03-pytorch-computer-vision-video

October 26, 2023

1 PyTorch Computer Vision

- See reference notebook - https://github.com/mrdbourke/pytorch-deep-learning/blob/main/03_pytorch_computer_vision.ipynb
- See reference online book - https://www.learnpytorch.io/03_pytorch_computer_vision/

1.1 0. Computer vision libaries in PyTorch

- `torchvision` - base domain library for PyTorch computer vision
- `torchvision.datasets` - get datasets and data loading functions for computer vision here
- `torchvision.models` - get pretrained computer vision models that you can leverage for your own problems
- `torchvision.transforms` - functions for manipulating your vision data (images) to be suitable for use with an ML model
- `torch.utils.data.Dataset` - Base dataset class for PyTorch.
- `torch.utils.data.DataLoader` - Creates a Python iterable over a dataset

[1]:
```
# Import PyTorch
import torch
from torch import nn

# Import torchvision
import torchvision
from torchvision import datasets
from torchvision import transforms
from torchvision.transforms import ToTensor

# Import matplotlib for visualization
import matplotlib.pyplot as plt

# Check versions
print(torch.__version__)
print(torchvision.__version__)
```

```
1.10.0+cu111
0.11.1+cu111
```

1.2 1. Getting a dataset

The dataset we'll be using is FashionMNIST from torchvision.datasets - https://pytorch.org/vision/stable/generated/torchvision.datasets.FashionMNIST.html#torchvision.datasets.Fashi

[2]:
```
# Setup training data
from torchvision import datasets
train_data = datasets.FashionMNIST(
    root="data", # where to download data to?
    train=True, # do we want the training dataset?
    download=True, # do we want to download yes/no?
    transform=torchvision.transforms.ToTensor(), # how do we want to transform␣
 ↪the data?
    target_transform=None # how do we want to transform the labels/targets?
)

test_data = datasets.FashionMNIST(
    root="data",
    train=False,
    download=True,
    transform=ToTensor(),
    target_transform=None
)
```

[3]:
```
len(train_data), len(test_data)
```

[3]:
```
(60000, 10000)
```

[4]:
```
# See the first training example
image, label = train_data[0]
image, label
```

[4]:
```
(tensor([[[0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000,
           0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000,
           0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000,
           0.0000, 0.0000, 0.0000, 0.0000],
          [0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000,
           0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000,
           0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000,
           0.0000, 0.0000, 0.0000, 0.0000],
          [0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000,
           0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000,
           0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000,
           0.0000, 0.0000, 0.0000, 0.0000],
          [0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000,
           0.0000, 0.0000, 0.0000, 0.0000, 0.0039, 0.0000, 0.0000, 0.0510,
           0.2863, 0.0000, 0.0000, 0.0039, 0.0157, 0.0000, 0.0000, 0.0000,
           0.0000, 0.0039, 0.0039, 0.0000],
```

```
[0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000,
 0.0000, 0.0000, 0.0000, 0.0000, 0.0118, 0.0000, 0.1412, 0.5333,
 0.4980, 0.2431, 0.2118, 0.0000, 0.0000, 0.0000, 0.0039, 0.0118,
 0.0157, 0.0000, 0.0000, 0.0118],
[0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000,
 0.0000, 0.0000, 0.0000, 0.0000, 0.0235, 0.0000, 0.4000, 0.8000,
 0.6902, 0.5255, 0.5647, 0.4824, 0.0902, 0.0000, 0.0000, 0.0000,
 0.0000, 0.0471, 0.0392, 0.0000],
[0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000,
 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.6078, 0.9255,
 0.8118, 0.6980, 0.4196, 0.6118, 0.6314, 0.4275, 0.2510, 0.0902,
 0.3020, 0.5098, 0.2824, 0.0588],
[0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000,
 0.0000, 0.0000, 0.0000, 0.0039, 0.0000, 0.2706, 0.8118, 0.8745,
 0.8549, 0.8471, 0.8471, 0.6392, 0.4980, 0.4745, 0.4784, 0.5725,
 0.5529, 0.3451, 0.6745, 0.2588],
[0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000,
 0.0000, 0.0039, 0.0039, 0.0039, 0.0000, 0.7843, 0.9098, 0.9098,
 0.9137, 0.8980, 0.8745, 0.8745, 0.8431, 0.8353, 0.6431, 0.4980,
 0.4824, 0.7686, 0.8980, 0.0000],
[0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000,
 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.7176, 0.8824, 0.8471,
 0.8745, 0.8941, 0.9216, 0.8902, 0.8784, 0.8706, 0.8784, 0.8667,
 0.8745, 0.9608, 0.6784, 0.0000],
[0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000,
 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.7569, 0.8941, 0.8549,
 0.8353, 0.7765, 0.7059, 0.8314, 0.8235, 0.8275, 0.8353, 0.8745,
 0.8627, 0.9529, 0.7922, 0.0000],
[0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000,
 0.0000, 0.0039, 0.0118, 0.0000, 0.0471, 0.8588, 0.8627, 0.8314,
 0.8549, 0.7529, 0.6627, 0.8902, 0.8157, 0.8549, 0.8784, 0.8314,
 0.8863, 0.7725, 0.8196, 0.2039],
[0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000,
 0.0000, 0.0000, 0.0235, 0.0000, 0.3882, 0.9569, 0.8706, 0.8627,
 0.8549, 0.7961, 0.7765, 0.8667, 0.8431, 0.8353, 0.8706, 0.8627,
 0.9608, 0.4667, 0.6549, 0.2196],
[0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000,
 0.0000, 0.0157, 0.0000, 0.0000, 0.2157, 0.9255, 0.8941, 0.9020,
 0.8941, 0.9412, 0.9098, 0.8353, 0.8549, 0.8745, 0.9176, 0.8510,
 0.8510, 0.8196, 0.3608, 0.0000],
[0.0000, 0.0000, 0.0039, 0.0157, 0.0235, 0.0275, 0.0078, 0.0000,
 0.0000, 0.0000, 0.0000, 0.0000, 0.9294, 0.8863, 0.8510, 0.8745,
 0.8706, 0.8588, 0.8706, 0.8667, 0.8471, 0.8745, 0.8980, 0.8431,
 0.8549, 1.0000, 0.3020, 0.0000],
[0.0000, 0.0118, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000,
 0.0000, 0.2431, 0.5686, 0.8000, 0.8941, 0.8118, 0.8353, 0.8667,
 0.8549, 0.8157, 0.8275, 0.8549, 0.8784, 0.8745, 0.8588, 0.8431,
```

```
 0.8784, 0.9569, 0.6235, 0.0000],
[0.0000, 0.0000, 0.0000, 0.0000, 0.0706, 0.1725, 0.3216, 0.4196,
 0.7412, 0.8941, 0.8627, 0.8706, 0.8510, 0.8863, 0.7843, 0.8039,
 0.8275, 0.9020, 0.8784, 0.9176, 0.6902, 0.7373, 0.9804, 0.9725,
 0.9137, 0.9333, 0.8431, 0.0000],
[0.0000, 0.2235, 0.7333, 0.8157, 0.8784, 0.8667, 0.8784, 0.8157,
 0.8000, 0.8392, 0.8157, 0.8196, 0.7843, 0.6235, 0.9608, 0.7569,
 0.8078, 0.8745, 1.0000, 1.0000, 0.8667, 0.9176, 0.8667, 0.8275,
 0.8627, 0.9098, 0.9647, 0.0000],
[0.0118, 0.7922, 0.8941, 0.8784, 0.8667, 0.8275, 0.8275, 0.8392,
 0.8039, 0.8039, 0.8039, 0.8627, 0.9412, 0.3137, 0.5882, 1.0000,
 0.8980, 0.8667, 0.7373, 0.6039, 0.7490, 0.8235, 0.8000, 0.8196,
 0.8706, 0.8941, 0.8824, 0.0000],
[0.3843, 0.9137, 0.7765, 0.8235, 0.8706, 0.8980, 0.8980, 0.9176,
 0.9765, 0.8627, 0.7608, 0.8431, 0.8510, 0.9451, 0.2549, 0.2863,
 0.4157, 0.4588, 0.6588, 0.8588, 0.8667, 0.8431, 0.8510, 0.8745,
 0.8745, 0.8784, 0.8980, 0.1137],
[0.2941, 0.8000, 0.8314, 0.8000, 0.7569, 0.8039, 0.8275, 0.8824,
 0.8471, 0.7255, 0.7725, 0.8078, 0.7765, 0.8353, 0.9412, 0.7647,
 0.8902, 0.9608, 0.9373, 0.8745, 0.8549, 0.8314, 0.8196, 0.8706,
 0.8627, 0.8667, 0.9020, 0.2627],
[0.1882, 0.7961, 0.7176, 0.7608, 0.8353, 0.7725, 0.7255, 0.7451,
 0.7608, 0.7529, 0.7922, 0.8392, 0.8588, 0.8667, 0.8627, 0.9255,
 0.8824, 0.8471, 0.7804, 0.8078, 0.7294, 0.7098, 0.6941, 0.6745,
 0.7098, 0.8039, 0.8078, 0.4510],
[0.0000, 0.4784, 0.8588, 0.7569, 0.7020, 0.6706, 0.7176, 0.7686,
 0.8000, 0.8235, 0.8353, 0.8118, 0.8275, 0.8235, 0.7843, 0.7686,
 0.7608, 0.7490, 0.7647, 0.7490, 0.7765, 0.7529, 0.6902, 0.6118,
 0.6549, 0.6941, 0.8235, 0.3608],
[0.0000, 0.0000, 0.2902, 0.7412, 0.8314, 0.7490, 0.6863, 0.6745,
 0.6863, 0.7098, 0.7255, 0.7373, 0.7412, 0.7373, 0.7569, 0.7765,
 0.8000, 0.8196, 0.8235, 0.8235, 0.8275, 0.7373, 0.7373, 0.7608,
 0.7529, 0.8471, 0.6667, 0.0000],
[0.0078, 0.0000, 0.0000, 0.0000, 0.2588, 0.7843, 0.8706, 0.9294,
 0.9373, 0.9490, 0.9647, 0.9529, 0.9569, 0.8667, 0.8627, 0.7569,
 0.7490, 0.7020, 0.7137, 0.7137, 0.7098, 0.6902, 0.6510, 0.6588,
 0.3882, 0.2275, 0.0000, 0.0000],
[0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.1569,
 0.2392, 0.1725, 0.2824, 0.1608, 0.1373, 0.0000, 0.0000, 0.0000,
 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000,
 0.0000, 0.0000, 0.0000, 0.0000],
[0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000,
 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000,
 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000,
 0.0000, 0.0000, 0.0000, 0.0000],
[0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000,
 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000,
```

```
            0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000,
            0.0000, 0.0000, 0.0000, 0.0000]]]), 9)
```

[5]:
```
class_names = train_data.classes
class_names
```

[5]:
```
['T-shirt/top',
 'Trouser',
 'Pullover',
 'Dress',
 'Coat',
 'Sandal',
 'Shirt',
 'Sneaker',
 'Bag',
 'Ankle boot']
```

[6]:
```
class_to_idx = train_data.class_to_idx
class_to_idx
```

[6]:
```
{'Ankle boot': 9,
 'Bag': 8,
 'Coat': 4,
 'Dress': 3,
 'Pullover': 2,
 'Sandal': 5,
 'Shirt': 6,
 'Sneaker': 7,
 'T-shirt/top': 0,
 'Trouser': 1}
```

[7]:
```
train_data.targets
```

[7]:
```
tensor([9, 0, 0,  …, 3, 0, 5])
```

1.2.1 1.1 Check input and output shapes of data

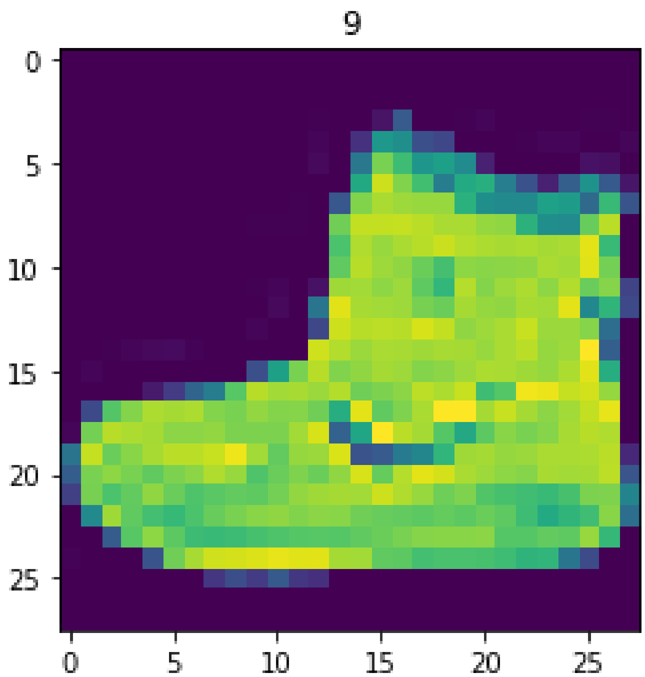
[8]:
```
# Check the shape of our image
print(f"Image shape: {image.shape} -> [color_channels, height, width]")
print(f"Image label: {class_names[label]}")
```

```
Image shape: torch.Size([1, 28, 28]) -> [color_channels, height, width]
Image label: Ankle boot
```

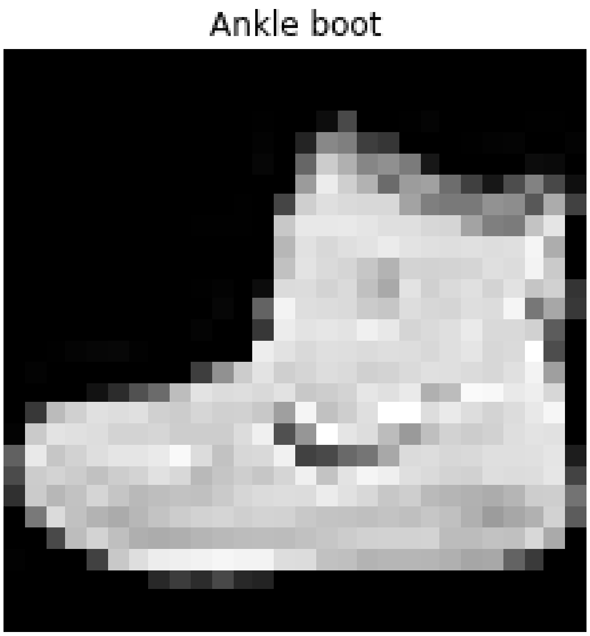
1.2.2 1.2 Visualizing our data

[9]:
```
import matplotlib.pyplot as plt
image, label = train_data[0]
print(f"Image shape: {image.shape}")
plt.imshow(image.squeeze())
plt.title(label);
# image
```

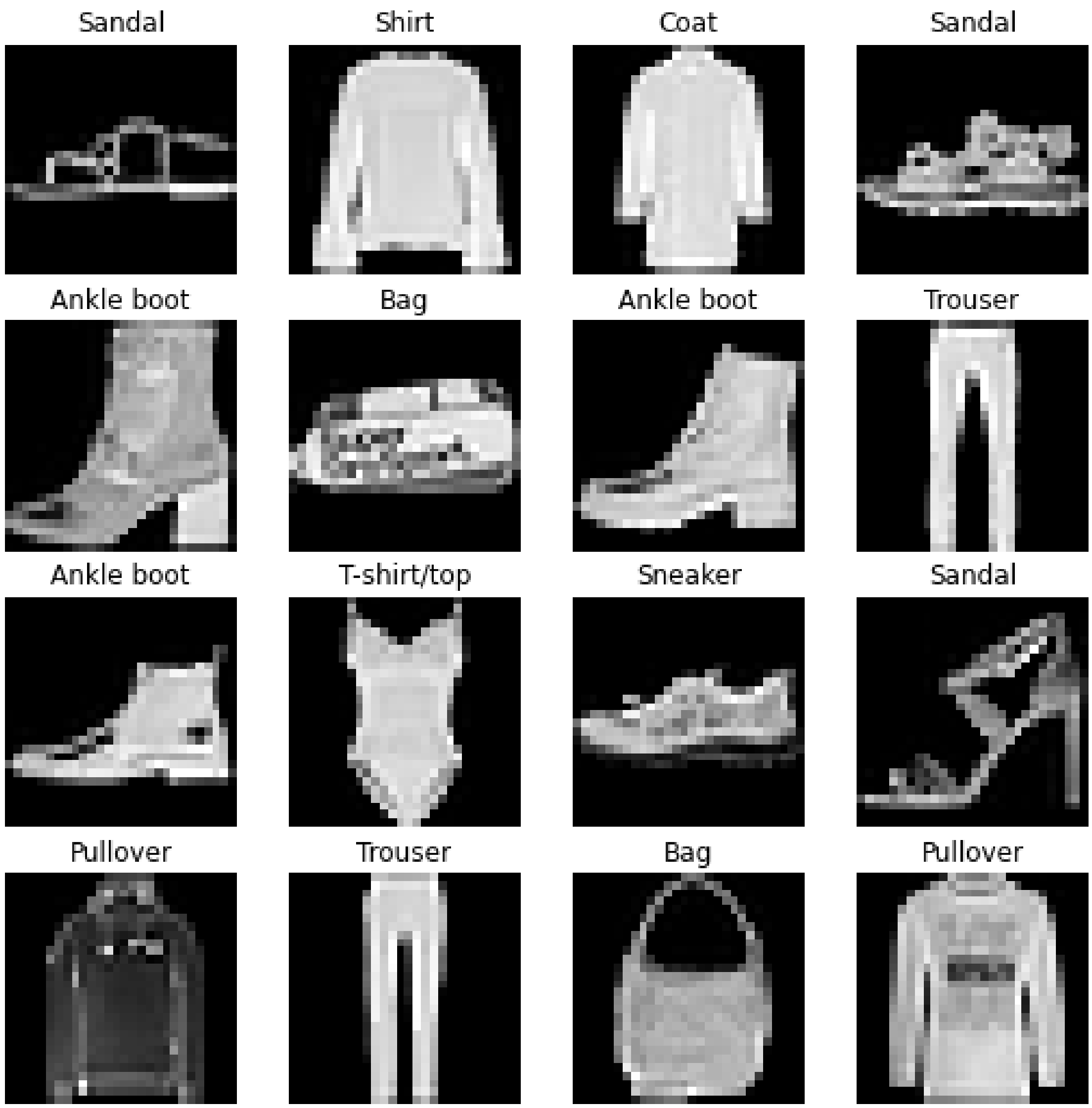
```
Image shape: torch.Size([1, 28, 28])
```



[10]:
```
plt.imshow(image.squeeze(), cmap="gray")
plt.title(class_names[label]);
plt.axis(False);
```



[11]:
```
# Plot more images
# torch.manual_seed(42)
fig = plt.figure(figsize=(9, 9))
rows, cols = 4, 4
for i in range(1, rows*cols+1):
  random_idx = torch.randint(0, len(train_data), size=[1]).item()
  img, label = train_data[random_idx]
  fig.add_subplot(rows, cols, i)
  plt.imshow(img.squeeze(), cmap="gray")
  plt.title(class_names[label])
  plt.axis(False);
```



Do you think these items of clothing (images) could be modelled with pure linear lines? Or do you think we'll need non-linearities?

[12]:
```
train_data, test_data
```

[12]:
```
(Dataset FashionMNIST
     Number of datapoints: 60000
     Root location: data
     Split: Train
     StandardTransform
 Transform: ToTensor(), Dataset FashionMNIST
     Number of datapoints: 10000
     Root location: data
```

```
    Split: Test
    StandardTransform
Transform: ToTensor())
```

1.3 2. Prepare DataLoader

Right now, our data is in the form of PyTorch Datasets.

DataLoader turns our dataset into a Python iterable.

More specifically, we want to turn our data into batches (or mini-batches).

Why would we do this?

1. It is more computationally efficient, as in, your computing hardware may not be able to look (store in memory) at 60000 images in one hit. So we break it down to 32 images at a time (batch size of 32).
2. It gives our neural network more chances to update its gradients per epoch.

For more on mini-batches, see here: https://youtu.be/l4lSUAcvHFs

[13]:
```python
from torch.utils.data import DataLoader

# Setup the batch size hyperparameter
BATCH_SIZE = 32

# Turn datasets into iterables (batches)
train_dataloader = DataLoader(dataset=train_data,
                              batch_size=BATCH_SIZE,
                              shuffle=True)

test_dataloader = DataLoader(dataset=test_data,
                             batch_size=BATCH_SIZE,
                             shuffle=False)

train_dataloader, test_dataloader
```

[13]:
```
(<torch.utils.data.dataloader.DataLoader at 0x7f8e42bb4fd0>,
 <torch.utils.data.dataloader.DataLoader at 0x7f8e42bb4150>)
```

[14]:
```python
# Let's check out what what we've created
print(f"DataLoaders: {train_dataloader, test_dataloader}")
print(f"Length of train_dataloader: {len(train_dataloader)} batches of␣
 ↪{BATCH_SIZE}...")
print(f"Length of test_dataloader: {len(test_dataloader)} batches of␣
 ↪{BATCH_SIZE}...")
```

```
DataLoaders: (<torch.utils.data.dataloader.DataLoader object at 0x7f8e42bb4fd0>,
<torch.utils.data.dataloader.DataLoader object at 0x7f8e42bb4150>)
```

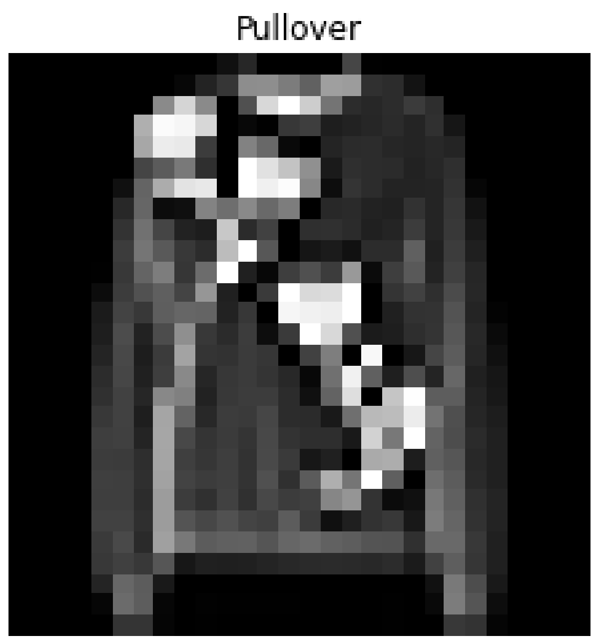
```
Length of train_dataloader: 1875 batches of 32…
Length of test_dataloader: 313 batches of 32…
```

[15]:
```python
# Check out what's inside the training dataloader
train_features_batch, train_labels_batch = next(iter(train_dataloader))
train_features_batch.shape, train_labels_batch.shape
```

[15]:
```
(torch.Size([32, 1, 28, 28]), torch.Size([32]))
```

[16]:
```python
# Show a sample
# torch.manual_seed(42)
random_idx = torch.randint(0, len(train_features_batch), size=[1]).item()
img, label = train_features_batch[random_idx], train_labels_batch[random_idx]
plt.imshow(img.squeeze(), cmap="gray")
plt.title(class_names[label])
plt.axis(False)
print(f"Image size: {img.shape}")
print(f"Label: {label}, label size: {label.shape}")
```

```
Image size: torch.Size([1, 28, 28])
Label: 2, label size: torch.Size([])
```



1.4 3. Model 0: Build a basline model

When starting to build a series of machine learning modelling experiments, it's best practice to start with a baseline model.

A baseline model is a simple model you will try and improve upon with subsequent models/experiments.

In other words: start simply and add complexity when necessary.

[17]:
```
# Create a flatten layer
flatten_model = nn.Flatten()

# Get a single sample
x = train_features_batch[0]

# Flatten the sample
output = flatten_model(x) # perform forward pass

# Print out what happened
print(f"Shape before flattening: {x.shape} -> [color_channels, height, width]")
print(f"Shape after flattening: {output.shape} -> [color_channels,␣
↪height*width]")
```

```
Shape before flattening: torch.Size([1, 28, 28]) -> [color_channels, height,
width]
Shape after flattening: torch.Size([1, 784]) -> [color_channels, height*width]
```

[18]:
```
from torch import nn
class FashionMNISTModelV0(nn.Module):
  def __init__(self,
               input_shape: int,
               hidden_units: int,
               output_shape: int):
    super().__init__()
    self.layer_stack = nn.Sequential(
        nn.Flatten(),
        nn.Linear(in_features=input_shape,
                  out_features=hidden_units),
        nn.Linear(in_features=hidden_units,
                  out_features=output_shape)
    )

  def forward(self, x):
    return self.layer_stack(x)
```

[19]:
```
torch.manual_seed(42)

# Setup model with input parameters
model_0 = FashionMNISTModelV0(
    input_shape=28*28, # this is 28*28
    hidden_units=10, # how mnay units in the hidden layer
    output_shape=len(class_names) # one for every class
```

```
).to("cpu")

model_0
```

[19]:
```
FashionMNISTModelV0(
  (layer_stack): Sequential(
    (0): Flatten(start_dim=1, end_dim=-1)
    (1): Linear(in_features=784, out_features=10, bias=True)
    (2): Linear(in_features=10, out_features=10, bias=True)
  )
)
```

[20]:
```
dummy_x = torch.rand([1, 1, 28, 28])
model_0(dummy_x)
```

[20]:
```
tensor([[-0.0315,  0.3171,  0.0531, -0.2525,  0.5959,  0.2112,  0.3233,  0.2694,
         -0.1004,  0.0157]], grad_fn=<AddmmBackward0>)
```

[21]:
```
model_0.state_dict()
```

[21]:
```
OrderedDict([('layer_stack.1.weight',
              tensor([[ 0.0273,  0.0296, -0.0084,  …, -0.0142,  0.0093,
0.0135],
                      [-0.0188, -0.0354,  0.0187,  …, -0.0106, -0.0001,
0.0115],
                      [-0.0008,  0.0017,  0.0045,  …, -0.0127, -0.0188,
0.0059],
                      …,
                      [-0.0116,  0.0273, -0.0344,  …,  0.0176,  0.0283,
-0.0011],
                      [-0.0230,  0.0257,  0.0291,  …, -0.0187, -0.0087,
0.0001],
                      [ 0.0176, -0.0147,  0.0053,  …, -0.0336, -0.0221,
0.0205]])),
             ('layer_stack.1.bias',
              tensor([-0.0093,  0.0283, -0.0033,  0.0255,  0.0017,  0.0037,
-0.0302, -0.0123,
                       0.0018,  0.0163])),
             ('layer_stack.2.weight',
              tensor([[ 0.0614, -0.0687,  0.0021,  0.2718,  0.2109,  0.1079,
-0.2279, -0.1063,
                        0.2019,  0.2847],
                      [-0.1495,  0.1344, -0.0740,  0.2006, -0.0475, -0.2514,
-0.3130, -0.0118,
                        0.0932, -0.1864],
                      [ 0.2488,  0.1500,  0.1907,  0.1457, -0.3050, -0.0580,
0.1643,  0.1565,
```

```
                        -0.2877, -0.1792],
                       [ 0.2305, -0.2618,  0.2397, -0.0610,  0.0232,  0.1542,
0.0851, -0.2027,
                         0.1030, -0.2715],
                       [-0.1596, -0.0555, -0.0633,  0.2302, -0.1726,  0.2654,
0.1473,  0.1029,
                         0.2252, -0.2160],
                       [-0.2725,  0.0118,  0.1559,  0.1596,  0.0132,  0.3024,
0.1124,  0.1366,
                        -0.1533,  0.0965],
                       [-0.1184, -0.2555, -0.2057, -0.1909, -0.0477, -0.1324,
0.2905,  0.1307,
                        -0.2629,  0.0133],
                       [ 0.2727, -0.0127,  0.0513,  0.0863, -0.1043, -0.2047,
-0.1185, -0.0825,
                         0.2488, -0.2571],
                       [ 0.0425, -0.1209, -0.0336, -0.0281, -0.1227,  0.0730,
0.0747, -0.1816,
                         0.1943,  0.2853],
                       [-0.1310,  0.0645, -0.1171,  0.2168, -0.0245, -0.2820,
0.0736,  0.2621,
                         0.0012, -0.0810]])),
             ('layer_stack.2.bias',
              tensor([-0.0087,  0.1791,  0.2712, -0.0791,  0.1685,  0.1762,
0.2825,  0.2266,
                       -0.2612, -0.2613]))])
```

1.4.1 3.1 Setup loss, optimizer and evaluation metrics

- Loss function - since we're working with multi-class data, our loss function will be `nn.CrossEntropyLoss()`
- Optimizer - our optimizer `torch.optim.SGD()` (stochastic gradient descent)
- Evaluation metric - since we're working on a classification problem, let's use accruacy as our evaluation metric

[22]:
```
import requests
from pathlib import Path

# Download helper functions from Learn PyTorch repo
if Path("helper_functions.py").is_file():
  print("helper_functions.py already exists, skipping download...")
else:
  print("Downloading helper_functions.py")
  request = requests.get("https://raw.githubusercontent.com/mrdbourke/
↪pytorch-deep-learning/main/helper_functions.py")
  with open("helper_functions.py", "wb") as f:
    f.write(request.content)
```

```
helper_functions.py already exists, skipping download…
```

[23]:
```python
# Import accuracy metric
from helper_functions import accuracy_fn

# Setup loss function and optimizer
loss_fn = nn.CrossEntropyLoss()
optimizer = torch.optim.SGD(params=model_0.parameters(),
                            lr=0.1)
```

1.4.2 3.2 Creating a function to time our experiments

Machine learning is very experimental.

Two of the main things you'll often want to track are: 1. Model's performance (loss and accuracy values etc) 2. How fast it runs

[24]:
```python
from timeit import default_timer as timer
def print_train_time(start: float,
                     end: float,
                     device: torch.device = None):
  """Prints difference between start and end time."""
  total_time = end - start
  print(f"Train time on {device}: {total_time:.3f} seconds")
  return total_time
```

[25]:
```python
start_time = timer()
# some code...
end_time = timer()
print_train_time(start=start_time, end=end_time, device="cpu")
```

```
Train time on cpu: 0.000 seconds
```

[25]:
```
2.397800017206464e-05
```

1.4.3 3.3 Creating a training loop and training a model on batches of data

1. Loop through epochs.
2. Loop through training batches, perform training steps, calculate the train loss *per batch*.
3. Loop through testing batches, perform testing steps, calculate the test loss *per batch*.
4. Print out what's happening.
5. Time it all (for fun).

Note: Because we are computing on *batches*, the optimizer will update the model's parameters once *per batch* rather than once per epoch.

[26]:
```python
# Import tqdm for progress bar
from tqdm.auto import tqdm
```

```
# Set the seed and start the timer
torch.manual_seed(42)
train_time_start_on_cpu = timer()

# Set the number of epochs (we'll keep this small for faster training time)
epochs = 3

# Create training and test loop
for epoch in tqdm(range(epochs)):
  print(f"Epoch: {epoch}\n------")
  ### Training
  train_loss = 0
  # Add a loop to loop through the training batches
  for batch, (X, y) in enumerate(train_dataloader):
    model_0.train()
    # 1. Forward pass
    y_pred = model_0(X)

    # 2. Calculate loss (per batch)
    loss = loss_fn(y_pred, y)
    train_loss += loss # accumulate train loss

    # 3. Optimizer zero grad
    optimizer.zero_grad()

    # 4. Loss backward
    loss.backward()

    # 5. Optimizer step (update the model's parameters once *per batch*)
    optimizer.step()

    # Print out what's happening
    if batch % 400 == 0:
        print(f"Looked at {batch * len(X)}/{len(train_dataloader.dataset)}␣
↪samples.")

  # Divide total train loss by length of train dataloader
  train_loss /= len(train_dataloader)

  ### Testing
  test_loss, test_acc = 0, 0
  model_0.eval()
  with torch.inference_mode():
    for X_test, y_test in test_dataloader:
      # 1. Forward pass
      test_pred = model_0(X_test)
```

```
        # 2. Calculate loss (accumulatively)
        test_loss += loss_fn(test_pred, y_test)

        # 3. Calculate accuracy
        test_acc += accuracy_fn(y_true=y_test, y_pred=test_pred.argmax(dim=1))

      # Calculate the test loss average per batch
      test_loss /= len(test_dataloader)

      # Calculate the test acc average per batch
      test_acc /= len(test_dataloader)

    # Print out what's happening
    print(f"\nTrain loss: {train_loss:.4f} | Test loss: {test_loss:.4f}, Test acc:
  ↪ {test_acc:.4f}")

# Calculate training time
train_time_end_on_cpu = timer()
total_train_time_model_0 = print_train_time(start=train_time_start_on_cpu,
                                            end=train_time_end_on_cpu,
                                            device=str(next(model_0.
  ↪parameters()).device))
```

```
  0%|          | 0/3 [00:00<?, ?it/s]

Epoch: 0
------
Looked at 0/60000 samples.
Looked at 12800/60000 samples.
Looked at 25600/60000 samples.
Looked at 38400/60000 samples.
Looked at 51200/60000 samples.

Train loss: 0.5904 | Test loss: 0.5095, Test acc: 82.0387
Epoch: 1
------
Looked at 0/60000 samples.
Looked at 12800/60000 samples.
Looked at 25600/60000 samples.
Looked at 38400/60000 samples.
Looked at 51200/60000 samples.

Train loss: 0.4763 | Test loss: 0.4799, Test acc: 83.1969
Epoch: 2
------
Looked at 0/60000 samples.
Looked at 12800/60000 samples.
Looked at 25600/60000 samples.
```

```
Looked at 38400/60000 samples.
Looked at 51200/60000 samples.

Train loss: 0.4550 | Test loss: 0.4766, Test acc: 83.4265
Train time on cpu: 26.749 seconds
```

1.5 4. Make predictions and get Model 0 results

[27]:
```python
torch.manual_seed(42)
def eval_model(model: torch.nn.Module,
               data_loader: torch.utils.data.DataLoader,
               loss_fn: torch.nn.Module,
               accuracy_fn):
  """Returns a dictionary containing the results of model predicting on␣
↪data_loader."""
  loss, acc = 0, 0
  model.eval()
  with torch.inference_mode():
    for X, y in tqdm(data_loader):
      # Make predictions
      y_pred = model(X)

      # Accumulate the loss and acc values per batch
      loss += loss_fn(y_pred, y)
      acc += accuracy_fn(y_true=y,
                         y_pred=y_pred.argmax(dim=1))

    # Scale loss and acc to find the average loss/acc per batch
    loss /= len(data_loader)
    acc /= len(data_loader)

  return {"model_name": model.__class__.__name__, # only works when model was␣
↪created with a class
          "model_loss": loss.item(),
          "model_acc": acc}

# Calculate model 0 results on test dataset
model_0_results = eval_model(model=model_0,
                             data_loader=test_dataloader,
                             loss_fn=loss_fn,
                             accuracy_fn=accuracy_fn)
model_0_results
```

```
  0%|          | 0/313 [00:00<?, ?it/s]
```

[27]:
```
{'model_acc': 83.42651757188499,
 'model_loss': 0.47663888335227966,
```

```
 'model_name': 'FashionMNISTModelV0'}
```

1.6 5. Setup device agnostic-code (for using a GPU if there is one)

[28]:
```
!nvidia-smi
```

```
Sat Apr 23 01:36:35 2022
+-----------------------------------------------------------------------------+
| NVIDIA-SMI 460.32.03    Driver Version: 460.32.03    CUDA Version: 11.2     |
|-------------------------------+----------------------+----------------------+
| GPU  Name        Persistence-M| Bus-Id        Disp.A | Volatile Uncorr. ECC |
| Fan  Temp  Perf  Pwr:Usage/Cap|         Memory-Usage | GPU-Util  Compute M. |
|                               |                      |               MIG M. |
|===============================+======================+======================|
|   0  Tesla P100-PCIE...  Off  | 00000000:00:04.0 Off |                    0 |
| N/A   37C    P0    29W / 250W |      2MiB / 16280MiB |      0%      Default |
|                               |                      |                  N/A |
+-------------------------------+----------------------+----------------------+

+-----------------------------------------------------------------------------+
| Processes:                                                                  |
|  GPU   GI   CI        PID   Type   Process name                  GPU Memory |
|        ID   ID                                                   Usage      |
|=============================================================================|
|  No running processes found                                                 |
+-----------------------------------------------------------------------------+
```

[29]:
```
torch.cuda.is_available()
```

[29]: True

[30]:
```
# Setup device-agnostic code
import torch
device = "cuda" if torch.cuda.is_available() else "cpu"
device
```

[30]: 'cuda'

1.7 6. Model 1: Building a better model with non-linearity

We learned about the power of non-linearity in notebook 02 - https://www.learnpytorch.io/02_pytorch_classification/#6-the-missing-piece-non-linearity

[31]:
```
# Create a model with non-linear and linear layers
class FashionMNISTModelV1(nn.Module):
  def __init__(self,
               input_shape: int,
```

```
                hidden_units: int,
                output_shape: int):
    super().__init__()
    self.layer_stack = nn.Sequential(
        nn.Flatten(), # flatten inputs into a single vector
        nn.Linear(in_features=input_shape,
                  out_features=hidden_units),
        nn.ReLU(),
        nn.Linear(in_features=hidden_units,
                  out_features=output_shape),
        nn.ReLU()
    )

  def forward(self, x: torch.Tensor):
    return self.layer_stack(x)
```

[32]:
```
# Create an instance of model_1
torch.manual_seed(42)
model_1 = FashionMNISTModelV1(input_shape=784, # this is the output of the␣
↪flatten after our 28*28 image goes in
                              hidden_units=10,
                              output_shape=len(class_names)).to(device) # send␣
↪to the GPU if it's available
next(model_1.parameters()).device
```

[32]:
```
device(type='cuda', index=0)
```

1.7.1 6.1 Setup loss, optimizer and evaluation metrics

[33]:
```
from helper_functions import accuracy_fn
loss_fn = nn.CrossEntropyLoss() # measure how wrong our model is
optimizer = torch.optim.SGD(params=model_1.parameters(), # tries to update our␣
↪model's parameters to reduce the loss
                            lr=0.1)
```

1.7.2 6.2 Functionizing training and evaluation/testing loops

Let's create a function for: * training loop - `train_step()` * testing loop - `test_step()`

[34]:
```
def train_step(model: torch.nn.Module,
               data_loader: torch.utils.data.DataLoader,
               loss_fn: torch.nn.Module,
               optimizer: torch.optim.Optimizer,
               accuracy_fn,
               device: torch.device = device):
  """Performs a training with model trying to learn on data_loader."""
  train_loss, train_acc = 0, 0
```

```
    # Put model into training mode
    model.train()

    # Add a loop to loop through the training batches
    for batch, (X, y) in enumerate(data_loader):
      # Put data on target device
      X, y = X.to(device), y.to(device)

      # 1. Forward pass (outputs the raw logits from the model)
      y_pred = model(X)

      # 2. Calculate loss and accuracy (per batch)
      loss = loss_fn(y_pred, y)
      train_loss += loss # accumulate train loss
      train_acc += accuracy_fn(y_true=y,
                               y_pred=y_pred.argmax(dim=1)) # go from logits ->␣
↪prediction labels

      # 3. Optimizer zero grad
      optimizer.zero_grad()

      # 4. Loss backward
      loss.backward()

      # 5. Optimizer step (update the model's parameters once *per batch*)
      optimizer.step()

    # Divide total train loss and acc by length of train dataloader
    train_loss /= len(data_loader)
    train_acc /= len(data_loader)
    print(f"Train loss: {train_loss:.5f} | Train acc: {train_acc:.2f}%")
```

[35]:
```
def test_step(model: torch.nn.Module,
              data_loader: torch.utils.data.DataLoader,
              loss_fn: torch.nn.Module,
              accuracy_fn,
              device: torch.device = device):
    """Performs a testing loop step on model going over data_loader."""
    test_loss, test_acc = 0, 0

    # Put the model in eval mode
    model.eval()

    # Turn on inference mode context manager
    with torch.inference_mode():
      for X, y in data_loader:
```

```
        # Send the data to the target device
        X, y = X.to(device), y.to(device)

        # 1. Forward pass (outputs raw logits)
        test_pred = model(X)

        # 2. Calculate the loss/acc
        test_loss += loss_fn(test_pred, y)
        test_acc += accuracy_fn(y_true=y,
                                y_pred=test_pred.argmax(dim=1)) # go from logits␣
↪-> prediction labels

    # Adjust metrics and print out
    test_loss /= len(data_loader)
    test_acc /= len(data_loader)
    print(f"Test loss: {test_loss:.5f} | Test acc: {test_acc:.2f}%\n")
```

[36]:
```
torch.manual_seed(42)

# Measure time
from timeit import default_timer as timer
train_time_start_on_gpu = timer()

# Set epochs
epochs = 3

# Create a optimization and evaluation loop using train_step() and test_step()
for epoch in tqdm(range(epochs)):
  print(f"Epoch: {epoch}\n----------")
  train_step(model=model_1,
             data_loader=train_dataloader,
             loss_fn=loss_fn,
             optimizer=optimizer,
             accuracy_fn=accuracy_fn,
             device=device)
  test_step(model=model_1,
            data_loader=test_dataloader,
            loss_fn=loss_fn,
            accuracy_fn=accuracy_fn,
            device=device)

train_time_end_on_gpu = timer()
total_train_time_model_1 = print_train_time(start=train_time_start_on_gpu,
                                            end=train_time_end_on_gpu,
                                            device=device)
```

```
0%|          | 0/3 [00:00<?, ?it/s]
```

```
Epoch: 0
----------
Train loss: 1.09199 | Train acc: 61.34%
Test loss: 0.95636 | Test acc: 65.00%

Epoch: 1
----------
Train loss: 0.78101 | Train acc: 71.93%
Test loss: 0.72227 | Test acc: 73.91%

Epoch: 2
----------
Train loss: 0.67027 | Train acc: 75.94%
Test loss: 0.68500 | Test acc: 75.02%

Train time on cuda: 20.042 seconds
```

> **Note:** Sometimes, depending on your data/hardware you might find that your model trains faster on CPU than GPU.
>
> Why is this?
>
> 1. It could be that the overhead for copying data/model to and from the GPU outweighs the compute benefits offered by the GPU.
> 2. The hardware you're using has a better CPU in terms compute capability than the GPU.
>
> For more on how to make your models compute faster, see here: https://horace.io/brrr_intro.html

[37]:
```
model_0_results
```

[37]:
```
{'model_acc': 83.42651757188499,
 'model_loss': 0.47663888335227966,
 'model_name': 'FashionMNISTModelV0'}
```

[38]:
```
# Train time on CPU
total_train_time_model_0
```

[38]:
```
26.74877341499996
```

[39]:
```
# Get model_1 results dictionary
model_1_results = eval_model(model=model_1,
                             data_loader=test_dataloader,
                             loss_fn=loss_fn,
                             accuracy_fn=accuracy_fn)
model_1_results
```

```
  0%|          | 0/313 [00:00<?, ?it/s]
```

```
---------------------------------------------------------------------------
RuntimeError                              Traceback (most recent call last)
<ipython-input-39-801e93364267> in <module>()
      3                               data_loader=test_dataloader,
      4                               loss_fn=loss_fn,
----> 5                               accuracy_fn=accuracy_fn)

      6 model_1_results

<ipython-input-27-c5b127dad9f6> in eval_model(model, data_loader, loss_fn,␣
 ↪accuracy_fn)
     10     for X, y in tqdm(data_loader):
     11       # Make predictions
---> 12       y_pred = model(X)
     13 
     14       # Accumulate the loss and acc values per batch

/usr/local/lib/python3.7/dist-packages/torch/nn/modules/module.py in␣
 ↪_call_impl(self, *input, **kwargs)
   1100         if not (self._backward_hooks or self._forward_hooks or self.
 ↪_forward_pre_hooks or _global_backward_hooks
   1101                 or _global_forward_hooks or _global_forward_pre_hooks):
-> 1102             return forward_call(*input, **kwargs)
   1103         # Do not call functions when jit is used
   1104         full_backward_hooks, non_full_backward_hooks = [], []

<ipython-input-31-2284727bcc95> in forward(self, x)
     17 
     18   def forward(self, x: torch.Tensor):
---> 19     return self.layer_stack(x)

/usr/local/lib/python3.7/dist-packages/torch/nn/modules/module.py in␣
 ↪_call_impl(self, *input, **kwargs)
   1100         if not (self._backward_hooks or self._forward_hooks or self.
 ↪_forward_pre_hooks or _global_backward_hooks
   1101                 or _global_forward_hooks or _global_forward_pre_hooks):
-> 1102             return forward_call(*input, **kwargs)
   1103         # Do not call functions when jit is used
   1104         full_backward_hooks, non_full_backward_hooks = [], []

/usr/local/lib/python3.7/dist-packages/torch/nn/modules/container.py in␣
 ↪forward(self, input)
    139     def forward(self, input):
    140         for module in self:
--> 141             input = module(input)
    142         return input
    143 
```

```
/usr/local/lib/python3.7/dist-packages/torch/nn/modules/module.py in␣
↪_call_impl(self, *input, **kwargs)
   1100         if not (self._backward_hooks or self._forward_hooks or self.
↪_forward_pre_hooks or _global_backward_hooks
   1101                 or _global_forward_hooks or _global_forward_pre_hooks):
-> 1102             return forward_call(*input, **kwargs)
   1103         # Do not call functions when jit is used
   1104         full_backward_hooks, non_full_backward_hooks = [], []

/usr/local/lib/python3.7/dist-packages/torch/nn/modules/linear.py in␣
↪forward(self, input)
    101
    102     def forward(self, input: Tensor) -> Tensor:
--> 103         return F.linear(input, self.weight, self.bias)
    104
    105     def extra_repr(self) -> str:

/usr/local/lib/python3.7/dist-packages/torch/nn/functional.py in linear(input,␣
↪weight, bias)
   1846     if has_torch_function_variadic(input, weight, bias):
   1847         return handle_torch_function(linear, (input, weight, bias),␣
↪input, weight, bias=bias)
-> 1848     return torch._C._nn.linear(input, weight, bias)
   1849
   1850

RuntimeError: Expected all tensors to be on the same device, but found at least␣
↪two devices, cuda:0 and cpu! (when checking argument for argument mat1 in␣
↪method wrapper_addmm)
```

[40]:

```
torch.manual_seed(42)
def eval_model(model: torch.nn.Module,
               data_loader: torch.utils.data.DataLoader,
               loss_fn: torch.nn.Module,
               accuracy_fn,
               device=device):
  """Returns a dictionary containing the results of model predicting on␣
 ↪data_loader."""
  loss, acc = 0, 0
  model.eval()
  with torch.inference_mode():
    for X, y in tqdm(data_loader):
      # Make our data device agnostic
      X, y = X.to(device), y.to(device)
      # Make predictions
      y_pred = model(X)
```

```
        # Accumulate the loss and acc values per batch
        loss += loss_fn(y_pred, y)
        acc += accuracy_fn(y_true=y,
                           y_pred=y_pred.argmax(dim=1))

    # Scale loss and acc to find the average loss/acc per batch
    loss /= len(data_loader)
    acc /= len(data_loader)

  return {"model_name": model.__class__.__name__, # only works when model was␣
↪created with a class
          "model_loss": loss.item(),
          "model_acc": acc}
```

[41]:
```
# Get model_1 results dictionary
model_1_results = eval_model(model=model_1,
                             data_loader=test_dataloader,
                             loss_fn=loss_fn,
                             accuracy_fn=accuracy_fn,
                             device=device)
model_1_results
```

```
0%|          | 0/313 [00:00<?, ?it/s]
```

[41]:
```
{'model_acc': 75.01996805111821,
 'model_loss': 0.6850008368492126,
 'model_name': 'FashionMNISTModelV1'}
```

[42]:
```
model_0_results
```

[42]:
```
{'model_acc': 83.42651757188499,
 'model_loss': 0.47663888335227966,
 'model_name': 'FashionMNISTModelV0'}
```

1.8 Model 2: Building a Convolutional Neural Network (CNN)

CNN's are also known ConvNets.

CNN's are known for their capabilities to find patterns in visual data.

To find out what's happening inside a CNN, see this website: https://poloclub.github.io/cnn-explainer/

[43]:
```
# Create a convolutional neural network
class FashionMNISTModelV2(nn.Module):
  """
  Model architecture that replicates the TinyVGG
```

```
    model from CNN explainer website.
    """
    def __init__(self, input_shape: int, hidden_units: int, output_shape: int):
      super().__init__()
      self.conv_block_1 = nn.Sequential(
          # Create a conv layer - https://pytorch.org/docs/stable/generated/torch.
↪nn.Conv2d.html
          nn.Conv2d(in_channels=input_shape,
                    out_channels=hidden_units,
                    kernel_size=3,
                    stride=1,
                    padding=1), # values we can set ourselves in our NN's are␣
↪called hyperparameters
          nn.ReLU(),
          nn.Conv2d(in_channels=hidden_units,
                    out_channels=hidden_units,
                    kernel_size=3,
                    stride=1,
                    padding=1),
          nn.ReLU(),
          nn.MaxPool2d(kernel_size=2)
      )
      self.conv_block_2 = nn.Sequential(
          nn.Conv2d(in_channels=hidden_units,
                    out_channels=hidden_units,
                    kernel_size=3,
                    stride=1,
                    padding=1),
          nn.ReLU(),
          nn.Conv2d(in_channels=hidden_units,
                    out_channels=hidden_units,
                    kernel_size=3,
                    stride=1,
                    padding=1),
          nn.ReLU(),
          nn.MaxPool2d(kernel_size=2)
      )
      self.classifier = nn.Sequential(
          nn.Flatten(),
          nn.Linear(in_features=hidden_units*7*7, # there's a trick to␣
↪calculating this...
                    out_features=output_shape)
      )

    def forward(self, x):
      x = self.conv_block_1(x)
      # print(f"Output shape of conv_block_1: {x.shape}")
```

```
        x = self.conv_block_2(x)
        # print(f"Output shape of conv_block_2: {x.shape}")
        x = self.classifier(x)
        # print(f"Output shape of classifier: {x.shape}")
        return x
```

[44]:
```
torch.manual_seed(42)
model_2 = FashionMNISTModelV2(input_shape=1,
                              hidden_units=10,
                              output_shape=len(class_names)).to(device)
```

[45]:
```
rand_image_tensor = torch.randn(size=(1, 28, 28))
rand_image_tensor.shape
```

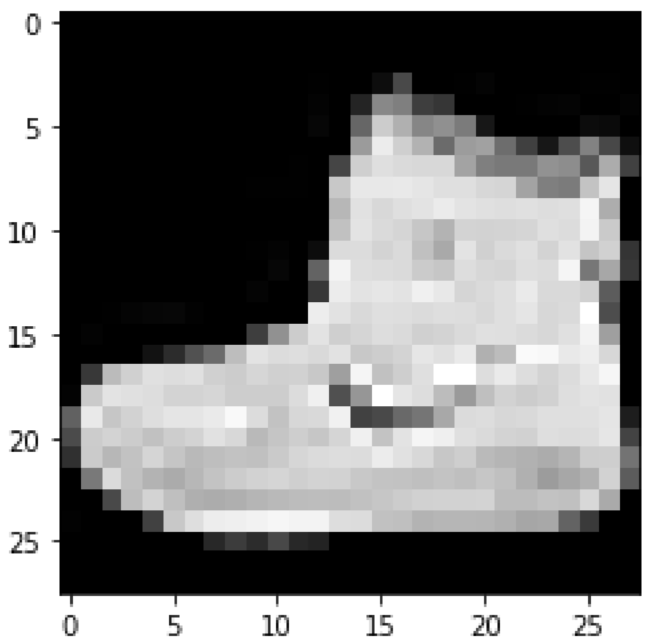
[45]:
```
torch.Size([1, 28, 28])
```

[46]:
```
# Pass image through model
model_2(rand_image_tensor.unsqueeze(0).to(device))
```

[46]:
```
tensor([[ 0.0366, -0.0940,  0.0686, -0.0485,  0.0068,  0.0290,  0.0132,  0.0084,
         -0.0030, -0.0185]], device='cuda:0', grad_fn=<AddmmBackward0>)
```

[47]:
```
plt.imshow(image.squeeze(), cmap="gray")
```

[47]:
```
<matplotlib.image.AxesImage at 0x7f8e43543a10>
```



[48]:
```
# model_2.state_dict()
```

1.8.1 7.1 Stepping through `nn.Conv2d()`

See the documentation for `nn.Conv2d()` here - https://pytorch.org/docs/stable/generated/torch.nn.Conv2d.html

[49]:
```
torch.manual_seed(42)

# Create a batch of images
images = torch.randn(size=(32, 3, 64, 64))
test_image = images[0]

print(f"Image batch shape: {images.shape}")
print(f"Single image shape: {test_image.shape}")
print(f"Test image:\n {test_image}")
```

```
Image batch shape: torch.Size([32, 3, 64, 64])
Single image shape: torch.Size([3, 64, 64])
Test image:
 tensor([[[ 1.9269,  1.4873,  0.9007,  …,  1.8446, -1.1845,  1.3835],
         [ 1.4451,  0.8564,  2.2181,  …,  0.3399,  0.7200,  0.4114],
         [ 1.9312,  1.0119, -1.4364,  …, -0.5558,  0.7043,  0.7099],
         …,
         [-0.5610, -0.4830,  0.4770,  …, -0.2713, -0.9537, -0.6737],
         [ 0.3076, -0.1277,  0.0366,  …, -2.0060,  0.2824, -0.8111],
         [-1.5486,  0.0485, -0.7712,  …, -0.1403,  0.9416, -0.0118]],

        [[-0.5197,  1.8524,  1.8365,  …,  0.8935, -1.5114, -0.8515],
         [ 2.0818,  1.0677, -1.4277,  …,  1.6612, -2.6223, -0.4319],
         [-0.1010, -0.4388, -1.9775,  …,  0.2106,  0.2536, -0.7318],
         …,
         [ 0.2779,  0.7342, -0.3736,  …, -0.4601,  0.1815,  0.1850],
         [ 0.7205, -0.2833,  0.0937,  …, -0.1002, -2.3609,  2.2465],
         [-1.3242, -0.1973,  0.2920,  …,  0.5409,  0.6940,  1.8563]],

        [[-0.7978,  1.0261,  1.1465,  …,  1.2134,  0.9354, -0.0780],
         [-1.4647, -1.9571,  0.1017,  …, -1.9986, -0.7409,  0.7011],
         [-1.3938,  0.8466, -1.7191,  …, -1.1867,  0.1320,  0.3407],
         …,
         [ 0.8206, -0.3745,  1.2499,  …, -0.0676,  0.0385,  0.6335],
         [-0.5589, -0.3393,  0.2347,  …,  2.1181,  2.4569,  1.3083],
         [-0.4092,  1.5199,  0.2401,  …, -0.2558,  0.7870,  0.9924]]])
```

[50]:
```
test_image.shape
```

[50]:
```
torch.Size([3, 64, 64])
```

[51]:
```
torch.manual_seed(42)
# Create a sinlge conv2d layer
conv_layer = nn.Conv2d(in_channels=3,
                       out_channels=10,
                       kernel_size=(3, 3),
                       stride=1,
                       padding=0)

# Pass the data through the convolutional layer
conv_output = conv_layer(test_image.unsqueeze(0))
conv_output.shape
```

[51]:
```
torch.Size([1, 10, 62, 62])
```

[52]:
```
test_image.unsqueeze(0).shape
```

[52]:
```
torch.Size([1, 3, 64, 64])
```

1.8.2 7.2 Stepping through `nn.MaxPool2d()`

https://pytorch.org/docs/stable/generated/torch.nn.MaxPool2d.html

[53]:
```
test_image.shape
```

[53]:
```
torch.Size([3, 64, 64])
```

[54]:
```
# Print out original image shape without unsqueezed dimension
print(f"Test image original shape: {test_image.shape}")
print(f"Test image with unsqueezed dimension: {test_image.unsqueeze(0).shape}")

# Create a sample nn.MaxPool2d layer
max_pool_layer = nn.MaxPool2d(kernel_size=2)

# Pass data through just the conv_layer
test_image_through_conv = conv_layer(test_image.unsqueeze(dim=0))
print(f"Shape after going through conv_layer(): {test_image_through_conv.
 ↪shape}")

# Pass data through the max pool layer
test_image_through_conv_and_max_pool = max_pool_layer(test_image_through_conv)
print(f"Shape after going through conv_layer() and max_pool_layer():␣
 ↪{test_image_through_conv_and_max_pool.shape}")
```

```
Test image original shape: torch.Size([3, 64, 64])
Test image with unsqueezed dimension: torch.Size([1, 3, 64, 64])
Shape after going through conv_layer(): torch.Size([1, 10, 62, 62])
Shape after going through conv_layer() and max_pool_layer(): torch.Size([1, 10,
31, 31])
```

[55]:
```
torch.manual_seed(42)
# Create a random tesnor with a similar number of dimensions to our images
random_tensor = torch.randn(size=(1, 1, 2, 2))
print(f"\nRandom tensor:\n{random_tensor}")
print(f"Random tensor shape: {random_tensor.shape}")

# Create a max pool layer
max_pool_layer = nn.MaxPool2d(kernel_size=2)

# Pass the random tensor through the max pool layer
max_pool_tensor = max_pool_layer(random_tensor)
print(f"\nMax pool tensor:\n {max_pool_tensor}")
print(f"Max pool tensor shape: {max_pool_tensor.shape}")
```

```
Random tensor:
tensor([[[[0.3367, 0.1288],
          [0.2345, 0.2303]]]])
Random tensor shape: torch.Size([1, 1, 2, 2])

Max pool tensor:
 tensor([[[[0.3367]]]])
Max pool tensor shape: torch.Size([1, 1, 1, 1])
```

1.8.3 7.3 Setup a loss function and optimizer for model_2

[56]:
```
# Setup loss function/eval metrics/optimizer
from helper_functions import accuracy_fn

loss_fn = nn.CrossEntropyLoss()
optimizer = torch.optim.SGD(params=model_2.parameters(),
                            lr=0.1)
```

1.8.4 7.4 Training and testing model_2 using our training and test functions

[57]:
```
torch.manual_seed(42)
torch.cuda.manual_seed(42)

# Measure time
from timeit import default_timer as timer
train_time_start_model_2 = timer()

# Train and test model
epochs = 3
for epoch in tqdm(range(epochs)):
  print(f"Epoch: {epoch}\n-------")
  train_step(model=model_2,
```

```
              data_loader=train_dataloader,
              loss_fn=loss_fn,
              optimizer=optimizer,
              accuracy_fn=accuracy_fn,
              device=device)
  test_step(model=model_2,
             data_loader=test_dataloader,
             loss_fn=loss_fn,
             accuracy_fn=accuracy_fn,
             device=device)

train_time_end_model_2 = timer()
total_train_time_model_2 = print_train_time(start=train_time_start_model_2,
                                            end=train_time_end_model_2,
                                            device=device)
```

```
  0%|          | 0/3 [00:00<?, ?it/s]

Epoch: 0
-------
Train loss: 0.59952 | Train acc: 78.09%
Test loss: 0.38754 | Test acc: 85.94%

Epoch: 1
-------
Train loss: 0.35734 | Train acc: 87.07%
Test loss: 0.34306 | Test acc: 87.63%

Epoch: 2
-------
Train loss: 0.31825 | Train acc: 88.42%
Test loss: 0.31359 | Test acc: 88.57%

Train time on cuda: 32.770 seconds
```

[58]:
```
# Get model_2 results
model_2_results = eval_model(
     model=model_2,
     data_loader=test_dataloader,
     loss_fn=loss_fn,
     accuracy_fn=accuracy_fn,
     device=device
)

model_2_results
```

```
  0%|          | 0/313 [00:00<?, ?it/s]
```

```
[58]: {'model_acc': 88.56829073482429,
 'model_loss': 0.31358689069747925,
 'model_name': 'FashionMNISTModelV2'}
```

1.9 8. Compare model results and training time

```
[59]: import pandas as pd
compare_results = pd.DataFrame([model_0_results,
                                model_1_results,
                                model_2_results])
compare_results
```

[59]:

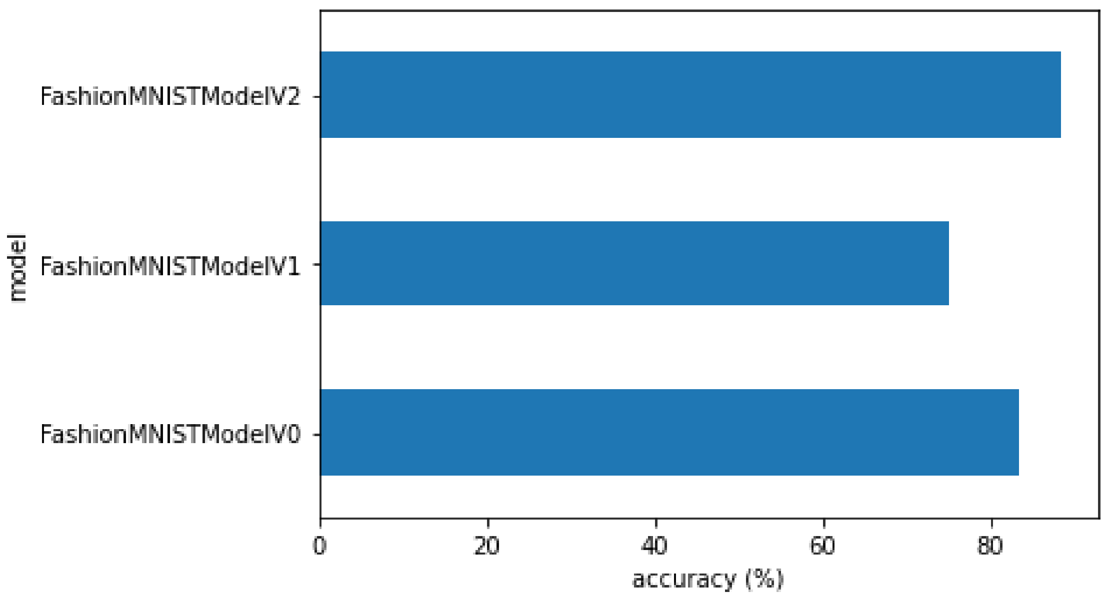
	model_name	model_loss	model_acc
0	FashionMNISTModelV0	0.476639	83.426518
1	FashionMNISTModelV1	0.685001	75.019968
2	FashionMNISTModelV2	0.313587	88.568291

```
[60]: # Add training time to results comparison
compare_results["training_time"] = [total_train_time_model_0,
                                    total_train_time_model_1,
                                    total_train_time_model_2]
compare_results
```

[60]:

	model_name	model_loss	model_acc	training_time
0	FashionMNISTModelV0	0.476639	83.426518	26.748773
1	FashionMNISTModelV1	0.685001	75.019968	20.041531
2	FashionMNISTModelV2	0.313587	88.568291	32.770459

```
[61]: # Visualize our model results
compare_results.set_index("model_name")["model_acc"].plot(kind="barh")
plt.xlabel("accuracy (%)")
plt.ylabel("model");
```



1.10 9. Make and evaluate random predictions with best model

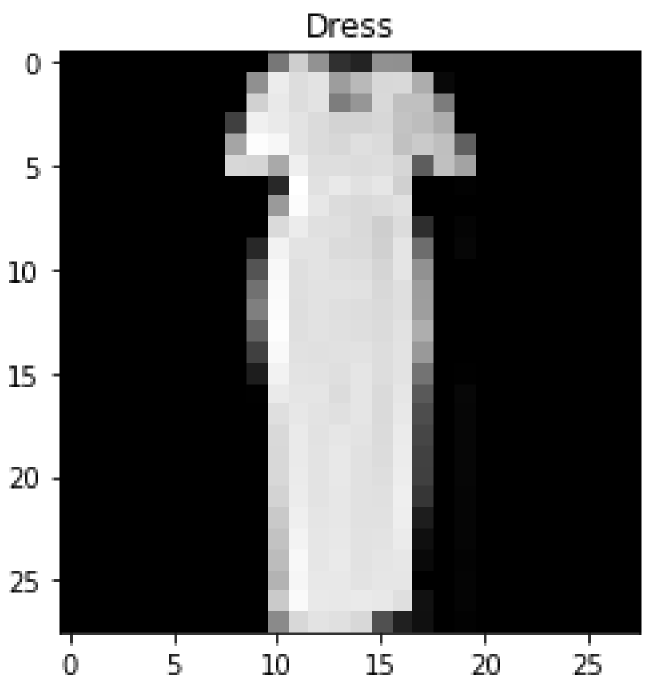
[62]:
```
def make_predictions(model: torch.nn.Module,
                     data: list,
                     device: torch.device = device):
  pred_probs = []
  model.to(device)
  model.eval()
  with torch.inference_mode():
    for sample in data:
      # Prepare the sample (add a batch dimension and pass to target device)
      sample = torch.unsqueeze(sample, dim=0).to(device)

      # Forward pass (model outputs raw logits)
      pred_logit = model(sample)

      # Get prediction probability (logit -> prediction probability)
      pred_prob = torch.softmax(pred_logit.squeeze(), dim=0)

      # Get pred_prob off the GPU for further calculations
      pred_probs.append(pred_prob.cpu())

  # Stack the pred_probs to turn list into a tensor
  return torch.stack(pred_probs)
```

[63]:
```
import random
# random.seed(42)
test_samples = []
test_labels = []
for sample, label in random.sample(list(test_data), k=9):
  test_samples.append(sample)
  test_labels.append(label)

# View the first sample shape
test_samples[0].shape
```

[63]: torch.Size([1, 28, 28])

[64]:
```
plt.imshow(test_samples[0].squeeze(), cmap="gray")
plt.title(class_names[test_labels[0]])
```

[64]: Text(0.5, 1.0, 'Dress')



[65]:
```
# Make predictions
pred_probs = make_predictions(model=model_2,
                              data=test_samples)

# View first two prediction probabilities
pred_probs[:2]
```

[65]: tensor([[1.2333e-03, 3.3934e-03, 4.5061e-05, 9.8818e-01, 6.3306e-03, 7.6291e-06,
          3.1144e-04, 3.5785e-04, 7.5017e-05, 6.2114e-05],
         [1.6455e-03, 2.8294e-05, 9.6235e-01, 2.9167e-04, 1.0726e-03, 3.6521e-06,
          3.4579e-02, 1.1791e-06, 2.2558e-05, 6.7034e-06]])

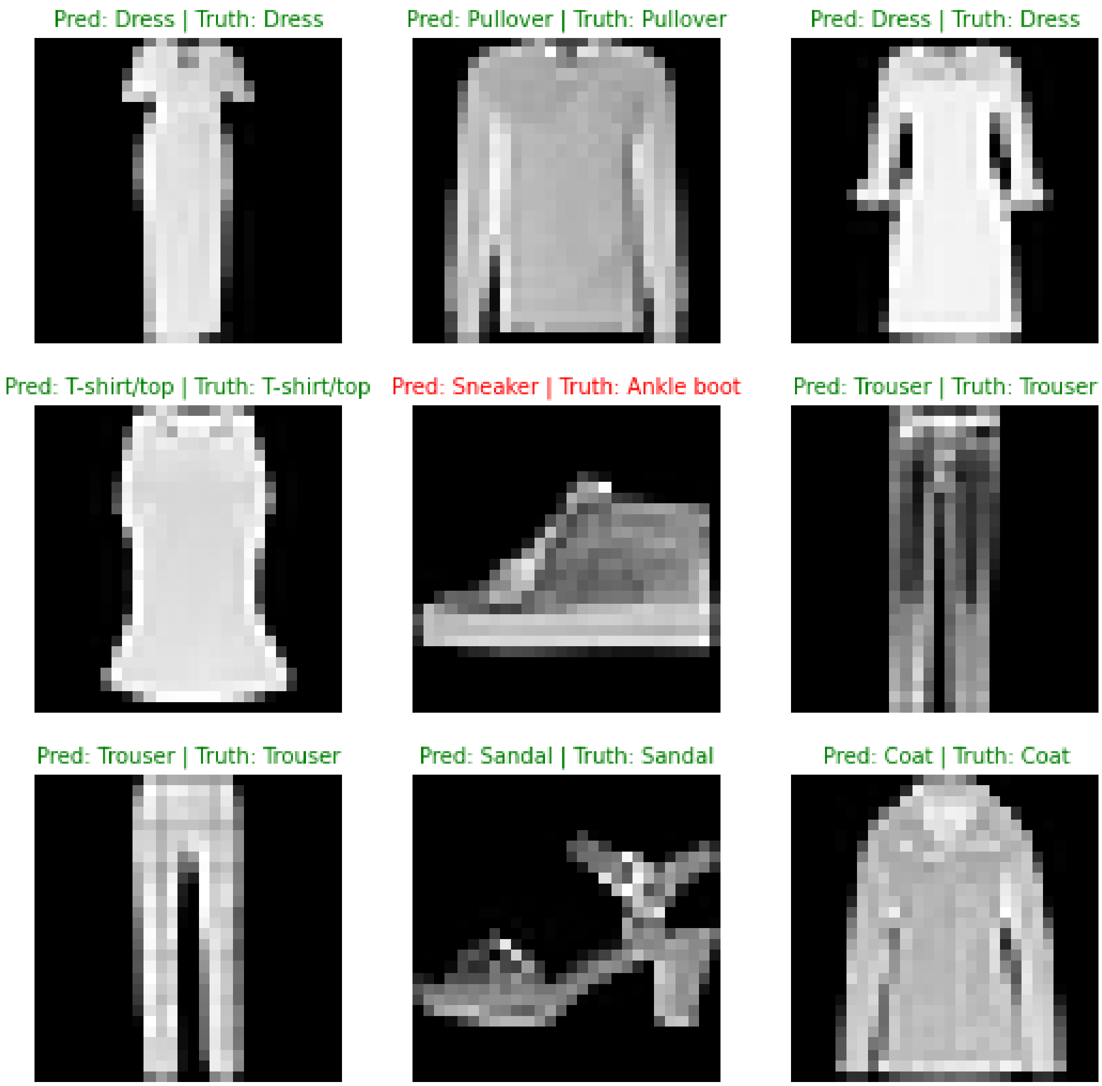
[66]:
```
# Convert prediction probabilities to labels
pred_classes = pred_probs.argmax(dim=1)
pred_classes
```

[66]: tensor([3, 2, 3, 0, 7, 1, 1, 5, 4])

[67]:
```
test_labels
```

[67]: [3, 2, 3, 0, 9, 1, 1, 5, 4]

[68]:
```
# Plot predictions
plt.figure(figsize=(9, 9))
nrows = 3
ncols = 3
for i, sample in enumerate(test_samples):
  # Create subplot
  plt.subplot(nrows, ncols, i+1)

  # Plot the target image
  plt.imshow(sample.squeeze(), cmap="gray")

  # Find the prediction (in text form, e.g "Sandal")
  pred_label = class_names[pred_classes[i]]

  # Get the truth label (in text form)
  truth_label = class_names[test_labels[i]]

  # Create a title for the plot
  title_text = f"Pred: {pred_label} | Truth: {truth_label}"

  # Check for equality between pred and truth and change color of title text
  if pred_label == truth_label:
    plt.title(title_text, fontsize=10, c="g") # green text if prediction same␣
↪as truth
  else:
    plt.title(title_text, fontsize=10, c="r")

  plt.axis(False);
```



1.11 10. Making a confusion matrix for further prediction evaluation

A confusion matrix is a fantastic way of evaluating your classification models visually: https://www.learnpytorch.io/02_pytorch_classification/#9-more-classification-evaluation-metrics

1. Make predictions with our trained model on the test dataset
2. Make a confusion matrix `torchmetrics.ConfusionMatrix` - https://torchmetrics.readthedocs.io/en/stable/classification/confusion_matrix.html
3. Plot the confusion matrix using `mlxtend.plotting.plot_confusion_matrix()` - http://rasbt.github.io/mlxtend/user_guide/plotting/plot_confusion_matrix/

[69]:
```
# Import tqdm.auto
from tqdm.auto import tqdm
```

```python
# 1. Make predictions with trained model
y_preds = []
model_2.eval()
with torch.inference_mode():
  for X, y in tqdm(test_dataloader, desc="Making predictions..."):
    # Send the data and targets to target device
    X, y = X.to(device), y.to(device)
    # Do the forward pass
    y_logit = model_2(X)
    # Turn predictions from logits -> prediction probabilities -> prediction␣
↪labels
    y_pred = torch.softmax(y_logit.squeeze(), dim=0).argmax(dim=1)
    # Put prediction on CPU for evaluation
    y_preds.append(y_pred.cpu())

# Concatenate list of predictions into a tensor
# print(y_preds)
y_pred_tensor = torch.cat(y_preds)
y_pred_tensor
```

```
Making predictions…:   0%|          | 0/313 [00:00<?, ?it/s]
```

[69]:
```
tensor([9, 2, 1,  …, 8, 1, 2])
```

[70]:
```python
len(y_pred_tensor)
```

[70]:
```
10000
```

[71]:
```python
# See if required packages are installed and if not, install them...
try:
  import torchmetrics, mlxtend
  print(f"mlxtend version: {mlxtend.__version__}")
  assert int(mlxtend.__version__.split(".")[1]) >= 19, "mlxtend version should␣
↪be 0.19.0 or higher")
except:
  !pip install torchmetrics -U mlxtend
  import torchmetrics, mlxtend
  print(f"mlxtend version: {mlxtend.__version__}")
```

```
mlxtend version: 0.19.0
Requirement already satisfied: torchmetrics in /usr/local/lib/python3.7/dist-
packages (0.8.0)
Requirement already satisfied: mlxtend in /usr/local/lib/python3.7/dist-packages
(0.19.0)
Requirement already satisfied: packaging in /usr/local/lib/python3.7/dist-
packages (from torchmetrics) (21.3)
```

```
Requirement already satisfied: pyDeprecate==0.3.* in
/usr/local/lib/python3.7/dist-packages (from torchmetrics) (0.3.2)
Requirement already satisfied: torch>=1.3.1 in /usr/local/lib/python3.7/dist-
packages (from torchmetrics) (1.10.0+cu111)
Requirement already satisfied: numpy>=1.17.2 in /usr/local/lib/python3.7/dist-
packages (from torchmetrics) (1.21.6)
Requirement already satisfied: typing-extensions in
/usr/local/lib/python3.7/dist-packages (from torch>=1.3.1->torchmetrics) (4.1.1)
Requirement already satisfied: matplotlib>=3.0.0 in
/usr/local/lib/python3.7/dist-packages (from mlxtend) (3.2.2)
Requirement already satisfied: scikit-learn>=0.20.3 in
/usr/local/lib/python3.7/dist-packages (from mlxtend) (1.0.2)
Requirement already satisfied: joblib>=0.13.2 in /usr/local/lib/python3.7/dist-
packages (from mlxtend) (1.1.0)
Requirement already satisfied: scipy>=1.2.1 in /usr/local/lib/python3.7/dist-
packages (from mlxtend) (1.4.1)
Requirement already satisfied: pandas>=0.24.2 in /usr/local/lib/python3.7/dist-
packages (from mlxtend) (1.3.5)
Requirement already satisfied: setuptools in /usr/local/lib/python3.7/dist-
packages (from mlxtend) (57.4.0)
Requirement already satisfied: cycler>=0.10 in /usr/local/lib/python3.7/dist-
packages (from matplotlib>=3.0.0->mlxtend) (0.11.0)
Requirement already satisfied: kiwisolver>=1.0.1 in
/usr/local/lib/python3.7/dist-packages (from matplotlib>=3.0.0->mlxtend) (1.4.2)
Requirement already satisfied: python-dateutil>=2.1 in
/usr/local/lib/python3.7/dist-packages (from matplotlib>=3.0.0->mlxtend) (2.8.2)
Requirement already satisfied: pyparsing!=2.0.4,!=2.1.2,!=2.1.6,>=2.0.1 in
/usr/local/lib/python3.7/dist-packages (from matplotlib>=3.0.0->mlxtend) (3.0.8)
Requirement already satisfied: pytz>=2017.3 in /usr/local/lib/python3.7/dist-
packages (from pandas>=0.24.2->mlxtend) (2022.1)
Requirement already satisfied: six>=1.5 in /usr/local/lib/python3.7/dist-
packages (from python-dateutil>=2.1->matplotlib>=3.0.0->mlxtend) (1.15.0)
Requirement already satisfied: threadpoolctl>=2.0.0 in
/usr/local/lib/python3.7/dist-packages (from scikit-learn>=0.20.3->mlxtend)
(3.1.0)
mlxtend version: 0.19.0
```

[78]:
```
import mlxtend
print(mlxtend.__version__)
```

```
0.19.0
```

[79]:
```
class_names
```

[79]:
```
['T-shirt/top',
 'Trouser',
 'Pullover',
```

```
 'Dress',
 'Coat',
 'Sandal',
 'Shirt',
 'Sneaker',
 'Bag',
 'Ankle boot']
```

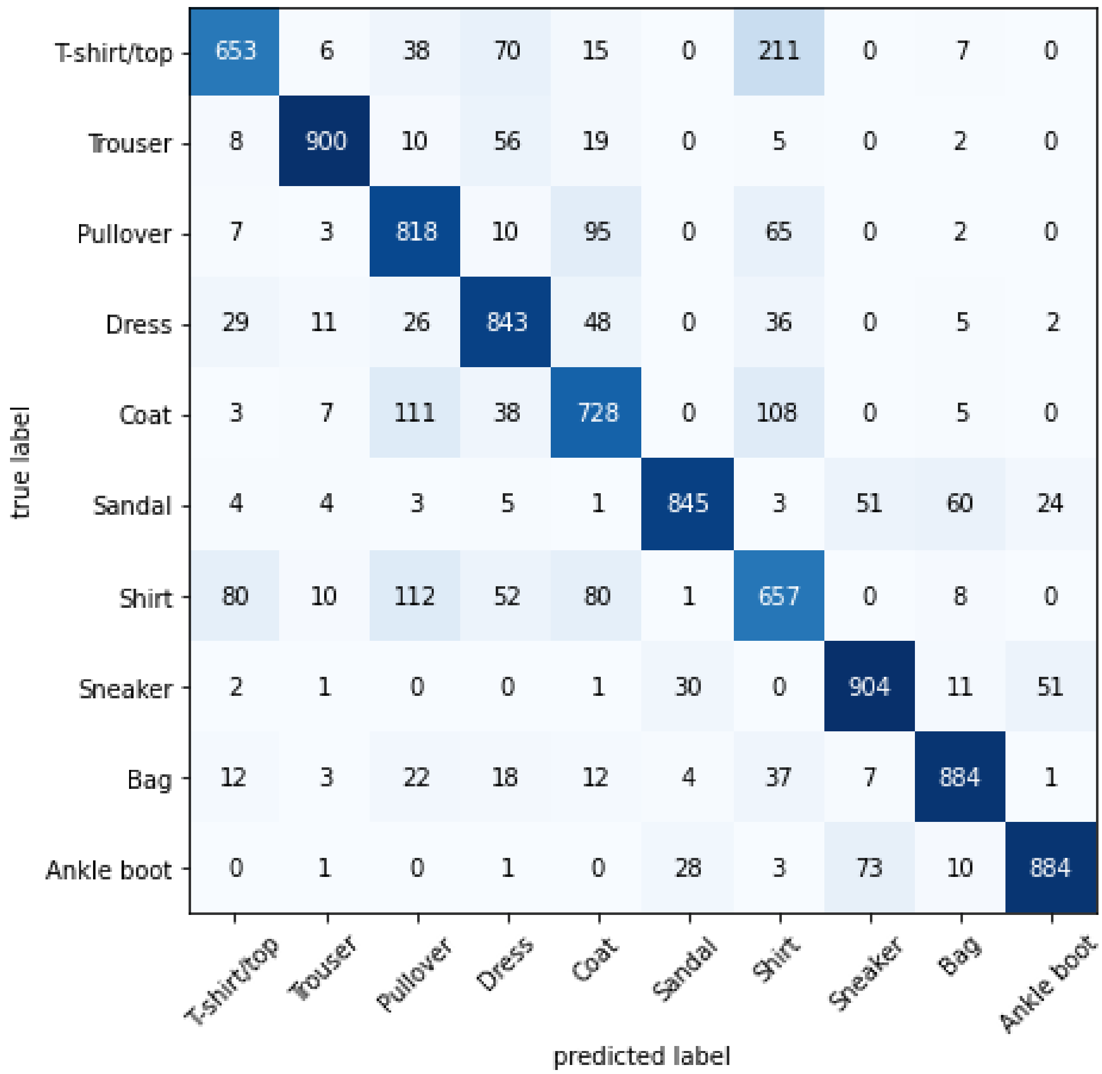
[80]:
```
y_pred_tensor[:10]
```

[80]:
```
tensor([9, 2, 1, 1, 6, 1, 4, 6, 5, 7])
```

[82]:
```
test_data.targets
```

[82]:
```
tensor([9, 2, 1,  …, 8, 1, 5])
```

[85]:
```
from torchmetrics import ConfusionMatrix
from mlxtend.plotting import plot_confusion_matrix

# 2. Setup confusion instance and compare predictions to targets
confmat = ConfusionMatrix(num_classes=len(class_names))
confmat_tensor = confmat(preds=y_pred_tensor,
                         target=test_data.targets)

# 3. Plot the confusion matrix
fig, ax = plot_confusion_matrix(
    conf_mat=confmat_tensor.numpy(), # matplotlib likes working with numpy
    class_names=class_names,
    figsize=(10, 7)
)
```



1.12 11. Save and load best performing model

[88]:
```
from pathlib import Path

# Create model dictory path
MODEL_PATH = Path("models")
MODEL_PATH.mkdir(parents=True,
                 exist_ok=True)

# Create model save
MODEL_NAME = "03_pytorch_computer_vision_model_2.pth"
MODEL_SAVE_PATH = MODEL_PATH / MODEL_NAME
```

```python
# Save the model state dict
print(f"Saving model to: {MODEL_SAVE_PATH}")
torch.save(obj=model_2.state_dict(),
           f=MODEL_SAVE_PATH)
```

```
Saving model to: models/03_pytorch_computer_vision_model_2.pth
```

[90]:
```python
image_shape = [1, 28, 28]
```

[91]:
```python
# Create a new instance
torch.manual_seed(42)

loaded_model_2 = FashionMNISTModelV2(input_shape=1,
                                     hidden_units=10,
                                     output_shape=len(class_names))

# Load in the save state_dict()
loaded_model_2.load_state_dict(torch.load(f=MODEL_SAVE_PATH))

# Send the model to the target device
loaded_model_2.to(device)
```

[91]:
```
FashionMNISTModelV2(
  (conv_block_1): Sequential(
    (0): Conv2d(1, 10, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (1): ReLU()
    (2): Conv2d(10, 10, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (3): ReLU()
    (4): MaxPool2d(kernel_size=2, stride=2, padding=0, dilation=1,
ceil_mode=False)
  )
  (conv_block_2): Sequential(
    (0): Conv2d(10, 10, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (1): ReLU()
    (2): Conv2d(10, 10, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (3): ReLU()
    (4): MaxPool2d(kernel_size=2, stride=2, padding=0, dilation=1,
ceil_mode=False)
  )
  (classifier): Sequential(
    (0): Flatten(start_dim=1, end_dim=-1)
    (1): Linear(in_features=490, out_features=10, bias=True)
  )
)
```

[93]:
```python
# Evaluate loaded model
torch.manual_seed(42)
```

```
loaded_model_2_results = eval_model(
    model=loaded_model_2,
    data_loader=test_dataloader,
    loss_fn=loss_fn,
    accuracy_fn=accuracy_fn
)

loaded_model_2_results
```

```
  0%|          | 0/313 [00:00<?, ?it/s]
```

[93]:
```
{'model_acc': 88.56829073482429,
 'model_loss': 0.31358689069747925,
 'model_name': 'FashionMNISTModelV2'}
```

[92]:
```
model_2_results
```

[92]:
```
{'model_acc': 88.56829073482429,
 'model_loss': 0.31358689069747925,
 'model_name': 'FashionMNISTModelV2'}
```

[94]:
```
# Check if model results are close to each other
torch.isclose(torch.tensor(model_2_results["model_loss"]),
              torch.tensor(loaded_model_2_results["model_loss"]),
              atol=1e-02)
```

[94]:
```
tensor(True)
```

1.13 Exercises

- See here for exercises and extra-curriculum: https://www.learnpytorch.io/03_pytorch_computer_vision/#e

[ ]:
```

```