

## importing libraries

```
In [5]: import numpy as np
import pandas as pd
import seaborn as sns
sns.set_style(style='whitegrid')
import matplotlib.pyplot as plt
from collections import Counter
%matplotlib inline
import os
for dirname, _, filenames in os.walk(r"C:\Users\user\Documents"):
    for filename in filenames:
        print(os.path.join(dirname,filename))
```

```
C:\Users\user\Documents\!qhlogs.doc
C:\Users\user\Documents\3D Objects - Shortcut.lnk
C:\Users\user\Documents\desktop.ini
C:\Users\user\Documents\FIFA.csv
C:\Users\user\Documents\heart.csv
C:\Users\user\Documents\Movie-Rating.csv
C:\Users\user\Documents\movie.csv
C:\Users\user\Documents\rating.csv
C:\Users\user\Documents\Rawdata.xlsx
C:\Users\user\Documents\Sample - Superstore_Orders.csv
C:\Users\user\Documents\sample1-json.json
C:\Users\user\Documents\sample1.xml
C:\Users\user\Documents\samplepdf.pdf
C:\Users\user\Documents\table.html
C:\Users\user\Documents>tag.csv
C:\Users\user\Documents\TASK -- convert raw data - clean data.xlsx
C:\Users\user\Documents\Tasks.txt
```

```
In [7]: import warnings
warnings.filterwarnings('ignore')
```

## Read dataset

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

```
In [10]: fifa=pd.read_csv(r"C:\Users\user\Documents\FIFA.csv")
```

## Exploratory Data Analysis

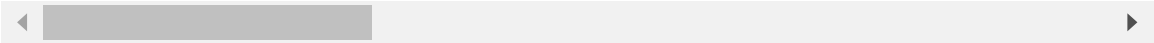
### Preview the dataset

```
In [14]: fifa.head()
```

Out[14]:

	Unnamed: 0	ID	Name	Age	Photo	Nationality
0	0	158023	L. Messi	31	https://cdn.sofifa.org/players/4/19/158023.png	Argentina
1	1	20801	Cristiano Ronaldo	33	https://cdn.sofifa.org/players/4/19/20801.png	Portugal
2	2	190871	Neymar Jr	26	https://cdn.sofifa.org/players/4/19/190871.png	Brazil
3	3	193080	De Gea	27	https://cdn.sofifa.org/players/4/19/193080.png	Spain
4	4	192985	K. De Bruyne	27	https://cdn.sofifa.org/players/4/19/192985.png	Belgium

5 rows × 89 columns



View summary of dataset

In [17]:

```
fifa.info()
```

```
<class 'pandas.core.frame.DataFrame'>
```

```
RangeIndex: 18207 entries, 0 to 18206
```

```
Data columns (total 89 columns):
```

#	Column	Non-Null Count	Dtype
0	Unnamed: 0	18207 non-null	int64
1	ID	18207 non-null	int64
2	Name	18207 non-null	object
3	Age	18207 non-null	int64
4	Photo	18207 non-null	object
5	Nationality	18207 non-null	object
6	Flag	18207 non-null	object
7	Overall	18207 non-null	int64
8	Potential	18207 non-null	int64
9	Club	17966 non-null	object
10	Club Logo	18207 non-null	object
11	Value	18207 non-null	object
12	Wage	18207 non-null	object
13	Special	18207 non-null	int64
14	Preferred Foot	18159 non-null	object
15	International Reputation	18159 non-null	float64
16	Weak Foot	18159 non-null	float64
17	Skill Moves	18159 non-null	float64
18	Work Rate	18159 non-null	object
19	Body Type	18159 non-null	object
20	Real Face	18159 non-null	object
21	Position	18147 non-null	object
22	Jersey Number	18147 non-null	float64
23	Joined	16654 non-null	object
24	Loaned From	1264 non-null	object
25	Contract Valid Until	17918 non-null	object
26	Height	18159 non-null	object
27	Weight	18159 non-null	object
28	LS	16122 non-null	object
29	ST	16122 non-null	object
30	RS	16122 non-null	object
31	LW	16122 non-null	object
32	LF	16122 non-null	object
33	CF	16122 non-null	object
34	RF	16122 non-null	object
35	RW	16122 non-null	object
36	LAM	16122 non-null	object
37	CAM	16122 non-null	object
38	RAM	16122 non-null	object
39	LM	16122 non-null	object
40	LCM	16122 non-null	object
41	CM	16122 non-null	object
42	RCM	16122 non-null	object
43	RM	16122 non-null	object
44	LWB	16122 non-null	object
45	LDM	16122 non-null	object
46	CDM	16122 non-null	object
47	RDM	16122 non-null	object
48	RWB	16122 non-null	object
49	LB	16122 non-null	object
50	LCB	16122 non-null	object
51	CB	16122 non-null	object
52	RCB	16122 non-null	object
53	RB	16122 non-null	object
54	Crossing	18159 non-null	float64

55	Finishing	18159	non-null	float64
56	HeadingAccuracy	18159	non-null	float64
57	ShortPassing	18159	non-null	float64
58	Volleys	18159	non-null	float64
59	Dribbling	18159	non-null	float64
60	Curve	18159	non-null	float64
61	FKAccuracy	18159	non-null	float64
62	LongPassing	18159	non-null	float64
63	BallControl	18159	non-null	float64
64	Acceleration	18159	non-null	float64
65	SprintSpeed	18159	non-null	float64
66	Agility	18159	non-null	float64
67	Reactions	18159	non-null	float64
68	Balance	18159	non-null	float64
69	ShotPower	18159	non-null	float64
70	Jumping	18159	non-null	float64
71	Stamina	18159	non-null	float64
72	Strength	18159	non-null	float64
73	LongShots	18159	non-null	float64
74	Aggression	18159	non-null	float64
75	Interceptions	18159	non-null	float64
76	Positioning	18159	non-null	float64
77	Vision	18159	non-null	float64
78	Penalties	18159	non-null	float64
79	Composure	18159	non-null	float64
80	Marking	18159	non-null	float64
81	StandingTackle	18159	non-null	float64
82	SlidingTackle	18159	non-null	float64
83	GKDivining	18159	non-null	float64
84	GKHandling	18159	non-null	float64
85	GK Kicking	18159	non-null	float64
86	GK Positioning	18159	non-null	float64
87	GK Reflexes	18159	non-null	float64
88	Release Clause	16643	non-null	object

dtypes: float64(38), int64(6), object(45)  
memory usage: 12.4+ MB

```
In [19]: fifa.info()
```

```
<class 'pandas.core.frame.DataFrame'>
```

```
RangeIndex: 18207 entries, 0 to 18206
```

```
Data columns (total 89 columns):
```

#	Column	Non-Null Count	Dtype
0	Unnamed: 0	18207 non-null	int64
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2	Name	18207 non-null	object
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4	Photo	18207 non-null	object
5	Nationality	18207 non-null	object
6	Flag	18207 non-null	object
7	Overall	18207 non-null	int64
8	Potential	18207 non-null	int64
9	Club	17966 non-null	object
10	Club Logo	18207 non-null	object
11	Value	18207 non-null	object
12	Wage	18207 non-null	object
13	Special	18207 non-null	int64
14	Preferred Foot	18159 non-null	object
15	International Reputation	18159 non-null	float64
16	Weak Foot	18159 non-null	float64
17	Skill Moves	18159 non-null	float64
18	Work Rate	18159 non-null	object
19	Body Type	18159 non-null	object
20	Real Face	18159 non-null	object
21	Position	18147 non-null	object
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32	LF	16122 non-null	object
33	CF	16122 non-null	object
34	RF	16122 non-null	object
35	RW	16122 non-null	object
36	LAM	16122 non-null	object
37	CAM	16122 non-null	object
38	RAM	16122 non-null	object
39	LM	16122 non-null	object
40	LCM	16122 non-null	object
41	CM	16122 non-null	object
42	RCM	16122 non-null	object
43	RM	16122 non-null	object
44	LWB	16122 non-null	object
45	LDM	16122 non-null	object
46	CDM	16122 non-null	object
47	RDM	16122 non-null	object
48	RWB	16122 non-null	object
49	LB	16122 non-null	object
50	LCB	16122 non-null	object
51	CB	16122 non-null	object
52	RCB	16122 non-null	object
53	RB	16122 non-null	object
54	Crossing	18159 non-null	float64

55	Finishing	18159	non-null	float64
56	HeadingAccuracy	18159	non-null	float64
57	ShortPassing	18159	non-null	float64
58	Volleys	18159	non-null	float64
59	Dribbling	18159	non-null	float64
60	Curve	18159	non-null	float64
61	FKAccuracy	18159	non-null	float64
62	LongPassing	18159	non-null	float64
63	BallControl	18159	non-null	float64
64	Acceleration	18159	non-null	float64
65	SprintSpeed	18159	non-null	float64
66	Agility	18159	non-null	float64
67	Reactions	18159	non-null	float64
68	Balance	18159	non-null	float64
69	ShotPower	18159	non-null	float64
70	Jumping	18159	non-null	float64
71	Stamina	18159	non-null	float64
72	Strength	18159	non-null	float64
73	LongShots	18159	non-null	float64
74	Aggression	18159	non-null	float64
75	Interceptions	18159	non-null	float64
76	Positioning	18159	non-null	float64
77	Vision	18159	non-null	float64
78	Penalties	18159	non-null	float64
79	Composure	18159	non-null	float64
80	Marking	18159	non-null	float64
81	StandingTackle	18159	non-null	float64
82	SlidingTackle	18159	non-null	float64
83	GKDivining	18159	non-null	float64
84	GKHandling	18159	non-null	float64
85	GKKicking	18159	non-null	float64
86	GKPositioning	18159	non-null	float64
87	GKReflexes	18159	non-null	float64
88	Release Clause	16643	non-null	object

dtypes: float64(38), int64(6), object(45)  
memory usage: 12.4+ MB

## 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.

```
In [22]: fifa['Body Type'].value_counts()
```

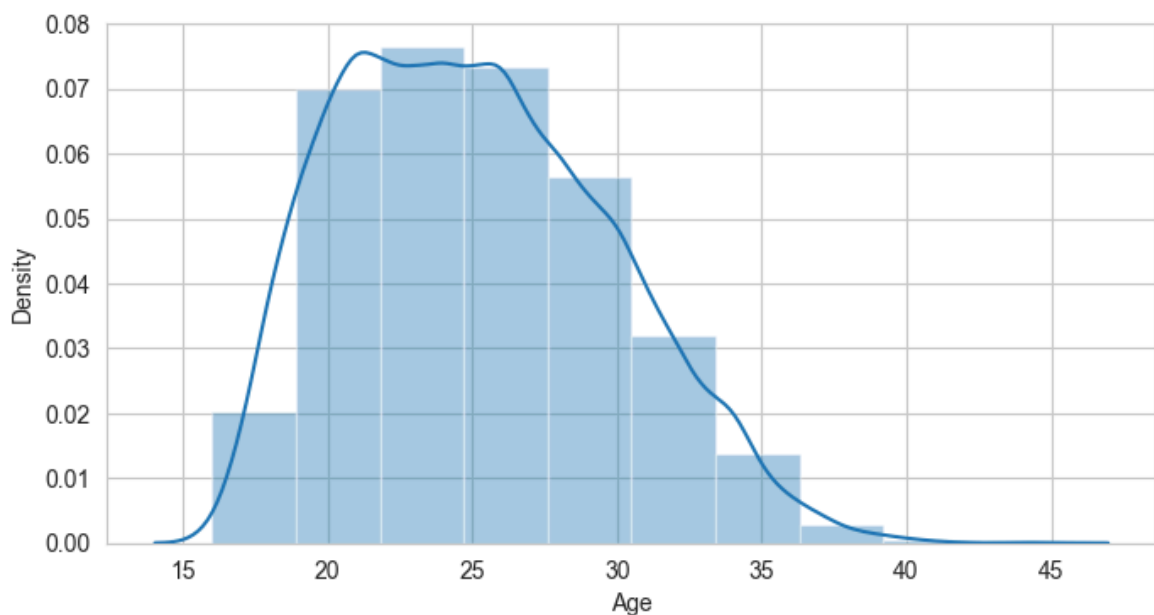
```
Out[22]: Body Type
Normal      10595
Lean        6417
Stocky      1140
Messi       1
C. Ronaldo  1
Neymar      1
Courtois    1
PLAYER_BODY_TYPE_25  1
Shaqiri     1
Akinfenwa   1
Name: count, dtype: int64
```

## Explore Age variable

### 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.

```
In [26]: f, ax = plt.subplots(figsize=(8,4))
x = fifa['Age']
ax = sns.distplot(x, bins=10)
plt.show()
```

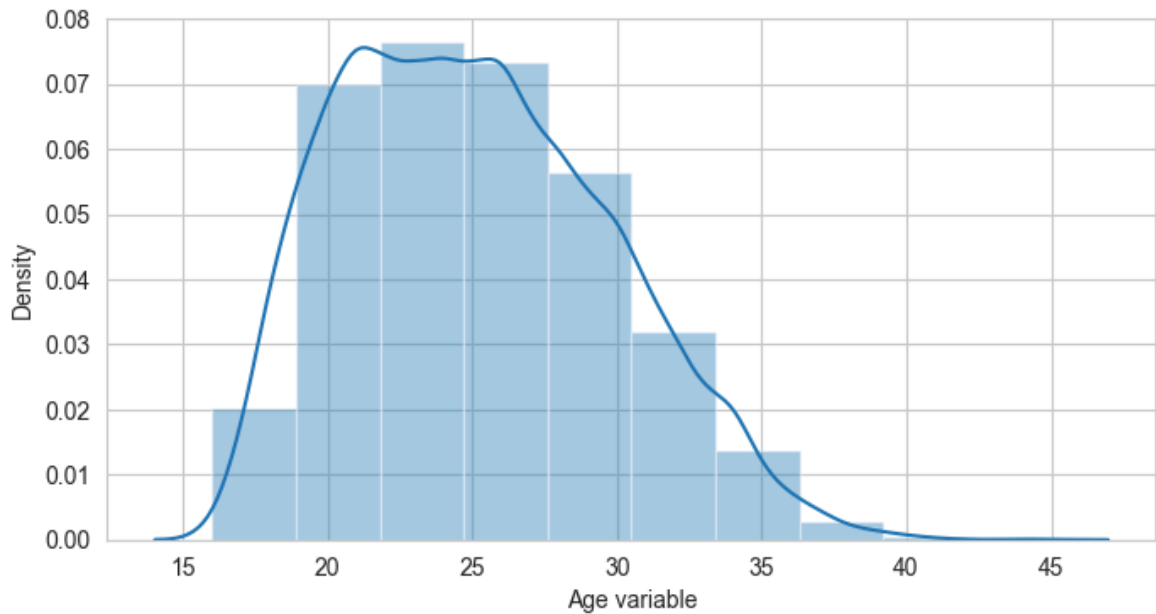


## Comment

- 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-

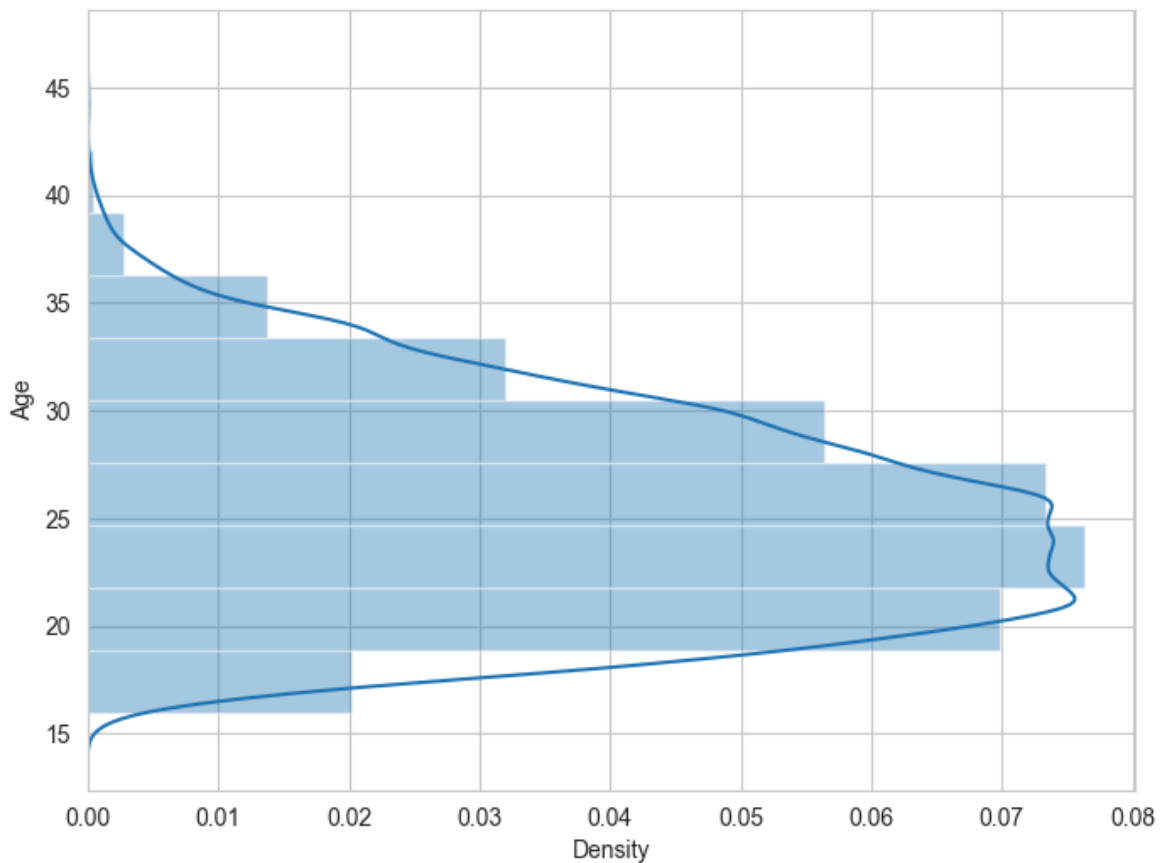
```
In [30]: f, ax = plt.subplots(figsize=(8,4))
x = fifa['Age']
x = pd.Series(x, name="Age variable")
ax = sns.distplot(x, bins=10)
plt.show()
```



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

```
In [33]: f, ax = plt.subplots(figsize=(8,6))
x = fifa['Age']
ax = sns.distplot(x, bins=10, vertical = True)
plt.show()
```

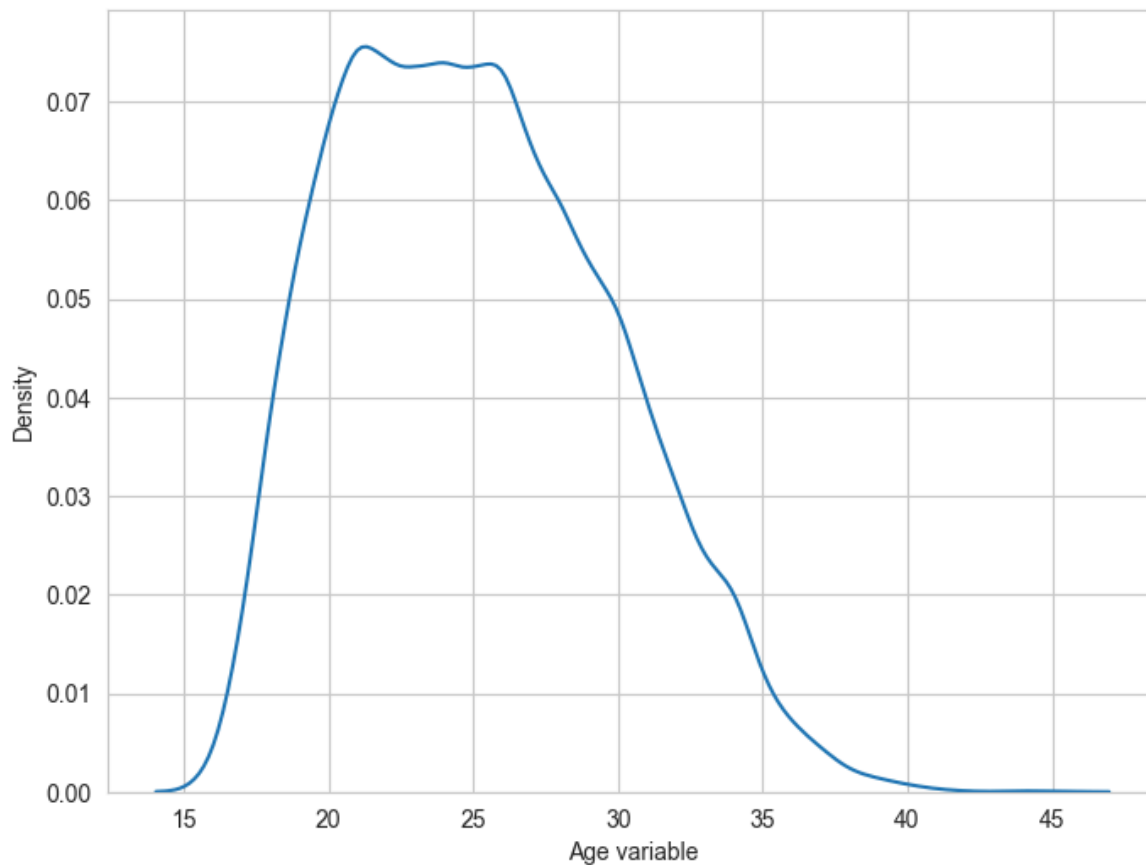




## Seaborn Kernel Density Estimation (KDE) Plot

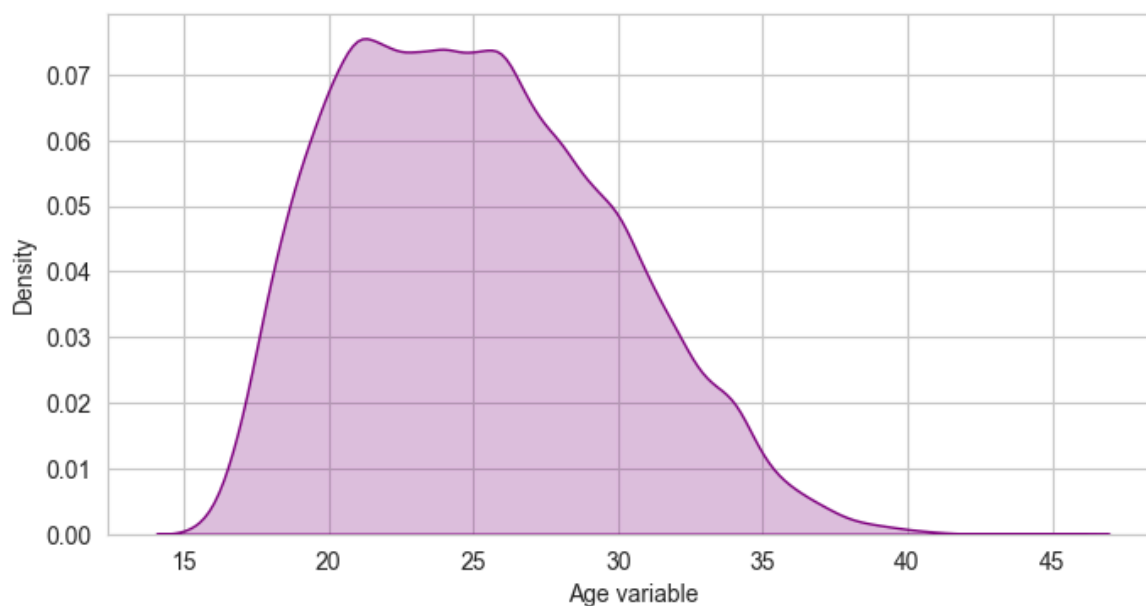
- The **kernel density estimate (KDE)** plot is a useful tool for plotting the shape of a distribution.
- Seaborn `kdeplot` is another seaborn plotting function that fits and plot a univariate or bivariate kernel density estimate.
- Like the histogram, the KDE plots encode the density of observations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

```
In [36]: f, ax = plt.subplots(figsize=(8,6))
x = fifa['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:-

```
In [39]: f, ax = plt.subplots(figsize=(8,4))
x = fifa['Age']
x = pd.Series(x, name="Age variable")
ax = sns.kdeplot(x, shade=True, color='purple')
plt.show()
```



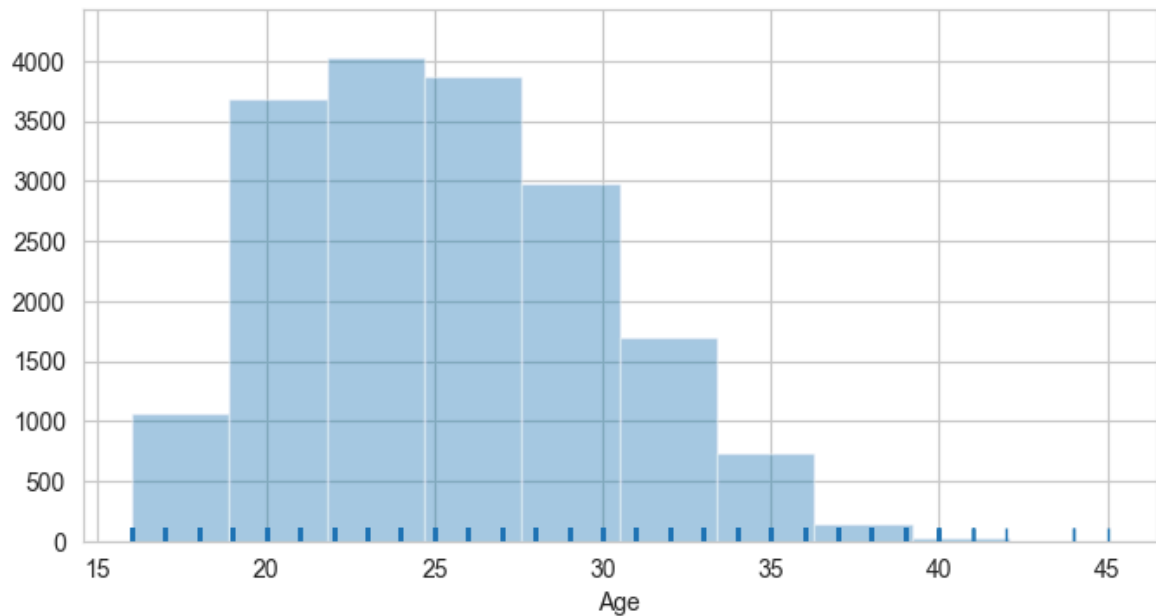
## Histograms

- 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.

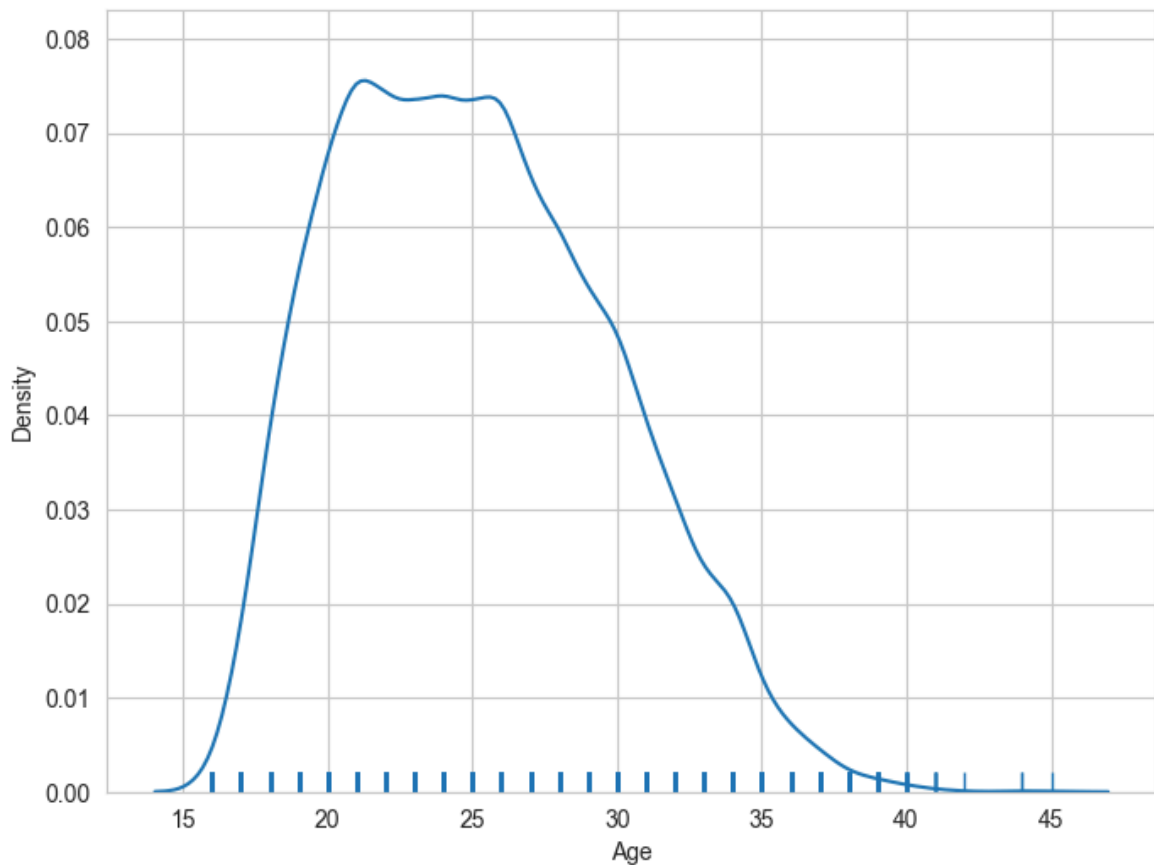
- A `hist()` function already exists in matplotlib.
- We can use Seaborn to plot a histogram.

```
In [41]: f,ax=plt.subplots(figsize=(8,4))  
x=fifa['Age']  
ax=sns.distplot(x,kde=False,rug=True,bins=10)  
plt.show()
```



We can plot a KDE plot alternatively as follows:-

```
In [44]: f, ax = plt.subplots(figsize=(8,6))  
x = fifa['Age']  
ax = sns.distplot(x, hist=False, rug=True, bins=10)  
plt.show()
```



## Explore Preferred Foot variable

### Check number of unique values in Preferred Foot variable

```
In [47]: fifa['Preferred Foot'].nunique()
```

```
Out[47]: 2
```

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

```
In [50]: fifa['Preferred Foot'].unique()
```

```
Out[50]: array(['Left', 'Right', nan], dtype=object)
```

### Check frequency distribution of values in Preferred Foot variable

```
In [52]: fifa['Preferred Foot'].value_counts()
```

```
Out[52]: Preferred Foot
Right    13948
Left     4211
Name: count, dtype: int64
```

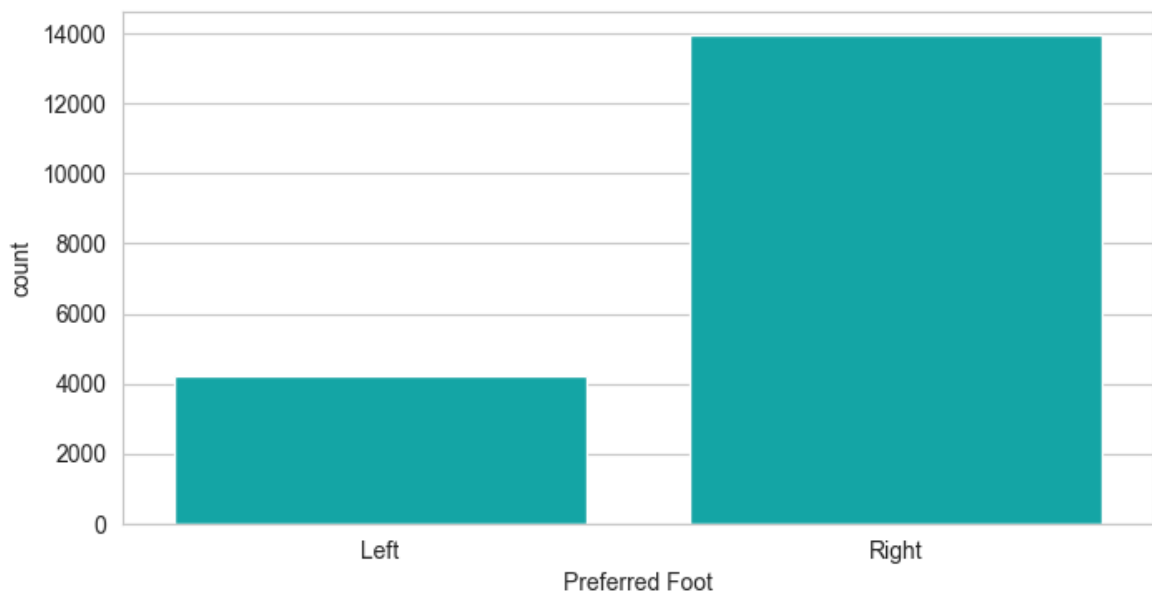
The Preferred Foot variable contains two types of values - Right and Left .

## 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.

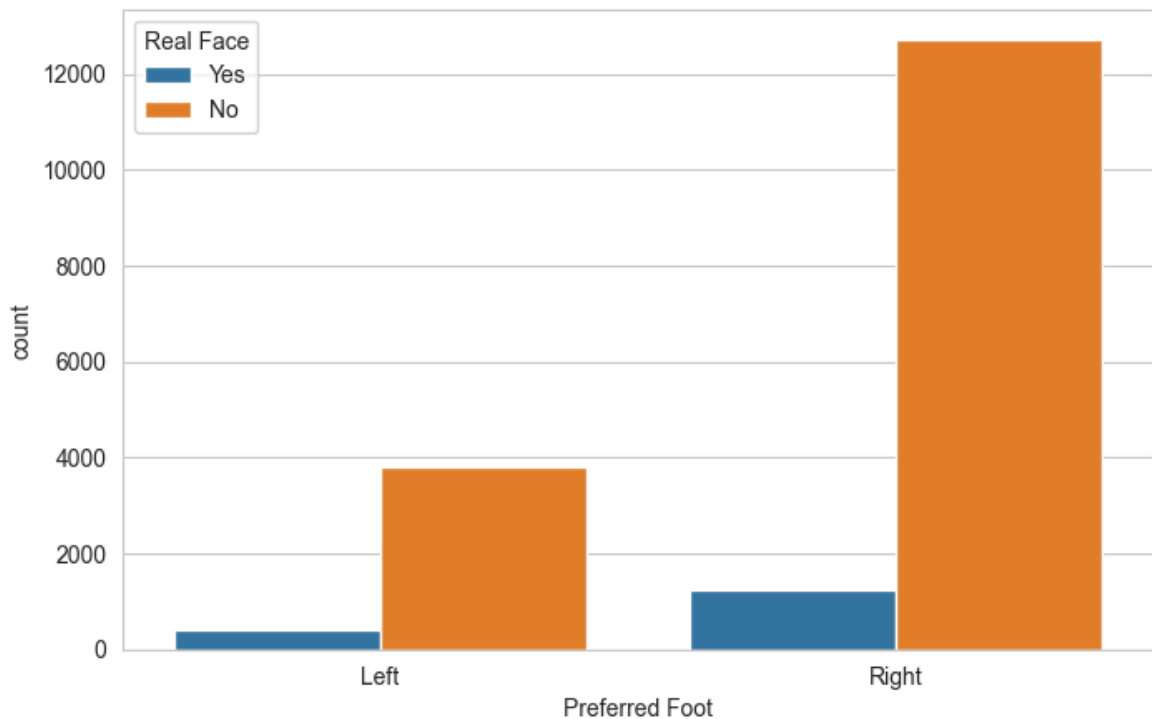
- We can visualize the distribution of values with Seaborn `countplot()` function as follows-

```
In [59]: f, ax = plt.subplots(figsize=(8, 4))  
sns.countplot(x="Preferred Foot", data=fifa, color="c")  
plt.show()
```



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

```
In [62]: f, ax=plt.subplots(figsize=(8,5))  
sns.countplot(x='Preferred Foot', hue='Real Face', data=fifa)  
plt.show()
```



We can draw plot vertically as follows-

```
f, ax = plt.subplots(figsize=(8, 6))
sns.countplot(y="Preferred Foot", data=fifa, color="c")
plt.show()
```

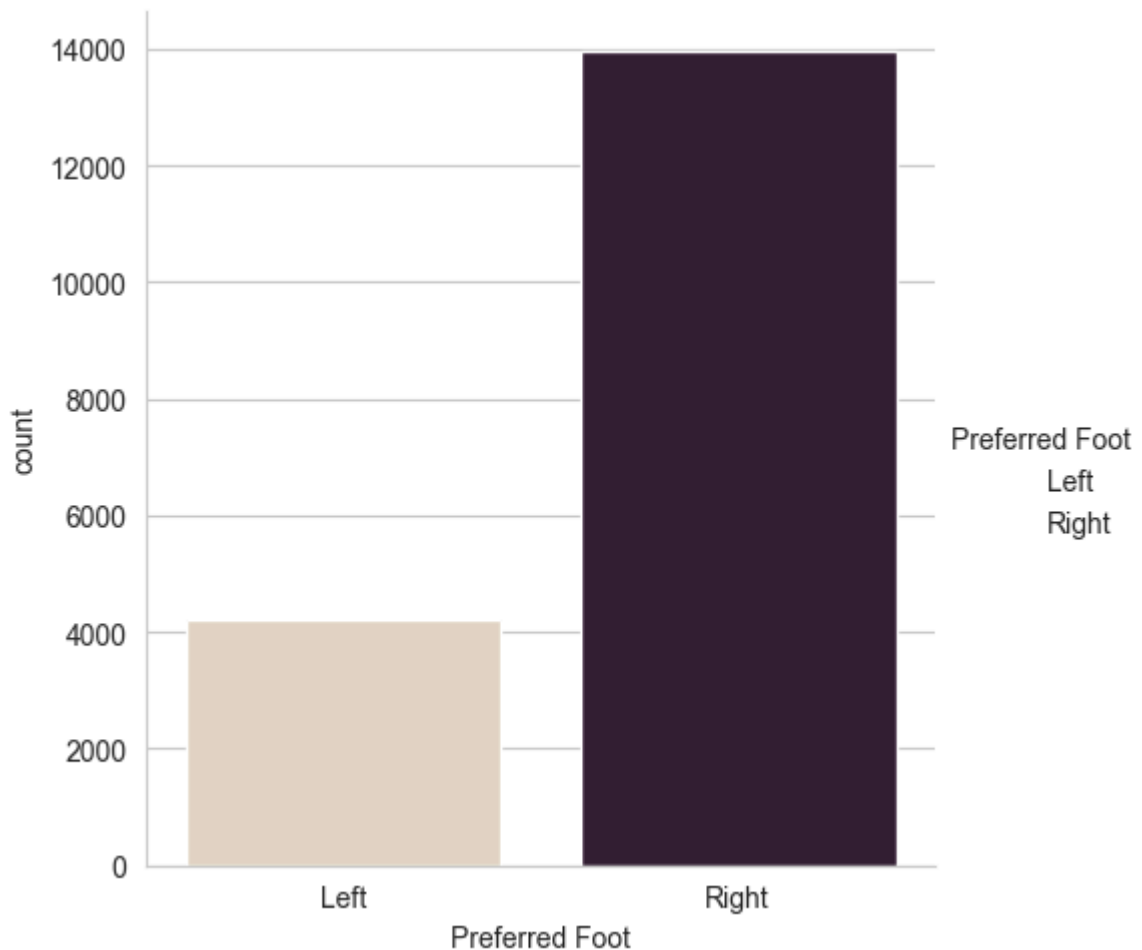
## Seaborn `Catplot()` function

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

```
In [68]: g=sns.catplot(x="Preferred Foot", kind="count", palette="ch:.25", data=fifa)
```

```
In [69]: plt.show()
```



## Explore International Reputation variable

### Check the number of unique values in International Reputation variable

```
In [73]: fifa['International Reputation'].nunique()
```

```
Out[73]: 5
```

```
In [74]: fifa['International Reputation'].unique()
```

```
Out[74]: array([ 5.,  4.,  3.,  2.,  1., nan])
```

### Check the distribution of values in International Reputation variable

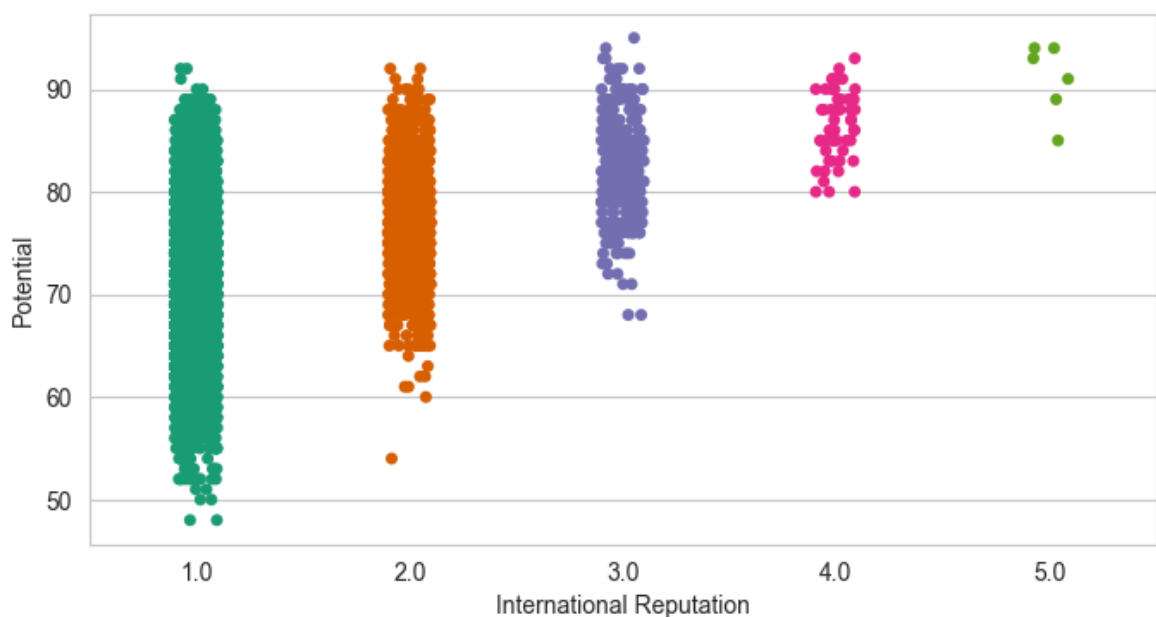
```
In [79]: fifa['International Reputation'].value_counts()
```

```
Out[79]: International Reputation
1.0    16532
2.0     1261
3.0      309
4.0       51
5.0        6
Name: count, dtype: int64
```

## Seaborn `Striplot()` 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.

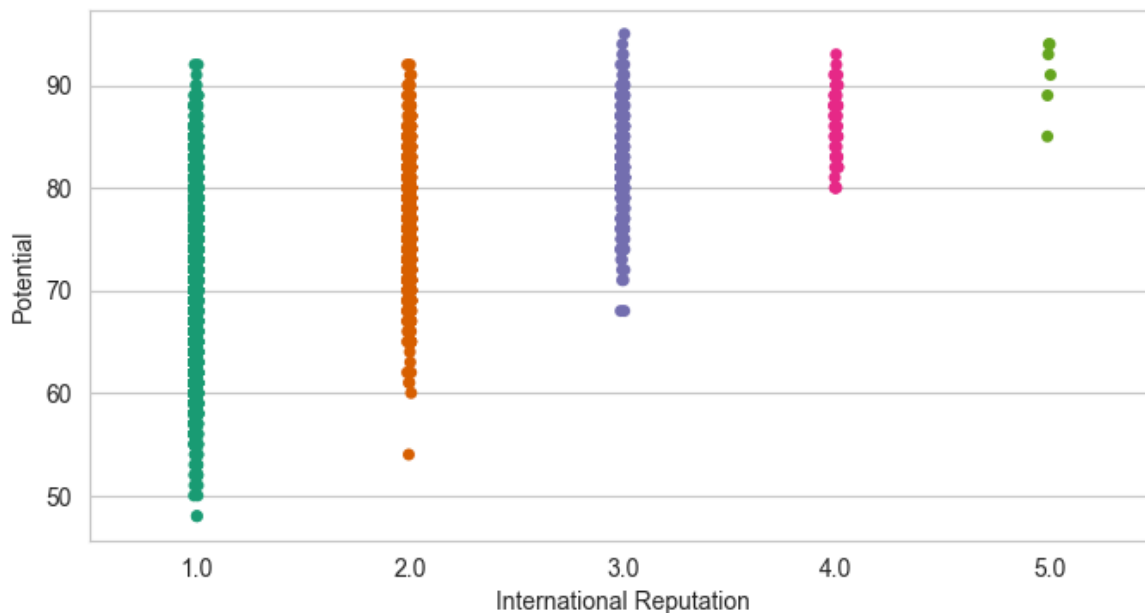
```
In [82]: f, ax = plt.subplots(figsize=(8, 4))
sns.stripplot(x="International Reputation", y="Potential", data=fifa, palette="Dark2")
plt.show()
```



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

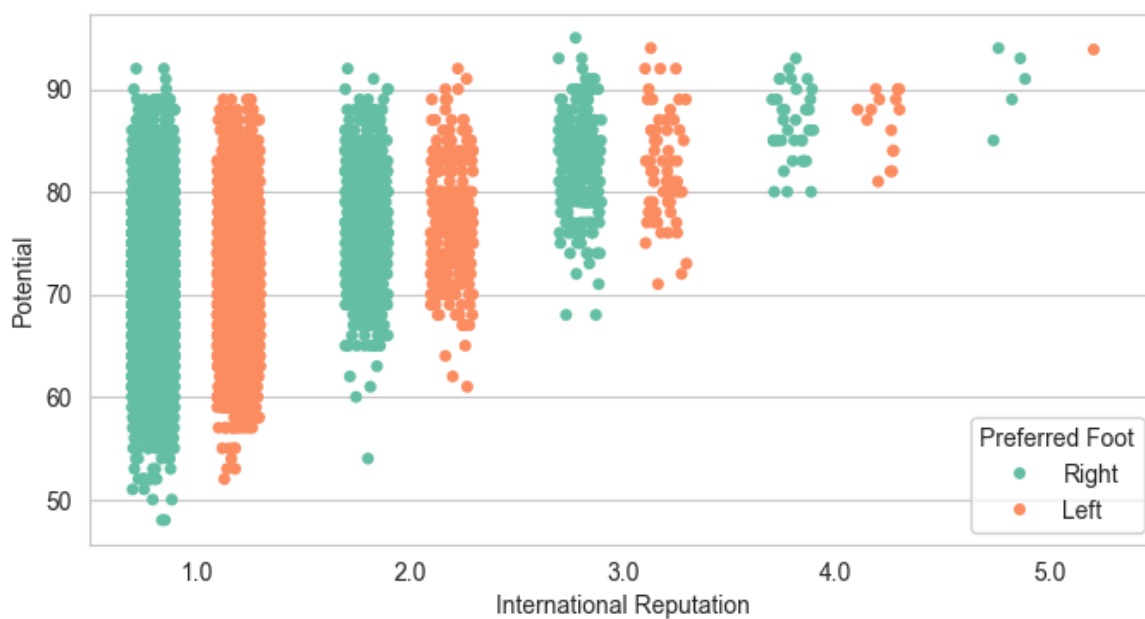
```
In [84]: f, ax = plt.subplots(figsize=(8, 4))
sns.stripplot(x='International Reputation', y='Potential', data=fifa, palette="Dark2", jitter=True)
plt.show()
```





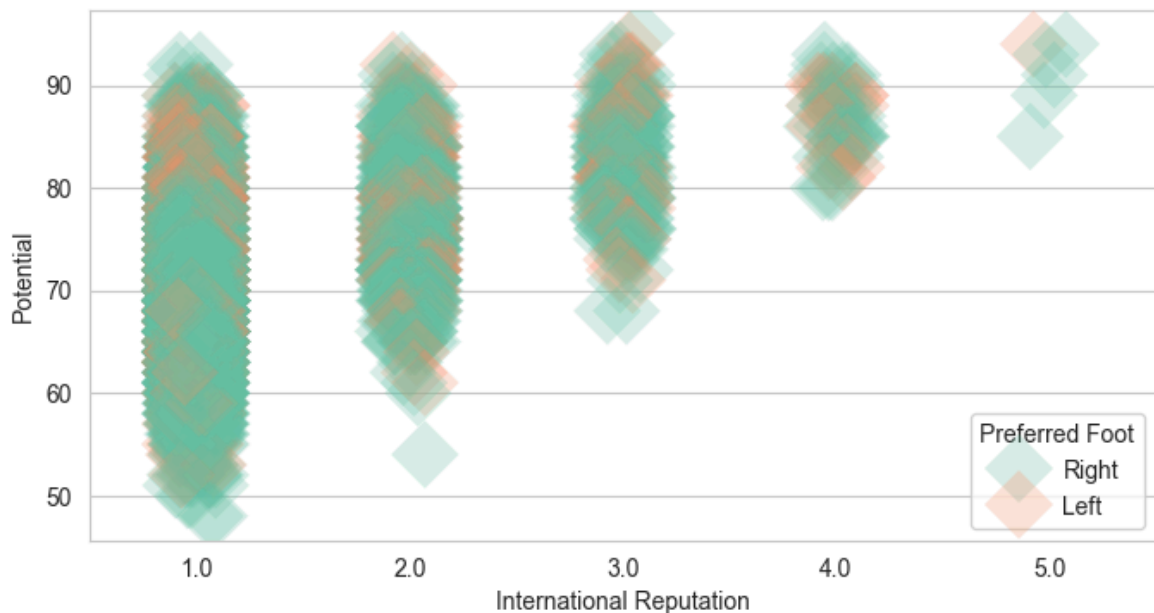
We can nest the strips within a second categorical variable - Preferred Foot - as follows-

```
In [87]: f,ax=plt.subplots(figsize=(8,4))
sns.stripplot(x="International Reputation",y="Potential",hue="Preferred Foot",da
plt.show()
```



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

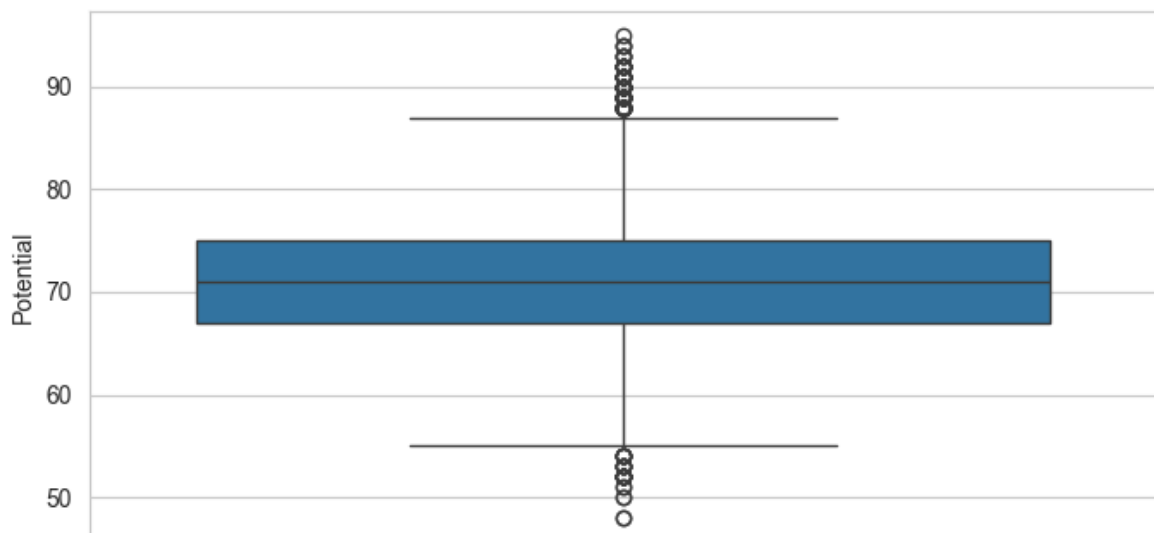
```
In [90]: f,ax=plt.subplots(figsize=(8,4))
sns.stripplot(x="International Reputation",y="Potential",hue="Preferred Foot",da
plt.show()
```



## Seaborn `boxplot()` function

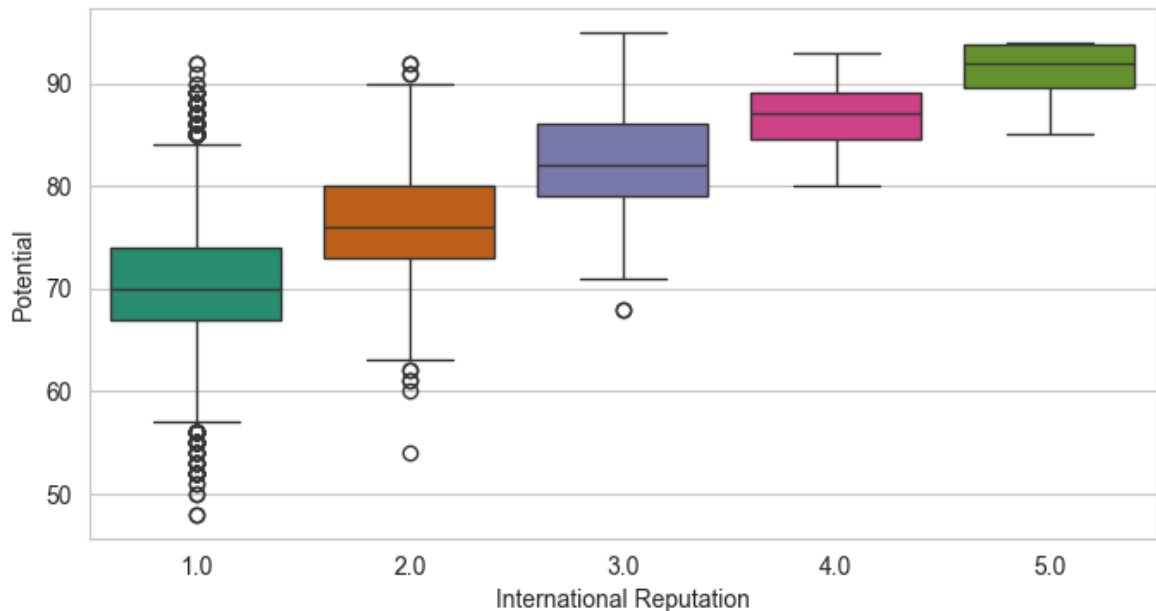
- This function draws a box plot to show distributions with respect to categories.
- A box plot (or box-and-whisker plot) shows the distribution of quantitative data in a way that facilitates comparisons between variables or across levels of a categorical variable.
- The box shows the quartiles of the 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-

```
In [92]: f,ax=plt.subplots(figsize=(8,4))
x=fifa['Potential']
sns.boxplot(x)
plt.show()
```



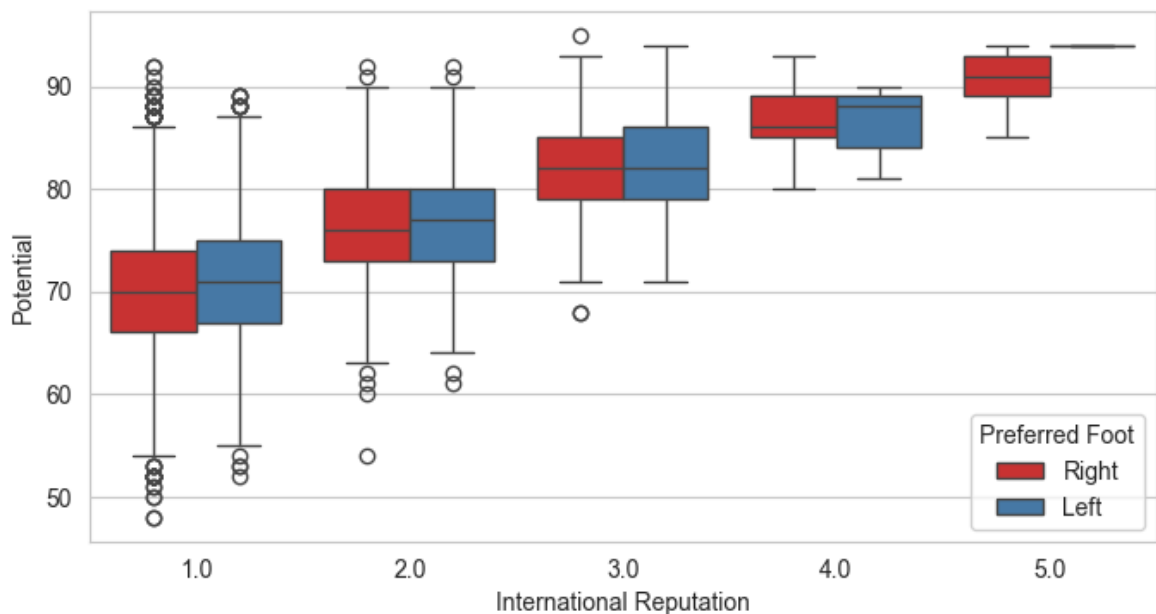
We can draw the vertical boxplot grouped by the categorical variable `International Reputation` as follows-

```
In [94]: f,ax=plt.subplots(figsize=(8,4))
sns.boxplot(x="International Reputation",y="Potential",data=fifa,palette="Dark2")
plt.show()
```



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

```
In [96]: f,ax=plt.subplots(figsize=(8,4))
sns.boxplot(x="International Reputation",y="Potential",hue="Preferred Foot",data=fifa)
plt.show()
```

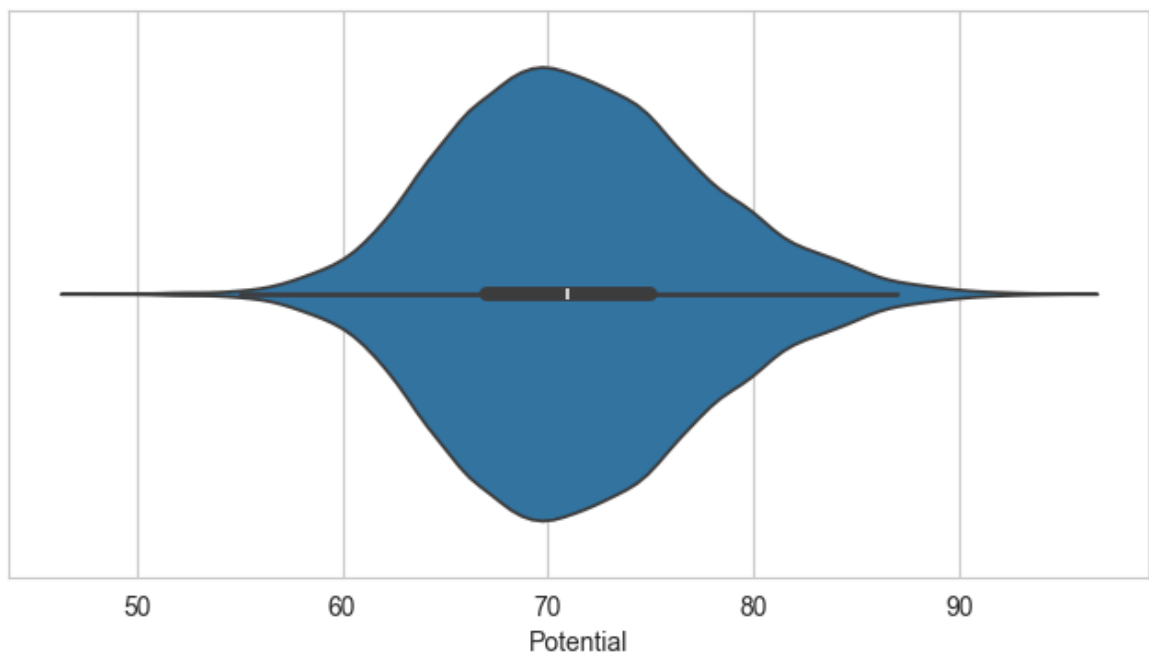


## Seaborn `violinplot()` function

- This function draws a combination of boxplot and kernel density estimate.
- A violin plot plays a similar role as a box and whisker plot.

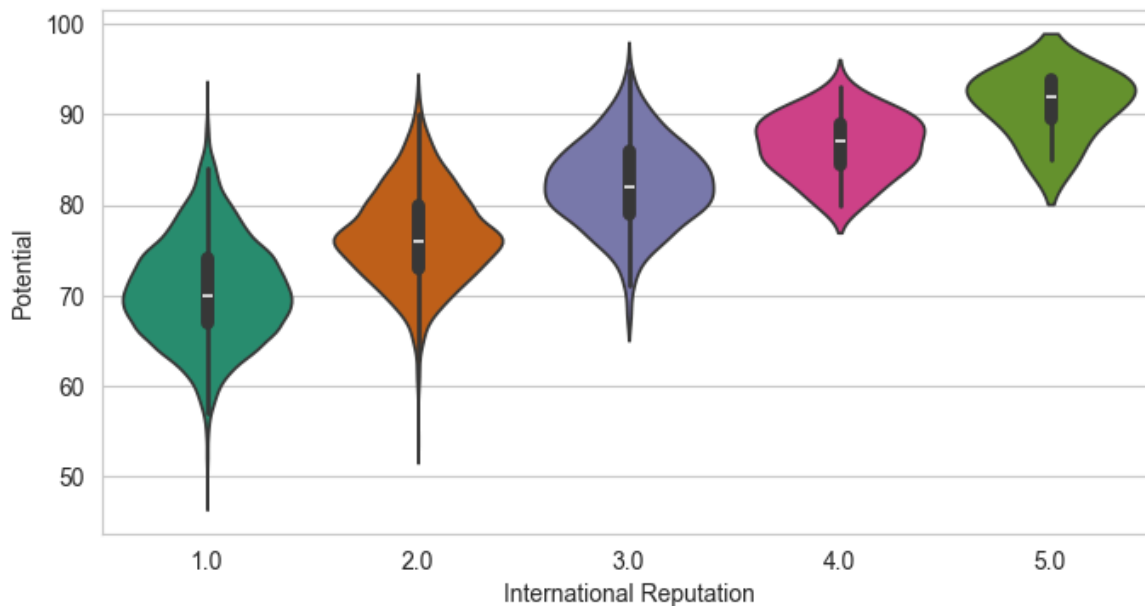
- It shows the distribution of quantitative data across several levels of one (or more) categorical variables such that those distributions can be compared.
- Unlike a box plot, in which all of the plot components correspond to actual datapoints, the violin plot features a kernel density estimation of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

```
In [99]: f, ax = plt.subplots(figsize=(8, 4))  
sns.violinplot(x=fifa["Potential"])  
plt.show()
```



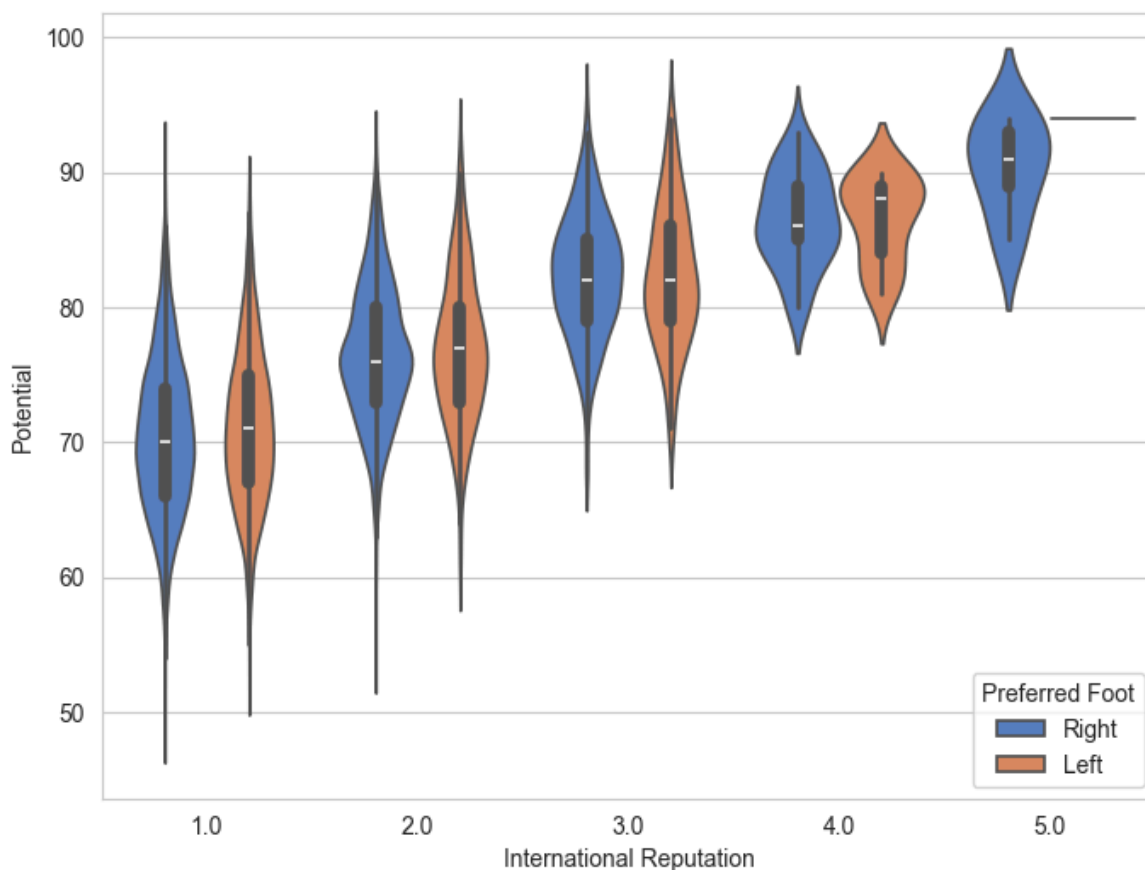
We can draw the vertical violinplot grouped by the categorical variable `International Reputation` as follows-

```
In [101]: f, ax=plt.subplots(figsize=(8,4))  
sns.violinplot(x="International Reputation", y="Potential", data=fifa,palette="D")  
plt.show()
```



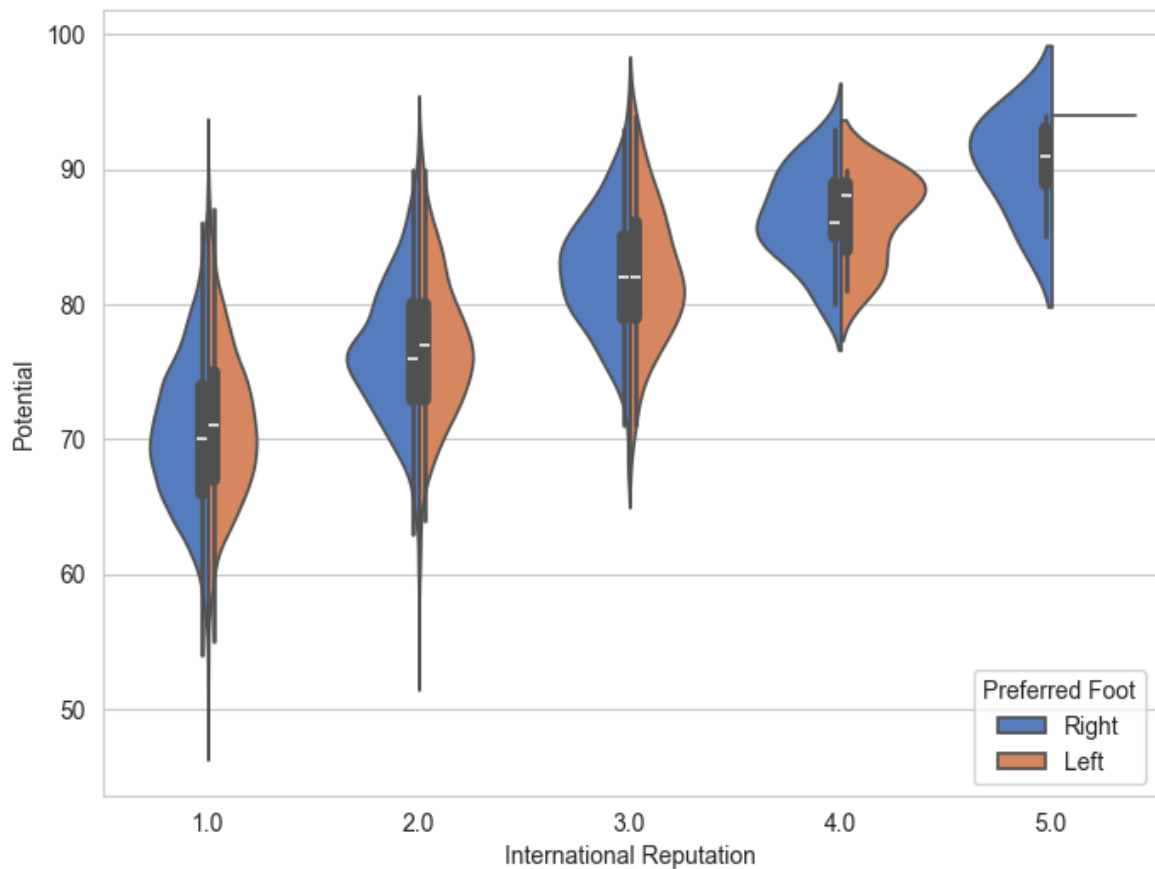
We can draw a violinplot with nested grouping by two categorical variables as follows-

```
In [103... f, ax = plt.subplots(figsize=(8, 6))
sns.violinplot(x="International Reputation", y="Potential", hue="Preferred Foot")
plt.show()
```



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

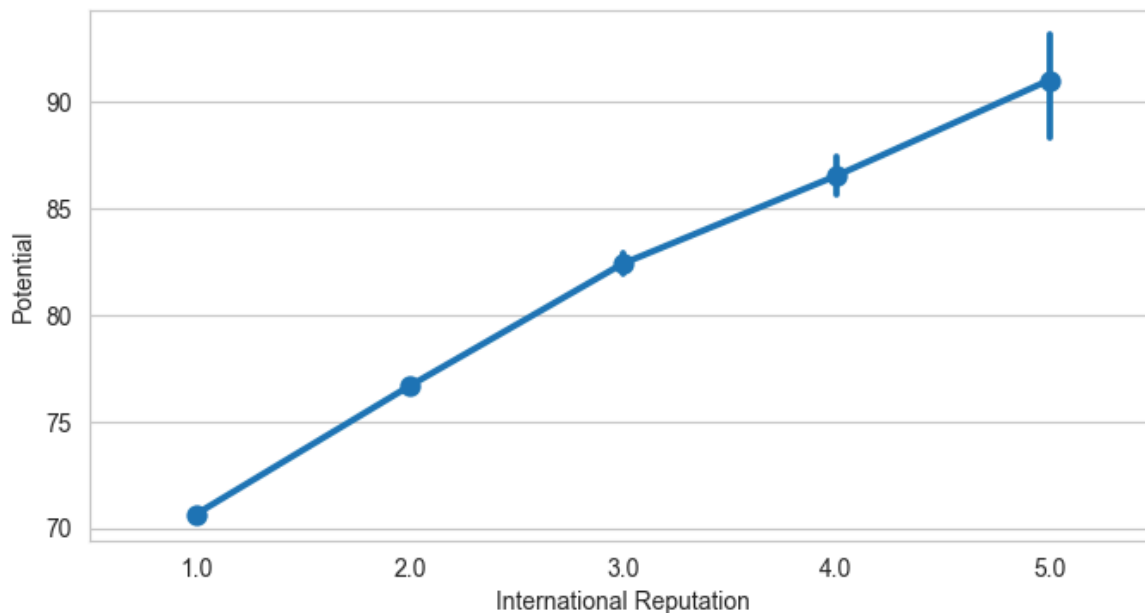
```
In [105... f, ax = plt.subplots(figsize=(8, 6))
sns.violinplot(x="International Reputation", y="Potential", hue="Preferred Foot",
               data=fifa, palette="muted", split=True)
plt.show()
```



## Seaborn `pointplot()` function

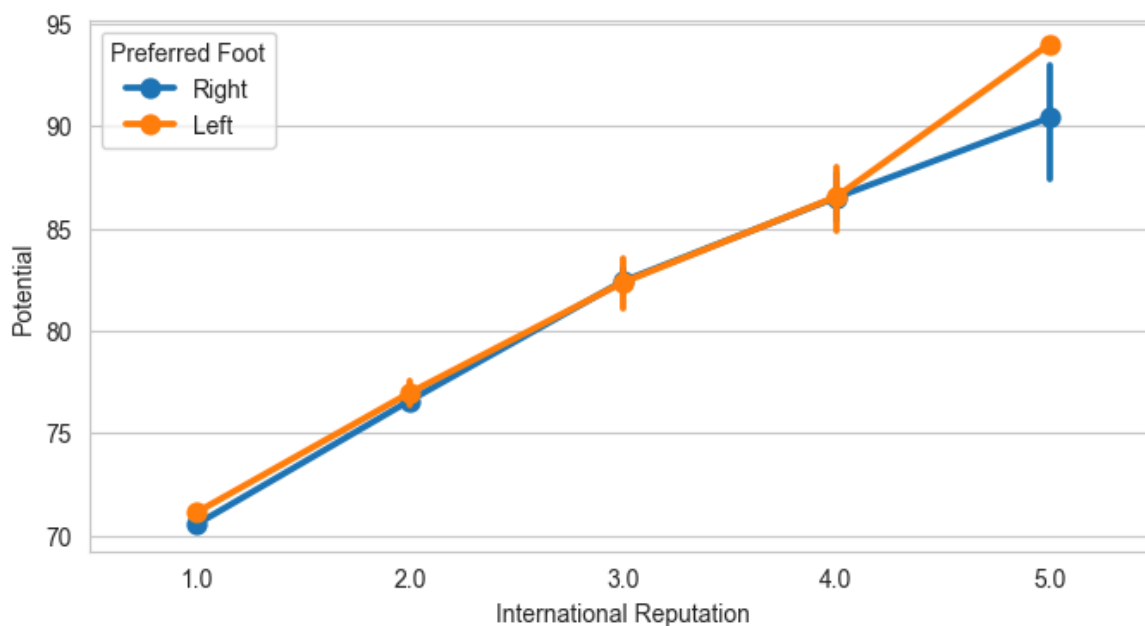
- This function show point estimates and confidence intervals using scatter plot graphs.
- A point plot represents an estimate of central tendency for a numeric variable by the position of scatter plot points and provides some indication of the uncertainty around that estimate using error bars.

```
In [107... f, ax = plt.subplots(figsize=(8, 4))
sns.pointplot(x="International Reputation", y="Potential", data=fifa)
plt.show()
```



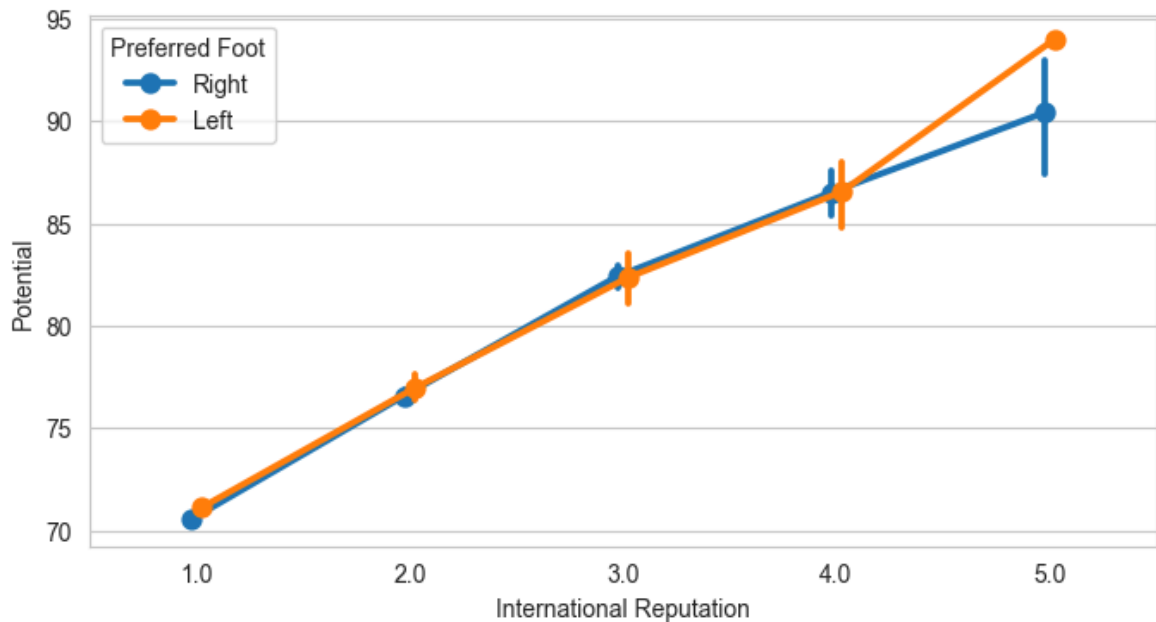
We can draw a set of vertical points with nested grouping by a two variables as follows-

```
In [110... f, ax = plt.subplots(figsize=(8, 4))
sns.pointplot(x="International Reputation", y="Potential", hue="Preferred Foot",
plt.show())
```



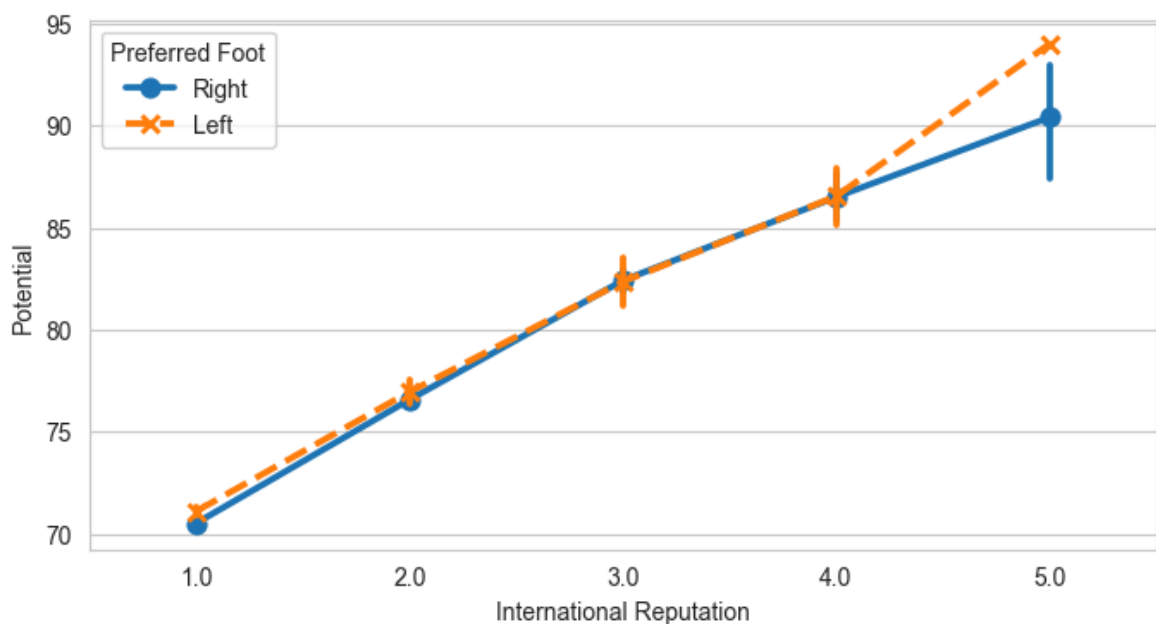
We can separate the points for different hue levels along the categorical axis as follows-

```
In [113... f, ax = plt.subplots(figsize=(8, 4))
sns.pointplot(x="International Reputation", y="Potential", hue="Preferred Foot",
plt.show())
```



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

```
In [116... f, ax = plt.subplots(figsize=(8, 4))
sns.pointplot(x="International Reputation", y="Potential", hue="Preferred Foot",
              data=fifa, markers=["o", "x"], linestyles=["-", "--"])
plt.show()
```



## Seaborn `barplot()` function

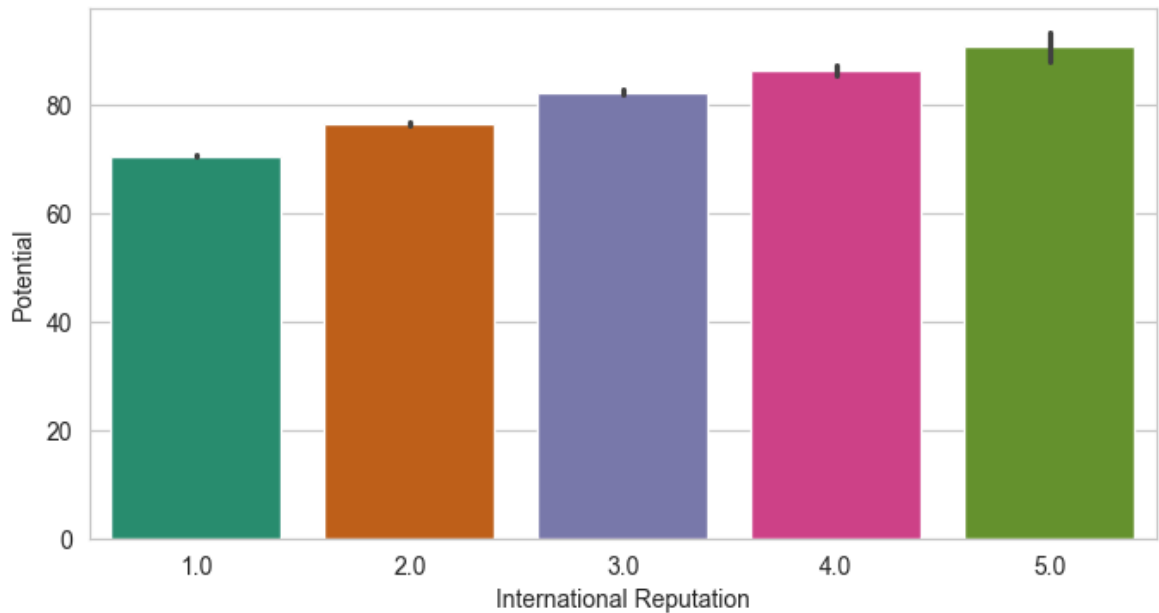
- This function show point estimates and confidence intervals as rectangular bars.
- A bar plot represents an estimate of central tendency for a numeric variable with the height of each rectangle and provides some indication of the uncertainty around that estimate using error bars.
- Bar plots include 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.

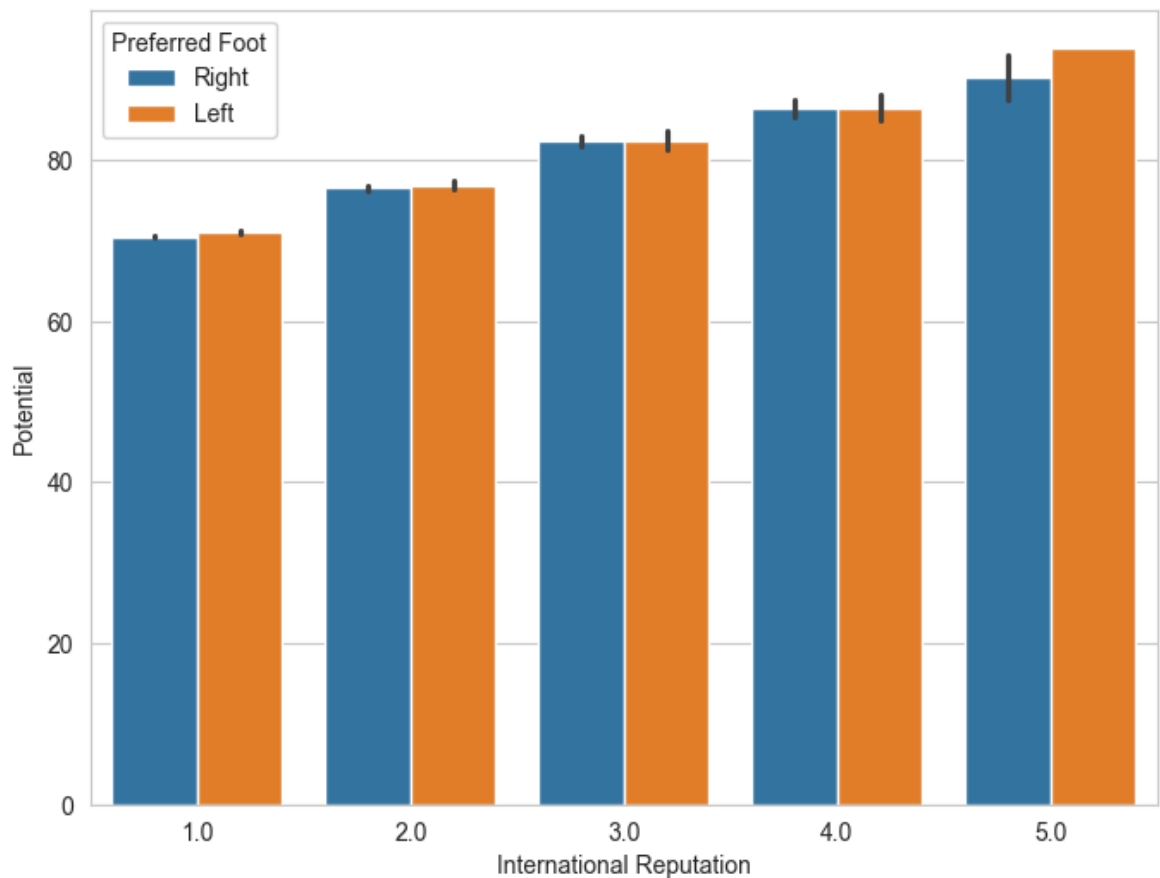
- We can plot a barplot as follows-

```
In [118... f, ax = plt.subplots(figsize=(8,4))
sns.barplot(x="International Reputation", y="Potential", data=fifa,palette="Dark
plt.show()
```



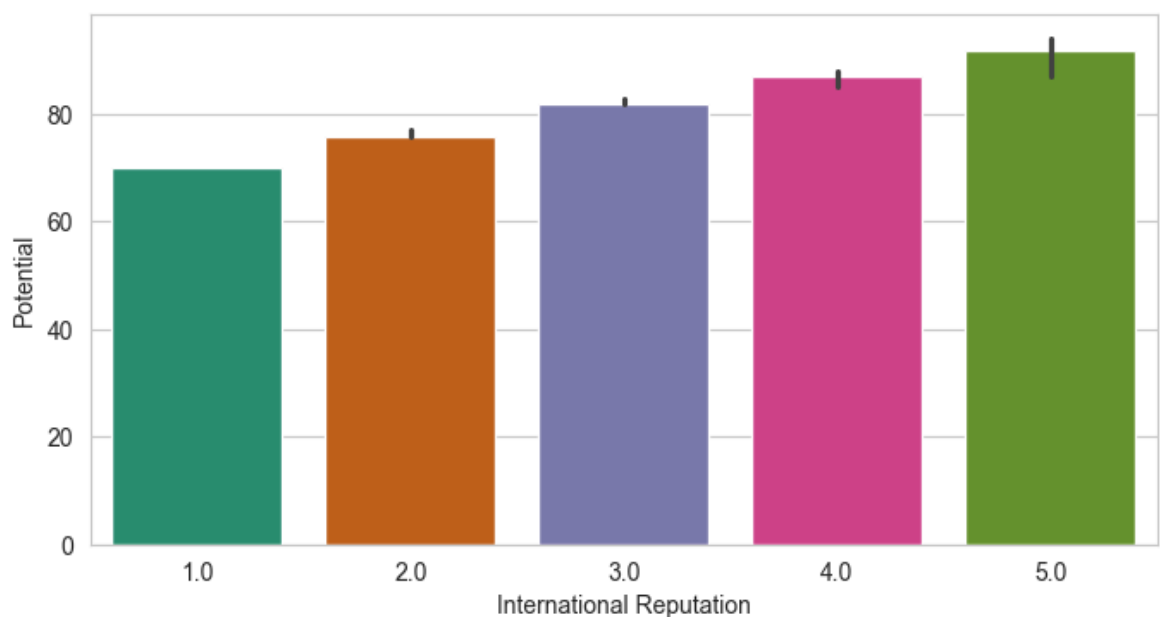
We can draw a set of vertical bars with nested grouping by a two variables as follows-

```
In [121... f, ax = plt.subplots(figsize=(8, 6))
sns.barplot(x="International Reputation", y="Potential", hue="Preferred Foot", d
plt.show()
```



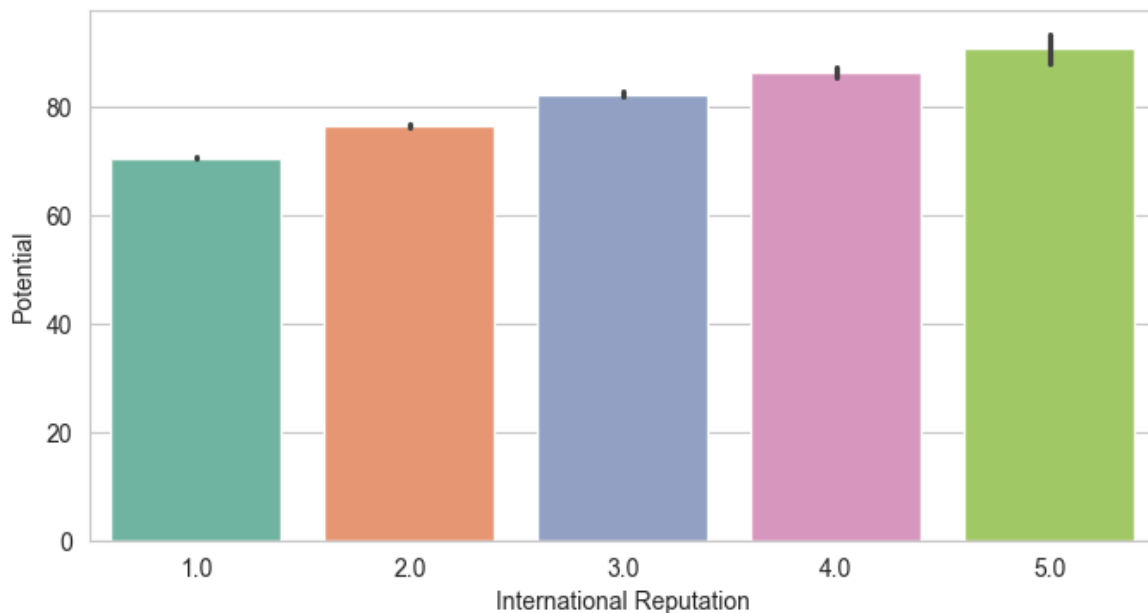
We can use median as the estimate of central tendency as follows-

```
In [124... from numpy import median
f, ax = plt.subplots(figsize=(8, 4))
sns.barplot(x="International Reputation", y="Potential", data=fifa, estimator=median)
plt.show()
```



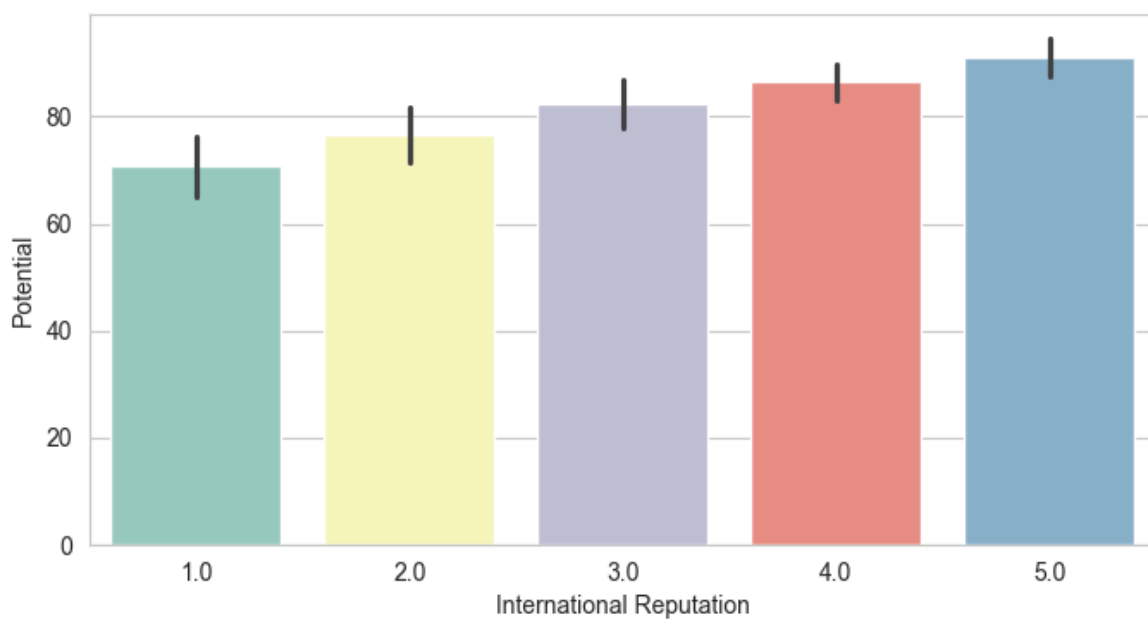
We can show the standard error of the mean with the error bars as follows-

```
In [136... f, ax=plt.subplots(figsize=(8, 4))
sns.barplot(x="International Reputation", y="Potential", data=fifa, ci=95, palette="magma")
plt.show()
```



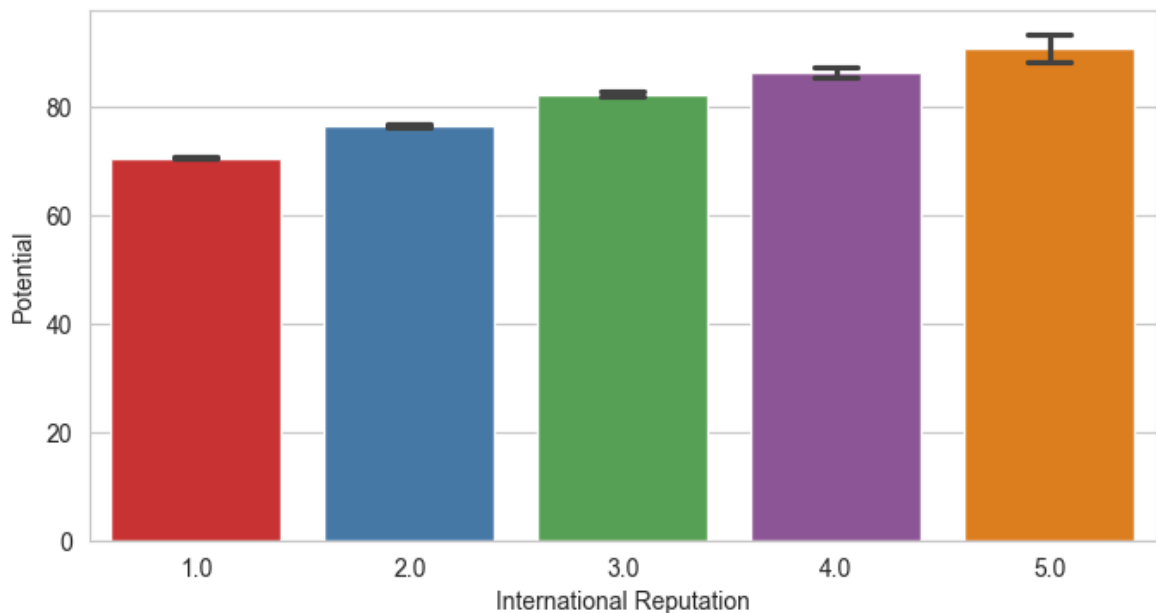
We can show standard deviation of observations instead of a confidence interval as follows-

```
In [144... f, ax = plt.subplots(figsize=(8, 4))
sns.barplot(x="International Reputation", y="Potential", data=fifa, ci="sd", palette=
plt.show()
```



We can add "caps" to the error bars as follows-

```
In [152... f, ax = plt.subplots(figsize=(8, 4))
sns.barplot(x="International Reputation", y="Potential", data=fifa, capsize=0.2,
plt.show()
```



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

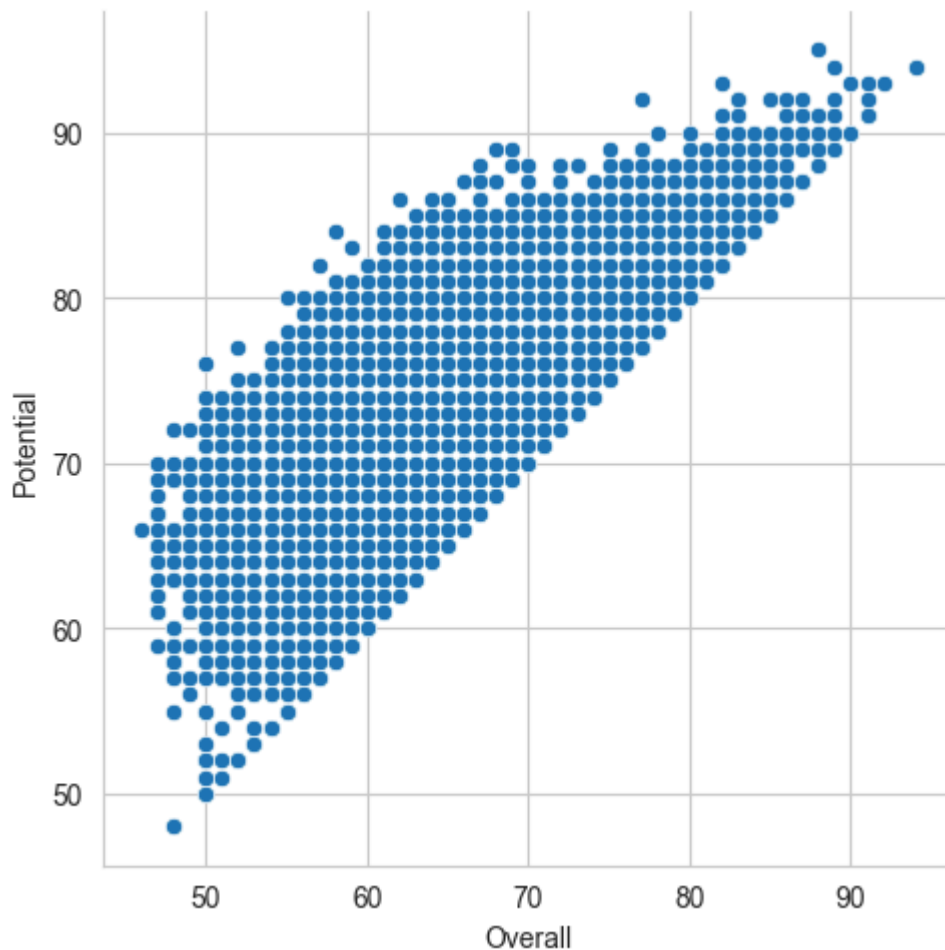
### Seaborn `relplot()` function

- 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 `Height` and `Weight` with Seaborn `relplot()` function as follows-

```
In [167... g = sns.relplot(x="Overall", y="Potential", data=fifa)
```

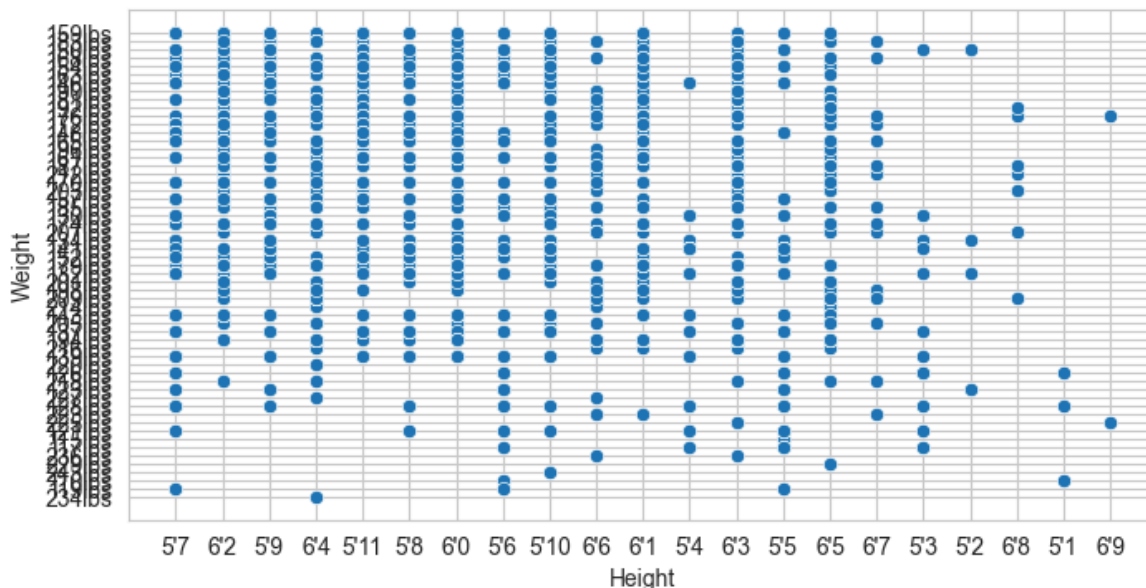
```
In [169... plt.show()
```



## 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.

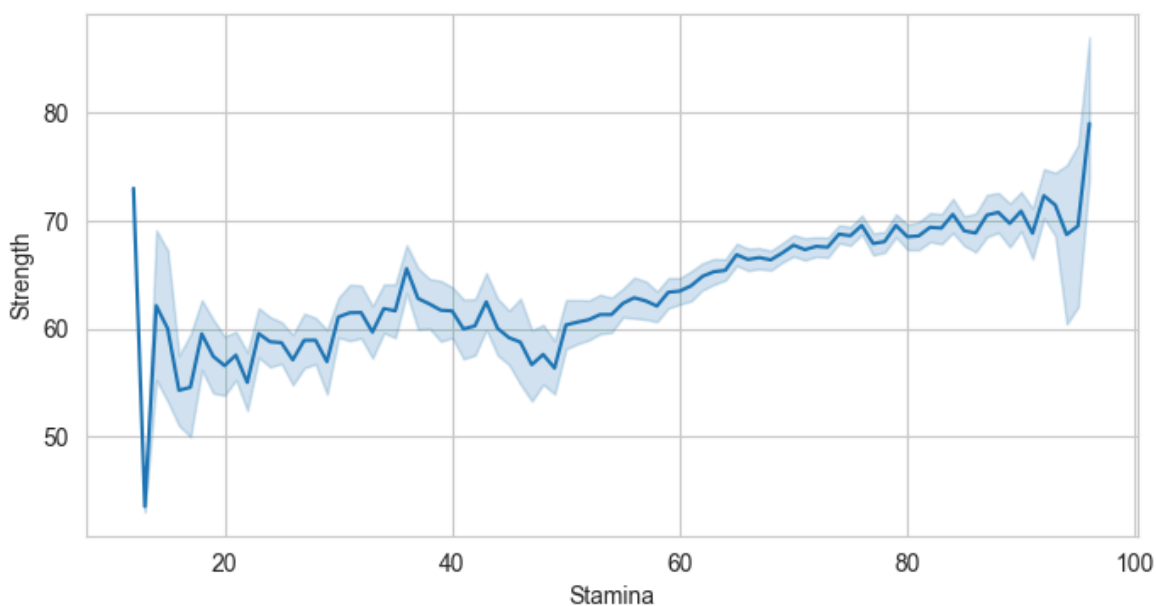
```
In [174... f, ax = plt.subplots(figsize=(8, 4))
sns.scatterplot(x="Height", y="Weight", data=fifa)
plt.show()
```



## 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.

```
In [179... f, ax = plt.subplots(figsize=(8, 4))
ax = sns.lineplot(x="Stamina", y="Strength", data=fifa)
plt.show()
```

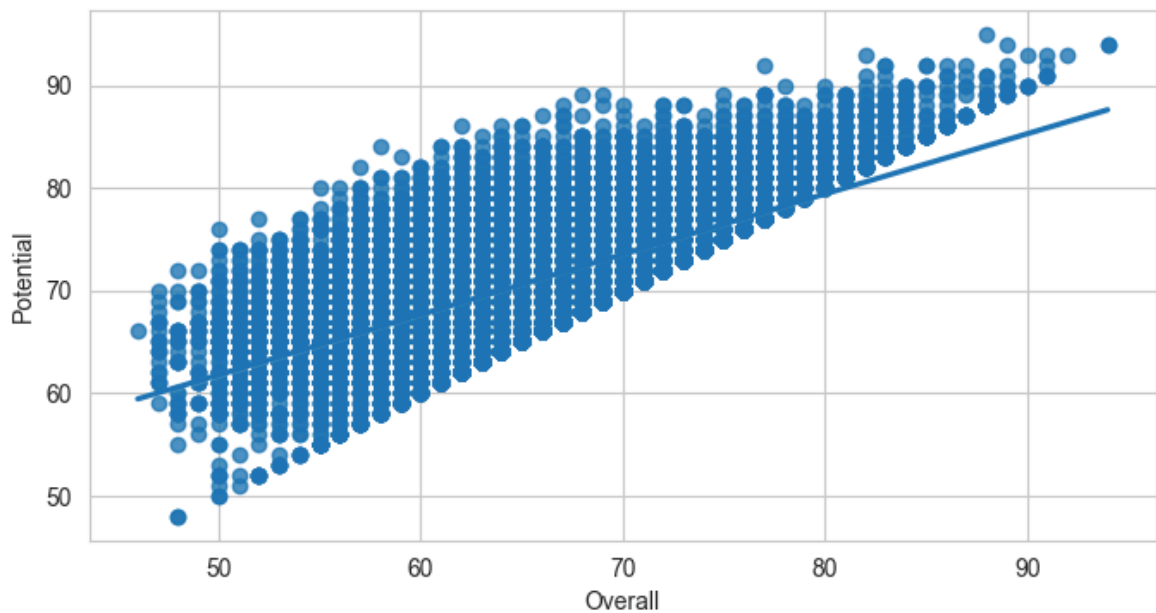


## Visualize linear relationship with Seaborn `regplot()` function

## Seaborn `regplot()` function

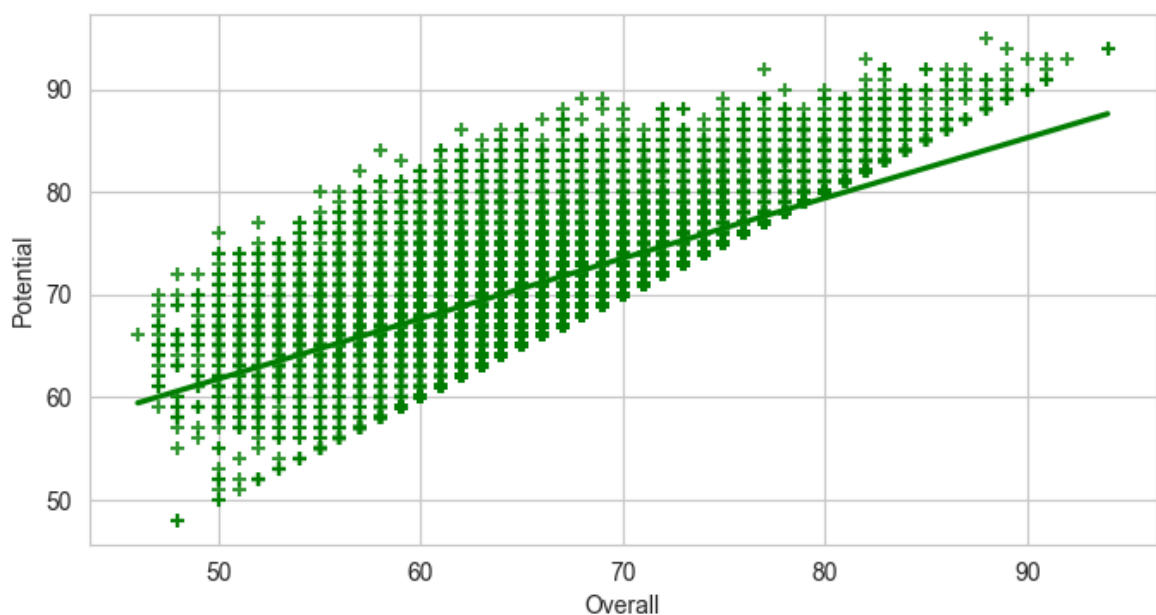
- This function plots data and a linear regression model fit.
- We can plot a linear regression model between `Overall` and `Potential` variable with `regplot()` function as follows-

```
In [220... f, ax = plt.subplots(figsize=(8, 4))  
ax = sns.regplot(x="Overall", y="Potential", data=fifa)  
plt.show()
```



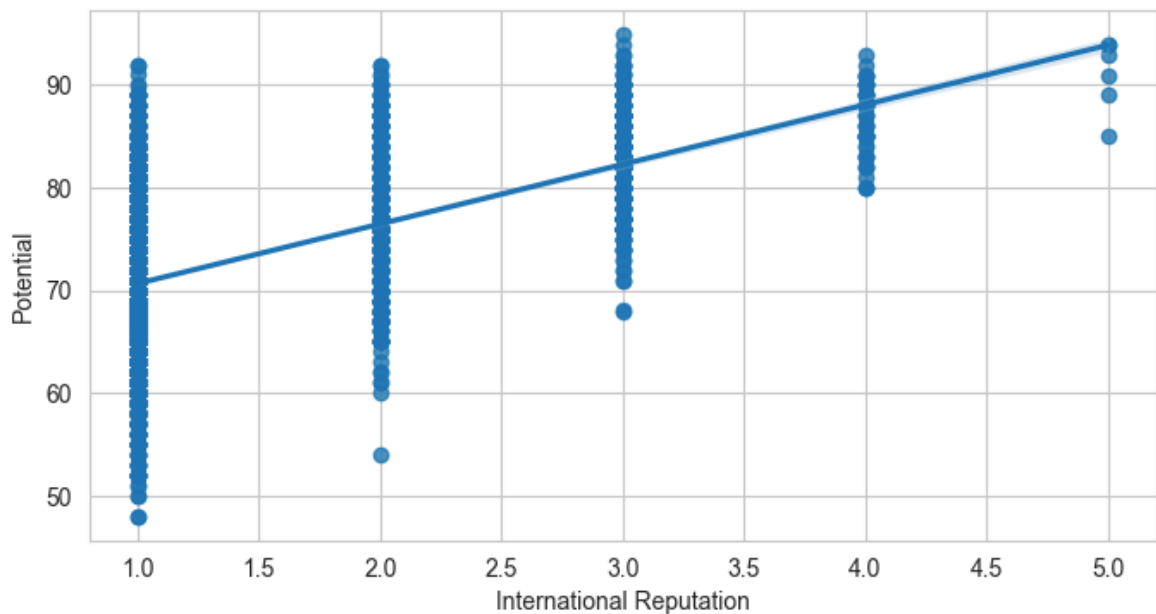
We can use a different color and marker as follows-

```
In [223... f, ax = plt.subplots(figsize=(8, 4))  
ax = sns.regplot(x="Overall", y="Potential", data=fifa, color="g", marker="+")  
plt.show()
```



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

```
In [226... f, ax = plt.subplots(figsize=(8, 4))
sns.regplot(x="International Reputation", y="Potential", data=fifa, y_jitter=.01)
plt.show()
```

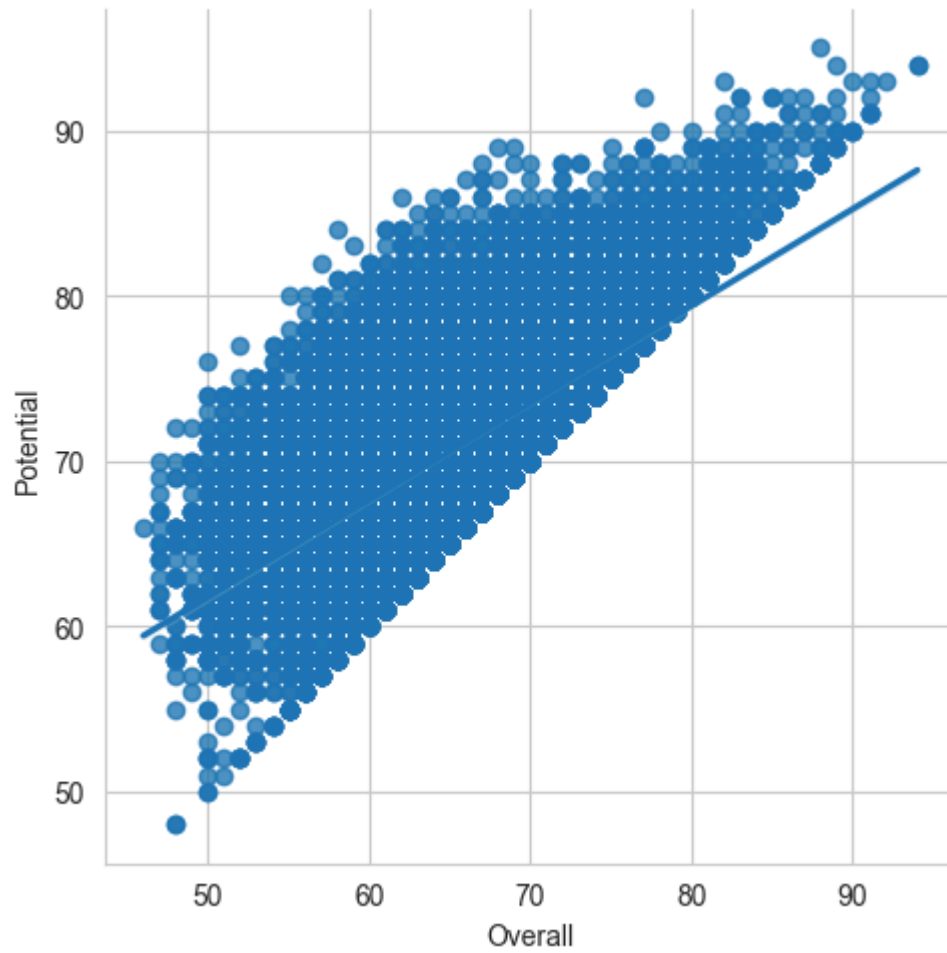


## Seaborn `lplot()` function

- 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 `lplot()` function as follows-

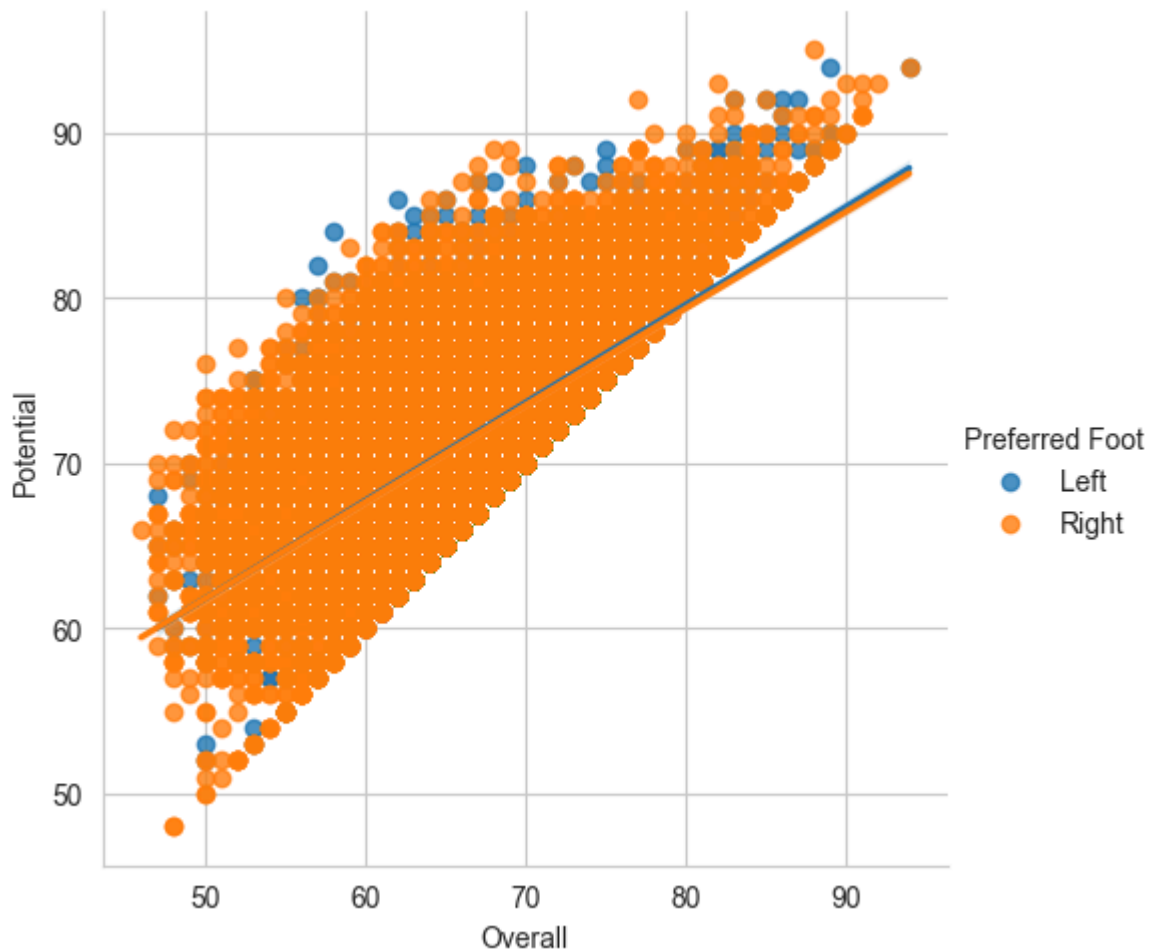
```
In [229... g = sns.lplot(x="Overall", y="Potential", data=fifa)
plt.show()
```





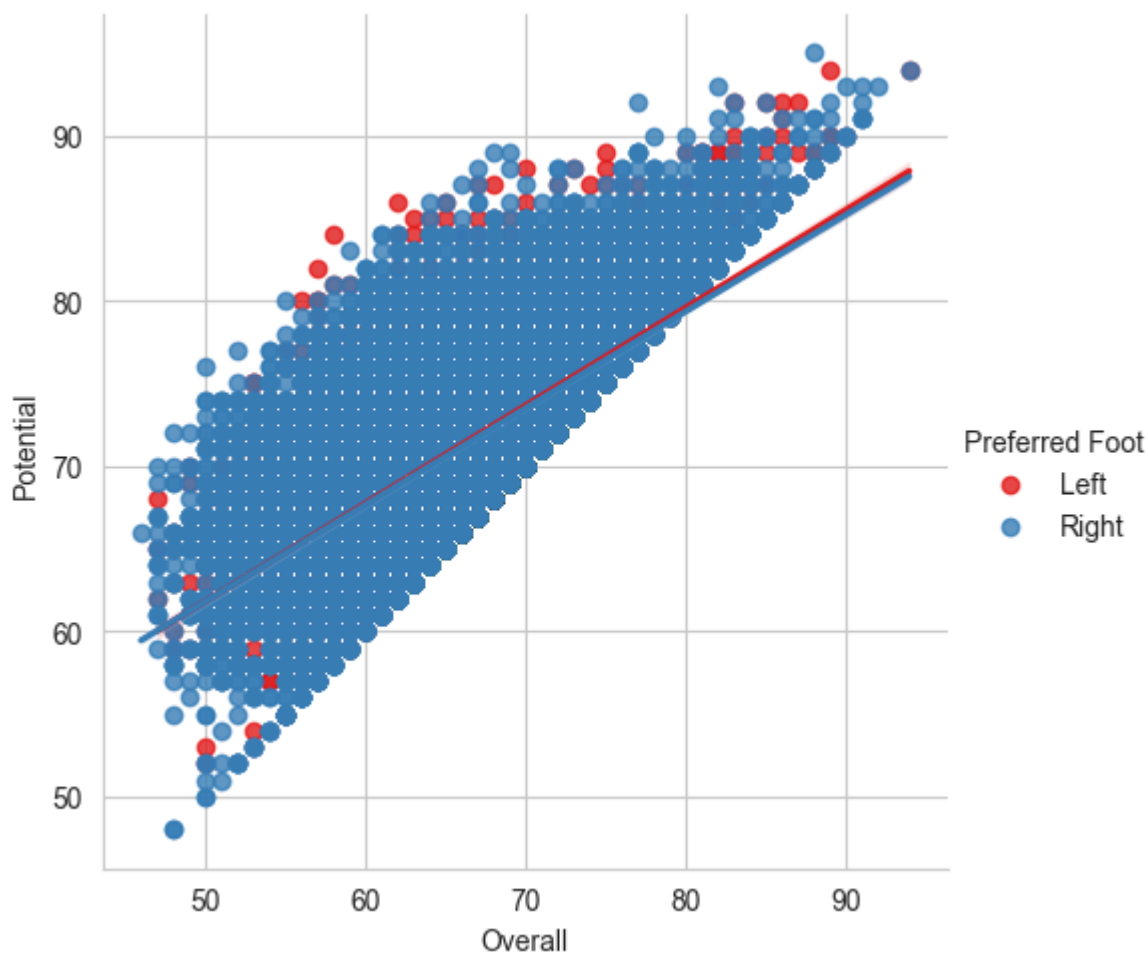
We can condition on a third variable and plot the levels in different colors as follows-

```
In [232... g= sns.lmplot(x="Overall", y="Potential", hue="Preferred Foot", data=fifa)
plt.show()
```



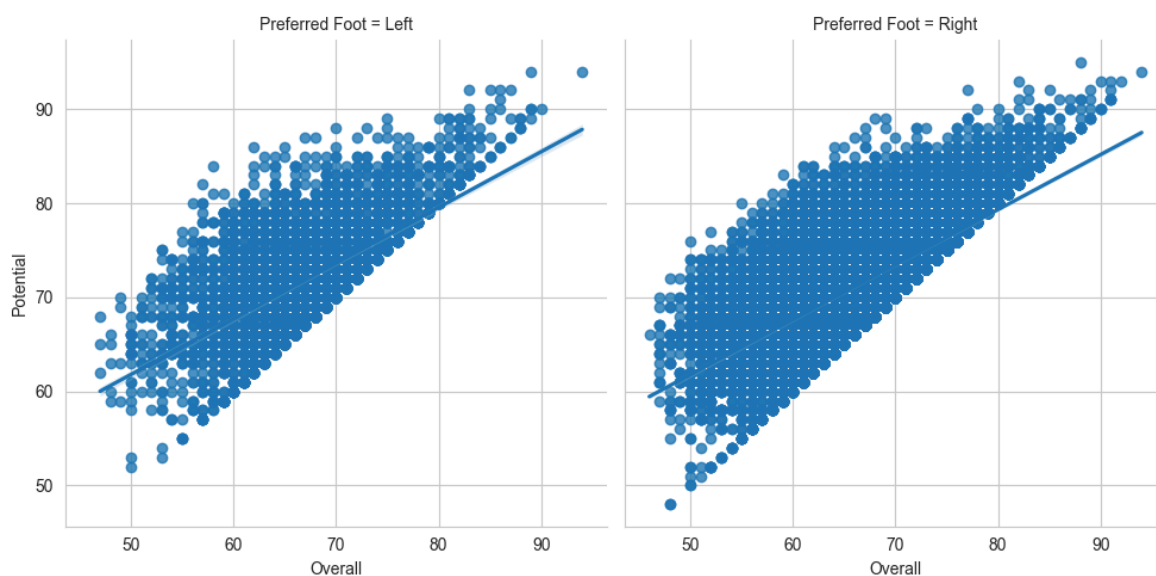
We can use a different color palette as follows-

```
In [246... g= sns.lmplot(x="Overall", y="Potential", hue="Preferred Foot", data=fifa, palet  
plt.show()
```



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

```
In [270... g= sns.lmplot(x="Overall", y="Potential", col="Preferred Foot", data=fifa)
plt.show()
```



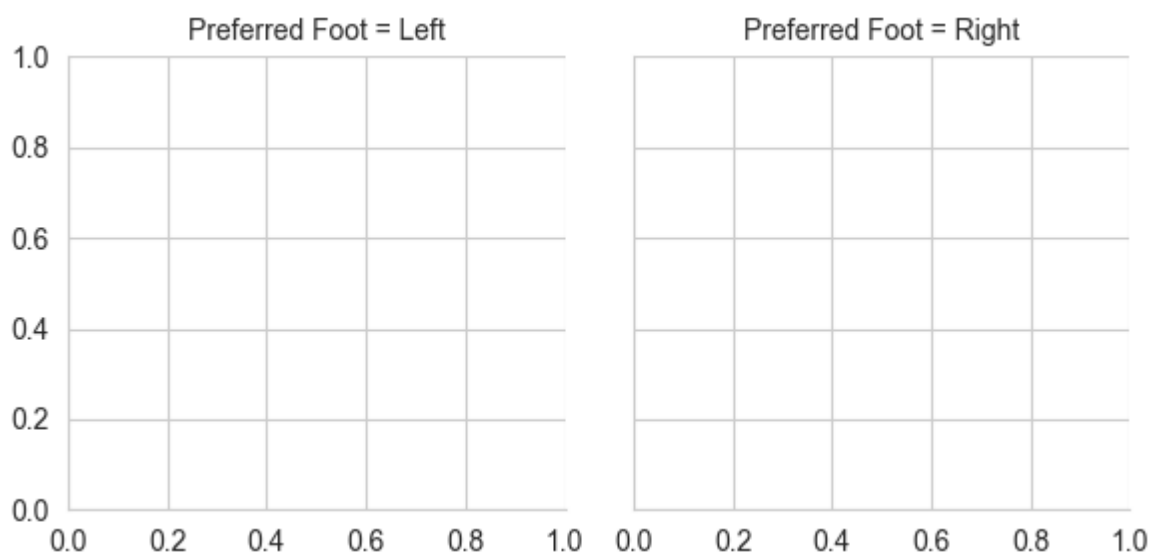
## Multi-plot grids

### 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.

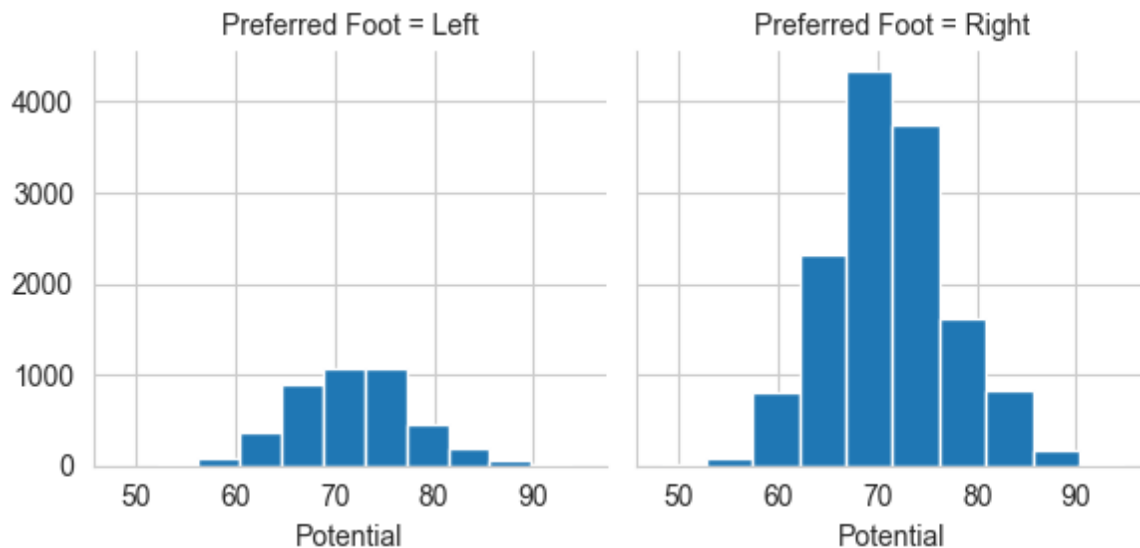
We can initialize a 1x2 grid of facets using the fifa dataset.

```
In [286... g = sns.FacetGrid(fifa, col="Preferred Foot")  
plt.show()
```

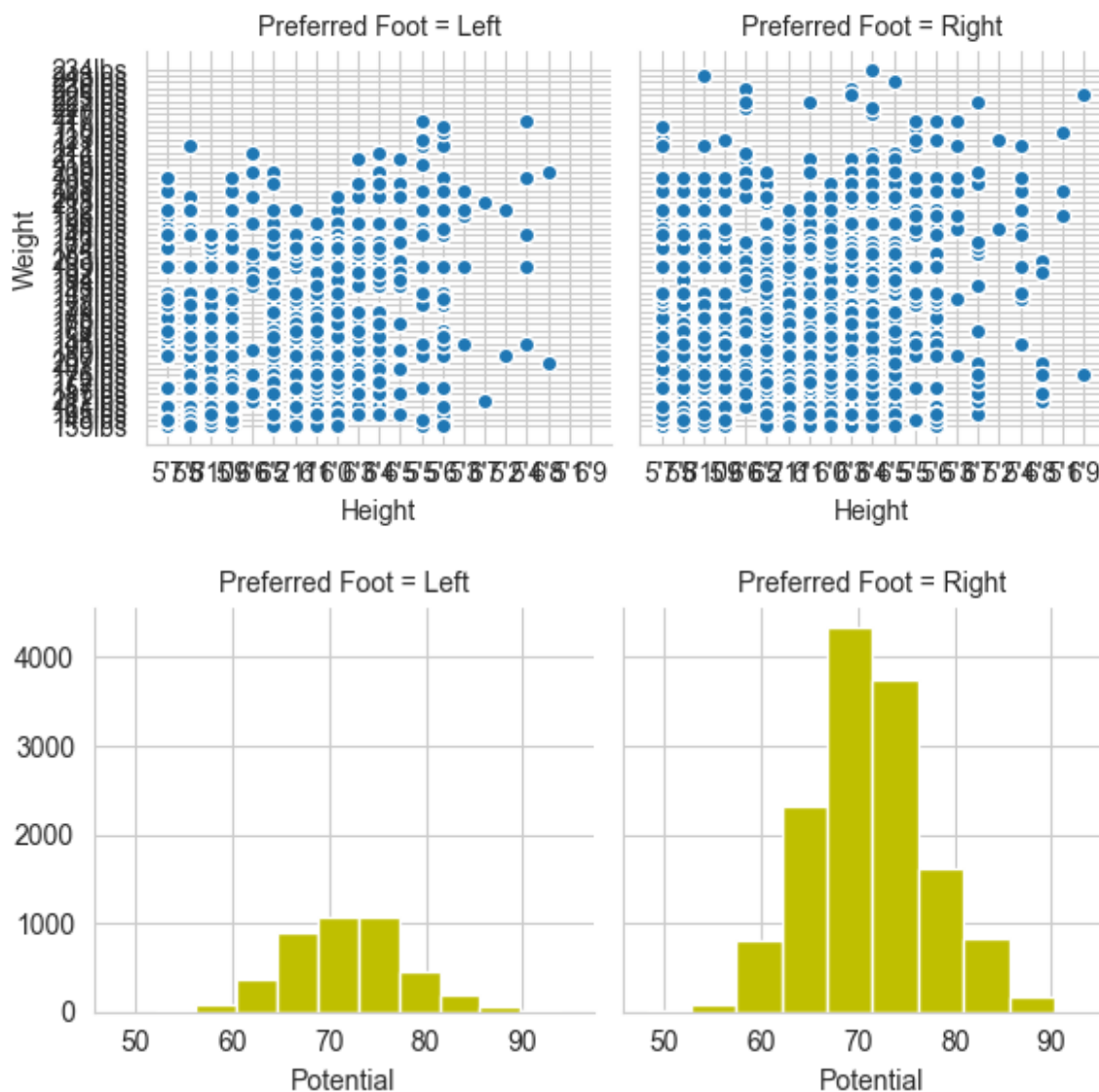


We can draw a univariate plot of `Potential` variable on each facet as follows-

```
In [301... g = sns.FacetGrid(fifa, col="Preferred Foot")  
g = g.map(plt.hist, "Potential")  
plt.show()
```

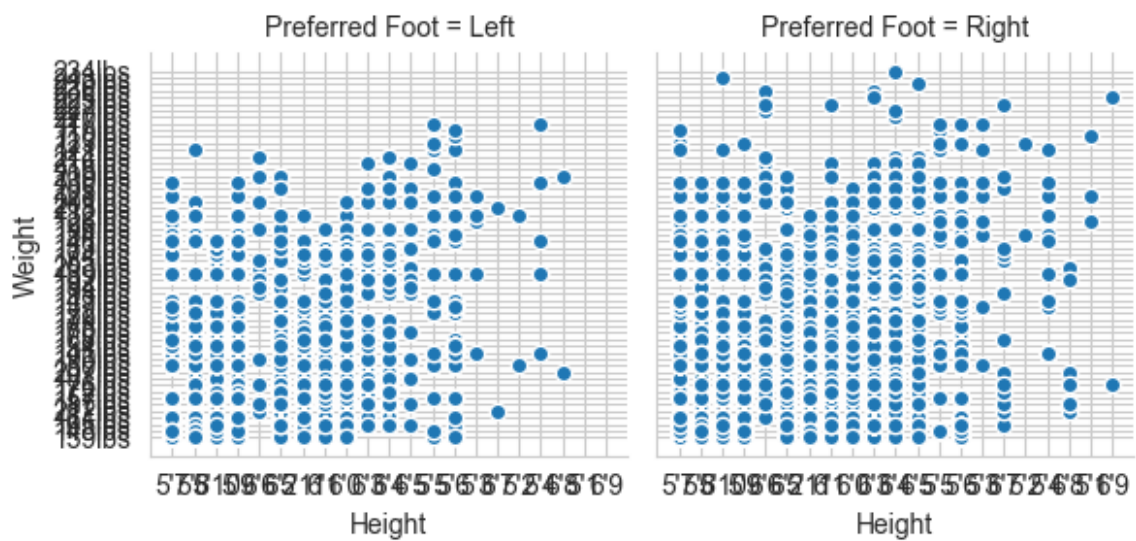


```
In [308... g = sns.FacetGrid(fifa, col="Preferred Foot")
g = g.map(plt.hist, "Potential", bins=10, color="y")
plt.show()
```



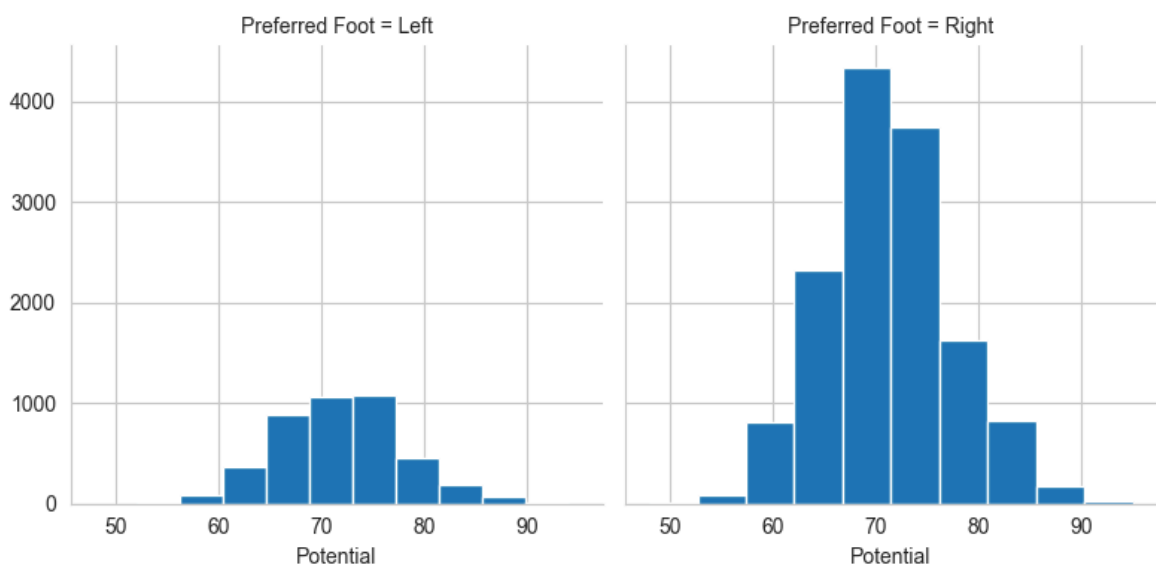
We can plot a bivariate function on each facet as follows-

```
In [310... g = sns.FacetGrid(fifa, col="Preferred Foot")
g = (g.map(plt.scatter, "Height", "Weight", edgecolor="w")).add_legend()
plt.show()
```



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

```
In [318... g = sns.FacetGrid(fifa, col="Preferred Foot", height=4, aspect=1)
g = g.map(plt.hist, "Potential")
plt.show()
```



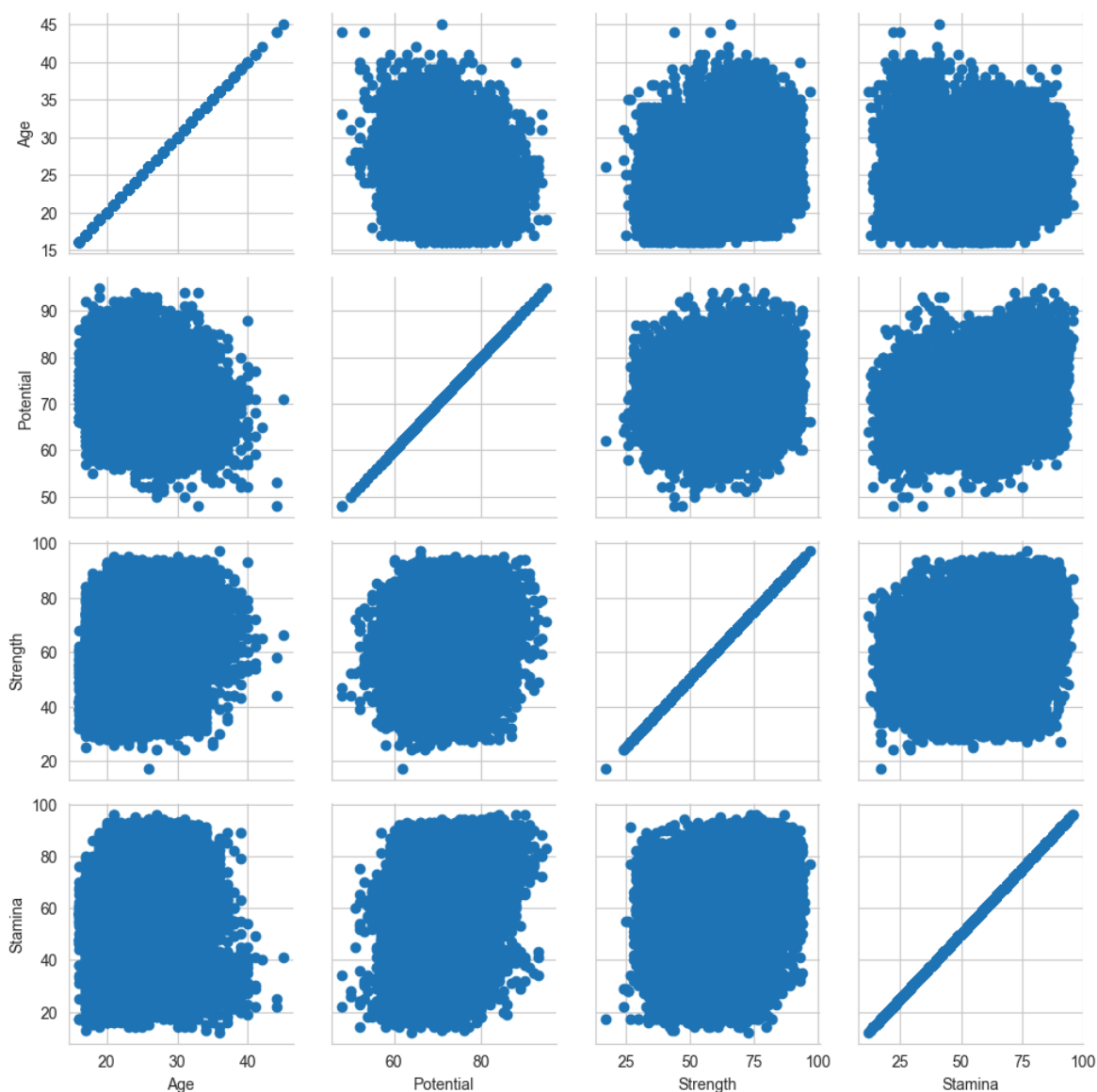
## Seaborn `Pairgrid()` function

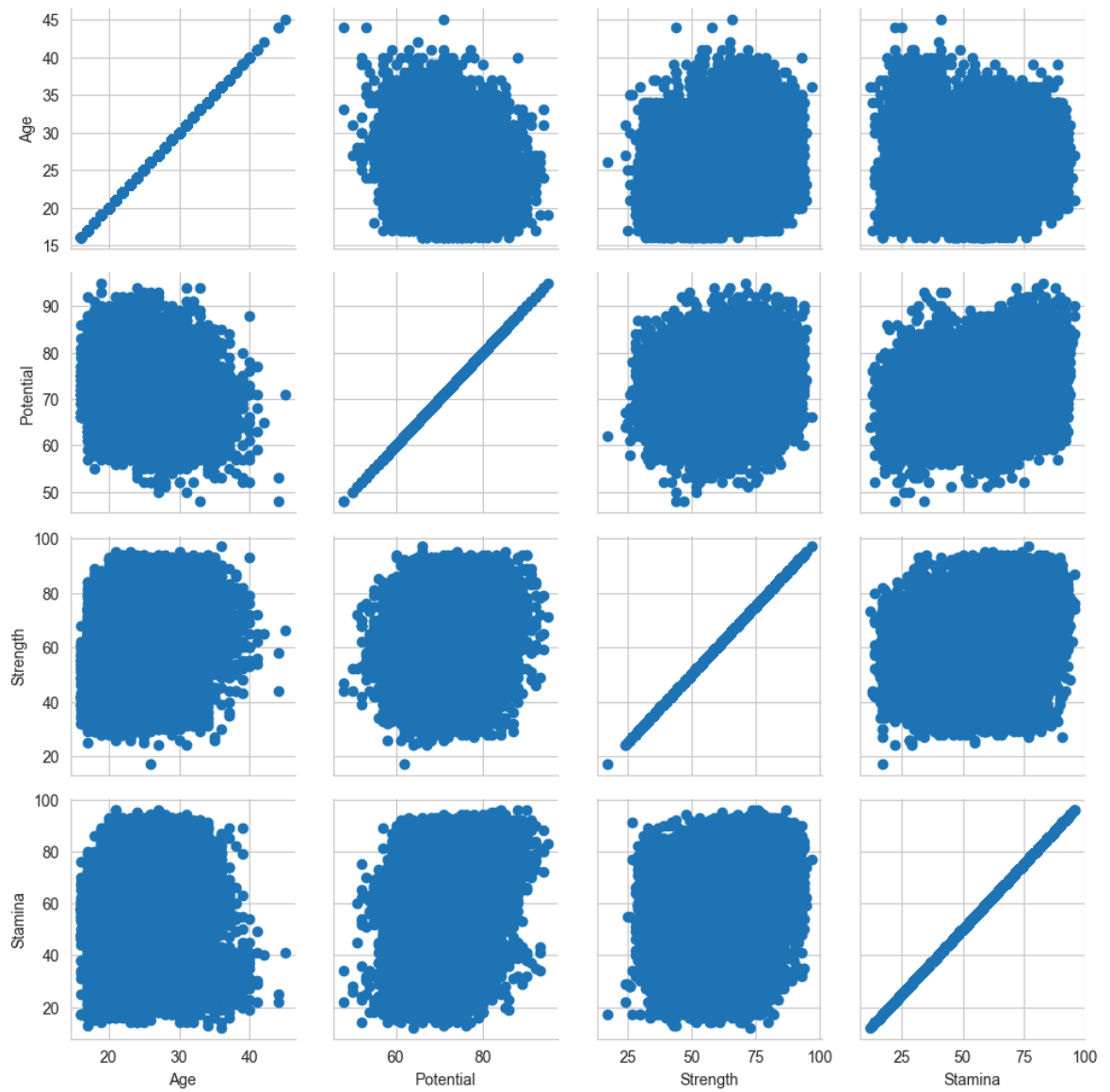
- This function plots subplot grid for plotting pairwise relationships in a dataset.
- This class maps each variable in a dataset onto a column and row in a grid of multiple axes.
- Different axes-level plotting functions can be used to draw bivariate plots in the upper and lower triangles, and the the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

```
In [325... fifa_new = fifa[['Age', 'Potential', 'Strength', 'Stamina', 'Preferred Foot']]
```

```
In [327... g = sns.PairGrid(fifa_new)  
g = g.map(plt.scatter)  
plt.show()
```

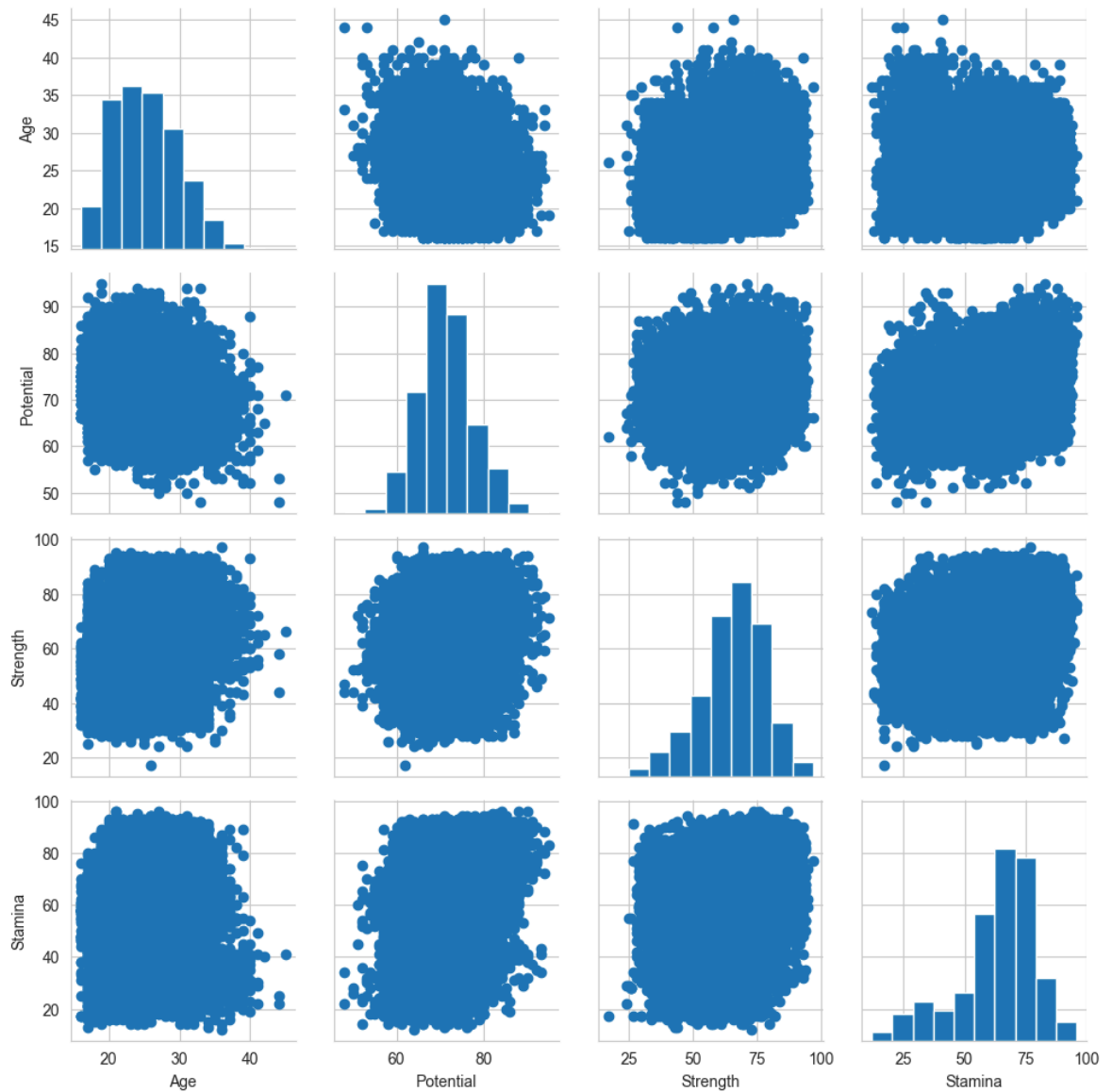




We can show a univariate distribution on the diagonal as follows-

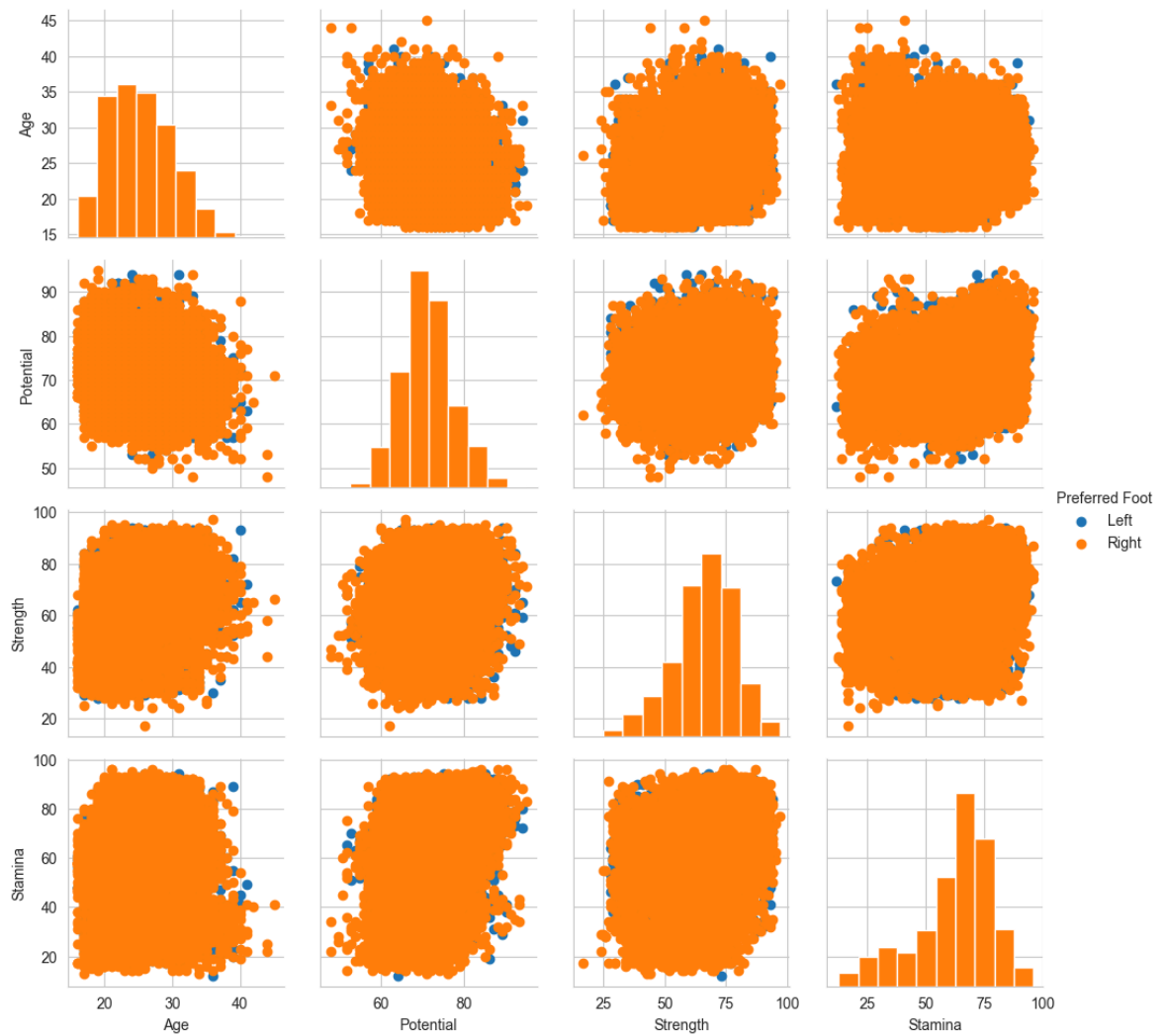
```
In [330... g = sns.PairGrid(fifa_new)
g = g.map_diag(plt.hist)
g = g.map_offdiag(plt.scatter)
plt.show()
```





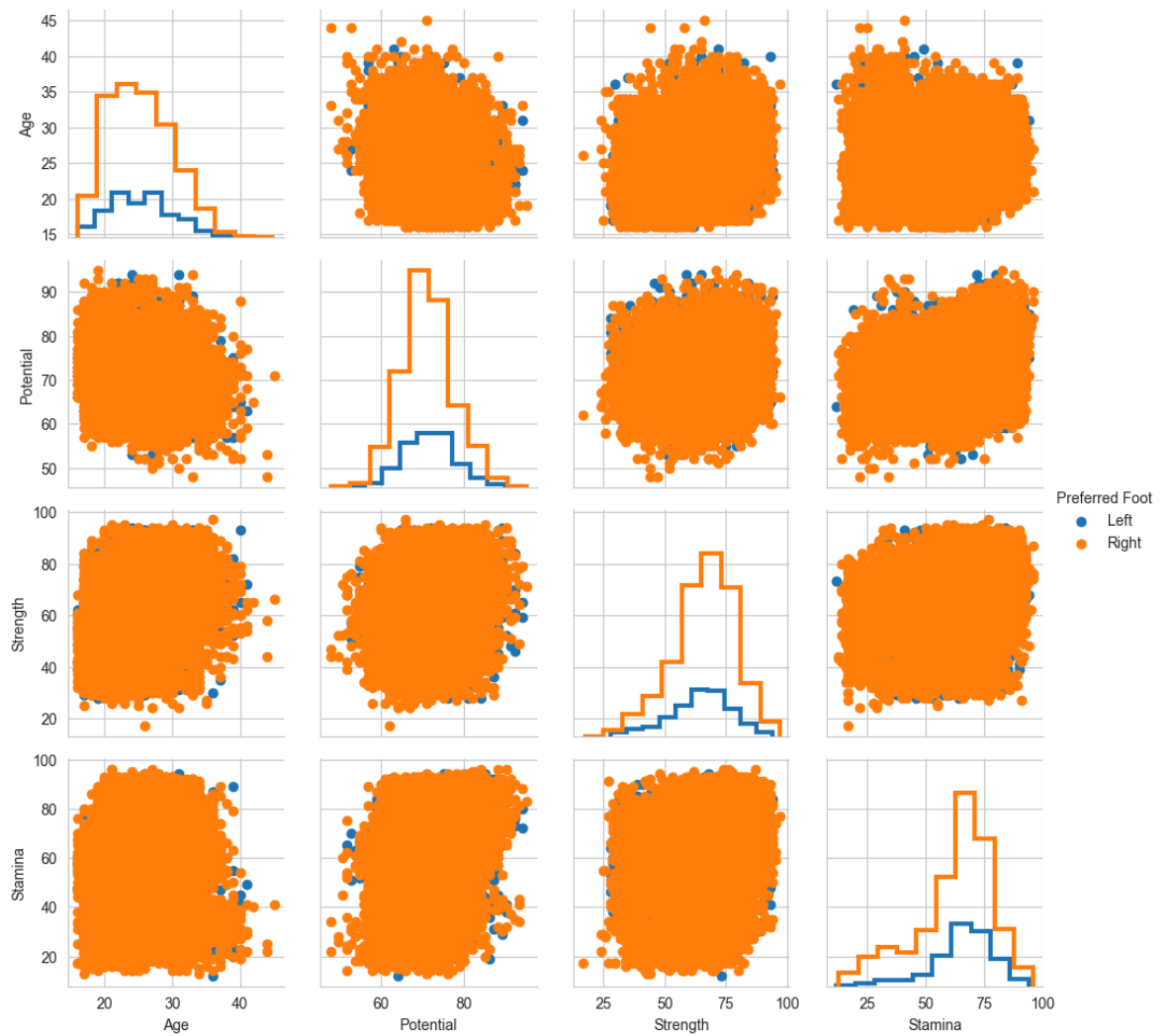
We can color the points using the categorical variable `Preferred Foot` as follows -

```
In [333... g = sns.PairGrid(fifa_new, hue="Preferred Foot")
g = g.map_diag(plt.hist)
g = g.map_offdiag(plt.scatter)
g = g.add_legend()
plt.show()
```



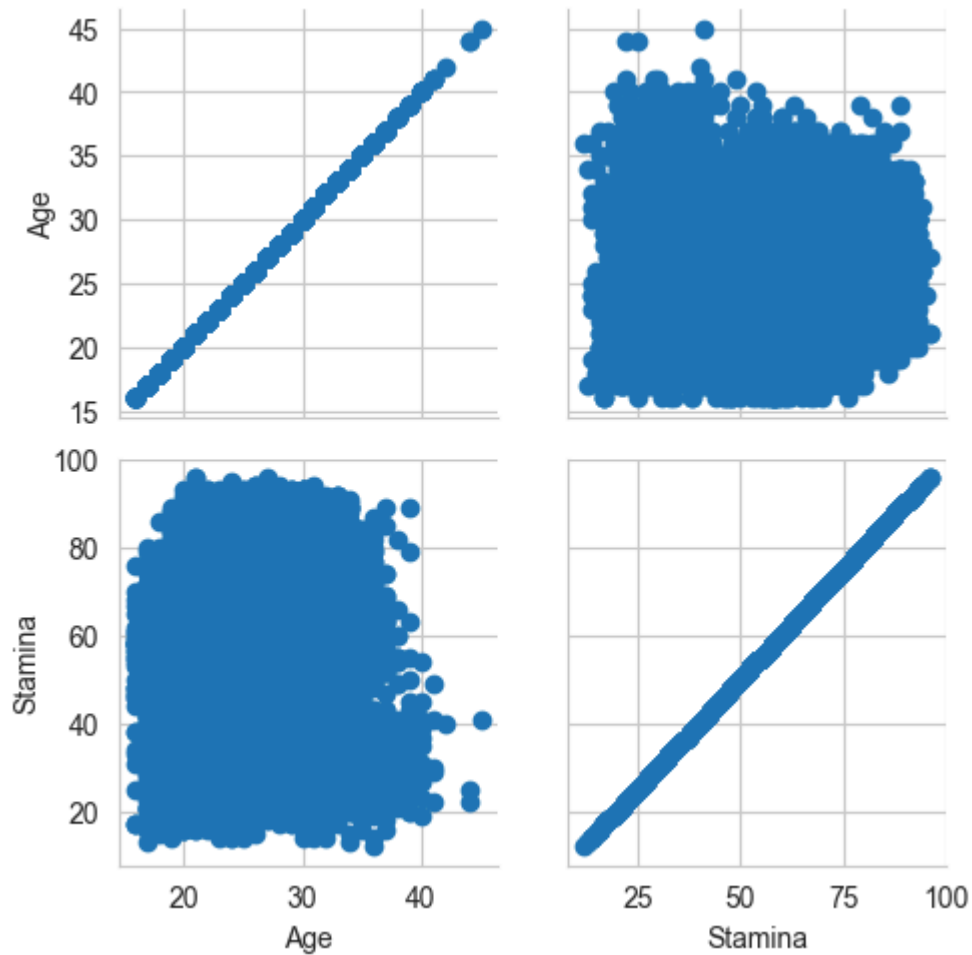
We can use a different style to show multiple histograms as follows-

```
In [336... g = sns.PairGrid(fifa_new, hue="Preferred Foot")
g = g.map_diag(plt.hist, histtype="step", linewidth=3)
g = g.map_offdiag(plt.scatter)
g = g.add_legend()
plt.show()
```



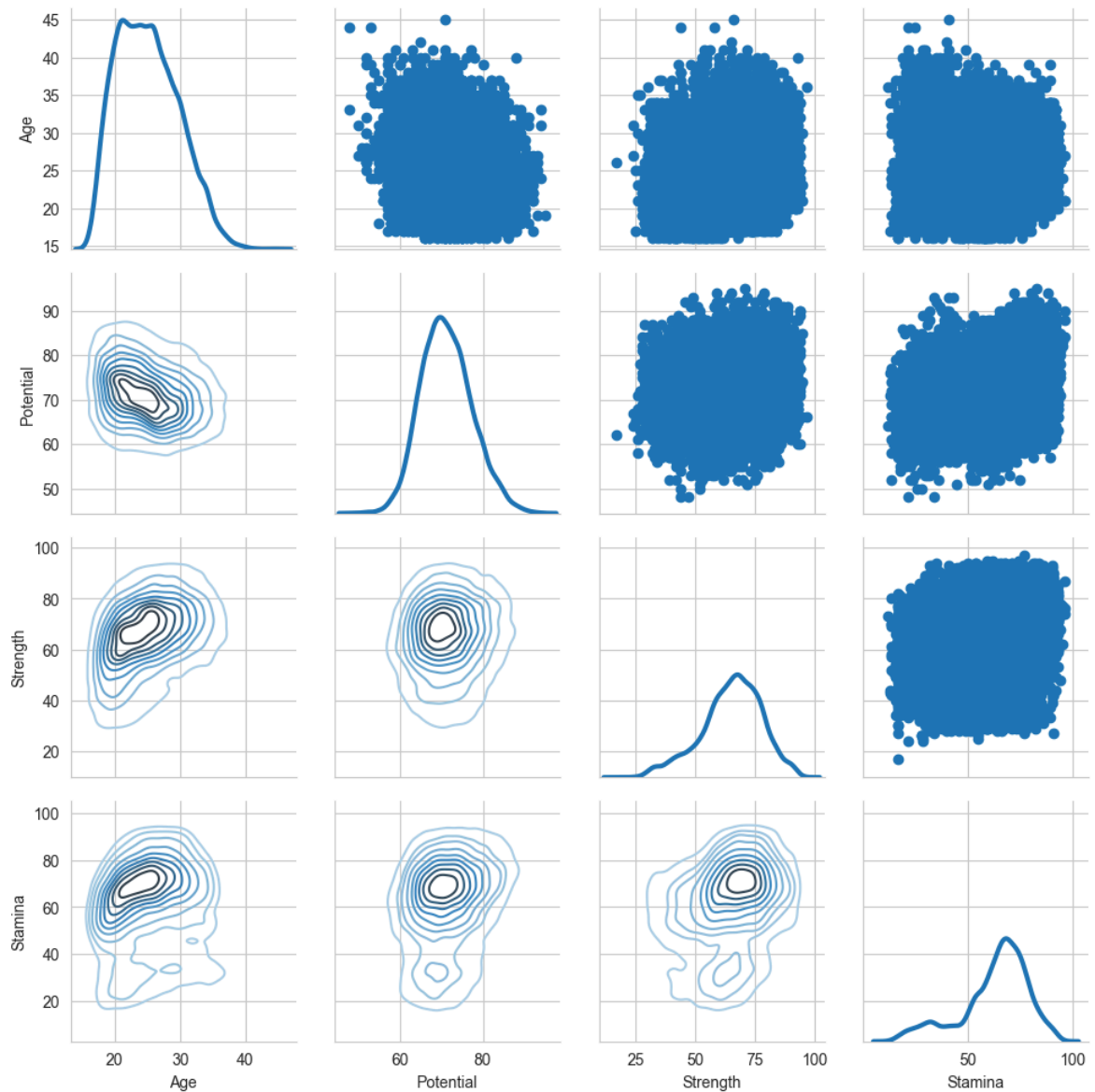
We can plot a subset of variables as follows-

```
In [339... g = sns.PairGrid(fifa_new, vars=['Age', 'Stamina'])
g = g.map(plt.scatter)
plt.show()
```



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

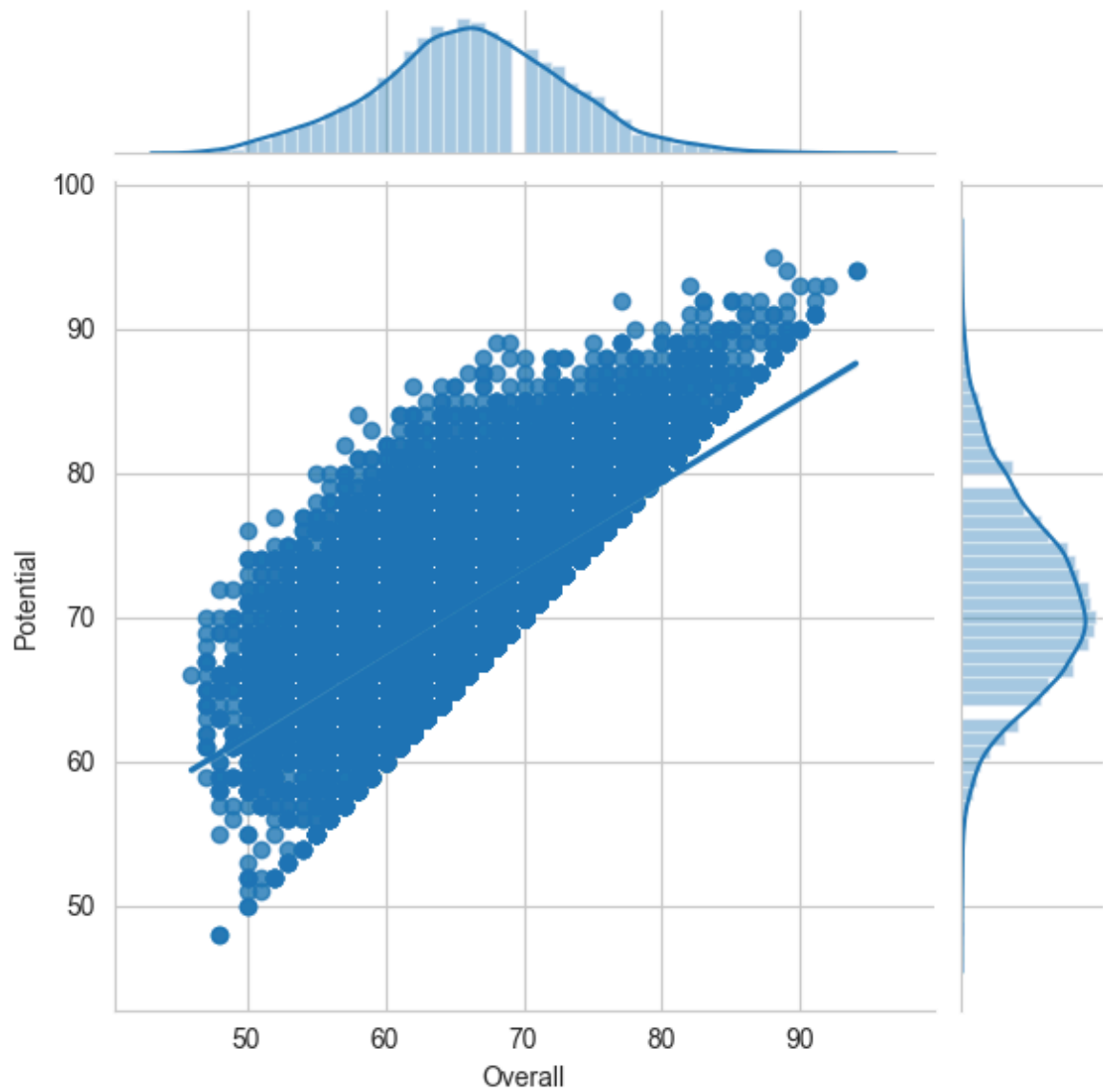
```
In [342... g = sns.PairGrid(fifa_new)
g = g.map_upper(plt.scatter)
g = g.map_lower(sns.kdeplot, cmap="Blues_d")
g = g.map_diag(sns.kdeplot, lw=3, legend=False)
plt.show()
```



## Seaborn `JointGrid()` function

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

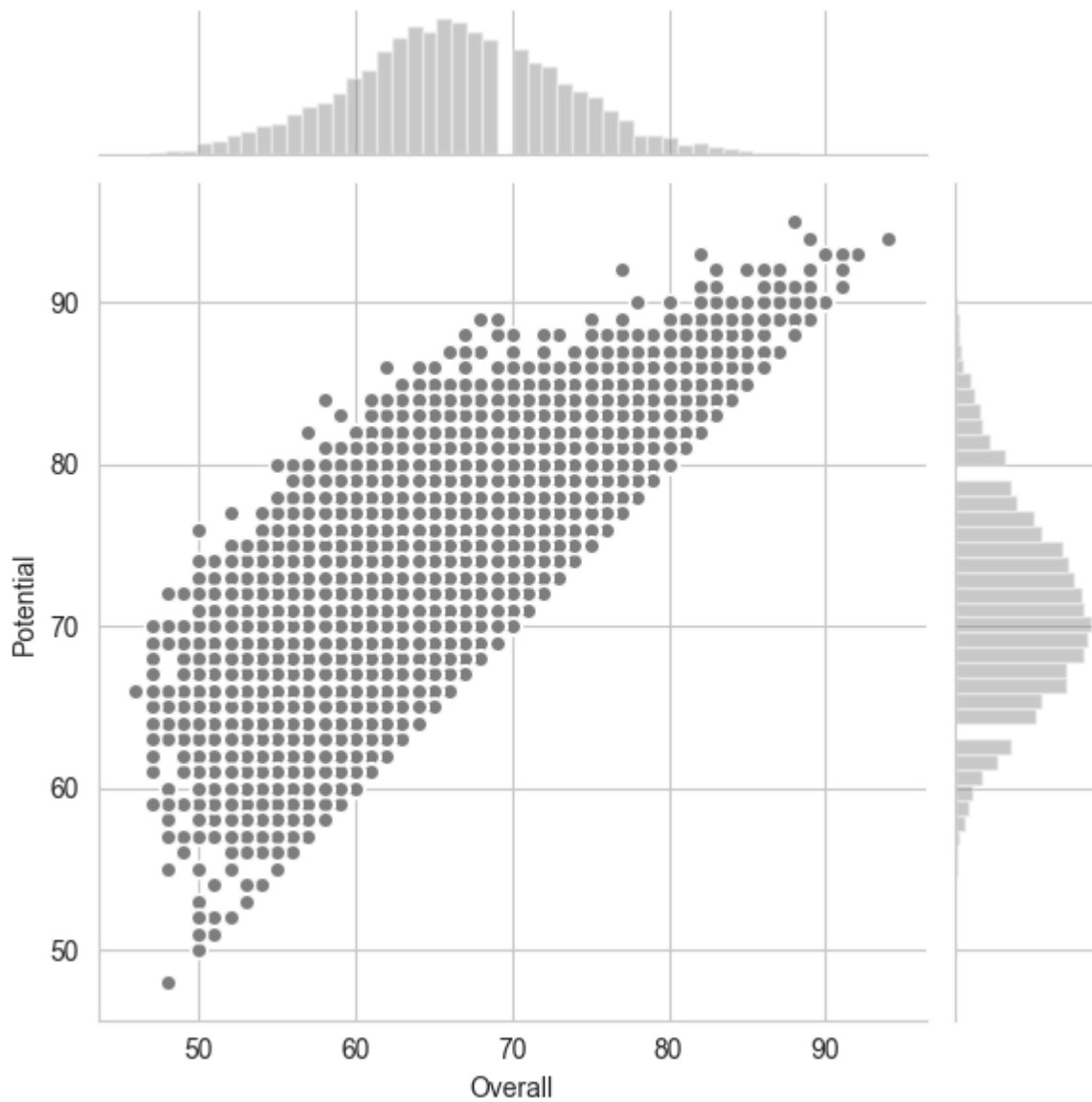
```
In [346... g = sns.JointGrid(x="Overall", y="Potential", data=fifa)
g = g.plot(sns.regplot, sns.distplot)
plt.show()
```



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

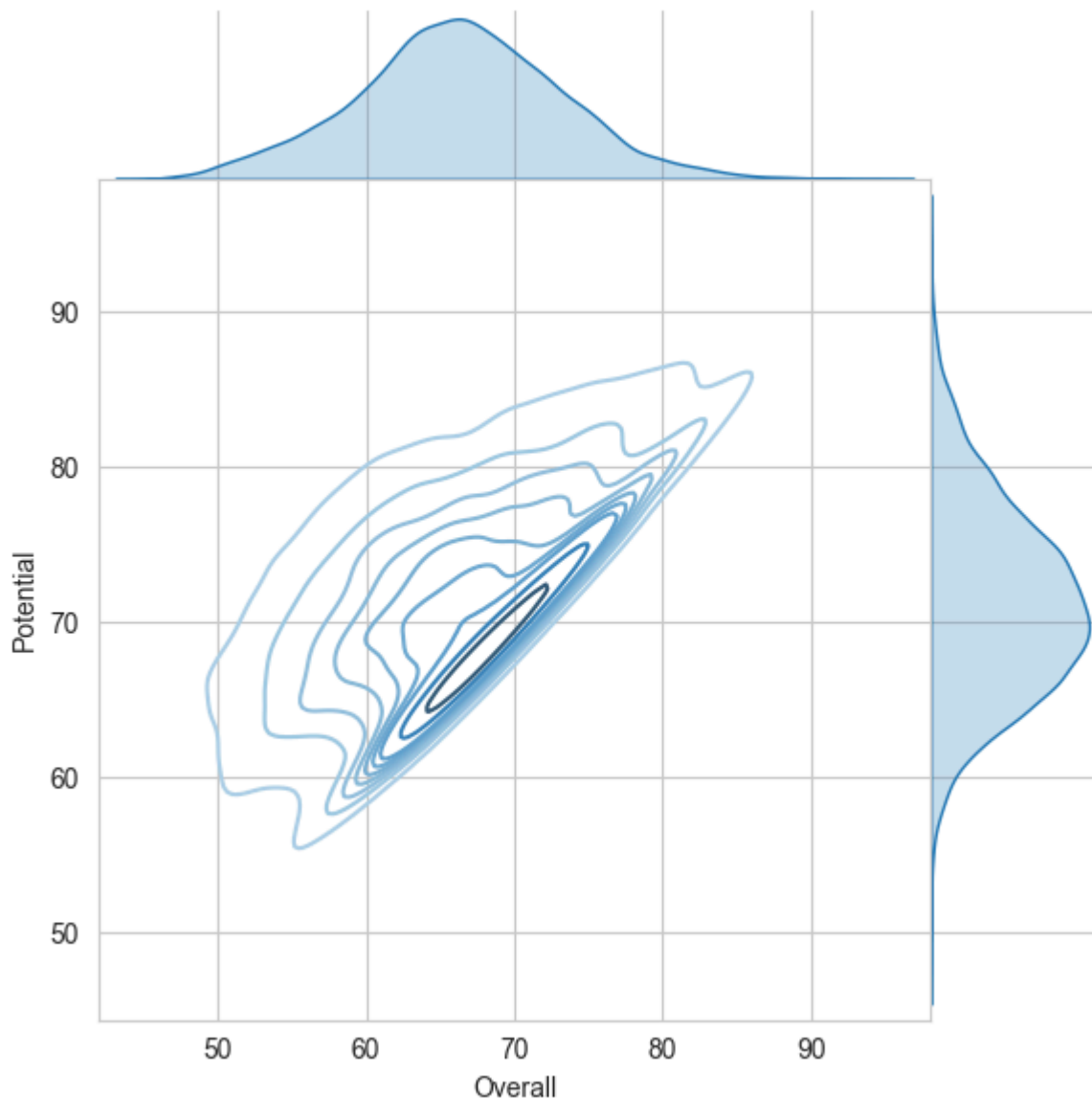
```
In [350...] import matplotlib.pyplot as plt
```

```
In [352...] g = sns.JointGrid(x="Overall", y="Potential", data=fifa)
g = g.plot_joint(plt.scatter, color=".5", edgecolor="white")
g = g.plot_marginals(sns.distplot, kde=False, color=".5")
plt.show()
```



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

```
In [355... g = sns.JointGrid(x="Overall", y="Potential", data=fifa, space=0)
g = g.plot_joint(sns.kdeplot, cmap="Blues_d")
g = g.plot_marginals(sns.kdeplot, shade=True)
plt.show()
```



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

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

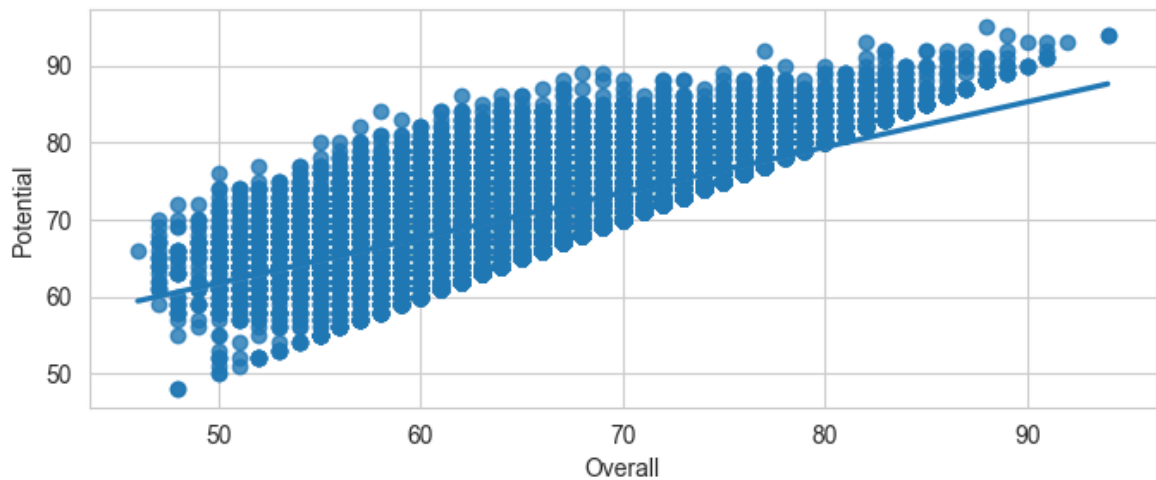
## Controlling the size and shape of the plot

- The default plots made by `regplot()` and `lmpplot()` 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.



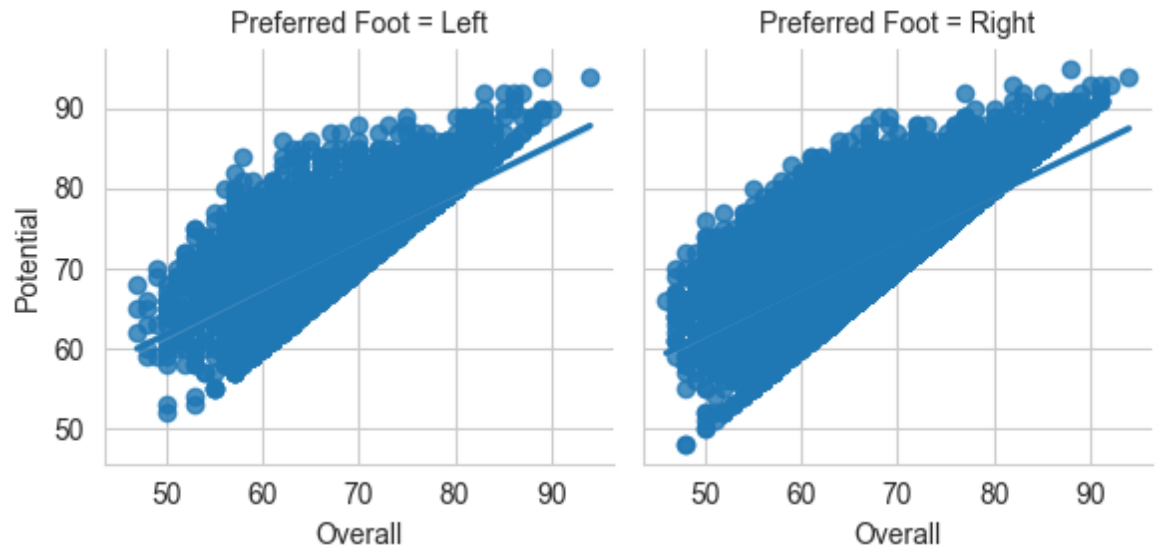
- To control the size, we need to create a figure object ourself as follows-

```
In [382... f, ax = plt.subplots(figsize=(8, 3))
ax = sns.regplot(x="Overall", y="Potential", data=fifa)
plt.show()
```



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.

```
In [392... sns.lmplot(x="Overall", y="Potential", col="Preferred Foot", data=fifa, col_wrap
plt.show())
```



## 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`.

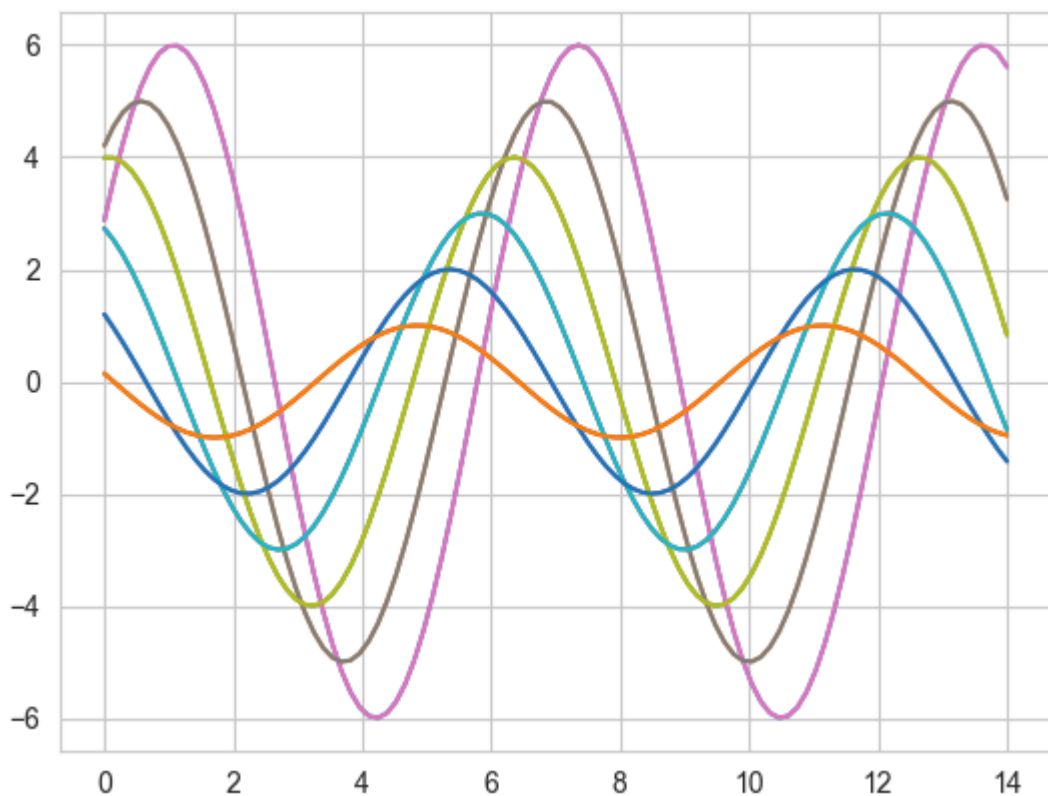
- The grid helps the plot serve as a lookup table for quantitative information, and the white-on grey helps to keep the grid from competing with lines that represent data.
- The whitegrid theme is similar, but it is better suited to plots with heavy data elements:

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

```
In [397... 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)
```

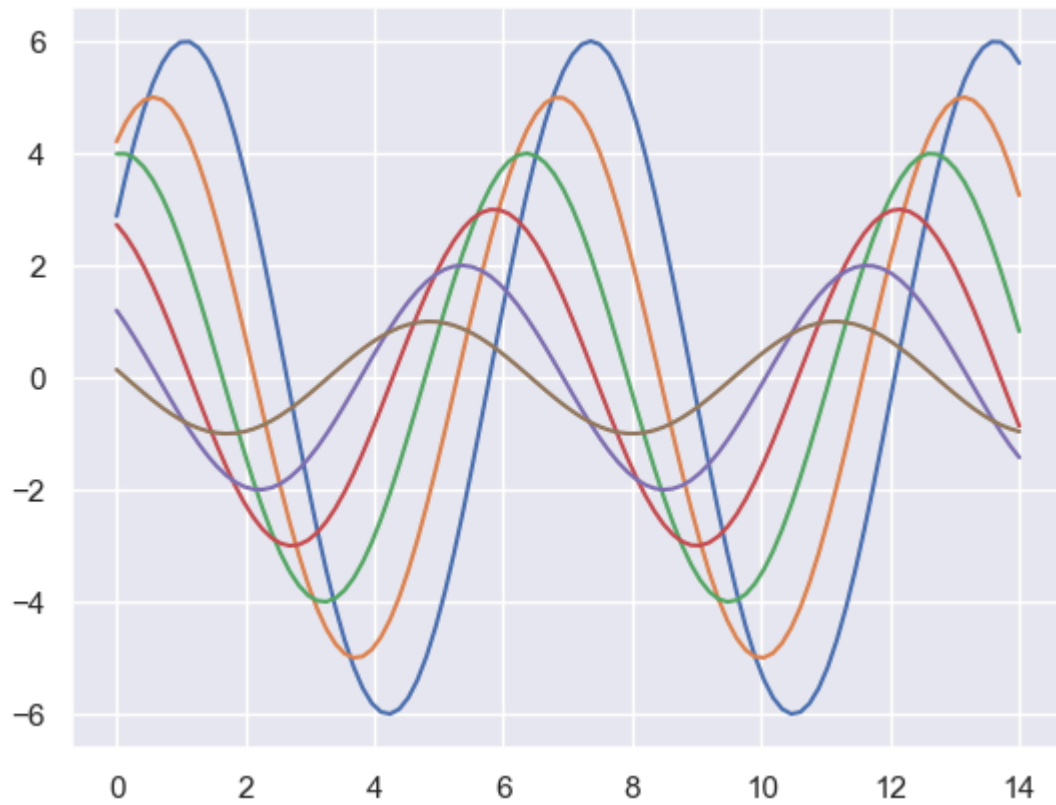
This is what the plot looks like with matplotlib default parameters.

```
In [400... sinplot()
plt.show()
```



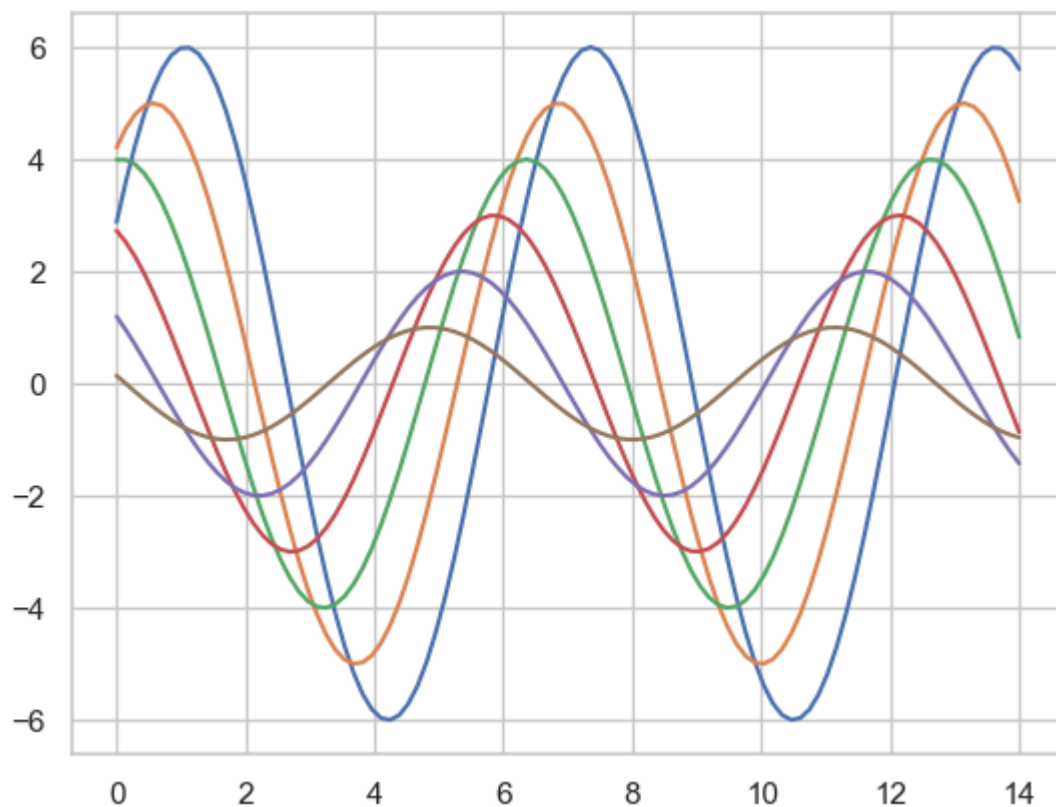
To switch to seaborn defaults, we need to call the `set()` function as follows -

```
In [403... sns.set()
sinplot()
plt.show()
```



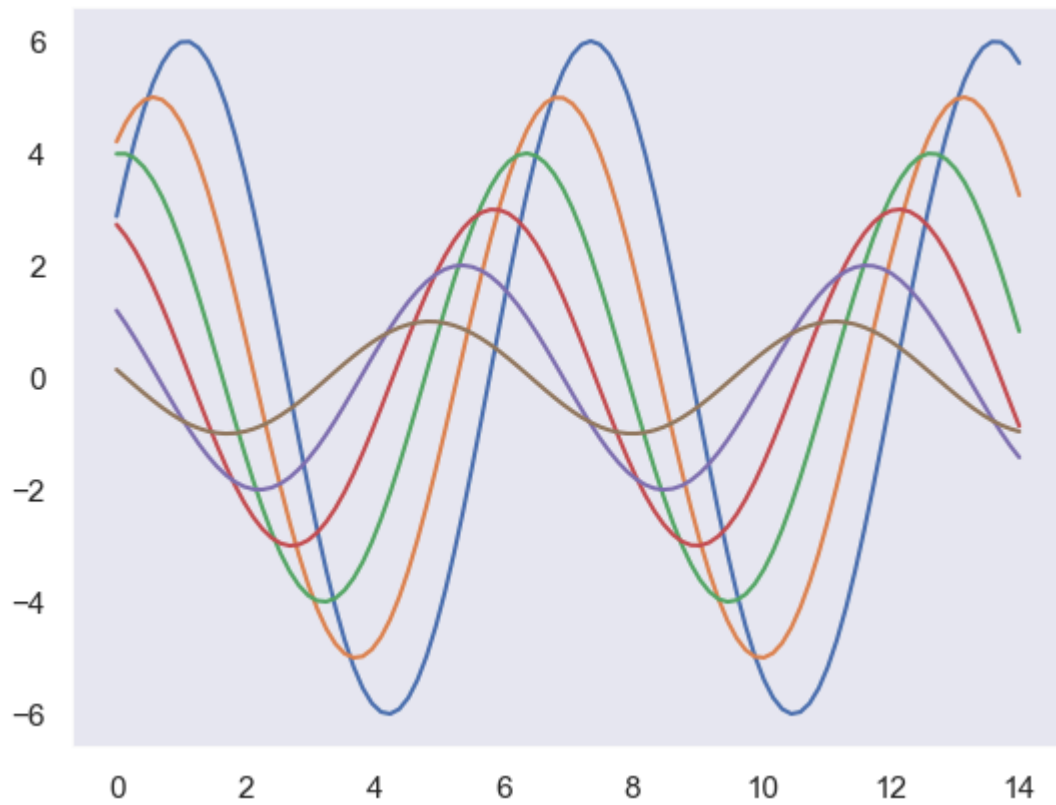
- We can set different styles as follows -

```
In [406... sns.set_style("whitegrid")  
sinplot()  
plt.show()
```



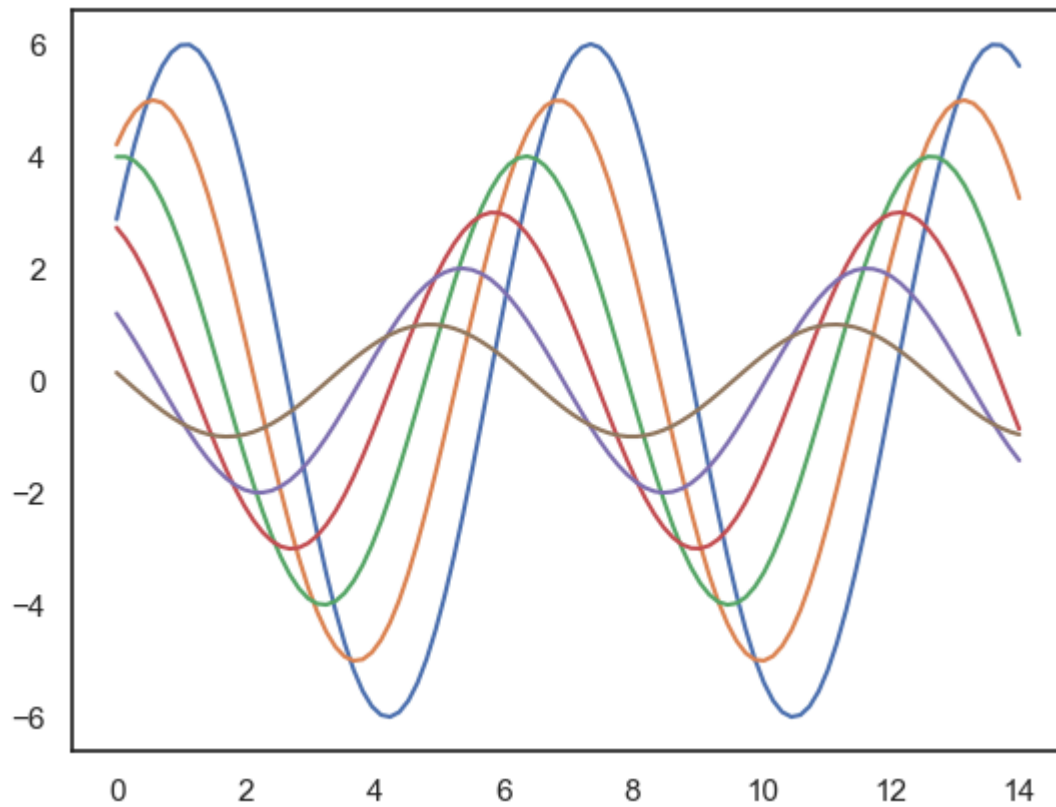
```
In [409... sns.set_style("dark")  
sinplot()
```

```
plt.show()
```



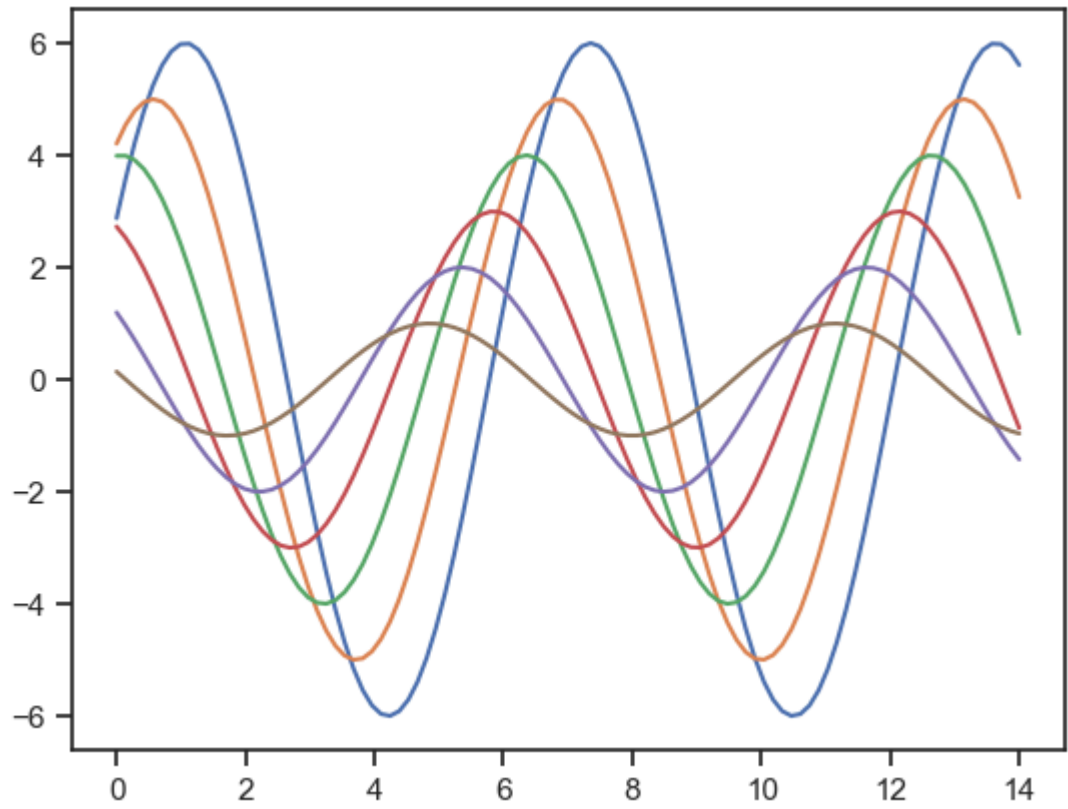
In [411...

```
sns.set_style("white")  
sinplot()  
plt.show()
```



In [413...

```
sns.set_style("ticks")  
sinplot()  
plt.show()
```



In [ ]:

In [ ]: