seaborn-tutorial-for-beginners

August 1, 2023

1 Seaborn tutorial for beginners

Hello friends,

This kernel introduces us to the basics of statistical data visualization. I have used the Seaborn library for the data visualization purpose.

Following references are used in this kernel.

References:

Seaborn Official Tutorial

http://seaborn.pydata.org/tutorial.html

Seaborn documentation and API reference

http://seaborn.pydata.org/

http://seaborn.pydata.org/api.html

Useful Seaborn tutorials

https://www.datacamp.com/community/tutorials/seaborn-python-tutorial

https://elitedatascience.com/python-seaborn-tutorial

https://www.tutorialspoint.com/seaborn/index.htm#

Data visualization helps us to discover hidden insights from our data.

So, let's get started.

1.0.1 Table of Contents

The table of contents for this tutorial is as follows -

- Import libraries
- Read dataset
- Exploratory data analysis
- Visualize distribution of Age variable with Seaborn distplot() function
- Seaborn Kernel Density Estimation (KDE) plot
- Histograms
- Visualize distribution of values in Preferred Foot variable with Seaborn countplot() function
- Seaborn catplot() function
- Seaborn stripplot() function

- Seaborn boxplot() function
- Seaborn violinplot() function
- Seaborn pointplot() function
- Seaborn barplot() function
- Visualizing statistical relationship with Seaborn relplot() function
- Seaborn scatterplot() function
- Seaborn lineplot() function
- Seaborn regplot() function
- Seaborn lmplot() function
- Multi-plot grids
- Seaborn Facetgrid() function
- Seaborn Pairgrid() function
- Seaborn Jointgrid() function
- Controlling the size and shape of the plot
- Seaborn figure styles

1.0.2 Import libraries

[1]:
```
# This Python 3 environment comes with many helpful analytics libraries␣
 ↪installed
# It is defined by the kaggle/python docker image: https://github.com/kaggle/
 ↪docker-python
# For example, here's several helpful packages to load in

import numpy as np # linear algebra
import pandas as pd # data processing, CSV file I/O (e.g. pd.read_csv)
import seaborn as sns
sns.set(style="whitegrid")
import matplotlib.pyplot as plt
from collections import Counter
%matplotlib inline

# Input data files are available in the "../input/" directory.
# For example, running this (by clicking run or pressing Shift+Enter) will list␣
 ↪all files under the input directory

import os
for dirname, _, filenames in os.walk('/kaggle/input'):
    for filename in filenames:
        print(os.path.join(dirname, filename))

# Any results you write to the current directory are saved as output.
```

```
/kaggle/input/fifa19/data.csv
```

[2]:
```
# ignore warnings
import warnings
```

```
warnings.filterwarnings('ignore')
```

1.0.3 Read dataset

In this kernel, I will focus on those datasets which help to explain various features of Seaborn. So, I will read the related datasets with pandas read_csv() function.

[3]:
```
fifa19 = pd.read_csv('/kaggle/input/fifa19/data.csv', index_col=0)
```

1.0.4 Exploratory Data Analysis

1.0.5 Preview the dataset

[4]:
```
fifa19.head()
```

[4]:
```
       ID               Name  Age  \
0  158023           L. Messi   31
1   20801  Cristiano Ronaldo   33
2  190871          Neymar Jr   26
3  193080             De Gea   27
4  192985       K. De Bruyne   27

                                              Photo Nationality  \
0  https://cdn.sofifa.org/players/4/19/158023.png   Argentina
1   https://cdn.sofifa.org/players/4/19/20801.png    Portugal
2  https://cdn.sofifa.org/players/4/19/190871.png      Brazil
3  https://cdn.sofifa.org/players/4/19/193080.png       Spain
4  https://cdn.sofifa.org/players/4/19/192985.png     Belgium

                                Flag  Overall  Potential  \
0  https://cdn.sofifa.org/flags/52.png       94         94
1  https://cdn.sofifa.org/flags/38.png       94         94
2  https://cdn.sofifa.org/flags/54.png       92         93
3  https://cdn.sofifa.org/flags/45.png       91         93
4   https://cdn.sofifa.org/flags/7.png       91         92

                 Club                                      Club Logo  …  \
0         FC Barcelona  https://cdn.sofifa.org/teams/2/light/241.png  …
1             Juventus   https://cdn.sofifa.org/teams/2/light/45.png  …
2  Paris Saint-Germain   https://cdn.sofifa.org/teams/2/light/73.png  …
3    Manchester United   https://cdn.sofifa.org/teams/2/light/11.png  …
4      Manchester City   https://cdn.sofifa.org/teams/2/light/10.png  …

  Composure Marking  StandingTackle SlidingTackle  GKDiving  GKHandling  \
0      96.0    33.0            28.0          26.0       6.0        11.0
1      95.0    28.0            31.0          23.0       7.0        11.0
2      94.0    27.0            24.0          33.0       9.0         9.0
```

```
3      68.0    15.0            21.0          13.0      90.0        85.0
4      88.0    68.0            58.0          51.0      15.0        13.0

   GKKicking GKPositioning GKReflexes Release Clause
0       15.0          14.0        8.0        €226.5M
1       15.0          14.0       11.0        €127.1M
2       15.0          15.0       11.0        €228.1M
3       87.0          88.0       94.0        €138.6M
4        5.0          10.0       13.0        €196.4M

[5 rows x 88 columns]
```

1.0.6 View summary of dataset

[5]:
```
fifa19.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 18207 entries, 0 to 18206
Data columns (total 88 columns):
ID                          18207 non-null int64
Name                        18207 non-null object
Age                         18207 non-null int64
Photo                       18207 non-null object
Nationality                 18207 non-null object
Flag                        18207 non-null object
Overall                     18207 non-null int64
Potential                   18207 non-null int64
Club                        17966 non-null object
Club Logo                   18207 non-null object
Value                       18207 non-null object
Wage                        18207 non-null object
Special                     18207 non-null int64
Preferred Foot              18159 non-null object
International Reputation    18159 non-null float64
Weak Foot                   18159 non-null float64
Skill Moves                 18159 non-null float64
Work Rate                   18159 non-null object
Body Type                   18159 non-null object
Real Face                   18159 non-null object
Position                    18147 non-null object
Jersey Number               18147 non-null float64
Joined                      16654 non-null object
Loaned From                 1264 non-null object
Contract Valid Until        17918 non-null object
Height                      18159 non-null object
Weight                      18159 non-null object
LS                          16122 non-null object
```

```
ST                     16122 non-null object
RS                     16122 non-null object
LW                     16122 non-null object
LF                     16122 non-null object
CF                     16122 non-null object
RF                     16122 non-null object
RW                     16122 non-null object
LAM                    16122 non-null object
CAM                    16122 non-null object
RAM                    16122 non-null object
LM                     16122 non-null object
LCM                    16122 non-null object
CM                     16122 non-null object
RCM                    16122 non-null object
RM                     16122 non-null object
LWB                    16122 non-null object
LDM                    16122 non-null object
CDM                    16122 non-null object
RDM                    16122 non-null object
RWB                    16122 non-null object
LB                     16122 non-null object
LCB                    16122 non-null object
CB                     16122 non-null object
RCB                    16122 non-null object
RB                     16122 non-null object
Crossing               18159 non-null float64
Finishing              18159 non-null float64
HeadingAccuracy        18159 non-null float64
ShortPassing           18159 non-null float64
Volleys                18159 non-null float64
Dribbling              18159 non-null float64
Curve                  18159 non-null float64
FKAccuracy             18159 non-null float64
LongPassing            18159 non-null float64
BallControl            18159 non-null float64
Acceleration           18159 non-null float64
SprintSpeed            18159 non-null float64
Agility                18159 non-null float64
Reactions              18159 non-null float64
Balance                18159 non-null float64
ShotPower              18159 non-null float64
Jumping                18159 non-null float64
Stamina                18159 non-null float64
Strength               18159 non-null float64
LongShots              18159 non-null float64
Aggression             18159 non-null float64
Interceptions          18159 non-null float64
Positioning            18159 non-null float64
```

```
Vision                    18159 non-null float64
Penalties                 18159 non-null float64
Composure                 18159 non-null float64
Marking                   18159 non-null float64
StandingTackle            18159 non-null float64
SlidingTackle             18159 non-null float64
GKDiving                  18159 non-null float64
GKHandling                18159 non-null float64
GKKicking                 18159 non-null float64
GKPositioning             18159 non-null float64
GKReflexes                18159 non-null float64
Release Clause            16643 non-null object
dtypes: float64(38), int64(5), object(45)
memory usage: 12.4+ MB
```

[6]:
```
fifa19['Body Type'].value_counts()
```

[6]:
```
Normal                10595
Lean                   6417
Stocky                 1140
Akinfenwa                 1
Courtois                  1
Messi                     1
PLAYER_BODY_TYPE_25       1
Shaqiri                   1
C. Ronaldo                1
Neymar                    1
Name: Body Type, dtype: int64
```

Comment

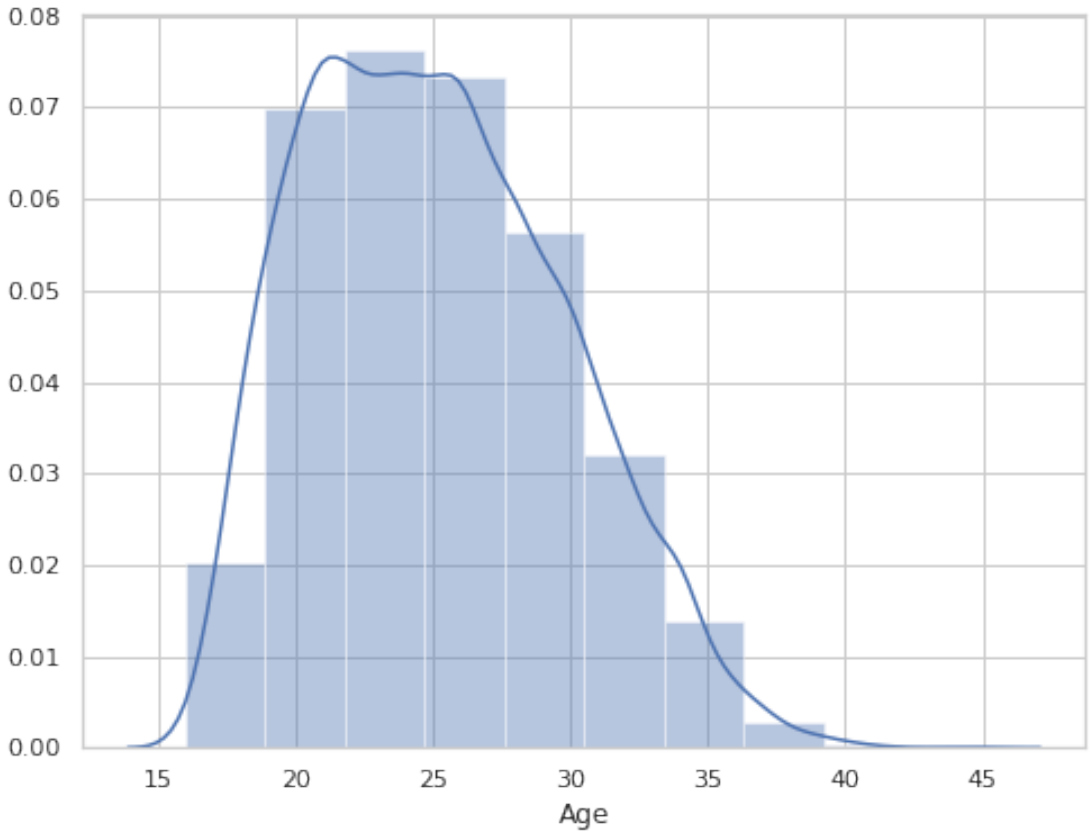
- This dataset contains 89 variables.
- Out of the 89 variables, 44 are numerical variables. 38 are of float64 data type and remaining 6 are of int64 data type.
- The remaining 45 variables are of character data type.
- Let's explore this further.

1.0.7 Explore `Age` variable

1.0.8 Visualize distribution of `Age` variable with Seaborn `distplot()` function

- Seaborn `distplot()` function flexibly plots a univariate distribution of observations.
- This function combines the matplotlib hist function (with automatic calculation of a good default bin size) with the seaborn kdeplot() and rugplot() functions.
- – So, let's visualize the distribution of `Age` variable with Seaborn `distplot()` function.

[7]:
```
f, ax = plt.subplots(figsize=(8,6))
x = fifa19['Age']
ax = sns.distplot(x, bins=10)
plt.show()
```

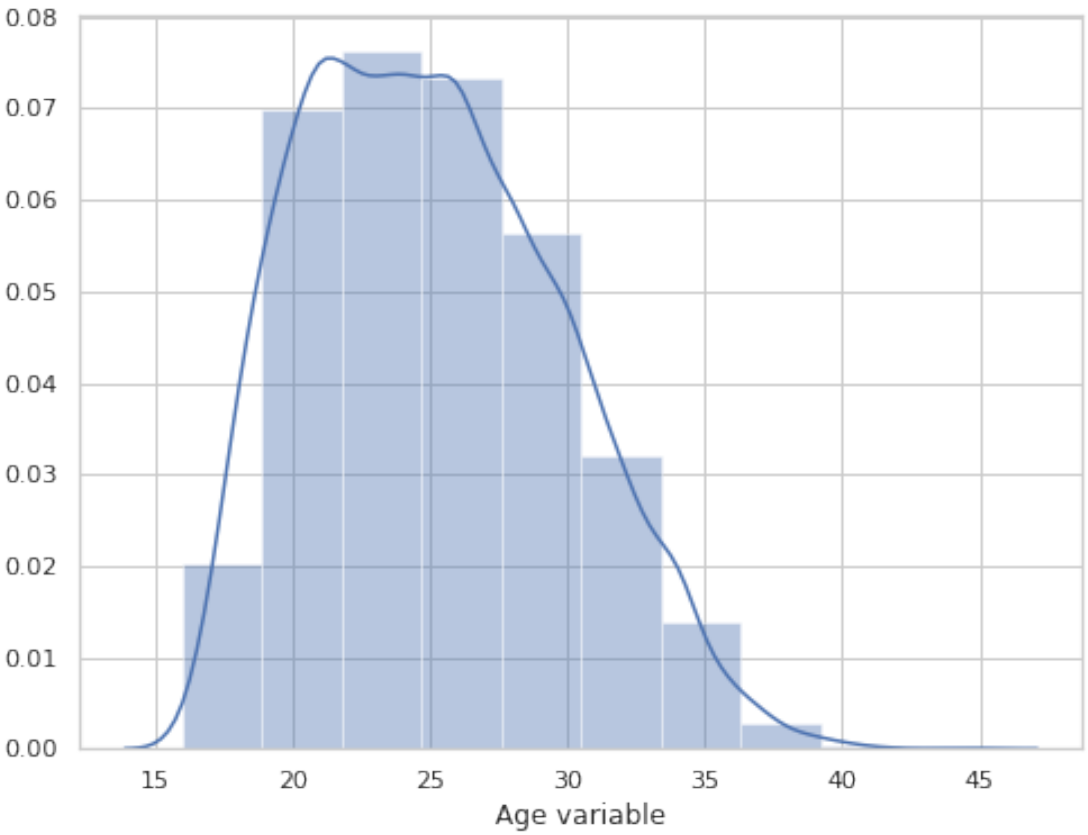


1.0.9 Comment

- It can be seen that the `Age` variable is slightly positively skewed.

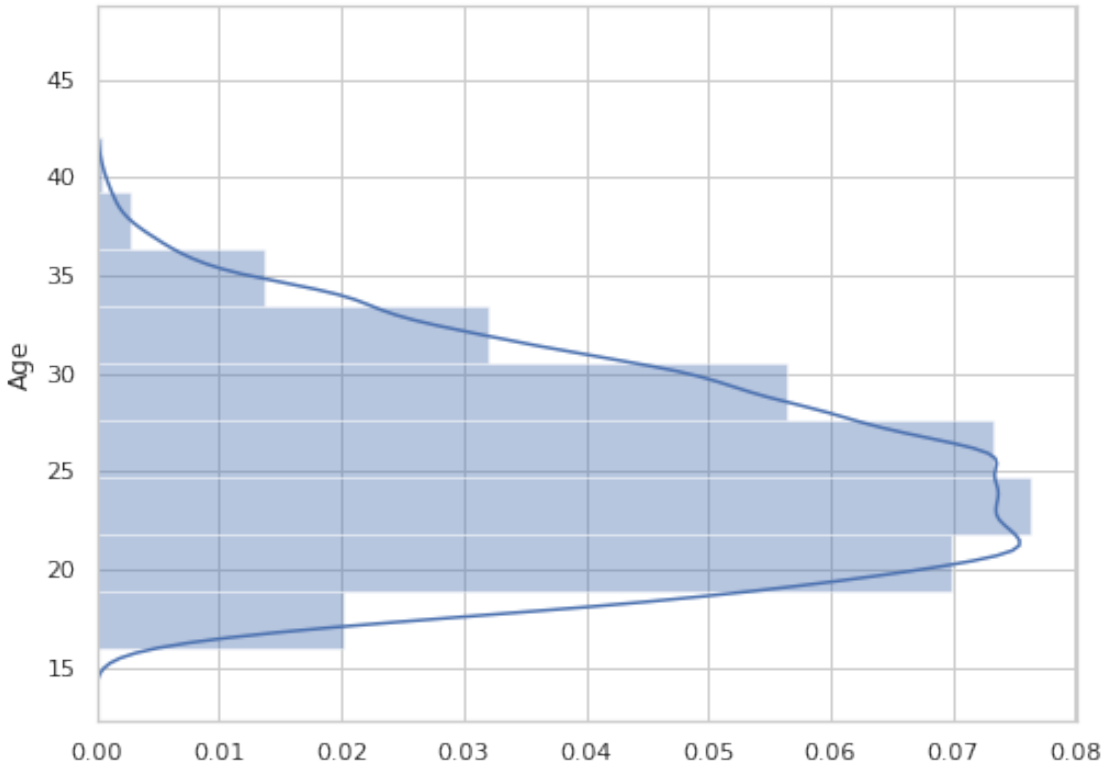
We can use Pandas series object to get an informative axis label as follows-

[8]:
```
f, ax = plt.subplots(figsize=(8,6))
x = fifa19['Age']
x = pd.Series(x, name="Age variable")
ax = sns.distplot(x, bins=10)
plt.show()
```



We can plot the distribution on the vertical axis as follows:-

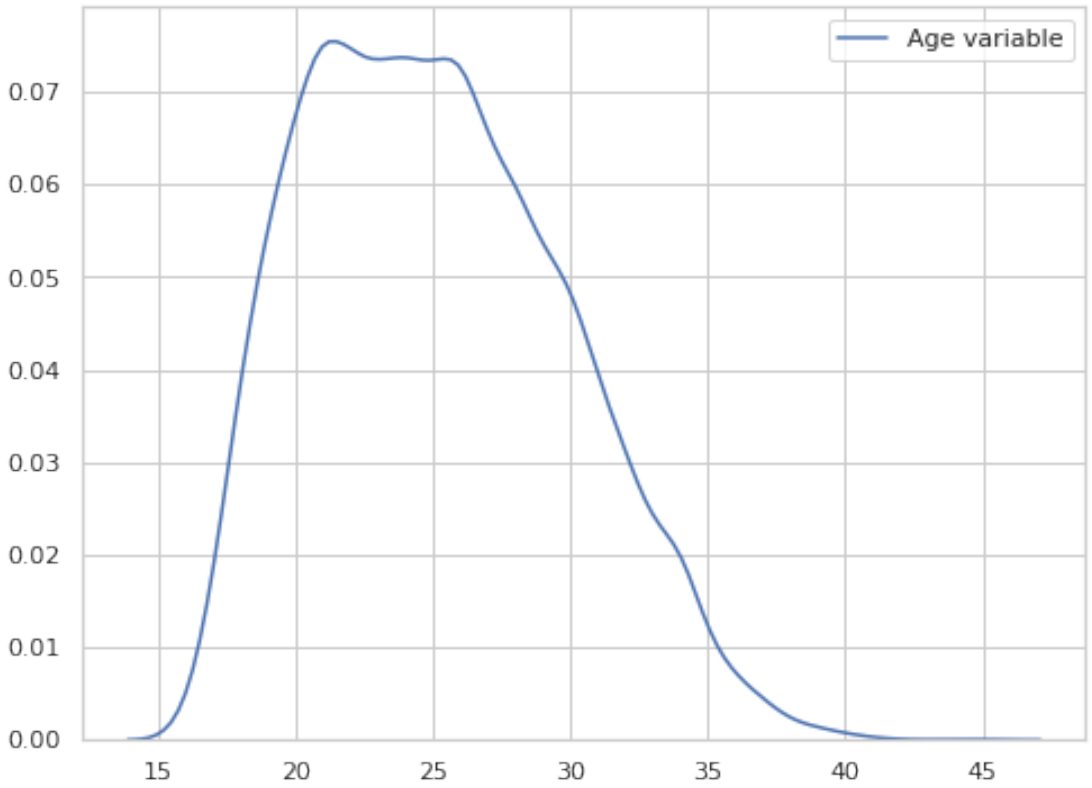
[9]:
```
f, ax = plt.subplots(figsize=(8,6))
x = fifa19['Age']
ax = sns.distplot(x, bins=10, vertical = True)
plt.show()
```



1.0.10 Seaborn Kernel Density Estimation (KDE) Plot

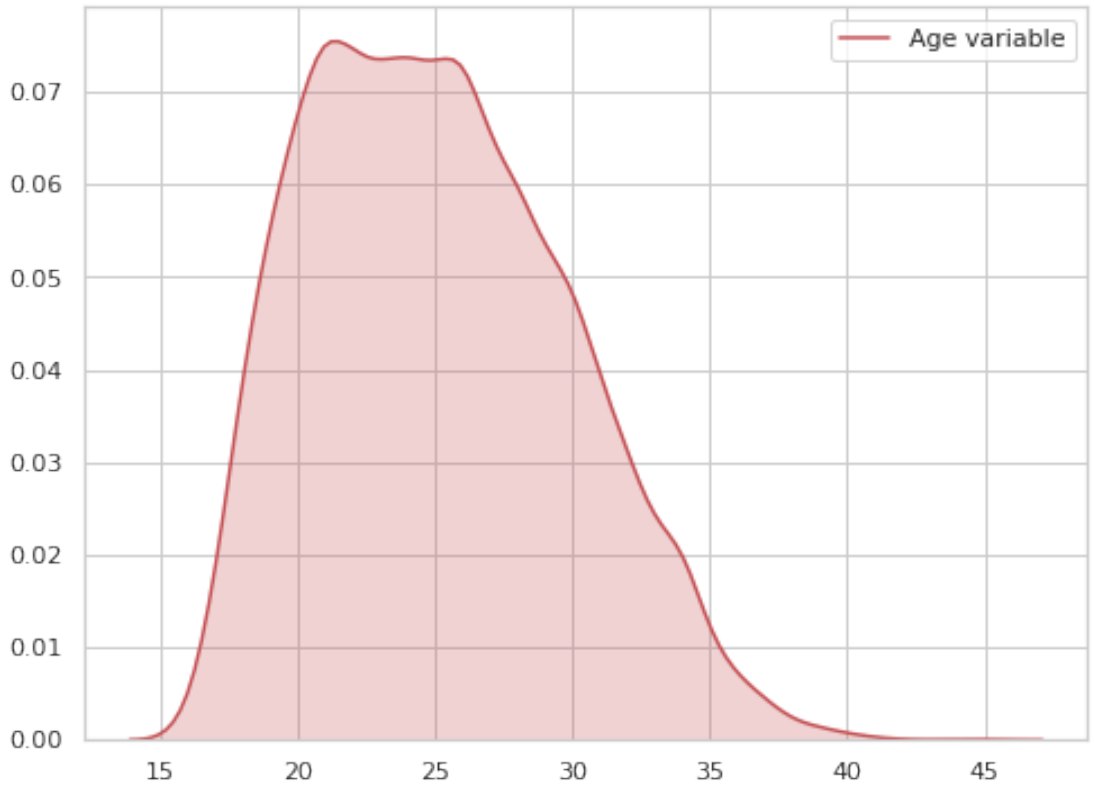
- The `kernel density estimate (KDE)` plot is a useful tool for plotting the shape of a distribution.
- Seaborn kdeplot is another seaborn plotting function that fits and plot a univariate or bivariate kernel density estimate.
- Like the histogram, the KDE plots encode the density of observations on one axis with height along the other axis.
- We can plot a KDE plot as follows-

[10]:
```
f, ax = plt.subplots(figsize=(8,6))
x = fifa19['Age']
x = pd.Series(x, name="Age variable")
ax = sns.kdeplot(x)
plt.show()
```



We can shade under the density curve and use a different color as follows:-

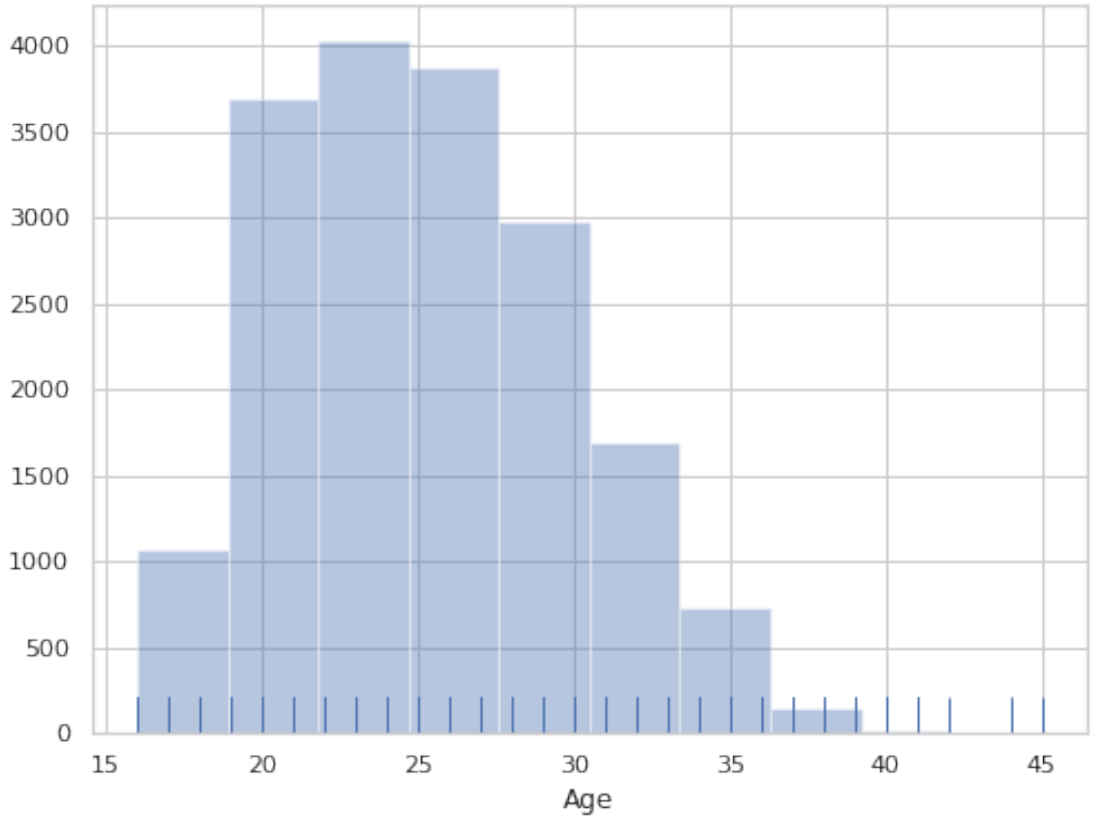
[11]:
```
f, ax = plt.subplots(figsize=(8,6))
x = fifa19['Age']
x = pd.Series(x, name="Age variable")
ax = sns.kdeplot(x, shade=True, color='r')
plt.show()
```



1.0.11 Histograms

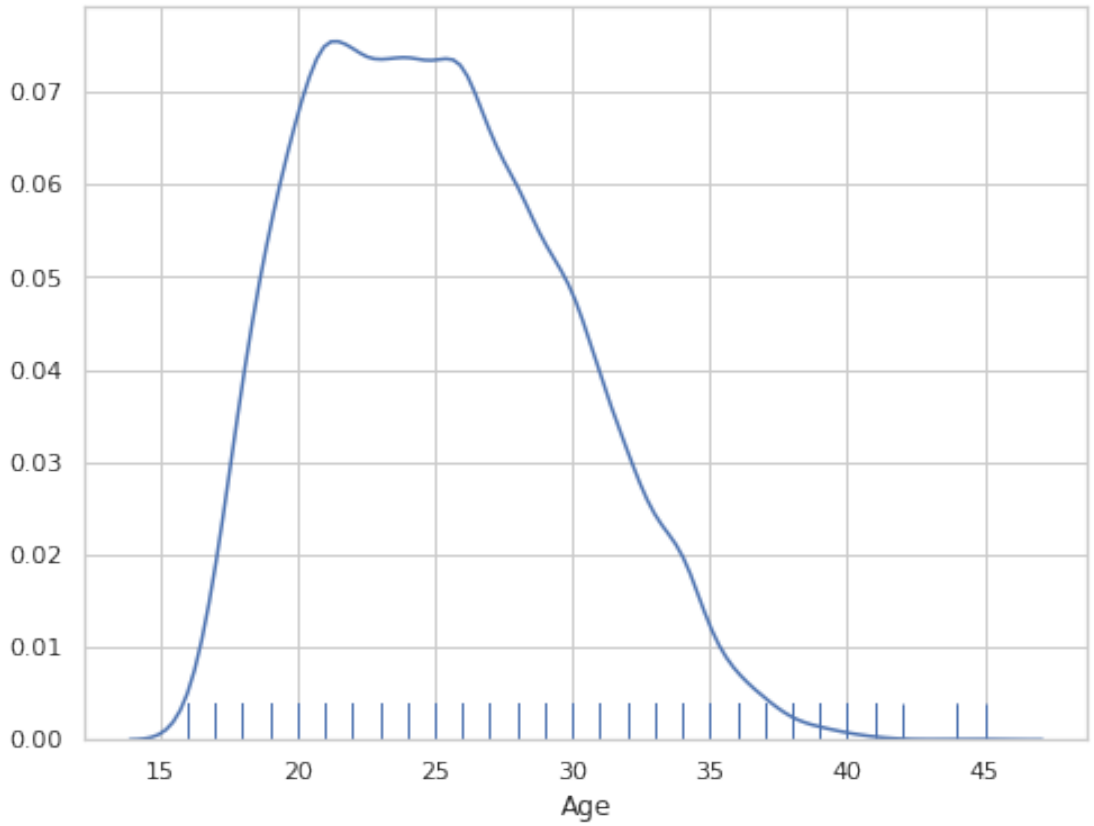
- A histogram represents the distribution of data by forming bins along the range of the data and then drawing bars to show the number of observations that fall in each bin.
- A `hist()` function already exists in matplotlib.
- We can use Seaborn to plot a histogram.

[12]:
```
f, ax = plt.subplots(figsize=(8,6))
x = fifa19['Age']
ax = sns.distplot(x, kde=False, rug=True, bins=10)
plt.show()
```



We can plot a KDE plot alternatively as follows:-

[13]:
```
f, ax = plt.subplots(figsize=(8,6))
x = fifa19['Age']
ax = sns.distplot(x, hist=False, rug=True, bins=10)
plt.show()
```



1.0.12 Explore `Preferred Foot` variable

1.0.13 Check number of unique values in `Preferred Foot` variable

[14]:
```
fifa19['Preferred Foot'].nunique()
```

[14]:
```
2
```

We can see that there are two types of unique values in `Preferred Foot` variable.

1.0.14 Check frequency distribution of values in `Preferred Foot` variable

[15]:
```
fifa19['Preferred Foot'].value_counts()
```

[15]:
```
Right    13948
Left      4211
Name: Preferred Foot, dtype: int64
```

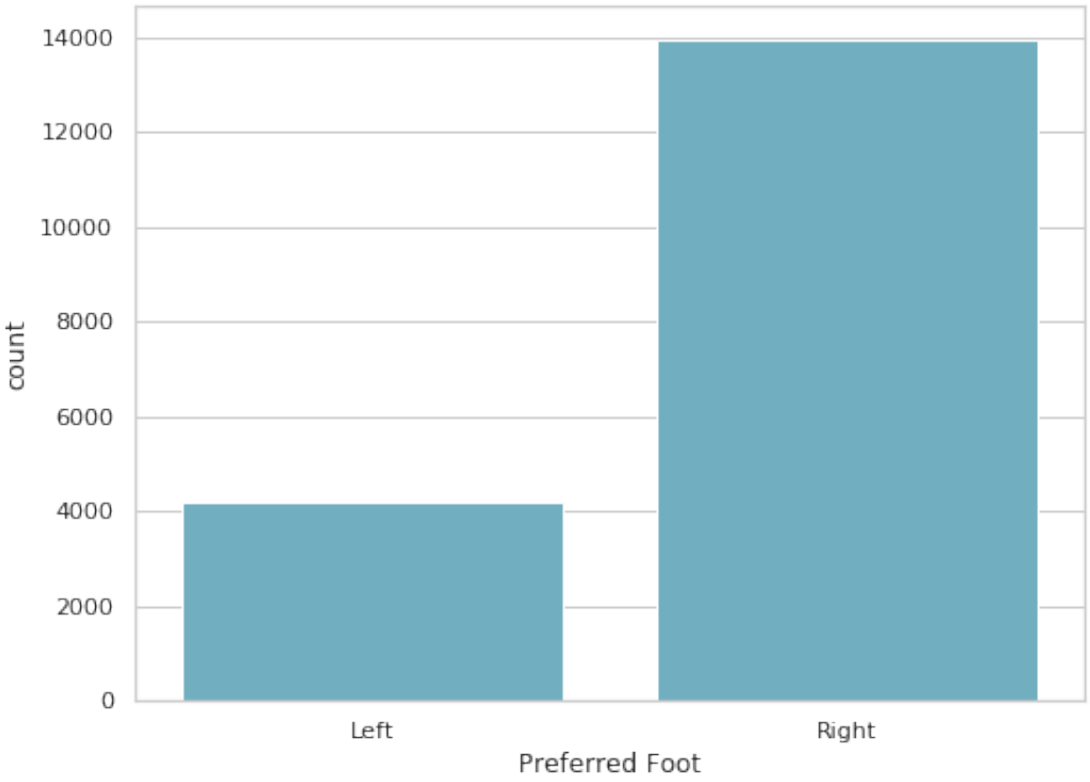
The `Preferred Foot` variable contains two types of values - `Right` and `Left`.

1.0.15 Visualize distribution of values with Seaborn `countplot()` function.

- A countplot shows the counts of observations in each categorical bin using bars.
- It can be thought of as a histogram across a categorical, instead of quantitative, variable.
- This function always treats one of the variables as categorical and draws data at ordinal positions (0, 1, … n) on the relevant axis, even when the data has a numeric or date type.

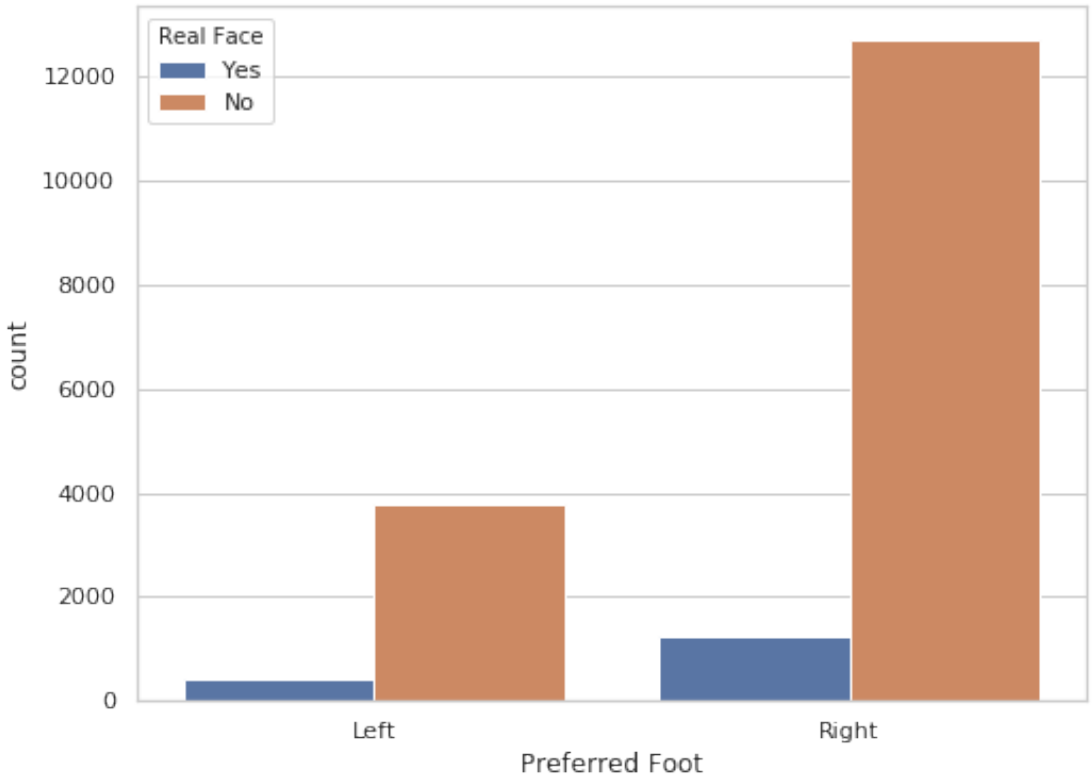
1. - We can visualize the distribution of values with Seaborn `countplot()` function as follows-

[16]:
```
f, ax = plt.subplots(figsize=(8, 6))
sns.countplot(x="Preferred Foot", data=fifa19, color="c")
plt.show()
```



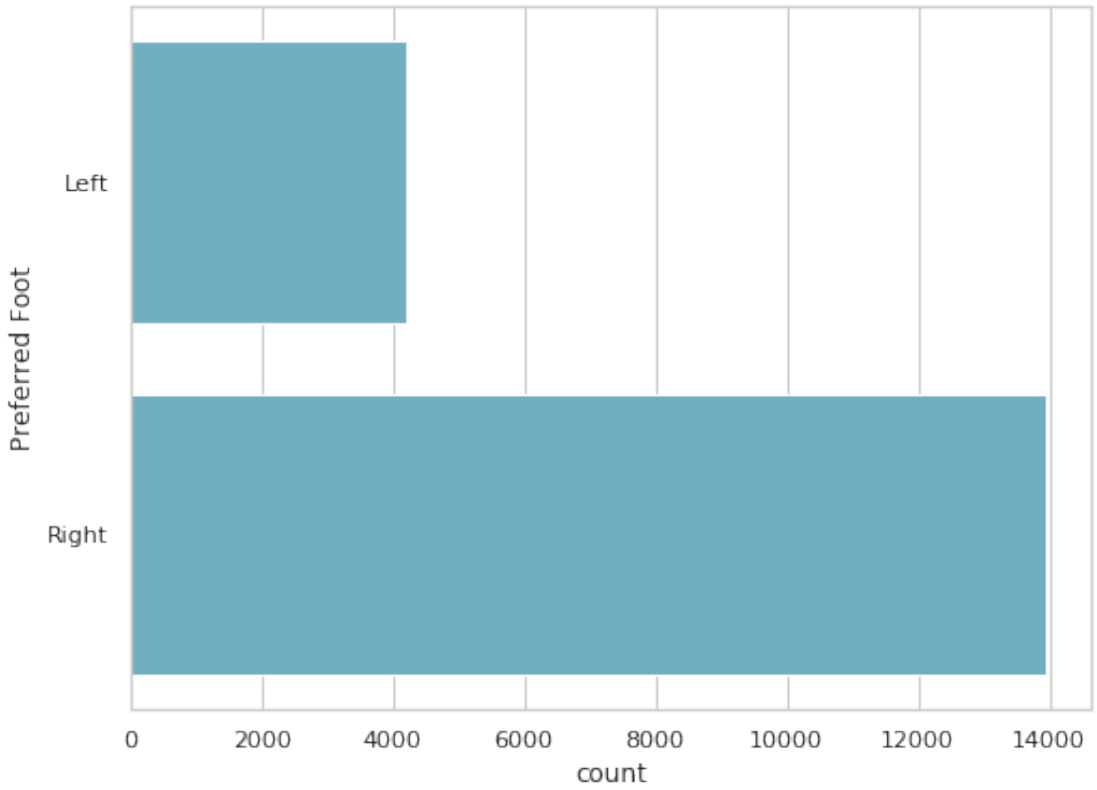
We can show value counts for two categorical variables as follows-

[17]:
```
f, ax = plt.subplots(figsize=(8, 6))
sns.countplot(x="Preferred Foot", hue="Real Face", data=fifa19)
plt.show()
```



We can draw plot vertically as follows-

[18]:
```
f, ax = plt.subplots(figsize=(8, 6))
sns.countplot(y="Preferred Foot", data=fifa19, color="c")
plt.show()
```

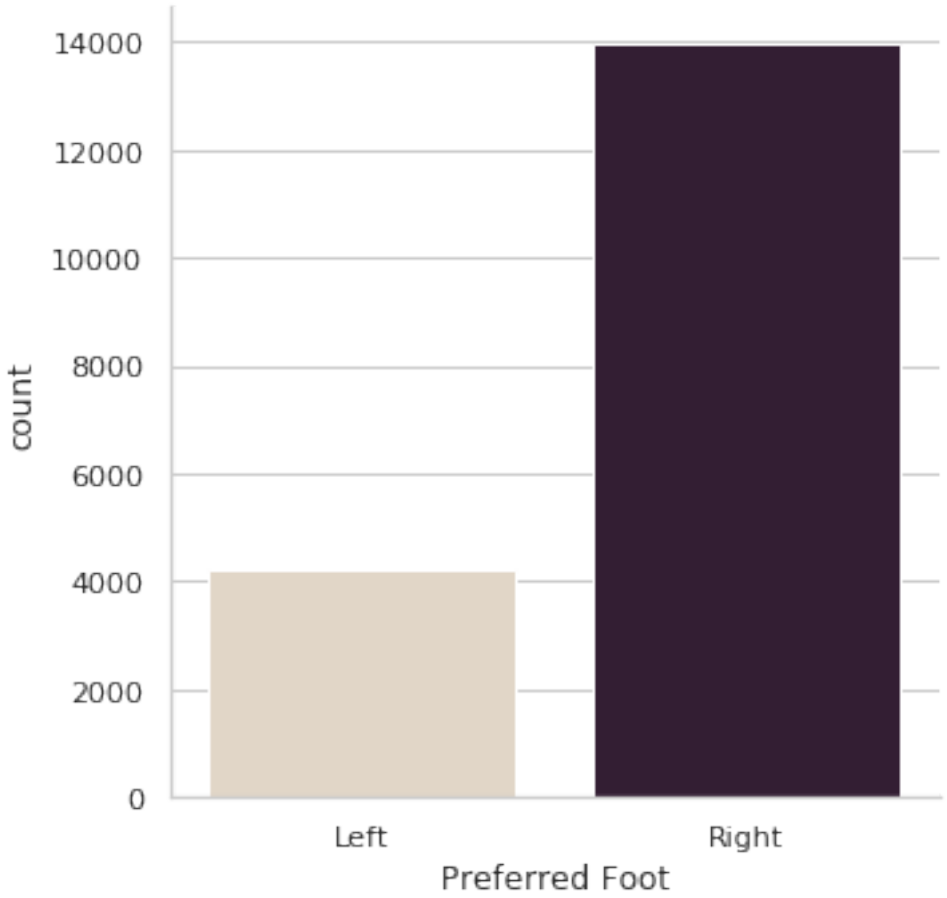


1.0.16 Seaborn `Catplot()` function

- We can use Seaborn `Catplot()` function to plot categorical scatterplots.
- The default representation of the data in `catplot()` uses a scatterplot.
- It helps to draw figure-level interface for drawing categorical plots onto a facetGrid.
- This function provides access to several axes-level functions that show the relationship between a numerical and one or more categorical variables using one of several visual representations.
- The `kind` parameter selects the underlying axes-level function to use.

We can use the kind parameter to draw different plot kin to visualize the same data. We can use the Seaborn `catplot()` function to draw a `countplot()` as follows-

[19]:
```
g = sns.catplot(x="Preferred Foot", kind="count", palette="ch:.25", data=fifa19)
```



1.0.17 Explore International Reputation variable

1.0.18 Check the number of unique values in International Reputation variable

[20]:
```
fifa19['International Reputation'].nunique()
```

[20]:
```
5
```

1.0.19 Check the distribution of values in International Reputation variable

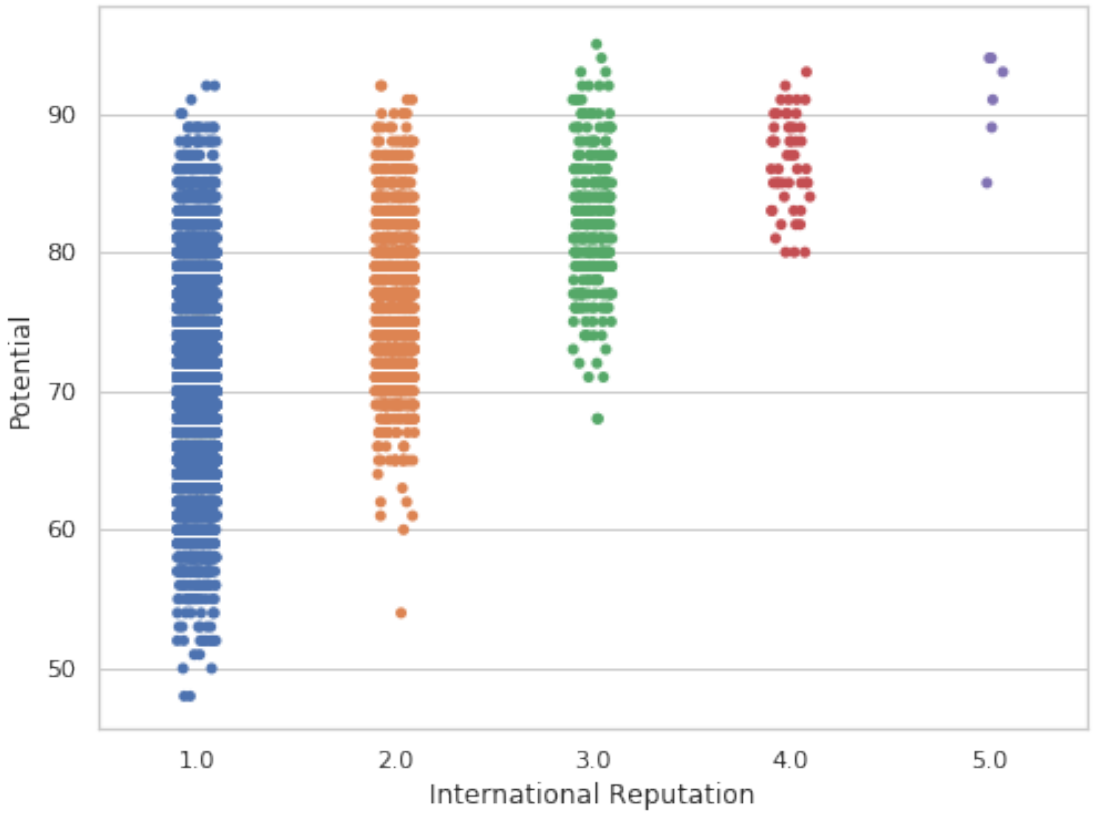
[21]:
```
fifa19['International Reputation'].value_counts()
```

[21]:
```
1.0    16532
2.0     1261
3.0      309
4.0       51
5.0        6
Name: International Reputation, dtype: int64
```

1.0.20 Seaborn `Stripplot()` function

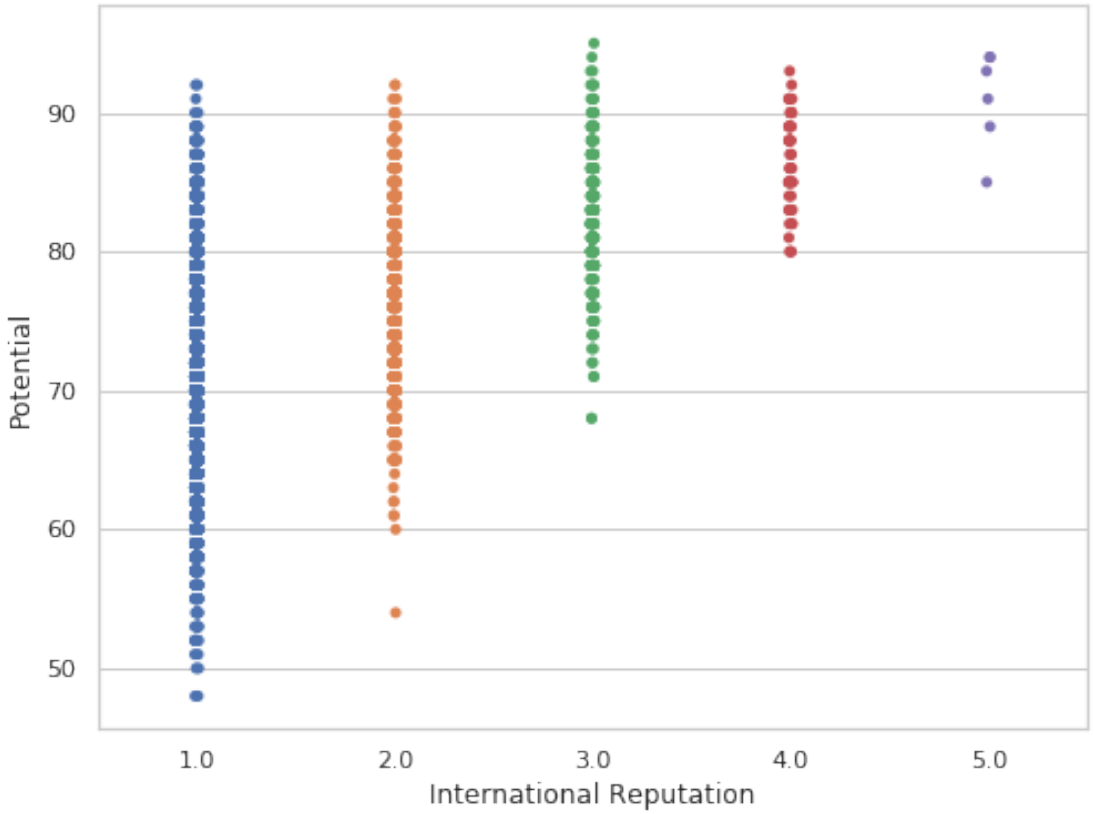
- This function draws a scatterplot where one variable is categorical.
- A strip plot can be drawn on its own, but it is also a good complement to a box or violin plot in cases where we want to show all observations along with some representation of the underlying distribution.
- I will plot a stripplot with `International Reputation` as categorical variable and `Potential` as the other variable.

[22]:
```
f, ax = plt.subplots(figsize=(8, 6))
sns.stripplot(x="International Reputation", y="Potential", data=fifa19)
plt.show()
```



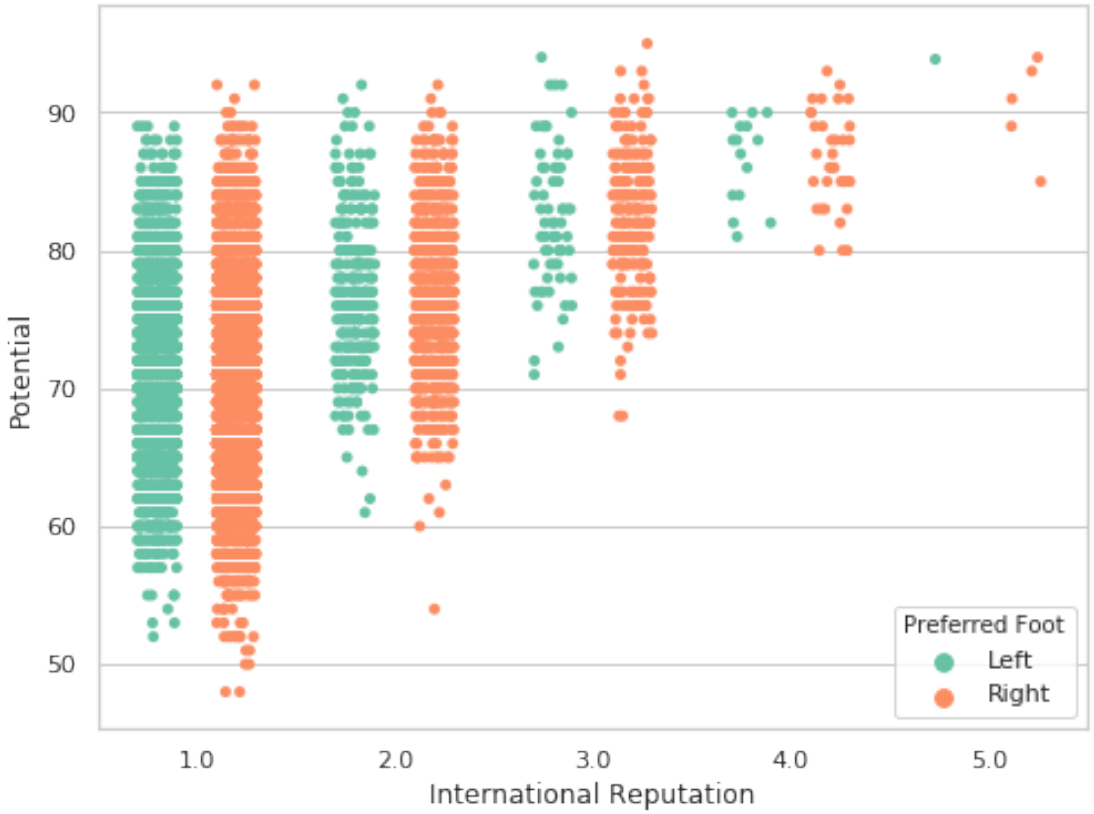
We can add jitter to bring out the distribution of values as follows-

[23]:
```
f, ax = plt.subplots(figsize=(8, 6))
sns.stripplot(x="International Reputation", y="Potential", data=fifa19,␣
 ↪jitter=0.01)
plt.show()
```



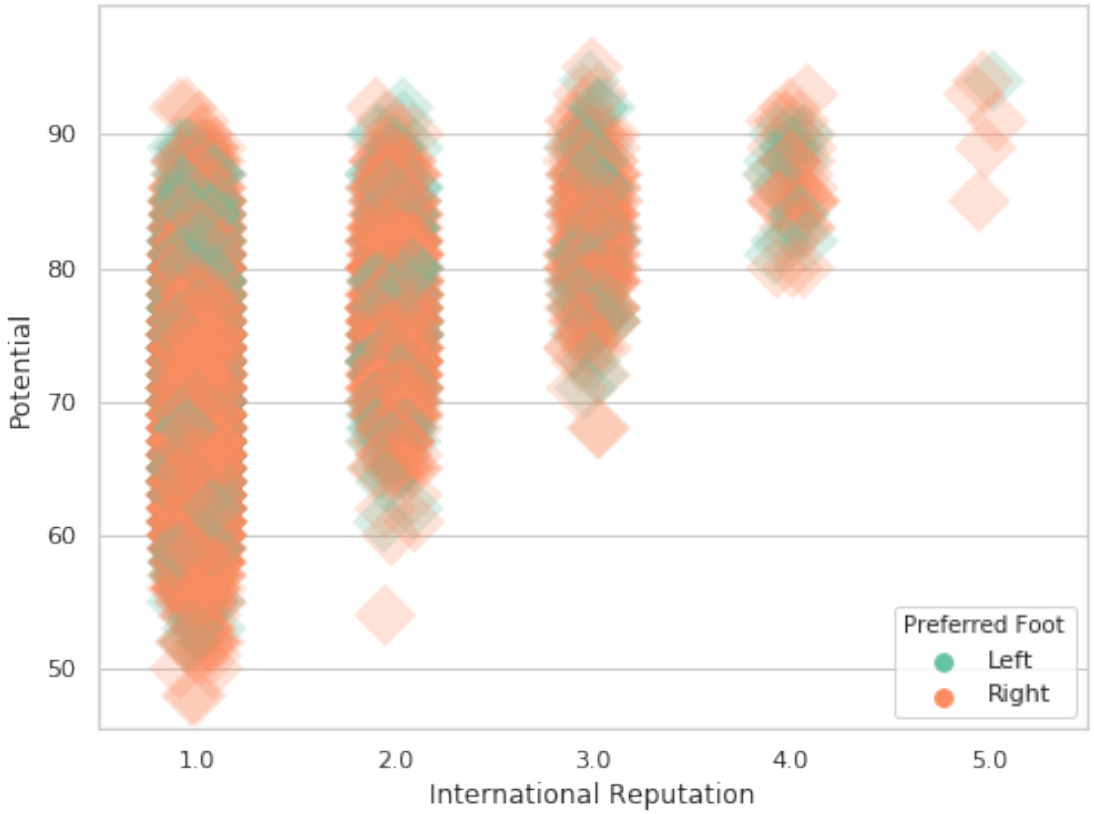
We can nest the strips within a second categorical variable - `Preferred Foot` as folows-

[24]:
```
f, ax = plt.subplots(figsize=(8, 6))
sns.stripplot(x="International Reputation", y="Potential", hue="Preferred Foot",
                    data=fifa19, jitter=0.2, palette="Set2", dodge=True)
plt.show()
```



We can draw strips with large points and different aesthetics as follows-

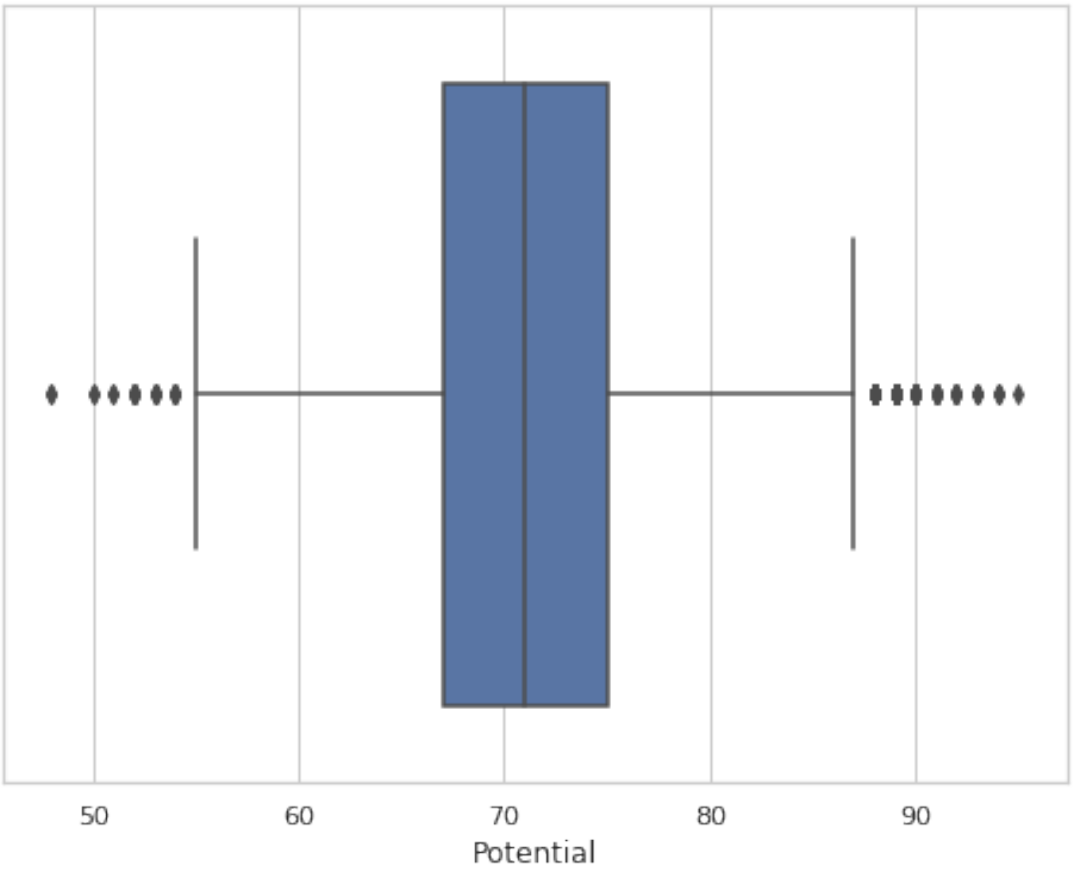
[25]:
```
f, ax = plt.subplots(figsize=(8, 6))
sns.stripplot(x="International Reputation", y="Potential", hue="Preferred Foot",
                    data=fifa19, palette="Set2", size=20, marker="D",
                    edgecolor="gray", alpha=.25)
plt.show()
```



1.0.21 Seaborn `boxplot()` function

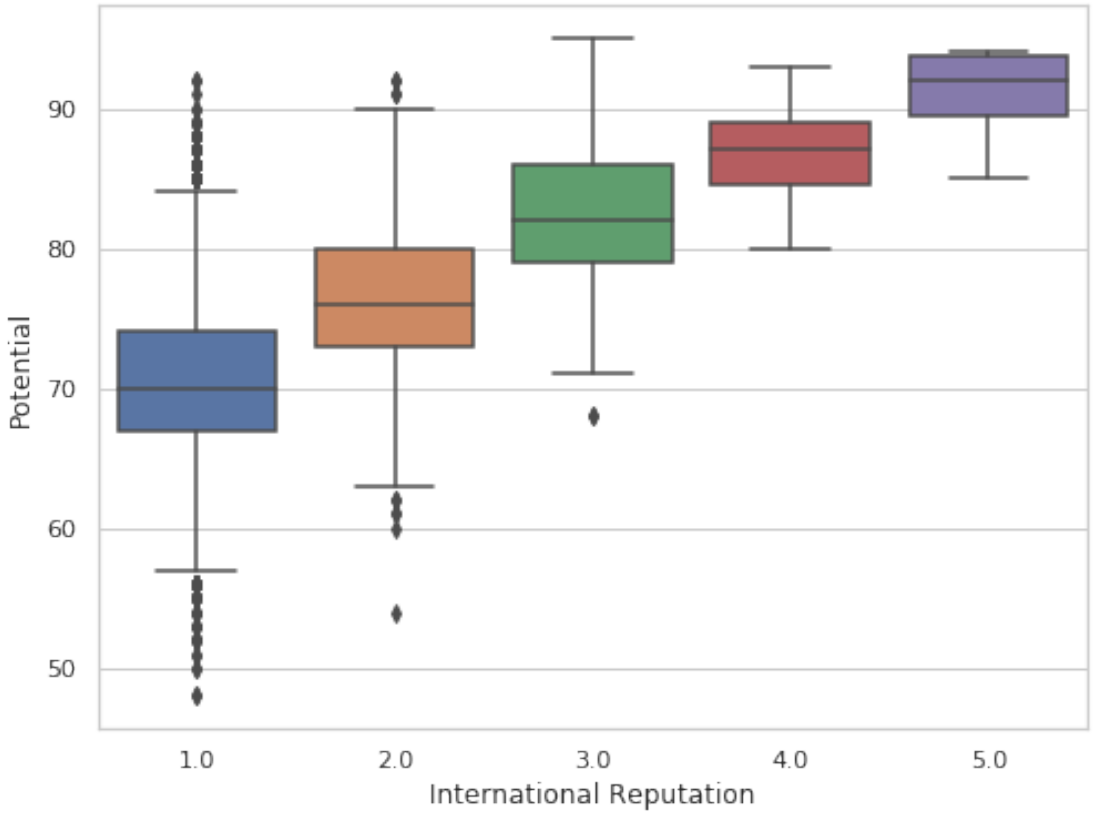
- This function draws a box plot to show distributions with respect to categories.
- A box plot (or box-and-whisker plot) shows the distribution of quantitative data in a way that facilitates comparisons between variables or across levels of a categorical variable.
- The box shows the quartiles of the dataset while the whiskers extend to show the rest of the distribution, except for points that are determined to be "outliers" using a method that is a function of the inter-quartile range.
- I will plot the boxplot of the `Potential` variable as follows-

[26]:
```
f, ax = plt.subplots(figsize=(8, 6))
sns.boxplot(x=fifa19["Potential"])
plt.show()
```



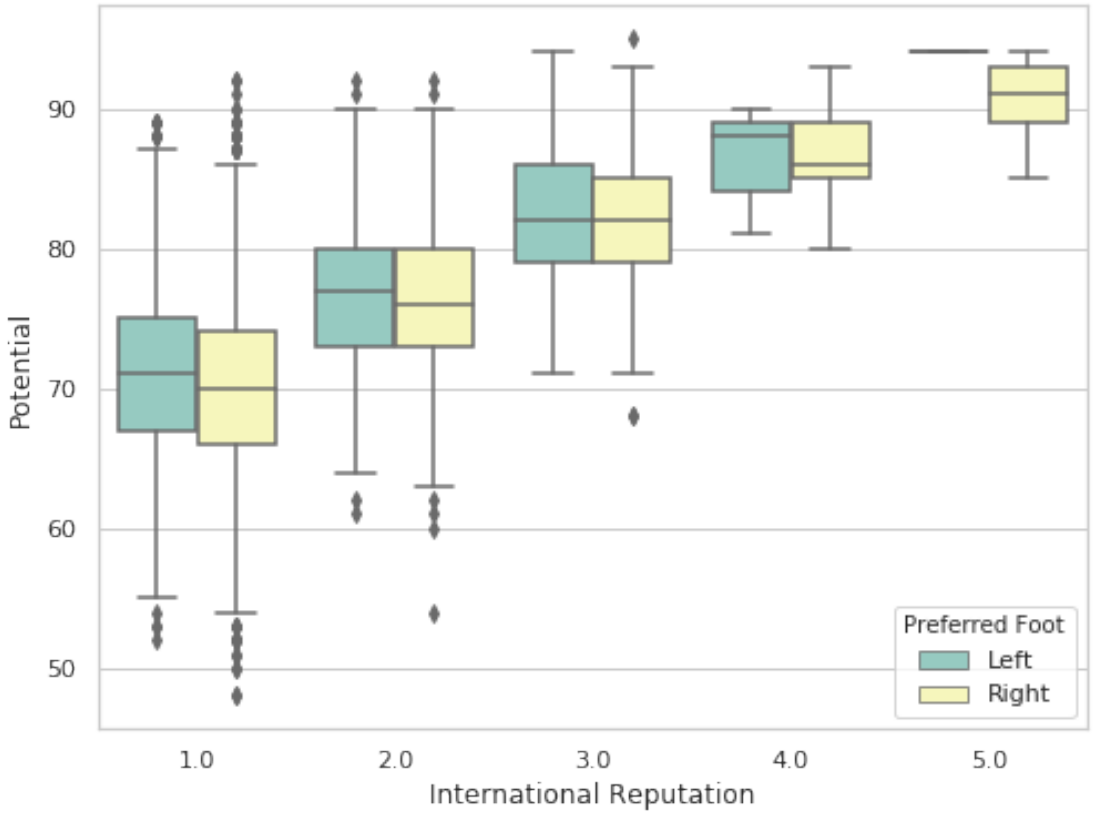
We can draw the vertical boxplot grouped by the categorical variable `International Reputation` as follows-

[27]:
```
f, ax = plt.subplots(figsize=(8, 6))
sns.boxplot(x="International Reputation", y="Potential", data=fifa19)
plt.show()
```



We can draw a boxplot with nested grouping by two categorical variables as follows-

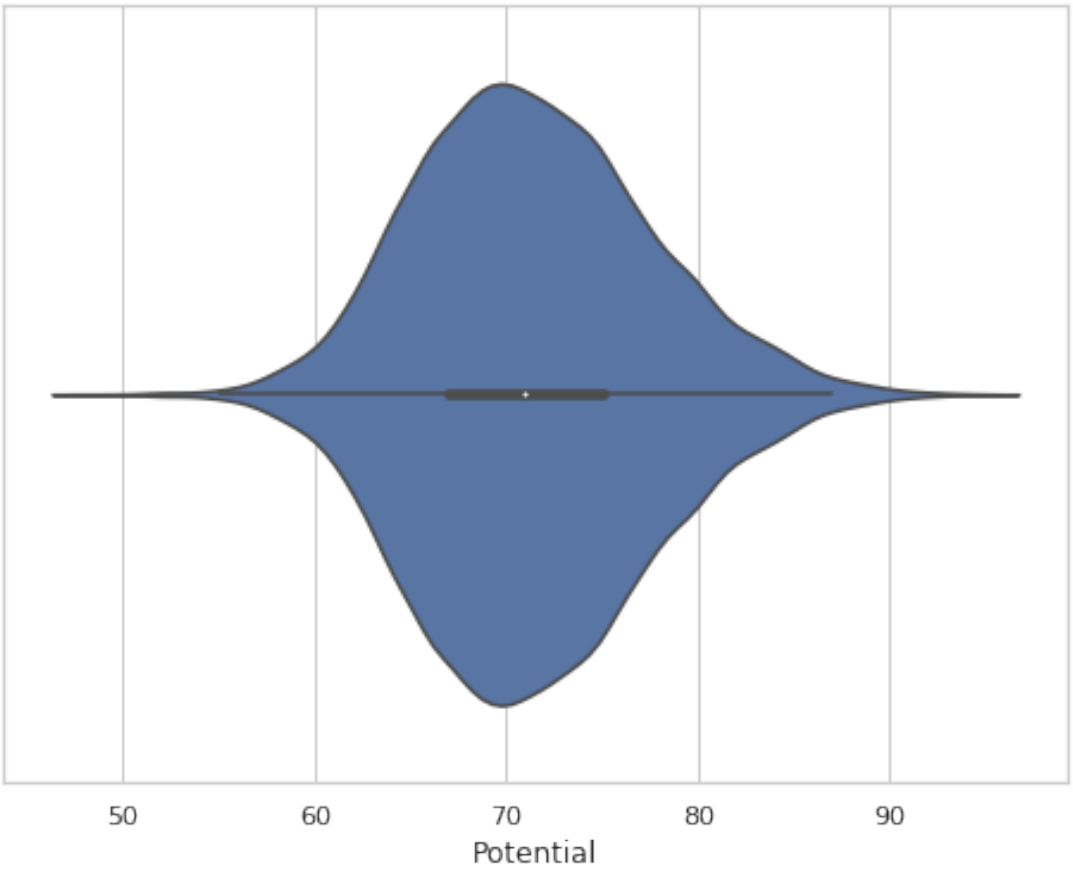
[28]:
```
f, ax = plt.subplots(figsize=(8, 6))
sns.boxplot(x="International Reputation", y="Potential", hue="Preferred Foot",␣
 ↪data=fifa19, palette="Set3")
plt.show()
```



1.0.22 Seaborn `violinplot()` function

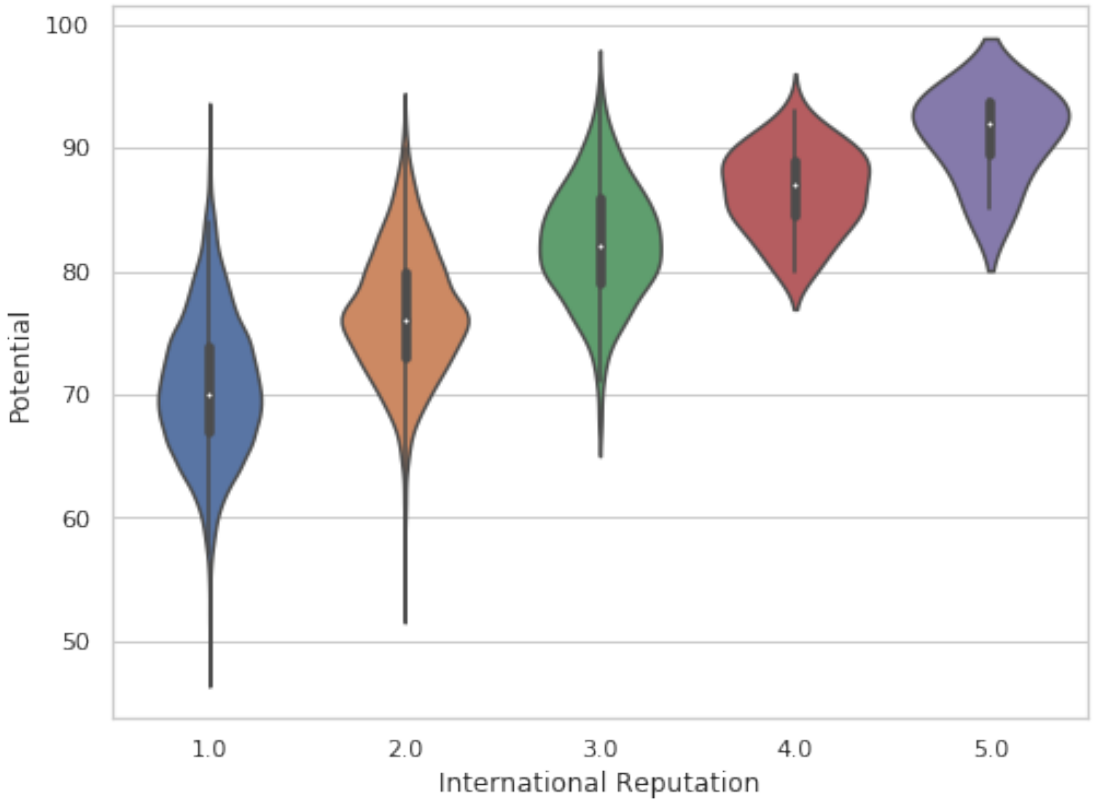
- This function draws a combination of boxplot and kernel density estimate.
- A violin plot plays a similar role as a box and whisker plot.
- It shows the distribution of quantitative data across several levels of one (or more) categorical variables such that those distributions can be compared.
- Unlike a box plot, in which all of the plot components correspond to actual datapoints, the violin plot features a kernel density estimation of the underlying distribution.
- I will plot the violinplot of `Potential` variable as follows-

[29]:
```
f, ax = plt.subplots(figsize=(8, 6))
sns.violinplot(x=fifa19["Potential"])
plt.show()
```



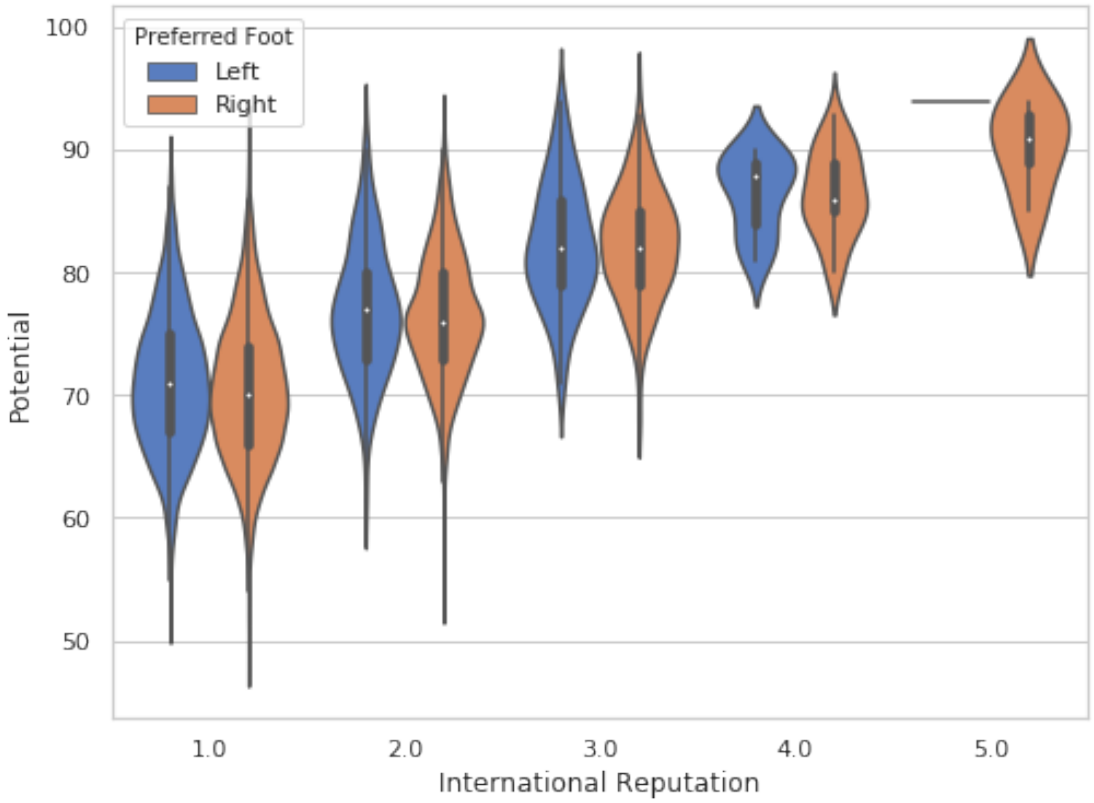
We can draw the vertical violinplot grouped by the categorical variable `International Reputation` as follows-

[30]:
```
f, ax = plt.subplots(figsize=(8, 6))
sns.violinplot(x="International Reputation", y="Potential", data=fifa19)
plt.show()
```



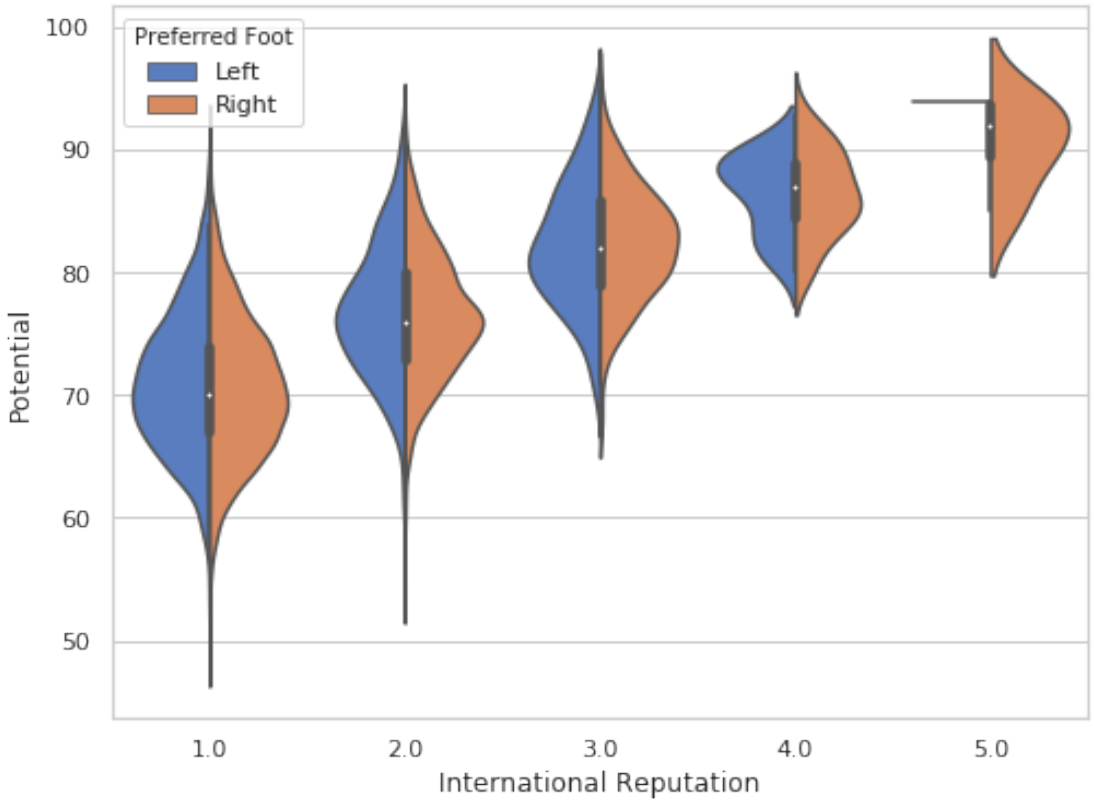
We can draw a violinplot with nested grouping by two categorical variables as follows-

[31]:
```
f, ax = plt.subplots(figsize=(8, 6))
sns.violinplot(x="International Reputation", y="Potential", hue="Preferred␣
↪Foot", data=fifa19, palette="muted")
plt.show()
```



We can draw split violins to compare the across the hue variable as follows-

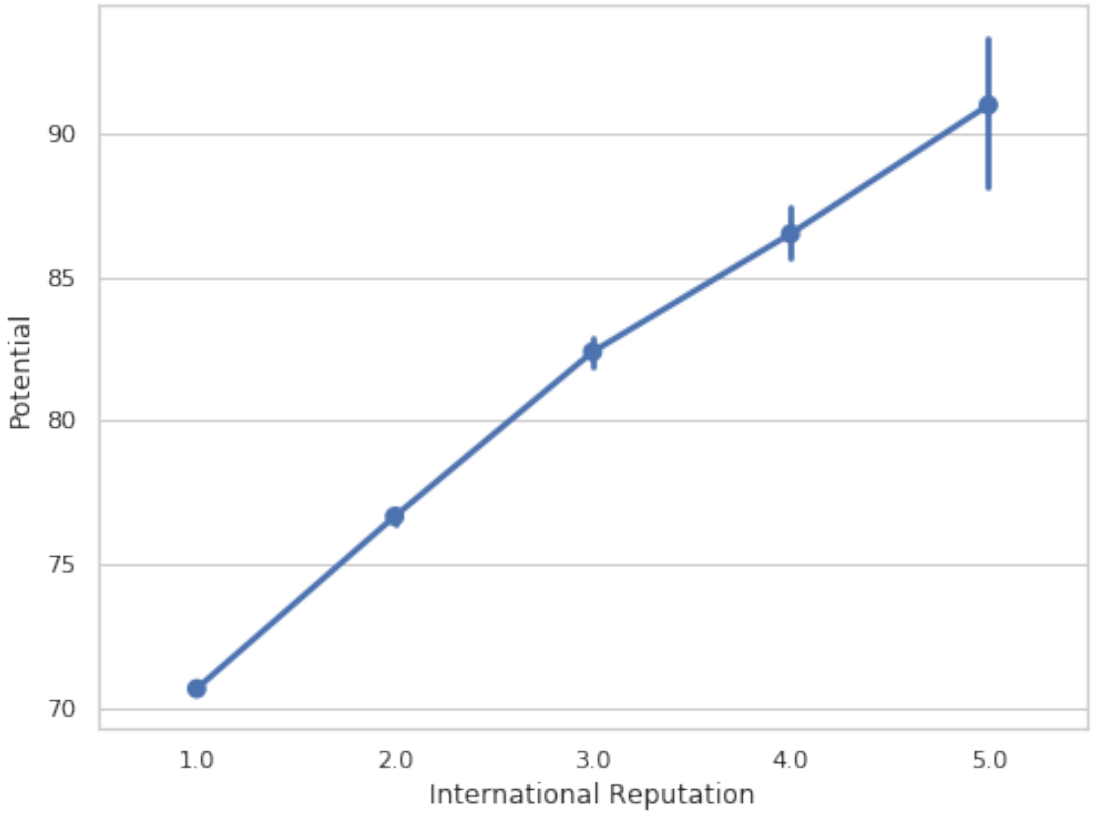
[32]:
```
f, ax = plt.subplots(figsize=(8, 6))
sns.violinplot(x="International Reputation", y="Potential", hue="Preferred␣
↪Foot",
               data=fifa19, palette="muted", split=True)
plt.show()
```



1.0.23 Seaborn `pointplot()` function

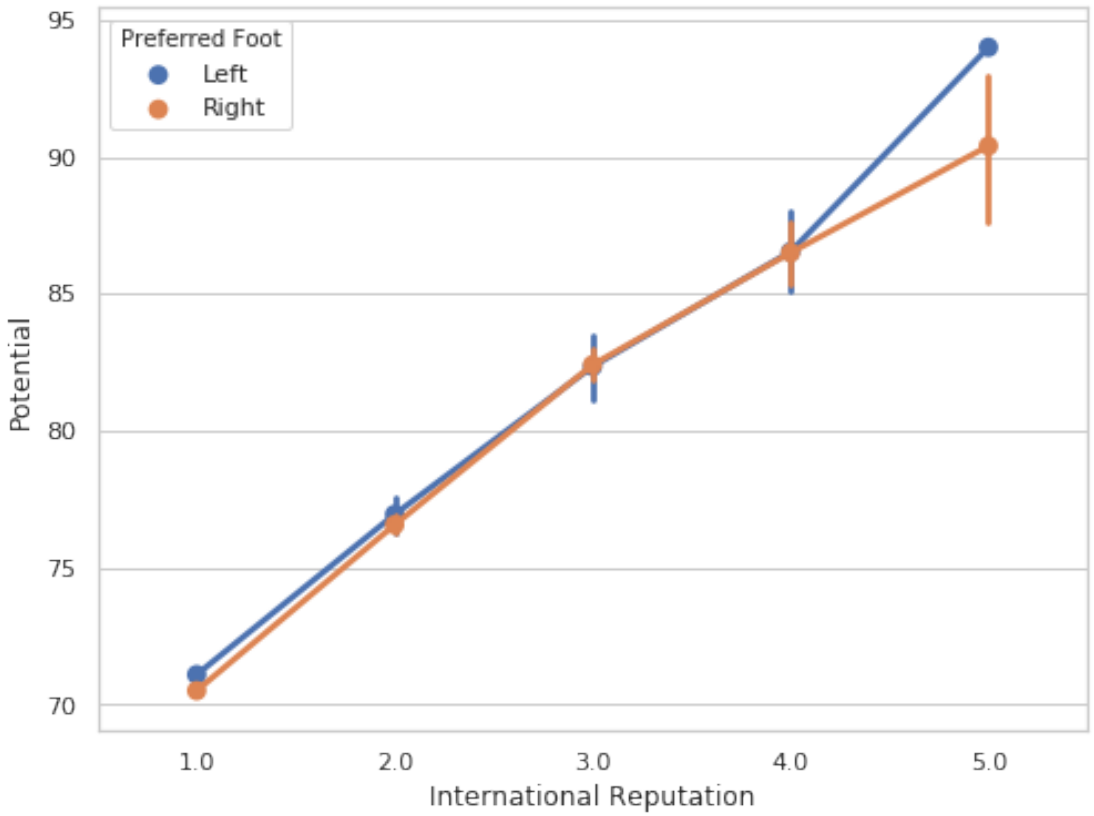
- This function show point estimates and confidence intervals using scatter plot glyphs.
- A point plot represents an estimate of central tendency for a numeric variable by the position of scatter plot points and provides some indication of the uncertainty around that estimate using error bars.

[33]:
```
f, ax = plt.subplots(figsize=(8, 6))
sns.pointplot(x="International Reputation", y="Potential", data=fifa19)
plt.show()
```



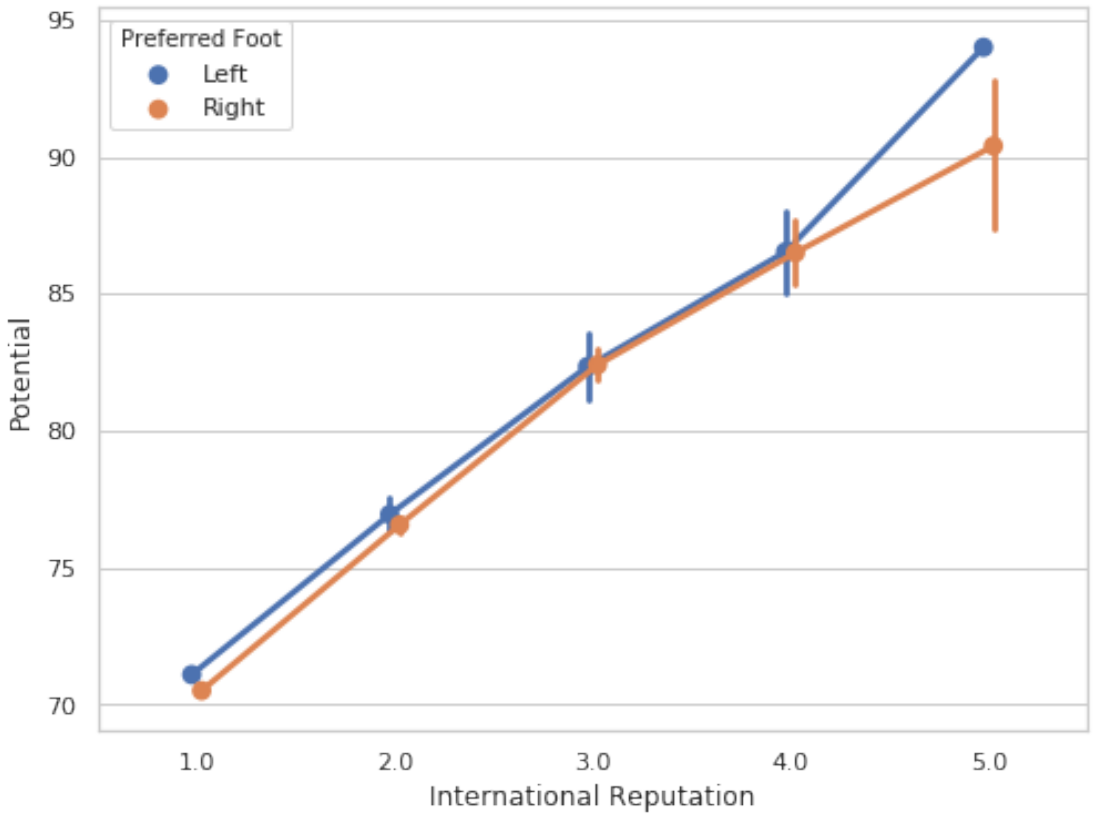
We can draw a set of vertical points with nested grouping by a two variables as follows-

[34]:
```
f, ax = plt.subplots(figsize=(8, 6))
sns.pointplot(x="International Reputation", y="Potential", hue="Preferred␣
↪Foot", data=fifa19)
plt.show()
```



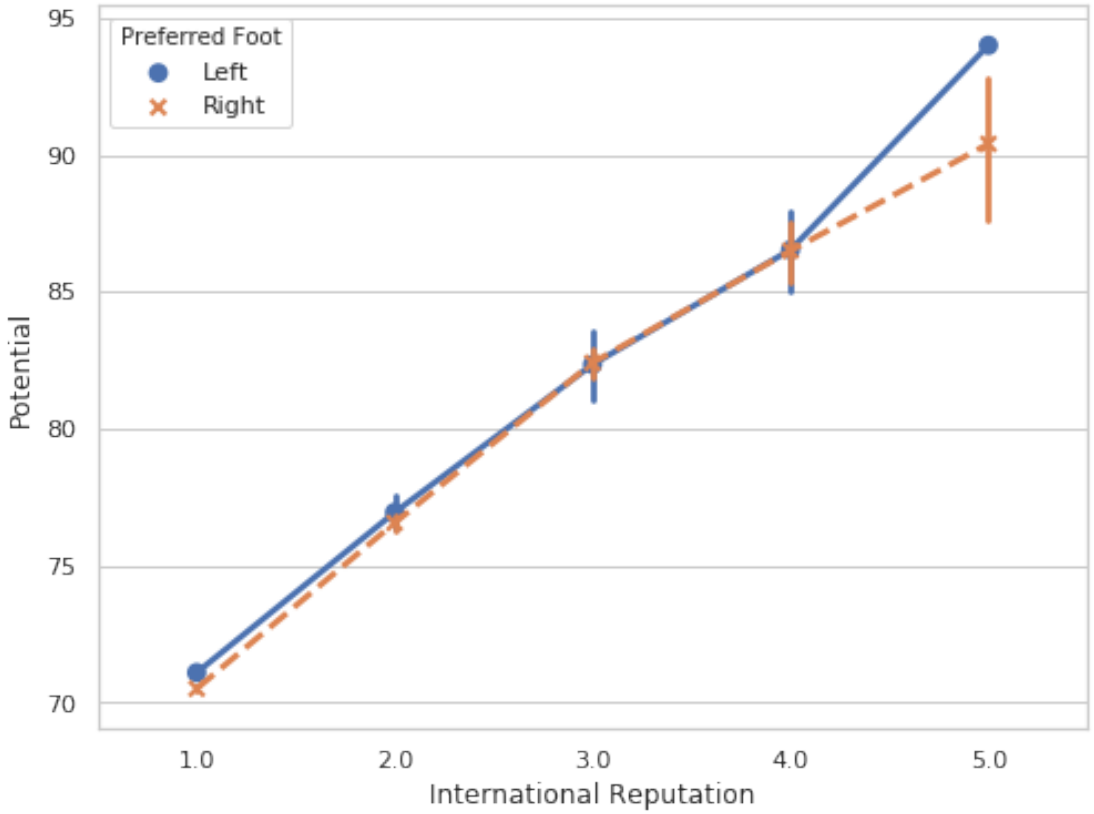
We can separate the points for different hue levels along the categorical axis as follows-

[35]:
```
f, ax = plt.subplots(figsize=(8, 6))
sns.pointplot(x="International Reputation", y="Potential", hue="Preferred␣
↪Foot", data=fifa19, dodge=True)
plt.show()
```



We can use a different marker and line style for the hue levels as follows-

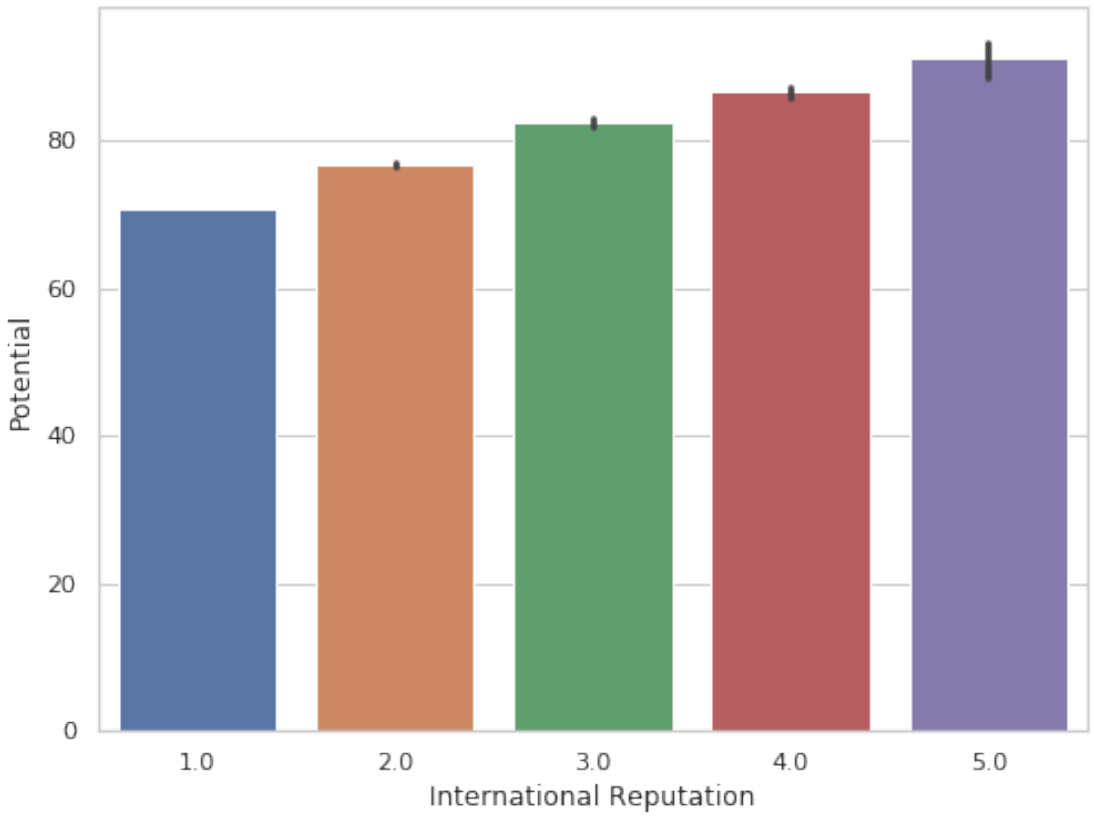
[36]:
```
f, ax = plt.subplots(figsize=(8, 6))
sns.pointplot(x="International Reputation", y="Potential", hue="Preferred Foot",
              data=fifa19, markers=["o", "x"], linestyles=["-", "--"])
plt.show()
```



1.0.24 Seaborn `barplot()` function

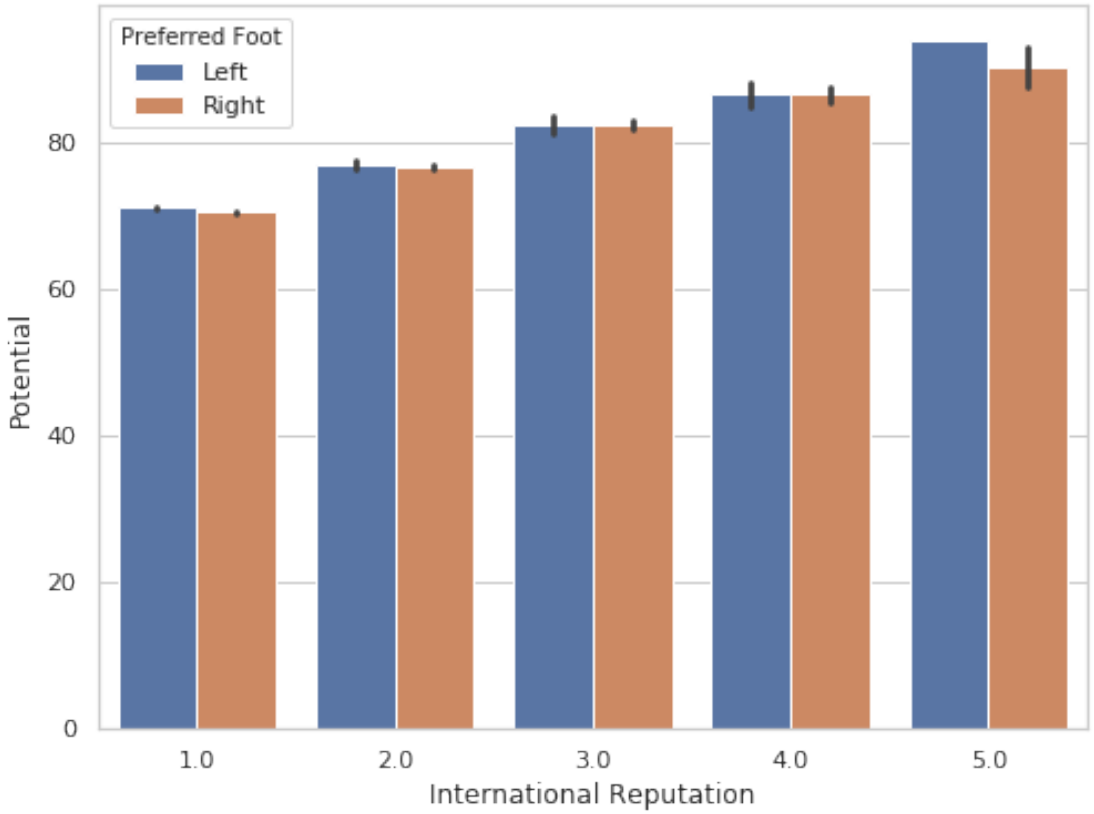
- This function show point estimates and confidence intervals as rectangular bars.
- A bar plot represents an estimate of central tendency for a numeric variable with the height of each rectangle and provides some indication of the uncertainty around that estimate using error bars.
- Bar plots include 0 in the quantitative axis range, and they are a good choice when 0 is a meaningful value for the quantitative variable, and you want to make comparisons against it.
- We can plot a barplot as follows-

[37]:
```
f, ax = plt.subplots(figsize=(8, 6))
sns.barplot(x="International Reputation", y="Potential", data=fifa19)
plt.show()
```



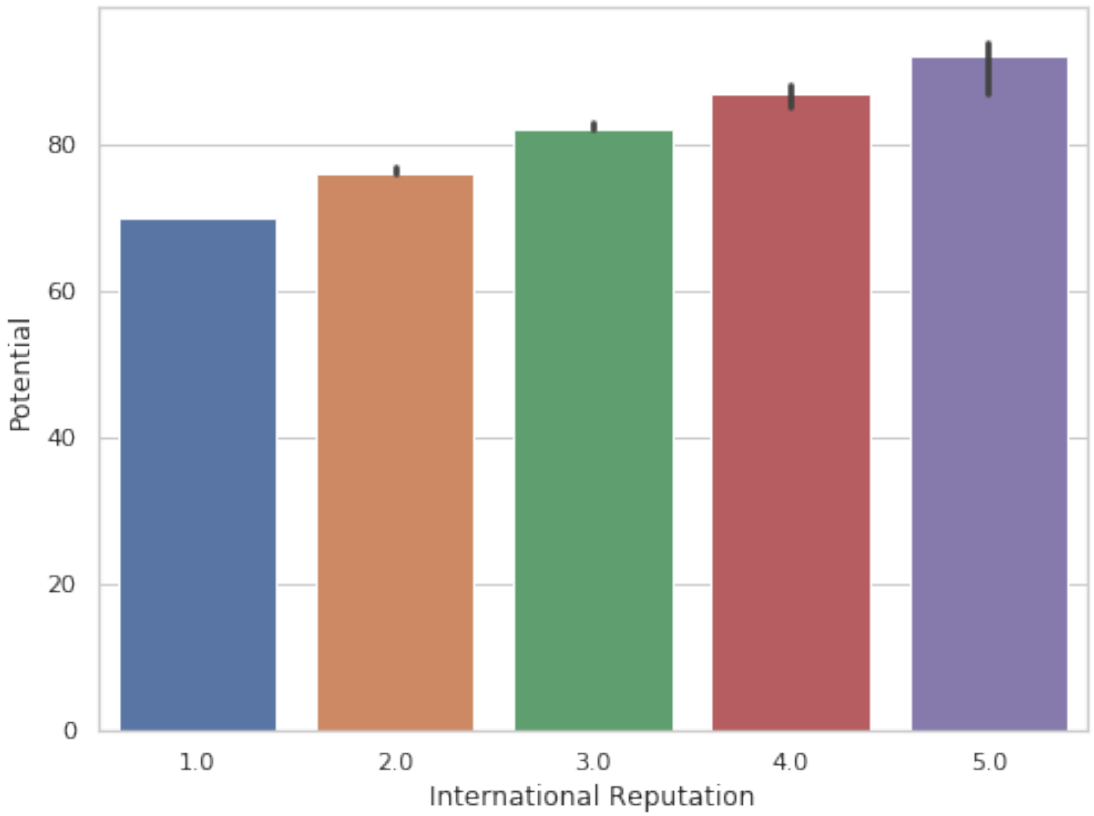
We can draw a set of vertical bars with nested grouping by a two variables as follows-

[38]:
```
f, ax = plt.subplots(figsize=(8, 6))
sns.barplot(x="International Reputation", y="Potential", hue="Preferred Foot",␣
 ↪data=fifa19)
plt.show()
```



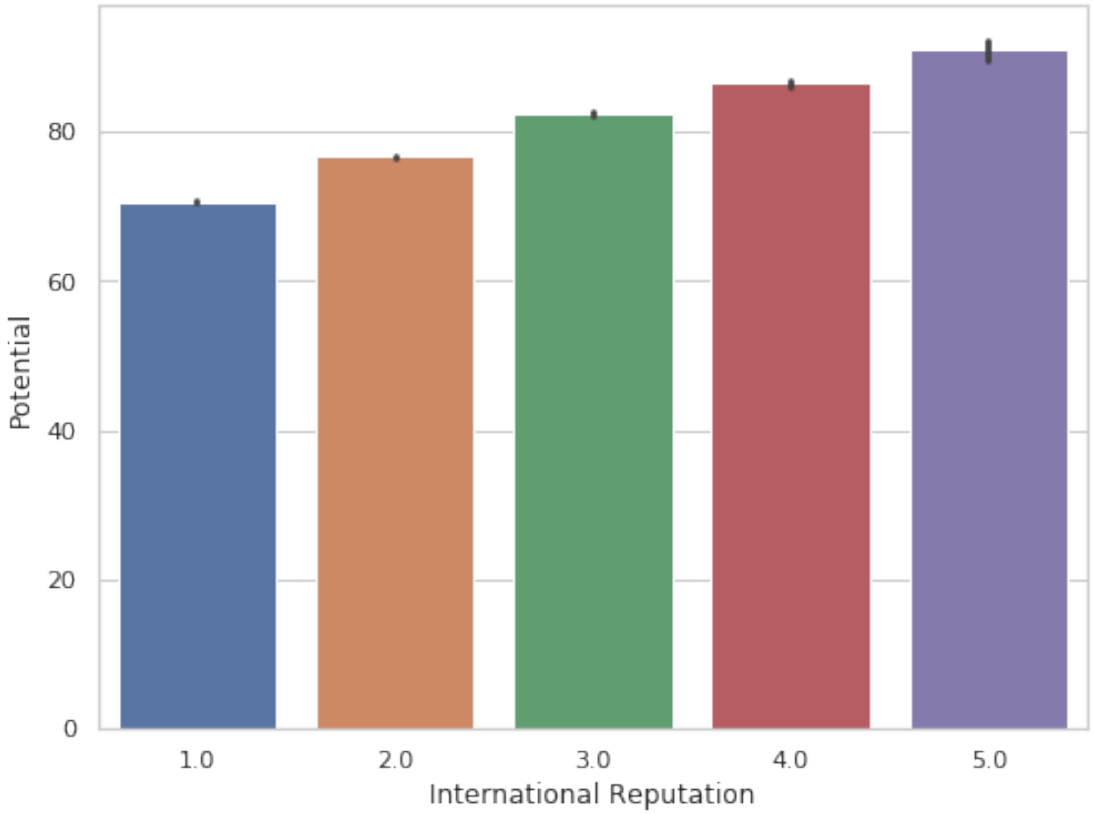
We can use median as the estimate of central tendency as follows-

[39]:
```
from numpy import median
f, ax = plt.subplots(figsize=(8, 6))
sns.barplot(x="International Reputation", y="Potential", data=fifa19,␣
 ↪estimator=median)
plt.show()
```



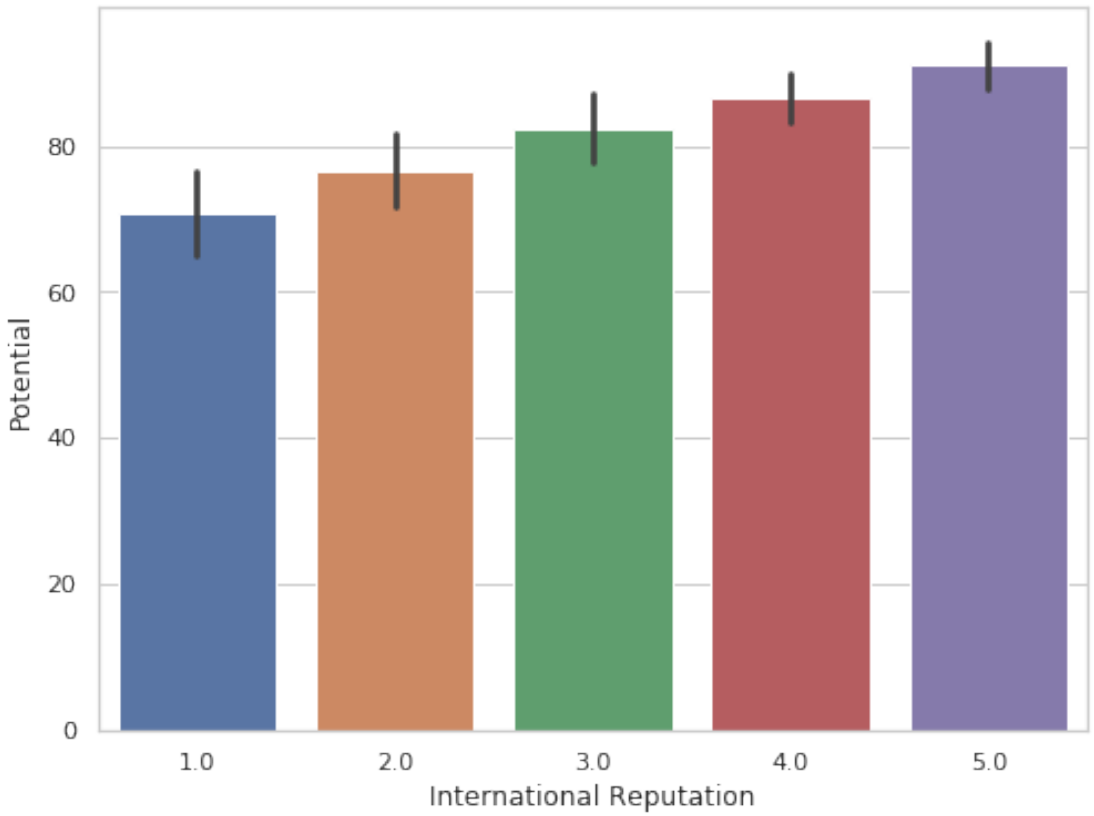
We can show the standard error of the mean with the error bars as follows-

[40]:
```
f, ax = plt.subplots(figsize=(8, 6))
sns.barplot(x="International Reputation", y="Potential", data=fifa19, ci=68)
plt.show()
```



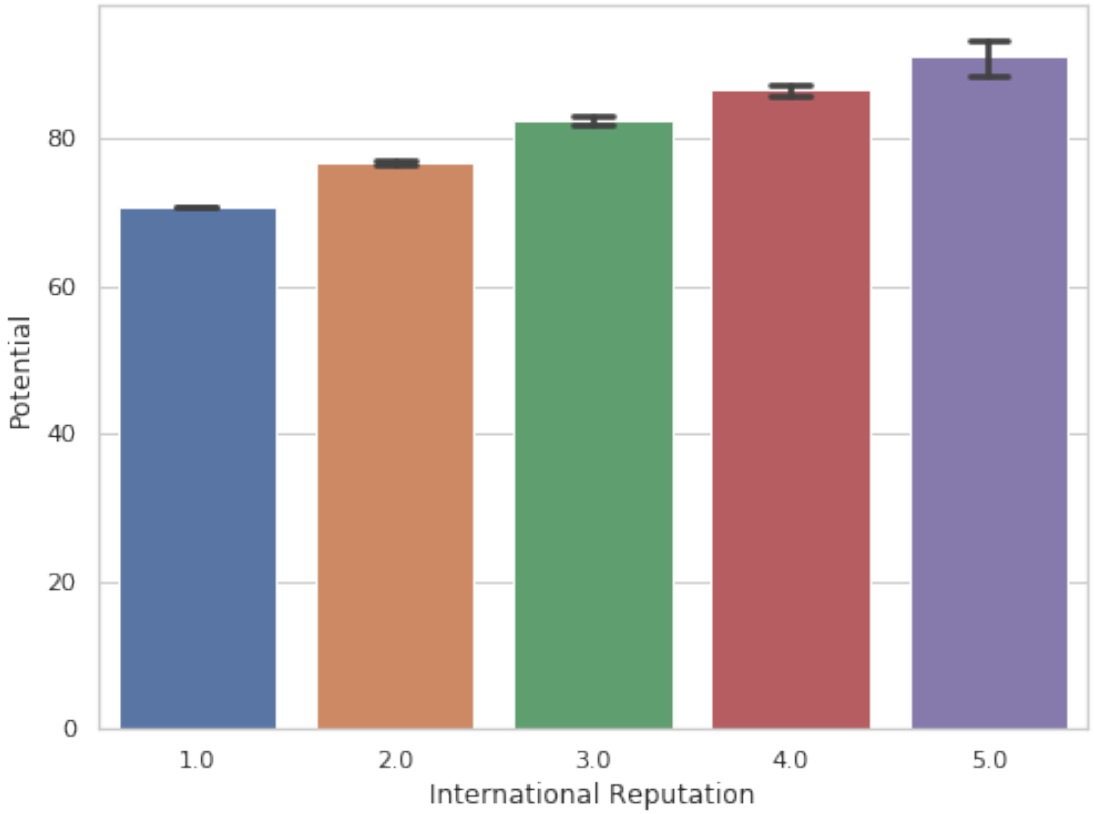
We can show standard deviation of observations instead of a confidence interval as follows-

[41]:
```
f, ax = plt.subplots(figsize=(8, 6))
sns.barplot(x="International Reputation", y="Potential", data=fifa19, ci="sd")
plt.show()
```



We can add “caps” to the error bars as follows-

[42]:
```
f, ax = plt.subplots(figsize=(8, 6))
sns.barplot(x="International Reputation", y="Potential", data=fifa19, capsize=0.
↪2)
plt.show()
```



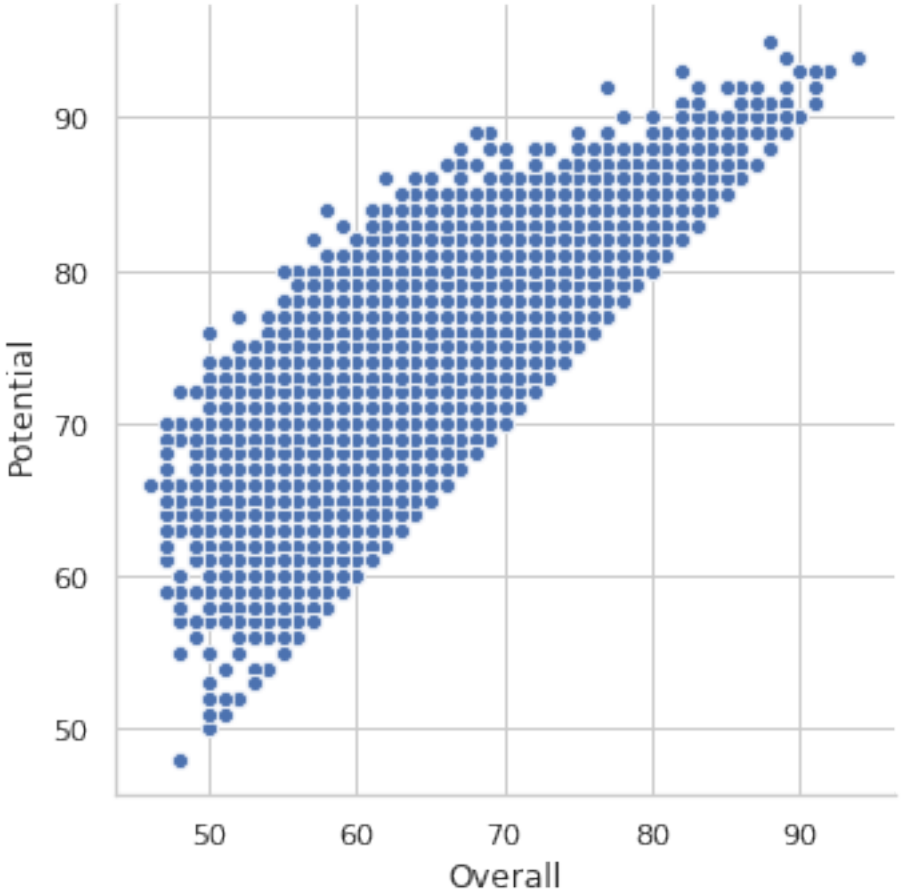
1.0.25 Visualizing statistical relationship with Seaborn `relplot()` function

1.0.26 Seaborn `relplot()` function

- Seaborn `relplot()` function helps us to draw figure-level interface for drawing relational plots onto a FacetGrid.
- This function provides access to several different axes-level functions that show the relationship between two variables with semantic mappings of subsets.
- The `kind` parameter selects the underlying axes-level function to use-
- scatterplot() (with kind="scatter"; the default)
- lineplot() (with kind="line")

We can plot a scatterplot with variables `Heigh` and `Weight` with Seaborn `relplot()` function as follows-

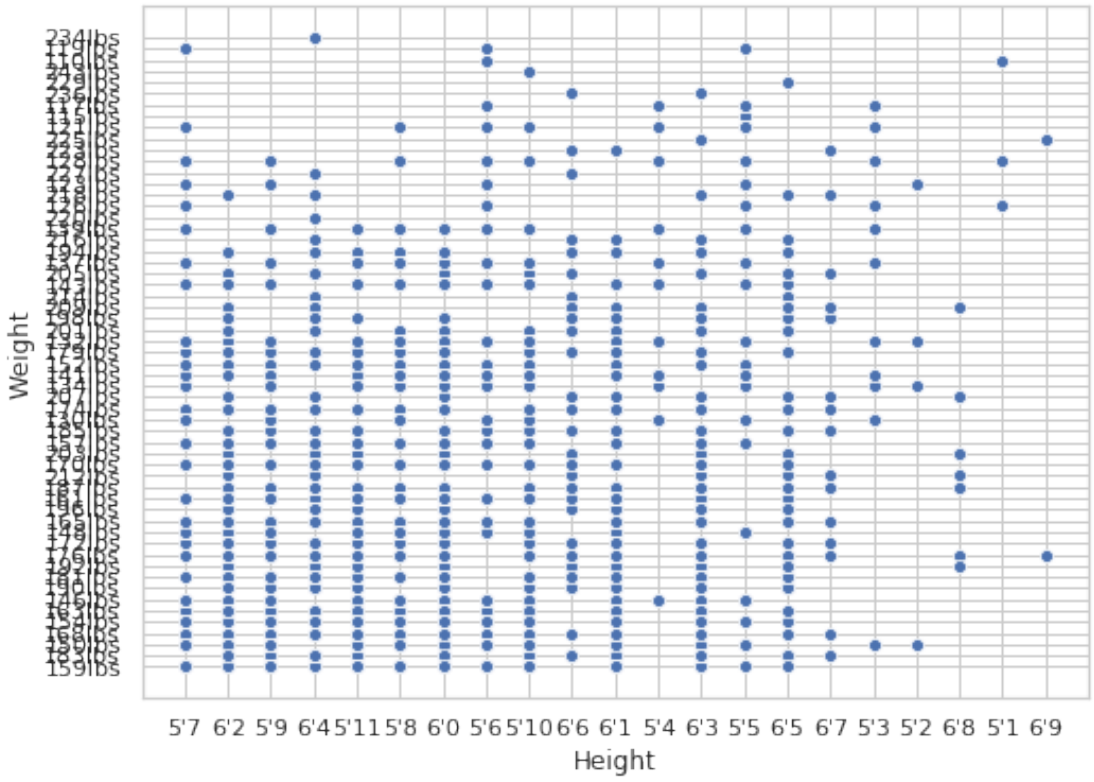
[43]:
```
g = sns.relplot(x="Overall", y="Potential", data=fifa19)
```



1.0.27 Seaborn `scatterplot()` function

- This function draws a scatter plot with possibility of several semantic groups.
- The relationship between x and y can be shown for different subsets of the data using the `hue`, `size` and `style` parameters.
- These parameters control what visual semantics are used to identify the different subsets.

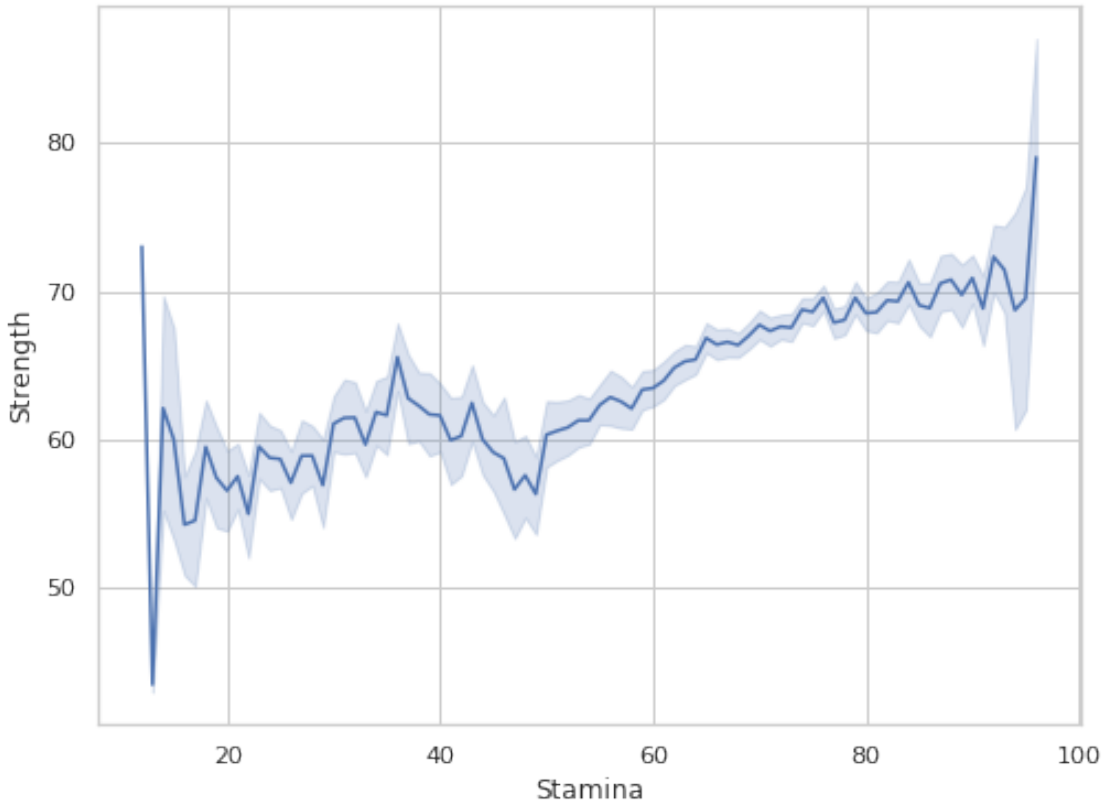
[44]:
```
f, ax = plt.subplots(figsize=(8, 6))
sns.scatterplot(x="Height", y="Weight", data=fifa19)
plt.show()
```



1.0.28 Seaborn `lineplot()` function

- THis function draws a line plot with possibility of several semantic groupings.
- The relationship between x and y can be shown for different subsets of the data using the `hue`, `size` and `style` parameters.
- These parameters control what visual semantics are used to identify the different subsets.

[45]:
```
f, ax = plt.subplots(figsize=(8, 6))
ax = sns.lineplot(x="Stamina", y="Strength", data=fifa19)
plt.show()
```

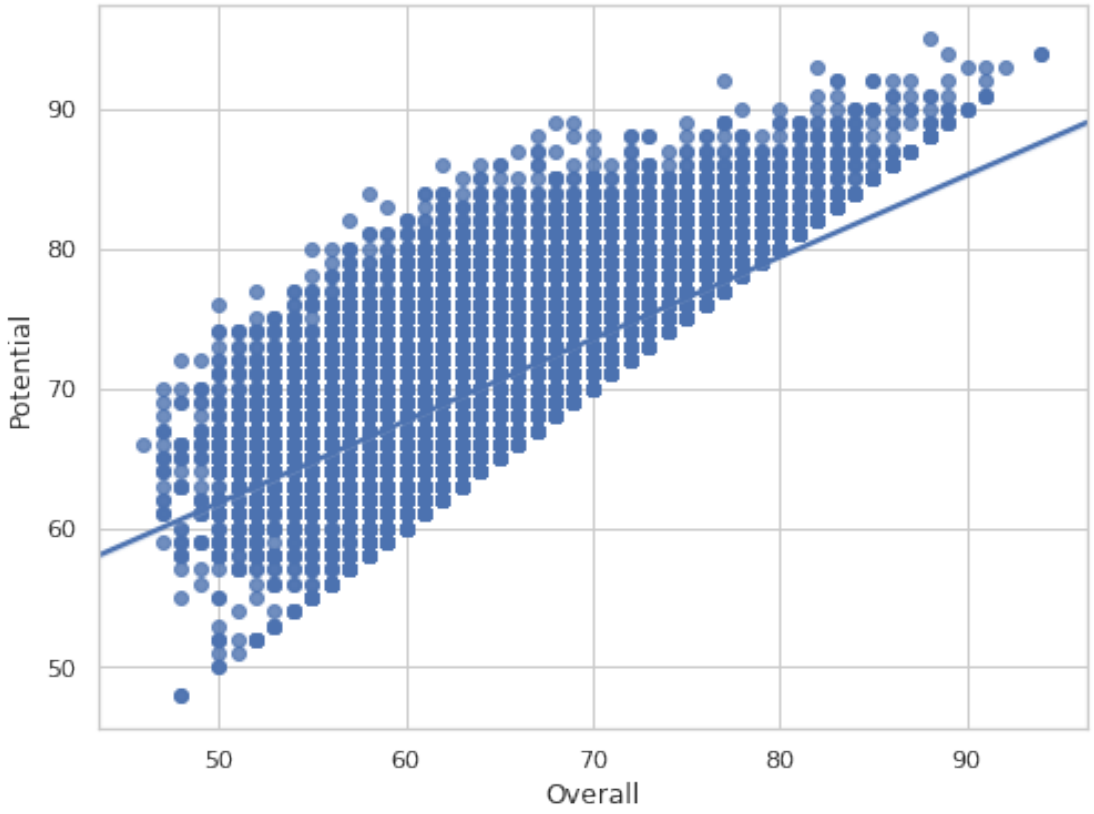


1.0.29 Visualize linear relationship with Seaborn `regplot()` function

1.0.30 Seaborn `regplot()` function

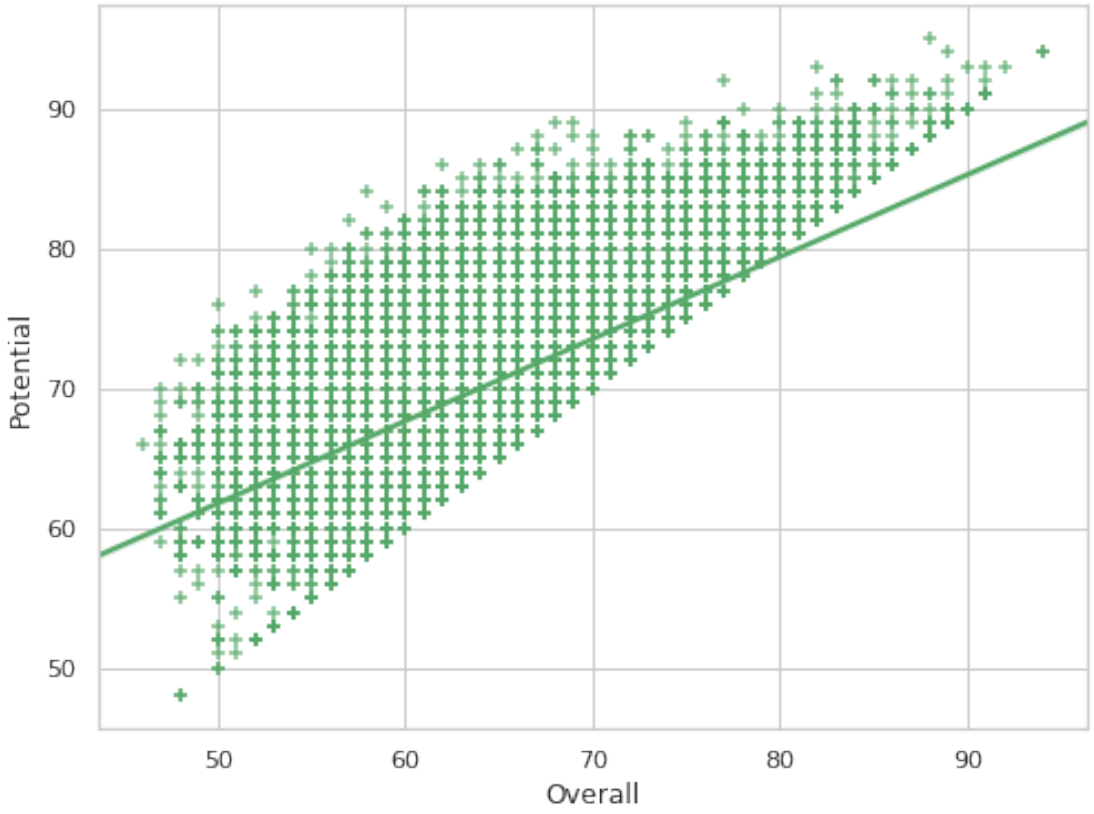
- This function plots data and a linear regression model fit.
- We can plot a linear regression model between `Overall` and `Potential` variable with `regplot()` function as follows-

[46]:
```
f, ax = plt.subplots(figsize=(8, 6))
ax = sns.regplot(x="Overall", y="Potential", data=fifa19)
plt.show()
```



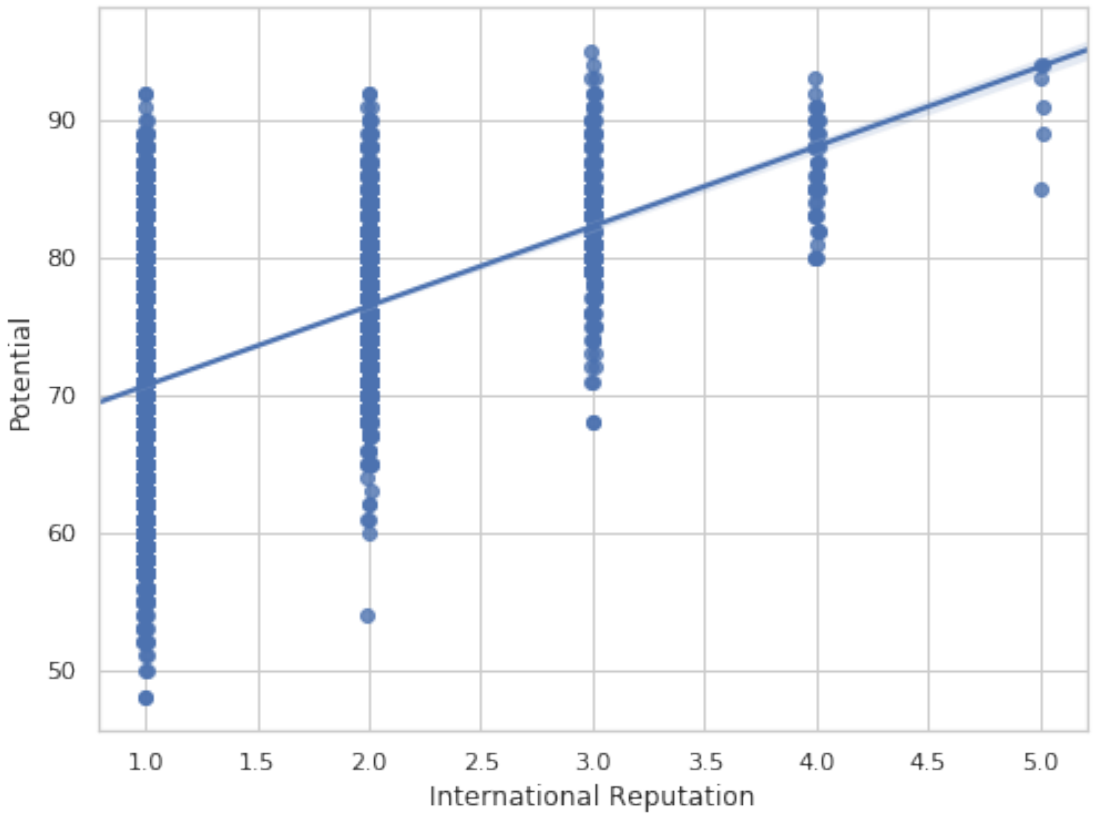
We can use a different color and marker as follows-

[47]:
```
f, ax = plt.subplots(figsize=(8, 6))
ax = sns.regplot(x="Overall", y="Potential", data=fifa19, color= "g",␣
 ↪marker="+")
plt.show()
```



We can plot with a discrete variable and add some jitter as follows-

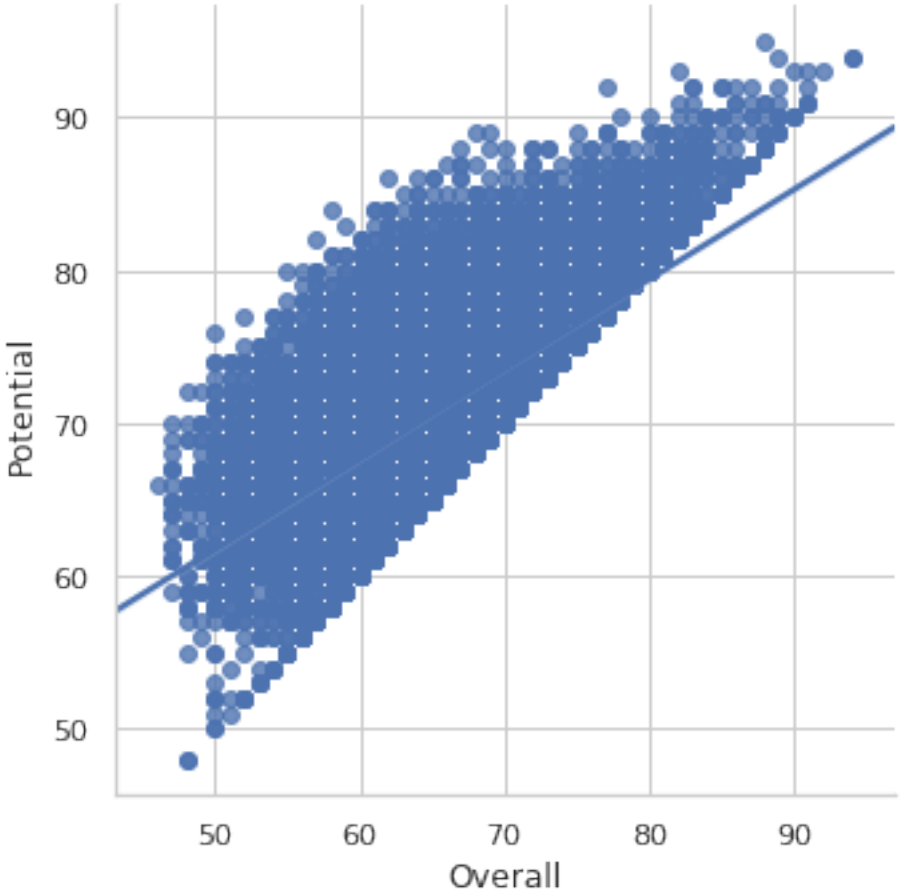
[48]:
```
f, ax = plt.subplots(figsize=(8, 6))
sns.regplot(x="International Reputation", y="Potential", data=fifa19, x_jitter=.
↪01)
plt.show()
```



1.0.31 Seaborn `lmplot()` function

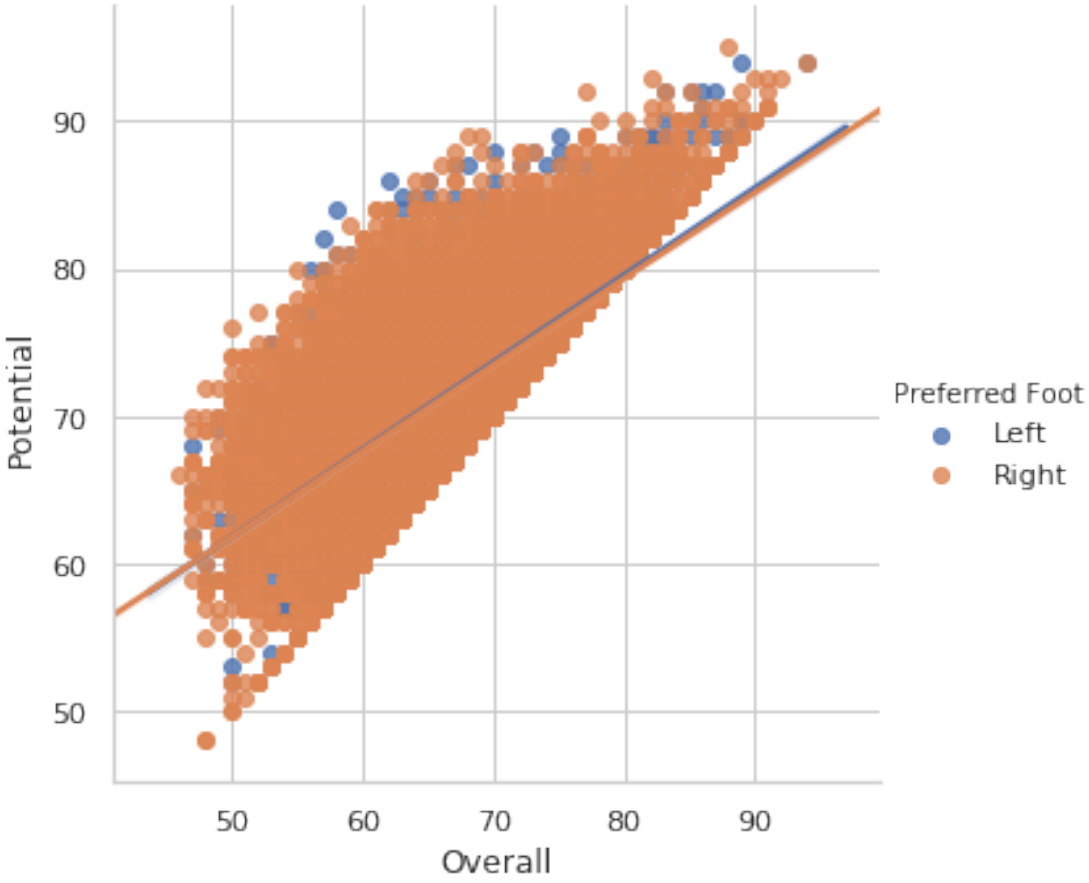
- This function plots data and regression model fits across a FacetGrid.
- This function combines `regplot()` and `FacetGrid`.
- It is intended as a convenient interface to fit regression models across conditional subsets of a dataset.
- We can plot a linear regression model between `Overall` and `Potential` variable with `lmplot()` function as follows-

[49]:
```
g= sns.lmplot(x="Overall", y="Potential", data=fifa19)
```



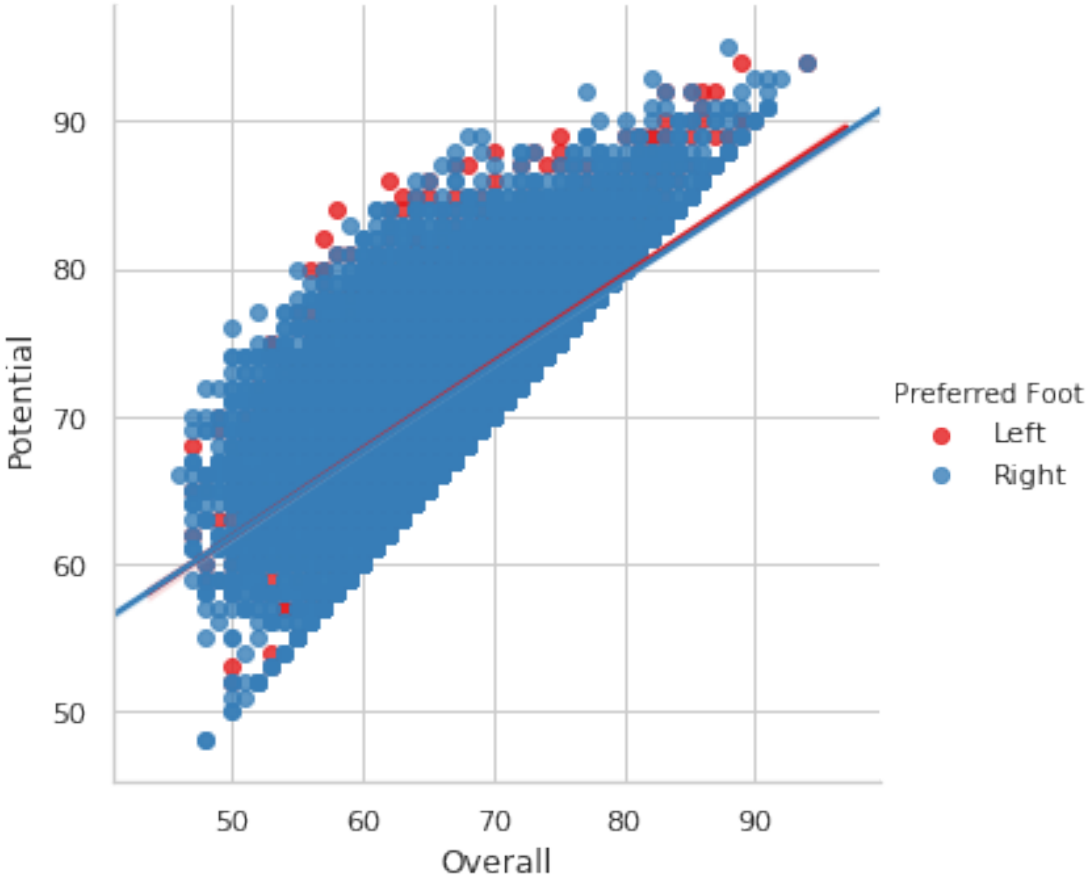
We can condition on a third variable and plot the levels in different colors as follows-

[50]:
```
g= sns.lmplot(x="Overall", y="Potential", hue="Preferred Foot", data=fifa19)
```



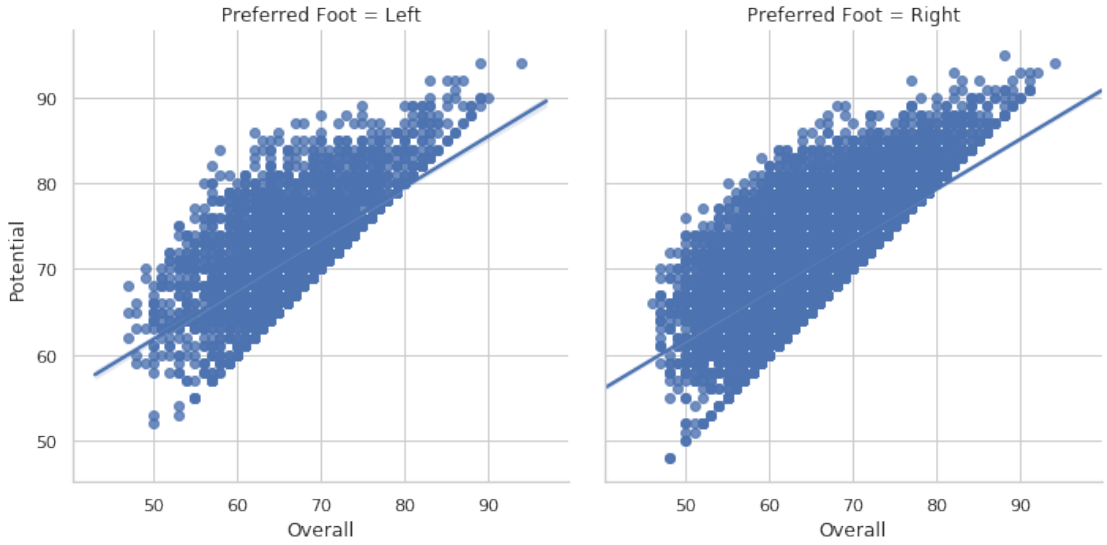
We can use a different color palette as follows-

[51]:
```
g= sns.lmplot(x="Overall", y="Potential", hue="Preferred Foot", data=fifa19,␣
↪palette="Set1")
```



We can plot the levels of the third variable across different columns as follows-

[52]:
```
g= sns.lmplot(x="Overall", y="Potential", col="Preferred Foot", data=fifa19)
```



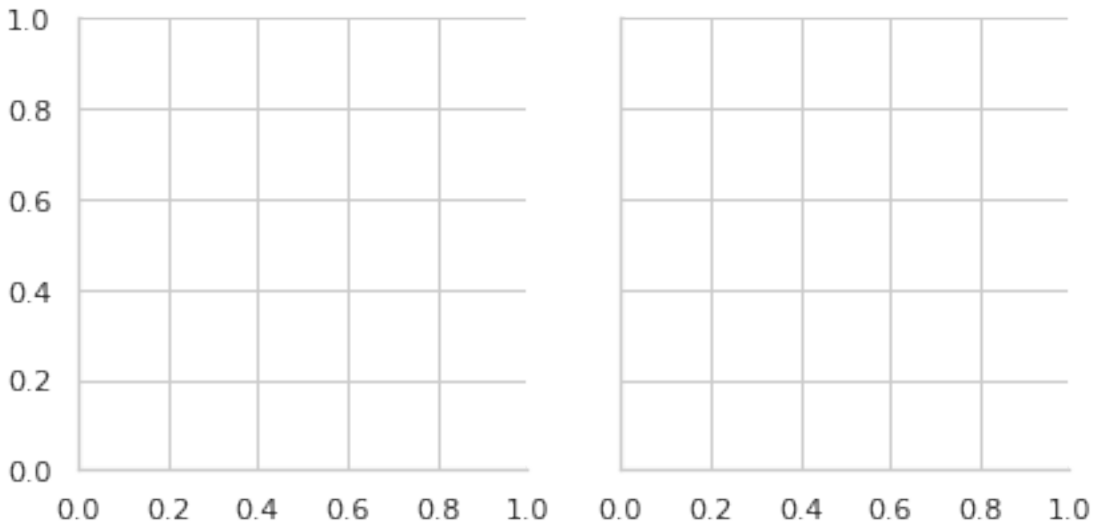
1.0.32 Multi-plot grids

1.0.33 Seaborn `FacetGrid()` function

- The FacetGrid class is useful when you want to visualize the distribution of a variable or the relationship between multiple variables separately within subsets of your dataset.
- A FacetGrid can be drawn with up to three dimensions - `row`, `col` and `hue`. The first two have obvious correspondence with the resulting array of axes - the `hue` variable is a third dimension along a depth axis, where different levels are plotted with different colors.
- The class is used by initializing a FacetGrid object with a dataframe and the names of the variables that will form the `row`, `column` or `hue` dimensions of the grid.
- These variables should be categorical or discrete, and then the data at each level of the variable will be used for a facet along that axis.

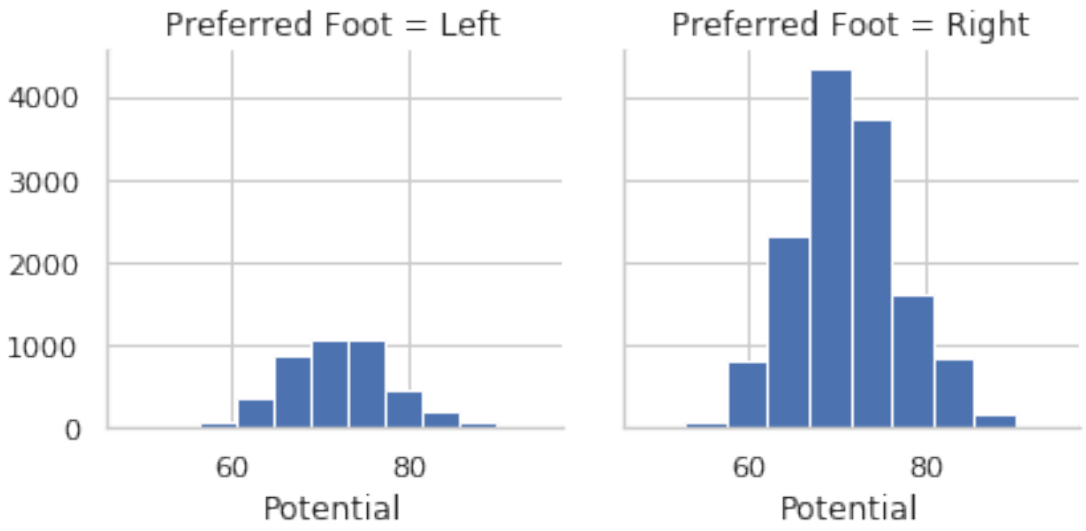
We can initialize a 1x2 grid of facets using the fifa19 dataset.

[53]:
```
g = sns.FacetGrid(fifa19, col="Preferred Foot")
```

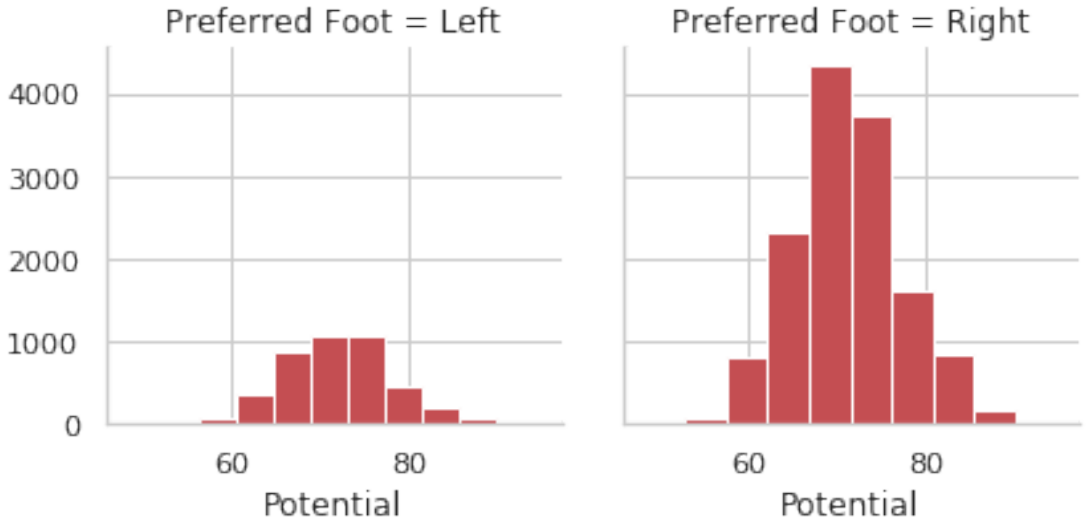


We can draw a univariate plot of `Potential` variable on each facet as follows-

[54]:
```
g = sns.FacetGrid(fifa19, col="Preferred Foot")
g = g.map(plt.hist, "Potential")
```

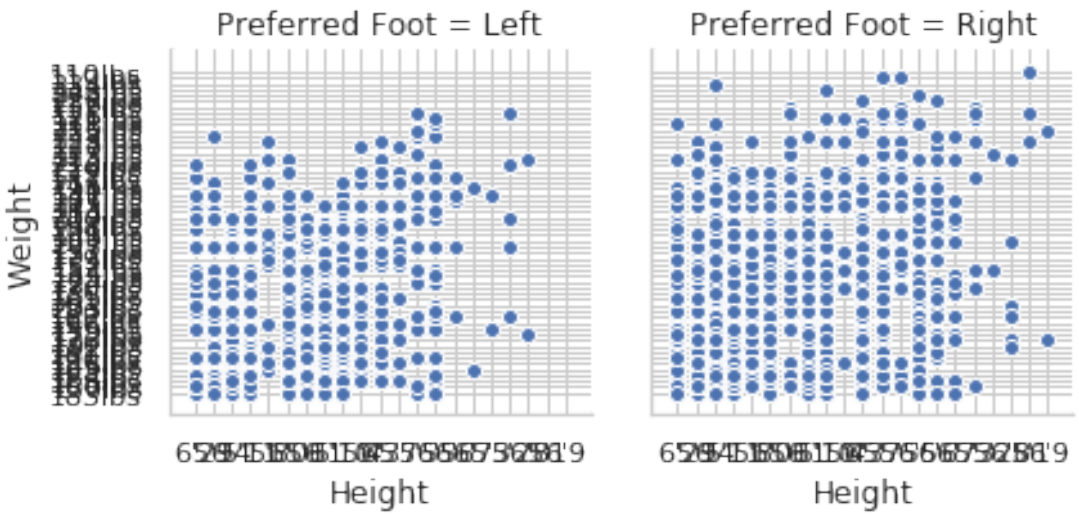


[55]:
```
g = sns.FacetGrid(fifa19, col="Preferred Foot")
g = g.map(plt.hist, "Potential", bins=10, color="r")
```



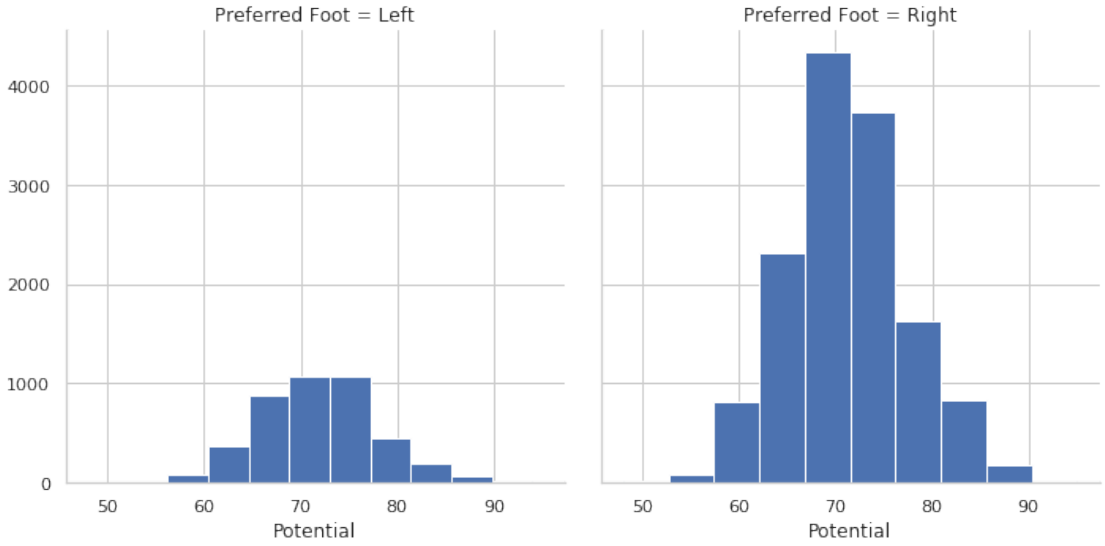
We can plot a bivariate function on each facet as follows-

[56]:
```
g = sns.FacetGrid(fifa19, col="Preferred Foot")
g = (g.map(plt.scatter, "Height", "Weight", edgecolor="w").add_legend())
```



The size of the figure is set by providing the height of each facet, along with the aspect ratio:

[57]:
```
g = sns.FacetGrid(fifa19, col="Preferred Foot", height=5, aspect=1)
g = g.map(plt.hist, "Potential")
```



1.0.34 Seaborn `Pairgrid()` function

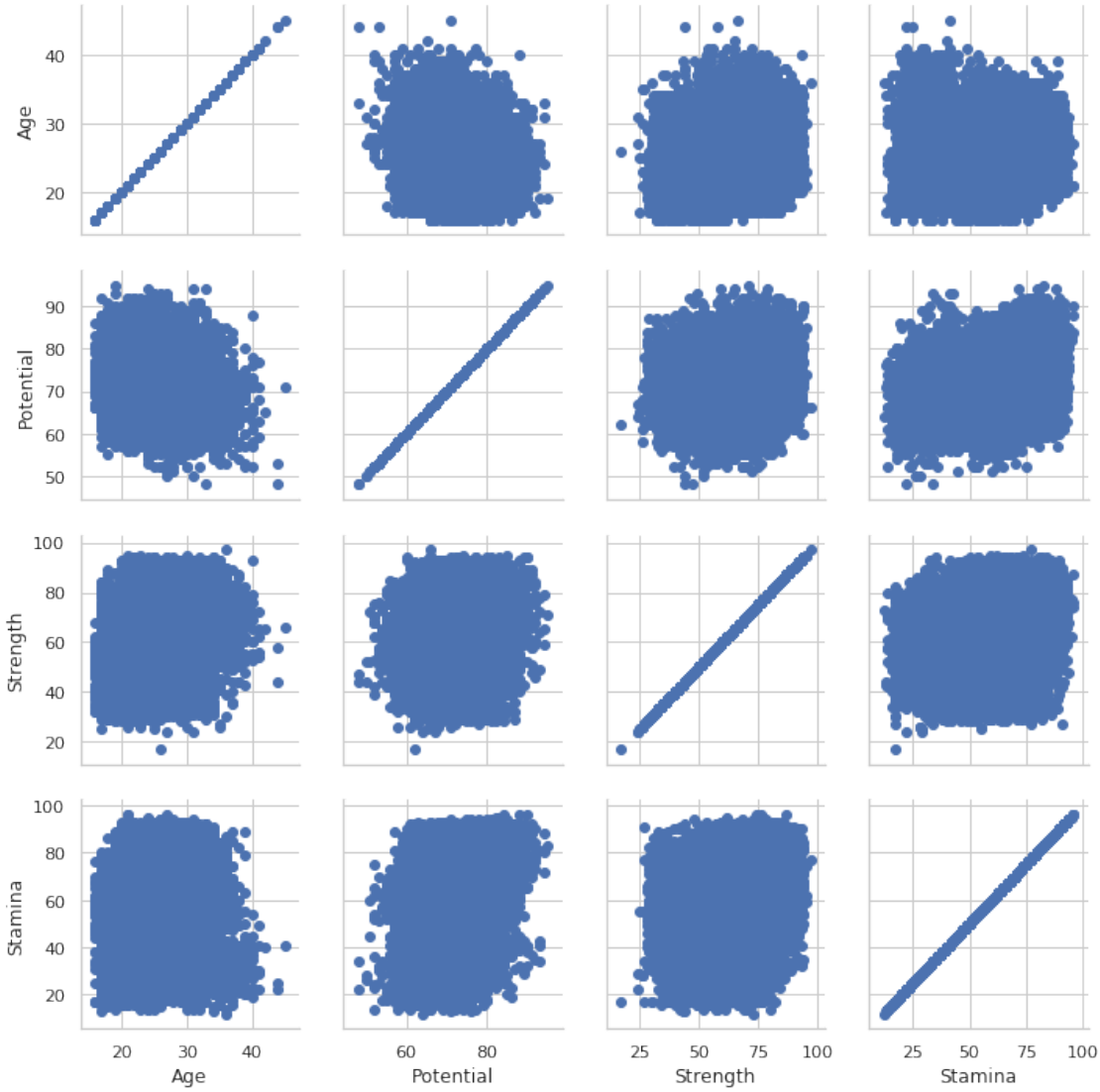
- This function plots subplot grid for plotting pairwise relationships in a dataset.
- This class maps each variable in a dataset onto a column and row in a grid of multiple axes.
- Different axes-level plotting functions can be used to draw bivariate plots in the upper and

lower triangles, and the the marginal distribution of each variable can be shown on the diagonal.

- It can also represent an additional level of conditionalization with the hue parameter, which plots different subets of data in different colors.
- This uses color to resolve elements on a third dimension, but only draws subsets on top of each other and will not tailor the hue parameter for the specific visualization the way that axes-level functions that accept hue will.

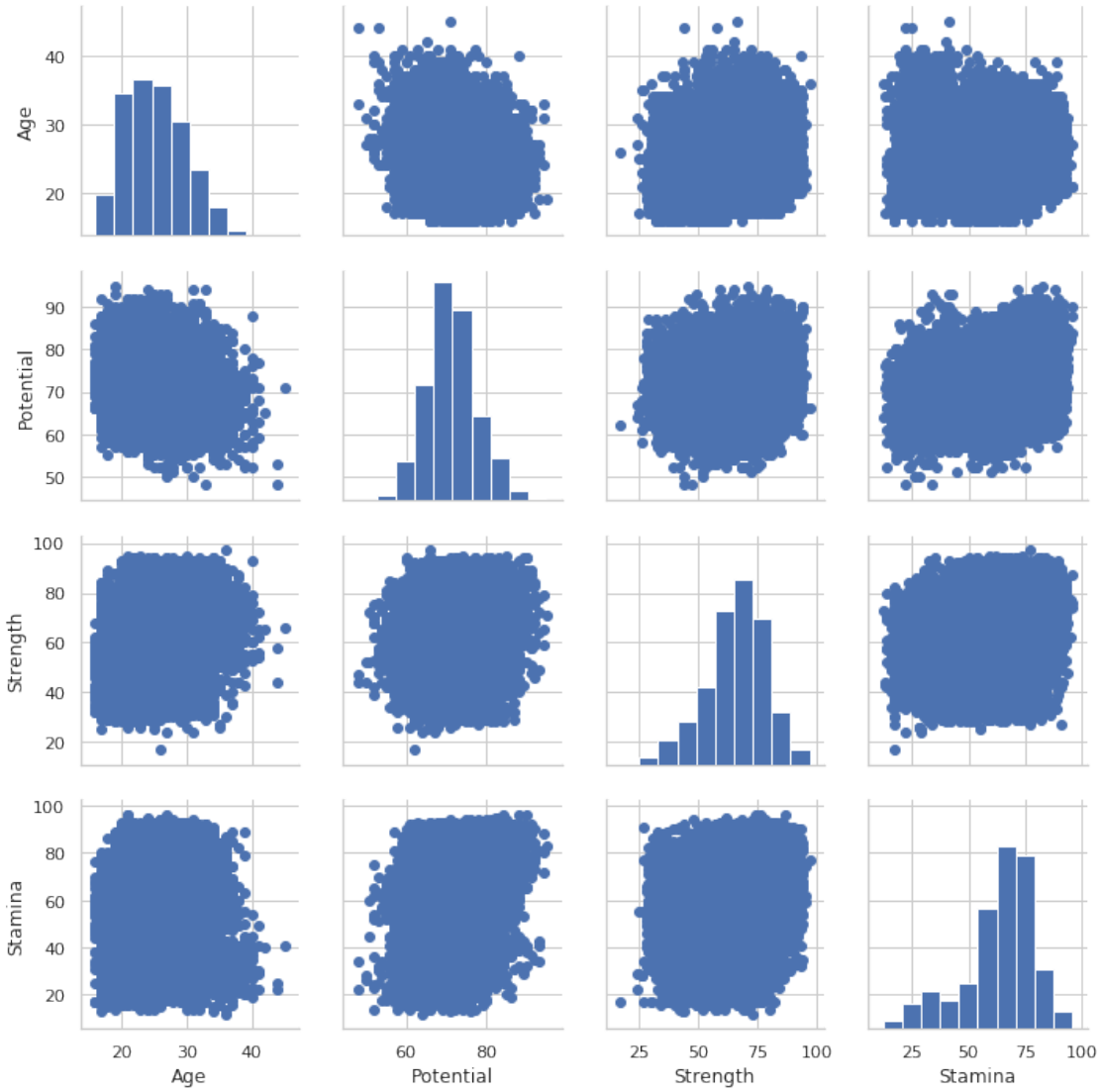
[58]:
```
fifa19_new = fifa19[['Age', 'Potential', 'Strength', 'Stamina', 'Preferred␣
↪Foot']]
```

[59]:
```
g = sns.PairGrid(fifa19_new)
g = g.map(plt.scatter)
```



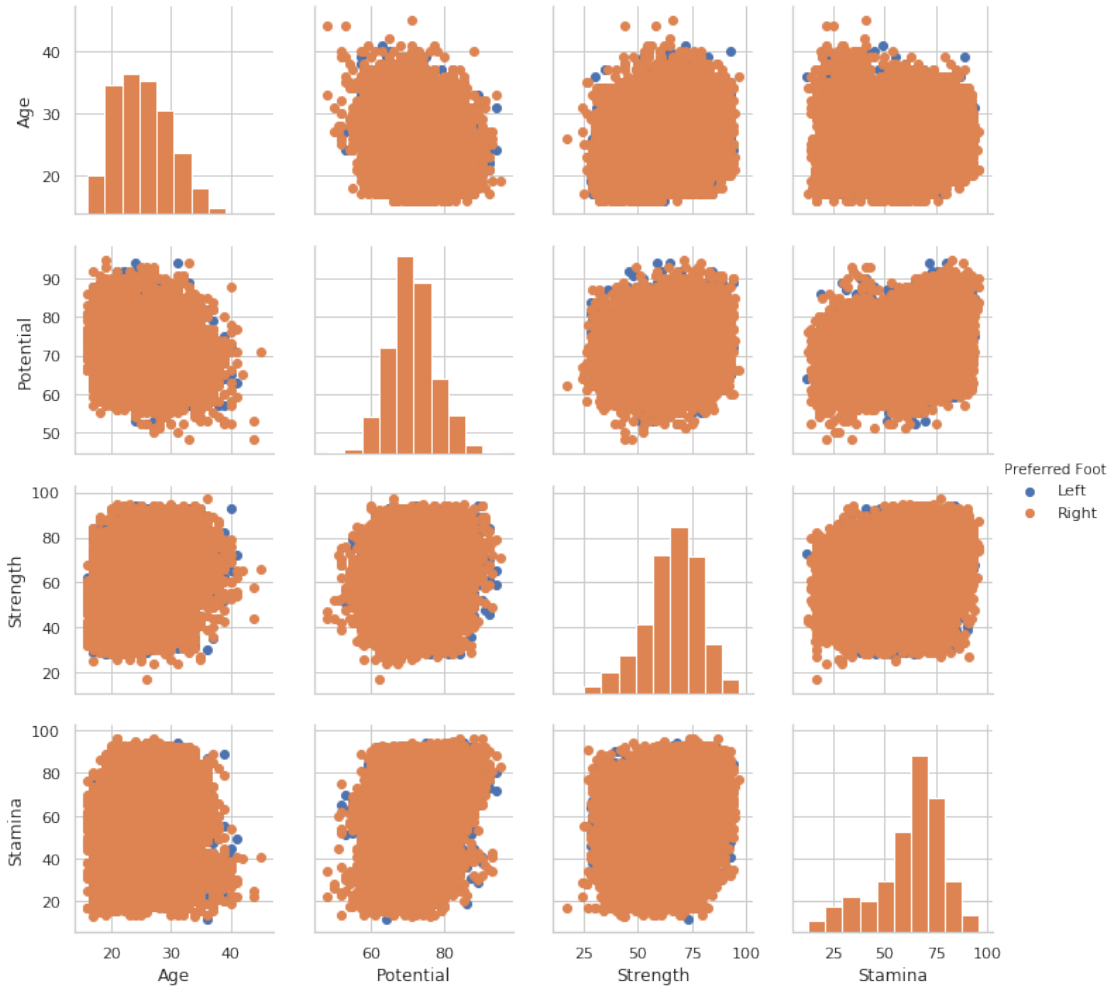
We can show a univariate distribution on the diagonal as follows-

[60]:
```
g = sns.PairGrid(fifa19_new)
g = g.map_diag(plt.hist)
g = g.map_offdiag(plt.scatter)
```



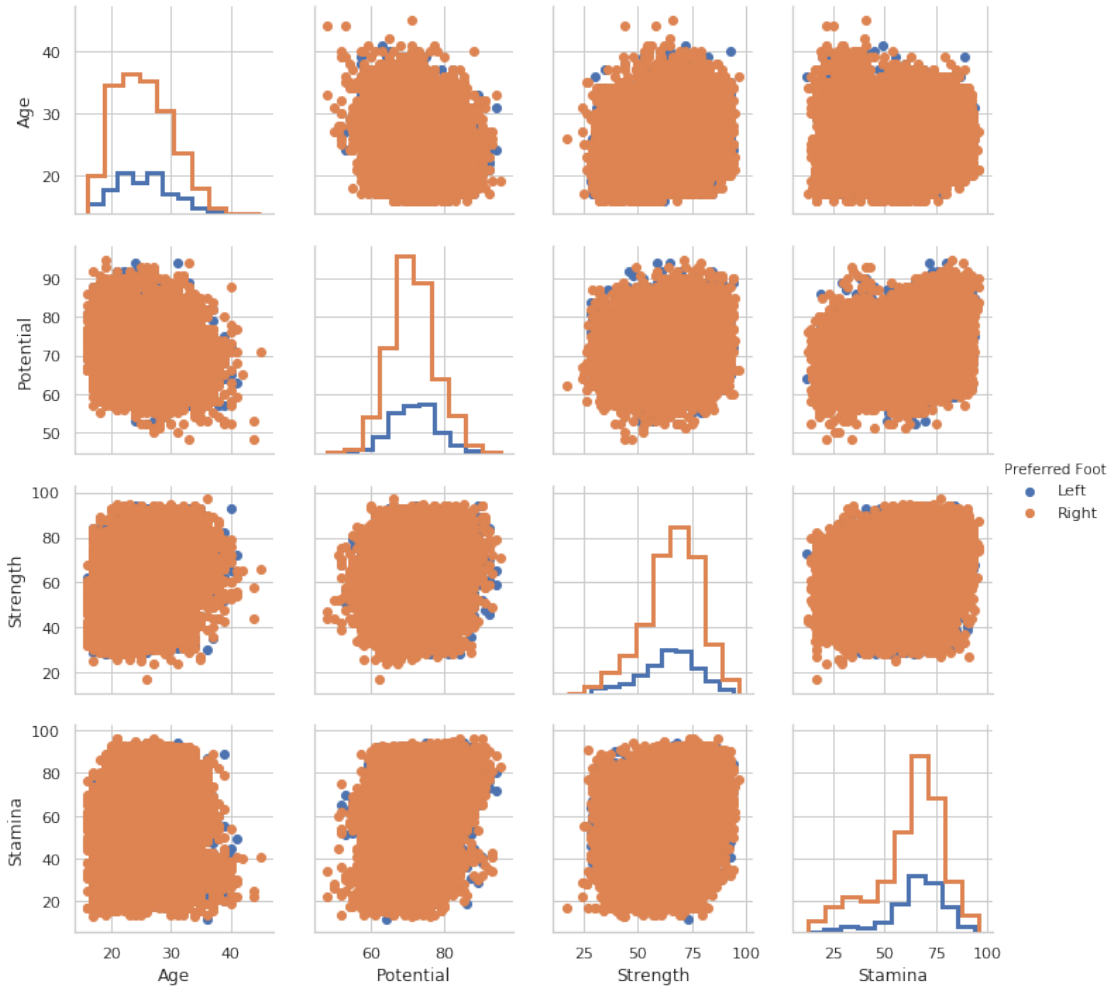
We can color the points using the categorical variable `Preferred Foot` as follows -

[61]:
```
g = sns.PairGrid(fifa19_new, hue="Preferred Foot")
g = g.map_diag(plt.hist)
g = g.map_offdiag(plt.scatter)
g = g.add_legend()
```



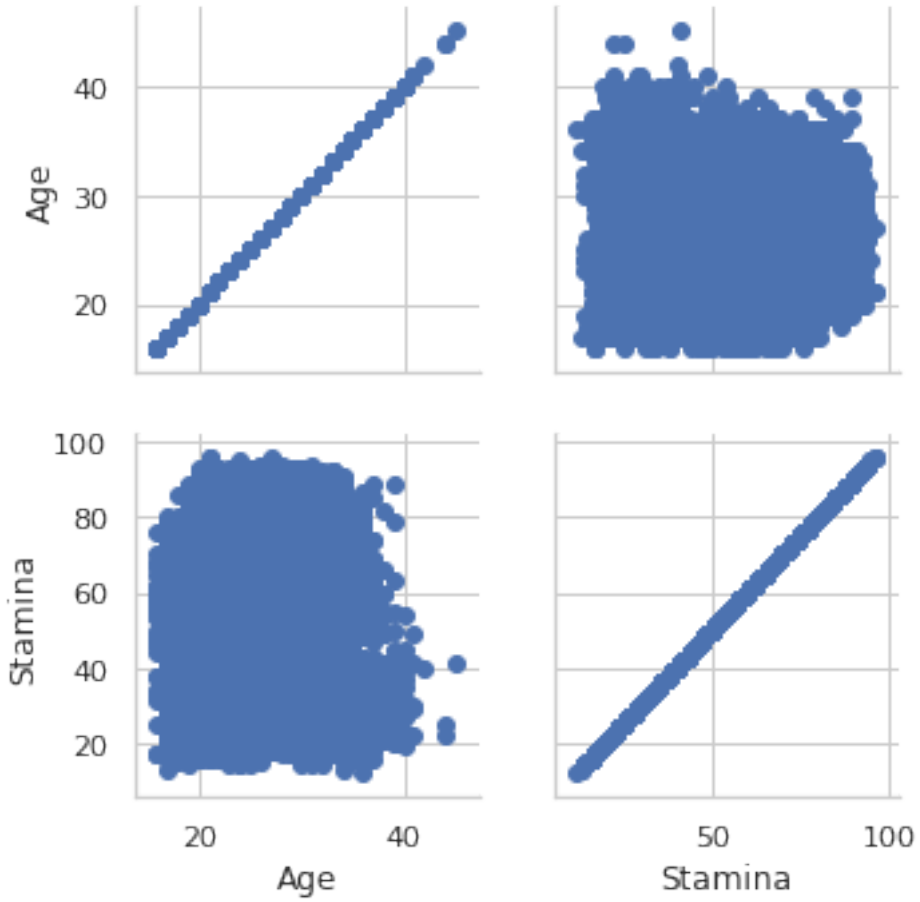
We can use a different style to show multiple histograms as follows-

[62]:
```
g = sns.PairGrid(fifa19_new, hue="Preferred Foot")
g = g.map_diag(plt.hist, histtype="step", linewidth=3)
g = g.map_offdiag(plt.scatter)
g = g.add_legend()
```



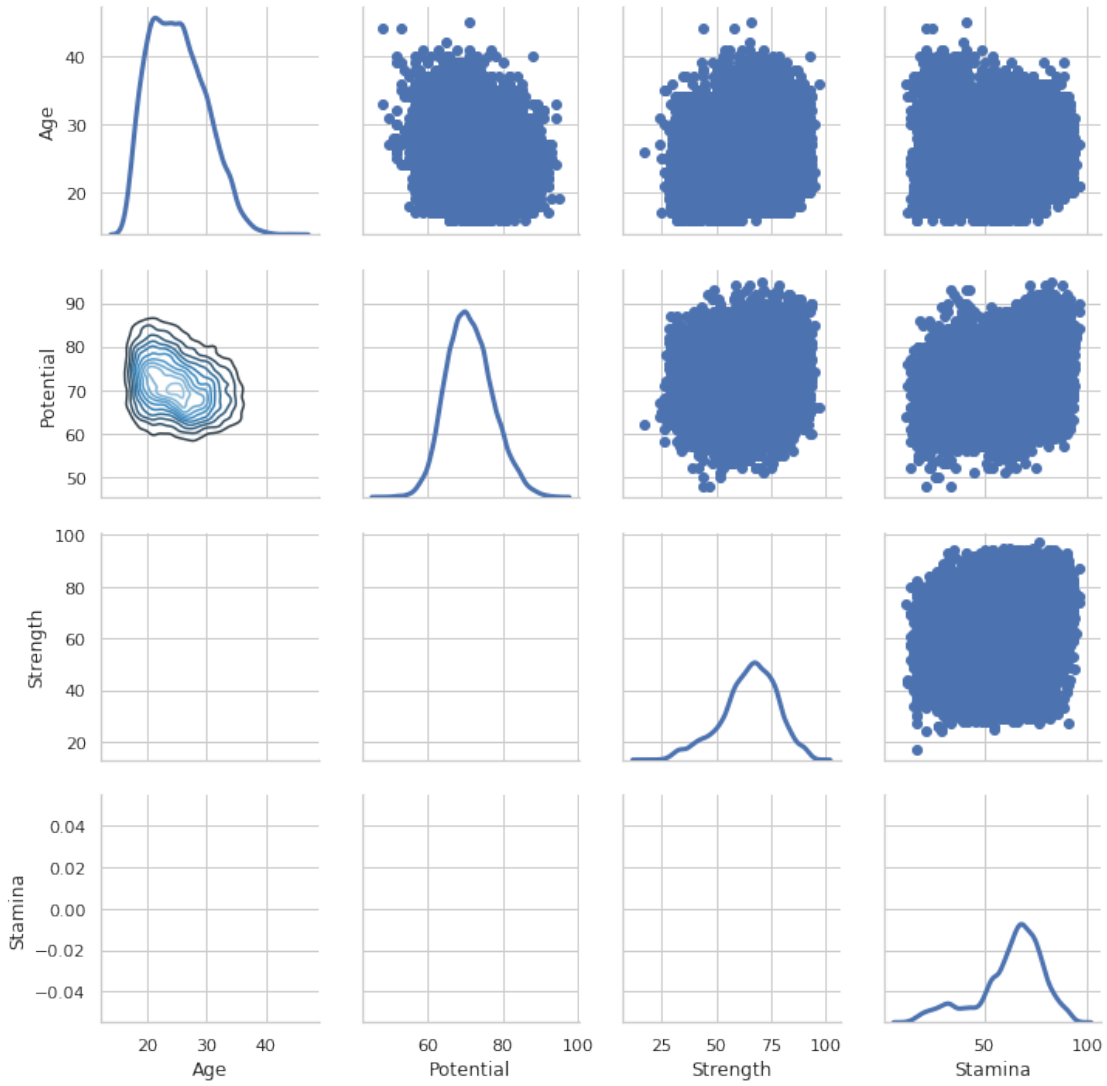
We can plot a subset of variables as follows-

[63]:
```
g = sns.PairGrid(fifa19_new, vars=['Age', 'Stamina'])
g = g.map(plt.scatter)
```



We can use different functions on the upper and lower triangles as follows-

[64]:
```
g = sns.PairGrid(fifa19_new)
g = g.map_upper(plt.scatter)
g = g.map_lower(sns.kdeplot, cmap="Blues_d")
g = g.map_diag(sns.kdeplot, lw=3, legend=False)
```

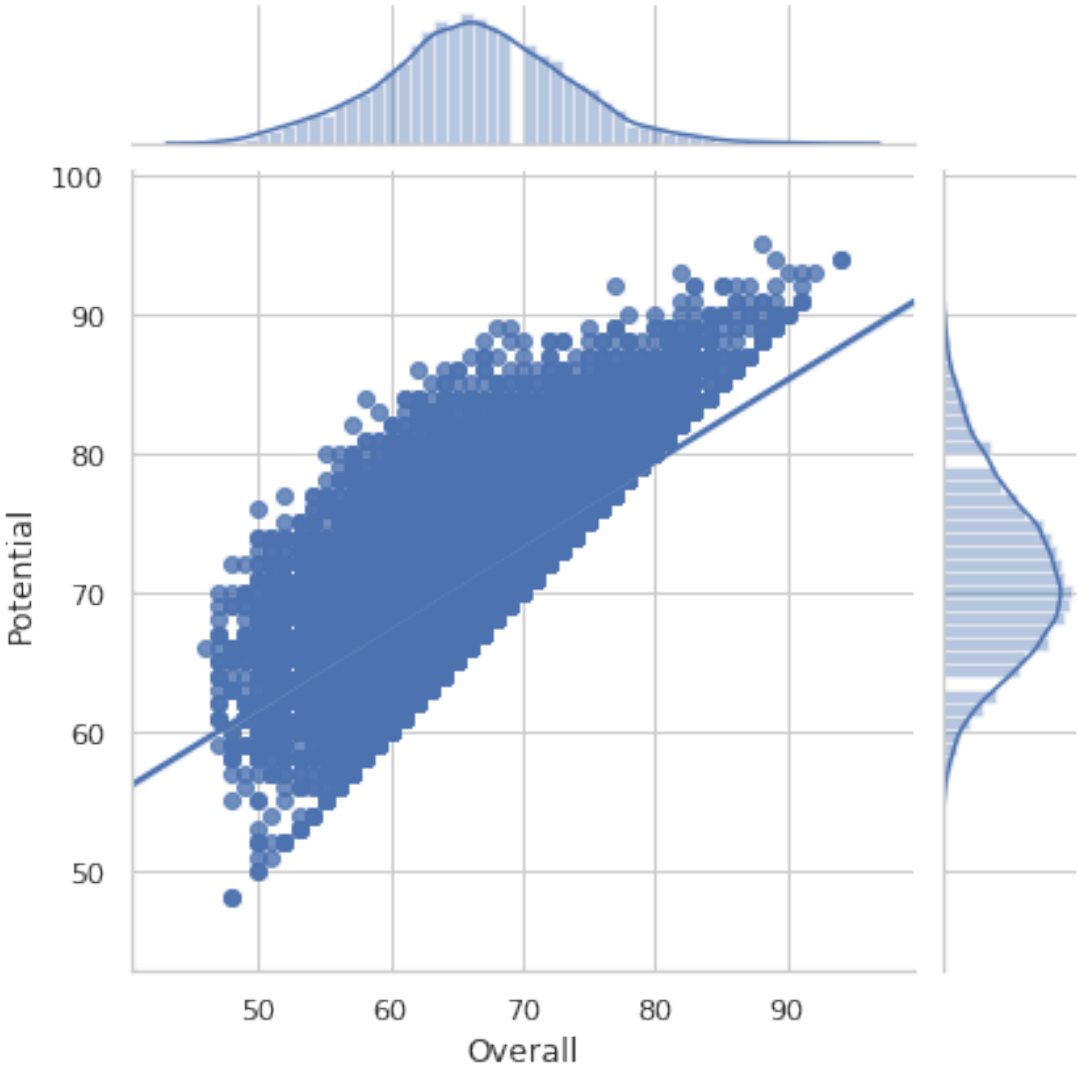


1.0.35 Seaborn `Jointgrid()` function

- This function provides a grid for drawing a bivariate plot with marginal univariate plots.
- It set up the grid of subplots.

We can initialize the figure and add plots using default parameters as follows-

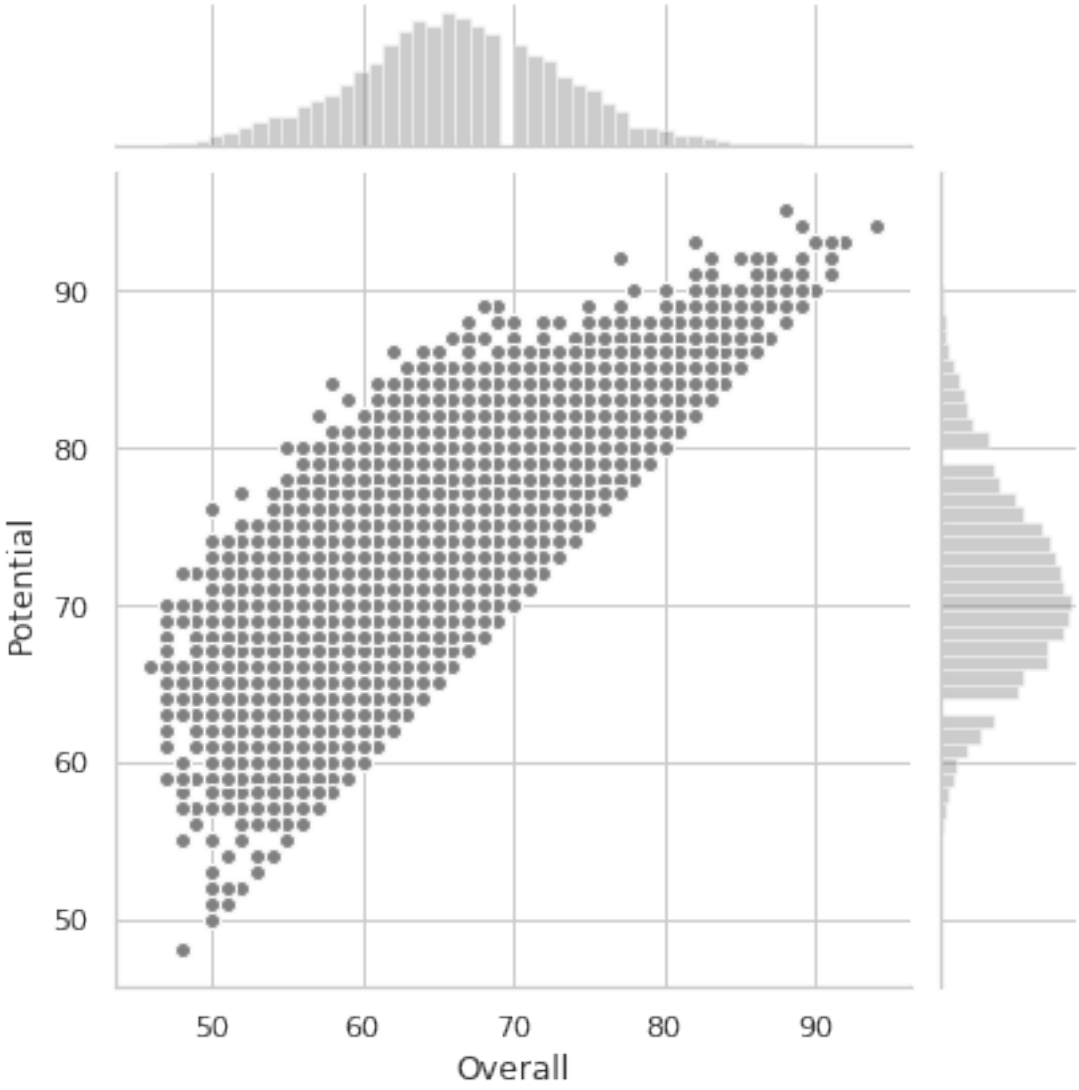
[65]:
```
g = sns.JointGrid(x="Overall", y="Potential", data=fifa19)
g = g.plot(sns.regplot, sns.distplot)
```



We can draw the join and marginal plots separately, which allows finer-level control other parameters as follows -

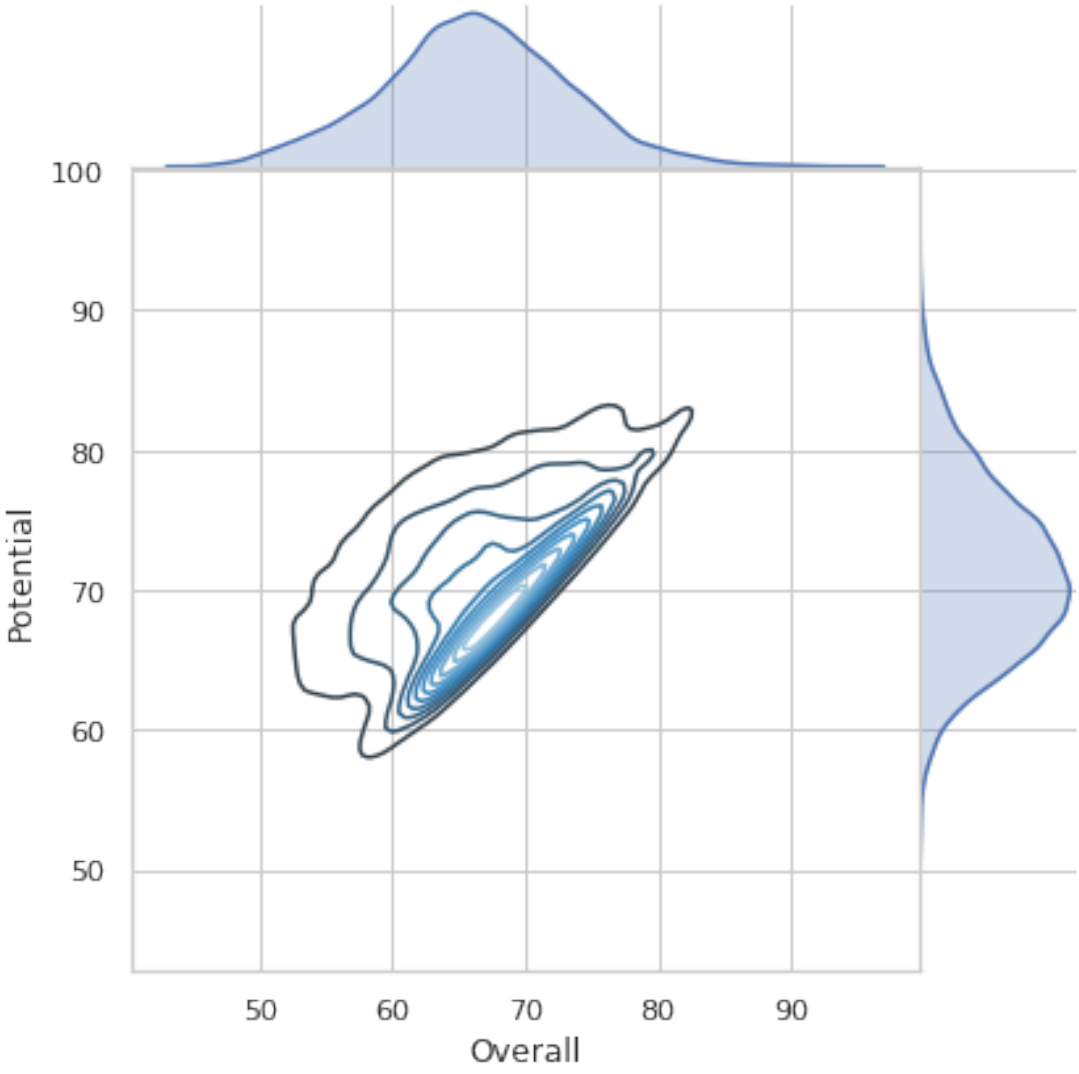
[66]:
```
import matplotlib.pyplot as plt
```

[67]:
```
g = sns.JointGrid(x="Overall", y="Potential", data=fifa19)
g = g.plot_joint(plt.scatter, color=".5", edgecolor="white")
g = g.plot_marginals(sns.distplot, kde=False, color=".5")
```



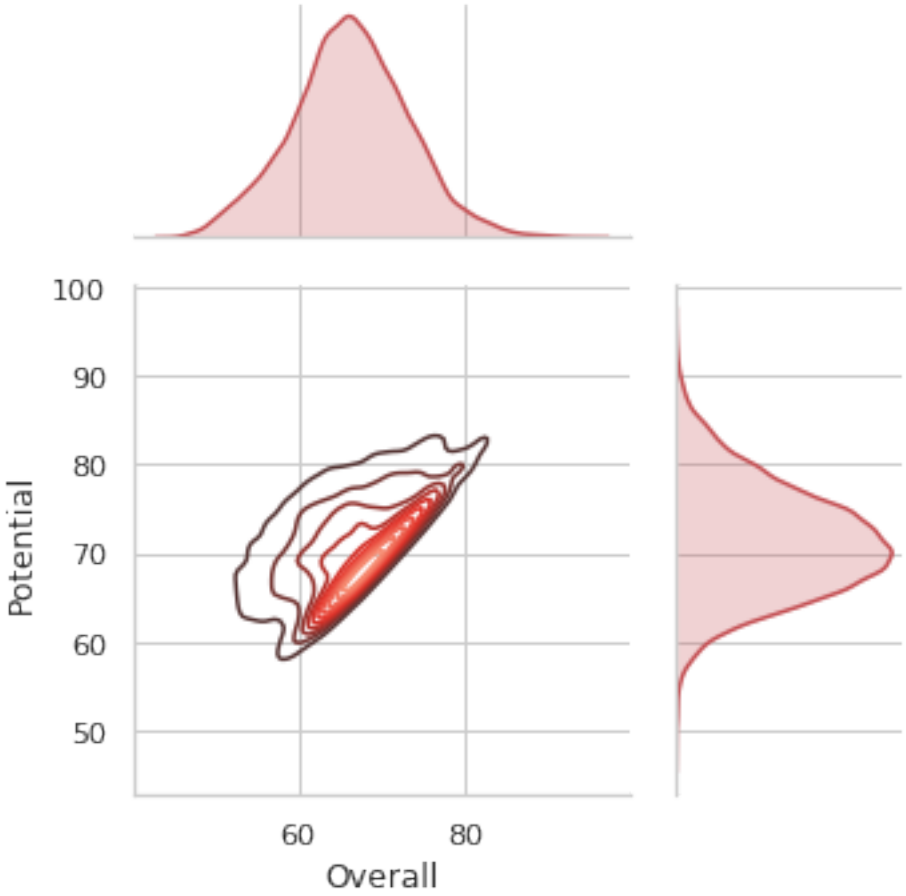
We can remove the space between the joint and marginal axes as follows -

[68]:
```
g = sns.JointGrid(x="Overall", y="Potential", data=fifa19, space=0)
g = g.plot_joint(sns.kdeplot, cmap="Blues_d")
g = g.plot_marginals(sns.kdeplot, shade=True)
```



We can draw a smaller plot with relatively larger marginal axes as follows -

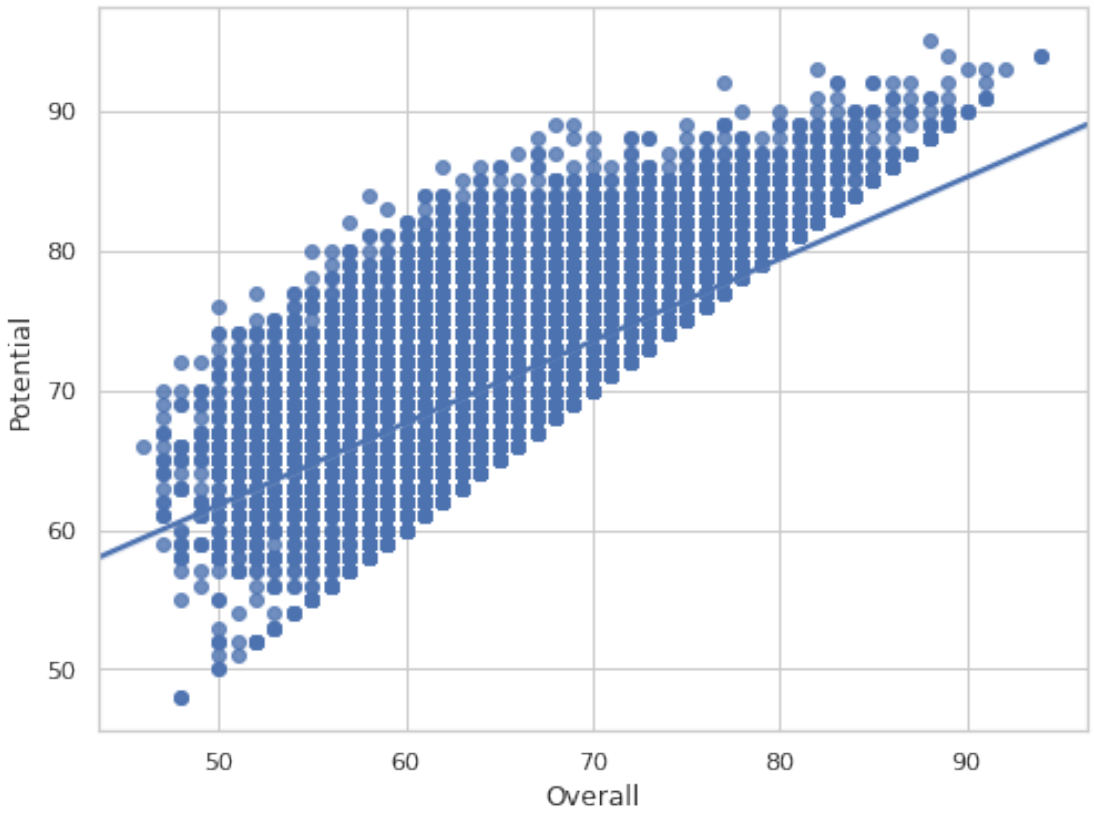
[69]:
```
g = sns.JointGrid(x="Overall", y="Potential", data=fifa19, height=5, ratio=2)
g = g.plot_joint(sns.kdeplot, cmap="Reds_d")
g = g.plot_marginals(sns.kdeplot, color="r", shade=True)
```



1.0.36 Controlling the size and shape of the plot

- The default plots made by `regplot()` and `lmplot()` look the same but on axes that have a different size and shape.
- This is because `regplot()` is an "axes-level" function draws onto a specific axes.
- This means that you can make multi-panel figures yourself and control exactly where the regression plot goes.
- If no axes object is explicitly provided, it simply uses the "currently active" axes, which is why the default plot has the same size and shape as most other matplotlib functions.
- To control the size, we need to create a figure object ourself as follows-

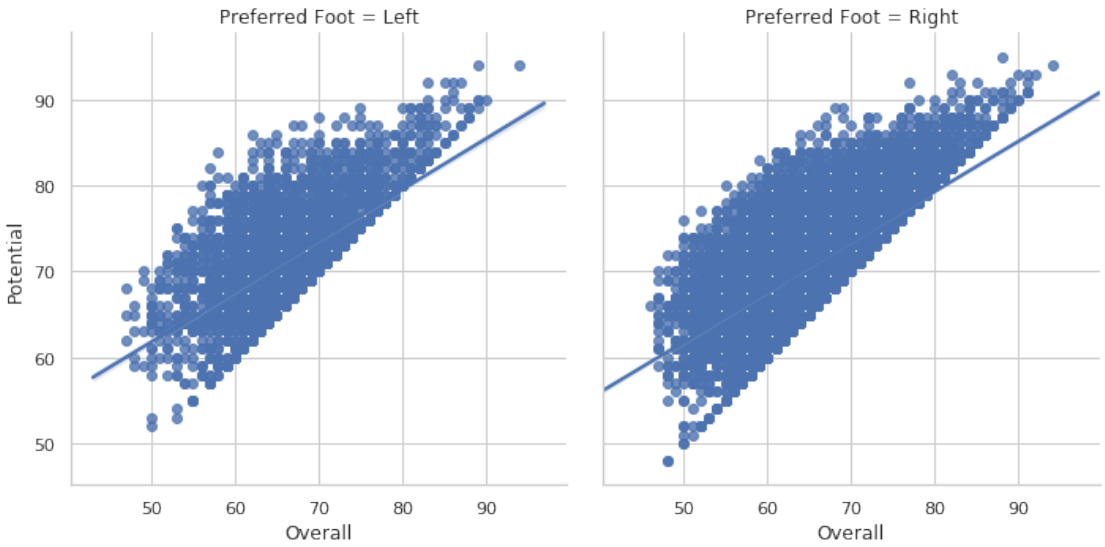
[70]:
```
f, ax = plt.subplots(figsize=(8, 6))
ax = sns.regplot(x="Overall", y="Potential", data=fifa19);
```



In contrast, the size and shape of the `lmplot()` figure is controlled through the FacetGrid interface using the size and aspect parameters, which apply to each facet in the plot, not to the overall figure itself.

[71]:
```
sns.lmplot(x="Overall", y="Potential", col="Preferred Foot", data=fifa19,␣
↪col_wrap=2, height=5, aspect=1)
```

[71]:
```
<seaborn.axisgrid.FacetGrid at 0x7fc7a26a51d0>
```



1.0.37 Seaborn figure styles

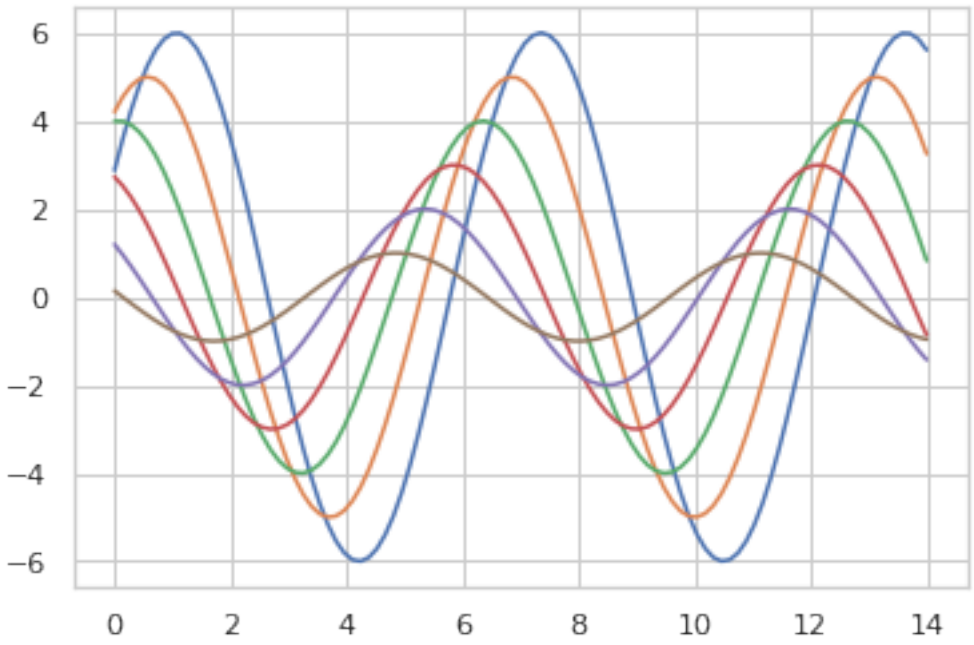
- There are five preset seaborn themes: `darkgrid`, `whitegrid`, `dark`, `white` and `ticks`.
- They are each suited to different applications and personal preferences.
- The default theme is darkgrid.
- The grid helps the plot serve as a lookup table for quantitative information, and the white-on grey helps to keep the grid from competing with lines that represent data.
- The whitegrid theme is similar, but it is better suited to plots with heavy data elements:

I will define a simple function to plot some offset sine waves, which will help us see the different stylistic parameters as follows -

[72]:
```
def sinplot(flip=1):
    x = np.linspace(0, 14, 100)
    for i in range(1, 7):
        plt.plot(x, np.sin(x + i * .5) * (7 - i) * flip)
```

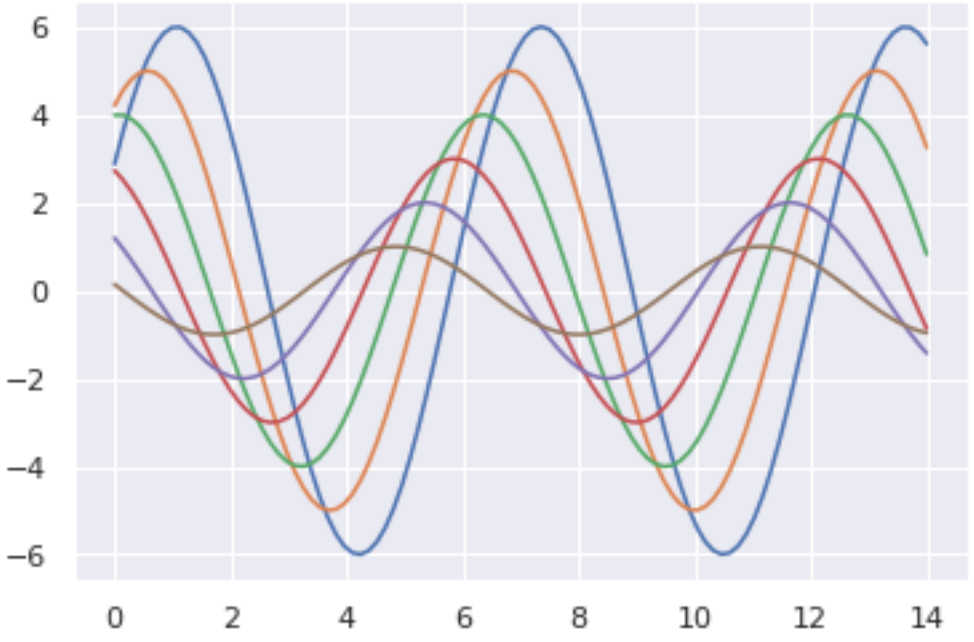
This is what the plot looks like with matplotlib default parameters.

[73]:
```
sinplot()
```



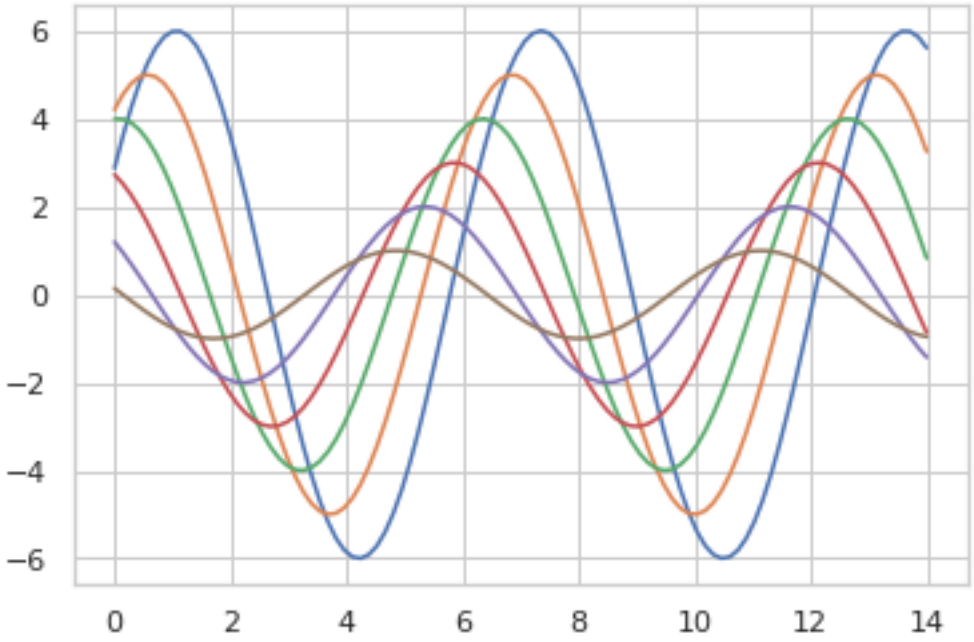
To switch to seaborn defaults, we need to call the `set()` function as follows -

[74]:
```
sns.set()
sinplot()
```

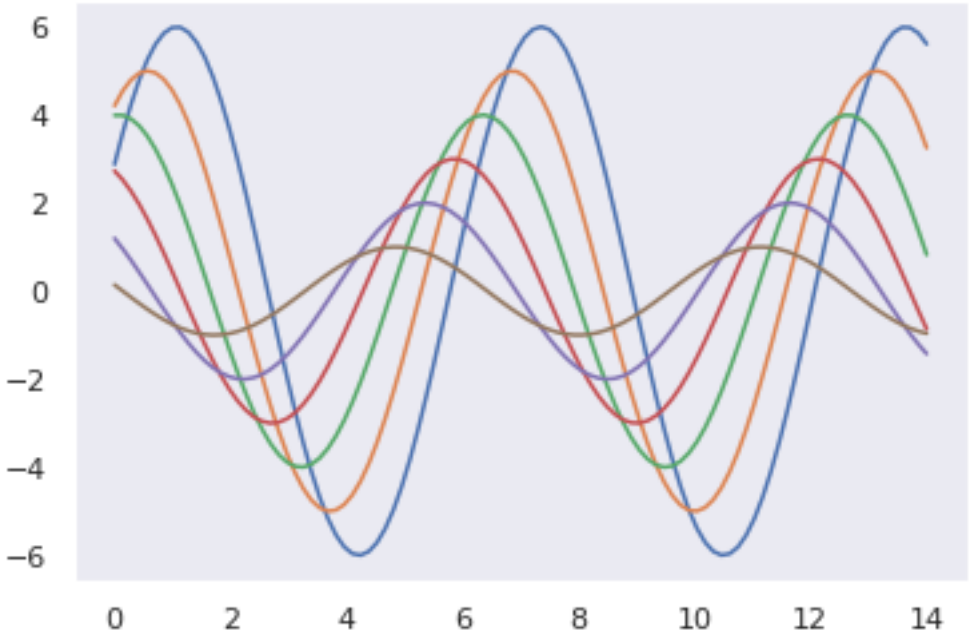


- We can set different styles as follows -

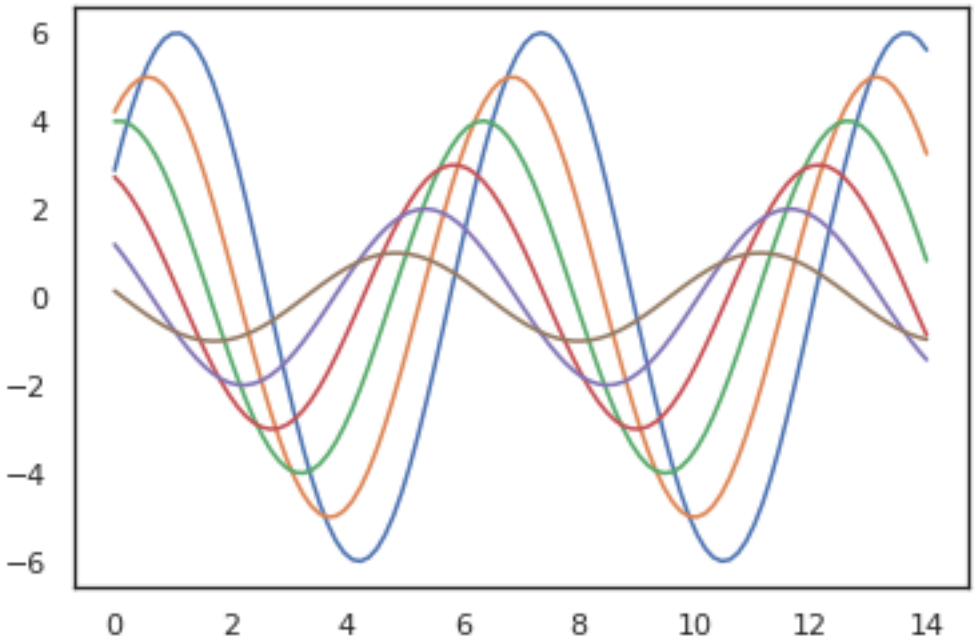
[75]:
```
sns.set_style("whitegrid")
sinplot()
```



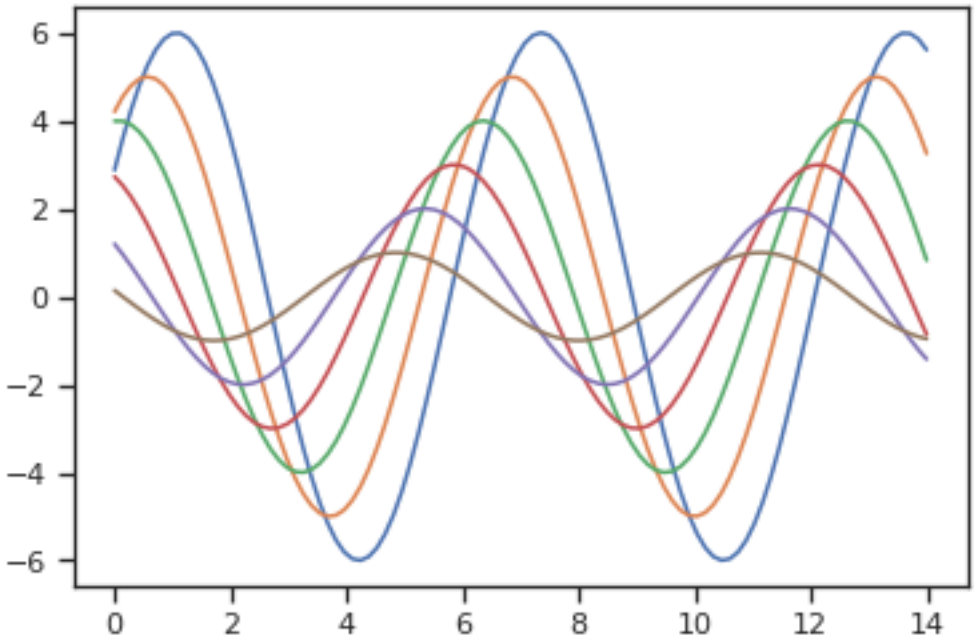
[76]:
```
sns.set_style("dark")
sinplot()
```



[77]:
```
sns.set_style("white")
sinplot()
```



[78]:
```
sns.set_style("ticks")
sinplot()
```



With that, we come to the end of this tutorial.

I hope you find it useful.

Please upvote it if it helps to learn Seaborn.