Soccer-Insights using ML

June 1, 2018

1 CSE-891 PROJECT: IDENTIFYING FACTORS CRITICAL FOR RESULTS IN THE ENGLISH PREMIER LEAGUE GAMES

1.0.1 IMPORTING NECESSARY LIBRARIES

I first import all the necessary libraries required for this notebook. As different parts of the notebook was completed, the libraries were consolidated in this location

```
In [1]: %pylab inline
```

```
Populating the interactive namespace from numpy and matplotlib
```

```
In [ ]: import json
        import seaborn as sns
        import pandas as pd
        import numpy as np
        import datetime
        from sklearn.model_selection import train_test_split
        from sklearn import tree
        from sklearn.metrics import accuracy_score
        from sklearn import cross_validation
        from sklearn.ensemble import RandomForestClassifier, RandomForestRegressor
        from sklearn import linear_model
        from sklearn.metrics import confusion_matrix
        from sklearn.feature_selection import RFE
        from sklearn.externals.six import StringIO
        from IPython.display import Image
        from sklearn.tree import export_graphviz
        import pydotplus
        pd.options.mode.chained_assignment = None
```

The main objectives of this project that I need to show: 1. API 1.1 EPL CSV 2015-2017 as Training and 2018 as Test Case 1.2 EPL Players 2018 1.3 LaLiga CSV 2018 1.4 Bundesliga CSV 2018

2. Show data transformation and preprocessing 2.1 Dictionary 2.2 Dictionary to PD 2.3 Changing column types 2.4 Changing to CSV

3. Loading CSV
4. Running different regression models
5. Finding the best models

Getting the EPL 2015-16 season data

1.1 DATA EXTRACTION AND PREPROCESSING

I create a function that I need to loop through dates. I require this for the API which gathers data for games based on dates. The daterange function uses 2 inputs: start and end date. It then calculates all the dates in between those with a step of 1 day until the end. The start date takes year, month and day as numerical arguments.

```
In [ ]: #create date function to loop through the API, it takes the start and end date as inpu
        def daterange( start_date, end_date ):
            if start_date <= end_date:
                for n in range( ( end_date - start_date ).days + 1 ):
                    yield start_date + datetime.timedelta( n )
            else:
                for n in range( ( start_date - end_date ).days + 1 ):
                    yield start_date - datetime.timedelta( n )
```

I create 2 empty pandas data frames to store all the games from the 2015 and 2016 seasons.

```
In [3]: #initialize empty dataframes
        epl_15_16=pd.DataFrame()
        epl_16_17=pd.DataFrame()
```

Here I extract data for all the data for all the games from 2015-2016. I input the year, month and days between which to gather the games data. For the API, I enter a subscription key, the format for data output (JSON). I then append the day to the request and run all the requests. I store all the data into a dataframe.

```
In [ ]: #specify start and end date and run the API
        start = datetime.date(year = 2015, month = 8, day = 7)
        end = datetime.date(year = 2016, month = 5, day = 18)
        import http.client, urllib.request, urllib.parse, urllib.error, base64
        for date in daterange(start, end):

            headers = {
                    # Request headers and add subscription key
                'Ocp-Apim-Subscription-Key': '8071cba1b2f140bc9cf342fbd2c76c23',
            }

            params = urllib.parse.urlencode({
            })

            try:
```

```
                conn = http.client.HTTPSConnection('api.fantasydata.net')
                #get data in json format, append the date as a link
                conn.request("GET", "/v3/soccer/stats/json/TeamGameStatsByDate/"+ str(date
                response = conn.getresponse()
                data = response.read()
                print(data)
                conn.close()
        except Exception as e:
                print("[Errno {0}] {1}".format(e.errno, e.strerror))

        game_data=json.loads(data.decode('utf-8'))
        game_df=pd.DataFrame.from_dict(game_data,orient='columns')
        epl_15_16=pd.concat([game_df, epl_15_16])
```

```
In [ ]: epl_15_16.to_csv('FullData15_16.csv')
```

I create an empty dataframe for the 2017-18 data. I then repeat the same procedure to get all the games from this season.

```
In [4]: #create empty data frame for 2017-18 data
        FullData17_18=pd.DataFrame()
```

```
In [ ]: start = datetime.date(year = 2017, month = 8, day = 10)
        end = datetime.date(year = 2018, month = 5, day = 3)
        import http.client, urllib.request, urllib.parse, urllib.error, base64
        for date in daterange(start, end):

            headers = {
                    # Request headers
                'Ocp-Apim-Subscription-Key': '9a5653a951ad41f4a1c020100b14b2b8',
            }

            params = urllib.parse.urlencode({
            })

            try:
                    conn = http.client.HTTPSConnection('api.fantasydata.net')
                    conn.request("GET", "/v3/soccer/stats/json/TeamGameStatsByDate/"+ str(date
                    response = conn.getresponse()
                    data1718 = response.read()
                    print(data1718)
                    conn.close()
            except Exception as e:
                    print("[Errno {0}] {1}".format(e.errno, e.strerror))

            game_data1718=json.loads(data1718.decode('utf-8'))
            game_df1718=pd.DataFrame.from_dict(game_data1718,orient='columns')
            FullData17_18=pd.concat([game_df1718, FullData17_18])
```

I append the data to a csv file for later usage.

```
In [ ]: FullData17_18.to_csv('FullData17_18.csv')
```

Here I extract the data that provides me information regarding the RoundId for different leagues and different seasons. I receive the following:

For 2015/16 EPL - 1
For 2016/17 EPL - 73
For 2017/18 EPL - 144
For 2017/18 LaLiga - 182
For 2017/18 Bundesliga - 145

```
In [ ]: import http.client, urllib.request, urllib.parse, urllib.error, base64

        headers = {
            # Request headers
            'Ocp-Apim-Subscription-Key': '8071cba1b2f140bc9cf342fbd2c76c23',
        }

        params = urllib.parse.urlencode({
        })

        try:
            conn = http.client.HTTPSConnection('api.fantasydata.net')
            conn.request("GET", "/v3/soccer/stats/json/Competitions?%s" % params, "{body}", hea
            response = conn.getresponse()
            leagues = response.read()
            print(leagues)
            conn.close()
        except Exception as e:
            print("[Errno {0}] {1}".format(e.errno, e.strerror))
```

This API is to extract data for player performance. This API gives player stats for the entire 2017-18 season. For this API I have to enter the file format - json and the Round Id - 144 (refers to season for a particular league)

```
In [ ]: headers = {
            # Request headers
            'Ocp-Apim-Subscription-Key': '8071cba1b2f140bc9cf342fbd2c76c23',
        }

        params = urllib.parse.urlencode({
        })

        try:
            conn = http.client.HTTPSConnection('api.fantasydata.net')
            conn.request("GET", "/v3/soccer/stats/json/PlayerSeasonStats/144?%s" % params, "{bo
            response = conn.getresponse()
            players = response.read()
```

```
        print(players)
        conn.close()
    except Exception as e:
        print("[Errno {0}] {1}".format(e.errno, e.strerror))
```

I convert the json data dump from the API to a dictionary first using the json.load function with utf-8 decoder. I then convert the dictionary into a pandas df using pandas library and finally store it as csv for later use.

```
In [ ]: #store data into dictionary then convert to df
        dict_players_epl=json.loads(players.decode('utf-8'))
        players_epl_df=pd.DataFrame.from_dict(dict_players_epl,orient='columns')
        players_epl_df.to_csv('Players_EPL_17_18.csv')
        players_epl_df.head()
```

Here I read into a pandas df all the data that I gathered from the API and stored in the csv

```
In [ ]: #Load all data as initial csv
        epl_15_16=pd.read_csv('epl_15_16.csv')
        epl_16_17=pd.read_csv('epl_16_17.csv')
        FullData17_18=pd.read_csv('FullData17_18.csv')
```

The API free trial provides scrambled data. So some data points are higher/lower by 10%. I select all the float/int columns, drop any columns with null values (none), convert all columns to int format. In the second set of code, I create class labels for goals scored, goals against, goals against unique

```
In [ ]: #look for only float and int type columns and convert all float to int
        epl_15_16_1=epl_15_16.select_dtypes(include=['float64','int64'])
        epl_15_16_Final=epl_15_16_1.dropna(axis=1,how='any')
        epl_15_16_Final=epl_15_16_Final.astype('int64')

        epl_16_17_1=epl_16_17.select_dtypes(include=['float64','int64'])
        epl_16_17_Final=epl_16_17_1.dropna(axis=1,how='any')
        epl_16_17_Final=epl_16_17_Final.astype('int64')

        FullData17_18_1=FullData17_18.select_dtypes(include=['float64','int64'])
        FullData17_18_Final=FullData17_18_1.dropna(axis=1,how='any')
        FullData17_18_Final=FullData17_18_Final.astype('int64')

        #create empty labels for goal against, goal for, goal against discrete
        epl_15_16_Final['goal_against_label']=[0]*len(epl_15_16_Final)
        epl_15_16_Final['GA_unique_label']=[0]*len(epl_15_16_Final)
        epl_15_16_Final['goal_label']=[0]*len(epl_15_16_Final)
        epl_16_17_Final['goal_against_label']=[0]*len(epl_16_17_Final)
        epl_16_17_Final['GA_unique_label']=[0]*len(epl_16_17_Final)
        epl_16_17_Final['goal_label']=[0]*len(epl_16_17_Final)
        FullData17_18_Final['goal_against_label']=[0]*len(FullData17_18_Final)
        FullData17_18_Final['GA_unique_label']=[0]*len(FullData17_18_Final)
```

```
FullData17_18_Final['goal_label']=[0]*len(FullData17_18_Final)

array(FullData17_18_Final.columns.values)
```

The function specified below takes a df and changes the values in the labels. I have three labels: 1. goal_against_label - 1 if goal was allowed, 0 if goal wasn't 2. GA_unique_label - value of goals allowed upto less than 3, then everything is 3 3. Goals - value of goals scored upto less than 3, then everything is 3

The 3 value was selected based on density distribution of these labels shown in the exploration section

```
In [ ]: #function for goal against, if goal is conceded,, then 0 else 1
        def goalagainst(df):
            for i in range(len(df)):
                pd.options.mode.chained_assignment = None
                if df['GoalkeeperGoalsAgainst'][i]<1:
                    df['goal_against_label'][i]=0
                else:
                    df['goal_against_label'][i]=1

        #function for goal against, if goal is conceded then 0,1,2 depending on how many, else
        def goalagainstunique(df):
            for i in range(len(df)):
                pd.options.mode.chained_assignment = None
                if df['GoalkeeperGoalsAgainst'][i]<3:
                    df['GA_unique_label'][i]=df['GoalkeeperGoalsAgainst'][i]
                else:
                    df['GA_unique_label'][i]=3
        #function for goal scored, if goal is scored then 0,1,2 depending on how many, else 3
        def goals(df):
            for i in range(len(df)):
                pd.options.mode.chained_assignment = None
                if df['Goals'][i]<3:
                    df['goal_label'][i]=df['Goals'][i]
                else:
                    df['goal_label'][i]=3
```

I run the functions on the three datasets of concern and then store the data into csv for later use

```
In [ ]: #run the above functions on the 2015, 16, 17 premier league data
        goalagainst(epl_15_16_Final)
        goalagainst(epl_16_17_Final)
        goalagainst(FullData17_18_Final)

        goalagainstunique(epl_15_16_Final)
        goalagainstunique(epl_16_17_Final)
        goalagainstunique(FullData17_18_Final)
```

```
goals(epl_15_16_Final)
goals(epl_16_17_Final)
goals(FullData17_18_Final)
```

In [ ]:
```
#save the data into csv again
epl_15_16_Final.to_csv('Data_1516.csv')
epl_16_17_Final.to_csv('Data_1617.csv')
FullData17_18_Final.to_csv('Data_1718.csv')
```

In [5]:
```
#read in the data
epl_15_16_Final=pd.read_csv('Data_1516.csv')
epl_16_17_Final=pd.read_csv('Data_1617.csv')
FullData17_18_Final=pd.read_csv('Data_1718.csv')
```

The data set for the 3 seasons contains games for all leagues. I am only interested in the english premier league as the style of play differs depening on the leagues. I use the loc function to look for all games with RoundID=1 which refers to (EPL, 15/16 season). I then select only the columns of interest (int columns) and labels. I do this for all three seasons and then verify my results. Each season 380 games are played and per game I should have 2 rows (one for each team). For 17/18 season, 354 games have been played as of May 1, 2018.

In [6]:
```
#Data updated as of May 1, 2018
EPL_2015_2016=epl_15_16_Final.loc[epl_15_16_Final['RoundId']==1]
EPL_2015_2016=EPL_2015_2016[['Assists', 'BlockedShots', 'CornersWon', 'Crosses','Fouled
                             'Fouls','GoalkeeperSaves','Goals', 'Interceptions', 'LastM
                             'Offsides', 'Passes','PassesCompleted', 'PenaltiesConceded
                             'PenaltiesWon', 'PenaltyKickMisses', 'PenaltyKickSaves','R
                             'Shots', 'ShotsOnGoal','TacklesWon','Touches','YellowCards
                             'goal_against_label','GA_unique_label', 'goal_label']]


EPL_2016_2017=epl_16_17_Final.loc[epl_16_17_Final['RoundId']==73]
EPL_2016_2017=EPL_2016_2017[['Assists', 'BlockedShots', 'CornersWon', 'Crosses','Fouled
                             'Fouls','GoalkeeperSaves','Goals', 'Interceptions', 'LastM
                             'Offsides', 'Passes','PassesCompleted', 'PenaltiesConceded
                             'PenaltiesWon', 'PenaltyKickMisses', 'PenaltyKickSaves','R
                             'Shots', 'ShotsOnGoal','TacklesWon','Touches','YellowCards
                             'goal_against_label','GA_unique_label', 'goal_label']]


EPL_2017_2018=FullData17_18_Final.loc[FullData17_18_Final['RoundId']==144]
EPL_2017_2018=EPL_2017_2018[['Assists', 'BlockedShots', 'CornersWon', 'Crosses','Fouled
                             'Fouls','GoalkeeperSaves','Goals', 'Interceptions', 'LastM
                             'Offsides', 'Passes','PassesCompleted', 'PenaltiesConceded
                             'PenaltiesWon', 'PenaltyKickMisses', 'PenaltyKickSaves','R
                             'Shots', 'ShotsOnGoal','TacklesWon','Touches','YellowCards
                             'goal_against_label','GA_unique_label', 'goal_label']]
```

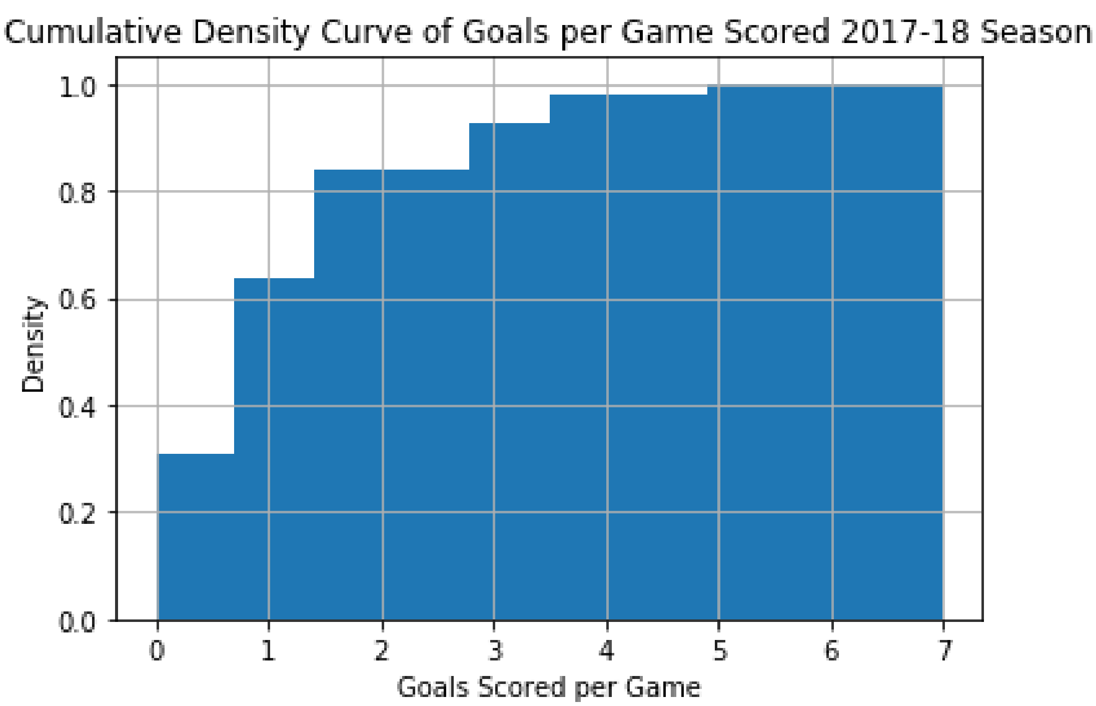
I create another dataset using the approach above. These ones I will use to classify wins/losses later.

```
In [7]: EPL_2017_2018_all=FullData17_18_Final.loc[FullData17_18_Final['RoundId']==144]
        EPL_2017_2018_WL=EPL_2017_2018_all[['Assists', 'BlockedShots', 'CornersWon', 'Crosses'
                                    'Fouls','GoalkeeperGoalsAgainst','GoalkeeperSaves','Goals
                                    'Offsides', 'Passes','PassesCompleted', 'PenaltiesConcede
                                    'PenaltiesWon', 'PenaltyKickMisses', 'PenaltyKickSaves','
                                    'Shots', 'ShotsOnGoal','TacklesWon','Touches','YellowCard
                                    'goal_against_label','GA_unique_label', 'goal_label']]

        EPL_2015_2016_all=epl_15_16_Final.loc[epl_15_16_Final['RoundId']==1]
        EPL_2015_2016_WL=EPL_2015_2016_all[['Assists', 'BlockedShots', 'CornersWon', 'Crosses'
                                    'Fouls','GoalkeeperGoalsAgainst','GoalkeeperSaves','Goals
                                    'Offsides', 'Passes','PassesCompleted', 'PenaltiesConcede
                                    'PenaltiesWon', 'PenaltyKickMisses', 'PenaltyKickSaves','
                                    'Shots', 'ShotsOnGoal','TacklesWon','Touches','YellowCard
                                    'goal_against_label','GA_unique_label', 'goal_label']]
```

2 DATA EXPLORATION

I use a histogram with a density to see the density distribution of goals scored per game in 17/18 season. About 85% of the time, 2 or less goals are scored by a team in a game.

```
In [8]: EPL_2017_2018_WL.Goals.hist(density=True, cumulative=True)
        plt.title('Cumulative Density Curve of Goals per Game Scored 2017-18 Season')
        plt.xlabel('Goals Scored per Game')
        plt.ylabel('Density')

Out[8]: Text(0,0.5,'Density')
```



I use a histogram with a density to see the density distribution of goals allowed per game in 17/18 season. About 85% of the time, 2 or less goals are conceded by a team in a game.

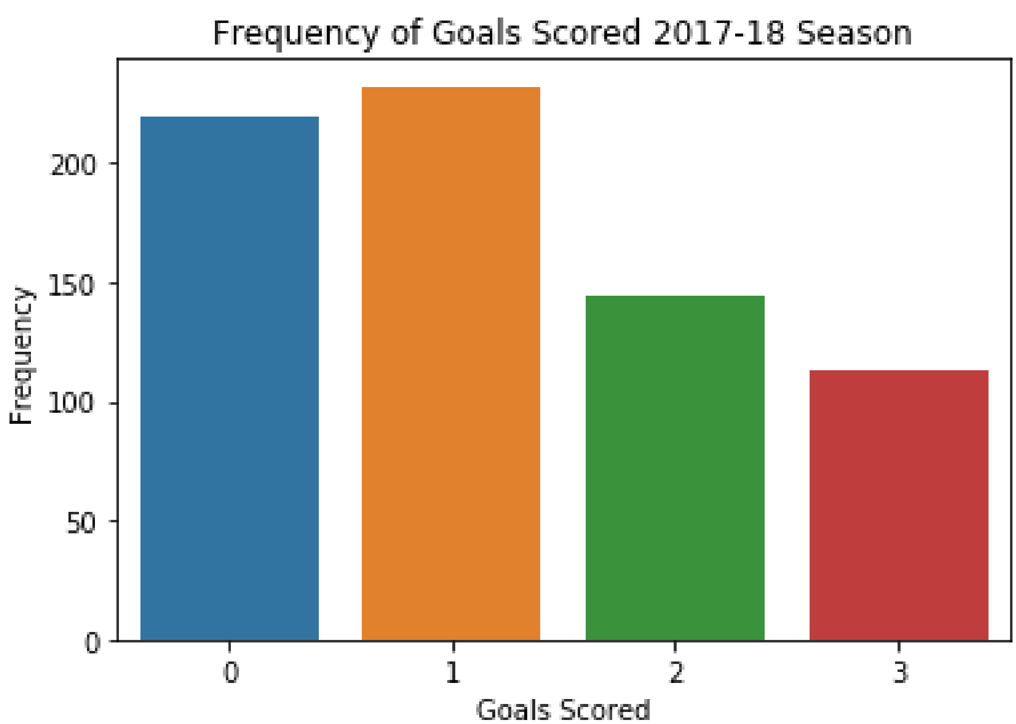
```
In [ ]: EPL_2017_2018_WL.GoalkeeperGoalsAgainst.hist(density=True, cumulative=True)
        plt.title('Cumulative Density Curve of Goals Allowed per Game 2017-18 Season')
        plt.xlabel('Goals Scored per Game')
        plt.ylabel('Density')
```

I wanted to check the frequency of labels for goal against. I conclude that the data and therefore outcomes are imbalanced. There are way more games where a goal is scored as opposed to games where a goal is not scored

```
In [ ]: sns.countplot(x='goal_against_label',data=EPL_2017_2018_WL)
        plt.title('Frequency of Goals Scored 2017-18 Season')
        plt.xlabel('Goals Scored')
        plt.ylabel('Frequency')
```

Visualization of the count by label for 2017/18 premier leagues season

```
In [16]: sns.countplot(x='goal_label',data=EPL_2017_2018_WL)
         plt.title('Frequency of Goals Scored 2017-18 Season')
         plt.xlabel('Goals Scored')
         plt.ylabel('Frequency')

Out[16]: Text(0,0.5,'Frequency')
```



2.1 REGRESSION ANALYSIS AND MODEL SELECTION FOR PREDICTIONS

2.1.1 PREDICTING CLEAN SHEETS

After preparing my datasets, I run some classification to see how accurately I can predict clean sheets (i.e. a team concedes 0 goals) The approach is as follows: 1. Start with 2015/16 data and split into train/test sets 2. Run various regression and classification models and find the best 3. Use the entire 2015/16 data as training set to check accuracy on the 2017-18 data. 4. Optimize the model

I start by creating my X matrix (predictors) and Y(outcome). I split the dataset into test and train using the function below. I try: 1. Logistic Regression 2. Decision Tree 3. Random Forest

```
In [9]: X = EPL_2015_2016.drop(columns=['goal_against_label','goal_label','GA_unique_label'])
        y = EPL_2015_2016['goal_against_label']

        X_train, X_test, y_train, y_test = train_test_split(X, y, random_state=1)
```

I define my models here for each classifier

```
In [10]: logreg = linear_model.LogisticRegression()
         dectree = tree.DecisionTreeClassifier()
         random_forest = RandomForestClassifier(n_estimators=30, max_depth=10, random_state=1)
```

I train a logistic regression model with the training set and make predictions with the test dataset. The outcome is 57.4% accuracy. More interestingly, 1 is easier and better to predict than 0. I create a confusion matrix to visualize the accuracy of different outcomes.

```
In [11]: logreg.fit(X_train,y_train)
         y_predict = logreg.predict(X_test)
         print(round(accuracy_score(y_test, y_predict),3))

         pd.DataFrame(
             confusion_matrix(y_test, y_predict),
             columns=['Predicted 0', 'Predicted 1'],
             index=['True 0', 'True 1'])
```

```
0.574
```

Out[11]:

	Predicted 0	Predicted 1
True 0	11	59
True 1	22	98

I train a decision tree with the training set and make predictions with the test dataset. The outcome is 53.2% accuracy. More interestingly, 1 is easier and better to predict than 0. I create a confusion matrix to visualize the accuracy of different outcomes.

```
In [12]: dectree.fit(X_train,y_train)
         y_predict = dectree.predict(X_test)
         print(round(accuracy_score(y_test, y_predict),3))
```

```
pd.DataFrame(
    confusion_matrix(y_test, y_predict),
    columns=['Predicted 0', 'Predicted 1'],
    index=['True 0', 'True 1'])
```

```
0.553
```

```
Out[12]:         Predicted 0  Predicted 1
         True 0           29           41
         True 1           44           76
```

I train a random forest classifier model with the training set and make predictions with the test dataset. The outcome is 61.1% accuracy. The random forest produces the best results for me.

```
In [13]: random_forest.fit(X_train,y_train)
         y_predict = random_forest.predict(X_test)
         print(round(accuracy_score(y_test, y_predict),3))
         pd.DataFrame(
             confusion_matrix(y_test, y_predict),
             columns=['Predicted 0', 'Predicted 1'],
             index=['True 0', 'True 1'])
```

```
0.611
```

```
Out[13]:         Predicted 0  Predicted 1
         True 0            8           62
         True 1           12          108
```

I utilize the models on 2016/17 and 2017/18 data and results are consistent. Random forest is the best model. The accuracy is as follows:
LogReg - 0.72
Decision Tree Classifier - 0.63
Random Forest - 0.72

Random Forest Performs best for all years. However, all the models are equally bad at predicting 0 goals while really good at predicting goals scored. I have narrowed the scope on to random forest and will to optimize the random forest I first create a large training data set by combining the 2015/16 and 2016/17 data. With a large training dataset, I expect to train with a variety of outcomes.

```
In [14]: big=EPL_2015_2016.append(EPL_2016_2017,ignore_index=True)
         X_big = big.drop(columns=['goal_against_label','goal_label','GA_unique_label'])
         y_big = big['goal_against_label']
```

```
In [15]: print(len(X_big))
         X1_train,X1_test,y1_train,y1_test=train_test_split(X_big,y_big,stratify=y_big)
```

```
1520
```

My test dataset will be the 2017/18 data

```
In [16]: X_final = EPL_2017_2018.drop(columns=['goal_against_label','goal_label','GA_unique_lal
         y_final = EPL_2017_2018['goal_against_label']
```

Fitting the random forest to the 2017/18 data produces an accuracy of 67%. Here i try to use a set of parameters within the random forest classifier that would best predict the desired outcome.

```
In [17]: forest = RandomForestClassifier(n_estimators=30, max_depth=5, random_state=42)
         forest.fit(X1_train,y1_train)
         y_predict = forest.predict(X1_test)
         print(round(accuracy_score(y1_test, y_predict),3))
         pd.DataFrame(
             confusion_matrix(y1_test, y_predict),
             columns=['Predicted 0', 'Predicted 1'],
             index=['True 0', 'True 1'])
```

```
0.671
```

Out[17]:

	Predicted 0	Predicted 1
True 0	5	118
True 1	7	250

The goal now is to optimize the random forest model. I start with feature selection to remove the undesired predictors and focus on the best possible set of predictors. This is also important as a less number of variables will make it easy for me to select players later. To do this, I use the RFE function within Sklearn library which essentially uses backward elimination to provide the predictors that best suit the model. It then provides me the support and ranking for the different predictors

```
In [18]: rfe = RFE(forest)
         rfe = rfe.fit(X_big,y_big)
         print(rfe.support_)
         print(rfe.ranking_)
```

```
[False False  True  True False False False False  True False False  True
  True  True False False False False  True  True  True  True  True]
[ 8  7  1  1  4  2  3  6  1  9  5  1  1  1 12 13 11 10  1  1  1  1  1]
```

I drop the False terms and continue with the selected terms.

```
In [ ]: X1_big_new=X_big.iloc[:, [2,3,8,11,12,13,18,19,20,21,22]]
        X1_big_new.head()
```

I run the random forest again and get an accuracy of 66%, only 1% lower but way less predictors. I also noticed the impact of the number of estimators and max depth that i use.

```
In [20]: X1_train,X1_test,y1_train,y1_test=train_test_split(X1_big_new,y_big,stratify=y_big)
         forest = RandomForestClassifier(n_estimators=30, max_depth=5, random_state=42)
         forest.fit(X1_train,y1_train)
         y_predict = forest.predict(X1_test)
         print(round(accuracy_score(y1_test, y_predict),3))
         pd.DataFrame(
             confusion_matrix(y1_test, y_predict),
             columns=['Predicted 0', 'Predicted 1'],
             index=['True 0', 'True 1'])
```

```
0.676
```

```
Out[20]:         Predicted 0  Predicted 1
         True 0            4          119
         True 1            4          253
```

```
In [ ]: X1_final=X_final.iloc[:, [2,3,8,11,12,13,18,19,20,21,22]]

        X1_final.head()
```

```
In [22]: forest
```

```
Out[22]: RandomForestClassifier(bootstrap=True, class_weight=None, criterion='gini',
                     max_depth=5, max_features='auto', max_leaf_nodes=None,
                     min_impurity_decrease=0.0, min_impurity_split=None,
                     min_samples_leaf=1, min_samples_split=2,
                     min_weight_fraction_leaf=0.0, n_estimators=30, n_jobs=1,
                     oob_score=False, random_state=42, verbose=0, warm_start=False)
```

Now the objective is to optimize the paramters of the random forest classifier. I create a paramter grid with different values to test different combinations of parameters to see what gives me the best outcome

```
In [ ]: param_grid = {
            'n_estimators': [10, 20, 30, 50, 100],
            'max_features': ['auto', 'sqrt', 'log2'],
            'max_depth' : [5,10,15, 20,30,50],
            'criterion' :['gini', 'entropy'],
            'min_samples_leaf':[1,2,3,5,10]
        }
```

I run a grid search CV function which essentially allows me to find the most optimal paramter set. It runs through multiple combinations estimators, features, depth, criterion and min leaf samples to find the best model.

```
In [ ]: CV_rfc = GridSearchCV(estimator=forest, param_grid=param_grid, cv=5)
        CV_rfc.fit(X1_big_new, y_big)
```

The following are found to be the best parameters based on my grid search model.

```
In [ ]: CV_rfc.best_params_
```

I implement the new random classifier model with newly tuned parameters on the 2017/18 data and the new accuracy is around 71.6%, much better. This is better than a 50% accuracy expected with random guessing.

```
In [23]: forest = RandomForestClassifier(n_estimators=100, max_depth=5, random_state=42, crite
                                          min_samples_leaf = 3, max_features = 'auto')
         forest.fit(X1_big_new,y_big)
         y_predict = forest.predict(X1_final)
         print(round(accuracy_score(y_final, y_predict),3))
         pd.DataFrame(
             confusion_matrix(y_final, y_predict),
             columns=['Predicted 0', 'Predicted 1'],
             index=['True 0', 'True 1'])
```

```
0.716
```

Out[23]:

	Predicted 0	Predicted 1
True 0	27	180
True 1	21	480

However I notice that when I keep things "simple" and run the random forest with high estimators and low depth, I get a similar result.

```
In [24]: forest1 = RandomForestClassifier(n_estimators=100, max_depth=5, random_state=42)
         forest1.fit(X1_big_new,y_big)
         y_predict = forest1.predict(X1_final)
         print(round(accuracy_score(y_final, y_predict),3))
         pd.DataFrame(
             confusion_matrix(y_final, y_predict),
             columns=['Predicted 0', 'Predicted 1'],
             index=['True 0', 'True 1'])
```

```
0.722
```

Out[24]:

	Predicted 0	Predicted 1
True 0	27	180
True 1	17	484

I plot one of the trees in the forest to visualize and observe. I utilize the graphviz library to create a visualization of the tree.

```
In [33]: tree1=forest1.estimators_[1]
```

```
In [34]: dot_data = StringIO()
         export_graphviz(tree1, out_file=dot_data,
                         filled=True, rounded=True,
                         special_characters=True, feature_names=X1_final.columns)
```

```
In [ ]: graph = pydotplus.graph_from_dot_data(dot_data.getvalue())
        Image(graph.create_png())
```

Conclusion: with the random forest model, I can predict 72% of the time if a goal will be scored or not. The prediction is a lot easier for a case where a goal will be scored. This is a fascinating finding. I will now focus on how accurately I can predict the number of goals that will be conceded.

2.1.2 Can I Classify Win/Loss

After completing my analysis, I realize that with all the findings I can actually try to classify a result in the game for the particular team based on their statistics. To do this I create a new label called result: 1. Draw or Win - 1 is label 2. Loss - 0 is label

```
In [25]: EPL_2015_2016_WL['Result']=[0]*len(EPL_2015_2016_WL)

         EPL_2017_2018_WL['Result']=[0]*len(EPL_2017_2018_WL)
         EPL_2017_2018_WL['Result'].head()

Out[25]: 12    0
         13    0
         62    0
         63    0
         80    0
         Name: Result, dtype: int64
```

This is a function to append the result label for different seasons.

```
In [26]: def result(df):
             for i in range(len(df)):
                 if ((df['Goals'].iloc[i])<(df['GoalkeeperGoalsAgainst'].iloc[i])):
                     df['Result'].iloc[i]=0
                 else:
                     df['Result'].iloc[i]=1

In [27]: result(EPL_2015_2016_WL)

         result(EPL_2017_2018_WL)

In [28]: EPL_2015_2016_WL[['Result','Goals','GoalkeeperGoalsAgainst']].head()

Out[28]:    Result  Goals  GoalkeeperGoalsAgainst
         0       1      0                       0
         1       1      3                       1
         2       0      1                       5
         3       1      5                       1
         4       0      0                       4

In [29]: EPL_2017_2018_WL[['Result','Goals','GoalkeeperGoalsAgainst']].head()
```

Out[29]:

	Result	Goals	GoalkeeperGoalsAgainst
12	0	0	2
13	1	2	0
62	1	3	1
63	0	1	4
80	0	1	2

I create the X and y data frames for the models. I create a train and test dataset.

In [38]:
```
X_WL = EPL_2015_2016_WL.drop(columns=['goal_against_label','goal_label','GA_unique_la
                                       'GoalkeeperGoalsAgainst','Result'])
y_WL = EPL_2015_2016_WL['Result']

X_WL_17 = EPL_2017_2018_WL.drop(columns=['goal_against_label','goal_label','GA_unique
                                       'GoalkeeperGoalsAgainst','Result'])
y_WL_17 = EPL_2017_2018_WL['Result']

X_train, X_test, y_train, y_test = train_test_split(X_WL, y_WL,stratify=y_WL)

array(X_WL.columns.values)
```

Out[38]:
```
array(['Assists', 'BlockedShots', 'CornersWon', 'Crosses', 'Fouled',
       'Fouls', 'GoalkeeperSaves', 'Interceptions', 'LastManTackle',
       'Offsides', 'Passes', 'PassesCompleted', 'PenaltiesConceded',
       'PenaltiesWon', 'PenaltyKickMisses', 'PenaltyKickSaves',
       'RedCards', 'Shots', 'ShotsOnGoal', 'TacklesWon', 'Touches',
       'YellowCards'], dtype=object)
```

Once I create my test and train data, I run the following models to predict outcomes: 1. Logistic Regression 2. Random Forest

The logistic regression produces an accuracy of 75% on average for the outcomes

In [39]:
```
logreg = linear_model.LogisticRegression()
logreg.fit(X_train,y_train)
y_predict = logreg.predict(X_test)
print(round(accuracy_score(y_test, y_predict),3))

pd.DataFrame(
    confusion_matrix(y_test, y_predict),
    columns=['Predicted 0', 'Predicted 1'],
    index=['True 0', 'True 1'])
```

```
0.763
```

Out[39]:

	Predicted 0	Predicted 1
True 0	34	27
True 1	18	111

The random forest produces an accuracy of 71% on average for the outcomes

```
In [40]: random_forest = RandomForestClassifier(n_estimators=60, max_depth=30, random_state=1,c
         random_forest.fit(X_train,y_train)
         y_predict = random_forest.predict(X_test)
         print(round(accuracy_score(y_test, y_predict),3))
         pd.DataFrame(
             confusion_matrix(y_test, y_predict),
             columns=['Predicted 0', 'Predicted 1'],
             index=['True 0', 'True 1'])
```

```
0.711
```

```
Out[40]:         Predicted 0  Predicted 1
         True 0           25           36
         True 1           19          110
```

Since the logistic model produces the best result, I try now to optimize it using feature selection.

```
In [41]: rfe = RFE(logreg)
         rfe = rfe.fit(X_WL,y_WL)
         print(rfe.support_)
         print(rfe.ranking_)
```

```
[ True False  True  True False  True False  True  True False False False
 False False  True  True  True  True  True False False False]
[ 1  4  1  1  6  1  2  1  1  7  9  8 11 12  1  1  1  1  1  3 10  5]
```

```
In [42]: rfe = RFE(random_forest)
         rfe = rfe.fit(X_WL,y_WL)
         print(rfe.support_)
         print(rfe.ranking_)
```

```
[ True False  True  True  True  True False  True False False  True  True
 False False False False False  True  True  True False False]
[ 1  3  1  1  1  1  2  1  7  4  1  1 11 10  9  8  6  1  1  1 12  5]
```

I then create the new dataframes with the newly selected features

```
In [43]: X_WL_log=X_WL.iloc[:, [0,2,3,5,7,8,14,15,16,17,18]]
         X_WL_rfc=X_WL.iloc[:, [0,2,3,4,5,7,10,11,17,18,19]]
         X_WL_17_log=X_WL_17.iloc[:, [0,2,3,5,7,8,14,15,16,17,18]]
         X_WL_17_rfc=X_WL_17.iloc[:, [0,2,3,4,5,7,10,11,17,18,19]]
```

```
In [44]: from scipy import stats
         stats.chisqprob = lambda chisq, df: stats.chi2.sf(chisq, df)
```

I run the results for the logistic regression fit to get the P values for all the different features. Some variables have a p-value greater than 0.05, I drop them and reevaluate the model

```
In [45]: import statsmodels.api as sm
         logit_model=sm.Logit(y_WL_17,X_WL_17_log)
         result=logit_model.fit()
         print(result.summary())
```

```
/anaconda3/envs/cse801/lib/python3.5/site-packages/statsmodels/compat/pandas.py:56: FutureWarn
  from pandas.core import datetools


Optimization terminated successfully.
         Current function value: 0.506973
         Iterations 7
                           Logit Regression Results
==============================================================================
Dep. Variable:                 Result   No. Observations:                  708
Model:                          Logit   Df Residuals:                      697
Method:                           MLE   Df Model:                           10
Date:                Fri, 01 Jun 2018   Pseudo R-squ.:                  0.2341
Time:                        13:27:00   Log-Likelihood:                -358.94
converged:                       True   LL-Null:                       -468.64
                                        LLR p-value:                 1.421e-41
=====================================================================================
                        coef    std err          z      P>|z|      [0.025      0.975]
-------------------------------------------------------------------------------------
Assists               1.0023      0.137      7.331      0.000       0.734       1.270
CornersWon           -0.0066      0.041     -0.160      0.873      -0.088       0.075
Crosses              -0.0473      0.014     -3.370      0.001      -0.075      -0.020
Fouls                -0.0134      0.021     -0.640      0.522      -0.055       0.028
Interceptions        -0.0447      0.014     -3.171      0.002      -0.072      -0.017
LastManTackle        -0.2740      0.330     -0.831      0.406      -0.920       0.372
PenaltyKickMisses     0.0453      0.557      0.081      0.935      -1.046       1.137
PenaltyKickSaves     -0.7879      0.573     -1.375      0.169      -1.911       0.335
RedCards             -1.2399      0.572     -2.169      0.030      -2.360      -0.119
Shots                 0.1025      0.026      3.922      0.000       0.051       0.154
ShotsOnGoal           0.0966      0.058      1.660      0.097      -0.017       0.211
=====================================================================================
```

I removed the variables that had a P-value higher than 0.05 and created a new X matrix with only 5 predictors

```
In [46]: X_WL_log_new=X_WL_log.iloc[:, [0,2,4,8,9]]
         X_WL_17_log_new=X_WL_17_log.iloc[:, [0,2,4,8,9]]
         X_WL_17_log_new.head()
```

Out[46]:

	Assists	Crosses	Interceptions	RedCards	Shots
12	0	7	18	0	14
13	2	22	20	0	14
62	3	14	13	0	21

63	0	11	18	0	4
80	1	6	15	0	9

I run the model on the 2017 data to test my predictions against the real outcomes. I get around a 69% accuracy.

```
In [47]: logreg.fit(X_WL_log,y_WL)
         y_predict = logreg.predict(X_WL_17_log)
         print(round(accuracy_score(y_WL_17, y_predict),3))

         pd.DataFrame(
             confusion_matrix(y_WL_17, y_predict),
             columns=['Predicted 0', 'Predicted 1'],
             index=['True 0', 'True 1'])
```

```
0.691
```

Out[47]:

	Predicted 0	Predicted 1
True 0	121	145
True 1	74	368

I then run the new logit model with 5 predictors on the 2017 data to test my predictions against the real outcomes. I get around a 70% accuracy. 70% with 5 predictors is a perfect balance to help me find players

```
In [48]: logreg.fit(X_WL_log_new,y_WL)
         y_predict = logreg.predict(X_WL_17_log_new)
         print(round(accuracy_score(y_WL_17, y_predict),3))

         pd.DataFrame(
             confusion_matrix(y_WL_17, y_predict),
             columns=['Predicted 0', 'Predicted 1'],
             index=['True 0', 'True 1'])
```

```
0.701
```

Out[48]:

	Predicted 0	Predicted 1
True 0	116	150
True 1	62	380

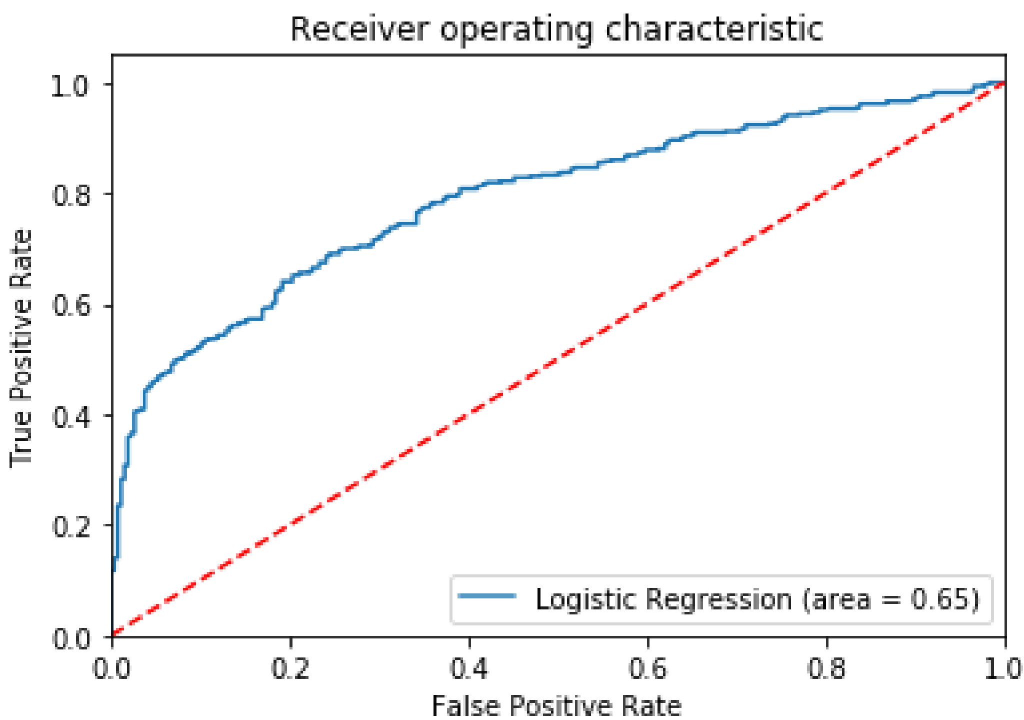
```
In [49]: from sklearn.metrics import classification_report
         print(classification_report(y_WL_17, y_predict))
```

```
             precision    recall  f1-score   support

          0       0.65      0.44      0.52       266
          1       0.72      0.86      0.78       442
```

```
avg / total       0.69      0.70      0.68       708
```

I created a ROC curve to visualize my binary classifer model. The dotted line represents the ROC curve of a random classifier while the blue line represents the current model. The current model is much further from the random classifier.

```
In [50]: from sklearn.metrics import roc_auc_score
         from sklearn.metrics import roc_curve
         logit_roc_auc = roc_auc_score(y_WL_17, y_predict)
         fpr, tpr, thresholds = roc_curve(y_WL_17, logreg.predict_proba(X_WL_17_log_new)[:,1])
         plt.figure()
         plt.plot(fpr, tpr, label='Logistic Regression (area = %0.2f)' % logit_roc_auc)
         plt.plot([0, 1], [0, 1],'r--')
         plt.xlim([0.0, 1.0])
         plt.ylim([0.0, 1.05])
         plt.xlabel('False Positive Rate')
         plt.ylabel('True Positive Rate')
         plt.title('Receiver operating characteristic')
         plt.legend(loc="lower right")
         plt.savefig('Log_ROC')
         plt.show()
```



I also run a random forest with the 5 predictors and receive a 71% accuracy.

```
In [51]: random_forest = RandomForestClassifier(n_estimators=200, max_depth=100, random_state=
         random_forest.fit(X_WL_rfc,y_WL)
         y_predict = random_forest.predict(X_WL_17_rfc)
         print(round(accuracy_score(y_WL_17, y_predict),3))

         pd.DataFrame(
             confusion_matrix(y_WL_17, y_predict),
             columns=['Predicted 0', 'Predicted 1'],
             index=['True 0', 'True 1'])
```

```
0.713
```

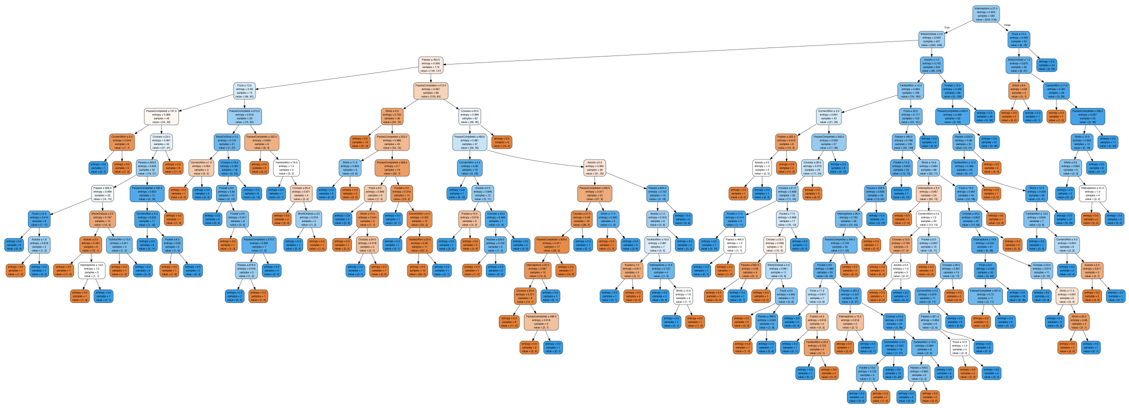
Out[51]:

	Predicted 0	Predicted 1
True 0	133	133
True 1	70	372

I visualize one of the trees from the random forest to visualize cutoff values

```
In [52]: tree_WL=random_forest.estimators_[100]
         dot_data = StringIO()
         export_graphviz(tree_WL, out_file=dot_data,
                         filled=True, rounded=True,
                         special_characters=True, feature_names=X_WL_17_rfc.columns)
         graph = pydotplus.graph_from_dot_data(dot_data.getvalue())
         Image(graph.create_png())
```

Out[52]:



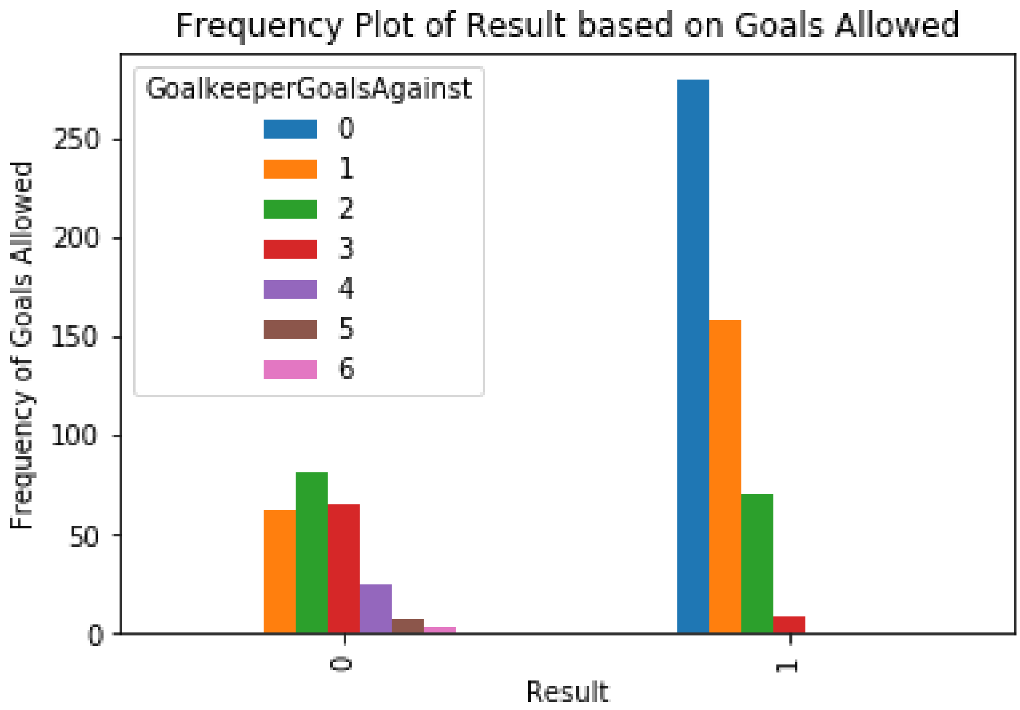
I wanted to create a frequency plot of the results in comparison to the amount of goals scored. It is interesting to see that majority of the time, scoring 1 or 2 goals

```
In [ ]: pd.crosstab(EPL_2015_2016_WL.Result,EPL_2015_2016_WL.Goals).plot(kind='bar')
        plt.title('Frequency Plot of Result based on Goals Scored')
        plt.xlabel('Result')
        plt.ylabel('Frequency of Goals')
```

Below is a frequency plot of the results in comparison to the amount of goals conceded. It is interesting to see that teams are still able to get a positive result after conceding upto 2 goals!

```
In [54]: pd.crosstab(EPL_2015_2016_WL.Result,EPL_2015_2016_WL.GoalkeeperGoalsAgainst).plot(kinc
         plt.title('Frequency Plot of Result based on Goals Allowed')
         plt.xlabel('Result')
         plt.ylabel('Frequency of Goals Allowed')
```

```
Out[54]: Text(0,0.5,'Frequency of Goals Allowed')
```



3 Player Selection for Better Results

My goal now is to do a player selection using player statistics from the 2017-18 season. Players that maximize the newly developed model are required. I use the logit model with 5 predictor variables that I create in the section above.

```
In [55]: array(X_WL_log_new.columns.values)
```

```
Out[55]: array(['Assists', 'Crosses', 'Interceptions', 'RedCards', 'Shots'],
               dtype=object)
```

I run a binomial regression similar to the one in the section above to create my logit model

```
In [56]: import statsmodels.api as sm
         import statsmodels.genmod.generalized_linear_model as stat
         logit_model=sm.Logit(y_WL_17,X_WL_17_log_new)
         #player_model=sm.GLM(y_WL_17,X_WL_17_log_new,sm.families.Binomial())
         result=logit_model.fit()
         print(result.summary())
```

```
Optimization terminated successfully.
         Current function value: 0.511137
         Iterations 7
                           Logit Regression Results
==============================================================================
Dep. Variable:                 Result   No. Observations:                  708
Model:                          Logit   Df Residuals:                      703
Method:                           MLE   Df Model:                            4
Date:                Fri, 01 Jun 2018   Pseudo R-squ.:                  0.2278
Time:                        13:27:32   Log-Likelihood:                -361.89
converged:                       True   LL-Null:                       -468.64
                                        LLR p-value:                 4.664e-45
=================================================================================
                    coef    std err          z      P>|z|      [0.025      0.975]
---------------------------------------------------------------------------------
Assists           1.0756      0.128      8.405      0.000       0.825       1.326
Crosses          -0.0517      0.011     -4.590      0.000      -0.074      -0.030
Interceptions    -0.0500      0.011     -4.532      0.000      -0.072      -0.028
RedCards         -1.2381      0.562     -2.203      0.028      -2.340      -0.136
Shots             0.1230      0.020      6.058      0.000       0.083       0.163
=================================================================================
```

I then use the csv file i created from the API to get the player info and visualize the player column labels

```
In [57]: players=pd.read_csv('Players_EPL_17_18.csv')
```

I keep only the 5 predictor variables of interest. Since the player results are aggregated over the season, I create new columns with the averages of the stats. The average is dependent on the number of games played (Started column)

```
In [59]: players=players[['Name','Assists','Crosses','Interceptions','RedCards','Shots','Team'
                          'Position']]
         players[['Assists']]=players[['Assists']].astype('int')
         players['Assists_Avg']=players['Assists']/players['Started']
         players[['Crosses']]=players[['Crosses']].astype('int')
         players['Crosses_Avg']=players['Crosses']/players['Started']
         players[['Interceptions']]=players[['Interceptions']].astype('int')
         players['Interceptions_Avg']=players['Interceptions']/players['Started']
         players[['RedCards']]=players[['RedCards']].astype('int')
         players['RedCards_Avg']=players['RedCards']/players['Started']
```

```
players[['Shots']]=players[['Shots']].astype('int')
players['Shots_Avg']=players['Shots']/players['Started']
```

I do some data cleaning in this section. I remove any players with null values or any players that have not played at least 10 games in the season

```
In [60]: players=players.dropna(axis=0,how='any')
         players_final=players.loc[players['Started']>10]
```

I save the data to a csv for later use

```
In [61]: players_final.to_csv('players_final.csv')
```

I write a function which is essentially the logit model and calculate the probability of success for each player.

```
In [63]: def points(a,b,c,d,e):
             A=(exp(1.0756*a - 0.0517*b - 0.05*c - 1.2381*d + 0.123*e)/
             (1 + exp((1.0756*a - 0.0517*b - 0.05*c - 1.2381*d + 0.123*e))))
             return A
```

I run the points function on the players data

```
In [64]: players_final['Points']=points(players_final.Assists_Avg,players_final.Crosses_Avg,pla
                    players_final.RedCards_Avg,players_final.Shots_Avg)
```

I store the Name, Position, Team and Points of the players in a new dataframe and sort them by points

```
In [65]: Player_Model=players_final[['Name','Position','Team','Points']].sort_values(by=['Poin
```

Best 10 Attackers of the 2017-18 Season

```
In [66]: Player_Model.loc[Player_Model['Position']=="A"].head(10)
```

```
Out[66]:                   Name Position                 Team    Points
         97       Sergio Agüero        A    Manchester City FC  0.696105
         100    Raheem Sterling        A    Manchester City FC  0.693325
         326         Harry Kane        A  Tottenham Hotspur FC  0.682254
         194      Álvaro Morata        A            Chelsea FC  0.662099
         220      Gabriel Jesus        A    Manchester City FC  0.635655
         92   Christian Benteke        A     Crystal Palace FC  0.630696
         309    Marcus Rashford        A  Manchester United FC  0.630633
         308    Anthony Martial        A  Manchester United FC  0.628193
         294      Romelu Lukaku        A  Manchester United FC  0.626859
         10       Danny Welbeck        A            Arsenal FC  0.623708
```

Best 10 Midfielders of the 2017-18 Season

```
In [67]: Player_Model.loc[Player_Model['Position']=="M"].head(10)
```

```
Out[67]:                     Name Position                 Team    Points
         439      Philippe Coutinho        M         Liverpool FC  0.683739
         190          Mohamed Salah        M         Liverpool FC  0.682976
         350             Paul Pogba        M  Manchester United FC  0.675582
         3             Aaron Ramsey        M           Arsenal FC  0.661845
         185             Leroy Sané        M    Manchester City FC  0.660980
         258  Dominic Calvert-Lewin        M           Everton FC  0.642752
         335              Dele Alli        M  Tottenham Hotspur FC  0.640633
         94             David Silva        M    Manchester City FC  0.635636
         349      Henrikh Mkhitaryan       M           Arsenal FC  0.634539
         8               Alex Iwobi        M           Arsenal FC  0.624033
```

Best 10 Defenders of the 2017-18 Season

```
In [68]: Player_Model.loc[Player_Model['Position']=="D"].head(10)
```

```
Out[68]:                Name Position                 Team    Points
         203            Danilo        D    Manchester City FC  0.547819
         35       Wilfred Ndidi       D     Leicester City FC  0.539823
         30      Sead Kolainac       D            Arsenal FC  0.536282
         395  Cheikhou Kouyaté        D     West Ham United FC  0.529894
         154        Kyle Walker       D    Manchester City FC  0.528242
         359    Florian Lejeune       D   Newcastle United FC  0.526372
         251         Kevin Long       D            Burnley FC  0.526026
         93     Vincent Kompany       D    Manchester City FC  0.520389
         131     Ryan Shawcross       D         Stoke City FC  0.520214
         332          Eric Dier       D  Tottenham Hotspur FC  0.519618
```

Conclusion: Using the logit model for player selection, the ideal team formation (4-4-2) barring goalkeeper would be the following. Right Back - Danilo
Center Back - Cheikhou Kouyate
Center Back - Wilfred Ndidi
Left Back - Sead Kolasinac
Right Mid - Mo Salah
Center Mid - Aaron Ramsey
Center Mid - Paul Pogba
Left Mid - Phillipe Coutinho
Striker - Sergio Aguero
Striker - Raheem Sterling

3.0.1 Now I'll try to predict the number of goals allowed as a discrete

The goal here is to see if I can accurately predict the number of goals that a team will concede. For this I use:

1. Multinomial Regression
2. Random Forest

The predictor variable in this case is different. I utilize the goal against unique label which has a different class label depending on the number of goals conceded: 1. 0 for 0 conceded 2. 1 for 1 conceded 3. 2 for 2 conceded 4. 3 for 3+ conceded

```
In [ ]: y_unique = big['GA_unique_label']

        y_final_unique = EPL_2017_2018['GA_unique_label']
```

I then run a multinomial regression model since the outcomes are multi-class. I create a train and test dataset using the "big dataset" (2015 and 16 seasons data) and then gather predictions. Result are poor, only around 38% accuracy for the number of goals scored predicted. Random guessing would be a 25% accuracy so this model is better.

```
In [ ]: X_train, X_test, y_train, y_test = train_test_split(X1_big_new, y_unique, stratify=y_un
        multi=linear_model.LogisticRegression(multi_class='multinomial', solver='newton-cg')
        multi.fit(X_train,y_train)
        y_predict = multi.predict(X_test)

        from sklearn.metrics import accuracy_score
        print(accuracy_score(y_test, y_predict))

        pd.DataFrame(
            confusion_matrix(y_test, y_predict),
            columns=['Predicted 0', 'Predicted 1','Predicted 2','Predicted 3'],
            index=['True 0', 'True 1','True 2','True 3'])
```

I then run a random forest since the outcomes are multi-class. I create a train and test dataset using the "big dataset" (2015 and 16 seasons data) and then gather predictions. Result are poor, only around 31% accuracy for the number of goals scored predicted.

```
In [ ]: X_train, X_test, y_train, y_test = train_test_split(X1_big_new, y_unique,stratify=y_uni
        forest2 = RandomForestClassifier(n_estimators=50, max_depth=100, random_state=42)
        forest2.fit(X_train,y_train)
        y_predict = forest2.predict(X_test)

        from sklearn.metrics import accuracy_score
        print(accuracy_score(y_test, y_predict))

        pd.DataFrame(
            confusion_matrix(y_test, y_predict),
            columns=['Predicted 0', 'Predicted 1','Predicted 2','Predicted 3'],
            index=['True 0', 'True 1','True 2','True 3'])
```

I then run the multinomial regression model I created to test the model predictions versus the real outcomes. I am able to predict with a 40% accuracy. This is better than random guessing of 25% accuracy.

```
In [ ]: multi=linear_model.LogisticRegression(multi_class='multinomial', solver='newton-cg')
        multi.fit(X1_big_new,y_unique)
```

```
y_predict = multi.predict(X1_final)

from sklearn.metrics import accuracy_score
print(accuracy_score(y_final_unique, y_predict))

pd.DataFrame(
    confusion_matrix(y_final_unique, y_predict),
    columns=['Predicted 0', 'Predicted 1','Predicted 2','Predicted 3'],
    index=['True 0', 'True 1','True 2','True 3'])
```

```
In [ ]: from sklearn.metrics import classification_report
        print(classification_report(y_final_unique, y_predict))
```

I then run the random forest model I created to test the model predictions versus the real outcomes. I am able to predict with a 33% accuracy. This is better than random guessing of 25% accuracy.

```
In [ ]: X_train, X_test, y_train, y_test = train_test_split(X1_big_new, y_unique,stratify=y_uni
        forest2 = RandomForestClassifier(n_estimators=50, max_depth=100, random_state=42,crite
        forest2.fit(X1_big_new,y_unique)
        y_predict = forest2.predict(X1_final)

        from sklearn.metrics import accuracy_score
        print(accuracy_score(y_final_unique, y_predict))

        pd.DataFrame(
            confusion_matrix(y_final_unique, y_predict),
            columns=['Predicted 0', 'Predicted 1','Predicted 2','Predicted 3'],
            index=['True 0', 'True 1','True 2','True 3'])
```

The conclusion from this analysis is that the multinomial regression is a much better model to predict the "actual" number of goals allowed. However the accuracy is only 40%. The accuracy is different for different classes however.

3.0.2 Now I'll try to predict the number of goals scored

I also wanted to explore if I could explore whether I could predict the outcome for the number of goals. I use multinomial logistic regression and random forest to determine the outcome. For this, I use a new label for the y called the "goal_label" which I created earlier.

```
In [ ]: y_goals = big['goal_label']

        y_final_goals = EPL_2017_2018['goal_label']
```

I run the multinomial regression model on the test and compare outcomes with the training data.

```
In [ ]: X_train, X_test, y_train, y_test = train_test_split(X1_big_new, y_goals, stratify=y_uni
        multi=linear_model.LogisticRegression(multi_class='multinomial', solver='newton-cg')
```

```
multi.fit(X_train,y_train)
y_predict = multi.predict(X_test)

from sklearn.metrics import accuracy_score
print(accuracy_score(y_test, y_predict))

pd.DataFrame(
    confusion_matrix(y_test, y_predict),
    columns=['Predicted 0', 'Predicted 1','Predicted 2','Predicted 3'],
    index=['True 0', 'True 1','True 2','True 3'])
```

I run the random forest model on the test and compare outcomes with the training data.

```
In [ ]: X_train, X_test, y_train, y_test = train_test_split(X1_big_new, y_goals,stratify=y_unic
        forest2 = RandomForestClassifier(n_estimators=50, max_depth=100, random_state=42,criter
        forest2.fit(X_train,y_train)
        y_predict = forest2.predict(X_test)

        from sklearn.metrics import accuracy_score
        print(accuracy_score(y_test, y_predict))

        pd.DataFrame(
            confusion_matrix(y_test, y_predict),
            columns=['Predicted 0', 'Predicted 1','Predicted 2','Predicted 3'],
            index=['True 0', 'True 1','True 2','True 3'])
```

I then run the multinomial model to get the predictions and compare with real outputs for the 2017-18 season.The accuracy is around 48% significantly higher than 25% accuracy on a random guess.

```
In [ ]: multi=linear_model.LogisticRegression(multi_class='multinomial', solver='newton-cg')
        multi.fit(X1_big_new,y_goals)
        y_predict = multi.predict(X1_final)

        from sklearn.metrics import accuracy_score
        print(accuracy_score(y_final_goals, y_predict))

        pd.DataFrame(
            confusion_matrix(y_final_goals, y_predict),
            columns=['Predicted 0', 'Predicted 1','Predicted 2','Predicted 3'],
            index=['True 0', 'True 1','True 2','True 3'])
```

I then run the random forest model to get the predictions and compare with real outputs for the 2017-18 season.The accuracy is around 44% significantly higher than 25% accuracy on a random guess.

```
In [ ]: forest2 = RandomForestClassifier(n_estimators=50, max_depth=100, random_state=42,criter
        forest2.fit(X1_big_new,y_goals)
        y_predict = forest2.predict(X1_final)
```

```python
from sklearn.metrics import accuracy_score
print(accuracy_score(y_final_goals, y_predict))

pd.DataFrame(
    confusion_matrix(y_final_goals, y_predict),
    columns=['Predicted 0', 'Predicted 1','Predicted 2','Predicted 3'],
    index=['True 0', 'True 1','True 2','True 3'])
```