AML Practical 1.1

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1) Read the text from given Image using tesseract

In [5]:
```python
from PIL import Image
import pytesseract as pt

img = Image.open('class.png')
imgText = pt.image_to_string(img,lang='eng')
print(imgText)
```

```
Classification - Machine Learning

Classification is a type of supervised learning. It specifies the class to which data elements belong
to and is best used when the output has finite and discrete values. It predicts a class

Types of Classification Algorithms
Let's have a quick look into the types of Classification Algorithm below.

-Linear Models
Logistic Regression
Support Vector Machines
-Nonlinear models
K-nearest Neighbors (KNN)
Kernel Support vector Machines (SVM)
Naive Bayes
Decision Tree Classification
Random Forest Classification
```

1.2 Linear Regression using sklearn.linear_model

In [97]:
```python
import numpy as np
import pandas as pd
from sklearn import datasets,metrics
from sklearn.linear_model import LinearRegression
from sklearn.model_selection import train_test_split
from sklearn.metrics import mean_absolute_error ,mean_squared_error
from sklearn.datasets import load_boston

bos = load_boston()
bos_df = pd.DataFrame(bos.data)
```

In [98]:
```python
bos_df.head()
```

Out[98]:

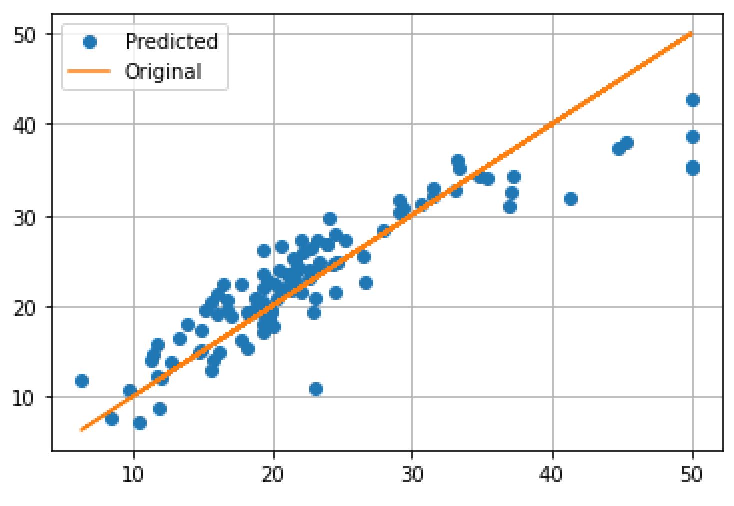
	0	1	2	3	4	5	6	7	8	9	10	11	12
0	0.00632	18.0	2.31	0.0	0.538	6.575	65.2	4.0900	1.0	296.0	15.3	396.90	4.98
1	0.02731	0.0	7.07	0.0	0.469	6.421	78.9	4.9671	2.0	242.0	17.8	396.90	9.14
2	0.02729	0.0	7.07	0.0	0.469	7.185	61.1	4.9671	2.0	242.0	17.8	392.83	4.03
3	0.03237	0.0	2.18	0.0	0.458	6.998	45.8	6.0622	3.0	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 [99]:
```python
bos_df.columns = bos.feature_names
bos_df['PRICE'] = bos.target
X = bos_df.drop('PRICE', axis = 1)
y = bos_df['PRICE']
X_train, X_test, y_train, y_test = train_test_split(X,y,test_size=0.21,random_state = 3)
```

In [100]:
```python
lr_model = LinearRegression()

lr_model.fit(X_train,y_train)
pre_y = lr_model.predict(X_test)
print("MAE = ",mean_absolute_error(y_test,pre_y))
print("MSE =",mean_squared_error(y_test,pre_y))
print("Model accuracy = " , (lr_model.score(X_test,y_test)*100))
```

```
MAE =  2.926678561960011
MSE = 16.255782909135814
Model accuracy =  80.2232232582644
```

In [101]:
```python
import matplotlib.pyplot as plt
plt.plot(y_test,pre_y,marker='o',linestyle='',label="Predicted")
plt.plot(y_test,y_test, label="Original")

plt.legend(loc='best')
plt.grid()
plt.show()
```



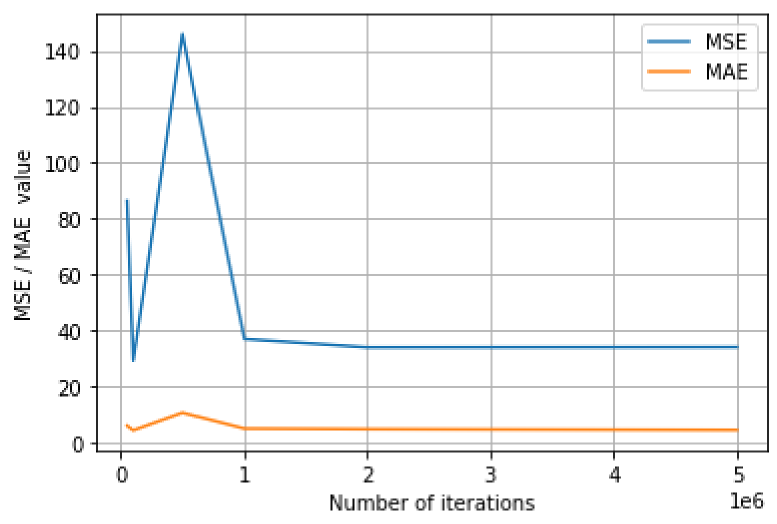
As we can see from the above graph predicted vs original values. We can see that our model performed well with 80% accuracy and very less MSE.

1.3 Linear Regression using SGDRegressor

In [6]:
```python
import numpy as np
from sklearn import datasets, metrics
from sklearn.preprocessing import StandardScaler
from sklearn import linear_model, metrics
from sklearn.model_selection import train_test_split

X, y = datasets.load_boston(return_X_y=True)
X_train=X[0:400,:]
y_train=y[0:400]
X_test=X[400:506,:]
y_test=y[400:506]

# X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)
scaler=StandardScaler()
scaler.fit(X_train[:,1:])
X_train[:,1:]=scaler.transform(X_train[:,1:])
X_test[:,1:]=scaler.transform(X_test[:,1:])


mae_list = []
mse_list = []
iter_list = [50000,100000,500000,1000000,2000000,5000000]
def linear_cal(intr):
        regr = linear_model.SGDRegressor(max_iter=intr,learning_rate='invscaling',eta0=0.01)
         # Train the model using the training sets
        regr.fit(X_train, y_train)
        pre_y=regr.predict(X_test)
        metrics.mean_squared_error(y_test,pre_y)
        mae = metrics.mean_absolute_error(y_test,pre_y)
        mse = metrics.mean_squared_error(y_test,pre_y)
        mae_list.append(mae)
        mse_list.append(mse)
        #print("MAE = ",mae)
        #print("MSE =",mse)

for iter_value in iter_list:
     linear_cal(iter_value)
```

Graph

In [7]:
```python
import matplotlib.pyplot as plt
plt.plot(iter_list,mse_list, label="MSE")
plt.plot(iter_list,mae_list, label="MAE")
plt.xlabel('Number of iterations')
plt.ylabel('MSE / MAE  value')
plt.legend(loc='best')
plt.grid()
plt.show()
```



Observation

As we can see from the above diagram (No of iterations vs error values), We can see that as the number of iterations increases the error starts decreasing up to a certain value then it's getting settling to a particular value.