Unlocking Potential: Identifying Data-Driven Ways for an Aspiring Player to Improve Their Perceived Value and Potential

Michael Govaerts

Dataset(s)

Soccer Dataset

(European Soccer Database from Kaggle – Author: Hugo Mathien)

https://www.kaggle.com/hugomathien/soccer

Motivation

Pre-professional athletes are often competing against a large pool of their peers for a very limited number of professional positions. In many cases, these players have worked for more than a decade to hone their sport-specific abilities and get noticed by teams that could take them on. As the probability of success in this regard is dishearteningly low, any evidence-based guidance in improving a player's odds for selection would be extremely valuable. Instead of operating off hunches, superstition and perceived trends; data-driven insights to help a player improve their perceived potential would be incredibly valuable for the player and what is often their dedicated network of supporters.

To help supply these insights, data science principles can be used to analyze data from current players and their potential rating to help determine if any particular player attributes are notably related. Armed with the European Soccer Database and its catalog of more than 10,000 players and their statistics, we hope our analyses can help identify any relationships that may help these players in their professional pursuits.

Research Question(s)

When comparing professional player attributes to a player’s rating and perceived potential, do any meaningful trends emerge when focusing on a large sample of European professional soccer players?

Can these conclusions be extended to the pre-professional community to help them select more valuable areas of improvement to enhance their rating and perceived potential in the hiring process?

Findings (1/6)

After cleaning the data set, correlations between the various player attributes and the two overall player quality measures, namely a player's overall rating and perceived potential, were calculated.

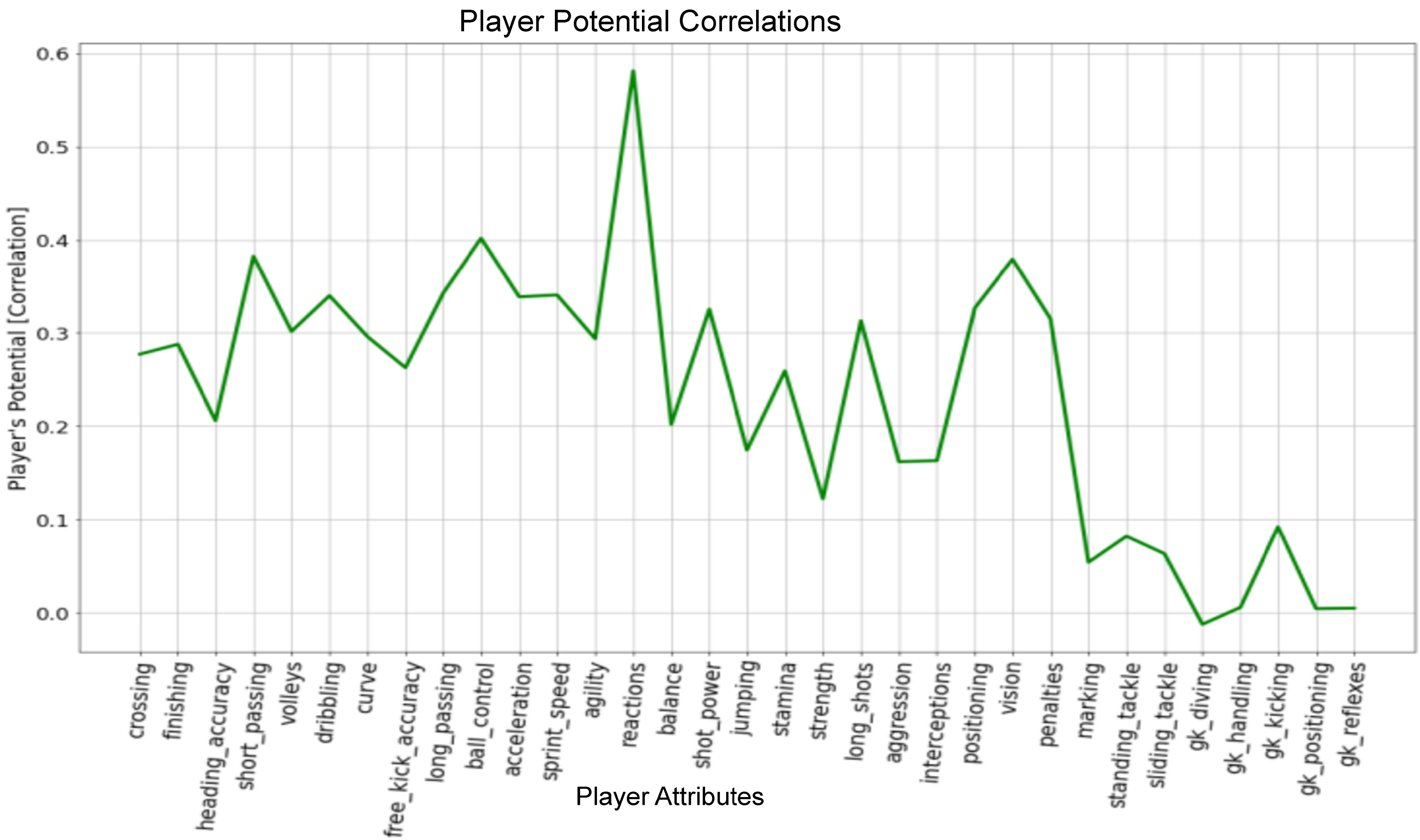
We created two graphs to help make the strongest correlations easier to identify across the numerous player attributes.   One graph was for attribute correlations with player potential, and the other was for attribute correlations with overall player rating. The strongest correlations visible in the the graphs and obtained from the data are listed below.

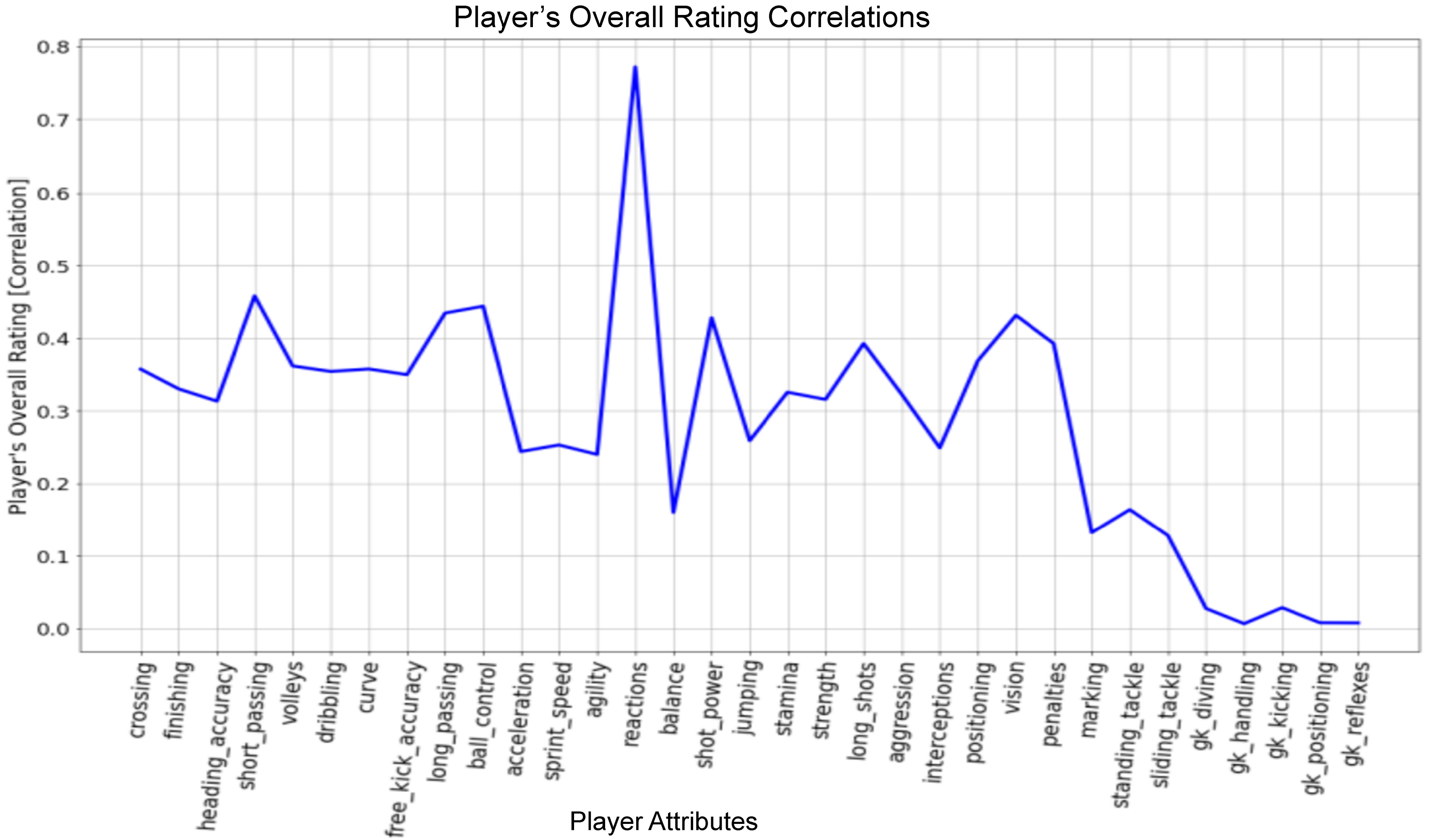
<u>Player Potential Correlations</u>

```
reactions: 0.580991
ball_control: 0.401803
vision: 0.379278
short_passing: 0.382538
long_passing: 0.343133
positioning: 0.326898
penalties: 0.315207
shot_power: 0.325459
```

<u>Player’s Overall Rating Correlations</u>

```
reactions: 0.771856
short_passing: 0.458243
ball_control: 0.443991
long_passing: 0.434525
vision: 0.431493
shot_power: 0.428053
```


Player Potential Correlations
Player's Potential [Correlation]
0.6
0.5
0.4
0.3
0.2
0.1
0.0
crossing
finishing
heading_accuracy
short_passing
volleys
dribbling
curve
free_kick_accuracy
long_passing
ball_control
acceleration
sprint_speed
agility
reactions
balance
shot_power
jumping
stamina
strength
long_shots
aggression
interceptions
positioning
vision
penalties
marking
standing_tackle
sliding_tackle
gk_diving
gk_handling
gk_kicking
gk_positioning
gk_reflexes
Player Attributes


Player's Overall Rating Correlations
Player's Overall Rating [Correlation]
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0.0
crossing
finishing
heading_accuracy
short_passing
volleys
dribbling
curve
free_kick_accuracy
long_passing
ball_control
acceleration
sprint_speed
agility
reactions
balance
shot_power
jumping
stamina
strength
long_shots
aggression
interceptions
positioning
vision
penalties
marking
standing_tackle
sliding_tackle
gk_diving
gk_handling
gk_kicking
gk_positioning
gk_reflexes
Player Attributes

Findings (2/6)

Through visualizing these two graphs, we identified that the strongest correlations between player attributes and overall player performance measures occurred in the attributes for 'short_passing', 'long_passing', 'ball_control', 'reactions', 'shot_power', 'positioning', 'vision', and 'penalties'.

The reactions attribute was correlated with player potential and overall player rating at 0.581 and 0.772, respectively. The reactions attribute is defined as follows:

Reactions: "Good reactions will allow you to latch onto loose balls & rebounds quicker than other players." [as defined by the sofifa.com website referenced by the Kaggle European Soccer Database page]

Findings (3/6)

Player’s Overall Rating Correlations

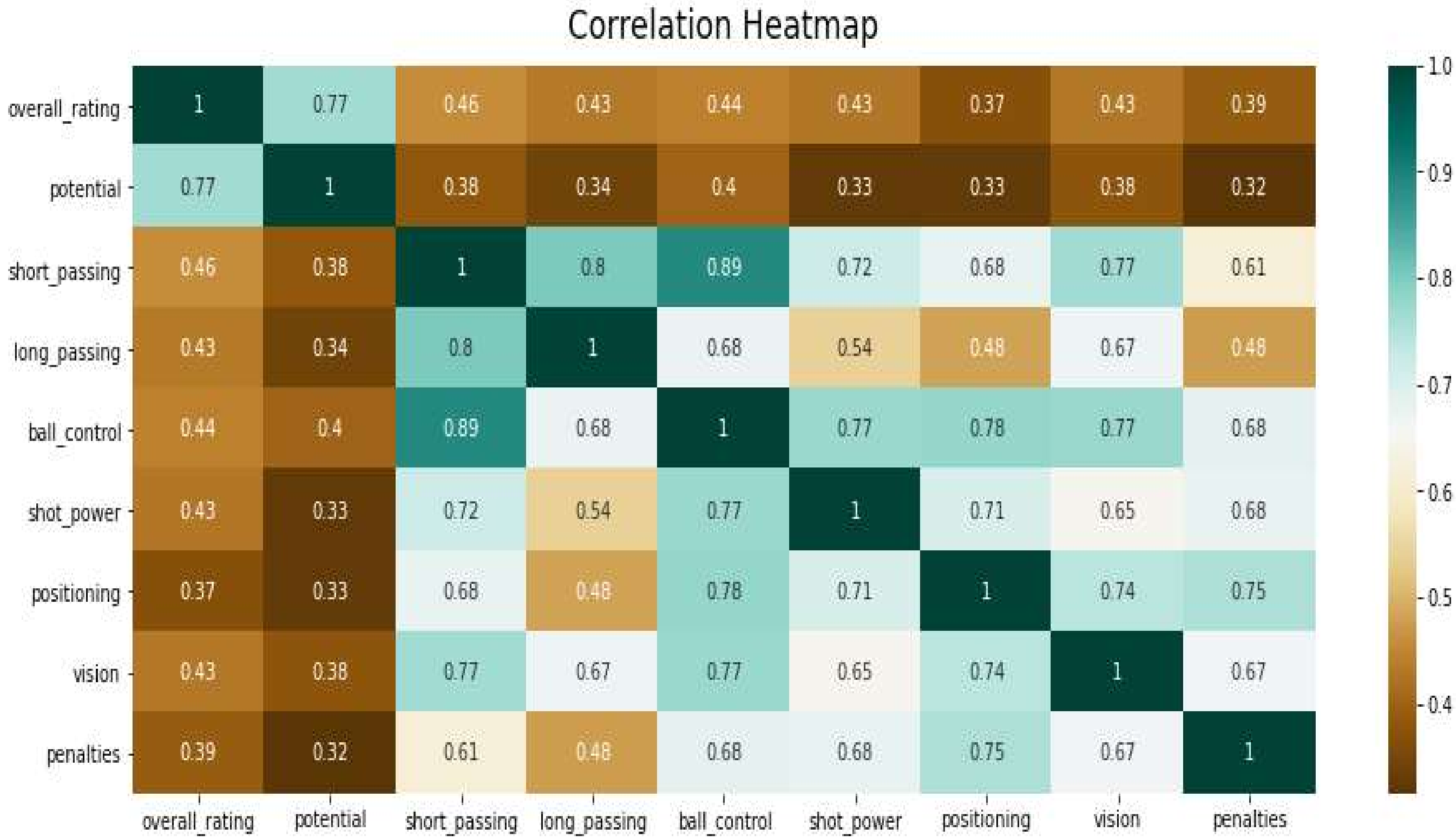
```
reactions: 0.771856
short_passing: 0.458243
ball_control: 0.443991
long_passing: 0.434525
vision: 0.431493
shot_power: 0.428053
```

Player Potential Correlations

```
reactions: 0.580991
ball_control: 0.401803
vision: 0.379278
short_passing: 0.382538
long_passing: 0.343133
positioning: 0.326898
penalties: 0.315207
shot_power: 0.325459
```

This reactions attribute was much more highly correlated than the next strongest correlated attribute for each performance value, namely short_passing (correlations of 0.458 with player rating and 0.382 with player potential) and ball_control (correlations of 0.444 with player rating and 0.402 with player potential).

Our correlation heatmap helps further visualize these relationships and their relative strengths.


Correlation Heatmap
overall_rating
potential
short_passing
long_passing
ball_control
shot_power
positioning
vision
penalties
1 0.77 0.46 0.43 0.44 0.43 0.37 0.43 0.39
0.77 1 0.38 0.34 0.4 0.33 0.33 0.38 0.32
0.46 0.38 1 0.8 0.89 0.72 0.68 0.77 0.61
0.43 0.34 0.8 1 0.68 0.54 0.48 0.67 0.48
0.44 0.4 0.89 0.68 1 0.77 0.78 0.77 0.68
0.43 0.33 0.72 0.54 0.77 1 0.71 0.65 0.68
0.37 0.33 0.68 0.48 0.78 0.71 1 0.74 0.75
0.43 0.38 0.77 0.67 0.77 0.65 0.74 1 0.67
0.39 0.32 0.61 0.48 0.68 0.68 0.75 0.67 1
1.0
0.9
0.8
0.7
0.6
0.5
0.4

Critical to our research questions, we can see the reactions attribute is notably more correlated with player potential and a player's overall rating than the other attributes. Specifically, the reactions attribute has an even stronger correlation with overall player rating, with a correlation of 0.77. Furthermore, this 0.77 correlation is much stronger than the second strongest overall player rating correlation with the short_passing attribute at 0.46, identifying a clear trend in these attributes.

Thus, our analysis has clearly identified that some player attributes are more strongly correlated with player potential and overall player rating than others. Therefore, we identified meaningful trends in the attributes' associations with overall player performance measures, which answers our first research question concerning the presence of any such trends.

Additionally, our analysis also suggests that our conclusions can be extended to the pre-professional community, addressing our second research question. Using our data, pre-professional athletes and their advocates can focus on improving player attributes most strongly associated with a professional player's overall quality and potential. By focusing on enhancing these more strongly correlated attributes, the pre-professional players can hopefully improve their chances of drawing professional soccer's attention and subsequently entering the professional soccer community. Based on the notable strength of the "reactions" attribute in this project, pre-professional players would likely be wise to improve their own abilities in the "reactions" attribute to enhance their own perceived overall player rating and potential in the eyes of professional soccer.

However, to draw more comprehensive and definitive conclusions, we would likely need to utilize more comprehensive statistical methods and analyses to effectively carry out sensitive statistical tasks like removing any confounders, identifying any issues with the data, and revealing more meaningful findings. Thus, further research with this data set and with additional data is likely needed to shed more light on our research questions and their implications for the professional and pre-professional soccer communities.

Acknowledgments

The author would like to thank the Kaggle for hosting the European Soccer Database data set used in this analysis. Also, we would like to thank Hugo Mathien for gathering the data, creating the data set, and sharing it publicly on Kaggle.

Also, we are incredibly grateful to the scientists, especially data scientists, who are kind enough to share their knowledge and expertise with the rest of us. Reviewing various data scientists' publicly available work and observing their online discussions significantly helped inform this project's direction.

Thank you, as well, to the instructors and participants in this course for allowing the author to become more proficient in data science.

References

European Soccer Database from Kaggle [Hugo Mathien]
https://www.kaggle.com/hugomathien/soccer

EdX / UC San Diego MicroMasters in Data Science: Python for Data Science
https://www.edx.org/course/subject/data-science

Unlocking Potential

Author: Michael Govaerts

In [332]:
```
# Import sqlite3 for interacting with the local relational database
# Import pandas and numpy for data manipulation and analysis
# Import matplotlib and seaborn for data visualization [Use magic function to ensure inline plotting]

import sqlite3
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
%matplotlib inline
```

In [333]:
```
# Ingest the data set

brn = sqlite3.connect('database.sqlite')
df = pd.read_sql_query("SELECT * FROM Player_Attributes", brn)
```

In [334]:
```
#Review data set in tabular form to confirm it has been processed correctly

df.head()
```

Out[334]:

	id	player_fifa_api_id	player_api_id	date	overall_rating	potential	preferred_foot	attacking_work_rate	defensive_work_rate	crossing	finish
0	1	218353	505942	2016-02-18 00:00:00	67.0	71.0	right	medium	medium	49.0	
1	2	218353	505942	2015-11-19 00:00:00	67.0	71.0	right	medium	medium	49.0	
2	3	218353	505942	2015-09-21 00:00:00	62.0	66.0	right	medium	medium	49.0	
3	4	218353	505942	2015-03-20 00:00:00	61.0	65.0	right	medium	medium	48.0	
4	5	218353	505942	2007-02-22 00:00:00	61.0	65.0	right	medium	medium	48.0	

In [335]:
```python
# Determine if we need to do any data cleaning by checking if any row contains null values

df.isnull().any().any(), df.shape
```

Out[335]: (True, (183978, 42))

In [336]:
```python
# Remove the rows with the null values that we identified

# Determine the initial number of rows for comparison purposes
rows = df.shape[0]

# Drop the rows that contain null values
df = df.dropna()
```

In [337]:
```python
# Confirm that all null values were successfully removed

print(rows)
df.isnull().any().any(), df.shape
```

183978

Out[337]: (False, (180354, 42))

In [338]:
```python
# Determine how many rows were removed

rows - df.shape[0]
```

Out[338]: 3624

In [339]:
```python
# Review descriptive statistics of our data to begin our analyses

df.describe()
```

Out[339]:

	id	player_fifa_api_id	player_api_id	overall_rating	potential	crossing	finishing	heading_accuracy	short_passing
count	180354.000000	180354.000000	180354.000000	180354.000000	180354.000000	180354.000000	180354.000000	180354.000000	180354.000000
mean	91995.886274	166822.125803	137653.145514	68.635317	73.479457	55.142071	49.962136	57.263476	62.486726
std	53092.657914	52821.443279	137599.735284	7.027950	6.581963	17.247231	19.041760	16.478716	14.172493
min	1.000000	2.000000	2625.000000	33.000000	39.000000	1.000000	1.000000	1.000000	3.000000

	id	player_fifa_api_id	player_api_id	overall_rating	potential	crossing	finishing	heading_accuracy	short_passing
25%	46074.250000	156616.000000	35451.000000	64.000000	69.000000	45.000000	34.000000	49.000000	57.000000
50%	92003.500000	183792.000000	80291.000000	69.000000	74.000000	59.000000	53.000000	60.000000	65.000000
75%	137935.750000	200138.000000	192841.000000	73.000000	78.000000	68.000000	65.000000	68.000000	72.000000
max	183978.000000	234141.000000	750584.000000	94.000000	97.000000	95.000000	97.000000	98.000000	97.000000

In [340]:

```python
# Review data to determine if there are any columns we want to omit before going deeper into our analysis

df.head()
```

Out[340]:

	id	player_fifa_api_id	player_api_id	date	overall_rating	potential	preferred_foot	attacking_work_rate	defensive_work_rate	crossing	finish
0	1	218353	505942	2016-02-18 00:00:00	67.0	71.0	right	medium	medium	49.0	
1	2	218353	505942	2015-11-19 00:00:00	67.0	71.0	right	medium	medium	49.0	
2	3	218353	505942	2015-09-21 00:00:00	62.0	66.0	right	medium	medium	49.0	
3	4	218353	505942	2015-03-20 00:00:00	61.0	65.0	right	medium	medium	48.0	
4	5	218353	505942	2007-02-22 00:00:00	61.0	65.0	right	medium	medium	48.0	

In [341]:

```python
# Drop id, api_id and date columns, as they don't add much to our analyses of the player attributes
df2 = df.drop(['id', 'player_fifa_api_id', 'player_api_id', 'date'], axis=1)

# Remove column display limitations and review dataframe
pd.set_option('display.max_columns', None)
df2.head()
```

Out[341]:

overall_rating	potential	preferred_foot	attacking_work_rate	defensive_work_rate	crossing	finishing	heading_accuracy	short_passing	volleys

	overall_rating	potential	preferred_foot	attacking_work_rate	defensive_work_rate	crossing	finishing	heading_accuracy	short_passing	volleys
0	67.0	71.0	right	medium	medium	49.0	44.0	71.0	61.0	44.0
1	67.0	71.0	right	medium	medium	49.0	44.0	71.0	61.0	44.0
2	62.0	66.0	right	medium	medium	49.0	44.0	71.0	61.0	44.0
3	61.0	65.0	right	medium	medium	48.0	43.0	70.0	60.0	43.0
4	61.0	65.0	right	medium	medium	48.0	43.0	70.0	60.0	43.0

In [342]:

```
# Identify any clear correlations in tabular form

df2.corr()
```

Out[342]:

	overall_rating	potential	crossing	finishing	heading_accuracy	short_passing	volleys	dribbling	curve	free_kick_accurac
overall_rating	1.000000	0.765435	0.357320	0.330079	0.313324	0.458243	0.361739	0.354191	0.357566	0.34980
potential	0.765435	1.000000	0.277284	0.287838	0.206063	0.382538	0.301678	0.339978	0.296050	0.26284
crossing	0.357320	0.277284	1.000000	0.576896	0.368956	0.790323	0.637527	0.809747	0.788924	0.70876
finishing	0.330079	0.287838	0.576896	1.000000	0.373459	0.580245	0.851482	0.784988	0.691082	0.63327
heading_accuracy	0.313324	0.206063	0.368956	0.373459	1.000000	0.548435	0.391129	0.400803	0.320384	0.30601
short_passing	0.458243	0.382538	0.790323	0.580245	0.548435	1.000000	0.639995	0.788935	0.731948	0.69349
volleys	0.361739	0.301678	0.637527	0.851482	0.391129	0.639995	1.000000	0.784247	0.752410	0.68290
dribbling	0.354191	0.339978	0.809747	0.784988	0.400803	0.788935	0.784247	1.000000	0.810353	0.70732
curve	0.357566	0.296050	0.788924	0.691082	0.320384	0.731948	0.752410	0.810353	1.000000	0.79784
free_kick_accuracy	0.349800	0.262842	0.708763	0.633274	0.306013	0.693490	0.682909	0.707322	0.797842	1.00000
long_passing	0.434525	0.343133	0.685649	0.341121	0.362741	0.803073	0.414520	0.579201	0.586313	0.60328
ball_control	0.443991	0.401803	0.807721	0.720694	0.550956	0.890622	0.749459	0.901730	0.798598	0.72067
acceleration	0.243998	0.338820	0.599439	0.529355	0.198164	0.502893	0.512931	0.698906	0.549135	0.43065
sprint_speed	0.253048	0.340698	0.579506	0.509647	0.265430	0.490562	0.493721	0.669779	0.516366	0.39400
agility	0.239963	0.293714	0.599561	0.554396	0.068570	0.510650	0.560021	0.703528	0.619243	0.50525
reactions	0.771856	0.580991	0.384999	0.354769	0.295601	0.460469	0.397448	0.377852	0.392756	0.36919

	overall_rating	potential	crossing	finishing	heading_accuracy	short_passing	volleys	dribbling	curve	free_kick_accura
balance	0.160211	0.202232	0.519778	0.394978	0.077255	0.462617	0.416578	0.547666	0.494479	0.43148
shot_power	0.428053	0.325459	0.656740	0.727835	0.541365	0.722320	0.746622	0.744960	0.694945	0.68419
jumping	0.258978	0.174532	0.021270	0.008948	0.286305	0.060067	0.023143	0.008645	-0.017059	-0.03355
stamina	0.325606	0.259432	0.565935	0.347853	0.477830	0.611422	0.382636	0.527134	0.454458	0.41676
strength	0.315684	0.122392	-0.072915	-0.054596	0.493543	0.089782	-0.037103	-0.114107	-0.115739	-0.05910
long_shots	0.392668	0.313059	0.716515	0.806895	0.406003	0.729741	0.814894	0.807175	0.783732	0.77388
aggression	0.322782	0.162137	0.324625	0.044465	0.577304	0.455426	0.127425	0.204592	0.203332	0.23239
interceptions	0.249094	0.163292	0.306446	-0.152560	0.454187	0.425764	-0.038534	0.106897	0.136119	0.17624
positioning	0.368978	0.326898	0.684803	0.803687	0.408972	0.679014	0.779166	0.798720	0.721106	0.65625
vision	0.431493	0.379278	0.693978	0.652376	0.336472	0.766401	0.690716	0.734119	0.728198	0.69794
penalties	0.392715	0.315207	0.574208	0.726234	0.431291	0.612511	0.713116	0.663420	0.649737	0.66901
marking	0.132185	0.054094	0.234886	-0.285416	0.460831	0.349578	-0.170094	0.004345	0.032956	0.07291
standing_tackle	0.163986	0.082073	0.285018	-0.230453	0.480054	0.415427	-0.108062	0.067306	0.094466	0.13314
sliding_tackle	0.128054	0.063284	0.274673	-0.262144	0.441134	0.380148	-0.127810	0.044988	0.080110	0.10589
gk_diving	0.027675	-0.012283	-0.604567	-0.479370	-0.665600	-0.694111	-0.508029	-0.654097	-0.556625	-0.49834
gk_handling	0.006717	0.005865	-0.595646	-0.465135	-0.649145	-0.689874	-0.486178	-0.650645	-0.544940	-0.49163
gk_kicking	0.028799	0.092299	-0.356728	-0.292349	-0.402865	-0.422659	-0.279492	-0.432452	-0.333784	-0.27971
gk_positioning	0.008029	0.004472	-0.597742	-0.470758	-0.648981	-0.691030	-0.490148	-0.653560	-0.549870	-0.49425
gk_reflexes	0.007804	0.004936	-0.601696	-0.473302	-0.652494	-0.693260	-0.492267	-0.656195	-0.551574	-0.49586

In [343]:

```
# It's not easy to see the correlations in tabular form.  Since player potential and player rating are our key
# attributes to measure correlations with, let's just visualize those correlations against the other player attributes

df2.columns
```

Out[343]:

```
Index(['overall_rating', 'potential', 'preferred_foot', 'attacking_work_rate',
       'defensive_work_rate', 'crossing', 'finishing', 'heading_accuracy',
       'short_passing', 'volleys', 'dribbling', 'curve', 'free_kick_accuracy',
       'long_passing', 'ball_control', 'acceleration', 'sprint_speed',
```

```
       'agility', 'reactions', 'balance', 'shot_power', 'jumping', 'stamina',
       'strength', 'long_shots', 'aggression', 'interceptions', 'positioning',
       'vision', 'penalties', 'marking', 'standing_tackle', 'sliding_tackle',
       'gk_diving', 'gk_handling', 'gk_kicking', 'gk_positioning',
       'gk_reflexes'],
      dtype='object')
```

In [344]:
```
#Create a list of features to correlate with player potential and rating

Comps = ['crossing', 'finishing', 'heading_accuracy',
       'short_passing', 'volleys', 'dribbling', 'curve', 'free_kick_accuracy',
       'long_passing', 'ball_control', 'acceleration', 'sprint_speed',
       'agility', 'reactions', 'balance', 'shot_power', 'jumping', 'stamina',
       'strength', 'long_shots', 'aggression', 'interceptions', 'positioning',
       'vision', 'penalties', 'marking', 'standing_tackle', 'sliding_tackle',
       'gk_diving', 'gk_handling', 'gk_kicking', 'gk_positioning',
       'gk_reflexes']
```

In [345]:
```
# create a list containing Pearson's correlation between 'overall_rating' with each column in list

correlations1 = [ df2['overall_rating'].corr(df2[f]) for f in Comps ]
```

In [346]:
```
#Confirm that the number of correlations we calculated match the number of features we wanted to correlate

len(correlations1), len(Comps)
```

Out[346]:
```
(33, 33)
```

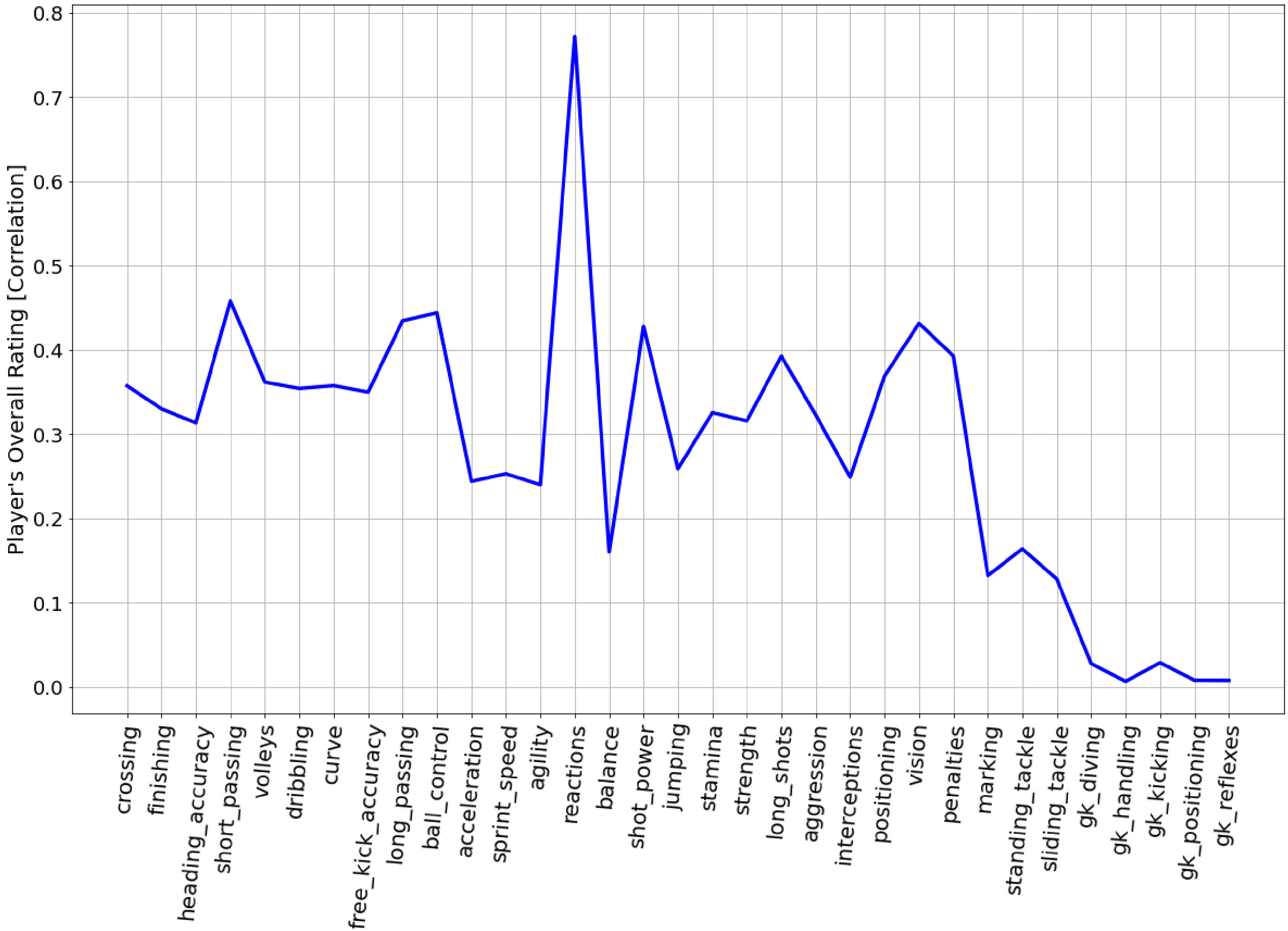
In [347]:
```
# create a function for plotting a dataframe with string columns and numeric values

def plot_dataframe(df2, y_label):
    color='blue'
    fig = plt.gcf()
    fig.set_size_inches(20, 12)
    plt.ylabel(y_label, fontsize=20)
    plt.yticks(fontsize=18)

    ax = df2.correlation.plot(linewidth=3.3, color=color)
    ax.set_xticks(df2.index)
    ax.set_xticklabels(df2.attributes, rotation=85, fontsize=20);
    plt.grid()
    plt.show()
```

In [348]:
```
# create an overall_rating dataframe using our Comps and correlations1 lists
```

```
df3 = pd.DataFrame({'attributes': Comps, 'correlation': correlations1})
```

In [349]:

```
# Plot the above dataframe using the created function

plot_dataframe(df3, 'Player\'s Overall Rating [Correlation]')
```



In [350]:

```
##From the graph above, the attributes with the strongest correlations to a player's rating are
## reactions (0.771856), short_passing (0.458243), ball_control (0.44391), long_passing (0.434525),
## vision (0.431493), and shot_power (0.428053)

strong1 = ['reactions','short_passing', 'ball_control','long_passing','vision','shot_power']
```

In [351]:
```
#List correlations to confirm our conclusions

for f in strong1:
    related = df2['overall_rating'].corr(df2[f])
    print("%s: %f" % (f,related))
```

```
reactions: 0.771856
short_passing: 0.458243
ball_control: 0.443991
long_passing: 0.434525
vision: 0.431493
shot_power: 0.428053
```

In [352]:
```
# Let's now repeat the process for Player Potential rating to see if the correlations are similar

# create a list containing Pearson's correlation between 'potential' with each column in list

correlations2 = [ df2['potential'].corr(df2[f]) for f in Comps ]
```

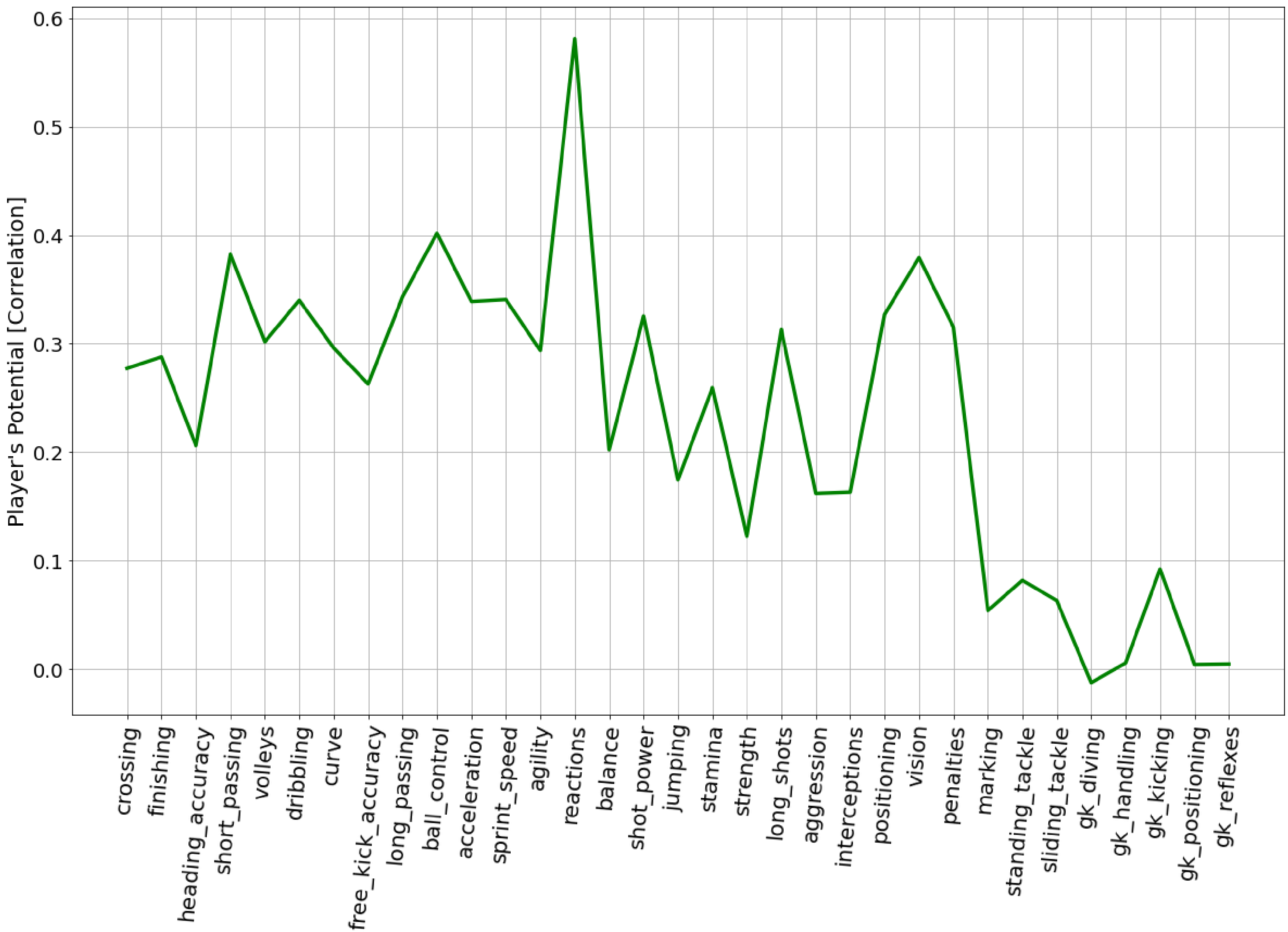
In [353]:
```
#Confirm that the number of correlations we calculated match the number of features we wanted to correlate

len(correlations2), len(Comps)
```

Out[353]:
```
(33, 33)
```

In [354]:
```
# create a function for plotting a dataframe with string columns and numeric values

def plot_dataframe2(df2, y_label):
    color='green'
    fig = plt.gcf()
    fig.set_size_inches(20, 12)
    plt.ylabel(y_label, fontsize=20)
    plt.yticks(fontsize=18)

    ax = df2.correlation.plot(linewidth=3.3, color=color)
    ax.set_xticks(df2.index)
    ax.set_xticklabels(df2.attributes, rotation=85, fontsize=20);
    plt.grid()
    plt.show()
```

In [355]:
```
#create a dataframe using our Comps and correlations2 lists

df4 = pd.DataFrame({'attributes': Comps, 'correlation': correlations2})
```

In [356]:
```
# Plot the 'potential' dataframe, above, using the function we created

plot_dataframe2(df4, 'Player\'s Potential [Correlation]')
```



In [357]:
```
#From the potential graph above, list the attributes with the strongest correlations to a player's potential
```

```
strong2 = ['reactions','ball_control','vision','short_passing','long_passing', 'positioning', 'penalties', 'shot_power']
```

In [358]:

```
#List correlations to confirm our conclusions

for f in strong2:
    related = df2['potential'].corr(df2[f])
    print("%s: %f" % (f,related))
```

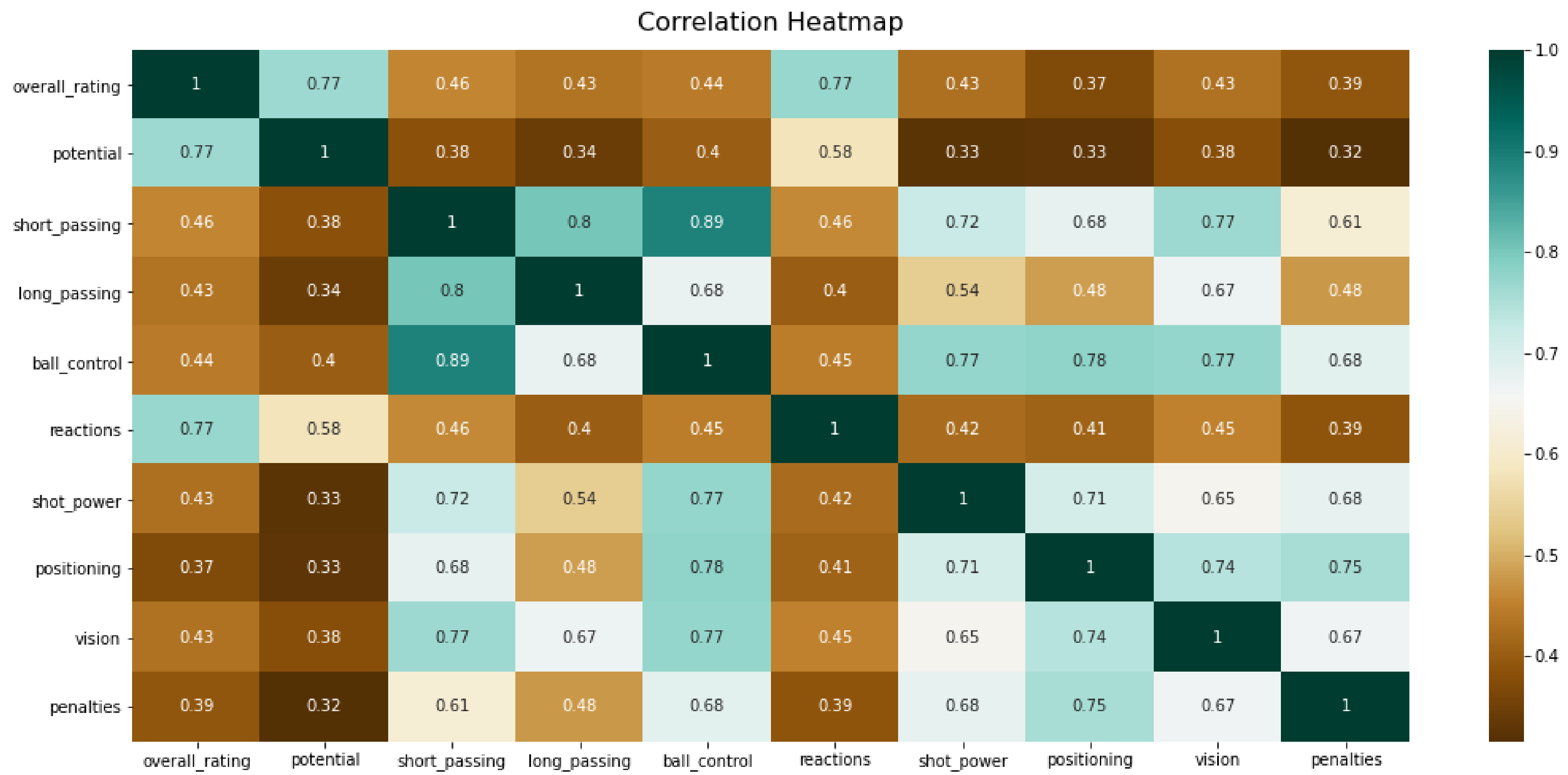
```
reactions: 0.580991
ball_control: 0.401803
vision: 0.379278
short_passing: 0.382538
long_passing: 0.343133
positioning: 0.326898
penalties: 0.315207
shot_power: 0.325459
```

In [359]:

```
# Create and display a correlation heatmap of highly correlated attributes to player potential and player rating
# by eliminating other attributes from the correlation

import seaborn as sns

corr_df2=df2.corr()
heatmap_df3=corr_df2.drop(['crossing', 'finishing', 'heading_accuracy','volleys', 'dribbling', 'curve', 'free_kick_accuracy
                           'acceleration', 'sprint_speed','agility', 'balance', 'jumping', 'stamina',
        'strength', 'long_shots', 'aggression', 'interceptions', 'marking', 'standing_tackle', 'sliding_tackle',
       'gk_diving', 'gk_handling', 'gk_kicking', 'gk_positioning',
       'gk_reflexes']).drop(['crossing', 'finishing', 'heading_accuracy',
'volleys', 'dribbling', 'curve', 'free_kick_accuracy',  'acceleration', 'sprint_speed',
       'agility', 'balance', 'jumping', 'stamina',
       'strength', 'long_shots', 'aggression', 'interceptions', 'marking', 'standing_tackle', 'sliding_tackle',
       'gk_diving', 'gk_handling', 'gk_kicking', 'gk_positioning',
       'gk_reflexes'],axis=1)
```

In [363]:

```
plt.figure(figsize=(18, 8))
heatmap = sns.heatmap(heatmap_df3,annot=True, cmap='BrBG',)
heatmap.set_title('Correlation Heatmap', fontdict={'fontsize':16}, pad=12);
```



Return to Presentation and Report Findings