Introduction

2020 MLB season has already been hard to predict given it's short nature. This research aims to build a perfect model using team batting stats of the past eight years and then use the model to predict which teams' stats on 08/13/2020 is worthy of getting into postseason on a traditional 10-team postseason format.

Methods

Model was built using the combination of 16 team regular season stats:PA, R, H, 2B, 3B, HR, RBI, SB, CS, BB, SO, BA, OBP, SLG, OPS, TB from 2012-2019 and whether that corresponding team went into postseason or not.

Using SQL Server and Python

XGBoost classification model

Step 1: Import data

import regular season stats from MLB teams who got into postseason during 2012-2019

items include Tm, PA, R, H, 2B, 3B, HR, RBI, SB, CS, BB, SO, BA, OBP, SLG, OPS, TB

total rows are 8(years)*10(teams each year)=80

In [1]:

```
import pandas as pd
import pyodbc
sql conn = pyodbc.connect('''DRIVER={ODBC Driver 13 for SQL Server);
                             SERVER=ALLENHO\MSSQLSERVER002;
                             DATABASE=Playoffbound;
                             Trusted Connection=yes''')
query = '''
select Tm, PA, R, H, HR, RBI, SB, CS, BB, SO, BA, OBP, SLG, OPS, TB
from [dbo].['19B$']
where Tm in ('WSN', 'LAD', 'MIL', 'ATL', 'STL', 'HOU', 'NYY', 'MIN', 'TBR', 'OAK')
select Tm, PA, R, H, HR, RBI, SB, CS, BB, SO, BA, OBP, SLG, OPS, TB
from [dbo].['18B$']
where Tm in ('BOS', 'LAD', 'MIL', 'ATL', 'CHC', 'HOU', 'NYY', 'CLE', 'COL', 'OAK')
UNTON ALL
select Tm, PA, R, H, HR, RBI, SB, CS, BB, SO, BA, OBP, SLG, OPS, TB
from [dbo].['17B$']
where Tm in ('BOS', 'LAD', 'COL', 'WSN', 'CHC', 'HOU', 'NYY', 'CLE', 'ARI', 'MIN')
UNION ALL
select Tm, PA, R, H, HR, RBI, SB, CS, BB, SO, BA, OBP, SLG, OPS, TB
from [dbo].['16B$']
where Tm in ('TOR','CLE','BOS','BAL','TEX','NYM','CHC','LAD','WSN','SFG')
UNTON ATIT
select Tm, PA, R, H, HR, RBI, SB, CS, BB, SO, BA, OBP, SLG, OPS, TB
from [dbo].['15B$']
where Tm in ('TOR', 'KCR', 'HOU', 'NYY', 'TEX', 'NYM', 'CHC', 'LAD', 'STL', 'PIT')
select Tm, PA, R, H, HR, RBI, SB, CS, BB, SO, BA, OBP, SLG, OPS, TB
from [dbo].['14B$']
where Tm in ('BAL', 'KCR', 'OAK', 'LAA', 'DET', 'WSN', 'STL', 'LAD', 'PIT', 'SFG')
UNTON ATIT
select Tm, PA, R, H, HR, RBI, SB, CS, BB, SO, BA, OBP, SLG, OPS, TB
from [dbo].['13B$']
where Tm in ('BOS', 'TBR', 'OAK', 'CLE', 'DET', 'ATL', 'STL', 'LAD', 'PIT', 'CIN')
UNION ALL
select Tm, PA, R, H, HR, RBI, SB, CS, BB, SO, BA, OBP, SLG, OPS, TB
from [dbo].['12B$']
where Tm in ('TEX', 'BAL', 'OAK', 'NYY', 'DET', 'ATL', 'STL', 'SFG', 'WSN', 'CIN')
df = pd.read_sql(query, sql_conn)
#stored as df_post
df post = df
```

import regular season stats from MLB teams who DIDN'T get into postseason during 2012-2019 items are the same as above total rows are 8(years)*20(teams each year)=160

In [2]:

```
sql conn = pyodbc.connect('''DRIVER={ODBC Driver 13 for SQL Server};
                             SERVER=ALLENHO\MSSQLSERVER002;
                             DATABASE=Playoffbound;
                             Trusted Connection=yes'
query = '''
select Tm, PA, R, H, HR, RBI, SB, CS, BB, SO, BA, OBP, SLG, OPS, TB
from [dbo].['19B$']
where Tm is not null and Tm not in ('WSN', 'LAD', 'MIL', 'ATL', 'STL', 'HOU', 'NYY', 'MIN', 'TBR', 'OAK', '
UNTON ALL
select Tm, PA, R, H, HR, RBI, SB, CS, BB, SO, BA, OBP, SLG, OPS, TB
from [dbo].['18B$']
where Tm is not null and Tm not in ('BOS', 'LAD', 'MIL', 'ATL', 'CHC', 'HOU', 'NYY', 'CLE', 'COL', 'OAK', '
LgAvg')
UNION ALL
select Tm, PA, R, H, HR, RBI, SB, CS, BB, SO, BA, OBP, SLG, OPS, TB
from [dbo].['17B$']
where Tm is not null and Tm not in ('BOS', 'LAD', 'COL', 'WSN', 'CHC', 'HOU', 'NYY', 'CLE', 'ARI', 'MIN', '
LaAva')
UNION ALL
select Tm, PA, R, H, HR, RBI, SB, CS, BB, SO, BA, OBP, SLG, OPS, TB
from [dbo].['16B$']
where Tm is not null and Tm not in ('TOR','CLE','BOS','BAL','TEX','NYM','CHC','LAD','WSN','SFG', '
LaAva')
UNION ALL
select Tm, PA, R, H, HR, RBI, SB, CS, BB, SO, BA, OBP, SLG, OPS, TB
from [dbo].['15B$']
where Tm is not null and Tm not in ('TOR', 'KCR', 'HOU', 'NYY', 'TEX', 'NYM', 'CHC', 'LAD', 'STL', 'PIT', '
LgAvg')
UNION ALL
select Tm, PA, R, H, HR, RBI, SB, CS, BB, SO, BA, OBP, SLG, OPS, TB
from [dbo].['14B$']
where Tm is not null and Tm not in ('BAL', 'KCR', 'OAK', 'LAA', 'DET', 'WSN', 'STL', 'LAD', 'PIT', 'SFG', '
LgAvg')
UNION ALL
select Tm, PA, R, H, HR, RBI, SB, CS, BB, SO, BA, OBP, SLG, OPS, TB
from [dbo].['13B$']
where Tm is not null and Tm not in ('BOS', 'TBR', 'OAK', 'CLE', 'DET', 'ATL', 'STL', 'LAD', 'PIT', 'CIN', '
LaAva')
UNION ALL
select Tm, PA, R, H, HR, RBI, SB, CS, BB, SO, BA, OBP, SLG, OPS, TB
from [dbo].['12B$']
where Tm is not null and Tm not in ('TEX', 'BAL', 'OAK', 'NYY', 'DET', 'ATL', 'STL', 'SFG', 'WSN', 'CIN', '
LgAvg')
df = pd.read_sql(query, sql_conn)
#stored as df_npost
df npost = df
#add each dataframe a new column named POST, which imply whether the team made the postseason that
vear
df post['POST']= 1
df_npost['POST']= 0
#append two dataframes together
df com=df post.append(df npost)
#take a look at the table we got
print(df com)
                                           RBI
                                                         CS
                                                                         SO
              PΑ
                              Η
                                     HR
                                                   SB
                                                                 BB
Ω
     ATL 6302.0 855.0 1432.0 249.0 824.0
                                                 89.0 28.0 619.0 1467.0
1
     HOII
          6394.0
                  920.0
                         1538.0
                                  288.0
                                         891.0
                                                 67.0
                                                       27.0
                                                              645.0
                                                                     1166.0
2
          6282.0
                  886.0
                         1414.0
                                  279.0
                                         861.0
                                                 57.0
                                                       10.0
                                                              607.0
                                                                    1356.0
         6309.0 769.0 1366.0 250.0
                                        744.0 101.0
                                                       25.0
                                                             629.0 1563.0
     MIL
3
     MIN 6392.0 939.0 1547.0 307.0 906.0
                                                28.0 21.0 525.0 1334.0
          CO14 O
                  CF1 A
                         1010 0
                                 170 0
                                         COO 0
                                                 72 0
                                                       F 0 0
```

```
/3.0 52.0 444.0 1354.0
155 PIT 6014.0 651.0 1313.0 1/0.0 620.0
        6112.0 651.0 1339.0 121.0 610.0 155.0 46.0 539.0 1238.0 6057.0 619.0 1285.0 149.0 584.0 104.0 35.0 466.0 1259.0
156 SDP
157 SEA
158 TBR 6105.0 697.0 1293.0 175.0 665.0 134.0 44.0 571.0 1323.0
159 TOR 6094.0 716.0 1346.0 198.0 677.0 123.0 41.0 473.0 1251.0
       ΒA
            OBP
                  SLG
                         OPS
                                  TB POST
    0.258 0.336 0.452 0.789 2514.0
0
    0.274 0.352 0.495 0.848 2781.0
1
    0.257 0.338 0.472 0.810 2593.0
   0.246 0.329 0.438 0.767 2429.0
   0.270 0.338 0.494 0.832 2832.0
                                         1
155 0.243 0.304 0.395 0.699 2138.0
156 0.247 0.319 0.380 0.699 2060.0
157 0.234 0.296 0.369 0.665 2027.0
                                        0
158 0.240 0.317 0.394 0.711 2128.0
159 0.245 0.309 0.407 0.716 2231.0
[240 rows x 16 columns]
```

Step 2: Train the XGBoost Model

```
In [3]:
```

```
from numpy import loadtxt
from xgboost import XGBClassifier
from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score

# split data into X and y
X = df_com.loc[:,'PA':'TB']
Y = df_com.loc[:,'POST']

# split data into train and test sets
seed = 7
test_size = 0.2
X_train, X_test, y_train, y_test = train_test_split(X, Y, test_size=test_size, random_state=seed)
```

In [4]:

```
# fit model no training data
model = XGBClassifier()
model.fit(X_train, y_train)
print(model)
```

In [5]:

```
# make predictions for test data
y_pred = model.predict(X_test)
predictions = [round(value) for value in y_pred]

# evaluate predictions
accuracy = accuracy_score(y_test, predictions)
print("Accuracy: %.2f%%" % (accuracy * 100.0))
```

Accuracy: 72.92%

Step 3: Make Predictions with XGBoost Model

import 2020 team stats as of 08/14/2020 normalized to 162 games, try to see which teams' stats on 08/13/2020 is worthy of getting

In [6]:

```
import pandas as pd
df 2020=pd.read excel(r'C:\Users\allen\Desktop\Baseball research\Postseason or bust\2020
projection for 0813.xlsx')
df_2020=df_2020.loc[:,['PA162', 'R162', 'H162', 'HR162', 'RBI162', 'SB162', 'CS162', 'BB162', 'S016
2', 'BA', 'OBP', 'SLG', 'OPS', 'TB162']]
df 2020['PA']=df 2020['PA162']
df 2020['R']=df 2020['R162']
df 2020['H']=df 2020['H162']
df 2020['HR']=df 2020['HR162']
df_2020['RBI']=df_2020['RBI162']
df 2020['SB']=df 2020['SB162']
   2020['CS']=df 2020['CS162']
df 2020['BB']=df 2020['BB162']
df 2020['SO']=df 2020['SO162']
df 2020['TB']=df 2020['TB162']
DF_2020=df_2020.loc[:, ['PA','R','H','HR','RBI','SB','CS','BB','SO','BA','OBP','SLG','OPS','TB']]
print(df_2020.head())
                                  H162
                                            HR162
                                                       RBI162
        PA162
                     R162
                                                                    SB162
0 \quad 6096.315789 \quad 750.315789 \quad 1347.157895 \quad 127.894737 \quad 707.684211 \quad 34.105263
1 5977.800000 842.400000 1312.200000 226.800000 826.200000 64.800000
2 \quad 6111.000000 \quad 864.000000 \quad 1467.000000 \quad 243.000000 \quad 846.000000 \quad 63.000000
  6096.315789
               724.736842
                           1415.368421
                                        196.105263 682.105263
                                                               34.105263
  6176.250000 840.375000 1296.000000 232.875000 789.750000 50.625000
                                         BA ...
       CS162
                  BB162
                               SO162
                                                           PΑ
0 \quad 25.578947 \quad 477.473684 \quad 1219.263158 \quad 0.245 \quad \dots \quad 6096.315789 \quad 750.315789
                                             ... 5977.800000 842.400000
  24.300000 526.500000 1644.300000 0.244
  45.000000 513.000000
                         1305.000000 0.269
                                                 6111.000000 864.000000
                                             . . .
                                             ... 6096.315789 724.736842
3 25.578947 426.315789 1492.105263 0.254
4 10.125000 658.125000 1620.000000 0.244
                                             ... 6176.250000 840.375000
                                  RBI
                                              SB
                                                                     BB
            Н
                       HR
                                                         CS
                                      34.105263 25.578947 477.473684
0 1347.157895 127.894737 707.684211
  1312.200000 226.800000 826.200000 64.800000 24.300000 526.500000
2 1467.000000 243.000000 846.000000 63.000000 45.000000 513.000000
3 1415.368421 196.105263 682.105263 34.105263 25.578947 426.315789
4 1296.000000 232.875000 789.750000 50.625000 10.125000 658.125000
            SO
0 1219.263158 2097.473684
1 1644.300000 2349.000000
2 1305.000000 2583.000000
3 1492.105263 2353.263158
  1620.000000 2288.250000
[5 rows x 24 columns]
In [7]:
### Calculate predictions: predictions
predictions 2020 = model.predict(DF 2020)
predictions 2020 = [round(value) for value in predictions 2020]
print (predictions 2020)
```

Result

The model we built has a roughly 72.9% accuracy on training data set(data from 2011-2019). When trying to see which teams' stats on 08/13/2020(normalized to 162 games) are worthy of getting into postseason on a traditional 10-team postseason format, it shows BAL, COL, HOU, LAA, LAD, NYM, NYY, PHI.

Conclusion

Though the list of teams might not be exactly the powerhouse of MLB on 8/13, but we have to keep in mind that this research only considered the offense part of baseball. And it's definitely good to see teams like HOU, LAD, NYY as huge favorite coming into the season making the list.