HW4

February 22, 2024

1 Problem 1

[18]:
```
import numpy as np
from datetime import datetime

import torch
import torch.nn as nn
import torch.nn.functional as F
from torch.utils.data import DataLoader

from torchvision import datasets, transforms

%matplotlib inline
import matplotlib.pyplot as plt
```

[19]:
```
# define transforms
transforms = transforms.Compose([transforms.Resize((32, 32)),
                                 transforms.ToTensor()])

# download and create datasets
train_dataset = datasets.MNIST(root='mnist_data',
                               train=True,
                               transform=transforms,
                               download=True)

valid_dataset = datasets.MNIST(root='mnist_data',
                               train=False,
                               transform=transforms)
```

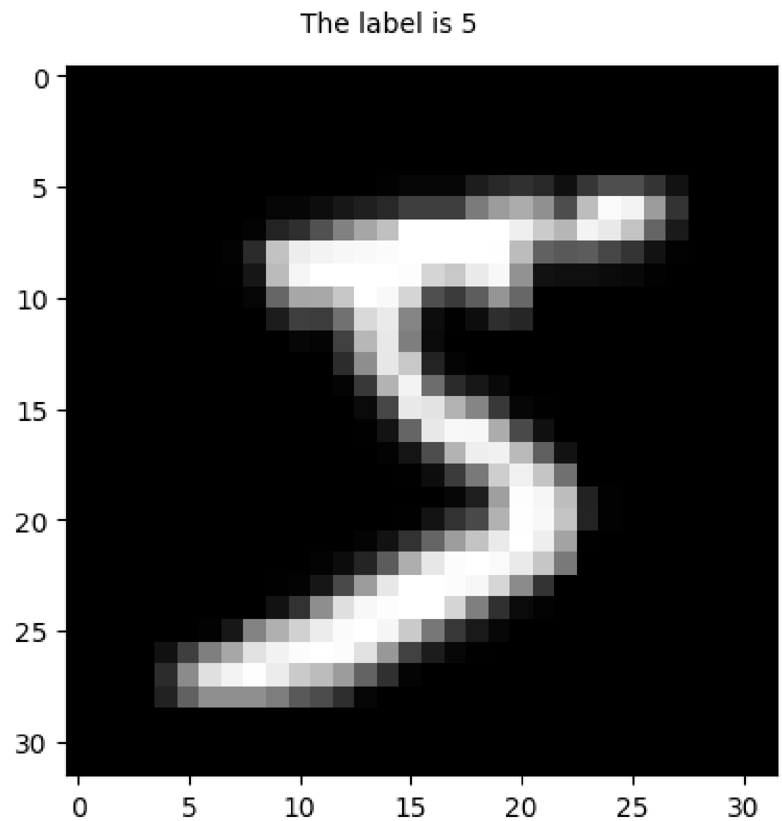
1.1 1.1.1

[20]:
```
print(train_dataset[0][0])
plt.imshow(train_dataset[0][0].squeeze(), cmap='gray')
plt.text(10, -2, 'The label is ' + str(train_dataset[0][1]))
```

```
tensor([[[0., 0., 0.,  …, 0., 0., 0.],
         [0., 0., 0.,  …, 0., 0., 0.],
         [0., 0., 0.,  …, 0., 0., 0.],
```

```
          …,
          [0., 0., 0.,  …, 0., 0., 0.],
          [0., 0., 0.,  …, 0., 0., 0.],
          [0., 0., 0.,  …, 0., 0., 0.]]])
```

[20]:
```
Text(10, -2, 'The label is 5')
```



[21]:
```python
# hyper parameters
RANDOM_SEED = 42
LEARNING_RATE = 0.001
BATCH_SIZE = 32
N_EPOCHS = 15

IMG_SIZE = 32
N_CLASSES = 10
```

1.2 1.1.2

[22]:
```
# define the data loaders
train_loader = DataLoader(dataset=train_dataset,
                          batch_size=BATCH_SIZE,
                          shuffle=True)

valid_loader = DataLoader(dataset=valid_dataset,
                          batch_size=BATCH_SIZE,
                          shuffle = False)
```

1.3 1.1.3

[23]:
```
def train(train_loader, model, criterion, optimizer):
    '''
    Train one epoch.
    '''

    model.train()
    running_loss = 0

    for X, y_true in train_loader:

        #gradient to zero
        optimizer.zero_grad()

        # Forward pass
        y_hat, _ = model(X)
        loss = criterion(y_hat, y_true)
        running_loss += loss.item() * X.size(0)

        # Backward pass
        loss.backward()
        optimizer.step()

    epoch_loss = running_loss / len(train_loader.dataset)
    return model, optimizer, epoch_loss
```

1.4 1.1.4

[24]:
```
def validate(valid_loader, model, criterion):
    '''
    Function for the validation step of the training loop.
    Returns the model and the loss on the test set.
    '''

    model.eval()
    running_loss = 0
```

```
    for X, y_true in valid_loader:

        # Forward pass and record loss
        y_hat, _ = model(X)
        loss = criterion(y_hat, y_true)
        # Update running loss to calculate the average
        running_loss += loss.item() * X.size(0)

    epoch_loss = running_loss / len(valid_loader.dataset)

    return model, epoch_loss
```

[25]:
```
def training_loop(model, criterion, optimizer, train_loader, valid_loader,␣
↪epochs, print_every=1):
    '''
    Function defining the entire training loop
    '''

    # set objects for storing metrics
    best_loss = 1e10
    train_losses = []
    valid_losses = []
    train_accs = []
    valid_accs = []

    # Train model
    for epoch in range(0, epochs):

        # training
        model, optimizer, train_loss = train(train_loader, model, criterion,␣
↪optimizer)
        train_losses.append(train_loss)

        # validation
        with torch.no_grad():
            model, valid_loss = validate(valid_loader, model, criterion)
            valid_losses.append(valid_loss)

        if epoch % print_every == (print_every - 1):

            train_acc = get_accuracy(model, train_loader,)
            train_accs.append(train_acc)
            valid_acc = get_accuracy(model, valid_loader)
            valid_accs.append(valid_acc)

            print(f'{datetime.now().time().replace(microsecond=0)} '
```

```
                  f'Epoch: {epoch}\t'
                  f'Train loss: {train_loss:.4f}\t'
                  f'Valid loss: {valid_loss:.4f}\t'
                  f'Train accuracy: {100 * train_acc:.2f}\t'
                  f'Valid accuracy: {100 * valid_acc:.2f}')

    performance = {
        'train_losses':train_losses,
        'valid_losses': valid_losses,
        'train_acc': train_accs,
        'valid_acc':valid_accs
    }

    return model, optimizer, performance
```

1.5 1.1.5

[26]:
```
def get_accuracy(model, data_loader):
    '''
    Function for computing the accuracy of the predictions over the entire␣
 ↪data_loader
    '''

    correct_pred = 0
    n = 0

    with torch.no_grad():
        model = model.eval()
        for X, y_true in data_loader:

            _, y_prob = model(X)
            _, predicted_labels = torch.max(y_prob, 1)

            n += y_true.size(0)
            correct_pred += (predicted_labels == y_true).sum()

    return correct_pred.float() / n



def plot_performance(performance):
    '''
    Function for plotting training and validation losses
    '''

    # temporarily change the style of the plots to seaborn
    plt.style.use('seaborn-v0_8')
```

```
fig, ax = plt.subplots(1, 2, figsize = (16, 4.5))
for key, value in performance.items():
    if 'loss' in key:
        ax[0].plot(value, label=key)
    else:
        ax[1].plot(value, label=key)
ax[0].set(title="Loss  over epochs",
        xlabel='Epoch',
        ylabel='Loss')
ax[1].set(title="accuracy over epochs",
        xlabel='Epoch',
        ylabel='Loss')
ax[0].legend()
ax[1].legend()
plt.show()

# change the plot style to default
plt.style.use('default')
```

1.6 1.2.1

[27]:
```
class LeNet5(nn.Module):

    def __init__(self, n_classes):
        super(LeNet5, self).__init__()

        self.feature_extractor = nn.Sequential(
            nn.Conv2d(in_channels=1, out_channels=6, kernel_size=5, stride=1),
            nn.Tanh(),
            nn.AvgPool2d(kernel_size=2),
            nn.Conv2d(in_channels=6, out_channels=16, kernel_size=5, stride=1),
            nn.Tanh(),
            nn.AvgPool2d(kernel_size=2),
            nn.Conv2d(in_channels=16, out_channels=120, kernel_size=5,␣
↪stride=1),
            nn.Tanh()
        )

        self.classifier = nn.Sequential(
            nn.Linear(in_features=120, out_features=84),
            nn.Tanh(),
            nn.Linear(in_features=84, out_features=n_classes),
        )

    def forward(self, x):
        x= self.feature_extractor(x)
```

```
        x = torch.flatten(x, 1)
        logits = self.classifier(x)
        probs = F.softmax(logits, dim=1)
        return logits, probs
```

1.7 1.2.2

[36]:
```
class MLP(nn.Module):

    def __init__(self, layers):
        super(MLP, self).__init__()

        self.all_layers = nn.ModuleList()
        for i in range(1, len(layers)):
            self.all_layers.append(
                nn.Linear(in_features=layers[i - 1], out_features=layers[i])
            )
            if i != len(layers) - 1:
                self.all_layers.append(nn.Tanh())
        self.all_layers = nn.Sequential(*self.all_layers)

    def forward(self, x):
        x = x.view(x.shape[0], -1)
        logits = self.all_layers(x)
        probs = F.softmax(logits, dim=1)
        return logits, probs
```

1.8 1.3.1

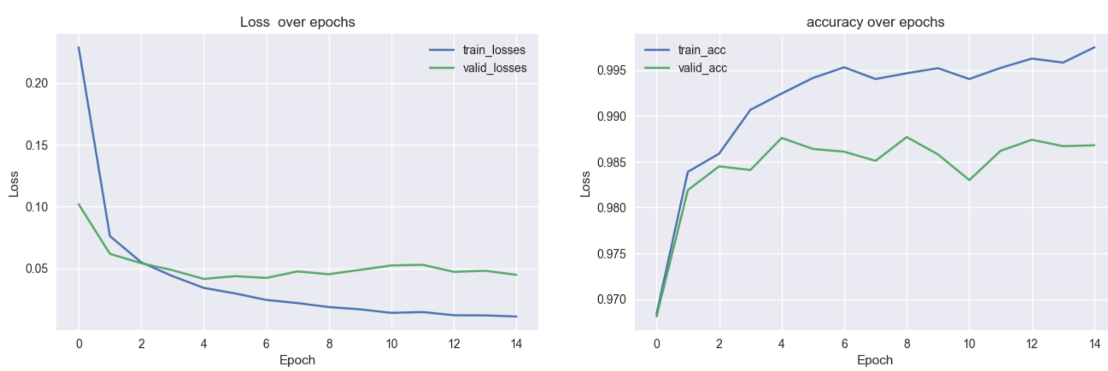
[29]:
```
torch.manual_seed(RANDOM_SEED)

model = LeNet5(N_CLASSES)
optimizer = torch.optim.Adam(model.parameters(), lr=LEARNING_RATE)
criterion = nn.CrossEntropyLoss()
```

[30]:
```
model, optimizer, performance_1 = training_loop(model, criterion, optimizer,␣
  ↪train_loader, valid_loader, N_EPOCHS)
```

```
21:28:06 Epoch: 0       Train loss: 0.2290      Valid loss: 0.1020      Train
accuracy: 96.84   Valid accuracy: 96.81
21:29:05 Epoch: 1       Train loss: 0.0762      Valid loss: 0.0619      Train
accuracy: 98.39   Valid accuracy: 98.19
21:30:05 Epoch: 2       Train loss: 0.0550      Valid loss: 0.0542      Train
accuracy: 98.59   Valid accuracy: 98.45
21:31:06 Epoch: 3       Train loss: 0.0438      Valid loss: 0.0486      Train
accuracy: 99.07   Valid accuracy: 98.41
21:32:07 Epoch: 4       Train loss: 0.0343      Valid loss: 0.0415      Train
accuracy: 99.25   Valid accuracy: 98.76
```

```
21:33:12 Epoch: 5       Train loss: 0.0298      Valid loss: 0.0438      Train
accuracy: 99.42   Valid accuracy: 98.64
21:34:17 Epoch: 6       Train loss: 0.0245      Valid loss: 0.0423      Train
accuracy: 99.53   Valid accuracy: 98.61
21:35:23 Epoch: 7       Train loss: 0.0220      Valid loss: 0.0476      Train
accuracy: 99.40   Valid accuracy: 98.51
21:36:28 Epoch: 8       Train loss: 0.0188      Valid loss: 0.0454      Train
accuracy: 99.47   Valid accuracy: 98.77
21:37:34 Epoch: 9       Train loss: 0.0170      Valid loss: 0.0489      Train
accuracy: 99.52   Valid accuracy: 98.58
21:38:38 Epoch: 10      Train loss: 0.0140      Valid loss: 0.0524      Train
accuracy: 99.40   Valid accuracy: 98.30
21:39:43 Epoch: 11      Train loss: 0.0147      Valid loss: 0.0530      Train
accuracy: 99.53   Valid accuracy: 98.62
21:40:48 Epoch: 12      Train loss: 0.0122      Valid loss: 0.0472      Train
accuracy: 99.63   Valid accuracy: 98.74
21:41:54 Epoch: 13      Train loss: 0.0120      Valid loss: 0.0481      Train
accuracy: 99.58   Valid accuracy: 98.67
21:43:06 Epoch: 14      Train loss: 0.0111      Valid loss: 0.0449      Train
accuracy: 99.75   Valid accuracy: 98.68
```

[31]:
```
plot_performance(performance_1)
```



1.9 1.3.2

[37]:
```
torch.manual_seed(RANDOM_SEED)
layers = [1024, 256, 64, 16, N_CLASSES]
model = MLP(layers)
print(model)
optimizer = torch.optim.Adam(model.parameters(), lr=LEARNING_RATE)
criterion = nn.CrossEntropyLoss()
```

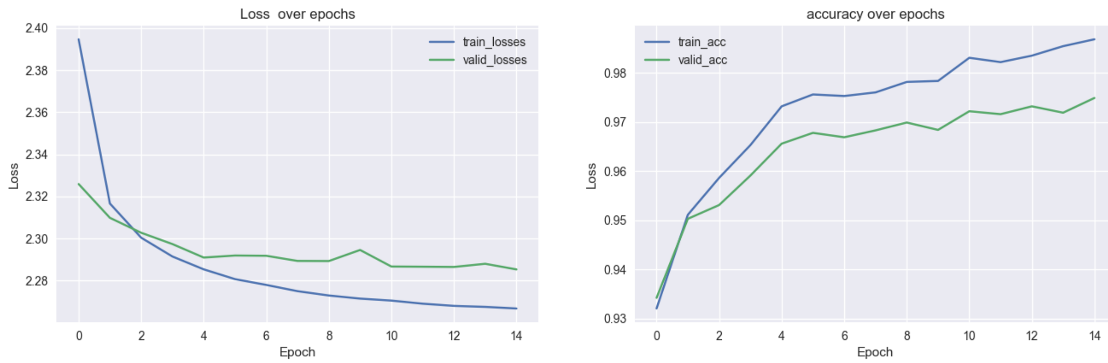
```
MLP(
  (all_layers): Sequential(
    (0): Linear(in_features=1024, out_features=256, bias=True)
```

```
    (1): Tanh()
    (2): Linear(in_features=256, out_features=64, bias=True)
    (3): Tanh()
    (4): Linear(in_features=64, out_features=16, bias=True)
    (5): Tanh()
    (6): Linear(in_features=16, out_features=10, bias=True)
  )
)
```

[38]:
```
model, optimizer, performance_2 = training_loop(model, criterion, optimizer,␣
↪train_loader, valid_loader, N_EPOCHS)
```

```
21:53:59 Epoch: 0       Train loss: 0.3575      Valid loss: 0.1636      Train
accuracy: 95.61   Valid accuracy: 95.23
21:54:53 Epoch: 1       Train loss: 0.1307      Valid loss: 0.1195      Train
accuracy: 97.27   Valid accuracy: 96.38
21:55:42 Epoch: 2       Train loss: 0.0924      Valid loss: 0.1024      Train
accuracy: 97.86   Valid accuracy: 96.99
21:56:28 Epoch: 3       Train loss: 0.0722      Valid loss: 0.0876      Train
accuracy: 98.29   Valid accuracy: 97.38
21:57:18 Epoch: 4       Train loss: 0.0594      Valid loss: 0.0877      Train
accuracy: 98.52   Valid accuracy: 97.36
21:58:05 Epoch: 5       Train loss: 0.0504      Valid loss: 0.0836      Train
accuracy: 98.79   Valid accuracy: 97.43
21:58:51 Epoch: 6       Train loss: 0.0438      Valid loss: 0.0819      Train
accuracy: 99.06   Valid accuracy: 97.66
21:59:37 Epoch: 7       Train loss: 0.0386      Valid loss: 0.0759      Train
accuracy: 99.20   Valid accuracy: 97.75
22:00:23 Epoch: 8       Train loss: 0.0339      Valid loss: 0.0871      Train
accuracy: 99.01   Valid accuracy: 97.60
22:01:09 Epoch: 9       Train loss: 0.0299      Valid loss: 0.0802      Train
accuracy: 99.23   Valid accuracy: 97.76
22:01:59 Epoch: 10      Train loss: 0.0290      Valid loss: 0.0985      Train
accuracy: 98.67   Valid accuracy: 97.47
22:02:51 Epoch: 11      Train loss: 0.0272      Valid loss: 0.0866      Train
accuracy: 99.34   Valid accuracy: 97.86
22:03:40 Epoch: 12      Train loss: 0.0251      Valid loss: 0.0891      Train
accuracy: 99.30   Valid accuracy: 97.56
22:04:27 Epoch: 13      Train loss: 0.0232      Valid loss: 0.0800      Train
accuracy: 99.50   Valid accuracy: 97.87
22:05:15 Epoch: 14      Train loss: 0.0242      Valid loss: 0.0874      Train
accuracy: 99.31   Valid accuracy: 97.88
```

[ ]:
```
plot_performance(performance_2)
```



1.10 1.4.1 Comparison of these two models.

Convolutional Layers 1:
nn.Conv2d(in_channels=1, out_channels=6, kernel_size=5, stride=1)
(5 * 5 * 1 + 1) * 6 = 156

Convolutional Layers 2:
nn.Conv2d(in_channels=6, out_channels=16, kernel_size=5, stride=1)
(5 * 5 * 6 + 1) * 16 = 2416

Convolutional Layers 3:
nn.Conv2d(in_channels=16, out_channels=120, kernel_size=5, stride=1)
(5 * 5 * 16 + 1) * 120 = 48120

Fully Connected 1:
nn.Linear(in_features=120, out_features=84)
(120 + 1) * 84 = 10164

Fully Connected 2:
nn.Linear(in_features=84, out_features=10)
(84 + 1) * 10 = 850

Total: 156+2416+48120+10164+850=61706

1.11 1.4.2 number of trainable parameters of MLP

Fully Connected Layers 1:
Linear(in_features=1024, out_features=256, bias=True)
(1024 + 1) * 256 = 262400

Fully Connected Layers 2:
Linear(in_features=256, out_features=64, bias=True)
(256 + 1) * 64 = 16448

Fully Connected Layers 3:
Linear(in_features=64, out_features=16, bias=True)
(64 + 1) * 16 = 1040

Last Fully Connected Layers:
Linear(in_features=16, out_features=10, bias=True)
(16 +1) * 10 = 170

Total: 262400+16448+1040+170=280058

1.12 1.4.3

LeNet is the better than MLP.

LeNet:
Epoch: 14 Train loss: 0.0111 Valid loss: 0.0449 Train accuracy: 99.75 Valid accuracy: 98.68
MLP:
Epoch: 14 Train loss: 0.0242 Valid loss: 0.0874 Train accuracy: 99.31 Valid accuracy: 97.88
Obviously, the CNN has higher train accuracy and valid accuracy.

CNNs generally perform better in handling high-dimensional data like images because they can automatically learn features and have better generalization capabilities. MLPs may perform well in some simple tasks or low-dimensional data

2 Statement of Collaboration

I do it by myself