Homework 5 – Report

Question 1

```python
import torch
from torchvision import datasets, transforms
from matplotlib import pyplot as plt
```

```python
# Define the transformation
transform = transforms.Compose([
    transforms.ToTensor(),
    transforms.Normalize((0.5,), (0.5,))
])

# Load datasets
trainset = datasets.FashionMNIST('~/.pytorch/F_MNIST_data/', download=True, train=True, transform=transform)
trainloader = torch.utils.data.DataLoader(trainset, batch_size=32, shuffle=True)

testset = datasets.FashionMNIST('~/.pytorch/F_MNIST_data/', download=True, train=False, transform=transform)
testloader = torch.utils.data.DataLoader(testset, batch_size=32, shuffle=False)

# Verify dataset loading
batch = next(iter(trainloader))
print(batch[0].shape, batch[1].shape)

# Visualize images
f, ax = plt.subplots(2, 5)
plt.subplots_adjust(bottom=0.3, top=0.7, hspace=0)

for i in range(2):
    for j in range(5):
        image, label = next(iter(trainloader))
        ax[i][j].set_axis_off()
        ax[i][j].imshow(image[0,0,:], cmap='gray')

plt.show()
```

```
Downloading http://fashion-mnist.s3-website.eu-central-1.amazonaws.com/train-images-idx3-ubyte.gz
Downloading http://fashion-mnist.s3-website.eu-central-1.amazonaws.com/train-images-idx3-ubyte.gz to /root/.pytorch/F_MNIST_data/FashionMNIST/raw/train-images-idx3-ubyte.gz
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Extracting /root/.pytorch/F_MNIST_data/FashionMNIST/raw/train-images-idx3-ubyte.gz to /root/.pytorch/F_MNIST_data/FashionMNIST/raw

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Downloading http://fashion-mnist.s3-website.eu-central-1.amazonaws.com/train-labels-idx1-ubyte.gz to /root/.pytorch/F_MNIST_data/FashionMNIST/raw/train-labels-idx1-ubyte.gz
100%|██████████| 29.5k/29.5k [00:00<00:00, 276kB/s]
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Downloading http://fashion-mnist.s3-website.eu-central-1.amazonaws.com/t10k-labels-idx1-ubyte.gz to /root/.pytorch/F_MNIST_data/FashionMNIST/raw/t10k-labels-idx1-ubyte.gz
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torch.Size([32, 1, 28, 28]) torch.Size([32])
```
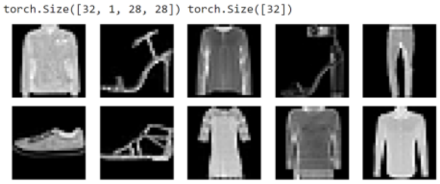



Question 2

```python
# Flatten the data (28x28 -> 784)
input_size = 784
num_classes = 10

# Define different network structures
class MLP(nn.Module):
    def __init__(self, structure, activation):
        super(MLP, self).__init__()
        layers = []
        for i in range(len(structure)-1):
            layers.append(nn.Linear(structure[i], structure[i+1]))
            if i < len(structure)-2:
                if activation == 'relu':
                    layers.append(nn.ReLU())
                elif activation == 'tanh':
                    layers.append(nn.Tanh())
                elif activation == 'sigmoid':
                    layers.append(nn.Sigmoid())
        self.model = nn.Sequential(*layers)

    def forward(self, x):
        x = x.view(-1, 784)  # Flatten the input
        return self.model(x)
```

```python
def train_and_evaluate(model, trainloader, testloader, epochs=10):
    criterion = nn.CrossEntropyLoss()
    optimizer = optim.Adam(model.parameters(), lr=0.001)

    # Training
    model.train()
    for epoch in range(epochs):
        running_loss = 0.0
        correct = 0
        total = 0
        for images, labels in trainloader:
            optimizer.zero_grad()
            outputs = model(images)
            loss = criterion(outputs, labels)
            loss.backward()
            optimizer.step()

            _, predicted = torch.max(outputs.data, 1)
            total += labels.size(0)
            correct += (predicted == labels).sum().item()
            running_loss += loss.item()

        train_accuracy = 100 * correct / total

        # Testing accuracy
        model.eval()
        correct = 0
        total = 0
        with torch.no_grad():
            for images, labels in testloader:
                outputs = model(images)
                _, predicted = torch.max(outputs.data, 1)
                total += labels.size(0)
                correct += (predicted == labels).sum().item()
        test_accuracy = 100 * correct / total
```

```python
        print(f'Epoch {epoch+1}: Train Acc: {train_accuracy:.2f}%, Test Acc: {test_accuracy:.2f}%')

# Different network structures to try
structures = [
    [784, 128, 10],
    [784, 256, 128, 10],
    [784, 512, 256, 128, 10],
    [784, 128, 64, 32, 10],
    [784, 1024, 512, 10]
]

print("Testing different network structures with ReLU activation:")
for structure in structures:
    print(f"\nStructure: {structure}")
    model = MLP(structure, 'relu')
    train_and_evaluate(model, trainloader, testloader)

# Test different activations on best structure
best_structure = [784, 512, 256, 128, 10]  # Replace with your best structure
activations = ['relu', 'tanh', 'sigmoid']

print("\nTesting different activation functions on best structure:")
for activation in activations:
    print(f"\nActivation: {activation}")
    model = MLP(best_structure, activation)
    train_and_evaluate(model, trainloader, testloader)
```

```
Testing different network structures with ReLU activation:

Structure: [784, 128, 10]
Epoch 1: Train Acc: 82.42%, Test Acc: 85.01%
Epoch 2: Train Acc: 86.18%, Test Acc: 85.50%
Epoch 3: Train Acc: 87.43%, Test Acc: 86.22%
Epoch 4: Train Acc: 88.29%, Test Acc: 86.36%
Epoch 5: Train Acc: 88.82%, Test Acc: 86.45%
Epoch 6: Train Acc: 89.44%, Test Acc: 86.95%
Epoch 7: Train Acc: 89.79%, Test Acc: 87.64%
Epoch 8: Train Acc: 90.26%, Test Acc: 87.48%
Epoch 9: Train Acc: 90.62%, Test Acc: 87.71%
Epoch 10: Train Acc: 90.97%, Test Acc: 88.44%

Structure: [784, 256, 128, 10]
Epoch 1: Train Acc: 82.23%, Test Acc: 83.26%
Epoch 2: Train Acc: 86.31%, Test Acc: 84.87%
Epoch 3: Train Acc: 87.65%, Test Acc: 86.50%
Epoch 4: Train Acc: 88.67%, Test Acc: 86.99%
Epoch 5: Train Acc: 89.25%, Test Acc: 87.59%
Epoch 6: Train Acc: 89.90%, Test Acc: 87.60%
Epoch 7: Train Acc: 90.27%, Test Acc: 88.65%
Epoch 8: Train Acc: 90.76%, Test Acc: 88.02%
Epoch 9: Train Acc: 91.00%, Test Acc: 88.38%
Epoch 10: Train Acc: 91.44%, Test Acc: 88.74%

Structure: [784, 512, 256, 128, 10]
Epoch 1: Train Acc: 81.77%, Test Acc: 84.12%
Epoch 2: Train Acc: 86.14%, Test Acc: 84.99%
Epoch 3: Train Acc: 87.65%, Test Acc: 85.27%
Epoch 4: Train Acc: 88.59%, Test Acc: 87.43%
Epoch 5: Train Acc: 89.17%, Test Acc: 87.88%
Epoch 6: Train Acc: 89.55%, Test Acc: 87.94%
Epoch 7: Train Acc: 90.23%, Test Acc: 87.55%
Epoch 8: Train Acc: 90.62%, Test Acc: 87.13%
Epoch 9: Train Acc: 91.03%, Test Acc: 88.81%
Epoch 10: Train Acc: 91.43%, Test Acc: 88.70%
```

```
Structure: [784, 128, 64, 32, 10]
Epoch 1: Train Acc: 80.93%, Test Acc: 84.62%
Epoch 2: Train Acc: 86.08%, Test Acc: 85.67%
Epoch 3: Train Acc: 87.27%, Test Acc: 86.08%
Epoch 4: Train Acc: 88.15%, Test Acc: 87.15%
Epoch 5: Train Acc: 88.79%, Test Acc: 86.67%
Epoch 6: Train Acc: 89.32%, Test Acc: 87.43%
Epoch 7: Train Acc: 89.65%, Test Acc: 87.81%
Epoch 8: Train Acc: 90.19%, Test Acc: 87.69%
Epoch 9: Train Acc: 90.61%, Test Acc: 87.75%
Epoch 10: Train Acc: 90.81%, Test Acc: 87.69%

Structure: [784, 1024, 512, 10]
Epoch 1: Train Acc: 82.25%, Test Acc: 84.61%
Epoch 2: Train Acc: 86.32%, Test Acc: 86.65%
Epoch 3: Train Acc: 87.77%, Test Acc: 87.08%
Epoch 4: Train Acc: 88.71%, Test Acc: 86.98%
Epoch 5: Train Acc: 89.34%, Test Acc: 87.68%
Epoch 6: Train Acc: 89.94%, Test Acc: 87.67%
Epoch 7: Train Acc: 90.41%, Test Acc: 87.52%
Epoch 8: Train Acc: 91.07%, Test Acc: 87.01%
Epoch 9: Train Acc: 91.47%, Test Acc: 88.40%
Epoch 10: Train Acc: 91.90%, Test Acc: 88.74%

Testing different activation functions on best structure:

Activation: relu
Epoch 1: Train Acc: 81.75%, Test Acc: 83.85%
Epoch 2: Train Acc: 86.28%, Test Acc: 85.52%
Epoch 3: Train Acc: 87.60%, Test Acc: 86.54%
Epoch 4: Train Acc: 88.47%, Test Acc: 86.38%
Epoch 5: Train Acc: 89.25%, Test Acc: 87.58%
Epoch 6: Train Acc: 89.83%, Test Acc: 87.23%
Epoch 7: Train Acc: 90.21%, Test Acc: 87.34%
Epoch 8: Train Acc: 90.76%, Test Acc: 87.89%
Epoch 9: Train Acc: 91.10%, Test Acc: 87.97%
Epoch 10: Train Acc: 91.53%, Test Acc: 88.74%
```

```
Activation: tanh
Epoch 1: Train Acc: 81.30%, Test Acc: 81.60%
Epoch 2: Train Acc: 84.85%, Test Acc: 85.19%
Epoch 3: Train Acc: 85.76%, Test Acc: 85.24%
Epoch 4: Train Acc: 86.41%, Test Acc: 85.27%
Epoch 5: Train Acc: 86.69%, Test Acc: 85.66%
Epoch 6: Train Acc: 87.07%, Test Acc: 85.70%
Epoch 7: Train Acc: 87.12%, Test Acc: 85.23%
Epoch 8: Train Acc: 87.18%, Test Acc: 84.59%
Epoch 9: Train Acc: 87.43%, Test Acc: 85.81%
Epoch 10: Train Acc: 87.53%, Test Acc: 85.47%

Activation: sigmoid
Epoch 1: Train Acc: 76.03%, Test Acc: 82.55%
Epoch 2: Train Acc: 85.69%, Test Acc: 85.03%
Epoch 3: Train Acc: 87.10%, Test Acc: 85.41%
Epoch 4: Train Acc: 88.05%, Test Acc: 86.52%
Epoch 5: Train Acc: 88.82%, Test Acc: 86.88%
Epoch 6: Train Acc: 89.26%, Test Acc: 87.12%
Epoch 7: Train Acc: 89.85%, Test Acc: 87.32%
Epoch 8: Train Acc: 90.34%, Test Acc: 87.94%
Epoch 9: Train Acc: 90.72%, Test Acc: 87.42%
Epoch 10: Train Acc: 90.89%, Test Acc: 87.24%
```

I observe that the best structures were [784, 1024, 512, 10] and [784, 256, 128, 10] since they both had approximately 88.74% test accuracy. ReLU also performed the best because it had 88.74% test accuracy.

Question 3

Implementation Parts a-e

I commented specifically the parts of the code that have to do with each part. There's some experimentation code as well.

```
# Set device
device = torch.device('cuda' if torch.cuda.is_available() else 'cpu')

# Implementation a-e: Baseline CNN
class CNN(nn.Module):
    def __init__(self, dropout_rate=0, num_conv_layers=1):
        super(CNN, self).__init__()

        # Implementation a: First conv layer
        self.conv1 = nn.Conv2d(1, 32, 3)

        # Implementation b: First maxpool
        self.pool = nn.MaxPool2d(2, 2)

        # Experimentation c: Optional second conv layer
        self.num_conv_layers = num_conv_layers
        if num_conv_layers > 1:
            self.conv2 = nn.Conv2d(32, 64, 3)

        # Calculate flattened size
        self.flat_size = 32 * 13 * 13 if num_conv_layers == 1 else 64 * 5 * 5

        # Experimentation b: Dropout layer
        self.dropout = nn.Dropout(dropout_rate)

        # Implementation d: Dense layer with ReLU
        self.fc1 = nn.Linear(self.flat_size, 100)

        # Implementation e: Output layer
        self.fc2 = nn.Linear(100, 10)
```

```
    def forward(self, x):
        x = self.pool(torch.relu(self.conv1(x)))

        if self.num_conv_layers > 1:
            x = self.pool(torch.relu(self.conv2(x)))

        # Implementation c: Flatten layer
        x = x.view(-1, self.flat_size)

        x = self.dropout(x)
        x = torch.relu(self.fc1(x))
        x = self.fc2(x)
        return x

def train_and_evaluate(model, trainloader, testloader, epochs, lr=0.01, store_metrics=False):
    model = model.to(device)
    criterion = nn.CrossEntropyLoss()
    optimizer = optim.SGD(model.parameters(), lr=lr, momentum=0.9)

    train_acc_history = []
    test_acc_history = []

    for epoch in range(epochs):
        # Training
        model.train()
        correct = 0
        total = 0
        for images, labels in trainloader:
            images, labels = images.to(device), labels.to(device)
            optimizer.zero_grad()
            outputs = model(images)
            loss = criterion(outputs, labels)
            loss.backward()
            optimizer.step()
```

```python
            _, predicted = torch.max(outputs.data, 1)
            total += labels.size(0)
            correct += (predicted == labels).sum().item()

        train_acc = 100 * correct / total

        # Testing
        model.eval()
        correct = 0
        total = 0
        with torch.no_grad():
            for images, labels in testloader:
                images, labels = images.to(device), labels.to(device)
                outputs = model(images)
                _, predicted = torch.max(outputs.data, 1)
                total += labels.size(0)
                correct += (predicted == labels).sum().item()

        test_acc = 100 * correct / total

        if store_metrics:
            train_acc_history.append(train_acc)
            test_acc_history.append(test_acc)

        if (epoch + 1) % 10 == 0 or epoch == epochs-1:
            print(f'Epoch {epoch+1}: Train Acc: {train_acc:.2f}%, Test Acc: {test_acc:.2f}%')

    if store_metrics:
        return train_acc_history, test_acc_history
    return test_acc
```

```python
def plot_accuracies(train_acc, test_acc, title):
    plt.figure(figsize=(10, 6))
    epochs = range(10, len(train_acc) * 10 + 1, 10)
    plt.plot(epochs, train_acc, 'b-', label='Training Accuracy')
    plt.plot(epochs, test_acc, 'r-', label='Validation Accuracy')
    plt.title(title)
    plt.xlabel('Epoch')
    plt.ylabel('Accuracy (%)')
    plt.legend()
    plt.grid(True)
    plt.savefig(f'{title}.png')
    plt.close()
```

```python
# Baseline training (10 epochs)
print("Training baseline CNN for 10 epochs:")
model = CNN()
test_acc = train_and_evaluate(model, trainloader, testloader, epochs=10)
print(f"Final test accuracy: {test_acc:.2f}%")
```

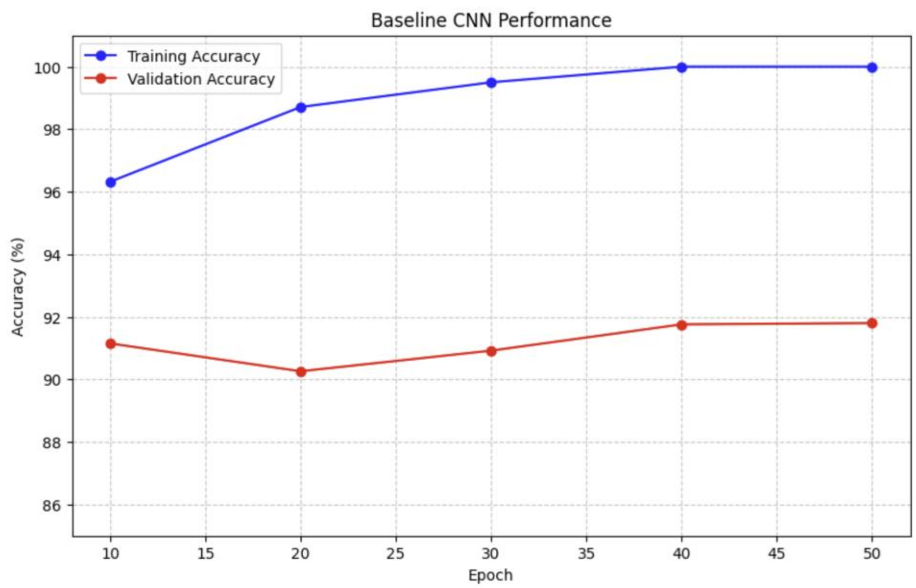
```
Training baseline CNN for 10 epochs:
Epoch 10: Train Acc: 96.27%, Test Acc: 90.80%
Final test accuracy: 90.80%
```

Experimentation:

Part a

```
# Experimentation a: 50 epochs baseline
print("\nTraining CNN for 50 epochs:")
model = CNN()
train_acc, test_acc = train_and_evaluate(model, trainloader, testloader, epochs=50, store_metrics=True)
plot_accuracies(train_acc[::10], test_acc[::10], "Baseline CNN Performance")
```

```
Training CNN for 50 epochs:
Epoch 10: Train Acc: 96.32%, Test Acc: 91.15%
Epoch 20: Train Acc: 98.71%, Test Acc: 90.26%
Epoch 30: Train Acc: 99.50%, Test Acc: 90.92%
Epoch 40: Train Acc: 100.00%, Test Acc: 91.76%
Epoch 50: Train Acc: 100.00%, Test Acc: 91.80%
```

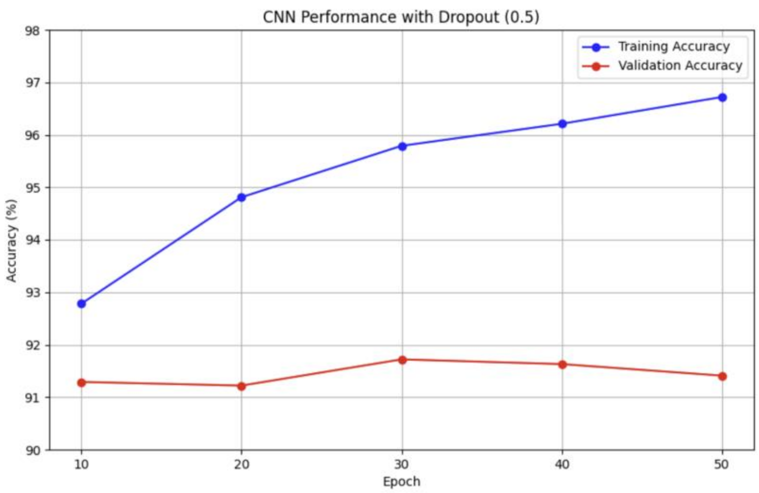


There is a steady increase in training accuracy that converges around 100% accuracy. However there is not steady improvement in the validation accuracy. A possible reason for this is that the model is overfitting the data and can't seem to generalize.

Part b

```
# Experimentation b: 50 epochs with dropout
print("\nTraining CNN for 50 epochs with dropout:")
model = CNN(dropout_rate=0.5)
train_acc, test_acc = train_and_evaluate(model, trainloader, testloader, epochs=50, store_metrics=True)
plot_accuracies(train_acc[::10], test_acc[::10], "CNN Performance with Dropout")
```

```
Training CNN for 50 epochs with dropout:
Epoch 10: Train Acc: 92.78%, Test Acc: 91.29%
Epoch 20: Train Acc: 94.81%, Test Acc: 91.22%
Epoch 30: Train Acc: 95.79%, Test Acc: 91.72%
Epoch 40: Train Acc: 96.21%, Test Acc: 91.63%
Epoch 50: Train Acc: 96.72%, Test Acc: 91.41%
```



Part c

```
# Experimentation c: Two conv layers
print("\nTraining CNN with two conv layers:")
model = CNN(dropout_rate=0.5, num_conv_layers=2)
test_acc = train_and_evaluate(model, trainloader, testloader, epochs=10)
print(f"Final test accuracy with two conv layers: {test_acc:.2f}%")
```

```
Training CNN with two conv layers:
Epoch 10: Train Acc: 90.89%, Test Acc: 90.72%
Final test accuracy with two conv layers: 90.72%
```

Part d

```
[20] # Experimentation d: Different learning rates
print("\nTesting different learning rates:")
for lr in [0.001, 0.1]:
    print(f"\nTraining with learning rate: {lr}")
    model = CNN(dropout_rate=0.5, num_conv_layers=2)
    test_acc = train_and_evaluate(model, trainloader, testloader, epochs=10, lr=lr)
    print(f"Final test accuracy: {test_acc:.2f}%")
```

```
Testing different learning rates:

Training with learning rate: 0.001
Epoch 10: Train Acc: 87.39%, Test Acc: 88.23%
Final test accuracy: 88.23%

Training with learning rate: 0.1
Epoch 10: Train Acc: 9.90%, Test Acc: 10.00%
Final test accuracy: 10.00%
```

Analysis:

Part a

I notice that without dropping, the training accuracy reaches 100% accuracy really fast and that the testing accuracy does not increase steadily. However, with dropout, the training accuracy increases much slower and reaches 97% instead of 100% and the testing accuracy seems to be a little more stable but still only reaches around 92%

Part b

The single layer definitely shows more overfitting than the CNN with two layers. I can prove this because the training accuracy for one layer was 96.32% while the training accuracy for two layers was 90.89% and the testing accuracy for the single layer was 91.15% and the testing accuracy for two layers was 90.72% which is much closer to its training accuracy than the single layer. However, I did notice that two layers performed slightly worse.

Part c

When the learning rate was 0.001, the test accuracy was 88.23% while the test accuracy of the 0.1 learning rate was only 10%, which is significantly worse. I think we could increase the test accuracy by choosing something a little higher, yet closer to 0.001 like 0.03. This will be more effective learning without overshooting the way 0.1 did.

Written Exercises

Question 1

Part a

Yes, a multilayer perceptron with one hidden layer of ReLU units represent any function that an MLP with linear hidden units can represent and you would need either the same or less amount of nodes since linear networks can be redundant.

Part b

No, MLP with linear units can't represent the mappings that an MLP with ReLU units can represent no matter how many hidden nodes you add.