STAT 231: Problem Set 9B

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due by 10 PM on Friday, May 14

This homework assignment is designed to help you further ingest, practice, and expand upon the material covered in class over the past week(s). You are encouraged to work with other students, but all code and text must be written by you, and you must indicate below who you discussed the assignment with (if anyone).

Steps to proceed:

1. In RStudio, go to File > Open Project, navigate to the folder with the course-content repo, select the course-content project (course-content.Rproj), and click "Open"
2. Pull the course-content repo (e.g. using the blue-ish down arrow in the Git tab in upper right window)
3. Copy ps9B.Rmd from the course repo to your repo (see page 6 of the GitHub Classroom Guide for Stat231 if needed)
4. Close the course-content repo project in RStudio
5. Open YOUR repo project in RStudio
6. In the ps9B.Rmd file in YOUR repo, replace "YOUR NAME HERE" with your name
7. Add in your responses, committing and pushing to YOUR repo in appropriate places along the way
8. Run "Knit PDF"
9. Upload the pdf to Gradescope. Don't forget to select which of your pages are associated with each problem. *You will not get credit for work on unassigned pages (e.g., if you only selected the first page but your solution spans two pages, you would lose points for any part on the second page that the grader can't see).*

If you discussed this assignment with any of your peers, please list who here:

ANSWER: TA Hours with Andrea

1. Ethics follow-up

(a) Thinking about the discussion you had with the first group you were with during class on Tuesday 5/4 (focused on either "Predicting Policing & Recidivism" or "Predicting Financial Risk"), did your perspective on, or understanding of, any of the questions shift? If so, please describe. If not, was there anything you found surprising in the resources or your first group discussion?

ANSWER: I think that my perspective on how we could solve biases in predicting policing and recidivism changed. Before the conversation I had the viewpoint that biases would always exist no matter what so people should accept a degree of bias in these algorithms. However, my group provided some very good points on how bias can be mitigated and people should not accept tools that disproportionately hurt one group of people compared to the general population.

(b) Thinking about the discussion you had with the second group you were with during class on Tuesday 5/4 (focused on considering the use of algorithms in the college admissions process), did your perspective on, or understanding of, the use of algorithms in these contexts shift? If not, was there anything you found surprising in the resources or your second group discussion?

ANSWER: One particular area of note in our discussion is the role of affirmative action and whether an algorithm designed the help one specific group may be tweaked or altered depending who is in charge of the government. While being race-blind would theoretically be the ideal in the admissions process, we discussed how no admissions process can be truly unbiased as many circumstances are tied to historical unjustices. It seems then that a more automated algorithm in the admissions process would actually amplify current biases as instead of perhaps one biased person affecting admissions for a group of students, the algorithm may exacerbate biases for all students if implemented.

CHOOSE ONE OF 2 (Clustering), 3 (Simulations) or 4 (SQL) to COMPLETE

2. Clustering

MDSR Exercise 9.5

Baseball players are voted into the Hall of Fame by the members of the Baseball Writers of America Association. Quantitative criteria are used by the voters, but they are also allowed wide discretion. The following code identifies the position players who have been elected to the Hall of Fame and tabulates a few basic statistics, include their number of career hits (`tH`), home runs (`tHR`), runs batted in (`tRBI`), and stolen bases (`tSB`). Use the `kmeans()` function to perform a cluster analysis on these players. Describe the properties that seem common to each cluster.

Don't forget to standardize the variables before clustering, if applicable.

ANSWER: In this case I thought that unstandardized clustering would be more interpretable, although I also did do k-means clustering with standardized variables as well. Overall, I decided to go with 4 clusters do to the elbow plot.

The first cluster is the green cluster, which players in the cluster appear to have the least number of hits and steals compared to the other clusters. The players in the green cluster also have a relatively low number of home runs and RBIs. The purple cluster as the second-least number of hits, between 2000 and 3500, the second most amount of home runs and RBIs, and the second least number of steals. The blue cluster has the second-most number of hits, the least amount of home runs, the second-least number of RBIs and the most number of steals (over 300 for all players). Lastly players in the red cluster have the highest number of hits, home runs, and RBIs while having the second-most in steals.

It seems that players in the red cluster are the "best". Players in this group are the most well-rounded and lead in the more important categories (home runs and hits).

```r
library(tidyverse)
library(mdsr)
library(Lahman)
library(GGally)

##### PLEASE DO NOT CHANGE THIS SEED NUMBER
##### keep set.seed(75)
set.seed(75)

hof <- Batting %>%
  group_by(playerID) %>%
  inner_join(HallOfFame, by = "playerID") %>%
  filter(inducted == "Y" & votedBy == "BBWAA") %>%
  summarize(tH = sum(H), tHR = sum(HR), tRBI = sum(RBI), tSB = sum(SB)) %>%
  filter(tH > 1000)
##create standardized variables of tH, tHR, tRBI, and tSB
hof_std <- hof %>%
  mutate_if(is.numeric, funs(`std`=scale(.) %>% as.vector())) %>%
  janitor::clean_names()
```

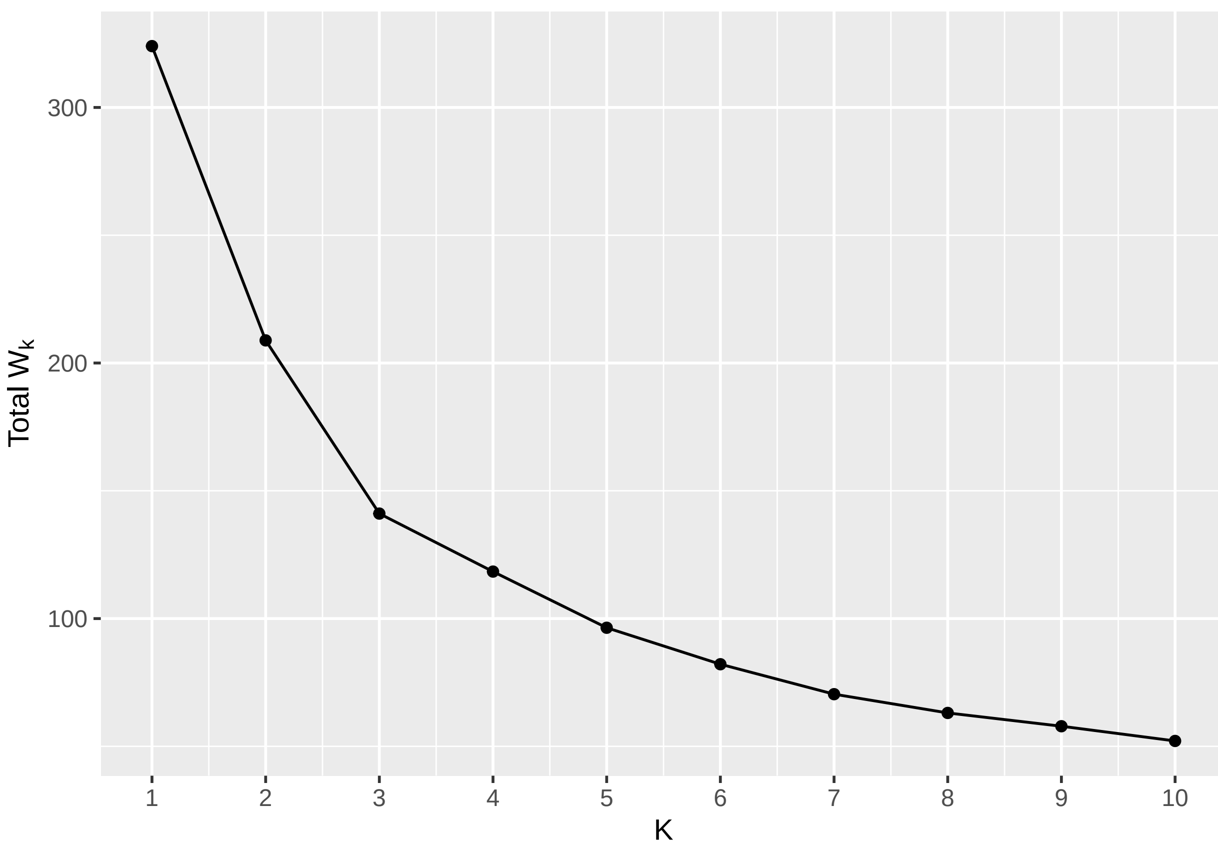
```
## Warning: `funs()` was deprecated in dplyr 0.8.0.
## Please use a list of either functions or lambdas:
##
##   # Simple named list:
##   list(mean = mean, median = median)
##
```

```
##   # Auto named with `tibble::lst()`:
##   tibble::lst(mean, median)
##
##   # Using lambdas
##   list(~ mean(., trim = .2), ~ median(., na.rm = TRUE))
```

```r
##Vector of standardized variables
vars_std <- c("t_h_std", "t_hr_std", "t_rbi_std", "t_sb_std")

fig <- matrix(NA, nrow=10, ncol=2)
for (i in 1:10){
  fig[i,1] <- i
  fig[i,2] <- kmeans(hof_std[,vars_std]
                 , centers=i
                 , nstart=20)$tot.withinss
}

ggplot(data=as.data.frame(fig), aes(x = V1, y = V2))+
  geom_point()+
  geom_line()+
  scale_x_continuous(breaks=c(1:10))+
  labs(x="K", y = expression("Total W"[k]))
```



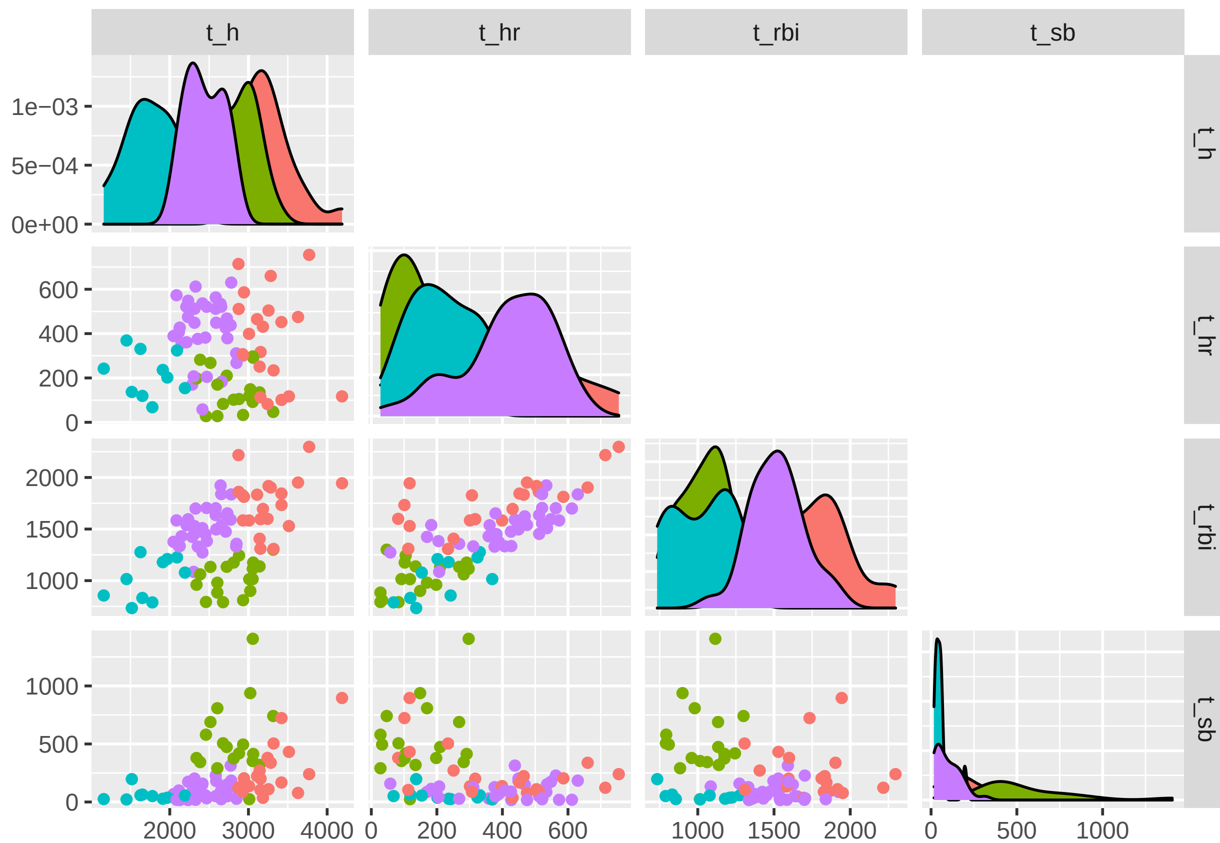

```r
##K-means with standardization
km4_out_std <- kmeans(hof_std[,vars_std]
                      , centers = 4
                      , nstart = 20)
hof_std_more <- hof_std %>%
```

```r
  mutate(clust4_std = as.character(km4_out_std$cluster))
```

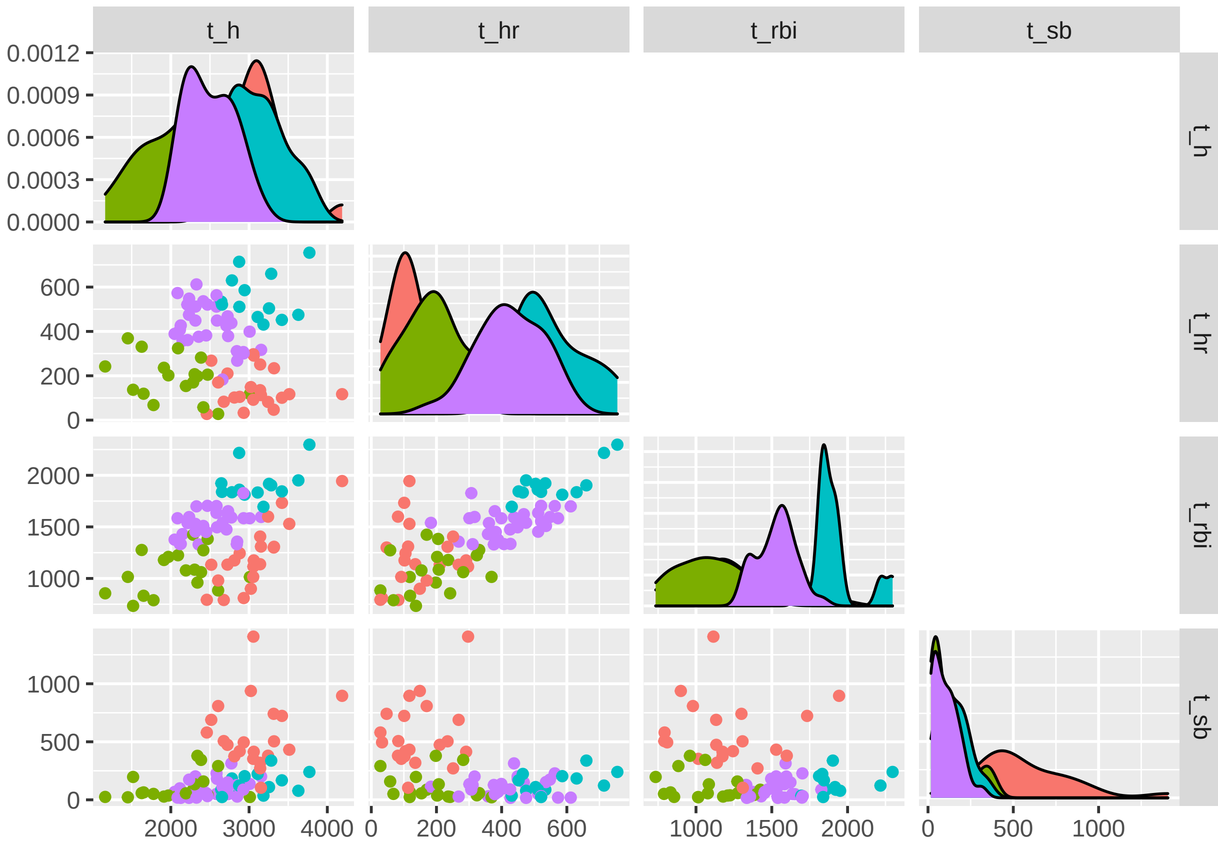
```r
##Unstandardized variable K-means
vars_unstd <- c("t_h", "t_hr", "t_rbi", "t_sb")
km4_out_unstd <- kmeans(hof_std[,vars_unstd]
                        , centers = 4
                        , nstart = 20)

hof_std_more <- hof_std_more %>%
  mutate(clust4_unstd = as.character(km4_out_unstd$cluster))
```

```r
#Unstandardized grid plot
ggpairs(data = hof_std_more
        , aes(color = clust4_unstd)
        , columns = vars_unstd
        , upper = list(continuous = "blank"))
```




```r
#Standardized Grid Plot
ggpairs(data = hof_std_more
        , aes(color = clust4_std)
        , columns = vars_unstd
        , upper = list(continuous = "blank"))
```


t_h
t_hr
t_rbi
t_sb
0.0012
0.0009
0.0006
0.0003
0.0000
600
400
200
0
2000
1500
1000
1000
500
0
2000
3000
4000
0
200
400
600
1000
1500
2000
0
500
1000

CHOOSE ONE OF 2 (Clustering), 3 (Simulations) or 4 (SQL) to COMPLETE

3. Simulation

MDSR Exercise 10.6 (modified)

Equal variance assumption: What is the impact of the violation of the equal variance assumption for linear regression models? Repeatedly generate data from two "true" models:

(1) where the equal variance assumption is met: $y_i \sim N(\mu_i, \sigma)$
(2) where the equal variance assumption is violated: $y_i \sim N(\mu_i, \sigma_i)$

, where $\mu_i = -1 + 0.5 * X_{1i} + 1.5 * X_{2i}$, σ=1 in (1), $\sigma_i = 1 + X_{2i}$ in (2), and X_1 is a binary predicator and X_2 is Uniform(0,5).

Code to get you started is given below. (Note that in (2) the standard deviation is dependent upon x2, which is random; i.e., the equal variance assumption is violated. The Ys are *not* generated from a distribution with the same variance in (2).)

For each simulation, fit the linear regression model and display the distribution of 1,000 estimates of the β_1 parameter. Does the distribution of the parameter follow a normal distribution in both cases? Is it centered around β_1? How does the variability in the distributions compare (variance in $\hat{\beta}_1$ when the equal variance assumption is met vs. when it is violated)?

ANSWER:

```
library(tidyverse)

# number of observations in each sample
n_obs <- 250

rmse <- 1
x1 <- rep(c(0,1), each=n_obs/2)
x2 <- runif(n_obs, min=0, max=5)
beta0 <- -1
beta1 <- 0.5
beta2 <- 1.5

# for scenario 1, where equal var assumption is met (sd is constant value, rmse)
y1 <- beta0 + beta1*x1 + beta2*x2 + rnorm(n=n_obs, mean=0, sd=rmse)
# for scenario 2, where equal var assumption is violated (sd depends on x2)
y2 <- beta0 + beta1*x1 + beta2*x2 + rnorm(n=n_obs, mean=0, sd=rmse + x2)

# for scenario 1
mod1 <- lm(y1 ~ x1 + x2)
# for scenario 2
mod2 <- lm(y2 ~ x1 + x2)

summary(mod1)$coeff["x1","Estimate"]
```

```
## [1] 0.3522719
```

```
# repeatedly generate data, fit the model, and extra the beta1 coefficient (1,000 times)
# number of simulations
n_sim <- 1000

# target visualization: sampling distribution of \hat{beta}_1
```

```
#                  (histogram or density plot of \beta_1 estimates), by scenario
# target summary numbers: mean and sd/variance of beta_1 estimates, by scenario

# loop through iterations

# create target visualization

# create target summaries
```

CHOOSE ONE OF 2 (Clustering), 3 (Simulations) or 4 (SQL) to COMPLETE

4. SQL

Airline flights

4a. Identify what years of data are available in the `flights` table of the airlines database using SQL code.

ANSWER:

```
library(RMySQL)
```

```
## Loading required package: DBI
```

```
library(mdsr)
# dbConnect_scidb is accesible from the mdsr package
aircon <- dbConnect_scidb("airlines")

# can use SHOW and EXPLAIN commands to explore what tables are available
# through this connection, and what variables/fields are in each table
dbGetQuery(aircon, "SHOW TABLES")
```

```
##   Tables_in_airlines
## 1           airports
## 2           carriers
## 3            flights
## 4             planes
```

```
dbGetQuery(aircon, "EXPLAIN airports")
```

```
##     Field          Type Null Key Default Extra
## 1     faa    varchar(3)   NO PRI
## 2    name  varchar(255)  YES        <NA>
## 3     lat decimal(10,7)  YES        <NA>
## 4     lon decimal(10,7)  YES        <NA>
## 5     alt       int(11)  YES        <NA>
## 6      tz   smallint(4)  YES        <NA>
## 7     dst       char(1)  YES        <NA>
## 8    city  varchar(255)  YES        <NA>
## 9 country  varchar(255)  YES        <NA>
```

```
# can view first few obs of a table to see what the fields look like
dbGetQuery(aircon, "SELECT *
                   FROM airports
                   LIMIT 0,5")
```

```
## Warning in .local(conn, statement, ...): Decimal MySQL column 2 imported as
## numeric
```

```
## Warning in .local(conn, statement, ...): Decimal MySQL column 3 imported as
## numeric
```

```
##   faa                           name      lat       lon  alt tz dst
## 1 04G              Lansdowne Airport 41.13047 -80.61958 1044 -5   A
## 2 06A Moton Field Municipal Airport 32.46057 -85.68003  264 -6   A
## 3 06C            Schaumburg Regional 41.98934 -88.10124  801 -6   A
## 4 06N                Randall Airport 41.43191 -74.39156  523 -5   A
## 5 09J          Jekyll Island Airport 31.07447 -81.42778   11 -5   A
```

```
##            city       country
## 1    Youngstown United States
## 2      Tuskegee United States
## 3    Schaumburg United States
## 4    Middletown United States
## 5 Jekyll Island United States
```

4b. How many domestic flights flew into Dallas-Fort Worth (DFW) on May 14, 2010? Use SQL to compute this number. (You can use R code to check it, if you wish.)

ANSWER:

4c. *Among the flights that flew into Dallas-Fort Worth (DFW) on May 14, 2010*, compute (using SQL) the number of flights and the average arrival delay time for each airline carrier. Among these flights, how many carriers had an average arrival delay of 60 minutes or longer?

ANSWER: