Deep_Learning_Lab_Exam_Unsolved_Fall_2022

November 8, 2024

1 CS 316: Introduction to Deep Learning

2 Lab Exam - Fall 2022

3 Dr. Abdul Samad

Total Duration: 2 Hours and 50 minutes Total Points: 100 Name: **Write your Name Here** ID: **Write your Student ID**

4 Instructions

1. Google Colab must be used for this exam.
2. You are not permitted to utilise the internet or any other source for this exam.
3. Any violation shall be treated as a plagarism case.
4. The error in one task will not carry to other tasks.
5. The marks for each task are stated explicitly.
6. Please carefully study the questions; they are self-explanatory.
7. Rename your file as `Lab_Exam_aa01234.ipynb` where `aa01234` will be replaced by your student id.

5 Exam Overview

In this Exam, we are implementing a neural network with 3-hidden layers and we will be using it to classify digits. Since each image is a greyscale image of size 8 x 8 it is flattened into a column vector of size 64 before being fed to the multi-layer pereceptron.

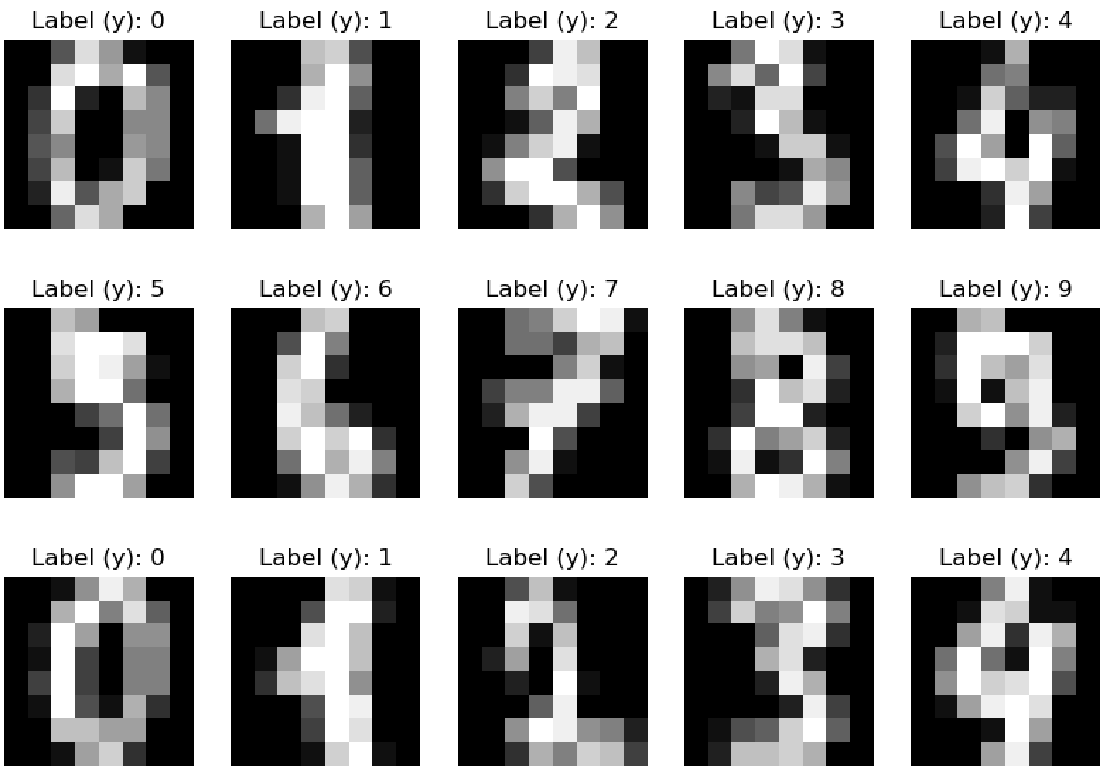
5.1 Setup

[1]:
```
import numpy as np
import matplotlib.pyplot as plt
np.random.seed(42)
from sklearn import datasets
import sklearn.model_selection
from IPython.display import clear_output
```

6 Dataset Overview

[2]:
```python
data = datasets.load_digits()
X = data["data"]
Y = data["target"]

fig = plt.figure(figsize=(10,7))
for i in range(15):
    ax = fig.add_subplot(3, 5, i+1)
    ax.imshow(X[i].reshape((8,8)), cmap=plt.get_cmap('gray'))
    ax.set_title('Label (y): {y}'.format(y=Y[i]))
    plt.axis('off')
```



7 [10 Points] Task 01 - Train Test Split

In Task 01, you are required to the implement the function `train_test_split` which splits the datasets into train and test set.

Hint: Use `rng.shuffle` to shuffle the dataset. Furthermore, instead of shuffling the dataset, shuffle the indexes.

[3]:
```python
#TODO: Implement the function train_test_split
def train_test_split(inputs,outputs,test_size,seed = 0):
    """
    Splits the data into training and test sets.
    Return 4 numpy arrays. X_train, X_test, Y_train, Y_test
    where training data is test_size proportion of data provided.

    Args:
        inputs [np.array] : numpy array of input data
        outputs [np.array]: numpy array of output labels
        test_size [float]: proportion of data to be used as test data. e.g. 0.2␣
↪means 20% of data is used for test data.
        seed [int]: A seed to create random number generator. (For␣
↪reproducability)
    """

    rng = np.random.default_rng(seed)
    assert(len(inputs) == len(outputs))
    assert(test_size <= 1.0)
    assert(test_size >= 0.0)
    num_samples = len(inputs)
    num_train = int(num_samples * (1.0 - test_size))
    # Write your code here
    indices = np.arange(num_samples)
    rng.shuffle(indices)
    train_indices = indices[:num_train]
    test_indices = indices[num_train:]
    X_train = inputs[train_indices]
    X_test = inputs[test_indices]
    Y_train = outputs[train_indices]
    Y_test = outputs[test_indices]

    return X_train,X_test,Y_train,Y_test
```

[4]:
```python
# DO NOT EDIT
# Test Case to check Train Test Split
np.random.seed(1)
x = np.random.randn(15,2)
y = np.random.randn(15)
X_train,X_test,Y_train,Y_test = train_test_split(x,y,test_size=0.2)
print(X_train.shape,X_test.shape,Y_train.shape,Y_test.shape)
assert np.allclose (X_train,np.array([[ 0.86540763, -2.3015387 ],[ 0.90159072, ␣
↪0.50249434],[ 1.74481176, -0.7612069 ],[-1.10061918,  1.14472371],[ 1.
↪62434536, -0.61175641],[ 0.3190391 , -0.24937038],[ 1.13376944, -1.
↪09989127],[ 1.46210794, -2.06014071],[-0.26788808,  0.53035547],[ 0.
↪90085595, -0.68372786],[-0.3224172 , -0.38405435],[ 0.04221375,  0.
↪58281521]]))
```

```
assert np.allclose (X_test,np.array([[-0.12289023, -0.93576943],[-0.17242821,␣
↪-0.87785842],[-0.52817175, -1.07296862]]))
assert np.allclose (Y_train,np.array([-0.6871727 , -0.88762896, -0.84520564, -0.
↪19183555, -0.69166075,-0.67124613,  0.2344157 , -0.0126646 ,  0.05080775, -0.
↪74715829,-1.11731035,  0.74204416]))
assert np.allclose (Y_test, np.array([ 1.6924546 ,  1.65980218, -0.39675353]))
```

```
(12, 2) (3, 2) (12,) (3,)
```

8 [10 Points] Task 02 - Activation Functions

In this task, you will be implementing the Sigmoid and ReLU activation fuctions.

8.1 [5 Points] Part A - Relu Activation Function

[5]:
```
#TODO: Implement the Relu class which implements the Relu activation function.
class Relu:
    """
    Implements the Relu activation
    """
    @staticmethod
    def activation(z):
        # Write your code here
        # Hint: Use np.maximum
        # Refer to equation (2.1)
        return np.maximum(z, 0)

    @staticmethod
    def prime(z):
        # Write your code here
        # Hint: Use np.where
        # Refer to equation (2.2)
        return np.where(z > 0, 1, 0)
```

[6]:
```
# DO NOT EDIT
# Test Case to Check ReLU
rng = np.random.default_rng(42)
input = rng.normal(size=(3,3))
print(f"Input: {input}")
output = Relu.activation(input)
print(f"Output: {output}")
assert np.allclose(output,np.array([[0.30471708,0.,0.7504512 ],[0.94056472,0.,0.
↪],[0.1278404, 0.,0.]]))
grad = Relu.prime(input)
print(f"Gradient: {grad}")
assert np.allclose(grad,np.array([[1,0,1],[1,0,0],[1,0,0]]))
```

```
Input: [[ 0.30471708 -1.03998411  0.7504512 ]
 [ 0.94056472 -1.95103519 -1.30217951]
 [ 0.1278404  -0.31624259 -0.01680116]]
Output: [[0.30471708 0.         0.7504512 ]
 [0.94056472 0.         0.        ]
 [0.1278404  0.         0.        ]]
Gradient: [[1 0 1]
 [1 0 0]
 [1 0 0]]
```

8.2 [5 Points] Part B - Sigmoid Activation Function

[7]:
```python
#TODO: Implement the Sigmoid class which implements the Sigmoid activation␣
 ↪function.
class Sigmoid:
    @staticmethod
    def activation(z):
      # Write your code here
      # Refer to equation (3.1)
      return 1 / np.add(1, np.exp(-z))

    @staticmethod
    def prime(z):
      # Write your code here
      # Refer to equation (3.2)
      return np.multiply(Sigmoid.activation(z), 1 - Sigmoid.activation(z))
```

[8]:
```python
# DO NOT EDIT
# Test Case to Check Sigmoid
rng = np.random.default_rng(42)
input = rng.normal(size=(3,3))
print(f"Input: {input}")
output = Sigmoid.activation(input)
print(f"Output: {output}")
assert np.allclose(output,np.array([[0.57559524, 0.26115306, 0.679277 ],[0.
 ↪71921371, 0.12444053, 0.21379844],[0.53191664, 0.42159173, 0.49579981]]))
grad = Sigmoid.prime(input)
print(f"Gradient: {grad}")
assert np.allclose(grad, np.array([[0.24428536, 0.19295214, 0.21785976],[0.
 ↪20194535, 0.10895508, 0.16808867],[0.24898133, 0.24385214, 0.24998236]]))
```

```
Input: [[ 0.30471708 -1.03998411  0.7504512 ]
 [ 0.94056472 -1.95103519 -1.30217951]
 [ 0.1278404  -0.31624259 -0.01680116]]
Output: [[0.57559524 0.26115306 0.679277  ]
 [0.71921371 0.12444053 0.21379844]
 [0.53191664 0.42159173 0.49579981]]
```

```
Gradient: [[0.24428536 0.19295214 0.21785976]
 [0.20194535 0.10895508 0.16808867]
 [0.24898133 0.24385214 0.24998236]]
```

9 [5 Points] Task 03 - Softmax

[9]:
```python
#TODO: Implement the Softmax class which implements the softmax activation␣
↪function.
class Softmax:
    @staticmethod
    def activation(z):
      # Write your code here
      # Refer to equation (4.1)
      return np.divide(np.exp(z), np.sum(np.exp(z), axis=1).reshape(-1, 1))
```

[10]:
```python
# DO NOT EDIT
# Test Case to check Softmax activation function
rng = np.random.default_rng(42)
input = rng.normal(size=(3,3))
print(f"Input: {input}")
output = Softmax.activation(input)
print(f"Output: {output}")
assert np.allclose(output, np.array([[0.35432675, 0.09234378, 0.55332948],[0.
↪86084143, 0.04776582, 0.09139274],[0.39892377, 0.25587457, 0.34520167]]))
```

```
Input: [[ 0.30471708 -1.03998411  0.7504512 ]
 [ 0.94056472 -1.95103519 -1.30217951]
 [ 0.1278404  -0.31624259 -0.01680116]]
Output: [[0.35432675 0.09234378 0.55332948]
 [0.86084143 0.04776582 0.09139274]
 [0.39892377 0.25587457 0.34520167]]
```

10 [10 Points] Task 04 - Cross Entropy Loss

[20]:
```python
#TODO: Implement the class CrossEntropy which represents the cross-entropy loss␣
↪function.
class CrossEntropy:
    """
    Used with Softmax activation in final layer
    """
    @staticmethod
    def activation(z):
        # DO NOT EDIT
        return Softmax.activation(z)

    @staticmethod
```

```
    def delta(y_true, y):
        n,c = y.shape
        y_hot = np.eye(c)[y_true]
        y_hat = Softmax.activation(y)
        # Write your code here
        # Refer to equation (5.3)
        grad = y_hat - y_hot
        return grad

    @staticmethod
    def loss(y_true, y):
        m,c = y.shape
        y_hot = np.eye(c)[y_true]
        y_hat = Softmax.activation(y)
        # Write your code here
        # Refer to equations (5.1) & (5.2)
        loss = np.divide(-np.sum(y_hot * np.log(y_hat)), m)
        return loss
```

[21]:

```
# DO NOT EDIT
# Test Case to check Softmax activation function
rng = np.random.default_rng(42)
y_hat = rng.normal(size=(3,3))
print(f"y_hat: {y_hat}")
y = np.arange(3)
print(f'y: {y}')
loss = CrossEntropy.loss(y,y_hat)
print(f"Cross Entropy Loss: {loss}")
assert loss == 1.714202378772346
delta = CrossEntropy.delta(y,y_hat)
print(f"Delta: {delta}")
assert np.allclose(delta, np.array([[-0.64567325,  0.09234378, 0.55332948],[ 0.
 ↪86084143, -0.95223418 , 0.09139274],[ 0.39892377 , 0.25587457 ,-0.
 ↪65479833]]))
```

```
y_hat: [[ 0.30471708 -1.03998411  0.7504512 ]
 [ 0.94056472 -1.95103519 -1.30217951]
 [ 0.1278404  -0.31624259 -0.01680116]]
y: [0 1 2]
Cross Entropy Loss: 1.714202378772346
Delta: [[-0.64567325  0.09234378  0.55332948]
 [ 0.86084143 -0.95223418  0.09139274]
 [ 0.39892377  0.25587457 -0.65479833]]
```

11 [10 Points] Task 05 - Network Initialisation

[53]:
```
#TODO: Implement the Network class which represents the neural network.
class Network:

    def __init__(self, dimensions, activations):
        """
        Args
          dimensions: (list) Dimensions of the neural net. (input, hidden␣
↪layer, output)
          activations: (list) Activations functions.
        """
        self.n_layers = len(dimensions)
        self.loss = None
        self.learning_rate = None

        # Weights and biases are initiated by index. For a one hidden layer net␣
↪you will have a w[1] and w[2]
        self.w = {}
        self.b = {}

        # Activations are also initiated by index. For the example we will have␣
↪activations[2] and activations[3]
        self.activations = {}

        for i in range(len(dimensions) - 1):
            # Hint: Use np.sqrt as scale represents standard deviation
            sddev = np.sqrt(2/(dimensions[i] + dimensions[i + 1]))
            self.w[i + 1] = np.random.normal(0, sddev, (dimensions[i],␣
↪dimensions[i + 1]))
            self.b[i + 1] = np.zeros(dimensions[i + 1])
            self.activations[i + 2] = activations[i]
```

[54]:
```
# DO NOT EDIT
# Test Case to check Network Initialisation
W = {1: np.array([[-0.26358081, -0.03558627, -1.35104904],[ 1.03739835, -1.
↪13426826, -0.53236778]]), 2: np.array([[ 0.35559086],[-0.88055165],[-0.
↪74808519]])}
B = {1: np.array([0., 0., 0.]), 2: np.array([0.])}
Activations = {2: Relu, 3: Sigmoid}
np.random.seed(2)
nn = Network((2, 3, 1), (Relu, Sigmoid))
for i in nn.w:
  print(f"W[{i}]: {nn.w[i]}\nW[{i}] Shape: {nn.w[i].shape}")
for i in nn.b:
  print(f"B[{i}]: {nn.b[i]}\nB[{i}] Shape: {nn.b[i].shape}")
for i in nn.activations:
```

```
    print(f"A[{i}]: {nn.activations[i]}")
for key,value in nn.w.items():
    assert np.allclose(nn.w[key],  W[key])
for key,value in nn.b.items():
    assert np.allclose(nn.b[key],  B[key])
for key,value in nn.activations.items():
    assert nn.activations[key] ==  Activations[key]
```

```
W[1]: [[-0.26358081 -0.03558627 -1.35104904]
 [ 1.03739835 -1.13426826 -0.53236778]]
W[1] Shape: (2, 3)
W[2]: [[ 0.35559086]
 [-0.88055165]
 [-0.74808519]]
W[2] Shape: (3, 1)
B[1]: [0. 0. 0.]
B[1] Shape: (3,)
B[2]: [0.]
B[2] Shape: (1,)
A[2]: <class '__main__.Relu'>
A[3]: <class '__main__.Sigmoid'>
```

12 [15 Points] Task 06 - Forward Pass

[55]:
```
#TODO: Implement the function forward which represents the forward pass of a␣
↪Neural Network.
def forward(model,X):
      """
      Args
        model: (Network) Network Object
        X: (array) Batch of input data vectors.
      Return
        (z,a): (tuple) Node outputs and activations per layer.
      """
      # w(x) + b
      z = {}
      # activations: f(z)
      # First layer has no activations as input. The input x is the input.
      a = {1: X}
      for i in range(1, model.n_layers):
          # current layer = i
          # activation layer = i + 1
          # Refer to equation (6.1)
          z[i + 1] = np.dot(a[i], model.w[i]) + model.b[i]
          # Pass the output from the layer z[i+1] to the model.activations[i+1]␣
↪activation
          # Refer to equation (6.2)
```

```
        a[i + 1] = model.activations[i + 1].activation(z[i + 1])
    return z, a
```

[56]:
```
# DO NOT EDIT
# Test Case to check forward pass
Z = {
2: np.array([[ 0.25129181, -0.52534809, -1.27929731],[ 0.49713851, -0.82155671,␣
↪-1.53126416],[ 0.98728567, -1.10996888, -0.64662812],[ 0.61483999, -0.
↪91869391, -1.44681237],[ 0.43346133, -0.51541756, -0.41285876],[ 0.86368923,␣
↪-1.06439543, -0.99434613],[ 0.68382105, -0.95614514, -1.30790512],[ 0.
↪1188616 , -0.27352912, -0.7200489 ],[-0.07997399, -0.09212149, -0.
↪78324549],[ 0.43713991, -0.74592918, -1.45444807]]),
3: np.array([[0.08935707],[0.17677791],[0.35106976],[0.21863148],[0.
↪15413489],[0.30711999],[0.24316052],[0.0422661 ],[0.],[0.15544296]])
}
A = {
1: np.array([[0.77395605, 0.43887844],[0.85859792, 0.69736803],[0.09417735, 0.
↪97562235],[0.7611397 , 0.78606431],[0.12811363, 0.45038594],[0.37079802, 0.
↪92676499],[0.64386512, 0.82276161],[0.4434142 , 0.22723872],[0.55458479, 0.
↪06381726],[0.82763117, 0.6316644 ]]),
2: np.array([[0.25129181, 0.        , 0.        ],[0.49713851, 0.        , 0.  ␣
↪     ],[0.98728567, 0.        , 0.        ],[0.61483999, 0.        , 0.      ␣
↪  ],[0.43346133, 0.        , 0.        ],[0.86368923, 0.        , 0.        ␣
↪],[0.68382105, 0.        , 0.        ],[0.1188616 , 0.        , 0.        ␣
↪],[0.        , 0.        , 0.        ],[0.43713991, 0.        , 0.        ␣
↪]]),
3: np.array([[0.52232442],[0.54407974],[0.58687697],[0.55444119],[0.
↪53845761],[0.57618213],[0.56049236],[0.51056495],[0.5       ],[0.53878268]])
}
np.random.seed(2)
nn = Network((2, 3, 1), (Relu, Sigmoid))
rng = np.random.default_rng(42)
input = rng.random((10,2))
print(f"Input: {input}")
z,a = forward(nn,input)
for key,value in a.items():
  print(f"A[{key}]: {value.shape}: {value}")
for key,value in z.items():
  print(f"Z[{key}]: {value.shape}: {value}")
for key,value in a.items():
  assert np.allclose(a[key],A[key])
for key,value in z.items():
  assert np.allclose(z[key],Z[key])
```

```
Input: [[0.77395605 0.43887844]
 [0.85859792 0.69736803]
 [0.09417735 0.97562235]
```

```
 [0.7611397  0.78606431]
 [0.12811363 0.45038594]
 [0.37079802 0.92676499]
 [0.64386512 0.82276161]
 [0.4434142  0.22723872]
 [0.55458479 0.06381726]
 [0.82763117 0.6316644 ]]
A[1]: (10, 2): [[0.77395605 0.43887844]
 [0.85859792 0.69736803]
 [0.09417735 0.97562235]
 [0.7611397  0.78606431]
 [0.12811363 0.45038594]
 [0.37079802 0.92676499]
 [0.64386512 0.82276161]
 [0.4434142  0.22723872]
 [0.55458479 0.06381726]
 [0.82763117 0.6316644 ]]
A[2]: (10, 3): [[0.25129181 0.         0.        ]
 [0.49713851 0.         0.        ]
 [0.98728567 0.         0.        ]
 [0.61483999 0.         0.        ]
 [0.43346133 0.         0.        ]
 [0.86368923 0.         0.        ]
 [0.68382105 0.         0.        ]
 [0.1188616  0.         0.        ]
 [0.         0.         0.        ]
 [0.43713991 0.         0.        ]]
A[3]: (10, 1): [[0.52232442]
 [0.54407974]
 [0.58687697]
 [0.55444119]
 [0.53845761]
 [0.57618213]
 [0.56049236]
 [0.51056495]
 [0.5       ]
 [0.53878268]]
Z[2]: (10, 3): [[ 0.25129181 -0.52534809 -1.27929731]
 [ 0.49713851 -0.82155671 -1.53126416]
 [ 0.98728567 -1.10996888 -0.64662812]
 [ 0.61483999 -0.91869391 -1.44681237]
 [ 0.43346133 -0.51541756 -0.41285876]
 [ 0.86368923 -1.06439543 -0.99434613]
 [ 0.68382105 -0.95614514 -1.30790512]
 [ 0.1188616  -0.27352912 -0.7200489 ]
 [-0.07997399 -0.09212149 -0.78324549]
 [ 0.43713991 -0.74592918 -1.45444807]]
Z[3]: (10, 1): [[0.08935707]
```

```
 [0.17677791]
 [0.35106976]
 [0.21863148]
 [0.15413489]
 [0.30711999]
 [0.24316052]
 [0.0422661 ]
 [0.        ]
 [0.15544296]]
```

13 [5 Points] Task 07 - Compute Prediction

[57]:

```python
#TODO: Implement the function predict which outputs the prediction of the model.
def predict(model, X):
    """
    Args
      model: (network) Neural
      X: (array) Input
    :return: (array) A 1D array of predicted labels
    """
    # Compute forward pass
    _, a = forward(model, X)
    pred= np.argmax(a[model.n_layers], axis=1)
    return pred
```

[58]:

```python
# DO NOT EDIT
# Test Case to check predict
np.random.seed(2)
nn_1 = Network((2, 3, 10), (Sigmoid, Softmax))
rng = np.random.default_rng(42)
input = rng.random((10,2))
print(f"Input: {input}")
pred = predict(nn_1,input)
print(f"Prediction: {pred}")
assert np.allclose(pred,np.array([5, 5, 5, 5, 5, 5, 5, 5, 5, 5]))
```

```
Input: [[0.77395605 0.43887844]
 [0.85859792 0.69736803]
 [0.09417735 0.97562235]
 [0.7611397  0.78606431]
 [0.12811363 0.45038594]
 [0.37079802 0.92676499]
 [0.64386512 0.82276161]
 [0.4434142  0.22723872]
 [0.55458479 0.06381726]
 [0.82763117 0.6316644 ]]
Prediction: [5 5 5 5 5 5 5 5 5 5]
```

#[5 Points] Task 08 - Compute accuracy

In this task, you are required to implement the function `compute_accuracy` which takes as parameters the actual and predicted labels, and then returns the accuracy.

[59]:
```
#TODO: Implement the function compute_accuracy which implements the
def compute_accuracy(y_pred,y_actual):
  acc = np.mean(y_pred == y_actual)
  return acc
```

[60]:
```
# DO NOT EDIT
# Test case to check the compute_accuracy function
accuracy = compute_accuracy(np.array([1,2,3,4,5]),np.ones(5))
print(accuracy)
```

```
0.2
```

14 [15 Points] Task 09 - Backpropagation

[63]:
```
def backprop(model, z, a, y_true):
    """
    The input dicts keys represent the layers of the net.
    a = { 1: x,
          2: f(w1(x) + b1)
          3: f(w2(a2) + b2)
    }
    Args
      model: (Network) Neural Network
      z: (dict) w(x) + b
      a: (dict) f(z)
      y_true: (array) One hot encoded truth vector.
    """

    # Determine partial derivative and delta for the output layer.
    # delta output layer
    # Refer to equation (7.1)
    delta = model.loss.delta(y_true, a[model.n_layers])
    # Refer to equation (7.3)
    dw = np.dot(a[model.n_layers - 1].T, delta)
    # Refer to equation (7.4)
    db = np.mean(delta, axis=0)

    update_params = {
        model.n_layers - 1: (dw, delta,db)
    }
    # In case of three layer net will iterate over i = 2 and i = 1
    # Determine partial derivative and delta for the rest of the layers.
```

```
    # Each iteration requires the delta from the previous layer, propagating␣
 ↪backwards.
    for i in reversed(range(2, model.n_layers)):
        # Refer to equation (7.2)
        # Hint: delta[i+1] refers to the current value of delta, and delta[i]␣
 ↪refers to the previous value of delta.
        delta = np.dot(delta, model.w[i].T) * model.activations[i].prime(z[i])
        # Refer to equation (7.3)
        dw = np.dot(a[i - 1].T, delta)
        # Refer to equation (7.4)
        # Hint: Use np.mean(axis=0)
        db = np.mean(delta, axis=0)
        update_params[i - 1] = (dw, delta,db)

    # Update the weights and biases
    for index, (dw,delta,db) in update_params.items():
      # w = w - lr * dw
      model.w[index] -= model.learning_rate * dw
      # b = b - lr * db
      model.b[index] -= model.learning_rate * db
```

[64]:
```
np.random.seed(2)
rng = np.random.default_rng(42)
nn_1 = Network((2, 3, 10), (Sigmoid, Softmax))
nn_1.learning_rate = 0.1
nn_1.loss = CrossEntropy
input = rng.random((10,2))
print(f"input: {input}")
y_true = np.arange(10)
print(f"y_true: {y_true}")
z,a = forward(nn_1,input)
backprop(nn_1,z,a,y_true)
W = {
1: np.array([[-0.27226824, -0.02672387, -1.35118418],[ 1.03448274, -1.13009851,␣
 ↪-0.53772292]]),
2: np.array([[ 1.91646819e-01, -4.86305495e-01, -4.01227553e-01,-3.
 ↪51851759e-01,  2.15498795e-01,  9.00262607e-01,2.23875820e-02, -4.
 ↪45063393e-01,  1.97099785e-01,-2.34362686e-01],[-3.99426762e-03,  4.
 ↪58680865e-01, -3.00731553e-01,-7.39663154e-04, -3.40449836e-01, -7.
 ↪32415400e-02,9.55499608e-02, -3.77044916e-01, -1.19112104e-01,-9.
 ↪38588043e-02],[-2.54866522e-01, -4.73815123e-01, -5.48427659e-01,-6.
 ↪70061155e-02, -9.20670733e-02,  8.72480316e-01,-9.59579240e-01,  5.
 ↪13972509e-02,  1.49910124e-01,5.25886653e-01]])
}
B = {
1: np.array([-0.00045843, -0.00015131, -0.00015516]),
```

```
2: np.array([-5.01683620e-05,  2.36204952e-04,  3.91689465e-04,  2.
↪11468706e-04,1.42539567e-05, -1.22402523e-03,  1.89624928e-04,  3.
↪22355945e-04,-1.28728315e-04,  3.73239533e-05])
}

for i in nn_1.w:
  print(f"W[{i}]: {nn_1.w[i]}\nW[{i}] Shape: {nn_1.w[i].shape}")
for i in nn_1.b:
  print(f"B[{i}]: {nn_1.b[i]}\nB[{i}] Shape: {nn_1.b[i].shape}")
for key,value in nn_1.w.items():
  assert np.allclose(nn_1.w[key],  W[key])
for key,value in nn_1.b.items():
  assert np.allclose(nn_1.b[key],  B[key])
```

```
input: [[0.77395605 0.43887844]
 [0.85859792 0.69736803]
 [0.09417735 0.97562235]
 [0.7611397  0.78606431]
 [0.12811363 0.45038594]
 [0.37079802 0.92676499]
 [0.64386512 0.82276161]
 [0.4434142  0.22723872]
 [0.55458479 0.06381726]
 [0.82763117 0.6316644 ]]
y_true: [0 1 2 3 4 5 6 7 8 9]
W[1]: [[-0.27226824 -0.02672387 -1.35118418]
 [ 1.03448274 -1.13009851 -0.53772292]]
W[1] Shape: (2, 3)
W[2]: [[ 1.91646819e-01 -4.86305495e-01 -4.01227553e-01 -3.51851759e-01
   2.15498795e-01  9.00262607e-01  2.23875820e-02 -4.45063393e-01
   1.97099785e-01 -2.34362686e-01]
 [-3.99426762e-03  4.58680865e-01 -3.00731553e-01 -7.39663154e-04
  -3.40449836e-01 -7.32415400e-02  9.55499608e-02 -3.77044916e-01
  -1.19112104e-01 -9.38588043e-02]
 [-2.54866522e-01 -4.73815123e-01 -5.48427659e-01 -6.70061155e-02
  -9.20670733e-02  8.72480316e-01 -9.59579240e-01  5.13972509e-02
   1.49910124e-01  5.25886653e-01]]
W[2] Shape: (3, 10)
B[1]: [-0.00045843 -0.00015131 -0.00015516]
B[1] Shape: (3,)
B[2]: [-5.01683620e-05  2.36204952e-04  3.91689465e-04  2.11468706e-04
  1.42539567e-05 -1.22402523e-03  1.89624928e-04  3.22355945e-04
 -1.28728315e-04  3.73239533e-05]
B[2] Shape: (10,)
```

[65]:

```
nn_1.b
```

[65]:
```
{1: array([-0.00045843, -0.00015131, -0.00015516]),
 2: array([-5.01683620e-05,  2.36204952e-04,  3.91689465e-04,  2.11468706e-04,
        1.42539567e-05, -1.22402523e-03,  1.89624928e-04,  3.22355945e-04,
       -1.28728315e-04,  3.73239533e-05])}
```

15 [5 Points] Task 10 - Create Minibatches

In this task, you are required to implement the function `create_minibatches` which splits the dataset into multiple batches

[66]:
```python
#TODO: Complete create_minibatches
def create_minibatches(x,y,batch_size):
   indices = np.arange(x.shape[0])
   np.random.shuffle(indices)
   X_shuffled = x[indices]
   Y_shuffled = y[indices]

   n_batches = int(np.ceil(x.shape[0] // batch_size))
   for i in range(n_batches):
     x_batch = X_shuffled[i * batch_size:(i + 1) * batch_size]
     y_batch = Y_shuffled[i * batch_size:(i + 1) * batch_size]
     yield x_batch, y_batch
```

[67]:
```python
# DO NOT EDIT
# Test case to check create_mini_batches
rng = np.random.default_rng(42)
input = rng.random((500,64))
output = np.arange(500)
batch = 1
for xbatch,ybatch in create_minibatches(input,output,32):
  print(f"Batch: {batch} xbatch.shape: {xbatch.shape}, ybatch.shape: {ybatch.
↪shape}")
  assert xbatch.shape == (32,64) and ybatch.shape ==(32,)
  batch+=1
```

```
Batch: 1 xbatch.shape: (32, 64), ybatch.shape: (32,)
Batch: 2 xbatch.shape: (32, 64), ybatch.shape: (32,)
Batch: 3 xbatch.shape: (32, 64), ybatch.shape: (32,)
Batch: 4 xbatch.shape: (32, 64), ybatch.shape: (32,)
Batch: 5 xbatch.shape: (32, 64), ybatch.shape: (32,)
Batch: 6 xbatch.shape: (32, 64), ybatch.shape: (32,)
Batch: 7 xbatch.shape: (32, 64), ybatch.shape: (32,)
Batch: 8 xbatch.shape: (32, 64), ybatch.shape: (32,)
Batch: 9 xbatch.shape: (32, 64), ybatch.shape: (32,)
Batch: 10 xbatch.shape: (32, 64), ybatch.shape: (32,)
Batch: 11 xbatch.shape: (32, 64), ybatch.shape: (32,)
Batch: 12 xbatch.shape: (32, 64), ybatch.shape: (32,)
Batch: 13 xbatch.shape: (32, 64), ybatch.shape: (32,)
```

```
Batch: 14 xbatch.shape: (32, 64), ybatch.shape: (32,)
Batch: 15 xbatch.shape: (32, 64), ybatch.shape: (32,)
```

16 [10 Points] Task 11 - Fit Function

In this task, you are required to implement the `fit` function which implements the main training loop for the model.

[68]:
```
#TODO: Complete the function which implements the training loop for the model.
def fit (model, x, y, loss, epochs, batch_size, learning_rate=1e-3):
        """
        Args
          x: (array) Containing parameters
          y: (array) Containing one hot encoded labels.
          loss: Loss class (MSE, CrossEntropy etc.)
          epochs: (int) Number of epochs.
          batch_size: (int)
          learning_rate: (flt)
        """
        if not x.shape[0] == y.shape[0]:
            raise ValueError("Length of x and y arrays don't match")
        # Initiate the loss object with the final activation function
        loss_plot = []
        model.loss = loss
        model.learning_rate = learning_rate


        for i in range(epochs + 1):
          for x_,y_ in create_minibatches(x,y,batch_size):
            # Compute forward pass on x_
            z,a = forward(model,x_)
            # Compute backward pass on y_
            backprop(model,z,a,y_)

          # Compute forward pass on the entire dataset
          _, a = forward(model, x)
          # Compute the loss using y and the output from the last activation␣
 ↪layer
          out = a[model.n_layers]
          l = loss.loss(y, out)
          loss_plot.append(l)
          print(f'Epoch: {i} , Loss: {l}')
        plt.figure(figsize=(10,8))
        plt.grid()
        plt.title("Cross Entropy Loss vs. Epochs")
        plt.xlabel("Epochs")
        plt.ylabel("Cross Entropy Loss")
```

```
        plt.plot(loss_plot)
        plt.show()
```

17 Combining it all together

[69]:
```
# DO NOT EDIT
X = data["data"]
y = data["target"]
```

[70]:
```
# DO NOT EDIT
X.shape,y.shape
```

[70]:
```
((1797, 64), (1797,))
```

[71]:
```
# DO NOT EDIT
X_train,X_test,Y_train,Y_test = sklearn.model_selection.
 ↪train_test_split(X,y,test_size=0.2,random_state=2)
```

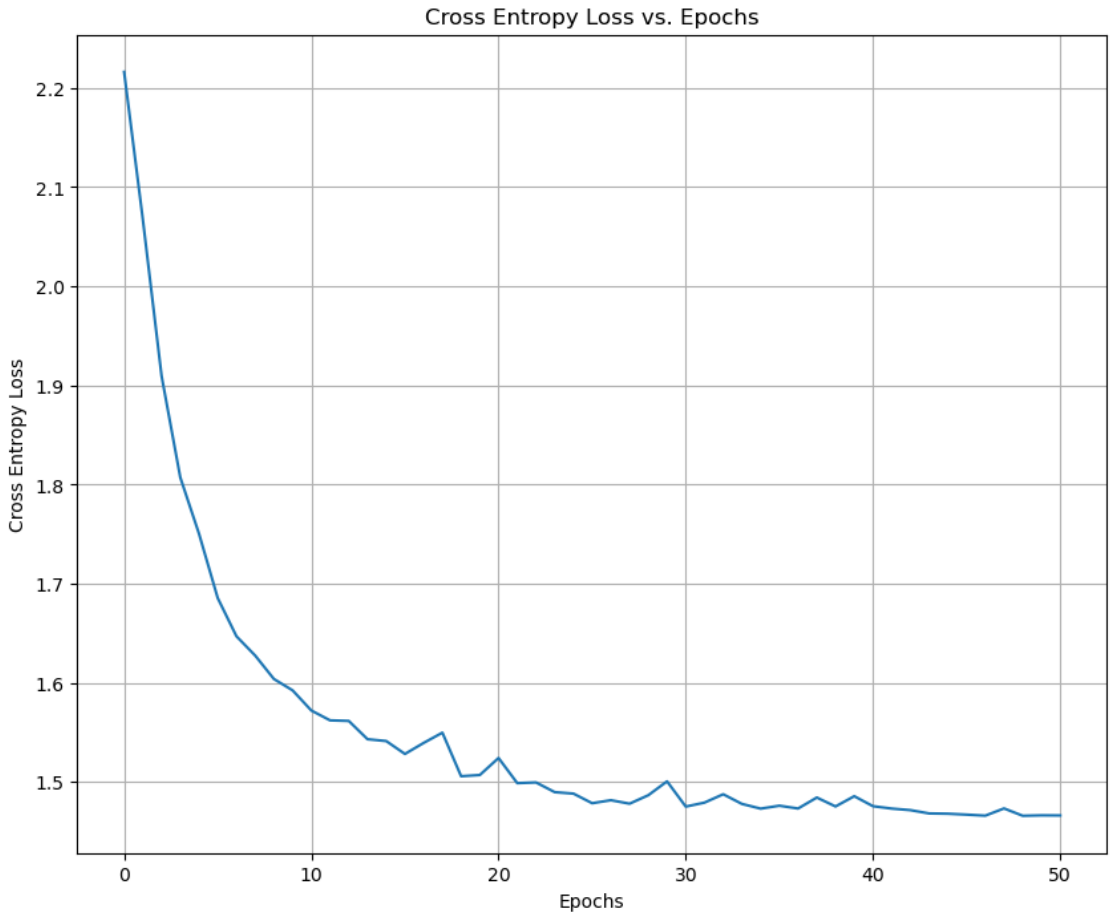
[72]:
```
# DO NOT EDIT
print(X_train.shape,X_test.shape,Y_train.shape,Y_test.shape)
```

```
(1437, 64) (360, 64) (1437,) (360,)
```

[73]:
```
# DO NOT EDIT
np.random.seed(2)
mlp = Network((64,32,64,128,10),(Relu,Relu,Sigmoid,Softmax))
fit(mlp,X_train,Y_train,CrossEntropy,batch_size=32,learning_rate=5e-4,epochs=50)
```

```
Epoch: 0 , Loss: 2.216244196200133
Epoch: 1 , Loss: 2.0674083135059895
Epoch: 2 , Loss: 1.909676163807208
Epoch: 3 , Loss: 1.8072546513720127
Epoch: 4 , Loss: 1.7504778162546484
Epoch: 5 , Loss: 1.6855998511499142
Epoch: 6 , Loss: 1.6470624860864551
Epoch: 7 , Loss: 1.6276287702147634
Epoch: 8 , Loss: 1.6040001579810566
Epoch: 9 , Loss: 1.5924993625888502
Epoch: 10 , Loss: 1.572198245330661
Epoch: 11 , Loss: 1.5622729277496898
Epoch: 12 , Loss: 1.5616771814870838
Epoch: 13 , Loss: 1.5432643738303884
Epoch: 14 , Loss: 1.54139646941511
Epoch: 15 , Loss: 1.5283856256772912
Epoch: 16 , Loss: 1.539507384313876
Epoch: 17 , Loss: 1.5498547783245613
Epoch: 18 , Loss: 1.5059223761910312
Epoch: 19 , Loss: 1.5071528491075667
```

```
Epoch: 20 , Loss: 1.5243048853531782
Epoch: 21 , Loss: 1.4989530640037267
Epoch: 22 , Loss: 1.4996621234242158
Epoch: 23 , Loss: 1.4898541133952006
Epoch: 24 , Loss: 1.4883979277633026
Epoch: 25 , Loss: 1.4786931892562762
Epoch: 26 , Loss: 1.4817314116884324
Epoch: 27 , Loss: 1.478234558457138
Epoch: 28 , Loss: 1.4867608525813492
Epoch: 29 , Loss: 1.5007571259006147
Epoch: 30 , Loss: 1.4752968049508732
Epoch: 31 , Loss: 1.4793041404296945
Epoch: 32 , Loss: 1.487746279573507
Epoch: 33 , Loss: 1.4780004929641952
Epoch: 34 , Loss: 1.4732295134872757
Epoch: 35 , Loss: 1.4761807604607273
Epoch: 36 , Loss: 1.4733501708453696
Epoch: 37 , Loss: 1.4844296371468297
Epoch: 38 , Loss: 1.4754240981873514
Epoch: 39 , Loss: 1.4857791774499696
Epoch: 40 , Loss: 1.4756915566366828
Epoch: 41 , Loss: 1.4732942788687895
Epoch: 42 , Loss: 1.471715500221115
Epoch: 43 , Loss: 1.4683970460198223
Epoch: 44 , Loss: 1.4680921046349267
Epoch: 45 , Loss: 1.46718721028455
Epoch: 46 , Loss: 1.4661474379725774
Epoch: 47 , Loss: 1.4734457384038377
Epoch: 48 , Loss: 1.4660248515054615
Epoch: 49 , Loss: 1.4664679629664792
Epoch: 50 , Loss: 1.4663579344014719
```



The expected plot of Cross Entropy loss vs Epochs

[74]:
```
#  DO NOT EDIT
y_pred = predict(mlp,X_test)
y_acc = compute_accuracy(y_pred,Y_test)
y_acc
```

[74]: 0.9555555555555556

The expected test accuracy is 95.5%