

# DAT565/DIT407 Assignment 6

Sebastian Miles  
miless@chalmers.se

Olle Lapidus  
ollelap@chalmers.se

2024-10-11

## Problem 1

We verify that the images are 28x28 pixels grayscale and plot some images from the train dataset and some from the test dataset. See figure 1 and 2.

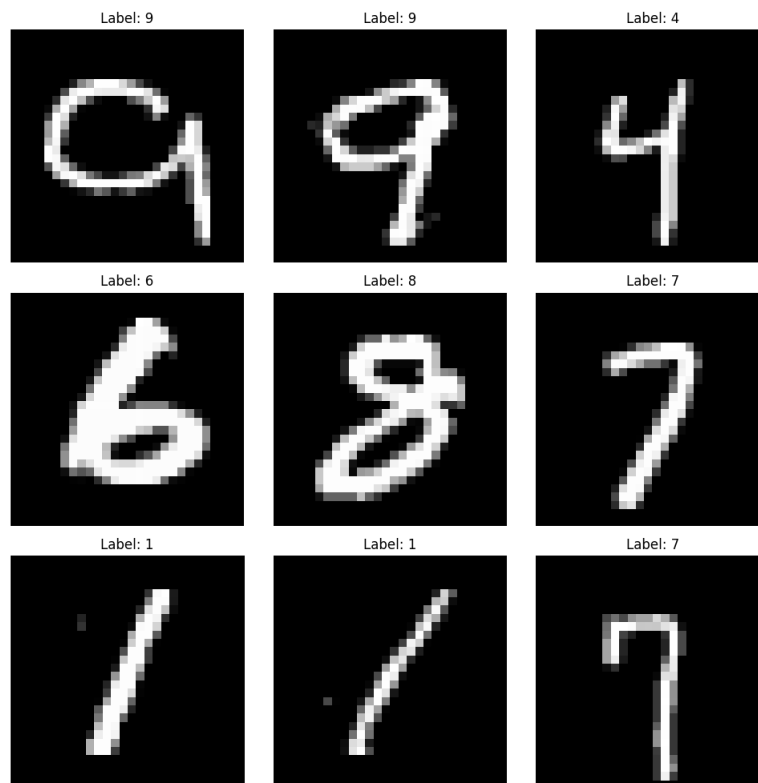


Figure 1: Various images from the train dataset

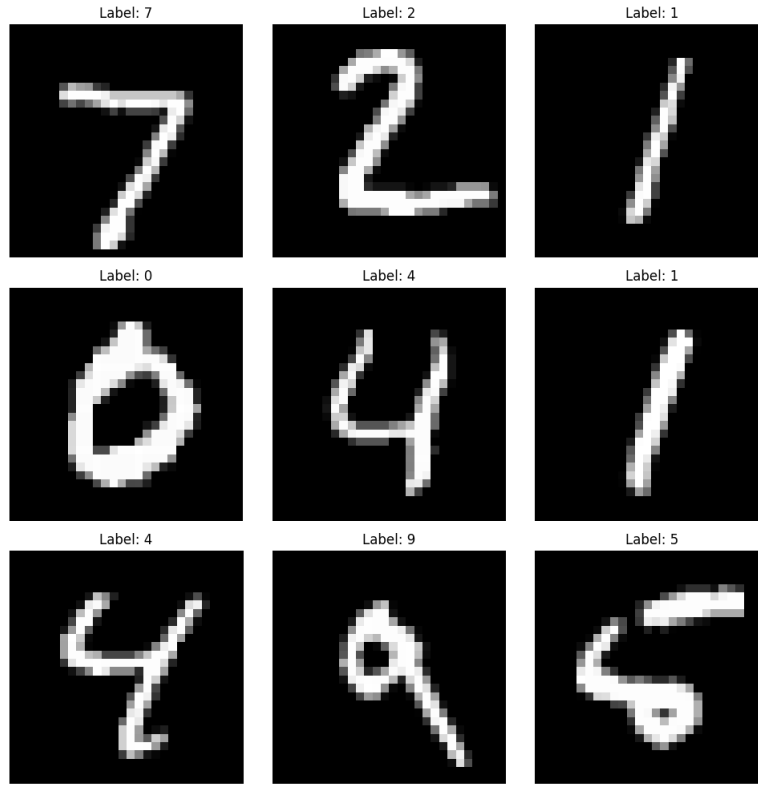


Figure 2: Various images from the test dataset

## Problem 2

We train the data with a single hidden layer. We put the hidden layer size as 128 and the learning rate for the SGD as 0.01. The accuracy over 10 epochs is shown in table 1.

Epoch	Accuracy
1	79.45%
2	82.06%
3	84.35%
4	83.96%
5	84.61%
6	85.36%
7	84.10%
8	85.57%
9	84.92%
10	86.75%

Table 1: Accuracy of the test data over 10 epochs.

### Problem 3

For this problem we used weight decay = 0.0001 and learning rate = 0.04. The accuracies are displayed in table 2. The accuracy seems to plateau at around 98%, which is also what we were supposed to reach.

Epoch	Accuracy
1	90.61%
2	94.65%
3	94.68%
4	95.81%
5	96.90%
6	94.19%
7	97.10%
8	97.29%
9	97.29%
10	97.19%
11	97.85%
12	97.76%
13	98.05%
14	97.92%
15	97.90%
16	97.21%
17	98.04%
18	98.12%
19	98.10%
20	98.07%
21	98.13%
22	98.02%
23	98.11%
24	97.80%
25	98.20%
26	98.23%
27	98.17%
28	98.21%
29	98.22%
30	98.24%
31	98.29%
32	98.22%
33	98.22%
34	98.28%
35	98.30%
36	98.30%
37	98.30%
38	98.36%
39	98.28%
40	98.34%

Table 2: Accuracy of the test data over 40 epochs with two hidden layers.

## Problem 4

In this model we first have a convolution layer with 32 filters and 3x3 kernel, and max pooling with a 2x2 window. In the second layer we have 64 filters with a 3x3 kernel and a 2x2 max pooling. Finally we have a hidden layer with 128 neurons. In between every layer we use ReLU activation which adds non-linearity to the model. We also used the same weight decay and learning rate as in problem 3. The accuracy for 40 epochs is shown in table 3. We note that the accuracies plateau at around 99.1% meaning that we have likely reached the best accuracy for the model, and running it for more epochs would be a waste.

The  $\vdots$  implies that the data continued roughly in the range 99% to 99.2%.

Epoch	Accuracy
1	97.34%
2	98.16%
3	98.50%
4	98.29%
5	98.80%
6	98.61%
7	98.88%
8	97.84%
9	98.76%
10	99.08%
11	99.17%
12	99.12%
13	99.04%
$\vdots$	$\vdots$
37	99.10%
38	99.11%
39	99.11%
40	99.15%

Table 3: Accuracy of the test data over 40 epochs with a convolution NN.

## Code

```
1 import torch
2 import torch.nn as nn
3 import torch.optim as optim
4 import torchvision.transforms as transforms
5 import torchvision.datasets as datasets
6 from torch.utils.data import DataLoader
7
8 input_size = 28 * 28
9 hidden_size = 128
10 output_size = 10
11 weight_decay = 0.0001
```

```

12 learning_rate = 0.04
13
14 transform = transforms.Compose([
15     transforms.ToTensor(),
16     transforms.Normalize((0.5,), (0.5,)) # Normalize
17     ↪ to [-1, 1]
18 ])
19 train_dataset = datasets.MNIST(root='./mnist_data',
20     ↪ train=True, download=True, transform=transform)
21 test_dataset = datasets.MNIST(root='./mnist_data',
22     ↪ train=False, download=True, transform=transform)
23
24 train_loader = DataLoader(train_dataset, batch_size
25     ↪ =64, shuffle=True)
26 test_loader = DataLoader(test_dataset, batch_size=64,
27     ↪ shuffle=False)
28
29 def train_model(model, train_loader, test_loader,
30     ↪ num_epochs):
31     criterion = nn.CrossEntropyLoss()
32     optimizer = optim.SGD(model.parameters(), lr=
33     ↪ learning_rate, weight_decay=weight_decay)
34
35     for epoch in range(1, num_epochs + 1):
36         model.train()
37         for batch_idx, (data, target) in enumerate(
38             ↪ train_loader):
39             optimizer.zero_grad()
40             #output = model(data.view(-1, 28*28)) #
41             ↪ Cant do this with model3
42             output = model(data)
43             loss = criterion(output, target)
44             loss.backward()
45             optimizer.step()
46
47         test_loss, accuracy = validate(model,
48             ↪ test_loader, criterion)
49         print(f'{epoch}<u>_</u>{accuracy:.2f}\\\\%')
50
51     return model
52
53 def validate(model, test_loader, criterion):
54     model.eval()
55     test_loss = 0
56     correct = 0
57     with torch.no_grad(): # disable gradient
58         ↪ calculation for validation
59         for data, target in test_loader:

```

```

51         #output = model(data.view(-1, 28*28)) #
           ↪ Cant do this with model3
52         output = model(data)
53         test_loss += criterion(output, target).
           ↪ item()
54         pred = output.argmax(dim=1, keepdim=True)
55         correct += pred.eq(target.view_as(pred)).
           ↪ sum().item()
56
57         test_loss /= len(test_loader.dataset)
58         accuracy = 100.0 * correct / len(test_loader.
           ↪ dataset)
59         return test_loss, accuracy
60
61
62 model1 = nn.Sequential(
63     nn.Linear(28*28, hidden_size),
64     nn.ReLU(),
65     nn.Linear(hidden_size, output_size)
66 )
67
68
69 #train_model(model1, train_loader, test_loader,
           ↪ num_epochs=10)
70
71 model2 = nn.Sequential(
72     nn.Linear(28*28, 500),
73     nn.ReLU(),
74     nn.Linear(500, 300),
75     nn.ReLU(),
76     nn.Linear(300, 10),
77 )
78
79 #train_model(model2, train_loader, test_loader,
           ↪ num_epochs=40)
80
81 model3 = nn.Sequential(
82     nn.Conv2d(in_channels=1, out_channels=32,
           ↪ kernel_size=3, stride=1, padding=1),
83     nn.ReLU(),
84     nn.MaxPool2d(kernel_size=2, stride=2),
85
86     nn.Conv2d(in_channels=32, out_channels=64,
           ↪ kernel_size=3, stride=1, padding=1),
87     nn.ReLU(),
88     nn.MaxPool2d(kernel_size=2, stride=2),
89
90     nn.Flatten(),
91     nn.Linear(64 * 7 * 7, 128),
92     nn.ReLU(),

```

```
93 |  
94 |     nn.Linear(128, 10)  
95 | )  
96 |  
97 | train_model(model3, train_loader, test_loader,  
    | ↪ num_epochs=40)
```