In [803…

```
import numpy as np
import matplotlib.pyplot as plt
import pickle
from hw2 import get_mnist_threes_nines, display_image
```

1.2a (finite differences checker, used to help implement `my_nn_finite_difference_checker` in 1.3a. Feel free to modify the function signature, or to skip this part and implement `my_nn_finite_difference_checker` without this helper function.)

In [ ]:

```
"Sanket Behera"
"I have collaborated with Dherik Jenitan Devakumar"
```

In [804…

```
epsilon = 10**(-5)
def finite_difference_checker(f, x, k):
    """Returns \frac{\partial f}{\partial x_k}(x)"""
    # YOUR CODE HERE
    x_add_epsilon = [0 for i in x]
    x_add_epsilon[k] = epsilon
    x_add_epsilon = x+x_add_epsilon
    x_sub_epsilon = [0 for i in x]
    x_sub_epsilon[k] = epsilon
    x_sub_epsilon = x-x_add_epsilon
    derivative = (f(x_add_epsilon)-f(x_sub_epsilon))/2*epsilon
    #derivative = (f(x+epsilon)-f(x-epsilon))/2*epsilon

    return derivative
```

1.2b (functions that implement neural network layers)

In [104…

```
from cmath import log
from functools import cache

from numpy import vectorize


def sigmoid(num):
    return 1/(1+np.exp(-num))

def sigmoid_activation(x):
    # YOUR CODE HERE
    out = np.where(x<0, np.exp(x), 1)/(1+np.where(x<0, np.exp(x), np.exp(-x)
    np.clip(out,10**(-15), 1-10**(-15))
    grad = out*(1-out)
    return out, grad


def log_loss(x):
    return -np.log((x[0]**x[1])*(1-x[0]**(1-x[1])))

def logistic_loss(g, y):
    """
    Computes the loss and gradient for binary classification with logistic
    loss

    Inputs:
    - g: Output of final layer with sigmoid activation,
         of shape (n, 1)

```

```
    - y: Vector of labels, of shape (n,) where y[i] is the label for x[i]
         and y[i] in {0, 1}

    Returns a tuple of:
    - loss: array of losses
    - dL_dg: Gradient of the loss with respect to g
    """
    # YOUR CODE HERE
    loss = -(y * np.log(g) + (1 - y) * np.log(1 - g))
    dL_dg =  -(((y / g) + (y - 1)/(1 - g)))/len(g)
    return loss, dL_dg

def relu_activation(s):
    # YOUR CODE HERE
    out = np.where(s<0, 0, s)
    ds = np.where(s<0, 0.0, 1.0)
    return out, ds

def layer_forward(x, W, b, activation_fn):
    # YOUR CODE HERE
    result = x@W+b
    out, grad = activation_fn(result)
    cache = (grad, x, W)
    return out, cache
```

1.3b i, ii (deliverables for the sigmoid activation)

In [105…

```
# 1.3b i
s = np.asarray([1., 0., -1])
out, grad = sigmoid_activation(s)

with np.printoptions(precision=2):
    print(out)
    print(grad)

print("="*80)

# 1.3b ii
s = np.asarray([-1000., 1000.])
out, grad = sigmoid_activation(s)
print(out)
print(grad)
```

```
[0.73 0.5  0.27]
[0.2  0.25 0.2 ]
============================================================================
====
[0. 1.]
[0. 0.]
```

```
/var/folders/vt/385jmswn461_nsyn68syvb9h0000gn/T/ipykernel_57966/3219974770.
py:12: RuntimeWarning: overflow encountered in exp
  out = np.where(x<0, np.exp(x), 1)/(1+np.where(x<0, np.exp(x), np.exp(-x)))
```

1.3b iii: What is the derivative of the negative log-likelihood loss with respect to g?

your answer here The derivative of the negative log-likelihood loss with respect to g is given by: -y/g +(1-y)/(1-g)

1.3b iv: Explain what is returned in `cache` in your `layer_forward` implementation. (Trying to answer this question before completing your implementation might help think about should go in `cache`, which should be stuff computed during the forward pass that is needed for backpropagation in the backward pass. Just make sure your final answer pertains to what you ultimately return in `cache`.)

your answer here

My cache is containing grad, x, W, out and b which corresponds to the gradient, the input x to the neurons, the weights W, the output of the actiation function and the bias.

After implementing backward pass, I changed my cache to only contain grad, x and W. The reason is that these are the variables I ended up needing in my backward pass algorithm to calculate the deltas, gradient of the weight and bias matrixes.

1.2c (in this part you will code functions that initialize the neural network's weights. You will also code the forward pass which ties everything together, computing the output of a neural network with weights given by `weight_matrices` + `biases`, activation functions given by `activations`, on the input `X_batch`, a 2d input where each row is an individual input vector)

In [105…

```
def create_weight_matrices(layer_dims):
    """
    Creates a list of weight matrices defining the weights of NN

    Inputs:
    - layer_dims: A list whose size is the number of layers. layer_dims[i] d
      the number of neurons in the i+1 layer.

    Returns a list of weight matrices
    """
    # YOUR CODE HERE
    #arr = np.vectorize(create_weight_layer)
    #weights = arr(layer_dims)
    weights = []
    for i in range (len(layer_dims)-1):
        rows = layer_dims[i]
        columns = layer_dims[i+1]
        weights.append(np.random.randn(rows, columns)*np.random.normal(0, 0.
    return weights

def create_bias_vectors(layer_dims):
    # YOUR CODE HERE
    biases = []
    #for i in range(len(layer_dims)-1):
    #    biases.append(np.random.randn(1,i)*np.random.normal(0, 0.01))
    biases = [np.random.randn(1, h)* 0.01 for h in layer_dims[1:]]
    return biases

def forward_pass(X_batch, weight_matrices, biases, activations):
    # YOUR CODE HERE

    caches = []
    for x in range(len(weight_matrices)):
        X_batch, cache_x = layer_forward(X_batch, weight_matrices[x], biases
        caches.append(cache_x)
    return X_batch.flatten(), caches
```

1.3c (deliverable which has you run a forward pass of your neural network and compute its logistic loss on some output)

In [105…
```
with open("test_batch_weights_biases.pkl", "rb") as fn:
    (X_batch, y_batch, weight_matrices, biases) = pickle.load(fn)
activations = [relu_activation, sigmoid_activation]
output, _ = forward_pass(X_batch, weight_matrices, biases,
                         activations)
loss, dL_dg = logistic_loss(output, y_batch)
print(loss.mean())
```

```
0.6985168038536878
```

1.3a (deliverable which has you compute the gradient w.r.t. `weight_matrices` and `biases` using a finite differences checker)

In [2]:
```
with open("test_batch_weights_biases.pkl", "rb") as fn:
    (X_batch, y_batch, weight_matrices, biases) = pickle.load(fn)

def my_nn_finite_difference_checker(X_batch, y_batch, weight_matrices, biase
    # YOUR CODE HERE
    ...
    return grad_Ws, grad_bs

grad_Ws, grad_bs = my_nn_finite_difference_checker(X_batch,
                                                    y_batch,
                                                    weight_matrices,
                                                    biases,
                                                    activations)

with np.printoptions(precision=2):
    print(grad_Ws[0])
    print()
    print(grad_Ws[1])
    print()
    print(grad_bs[0])
    print()
    print(grad_bs[1])
```

```
---------------------------------------------------------------------------
FileNotFoundError                         Traceback (most recent call last)
/tmp/ipykernel_179/3523402699.py in <module>
----> 1 with open("test_batch_weights_biases.pkl", "rb") as fn:
      2     (X_batch, y_batch, weight_matrices, biases) = pickle.load(fn)
      3 
      4 def my_nn_finite_difference_checker(X_batch, y_batch, weight_matrice
s, biases, activations):
      5     # YOUR CODE HERE

FileNotFoundError: [Errno 2] No such file or directory: 'test_batch_weights_
biases.pkl'
```

1.2d (the backward pass!!!!)

In [105…
```
def backward_pass(dL_dg, layer_caches):
    grad, x, W = layer_caches[::-1][0]
    ### 0 = grad, 1 = x, 2 = W, 3 = b ###
    depth = len(layer_caches)
    delta = np.multiply(dL_dg.reshape(len(dL_dg), -1), grad)
    grad_Ws = [np.dot(x.T, delta)]
    #grad_Ws = [np.dot(layer_caches[depth-1][4].T, dW)]
    grad_bs = [np.sum(delta, axis=0)]

    for l in reversed(list(layer_caches[:-1])):

     grad, x, W = l
```

```
        delta = np.multiply(delta, grad)
        gradW = np.dot(x.T, delta)
        grad_Ws.insert(0, gradW)
        grad_bs.insert(0, np.sum(delta))
        delta = np.dot(delta, W.T).reshape(x.shape)


    return grad_Ws, grad_bs
```

1.3d (test your backward pass! compare it with 1.3a, the gradient computed by the finite difference checker. The answers should match!)

In [105…

```
with open("test_batch_weights_biases.pkl", "rb") as fn:
    (X_batch, y_batch, weight_matrices, biases) = pickle.load(fn)

activations = [relu_activation, sigmoid_activation]
output, layer_caches = forward_pass(X_batch, weight_matrices, biases,
                                    activations)
loss, dL_dg = logistic_loss(output, y_batch)

grad_Ws, grad_bs = backward_pass(dL_dg, layer_caches)

with np.printoptions(precision=2):
    print(grad_Ws[0])
    print()
    print(grad_Ws[1])
    print()
    print(grad_bs[0])
    print()
    print(grad_bs[1])
```

```
[[ 0.09 -0.16]
 [-0.01 -0.1 ]
 [-0.27 -0.37]
 [ 0.05  0.01]]

[[-0.  ]
 [-0.01]]

-0.7540152986252404

[-0.5]
```

1.2e (train your neural network on MNIST! save the training and test losses and accuracies at each iteration to use in 1.3e)

In [103…

```
from itertools import count
from multiprocessing.sharedctypes import Value
from nis import cat
import random

(X_train, y_train), (X_test, y_test) = get_mnist_threes_nines()
# YOUR CODE HERE
layer_dims = [784, 200,1]
step_size = 0.1
weights = create_weight_matrices(layer_dims)
biases = create_bias_vectors(layer_dims)
activations = [relu_activation, sigmoid_activation]
batch_size = 100
traning = []
traning_loss = []
test = []
```

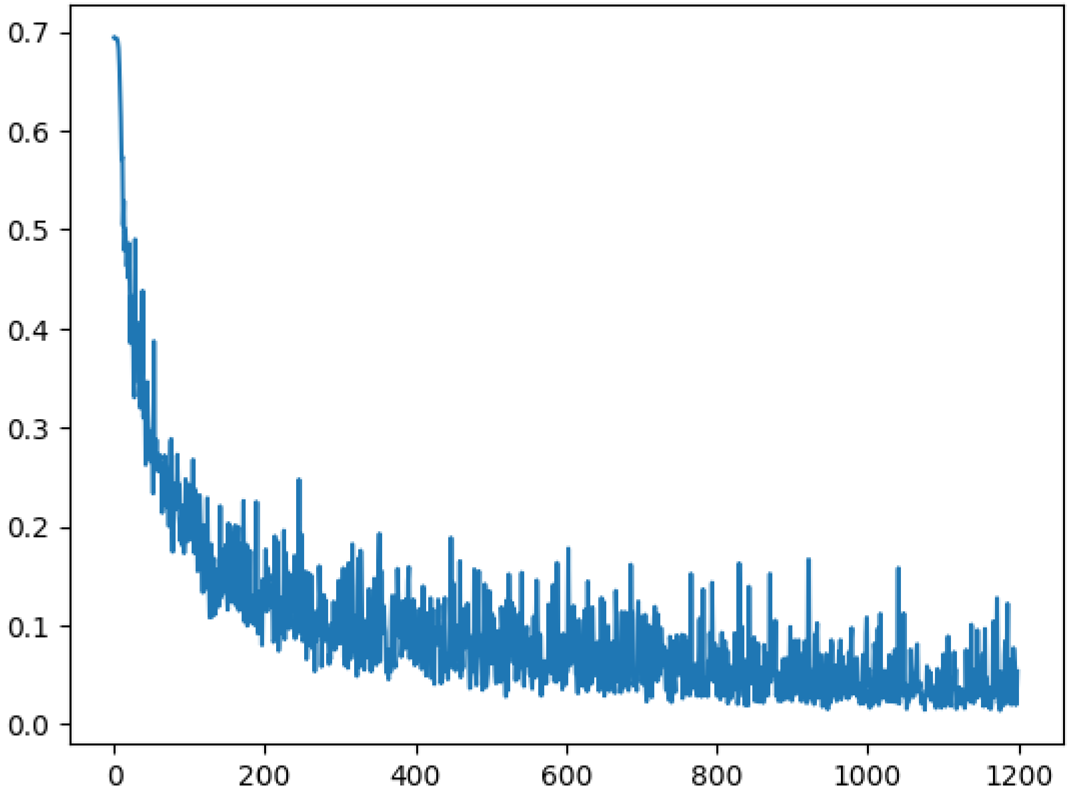
```
test_loss = []
xbatch_test = X_test
ybatch = y_train
ybatch_test = y_test
epochs = 10

def calculate_accuracy_and_loss(xbatch, ybatch, trainingdata):
     for m_batch in range(int(xbatch.shape[0]/batch_size)):
        #creating minibatches
        #Computation of batch size, inspiration from
        #https://realpython.com/gradient-descent-algorithm-python/#stochasti
        start = m_batch * batch_size
        stop = start+batch_size
        minibatch = random_x[start : stop]
        Xbatch = xbatch[minibatch].reshape(xbatch[minibatch].shape[0], -1)
        Ybatch = ybatch[minibatch]
        #Computing forward pass
        output, layer_caches = forward_pass(Xbatch, weights, biases, activat
        #Computing loss
        loss, dL_dg = logistic_loss(output, Ybatch)
        if trainingdata:
            traning_loss.append(loss.mean())
        else:
            test_loss.append(loss.mean())
        #Computing backward pass
        grad_Ws, grad_bs = backward_pass(dL_dg, layer_caches)
        #Updating weights
        for layer in range(len(weights)):
            weights[layer] -= step_size*grad_Ws[layer]
            biases[layer] -= step_size* grad_bs[layer]
        output_classification = []
        count = 0
        for i in output:
            if i >=0.5:
                output_classification.append(1)
            else:
                output_classification.append(0)
        for i in range(len(Ybatch)):
            if Ybatch[i]==output_classification[i]:
                count+=1
        accuracy = count/len(Ybatch)
        if trainingdata:
            traning.append(accuracy)
        else:
            test.append(accuracy)

for e in range(epochs):
    random_x = np.random.permutation(X_train.shape[0])
    #for i in range (xbatch.shape[0]):
    #    random_x.append(random.randint(0,xbatch.shape[0]))
    calculate_accuracy_and_loss(X_train, y_train, True)
    random_x = np.random.permutation(X_test.shape[0])
    calculate_accuracy_and_loss(X_test, y_test, False)
```

1.3e code answers for i, ii, iii

In [104…

```
# i
# Plot the train and test losses from the MNIST network with step size = 0.1
# YOUR CODE HERE
#I am plotting all 4 plots individually. This is plot for training loss
plt.plot(traning_loss, label="Training loss")
plt.show()
```

```
# iii
# Visualize (plot) some images that are misclassified by your network
```

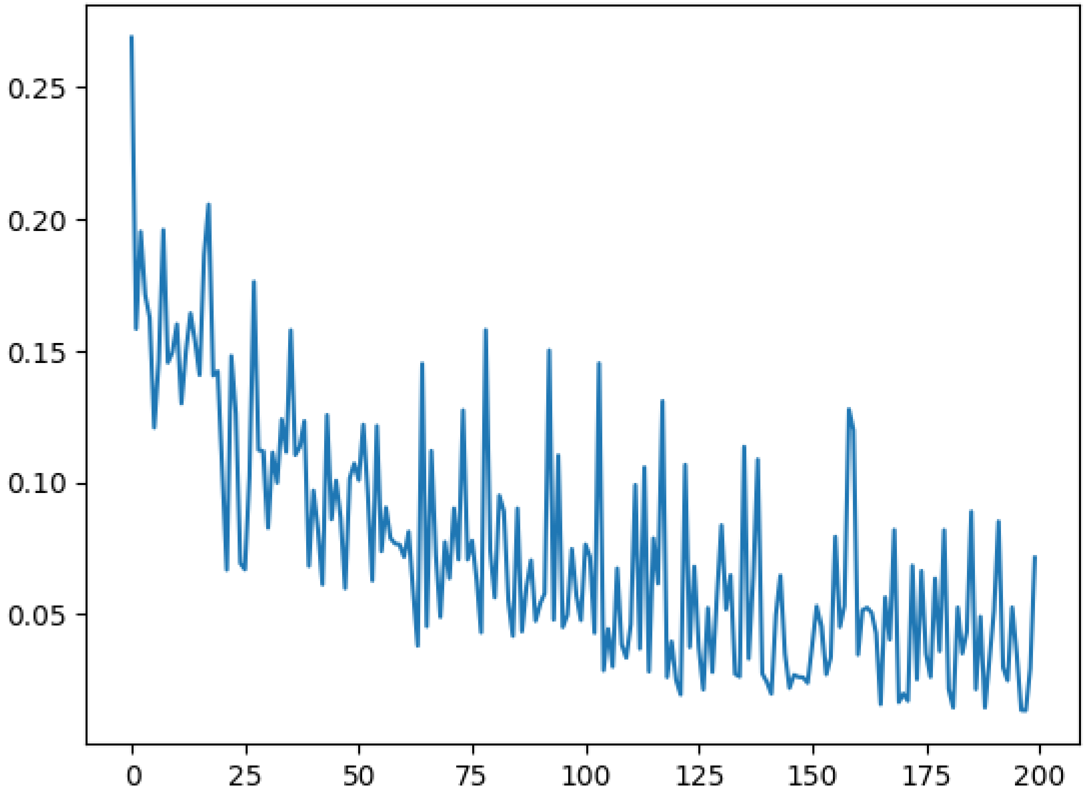


In [104…

```
# i
# Plot the train and test losses from the MNIST network with step size = 0.1
# YOUR CODE HERE
plt.plot(test_loss, label="Test loss")
plt.show
```

Out[1042]:

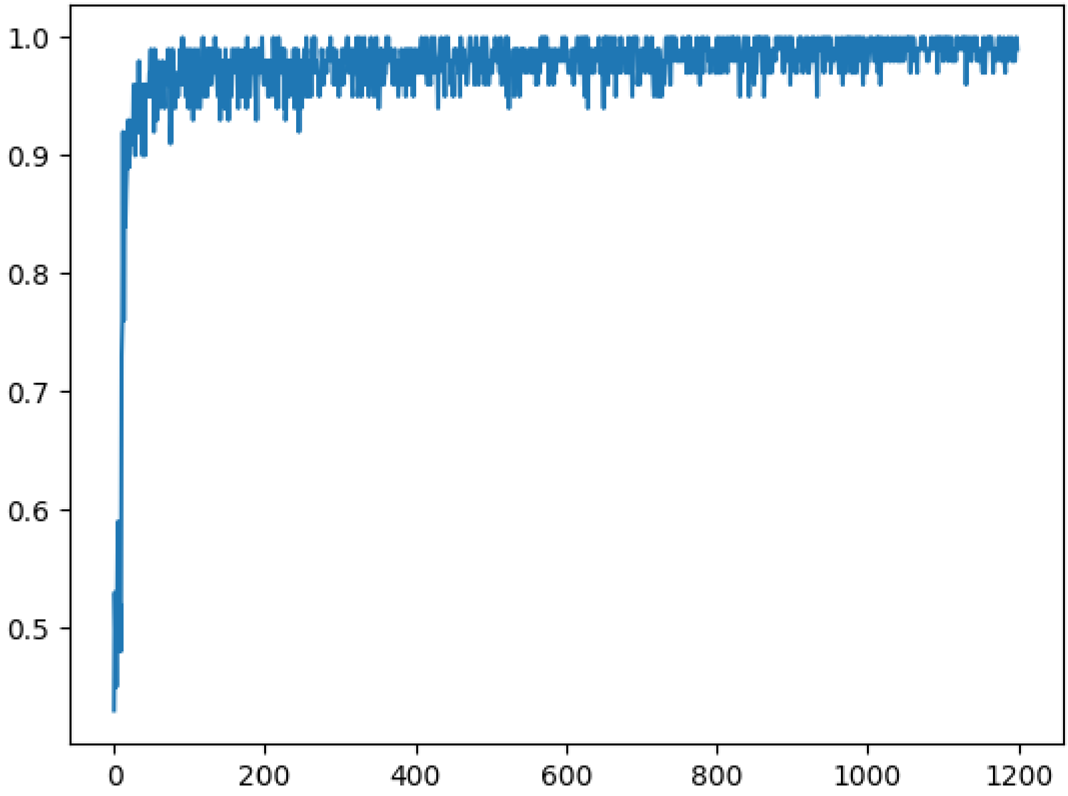
```
<function matplotlib.pyplot.show(close=None, block=None)>
```




```
# ii
```

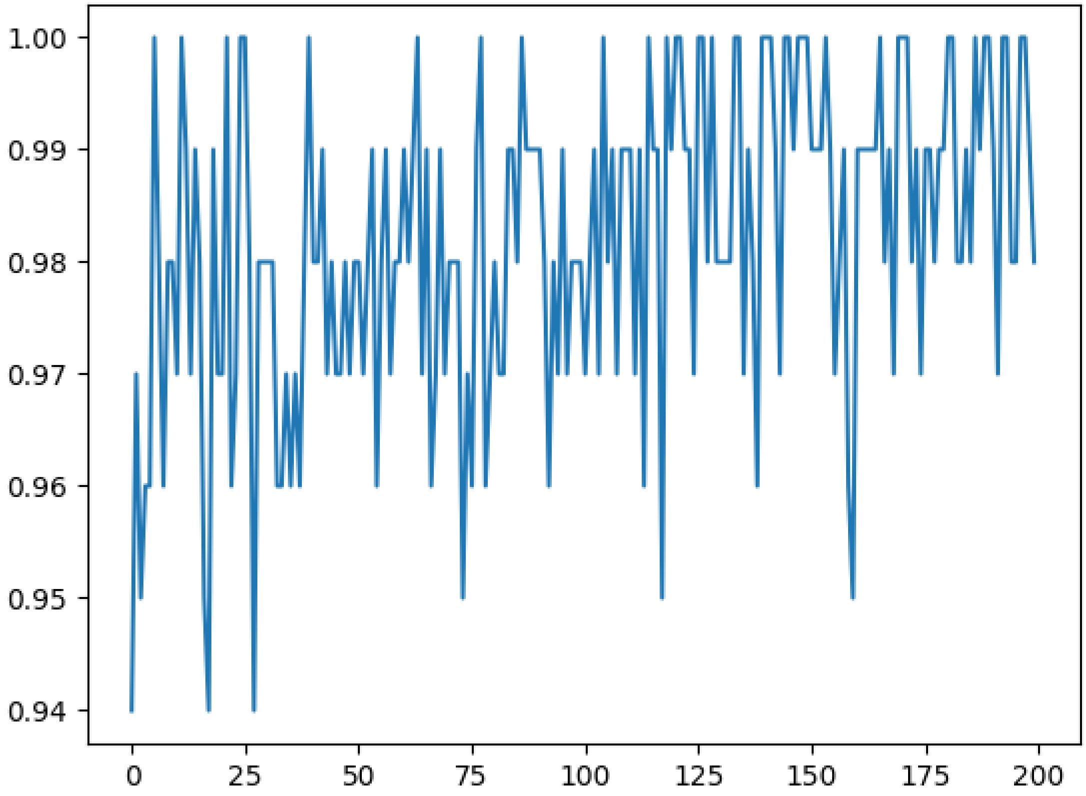
In [104…

```
# Plot the train and test accuracies from the MNIST network with step size =
# YOUR CODE HERE
plt.plot(traning, label="Training accuracy")
plt.show()
```



In [104…

```
# ii
# Plot the train and test accuracies from the MNIST network with step size =
# YOUR CODE HERE
plt.plot(test, label="Test accuracy")
plt.show()
```



1.3e iii: Examine the images that your network guesses incorrectly, and explain at a high level what patterns you see in those images.

your answer here

1.3e iv: Rerun the neural network training but now increase the step size to 10.0. What happens? You do not need to include plots here.

your answer here

1.3f (optional) (Train a network to fit 100 random images to the first 100 original labels! How fast can you memorize the dataset?)

In [102…

```
X_train = np.random.rand(100, 784)
# YOUR CODE HERE
```