Predicting HOF Members

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Author: Mitchell vom Scheidt

1 Question: How accurately can we predict MLB Hall of Fame members based on their offensive performance?

1.0.1 Type of Problem: Supervised, Classification Machine Learning

1.0.2 Steps involved in this classification machine learning problem:

1. Find/import the data
2. Data preprocessing
3. Exploratory data analysis (EDA)
4. Feature engineering & selection
5. Model training
6. Model evaluation
7. Conclusion

1.1 Find/Import The Data

Dataset Description:
The data used in this project was taken from baseball reference. Specifically, the dataset contains MLB position players who debuted after 1946 (In order to include non-white players) and played their final game before 2018. Every player in the dataset played in >= 750 games in their career (Since the hall of fame requires members to play at minimum 764 games). The dataset contains 43 features including a wide range of statistics such as batting average (BA), wins above replacement (WAR), home runs (HR), and so on.

Target Variable: 'HOF Status'

[1]:
```
import numpy as np
import pandas as pd
pd.options.display.max_columns = 50

data = pd.read_csv('data/past_player_data.csv')
data.head()
```

[1]:
```
            Player  HOF Status  Suspended  Suspected Steroids   WAR  \
0   Wayne Tolleson       False      False               False   2.3
1   Gary Disarcina       False      False               False  11.2
```

```
2     Darren Lewis       False      False               False  10.5
3     Brian Hunter       False      False               False   7.4
4  Alvaro Espinoza       False      False               False   3.9

   First Season  Last Season  Debut Age  Final Season Age     G    PA    AB  \
0          1981         1990         25                34   863  2614  2322
1          1989         2000         21                32  1086  4032  3744
2          1990         2002         22                34  1354  4654  4081
3          1994         2003         23                32  1000  3659  3347
4          1984         1997         22                35   942  2659  2478

     R     H   1B   2B  3B  HR  xbh  RBI   SB   CS   BB   SO     BA    OBP  \
0  301   559  473   60  17   9   86  133  108   41  219  384  0.241  0.307
1  444   966  732  186  20  28  234  355   47   44  154  306  0.258  0.292
2  607  1021  820  137  37  27  201  342  247  107  403  514  0.250  0.323
3  500   882  683  146  28  25  199  241  260   61  243  581  0.264  0.313
4  252   630  494  105   9  22  136  201   13   19   76  324  0.254  0.279

     SLG    OPS  OPS+    TB  GIDP  HBP   SH  SF  IBB  WAA  oWAR  dWAR  Rbat  \
0  0.293  0.600    66   680    40    8   53  11    0 -6.1   3.3   2.9   -98
1  0.341  0.633    66  1276   105   36   77  21    0 -2.9   5.2  12.8  -164
2  0.322  0.645    73  1313    58   48  101  19    1 -4.5   5.2   6.2  -123
3  0.346  0.660    72  1159    46   13   27  29    1 -4.4   5.1   3.2  -119
4  0.331  0.610    66   819    66   16   73  16    1 -5.1   1.0   7.3  -123

   Rdp  Rbaser  Rbaser + Rdp  Rfield
0    8       3            11      -7
1    2      -1             2      63
2   14       2            16      53
3   11      30            41      27
4   -1       0            -1      31
```

1.2 Data Preprocessing

[2]:

```python
from matplotlib import pyplot as plt
%matplotlib inline
import seaborn as sns
from sklearn.model_selection import train_test_split, GridSearchCV
from sklearn.preprocessing import StandardScaler
from sklearn.metrics import accuracy_score, confusion_matrix
from sklearn.linear_model import LogisticRegression
from sklearn.neighbors import KNeighborsClassifier
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier
```

Due to the real-world bias imposed on players who have been guilty or suspects of steroid use, we can remove those players from our dataset. After which, we can drop the 2 columns relating to this from the dataset.

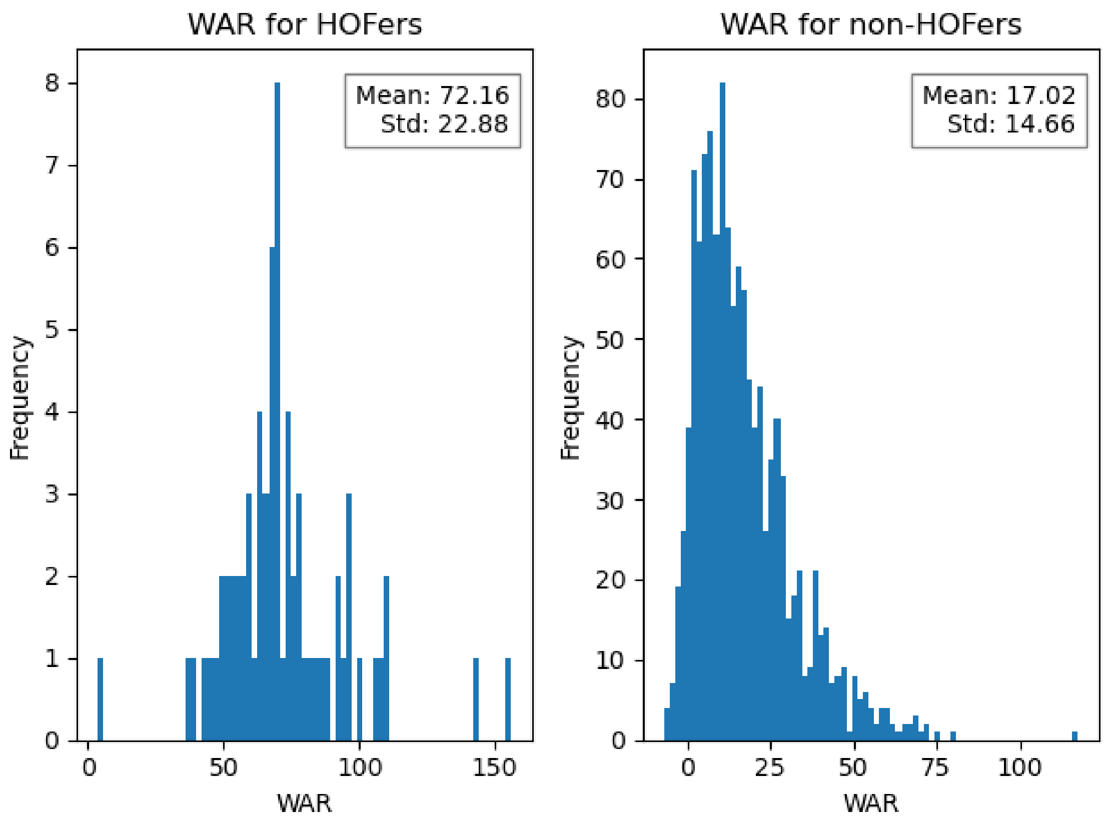
[3]:
```python
data = data[(data['Suspended'] == False) & data['Suspected Steroids'] == False]
data = data.drop(columns=['Suspended', 'Suspected Steroids'])
```

1.3 Exploratory Data Analysis (EDA)

Let's explore how the values of some of the features in our dataset differ between players who are members of the hall of fame, and those which are not.

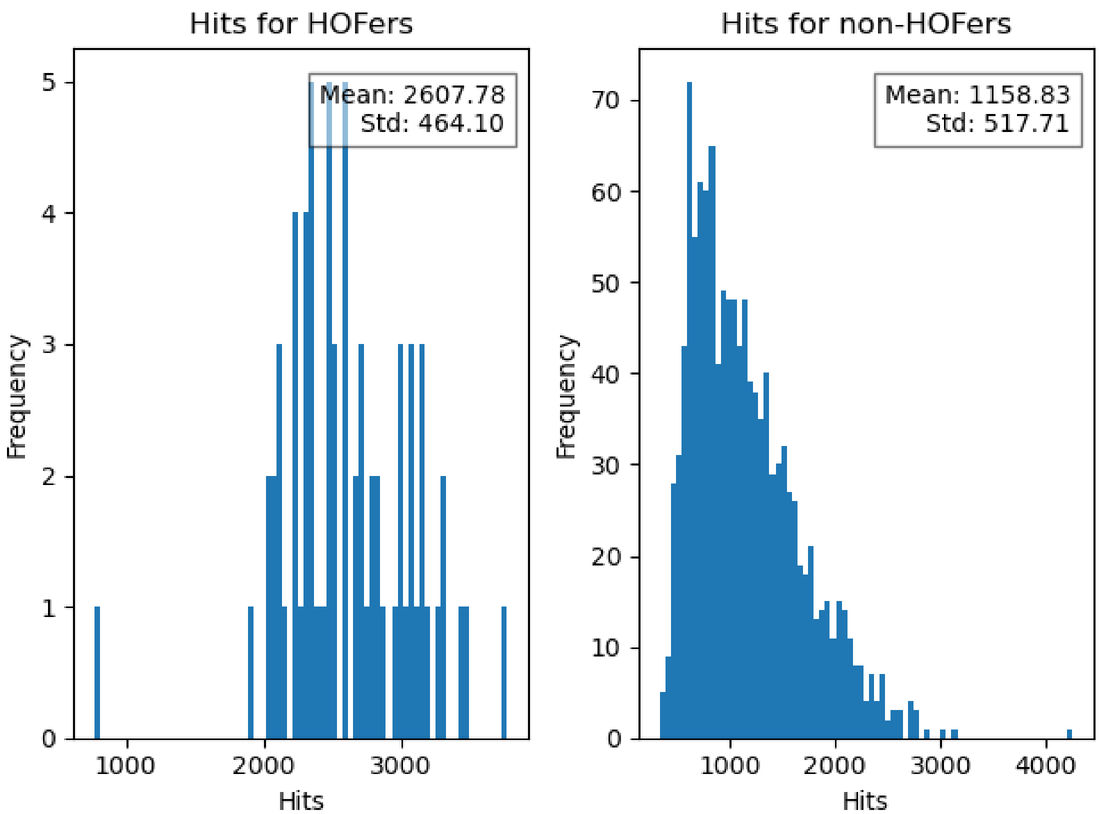
[4]:
```python
# helper function to creating histogram plot
def plotHist(var, bins, title, x_label, y_label):
    plt.hist(var, bins=bins)
    plt.title(title)
    plt.ylabel(y_label)
    plt.xlabel(x_label)
```

[5]:
```python
plt.subplot(1,2,1)
hof_war = data.loc[data['HOF Status'] == True, 'WAR']
# Creating plot
plotHist(hof_war, 75, 'WAR for HOFers', 'WAR', 'Frequency')
mean = np.mean(hof_war)
std = np.std(hof_war)
# Adding mean/std to plot
plt.text(0.95, 0.95, f'Mean: {mean:.2f}\nStd: {std:.2f}',
         transform=plt.gca().transAxes,
         verticalalignment='top',
         horizontalalignment='right',
         bbox=dict(facecolor='white', alpha=0.5))

plt.subplot(1,2,2)
non_hof_war = data.loc[data['HOF Status'] == False, 'WAR']
# Creating plot
plotHist(non_hof_war, 75, 'WAR for non-HOFers', 'WAR', 'Frequency')
mean = np.mean(non_hof_war)
std = np.std(non_hof_war)
# Adding mean/std to plot
plt.text(0.95, 0.95, f'Mean: {mean:.2f}\nStd: {std:.2f}',
         transform=plt.gca().transAxes,
         verticalalignment='top',
         horizontalalignment='right',
         bbox=dict(facecolor='white', alpha=0.5))

plt.tight_layout()
plt.show()
```



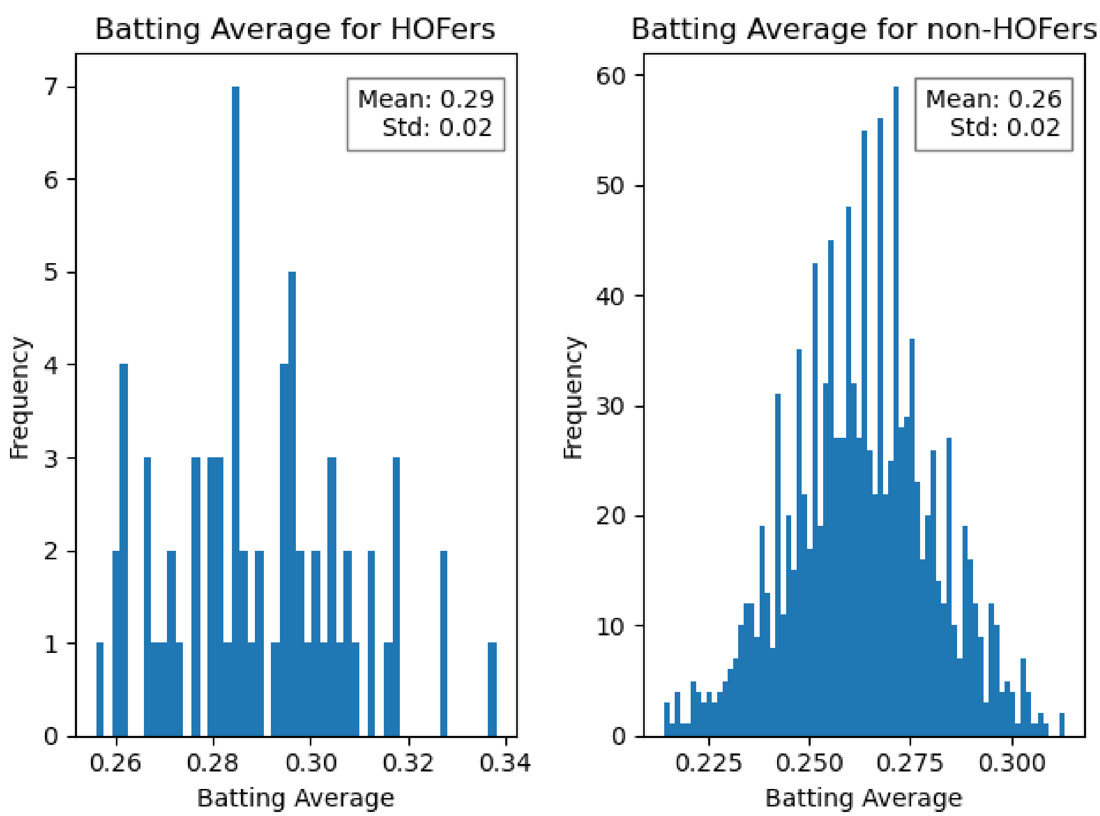
[6]:
```
plt.subplot(1,2,1)
hof_hits = data.loc[data['HOF Status'] == True, 'H']
# Creating plot
plotHist(hof_hits, 75, 'Hits for HOFers', 'Hits', 'Frequency')
mean = np.mean(hof_hits)
std = np.std(hof_hits)
# Adding mean/std to plot
plt.text(0.95, 0.95, f'Mean: {mean:.2f}\nStd: {std:.2f}',
         transform=plt.gca().transAxes,
         verticalalignment='top',
         horizontalalignment='right',
         bbox=dict(facecolor='white', alpha=0.5))

plt.subplot(1,2,2)
non_hof_hits = data.loc[data['HOF Status'] == False, 'H']
# Creating plot
plotHist(non_hof_hits, 75, 'Hits for non-HOFers', 'Hits', 'Frequency')
mean = np.mean(non_hof_hits)
std = np.std(non_hof_hits)
# Adding mean/std to plot
```

```
plt.text(0.95, 0.95, f'Mean: {mean:.2f}\nStd: {std:.2f}',
         transform=plt.gca().transAxes,
         verticalalignment='top',
         horizontalalignment='right',
         bbox=dict(facecolor='white', alpha=0.5))

plt.tight_layout()
plt.show()
```



[7]:
```
plt.subplot(1,2,1)
hof_avg = data.loc[data['HOF Status'] == True, 'BA']
# Creating plot
plotHist(hof_avg, 50, 'Batting Average for HOFers', 'Batting Average',␣
 ↪'Frequency')
mean = np.mean(hof_avg)
std = np.std(hof_avg)
# Adding mean/std to plot
plt.text(0.95, 0.95, f'Mean: {mean:.2f}\nStd: {std:.2f}',
         transform=plt.gca().transAxes,
         verticalalignment='top',
```

```
        horizontalalignment='right',
        bbox=dict(facecolor='white', alpha=0.5))

plt.subplot(1,2,2)
non_hof_avg = data.loc[data['HOF Status'] == False, 'BA']
# Creating plot
plotHist(non_hof_avg, 75, 'Batting Average for non-HOFers', 'Batting Average',␣
 ↪'Frequency')
mean = np.mean(non_hof_avg)
std = np.std(non_hof_avg)
# Adding mean/std to plot
plt.text(0.95, 0.95, f'Mean: {mean:.2f}\nStd: {std:.2f}',
        transform=plt.gca().transAxes,
        verticalalignment='top',
        horizontalalignment='right',
        bbox=dict(facecolor='white', alpha=0.5))

plt.tight_layout()
plt.show()
```



As you can see, for those statistics which are cumulative over a player's entire career, such as WAR and Hits, the average and distribution of the values are drastically different between players which are members of the hall of fame and players which are not. In other words, these plots demonstrate the degree of seperations between the two categories of players.

This will become important when we get to the feature engineering and selection process.

1.4 Feature Engineering & Selection

To start off, I have selected a subset of features which I will use and have discarded the rest of the features.

[8]:
```python
features = ['R', 'H', '1B', '2B', '3B', 'HR', 'xbh', 'RBI', 'SB', 'CS', 'BB',␣
 ↪'IBB', 'SO', 'TB', 'WAR', 'WAA']
other_cols = ['Player', 'HOF Status', 'G', 'BA', 'OBP', 'SLG', 'OPS']

data = data[other_cols + features]

data.head()
```

[8]:
```
            Player  HOF Status     G     BA    OBP    SLG    OPS    R     H  \
0   Wayne Tolleson       False   863  0.241  0.307  0.293  0.600  301   559
1   Gary Disarcina       False  1086  0.258  0.292  0.341  0.633  444   966
2     Darren Lewis       False  1354  0.250  0.323  0.322  0.645  607  1021
3     Brian Hunter       False  1000  0.264  0.313  0.346  0.660  500   882
4  Alvaro Espinoza       False   942  0.254  0.279  0.331  0.610  252   630

    1B   2B  3B  HR  xbh  RBI   SB   CS   BB  IBB   SO    TB   WAR  WAA
0  473   60  17   9   86  133  108   41  219    0  384   680   2.3 -6.1
1  732  186  20  28  234  355   47   44  154    0  306  1276  11.2 -2.9
2  820  137  37  27  201  342  247  107  403    1  514  1313  10.5 -4.5
3  683  146  28  25  199  241  260   61  243    1  581  1159   7.4 -4.4
4  494  105   9  22  136  201   13   19   76    1  324   819   3.9 -5.1
```

Looking back to the EDA process, the feature values are different for the two classes of player (hall of fame & non-hall of fame). To eliminate this effect, I engineered features which average the features over a 162 game season.

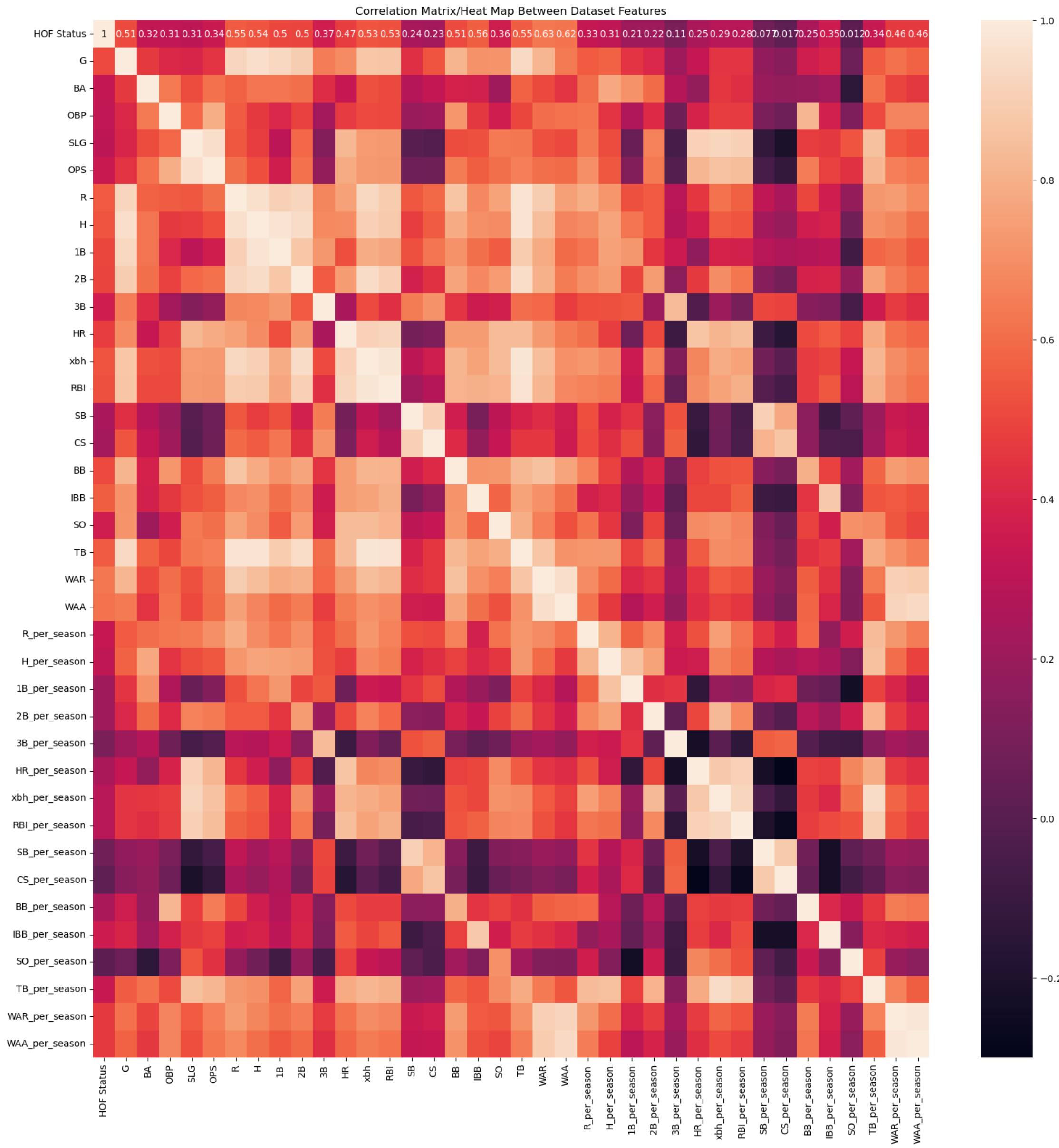
[9]:
```python
for feature in features:
    data[f'{feature}_per_season'] = (data[feature] / data['G']) * 162

data.head()
```

[9]:
```
            Player  HOF Status     G     BA    OBP    SLG    OPS    R     H  \
0   Wayne Tolleson       False   863  0.241  0.307  0.293  0.600  301   559
1   Gary Disarcina       False  1086  0.258  0.292  0.341  0.633  444   966
2     Darren Lewis       False  1354  0.250  0.323  0.322  0.645  607  1021
3     Brian Hunter       False  1000  0.264  0.313  0.346  0.660  500   882
4  Alvaro Espinoza       False   942  0.254  0.279  0.331  0.610  252   630
```

```
    1B   2B  3B  HR  xbh  RBI   SB   CS   BB  IBB   SO    TB   WAR   WAA  \
0  473   60  17   9   86  133  108   41  219    0  384   680   2.3  -6.1
1  732  186  20  28  234  355   47   44  154    0  306  1276  11.2  -2.9
2  820  137  37  27  201  342  247  107  403    1  514  1313  10.5  -4.5
3  683  146  28  25  199  241  260   61  243    1  581  1159   7.4  -4.4
4  494  105   9  22  136  201   13   19   76    1  324   819   3.9  -5.1

   R_per_season  H_per_season  1B_per_season  2B_per_season  3B_per_season  \
0     56.502897    104.933951      88.790267      11.263036       3.191194
1     66.232044    144.099448     109.193370      27.745856       2.983425
2     72.624815    122.158050      98.109306      16.391433       4.426883
3     81.000000    142.884000     110.646000      23.652000       4.536000
4     43.337580    108.343949      84.955414      18.057325       1.547771

   HR_per_season  xbh_per_season  RBI_per_season  SB_per_season  \
0       1.689455       16.143685       24.966396      20.273465
1       4.176796       34.906077       52.955801       7.011050
2       3.230428       24.048744       40.918759      29.552437
3       4.050000       32.238000       39.042000      42.120000
4       3.783439       23.388535       34.566879       2.235669

   CS_per_season  BB_per_season  IBB_per_season  SO_per_season  TB_per_season  \
0       7.696408      41.110081        0.000000      72.083430     127.647740
1       6.563536      22.972376        0.000000      45.646409     190.342541
2      12.802068      48.217134        0.119645      61.497784     157.094535
3       9.882000      39.366000        0.162000      94.122000     187.758000
4       3.267516      13.070064        0.171975      55.719745     140.847134

   WAR_per_season  WAA_per_season
0        0.431750       -1.145075
1        1.670718       -0.432597
2        1.256278       -0.538405
3        1.198800       -0.712800
4        0.670701       -0.877070
```

Looking at a correlation matrix now using a heatmap we can see which features look promising and important to keep.

[10]:
```python
# Creating correlation matrix heatmap
plt.figure(figsize=(20,20))
sns.heatmap(data.corr(numeric_only=True), annot=True)
plt.title('Correlation Matrix/Heat Map Between Dataset Features')
plt.show()
```



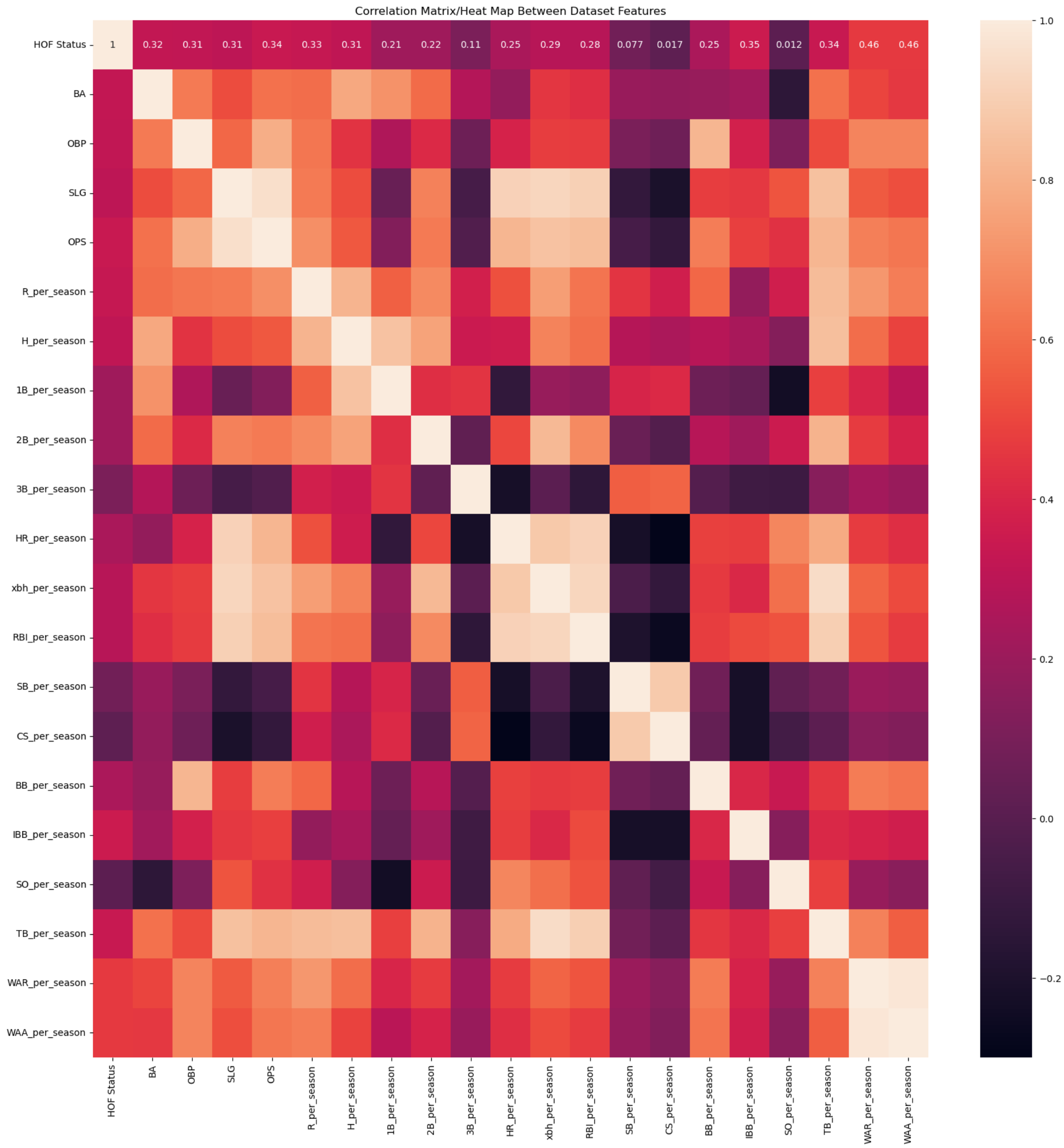

```
[11]: data = data.drop(columns=features + ['G'])
      data.head()
```

```
[11]:              Player  HOF Status     BA    OBP    SLG    OPS  R_per_season  \
      0    Wayne Tolleson       False  0.241  0.307  0.293  0.600     56.502897
      1    Gary Disarcina       False  0.258  0.292  0.341  0.633     66.232044
      2      Darren Lewis       False  0.250  0.323  0.322  0.645     72.624815
      3      Brian Hunter       False  0.264  0.313  0.346  0.660     81.000000
      4  Alvaro Espinoza       False  0.254  0.279  0.331  0.610     43.337580
```

```
   H_per_season  1B_per_season  2B_per_season  3B_per_season  HR_per_season  \
0    104.933951      88.790267      11.263036       3.191194       1.689455
1    144.099448     109.193370      27.745856       2.983425       4.176796
2    122.158050      98.109306      16.391433       4.426883       3.230428
3    142.884000     110.646000      23.652000       4.536000       4.050000
4    108.343949      84.955414      18.057325       1.547771       3.783439

   xbh_per_season  RBI_per_season  SB_per_season  CS_per_season  \
0       16.143685       24.966396      20.273465       7.696408
1       34.906077       52.955801       7.011050       6.563536
2       24.048744       40.918759      29.552437      12.802068
3       32.238000       39.042000      42.120000       9.882000
4       23.388535       34.566879       2.235669       3.267516

   BB_per_season  IBB_per_season  SO_per_season  TB_per_season  \
0      41.110081        0.000000      72.083430     127.647740
1      22.972376        0.000000      45.646409     190.342541
2      48.217134        0.119645      61.497784     157.094535
3      39.366000        0.162000      94.122000     187.758000
4      13.070064        0.171975      55.719745     140.847134

   WAR_per_season  WAA_per_season
0        0.431750       -1.145075
1        1.670718       -0.432597
2        1.256278       -0.538405
3        1.198800       -0.712800
4        0.670701       -0.877070
```

Since we averaged the features in the engineering process on a per season basis, we can remove all the aggregate features and look at the correlation matrix heatmap again.

[12]:
```
# Creating correlation matrix heatmap
plt.figure(figsize=(20,20))
sns.heatmap(data.corr(numeric_only=True), annot=True)
plt.title('Correlation Matrix/Heat Map Between Dataset Features')
plt.show()
```



Lastly, we need to change the 'HOF Status' column of our dataset, which is our target variable, to type integer instead of it being boolean.

[13]:
```python
# Converting boolean column to type integer
data['HOF Status'] = data['HOF Status'].astype(int)

final_data = data
final_data.head()
```

[13]:
```
            Player  HOF Status     BA    OBP    SLG    OPS  R_per_season  \
0   Wayne Tolleson           0  0.241  0.307  0.293  0.600     56.502897
```

```
1   Gary Disarcina           0  0.258  0.292  0.341  0.633     66.232044
2     Darren Lewis           0  0.250  0.323  0.322  0.645     72.624815
3     Brian Hunter           0  0.264  0.313  0.346  0.660     81.000000
4  Alvaro Espinoza           0  0.254  0.279  0.331  0.610     43.337580

   H_per_season  1B_per_season  2B_per_season  3B_per_season  HR_per_season  \
0    104.933951      88.790267      11.263036       3.191194       1.689455
1    144.099448     109.193370      27.745856       2.983425       4.176796
2    122.158050      98.109306      16.391433       4.426883       3.230428
3    142.884000     110.646000      23.652000       4.536000       4.050000
4    108.343949      84.955414      18.057325       1.547771       3.783439

   xbh_per_season  RBI_per_season  SB_per_season  CS_per_season  \
0       16.143685       24.966396      20.273465       7.696408
1       34.906077       52.955801       7.011050       6.563536
2       24.048744       40.918759      29.552437      12.802068
3       32.238000       39.042000      42.120000       9.882000
4       23.388535       34.566879       2.235669       3.267516

   BB_per_season  IBB_per_season  SO_per_season  TB_per_season  \
0      41.110081        0.000000      72.083430     127.647740
1      22.972376        0.000000      45.646409     190.342541
2      48.217134        0.119645      61.497784     157.094535
3      39.366000        0.162000      94.122000     187.758000
4      13.070064        0.171975      55.719745     140.847134

   WAR_per_season  WAA_per_season
0        0.431750       -1.145075
1        1.670718       -0.432597
2        1.256278       -0.538405
3        1.198800       -0.712800
4        0.670701       -0.877070
```

1.5 Model Training

As this is a classification problem, we need to use the appropriate machine learning models. The model's we will compare in this analysis are: 1. Logistic regression 2. K-nearest neighbors classifier 3. Decision tree classifier 4. Random forest classifier

Something important to note in the training process is stratification of the training data. We need to stratify our train/test datasets over the target variable since there are significantly more data entries which are non-hall of fame player than hall-of-fame players. Statifying the data means the proportion of data entries which are non-hall of fame to hall-of-fame is the same for both the train and test datasets.

I am using a 80/20 train/test split.

[14]:
```
X = final_data.drop(columns=['Player', 'HOF Status'])
y = final_data['HOF Status']

# Creating train/test split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,␣
 ↪stratify=y, random_state=42)
```

We need to scale the data in order to standardize the features. We use the sklearn.preprocessing.StandardScaler which uses z-score standardization (z = (x - u) / s). It is necessary to standardize the features to ensure each feature is equally weighted. It also helps models such as logistic regression and k-nearest neighbors to converge faster and perform better.

[15]:
```
# Scaling the data
scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)
```

When training some of the models, there is an opportunity for tuning/optimizing the hyperparameters. in this analysis, I chose to use GridSearchCV (grid search cross-validation), to optimize the hyperparameters for K-NN, Decision Tree, and Random Forest.

Logistic Regression:

[16]:
```
# Creating & training model
reg_model = LogisticRegression(max_iter=10000)
reg_model.fit(X_train_scaled, y_train)
```

[16]:
```
LogisticRegression(max_iter=10000)
```

K-Nearest Neighbors Classifier:

[17]:
```
# Tuning hyperparameter n_nieghbors (k)
knn_model = KNeighborsClassifier()

param_gird = {'n_neighbors': [1,3,5,7,8,11,13,15]}

grid_search = GridSearchCV(estimator=knn_model, param_grid=param_gird, cv=10,␣
 ↪scoring='accuracy')
grid_search.fit(X_train_scaled, y_train)

optimal_n_neighbors = grid_search.best_params_['n_neighbors']
print(f'Optimal number of neighbors: {optimal_n_neighbors}')

# Creating & training model
optimal_knn_model = KNeighborsClassifier(n_neighbors=optimal_n_neighbors)
optimal_knn_model.fit(X_train_scaled, y_train)
```

```
Optimal number of neighbors: 15
```

[17]:
```
KNeighborsClassifier(n_neighbors=15)
```

Decision Tree Classifier:

[18]:
```
# Tuning hyperparameter max_depth
tree_model = DecisionTreeClassifier()

param_grid = {'max_depth': range(1, 20)}

grid_search = GridSearchCV(tree_model, param_grid, cv=10, scoring='accuracy')
grid_search.fit(X_train_scaled, y_train)

optimal_max_depth = grid_search.best_params_['max_depth']
print(f'Optimal max depth: {optimal_max_depth}')

# Creating & training model
optimal_tree_model = DecisionTreeClassifier(max_depth=optimal_max_depth,␣
 ↪random_state=42)
optimal_tree_model.fit(X_train_scaled, y_train)
```

```
Optimal max depth: 1
```

[18]:
```
DecisionTreeClassifier(max_depth=1, random_state=42)
```

Random Forest Classifier:

[19]:
```
# Tuning hyperparameter n_estimators
rf_model = RandomForestClassifier()

param_grid = {'n_estimators': [50, 100, 150, 200]}

grid_search = GridSearchCV(rf_model, param_grid, cv=10, scoring='accuracy')
grid_search.fit(X_train_scaled, y_train)

optimal_n_estimators = grid_search.best_params_['n_estimators']
print(f'Optimal n estimators: {optimal_n_estimators}')

# Creating & training model
optimal_rf_model = RandomForestClassifier(n_estimators=optimal_n_estimators,␣
 ↪random_state=42)
optimal_rf_model.fit(X_train_scaled, y_train)
```

```
Optimal n estimators: 200
```

[19]:
```
RandomForestClassifier(n_estimators=200, random_state=42)
```

1.6 Model Evaluation

For classification problems, there are many ways to evaluate the performance of a model. The ones I will use are: 1. Accuracy 2. Precision 3. Recall 4. F1-Score

[20]:
```
# Logistic Regression
y_pred_reg = reg_model.predict(X_test_scaled)

accuracy_reg = accuracy_score(y_test, y_pred_reg) * 100
conf_matrix_reg = confusion_matrix(y_test, y_pred_reg)
precision_reg = conf_matrix_reg[0,0] / (conf_matrix_reg[0,0] +␣
↪conf_matrix_reg[0,1]) * 100
recall_reg = conf_matrix_reg[0,0] / (conf_matrix_reg[0,0] +␣
↪conf_matrix_reg[1,0]) * 100
f1_reg = 2 * ((precision_reg * recall_reg) / (precision_reg + recall_reg)) / 100

# K-Nearest Neighbors Classifier
y_pred_knn = optimal_knn_model.predict(X_test_scaled)

accuracy_knn = accuracy_score(y_test, y_pred_knn) * 100
conf_matrix_knn = confusion_matrix(y_test, y_pred_knn)
precision_knn = conf_matrix_knn[0,0] / (conf_matrix_knn[0,0] +␣
↪conf_matrix_knn[0,1]) * 100
recall_knn = conf_matrix_knn[0,0] / (conf_matrix_knn[0,0] +␣
↪conf_matrix_knn[1,0]) * 100
f1_knn = 2 * ((precision_knn * recall_knn) / (precision_knn + recall_knn)) / 100

# Decision Tree Classifier
y_pred_tree = optimal_tree_model.predict(X_test_scaled)

accuracy_tree = accuracy_score(y_test, y_pred_tree) * 100
conf_matrix_tree = confusion_matrix(y_test, y_pred_tree)
precision_tree = conf_matrix_tree[0,0] / (conf_matrix_tree[0,0] +␣
↪conf_matrix_tree[0,1]) * 100
recall_tree = conf_matrix_tree[0,0] / (conf_matrix_tree[0,0] +␣
↪conf_matrix_tree[1,0]) * 100
f1_tree = 2 * ((precision_tree * recall_tree) / (precision_tree + recall_tree))␣
↪/ 100

# Random Forest Classifier
y_pred_rf = optimal_rf_model.predict(X_test_scaled)

accuracy_rf = accuracy_score(y_test, y_pred_rf) * 100
conf_matrix_rf = confusion_matrix(y_test, y_pred_rf)
precision_rf = conf_matrix_rf[0,0] / (conf_matrix_rf[0,0] +␣
↪conf_matrix_rf[0,1]) * 100
recall_rf = conf_matrix_rf[0,0] / (conf_matrix_rf[0,0] + conf_matrix_rf[1,0]) *␣
↪100
f1_rf = 2 * ((precision_rf * recall_rf) / (precision_rf + recall_rf)) / 100
```

```
# Creating a dataframe to display the results
results = pd.DataFrame({'Model':
                        ['Logistic Regression', 'K-Nearest Neighbors␣
 ↪Classifier', 'Decision Tree Classifier', 'Random Forest Classifier'],
                        'Accuracy (%)':
                        [accuracy_reg , accuracy_knn, accuracy_tree,␣
 ↪accuracy_rf],
                        'Precision (%)':
                        [precision_reg, precision_knn, precision_tree,␣
 ↪precision_rf],
                        'Recall (%)':
                        [recall_reg, recall_knn, recall_tree, recall_rf],
                        'F1 Score':
                        [f1_reg, f1_knn, f1_tree, f1_rf]
                       })

results
```

[20]:

```
                              Model  Accuracy (%)  Precision (%)  Recall (%)  \
0               Logistic Regression     94.531250      97.520661   96.721311
1  K-Nearest Neighbors Classifier     95.312500      99.586777   95.634921
2          Decision Tree Classifier     92.578125      95.041322   97.046414
3          Random Forest Classifier     94.921875      98.347107   96.356275

   F1 Score
0  0.971193
1  0.975709
2  0.960334
3  0.973415
```

1.7 Conclusion

The table above containing the various evalaution tools gives us a lot of insight. From it, we can tell: 1. Best overall model: K-Nearest Neighbors Classifier - Highest accuracy, precision, and F1 score 2. Highest Precision: K-Nearest Neighbors Classifier - Best for applications of minimizing false positives is needed 3. Highest Recall: Decision Tree Classifier - Best for applications where maximizing true positives is needed 4. Highest F1 Score: K-Nearest Neighbors Classifier - Best for applications where balancing precision and recall is needed

Overall, KNN came out to be the most effective model. Meaning it generalizes to new data well, and it is likely to perform reliably accross different datasets. This project is a demonstration of key aspects of machine learning in general, however the model created could be used for, or tweaked slightly to then be used for, player analytics within baseball. That is, the evaluation of players to determine predicted future performance, and the suggested value of a given player.