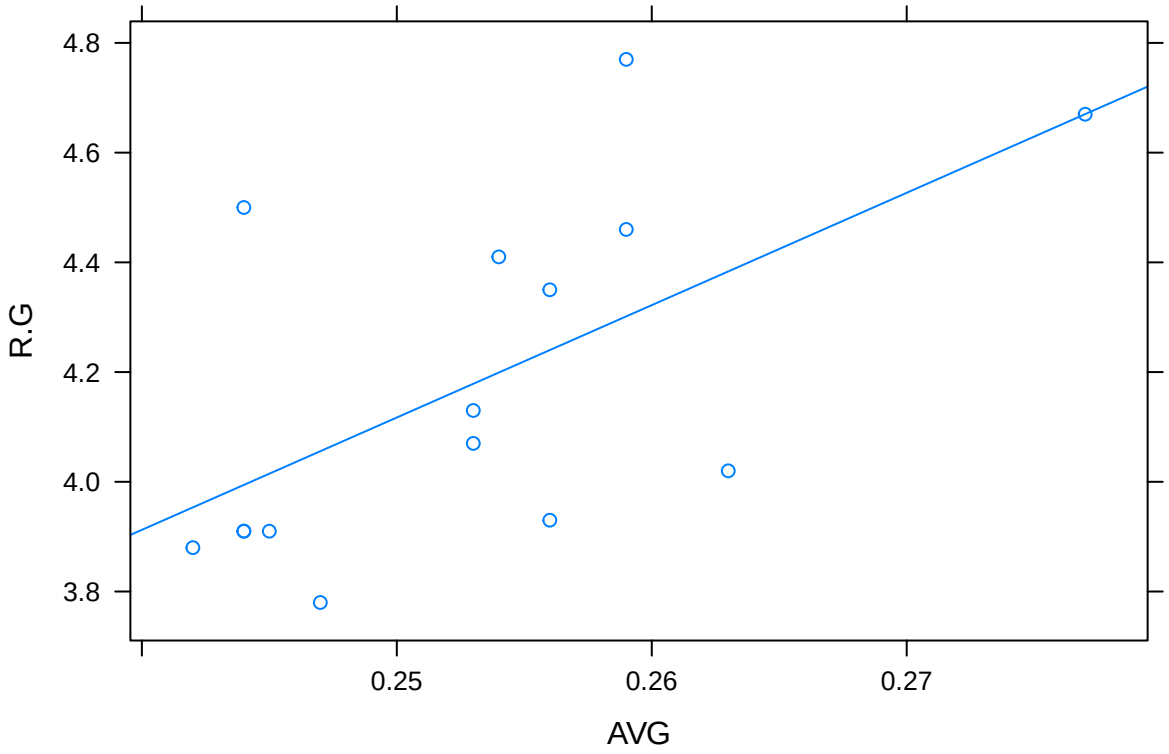
```
     coef(lm(R.G~AVG, data=case.4.3))
```

```
## (Intercept)         AVG
##   -1.002905   20.480394
```

```
# Albert starts looking at goodness of fit.  R helps us with this.
rpg.lm.avg = lm(R.G~AVG, data=case.4.3)     ### Fit and save the regression equation (and some other
case.4.3$predrpg = predict(rpg.lm.avg)      ### Get the predicted values
case.4.3$residrpg = resid(rpg.lm.avg)       ### Get the residuals or errors

# Figure 4.7
plot(R.G~AVG, data=case.4.3)                                                                    ### F
abline(rpg.lm.avg)                                                                              ### A
segments(case.4.3$AVG, case.4.3$R.G, case.4.3$AVG, case.4.3$predrpg, col="red")                 ### A
text(case.4.3$AVG[c(8,7)]+0.0025, case.4.3$R.G[c(8,7)] , case.4.3$teamID[c(8,7)], cex=0.75)     ### F
```

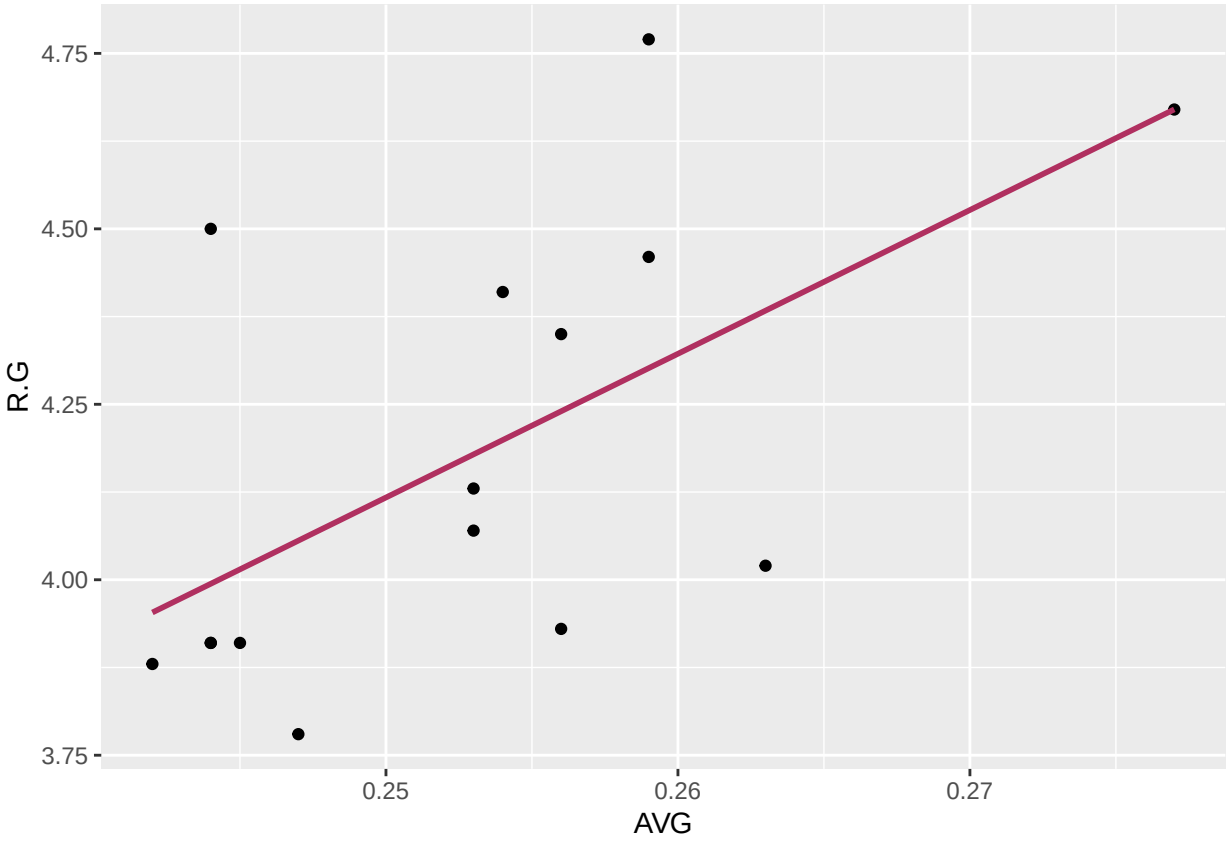



```
### Other methods for getting points and the regression line
  # lattice
  p_load(lattice)
  xyplot(R.G ~ AVG, data=case.4.3, type=c("p","r"))   ### Get p=points and r=regression
```



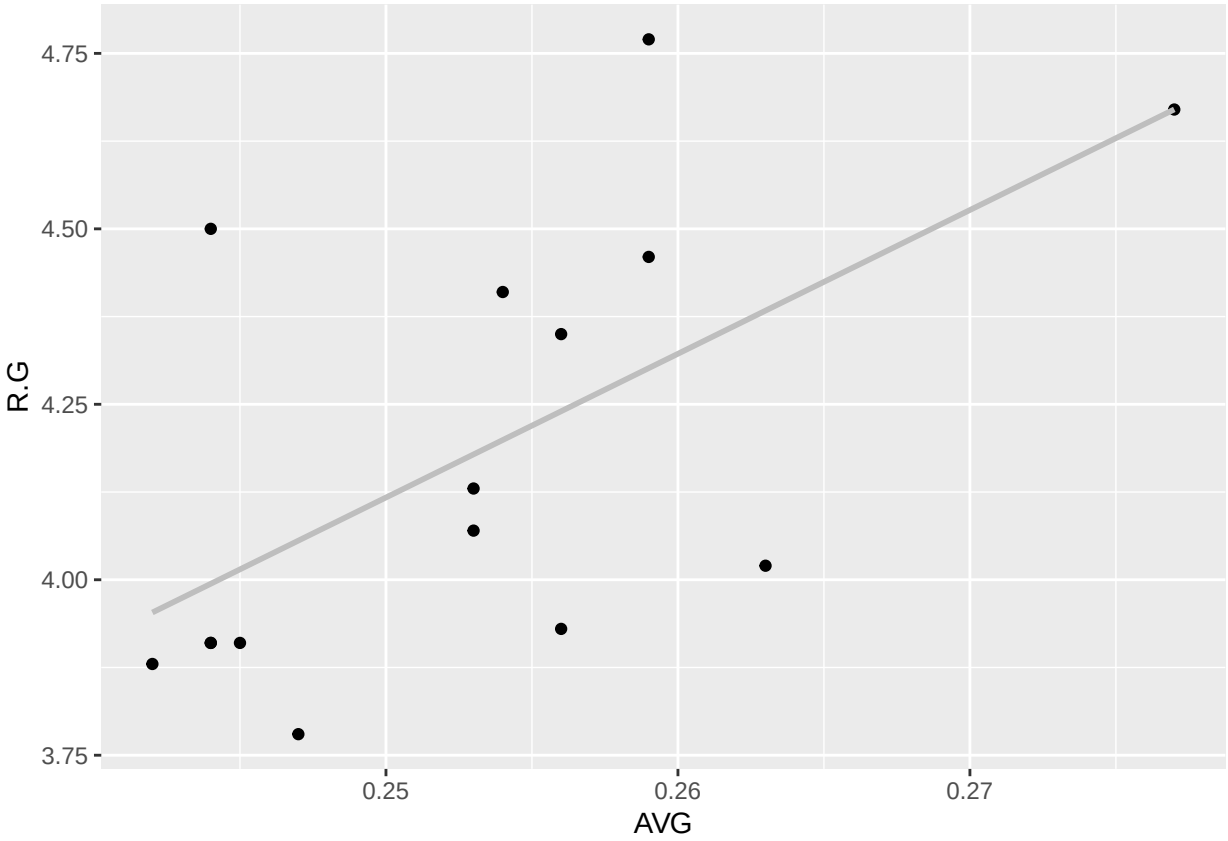

```
# ggplot2
p_load(ggplot2)

ggplot(data=case.4.3, aes(x=AVG, y=R.G)) +              ### Define the data, set the aesthetics
  geom_point() +                                        ### Plot the points, "+" continues the
  geom_smooth(method ="lm", se=FALSE, color="maroon")   ### Add the regression line without con
```

```
## `geom_smooth()` using formula 'y ~ x'
```




```
      case.4.3 %>%                                          ### Pipe the data to ggplot using %>%
        ggplot(aes(x=AVG, y=R.G)) +                         ### The rest is the same as above excep
        geom_point() +
        geom_smooth(method="lm", se=FALSE, color="gray")
```

```
## `geom_smooth()` using formula 'y ~ x'
```



Mean squared error (MSE) is a measure of the quality of the fit of the regression line. It is the average of the *squared* errors or residuals. The root mean squared error (RMSE) is the almost average error — almost because the square root of a sum is not equal to the summ of the square roots.

```
     # Compute the Mean Squared Error (MSE)
    case.4.3$sqresidrpg = case.4.3$residrpg^2   ### Square the residuals found above
    n = nrow(case.4.3)                          ### Count the number of observations
    mse = sum(case.4.3$sqresidrpg)/n            ### Sum the squared residuals and divide by n.  This r
    mse
```

```
## [1] 0.06039262
```

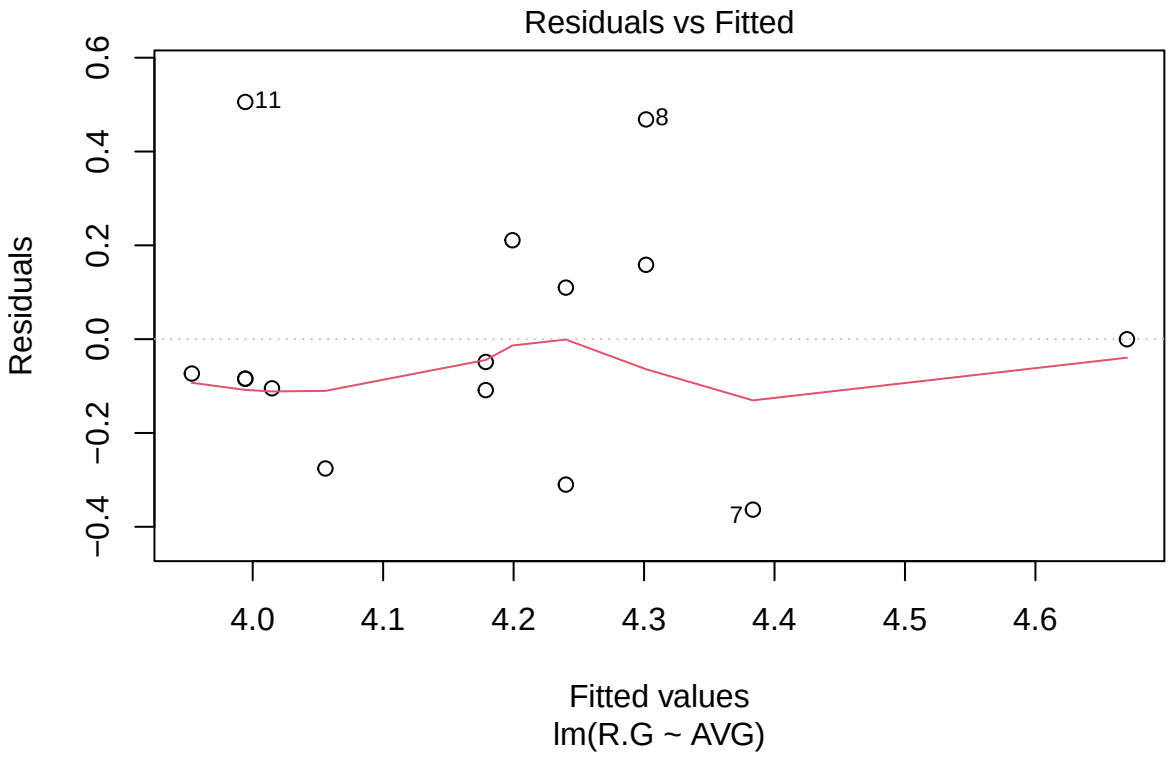
```
    rmse = sqrt(mse)
    rmse
```

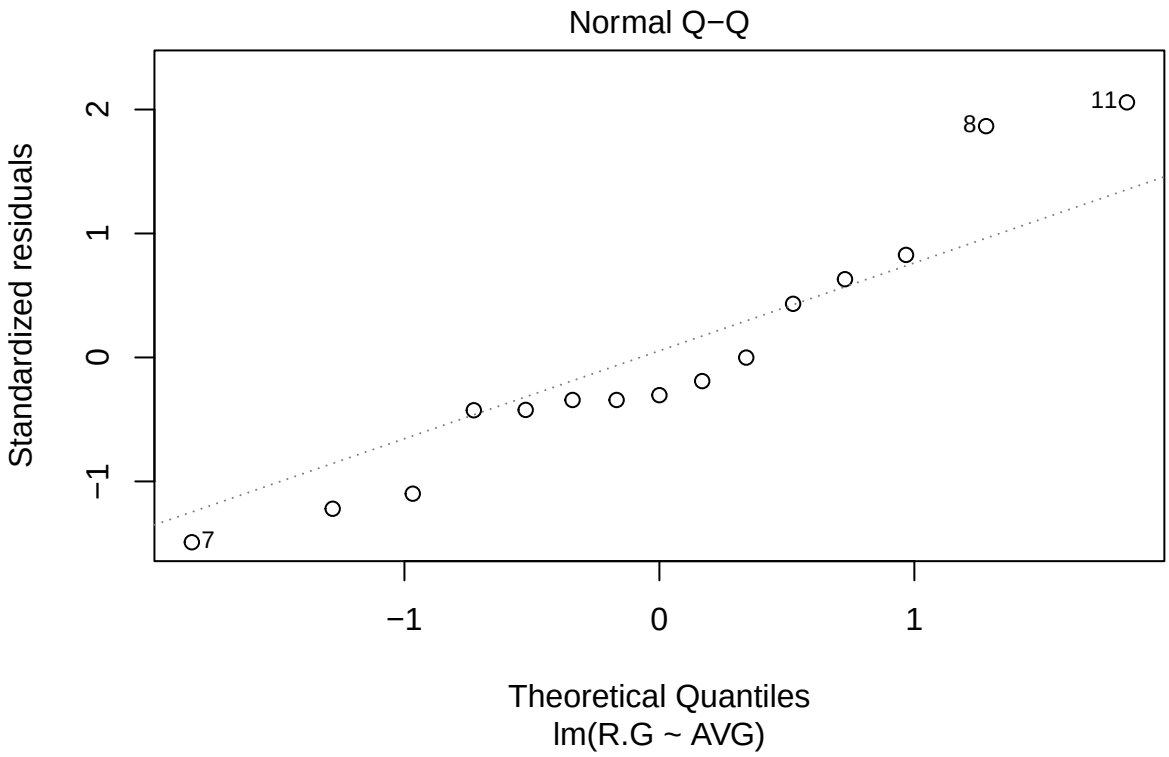
```
## [1] 0.2457491
```

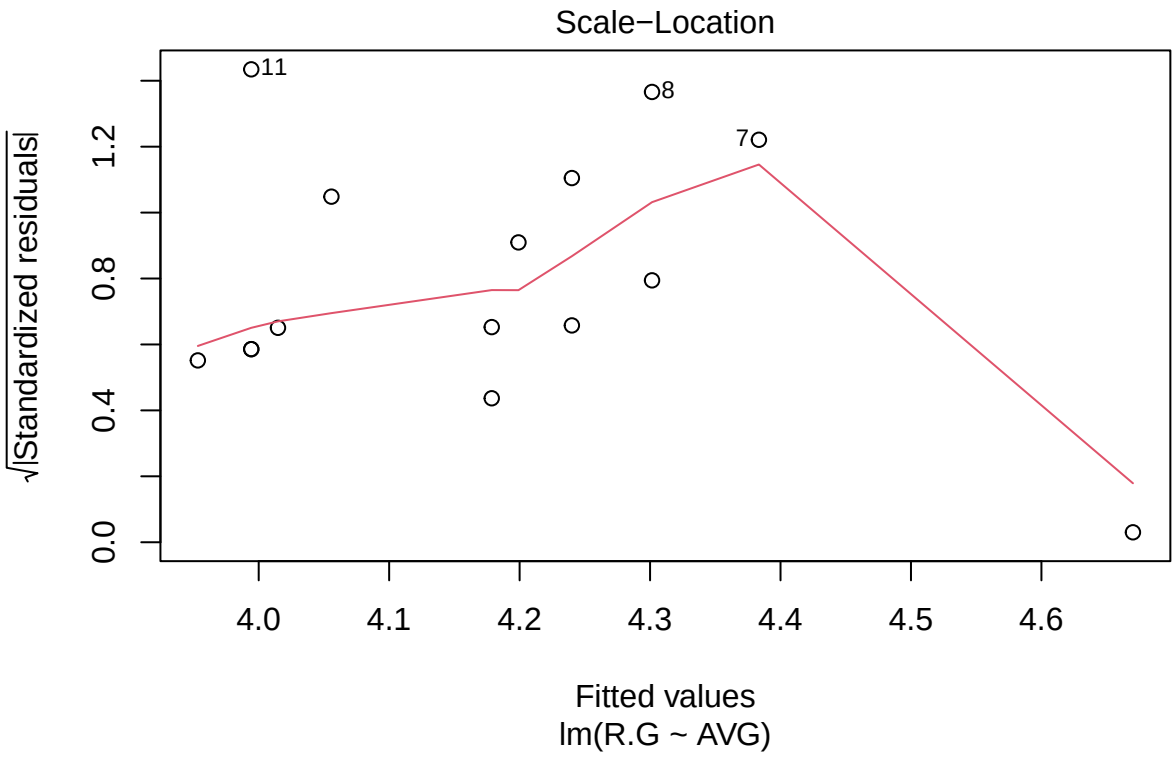
```
    sort(case.4.3$residrpg)
```

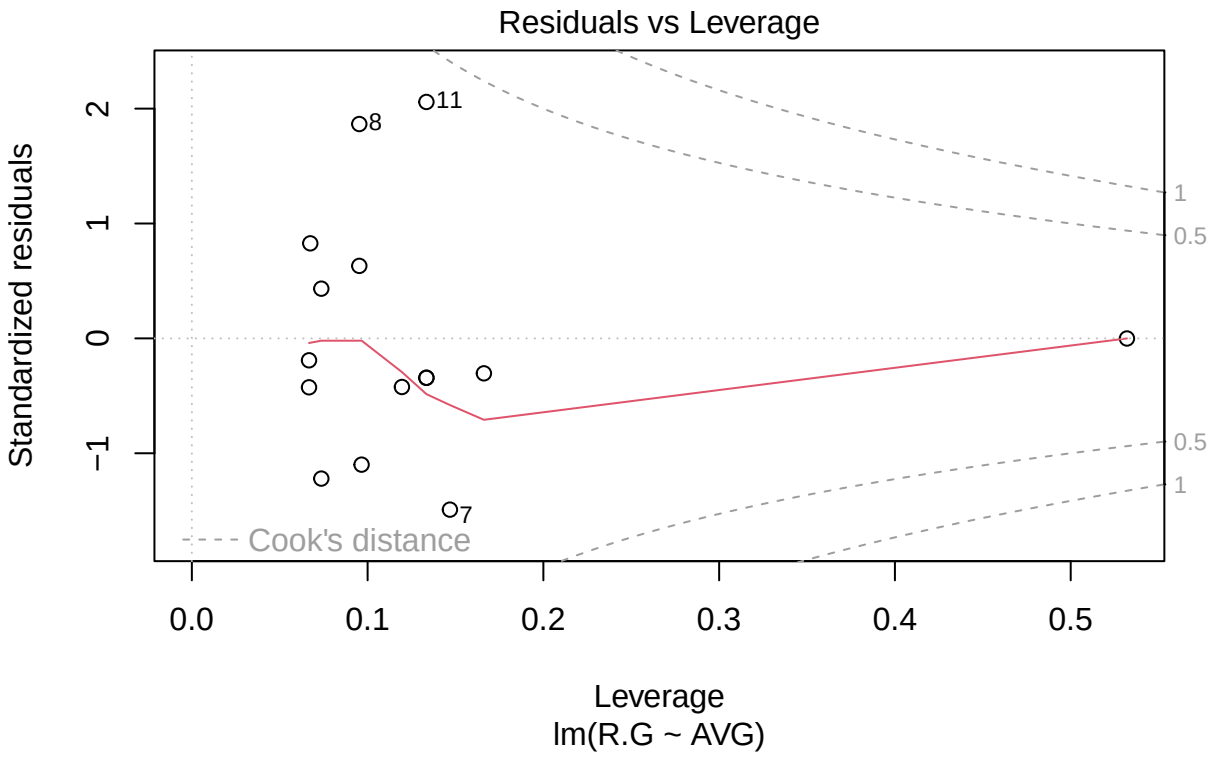
```
##  [1] -0.3634385832 -0.3100758232 -0.2757522747 -0.1086346404 -0.1047914861
##  [6] -0.0843110919 -0.0843110919 -0.0733503033 -0.0486346404 -0.0001641031
## [11]  0.1099241768  0.1584829939  0.2108849653  0.4684829939  0.5056889081
```

```
    # Albert suggests that the residuals are normally distributed.  R helps us
    # check this.
     plot(rpg.lm.avg)
```

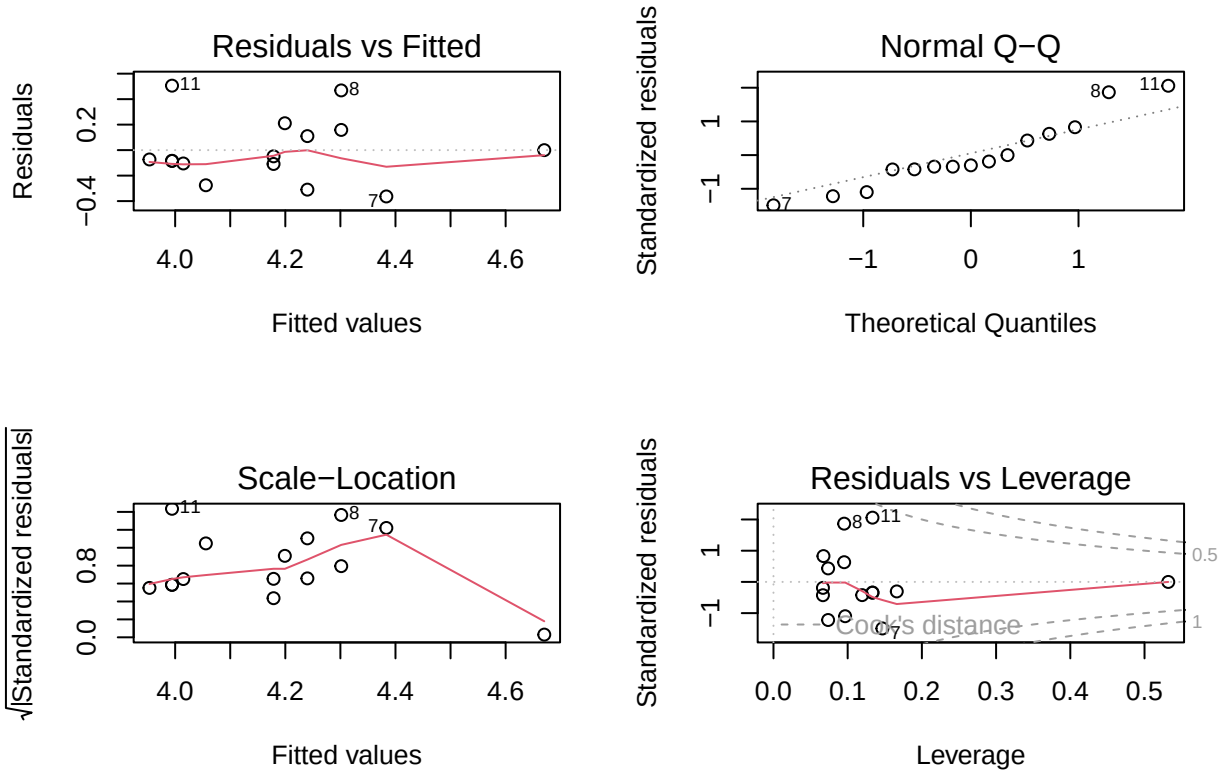

Residuals vs Fitted
Residuals
0.6
0.4
0.2
0.0
−0.2
−0.4
11
8
7
4.0
4.1
4.2
4.3
4.4
4.5
4.6
Fitted values
lm(R.G ~ AVG)


Normal Q−Q
Standardized residuals
2
1
0
−1
11
8
7
−1
0
1
Theoretical Quantiles
lm(R.G ~ AVG)


Scale−Location
√|Standardized residuals|
0.0
0.4
0.8
1.2
11
8
7
4.0
4.1
4.2
4.3
4.4
4.5
4.6
Fitted values
lm(R.G ~ AVG)




```
# Or on one page...
par(mfrow=c(2,2))
plot(rpg.lm.avg)
```




```
    par(mfrow=c(1,1))

    # Next we try OBP
    rpg.lm.obp = lm(R.G~OBP, data=case.4.3)
    coef(rpg.lm.obp)
```

```
## (Intercept)         OBP
##   -5.155568   29.574132
```

Tables 4.6 and 4.7 give the values used in computing the RMSE.

```
    ### Table 4.7 uses AVG
    cbind(case.4.3$teamID, round(case.4.3[,c("AVG","R.G")],3), pred=round(predict(rpg.lm.avg),3),
              res=round(resid(rpg.lm.avg),3), sqrres=round(resid(rpg.lm.avg)^2,3))
```

```
##    case.4.3$teamID   AVG  R.G  pred    res sqrres
## 1              BAL 0.256 4.35 4.240  0.110  0.012
## 2              BOS 0.244 3.91 3.994 -0.084  0.007
## 3              CHA 0.253 4.07 4.179 -0.109  0.012
## 4              CLE 0.253 4.13 4.179 -0.049  0.002
## 5              DET 0.277 4.67 4.670  0.000  0.000
## 6              HOU 0.242 3.88 3.953 -0.073  0.005
## 7              KCA 0.263 4.02 4.383 -0.363  0.132
## 8              LAA 0.259 4.77 4.302  0.468  0.219
## 9              MIN 0.254 4.41 4.199  0.211  0.044
## 10             NYA 0.245 3.91 4.015 -0.105  0.011
## 11             OAK 0.244 4.50 3.994  0.506  0.256
## 12             SEA 0.244 3.91 3.994 -0.084  0.007
```

```
## 13             TBA 0.247 3.78 4.056 -0.276  0.076
## 14             TEX 0.256 3.93 4.240 -0.310  0.096
## 15             TOR 0.259 4.46 4.302  0.158  0.025
```

```
    mse = sum(resid(rpg.lm.avg)^2)/(nrow(case.4.3)-2)  ### We divide by n-2 because we used 2 pieces o
    rmse = sqrt(mse)
    c(mse, rmse)
```

```
## [1] 0.06968379 0.26397687
```

```
    anova(rpg.lm.avg)
```

```
## Analysis of Variance Table
##
## Response: R.G
##           Df  Sum Sq Mean Sq F value  Pr(>F)
## AVG        1 0.51631 0.51631  7.4093 0.01745 *
## Residuals 13 0.90589 0.06968
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
    ### Table 4.7 uses OBP
    cbind(case.4.3$teamID, round(case.4.3[,c("OBP","R.G")],3), pred=round(predict(rpg.lm.obp),3),
              res=round(resid(rpg.lm.obp),3), sqrres=round(resid(rpg.lm.obp)^2,3))
```

```
##    case.4.3$teamID   OBP  R.G  pred    res sqrres
## 1              BAL 0.311 4.35 4.042  0.308  0.095
## 2              BOS 0.316 3.91 4.190 -0.280  0.078
## 3              CHA 0.310 4.07 4.012  0.058  0.003
## 4              CLE 0.317 4.13 4.219 -0.089  0.008
## 5              DET 0.331 4.67 4.633  0.037  0.001
## 6              HOU 0.309 3.88 3.983 -0.103  0.011
## 7              KCA 0.314 4.02 4.131 -0.111  0.012
## 8              LAA 0.322 4.77 4.367  0.403  0.162
## 9              MIN 0.324 4.41 4.426 -0.016  0.000
## 10             NYA 0.307 3.91 3.924 -0.014  0.000
## 11             OAK 0.320 4.50 4.308  0.192  0.037
## 12             SEA 0.300 3.91 3.717  0.193  0.037
## 13             TBA 0.317 3.78 4.219 -0.439  0.193
## 14             TEX 0.314 3.93 4.131 -0.201  0.040
## 15             TOR 0.323 4.46 4.397  0.063  0.004
```

```
    mse = sum(resid(rpg.lm.obp)^2)/(nrow(case.4.3)-2)  ### We divide by n-2 because we used 2 pieces o
    rmse = sqrt(mse)
    c(mse, rmse)
```

```
## [1] 0.05252667 0.22918697
```

```
    anova(rpg.lm.obp)
```

```
## Analysis of Variance Table
##
## Response: R.G
##           Df  Sum Sq Mean Sq F value   Pr(>F)
## OBP        1 0.73935 0.73935  14.076 0.002419 **
## Residuals 13 0.68285 0.05253
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

As noted in the comments, the proper formula for mean squared error divides by $n-2$ and not n. This is a correction to the amount of information that we have left over after computing the intercept and slope. We call these leftover pieces of information *degrees of freedom*. The correct formula is thus

$$\text{MSE} = \frac{\sum_{i=1}^{n} (\text{OBSERVED}_i - \text{PREDICTED}_i)^2}{n-2}$$

]

$$\text{MSE} = \frac{\sum_{i=1}^{n} (y_i - \widehat{y}_i)^2}{n-2}$$

Case 4.4

We now switch to looking at multiple predictor variables by using multiple linear regression. Albert fits a model using the six batting events (Singles, doubles, triples, home runs, walks, and hit by pitch) to predict runs per game.

```
### The initial model that Albert fits uses the 2014 data from Case 4.1.  This is the same as case_4_
MLB2014 = case_4_4
### We called this MLB2014
head(MLB2014)
```

```
##    Tm NBat BatAge  R.G   G   PA   AB   R    H X2B X3B  HR RBI SB CS  BB   SO
## 1 ARI   52   27.6 3.80 162 6089 5552 615 1379 259  47 118 573 86 33 398 1165
## 2 ATL   39   26.8 3.54 162 6064 5468 573 1316 240  22 123 545 95 33 472 1369
## 3 BAL   44   28.3 4.35 162 6130 5596 705 1434 264  16 211 681 44 20 401 1285
## 4 BOS   55   29.2 3.91 162 6226 5551 634 1355 282  20 123 601 63 25 535 1337
## 5 CHC   48   26.8 3.79 162 6102 5508 614 1315 270  31 157 590 65 40 442 1477
## 6 CHW   44   27.7 4.07 162 6077 5543 660 1400 279  32 155 625 85 36 417 1362
##      BA   OBP   SLG   OPS OPS.   TB GDP HBP SH SF IBB  LOB
## 1 0.248 0.302 0.376 0.678   88 2086 115  43 56 36  31 1092
## 2 0.241 0.305 0.360 0.665   87 1969 121  43 53 27  31 1128
## 3 0.256 0.311 0.422 0.734  106 2363 112  62 35 36  29 1088
## 4 0.244 0.316 0.369 0.684   92 2046 138  68 20 52  36 1168
## 5 0.239 0.300 0.385 0.684   88 2118  94  54 57 41  29 1069
## 6 0.253 0.310 0.398 0.708  100 2208 127  60 19 38  33 1071
```

```
names(MLB2014)
```

```
##  [1] "Tm"     "NBat"   "BatAge" "R.G"    "G"      "PA"     "AB"     "R"
##  [9] "H"      "X2B"    "X3B"    "HR"     "RBI"    "SB"     "CS"     "BB"
## [17] "SO"     "BA"     "OBP"    "SLG"    "OPS"    "OPS."   "TB"     "GDP"
## [25] "HBP"    "SH"     "SF"     "IBB"    "LOB"
```

```
### We can now fit the optimized average
MLB2014$X1B = MLB2014$H - (MLB2014$X2B + MLB2014$X3B + MLB2014$HR)
rpg.lm.optavg = lm(R.G ~ X1B + X2B + X3B + HR + BB + HBP, data=MLB2014)
coef(rpg.lm.optavg)
```

```
##   (Intercept)           X1B           X2B           X3B            HR
## -1.8352666443  0.0025173114  0.0056001510  0.0076324824  0.0072430677
##            BB           HBP
##  0.0017538445 -0.0009130335
```

It is likely that the differences that we are seeing here are the result of Albert having rounded his data. The RMSE is

```
   mse = sum(resid(rpg.lm.optavg)^2)/(nrow(MLB2014)-7)
   rmse = sqrt(mse)
   c(mse, rmse)
```

```
## [1] 0.01730754 0.13155812
```

```
   anova(rpg.lm.optavg)
```

```
## Analysis of Variance Table
##
## Response: R.G
##           Df  Sum Sq Mean Sq F value    Pr(>F)
## X1B        1 1.15388 1.15388 66.6693 3.016e-08 ***
## X2B        1 0.90625 0.90625 52.3614 2.295e-07 ***
## X3B        1 0.02087 0.02087  1.2060  0.283496
## HR         1 0.76495 0.76495 44.1975 8.790e-07 ***
## BB         1 0.23774 0.23774 13.7363  0.001163 **
## HBP        1 0.00278 0.00278  0.1607  0.692214
## Residuals 23 0.39807 0.01731
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Albert fits other single variable models to fill Table 4.10.

```
   n = nrow(MLB2014)
   MLB2014$avg = MLB2014$H/MLB2014$AB
   rpg.lm.avg = lm(R.G ~ avg, data=MLB2014)
   rmse.avg = sqrt(sum(resid(rpg.lm.avg)^2)/(n-2))
   MLB2014$tb = 1*MLB2014$X1B + 2*MLB2014$X2B + 3*MLB2014$X3B + 4*MLB2014$HR
   MLB2014$slg = MLB2014$tb/MLB2014$AB
   rpg.lm.slg = lm(R.G ~ slg, data=MLB2014)
   rmse.slg = sqrt(sum(resid(rpg.lm.slg)^2)/(n-2))
   MLB2014$obp = (MLB2014$H + MLB2014$BB + MLB2014$HBP)/(MLB2014$AB + MLB2014$BB + MLB2014$HBP + MLB2014
   rpg.lm.obp = lm(R.G ~ obp, data=MLB2014)
   rmse.obp = sqrt(sum(resid(rpg.lm.obp)^2)/(n-2))
   MLB2014$rc = (MLB2014$H + MLB2014$BB)*MLB2014$tb/(MLB2014$AB + MLB2014$BB)
   rpg.lm.rc = lm(R.G ~ rc, data=MLB2014)
   rmse.rc = sqrt(sum(resid(rpg.lm.rc)^2)/(n-2))
   MLB2014$ops = MLB2014$obp + MLB2014$slg
   rpg.lm.ops = lm(R.G ~ ops, data=MLB2014)
   rmse.ops = sqrt(sum(resid(rpg.lm.ops)^2)/(n-2))
   rmse.rpg = round(c(rmse.avg, rmse.obp, rmse.slg, rmse.ops, rmse.rc),3)
   data.frame(Statistic=c("AVG","OBP","SLG","OPS","RC"), rmse.rpg, rmse.n = round(rmse.rpg*sqrt((n-2)/n)
```

```
##   Statistic rmse.rpg rmse.n
## 1       AVG    0.212  0.205
## 2       OBP    0.212  0.205
## 3       SLG    0.182  0.176
## 4       OPS    0.150  0.145
## 5        RC    0.133  0.128
```

Table 4.11 is easy to create using information from above. Albert takes the coefficients, which he views as weights of the events, and standardizes them by dividing by the "weight" of a single.

```
   t(round(rbind(coef(rpg.lm.optavg)[-1],coef(rpg.lm.optavg)[-1]/coef(rpg.lm.optavg)[2]),5))
```

```
##         [,1]     [,2]
```

```
## X1B  0.00252  1.00000
## X2B  0.00560  2.22466
## X3B  0.00763  3.03200
## HR   0.00724  2.87730
## BB   0.00175  0.69671
## HBP -0.00091 -0.36270
```

Case 4.5

We now switch to looking at multiple predictor variables by using non-linear (in the coefficients) regression.

```
  ### We get the Table 4.11 data from ALbert's tsub package.
     case.4.5 =  case_4_5
     head(case.4.5)
```

```
##   teamID  W  L   R  RA
## 1    ARI 64 98 615 742
## 2    ATL 79 83 573 597
## 3    BAL 96 66 705 593
## 4    BOS 71 91 634 715
## 5    CHA 73 89 660 758
## 6    CHN 73 89 614 707
```

```
  ### Alternatively, we could pull the table from Lahman's data.
   require(pacman)
   p_load(Lahman, sqldf)
   data(Teams)
   tbl.4.12 = sqldf("SELECT teamId, W, L, R, RA FROM Teams WHERE (yearID=2014 AND (lgID='AL' OR lgID='N
   head(tbl.4.12)
```

```
##   teamID  W  L   R  RA
## 1    ARI 64 98 615 742
## 2    ATL 79 83 573 597
## 3    BAL 96 66 705 593
## 4    BOS 71 91 634 715
## 5    CHA 73 89 660 758
## 6    CHN 73 89 614 707
```

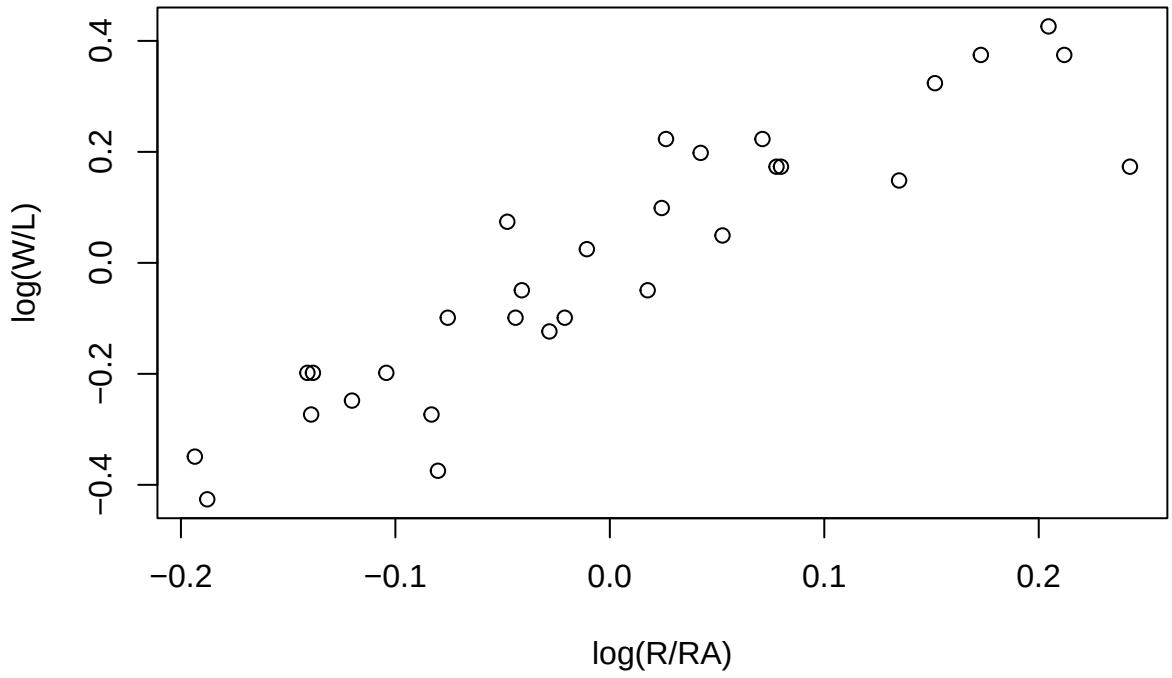
It's nice to see that the values are the same. We continue by creating Figure 4.8

```
  ### Create Figure 4.8 using Lahman data
   tbl.4.12$lnwl = log(tbl.4.12$W/tbl.4.12$L)
   tbl.4.12$lnrra = log(tbl.4.12$R/tbl.4.12$RA)
   plot(lnwl~lnrra, data=tbl.4.12, xlab="log(R/RA)", ylab="log(W/L)")
  ### Fit the linearized model through the point (0,0)---i.e. without intercept
   tbl.4.12.lm = lm(lnwl ~ lnrra - 1, data=tbl.4.12)
   summary(tbl.4.12.lm)
```

```
##
## Call:
## lm(formula = lnwl ~ lnrra - 1, data = tbl.4.12)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -0.26466 -0.05703  0.01246  0.05430  0.17586
##
## Coefficients:
```

```
##       Estimate Std. Error t value Pr(>|t|)
## lnrra   1.8057     0.1509   11.97 9.65e-13 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.09813 on 29 degrees of freedom
## Multiple R-squared:  0.8316, Adjusted R-squared:  0.8258
## F-statistic: 143.2 on 1 and 29 DF,  p-value: 9.655e-13
```

```
### Try again using data from Albert's tsub
   ### Create Figure 4.8
   case.4.5$lnwl = log(case.4.5$W/case.4.5$L)
   case.4.5$lnrra = log(case.4.5$R/case.4.5$RA)
   plot(lnwl~lnrra, data=case.4.5, xlab="log(R/RA)", ylab="log(W/L)")
```




```
   # Fit the linearized model through the point (0,0)---i.e. without intercept
   case.4.5.lm = lm(lnwl ~ lnrra - 1, data=case.4.5)
   summary(case.4.5.lm)
```

```
##
## Call:
## lm(formula = lnwl ~ lnrra - 1, data = case.4.5)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -0.26466 -0.05703  0.01246  0.05430  0.17586
##
```

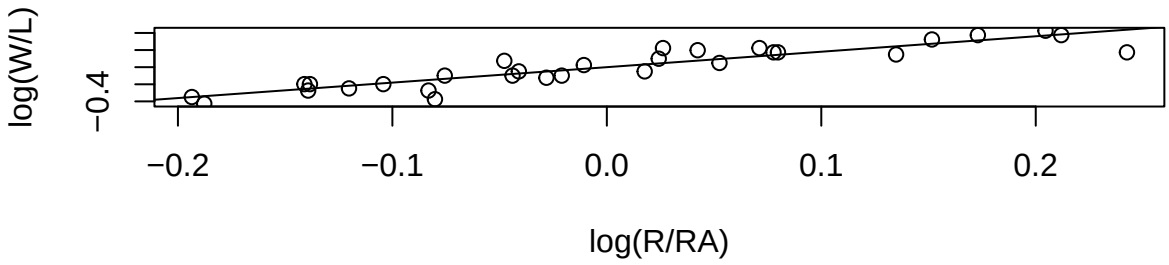
```
## Coefficients:
##       Estimate Std. Error t value Pr(>|t|)
## lnrra   1.8057     0.1509   11.97 9.65e-13 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.09813 on 29 degrees of freedom
## Multiple R-squared:  0.8316, Adjusted R-squared:  0.8258
## F-statistic: 143.2 on 1 and 29 DF,  p-value: 9.655e-13
```

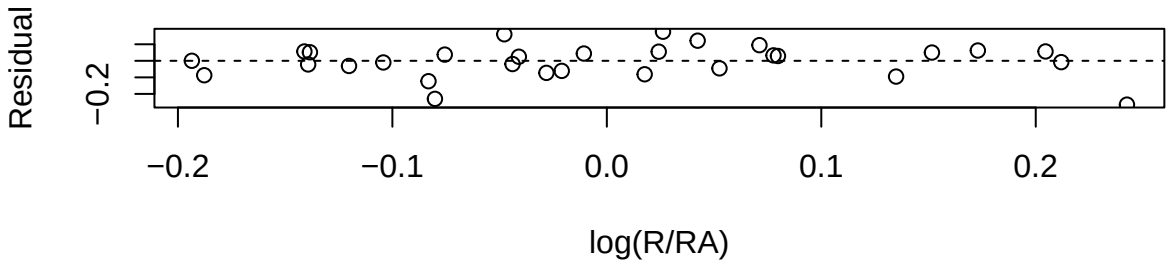
```
  coef(tbl.4.12.lm)
```

```
##    lnrra
## 1.805664
```

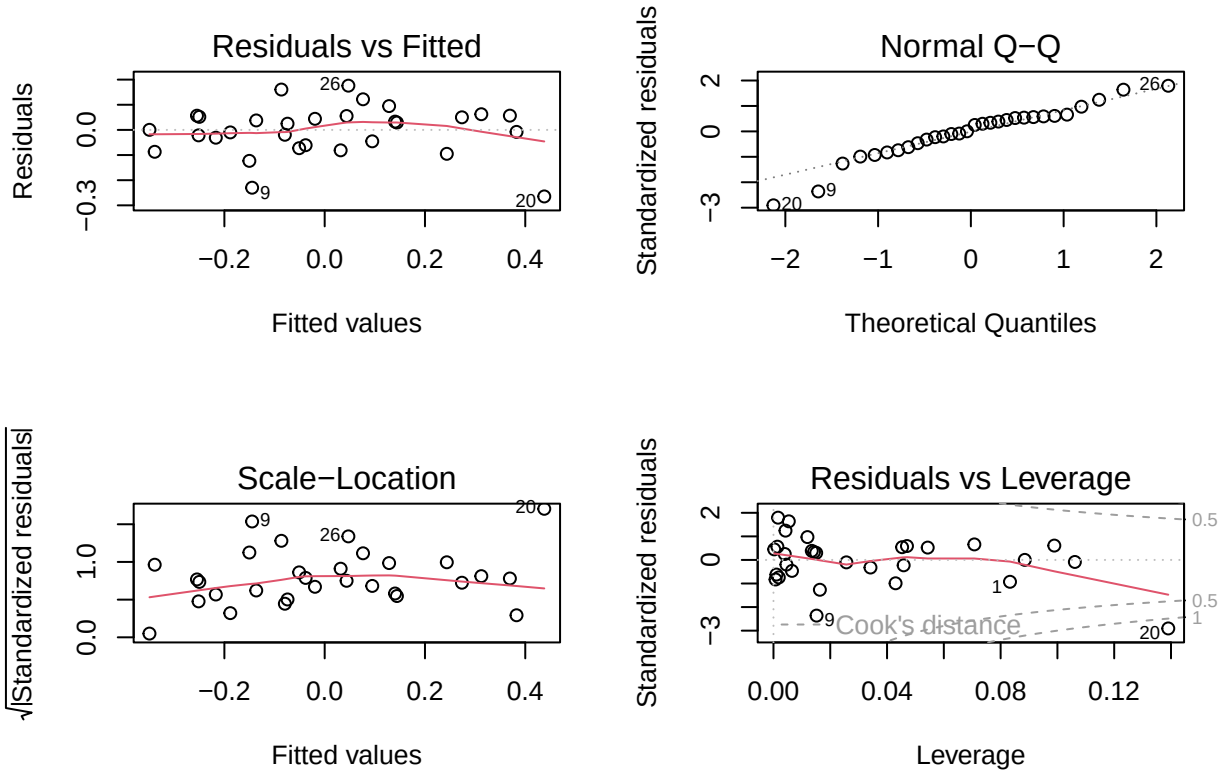
As found in the text, the observed coefficient (1.81) is approximately 2.

```
 # Figure 4.9 can be plotted as
  par(mfrow=c(2,1))
  plot(lnwl ~ lnrra, data=tbl.4.12, xlab="log(R/RA)", ylab="log(W/L)")
  abline(tbl.4.12.lm)
  plot(resid(tbl.4.12.lm)~tbl.4.12$lnrra, xlab="log(R/RA)", ylab="Residual")
  abline(h=0, lty=2)
```






```
  par(mfrow=c(1,1))
 # Note that R has the default diagnostic plots
  par(mfrow=c(2,2))
  plot(tbl.4.12.lm)
```




```
   par(mfrow=c(1,1))
```

Table 4.13 is generated using R functions "pred" and "resid".

```
   tbl.4.12$predw = tbl.4.12$L*(tbl.4.12$R/tbl.4.12$RA)^coef(tbl.4.12.lm) ###coef is 1.805
   tbl.4.12$residw = tbl.4.12$W - tbl.4.12$predw
   tbl.4.13 = cbind(tbl.4.12[,c("teamID","W","L")], Predicted=round(tbl.4.12$predw,1), Residual=round(tb
   print(tbl.4.13)
```

```
##    teamID  W  L Predicted Residual
## 1     ARI 64 98      69.8   -5.825
## 2     ATL 79 83      77.1    1.927
## 3     BAL 96 66      90.2    5.799
## 4     BOS 71 91      73.2   -2.241
## 5     CHA 73 89      69.3    3.686
## 6     CHN 73 89      69.0    4.009
## 7     CIN 76 86      81.7   -5.735
## 8     CLE 85 77      80.4    4.560
## 9     COL 66 96      83.1  -17.066
## 10    DET 90 72      81.9    8.127
## 11    HOU 70 92      71.5   -1.543
## 12    KCA 89 73      78.8   10.197
## 13    LAA 98 64      92.6    5.404
## 14    LAN 94 68      89.4    4.589
## 15    MIA 77 85      78.5   -1.511
## 16    MIL 82 80      78.5    3.532
## 17    MIN 70 92      79.2   -9.173
```

```
## 18    NYA 84 78      71.5   12.451
## 19    NYN 79 83      85.7   -6.687
## 20    OAK 88 74     114.7  -26.663
## 21    PHI 73 89      73.7   -0.732
## 22    PIT 88 74      85.1    2.851
## 23    SDN 77 85      74.2    2.843
## 24    SEA 87 75      95.7   -8.683
## 25    SFN 88 74      85.5    2.532
## 26    SLN 90 72      75.5   14.514
## 27    TBA 77 85      81.8   -4.834
## 28    TEX 67 95      67.0    0.015
## 29    TOR 83 79      86.9   -3.860
## 30    WAS 96 66      96.8   -0.766
```

These values do not match Albert's. We can try using the Pythagorean approach of $k = 2$.

```
tbl.4.12$predw = tbl.4.12$L*(tbl.4.12$R/tbl.4.12$RA)^2  ### coef is 2
tbl.4.12$residw = tbl.4.12$W - tbl.4.12$predw
cbind(tbl.4.12[,c("teamID","W","L")], Predicted=round(tbl.4.12$predw,1), Pythag=round(tbl.4.12$residw
```

```
##    teamID  W  L Predicted  Pythag
## 1     ARI 64 98      67.3  -3.324
## 2     ATL 79 83      76.5   2.539
## 3     BAL 96 66      93.3   2.715
## 4     BOS 71 91      71.5  -0.550
## 5     CHA 73 89      67.5   5.526
## 6     CHN 73 89      67.1   5.874
## 7     CIN 76 86      81.3  -5.289
## 8     CLE 85 77      80.8   4.180
## 9     COL 66 96      81.8 -15.782
## 10    DET 90 72      83.0   6.987
## 11    HOU 70 92      69.6   0.367
## 12    KCA 89 73      79.5   9.546
## 13    LAA 98 64      96.4   1.649
## 14    LAN 94 68      92.1   1.915
## 15    MIA 77 85      77.8  -0.843
## 16    MIL 82 80      78.3   3.696
## 17    MIN 70 92      77.9  -7.904
## 18    NYA 84 78      70.9  13.113
## 19    NYN 79 83      86.0  -6.981
## 20    OAK 88 74     120.2 -32.197
## 21    PHI 73 89      72.3   0.747
## 22    PIT 88 74      86.4   1.555
## 23    SDN 77 85      73.1   3.924
## 24    SEA 87 75      98.2 -11.225
## 25    SFN 88 74      86.8   1.196
## 26    SLN 90 72      75.9  14.128
## 27    TBA 77 85      81.5  -4.501
## 28    TEX 67 95      64.5   2.488
## 29    TOR 83 79      87.8  -4.752
## 30    WAS 96 66     100.8  -4.834
```

Still not right. Let's try figuring out what Albert used for k.

```
### Find k using our estimates
log(95.8/64)/log(773/630) # Angels
```

```
## [1] 1.971945
```

```
log(92.0/68)/log(718/617) # Dodgers
```

```
## [1] 1.99393
```

```
# Both should have been 1.81 which is the "right" answer on average.

### Try the same for our predicted values.
log(96.4/64)/log(773/630) # Angels
```

```
## [1] 2.002467
```

```
log(92.1/68)/log(718/617) # Dodgers
```

```
## [1] 2.001096
```

```
# Both appear to be 2 and not 1.81.  Maybe he used the Pythagorean approach.
```

It looks like Albert used $k = 2$ instead of $k = 1.81$ in his estimates and residuals.

Based on our results, Albert's contention that we hit 80% prediction within 4 runs is a joke. It's more like 13/30 or 43%.

```
p_load(aplpack)
stem.leaf(abs(tbl.4.13$Residual))
```

```
## 1 | 2: represents 12
##  leaf unit: 1
##             n: 30
##    6    0* | 000111
##   13     t | 2222333
##   (8)    f | 44445555
##    9     s | 6
##    8    0. | 889
##    5    1* | 0
##    4     t | 2
##    3     f | 4
##    2     s | 7
## HI: 26.663
```

```
tbl.4.13 %>%
   mutate(abs.resid = abs(Residual)) %>%
   filter(abs.resid <= 4) %>%
   summarize(n = n())
```

```
##    n
## 1 13
```

```
table(abs(tbl.4.13$Residual) <= 4)/30*100
```

```
##
##    FALSE     TRUE
## 56.66667 43.33333
```

```
quantile(abs(tbl.4.13$Residual))
```

```
##       0%      25%      50%      75%     100%
##  0.01500  2.60975  4.57450  7.76700 26.66300
```

Case 4.6

Albert now brings up the concept of regression to the mean — those things that were big will get smaller and those that were small will get bigger. He focuses on slugging (***SLG***), but could have used any baseball stat.

```
  ### We get the Table 4.14 data from ALbert's tsub package.
     case.4.6 =  case_4_6   ### Make a local copy
     head(case.4.6)
```

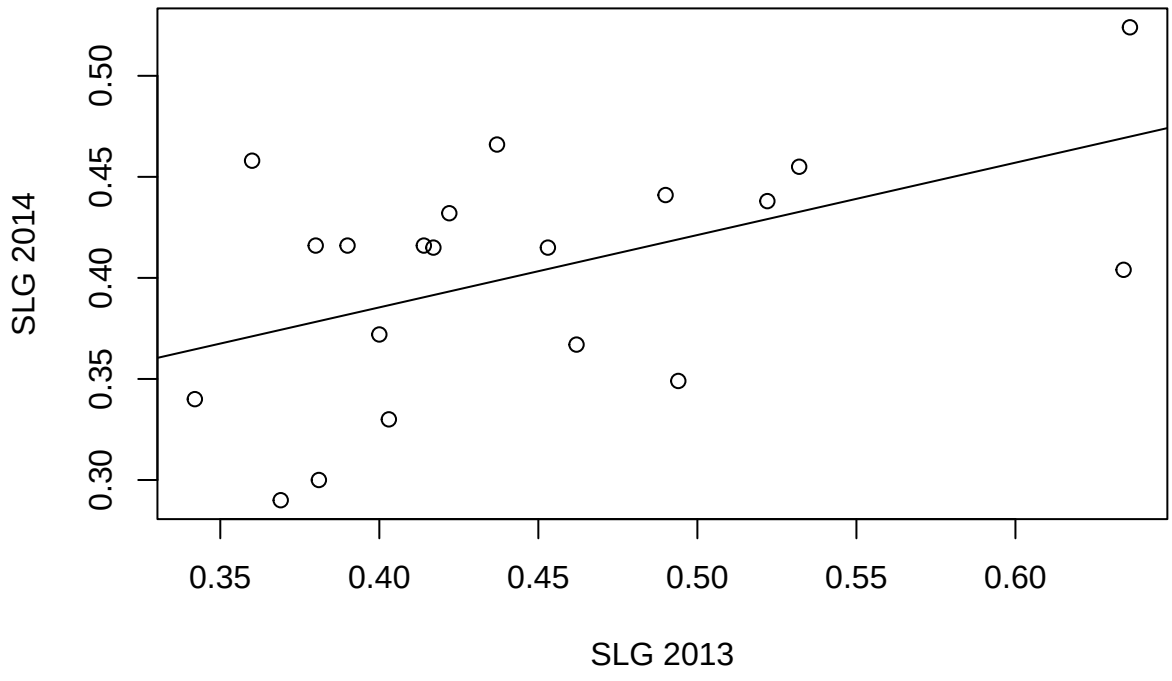
```
##               Name SLG.2013 SLG.2014 Improvement
## 1    Domonic_Brown    0.494    0.349      -0.145
## 2    Melky_Cabrera    0.360    0.458       0.098
## 3   Miguel_Cabrera    0.636    0.524      -0.112
## 4 Alberto_Callaspo    0.369    0.290      -0.079
## 5      Zack_Cozart    0.381    0.300      -0.081
## 6      Chris_Davis    0.634    0.404      -0.230
```

```
     names(case.4.6)
```

```
## [1] "Name"        "SLG.2013"    "SLG.2014"    "Improvement"
```

Figure 4.11 and the regression line are computed using the methods from above.

```
     plot(SLG.2014 ~ SLG.2013, data=case.4.6, xlab="SLG 2013", ylab="SLG 2014")
     case.4.6.lm1 = lm(SLG.2014 ~ SLG.2013, case.4.6)
     abline(case.4.6.lm1)
```




```
     coef(case.4.6.lm1)
```

```
## (Intercept)    SLG.2013
```

```
##   0.2421790   0.3580688
```

```
summary(case.4.6.lm1)
```

```
##
## Call:
## lm(formula = SLG.2014 ~ SLG.2013, data = case.4.6)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -0.08431 -0.04457  0.01647  0.03507  0.08692
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept)  0.24218    0.06577   3.682   0.0017 **
## SLG.2013     0.35807    0.14480   2.473   0.0236 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.05251 on 18 degrees of freedom
## Multiple R-squared:  0.2536, Adjusted R-squared:  0.2121
## F-statistic: 6.115 on 1 and 18 DF,  p-value: 0.0236
```

```
# Compute Davis's predicted 2014 value
c(1,.634)%*%coef(case.4.6.lm1)
```

```
##           [,1]
## [1,] 0.4691947
```

```
mean(case.4.6$SLG.2013)  ### Albert says 0.469 not 0.4469
```

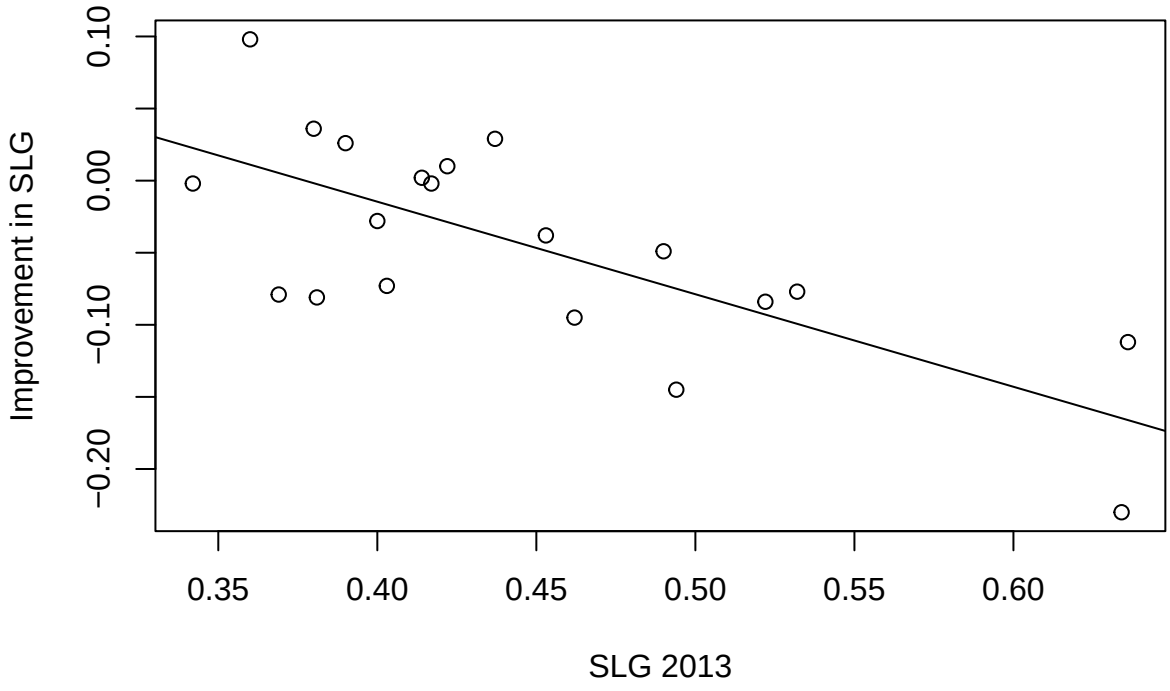
```
## [1] 0.4469
```

```
c(1,.634)%*%coef(case.4.6.lm1)-mean(case.4.6$SLG.2014) ### Albert got this one right at .067
```

```
##            [,1]
## [1,] 0.06699468
```

Now look at improvement in Figure 4.11 and the regression model.

```
plot(Improvement ~ SLG.2013, data=case.4.6, xlab="SLG 2013", ylab="Improvement in SLG")
case.4.6.lm2 = lm(Improvement ~ SLG.2013, case.4.6)
abline(case.4.6.lm2)
```




```
    cor(case.4.6[,-1])  ### Remove the Team column
```

```
##                SLG.2013  SLG.2014 Improvement
## SLG.2013     1.0000000 0.5035738  -0.7224750
## SLG.2014     0.5035738 1.0000000   0.2335145
## Improvement -0.7224750 0.2335145   1.0000000
```

```
    coef(case.4.6.lm2)
```

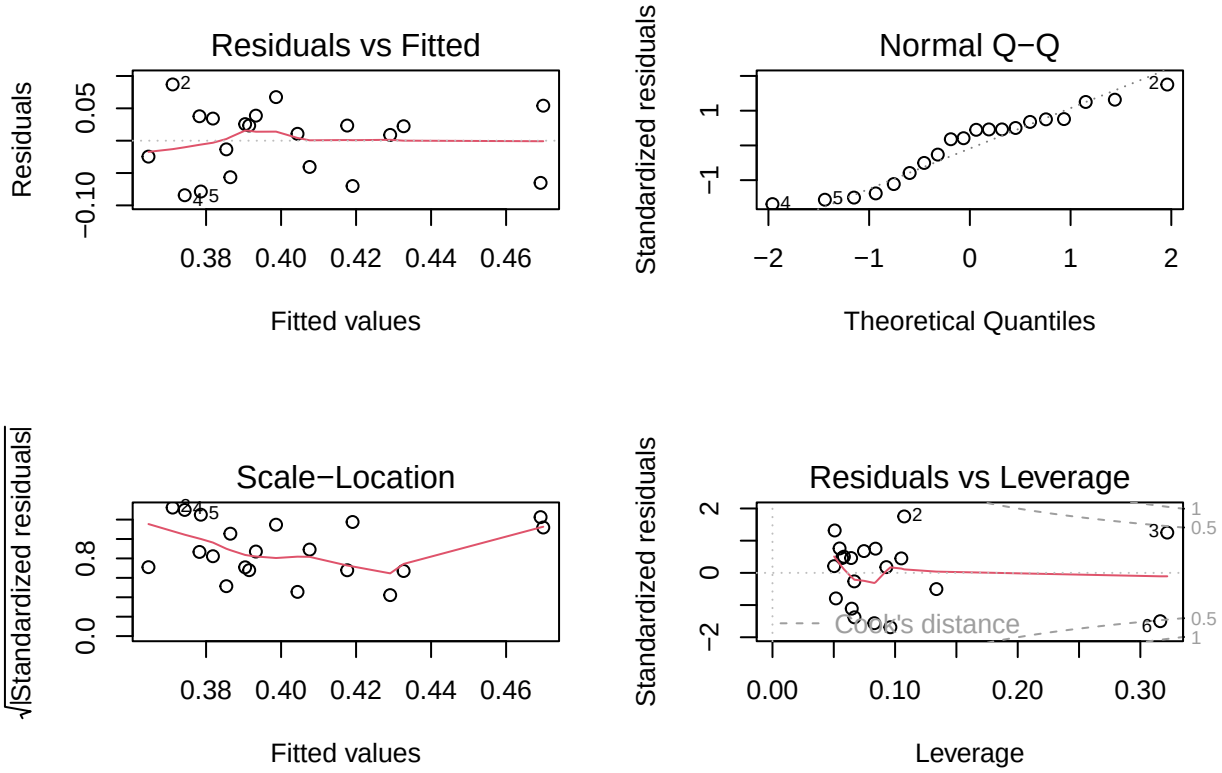
```
## (Intercept)    SLG.2013
##   0.2421790  -0.6419312
```

```
    summary(case.4.6.lm2)
```

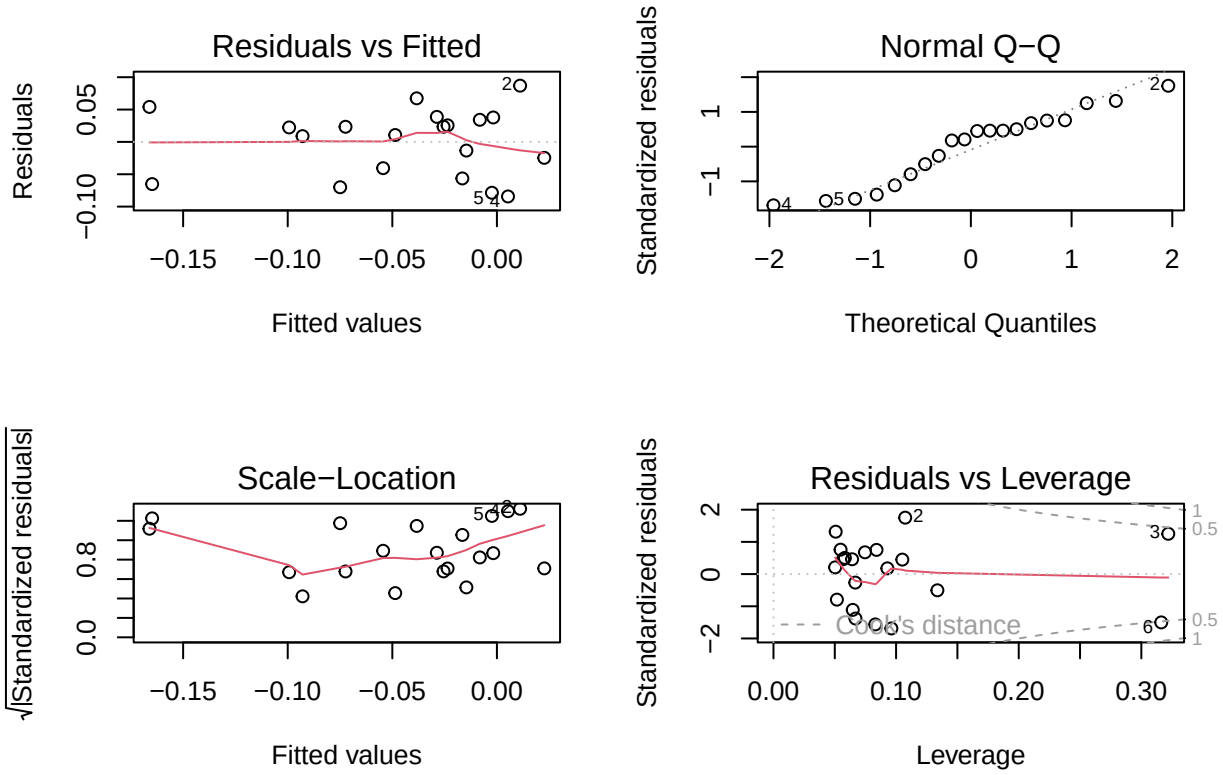
```
##
## Call:
## lm(formula = Improvement ~ SLG.2013, data = case.4.6)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -0.08431 -0.04457  0.01647  0.03507  0.08692
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept)  0.24218    0.06577   3.682 0.001704 **
## SLG.2013    -0.64193    0.14480  -4.433 0.000321 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
##
## Residual standard error: 0.05251 on 18 degrees of freedom
## Multiple R-squared:  0.522,  Adjusted R-squared:  0.4954
## F-statistic: 19.65 on 1 and 18 DF,  p-value: 0.0003209
```

```
  ### Albert doesn't look at residuals, but you ought to.
    par(mfrow=c(2,2))
    plot(case.4.6.lm1)
```




```
    plot(case.4.6.lm2)
```




```
par(mfrow=c(1,1))
```

Note

The above code is intended to show one or two ways of computing some of the statistics that might be used in looking at sports related data. In a few cases, our results differed from Albert's. While this is unfortunate, the process of identifying possible reasons for these differences is very informative. In the real world it is important to verify results. Having experience in debugging analyses is a good thing. While I am pretty sure that Albert did not intend to include the errors that we found, we should be glad that we had the opportunity to find them.