

Chapter7

April 29, 2019

D2L Textbook Solution

```
In [2]: import d2l
import mxnet as mx
from mxnet import autograd, gluon, init, nd
from mxnet.gluon import loss as gloss, data as gdata, nn

import time

import numpy as np

from IPython.core.interactiveshell import InteractiveShell
InteractiveShell.ast_node_interactivity = "all"
```

0.0.1 Chapter 7

7.1 (AlexNet) Exercises

1. Try increasing the number of epochs. Compared with LeNet, how are the results different? Why?
2. AlexNet may be too complex for the Fashion-MNIST data set.
 - a. Try to simplify the model to make the training faster, while ensuring that the accuracy does not drop significantly.
 - b. Can you design a better model that works directly on 28 x 28 images.
3. Modify the batch size, and observe the changes in accuracy and GPU memory.
4. Rooflines
 - a. What is the dominant part for the memory footprint of AlexNet?
Dense1 - 26 millions of parameters
 - b. What is the dominant part for computation in AlexNet?
Conv2 - 16 millions of FLOP
 - c. How about memory bandwidth when computing the results?
5. Apply dropout and ReLU to LeNet5. Does it improve? How about preprocessing?

7.2 (VGG) Exercises

1. When printing out the dimensions of the layers we only saw 8 results rather than 11. Where did the remaining 3 layer informations go?

There are 3 pairs of CNN (3 vgg blocks) has the same shape

2. Compared with AlexNet, VGG is much slower in terms of computation, and it also needs more GPU memory. Try to analyze the reasons for this.

As shown in the summary results below, VGG needs to train much more parameters than AlexNet.

```
In [5]: def vgg_block(num_convs, num_channels):
        blk = nn.Sequential()
        for _ in range(num_convs):
            blk.add(nn.Conv2D(num_channels, kernel_size=3,
                               padding=1, activation='relu'))
        blk.add(nn.MaxPool2D(pool_size=2, strides=2))
        return blk

    def VGG11(conv_arch):
        net = nn.Sequential()
        # The convolutional layer part
        for (num_convs, num_channels) in conv_arch:
            net.add(vgg_block(num_convs, num_channels))
        # The fully connected layer part
        net.add(nn.Dense(4096, activation='relu'), nn.Dropout(0.5),
                  nn.Dense(4096, activation='relu'), nn.Dropout(0.5),
                  nn.Dense(10))
        return net

    conv_arch = ((1, 64), (1, 128), (2, 256), (2, 512), (2, 512))
    vgg = VGG11(conv_arch)
    vgg.initialize()
    X = nd.random.uniform(shape=(1, 1, 224, 224))
    for blk in vgg:
        X = blk(X)
        print(blk.name, 'output shape:\t', X.shape)
    vgg.summary(mx.nd.random.uniform(shape=(1, 1, 244, 244)))
```

```
sequential2 output shape:      (1, 64, 112, 112)
sequential3 output shape:      (1, 128, 56, 56)
sequential4 output shape:      (1, 256, 28, 28)
sequential5 output shape:      (1, 512, 14, 14)
sequential6 output shape:      (1, 512, 7, 7)
dense1 output shape:           (1, 4096)
dropout0 output shape:         (1, 4096)
dense2 output shape:           (1, 4096)
dropout1 output shape:         (1, 4096)
```

dense3 output shape: (1, 10)

Layer (type)	Output Shape	Param #
Input	(1, 1, 244, 244)	0
Activation-1	(1, 64, 244, 244)	0
Conv2D-2	(1, 64, 244, 244)	640
MaxPool2D-3	(1, 64, 122, 122)	0
Activation-4	(1, 128, 122, 122)	0
Conv2D-5	(1, 128, 122, 122)	73856
MaxPool2D-6	(1, 128, 61, 61)	0
Activation-7	(1, 256, 61, 61)	0
Conv2D-8	(1, 256, 61, 61)	295168
Activation-9	(1, 256, 61, 61)	0
Conv2D-10	(1, 256, 61, 61)	590080
MaxPool2D-11	(1, 256, 30, 30)	0
Activation-12	(1, 512, 30, 30)	0
Conv2D-13	(1, 512, 30, 30)	1180160
Activation-14	(1, 512, 30, 30)	0
Conv2D-15	(1, 512, 30, 30)	2359808
MaxPool2D-16	(1, 512, 15, 15)	0
Activation-17	(1, 512, 15, 15)	0
Conv2D-18	(1, 512, 15, 15)	2359808
Activation-19	(1, 512, 15, 15)	0
Conv2D-20	(1, 512, 15, 15)	2359808
MaxPool2D-21	(1, 512, 7, 7)	0
Activation-22	(1, 4096)	0
Dense-23	(1, 4096)	102764544
Dropout-24	(1, 4096)	0
Activation-25	(1, 4096)	0
Dense-26	(1, 4096)	16781312
Dropout-27	(1, 4096)	0
Dense-28	(1, 10)	40970

Parameters in forward computation graph, duplicate included

Total params: 128806154

Trainable params: 128806154

Non-trainable params: 0

Shared params in forward computation graph: 0

Unique parameters in model: 128806154

3. Try to change the height and width of the images in Fashion-MNIST from 224 to 96. What influence does this have on the experiments?

As it shows below, there will be 45M params in the model with resized images, compared with 129M params in the origin $224 \times 224 \times 3$ size images.

```
In [7]: vgg11 = VGG11(conv_arch)
        vgg11.initialize()
        vgg11.summary(mx.nd.random.uniform(shape=(1, 1, 96, 96)))
```

Layer (type)	Output Shape	Param #
Input	(1, 1, 96, 96)	0
Activation-1	<Symbol conv65_relu_fwd>	0
Activation-2	(1, 64, 96, 96)	0
Conv2D-3	(1, 64, 96, 96)	640
MaxPool2D-4	(1, 64, 48, 48)	0
Activation-5	<Symbol conv66_relu_fwd>	0
Activation-6	(1, 128, 48, 48)	0
Conv2D-7	(1, 128, 48, 48)	73856
MaxPool2D-8	(1, 128, 24, 24)	0
Activation-9	<Symbol conv67_relu_fwd>	0
Activation-10	(1, 256, 24, 24)	0
Conv2D-11	(1, 256, 24, 24)	295168
Activation-12	<Symbol conv68_relu_fwd>	0
Activation-13	(1, 256, 24, 24)	0
Conv2D-14	(1, 256, 24, 24)	590080
MaxPool2D-15	(1, 256, 12, 12)	0
Activation-16	<Symbol conv69_relu_fwd>	0
Activation-17	(1, 512, 12, 12)	0
Conv2D-18	(1, 512, 12, 12)	1180160
Activation-19	<Symbol conv70_relu_fwd>	0
Activation-20	(1, 512, 12, 12)	0
Conv2D-21	(1, 512, 12, 12)	2359808
MaxPool2D-22	(1, 512, 6, 6)	0
Activation-23	<Symbol conv71_relu_fwd>	0
Activation-24	(1, 512, 6, 6)	0
Conv2D-25	(1, 512, 6, 6)	2359808
Activation-26	<Symbol conv72_relu_fwd>	0
Activation-27	(1, 512, 6, 6)	0
Conv2D-28	(1, 512, 6, 6)	2359808
MaxPool2D-29	(1, 512, 3, 3)	0
Activation-30	<Symbol dense4_relu_fwd>	0
Activation-31	(1, 4096)	0
Dense-32	(1, 4096)	18878464
Dropout-33	(1, 4096)	0
Activation-34	<Symbol dense5_relu_fwd>	0
Activation-35	(1, 4096)	0
Dense-36	(1, 4096)	16781312
Dropout-37	(1, 4096)	0
Dense-38	(1, 10)	40970

Parameters in forward computation graph, duplicate included

```

Total params: 44920074
Trainable params: 44920074
Non-trainable params: 0
Shared params in forward computation graph: 0
Unique parameters in model: 44920074
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```

4. Refer to Table 1 in the original VGG Paper to construct other common models, such as VGG-16 or VGG-19.

7.3 (NiN) Exercises

1. Tune the hyper-parameters to improve the classification accuracy.
See STAT157 Homework4 for details.
2. Why are there two 1×1 convolutional layers in the NiN block? Remove one of them, and then observe and analyze the experimental phenomena.
3. Calculate the resource usage for NiN:
 - a. What is the number of parameters? ~2M.
 - b. What is the amount of computation?
 - c. What is the amount of memory needed during training?
 - d. What is the amount of memory needed during inference?

```

In [8]: def nin_block(num_channels, kernel_size, strides, padding):
        blk = nn.Sequential()
        blk.add(nn.Conv2D(num_channels, kernel_size, strides, padding, activation='relu'),
                nn.Conv2D(num_channels, kernel_size=1, activation='relu'),
                nn.Conv2D(num_channels, kernel_size=1, activation='relu'))
        return blk

NiNnet = nn.Sequential()
NiNnet.add(nin_block(96, kernel_size=11, strides=4, padding=0),
           nn.MaxPool2D(pool_size=3, strides=2),
           nin_block(256, kernel_size=5, strides=1, padding=2), nn.MaxPool2D(pool_size=3,
           nin_block(384, kernel_size=3, strides=1, padding=1), nn.MaxPool2D(pool_size=3,
           nn.Dropout(0.5),
           # There are 10 label classes
           nin_block(10, kernel_size=3, strides=1, padding=1),
           # The global average pooling layer automatically sets the window shape # to th
           nn.GlobalAvgPool2D(),
           # Transform the four-dimensional output into two-dimensional output
           # with a shape of (batch size, 10)
           nn.Flatten())

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```

X = nd.random.uniform(shape=(1, 1, 224, 224))
NiNnet.initialize()
for layer in NiNnet:
    X = layer(X)
    print(layer.name, 'output shape:\t', X.shape)

NiNnet.summary(mx.nd.random.uniform(shape=(1, 1, 244, 244)))

```

```

sequential14 output shape:      (1, 96, 54, 54)
pool24 output shape:           (1, 96, 26, 26)
sequential15 output shape:      (1, 256, 26, 26)
pool25 output shape:           (1, 256, 12, 12)
sequential16 output shape:      (1, 384, 12, 12)
pool26 output shape:           (1, 384, 5, 5)
dropout4 output shape:          (1, 384, 5, 5)
sequential17 output shape:      (1, 10, 5, 5)
pool27 output shape:           (1, 10, 1, 1)
flatten0 output shape:         (1, 10)

```

Layer (type)	Output Shape	Param #
Input	(1, 1, 244, 244)	0
Activation-1	(1, 96, 59, 59)	0
Conv2D-2	(1, 96, 59, 59)	11712
Activation-3	(1, 96, 59, 59)	0
Conv2D-4	(1, 96, 59, 59)	9312
Activation-5	(1, 96, 59, 59)	0
Conv2D-6	(1, 96, 59, 59)	9312
MaxPool2D-7	(1, 96, 29, 29)	0
Activation-8	(1, 256, 29, 29)	0
Conv2D-9	(1, 256, 29, 29)	614656
Activation-10	(1, 256, 29, 29)	0
Conv2D-11	(1, 256, 29, 29)	65792
Activation-12	(1, 256, 29, 29)	0
Conv2D-13	(1, 256, 29, 29)	65792
MaxPool2D-14	(1, 256, 14, 14)	0
Activation-15	(1, 384, 14, 14)	0
Conv2D-16	(1, 384, 14, 14)	885120
Activation-17	(1, 384, 14, 14)	0
Conv2D-18	(1, 384, 14, 14)	147840
Activation-19	(1, 384, 14, 14)	0
Conv2D-20	(1, 384, 14, 14)	147840
MaxPool2D-21	(1, 384, 6, 6)	0
Dropout-22	(1, 384, 6, 6)	0
Activation-23	(1, 10, 6, 6)	0
Conv2D-24	(1, 10, 6, 6)	34570
Activation-25	(1, 10, 6, 6)	0
Conv2D-26	(1, 10, 6, 6)	110

Activation-27	(1, 10, 6, 6)	0
Conv2D-28	(1, 10, 6, 6)	110
GlobalAvgPool2D-29	(1, 10, 1, 1)	0
Flatten-30	(1, 10)	0

Parameters in forward computation graph, duplicate included

Total params: 1992166

Trainable params: 1992166

Non-trainable params: 0

Shared params in forward computation graph: 0

Unique parameters in model: 1992166

4. What are possible problems with reducing the $384 \times 5 \times 5$ representation to a $10 \times 5 \times 5$ representation in one step?

Loss too much information at one dimension in one step.

7.4 (GoogLeNet) Exercises

1. There are several iterations of GoogLeNet. Try to implement and run them. Some of them include the following:

- Add a batch normalization layer, as described later in this chapter.**
- Make adjustments to the Inception block.**
- Use “label smoothing” for model regularization.**

“label smoothing” has the advantage of preventing the pursuit of hard probabilities without discouraging correct classification.

Check `smooth_alpha` in `mxnet.ndarray.Softmax`.

<https://mxnet.incubator.apache.org/api/python/ndarray/ndarray.html?highlight=softmaxoutput#mxne>

- Include it in the residual connection, as described later in this chapter.**

```
In [4]: class Inception(nn.Block):
        # c1 - c4 are the number of output channels for each layer in the path
        def __init__(self, c1, c2, c3, c4, **kwargs):
            super(Inception, self).__init__(**kwargs)
            self.p1_1 = nn.Conv2D(c1, kernel_size=1, activation='relu')
            self.p2_1 = nn.Conv2D(c2[0], kernel_size=1, activation='relu')
            self.p2_2 = nn.Conv2D(c2[1], kernel_size=3, padding=1, activation='relu')
            self.p3_1 = nn.Conv2D(c3[0], kernel_size=1, activation='relu')
            self.p3_2 = nn.Conv2D(c3[1], kernel_size=5, padding=2,
                                   activation='relu')
            self.p4_1 = nn.MaxPool2D(pool_size=3, strides=1, padding=1)
            self.p4_2 = nn.Conv2D(c4, kernel_size=1, activation='relu')
```

```

def forward(self, x):
    p1 = self.p1_1(x)
    p2 = self.p2_2(self.p2_1(x))
    p3 = self.p3_2(self.p3_1(x))
    p4 = self.p4_2(self.p4_1(x))
    # Concatenate the outputs on the channel dimension
    return nd.concat(p1, p2, p3, p4, dim=1)

def GoogLeNet():
    net = nn.Sequential()
    net.add(nn.Conv2D(64, kernel_size=7, strides=2, padding=3, activation='relu'),
            nn.MaxPool2D(pool_size=3, strides=2, padding=1))
    net.add(nn.Conv2D(64, kernel_size=1, activation='relu'),
            nn.Conv2D(192, kernel_size=3, padding=1, activation='relu'),
            nn.MaxPool2D(pool_size=3, strides=2, padding=1))
    net.add(Inception(64, (96, 128), (16, 32), 32),
            Inception(128, (128, 192), (32, 96), 64),
            nn.MaxPool2D(pool_size=3, strides=2, padding=1))
    net.add(Inception(192, (96, 208), (16, 48), 64),
            Inception(160, (112, 224), (24, 64), 64),
            Inception(128, (128, 256), (24, 64), 64),
            Inception(112, (144, 288), (32, 64), 64),
            Inception(256, (160, 320), (32, 128), 128),
            nn.MaxPool2D(pool_size=3, strides=2, padding=1))
    net.add(Inception(256, (160, 320), (32, 128), 128),
            Inception(384, (192, 384), (48, 128), 128),
            nn.GlobalAvgPool2D(), nn.Dense(10))
    return net

X = nd.random.uniform(shape=(1, 1, 96, 96))
googlenet = GoogLeNet()
googlenet.initialize()
out = googlenet(X)
googlenet.summary(mx.nd.random.uniform(shape=(1, 1, 244, 244)))

```

Layer (type)	Output Shape	Param #
Input	(1, 1, 244, 244)	0
Activation-1	(1, 64, 122, 122)	0
Conv2D-2	(1, 64, 122, 122)	3200
MaxPool2D-3	(1, 64, 61, 61)	0
Activation-4	(1, 64, 61, 61)	0
Conv2D-5	(1, 64, 61, 61)	4160
Activation-6	(1, 192, 61, 61)	0
Conv2D-7	(1, 192, 61, 61)	110784
MaxPool2D-8	(1, 192, 31, 31)	0

Activation-9	(1, 64, 31, 31)	0
Conv2D-10	(1, 64, 31, 31)	12352
Activation-11	(1, 96, 31, 31)	0
Conv2D-12	(1, 96, 31, 31)	18528
Activation-13	(1, 128, 31, 31)	0
Conv2D-14	(1, 128, 31, 31)	110720
Activation-15	(1, 16, 31, 31)	0
Conv2D-16	(1, 16, 31, 31)	3088
Activation-17	(1, 32, 31, 31)	0
Conv2D-18	(1, 32, 31, 31)	12832
MaxPool2D-19	(1, 192, 31, 31)	0
Activation-20	(1, 32, 31, 31)	0
Conv2D-21	(1, 32, 31, 31)	6176
Inception-22	(1, 256, 31, 31)	0
Activation-23	(1, 128, 31, 31)	0
Conv2D-24	(1, 128, 31, 31)	32896
Activation-25	(1, 128, 31, 31)	0
Conv2D-26	(1, 128, 31, 31)	32896
Activation-27	(1, 192, 31, 31)	0
Conv2D-28	(1, 192, 31, 31)	221376
Activation-29	(1, 32, 31, 31)	0
Conv2D-30	(1, 32, 31, 31)	8224
Activation-31	(1, 96, 31, 31)	0
Conv2D-32	(1, 96, 31, 31)	76896
MaxPool2D-33	(1, 256, 31, 31)	0
Activation-34	(1, 64, 31, 31)	0
Conv2D-35	(1, 64, 31, 31)	16448
Inception-36	(1, 480, 31, 31)	0
MaxPool2D-37	(1, 480, 16, 16)	0
Activation-38	(1, 192, 16, 16)	0
Conv2D-39	(1, 192, 16, 16)	92352
Activation-40	(1, 96, 16, 16)	0
Conv2D-41	(1, 96, 16, 16)	46176
Activation-42	(1, 208, 16, 16)	0
Conv2D-43	(1, 208, 16, 16)	179920
Activation-44	(1, 16, 16, 16)	0
Conv2D-45	(1, 16, 16, 16)	7696
Activation-46	(1, 48, 16, 16)	0
Conv2D-47	(1, 48, 16, 16)	19248
MaxPool2D-48	(1, 480, 16, 16)	0
Activation-49	(1, 64, 16, 16)	0
Conv2D-50	(1, 64, 16, 16)	30784
Inception-51	(1, 512, 16, 16)	0
Activation-52	(1, 160, 16, 16)	0
Conv2D-53	(1, 160, 16, 16)	82080
Activation-54	(1, 112, 16, 16)	0
Conv2D-55	(1, 112, 16, 16)	57456
Activation-56	(1, 224, 16, 16)	0

Conv2D-57	(1, 224, 16, 16)	226016
Activation-58	(1, 24, 16, 16)	0
Conv2D-59	(1, 24, 16, 16)	12312
Activation-60	(1, 64, 16, 16)	0
Conv2D-61	(1, 64, 16, 16)	38464
MaxPool2D-62	(1, 512, 16, 16)	0
Activation-63	(1, 64, 16, 16)	0
Conv2D-64	(1, 64, 16, 16)	32832
Inception-65	(1, 512, 16, 16)	0
Activation-66	(1, 128, 16, 16)	0
Conv2D-67	(1, 128, 16, 16)	65664
Activation-68	(1, 128, 16, 16)	0
Conv2D-69	(1, 128, 16, 16)	65664
Activation-70	(1, 256, 16, 16)	0
Conv2D-71	(1, 256, 16, 16)	295168
Activation-72	(1, 24, 16, 16)	0
Conv2D-73	(1, 24, 16, 16)	12312
Activation-74	(1, 64, 16, 16)	0
Conv2D-75	(1, 64, 16, 16)	38464
MaxPool2D-76	(1, 512, 16, 16)	0
Activation-77	(1, 64, 16, 16)	0
Conv2D-78	(1, 64, 16, 16)	32832
Inception-79	(1, 512, 16, 16)	0
Activation-80	(1, 112, 16, 16)	0
Conv2D-81	(1, 112, 16, 16)	57456
Activation-82	(1, 144, 16, 16)	0
Conv2D-83	(1, 144, 16, 16)	73872
Activation-84	(1, 288, 16, 16)	0
Conv2D-85	(1, 288, 16, 16)	373536
Activation-86	(1, 32, 16, 16)	0
Conv2D-87	(1, 32, 16, 16)	16416
Activation-88	(1, 64, 16, 16)	0
Conv2D-89	(1, 64, 16, 16)	51264
MaxPool2D-90	(1, 512, 16, 16)	0
Activation-91	(1, 64, 16, 16)	0
Conv2D-92	(1, 64, 16, 16)	32832
Inception-93	(1, 528, 16, 16)	0
Activation-94	(1, 256, 16, 16)	0
Conv2D-95	(1, 256, 16, 16)	135424
Activation-96	(1, 160, 16, 16)	0
Conv2D-97	(1, 160, 16, 16)	84640
Activation-98	(1, 320, 16, 16)	0
Conv2D-99	(1, 320, 16, 16)	461120
Activation-100	(1, 32, 16, 16)	0
Conv2D-101	(1, 32, 16, 16)	16928
Activation-102	(1, 128, 16, 16)	0
Conv2D-103	(1, 128, 16, 16)	102528
MaxPool2D-104	(1, 528, 16, 16)	0

Activation-105	(1, 128, 16, 16)	0
Conv2D-106	(1, 128, 16, 16)	67712
Inception-107	(1, 832, 16, 16)	0
MaxPool2D-108	(1, 832, 8, 8)	0
Activation-109	(1, 256, 8, 8)	0
Conv2D-110	(1, 256, 8, 8)	213248
Activation-111	(1, 160, 8, 8)	0
Conv2D-112	(1, 160, 8, 8)	133280
Activation-113	(1, 320, 8, 8)	0
Conv2D-114	(1, 320, 8, 8)	461120
Activation-115	(1, 32, 8, 8)	0
Conv2D-116	(1, 32, 8, 8)	26656
Activation-117	(1, 128, 8, 8)	0
Conv2D-118	(1, 128, 8, 8)	102528
MaxPool2D-119	(1, 832, 8, 8)	0
Activation-120	(1, 128, 8, 8)	0
Conv2D-121	(1, 128, 8, 8)	106624
Inception-122	(1, 832, 8, 8)	0
Activation-123	(1, 384, 8, 8)	0
Conv2D-124	(1, 384, 8, 8)	319872
Activation-125	(1, 192, 8, 8)	0
Conv2D-126	(1, 192, 8, 8)	159936
Activation-127	(1, 384, 8, 8)	0
Conv2D-128	(1, 384, 8, 8)	663936
Activation-129	(1, 48, 8, 8)	0
Conv2D-130	(1, 48, 8, 8)	39984
Activation-131	(1, 128, 8, 8)	0
Conv2D-132	(1, 128, 8, 8)	153728
MaxPool2D-133	(1, 832, 8, 8)	0
Activation-134	(1, 128, 8, 8)	0
Conv2D-135	(1, 128, 8, 8)	106624
Inception-136	(1, 1024, 8, 8)	0
GlobalAvgPool2D-137	(1, 1024, 1, 1)	0
Dense-138	(1, 10)	10250

=====

Parameters in forward computation graph, duplicate included

Total params: 5977530

Trainable params: 5977530

Non-trainable params: 0

Shared params in forward computation graph: 0

Unique parameters in model: 5977530

2. What is the minimum image size for GoogLeNet to work?

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3. Compare the model parameter sizes of AlexNet, VGG, and NiN with GoogLeNet. How

do the latter two network architectures significantly reduce the model parameter size?

- GoogLeNet has 5977530 ~ 6M params;
- NiN has ~ 2M paras;
- VGG has ~ 129M paras;
- AlexNet has ~46M params;

Dense layer in AlexNet and VGG are the one which needs the most parameters. While NiN and GoogLeNet use GlobalAvgPool2D to pool the weights to one dimension first, then apply a Dense layer.

4. Why do we need a large range convolution initially?