Project EDA

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A Brief Description of the Dataset

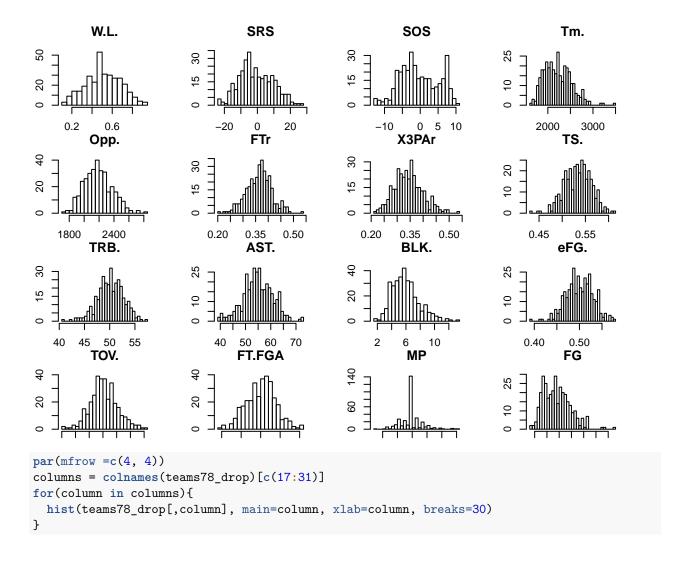
Our dataset was exported from the Sports Reference College Basketball website. Sports Reference College Basketball states that their contemporary data is "is provided by data companies on an ongoing basis." Assuming that this data is reliable, we extracted basic and advanced team statistics for the 330 NCAA Division 1 teams in the 2007-2008, 2009-2010 and 2017-2018 college basketball seasons. We will team statistics from the 2007-2008 (and possibly the 2008-2009) basketball seasons as our training set with the 2008-2009 W-L% as our response variable. This training set will be split into training and validation datasets to be used for model selection. The 2017-2018 dataset (and possibly 2019-2020) will be used as our test set. The accuracy of our model on this dataset will be unknown until the completion of the 2019-2020 season.

Jess, Anna and Seth Project

11/6/19

```
library(tidyverse)
## -- Attaching packages
## v ggplot2 3.2.1
                       v purrr
                                  0.3.3
## v tibble 2.1.3
                       v dplyr
                                  0.8.3
             1.0.0
## v tidyr
                       v stringr 1.4.0
## v readr
             1.3.1
                       v forcats 0.4.0
## -- Conflicts -----
## x dplyr::filter() masks stats::filter()
## x dplyr::lag()
                     masks stats::lag()
library(dplyr)
library(glmnet)
## Loading required package: Matrix
##
## Attaching package: 'Matrix'
## The following objects are masked from 'package:tidyr':
##
##
       expand, pack, unpack
## Loading required package: foreach
##
## Attaching package: 'foreach'
## The following objects are masked from 'package:purrr':
##
##
       accumulate, when
## Loaded glmnet 2.0-18
```

```
library(rpart)
rm(list = ls())
teams78 = read.csv('data/teams0708.csv')
teams89 = read.csv('data/teams0809.csv')
RMSE = function(y,yhat){
 SSE = sum((y-yhat)^2)
  return(sqrt(SSE/length(y)))
names(teams78)[1] = "Rk"
names(teams89)[1] = "Rk"
teams78_drop = subset(teams78, select = -c(Rk, TeamW, TeamL, ConfW, ConfL, HomeW, HomeL, AwayW, AwayL,
teams89_drop = subset(teams89, select = -c(Rk, TeamW, TeamL, ConfW, ConfL, HomeW, HomeL, AwayW, AwayL,
# inpute the data with the column means
for(i in 1:ncol(teams78_drop)){
  teams78_drop[is.na(teams78_drop[,i]), i] <- mean(teams78_drop[,i], na.rm = TRUE)</pre>
}
for(i in 1:ncol(teams89_drop)){
  teams89_drop[is.na(teams89_drop[,i]), i] <- mean(teams89_drop[,i], na.rm = TRUE)</pre>
}
#explore data
summary(teams78_drop)
summary(teams89_drop)
par(mfrow = c(4, 4))
par(mar=c(1,2,3,3))
columns = colnames(teams78_drop)[c(1:16)]
for(column in columns){
  hist(teams78_drop[,column], main=column, xlab=column, breaks=30)
}
```



```
FGA
                                FG.
                                                        X<sub>3</sub>P
                                                                               X3PA
                       30
                                               30
30
                       2
                                               2
15
                                                                       9
                                                                       0
        1800 2400
                                                      200 300
                                                                                700
                                                                                     1000
  1200
                         0.35
                                  0.45
                                                  100
                                                                          400
                                                                                FT.
        X3P.
                                 FT
                                                        FTA
                                               30
                                                                       25
20
                       20
                                               15
9
                                                                       9
             0.40
                                                                          0.60
     0.30
                          200
                               400
                                   600
                                                   400
                                                         700
                                                               1000
                                                                                0.70
                                                                                       0.80
        ORB
                                TRB
                                                        AST
                                                                                STL
                       50
4
                                               2
                                                                       15
20
                       20
    200
         400
               600
                            800
                                1200
                                     1600
                                                   300
                                                        500
                                                              700
                                                                         100
                                                                              200
                                                                                   300
        BLK
                                                        PF
                                TOV
4
                       25
                                               20
20
                       9
                                               9
#linear model with main effects of all included predictors
lm1 = lm(W.L. ~., data=teams78_drop)
lm1rmse_train = RMSE(teams78_drop$W.L, predict(lm1, teams78_drop))
## Warning in predict.lm(lm1, teams78_drop): prediction from a rank-deficient
## fit may be misleading
lm1rmse_test = RMSE(teams89_drop$W.L, predict(lm1, teams89_drop))
## Warning in predict.lm(lm1, teams89_drop): prediction from a rank-deficient
## fit may be misleading
cat('lm1 train RMSE: ', lm1rmse_train, '\n', 'lm1 test RMSE: ', lm1rmse_test, sep='')
## lm1 train RMSE: 0.05182295
## lm1 test RMSE: 0.05492276
#backward sequential variable selection regression model
lm2 = step(lm1, direction = "backward", k=2, trace = 0)
lm2rmse_train = RMSE(teams78_drop$W.L, predict(lm2, teams78_drop))
lm2rmse_test = RMSE(teams89_drop$W.L, predict(lm2, teams89_drop))
cat('lm2 train RMSE: ', lm2rmse_train, '\n', 'lm2 test RMSE: ', lm2rmse_test, sep='')
## lm2 train RMSE: 0.05214415
## lm2 test RMSE: 0.05404892
#forward sequential variable selection regression model
lm3 = step(lm1, scope = list(upper = formula(lm1)), direction = "forward", trace=0)
lm3rmse_train = RMSE(teams78_drop$W.L, predict(lm3, teams78_drop))
```

```
## Warning in predict.lm(lm3, teams78_drop): prediction from a rank-deficient
## fit may be misleading
lm3rmse_test = RMSE(teams89_drop$W.L, predict(lm3, teams89_drop))
## Warning in predict.lm(lm3, teams89_drop): prediction from a rank-deficient
## fit may be misleading
cat('lm3 train RMSE: ', lm3rmse_train, '\n', 'lm3 test RMSE: ', lm3rmse_test, sep='')
## lm3 train RMSE: 0.05182295
## 1m3 test RMSE: 0.05492276
#well-tuned Ridge regression model
set.seed(2)
X_train = model.matrix(formula(lm1), data=teams78_drop)[,-1]
X_test = model.matrix(formula(lm1), data=teams89_drop)[,-1]
ridges = cv.glmnet(X_train, teams78_drop$W.L, alpha=0, lambda=10^seq(-4,4,0.1), nfolds=5)
best_lambda = ridges$lambda.min
ridge1 = glmnet(X_train, teams78_drop$W.L, alpha=0, lambda=best_lambda)
ridgermse_train = RMSE(teams78_drop$W.L, predict(ridge1, X_train))
ridgermse_test = RMSE(teams89_drop$W.L, predict(ridge1, X_test))
cat('ridge train RMSE: ', ridgermse_train, '\n', 'ridge test RMSE: ', ridgermse_test, sep='')
## ridge train RMSE: 0.05234369
## ridge test RMSE: 0.05412679
#well-tuned Lasso regression model
lassos = cv.glmnet(X_train, teams78_drop$W.L, alpha=0, lambda=10^seq(-4,4,0.1), nfolds=5)
best_lambda = lassos$lambda.min
lasso1 = glmnet(X_train, teams78_drop$W.L, alpha=1, lambda=best_lambda)
lassormse_train = RMSE(teams78_drop$W.L, predict(lasso1, X_train))
lassormse test = RMSE(teams89 drop$W.L, predict(lasso1, X test))
cat('lasso train RMSE: ', lassormse_train, '\n', 'lasso test RMSE: ', lassormse_test, sep='')
## lasso train RMSE: 0.05390289
## lasso test RMSE: 0.0546133
#regresion tree
tree1 = rpart(W.L. ~ . , data=teams78_drop, control=list(minsplit=1,cp=0.00001,maxdepth=20))
tree1RMSE_train = RMSE(teams78_drop$W.L, predict(tree1, teams78_drop))
tree1RMSE_test = RMSE(teams89_drop$W.L., predict(tree1, teams89_drop))
cat('tree1 train RMSE: ', tree1RMSE_train, '\n', 'tree1 test RMSE: ', tree1RMSE_test, sep='')
## tree1 train RMSE: 0.05522243
## tree1 test RMSE: 0.09639657
#tuned pruned regression tree
cps = 10^{(seq(-10, 2, .1))}
rmses = rep(NA,length(cps))
for(i in 1:length(cps)){
  cp=cps[i]
 temptree = prune(tree1,cp)
 rmses[i] = RMSE(teams89_drop$W.L., predict(temptree,new=teams89_drop))
}
tree2 = rpart(W.L. ~ ., data=teams78_drop, control=list(minsplit=1,cp=cps[which.min(which.min(rmses))],
tree2RMSE_train = RMSE(teams78_drop$\$W.L, predict(tree2, teams78_drop))
```

```
tree2RMSE_test = RMSE(teams89_drop$W.L., predict(tree2, teams89_drop))
cat('tree2 train RMSE: ', tree2RMSE_train, '\n', 'tree2 test RMSE: ', tree2RMSE_test, sep='')
## tree2 train RMSE: 0.05522243
## tree2 test RMSE: 0.09639657
```