Lab Course Machine Learning

Exercise Sheet 5

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Exercise 1: Backward search for variable selection

In [23]:
```
import numpy as np
import math
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from matplotlib import cm
from matplotlib.ticker import LinearLocator
plt.rcParams['figure.figsize'] = (10 ,8)
from sympy import symbols, diff
import pandas as pd
import math
import warnings
import itertools
warnings.filterwarnings('ignore')
```

In [24]:
```
df = pd.read_csv('bank.csv',sep = ';')
df.columns
```

Out[24]:
```
Index(['age', 'job', 'marital', 'education', 'default', 'balance', 'housing',
       'loan', 'contact', 'day', 'month', 'duration', 'campaign', 'pdays',
       'previous', 'poutcome', 'y'],
      dtype='object')
```

If required drop out the rows with missing values or NA. (hope) in next lectures we will handle sparse data, which will allow us to use records with missing values.

In [25]:
```
is_NaN = df.isnull()
row_has_NaN = is_NaN.any(axis=1)
rows_with_NaN = df[row_has_NaN]
rows_with_NaN
```

Out[25]:

age	job	marital	education	default	balance	housing	loan	contact	day	month	duration	campaign	pdays	previous	poutcome	y

In [26]:
```
df[(df == 'unknown').any(axis='columns')]
```

Out[26]:

	age	job	marital	education	default	balance	housing	loan	contact	day	month	duration	campaign	pdays	previous
0	30	unemployed	married	primary	no	1787	no	no	cellular	19	oct	79	1	-1	0
3	30	management	married	tertiary	no	1476	yes	yes	unknown	3	jun	199	4	-1	0
4	59	blue-collar	married	secondary	no	0	yes	no	unknown	5	may	226	1	-1	0
7	39	technician	married	secondary	no	147	yes	no	cellular	6	may	151	2	-1	0
8	41	entrepreneur	married	tertiary	no	221	yes	no	unknown	14	may	57	2	-1	0
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
4513	49	blue-collar	married	secondary	no	322	no	no	cellular	14	aug	356	2	-1	0
4515	32	services	single	secondary	no	473	yes	no	cellular	7	jul	624	5	-1	0
4516	33	services	married	secondary	no	-333	yes	no	cellular	30	jul	329	5	-1	0
4517	57	self-employed	married	tertiary	yes	-3313	yes	yes	unknown	9	may	153	1	-1	0
4518	57	technician	married	secondary	no	295	no	no	cellular	19	aug	151	11	-1	0

3757 rows × 17 columns

1 Convert any non-numeric values to numeric values. For example you can replace a country name with an integer value or more appropriately use hot-one encoding.

transformData() takes a dataframe and for each column gets uniques values in that column and assign a value from zero to number of possible values in that columns. Finally, append this dictionary for one column to next columns. In this way it creates a hashmap for dataframe.

In [27]:
```
def transformData (df):
    cols = df.columns
    num_cols = df._get_numeric_data().columns
    colList = list(set(cols) - set(num_cols))
    dictMap = dict()
    for c in colList :

        keys = df[c].unique()
        values = list(range(0, len(keys)))
        dictionary = dict(zip(keys, values))
        dictMap.update(dictionary)

    df= df.replace(dictMap)

    return df,dictMap
```

In [28]:
```
ds,dictMap = transformData(df)
```

In [29]:
```
dictMap
```

Out[29]:
```
{'married': 0,
 'single': 1,
 'divorced': 2,
 'no': 0,
 'yes': 1,
 'cellular': 0,
 'unknown': 3,
 'telephone': 2,
 'failure': 1,
 'other': 2,
 'success': 3,
 'unemployed': 0,
 'services': 1,
 'management': 2,
 'blue-collar': 3,
 'self-employed': 4,
 'technician': 5,
 'entrepreneur': 6,
 'admin.': 7,
 'student': 8,
 'housemaid': 9,
 'retired': 10,
 'primary': 0,
 'secondary': 1,
 'tertiary': 2,
 'oct': 0,
 'may': 1,
 'apr': 2,
 'jun': 3,
 'feb': 4,
 'aug': 5,
 'jan': 6,
 'jul': 7,
 'nov': 8,
 'sep': 9,
 'mar': 10,
 'dec': 11}
```

4 Normalize (Standardize) the data

In [30]:
```
dsy = ds.loc[:, ds.columns != 'y']
nds = (dsy-dsy.mean())/dsy.std()
nds
```

Out[30]:

	age	job	marital	education	default	balance	housing	loan	contact	day	month	duration	campaig
0	-1.056153	-1.595307	-0.716234	-1.644573	-0.130744	0.121058	-1.141925	-0.424709	-0.738102	0.374011	-1.444582	-0.711782	-0.5767
1	-0.772497	-1.199305	-0.716234	-0.309004	-0.130744	1.118521	0.875521	2.354032	-0.738102	-0.595961	-1.076641	-0.169175	-0.5767
2	-0.583394	-0.803303	0.721640	1.026566	-0.130744	-0.024142	0.875521	-0.424709	-0.738102	0.010271	-0.708700	-0.303865	-0.5767
3	-1.056153	-0.803303	-0.716234	1.026566	-0.130744	0.017724	0.875521	2.354032	1.450546	-1.565932	-0.340759	-0.249989	0.3879
4	1.685850	-0.407301	-0.716234	-0.309004	-0.130744	-0.472701	0.875521	-0.424709	1.450546	-1.323439	-1.076641	-0.146086	-0.5767
...	...	...	...	...	...	...	...	...	...	...	...	...	
4516	-0.772497	-1.199305	-0.716234	-0.309004	-0.130744	-0.583345	0.875521	-0.424709	-0.738102	1.707721	1.131006	0.250287	0.7094
4517	1.496746	-0.011299	-0.716234	1.026566	7.646823	-1.573497	0.875521	2.354032	1.450546	-0.838453	-1.076641	-0.427010	-0.5767
4518	1.496746	0.384703	-0.716234	-0.309004	-0.130744	-0.374682	-1.141925	-0.424709	-0.738102	0.374011	0.395124	-0.434706	2.6388
4519	-1.245256	-0.407301	-0.716234	-0.309004	-0.130744	-0.094914	-1.141925	-0.424709	-0.738102	-1.202193	0.027183	-0.519368	0.3879
4520	0.267573	0.780704	0.721640	1.026566	-0.130744	-0.095247	0.875521	2.354032	-0.738102	-1.565932	-0.708700	0.311859	-0.2552

4521 rows × 16 columns

In [31]:
```
# no need to normalize target Y
nds['y'] = ds[['y']]
nds
```

Out[31]:

	age	job	marital	education	default	balance	housing	loan	contact	day	month	duration	campaig
0	-1.056153	-1.595307	-0.716234	-1.644573	-0.130744	0.121058	-1.141925	-0.424709	-0.738102	0.374011	-1.444582	-0.711782	-0.5767
1	-0.772497	-1.199305	-0.716234	-0.309004	-0.130744	1.118521	0.875521	2.354032	-0.738102	-0.595961	-1.076641	-0.169175	-0.5767
2	-0.583394	-0.803303	0.721640	1.026566	-0.130744	-0.024142	0.875521	-0.424709	-0.738102	0.010271	-0.708700	-0.303865	-0.5767
3	-1.056153	-0.803303	-0.716234	1.026566	-0.130744	0.017724	0.875521	2.354032	1.450546	-1.565932	-0.340759	-0.249989	0.3879
4	1.685850	-0.407301	-0.716234	-0.309004	-0.130744	-0.472701	0.875521	-0.424709	1.450546	-1.323439	-1.076641	-0.146086	-0.5767
...	...	...	...	...	...	...	...	...	...	...	...	...	
4516	-0.772497	-1.199305	-0.716234	-0.309004	-0.130744	-0.583345	0.875521	-0.424709	-0.738102	1.707721	1.131006	0.250287	0.7094
4517	1.496746	-0.011299	-0.716234	1.026566	7.646823	-1.573497	0.875521	2.354032	1.450546	-0.838453	-1.076641	-0.427010	-0.5767
4518	1.496746	0.384703	-0.716234	-0.309004	-0.130744	-0.374682	-1.141925	-0.424709	-0.738102	0.374011	0.395124	-0.434706	2.6388
4519	-1.245256	-0.407301	-0.716234	-0.309004	-0.130744	-0.094914	-1.141925	-0.424709	-0.738102	-1.202193	0.027183	-0.519368	0.3879
4520	0.267573	0.780704	0.721640	1.026566	-0.130744	-0.095247	0.875521	2.354032	-0.738102	-1.565932	-0.708700	0.311859	-0.2552

4521 rows × 17 columns

3 Split the data into a train/test splits according to the ratios 80%:20%.

In [33]:
```
nds_train = nds.loc[0:math.floor(len(nds)*0.8)]
nds_test = nds.loc[math.floor(len(nds)*0.8)+1:]
len(nds) == len(nds_train)+ len(nds_test)
nds_test
```

Out[33]:

	age	job	marital	education	default	balance	housing	loan	contact	day	month	duration	campaig
3617	0.078469	-0.407301	-0.716234	-0.309004	-0.130744	-0.612917	-1.141925	-0.424709	-0.738102	-0.838453	1.131006	-0.896499	-0.5767
3618	0.362124	1.176706	-0.716234	-0.309004	-0.130744	-0.390299	-1.141925	-0.424709	-0.738102	0.010271	1.131006	-0.199961	-0.2552
3619	0.551228	0.384703	-0.716234	-1.644573	-0.130744	-0.424522	0.875521	-0.424709	1.450546	-1.080946	-1.076641	-0.411617	1.0310
3620	1.780402	2.364712	2.159515	-0.309004	-0.130744	-0.274006	-1.141925	2.354032	-0.738102	-0.959700	1.131006	-0.646361	-0.5767
3621	-0.583394	-0.803303	-0.716234	1.026566	-0.130744	-0.157380	0.875521	-0.424709	1.450546	1.343982	-1.076641	-0.072968	-0.2552
...	...	...	...	...	...	...	...	...	...	...	...	...	
4516	-0.772497	-1.199305	-0.716234	-0.309004	-0.130744	-0.583345	0.875521	-0.424709	-0.738102	1.707721	1.131006	0.250287	0.7094
4517	1.496746	-0.011299	-0.716234	1.026566	7.646823	-1.573497	0.875521	2.354032	1.450546	-0.838453	-1.076641	-0.427010	-0.5767
4518	1.496746	0.384703	-0.716234	-0.309004	-0.130744	-0.374682	-1.141925	-0.424709	-0.738102	0.374011	0.395124	-0.434706	2.6388
4519	-1.245256	-0.407301	-0.716234	-0.309004	-0.130744	-0.094914	-1.141925	-0.424709	-0.738102	-1.202193	0.027183	-0.519368	0.3879
4520	0.267573	0.780704	0.721640	1.026566	-0.130744	-0.095247	0.875521	2.354032	-0.738102	-1.565932	-0.708700	0.311859	-0.2552

904 rows × 17 columns

5 Implement logistic regression and mini-batch Gradient Ascent.

The implementation of Gradient Acent and logistic regression is same as last lab, for mini batches I am splitting data in N number of batches of size 50, and for each batch calling Gradient Ascent Func(), Beta returned from last batch will be used as initial Beta for the next batch.

In [34]:
```
def sig(X,B):
    return (1  / (1 + np.exp((-1)*(np.dot(X,B)))))


def logLike(X,Y,B):
    return np.sum((Y*sig(X,B))-np.log(1+np.exp(sig(X,B))))
# for logloss: https://ml-cheatsheet.readthedocs.io/en/latest/loss_functions.html
# ref given in exercise was not running
def logloss(yHat, y):
    sum=0
    for i in range(len(yHat)):
        if y[i] == 1:
            sum = sum - np.log(yHat[i] )
        else:
            sum = sum -np.log(1 - yHat[i] )
    return sum
def miniBatch(X,Y,batchSize):
    totalRecords = len(X)
    numberOfbatches = np.ceil(totalRecords/ batchSize)

    X_mini = np.array_split(X, numberOfbatches)
    Y_mini = np.array_split(Y, numberOfbatches)
    B = np.zeros(shape=(len(X[0]),1))
    for i in range (len(X_mini)):
        B = GradAscent(X_mini[i],Y_mini[i])
    return B
def aicScore(X,Y,B):
    return (-2)*(logLike(X,Y,B)) +2*(len(B))

def mapProbablity(Y_prob):
    y=np.zeros(shape=(len(Y_prob),1))
    for i in range(len(Y_prob)):
        if(Y_prob[i]>=0.5):
            y[i]=1
        else:
            y[i]=0
    return y

def errorEval(Y_pred,Y_test):
    error = 0
    for i in range(len(Y_pred)):

        if(Y_pred[i]!=Y_test[i]):
            error +=1
    return (error/len(Y_pred))*100

def GradAscent(X,Y):
    μ=10**(-10)
    B_old = np.zeros(shape=(len(X[0]),1))
    fold_min_fnew_List =[]
    numberIterations = 100
    L= logLike(X,Y,B_old)
    Log_loss = []
    for i in range (numberIterations):
        y_hat = sig(X,B_old)


        B_hat =B_old +(μ* np.dot(X.T,(Y-y_hat)))
        L_old = L
        L = logLike(X,Y,B_hat)
        B_old = B_hat
    return B_hat


def kFoldCrossValitaion(X,Y,k):
    X_splits = np.array_split(X, k)
    Y_splits = np.array_split(Y, k)
    for i in range (len(Y_splits)):
        print(len(Y_splits[i]))
```

Keep the hyperparameters of learning rate and batch size fixed (good guesses) and iteratively do backward selection keeping track of the AIC metric.

For backward search to eliminate less effective params, We first find AIC with all columns then iteratively drop columns and check AIC again, Here we are using AIC formula for minimization, It means if after dropping that column value of AIC is minimum than before. It means there is an improvement and we will drop the column with maximum improvement. We will do this iterative until when there is no improvement. Final parameter list give all the columns for which AIC is not dropped after removing.

In [35]:
```
def backwardSearch(Xtrain,Ytrain):
    V = Xtrain.columns
    batchSize = 50
    Vused = V.tolist()
    improvement = True
    while (improvement):
        gainBest = 0

        #for AIC when all columns are there
        X_used = Xtrain[Vused].to_numpy()
        bias_column = np.ones(shape=(len(X_used),1))
        X_used = np.append(bias_column,X_used,axis=1)
        B_used = miniBatch(X_used,Ytrain.to_numpy(),batchSize)
        aic_used = aicScore(X_used,Ytrain.to_numpy(),B_used)
        for v in Vused:
            #for AIC when V column is droped
            X_without_v = Xtrain.loc[:, Xtrain.columns != v ].to_numpy()
            bias_column = np.ones(shape=(len(X_without_v),1))
            X_without_v = np.append(bias_column,X_without_v,axis=1)
            B_without_v = miniBatch(X_without_v,Ytrain.to_numpy(),batchSize)
            aic_without_v = aicScore(X_without_v,Ytrain.to_numpy(),B_without_v)

            gain = aic_used - aic_without_v

            if ( gain > gainBest):
                gainBest = gain
                v_best = v
        improvement = (gain > 0)
        if(improvement):

            Vused.remove(v_best)

    return Vused
```

In [36]:
```
X_train = nds_train.loc[:, nds_train.columns != 'y']
Y_train = nds_train[['y']]

params = backwardSearch(X_train,Y_train)
X_train = nds_train[params]
Y_train = nds_train[['y']]

X_test = (nds_train[params]).to_numpy()
bias_column = np.ones(shape=(len(X_test),1))
X_test = np.append(bias_column,X_test,axis=1)
Y_test = (nds_train[['y']]).to_numpy()

X = X_train.to_numpy()
Y = Y_train.to_numpy()
bias_column = np.ones(shape=(len(X_train),1))
X = np.append(bias_column,X,axis=1)

B = np.zeros(len(X[0]))

B_hat=miniBatch(X,Y,50)
```

Report the final error on Test set.

In [37]:
```
Y_hat = sig(X_test,B_hat)
y_pred = mapProbablity(Y_hat)

error = errorEval(y_pred,Y_test)
print (error)
```

```
11.169477467514515
```

Exercise 2: Regularization for Logistic Regression

1. Pick a range of α0 and λ defined on grid. You can choose fixed batchsize

In [162…:
```
μ =[10**(-4),10**(-7),10**(-10),10**(-14),10**(-17)]
μ
```

Out[162…:
```
[0.0001, 1e-07, 1e-10, 1e-14, 1e-17]
```

In [163…:
```
lamda = [np.exp(-4),np.exp(-6),np.exp(-8),np.exp(-10)]
lamda
```

Out[163…:
```
[0.01831563888873418,
 0.0024787521766663585,
 0.00033546262790251185,
 4.5399929762484854e-05]
```

In [164…:
```
grid =list(itertools.product(μ, lamda))
```

In [165…:
```
def acuuracyValue(Y_pred,Y_test):
    acc = 0
    for i in range(len(Y_pred)):

        if(Y_pred[i]==Y_test[i]):
            acc +=1
    return (acc/len(Y_pred))*100

def logLike(X,Y,B,lamda):
    return np.sum((Y*sig(X,B))-np.log(1+np.exp(sig(X,B))))-(lamda*(np.linalg.norm(B))**2)


def miniBatch(X,Y,batchSize,μ,lamda,numberIterations):
    totalRecords = len(X)
    numberOfbatches = np.ceil(totalRecords/ batchSize)

    X_mini = np.array_split(X, numberOfbatches)
    Y_mini = np.array_split(Y, numberOfbatches)
    B = np.zeros(shape=(len(X[0]),1))
    for i in range (len(X_mini)):
        B = GradAscent(X_mini[i],Y_mini[i],μ,lamda,numberIterations)
    return B

def logloss(yHat, y):
    sum=0
    for i in range(len(yHat)):
        if y[i] == 1:
            sum = sum - np.log(yHat[i] )
        else:
            sum = sum -np.log(1 - yHat[i] )
    return sum


def GradAscent(X,Y,μ,lamda,numberIterations):
    B_old = np.zeros(shape=(len(X[0]),1))
    fold_min_fnew_List =[]
    numberIterations = 100
    L= logLike(X,Y,B_old,lamda)
    Log_loss = []
    for i in range (numberIterations):
        y_hat = sig(X,B_old)
        B_hat =B_old +(μ* (np.dot(X.T,(Y-y_hat))-(2*lamda*B_old)))
        L_old = L
        L = logLike(X,Y,B_hat,lamda)
        B_old = B_hat
    return B_hat
```

2. Implement k-fold cross-validation protocol for grid search.

For k−folds divinding whole dataset into equal 5 parts and in one iteration taking one part as test and other 4 parts as training.Finding Accuracy for each iteration.

In [223…:
```
def kFoldCrossValitaion(X,Y,k,μ,lamda,numberIterations,batchSize):
    chunkSize = int(np.floor(len(X)/k))
    meanAcc =0
    accLogList = []

    for i in range (k):

        x_test = X[i*chunkSize:(i*chunkSize)+chunkSize,:]
        y_test = Y[i*chunkSize:(i*chunkSize)+chunkSize,:]
        index = list(range(i*chunkSize,(i*chunkSize)+chunkSize))

        x_train = np.delete(X,index,0)
        y_train = np.delete(Y,index,0)

        B = miniBatch(x_train,y_train,batchSize,μ,lamda,numberIterations)
        #for training data
        Y_hat_train = sig(x_train,B)
        y_pred_train = mapProbablity(Y_hat_train)
        train_accuracy = acuuracyValue(y_pred_train,y_train)
        logLossTrain = logloss(Y_hat_train, y_train)

        #for test data
        Y_hat = sig(x_test,B)
        y_pred = mapProbablity(Y_hat)
        meanAcc += acuuracyValue(y_pred,y_test)
        test_accuracy = acuuracyValue(y_pred,y_test)
        logLosstest = logloss(Y_hat, y_test)

        accLogList.append([train_accuracy,test_accuracy,logLossTrain[0],logLosstest[0]])

    return (meanAcc/k),np.array(accLogList)
```

For each pair value of μ and lamda in grid, calling kFoldCrossValitaion() which gives mean for that pair. Getting best accuracy and getting best μ and lamda values corresponding to that accuracy.

In [168…:
```
X = nds.loc[:, nds.columns != 'y'].to_numpy()
Y = nds[['y']].to_numpy()
bias_column = np.ones(shape=(len(X),1))
X = np.append(bias_column,X,axis=1)
listMeanError = 0
i=0
numberIterations=100
meanList =[]
for (μ,lamda) in grid:
    meanError,accLogList = kFoldCrossValitaion(X,Y,5,μ,lamda,numberIterations)

    meanList.append(list([meanError,μ,lamda]))
```

In [169…:
```
print(max(meanList))
```

```
[86.06194690265487, 0.0001, 0.01831563888873418]
```

In [170…:
```
print(np.array(meanList))
```

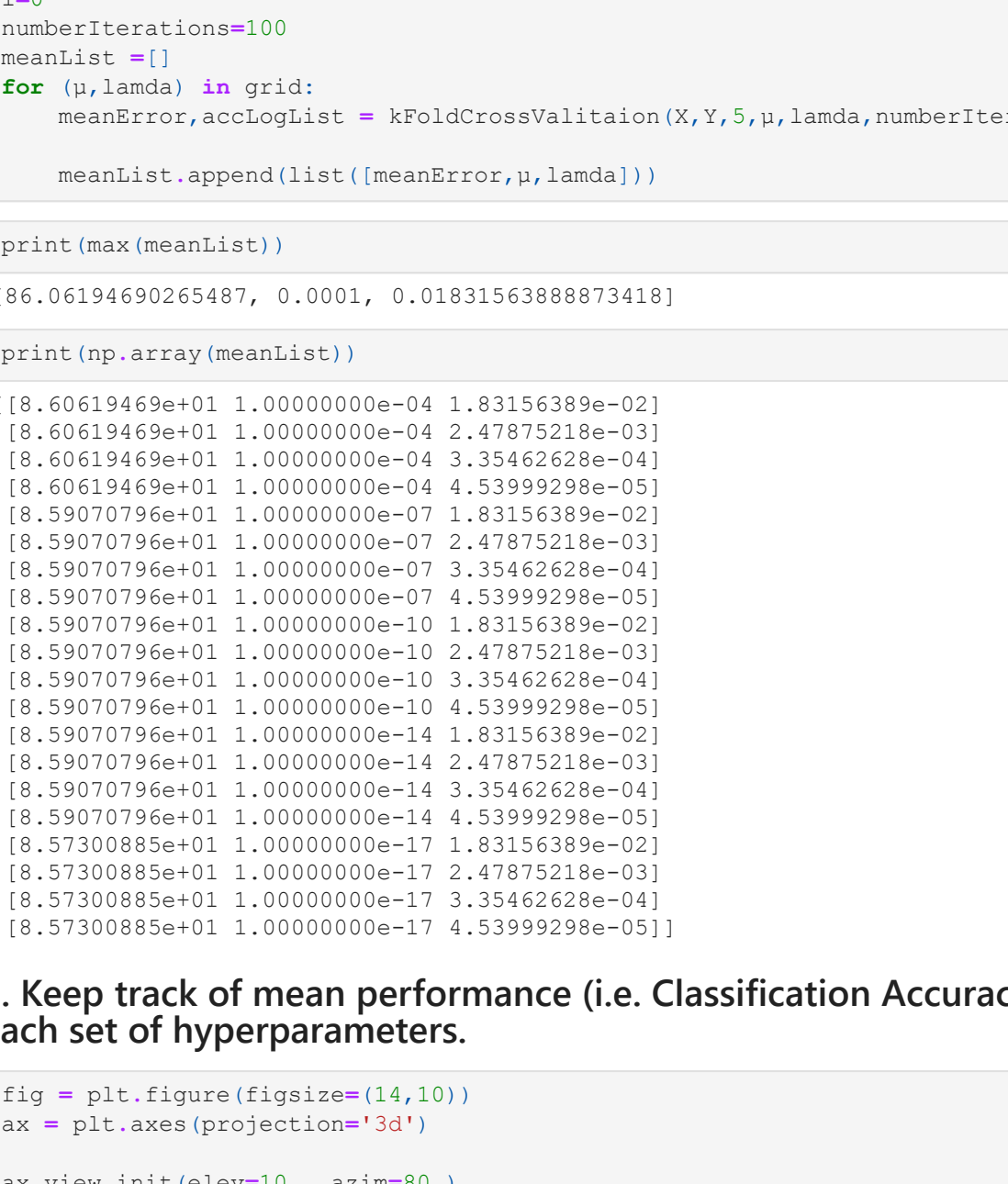
```
[[8.60619469e+01 1.00000000e-04 1.83156389e-02]
 [8.60619469e+01 1.00000000e-04 2.47875218e-03]
 [8.60619469e+01 1.00000000e-04 3.35462628e-04]
 [8.60619469e+01 1.00000000e-04 4.53999298e-05]
 [8.59070796e+01 1.00000000e-07 1.83156389e-02]
 [8.59070796e+01 1.00000000e-07 2.47875218e-03]
 [8.59070796e+01 1.00000000e-07 3.35462628e-04]
 [8.59070796e+01 1.00000000e-07 4.53999298e-05]
 [8.59070796e+01 1.00000000e-10 1.83156389e-02]
 [8.59070796e+01 1.00000000e-10 2.47875218e-03]
 [8.59070796e+01 1.00000000e-10 3.35462628e-04]
 [8.59070796e+01 1.00000000e-10 4.53999298e-05]
 [8.59070796e+01 1.00000000e-14 1.83156389e-02]
 [8.59070796e+01 1.00000000e-14 2.47875218e-03]
 [8.59070796e+01 1.00000000e-14 3.35462628e-04]
 [8.59070796e+01 1.00000000e-14 4.53999298e-05]
 [8.57300885e+01 1.00000000e-17 1.83156389e-02]
 [8.57300885e+01 1.00000000e-17 2.47875218e-03]
 [8.57300885e+01 1.00000000e-17 3.35462628e-04]
 [8.57300885e+01 1.00000000e-17 4.53999298e-05]]
```

3. Keep track of mean performance (i.e. Classification Accuracy value) across k − folds for each set of hyperparameters.

In [171…:
```
fig = plt.figure(figsize=(14,10))
ax = plt.axes(projection='3d')

ax.view_init(elev=10., azim=80.)

ax.scatter(np.array(meanList)[:,1], np.array(meanList)[:,2], np.array(meanList)[:,0], c='r', marker='o')
ax.set_xlabel('μ')
ax.set_ylabel('Lamda')
ax.set_zlabel('Accuracy Perc')
plt.show()
```



4. Finally, for the optimal value of alpha0 and λ, train your model on complete training data and evaluate on Test data.

In [172…:
```
μBest = max(meanList)[1]
lamdaBest = max(meanList)[2]
```

In [173…:
```
print(μBest)
```

```
0.0001
```

In [174…:
```
print(lamdaBest)
```

```
0.01831563888873418
```

In [175…:
```
X_train = nds_train.loc[:, nds_train.columns != 'y']
Y_train = nds_train[['y']]

X_train = nds_train[params]
Y_train = nds_train[['y']]

X_test = (nds_train[params]).to_numpy()
bias_column = np.ones(shape=(len(X_test),1))
X_test = np.append(bias_column,X_test,axis=1)
Y_test = (nds_train[['y']]).to_numpy()

X = X_train.to_numpy()
Y = Y_train.to_numpy()
bias_column = np.ones(shape=(len(X_train),1))
X = np.append(bias_column,X,axis=1)

B = np.zeros(len(X[0]))
numberIterations = 100
B_hat=miniBatch(X,Y,50,μBest,lamdaBest,numberIterations)

Y_hat = sig(X_test,B_hat)
y_pred = mapProbablity(Y_hat)
logLoss = logloss(Y_hat, Y_test)

acc = acuuracyValue(y_pred,Y_test)
print('Accuracy:',acc)
print('Log-likelihood:',logLoss)
```

```
Accuracy: 89.13464196848217
Log-likelihood: [2204.40501852]
```

5. Plot Train and Validation Accuracy and Log-likelihood metrics per k − fold iteration.

In [177…:
```
X = nds.loc[:, nds.columns != 'y'].to_numpy()
Y = nds[['y']].to_numpy()
bias_column = np.ones(shape=(len(X),1))
X = np.append(bias_column,X,axis=1)

meanError,accLogList = kFoldCrossValitaion(X,Y,5,μBest,lamdaBest,numberIterations)
iterations =list(range(0,5))
```

In [178…:
```
#[train_accuracy,test_accuracy,logLossTrain[0],logLosstest[0]]
accLogList
```

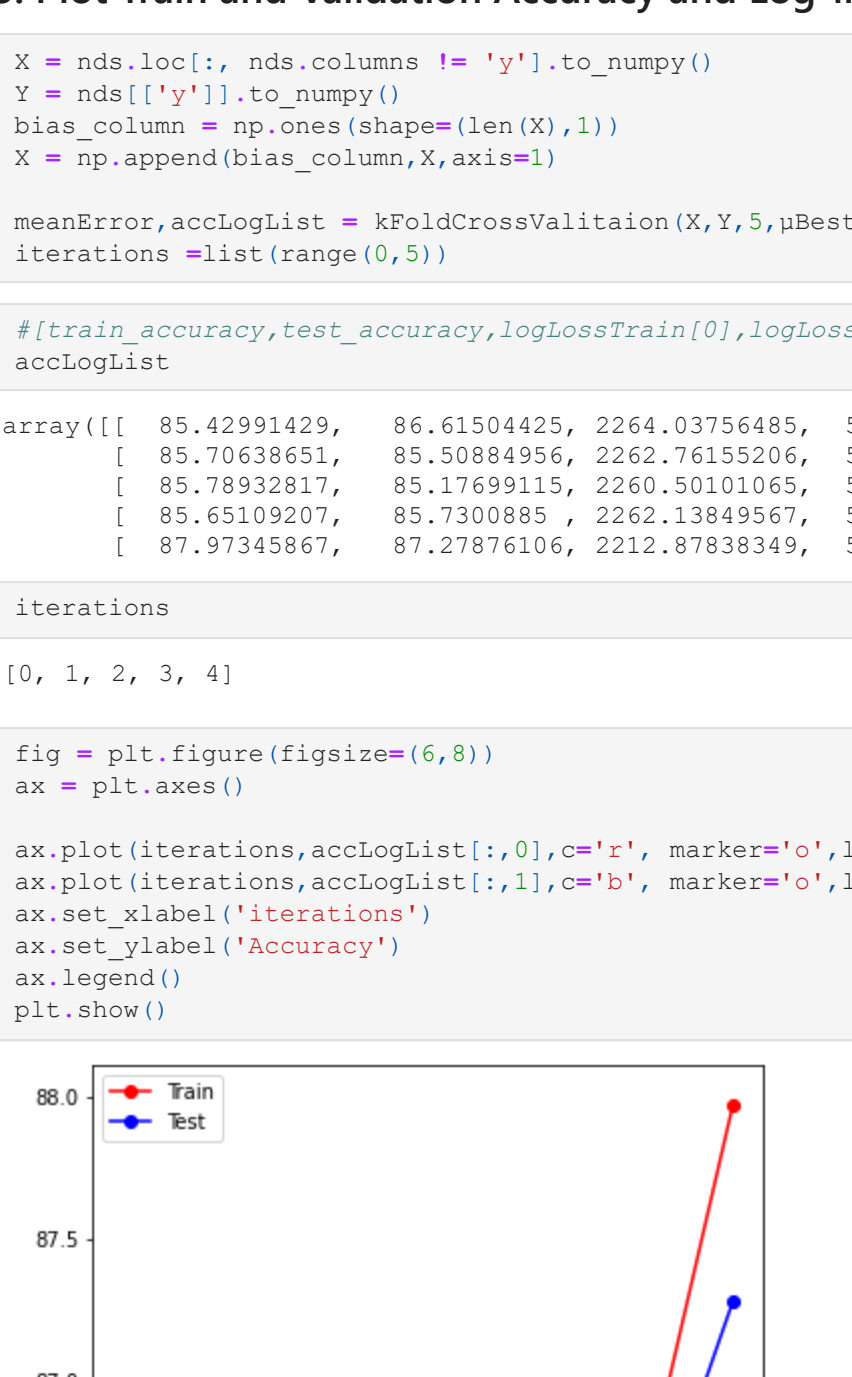
Out[178…:
```
array([[  85.42991429,   86.61504425, 2264.03756485,  563.37799364],
       [  85.70638651,   85.50884956, 2262.76155206,  564.65400643],
       [  85.78932817,   85.17699115, 2260.50101065,  566.91454783],
       [  85.65109207,   85.7300885 , 2262.13849567,  565.27706281],
       [  87.97345867,   87.27876106, 2212.87838349,  554.53023419]])
```

In [179…:
```
iterations
```

Out[179…:
```
[0, 1, 2, 3, 4]
```

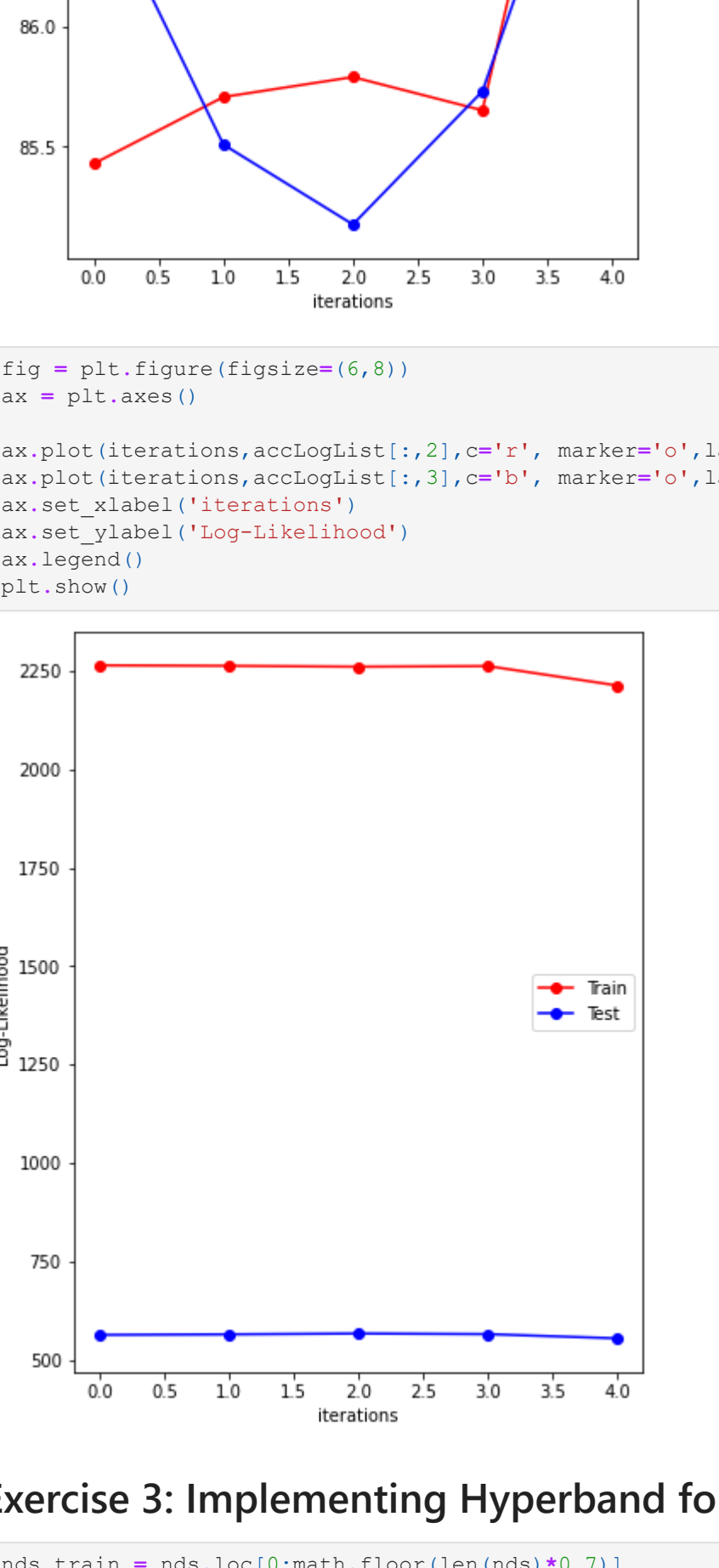
In [180…:
```
fig = plt.figure(figsize=(6,8))
ax = plt.axes()

ax.plot(iterations,accLogList[:,0],c='r', marker='o',label='Train')
ax.plot(iterations,accLogList[:,1],c='b', marker='o',label = 'Test')
ax.set_xlabel('iterations')
ax.set_ylabel('Accuracy')
ax.legend()
plt.show()
```



In [181…:
```
fig = plt.figure(figsize=(6,8))
ax = plt.axes()

ax.plot(iterations,accLogList[:,2],c='r', marker='o',label='Train')
ax.plot(iterations,accLogList[:,3],c='b', marker='o',label = 'Test')
ax.set_xlabel('iterations')
ax.set_ylabel('Log-Likelihood')
ax.legend()
plt.show()
```



Exercise 3: Implementing Hyperband for Logistic Regression

In [ ]:
```
nds_train = nds.loc[0:math.floor(len(nds)*0.7)]
nds_validation = nds.loc[math.floor(len(nds)*0.7)+1:math.floor(len(nds)*0.85)]
nds_test = nds.loc[math.floor(len(nds)*0.85)+1:]
len(nds) == len(nds_train)+ len(nds_test)
nds_test
```

In [227…:
```
max_iter = 81
eta =
logeta = lambda x: np.log(x)/np.log(eta)
s_max = int(logeta(max_iter))
B = (s_max+1)*max_iter


for s in reversed(range(s_max+1)):

    n = int(np.ceil(int(B/max_iter/(s+1))*eta**s))
    r = max_iter*eta**(-s)

    lamdaList =np.random.uniform(np.exp(-9),np.exp(-4),n)
    batches = np.random.randint(25,800,n)
    μList = np.random.uniform(10**(-7),10**(-5),n)
    hyperParamConfigs = []
    for i in range (len(batches)):
        hyperParamConfigs.append([μList[i],lamdaList[i],batches[i]])
    print(s,n,r, len(hyperParamConfigs) )

    finalList = []
    for i in range(s+1):

        n_i = n*eta**(-i)
        r_i = r*eta**(i)
        print(n_i,r_i)
        for i in range(len(hyperParamConfigs)):


            meanAcc,accLogList = kFoldCrossValitaion(X,Y,5,hyperParamConfigs[i][0],hyperParamConfigs[i][1],r_i,
            finalList.append([meanAcc,hyperParamConfigs[i][0],hyperParamConfigs[i][1],hyperParamConfigs[i][2]])


print(min(finalList))
```

```
4 81 1.0 81
81 1.0
27.0 3.0
9.0 9.0
3.0 27.0
1.0 81.0
3 27 3.0 27
27 3.0
9.0 9.0
3.0 27.0
1.0 81.0
2 9 9.0 9
9 9.0
3.0 27.0
1.0 81.0
1 6 27.0 6
6 27.0
2.0 81.0
0 5 81 5
5 81
[87.43362831858407, 3.932222350837884e-06, 0.006565918243638579, 94]
```

In [229…:
```
print(max(finalList))
```

```
[88.93805309734513, 8.16389535376992e-06, 0.007979239671917002, 580]
```

In [234…:
```
μBest = max(finalList)[1]
print(μBest)
```

```
8.16389535376992e-06
```

In [235…:
```
batchSizeBest = max(finalList)[3]
print(batchSizeBest)
```

```
580
```

In [236…:
```
lamdaBest = max(finalList)[2]
print(lamdaBest)
```

```
0.007979239671917002
```

In [ ]: