```
from google.colab import drive
drive.mount('/content/gdrive')
    Mounted at /content/gdrive
main_directory = '/content/gdrive/MyDrive/Pattern Lab/Assignment1/train-perceptron.txt'
df1 = pd.read_csv(main_directory, sep=" " , header = None)
print(df1)
            1 2
    0 1 1.0 1
    1 1 -1.0 1
    2 2 2.5 2
    3 0 2.0 2
    4 2 3.0 2
    5 4 5.0 1
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
```

Part 1

▼ Training and Testing Data

Retriving training and testing data and dividing them into features and labels

Splitting Training Data

Splitting training data into classes according to labels

```
class1_X1, class1_X2, class2_X1, class2_X2 = [], [], [], []
for i in range(train_X.shape[0]):
  if train_Y[i] == 1:
   class1_X1.append(train_X[i, 0])
    class1_X2.append(train_X[i, 1])
  else:
    class2_X1.append(train_X[i, 0])
    class2_X2.append(train_X[i, 1])
# To check if data is successfully retrieved
print(class1_X1)
print(class1_X2)
print(class2_X1)
print(class2_X2)
     [1.0, 1.0, 4.0]
     [1.0, -1.0, 5.0]
     [2.0, 0.0, 2.0]
     [2.5, 2.0, 3.0]
```

Plotting Training Data

Plotting the training data. There are two classes and they are shown.

```
limit_X1 = list(map(int, class1_X1 + class2_X1))
limit_X2 = list(map(int, class1_X2 + class2_X2))

plt.figure(figsize = (10, 5))
# Training Data
plt.scatter(class1_X1, class1_X2, label = 'Train Class 1', color = 'red', marker = 'o')
plt.scatter(class2_X1, class2_X2, label = 'Train Class 2', color = 'black', marker = '*')
# Plot Accessory
plt.xticks([i for i in range(min(limit_X1) - 1, max(limit_X1) + 1)])
plt.yticks([i for i in range(min(limit_X2) - 1, max(limit_X2) + 1)])
plt.legend(loc = 'upper center')
plt.show()
```



Part 2

Dimension Increase

Higher dimensional sample points are constructed using given matrix represented as,

$$y=egin{bmatrix} x_1^2 & x_2^2 & x_1 imes x_2 & x_1 & x_2 & 1 \end{bmatrix}$$

```
trainPoints = np.zeros((train_X.shape[0], 6))
j = len(class1_X1)
for i in range(j):
  trainPoints[i, :] = np.array([class1_X1[i] ** 2, class1_X2[i] ** 2,
                                class1_X1[i] * class1_X2[i], class1_X1[i],
                                class1_X2[i], 1])
for i in range(len(class2_X1)):
  trainPoints[i + j, :] = np.array([class2_X1[i] ** 2, class2_X2[i] ** 2,
                                     class2_X1[i] * class2_X2[i], class2_X1[i],
                                     class2_X2[i], 1])
# To check if data is successfully retrieved
print(trainPoints)
     [[ 1.
                                1.
             1.
                               -1.
      [ 1.
                   -1.
             25. 20. 4. 5.
6.25 5. 2. 2.5
4. 0. 0. 2.
      [16.
      [ 4.
      [ 0.
                                3.
                                       1. ]]
      [ 4.
              9. 6.
```

▼ Normalize Class 2

Among the two classes, Class 2 features are negated to normalize the data

Also, data are converted to NumPy format for easier use in future.

```
for i in range(j, 0, -1):
    trainPoints[-i, :] *= -1
```

```
# To check if data is successfully retrieved
print(trainPoints)
               1. 1. 1.
    [[ 1.
           1.
                               1.
                                  ]
    [ 1.
           1.
               -1. 1. -1.
                               1. ]
    [16.
          25.
               20. 4. 5.
                              1. ]
          -6.25 -5. -2. -2.5 -1.
```

-4. -0. -0. -2. -1.]

-3. -1.]]

-6. -2.

Part 3

[-4.

[-0. [-4.

-9.

```
def updateWeight(w, alpha, y_mc, update_cnt):
 return w + alpha * y_mc, update_cnt + 1 * (1 if sum(y_mc) != 0 else 0)
def oneTime(y, w, alpha, iteration = 150):
 it = 0
 update cnt = 0
 points = y.shape[0]
 while it < iteration:
   res = np.zeros((points, 1))
   for i in range(points):
     val = np.dot(y[i],w.T )
     res[i] = 0 if val > 0 else 1
     w, update_cnt = updateWeight(w, alpha, res[i] * y[i], update_cnt)
   it += 1
   if sum(res) == 0:
     break
  return it, update_cnt
def manyTime(y, w, alpha, iteration = 150):
  it = 0
 update cnt = 0
  points = y.shape[0]
 while it < iteration:
   res = np.zeros((points, 1))
   for i in range(points):
     val = np.dot(y[i], w.T)
     res[i] = 0 if val > 0 else 1
    it += 1
    if sum(res) == 0:
     break
     w, update_cnt = updateWeight(w, alpha, sum(res * y), update_cnt)
  return it, update_cnt
```

Part 4

Given Value Generation

As per requirement, values of w and α are pre-determined. Here the lists are generated to prepare those values

```
alphaAll = [i / 10 for i in range(1, 11, 1)]
np.random.seed(14)
initialweightAll = np.zeros((3, 6))
initialweightAll[1, :] = np.ones((1, 6))
initialweightAll[2, :] = np.random.rand(1, 6)
# To check if data is successfully retrieved
print(alphaAll)
print(initialweightAll)
     [0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, 0.9, 1.0]
     [[0.
                  0.
                                        0.
                             0.
                                                    0.
                                                               0.
      [1.
                  1.
                             1.
                                         1.
                                                    1.
      [0.51394334 0.77316505 0.87042769 0.00804695 0.30973593 0.95760374]]
```

▼ Implementing Perceptron

Finally the perceptron algorithm is used and generate results for the different situations given as requirements.

```
output = np.zeros((30, 6))
wType = {0: 'All Zeros', 1: 'All Ones', 2: 'Random'}
for i in range(output.shape[0]):
  alpha = alphaAll[i % 10]
 weight = initialweightAll[i // 10, :].copy()
  itOne, updateOne = oneTime(trainPoints, weight, alpha)
  itMany, updateMany = manyTime(trainPoints, weight, alpha)
 output[i, :] = alpha, i // 10, itOne, updateOne, itMany, updateMany
np.set_printoptions(suppress=True)
print(output)
     ΓΓ
        0.1
              0.
                   94. 184.
                              105. 104. ]
        0.2
              0.
                   94.
                        184.
                              105.
                                    104. ]
        0.3
                   94.
                       184. 105. 104.
              0.
        0.4
              0.
                   94.
                       184. 105. 104.
                   94.
                              92.
        0.5
              0.
                        184.
                                    91. ]
                   94.
        0.6
              0.
                       184. 105. 104.
        0.7
              0.
                   94.
                       184.
                              92.
                                    91. ]
        0.8
                   94.
                        184. 105. 104.
              0.
                   94.
                       184.
                             105.
        0.9
              0.
                                   104.
                       184.
                             92.
        1.
              0.
                   94.
                                   91. ]
        0.1
                        13.
                              102.
                                    101. ]
              1.
                   6.
        0.2
                   92.
                        179.
                              104.
                                    103. ]
```

```
1. 104. 199.
                       91.
                              90. ]
  0.3
  0.4
        1.
            106.
                 202.
                       116.
                             115.
  0.5
        1.
             93.
                  182.
                       105.
                             104. ]
  0.6
        1.
             93.
                 180.
                      114.
                             113. ]
  0.7
        1.
            108.
                  203.
                        91.
                              90. ]
  0.8
        1.
            115.
                  215.
                        91.
                              90.
  0.9
             94.
                 183.
                      105.
        1.
                             104. ]
  1.
        1.
             94.
                  183.
                        93.
                              92. ]
                       108.
  0.1
        2.
             94.
                  181.
                             107.
                             122. ]
            107.
                 200. 123.
  0.2
        2.
  0.3
        2.
             93.
                 182. 100.
                              99. ]
  0.4
        2.
            105.
                  195.
                       117.
                             116.
  0.5
             85.
                 163.
                      106.
2.
                            105. ]
             94.
                 183.
                       92.
  0.6
       2.
                              91. 1
            94.
                 183.
                       106. 105.
  0.7
        2.
  0.8
        2.
             84.
                 161. 121. 120. ]
0.9
        2.
             96. 181. 106. 105.
                              87.]]
1.
        2.
            105.
                  201.
                       88.
```

Display Using Plots

In this section, found results are shown in Tabular and Charts

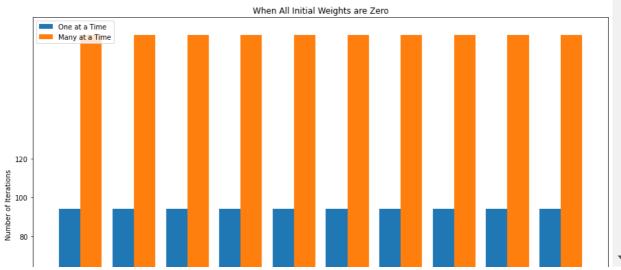
```
print('Found Values')
fig, ax = plt.subplots()
table_data = []
for i in range(output.shape[0]):
 table_data.append([output[i, 0], wType[output[i, 1]], int(output[i, 2]), int(output[i, 4
colHeader = ['Learning Rate', 'Initial Weight', 'One at a Time', 'Many at a Time']
table = ax.table(cellText = table_data, colLabels = colHeader, cellLoc = 'center', loc = '
table.set_fontsize(25)
table.scale(2,2)
ax.axis('off')
plt.show()
print('\nCharts')
alphaDist = np.arange(len(alphaAll))
plt.figure(figsize = (15, 10))
plt.bar(alphaDist - 0.2, output[0:10, 2], 0.4, label = 'One at a Time')
plt.bar(alphaDist + 0.2, output[0:10, 3], 0.4, label = 'Many at a Time')
plt.xticks(alphaDist, alphaAll)
plt.yticks([i for i in range(0, 121, 20)])
plt.xlabel("Values of Alpha")
plt.ylabel("Number of Iterations")
plt.title("When All Initial Weights are Zero")
plt.legend(loc = 'best')
plt.show()
```

```
plt.figure(figsize = (15, 10))
plt.bar(alphaDist - 0.2, output[10:20, 2], 0.4, label = 'One at a Time')
plt.bar(alphaDist + 0.2, output[10:20, 3], 0.4, label = 'Many at a Time')
plt.xticks(alphaDist, alphaAll)
plt.yticks([i for i in range(0, 121, 20)])
plt.xlabel("Values of Alpha")
plt.ylabel("Number of Iterations")
plt.title("When All Initial Weights are One")
plt.legend(loc = 'best')
plt.show()
plt.figure(figsize = (15, 10))
plt.bar(alphaDist - 0.2, output[20:30, 2], 0.4, label = 'One at a Time')
plt.bar(alphaDist + 0.2, output[20:30, 3], 0.4, label = 'Many at a Time')
plt.xticks(alphaDist, alphaAll)
plt.yticks([i for i in range(0, 121, 20)])
plt.xlabel("Values of Alpha")
plt.ylabel("Number of Iterations")
plt.title("When All Initial Weights are Random")
plt.legend(loc = 'best')
plt.show()
```

Found Values

Learning Rate	Initial Weight	One at a Time	Many at a Time
0.1	All Zeros	94	105
0.2	All Zeros	94	105
0.3	All Zeros	94	105
0.4	All Zeros	94	105
0.5	All Zeros	94	92
0.6	All Zeros	94	105
0.7	All Zeros	94	92
0.8	All Zeros	94	105
0.9	All Zeros	94	105
1.0	All Zeros	94	92
0.1	All Ones	6	102
0.2	All Ones	92	104
0.3	All Ones	104	91
0.4	All Ones	106	116
0.5	All Ones	93	105
0.6	All Ones	93	114
0.7	All Ones	108	91
0.8	All Ones	115	91
0.9	All Ones	94	105
1.0	All Ones	94	93
0.1	Random	94	108
0.2	Random	107	123
0.3	Random	93	100
0.4	Random	105	117
0.5	Random	85	106
0.6	Random	94	92
0.7	Random	94	106
0.8	Random	84	121
0.9	Random	96	106
1.0	Random	105	88

Charts



Question Answer

Question (a): In Task 2, why do we need to take the sample points to a high dimension?

Answer: From the image seen while trying to plot the training points, it can be seen that the two classes are quite scattered.

It looks quite imposible to separate the two classes using a **Linear Line**.

So, in order to separate the classes, the sampl points were taken to higher points using ϕ function.

Question (b): In each of the three initial weight cases and for each learning rate, how many updates does the algorithm take before converging?

Answer:

```
fig, ax = plt.subplots()
table_data = []

for i in range(output.shape[0]):
    table_data.append([output[i, 0], wType[output[i, 1]], int(output[i, 3]), int(output[i, 5]))
colHeader = ['Learning Rate', 'Initial Weight', 'One at a Time', 'Many at a Time']

table = ax.table(cellText = table_data, colLabels = colHeader, cellLoc = 'center', loc = 'table.set_fontsize(25)
table.scale(2,2)
ax.axis('off')
plt.show()
```