CNN Using Pretrained Models

Text and explanations credit to: Chapter 5, Section 3 of Deep Learning with Python.

Dependencies

In [ ]:
```
!pip install torchinfo
! pip install gdown  # download large file from Google Drive
```

```
Collecting torchinfo
  Downloading torchinfo-1.5.3-py3-none-any.whl (19 kB)
Installing collected packages: torchinfo
Successfully installed torchinfo-1.5.3
Requirement already satisfied: gdown in /usr/local/lib/python3.7/dist-packages (3.6.4)
Requirement already satisfied: tqdm in /usr/local/lib/python3.7/dist-packages (from gdown) (4.6
2.3)
Requirement already satisfied: requests in /usr/local/lib/python3.7/dist-packages (from gdown)
(2.23.0)
Requirement already satisfied: six in /usr/local/lib/python3.7/dist-packages (from gdown) (1.15.
0)
Requirement already satisfied: idna<3,>=2.5 in /usr/local/lib/python3.7/dist-packages (from requ
ests->gdown) (2.10)
Requirement already satisfied: chardet<4,>=3.0.2 in /usr/local/lib/python3.7/dist-packages (from
requests->gdown) (3.0.4)
Requirement already satisfied: certifi>=2017.4.17 in /usr/local/lib/python3.7/dist-packages (fro
m requests->gdown) (2021.5.30)
Requirement already satisfied: urllib3!=1.25.0,!=1.25.1,<1.26,>=1.21.1 in /usr/local/lib/python
3.7/dist-packages (from requests->gdown) (1.24.3)
```

In [ ]:
```
import os
import shutil
import glob
import random
import concurrent
import zipfile
import torch
import PIL
import numpy as np
import torch.nn as nn
import torchvision.transforms as transforms
import matplotlib.pyplot as plt
from torch.utils.data import DataLoader, random_split, Dataset
from IPython.display import Image
from torchinfo import summary

device = torch.device("cuda" if torch.cuda.is_available() else "cpu")
```

Load Convnet Models from torchvision

A common and highly effective approach to deep learning on small image datasets is to leverage a pre-trained network. A pre-trained network is simply a saved network previously trained on a large dataset, typically on a large-scale image classification task. If this original dataset is large enough and general enough, then the spatial feature hierarchy learned by the pre-trained network can effectively act as a generic model of our visual world, and hence its features can prove useful for many different computer vision problems, even though these new problems might involve completely different classes from those of the original task. For instance, one might train a network on ImageNet (where classes are mostly animals and everyday objects) and then re-purpose this trained network for something as remote as identifying furniture items in images. Such portability of learned features across different problems is a key advantage of deep learning compared to many older shallow learning approaches, and it makes deep learning very effective for small-data problems.

In our case, we will consider a large convnet trained on the ImageNet dataset (1.4 million labeled images and 1000 different classes). ImageNet contains many animal classes, including different species of cats and dogs, and we can thus expect to perform very well on our cat vs. dog classification problem.

We will use the VGG16 architecture, developed by Karen Simonyan and Andrew Zisserman in 2014, a simple and widely used convnet architecture for ImageNet. Although it is a bit of an older model, far from the current state of the art and somewhat heavier than many other recent models, we chose it because its architecture is similar to what you are already familiar with, and easy to understand without introducing any new concepts. This may be your first encounter with one of these cutesie model names -- VGG, ResNet, Inception, Inception-ResNet, Xception... you will get used to them, as they will come up frequently if you keep doing deep learning for computer vision.

There are two ways to leverage a pre-trained network: *feature extraction* and *fine-tuning*. We will cover both of them. Let's start with feature extraction.

Load datasetL Dog&Cat

In [ ]:
```
! gdown https://drive.google.com/uc?id=1ItGv65UmiQKnett7vxY1qNPTXRg4hSfW
```

```
Downloading...
From: https://drive.google.com/uc?id=1ItGv65UmiQKnett7vxY1qNPTXRg4hSfW
To: /content/dog_cat.zip
100% 570M/570M [00:06<00:00, 86.3MB/s]
```

In [ ]:
```
with zipfile.ZipFile('/content/dog_cat.zip', 'r') as zip_ref:
    zip_ref.extractall('./')
```

In [ ]:
```
# cwd
cwd = os.getcwd()

# dirs
dog_cat_dir = os.path.join(cwd, 'dog_cat')
if not os.path.exists(dog_cat_dir):
    os.mkdir(dog_cat_dir)

cat_dir = os.path.join(dog_cat_dir, 'cat')
if not os.path.exists(cat_dir):
    os.mkdir(cat_dir)

dog_dir = os.path.join(dog_cat_dir, 'dog')
if not os.path.exists(dog_dir):
    os.mkdir(dog_dir)

# sample random 1000 pics for cats & dogs
cat_pics = np.random.choice(glob.glob(os.path.join(cwd, 'train', 'cat.*.jpg')), size=1000, repla
dog_pics = np.random.choice(glob.glob(os.path.join(cwd, 'train', 'dog.*.jpg')), size=1000, repla
```

```python
# move to dir
def move_to_folder(scr_file, des_folder):
    des_name = os.path.basename(scr_file)
    shutil.copyfile(scr_file, os.path.join(des_folder, des_name))
# cats
with concurrent.futures.ThreadPoolExecutor(max_workers=4) as pool:
    [pool.submit(move_to_folder, file_name, cat_dir) for file_name in cat_pics]
# dogs
with concurrent.futures.ThreadPoolExecutor(max_workers=4) as pool:
    [pool.submit(move_to_folder, file_name, dog_dir) for file_name in dog_pics]
```

In [ ]:
```python
class ImgDataset(Dataset):
    def __init__(self, img_path, img_labels, img_transforms=None):
        self.img_path = img_path
        self.img_labels = torch.Tensor(img_labels)
        if img_transforms is None:
            self.transforms = transforms.ToTensor()
        else:
            self.transforms = img_transforms

    def __getitem__(self, index):
        # load image
        cur_path = self.img_path[index]
        cur_img = PIL.Image.open(cur_path)
        cur_img = self.transforms(cur_img)

        return cur_img, self.img_labels[index]

    def __len__(self):
        return len(self.img_path)
```

In [ ]:
```python
images_list = glob.glob(os.path.join(dog_cat_dir, '*', '*.jpg'))
# label: 0 for cat, 1 for dog
def extract_class(img_path):
    base_path = os.path.basename(img_path)
    return base_path.split('.')[0]

labels = [0 if extract_class(cur_path) == 'cat' else 1 for cur_path in images_list]
```

In [ ]:
```python
transformations = transforms.Compose([transforms.Resize((150, 150)),  # resize to input shape of
                                      transforms.ColorJitter(brightness=0.3, contrast=0.3, satura
                                      transforms.RandomRotation(40),
                                      transforms.RandomAffine(degrees=0, scale=(0.8, 1.2), shear
                                      transforms.RandomHorizontalFlip(p=0.5),
                                      transforms.ToTensor()  # convert PIL to Tensor
                                      ])
```

In [ ]:
```python
dog_cat_dataset = ImgDataset(img_path=images_list, img_labels=labels, img_transforms=transformat
```

In [ ]:
```python
split_size = (np.array([0.6, 0.2, 0.2]) * len(dog_cat_dataset)).round().astype(np.int)
train_data, valid_data, test_data = random_split(dog_cat_dataset, split_size)
```

Train Function

In [ ]:
```python
def train_model(model, train_dataset, test_dataset, device,
                lr=0.0001, epochs=30, batch_size=256):

    # construct dataloader
```

```python
    train_loader = DataLoader(train_dataset, batch_size=batch_size, shuffle=True)
    test_loader = DataLoader(test_dataset, batch_size=batch_size, shuffle=False)

    # move model to device
    model = model.to(device)

    # history
    history = {'train_loss': [],
               'train_acc': [],
               'test_loss': [],
               'test_acc': []}
    # setup loss function and optimizer
    criterion = nn.BCEWithLogitsLoss()
    optimizer = torch.optim.Adam(model.parameters(), lr=lr)
    # training loop
    print('Training Start')
    for epoch in range(epochs):
        model.train()
        train_loss = 0
        train_acc = 0
        test_loss = 0
        test_acc = 0

        for x, y in train_loader:
            # move data to device
            x = x.to(device)
            y = y.to(device)
            # forward
            outputs = model(x).view(-1)  # (num_batch)
            cur_train_loss = criterion(outputs, y)
            pred = torch.sigmoid(outputs)
            pred = torch.round(pred)
            cur_train_acc = (pred == y).sum().item() / batch_size
            # backward
            cur_train_loss.backward()
            optimizer.step()
            optimizer.zero_grad()
            # loss and acc
            train_loss += cur_train_loss
            train_acc += cur_train_acc

        # test start
        model.eval()
        with torch.no_grad():
            for x, y in test_loader:
                # move
                x = x.to(device)
                y = y.to(device)
                # predict
                outputs = model(x).view(-1)
                pred = torch.round(torch.sigmoid(outputs))
                cur_test_loss = criterion(outputs, y)
                cur_test_acc = (pred == y).sum().item() / batch_size
                # loss and acc
                test_loss += cur_test_loss
                test_acc += cur_test_acc

        # epoch output
        train_loss = (train_loss/len(train_loader)).item()
        train_acc = train_acc/len(train_loader)
        val_loss = (test_loss/len(test_loader)).item()
        val_acc = test_acc/len(test_loader)
```

```
        history['train_loss'].append(train_loss)
        history['train_acc'].append(train_acc)
        history['test_loss'].append(val_loss)
        history['test_acc'].append(val_acc)
        print(f"Epoch:{epoch + 1} / {epochs}, train loss:{train_loss:.4f} train_acc:{train_acc:.

    return history
```

Feature extraction

Feature extraction consists of using the representations learned by a previous network to extract interesting features from new samples. These features are then run through a new classifier, which is trained from scratch.

As we saw previously, convnets used for image classification comprise two parts: they start with a series of pooling and convolution layers, and they end with a densely-connected classifier. The first part is called the "convolutional base" of the model. In the case of convnets, "feature extraction" will simply consist of taking the convolutional base of a previously-trained network, running the new data through it, and training a new classifier on top of the output.

Why only reuse the convolutional base? Could we reuse the densely-connected classifier as well? In general, it should be avoided. The reason is simply that the representations learned by the convolutional base are likely to be more generic and therefore more reusable: the feature maps of a convnet are presence maps of generic concepts over a picture, which is likely to be useful regardless of the computer vision problem at hand. On the other end, the representations learned by the classifier will necessarily be very specific to the set of classes that the model was trained on -- they will only contain information about the presence probability of this or that class in the entire picture. Additionally, representations found in densely-connected layers no longer contain any information about *where* objects are located in the input image: these layers get rid of the notion of space, whereas the object location is still described by convolutional feature maps. For problems where object location matters, densely-connected features would be largely useless.

Note that the level of generality (and therefore reusability) of the representations extracted by specific convolution layers depends on the depth of the layer in the model. Layers that come earlier in the model extract local, highly generic feature maps (such as visual edges, colors, and textures), while layers higher-up extract more abstract concepts (such as "cat ear" or "dog eye"). So if your new dataset differs a lot from the dataset that the original model was trained on, you may be better off using only the first few layers of the model to do feature extraction, rather than using the entire convolutional base.

In our case, since the ImageNet class set did contain multiple dog and cat classes, it is likely that it would be beneficial to reuse the information contained in the densely-connected layers of the original model. However, we will chose not to, in order to cover the more general case where the class set of the new problem does not overlap with the class set of the original model

Load models from torch.vision

Let's put this in practice by using the convolutional base of the VGG16 network, trained on ImageNet, to extract interesting features from our cat and dog images, and then training a cat vs. dog classifier on top of these features.

The VGG16 model, among others, comes pre-packaged with `torchvision.models`. Here's the list of image classification models (all pre-trained on the ImageNet dataset) that are available as part of `torchvision.models`:

- AlexNet
- VGG-11
- VGG-16
- ResNet-18
- SqueezeNet 1.0
- MGoogleNet

Let's instantiate the VGG16 model:

In [ ]:
```
import torchvision.models as models

VGG_model = models.vgg16(pretrained=True)
```

`pretrained=True` will load the pretrained set of weights of VGG16 model. If `pretrained=False`, then only the structure will be loaded.

Here's the detail of the architecture of the VGG16 convolutional base, it's very similar to the simple convnets that you are already:

In [ ]:
```
print(VGG_model)
```

```
VGG(
  (features): Sequential(
    (0): Conv2d(3, 64, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (1): ReLU(inplace=True)
    (2): Conv2d(64, 64, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (3): ReLU(inplace=True)
    (4): MaxPool2d(kernel_size=2, stride=2, padding=0, dilation=1, ceil_mode=False)
    (5): Conv2d(64, 128, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (6): ReLU(inplace=True)
    (7): Conv2d(128, 128, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (8): ReLU(inplace=True)
    (9): MaxPool2d(kernel_size=2, stride=2, padding=0, dilation=1, ceil_mode=False)
    (10): Conv2d(128, 256, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (11): ReLU(inplace=True)
    (12): Conv2d(256, 256, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (13): ReLU(inplace=True)
    (14): Conv2d(256, 256, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (15): ReLU(inplace=True)
    (16): MaxPool2d(kernel_size=2, stride=2, padding=0, dilation=1, ceil_mode=False)
    (17): Conv2d(256, 512, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (18): ReLU(inplace=True)
    (19): Conv2d(512, 512, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (20): ReLU(inplace=True)
    (21): Conv2d(512, 512, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (22): ReLU(inplace=True)
    (23): MaxPool2d(kernel_size=2, stride=2, padding=0, dilation=1, ceil_mode=False)
    (24): Conv2d(512, 512, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (25): ReLU(inplace=True)
    (26): Conv2d(512, 512, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (27): ReLU(inplace=True)
    (28): Conv2d(512, 512, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (29): ReLU(inplace=True)
    (30): MaxPool2d(kernel_size=2, stride=2, padding=0, dilation=1, ceil_mode=False)
  )
  (avgpool): AdaptiveAvgPool2d(output_size=(7, 7))
  (classifier): Sequential(
    (0): Linear(in_features=25088, out_features=4096, bias=True)
    (1): ReLU(inplace=True)
    (2): Dropout(p=0.5, inplace=False)
    (3): Linear(in_features=4096, out_features=4096, bias=True)
    (4): ReLU(inplace=True)
    (5): Dropout(p=0.5, inplace=False)
    (6): Linear(in_features=4096, out_features=1000, bias=True)
  )
)
```

In [ ]:

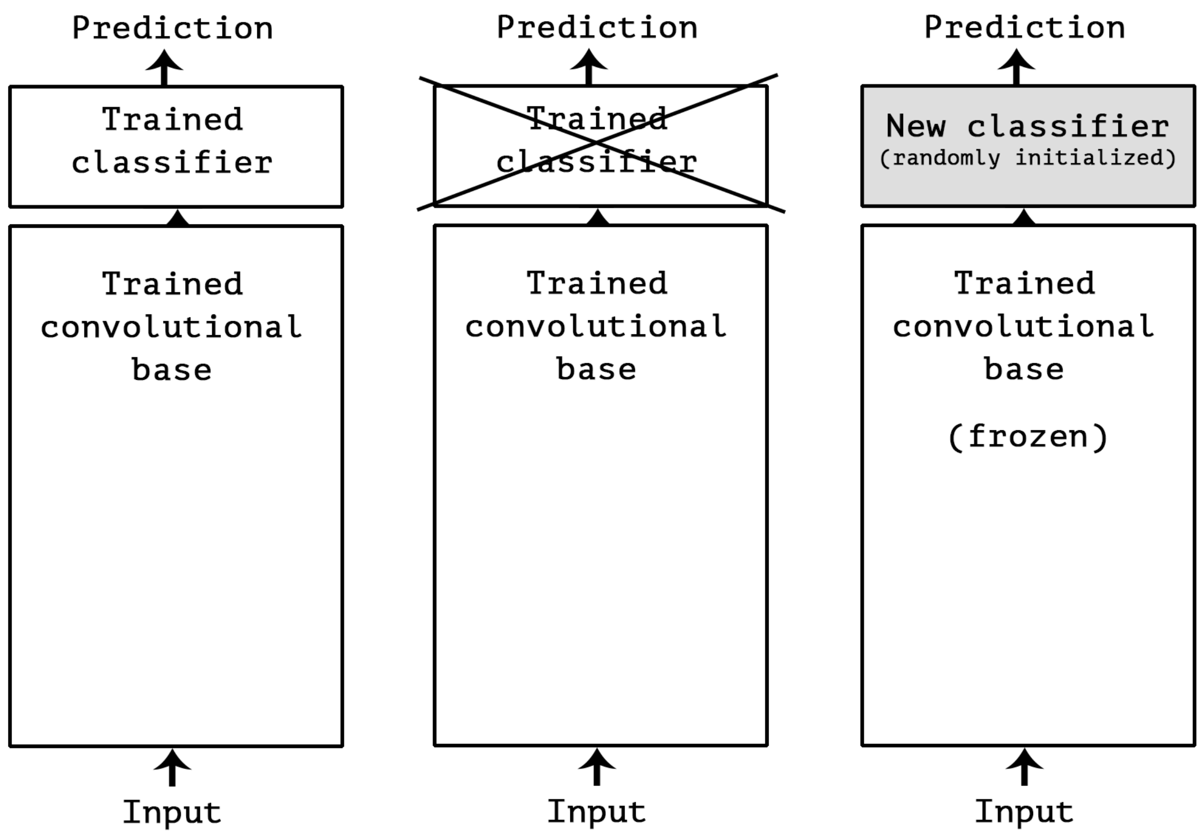
```
summary(VGG_model, (10, 3, 150, 150))
```

Out[ ]:
```
==========================================================================================
Layer (type:depth-idx)                   Output Shape              Param #
==========================================================================================
VGG                                      --                        --
├─Sequential: 1-1                        [10, 512, 4, 4]           --
│    └─Conv2d: 2-1                       [10, 64, 150, 150]        1,792
│    └─ReLU: 2-2                         [10, 64, 150, 150]        --
│    └─Conv2d: 2-3                       [10, 64, 150, 150]        36,928
│    └─ReLU: 2-4                         [10, 64, 150, 150]        --
│    └─MaxPool2d: 2-5                    [10, 64, 75, 75]          --
│    └─Conv2d: 2-6                       [10, 128, 75, 75]         73,856
│    └─ReLU: 2-7                         [10, 128, 75, 75]         --
│    └─Conv2d: 2-8                       [10, 128, 75, 75]         147,584
│    └─ReLU: 2-9                         [10, 128, 75, 75]         --
│    └─MaxPool2d: 2-10                   [10, 128, 37, 37]         --
│    └─Conv2d: 2-11                      [10, 256, 37, 37]         295,168
│    └─ReLU: 2-12                        [10, 256, 37, 37]         --
│    └─Conv2d: 2-13                      [10, 256, 37, 37]         590,080
│    └─ReLU: 2-14                        [10, 256, 37, 37]         --
│    └─Conv2d: 2-15                      [10, 256, 37, 37]         590,080
│    └─ReLU: 2-16                        [10, 256, 37, 37]         --
│    └─MaxPool2d: 2-17                   [10, 256, 18, 18]         --
│    └─Conv2d: 2-18                      [10, 512, 18, 18]         1,180,160
│    └─ReLU: 2-19                        [10, 512, 18, 18]         --
│    └─Conv2d: 2-20                      [10, 512, 18, 18]         2,359,808
│    └─ReLU: 2-21                        [10, 512, 18, 18]         --
│    └─Conv2d: 2-22                      [10, 512, 18, 18]         2,359,808
│    └─ReLU: 2-23                        [10, 512, 18, 18]         --
│    └─MaxPool2d: 2-24                   [10, 512, 9, 9]           --
│    └─Conv2d: 2-25                      [10, 512, 9, 9]           2,359,808
│    └─ReLU: 2-26                        [10, 512, 9, 9]           --
│    └─Conv2d: 2-27                      [10, 512, 9, 9]           2,359,808
│    └─ReLU: 2-28                        [10, 512, 9, 9]           --
│    └─Conv2d: 2-29                      [10, 512, 9, 9]           2,359,808
│    └─ReLU: 2-30                        [10, 512, 9, 9]           --
│    └─MaxPool2d: 2-31                   [10, 512, 4, 4]           --
├─AdaptiveAvgPool2d: 1-2                 [10, 512, 7, 7]           --
├─Sequential: 1-3                        [10, 1000]                --
│    └─Linear: 2-32                      [10, 4096]                102,764,544
│    └─ReLU: 2-33                        [10, 4096]                --
│    └─Dropout: 2-34                     [10, 4096]                --
│    └─Linear: 2-35                      [10, 4096]                16,781,312
│    └─ReLU: 2-36                        [10, 4096]                --
│    └─Dropout: 2-37                     [10, 4096]                --
│    └─Linear: 2-38                      [10, 1000]                4,097,000
==========================================================================================
Total params: 138,357,544
Trainable params: 138,357,544
Non-trainable params: 0
Total mult-adds (G): 67.45
==========================================================================================
Input size (MB): 2.70
Forward/backward pass size (MB): 480.21
Params size (MB): 553.43
Estimated Total Size (MB): 1036.34
==========================================================================================
```

To apply the model on our cat&dog dataset, we will need to:

1. Change the classifier
2. Determine if we want to freeze the weights or not(pre-trained or fine tuning)

Using the pre-trained model: Weights are frozen



0. Model

In [ ]:
```
VGG_model = models.vgg16(pretrained=True)
```

1. Freeze Weights

In [ ]:
```
for name, param in VGG_model.named_parameters():
  param.requires_grad = False
```

2. Rewrite Classifier:
As we can see from the output shape of the previous model, it classifies the image into 1000 classes. To make the model fit to our binary classification case, let's rewrite the classifier:

In [ ]:
```
# define out classifier
binary_classifier = nn.Sequential(
   nn.Linear(in_features=25088, out_features=2048),
   nn.ReLU(),
   nn.Linear(in_features=2048, out_features=1024),
   nn.ReLU(),
   nn.Linear(in_features=1024, out_features=512),
   nn.ReLU(),
   nn.Linear(in_features=512, out_features=1)
)

# replace model class classifier attribute:
VGG_model.classifier = binary_classifier
```

In [ ]:
```
VGG_model
```

Out[ ]:
```
VGG(
  (features): Sequential(
    (0): Conv2d(3, 64, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (1): ReLU(inplace=True)
    (2): Conv2d(64, 64, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (3): ReLU(inplace=True)
    (4): MaxPool2d(kernel_size=2, stride=2, padding=0, dilation=1, ceil_mode=False)
    (5): Conv2d(64, 128, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (6): ReLU(inplace=True)
    (7): Conv2d(128, 128, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (8): ReLU(inplace=True)
    (9): MaxPool2d(kernel_size=2, stride=2, padding=0, dilation=1, ceil_mode=False)
    (10): Conv2d(128, 256, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (11): ReLU(inplace=True)
    (12): Conv2d(256, 256, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (13): ReLU(inplace=True)
    (14): Conv2d(256, 256, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (15): ReLU(inplace=True)
    (16): MaxPool2d(kernel_size=2, stride=2, padding=0, dilation=1, ceil_mode=False)
    (17): Conv2d(256, 512, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (18): ReLU(inplace=True)
    (19): Conv2d(512, 512, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (20): ReLU(inplace=True)
    (21): Conv2d(512, 512, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
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    (27): ReLU(inplace=True)
    (28): Conv2d(512, 512, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (29): ReLU(inplace=True)
    (30): MaxPool2d(kernel_size=2, stride=2, padding=0, dilation=1, ceil_mode=False)
  )
  (avgpool): AdaptiveAvgPool2d(output_size=(7, 7))
  (classifier): Sequential(
    (0): Linear(in_features=25088, out_features=2048, bias=True)
    (1): ReLU()
    (2): Linear(in_features=2048, out_features=1024, bias=True)
    (3): ReLU()
    (4): Linear(in_features=1024, out_features=512, bias=True)
    (5): ReLU()
    (6): Linear(in_features=512, out_features=1, bias=True)
  )
)
```

3. Train the model

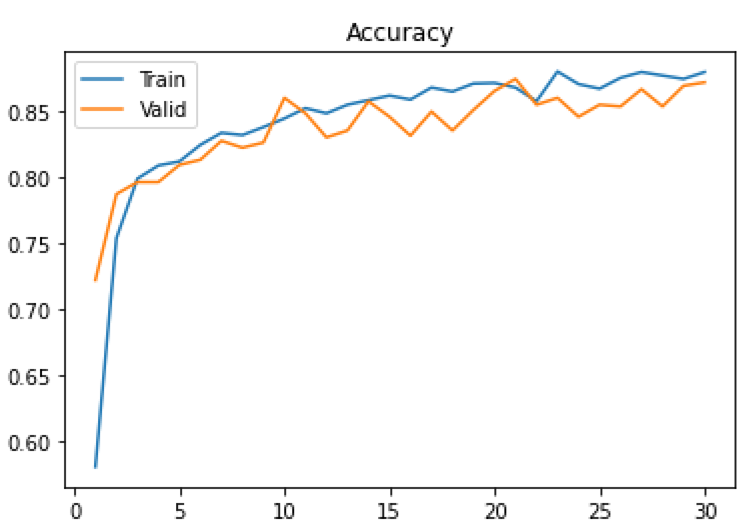
In [ ]:
```
history = train_model(VGG_model, train_data, valid_data, device, batch_size=32, epochs=30, lr=0.(
```

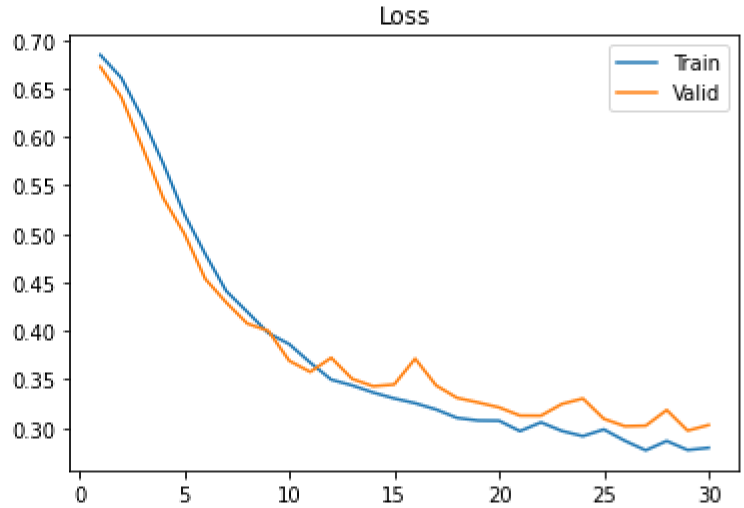
```
Training Start
Epoch:1 / 30, train loss:0.6845 train_acc:0.5812, valid loss:0.6723 valid acc:0.7227
Epoch:2 / 30, train loss:0.6610 train_acc:0.7543, valid loss:0.6409 valid acc:0.7878
Epoch:3 / 30, train loss:0.6197 train_acc:0.7995, valid loss:0.5895 valid acc:0.7969
Epoch:4 / 30, train loss:0.5724 train_acc:0.8095, valid loss:0.5368 valid acc:0.7969
Epoch:5 / 30, train loss:0.5204 train_acc:0.8125, valid loss:0.5003 valid acc:0.8099
Epoch:6 / 30, train loss:0.4792 train_acc:0.8251, valid loss:0.4536 valid acc:0.8138
Epoch:7 / 30, train loss:0.4411 train_acc:0.8342, valid loss:0.4293 valid acc:0.8281
Epoch:8 / 30, train loss:0.4197 train_acc:0.8325, valid loss:0.4076 valid acc:0.8229
Epoch:9 / 30, train loss:0.3978 train_acc:0.8385, valid loss:0.4001 valid acc:0.8268
Epoch:10 / 30, train loss:0.3864 train_acc:0.8451, valid loss:0.3692 valid acc:0.8607
Epoch:11 / 30, train loss:0.3674 train_acc:0.8529, valid loss:0.3578 valid acc:0.8490
Epoch:12 / 30, train loss:0.3498 train_acc:0.8490, valid loss:0.3723 valid acc:0.8307
Epoch:13 / 30, train loss:0.3439 train_acc:0.8555, valid loss:0.3506 valid acc:0.8359
Epoch:14 / 30, train loss:0.3365 train_acc:0.8589, valid loss:0.3430 valid acc:0.8581
Epoch:15 / 30, train loss:0.3305 train_acc:0.8624, valid loss:0.3448 valid acc:0.8464
Epoch:16 / 30, train loss:0.3255 train_acc:0.8594, valid loss:0.3714 valid acc:0.8320
Epoch:17 / 30, train loss:0.3190 train_acc:0.8685, valid loss:0.3438 valid acc:0.8503
Epoch:18 / 30, train loss:0.3104 train_acc:0.8655, valid loss:0.3310 valid acc:0.8359
Epoch:19 / 30, train loss:0.3077 train_acc:0.8715, valid loss:0.3263 valid acc:0.8516
Epoch:20 / 30, train loss:0.3075 train_acc:0.8720, valid loss:0.3212 valid acc:0.8659
Epoch:21 / 30, train loss:0.2967 train_acc:0.8685, valid loss:0.3128 valid acc:0.8750
Epoch:22 / 30, train loss:0.3058 train_acc:0.8581, valid loss:0.3126 valid acc:0.8555
Epoch:23 / 30, train loss:0.2969 train_acc:0.8806, valid loss:0.3247 valid acc:0.8607
Epoch:24 / 30, train loss:0.2916 train_acc:0.8711, valid loss:0.3304 valid acc:0.8464
Epoch:25 / 30, train loss:0.2985 train_acc:0.8676, valid loss:0.3094 valid acc:0.8555
Epoch:26 / 30, train loss:0.2868 train_acc:0.8759, valid loss:0.3018 valid acc:0.8542
Epoch:27 / 30, train loss:0.2769 train_acc:0.8802, valid loss:0.3023 valid acc:0.8672
Epoch:28 / 30, train loss:0.2866 train_acc:0.8776, valid loss:0.3185 valid acc:0.8542
Epoch:29 / 30, train loss:0.2773 train_acc:0.8750, valid loss:0.2972 valid acc:0.8698
Epoch:30 / 30, train loss:0.2795 train_acc:0.8802, valid loss:0.3030 valid acc:0.8724
```

In [ ]:

```python
# acc
plt.plot(range(1, 31), history['train_acc'], label='Train')
plt.plot(range(1, 31), history['test_acc'], label='Valid')
plt.title('Accuracy')
plt.legend()
plt.show()

# loss
plt.plot(range(1, 31), history['train_loss'], label='Train')
plt.plot(range(1, 31), history['test_loss'], label='Valid')
plt.title('Loss')
plt.legend()
plt.show()
```





Fine-turning the Model: Weights are not frozen

Another widely used technique for model reuse, complementary to feature extraction, is *fine-tuning*. Fine-tuning consists in unfreezing a few of the top layers of a frozen model base used for feature extraction, and jointly training both the newly added part of the model (in our case, the fully-connected classifier) and these top layers. This is called "fine-tuning" because it slightly adjusts the more abstract representations of the model being reused, in order to make them more relevant for the problem at hand.

1. Freeze the layers:

We will fine-tune the last 3 convolutional layers, why not fine-tune more layers? Why not fine-tune the entire convolutional base? We could. However, we need to consider that:

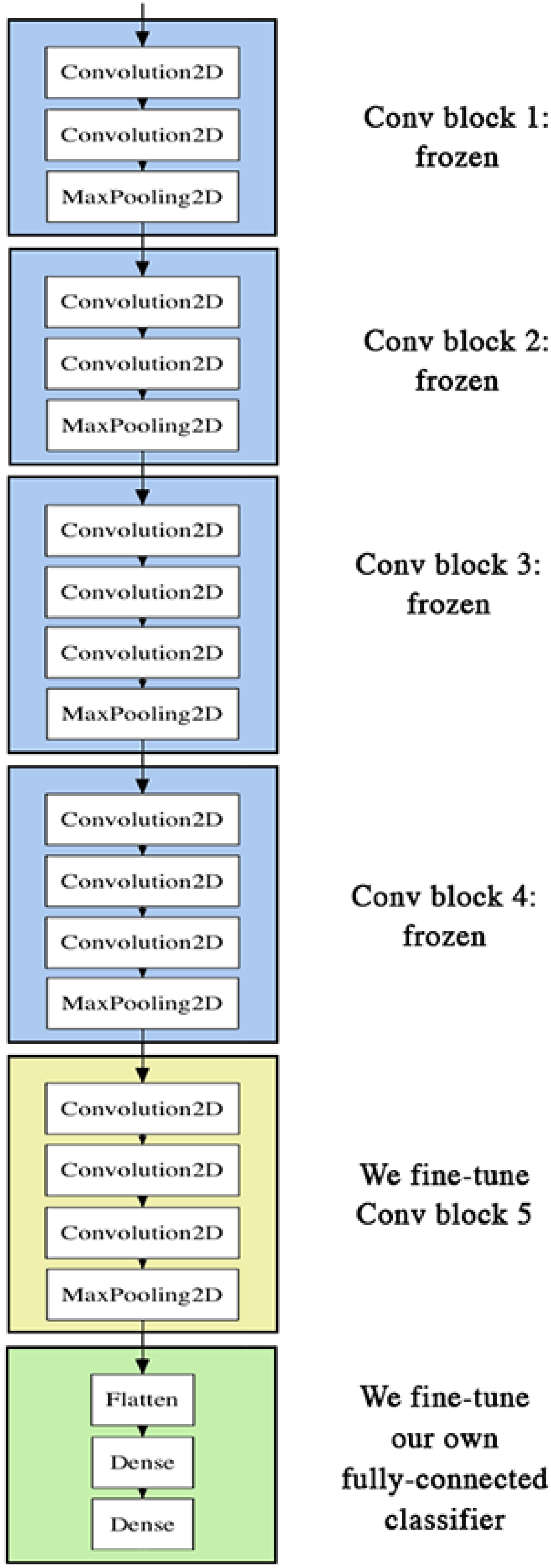
- Earlier layers in the convolutional base encode more generic, reusable features, while layers higher up encode more specialized features. It is

more useful to fine-tune the more specialized features, as these are the ones that need to be repurposed on our new problem. There would be fast-decreasing returns in fine-tuning lower layers.

- The more parameters we are training, the more we are at risk of overfitting. The convolutional base has 15M parameters, so it would be

risky to attempt to train it on our small dataset.

Thus, in our situation, it is a good strategy to only fine-tune the top 3 layers in the convolutional base.



0. Model

In [ ]:
```
# get a new model
import torchvision.models as models
```

```python
VGG_model = models.vgg16(pretrained=True)

print(VGG_model)
```

```
VGG(
  (features): Sequential(
    (0): Conv2d(3, 64, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (1): ReLU(inplace=True)
    (2): Conv2d(64, 64, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (3): ReLU(inplace=True)
    (4): MaxPool2d(kernel_size=2, stride=2, padding=0, dilation=1, ceil_mode=False)
    (5): Conv2d(64, 128, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (6): ReLU(inplace=True)
    (7): Conv2d(128, 128, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (8): ReLU(inplace=True)
    (9): MaxPool2d(kernel_size=2, stride=2, padding=0, dilation=1, ceil_mode=False)
    (10): Conv2d(128, 256, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (11): ReLU(inplace=True)
    (12): Conv2d(256, 256, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (13): ReLU(inplace=True)
    (14): Conv2d(256, 256, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (15): ReLU(inplace=True)
    (16): MaxPool2d(kernel_size=2, stride=2, padding=0, dilation=1, ceil_mode=False)
    (17): Conv2d(256, 512, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (18): ReLU(inplace=True)
    (19): Conv2d(512, 512, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (20): ReLU(inplace=True)
    (21): Conv2d(512, 512, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (22): ReLU(inplace=True)
    (23): MaxPool2d(kernel_size=2, stride=2, padding=0, dilation=1, ceil_mode=False)
    (24): Conv2d(512, 512, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (25): ReLU(inplace=True)
    (26): Conv2d(512, 512, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (27): ReLU(inplace=True)
    (28): Conv2d(512, 512, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (29): ReLU(inplace=True)
    (30): MaxPool2d(kernel_size=2, stride=2, padding=0, dilation=1, ceil_mode=False)
  )
  (avgpool): AdaptiveAvgPool2d(output_size=(7, 7))
  (classifier): Sequential(
    (0): Linear(in_features=25088, out_features=4096, bias=True)
    (1): ReLU(inplace=True)
    (2): Dropout(p=0.5, inplace=False)
    (3): Linear(in_features=4096, out_features=4096, bias=True)
    (4): ReLU(inplace=True)
    (5): Dropout(p=0.5, inplace=False)
    (6): Linear(in_features=4096, out_features=1000, bias=True)
  )
)
```

1. Freeze the weights except for the top 3 layers

In [ ]:

```python
for name, param in VGG_model.named_parameters():
  print(f'Name {name}')
```

```
Name features.0.weight
Name features.0.bias
Name features.2.weight
Name features.2.bias
Name features.5.weight
Name features.5.bias
Name features.7.weight
Name features.7.bias
Name features.10.weight
Name features.10.bias
Name features.12.weight
Name features.12.bias
Name features.14.weight
Name features.14.bias
Name features.17.weight
Name features.17.bias
Name features.19.weight
Name features.19.bias
Name features.21.weight
Name features.21.bias
Name features.24.weight
Name features.24.bias
Name features.26.weight
Name features.26.bias
Name features.28.weight
Name features.28.bias
Name classifier.0.weight
Name classifier.0.bias
Name classifier.3.weight
Name classifier.3.bias
Name classifier.6.weight
Name classifier.6.bias
```

Freeze:

In [ ]:

```
layers_not_to_freeze = ['24', '26', '28']

for name, param in VGG_model.named_parameters():
    layer_type, layer_index = name.split('.')[0], name.split('.')[1]

    if layer_type != "classifier":
        if layer_index not in layers_not_to_freeze:
            print(f"Layer {layer_index}: {name} freezed")
            param.requires_grad = False
        else:
            print(f"Layer {layer_index}: {name} not freezed")
            param.requires_grad = True
```

```
Layer 0: features.0.weight freezed
Layer 0: features.0.bias freezed
Layer 2: features.2.weight freezed
Layer 2: features.2.bias freezed
Layer 5: features.5.weight freezed
Layer 5: features.5.bias freezed
Layer 7: features.7.weight freezed
Layer 7: features.7.bias freezed
Layer 10: features.10.weight freezed
Layer 10: features.10.bias freezed
Layer 12: features.12.weight freezed
Layer 12: features.12.bias freezed
Layer 14: features.14.weight freezed
Layer 14: features.14.bias freezed
Layer 17: features.17.weight freezed
Layer 17: features.17.bias freezed
Layer 19: features.19.weight freezed
Layer 19: features.19.bias freezed
Layer 21: features.21.weight freezed
Layer 21: features.21.bias freezed
Layer 24: features.24.weight not freezed
Layer 24: features.24.bias not freezed
Layer 26: features.26.weight not freezed
Layer 26: features.26.bias not freezed
Layer 28: features.28.weight not freezed
Layer 28: features.28.bias not freezed
```

2. Rewrite the classifier:

In [ ]:
```
# define out classifier
binary_classifier = nn.Sequential(
   nn.Linear(in_features=25088, out_features=2048),
   nn.ReLU(),
   nn.Linear(in_features=2048, out_features=1024),
   nn.ReLU(),
   nn.Linear(in_features=1024, out_features=512),
   nn.ReLU(),
   nn.Linear(in_features=512, out_features=1)
)

# replace model class classifier attribute:
VGG_model.classifier = binary_classifier
```

In [ ]:
```
VGG_model
```

Out[ ]:
```
VGG(
  (features): Sequential(
    (0): Conv2d(3, 64, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (1): ReLU(inplace=True)
    (2): Conv2d(64, 64, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (3): ReLU(inplace=True)
    (4): MaxPool2d(kernel_size=2, stride=2, padding=0, dilation=1, ceil_mode=False)
    (5): Conv2d(64, 128, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (6): ReLU(inplace=True)
    (7): Conv2d(128, 128, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (8): ReLU(inplace=True)
    (9): MaxPool2d(kernel_size=2, stride=2, padding=0, dilation=1, ceil_mode=False)
    (10): Conv2d(128, 256, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (11): ReLU(inplace=True)
    (12): Conv2d(256, 256, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (13): ReLU(inplace=True)
    (14): Conv2d(256, 256, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (15): ReLU(inplace=True)
    (16): MaxPool2d(kernel_size=2, stride=2, padding=0, dilation=1, ceil_mode=False)
    (17): Conv2d(256, 512, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (18): ReLU(inplace=True)
    (19): Conv2d(512, 512, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (20): ReLU(inplace=True)
    (21): Conv2d(512, 512, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (22): ReLU(inplace=True)
    (23): MaxPool2d(kernel_size=2, stride=2, padding=0, dilation=1, ceil_mode=False)
    (24): Conv2d(512, 512, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (25): ReLU(inplace=True)
    (26): Conv2d(512, 512, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (27): ReLU(inplace=True)
    (28): Conv2d(512, 512, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (29): ReLU(inplace=True)
    (30): MaxPool2d(kernel_size=2, stride=2, padding=0, dilation=1, ceil_mode=False)
  )
  (avgpool): AdaptiveAvgPool2d(output_size=(7, 7))
  (classifier): Sequential(
    (0): Linear(in_features=25088, out_features=2048, bias=True)
    (1): ReLU()
    (2): Linear(in_features=2048, out_features=1024, bias=True)
    (3): ReLU()
    (4): Linear(in_features=1024, out_features=512, bias=True)
    (5): ReLU()
    (6): Linear(in_features=512, out_features=1, bias=True)
  )
)
```

2. Train the model:

In [ ]:
```
history = train_model(VGG_model, train_data, valid_data, device, batch_size=32, epochs=30, lr=0.0
```

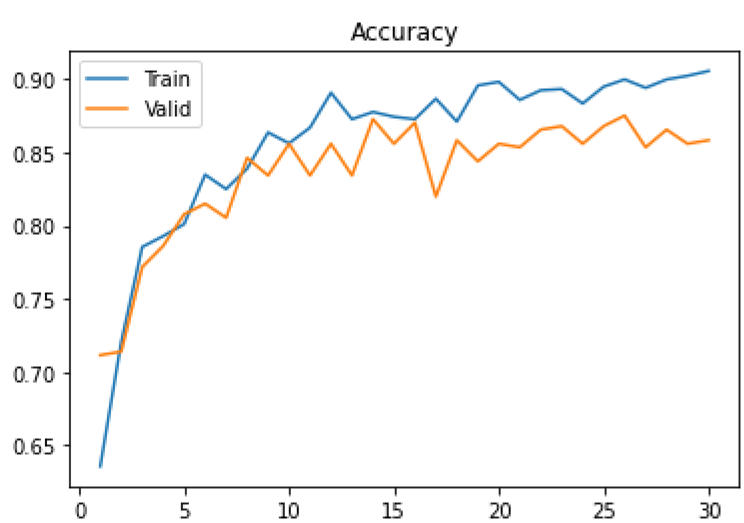
```
Training Start
/usr/local/lib/python3.7/dist-packages/torch/nn/functional.py:718: UserWarning: Named tensors an
d all their associated APIs are an experimental feature and subject to change. Please do not use
them for anything important until they are released as stable. (Triggered internally at  /pytorc
h/c10/core/TensorImpl.h:1156.)
  return torch.max_pool2d(input, kernel_size, stride, padding, dilation, ceil_mode)
```

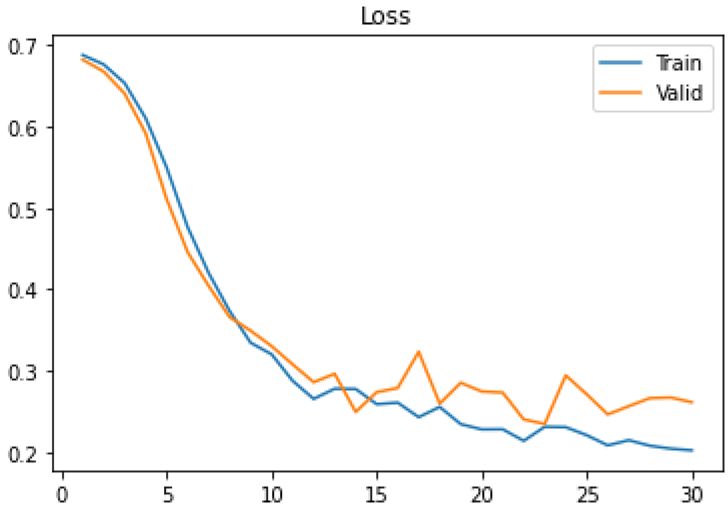
```
Epoch:1 / 30, train loss:0.6879 train_acc:0.6357, valid loss:0.6821 valid acc:0.7115
Epoch:2 / 30, train loss:0.6763 train_acc:0.7204, valid loss:0.6675 valid acc:0.7139
Epoch:3 / 30, train loss:0.6534 train_acc:0.7854, valid loss:0.6405 valid acc:0.7716
Epoch:4 / 30, train loss:0.6102 train_acc:0.7928, valid loss:0.5917 valid acc:0.7861
Epoch:5 / 30, train loss:0.5496 train_acc:0.8010, valid loss:0.5107 valid acc:0.8077
Epoch:6 / 30, train loss:0.4763 train_acc:0.8347, valid loss:0.4456 valid acc:0.8149
Epoch:7 / 30, train loss:0.4200 train_acc:0.8248, valid loss:0.4041 valid acc:0.8053
Epoch:8 / 30, train loss:0.3732 train_acc:0.8388, valid loss:0.3657 valid acc:0.8462
Epoch:9 / 30, train loss:0.3343 train_acc:0.8635, valid loss:0.3490 valid acc:0.8341
Epoch:10 / 30, train loss:0.3201 train_acc:0.8561, valid loss:0.3300 valid acc:0.8558
Epoch:11 / 30, train loss:0.2875 train_acc:0.8668, valid loss:0.3077 valid acc:0.8341
Epoch:12 / 30, train loss:0.2653 train_acc:0.8906, valid loss:0.2858 valid acc:0.8558
Epoch:13 / 30, train loss:0.2778 train_acc:0.8725, valid loss:0.2961 valid acc:0.8341
Epoch:14 / 30, train loss:0.2775 train_acc:0.8775, valid loss:0.2493 valid acc:0.8726
Epoch:15 / 30, train loss:0.2588 train_acc:0.8742, valid loss:0.2736 valid acc:0.8558
Epoch:16 / 30, train loss:0.2607 train_acc:0.8725, valid loss:0.2787 valid acc:0.8702
Epoch:17 / 30, train loss:0.2429 train_acc:0.8865, valid loss:0.3232 valid acc:0.8197
Epoch:18 / 30, train loss:0.2555 train_acc:0.8709, valid loss:0.2595 valid acc:0.8582
Epoch:19 / 30, train loss:0.2343 train_acc:0.8956, valid loss:0.2851 valid acc:0.8438
Epoch:20 / 30, train loss:0.2278 train_acc:0.8980, valid loss:0.2744 valid acc:0.8558
Epoch:21 / 30, train loss:0.2280 train_acc:0.8857, valid loss:0.2731 valid acc:0.8534
Epoch:22 / 30, train loss:0.2138 train_acc:0.8923, valid loss:0.2401 valid acc:0.8654
Epoch:23 / 30, train loss:0.2311 train_acc:0.8931, valid loss:0.2345 valid acc:0.8678
Epoch:24 / 30, train loss:0.2306 train_acc:0.8832, valid loss:0.2942 valid acc:0.8558
Epoch:25 / 30, train loss:0.2207 train_acc:0.8947, valid loss:0.2710 valid acc:0.8678
Epoch:26 / 30, train loss:0.2082 train_acc:0.8997, valid loss:0.2463 valid acc:0.8750
Epoch:27 / 30, train loss:0.2146 train_acc:0.8939, valid loss:0.2563 valid acc:0.8534
Epoch:28 / 30, train loss:0.2078 train_acc:0.8997, valid loss:0.2662 valid acc:0.8654
Epoch:29 / 30, train loss:0.2041 train_acc:0.9021, valid loss:0.2670 valid acc:0.8558
Epoch:30 / 30, train loss:0.2021 train_acc:0.9054, valid loss:0.2612 valid acc:0.8582
```

In [ ]:

```python
# acc
plt.plot(range(1, 31), history['train_acc'], label='Train')
plt.plot(range(1, 31), history['test_acc'], label='Valid')
plt.title('Accuracy')
plt.legend()
plt.show()

# loss
plt.plot(range(1, 31), history['train_loss'], label='Train')
plt.plot(range(1, 31), history['test_loss'], label='Valid')
plt.title('Loss')
plt.legend()
plt.show()
```




Loss
Train
Valid
0.7
0.6
0.5
0.4
0.3
0.2
0
5
10
15
20
25
30