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8.1. Deep Convolutional Neural Networks (AlexNet)

SAGEMAKER STUDIO LAB COLAB [PYTORCH]

Although CNNs were well known in the computer vision and machine learning communities following the introduction of LeNet (LeCun *et al.*, 1995), they did not immediately dominate the field. Although LeNet achieved good results on early small datasets, the performance and feasibility of training CNNs on larger, more realistic datasets had yet to be established. In fact, for much of the intervening time between the early 1990s and the watershed results of 2012 (Krizhevsky *et al.*, 2012), neural networks were often surpassed by other machine learning methods, such as kernel methods (Schölkopf and Smola, 2002), ensemble methods (Freund and Schapire, 1996), and structured estimation (Taskar *et al.*, 2004).

For computer vision, this comparison is perhaps not entirely accurate. That is, although the inputs to convolutional networks consist of raw or lightly-processed (e.g., by centering) pixel values, practitioners would never feed raw pixels into traditional models. Instead, typical computer vision pipelines consisted of manually engineering feature extraction pipelines, such as SIFT (Lowe, 2004), SURF (Bay *et al.*, 2006), and bags of visual words (Sivic and Zisserman, 2003). Rather than *learning* the features, the features were *crafted*. Most of the progress came from having more clever ideas for feature extraction on the one hand and deep insight into geometry (Hartley and Zisserman, 2000) on the other. The learning algorithm was often considered an afterthought.

Although some neural network accelerators were available in the 1990s, they were not yet sufficiently powerful to make deep multichannel, multilayer CNNs with a large number of parameters. For instance, NVIDIA's GeForce 256 from 1999 was able to process at most 480 million floating-point operations, such as additions and multiplications, per second (MFLOPS), without any meaningful programming framework for operations beyond games. Today's accelerators are able to perform in excess of 1000 TFLOPs per device. Moreover, datasets were still relatively small: OCR on 60,000 low-resolution 28×28 pixel images was considered a highly challenging task. Added to these obstacles, key tricks for training neural networks including parameter initialization heuristics (Glorot and Bengio, 2010), clever variants of stochastic gradient descent (Kingma and Ba, 2014), non-squashing activation functions (Nair and Hinton, 2010), and effective regularization techniques (Srivastava *et al.*, 2014) were still missing.

Thus, rather than training *end-to-end* (pixel to classification) systems, classical pipelines looked more like this:

1. Obtain an interesting dataset. In the early days, these datasets required expensive sensors. For instance, the Apple QuickTake 100 of 1994 sported a whopping 0.3 megapixel (VGA) resolution, capable of storing up to 8 images, all for the price of $1000.
2. Preprocess the dataset with hand-crafted features based on some knowledge of optics, geometry, other analytic tools, and occasionally on the serendipitous discoveries by lucky graduate students.
3. Feed the data through a standard set of feature extractors such as the SIFT (scale-invariant feature transform) (Lowe, 2004), the SURF (speeded up robust features) (Bay *et al.*, 2006), or any number of other hand-tuned pipelines. OpenCV still provides SIFT extractors to this day!
4. Dump the resulting representations into your favorite classifier, likely a linear model or kernel method, to train a classifier.

If you spoke to machine learning researchers, they would reply that machine learning was both important and beautiful. Elegant theories proved the properties of various classifiers (Boucheron *et al.*, 2005) and convex optimization (Boyd and Vandenberghe, 2004) had become the mainstay for obtaining them. The field of machine learning was thriving, rigorous, and eminently useful. However, if you spoke to a computer vision researcher, you would hear a very different story. The dirty truth of image recognition, they would tell you, is that features, geometry (Hartley and Zisserman, 2000, Hartley and Kahl, 2009), and engineering, rather than novel learning algorithms, drove progress. Computer vision researchers justifiably believed that a slightly bigger or cleaner dataset or a slightly improved feature-extraction pipeline mattered far more to the final accuracy than any learning algorithm.

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

8.1.1. Representation Learning

Another way to cast the state of affairs is that the most important part of the pipeline was the representation. And up until 2012 the representation was calculated mostly mechanically. In fact, engineering a new set of feature functions, improving results, and writing up the method all featured prominently in papers. SIFT (Lowe, 2004), SURF (Bay *et al.*, 2006), HOG (histograms of oriented gradient) (Dalal and Triggs, 2005), bags of visual words (Sivic and Zisserman, 2003), and similar feature extractors ruled the roost.

Another group of researchers, including Yann LeCun, Geoff Hinton, Yoshua Bengio, Andrew Ng, Shun-ichi Amari, and Juergen Schmidhuber, had different plans. They believed that features themselves ought to be learned. Moreover, they believed that to be reasonably complex, the features ought to be hierarchically composed with multiple jointly learned layers, each with learnable parameters. In the case of an image, the lowest layers might come to detect edges, colors, and textures, by analogy with how the visual system in animals processes its input. In particular, the automatic design of visual features such as those obtained by sparse coding (Olshausen and Field, 1996) remained an open challenge until the advent of modern CNNs. It was not until Dean *et al.* (2012), Le (2013) that the idea of generating features from image data automatically gained significant traction.

The first modern CNN (Krizhevsky *et al.*, 2012), named *AlexNet* after one of its inventors, Alex Krizhevsky, is largely an evolutionary improvement over LeNet. It achieved excellent performance in the 2012 ImageNet challenge.

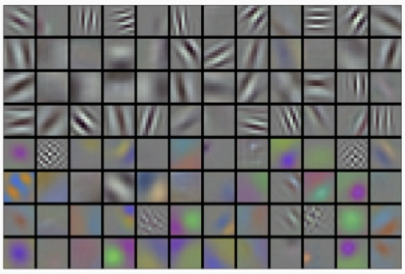

Fig. 8.1.1 Image filters learned by the first layer of AlexNet. Reproduction courtesy of Krizhevsky *et al.* (2012).

Interestingly, in the lowest layers of the network, the model learned feature extractors that resembled some traditional filters. Fig. 8.1.1 shows lower-level image descriptors. Higher layers in the network might build upon these representations to represent larger structures, like eyes, noses, blades of grass, and so on. Even higher layers might represent whole objects like people, airplanes, dogs, or frisbees. Ultimately, the final hidden state learns a compact representation of the image that summarizes its contents such that data belonging to different categories can be easily separated.

AlexNet (2012) and its precursor LeNet (1995) share many architectural elements. This begs the question: why did it take so long? A key difference was that, over the previous

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Interestingly, in the lowest layers of the network, the model learned feature extractors that resembled some traditional filters. Fig. 8.1.1 shows lower-level image descriptors. Higher layers in the network might build upon these representations to represent larger structures, like eyes, noses, blades of grass, and so on. Even higher layers might represent whole objects like people, airplanes, dogs, or frisbees. Ultimately, the final hidden state learns a compact representation of the image that summarizes its contents such that data belonging to different categories can be easily separated.

AlexNet (2012) and its precursor LeNet (1995) share many architectural elements. This begs the question: why did it take so long? A key difference was that, over the previous two decades, the amount of data and the computing power available had increased significantly. As such AlexNet was much larger: it was trained on much more data, and on much faster GPUs compared to the CPUs available in 1995.

8.1.1.1. Missing Ingredient: Data

Deep models with many layers require large amounts of data in order to enter the regime where they significantly outperform traditional methods based on convex optimizations (e.g., linear and kernel methods). However, given the limited storage capacity of computers, the relative expense of (imaging) sensors, and the comparatively tighter research budgets in the 1990s, most research relied on tiny datasets. Numerous papers relied on the UCI collection of datasets, many of which contained only hundreds or (a few) thousands of images captured in low resolution and often with an artificially clean background.

In 2009, the ImageNet dataset was released (Deng *et al.*, 2009), challenging researchers to learn models from 1 million examples, 1000 each from 1000 distinct categories of objects. The categories themselves were based on the most popular noun nodes in WordNet (Miller, 1995). The ImageNet team used Google Image Search to prefilter large candidate sets for each category and employed the Amazon Mechanical Turk crowdsourcing pipeline to confirm for each image whether it belonged to the associated category. This scale was unprecedented, exceeding others by over an order of magnitude (e.g., CIFAR-100 has 60,000 images). Another aspect was that the images were at relatively high resolution of 224×224 pixels, unlike the 80 million-sized TinyImages dataset (Torralba *et al.*, 2008), consisting of 32×32 pixel thumbnails. This allowed for the formation of higher-level features. The associated competition, dubbed the ImageNet Large Scale Visual Recognition Challenge (Russakovsky *et al.*, 2015), pushed computer vision and machine learning research forward, challenging researchers to identify which models performed best at a greater scale than academics had previously considered. The largest vision datasets, such as LAION-5B (Schuhmann *et al.*, 2022) contain billions of images with additional metadata.

8.1.1.2. Missing Ingredient: Hardware

Deep learning models are voracious consumers of compute cycles. Training can take hundreds of epochs, and each iteration requires passing data through many layers of computationally expensive linear algebra operations. This is one of the main reasons why in the 1990s and early 2000s, simple algorithms based on the more-efficiently optimized convex objectives were preferred.

Graphical processing units (GPUs) proved to be a game changer in making deep learning feasible. These chips had earlier been developed for accelerating graphics processing to benefit computer games. In particular, they were optimized for high throughput 4×4 matrix–vector products, which are needed for many computer graphics tasks. Fortunately, the math is strikingly similar to that required for calculating convolutional layers. Around that time, NVIDIA and ATI had begun optimizing GPUs for general computing operations (Fernando, 2004), going as far as to market them as *general-purpose GPUs* (GPGPUs).

To provide some intuition, consider the cores of a modern microprocessor (CPU). Each of the cores is fairly powerful running at a high clock frequency and sporting large caches (up to several megabytes of L3). Each core is well-suited to executing a wide range of instructions, with branch predictors, a deep pipeline, specialized execution units, speculative execution, and many other bells and whistles that enable it to run a large variety of programs with sophisticated control flow. This apparent strength, however, is also its Achilles heel: general-purpose cores are very expensive to build. They excel at general-purpose code with lots of control flow. This requires lots of chip area, not just for the actual ALU (arithmetic logical unit) where computation happens, but also for all the aforementioned bells and whistles, plus memory interfaces, caching

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By comparison, GPUs can consist of thousands of small processing elements (NIVIDA's latest Ampere chips have up to 6912 CUDA cores), often grouped into larger groups (NVIDIA calls them warps). The details differ somewhat between NVIDIA, AMD, ARM and other chip vendors. While each core is relatively weak, running at about 1GHz clock frequency, it is the total number of such cores that makes GPUs orders of magnitude faster than CPUs. For instance, NVIDIA's recent Ampere A100 GPU offers over 300 TFLOPs per chip for specialized 16-bit precision (BFLOAT16) matrix-matrix multiplications, and up to 20 TFLOPs for more general-purpose floating point operations (FP32). At the same time, floating point performance of CPUs rarely exceeds 1 TFLOPs. For instance, Amazon's Graviton 3 reaches 2 TFLOPs peak performance for 16-bit precision operations, a number similar to the GPU performance of Apple's M1 processor.

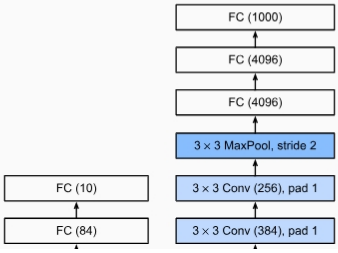
There are many reasons why GPUs are much faster than CPUs in terms of FLOPs. First, power consumption tends to grow *quadratically* with clock frequency. Hence, for the power budget of a CPU core that runs four times faster (a typical number), you can use 16 GPU cores at $\frac{1}{4}$ the speed, which yields $16 \times \frac{1}{4} = 4$ times the performance. Second, GPU cores are much simpler (in fact, for a long time they were not even *able* to execute general-purpose code), which makes them more energy efficient. For instance, (i) they tend not to support speculative evaluation, (ii) it typically is not possible to program each processing element individually, and (iii) the caches per core tend to be much smaller. Last, many operations in deep learning require high memory bandwidth. Again, GPUs shine here with buses that are at least 10 times as wide as many CPUs.

Back to 2012. A major breakthrough came when Alex Krizhevsky and Ilya Sutskever implemented a deep CNN that could run on GPUs. They realized that the computational bottlenecks in CNNs, convolutions and matrix multiplications, are all operations that could be parallelized in hardware. Using two NVIDIA GTX 580s with 3GB of memory, either of which was capable of 1.5 TFLOPs (still a challenge for most CPUs a decade later), they implemented fast convolutions. The cuda-convnet code was good enough that for several years it was the industry standard and powered the first couple of years of the deep learning boom.

8.1.2. AlexNet

AlexNet, which employed an 8-layer CNN, won the ImageNet Large Scale Visual Recognition Challenge 2012 by a large margin (Russakovsky *et al.*, 2013). This network showed, for the first time, that the features obtained by learning can transcend manually-designed features, breaking the previous paradigm in computer vision.

The architectures of AlexNet and LeNet are strikingly similar, as Fig. 8.1.2 illustrates. Note that we provide a slightly streamlined version of AlexNet removing some of the design quirks that were needed in 2012 to make the model fit on two small GPUs.



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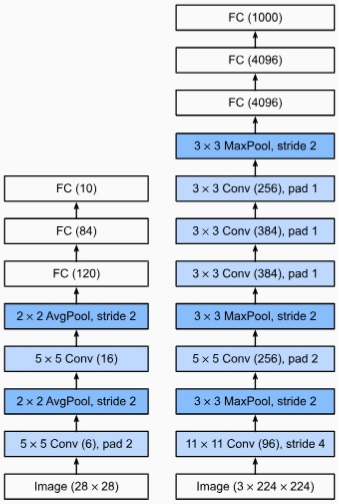

Fig. 8.1.2 From LeNet (left) to AlexNet (right).

There are also significant differences between AlexNet and LeNet. First, AlexNet is much deeper than the comparatively small LeNet-5. AlexNet consists of eight layers: five convolutional layers, two fully connected hidden layers, and one fully connected output layer. Second, AlexNet used the ReLU instead of the sigmoid as its activation function. Let's delve into the details below.

8.1.2.1. Architecture

In AlexNet's first layer, the convolution window shape is 11×11. Since the images in ImageNet are eight times taller and wider than the MNIST images, objects in ImageNet data tend to occupy more pixels with more visual detail. Consequently, a larger convolution window is needed to capture the object. The convolution window shape in the second layer is reduced to 5×5, followed by 3×3. In addition, after the first, second, and fifth convolutional layers, the network adds max-pooling layers with a window shape of 3×3 and a stride of 2. Moreover, AlexNet has ten times more convolution channels than LeNet.

After the final convolutional layer, there are two huge fully connected layers with 4096 outputs. These layers require nearly 1GB model parameters. Because of the limited memory in early GPUs, the original AlexNet used a dual data stream design, so that each of their two GPUs could be responsible for storing and computing only its half of the model. Fortunately, GPU memory is comparatively abundant now, so we rarely need to break up models across GPUs these days (our version of the AlexNet model deviates from the original paper in this aspect).

8.1.2.2. Activation Functions

Furthermore, AlexNet changed the sigmoid activation function to a simpler ReLU activation function. On the one hand, the computation of the ReLU activation function is simpler. For example, it does not have the exponentiation operation found in the sigmoid activation function. On the other hand, the ReLU activation function makes model training easier when using different parameter initialization methods. This is because, when the output of the sigmoid activation function is very close to 0 or 1, the gradient of these regions is almost 0, so that backpropagation cannot continue to update some of the model parameters. By contrast, the gradient of the ReLU activation function in the positive interval is always 1 (Section 5.1.2). Therefore, if the model parameters are not properly initialized, the sigmoid function may obtain a gradient of almost 0 in the positive interval, meaning that the model cannot be effectively trained.

8.1.2.3. Capacity Control and Preprocessing

AlexNet controls the model complexity of the fully connected layer by dropout (Section

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parameters are not properly initialized, the sigmoid function may obtain a gradient of almost 0 in the positive interval, meaning that the model cannot be effectively trained.

8.1.2.3. Capacity Control and Preprocessing

AlexNet controls the model complexity of the fully connected layer by dropout (Section 5.6), while LeNet only uses weight decay. To augment the data even further, the training loop of AlexNet added a great deal of image augmentation, such as flipping, clipping, and color changes. This makes the model more robust and the larger sample size effectively reduces overfitting. See Buslaev *et al.* (2020) for an in-depth review of such preprocessing steps.

PYTORCH MXNET JAX TENSORFLOW

```
class AlexNet(d2l.Classifier):
    def __init__(self, lr=0.1, num_classes=10):
        super().__init__()
        self.save_hyperparameters()
        self.net = nn.Sequential(
            nn.LazyConv2d(96, kernel_size=11, stride=4, padding=1),
            nn.ReLU(), nn.MaxPool2d(kernel_size=3, stride=2),
            nn.LazyConv2d(256, kernel_size=5, padding=2), nn.ReLU(),
            nn.MaxPool2d(kernel_size=3, stride=2),
            nn.LazyConv2d(384, kernel_size=3, padding=1), nn.ReLU(),
            nn.LazyConv2d(384, kernel_size=3, padding=1), nn.ReLU(),
            nn.LazyConv2d(256, kernel_size=3, padding=1), nn.ReLU(),
            nn.MaxPool2d(kernel_size=3, stride=2), nn.Flatten(),
            nn.LazyLinear(4096), nn.ReLU(), nn.Dropout(p=0.5),
            nn.LazyLinear(4096), nn.ReLU(),nn.Dropout(p=0.5),
            nn.LazyLinear(num_classes))
        self.net.apply(d2l.init_cnn)
```

We construct a single-channel data example with both height and width of 224 to observe the output shape of each layer. It matches the AlexNet architecture in Fig. 8.1.2.

PYTORCH MXNET JAX TENSORFLOW

```
AlexNet().layer_summary((1, 1, 224, 224))
```

```
Conv2d output shape:         torch.Size([1, 96, 54, 54])
ReLU output shape:   torch.Size([1, 96, 54, 54])
MaxPool2d output shape:      torch.Size([1, 96, 26, 26])
Conv2d output shape:         torch.Size([1, 256, 26, 26])
ReLU output shape:   torch.Size([1, 256, 26, 26])
MaxPool2d output shape:      torch.Size([1, 256, 12, 12])
Conv2d output shape:         torch.Size([1, 384, 12, 12])
ReLU output shape:   torch.Size([1, 384, 12, 12])
Conv2d output shape:         torch.Size([1, 384, 12, 12])
ReLU output shape:   torch.Size([1, 384, 12, 12])
Conv2d output shape:         torch.Size([1, 256, 12, 12])
ReLU output shape:   torch.Size([1, 256, 12, 12])
MaxPool2d output shape:      torch.Size([1, 256, 5, 5])
Flatten output shape:        torch.Size([1, 6400])
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])
```

8.1.3. Training

Although AlexNet was trained on ImageNet in Krizhevsky *et al.* (2012), we use Fashion-MNIST here since training an ImageNet model to convergence could take hours or days even on a modern GPU. One of the problems with applying AlexNet directly on Fashion-MNIST is that its images have lower resolution (28×28 pixels) than ImageNet images. To make things work, we upsample them to 224×224. This is generally not a smart practice, as it simply increases the computational complexity without adding information. Nonetheless, we do it here to be faithful to the AlexNet architecture. We perform this resizing with the `resize` argument in the `d2l.FashionMNIST` constructor.

Now, we can start training AlexNet. Compared to LeNet in Section 7.6, the main change here is the use of a smaller learning rate and much slower training due to the deeper and wider network, the higher image resolution, and the more costly convolutions.

PYTORCH MXNET JAX TENSORFLOW

```
model = AlexNet(lr=0.01)
```

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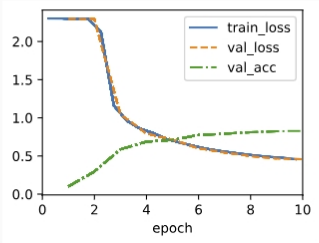
Now, we can start training AlexNet. Compared to LeNet in Section 7.6, the main change here is the use of a smaller learning rate and much slower training due to the deeper and wider network, the higher image resolution, and the more costly convolutions.

PYTORCH MXNET JAX TENSORFLOW

```
model = AlexNet(lr=0.01)
data = d2l.FashionMNIST(batch_size=128, resize=(224, 224))
trainer = d2l.Trainer(max_epochs=10, num_gpus=1)
trainer.fit(model, data)
```



8.1.4. Discussion

AlexNet's structure bears a striking resemblance to LeNet, with a number of critical improvements, both for accuracy (dropout) and for ease of training (ReLU). What is equally striking is the amount of progress that has been made in terms of deep learning tooling. What was several months of work in 2012 can now be accomplished in a dozen lines of code using any modern framework.

Reviewing the architecture, we see that AlexNet has an Achilles heel when it comes to efficiency: the last two hidden layers require matrices of size 6400×4096 and 4096×4096, respectively. This corresponds to 164 MB of memory and 81 MFLOPs of computation, both of which are a nontrivial outlay, especially on smaller devices, such as mobile phones. This is one of the reasons why AlexNet has been surpassed by much more effective architectures that we will cover in the following sections. Nonetheless, it is a key step from shallow to deep networks that are used nowadays. Note that even though the number of parameters exceeds by far the amount of training data in our experiments (the last two layers have more than 40 million parameters, trained on a datasets of 60 thousand images), there is hardly any overfitting: training and validation loss are virtually identical throughout training. This is due to the improved regularization, such as dropout, inherent in modern deep network designs.

Although it seems that there are only a few more lines in AlexNet's implementation than in LeNet's, it took the academic community many years to embrace this conceptual change and take advantage of its excellent experimental results. This was also due to the lack of efficient computational tools. At the time neither DistBelief (Dean *et al.*, 2012) nor Caffe (Jia *et al.*, 2014) existed, and Theano (Bergstra *et al.*, 2010) still lacked many distinguishing features. It was the availability of TensorFlow (Abadi *et al.*, 2016) that dramatically changed the situation.

8.1.5. Exercises

1. Following up on the discussion above, analyze the computational properties of AlexNet.
    1. Compute the memory footprint for convolutions and fully connected layers, respectively. Which one dominates?
    2. Calculate the computational cost for the convolutions and the fully connected layers.
    3. How does the memory (read and write bandwidth, latency, size) affect computation? Is there any difference in its effects for training and inference?
2. You are a chip designer and need to trade off computation and memory bandwidth. For example, a faster chip requires more power and possibly a larger chip area. More memory bandwidth requires more pins and control logic, thus also more area. How do you optimize?
3. Why do engineers no longer report performance benchmarks on AlexNet?
4. Try increasing the number of epochs when training AlexNet. Compared with LeNet, how do the results differ? Why?
5. AlexNet may be too complex for the Fashion-MNIST dataset, in particular due to

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4. Try increasing the number of epochs when training AlexNet. Compared with LeNet, how do the results differ? Why?
5. AlexNet may be too complex for the Fashion-MNIST dataset, in particular due to the low resolution of the initial images.
   1. Try simplifying the model to make the training faster, while ensuring that the accuracy does not drop significantly.
   2. Design a better model that works directly on 28×28 images.
6. Modify the batch size, and observe the changes in throughput (images/s), accuracy, and GPU memory.
7. Apply dropout and ReLU to LeNet-5. Does it improve? Can you improve things further by preprocessing to take advantage of the invariances inherent in the images?
8. Can you make AlexNet overfit? Which feature do you need to remove or change to break training?

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PYTORCH MXNET JAX TENSORFLOW

Continue Discussion 16 replies

StevenJokes Jun '20

```
lr, num_epochs = 0.01, 10
d2l.train_ch6(net, train_iter, test_iter, num_epochs, lr)
```

training on cpu

no other results?
no pic?

so slow?

1 reply

ChenYangyao ▶ StevenJokes Aug '20

Please use a GPU for deep nets. A CPU could be 100 times slower than a GPU.

For the AlexNet on Fashion-MNIST, a GPU takes ~ 20 seconds per epoch, which means a CPU would take 2000 seconds ~ 30 minutes.

2 replies

StevenJokes ▶ ChenYangyao Aug '20

@ChenYangyao thank for your reply. I don't have gpus. I'm using colab for learning.
And now I can't find any exercitations because of my finance undergraduate diploma.

1 reply

Nish ▶ StevenJokes Aug '20

@StevenJokes I think colab lets you use a GPU for free? Tools -> Change runtime type -> choose 'GPU' under Hardware Accelerator

1 reply

StevenJokes Aug '20

@Nish
I have known it. But 12 hours will disconnect. 😁
And you can find why colab is not so friendly in my discussion:
http://d2l.ai/chapter_appendix-tools-for-deep-learning/colab.html

And there is an issue of python 3.6:

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And you can find why colab is not so friendly in my discussion:
http://d2l.ai/chapter_appendix-tools-for-deep-learning/colab.html

And there is an issue of python 3.6:

github.com/d2l-ai/d2l-tvm

colab's python 3.6 doesn't support `pip install`
And tvm py36 is denied.
opened 07:14AM - 19 Aug 20 UTC StevenJokes

1 reply

Nish ▶ StevenJokes Aug '20

aha, I see. maybe you can try the kaggle.com free kernel? It allows 30 hours a week of GPU use for its contests I think.

1 reply

StevenJokes ▶ Nish Aug '20

I'll try. @Nish
Thanks.

Rameen ▶ ChenYangyao Jul '21

Hi!!
If I change Dataset then how do I change the below statement like dataset of Animals?

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StevenJokes ▶ Nish Aug '20

I'll try. @Nish
Thanks.

Rameen ▶ ChenYangyao Jul '21

Hi!!
If I change Dataset then how do I change the below statement like dataset of Animals?

train_iter, test_iter = d2l.load_data_fashion_mnist(batch_size, resize=224)
Any Suggestion??

1 reply

DXD Aug '21

For Exercise 4, I'm guessing the dominant part of computation is the block of fully connected layers at the end. Is the dominant part of the memory footprint the largest convolution layer?

fanbyprinciple ▶ Rameen Aug '21

If you are using custom dataset then you might have to use the `torch.utils.data.Dataset` to create a custom class. Writing Custom Datasets, DataLoaders and Transforms — PyTorch Tutorials 1.9.0+cu102 documentation

fanbyprinciple Aug '21

Exercises

1. Try increasing the number of epochs. Compared with LeNet, how are the results different? Why?

Finally was able to "train" it but it looks more like a heartbeat than anything

- The result is a very noisy function, it is like its not getting trained at all.

2. AlexNet may be too complex for the Fashion-MNIST dataset.

   1. Try simplifying the model to make the training faster, while ensuring that the accuracy
   does not drop significantly.

   - done but accuracy has still not improved.
   2. Design a better model that works directly on 28 × 28 images.
   - done.
3. Modify the batch size, and observe the changes in accuracy and GPU memory.

- more batch size more consumption

4. Analyze computational performance of AlexNet.

   - any idea how to do it ?
   1. What is the dominant part for the memory footprint of AlexNet?

      - Linear network and 3 cnns
   2. What is the dominant part for computation in AlexNet?

      - the neuralnetwork 3 cnns
   3. How about memory bandwidth when computing the results?

      - more than 100 mb
5. Apply dropout and ReLU to LeNet-5. Does it improve? How about preprocessing?

```
 lenet_5 = nn.Sequential(nn.Conv2d(1, 6, kernel_size=5,
padding=2), nn.ReLU(),

                    nn.AvgPool2d(kernel_size=2, stride=2),

                    nn.Conv2d(6, 16, kernel_size=5),
nn.ReLU(),

                    nn.AvgPool2d(kernel_size=2, stride=2),
nn.Flatten(),

                    nn.Linear(16 * 5 * 5, 120), nn.ReLU(),
nn.Dropout(p=0.5),

                    nn.Linear(120, 84), nn.ReLU(),
nn.Linear(84, 10))
```

its not training well as well.

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its not training well as well.

FInally able to train , here is the network summary

```
In [19]: from torchsummary import summary
         summary(net, (1,224,224))

----------------------------------------------------------------
        Layer (type)               Output Shape         Param #
================================================================
            Conv2d-1           [-1, 96, 54, 54]          11,712
              ReLU-2           [-1, 96, 54, 54]               0
         MaxPool2d-3           [-1, 96, 26, 26]               0
            Conv2d-4          [-1, 256, 26, 26]         614,656
              ReLU-5          [-1, 256, 26, 26]               0
         MaxPool2d-6          [-1, 256, 12, 12]               0
            Conv2d-7          [-1, 384, 12, 12]         885,120
              ReLU-8          [-1, 384, 12, 12]               0
            Conv2d-9          [-1, 384, 12, 12]       1,327,488
             ReLU-10          [-1, 384, 12, 12]               0
           Conv2d-11          [-1, 256, 12, 12]         884,992
             ReLU-12          [-1, 256, 12, 12]               0
        MaxPool2d-13            [-1, 256, 5, 5]               0
          Flatten-14                 [-1, 6400]               0
           Linear-15                 [-1, 4096]      26,218,496
          Dropout-16                 [-1, 4096]               0
           Linear-17                  [-1, 256]       1,048,832
          Dropout-18                  [-1, 256]               0
           Linear-19                   [-1, 10]           2,570
================================================================
Total params: 30,993,866
Trainable params: 30,993,866
Non-trainable params: 0
----------------------------------------------------------------
Input size (MB): 0.19
Forward/backward pass size (MB): 10.10
Params size (MB): 118.23
Estimated Total Size (MB): 128.53
----------------------------------------------------------------
```

it took me 6m 21 sec to get an accuracy of 88.7, in just 3 epochs.

thainq Feb '22

When i have learned the CNN network, the question always in my mind is how to design the good architecture and also how many filter, layer is enough?

pandalabme Aug '23

My solutions to the exs: 8.1

dingcurie Sep '23

```
class AlexNet(d2l.Classifier):
    def __init__(self, lr=0.1, num_classes=10):
        super().__init__()
        self.save_hyperparameters()
        self.net = nn.Sequential(
            nn.LazyConv2d(96, kernel_size=11, stride=4,
padding=1),
            nn.ReLU(), nn.MaxPool2d(kernel_size=3, stride=2),
            ...
            nn.LazyLinear(4096), nn.ReLU(),nn.Dropout(p=0.5),
            nn.LazyLinear(num_classes))
        self.net.apply(d2l.init_cnn)     # <-----
```

The last line has no effect since a dry run has not been performed yet and hence the lazy layers have not been reified into regular (non-lazy) layers.

Mohamed_Ahmed_Naji Jun '24

Why ReLU activation is not applied after MaxPool2d?
does it may save memory and computation in forward and backward propagation

what this line "self.net.apply(d2l.init_cnn)" in the AlexNet class do?
is it will not be executed?

Juu_Hu Sep '24

self.net.apply(d2l.init_cnn)

It seems that this line will not work, since the layer dimensions are not initialized until input data is passed through the network for the first time.

my solution is :

1. Defining an initial function in the class

```
def para_init(self):
    self.net.apply(d2l.init_cnn)
```

2. Conducting a forward, then initial the parameters

```
model = AlexNet(lr = 0.01)
```

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```
         Conv2d-11        [-1, 256, 12, 12]         884,992
           ReLU-12        [-1, 256, 12, 12]               0
      MaxPool2d-13          [-1, 256, 5, 5]               0
        Flatten-14               [-1, 6400]               0
         Linear-15               [-1, 4096]      26,218,496
        Dropout-16               [-1, 4096]               0
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            ...
            nn.LazyLinear(4096), nn.ReLU(),nn.Dropout(p=0.5),
            nn.LazyLinear(num_classes))
        self.net.apply(d2l.init_cnn)     # <-----
```

The last line has no effect since a dry run has not been performed yet and hence the lazy layers have not been reified into regular (non-lazy) layers.

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def para_init(self):
    self.net.apply(d2l.init_cnn)
```

2. Conducting a forward, then initial the parameters

```
model = AlexNet(lr = 0.01)
data = d2l.FashionMNIST(batch_size=128,resize=(224,224))
model(next(iter(data.get_dataloader(True)))[0])
model.para_init()
```

Continue Discussion

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