Exercise 2 - Part A

November 19, 2021

Machine Learning Lab

Lab 02

Exercise 2 - Part A

Importing Packages

[1]:
```
import numpy as np            #Importing Numpy
```

Initializing Normal Distribution Parameters and Matrix X and Matrix Y Shapes

[2]:
```
mu = 2                      #Mean of Distribution
sigma = 0.01                #Standard Deviation of Data points
matX_shape = (100,10)       #Dimensions for Matrix X
matY_shape = (100,1)        #Dimensions for Matrix Y
```

Creating a Bias column to be added in Matrix X

[3]:
```
#Initializing the bias column for b0
bias_column = np.ones(shape=(100,1))
```

Initializing Matrix X and Matrix Y

[4]:
```
matX = [[np.random.normal(mu,sigma) for i in range(matX_shape[1])] for j in␣
 ↪range(matX_shape[0])]
matX = np.array(matX)

#Appending bias column in the Matrix X for calculating b0
matX = np.append(bias_column,matX,axis=1)
```

[5]:
```
matY = [[np.random.uniform(1,2) for i in range(matY_shape[1])] for j in␣
 ↪range(matY_shape[0])]
matY = np.array(matY)
```

Function to Transpose the given Matrix

[6]:
```
def transpose_matrix(matrix):
    result = []

    #Taking individual columns, flatten it into a single dimension
    #row and then append it into our result matrix
    for i in range(matrix.shape[1]):
```

```
        curr_col = matrix[:,i]
        curr_col = curr_col.flatten()
        result.append(curr_col)

    return np.array(result)
```

Function to Multiply Two Matrices

[7]:
```
def multiply_matrices(matA,matB):
    #Validates if matrix A columns are same as matrix B rows
    if matA.shape[1] != matB.shape[0]:
        raise Exception('Invalid Matrix Dimensions')

    matC = np.zeros(shape=(matA.shape[0],matB.shape[1]))
    for i in range(len(matA)):
        for j in range(len(matB[0])):
            for k in range(len(matB)):
                matC[i][j] += matA[i][k] * matB[k][j]
    return matC
```

Implementing Guassain Elimination Functions

[8]:
```
def guassian_elimination(A,b):
    for k in range(len(A)-1):
        for i in range(k+1,len(A)):
            A[i][k] = A[i][k]/A[k][k]
            for j in range(k+1,len(A)):
                A[i][j] = A[i][j] - A[i][k] * A[k][j]
            b[i] = b[i] - A[i][k] * b[k]
    return (A,b)
```

[9]:
```
def backward_substitution(A,b):
    x = np.zeros(shape=(len(A),1))
    for i in range(len(A)-1,-1,-1):
        s = b[i]
        for j in range(i+1,len(A)):
            s = s - A[i][j] * x[j]
        x[i] = s/A[i][i]
    return x
```

A Wrapper function which uses Guassian Elimination and Backward Substitution to calculate Beta values

[10]:
```
def solve_linear_equations(A,b):
    #Using Guassian Elimination to simplify Matrix A and b
    A , b = guassian_elimination(A,b)
    #Using Backward Substitution to calculate the vector x which is our Beta␣
 ↪values
    return backward_substitution(A,b)
```

Function to Learn Linear Regression model and Returns Beta Vector

[11]:
```
def learn_simple_linreg(X,Y):
    X_tran = transpose_matrix(matX)
    # A = X^T.X
    A = multiply_matrices(X_tran,X)
    # b = X*T.Y
    b = multiply_matrices(X_tran,Y)
    beta = solve_linear_equations(A,b)
    return beta
```

Function which takes Matrix X and beta to predict our Predicted Y (y hat)

[12]:
```
def predict_simple_linreg(X,beta):
    #Calculating yhat using equation y_hat = X.b
    y_hat = multiply_matrices(X,beta)
    return y_hat
```

Calculating Beta values using the Guassian Elimination method

[13]:
```
#Calculating our beta values
beta = learn_simple_linreg(matX,matY)
print(beta)
```

```
[[12.38347074]
 [ 0.54140055]
 [-0.59475465]
 [ 2.57500107]
 [-1.65599471]
 [ 2.35415863]
 [-0.24840299]
 [ 0.56046431]
 [-2.96177026]
 [-4.45959388]
 [-1.55567627]]
```

Using Matrix X and Beta values calculating Predicted Y

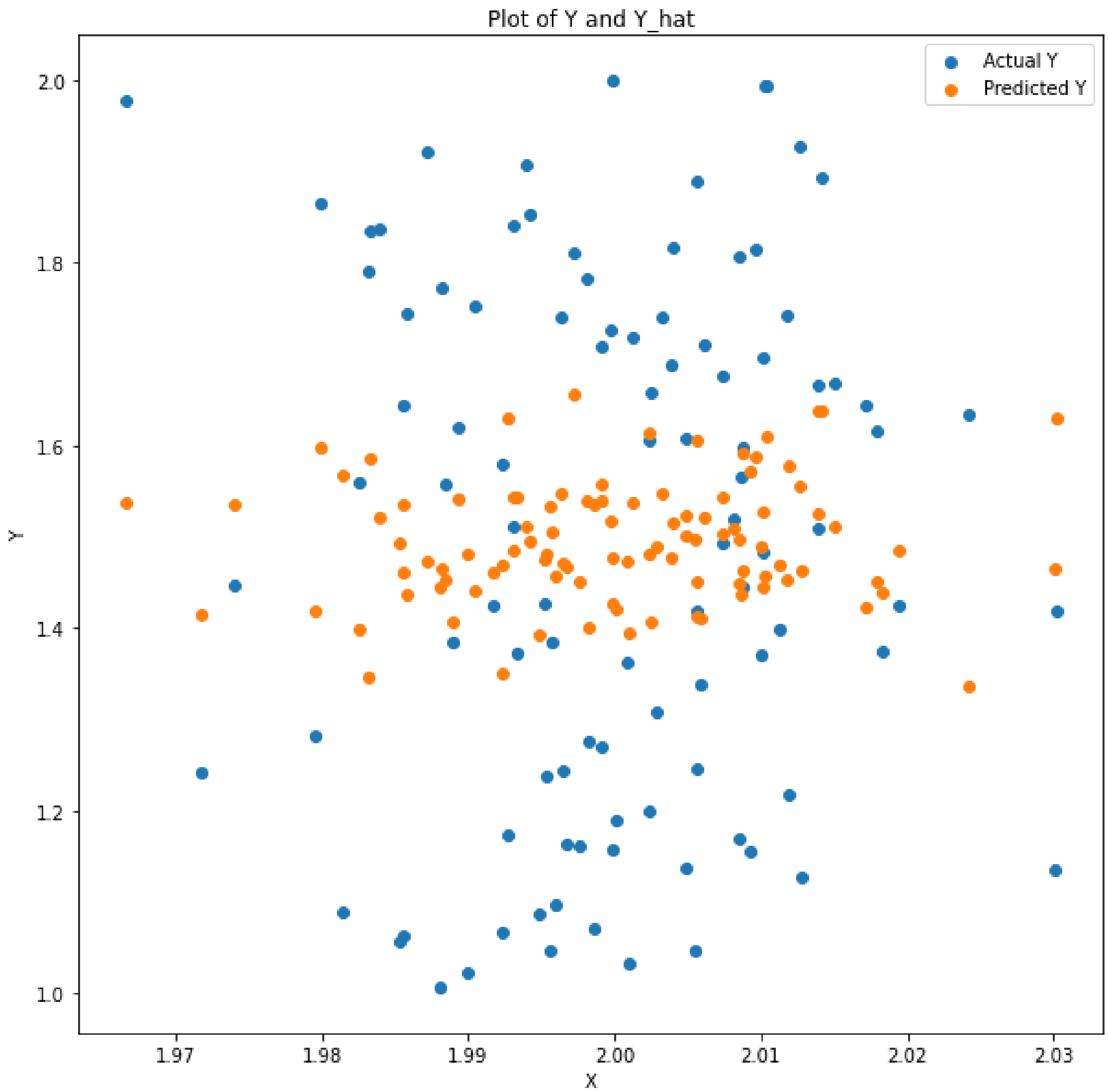
[14]:
```
#Calculating y_hat
y_hat = predict_simple_linreg(matX,beta)
```

Plot the training points from matrix Y and predicted values Y in the form of scatter graph.

[15]:
```
import matplotlib.pyplot as plt      #Importing Matplotlib
```

[16]:
```
fig = plt.figure(figsize=(10,10))
ax = fig.add_subplot(111)
ax.scatter(matX[:,1].reshape(-1,1),matY,label='Actual Y')
ax.scatter(matX[:,1].reshape(-1,1),y_hat,label='Predicted Y')
ax.set_xlabel('X')
ax.set_ylabel('Y')
```

```
ax.set_title('Plot of Y and Y_hat')
plt.legend()
plt.show()
```



In the end use numpy.linalg.lstsq to learn 0:10 and plot the predictions from these parameters.

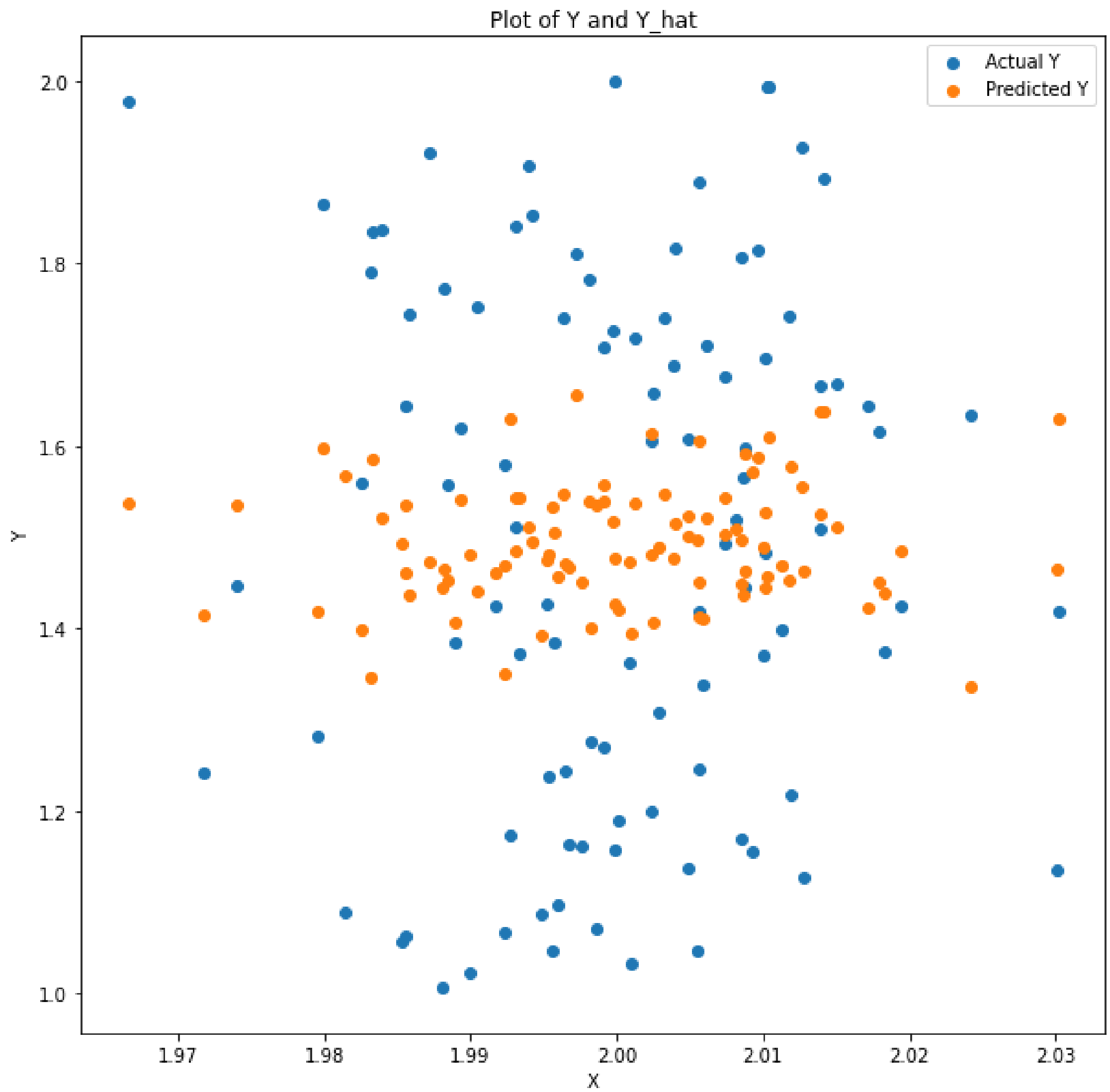
[17]:
```
np_beta = np.linalg.lstsq(matX,matY,rcond=None)[0]
print(np_beta)
```

```
[[12.38347074]
 [ 0.54140055]
 [-0.59475465]
 [ 2.57500107]
```

```
 [-1.65599471]
 [ 2.35415863]
 [-0.24840299]
 [ 0.56046431]
 [-2.96177026]
 [-4.45959388]
 [-1.55567627]]
```

[18]:
```
#Calculating y_hat with numpy beta values
y_hat = predict_simple_linreg(matX,np_beta)
```

[19]:
```
fig = plt.figure(figsize=(10,10))
ax = fig.add_subplot(111)
ax.scatter(matX[:,1].reshape(-1,1),matY,label='Actual Y')
ax.scatter(matX[:,1].reshape(-1,1),y_hat,label='Predicted Y')
ax.set_xlabel('X')
ax.set_ylabel('Y')
ax.set_title('Plot of Y and Y_hat')
plt.legend()
plt.show()
```



Plot of Y and Y_hat
Actual Y
Predicted Y
2.0
1.8
1.6
1.4
1.2
1.0
Y
1.97
1.98
1.99
2.00
2.01
2.02
2.03
X