```
!pip install d2l==1.0.3
```

Show hidden output

COSE474-2024F: Deep Learning

8.6. Residual Networks (ResNet) and ResNeXt

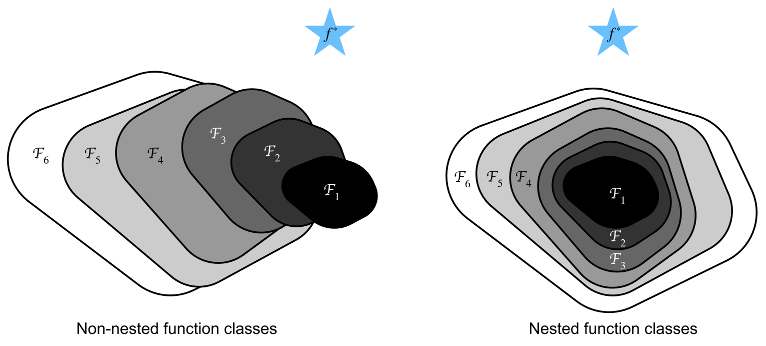
```
import torch
from torch import nn
from torch.nn import functional as F
from d2l import torch as d2l
```

Consider $\mathcal{F}$, the class of functions that a specific network architecture (together with learning rates and other hyperparameter settings) can reach. That is, for all $f \in \mathcal{F}$ there exists some set of parameters (e.g., weights and biases) that can be obtained through training on a suitable dataset. Let's assume that f^* is the "truth" function that we really would like to find. If it is in $\mathcal{F}$, we are in good shape but typically we will not be quite so lucky. Instead, we will try to find some $f^*_\mathcal{F}$ which is our best bet within $\mathcal{F}$. For instance, given a dataset with features $\mathbf{X}$ and labels $\mathbf{y}$, we might try finding it by solving the following optimization problem:

$$f^*_\mathcal{F} \stackrel{\textrm{def}}{=} \mathop{\mathrm{argmin}}_f L(\mathbf{X}, \mathbf{y}, f) \textrm{ subject to } f \in \mathcal{F}.$$

(Fig. 8.6.1)

We know that regularization (Morozov, 1984, Tikhonov and Arsenin, 1977) may control complexity of $\mathcal{F}$ and achieve consistency, so a larger size of training data generally leads to better $f^*_\mathcal{F}$. It is only reasonable to assume that if we design a different and more powerful architecture $\mathcal{F}'$ we should arrive at a better outcome. In other words, we would expect that $f^*_{\mathcal{F}'}$ is "better" than $f^*_\mathcal{F}$. However, if $\mathcal{F} \not\subseteq \mathcal{F}'$ there is no guarantee that this should even happen. In fact, $f^*_{\mathcal{F}'}$ might well be worse. As illustrated by Fig. 8.6.1, for non-nested function classes, a larger function class does not always move closer to the "truth" function f^*. For instance, on the left of Fig. 8.6.1, though $\mathcal{F}_3$ is closer to f^* than $\mathcal{F}_1$, $\mathcal{F}_6$ moves away and there is no guarantee that further increasing the complexity can reduce the distance from f^*. With nested function classes where $\mathcal{F}_1 \subseteq \cdots \subseteq \mathcal{F}_6$ on the right of Fig. 8.6.1, we can avoid the aforementioned issue from the non-nested function classes.



:label: `fig_functionclasses`

Fig. 8.6.1 For non-nested function classes, a larger (indicated by area) function class does not guarantee we will get closer to the “truth” function (f^*). This does not happen in nested function classes.

Thus, only if larger function classes contain the smaller ones are we guaranteed that increasing them strictly increases the expressive power of the network. For deep neural networks, if we can train the newly-added layer into an identity function $f(\mathbf{x}) = \mathbf{x}$, the new model will be as effective as the original model. As the new model may get a better solution to fit the training dataset, the added layer might make it easier to reduce training errors.

This is the question that He et al. (2016) considered when working on very deep computer vision models. At the heart of their proposed residual network (ResNet) is the idea that every additional layer should more easily contain the identity function as one of its elements. These considerations are rather profound but they led to a surprisingly simple solution, a residual block. With it, ResNet won the ImageNet Large Scale Visual Recognition Challenge in 2015. The design had a profound influence on how to build deep neural networks. For instance, residual blocks have been added to recurrent networks (Kim et al., 2017, Prakash et al., 2016). Likewise, Transformers (Vaswani et al., 2017) use them to stack many layers of networks efficiently. It is also used in graph neural networks (Kipf and Welling, 2016) and, as a basic concept, it has been used extensively in computer vision (Redmon and Farhadi, 2018, Ren et al., 2015). Note that residual networks are predated by highway networks (Srivastava et al., 2015) that share some of the motivation, albeit without the elegant parametrization around the identity function.

8.6.2. Residual Blocks

Let's focus on a local part of a neural network, as depicted in :numref: `fig_residual_block`. Denote the input by $\mathbf{x}$. We assume that $f(\mathbf{x})$, the desired underlying mapping we want to obtain by learning, is to be used as input to the activation function on the top. On the left, the portion within the dotted-line box must directly learn $f(\mathbf{x})$. On the right, the portion within the dotted-line box needs to learn the *residual mapping* $g(\mathbf{x}) = f(\mathbf{x}) - \mathbf{x}$, which is how the residual block derives its name. If the identity mapping $f(\mathbf{x}) = \mathbf{x}$ is the desired underlying mapping, the residual mapping amounts to $g(\mathbf{x}) = 0$ and it is thus easier to learn: we only need to push the weights and biases of the upper weight layer (e.g., fully connected layer and convolutional layer) within the dotted-line box to zero. The right figure illustrates the *residual block* of ResNet, where the solid line carrying the layer input $\mathbf{x}$ to the addition operator is called a *residual connection* (or *shortcut connection*). With residual blocks, inputs can forward propagate faster through the residual connections across layers. In fact, the residual block can be thought of as a special case of the multi-branch Inception block: it has two branches one of which is the identity mapping.

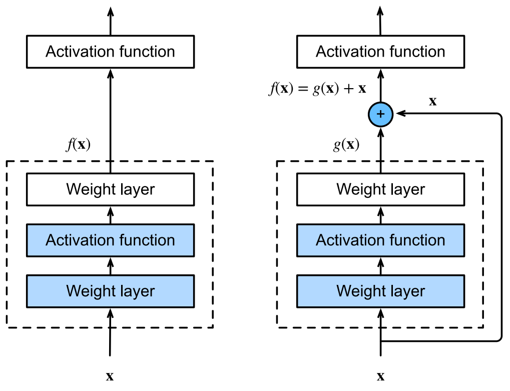


Fig. 8.6.2 In a regular block (left), the portion within the dotted-line box must directly learn the mapping $f(\mathbf{x})$. In a residual block (right), the portion within the dotted-line box needs to learn the residual mapping $g(\mathbf{x}) = f(\mathbf{x}) - \mathbf{x}$, making the identity mapping $f(\mathbf{x}) = \mathbf{x}$ easier to learn.

ResNet has VGG's full 3×3 convolutional layer design. The residual block has two 3×3 convolutional layers with the same number of output channels. Each convolutional layer is followed by a batch normalization layer and a ReLU activation function. Then, we skip these two convolution operations and add the input directly before the final ReLU activation function. This kind of design requires that the output of the two convolutional layers has to be of the same shape as the input, so that they can be added together. If we want to change the number of channels, we need to introduce an additional 1×1 convolutional layer to transform the input into the desired shape for the addition operation. Let's have a look at the code below.

```
class Residual(nn.Module):  #@save
    """The Residual block of ResNet models."""
    def __init__(self, num_channels, use_1x1conv=False, strides=1):
        super().__init__()
        self.conv1 = nn.LazyConv2d(num_channels, kernel_size=3, paddi
                                   stride=strides)
        self.conv2 = nn.LazyConv2d(num_channels, kernel_size=3, paddi
        if use_1x1conv:
            self.conv3 = nn.LazyConv2d(num_channels, kernel_size=1,
                                       stride=strides)
        else:
            self.conv3 = None
        self.bn1 = nn.LazyBatchNorm2d()
        self.bn2 = nn.LazyBatchNorm2d()

    def forward(self, X):
        Y = F.relu(self.bn1(self.conv1(X)))
        Y = self.bn2(self.conv2(Y))
        if self.conv3:
            X = self.conv3(X)
        Y += X
        return F.relu(Y)
```

"@save" is not an allowed annotation - allowed values include [@param, @title, @markdown].

This code generates two types of networks: one where we add the input to the output before applying the ReLU nonlinearity whenever use_1x1conv=False; and one where we adjust channels and resolution by means of a 1×1 convolution before adding. Fig. 8.6.3 illustrates this.

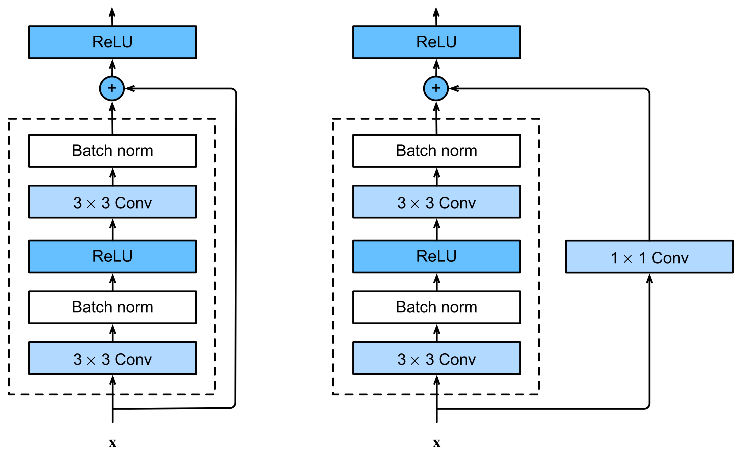


Fig. 8.6.3 ResNet block with and without 1×1 convolution, which transforms the input into the desired shape for the addition operation.

Now let's look at a situation where the input and output are of the same shape, where 1×1 convolution is not needed.

```
blk = Residual(3)
X = torch.randn(4, 3, 6, 6)
blk(X).shape
```

```
torch.Size([4, 3, 6, 6])
```

We also have the option to [**halve the output height and width while increasing the number of output channels**]. In this case we use 1×1 convolutions via `use_1x1conv=True`. This comes in handy at the beginning of each ResNet block to reduce the spatial dimensionality via `strides=2`.

```
blk = Residual(6, use_1x1conv=True, strides=2)
blk(X).shape
```

```
torch.Size([4, 6, 3, 3])
```

8.6.3. ResNet Model

The first two layers of ResNet are the same as those of the GoogLeNet we described before: the 7×7 convolutional layer with 64 output channels and a stride of 2 is followed by the 3×3 max-pooling layer with a stride of 2. The difference is the batch normalization layer added after each convolutional layer in ResNet.

```
class ResNet(d2l.Classifier):
    def b1(self):
        return nn.Sequential(
            nn.LazyConv2d(64, kernel_size=7, stride=2, padding=3),
            nn.LazyBatchNorm2d(), nn.ReLU(),
            nn.MaxPool2d(kernel_size=3, stride=2, padding=1))
```

GoogLeNet uses four modules made up of Inception blocks. However, ResNet uses four modules made up of residual blocks, each of which uses several residual blocks with the same number of output channels. The number of channels in the first module is the same as the number of input channels. Since a max-pooling layer with a stride of 2 has already been used, it is not necessary to reduce the height and width. In the first residual block for each of the subsequent modules, the number of channels is doubled compared with that of the previous module, and the height and width are halved.

```
@d2l.add_to_class(ResNet)
def block(self, num_residuals, num_channels, first_block=False):
    blk = []
    for i in range(num_residuals):
        if i == 0 and not first_block:
            blk.append(Residual(num_channels, use_1x1conv=True, strides=2))
        else:
            blk.append(Residual(num_channels))
    return nn.Sequential(*blk)
```

Then, we add all the modules to ResNet. Here, two residual blocks are used for each module. Lastly, just like GoogLeNet, we add a global average pooling layer, followed by the fully connected layer output.

```
@d2l.add_to_class(ResNet)
def __init__(self, arch, lr=0.1, num_classes=10):
    super(ResNet, self).__init__()
    self.save_hyperparameters()
    self.net = nn.Sequential(self.b1())
    for i, b in enumerate(arch):
        self.net.add_module(f'b{i+2}', self.block(*b, first_block=(i==0)))
    self.net.add_module('last', nn.Sequential(
        nn.AdaptiveAvgPool2d((1, 1)), nn.Flatten(),
        nn.LazyLinear(num_classes)))
    self.net.apply(d2l.init_cnn)
```

There are four convolutional layers in each module (excluding the 1×1 convolutional layer). Together with the first 7×7 convolutional layer and the final fully connected layer, there are 18 layers in total. Therefore, this model is commonly known as ResNet-18. By configuring different numbers of channels and residual blocks in the module, we can create different ResNet models, such as the deeper 152-layer ResNet-152. Although the main architecture of ResNet is similar to that of GoogLeNet, ResNet's structure is simpler and easier to modify. All these factors have resulted in the rapid and widespread use of ResNet. Fig. 8.6.4 depicts the full ResNet-18.

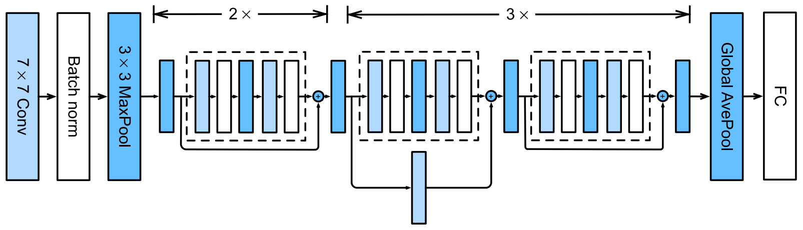


Fig. 8.6.4 The ResNet-18 architecture.

Before training ResNet, let's [**observe how the input shape changes across different modules in ResNet**]. As in all the previous architectures, the resolution decreases while the number of channels increases up until the point where a global average pooling layer aggregates all features.

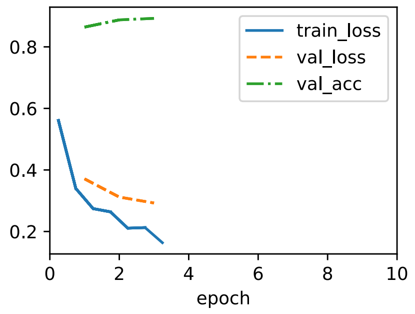
```
class ResNet18(ResNet):
    def __init__(self, lr=0.1, num_classes=10):
        super().__init__(((2, 64), (2, 128), (2, 256), (2, 512)),
                       lr, num_classes)

ResNet18().layer_summary((1, 1, 96, 96))
```

```
Sequential output shape:         torch.Size([1, 64, 24, 24])
Sequential output shape:         torch.Size([1, 64, 24, 24])
Sequential output shape:         torch.Size([1, 128, 12, 12])
Sequential output shape:         torch.Size([1, 256, 6, 6])
Sequential output shape:         torch.Size([1, 512, 3, 3])
Sequential output shape:         torch.Size([1, 10])
```

8.6.4. Training

We train ResNet on the Fashion-MNIST dataset, just like before. ResNet is quite a powerful and flexible architecture. The plot capturing training and validation loss illustrates a significant gap between both graphs, with the training loss being considerably lower. For a network of this flexibility, more training data would offer distinct benefit in closing the gap and improving accuracy.

```
model = ResNet18(lr=0.01)
trainer = d2l.Trainer(max_epochs=10, num_gpus=1)
data = d2l.FashionMNIST(batch_size=128, resize=(96, 96))
model.apply_init([next(iter(data.get_dataloader(True)))[0]], d2l.init_cnn)
trainer.fit(model, data)
```



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