Simple Linear Regression

In this example, we will consider sales based on 'TV' marketing budget.
We'll build a linear regression model to predict 'Sales' using 'TV' as the predictor variable.

Understanding the data

Import pandas

In [1]:
```
import pandas as pd
```

Read the dataset with pandas

In [2]:
```
df = pd.read_csv('tvmarketing.csv')
```

View the first five rows of the dataset

In [3]:
```
df.head()
```

Out[3]:

	TV	Sales
0	230.1	22.1
1	44.5	10.4
2	17.2	9.3
3	151.5	18.5
4	180.8	12.9

View the last 5 rows

In [4]:
```
df.tail()
```

Out[4]:

	TV	Sales
195	38.2	7.6
196	94.2	9.7
197	177.0	12.8
198	283.6	25.5
199	232.1	13.4

Check info about the dataset

In [5]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 200 entries, 0 to 199
Data columns (total 2 columns):
 #   Column  Non-Null Count  Dtype
---  ------  --------------  -----
 0   TV      200 non-null    float64
 1   Sales   200 non-null    float64
dtypes: float64(2)
memory usage: 3.2 KB
```

Check the number of rows and columns in the dataset

In [6]:
```
df.shape
```

Out[6]:
```
(200, 2)
```

Quick view the basic statistical information about the dataset

In [7]:
```
df.describe()
```

Out[7]:

	TV	Sales
count	200.000000	200.000000
mean	147.042500	14.022500
std	85.854236	5.217457
min	0.700000	1.600000
25%	74.375000	10.375000
50%	149.750000	12.900000
75%	218.825000	17.400000
max	296.400000	27.000000

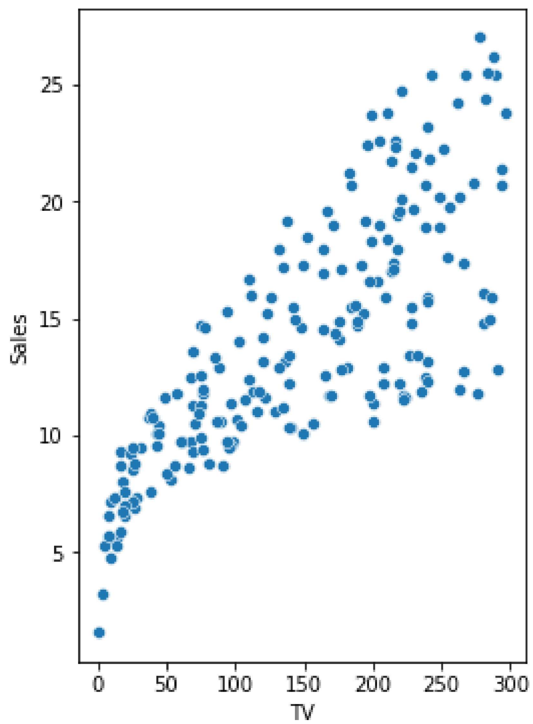
Visualising the data using Seaborn Library

Import Matplotlib, Seaborn and set matplotlib inline

In [8]:
```
import matplotlib.pyplot as plt
import seaborn as sns
%matplotlib inline
```

Visualize the relationship between the features and the response using scatterplots

In [9]:
```
plt.figure(figsize = (4,6))
sns.scatterplot(x = "TV", y = "Sales", data = df)
plt.show()
```



Performing Simple Linear Regression

Equation of linear regression
$y = c + m_1x_1 + m_2x_2 + \ldots + m_nx_n$

- y is the response
- c is the intercept
- m_1 is the coefficient for the first feature
- m_n is the coefficient for the nth feature

In our case:

$y = c + m_1 \times TV$

The m values are called the model **coefficients** or **model parameters**.

Generic Steps in Model Building using `sklearn`

Before you read further, it is good to understand the generic structure of modeling using the scikit-learn library. Broadly, the steps to build any model can be divided as follows:

Preparing X and y (Independent and Dependent variables)

- The scikit-learn library expects X (feature variable) and y (response variable) to be NumPy arrays.
- However, X can be a dataframe as Pandas is built over NumPy.

Assign feature variable(Independent variable) to X

In [10]:
```
X = df[['TV']]
```

Print the first five rows of X

In [11]:
```
X.head()
```

Out[11]:

	TV
0	230.1
1	44.5
2	17.2
3	151.5
4	180.8

Assign response variable(Dependent variable or target variable) to y

In [12]:
```
y = df['Sales']
```

Split the data into Training and testing Sets

In [13]:
```
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X,y , test_size = 0.3, rar
```

In [14]:
```
# random_state is the seed used by the random number generator, it can be any
# If we don't specify a random state integer, we get different training and te
```

In [ ]:
```
train_test_split   #Press Tab to auto-fill the code
#Press Tab+Shift to read the documentationy
```

Check the shape of training and testing set

In [20]:
```
print(X_train.shape)
print(y_train.shape)
print(X_test.shape)
print(y_test.shape)
```

```
(140, 1)
(140,)
(60, 1)
(60,)
```

Performing Linear Regression

Import LinearRegression from sklearn linear model

In [21]:
```
from sklearn.linear_model import LinearRegression
```

Create a LinearRegression object

In [22]:
```
lr = LinearRegression()
```

Train the model (lr) using fit

In [23]:
```
lr.fit(X_train, y_train)
```

Out[23]:
```
LinearRegression()
```

Print the coefficient and Intercept

In [24]:
```
print(lr.coef_)
print(lr.intercept_)
```

```
[0.04649736]
6.989665857411679
```

Check the score of our model

In [27]:
```
lr.score(X_train, y_train)
```

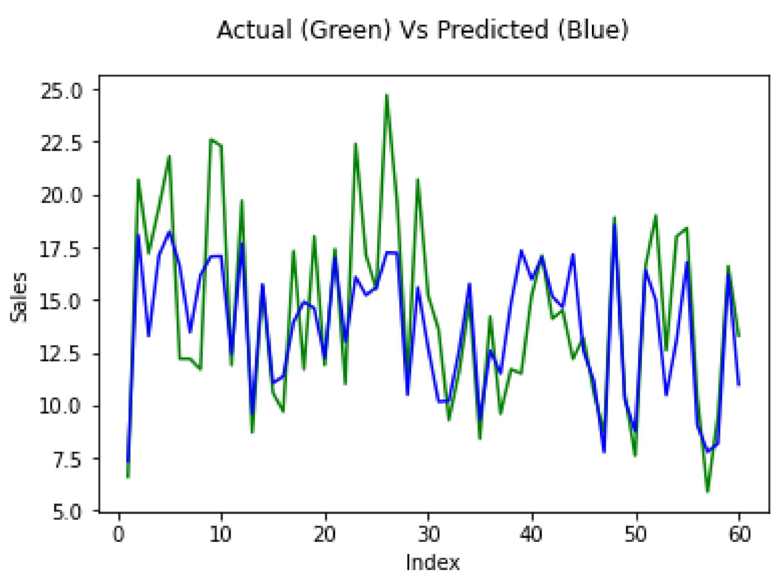
Out[27]:
```
0.6134312469429994
```

Make predictions on the testing set

In [25]:
```
y_pred = lr.predict(X_test)
```

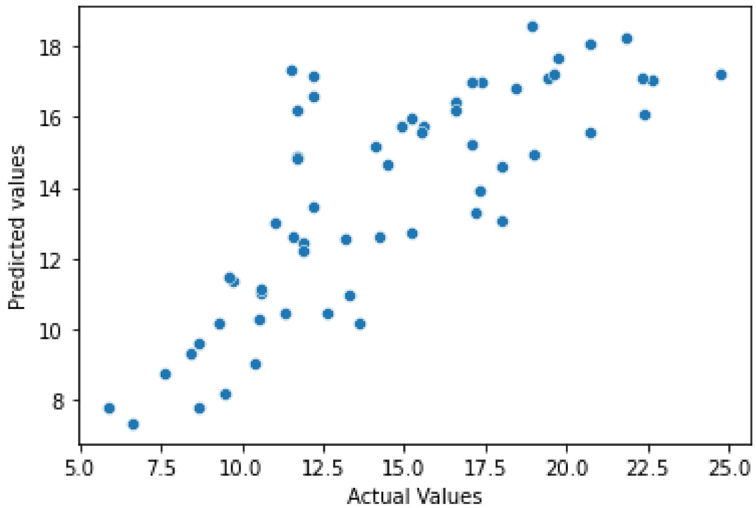
Plot a graph to check the accuracy of our prediction

In [26]:
```
c = [i for i in range(1,61,1)]    #Creating an Index, 61 is used because we hav
fig = plt.figure()
plt.plot(c,y_test, color = 'green') # Plotting y test
plt.plot(c,y_pred, color = 'blue') # Plotting predicted values
fig.suptitle('Actual (Green) Vs Predicted (Blue)') # Set title
plt.xlabel('Index') # Set X label
plt.ylabel('Sales') # Set Y label
plt.show()
```



Plot a scatterplot of actual values vs predicted

In [36]:
```
sns.scatterplot(x = y_test, y = y_pred)
plt.xlabel('Actual Values')
plt.ylabel('Predicted values')
plt.show()
```



Calculate mean squared error and r2_score

Mean Squared Error:It is the sum, over all the data points, of the square of the difference between the predicted and actual target variables, divided by the number of data points.

y-ypred^2

$$e_i = YPred - Yi$$
$$Ypred = mx + c$$

i.e,

$$e_1 = ((m_i * x + c) - y_i)$$

i.e,

$$e_1^2 = (y_1 - (m_i * x + c))^2$$

Import mean_squared_error and r2_score from sklearn.metrics

In [30]:
```
from sklearn.metrics import mean_squared_error,r2_score
```

Calculate the mean squared error

In [33]:
```
mean_squared_error(y_test, y_pred)
```

Out[33]:
```
7.97579853285485
```

Calculate r2_score

In [34]:
```
r2_score(y_test, y_pred)
```

Out[34]:
```
0.5942987267783302
```