Practice Set 2

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Due by 10pm ET on Friday

Practice Set Information

During the week, you will get further practice with the material by working through the Practice Set, a set of problems designed to give you practice beyond the examples produced in the text.

You may work through these problems with peers, but all work must be completed by you (see the Honor Code in the syllabus) and you must indicate who you worked with below.

Even then, the best approach here is to try the problems on your own before discussing them with peers, and then write your final solutions yourself.

GitHub Workflow

- 1. Before editing this file, verify you are working on the copy saved in *your* repo for the course (check the filepath and the project name in the top right corner).
- 2. Before editing this file, make an initial commit of the file to your repo to add your copy of the problem set.
- 3. Change your name at the top of the file and get started!
- 4. You should *save*, *knit*, *and commit* the .Rmd file each time you've finished a question, if not more often. You should also *push* your commits back onto GitHub occasionally (you can do this after each commit).
- 5. When you think you are done with the assignment, save the pdf as "Name_thisfilename_date.pdf" before committing and pushing (this is generally good practice but also helps me in those times where I need to download all student homework files).

Gradescope Upload

For each question (e.g., 3.1), allocate all pages associated with the specific question. If your work for a question runs onto a page that you did not select, you may not get credit for the work. If you do not allocate *any* pages when you upload your pdf, you may get a zero for the assignment.

You can resubmit your work as many times as you want before the deadline, so you should not wait until the last minute to submit some version of your work. Unexpected delays/crises that occur on the day the assignment is due do not warrant extensions (please submit whatever you have done to receive partial credit).

Practicing Academic Integrity

If you worked with others or used resources outside of provided course material (notes, textbook, etc) to complete this assignment, please acknowledge them below using a bulleted list.

 $\it I$ acknowledge the following individuals with whom $\it I$ worked on this assignment:

Name(s) and corresponding problem(s)

- SDS Fellows
- Kayla Ko

I used the following sources to help complete this assignment:

Source(s) and corresponding problem(s)

• N/A

- Problem 1 MDSR 5.2 Use the Batting, Pitching, and Master tables in the Lahman package to answer the following questions.
- 1.1 List the name of every player in baseball history who has accumulated at least 300 home runs (HR) and at least 300 stolen bases (SB). You can find the first and last name of the player in the Master data frame. Join this to your result along with the total home runs and total bases stolen for each of these elite players.

```
library(Lahman)
JoinedData<-full_join(Batting, Master)
BattingGrouped<-Batting%>%
    group_by(playerID) %>%
    summarize(
        totalHR = sum(HR),
        totalSB = sum(SB)
    )

JoinedData<-full_join(Master,BattingGrouped)
JoinedData%>%
    select(totalHR, totalSB, nameFirst, nameLast) %>%
    filter(totalHR >300 & totalSB > 300)
```

```
totalHR totalSB nameFirst nameLast
    435 312 Carlos Beltran
1
    762 514 Barry Bonds
2
    332 461
               Bobby
                       Bonds
3
               Andre
4
    438 314
                     Dawson
5
    304
         320
               Steve Finley
6
    660
          338 Willie
                        Mays
7
    696
          329
               Alex Rodriguez
    305
          304 Reggie Sanders
```

1.2 Similarly, list the names every pitcher in baseball history who has accumulated at least 300 wins (W) and at least 3,000 strikeouts (SO).

```
PitchingGrouped <- Pitching %>%
  group_by(playerID) %>%
  summarize(
    totalW = sum(W),
    totalSO = sum(SO)
)
PitchingGrouped<-full_join(Master,PitchingGrouped)
PitchingGrouped%>%
  select(totalW, totalSO, nameFirst, nameLast) %>%
  filter(totalW >300 & totalSO > 3000)
```

totalW totalSO nameFirst nameLast

```
1
      329
              4136
                        Steve
                               Carlton
      354
2
                               Clemens
              4672
                        Roger
                        Randy
3
      303
              4875
                               Johnson
4
      417
              3509
                       Walter
                               Johnson
5
      355
              3371
                         Greg
                                Maddux
6
                         Phil
                                Niekro
      318
              3342
7
                     Gaylord
      314
              3534
                                 Perry
                        Nolan
8
      324
              5714
                                   Ryan
9
      311
              3640
                          Tom
                                Seaver
                          Don
10
      324
              3574
                                Sutton
```

1.3 Finally, list the name and year of every player who has hit at least 50 home runs in a single season. Which player had the lowest batting average in that season? Note: Batting average is calculated as the number of hits (H) divided by the number of at bats (AB).

```
ModBatting <- full_join(Master, Batting) %>%
  mutate(BattingAverage = H/AB) %>%
  select(yearID, HR, BattingAverage, nameFirst, nameLast) %>%
  filter(HR >50)
ModBatting
```

```
yearID HR BattingAverage nameFirst
                                         nameLast
1
     2019 53
                   0.2596315
                                   Pete
                                            Alonso
2
     2010 54
                   0.2601054
                                   Jose
                                         Bautista
3
     2001 73
                   0.3277311
                                  Barry
                                            Bonds
4
     2013 53
                   0.2859589
                                  Chris
                                            Davis
5
     1990 51
                   0.2774869
                                  Cecil
                                          Fielder
                                           Foster
6
     1977 52
                   0.3203252
                                 George
7
     1932 58
                   0.3641026
                                 Jimmie
                                              Foxx
8
     2001 57
                   0.3251232
                                   Luis
                                         Gonzalez
9
     1938 58
                   0.3147482
                                   Hank Greenberg
10
     1997 56
                   0.3042763
                                    Ken
                                          Griffey
     1998 56
11
                   0.2843602
                                    Ken
                                          Griffey
12
     2006 58
                                   Ryan
                                           Howard
                   0.3132530
13
     2005 51
                   0.2627986
                                 Andruw
                                            Jones
14
     2017 52
                   0.2841328
                                  Aaron
                                            Judge
15
     1947 51
                   0.3132743
                                  Ralph
                                            Kiner
     1949 54
                                  Ralph
16
                   0.3096539
                                            Kiner
17
     1956 52
                   0.3527205
                                 Mickey
                                           Mantle
18
     1961 54
                   0.3171206
                                 Mickey
                                           Mantle
19
     1961 61
                   0.2694915
                                  Roger
                                            Maris
20
     1955 51
                   0.3189655
                                 Willie
                                              Mays
21
     1965 52
                                 Willie
                   0.3172043
                                              Mays
22
     1996 52
                   0.3120567
                                   Mark
                                          McGwire
23
     1998 70
                                   Mark
                   0.2986248
                                          McGwire
24
     1999 65
                   0.2783109
                                   Mark
                                          McGwire
25
     1947 51
                   0.3020478
                                 Johnny
                                             Mize
26
     2006 54
                   0.2867384
                                  David
                                            Ortiz
27
     2001 52
                                   Alex Rodriguez
                   0.3180380
```

28	2002	57	0.2996795	Alex	Rodriguez
29	2007	54	0.3138937	Alex	Rodriguez
30	1920	54	0.3763676	Babe	Ruth
31	1921	59	0.3777778	Babe	Ruth
32	1927	60	0.355556	Babe	Ruth
33	1928	54	0.3227612	Babe	Ruth
34	1998	66	0.3079316	Sammy	Sosa
35	1999	63	0.2880000	Sammy	Sosa
36	2001	64	0.3275563	Sammy	Sosa
37	2017	59	0.2814070	${\tt Giancarlo}$	Stanton
38	2002	52	0.3041667	Jim	Thome
39	1930	56	0.355556	Hack	Wilson

min(ModBatting\$BattingAverage)

[1] 0.2596315

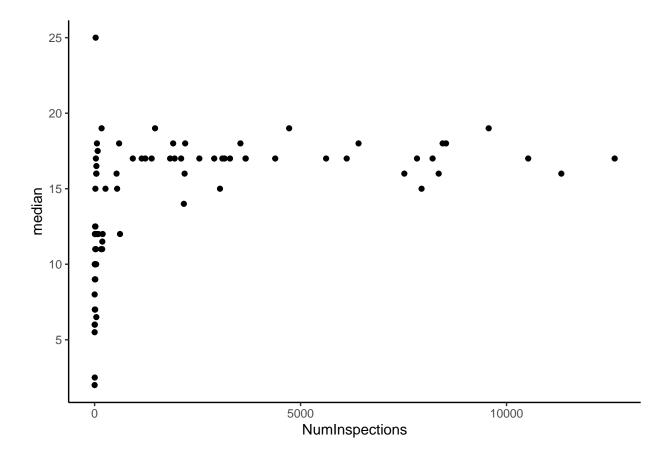
```
GetMin <- ModBatting %>%
  filter(BattingAverage == min(ModBatting$BattingAverage))
GetMin
```

yearID HR BattingAverage nameFirst nameLast 1 2019 53 0.2596315 Pete Alonso

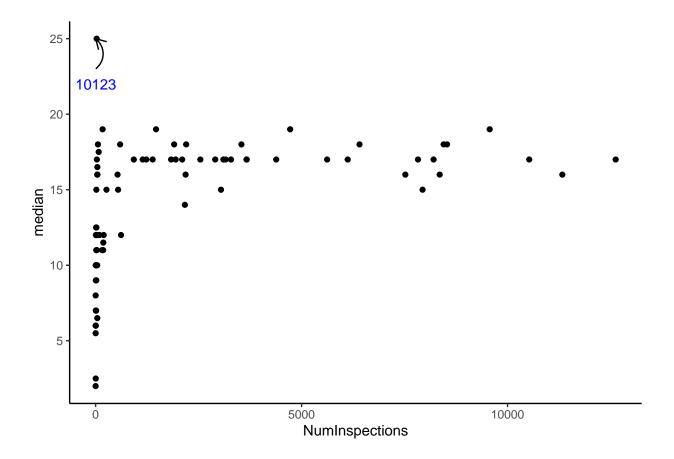
- Problem 2 MDSR 4.11 (modified) The Violations data set in the mdsr package contains information regarding the outcome of health inspections of restaurants in New York City. Note that higher inspection scores indicate worse violations: "restaurants with an inspection score between 0 and 13 points earn an A, those with 14 to 27 points receive a B and those with 28 or more a C" (nyc.gov).
- 2.1 Use these data to calculate the median violation score by zip code for zip codes in Manhattan. What pattern, if any, do you see between the number of inspections and the median score? Generate a visualization to support your response.

```
Violations_median <- Violations %>%
  select(boro, zipcode, score) %>%
  na.omit() %>%
  filter(boro == "MANHATTAN") %>%
  group_by(zipcode)%>%
  summarise(
    median=median(score),
    NumInspections=n()
  )
Violations_median
```

```
# A tibble: 81 x 3
  zipcode median NumInspections
    <int> <dbl>
                           <int>
    10001
               15
                            7937
 2
    10002
               18
                            8449
 3
    10003
               17
                           12625
    10004
               14
                            2167
5
    10005
               17
                            1144
6
    10006
               17
                             928
7
    10007
               16
                            2185
8
    10009
               17
                            5620
9
    10010
               17
                            4385
10
    10011
               17
                            8205
# ... with 71 more rows
```



2.2 In your visualization above, there are several potential outliers but there is one zipcode in particular that does not seem to fall along the general trend. Add text to the outlier identifying what zipcode it is, and add an arrow pointing from the text to the observation. Note: first, you may want to filter() to identify the zipcode (so you know what text to add to the plot).



Problem 3 MDSR 6.5 Generate the code to convert the data frame from the starting point (Figure 1) to the results (Figure 2). Hint: use pivot_longer() in conjunction with pivot_wider().

grp	sex	meanL	sdL	meanR	sdR
A	F	0.225	0.106	0.340	0.085
A	M	0.470	0.325	0.570	0.325
В	F	0.325	0.106	0.400	0.071
В	M	0.547	0.308	0.647	0.274

Figure 1: Starting point

	grp	F.meanL	F.meanR	F.sdL	F.sdR	M.meanL	M.meanR	M.sdL	M.sdR
1	A	0.22	0.34	0.11	0.08	0.47	0.57	0.33	0.33
2	В	0.33	0.40	0.11	0.07	0.55	0.65	0.31	0.27

Figure 2: Results

```
 \begin{split} & g < -\text{data.frame}(\text{grp} = \text{c}(\text{"A", "A", "B", "B")}, \\ & \text{sex} = \text{c}(\text{"F", "M", "F", "M")}, \\ & \text{meanL} = \text{c}(0.225, 0.470, 0.325, 0.547), \\ & \text{sdL} = \text{c}(0.106, 0.325, 0.106, 0.308), \\ & \text{meanR} = \text{c}(0.340, 0.570, 0.400, 0.647), \\ & \text{sdR} = \text{c}(0.085, 0.325, 0.071, 0.274)) \end{split}
```

```
grp sex meanL sdL meanR sdR

1 A F 0.225 0.106 0.340 0.085

2 A M 0.470 0.325 0.570 0.325

3 B F 0.325 0.106 0.400 0.071

4 B M 0.547 0.308 0.647 0.274
```

```
longtable <- g %>%
  pivot_longer(
    cols = meanL:sdR,
    names_to = "measurement",
    values_to = "value"
)
widetable <- longtable %>%
  pivot_wider(
    names_from = c(sex, measurement),
    values_from = value,
    names_sep = "."
)
widetable %>% kable()
```

grp	F.meanL	F.sdL	F.meanR	F.sdR	M.meanL	M.sdL	M.meanR	M.sdR
A	0.225	0.106	0.34	0.085	0.470	0.325	0.570	0.325
В	0.325	0.106	0.40	0.071	0.547	0.308	0.647	0.274