```
from google.colab import drive
drive.mount('/content/drive')
```

```
Drive already mounted at /content/drive; to attempt to forcibly remount, call drive.m
```

```
import pandas as pd
import math
import numpy as np
import matplotlib.pyplot as plt
```

Linear Regression with L2 norm regularization commented

```
def cost_function(X,y,w):
  hypothesis = np.dot(X,w.T) ###calculation of hypothesis for all instances
  J = (1/(2*len(y))) * np.sum((hypothesis - y) ** 2) ####as mention in the class notes
  # J = (1/(2*len(y))) * np.sum((hypothesis - y) ** 2)+(lamb/2)*np.sum(w**2) ####as mentio
  return J
```

```
def batch_gradient_descent(X,y,w,alpha,iters,lamb):
  cost_history = np.zeros(iters) # cost function for each iteration
  #initalize our cost history list to store the cost function on every iteration
  for i in range(iters):
    hypothesis = np.dot(X,w.T)
    #w = (w*(1-alpha*lamb)) -(alpha/len(y)) * np.dot(hypothesis - y, X)
    w = w - (alpha/len(y)) * np.dot(hypothesis - y, X)
    #cost_history[i] = cost_function(X,y,w,lamb)
    cost_history[i] = cost_function(X,y,w)
  return w,cost_history
```

```
def MB_gradient_descent(X,y,w,alpha, iters, batch_size):
  cost_history = np.zeros(iters)
  for i in range(iters):
    rand_index = np.random.randint(len(y)-batch_size)
    ind_x = X[rand_index:rand_index+batch_size]
    ind_y = y[rand_index:rand_index+batch_size]
    w = w - (alpha/batch_size) * (ind_x.T.dot(ind_x.dot(w) - ind_y))
    cost_history[i] = cost_function(ind_x,ind_y,w)
  return w, cost_history
```

```
def stochastic_gradient_descent(X,y,w,alpha, iters):
  cost_history = np.zeros(iters)
  for i in range(iters):
    rand_index = np.random.randint(len(y)-1)
    ind_x = X[rand_index:rand_index+1]
    ind_y = y[rand_index:rand_index+1]
    w = w - alpha * (ind_x.T.dot(ind_x.dot(w) - ind_y))
    cost_history[i] = cost_function(ind_x,ind_y,w)
  return w, cost_history
```

Linear Regression with L2 norm regularization

```
def cost_function_l2(X,y,w,lamb):
    hypothesis = np.dot(X,w.T)
    #J = (1/(2*len(y)))*np.sum((hypothesis-y)**2)
    J= (1/(2*len(y)))*np.sum((hypothesis-y)**2) + (lamb/2)*np.sum(w**2)
    return J


def batch_gradient_descent_l2(X,y,w,alpha,iters,lamb):
    cost_history = np.zeros(iters)
    for i in range(iters):
        hypothesis = np.dot(X,w.T)
        w = (w*(1-alpha*lamb)) - (alpha/len(y)) * (np.dot(hypothesis - y, X))
        cost_history[i] = cost_function_l2(X,y,w,lamb)
    return w, cost_history


def MB_gradient_descent_l2(X,y,w,alpha, iters, batch_size,lamb):
    cost_history = np.zeros(iters)
    for i in range(iters):
        rand_index = np.random.randint(len(y)-batch_size)
        ind_x = X[rand_index:rand_index+batch_size]
        ind_y = y[rand_index:rand_index+batch_size]

        w = w*int((1-(alpha*lamb))) - (alpha/batch_size) * (np.dot((np.dot(ind_x,w) - ind_
        cost_history[i] = cost_function_l2(ind_x,ind_y,w,lamb)
    return w, cost_history


def stochastic_gradient_descent_l2(X,y,w,alpha, iters,lamb):
    cost_history = np.zeros(iters)
    for i in range(iters):
        rand_index = np.random.randint(len(y)-1)
        ind_x = X[rand_index:rand_index+1]
        ind_y = y[rand_index:rand_index+1]
        w = w*(1-alpha*lamb) - alpha * (ind_x.T.dot(ind_x.dot(w) - ind_y))
        cost_history[i] = cost_function_l2(ind_x,ind_y,w,lamb)
    return w, cost_history
```

Linear Regression with Least Angle Regression Model

```
def cost_function_l1(X,y,w,lamb):
    hypothesis = np.dot(X,np.transpose(w))
    #J = (1/(2*len(y)))*np.sum((hypothesis-y)**2)
    J= (1/(2*len(y)))*np.sum((hypothesis-y)**2) + (lamb/2)*np.sum(abs(w))
    return J


def batch_gradient_descent_l1(X,y,w,alpha,iters,lamb):
    cost_history = np.zeros(iters)
```

```
    for i in range(iters):
        hypothesis = np.dot(X,w.T)
        w = w - (alpha/len(y)) * (np.dot(hypothesis - y, X) - (lamb/2)*np.sign(w))
        cost_history[i] = cost_function_l2(X,y,w,lamb)
    return w, cost_history

def stochastic_gradient_descent_l1(X,y,w,alpha, iters,lamb):
    cost_history = np.zeros(iters)
    for i in range(iters):
        rand_index = np.random.randint(len(y)-1)
        ind_x = X[rand_index:rand_index+1]
        ind_y = y[rand_index:rand_index+1]
        w = w - alpha * (ind_x.T.dot(ind_x.dot(w) - ind_y) - (lamb/2)*np.sign(w))
        cost_history[i] = cost_function_l1(ind_x,ind_y,w,lamb)
    return w, cost_history


def MB_gradient_descent(X,y,w,alpha, iters, batch_size):
    cost_history = np.zeros(iters)
    for i in range(iters):
        rand_index = np.random.randint(len(y)-batch_size)
        ind_x = X[rand_index:rand_index+batch_size]
        ind_y = y[rand_index:rand_index+batch_size]

        # print((ind_x.T@(ind_x@w - ind_y)).sum(axis=1).shape)
        w = w - (alpha/batch_size) * (ind_x.T@(ind_x@w - ind_y)).sum(axis=1)
        cost_history[i] = cost_function(ind_x,ind_y,w)
    return w, cost_history
```

TrainingData

```
dataxtr = pd.read_csv('/content/drive/MyDrive/xtr.csv',header=None)
dataytr = pd.read_csv('/content/drive/MyDrive/ytr.csv',header=None)
```

TestingData

```
dataxte = pd.read_csv('/content/drive/MyDrive/xte.csv',header=None)
datayte = pd.read_csv('/content/drive/MyDrive/yte.csv',header=None)
```

```
data_XTraining=dataxtr.values
X=data_XTraining[:,:]
# print(X)
m=X.shape[0]
xmin=np.min(X,axis=0)
xmax=np.max(X,axis=0)
# print(xmin , xmax)
```

```
X = (X- xmin)/(xmax-xmin) #Normalization
# print(X)

pp = np.ones([m, 1]) # vector containg ones as all elements
X = np.append(pp,X, axis=1) #Column of ones
# print(X)
```

```
X.shape
```

```
(55, 3)
```

```
data_YTraining=dataytr.values
Y=data_YTraining[:,:]
# print(Y)
m=X.shape[0]
ymin=np.min(Y,axis=0)
ymax=np.max(Y,axis=0)
# print(ymin , ymax)
y = (Y- ymin)/(ymax-ymin) #Normalization
#print(Y)
```

```
datayte_=datayte.values
k=datayte_.shape[0]
Yte=np.ones([k,1])
Yte=np.append(Yte,dataxte_,axis=1)
```

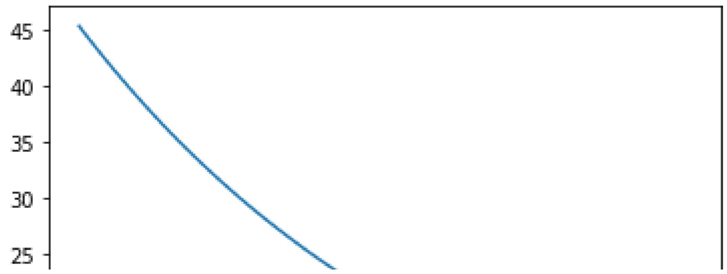
```
#Linear regression starts from here
w= np.zeros(X.shape[1]) ##weight initialization
#w=[0.5, 0.5, 0.5]
w1=np.zeros((X.shape[1]))
print(w)
```

```
[0. 0. 0.]
```

Batch Gradient Descent

```
alpha=0.005 ##learning rate
iters=100 ###iterations
lamb=5
batch_w,J_his = batch_gradient_descent(X,Y,w,alpha,iters,lamb)
```

```
plt.plot(range(iters),J_his)
plt.show()
```



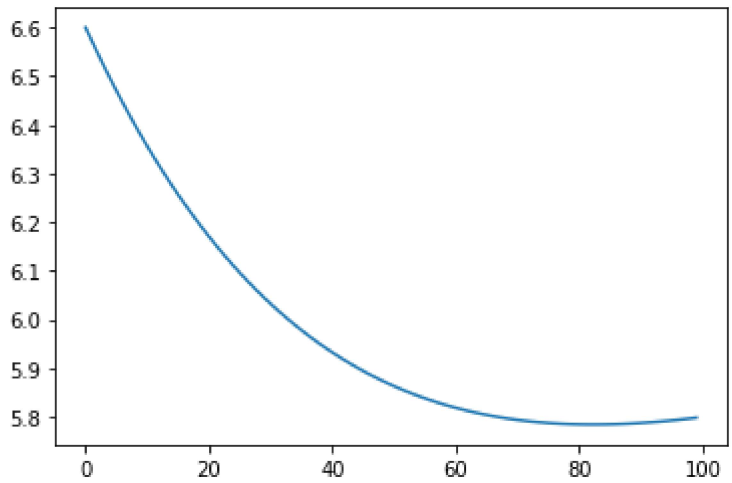

```
print(batch_w[0])
```

```
[0.45651057 0.23564335 0.26581355]
```


```
# print(y)
```

Batch Gradient Descent with L2 norm regularization

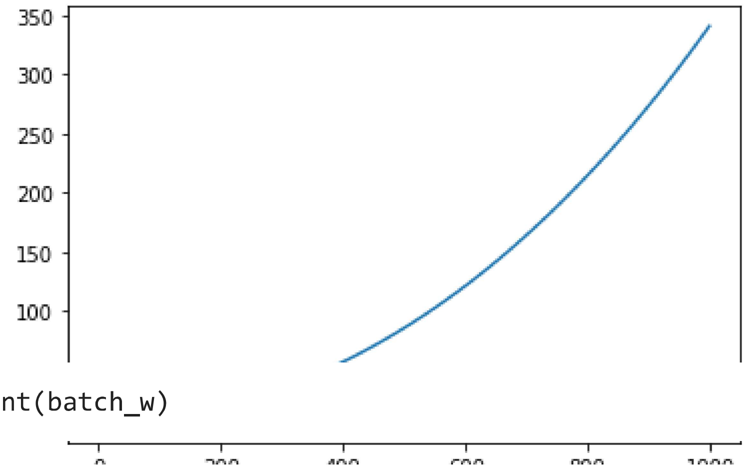
```
alpha=0.002 ##learning rate
iters=100 ###iterations
lamb=3.5
batch_w_l2,J_his_l2 = batch_gradient_descent_l2(X,y,w,alpha,iters,lamb)
plt.plot(range(iters),J_his_l2)
plt.show()
```



Batch Gradient Descent with L1 norm regularization

```
alpha=0.004 ##learning rate
iters=1000 ###iterations
lamb=3
batch_w,J_his = batch_gradient_descent_l1(X,y,w,alpha,iters,lamb)

plt.plot(range(iters),J_his)
plt.show()
```



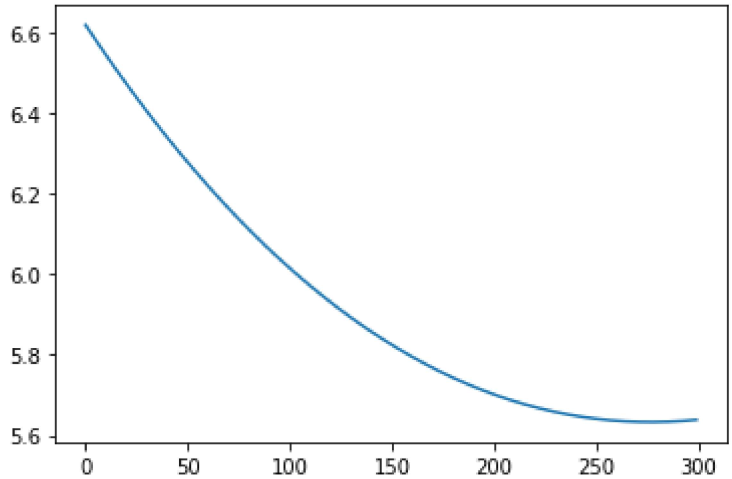

```
# print(batch_w)
```

```
bgd=batch_w[-1:]
print(bgd)
```

    [[1.78991329 1.15029434 1.18273904]]

```
alpha=0.0005#learning rate
iters=300 ###iterations
lamb=3
batch_w_l1,J_his_l1 = batch_gradient_descent_l1(X,y,w,alpha,iters,lamb)

plt.plot(range(iters),J_his_l1)
plt.show()
```



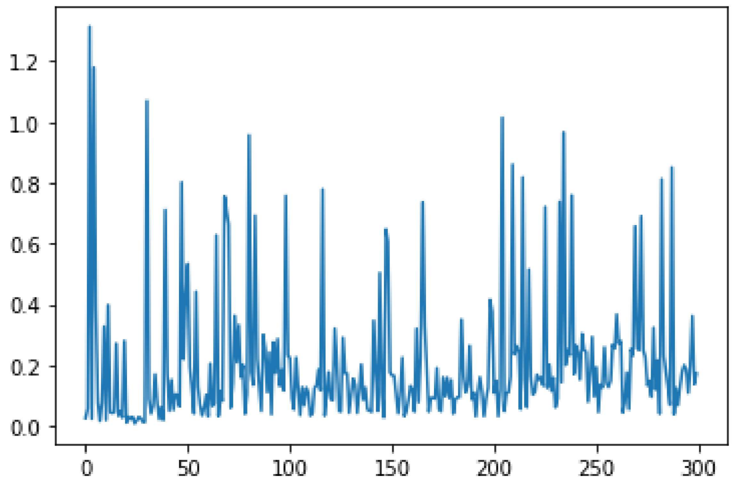

```
# print(batch_w_l1)
```

```
bgd_l1=batch_w_l1[-1:]
print(bgd_l1)
```

    [[0.09544143 0.05084858 0.05689333]]

```
alpha=0.05
iters=300 ###iterations
lamb=1
w_n,J_sgd = stochastic_gradient_descent(X,y,w,alpha, iters)
```

```
plt.plot(range(iters),J_sgd)
plt.show()
```




```
print(w_n)
```

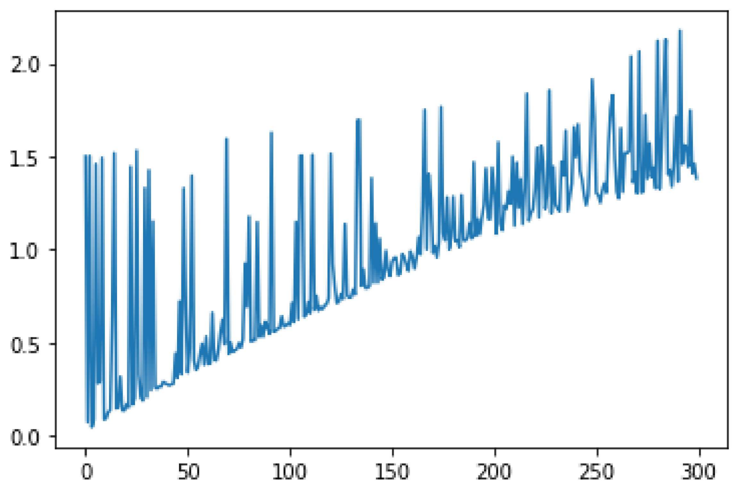
```
[[ 0.27939833  0.27939833  0.27939833]
 [-0.02090169 -0.02090169 -0.02090169]
 [ 0.09714084  0.09714084  0.09714084]]
```

```
sgd=w_n[-1:]
print(sgd)
```

```
[[0.09714084 0.09714084 0.09714084]]
```

```
alpha=0.002
iters=300 ###iterations
lamb=1
w_n_l1,J_sgd_l1 = stochastic_gradient_descent_l1(X,y,w,alpha, iters,lamb)

plt.plot(range(iters),J_sgd_l1)
plt.show()
```



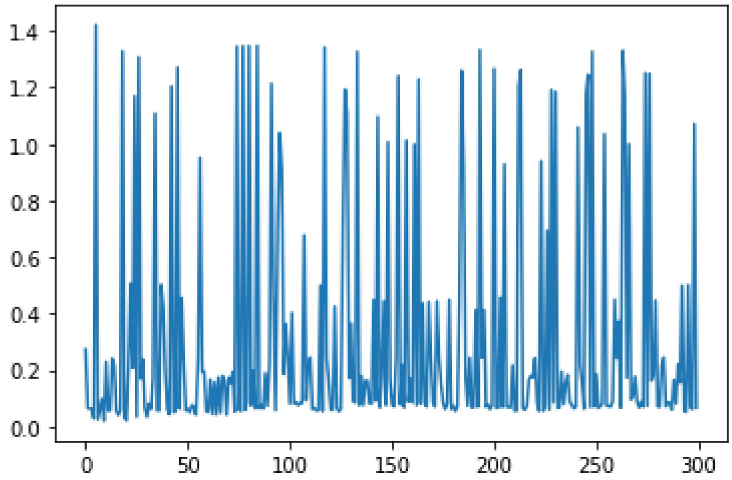

```
print(w_n_l1)
```

```
[[0.32180733 0.32180733 0.32180733]
 [0.29396355 0.29396355 0.29396355]
 [0.30018099 0.30018099 0.30018099]]
```

```
sgd_l1=w_n_l1[-1:]
print(sgd_l1)
```

```
[[0.30018099 0.30018099 0.30018099]]
```

```
alpha=0.01
iters=300 ###iterations
lamb=3
w_n_l2,J_sgd_l2 = stochastic_gradient_descent_l2(X,y,w,alpha, iters,lamb)
plt.plot(range(iters),J_sgd_l2)
plt.show()
```




```
print(w_n_l2)
```

```
[[0.08481359 0.08481359 0.08481359]
 [0.04128165 0.04128165 0.04128165]
 [0.05071442 0.05071442 0.05071442]]
```

```
sgd_l2=w_n_l2[-1:]
print(sgd_l2)
```

```
[[0.05071442 0.05071442 0.05071442]]
```

```
alpha=0.05
iters=300 ###iterations
lamb=3
batch_size=25
mb_w,J_mb = MB_gradient_descent(X,y,w1,alpha, iters, batch_size)

plt.plot(range(iters),J_mb)
plt.show()
```

Performance Measures for Regression(Self Defined functions)

Have defined these functions but have not used them because sklearn libraries were allowed to be used which I have used to find the three errors.

Mean Absolute Error

```
def mean_abs_error(Ypre,Yact):
  sum_err=abs(Yact - Ypre)
  ma_err=sum_err/Ypre.shape[0]
  return ma_err
```

Mean Square Error

```
def mean_square_error(Ypre,Yact):
  sum_error=((Yact - Ypre)**2)
  ms_err=sum_error/Ypre.shape[0]
  return ms_err
```

Correlation Coefficient

```
def correlation_coeff(test_instances,Ypred,Yact):
  ypm=np.mean(Ypred)##mean of Ypred data
  yam=np.mean(Yact)##mean of Yactual data
  num=((Yact - yam)*(Ypred-ypm))
  d1=pow(((Yact - yam)**2),1/2)
  d2=pow(((Ypred - ypm)**2),1/2)
  c_c=num/(d1*d2)
  return c_c
```

Finding Errors

Using sklearn libraries(was allowed)

```
from sklearn.metrics import mean_squared_error
from sklearn.metrics import mean_absolute_error
from sklearn.metrics import matthews_corrcoef


dataxte_=dataxte.values
k=dataxte_.shape[0]
Xte=np.ones([k,1])
Xte=np.append(Xte,dataxte_,axis=1)
print(Xte)
print(bgd.T)
```

```
[[ 1.   17.4   8.58]
 [ 1.   17.86  9.08]
 [ 1.   18.3   9.58]
 [ 1.   16.97  8.08]
 [ 1.   16.46  7.58]
 [ 1.   17.4   8.58]
 [ 1.   17.85  9.08]
 [ 1.   18.3   9.58]
 [ 1.   16.9   8.08]
 [ 1.   16.42  7.58]]
[[1.78991329]
 [1.15029434]
 [1.18273904]]
```

```
# Xte = np.hstack((np.ones((Xte.shape[0],1)) , Xte))
# Xte.shape
# print(Xte)



y_pred_bgd=Xte.dot(bgd.T)
print(mean_squared_error(y_pred_bgd, Yte))
print(mean_absolute_error(y_pred_bgd, Yte))
# print(matthews_corrcoef(y_pred_bgd, Yte))


# y_pred_bgd_l1=Xte.dot(bgd_l1.T)
# print(mean_squared_error(y_pred_bgd_l1, Yte))
# print(mean_absolute_error(y_pred_bgd_l1, Yte))
# print(matthews_corrcoef(y_pred_bgd_l1, Yte))

# y_pred_bgd_l2=Xte.dot(bgd_l2.T)
# print(mean_squared_error(y_pred_bgd_l2, Yte))
# print(mean_absolute_error(y_pred_bgd_l2, Yte))
# print(matthews_corrcoef(y_pred_bgd_l2, Yte))
```

```
---------------------------------------------------------------------------
ValueError                                Traceback (most recent call last)
<ipython-input-359-5a96d7ea412b> in <module>()
      1 y_pred_bgd=Xte.dot(bgd.T)
----> 2 print(mean_squared_error(y_pred_bgd, Yte))
      3 print(mean_absolute_error(y_pred_bgd, Yte))
      4 # print(matthews_corrcoef(y_pred_bgd, Yte))
      5

1 frames

/usr/local/lib/python3.7/dist-packages/sklearn/metrics/_regression.py in
_check_reg_targets(y_true, y_pred, multioutput, dtype)
```

Stochastic Gradient descent

```
y_pred_sgd=Xte.dot(sgd.T)
print(mean_squared_error(y_pred_sgd, Yte))
print(mean_absolute_error(y_pred_sgd, Yte))
print(matthews_corrcoef(y_pred_sgd, Yte))

y_pred_sgd_l1=Xte.dot(sgd_l1.T)
print(mean_squared_error(y_pred_sgd_l1, Yte))
print(mean_absolute_error(y_pred_sgd_l1, Yte))
print(matthews_corrcoef(y_pred_sgd_l1, Yte))

y_pred_sgd_l2=Xte.dot(sgd_l2.T)
print(mean_squared_error(y_pred_sgd_l2, Yte))
print(mean_absolute_error(y_pred_sgd_l2, Yte))
print(matthews_corrcoef(y_pred_sgd_l2, Yte))
```

```
---------------------------------------------------------------------------
ValueError                                Traceback (most recent call last)
<ipython-input-357-d5771ea10559> in <module>()
      1 y_pred_sgd=Xte.dot(sgd.T)
----> 2 print(mean_squared_error(y_pred_sgd, Yte))
      3 print(mean_absolute_error(y_pred_sgd, Yte))
      4 print(matthews_corrcoef(y_pred_sgd, Yte))
      5

1 frames

/usr/local/lib/python3.7/dist-packages/sklearn/metrics/_regression.py in
_check_reg_targets(y_true, y_pred, multioutput, dtype)
    105         raise ValueError(
    106             "y_true and y_pred have different number of output ({0}!=
{1})".format(
--> 107                 y_true.shape[1], y_pred.shape[1]
    108             )
    109         )

ValueError: y_true and y_pred have different number of output (1!=3)
```

Mini Batch Gradient Descent

0s completed at 3:00 AM

Could not connect to the reCAPTCHA service. Please check your internet connection and reload to get a reCAPTCHA challenge.