

HW2

0 Intallation

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

```
Requirement already satisfied: ipython-genutils in /usr/local/lib/python3.10/dist-packages (from ipykernel->jupyter==1.0.0->d2l==1.0.3) (0.2.0)
Requirement already satisfied: ipython>=5.0.0 in /usr/local/lib/python3.10/dist-packages (from ipykernel->jupyter==1.0.0->d2l==1.0.3) (7.34.0)
Requirement already satisfied: jupyter-client in /usr/local/lib/python3.10/dist-packages (from ipykernel->jupyter==1.0.0->d2l==1.0.3) (6.1.12)
Requirement already satisfied: tornado>=4.2 in /usr/local/lib/python3.10/dist-packages (from ipykernel->jupyter==1.0.0->d2l==1.0.3) (6.3.3)
Requirement already satisfied: widgetsnbextension~=3.6.0 in /usr/local/lib/python3.10/dist-packages (from ipywidgets->jupyter==1.0.0->d2l==1.0.0)
Requirement already satisfied: jupyterlab-widgets>=1.0.0 in /usr/local/lib/python3.10/dist-packages (from ipywidgets->jupyter==1.0.0->d2l==1.0.0)
Requirement already satisfied: prompt-toolkit!=3.0.0,!<3.0.1,<3.1.0,>=2.0.0 in /usr/local/lib/python3.10/dist-packages (from jupyter-console->jupyter==1.0.0->d2l==1.0.3) (2.18.0)
Requirement already satisfied: pygments in /usr/local/lib/python3.10/dist-packages (from jupyter-console->jupyter==1.0.0->d2l==1.0.3) (2.18.0)
Requirement already satisfied: lxml in /usr/local/lib/python3.10/dist-packages (from nbconvert->jupyter==1.0.0->d2l==1.0.3) (4.9.4)
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Requirement already satisfied: bleach in /usr/local/lib/python3.10/dist-packages (from nbconvert->jupyter==1.0.0->d2l==1.0.3) (6.1.0)
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Requirement already satisfied: terminado>=0.8.3 in /usr/local/lib/python3.10/dist-packages (from notebook->jupyter==1.0.0->d2l==1.0.3) (0.18.1)
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Requirement already satisfied: jedi>=0.16 in /usr/local/lib/python3.10/dist-packages (from ipython>=5.0.0->ipykernel->jupyter==1.0.0->d2l==1.0.3) (0.19.0)
Requirement already satisfied: decorator in /usr/local/lib/python3.10/dist-packages (from ipython>=5.0.0->ipykernel->jupyter==1.0.0->d2l==1.0.3) (5.1.1)
Requirement already satisfied: pickleshare in /usr/local/lib/python3.10/dist-packages (from ipython>=5.0.0->ipykernel->jupyter==1.0.0->d2l==1.0.3) (0.7.5)
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Requirement already satisfied: argon2-cffi-bindings in /usr/local/lib/python3.10/dist-packages (from argon2-cffi->notebook->jupyter==1.0.0->d2l==1.0.3) (21.2.0)
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Requirement already satisfied: webencodings in /usr/local/lib/python3.10/dist-packages (from bleach->nbconvert->jupyter==1.0.0->d2l==1.0.3) (0.5.1)
Requirement already satisfied: parso<0.9.0,>=0.8.3 in /usr/local/lib/python3.10/dist-packages (from jedi>=0.16->ipython>=5.0.0->ipykernel->jupyter==1.0.0->d2l==1.0.3) (0.8.4)
Requirement already satisfied: attrs>=22.2.0 in /usr/local/lib/python3.10/dist-packages (from jsonschema>=2.6->nbformat>=5.1->nbconvert->jupyter==1.0.0->d2l==1.0.3) (23.2.0)
Requirement already satisfied: jsonschema-specifications>=2023.03.6 in /usr/local/lib/python3.10/dist-packages (from jsonschema>=2.6->nbformat>=5.1->nbconvert->jupyter==1.0.0->d2l==1.0.3) (2023.12.1)
Requirement already satisfied: referencing>=0.28.4 in /usr/local/lib/python3.10/dist-packages (from jsonschema>=2.6->nbformat>=5.1->nbconvert->jupyter==1.0.0->d2l==1.0.3) (0.35.0)
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Requirement already satisfied: jupyter-server<3,>=1.8 in /usr/local/lib/python3.10/dist-packages (from notebook-shim>=0.2.3->nbclassic>=0.4.7->notebook->jupyter==1.0.0->d2l==1.0.3) (2.14.1)
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Requirement already satisfied: anyio<4,>=3.1.0 in /usr/local/lib/python3.10/dist-packages (from jupyter-server<3,>=1.8->notebook-shim>=0.2.3->notebook->jupyter==1.0.0->d2l==1.0.3) (3.7.1)
Requirement already satisfied: websocket-client in /usr/local/lib/python3.10/dist-packages (from jupyter-server<3,>=1.8->notebook-shim>=0.2.3->notebook->jupyter==1.0.0->d2l==1.0.3) (1.7.0)
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Requirement already satisfied: exceptiongroup in /usr/local/lib/python3.10/dist-packages (from anyio<4,>=3.1.0->jupyter-server<3,>=1.8->notebook-shim>=0.2.3->notebook->jupyter==1.0.0->d2l==1.0.3) (1.2.0)
```

Ch 7

7.1. From Fully Connected Layers to Convolutions

Translation invariance (or translation equivariance): In the earliest layers, our network should respond similarly to the same patch, regardless of where it appears in the image.

Locality principle: The earliest layers of the network should focus on local regions, without regard for the contents of the image in distant regions. Eventually, these local representations can be aggregated to make predictions at the whole image level.

Deeper layers: As we proceed, deeper layers should be able to capture longer-range features of the image, in a way similar to higher level vision in nature.

7.2. Convolutions for Images

```
import torch
from torch import nn
from d2l import torch as d2l
```

Recall that strictly speaking, convolutional layers are a misnomer, since the operations they express are more accurately described as cross-correlations

```
def corr2d(X, K):
    h, w = K.shape
    Y = torch.zeros((X.shape[0] - h + 1, X.shape[1] - w + 1))
    for i in range(Y.shape[0]):
        for j in range(Y.shape[1]):
            Y[i, j] = (X[i:i + h, j:j + w] * K).sum()
    return Y

X = torch.tensor([[0.0, 1.0, 2.0], [3.0, 4.0, 5.0], [6.0, 7.0, 8.0]])
K = torch.tensor([[0.0, 1.0], [2.0, 3.0]])
corr2d(X, K)
```

```
↗ tensor([[19., 25.],
          [37., 43.]])
```

```
def corr2d(X, K):
    h, w = K.shape
    Y = torch.zeros((X.shape[0] - h + 1, X.shape[1] - w + 1))
    for i in range(Y.shape[0]):
        for j in range(Y.shape[1]):
            Y[i, j] = (X[i:i + h, j:j + w] * K).sum()
    return Y

X = torch.tensor([[0.0, 1.0, 2.0], [3.0, 4.0, 5.0], [6.0, 7.0, 8.0]])
K = torch.tensor([[0.0, 1.0], [2.0, 3.0]])
corr2d(X, K)
```

```
↗ tensor([[19., 25.],
          [37., 43.]])
```

```
class Conv2D(nn.Module):
    def __init__(self, kernel_size):
        super().__init__()
        self.weight = nn.Parameter(torch.rand(kernel_size))
        self.bias = nn.Parameter(torch.zeros(1))

    def forward(self, x):
        return corr2d(x, self.weight) + self.bias
```

```
class Conv2D(nn.Module):
    def __init__(self, kernel_size):
        super().__init__()
        self.weight = nn.Parameter(torch.rand(kernel_size))
        self.bias = nn.Parameter(torch.zeros(1))

    def forward(self, x):
        return corr2d(x, self.weight) + self.bias
```

```
X = torch.ones((6, 8))
X[:, 2:6] = 0
X
```

```
↗ tensor([[1., 1., 0., 0., 0., 0., 1., 1.],
          [1., 1., 0., 0., 0., 0., 1., 1.],
          [1., 1., 0., 0., 0., 0., 1., 1.]])
```

```

[1., 1., 0., 0., 0., 0., 1., 1.],
[1., 1., 0., 0., 0., 0., 1., 1.],
[1., 1., 0., 0., 0., 0., 1., 1]])

K = torch.tensor([[1.0, -1.0]])

Y = corr2d(X, K)
Y

↔ tensor([[ 0.,  1.,  0.,  0.,  0., -1.,  0.],
          [ 0.,  1.,  0.,  0.,  0., -1.,  0.],
          [ 0.,  1.,  0.,  0.,  0., -1.,  0.],
          [ 0.,  1.,  0.,  0.,  0., -1.,  0.],
          [ 0.,  1.,  0.,  0.,  0., -1.,  0.],
          [ 0.,  1.,  0.,  0.,  0., -1.,  0.]])

# my exercise
# horizontal edge에 대한 filter
K_horizontal = torch.tensor([[1.0], [-1.0]])

X2 = torch.ones((6, 8))
X2[2:4, :] = 0
print(X2)

Y2 = corr2d(X2, K_horizontal)
print(Y2)

↔ tensor([[1., 1., 1., 1., 1., 1., 1., 1.],
          [1., 1., 1., 1., 1., 1., 1., 1.],
          [0., 0., 0., 0., 0., 0., 0., 0.],
          [0., 0., 0., 0., 0., 0., 0., 0.],
          [1., 1., 1., 1., 1., 1., 1., 1.],
          [1., 1., 1., 1., 1., 1., 1., 1.]])
tensor([[ 0.,  0.,  0.,  0.,  0.,  0.,  0.,  0.],
        [ 1.,  1.,  1.,  1.,  1.,  1.,  1.,  1.],
        [ 0.,  0.,  0.,  0.,  0.,  0.,  0.,  0.],
        [-1., -1., -1., -1., -1., -1., -1., -1.],
        [ 0.,  0.,  0.,  0.,  0.,  0.,  0.,  0.]])

corr2d(X.t(), K)

↔ tensor([[0., 0., 0., 0., 0.],
          [0., 0., 0., 0., 0.],
          [0., 0., 0., 0., 0.],
          [0., 0., 0., 0., 0.],
          [0., 0., 0., 0., 0.],
          [0., 0., 0., 0., 0.],
          [0., 0., 0., 0., 0.],
          [0., 0., 0., 0., 0.]])

conv2d = nn.LazyConv2d(1, kernel_size=(1, 2), bias=False)

X = X.reshape((1, 1, 6, 8))
Y = Y.reshape((1, 1, 6, 7))
lr = 3e-2

for i in range(10):
    Y_hat = conv2d(X)
    l = (Y_hat - Y) ** 2
    conv2d.zero_grad()
    l.sum().backward()
    conv2d.weight.data[:] -= lr * conv2d.weight.grad
    if (i + 1) % 2 == 0:
        print(f'epoch {i + 1}, loss {l.sum():.3f}')

↔ epoch 2, loss 6.672
epoch 4, loss 1.131
epoch 6, loss 0.194
epoch 8, loss 0.034
epoch 10, loss 0.007

conv2d.weight.data.reshape((1, 2))

↔ tensor([[ 0.9903, -0.9829]])

```

✓ 7.3. Padding and Stride

Padding: add extra pixels of filler around the boundary of our input image, thus increasing the effective size of the image

```
import torch
from torch import nn

def comp_conv2d(conv2d, X):
    X = X.reshape((1, 1) + X.shape)
    Y = conv2d(X)
    return Y.reshape(Y.shape[2:])

conv2d = nn.LazyConv2d(1, kernel_size=3, padding=1)
X = torch.rand(size=(8, 8))
comp_conv2d(conv2d, X).shape

↔ torch.Size([8, 8])

conv2d = nn.LazyConv2d(1, kernel_size=(5, 3), padding=(2, 1))
comp_conv2d(conv2d, X).shape

↔ torch.Size([8, 8])

conv2d = nn.LazyConv2d(1, kernel_size=3, padding=1, stride=2)
comp_conv2d(conv2d, X).shape

↔ torch.Size([4, 4])

conv2d = nn.LazyConv2d(1, kernel_size=(3, 5), padding=(0, 1), stride=(3, 4))
comp_conv2d(conv2d, X).shape

↔ torch.Size([2, 2])
```

✓ 7.4. Multiple Input and Multiple Output Channels

```
import torch
from d2l import torch as d2l

def corr2d_multi_in(X, K):
    return sum(d2l.corr2d(x, k) for x, k in zip(X, K))

X = torch.tensor([[[[0.0, 1.0, 2.0], [3.0, 4.0, 5.0], [6.0, 7.0, 8.0]],
                    [[1.0, 2.0, 3.0], [4.0, 5.0, 6.0], [7.0, 8.0, 9.0]]]])
K = torch.tensor([[[[0.0, 1.0], [2.0, 3.0]], [[1.0, 2.0], [3.0, 4.0]]]])

corr2d_multi_in(X, K)

↔ tensor([[ 56.,  72.],
          [104., 120.]])

def corr2d_multi_in_out(X, K):
    return torch.stack([corr2d_multi_in(X, k) for k in K], 0)

K = torch.stack((K, K + 1, K + 2), 0)
K.shape

↔ torch.Size([3, 2, 2, 2])

corr2d_multi_in_out(X, K)

↔ tensor([[[[ 56.,  72.],
              [104., 120.]],
           [[ 76., 100.],
              [148., 172.]],
           [[ 96., 128.],
              [192., 224.]]]])

def corr2d_multi_in_out_1x1(X, K):
    c_i, h, w = X.shape
    c_o = K.shape[0]
    X = X.reshape((c_i, h * w))
    K = K.reshape((c_o, c_i))
```

```

Y = torch.matmul(K, X)
return Y.reshape((c_o, h, w))

X = torch.normal(0, 1, (3, 3, 3))
K = torch.normal(0, 1, (2, 3, 1, 1))
Y1 = corr2d_multi_in_out_1x1(X, K)
Y2 = corr2d_multi_in_out(X, K)
assert float(torch.abs(Y1 - Y2).sum()) < 1e-6

```

7.5. Pooling

Consequently, the units of our final layer should be sensitive to the entire input. Reducing spatial resolution makes convolution kernels cover a larger effective area.

```

import torch
from torch import nn
from d2l import torch as d2l

def pool2d(X, pool_size, mode='max'):
    p_h, p_w = pool_size
    Y = torch.zeros((X.shape[0] - p_h + 1, X.shape[1] - p_w + 1))
    for i in range(Y.shape[0]):
        for j in range(Y.shape[1]):
            if mode == 'max':
                Y[i, j] = X[i:i + p_h, j:j + p_w].max()
            elif mode == 'avg':
                Y[i, j] = X[i:i + p_h, j:j + p_w].mean()
    return Y

X = torch.tensor([[0.0, 1.0, 2.0], [3.0, 4.0, 5.0], [6.0, 7.0, 8.0]])
pool2d(X, (2, 2))

↩ tensor([[4., 5.],
          [7., 8.]])

# my exercise
# 3-dimecsional data에 대한 pooling

import torch

def pool3d(X, pool_size, mode='max'):
    p_d, p_h, p_w = pool_size
    Y = torch.zeros((X.shape[0] - p_d + 1, X.shape[1] - p_h + 1, X.shape[2] - p_w + 1))

    for i in range(Y.shape[0]):
        for j in range(Y.shape[1]):
            for k in range(Y.shape[2]):
                region = X[i:i + p_d, j:j + p_h, k:k + p_w]
                if mode == 'max':
                    Y[i, j, k] = region.max()
                elif mode == 'avg':
                    Y[i, j, k] = region.mean()

    return Y

X_3d = torch.tensor([
    [[0.0, 1.0, 2.0], [3.0, 4.0, 5.0], [6.0, 7.0, 8.0]],
    [[9.0, 10.0, 11.0], [12.0, 13.0, 14.0], [15.0, 16.0, 17.0]],
    [[18.0, 19.0, 20.0], [21.0, 22.0, 23.0], [24.0, 25.0, 26.0]]
])
result = pool3d(X_3d, (2, 2, 2), mode='max')
print(result)

↩ tensor([[[[13., 14.],
            [16., 17.]],

           [[22., 23.],
            [25., 26.]]]])

pool2d(X, (2, 2), 'avg')

↩ tensor([[2., 3.],
          [5., 6.]])

```

```
X = torch.arange(16, dtype=torch.float32).reshape((1, 1, 4, 4))
X
```

```
↔ tensor([[[[ 0.,  1.,  2.,  3.],
              [ 4.,  5.,  6.,  7.],
              [ 8.,  9., 10., 11.],
              [12., 13., 14., 15.]]]]])
```

```
pool2d = nn.MaxPool2d(3)
pool2d(X)
```

```
↔ tensor([[[[10.]]]]])
```

```
pool2d = nn.MaxPool2d(3, padding=1, stride=2)
pool2d(X)
```

```
↔ tensor([[[[ 5.,  7.],
              [13., 15.]]]]])
```

```
pool2d = nn.MaxPool2d((2, 3), stride=(2, 3), padding=(0, 1))
pool2d(X)
```

```
↔ tensor([[[[ 5.,  7.],
              [13., 15.]]]]])
```

```
X = torch.cat((X, X + 1), 1)
X
```

```
↔ tensor([[[[ 0.,  1.,  2.,  3.],
              [ 4.,  5.,  6.,  7.],
              [ 8.,  9., 10., 11.],
              [12., 13., 14., 15.]],

           [[ 1.,  2.,  3.,  4.],
            [ 5.,  6.,  7.,  8.],
            [ 9., 10., 11., 12.],
            [13., 14., 15., 16.]]]]])
```

```
pool2d = nn.MaxPool2d(3, padding=1, stride=2)
pool2d(X)
```

```
↔ tensor([[[[ 5.,  7.],
              [13., 15.]],

           [[ 6.,  8.],
            [14., 16.]]]]])
```

✓ 7.6. Convolutional Neural Networks (LeNet)

```
import torch
from torch import nn
from d2l import torch as d2l
```

```
def init_cnn(module):
    """Initialize weights for CNNs."""
    if type(module) == nn.Linear or type(module) == nn.Conv2d:
        nn.init.xavier_uniform_(module.weight)
```

```
class LeNet(d2l.Classifier):
    """The LeNet-5 model."""
    def __init__(self, lr=0.1, num_classes=10):
        super().__init__()
        self.save_hyperparameters()
        self.net = nn.Sequential(
            nn.LazyConv2d(6, kernel_size=5, padding=2), nn.Sigmoid(),
            nn.AvgPool2d(kernel_size=2, stride=2),
            nn.LazyConv2d(16, kernel_size=5), nn.Sigmoid(),
            nn.AvgPool2d(kernel_size=2, stride=2),
            nn.Flatten(),
            nn.LazyLinear(120), nn.Sigmoid(),
            nn.LazyLinear(84), nn.Sigmoid(),
            nn.LazyLinear(num_classes))
```

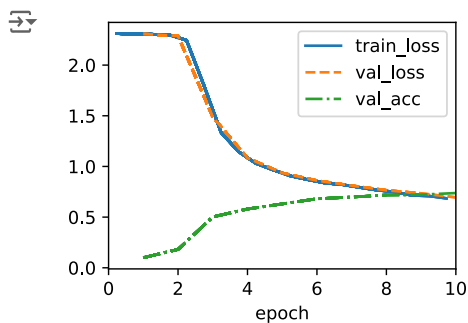
```
@d2l.add_to_class(d2l.Classifier)
def layer_summary(self, X_shape):
    X = torch.randn(*X_shape)
    for layer in self.net:
```

```
X = layer(X)
print(layer.__class__.__name__, 'output shape:Wt', X.shape)
```

```
model = LeNet()
model.layer_summary((1, 1, 28, 28))
```

```
Conv2d output shape: torch.Size([1, 6, 28, 28])
Sigmoid output shape: torch.Size([1, 6, 28, 28])
AvgPool2d output shape: torch.Size([1, 6, 14, 14])
Conv2d output shape: torch.Size([1, 16, 10, 10])
Sigmoid output shape: torch.Size([1, 16, 10, 10])
AvgPool2d output shape: torch.Size([1, 16, 5, 5])
Flatten output shape: torch.Size([1, 400])
Linear output shape: torch.Size([1, 120])
Sigmoid output shape: torch.Size([1, 120])
Linear output shape: torch.Size([1, 84])
Sigmoid output shape: torch.Size([1, 84])
Linear output shape: torch.Size([1, 10])
```

```
trainer = d2l.Trainer(max_epochs=10, num_gpus=1)
data = d2l.FashionMNIST(batch_size=128)
model = LeNet(lr=0.1)
model.apply_init([next(iter(data.get_dataloader(True)))[0]), init_cnn]
trainer.fit(model, data)
```



✓ Ch 8

✓ 8.2. Networks Using Blocks (VGG)

```
import torch
from torch import nn
from d2l import torch as d2l
```

```
def vgg_block(num_convs, out_channels):
    layers = []
    for _ in range(num_convs):
        layers.append(nn.LazyConv2d(out_channels, kernel_size=3, padding=1))
        layers.append(nn.ReLU())
    layers.append(nn.MaxPool2d(kernel_size=2, stride=2))
    return nn.Sequential(*layers)
```

```
class VGG(d2l.Classifier):
    def __init__(self, arch, lr=0.1, num_classes=10):
        super().__init__()
        self.save_hyperparameters()
        conv_blks = []
        for (num_convs, out_channels) in arch:
            conv_blks.append(vgg_block(num_convs, out_channels))
        self.net = nn.Sequential(
            *conv_blks, nn.Flatten(),
            nn.LazyLinear(4096), nn.ReLU(), nn.Dropout(0.5),
            nn.LazyLinear(4096), nn.ReLU(), nn.Dropout(0.5),
            nn.LazyLinear(num_classes))
        self.net.apply(d2l.init_cnn)
```

```
VGG(arch=((1, 64), (1, 128), (2, 256), (2, 512), (2, 512))).layer_summary(
    (1, 1, 224, 224))
```

```
Sequential output shape: torch.Size([1, 64, 112, 112])
Sequential output shape: torch.Size([1, 128, 56, 56])
Sequential output shape: torch.Size([1, 256, 28, 28])
Sequential output shape: torch.Size([1, 512, 14, 14])
```

```

Sequential output shape:      torch.Size([1, 512, 7, 7])
Flatten output shape:         torch.Size([1, 25088])
Linear output shape:          torch.Size([1, 4096])
ReLU output shape:            torch.Size([1, 4096])
Dropout output shape:         torch.Size([1, 4096])
Linear output shape:          torch.Size([1, 4096])
ReLU output shape:            torch.Size([1, 4096])
Dropout output shape:         torch.Size([1, 4096])
Linear output shape:          torch.Size([1, 10])

```

```

model = VGG(arch=((1, 16), (1, 32), (2, 64), (2, 128), (2, 128)), lr=0.01)
trainer = d2l.Trainer(max_epochs=10, num_gpus=1)
data = d2l.FashionMNIST(batch_size=128, resize=(224, 224))
model.apply_init([next(iter(data.get_dataloader(True)))[0]], d2l.init_cnn)
trainer.fit(model, data)

```



```

KeyboardInterrupt                                Traceback (most recent call last)
<ipython-input-7-8d3dfa6be93b> in <cell line: 5>()
      3 data = d2l.FashionMNIST(batch_size=128, resize=(224, 224))
      4 model.apply_init([next(iter(data.get_dataloader(True)))[0]], d2l.init_cnn)
----> 5 trainer.fit(model, data)

```

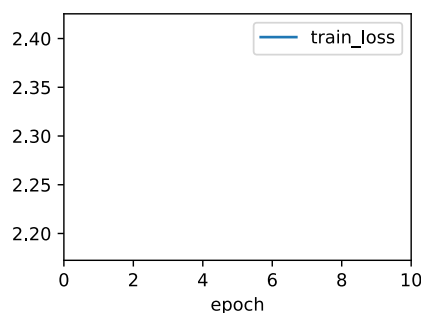
15 frames

```

/usr/local/lib/python3.10/dist-packages/torch/nn/functional.py in relu(input, inplace)
    1498     result = torch.relu(input)
    1499     else:
-> 1500         result = torch.relu(input)
    1501     return result
    1502

```

KeyboardInterrupt:



8.6. Residual Networks (ResNet) and ResNeXt

only if larger function classes contain the smaller ones are we guaranteed that increasing them strictly increases the expressive power of the network.

Residual Networks: $f(x) = g(x) + x$

If the identity mapping $f(x) = x$ is the desired underlying mapping, the residual mapping amounts to $g(x) = x$

use 1x1 convolution layer to transform x into desired shape (output shape)

```

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

```

```

class Residual(nn.Module):
    def __init__(self, num_channels, use_1x1conv=False, strides=1):
        super().__init__()
        self.conv1 = nn.Conv2d(num_channels, kernel_size=3, padding=1,
                                stride=strides)
        self.conv2 = nn.Conv2d(num_channels, kernel_size=3, padding=1)
        if use_1x1conv:
            self.conv3 = nn.Conv2d(num_channels, kernel_size=1,
                                    stride=strides)
        else:
            self.conv3 = None
        self.bn1 = nn.BatchNorm2d()
        self.bn2 = nn.BatchNorm2d()

```



```

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)

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

↔ torch.Size([4, 3, 6, 6])

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

↔ torch.Size([4, 6, 3, 3])

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))

@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)

@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)

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])

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)

```

```

KeyboardInterrupt                                Traceback (most recent call last)
<ipython-input-16-02b532dcfd80> in <cell line: 5>()
      3 data = d2l.FashionMNIST(batch_size=128, resize=(96, 96))
      4 model.apply_init([next(iter(data.get_dataloader(True)))[0]], d2l.init_cnn)
----> 5 trainer.fit(model, data)

4 frames
/usr/local/lib/python3.10/dist-packages/torch/autograd/graph.py in _engine_run_backward(t_outputs, *args, **kwargs)
    767     unregister_hooks = _register_logging_hooks_on_whole_graph(t_outputs)
    768     try:
--> 769         return Variable._execution_engine.run_backward( # Calls into the C++ engine to run the backward pass
    770             t_outputs, *args, **kwargs
    771         ) # Calls into the C++ engine to run the backward pass

KeyboardInterrupt:

```

Discussion & Exercise

Translation invariance (or translation equivariance): In the earliest layers, our network should respond similarly to the same patch, regardless of where it appears in the image.

Locality principle: The earliest layers of the network should focus on local regions, without regard for the contents of the image in distant regions. Eventually, these local representations can be aggregated to make predictions at the whole image level.

Deeper layers: As we proceed, deeper layers should be able to capture longer-range features of the image, in a way similar to higher level vision in nature.

Recall that strictly speaking, convolutional layers are a misnomer, since the operations they express are more accurately described as cross-correlations

```

# my exercise
# horizontal edge에 대한 filter
K_horizontal = torch.tensor([[1.0], [-1.0]])

```

```

X2 = torch.ones((6, 8))
X2[2:4, :] = 0
print(X2)

```

```

Y2 = corr2d(X2, K_horizontal)
print(Y2)

```

```

tensor([[[1., 1., 1., 1., 1., 1., 1., 1.],
         [1., 1., 1., 1., 1., 1., 1., 1.],
         [0., 0., 0., 0., 0., 0., 0., 0.],
         [0., 0., 0., 0., 0., 0., 0., 0.],
         [1., 1., 1., 1., 1., 1., 1., 1.],
         [1., 1., 1., 1., 1., 1., 1., 1.]])
tensor([[ 0.,  0.,  0.,  0.,  0.,  0.,  0.,  0.],
        [ 1.,  1.,  1.,  1.,  1.,  1.,  1.,  1.],
        [ 0.,  0.,  0.,  0.,  0.,  0.,  0.,  0.],
        [-1., -1., -1., -1., -1., -1., -1., -1.],
        [ 0.,  0.,  0.,  0.,  0.,  0.,  0.,  0.]])

```

Padding: add extra pixels of filler around the boundary of our input image, thus increasing the effective size of the image

Consequently, the units of our final layer should be sensitive to the entire input. Reducing spatial resolution makes convolution kernels cover a larger effective area.

```

# my exercise
# 3-dimeccsional data에 대한 pooling

import torch

def pool3d(X, pool_size, mode='max'):
    p_d, p_h, p_w = pool_size
    Y = torch.zeros((X.shape[0] - p_d + 1, X.shape[1] - p_h + 1, X.shape[2] - p_w + 1))

    for i in range(Y.shape[0]):
        for j in range(Y.shape[1]):
            for k in range(Y.shape[2]):
                region = X[i:i + p_d, j:j + p_h, k:k + p_w]
                if mode == 'max':
                    Y[i, j, k] = region.max()

```

```

        elif mode == 'avg':
            Y[i, j, k] = region.mean()

    return Y

X_3d = torch.tensor([
    [[0.0, 1.0, 2.0], [3.0, 4.0, 5.0], [6.0, 7.0, 8.0]],
    [[9.0, 10.0, 11.0], [12.0, 13.0, 14.0], [15.0, 16.0, 17.0]],
    [[18.0, 19.0, 20.0], [21.0, 22.0, 23.0], [24.0, 25.0, 26.0]]
])
result = pool3d(X_3d, (2, 2, 2), mode='max')
print(result)

↔ tensor([[[[13., 14.],
            [16., 17.]],
          [[22., 23.],
            [25., 26.]]]])

```

only if larger function classes contain the smaller ones are we guaranteed that increasing them strictly increases the expressive power of the network.