

# 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

logistic regression  
k-nearest neighbors  
support vector machine  
decision tree  
random forest  
gradient boosting

## 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$']
where Tm in ('WSN','LAD','MIL','ATL','STL','HOU','NYY','MIN','TBR','OAK')
UNION ALL
select Tm, PA, R, H, HR, RBI, SB, CS, BB, SO, BA, OBP, SLG, OPS, TB
from [dbo].['18B$']
where Tm in ('BOS','LAD','MIL','ATL','CHC','HOU','NYY','CLE','COL','OAK')
UNION 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')
UNION ALL
select Tm, PA, R, H, HR, RBI, SB, CS, BB, SO, BA, OBP, SLG, OPS, TB
from [dbo].['15B$']
where Tm in ('TOR','KCR','HOU','NYY','TEX','NYM','CHC','LAD','STL','PIT')
UNION ALL
select Tm, PA, R, H, HR, RBI, SB, CS, BB, SO, BA, OBP, SLG, OPS, TB
from [dbo].['14B$']
where Tm in ('BAL','KCR','OAK','LAA','DET','WSN','STL','LAD','PIT','SFG')
UNION ALL
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$']
where Tm is not null and Tm not in ('WSN','LAD','MIL','ATL','STL','HOU','NYY','MIN','TBR','OAK',' '
LgAvg')
UNION ALL
select Tm, PA, R, H, HR, RBI, SB, CS, BB, SO, BA, OBP, SLG, OPS, TB
from [dbo].['18B$']
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$']
where Tm is not null and Tm not in ('BOS','LAD','COL','WSN','CHC','HOU','NYY','CLE','ARI','MIN',' '
LgAvg')
UNION ALL
select Tm, PA, R, H, HR, RBI, SB, CS, BB, SO, BA, OBP, SLG, OPS, TB
from [dbo].['16B$']
where Tm is not null and Tm not in ('TOR','CLE','BOS','BAL','TEX','NYM','CHC','LAD','WSN','SFG',' '
LgAvg')
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$']
where Tm is not null and Tm not in ('BOS','TBR','OAK','CLE','DET','ATL','STL','LAD','PIT','CIN',' '
LgAvg')
UNION ALL
select Tm, PA, R, H, HR, RBI, SB, CS, BB, SO, BA, OBP, SLG, OPS, TB
from [dbo].['12B$']
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
year
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)

```

	Team	PA	R	H	HR	RBI	SB	CS	BB	SO	\
0	ATL	6302.0	855.0	1432.0	249.0	824.0	89.0	28.0	619.0	1467.0	
1	HOU	6394.0	920.0	1538.0	288.0	891.0	67.0	27.0	645.0	1166.0	
2	LAD	6282.0	886.0	1414.0	279.0	861.0	57.0	10.0	607.0	1356.0	
3	MIL	6309.0	769.0	1366.0	250.0	744.0	101.0	25.0	629.0	1563.0	
4	MIN	6392.0	939.0	1547.0	307.0	906.0	28.0	21.0	525.0	1334.0	
..	...	...	...	...	...	...	...	...	...	...	
155	PIT	6014.0	651.0	1313.0	170.0	620.0	73.0	52.0	444.0	1354.0	
156	SDP	6112.0	651.0	1339.0	121.0	610.0	155.0	46.0	539.0	1238.0	
157	SEA	6057.0	619.0	1285.0	149.0	584.0	104.0	35.0	466.0	1259.0	
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	

	BA	OBP	SLG	OPS	TB	POST
0	0.258	0.336	0.452	0.789	2514.0	1
1	0.274	0.352	0.495	0.848	2781.0	1
2	0.257	0.338	0.472	0.810	2593.0	1
3	0.246	0.329	0.438	0.767	2429.0	1
4	0.270	0.338	0.494	0.832	2832.0	1
..	...	...	...	...	...	...
155	0.243	0.304	0.395	0.699	2138.0	0
156	0.247	0.319	0.380	0.699	2060.0	0
157	0.234	0.296	0.369	0.665	2027.0	0
158	0.240	0.317	0.394	0.711	2128.0	0
159	0.245	0.309	0.407	0.716	2231.0	0

[240 rows x 16 columns]

## Step 2: Train the Models

In [3]:

```
from sklearn.preprocessing import StandardScaler

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

# scale and center numeric columns
X = StandardScaler().fit_transform(X)
```

In [4]:

```
from imblearn.pipeline import Pipeline
from sklearn.model_selection import cross_validate
from sklearn.metrics import f1_score, accuracy_score, log_loss, roc_auc_score, make_scorer
from sklearn.linear_model import LogisticRegression
from sklearn.neighbors import KNeighborsClassifier
from sklearn.svm import SVC
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier, GradientBoostingClassifier
from xgboost import XGBClassifier

# scoring metrics
scoring = {
    'f1_weighted': 'f1_weighted',
    'accuracy': 'balanced_accuracy',
    'roc_auc': 'roc_auc_ovr_weighted',
    'neg_log_loss': 'neg_log_loss'
}

# for results df
eval_cols = [
    'models',
    'F1 Score',
    'Balanced Accuracy',
    'ROC AUC',
    'Neg Log Loss'
]

# define classifier models
classifiers = [
    LogisticRegression(multi_class='multinomial', max_iter=10000),
```

```
LogisticRegression(max_iter=MAX_ITER, max_fun=MAX_FUN,
KNeighborsClassifier(n_neighbors=50),
SVC(probability=True),
DecisionTreeClassifier(),
RandomForestClassifier(),
GradientBoostingClassifier(),
XGBClassifier()
]
```

```
# classifier names
```

```
clf_names = [
    'Logistic Regression',
    'KNN',
    'SVM',
    'Decision Tree',
    'Random Forest',
    'Gradient Boosting',
    'XGBClassifier'
]
```

C:\Users\allen\anaconda3\lib\site-packages\sklearn\externals\six.py:31: FutureWarning: The module is deprecated in version 0.21 and will be removed in version 0.23 since we've dropped support for Python 2.7. Please rely on the official version of six (<https://pypi.org/project/six/>).

"(<https://pypi.org/project/six/>).", FutureWarning)

C:\Users\allen\anaconda3\lib\site-packages\sklearn\utils\deprecation.py:144: FutureWarning: The sklearn.neighbors.base module is deprecated in version 0.22 and will be removed in version 0.24. The corresponding classes / functions should instead be imported from sklearn.neighbors. Anything that cannot be imported from sklearn.neighbors is now part of the private API.

warnings.warn(message, FutureWarning)

In [5]:

```
from imblearn.over_sampling import SMOTE
import time as time
import numpy as np

f1, acc, roc_auc, log_loss = [], [], [], []
for clf, clf_nm in zip(classifiers, clf_names):

    # setup pipeline to oversample, then fit model
    pipe = Pipeline([
        ('smote', SMOTE()),
        ('classify', clf)
    ])

    start = time.time()

    # cross-validate 5 times
    res_smote = cross_validate(pipe, X, Y, cv=5, scoring=scoring)
    results_smote = pd.DataFrame(res_smote)

    stop = time.time()

    print('Time to cross-validate %s = %0.3f min.' % (clf_nm, (stop - start) / 60))

    # save average scores
    f1.append(np.mean(results_smote.test_f1_weighted))
    acc.append(np.mean(results_smote.test_accuracy))
    roc_auc.append(np.mean(results_smote.test_roc_auc))
    log_loss.append(np.mean(results_smote.test_neg_log_loss))

# save results to df
model_eval_smote = pd.DataFrame(data=zip(clf_names, f1, acc, roc_auc, log_loss),
                                columns=eval_cols)

display(model_eval_smote)
```

C:\Users\allen\anaconda3\lib\site-packages\sklearn\utils\deprecation.py:87: FutureWarning: Function safe\_indexing is deprecated; safe\_indexing is deprecated in version 0.22 and will be removed in version 0.24.

warnings.warn(msg, category=FutureWarning)

C:\Users\allen\anaconda3\lib\site-packages\sklearn\utils\deprecation.py:87: FutureWarning: Function safe\_indexing is deprecated; safe\_indexing is deprecated in version 0.22 and will be removed in version 0.24.

warnings.warn(msg, category=FutureWarning)





	models	F1 Score	Balanced Accuracy	ROC AUC	Neg Log Loss
0	Logistic Regression	0.705002	0.706250	0.832812	-0.535090
1	KNN	0.669356	0.696875	0.835547	-0.574364
2	SVM	0.639647	0.631250	0.741797	-0.611696
3	Decision Tree	0.714471	0.687500	0.687500	-9.642188
4	Random Forest	0.728670	0.712500	0.807813	-0.559156
5	Gradient Boosting	0.709187	0.690625	0.789062	-0.628873
6	XGBClassifier	0.733194	0.721875	0.774219	-0.638473

In [6]:

```
import time as time
f1, acc, roc_auc, log_loss = [], [], [], []
for clf, clf_nm in zip(classifiers, clf_names):

    start = time.time()

    # cross-validate 5 times
    res = cross_validate(clf, X, Y, cv=5, scoring=scoring)
    results = pd.DataFrame(res)

    stop = time.time()

    print('Time to cross-validate %s = %0.3f min.' % (clf_nm, (stop - start) / 60))

    # save average scores
    f1.append(np.mean(results.test_f1_weighted))
    acc.append(np.mean(results.test_accuracy))
    roc_auc.append(np.mean(results.test_roc_auc))
    log_loss.append(np.mean(results.test_neg_log_loss))

# save results to df
model_eval = pd.DataFrame(data=zip(clf_names, f1, acc, roc_auc, log_loss),
                           columns=eval_cols)

display(model_eval)
```

Time to cross-validate Logistic Regression = 0.003 min.  
Time to cross-validate KNN = 0.001 min.  
Time to cross-validate SVM = 0.001 min.  
Time to cross-validate Decision Tree = 0.001 min.  
Time to cross-validate Random Forest = 0.027 min.  
Time to cross-validate Gradient Boosting = 0.017 min.  
Time to cross-validate XGBClassifier = 0.005 min.

	models	F1 Score	Balanced Accuracy	ROC AUC	Neg Log Loss
0	Logistic Regression	0.748284	0.715625	0.828516	-0.491554
1	KNN	0.711105	0.675000	0.830469	-0.520010
2	SVM	0.731454	0.684375	0.751563	-0.548995
3	Decision Tree	0.684726	0.650000	0.650000	-10.649576
4	Random Forest	0.708330	0.671875	0.805859	-0.535242
5	Gradient Boosting	0.727597	0.696875	0.792969	-0.623737
6	XGBClassifier	0.734542	0.703125	0.785547	-0.602285

It looks like not performing oversampling is the way to go here. The non-SMOTE'd data built models that slightly outperformed the SMOTE'd models. sklearn defines balanced accuracy as the average of recall on each class. Recall only considers false negatives and true positives -- and since SMOTE creates more data to help a model recognize minority classes, it should reduce false negatives. So, it's no surprise the SMOTE'd data performs better in balanced accuracy.

Overall, the Logistic Regression model was the best.

### Step 3: Make Predictions with Logistic Regression 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 into postseason on a traditional 10-team postseason format.

In [7]:

```
model = LogisticRegression(multi_class='multinomial', max_iter=10000)
model.fit(X, Y)
```

Out[7]:

```
LogisticRegression(C=1.0, class_weight=None, dual=False, fit_intercept=True,
intercept_scaling=1, l1_ratio=None, max_iter=10000,
multi_class='multinomial', n_jobs=None, penalty='l2',
random_state=None, solver='lbfgs', tol=0.0001, verbose=0,
warm_start=False)
```

In [8]:

```
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', 'SO16
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']
df_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())
```

	PA162	R162	H162	HR162	RBI162	SB162	\
0	6096.315789	750.315789	1347.157895	127.894737	707.684211	34.105263	
1	5977.800000	842.400000	1312.200000	226.800000	826.200000	64.800000	
2	6111.000000	864.000000	1467.000000	243.000000	846.000000	63.000000	
3	6096.315789	724.736842	1415.368421	196.105263	682.105263	34.105263	
4	6176.250000	840.375000	1296.000000	232.875000	789.750000	50.625000	

	CS162	BB162	SO162	BA	...	PA	R	\
0	25.578947	477.473684	1219.263158	0.245	...	6096.315789	750.315789	
1	24.300000	526.500000	1644.300000	0.244	...	5977.800000	842.400000	
2	45.000000	513.000000	1305.000000	0.269	...	6111.000000	864.000000	
3	25.578947	426.315789	1492.105263	0.254	...	6096.315789	724.736842	
4	10.125000	658.125000	1620.000000	0.244	...	6176.250000	840.375000	

	H	HR	RBI	SB	CS	BB	\
0	1347.157895	127.894737	707.684211	34.105263	25.578947	477.473684	
1	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	TB
0	1219.263158	2097.473684
1	1644.300000	2349.000000
2	1305.000000	2583.000000
3	1492.105263	2353.263158
4	1620.000000	2288.250000

[5 rows x 24 columns]

In [9]:

```
### Calculate predictions: predictions
predictions_2020 = model.predict(DF_2020)
```



```
predictions_2020 = [round(value) for value in predictions_2020]

print(predictions_2020)
```

```
[1, 0, 0, 0, 0, 0, 1, 1, 0, 0, 1, 0, 1, 0, 1, 1, 0, 0, 0, 1, 0, 1, 0, 1, 0, 0, 0, 1, 0, 0]
```

## Result

When trying to see which teams' offensive stats on 08/13/2020(normalized to 162 games) are worthy of getting into postseason on a traditional 10-team postseason format, it shows ARI, CIN, CLE, HOU, LAA, MIA, MIL, OAK, PIT, SEA, TEX.

## 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 offensive part of baseball.