practical_3.ipynb

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[65]
```python
# Importing packages

import numpy as np
import pandas as pd
import sklearn
import matplotlib.pyplot as plt
from sklearn.datasets import load_boston
from sklearn.model_selection import train_test_split
from sklearn.metrics import mean_squared_error
from sklearn.preprocessing import StandardScaler
```

[66]
```python
# Loading datasets

X, y = load_boston(return_X_y=True)
print(f"No of data samples : {X.shape[0]}")
```

```
No of data samples : 506
```

[67]
```python
# Spliting into training and testing datasets
M = 400                    # No. of samples in the training dataset
N = X.shape[0] - M         # No. of samples in the testing dataset
X_train, y_train = X[:M,:], y[:M]
X_test , y_test  = X[M:,:], y[M:]
```

[68]
```python
# Reshape the data (sklearn is pedantic)
y_train, y_test = y_train[:, None], y_test[:, None]
```

[69]
```python
# Normalize the data
scaler = StandardScaler() # To scale the X_train and X_test datasets

# Let's transform the X_train and X_test data
X_train = scaler.fit_transform(X_train)
X_test  = scaler.transform(X_test)
```

[70]
```python
X_train = np.c_[np.ones_like(X_train[:, 0]) , X_train]
X_test  = np.c_[np.ones_like(X_test[:, 0])  , X_test ]
```

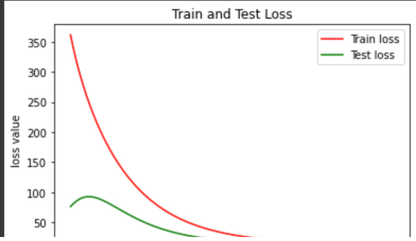
[71]
```python
# Let's initialize our weights
w = np.random.randn(X_train.shape[-1], 1)
```

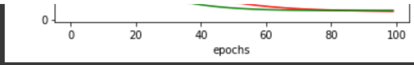
[72]
```python
def loss(y, y_pred):
    return 0.5 * np.mean((y - y_pred) ** 2)

def loss_grad(X, y, y_pred):
    return (1./X.shape[0]) * X.T @ (y_pred - y)
```

[73]
```python
# Start training now!
import time
import sys

epochs = 100
alpha  = 0.03
train_losses = []
test_losses  = []
for _ in range(epochs):
    y_pred = X_train @ w
    w_grad = loss_grad(X_train, y_train, y_pred)
    w = w - alpha * w_grad
    sys.stdout.write(f"\rEpochs : {_}, loss_train : {loss(y_train, y_pred):.4f}, loss_test : {loss(y_test, X_test @ w):.4f}")
    train_losses.append(loss(y_train, y_pred))
    test_losses.append(loss(y_test, X_test @ w))
    time.sleep(0.05)
```

```
Epochs : 99, loss_train : 13.5612, loss_test : 15.0852
```

[74]
```python
import matplotlib.pyplot as plt

plt.plot(train_losses, color='r', label="Train loss")
plt.plot(test_losses, color='g', label="Test loss")
plt.title("Train and Test Loss")
plt.xlabel("epochs")
plt.ylabel("loss value")
plt.legend()
plt.show()
```





[75]

```python
#for saving values for table generation
thetas = []
MAEs = []
MSEs = []

epochs = 100
# alphas  = [0.01, 0.03, 0.05, 0.1, 0.37]
alphas  = [0.0001, 0.0003, 0.001, 0.003, 0.01, 0.03, 0.037, 0.05, 0.1, 0.37]
for alpha in alphas:
    w = np.random.randn(X_train.shape[-1], 1)
    train_losses = []
    for _ in range(epochs):
        y_pred = X_train @ w
        w_grad = loss_grad(X_train, y_train, y_pred)
        w = w - alpha * w_grad
        train_losses.append(loss(y_train, y_pred))
#         test_losses.append(loss(y_test, X_test @ w))
    plt.plot(train_losses, label=f"$\\alpha$={alpha}")

    predictions=np.dot(X_test,w)
    print("For alpha",alpha,":")
    print("\tTheta:", w)
    thetas.append(w)

    this_MAE = sklearn.metrics.mean_absolute_error(y_true=y_test,y_pred=predictions)
    print("\tMAE:", this_MAE)
    MAEs.append(this_MAE)

    this_MSE = sklearn.metrics.mean_squared_error(y_true=y_test,y_pred=predictions)
    print("\tMSE:", this_MSE)
    MSEs.append(this_MSE)

# plt.legend()
plt.title("Loss for different hyperparameters")
plt.show()
```

```
For alpha 0.0001 :
        Theta: [[-0.39925526]
 [ 0.50000383]
 [ 2.07775593]
 [ 0.74895147]
 [ 0.58949543]
 [-0.25972503]
 [ 2.33375756]
 [-1.68370803]
 [ 0.42818343]
 [ 0.31342742]
 [ 0.01400306]
 [-0.53351756]
 [-1.20346038]
 [-0.00855802]]
        MAE: 15.18930152842787
        MSE: 299.6740767572498
For alpha 0.0003 :
        Theta: [[-0.35640997]
 [-0.48481105]
 [-0.64248745]
 [-1.46278109]
 [-0.43574326]
 [ 0.24613746]
 [-0.8418798 ]
 [ 1.43630306]
 [-1.0041252 ]
 [-0.26197713]
 [-0.55131567]
 [ 1.8752137 ]
 [-0.52610099]
 [-1.20843902]]
        MAE: 15.392293944333394
        MSE: 270.2328400596714
For alpha 0.001 :
        Theta: [[ 2.9952745 ]
 [-1.37389219]
 [ 2.5185879 ]
 [-0.81442255]
 [-0.1321475 ]
 [ 0.45778958]
 [-0.05785604]
 [ 0.39880353]
 [-0.5653267 ]
 [-0.77728479]
 [-0.74673891]
 [ 0.01382263]
 [ 0.14462914]
 [-0.10306591]]
        MAE: 19.74248159353918
        MSE: 413.2464491751797
For alpha 0.003 :
        Theta: [[ 6.36287451]
 [ 0.07990647]
 [ 0.12907113]
 [-0.90923247]
 [-1.46059024]
 [-1.06121614]
```

Extra Lab work

Plotting graph for 10 alpha values and calculating their MAE and MSE. Also generating table of alpha values along with their respective theta values, MSE and MAB.

```python
# Generating table of 10x17 for each of 10 alpha values in which parameters like MSE, MAE, 14 Theta values are included.
from prettytable import PrettyTable
myTable = PrettyTable(["Alpha values", "MAE", "MSE", "θ0", "θ1", "θ2", "θ3", "θ4", "θ5", "θ6", "θ7", "θ8", "θ9", "θ10", "θ11", "θ12", "θ13" ])

for i in range(len(alphas)):
  myTable.add_row([str(alphas[i]), str(MAEs[i]), str(MSEs[i]), str(thetas[i][0]), str(thetas[i][1]), str(thetas[i][2]), str(thetas[i][3]), str(thetas[i][4
print(myTable)
```

Alpha values	MAE	MSE	θ0	θ1	θ2	θ3	θ4	θ5	
0.0001	15.18930152842787	299.6740767572498	[-0.39925526]	[0.50000383]	[2.07775593]	[0.74895147]	[0.58949543]	[-0.25972503]	[2
0.0003	15.392293944333394	270.2328400596714	[-0.35640997]	[-0.48481105]	[-0.64248745]	[-1.46278109]	[-0.43574326]	[0.24613746]	[-
0.001	19.74248159353918	413.2464491751797	[2.9952745]	[-1.37389219]	[2.5185879]	[-0.81442255]	[-0.1321475]	[0.45778958]	[-0
0.003	12.900447713767893	187.50135720265695	[6.36287451]	[0.07990647]	[0.12907113]	[-0.90923247]	[-1.46059024]	[-1.06121614]	[0
0.01	7.965204265664068	79.74723131911446	[15.51448212]	[-0.91271604]	[0.96980842]	[0.03792848]	[1.05911199]	[-1.26733162]	[2
0.03	4.077712394609106	25.098154452856157	[23.1620726]	[-0.77241619]	[1.05638024]	[-0.43039596]	[0.72208168]	[-0.41364796]	[3
0.037	3.6314912539454416	20.774716636762882	[23.74088067]	[-0.46742962]	[1.28283529]	[-0.66603044]	[0.73368274]	[-0.62749466]	[3
0.05	4.44883841979193	29.1306742147603	[24.19371371]	[-0.83489091]	[0.91392928]	[0.11553724]	[0.635306]	[-1.30171861]	[3
0.1	4.852705090072671	33.89109167985263	[24.33390309]	[-1.05448047]	[0.99043565]	[0.05031823]	[0.5453088]	[-1.4447727]	[3
0.37	74.06609687969615	6405.995051728531	[24.3345]	[3.00655517]	[-3.47589409]	[6.44849831]	[1.61660424]	[4.5607586]	[-

Linear Regression using normal equation :

[77]

```python
import numpy as np
from sklearn import datasets, metrics
from numpy.linalg import inv, pinv, LinAlgError

X, y = datasets.load_boston(return_X_y=True)
X_train_temp1=X[0:400,:]
X_train=np.zeros((X_train_temp1.shape[0],X_train_temp1.shape[1]+1))
X_train[:,0]=np.ones((X_train_temp1.shape[0]))
X_train[:,1:]=X_train_temp1
print("Type of X_train:", type(X_train), "Shape of X_train:", X_train.shape)
y_train=y[0:400]
X_test_temp1=X[400:506,:]
X_test=np.zeros((X_test_temp1.shape[0],X_test_temp1.shape[1]+1))
X_test[:,0]=np.ones((X_test_temp1.shape[0]))
X_test[:,1:]=X_test_temp1
print("Type of X_test:", type(X_test), "Shape of X_test:", X_test.shape)
y_test=y[400:506]
theta=np.zeros(X_train.shape[1])
try:
  XTXi=inv(np.dot(X_train.T,X_train))
except LinAlgError:
  XTXi=pinv(np.dot(X_train.T,X_train))
XTy=np.dot(X_train.T,y_train)
theta=np.dot(XTXi,XTy)
print("Thetas:", theta)
print("Thetas Shape:", theta.shape)
predictions=np.dot(theta,X_test.T)
print("MAE:", metrics.mean_absolute_error(y_true=y_test,y_pred=predictions))
print("MSE:", metrics.mean_squared_error(y_true=y_test,y_pred=predictions))
```

```
Type of X_train: <class 'numpy.ndarray'> Shape of X_train: (400, 14)
Type of X_test: <class 'numpy.ndarray'> Shape of X_test: (106, 14)
Thetas: [ 2.86725996e+01 -1.91246374e-01  4.42289967e-02  5.52207977e-02
  1.71631351e+00 -1.49957220e+01  4.88773025e+00  2.60921031e-03
 -1.29480799e+00  4.84787214e-01 -1.54006673e-02 -8.08795026e-01
 -1.29230427e-03 -5.17953791e-01]
Thetas Shape: (14,)
MAE: 5.142232214464314
MSE: 37.89377859958516
```

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