CIND820 Initial Results and Code

Summary of Questions

• How have NBA players been transforming the game of basketball to take advantage of the different types of scoring methods in the last 40 years?
• How accurate are the player positions classified? Does the skillset of the player match up with the position that they are labelled?
• Should the player positions remain the same or should they be revised?

GitHub Link - https://github.com/priscillachan28/Evolution-of-NBA

Import Libaries

In [1]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from scipy import stats
from sklearn import linear_model
from sklearn.linear_model import LogisticRegression
from sklearn import preprocessing
import pandas
from collections import Counter
from sklearn.datasets import make_classification
from sklearn.model_selection import train_test_split
from sklearn.metrics import classification_report
from sklearn import metrics
from sklearn.metrics import confusion_matrix
from sklearn.metrics import matthews_corrcoef
from sklearn.model_selection import RepeatedKFold
from sklearn.model_selection import cross_val_score
from numpy import mean
from numpy import std
```

Data Preparation

Dataset was taken from kaggle: https://www.kaggle.com/datasets/drgilermo/nba-players-stats. This dataset shows the individual NBA player stats since 1950.

Downloaded .xlsx file from Kaggle and read Excel file

In [2]:
```
season_stats = pd.read_csv('C:/Users/priis/Documents/CIND820/nba player stats/Seasons_St
player_data = pd.read_csv('C:/Users/priis/Documents/CIND820/nba player stats/Players.csv
```

In [3]:
```
season_stats.head()
```

Out[3]:

	Unnamed: 0	Year	Player	Pos	Age	Tm	G	GS	MP	PER	...	FT%	ORB	DRB	TRB	AST	ST
0	0	1950.0	Curly Armstrong	G-F	31.0	FTW	63.0	NaN	NaN	NaN	...	0.705	NaN	NaN	NaN	176.0	Na
1	1	1950.0	Cliff Barker	SG	29.0	INO	49.0	NaN	NaN	NaN	...	0.708	NaN	NaN	NaN	109.0	Na

2	2	1950.0	Leo Barnhorst	SF	25.0	CHS	67.0	NaN	NaN	NaN	...	0.698	NaN	NaN	NaN	140.0	Na
3	3	1950.0	Ed Bartels	F	24.0	TOT	15.0	NaN	NaN	NaN	...	0.559	NaN	NaN	NaN	20.0	Na
4	4	1950.0	Ed Bartels	F	24.0	DNN	13.0	NaN	NaN	NaN	...	0.548	NaN	NaN	NaN	20.0	Na

5 rows × 53 columns

In [4]:

```
player_data.head()
```

Out[4]:

	Unnamed: 0	Player	height	weight	collage	born	birth_city	birth_state
0	0	Curly Armstrong	180.0	77.0	Indiana University	1918.0	NaN	NaN
1	1	Cliff Barker	188.0	83.0	University of Kentucky	1921.0	Yorktown	Indiana
2	2	Leo Barnhorst	193.0	86.0	University of Notre Dame	1924.0	NaN	NaN
3	3	Ed Bartels	196.0	88.0	North Carolina State University	1925.0	NaN	NaN
4	4	Ralph Beard	178.0	79.0	University of Kentucky	1927.0	Hardinsburg	Kentucky

After showing the summary of the two Excel spreadsheets, we will be merging them together to create one dataset.

In [5]:

```
df = season_stats.merge(player_data, left_on='Player', right_on='Player')
df.head()
```

Out[5]:

	Unnamed: 0_x	Year	Player	Pos	Age	Tm	G	GS	MP	PER	...	TOV	PF	PTS	Unnamed: 0_y	hei
0	0	1950.0	Curly Armstrong	G-F	31.0	FTW	63.0	NaN	NaN	NaN	...	NaN	217.0	458.0	0	18
1	314	1951.0	Curly Armstrong	G-F	32.0	FTW	38.0	NaN	NaN	NaN	...	NaN	97.0	202.0	0	18
2	1	1950.0	Cliff Barker	SG	29.0	INO	49.0	NaN	NaN	NaN	...	NaN	99.0	279.0	1	18
3	315	1951.0	Cliff Barker	SG	30.0	INO	56.0	NaN	NaN	NaN	...	NaN	98.0	152.0	1	18
4	489	1952.0	Cliff Barker	SG	31.0	INO	44.0	NaN	494.0	10.8	...	NaN	56.0	126.0	1	18

5 rows × 60 columns

In [6]:

```
df.drop_duplicates(keep='first')
```

Out[6]:

	Unnamed: 0_x	Year	Player	Pos	Age	Tm	G	GS	MP	PER	...	TOV	PF	PTS	Unnamed 0_
0	0	1950.0	Curly Armstrong	G-F	31.0	FTW	63.0	NaN	NaN	NaN	...	NaN	217.0	458.0	
1	314	1951.0	Curly Armstrong	G-F	32.0	FTW	38.0	NaN	NaN	NaN	...	NaN	97.0	202.0	
2	1	1950.0	Cliff Barker	SG	29.0	INO	49.0	NaN	NaN	NaN	...	NaN	99.0	279.0	

3	315	1951.0	Cliff Barker	SG	30.0	INO	56.0	NaN	NaN	NaN	...	NaN	98.0	152.0	
4	489	1952.0	Cliff Barker	SG	31.0	INO	44.0	NaN	494.0	10.8	...	NaN	56.0	126.0	
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	
24685	24674	2017.0	Troy Williams	SF	22.0	HOU	6.0	3.0	139.0	12.8	...	6.0	18.0	58.0	391
24686	24675	2017.0	Kyle Wiltjer	PF	24.0	HOU	14.0	0.0	44.0	6.7	...	5.0	4.0	13.0	391
24687	24688	2017.0	Stephen Zimmerman	C	20.0	ORL	19.0	0.0	108.0	7.3	...	3.0	17.0	23.0	391
24688	24689	2017.0	Paul Zipser	SF	22.0	CHI	44.0	18.0	843.0	6.9	...	40.0	78.0	240.0	392
24689	24690	2017.0	Ivica Zubac	C	19.0	LAL	38.0	11.0	609.0	17.0	...	30.0	66.0	284.0	392

24690 rows × 60 columns

This dataset has 24,690 entries and a total of 60 variables.

In [7]:

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 24690 entries, 0 to 24689
Data columns (total 60 columns):
 #   Column         Non-Null Count  Dtype
---  ------         --------------  -----
 0   Unnamed: 0_x   24690 non-null  int64
 1   Year           24623 non-null  float64
 2   Player         24623 non-null  object
 3   Pos            24623 non-null  object
 4   Age            24615 non-null  float64
 5   Tm             24623 non-null  object
 6   G              24623 non-null  float64
 7   GS             18232 non-null  float64
 8   MP             24137 non-null  float64
 9   PER            24100 non-null  float64
 10  TS%            24538 non-null  float64
 11  3PAr           18839 non-null  float64
 12  FTr            24525 non-null  float64
 13  ORB%           20791 non-null  float64
 14  DRB%           20791 non-null  float64
 15  TRB%           21570 non-null  float64
 16  AST%           22554 non-null  float64
 17  STL%           20791 non-null  float64
 18  BLK%           20791 non-null  float64
 19  TOV%           19582 non-null  float64
 20  USG%           19639 non-null  float64
 21  blanl          0 non-null      float64
 22  OWS            24584 non-null  float64
 23  DWS            24584 non-null  float64
```

```
 24  WS              24584 non-null  float64
 25  WS/48           24100 non-null  float64
 26  blank2          0 non-null      float64
 27  OBPM            20796 non-null  float64
 28  DBPM            20796 non-null  float64
 29  BPM             20796 non-null  float64
 30  VORP            20796 non-null  float64
 31  FG              24623 non-null  float64
 32  FGA             24623 non-null  float64
 33  FG%             24525 non-null  float64
 34  3P              18926 non-null  float64
 35  3PA             18926 non-null  float64
 36  3P%             15416 non-null  float64
 37  2P              24623 non-null  float64
 38  2PA             24623 non-null  float64
 39  2P%             24496 non-null  float64
 40  eFG%            24525 non-null  float64
 41  FT              24623 non-null  float64
 42  FTA             24623 non-null  float64
 43  FT%             23766 non-null  float64
 44  ORB             20796 non-null  float64
 45  DRB             20796 non-null  float64
 46  TRB             24311 non-null  float64
 47  AST             24623 non-null  float64
 48  STL             20796 non-null  float64
 49  BLK             20796 non-null  float64
 50  TOV             19644 non-null  float64
 51  PF              24623 non-null  float64
 52  PTS             24623 non-null  float64
 53  Unnamed: 0_y    24690 non-null  int64
 54  height          24623 non-null  float64
 55  weight          24623 non-null  float64
 56  collage         22400 non-null  object
 57  born            24623 non-null  float64
 58  birth_city      22977 non-null  object
 59  birth_state     22934 non-null  object
dtypes: float64(52), int64(2), object(6)
memory usage: 11.5+ MB
```

We will be selecting only the attributes that we want and are relevant to this project.

In [8]:
```
data_frame = df[["Player","Year","2PA", "2P%", "3PA", "3P%", "AST%", "BLK%", "eFG%",
                 "FG%", "FT%", "height", "PER", "Pos", "STL%", "TOV%", "TRB%", "weight"]
```

In [9]:
```
data_frame.head()
```

Out[9]:

	Player	Year	2PA	2P%	3PA	3P%	AST%	BLK%	eFG%	FG%	FT%	height	PER	Pos	STL%	TO\
0	Curly Armstrong	1950.0	516.0	0.279	NaN	NaN	NaN	NaN	0.279	0.279	0.705	180.0	NaN	G-F	NaN	N
1	Curly Armstrong	1951.0	232.0	0.310	NaN	NaN	NaN	NaN	0.310	0.310	0.644	180.0	NaN	G-F	NaN	N
2	Cliff Barker	1950.0	274.0	0.372	NaN	NaN	NaN	NaN	0.372	0.372	0.708	188.0	NaN	SG	NaN	N
3	Cliff Barker	1951.0	202.0	0.252	NaN	NaN	NaN	NaN	0.252	0.252	0.649	188.0	NaN	SG	NaN	N
4	Cliff Barker	1952.0	161.0	0.298	NaN	NaN	NaN	NaN	0.298	0.298	0.588	188.0	10.8	SG	NaN	N

As mentioned in the Literature Review, we will be selecting data after 1980 due to a lot of missing values prior to 1980.

In [10]:
```
data_frame = data_frame[data_frame["Year"] >= 1980.0]
```

In [11]:
```
data_frame.head()
```

Out[11]:

	Player	Year	2PA	2P%	3PA	3P%	AST%	BLK%	eFG%	FG%	FT%	height	PER	Pos	STL%	TC
1642	Jim Paxson	1980.0	438.0	0.429	22.0	0.045	15.9	0.2	0.412	0.411	0.711	198.0	9.1	SG	1.8	
1643	Jim Paxson	1981.0	1062.0	0.549	30.0	0.067	15.3	0.2	0.537	0.536	0.734	198.0	16.9	SG	2.4	
1644	Jim Paxson	1982.0	1223.0	0.535	35.0	0.229	14.8	0.2	0.529	0.526	0.767	198.0	18.0	SG	2.2	
1645	Jim Paxson	1983.0	1298.0	0.522	25.0	0.160	13.5	0.3	0.517	0.515	0.812	198.0	20.1	SG	2.4	
1646	Jim Paxson	1984.0	1263.0	0.525	59.0	0.288	14.1	0.2	0.521	0.514	0.841	198.0	19.5	SG	2.2	

In the NBA, there are 5 main positions to be played (Centre (C), Power Forward (PF), Point Guard (PG), Small Forward (SF) and Shooting Guard (SG)). This dataset contains some players who can play multiple positions but since there are not a lot of players who play multiple positions, we will be narrowing down those players to be the prominent position that they normally play. For example, for C-PF, we will be categorizing them to play the centre position instead.

In [12]:
```
data_frame = data_frame.replace(['C-PF'],'C')
data_frame = data_frame.replace(['PF-SF'],'PF')
data_frame = data_frame.replace(['SF-SG'],'SF')
data_frame = data_frame.replace(['SG-PG'],'SG')
data_frame = data_frame.replace(['SG-PF'],'SG')
data_frame = data_frame.replace(['C-SF'],'C')
data_frame = data_frame.replace(['SG-SF'],'SG')
data_frame = data_frame.replace(['PG-SG'],'PG')
data_frame = data_frame.replace(['SF-PF'],'SF')
data_frame = data_frame.replace(['PG-SF'],'PG')
data_frame = data_frame.replace(['PF-C'],'PF')
```

In [13]:
```
data_frame.shape
```

Out[13]:
```
(18926, 18)
```

In [14]:
```
##Missing Value
data_frame.isnull().sum()
```

Out[14]:
```
Player       0
Year         0
2PA          0
2P%        116
3PA          0
3P%       3510
AST%         5
BLK%         5
eFG%        87
FG%         87
FT%        744
height       0
PER          5
Pos          0
```

```
STL%          5
TOV%         60
TRB%          5
weight        0
dtype: int64
```

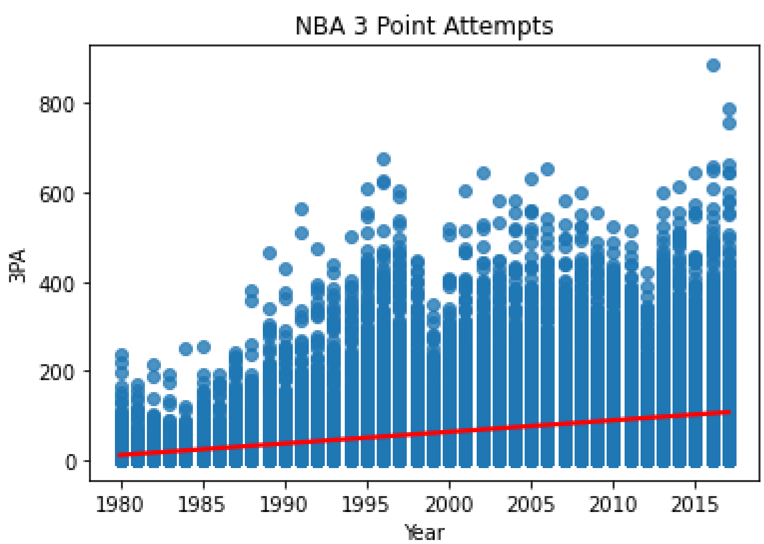
There are several attributes that have missing values (2P%, 3P%, eFG%, FG%, FT%, PER, TOV%, TRB%). Some of these missing values are due to the fact that the player did not attempt that shot for the season making it NaN. For example - a player may not attempt a 3 point shot or free throw for the season so they do not have a 3 point percentage. Since we know the reason as to why these missing values occur, we will not be removing the entire row from the dataset but instead replacing missing values with the mean or median value of that attribute later on in the project.

Initial Results for Question 1

Below is a scatter plot of the amount of 3 point attempts from 1980 to 2017. 1980 was when the three point shot was first introduced and we can see by looking at the scatterplot and the regression line? that the 3 point attempt has increased over the 35 years. This means that more players are utilizing the 3 point shot as a way to score in the game.

In [15]:
```python
sns.regplot(x='Year', y='3PA', data=data_frame,
            line_kws={"color": "red"}).set(title='NBA 3 Point Attempts')
```

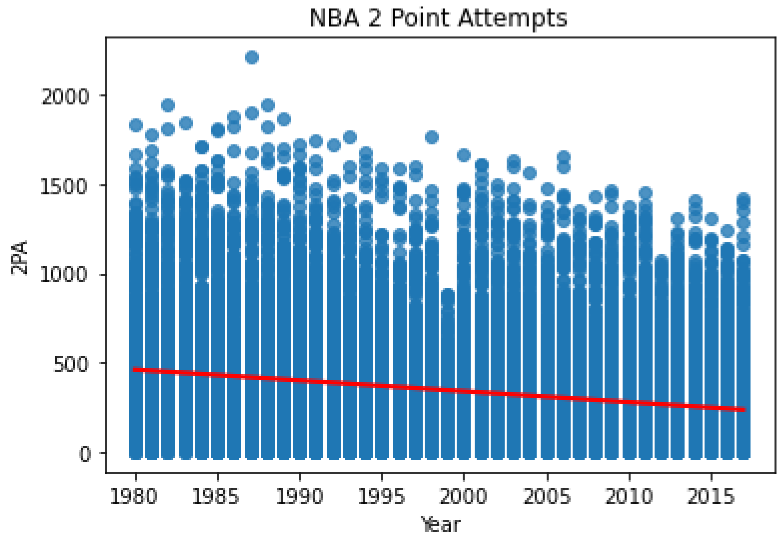
Out[15]:
```
[Text(0.5, 1.0, 'NBA 3 Point Attempts')]
```



We can see that with a rise of 3 point attempts over the years, this caused a decrease in the amount of 2 point attempts as well. From our literature review, a study noticed that there has been a decrease in 2 point attempts due to the fact that many teams are looking for players who have an empty shot at shooting a 3 point ball. The below scatter plot proves that theory.

In [16]:
```python
sns.regplot(x='Year', y='2PA', data=data_frame,
            line_kws={"color": "red"}).set(title='NBA 2 Point Attempts')
```

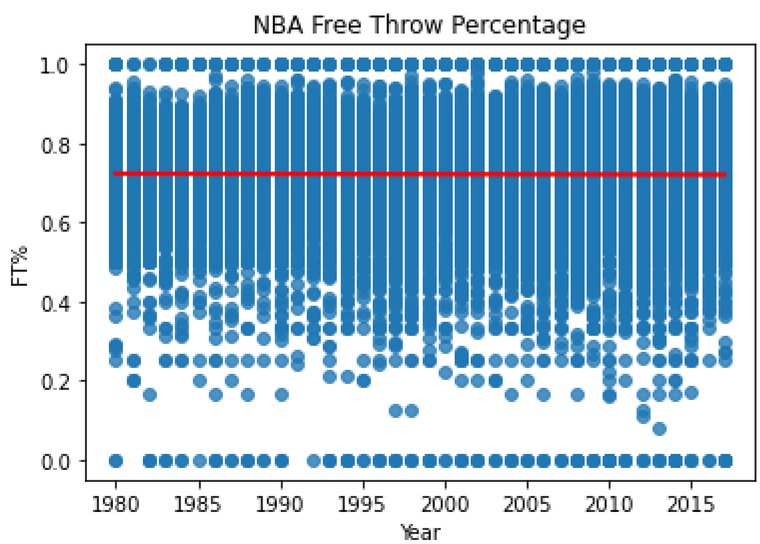
Out[16]:
```
[Text(0.5, 1.0, 'NBA 2 Point Attempts')]
```



Free throw percentages have been pretty stagnant over the 35 years. This shows that players have been making sure that their free throw attempts are at a good level as it is a quick and easy way to help the team score additional points.

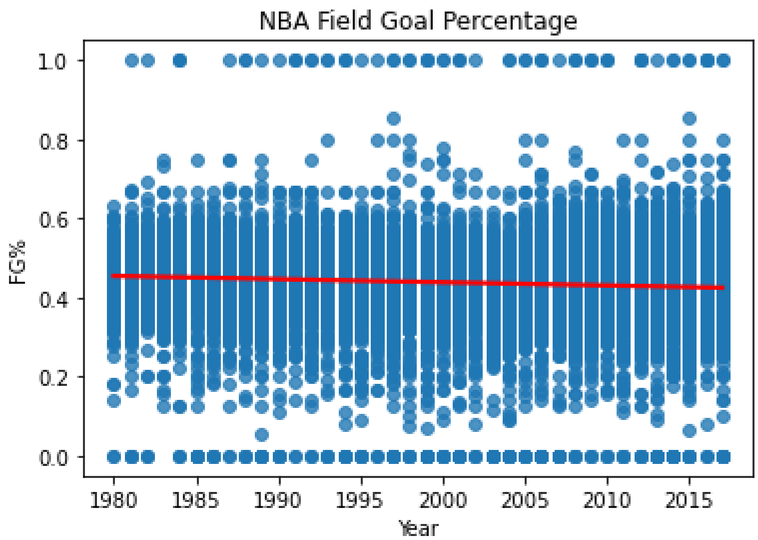
In [17]:
```
sns.regplot(x='Year', y='FT%', data=data_frame,
            line_kws={"color": "red"}).set(title='NBA Free Throw Percentage')
```

Out[17]:
```
[Text(0.5, 1.0, 'NBA Free Throw Percentage')]
```



In [18]:
```
sns.regplot(x='Year', y='FG%', data=data_frame,
            line_kws={"color": "red"}).set(title='NBA Field Goal Percentage')
```

Out[18]:
```
[Text(0.5, 1.0, 'NBA Field Goal Percentage')]
```



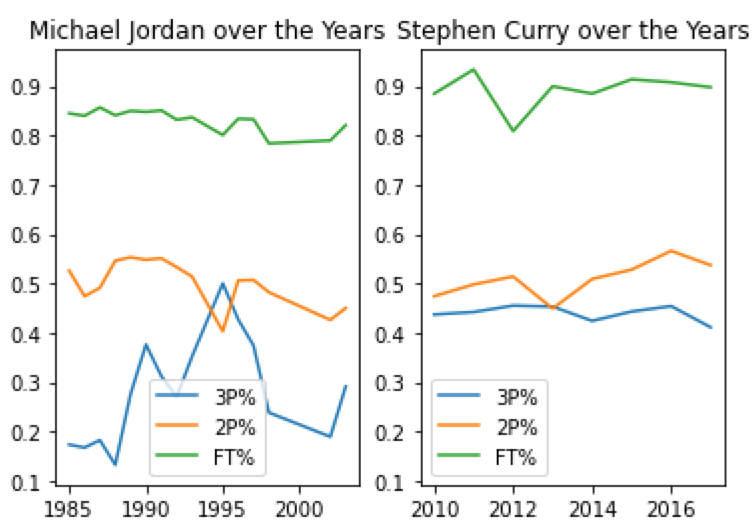
To see how basketball techniques have evolved throughout the years, we will be comparing two of the most popular players over the decades. We will be comparing Michael Jordan and Stephen Curry. Both of these players have been known as being the best players in the NBA to date.

In [19]:
```
michael = data_frame[data_frame["Player"] == 'Michael Jordan*']
steph = data_frame[data_frame["Player"] == 'Stephen Curry']
```

In [20]:
```
ax1 = plt.subplot(1, 2, 1)
plt.plot(michael['Year'], michael['3P%'])
plt.plot(michael['Year'], michael['2P%'])
plt.plot(michael['Year'], michael['FT%'])
plt.legend(["3P%", "2P%", "FT%"])
plt.title("Michael Jordan over the Years")

ax2 = plt.subplot(1, 2, 2, sharey=ax1)
plt.plot(steph['Year'], steph['3P%'])
plt.plot(steph['Year'], steph['2P%'])
plt.plot(steph['Year'], steph['FT%'])
plt.legend(["3P%", "2P%", "FT%"])
plt.title("Stephen Curry over the Years")
```

Out[20]:
```
Text(0.5, 1.0, 'Stephen Curry over the Years')
```



From looking at the graph above, it's clear that Stephen Curry has put a lot more focus and attention on 3 Point throws. There is the spike in 1995 where Michael Jordan's three point percentaged increased but caused a drop in his two point percentage. A reason for this increase in 3P% may be due to the fact that the NBA changed the three point line to be closer for a few years before ultimately moving the three point line back. Stephen Curry has been consistent in all types of shots. Over the years, players have realized that it is important to be consistent in all types of shooting instead of focusing to excel on a certain type.

Initial Results for Question 2

In [21]:
```
## Replace NaN Values
data_frame['2P%'].fillna(int(data_frame['2P%'].mean()), inplace=True)
data_frame['3P%'].fillna(int(data_frame['3P%'].mean()), inplace=True)
data_frame['AST%'].fillna(int(data_frame['AST%'].median()), inplace=True)
data_frame['BLK%'].fillna(int(data_frame['BLK%'].median()), inplace=True)
data_frame['eFG%'].fillna(int(data_frame['eFG%'].median()), inplace=True)
data_frame['FG%'].fillna(int(data_frame['FG%'].mean()), inplace=True)
data_frame['FT%'].fillna(int(data_frame['FT%'].median()), inplace=True)
data_frame['PER'].fillna(int(data_frame['PER'].mean()), inplace=True)
data_frame['STL%'].fillna(int(data_frame['STL%'].median()), inplace=True)
data_frame['TOV%'].fillna(int(data_frame['TOV%'].median()), inplace=True)
data_frame['TRB%'].fillna(int(data_frame['TRB%'].median()), inplace=True)
```

Multinomial Logistic Regression

In [22]:
```
X = data_frame[list(set(list(data_frame)) - set(['Pos','Player']))]
y = data_frame['Pos']
x_train, x_test, y_train, y_test = train_test_split(X, y, test_size=0.30, random_state=4
```

In [23]:
```
model1 = LogisticRegression(random_state=0, multi_class='multinomial', penalty='none',
                            solver='saga', max_iter = 10000).fit(x_train, y_train)
model1
```

Out[23]:
```
LogisticRegression(max_iter=10000, multi_class='multinomial', penalty='none',
                   random_state=0, solver='saga')
```

In [24]:
```
y_pred = model1.predict(x_test)
y_pred
```

Out[24]:
```
array(['PG', 'SG', 'SF', ..., 'PG', 'PF', 'SG'], dtype=object)
```

In [25]:
```
confusion_matrix = pd.crosstab(y_test, y_pred, rownames=['Actual'], colnames=['Predicted
confusion_matrix
```

Out[25]:

Predicted Actual	C	PF	PG	SF	SG
C	882	197	3	50	3
PF	254	789	1	155	24
PG	1	0	979	9	174
SF	16	187	10	637	207
SG	3	18	154	199	726

In [26]:
```
print(classification_report(y_test, y_pred))
```

```
              precision    recall  f1-score   support

           C       0.76      0.78      0.77      1135
          PF       0.66      0.65      0.65      1223
          PG       0.85      0.84      0.85      1163
          SF       0.61      0.60      0.60      1057
```

```
          SG       0.64      0.66      0.65      1100

    accuracy                           0.71      5678
   macro avg       0.71      0.71      0.71      5678
weighted avg       0.71      0.71      0.71      5678
```

In [27]:
```
# Matthews Correlation Score
matthews_corrcoef(y_test, y_pred)
```

Out[27]:
```
0.6333200394980081
```

In [28]:
```
#Repeated K Fold Cross Validation with a 10 split
cv = RepeatedKFold(n_splits=10, n_repeats=3, random_state=1)
scores = cross_val_score(model1, X, y, scoring='accuracy', cv=cv, n_jobs=-1)
```

In [29]:
```
print('Accuracy: %.3f (%.3f)' % (mean(scores), std(scores)))
```

```
Accuracy: 0.704 (0.006)
```

In [30]:
```
#Repeated K Fold Cross Validation with a 15 split
cv_15 = RepeatedKFold(n_splits=15, n_repeats=3, random_state=1)
scores_15 = cross_val_score(model1, X, y, scoring='accuracy', cv=cv_15, n_jobs=-1)
```

In [31]:
```
print('Accuracy: %.3f (%.3f)' % (mean(scores_15), std(scores_15)))
```

```
Accuracy: 0.704 (0.011)
```