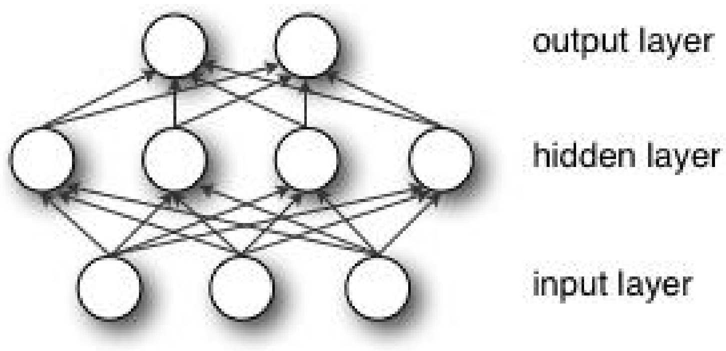
<u>Machine Learning Lab 6</u>

Multilayer Perceptron

A multilayer perceptron (MLP) is a class of feedforward artificial neural network. An MLP consists of, at least, three layers of nodes: an input layer, a hidden layer and an output layer. Except for the input nodes, each node is a neuron that uses a nonlinear activation function. MLP utilizes a supervised learning technique called backpropagation for training. Its multiple layers and non-linear activation distinguish MLP from a linear perceptron. It can distinguish data that is not linearly separable.



The dataset

The dataset used to perform this experiment is the wine quality dataset, it is a combination of data on two types of wine variants, namely red wine and white wine, of the portuguese "Vinho Verde" wine. The dataset contains information on the parameters for fixed acidity, volatile acidity, citric acid, residual sugar, chlorides, free sulfur dioxide, total sulfur dioxide, density, pH, sulphates, alcohol.

Experiment

In this experiment I used the sklearn's multi-layer perceptron algorithm to predict if a wine is fit to drink or not.

Using the pandas library in I loaded the red wine and white wine datasets into the memory from their respective csv files and then merged the two datasets into one single pandas dataframe. Then using a threshold quality values, in this case 6, I segregated the data points for each sample of wine in the good wine and bad wine. That is the points with quality levels more than or equal to 6 are good and the rest are bad. This also helps in reducing the skewness of the data.

Using the pandas.Dataframe.describe() function in pandas I calculated the various statistical measures of each of the columns of the dataset.

For performing the experiment I started with plotting the distribution of the quality of wine with respect to the various levels of alcohol in the dataset. The inference that can be made out of this graph is that the good quality wine has a moderate level of alcohol in it whereas the bad quality wine has extremely high quantity of alcohols in it.

Next I used a multi-layer perceptron based classifier with 10 hidden units to classify the data. I am able to achieve a score of 0.80 on the training set.

Finally I increased the number of hidden units from 10 to 20 and 15, i.e. two layers of hidden unit first with 10 and the second with 15 and the score increased to 0.815.

Finally, I plotted the decision surface for the good and bad quality wine. The activation function I used all along was 'relu' and the value of alpha was 10^-5 with an adaptive learning rate and a maximum iteration of 3000.

The code and plots can be found in the accompanying jupyter notebook.

Multi-layer Perceptron

November 1, 2018

1 Lab 6

2 Multi-layer Perceptron

2.1 Submitted to : Prof. Sweetlin Hemlatha

2.2 Submitted by: Prateek Singh (15BCE1091)

```
In [22]: import numpy as np
         import pandas as pd
         import seaborn as sb

         from sklearn.preprocessing import LabelEncoder
         from sklearn.neural_network import MLPClassifier
         from sklearn.model_selection import train_test_split
         from sklearn.preprocessing import StandardScaler
         from sklearn.metrics import accuracy_score, classification_report, confusion_matrix

         import matplotlib.pyplot as plt
         from matplotlib.colors import ListedColormap
         %matplotlib inline
```

```
In [4]: banknote_data = pd.read_csv("banknote.csv")
```

```
In [5]: banknote_data.head()
```

```
Out[5]:    Variance  Skewness  Kurtosis  Entropy  class
        0   3.62160    8.6661   -2.8073 -0.44699      0
        1   4.54590    8.1674   -2.4586 -1.46210      0
        2   3.86600   -2.6383    1.9242  0.10645      0
        3   3.45660    9.5228   -4.0112 -3.59440      0
        4   0.32924   -4.4552    4.5718 -0.98880      0
```

```
In [6]: X = banknote_data.values[:, :4]
        Y = banknote_data.values[:, 4]
        X_train, X_test, Y_train, Y_test = train_test_split(X, Y, test_size=0.2, random_state=
```

```
In [7]: mlp = MLPClassifier(hidden_layer_sizes=(4), max_iter=50)
        mlp.fit(X_train, Y_train)
```

```
/usr/local/lib64/python3.6/site-packages/sklearn/neural_network/multilayer_perceptron.py:564: C
  % self.max_iter, ConvergenceWarning)
```

```
Out[7]: MLPClassifier(activation='relu', alpha=0.0001, batch_size='auto', beta_1=0.9,
               beta_2=0.999, early_stopping=False, epsilon=1e-08,
               hidden_layer_sizes=4, learning_rate='constant',
               learning_rate_init=0.001, max_iter=50, momentum=0.9,
               nesterovs_momentum=True, power_t=0.5, random_state=None,
               shuffle=True, solver='adam', tol=0.0001, validation_fraction=0.1,
               verbose=False, warm_start=False)
```

```
In [8]: predictions = mlp.predict(X_test)
        print(confusion_matrix(Y_test, predictions))
```

```
[[83 80]
 [83 29]]
```

```
In [9]: mlp = MLPClassifier(hidden_layer_sizes=(10,8), max_iter=50)
        mlp.fit(X_train, Y_train)
```

```
/usr/local/lib64/python3.6/site-packages/sklearn/neural_network/multilayer_perceptron.py:564: C
  % self.max_iter, ConvergenceWarning)
```

```
Out[9]: MLPClassifier(activation='relu', alpha=0.0001, batch_size='auto', beta_1=0.9,
               beta_2=0.999, early_stopping=False, epsilon=1e-08,
               hidden_layer_sizes=(10, 8), learning_rate='constant',
               learning_rate_init=0.001, max_iter=50, momentum=0.9,
               nesterovs_momentum=True, power_t=0.5, random_state=None,
               shuffle=True, solver='adam', tol=0.0001, validation_fraction=0.1,
               verbose=False, warm_start=False)
```

```
In [10]: predictions = mlp.predict(X_test)
         print(confusion_matrix(Y_test, predictions))
```

```
[[163   0]
 [  0 112]]
```

2.3 On my own dataset

```
In [3]: red_wine_data = pd.read_csv('../Dataset/winequality-red.csv', sep=';')
        white_wine_data = pd.read_csv('../Dataset/winequality-white.csv', sep=';')

        wine_data = pd.concat([red_wine_data, white_wine_data])

        bins = (2, 6.5, 10)
```

```
group_names = ['bad', 'good']
wine_data['quality'] = pd.cut(wine_data['quality'], bins = bins, labels = group_names)

wine_data.head()
```

Out[3]:

```
   fixed acidity  volatile acidity  citric acid  residual sugar  chlorides  \
0            7.4              0.70         0.00             1.9      0.076
1            7.8              0.88         0.00             2.6      0.098
2            7.8              0.76         0.04             2.3      0.092
3           11.2              0.28         0.56             1.9      0.075
4            7.4              0.70         0.00             1.9      0.076

   free sulfur dioxide  total sulfur dioxide  density    pH  sulphates  \
0                 11.0                  34.0   0.9978  3.51       0.56
1                 25.0                  67.0   0.9968  3.20       0.68
2                 15.0                  54.0   0.9970  3.26       0.65
3                 17.0                  60.0   0.9980  3.16       0.58
4                 11.0                  34.0   0.9978  3.51       0.56

   alcohol quality
0      9.4     bad
1      9.8     bad
2      9.8     bad
3      9.8     bad
4      9.4     bad
```

In [4]:

```
label_quality = LabelEncoder()
wine_data['quality'] = label_quality.fit_transform(wine_data['quality'])
wine_data.head()
```

Out[4]:

```
   fixed acidity  volatile acidity  citric acid  residual sugar  chlorides  \
0            7.4              0.70         0.00             1.9      0.076
1            7.8              0.88         0.00             2.6      0.098
2            7.8              0.76         0.04             2.3      0.092
3           11.2              0.28         0.56             1.9      0.075
4            7.4              0.70         0.00             1.9      0.076

   free sulfur dioxide  total sulfur dioxide  density    pH  sulphates  \
0                 11.0                  34.0   0.9978  3.51       0.56
1                 25.0                  67.0   0.9968  3.20       0.68
2                 15.0                  54.0   0.9970  3.26       0.65
3                 17.0                  60.0   0.9980  3.16       0.58
4                 11.0                  34.0   0.9978  3.51       0.56

   alcohol  quality
0      9.4        0
1      9.8        0
2      9.8        0
```

```
3      9.8        0
4      9.4        0
```

In [6]:
```
wine_data['quality'].value_counts()
```

Out[6]:
```
0    5220
1    1277
Name: quality, dtype: int64
```

In [30]:
```
scaler = StandardScaler()
scaled_features = scaler.fit_transform(wine_data.iloc[:,:11].values)

wine_data_scaled = pd.DataFrame(scaled_features, index=wine_data.index, columns=wine_d
wine_data_scaled.head()
```

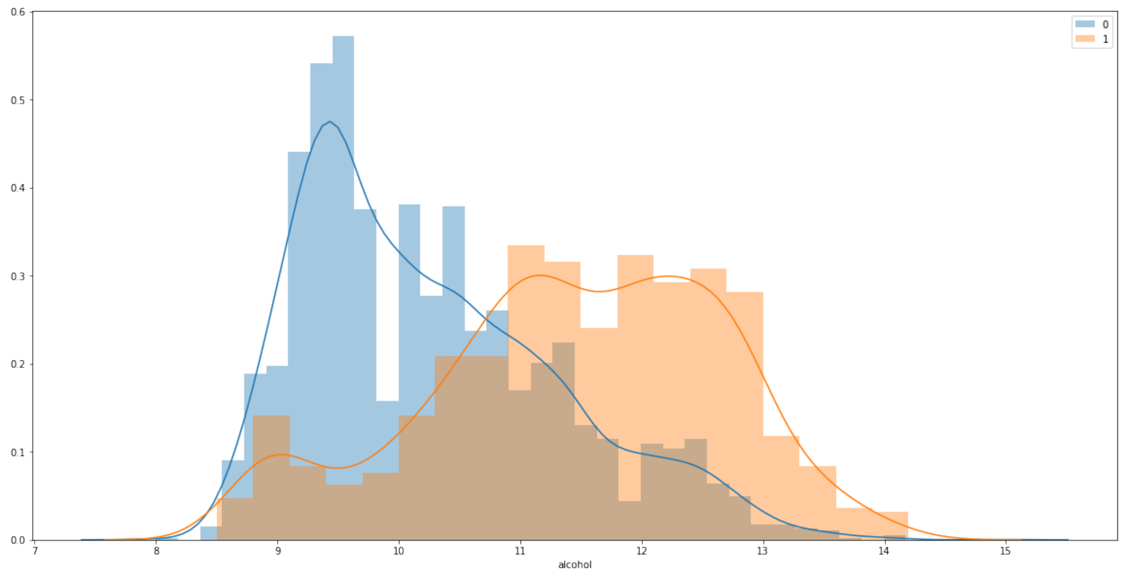
Out[30]:
```
   fixed acidity  volatile acidity  citric acid  residual sugar  chlorides  \
0       0.142473          2.188833    -2.192833       -0.744778   0.569958
1       0.451036          3.282235    -2.192833       -0.597640   1.197975
2       0.451036          2.553300    -1.917553       -0.660699   1.026697
3       3.073817         -0.362438     1.661085       -0.744778   0.541412
4       0.142473          2.188833    -2.192833       -0.744778   0.569958

   free sulfur dioxide  total sulfur dioxide   density        pH  sulphates  \
0            -1.100140             -1.446359  1.034993  1.813090   0.193097
1            -0.311320             -0.862469  0.701486 -0.115073   0.999579
2            -0.874763             -1.092486  0.768188  0.258120   0.797958
3            -0.762074             -0.986324  1.101694 -0.363868   0.327510
4            -1.100140             -1.446359  1.034993  1.813090   0.193097

    alcohol
0 -0.915464
1 -0.580068
2 -0.580068
3 -0.580068
4 -0.915464
```

2.4 Plotting the distribution of quality w.r.t various levels of alcohol in the data

In [7]:
```
plt.figure(figsize = (20,10))
for i in wine_data.quality.unique():
    sb.distplot(wine_data['alcohol'][wine_data.quality == i], kde=1, label='{}'.format

plt.legend()
```

```
/home/prateek/anaconda3/envs/dltf/lib/python3.6/site-packages/matplotlib/axes/_axes.py:6462: Us
  warnings.warn("The 'normed' kwarg is deprecated, and has been "
/home/prateek/anaconda3/envs/dltf/lib/python3.6/site-packages/matplotlib/axes/_axes.py:6462: Us
  warnings.warn("The 'normed' kwarg is deprecated, and has been "
```

Out[7]: <matplotlib.legend.Legend at 0x7f2bb0471ef0>




```
In [69]: X_train, X_test, Y_train, Y_test = train_test_split(wine_data_scaled,
                                                              wine_data.iloc[:,11],
                                                              test_size=0.2,
                                                              random_state=42)
```

```
In [77]: a = np.array(X_train.iloc[:, [1, 10]])
         a.shape
```

```
Out[77]: (5197, 2)
```

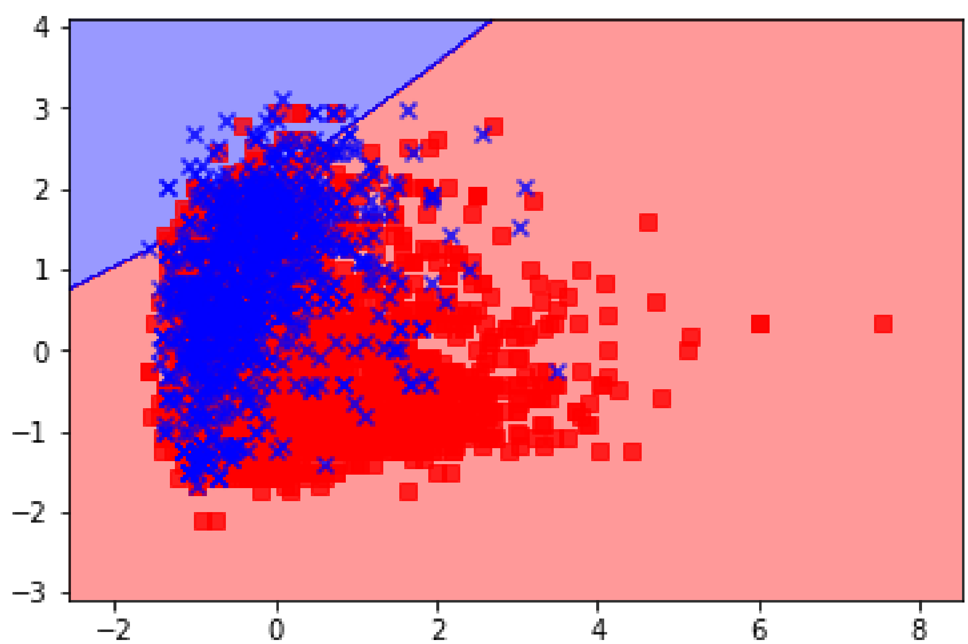
```
In [63]: def plot_decision_surface(X, y, classifier, test_idx=None, resolution=0.02):

             markers = ('s', 'x', 'o', '^', 'v')
             colors = ('red', 'blue', 'lightgreen', 'gray', 'cyan')
             cmap = ListedColormap(colors[:len(np.unique(y))])

             x1_min, x1_max = X[:, 0].min() - 1, X[:, 0].max() + 1
             x2_min, x2_max = X[:, 1].min() - 1, X[:, 1].max() + 1
             xx1, xx2 = np.meshgrid(np.arange(x1_min, x1_max, resolution), np.arange(x2_min, x2

             Z = classifier.predict(np.array([xx1.ravel(), xx2.ravel()]).T)
             Z = Z.reshape(xx1.shape)

             plt.contourf(xx1, xx2, Z, alpha=0.4, cmap=cmap)
             plt.xlim(xx1.min(), xx1.max())
             plt.ylim(xx2.min(), xx2.max())
```

```
    X_test, y_test = X[test_idx, :], y[test_idx]

    for idx, cl in enumerate(np.unique(y)):
        plt.scatter(x=X[y == cl, 0], y=X[y == cl, 1],
        alpha=0.8, c=cmap(idx),
        marker=markers[idx], label=cl)
        if test_idx:
            X_test, y_test = X[test_idx, :], y[test_idx]
            plt.scatter(X_test[:, 0], X_test[:, 1], c='',
            alpha=1.0, linewidth=1, marker='o',
            s=55, label='test set')
```

First lets plot the data on just two most important features from the dataset and observe the performance. From the logistic regression experiment we know that feature number 1 which is volatile acidity and feature 10, which is the fixed acidity are most important features in the dataset. And thus we train an mlp classifier over these two features so as to visualize the results and then we use the full dataset to obtain better accuracy

```
In [97]: hidden_layers = (10)

         mlp_2 = MLPClassifier(activation='logistic', alpha=1e-05,
                               batch_size='auto',
                               hidden_layer_sizes=hidden_layers,
                               learning_rate='adaptive',
                               learning_rate_init=0.0001,
                               max_iter=2000, warm_start=True)
```

```
In [98]: mlp_2.fit(X_train.iloc[:, [1, 10]], Y_train)
         plot_decision_regions(X=a, y = np.array(Y_train.values), classifier=mlp_2)
```



In [99]:
```
mlp.score(X_train.iloc[:, [1, 10]], Y_train)
```

Out[99]:
```
0.8027708293246103
```

In [113]:
```
hidden_layers = (20, 15)

mlp = MLPClassifier(activation='logistic', alpha=1e-05,
                    batch_size='auto',
                    hidden_layer_sizes=hidden_layers,
                    learning_rate='adaptive',
                    learning_rate_init=0.0001,
                    max_iter=3000, warm_start=True)
```

In [114]:
```
mlp.fit(X_train, Y_train)
```

Out[114]:
```
MLPClassifier(activation='logistic', alpha=1e-05, batch_size='auto',
       beta_1=0.9, beta_2=0.999, early_stopping=False, epsilon=1e-08,
       hidden_layer_sizes=(20, 15), learning_rate='adaptive',
       learning_rate_init=0.0001, max_iter=3000, momentum=0.9,
       nesterovs_momentum=True, power_t=0.5, random_state=None,
       shuffle=True, solver='adam', tol=0.0001, validation_fraction=0.1,
       verbose=False, warm_start=True)
```

In [115]:
```
mlp.score(X_train, Y_train)
```

Out[115]:
```
0.8158553011352704
```