Information about the data:

```
-> The dataset has benn taken from sklearn.datasets

-> This is the Boston House price dataset

-> The dataset consist of 506 rown with 13 attributes
```

Objective:

```
-> Implementing Logistic Regression on the Boston House price datase
t and checking the accuracy

-> Implementing Logistic Regression with Stochastic Gradient Descent
and check the accuracy

-> Evaluating Logistic Regression model with and with out Stochastic
Gradient Descent
   Optimization
```

Importing the dataset

In [1]:

```
from sklearn.datasets import load_boston
boston_data = load_boston()
```

Information from the dataset:

```
-> Shape of the dataset

-> Features of the dataset

-> Dimensionality of the dataset
```

In [2]:

```
print(boston_data.data.shape)
print(boston_data.feature_names)
print(boston_data.data.ndim)
```

```
(506, 13)
['CRIM' 'ZN' 'INDUS' 'CHAS' 'NOX' 'RM' 'AGE' 'DIS' 'RAD' 'TAX' 'PTRATIO'
 'B' 'LSTAT']
2
```

The class label of the dataset were:

In [3]:

```
print(boston_data.target.shape)
```

```
(506,)
```

In [4]:

```
print(boston_data.DESCR)
```

```
Boston House Prices dataset
===========================

Notes
------
Data Set Characteristics:

    :Number of Instances: 506

    :Number of Attributes: 13 numeric/categorical predictive

    :Median Value (attribute 14) is usually the target

    :Attribute Information (in order):
        - CRIM     per capita crime rate by town
        - ZN       proportion of residential land zoned for lots over
25,000 sq.ft.
        - INDUS    proportion of non-retail business acres per town
        - CHAS     Charles River dummy variable (= 1 if tract bounds river;
0 otherwise)
        - NOX      nitric oxides concentration (parts per 10 million)
        - RM       average number of rooms per dwelling
        - AGE      proportion of owner-occupied units built prior to 1940
        - DIS      weighted distances to five Boston employment centres
        - RAD      index of accessibility to radial highways
        - TAX      full-value property-tax rate per $10,000
        - PTRATIO  pupil-teacher ratio by town
        - B        1000(Bk - 0.63)^2 where Bk is the proportion of blacks by
town
        - LSTAT    % lower status of the population
        - MEDV     Median value of owner-occupied homes in $1000's

    :Missing Attribute Values: None

    :Creator: Harrison, D. and Rubinfeld, D.L.

This is a copy of UCI ML housing dataset.
http://archive.ics.uci.edu/ml/datasets/Housing


This dataset was taken from the StatLib library which is maintained at Carn
egie Mellon University.

The Boston house-price data of Harrison, D. and Rubinfeld, D.L. 'Hedonic
prices and the demand for clean air', J. Environ. Economics & Management,
vol.5, 81-102, 1978.   Used in Belsley, Kuh & Welsch, 'Regression diagnosti
cs
...', Wiley, 1980.   N.B. Various transformations are used in the table on
pages 244-261 of the latter.

The Boston house-price data has been used in many machine learning papers t
hat address regression
```

```
hat address regression
problems.

**References**

   - Belsley, Kuh & Welsch, 'Regression diagnostics: Identifying Influentia
l Data and Sources of Collinearity', Wiley, 1980. 244-261.
   - Quinlan,R. (1993). Combining Instance-Based and Model-Based Learning.
In Proceedings on the Tenth International Conference of Machine Learning, 2
36-243, University of Massachusetts, Amherst. Morgan Kaufmann.
   - many more! (see http://archive.ics.uci.edu/ml/datasets/Housing)
```

In [5]:

```
import pandas as pd
df = pd.DataFrame(boston_data.data)
df.head(5)
```

Out[5]:

	0	1	2	3	4	5	6	7	8	9	10	11	12
0	0.00632	18.0	2.31	0.0	0.538	6.575	65.2	4.0900	1.0	296.0	15.3	396.90	4.98
1	0.02731	0.0	7.07	0.0	0.469	6.421	78.9	4.9671	2.0	242.0	17.8	396.90	9.14
2	0.02729	0.0	7.07	0.0	0.469	7.185	61.1	4.9671	2.0	242.0	17.8	392.83	4.03
3	0.03237	0.0	2.18	0.0	0.458	6.998	45.8	6.0622	3.0	222.0	18.7	394.63	2.94
4	0.06905	0.0	2.18	0.0	0.458	7.147	54.2	6.0622	3.0	222.0	18.7	396.90	5.33

In [6]:

```
df["price"] = boston_data.target
```

In [7]:

```
df.head(5)
```

Out[7]:

	0	1	2	3	4	5	6	7	8	9	10	11	12	price
0	0.00632	18.0	2.31	0.0	0.538	6.575	65.2	4.0900	1.0	296.0	15.3	396.90	4.98	24.0
1	0.02731	0.0	7.07	0.0	0.469	6.421	78.9	4.9671	2.0	242.0	17.8	396.90	9.14	21.6
2	0.02729	0.0	7.07	0.0	0.469	7.185	61.1	4.9671	2.0	242.0	17.8	392.83	4.03	34.7
3	0.03237	0.0	2.18	0.0	0.458	6.998	45.8	6.0622	3.0	222.0	18.7	394.63	2.94	33.4
4	0.06905	0.0	2.18	0.0	0.458	7.147	54.2	6.0622	3.0	222.0	18.7	396.90	5.33	36.2

Seperating the Dependent feature and Independent feature

In [8]:

```
x = df.drop('price',axis=1)
```

```
y = df['price']
```

In [9]:

```
print(x.shape)
print(y.shape)
```

```
(506, 13)
(506,)
```

In [10]:

```
from sklearn.cross_validation import train_test_split
```

```
C:\Users\Anil Chowdary\Anaconda3\lib\site-
packages\sklearn\cross_validation.py:41: DeprecationWarning: This module wa
s deprecated in version 0.18 in favor of the model_selection module into wh
ich all the refactored classes and functions are moved. Also note that the
interface of the new CV iterators are different from that of this module. T
his module will be removed in 0.20.
  "This module will be removed in 0.20.", DeprecationWarning)
```

In [11]:

```
xtrain,xtest,ytrain,ytest =
train_test_split(x,y,test_size=0.25,random_state=1)
```

In [12]:

```
print(xtrain.shape)
print(xtest.shape)
print(ytrain.shape)
print(ytest.shape)
```

```
(379, 13)
(127, 13)
(379,)
(127,)
```

In [13]:

```
from sklearn.linear_model import LinearRegression
```

In [613]:

```
lrm = LinearRegression()
```

In [614]:

```
lrm.fit(xtrain,ytrain)
```

Out[614]:

```
LinearRegression(copy_X=True, fit_intercept=True, n_jobs=1,
normalize=False)
```

In [615]:

```
pred = lrm.predict(xtest)
```

In [616]:

```
from sklearn.metrics import r2_score
```

In [617]:

```
score = r2_score(pred,ytest)
```

In [618]:

```
score
```

Out[618]:

```
0.6213821726369473
```

Visualization between the Actual values and Predicted values

In [20]:

```
import matplotlib.pyplot as mp
mp.scatter(ytest,pred)
mp.xlabel('ytest')
mp.ylabel('pred')
mp.title('Actual vs Predicted')
```

Out[20]:

```
Text(0.5,1,'Actual vs Predicted')
```

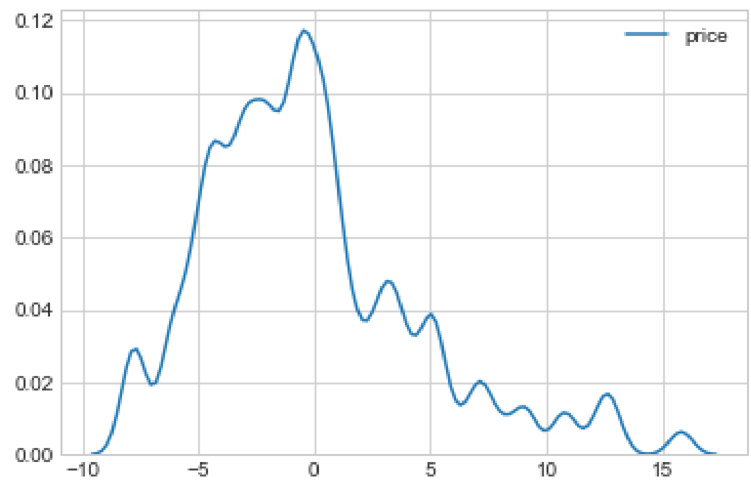
Distribution of Errors:

In [21]:

```
ydelta = ytest - pred
import seaborn as s
s.set_style("whitegrid")
s.kdeplot(ydelta,bw=0.5)
```

Out[21]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x177fcce0208>
```



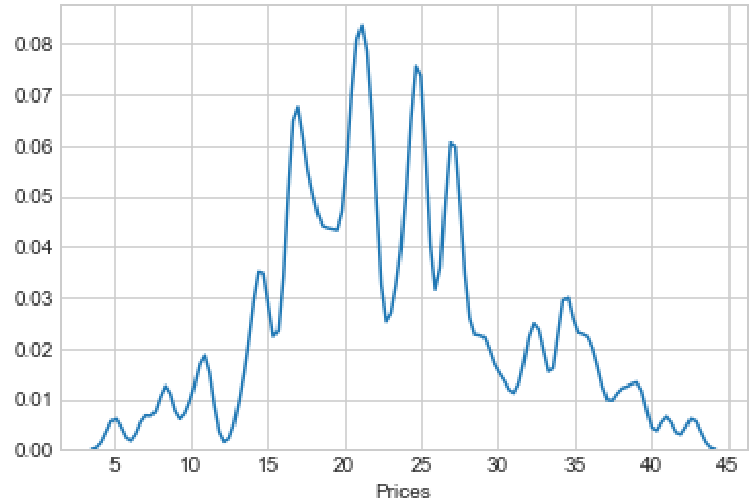
Distribution of Predicted prices and Actual prices

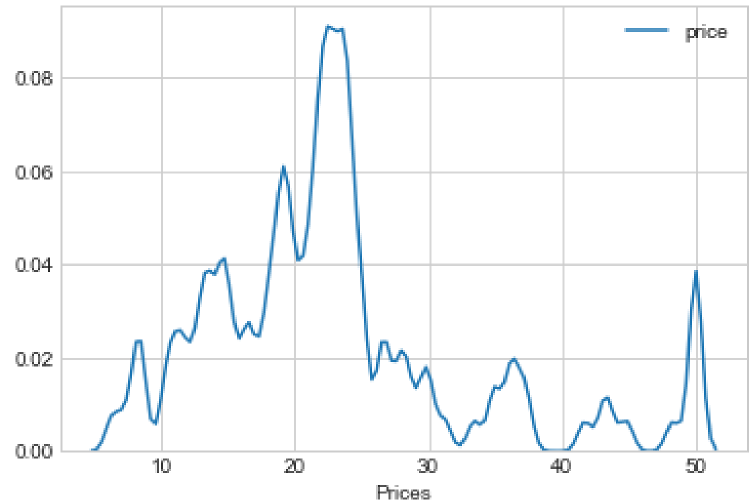
In [22]:

```
mp.figure(211)
s.kdeplot(pred,bw=0.5)
mp.xlabel("Prices")
mp.figure(212)
s.kdeplot(ytest,bw=0.5)
mp.xlabel("Prices")
```

Out[22]:

```
Text(0.5,0,'Prices')
```





Observation:

```
-> The actual values have spread between 3 and 44

-> The predicted values have spread between 3 and 53

-> The error distribution have more negative skewness, this means th
at the model is preiciting
    more than the actual values

-> I have used R-Squared as the performance measure which resulted i
n 62.1 percent
```

Linear Regression with Stochastic Gradient Descent Optimization

In [784]:

```
print(xtrain.shape)
print(xtest.shape)
print(ytrain.shape)
print(ytest.shape)
```

```
(379, 13)
(127, 13)
(379,)
(127,)
```

Scaling the features

In [785]:

```
scale  =StandardScaler()
```

In [786]:

```
xtrain = scale.fit_transform(xtrain)
xtest = scale.fit_transform(xtest)
```

In [787]:

```
from sklearn.linear_model import SGDRegressor
```

In [788]:

```
from sklearn import linear_model
```

SGD with learning rate 1 and number of iterations = 1

In [866]:

```
sgdr = SGDRegressor(alpha=1,n_iter=1,loss='squared_loss')
sgdr.fit(xtrain,ytrain)
pred = sgdr.predict(xtest)
score = r2_score(pred,ytest)*100
print(score)
```

```
-289.8165364388144
```

```
C:\Users\Anil Chowdary\Anaconda3\lib\site-
packages\sklearn\linear_model\stochastic_gradient.py:117:
DeprecationWarning: n_iter parameter is deprecated in 0.19 and will be remo
ved in 0.21. Use max_iter and tol instead.
  DeprecationWarning)
```

SGD with learning rate 0.5 and number of iterations = 2

In [867]:

```
sgdr = SGDRegressor(alpha=0.5,n_iter=2,random_state=1,loss='squared_loss')
sgdr.fit(xtrain,ytrain)
pred = sgdr.predict(xtest)
score = r2_score(pred,ytest)*100
print(score)
```

```
-18.481088609809902
```

```
C:\Users\Anil Chowdary\Anaconda3\lib\site-
packages\sklearn\linear_model\stochastic_gradient.py:117:
DeprecationWarning: n_iter parameter is deprecated in 0.19 and will be remo
ved in 0.21. Use max_iter and tol instead.
  DeprecationWarning)
```

SGD with learning rate 0.25 and number of iterations = 3

In [868]:

```
sgdr = SGDRegressor(alpha=0.25,n_iter=3,random_state=2,loss='squared_loss')
sgdr.fit(xtrain,ytrain)
pred = sgdr.predict(xtest)
score = r2_score(pred,ytest)*100
print(score)
```

```
28.60078816790762
```

```
C:\Users\Anil Chowdary\Anaconda3\lib\site-
packages\sklearn\linear_model\stochastic_gradient.py:117:
DeprecationWarning: n_iter parameter is deprecated in 0.19 and will be remo
ved in 0.21. Use max_iter and tol instead.
  DeprecationWarning)
```

SGD with learning rate 0.12 and number of iterations = 4

In [869]:

```
sgdr = SGDRegressor(alpha=0.12,n_iter=4,random_state=3,loss='squared_loss')
sgdr.fit(xtrain,ytrain)
pred = sgdr.predict(xtest)
score = r2_score(pred,ytest)*100
print(score)
```

```
55.000206266037296
```

```
C:\Users\Anil Chowdary\Anaconda3\lib\site-
packages\sklearn\linear_model\stochastic_gradient.py:117:
DeprecationWarning: n_iter parameter is deprecated in 0.19 and will be remo
ved in 0.21. Use max_iter and tol instead.
  DeprecationWarning)
```

In [ ]:

```
SGD with learning rate 0.06 and number of iterations = 5
```

In [870]:

```
sgdr = SGDRegressor(alpha=0.06,n_iter=5,random_state=4,loss='squared_loss')
sgdr.fit(xtrain,ytrain)
pred = sgdr.predict(xtest)
score = r2_score(pred,ytest)*100
print(score)
```

```
53.57293449043019
```

```
C:\Users\Anil Chowdary\Anaconda3\lib\site-
packages\sklearn\linear_model\stochastic_gradient.py:117:
DeprecationWarning: n_iter parameter is deprecated in 0.19 and will be remo
ved in 0.21. Use max_iter and tol instead.
```

```
ved in 0.21. Use max_iter and tol instead.
  DeprecationWarning)
```

SGD with learning rate 0.03 and number of iterations = 6

In [871]:

```
sgdr = SGDRegressor(alpha=0.03,n_iter=6,random_state=5,loss='squared_loss')
sgdr.fit(xtrain,ytrain)
pred = sgdr.predict(xtest)
score = r2_score(pred,ytest)*100
print(score)
```

```
62.04614151659265
```

```
C:\Users\Anil Chowdary\Anaconda3\lib\site-
packages\sklearn\linear_model\stochastic_gradient.py:117:
DeprecationWarning: n_iter parameter is deprecated in 0.19 and will be remo
ved in 0.21. Use max_iter and tol instead.
  DeprecationWarning)
```

SGD with learning rate 0.02 and number of iterations = 7

In [872]:

```
sgdr = SGDRegressor(alpha=0.02,n_iter=7,random_state=6,loss='squared_loss')
sgdr.fit(xtrain,ytrain)
pred = sgdr.predict(xtest)
score = r2_score(pred,ytest)*100
print(score)
```

```
64.54798575686078
```

```
C:\Users\Anil Chowdary\Anaconda3\lib\site-
packages\sklearn\linear_model\stochastic_gradient.py:117:
DeprecationWarning: n_iter parameter is deprecated in 0.19 and will be remo
ved in 0.21. Use max_iter and tol instead.
  DeprecationWarning)
```

SGD with learning rate 0.01 and number of iterations = 8

In [873]:

```
sgdr = SGDRegressor(alpha=0.01,n_iter=8,random_state=7,loss='squared_loss')
sgdr.fit(xtrain,ytrain)
pred = sgdr.predict(xtest)
score = r2_score(pred,ytest)*100
print(score)
```

```
59.081650022913855
```

```
C:\Users\Anil Chowdary\Anaconda3\lib\site-
packages\sklearn\linear_model\stochastic_gradient.py:117:
DeprecationWarning: n_iter parameter is deprecated in 0.19 and will be remo
ved in 0.21. Use max_iter and tol instead.
  DeprecationWarning)
```

Observation:

```
    By trying different combinations of Learning rates and Number of Ite
```

```
rations we can see that by
increasing learning rate from 0.02 there is decreasing in the perfor
mance score
```

In [833]:

```
print(pred.shape)
print(ytest.shape)
```

```
(127,)
(127,)
```

In [834]:

```
print(type(ytest))
print(type(pred))
```

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

Mean difference between the Actual price and Predicted price

In [836]:

```
print(ytest.mean())
print(pred.mean())
```

```
23.09448818897638
22.22302364393628
```

In [837]:

```
t = pd.DataFrame(data=pred)
```

Median difference between Actual price and Predicted price

In [840]:

```
print(ytest.median())
print(t.median())
```

```
22.0
0    22.417535
dtype: float64
```

In [841]:

```
print(ytest.std())
print(pred.std())
```

```
9.992229576951791
7.421183114166382
```

In [842]:

```
import numpy as np
```

In [843]:

```
print(np.sum(ytest))
print(np.sum(pred))
```

```
2933.0
2822.3240027799075
```

Weight of the features from the Model

In [844]:

```
sgdr.coef_
```

Out[844]:

```
array([-0.76933981,  0.70170576, -0.2440426 ,  0.68822587, -1.30061069,
        2.44441636, -0.16806442, -2.07190516,  0.89617887, -0.31317425,
       -1.8610315 ,  0.6094922 , -3.57303014])
```

-> Error is the difference between the Actual prices and Predicted prices

In [852]:

```
error = ytest-pred
print(error.max())
print(error.min())
print(np.sum(error))
```

```
16.91771118510735
-7.495529208285134
110.67599722009287
```

Observation:

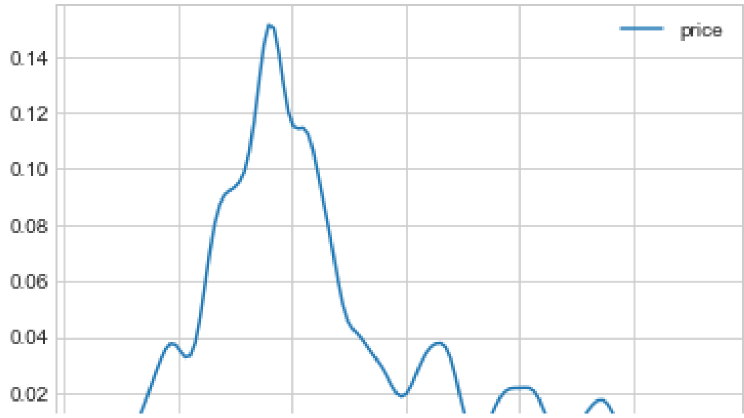
```
The maximun error is 16.9177

The minimum error is -7.45

The sum of all the errors is 110.67599
```

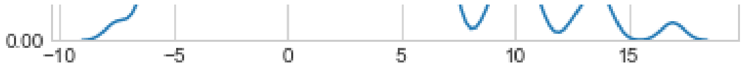
In [853]:

```
s.kdeplot(error,bw=0.5)
```

Out[853]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x177fe62d208>
```





In [854]:

```
sgdr.intercept_
```

Out[854]:

```
array([22.22302364])
```

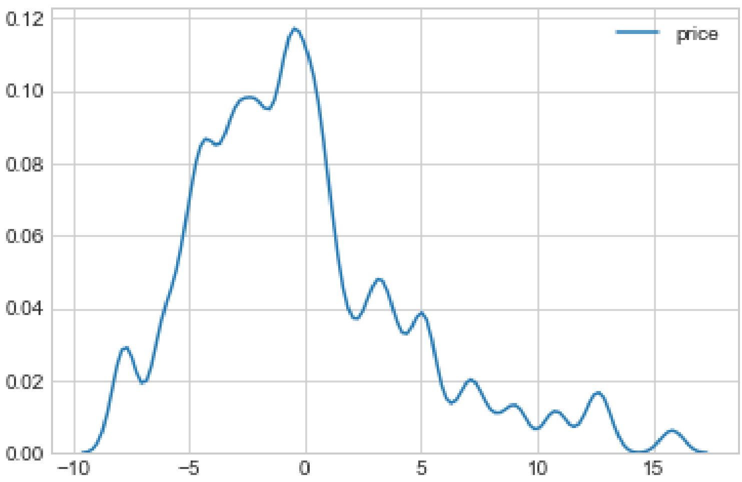
Distribution of Errors

In [855]:

```
import seaborn as s
s.set_style("whitegrid")
s.kdeplot(ydelta,bw=0.5)
```

Out[855]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x177fe5c39b0>
```



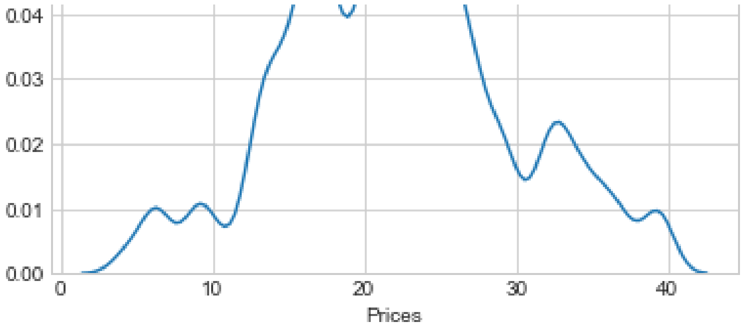
Distribution of Predicted prices and Actual prices

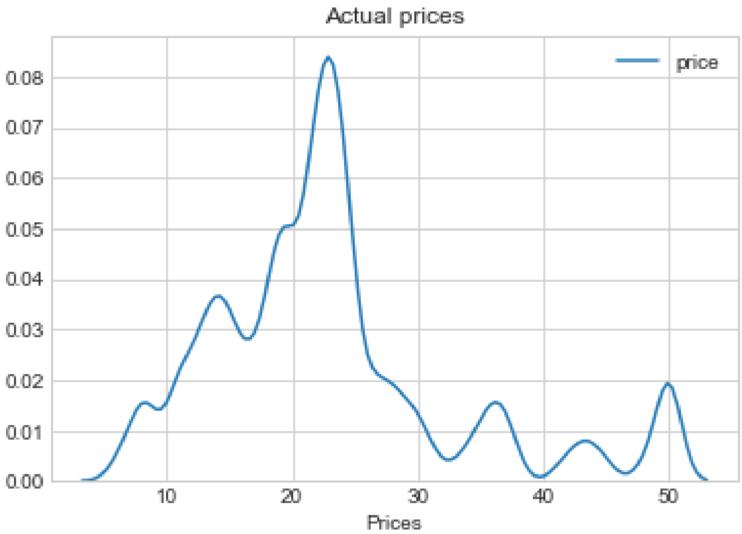
In [859]:

```
mp.figure(211)
s.kdeplot(pred,bw=1)
mp.xlabel("Prices")
mp.title("Predicted prices")
mp.figure(212)
s.kdeplot(ytest,bw=1)
mp.xlabel("Prices")
mp.title("Actual prices")
```

Out[859]:

```
Text(0.5,1,'Actual prices')
```





Observation:

```
Both the predicted prices and actual prices have more spread in the
region of 10 and 30
```

Conclusion:

```
-> The best performance measure for regression model is R-Squared

-> The value of R-Square in the range of 0 to 1 is a good model

-> If the R-Square value is equal to zero then the model is simple m
ean model

-> If R-Square value is negative then the model is performing very b
ad

-> By using simple Linear Regression we got R-Square value as 0.62

-> By using Stochastic Gradient Descent with different combination o
f learning rates and

   number of iterations we got the best R-Square value as 0.645
```