Copa America 2019 Prediction

The purpose of this is to try and predict the top 3 teams for Copa America 2019 using classification models coupled with poisson distribution to predict the exact results of the semi-finals, third place playoff and final.

Final Predictions

Winner: Brazil
Runners-up: Argentina
Third Place: Uruguay
Fourth Place: Colombia
Final Score: Brazil 2:1 Argentina
Third Place Playoff Score: Uruguay 1:0 Colombia

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     - **Importance** of match (0-Friendly, 1-Others).
     - How much the Home Team's **Points** have changed.
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7. Predicting Copa America 2019

1. Importing Necessary Packages/Datasets

In [1]:

```
%matplotlib inline
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from sklearn.model_selection import train_test_split, KFold, cross_val_score, GridSearc
hCV
from sklearn.metrics import confusion_matrix, accuracy_score, precision_score, f1_score
from sklearn.preprocessing import StandardScaler
from scipy.stats import poisson
import random
import warnings
warnings.filterwarnings('ignore')
```

Classifiers Libraries

In [2]:

```
from sklearn.linear_model import LogisticRegression
from sklearn.svm import SVC
from sklearn.neighbors import KNeighborsClassifier
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier
import xgboost as xgb
```

In [3]:

```
result=pd.read_csv(r"E:\ML\Project\results.csv")
ranking=pd.read_csv(r"E:\ML\Project\ranking.csv",encoding='latin-1')
squads = pd.read_csv(r'E:\ML\Project\squads_upd.csv')
fifa19 = pd.read_csv(r'E:\ML\Project\fifa19_cleaned.csv')
df=pd.read_csv(r"E:\ML\Project\spi.csv")
history=pd.read_csv(r'E:\ML\Project\history team.csv',delimiter='\t')
fixtures=pd.read_csv(r'E:\ML\Project\copa_fixtures.csv')
```

2. Data Cleaning

Function to calculate **Mean Weighted Points** over the past 3 years.

In [4]:

```
def meanWeighted(l,year,country):
    if l>2:
        currentYear = int(ranking.ix[(ranking['country_full']==country) & (ranking['yea
r']==[year])]['mean_pts'].head(1))
        previousYear = int(ranking.ix[(ranking['country_full']==country) & (ranking['ye
ar']==[year-1])]['mean_pts'].head(1))
        previous2Year = int(ranking.ix[(ranking['country_full']==country) & (ranking['y
ear']==[year-2])]['mean_pts'].head(1))
        weighted = (0.5*currentYear)+(0.3*previousYear)+(0.2*previous2Year)
    elif l==2 and year>=2012:
        currentYear = int(ranking.ix[(ranking['country_full']==country) & (ranking['yea
r']==[year])]['mean_pts'].head(1))
        previousYear = int(ranking.ix[(ranking['country_full']==country) & (ranking['ye
ar']==[year-1])]['mean_pts'].head(1))
        weighted = (0.6*currentYear)+(0.4*previousYear)
    else:
        weighted = int(ranking[(ranking['year']==year)]['mean_pts'].head(1))
    return weighted
```

In [5]:

```
countries = ranking.country_full.unique().tolist()
countries.sort()

result = result[result.home_team.isin(countries)]
result = result[result.away_team.isin(countries)]
```

In [6]:

```
ranking['pts_diff'] = round(ranking['total_points'] - ranking['previous_points'])
ranking['rank_date'] = pd.to_datetime(ranking['rank_date'], format='%d-%m-%Y')
ranking.rename(columns={'rank_date':'date'},inplace=True)
ranking['day'] = ranking['date'].dt.day
ranking['month'] = ranking['date'].dt.month
ranking['year'] = ranking['date'].dt.year
ranking['mean_pts'] = ranking.groupby(['country_full','year']).transform(lambda x: x.me
an())['total_points']
ranking['mean_weighted'] = 0
for country in countries:
    years = ranking.ix[ranking['country_full']==country]['year'].unique().tolist()
    years.sort(reverse=True)
    l = len(years)
    for year in years:
        ranking['mean_weighted'] = np.where((ranking['year']==year) & (ranking['country
_full']==country),meanWeighted(l,year,country),ranking['mean_weighted'])
        l -= 1
```

In [7]:

```
current_ranking = ranking[ranking['date']=='2019-06-14']
ranking.drop(['date','previous_points'],axis=1,inplace=True)
ranking.head(3)
```

Out[7]:

	rank	country_full	total_points	confederation	pts_diff	day	month	year	mean_pts	mea
0	1	Netherlands	1596.13	UEFA	54.0	24	8	2011	1464.624	
1	2	Spain	1563.45	UEFA	-25.0	24	8	2011	1584.144	
2	3	Germany	1329.86	UEFA	25.0	24	8	2011	1332.530	

In [8]:

```
current_ranking.head(3)
```

Out[8]:

	date	rank	country_full	total_points	previous_points	confederation	pts_diff	day
19524	2019-06-14	1	Belgium	1746.0	1737	UEFA	9.0	14
19525	2019-06-14	2	France	1718.0	1734	UEFA	-16.0	14
19526	2019-06-14	3	Brazil	1681.0	1676	CONMEBOL	5.0	14

In [9]:

```
result['date'] = pd.to_datetime(result['date'], format='%d-%m-%Y')
result['day'] = result['date'].dt.day
result['month'] = result['date'].dt.month
result['year'] = result['date'].dt.year

result['results'] = np.where(result['home_score']>result['away_score'],2,np.where(resul
t['home_score']==result['away_score'],1,0))
result['impt'] = np.where(result['tournament']=='Friendly',0,1)
result['host'] = np.where((result['country']==result['home_team']) | (result['country']
==result['away_team']),1,0)
result.drop(['date','city','tournament','country'],axis=1,inplace=True)
```

In [10]:

```
result = pd.merge(left=result, right=ranking, how='left', left_on=['home_team','year',
'month'], right_on=['country_full','year','month'], suffixes=('_x','_y')).drop(['countr
y_full','day_y','total_points','confederation'],axis=1)
result = pd.merge(left=result, right=ranking, how='left', left_on=['away_team','year',
'month'], right_on=['country_full','year','month'], suffixes=('_x','_y')).drop(['countr
y_full','day','total_points','confederation'],axis=1)
result.rename(columns={'day_x':'day','rank_x':'home_rank','rank_y':'away_rank','pts_dif
f_x':'home_pts_diff','pts_diff_y':'away_pts_diff','mean_pts_x':'home_mean','mean_pts_y'
:'away_mean','mean_weighted_x':'home_weighted','mean_weighted_y':'away_weighted'},inpla
ce=True)
result.update(result[['home_rank','away_rank','home_pts_diff','away_pts_diff','home_mea
n','away_mean','home_weighted','away_weighted']].fillna(0))
result['rank_diff'] = result['home_rank'] - result['away_rank']
result['mean_diff'] = result['home_mean'] - result['away_mean']
result['weighted_diff'] = result['home_weighted'] - result['away_weighted']
result.drop(['home_rank','away_rank','home_mean','away_mean','home_weighted','away_weig
hted'],axis=1,inplace=True)
result.tail()
```

Out[10]:

	home_team	away_team	home_score	away_score	neutral	day	month	year	result
6658	Norway	Sweden	3	3	False	26	3	2019	
6659	Romania	Faroe Islands	4	1	False	26	3	2019	
6660	Bosnia and Herzegovina	Greece	2	2	False	26	3	2019	
6661	Italy	Liechtenstein	6	0	False	26	3	2019	
6662	Armenia	Finland	0	2	False	26	3	2019	

3. Predicting Match Results (Win/Draw/Lose)

- Variables Used:
  - Which Stadium the match is played in **(0-Neutral, 1-Otherwise)**.
  - **Importance** of match (0-Friendly, 1-Others).
  - How much the Home Team's **Points** have changed.
  - How much the Away Team's **Points** have changed.
  - Difference in team's **Ranking**.
  - Difference in **Mean Weighted Points** over the past 3 years.
- We shall scale the features to speed up the process for **Distance** based classifiers and also use 5-fold Cross Validation for Accuracy.

3.1 Splitting into Training and Test Sets

In [11]:

```
features = result.loc[0:,['host','impt','home_pts_diff','away_pts_diff','rank_diff','we
ighted_diff']]
labels = result.loc[:,['results']]

sc = StandardScaler()
features = sc.fit_transform(features)
x_train,x_test,y_train,y_test = train_test_split(features, labels, test_size=0.2, rando
m_state=0)
x_train = pd.DataFrame(x_train,columns=['host','impt','home_pts_diff','away_pts_diff',
'rank_diff','weighted_diff'])
x_test = pd.DataFrame(x_test,columns=['host','impt','home_pts_diff','away_pts_diff','ra
nk_diff','weighted_diff'])

k_fold = KFold(n_splits=5, shuffle=True, random_state=0)
```

3.2 Building Classification Models

The models will be optimised using GridSearchCV based on F1 score. F1 score gives a weighted average between precision and accuracy/recall. It tells you how precise your classifier is (how many instances it classifies correctly), as well as how robust it is (it does not miss a significant number of instances).

I have typed in some of the optimised parameters based on the GridSearchCV code output.

Confusion matrix table and details will only be shown for the final selected models in order to save space. There would be a summary of each models in the evaluation section below.

Logistic Regression

In [12]:

```
Logistic_Reg = dict()
lr_class = LogisticRegression(C=0.001,n_jobs=-1)
lr_class.fit(x_train,y_train)
res_predict = lr_class.predict(x_test)
train_predict = lr_class.predict(x_train)
Logistic_Reg['Train Accuracy'] = round(np.mean(cross_val_score(lr_class,x_train,y_train
,cv=k_fold,scoring="accuracy")),2)
Logistic_Reg['Test Accuracy'] = round(accuracy_score(y_test,res_predict),2)
Logistic_Reg['Train Precision'] = round(precision_score(y_train,train_predict,average=
'macro'),2)
Logistic_Reg['Test Precision'] = round(precision_score(y_test,res_predict,average='macr
o'),2)
Logistic_Reg['Train F1-Score'] = round(f1_score(y_train,train_predict,average='macro'),
2)
Logistic_Reg['Test F1-Score'] = round(f1_score(y_test,res_predict,average='macro'),2)
```

Support Vector Machine (RBF Kernel)

In [13]:

```
SVM = dict()
svm_class = SVC(kernel='rbf',gamma=0.001,C=2,probability=True)
svm_class.fit(x_train,y_train)
res_predict = svm_class.predict(x_test)
train_predict = svm_class.predict(x_train)
SVM['Train Accuracy'] = round(np.mean(cross_val_score(svm_class,x_train,y_train,cv=k_fo
ld,scoring="accuracy")),2)
SVM['Test Accuracy'] = round(accuracy_score(y_test,res_predict),2)
SVM['Train Precision'] = round(precision_score(y_train,train_predict,average='macro'),2
)
SVM['Test Precision'] = round(precision_score(y_test,res_predict,average='macro'),2)
SVM['Train F1-Score'] = round(f1_score(y_train,train_predict,average='macro'),2)
SVM['Test F1-Score'] = round(f1_score(y_test,res_predict,average='macro'),2)
```

Support Vector Machine (Linear Kernel)

In [14]:

```
SVML = dict()
svml_class = SVC(kernel='linear', gamma=0.001, C=0.5, probability=True)
svml_class.fit(x_train,y_train)
res_predict = svml_class.predict(x_test)
train_predict = svml_class.predict(x_train)
SVML['Train Accuracy'] = round(np.mean(cross_val_score(svml_class,x_train,y_train,cv=k_
fold,scoring="accuracy")),2)
SVML['Test Accuracy'] = round(accuracy_score(y_test,res_predict),2)
SVML['Train Precision'] = round(precision_score(y_train,train_predict,average='macro'),
2)
SVML['Test Precision'] = round(precision_score(y_test,res_predict,average='macro'),2)
SVML['Train F1-Score'] = round(f1_score(y_train,train_predict,average='macro'),2)
SVML['Test F1-Score'] = round(f1_score(y_test,res_predict,average='macro'),2)
```

K-Nearest Neighbors

In [15]:

```
KNN = dict()
knn_class = KNeighborsClassifier(n_neighbors=11,p=2,weights='distance',n_jobs=-1)
knn_class.fit(x_train,y_train)
res_predict = knn_class.predict(x_test)
train_predict = knn_class.predict(x_train)
KNN['Train Accuracy'] = round(np.mean(cross_val_score(knn_class,x_train,y_train,cv=k_fo
ld,scoring="accuracy")),2)
KNN['Test Accuracy'] = round(accuracy_score(y_test,res_predict),2)
KNN['Train Precision'] = round(precision_score(y_train,train_predict,average='macro'),2
)
KNN['Test Precision'] = round(precision_score(y_test,res_predict,average='macro'),2)
KNN['Train F1-Score'] = round(f1_score(y_train,train_predict,average='macro'),2)
KNN['Test F1-Score'] = round(f1_score(y_test,res_predict,average='macro'),2)
```

Decision Tree

In [16]:

```
DT = dict()
dt_class = DecisionTreeClassifier(max_depth= 9, max_leaf_nodes= 80, min_samples_leaf= 6
, min_samples_split= 2)
dt_class.fit(x_train,y_train)
res_predict = dt_class.predict(x_test)
train_predict = dt_class.predict(x_train)
DT['Train Accuracy'] = round(np.mean(cross_val_score(dt_class,x_train,y_train,cv=k_fold
,scoring="accuracy")),2)
DT['Test Accuracy'] = round(accuracy_score(y_test,res_predict),2)
DT['Train Precision'] = round(precision_score(y_train,train_predict,average='macro'),2)
DT['Test Precision'] = round(precision_score(y_test,res_predict,average='macro'),2)
DT['Train F1-Score'] = round(f1_score(y_train,train_predict,average='macro'),2)
DT['Test F1-Score'] = round(f1_score(y_test,res_predict,average='macro'),2)
```

Random Forest

In [17]:

```
RF = dict()
rf_class = RandomForestClassifier(n_estimators=250,max_depth= 8, max_leaf_nodes=100, mi
n_samples_leaf= 5, min_samples_split= 5, n_jobs=-1)
rf_class.fit(x_train,y_train)
res_predict = rf_class.predict(x_test)
train_predict = rf_class.predict(x_train)
RF['Train Accuracy'] = round(np.mean(cross_val_score(rf_class,x_train,y_train,cv=k_fold
,scoring="accuracy")),2)
RF['Test Accuracy'] = round(accuracy_score(y_test,res_predict),2)
RF['Train Precision'] = round(precision_score(y_train,train_predict,average='macro'),2)
RF['Test Precision'] = round(precision_score(y_test,res_predict,average='macro'),2)
RF['Train F1-Score'] = round(f1_score(y_train,train_predict,average='macro'),2)
RF['Test F1-Score'] = round(f1_score(y_test,res_predict,average='macro'),2)
```

XGBoost

In [18]:

```
XGB = dict()
xgb_class = xgb.XGBClassifier(max_depth=10, n_estimators=50, learning_rate=0.1, n_jobs=
-1)
xgb_class.fit(x_train,y_train)
res_predict = xgb_class.predict(x_test)
train_predict = xgb_class.predict(x_train)
XGB['Train Accuracy'] = round(np.mean(cross_val_score(xgb_class,x_train,y_train,cv=k_fo
ld,scoring="accuracy")),2)
XGB['Test Accuracy'] = round(accuracy_score(y_test,res_predict),2)
XGB['Train Precision'] = round(precision_score(y_train,train_predict,average='macro'),2
)
XGB['Test Precision'] = round(precision_score(y_test,res_predict,average='macro'),2)
XGB['Train F1-Score'] = round(f1_score(y_train,train_predict,average='macro'),2)
XGB['Test F1-Score'] = round(f1_score(y_test,res_predict,average='macro'),2)
```

3.3 Model Evaluation

In [19]:

```
clfResults = pd.DataFrame.from_records([Logistic_Reg,SVM,SVML,KNN,DT,RF,XGB],index=['Lo
gistic Regession','Support Vector Machine (RBF)','Support Vector Machine (Linear)','K-N
earest Neighbors','Decision Tree','Random Forest','XGBoost'])
col = clfResults.columns.tolist()
col = [col[i] for i in [3,0,5,2,4,1]]
clfResults = clfResults[col]
clfResults
```

Out[19]:

	Train Accuracy	Test Accuracy	Train Precision	Test Precision	Train F1-Score	Test F1-Score
Logistic Regession	0.59	0.59	0.39	0.38	0.44	0.44
Support Vector Machine (RBF)	0.59	0.60	0.39	0.39	0.43	0.44
Support Vector Machine (Linear)	0.59	0.60	0.39	0.39	0.44	0.44
K-Nearest Neighbors	0.56	0.57	0.99	0.51	0.99	0.50
Decision Tree	0.57	0.58	0.62	0.49	0.55	0.47
Random Forest	0.60	0.61	0.70	0.55	0.57	0.49
XGBoost	0.58	0.59	0.92	0.53	0.89	0.52

Although **XGBoost** has the highest **F1-Score**, we will use **Random Forest Classifier** as it has higher **Test Accuracy** and **Test Precision** values with **F1-Score** almost being the same as XGBoost. In XGboost, the difference between Training and Test Precision, and Train and Test F1-Score is higher, which makes it overfitted.

Confusion Matrix for the Selected Model

In [20]:

```
cm=confusion_matrix(y_train,rf_class.predict(x_train))
col=["Predicted Away Win","Predicted Draw","Predicted Home Win"]
cm=pd.DataFrame(cm)
cm.columns=["Predicted Away Win","Predicted Draw","Predicted Home Win"]
cm.index=["Actual Away Win","Actual Draw","Actual Home Win"]
cm.T
```

Out[20]:

	Actual Away Win	Actual Draw	Actual Home Win
Predicted Away Win	1062	324	215
Predicted Draw	25	215	36
Predicted Home Win	445	753	2255

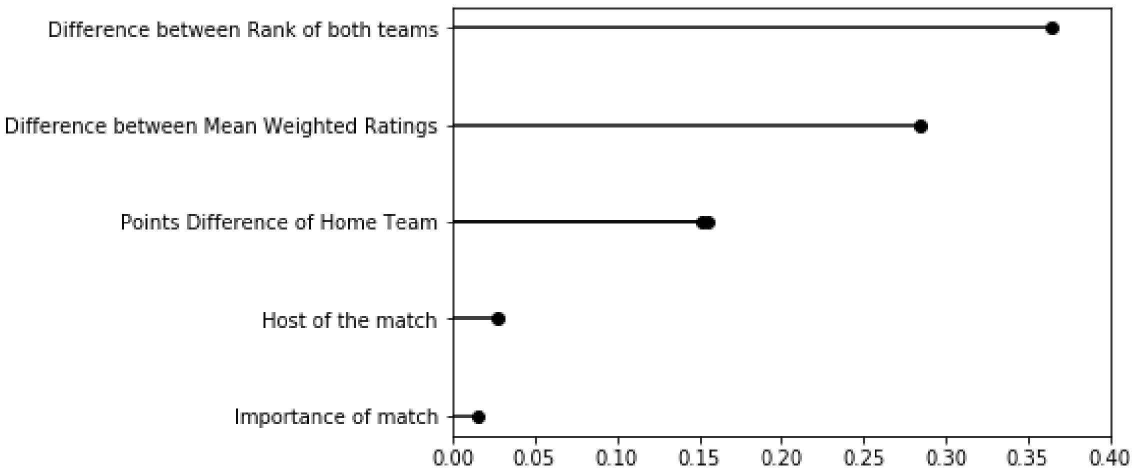
Important Features for the Selected Model

In [21]:

```
impFeatures = pd.DataFrame()
impFeatures['Feature'] = ['Host of the match', 'Importance of match', 'Points Differenc
e of Home Team', 'Points Difference of Home Team', 'Difference between Rank of both tea
ms', 'Difference between Mean Weighted Ratings']
impFeatures['Feature Importance'] = rf_class.feature_importances_
impFeatures.sort_values(by=['Feature Importance'], ascending=True, inplace=True)
fig, ax = plt.subplots(figsize=(6,4))
ax.hlines(impFeatures['Feature'], xmin=0, xmax=impFeatures['Feature Importance'])
ax.plot(impFeatures['Feature Importance'],impFeatures['Feature'],"o",color='black')
ax.set_xlim(0,0.4)
```

Out[21]:

```
(0, 0.4)
```



4. Predicting Goals Scored by Home and Away Teams

Variables used are same as in **3**.

4.1 Splitting into Training and Test Sets

In [22]:

```
features = result.loc[0:,['host','impt','home_pts_diff','away_pts_diff','rank_diff','weighted_diff']]
labels_home = result.loc[:,['home_score']]
labels_away = result.loc[:,['away_score']]

sc = StandardScaler()
features = sc.fit_transform(features)
x_home_train,x_home_test,y_home_train,y_home_test = train_test_split(features, labels_home, test_size=0.2, random_state=0)
x_away_train,x_away_test,y_away_train,y_away_test = train_test_split(features, labels_away, test_size=0.2, random_state=0)

x_home_train = pd.DataFrame(x_train,columns=['host','impt','home_pts_diff','away_pts_diff','rank_diff','weighted_diff'])
x_home_test = pd.DataFrame(x_test,columns=['host','impt','home_pts_diff','away_pts_diff','rank_diff','weighted_diff'])
x_away_train = pd.DataFrame(x_train,columns=['host','impt','home_pts_diff','away_pts_diff','rank_diff','weighted_diff'])
x_away_test = pd.DataFrame(x_test,columns=['host','impt','home_pts_diff','away_pts_diff','rank_diff','weighted_diff'])

k_fold = KFold(n_splits=5, shuffle=True, random_state=0)
```

4.2 Predicting goals scored by Home team

As done in previous section, models will be optimised using GridSearchCV based on F1-Score.

I have typed in some of the optimised parameters based on the GridSearchCV code output.

There would be a summary of each models in the evaluation section below.

Logistic Regression

In [23]:

```
Logistic_Reg_Home = dict()
lr_home = LogisticRegression(C=0.0001, n_jobs=-1)
lr_home.fit(x_home_train,y_home_train)
res_predict = lr_home.predict(x_home_test)
train_predict = lr_home.predict(x_home_train)
Logistic_Reg_Home['Train Accuracy'] = round(np.mean(cross_val_score(lr_home,x_home_train,y_home_train,cv=k_fold,scoring="accuracy")),2)
Logistic_Reg_Home['Test Accuracy'] = round(accuracy_score(y_home_test,res_predict),2)
Logistic_Reg_Home['Train Precision'] = round(precision_score(y_home_train,train_predict,average='macro'),2)
Logistic_Reg_Home['Test Precision'] = round(precision_score(y_home_test,res_predict,average='macro'),2)
Logistic_Reg_Home['Train F1-Score'] = round(f1_score(y_home_train,train_predict,average='macro'),2)
Logistic_Reg_Home['Test F1-Score'] = round(f1_score(y_home_test,res_predict,average='macro'),2)
```

Support Vector Machine (RBF Kernel)

In [24]:

```
SVM_Home = dict()
svm_home = SVC(kernel='rbf', gamma=0.001, C=2, probability=True)
svm_home.fit(x_home_train,y_home_train)
res_predict = svm_home.predict(x_home_test)
train_predict = svm_home.predict(x_home_train)
SVM_Home['Train Accuracy'] = round(np.mean(cross_val_score(svm_home,x_home_train,y_home
_train,cv=k_fold,scoring="accuracy")),2)
SVM_Home['Test Accuracy'] = round(accuracy_score(y_home_test,res_predict),2)
SVM_Home['Train Precision'] = round(precision_score(y_home_train,train_predict,average=
'macro'),2)
SVM_Home['Test Precision'] = round(precision_score(y_home_test,res_predict,average='mac
ro'),2)
SVM_Home['Train F1-Score'] = round(f1_score(y_home_train,train_predict,average='macro'
),2)
SVM_Home['Test F1-Score'] = round(f1_score(y_home_test,res_predict,average='macro'),2)
```

K-Nearest Neighbors

In [25]:

```
KNN_Home = dict()
knn_home = KNeighborsClassifier(n_neighbors=19, p=1, weights='distance', n_jobs=-1)
knn_home.fit(x_home_train,y_home_train)
res_predict = knn_home.predict(x_home_test)
train_predict = knn_home.predict(x_home_train)
KNN_Home['Train Accuracy'] = round(np.mean(cross_val_score(knn_home,x_home_train,y_home
_train,cv=k_fold,scoring="accuracy")),2)
KNN_Home['Test Accuracy'] = round(accuracy_score(y_home_test,res_predict),2)
KNN_Home['Train Precision'] = round(precision_score(y_home_train,train_predict,average=
'macro'),2)
KNN_Home['Test Precision'] = round(precision_score(y_home_test,res_predict,average='mac
ro'),2)
KNN_Home['Train F1-Score'] = round(f1_score(y_home_train,train_predict,average='macro'
),2)
KNN_Home['Test F1-Score'] = round(f1_score(y_home_test,res_predict,average='macro'),2)
```

Decision Tree

In [26]:

```
DT_Home = dict()
dt_home = DecisionTreeClassifier(max_depth= 5, max_leaf_nodes= 50, min_samples_leaf= 5,
min_samples_split= 2)
dt_home.fit(x_home_train,y_home_train)
res_predict = dt_home.predict(x_home_test)
train_predict = dt_home.predict(x_home_train)
DT_Home['Train Accuracy'] = round(np.mean(cross_val_score(dt_home,x_home_train,y_home_t
rain,cv=k_fold,scoring="accuracy")),2)
DT_Home['Test Accuracy'] = round(accuracy_score(y_home_test,res_predict),2)
DT_Home['Train Precision'] = round(precision_score(y_home_train,train_predict,average=
'macro'),2)
DT_Home['Test Precision'] = round(precision_score(y_home_test,res_predict,average='macr
o'),2)
DT_Home['Train F1-Score'] = round(f1_score(y_home_train,train_predict,average='macro'),
2)
DT_Home['Test F1-Score'] = round(f1_score(y_home_test,res_predict,average='macro'),2)
```

Random Forest

In [27]:

```
RF_Home = dict()
rf_home = RandomForestClassifier(n_estimators=100,max_depth= 7, max_leaf_nodes=110, min
_samples_leaf= 3, min_samples_split= 2, n_jobs=-1)
rf_home.fit(x_home_train,y_home_train)
res_predict = rf_home.predict(x_home_test)
train_predict = rf_home.predict(x_home_train)
RF_Home['Train Accuracy'] = round(np.mean(cross_val_score(rf_home,x_home_train,y_home_t
rain,cv=k_fold,scoring="accuracy")),2)
RF_Home['Test Accuracy'] = round(accuracy_score(y_home_test,res_predict),2)
RF_Home['Train Precision'] = round(precision_score(y_home_train,train_predict,average=
'macro'),2)
RF_Home['Test Precision'] = round(precision_score(y_home_test,res_predict,average='macr
o'),2)
RF_Home['Train F1-Score'] = round(f1_score(y_home_train,train_predict,average='macro'),
2)
RF_Home['Test F1-Score'] = round(f1_score(y_home_test,res_predict,average='macro'),2)
```

XGBoost

In [28]:

```
XGB_Home = dict()
xgb_home = xgb.XGBClassifier(max_depth=6, n_estimators=150, learning_rate=0.01, n_jobs=
-1)
xgb_home.fit(x_home_train,y_home_train)
res_predict = xgb_home.predict(x_home_test)
train_predict = xgb_home.predict(x_home_train)
XGB_Home['Train Accuracy'] = round(np.mean(cross_val_score(xgb_home,x_home_train,y_home
_train,cv=k_fold,scoring="accuracy")),2)
XGB_Home['Test Accuracy'] = round(accuracy_score(y_home_test,res_predict),2)
XGB_Home['Train Precision'] = round(precision_score(y_home_train,train_predict,average=
'macro'),2)
XGB_Home['Test Precision'] = round(precision_score(y_home_test,res_predict,average='mac
ro'),2)
XGB_Home['Train F1-Score'] = round(f1_score(y_home_train,train_predict,average='macro'
),2)
XGB_Home['Test F1-Score'] = round(f1_score(y_home_test,res_predict,average='macro'),2)
```

4.3 Model evaluation for classifiers used to predict goals for Home team

In [29]:

```
clfResultsHome = pd.DataFrame.from_records([Logistic_Reg_Home,SVM_Home,KNN_Home,DT_Home
,RF_Home,XGB_Home],index=['Logistic Regession','Support Vector Machine (RBF)','K-Neares
t Neighbors','Decision Tree','Random Forest','XGBoost'])
col = clfResultsHome.columns.tolist()
col = [col[i] for i in [3,0,5,2,4,1]]
clfResultsHome = clfResultsHome[col]
clfResultsHome
```

Out[29]:

	Train Accuracy	Test Accuracy	Train Precision	Test Precision	Train F1-Score	Test F1-Score
Logistic Regession	0.35	0.33	0.08	0.08	0.09	0.09
Support Vector Machine (RBF)	0.35	0.33	0.06	0.06	0.07	0.07
K-Nearest Neighbors	0.33	0.33	1.00	0.13	1.00	0.11
Decision Tree	0.35	0.34	0.15	0.11	0.11	0.10
Random Forest	0.36	0.33	0.31	0.11	0.15	0.10
XGBoost	0.35	0.35	0.40	0.12	0.23	0.11

K-Nearest Neighbors has the highest F1-Score, but the difference between Training and Test F1-Score is very large, which makes it overfitted.

4.4 Predicting goals scored by Away team

Logistic Regression

In [30]:

```
Logistic_Reg_Away = dict()
lr_away = LogisticRegression(C=0.001, n_jobs=-1)
lr_away.fit(x_away_train,y_away_train)
res_predict = lr_away.predict(x_away_test)
train_predict = lr_away.predict(x_away_train)
Logistic_Reg_Away['Train Accuracy'] = round(np.mean(cross_val_score(lr_away,x_away_trai
n,y_away_train,cv=k_fold,scoring="accuracy")),2)
Logistic_Reg_Away['Test Accuracy'] = round(accuracy_score(y_away_test,res_predict),2)
Logistic_Reg_Away['Train Precision'] = round(precision_score(y_away_train,train_predict
,average='macro'),2)
Logistic_Reg_Away['Test Precision'] = round(precision_score(y_away_test,res_predict,ave
rage='macro'),2)
Logistic_Reg_Away['Train F1-Score'] = round(f1_score(y_away_train,train_predict,average
='macro'),2)
Logistic_Reg_Away['Test F1-Score'] = round(f1_score(y_away_test,res_predict,average='ma
cro'),2)
```

Support Vector Machine (RBF Kernel)

In [31]:

```
SVM_Away = dict()
svm_away = SVC(kernel='rbf', gamma=0.001, C=2, probability=True)
svm_away.fit(x_away_train,y_away_train)
res_predict = svm_away.predict(x_away_test)
train_predict = svm_away.predict(x_away_train)
SVM_Away['Train Accuracy'] = round(np.mean(cross_val_score(svm_away,x_away_train,y_away
_train,cv=k_fold,scoring="accuracy")),2)
SVM_Away['Test Accuracy'] = round(accuracy_score(y_away_test,res_predict),2)
SVM_Away['Train Precision'] = round(precision_score(y_away_train,train_predict,average=
'macro'),2)
SVM_Away['Test Precision'] = round(precision_score(y_away_test,res_predict,average='mac
ro'),2)
SVM_Away['Train F1-Score'] = round(f1_score(y_away_train,train_predict,average='macro'
),2)
SVM_Away['Test F1-Score'] = round(f1_score(y_away_test,res_predict,average='macro'),2)
```

K-Nearest Neighbors

In [32]:

```
KNN_Away = dict()
knn_away = KNeighborsClassifier(n_neighbors=10, p=2, weights='distance', n_jobs=-1)
knn_away.fit(x_away_train,y_away_train)
res_predict = knn_away.predict(x_away_test)
train_predict = knn_away.predict(x_away_train)
KNN_Away['Train Accuracy'] = round(np.mean(cross_val_score(knn_away,x_away_train,y_away
_train,cv=k_fold,scoring="accuracy")),2)
KNN_Away['Test Accuracy'] = round(accuracy_score(y_away_test,res_predict),2)
KNN_Away['Train Precision'] = round(precision_score(y_away_train,train_predict,average=
'macro'),2)
KNN_Away['Test Precision'] = round(precision_score(y_away_test,res_predict,average='mac
ro'),2)
KNN_Away['Train F1-Score'] = round(f1_score(y_away_train,train_predict,average='macro'
),2)
KNN_Away['Test F1-Score'] = round(f1_score(y_away_test,res_predict,average='macro'),2)
```

Decision Tree

In [33]:

```
DT_Away = dict()
dt_away = DecisionTreeClassifier(max_depth= 6, max_leaf_nodes= 90, min_samples_leaf= 6,
min_samples_split= 2)
dt_away.fit(x_away_train,y_away_train)
res_predict = dt_away.predict(x_away_test)
train_predict = dt_away.predict(x_away_train)
DT_Away['Train Accuracy'] = round(np.mean(cross_val_score(dt_away,x_away_train,y_away_t
rain,cv=k_fold,scoring="accuracy")),2)
DT_Away['Test Accuracy'] = round(accuracy_score(y_away_test,res_predict),2)
DT_Away['Train Precision'] = round(precision_score(y_away_train,train_predict,average=
'macro'),2)
DT_Away['Test Precision'] = round(precision_score(y_away_test,res_predict,average='macr
o'),2)
DT_Away['Train F1-Score'] = round(f1_score(y_away_train,train_predict,average='macro'),
2)
DT_Away['Test F1-Score'] = round(f1_score(y_away_test,res_predict,average='macro'),2)
```

Random Forest

In [34]:

```
RF_Away = dict()
rf_away = RandomForestClassifier(n_estimators=100,max_depth= 7, max_leaf_nodes=90, min_samples_leaf= 4, min_samples_split= 2, n_jobs=-1)
rf_away.fit(x_away_train,y_away_train)
res_predict = rf_away.predict(x_away_test)
train_predict = rf_away.predict(x_away_train)
RF_Away['Train Accuracy'] = round(np.mean(cross_val_score(rf_away,x_away_train,y_away_train,cv=k_fold,scoring="accuracy")),2)
RF_Away['Test Accuracy'] = round(accuracy_score(y_away_test,res_predict),2)
RF_Away['Train Precision'] = round(precision_score(y_away_train,train_predict,average='macro'),2)
RF_Away['Test Precision'] = round(precision_score(y_away_test,res_predict,average='macro'),2)
RF_Away['Train F1-Score'] = round(f1_score(y_away_train,train_predict,average='macro'),2)
RF_Away['Test F1-Score'] = round(f1_score(y_away_test,res_predict,average='macro'),2)
```

XGBoost

In [35]:

```
XGB_Away = dict()
xgb_away = xgb.XGBClassifier(max_depth=6, n_estimators=100, learning_rate=0.01, n_jobs=-1)
xgb_away.fit(x_away_train,y_away_train)
res_predict = xgb_away.predict(x_away_test)
train_predict = xgb_away.predict(x_away_train)
XGB_Away['Train Accuracy'] = round(np.mean(cross_val_score(xgb_away,x_away_train,y_away_train,cv=k_fold,scoring="accuracy")),2)
XGB_Away['Test Accuracy'] = round(accuracy_score(y_away_test,res_predict),2)
XGB_Away['Train Precision'] = round(precision_score(y_away_train,train_predict,average='macro'),2)
XGB_Away['Test Precision'] = round(precision_score(y_away_test,res_predict,average='macro'),2)
XGB_Away['Train F1-Score'] = round(f1_score(y_away_train,train_predict,average='macro'),2)
XGB_Away['Test F1-Score'] = round(f1_score(y_away_test,res_predict,average='macro'),2)
```

4.3 Model evaluation for classifiers used to predict goals for Away team

In [36]:

```
clfResultsAway = pd.DataFrame.from_records([Logistic_Reg_Away,SVM_Away,KNN_Away,DT_Away
,RF_Away,XGB_Away],index=['Logistic Regession','Support Vector Machine (RBF)','K-Neares
t Neighbors','Decision Tree','Random Forest','XGBoost'])
col = clfResultsAway.columns.tolist()
col = [col[i] for i in [3,0,5,2,4,1]]
clfResultsAway = clfResultsAway[col]
clfResultsAway
```

Out[36]:

	Train Accuracy	Test Accuracy	Train Precision	Test Precision	Train F1-Score	Test F1-Score
Logistic Regession	0.43	0.45	0.10	0.15	0.09	0.14
Support Vector Machine (RBF)	0.41	0.42	0.05	0.05	0.05	0.07
K-Nearest Neighbors	0.39	0.41	1.00	0.13	1.00	0.13
Decision Tree	0.41	0.44	0.26	0.15	0.17	0.14
Random Forest	0.43	0.45	0.35	0.17	0.19	0.14
XGBoost	0.42	0.45	0.60	0.19	0.32	0.14

Random Forest Classifier has the highest value for all the 3 metrics, hence we will use Random Forest Classifier to predict goals scored by Away Team.

5. Current Ability and Potential of Teams

We will use the current **Overall** and **Potential** ratings for each player in the squad of each team.

Each team has a squad of 23 players.

We take the ratings of each player from **FIFA 19** and **PES 19** dataset to calculate the current Ability and Potential of each team.

In [37]:

```
teams = squads.team.unique().tolist()
fifa19 = fifa19[fifa19.Nationality.isin(teams)].reset_index(drop=True)
fifa19_stats = fifa19[fifa19.Nationality.isin(squads.team) & (fifa19['Full Name'].isin(
squads['player']) |
        fifa19['Name'].isin(squads['player']) | fifa19['First Name'].isin(squads['Last
 Name']) )]
fifa19_stats.reset_index(inplace=True,drop=True)
fifa19_stats = fifa19_stats.groupby('Nationality').apply(lambda x: (x.sort_values('Over
all',ascending=False)).head(23)).reset_index(drop=True)
fifa19.head()
```

Out[37]:

	Name	Full Name	Age	Height	Nationality	Overall	Potential	First Name	Last Name
0	L. Messi	Lionel Messi	31	170.0	Argentina	94	94	Lionel	Messi
1	Neymar Jr	Neymar Jr	26	175.0	Brazil	92	93	Neymar	Jr
2	L. Suárez	Luis Suárez	31	183.0	Uruguay	91	91	Luis	Suárez
3	D. Godín	Diego Godín	32	188.0	Uruguay	90	90	Diego	Godín
4	P. Dybala	Paulo Dybala	24	178.0	Argentina	89	94	Paulo	Dybala

In [38]:

```
for team in teams:
    count = fifa19_stats[fifa19_stats.Nationality==team]['Full Name'].count()
    if count >= 23:
        continue
    squadUpdate = fifa19[(fifa19.Nationality==team) & ( ~fifa19['Full Name'].isin(fifa1
9_stats['Full Name']) )].sort_values('Overall',ascending=False).head(23-count)
    fifa19_stats = pd.concat([fifa19_stats,squadUpdate]).drop_duplicates().reset_index(
drop=True)
```

In [39]:

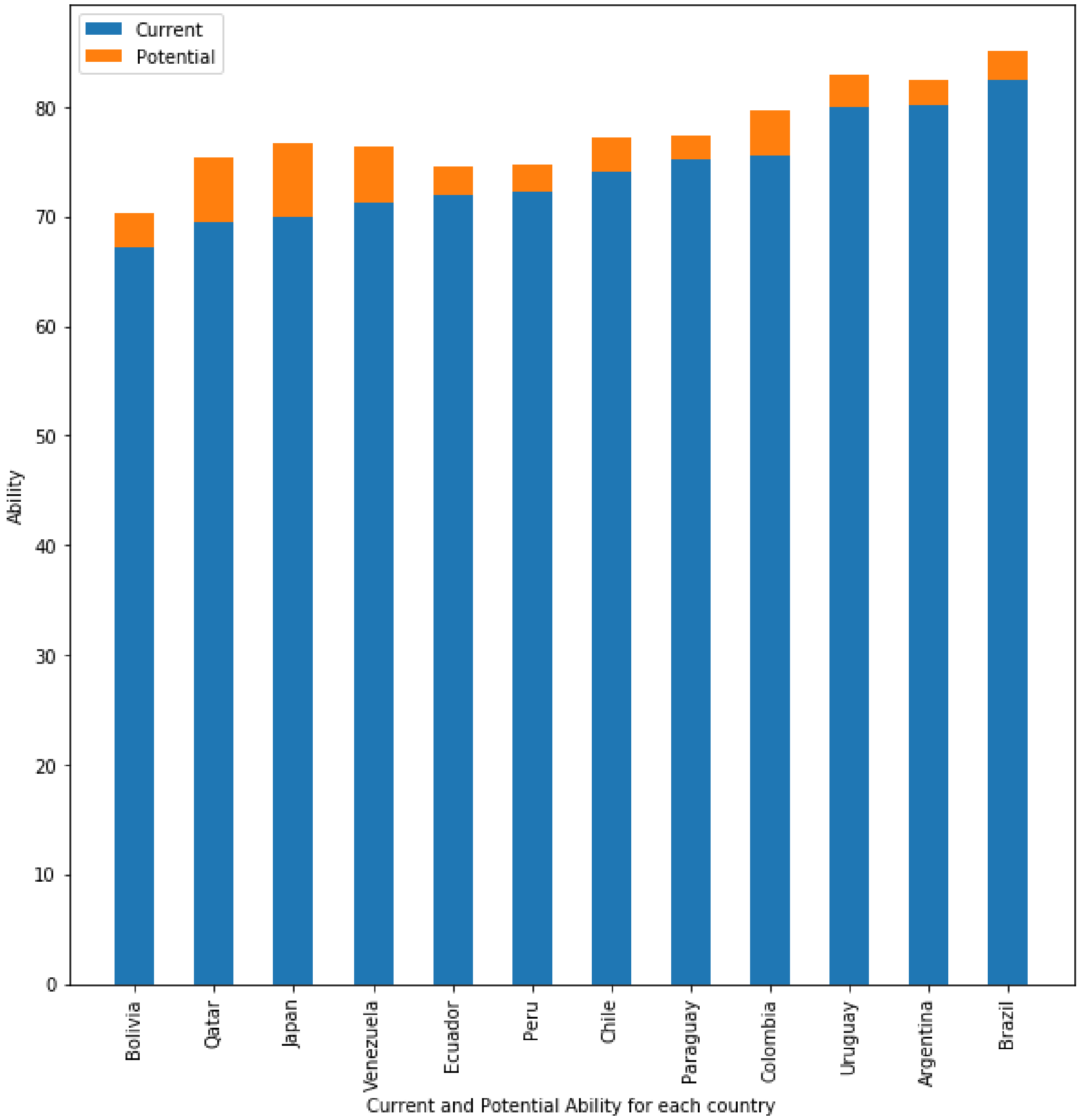
```
grp = fifa19_stats.groupby('Nationality').apply(lambda x: round((x.sort_values('Overal
l',ascending=False)).mean(),2)).sort_values('Potential')
grp['Points to potential'] = grp['Potential'] - grp['Overall']
grp = grp.sort_values(by = 'Overall')
grp.head(3)
```

Out[39]:

	Age	Height	Overall	Potential	Points to potential
Nationality					
Bolivia	26.48	176.83	67.09	70.22	3.13
Qatar	27.26	177.65	69.43	75.43	6.00
Japan	24.35	178.17	70.00	76.70	6.70

In [40]:

```
current = grp['Overall']
potential = grp['Points to potential']
ind = np.arange(12)
width = 0.5
plt.figure(figsize=(10,10))
p1 = plt.bar(ind,current,width)
p2 = plt.bar(ind,potential,width,bottom=current)
plt.ylabel('Ability')
plt.xlabel('Current and Potential Ability for each country')
plt.xticks(ind,(grp.index),rotation=90)
plt.legend((p1[0],p2[0]),('Current','Potential'))
plt.show()
```



We can see that **Brazil** has the highest current ability while **Japan** is most under potential.

6. Variables to build Poisson Model

- Soccer Power Index
- Average Age
- Average Height
- Past Participation
- Average goals scored per game
- Average goals conceded per game
- Potential
- Current Ability

In [41]:

```
grp.reset_index(inplace=True)
spi=pd.merge(left=df,right=grp,how='left',left_on=['Name'],right_on=['Nationality']).dr
opna().drop(['Nationality'],axis=1)
spi=pd.merge(left=spi,right=history,how='left',left_on=['Name'],right_on=['Team']).drop
(['Team'],axis=1)
fixtures=pd.merge(left=fixtures,right=spi,how='left',left_on=['Team'],right_on=['Name'
]).drop(['Name'],axis=1).fillna(0)
fixtures["avg score"] = round(fixtures['GF'] / fixtures['GP'],2)
fixtures["avg conceded"] = round(fixtures['GA'] / fixtures['GP'],2)
fixtures.iloc[0:,[5,6,7,9,-2,-1]].fillna(0,inplace=True)
sc=StandardScaler()
fixtures[['Part.','Overall','Potential']]=sc.fit_transform(fixtures[['Part.','Overall',
'Potential']])
fixtures.head()
```

Out[41]:

	Team	Group	First_match_Against	Second_match_Against	Third_match_Against	SPI
0	Brazil	A	Bolivia	Venezuela	Peru	2.39
1	Bolivia	A	Brazil	Peru	Venezuela	0.17
2	Venezuela	A	Peru	Brazil	Bolivia	0.73
3	Peru	A	Venezuela	Bolivia	Brazil	1.25
4	Argentina	B	Colombia	Paraguay	Qatar	1.59

5 rows × 24 columns

7. Predicting Copa America 2019

Combination of Poisson Distribution and Random Forest to Predict Goals Scored

- **Base Goals** = Average goals scored by X against Y = min(Ave_goals_scored_per_game (X), Ave_goals_conceded_per_game(Y))
- **Difference in Teams** = 0.35*(diff. in Soccer_Power_index) + 0.20*(diff. in Potential) + 0.20*(diff. in total_participation) + 0.05 (diff. in Average_height) - 0.05* (diff. in Average_age) + 0.15*(diff. in current overall ability)

The current ability plays an important role as to how much the teams differ in quality.

The potential of the players and the experience (total_participation) would also play a important role in a match, especially in a semi-final/final.

Least weights were given to the height (Headers advantage) and age (might be correlated with their stamina) as they might play a small part in some parts of the match. Age difference was "subtracted" because the younger the player is, there is a higher change of having more stamina, hence lower age is "better".

- **Mean Goals Scored** = max(0, Base Goals + Difference in Teams)

Now to calculate probability of goals scored, we will combine Poisson Distribution and Random Forest Classifier as, Probability(i Goals Scored) = 0.7*(poisson.pmf(i, Mean Goals Scored)) + 0.3*(Random Forest Probability of i Goals)

Eg. P(0 goals) = 0.7*(poisson.pmf(0, Mean Goals Scored)) + 0.3*(Random Forest Probability of 0 Goals)

We then calculate the probability for 0,1,2,3,4,5,6 Goals using above equation.

Predicted no. of goals will be the one with highest probability.

Training the selected classifier(s) for Group Matches

In [42]:

```
features = result.loc[0:,['host','impt','home_pts_diff','away_pts_diff','rank_diff','we
ighted_diff']]
labels = result.loc[:,['results']]
rf_class = RandomForestClassifier(n_estimators=250,max_depth= 8, max_leaf_nodes=100, mi
n_samples_leaf= 5, min_samples_split= 5, n_jobs=-1)
rf_class.fit(features,labels)

from itertools import combinations
opponents = ['First match \nagainst', 'Second match\n against', 'Third match\n against'
]
fixtures['Points'] = 0
fixtures['Total_Prob'] = 0
fixtures.set_index('Team',inplace=True)
current_ranking.set_index('country_full',inplace=True)
```

Group Stage

In [43]:

```
for group in list(fixtures['Group'].unique()):
    print('___Group {}___'.format(group))
    for home, away in combinations(fixtures.query('Group == "{}"'.format(group)).index,
2):
        print('{} vs. {}: '.format(home, away), end='')
        match = pd.DataFrame(np.array([[np.nan, np.nan, np.nan, np.nan, np.nan, np.nan
]]), columns=['host','impt','home_pts_diff','away_pts_diff','rank_diff','weighted_diff'
])
        match['host'] = 1 if home=='Brazil' or away=='Brazil' else 0
        match['impt'] = 1
        match['home_pts_diff'] = current_ranking.loc[home,'pts_diff']
        match['away_pts_diff'] = current_ranking.loc[away,'pts_diff']
        match['rank_diff'] = current_ranking.loc[home,'rank'] - current_ranking.loc[awa
y,'rank']
        match['weighted_diff'] = current_ranking.loc[home,'mean_weighted'] - current_ra
nking.loc[away,'mean_weighted']

        home_win_prob = rf_class.predict_proba(match)[:,2][0]
        away_win_prob = rf_class.predict_proba(match)[:,0][0]
        draw_prob = rf_class.predict_proba(match)[:,1][0]

        points = 0
        if max(home_win_prob,away_win_prob,draw_prob) == away_win_prob:
            print("{} wins with a probability of {:.2f}% ".format(away, away_win_prob))
            fixtures.loc[away, 'Points'] += 3
            fixtures.loc[home, 'Total_Prob'] += home_win_prob
            fixtures.loc[away, 'Total_Prob'] += away_win_prob
        elif max(home_win_prob,away_win_prob,draw_prob) == draw_prob:
            points = 1
            print("Draw with probability of {:.2f}%".format(draw_prob))
            fixtures.loc[home, 'Points'] += 1
            fixtures.loc[away, 'Points'] += 1
            fixtures.loc[home, 'Total_Prob'] += draw_prob
            fixtures.loc[away, 'Total_Prob'] += draw_prob
        elif max(home_win_prob,away_win_prob,draw_prob) == home_win_prob:
            points = 3
            fixtures.loc[home, 'Points'] += 3
            fixtures.loc[home, 'Total_Prob'] += home_win_prob
            fixtures.loc[away, 'Total_Prob'] += away_win_prob
            print("{} wins with a probability of {:.2f}%".format(home, home_win_prob))
    print()
```

```
___Group A___
Brazil vs. Bolivia: Brazil wins with a probability of 0.85%
Brazil vs. Venezuela: Brazil wins with a probability of 0.72%
Brazil vs. Peru: Brazil wins with a probability of 0.71%
Bolivia vs. Venezuela: Venezuela wins with a probability of 0.41%
Bolivia vs. Peru: Peru wins with a probability of 0.62%
Venezuela vs. Peru: Peru wins with a probability of 0.57%

___Group B___
Argentina vs. Colombia: Argentina wins with a probability of 0.50%
Argentina vs. Paraguay: Argentina wins with a probability of 0.62%
Argentina vs. Qatar: Argentina wins with a probability of 0.71%
Colombia vs. Paraguay: Colombia wins with a probability of 0.69%
Colombia vs. Qatar: Colombia wins with a probability of 0.75%
Paraguay vs. Qatar: Paraguay wins with a probability of 0.66%

___Group C___
Uruguay vs. Ecuador: Uruguay wins with a probability of 0.68%
Uruguay vs. Japan: Uruguay wins with a probability of 0.61%
Uruguay vs. Chile: Uruguay wins with a probability of 0.38%
Ecuador vs. Japan: Japan wins with a probability of 0.38%
Ecuador vs. Chile: Chile wins with a probability of 0.61%
Japan vs. Chile: Chile wins with a probability of 0.59%
```

Some probabilities are not more than 50% because the maximum of (Win Probability, Draw Probability and Loss Probability) is taken to make the decision, and hence the maximum probability selected might not be more than 50%.

Function to simulate a knockout match

In [44]:

```
def knockout(home,away):
    print("{} vs. {}: ".format(home, away), end='')
    match = pd.DataFrame(np.array([[np.nan, np.nan, np.nan, np.nan, np.nan, np.nan]]),
columns=['host','impt','home_pts_diff','away_pts_diff','rank_diff','weighted_diff'])
    match['host'] = 1 if home=='Brazil' or away=='Brazil' else 0
    match['impt'] = 1
    match['home_pts_diff'] = current_ranking.loc[home,'pts_diff']
    match['away_pts_diff'] = current_ranking.loc[away,'pts_diff']
    match['rank_diff'] = current_ranking.loc[home,'rank'] - current_ranking.loc[away,'r
ank']
    match['weighted_diff'] = current_ranking.loc[home,'mean_weighted'] - current_rankin
g.loc[away,'mean_weighted']
    base_home_goals = max(fixtures.loc[home,'avg score'],fixtures.loc[away,'avg concede
d'])
    base_away_goals = max(fixtures.loc[home,'avg conceded'],fixtures.loc[away,'avg scor
e'])
    home_diff_in_countries = (0.35*(fixtures.loc[home,'SPI']-fixtures.loc[away,'SPI'])
+
                              0.20*(fixtures.loc[home,'Potential']-fixtures.loc[away,'P
otential'])+
                              0.20*(fixtures.loc[home,'Part.']-fixtures.loc[away,'Par
t.'])-
                              0.05*(fixtures.loc[home,'Age']-fixtures.loc[away,'Age'])+
                              0.05*(fixtures.loc[home,'Height']-fixtures.loc[away,'Heig
ht'])+
                              0.15*(fixtures.loc[home,'Overall']-fixtures.loc[away,'Ove
rall']))

    away_diff_in_countries = (0.35*(fixtures.loc[away,'SPI']-fixtures.loc[home,'SPI'])
+
                              0.20*(fixtures.loc[away,'Potential']-fixtures.loc[home,'P
otential'])+
                              0.20*(fixtures.loc[away,'Part.']-fixtures.loc[home,'Par
t.'])-
                              0.05*(fixtures.loc[away,'Age']-fixtures.loc[home,'Age'])+
                              0.05*(fixtures.loc[away,'Height']-fixtures.loc[home,'Heig
ht'])+
                              0.15*(fixtures.loc[away,'Overall']-fixtures.loc[home,'Ove
rall']))

    mean_home_goals = max(0,base_home_goals + home_diff_in_countries)
    mean_away_goals = max(0,base_away_goals + away_diff_in_countries)
    home_prob_goals = list()
    away_prob_goals = list()
    home_prob_goals_rfmodel = list(rf_home.predict_proba(match)[0])
    away_prob_goals_rfmodel = list(rf_away.predict_proba(match)[0])
    for i in range(7):
        home_prob_goals.append(0.7*poisson.pmf(i,mean_home_goals) + 0.3*home_prob_goals
_rfmodel[i])
        away_prob_goals.append(0.7*poisson.pmf(i,mean_away_goals) + 0.3*away_prob_goals
_rfmodel[i])

    home_goals = np.argmax(home_prob_goals)
    away_goals = np.argmax(away_prob_goals)

    if home_goals>away_goals:
        print("{} wins {} with score of {}:{}".format(home,away,str(home_goals),str(awa
y_goals)),end='')
        winners.append(home)
```

```
        losers.append(away)
    elif home_goals<away_goals:
        print("{} wins {} with score of {}:{}".format(away,home,str(away_goals),str(hom
e_goals)),end='')
        winners.append(away)
        losers.append(home)
    else:
        team = [home,away]
        win = random.choice(team)
        team.remove(win)
        loser = team[0]
        print("{} draws with {} with a score of {}:{} after Extra-Time and {} wins the
 Penalty Shootout".format(home,away,str(home_goals),str(away_goals),win),end='')
        winners.append(win)
        losers.append(loser)
    print()
```

Training the selected classifier(s) for Knockout Matches

In [45]:

```
features = result.loc[0:,['host','impt','home_pts_diff','away_pts_diff','rank_diff','we
ighted_diff']]
labels_home = result.loc[:,['home_score']]
labels_away = result.loc[:,['away_score']]

rf_home = RandomForestClassifier(n_estimators=100,max_depth= 8, max_leaf_nodes=110, min
_samples_leaf= 2, min_samples_split= 2, n_jobs=-1)
rf_home.fit(features,labels_home)
rf_away = RandomForestClassifier(n_estimators=100,max_depth= 7, max_leaf_nodes=90, min_
samples_leaf= 4, min_samples_split= 2, n_jobs=-1)
rf_away.fit(features,labels_away)

print()
```

Creating fixtures for Knockout Stages

In [46]:

```
pairing = [0,7,3,4,1,5,2,6]
fixtures = fixtures.sort_values(['Points','Group'],ascending=[False,True]).reset_index
()
Finals = fixtures.groupby('Group').nth([0,1]).reset_index().set_index('Team')
#Finals.sort_values(['Points','Group'],ascending=[False,True],inplace=True)
thirdPlaced=fixtures.groupby('Group').nth([2]).sort_values(['Points','Total_Prob'],asce
nding=[False,False]).reset_index().set_index('Team')
Finals=Finals.append(thirdPlaced.iloc[:2,:])
Finals.sort_values(['Points','Group'],ascending=[False,True],inplace=True)
Finals.reset_index(inplace=True)
Finals = Finals.loc[pairing].set_index('Team')
fixtures.set_index('Team',inplace=True)
Finals.head()
```

Out[46]:

	Group	Age	D	Dif	First_match_Against	GA	GF	GP	Height	L
Team										
Brazil	A	27.00	35.0	205.0	Bolivia	200.0	405.0	178.0	180.09	44.0
Paraguay	B	27.52	39.0	-40.0	Qatar	293.0	253.0	168.0	178.48	67.0
Peru	A	26.57	35.0	-19.0	Venezuela	232.0	213.0	148.0	177.35	59.0
Colombia	B	25.52	24.0	-53.0	Argentina	184.0	131.0	113.0	182.22	47.0
Argentina	B	26.70	38.0	282.0	Colombia	173.0	455.0	189.0	180.30	31.0

5 rows × 25 columns

Quarterfinals and Semifinals

In [47]:

```
finals = ['Quarter-Finals','Semi-Finals']

for f in finals:
    print("___Starting of the {}___".format(f))
    iterations = int(len(Finals) / 2)
    winners = list()
    losers = list()
    for i in range(iterations):
        home = Finals.index[i*2]
        away = Finals.index[i*2+1]
        knockout(home,away)
    Finals = Finals.loc[winners]
    if len(winners)>2:
        print('\nSemi-Finalists: ' + winners[0] + ',' + winners[1] + ',' + winners[2] +
',' + winners[3] + '\n')
    else:
        print('\nFinalists: ' + winners[0] + ',' + winners[1] + '\n')

finalists = winners
```

```
___Starting of the Quarter-Finals___
Brazil vs. Paraguay: Brazil wins Paraguay with score of 2:0
Peru vs. Colombia: Colombia wins Peru with score of 1:0
Argentina vs. Chile: Argentina wins Chile with score of 2:0
Uruguay vs. Venezuela: Uruguay wins Venezuela with score of 2:0

Semi-Finalists: Brazil,Colombia,Argentina,Uruguay

___Starting of the Semi-Finals___
Brazil vs. Colombia: Brazil wins Colombia with score of 2:0
Argentina vs. Uruguay: Argentina wins Uruguay with score of 2:1

Finalists: Brazil,Argentina
```

Third Place Playoff and Final

In [48]:

```
print("___Third Place Playoff___")
home = losers[0]
away = losers[1]
winners = list()
losers = list()
knockout(home,away)
third = winners[0]
fourth = losers[0]

print("\n___Copa America Final___")
home = finalists[0]
away = finalists[1]
knockout(home,away)
champion = winners[1]
runners_up = losers[1]

print("\n{} wins the Copa America 2019.\n".format(champion))
print("{} are Runners-up.\n".format(runners_up))
print("{} secures Third place.\n".format(third))
print("{} secures Fourth place after losing from {} in the Playoff\n".format(fourth,thi
rd))
```

```
___Third Place Playoff___
Colombia vs. Uruguay: Uruguay wins Colombia with score of 1:0

___Copa America Final___
Brazil vs. Argentina: Brazil wins Argentina with score of 2:1

Brazil wins the Copa America 2019.

Argentina are Runners-up.

Uruguay secures Third place.

Colombia secures Fourth place after losing from Uruguay in the Playoff
```