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Problem 1: Part A

F(x) = $||X||_2^2$

F(x) = $((\sum_{i=1}^{n} x_i^2)^{1/2})2$

F(x) = $\sum_{i=1}^{n} x_i^2$

Can ignore the summation as n is 1.

$\frac{\partial}{\partial x}$ = 2x

Problem 1: Part B

$\sum_{i=1}^{n} ||x_i - \mu||_2^2$

$\frac{\partial}{\partial x}$ = 2(x- μ) Got the derivative, could just put it in the answer for Part A but accounting for μ. This works because this is the derivative at each point, and we have the summation of all of the points already in the expression.

Now we set the derivative with summation $= 0$

$\sum_{i=1}^{n} 2(x_i - \mu) = 0$

Do some algebra and we end up with:

$\mu = (\sum_{i=1}^{n} x_i)/n$

Problem 2: Part A

L(w) = $||x||_1$

L(w) = $||Xw - y||_1$

Sizes: X(data) -> n*c, w(weights) -> c*1, y(labels) -> n*1

Problem 2: Part B

No, because L1 norm isn't differentiable at zero therefore gradient optimization cannot be used. The explanation is partly explained in Part C as well.

Problem 2: Part C

Part A was straightforward since we just need the difference from the estimate and actual value. Since L1 is the summation of ||x||, we can just replace Xw-y for x. For part B, it wouldn't have a value

at zero if we took the derivative as it's non-convex there, there would be no unique global minimum so we can't minimize the loss function. This would mostly be concerned with the loss function part of the 3-step recipe as we are calculating the losses from the prediction regarding the label.

Problem 3: Part A

I do not have an answer for this question:

I first tried to do the math by having it all listed out in vectors and matrices but there's just a lot of numbers I would have to brute force. I did:

$[X][W_{HI}]+[B_{HI}] = Z_I$ where X is the input data and W_{HI} and B_{HI} is the weights and biases for each neuron in the hidden layer and Z_I is the output the ReLu activation function will take in. I then wrapped the ReLu function around that so that it would either be zero or Z_I, I then did the following:

$[B_O]+ \sum_{i=1}^{n} [W_{OI}][Z_I] = y$, where B_O is the bias for the output layer, W_{OI} is the weights of the output layer, and Z_I is either o or the Z_I from before and y is the predicted output.

The problem I keep running into is that this just leads to a method where I have to brute force numbers for a solution, and this is a lot of trial and error.

I also tried just calculating it out straightforward for each x value listed on the datasets. This doesn't work out because that is even more brute forcing then the previous method.

I found it easier to setup an optimization using excel solver to find a solution than to do the math or code so I did that first.
My computer actually ran out of RAM for both datasets before finding a solution and I have 128 GB of RAM.

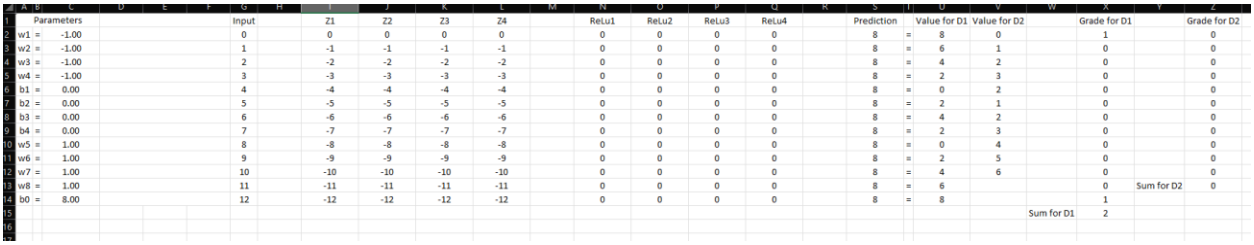
I also tried to code a solution in python, and I let it run for a few hours and nothing came from it.

The closest I got was just trying random numbers and I got 7/11 for dataset 2:

	Parameters		Input	Z1	Z2	Z3	Z4	ReLu1	ReLu2	ReLu3	ReLu4	Prediction		Value for D1	Value for D2		Grade for D1		Grade for D2
w1	=	1.00	0	-10	-10	-10	-4	0	0	0	0	0	=	8	0		0		1
w2	=	1.00	1	-9	-9	-9	-3	0	0	0	0	0	=	6	1		0		0
w3	=	1.00	2	-8	-8	-8	-2	0	0	0	0	0	=	4	2		0		0
w4	=	1.00	3	-7	-7	-7	-1	0	0	0	0	0	=	2	3		0		0
b1	=	-10.00	4	-6	-6	-6	0	0	0	0	0	0	=	0	2		1		0
b2	=	-10.00	5	-5	-5	-5	1	0	0	0	1	1	=	2	1		0		1
b3	=	-10.00	6	-4	-4	-4	2	0	0	0	2	2	=	4	2		0		1
b4	=	-4.00	7	-3	-3	-3	3	0	0	0	3	3	=	2	3		0		1
w5	=	1.00	8	-2	-2	-2	4	0	0	0	4	4	=	0	4		0		1
w6	=	1.00	9	-1	-1	-1	5	0	0	0	5	5	=	2	5		0		1
w7	=	1.00	10	0	0	0	6	0	0	0	6	6	=	4	6		0		1
w8	=	1.00	11	1	1	1	7	1	1	1	7	10	=	6			0	Sum for D2	7
b0	=	0.00	12	2	2	2	8	2	2	2	8	14	=	8			0		
																Sum for D1	1		

That was with w1= 1, w2 = 1 w3 = 1, w4 = 1, b1 = -10, b2 = -10, b3 = -10, b4 = -4, w5 = 1, w6 = 1, w7 = 1, w8 = 1, and b0 = 0.

The closest I for was dataset 1 was 2/13:



	Parameters		Input	Z1	Z2	Z3	Z4	ReLu1	ReLu2	ReLu3	ReLu4	Prediction		Value for D1	Value for D2		Grade for D1		Grade for D2
w1 =	-1.00		0	0	0	0	0	0	0	0	0	8	=	8	0		1		0
w2 =	-1.00		1	-1	-1	-1	-1	0	0	0	0	8	=	6	1		0		0
w3 =	-1.00		2	-2	-2	-2	-2	0	0	0	0	8	=	4	2		0		0
w4 =	-1.00		3	-3	-3	-3	-3	0	0	0	0	8	=	2	3		0		0
b1 =	0.00		4	-4	-4	-4	-4	0	0	0	0	8	=	0	2		0		0
b2 =	0.00		5	-5	-5	-5	-5	0	0	0	0	8	=	2	1		0		0
b3 =	0.00		6	-6	-6	-6	-6	0	0	0	0	8	=	4	2		0		0
b4 =	0.00		7	-7	-7	-7	-7	0	0	0	0	8	=	2	3		0		0
w5 =	1.00		8	-8	-8	-8	-8	0	0	0	0	8	=	0	4		0		0
w6 =	1.00		9	-9	-9	-9	-9	0	0	0	0	8	=	2	5		0		0
w7 =	1.00		10	-10	-10	-10	-10	0	0	0	0	8	=	4	6		0		0
w8 =	1.00		11	-11	-11	-11	-11	0	0	0	0	8	=	6			0	Sum for D2	0
b0 =	8.00		12	-12	-12	-12	-12	0	0	0	0	8	=	8			1		
																Sum for D1	2		

That was with w1= -1, w2 = -1 w3 = -1, w4 = -1, b1 = 0, b2 = 0, b3 = 0, b4 = 0, w5 = 1, w6 = 1, w7 = 1, w8 = 1, and b0 = 8.

Problem 3: Part B

This is just mean squares, so the derivative is straightforward:

$L(\vec{\theta}) = \sum_{i=1}^{n} (y_i - f(x_i, \vec{\Theta}))^2$

$\nabla L(\vec{\theta}) = -2 \sum_{i=1}^{n} ((y_i - f(x_i, \vec{\Theta})) * \nabla f(x_i, \vec{\Theta}))$

I left it in terms of $\nabla f(x_i, \vec{\Theta})$ since that's what the question asked for.

Problem 3: Part C

First layer values after plugging in the input(x) and parameters.

$Z_1 = -1$

$Z_2 = 3$

$Z_3 = 1$

$Z_4 = -1$

After ReLu

$Z_1 = 0$

$Z_2 = 3$

$Z_3 = 1$

$Z_4 = 0$

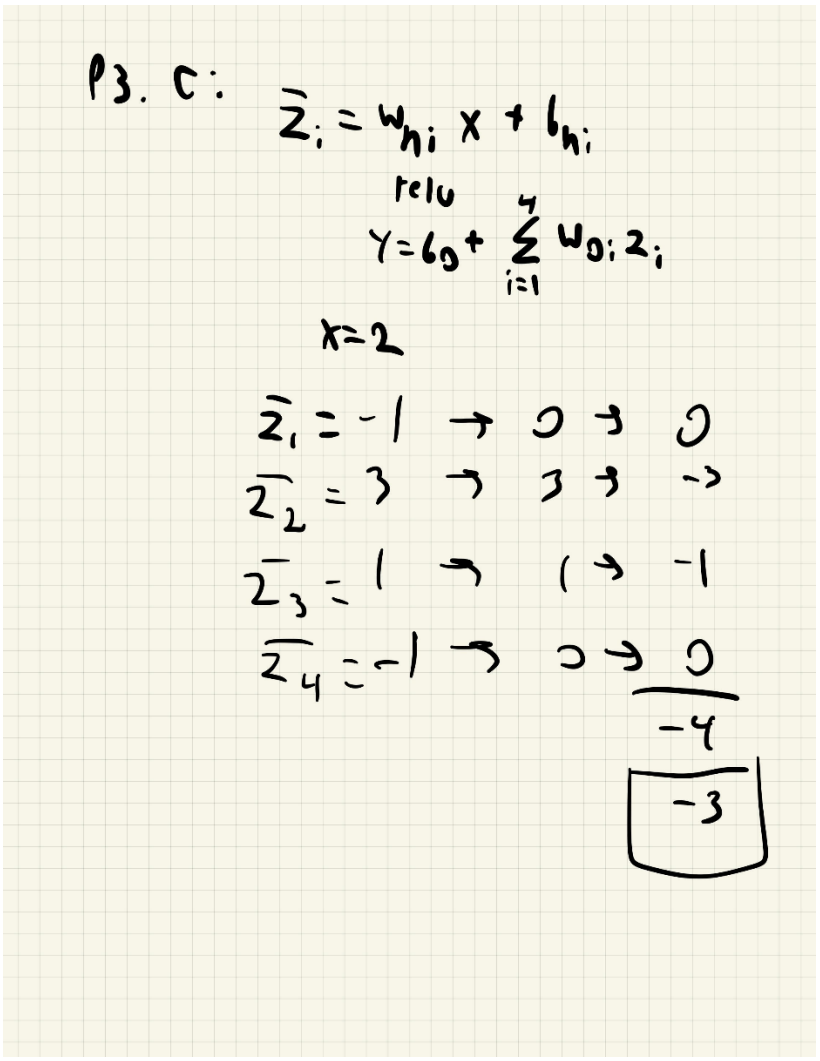
After summation in output layer

-4

After adding final bias

-3

Did this both manually and on the excel calculator I made:



		Parameters				Input		Z1	Z2	Z3	Z4		ReLu1	ReLu2	ReLu3	ReLu4		Prediction
w1	=	-1				0		1	1	-1	1		1	1	0	1		0
w2	=	1				1		0	2	0	0		0	2	0	0		-1
w3	=	1				2		-1	3	1	-1		0	3	1	0		-3
w4	=	-1				3		-2	4	2	-2		0	4	2	0		-5

Problem 3: Part D

I have all the formulas written out but am not sure what the parameters are supposed to be. But once I'm given those, I can figure out what the derivative at x=2 is with no problem.

$$\frac{\partial L}{\partial w0} = \frac{\partial L}{\partial y} * \frac{\partial y}{\partial w0}$$

$$\frac{\partial y}{\partial w0} = \sum_{i=1}^{4} z_i$$

$$\frac{\partial L}{\partial y} = 2 \sum_{i=1}^{n} (y0 - f(x, \theta))$$

$\frac{\partial L}{\partial \mathrm{w0}}$ = 2 * $\sum_{i=1}^{4} z$ * $\sum_{i=1}^{n}(y0 - f(x,\theta))$

$\frac{\partial L}{\partial b0}$ = $\frac{\partial L}{\partial \mathrm{y}} * \frac{\partial y}{\partial \mathrm{b0}}$

$\frac{\partial y}{\partial \mathrm{b0}}$ = 1

$\frac{\partial L}{\partial \mathrm{y}}$ = 2 $\sum_{i=1}^{n}(y0 - f(x,\theta))$

$\frac{\partial L}{\partial b0}$ = 2 $\sum_{i=1}^{n}(y0 - f(x,\theta))$

$\frac{\partial L}{\partial \mathrm{w1}}$ = $\frac{\partial L}{\partial \mathrm{y}}$ * $\frac{\partial y}{\partial \mathrm{z}}$ * max(0,z) * $\frac{\partial z}{\partial \mathrm{wo}}$

$\frac{\partial z}{\partial \mathrm{wo}}$ = x -> max(0,z) = max(0,x)

$\frac{\partial y}{\partial \mathrm{z}}$ = $\sum_{i=1}^{4} wo_{\mathrm{i}}$

$\frac{\partial L}{\partial \mathrm{y}}$ = 2 $\sum_{i=1}^{n}(y0 - f(x,\theta))$

$\frac{\partial L}{\partial \mathrm{w1}}$ 2 * $\sum_{i=1}^{4} wo$ * max(0,x) * $\sum_{i=1}^{n}(y0 - f(x,\theta))$

$\frac{\partial L}{\partial \mathrm{b1}}$ = $\frac{\partial L}{\partial \mathrm{y}}$ * $\frac{\partial y}{\partial \mathrm{z}}$ * max(0,z) * $\frac{\partial z}{\partial \mathrm{bo}}$

$\frac{\partial z}{\partial \mathrm{bo}}$ = 1 -> max(0,z) = 1

$\frac{\partial y}{\partial \mathrm{z}}$ = $\sum_{i=1}^{4} wo_{\mathrm{i}}$

$\frac{\partial L}{\partial \mathrm{y}}$ = 2 $\sum_{i=1}^{n}(y0 - f(x,\theta))$

$\frac{\partial L}{\partial \mathrm{w1}}$ 2 * $\sum_{i=1}^{4} wo$ * $\sum_{i=1}^{n}(y0 - f(x,\theta))$

hw1p4

September 21, 2023

[1]:
```
import numpy as np
import torch
import torchvision
import matplotlib.pyplot as plt
```

[2]:
```
trainingdata = torchvision . datasets. FashionMNIST ('./FashionMNIST/',␣
 ↪train=True ,download=True , transform = torchvision . transforms . ToTensor␣
 ↪())
testdata = torchvision .datasets. FashionMNIST ('./FashionMNIST/', train=False␣
 ↪,download=True , transform = torchvision . transforms . ToTensor ())
```

[3]:
```
print(len(trainingdata)) #Training data length
print(len(testdata)) #Testing data length
```

```
60000
10000
```

[4]:
```
trainDataLoader = torch.utils.data.
 ↪DataLoader(trainingdata,batch_size=64,shuffle=True) #Making it iterable
testDataLoader = torch.utils.data.
 ↪DataLoader(testdata,batch_size=64,shuffle=False)
images, labels = next(iter(trainDataLoader))
print(images.shape)
print(labels.shape)
```

```
torch.Size([64, 1, 28, 28])
torch.Size([64])
```

[5]:
```
class Model(torch.nn.Module):
  def __init__(self):
    super(Model, self).__init__()
    self.linear = torch.nn.Linear(784, 256) #764 inputs and 256 outputs
    self.activation = torch.nn.ReLU() #Activation function
    self.linear2 = torch.nn.Linear(256, 128)
    self.activation2 = torch.nn.ReLU()
    self.linear3 = torch.nn.Linear(128, 64)
    self.activation3 = torch.nn.ReLU()
    self.linear4 = torch.nn.Linear(64, 10) #10 categories
```

```
  def forward(self, x):
    x = x.view(-1, 28*28) #Vectorize
    x = self.linear(x)
    x = self.activation(x)
    x = self.linear2(x)
    x = self.activation2(x)
    x = self.linear3(x)
    x = self.activation3(x)
    x = self.linear4(x)
    return x
```

[6]:
```
model = Model()
loss = torch.nn.CrossEntropyLoss()
optimizer = torch.optim.SGD(model.parameters(), lr=0.01)
```

[7]:
```
device = torch.device('cuda' if torch.cuda.is_available() else 'cpu') #Mine␣
 ↪isn't setup as I have a new computer
#Note to follow this guide for setup: https://youtu.be/hHWkvEcDBO0?
 ↪si=MnJQsm7fIhbEes74
model = model.to(device)
```

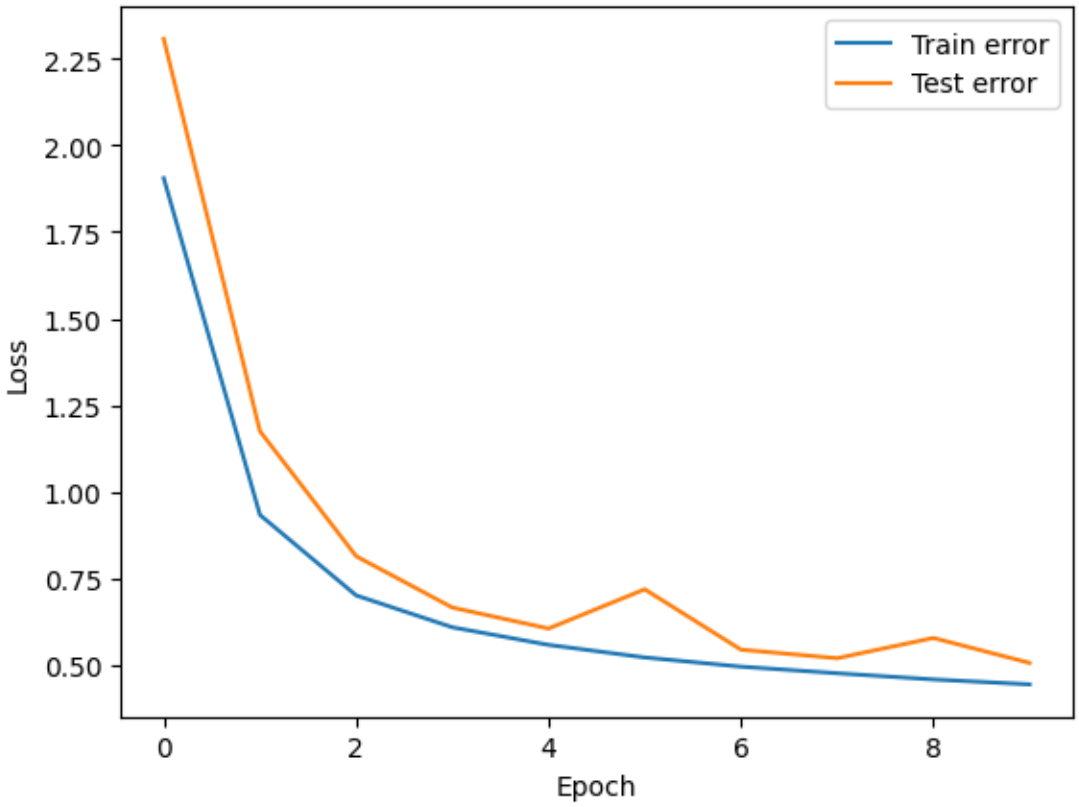
[8]:
```
train_losses = []
test_losses = []
```

[9]:
```
for epoch in range(10): # We'll train for 10 "epochs"
  train_loss = 0
  test_loss = 0

  for data in testDataLoader: #Predicts test data
    images, labels = data
    images, labels = images.to(device), labels.to(device)
    predicted_output = model(images)
    fit = loss(predicted_output, labels)
    test_loss += fit.item()

  for data in trainDataLoader: #Predicts train data
    images, labels = data
    images, labels = images.to(device), labels.to(device)
    optimizer.zero_grad() # Zero out the gradient values
    predicted_output = model(images)
    fit = loss(predicted_output, labels) # Measure how well the predicted␣
 ↪output matches the labels
    fit.backward() # Compute the gradient of the fit with respect to the model␣
 ↪parameters
    optimizer.step() # Update the weights in the model using gradient descent
    train_loss += fit.item()
```

```
    train_losses += [train_loss/len(trainDataLoader)]
    test_losses += [test_loss/len(testDataLoader)]

    print(f'Epoch {epoch}, Train loss {train_loss}, Test loss {test_loss}')
```

```
Epoch 0, Train loss 1787.3244709968567, Test loss 362.3181862831116
Epoch 1, Train loss 875.131316781044, Test loss 184.43580251932144
Epoch 2, Train loss 657.0507292747498, Test loss 127.7506094276905
Epoch 3, Train loss 570.6527071595192, Test loss 104.46469113230705
Epoch 4, Train loss 523.0395578444004, Test loss 94.95994547009468
Epoch 5, Train loss 489.00073251128197, Test loss 112.74039062857628
Epoch 6, Train loss 464.0913973748684, Test loss 85.38151663541794
Epoch 7, Train loss 446.2029498517513, Test loss 81.49660468101501
Epoch 8, Train loss 429.4090850651264, Test loss 90.68424804508686
Epoch 9, Train loss 416.1134061217308, Test loss 79.3811206817627
```

[10]:
```
plt.plot(range(10),train_losses, label='Train error')
plt.plot(range(10),test_losses, label='Test error')
plt.xlabel('Epoch')
plt.ylabel('Loss')
plt.legend()
plt.show()
```



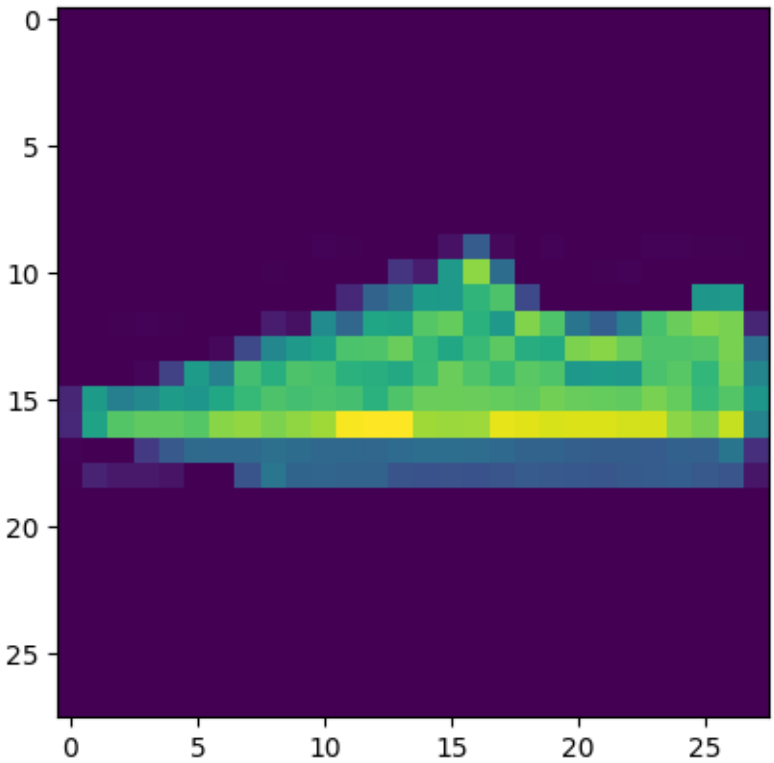
[11]:
```
predicted_classes = torch.max(predicted_output, 1)[1] #Isn't perfect
print('Predicted:', predicted_classes)
print('Labels:', labels)
```

```
Predicted: tensor([0, 3, 7, 1, 9, 8, 4, 3, 0, 2, 5, 6, 9, 0, 9, 2, 1, 1, 9, 7,
6, 8, 2, 2,
        0, 3, 2, 0, 7, 4, 7, 0])
Labels: tensor([6, 3, 7, 1, 9, 8, 4, 3, 0, 2, 5, 0, 9, 0, 9, 6, 1, 1, 7, 7, 6,
8, 2, 2,
        0, 3, 4, 0, 7, 4, 7, 0])
```

[12]:
```
i = 30
j = 20
k = 10
```

[13]:
```
print('Predicted:', predicted_classes[i].item())
print('Labels:', labels[i].item())
plt.imshow(images[i].squeeze().cpu()) # Visualize iamge
plt.show()
```

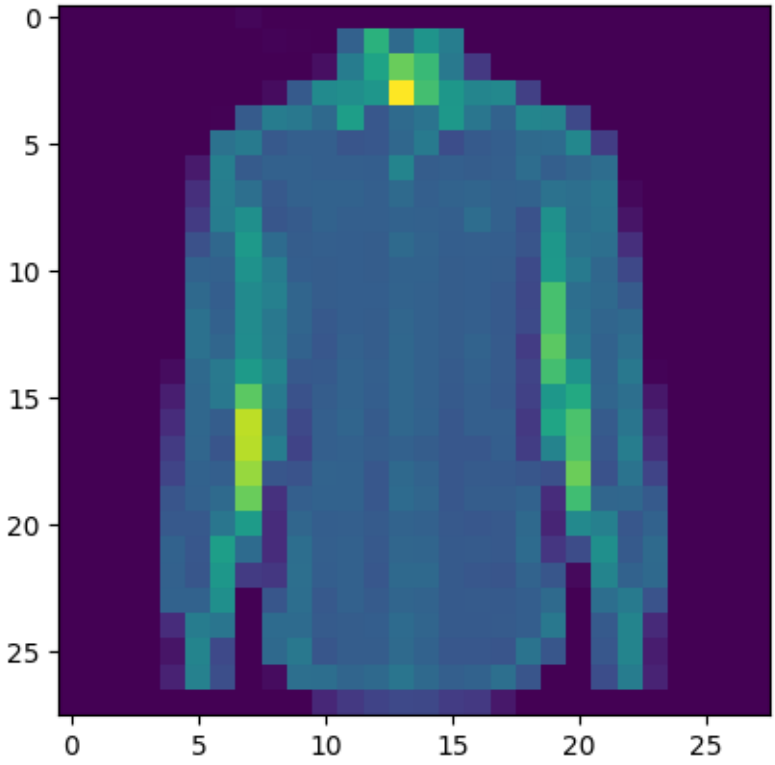
```
Predicted: 7
Labels: 7
```



The prediction for item 30 is correct since it was categorized as a shoe and it is predicted to be a shoe.

[17]:
```
print('Predicted:', predicted_classes[j].item())
print('Labels:', labels[j].item())
plt.imshow(images[j].squeeze().cpu()) # Visualize iamge
plt.show()
```

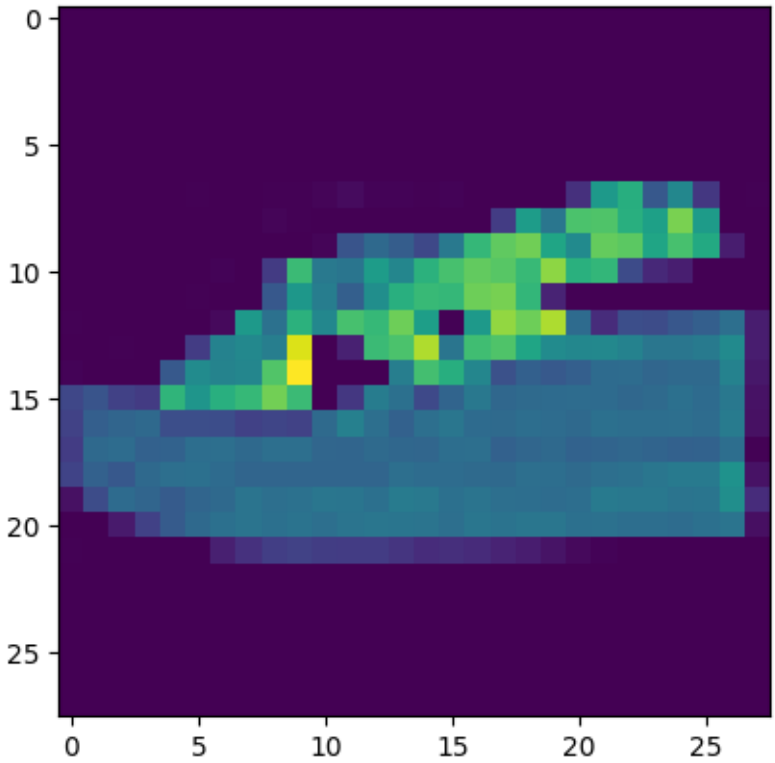
```
Predicted: 6
Labels: 6
```



The prediction for item 20 is correct since it was categorized as a shirt and it is predicted to be a shirt.

[18]:
```
print('Predicted:', predicted_classes[k].item())
print('Labels:', labels[k].item())
plt.imshow(images[k].squeeze().cpu()) # Visualize iamge
plt.show()
```

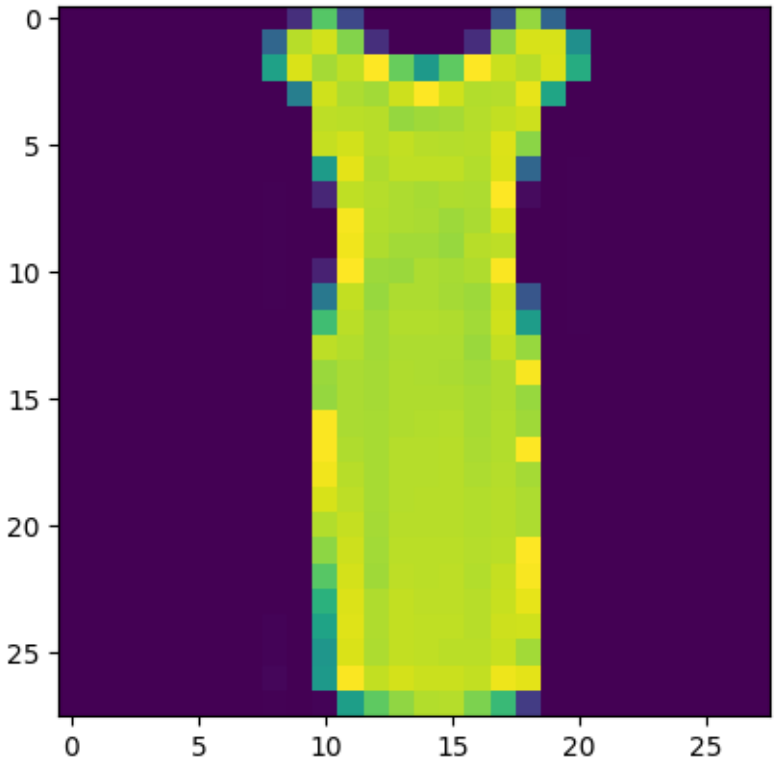
```
Predicted: 5
Labels: 5
```



The prediction for item 10 is correct since although I do not know what it is.

[20]:
```
x = 1
print('Predicted:', predicted_classes[x].item())
print('Labels:', labels[x].item())
plt.imshow(images[x].squeeze().cpu()) # Visualize iamge
plt.show()
```

```
Predicted: 3
Labels: 3
```



The prediction for item 1 is correct since it was categorized as a dress and it is predicted to be a dress.

[ ]:

dlf23-hw1-prob5

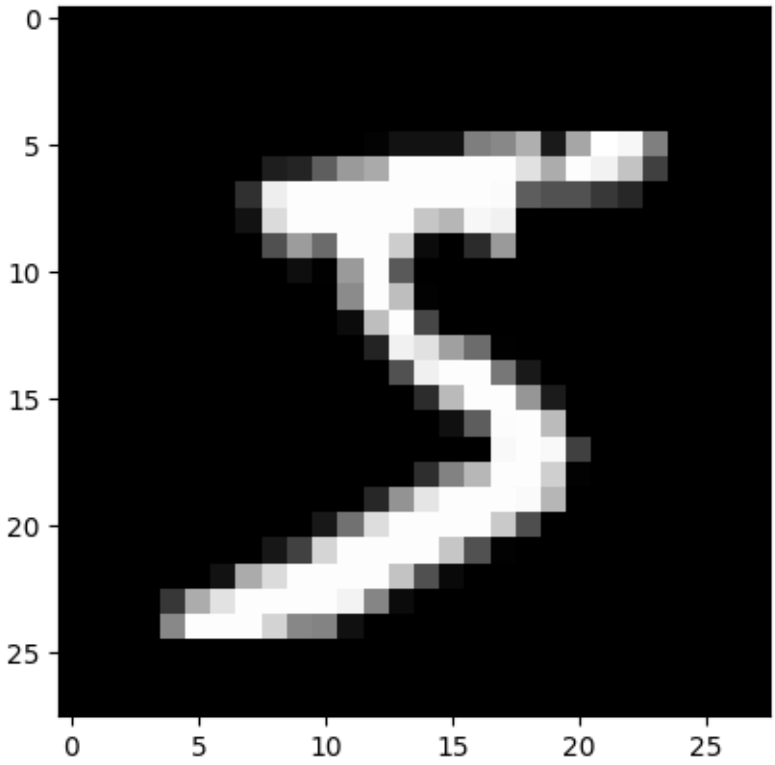
September 21, 2023

In this problem we will train a neural network from scratch using numpy. In practice, you will never need to do this (you'd just use TensorFlow or PyTorch). But hopefully this will give us a sense of what's happening under the hood.

For training/testing, we will use the standard MNIST benchmark consisting of images of handwritten images.

In the second demo, we worked with autodiff. Autodiff enables us to implicitly store how to calculate the gradient when we call backward. We implemented some basic operations (addition, multiplication, power, and ReLU). In this homework problem, you will implement backprop for more complicated operations directly. Instead of using autodiff, you will manually compute the gradient of the loss function for each parameter.

[7]:
```
import tensorflow as tf
import matplotlib.pyplot as plt

(x_train, y_train), (x_test, y_test) = tf.keras.datasets.mnist.
 ↪load_data(path="mnist.npz") #Loading dataset

plt.imshow(x_train[0],cmap='gray'); #One of the data points
```



Loading MNIST is the only place where we will use TensorFlow; the rest of the code will be pure numpy.

Let us now set up a few helper functions. We will use sigmoid activations for neurons, the softmax activation for the last layer, and the cross entropy loss.

I understand what is happening here but I found this demo helped a lot: https://www.youtube.com/watch?v=w8yWXqWQYmU

Everything I referenced for help outside of this course is from that video.

[8]:
```
import numpy as np

def sigmoid(x): #For hidden layers
  # Numerically stable sigmoid function based on
  # http://timvieira.github.io/blog/post/2014/02/11/exp-normalize-trick/

  x = np.clip(x, -500, 500) # We get an overflow warning without this

  return np.where(
    x >= 0,
    1 / (1 + np.exp(-x)),
    np.exp(x) / (1 + np.exp(x))
  )
```

```
def dsigmoid(x): # Derivative of sigmoid
  return sigmoid(x) * (1 - sigmoid(x))

def softmax(x): #For output layer
  # Numerically stable softmax based on (same source as sigmoid)
  # http://timvieira.github.io/blog/post/2014/02/11/exp-normalize-trick/
  b = x.max()
  y = np.exp(x - b)
  return y / y.sum()

def cross_entropy_loss(y, yHat): #Loss function
  return -np.sum(y * np.log(yHat))

def integer_to_one_hot(x, max): #Categorical to numerical
  # x: integer to convert to one hot encoding
  # max: the size of the one hot encoded array
  result = np.zeros(10)
  result[x] = 1
  return result
```

OK, we are now ready to build and train our model. The input is an image of size 28x28, and the output is one of 10 classes. So, first:

Q1. Initialize a 2-hidden layer neural network with 32 neurons in each hidden layer, i.e., your layer sizes should be:

784 -> 32 -> 32 -> 10

If the layer is $n_{in} \times n_{out}$ your layer weights should be initialized by sampling from a normal distribution with mean zero and variance $1/\max(n_{in}, n_{out})$.

[9]:
```
import math

# Initialize weights of each layer with a normal distribution of mean 0 and
# standard deviation 1/sqrt(n), where n is the number of inputs.
# This means the weighted input will be a random variable itself with mean
# 0 and standard deviation close to 1 (if biases are initialized as 0, standard
# deviation will be exactly 1)

from numpy.random import default_rng

rng = default_rng(80085)

# Q1. Fill initialization code here.
# ...

weights = []
biases = []
```

```
l1w=rng.normal(loc=0,scale=1/math.sqrt(784),size=(784,32)) #784 input and 32␣
 ↪output
l1b=np.zeros(32) #A bunch of zeroes
l2w=rng.normal(loc=0,scale=1/math.sqrt(32),size=(32,32))
l2b=np.zeros(32)
l3w=rng.normal(loc=0,scale=1/math.sqrt(32),size=(32,10)) #10 outputs
l3b=np.zeros(10)

weights.append(l1w)
weights.append(l2w)
weights.append(l3w)
biases.append(l1b)
biases.append(l2b)
biases.append(l3b)
```

Next, we will set up the forward pass. We will implement this by looping over the layers and successively computing the activations of each layer.

Q2. Implement the forward pass for a single sample, and for the entire dataset.

Right now, your network weights should be random, so doing a forward pass with the data should not give you any meaningful information. Therefore, in the last line, when you calculate test accuracy, it should be somewhere around 1/10 (i.e., a random guess).

[10]:
```
def feed_forward_sample(sample, y):
  """ Forward pass through the neural network.
    Inputs:
      sample: 1D numpy array. The input sample (an MNIST digit).
      label: An integer from 0 to 9.

    Returns: the cross entropy loss, most likely class
  """
  # Q2. Fill code here.
  # ...
  dummy=sample
  for i in range(len(weights)): #Each weight set
    z=np.matmul(dummy,weights[i])+biases[i] #dataset times weights plus biases
    if i==(len(weights)-1): #last weight set, output layer
        activation=softmax(z)
        output=activation
    else:
        activation=sigmoid(z)
    dummy=activation #Updates input for loop

  one_hot=integer_to_one_hot(y,10) #Make categorical data numerical
  loss=cross_entropy_loss(one_hot,output) #Loss function
  two_hot=integer_to_one_hot(np.argmax(output),10)
```

```
  return loss, two_hot


def feed_forward_dataset(x, y):
  losses = np.empty(x.shape[0])
  one_hot_guesses = np.empty((x.shape[0], 10))


  # ...
  # Q2. Fill code here to calculate losses, one_hot_guesses
  # ...
  for i in range(x.shape[0]): #Makes images into vectors
      dummy=x[i].reshape(-1)
      label=y[i]
      loss,one_hot=feed_forward_sample(dummy,label)
      losses[i]=loss
      one_hot_guesses[i]=one_hot

  y_one_hot = np.zeros((y.size, 10))
  y_one_hot[np.arange(y.size), y] = 1

  correct_guesses = np.sum(y_one_hot * one_hot_guesses)
  correct_guess_percent = format((correct_guesses / y.shape[0]) * 100, ".2f")

  print("\nAverage loss:", np.round(np.average(losses), decimals=2))
  print("Accuracy (# of correct guesses):", correct_guesses, "/", y.shape[0],␣
 ↪"(", correct_guess_percent, "%)")

def feed_forward_training_data():
  print("Feeding forward all training data...")
  feed_forward_dataset(x_train, y_train)
  print("")

def feed_forward_test_data():
  print("Feeding forward all test data...")
  feed_forward_dataset(x_test, y_test)
  print("")

feed_forward_test_data()
```

```
Feeding forward all test data…

Average loss: 2.37
Accuracy (# of correct guesses): 880.0 / 10000 ( 8.80 %)
```

OK, now we will implement the backward pass using backpropagation. We will keep it simple and

just do training sample-by-sample (no minibatching, no randomness).

Q3: Compute the gradient of all the weights and biases by backpropagating derivatives all the way from the output to the first layer.

[11]:
```
def train_one_sample(sample, y, learning_rate=0.003):
  a = sample.flatten()

  # We will store each layer's activations to calculate gradient
  activations = []

  # Forward pass

  # Q3. This should be the same as what you did in feed_forward_sample above.
  # ...
  weight_gradients=[None]*3 #3 of each
  bias_gradients=[None]*3
  # Forward pass
  dummy=a
  for i in range(len(weights)):
    dummy2=np.matmul(dummy,weights[i])+biases[i] #Same as before just with␣
 ↪activations
    if i==(len(weights)-1):
        activation=softmax(dummy2)
        output=activation
    else:
        activation=sigmoid(dummy2)
    dummy=activation
    activations.append(dummy)

# Backward pass
  one_hot=integer_to_one_hot(y,10)

  for index in range(len(weights)): #Getting the gradients, derivatives are␣
 ↪written out
      i=len(weights)-index-1
      if index==0:
          dl_dz=activations[i]-one_hot #For output layer
      else:
          dl_dac=np.matmul(weights[i+1],dl_dz.T).reshape(-1) #Hidden layers
          dl_dz=dl_dac*(activations[i]*(1-activations[i]))


      if i==0: #To the end
          dl_dw=np.matmul(a[:,np.newaxis],dl_dz[np.newaxis,:]) #First layer
      else:
          dl_dw=np.matmul(activations[i-1][:,np.newaxis],dl_dz[np.newaxis,:])␣
 ↪#Others
```

```
        dl_db=dl_dz
        weight_gradients[i]=dl_dw
        bias_gradients[i]=dl_db


    # Q3. Implement backpropagation by backward-stepping gradients through each␣
    ↪layer.
    # You may need to be careful to make sure your Jacobian matrices are the␣
    ↪right shape.
    # At the end, you should get two vectors: weight_gradients and bias_gradients.
    # ...

    # Update weights & biases based on your calculated gradient
    for i in range(len(weights)):
        weights[i] -= weight_gradients[i] * learning_rate
        biases[i] -= bias_gradients[i].flatten() * learning_rate
```

Finally, train for 3 epochs by looping over the entire training dataset 3 times.

Q4. Train your model for 3 epochs.

[12]:
```
def train_one_epoch(learning_rate=0.003):
    print("Training for one epoch over the training dataset...")

    # Q4. Write the training loop over the epoch here.
    # ...
    for j in range(x_train.shape[0]): #3 epochs
        train_one_sample(x_train[j],y_train[j],learning_rate=0.003)
    feed_forward_training_data()

    print("Finished training.\n")

feed_forward_test_data()

def test_and_train():
    train_one_epoch()
    feed_forward_test_data()

for i in range(3):
    test_and_train()
```

```
Feeding forward all test data…

Average loss: 2.37
Accuracy (# of correct guesses): 880.0 / 10000 ( 8.80 %)

Training for one epoch over the training dataset…
```

```
Feeding forward all training data…

Average loss: 1.04
Accuracy (# of correct guesses): 39068.0 / 60000 ( 65.11 %)

Finished training.

Feeding forward all test data…

Average loss: 1.04
Accuracy (# of correct guesses): 6505.0 / 10000 ( 65.05 %)

Training for one epoch over the training dataset…
Feeding forward all training data…

Average loss: 0.84
Accuracy (# of correct guesses): 43749.0 / 60000 ( 72.91 %)

Finished training.

Feeding forward all test data…

Average loss: 0.83
Accuracy (# of correct guesses): 7330.0 / 10000 ( 73.30 %)

Training for one epoch over the training dataset…
Feeding forward all training data…

Average loss: 0.9
Accuracy (# of correct guesses): 41467.0 / 60000 ( 69.11 %)

Finished training.

Feeding forward all test data…

Average loss: 0.88
Accuracy (# of correct guesses): 6994.0 / 10000 ( 69.94 %)
```

That's it!

Your code is probably very time- and memory-inefficient; that's ok. There is a ton of optimization under the hood in professional deep learning frameworks which we won't get into.

If everything is working well, you should be able to raise the accuracy from ~10% to ~70% accuracy after 3 epochs.

[ ]: