CIND820_project

December 1, 2021

INITIALIZE - import Python modules ************************************

[1]:
```
import pandas as pd
import numpy as np
from sklearn.model_selection import train_test_split
from sklearn import metrics
from sklearn import linear_model
import matplotlib.pyplot as plt
from sklearn.linear_model import Ridge, RidgeCV
```

[2]:
```
pip install xgboost
```

```
Requirement already satisfied: xgboost in /opt/conda/lib/python3.7/site-packages
(1.5.1)
Requirement already satisfied: scipy in /opt/conda/lib/python3.7/site-packages
(from xgboost) (1.4.1)
Requirement already satisfied: numpy in /opt/conda/lib/python3.7/site-packages
(from xgboost) (1.18.4)
Note: you may need to restart the kernel to use updated packages.
```

[3]:
```
import xgboost
from xgboost import XGBRegressor
```

IMPORT DATA - import data from csv files - combine into 2 dataframes: - Regular season - Postseason - check summary statistics for resulting dataframes **

[4]:
```
#Import data

df_RS_sum = pd.read_csv('Summary_RS.csv', encoding='latin-1')
df_RS_pen = pd.read_csv('Penalties_RS.csv', encoding='latin-1')
df_RS_tgg = pd.read_csv('Team Goal-Games_RS.csv', encoding='latin-1')
df_RS_satc = pd.read_csv('SAT Counts_RS.csv', encoding='latin-1')
df_RS_satp = pd.read_csv('SAT Percentages_RS.csv', encoding='latin-1')

df_PS_sum = pd.read_csv('Summary_PS.csv', encoding='latin-1')
```

```python
df_PS_pen = pd.read_csv('Penalties_PS.csv', encoding='latin-1')
df_PS_tgg = pd.read_csv('Team Goal-Games_PS.csv', encoding='latin-1')
df_PS_satc = pd.read_csv('SAT Counts_PS.csv', encoding='latin-1')
df_PS_satp = pd.read_csv('SAT Percentages_PS.csv', encoding='latin-1')
```

[5]:
```python
#Check import sample
df_PS_sum.head()
```

[5]:
```
                  Team    Season  GP   W  L   T  OT     P     P%  RW  …  \
0   Tampa Bay Lightning  20202021  23  16  7  --  --  32.0  0.696  16  …
1    Montréal Canadiens  20202021  22  13  9  --  --  26.0  0.591   7  …
2    New York Islanders  20202021  19  11  8  --  --  22.0  0.579   7  …
3  Vegas Golden Knights  20202021  19  10  9  --  --  20.0  0.526   8  …
4         Boston Bruins  20202021  11   6  5  --  --  12.0  0.545   3  …

     GA  GF/GP  GA/GP   PP%   PK%  Net PP%  Net PK%  Shots/GP  SA/GP  FOW%
0  45.0   3.26   1.96  32.4  84.1     32.4     87.3      29.6   30.4  48.1
1  54.0   2.32   2.45  18.9  91.8     17.0     98.4      28.9   30.7  49.4
2  53.0   2.84   2.79  20.4  65.1     16.3     65.1      28.5   35.2  51.8
3  46.0   2.79   2.42   9.3  71.8      9.3     74.4      32.1   26.4  53.5
4  32.0   3.00   2.91  36.4  75.7     36.4     75.7      35.8   31.0  52.3

[5 rows x 23 columns]
```

[6]:
```python
#Create regular season dataframe

#Rename column with shared name but different data
df_RS_satp = df_RS_satp.rename({'GF':'5v5 GF', 'GA':'5v5 GA'}, axis=1)

#Drop duplicate columns
df_RS_pen = df_RS_pen.drop(['GP','W','L','T','OT','P'], axis=1)
df_RS_satc = df_RS_satc.drop(['GP'], axis=1)
df_RS_satp = df_RS_satp.drop(['GP','P','P%'], axis=1)
df_RS_tgg = df_RS_tgg.drop(['GP','W','L','T','OT','P','P%'], axis=1)

#Merge dataframes to create one regular season dataframe
df = pd.merge(df_RS_sum, df_RS_pen, how='inner', on=['Team','Season'])
df = pd.merge(df, df_RS_satc, how='inner', on=['Team','Season'])
df = pd.merge(df, df_RS_satp, how='inner', on=['Team','Season'])
df = pd.merge(df, df_RS_tgg, how='inner', on=['Team','Season'])

#Drop irrelevant columns (Ties not applicable in seasons being studied)
df = df.drop(['T'], axis=1)

#Convert season column to string
df['Season'] = df['Season'].apply(str)
```

```python
#Convert SAT for/against to rate per game
df['SAT For/GP'] = df['SAT For'] / df['GP']
df['SAT Agst/GP'] = df['SAT Agst'] / df['GP']
```

[7]:
```python
#Check summary statistics for regular season dataframe
df.describe()
```

[7]:
```
               GP           W           L          OT           P          P%  \
count  154.000000  154.000000  154.000000  154.000000  154.000000  154.000000
mean    74.311688   37.155844   28.707792    8.448052   82.759740    0.556929
std     10.380676    8.935594    7.828994    2.906028   17.944379    0.094176
min     56.000000   15.000000   12.000000    2.000000   37.000000    0.275000
25%     69.000000   31.000000   24.000000    7.000000   72.000000    0.488000
50%     82.000000   37.000000   28.000000    8.000000   81.500000    0.569000
75%     82.000000   44.000000   34.000000   10.000000   97.750000    0.622750
max     82.000000   62.000000   56.000000   15.000000  128.000000    0.780000

               RW         ROW     S/O Win          GF  …  Win% 3 Goal Game  \
count  154.000000  154.000000  154.000000  154.000000  …        154.000000
mean    28.707792   34.298701    2.857143  215.642857  …          0.499370
std      8.100613    8.792547    1.693620   38.727923  …          0.163777
min     11.000000   11.000000    0.000000  124.000000  …          0.032000
25%     23.000000   28.000000    2.000000  189.250000  …          0.385500
50%     29.000000   34.000000    3.000000  221.000000  …          0.515500
75%     35.000000   41.000000    4.000000  243.000000  …          0.618000
max     49.000000   56.000000    9.000000  319.000000  …          0.875000

       Wins 1 Goal Game  Wins 2 Goal Game  Wins 3 Goal Game  Loss 1 Goal Game  \
count        154.000000        154.000000        154.000000        154.000000
mean          16.012987          7.733766         13.409091          7.564935
std            4.216350          2.985898          5.188743          2.976872
min            5.000000          0.000000          1.000000          1.000000
25%           13.000000          6.000000         10.000000          5.000000
50%           16.000000          7.000000         14.000000          8.000000
75%           19.000000         10.000000         17.000000          9.000000
max           25.000000         16.000000         30.000000         15.000000

       Loss 2 Goal Game  Loss 3 Goal Game  OT Loss 1 Goal Game  SAT For/GP  \
count        154.000000        154.000000           154.000000  154.000000
mean           7.733766         13.409091             8.448052   44.869488
std            3.031517          5.099806             2.906028    3.125934
min            2.000000          2.000000             2.000000   37.321429
25%            5.250000         10.000000             7.000000   42.664634
50%            8.000000         13.000000             8.000000   44.622570
75%           10.000000         16.000000            10.000000   46.908537
max           16.000000         30.000000            15.000000   53.609756
```

```
       SAT Agst/GP
count   154.000000
mean     44.867717
std       3.010061
min      35.053571
25%      42.871951
50%      45.009364
75%      47.088415
max      53.914634

[8 rows x 75 columns]
```

[8]:
```python
#Create postseason dataframe following same process as regular season

df_PS_satp = df_PS_satp.rename({'GF':'5v5 GF', 'GA':'5v5 GA'}, axis=1)

df_PS_pen = df_PS_pen.drop(['GP','W','L','T','OT','P'], axis=1)
df_PS_satc = df_PS_satc.drop(['GP'], axis=1)
df_PS_satp = df_PS_satp.drop(['GP','P','P%'], axis=1)
df_PS_tgg = df_PS_tgg.drop(['GP','W','L','T','P','P%'], axis=1)

df2 = pd.merge(df_PS_sum, df_PS_pen, how='inner', on=['Team','Season'])
df2 = pd.merge(df2, df_PS_satc, how='inner', on=['Team','Season'])
df2 = pd.merge(df2, df_PS_satp, how='inner', on=['Team','Season'])
df2 = pd.merge(df2, df_PS_tgg, how='inner', on=['Team','Season'])

df2 = df2.drop(['T'], axis=1)

df2['Season'] = df2['Season'].apply(str)

df2['SAT For/GP'] = df2['SAT For'] / df2['GP']
df2['SAT Agst/GP'] = df2['SAT Agst'] / df2['GP']
```

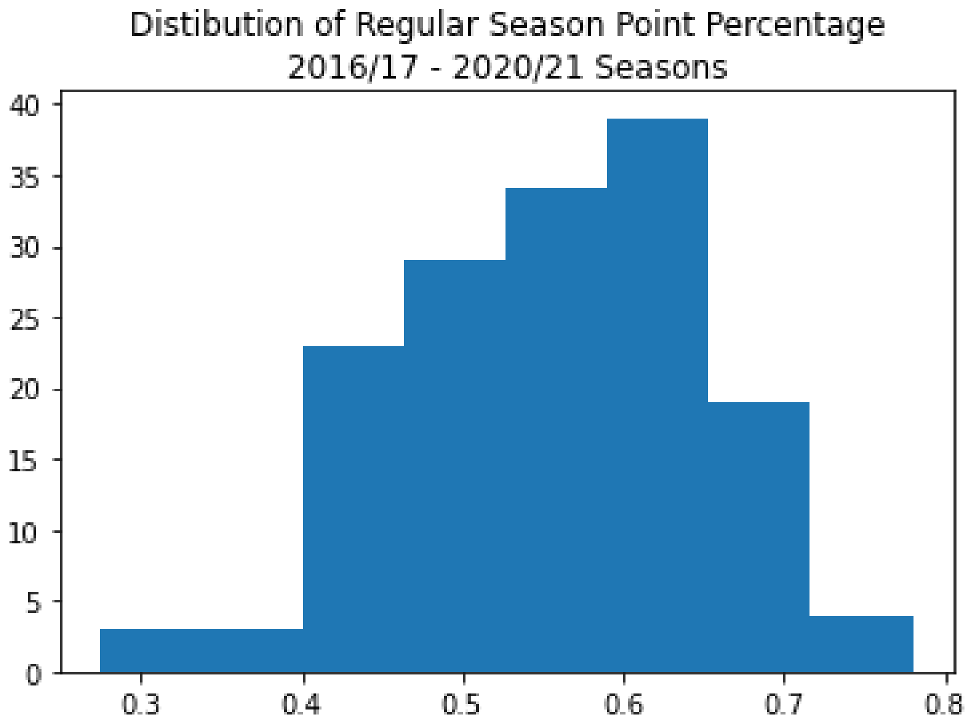
[9]:
```python
df2.describe()
```

[9]:
```
              GP          W          L          P         P%         RW  \
count  88.000000  88.000000  88.000000  88.000000  88.000000  88.000000
mean   10.727273   5.363636   5.329545   5.117261   2.505977   4.738636
std     6.629310   4.849889   1.981069   8.387413   3.631763   4.450221
min     3.000000   0.000000   3.000000   0.000000   0.000000   0.000000
25%     5.750000   2.000000   4.000000   0.333000   0.333000   1.000000
50%     8.500000   4.000000   4.000000   0.607500   0.612500   3.000000
75%    15.000000   8.250000   6.250000   6.500000   3.250000   7.000000
max    27.000000  18.000000  12.000000  36.000000  14.000000  16.000000

             ROW    S/O Win         GF         GA  …  5v5 S%+Sv%  \
count  88.000000  88.000000  88.000000  88.000000  …   88.000000
```

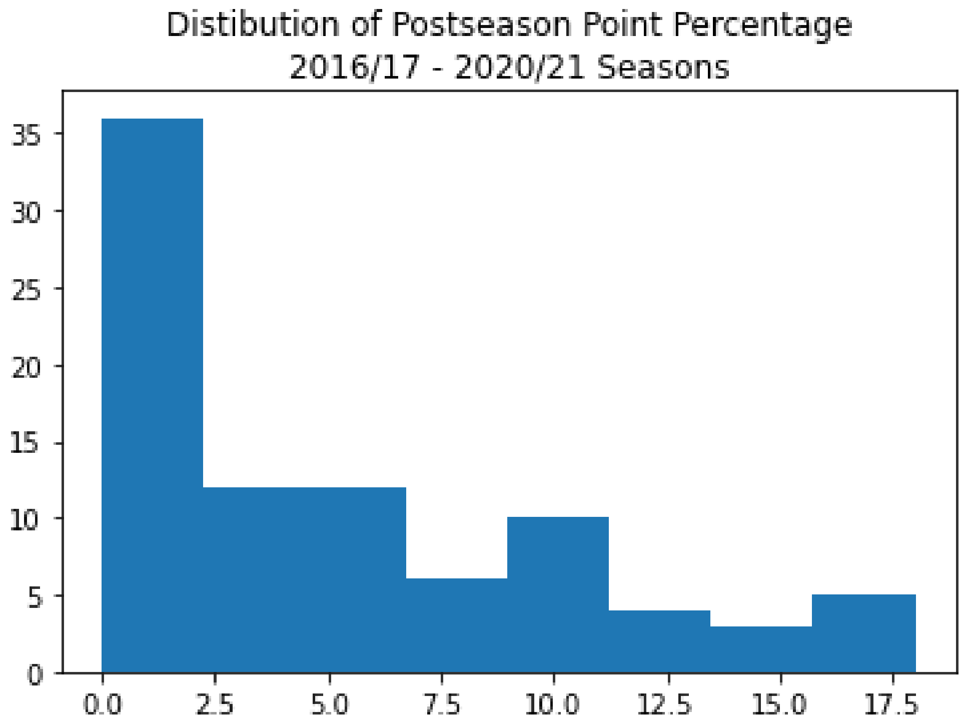
```
mean    2.409091  16.272727  29.534091  14.671023  …   98.932955
std     4.173359  21.981041  18.536047  17.144004  …    3.018781
min     0.000000   0.000000   4.000000   0.750000  …   90.600000
25%     0.000000   0.000000  16.000000   2.652500  …   97.150000
50%     0.000000   7.000000  23.000000   3.355000  …   99.850000
75%     3.250000  26.250000  42.000000  22.250000  …  101.000000
max    17.000000  86.000000  77.000000  82.000000  …  103.800000

       Wins 2 Goal Game  Wins 3 Goal Game  Loss 1 Goal Game  Loss 2 Goal Game  \
count         88.000000         88.000000         88.000000         88.000000
mean           1.829545          1.397727          2.136364          1.795455
std            2.354851          1.847893          1.709889          1.576837
min            0.000000          0.000000          0.000000          0.000000
25%            0.000000          0.000000          1.000000          1.000000
50%            1.000000          1.000000          2.000000          1.500000
75%            2.000000          2.000000          3.000000          3.000000
max           12.000000          9.000000          6.000000          7.000000

       Loss 3 Goal Game  OT Loss 1 Goal Game  Unnamed: 18  SAT For/GP  \
count         88.000000            88.000000    40.000000   88.000000
mean           1.397727             0.806818     0.075000   47.657206
std            1.255240             1.239744     0.266747    6.483257
min            0.000000             0.000000     0.000000   36.571429
25%            0.000000             0.000000     0.000000   43.221429
50%            1.000000             0.000000     0.000000   46.900219
75%            2.000000             1.250000     0.000000   51.723214
max            5.000000             5.000000     1.000000   69.500000

       SAT Agst/GP
count    88.000000
mean     47.749411
std       6.219736
min      36.400000
25%      44.250000
50%      47.431373
75%      50.987500
max      66.900000

[8 rows x 72 columns]
```

[10]:

```
fig, ax = plt.subplots()

plt.hist(df['P%'], bins=8)

plt.title('Distibution of Regular Season Point Percentage\n2016/17 - 2020/21 Seasons')
plt.savefig('hist_RS_Ppct.png', dpi=144)
```



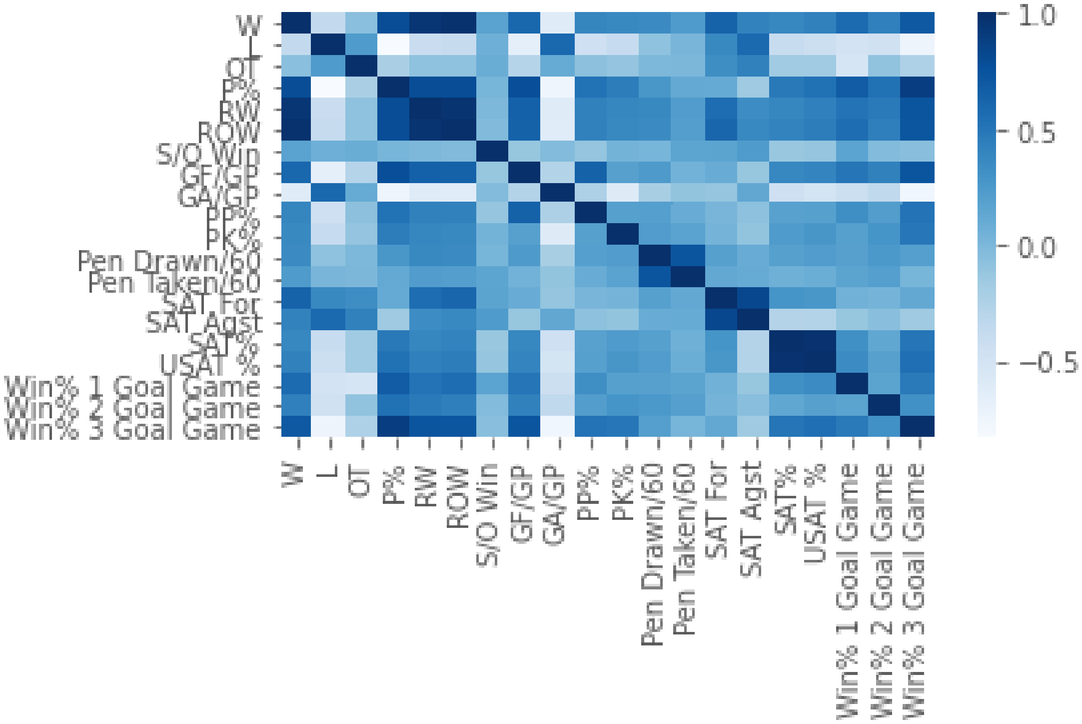
[11]:
```
fig, ax = plt.subplots()

plt.hist(df2['W'], bins=8)

plt.title('Distibution of Postseason Point Percentage\n2016/17 - 2020/21␣
 ↪Seasons')
plt.savefig('hist_PS_W.png', dpi=144)
```



INITIAL DATA ASSESSMENT - reduce dataframes to set of variables expected to be of primary interest. Preferentially select variables as rates or ratios from each category of statistics. - create heat map to check correlation between selected variables ************************************

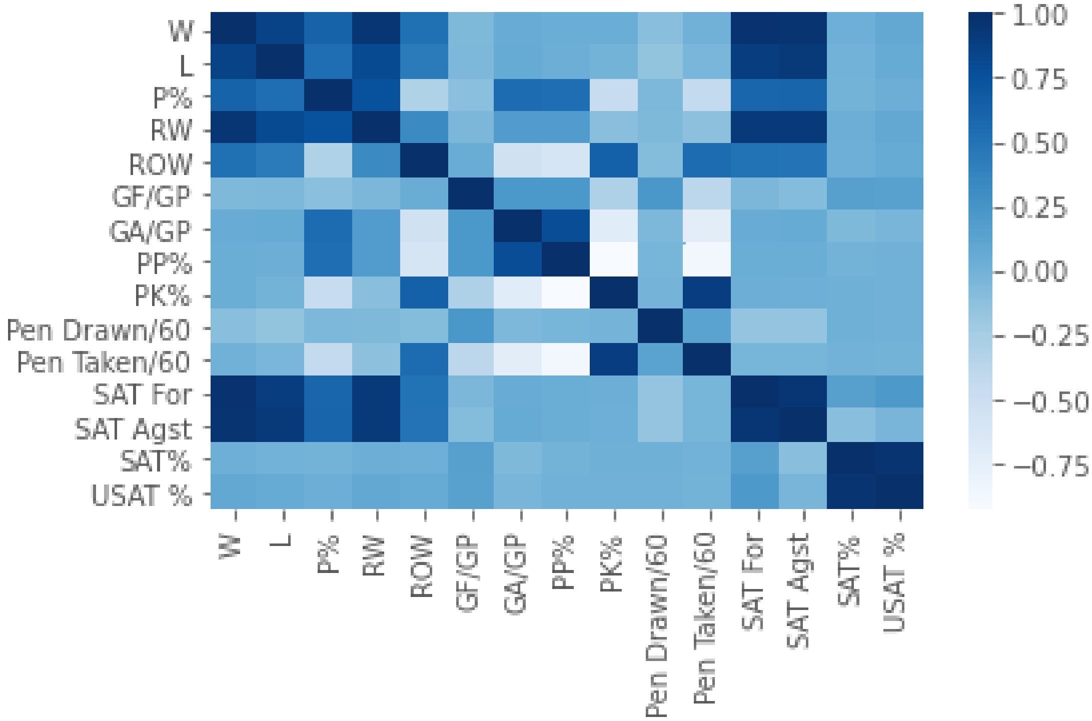
[12]:
```
#Reduce regular season dataframe for initial heatmap
df_reg = df[['W','L','OT','P%', 'RW','ROW','S/O Win','GF/GP','GA/
↪GP','PP%','PK%','Pen Drawn/60','Pen Taken/60','SAT For','SAT␣
↪Agst','SAT%','USAT %','Win% 1 Goal Game','Win% 2 Goal Game', 'Win% 3 Goal␣
↪Game']]
```

[13]:
```
#Create correlation heat map for regular season
import matplotlib
matplotlib.use('Agg')
import matplotlib.pyplot as plt
matplotlib.style.use('ggplot')
import seaborn as sns
corr = df_reg.corr()
sns_plot = sns.heatmap(corr, cmap="Blues", annot=False)

fig = sns_plot.get_figure()
fig.tight_layout()
fig.savefig("reg_heat.png")
```



[14]:
```
#Reduce postseason dataframe for initial heatmap
df_post = df2[['W','L','OT','P%', 'RW','ROW','GF/GP','GA/GP','PP%','PK%','Pen␣
↪Drawn/60','Pen Taken/60','SAT For','SAT Agst','SAT%','USAT %','Win% 1 Goal␣
↪Game','Win% 2 Goal Game', 'Win% 3 Goal Game']]
```

[15]:
```
#Create correlation heat map for postseason
corr = df_post.corr()
sns_plot = sns.heatmap(corr, cmap="Blues", annot=False)

fig = sns_plot.get_figure()
fig.tight_layout()
fig.savefig("post_heat.png")
```



MODELLING: REGULAR SEASON Initial model: - Train initial model for regular season using goal-based input variables - Test multiple types of regression models to find best fit. Considering linear regression, XGBoost regression, ridge regression Additional models: - Add additional variables to inital model in categorical groups to test for improved models.
- Additional categorical groups include shot metrics, penalties, special teams, records in close games - Additional models without using goal metrics
****

[16]:
```
#TRAIN INITIAL MODEL MO
#Linear Regression
#Inputs: goal based variables
#Target: Regular season P%
#70/30 Train/test split

#Target Variable = Roint Percentage
reg_col_name = 'P%'

#Select feature variables
feature_names = ['GF/GP','GA/GP']

#Use 70/30 train/test split
```

```
X_train, X_test, y_train, y_test = train_test_split(df.loc[:, feature_names],␣
 ↪df[reg_col_name], test_size=0.3,random_state=2)

#Train model & predict test set
M0 = linear_model.LinearRegression()
M0.fit(X_train,y_train)

y_pred = M0.predict(X_test)
```

[17]:
```
#Check model metrics
print('Mean Absolute Error:', metrics.mean_absolute_error(y_test, y_pred))
print('Mean Squared Error:', metrics.mean_squared_error(y_test, y_pred))
print('Root Mean Squared Error:', np.sqrt(metrics.mean_squared_error(y_test,␣
 ↪y_pred)))
print('R-Squared:', metrics.r2_score(y_test, y_pred))
print('Adjusted R-Squared:', 1 - (1-metrics.r2_score(y_test,␣
 ↪y_pred))*(len(y_train)-1)/(len(y_train)-X_train.shape[1]-1))
```

```
Mean Absolute Error: 0.019301933879415853
Mean Squared Error: 0.0005326454997485497
Root Mean Squared Error: 0.02307911392901707
R-Squared: 0.9331582772976956
Adjusted R-Squared: 0.9318728595534206
```

[18]:
```
#TRAIN INITIAL MODEL M0 with kfold cross validation
#Linear Regression
#Inputs: goal based variables
#Target: Regular season P%
#kfold cross validation

X, y = df[['GF/GP', 'GA/GP']], df['P%']

#Train model & predict test set
M0k = linear_model.LinearRegression()
#M0k.fit(X,y)

#y_pred = M0k.predict(X)

from sklearn.model_selection import RepeatedKFold

cv = RepeatedKFold(n_splits=10, n_repeats=3, random_state=1)

from sklearn.model_selection import cross_val_score

scores = cross_val_score(M0k, X, y, scoring='neg_mean_absolute_error', cv=cv)
scores.mean()
```

[18]: -0.019066608315764132

[19]:
```
#MODEL MO_XGB
#XGBoost Regression
#Inputs: goal based variables
#Target: Regular season P%

reg_col_name = 'P%'

feature_names = ['GF/GP','GA/GP']

X_train, X_test, y_train, y_test = train_test_split(df.loc[:, feature_names],␣
↪df[reg_col_name], test_size=0.3,random_state=2)

MO_XGB = XGBRegressor(objective ='reg:squarederror', colsample_bytree = 1.0,␣
↪learning_rate = 0.1,
                max_depth = 4, n_estimators = 100)

MO_XGB.fit(X_train,y_train)

y_pred = MO_XGB.predict(X_test)
```

[20]:
```
print('Mean Absolute Error:', metrics.mean_absolute_error(y_test, y_pred))
print('Mean Squared Error:', metrics.mean_squared_error(y_test, y_pred))
print('Root Mean Squared Error:', np.sqrt(metrics.mean_squared_error(y_test,␣
↪y_pred)))
print('R-Squared:', metrics.r2_score(y_test, y_pred))
print('Adjusted R-Squared:', 1 - (1-metrics.r2_score(y_test,␣
↪y_pred))*(len(y_train)-1)/(len(y_train)-X_train.shape[1]-1))
```

```
Mean Absolute Error: 0.024832683020449716
Mean Squared Error: 0.0010186796962558568
Root Mean Squared Error: 0.031916761995162614
R-Squared: 0.8721658104466374
Adjusted R-Squared: 0.8697074606475343
```

[21]:
```
#MODEL MORR
#Ridge Regression
#Inputs: goal based variables
#Target: Regular season P%

reg_col_name = 'P%'

feature_names = ['GF/GP','GA/GP']

X_train, X_test, y_train, y_test = train_test_split(df.loc[:, feature_names],␣
↪df[reg_col_name], test_size=0.3,random_state=2)
```

```
MORR = Ridge(alpha=0.1)
MORR.fit(X_train,y_train)

y_pred = MORR.predict(X_test)
```

[22]:
```
print('Mean Absolute Error:', metrics.mean_absolute_error(y_test, y_pred))
print('Mean Squared Error:', metrics.mean_squared_error(y_test, y_pred))
print('Root Mean Squared Error:', np.sqrt(metrics.mean_squared_error(y_test,␣
 ↪y_pred)))
print('R-Squared:', metrics.r2_score(y_test, y_pred))
print('Adjusted R-Squared:', 1 - (1-metrics.r2_score(y_test,␣
 ↪y_pred))*(len(y_train)-1)/(len(y_train)-X_train.shape[1]-1))
```

```
Mean Absolute Error: 0.019349022473394435
Mean Squared Error: 0.0005375438606248156
Root Mean Squared Error: 0.02318499214200461
R-Squared: 0.93254358163324
Adjusted R-Squared: 0.9312463428184946
```

[23]:
```
#Continue regular season prediction adding additional variables to goal-based␣
 ↪model.  Linear Regression dropped due to suspected overfitting in M0.
```

[24]:
```
#Does adding shot metric variables improve goal based model?
#MODEL M1
#XGBoost Regression
#Inputs: goal based variables + shot-based metrics
#Target: Regular season P%

reg_col_name = 'P%'

feature_names = ['GF/GP','GA/GP','SAT For/GP', 'SAT Agst/GP', 'SAT%']

X_train, X_test, y_train, y_test = train_test_split(df.loc[:, feature_names],␣
 ↪df[reg_col_name], test_size=0.3,random_state=2)

M1 = XGBRegressor(objective ='reg:squarederror', colsample_bytree = 1.0,␣
 ↪learning_rate = 0.1,
                max_depth = 2, n_estimators = 100)
M1.fit(X_train,y_train)

y_pred = M1.predict(X_test)
```

[25]:
```
print('Mean Absolute Error:', metrics.mean_absolute_error(y_test, y_pred))
print('Mean Squared Error:', metrics.mean_squared_error(y_test, y_pred))
print('Root Mean Squared Error:', np.sqrt(metrics.mean_squared_error(y_test,␣
 ↪y_pred)))
```

```
print('R-Squared:', metrics.r2_score(y_test, y_pred))
print('Adjusted R-Squared:', 1 - (1-metrics.r2_score(y_test,␣
↪y_pred))*(len(y_train)-1)/(len(y_train)-X_train.shape[1]-1))
```

```
Mean Absolute Error: 0.024218783079309674
Mean Squared Error: 0.0010224722293729596
Root Mean Squared Error: 0.03197611967348383
R-Squared: 0.8716898851885204
Adjusted R-Squared: 0.865337899306764
```

[26]:
```
#MODEL M1RR
#Ridge Regression
#Inputs: goal based variables + shot-based metrics
#Target: Regular season P%

reg_col_name = 'P%'

feature_names = ['GF/GP','GA/GP','SAT For/GP', 'SAT Agst/GP', 'SAT%']

X_train, X_test, y_train, y_test = train_test_split(df.loc[:, feature_names],␣
↪df[reg_col_name], test_size=0.3,random_state=2)

M1RR = Ridge(alpha=1)
M1RR.fit(X_train,y_train)

y_pred = M1RR.predict(X_test)
```

[27]:
```
print('Mean Absolute Error:', metrics.mean_absolute_error(y_test, y_pred))
print('Mean Squared Error:', metrics.mean_squared_error(y_test, y_pred))
print('Root Mean Squared Error:', np.sqrt(metrics.mean_squared_error(y_test,␣
↪y_pred)))
print('R-Squared:', metrics.r2_score(y_test, y_pred))
print('Adjusted R-Squared:', 1 - (1-metrics.r2_score(y_test,␣
↪y_pred))*(len(y_train)-1)/(len(y_train)-X_train.shape[1]-1))
```

```
Mean Absolute Error: 0.020269714102022034
Mean Squared Error: 0.0006176650868208685
Root Mean Squared Error: 0.024852868784526035
R-Squared: 0.9224891631006638
Adjusted R-Squared: 0.9186519929571323
```

[28]:
```
#Can shot metrics provide predictive ability without goal based data?
#MODEL M2
#XGBoost Regression
#Inputs: shot metrics
#Target: Regular season P%
```

```
reg_col_name = 'P%'

feature_names = ['SAT For/GP', 'SAT Agst/GP', 'SAT%']

X_train, X_test, y_train, y_test = train_test_split(df.loc[:, feature_names],␣
↪df[reg_col_name], test_size=0.3,random_state=2)

M2 = XGBRegressor(objective ='reg:squarederror', colsample_bytree = 1.0,␣
↪learning_rate = 0.3,
                max_depth = 5, n_estimators = 100)
M2.fit(X_train,y_train)

y_pred = M2.predict(X_test)
```

[29]:
```
print('Mean Absolute Error:', metrics.mean_absolute_error(y_test, y_pred))
print('Mean Squared Error:', metrics.mean_squared_error(y_test, y_pred))
print('Root Mean Squared Error:', np.sqrt(metrics.mean_squared_error(y_test,␣
↪y_pred)))
print('R-Squared:', metrics.r2_score(y_test, y_pred))
print('Adjusted R-Squared:', 1 - (1-metrics.r2_score(y_test,␣
↪y_pred))*(len(y_train)-1)/(len(y_train)-X_train.shape[1]-1))
```

```
Mean Absolute Error: 0.06372146529847003
Mean Squared Error: 0.005699138319216351
Root Mean Squared Error: 0.07549263751662377
R-Squared: 0.28481471568806993
Adjusted R-Squared: 0.26398407633917875
```

[30]:
```
#MODEL M2RR
#Ridge Regression
#Inputs: shot metrics
#Target: Regular season P%

reg_col_name = 'P%'

feature_names = ['SAT For/GP', 'SAT Agst/GP', 'SAT%']

X_train, X_test, y_train, y_test = train_test_split(df.loc[:, feature_names],␣
↪df[reg_col_name], test_size=0.3,random_state=2)

M2RR = Ridge(alpha=0.1)
M2RR.fit(X_train,y_train)

y_pred = M2RR.predict(X_test)
```

[31]:
```
print('Mean Absolute Error:', metrics.mean_absolute_error(y_test, y_pred))
print('Mean Squared Error:', metrics.mean_squared_error(y_test, y_pred))
```

```
print('Root Mean Squared Error:', np.sqrt(metrics.mean_squared_error(y_test,␣
 ↪y_pred)))
print('R-Squared:', metrics.r2_score(y_test, y_pred))
print('Adjusted R-Squared:', 1 - (1-metrics.r2_score(y_test,␣
 ↪y_pred))*(len(y_train)-1)/(len(y_train)-X_train.shape[1]-1))
```

```
Mean Absolute Error: 0.07074727860750397
Mean Squared Error: 0.006334153385074077
Root Mean Squared Error: 0.0795873946368021
R-Squared: 0.20512662865103448
Adjusted R-Squared: 0.1819749770583462
```

[32]:
```
#Do S% and SV% improve shot based model?
#MODEL M4
#XGBoost Regression
#Inputs: shot metrics, shooting/save percentage
#Target: Regular season P%

reg_col_name = 'P%'

feature_names = ['SAT For/GP', 'SAT Agst/GP', 'SAT%', '5v5 S%', '5v5 Sv%']

X_train, X_test, y_train, y_test = train_test_split(df.loc[:, feature_names],␣
 ↪df[reg_col_name], test_size=0.3,random_state=2)

M4 = XGBRegressor(objective ='reg:squarederror', colsample_bytree = 1.0,␣
 ↪learning_rate = 0.3,
                max_depth = 3, n_estimators = 10)
M4.fit(X_train,y_train)

y_pred = M4.predict(X_test)
```

[33]:
```
print('Mean Absolute Error:', metrics.mean_absolute_error(y_test, y_pred))
print('Mean Squared Error:', metrics.mean_squared_error(y_test, y_pred))
print('Root Mean Squared Error:', np.sqrt(metrics.mean_squared_error(y_test,␣
 ↪y_pred)))
print('R-Squared:', metrics.r2_score(y_test, y_pred))
print('Adjusted R-Squared:', 1 - (1-metrics.r2_score(y_test,␣
 ↪y_pred))*(len(y_train)-1)/(len(y_train)-X_train.shape[1]-1))
```

```
Mean Absolute Error: 0.04410175598935877
Mean Squared Error: 0.003107177336544678
Root Mean Squared Error: 0.05574206074899526
R-Squared: 0.6100800888879196
Adjusted R-Squared: 0.590777122991282
```

[34]:
```
#MODEL M4RR
#Ridge Regression
#Inputs: shot metrics, shooting/save percentage
#Target: Regular season P%

reg_col_name = 'P%'

feature_names = ['SAT For/GP', 'SAT Agst/GP', 'SAT%', '5v5 S%', '5v5 Sv%']

X_train, X_test, y_train, y_test = train_test_split(df.loc[:, feature_names],␣
↪df[reg_col_name], test_size=0.3,random_state=2)

M4RR = Ridge(alpha=0.1)
M4RR.fit(X_train,y_train)

y_pred = M4RR.predict(X_test)
```

[35]:
```
print('Mean Absolute Error:', metrics.mean_absolute_error(y_test, y_pred))
print('Mean Squared Error:', metrics.mean_squared_error(y_test, y_pred))
print('Root Mean Squared Error:', np.sqrt(metrics.mean_squared_error(y_test,␣
↪y_pred)))
print('R-Squared:', metrics.r2_score(y_test, y_pred))
print('Adjusted R-Squared:', 1 - (1-metrics.r2_score(y_test,␣
↪y_pred))*(len(y_train)-1)/(len(y_train)-X_train.shape[1]-1))
```

```
Mean Absolute Error: 0.03219329522690666
Mean Squared Error: 0.0017621542671799556
Root Mean Squared Error: 0.041978021239452865
R-Squared: 0.7788671321899294
Adjusted R-Squared: 0.7679199605161635
```

[36]:
```
#Does adding special teams performance improve previous model?
#MODEL M5
#XGBoost Regression
#Inputs: shot metrics, shooting/save percentage, special teams
#Target: Regular season P%

reg_col_name = 'P%'

feature_names = ['SAT For/GP', 'SAT Agst/GP', 'SAT%', '5v5 S%', '5v5 Sv%',␣
↪'PP%','PK%']

X_train, X_test, y_train, y_test = train_test_split(df.loc[:, feature_names],␣
↪df[reg_col_name], test_size=0.3,random_state=2)

M5 = XGBRegressor(objective ='reg:squarederror', colsample_bytree = 0.5,␣
↪learning_rate = 0.1,
```

```
                max_depth = 4, n_estimators = 100)
M5.fit(X_train,y_train)

y_pred = M5.predict(X_test)
```

[37]:
```
print('Mean Absolute Error:', metrics.mean_absolute_error(y_test, y_pred))
print('Mean Squared Error:', metrics.mean_squared_error(y_test, y_pred))
print('Root Mean Squared Error:', np.sqrt(metrics.mean_squared_error(y_test,␣
 ↪y_pred)))
print('R-Squared:', metrics.r2_score(y_test, y_pred))
print('Adjusted R-Squared:', 1 - (1-metrics.r2_score(y_test,␣
 ↪y_pred))*(len(y_train)-1)/(len(y_train)-X_train.shape[1]-1))
```

```
Mean Absolute Error: 0.037449044826182915
Mean Squared Error: 0.002268004998376496
Root Mean Squared Error: 0.04762357607715422
R-Squared: 0.7153878869520387
Adjusted R-Squared: 0.6952637981506677
```

[38]:
```
#MODEL M5RR
#Ridge Regression
#Inputs: shot metrics, shooting/save percentage, special teams
#Target: Regular season P%

reg_col_name = 'P%'

feature_names = ['SAT For/GP', 'SAT Agst/GP', 'SAT%', '5v5 S%', '5v5 Sv%',␣
 ↪'PP%','PK%']

X_train, X_test, y_train, y_test = train_test_split(df.loc[:, feature_names],␣
 ↪df[reg_col_name], test_size=0.3,random_state=2)

M5RR = Ridge(alpha=0.1)
M5RR.fit(X_train,y_train)

y_pred = M5RR.predict(X_test)
```

[39]:
```
print('Mean Absolute Error:', metrics.mean_absolute_error(y_test, y_pred))
print('Mean Squared Error:', metrics.mean_squared_error(y_test, y_pred))
print('Root Mean Squared Error:', np.sqrt(metrics.mean_squared_error(y_test,␣
 ↪y_pred)))
print('R-Squared:', metrics.r2_score(y_test, y_pred))
print('Adjusted R-Squared:', 1 - (1-metrics.r2_score(y_test,␣
 ↪y_pred))*(len(y_train)-1)/(len(y_train)-X_train.shape[1]-1))
```

```
Mean Absolute Error: 0.02511585765061583
Mean Squared Error: 0.0011778810039069912
```

```
Root Mean Squared Error: 0.03432027103487079
R-Squared: 0.8521876267111418
Adjusted R-Squared: 0.8417362467816265
```

[40]:

```
#Does adding penalty rates improve the previous model?
#MODEL M6
#XGBoost Regression
#Inputs: shot metrics, shooting/save percentage, special teams, penatly rates
#Target: Regular season P%

reg_col_name = 'P%'

feature_names = ['SAT For/GP', 'SAT Agst/GP', 'SAT%', '5v5 S%', '5v5 Sv%',␣
↪'PP%','PK%', 'Pen Drawn/60','Pen Taken/60']

X_train, X_test, y_train, y_test = train_test_split(df.loc[:, feature_names],␣
↪df[reg_col_name], test_size=0.3,random_state=2)

M6 = XGBRegressor(objective ='reg:squarederror', colsample_bytree = 0.5,␣
↪learning_rate = 0.1,
                max_depth = 40, n_estimators = 100)
M6.fit(X_train,y_train)

y_pred = M6.predict(X_test)
```

[41]:

```
print('Mean Absolute Error:', metrics.mean_absolute_error(y_test, y_pred))
print('Mean Squared Error:', metrics.mean_squared_error(y_test, y_pred))
print('Root Mean Squared Error:', np.sqrt(metrics.mean_squared_error(y_test,␣
↪y_pred)))
print('R-Squared:', metrics.r2_score(y_test, y_pred))
print('Adjusted R-Squared:', 1 - (1-metrics.r2_score(y_test,␣
↪y_pred))*(len(y_train)-1)/(len(y_train)-X_train.shape[1]-1))
```

```
Mean Absolute Error: 0.04500114227355795
Mean Squared Error: 0.0030528095528431706
Root Mean Squared Error: 0.05525223572710131
R-Squared: 0.6169027060391592
Adjusted R-Squared: 0.5813575962902152
```

[42]:

```
#MODEL M6RR
#Ridge Regression
#Inputs: shot metrics, shooting/save percentage, special teams, penatly rates
#Target: Regular season P%

reg_col_name = 'P%'
```

```
feature_names = ['SAT For/GP', 'SAT Agst/GP', 'SAT%', '5v5 S%', '5v5 Sv%',␣
↪'PP%','PK%', 'Pen Drawn/60','Pen Taken/60']

X_train, X_test, y_train, y_test = train_test_split(df.loc[:, feature_names],␣
↪df[reg_col_name], test_size=0.3,random_state=2)

M6RR = Ridge(alpha=0.1)
M6RR.fit(X_train,y_train)

y_pred = M6RR.predict(X_test)
```

[43]:

```
print('Mean Absolute Error:', metrics.mean_absolute_error(y_test, y_pred))
print('Mean Squared Error:', metrics.mean_squared_error(y_test, y_pred))
print('Root Mean Squared Error:', np.sqrt(metrics.mean_squared_error(y_test,␣
↪y_pred)))
print('R-Squared:', metrics.r2_score(y_test, y_pred))
print('Adjusted R-Squared:', 1 - (1-metrics.r2_score(y_test,␣
↪y_pred))*(len(y_train)-1)/(len(y_train)-X_train.shape[1]-1))
```

```
Mean Absolute Error: 0.025264003393739975
Mean Squared Error: 0.0011659666653443162
Root Mean Squared Error: 0.03414625404556576
R-Squared: 0.8536827579283653
Adjusted R-Squared: 0.8401069313443992
```

[44]:

```
#Does kfold cross validation help model M5RR?
#MODEL M5RR
#Ridge Regression
#Inputs: shot metrics, shooting/save percentage, special teams
#Target: Regular season P%

X, y = df[['SAT For/GP', 'SAT Agst/GP', 'SAT%', '5v5 S%', '5v5 Sv%',␣
↪'PP%','PK%']], df['P%']

#Train model & predict test set
M5RRk = Ridge(alpha=0.1)
#M0k.fit(X,y)

#y_pred = M0k.predict(X)

from sklearn.model_selection import RepeatedKFold

cv = RepeatedKFold(n_splits=10, n_repeats=3, random_state=1)

from sklearn.model_selection import cross_val_score

scores = cross_val_score(M5RRk, X, y, scoring='neg_mean_absolute_error', cv=cv)
```

```
scores.mean()
```

[44]: -0.02964831601405144

POSTSEASON MODELS - Model postseason, using wins as target variable. - Use input variables matching regular season models: initial base model and other most successful regular season models - Results to be compared with regular season models to assess impact of small postseason sample sizes ***

[45]:
```
#Can the inputs for the most successful regular season model M5 provide similar␣
↪results on postseason data?  Use W instead of P% for target variable for␣
↪postseason.
#MODEL P5
#XGBoost Regression
#Inputs: shot metrics, shooting/save percentage, special teams, penatly rates
#Target: Postseason W

reg_col_name = 'W'

feature_names = ['SAT For/GP', 'SAT Agst/GP', 'SAT%', '5v5 S%', '5v5 Sv%',␣
↪'PP%','PK%']

X_train, X_test, y_train, y_test = train_test_split(df2.loc[:, feature_names],␣
↪df2[reg_col_name], test_size=0.3,random_state=2)

P5 = XGBRegressor(objective ='reg:squarederror', colsample_bytree = 1.0,␣
↪learning_rate = 0.1,
                max_depth = 4, n_estimators = 100)
P5.fit(X_train,y_train)

y_pred = P5.predict(X_test)
```

[46]:
```
print('Mean Absolute Error:', metrics.mean_absolute_error(y_test, y_pred))
print('Mean Squared Error:', metrics.mean_squared_error(y_test, y_pred))
print('Root Mean Squared Error:', np.sqrt(metrics.mean_squared_error(y_test,␣
↪y_pred)))
print('R-Squared:', metrics.r2_score(y_test, y_pred))
print('Adjusted R-Squared:', 1 - (1-metrics.r2_score(y_test,␣
↪y_pred))*(len(y_train)-1)/(len(y_train)-X_train.shape[1]-1))
```

```
Mean Absolute Error: 2.841516375541687
Mean Squared Error: 15.753672860832477
Root Mean Squared Error: 3.9690896765924144
R-Squared: 0.272492872447303
Adjusted R-Squared: 0.17640702541204112
```

[47]:
```
#MODEL P5RR
#Ridge Regression
#Inputs: shot metrics, shooting/save percentage, special teams, penatly rates
#Target: Postseason W

reg_col_name = 'W'

feature_names = ['SAT For/GP', 'SAT Agst/GP', 'SAT%', '5v5 S%', '5v5 Sv%',␣
↪'PP%','PK%']

X_train, X_test, y_train, y_test = train_test_split(df2.loc[:, feature_names],␣
↪df2[reg_col_name], test_size=0.3,random_state=2)

P5RR = Ridge(alpha=0.1)
P5RR.fit(X_train,y_train)

y_pred = P5RR.predict(X_test)
```

[48]:
```
print('Mean Absolute Error:', metrics.mean_absolute_error(y_test, y_pred))
print('Mean Squared Error:', metrics.mean_squared_error(y_test, y_pred))
print('Root Mean Squared Error:', np.sqrt(metrics.mean_squared_error(y_test,␣
↪y_pred)))
print('R-Squared:', metrics.r2_score(y_test, y_pred))
print('Adjusted R-Squared:', 1 - (1-metrics.r2_score(y_test,␣
↪y_pred))*(len(y_train)-1)/(len(y_train)-X_train.shape[1]-1))
```

```
Mean Absolute Error: 2.8316068910219565
Mean Squared Error: 12.136678677422992
Root Mean Squared Error: 3.4837736260301115
R-Squared: 0.43952624123645256
Adjusted R-Squared: 0.3655014051733426
```

[49]:
```
#Does goal based model have similar reduction in results?
#MODEL P0
#XGBoost Regression
#Inputs: shot metrics, shooting/save percentage, special teams, penatly rates
#Target: Postseason W

reg_col_name = 'W'

feature_names = ['GF/GP', 'GA/GP']

X_train, X_test, y_train, y_test = train_test_split(df2.loc[:, feature_names],␣
↪df2[reg_col_name], test_size=0.3,random_state=2)

P0 = XGBRegressor(objective ='reg:squarederror', colsample_bytree = 1.0,␣
↪learning_rate = 0.1,
```

```
                max_depth = 4, n_estimators = 100)
PO.fit(X_train,y_train)

y_pred = PO.predict(X_test)
```

[50]:
```
print('Mean Absolute Error:', metrics.mean_absolute_error(y_test, y_pred))
print('Mean Squared Error:', metrics.mean_squared_error(y_test, y_pred))
print('Root Mean Squared Error:', np.sqrt(metrics.mean_squared_error(y_test,␣
 ↪y_pred)))
print('R-Squared:', metrics.r2_score(y_test, y_pred))
print('Adjusted R-Squared:', 1 - (1-metrics.r2_score(y_test,␣
 ↪y_pred))*(len(y_train)-1)/(len(y_train)-X_train.shape[1]-1))
```

```
Mean Absolute Error: 3.720087496218858
Mean Squared Error: 20.83882289016658
Root Mean Squared Error: 4.564955957089463
R-Squared: 0.03765983232412051
Adjusted R-Squared: 0.004475688611159212
```

[51]:
```
#MODEL PORR
#Ridge Regression
#Inputs: shot metrics, shooting/save percentage, special teams, penatly rates
#Target: Postseason W

reg_col_name = 'W'

feature_names = ['GF/GP', 'GA/GP']

X_train, X_test, y_train, y_test = train_test_split(df2.loc[:, feature_names],␣
 ↪df2[reg_col_name], test_size=0.3,random_state=2)

PORR = Ridge(alpha=0.5)
PORR.fit(X_train,y_train)

y_pred = PORR.predict(X_test)
```

[52]:
```
print('Mean Absolute Error:', metrics.mean_absolute_error(y_test, y_pred))
print('Mean Squared Error:', metrics.mean_squared_error(y_test, y_pred))
print('Root Mean Squared Error:', np.sqrt(metrics.mean_squared_error(y_test,␣
 ↪y_pred)))
print('R-Squared:', metrics.r2_score(y_test, y_pred))
print('Adjusted R-Squared:', 1 - (1-metrics.r2_score(y_test,␣
 ↪y_pred))*(len(y_train)-1)/(len(y_train)-X_train.shape[1]-1))
```

```
Mean Absolute Error: 3.76161208247753
Mean Squared Error: 23.979697311732068
Root Mean Squared Error: 4.896906912708477
```

```
R-Squared: -0.10738624985763812
Adjusted R-Squared: -0.14557198261134996
```

PREDICT POSTSEASON SUCCESS USING REGULAR SEASON INPUT VARIABLES - Use regular season input variables to predict postseason success. Chose variables based on results of previous models. **

[53]:
```
#Use regular season statistics for input variables
RS = df[['Team', 'Season', 'RW', 'P', 'GF/GP', 'GA/GP','Win% 1 Goal Game',␣
↪'Win% 2 Goal Game', 'Win% 3 Goal Game', 'SAT For/GP', 'SAT Agst/GP', 'SAT%',␣
↪'5v5 S%', '5v5 Sv%', 'PP%','PK%', 'Pen Drawn/60','Pen Taken/60']]

#Use postseason W as target variable
PS = df2[['Team', 'Season', 'P%', 'W']]

#Create new dataframe
df3 = pd.merge(RS, PS, on=['Team','Season'])
```

[54]:
```
#Can regular season inputs be used to predict postseason W?
#MODEL RP5
#XGBoost Regression
#Inputs: shot metrics, shooting/save percentage, special teams, penatly rates
#Target: Postseason W

reg_col_name = 'W'

feature_names = ['SAT For/GP', 'SAT Agst/GP', 'SAT%', '5v5 S%', '5v5 Sv%',␣
↪'PP%','PK%']

X_train, X_test, y_train, y_test = train_test_split(df3.loc[:, feature_names],␣
↪df3[reg_col_name], test_size=0.3,random_state=2)

RP5 = XGBRegressor(objective ='reg:squarederror', colsample_bytree = 0.5,␣
↪learning_rate = 0.1,
                max_depth = 2, n_estimators = 100)
RP5.fit(X_train,y_train)

y_pred = RP5.predict(X_test)
```

[55]:
```
print('Mean Absolute Error:', metrics.mean_absolute_error(y_test, y_pred))
print('Mean Squared Error:', metrics.mean_squared_error(y_test, y_pred))
print('Root Mean Squared Error:', np.sqrt(metrics.mean_squared_error(y_test,␣
↪y_pred)))
print('R-Squared:', metrics.r2_score(y_test, y_pred))
print('Adjusted R-Squared:', 1 - (1-metrics.r2_score(y_test,␣
↪y_pred))*(len(y_train)-1)/(len(y_train)-X_train.shape[1]-1))
```

```
Mean Absolute Error: 5.222498823095251
Mean Squared Error: 42.04227377577858
Root Mean Squared Error: 6.484001370741572
R-Squared: -0.5449550147465765
Adjusted R-Squared: -0.749005677071596
```

[56]:
```
#MODEL RP5RR
#Ridge Regression
#Inputs: shot metrics, shooting/save percentage, special teams, penatly rates
#Target: Postseason W

reg_col_name = 'W'

feature_names = ['SAT For/GP', 'SAT Agst/GP', 'SAT%', '5v5 S%', '5v5 Sv%',␣
↪'PP%','PK%']

X_train, X_test, y_train, y_test = train_test_split(df3.loc[:, feature_names],␣
↪df3[reg_col_name], test_size=0.3,random_state=2)

RP5RR = Ridge(alpha=0.1)
RP5RR.fit(X_train,y_train)

y_pred = RP5RR.predict(X_test)
```

[57]:
```
print('Mean Absolute Error:', metrics.mean_absolute_error(y_test, y_pred))
print('Mean Squared Error:', metrics.mean_squared_error(y_test, y_pred))
print('Root Mean Squared Error:', np.sqrt(metrics.mean_squared_error(y_test,␣
↪y_pred)))
print('R-Squared:', metrics.r2_score(y_test, y_pred))
print('Adjusted R-Squared:', 1 - (1-metrics.r2_score(y_test,␣
↪y_pred))*(len(y_train)-1)/(len(y_train)-X_train.shape[1]-1))
```

```
Mean Absolute Error: 5.132641301308711
Mean Squared Error: 39.62557528535863
Root Mean Squared Error: 6.294884850841883
R-Squared: -0.45614700993176927
Adjusted R-Squared: -0.6484683131303048
```

[58]:
```
#MODEL RP0
#XGBoost Regression
#Inputs: goal rates
#Target: Postseason W

reg_col_name = 'W'

feature_names = ['GF/GP', 'GA/GP']
```

```
X_train, X_test, y_train, y_test = train_test_split(df3.loc[:, feature_names],␣
↪df3[reg_col_name], test_size=0.3,random_state=2)

RPO = XGBRegressor(objective ='reg:squarederror', colsample_bytree = 0.5,␣
↪learning_rate = 0.1,
                max_depth = 10, n_estimators = 100)
RPO.fit(X_train,y_train)

y_pred = RPO.predict(X_test)
```

[59]:
```
print('Mean Absolute Error:', metrics.mean_absolute_error(y_test, y_pred))
print('Mean Squared Error:', metrics.mean_squared_error(y_test, y_pred))
print('Root Mean Squared Error:', np.sqrt(metrics.mean_squared_error(y_test,␣
↪y_pred)))
print('R-Squared:', metrics.r2_score(y_test, y_pred))
print('Adjusted R-Squared:', 1 - (1-metrics.r2_score(y_test,␣
↪y_pred))*(len(y_train)-1)/(len(y_train)-X_train.shape[1]-1))
```

```
Mean Absolute Error: 5.422038421862656
Mean Squared Error: 48.07547664870346
Root Mean Squared Error: 6.933648148608599
R-Squared: -0.7666610785817534
Adjusted R-Squared: -0.8275804261190554
```

[60]:
```
#MODEL RPORR
#Ridge Regression
#Inputs: goal rates
#Target: Postseason W

reg_col_name = 'W'

feature_names = ['GF/GP', 'GA/GP']

X_train, X_test, y_train, y_test = train_test_split(df3.loc[:, feature_names],␣
↪df3[reg_col_name], test_size=0.3,random_state=2)

RPO = Ridge(alpha=0.1)
RPO.fit(X_train,y_train)

y_pred = RPO.predict(X_test)
```

[61]:
```
print('Mean Absolute Error:', metrics.mean_absolute_error(y_test, y_pred))
print('Mean Squared Error:', metrics.mean_squared_error(y_test, y_pred))
print('Root Mean Squared Error:', np.sqrt(metrics.mean_squared_error(y_test,␣
↪y_pred)))
print('R-Squared:', metrics.r2_score(y_test, y_pred))
```

```
print('Adjusted R-Squared:', 1 - (1-metrics.r2_score(y_test,␣
↪y_pred))*(len(y_train)-1)/(len(y_train)-X_train.shape[1]-1))
```

```
Mean Absolute Error: 4.693376720415959
Mean Squared Error: 35.838794498087864
Root Mean Squared Error: 5.986551135510985
R-Squared: -0.3169916921618132
Adjusted R-Squared: -0.3624051987880825
```

CHECK REGULAR SEASON TO POSTSEASON CORRELATIONS - check correlation of each variable used as input variable to previous model between regular season and postseason. - higher correlation may suggest higher predictive power in postseason prediction models. **

[62]:
```
#Check correlation between key variables: regular season vs postseason

#Combine data
reg_shot = df[['Team', 'Season', 'SAT For/GP', 'SAT Agst/GP', 'SAT%', '5v5 S%',␣
↪'5v5 Sv%', 'PP%','PK%', 'Pen Drawn/60','Pen Taken/60']]
post_shot = df2[['Team', 'Season', 'SAT For/GP', 'SAT Agst/GP', 'SAT%', '5v5␣
↪S%', '5v5 Sv%', 'PP%','PK%', 'Pen Drawn/60','Pen Taken/60']]
post_shot = post_shot.rename(columns={'SAT For/GP':'SAT For/GP P', 'SAT Agst/
↪GP':'SAT Agst/GP P', 'SAT%':'SAT% P', '5v5 S%':'5v5 S% P', '5v5 Sv%':'5v5␣
↪Sv% P', 'PP%':'PP% P','PK%':'PK% P', 'Pen Drawn/60':'Pen Drawn/60 P','Pen␣
↪Taken/60':'Pen Taken/60 P'})
compare = pd.merge(reg_shot, post_shot, on=['Team', 'Season'])

#Check correlations
from scipy.stats import pearsonr
stats = ['SAT For/GP', 'SAT Agst/GP', 'SAT%', '5v5 S%', '5v5 Sv%', 'PP%','PK%',␣
↪'Pen Drawn/60','Pen Taken/60']

for i in stats:
    list1 = compare[i]
    list2 = compare[i + ' P']

    corr, _ = pearsonr(list1, list2)
    print('Pearsons correlation (' + i +'): %.3f' % corr)
```

```
Pearsons correlation (SAT For/GP): 0.261
Pearsons correlation (SAT Agst/GP): 0.254
Pearsons correlation (SAT%): 0.466
Pearsons correlation (5v5 S%): -0.080
Pearsons correlation (5v5 Sv%): 0.043
Pearsons correlation (PP%): -0.063
Pearsons correlation (PK%): -0.106
Pearsons correlation (Pen Drawn/60): 0.393
```

```
Pearsons correlation (Pen Taken/60): -0.125
```

[63]:
```python
#Does model improve by removing variables with poor regular season to␣
↪postseason correlation?
#MODEL RP5RR_simple
#Ridge Regression
#Inputs: shot metrics, shooting/save percentage, special teams, penatly rates
#Target: Postseason W

reg_col_name = 'W'

feature_names = ['SAT%']

X_train, X_test, y_train, y_test = train_test_split(df3.loc[:, feature_names],␣
↪df3[reg_col_name], test_size=0.3,random_state=2)

RP5RR_simple = Ridge(alpha=0.1)
RP5RR_simple.fit(X_train,y_train)

y_pred = RP5RR_simple.predict(X_test)
```

[64]:
```python
print('Mean Absolute Error:', metrics.mean_absolute_error(y_test, y_pred))
print('Mean Squared Error:', metrics.mean_squared_error(y_test, y_pred))
print('Root Mean Squared Error:', np.sqrt(metrics.mean_squared_error(y_test,␣
↪y_pred)))
print('R-Squared:', metrics.r2_score(y_test, y_pred))
print('Adjusted R-Squared:', 1 - (1-metrics.r2_score(y_test,␣
↪y_pred))*(len(y_train)-1)/(len(y_train)-X_train.shape[1]-1))
```

```
Mean Absolute Error: 4.992943710259225
Mean Squared Error: 38.76544416640514
Root Mean Squared Error: 6.226190180712853
R-Squared: -0.4245392074457781
Adjusted R-Squared: -0.44868393977536747
```

[65]:
```python
#MODEL RP5RR_simple
#Ridge Regression
#Inputs: shot metrics, shooting/save percentage, special teams, penatly rates
#Target: Postseason W

reg_col_name = 'W'

feature_names = ['SAT%']

X_train, X_test, y_train, y_test = train_test_split(df3.loc[:, feature_names],␣
↪df3[reg_col_name], test_size=0.3,random_state=2)
```

```
RP_simple = XGBRegressor(objective ='reg:squarederror', colsample_bytree = 0.5,␣
↪learning_rate = 0.1,
                max_depth = 10, n_estimators = 100)
RP_simple.fit(X_train,y_train)

y_pred = RP_simple.predict(X_test)
```

[66]:
```
print('Mean Absolute Error:', metrics.mean_absolute_error(y_test, y_pred))
print('Mean Squared Error:', metrics.mean_squared_error(y_test, y_pred))
print('Root Mean Squared Error:', np.sqrt(metrics.mean_squared_error(y_test,␣
↪y_pred)))
print('R-Squared:', metrics.r2_score(y_test, y_pred))
print('Adjusted R-Squared:', 1 - (1-metrics.r2_score(y_test,␣
↪y_pred))*(len(y_train)-1)/(len(y_train)-X_train.shape[1]-1))
```

```
Mean Absolute Error: 6.059022011718264
Mean Squared Error: 56.448535744619136
Root Mean Squared Error: 7.513224057927404
R-Squared: -1.074351374020937
Adjusted R-Squared: -1.1095098718856988
```

CHECK SENSITIVITY: COVID AFFECTED SEASONS - remove Covid-19 affected seasons from dataset (2019-2020, 2020/2021) - re-train best model and compare to previous result with full dataset to assess whether Covid affected seasons have different driving forces **

[67]:
```
#Remove Covid-19 shortened season from dataset
df_reduced = df[df['Season'] != '20202021']
df_reduced = df_reduced[df_reduced['Season'] != '20192020']
df_reduced.head()
```

[67]:
```
                   Team    Season  GP   W   L  OT    P     P%  RW  ROW  …  \
62  Tampa Bay Lightning  20182019  82  62  16   4  128  0.780  49   56  …
63       Calgary Flames  20182019  82  50  25   7  107  0.652  45   50  …
64        Boston Bruins  20182019  82  49  24   9  107  0.652  38   47  …
65  Washington Capitals  20182019  82  48  26   8  104  0.634  39   44  …
66   New York Islanders  20182019  82  48  27   7  103  0.628  37   43  …

    Win% 3 Goal Game  Wins 1 Goal Game  Wins 2 Goal Game  Wins 3 Goal Game  \
62             0.789                24                 8                30
63             0.786                16                12                22
64             0.676                21                 5                23
65             0.533                19                13                16
66             0.613                19                10                19

    Loss 1 Goal Game  Loss 2 Goal Game  Loss 3 Goal Game  OT Loss 1 Goal Game  \
```

```
62                   3                  5                  8                      4
63                   8                 11                  6                      7
64                   6                  7                 11                      9
65                   5                  7                 14                      8
66                   6                  9                 12                      7

    SAT For/GP  SAT Agst/GP
62   46.658537    43.780488
63   48.073171    41.256098
64   47.158537    41.707317
65   45.292683    47.060976
66   43.231707    47.121951

[5 rows x 80 columns]
```

[68]:

```
#TRAIN BEST MODEL (M5_reduced)

#MODEL M5RR
#Ridge Regression
#Inputs: shot metrics, shooting/save percentage
#Target: Regular season P%

reg_col_name = 'P%'

feature_names = ['SAT For/GP', 'SAT Agst/GP', 'SAT%', '5v5 S%', '5v5 Sv%',␣
 ↪'PP%','PK%']

X_train, X_test, y_train, y_test = train_test_split(df.loc[:, feature_names],␣
 ↪df[reg_col_name], test_size=0.3,random_state=2)

M5RR_reduced = Ridge(alpha=0.1)
M5RR_reduced.fit(X_train,y_train)

y_pred = M5RR_reduced.predict(X_test)
```

[69]:

```
print('Mean Absolute Error:', metrics.mean_absolute_error(y_test, y_pred))
print('Mean Squared Error:', metrics.mean_squared_error(y_test, y_pred))
print('Root Mean Squared Error:', np.sqrt(metrics.mean_squared_error(y_test,␣
 ↪y_pred)))
print('R-Squared:', metrics.r2_score(y_test, y_pred))
print('Adjusted R-Squared:', 1 - (1-metrics.r2_score(y_test,␣
 ↪y_pred))*(len(y_train)-1)/(len(y_train)-X_train.shape[1]-1))
```

```
Mean Absolute Error: 0.02511585765061583
Mean Squared Error: 0.0011778810039069912
Root Mean Squared Error: 0.03432027103487079
R-Squared: 0.8521876267111418
```

```
Adjusted R-Squared: 0.8417362467816265
```

[ ]:

```

```