Problem3

November 1, 2024

[1]:
```
#Library Imports
from torchvision import datasets
from torchvision.transforms import ToTensor
from torch.utils.data import DataLoader
import torch
from torch import nn
import numpy as np
import matplotlib.pyplot as plt
```

[2]:
```
train_data = datasets.USPS(root='usps', download=True, transform=ToTensor(),␣
 ↪train=True)
test_data = datasets.USPS(root='usps', download=True, transform=ToTensor(),␣
 ↪train=False)

# Create DataLoaders for training and testing
train_loader = DataLoader(train_data, batch_size=128, shuffle=True)
test_loader = DataLoader(test_data, batch_size=len(test_data), shuffle=False)
```

[3]:
```
# Define the MLP model with 2 hidden layers, both with 128 units
class MLP(nn.Module):
    def __init__(self):
        super().__init__()
        self.flatten = nn.Flatten()
        self.mlp = nn.Sequential(
            nn.Linear(16 * 16, 128),  # Input layer to first hidden layer
            nn.ReLU(),
            nn.Linear(128, 128),      # First hidden layer to second hidden␣
 ↪layer
            nn.ReLU(),
            nn.Linear(128, 128),      # Second hidden layer
            nn.ReLU(),
            nn.Linear(128, 10)        # Output layer for 10 classes
        )

    def forward(self, X):
        return self.mlp(self.flatten(X))
```

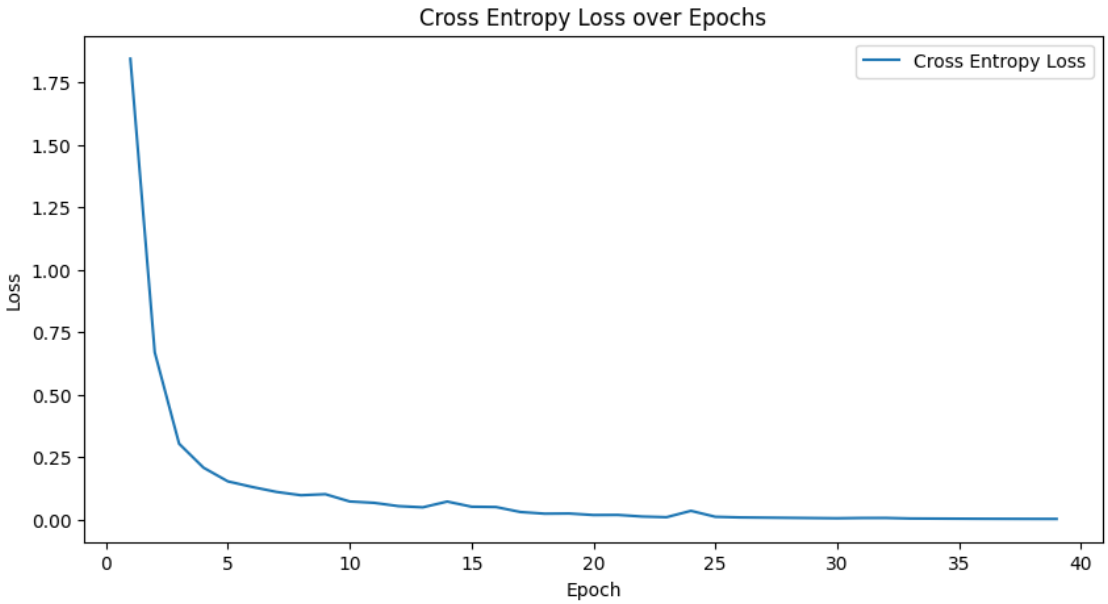
```
model = MLP().to('cuda:1')
loss_fn = nn.CrossEntropyLoss()
optimizer = torch.optim.SGD(model.parameters(), lr=0.5)
```

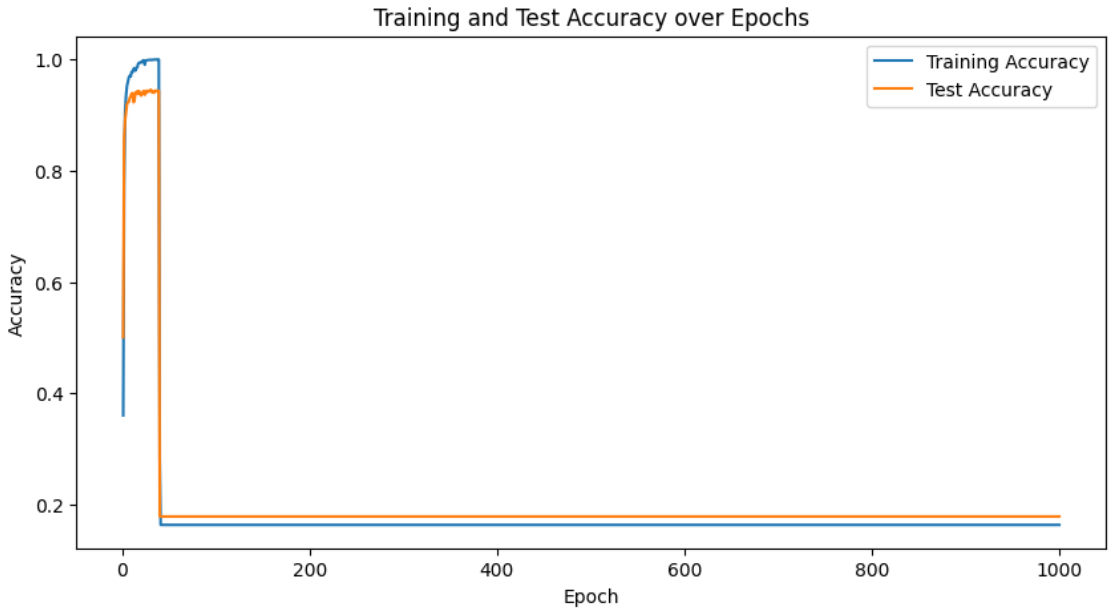
[4]:
```
%%time
epochs = 1000
training_accuracy = []
test_accuracy = []
epoch_loss = []

for epoch in range(epochs):
    cumulative_accuracy = 0
    cumulative_loss = 0
    for X, Y in train_loader:
        X, Y = X.to('cuda:1'), Y.to('cuda:1')
        out = model(X)
        loss = loss_fn(out, Y)
        optimizer.zero_grad()
        loss.backward()
        optimizer.step()
        cumulative_loss += loss.item()
        cumulative_accuracy += (out.argmax(axis=1) == Y).sum().item()

    epoch_loss.append(cumulative_loss / len(train_loader))
    training_accuracy.append(cumulative_accuracy / len(train_data))

    with torch.no_grad():
        for Xt, Yt in test_loader:
            Xt, Yt = Xt.to('cuda:1'), Yt.to('cuda:1')
            test_out = model(Xt)
            test_accuracy_epoch = (test_out.argmax(axis=1) == Yt).sum().item() /
 ↪ len(test_data)
        test_accuracy.append(test_accuracy_epoch)

    if (epoch + 1) % 100 == 0:
        print(f"Epoch {epoch + 1}/{epochs} | Loss: {epoch_loss[-1]:.4f} |␣
 ↪Training Accuracy: {training_accuracy[-1]:.4f} | Test Accuracy:␣
 ↪{test_accuracy[-1]:.4f}")
```

```
Epoch 100/1000 | Loss: nan | Training Accuracy: 0.1638 | Test Accuracy: 0.1789
Epoch 200/1000 | Loss: nan | Training Accuracy: 0.1638 | Test Accuracy: 0.1789
Epoch 300/1000 | Loss: nan | Training Accuracy: 0.1638 | Test Accuracy: 0.1789
Epoch 400/1000 | Loss: nan | Training Accuracy: 0.1638 | Test Accuracy: 0.1789
Epoch 500/1000 | Loss: nan | Training Accuracy: 0.1638 | Test Accuracy: 0.1789
Epoch 600/1000 | Loss: nan | Training Accuracy: 0.1638 | Test Accuracy: 0.1789
Epoch 700/1000 | Loss: nan | Training Accuracy: 0.1638 | Test Accuracy: 0.1789
Epoch 800/1000 | Loss: nan | Training Accuracy: 0.1638 | Test Accuracy: 0.1789
```

```
Epoch 900/1000 | Loss: nan | Training Accuracy: 0.1638 | Test Accuracy: 0.1789
Epoch 1000/1000 | Loss: nan | Training Accuracy: 0.1638 | Test Accuracy: 0.1789
CPU times: user 11min 55s, sys: 1.48 s, total: 11min 56s
Wall time: 11min 56s
```

[5]:
```
plt.figure(figsize=(10, 5))
plt.plot(np.arange(1, epochs + 1), epoch_loss, label="Cross Entropy Loss")
plt.xlabel("Epoch")
plt.ylabel("Loss")
plt.title("Cross Entropy Loss over Epochs")
plt.legend()
plt.show()

plt.figure(figsize=(10, 5))
plt.plot(np.arange(1, epochs + 1), training_accuracy, label="Training Accuracy")
plt.plot(np.arange(1, epochs + 1), test_accuracy, label="Test Accuracy")
plt.xlabel("Epoch")
plt.ylabel("Accuracy")
plt.title("Training and Test Accuracy over Epochs")
plt.legend()
plt.show()
```




Training and Test Accuracy over Epochs
Training Accuracy
Test Accuracy
Accuracy
Epoch
1.0
0.8
0.6
0.4
0.2
0
200
400
600
800
1000