Multi-layer Perceptron

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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)
```

```python
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]:

```python
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()
```

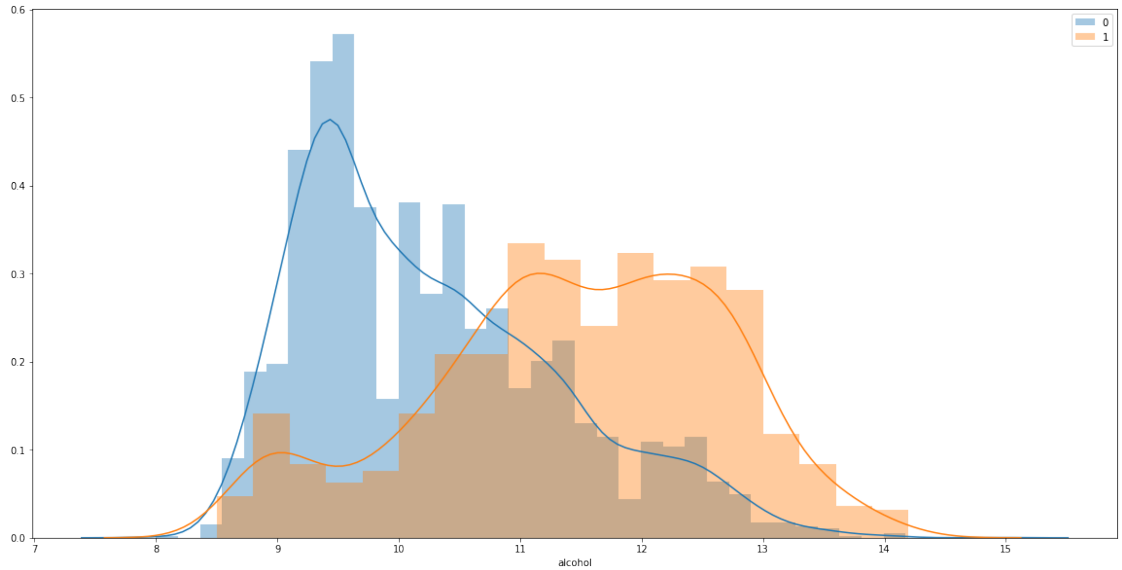
Out[30]:
```
   fixed acidity  volatile acidity  citric acid  residual sugar  chlorides  \
0       0.142473          2.188833    -2.192833       -0.744778   0.569958
1       0.451036          3.282235    -2.192833       -0.597640   1.197975
2       0.451036          2.553300    -1.917553       -0.660699   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)

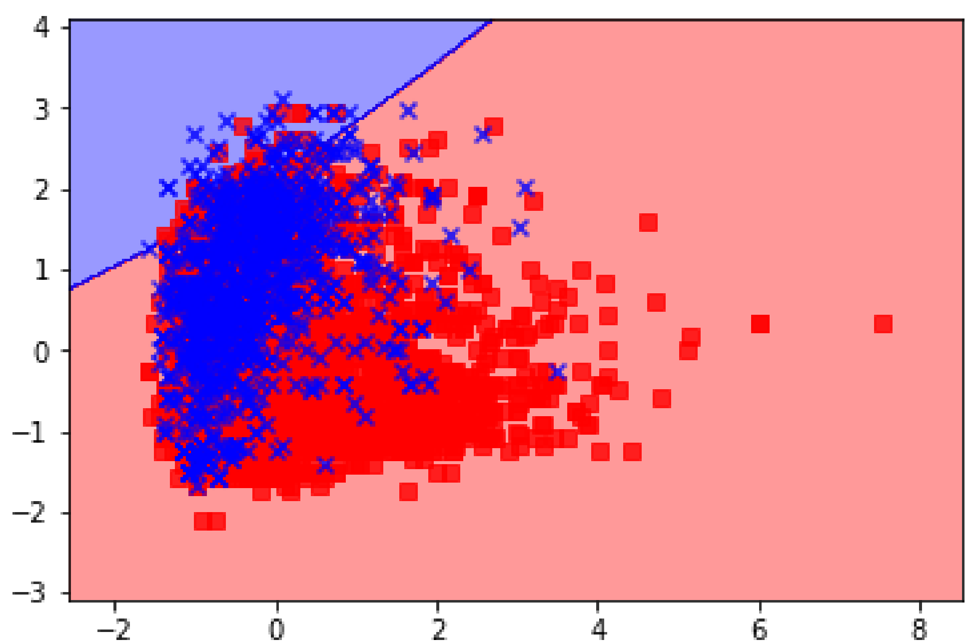
```
In [63]: def plot_decision_surface(X, y, classifier, test_idx=None, resolution=0.02):

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

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

In [113]:
```python
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]:
```python
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]:
```python
mlp.score(X_train, Y_train)
```

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