# Player Overall Scores Analysis and Prediction by FIFA 18 player dataset

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## 1. Introduction

FIFA 18 is the last-year version of a famous series of soccer video games, FIFA soccer. In order to reproduce the reality in the virtual world, the game developers track the performance of every player in the real matches and assess their abilities by assigning ratings from 0 to 100 for their attributes such as finishing or dribbling. Each player is also assigned an overall score from 0 to 100, one number summarizing all abilities. We were very interested with the rating calculation of this one-number overall score from all player's attributes.

In this project, we utilized the FIFA 18 player dataset from Kaggle (https://www.kaggle.com/thec03u5/fifa-18-demo-player-dataset) to unravel the hidden rating calculation of overall scores. We wanted to find the most determining attributes in the calculation by implementing the thesis of correlation and the technique of machine learning. We were also curious about whether the set of determining attributes would vary among different player's positions (forward, midfield, defender and goalkeeper). Our result included:

1. The distribution of overall scores in the player dataset
2. The correlation between overall scores and individual attribute.
3. The search of determining attributes by machine learning for all players generally.
4. The deeper exploration of determining attributes for specific positions.

## 2. Data processing

The raw dataset was a complete FIFA18 player dataset from Kaggle, 17981 players in total. It had 75 columns of information for each player including player personal attributes (Nationality, Club, Age, etc.), player performance attributes (Overall, Finishing, Dribbling, etc.) and player preferred subdivided positions (CF, CM, CB, etc.).

The code doing the data processing can be found in appendix part 1 "Data processing", which includes:

1. Extraction of player performance attributes and preferred subdivided positions from all information, which we considered as the most relevant to our project. There were 29 individual attributes and 1 overall score in the player performance attributes categories.
2. Conversion of calculations to its integer results. This step was necessary since in some columns not one-number rating, but a math calculation was given.
3. Filling of null space by 0.
4. Assignment of one preferred position (only four categories: forward, midfield, defender and goalkeeper) for each player based on preferred subdivided positions.

## 3. Result

### 3.1 Distribution of overall scores

We first investigated the distribution of overall scores. Simple statistics showed that there were 17981 players with mean 66.25 and standard deviation 6.99 in overall scores.

We plotted overall scores for all players in Figure 1, which inspired our hypothesis that the distribution could be approximated as a normal distribution. Thus, we fitted a gaussian distribution N ~ (66.25, 49) onto the overall score distribution, where 66.25 and 49 were the mean and variance we directly got from simple statistics. The perfect fitting confirmed our hypothesis. This normal distribution also made sense in reality since most of the players are just mid-class and only few players can reach the top-class.

The code for this part could be found in appendix part 2 “Distribution of overall scores”.

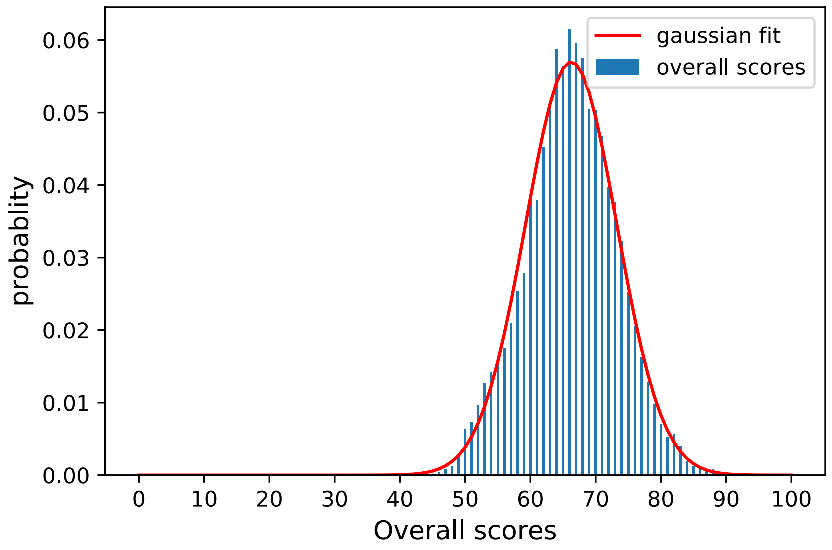


Figure 1. The distribution of overall scores of all players. Total 17981 players were examined with the mean 66.25 and standard deviation 6.99 in overall score. We fitted a Gaussian distribution N ~ (66.25, 49) to the overall score distribution. The fitted result confirmed the hypothesis that the overall score rating in FIFA18 can be approximated as a normal distribution.

## 3.2 Correlation between overall score and attributes

There are 29 attributes of interest in total in the dataset including finishing, dribbling, reaction and etc. We calculated the correlation between overall score and each of 29 attributes. The correlation is a function as:

$$\text{corr} = \mathrm{E}[(x - \mu x)(y - \mu y)]$$

where x represents overall score and y represents individual attribute. Larger correlation indicated that individual attribute is more determining in the rating calculation of overall scores. Figure 2 plotted all the correlations in descending order, in which we realized top 10 determining ones were Reactions (0.84), Composure (0.63), Short passing (0.49), Vision (0.48), Long passing (0.47), Ball control (0.45), Shot power (0.43), Curve (0.41), Long shots (0.41) and Aggression (0.40). It was interesting that reactions had such an importance.

In next section we were going to show the top 10 determining attributes examined by machine learning technique and compared with those examined by correlation. The code for correlation could be found in appendix part 3, “Correlation between overall score and attributes”.

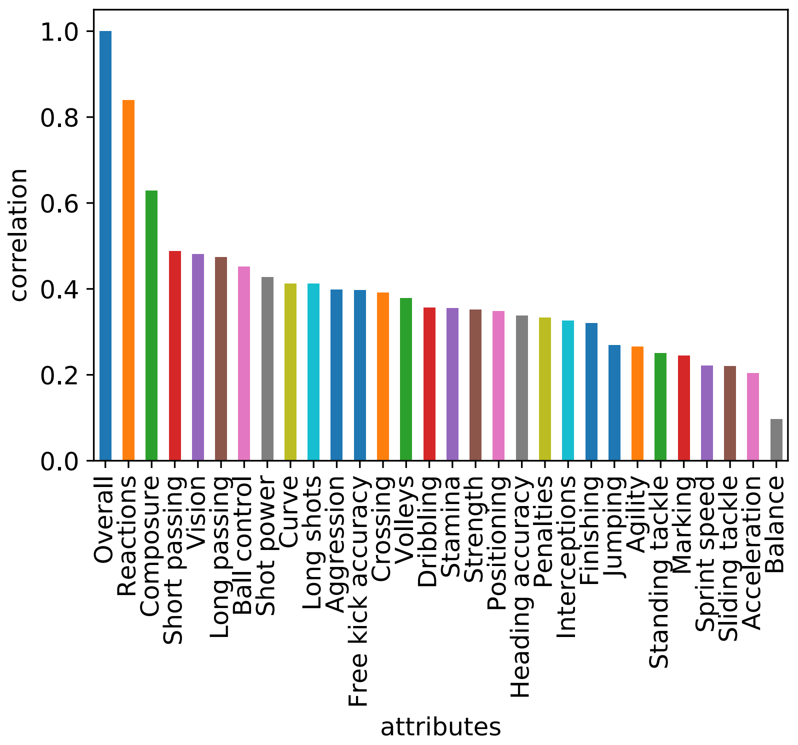


Figure 2. The correlation between overall score and each of 29 attributes plotted in descending order.

## 3.3 Machine Learning Prediction

In this section we used the machine learning technique to assess the top 10 determining attributes. First, we used linear regression to predict overall score, generating a generalized model for all players with weights of each attribute. Second, we divided all players into four different types of positions to improve the accuracy of AI prediction. Four types of positions were also investigated by logistic regression to be a reasonable category classification. Third, we used regression to predict overall score for players in each type of positions, generating a position-specific model with weights of each attribute. It turned out that the position-specific model compared to the generalized model was more accurate in prediction and more reasonable in weight assignment of each attribute.

### 3.3.1. A generalized model for all players

To generate a generalized model for all players, we decided to apply linear regression. It brought two main advantages, ease of implementation and capacity of interpretation. We used a linear regression model with 29 features of integer type (29 individual attributes) and a single integer (overall score) as label. As for statistical measurement, we used R-squared as metric. R closer to 1 means more accurate prediction. In addition to prediction accuracy, we also paid attention to weight corresponding to every attribute showing how importantly they contributed to overall score.

The R-squared result of this model turned out to be 0.770. The top 10 determining attributes according to their absolute values of weights in descending order is plotted in Figure 3.1.

Compared to the top 10 we got by correlation, we could see the machine learning technique gave us some similar results such as Reactions, Composure or Ball control as well as some different ones such as Acceleration and Sprint speed. It was also surprising that Reactions has much heavier impact than other attributes. To some extent, it could not reflect human heuristic on soccer player precisely.

The code for this part could be found in appendix “predict overall – linear regression”.

### 3.3.2. Position division

It is obvious that the determining attributes should be varied among different player positions. A forward should be expert in finishing, but a defender should be good at dribbling. Not satisfied with the generalized model, we started to think whether a position-specific model could be more helpful. We came up with the idea of dividing all subdivided positions into four types/ categories: forward, midfield, defender and goalkeeper. One thing we would like to state here is that we didn’t take the side into consideration since that would not largely affect the result of determining attributes. For example, the left midfield and the right midfield would be assumed to have very similar abilities so that they could both be classified into one type: midfield.

In order to investigate whether this four-type-position classification was suitable for all players, we implemented a multi-class classification using logistic regression, in which we had 29 features of integer type (29 individual attributes) and a single integer (numerical representation of four-type-position classification) as label. We got 81.3% in accuracy in this classification model, which looked satisfactory to us given the fact that a single player may suit multiple positions in real world.

The code for this part could be found in appendix “classify position – logistic regression”.

### 3.3.3. A position-specific model

After dividing all players into four position types, we generated four position-specific models for players in each position type using linear regression. Same as before, we had 29 features of integer type (29 individual attributes) and a single integer (overall score) as label. The R-square results were 0.971, 0.899, 0.933, 0.784 for forward, midfield, defender and goalkeeper respectively, which were much better than the result of the generalized model in section 3.3.1, showing our position division strategy was helpful.

The top 10 determining attributes for each position type were shown in Figure 3.2. This time we had more reasonable outputs compared to the generalized model which showed the Reactions outweighed other attributes. It was confirmed that the top 10 attributes would vary among different positions. Forward players are largely determined by finishing skills such as positioning, finishing or shot power; midfield players are largely determined by passing skill and strength; defenders are largely determined by defending skills such as standing tackle, marking or interception; Goalkeepers are largely determined by their reactions, volley and vision.

The code for this part could be found in appendix “predict overall – linear regression”.

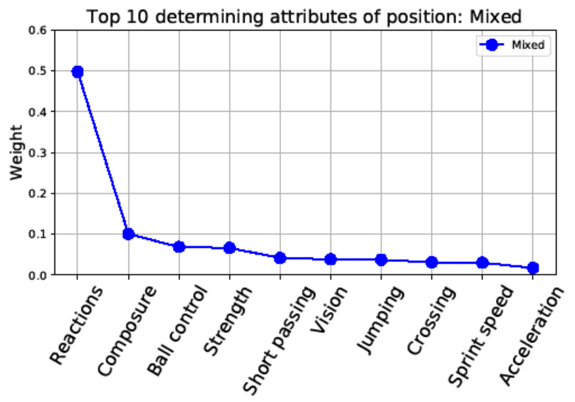


Figure 3.1 The top 10 determining attributes in a generalized model for all players. We used a linear regression model with 29 features of integer type (29 individual attributes) and a single integer (overall score) as label. It was surprising to see that Reactions outweighed other attributes

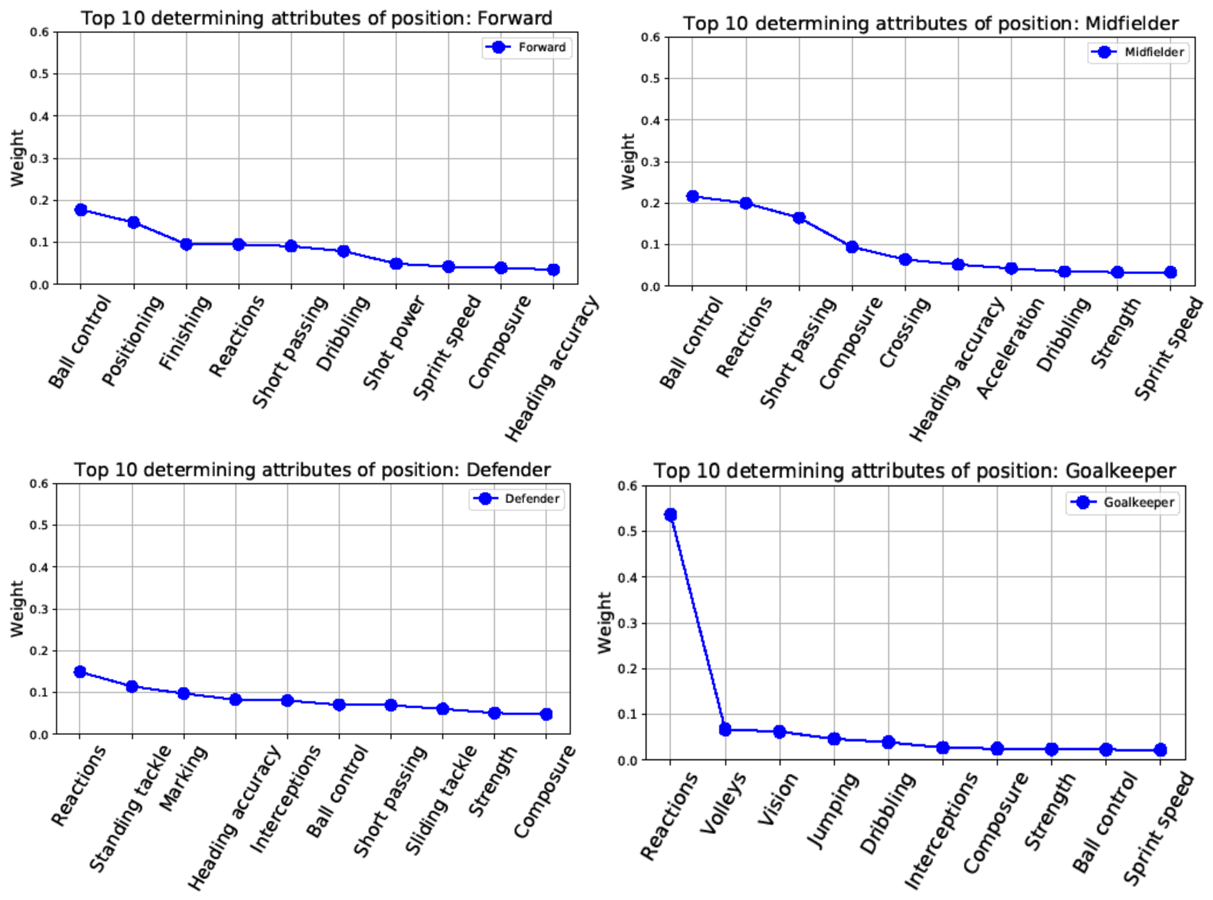


Figure 3.2 The top 10 determining attributes in four position-specific models for each position type. It could be confirmed that the top 10 attributes would vary among different positions. The result here compared to the result in Figure 3.1 looked more consistent with the common knowledge about soccer in the real world.

## 4. Conclusion

In this project, we analyzed the distribution and statistics of overall scores in FIFA 18 dataset, and then focused on finding the top 10 determining attributes in the rating calculation of overall score by two approaches: correlation thesis and machine learning technique (linear regression). The top 10 attributes obtained by correlation and the generalized model for all players were very similar. We also found that by dividing players into four position types and generated position-specific models, we could have more reasonable top 10 attributes for each position, consistent with our common knowledge and cognition about soccer.

## 5. Appendix (see next page)

In [1]:
```
# Import all the necessary packages:
import pandas as pd
import statistics
import numpy as np
import math
import csv
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
from sklearn.linear_model import LogisticRegression
```

## Part 1: Data processing

In [2]:
```
# Load the data, use first column as the index of the dataframe
df=pd.read_csv("data/CompleteDataset.csv",index_col=0)
```

```
D:\Anaconda3\lib\site-packages\IPython\core\interactiveshell.py:2785: DtypeWarning: C
olumns (23,35) have mixed types. Specify dtype option on import or set low_memory=Fal
se.
  interactivity=interactivity, compiler=compiler, result=result)
```

In [3]:

```
# Clean data:
# Conversion of calculations to its integer results easier for further processing.
# Filling of null space by 0.
# Conversion of float numbers to integers

#Function for cleaning:
def clean(x):
    # evaluate sum
    if('+' in str(x).strip()):
        cal = x.split('+')
        return int(cal[0]) + int(cal[1])
    # evaluate subtraction
    elif('-' in str(x).strip()):
        cal = x.split('-')
        return int(cal[0]) + int(cal[1])
    # convert to all float points to integer
    elif str(x).strip().isdigit():
        return int(x)
    # return as 0 if null values or NaN values
    elif pd.isnull(x):
         return 0
    # return other type (e.g. object) as the way it is.
    else:
        return x
# Clean the columns of interest
for column in df.iloc[:,11:74]:
    df[column] = df[column].apply(clean)
for column in df.iloc[:,5:7]:
    df[column] = df[column].apply(clean)
# Save the modfied dataframe
df.to_csv("data/CompleteDataset_clean.csv")
```

In [4]:

```
# Read data from cleaned dataset
filename = "data/CompleteDataset_clean.csv"
df = pd.read_csv(filename)
```

In [5]:

```
# Extract columns of interest:player performance attributes
# (Overall, Finishing, Dribbling, etc.) and player preferred
# subdivided positions (CF, CM, CB, etc.).

columns_needed = ['Acceleration', 'Aggression', 'Agility', 'Balance', 'Ball control',
       'Composure', 'Crossing', 'Curve', 'Dribbling', 'Finishing',
       'Free kick accuracy', 'Heading accuracy', 'Interceptions',
       'Jumping', 'Long passing', 'Long shots', 'Marking', 'Penalties',
       'Positioning', 'Reactions', 'Short passing', 'Shot power',
       'Sliding tackle', 'Sprint speed', 'Stamina', 'Standing tackle',
       'Strength', 'Vision', 'Volleys', 'Overall', 'Value', 'Preferred Positions']
df = df[columns_needed]
```

In [6]:
```
# Assign a preferred postion to each player:
# Each playerat has multiple subdivided under'Preferred Positions' , the first one is s
elected as target.

df['Target_Position'] = df['Preferred Positions'].str.split().str[0]
df = df.drop('Preferred Positions', 1)
# Transform target position into number representation in which
# 0 to 3 represents four categories of positions:
# Forward(0), Midfield(1), Defender(2) and Goalkeeper(3).

mapping = {'CF': 0,'ST': 0, 'RW': 0, 'LW': 0, 'RM': 1, 'CM': 1, 'LM': 1, 'CAM': 1, 'CD
M': 1, 'CB': 2, 'LB': 2, 'RB': 2, 'RWB': 2, 'LWB': 2, 'GK': 3}
df = df.replace({'Target_Position': mapping})
df.isnull().values.any()
```

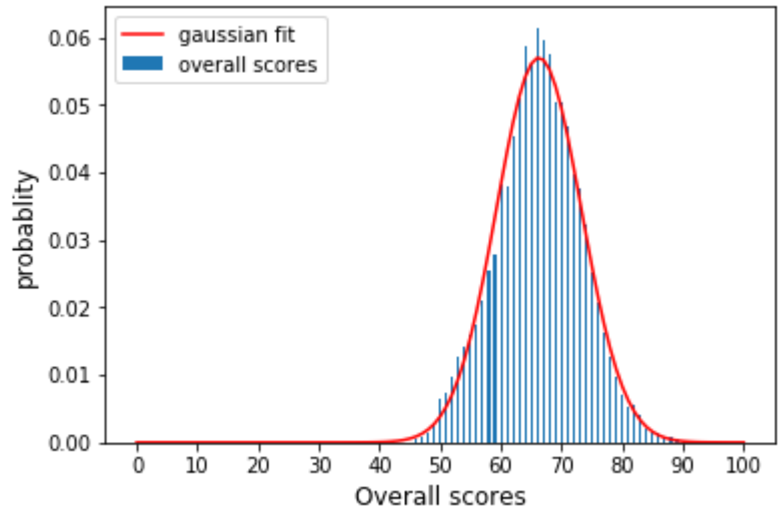
Out[6]:
```
False
```

## Part 2: Distribution of Overall scores

In [7]:
```
#simple statistics for overall scores
overall=df.iloc[:,29]
print(overall.describe())
```

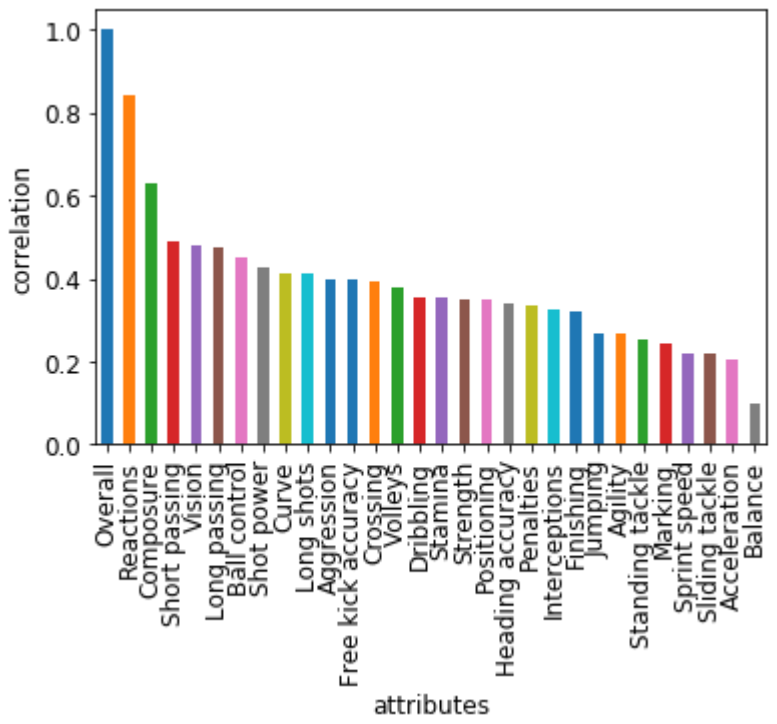
```
count    17981.000000
mean        66.247984
std          6.987965
min         46.000000
25%         62.000000
50%         66.000000
75%         71.000000
max         94.000000
Name: Overall, dtype: float64
```

In [8]:
```
# Plot the overall distribution
# Fit a Gaussian function onto the plot to show the distribution can be approximated as
 a normal distribution.
x=np.linspace(0,100,101)
y=np.array([0]*101)
for i in range(0,len(overall)):
      y[overall[i]]+=1
summation=overall.value_counts().sum()
y_prob=np.zeros(101)
for i in range(0,len(y)):
    y_prob[i] =y[i]*1.0/summation

mean=66.25
variance=49
x=np.linspace(0.0,100.0,101)
y_gaus=np.zeros(101)
for i in range(0,len(y)):
    y_gaus[i]=1/(math.sqrt(2*math.pi*variance))*np.exp(-((i-mean)**2)/(2*variance))


plt.bar(x,y_prob,width=0.35,label='overall scores')
plt.plot(x,y_gaus,'r',label='gaussian fit')
plt.legend()
plt.ylabel('probablity',fontsize=12)
plt.xlabel('Overall scores',fontsize=12);
plt.xticks(np.arange(0,101,10))
plt.savefig('overall score distribution gaussian fitted.pdf',bbox_inches = 'tight')
```



## Part 3: Correlation between Overall scores and attributes

In [9]:
```
attributes=np.concatenate([np.array([29]),np.arange(0,29)])
df_performance=df.iloc[:,attributes]
corr=df_performance.corr()
overall_corr=corr.iloc[0,:].sort_values(ascending=False)
overall_corr.plot.bar(fontsize=12)
plt.ylabel("correlation",fontsize=12)
plt.xlabel("attributes",fontsize=12)
plt.savefig('correlation of attributes.pdf',bbox_inches = 'tight')
```



## Predict Overall -- linear regression

In [15]:
```
df_F = df[df.Target_Position == 0]
df_M = df[df.Target_Position == 1]
df_D = df[df.Target_Position == 2]
df_G = df[df.Target_Position == 3]
position_names = ["Mixed", "Forward", "Midfielder", "Defender", "Goalkeeper"]
df_list = [df, df_F, df_M, df_D, df_G]

for i,t_name in enumerate(position_names):
    df_t = df_list[i]
    print("#", t_name,"\t", df_t.shape[0])
```

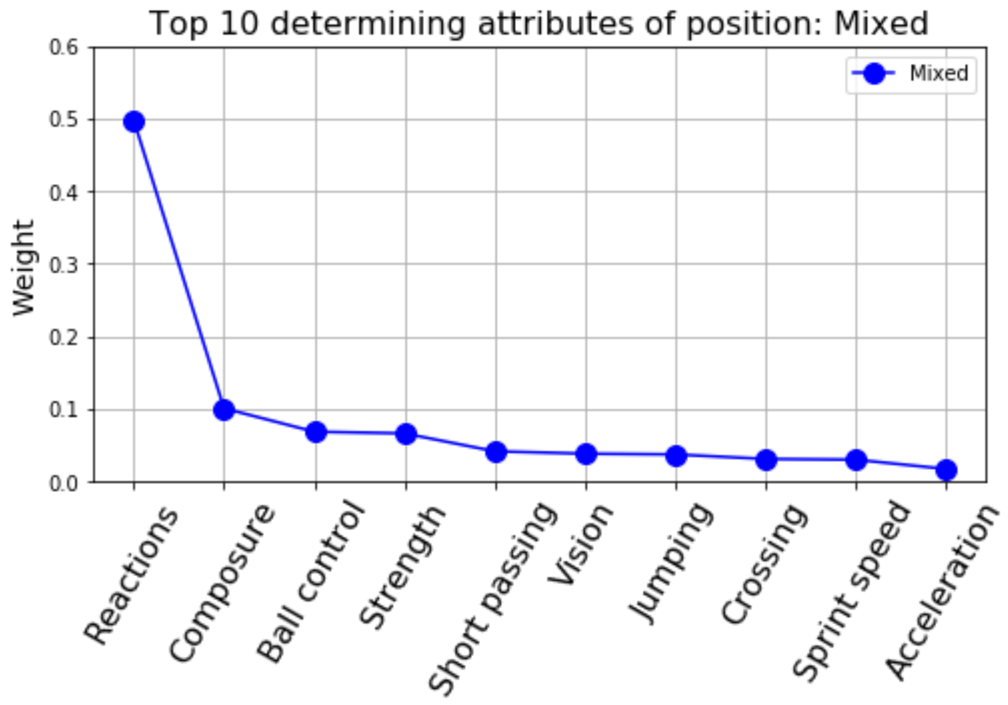
```
# Mixed         17981
# Forward       3338
# Midfielder    7174
# Defender      5440
# Goalkeeper    2029
```

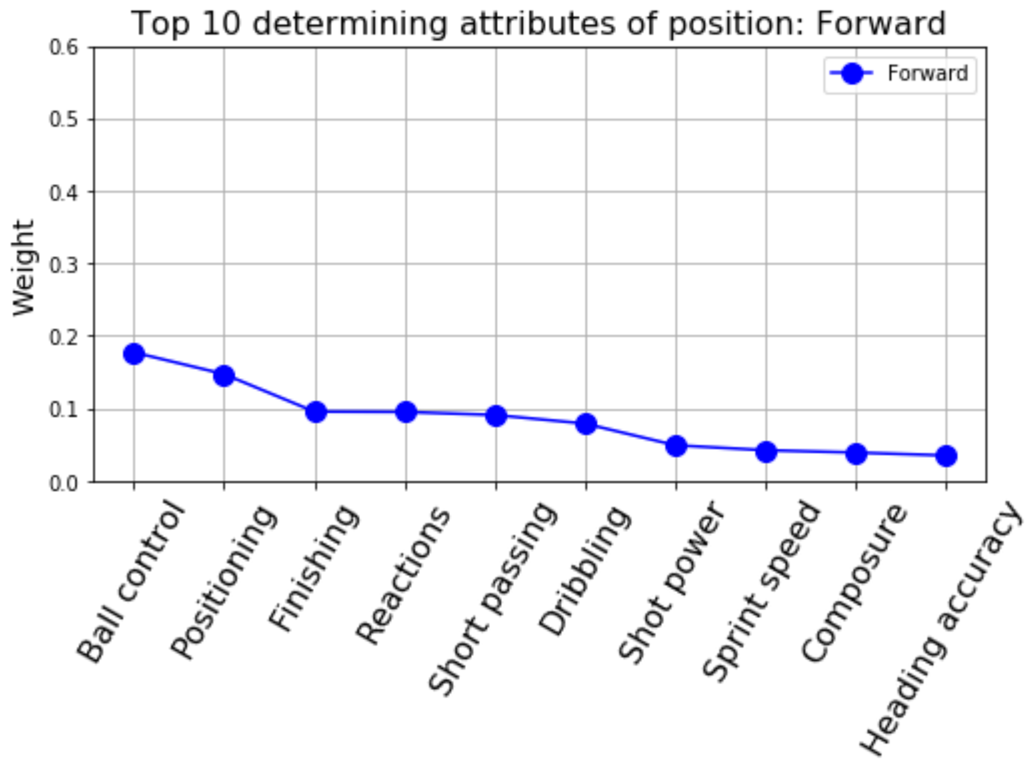
In [16]:
```
data_to_plot = [[] for i in range(5)]

# select which types of position
for i,t_name in enumerate(position_names):
    print("\n")
    print(t_name)
    print('Preparing data for training and testing...')

    df_sin = df_list[i]
    X_train, X_test, y_train, y_test = train_test_split(df_sin.iloc[:,:-3], df_sin.iloc
[:,-3], test_size=0.1, random_state=0)
    print('X train shape: {}'.format(X_train.shape))
    print('X test shape: {}'.format(X_test.shape))
    print('y train shape: {}'.format(y_train.shape))
    print('y test shape: {}'.format(y_test.shape))

    clf = LinearRegression().fit(X_train, y_train)
    acc = clf.score(X_test, y_test)
    print ('Linear Regression R^2 coef: {}'.format(acc))

    feature_result = [(X_train.columns[i], clf.coef_[i]) for i in range(len(clf.coef_
))]
    feature_result_sort = sorted(feature_result, key = lambda x : x[1], reverse = True
)
    for pair in (feature_result_sort[:10]):
        print(pair)

    data_to_plot[i] = feature_result_sort[:10]
```

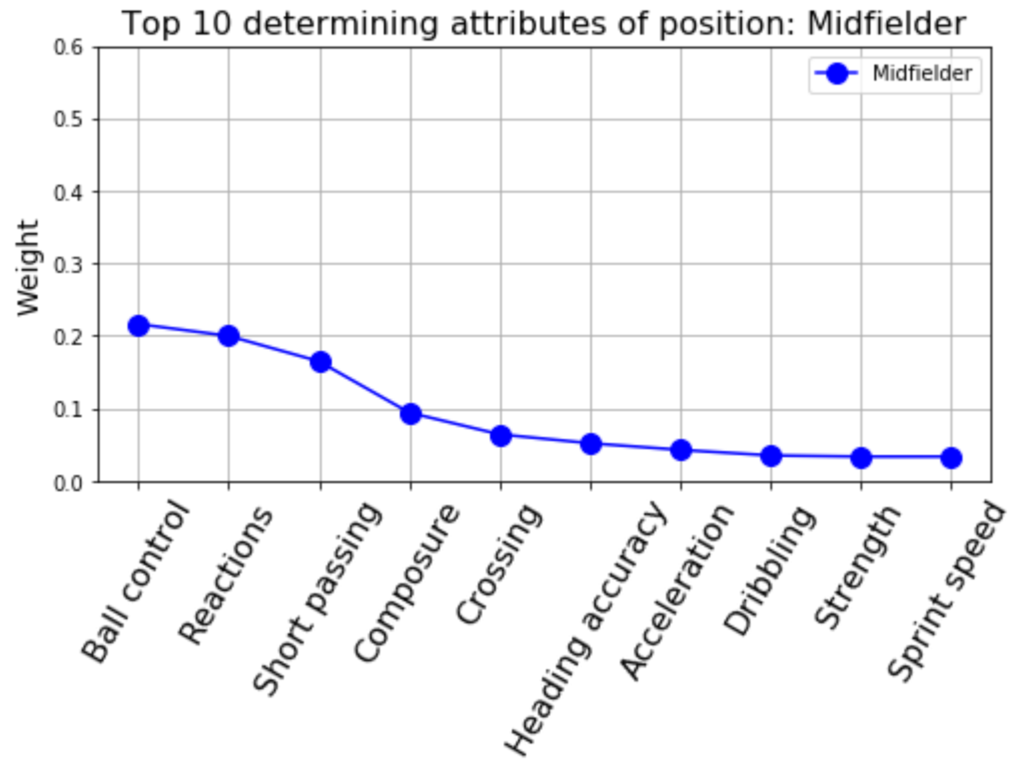
```
Mixed
Preparing data for training and testing...
X train shape: (16182, 29)
X test shape: (1799, 29)
y train shape: (16182,)
y test shape: (1799,)
Linear Regression R^2 coef: 0.7700273879214501
('Reactions', 0.4976124208480736)
('Composure', 0.10070997666906735)
('Ball control', 0.06857163291770287)
('Strength', 0.06624314222754851)
('Short passing', 0.04159958257420677)
('Vision', 0.03829656644653301)
('Jumping', 0.03725527572093278)
('Crossing', 0.031012417321654773)
('Sprint speed', 0.03005699867511938)
('Acceleration', 0.017230757274359555)


Forward
Preparing data for training and testing...
X train shape: (3004, 29)
X test shape: (334, 29)
y train shape: (3004,)
y test shape: (334,)
Linear Regression R^2 coef: 0.9705404535361363
('Ball control', 0.17732490401785622)
('Positioning', 0.1473182562638019)
('Finishing', 0.09569358044454984)
('Reactions', 0.09518441428884088)
('Short passing', 0.09096897079926951)
('Dribbling', 0.07914394954146871)
('Shot power', 0.04927934592523177)
('Sprint speed', 0.04239753494045078)
('Composure', 0.03922582973524693)
('Heading accuracy', 0.03519380255840841)


Midfielder
Preparing data for training and testing...
X train shape: (6456, 29)
X test shape: (718, 29)
y train shape: (6456,)
y test shape: (718,)
Linear Regression R^2 coef: 0.8998457216695079
('Ball control', 0.216272682862331)
('Reactions', 0.1999465502661954)
('Short passing', 0.16494574355280603)
('Composure', 0.09431280906348814)
('Crossing', 0.06431197585008698)
('Heading accuracy', 0.052081537089898294)
('Acceleration', 0.04292410002580306)
('Dribbling', 0.03527165446993157)
('Strength', 0.03362792762771143)
('Sprint speed', 0.03358937644197347)
```

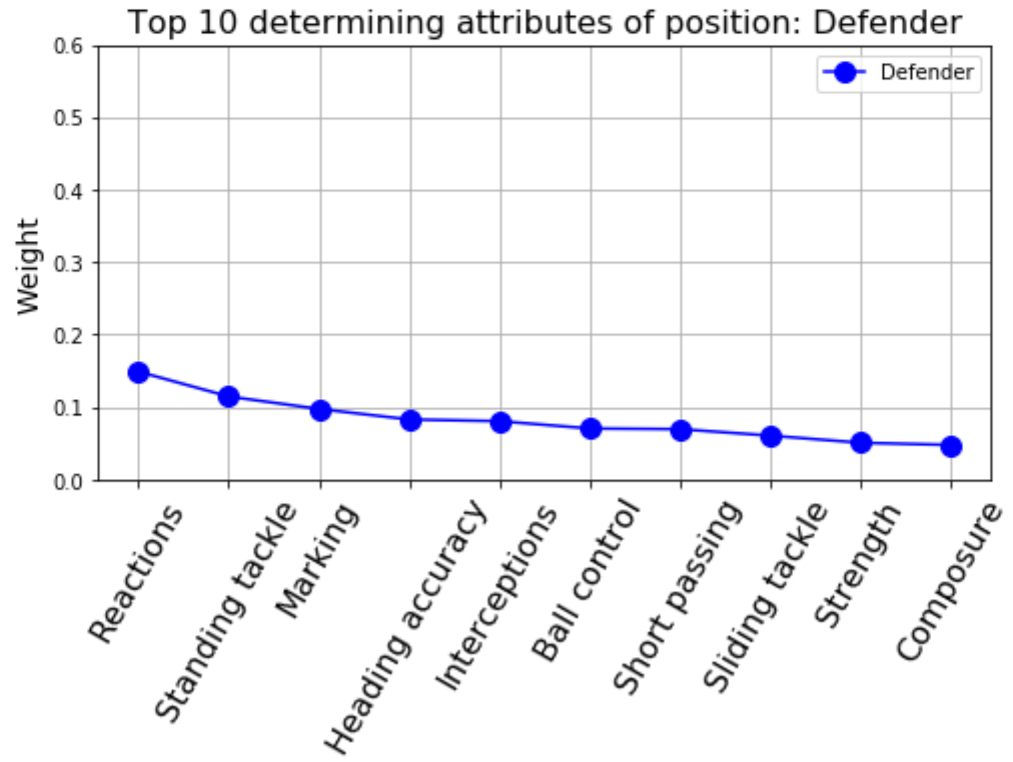
```
Defender
Preparing data for training and testing...
X train shape: (4896, 29)
X test shape: (544, 29)
y train shape: (4896,)
y test shape: (544,)
Linear Regression R^2 coef: 0.9330976484982253
('Reactions', 0.1490617719761642)
('Standing tackle', 0.11473428250519126)
('Marking', 0.0975329854790554)
('Heading accuracy', 0.08303701553291024)
('Interceptions', 0.08070460888703632)
('Ball control', 0.07061401385512571)
('Short passing', 0.06970442249698793)
('Sliding tackle', 0.06076803187412069)
('Strength', 0.05091871316557301)
('Composure', 0.047896292381827694)


Goalkeeper
Preparing data for training and testing...
X train shape: (1826, 29)
X test shape: (203, 29)
y train shape: (1826,)
y test shape: (203,)
Linear Regression R^2 coef: 0.7845672544274247
('Reactions', 0.5366588288391403)
('Volleys', 0.06712244740434369)
('Vision', 0.06231215527577779)
('Jumping', 0.04640943358575749)
('Dribbling', 0.03916041900406958)
('Interceptions', 0.027091080968377982)
('Composure', 0.025111832217296296)
('Strength', 0.023664130204054907)
('Ball control', 0.02301121733730714)
('Sprint speed', 0.022350000799053284)
```

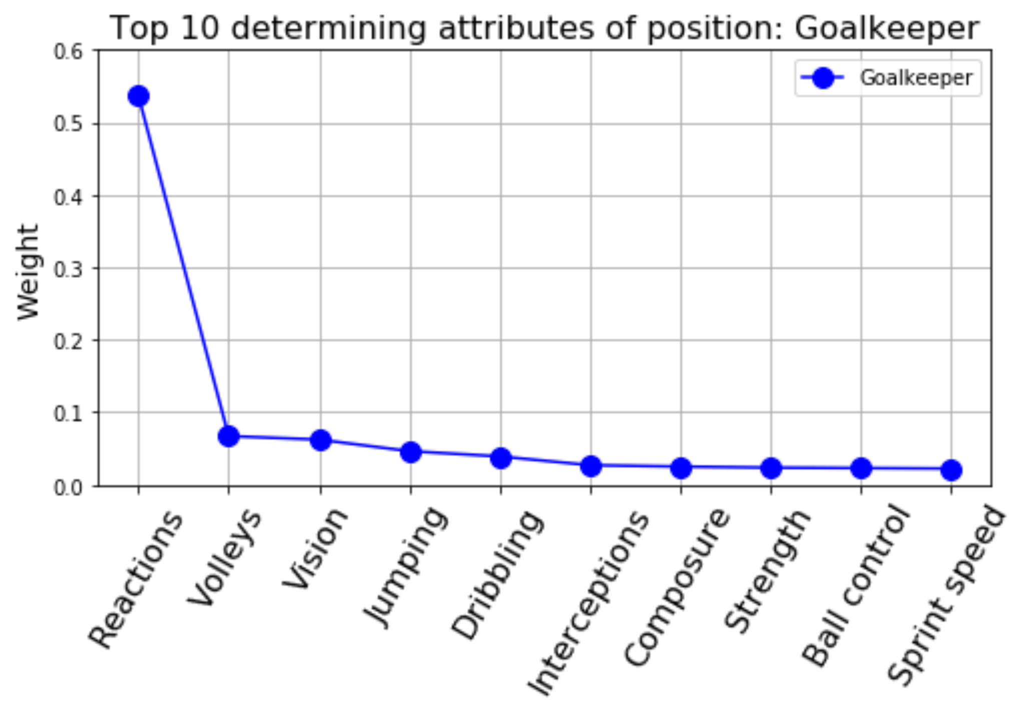
In [17]:
```
%matplotlib inline

for i,t_name in enumerate(position_names):

    name_list = [p[0] for p in data_to_plot[i]]
    coef_list = [p[1] for p in data_to_plot[i]]

    plt.figure(figsize=(8,4))
    plt.plot(name_list, coef_list, 'b-o', markersize=10, label=t_name)
    plt.ylim([0,0.6])
    plt.title("Top 10 determining attributes of position: " + t_name, fontsize=16)
    plt.ylabel('Weight', fontsize=14)
    plt.legend()
    plt.grid(True)
    plt.xticks(fontsize=16, rotation=60)
    plt.savefig('fig/top10'+t_name+'.pdf',bbox_inches = 'tight')
```


Top 10 determining attributes of position: Mixed
Mixed
Weight
0.0
0.1
0.2
0.3
0.4
0.5
0.6
Reactions
Composure
Ball control
Strength
Short passing
Vision
Jumping
Crossing
Sprint speed
Acceleration


Top 10 determining attributes of position: Forward
Forward
Weight
0.0
0.1
0.2
0.3
0.4
0.5
0.6
Ball control
Positioning
Finishing
Reactions
Short passing
Dribbling
Shot power
Sprint speed
Composure
Heading accuracy


Top 10 determining attributes of position: Midfielder
Midfielder
Weight
0.0
0.1
0.2
0.3
0.4
0.5
0.6
Ball control
Reactions
Short passing
Composure
Crossing
Heading accuracy
Acceleration
Dribbling
Strength
Sprint speed


Top 10 determining attributes of position: Defender
Defender
Weight
0.0
0.1
0.2
0.3
0.4
0.5
0.6
Reactions
Standing tackle
Marking
Heading accuracy
Interceptions
Ball control
Short passing
Sliding tackle
Strength
Composure



## Classify position -- logistic regression

In [18]:
```
X_train, X_test, y_train, y_test = train_test_split(df.iloc[:,:-3], df.iloc[:,-1], test
_size=0.1, random_state=0)

print('X train shape: {}'.format(X_train.shape))
print('X test shape: {}'.format(X_test.shape))
print('y train shape: {}'.format(y_train.shape))
print('y test shape: {}'.format(y_test.shape))
```

```
X train shape: (16182, 29)
X test shape: (1799, 29)
y train shape: (16182,)
y test shape: (1799,)
```

In [19]:
```
clf = LogisticRegression().fit(X_train, y_train)
acc = clf.score(X_test, y_test)
print ('Logistic Regression accuracy: {}'.format(acc))
```

```
Logistic Regression accuracy: 0.8132295719844358
```

In [ ]: