Unlocking Potential

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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]:

```
# 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]:

```
# 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_accura
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	0.4314
shot_power	0.428053	0.325459	0.656740	0.727835	0.541365	0.722320	0.746622	0.744960	0.694945	0.6841
jumping	0.258978	0.174532	0.021270	0.008948	0.286305	0.060067	0.023143	0.008645	-0.017059	-0.0335
stamina	0.325606	0.259432	0.565935	0.347853	0.477830	0.611422	0.382636	0.527134	0.454458	0.4167
strength	0.315684	0.122392	-0.072915	-0.054596	0.493543	0.089782	-0.037103	-0.114107	-0.115739	-0.0591
long_shots	0.392668	0.313059	0.716515	0.806895	0.406003	0.729741	0.814894	0.807175	0.783732	0.7738
aggression	0.322782	0.162137	0.324625	0.044465	0.577304	0.455426	0.127425	0.204592	0.203332	0.2323
interceptions	0.249094	0.163292	0.306446	-0.152560	0.454187	0.425764	-0.038534	0.106897	0.136119	0.1762
positioning	0.368978	0.326898	0.684803	0.803687	0.408972	0.679014	0.779166	0.798720	0.721106	0.6562
vision	0.431493	0.379278	0.693978	0.652376	0.336472	0.766401	0.690716	0.734119	0.728198	0.6979
penalties	0.392715	0.315207	0.574208	0.726234	0.431291	0.612511	0.713116	0.663420	0.649737	0.6690
marking	0.132185	0.054094	0.234886	-0.285416	0.460831	0.349578	-0.170094	0.004345	0.032956	0.0729
standing_tackle	0.163986	0.082073	0.285018	-0.230453	0.480054	0.415427	-0.108062	0.067306	0.094466	0.1331
sliding_tackle	0.128054	0.063284	0.274673	-0.262144	0.441134	0.380148	-0.127810	0.044988	0.080110	0.1058
gk_diving	0.027675	-0.012283	-0.604567	-0.479370	-0.665600	-0.694111	-0.508029	-0.654097	-0.556625	-0.4983
gk_handling	0.006717	0.005865	-0.595646	-0.465135	-0.649145	-0.689874	-0.486178	-0.650645	-0.544940	-0.4916
gk_kicking	0.028799	0.092299	-0.356728	-0.292349	-0.402865	-0.422659	-0.279492	-0.432452	-0.333784	-0.2797
gk_positioning	0.008029	0.004472	-0.597742	-0.470758	-0.648981	-0.691030	-0.490148	-0.653560	-0.549870	-0.4942
gk_reflexes	0.007804	0.004936	-0.601696	-0.473302	-0.652494	-0.693260	-0.492267	-0.656195	-0.551574	-0.4958

In [343]:

```python
# 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()
```

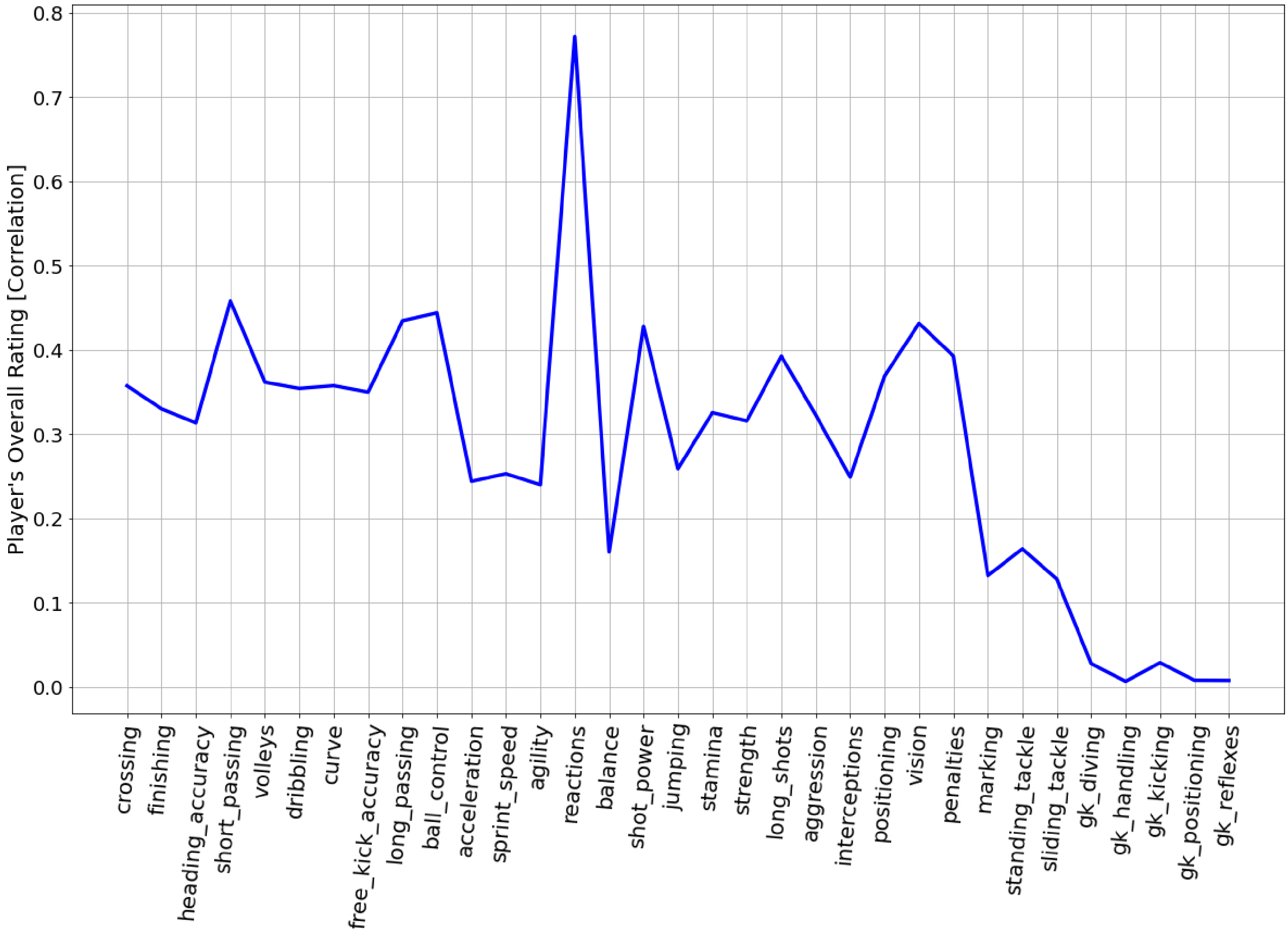
In [348]:
```
# create an overall_rating dataframe using our Comps and correlations1 lists
```

```
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()
```

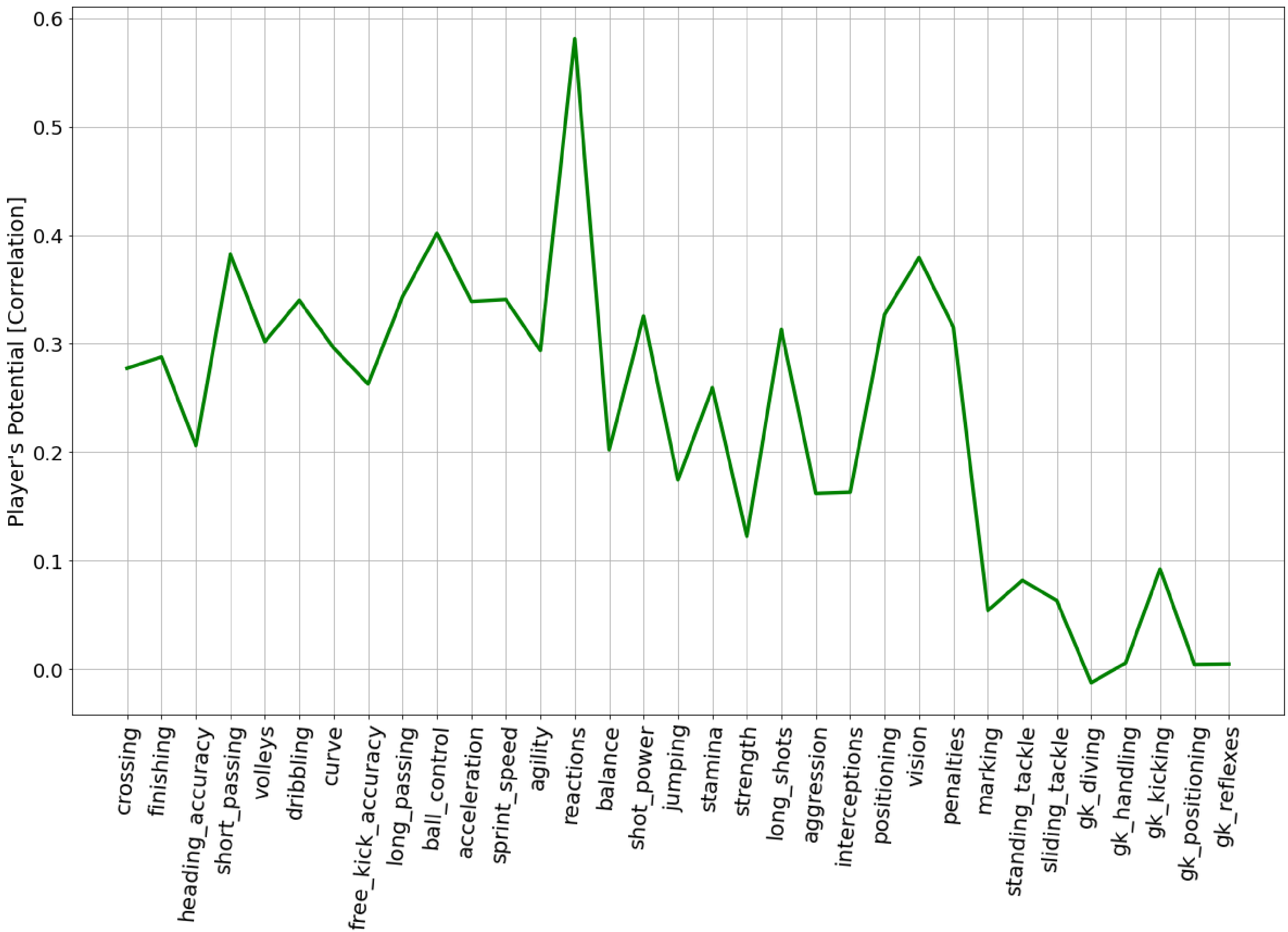
In [355]:
```
#create a dataframe using our Comps and correlations2 lists

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]:

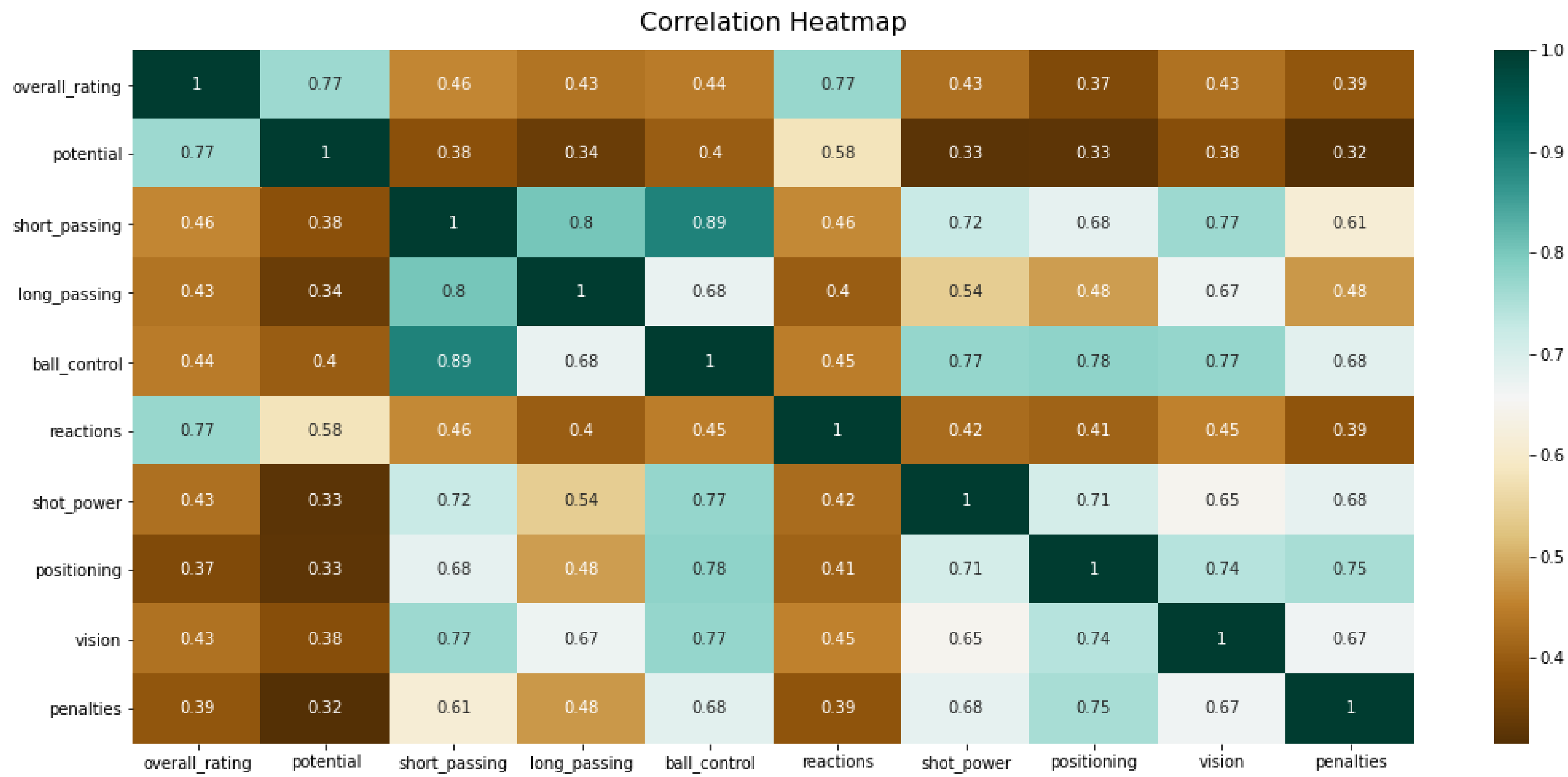
```
# Create and display a correlation heatmap of highly correlated attributes to player potential and player rating
# by eliminating other attributes from the correlation

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