2.Linear Regression From Scrach

October 17, 2021

Simple Linear Regression without Sci-Kit Learn

[1]:
```python
# Import necessary package
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
```

0.0.1 Step 1: Load the dataset

[2]:
```python
# Load the dataset into pandas dataframe
df = pd.read_csv("E:\\MY LECTURES\\DATA SCIENCE\\3.
↪Programs\\dataset\\Advertising.csv")
# Change this location based on the location of dataset in your machine
```

[3]:
```python
# Display the first five records
df.head()
```

[3]:

	TV	radio	newspaper	sales
0	230.1	37.8	69.2	22.1
1	44.5	39.3	45.1	10.4
2	17.2	45.9	69.3	9.3
3	151.5	41.3	58.5	18.5
4	180.8	10.8	58.4	12.9

Advertising data comprises four features: TV, radio, newspaper, and sales. It explains the budget (in 1000$) spent on different mass media and the net outcome for every week.

sales for a product (output/dependent/target variable).

advertising budget for TV, radio, and newspaper media (input/independent/target variable).

Planning to perform regression on TV budget (X) as input and sales (Y) as output.

[4]:
```python
# Load TV into X and sales into Y variable
X = df.iloc[:,0].values                         # Budget spent on TV
Y = df.iloc[:,3].values                         # Sales
```

[5]:
```
def disp_data(feature1,feature2):
    print('Displaying first 10 records')
    print('-------------------------')
    print('TV budget (X)','|','Sales (Y)')
    print('-------------------------')
    count = 0
    for x,y in zip(feature1,feature2):
        if count == 10:
            break
        else:
            print(x,'           ',y)
            count = count + 1
disp_data(X,Y)
```

```
Displaying first 10 records
-------------------------
TV budget (X) | Sales (Y)
-------------------------
230.1             22.1
44.5             10.4
17.2             9.3
151.5             18.5
180.8             12.9
8.7             7.2
57.5             11.8
120.2             13.2
8.6             4.8
199.8             10.6
```

Row <=> record, tuple, instance, sample, observation, object, case, entity Column <=> attribute, variable, field, feature, characteristic, dimension input feature <=> independent feature or predictor feature. Here, X1 (TV) is the input feature. output feature <=> dependent feature or response feature or target feature. Here, Y (sales) is the output feature.

0.0.2 Step 2: Split the data for training and testing

[6]:
```
# Dataset shape (number of rows and columns)
df.shape
```

[6]: (200, 4)

[7]:
```
# Splitting dataset into training set (80%) and testing set (20%)
x_train = X[0:160]
x_test = X[160:]
y_train = Y[0:160]
y_test = Y[160:]
```

[8]:
```
print("Training data")
print("===========================")
disp_data(x_train,y_train)
```

```
Training data
===========================
Displaying first 10 records
-------------------------
TV budget (X) | Sales (Y)
-------------------------
230.1            22.1
44.5            10.4
17.2            9.3
151.5            18.5
180.8            12.9
8.7            7.2
57.5            11.8
120.2            13.2
8.6            4.8
199.8            10.6
```

[9]:
```
print("Testing data")
print("===========================")
disp_data(x_test,y_test)
```

```
Testing data
===========================
Displaying first 10 records
-------------------------
TV budget (X) | Sales (Y)
-------------------------
172.5            14.4
85.7            13.3
188.4            14.9
163.5            18.0
117.2            11.9
234.5            11.9
17.9            8.0
206.8            12.2
215.4            17.1
284.3            15.0
```

0.0.3 Step 3: Training phase (bulding a model)

Variance function

[10]:
```
def variance(values, mean):
    var = 0
    for val in values:
        var = var + (val-mean)**2
    return var
```

Co-variance function

[11]:
```
def covariance(X_val, X_val_mean, Y_val , Y_val_mean):
    covariance = 0
    for r in range(len(X_val)):
        covariance = covariance + (X_val[r] - X_val_mean) * (Y_val[r] -␣
↪Y_val_mean)
    return covariance
```

The linear model Y = m X + b

[12]:
```
x_train_mean = np.mean(x_train)
y_train_mean = np.mean(y_train)
x_train_var = variance(x_train,x_train_mean)
x_train_y_test_cov = covariance(x_train, x_train_mean, y_train, y_train_mean)
```

$$m = \frac{\sum_{i=1}^{n}(x_i - \bar{x})(y_i - \bar{y})}{\sum_{i=1}^{n}(x_i - \bar{x})^2} \tag{1}$$

[13]:
```
m = x_train_y_test_cov / x_train_var
b = y_train_mean - m * x_train_mean
```

[14]:
```
print('Y = ',round(m,3),'X + ',round(b,3))
```

```
Y =  0.049 X +  7.069
```

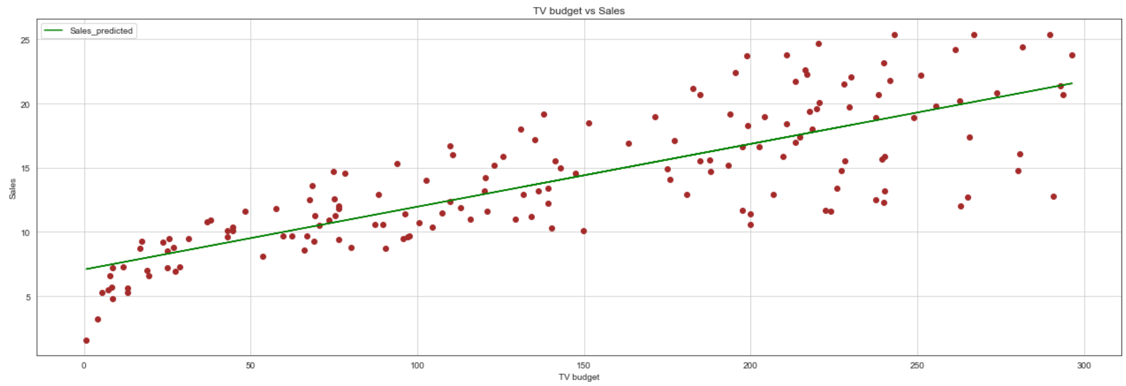
Predicting value for training set using the model above

[15]:
```
# Predicting the Training set results
y_train_pred = np.zeros(len(x_train)).reshape(len(x_train),1)
for x in range(len(x_train)):
    y_train_pred[x] = m * x_train[x] + b
```

Visualizing the model

[16]:
```
sns.set_style(style='white')
fig = plt.figure(figsize=(22,7))
plt.scatter(x_train,y_train,color="brown")
plt.grid(b=None)
plt.plot(x_train,y_train_pred,"g",label="Sales_predicted")
```

```
plt.xlabel("TV budget")
plt.ylabel("Sales")
plt.title("TV budget vs Sales")
plt.legend()
plt.show()
```

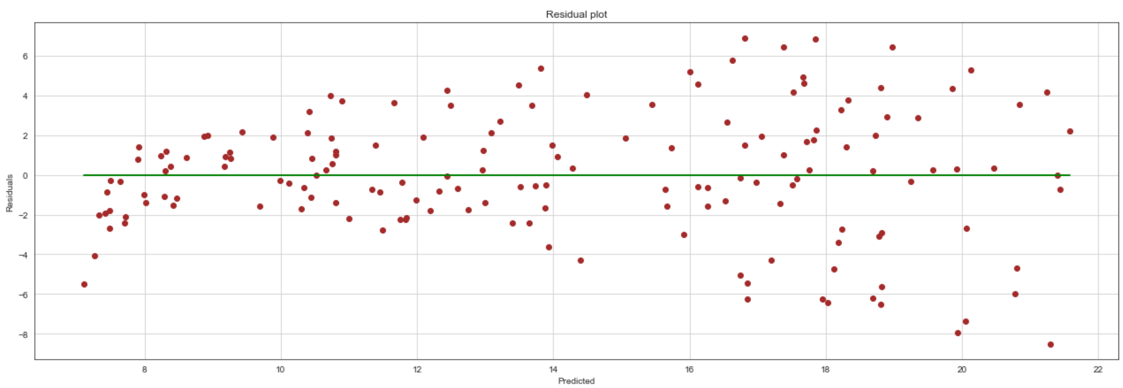


Plotting observed sale (x) and predicted sale (y) for training set

[17]:
```
# Predicting the Test set results
x = np.arange(len(y_train_pred))
fig = plt.figure(figsize=(22,7))
plt.plot(x,y_train,"g-+",label="Sales_observed")
plt.plot(x,y_train_pred,"r-*",label="Sales_predicted")
plt.grid(b=None)
plt.xlabel("TV budget")
plt.ylabel("Sales")
plt.title("TV budget vs Sales")
plt.legend()
plt.show()
```

Residual (Error) plot If the model has done good predictions, then the datapoints must be near around to horizontal line.

[18]:
```
sns.set_style(style='white')
fig = plt.figure(figsize=(22,7))
residuals = y_train.reshape((-1, 1))-y_train_pred
zeros = y_train-y_train
plt.scatter(y_train_pred,residuals,color="brown")
plt.grid(b=None)
plt.plot(y_train_pred,zeros,"g")
plt.xlabel("Predicted")
plt.ylabel("Residuals")
plt.title("Residual plot")
plt.show()
```



0.0.4 Different error calculations to asses the model for training set

1. Sum of Squared Error (SSE)

$$SSE(m,b) = \sum_{i=1}^{n}(y_i - \hat{y})^2 = \sum_{i=1}^{n}(y_i - (m * x_i + b))^2 \tag{2}$$

[19]:
```
sum = 0
n = len(x_train)
for i in range (0,n):
  diff = y_train[i] - y_train_pred[i]
  squ_diff = diff**2
  sum = sum + squ_diff
Train_SSE = np.round(sum,2)
print("Sum of Squared Error (SSE) :",Train_SSE)
```

```
Sum of Squared Error (SSE) : [1551.95]
```

2. **Mean Squared Error (MSE)**

$$MSE(m,b) = \frac{\sum_{i=1}^{n}(y_i - \hat{y})^2}{n} = \frac{\sum_{i=1}^{n}(y_i - (m * x_i + b))^2}{n} \tag{3}$$

[20]:
```
Train_MSE = np.round(Train_SSE/n,2)
print("Mean Squared Error (MSE) :",Train_MSE)
```

```
Mean Squared Error (MSE) : [9.7]
```

3. **Root Mean Squared Error (RMSE)**

$$RMSE(m,b) = \sqrt{\frac{\sum_{i=1}^{n}(y_i - \hat{y})^2}{n}} = \sqrt{\frac{\sum_{i=1}^{n}(y_i - (m * x_i + b))^2}{n}} \tag{4}$$

[21]:
```
Train_RMSE = np.round(np.sqrt(Train_MSE),2)
print("Root Mean Squared Error (RMSE) :",Train_RMSE)
```

```
Root Mean Squared Error (RMSE) : [3.11]
```

4. **Mean Absolute Error (MAE)**

$$MAE(m,b) = \frac{\sum_{i=1}^{n}|(y_i - \hat{y})|}{n} \tag{5}$$

[22]:
```
sum = 0
n = len(x_train)
for i in range (0,n):
  diff = y_train[i] - y_train_pred[i]
  sum = sum + np.abs(diff)
Train_MAE = np.round(sum/n,2)
print("Mean Absolute Error (MAE) :",Train_MAE)
```

```
Mean Absolute Error (MAE) : [2.43]
```

5. **Mean Absolute Percentage Error (MAPE)**

$$MAPE(m,b) = \frac{100\%}{n}\sum_{i=1}^{n}\left|\frac{(y_i - \hat{y})}{y_i}\right| = \frac{100\%}{n}\sum_{i=1}^{n}\left|\frac{(y_i - (m * x_i + b))}{y_i}\right| \tag{6}$$

[23]:
```
sum = 0
n = len(x_train)
for i in range (0,n):
  diff = (y_train[i] - y_train_pred[i])/y_train[i]
  sum = sum + np.abs(diff)
```

```python
Train_MAPE = np.round(sum/n*100,2)
print("Mean Absolute Percentage Error (MAPE) :",Train_MAPE)
```

```
Mean Absolute Percentage Error (MAPE) : [20.43]
```

0.0.5 Calculating R-Squred value (goodness of model) using SSE

$$R^2 = 1 - \frac{SSE}{SST} = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y})^2}{\sum_{i=1}^{n}(y_i - \bar{y})^2} \tag{7}$$

[24]:
```python
# SSE variance for mean model
y_train_mean = np.mean(y_train)
SSE_mean = variance(y_train,y_train_mean)
# SSE variance for fit model
y_train_pred_mean = np.mean(y_train_pred)
SSE_fit = variance(y_train_pred,y_train_pred_mean)
# calculating R_square
R = 1 - (SSE_fit/SSE_mean)
Train_RS = np.round(R,2)*100
print("R-Squred value (goodness of model) for training set :",Train_RS,"%")
```

```
R-Squred value (goodness of model) for training set : [36.] %
```

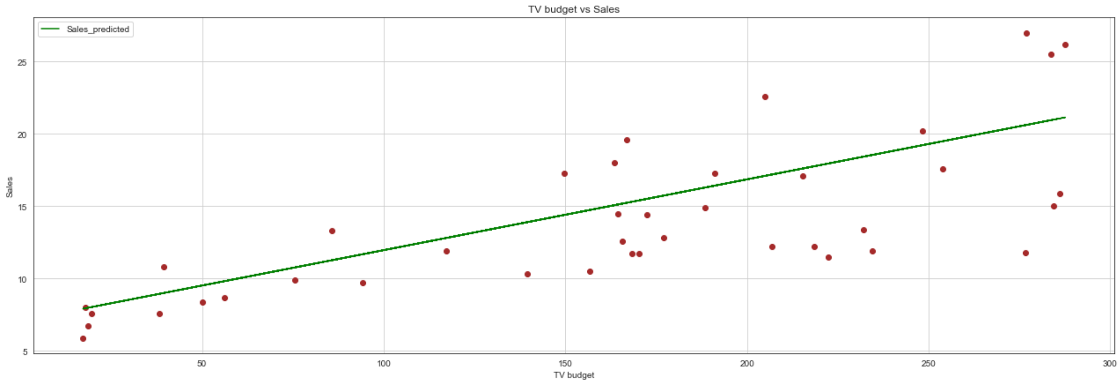
0.0.6 Step 6: Testing phase

Predicting value for training set using the model above

[25]:
```python
# Predicting values for test input set
y_test_pred = np.zeros(len(x_test)).reshape(len(x_test),1)
for x in range(len(x_test)):
    y_test_pred[x] = m * x_test[x] + b
```

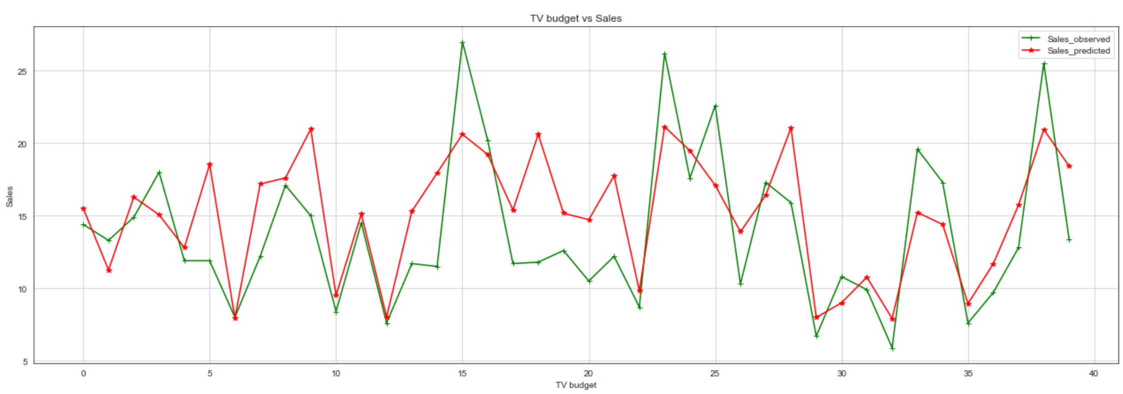
Visualizing the model

[26]:
```python
# Plotting the predicted values
sns.set_style(style='white')
fig = plt.figure(figsize=(22,7))
plt.scatter(x_test,y_test,color="brown")
plt.grid(b=None)
plt.plot(x_test,y_test_pred,"g",label="Sales_predicted")
plt.xlabel("TV budget")
plt.ylabel("Sales")
plt.title("TV budget vs Sales")
plt.legend()
plt.show()
```



Plotting observed sale (x) and predicted sale (y) for training set

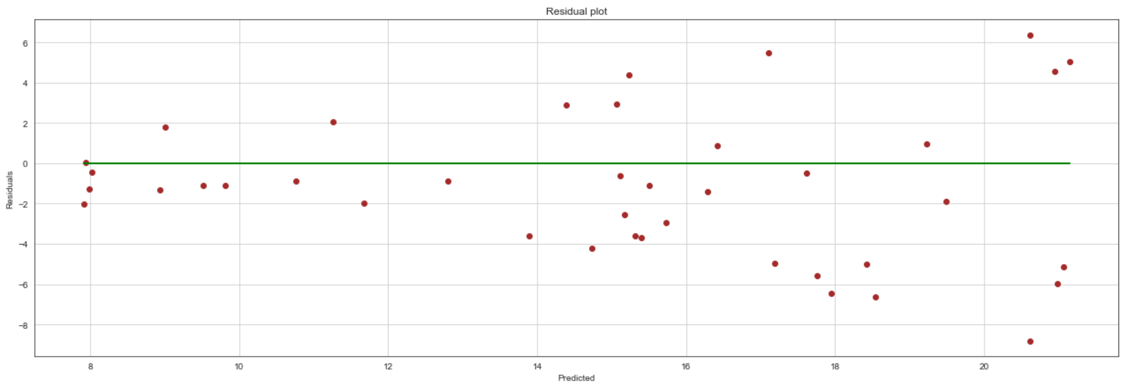
[27]:
```
x = np.arange(len(y_test_pred))
fig = plt.figure(figsize=(22,7))
plt.plot(x,y_test,"g-+",label="Sales_observed")
plt.plot(x,y_test_pred,"r-*",label="Sales_predicted")
plt.grid(b=None)
plt.xlabel("TV budget")
plt.ylabel("Sales")
plt.title("TV budget vs Sales")
plt.legend()
plt.show()
```



Residual (Error) plot If the model has done good predictions, then the datapoints must be near around to horizontal line.

[28]:
```
sns.set_style(style='white')
fig = plt.figure(figsize=(22,7))
residuals = y_test.reshape((-1, 1))-y_test_pred
```

```
zeros = y_test-y_test
plt.scatter(y_test_pred,residuals,color="brown")
plt.grid(b=None)
plt.plot(y_test_pred,zeros,"g")
plt.xlabel("Predicted")
plt.ylabel("Residuals")
plt.title("Residual plot")
plt.show()
```



0.0.7 Different error calculations to asses the model for the test set

1. Sum of Squared Error (SSE)

$$SSE(m,b) = \sum_{i=1}^{n}(y_i - \hat{y})^2 = \sum_{i=1}^{n}(y_i - (m * x_i + b))^2 \tag{8}$$

[29]:
```
sum = 0
n = len(x_test)
for i in range (0,n):
  diff = y_test[i] - y_test_pred[i]
  squ_diff = diff**2
  sum = sum + squ_diff
Test_SSE = np.round(sum,2)
print("Sum of Squared Error (SSE) :",Test_SSE)
```

```
Sum of Squared Error (SSE) : [565.15]
```

2. Mean Squared Error (MSE)

$$MSE(m,b) = \frac{\sum_{i=1}^{n}(y_i - \hat{y})^2}{n} = \frac{\sum_{i=1}^{n}(y_i - (m * x_i + b))^2}{n} \tag{9}$$

[30]:
```python
Test_MSE = np.round(Train_SSE/n,2)
print("Mean Squared Error (MSE) :",Test_MSE)
```

```
Mean Squared Error (MSE) : [38.8]
```

3. Root Mean Squared Error (RMSE)

$$RMSE(m,b) = \sqrt{\frac{\sum_{i=1}^{n}(y_i - \hat{y})^2}{n}} = \sqrt{\frac{\sum_{i=1}^{n}(y_i - (m * x_i + b))^2}{n}} \tag{10}$$

[31]:
```python
Test_RMSE = np.round(np.sqrt(Test_MSE),2)
print("Root Mean Squared Error (RMSE) :",Test_RMSE)
```

```
Root Mean Squared Error (RMSE) : [6.23]
```

4. Mean Absolute Error (MAE)

$$MAE(m,b) = \frac{\sum_{i=1}^{n}|(y_i - \hat{y})|}{n} \tag{11}$$

[32]:
```python
sum = 0
n = len(x_test)
for i in range (0,n):
  diff = y_test[i] - y_test_pred[i]
  sum = sum + np.abs(diff)
Test_MAE = np.round(sum/n,2)
print("Mean Absolute Error (MAE) :",Test_MAE)
```

```
Mean Absolute Error (MAE) : [3.08]
```

5. Mean Absolute Percentage Error (MAPE)

$$MAPE(m,b) = \frac{100\%}{n}\sum_{i=1}^{n}\left|\frac{(y_i - \hat{y})}{y_i}\right| = \frac{100\%}{n}\sum_{i=1}^{n}\left|\frac{(y_i - (m * x_i + b))}{y_i}\right| \tag{12}$$

[33]:
```python
sum = 0
n = len(x_test)
for i in range (0,n):
  diff = (y_test[i] - y_test_pred[i])/y_test[i]
  sum = sum + np.abs(diff)
Test_MAPE = np.round(sum/n*100,2)
print("Mean Absolute Percentage Error (MAPE) :",Test_MAPE)
```

```
Mean Absolute Percentage Error (MAPE) : [23.03]
```

0.0.8 Calculating R-Squred value (goodness of model) using SSE

$$R^2 = 1 - \frac{SSE}{SST} = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y})^2}{\sum_{i=1}^{n}(y_i - \bar{y})^2} \tag{13}$$

[34]:
```
# SSE variance for mean model
y_test_mean = np.mean(y_test)
SSE_mean = variance(y_test,y_test_mean)
# SSE variance for fit model
y_test_pred_mean = np.mean(y_test_pred)
SSE_fit = variance(y_test_pred,y_test_pred_mean)
# calculating R_square
R = 1 - (SSE_fit/SSE_mean)
Test_RS = np.round(R,2)*100
print("R-Squred value (goodness of model) for testing set :",Test_RS,"%")
```

```
R-Squred value (goodness of model) for testing set : [36.] %
```

0.0.9 Underfitting and overfitting observation

[35]:
```
print("Error \t Train     \t Test")
print("=================================")
print("SSE   \t",Train_SSE,"\t", Test_SSE)
print("MSE   \t",Train_MSE,"\t\t", Test_MSE)
print("RMSE   \t",Train_RMSE,"\t", Test_RMSE)
print("MAE   \t",Train_MAE,"\t", Test_MAE)
print("RS   \t",Train_RS,"\t\t", Test_RS)
```

```
Error    Train            Test
================================
SSE      [1551.95]        [565.15]
MSE      [9.7]            [38.8]
RMSE     [3.11]           [6.23]
MAE      [2.43]           [3.08]
RS       [36.]            [36.]
```

Repeat this process by changing the values of parameters m and b until you get least SSE

Painful process, so we use Sci-Kit (SK) Learn library.