COSE432-2024F Deep Learning HW2:CNN

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7.1 From Fully Connected Layers to Convolutions

Memo

- we have ignored the image's rich structure and treated images as vectors (we flatted them)
- Flattening was necessary to feed the resulting one-dimensional vectors through fully connected MLP
- the order of features doesn't change. the idea came from image data, near pixels would be similar

> Why we use CNN?

- it has fewer parameters and We can parallel compute the convolution in GPU It became effective
- learning a classifier by fitting so many parameters might require collecting an enormous dataset

where is waldo? CNN systematize the idea of **spatial invariance**

> **what Waldo looks like does not depend upon where Waldo is located**

1. In the earliest layers, our network should respond similarly to the same patch, regardless of where it appears in the image. This principle is called translation invariance (or translation equivariance).
2. The earliest layers of the network should focus on local regions, without regard for the contents of the image in distant regions. This is the locality principle. Eventually, these local representations can be aggregated to make predictions at the whole image level.
3. As we proceed, deeper layers should be able to capture longer-range features of the image, similar to higher-level vision in nature.

- 7.1.2 Constraining the MLP

X as inputs(2-dimensional) and their immediate hidden representation H similarly represented as matrices. U is biases, W is fourth-order weight tensors.

$$\begin{aligned}[\mathbf{H}]_{i,j} &= [\mathbf{U}]_{i,j} + \sum_k \sum_l [\mathbf{W}]_{i,j,k,l}[\mathbf{X}]_{k,l} \\ &= [\mathbf{U}]_{i,j} + \sum_a \sum_b [\mathbf{V}]_{i,j,a,b}[\mathbf{X}]_{i+a,j+b}\end{aligned}$$

1000 X 1000 image(1megapixal) has mapped to a 1000 X 1000 hidden representation. This requires 10^12 parameters

- 7.1.2.1 Translation Invariance

simply lead to a shift in the Hidden represenation H

$$[\mathbf{H}]_{i,j} = u + \sum_a \sum_b [\mathbf{V}]_{a,b}[\mathbf{X}]_{i+a,j+b}$$

- 7.1.2.2 Locality

To understand the local space. We think we don't need information from a large distance. /delta is much smaller than the image size.

$$[\mathbf{H}]_{i,j} = u + \sum_{a=-\Delta}^{\Delta} \sum_{b=-\Delta}^{\Delta} [\mathbf{V}]_{a,b}[\mathbf{X}]_{i+a,j+b}$$

- 7.1.3. Convolutions

$$(f * g)(\mathbf{x}) = \int f(\mathbf{z})g(\mathbf{x}-\mathbf{z})\,d\mathbf{z}.$$

$$(f * g)(i) = \sum_a f(a)g(i-a).$$

$$(f * g)(i,j) = \sum_a \sum_b f(a,b)g(i-a,j-b).$$

- 7.1.4 Channels

It emphasize the image has 3 channel.

7.1 Discussion & Exercises

> With the Translation Invariance why the parameters are 4 X 10^6

First, if input is 1000 X 1000, it would have 10^6 pixels. Because it is fully connected MLP. input should be connected to all of the nodes. If the hidden layer's size is also 1000 X 1000, parameter should be 10^6 X 10^6 = 10^12

Second, It's depend on which filter will be used.

7.2 Convolutions for Images

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

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Requirement already satisfied: ipython>=5.0.0 in /usr/local/lib/python3.10/dist-packages (from ipykernel->jupyter==1
Requirement already satisfied: jupyter-client in /usr/local/lib/python3.10/dist-packages (from ipykernel->jupyter==1
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Requirement already satisfied: exceptiongroup in /usr/local/lib/python3.10/dist-packages (from anyio<4,>=3.1.0->jupyt
```

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

$$\text{output size} = (n_h - k_h + 1) \times (n_w - k_w + 1)$$

```
def corr2d(X, K):
    h, w = K.shape #kernel hight and wide
    Y = torch.zeros((X.shape[0] - h +1, X.shape[1] - w + 1)) #size of output
    for i in range(Y.shape[0]): # size of rows
        for j in range(Y.shape[1]): #size of columns
            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
```

```
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.]])
```

```
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 4.554
epoch 4, loss 0.878
epoch 6, loss 0.194
epoch 8, loss 0.052
epoch 10, loss 0.017
```

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

```
tensor([[ 1.0014, -0.9776]])
```

Discussion

> Why do we need to use random with initializing the kernel.

- if all the weights are initialized in same integer(e.g. 0), all kinds of neuron learns same parameter. it means that learning is not possible. That's fir **Breaking Symmetry**
- It's also used for avoiding local minima.

> What's difference between conv2d, and LazyConv2d

- generally we need to anotate the input channel size and output channel size. However, in some case there is complicate input(that we don't know the input zie). With LazyConv2d, we can automatically predict the size of input.

7.3. Padding and Stride

```
import torch
from torch import nn
```

$$(n_h - k_h + p_h + 1) \times (n_w - k_w + p_w + 1)$$
$$p_h = k_h - 1 p_w = k_w - 1$$

```
def comp_conv2d(conv2d, X):
    # (1,1) indicates that batch size and the number of channels are both 1
    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])
```

$$\left\lfloor \frac{(n_h - k_h + p_h + s_h)}{s_h} \right\rfloor \times \left\lfloor \frac{(n_w - k_w + p_w + s_w)}{s_w} \right\rfloor$$

```
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])
```

Discussion

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
```

Discussion

> Why do we increase the channel depth

- to learn about more features. For details we can get high-level feature with the deep depth.
  - complicate pattern
  - increase representation
  - spatial resolution could be downgraded, but still important information can be maintained

> What will be the typical purpose to use 1x1 convolution area

- just to learn interaction between channels with maintaining the spatial information and
- it can compresss to smaller output channel
- to add non-linearilty

7.5 Pooling

```
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.]])
```

```
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.]]]])
```

Disscusion

> Why Pooling layer is used to decrease the location Sensitivity

- Because it summarize the local information and extracts the certain attribute.
  - maxpooling selects the largest nummber in the window. this means we lose the partical information but, we important points will be maintained.

7.6 Convolutional Neural Networks (LeNet)

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


def init_cnn(module):
    if type(module) == nn.Linear or type(module) == nn.Conv2d:
        nn.init.xavier_uniform_(module.weight)

class LeNet(d2l.Classifier):
    def __init__(self, lr=0.1, num_classes=10):
        super().__init__()
```

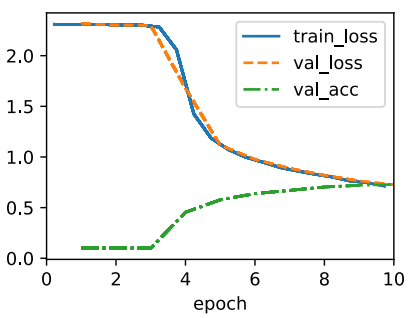
```
        self.save_hyperparameters()
        self.net = nn.Sequential(
            nn.LazyConv2d(6, kernel_size=5, padding=2), nn.Sigmoid(),
            nn.AvgPool2d(kernel_size=2, stride=2),
            nn.LazyConv2d(16, kernel_size=5), nn.Sigmoid(),
            nn.AvgPool2d(kernel_size=2, stride=2),
            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:\t', 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)
```



Discussion

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)

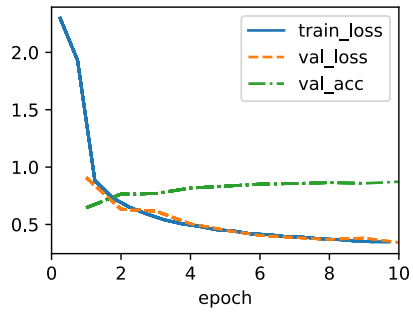

class VGG(d2l.Classifier):
    def __init__(self, arch, lr=0.1, num_classes=10):
        super().__init__()
        self.save_hyperparameters()
        conv_blks = []
        for (num_convs, out_channels) in arch:
            conv_blks.append(vgg_block(num_convs, out_channels))
```

```
        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)
```



Disccusion

> What points make VGG Block better in CNN?

- simple structure
  - instead of complicate un-symmetric kernel, using same small kernel makes deeper Network.
- We could use less parameter.5X5 kernel needs 25 parameters but using 3X3 two need onely 18 parameters.
- we can train in smaller local position and gain the complicate attributes.

8.6(1-4) Residual Networks (ResNet) and ResNeXt

```
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.LazyConv2d(num_channels, kernel_size=3, padding=1, stride=strides)
    self.conv2 = nn.LazyConv2d(num_channels, kernel_size=3, padding=1)
    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)


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)

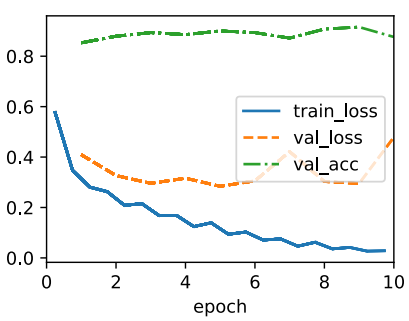

@d2l.add_to_class(ResNet)
def __init__(self, arch, lr=0.1, num_classes=10):
  super(ResNet, self).__init__()
  self.save_hyperparameters()
  self.net = nn.Sequential(self.b1())
  for i, b in enumerate(arch):
    self.net.add_module(f'b{i+2}', self.block(*b, first_block=(i==0)))
  self.net.add_module('last',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



Discussion

> What's the diffrence between LeNet and ResNet

- LeNet is constructed to precept the handwriting number
  - so it is appropriate to small simple image
  - it use sigmoid as activate function
  - 5-7 layers
- ResNet is used to train much deeper Neural Network stably
  - so it can be used in complicated visual perception
  - it use ReLU and batch normalization
  - much deeper layer 50, 101, 152
  - Also it solved the vanishing gradient problem