Assignment 7: Neural Networks and a Glimpse at Pytorch

Copyrighting and Fair Use

Automatic Testing Guidelines

Automatic unittesting requires you, as a student, to submit a notebook which contains strictly defined objects. Strictness of definition consists of unified shapes, dtypes, variable names and more.

Within the notebook, we provide detailed instruction which you should follow in order to maximise your final grade.

Name your notebook properly, follow the pattern in template name:

Assignment_N_NameSurname_matrnumber

1. N - number of assignment
2. NameSurname - your full name where every part of the name starts with a capital letter, no spaces
3. matrnumber - your 8-digit student number on ID card (without k)

Example:
✅ Assignment_0_RenéDescartes_12345678
✅ Assignment_0_SørenAabyeKierkegaard_12345678
❌ Assignment0_Peter_Pan_k12345678

Don't add any cells but use the ones provided by us. You may notice that most cells are tagged such that the unittest routine can recognise them.

We highly recommend you to develop your code within the provided cells. You can implement helper functions where needed unless you put them in the same cell they are actually called. Always make sure that implemented functions have the correct output and given variables contain the correct data type. Don't import any other packages than listed in the cell with the "imports" tag.

Note: Never use variables you defined in another cell in your functions directly; always pass them to the function as a parameter. In the unitest they won't be available either.

Good luck!

Task 1: The XOR Problem

Task 1.1.

In this task we try to formalize the fact that a single layer neural network (NN) cannot solve the XOR problem, but a two layer network can.

Let us assume that we only have four possible inputs $\mathbf{x}_1 = (0,0)$, $\mathbf{x}_2 = (1,0)$, $\mathbf{x}_3 = (0,1)$, and $\mathbf{x}_4 = (1,1)$ with the following labels $y_1 = 0$, $y_2 = 1$, $y_3 = 1$, and $y_4 = 0$, respectively. Note that this exactly describes the XOR function: it outputs 1 (=true) if and only if exactly one of the input components equals 1 (=true).

- As a first task show that if we use a linear network

$g_1(\mathbf{x};\mathbf{w}) = \mathbf{x}\cdot\mathbf{w} = x^{(1)}w_1 + x^{(2)}w_2$, it is impossible to find parameters w_1 and w_2 that solve this problem exactly.

Please provide reasoning and explanations in full sentences. Grading of the task will heavily depend on it.

Calculation (10 points):

$$\begin{gathered}
\text{Let's take the four possible inputs separately:}\\
g_1(\mathbf{x}_1;\mathbf{w}) = 0\cdot w_1 + 0\cdot w_2 = 0\\
g_1(\mathbf{x}_2;\mathbf{w}) = 1\cdot w_1 + 0\cdot w_2 = 1\\
g_1(\mathbf{x}_3;\mathbf{w}) = 0\cdot w_1 + 1\cdot w_2 = 1\\
g_1(\mathbf{x}_4;\mathbf{w}) = 1\cdot w_1 + 1\cdot w_2 = 0
\end{gathered}$$

$$\begin{gathered}
\text{Let the values of } \mathbf{x}^{(1)} \text{and } \mathbf{x}^{(2)} \text{would be 0 and 0, then } g_1(\mathbf{x},\mathbf{w}) = 0.\\
\text{So, we would have a threshold t>0. The condition is also satisfied if either of } \mathbf{x}^{(1)} \text{and } \mathbf{x}^{(2)} \text{is 1.}\\
\text{But if the values of } \mathbf{x}^{(1)} \text{and } \mathbf{x}^{(2)} \text{are simultaneously 1, the sum of them would be 0 which is not greater than the threshold t.}\\
\text{Thus, it is impossible to find the parameteres } \mathbf{w}_1 \text{and } \mathbf{w}_2 \text{ that solve this problem exactly, meaning one single layer network is impossible for this problem.}
\end{gathered}$$

Task 1.2.

Even by adding bias units or by applying a sigmoid, the problem cannot be solved.

However, as soon as we use a two-layer network with a simple non-linear activation function (ReLU):

$$g_2(\mathbf{x};\mathbf{W}^{[1]},\mathbf{W}^{[2]},\mathbf{b}) = \mathbf{W}^{[2]T}\max(0,\mathbf{W}^{[1]}\mathbf{x}+\mathbf{b}),$$

we can find parameters, that solve the problem.

- Precisely, show that $\mathbf{W}^{[1]} = \begin{pmatrix}1 & 1\\ 1 & 1\end{pmatrix}$,

```
$\mathbf{b}=\begin{pmatrix} 0 \\ -1 \end{pmatrix}$, and $\mathbf{W}^{[2]}=\begin{pmatrix} 1 \\ -2 \end{pmatrix}$ solve the problem
in an exact way. The transformation $\max(0,\mathbf{W}^{[1]} \mathbf{x} + \mathbf{b})$ has
mapped the points $ \mathbf{x}_1,\ldots,  \mathbf{x}_4$ into a space, in which those data points are
linearly separable.
```

Please provide reasoning and explanations in full sentences. Grading of the task will heavily depend on it.

Calculation (15 points):

$$\begin{gathered}
\text{We are going to take the outputs for each of the inputs:}\\
g_2(\mathbf{x}_1,\mathbf{W}^{[1]},\mathbf{W}^{[2]},\mathbf{b}) = (1\ \ -2)\cdot\max\left(\begin{pmatrix}0\\0\end{pmatrix},\begin{pmatrix}1&1\\1&1\end{pmatrix}\cdot\begin{pmatrix}0\\0\end{pmatrix}+\begin{pmatrix}0\\-1\end{pmatrix}\right) = (1\ \ -2)\cdot\max\left(\begin{pmatrix}0\\0\end{pmatrix},\begin{pmatrix}0\\-1\end{pmatrix}\right) = (1\ \ -2)\cdot\begin{pmatrix}0\\0\end{pmatrix} = 0\\
g_2(\mathbf{x}_2,\mathbf{W}^{[1]},\mathbf{W}^{[2]},\mathbf{b}) = (1\ \ -2)\cdot\max\left(\begin{pmatrix}0\\0\end{pmatrix},\begin{pmatrix}1&1\\1&1\end{pmatrix}\cdot\begin{pmatrix}1\\0\end{pmatrix}+\begin{pmatrix}0\\-1\end{pmatrix}\right) = (1\ \ -2)\cdot\begin{pmatrix}1\\0\end{pmatrix} = 1\\
g_2(\mathbf{x}_3,\mathbf{W}^{[1]},\mathbf{W}^{[2]},\mathbf{b}) = (1\ \ -2)\cdot\max\left(\begin{pmatrix}0\\0\end{pmatrix},\begin{pmatrix}1&1\\1&1\end{pmatrix}\cdot\begin{pmatrix}0\\1\end{pmatrix}+\begin{pmatrix}0\\-1\end{pmatrix}\right) = (1\ \ -2)\cdot\begin{pmatrix}1\\0\end{pmatrix} = 1\\
g_2(\mathbf{x}_4,\mathbf{W}^{[1]},\mathbf{W}^{[2]},\mathbf{b}) = (1\ \ -2)\cdot\max\left(\begin{pmatrix}0\\0\end{pmatrix},\begin{pmatrix}1&1\\1&1\end{pmatrix}\cdot\begin{pmatrix}1\\1\end{pmatrix}+\begin{pmatrix}0\\-1\end{pmatrix}\right) = (1\ \ -2)\cdot\begin{pmatrix}2\\1\end{pmatrix} = 0\\
\text{Since the results are the same with the actual truth values, the two-layer networks solves the problem in an exact way}
\end{gathered}$$

Task 2: Backprop of a Simple NN

Consider the following neural network (we try to adapt to the notation from the lecture):

The preactivations of the hidden units are denoted as s_3, s_4 and s_5 from left to right, their activations as a_3, a_4 and a_5, respectively. In the hidden layer we use ReLU as activation function, i.e. $f_3(x) = f_4(x) = f_5(x) = \mathrm{ReLU}(x)$, and in the output layer the activation is the identity function. The preactivation of the output layer is denoted as s_6 and the output as $\hat{y}$. The delta at the output is denoted as δ_6, and the hidden deltas as δ_3, δ_4 and δ_5 from left to right, respectively. The true label is $y = 1$ and as loss function we use the mean-squared loss, i.e $L(y,\hat{y}) = \frac{1}{2}(y-\hat{y})^2$. * Compute all outputs, preactivations, activations, and delta errors! Also compute $\frac{\partial L}{\partial w_{32}}$. Write down formulas (not only the numerical result) that indicate your computations at least for s_3, δ_3 and $\frac{\partial L}{\partial w_{32}}$.
Please provide reasoning and explanations in full sentences. Grading of the task will heavily depend on it.

Calculation (25 points):

$$\begin{gathered}
a_1 = x_1 = 1 \text{ and } a_2 = x_2 = 2 \text{ (for the input layer)}\\
a_3 = \mathrm{ReLu}(s_3), a_4 = \mathrm{ReLu}(s_4), a_5 = \mathrm{ReLu}(s_5)\\
s_3 = \mathbf{w}_{31}a_1 + \mathbf{w}_{32}a_2 = -0.1\cdot 1 + 0.5\cdot 2 = 0.9 \text{ and } a_3 = \mathrm{ReLu}(s_3) = \max(0,0.9) = 0.9\\
s_4 = \mathbf{w}_{41}a_1 + \mathbf{w}_{42}a_2 = -1\cdot 1 + 0\cdot 2 = -1 \text{ and } a_4 = \mathrm{ReLu}(s_4) = \max(0,-1) = 0\\
s_5 = \mathbf{w}_{51}a_1 + \mathbf{w}_{52}a_2 = 0\cdot 1 + (-2)\cdot 2 = -4 \text{ and } a_5 = \mathrm{ReLu}(s_5) = \max(0,-4) = 0\\
s_6 = \mathbf{w}_{63}a_3 + \mathbf{w}_{64}a_4 + \mathbf{w}_{65}a_5 = 1\cdot 0.9 - 1\cdot 0 + 0.5\cdot 0 = 0.9\\
a_6 \text{ (needed for further calculations, as the output)} = \mathrm{ReLu}(s_6) = \max(0,0.9) = 0.9\\
\delta_6 = \frac{\partial}{\partial s_6}L(y,\hat{y}) = \frac{\partial}{\partial a_6}L(y,\hat{y})f'(s_6) = \frac{\partial}{\partial a_6}\left(\frac{1}{2}(1-a_6)^2\right)f'(s_6) = 2\cdot\frac{1}{2}(1-a_6)(-1) = a_6 - 1 = -0.1\\
\delta_5 = f'(s_5)\sum_i \delta_i\mathbf{w}_{i5} = 0 \text{ (because f'(x)=0 when x<0)}\\
\delta_4 = f'(s_4)\sum_i \delta_i\mathbf{w}_{i4} = 0 \text{ (because f'(x)=0 when x<0)}\\
\delta_3 = f'(s_3)\sum_i \delta_i\mathbf{w}_{i3} = \delta_6\mathbf{w}_{63} = -0.1\cdot 1 = -0.1 \text{ (because f'(x)=1 when x>0)}\\
\frac{\partial L}{\partial w_{32}} = \frac{\partial}{\partial s_3}L(y,\hat{y})\frac{\partial s_3}{\partial \mathbf{w}_{32}} = \frac{\partial}{\partial s_3}L(y,\hat{y})a_2\\
\text{Since } \delta_3 = \frac{\partial}{\partial s_3}L(y,\hat{y})\\
\Rightarrow \frac{\partial L}{\partial \mathbf{w}_{32}} = \delta_3 a_2 = (-0.1)\cdot 2 = -0.2
\end{gathered}$$

Task 2: Pytorch and a Visualization of the Vanishing Gradient Problem

The aim of this task is to provide you with some familiarity with Pytorch, a Python-package which is nowadays heavily used for tasks that involve computations with neural networks. It has the nice feature that it incorporates automatic differentiation, so that you don't have to implement the backward pass for a NN any more. It also allows for transferring more involved experiments to GPUs easily, however, we won't need this nice feature here. We will again work with the Fashion MNIST data set, but this time we provide you with a Pytorch routine that can download it for you and even transforms it appropriately.

- Your first task will be to just let the code run and plot some images. To this end you will need to install Pytorch appropriately in your Python library!

Code (10 points)

In [1]:
```python
import torch
import torch.nn as nn
import torch.nn.functional as F
from torch.autograd import Variable
import torch.optim as optim
from torchvision import datasets, transforms
from types import SimpleNamespace
import matplotlib.pyplot as plt
import numpy as np
import os
```

In [2]:
```python
# Here we collect the hyperparameters we are going to use
args = SimpleNamespace(batch_size=64, test_batch_size=1000, epochs=1,
                       lr=0.01, momentum=0.5, seed=1, log_interval=100)
torch.manual_seed(args.seed)
use_cuda = torch.cuda.is_available()
device = torch.device('cuda' if use_cuda else 'cpu')
```

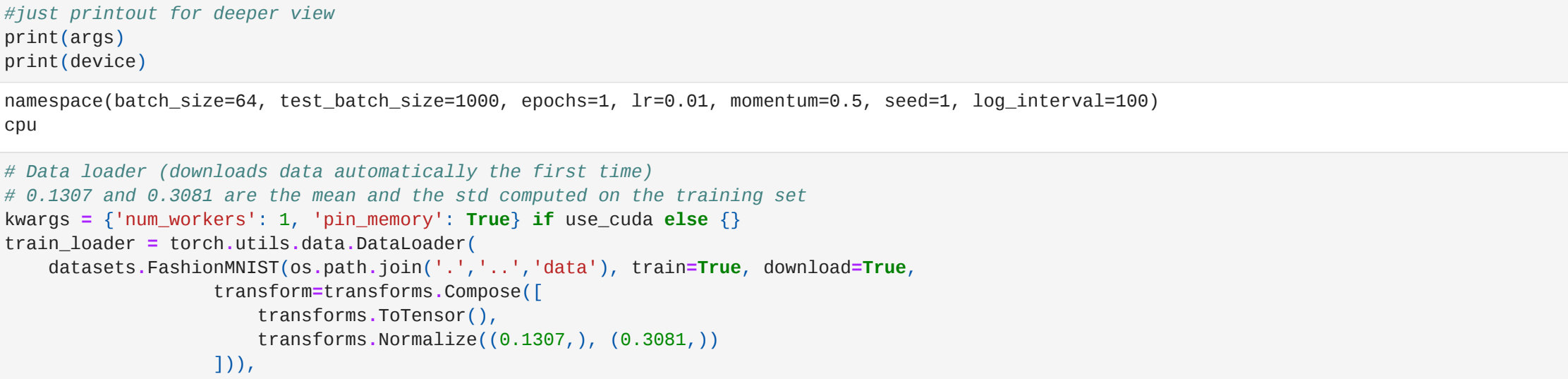
In [3]:
```python
#just printout for deeper view
print(args)
print(device)
```

```
namespace(batch_size=64, test_batch_size=1000, epochs=1, lr=0.01, momentum=0.5, seed=1, log_interval=100)
cpu
```

In [4]:
```python
# Data loader (downloads data automatically the first time)
# 0.1307 and 0.3081 are the mean and the std computed on the training set
kwargs = {'num_workers': 1, 'pin_memory': True} if use_cuda else {}
train_loader = torch.utils.data.DataLoader(
    datasets.FashionMNIST(os.path.join('.','..','data'), train=True, download=True,
                   transform=transforms.Compose([
                       transforms.ToTensor(),
                       transforms.Normalize((0.1307,), (0.3081,))
                   ])),
    batch_size=args.batch_size, shuffle=True, **kwargs)
test_loader = torch.utils.data.DataLoader(
    datasets.FashionMNIST(os.path.join('.','..','data'), train=False, transform=transforms.Compose([
                       transforms.ToTensor(),
                       transforms.Normalize((0.1307,), (0.3081,))
                   ])),
        batch_size=args.test_batch_size, shuffle=True, **kwargs)
```

In [5]:
```python
print(train_loader.dataset.targets.shape)
print(train_loader.dataset.data.shape)
input_dim = train_loader.dataset.data.shape[1]*train_loader.dataset.data.shape[2]
print("Input dimension is {}.".format(input_dim))
output_dim = 10

# Plot example images
fig=plt.figure(figsize=(15,3))
for image in range(20):
    show_img = train_loader.dataset.data[image].numpy().reshape(28, 28)
    fig.add_subplot(2,10,image+1)
    plt.xticks([]),plt.yticks([])
    plt.imshow(show_img, cmap='gray')
plt.show()
```

```
torch.Size([60000])
torch.Size([60000, 28, 28])
Input dimension is 784.
```



Next, we provide you with code that you can use to create your own artificial neural network (ANN) in terms of a class. We will use a 3-hidden-layer NN with sigmoid activation here. As you should know from the lecture, sigmoid is not a very good choice as it induces vanishing gradients.

- To overcome this issue, create a second nework class in a similar way that again has the same three linear layers but instead uses the ReLU activation function which is known to prevent the gradients from vanishing. Don't change the output activation function.

Code (10 points)

In [6]:
```python
class ANN_sigmoid(nn.Module):
    def __init__(self, D_in, D_out):
        super(ANN_sigmoid, self).__init__()
        self.linear1 = nn.Linear(D_in, 512)
        self.linear2 = nn.Linear(512, 1024)
        self.linear3 = nn.Linear(1024, 512)
        self.linear4 = nn.Linear(512, D_out)

    def forward(self, x):
        x = self.linear1(x)
        x = torch.sigmoid(x)
        x = self.linear2(x)
        x = torch.sigmoid(x)
        x = self.linear3(x)
        x = torch.sigmoid(x)
        x = self.linear4(x)
        return F.log_softmax(x, dim=1)
```

In [7]:
```python
class ANN_relu(nn.Module):
    #Your code for ReLU NN

    ## Solution start
    def __init__(self, D_in, D_out):
        super(ANN_relu,self).__init__()
        self.linear1=nn.Linear(D_in,512)
        self.linear2=nn.Linear(512,1024)
        self.linear3=nn.Linear(1024,512)
        self.linear4=nn.Linear(512,D_out)

    def forward(self, x):
        x = self.linear1(x)
        x = F.relu(x)
        x = self.linear2(x)
        x = F.relu(x)
        x = self.linear3(x)
        x = F.relu(x)
        x = self.linear4(x)
    ## Solution end
        return F.log_softmax(x, dim=1)
```

Next, we provide you with a routine for training a neural network with Pytorch. For each layer, it outputs a list where one entry indicates the averaged absolute sum of the gradient magnitudes of the activations for a particular mini batch of this particular layer. Note that the command loss.backward() automatically computes and stores the gradients of all the activations. It also prints accuracy and the loss value for each epoch.

In [8]:
```python
# This function trains the model for one epoch
# Nothing to do here
def train(args, model, device, train_loader, optimizer, epoch):
    model.train()
    grads1_list = []
    grads2_list = []
    grads3_list = []
    correct=0
    for batch_idx, (data, target) in enumerate(train_loader):
        data = Variable(data.view(-1, input_dim))
        data, target = data.to(device), target.to(device)
        optimizer.zero_grad()
        output = model(data)
        loss = F.nll_loss(output, target)
        loss.backward()

        # This part of the code gets the weights in the different layers
        grads3 = abs(model.linear3.weight.grad)
        grads2 = abs(model.linear2.weight.grad)
        grads1 = abs(model.linear1.weight.grad)
        grads3_list.append(torch.mean(grads3).item())
        grads2_list.append(torch.mean(grads2).item())
        grads1_list.append(torch.mean(grads1).item())

        optimizer.step()
        if batch_idx % args.log_interval == 0:
            print('Train Epoch: {} [{}/{} ({:.0f}%)]\tLoss: {:.6f}'.format(
                epoch, batch_idx * len(data), len(train_loader.dataset),
                100. * batch_idx / len(train_loader), loss.item()))
        pred = output.max(1, keepdim=True)[1] # get the index of the max log-probability
        correct += pred.eq(target.view_as(pred)).sum().item()
    print('\nTraining set: Accuracy: {}/{} ({:.2f}%)\n'.format(
    correct, len(train_loader.dataset),
    100. * correct / len(train_loader.dataset)))
    return grads1_list, grads2_list, grads3_list
```

Here is a similar routine for the test procedure.

In [9]:
```python
# This function evaluates the model on the test data
def test(args, model, device, test_loader):
    model.eval()
    test_loss = 0
    correct = 0
    with torch.no_grad():
        for data, target in test_loader:
            data = Variable(data.view(-1, input_dim))
            data, target = data.to(device), target.to(device)
            output = model(data)
            test_loss += F.nll_loss(output, target, reduction='sum').item() # sum up batch loss
            pred = output.max(1, keepdim=True)[1] # get the index of the max log-probability
            correct += pred.eq(target.view_as(pred)).sum().item()
    test_loss /= len(test_loader.dataset)

    print('\nTest set: Average loss: {:.4f}, Accuracy: {}/{} ({:.2f}%)\n'.format(
        test_loss, correct, len(test_loader.dataset),
        100. * correct / len(test_loader.dataset)))
```

Finally, you are asked to execute the previously built functions. To this end, perform the following tasks:

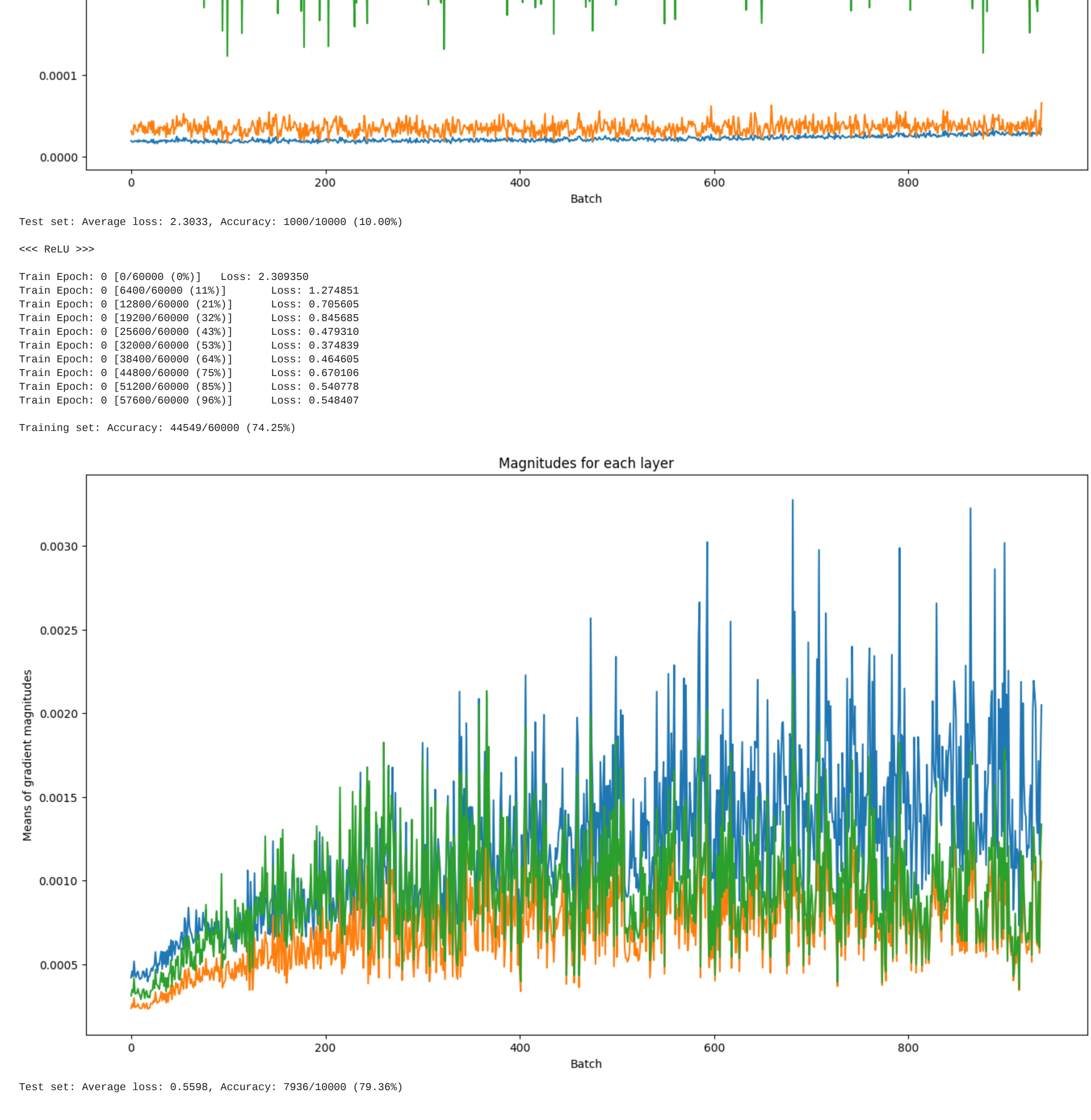
- We provided the routine for creating the model with the sigmoid function and executing it on the cpu per default. As a first task, you are now asked to create an appropriate optimizer (take a look into imports cell). Use SGD with the parameters of the model and the learning rate and momentum from the hyperparameterlist args created in the beginning.
- Now write a code where you **the function `train` for number of `epochs` in our hyperparameters collection `args`** with the required arguments for the **sigmoid model** and create a routine that **plots the output list of means of gradient magnitudes** for each layer appropriately. It should also output the test accuracy.
- Repeat the previous task but for ReLU model.

Code (20 points)

In [10]:
```python
print("<<< Sigmoid >>>\n")
model = ANN_sigmoid(input_dim, output_dim).to(device)

#please use only predefined variables names
optimizer = optim.SGD(model.parameters(),lr=args.lr,momentum=args.momentum) #define SGD optimizer
epochs_range = range(args.epochs) #range you will iterate over

for epoch in epochs_range:
    grads1_list, grads2_list, grads3_list = train(args, model, device, train_loader, optimizer, epoch)

    #plot here together 3 different magnitudes
    # plt.figure(figsize=(16,9))
    # plt.title("Layer 1")
    # plt.plot(grads1_list)
    # plt.show()
    # plt.figure(figsize=(16,9))
    # plt.title("Layer 2")
    # plt.plot(grads2_list)
    # plt.show()
    # plt.figure(figsize=(16,9))
    # plt.title("Layer 3")
    # plt.plot(grads3_list)
    # plt.show()

    plt.figure(figsize=(16,9))
    plt.title("Magnitudes for each layer")
    plt.xlabel("Batch")
    plt.ylabel("Means of gradient magnitudes")
    plt.plot(grads1_list)
    plt.plot(grads2_list)
    plt.plot(grads3_list)
    plt.show()

    #now test your model
    test(args,model,device,test_loader)

######################################################################################
print("<<< ReLU >>>\n")
model = ANN_relu(input_dim,output_dim).to(device) #define your ReLU model
optimizer = optim.SGD(model.parameters(),lr=args.lr,momentum=args.momentum) #redefine SGD optimizer

for epoch in epochs_range:
    #repeat operations of the loop above, but for ReLU model
    grads1_list, grads2_list, grads3_list = train(args, model, device, train_loader, optimizer, epoch)

    # plt.figure(figsize=(16,9))
    # plt.title("Layer 1")
    # plt.plot(grads1_list)
    # plt.show()
    # plt.figure(figsize=(16,9))
    # plt.title("Layer 2")
    # plt.plot(grads2_list)
    # plt.show()
    # plt.figure(figsize=(16,9))
    # plt.title("Layer 3")
    # plt.plot(grads3_list)
    # plt.show()

    plt.figure(figsize=(16,9))
    plt.title("Magnitudes for each layer")
    plt.xlabel("Batch")
    plt.ylabel("Means of gradient magnitudes")
    plt.plot(grads1_list)
    plt.plot(grads2_list)
    plt.plot(grads3_list)
    plt.show()

    test(args,model,device,test_loader)
```

```
<<< Sigmoid >>>

Train Epoch: 0 [0/60000 (0%)]	Loss: 2.277038
Train Epoch: 0 [6400/60000 (11%)]	Loss: 2.317646
Train Epoch: 0 [12800/60000 (21%)]	Loss: 2.291698
Train Epoch: 0 [19200/60000 (32%)]	Loss: 2.326507
Train Epoch: 0 [25600/60000 (43%)]	Loss: 2.294538
Train Epoch: 0 [32000/60000 (53%)]	Loss: 2.306917
Train Epoch: 0 [38400/60000 (64%)]	Loss: 2.309593
Train Epoch: 0 [44800/60000 (75%)]	Loss: 2.314287
Train Epoch: 0 [51200/60000 (85%)]	Loss: 2.309519
Train Epoch: 0 [57600/60000 (96%)]	Loss: 2.285814

Training set: Accuracy: 6477/60000 (10.79%)
```


```
Test set: Average loss: 2.3033, Accuracy: 1000/10000 (10.00%)

<<< ReLU >>>

Train Epoch: 0 [0/60000 (0%)]	Loss: 2.309350
Train Epoch: 0 [6400/60000 (11%)]	Loss: 1.274851
Train Epoch: 0 [12800/60000 (21%)]	Loss: 0.705605
Train Epoch: 0 [19200/60000 (32%)]	Loss: 0.845685
Train Epoch: 0 [25600/60000 (43%)]	Loss: 0.479310
Train Epoch: 0 [32000/60000 (53%)]	Loss: 0.374839
Train Epoch: 0 [38400/60000 (64%)]	Loss: 0.464605
Train Epoch: 0 [44800/60000 (75%)]	Loss: 0.670106
Train Epoch: 0 [51200/60000 (85%)]	Loss: 0.540778
Train Epoch: 0 [57600/60000 (96%)]	Loss: 0.548407

Training set: Accuracy: 44549/60000 (74.25%)
```




```
Test set: Average loss: 0.5598, Accuracy: 7936/10000 (79.36%)
```

Question (10 points):

What observations for the sigmoid network and the ReLU network can you make? Tick the correct boxes (several may be correct):

a_) The sigmoid network trains poorly in only one epoch.
b_) The means of magnitudes of the gradients for the sigmoid network are significantly higher for lower layers. This is an indication of the vanishing gradient problem.
c_) One reason why the sigmoid network can lead to vanishing gradients might be that the derivative of the sigmoid does not exceed 1/4.
d_) When you use the ReLU activation function, the resulting network trains well in only one epoch.
e_) One reason why several well-known activation functions different from sigmoid can lead to more stable training can be the fact that their derivatives are always larger than 1.

To answer the question, assign "True" or "False" boolean values to variables in the next cell. A non-correctly answered question yields negative points and no answer (i.e. answer "None") gives 0 points for a question. More details on grading can be found in the FAQ sheet.
Note: Do not reuse these variable names. They are used for testing.

In [11]:
```python
#your answers go here ↓↓↓
a_=True
b_=False
c_=True
d_=True
e_=False
```

Note, however, there are possible ways to improve the learning of the sigmoid network without changing the activation function and the network size (you are encouraged to make an educated guess and try out several choices), but still, the network archictecture seems to be too simple to really lead to a satisfying performance. In the upcoming assignment, we will further ellaborate on this issue.