06-pytorch-transfer-learning-video

October 26, 2023

1 06. PyTorch Transfer Learning

What is transfer learning?

Transfer learning involves taking the parameters of what one model has learned on another dataset and applying to our own problem.

- Pretrained model = foundation models

[ ]:
```
import torch
import torchvision

print(torch.__version__) # want 1.12+
print(torchvision.__version__) # want 0.13+
```

```
1.13.0.dev20220624+cu113
0.14.0.dev20220624+cu113
```

[ ]:
```
# For this notebook to run with updated APIs, we need torch 1.12+ and␣
↪torchvision 0.13+
try:
    import torch
    import torchvision
    assert int(torch.__version__.split(".")[1]) >= 12, "torch version should be␣
↪1.12+"
    assert int(torchvision.__version__.split(".")[1]) >= 13, "torchvision␣
↪version should be 0.13+"
    print(f"torch version: {torch.__version__}")
    print(f"torchvision version: {torchvision.__version__}")
except:
    print(f"[INFO] torch/torchvision versions not as required, installing␣
↪nightly versions.")
    !pip3 install -U --pre torch torchvision --extra-index-url https://download.
↪pytorch.org/whl/nightly/cu113
    import torch
    import torchvision
    print(f"torch version: {torch.__version__}")
    print(f"torchvision version: {torchvision.__version__}")
```

```
torch version: 1.13.0.dev20220624+cu113
torchvision version: 0.14.0.dev20220624+cu113
```

Now we've got the versions of torch and torchvision, we're after, let's import the code we've written in previous sections so that we don't have to write it all again.

[4]:
```
# Continue with regular imports
import matplotlib.pyplot as plt
import torch
import torchvision

from torch import nn
from torchvision import transforms

# Try to get torchinfo, install it if it doesn't work
try:
    from torchinfo import summary
except:
    print("[INFO] Couldn't find torchinfo... installing it.")
    !pip install -q torchinfo
    from torchinfo import summary

# Try to import the going_modular directory, download it from GitHub if it␣
↪doesn't work
try:
    from going_modular.going_modular import data_setup, engine
except:
    # Get the going_modular scripts
    print("[INFO] Couldn't find going_modular scripts... downloading them from␣
↪GitHub.")
    !git clone https://github.com/mrdbourke/pytorch-deep-learning
    !mv pytorch-deep-learning/going_modular .
    !rm -rf pytorch-deep-learning
    from going_modular.going_modular import data_setup, engine
```

```
[INFO] Couldn't find going_modular scripts… downloading them from GitHub.
Cloning into 'pytorch-deep-learning'…
remote: Enumerating objects: 1964, done.
remote: Counting objects: 100% (217/217), done.
remote: Compressing objects: 100% (111/111), done.
remote: Total 1964 (delta 96), reused 207 (delta 94), pack-reused 1747
Receiving objects: 100% (1964/1964), 284.02 MiB | 13.81 MiB/s, done.
Resolving deltas: 100% (1084/1084), done.
Checking out files: 100% (143/143), done.
```

[5]:
```
# Setup device agnostic code
device = "cuda" if torch.cuda.is_available() else "cpu"
device
```

[5]: 'cuda'

1.1 1. Get data

We need our pizza, steak, sushi data to build a transfer learning model on.

[6]:
```
import os
import zipfile

from pathlib import Path

import requests

# Setup data path
data_path = Path("data/")
image_path = data_path / "pizza_steak_sushi" # images from a subset of classes␣
↪from the Food101 dataset

# If the image folder doesn't exist, download it and prepare it...
if image_path.is_dir():
  print(f"{image_path} directory exists, skipping re-download.")
else:
  print(f"Did not find {image_path}, downloading it...")
  image_path.mkdir(parents=True, exist_ok=True)

  # Download pizza, steak, sushi data
  with open(data_path / "pizza_steak_sushi.zip", "wb") as f:
    request = requests.get("https://github.com/mrdbourke/pytorch-deep-learning/
↪raw/main/data/pizza_steak_sushi.zip")
    print("Downloading pizza, steak, sushi data...")
    f.write(request.content)

  # unzip pizza, steak, sushi data
  with zipfile.ZipFile(data_path / "pizza_steak_sushi.zip", "r") as zip_ref:
    print("Unzipping pizza, steak, sushi data...")
    zip_ref.extractall(image_path)

  # Remove .zip file
  os.remove(data_path / "pizza_steak_sushi.zip")
```

```
Did not find data/pizza_steak_sushi, downloading it…
Downloading pizza, steak, sushi data…
Unzipping pizza, steak, sushi data…
```

[7]:
```
# Setup directory path
train_dir = image_path / "train"
test_dir = image_path / "test"
```

```
train_dir, test_dir
```

[7]:
```
(PosixPath('data/pizza_steak_sushi/train'),
 PosixPath('data/pizza_steak_sushi/test'))
```

1.2 2. Create Datasets and DataLoaders

Now we've got some data, want to turn it into PyTorch DataLoaders.

To do so, we can use `data_setup.py` and the `create_dataloaders()` function we made in 05. PyTorch Going Modular.

There's one thing we have to think about when loading: how to **transform** it?

And with `torchvision` 0.13+ there's two ways to do this:

1. Manually created transforms - you define what transforms you want your data to go through.
2. Automatically created transforms - the transforms for your data are defined by the model you'd like to use.

Important point: when using a pretrained model, it's important that the data (including your custom data) that you pass through it is **transformed** in the same way that the data the model was trained on.

1.2.1 2.1 Creating a transform for `torchvision.models` (manual creation)

`torchvision.models` contains pretrained models (models ready for transfer learning) right within `torchvision`.

> All pre-trained models expect input images normalized in the same way, i.e. mini-batches of 3-channel RGB images of shape (3 x H x W), where H and W are expected to be at least 224. The images have to be loaded in to a range of [0, 1] and then normalized using mean = [0.485, 0.456, 0.406] and std = [0.229, 0.224, 0.225]. You can use the following transform to normalize.

[8]:
```
from torchvision import transforms
normalize = transforms.Normalize(mean=[0.485, 0.456, 0.406],
                                 std=[0.229, 0.224, 0.225])

manual_transforms = transforms.Compose([
                                        transforms.Resize((224, 224)), # resize␣
 ↪image to 224, 224 (height x width)
                                        transforms.ToTensor(), # get images␣
 ↪into range [0, 1]
                                        normalize]) # make sure images have the␣
 ↪same distribution as ImageNet (where our pretrained models have been trained)
```

[9]:
```
from going_modular.going_modular import data_setup
```

```
train_dataloader, test_dataloader, class_names = data_setup.
 ↪create_dataloaders(train_dir=train_dir,
                                                                          ␣
 ↪test_dir=test_dir,
                                                                          ␣
 ↪transform=manual_transforms,
                                                                          ␣
 ↪batch_size=32)
train_dataloader, test_dataloader, class_names
```

[9]:
```
(<torch.utils.data.dataloader.DataLoader at 0x7f795b3aa850>,
 <torch.utils.data.dataloader.DataLoader at 0x7f795b354910>,
 ['pizza', 'steak', 'sushi'])
```

1.2.2 2.2 Creating a transform for `torchvision.models` (auto creation)

As of `torchvision` v0.13+ there is now support for automatic data transform creation based on the pretrained model weights you're using.

[10]:
```
import torchvision
torchvision.__version__
```

[10]:
```
'0.14.0.dev20220624+cu113'
```

[11]:
```
# Get a set of pretrained model weights
weights = torchvision.models.EfficientNet_B0_Weights.DEFAULT # "DEFAULT" = best␣
 ↪available weights
weights
```

[11]:
```
EfficientNet_B0_Weights.IMAGENET1K_V1
```

[12]:
```
# Get the transforms used to create our pretrained weights
auto_transforms = weights.transforms()
auto_transforms
```

[12]:
```
ImageClassification(
    crop_size=[224]
    resize_size=[256]
    mean=[0.485, 0.456, 0.406]
    std=[0.229, 0.224, 0.225]
    interpolation=InterpolationMode.BICUBIC
)
```

[13]:
```
# Create DataLoaders using automatic transforms
train_dataloader, test_dataloader, class_names = data_setup.
 ↪create_dataloaders(train_dir=train_dir,
```

```
↪test_dir=test_dir,
↪transform=auto_transforms,
↪batch_size=32)
train_dataloader, test_dataloader, class_names
```

[13]:
```
(<torch.utils.data.dataloader.DataLoader at 0x7f795af1ee50>,
 <torch.utils.data.dataloader.DataLoader at 0x7f795af1ef90>,
 ['pizza', 'steak', 'sushi'])
```

1.3 3. Getting a pretrained model

There are various places to get a pretrained model, such as: 1. PyTorch domain libraries 2. Libraries like `timm` (torch image models) 3. HuggingFace Hub (for plenty of different models) 4. Paperswithcode (for models across different problem spaces/domains)

1.3.1 3.1 Which pretrained model should you use?

Experiment, experiment, experiment!

The whole idea of transfer learning: take an already well-performing model from a problem space similar to your own and then customize to your own problem.

Three things to consider: 1. Speed - how fast does it need to run? 2. Size - how big is the model? 3. Performance - how well does it go on your chosen problem (e.g. how well does it classify food images? for FoodVision Mini)?

Where does the model live?

Is it on device? (like a self-driving car)

Or does it live on a server?

Looking at https://pytorch.org/vision/main/models.html#table-of-all-available-classification-weights

Which model should we chose?

For our case (deploying FoodVision Mini on a mobile device), it looks like EffNetB0 is one of our best options in terms performance vs size.

However, in light of The Bitter Lesson, if we had infinite compute, we'd likely pick the biggest model + most parameters + most general we could - http://www.incompleteideas.net/IncIdeas/BitterLesson.html

1.3.2 3.2 Setting up a pretrained model

Want to create an instance of a pretrained EffNetB0 - https://pytorch.org/vision/main/models/generated/torchvision.models.efficientnet_b0.html#torchvision.models.

[14]:
```python
# OLD method of creating a pretrained model (prior to torchvision v0.13)
# model = torchvision.models.efficientnet_b0(pretrained=True)

# New method of creating a pretrained model (torchvision v0.13+)
weights = torchvision.models.EfficientNet_B0_Weights.DEFAULT # ".DEFAULT" =
 ↪best available weights
model = torchvision.models.efficientnet_b0(weights=weights).to(device)
model
```

```
Downloading:
"https://download.pytorch.org/models/efficientnet_b0_rwightman-3dd342df.pth" to
/root/.cache/torch/hub/checkpoints/efficientnet_b0_rwightman-3dd342df.pth

  0%|          | 0.00/20.5M [00:00<?, ?B/s]
```

[14]:
```
EfficientNet(
  (features): Sequential(
    (0): Conv2dNormActivation(
      (0): Conv2d(3, 32, kernel_size=(3, 3), stride=(2, 2), padding=(1, 1),
bias=False)
      (1): BatchNorm2d(32, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
      (2): SiLU(inplace=True)
    )
    (1): Sequential(
      (0): MBConv(
        (block): Sequential(
          (0): Conv2dNormActivation(
            (0): Conv2d(32, 32, kernel_size=(3, 3), stride=(1, 1), padding=(1,
1), groups=32, bias=False)
            (1): BatchNorm2d(32, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
            (2): SiLU(inplace=True)
          )
          (1): SqueezeExcitation(
            (avgpool): AdaptiveAvgPool2d(output_size=1)
            (fc1): Conv2d(32, 8, kernel_size=(1, 1), stride=(1, 1))
            (fc2): Conv2d(8, 32, kernel_size=(1, 1), stride=(1, 1))
            (activation): SiLU(inplace=True)
            (scale_activation): Sigmoid()
          )
          (2): Conv2dNormActivation(
            (0): Conv2d(32, 16, kernel_size=(1, 1), stride=(1, 1), bias=False)
            (1): BatchNorm2d(16, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
          )
        )
        (stochastic_depth): StochasticDepth(p=0.0, mode=row)
```

```
      )
    )
    (2): Sequential(
      (0): MBConv(
        (block): Sequential(
          (0): Conv2dNormActivation(
            (0): Conv2d(16, 96, kernel_size=(1, 1), stride=(1, 1), bias=False)
            (1): BatchNorm2d(96, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
            (2): SiLU(inplace=True)
          )
          (1): Conv2dNormActivation(
            (0): Conv2d(96, 96, kernel_size=(3, 3), stride=(2, 2), padding=(1,
1), groups=96, bias=False)
            (1): BatchNorm2d(96, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
            (2): SiLU(inplace=True)
          )
          (2): SqueezeExcitation(
            (avgpool): AdaptiveAvgPool2d(output_size=1)
            (fc1): Conv2d(96, 4, kernel_size=(1, 1), stride=(1, 1))
            (fc2): Conv2d(4, 96, kernel_size=(1, 1), stride=(1, 1))
            (activation): SiLU(inplace=True)
            (scale_activation): Sigmoid()
          )
          (3): Conv2dNormActivation(
            (0): Conv2d(96, 24, kernel_size=(1, 1), stride=(1, 1), bias=False)
            (1): BatchNorm2d(24, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
          )
        )
        (stochastic_depth): StochasticDepth(p=0.0125, mode=row)
      )
      (1): MBConv(
        (block): Sequential(
          (0): Conv2dNormActivation(
            (0): Conv2d(24, 144, kernel_size=(1, 1), stride=(1, 1), bias=False)
            (1): BatchNorm2d(144, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
            (2): SiLU(inplace=True)
          )
          (1): Conv2dNormActivation(
            (0): Conv2d(144, 144, kernel_size=(3, 3), stride=(1, 1), padding=(1,
1), groups=144, bias=False)
            (1): BatchNorm2d(144, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
            (2): SiLU(inplace=True)
```

```
          )
          (2): SqueezeExcitation(
            (avgpool): AdaptiveAvgPool2d(output_size=1)
            (fc1): Conv2d(144, 6, kernel_size=(1, 1), stride=(1, 1))
            (fc2): Conv2d(6, 144, kernel_size=(1, 1), stride=(1, 1))
            (activation): SiLU(inplace=True)
            (scale_activation): Sigmoid()
          )
          (3): Conv2dNormActivation(
            (0): Conv2d(144, 24, kernel_size=(1, 1), stride=(1, 1), bias=False)
            (1): BatchNorm2d(24, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
          )
        )
        (stochastic_depth): StochasticDepth(p=0.025, mode=row)
      )
    )
    (3): Sequential(
      (0): MBConv(
        (block): Sequential(
          (0): Conv2dNormActivation(
            (0): Conv2d(24, 144, kernel_size=(1, 1), stride=(1, 1), bias=False)
            (1): BatchNorm2d(144, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
            (2): SiLU(inplace=True)
          )
          (1): Conv2dNormActivation(
            (0): Conv2d(144, 144, kernel_size=(5, 5), stride=(2, 2), padding=(2,
2), groups=144, bias=False)
            (1): BatchNorm2d(144, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
            (2): SiLU(inplace=True)
          )
          (2): SqueezeExcitation(
            (avgpool): AdaptiveAvgPool2d(output_size=1)
            (fc1): Conv2d(144, 6, kernel_size=(1, 1), stride=(1, 1))
            (fc2): Conv2d(6, 144, kernel_size=(1, 1), stride=(1, 1))
            (activation): SiLU(inplace=True)
            (scale_activation): Sigmoid()
          )
          (3): Conv2dNormActivation(
            (0): Conv2d(144, 40, kernel_size=(1, 1), stride=(1, 1), bias=False)
            (1): BatchNorm2d(40, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
          )
        )
        (stochastic_depth): StochasticDepth(p=0.037500000000000006, mode=row)
```

```
      )
      (1): MBConv(
        (block): Sequential(
          (0): Conv2dNormActivation(
            (0): Conv2d(40, 240, kernel_size=(1, 1), stride=(1, 1), bias=False)
            (1): BatchNorm2d(240, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
            (2): SiLU(inplace=True)
          )
          (1): Conv2dNormActivation(
            (0): Conv2d(240, 240, kernel_size=(5, 5), stride=(1, 1), padding=(2,
2), groups=240, bias=False)
            (1): BatchNorm2d(240, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
            (2): SiLU(inplace=True)
          )
          (2): SqueezeExcitation(
            (avgpool): AdaptiveAvgPool2d(output_size=1)
            (fc1): Conv2d(240, 10, kernel_size=(1, 1), stride=(1, 1))
            (fc2): Conv2d(10, 240, kernel_size=(1, 1), stride=(1, 1))
            (activation): SiLU(inplace=True)
            (scale_activation): Sigmoid()
          )
          (3): Conv2dNormActivation(
            (0): Conv2d(240, 40, kernel_size=(1, 1), stride=(1, 1), bias=False)
            (1): BatchNorm2d(40, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
          )
        )
        (stochastic_depth): StochasticDepth(p=0.05, mode=row)
      )
    )
    (4): Sequential(
      (0): MBConv(
        (block): Sequential(
          (0): Conv2dNormActivation(
            (0): Conv2d(40, 240, kernel_size=(1, 1), stride=(1, 1), bias=False)
            (1): BatchNorm2d(240, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
            (2): SiLU(inplace=True)
          )
          (1): Conv2dNormActivation(
            (0): Conv2d(240, 240, kernel_size=(3, 3), stride=(2, 2), padding=(1,
1), groups=240, bias=False)
            (1): BatchNorm2d(240, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
            (2): SiLU(inplace=True)
```

```
          )
          (2): SqueezeExcitation(
            (avgpool): AdaptiveAvgPool2d(output_size=1)
            (fc1): Conv2d(240, 10, kernel_size=(1, 1), stride=(1, 1))
            (fc2): Conv2d(10, 240, kernel_size=(1, 1), stride=(1, 1))
            (activation): SiLU(inplace=True)
            (scale_activation): Sigmoid()
          )
          (3): Conv2dNormActivation(
            (0): Conv2d(240, 80, kernel_size=(1, 1), stride=(1, 1), bias=False)
            (1): BatchNorm2d(80, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
          )
        )
        (stochastic_depth): StochasticDepth(p=0.0625, mode=row)
      )
      (1): MBConv(
        (block): Sequential(
          (0): Conv2dNormActivation(
            (0): Conv2d(80, 480, kernel_size=(1, 1), stride=(1, 1), bias=False)
            (1): BatchNorm2d(480, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
            (2): SiLU(inplace=True)
          )
          (1): Conv2dNormActivation(
            (0): Conv2d(480, 480, kernel_size=(3, 3), stride=(1, 1), padding=(1,
1), groups=480, bias=False)
            (1): BatchNorm2d(480, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
            (2): SiLU(inplace=True)
          )
          (2): SqueezeExcitation(
            (avgpool): AdaptiveAvgPool2d(output_size=1)
            (fc1): Conv2d(480, 20, kernel_size=(1, 1), stride=(1, 1))
            (fc2): Conv2d(20, 480, kernel_size=(1, 1), stride=(1, 1))
            (activation): SiLU(inplace=True)
            (scale_activation): Sigmoid()
          )
          (3): Conv2dNormActivation(
            (0): Conv2d(480, 80, kernel_size=(1, 1), stride=(1, 1), bias=False)
            (1): BatchNorm2d(80, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
          )
        )
        (stochastic_depth): StochasticDepth(p=0.07500000000000001, mode=row)
      )
      (2): MBConv(
```

```
        (block): Sequential(
          (0): Conv2dNormActivation(
            (0): Conv2d(80, 480, kernel_size=(1, 1), stride=(1, 1), bias=False)
            (1): BatchNorm2d(480, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
            (2): SiLU(inplace=True)
          )
          (1): Conv2dNormActivation(
            (0): Conv2d(480, 480, kernel_size=(3, 3), stride=(1, 1), padding=(1,
1), groups=480, bias=False)
            (1): BatchNorm2d(480, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
            (2): SiLU(inplace=True)
          )
          (2): SqueezeExcitation(
            (avgpool): AdaptiveAvgPool2d(output_size=1)
            (fc1): Conv2d(480, 20, kernel_size=(1, 1), stride=(1, 1))
            (fc2): Conv2d(20, 480, kernel_size=(1, 1), stride=(1, 1))
            (activation): SiLU(inplace=True)
            (scale_activation): Sigmoid()
          )
          (3): Conv2dNormActivation(
            (0): Conv2d(480, 80, kernel_size=(1, 1), stride=(1, 1), bias=False)
            (1): BatchNorm2d(80, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
          )
        )
        (stochastic_depth): StochasticDepth(p=0.08750000000000001, mode=row)
      )
    )
    (5): Sequential(
      (0): MBConv(
        (block): Sequential(
          (0): Conv2dNormActivation(
            (0): Conv2d(80, 480, kernel_size=(1, 1), stride=(1, 1), bias=False)
            (1): BatchNorm2d(480, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
            (2): SiLU(inplace=True)
          )
          (1): Conv2dNormActivation(
            (0): Conv2d(480, 480, kernel_size=(5, 5), stride=(1, 1), padding=(2,
2), groups=480, bias=False)
            (1): BatchNorm2d(480, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
            (2): SiLU(inplace=True)
          )
          (2): SqueezeExcitation(
```

```
            (avgpool): AdaptiveAvgPool2d(output_size=1)
            (fc1): Conv2d(480, 20, kernel_size=(1, 1), stride=(1, 1))
            (fc2): Conv2d(20, 480, kernel_size=(1, 1), stride=(1, 1))
            (activation): SiLU(inplace=True)
            (scale_activation): Sigmoid()
          )
          (3): Conv2dNormActivation(
            (0): Conv2d(480, 112, kernel_size=(1, 1), stride=(1, 1), bias=False)
            (1): BatchNorm2d(112, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
          )
        )
        (stochastic_depth): StochasticDepth(p=0.1, mode=row)
      )
      (1): MBConv(
        (block): Sequential(
          (0): Conv2dNormActivation(
            (0): Conv2d(112, 672, kernel_size=(1, 1), stride=(1, 1), bias=False)
            (1): BatchNorm2d(672, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
            (2): SiLU(inplace=True)
          )
          (1): Conv2dNormActivation(
            (0): Conv2d(672, 672, kernel_size=(5, 5), stride=(1, 1), padding=(2,
2), groups=672, bias=False)
            (1): BatchNorm2d(672, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
            (2): SiLU(inplace=True)
          )
          (2): SqueezeExcitation(
            (avgpool): AdaptiveAvgPool2d(output_size=1)
            (fc1): Conv2d(672, 28, kernel_size=(1, 1), stride=(1, 1))
            (fc2): Conv2d(28, 672, kernel_size=(1, 1), stride=(1, 1))
            (activation): SiLU(inplace=True)
            (scale_activation): Sigmoid()
          )
          (3): Conv2dNormActivation(
            (0): Conv2d(672, 112, kernel_size=(1, 1), stride=(1, 1), bias=False)
            (1): BatchNorm2d(112, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
          )
        )
        (stochastic_depth): StochasticDepth(p=0.1125, mode=row)
      )
      (2): MBConv(
        (block): Sequential(
          (0): Conv2dNormActivation(
```

```
            (0): Conv2d(112, 672, kernel_size=(1, 1), stride=(1, 1), bias=False)
            (1): BatchNorm2d(672, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
            (2): SiLU(inplace=True)
          )
          (1): Conv2dNormActivation(
            (0): Conv2d(672, 672, kernel_size=(5, 5), stride=(1, 1), padding=(2,
2), groups=672, bias=False)
            (1): BatchNorm2d(672, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
            (2): SiLU(inplace=True)
          )
          (2): SqueezeExcitation(
            (avgpool): AdaptiveAvgPool2d(output_size=1)
            (fc1): Conv2d(672, 28, kernel_size=(1, 1), stride=(1, 1))
            (fc2): Conv2d(28, 672, kernel_size=(1, 1), stride=(1, 1))
            (activation): SiLU(inplace=True)
            (scale_activation): Sigmoid()
          )
          (3): Conv2dNormActivation(
            (0): Conv2d(672, 112, kernel_size=(1, 1), stride=(1, 1), bias=False)
            (1): BatchNorm2d(112, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
          )
        )
        (stochastic_depth): StochasticDepth(p=0.125, mode=row)
      )
    )
    (6): Sequential(
      (0): MBConv(
        (block): Sequential(
          (0): Conv2dNormActivation(
            (0): Conv2d(112, 672, kernel_size=(1, 1), stride=(1, 1), bias=False)
            (1): BatchNorm2d(672, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
            (2): SiLU(inplace=True)
          )
          (1): Conv2dNormActivation(
            (0): Conv2d(672, 672, kernel_size=(5, 5), stride=(2, 2), padding=(2,
2), groups=672, bias=False)
            (1): BatchNorm2d(672, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
            (2): SiLU(inplace=True)
          )
          (2): SqueezeExcitation(
            (avgpool): AdaptiveAvgPool2d(output_size=1)
            (fc1): Conv2d(672, 28, kernel_size=(1, 1), stride=(1, 1))
```

```
            (fc2): Conv2d(28, 672, kernel_size=(1, 1), stride=(1, 1))
            (activation): SiLU(inplace=True)
            (scale_activation): Sigmoid()
          )
          (3): Conv2dNormActivation(
            (0): Conv2d(672, 192, kernel_size=(1, 1), stride=(1, 1), bias=False)
            (1): BatchNorm2d(192, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
          )
        )
        (stochastic_depth): StochasticDepth(p=0.1375, mode=row)
      )
      (1): MBConv(
        (block): Sequential(
          (0): Conv2dNormActivation(
            (0): Conv2d(192, 1152, kernel_size=(1, 1), stride=(1, 1),
bias=False)
            (1): BatchNorm2d(1152, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
            (2): SiLU(inplace=True)
          )
          (1): Conv2dNormActivation(
            (0): Conv2d(1152, 1152, kernel_size=(5, 5), stride=(1, 1),
padding=(2, 2), groups=1152, bias=False)
            (1): BatchNorm2d(1152, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
            (2): SiLU(inplace=True)
          )
          (2): SqueezeExcitation(
            (avgpool): AdaptiveAvgPool2d(output_size=1)
            (fc1): Conv2d(1152, 48, kernel_size=(1, 1), stride=(1, 1))
            (fc2): Conv2d(48, 1152, kernel_size=(1, 1), stride=(1, 1))
            (activation): SiLU(inplace=True)
            (scale_activation): Sigmoid()
          )
          (3): Conv2dNormActivation(
            (0): Conv2d(1152, 192, kernel_size=(1, 1), stride=(1, 1),
bias=False)
            (1): BatchNorm2d(192, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
          )
        )
        (stochastic_depth): StochasticDepth(p=0.15000000000000002, mode=row)
      )
      (2): MBConv(
        (block): Sequential(
          (0): Conv2dNormActivation(
```

```
            (0): Conv2d(192, 1152, kernel_size=(1, 1), stride=(1, 1),
bias=False)
            (1): BatchNorm2d(1152, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
            (2): SiLU(inplace=True)
          )
          (1): Conv2dNormActivation(
            (0): Conv2d(1152, 1152, kernel_size=(5, 5), stride=(1, 1),
padding=(2, 2), groups=1152, bias=False)
            (1): BatchNorm2d(1152, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
            (2): SiLU(inplace=True)
          )
          (2): SqueezeExcitation(
            (avgpool): AdaptiveAvgPool2d(output_size=1)
            (fc1): Conv2d(1152, 48, kernel_size=(1, 1), stride=(1, 1))
            (fc2): Conv2d(48, 1152, kernel_size=(1, 1), stride=(1, 1))
            (activation): SiLU(inplace=True)
            (scale_activation): Sigmoid()
          )
          (3): Conv2dNormActivation(
            (0): Conv2d(1152, 192, kernel_size=(1, 1), stride=(1, 1),
bias=False)
            (1): BatchNorm2d(192, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
          )
        )
        (stochastic_depth): StochasticDepth(p=0.1625, mode=row)
      )
      (3): MBConv(
        (block): Sequential(
          (0): Conv2dNormActivation(
            (0): Conv2d(192, 1152, kernel_size=(1, 1), stride=(1, 1),
bias=False)
            (1): BatchNorm2d(1152, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
            (2): SiLU(inplace=True)
          )
          (1): Conv2dNormActivation(
            (0): Conv2d(1152, 1152, kernel_size=(5, 5), stride=(1, 1),
padding=(2, 2), groups=1152, bias=False)
            (1): BatchNorm2d(1152, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
            (2): SiLU(inplace=True)
          )
          (2): SqueezeExcitation(
            (avgpool): AdaptiveAvgPool2d(output_size=1)
```

```
            (fc1): Conv2d(1152, 48, kernel_size=(1, 1), stride=(1, 1))
            (fc2): Conv2d(48, 1152, kernel_size=(1, 1), stride=(1, 1))
            (activation): SiLU(inplace=True)
            (scale_activation): Sigmoid()
          )
          (3): Conv2dNormActivation(
            (0): Conv2d(1152, 192, kernel_size=(1, 1), stride=(1, 1),
bias=False)
            (1): BatchNorm2d(192, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
          )
        )
        (stochastic_depth): StochasticDepth(p=0.17500000000000002, mode=row)
      )
    )
    (7): Sequential(
      (0): MBConv(
        (block): Sequential(
          (0): Conv2dNormActivation(
            (0): Conv2d(192, 1152, kernel_size=(1, 1), stride=(1, 1),
bias=False)
            (1): BatchNorm2d(1152, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
            (2): SiLU(inplace=True)
          )
          (1): Conv2dNormActivation(
            (0): Conv2d(1152, 1152, kernel_size=(3, 3), stride=(1, 1),
padding=(1, 1), groups=1152, bias=False)
            (1): BatchNorm2d(1152, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
            (2): SiLU(inplace=True)
          )
          (2): SqueezeExcitation(
            (avgpool): AdaptiveAvgPool2d(output_size=1)
            (fc1): Conv2d(1152, 48, kernel_size=(1, 1), stride=(1, 1))
            (fc2): Conv2d(48, 1152, kernel_size=(1, 1), stride=(1, 1))
            (activation): SiLU(inplace=True)
            (scale_activation): Sigmoid()
          )
          (3): Conv2dNormActivation(
            (0): Conv2d(1152, 320, kernel_size=(1, 1), stride=(1, 1),
bias=False)
            (1): BatchNorm2d(320, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
          )
        )
        (stochastic_depth): StochasticDepth(p=0.1875, mode=row)
```

```
        )
      )
      (8): Conv2dNormActivation(
        (0): Conv2d(320, 1280, kernel_size=(1, 1), stride=(1, 1), bias=False)
        (1): BatchNorm2d(1280, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
        (2): SiLU(inplace=True)
      )
    )
    (avgpool): AdaptiveAvgPool2d(output_size=1)
    (classifier): Sequential(
      (0): Dropout(p=0.2, inplace=True)
      (1): Linear(in_features=1280, out_features=1000, bias=True)
    )
)
```

[15]:
```
model.classifier
```

[15]:
```
Sequential(
  (0): Dropout(p=0.2, inplace=True)
  (1): Linear(in_features=1280, out_features=1000, bias=True)
)
```

1.3.3 3.3 Getting a summary of our model with `torchinfo.summary()`

[16]:
```
# Print with torchinfo
from torchinfo import summary

summary(model=model,
        input_size=(1, 3, 224, 224), # example of [batch_size, color_channels,␣
 ↪height, width]
        col_names=["input_size", "output_size", "num_params", "trainable"],
        col_width=20,
        row_settings=["var_names"])
```

[16]:
```
================================================================================
============================================================
Layer (type (var_name))                                     Input Shape
Output Shape         Param #              Trainable
================================================================================
============================================================
EfficientNet (EfficientNet)                                  [1, 3, 224, 224]
[1, 1000]            --                   True
 Sequential (features)                                      [1, 3, 224, 224]
[1, 1280, 7, 7]      --                   True
     Conv2dNormActivation (0)                              [1, 3, 224, 224]
[1, 32, 112, 112]    --                   True
```

```
          Conv2d (0)                                              [1, 3, 224, 224]
[1, 32, 112, 112]    864                     True
          BatchNorm2d (1)                                         [1, 32, 112, 112]
[1, 32, 112, 112]    64                      True
          SiLU (2)                                                [1, 32, 112, 112]
[1, 32, 112, 112]    --                      --
     Sequential (1)                                               [1, 32, 112, 112]
[1, 16, 112, 112]    --                      True
          MBConv (0)                                              [1, 32, 112, 112]
[1, 16, 112, 112]    1,448                   True
     Sequential (2)                                               [1, 16, 112, 112]
[1, 24, 56, 56]      --                      True
          MBConv (0)                                              [1, 16, 112, 112]
[1, 24, 56, 56]      6,004                   True
          MBConv (1)                                              [1, 24, 56, 56]
[1, 24, 56, 56]      10,710                  True
     Sequential (3)                                               [1, 24, 56, 56]
[1, 40, 28, 28]      --                      True
          MBConv (0)                                              [1, 24, 56, 56]
[1, 40, 28, 28]      15,350                  True
          MBConv (1)                                              [1, 40, 28, 28]
[1, 40, 28, 28]      31,290                  True
     Sequential (4)                                               [1, 40, 28, 28]
[1, 80, 14, 14]      --                      True
          MBConv (0)                                              [1, 40, 28, 28]
[1, 80, 14, 14]      37,130                  True
          MBConv (1)                                              [1, 80, 14, 14]
[1, 80, 14, 14]      102,900                 True
          MBConv (2)                                              [1, 80, 14, 14]
[1, 80, 14, 14]      102,900                 True
     Sequential (5)                                               [1, 80, 14, 14]
[1, 112, 14, 14]     --                      True
          MBConv (0)                                              [1, 80, 14, 14]
[1, 112, 14, 14]     126,004                 True
          MBConv (1)                                              [1, 112, 14, 14]
[1, 112, 14, 14]     208,572                 True
          MBConv (2)                                              [1, 112, 14, 14]
[1, 112, 14, 14]     208,572                 True
     Sequential (6)                                               [1, 112, 14, 14]
[1, 192, 7, 7]       --                      True
          MBConv (0)                                              [1, 112, 14, 14]
[1, 192, 7, 7]       262,492                 True
          MBConv (1)                                              [1, 192, 7, 7]
[1, 192, 7, 7]       587,952                 True
          MBConv (2)                                              [1, 192, 7, 7]
[1, 192, 7, 7]       587,952                 True
          MBConv (3)                                              [1, 192, 7, 7]
```

```
[1, 192, 7, 7]        587,952               True
     Sequential (7)                                                  [1, 192, 7, 7]
[1, 320, 7, 7]        --                    True
          MBConv (0)                                                 [1, 192, 7, 7]
[1, 320, 7, 7]        717,232               True
     Conv2dNormActivation (8)                                        [1, 320, 7, 7]
[1, 1280, 7, 7]       --                    True
          Conv2d (0)                                                 [1, 320, 7, 7]
[1, 1280, 7, 7]       409,600               True
          BatchNorm2d (1)                                            [1, 1280, 7, 7]
[1, 1280, 7, 7]       2,560                 True
          SiLU (2)                                                   [1, 1280, 7, 7]
[1, 1280, 7, 7]       --                    --
 AdaptiveAvgPool2d (avgpool)                                          [1, 1280, 7, 7]
[1, 1280, 1, 1]       --                    --
 Sequential (classifier)                                              [1, 1280]
[1, 1000]             --                    True
     Dropout (0)                                                     [1, 1280]
[1, 1280]             --                    --
     Linear (1)                                                      [1, 1280]
[1, 1000]             1,281,000             True
================================================================================
============================================================
Total params: 5,288,548
Trainable params: 5,288,548
Non-trainable params: 0
Total mult-adds (M): 385.87
================================================================================
============================================================
Input size (MB): 0.60
Forward/backward pass size (MB): 107.89
Params size (MB): 21.15
Estimated Total Size (MB): 129.64
================================================================================
============================================================
```

1.3.4 3.4 Freezing the base model and changing the output layer to suit our needs

With a feature extractor model, typically you will "freeze" the base layers of a pretrained/foundation model and update the output layers to suit your own problem.

[17]:
```
# Freeze all of the base layers in EffNetB0
for param in model.features.parameters():
  # print(param)
  param.requires_grad = False
```

[18]:
```
len(class_names)
```

[18]: 3

[19]:
```
# Update the classifier head of our model to suit our problem
from torch import nn

torch.manual_seed(42)
torch.cuda.manual_seed(42)

model.classifier = nn.Sequential(
    nn.Dropout(p=0.2, inplace=True),
    nn.Linear(in_features=1280, # feature vector coming in
              out_features=len(class_names))).to(device) # how many classes do␣
↪we have?

model.classifier
```

[19]:
```
Sequential(
  (0): Dropout(p=0.2, inplace=True)
  (1): Linear(in_features=1280, out_features=3, bias=True)
)
```

[20]:
```
summary(model=model,
        input_size=(1, 3, 224, 224), # example of [batch_size, color_channels,␣
↪height, width]
        col_names=["input_size", "output_size", "num_params", "trainable"],
        col_width=20,
        row_settings=["var_names"])
```

[20]:
```
================================================================================
============================================================
Layer (type (var_name))                                      Input Shape
Output Shape         Param #              Trainable
================================================================================
============================================================
EfficientNet (EfficientNet)                                   [1, 3, 224, 224]
[1, 3]               --                   Partial
 Sequential (features)                                       [1, 3, 224, 224]
[1, 1280, 7, 7]      --                   False
     Conv2dNormActivation (0)                                [1, 3, 224, 224]
[1, 32, 112, 112]    --                   False
         Conv2d (0)                                         [1, 3, 224, 224]
[1, 32, 112, 112]    (864)                False
         BatchNorm2d (1)                                    [1, 32, 112, 112]
[1, 32, 112, 112]    (64)                 False
         SiLU (2)                                           [1, 32, 112, 112]
[1, 32, 112, 112]    --                   --
     Sequential (1)                                          [1, 32, 112, 112]
```

```
[1, 16, 112, 112]    --                    False
          MBConv (0)                                         [1, 32, 112, 112]
[1, 16, 112, 112]    (1,448)               False
     Sequential (2)                                           [1, 16, 112, 112]
[1, 24, 56, 56]      --                    False
          MBConv (0)                                         [1, 16, 112, 112]
[1, 24, 56, 56]      (6,004)               False
          MBConv (1)                                         [1, 24, 56, 56]
[1, 24, 56, 56]      (10,710)              False
     Sequential (3)                                           [1, 24, 56, 56]
[1, 40, 28, 28]      --                    False
          MBConv (0)                                         [1, 24, 56, 56]
[1, 40, 28, 28]      (15,350)              False
          MBConv (1)                                         [1, 40, 28, 28]
[1, 40, 28, 28]      (31,290)              False
     Sequential (4)                                           [1, 40, 28, 28]
[1, 80, 14, 14]      --                    False
          MBConv (0)                                         [1, 40, 28, 28]
[1, 80, 14, 14]      (37,130)              False
          MBConv (1)                                         [1, 80, 14, 14]
[1, 80, 14, 14]      (102,900)             False
          MBConv (2)                                         [1, 80, 14, 14]
[1, 80, 14, 14]      (102,900)             False
     Sequential (5)                                           [1, 80, 14, 14]
[1, 112, 14, 14]     --                    False
          MBConv (0)                                         [1, 80, 14, 14]
[1, 112, 14, 14]     (126,004)             False
          MBConv (1)                                         [1, 112, 14, 14]
[1, 112, 14, 14]     (208,572)             False
          MBConv (2)                                         [1, 112, 14, 14]
[1, 112, 14, 14]     (208,572)             False
     Sequential (6)                                           [1, 112, 14, 14]
[1, 192, 7, 7]       --                    False
          MBConv (0)                                         [1, 112, 14, 14]
[1, 192, 7, 7]       (262,492)             False
          MBConv (1)                                         [1, 192, 7, 7]
[1, 192, 7, 7]       (587,952)             False
          MBConv (2)                                         [1, 192, 7, 7]
[1, 192, 7, 7]       (587,952)             False
          MBConv (3)                                         [1, 192, 7, 7]
[1, 192, 7, 7]       (587,952)             False
     Sequential (7)                                           [1, 192, 7, 7]
[1, 320, 7, 7]       --                    False
          MBConv (0)                                         [1, 192, 7, 7]
[1, 320, 7, 7]       (717,232)             False
     Conv2dNormActivation (8)                                 [1, 320, 7, 7]
[1, 1280, 7, 7]      --                    False
```

```
          Conv2d (0)                                       [1, 320, 7, 7]
[1, 1280, 7, 7]      (409,600)            False
          BatchNorm2d (1)                                  [1, 1280, 7, 7]
[1, 1280, 7, 7]      (2,560)              False
          SiLU (2)                                         [1, 1280, 7, 7]
[1, 1280, 7, 7]      --                   --
 AdaptiveAvgPool2d (avgpool)                                [1, 1280, 7, 7]
[1, 1280, 1, 1]      --                   --
 Sequential (classifier)                                    [1, 1280]
[1, 3]               --                   True
     Dropout (0)                                           [1, 1280]
[1, 1280]            --                   --
     Linear (1)                                            [1, 1280]
[1, 3]               3,843                True
================================================================================
============================================================
Total params: 4,011,391
Trainable params: 3,843
Non-trainable params: 4,007,548
Total mult-adds (M): 384.59
================================================================================
============================================================
Input size (MB): 0.60
Forward/backward pass size (MB): 107.88
Params size (MB): 16.05
Estimated Total Size (MB): 124.53
================================================================================
============================================================
```

1.4 4. Train model

[22]:
```python
# Define loss and optimizer
loss_fn = nn.CrossEntropyLoss()
optimizer = torch.optim.Adam(model.parameters(), lr=0.001)
```

[24]:
```python
# Import train function
from going_modular.going_modular import engine

# Set the manual seeds
torch.manual_seed(42)
torch.cuda.manual_seed(42)

# Start the timer
from timeit import default_timer as timer
start_time = timer()

# Setup training and save the results
```

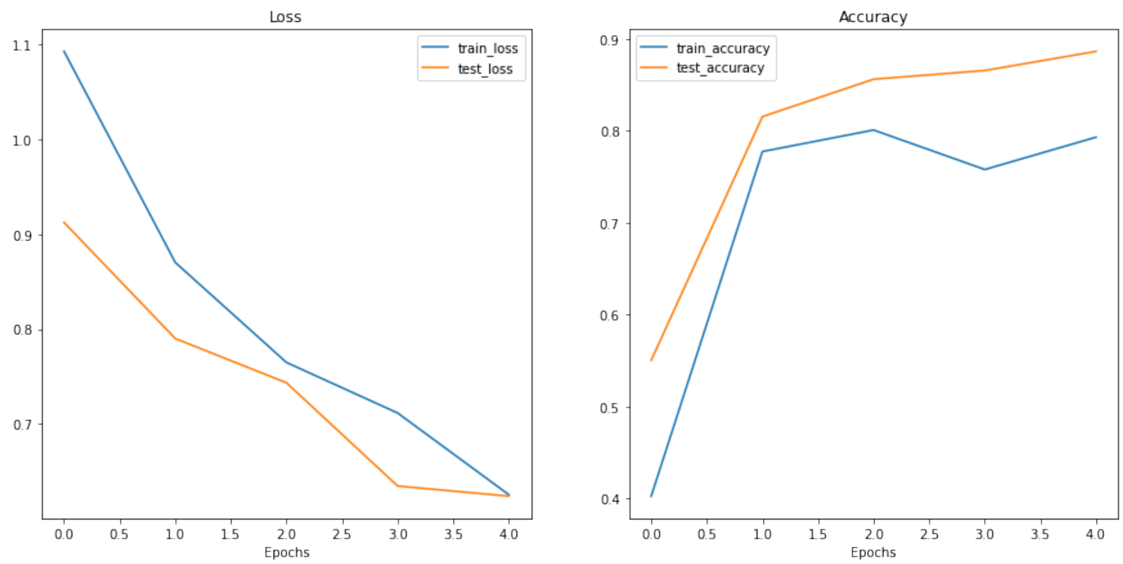
```
results = engine.train(model=model,
                       train_dataloader=train_dataloader,
                       test_dataloader=test_dataloader,
                       optimizer=optimizer,
                       loss_fn=loss_fn,
                       epochs=5,
                       device=device)

# End the timer and print out how long it took
end_time = timer()
print(f"[INFO] Total training time: {end_time-start_time:.3f} seconds")
```

```
  0%|          | 0/5 [00:00<?, ?it/s]

Epoch: 1 | train_loss: 1.0929 | train_acc: 0.4023 | test_loss: 0.9125 |
test_acc: 0.5502
Epoch: 2 | train_loss: 0.8703 | train_acc: 0.7773 | test_loss: 0.7900 |
test_acc: 0.8153
Epoch: 3 | train_loss: 0.7648 | train_acc: 0.8008 | test_loss: 0.7433 |
test_acc: 0.8561
Epoch: 4 | train_loss: 0.7114 | train_acc: 0.7578 | test_loss: 0.6344 |
test_acc: 0.8655
Epoch: 5 | train_loss: 0.6252 | train_acc: 0.7930 | test_loss: 0.6238 |
test_acc: 0.8864
[INFO] Total training time: 13.046 seconds
```

1.5 5. Evalaute model by plotting loss curves

[28]:
```
try:
  from helper_functions import plot_loss_curves
except:
  print(f"[INFO] Couldn't find helper_functions.py, downloading...")
  with open("helper_functions.py", "wb") as f:
    import requests
    request = requests.get("https://github.com/mrdbourke/pytorch-deep-learning/
↪raw/main/helper_functions.py")
    f.write(request.content)
  from helper_functions import plot_loss_curves

# Plot the loss curves of our model
plot_loss_curves(results)
```

```
[INFO] Couldn't find helper_functions.py, downloading…
```



What do our loss curves look like in terms of the ideal loss curve?

See here for more: https://www.learnpytorch.io/04_pytorch_custom_datasets/#8-what-should-an-ideal-loss-curve-look-like

1.6 6. Make predictions on images from the test set

Let's adhere to the data explorer's motto of *visualize, visualize, visualize*!

And make some qualitiative predictions on our test set.

Some things to keep in mind when making predictions/inference on test data/custom data.

We have to make sure that our test/custom data is: * Same shape - images need to be same shape as model was trained on * Same datatype - custom data should be in the same data type * Same device - custom data/test data should be on the same device as the model * Same transform - if you've transformed your custom data, ideally you will transform the test data and custom data the same

To do all of this automagically, let's create a function called `pred_and_plot_image()`:

The function will be similar to the one here: https://www.learnpytorch.io/04_pytorch_custom_datasets/#113-putting-custom-image-prediction-together-building-a-function

1. Take in a trained model, a list of class names, a filepath to a target image, an image size, a transform and a target device
2. Open the image with `PIL.Image.Open()`
3. Create a transform if one doesn't exist
4. Make sure the model is on the target device
5. Turn the model to `model.eval()` mode to make sure it's ready for inference (this will turn off things like `nn.Dropout()`)
6. Transform the target image and make sure its dimensionality is suited for the model (this mainly relates to batch size)

7. Make a prediction on the image by passing to the model
8. Convert the model's output logits to prediction probabilities using `torch.softmax()`
9. Convert model's prediction probabilities to prediction labels using `torch.argmax()`
10. Plot the image with `matplotlib` and set the title to the prediction label from step 9 and prediction probability from step 8

[48]:
```
from typing import List, Tuple

from PIL import Image

from torchvision import transforms

# 1. Take in a trained model...
def pred_and_plot_image(model: torch.nn.Module,
                        image_path: str,
                        class_names: List[str],
                        image_size: Tuple[int, int] = (224, 224),
                        transform: torchvision.transforms = None,
                        device: torch.device=device):
  # 2. Open the image with PIL
  img = Image.open(image_path)

  # 3. Create a transform if one doesn't exist
  if transform is not None:
    image_transform = transform
  else:
    image_transform = transforms.Compose([
                                          transforms.Resize(image_size),
                                          transforms.ToTensor(),
                                          transforms.Normalize(mean=[0.485, 0.
↪456, 0.406],
                                                               std=[0.229, 0.
↪224, 0.225])
    ])

  ### Predict on image ###
  # 4. Make sure the model is on the target device
  model.to(device)

  # 5. Turn on inference mode and eval mode
  model.eval()
  with torch.inference_mode():
    # 6. Transform the image and add an extra batch dimension
    transformed_image = image_transform(img).unsqueeze(dim=0) # [batch_size,␣
↪color_channels, height, width]
```

```
    # 7. Make a prediction on the transformed image by passing it to the model␣
↪(also ensure it's on the target device)
    target_image_pred = model(transformed_image.to(device))

  # 8. Convert the model's output logits to pred probs
  target_image_pred_probs = torch.softmax(target_image_pred, dim=1)
  # print(target_image_pred_probs.max())

  # 9. Convert the model's pred probs to pred labels
  target_image_pred_label = torch.argmax(target_image_pred_probs, dim=1)

  # 10. Plot image with predicted label and probability
  plt.figure()
  plt.imshow(img)
  plt.title(f"Pred: {class_names[target_image_pred_label]} | Prob:␣
↪{target_image_pred_probs.max():.3f}")
  plt.axis(False);
```

[49]:
```
test_dir
```

[49]: PosixPath('data/pizza_steak_sushi/test')

[50]:
```
class_names
```

[50]: ['pizza', 'steak', 'sushi']

[54]:
```
# Get a random list of image paths from the test set
import random
num_images_to_plot = 3
test_image_path_list = list(Path(test_dir).glob("*/*.jpg"))
test_image_path_sample = random.sample(population=test_image_path_list,
                                       k=num_images_to_plot)

# Make predictions on and plot the images
for image_path in test_image_path_sample:
  pred_and_plot_image(model=model,
                      image_path=image_path,
                      class_names=class_names,
                      image_size=(224, 224))
```

Pred: pizza | Prob: 0.707

Pred: steak | Prob: 0.407

1.6.1 6.1 Making predictions on a custom image

Let's make a prediction on the pizza dad image - https://github.com/mrdbourke/pytorch-deep-learning/blob/main/images/04-pizza-dad.jpeg

[56]:
```
# Download the image
import requests

# Setup custom image path
custom_image_path = data_path / "04-pizza-dad.jpeg"

# Download the image if it doesn't exist
if not custom_image_path.is_file():
  with open(custom_image_path, "wb") as f:
    # Download image from GitHub with "raw" link
    request = requests.get("https://github.com/mrdbourke/pytorch-deep-learning/
↪raw/main/images/04-pizza-dad.jpeg")
    print(f"Download {custom_image_path}...")
    f.write(request.content)
else:
  print(f"{custom_image_path} already exists, skipping download...")
```

```
Download data/04-pizza-dad.jpeg…
```

[57]:
```
# Predict on custom image
pred_and_plot_image(model=model,
```

```
                      image_path=custom_image_path,
                      class_names=class_names)
```

1.7 Exercises

See exercises and extra-curriculum to practice what you've learned here: https://www.learnpytorch.io/06_pytorch_transfer_learning/#exercises

[ ]:
```

```