Simple Linear Regression

In this example we will consider sales based on 'TV' marketing budget.

In this notebook, we'll build a linear regression model to predict 'Sales' using 'TV' as the predictor variable.

Understanding the Data

Let's start with the following steps:

1. Importing data using the pandas library
2. Understanding the structure of the data

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

In [33]:
```
advertising = pd.read_csv("tvmarketing.csv")
```

Now, let's check the structure of the advertising dataset.

In [34]:
```
# Display the first 5 rows
advertising.head()
```

Out[34]:

	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

In [35]:
```
# Display the last 5 rows
advertising.tail()
```

Out[35]:

	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

In [36]:
```
# Let's check the columns
advertising.info()
```

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

In [37]:
```
# Check the shape of the DataFrame (rows, columns)
advertising.shape
```

Out[37]:
```
(200, 2)
```

In [38]:
```
# Let's look at some statistical information about the dataframe.
advertising.describe()
```

Out[38]:

	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

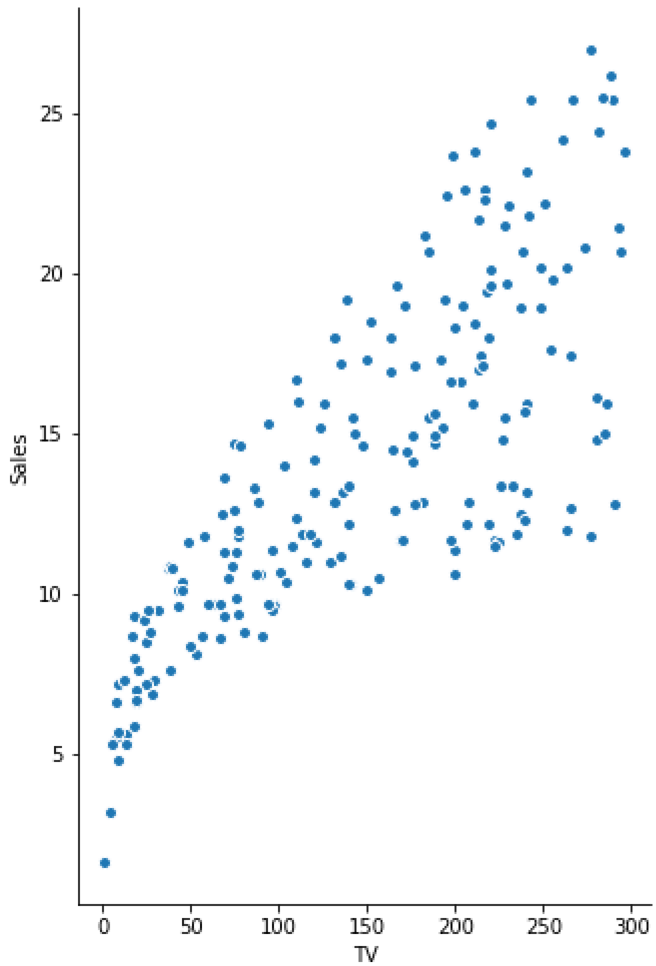
Visualising Data Using Seaborn

In [39]:
```
# Conventional way to import seaborn
import seaborn as sns

# To visualise in the notebook
%matplotlib inline
```

In [40]:
```python
# Visualise the relationship between the features and the response using scatterplots
sns.pairplot(advertising, x_vars=['TV'], y_vars='Sales',size=7, aspect=0.7, kind='scatter')
```

Out[40]: <seaborn.axisgrid.PairGrid at 0x1106ab128>



Perfroming 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

- 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.

In [41]:
```
# Putting feature variable to X
X = advertising['TV']

# Print the first 5 rows
X.head()
```

Out[41]:
```
0    230.1
1     44.5
2     17.2
3    151.5
4    180.8
Name: TV, dtype: float64
```

In [42]:
```
# Putting response variable to y
y = advertising['Sales']

# Print the first 5 rows
y.head()
```

Out[42]:
```
0    22.1
1    10.4
2     9.3
3    18.5
4    12.9
Name: Sales, dtype: float64
```

Splitting Data into Training and Testing Sets

In [43]:
```
#random_state is the seed used by the random number generator, it can be any integer.

from sklearn.cross_validation import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, y, train_size=0.7 , random_state=100)
```

In [44]:
```
print(type(X_train))
print(type(X_test))
print(type(y_train))
print(type(y_test))
```

```
<class 'pandas.core.series.Series'>
<class 'pandas.core.series.Series'>
<class 'pandas.core.series.Series'>
<class 'pandas.core.series.Series'>
```

In [45]:
```
train_test_split   #Press Tab to auto-fill the code
#Press Tab+Shift to read the documentation
```

In [46]:
```
print(X_train.shape)
print(y_train.shape)
print(X_test.shape)
print(y_test.shape)
```

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

In [47]:
```
#It is a general convention in scikit-learn that observations are rows, while features are columns.
#This is needed only when you are using a single feature; in this case, 'TV'.

import numpy as np

X_train = X_train[:, np.newaxis]
X_test = X_test[:, np.newaxis]
```

In [48]:
```
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

In [49]:
```
# import LinearRegression from sklearn
from sklearn.linear_model import LinearRegression

# Representing LinearRegression as lr(Creating LinearRegression Object)
lr = LinearRegression()

# Fit the model using lr.fit()
lr.fit(X_train, y_train)
```

Out[49]:
```
LinearRegression(copy_X=True, fit_intercept=True, n_jobs=1, normalize=False)
```

Coefficients Calculation

In [50]:
```
# Print the intercept and coefficients
print(lr.intercept_)
print(lr.coef_)
```

```
6.98966585741
[ 0.04649736]
```

$$y = 6.989 + 0.0464 \times TV$$

Now, let's use this equation to predict our sales.

Predictions

In [51]:
```
# Making predictions on the testing set
y_pred = lr.predict(X_test)
```

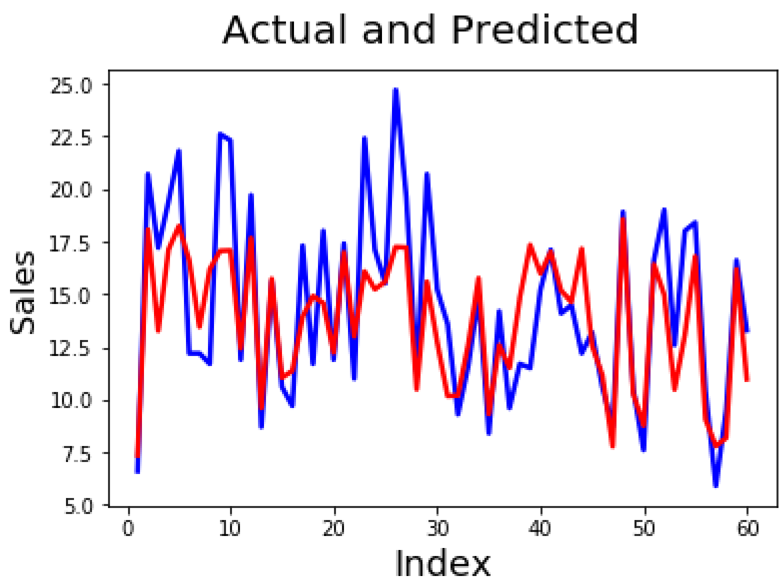
In [52]:
```
type(y_pred)
```

Out[52]:
```
numpy.ndarray
```

Computing RMSE and R^2 Values

In [53]:
```python
# Actual vs Predicted
import matplotlib.pyplot as plt
c = [i for i in range(1,61,1)]          # generating index
fig = plt.figure()
plt.plot(c,y_test, color="blue", linewidth=2.5, linestyle="-")
plt.plot(c,y_pred, color="red",  linewidth=2.5, linestyle="-")
fig.suptitle('Actual and Predicted', fontsize=20)              # Plot heading
plt.xlabel('Index', fontsize=18)                               # X-label
plt.ylabel('Sales', fontsize=16)                       # Y-label
```

Out[53]: Text(0,0.5,'Sales')



In [54]:
```python
# Error terms
c = [i for i in range(1,61,1)]
fig = plt.figure()
plt.plot(c,y_test-y_pred, color="blue", linewidth=2.5, linestyle="-")
fig.suptitle('Error Terms', fontsize=20)              # Plot heading
plt.xlabel('Index', fontsize=18)                      # X-label
plt.ylabel('ytest-ypred', fontsize=16)                # Y-label
```

Out[54]:
```
Text(0,0.5,'ytest-ypred')
```

In [55]:
```python
from sklearn.metrics import mean_squared_error, r2_score
mse = mean_squared_error(y_test, y_pred)
```

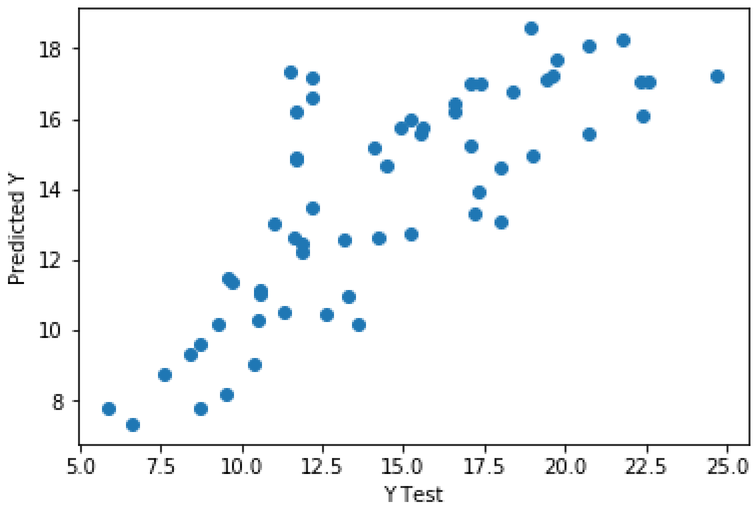
In [56]:
```python
r_squared = r2_score(y_test, y_pred)
```

In [57]:
```python
print('Mean_Squared_Error :' ,mse)
print('r_square_value :',r_squared)
```

```
Mean_Squared_Error : 7.97579853285
r_square_value : 0.594298726778
```

In [58]:
```
import matplotlib.pyplot as plt
plt.scatter(y_test,y_pred)
plt.xlabel('Y Test')
plt.ylabel('Predicted Y')
```

Out[58]: Text(0,0.5,'Predicted Y')



In [ ]: