HW1-2 Classification

November 4, 2019

[203]:
```
#author = 0712238@NCTU, Maxwill Lin, YT Lin
#last update = 2019.11.4
#usage = HW1 of Deep Learning 2019 fall @ NCTU
#classification part
#preprocess
#NN(2D) architectur = NN([34, 17, 2, 1],activations=['relu', 'relu', 'sigmoid'], usage = 'classification')
#NN2(3D) architectur = NN([34, 17, 3, 1],activations=['relu', 'relu', 'sigmoid'], usage = 'classification')
#train and test with split data set
#learning curve + train/test CE + train/test accuracy/error rate
#visualization with 2D/3D scatters
#save files
```

[178]:
```
import numpy as np
import math
import pandas as pd
from model2 import *
import csv
import matplotlib.pyplot as plt
import pickle
```

[180]:
```
df =  pd.read_csv("ionosphere_csv.csv")
df
```

[180]:
```
     a01  a02      a03      a04      a05      a06      a07      a08      a09  \
0      1    0  0.99539 -0.05889  0.85243  0.02306  0.83398 -0.37708  1.00000
1      1    0  1.00000 -0.18829  0.93035 -0.36156 -0.10868 -0.93597  1.00000
2      1    0  1.00000 -0.03365  1.00000  0.00485  1.00000 -0.12062  0.88965
3      1    0  1.00000 -0.45161  1.00000  1.00000  0.71216 -1.00000  0.00000
4      1    0  1.00000 -0.02401  0.94140  0.06531  0.92106 -0.23255  0.77152
..   …    …        …        …        …        …        …        …        …
346    1    0  0.83508  0.08298  0.73739 -0.14706  0.84349 -0.05567  0.90441
347    1    0  0.95113  0.00419  0.95183 -0.02723  0.93438 -0.01920  0.94590
348    1    0  0.94701 -0.00034  0.93207 -0.03227  0.95177 -0.03431  0.95584
349    1    0  0.90608 -0.01657  0.98122 -0.01989  0.95691 -0.03646  0.85746
350    1    0  0.84710  0.13533  0.73638 -0.06151  0.87873  0.08260  0.88928
```

```
         a10  …       a26       a27       a28       a29       a30       a31  \
0    0.03760  … -0.51171  0.41078 -0.46168  0.21266 -0.34090  0.42267
1   -0.04549  … -0.26569 -0.20468 -0.18401 -0.19040 -0.11593 -0.16626
2    0.01198  … -0.40220  0.58984 -0.22145  0.43100 -0.17365  0.60436
3    0.00000  …  0.90695  0.51613  1.00000  1.00000 -0.20099  0.25682
4   -0.16399  … -0.65158  0.13290 -0.53206  0.02431 -0.62197 -0.05707
..       …  …       …       …       …       …       …       …
346 -0.04622  … -0.04202  0.83479  0.00123  1.00000  0.12815  0.86660
347  0.01606  …  0.01361  0.93522  0.04925  0.93159  0.08168  0.94066
348  0.02446  …  0.03193  0.92489  0.02542  0.92120  0.02242  0.92459
349  0.00110  … -0.02099  0.89147 -0.07760  0.82983 -0.17238  0.96022
350 -0.09139  … -0.15114  0.81147 -0.04822  0.78207 -0.00703  0.75747

         a32      a33      a34  class
0   -0.54487  0.18641 -0.45300      g
1   -0.06288 -0.13738 -0.02447      b
2   -0.24180  0.56045 -0.38238      g
3    1.00000 -0.32382  1.00000      b
4   -0.59573 -0.04608 -0.65697      g
..       …       …       …    …
346 -0.10714  0.90546 -0.04307      g
347 -0.00035  0.91483  0.04712      g
348  0.00442  0.92697 -0.00577      g
349 -0.03757  0.87403 -0.16243      g
350 -0.06678  0.85764 -0.06151      g

[351 rows x 35 columns]
```

[186]:

```python
def normalize(X):
    s = [ np.mean(dim) for dim in X.T]
    X = np.asarray([np.divide(x, s) for x in X])
    return X

y = df["class"].values
y = np.asarray([[float(yi == 'g')] for yi in y])
#print(y.shape) (351,1)
X = df.drop(["class"], axis=1).values

def partition(X, y, ratio=0.8):
    n = X.shape[0]
    indices = np.arange(n)
    np.random.shuffle(indices)
    X = X[indices]
    y = y[indices]
    p = int(n*ratio)
    train_X = X[:p]
    test_X = X[p:]
    train_y = y[:p]
    test_y = y[p:]
    return train_X, train_y, test_X, test_y

train_X, train_y, test_X, test_y = partition(X, y, ratio=0.8)
```

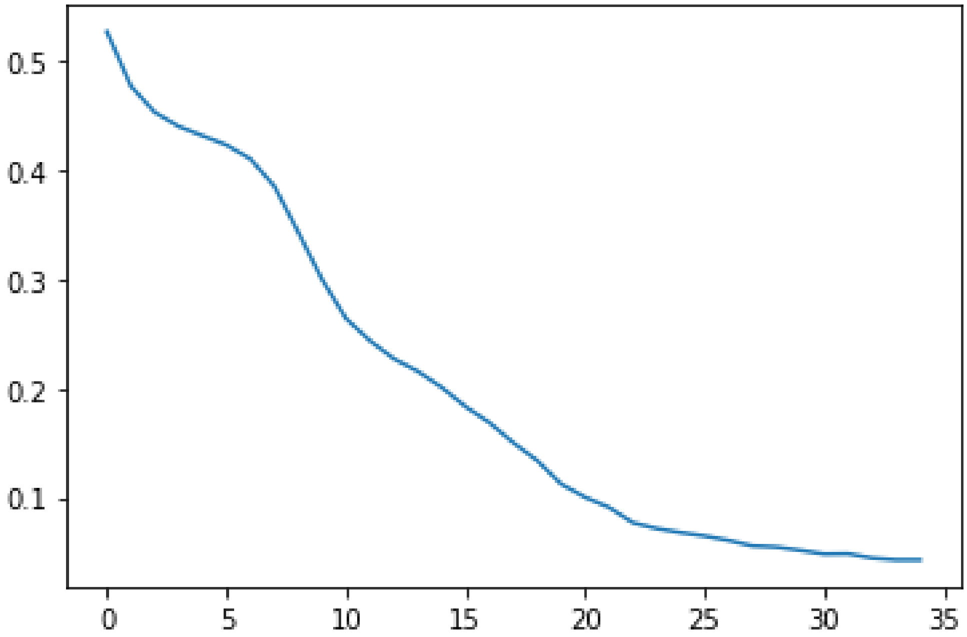
[191]:

```
nn = NN([34, 17, 2, 1],activations=['relu', 'relu', 'sigmoid'], usage =␣
 ↪'classification')
#the network architecture is as the constructer

learning_curve = nn.train(train_X, train_y, epochs=35, batch_size=10, lr = .1)

train_CE = nn.calc_error(train_X, train_y)
train_accuracy = nn.calc_accuracy(train_X, train_y)
test_CE = nn.calc_error(test_X, test_y)
test_accuracy = nn.calc_accuracy(test_X, test_y)
```

[192]:

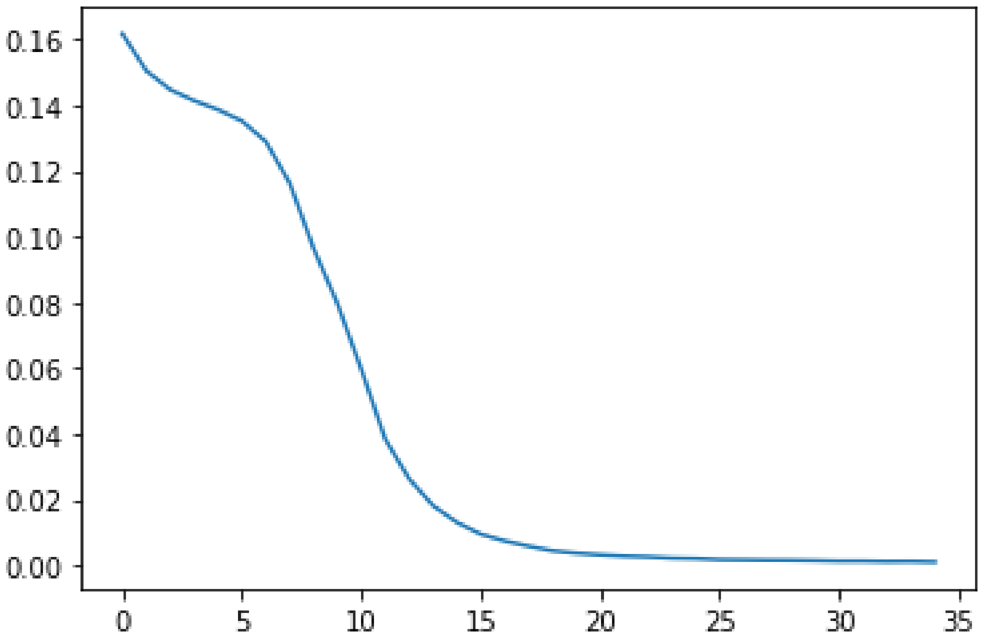
```
plt.plot(np.arange(len(learning_curve)), learning_curve)
print('train_CE = ', train_CE, '\n', 'test_RMS = ', test_CE)
print('train_Accuracy = ', train_accuracy, '\n', 'test_Accuracy = ',␣
 ↪test_accuracy)
print('train_ErrorRate = ', 1-train_accuracy, '\n', 'test_ErrorRate = ',␣
 ↪1-test_accuracy)
```

```
train_CE =  0.015342545071686l9
 test_RMS =  0.039579250130772736
train_Accuracy =  0.9821428571428571
 test_Accuracy =  0.9577464788732394
train_ErrorRate =  0.017857142857142905
 test_ErrorRate =  0.04225352112676062
```



```
[193]: nn2 = NN([34, 17, 3, 1],activations=['relu', 'relu',  'sigmoid'], usage =␣
        ↪'classification')
       #the network architecture is as the constructer

       learning_curve = nn2.train(train_X, train_y, epochs=35, batch_size=10, lr = .1)

       train_CE = nn2.calc_error(train_X, train_y)
       train_accuracy = nn2.calc_accuracy(train_X, train_y)
       test_CE = nn2.calc_error(test_X, test_y)
       test_accuracy = nn2.calc_accuracy(test_X, test_y)

       plt.plot(np.arange(len(learning_curve)), learning_curve)

       print('train_CE = ', train_CE, '\n', 'test_RMS = ', test_CE)
       print('train_Accuracy = ', train_accuracy, '\n', 'test_Accuracy = ',␣
        ↪test_accuracy)
       print('train_ErrorRate = ', 1-train_accuracy, '\n', 'test_ErrorRate = ',␣
        ↪1-test_accuracy)
```

```
train_CE =  0.015115380284795173
 test_RMS =  0.043591903771260448
train_Accuracy =  0.9892857142857143
 test_Accuracy =  0.9577464788732394
train_ErrorRate =  0.010714285714285676
 test_ErrorRate =  0.04225352112676062
```

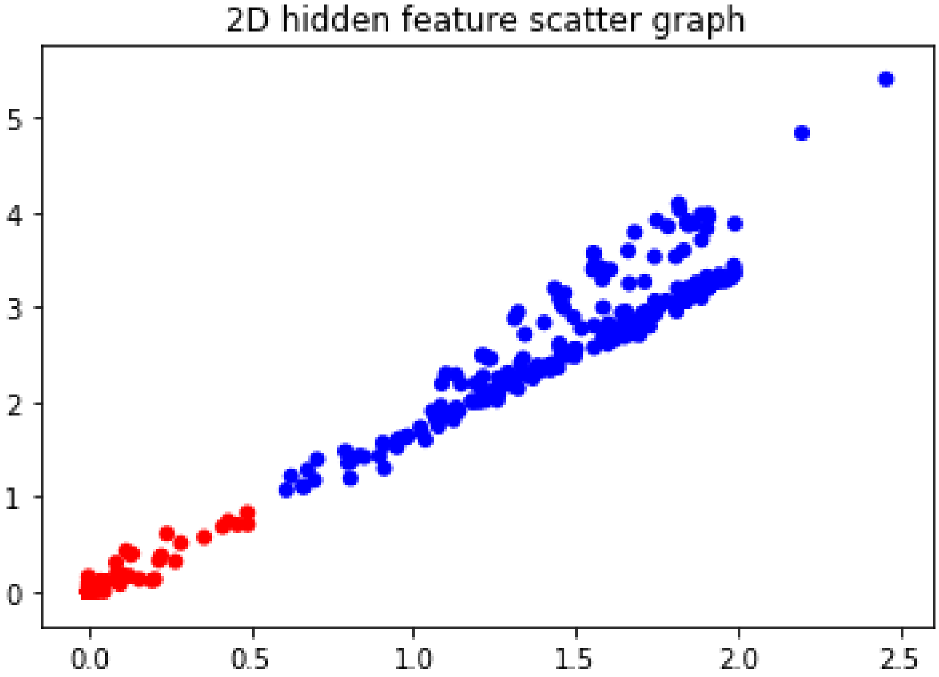


[194]:

```python
def plot2D(nn, X):
    _, a_s = nn.feedforward(X.T)
    cos = a_s[-2]
    label = a_s[-1]
    n = a_s[-2].shape[1]
    assert(a_s[-2].shape[0] == 2)
    colors = ("red", "blue")
    groups = ("good", "bad")

    for i in range(n):
        k = int(label[0][i]>=0.5)
        plt.scatter(cos[0][i], cos[1][i], c=colors[k], edgecolors='none')

    plt.title('2D hidden feature scatter graph')
    plt.show()

from mpl_toolkits.mplot3d import Axes3D

def plot3D(nn, X):
    _, a_s = nn.feedforward(X.T)
    cos = a_s[-2]
    label = a_s[-1]
    n = a_s[-2].shape[1]
    assert(a_s[-2].shape[0] == 3)
    colors = ("red", "blue")
    groups = ("good", "bad")
    fig = plt.figure()
    ax = Axes3D(fig)
    for i in range(n):
        k = int(label[0][i]>=0.5)
        ax.scatter(cos[0][i], cos[1][i], cos[2][i], c=colors[k])

    plt.title('3D hidden feature scatter graph')
    plt.show()
```

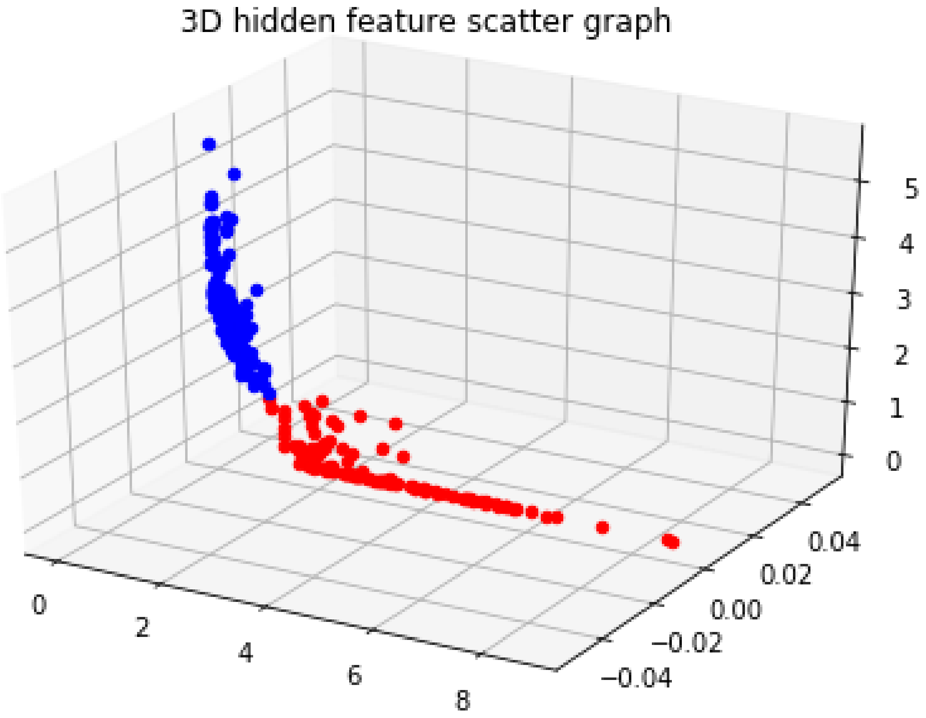
[195]:

```
plot2D(nn, X)
```



[196]:

```
plot3D(nn2, X)
```



```
[200]: file_train_csv = "class_trainning_pred.csv"
       file_test_csv = "class_testing_pred.csv"
       with open(file_train_csv, 'w', newline='') as csvFile:
           writer = csv.writer(csvFile)
           writer.writerow(['prediction', 'label'])
           for i in range(train_X.shape[0]):
               writer.writerow([nn.prediction(np.asarray([train_X[i]]))[0][0],␣
        ↪train_y[i][0]])
       with open(file_test_csv, 'w', newline='') as csvFile:
           writer = csv.writer(csvFile)
           writer.writerow(['prediction', 'label'])
           for i in range(test_X.shape[0]):
               writer.writerow([nn.prediction(np.asarray([test_X[i]]))[0][0],␣
        ↪test_y[i][0]])
```

```
[202]: #savefilename = "save_class_2D"
       #savefilename2 = "save_class_3D"
       #with open(savefilename, 'wb') as fo:
       #    pickle.dump(nn, fo)
       #with open(savefilename2, 'wb') as fo:
       #    pickle.dump(nn2, fo)
```

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[ ]:
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