## **CSE 598: Machine Learning Security and Fairness**

#### Assignment 1. Train and attack classifier

### **PART 1: Train a Fashion-MNIST Classification**

#### Dataset:

The dataset used is Fashion-MNIST dataset. It consists of 10 classes. The 10 classes are T-shirt/Top, Trouser, Pullover, Dress, Coat, Sandal, Shirt, Sneaker, Bag, Ankle Boot.

The dataset consists of 60000 images in the training set and 10000 images in the test set. Each image is of size 28\*28. Each image is a gray scale image.

The dataset is split into three parts: Training set, Validation set and Testing set.

The training set consists of 50000 images, validation set consists of 10000 images and test set consists of 10000 images.

#### Architecture of the network:

The Lenet network is used for training the Fashion-MNIST. Lenet consists of total 5 layers: 3 convolutional layers and 2 fully connected layers.

The network is defined in the forward function of the part1.py file.

Detailed description of each layer:

- 1. Convolution Layer 1:
  - a. Input channels: 1
  - b. Output channels: 6
  - c. Kernel size: 5\*5
  - d. Stride: 1\*1
- 2. Convolution Layer 2:
  - a. Input channels: 6
  - b. Output channels: 16
  - c. Kernel size: 5\*5
  - d. Stride: 1\*1
- 3. Convolution Layer 3:
  - a. Input channels: 16
  - b. Output channels: 120
  - c. Kernel size: 4\*4
  - d. Stride: 1\*1
- 4. Fully Connected layer 1:
  - a. Input features: 120

b. Output features: 84

5. Fully Connected layer 2:

a. Input features: 84b. Output features: 10

```
#Convolution Layer 1
x = self.conv1(x)
x = self.relu(x)
x = self.pooling_layer(x)

#Convolution Layer 2
x = self.conv2(x)
x = self.relu(x)
x = self.pooling_layer(x)
x = self.dropout(x)

#Convolution Layer 3
x = self.conv3(x)
x = self.relu(x)

#flatten x
x = x.view(-1, 120)

#Fully connected layer 1
x = self.fully_connected1(x)
x = self.relu(x)

#Fully connected layer 2
x = self.fully_connected2(x)

return x
```

Activation function used is ReLU.

A dropout layer is used after second convolution layer in the network with dropout percent set to 25%.

## **Optimizers and its parameters:**

The optimizer that is used is ADAM optimizer.

The parameters of the optimizers that are used for training the model are:

Learning Rate: 0.001 Weight Decay: 1e-4

```
optimizer = optim.Adam(model.parameters(), lr=learning_rate, weight_decay=weight_decay)
```

## **Training Parameters:**

Batch size: 32 Epoch: 40

Learning Rate: 0.001

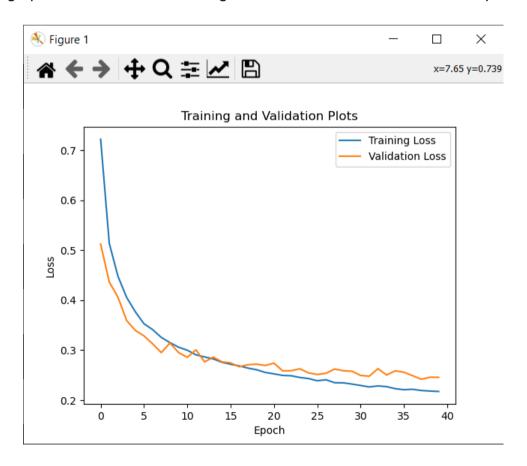
The model achieves best accuracy using the above-mentioned network, optimizer and training parameters.

#### **Key Choices made:**

- 1. Higher learning rate was not giving good accuracy on the test set even when it could achieve higher accuracy on training set.
- 2. Higher batch size for E.g.: 512, 1024 was not giving good accuracy. So a lower batch size was chosen for the best model.
- 3. Increasing the number of epochs to more than 100 was resulting in overfitting of the model. This was evident because as the epoch was increasing the training accuracy was increasing but the validation accuracy was decreasing.
- 4. Adam optimizer showed best result among SGD, RMSProp.
- 5. The model was overfitting so using a dropout layer was a way to deal with the overfitting of the model. Other method like augmenting the data using different augmentations like rotation at different angles which will increase the total number of training samples and reduce the overfitting problem can also be used.

#### **Loss Curves:**

The graph below shows the training loss and validation loss for the best parameters.

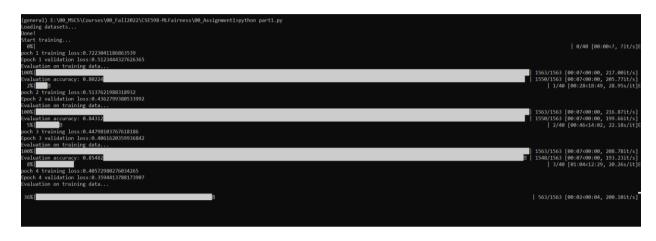


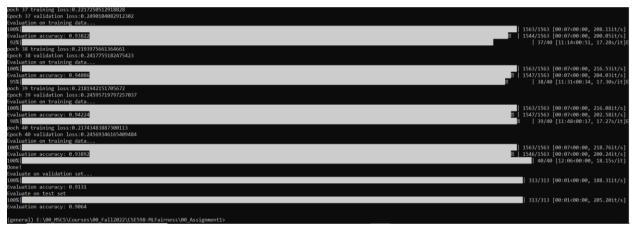
## **Training and Results:**

The model is able to achieve an accuracy of 90.64% on the test dataset.

Test Accuracy: 90.64%

Validation Accuracy: 91.31%





#### **PART 2 Implement attacks for Fashion-MNIST Classification:**

The implementation of both the attacks are present in part2.py file.

The python function generates perturbed images and performs the attack on the test dataset only.

```
def generate_perturbed_image(img, epsilon, loss_gradient):
    img - original image
    epsilon - used to adjust the input data by small step
    loss_gradient - gradient of the network
    ...

perturbed_image = img + epsilon * loss_gradient.sign()
    #to maintain the range of the image in [0, 1]
    perturbed_image = torch.clamp(perturbed_image, 0, 1)

return perturbed_image
```

The functions evaluate\_fsgm() and evaluate\_pgd() has the implementation of fast sign gradient method and PDG evasion attack.

The following epsilon and alpha values are used:

Epsilon: 25/255 Alpha: 2/255

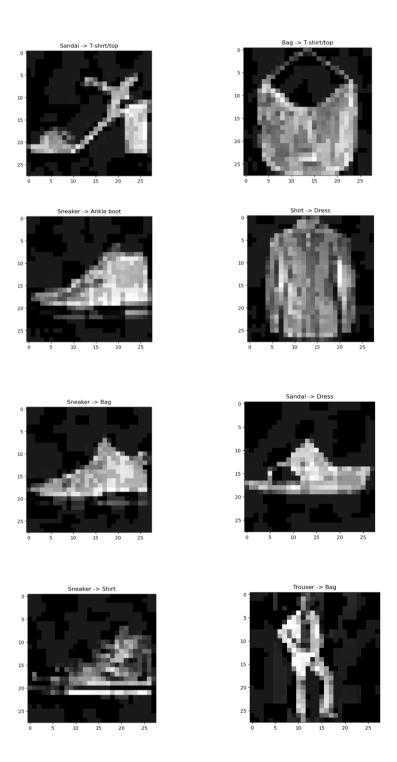
```
(general) E:\00_PKSS\Courses\00_Fall2022\CSE598-MEairnes\00_Assignment1>python part2.py
Loading datasets...

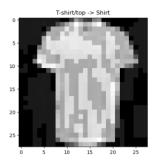
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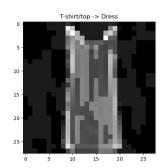
## **Fast Sign Gradient Method:**

The attack accuracy of the fast sign gradient method is: 85.21%

# Sample Adversarial Images and its Prediction for FSGM attack:







## **PGD Evasion Attack:**

Step sizes used are 1, 2, 5, 10.

Accuracy for Step 1: 9.17%
Accuracy for Step 2: 22.17%
Accuracy for Step 5: 63.67%
Accuracy for Step 10: 94.56%

# Sample Adversarial images for PGD Evasion Attack with step size 10:

