Mustererkennung/Machine Learning - Assignment 8

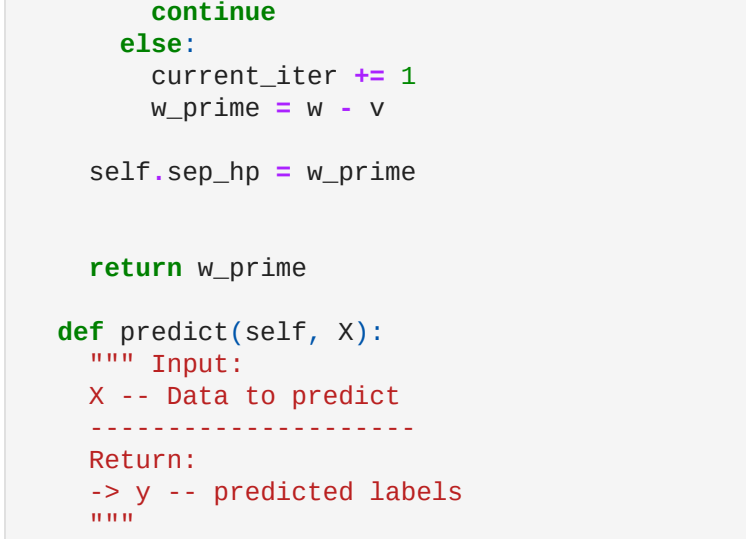
```python
import numpy as np
import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.utils import shuffle
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.preprocessing import StandardScaler
%matplotlib inline
```

Excercise 1 Solution: Perceptron

```python
import numpy as np
import matplotlib.pyplot as plt

class MyPerceptron():
  def __init__(self, tol, max_iter=100):
    self.tol = tol
    self.sep_hp = 0
    self.max_iter = max_iter

  def fit(self, X, y):
    """ Input:
    X -- Training data
    y -- Training labels
    --------------------
    Return:
    -> w_prime -- vector defining the separating hyperplane
    """

    X = X - np.mean(X, axis=0)  # normalize data

    n, m = X.shape

    w_prime = np.mean(X, axis=0)
    w = 0
    current_iter = 0

    while (np.linalg.norm(w_prime - w) <= self.tol) and (current_iter < self.max_iter)
      w = w_prime
      ix = np.random.randint(n)
      v = X[ix]
      if y[ix] == 1 and np.dot(w, v.T) > 0:
        current_iter += 1
        continue
      elif y[ix]==1 and np.dot(w, v.T) <= 0:
        current_iter += 1
        w_prime = w + v
      elif y[ix]==-1 and np.dot(w,v.T) < 0:
        current_iter += 1
        continue
      else:
        current_iter += 1
        w_prime = w - v

    self.sep_hp = w_prime


    return w_prime

  def predict(self, X):
    """ Input:
    X -- Data to predict
    ---------------------
    Return:
    -> y -- predicted labels
    """
    X = X - np.mean(X, axis=0)  # normalize data
    return np.sign(np.dot(X, self.sep_hp))

  def accuracy(self, X, y):
    """ Input:
    X -- Test data
    y -- Test labels
    -----------------------
    Return:
    -> p -- percentage of correct predictions
    """
    n = y.shape
    y_prediction = self.predict(X)

    return np.sum(y==y_prediction)/n
```

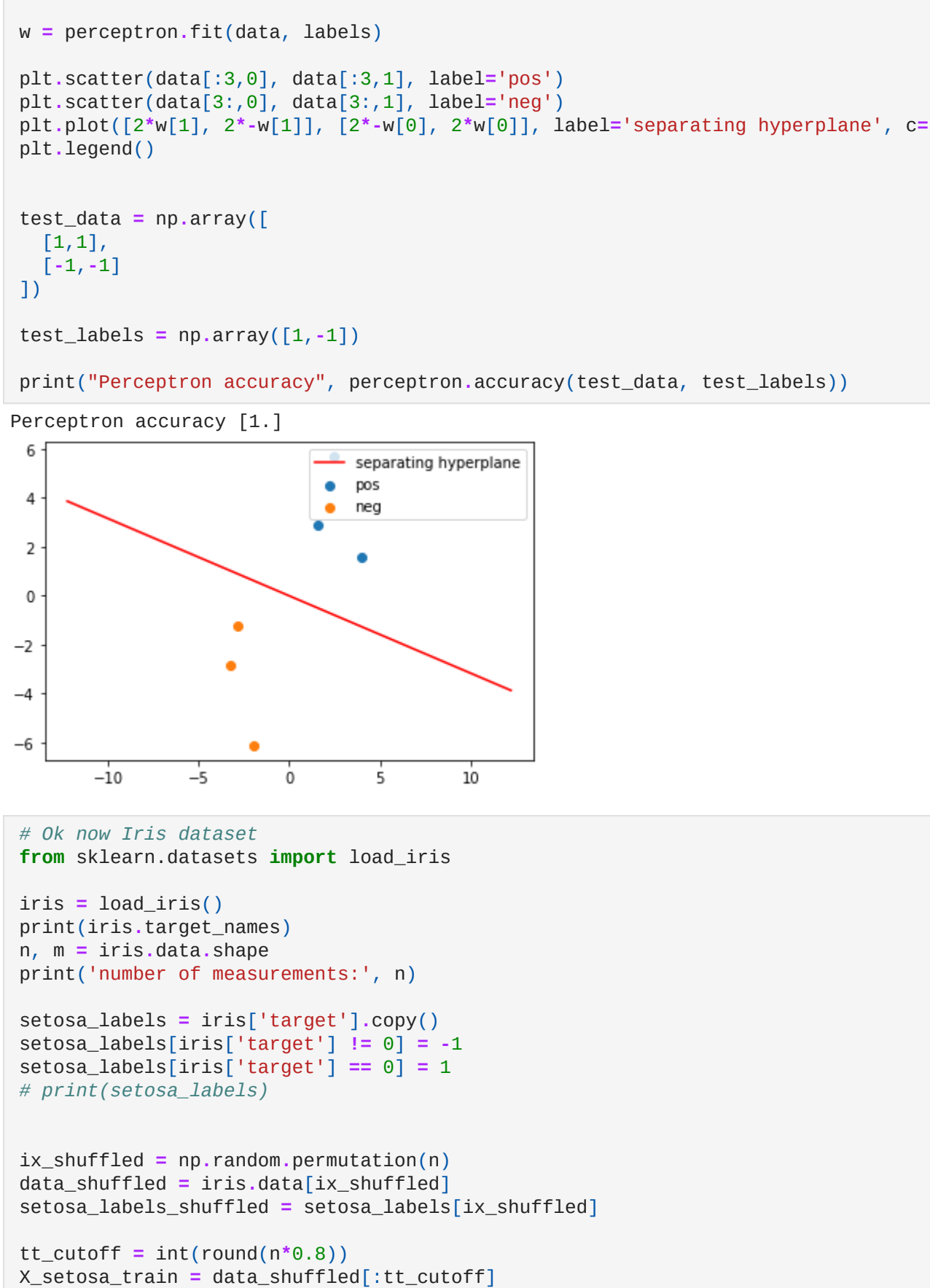
```python
# Small test

data = np.array([
  [2.3,2.5],
  [4.7,1.2],
  [3.2,5.3],
  [-2.1,-1.6],
  [-1.2,-6.5],
  [-2.5,-3.2]
])

data = data - np.mean(data, axis=0)

labels = np.array([1,1,1,-1,-1,-1])

perceptron = MyPerceptron(tol=1e-2)

w = perceptron.fit(data, labels)

plt.scatter(data[:3,0], data[:3,1], label='pos')
plt.scatter(data[3:,0], data[3:,1], label='neg')
plt.plot([2*w[1], 2*-w[1]], [2*-w[0], 2*w[0]], label='separating hyperplane', c='r')
plt.legend()


test_data = np.array([
  [1,1],
  [-1,-1]
])

test_labels = np.array([1,-1])

print("Perceptron accuracy", perceptron.accuracy(test_data, test_labels))
```

```
Perceptron accuracy [1.]
```




```python
# Ok now Iris dataset
from sklearn.datasets import load_iris

iris = load_iris()
print(iris.target_names)
n, m = iris.data.shape
print('number of measurements:', n)

setosa_labels = iris['target'].copy()
setosa_labels[iris['target'] != 0] = -1
setosa_labels[iris['target'] == 0] = 1
# print(setosa_labels)


ix_shuffled = np.random.permutation(n)
data_shuffled = iris.data[ix_shuffled]
setosa_labels_shuffled = setosa_labels[ix_shuffled]

tt_cutoff = int(round(n*0.8))
X_setosa_train = data_shuffled[:tt_cutoff]
y_setosa_train = setosa_labels_shuffled[:tt_cutoff]

X_setosa_test = data_shuffled[tt_cutoff:]
y_setosa_test = setosa_labels_shuffled[tt_cutoff:]

# print(X_setosa_test)
# print(y_setosa_test)


accuracy_in_runs = []
for i in range(100):
  perceptron = MyPerceptron(tol=1e-3)
  perceptron.fit(X_setosa_train, y_setosa_train)
  accuracy = perceptron.accuracy(X_setosa_test, y_setosa_test)
  accuracy_in_runs.append(accuracy)
print('setosa, non-setosa classification accuracy:', max(accuracy_in_runs))
fig =  plt.figure(figsize=(10,8))
plt.plot(range(0,100),[100*i for i in accuracy_in_runs])
plt.ylabel('Accuracy, %', fontsize = 14)
plt.xlabel('run',fontsize =14)
plt.title("Accuracy in 100 runs", fontsize =16)
```

```
['setosa' 'versicolor' 'virginica']
number of measurements: 150
setosa, non-setosa classification accuracy: [1.]
Text(0.5, 1.0, 'Accuracy in 100 runs')
```



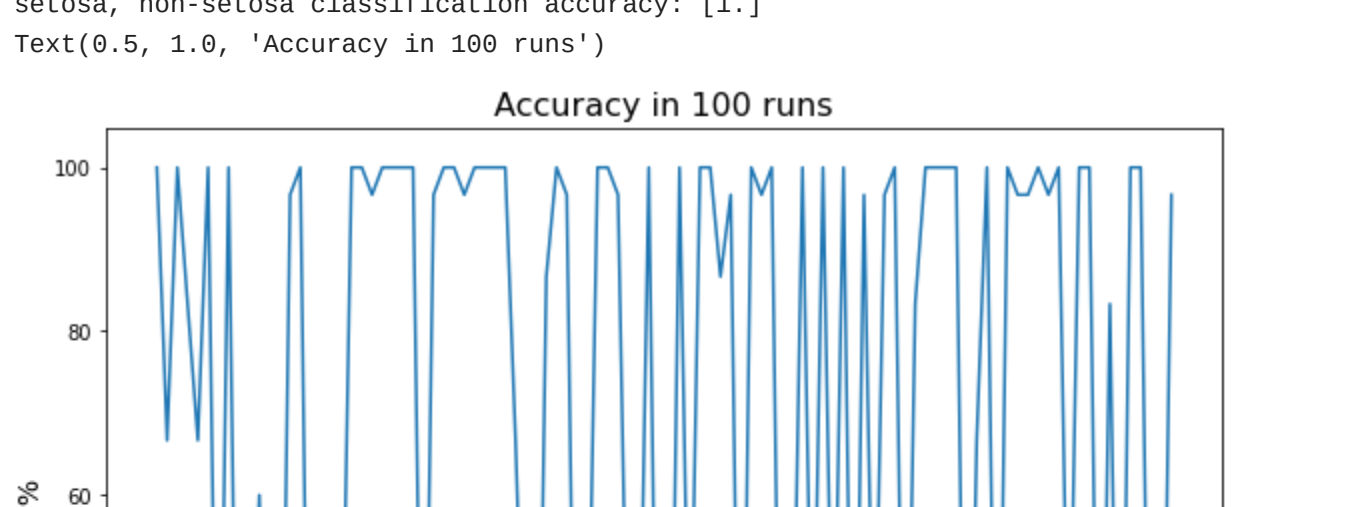

```python
from sklearn.model_selection import train_test_split

versicolor_labels = iris['target'][iris['target'] != 0].copy()
versicolor_labels[versicolor_labels == 2] = -1

data = iris['data'][iris['target'][iris['target'] != 0]] # Ok this line is a bit ridic

# print(versicolor_labels)
# print(data)

X_train, X_test, y_train, y_test = train_test_split(data, versicolor_labels, test_size

perceptron = MyPerceptron(tol=1e-1)
perceptron.fit(X_train, y_train)
accuracy = perceptron.accuracy(X_test, y_test)

print('versicolor-virignica accuracy:', accuracy)
```

```
versicolor-virignica accuracy: [1.]
```

Excercise 2 Solution: Multilayer-Perceptron (MLP)

Splitting the data into training/test and according to their class memberships

```python
training_data = np.array(pd.read_csv('zip.train', sep=' ', header=None))
test_data = np.array(pd.read_csv('zip.test', sep =' ',header=None))

X_train, y_train = training_data[:,1:-1], training_data[:,0]
X_test, y_test = test_data[:,1:], test_data[:,0]
def show_numbers(X):
    num_samples = 90
    indices = np.random.choice(range(len(X)), num_samples)
    sample_digits = X[indices]

    fig = plt.figure(figsize=(20, 6))

    for i in range(num_samples):
        ax = plt.subplot(6, 15, i + 1)
        img = 255 - sample_digits[i].reshape((16, 16))
        plt.imshow(img, cmap='gray')
        plt.axis('off')
show_numbers(X_train)
```



```python
#y_labels in form of vector  for digits for multiclass
enc = OneHotEncoder()
# 0 -> (1, 0, 0, 0), 1 -> (0, 1, 0, 0), 2 -> (0, 0, 1, 0), 3 -> (0, 0, 0, 1)
y_OH_train = enc.fit_transform(np.expand_dims(y_train,1)).toarray()
y_OH_test = enc.fit_transform(np.expand_dims(y_test,1)).toarray()
#print( X_train)
```

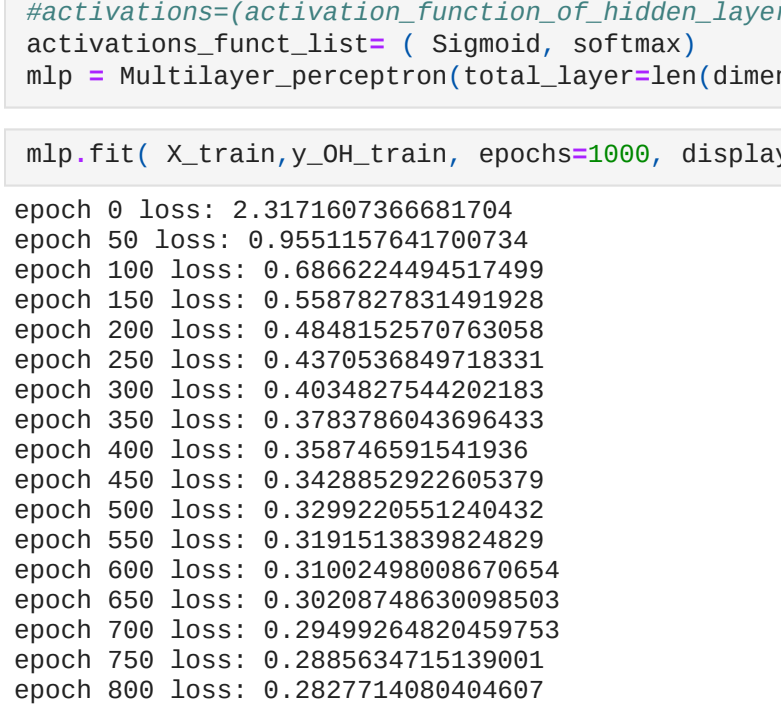
```python
#Data Normalization/standardization
scaler = StandardScaler()
scaler.fit(X_train)
X_train=scaler.transform(X_train)
X_test=scaler.transform(X_test)
```

```python
class Sigmoid:
    def activation(z):
        return 1 / (1 + np.exp(-z))
    def gradient(z):
        return Sigmoid.activation(z) * (1 - Sigmoid.activation(z))
class Relu:
    def activation(z):
        z[z < 0] = 0
        return z
    def gradient(x):
        x[x<=0] = 0
        x[x>0] = 1
        return x

class softmax:
    def activation(x):
        exps = np.exp(x)
        return exps / np.sum(exps)
class Multilayer_perceptron:
    def __init__(self, total_layer=2,dimensions=None, activations=None, learning_rate=
        """
        parameters
        1. total_layer: no of layers including input layer, hidden layers and output l
        2. dimensions: Dimensions of the neural net. (no of input, no of nodes in hidd
        3. activations:Activations functions for each layer.
        4. learning_rate: learning

        """

        self.n_layers = total_layer
        self.loss = None
        self.learning_rate = learning_rate
        self.sizes=dimensions

        # Weights and biases are initiated by index. For a one hidden layer net you wi
        self.w = {}
        self.b = {}

        # Activations are also initiated by index. For the example we will have activa
        self.activations = {}

        for i in range(len(dimensions) - 1):
            self.w[i + 1] = np.random.randn(dimensions[i], dimensions[i + 1]) / np.sqr
            self.b[i + 1] = np.zeros((1,dimensions[i + 1]))
            self.activations[i + 2] = activations[i]

    def _feed_forward(self, x):
        """
        Execute a forward feed through the network.

         x:input data vectors.
        return:  Node outputs and activations per layer.
                 The numbering of the output is equivalent to the layer numbers.
        """

        # w(x) + b
        z = {}

        # activations: f(z)
        a = {1: x.reshape(1,-1)}  # First layer has no activations as input. The input

        for i in range(1, self.n_layers):
            # current layer = i
            # activation layer = i + 1
            z[i + 1] = np.matmul(a[i], self.w[i]) + self.b[i]
            a[i + 1] = self.activations[i + 1].activation(z[i + 1])

        return z, a
    #gradient calculation
    def grad(self, x, y):
        self.Z,self.A=self._feed_forward(x)
        self.dW = {}
        self.dB = {}
        self.dZ = {}
        self.dA = {}
        L = self.n_layers
        self.dZ[L] = (self.A[L] - y)

        for k in range(L, 1, -1):
          #print('iter',k)
          #self.A[k-1]=np.array(self.A[k-1]).reshape(self.A[k-1].shape[0],1)
          self.dW[k-1] = np.matmul(self.A[k-1].T, self.dZ[k])
          #print('dw',self.dW[k-1])
          self.dB[k-1] = self.dZ[k]
          #print('dB',self.dB[k-1])
          self.dA[k-1] = np.matmul(self.dZ[k], self.w[k-1].T)
          self.dZ[k-1] = np.multiply(self.dA[k-1], Sigmoid.gradient(self.A[k-1]))

    def fit(self, X, Y, epochs=100, display_loss=True):

        if display_loss:
          loss = {}

        for epoch in range(epochs):
          dW = {}
          dB = {}
          for i in range(self.n_layers - 1):
            dW[i+1] = np.zeros((self.sizes[i], self.sizes[i+1]))
            dB[i+1] = np.zeros((1, self.sizes[i+1]))
          for x, y in zip(X, Y):
            self.grad(x, y)
            for i in range(self.n_layers-1):
              dW[i+1] += self.dW[i+1]
              dB[i+1] += self.dB[i+1]

          total_samples = X.shape[1]
          #print(total_samples)
          for i in range(self.n_layers-1):
            #self.b[i+1]=self.b[i+1].reshape(1,-1)
            #print(dB[i+1].shape)
            self.w[i+1] -= self.learning_rate * (dW[i+1]/total_samples)
            self.b[i+1] -= self.learning_rate * (dB[i+1]/total_samples)

          if display_loss:
            Y_pred = self.predict(X)
            loss[epoch] = self.cross_entropy(Y, Y_pred)
            if epoch%50==0:
                print("epoch",epoch,'loss:',loss[epoch])
        #loss plot
        if display_loss:
          plt.plot(loss.values())
          plt.xlabel('Epochs')
          plt.ylabel('CE')
          plt.show()
    #prediction method
    def predict(self, X):
        Y_pred = []
        for x in X:
          lin_sum,output = self._feed_forward(x)
          Y_pred.append(output[self.n_layers])
        return np.array(Y_pred).squeeze()
    #cross entropy calculation function
    def cross_entropy(self,label,pred):
        yl=np.multiply(pred,label)
        yl=yl[yl!=0]
        yl=-np.log(yl)
        yl=np.mean(yl)
        return yl
```

```python
#dimenstions=(nodes_inputlayer,nodes_hidden_layer1,nodes_hidden_layer2, ....., nodes_l
dimenstions=(X_train.shape[1], 16, len(np.unique(y_train)))
#activations=(activation_function_of_hidden_layer1,activation_function_of_hidden_layer
activations_funct_list= ( Sigmoid, softmax)
mlp = Multilayer_perceptron(total_layer=len(dimenstions),dimensions=dimenstions, activ
```

```python
mlp.fit( X_train,y_OH_train, epochs=1000, display_loss=True)
```

```
epoch 0 loss: 2.3171607366681704
epoch 50 loss: 0.9551157641700734
epoch 100 loss: 0.6866224494517499
epoch 150 loss: 0.5587827831491928
epoch 200 loss: 0.4848152570763058
epoch 250 loss: 0.4370536849718331
epoch 300 loss: 0.4034827544202183
epoch 350 loss: 0.3783786043696433
epoch 400 loss: 0.358746591541936
epoch 450 loss: 0.3428852922605379
epoch 500 loss: 0.3299220551240432
epoch 550 loss: 0.3191513839824829
epoch 600 loss: 0.31002498008670654
epoch 650 loss: 0.30208748630098503
epoch 700 loss: 0.29499264820459753
epoch 750 loss: 0.2885634715139001
epoch 800 loss: 0.2827714080404607
epoch 850 loss: 0.2775670810933319
epoch 900 loss: 0.272884989024984
epoch 950 loss: 0.268600455105745
```




```python
import sklearn
Y_pred_train = mlp.predict(X_train)
Y_pred_train = np.argmax(Y_pred_train,1)

Y_pred_test = mlp.predict(X_test)
Y_pred_test = np.argmax(Y_pred_test,1)

accuracy_train = accuracy_score(Y_pred_train, y_train)
accuracy_test = accuracy_score(Y_pred_test, y_test)

print("Training accuracy", round(accuracy_train, 2))
print("Test Dataset accuracy", round(accuracy_test, 2))
print(sklearn.metrics.classification_report(y_test, Y_pred_test))
```

```
Training accuracy 0.93
Test Dataset accuracy 0.88
              precision    recall  f1-score   support

         0.0       0.92      0.96      0.94       359
         1.0       0.97      0.95      0.96       264
         2.0       0.88      0.79      0.83       198
         3.0       0.88      0.83      0.85       166
         4.0       0.82      0.84      0.83       200
         5.0       0.82      0.86      0.84       160
         6.0       0.85      0.92      0.88       170
         7.0       0.89      0.90      0.89       147
         8.0       0.85      0.77      0.81       166
         9.0       0.85      0.88      0.86       177

    accuracy                           0.88      2007
   macro avg       0.87      0.87      0.87      2007
weighted avg       0.88      0.88      0.88      2007
```