hw8

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1 CSCE 421 :: Machine Learning :: Texas A&M University :: Fall 2021

2 Programming Assignment 5 (PA 5) + Competition

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3 Convolutional Neural Networks

In this assignment, you'll be coding up a convolutional neural network from scratch to classify images using PyTorch.

3.0.1 Instructions

- Install PyTorch following the instructions here.
- Install the `torchinfo` package to visualize the network architecture and the number of parameters. The maximum number of parameters you are allowed to use for your network is **100,000**.
- You are required to complete the functions defined in the code blocks following each question. Fill out sections of the code marked `"YOUR CODE HERE"`.
- You're free to add any number of methods within each class.
- You may also add any number of additional code blocks that you deem necessary.
- Once you've filled out your solutions, submit the notebook on Canvas following the instructions here.
- Do **NOT** forget to type in your name and UIN at the beginning of the notebook.

3.1 Data Preparation

[2]:
```
# Importing the libraries
import os
import torch
import torchvision
from torchvision.utils import make_grid

import numpy as np
```

In this assignment, we will use the Fashion-MNIST dataset. Fashion-MNIST is a dataset of Zalando's article images—consisting of a training set of 60,000 examples and a test set of 10,000 examples. Each example is a 28x28 grayscale image, associated with a label from 10 classes.

3.1.1 Data

Each image is 28 pixels in height and 28 pixels in width, for a total of 784 pixels in total. Each pixel has a single pixel-value associated with it, indicating the lightness or darkness of that pixel, with higher numbers meaning darker. This pixel-value is an integer between 0 and 255.

3.1.2 Labels

Each training and test example is assigned to one of the following labels:

Label	Description
0	T-shirt/top
1	Trouser
2	Pullover
3	Dress
4	Coat
5	Sandal
6	Shirt
7	Sneaker
8	Bag
9	Ankle boot

Fashion-MNIST is included in the `torchvision` library.

[3]:
```
from torchvision.datasets import FashionMNIST
from torchvision.transforms import Compose, ToTensor, Normalize
```

[4]:
```
# Transform to normalize the data and convert to a tensor
transform = Compose([ToTensor(),
    Normalize((0.5,), (0.5,))
    ])

# Download the data
dataset = FashionMNIST('MNIST_data/', download = True, train = True, transform␣
 ↪= transform)
```

```
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 MNIST_data/FashionMNIST/raw/train-images-idx3-ubyte.gz

100%|      | 26421880/26421880 [00:02<00:00, 13118544.47it/s]

Extracting MNIST_data/FashionMNIST/raw/train-images-idx3-ubyte.gz to
MNIST_data/FashionMNIST/raw

Downloading http://fashion-mnist.s3-website.eu-central-1.amazonaws.com/train-
```

```
labels-idx1-ubyte.gz
Downloading http://fashion-mnist.s3-website.eu-central-1.amazonaws.com/train-
labels-idx1-ubyte.gz to MNIST_data/FashionMNIST/raw/train-labels-idx1-ubyte.gz

100%|      | 29515/29515 [00:00<00:00, 223151.55it/s]

Extracting MNIST_data/FashionMNIST/raw/train-labels-idx1-ubyte.gz to
MNIST_data/FashionMNIST/raw

Downloading http://fashion-mnist.s3-website.eu-
central-1.amazonaws.com/t10k-images-idx3-ubyte.gz
Downloading http://fashion-mnist.s3-website.eu-
central-1.amazonaws.com/t10k-images-idx3-ubyte.gz to
MNIST_data/FashionMNIST/raw/t10k-images-idx3-ubyte.gz

100%|      | 4422102/4422102 [00:01<00:00, 3664399.48it/s]

Extracting MNIST_data/FashionMNIST/raw/t10k-images-idx3-ubyte.gz to
MNIST_data/FashionMNIST/raw

Downloading http://fashion-mnist.s3-website.eu-
central-1.amazonaws.com/t10k-labels-idx1-ubyte.gz
Downloading http://fashion-mnist.s3-website.eu-
central-1.amazonaws.com/t10k-labels-idx1-ubyte.gz to
MNIST_data/FashionMNIST/raw/t10k-labels-idx1-ubyte.gz

100%|      | 5148/5148 [00:00<00:00, 2898681.30it/s]

Extracting MNIST_data/FashionMNIST/raw/t10k-labels-idx1-ubyte.gz to
MNIST_data/FashionMNIST/raw
```

NOTE: You may add more operations to `Compose` if you're performing data augmentation.

3.2 Data Exploration

Let's take a look at the classes in our dataset.

[5]:
```python
print(dataset.classes)
```

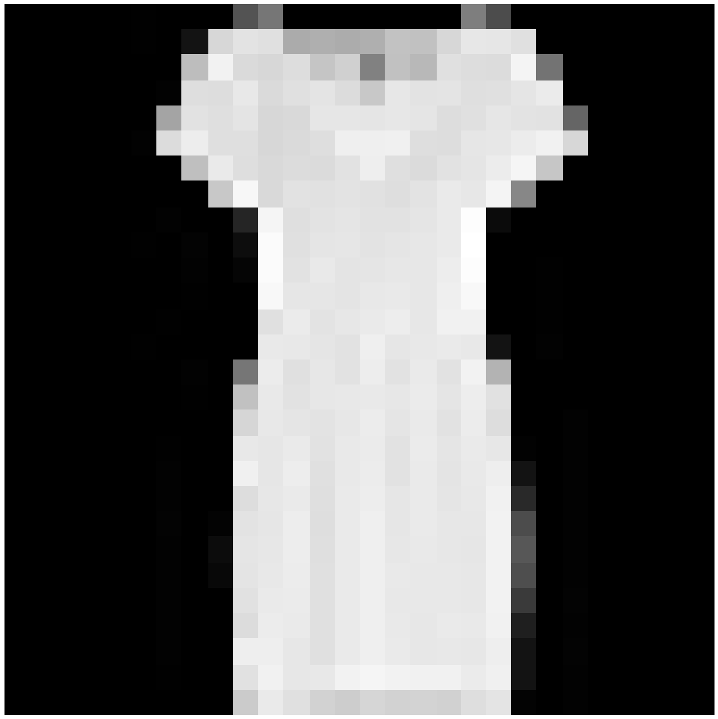
```
['T-shirt/top', 'Trouser', 'Pullover', 'Dress', 'Coat', 'Sandal', 'Shirt',
'Sneaker', 'Bag', 'Ankle boot']
```

[6]:
```python
import matplotlib.pyplot as plt

def show_example(img, label):
    print('Label: {} ({})'.format(dataset.classes[label], label))
    plt.imshow(img.squeeze(), cmap='Greys_r')
    plt.axis(False)
```

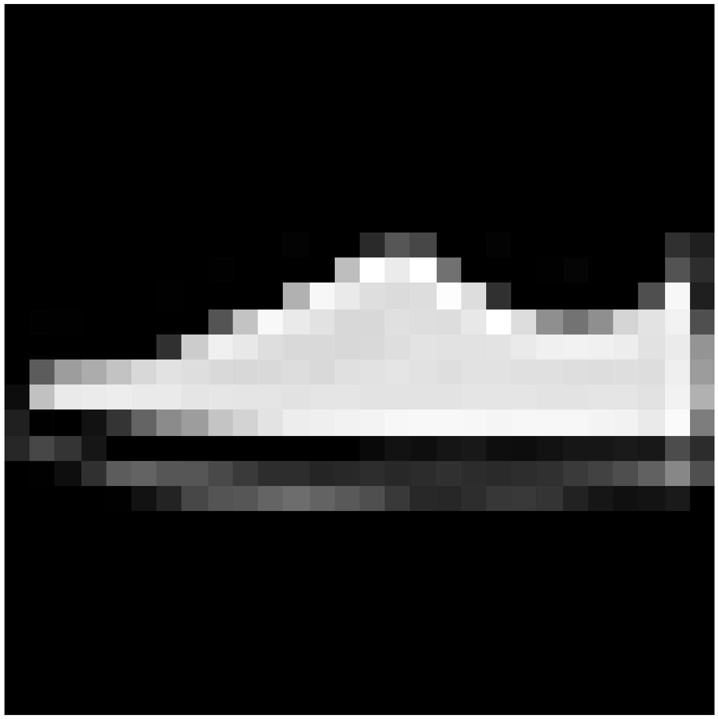
[7]:
```
show_example(*dataset[20])
```

Label: Dress (3)



[8]:
```
show_example(*dataset[20000])
```

Label: Sneaker (7)



3.3 Question 1 (10 points)

3.4 Creating Training and Validation Datasets

The `split_indices` function takes in the size of the entire dataset, `n`, the fraction of data to be used as validation set, `val_frac`, and the random seed and returns the indices of the data points to be added to the validation dataset.

Choose a suitable fraction for your validation set and experiment with the seed. Remember that the better your validation set, the higher the chances that your model would do well on the test set.

[9]:
```
def split_indices(n, val_frac, seed):
    # Determine the size of the validation set
    n_val = int(val_frac * n)
    np.random.seed(seed)
    # Create random permutation between 0 to n-1
    idxs = np.random.permutation(n)
    # Pick first n_val indices for validation set
    return idxs[n_val:], idxs[:n_val]
```

[10]:
```
val_frac = 0.2  # Use 20% of data for validation
rand_seed = 42  # Standard random seed that works well for reproducibility
```

```
train_indices, val_indices = split_indices(len(dataset), val_frac, rand_seed)
print("#samples in training set: {}".format(len(train_indices)))
print("#samples in validation set: {}".format(len(val_indices)))
```

```
#samples in training set: 48000
#samples in validation set: 12000
```

Next, we make use of the built-in dataloaders in PyTorch to create iterables of our our training and validation sets. This helps in avoiding fitting the whole dataset into memory and only loads a batch of the data that we can decide.

Set the `batch_size` depending on the hardware resource (GPU/CPU RAM) you are using for the assignment.

[11]:
```
from torch.utils.data.sampler import SubsetRandomSampler
from torch.utils.data.dataloader import DataLoader
```

[14]:
```
# Set the batch size based on available hardware resources
batch_size = 64  # Standard batch size that works well for most hardware setups
```

[15]:
```
# Training sampler and data loader
train_sampler = SubsetRandomSampler(train_indices)
train_dl = DataLoader(dataset,
                      batch_size,
                      sampler=train_sampler)

# Validation sampler and data loader
val_sampler = SubsetRandomSampler(val_indices)
val_dl = DataLoader(dataset,
                    batch_size,
                    sampler=val_sampler)
```

Plot images in a sample batch of data.

[16]:
```
def show_batch(dl):
    for images, labels in dl:
        fig, ax = plt.subplots(figsize=(10,10))
        ax.set_xticks([]); ax.set_yticks([])
        ax.imshow(make_grid(images, 8).permute(1, 2, 0), cmap='Greys_r')
        break
```

[17]:
```
show_batch(train_dl)
```

```
Clipping input data to the valid range for imshow with RGB data ([0..1] for
floats or [0..255] for integers).
```

3.5 Question 2 (40 points)

3.6 Building the Model

Create your model by defining the network architecture in the `ImageClassifierNet` class.
NOTE: The number of parameters in your network must be $\leq$ 100,000.

[19]:
```
# Import the libraries
import torch.nn as nn
import torch.nn.functional as F

# Install torchinfo if not already installed
```

```
%pip install torchinfo -q

from torchinfo import summary
```

```
Note: you may need to restart the kernel to use updated packages.
```

[27]:
```python
class ImageClassifierNet(nn.Module):
    def __init__(self, n_channels=1):
        super(ImageClassifierNet, self).__init__()

        # First convolutional block - reduced filters
        self.conv1 = nn.Conv2d(n_channels, 16, kernel_size=3, padding=1)
        self.bn1 = nn.BatchNorm2d(16)
        self.pool1 = nn.MaxPool2d(2, 2)

        # Second convolutional block - reduced filters
        self.conv2 = nn.Conv2d(16, 32, kernel_size=3, padding=1)
        self.bn2 = nn.BatchNorm2d(32)
        self.pool2 = nn.MaxPool2d(2, 2)

        # Fully connected layers - further reduced size
        # After 2 max-pooling layers, the image size is reduced to 7x7
        self.fc1 = nn.Linear(32 * 7 * 7, 50)  # Reduced from 64 to 50
        self.dropout = nn.Dropout(0.5)
        self.fc2 = nn.Linear(50, 10)  # 10 classes in Fashion MNIST

    def forward(self, X):
        # First block
        X = self.pool1(F.relu(self.bn1(self.conv1(X))))

        # Second block
        X = self.pool2(F.relu(self.bn2(self.conv2(X))))

        # Flatten
        X = X.view(X.size(0), -1)

        # Fully connected layers
        X = F.relu(self.fc1(X))
        X = self.dropout(X)
        X = self.fc2(X)

        return X
```

[28]:
```python
model = ImageClassifierNet()
```

The following code block prints your network architecture. It also shows the total number of parameters in your network (see `Total params`).

NOTE: The total number of parameters in your model should be <= 100,000.

[29]:
```
summary(model, input_size=(batch_size, 1, 28, 28))
```

[29]:
```
================================================================================
==========
Layer (type:depth-idx)                   Output Shape              Param #
================================================================================
==========
ImageClassifierNet                        [64, 10]                  --
 Conv2d: 1-1                             [64, 16, 28, 28]          160
 BatchNorm2d: 1-2                        [64, 16, 28, 28]          32
 MaxPool2d: 1-3                          [64, 16, 14, 14]          --
 Conv2d: 1-4                             [64, 32, 14, 14]          4,640
 BatchNorm2d: 1-5                        [64, 32, 14, 14]          64
 MaxPool2d: 1-6                          [64, 32, 7, 7]            --
 Linear: 1-7                             [64, 50]                  78,450
 Dropout: 1-8                            [64, 50]                  --
 Linear: 1-9                             [64, 10]                  510
================================================================================
==========
Total params: 83,856
Trainable params: 83,856
Non-trainable params: 0
Total mult-adds (Units.MEGABYTES): 71.29
================================================================================
==========
Input size (MB): 0.20
Forward/backward pass size (MB): 19.30
Params size (MB): 0.34
Estimated Total Size (MB): 19.83
================================================================================
==========
```

3.7 Enable training on a GPU

NOTE: This section is necessary if you're training your model on a GPU.

[30]:
```
def get_default_device():
    """Use GPU if available, else CPU"""
    if torch.cuda.is_available():
        return torch.device('cuda')
    else:
        return torch.device('cpu')

def to_device(data, device):
    """Move tensor(s) to chosen device"""
    if isinstance(data, (list,tuple)):
        return [to_device(x, device) for x in data]
    return data.to(device, non_blocking=True)
```

```python
class DeviceDataLoader():
    """Wrap a dataloader to move data to a device"""
    def __init__(self, dl, device):
        self.dl = dl
        self.device = device

    def __iter__(self):
        """Yield a batch of data after moving it to device"""
        for b in self.dl:
            yield to_device(b, self.device)

    def __len__(self):
        """Number of batches"""
        return len(self.dl)
```

[31]:
```python
device = get_default_device()

train_dl = DeviceDataLoader(train_dl, device)
val_dl = DeviceDataLoader(val_dl, device)

to_device(model, device)
```

[31]:
```
ImageClassifierNet(
  (conv1): Conv2d(1, 16, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
  (bn1): BatchNorm2d(16, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
  (pool1): MaxPool2d(kernel_size=2, stride=2, padding=0, dilation=1,
ceil_mode=False)
  (conv2): Conv2d(16, 32, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
  (bn2): BatchNorm2d(32, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
  (pool2): MaxPool2d(kernel_size=2, stride=2, padding=0, dilation=1,
ceil_mode=False)
  (fc1): Linear(in_features=1568, out_features=50, bias=True)
  (dropout): Dropout(p=0.5, inplace=False)
  (fc2): Linear(in_features=50, out_features=10, bias=True)
)
```

3.8 Question 3 (40 points)

3.9 Train the model

Complete the `train_model` function to train your model on a dataset. Tune your network architecture and hyperparameters on the validation set.

[32]:
```python
def train_model(n_epochs, model, train_dl, val_dl, loss_fn, opt_fn, lr):
    """
```

```
    Trains the model on a dataset.

    Args:
        n_epochs: number of epochs
        model: ImageClassifierNet object
        train_dl: training dataloader
        val_dl: validation dataloader
        loss_fn: the loss function
        opt_fn: the optimizer
        lr: learning rate

    Returns:
        The trained model.
        A tuple of (model, train_losses, val_losses, train_accuracies,␣
↪val_accuracies)
    """
    # Record these values the end of each epoch
    train_losses, val_losses, train_accuracies, val_accuracies = [], [], [], []

    # Initialize the optimizer
    optimizer = opt_fn(model.parameters(), lr=lr)

    for epoch in range(n_epochs):
        # Training phase
        model.train()
        train_loss = 0
        correct = 0
        total = 0

        for batch_idx, (images, labels) in enumerate(train_dl):
            # Forward pass
            outputs = model(images)
            loss = loss_fn(outputs, labels)

            # Backward pass and optimize
            optimizer.zero_grad()
            loss.backward()
            optimizer.step()

            # Track loss and accuracy
            train_loss += loss.item()
            _, predicted = outputs.max(1)
            total += labels.size(0)
            correct += predicted.eq(labels).sum().item()

            # Print progress
            if batch_idx % 100 == 0:
```

```
                print(f'Epoch: {epoch+1}/{n_epochs}, Batch: {batch_idx}/
↪{len(train_dl)}, Loss: {loss.item():.4f}')

        # Calculate average training metrics for the epoch
        avg_train_loss = train_loss / len(train_dl)
        train_accuracy = correct / total
        train_losses.append(avg_train_loss)
        train_accuracies.append(train_accuracy)

        # Validation phase (if validation data is provided)
        if len(val_dl) > 0:
            model.eval()
            val_loss = 0
            correct = 0
            total = 0

            with torch.no_grad():
                for images, labels in val_dl:
                    outputs = model(images)
                    loss = loss_fn(outputs, labels)

                    val_loss += loss.item()
                    _, predicted = outputs.max(1)
                    total += labels.size(0)
                    correct += predicted.eq(labels).sum().item()

            # Calculate average validation metrics
            avg_val_loss = val_loss / len(val_dl)
            val_accuracy = correct / total
            val_losses.append(avg_val_loss)
            val_accuracies.append(val_accuracy)

            print(f'Epoch {epoch+1}/{n_epochs}, Train Loss: {avg_train_loss:.
↪4f}, Train Acc: {train_accuracy:.4f}, Val Loss: {avg_val_loss:.4f}, Val Acc:␣
↪{val_accuracy:.4f}')
        else:
            print(f'Epoch {epoch+1}/{n_epochs}, Train Loss: {avg_train_loss:.
↪4f}, Train Acc: {train_accuracy:.4f}')

    return model, train_losses, val_losses, train_accuracies, val_accuracies
```

Set the maximum number of training epochs, the loss function, the optimizer, and the learning rate.

[33]:
```
import torch.optim as optim

# Standard values for training the model
```

```
num_epochs = 10  # Max number of training epochs
loss_fn = nn.CrossEntropyLoss()  # Standard loss function for classification␣
 ↪tasks
opt_fn = optim.Adam  # Adam optimizer typically works well for CNNs
lr = 0.001  # Standard learning rate for Adam optimizer
```

[34]:
```
history = train_model(num_epochs, model, train_dl, val_dl, loss_fn, opt_fn, lr)
model, train_losses, val_losses, train_accuracies, val_accuracies = history
```

```
Epoch: 1/10, Batch: 0/750, Loss: 2.3764
Epoch: 1/10, Batch: 100/750, Loss: 0.7478
Epoch: 1/10, Batch: 200/750, Loss: 0.6516
Epoch: 1/10, Batch: 300/750, Loss: 0.8996
Epoch: 1/10, Batch: 400/750, Loss: 0.5218
Epoch: 1/10, Batch: 500/750, Loss: 0.6532
Epoch: 1/10, Batch: 600/750, Loss: 0.4972
Epoch: 1/10, Batch: 700/750, Loss: 0.3668
Epoch 1/10, Train Loss: 0.7305, Train Acc: 0.7277, Val Loss: 0.3747, Val Acc:
0.8645
Epoch: 2/10, Batch: 0/750, Loss: 0.6157
Epoch: 2/10, Batch: 100/750, Loss: 0.5253
Epoch: 2/10, Batch: 200/750, Loss: 0.4360
Epoch: 2/10, Batch: 300/750, Loss: 0.4420
Epoch: 2/10, Batch: 400/750, Loss: 0.4793
Epoch: 2/10, Batch: 500/750, Loss: 0.5572
Epoch: 2/10, Batch: 600/750, Loss: 0.6899
Epoch: 2/10, Batch: 700/750, Loss: 0.5185
Epoch 2/10, Train Loss: 0.5365, Train Acc: 0.7947, Val Loss: 0.3252, Val Acc:
0.8817
Epoch: 3/10, Batch: 0/750, Loss: 0.4632
Epoch: 3/10, Batch: 100/750, Loss: 0.4898
Epoch: 3/10, Batch: 200/750, Loss: 0.5532
Epoch: 3/10, Batch: 300/750, Loss: 0.4883
Epoch: 3/10, Batch: 400/750, Loss: 0.5430
Epoch: 3/10, Batch: 500/750, Loss: 0.3901
Epoch: 3/10, Batch: 600/750, Loss: 0.4877
Epoch: 3/10, Batch: 700/750, Loss: 0.4395
Epoch 3/10, Train Loss: 0.4911, Train Acc: 0.8142, Val Loss: 0.3011, Val Acc:
0.8888
Epoch: 4/10, Batch: 0/750, Loss: 0.3620
Epoch: 4/10, Batch: 100/750, Loss: 0.4855
Epoch: 4/10, Batch: 200/750, Loss: 0.4504
Epoch: 4/10, Batch: 300/750, Loss: 0.4259
Epoch: 4/10, Batch: 400/750, Loss: 0.5133
Epoch: 4/10, Batch: 500/750, Loss: 0.4626
Epoch: 4/10, Batch: 600/750, Loss: 0.4785
Epoch: 4/10, Batch: 700/750, Loss: 0.4472
Epoch 4/10, Train Loss: 0.4575, Train Acc: 0.8261, Val Loss: 0.2940, Val Acc:
```

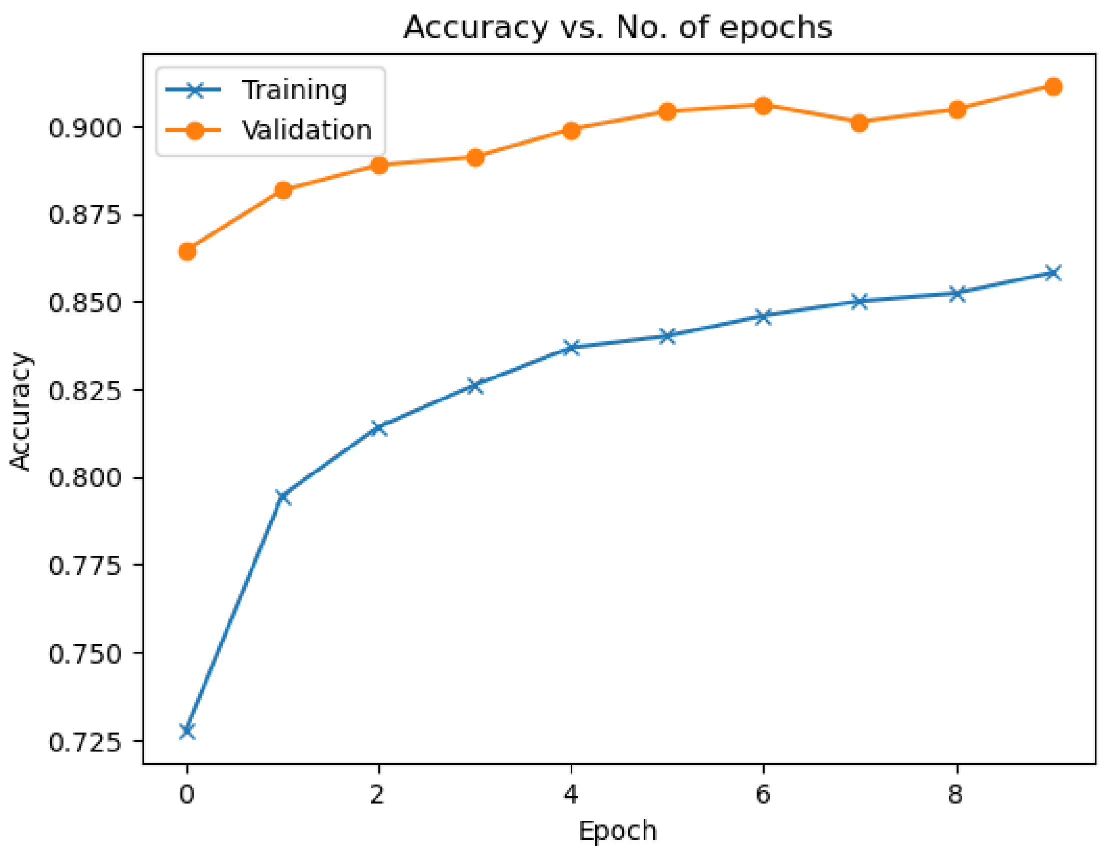
```
0.8912
Epoch: 5/10, Batch: 0/750, Loss: 0.5194
Epoch: 5/10, Batch: 100/750, Loss: 0.3233
Epoch: 5/10, Batch: 200/750, Loss: 0.4221
Epoch: 5/10, Batch: 300/750, Loss: 0.4900
Epoch: 5/10, Batch: 400/750, Loss: 0.3788
Epoch: 5/10, Batch: 500/750, Loss: 0.5298
Epoch: 5/10, Batch: 600/750, Loss: 0.5016
Epoch: 5/10, Batch: 700/750, Loss: 0.2563
Epoch 5/10, Train Loss: 0.4300, Train Acc: 0.8368, Val Loss: 0.2808, Val Acc:
0.8991
Epoch: 6/10, Batch: 0/750, Loss: 0.3535
Epoch: 6/10, Batch: 100/750, Loss: 0.5220
Epoch: 6/10, Batch: 200/750, Loss: 0.5129
Epoch: 6/10, Batch: 300/750, Loss: 0.4765
Epoch: 6/10, Batch: 400/750, Loss: 0.3781
Epoch: 6/10, Batch: 500/750, Loss: 0.3025
Epoch: 6/10, Batch: 600/750, Loss: 0.3441
Epoch: 6/10, Batch: 700/750, Loss: 0.2986
Epoch 6/10, Train Loss: 0.4175, Train Acc: 0.8401, Val Loss: 0.2664, Val Acc:
0.9042
Epoch: 7/10, Batch: 0/750, Loss: 0.3445
Epoch: 7/10, Batch: 100/750, Loss: 0.4724
Epoch: 7/10, Batch: 200/750, Loss: 0.4027
Epoch: 7/10, Batch: 300/750, Loss: 0.6315
Epoch: 7/10, Batch: 400/750, Loss: 0.2934
Epoch: 7/10, Batch: 500/750, Loss: 0.2824
Epoch: 7/10, Batch: 600/750, Loss: 0.4078
Epoch: 7/10, Batch: 700/750, Loss: 0.5848
Epoch 7/10, Train Loss: 0.4024, Train Acc: 0.8459, Val Loss: 0.2579, Val Acc:
0.9061
Epoch: 8/10, Batch: 0/750, Loss: 0.2634
Epoch: 8/10, Batch: 100/750, Loss: 0.2089
Epoch: 8/10, Batch: 200/750, Loss: 0.3317
Epoch: 8/10, Batch: 300/750, Loss: 0.4412
Epoch: 8/10, Batch: 400/750, Loss: 0.5859
Epoch: 8/10, Batch: 500/750, Loss: 0.3766
Epoch: 8/10, Batch: 600/750, Loss: 0.3540
Epoch: 8/10, Batch: 700/750, Loss: 0.3612
Epoch 8/10, Train Loss: 0.3886, Train Acc: 0.8501, Val Loss: 0.2601, Val Acc:
0.9012
Epoch: 9/10, Batch: 0/750, Loss: 0.3501
Epoch: 9/10, Batch: 100/750, Loss: 0.5489
Epoch: 9/10, Batch: 200/750, Loss: 0.4703
Epoch: 9/10, Batch: 300/750, Loss: 0.2627
Epoch: 9/10, Batch: 400/750, Loss: 0.4569
Epoch: 9/10, Batch: 500/750, Loss: 0.4592
Epoch: 9/10, Batch: 600/750, Loss: 0.3788
```

```
Epoch: 9/10, Batch: 700/750, Loss: 0.1966
Epoch 9/10, Train Loss: 0.3808, Train Acc: 0.8523, Val Loss: 0.2603, Val Acc:
0.9048
Epoch: 10/10, Batch: 0/750, Loss: 0.2645
Epoch: 10/10, Batch: 100/750, Loss: 0.4604
Epoch: 10/10, Batch: 200/750, Loss: 0.2527
Epoch: 10/10, Batch: 300/750, Loss: 0.2029
Epoch: 10/10, Batch: 400/750, Loss: 0.2589
Epoch: 10/10, Batch: 500/750, Loss: 0.4297
Epoch: 10/10, Batch: 600/750, Loss: 0.2230
Epoch: 10/10, Batch: 700/750, Loss: 0.2987
Epoch 10/10, Train Loss: 0.3689, Train Acc: 0.8582, Val Loss: 0.2428, Val Acc:
0.9115
```

3.10 Plot loss and accuracy

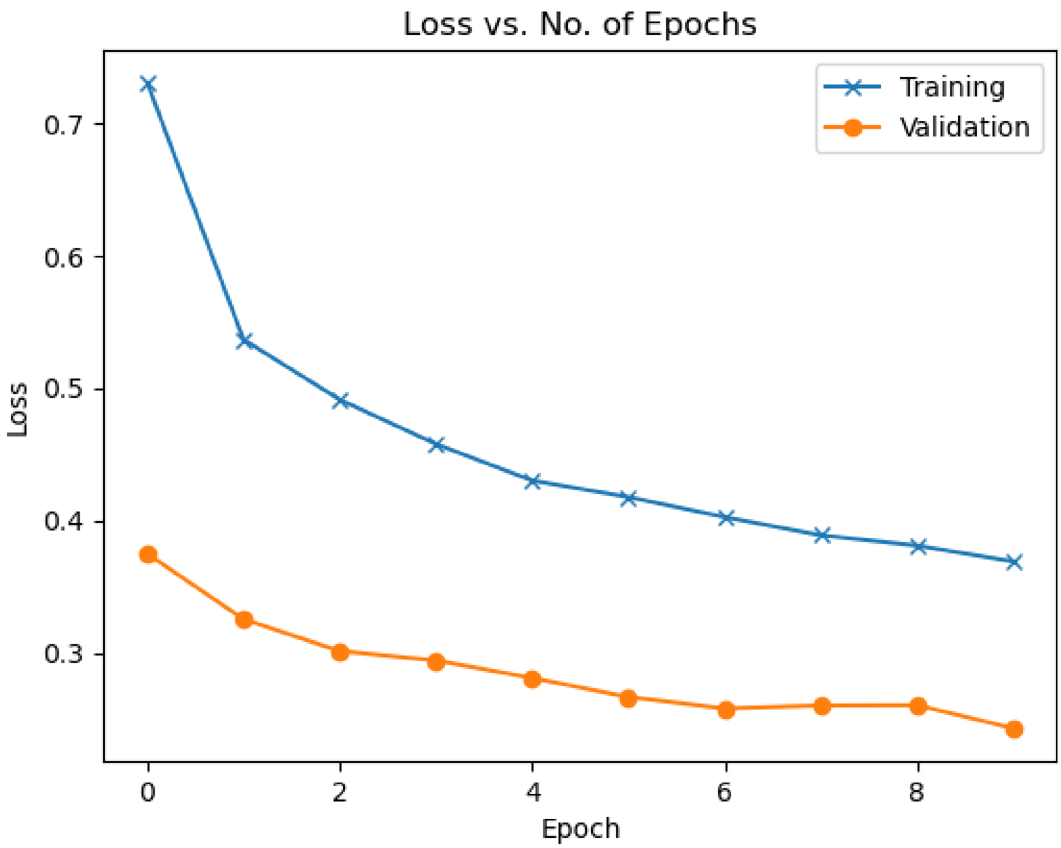
[35]:
```python
def plot_accuracy(train_accuracies, val_accuracies):
    """Plot accuracies"""
    plt.plot(train_accuracies, "-x")
    plt.plot(val_accuracies, "-o")
    plt.xlabel("Epoch")
    plt.ylabel("Accuracy")
    plt.legend(["Training", "Validation"])
    plt.title("Accuracy vs. No. of epochs")
```

[36]:
```python
plot_accuracy(train_accuracies, val_accuracies)
```



[37]:
```
def plot_losses(train_losses, val_losses):
    """Plot losses"""
    plt.plot(train_losses, "-x")
    plt.plot(val_losses, "-o")
    plt.xlabel("Epoch")
    plt.ylabel("Loss")
    plt.legend(["Training", "Validation"])
    plt.title("Loss vs. No. of Epochs")
```

[38]:
```
plot_losses(train_losses, val_losses)
```



3.11 Train a model on the entire dataset

[39]:
```
indices, _ = split_indices(len(dataset), 0, rand_seed)

sampler = SubsetRandomSampler(indices)
dl = DataLoader(dataset, batch_size, sampler=sampler)
dl = DeviceDataLoader(dl, device)
```

Set the maximum number of training epochs and the learning rate for finetuning your model.

[40]:
```
# For final training on the full dataset
num_epochs = 15  # Increased from 10 to 15 for better convergence
lr = 0.001  # Maintain the same learning rate as it was effective in previous
 ↪training
```

[41]:
```
history = train_model(num_epochs, model, dl, [], loss_fn, opt_fn, lr)
model = history[0]
```

```
Epoch: 1/15, Batch: 0/938, Loss: 0.3149
Epoch: 1/15, Batch: 100/938, Loss: 0.2238
```

```
Epoch: 1/15, Batch: 200/938, Loss: 0.2612
Epoch: 1/15, Batch: 300/938, Loss: 0.5824
Epoch: 1/15, Batch: 400/938, Loss: 0.4169
Epoch: 1/15, Batch: 500/938, Loss: 0.3996
Epoch: 1/15, Batch: 600/938, Loss: 0.3777
Epoch: 1/15, Batch: 700/938, Loss: 0.3292
Epoch: 1/15, Batch: 800/938, Loss: 0.2829
Epoch: 1/15, Batch: 900/938, Loss: 0.5688
Epoch 1/15, Train Loss: 0.3745, Train Acc: 0.8569
Epoch: 2/15, Batch: 0/938, Loss: 0.2678
Epoch: 2/15, Batch: 100/938, Loss: 0.3784
Epoch: 2/15, Batch: 200/938, Loss: 0.2788
Epoch: 2/15, Batch: 300/938, Loss: 0.4844
Epoch: 2/15, Batch: 400/938, Loss: 0.4752
Epoch: 2/15, Batch: 500/938, Loss: 0.5075
Epoch: 2/15, Batch: 600/938, Loss: 0.4028
Epoch: 2/15, Batch: 700/938, Loss: 0.3500
Epoch: 2/15, Batch: 800/938, Loss: 0.4372
Epoch: 2/15, Batch: 900/938, Loss: 0.4547
Epoch 2/15, Train Loss: 0.3623, Train Acc: 0.8609
Epoch: 3/15, Batch: 0/938, Loss: 0.3187
Epoch: 3/15, Batch: 100/938, Loss: 0.3581
Epoch: 3/15, Batch: 200/938, Loss: 0.2211
Epoch: 3/15, Batch: 300/938, Loss: 0.3200
Epoch: 3/15, Batch: 400/938, Loss: 0.5123
Epoch: 3/15, Batch: 500/938, Loss: 0.3663
Epoch: 3/15, Batch: 600/938, Loss: 0.2823
Epoch: 3/15, Batch: 700/938, Loss: 0.4016
Epoch: 3/15, Batch: 800/938, Loss: 0.2474
Epoch: 3/15, Batch: 900/938, Loss: 0.4137
Epoch 3/15, Train Loss: 0.3447, Train Acc: 0.8688
Epoch: 4/15, Batch: 0/938, Loss: 0.2812
Epoch: 4/15, Batch: 100/938, Loss: 0.4247
Epoch: 4/15, Batch: 200/938, Loss: 0.2988
Epoch: 4/15, Batch: 300/938, Loss: 0.2612
Epoch: 4/15, Batch: 400/938, Loss: 0.3391
Epoch: 4/15, Batch: 500/938, Loss: 0.2543
Epoch: 4/15, Batch: 600/938, Loss: 0.3558
Epoch: 4/15, Batch: 700/938, Loss: 0.2113
Epoch: 4/15, Batch: 800/938, Loss: 0.5803
Epoch: 4/15, Batch: 900/938, Loss: 0.4973
Epoch 4/15, Train Loss: 0.3354, Train Acc: 0.8750
Epoch: 5/15, Batch: 0/938, Loss: 0.3548
Epoch: 5/15, Batch: 100/938, Loss: 0.2423
Epoch: 5/15, Batch: 200/938, Loss: 0.3646
Epoch: 5/15, Batch: 300/938, Loss: 0.1911
Epoch: 5/15, Batch: 400/938, Loss: 0.2589
Epoch: 5/15, Batch: 500/938, Loss: 0.3211
```

```
Epoch: 5/15, Batch: 600/938, Loss: 0.2076
Epoch: 5/15, Batch: 700/938, Loss: 0.2557
Epoch: 5/15, Batch: 800/938, Loss: 0.4110
Epoch: 5/15, Batch: 900/938, Loss: 0.3380
Epoch 5/15, Train Loss: 0.3276, Train Acc: 0.8769
Epoch: 6/15, Batch: 0/938, Loss: 0.2270
Epoch: 6/15, Batch: 100/938, Loss: 0.3094
Epoch: 6/15, Batch: 200/938, Loss: 0.3613
Epoch: 6/15, Batch: 300/938, Loss: 0.4174
Epoch: 6/15, Batch: 400/938, Loss: 0.4055
Epoch: 6/15, Batch: 500/938, Loss: 0.2935
Epoch: 6/15, Batch: 600/938, Loss: 0.2257
Epoch: 6/15, Batch: 700/938, Loss: 0.2435
Epoch: 6/15, Batch: 800/938, Loss: 0.2455
Epoch: 6/15, Batch: 900/938, Loss: 0.3271
Epoch 6/15, Train Loss: 0.3235, Train Acc: 0.8773
Epoch: 7/15, Batch: 0/938, Loss: 0.4811
Epoch: 7/15, Batch: 100/938, Loss: 0.2375
Epoch: 7/15, Batch: 200/938, Loss: 0.3122
Epoch: 7/15, Batch: 300/938, Loss: 0.1948
Epoch: 7/15, Batch: 400/938, Loss: 0.2648
Epoch: 7/15, Batch: 500/938, Loss: 0.2197
Epoch: 7/15, Batch: 600/938, Loss: 0.3354
Epoch: 7/15, Batch: 700/938, Loss: 0.4398
Epoch: 7/15, Batch: 800/938, Loss: 0.2080
Epoch: 7/15, Batch: 900/938, Loss: 0.1889
Epoch 7/15, Train Loss: 0.3134, Train Acc: 0.8802
Epoch: 8/15, Batch: 0/938, Loss: 0.4033
Epoch: 8/15, Batch: 100/938, Loss: 0.3862
Epoch: 8/15, Batch: 200/938, Loss: 0.3437
Epoch: 8/15, Batch: 300/938, Loss: 0.1960
Epoch: 8/15, Batch: 400/938, Loss: 0.3024
Epoch: 8/15, Batch: 500/938, Loss: 0.2061
Epoch: 8/15, Batch: 600/938, Loss: 0.4126
Epoch: 8/15, Batch: 700/938, Loss: 0.2036
Epoch: 8/15, Batch: 800/938, Loss: 0.3553
Epoch: 8/15, Batch: 900/938, Loss: 0.5620
Epoch 8/15, Train Loss: 0.3049, Train Acc: 0.8827
Epoch: 9/15, Batch: 0/938, Loss: 0.2298
Epoch: 9/15, Batch: 100/938, Loss: 0.3481
Epoch: 9/15, Batch: 200/938, Loss: 0.1775
Epoch: 9/15, Batch: 300/938, Loss: 0.2317
Epoch: 9/15, Batch: 400/938, Loss: 0.3120
Epoch: 9/15, Batch: 500/938, Loss: 0.3873
Epoch: 9/15, Batch: 600/938, Loss: 0.2975
Epoch: 9/15, Batch: 700/938, Loss: 0.3756
Epoch: 9/15, Batch: 800/938, Loss: 0.2929
Epoch: 9/15, Batch: 900/938, Loss: 0.3330
```

```
Epoch 9/15, Train Loss: 0.2981, Train Acc: 0.8866
Epoch: 10/15, Batch: 0/938, Loss: 0.3715
Epoch: 10/15, Batch: 100/938, Loss: 0.3772
Epoch: 10/15, Batch: 200/938, Loss: 0.2333
Epoch: 10/15, Batch: 300/938, Loss: 0.2683
Epoch: 10/15, Batch: 400/938, Loss: 0.2522
Epoch: 10/15, Batch: 500/938, Loss: 0.2224
Epoch: 10/15, Batch: 600/938, Loss: 0.2724
Epoch: 10/15, Batch: 700/938, Loss: 0.5812
Epoch: 10/15, Batch: 800/938, Loss: 0.1942
Epoch: 10/15, Batch: 900/938, Loss: 0.2943
Epoch 10/15, Train Loss: 0.2911, Train Acc: 0.8908
Epoch: 11/15, Batch: 0/938, Loss: 0.3243
Epoch: 11/15, Batch: 100/938, Loss: 0.1997
Epoch: 11/15, Batch: 200/938, Loss: 0.2326
Epoch: 11/15, Batch: 300/938, Loss: 0.2631
Epoch: 11/15, Batch: 400/938, Loss: 0.2524
Epoch: 11/15, Batch: 500/938, Loss: 0.4095
Epoch: 11/15, Batch: 600/938, Loss: 0.2419
Epoch: 11/15, Batch: 700/938, Loss: 0.3694
Epoch: 11/15, Batch: 800/938, Loss: 0.2937
Epoch: 11/15, Batch: 900/938, Loss: 0.3507
Epoch 11/15, Train Loss: 0.2831, Train Acc: 0.8924
Epoch: 12/15, Batch: 0/938, Loss: 0.2126
Epoch: 12/15, Batch: 100/938, Loss: 0.1376
Epoch: 12/15, Batch: 200/938, Loss: 0.2524
Epoch: 12/15, Batch: 300/938, Loss: 0.2756
Epoch: 12/15, Batch: 400/938, Loss: 0.2545
Epoch: 12/15, Batch: 500/938, Loss: 0.2321
Epoch: 12/15, Batch: 600/938, Loss: 0.2486
Epoch: 12/15, Batch: 700/938, Loss: 0.3324
Epoch: 12/15, Batch: 800/938, Loss: 0.2061
Epoch: 12/15, Batch: 900/938, Loss: 0.3269
Epoch 12/15, Train Loss: 0.2756, Train Acc: 0.8959
Epoch: 13/15, Batch: 0/938, Loss: 0.2557
Epoch: 13/15, Batch: 100/938, Loss: 0.2493
Epoch: 13/15, Batch: 200/938, Loss: 0.2012
Epoch: 13/15, Batch: 300/938, Loss: 0.1542
Epoch: 13/15, Batch: 400/938, Loss: 0.1991
Epoch: 13/15, Batch: 500/938, Loss: 0.5044
Epoch: 13/15, Batch: 600/938, Loss: 0.1799
Epoch: 13/15, Batch: 700/938, Loss: 0.1552
Epoch: 13/15, Batch: 800/938, Loss: 0.2061
Epoch: 13/15, Batch: 900/938, Loss: 0.1784
Epoch 13/15, Train Loss: 0.2730, Train Acc: 0.8949
Epoch: 14/15, Batch: 0/938, Loss: 0.1877
Epoch: 14/15, Batch: 100/938, Loss: 0.2959
Epoch: 14/15, Batch: 200/938, Loss: 0.3914
```

```
Epoch: 14/15, Batch: 300/938, Loss: 0.3541
Epoch: 14/15, Batch: 400/938, Loss: 0.3192
Epoch: 14/15, Batch: 500/938, Loss: 0.1972
Epoch: 14/15, Batch: 600/938, Loss: 0.2817
Epoch: 14/15, Batch: 700/938, Loss: 0.2539
Epoch: 14/15, Batch: 800/938, Loss: 0.2635
Epoch: 14/15, Batch: 900/938, Loss: 0.2593
Epoch 14/15, Train Loss: 0.2697, Train Acc: 0.8975
Epoch: 15/15, Batch: 0/938, Loss: 0.2255
Epoch: 15/15, Batch: 100/938, Loss: 0.2404
Epoch: 15/15, Batch: 200/938, Loss: 0.3253
Epoch: 15/15, Batch: 300/938, Loss: 0.1418
Epoch: 15/15, Batch: 400/938, Loss: 0.1864
Epoch: 15/15, Batch: 500/938, Loss: 0.2514
Epoch: 15/15, Batch: 600/938, Loss: 0.1878
Epoch: 15/15, Batch: 700/938, Loss: 0.2495
Epoch: 15/15, Batch: 800/938, Loss: 0.1484
Epoch: 15/15, Batch: 900/938, Loss: 0.1735
Epoch 15/15, Train Loss: 0.2666, Train Acc: 0.8979
```

3.12 Check Predictions

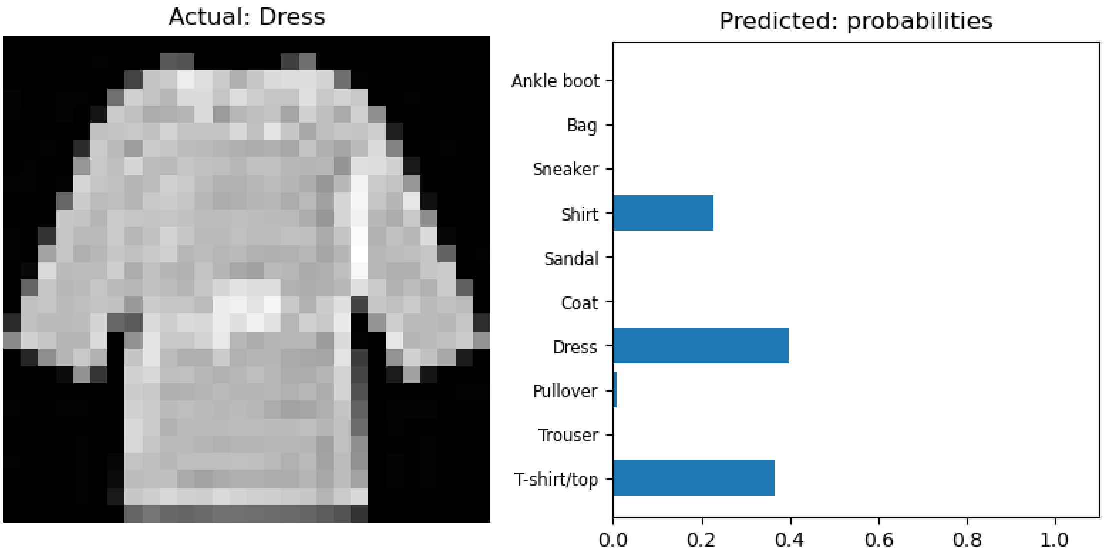
[42]:
```python
def view_prediction(img, label, probs, classes):
    """
    Visualize predictions.
    """
    probs = probs.cpu().numpy().squeeze()

    fig, (ax1, ax2) = plt.subplots(figsize=(8,15), ncols=2)
    ax1.imshow(img.resize_(1, 28, 28).cpu().numpy().squeeze(), cmap='Greys_r')
    ax1.axis('off')
    ax1.set_title('Actual: {}'.format(classes[label]))
    ax2.barh(np.arange(10), probs)
    ax2.set_aspect(0.1)
    ax2.set_yticks(np.arange(10))
    ax2.set_yticklabels(classes, size='small');
    ax2.set_title('Predicted: probabilities')
    ax2.set_xlim(0, 1.1)

    plt.tight_layout()
```

[43]:
```python
# Calculate the class probabilites (log softmax) for img
images = iter(dl)
for imgs, labels in images:
    with torch.no_grad():
        model.eval()
        # Calculate the class probabilites (log softmax) for img
```

```
        probs = torch.nn.functional.softmax(model(imgs[0].unsqueeze(0)), dim=1)
        # Plot the image and probabilites
        view_prediction(imgs[0], labels[0], probs, dataset.classes)
    break
```



3.13 Save the model

[44]:
```
# Very important
torch.save(model, 'model')
```

3.14 Question 4 (10 points)

3.15 Compute accuracy on the test set

[45]:
```
test_dataset = FashionMNIST('MNIST_data/', download = True, train = False,␣
 ↪transform = transform)
```

[46]:
```
test_dl = DataLoader(test_dataset, batch_size)
test_dl = DeviceDataLoader(test_dl, device)
```

[47]:
```
def evaluate(model, test_dl):
    """
    Evaluates your model on the test data.

    Args:
        model: ImageClassifierNet object
        test_dl: test dataloader
```

```
    Returns:
        Test accuracy.
    """
    model.eval()  # Set the model to evaluation mode
    correct = 0
    total = 0

    with torch.no_grad():  # Disable gradient computation
        for images, labels in test_dl:
            # Forward pass
            outputs = model(images)

            # Get predictions
            _, predicted = outputs.max(1)

            # Count correct predictions
            total += labels.size(0)
            correct += predicted.eq(labels).sum().item()

    # Calculate and return accuracy
    accuracy = correct / total
    return accuracy
```

[48]:
```
print("Test Accuracy = {:.4f}".format(evaluate(model, test_dl)))
```

```
Test Accuracy = 0.9118
```

3.16 Tips to increase the test accuracy

- **Data augmentation:** Diversifies your training set and leads to better generalization
  - Flipping
  - Rotation
  - Shifting
  - Cropping
  - Adding noise
  - Blurring
- **Regularization:** Reduces overfitting on the training set
  - Early stopping
  - Dropout
  - l_2 regularization
  - Batch normalization
- **Hyperparameter tuning:**
  - Weight initialization
  - Learning rate
  - Activation functions
  - Optimizers