```
In [1]:
```

```
%matplotlib inline
import warnings
warnings.filterwarnings("ignore")
import sqlite3
import pandas as pd
import numpy as np
import nltk
import string
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.feature_extraction.text import TfidfTransformer
from sklearn.feature extraction.text import TfidfVectorizer
from sklearn.feature_extraction.text import CountVectorizer
from sklearn.metrics import confusion matrix
from sklearn import metrics
from sklearn.metrics import roc curve, auc
from nltk.stem.porter import PorterStemmer
import re
# Tutorial about Python regular expressions: https://pymotw.com/2/re/
import string
from nltk.corpus import stopwords
from nltk.stem import PorterStemmer
from nltk.stem.wordnet import WordNetLemmatizer
from gensim.models import Word2Vec
from gensim.models import KeyedVectors
import pickle
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
from sklearn.model_selection import train test split
from tqdm import tqdm
import os
from plotly import plotly
import plotly.offline as offline
import plotly.graph objs as go
offline.init notebook mode()
from collections import Counter
import pickle
from sklearn.datasets import load boston
```

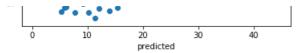
In [0]:

```
#loading the dataset
boston=load_boston()
X=boston.data
Y=boston.target

#splitting the dataset into train, test datasets
X_train, X_test, Y_train, Y_test=train_test_split(X,Y,test_size=0.3, random_state=0)

#feature scaling
scaler=preprocessing.StandardScaler().fit(X_train)
X_train=scaler.transform(X_train)
Y_test=scaler_transform(Y_test)
```

```
v rest-scatet. rranstorm (v rest)
In [31:
print(X_train.shape, X_test.shape)
(354, 13) (152, 13)
SGDRegressor (SkLearn)
In [4]:
sklearn model = SGDRegressor(penalty=None,loss='squared loss',alpha=0,max iter=1000,verbose=0)
sklearn_model.fit(X_train, Y_train)
Out[4]:
SGDRegressor(alpha=0, average=False, early_stopping=False, epsilon=0.1,
             eta0=0.01, fit intercept=True, l1 ratio=0.15,
             learning_rate='invscaling', loss='squared_loss', max_iter=1000,
             n_iter_no_change=5, penalty=None, power_t=0.25, random_state=None,
             shuffle=True, tol=0.001, validation fraction=0.1, verbose=0,
             warm start=False)
In [5]:
w sklearn = sklearn model.coef
b sklearn = sklearn_model.intercept_
print("w",sklearn model.coef )
print("b",sklearn_model.intercept_)
 \text{w } [-0.92067857 \quad 0.89159757 \quad -0.19854314 \quad 0.64819434 \quad -1.61035048 \quad 2.80469925 
-0.35168169 -2.93746844 1.32477611 -1.04757732 -2.2043927 0.58077839
 -3.361114571
b [22.73861763]
MeanSquaredError for test-Data
In [6]:
#mean squared error
Y predicted=sklearn model.predict(X test)
sklearn model MSE=mean squared error(Y test, Y predicted)
print("Mean Squared Error ",sklearn_model_MSE)
Mean Squared Error 27.5665152774417
In [7]:
#predicted values vs actual values
plt.plot(Y_predicted,Y_test,linestyle='',marker='o')
plt.xlabel('predicted')
plt.ylabel('actual')
plt.show()
  40
actual
08
  20
```



Custom Implementation of SGD

```
In [0]:
```

```
def loss(X,Y,W,b):
   Y_predicted=np.dot(X,W)+b
   mse_loss = mean_squared_error(Y,Y_predicted)
   return mse_loss
```

In [0]:

```
def SGDLinearRegression(X_train,Y_train,X_test,Y_test,W,b,r,iterations=2000,batch_size=128):
 n = len(Y train)
  mse train list =[]
 MSE test list = []
  for j in range(iterations):
    #we are choosing random index's from X-train so that we can form batches from X train
    \verb|index=np.random.choice(np.arange(len(X\_train)), size=batch\_size, replace={\bf False})|
    # X batch has a set of random elements from X train
    X batch=X train[index]
    Y batch=Y train[index]
   # y and mean squared error is predicted at the start of each iteration which means for each e
poch for Train DATA
    Y predicted=np.dot(X batch, W)+b
    mse train = loss(X batch, Y batch, W,b)
    mse train list.append(mse train)
    # We calculate the test mean squared loss for each updated Weights and Updated b intercept
    Y predicted=np.dot(X test,W)+b
   MSE_test=mean_squared_error(Y_test,Y_predicted)
    MSE test list.append(MSE test)
     #we could try if the difference between <code>mse_previous</code> and <code>mse_present value</code> is less than 0.1
we need to stop the loop,
     #we could also try other metrics like if mse does not change for few iterations we could sto
p the outer loop
      # If the test loss is greater than SKLEARN MODEL loss then Updated the Gradient,
      # If the test loss is less than SKLEARN MODEL that is the Optimal MODEL. and Store the
weights and Gradients
    if (MSE test list[j] > sklearn model MSE):
          # we need to calculated the loss of the first batch and then update the (w,b) parameters
and then pass the second batch and so..on
          \# We need to completer the first epoch and then calculate the MSE
          for i in range(batch size):
            # calculating the y_predicted for first element in the batch and so..on
            y_predicted = np.dot(W.T,X batch[i]) + b
            # updating the W parameter
            W = W - (-2) *r*X_batch[i] * (Y_batch[i] - y_predicted)
            # updating the b parameter
            b = b - (-2) *r* (Y_batch[i] - y_predicted)
          # we can decrease the learning rate based on weighted decay or exponential decay or
based on the epoch number
          # but here we are decresing r for each iteration
          r = r/np.exp(j)
    else:
  return W,b,mse_train_list,MSE_test_list
```

```
In [104]:
```

In [105]:

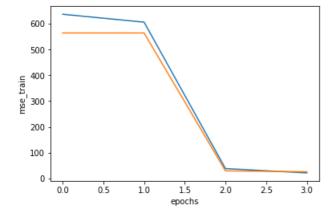
```
MSE_test_list
```

Out[105]:

[564.0665085299725, 564.0665085299725, 29.727041180223104, 26.371755430581246]

In [107]:

```
#predicted values vs actual values
n=4
plt.plot(range(0,n),mse_list[:n])
plt.plot(range(0,n),MSE_test_list[:n])
plt.xlabel('epochs')
plt.ylabel('mse_train')
plt.show()
```



In [108]:

```
Y_predicted=np.dot(X_test,W_updated)+b_updated
MSE_custom=mean_squared_error(Y_test,Y_predicted)
MSE_custom
```

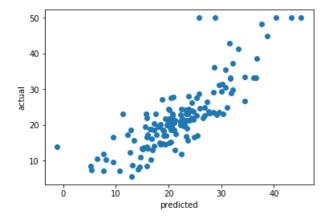
Out[108]:

26.371755430581246

In [109]:

```
#predicted values vs actual values
plt.plot(Y_predicted,Y_test,linestyle='',marker='o')
plt.xlabel('predicted')
```

```
plt.ylabel('actual')
plt.show()
```



In [110]:

```
from prettytable import PrettyTable

x = PrettyTable()

x.field_names = ["Weights", "sklear implementation", "my implementation"]

for i in range(13):
    x.add_row(["W"+str(i+1),w_sklearn[i],W_updated[i]])

x.add_row(["b",b_sklearn,b_updated])
print(x)
```

```
+----+
| Weights | sklear implementation | my implementation |
+-----
   W1 | -0.9206785659209031 | -0.1255767996530609 |
        | 0.891597567281791 | 0.8287376587046171 |
        | -0.1985431353855247 | -0.6848169874669686 |
   WЗ
        | 0.6481943432228289 | 1.138404818728685
| -1.610350477195073 | -0.9352746581330771
   W4
    W5
            2.8046992476392436
   W6
         2.976845256521955
        -0.3516816935278904 | 0.40426712504966494 |
   W7
   W8
        | -2.9374684425134485 | -2.1919289305658056 |
        | 1.3247761126708053 | 1.276048994583615 |
| -1.0475773200174825 | -0.3108737825818627 |
| -2.2043927049301333 | -1.7253414316463378 |
| 0.5807783859932566 | 0.6243120954743967 |
   W 9
   W10
   W11
   W12
  W13 | -3.3611145726488365 | -4.455934359649436 |
   b |
              [22.73861763] | [22.83036686]
```

In [111]:

```
y = PrettyTable()

y.field_names = ["MSE", "Model"]
y.add_row([27.5665,"Sklearn Model"])
y.add_row([26.3717,"Custom Model"])
print(y)
```

```
| MSE | Model |
|------+
| 27.5665 | Sklearn Model |
| 26.3717 | Custom Model |
```