Fashion-MNIST Classification using Neural Network

In this notebook, we'll build a neural network to classify Fashion-MNIST images

In [96]:
```
import numpy as np
import torch
import torch.nn as nn
import torch.optim as optim
from torchvision import datasets, transforms
import matplotlib.pyplot as plt
from collections import OrderedDict

# Download training and testing data
transform = transforms.Compose([transforms.ToTensor(),
                                transforms.Normalize((0.5,), (0.5,))])
train_ds = datasets.FashionMNIST('F_MNIST_data', download=True, train=True, transform=
test_ds = datasets.FashionMNIST('F_MNIST_data', download=True, train=False, transform=
```

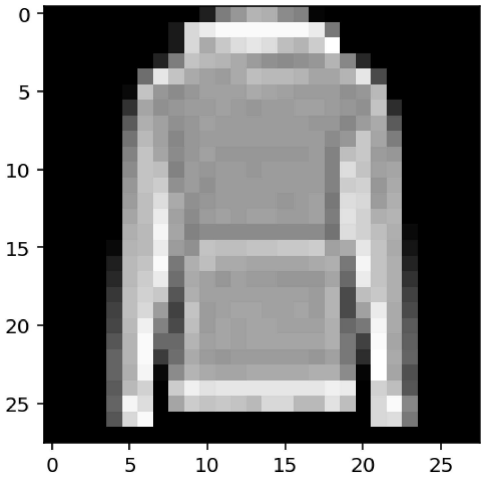
In [98]:
```
# split train set into training (80%) and validation set (20%)
train_num = len(train_ds)
indices = list(range(train_num))
np.random.shuffle(indices)
split = int(np.floor(0.2 * train_num))
val_idx, train_idx = indices[:split], indices[split:]
len(val_idx), len(train_idx)
```

Out[98]:
```
(12000, 48000)
```

In [103…
```
# prepare dataloaders
train_sampler = torch.utils.data.sampler.SubsetRandomSampler(train_idx)
train_dl = torch.utils.data.DataLoader(train_ds, batch_size=64, sampler=train_sampler)
val_sampler = torch.utils.data.sampler.SubsetRandomSampler(val_idx)
val_dl = torch.utils.data.DataLoader(train_ds, batch_size=64, sampler=val_sampler)
test_dl = torch.utils.data.DataLoader(test_ds, batch_size=64, shuffle=True)
```

In [104…
```
image, label = next(iter(train_dl))
print(image[0].shape, label.shape)
desc = ['T-shirt/top','Trouser','Pullover','Dress','Coat','Sandal','Shirt','Sneaker','
print(desc[label[0].item()])
plt.imshow(image[0].numpy().squeeze(), cmap='gray');
```

```
torch.Size([1, 28, 28]) torch.Size([64])
Pullover
```



Build the network

In [111…

```
def network():
    model = nn.Sequential(OrderedDict([('fc1', nn.Linear(784, 128)),
                                       ('relu1', nn.ReLU()),
                                       ('drop1', nn.Dropout(0.25)),
                                       ('fc2', nn.Linear(128, 64)),
                                       ('relu2', nn.ReLU()),
                                       ('drop1', nn.Dropout(0.25)),
                                       ('output', nn.Linear(64, 10)),
                                       ('logsoftmax', nn.LogSoftmax(dim=1))]))
    # Use GPU if available
    device = 'cuda' if torch.cuda.is_available() else 'cpu'
    model = model.to(device)

    # define the criterion and optimizer
    loss_fn = nn.NLLLoss()
    optimizer = optim.Adam(model.parameters(), lr=0.003)

    return model, loss_fn, optimizer, device
```

In [112…

```
model, loss_fn, optimizer, device = network()
print(model)
```

```
Sequential(
  (fc1): Linear(in_features=784, out_features=128, bias=True)
  (relu1): ReLU()
  (drop1): Dropout(p=0.25, inplace=False)
  (fc2): Linear(in_features=128, out_features=64, bias=True)
  (relu2): ReLU()
  (output): Linear(in_features=64, out_features=10, bias=True)
  (logsoftmax): LogSoftmax(dim=1)
)
```

Train the network

In [113…

```
def train_validate(model, loss_fn, optimizer, trainloader, testloader, device, n_epoch
    train_losses = []
    test_losses = []
    for epoch in range(n_epochs):
```

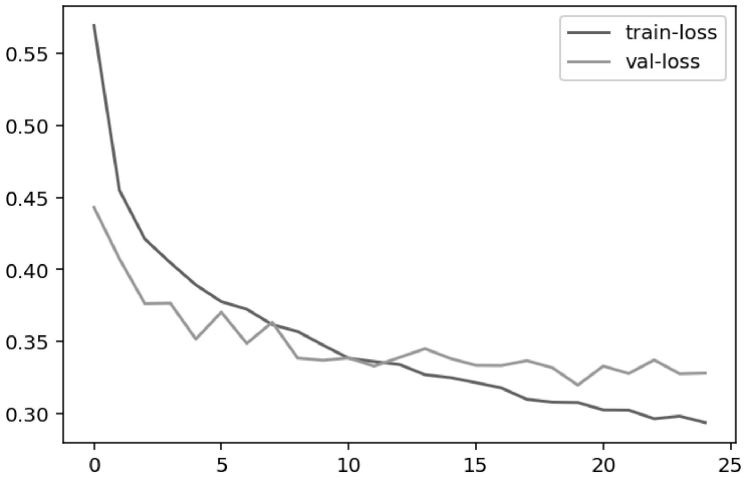
```
        # Set mode to training - Dropouts will be used here
        model.train()
        train_epoch_loss = 0
        for images, labels in trainloader:
            images, labels = images.to(device), labels.to(device)
            # flatten the images to batch_size x 784
            images = images.view(images.shape[0], -1)
            # forward pass
            outputs = model(images)
            # backpropogation
            train_batch_loss = loss_fn(outputs, labels)
            optimizer.zero_grad()
            train_batch_loss.backward()
            # Weight updates
            optimizer.step()
            train_epoch_loss += train_batch_loss.item()
        else:
            # One epoch of training complete
            # calculate average training epoch loss
            train_epoch_loss = train_epoch_loss/len(trainloader)

            # Now Validate on testset
            with torch.no_grad():
                test_epoch_acc = 0
                test_epoch_loss = 0
                # Set mode to eval - Dropouts will NOT be used here
                model.eval()
                for images, labels in testloader:
                    images, labels = images.to(device), labels.to(device)
                    # flatten images to batch_size x 784
                    images = images.view(images.shape[0], -1)
                    # make predictions
                    test_outputs = model(images)
                    # calculate test loss
                    test_batch_loss = loss_fn(test_outputs, labels)
                    test_epoch_loss += test_batch_loss

                    # get probabilities, extract the class associated with highest pro
                    proba = torch.exp(test_outputs)
                    _, pred_labels = proba.topk(1, dim=1)

                    # compare actual labels and predicted labels
                    result = pred_labels == labels.view(pred_labels.shape)
                    batch_acc = torch.mean(result.type(torch.FloatTensor))
                    test_epoch_acc += batch_acc.item()
                else:
                    # One epoch of training and validation done
                    # calculate average testing epoch loss
                    test_epoch_loss = test_epoch_loss/len(testloader)
                    # calculate accuracy as correct_pred/total_samples
                    test_epoch_acc = test_epoch_acc/len(testloader)
                    # save epoch losses for plotting
                    train_losses.append(train_epoch_loss)
                    test_losses.append(test_epoch_loss)
                    # print stats for this epoch
                    print(f'Epoch: {epoch} -> train_loss: {train_epoch_loss:.19f}, val
                          f'val_acc: {test_epoch_acc*100:.2f}%')
    # Finally plot losses
    plt.plot(train_losses, label='train-loss')
    plt.plot(test_losses, label='val-loss')
```

```
    plt.legend()
    plt.show()
```

In [114…

```
# Train and validate
train_validate(model, loss_fn, optimizer, train_dl, val_dl, device)
```

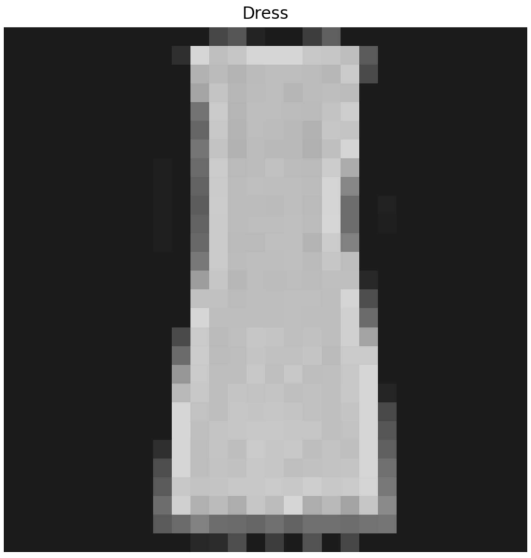
```
Epoch: 0 -> train_loss: 0.5692988239328066191, val_loss: 0.4430967867374420166,  val_
acc: 83.27%
Epoch: 1 -> train_loss: 0.4549953033725420704, val_loss: 0.4073663055896759033,  val_
acc: 84.97%
Epoch: 2 -> train_loss: 0.4211076561212539482, val_loss: 0.3762904107570648193,  val_
acc: 86.11%
Epoch: 3 -> train_loss: 0.4046927829583485958, val_loss: 0.3766101896762847900,  val_
acc: 86.46%
Epoch: 4 -> train_loss: 0.3892695648074150361, val_loss: 0.3516367673873901367,  val_
acc: 87.34%
Epoch: 5 -> train_loss: 0.3776730005542437429, val_loss: 0.3703932464122772217,  val_
acc: 86.71%
Epoch: 6 -> train_loss: 0.3724320774773756670, val_loss: 0.3486533761024475098,  val_
acc: 87.37%
Epoch: 7 -> train_loss: 0.3617128521899382054, val_loss: 0.3633341491222381592,  val_
acc: 87.08%
Epoch: 8 -> train_loss: 0.3569285793701807430, val_loss: 0.3384532332420349121,  val_
acc: 87.58%
Epoch: 9 -> train_loss: 0.3474347092111905178, val_loss: 0.3369818329811096191,  val_
acc: 87.88%
Epoch: 10 -> train_loss: 0.3383618565599123551, val_loss: 0.3385397493839263916,  val
_acc: 87.97%
Epoch: 11 -> train_loss: 0.3360619519948959133, val_loss: 0.3329190611839294434,  val
_acc: 87.97%
Epoch: 12 -> train_loss: 0.3340372469524542365, val_loss: 0.3389228284358978271,  val
_acc: 88.00%
Epoch: 13 -> train_loss: 0.3269288233717282388, val_loss: 0.3449897170066833496,  val
_acc: 87.77%
Epoch: 14 -> train_loss: 0.3249198505381742930, val_loss: 0.3381777107715606689,  val
_acc: 87.75%
Epoch: 15 -> train_loss: 0.3214456404149532154, val_loss: 0.3334679007530212402,  val
_acc: 87.97%
Epoch: 16 -> train_loss: 0.3177473722100258025, val_loss: 0.3333184421062469482,  val
_acc: 87.75%
Epoch: 17 -> train_loss: 0.3098344492912292747, val_loss: 0.3366726040840148926,  val
_acc: 88.12%
Epoch: 18 -> train_loss: 0.3078885127405325828, val_loss: 0.3318108916282653809,  val
_acc: 88.41%
Epoch: 19 -> train_loss: 0.3075984100500742668, val_loss: 0.3197179138660430908,  val
_acc: 88.56%
Epoch: 20 -> train_loss: 0.3024848873019218565, val_loss: 0.3329302072525024414,  val
_acc: 88.16%
Epoch: 21 -> train_loss: 0.3023494395713011151, val_loss: 0.3277964591979980469,  val
_acc: 88.35%
Epoch: 22 -> train_loss: 0.2963562680284182460, val_loss: 0.3371585309505462646,  val
_acc: 88.25%
Epoch: 23 -> train_loss: 0.2981447652975718343, val_loss: 0.3276244103908538818,  val
_acc: 88.55%
Epoch: 24 -> train_loss: 0.2937244445780913260, val_loss: 0.3280715346336364746,  val
_acc: 88.67%
```

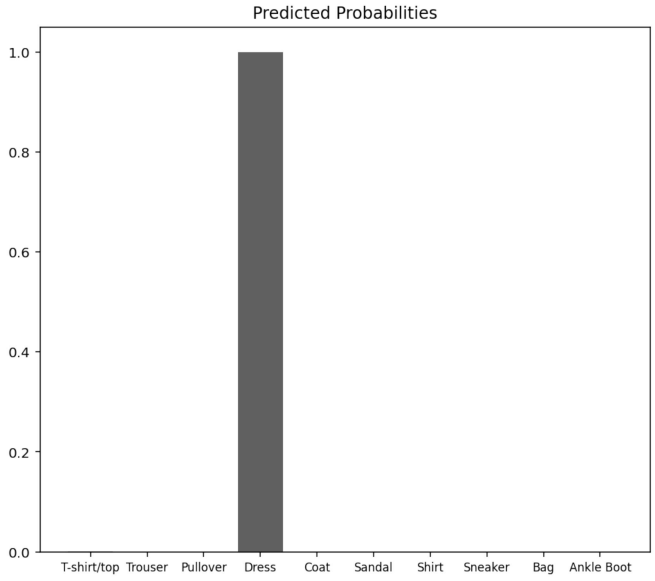


Predict a single image

In [115…

```
%matplotlib inline
%config InlineBackend.figure_format = 'retina'

# Test out the network!
dataiter = iter(test_dl)
images, labels = dataiter.next()
images, labels = images.to(device), labels.to(device)
index = 49
img, label = images[index], labels[index]
# Convert 2D image to 1D vector
img = img.view(img.shape[0], -1)

# Calculate the class probabilities (softmax) for img
proba = torch.exp(model(img))

# Plot the image and probabilities
desc = ['T-shirt/top','Trouser','Pullover','Dress','Coat','Sandal','Shirt','Sneaker','
fig, (ax1, ax2) =  plt.subplots(figsize=(13, 6), nrows=1, ncols=2)
ax1.axis('off')
ax1.imshow(images[index].cpu().numpy().squeeze())
ax1.set_title(desc[label.item()])
ax2.bar(range(10), proba.detach().cpu().numpy().squeeze())
ax2.set_xticks(range(10))
ax2.set_xticklabels(desc, size='small')
ax2.set_title('Predicted Probabilities')
plt.tight_layout()
```





Validate on test set

In [116…

```
# Validate
with torch.no_grad():
    batch_acc = []
    model.eval()
    for images, labels in test_dl:
        images, labels = images.to(device), labels.to(device)
        # flatten images to batch_size x 784
        images = images.view(images.shape[0], -1)
        # make predictions and get probabilities
        proba = torch.exp(model(images))
        # extract the class associted with highest probability
        _, pred_labels = proba.topk(1, dim=1)
        # compare actual labels and predicted labels
        result = pred_labels == labels.view(pred_labels.shape)
        acc = torch.mean(result.type(torch.FloatTensor))
        batch_acc.append(acc.item())
    else:
        print(f'Test Accuracy: {torch.mean(torch.tensor(batch_acc))*100:.2f}%')
```

```
Test Accuracy: 87.42%
```

More powerful model

In [131…

```
# Redefine network with dropout layers in between
def network():
    model = nn.Sequential(OrderedDict([('fc1', nn.Linear(784, 392)),
                                       ('relu1', nn.ReLU()),
                                       ('drop1', nn.Dropout(0.25)),
                                       ('fc12', nn.Linear(392, 196)),
                                       ('relu2', nn.ReLU()),
                                       ('drop2', nn.Dropout(0.25)),
                                       ('fc3', nn.Linear(196, 98)),
                                       ('relu3', nn.ReLU()),
                                       ('drop3', nn.Dropout(0.25)),
                                       ('fc4', nn.Linear(98, 49)),
                                       ('relu4', nn.ReLU()),
```

```
                                        ('output', nn.Linear(49, 10)),
                                        ('logsoftmax', nn.LogSoftmax(dim=1))]))

    # Use GPU if available
    device = 'cuda' if torch.cuda.is_available() else 'cpu'
    model = model.to(device)

    # define the criterion and optimizer
    loss_fn = nn.NLLLoss()
    optimizer = optim.Adam(model.parameters(), lr=0.0007)

    return model, loss_fn, optimizer, device
```

In [132…

```
model, loss_fn, optimizer, device = network()
model
```

Out[132]:

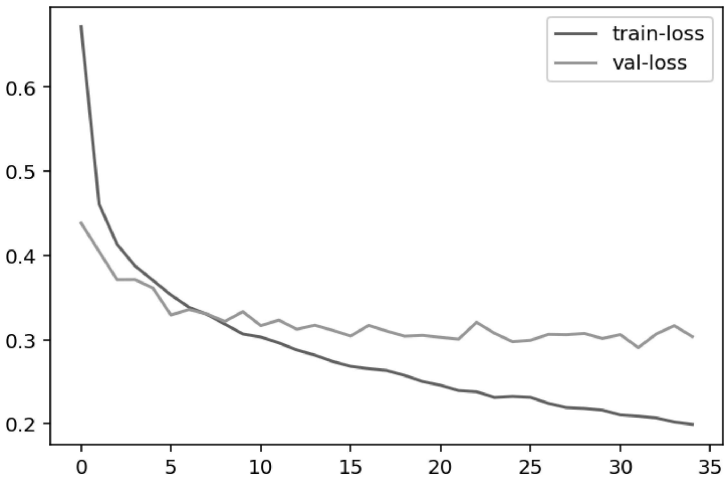
```
Sequential(
  (fc1): Linear(in_features=784, out_features=392, bias=True)
  (relu1): ReLU()
  (drop1): Dropout(p=0.25, inplace=False)
  (fc12): Linear(in_features=392, out_features=196, bias=True)
  (relu2): ReLU()
  (drop2): Dropout(p=0.25, inplace=False)
  (fc3): Linear(in_features=196, out_features=98, bias=True)
  (relu3): ReLU()
  (drop3): Dropout(p=0.25, inplace=False)
  (fc4): Linear(in_features=98, out_features=49, bias=True)
  (relu4): ReLU()
  (output): Linear(in_features=49, out_features=10, bias=True)
  (logsoftmax): LogSoftmax(dim=1)
)
```

In [133…

```
# Train and validate again with new architecture
train_validate(model, loss_fn, optimizer, train_dl, val_dl, device, n_epochs=35)
```

```
Epoch: 0 -> train_loss: 0.6715717662970225321, val_loss: 0.4384306371212005615,  val_
acc: 83.58%
Epoch: 1 -> train_loss: 0.4610257453123728366, val_loss: 0.4046924412250518799,  val_
acc: 84.90%
Epoch: 2 -> train_loss: 0.4132076732317606638, val_loss: 0.3710882067680358887,  val_
acc: 86.29%
Epoch: 3 -> train_loss: 0.3874667741258939202, val_loss: 0.3711968660354614258,  val_
acc: 86.47%
Epoch: 4 -> train_loss: 0.3702941476901372431, val_loss: 0.3610889613628387451,  val_
acc: 87.08%
Epoch: 5 -> train_loss: 0.3529314926067987912, val_loss: 0.3292031884193420410,  val_
acc: 88.07%
Epoch: 6 -> train_loss: 0.3384442613820234924, val_loss: 0.3356113731861114502,  val_
acc: 87.88%
Epoch: 7 -> train_loss: 0.3299360174735387341, val_loss: 0.3304152488708496094,  val_
acc: 88.25%
Epoch: 8 -> train_loss: 0.3183699831465879870, val_loss: 0.3215932250022888184,  val_
acc: 88.32%
Epoch: 9 -> train_loss: 0.3066120248536268744, val_loss: 0.3331522047519683838,  val_
acc: 88.21%
Epoch: 10 -> train_loss: 0.3030157501995563440, val_loss: 0.3165770173072814941,  val
_acc: 88.86%
Epoch: 11 -> train_loss: 0.2961013345122337492, val_loss: 0.3231025636196136475,  val
_acc: 88.11%
Epoch: 12 -> train_loss: 0.2876731425921122409, val_loss: 0.3123144209384918213,  val
_acc: 88.69%
Epoch: 13 -> train_loss: 0.2815732069909572810, val_loss: 0.3170706033706665039,  val
_acc: 88.46%
Epoch: 14 -> train_loss: 0.2739904375871022313, val_loss: 0.3109590411186218262,  val
_acc: 88.96%
Epoch: 15 -> train_loss: 0.2682814720571041200, val_loss: 0.3042424619197845459,  val
_acc: 89.29%
Epoch: 16 -> train_loss: 0.2654960344235102188, val_loss: 0.3168744444847106934,  val
_acc: 89.11%
Epoch: 17 -> train_loss: 0.2633762069841226183, val_loss: 0.3101049065589904785,  val
_acc: 88.79%
Epoch: 18 -> train_loss: 0.2575348454515139496, val_loss: 0.3040629029273986816,  val
_acc: 89.22%
Epoch: 19 -> train_loss: 0.2502811358968416999, val_loss: 0.3050162196159362793,  val
_acc: 89.39%
Epoch: 20 -> train_loss: 0.2457498750587304437, val_loss: 0.3026749193668365479,  val
_acc: 89.45%
Epoch: 21 -> train_loss: 0.2395246799389521286, val_loss: 0.3004771769046783447,  val
_acc: 89.69%
Epoch: 22 -> train_loss: 0.2380762482732534380, val_loss: 0.3205380141735076904,  val
_acc: 89.53%
Epoch: 23 -> train_loss: 0.2313262286484241426, val_loss: 0.3075141012668609619,  val
_acc: 89.69%
Epoch: 24 -> train_loss: 0.2325393498738606846, val_loss: 0.2975164949893951416,  val
_acc: 89.84%
Epoch: 25 -> train_loss: 0.2314718961914380424, val_loss: 0.2991222441196441650,  val
_acc: 89.60%
Epoch: 26 -> train_loss: 0.2241996667136748611, val_loss: 0.3062023818492889404,  val
_acc: 89.69%
Epoch: 27 -> train_loss: 0.2192408299843470187, val_loss: 0.3058206140995025635,  val
_acc: 89.56%
Epoch: 28 -> train_loss: 0.2181850755562385058, val_loss: 0.3072552680969238281,  val
_acc: 89.46%
Epoch: 29 -> train_loss: 0.2161911162187655777, val_loss: 0.3013016283512115479,  val
_acc: 90.00%
```

```
Epoch: 30 -> train_loss: 0.2105504951179027473, val_loss: 0.3058974742889404297,  val
_acc: 89.90%
Epoch: 31 -> train_loss: 0.2090706681162118885, val_loss: 0.2904951870441436768,  val
_acc: 89.88%
Epoch: 32 -> train_loss: 0.2068803765972455355, val_loss: 0.3066459596157073975,  val
_acc: 89.62%
Epoch: 33 -> train_loss: 0.2020631300210952719, val_loss: 0.3165600001811981201,  val
_acc: 89.64%
Epoch: 34 -> train_loss: 0.1992565853993097935, val_loss: 0.3035983443260192871,  val
_acc: 89.69%
```



Validate on test set

In [134…

```python
# Validate
with torch.no_grad():
    model.eval()
    batch_acc = []
    for images, labels in test_dl:
        images, labels = images.to(device), labels.to(device)
        # flatten images to batch_size x 784
        images = images.view(images.shape[0], -1)
        # make predictions and get probabilities
        proba = torch.exp(model(images))
        # extract the class associted with highest probability
        _, pred_labels = proba.topk(1, dim=1)
        # compare actual labels and predicted labels
        result = pred_labels == labels.view(pred_labels.shape)
        acc = torch.mean(result.type(torch.FloatTensor))
        batch_acc.append(acc.item())
    else:
        print(f'Accuracy: {torch.mean(torch.tensor(batch_acc))*100:.2f}%')
```

```
Accuracy: 88.65%
```