Ain Shams University

Faculty of Engineering

Computer and Systems Department

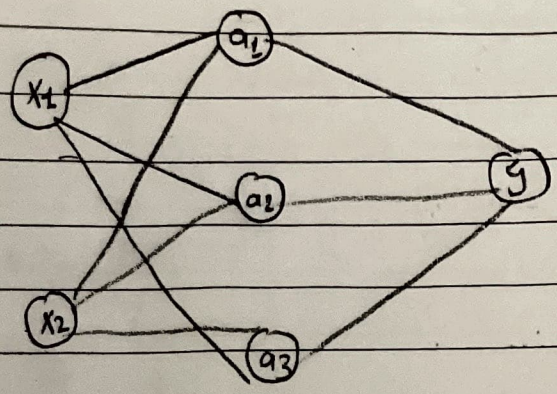
CSE 616: Neural Networks and their applications

Assignment 1

Report

Name	Diaa Ahmed Abdelzaher Abdelaziz
Code	1902558

Assignment 1



$$x = \begin{bmatrix} 1 \\ 3 \end{bmatrix}, \quad y = 32$$

$$W_{1st\ layer} = \begin{bmatrix} 2 & 1 & 3 \\ 2 & -1 & 1 \end{bmatrix}, \quad b_{1st} = \begin{bmatrix} 1 \\ 0 \\ -1 \end{bmatrix}$$

$$W_{2nd\ layer} = \begin{bmatrix} 3 \\ 1 \\ 2 \end{bmatrix}, \quad b_1^{[2]} = 1$$

1.a. activation functions are identity functions.

$$\therefore a_1 = w_{11}^{[1]} x_1 + w_{21}^{[1]} x_2 + b_1^{[1]} = 2*1 + 2*3 + 1 = 9$$

$$a_2 = w_{12}^{[1]} x_1 + w_{22}^{[1]} x_2 + b_2^{[1]} = 1*1 - 1*3 + 0 = -2$$

$$a_3 = w_{13}^{[1]} x_1 + w_{23}^{[1]} x_2 + b_3^{[1]} = 3*1 + 1*3 - 1 = 5$$

$$\therefore \hat{y} = w_{11}^{[2]} a_1 + w_{21}^{[2]} a_2 + w_{31}^{[2]} a_3 + b_1^{[2]}$$

$$= 3*9 - 2*1 + 2*5 + 1 = 36$$

1b. activation functions are Relu.

$a_1 = \max(0, (w_{11}^{[1]} x_1 + w_{21}^{[1]} x_2 + b_1^{[1]})) = 9$

$a_2 = \max(0, (w_{12}^{[1]} x_1 + w_{22}^{[1]} x_2 + b_2^{[1]})) = 0$

$a_3 = \max(0, (w_{13}^{[1]} x_1 + w_{23}^{[1]} x_2 + b_3^{[1]})) = 5$

$\therefore \hat{y} = \max(0, (w_{11}^{[2]} a_1 + w_{21}^{[2]} a_2 + w_{31}^{[2]} a_3)) =$

$\max(0, 38) = 38.$

1c. $J = (\hat{y} - y)^2$ $\quad \frac{\partial J}{\partial \hat{y}} = 2(\hat{y} - y) = 2 * (\quad)$

$= 2(36 - 32)$

$= 8$

$\frac{\partial J}{\partial b_1^{[2]}} = \frac{\partial J}{\partial \hat{y}} \cdot \frac{\partial \hat{y}}{\partial b_1^{[2]}}$

$= 8 * 1 = 8$

$\frac{\partial J}{\partial w_{21}^{[2]}} = \frac{\partial J}{\partial \hat{y}} * \frac{\partial \hat{y}}{\partial w_{21}^{[2]}}$, $\frac{\partial \hat{y}}{\partial w_{21}^{[2]}} = a_2 = 2$

$= 8 * 2 = 16$

$\frac{\partial J}{\partial b_2^{[1]}} = \frac{\partial J}{\partial \hat{y}} \cdot \frac{\partial \hat{y}}{\partial a_2} \cdot \frac{\partial a_2}{\partial b_2^{[1]}}$, $\frac{\partial \hat{y}}{\partial a_2} = w_{21}^{[2]} = 1$

$\frac{\partial a_2}{\partial b_2^{[1]}} = 1$

$\therefore \frac{\partial J}{\partial b_2^{[1]}} = 8 * 1 * 1 = 8$

$$\frac{\partial J}{\partial w_{13}^{[1]}} = \frac{\partial J}{\partial \hat{y}} \cdot \frac{\partial \hat{y}}{\partial a_3} \cdot \frac{\partial a_3}{\partial w_{13}^{[1]}} \rightarrow \frac{\partial \hat{y}}{\partial a_3} = w_{31}^{[2]} = 2$$

$$\frac{\partial a_3}{\partial w_{13}^{[1]}} = x_1 = 1$$

$$\therefore \frac{\partial J}{\partial w_{13}^{[1]}} = 8 * 2 \times 1 = 16.$$

1d.

$$b_2^{[1]}\Big|_{new} = b_2^{[1]}\Big|_{old} - \eta \frac{\partial J}{\partial b_2^{[1]}}$$

$$= 0 - 2 * 8 = -16$$

$$w_{13}^{[1]}\Big|_{new} = w_{13}^{[1]}\Big|_{old} - \eta * \frac{\partial J}{\partial w_{13}^{[1]}}$$

$$= 3 - 2 * 16 = -29$$

1e. No, it won't be a good indicator of out-of-sample error (generalization error) as there is still a risk of over fitting on the test set because the parameter can be changed until the model performs optimally. This way knowledge about test set can leak into the model and the evaluation metrics may not be able to indicate how the much generalization we performed. The issue can be solved by having another part of the data set which is called validation set.

2.

$$f = \sin g_1 + g_2^2 \;,\; g_1 = x_1 e^{x_2} \;,\; g_2 = x_1 + x_2^2$$

a. $$\frac{\partial f}{\partial x_1} = \frac{\partial f}{\partial g_1} \cdot \frac{\partial g_1}{\partial x_1} + \frac{\partial f}{\partial g_2} \cdot \frac{\partial g_2}{\partial x_1}$$

$$= \cos g_1 \cdot e^{x_2} + 2g_2 \cdot 1$$

$$\therefore \frac{\partial f}{\partial x_1} = \cos g_1 \cdot e^{x_2} + 2g_2 \quad -2.$$

$$\frac{\partial f}{\partial x_2} = \frac{\partial f}{\partial g_1} \cdot \frac{\partial g_1}{\partial x_2} + \frac{\partial f}{\partial g_2} \cdot \frac{\partial g_2}{\partial x_2}$$

$$= \cos g_1 \cdot \underbrace{x_1 e^{x_2}}_{\hookrightarrow g_1} + 2g_2 \cdot 2x_2$$

$$\therefore \frac{\partial f}{\partial x_2} = g_1 \cos g_1 + 4 g_2 x_2$$

3.

1. $f(z) = \frac{1}{1+e^{-z}}$

$$\frac{\partial f}{\partial z} = \frac{e^{-z}}{(1+e^{-z})^2} = \frac{1+e^{-z}}{(1+e^{-z})^2} - \frac{1}{(1+e^{-z})^2}$$

$$= f - f^2 = f(1-f).$$

2. $f(w) = \frac{1}{1+e^{-w^T x}}$

Let $w^T x = z$

$$\therefore \frac{\partial f}{\partial w} = \frac{\partial f}{\partial z} \cdot \frac{\partial z}{\partial w}$$

if we have:

$$x = \begin{bmatrix} x_1 \\ \vdots \\ x_D \end{bmatrix}, \quad w = \begin{bmatrix} w_1 \\ \vdots \\ w_D \end{bmatrix}$$

$$\therefore \frac{\partial z}{\partial w_i} = x_i \qquad \therefore z = w_1 x_1 + w_2 x_2 + \cdots w_n x_n$$

$$\therefore \frac{\partial z}{\partial w} = \begin{bmatrix} x_1 \\ \vdots \\ x_n \end{bmatrix} = x$$

$$\therefore \frac{\partial f}{\partial w} = f(1-f)x. \qquad \therefore \frac{\partial f}{\partial w_i} = f(1-f)x_i$$

3. $J(w) = \frac{1}{2} \sum_{i=1}^{m} |w^T x^{(i)} - y^{(i)}| = \frac{1}{2} \sum_{i=1}^{m} \sqrt{(w^T x^{(i)} - y^{(i)})^2}$

Let $f_i = w^T x^{(i)} - y^{(i)}$ $\quad \therefore J(w) = \frac{1}{2} \sum_{i=1}^{m} \sqrt{f_i^2}$

$$\therefore \frac{\partial J}{\partial f_i} = \frac{2 f_i}{2\sqrt{f_i^2}} = \frac{f_i}{\sqrt{f_i^2}} = \frac{f_i}{|f_i|}$$

$$\therefore \frac{\partial f_i}{\partial w} = x^{(i)}$$

$$\therefore \frac{\partial J}{\partial w} = \frac{1}{2} \sum_{i=1}^{m} \frac{w^T x^{(i)} - y^{(i)}}{|w^T x^{(i)} - y^{(i)}|} \cdot x^{(i)}$$

4. $$J(w) = \frac{1}{2} \left[\sum_{i=1}^{m} (w^T x^{(i)} - y^{(i)})^2 \right] + 2 \|w\|_2^2$$

$$= \frac{1}{2} \left[\sum_{i=1}^{m} (w^T x^{(i)} - y^{(i)})^2 \right] + 2 (w^T w)$$

$$\frac{\partial J}{\partial w} = \sum_{i=1}^{m} (w^T x^{(i)} - y^{(i)}) x^{(i)} + 2 \cdot 2w$$

5.

$$J(w) = \sum_{i=1}^{m} \left[y^{(i)} \log\left(\frac{1}{1+e^{-wTx^{(i)}}} \right) + (1-y^{(i)}) \log\left(1 - \frac{1}{1+e^{-wTx^{(i)}}}\right) \right]$$

Let $\frac{1}{1+e^{-wTx^{(i)}}} = f_i$

$$\therefore J(w) = \sum_{i=1}^{m} \left[y^{(i)} \log(f_i) + (1-y^{(i)}) \log(1-f_i) \right]$$

$$\frac{\partial J}{\partial w} = \sum_{i=1}^{m} \left[y^{(i)} \cdot \frac{1}{f_i} * \frac{\partial f_i}{\partial w} + (1-y^{(i)}) * \frac{1}{(1-f_i)} * \frac{\partial f_i}{\partial w} \right]$$

$$= \sum_{i=1}^{n} \left[y^{(i)} \cdot \frac{1}{f_i} * f_i(1-f_i) x^{(i)} + (1-y^{(i)}) * \frac{1}{1-f_i} * f_i(1-f_i) x^{(i)} \right]$$

$$= \sum_{i=1}^{m} \left[y^{(i)} (1-f_i) x^{(i)} + (1-y^{(i)}) * f_i x^{(i)} \right]$$

$$= \sum_{i=1}^{n} \left[y^{(i)} \left(1 - \frac{1}{1+e^{-wTx^{(i)}}}\right) x^{(i)} + (1-y^{(i)}) * \frac{x^{(i)}}{1+e^{-wTx^{(i)}}} \right]$$

6. $f(w) = \tanh[w^T x]$

Let $w^T x = z$

$$\tanh(z) = \frac{e^z - e^{-z}}{e^z + e^{-z}}$$

$$\frac{\partial}{\partial z}\tanh(z) = \frac{(e^z + e^{-z})(e^z + e^{-z}) - (e^z - e^{-z})(e^z - e^{-z})}{(e^z + e^{-z})^2}$$

$$= \frac{(e^z + e^{-z})^2 - (e^z - e^{-z})^2}{(e^z + e^{-z})^2}$$

$\therefore f = \tanh z = \tanh w^T x$

$$\frac{\partial f}{\partial z} = 1 - f^2 \quad , \frac{\partial z}{w^T} = x$$

$$\therefore \nabla_w f = (1 - f^2)\, x$$

Programming Question

April 9, 2022

1 Artificial Neural Network For Multi-Classification - Python Implementation

Diaa Ahmed Abdelzaher Abdelaziz 1902558@eng.asu.edu.eg

1.0.1 General steps for a classification problem:

1. Importing Necessary Libraries
2. Read, analyze and visualize the dataset
3. Define helper functions
4. Prepare the dataset for training
5. Build neural network model
6. Train and plot the accuracy of the model

1. Importing Necessary Libraries

[1]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
from scipy import stats
```

2. Read, analyze and visualize the dataset

[2]:
```
data = pd.read_csv('winequality-red.csv', sep=';')
data.head()
```

[2]:

	fixed acidity	volatile acidity	citric acid	residual sugar	chlorides	free sulfur dioxide	total sulfur dioxide	density	pH	sulphates
0	7.4	0.70	0.00	1.9	0.076	11.0	34.0	0.9978	3.51	0.56
1	7.8	0.88	0.00	2.6	0.098	25.0	67.0	0.9968	3.20	0.68
2	7.8	0.76	0.04	2.3	0.092	15.0	54.0	0.9970	3.26	0.65
3	11.2	0.28	0.56	1.9	0.075	17.0	60.0	0.9980	3.16	0.58
4	7.4	0.70	0.00	1.9	0.076	11.0	34.0	0.9978	3.51	0.56

```
   alcohol  quality
0      9.4        5
1      9.8        5
2      9.8        5
3      9.8        6
4      9.4        5
```

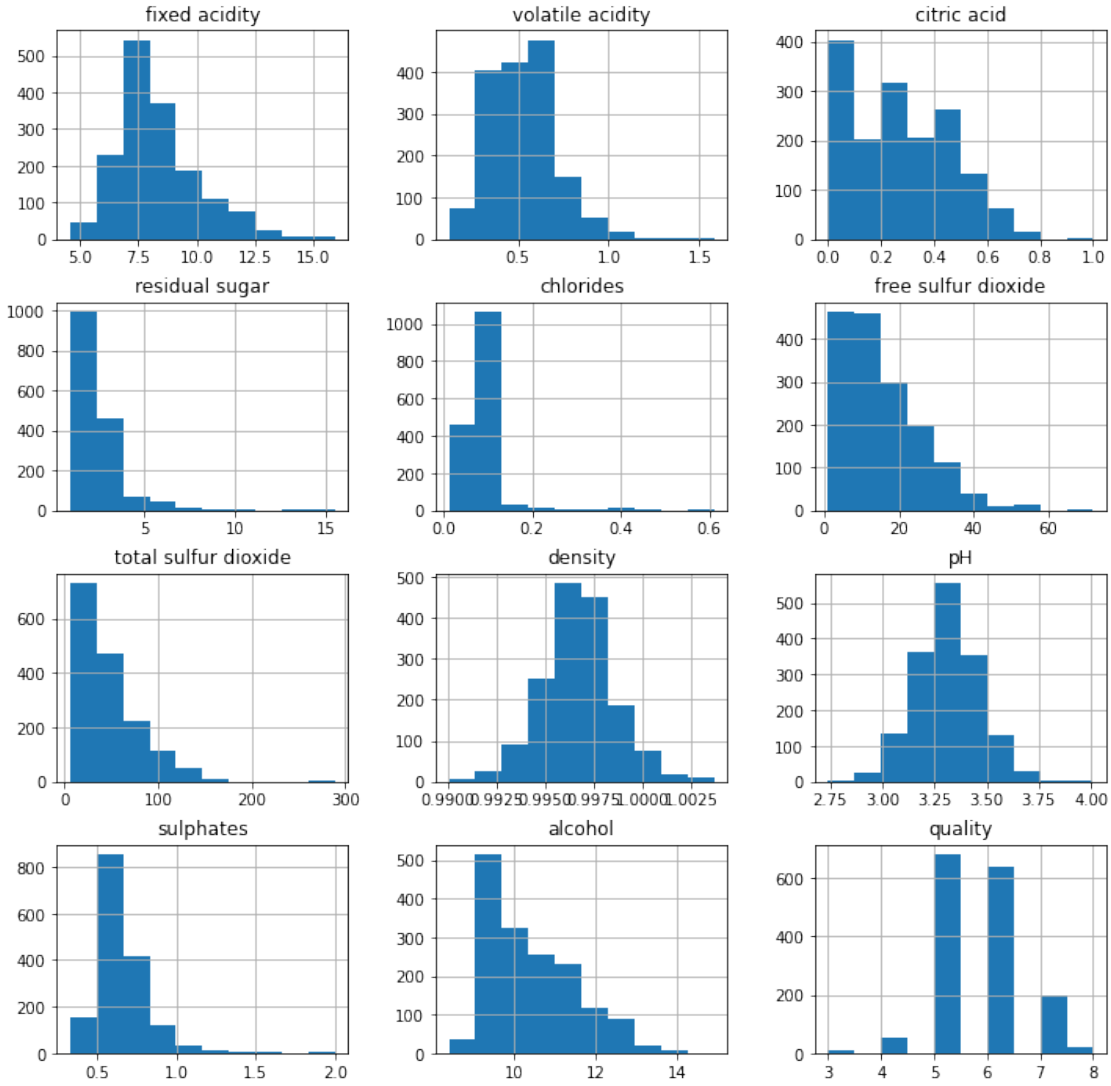
[3]:
```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1599 entries, 0 to 1598
Data columns (total 12 columns):
 #   Column                Non-Null Count  Dtype  
---  ------                --------------  -----  
 0   fixed acidity         1599 non-null   float64
 1   volatile acidity      1599 non-null   float64
 2   citric acid           1599 non-null   float64
 3   residual sugar        1599 non-null   float64
 4   chlorides             1599 non-null   float64
 5   free sulfur dioxide   1599 non-null   float64
 6   total sulfur dioxide  1599 non-null   float64
 7   density               1599 non-null   float64
 8   pH                    1599 non-null   float64
 9   sulphates             1599 non-null   float64
 10  alcohol               1599 non-null   float64
 11  quality               1599 non-null   int64  
dtypes: float64(11), int64(1)
memory usage: 150.0 KB
```

Our dataset contain **1559** data samples and **12** columns/features with numerical float values.

[4]:
```
data.hist(figsize=(12,12))
```

[4]:
```
array([[<AxesSubplot:title={'center':'fixed acidity'}>,
        <AxesSubplot:title={'center':'volatile acidity'}>,
        <AxesSubplot:title={'center':'citric acid'}>],
       [<AxesSubplot:title={'center':'residual sugar'}>,
        <AxesSubplot:title={'center':'chlorides'}>,
        <AxesSubplot:title={'center':'free sulfur dioxide'}>],
       [<AxesSubplot:title={'center':'total sulfur dioxide'}>,
        <AxesSubplot:title={'center':'density'}>,
        <AxesSubplot:title={'center':'pH'}>],
       [<AxesSubplot:title={'center':'sulphates'}>,
        <AxesSubplot:title={'center':'alcohol'}>,
        <AxesSubplot:title={'center':'quality'}>]], dtype=object)
```



The target feature is ***quality*** and it has 6 discrete values {3,4,5,6,7,8}

3. Define helper functions

shuffle_split_data function which split the dataset into training and testing sets according to defined split ratio

[5]:
```
def shuffle_split_data(X, y, ratio):
    arr_rand = np.random.rand(X.shape[0])
    split = arr_rand < np.percentile(arr_rand, ratio)
    #split = np.random.choice(range(X.shape[0]), int((ratio/100)*X.shape[0]))
    X_train = X[~split]
    y_train = y[~split]
    X_test =  X[split]
    y_test = y[split]
```

```
    #print (len(X_train), len(y_train), len(X_test), len(y_test))
    return X_train, y_train, X_test, y_test
```

encode_and_bind function which apply One Hot encoding on the target feature

[6]:
```
def one_hot_encode(array):
    """Convert an iterable of indices to one-hot encoded labels."""
    unique, inverse = np.unique(array, return_inverse=True)
    onehot = np.eye(unique.shape[0])[inverse]
    return onehot
```

standardize_data function which normalize the data by subtracting the mean and dividing by the stdev for each feature and each sample

[7]:
```
def standardize_data(data):
    #Compute the mean
    data_mean = data.sum(axis=0)/data.shape[0]
    #Compute the standard deviation
    data_std = np.std(data, axis=0, dtype=np.float64)
    #Standardize the data
    data_standard = (data - data_mean)/data_std

    return data_standard
```

4. Prepare the dataset for training

Check for duplicates

[8]:
```
duplicates = data[data.duplicated(keep=False)]
duplicates = duplicates.sort_values(by=['quality'], ascending= False)
duplicates.head()
```

[8]:

	fixed acidity	volatile acidity	citric acid	residual sugar	chlorides	free sulfur dioxide	total sulfur dioxide	density	pH	sulphates	alcohol	quality
498	10.7	0.35	0.53	2.60	0.070	5.0	16.0	0.99720	3.15	0.65		
495	10.7	0.35	0.53	2.60	0.070	5.0	16.0	0.99720	3.15	0.65		
290	8.7	0.52	0.09	2.50	0.091	20.0	49.0	0.99760	3.34	0.86		
1002	9.1	0.29	0.33	2.05	0.063	13.0	27.0	0.99516	3.26	0.84		
997	5.6	0.66	0.00	2.20	0.087	3.0	11.0	0.99378	3.71	0.63		

```
498      11.0        8
495      11.0        8
290      10.6        7
1002     11.7        7
997      12.8        7
```

[9]:
```
print("There is {} duplicated datapoints in our dataset".format(data.
↪duplicated().sum()))
```

```
There is 240 duplicated datapoints in our dataset
```

Duplicate Records doesn't contribue to our prediction. Rather they just increase the training size. It's usual to get rid of duplicates from our dataset.

[10]:
```
data.drop_duplicates(keep = 'first', inplace = True)
print('Total {} datapoints remaining with {} features'.format(data.shape[0],␣
↪data.shape[1]))
```

```
Total 1359 datapoints remaining with 12 features
```

[11]:
```
columns = list(data.columns.values)

labels = data[columns[-1:]]
labels = np.array(labels, dtype='int64')
features = data[columns[0:-1]]
features = np.array(features, dtype='float64')
```

Use describe() function to show the statistics of each feature.

[12]:
```
dataset = pd.DataFrame({'fixed acidity': features[:, 0], 'volatile acidity':␣
↪features[:, 1], 'citric acid': features[:, 2]
                        , 'residual sugar': features[:, 3], 'chlorides':␣
↪features[:, 4], 'free sulfur dioxide': features[:, 5]
                       , 'total sulfur dioxide': features[:, 6], 'density':␣
↪features[:, 7], 'pH': features[:, 8]
                       , 'sulphates': features[:, 9], 'alcohol': features[:,␣
↪10]})
dataset.describe()
```

[12]:

	fixed acidity	volatile acidity	citric acid	residual sugar	\
count	1359.000000	1359.000000	1359.000000	1359.000000	
mean	8.310596	0.529478	0.272333	2.523400	
std	1.736990	0.183031	0.195537	1.352314	
min	4.600000	0.120000	0.000000	0.900000	
25%	7.100000	0.390000	0.090000	1.900000	
50%	7.900000	0.520000	0.260000	2.200000	
75%	9.200000	0.640000	0.430000	2.600000	
max	15.900000	1.580000	1.000000	15.500000	

```
         chlorides  free sulfur dioxide  total sulfur dioxide      density  \
count  1359.000000          1359.000000           1359.000000  1359.000000
mean      0.088124            15.893304             46.825975     0.996709
std       0.049377            10.447270             33.408946     0.001869
min       0.012000             1.000000              6.000000     0.990070
25%       0.070000             7.000000             22.000000     0.995600
50%       0.079000            14.000000             38.000000     0.996700
75%       0.091000            21.000000             63.000000     0.997820
max       0.611000            72.000000            289.000000     1.003690

                pH    sulphates      alcohol
count  1359.000000  1359.000000  1359.000000
mean      3.309787     0.658705    10.432315
std       0.155036     0.170667     1.082065
min       2.740000     0.330000     8.400000
25%       3.210000     0.550000     9.500000
50%       3.310000     0.620000    10.200000
75%       3.400000     0.730000    11.100000
max       4.010000     2.000000    14.900000
```

It seems that the dataset is not normalized (the mean if features not zero)
Let's standardize the dataset

[13]:
```
features_standardize = standardize_data(features)
#features_standardize = np.round(features_standardize, 6)
```

[14]:
```
dataset_standardize = pd.DataFrame({'fixed acidity': features_standardize[:,␣
↪0], 'volatile acidity': features_standardize[:, 1]
                        , 'citric acid': features_standardize[:, 2], 'residual␣
↪sugar': features_standardize[:, 3]
                        , 'chlorides': features_standardize[:, 4], 'free sulfur␣
↪dioxide': features_standardize[:, 5]
                       , 'total sulfur dioxide': features_standardize[:, 6],␣
↪'density': features_standardize[:, 7]
                        , 'pH': features_standardize[:, 8], 'sulphates':␣
↪features_standardize[:, 9]
                        , 'alcohol': features_standardize[:, 10]})
dataset_standardize.describe().round(decimals=4)
```

[14]:
```
       fixed acidity  volatile acidity  citric acid  residual sugar  \
count      1359.0000         1359.0000    1359.0000       1359.0000
mean         -0.0000            0.0000       0.0000         -0.0000
std           1.0004            1.0004       1.0004          1.0004
min          -2.1370           -2.2380      -1.3933         -1.2009
25%          -0.6972           -0.7623      -0.9328         -0.4612
50%          -0.2365           -0.0518      -0.0631         -0.2392
```

```
75%           0.5122            0.6041       0.8066          0.0567
max           4.3709            5.7417       3.7228          9.5994

       chlorides  free sulfur dioxide  total sulfur dioxide    density  \
count  1359.0000            1359.0000             1359.0000  1359.0000
mean      0.0000              -0.0000                0.0000     0.0000
std       1.0004               1.0004                1.0004     1.0004
min      -1.5423              -1.4261               -1.2225    -3.5536
25%      -0.3672              -0.8516               -0.7434    -0.5936
50%      -0.1848              -0.1813               -0.2643    -0.0048
75%       0.0583               0.4890                0.4843     0.5947
max      10.5934               5.3724                7.2514     3.7367

              pH  sulphates    alcohol
count  1359.0000  1359.0000  1359.0000
mean     -0.0000    -0.0000     0.0000
std       1.0004     1.0004     1.0004
min      -3.6765    -1.9267    -1.8789
25%      -0.6439    -0.6372    -0.8619
50%       0.0014    -0.2269    -0.2148
75%       0.5821     0.4179     0.6173
max       4.5181     7.8620     4.1304
```

It seems that the data is standardized, the **mean** of each feature = 0 and the **std** = 1.

Append another column of ones to the feature space which maps adding the bias

[15]:
```
features_final = np.c_[ features_standardize, np.ones(features_standardize.
↪shape[0]) ]
```

One Hot encode the target feature ***labels***

[16]:
```
labels_final = one_hot_encode(labels)
```

[17]:
```
#test the label array after applying hot encoding
labels_final[0]
```

[17]:
```
array([0., 0., 1., 0., 0., 0.])
```

Let's split the dataset into training and testing sets

[18]:
```
X_train, y_train, X_test, y_test = shuffle_split_data(features_final,␣
↪labels_final, 50)
```

[19]:
```
print("Training Set shape: " + str(X_train.shape))
print("Testing Set shape: " + str(X_test.shape))
```

```
Training Set shape: (680, 12)
Testing Set shape: (679, 12)
```

5. Build neural network model #### General steps to build neural network: 1. Define the neural network structure (# of input units, # of hidden units, etc) 2. Initialize the model's parameters 3. Loop: - Implement forward propagation - Compute loss - Implement backward propagation to get the gradients - Update parameters

[20]:
```
class ANN:
    def __init__(self, layers_size):
        self.layers_size = layers_size
        self.parameters = {}
        self.L = len(self.layers_size)
        self.n = 0
        self.costs = []

    def relu(self,Z):
        '''
        The ReLu activation function is to performs a threshold
        operation to each input element where values less
        than zero are set to zero.
        '''
        return np.maximum(0,Z)

    def dRelu(self, x):
        x[x<=0] = 0
        x[x>0] = 1
        return x

    def softmax(self, Z):
        expZ = np.exp(Z - np.max(Z))
        return expZ / expZ.sum(axis=0, keepdims=True)

    def initialize_parameters(self):
        np.random.seed(1)

        for l in range(1, len(self.layers_size)):
            self.parameters["W" + str(l)] = np.random.randn(self.
↪layers_size[l], self.layers_size[l - 1]) / np.sqrt(
                self.layers_size[l - 1])

    def forward(self, X):
        store = {}

        A = X.T
        for l in range(self.L - 1):
            Z = self.parameters["W" + str(l + 1)].dot(A)
            A = self.relu(Z)
            store["A" + str(l + 1)] = A
            store["W" + str(l + 1)] = self.parameters["W" + str(l + 1)]
```

```
            store["Z" + str(l + 1)] = Z

        Z = self.parameters["W" + str(self.L)].dot(A)
        A = self.softmax(Z)
        store["A" + str(self.L)] = A
        store["W" + str(self.L)] = self.parameters["W" + str(self.L)]
        store["Z" + str(self.L)] = Z
        return A, store


    def backward(self, X, Y, store):
        derivatives = {}
        store["A0"] = X.T

        A = store["A" + str(self.L)]
        dZ = A - Y.T

        dW = dZ.dot(store["A" + str(self.L - 1)].T) / self.n
        dAPrev = store["W" + str(self.L)].T.dot(dZ)

        derivatives["dW" + str(self.L)] = dW

        for l in range(self.L - 1, 0, -1):
            dZ = dAPrev * self.dRelu(store["Z" + str(l)])
            dW = 1. / self.n * dZ.dot(store["A" + str(l - 1)].T)
            if l > 1:
                dAPrev = store["W" + str(l)].T.dot(dZ)

            derivatives["dW" + str(l)] = dW

        return derivatives

    def fit(self, X, Y, learning_rate, n_iterations):
        np.random.seed(1)

        self.n = X.shape[0]
        self.layers_size.insert(0, X.shape[1])
        self.initialize_parameters()
        for loop in range(n_iterations):
            A, store = self.forward(X)
            cost = np.sum((Y - A.T) ** 2)/ self.n  ##Mean Square Error

            derivatives = self.backward(X, Y, store)

            for l in range(1, self.L + 1):
                self.parameters["W" + str(l)] = self.parameters["W" + str(l)] -␣
↪learning_rate * derivatives[
```

```
                    "dW" + str(l)]

            if loop % 100 == 0:
                print("Loss: ", cost, "Train Accuracy:", self.predict(X, Y))

            if loop % 10 == 0:
                self.costs.append(cost)

    def predict(self, X, Y):
        A, cache = self.forward(X)
        y_hat = np.argmax(A, axis=0)
        Y = np.argmax(Y, axis=1)
        accuracy = (y_hat == Y).mean()
        return accuracy * 100

    def plot_loss(self):
        plt.figure()
        plt.plot(np.arange(len(self.costs)), self.costs)
        plt.xlabel("Iterations")
        plt.ylabel("Loss")
        plt.show()
```

6. Train and plot the accuracy of the model

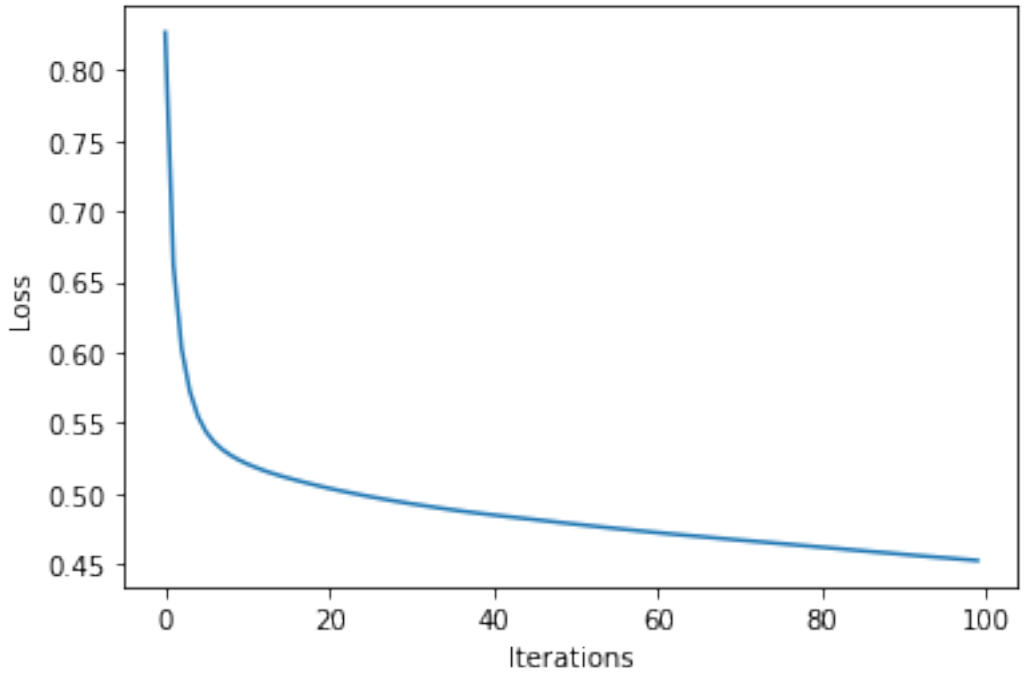
Set the number of neurons in hidden and ouptut layers

[21]:
```
layersDims = [30, 6]
```

For learning_rate = 0.1

[22]:
```
ann1 = ANN(layersDims)
ann1.fit(X_train, y_train, learning_rate=0.1, n_iterations=1000)
print("Train Accuracy:", ann1.predict(X_train, y_train))
print("Test Accuracy:", ann1.predict(X_test, y_test))
ann1.plot_loss()
```

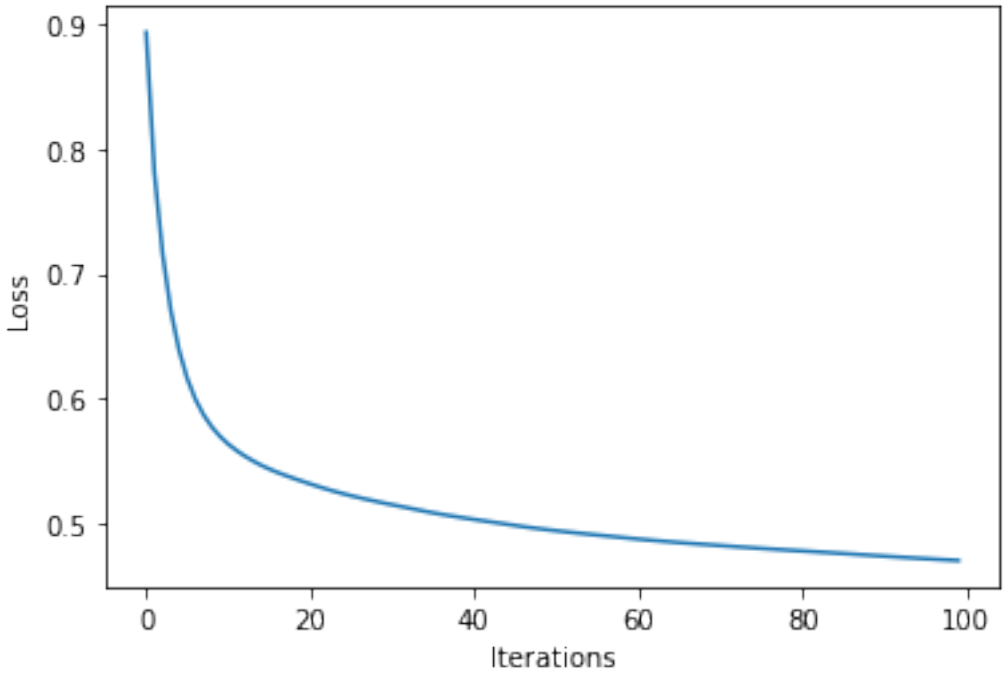
```
Loss:  0.8265431653608578 Train Accuracy: 32.35294117647059
Loss:  0.5208093887402137 Train Accuracy: 59.26470588235294
Loss:  0.5035208738393832 Train Accuracy: 61.1764705882353
Loss:  0.4925939227409262 Train Accuracy: 62.794117647058826
Loss:  0.48464239119310715 Train Accuracy: 63.52941176470588
Loss:  0.47812493753945545 Train Accuracy: 64.11764705882354
Loss:  0.4721271536954926 Train Accuracy: 64.41176470588236
Loss:  0.46687353209413784 Train Accuracy: 64.55882352941177
Loss:  0.46181360703714724 Train Accuracy: 64.8529411764706
Loss:  0.4567332626977856 Train Accuracy: 65.73529411764706
Train Accuracy: 66.76470588235294
Test Accuracy: 57.14285714285714
```



For learning_rate = 0.05

[23]:
```
ann2 = ANN(layersDims)
ann2.fit(X_train, y_train, learning_rate=0.05, n_iterations=1000)
print("Train Accuracy:", ann2.predict(X_train, y_train))
print("Test Accuracy:", ann2.predict(X_test, y_test))
ann2.plot_loss()
```

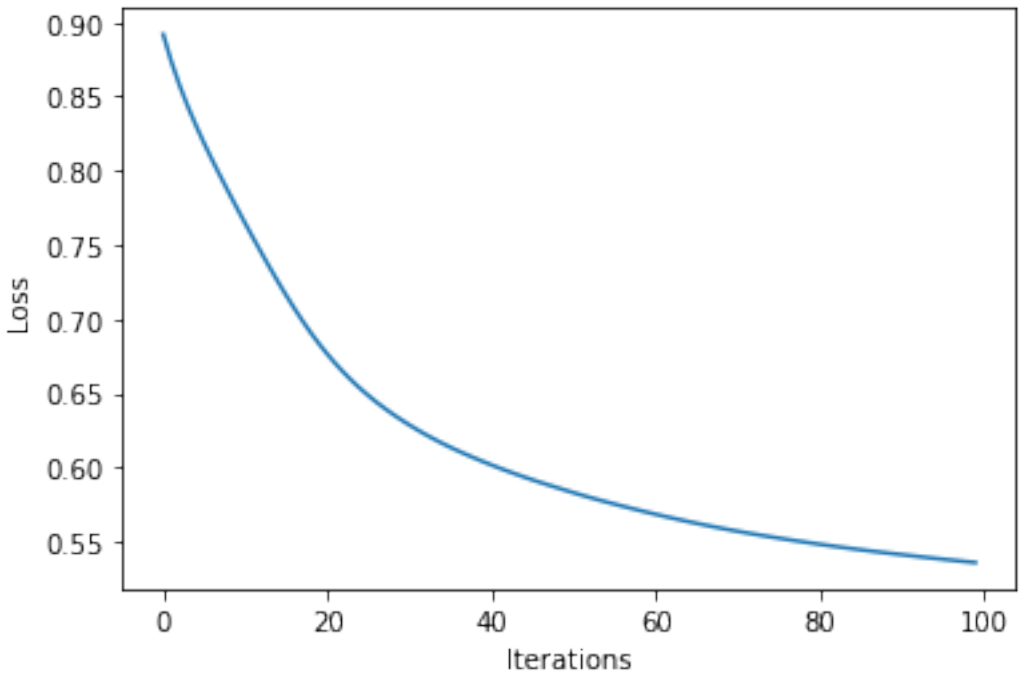
```
Loss:  0.8929065327221574 Train Accuracy: 4.411764705882353
Loss:  0.5638301233676902 Train Accuracy: 56.61764705882353
Loss:  0.5319516380698833 Train Accuracy: 59.85294117647059
Loss:  0.5153169529477301 Train Accuracy: 59.85294117647059
Loss:  0.5035307146165067 Train Accuracy: 61.029411764705884
Loss:  0.4945548937734092 Train Accuracy: 62.05882352941177
Loss:  0.4878839676659328 Train Accuracy: 63.67647058823529
Loss:  0.48268714719881795 Train Accuracy: 64.41176470588236
Loss:  0.47838486782921336 Train Accuracy: 64.26470588235294
Loss:  0.474200182949223 Train Accuracy: 65.44117647058823
Train Accuracy: 66.02941176470588
Test Accuracy: 57.437407952871865
```



For learning_rate = 0.01

[24]:
```
ann3 = ANN(layersDims)
ann3.fit(X_train, y_train, learning_rate=0.01, n_iterations=1000)
print("Train Accuracy:", ann3.predict(X_train, y_train))
print("Test Accuracy:", ann3.predict(X_test, y_test))
ann3.plot_loss()
```

```
Loss:  0.8918401846756474 Train Accuracy: 12.647058823529411
Loss:  0.7644633187245548 Train Accuracy: 46.32352941176471
Loss:  0.6765146202997322 Train Accuracy: 48.8235294117647
Loss:  0.6287759426611269 Train Accuracy: 53.088235294117645
Loss:  0.6018526712044446 Train Accuracy: 54.11764705882353
Loss:  0.5831539749332968 Train Accuracy: 57.205882352941174
Loss:  0.5686389632156069 Train Accuracy: 57.79411764705882
Loss:  0.5571811582074602 Train Accuracy: 58.6764705882353
Loss:  0.5484188704597996 Train Accuracy: 59.85294117647059
Loss:  0.541420091025964 Train Accuracy: 60.147058823529406
Train Accuracy: 60.147058823529406
Test Accuracy: 55.52282768777614
```


0.90
0.85
0.80
0.75
0.70
0.65
0.60
0.55
Loss
0
20
40
60
80
100
Iterations

[ ]: