Assignment1

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1 Programming Assignment 1: MNIST Classification using MLP

1.1 EE5179:Deep Learning for Imaging

1.2 Classification using MLP

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2 All imports

[1]:
```
import numpy as np
from scipy.special import expit
import matplotlib.pyplot as plt
from sklearn.metrics import classification_report
from datetime import datetime
import torch
from torchvision import datasets
from torch.utils.data import DataLoader, random_split, TensorDataset
from torchvision.transforms import ToTensor
```

3 Helper classes and functions.

We will first get some helper classes and functions which will be used for implementing the back-propogation algorithm from scratch

3.1 Loss functions

We define a class on various loss functions

[ ]:
```
class LossFunctions:

    class SquaredErrorLoss:
        def __init__(self, alpha=0.01, regularization='l2'):
            """
            Initializes the SquaredErrorLoss with optional L1 or L2␣
↪regularization.
```

```
        Parameters:
        alpha (float): Regularization constant.
        regularization (str): Type of regularization ('l1' for L1, 'l2' for␣
↪L2, or None).
        """
        self.alpha = alpha
        self.regularization = regularization

    def __call__(self, y_pred, y_true, model_weights=None):
        """
        Computes the Mean Squared Error (MSE) with optional L1 or L2␣
↪regularization.

        Parameters:
        y_pred (ndarray): The predicted values.
        y_true (ndarray): The true values.
        model_weights (list): A list of model weights (e.g., numpy arrays).

        Returns:
        float: The regularized mean squared error.
        """
        mse_loss = 0.5 * np.mean((y_pred - y_true) ** 2)

        # Regularization term
        if self.regularization == 'l2':
            reg_term = self.alpha * sum(np.sum(w ** 2) for w in␣
↪model_weights)
        elif self.regularization == 'l1':
            reg_term = self.alpha * sum(np.sum(np.abs(w)) for w in␣
↪model_weights)
        else:
            reg_term = 0  # No regularization

        return mse_loss + reg_term

    def gradient(self, y_pred, y_true, model_weights=None):
        """
        Computes the gradient of the Mean Squared Error (MSE) Loss with␣
↪respect to y_pred,
        including the gradient of the regularization term.

        Parameters:
        y_pred (ndarray): The predicted values.
        y_true (ndarray): The true values.
        model_weights (list): A list of model weights (e.g., numpy arrays).

        Returns:
```

```python
            tuple: The gradient with respect to y_pred and the gradients with respect to the model weights.
        """
        gradient_y_pred = 2 * (y_pred - y_true)


        gradients_weights = []
        if model_weights is not None:
            for w in model_weights:
                if self.regularization == 'l2':
                    grad_w = self.alpha * w
                elif self.regularization == 'l1':
                    grad_w = self.alpha * np.sign(w)
                else:
                    grad_w = np.zeros_like(w)
                gradients_weights.append(grad_w)

        return gradient_y_pred, gradients_weights

    def __repr__(self):
        return f"SquaredErrorLoss(alpha={self.alpha}, regularization={self.regularization})"



class CrossEntropyLoss:
    def __init__(self, alpha=0.01, regularization=None):
        self.alpha = alpha
        self.regularization = regularization

    def __call__(self, y_pred, y_true, model_weights):

        y_pred = np.clip(y_pred, 1e-15, 1 - 1e-15)
        ce_loss = -np.sum(y_true * np.log(y_pred))


        if self.regularization == 'l2':
            reg_term = self.alpha * sum(np.sum(w ** 2) for w in model_weights)
        elif self.regularization == 'l1':
            reg_term = self.alpha * sum(np.sum(np.abs(w)) for w in model_weights)
        else:
            reg_term = 0

        return ce_loss + reg_term
```

```
    def gradient(self, y_pred, y_true, model_weights):
        """
        Compute the gradient of the Cross-Entropy Loss with respect to␣
↪y_pred,
        including the gradient of the regularization term.

        Parameters:
        y_pred (ndarray): The predicted probabilities (output of softmax)␣
↪of shape (num_classes,).
        y_true (ndarray): The one-hot encoded true labels of shape␣
↪(num_classes,).
        model_weights (list): A list of model weights (e.g., numpy arrays).

        Returns:
        list: A list containing the gradient with respect to y_pred and the␣
↪gradients
              with respect to the model weights.
        """

        y_pred = np.clip(y_pred, 1e-15, 1 - 1e-15)
        gradient_y_pred = -(y_true / y_pred)


        gradients_weights = []
        for w in model_weights:
            if self.regularization == 'l2':
                grad_w = self.alpha * w
            elif self.regularization == 'l1':
                grad_w = self.alpha * np.sign(w)
            else:
                grad_w = np.zeros_like(w)
            gradients_weights.append(grad_w)


        return gradient_y_pred, gradients_weights


    def __repr__(self):
        return f"CrossEntropyLoss(alpha={self.alpha}, regularization={self.
↪regularization})"
```

3.2 Activation functions

We define the activation functions and its gradients.

[ ]:
```
class Activations:
```

```
class ReLU:
    def __call__(self, x):
        """
        Applies the ReLU activation function element-wise to the given␣
↪input x.

        Args:
            x (numpy array): The input array.

        Returns:
            numpy array: The output of the ReLU activation function, which␣
↪is element-wise max(0, x).
        """
        return np.maximum(0, x)

    def gradient(self, x):
        """
        Computes the gradient (derivative) of the ReLU function for␣
↪backpropagation.

        Args:
            x (numpy array): The input array.

        Returns:
            numpy array: The gradient of ReLU, which is 1 for x > 0 and 0␣
↪otherwise.
        """
        return np.where(x > 0, 1, 0)



class Sigmoid:

    def __call__(self, x):
        """
        Applies the Sigmoid activation function to the given input x.

        Args:
            x (float): The input value.

        Returns:
            float: The output of the Sigmoid activation function.
        """
        return expit(x)

    def gradient(self, x):
        """
```

```python
        Computes the gradient of the Sigmoid activation function.

        Args:
            x (float): The input value.

        Returns:
            float: The gradient of the Sigmoid activation function.
        """
        return self.__call__(x) * (1 - self.__call__(x))




class Softmax:

    def __call__(self, x):
        """
        Applies the Softmax activation function to the given input x.

        Args:
            x (numpy.ndarray): The input array.

        Returns:
            numpy.ndarray: The output of the Softmax activation function.
        """
        exp_x = np.exp(x - np.max(x))  # Subtracting max(x) for numerical␣
↪stability
        return exp_x / np.sum(exp_x, axis=0)

    def gradient(self, x):
        """
        Computes the gradient of the Softmax activation function.

        Args:
            x (numpy.ndarray): The input array.

        Returns:
            numpy.ndarray: The Jacobian matrix of the Softmax activation␣
↪function.
        """
        s = self.__call__(x)
        jacobian_matrix = np.diagflat(s) - np.outer(s, s)
        return jacobian_matrix

    def __repr__(self):
        return "Softmax"
```

```python
class Tanh:

    def __call__(self, x):
        """
        Applies the Tanh activation function to the given input x.

        Args:
            x (numpy.ndarray): The input array.

        Returns:
            numpy.ndarray: The output of the Tanh activation function.
        """
        return np.tanh(x)

    def gradient(self, x):
        """
        Computes the gradient of the Tanh activation function.

        Args:
            x (numpy.ndarray): The input array.

        Returns:
            numpy.ndarray: The derivative of the Tanh activation function.
        """
        return 1 - np.power(self.__call__(x), 2)

class Linear:

    def __call__(self, x):
        """
        Returns the input value.

        Parameters:
            x (Any): The input value.

        Returns:
            Any: The input value.
        """
        return x

    def gradient(self, x):
        """
        Computes the gradient of the Linear activation function.

        Args:
            x (Any): The input value.
```

```
        Returns:
            int: The derivative of the Linear activation function, which is␣
↪always 1.
        """
        return 1
```

3.3 Initialization

We define various initialization methods here

[ ]:
```
import numpy as np

class ParameterInitializer:
    def __init__(self, initialization='random'):
        """
        Parameters:
        initialization (str): 'random' for uniform random initialization,
                              'gaussian' for Gaussian distribution,
                              'glorot' for Glorot initialization.
        """
        self.initialization = initialization

    def initialize_parameters(self, inputs, hidden_layers, outputs):
        """
        Initializes the parameters for a neural network.

        Args:
            inputs (int): The number of input nodes.
            hidden_layers (list): A list of integers representing the number of␣
↪nodes in each hidden layer.
            outputs (int): The number of output nodes.

        Returns:
            dict: A dictionary containing the initialized parameters, with keys␣
↪"W1" and "b1" for the first layer, and "W{i+1}" and "b{i+1}" for each hidden␣
↪layer, where i is the index of the layer. The last two keys are␣
↪"W{len(hidden_layers) + 1}" and "b{len(hidden_layers) + 1}" for the output␣
↪layer.

        Raises:
            None.
        """
        parameters = {}

        if self.initialization == 'random':
            parameters["W1"] = np.random.rand(hidden_layers[0], inputs)
```

```
            parameters["b1"] = np.random.rand(hidden_layers[0])

        elif self.initialization == 'gaussian':
            parameters["W1"] = np.random.randn(hidden_layers[0], inputs)
            parameters["b1"] = np.random.randn(hidden_layers[0])

        elif self.initialization == 'glorot':
            parameters["W1"] = np.random.uniform(-np.sqrt(6 / (inputs +␣
↪hidden_layers[0])),
                                                  np.sqrt(6 / (inputs +␣
↪hidden_layers[0])),
                                                  (hidden_layers[0], inputs))
            parameters["b1"] = np.zeros(hidden_layers[0])

        for i in range(1, len(hidden_layers)):
            if self.initialization == 'random':
                parameters[f"W{i+1}"] = np.random.rand(hidden_layers[i],␣
↪hidden_layers[i - 1])
                parameters[f"b{i+1}"] = np.random.rand(hidden_layers[i])
            elif self.initialization == 'gaussian':
                parameters[f"W{i+1}"] = np.random.randn(hidden_layers[i],␣
↪hidden_layers[i - 1])
                parameters[f"b{i+1}"] = np.random.randn(hidden_layers[i])
            elif self.initialization == 'glorot':
                parameters[f"W{i+1}"] = np.random.uniform(-np.sqrt(6 /␣
↪(hidden_layers[i - 1] + hidden_layers[i])),
                                                          np.sqrt(6 /␣
↪(hidden_layers[i - 1] + hidden_layers[i])),
                                                          (hidden_layers[i],␣
↪hidden_layers[i - 1]))
                parameters[f"b{i+1}"] = np.zeros(hidden_layers[i])

        if self.initialization == 'random':
            parameters[f"W{len(hidden_layers) + 1}"] = np.random.rand(outputs,␣
↪hidden_layers[-1])
            parameters[f"b{len(hidden_layers) + 1}"] = np.random.rand(outputs)
        elif self.initialization == 'gaussian':
            parameters[f"W{len(hidden_layers) + 1}"] = np.random.randn(outputs,␣
↪hidden_layers[-1])
            parameters[f"b{len(hidden_layers) + 1}"] = np.random.randn(outputs)
        elif self.initialization == 'glorot':
            parameters[f"W{len(hidden_layers) + 1}"] = np.random.uniform(-np.
↪sqrt(6 / (hidden_layers[-1] + outputs)),
                                                                          np.
↪sqrt(6 / (hidden_layers[-1] + outputs)),
```

```
↪(outputs, hidden_layers[-1]))
            parameters[f"b{len(hidden_layers) + 1}"] = np.zeros(outputs)

        return parameters
```

4 Feed Forward Neural Netowrk Implementation

[ ]:
```
softmax = Activations.Softmax()
sigmoid = Activations.Sigmoid()
crossentropy = LossFunctions.CrossEntropyLoss()

class FeedForwardNeuralNets:
    def __init__(self, inputs, hidden_layers, outputs, g=sigmoid,␣
↪L=crossentropy, O=softmax, eta=0.01,
                 optimizer="gd", initialization_method="glorot", batch_size=32,
                 beta1=0.9, beta2=0.999, epsilon=1e-8, t=0):
        self.inputs = inputs
        self.outputs = outputs
        self.batch_size = min(batch_size, inputs.shape[0])
        if len(self.outputs.shape) < 2:
            self.parameters = ParameterInitializer(initialization_method).
↪initialize_parameters(
            inputs[0].shape[0], hidden_layers, 1)
        else:
            self.parameters = ParameterInitializer(initialization_method).
↪initialize_parameters(
                inputs[0].shape[0], hidden_layers, outputs[0].shape[0])
        self.g = g
        self.O = O
        self.L = L
        self.eta = eta
        self.losses = {}
        self.activations = {}
        self.beta1 = beta1
        self.beta2 = beta2
        self.epsilon = epsilon
        self.t = t
        self.v = {key: np.zeros_like(value) for key, value in self.parameters.
↪items()}
        self.s = {key: np.zeros_like(value) for key, value in self.parameters.
↪items()}
        self.training_loss = []
        self.validation_loss = []
```

```
        if optimizer == "gd":
            self.optimizer = self.gradient_descent
        elif optimizer == "adam":
            self.optimizer = self.adam

    def forward_propogation(self, x):
        """
        Performs forward propagation through the neural network.

        Parameters:
            x (numpy array): The input to the neural network.

        Returns:
            y_pred (numpy array): The predicted output of the neural network.
        """

        self.activations["a1"] = self.parameters["W1"] @ x + self.
↪parameters["b1"]
        self.activations["h1"] = self.g(self.activations["a1"])
        for i in range(2, len(self.parameters) // 2):
            self.activations[f"a{i}"] = self.parameters[f"W{i}"] @ self.
↪activations[f"h{i - 1}"] + self.parameters[f"b{i}"]
            self.activations[f"h{i}"] = self.g(self.activations[f"a{i}"])

        self.activations[f"a{len(self.parameters) // 2}"] = self.
↪parameters[f"W{len(self.parameters) // 2}"] @ self.activations[f"h{len(self.
↪parameters) // 2 - 1}"] + self.parameters[f"b{len(self.parameters) // 2}"]
        y_pred = self.O(self.activations[f"a{len(self.parameters) // 2}"])
        return y_pred

    def backPropogation(self, y_pred, y, x):
        """
        Performs backpropagation through the neural network.

        Parameters:
            y_pred (numpy array): The predicted output of the neural network.
            y (numpy array): The actual output of the neural network.
            x (numpy array): The input to the neural network.

        Returns:
            None
        """
        n = len(self.parameters) // 2
        m = len(self.activations) // 2

        La = y_pred - y
```

```python
        Lh = La @ self.parameters[f"W{n}"]

        da = self.g.gradient(self.activations[f"a{m}"])
        self.losses[f"W{n}"] = np.outer(La, self.activations[f"h{m}"])
        self.losses[f"b{n}"] = La.copy()

        for i in range(1, m):
            La = Lh * da
            Lh = La @ self.parameters[f"W{m - i + 1}"]
            da = self.g.gradient(self.activations[f"a{m - i}"])
            self.losses[f"W{m - i + 1}"] = np.outer(La, self.activations[f"h{m␣
↪- i}"])
            self.losses[f"b{m - i + 1}"] = La.copy()

        La = Lh * da
        self.losses["W1"] = np.outer(La, x)
        self.losses["b1"] = La.copy()

        _, gradients_weights = self.L.gradient(y_pred, y, list(self.parameters.
↪values()))

        for i, key in enumerate(self.parameters.keys()):
            if key.startswith('W'):
                self.losses[key] += gradients_weights[i]



    def gradient_descent(self):
        """
        Performs gradient descent optimization on the neural network's␣
↪parameters.

        Updates the weights (W) and biases (b) of the neural network by␣
↪subtracting the product of the learning rate (eta) and the corresponding␣
↪losses.

        Parameters:
            None

        Returns:
            None
        """
        for i in range(len(self.parameters) // 2):
            self.parameters[f"W{i + 1}"] = self.parameters[f"W{i + 1}"] - self.
↪eta * self.losses[f"W{i + 1}"]
            self.parameters[f"b{i + 1}"] = self.parameters[f"b{i + 1}"] - self.
↪eta * self.losses[f"b{i + 1}"]
```

```
    def adam(self):
        """
        Performs Adam optimization on the neural network's parameters.

        Updates the weights (W) and biases (b) of the neural network using the␣
↪Adam optimization algorithm.

        Parameters:
            None

        Returns:
            None
        """
        self.t += 1
        for key in self.parameters.keys():
            if key.startswith("W") or key.startswith("b"):
                gradient = self.losses[key]

                self.v[key] = self.beta1 * self.v[key] + (1 - self.beta1) *␣
↪gradient
                self.s[key] = self.beta2 * self.s[key] + (1 - self.beta2) *␣
↪(gradient ** 2)

                v_corrected = self.v[key] / (1 - self.beta1 ** self.t)
                s_corrected = self.s[key] / (1 - self.beta2 ** self.t)

                self.parameters[key] -= self.eta * v_corrected / (np.
↪sqrt(s_corrected) + self.epsilon)

    def train(self, epochs, validation_data=None):
        """
        Trains the neural network model for a specified number of epochs.

        This function takes in the number of epochs as input and performs the␣
↪following operations:
            - Shuffles the input data and corresponding outputs.
            - Divides the shuffled data into batches based on the batch size.
            - For each batch, it calculates the total gradient loss by␣
↪iterating over each input and output pair.
            - It then updates the model parameters using the optimizer function.
            - If validation data is provided, calculates and appends the␣
↪validation loss every 200 iterations.

        Parameters:
```

```
            epochs (int): The number of epochs to train the model for.
            validation_data (tuple): A tuple containing validation inputs and␣
↪outputs.

        Returns:
            None
        """
        for epoch in range(epochs):
            permutation = np.random.permutation(self.inputs.shape[0])
            inputs_shuffled = self.inputs[permutation]
            outputs_shuffled = self.outputs[permutation]

            total_loss = 0

            for i in range(0, self.inputs.shape[0], self.batch_size):
                batch_inputs = inputs_shuffled[i:i + self.batch_size]
                batch_outputs = outputs_shuffled[i:i + self.batch_size]

                total_gradient_loss = {key: 0 for key in self.parameters.keys()}
                batch_loss = 0

                for x, y in zip(batch_inputs, batch_outputs):
                    y_pred = self.forward_propogation(x)
                    batch_loss += self.L(y_pred, y, list(self.parameters.
↪values()))
                    self.backPropogation(y_pred, y, x)

                    for key in total_gradient_loss:
                        total_gradient_loss[key] += self.losses.get(key, 0)

                for key in total_gradient_loss:
                    total_gradient_loss[key] /= self.batch_size

                self.optimizer()

                total_loss += batch_loss / self.batch_size


                if (i // self.batch_size) % 200 == 0:
                    iteration_loss = batch_loss / self.batch_size
                    self.training_loss.append(iteration_loss)

                    if validation_data is not None:
                        val_inputs, val_outputs = validation_data
                        val_loss = 0
                        for x_val, y_val in zip(val_inputs, val_outputs):
                            y_pred_val = self.forward_propogation(x_val)
```

```
                                val_loss += self.L(y_pred_val, y_val, list(self.
↪parameters.values()))
                            val_loss /= val_inputs.shape[0]
                            self.validation_loss.append(val_loss)

            epoch_loss = total_loss / (self.inputs.shape[0] // self.batch_size)
            if validation_data is not None:
                val_loss = self.validation_loss[-1] if self.validation_loss␣
↪else None
                print(f'Epoch {epoch + 1}/{epochs}, Training Loss: {epoch_loss:.
↪4f}, Validation Loss: {val_loss:.4f}')
            else:
                print(f'Epoch {epoch + 1}/{epochs}, Training Loss: {epoch_loss:.
↪4f}')


    def evaluate(self, X):
        """
        Evaluates the neural network model for the given input X.

        Parameters:
            X (numpy array): The input to the neural network.

        Returns:
            numpy array: The predicted output of the neural network.
        """
        return np.array(self.forward_propogation(X))

    def predict(self, X):
        """
        Uses evaluate function and get arg max and get the prediction

        Parameters:
            X (numpy array): The input to the neural network

        Returns:
            Class label: The label that has the highest probabiltiy
        """
        return np.argmax(self.evaluate(X))
```

5 Example Implementation

[ ]:
```
X = np.array([
    [0.1, 0.5, 0.2, 0.9, 0.3, 0.6, 0.4, 0.8, 0.7, 0.2],
    [0.3, 0.2, 0.7, 0.4, 0.6, 0.8, 0.9, 0.5, 0.1, 0.3],
    [0.8, 0.9, 0.4, 0.1, 0.5, 0.2, 0.7, 0.6, 0.3, 0.9],
```

```
    [0.6, 0.2, 0.3, 0.7, 0.4, 0.1, 0.8, 0.9, 0.5, 0.6],
    [0.5, 0.1, 0.8, 0.2, 0.9, 0.7, 0.3, 0.4, 0.6, 0.5],
    [0.7, 0.3, 0.6, 0.5, 0.8, 0.4, 0.1, 0.2, 0.9, 0.7],
    [0.2, 0.8, 0.1, 0.6, 0.4, 0.5, 0.7, 0.3, 0.2, 0.8],
    [0.9, 0.6, 0.5, 0.3, 0.7, 0.2, 0.4, 0.1, 0.8, 0.6],
    [0.4, 0.7, 0.9, 0.8, 0.2, 0.3, 0.6, 0.5, 0.1, 0.4],
    [0.5, 0.3, 0.7, 0.4, 0.1, 0.8, 0.2, 0.6, 0.7, 0.5]
])

y = np.array([1, 0, 1, 0, 1, 0, 1, 0, 1, 0])
num_classes = len(np.unique(y))
y_one_hot = np.eye(num_classes)[y]

print("One-hot encoded y:")
print(y_one_hot)
```

```
One-hot encoded y:
[[0. 1.]
 [1. 0.]
 [0. 1.]
 [1. 0.]
 [0. 1.]
 [1. 0.]
 [0. 1.]
 [1. 0.]
 [0. 1.]
 [1. 0.]]
```

[ ]:
```
g_1 = LossFunctions.CrossEntropyLoss()
g_2 = LossFunctions.CrossEntropyLoss(regularization='l2')

model = FeedForwardNeuralNets(X, [50], y_one_hot, L=g_2, optimizer="adam",␣
 ↪g=Activations.ReLU(), eta=0.01,
                             )
model.train(epochs=500, validation_data=[X, y_one_hot])
```

[ ]:
```
for i in X:
    print(model.evaluate(i))
```

```
[0.07989294 0.92010706]
[0.77283669 0.22716331]
[0.04117688 0.95882312]
[0.93341553 0.06658447]
[0.34602394 0.65397606]
[0.94823665 0.05176335]
[0.0046353 0.9953647]
[0.93805742 0.06194258]
[0.04854306 0.95145694]
```

```
[0.76807655 0.23192345]
```

[ ]:
```
model.parameters
```

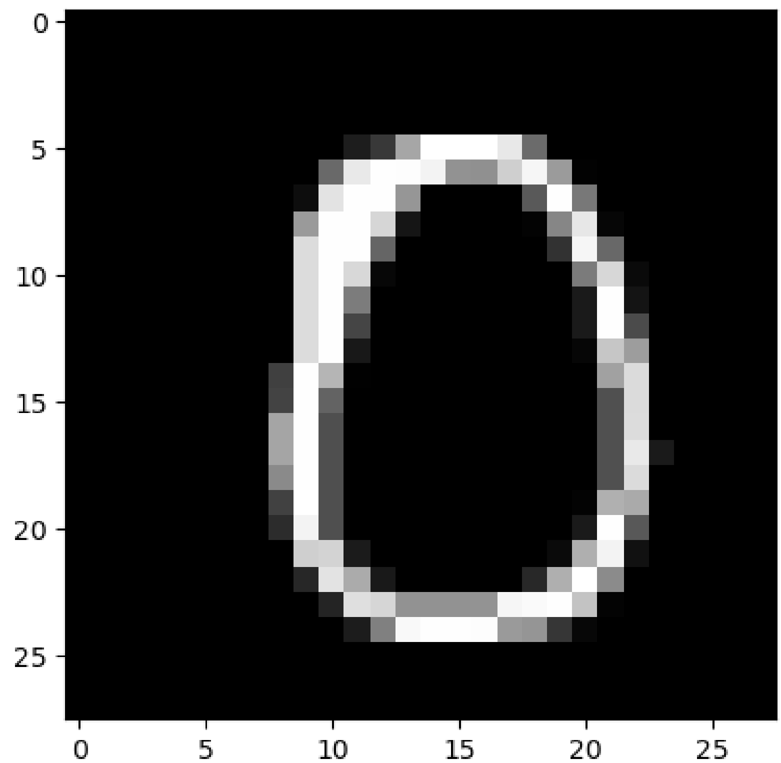
6 Importing MNIST Dataset

[2]:
```
training_data = datasets.MNIST(
    root="data",
    train=True,
    download=True,
    transform=ToTensor()
)

test_data = datasets.MNIST(
    root="data",
    train=False,
    download=True,
    transform=ToTensor()
)
```

[3]:
```
validation_size = 10000
training_size = len(training_data) - validation_size

train_dataset, val_dataset = random_split(training_data, [training_size,␣
 ↪validation_size])

train_loader = DataLoader(training_data, batch_size=training_size, shuffle=True)
val_loader = DataLoader(val_dataset, batch_size=validation_size, shuffle=False)

train_data = next(iter(train_loader))
X_train = train_data[0].numpy()
y_train = train_data[1].numpy()

val_data = next(iter(val_loader))
X_val = val_data[0].numpy()
y_val = val_data[1].numpy()
```

[ ]:
```
plt.imshow(X_train[6].reshape(28, 28), cmap="gray"), y_train[6]
```

[ ]:
```
(<matplotlib.image.AxesImage at 0x7f9c7aaad280>, 0)
```



7 Normalize the inputs to zero mean and unit variance

[ ]:
```
def preprocess(X, y):

    X = X / 255.0
    mean = X.mean()
    std = X.std()
    X = (X - mean) / std

    X = X.reshape(X.shape[0], -1)

    num_classes = len(np.unique(y))
    return X, np.eye(num_classes)[y]

X_train, y_train_one_hot = preprocess(X_train, y_train)
X_val, y_val_one_hot = preprocess(X_val, y_val)
```

8 Train the network with given configuration

As given as the base line model we will train the network according to the given configuration.

Default : - $\eta = 0.01$ - Initialization method : Glorot - Activation : Sigmoid - Loss function : Cross Entropy - Output function : Softmax

Hidden Layers : - $h_1 = 500$ - $h_2 = 250$ - $h_3 = 100$ - $i/p = 28 \times 28 = 764 \times 1$ (After flattening) - $o/p = 10 \times 1$ (Number of classes)

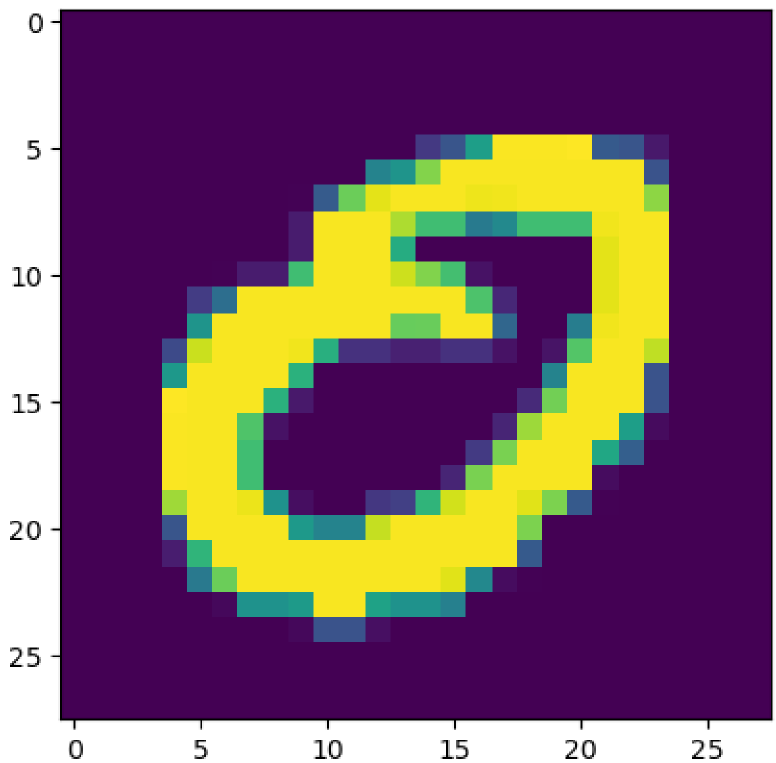
Number of epochs : 15

[ ]:
```
baselineModel = FeedForwardNeuralNets(X_train, [500, 250, 100],␣
 ↪y_train_one_hot, optimizer="gd", batch_size=64)


start_time = datetime.now()



baselineModel.train(epochs=15, validation_data=[X_val, y_val_one_hot])


end_time = datetime.now()

time_taken = end_time - start_time
print(f"Total time taken for training: {time_taken}")

# This cell takes to run approx. 44 mins with a 8 core CPU
```

```
Epoch 1/15, Training Loss: 2.3346, Validation Loss: 2.3094
Epoch 2/15, Training Loss: 2.2171, Validation Loss: 2.1922
Epoch 3/15, Training Loss: 1.9972, Validation Loss: 1.8870
Epoch 4/15, Training Loss: 1.5686, Validation Loss: 1.4182
Epoch 5/15, Training Loss: 1.1994, Validation Loss: 1.1047
Epoch 6/15, Training Loss: 0.9789, Validation Loss: 0.9207
Epoch 7/15, Training Loss: 0.8371, Validation Loss: 0.7936
Epoch 8/15, Training Loss: 0.7298, Validation Loss: 0.7354
Epoch 9/15, Training Loss: 0.6592, Validation Loss: 0.6320
Epoch 10/15, Training Loss: 0.5953, Validation Loss: 0.5839
Epoch 11/15, Training Loss: 0.5517, Validation Loss: 0.5399
Epoch 12/15, Training Loss: 0.5212, Validation Loss: 0.5037
Epoch 13/15, Training Loss: 0.4858, Validation Loss: 0.5226
Epoch 14/15, Training Loss: 0.4673, Validation Loss: 0.4718
Epoch 15/15, Training Loss: 0.4487, Validation Loss: 0.4499
Total time taken for training: 0:44:24.319133
```

[ ]:
```
plt.imshow(X_val[6].reshape(28, 28))
```

[ ]:
```
<matplotlib.image.AxesImage at 0x7f9c78739490>
```



[ ]:
```
baselineModel.predict(X_val[600]), y_val[600]
```

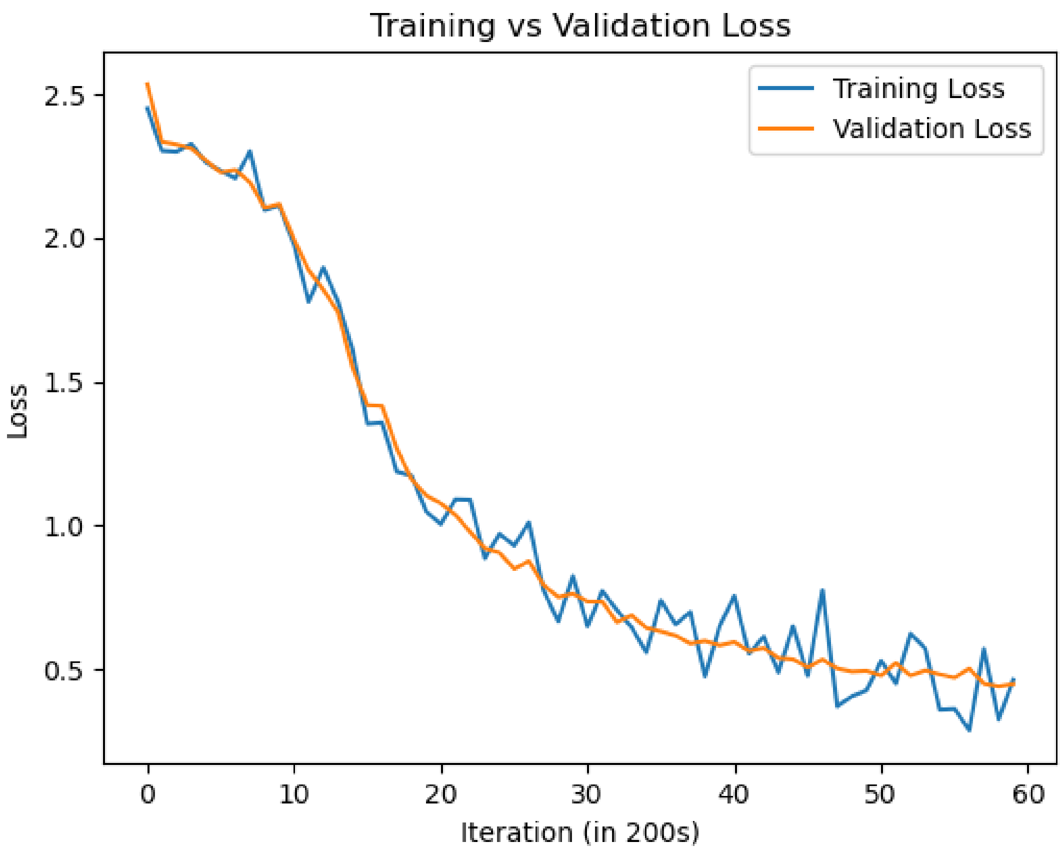
[ ]: (5, 5)

9 Plotting the Train and validation loss for every 200 iterations for baseline model

We will try to plot how the loss varies for every 200 iterations.

[ ]:
```
x_axis = np.arange(60)
train_loss = np.array(baselineModel.training_loss)
validation_loss = np.array(baselineModel.validation_loss)

plt.plot(x_axis, train_loss, label='Training Loss')
plt.plot(x_axis, validation_loss, label='Validation Loss')

plt.title('Training vs Validation Loss')
plt.xlabel('Iteration (in 200s)')
plt.ylabel('Loss')
```

```
plt.legend()
plt.savefig('training_vs_validation_loss.png')
plt.show()
```



10 Testing with actualy test data

[ ]:
```
test_loader = DataLoader(test_data, batch_size=len(test_data), shuffle=False)


X_test, y_test = next(iter(test_loader))
X_test = X_test.numpy()
y_test = y_test.numpy()

X_test, y_test_one_hot = preprocess(X_test, y_test)
```

[ ]:
```
X_train.shape, X_test.shape
```

[ ]: ((50000, 784), (10000, 784))

[ ]:
```
baselineModel.predict(X_test[6]), y_test[6]
```

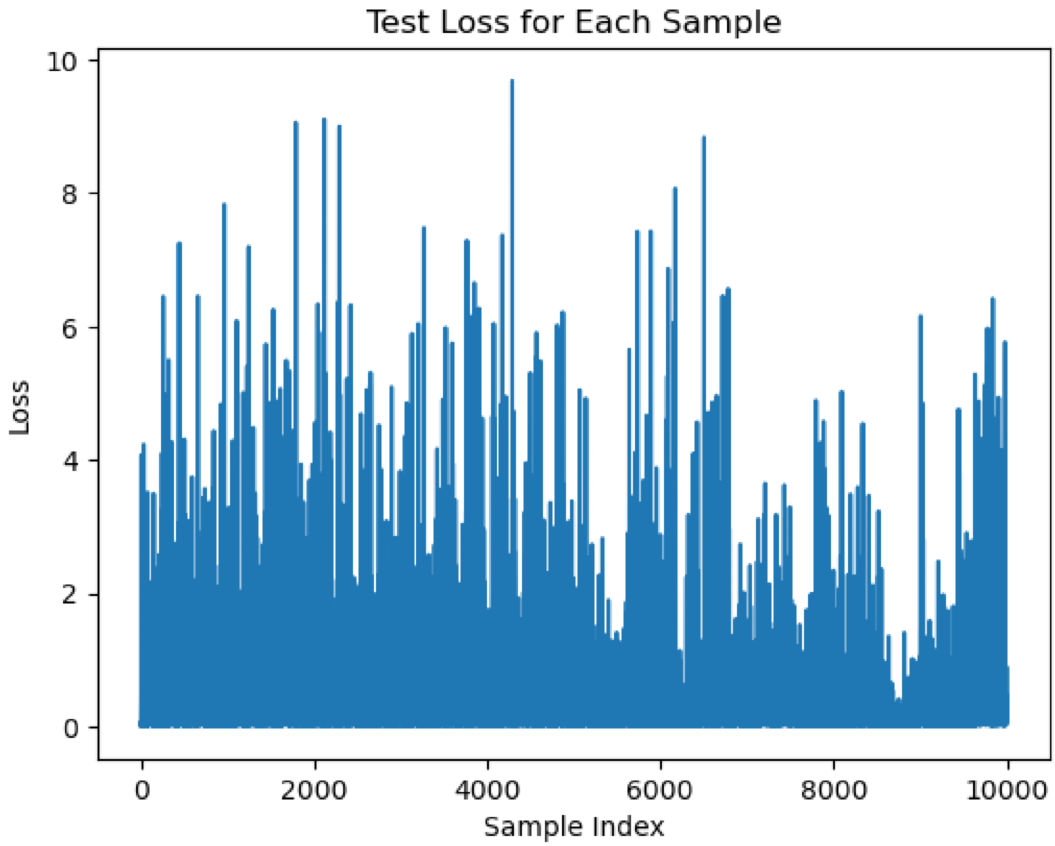
[ ]:
```
(4, 4)
```

11 Calculate Loss for test data and plot it

[ ]:
```
test_losses = []


for x, y_true in zip(X_test, y_test_one_hot):
    y_pred = baselineModel.forward_propogation(x)
    loss = baselineModel.L(y_pred, y_true, list(baselineModel.parameters))
    test_losses.append(loss)


test_losses = np.array(test_losses)
test_losses
```

[ ]:
```
array([0.01107608, 0.07231415, 0.03132954, …, 0.90026971, 0.14412548,
       0.10986916])
```

[ ]:
```
plt.plot(test_losses)
plt.title('Test Loss for Each Sample')
plt.xlabel('Sample Index')
plt.ylabel('Loss')
plt.show()
```



12 Classification Report

12.1 Train Data

[ ]:
```
y_train_pred = []
for x in X_train:
    y_pred = baselineModel.predict(x)
    y_train_pred.append(y_pred)

y_train_pred = np.array(y_train_pred)
print(classification_report(y_train, y_train_pred))
```

```
              precision    recall  f1-score   support

           0       0.90      0.97      0.93      4968
           1       0.87      0.98      0.92      5689
           2       0.86      0.86      0.86      4967
           3       0.84      0.86      0.85      5141
           4       0.92      0.78      0.84      4872
           5       0.85      0.79      0.82      4524
```

```
           6       0.97      0.86      0.91      4932
           7       0.72      0.96      0.83      5192
           8       0.90      0.77      0.83      4832
           9       0.77      0.68      0.72      4883

    accuracy                           0.85     50000
   macro avg       0.86      0.85      0.85     50000
weighted avg       0.86      0.85      0.85     50000
```

12.2 Test data

[ ]:
```
y_test_pred = []
for x in X_test:
    y_pred = baselineModel.predict(x)
    y_test_pred.append(y_pred)

y_test_pred = np.array(y_test_pred)
print(classification_report(y_test, y_test_pred))
```

```
              precision    recall  f1-score   support

           0       0.89      0.98      0.93       980
           1       0.90      0.99      0.94      1135
           2       0.87      0.86      0.86      1032
           3       0.83      0.88      0.86      1010
           4       0.90      0.78      0.84       982
           5       0.85      0.77      0.81       892
           6       0.97      0.84      0.90       958
           7       0.73      0.95      0.83      1028
           8       0.91      0.77      0.84       974
           9       0.79      0.72      0.76      1009

    accuracy                           0.86     10000
   macro avg       0.86      0.86      0.86     10000
weighted avg       0.86      0.86      0.86     10000
```

13 Using different activation functions to train the model

We will use two activation functions mentioned below and train our model

- Tanh
- ReLU

13.1 Using Tanh

[ ]:
```
model_tanh = FeedForwardNeuralNets(X_train, [500, 250, 100], y_train_one_hot,
    optimizer="gd", batch_size=64, g=Activations.Tanh())


start_time = datetime.now()



model_tanh.train(epochs=15, validation_data=[X_val, y_val_one_hot])


end_time = datetime.now()

time_taken = end_time - start_time
print(f"Total time taken for training: {time_taken}")

# This cell runs for 57 mins
```

```
Epoch 1/15, Training Loss: 0.8020, Validation Loss: 0.6118
Epoch 2/15, Training Loss: 0.4991, Validation Loss: 0.6735
Epoch 3/15, Training Loss: 0.4243, Validation Loss: 0.3930
Epoch 4/15, Training Loss: 0.3991, Validation Loss: 0.4073
Epoch 5/15, Training Loss: 0.3590, Validation Loss: 0.3651
Epoch 6/15, Training Loss: 0.3477, Validation Loss: 0.3610
Epoch 7/15, Training Loss: 0.3028, Validation Loss: 0.2737
Epoch 8/15, Training Loss: 0.2937, Validation Loss: 0.2821
Epoch 9/15, Training Loss: 0.2928, Validation Loss: 0.2897
Epoch 10/15, Training Loss: 0.2627, Validation Loss: 0.2608
Epoch 11/15, Training Loss: 0.2649, Validation Loss: 0.2623
Epoch 12/15, Training Loss: 0.2462, Validation Loss: 0.2625
Epoch 13/15, Training Loss: 0.2376, Validation Loss: 0.2231
Epoch 14/15, Training Loss: 0.2520, Validation Loss: 0.2511
Epoch 15/15, Training Loss: 0.2275, Validation Loss: 0.2076
Total time taken for training: 0:57:37.176801
```

13.2 Using ReLU

[ ]:
```
model_relu = FeedForwardNeuralNets(X_train, [500, 250, 100], y_train_one_hot,
    optimizer="gd", batch_size=64, g=Activations.ReLU())


start_time = datetime.now()



model_relu.train(epochs=15, validation_data=[X_val, y_val_one_hot])
```

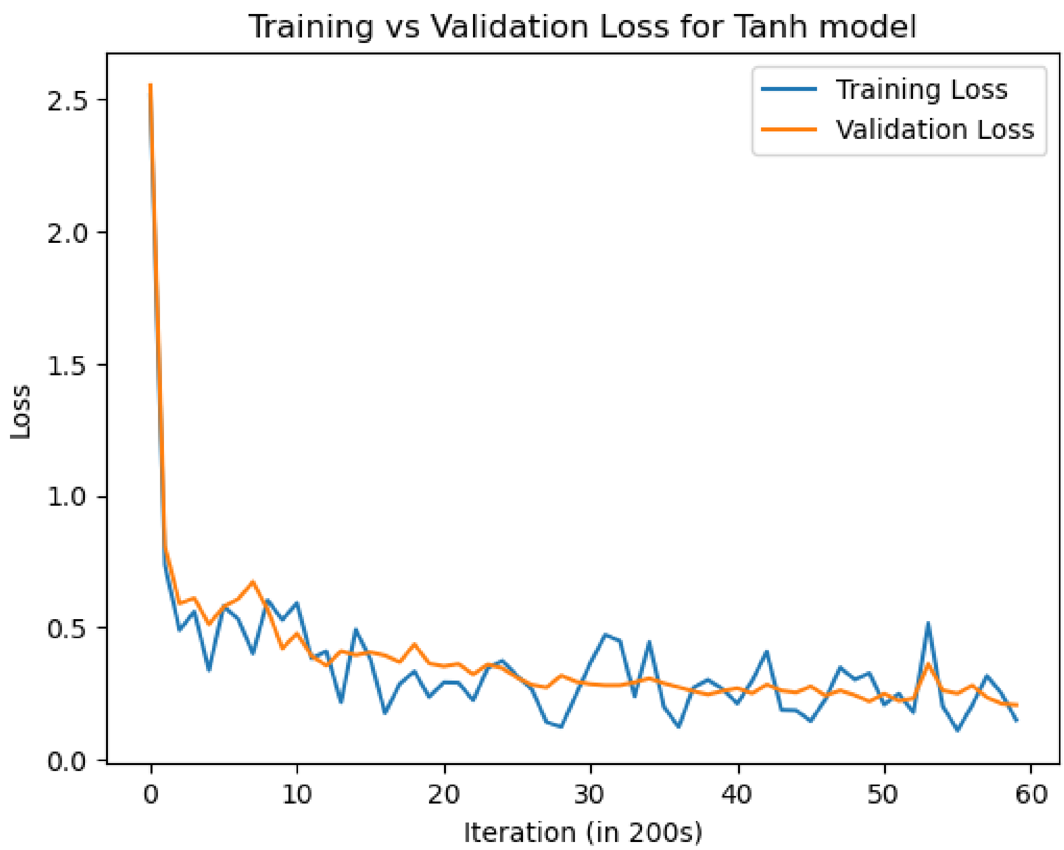
```
end_time = datetime.now()

time_taken = end_time - start_time
print(f"Total time taken for training: {time_taken}")

# This cell takes 57 mins 53 seconds in total
```

```
Epoch 1/15, Training Loss: 0.9837, Validation Loss: 0.6321
Epoch 2/15, Training Loss: 0.5767, Validation Loss: 0.4795
Epoch 3/15, Training Loss: 0.4467, Validation Loss: 0.4052
Epoch 4/15, Training Loss: 0.4186, Validation Loss: 0.3829
Epoch 5/15, Training Loss: 0.4126, Validation Loss: 0.4309
Epoch 6/15, Training Loss: 0.3590, Validation Loss: 0.3217
Epoch 7/15, Training Loss: 0.3294, Validation Loss: 0.3133
Epoch 8/15, Training Loss: 0.3318, Validation Loss: 0.3401
Epoch 9/15, Training Loss: 0.2767, Validation Loss: 0.2654
Epoch 10/15, Training Loss: 0.3018, Validation Loss: 0.2672
Epoch 11/15, Training Loss: 0.2871, Validation Loss: 0.2572
Epoch 12/15, Training Loss: 0.2847, Validation Loss: 0.3320
Epoch 13/15, Training Loss: 0.2931, Validation Loss: 0.2698
Epoch 14/15, Training Loss: 0.2455, Validation Loss: 0.2559
Epoch 15/15, Training Loss: 0.2233, Validation Loss: 0.2131
Total time taken for training: 0:57:53.821745
```

14 Plotting the Train and validation loss for every 200 iterations for Tanh model

We will try to plot how the loss varies for every 200 iterations.

[ ]:
```
x_axis = np.arange(60)
train_loss = np.array(model_tanh.training_loss)
validation_loss = np.array(model_tanh.validation_loss)

plt.plot(x_axis, train_loss, label='Training Loss')
plt.plot(x_axis, validation_loss, label='Validation Loss')

plt.title('Training vs Validation Loss for Tanh model')
plt.xlabel('Iteration (in 200s)')
plt.ylabel('Loss')


plt.legend()
plt.savefig('training_vs_validation_loss_tanh.png')
plt.show()
```

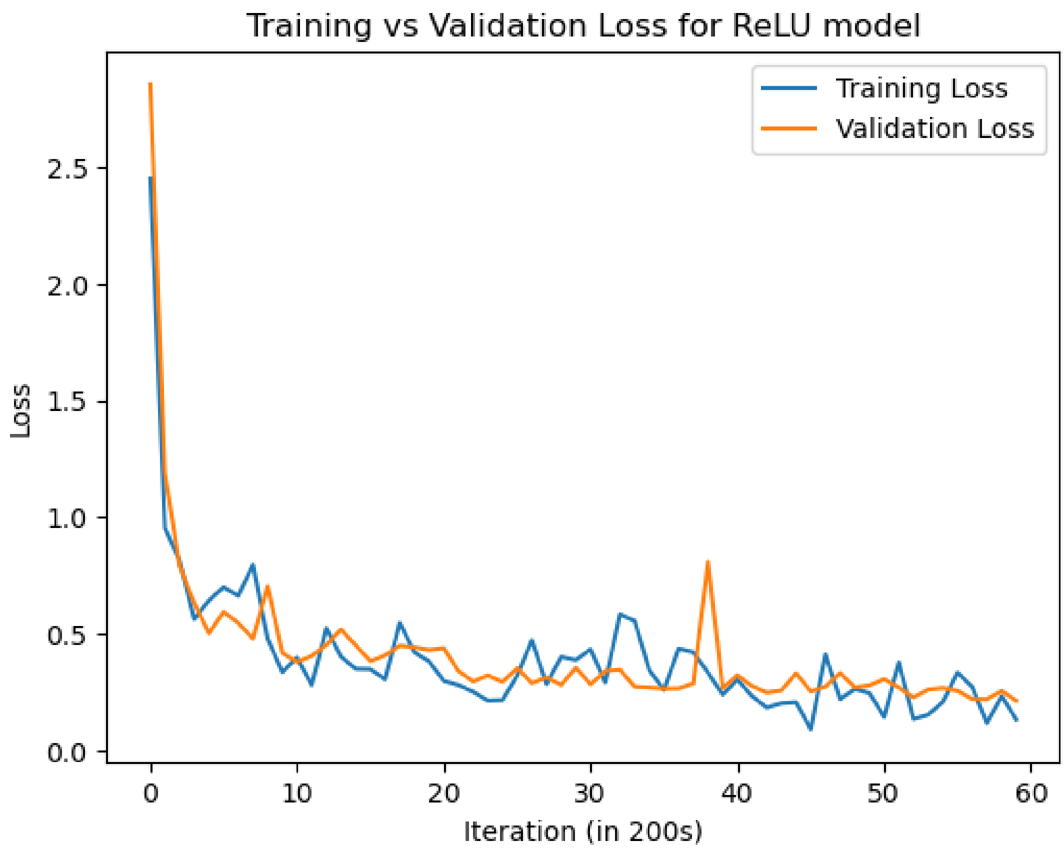


15 Plotting the Train and validation loss for every 200 iterations for ReLU model

We will try to plot how the loss varies for every 200 iterations.

[ ]:
```
x_axis = np.arange(60)
train_loss = np.array(model_relu.training_loss)
validation_loss = np.array(model_relu.validation_loss)

plt.plot(x_axis, train_loss, label='Training Loss')
plt.plot(x_axis, validation_loss, label='Validation Loss')

plt.title('Training vs Validation Loss for ReLU model')
plt.xlabel('Iteration (in 200s)')
plt.ylabel('Loss')


plt.legend()
plt.savefig('training_vs_validation_loss_relu.png')
```

```
plt.show()
```



16 Classification report for Tanh and ReLU

16.1 Tanh

Train Data

```
[ ]: y_train_pred_tanh = []
for x in X_train:
    y_pred = model_tanh.predict(x)
    y_train_pred_tanh.append(y_pred)

y_train_pred_tanh = np.array(y_train_pred_tanh)
print(classification_report(y_train, y_train_pred_tanh))
```

```
              precision    recall  f1-score   support

           0       0.96      0.97      0.96      4968
           1       0.98      0.98      0.98      5689
```

```
           2       0.93      0.95      0.94      4967
           3       0.94      0.90      0.92      5141
           4       0.96      0.89      0.92      4872
           5       0.95      0.89      0.92      4524
           6       0.98      0.93      0.95      4932
           7       0.97      0.90      0.93      5192
           8       0.85      0.94      0.89      4832
           9       0.82      0.96      0.88      4883

    accuracy                           0.93     50000
   macro avg       0.93      0.93      0.93     50000
weighted avg       0.93      0.93      0.93     50000
```

16.2 Tanh

Test Data

[ ]:
```
y_test_pred_tanh = []
for x in X_test:
    y_pred = model_tanh.predict(x)
    y_test_pred_tanh.append(y_pred)

y_test_pred_tanh = np.array(y_test_pred_tanh)
print(classification_report(y_test, y_test_pred_tanh))
```

```
              precision    recall  f1-score   support

           0       0.94      0.99      0.96       980
           1       0.98      0.98      0.98      1135
           2       0.92      0.94      0.93      1032
           3       0.93      0.91      0.92      1010
           4       0.96      0.89      0.93       982
           5       0.94      0.89      0.91       892
           6       0.98      0.91      0.94       958
           7       0.95      0.88      0.92      1028
           8       0.87      0.93      0.90       974
           9       0.83      0.95      0.89      1009

    accuracy                           0.93     10000
   macro avg       0.93      0.93      0.93     10000
weighted avg       0.93      0.93      0.93     10000
```

16.3 ReLU

Train data

```
[ ]: y_train_pred_relu = []
for x in X_train:
    y_pred = model_relu.predict(x)
    y_train_pred_relu.append(y_pred)

y_train_pred_relu = np.array(y_train_pred_relu)
print(classification_report(y_train, y_train_pred_relu))
```

```
              precision    recall  f1-score   support

           0       0.93      0.99      0.96      4968
           1       0.99      0.97      0.98      5689
           2       0.91      0.96      0.94      4967
           3       0.96      0.92      0.94      5141
           4       0.94      0.95      0.94      4872
           5       0.88      0.95      0.91      4524
           6       0.96      0.96      0.96      4932
           7       0.96      0.93      0.95      5192
           8       0.95      0.88      0.91      4832
           9       0.92      0.91      0.91      4883

    accuracy                           0.94     50000
   macro avg       0.94      0.94      0.94     50000
weighted avg       0.94      0.94      0.94     50000
```

```
[ ]: y_test_pred_relu = []
for x in X_test:
    y_pred = model_relu.predict(x)
    y_test_pred_relu.append(y_pred)

y_test_pred_relu = np.array(y_test_pred_relu)
print(classification_report(y_test, y_test_pred_relu))

# The output is there in the report. Please look at that
```

17 Regularization on the better model

We see that ReLU performs better than sigmoid and Tanh. So we will perform L_2 regularization on model ReLU

```
[ ]: cross_entropy_reg_l2 = LossFunctions.CrossEntropyLoss(regularization='l2',␣
 ↪alpha=0.01)

model_relu_l2 = FeedForwardNeuralNets(X_train, [500, 250, 100],␣
 ↪y_train_one_hot, optimizer="gd", batch_size=64, g=Activations.ReLU(),
                                  L=cross_entropy_reg_l2)
```

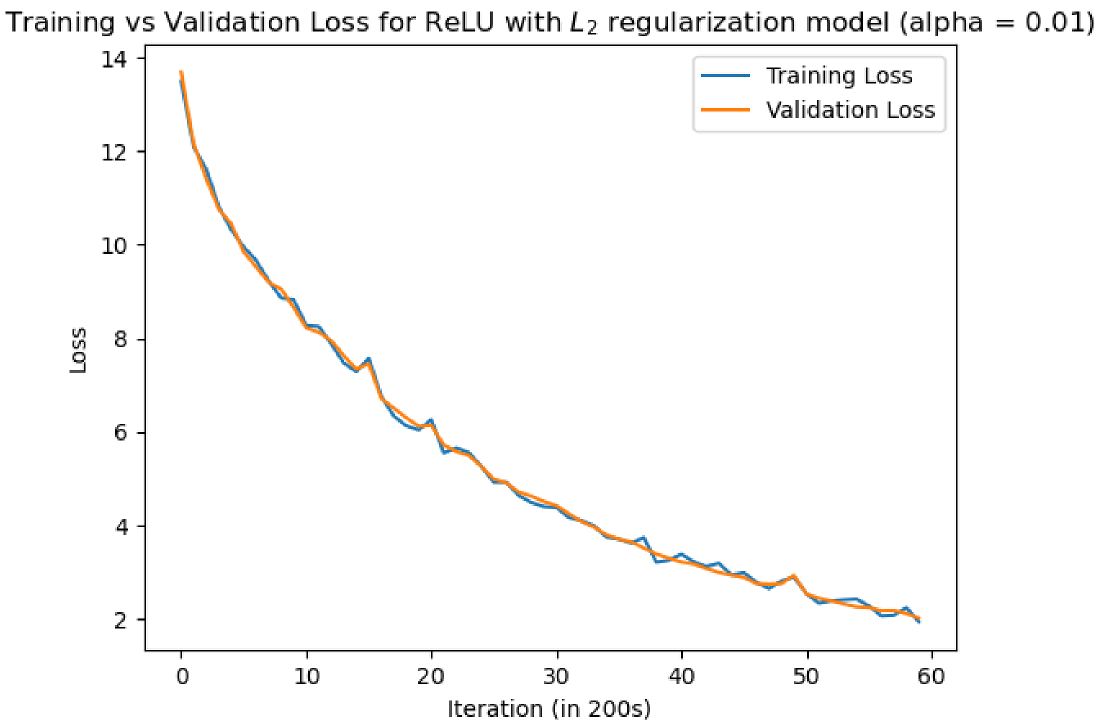
```
start_time = datetime.now()



model_relu_l2.train(epochs=15, validation_data=[X_val, y_val_one_hot])


end_time = datetime.now()

time_taken = end_time - start_time
print(f"Total time taken for training: {time_taken}")

# Total time taken : 1 hr 06 mins
```

```
Epoch 1/15, Training Loss: 11.3984, Validation Loss: 10.7624
Epoch 2/15, Training Loss: 9.5719, Validation Loss: 9.1938
Epoch 3/15, Training Loss: 8.3015, Validation Loss: 8.1260
Epoch 4/15, Training Loss: 7.2534, Validation Loss: 7.4504
Epoch 5/15, Training Loss: 6.3233, Validation Loss: 6.1156
Epoch 6/15, Training Loss: 5.5729, Validation Loss: 5.4898
Epoch 7/15, Training Loss: 4.9239, Validation Loss: 4.7039
Epoch 8/15, Training Loss: 4.3336, Validation Loss: 4.2440
Epoch 9/15, Training Loss: 3.8721, Validation Loss: 3.6975
Epoch 10/15, Training Loss: 3.4169, Validation Loss: 3.2924
Epoch 11/15, Training Loss: 3.0496, Validation Loss: 2.9853
Epoch 12/15, Training Loss: 2.7812, Validation Loss: 2.7342
Epoch 13/15, Training Loss: 2.5181, Validation Loss: 2.4351
Epoch 14/15, Training Loss: 2.2807, Validation Loss: 2.2350
Epoch 15/15, Training Loss: 2.0902, Validation Loss: 2.0112
Total time taken for training: 1:03:26.456915
```

18 Plotting graphs and getting classification report

[ ]:
```
x_axis = np.arange(60)
train_loss = np.array(model_relu_l2.training_loss)
validation_loss = np.array(model_relu_l2.validation_loss)

plt.plot(x_axis, train_loss, label='Training Loss')
plt.plot(x_axis, validation_loss, label='Validation Loss')

plt.title('Training vs Validation Loss for ReLU with $L_2$ regularization model␣
  ↪(alpha = 0.01)')
plt.xlabel('Iteration (in 200s)')
plt.ylabel('Loss')
```

```
plt.legend()
plt.savefig('training_vs_validation_loss_relu_l2.png')
plt.show()
```



[ ]:
```
y_train_pred_relu_l2 = []
for x in X_train:
    y_pred = model_relu_l2.predict(x)
    y_train_pred_relu_l2.append(y_pred)

y_train_pred_relu_l2 = np.array(y_train_pred_relu_l2)
print(classification_report(y_train, y_train_pred_relu_l2))
```

```
              precision    recall  f1-score   support

           0       0.89      0.94      0.92      4968
           1       0.65      0.98      0.79      5689
           2       0.87      0.72      0.79      4967
           3       0.89      0.62      0.73      5141
           4       0.77      0.85      0.81      4872
           5       0.73      0.78      0.76      4524
           6       0.82      0.92      0.87      4932
           7       0.72      0.89      0.80      5192
           8       0.78      0.58      0.66      4832
```

```
           9       0.84      0.47      0.60      4883

    accuracy                           0.78     50000
   macro avg       0.80      0.78      0.77     50000
weighted avg       0.79      0.78      0.77     50000
```

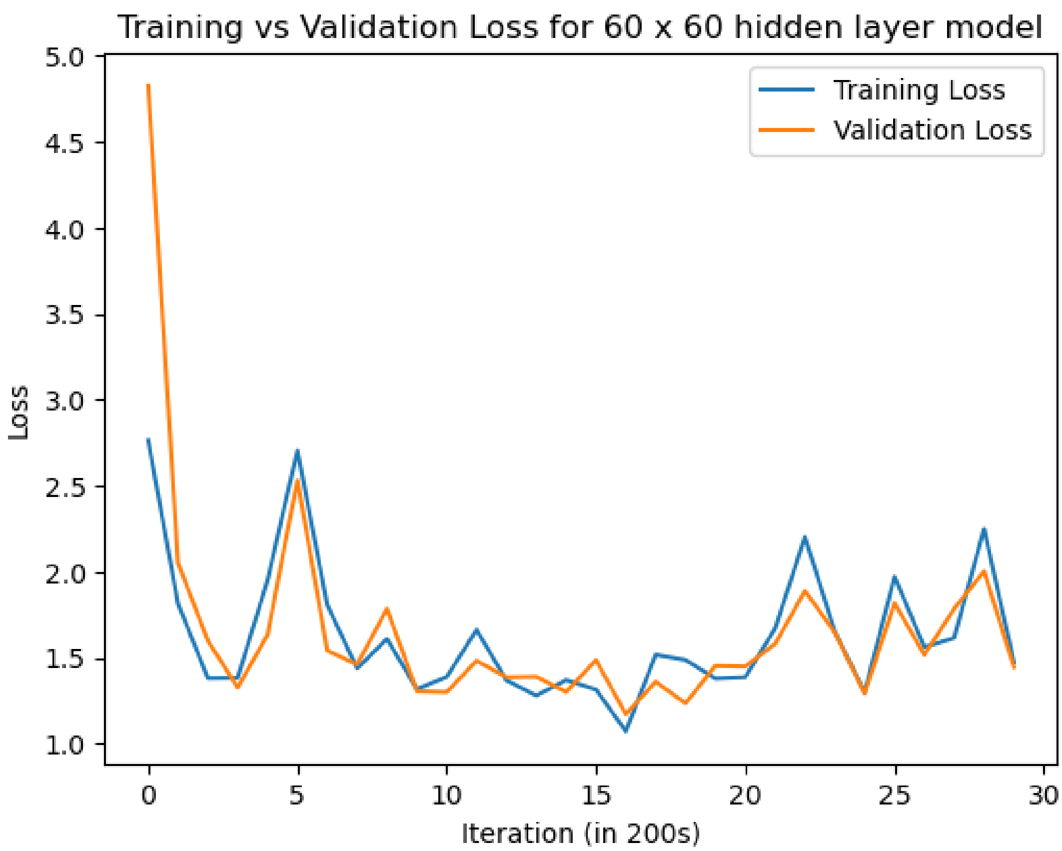
19 Experiments with different models

[ ]:
```
simple_model = FeedForwardNeuralNets(X_train, [60, 60], y_train_one_hot,␣
 ↪optimizer='adam', batch_size=128, g=Activations.ReLU())

start_time = datetime.now()



simple_model.train(epochs=15, validation_data=[X_val, y_val_one_hot])


end_time = datetime.now()

time_taken = end_time - start_time
print(f"Total time taken for training: {time_taken}")

# Total time taken : 5 min 54 sec
```

```
Epoch 1/15, Training Loss: 2.0271, Validation Loss: 2.0511
Epoch 2/15, Training Loss: 1.6989, Validation Loss: 1.3248
Epoch 3/15, Training Loss: 1.9417, Validation Loss: 2.5326
Epoch 4/15, Training Loss: 1.7098, Validation Loss: 1.4595
Epoch 5/15, Training Loss: 1.5395, Validation Loss: 1.3042
Epoch 6/15, Training Loss: 1.4193, Validation Loss: 1.4811
Epoch 7/15, Training Loss: 1.3879, Validation Loss: 1.3884
Epoch 8/15, Training Loss: 1.2468, Validation Loss: 1.4849
Epoch 9/15, Training Loss: 1.3437, Validation Loss: 1.3594
Epoch 10/15, Training Loss: 1.5493, Validation Loss: 1.4520
Epoch 11/15, Training Loss: 1.6902, Validation Loss: 1.5791
Epoch 12/15, Training Loss: 1.5291, Validation Loss: 1.6458
Epoch 13/15, Training Loss: 1.6245, Validation Loss: 1.8170
Epoch 14/15, Training Loss: 1.6224, Validation Loss: 1.7843
Epoch 15/15, Training Loss: 1.8279, Validation Loss: 1.4440
Total time taken for training: 0:05:54.533827
```

[ ]:
```
x_axis = np.arange(30)
train_loss = np.array(simple_model.training_loss)
validation_loss = np.array(simple_model.validation_loss)
```

```
plt.plot(x_axis, train_loss, label='Training Loss')
plt.plot(x_axis, validation_loss, label='Validation Loss')

plt.title('Training vs Validation Loss for 60 x 60 hidden layer model')
plt.xlabel('Iteration (in 200s)')
plt.ylabel('Loss')


plt.legend()
plt.savefig('training_vs_validation_loss_rsimple.png')
plt.show()
```



[ ]:
```
y_train_pred_simple = []
for x in X_train:
    y_pred = simple_model.predict(x)
    y_train_pred_simple.append(y_pred)

y_train_pred_simple = np.array(y_train_pred_simple)
print(classification_report(y_train, y_train_pred_simple))
```

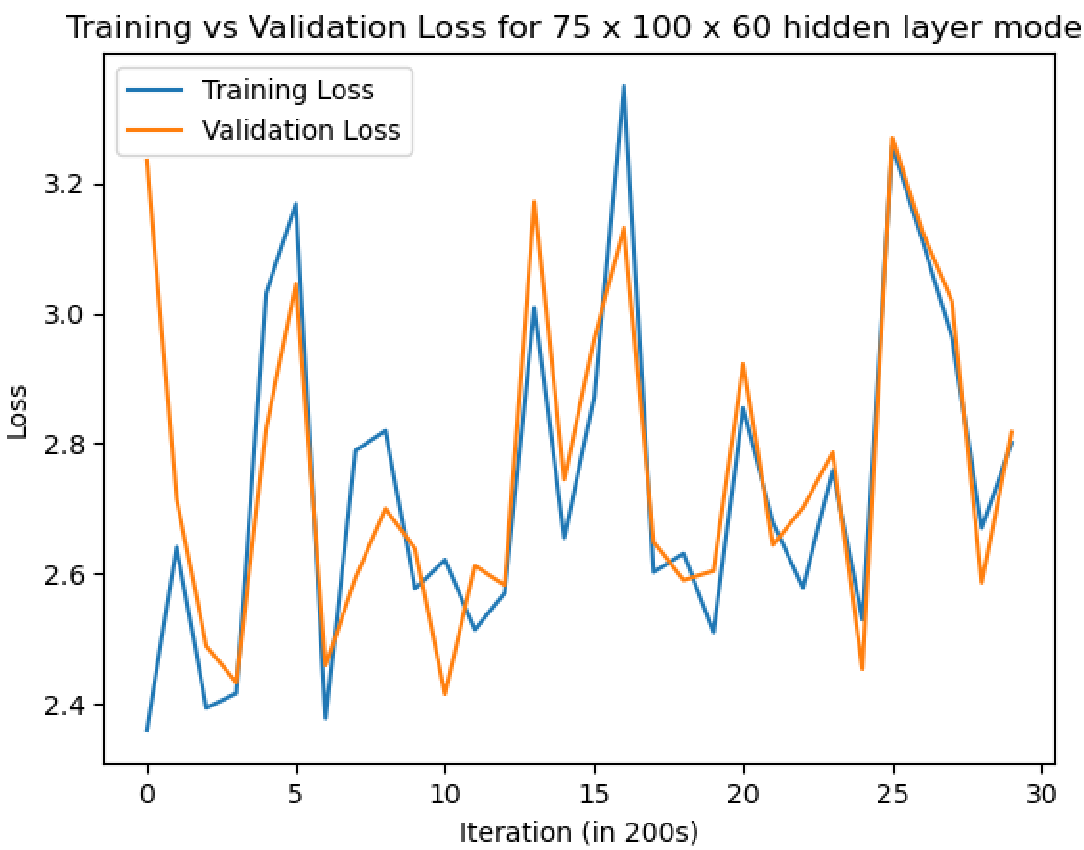
```
              precision    recall  f1-score   support

           0       0.98      0.66      0.79      4968
           1       0.24      0.99      0.39      5689
           2       0.90      0.55      0.68      4967
           3       0.87      0.36      0.51      5141
           4       0.47      0.79      0.59      4872
           5       0.03      0.00      0.00      4524
           6       1.00      0.12      0.21      4932
           7       0.96      0.72      0.83      5192
           8       0.01      0.00      0.00      4832
           9       0.20      0.18      0.19      4883

    accuracy                           0.45     50000
   macro avg       0.57      0.44      0.42     50000
weighted avg       0.57      0.45      0.43     50000
```

[ ]:
```
simple_model_tanh = FeedForwardNeuralNets(X_train, [75, 100, 60],␣
 ↪y_train_one_hot, optimizer='adam', batch_size=128, g=Activations.Tanh())

start_time = datetime.now()



simple_model_tanh.train(epochs=15, validation_data=[X_val, y_val_one_hot])


end_time = datetime.now()

time_taken = end_time - start_time
print(f"Total time taken for training: {time_taken}")

# Total time taken :
```

```
Epoch 1/15, Training Loss: 2.8796, Validation Loss: 2.7155
Epoch 2/15, Training Loss: 2.7369, Validation Loss: 2.4332
Epoch 3/15, Training Loss: 2.7762, Validation Loss: 3.0455
Epoch 4/15, Training Loss: 2.8017, Validation Loss: 2.5939
Epoch 5/15, Training Loss: 2.6731, Validation Loss: 2.6385
Epoch 6/15, Training Loss: 2.7330, Validation Loss: 2.6124
Epoch 7/15, Training Loss: 2.8385, Validation Loss: 3.1715
Epoch 8/15, Training Loss: 2.8315, Validation Loss: 2.9605
Epoch 9/15, Training Loss: 2.7560, Validation Loss: 2.6486
Epoch 10/15, Training Loss: 2.7437, Validation Loss: 2.6045
Epoch 11/15, Training Loss: 2.7349, Validation Loss: 2.6444
Epoch 12/15, Training Loss: 2.7772, Validation Loss: 2.7866
Epoch 13/15, Training Loss: 2.8654, Validation Loss: 3.2698
```

```
Epoch 14/15, Training Loss: 2.7987, Validation Loss: 3.0186
Epoch 15/15, Training Loss: 2.7348, Validation Loss: 2.8175
Total time taken for training: 0:07:12.886348
```

[ ]:
```python
x_axis = np.arange(30)
train_loss = np.array(simple_model_tanh.training_loss)
validation_loss = np.array(simple_model_tanh.validation_loss)

plt.plot(x_axis, train_loss, label='Training Loss')
plt.plot(x_axis, validation_loss, label='Validation Loss')

plt.title('Training vs Validation Loss for 75 x 100 x 60 hidden layer model')
plt.xlabel('Iteration (in 200s)')
plt.ylabel('Loss')


plt.legend()
plt.savefig('training_vs_validation_loss_rsimple.png')
plt.show()
```



[ ]:
```
y_train_pred_simple = []
for x in X_train:
    y_pred = simple_model.predict(x)
    y_train_pred_simple.append(y_pred)

y_train_pred_simple = np.array(y_train_pred_simple)
print(classification_report(y_train, y_train_pred_simple))
```

```
              precision    recall  f1-score   support

           0       0.98      0.66      0.79      4968
           1       0.24      0.99      0.39      5689
           2       0.90      0.55      0.68      4967
           3       0.87      0.36      0.51      5141
           4       0.47      0.79      0.59      4872
           5       0.03      0.00      0.00      4524
           6       1.00      0.12      0.21      4932
           7       0.96      0.72      0.83      5192
           8       0.01      0.00      0.00      4832
           9       0.20      0.18      0.19      4883

    accuracy                           0.45     50000
   macro avg       0.57      0.44      0.42     50000
weighted avg       0.57      0.45      0.43     50000
```

20 Using packages to mimic the same network

[4]:
```
import torch.nn as nn
import torch.optim as optim
from torch.utils.data import DataLoader, TensorDataset

class MLP(nn.Module):
    def __init__(self, input_size, hidden_layers, output_size, g=nn.Sigmoid(),␣
 ↪O=nn.Softmax(dim=1)):
        super(MLP, self).__init__()
        layers = []
        layer_sizes = [input_size] + hidden_layers
        for i in range(len(layer_sizes) - 1):
            layers.append(nn.Linear(layer_sizes[i], layer_sizes[i + 1]))
            layers.append(g)

        layers.append(nn.Linear(layer_sizes[-1], output_size))
        layers.append(O)

        self.model = nn.Sequential(*layers)
```

```python
    def forward(self, x):
        return self.model(x)
```

21 Trial Run

[5]:
```python
import torch
from torch.utils.data import DataLoader, random_split


batch_size = 64




train_size = int(0.8 * len(training_data))
val_size = len(training_data) - train_size
train_data, val_data = random_split(training_data, [train_size, val_size])


train_loader = DataLoader(dataset=train_data, batch_size=batch_size,␣
 ↪shuffle=True)
val_loader = DataLoader(dataset=val_data, batch_size=batch_size, shuffle=False)
test_loader = DataLoader(dataset=test_data, batch_size=batch_size,␣
 ↪shuffle=False)
```

[6]:
```python
def train(model, train_loader, val_loader, criterion, optimizer, epochs,␣
 ↪input_size=28*28, device='cpu'):
    """
    Trains the given model on the provided dataset using GPU if available.

    Args:
    - model: The neural network model (an instance of nn.Module).
    - train_loader: DataLoader for the training dataset.
    - val_loader: DataLoader for the validation/test dataset.
    - criterion: Loss function.
    - optimizer: Optimizer.
    - epochs: Number of epochs to train the model.
    - input_size: Size of the flattened input (e.g., 28*28 for MNIST).
    - device: Device to use for computation ('cpu' or 'cuda').

    Returns:
    - train_losses: List of training losses per epoch.
    - val_losses: List of validation losses per epoch.
    """

    model.to(device)
```

```
    train_losses = []
    val_losses = []

    for epoch in range(epochs):
        model.train()
        running_loss = 0.0

        for images, labels in train_loader:

            images, labels = images.view(-1, input_size).to(device), labels.
↪to(device)


            outputs = model(images)
            loss = criterion(outputs, labels)


            optimizer.zero_grad()
            loss.backward()
            optimizer.step()

            running_loss += loss.item()

        train_loss = running_loss / len(train_loader)
        train_losses.append(train_loss)


        model.eval()
        val_loss = 0.0
        with torch.no_grad():
            for images, labels in val_loader:
                images, labels = images.view(-1, input_size).to(device), labels.
↪to(device)
                outputs = model(images)
                loss = criterion(outputs, labels)
                val_loss += loss.item()

        val_loss = val_loss / len(val_loader)
        val_losses.append(val_loss)

        print(f"Epoch [{epoch+1}/{epochs}], Training Loss: {train_loss:.4f},␣
↪Validation Loss: {val_loss:.4f}")



    return train_losses, val_losses
```

[8]:
```python
device = torch.device('cuda' if torch.cuda.is_available() else 'cpu')


baseline_torch_model = MLP(input_size=28*28, hidden_layers=[500, 250, 100],
    output_size=10)
criterion = nn.CrossEntropyLoss()
optimizer = optim.Adam(baseline_torch_model.parameters(), lr=0.01)


baseline_torch_model
```

[8]:
```
MLP(
  (model): Sequential(
    (0): Linear(in_features=784, out_features=500, bias=True)
    (1): Sigmoid()
    (2): Linear(in_features=500, out_features=250, bias=True)
    (3): Sigmoid()
    (4): Linear(in_features=250, out_features=100, bias=True)
    (5): Sigmoid()
    (6): Linear(in_features=100, out_features=10, bias=True)
    (7): Softmax(dim=1)
  )
)
```

[9]:
```python
optimizer.defaults
```

[9]:
```
{'lr': 0.01,
 'betas': (0.9, 0.999),
 'eps': 1e-08,
 'weight_decay': 0,
 'amsgrad': False,
 'maximize': False,
 'foreach': None,
 'capturable': False,
 'differentiable': False,
 'fused': None}
```

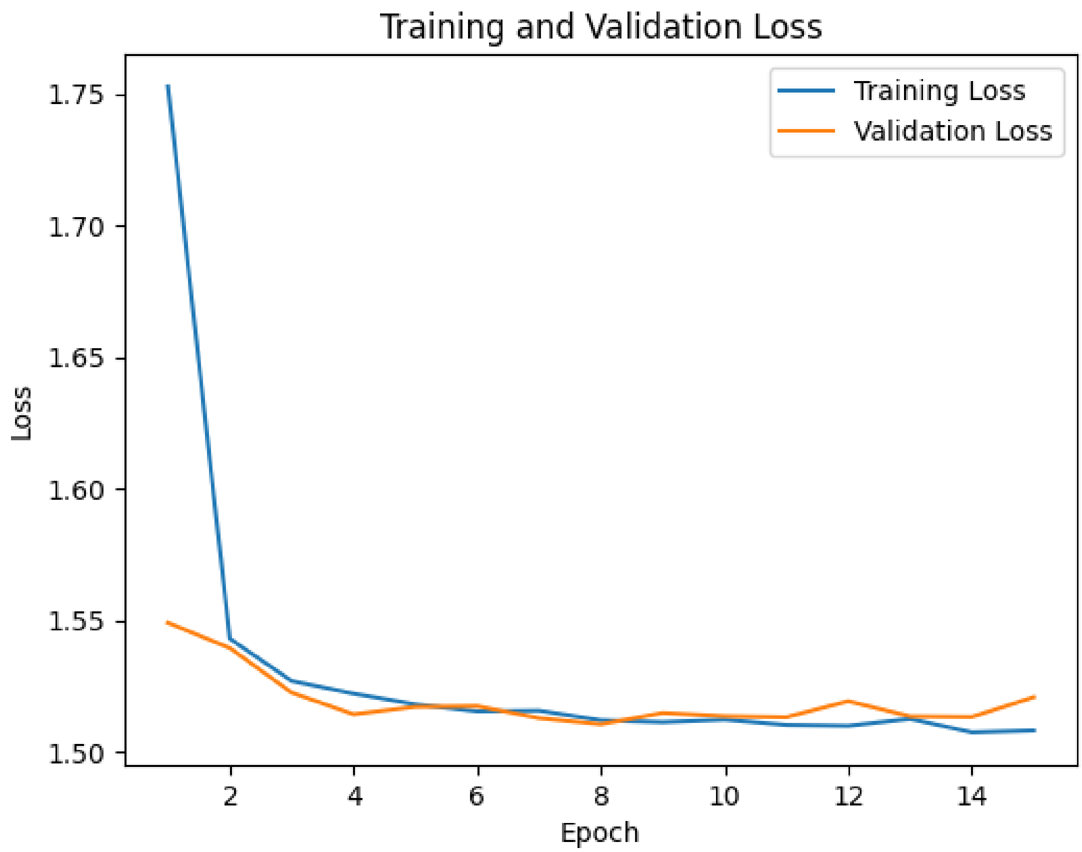
[11]:
```python
train_losses, val_losses = train(baseline_torch_model, train_loader,
    val_loader, criterion, optimizer, epochs=15, device=device)
```

```
Epoch [1/15], Training Loss: 1.7528, Validation Loss: 1.5491
Epoch [2/15], Training Loss: 1.5431, Validation Loss: 1.5396
Epoch [3/15], Training Loss: 1.5271, Validation Loss: 1.5226
Epoch [4/15], Training Loss: 1.5223, Validation Loss: 1.5144
Epoch [5/15], Training Loss: 1.5182, Validation Loss: 1.5173
Epoch [6/15], Training Loss: 1.5156, Validation Loss: 1.5175
Epoch [7/15], Training Loss: 1.5158, Validation Loss: 1.5130
Epoch [8/15], Training Loss: 1.5122, Validation Loss: 1.5107
```

```
Epoch [9/15], Training Loss: 1.5115, Validation Loss: 1.5149
Epoch [10/15], Training Loss: 1.5124, Validation Loss: 1.5137
Epoch [11/15], Training Loss: 1.5104, Validation Loss: 1.5134
Epoch [12/15], Training Loss: 1.5100, Validation Loss: 1.5194
Epoch [13/15], Training Loss: 1.5127, Validation Loss: 1.5137
Epoch [14/15], Training Loss: 1.5076, Validation Loss: 1.5134
Epoch [15/15], Training Loss: 1.5082, Validation Loss: 1.5209
```

21.1 Plotting a train and validation curve

[12]:
```
plt.plot(range(1, len(train_losses)+1), train_losses, label='Training Loss')
plt.plot(range(1, len(val_losses)+1), val_losses, label='Validation Loss')
plt.xlabel('Epoch')
plt.ylabel('Loss')
plt.title('Training and Validation Loss')
plt.legend()
plt.show()
```



[25]:

```
def evaluate_data_with_predictions(model, data_loader, criterion,␣
↪input_size=28*28, device='cpu'):
    """
    Evaluates the model on the entire dataset and returns predictions, test␣
↪loss, and accuracy.

    Args:
    - model: The trained neural network model.
    - test_loader: DataLoader for the test dataset.
    - criterion: The loss function to calculate the test loss.
    - input_size: Size of the flattened input (e.g., 28*28 for MNIST).
    - device: Device to use for computation ('cpu' or 'cuda').

    Returns:
    - avg_test_loss: The average test loss over the test dataset.
    - accuracy: The accuracy of the model on the test dataset.
    - all_predictions: The list of all predicted labels for the test dataset.
    - all_true_labels: The list of all true labels from the test dataset.
    """
    model.eval()
    model.to(device)

    test_loss = 0.0
    correct = 0
    total = 0
    all_predictions = []
    all_true_labels = []

    with torch.no_grad():
        for images, labels in data_loader:

            images, labels = images.view(-1, input_size).to(device), labels.
↪to(device)
            outputs = model(images)
            loss = criterion(outputs, labels)
            test_loss += loss.item()
            _, predicted = torch.max(outputs, 1)
            all_predictions.extend(predicted.cpu().numpy())
            all_true_labels.extend(labels.cpu().numpy())


            correct += (predicted == labels).sum().item()
            total += labels.size(0)



    return all_predictions, all_true_labels
```

[26]:
```
y_pred_train, y_true_train =␣
↪evaluate_data_with_predictions(baseline_torch_model, train_loader,␣
↪criterion=criterion, device=device)
print(classification_report(y_true_train, y_pred_train))
```

```
              precision    recall  f1-score   support

           0       0.98      0.97      0.97      4768
           1       0.97      0.99      0.98      5410
           2       0.97      0.94      0.95      4793
           3       0.99      0.87      0.93      4953
           4       0.92      0.96      0.94      4558
           5       0.95      0.96      0.95      4323
           6       0.92      0.99      0.95      4710
           7       0.97      0.95      0.96      5044
           8       0.94      0.89      0.91      4755
           9       0.86      0.93      0.89      4686

    accuracy                           0.94     48000
   macro avg       0.95      0.94      0.94     48000
weighted avg       0.95      0.94      0.94     48000
```

[27]:
```
y_pred_test, y_true_test = evaluate_data_with_predictions(baseline_torch_model,␣
↪test_loader, criterion=criterion, device=device)
print(classification_report(y_true_test, y_pred_test))
```

```
              precision    recall  f1-score   support

           0       0.97      0.98      0.97       980
           1       0.97      0.99      0.98      1135
           2       0.97      0.94      0.96      1032
           3       0.98      0.88      0.92      1010
           4       0.92      0.97      0.95       982
           5       0.94      0.94      0.94       892
           6       0.90      0.97      0.93       958
           7       0.96      0.93      0.94      1028
           8       0.95      0.88      0.92       974
           9       0.86      0.93      0.89      1009

    accuracy                           0.94     10000
   macro avg       0.94      0.94      0.94     10000
weighted avg       0.94      0.94      0.94     10000
```