40216952_2023_A1_Jupyter

March 7, 2023

1 Question 1

1.0.1 Exercise 1.(b)

[ ]:
```
#1-hidden layer neural network y=w2^T*tanh(w1*x+b1)+b2
#W1: 20 *10
#W2: 1 * 20

import numpy as np
import matplotlib.pyplot as plt
import math
import random
import time
import torch

#generate data
device = torch.device("cuda:0" if torch.cuda.is_available() else "cpu")

h_1 = 20
h_2 = 1
param_dict = {"W1": torch.randn(h_1,10,device=device,requires_grad=True),
              "b1":torch.randn(h_1,1,device=device,requires_grad=True),
              "W2":torch.randn(h_1,h_2,device=device,requires_grad=True),
              "b2":torch.randn(1, device=device,requires_grad=True)}

#generate data
x = torch.randn(100,10,1,device=device)
y = torch.randn(100,1,1,device=device)


def my_nn(x,param_dict):

    x = x.clone().detach().requires_grad_(True)
    x = torch.tanh(param_dict["W1"]@x+param_dict["b1"])
    x = param_dict["W2"].T@x+param_dict["b2"]
    return x

def my_MAE(y_hat,y):
```

```
    # abs value
    return torch.mean(torch.abs(y_hat-y))

def my_loss_grad(y_hat,y):
    return torch.sign(y_hat-y)

def my_nn_grad(x,y_hat,y,param_dict):

    x = x.clone().detach().requires_grad_(True)
    y_hat = y_hat.clone().detach().requires_grad_(True)
    y = y.clone().detach().requires_grad_(True)

    grad_dict = {}
    mlg = my_loss_grad(y_hat,y)
    grad_dict["b2"] = torch.mean(mlg)
    # my_loss_grad(y_hat,y) is 100*1*1
    # torch.tanh(param_dict["W1"]@x+param_dict["b1"]) is 100*20*1
    pre_w2 = mlg * torch.tanh(param_dict["W1"]@x+param_dict["b1"])
    grad_dict["W2"] = torch.mean(pre_w2,dim=0)
    pre_b1 = mlg * param_dict["W2"] * (1-torch.
↪tanh(param_dict["W1"]@x+param_dict["b1"])**2)
    grad_dict["b1"] = torch.mean(pre_b1,dim=0)
    pre_w1 = pre_b1 @ x.permute(0,2,1)
    grad_dict["W1"] = torch.mean(pre_w1,dim=0)

    return grad_dict

def torch_grad_check(x,y,param_dict,eps=1e-6):
    # check my_nn_grad and torch.autograd.grad
    print("Floating point error tolerance is: ", eps)
    y_hat = my_nn(x,param_dict)
    #backwards
    loss = my_MAE(y_hat,y)
    loss.backward()
    grad_dict = my_nn_grad(x,y_hat,y,param_dict)
    for key in param_dict.keys():
        #use torch.linalg.norm to compare if smaller than eps
        print ("Key is: ", key)
        #print ("My grad is: ", grad_dict[key])
        #print ("Torch grad is: ", param_dict[key].grad)
        diff = torch.linalg.norm(grad_dict[key]-param_dict[key].grad)
        print ("Difference is: ", diff)
        #assert diff < eps, print error message if failed, print success␣
↪message if passed
        assert diff < eps, "error in "+key
        print("Success in "+key)
```

```
#check my_nn_grad and torch.autograd
torch_grad_check(x,y,param_dict)
```

```
Floating point error tolerance is:  1e-06
Key is:  W1
Difference is:  tensor(1.0802e-07, device='cuda:0',
grad_fn=<LinalgVectorNormBackward0>)
Success in W1
Key is:  b1
Difference is:  tensor(2.3591e-08, device='cuda:0',
grad_fn=<LinalgVectorNormBackward0>)
Success in b1
Key is:  W2
Difference is:  tensor(9.8421e-08, device='cuda:0',
grad_fn=<LinalgVectorNormBackward0>)
Success in W2
Key is:  b2
Difference is:  tensor(0., device='cuda:0', grad_fn=<LinalgVectorNormBackward0>)
Success in b2
```

1.0.2 Exercise 1.(c)

[ ]:
```
# Train this model on the sklearn California Housing Prices datasets
# https://scikit-learn.org/stable/modules/generated/sklearn.datasets.
↪fetch_california_housing.html#sklearn.datasets.fetch_california_housing

import scipy
import sklearn
import sklearn.datasets
import sklearn.linear_model
from torch.utils import data


# Generate a random California housing dataset
# half of the data is used for training, the other half for testing
# the data is normalized to have zero mean and unit variance
scaler = sklearn.preprocessing.StandardScaler()
X_train, X_test, y_train, y_test = sklearn.model_selection.train_test_split(
    scaler.fit_transform(sklearn.datasets.fetch_california_housing().data),
    sklearn.datasets.fetch_california_housing().target,
    test_size=0.5,
    random_state=42)
```

```python
train_batch_size = 64
test_batch_size = 64

# dataloader to gpu
train_dataset = data.TensorDataset(torch.tensor(X_train,device=device, dtype=torch.float32), torch.tensor(y_train,device=device, dtype=torch.float32))
train_loader = data.DataLoader(train_dataset, batch_size=train_batch_size, shuffle=True)
test_dataset = data.TensorDataset(torch.tensor(X_test,device=device, dtype=torch.float32), torch.tensor(y_test,device=device, dtype=torch.float32))
test_loader = data.DataLoader(test_dataset, batch_size=test_batch_size, shuffle=True)

#validation set from training set
train_dataset, val_dataset = torch.utils.data.random_split(train_dataset, [int(0.8*len(train_dataset)), int(0.2*len(train_dataset))])
val_loader = data.DataLoader(val_dataset, batch_size=test_batch_size, shuffle=True)



# convenient xavier initialization, taking an existing dictionary of parameters

def xavier_init(param_dict):
    for key in param_dict.keys():
        if "W" in key:
            torch.nn.init.xavier_uniform_(param_dict[key])
        else:
            torch.nn.init.zeros_(param_dict[key])
        param_dict[key].requires_grad_(True)
    return param_dict

num_epochs = 40
optimizer = torch.optim.Adam(param_dict.values(), lr=0.001)
lr_scehudler = torch.optim.lr_scheduler.ReduceLROnPlateau(optimizer, mode='min', factor=0.5, patience=5, verbose=True)
loss_fn = torch.nn.MSELoss()


#change w1 to 20*8 instead of 20*10
param_dict["W1"] = torch.randn(h_1,8,device=device,requires_grad=True)
param_dict = xavier_init(param_dict)
```

```
train_loss_per_epoch = []
val_loss_per_epoch = []
test_loss_per_epoch = []

for epoch in range(num_epochs):
    train_loss = 0
    for batch_idx, (x, y) in enumerate(train_loader):
        y_hat = my_nn(x.T,param_dict)
        y_hat = y_hat.squeeze()
        loss = loss_fn(y_hat,y)
        train_loss += loss.item()
        optimizer.zero_grad()
        loss.backward()
        optimizer.step()
    train_loss_per_epoch.append(train_loss/len(train_loader))

    #validation
    val_loss = 0
    for batch_idx, (x, y) in enumerate(val_loader):
        y_hat = my_nn(x.T,param_dict)
        y_hat = y_hat.squeeze()
        loss = loss_fn(y_hat,y)
        val_loss += loss.item()
    val_loss_per_epoch.append(val_loss/len(val_loader))

    #test
    test_loss = 0
    for batch_idx, (x, y) in enumerate(test_loader):
        y_hat = my_nn(x.T,param_dict)
        y_hat = y_hat.squeeze()
        loss = loss_fn(y_hat,y)
        test_loss += loss.item()
    test_loss_per_epoch.append(test_loss/len(test_loader))

    lr_scehudler.step(val_loss_per_epoch[-1])

    print("Epoch: ", epoch+1, "Train loss: ", train_loss_per_epoch[-1], "Val␣
↪loss: ", val_loss_per_epoch[-1], "Test loss: ", test_loss_per_epoch[-1])
```

```
Epoch:  1 Train loss:  5.044032322035895 Val loss:  3.3316544691721597 Test
loss:  3.393525270768154
Epoch:  2 Train loss:  2.5859341290262012 Val loss:  1.9377626036152695 Test
loss:  1.9524018433358934
Epoch:  3 Train loss:  1.721601414091793 Val loss:  1.5419075886408489 Test
loss:  1.4871438531963914
Epoch:  4 Train loss:  1.3943074684084198 Val loss:  1.2730701330936316 Test
loss:  1.2506829032927385
Epoch:  5 Train loss:  1.197239801471616 Val loss:  1.115936729041013 Test loss:
```

```
1.09769755307539
Epoch:  6 Train loss:  1.0572793358637962 Val loss:  0.9786306204217853 Test
loss:  0.9740997012014743
Epoch:  7 Train loss:  0.9532213448374359 Val loss:  0.8838369701847886 Test
loss:  0.8931483902313091
Epoch:  8 Train loss:  0.879164864803538 Val loss:  0.8152112274458914 Test
loss:  0.8267838559400889
Epoch:  9 Train loss:  0.8241120387374619 Val loss:  0.7637008609193744 Test
loss:  0.7833703031510483
Epoch:  10 Train loss:  0.7845521986852457 Val loss:  0.7297153779954622 Test
loss:  0.7470582377763442
Epoch:  11 Train loss:  0.7528036900876481 Val loss:  0.7253795257120421 Test
loss:  0.7179016147130801
Epoch:  12 Train loss:  0.7261243872804406 Val loss:  0.6736350890361902 Test
loss:  0.7003690690538029
Epoch:  13 Train loss:  0.7043016736890063 Val loss:  0.6553660956296053 Test
loss:  0.6786355808561231
Epoch:  14 Train loss:  0.6842405130097895 Val loss:  0.6433809038364526 Test
loss:  0.6633080869545172
Epoch:  15 Train loss:  0.6673020146511219 Val loss:  0.6208234637072592 Test
loss:  0.6473549278797927
Epoch:  16 Train loss:  0.6518398451584356 Val loss:  0.6257883617372224 Test
loss:  0.6334221640854706
Epoch:  17 Train loss:  0.6373407068075957 Val loss:  0.6025128427780035 Test
loss:  0.6211050255798999
Epoch:  18 Train loss:  0.6267520095463153 Val loss:  0.5792950581420552 Test
loss:  0.6134037903429549
Epoch:  19 Train loss:  0.6121738332289236 Val loss:  0.5672783535538297 Test
loss:  0.5998080964257688
Epoch:  20 Train loss:  0.6039698449549852 Val loss:  0.5628748201962673 Test
loss:  0.5916449381613437
Epoch:  21 Train loss:  0.5899881072986273 Val loss:  0.5591041689569299 Test
loss:  0.5856422231889066
Epoch:  22 Train loss:  0.5826923085583581 Val loss:  0.5524021495472301 Test
loss:  0.5753879381550683
Epoch:  23 Train loss:  0.5767295936375488 Val loss:  0.54508622397076 Test
loss:  0.5705345502974074
Epoch:  24 Train loss:  0.5666191531920138 Val loss:  0.5307529532548153 Test
loss:  0.5618704901433286
Epoch:  25 Train loss:  0.5597873111197977 Val loss:  0.5259086300026287 Test
loss:  0.5563819309075674
Epoch:  26 Train loss:  0.554042245870755 Val loss:  0.5206093580433817 Test
loss:  0.5521462962583259
Epoch:  27 Train loss:  0.5501569836963842 Val loss:  0.508394720879468 Test
loss:  0.5492178904421535
Epoch:  28 Train loss:  0.5428346321906572 Val loss:  0.5212305377830159 Test
loss:  0.5424251720125293
Epoch:  29 Train loss:  0.5377390726848885 Val loss:  0.5135678242553364 Test
```

```
loss:  0.537404578960972
Epoch:  30 Train loss:  0.5349510317599332 Val loss:  0.5021451169794257 Test
loss:  0.5358283481112233
Epoch:  31 Train loss:  0.5309245376675217 Val loss:  0.4959628970334024 Test
loss:  0.5323892357172789
Epoch:  32 Train loss:  0.5266576563870465 Val loss:  0.48921683882222033 Test
loss:  0.5283976944140446
Epoch:  33 Train loss:  0.5225555409251907 Val loss:  0.4931635901783452 Test
loss:  0.5227267550833431
Epoch:  34 Train loss:  0.5180010208745062 Val loss:  0.48791271538445447 Test
loss:  0.5207540957648077
Epoch:  35 Train loss:  0.5149259470679142 Val loss:  0.48354241251945496 Test
loss:  0.5174984735103301
Epoch:  36 Train loss:  0.5131255129789128 Val loss:  0.4836010418154977 Test
loss:  0.5138383341240295
Epoch:  37 Train loss:  0.5124582295064573 Val loss:  0.4761627876397335 Test
loss:  0.5123441249684051
Epoch:  38 Train loss:  0.5067326539644489 Val loss:  0.4771790450269526 Test
loss:  0.5125919190453895
Epoch:  39 Train loss:  0.5053969733876946 Val loss:  0.47334257851947437 Test
loss:  0.5084010419654258
Epoch:  40 Train loss:  0.503074386421545 Val loss:  0.4950639352653966 Test
loss:  0.5070931996092384
```

2 Question 2

2.0.1 Exercise 2.(a)

[ ]:
```
def generate_dict(L,D,K,P):
    param_dict = {}
    param_dict["W1"] = torch.randn(K,D,device=device)
    for i in range(2,L+1):
        param_dict["W"+str(i)] = torch.randn(K,K,device=device)
    param_dict["WF"] = torch.randn(P,K,device=device)
    return param_dict

def my_nn_2a(x,L,param_dict):
    x = param_dict["W1"]@x
    for i in range(2,L+1):
        x = param_dict["W"+str(i)]@torch.tanh(x)
    x = param_dict["WF"]@torch.tanh(x)
    return x

# backward automatic differentiation from scratch
# using the chain rule

def my_backward_2a(x,L,param_dict):
```

```
    P = param_dict["WF"].shape[0]
    D = x.shape[0]
    #forward pass
    x = x.clone().detach().requires_grad_(True)
    x = param_dict["W1"]@x
    tanh_outputs =[x]
    for i in range(2,L+1):
        x = param_dict["W"+str(i)]@torch.tanh(x)
        tanh_outputs.append(x)
    x = param_dict["WF"]@torch.tanh(x)
    #backward pass for jacobian
    df_intermediate = torch.diag(1-torch.tanh(tanh_outputs[-1])**2)
    df_intermediate = param_dict["WF"]@df_intermediate
    for i in range(L,1,-1):
        df_intermediate = df_intermediate@ param_dict["W"+str(i)]@torch.
 ↪diag(1-torch.tanh(tanh_outputs[i-2])**2)
    df_intermediate = df_intermediate@param_dict["W1"]
    #copy df_intermediate to df_dx
    return df_intermediate





epsilon = 1e-2



D = 2
K= 30
P = 10
L = 10
param_dict = generate_dict(L,D,K,P)

start = time.time()
for i in range(1000):
    test = torch.randn(D,device=device,requires_grad=True)
    my_J = my_backward_2a(test,L,param_dict)
    J_autograd = torch.autograd.functional.jacobian(lambda x:␣
 ↪my_nn_2a(x,L,param_dict),test,create_graph=True,strategy="reverse-mode")
    #assert, print two jacobians if they are not equal
    assert torch.allclose(my_J,J_autograd,atol=epsilon), print(my_J,J_autograd)
    #Get time taken
end = time.time()
print("Time taken for 1000 iterations: ", end-start)
print ("Jacobian is correct")
```

```
Time taken for 1000 iterations:  9.11955213546753
Jacobian is correct
```

2.0.2 Exercise 2.(b)

```
[ ]: def my_forward_2b(x,L,param_dict):
         x = param_dict["W1"]@x
         df_dx = param_dict["W1"]
         for i in range(2,L+1):
             x = torch.tanh(x)
             #foward automatic differentiation
             df_intermediate = torch.diag(1-x**2)
             df_dx = param_dict["W"+str(i)]@df_intermediate@df_dx
             x = param_dict["W"+str(i)]@x
         x = torch.tanh(x)
         df_intermediate = torch.diag(1-x**2)
         df_dx = param_dict["WF"]@df_intermediate@df_dx
         x = param_dict["WF"]@x
         return df_dx

     param_dict = generate_dict(L,D,K,P)

     start = time.time()
     for i in range(1000):
         test_2b = torch.randn(D,device=device,requires_grad=True)
         my_J_2b = my_forward_2b(test_2b,L,param_dict)
         J_autograd_2b = torch.autograd.functional.jacobian(lambda x:␣
      ↪my_nn_2a(x,L,param_dict),test_2b, strategy="forward-mode", vectorize=True)
         #assert, print two jacobians if they are not equal
         assert torch.allclose(my_J_2b,J_autograd_2b,atol=epsilon),␣
      ↪print(my_J_2b,J_autograd_2b)
     end = time.time()
     print("Time taken for 1000 iterations: ", end-start)
     print ("Jacobian is correct")
```

```
Time taken for 1000 iterations:  4.200482368469238
Jacobian is correct
```

2.0.3 Exercise 2(c)

[ ]:
```
#Run on GPU
device = torch.device("cuda:0" if torch.cuda.is_available() else "cpu")
print("Running on GPU: ", torch.cuda.is_available())

test_l = [3,5,10]

D= 1000
K = 1000
P =1

test = torch.randn(D,device=device,requires_grad=True)



print("""When D,K,P are large (1000,1000,1), the reverse mode is faster than␣
 ↪the forward mode.""")

for L in test_l:
    print("L = ", L)
    param_dict = generate_dict(L,D,K,P)

    start = time.time()
    for i in range(1000):
        my_J = my_backward_2a(test,L,param_dict)
    end = time.time()
    print ("Time taken for 1000 iterations of backward with L = ", L, " is ",␣
 ↪time.time()-start)
    start = time.time()
    for i in range(1000):
        my_J_2b = my_forward_2b(test,L,param_dict)
    end = time.time()
    print ("Time taken for 1000 iterations of forward with L =  ", L, " is ",␣
 ↪time.time()-start)
```

```
Running on GPU:  True
When D,K,P are large (1000,1000,1), the reverse mode is faster than the forward
mode.
L =  3
Time taken for 1000 iterations of backward with L =  3  is  0.5629339218139648
Time taken for 1000 iterations of forward with L =   3  is  0.7463889122009277
L =  5
Time taken for 1000 iterations of backward with L =  5  is  0.8709812164306641
Time taken for 1000 iterations of forward with L =   5  is  1.5786635875701904
L =  10
Time taken for 1000 iterations of backward with L =  10  is  1.6397125720977783
```

```
Time taken for 1000 iterations of forward with L =   10  is  3.675320863723755
```

[ ]:
```
#Run on CPU
device = "cpu"
print("Running on CPU:")

test_l = [3,5,10]

D=1000
P=1
K=1000

test= torch.randn(D,device=device,requires_grad=True)


print("""When D,K,P are large (1000,1000,1), the reverse mode is faster than␣
↪the forward mode.""")



for L in test_l:
    print("L = ", L)
    param_dict = generate_dict(L,D,K,P)
    start = time.time()
    for i in range(1000):
        my_J = my_backward_2a(test,L,param_dict)
    end = time.time()
    print ("Time taken for 1000 iterations of backward with L = ", L, " is ",␣
↪(end-start))
    start = time.time()
    for i in range(1000):
        my_J_2b = my_forward_2b(test,L,param_dict)
    end = time.time()
    print ("Time taken for 1000 iterations of forward with L =  ", L, " is ",␣
↪(end-start))
```

```
Running on CPU:
When D,K,P are large (1000,1000,1), the reverse mode is faster than the forward
mode.
L =  3
Time taken for 1000 iterations of backward with L =  3  is  3.24117112159729
Time taken for 1000 iterations of forward with L =   3  is  21.133321046829224
L =  5
Time taken for 1000 iterations of backward with L =  5  is  5.777544736862183
Time taken for 1000 iterations of forward with L =   5  is  41.2066969871521
L =  10
Time taken for 1000 iterations of backward with L =  10  is  11.320931434631348
```

```
Time taken for 1000 iterations of forward with L =   10  is  91.34891438484192
```

3 Question 4

3.0.1 Exercise 4a) & 4b)

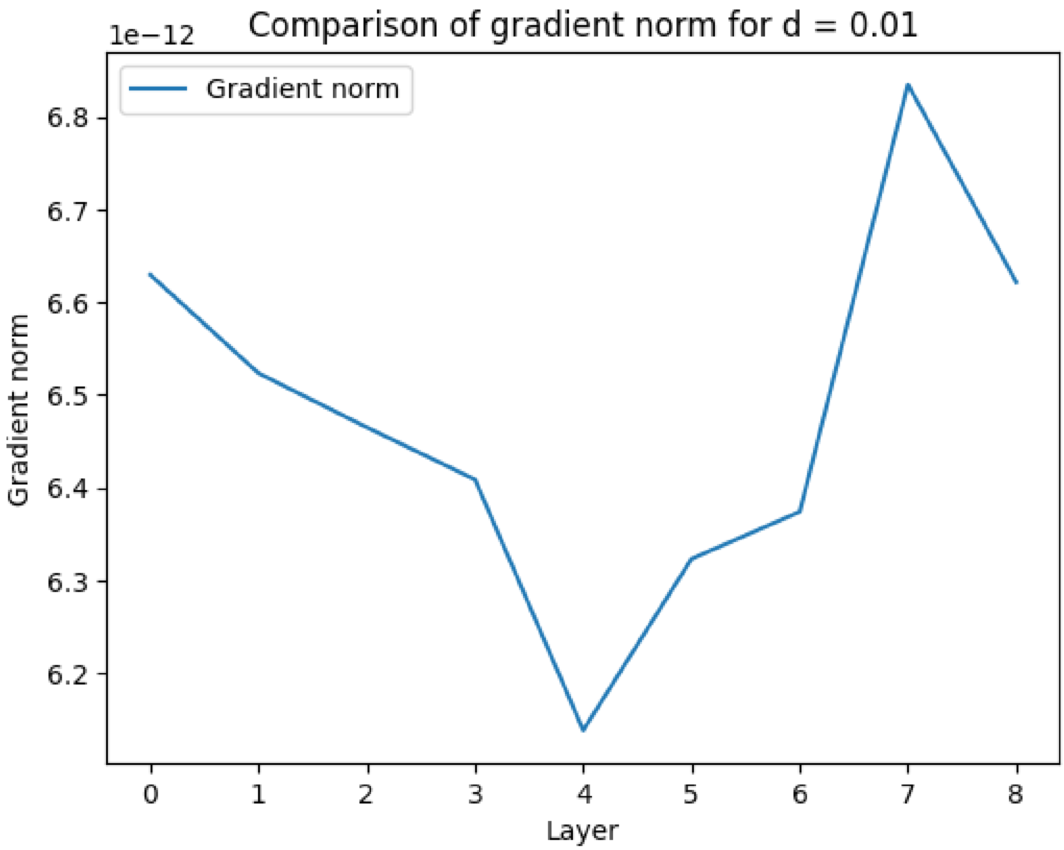
[ ]:
```python
device = torch.device("cuda:0" if torch.cuda.is_available() else "cpu")

import torch.nn as nn

class My_nn_4a(nn.Module):
    def __init__(self,depth):
        super(My_nn_4a,self).__init__()
        self.depth = depth
        self.input_layer = nn.Linear(784,50)
        self.layers = nn.ModuleList([nn.Linear(50,50) for i in range(depth-1)])
        self.output_layer = nn.Linear(50,10)
        self.activation = nn.Tanh()

    def forward(self,x):
        x = x.view(-1,784)
        x= self.input_layer(x)
        x = self.activation(x)
        #x.retain_grad()
        for i in range(self.depth-1):
            x = self.layers[i](x)
            x = self.activation(x)
            #x.retain_grad()
        x = self.output_layer(x)
        return x

    def initialize_weights(self,d, xavier = False):
        #use torch.nn.init
        for m in self.modules():
            if isinstance(m, nn.Linear):
                if xavier:
                    d = np.sqrt(6/(m.in_features + m.out_features))
                    nn.init.uniform_(m.weight, -d, d)
                    nn.init.zeros_(m.bias)
                else:
                    nn.init.uniform_(m.weight, -d, d)
                    nn.init.zeros_(m.bias)

    # use cross entropy loss
    def loss(self, x, y):
        return nn.CrossEntropyLoss()(self.forward(x), y)
```

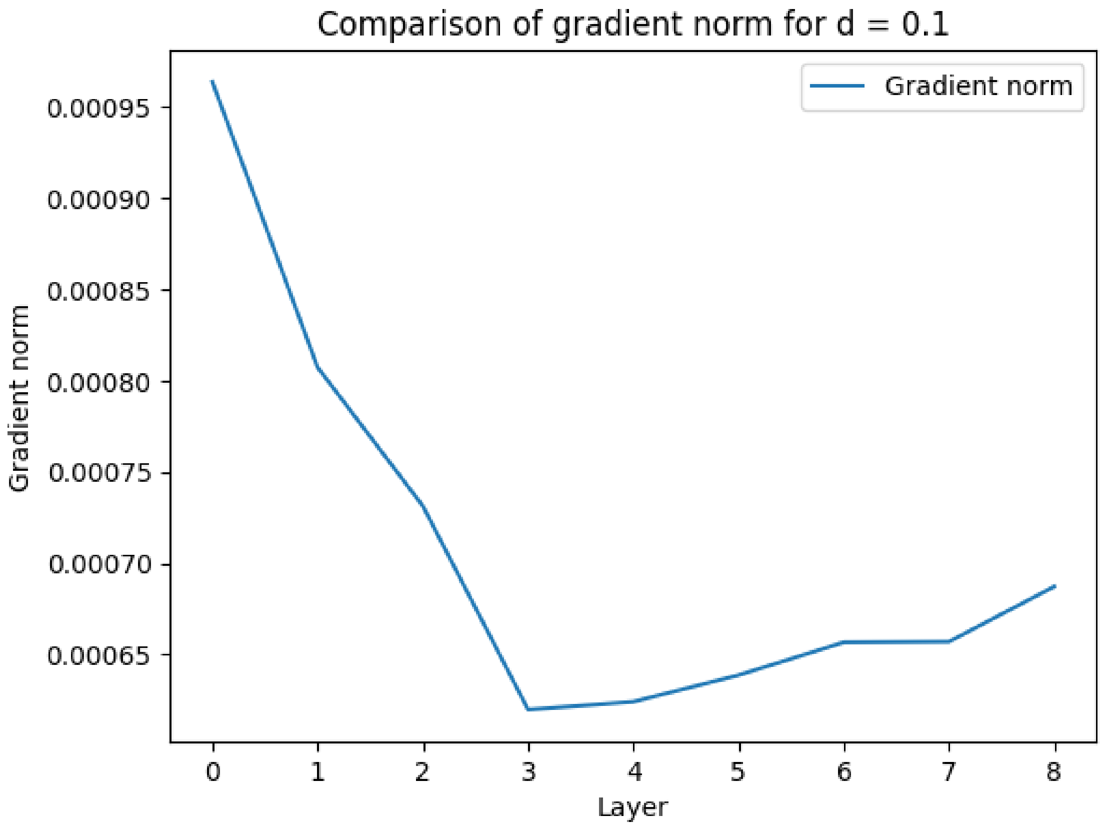
```
```

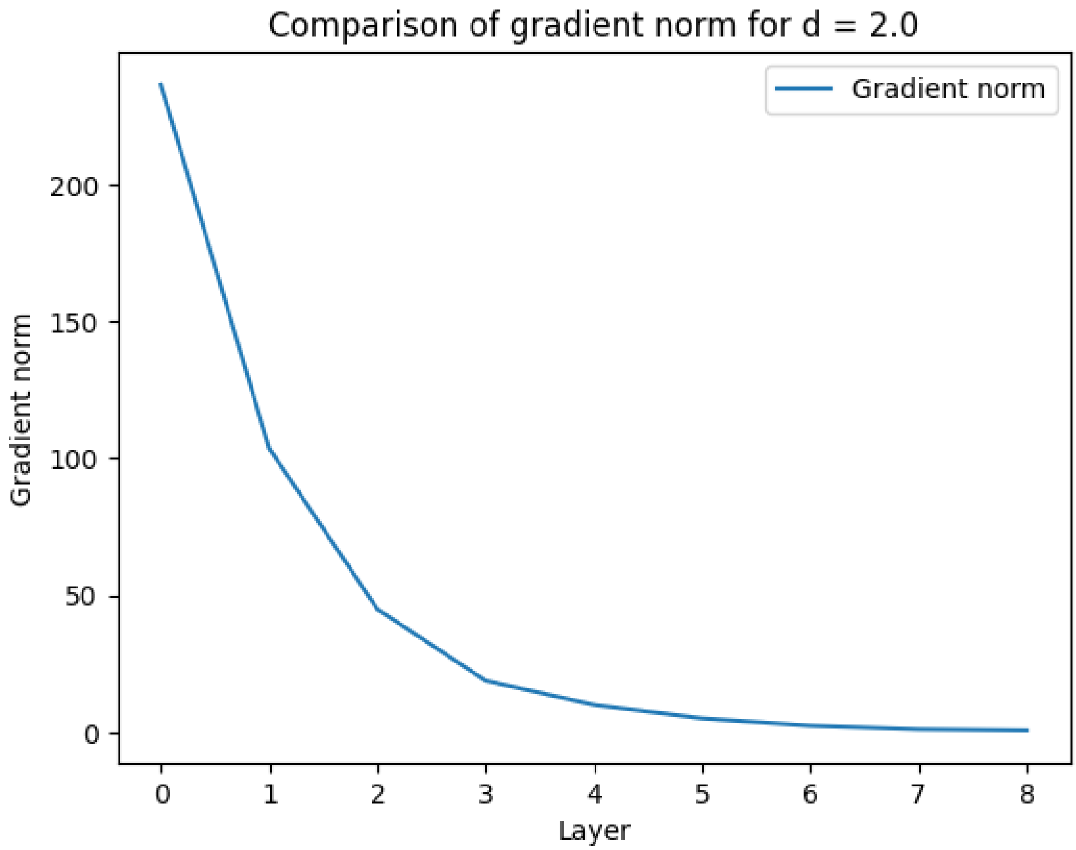
3.0.2 Exercise 4c)

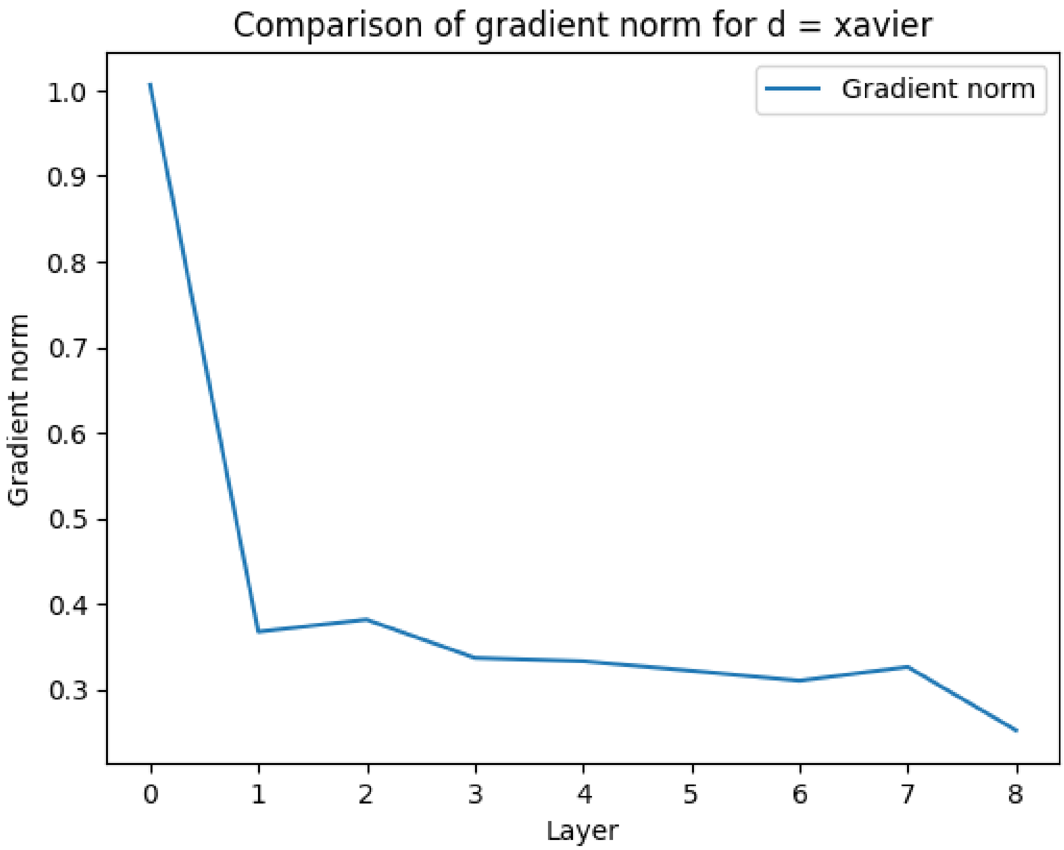
[ ]:
```
#forward and backward a minibatch of 256 MNIST digits through the network with␣
↪depth 8.


from torchvision import datasets, transforms
#load MNIST data
transform=transforms.Compose([
        transforms.ToTensor()
        ])

train_batch_size = 256
test_batch_size = 256

# load MNIST train and test sets
mnist_train = datasets.MNIST(root='.',
                             train=True,
                             download=True,
                              transform=transform)
mnist_test = datasets.MNIST(root='.',
                            train=False,
                            download=True,
                            transform=transform)

# initialize dataloaders for MNIST train and test sets
train_dataloader = data.
 ↪DataLoader(mnist_train,batch_size=train_batch_size,drop_last=True)
test_dataloader = data.
 ↪DataLoader(mnist_test,batch_size=test_batch_size,drop_last=True)

device = torch.device("cuda:0" if torch.cuda.is_available() else "cpu")

network = My_nn_4a(8).to(device)

#"""Just to check if the network is working"""
# def test(test_dataloader):
#     loss = 0
#     accuracy = 0
#     for x,y in test_dataloader:
#         x = x.to(device)
#         y = y.to(device)
#         output = network.forward(x)
#         prediciton = torch.argmax(output,dim=1)
#         accuracy += torch.sum(prediciton==y).item()/test_batch_size
```

```python
#         loss += nn.functional.cross_entropy(output,y).item()
#     print(f'test loss: {loss/len(test_dataloader):4f}')
#     print(f'test accuracy: {accuracy/len(test_dataloader)*100:.2f}%')

# test(test_dataloader)

#Compute and visualize the gradient norm at each layer
def compute_grad_norm(network):
    grad_norm = []
    for m in network.modules():
        if isinstance(m, nn.Linear):
            grad_norm.append(torch.norm(m.weight.grad).item())
    return grad_norm

def visualize_grad_norm(grad_norm,title):
    plt.figure()
    plt.title(title)
    plt.plot(grad_norm, label="Gradient norm")
    plt.xlabel("Layer")
    plt.ylabel("Gradient norm")
    plt.legend()
    plt.show()

d_list = [0.01,0.1,2.0,"xavier"]



for d in d_list:
    if d == "xavier":
        network.initialize_weights(1,xavier=True)
    else:
        network.initialize_weights(d)

    title = "Comparison of gradient norm for d = " + str(d)

    for x,y in test_dataloader:
        x = x.to(device)
        y = y.to(device)
        loss = network.loss(x,y)
        loss.backward()
        grad_norm = compute_grad_norm(network)
        visualize_grad_norm(grad_norm,title)
        network.zero_grad()
        break
```


Comparison of gradient norm for d = 0.01
1e−12
Gradient norm
6.8
6.7
6.6
6.5
6.4
6.3
6.2
Gradient norm
0
1
2
3
4
5
6
7
8
Layer


Comparison of gradient norm for d = 0.1
Gradient norm
0.00095
0.00090
0.00085
0.00080
0.00075
0.00070
0.00065
Gradient norm
0
1
2
3
4
5
6
7
8
Layer


Comparison of gradient norm for d = 2.0
Gradient norm
Gradient norm
0
50
100
150
200
0
1
2
3
4
5
6
7
8
Layer



3.0.3 Exercise 4 d)

[ ]:
```
#Train the model for 5 epochs, minibatch size 128, and learning rate 0.01

import torch.optim as optim

train_batch_size = 128
test_batch_size = 128

train_dataloader = data.
 ↪DataLoader(mnist_train,batch_size=train_batch_size,drop_last=True)
test_dataloader = data.
 ↪DataLoader(mnist_test,batch_size=test_batch_size,drop_last=True)

def train(train_dataloader, test_dataloader, network, epochs, learning_rate):
    optimizer = optim.SGD(network.parameters(), lr=learning_rate)
    train_loss = []
    train_accuracy = []
    test_loss = []
```

```
    test_accuracy = []
    for epoch in range(epochs):
        # training
        network.train()
        for x,y in train_dataloader:
            optimizer.zero_grad()
            x = x.to(device)
            y = y.to(device)
            output = network.forward(x)
            loss = nn.functional.cross_entropy(output,y)
            loss.backward()
            optimizer.step()
            train_loss.append(loss.item())
            prediciton = output.argmax(dim=1)
            #print(prediciton)
            #print(network.layers[0].weight)
            train_accuracy.append(torch.sum(prediciton==y).item()/
 ↪train_batch_size)
        # testing
        network.eval()
        for x,y in test_dataloader:
            x = x.to(device)
            y = y.to(device)
            output = network.forward(x)
            prediciton = torch.argmax(output,dim=1)
            test_accuracy.append(torch.sum(prediciton==y).item()/
 ↪test_batch_size)
            test_loss.append(nn.functional.cross_entropy(output,y).item())
        print(f'epoch: {epoch+1}')
        print(f'train loss: {sum(train_loss)/ (len(train_dataloader) *␣
 ↪(epoch+1)):4f} - train accuracy: {sum(train_accuracy)/␣
 ↪(len(train_dataloader) * (epoch+1))*100:.2f}%')
        print(f'test loss: {sum(test_loss)/ (len(test_dataloader) * (epoch+1)):
 ↪4f} - test accuracy: {sum(test_accuracy)/ (len(test_dataloader) *␣
 ↪(epoch+1))*100:.2f}%')
for d in d_list:
    network = My_nn_4a(8).to(device)
    if d == "xavier":
        network.initialize_weights(1,xavier=True)
    else:
        network.initialize_weights(d)
    train(train_dataloader, test_dataloader, network, 5, 0.01)
```

```
epoch: 1
train loss: 2.302108 - train accuracy: 11.19%
test loss: 2.301665 - test accuracy: 11.35%
epoch: 2
```

```
train loss: 2.301826 - train accuracy: 11.21%
test loss: 2.301479 - test accuracy: 11.35%
epoch: 3
train loss: 2.301659 - train accuracy: 11.22%
test loss: 2.301366 - test accuracy: 11.35%
epoch: 4
train loss: 2.301553 - train accuracy: 11.23%
test loss: 2.301293 - test accuracy: 11.35%
epoch: 5
train loss: 2.301483 - train accuracy: 11.23%
test loss: 2.301243 - test accuracy: 11.35%
epoch: 1
train loss: 2.302034 - train accuracy: 11.36%
test loss: 2.301557 - test accuracy: 11.35%
epoch: 2
train loss: 2.301740 - train accuracy: 11.30%
test loss: 2.301373 - test accuracy: 11.35%
epoch: 3
train loss: 2.301572 - train accuracy: 11.28%
test loss: 2.301264 - test accuracy: 11.35%
epoch: 4
train loss: 2.301468 - train accuracy: 11.27%
test loss: 2.301193 - test accuracy: 11.35%
epoch: 5
train loss: 2.301397 - train accuracy: 11.26%
test loss: 2.301144 - test accuracy: 11.35%
epoch: 1
train loss: 6.039689 - train accuracy: 11.67%
test loss: 2.480055 - test accuracy: 12.66%
epoch: 2
train loss: 4.200424 - train accuracy: 12.47%
test loss: 2.397484 - test accuracy: 14.90%
epoch: 3
train loss: 3.554068 - train accuracy: 14.34%
test loss: 2.338540 - test accuracy: 16.49%
epoch: 4
train loss: 3.215720 - train accuracy: 15.50%
test loss: 2.286135 - test accuracy: 17.93%
epoch: 5
train loss: 3.001272 - train accuracy: 16.82%
test loss: 2.239740 - test accuracy: 19.48%
epoch: 1
train loss: 1.190881 - train accuracy: 70.15%
test loss: 0.639273 - test accuracy: 85.36%
epoch: 2
train loss: 0.856330 - train accuracy: 78.54%
test loss: 0.528139 - test accuracy: 87.41%
epoch: 3
```

```
train loss: 0.700018 - train accuracy: 82.28%
test loss: 0.464706 - test accuracy: 88.60%
epoch: 4
train loss: 0.606552 - train accuracy: 84.49%
test loss: 0.422158 - test accuracy: 89.43%
epoch: 5
train loss: 0.542731 - train accuracy: 86.02%
test loss: 0.390663 - test accuracy: 90.06%
```