

▼ Classification for Multiple Categories using Pytorch

Build a classifier for the digit classification task with 10 classes on the MNIST dataset

```
1  import os
2
3  # load data
4  from torch.utils.data import DataLoader
5  from torchvision import datasets, transforms
6
7  # train
8  import torch
9  from torch import nn
10 from torch.nn import functional as F
11 import numpy as np
12
13 # visualization
14 import matplotlib.pyplot as plt
15 import pandas as pd
```

▼ 1. Data

- apply normalization

```
1  transform = transforms.Compose([
2      transforms.ToTensor(),
3      transforms.Normalize((0.1307,), (0.3081,)), # mean value = 0.1307, standard deviation value = 0.3081
4  ])
```

- load the MNIST dataset

```
1  data_path = './MNIST'
2
3  training_set = datasets.MNIST(root = data_path, train= True, download=True, transform= transform)
4  testing_set = datasets.MNIST(root = data_path, train= False, download=True, transform= transform)
```

▼ 2. Model

- design a neural network that consists of three fully connected layers with an activation function of Sigmoid
- the activation function for the output layer is LogSoftmax

```
1  class classification(nn.Module):
2      def __init__(self):
3          super(classification, self).__init__()
4
5          # construct layers for a neural network
6          self.classifier1 = nn.Sequential(
7              nn.Linear(in_features=28*28, out_features=20*20),
8              nn.Sigmoid(),
9          )
10         self.classifier2 = nn.Sequential(
11             nn.Linear(in_features=20*20, out_features=10*10),
12             nn.Sigmoid(),
13         )
```

```

14         self.classifier3 = nn.Sequential(
15             nn.Linear(in_features=10*10, out_features=10),
16             nn.LogSoftmax(dim=1),
17         )
18
19
20     def forward(self, inputs):                # [batchSize, 1, 28, 28]
21         x = inputs.view(inputs.size(0), -1)  # [batchSize, 28*28]
22         x = self.classifier1(x)              # [batchSize, 20*20]
23         x = self.classifier2(x)              # [batchSize, 10*10]
24         out = self.classifier3(x)            # [batchSize, 10]
25
26         return out

```

▼ 3. Loss function

- the log of softmax
- the negative log likelihood loss

```

1 criterion = nn.NLLLoss()

```

▼ 4. Optimization

- use a stochastic gradient descent algorithm with different mini-batch sizes of 32, 64, 128
- use a constant learning rate for all the mini-batch sizes
- do not use any regularization algorithm such as dropout or weight decay
- compute the average loss and the average accuracy for all the mini-batches within each epoch

```

1 def init_optimizer(learning_rate_value):
2     device = torch.device('cuda:0' if torch.cuda.is_available() else 'cpu')
3     print(device)
4     classifier = classification().to(device)
5     optimizer = torch.optim.SGD(classifier.parameters(), lr=learning_rate_value)
6
7     return device, classifier, optimizer

```

▼ 5. Train

```

1 def train(model, batch_size, optimizer, criterion):
2     model.train()
3     train_accuracy = 0.0
4     train_loss = 0.0
5     total = 0
6     train_loader = torch.utils.data.DataLoader(dataset=training_set, batch_size=batch_size, shuffle=True)
7
8     for train_img, train_label in train_loader:
9         train_img, train_label = train_img.to(device), train_label.to(device)
10
11         optimizer.zero_grad()
12         train_output = model(train_img)
13         loss = criterion(train_output, train_label)
14         loss.backward()
15         optimizer.step()
16
17         train_loss += loss
18         _, argmax = torch.max(train_output, 1)

```

```

19         total += train_label.size(0)
20         train_accuracy += (train_label == argmax).sum().item()
21
22     print("Training Loss: {:.4f} ".format(train_loss/len(train_loader)),
23           "Train Accuracy: {:.4f}".format(train_accuracy/total))
24
25     return train_loss/len(train_loader), train_accuracy/total
26
27
28 def test(model, batch_size, optimizer, criterion):
29     model.eval()
30     total = 0
31     test_loss = 0.0
32     test_accuracy = 0.0
33     test_loader = torch.utils.data.DataLoader(dataset=testing_set, batch_size=batch_size, shuffle=True)
34     with torch.no_grad():
35         for test_img, test_label in test_loader:
36             test_img, test_label = test_img.to(device), test_label.to(device)
37             test_output = model(test_img)
38             test_loss += criterion(test_output, test_label)
39
40             _, argmax = torch.max(test_output, 1)
41             total += test_label.size(0)
42             test_accuracy += (test_label == argmax).sum().item()
43
44     print("Test Loss: {:.4f} ".format(test_loss/len(test_loader)),
45           "Test Accuracy: {:.4f}".format(test_accuracy / total))
46
47     return test_loss/len(test_loader), test_accuracy /total
48
49
50 def run_epoch(model, batch_size, optimizer, criterion):
51     train_loss_list, train_acc_list, test_loss_list, test_acc_list = [], [], [], []
52     for epoch in range(epochs):
53         print("Epoch: {}/{} : ".format(epoch+1, epochs))
54         train_loss, train_acc = train(model, batch_size, optimizer, criterion)
55         test_loss, test_acc = test(model, batch_size, optimizer, criterion)
56
57         train_loss_list.append(train_loss)
58         train_acc_list.append(train_acc)
59         test_loss_list.append(test_loss)
60         test_acc_list.append(test_acc)
61
62     return train_loss_list, test_loss_list, train_acc_list, test_acc_list

```

▼ 6. Visualization

```

1 def draw_graph(idx, train_data, test_data, batch_size):
2     fig = plt.figure(figsize=(8,8))
3     # plot the loss curve
4     if (idx == 0):
5         train_label = 'train loss'
6         test_label = 'test loss'
7         title = 'loss (Batch size = '+str(batch_size)+')'
8         legend_loc = 'upper right'
9     # plot the accuracy curve
10    elif (idx == 1):
11        train_label = 'train accuracy'
12        test_label = 'test accuracy'
13        title = 'accuracy (Batch size = '+str(batch_size)+')'
14        legend_loc = 'lower right'
15
16    plt.plot(np.array(range(epochs)), train_data, c = 'r', label = train_label)

```

```

17     plt.plot(np.array(range(epochs)), test_data, c = 'b', label = test_label)
18     plt.legend(loc = legend_loc)
19     plt.title(title)
20     plt.show()
21
22     return fig

```

▼ 7. Start Learning

▼ Init learning value

```

1     train_loss_result, test_loss_result, train_acc_result, test_acc_result= [], [], [], []

1     def final_result(train_loss_list, test_loss_list, train_acc_list, test_acc_list):
2         train_loss_result.append(train_loss_list[-1])
3         test_loss_result.append(test_loss_list[-1])
4         train_acc_result.append(train_acc_list[-1])
5         test_acc_result.append(test_acc_list[-1])

1     epochs = 70
2     lr = 0.01

```

▼ Learning All

```

1     # mini-batch size = 32
2     device, classifier, optimizer = init_optimizer(lr)
3     train_loss_list, test_loss_list, train_acc_list, test_acc_list = run_epoch(classifier, 32, optimizer, criterion)
4     final_result(train_loss_list, test_loss_list, train_acc_list, test_acc_list)
5     fig_1 = draw_graph(0, train_loss_list, test_loss_list, 32)
6     fig_1.savefig('loss curve (Batch size =32).png')
7     fig_2 = draw_graph(1, train_acc_list, test_acc_list, 32)
8     fig_2.savefig('accuracy curve (Batch size =32).png')
9
10    # mini-batch size = 64
11    device, classifier, optimizer = init_optimizer(lr)
12    train_loss_list, test_loss_list, train_acc_list, test_acc_list = run_epoch(classifier, 64, optimizer, criterion)
13    final_result(train_loss_list, test_loss_list, train_acc_list, test_acc_list)
14    fig_3 = draw_graph(0, train_loss_list, test_loss_list, 64)
15    fig_3.savefig('loss curve (Batch size = 64).png')
16    fig_4 = draw_graph(1, train_acc_list, test_acc_list, 64)
17    fig_4.savefig('accuracy curve (Batch size = 64).png')
18
19    # mini-batch size = 128
20    device, classifier, optimizer = init_optimizer(lr)
21    train_loss_list, test_loss_list, train_acc_list, test_acc_list = run_epoch(classifier, 128, optimizer, criterion)
22    final_result(train_loss_list, test_loss_list, train_acc_list, test_acc_list)
23    fig_5 = draw_graph(0, train_loss_list, test_loss_list, 128)
24    fig_5.savefig('loss curve (Batch size = 128).png')
25    fig_6 = draw_graph(1, train_acc_list, test_acc_list, 128)
26    fig_6.savefig('accuracy curve (Batch size = 128).png')

```

▼ Learning Each mini-batch

```

1     # mini-batch size = 32
2     device, classifier, optimizer = init_optimizer(lr)

```

```

2 device, classifier, optimizer = init_optimizer(lr)
3 train_loss_list, test_loss_list, train_acc_list, test_acc_list = run_epoch(classifier, 32, optimizer, criterion)

1 final_result(train_loss_list, test_loss_list, train_acc_list, test_acc_list)
2 fig_1 = draw_graph(0, train_loss_list, test_loss_list, 32)
3 fig_1.savefig('loss curve (Batch size =32).png')
4 fig_2 = draw_graph(1, train_acc_list, test_acc_list, 32)
5 fig_2.savefig('accuracy curve (Batch size =32).png')

1 # mini-batch size = 64
2 device, classifier, optimizer= init_optimizer(lr)
3 train_loss_list, test_loss_list, train_acc_list, test_acc_list = run_epoch(classifier, 64, optimizer, criterion)

1 final_result(train_loss_list, test_loss_list, train_acc_list, test_acc_list)
2 fig_3 = draw_graph(0, train_loss_list, test_loss_list, 64)
3 fig_3.savefig('loss curve (Batch size = 64).png')
4 fig_4 = draw_graph(1, train_acc_list, test_acc_list, 64)
5 fig_4.savefig('accuracy curve (Batch size = 64).png')

1 # mini-batch size =
2 device, classifier, optimizer = init_optimizer(lr)
3 train_loss_list, test_loss_list, train_acc_list, test_acc_list = run_epoch(classifier, 128, optimizer, criterion)

```

+ 코드
+ 텍스트

```

1 final_result(train_loss_list, test_loss_list, train_acc_list, test_acc_list)
2 fig_5 = draw_graph(0, train_loss_list, test_loss_list, 128)
3 fig_5.savefig('loss curve (Batch size = 128).png')
4 fig_6 = draw_graph(1, train_acc_list, test_acc_list, 128)
5 fig_6.savefig('accuracy curve (Batch size = 128).png')

```

▼ Print learning results as a table using pandas

```

1 result_loss = pd.DataFrame({'32':[train_loss_result[0].item(), test_loss_result[0].item()],
2                               '64':[train_loss_result[1].item(), test_loss_result[1].item()],
3                               '128':[train_loss_result[2].item(), test_loss_result[2].item()]} , index = ['training loss', 'testing loss'])
4 result_loss

```

	32	64	128
training loss	0.074559	0.151474	0.249550
testing loss	0.093673	0.158547	0.250557

```

1 result_acc = pd.DataFrame({'32':[train_acc_result[0], test_acc_result[0]],
2                               '64':[train_acc_result[1], test_acc_result[1]],
3                               '128':[train_acc_result[2], test_acc_result[2]]} , index = ['training accuracy', 'testing accuracy'])
4 result_acc

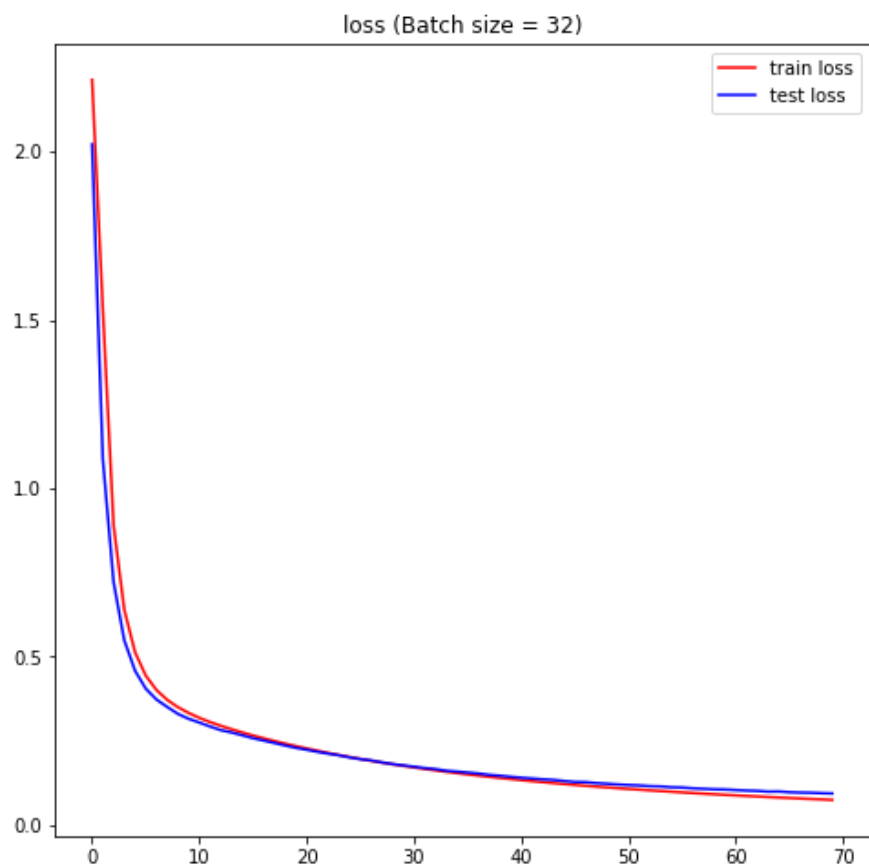
```

	32	64	128
training accuracy	0.98025	0.957133	0.92815
testing accuracy	0.97160	0.955300	0.92840

▼ Output

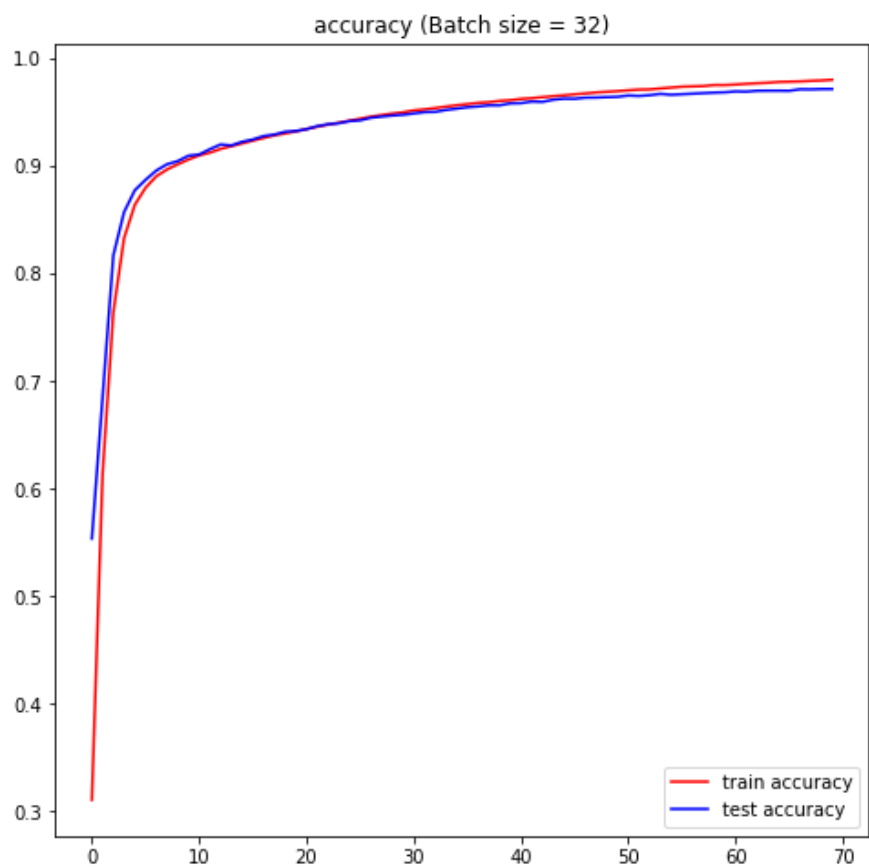
1. Plot the training and testing losses with a batch size of 32 [4pt]

1 fig_1



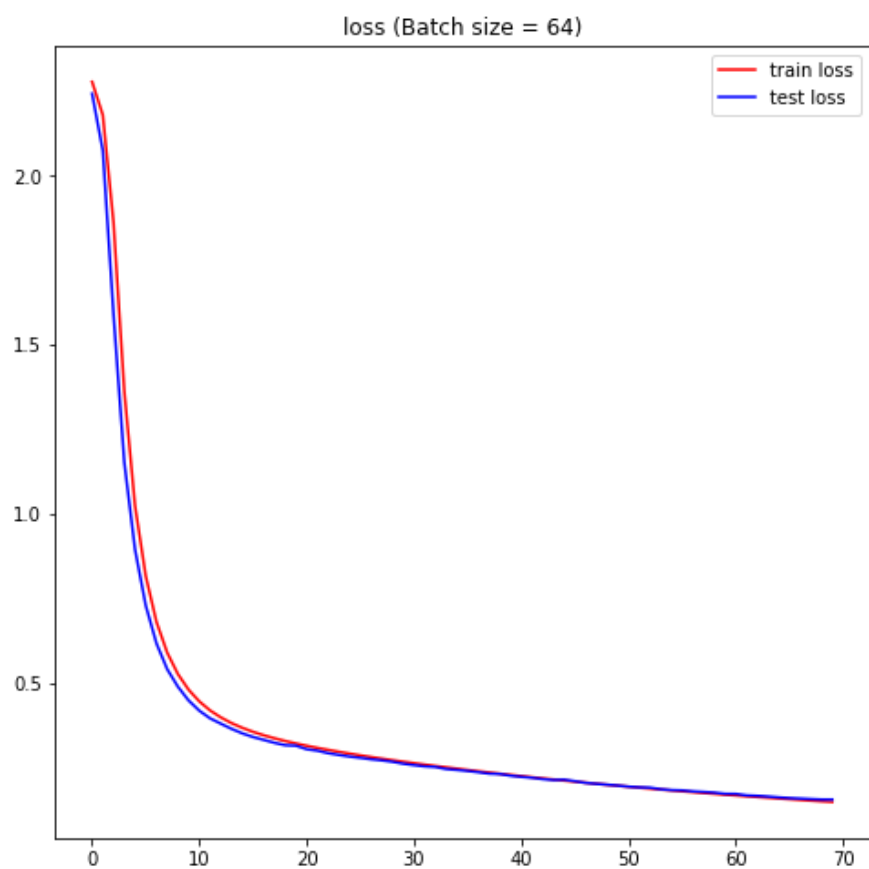
2. Plot the training and testing accuracies with a batch size of 32 [4pt]

1 fig_2



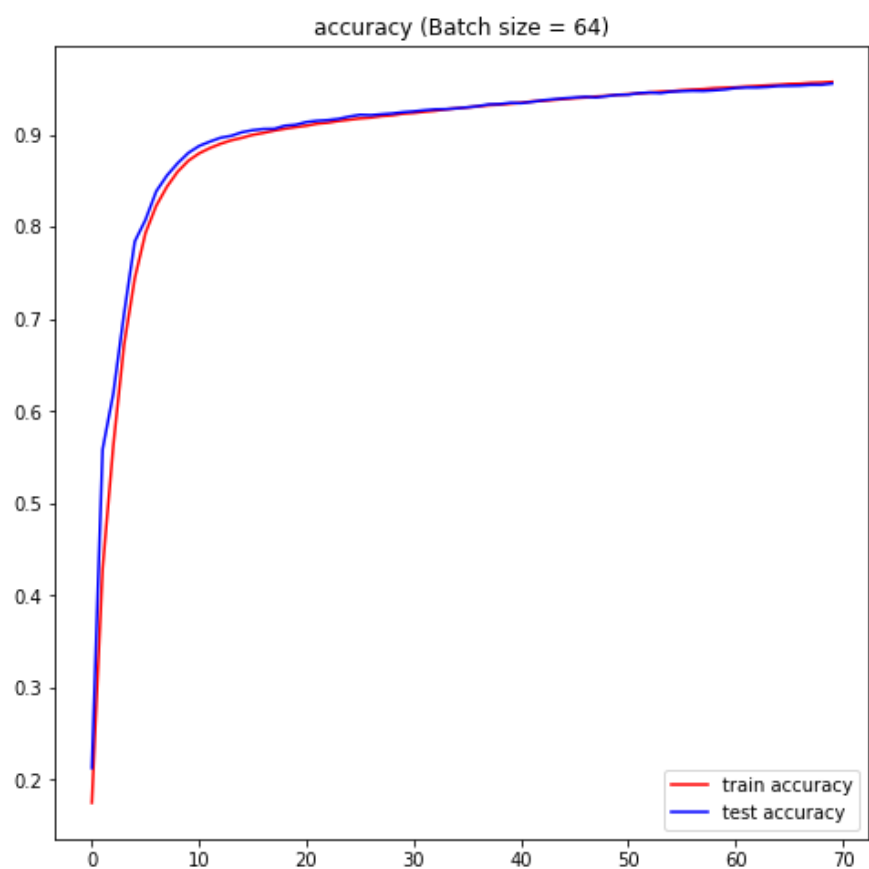
3. Plot the training and testing losses with a batch size of 64 [4pt]

1 fig_3



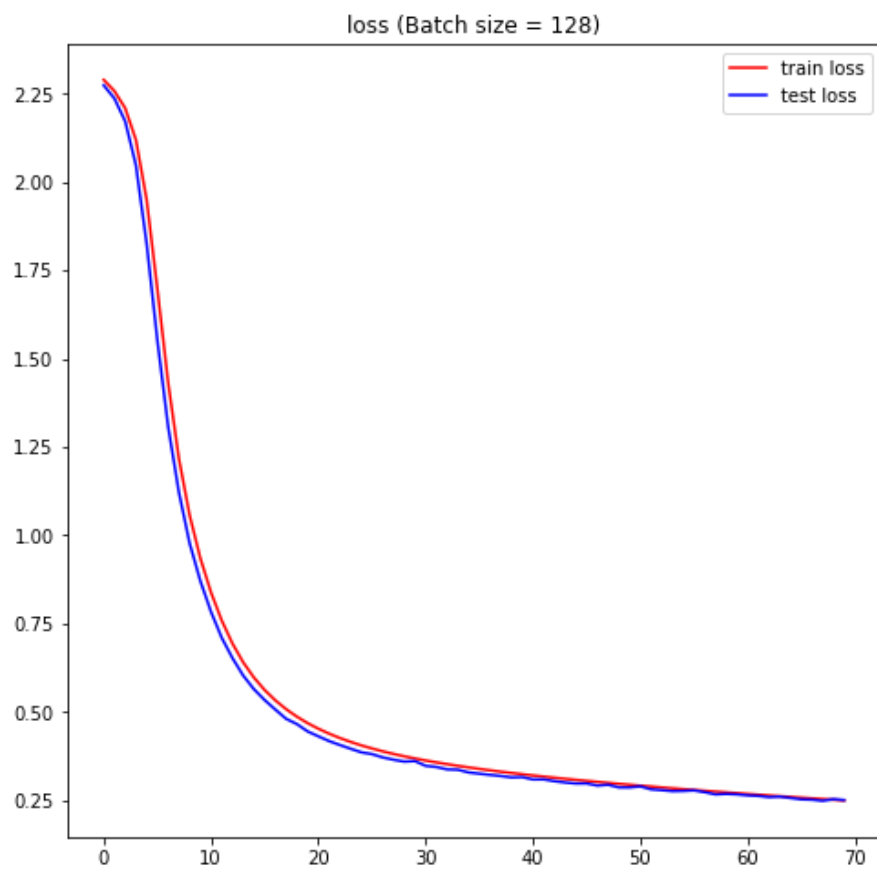
4. Plot the training and testing accuracies with a batch size of 64 [4pt]

1 fig_4



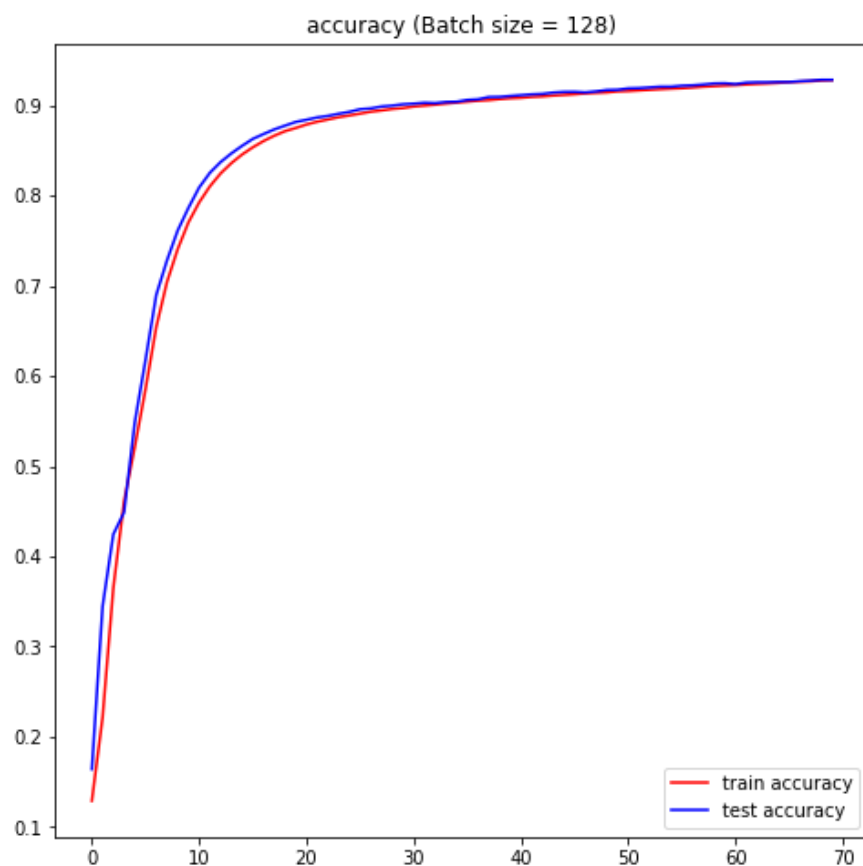
5. Plot the training and testing losses with a batch size of 128 [4pt]

1 fig_5



6. Plot the training and testing accuracies with a batch size of 128 [4pt]

1 fig_6



7. Print the loss at convergence with different mini-batch sizes [3pt]

1 result_loss

	32	64	128
training loss	0.074559	0.151474	0.249550
testing loss	0.093673	0.158547	0.250557

8. Print the accuracy at convergence with different mini-batch sizes [3pt]

1 result_acc

	32	64	128
training accuracy	0.98025	0.957133	0.92815
testing accuracy	0.97160	0.955300	0.92840