CNN_from_scratch.ipynb

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So, how are we going to proceed with this?

1. Getting a Dataset
2. Prepare DataLoader
3. Model 0: Build a baseline model

[1]

```python
# Import PyTorch
import torch
from torch import nn

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

# Import matplotlib for visualization
import matplotlib.pyplot as plt
```

1. Getting a Dataset

We need a dataset to work with. We're going to start with FashionMNIST.

MNIST stands for Modified National Institute of Standards and Technology.

[2] 8s

```python
train_data = datasets.FashionMNIST(
    root = "data",  # where to download data to?
    train = True,   # get training data
    download = True, # download the data if it doesn't already exists
    transform = ToTensor(),
    target_transform = None
)

test_data = datasets.FashionMNIST(
    root = "data",
    train = False,
    download = True,
    transform = ToTensor()
)
```

```
100%|██████████| 26.4M/26.4M [00:02<00:00, 9.44MB/s]
100%|██████████| 29.5k/29.5k [00:00<00:00, 139kB/s]
100%|██████████| 4.42M/4.42M [00:01<00:00, 2.62MB/s]
100%|██████████| 5.15k/5.15k [00:00<00:00, 1.67MB/s]
```

0s

```python
# See first training sample
image, label = train_data[0]
image, label
```

```
(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,
```

1.1 Input and output shapes of a computer vision model

```
[4]  1 image.shape # [color_channels=1, height=28, width=28]
```

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

```
[5]  1 len(train_data.data), len(test_data.data)  # we have 60000 training data and 10000 testing data
```

```
(60000, 10000)
```

```
[6]  1 # checking diff classes
     2
     3 class_names = train_data.classes
     4 class_names
```

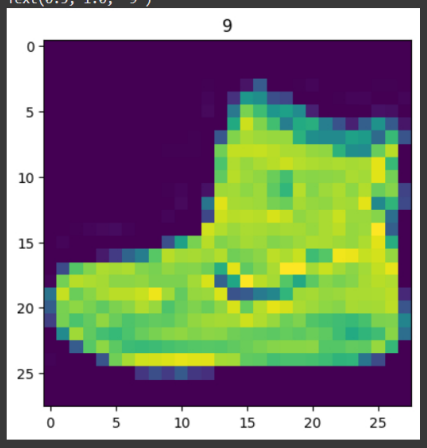
```
['T-shirt/top',
 'Trouser',
 'Pullover',
 'Dress',
 'Coat',
 'Sandal',
 'Shirt',
 'Sneaker',
 'Bag',
 'Ankle boot']
```

```
[ ]  1 ## we're working with 10 different classes, it means our problem is multi-class classification.
```

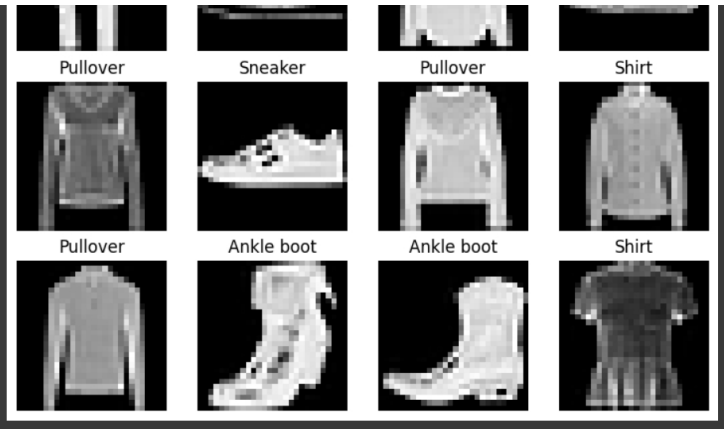
1.2 Visualizing our data

```
[8]  1 image, label = train_data[0]
     2 print(f"Image Size: {image.shape}")
     3 plt.imshow(image.squeeze())
     4 plt.title(label)
```

```
Image Size: torch.Size([1, 28, 28])
Text(0.5, 1.0, '9')
```




```
[9]  1 # plot more images
     2
     3 torch.manual_seed(42)
     4 fig = plt.figure(figsize=(9, 9))
     5 rows, cols = 4, 4
     6
     7 for i in range (1, rows*cols + 1):
     8   random_idx = torch.randint(0, len(train_data), size=[1]).item()
     9   image, label = train_data[random_idx]
    10   fig.add_subplot(rows, cols, i)
    11   plt.imshow(image.squeeze(), cmap="gray")
    12   plt.title(class_names[label])
    13   plt.axis(False)
```



2. Prepare DataLoader

It helps load data into a model. For training and for inference.

It turns a large Dataset into a Python iterable of smaller chunks. These smaller chunks are called batches or mini-batches and can be set by the batch_size parameter.

[10]
```python
from torch.utils.data import DataLoader

# set the batch_size hyper parameter
BATCH_SIZE = 32

# turn datasets into iterables
train_dataloader = DataLoader(train_data,  # data you want to turn into iterables
                              batch_size = BATCH_SIZE,
                              shuffle = True)  # shuffle data every epoch

test_dataloader = DataLoader(test_data,
                             batch_size = BATCH_SIZE,
                             shuffle = False) # we dont necessarily have to shuffle the testing data
```

[11]
```python
len(train_dataloader), len(test_dataloader)
```

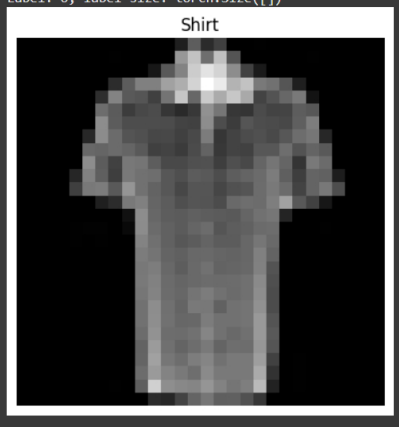
```
(1875, 313)
```

[12]
```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
```

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

[13]
```python
## And we can see that the data remains unchanged by checking a single sample.

# 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("Off");
print(f"Image size: {img.shape}")
print(f"Label: {label}, label size: {label.shape}")
```

```
Image size: torch.Size([1, 28, 28])
Label: 6, label size: torch.Size([])
```



3. Model 0: Build a baseline model

[14]
```python
# create a flatten layer
flatten_model = nn.Flatten() # nn.Flatten() compresses the dimensions of a tensor into a single vector

# get a single sample
x = train_features_batch[0]
```

```
# flatten the sample
output = flatten_model(x)

# lets see now
print(f"Shape before flattening: {x.shape}")
print(f"Shape after flattening: {output.shape}")
```

```
Shape before flattening: torch.Size([1, 28, 28])
Shape after flattening: torch.Size([1, 784])
```

Why do this?

Why do this?

Because we've now turned our pixel data from height and width dimensions into one long feature vector.

And nn.Linear() layers like their inputs to be in the form of feature vectors.

[15]
```
from torch import nn
class FashionMNISTModelV0(nn.Module):
    def __init__(self, input_shape: int, hidden_units: int, output_shape: int): # takes 3 args
        super().__init__()
        self.layer_stack = nn.Sequential(
            nn.Flatten(), # neural networks like their inputs in vector form
            nn.Linear(in_features=input_shape, out_features=hidden_units), # in_features = number of features in a data sample (784 pixels)
            nn.Linear(in_features=hidden_units, out_features=output_shape)
        )

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

torch.manual_seed(42)

# Need to setup model with input parameters
model_0 = FashionMNISTModelV0(input_shape=784, # one for every pixel (28x28)
    hidden_units=10, # how many units in the hidden layer
    output_shape=len(class_names) # one for every class
)
model_0.to("cpu") # keep model on CPU to begin with
```

```
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)
  )
)
```

3.1 Setup loss, optimizer and evaluation metrics

[16]
```
import requests
from pathlib import Path

# Download helper functions from Learn PyTorch repo (if not already downloaded)
if Path("helper_functions.py").is_file():
  print("helper_functions.py already exists, skipping download")
else:
  print("Downloading helper_functions.py")
  # Note: you need the "raw" GitHub URL for this to work
  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)
```

```
Downloading helper_functions.py
```

[17]
```
# Import accuracy metric
from helper_functions import accuracy_fn # Note: could also use torchmetrics.Accuracy(task = 'multiclass', num_classes=len(class_names)).to(device)

# Setup loss function and optimizer
loss_fn = nn.CrossEntropyLoss() # this is also called "criterion"/"cost function" in some places
optimizer = torch.optim.SGD(params=model_0.parameters(), lr=0.1)
```

3.2 Creating a function to time our experiments

[18]
```
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.

    Args:
        start (float): Start time of computation (preferred in timeit format).
        end (float): End time of computation.
        device ([type], optional): Device that compute is running on. Defaults to None.

    Returns:
        float: time between start and end in seconds (higher is longer).
    """
    total_time = end - start
    print(f"Train time on {device}: {total_time:.3f} seconds")
    return total_time
```

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

Let's step through it:

- Loop through epochs.
- Loop through training batches, perform training steps, calculate the train - loss per batch

- Loop through testing batches, perform testing steps, calculate the test loss per batch.
- Print out what's happening.
- Time it all (for fun).

[19]

```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 times)
epochs = 3

# Create training and testing loop
for epoch in tqdm(range(epochs)):
    print(f"Epoch: {epoch}\n-------")
    ### Training
    train_loss = 0
    # Add a loop to loop through 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 # accumulatively add up the loss per epoch

        # 3. Optimizer zero grad
        optimizer.zero_grad()

        # 4. Loss backward
        loss.backward()

        # 5. Optimizer step
        optimizer.step()

        # Print out how many samples have been seen
        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 (average loss per batch per epoch)
    train_loss /= len(train_dataloader)

    ### Testing
    # Setup variables for accumulatively adding up loss and accuracy
    test_loss, test_acc = 0, 0
    model_0.eval()
    with torch.inference_mode():
        for X, y in test_dataloader:
            # 1. Forward pass
            test_pred = model_0(X)

            # 2. Calculate loss (accumulatively)
            test_loss += loss_fn(test_pred, y) # accumulatively add up the loss per epoch

            # 3. Calculate accuracy (preds need to be same as y_true)
            test_acc += accuracy_fn(y_true=y, y_pred=test_pred.argmax(dim=1))

        # Calculations on test metrics need to happen inside torch.inference_mode()
        # Divide total test loss by length of test dataloader (per batch)
        test_loss /= len(test_dataloader)

        # Divide total accuracy by length of test dataloader (per batch)
        test_acc /= len(test_dataloader)

    ## Print out what's happening
    print(f"\nTrain loss: {train_loss:.5f} | Test loss: {test_loss:.5f}, Test acc: {test_acc:.2f}%\n")

# 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))
```

```
100% 3/3 [00:28<00:00, 9.49s/it]
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: 0.59039 | Test loss: 0.50954, Test acc: 82.04%

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: 0.47633 | Test loss: 0.47989, Test acc: 83.20%

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: 0.45503 | Test loss: 0.47664, Test acc: 83.43%
```

```
Train time on cpu: 28.527 seconds
```

4. Make predictions and get Model 0 results

```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.

    Args:
        model (torch.nn.Module): A PyTorch model capable of making predictions on data_loader.
        data_loader (torch.utils.data.DataLoader): The target dataset to predict on.
        loss_fn (torch.nn.Module): The loss function of model.
        accuracy_fn: An accuracy function to compare the models predictions to the truth labels.

    Returns:
        (dict): Results of model making predictions on data_loader.
    """
    loss, acc = 0, 0
    model.eval()
    with torch.inference_mode():
        for X, y in data_loader:
            # Make predictions with the model
            y_pred = model(X)

            # Accumulate the loss and accuracy values per batch
            loss += loss_fn(y_pred, y)
            acc += accuracy_fn(y_true=y,
                               y_pred=y_pred.argmax(dim=1)) # For accuracy, need the prediction labels (logits -> pred_prob -> pred_labels)

        # 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
```

```
{'model_name': 'FashionMNISTModelV0',
 'model_loss': 0.4766389429569244,
 'model_acc': 83.42651757188499}
```

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

```python
# Setup device agnostic code
import torch
device = "cuda" if torch.cuda.is_available() else "cpu"
device
```

```
'cpu'
```

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

```python
# 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 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)
```

```python
torch.manual_seed(42)
model_1 = FashionMNISTModelV1(input_shape=784, # number of input features
    hidden_units=10,
    output_shape=len(class_names) # number of output classes desired
).to(device) # send model to GPU if it's available
next(model_1.parameters()).device # check model device
```

```
device(type='cpu')
```

6.1 Setup loss, optimizer and evaluation metrics

```python
from helper_functions import accuracy_fn
loss_fn = nn.CrossEntropyLoss()
optimizer = torch.optim.SGD(params=model_1.parameters(),
                            lr=0.1)
```

6.2 Functionizing training and test loops

[25]

```python
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):
    train_loss, train_acc = 0, 0
    model.to(device)
    for batch, (X, y) in enumerate(data_loader):
        # Send data to GPU
        X, y = X.to(device), y.to(device)

        # 1. Forward pass
        y_pred = model(X)

        # 2. Calculate loss
        loss = loss_fn(y_pred, y)
        train_loss += loss
        train_acc += accuracy_fn(y_true=y,
                                 y_pred=y_pred.argmax(dim=1)) # Go from logits -> pred labels

        # 3. Optimizer zero grad
        optimizer.zero_grad()

        # 4. Loss backward
        loss.backward()

        # 5. Optimizer step
        optimizer.step()

    # Calculate loss and accuracy per epoch and print out what's happening
    train_loss /= len(data_loader)
    train_acc /= len(data_loader)
    print(f"Train loss: {train_loss:.5f} | Train accuracy: {train_acc:.2f}%")

def test_step(data_loader: torch.utils.data.DataLoader,
              model: torch.nn.Module,
              loss_fn: torch.nn.Module,
              accuracy_fn,
              device: torch.device = device):
    test_loss, test_acc = 0, 0
    model.to(device)
    model.eval() # put model in eval mode
    # Turn on inference context manager
    with torch.inference_mode():
        for X, y in data_loader:
            # Send data to GPU
            X, y = X.to(device), y.to(device)

            # 1. Forward pass
            test_pred = model(X)

            # 2. Calculate loss and accuracy
            test_loss += loss_fn(test_pred, y)
            test_acc += accuracy_fn(y_true=y,
                y_pred=test_pred.argmax(dim=1) # Go from logits -> pred labels
            )

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

[26] 28s

```python
torch.manual_seed(42)

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

epochs = 3
for epoch in tqdm(range(epochs)):
    print(f"Epoch: {epoch}\n---------")
    train_step(data_loader=train_dataloader,
        model=model_1,
        loss_fn=loss_fn,
        optimizer=optimizer,
        accuracy_fn=accuracy_fn
    )
    test_step(data_loader=test_dataloader,
        model=model_1,
        loss_fn=loss_fn,
        accuracy_fn=accuracy_fn
    )

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)
```

```
100% 3/3 [00:28<00:00,  9.37s/it]
Epoch: 0
---------
Train loss: 1.09199 | Train accuracy: 61.34%
Test loss: 0.95636 | Test accuracy: 65.00%

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

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

```
Train time on cpu: 28.042 seconds
```

[32]
```python
torch.manual_seed(42)

# Note: This will error due to `eval_model()` not using device agnostic code
model_1_results = eval_model(model=model_1,
    data_loader=test_dataloader,
    loss_fn=loss_fn,
    accuracy_fn=accuracy_fn)
model_1_results
```

```
{'model_name': 'FashionMNISTModelV1',
 'model_loss': 0.685000956058502,
 'model_acc': 75.0199680511182}
```

7. Model 2: Building a Convolutional Neural Network (CNN)

[27]
```python
# Create a convolutional neural network
class FashionMNISTModelV2(nn.Module):
    """
    Model architecture copying TinyVGG from:
    https://poloclub.github.io/cnn-explainer/
    """
    def __init__(self, input_shape: int, hidden_units: int, output_shape: int):
        super().__init__()
        self.block_1 = nn.Sequential(
            nn.Conv2d(in_channels=input_shape,
                      out_channels=hidden_units,
                      kernel_size=3, # how big is the square that's going over the image?
                      stride=1, # default
                      padding=1),# options = "valid" (no padding) or "same" (output has same shape as input) or int for specific number
            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,
                         stride=2) # default stride value is same as kernel_size
        )
        self.block_2 = nn.Sequential(
            nn.Conv2d(hidden_units, hidden_units, 3, padding=1),
            nn.ReLU(),
            nn.Conv2d(hidden_units, hidden_units, 3, padding=1),
            nn.ReLU(),
            nn.MaxPool2d(2)
        )
        self.classifier = nn.Sequential(
            nn.Flatten(),
            # Where did this in_features shape come from?
            # It's because each layer of our network compresses and changes the shape of our input data.
            nn.Linear(in_features=hidden_units*7*7,
                      out_features=output_shape)
        )

    def forward(self, x: torch.Tensor):
        x = self.block_1(x)
        # print(x.shape)
        x = self.block_2(x)
        # print(x.shape)
        x = self.classifier(x)
        # print(x.shape)
        return x

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

```
FashionMNISTModelV2(
  (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)
  )
  (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)
  )
)
```

7.1 Setup a loss function and optimizer for model_2

[28]
```python
# Setup loss and optimizer
loss_fn = nn.CrossEntropyLoss()
optimizer = torch.optim.SGD(params=model_2.parameters(),
                            lr=0.1)
```

7.2 Training and testing model_2 using our training and test functions

[29]
```python
torch.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(data_loader=train_dataloader,
        model=model_2,
        loss_fn=loss_fn,
        optimizer=optimizer,
        accuracy_fn=accuracy_fn,
        device=device
    )
    test_step(data_loader=test_dataloader,
        model=model_2,
        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)
```

```
100% 3/3 [02:19<00:00, 46.34s/it]
Epoch: 0
---------
Train loss: 0.58653 | Train accuracy: 78.74%
Test loss: 0.39255 | Test accuracy: 86.04%

Epoch: 1
---------
Train loss: 0.36231 | Train accuracy: 86.89%
Test loss: 0.35723 | Test accuracy: 86.70%

Epoch: 2
---------
Train loss: 0.32485 | Train accuracy: 88.22%
Test loss: 0.32124 | Test accuracy: 88.02%

Train time on cpu: 139.285 seconds
```

[30]
```python
# Get model_2 results
model_2_results = eval_model(
    model=model_2,
    data_loader=test_dataloader,
    loss_fn=loss_fn,
    accuracy_fn=accuracy_fn
)
model_2_results
```

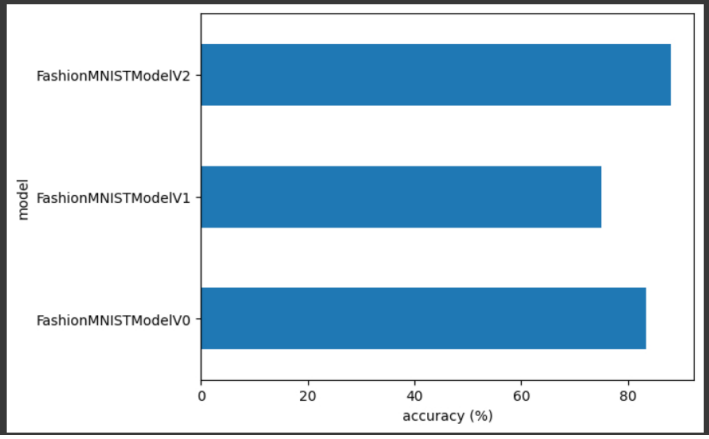
```
{'model_name': 'FashionMNISTModelV2',
 'model_loss': 0.321236508079529,
 'model_acc': 88.01916932907348}
```

8. Compare model results and training time

[33]
```python
import pandas as pd
compare_results = pd.DataFrame([model_0_results, model_1_results, model_2_results])
compare_results
```

	model_name	model_loss	model_acc
0	FashionMNISTModelV0	0.476639	83.426518
1	FashionMNISTModelV1	0.685001	75.019968
2	FashionMNISTModelV2	0.321237	88.019169

[34]
```python
# Visualize our model results
compare_results.set_index("model_name")["model_acc"].plot(kind="barh")
plt.xlabel("accuracy (%)")
plt.ylabel("model");
```



9. Make and evaluate random predictions with best model

[35]
```python
def make_predictions(model: torch.nn.Module, data: list, device: torch.device = device):
    pred_probs = []
    model.eval()
    with torch.inference_mode():
        for sample in data:
            # Prepare sample
            sample = torch.unsqueeze(sample, dim=0).to(device) # Add an extra dimension and send sample to device

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

            # Get prediction probability (logit -> prediction probability)
            pred_prob = torch.softmax(pred_logit.squeeze(), dim=0) # note: perform softmax on the "logits" dimension, not "batch" dimension (in this case we have a batch size of 1,

            # Get pred_prob off 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)
```

[36]
```python
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 test sample shape and label
print(f"Test sample image shape: {test_samples[0].shape}\nTest sample label: {test_labels[0]} ({class_names[test_labels[0]]})")
```

```
Test sample image shape: torch.Size([1, 28, 28])
Test sample label: 5 (Sandal)
```

[37]
```python
# Make predictions on test samples with model 2
pred_probs= make_predictions(model=model_2,
                             data=test_samples)

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

```
tensor([[1.7889e-07, 3.0100e-07, 7.4711e-08, 2.9112e-07, 4.0070e-08, 9.9988e-01,
         9.7217e-07, 1.5529e-05, 4.1133e-05, 6.1028e-05],
        [8.4885e-02, 5.9099e-01, 1.6154e-03, 1.5859e-01, 3.7294e-02, 1.3594e-04,
         1.2469e-01, 3.1763e-04, 1.2822e-03, 1.8921e-04]])
```

[38]
```python
# Make predictions on test samples with model 2
pred_probs= make_predictions(model=model_2,
                             data=test_samples)

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

```
tensor([[1.7889e-07, 3.0100e-07, 7.4711e-08, 2.9112e-07, 4.0070e-08, 9.9988e-01,
         9.7217e-07, 1.5529e-05, 4.1133e-05, 6.1028e-05],
        [8.4885e-02, 5.9099e-01, 1.6154e-03, 1.5859e-01, 3.7294e-02, 1.3594e-04,
         1.2469e-01, 3.1763e-04, 1.2822e-03, 1.8921e-04]])
```

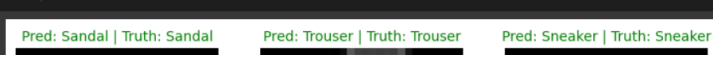
[39]
```python
# Turn the prediction probabilities into prediction labels by taking the argmax()
pred_classes = pred_probs.argmax(dim=1)
pred_classes
```

```
tensor([5, 1, 7, 4, 3, 0, 4, 7, 1])
```

[40]
```python
# Are our predictions in the same form as our test labels?
test_labels, pred_classes
```

```
([5, 1, 7, 4, 3, 0, 4, 7, 1], tensor([5, 1, 7, 4, 3, 0, 4, 7, 1]))
```

[41]
```python
# Plot predictions
plt.figure(figsize=(9, 9))
nrows = 3
ncols = 3
for i, sample in enumerate(test_samples):
  # Create a subplot
  plt.subplot(nrows, ncols, i+1)

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

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

  # Get the truth label (in text form, e.g. "T-shirt")
  truth_label = class_names[test_labels[i]]

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

  # Check for equality and change title colour accordingly
  if pred_label == truth_label:
      plt.title(title_text, fontsize=10, c="g") # green text if correct
  else:
      plt.title(title_text, fontsize=10, c="r") # red text if wrong
  plt.axis(False);
```



10. Making a confusion matrix for further prediction evaluation

[42]
```python
# Import tqdm for progress bar
from tqdm.auto import tqdm

# 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 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 -> predictions labels
    y_pred = torch.softmax(y_logit, dim=1).argmax(dim=1) # note: perform softmax on the "logits" dimension, not "batch" dimension (in this case we have a batch size of 32, so can p
    # Put predictions on CPU for evaluation
    y_preds.append(y_pred.cpu())
# Concatenate list of predictions into a tensor
y_pred_tensor = torch.cat(y_preds)
```

```
Making predictions: 100% 313/313 [00:03<00:00, 90.53it/s]
```

[43]
```python
# See if torchmetrics exists, if not, install it
try:
    import torchmetrics, mlxtend
    print(f"mlxtend version: {mlxtend.__version__}")
    assert int(mlxtend.__version__.split(".")[1]) >= 19, "mlxtend verison should be 0.19.0 or higher"
except:
    !pip install -q torchmetrics -U mlxtend # <- Note: If you're using Google Colab, this may require restarting the runtime
    import torchmetrics, mlxtend
    print(f"mlxtend version: {mlxtend.__version__}")
```

```
━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 962.6/962.6 kB 14.7 MB/s eta 0:00:00
━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 363.4/363.4 MB 4.5 MB/s eta 0:00:00
━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 13.8/13.8 MB 101.9 MB/s eta 0:00:00
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━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 664.8/664.8 MB 1.4 MB/s eta 0:00:00
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━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 56.3/56.3 MB 14.5 MB/s eta 0:00:00
━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 127.9/127.9 MB 7.8 MB/s eta 0:00:00
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━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 21.1/21.1 MB 86.7 MB/s eta 0:00:00
mlxtend version: 0.23.4
```
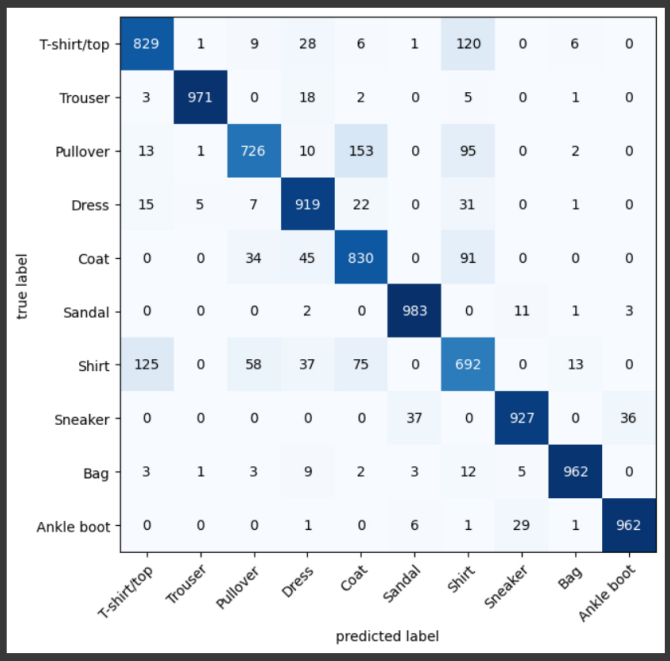

[44]
```python
# Import mlxtend upgraded version
import mlxtend
print(mlxtend.__version__)
assert int(mlxtend.__version__.split(".")[1]) >= 19 # should be version 0.19.0 or higher
```

```
0.23.4
```

[45]
```python
from torchmetrics import ConfusionMatrix
from mlxtend.plotting import plot_confusion_matrix

# 2. Setup confusion matrix instance and compare predictions to targets
confmat = ConfusionMatrix(num_classes=len(class_names), task='multiclass')
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, # turn the row and column labels into class names
```

```
    class_names=class_names, # turn the row and column labels into class names
    figsize=(10, 7)
);
```



[51]
```
!pip install nbstripout
```

```
Requirement already satisfied: nbstripout in /usr/local/lib/python3.11/dist-packages (0.8.1)
Requirement already satisfied: nbformat in /usr/local/lib/python3.11/dist-packages (from nbstripout) (5.10.4)
Requirement already satisfied: fastjsonschema>=2.15 in /usr/local/lib/python3.11/dist-packages (from nbformat->nbstripout) (2.21.1)
Requirement already satisfied: jsonschema>=2.6 in /usr/local/lib/python3.11/dist-packages (from nbformat->nbstripout) (4.24.0)
Requirement already satisfied: jupyter-core!=5.0.*,>=4.12 in /usr/local/lib/python3.11/dist-packages (from nbformat->nbstripout) (5.8.1)
Requirement already satisfied: traitlets>=5.1 in /usr/local/lib/python3.11/dist-packages (from nbformat->nbstripout) (5.7.1)
Requirement already satisfied: attrs>=22.2.0 in /usr/local/lib/python3.11/dist-packages (from jsonschema>=2.6->nbformat->nbstripout) (25.3.0)
Requirement already satisfied: jsonschema-specifications>=2023.03.6 in /usr/local/lib/python3.11/dist-packages (from jsonschema>=2.6->nbformat->nbstripout) (2025.4.1)
Requirement already satisfied: referencing>=0.28.4 in /usr/local/lib/python3.11/dist-packages (from jsonschema>=2.6->nbformat->nbstripout) (0.36.2)
Requirement already satisfied: rpds-py>=0.7.1 in /usr/local/lib/python3.11/dist-packages (from jsonschema>=2.6->nbformat->nbstripout) (0.25.1)
Requirement already satisfied: platformdirs>=2.5 in /usr/local/lib/python3.11/dist-packages (from jupyter-core!=5.0.*,>=4.12->nbformat->nbstripout) (4.3.8)
Requirement already satisfied: typing-extensions>=4.4.0 in /usr/local/lib/python3.11/dist-packages (from referencing>=0.28.4->jsonschema>=2.6->nbformat->nbstripout) (4.14.0)
```

[52]
```
!nbstripout your_notebook.ipynb
```

```
Could not strip 'your_notebook.ipynb': file not found
```

[53]
```
!nbstripout CNN_from_scratch.ipynb
```

```
Could not strip 'CNN_from_scratch.ipynb': file not found
```

[54]
```
!ls
```

```
data  helper_functions.py  __pycache__  sample_data
```

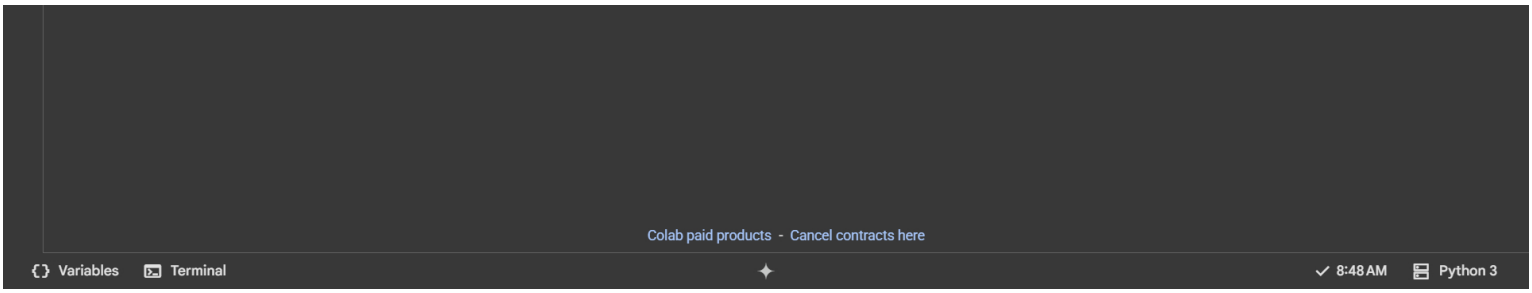
[55]
```
from pathlib import Path

# Create models directory (if it doesn't already exist), see: https://docs.python.org/3/library/pathlib.html#pathlib.Path.mkdir
MODEL_PATH = Path("models")
MODEL_PATH.mkdir(parents=True, # create parent directories if needed
                 exist_ok=True # if models directory already exists, don't error
)

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

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

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

[72]
```
Start coding or generate with AI.
```

```
Could not strip 'content/models/03_pytorch_computer_vision_model.ipynb': file not found
```

[ ]
```
Start coding or generate with AI.
```


Colab paid products - Cancel contracts here
Variables
Terminal
8:48 AM
Python 3