In [1]:
```
# Imports
import warnings
warnings.filterwarnings("ignore")
from sklearn.datasets import load_boston
from random import seed
from random import randrange
from csv import reader
from math import sqrt
from sklearn import preprocessing
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from prettytable import PrettyTable
from sklearn.linear_model import SGDRegressor
from sklearn import preprocessing
from sklearn.metrics import mean_squared_error
```

sklearn Boston Dataset

In [2]:
```
boston = load_boston()
```

In [3]:
```
boston.keys()
```

Out[3]:
```
dict_keys(['data', 'target', 'feature_names', 'DESCR', 'filename'])
```

In [4]:
```
boston.data.shape
```

Out[4]:
```
(506, 13)
```

506 data samples, with 13 features each

In [5]:
```
boston.feature_names
```

Out[5]:
```
array(['CRIM', 'ZN', 'INDUS', 'CHAS', 'NOX', 'RM', 'AGE', 'DIS', 'RAD',
       'TAX', 'PTRATIO', 'B', 'LSTAT'], dtype='<U7')
```

In [6]:
```
print (boston.DESCR)
```

```
.. _boston_dataset:

Boston house prices dataset
---------------------------

**Data Set Characteristics:**

    :Number of Instances: 506

    :Number of Attributes: 13 numeric/categorical predictive. Median Value (a
ttribute 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.
https://archive.ics.uci.edu/ml/machine-learning-databases/housing/


This dataset was taken from the StatLib library which is maintained at Carneg
ie 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 diagnostics
...', 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 tha
t address regression
problems.

.. topic:: References

   - Belsley, Kuh & Welsch, 'Regression diagnostics: Identifying Influential
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, 236-24
3, University of Massachusetts, Amherst. Morgan Kaufmann.

In [7]:
```
df = pd.DataFrame(boston.data)
```

In [8]:
```
df.head(5)
```

Out[8]:

	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 [9]:
```
# sklearn Train Test split
from sklearn.model_selection import train_test_split
```

In [10]:
```
X_train, X_test, Y_train, Y_test = train_test_split(boston.data, boston.target
, test_size=0.3, random_state=4)
```

In [11]:
```
# Standardizing the Train and Test Data
# Perform fit on Train data and Transform on both Train and Test Data
scaler = preprocessing.StandardScaler()
X_train = scaler.fit_transform(X_train)
X_test = scaler.transform(X_test)
```

In [12]:
```
# To visualize how the data looks post standardization, lets convert it into a
pandas dataframe
standardized_df = pd.DataFrame(X_train)
standardized_df.head(5)
```

Out[12]:

	0	1	2	3	4	5	6	7	
0	-0.425469	-0.470768	-0.954686	-0.231455	-0.919581	0.215100	-0.747410	0.454022	-0.7644
1	-0.426323	2.992576	-1.330157	-0.231455	-1.227311	-0.883652	-1.691588	3.163428	-0.6515
2	-0.385190	-0.470768	-0.705828	4.320494	-0.423795	-0.125423	0.818985	-0.353904	-0.1999
3	-0.249268	-0.470768	-0.423497	-0.231455	-0.158805	-0.228336	1.021567	-0.021755	-0.6515
4	-0.365945	0.395068	-1.030363	-0.231455	0.157472	3.102729	-0.060078	-0.646202	-0.5386

In [13]:
```
standardized_df['house_price'] = Y_train
standardized_df.head(5)
```

Out[13]:

	0	1	2	3	4	5	6	7	
0	-0.425469	-0.470768	-0.954686	-0.231455	-0.919581	0.215100	-0.747410	0.454022	-0.7644
1	-0.426323	2.992576	-1.330157	-0.231455	-1.227311	-0.883652	-1.691588	3.163428	-0.6515
2	-0.385190	-0.470768	-0.705828	4.320494	-0.423795	-0.125423	0.818985	-0.353904	-0.1999
3	-0.249268	-0.470768	-0.423497	-0.231455	-0.158805	-0.228336	1.021567	-0.021755	-0.6515
4	-0.365945	0.395068	-1.030363	-0.231455	0.157472	3.102729	-0.060078	-0.646202	-0.5386

In [14]:
```
# Retrieving Random 5 samples from dataset
standardized_df.sample(5)
```

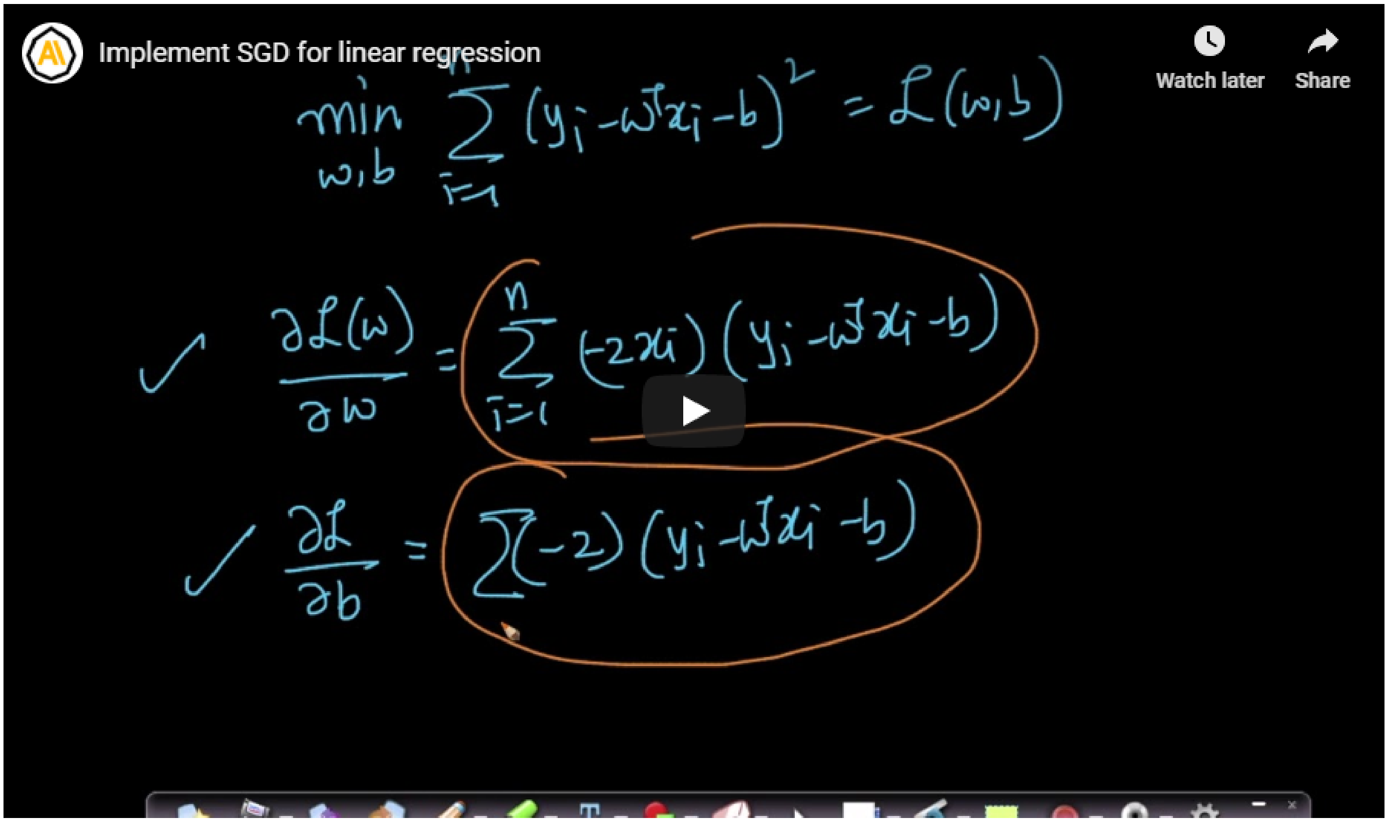
Out[14]:

	0	1	2	3	4	5	6	7	
352	-0.421647	-0.470768	-1.018720	-0.231455	-0.398151	-0.587019	0.001420	-0.515405	-0.538
205	-0.168268	-0.470768	1.241383	-0.231455	2.687694	-1.605559	0.909423	-1.062438	-0.538
191	-0.155219	-0.470768	1.241383	-0.231455	2.687694	-1.475404	0.916658	-0.965939	-0.538
35	-0.407931	0.481652	-0.755308	-0.231455	-1.073446	-0.989592	0.283589	1.935812	-0.312
59	0.443181	-0.470768	1.025997	-0.231455	1.337103	0.081918	0.544051	-0.477515	1.606

In [15]:
```
standardized_df.sample(5)
```

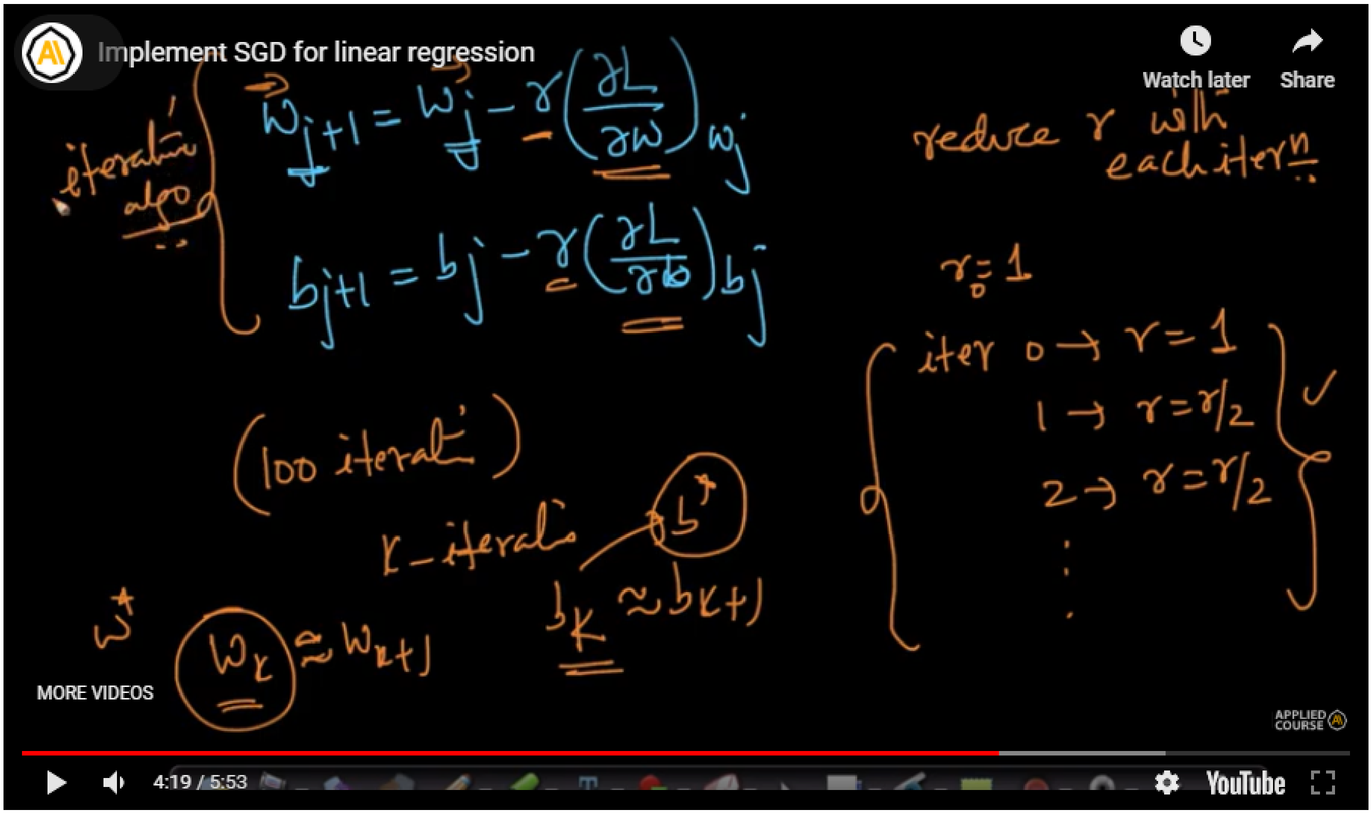
Out[15]:

	0	1	2	3	4	5	6	7	
111	0.111574	-0.470768	1.025997	-0.231455	1.337103	0.687291	0.771956	-0.564122	1.606
75	-0.392820	-0.470768	1.577561	-0.231455	0.576327	0.319527	1.093918	-0.787639	-0.651
250	-0.424806	-0.470768	0.259046	-0.231455	-1.022158	-0.022509	-0.541211	0.563541	-0.538
13	0.225702	-0.470768	1.025997	-0.231455	-0.210094	-0.007375	-0.143281	-0.178357	1.606
106	2.055917	-0.470768	1.025997	-0.231455	1.567900	-0.649070	0.858777	-0.905370	1.606



From the optimization function above, we need to compute weights (W) and Bias (B) for the linear regression model. For a two feature input system, the model is a line equation. In the current problem, we have 13 features, so the model is a hyper plane

We need to compute partial derivatives with respect to Weights and Bias for the optimization problem


Implement SGD for linear regression
Watch later
Share
reduce r with each itern
iter 0 → r = 1
(100 iterations)
MORE VIDEOS
4:19 / 5:53
YouTube

In [68]:
```
def _customSGD(dataset, learning_rate, n_epochs, batch_size, initialize_random
_coefs=False, variable_learning=False):
    """
    # Stochastic Gradient Descent
    -- Gradient Descent computes the cost gradient for all the samples involve
d in the dataset
       where as the SGD computes cost gradient of 1 sample at each iteration.
    -- Instead of one sample at a time, if a batch_size is provided it then be
comes Batch GD

    Expectations:
        dataset - a pandas dataframe
        learning_rate - an intezer or float
        n_epochs - an intezer
        batch_Size - an intezer

    """

    # Raise TypeErrors when required inputs are of not desired format

    no_of_training_sample, no_of_features = dataset.shape
    no_of_features -= 1 # subtracing the labels column from features

    if initialize_random_coefs:
        # Random initialization
        bias = np.random.rand(1)
        weights = np.random.rand(no_of_features)
    else:
        # Initialization with zeros
        bias = 0
        weights = np.zeros(shape=(1,no_of_features),dtype="double")

    # for future add tqdm function hear to know the progress of epochs
    for _epoch in range(n_epochs):
        # updating learning rate for every 100 epochs
        if variable_learning == True:
            if _epoch%100 == 0:
                learning_rate /= 2.0

        # local variables for needing to predict and compute error
        _b, _w, _parderivateW, _parderivateB = bias, weights, np.zeros(shape=(
1,no_of_features)), 0

        # since this going to be mini batch SGD
        miniBatch = dataset.sample(batch_size)

        #  reference - https://stackoverflow.com/questions/40144769/how-to-sel
ect-the-last-column-of-dataframe
        ylabels = np.array(miniBatch.iloc[:,-1]) # labels column
        xfeatures = np.array(miniBatch.drop(miniBatch.columns[len(miniBatch.co
lumns)-1], axis=1))

        for index in range(batch_size):
            # Refer first image for formulae
            # partial derivative w.r.t Weights
            # dl/dw = Summation(-2x * (y - (wTx+b)))
```

```
            _parderivateW += (-2) * (xfeatures[index]) * (ylabels[index] - (np
.dot(_w,xfeatures[index]) + _b))

            # partial derivate w.r.t bias
            # dL/db = Summation(-2 * (y - (wTx+b)))
            _parderivateB += (-2) * (ylabels[index] - (np.dot(_w, xfeatures[in
dex]) + _b))

        # Updating the weights, bias at the end of epoch
        # refer second image for formulae
        bias = (_b - learning_rate*(_parderivateB)/batch_size)
        weights = (_w - learning_rate*(_parderivateW)/batch_size)

        # print (bias, weights, f"At the end of epoch {_epoch} out of {n_epoch
s}")


    return weights, bias
```

In [69]:

```
fweights, fbias = _customSGD(standardized_df, 0.01, 750, 25) # fixed learning
 rate
```

In [70]:

```
print (f"Weights\n================\n{fweights}")
```

```
Weights
================
[[-0.89519037  1.12956652 -0.35030211  1.13923212 -1.35240868  2.366946
  -0.23322673 -3.29670507  2.01243158 -1.33301936 -1.6670795   0.73886308
  -3.70065531]]
```

In [71]:

```
print (f"Bias\n================\n{fbias}")
```

```
Bias
================
[22.19157247]
```

In [82]:

```
# variable learning rate
vweights, vbias = _customSGD(standardized_df, 0.01, 750, 25, False, True) # fi
xed learning rate
```

In [83]:

```
print (f"Weights\n================\n{vweights}")
```

```
Weights
================
[[-0.70785641  0.42531237 -0.56623238  1.08724266 -0.43664337  2.76976657
  -0.21268316 -1.31358926  0.44666002 -0.37973611 -1.54300038  0.76709466
  -2.62892823]]
```

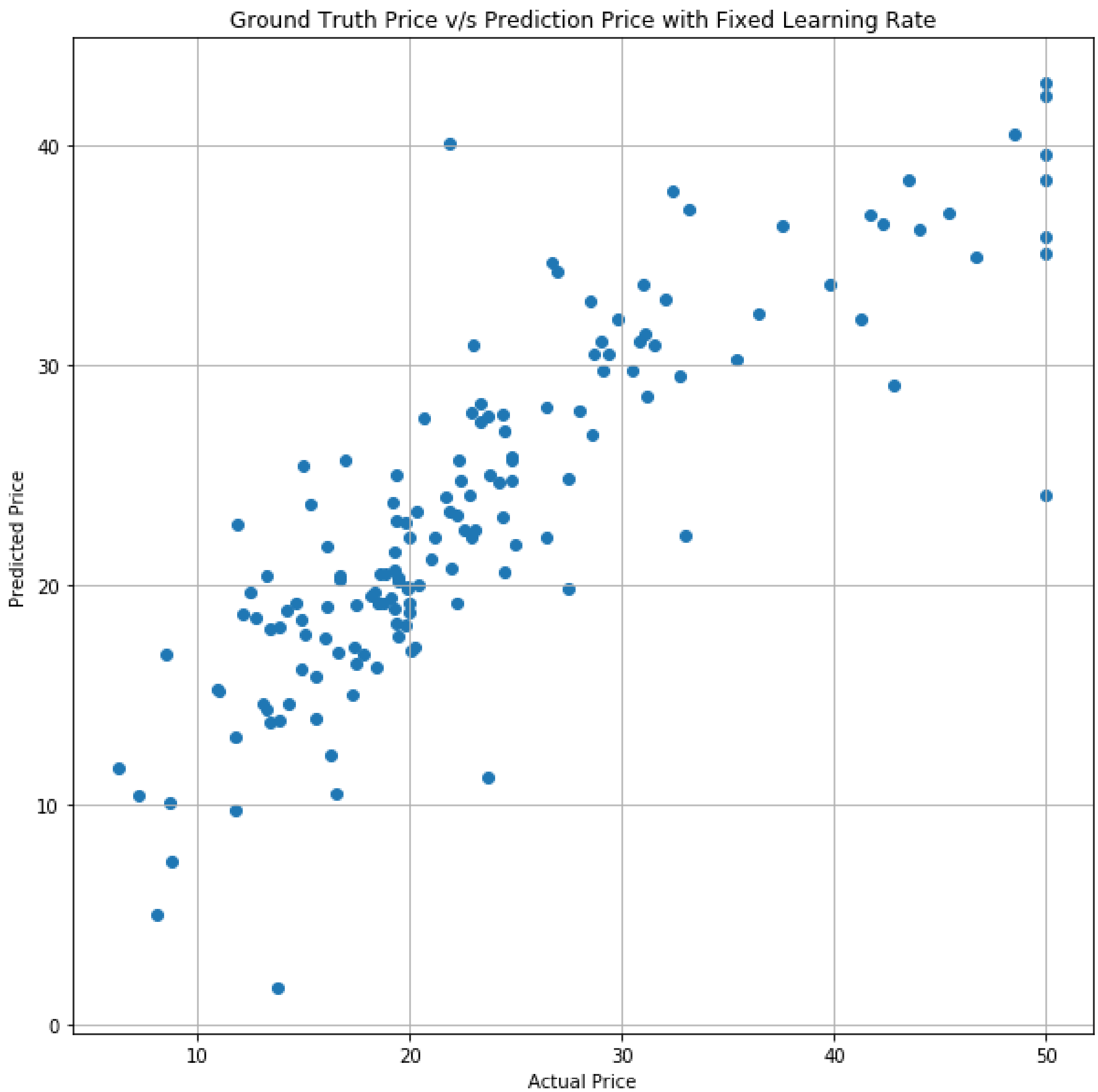
In [84]:

```
print (f"Bias\n================\n{vbias}")
```

```
Bias
================
[19.11943868]
```

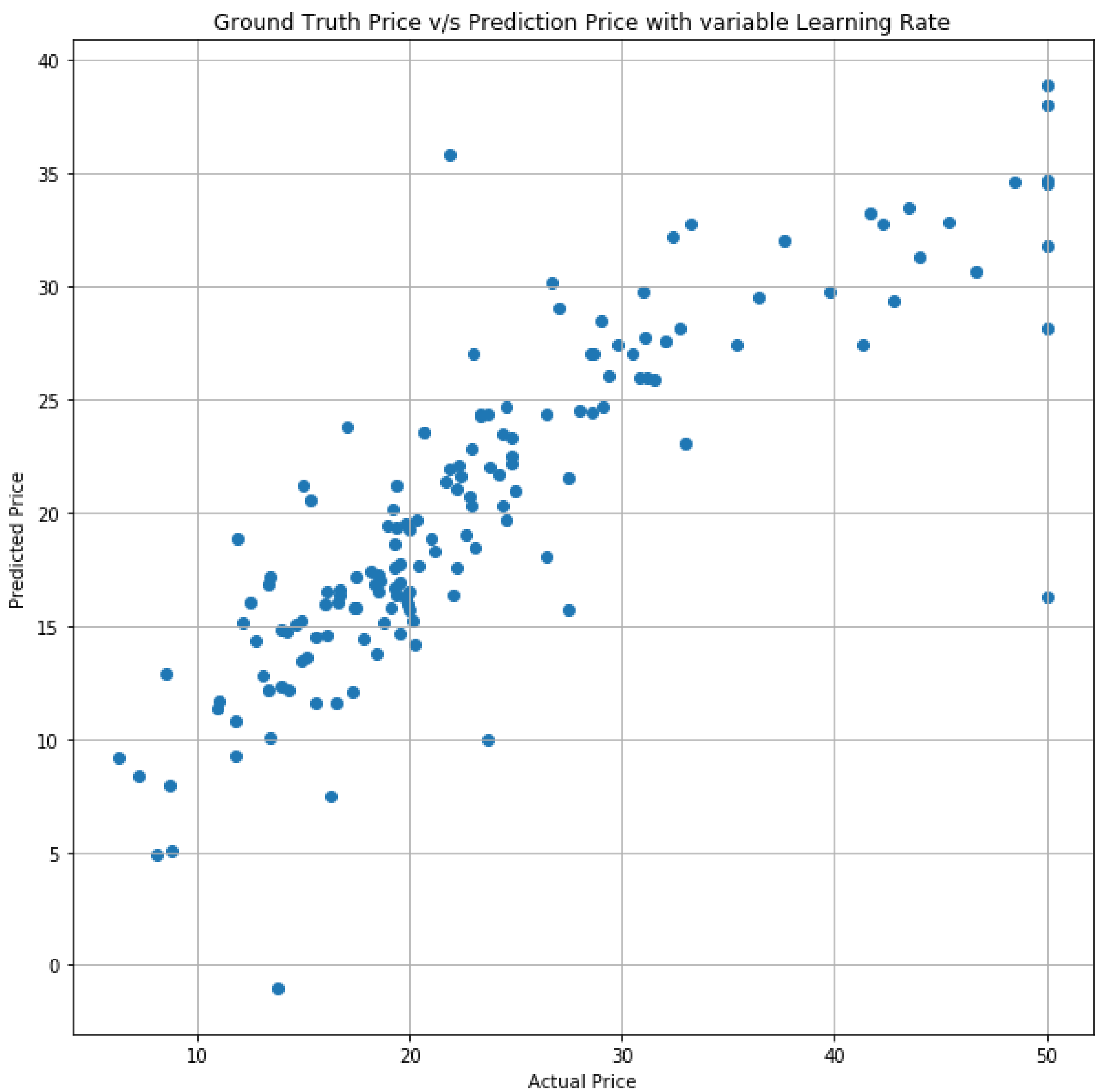
In [72]:
```
# since we are done with the training lets do inference
# with fixed learning rate
predicted_house_yhat_list = []
for index in range (len(X_test)):
    yhat = np.dot(fweights, X_test[index]) + fbias
    predicted_house_yhat_list.append(np.asscalar(yhat)) # converting the yhat
 prediction into a scalar value
    # >>> np.asscalar(np.array([24]))
    # 24
```

In [73]:
```
# Lets plot Ground Truth Price v/s Predictions
plt.figure(figsize=(10,10))
plt.title("Ground Truth Price v/s Prediction Price with Fixed Learning Rate")
plt.scatter(Y_test, predicted_house_yhat_list)
plt.xlabel("Actual Price")
plt.ylabel("Predicted Price")
plt.grid()
plt.show()
```



In [85]:
```
# with Variable Learning rate
vpredicted_house_yhat_list = []
for index in range (len(X_test)):
    yhat = np.dot(vweights, X_test[index]) + vbias
    vpredicted_house_yhat_list.append(np.asscalar(yhat)) # converting the yhat
prediction into a scalar value
    # >>> np.asscalar(np.array([24]))
    # 24
```

In [86]:
```
# Lets plot Ground Truth Price v/s Predictions
plt.figure(figsize=(10,10))
plt.title("Ground Truth Price v/s Prediction Price with variable Learning Rat
e")
plt.scatter(Y_test, vpredicted_house_yhat_list)
plt.xlabel("Actual Price")
plt.ylabel("Predicted Price")
plt.grid()
plt.show()
```

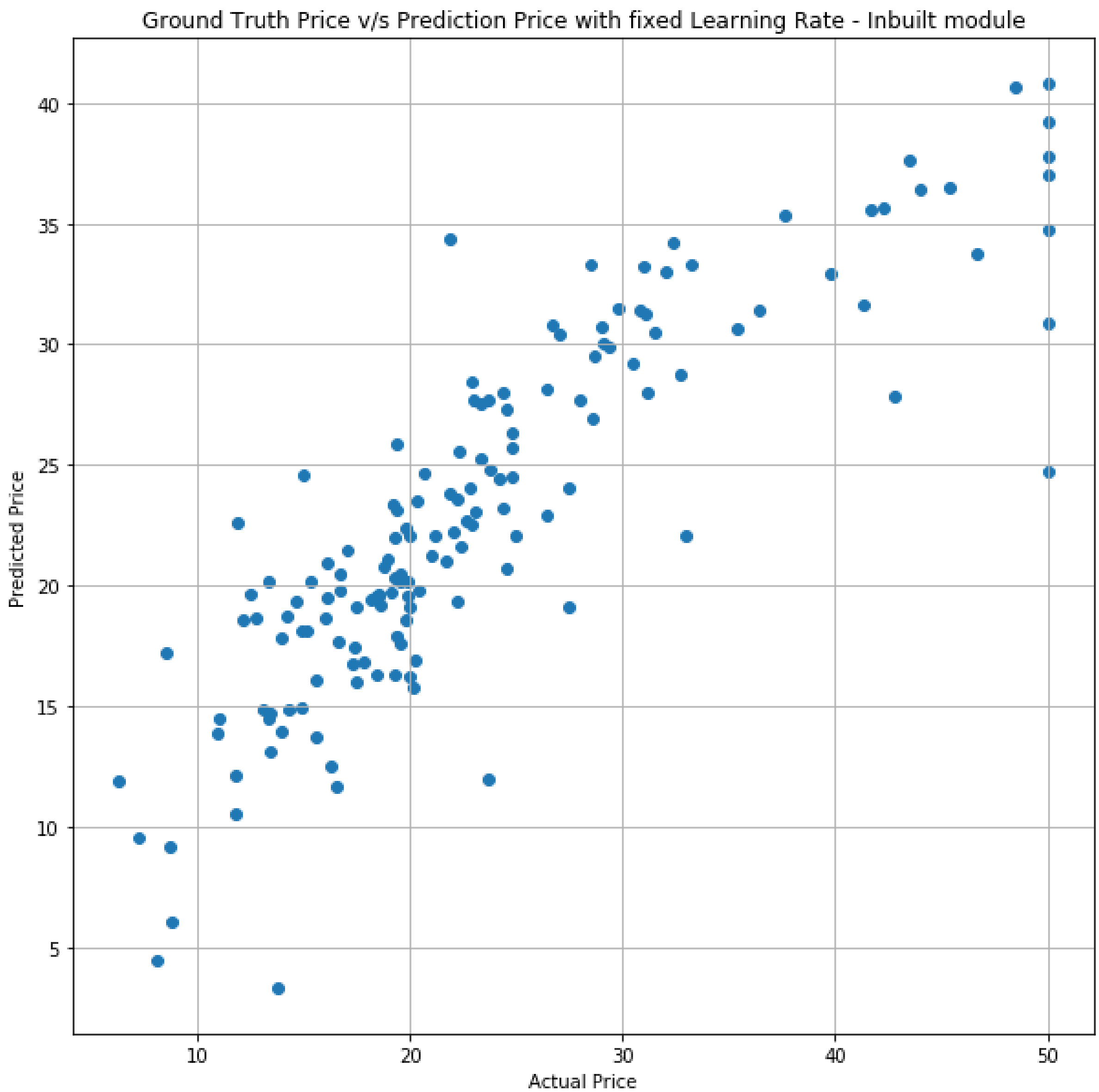


In [87]:
```
# Mean Squared Error - Fixed LR, Variable LR
MSE_flr = mean_squared_error(Y_test, predicted_house_yhat_list)
MSE_vlr = mean_squared_error(Y_test, vpredicted_house_yhat_list)

print (f"Fixed LR MSE {MSE_flr}")
print (f"Variable LR MSE {MSE_vlr}")
```

```
Fixed LR MSE 30.64473411784173
Variable LR MSE 42.52533567999639
```

In [75]:
```
# Lets perform the same with inbuilt module of sklearn

sgd = SGDRegressor(learning_rate="constant", eta0=0.01, penalty=None, max_iter
=50)
sgd.fit(X_train,Y_train)
y_hat_sgd=sgd.predict(X_test)
```

In [76]:
```
# Lets plot Ground Truth Price v/s Predictions
plt.figure(figsize=(10,10))
plt.title("Ground Truth Price v/s Prediction Price with fixed Learning Rate -
 Inbuilt module")
plt.scatter(Y_test, y_hat_sgd)
plt.xlabel("Actual Price")
plt.ylabel("Predicted Price")
plt.grid()
plt.show()
```



In [77]:
```
# Mean Squared Error - Fixed LR, Variable LR
MSE_flr_inbuilt = mean_squared_error(Y_test, y_hat_sgd)

print (f"Fixed LR MSE {MSE_flr_inbuilt}")
```

```
Fixed LR MSE 29.7729382260675
```

Summarizing the results

In [78]:
```
# A tabular representation of weights for all four modes
from prettytable import PrettyTable

x = PrettyTable()
x.field_names = ["Weights - Custom", "Weights - Inbuilt"]
```

In [79]:
```
weights_sgd = sgd.coef_
```

In [80]:
```
for i in range(12):
    x.add_row([fweights[0][i],weights_sgd[i]])
print(x)
```

```
+---------------------+---------------------+
|   Weights - Custom  |  Weights - Inbuilt  |
+---------------------+---------------------+
| -0.8951903669319022 | -0.9957863796826973  |
|  1.129566519981019  |  1.3733331426243682  |
| -0.3503021113827559 | 0.043633719299515004 |
|  1.139232115194231  |  0.3210297525187523  |
| -1.3524086841272596 | -1.6073743441292732  |
|  2.366946004315772  |  1.9590627259886977  |
| -0.23322673440138084 | -0.0808845687432791 |
|  -3.296705073959816 |  -3.231395894872585  |
|  2.012431578586961  |  2.8169369696694315  |
| -1.3330193563306263 |  -2.268061926237042  |
| -1.6670794991024582 |  -1.752852491026695  |
|  0.7388630842189096 |  0.9634424018569003  |
+---------------------+---------------------+
```

In [81]:
```
# Custom SGD v/s SGD sklearn implementation
print('MSE of manual implementation = ',MSE_flr)
print('-'*50)
print('MSE of SGD sklearn implementation = ',MSE_flr_inbuilt)
```

```
MSE of manual implementation =  30.64473411784173
--------------------------------------------------
MSE of SGD sklearn implementation =  29.7729382260675
```

Summary

When compared manual SGD implementation with that of third party module of sklearn we pretty much see the same weights and MSE