INF 552 MACHINE LEARNING FOR DATA SCIENCE

HOMEWORK 4

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Part 1:

Language used:

Python 3, jupyter notebook

Data structures used:

Numpy array to store data

Code-level optimization:

For linear and logistic regression, I implemented matrix multiplication instead of using a loop to calculate updates. It reduced the run time.

Challenges:

When implementing pocket algorithm, there was 2 methods of doing it. 1) calculating best weights at the end of each iteration 2) calculating best weight at the end of every update of a data point.

The 1st method takes less time because the best weight is calculated only at the end and not at every step of the algorithm. One iteration of the first method takes O(n) time while the 2nd method takes O(n^2). Even though the 2nd method could give the best weight, 1st method is preferred as the run time is less and also the difference in accuracy etween the two methods is not so significant.

Part 2:

Library used: Scikit learn

Almost all the implementations gave similar result to the library function but the library functions gives a slightly better output because it reruns the algorithm with different parameters like initial weight, learning rate etc.

The results of the implementation can be improved by using different local search heuristics like different starting points and choosing the best output(random restart), stochastic gradient descent(choose a random neighbour) etc. to improve the accuracy.

Also, different learning rate can be used to find the most optimal possible solution.

Part 3:

Linear Classification is used to filter out spam or non-spam email, handwritten digit recognition, credit card fraud detection etc.

Linear regression is used for predictive analysis like predict future sales of an item or its price. It Is also used by insurane companies to estimate the number of claims at a certain time in the future

Logistic regression is used in medical field to predict mortality in injured patients. It is called Trauma and Injury Severity Score.It is also used to find the probability that a person will develop a certain disease like cancer.It is also used in marketing field to find thechances that a person will buy a certain product.

In [1]:
```python
#Done by SANJAY MALLASAMUDRAM SANTHANAM ; USC ID:3124715393
#perceptron learning algo
import pandas as pd
import numpy as np
import math
from operator import truediv,add
import copy
```

In [2]:
```python
#read data
data=np.loadtxt('C:/Users/Lenovo/Desktop/classification.txt',delimiter=",")
```

In [3]:
```python
#Check data
np.shape(data)
```

Out[3]:
```
(2000, 5)
```

In [4]:
```python
data
```

Out[4]:
```
array([[ 0.750072  ,  0.97740794,  0.88565752, -1.        ,  1.        ],
       [ 0.87791369,  0.01925101,  0.50671112,  1.        , -1.        ],
       [ 0.7773246 ,  0.99406596,  0.82224385, -1.        ,  1.        ],
       ...,
       [ 0.5155064 ,  0.15354364,  0.01275495,  1.        ,  1.        ],
       [ 0.2282263 ,  0.97155357,  0.18305906, -1.        ,  1.        ],
       [ 0.36391513,  0.49207061,  0.71952659, -1.        ,  1.        ]])
```

In [5]:
```python
#take first 4 columns for data points and labels
data=data[:,0:4]
```

In [6]:
```python
#cross verify correctness
data
```

Out[6]:
```
array([[ 0.750072  ,  0.97740794,  0.88565752, -1.        ],
       [ 0.87791369,  0.01925101,  0.50671112,  1.        ],
       [ 0.7773246 ,  0.99406596,  0.82224385, -1.        ],
       ...,
       [ 0.5155064 ,  0.15354364,  0.01275495,  1.        ],
       [ 0.2282263 ,  0.97155357,  0.18305906, -1.        ],
       [ 0.36391513,  0.49207061,  0.71952659, -1.        ]])
```

In [7]:
```python
np.shape(data)
```

Out[7]:
```
(2000, 4)
```

In [8]:
```python
#N is total number of data points
N= len(data)
```

In [9]:
```python
#assigning data points and labels
X=data[:,0:3].T
# d is numner of dimensions
d=len(X[:,0])
#Add x0=1 to all data points
X=np.vstack((np.ones((1,2000)),X))
y=data[:,3]
# assign weights to be zero vector
#w=np.random.random(size=(d+1,1))
w=np.zeros((d+1,1))
```

In [10]:
```
#count measures how many data points passed without change in weight w. If if comes equal to N i.e. we completed one full
#round of data without changing weights w, it means we have reached convergence.In case data is not linearly separable, break
#after 7000 iterations.
#alpha is learning rate
alpha=0.0001
#counts how many data points seen afer last modification of weights. If count=N, it means the whole of dataset is seen
#without modifying the weights and hence convergence.
count=0
#used to break loop in case the convergence takes long time or when the data is not linearly separable
itr=7000
while(count!=N and itr):
    i=0
    while(i<N and count!=N):
        flag=0
        if(np.matmul(w.T,X[:,i])>=0 and y[i]<0):
            w-=alpha*np.reshape(X[:,i],(d+1,1))
            flag=1
        elif(np.matmul(w.T,X[:,i])<0 and y[i]>0):
            w+=alpha*np.reshape(X[:,i],(d+1,1))
            flag=1
        if(flag):
            count=0
        else:
            count+=1
        i+=1
        #print(w)
    itr-=1
print("Converged after ",7000-itr," iterations")
print("Final weight: ",w)
#y_hat is predicted values
y_hat=np.zeros(shape=(np.shape(y)))
err=0
for i in range(N):
    y_hat[i]=np.sign(np.matmul(w.T,X[:,i]))
    if(y_hat[i]!=y[i]):
        err+=1

print('Accuracy:', (N-err)/N)
print("Number of misclassified points: ",err)
#print("Mean accuracy: ",(N-err)/N)
```

```
Converged after  1238  iterations
Final weight:  [[ 0.        ]
 [ 0.00939936]
 [-0.00753947]
 [-0.00563132]]
Accuracy: 1.0
Number of misclassified points:  0
```

In [11]:
```
#library function for perceptron learning
from sklearn.linear_model import Perceptron
clf = Perceptron()
clf.fit(X.T, y)
print("Weights calculated by library function:\n",clf.coef_)
```

```
Weights calculated by library function:
 [[  0.          24.35173999 -18.56164074 -14.10260498]]
```

In [12]:
```
#accuracy score
clf.score(X.T,y)
```

Out[12]: 0.98

In [13]:
```
#It can be seen that the weight calculated by the libray function is almost a multiple(by a
 factor of 2500) of the weight calulated by implementation.
#Since multiples of weights give the same result as the original, the accuracy wont change a
s the sign() of the final result
#is only required, not the numerical value.
```

In [14]:
```
#pocket algo
#read data
data=np.loadtxt('C:/Users/Lenovo/Desktop/classification.txt',delimiter=",")
N=len(data)
#assign data points
X=data[:,0:3].T
#number fo dimensions of data points
d=len(X[:,0])
#Add x0=1 to all data points
X=np.vstack((np.ones((1,2000)),X))
y=data[:,4]
#randomnly assign weights
w=np.zeros(shape=(d+1,1))
```

In [15]:

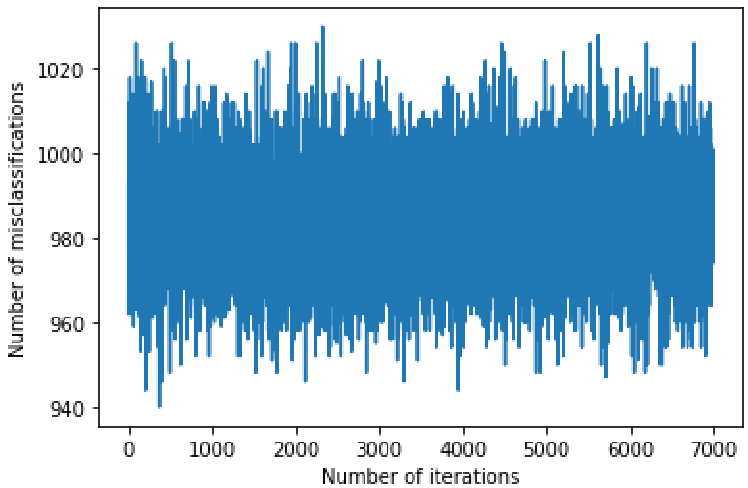
```
#count measures how many data points passed without change in weight w. If if comes equal to
N i.e. we completed one full
#round of data without changing weights w, it means we have reached convergence
#alpha is learning rate
alpha=0.0001
#counts how many data points seen afer last modification of weights. If count=N, it means th
e whole of dataset is seen
#without modifying the weights and hence convergence.
count=0
#used to break loop in case the convergence takes long time or when the data is not linearly
separable
itr=7000
#stores minimum value of number of misclassifications across all iterations.Initialised with
-1 before 1st iteration
misc=-1
#array to store no of misclassified points in each iteration
mis_arr=[]
#stores best weight .Initialised with zero
weig=np.zeros(shape=(d+1,1))
while(count!=N and itr):
    i=0
    #number of miclassifications in current iteration
    M=0
    while(i<N and count!=N):
        #flag denotes is there is a misclassification
        flag=0
        if(np.matmul(w.T,X[:,i])>=0 and y[i]<0):
            w-=alpha*np.reshape(X[:,i],(d+1,1))
            flag=1
        elif(np.matmul(w.T,X[:,i])<0 and y[i]>0):
            w+=alpha*np.reshape(X[:,i],(d+1,1))
            flag=1
        if(flag):
            count=0
            M+=1
        else:
            count+=1
        i+=1
        #print(w)
    itr-=1
    mis_arr.append(M)
    if(misc==-1 or M<misc):
        misc=M
        weig=copy.deepcopy(w)

print("best weight: ",weig)
print("best accuracy:",(N-misc)/N)
print("Lowest misclassification:",misc)
print("Weight after final iteration:,",w)
y_hat=np.zeros(shape=(np.shape(y)))
#stores number of misclassifications
err=0
#calculate number of misclassifications
for i in range(N):
    y_hat[i]=np.sign(np.matmul(w.T,X[:,i]))
    if(y_hat[i]!=y[i]):
        err+=1

print('Accuracy after final iteration:', (N-err)/N)
print("Number of misclassified points after final iteration: ",err)
#print("Mean accuracy: ",(N-err)/N)
```

```
best weight:  [[ 1.00000000e-04]
 [ 6.09348532e-05]
 [ 1.62586130e-04]
 [-3.65629844e-05]]
best accuracy: 0.53
Lowest misclassification: 940
Weight after final iteration:, [[1.00000000e-04]
 [2.81760345e-05]
 [1.19863056e-04]
 [5.45141147e-06]]
Accuracy after final iteration: 0.494
Number of misclassified points after final iteration:  1012
```

In [31]:
```python
#graph of number of misclassification pts vs number of iterations
import matplotlib.pyplot as plt
plt.xlabel("Number of iterations")
plt.ylabel("Number of misclassifications")
plt.plot(mis_arr)
plt.show()
"""
NOTE: rerun this cell if the plot doesnt show. Sometimes rerunning the cell gives correct ou
tput.
"""
```



Out[31]:
```
'\nNOTE: rerun this cell if the plot doesnt show. Sometimes rerunning the cell gives correct
output. \n'
```

In [17]:
```python
#range of no. of miscalssification pts
np.unique(mis_arr)
```

Out[17]:
```
array([ 940,  944,  946,  947,  948,  950,  951,  952,  953,  954,  955,
        956,  957,  958,  959,  960,  961,  962,  963,  964,  965,  966,
        967,  968,  969,  970,  971,  972,  973,  974,  975,  976,  977,
        978,  979,  980,  981,  982,  983,  984,  985,  986,  987,  988,
        989,  990,  991,  992,  993,  994,  995,  996,  997,  998,  999,
       1000, 1001, 1002, 1003, 1004, 1005, 1006, 1007, 1008, 1009, 1010,
       1011, 1012, 1014, 1016, 1017, 1018, 1020, 1022, 1024, 1026, 1028,
       1030])
```

In [18]:
```python
#It is seen that the pocket algorithms stores the best weights obtained and it can also be s
een that the weight after final
#itertion of perceptron algorithm is less accurate than the best weight returned by the pock
et algorithm
```

In [19]:
```
#library function to test how accurate the pocket algorithm implementation is with the perce
ptron learning algo
from sklearn.linear_model import Perceptron
clf = Perceptron()
clf.fit(X.T, y)
print("Weights calculated by library function:\n",clf.coef_)
print("Accuracy returned by pocket algo library function:",clf.score(X.T,y))
```

```
Weights calculated by library function:
 [[ 0.         -1.67159882 -1.89735341 -0.81731086]]
Accuracy returned by pocket algo library function: 0.506
```

In [20]:
```
#thus pocket algorithm implementation gives better result than standard perceptron learning
 algo
```

In [21]:
```
#logistic regression
data=np.loadtxt('C:/Users/Lenovo/Desktop/classification.txt',delimiter=",")
N=len(data)
#first 3 columns are data points
X=data[:,0:3].T
d=len(X[:,0])
#assign x0=1 to all data points
X=np.vstack((np.ones((1,2000)),X))
#last column is label
y=data[:,4]
#randomnly assign weights
#w=np.random.rand(d+1,1)
w=np.zeros((d+1,1))
```

In [22]:
```
#number of iterations
itr=7000
#learning rate
alpha=0.1
for i in range(itr):
    """
    #predict y labels for current weight assignment w.
    y_pred=np.exp(np.matmul(w.T,X))/(1+np.exp(np.matmul(w.T,X)))
    #update weights w. simultaneous update is done for all coefficients w0,w1,...,wd
    w-=alpha*np.dot(X,np.reshape((y_pred-y),(N,1)))/N
    #print loss every 1000 iterations to check if it nearing convergence
    if(i%1000==0):
        print("Loss:",(-y * np.log(y_pred) - (1 - y) * np.log(1 - y_pred)).mean())
    """
    #stores derivative value which is sued to update weight w
    delta=np.zeros((d+1,1))
    #for j in range(N):
        #delta+=y[j]*np.reshape(X[:,j],(d+1,1))/(1+np.exp(y[j]*np.matmul(w.T,np.reshape(X[:,
j],(d+1,1)))))
    #delta*=-1/N
    delta=-np.matmul(y.T/(1+np.exp(y.T*np.matmul(w.T,X))),X.T).T/N

    w-=alpha*delta

print("Final weight: ",w)
#final prediction of lables
y_hat=np.zeros(shape=(np.shape(y)))
#used to count number of misclassified points
err=0
#find number of misclassified points
for i in range(N):
    y_hat[i]=np.sign(np.matmul(w.T,X[:,i]))
    if(np.sign(y_hat[i])!=np.sign(y[i])):
        err+=1

print('Accuracy:', (N-err)/N)
print("Number of misclassified points: ",err)
```

```
Final weight:  [[-0.03149498]
 [-0.17769975]
 [ 0.11444872]
 [ 0.07669738]]
Accuracy: 0.5295
Number of misclassified points:  941
```

In [23]:
```
#library function
from sklearn.linear_model import LogisticRegression
clf = LogisticRegression(random_state=0).fit(X.T, y)
print("Score:",clf.score(X.T, y))
print("Weights calculated by library function",clf.coef_)
```

```
Score: 0.5295
Weights calculated by library function [[-0.01550526 -0.17376308  0.11159028  0.07474653]]

C:\Users\Lenovo\Anaconda3\lib\site-packages\sklearn\linear_model\logistic.py:432: FutureWarn
ing: Default solver will be changed to 'lbfgs' in 0.22. Specify a solver to silence this war
ning.
  FutureWarning)
```

In [24]:
```
#Weights  of both the library version and implementation are pretty similar.Accuracy of both versions are exactly the same
```

In [25]:
```
import numpy as np
```

In [26]:
```
#linear regression
data=np.loadtxt('C:/Users/Lenovo/Desktop/linear-regression.txt',delimiter=",")
N=len(data)
#first 2 data columns are x and y independent variables
X=data[:,0:2].T
d=len(X[:,0])
X=np.vstack((np.ones((1,N)),X))
#3rd column is z dependent variable
y=data[:,2]
#randomnly assign weights
w=np.random.rand(d+1,1)
```

In [27]:
```
#analytical solution for linear regression.
w=np.matmul(np.matmul(np.linalg.inv(np.matmul(X,X.T)),X),np.reshape(y,(N,1)))
```

In [28]:
```
print("Weights",w)
```

```
Weights [[0.01523535]
 [1.08546357]
 [3.99068855]]
```

In [29]:
```
from sklearn.linear_model import LinearRegression
reg = LinearRegression().fit(X.T, y)
print("Weights calculated by library function",reg.coef_)
```

```
Weights calculated by library function [0.         1.08546357 3.99068855]
```

In [30]:
```
#It can be seen that the weight calculated by the libray function is same as the weight calculated by implementation
```