Deep learning

1.1. From neural networks to deep learning

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Many applications require the automatic extraction of “refined” information from raw signal (e.g. image recognition, automatic speech processing, natural language processing, robotic control, geometry reconstruction).
Our brain is so good at interpreting visual information that the “semantic gap” is hard to assess intuitively.
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This: is a horse
```python
>>> from torchvision.datasets import CIFAR10
>>> cifar = CIFAR10('./data/cifar10/', train=True, download=True)
Files already downloaded and verified
>>> x = torch.from_numpy(cifar.data)[43].permute(2, 0, 1)
>>> x[:, :4, :8]
tensor([[ 99, 98, 100, 103, 105, 107, 108, 110],
        [100, 100, 102, 105, 107, 109, 110, 112],
        [104, 104, 106, 109, 111, 112, 114, 116],
        [109, 109, 111, 113, 116, 117, 118, 120]],
       [[166, 165, 167, 169, 171, 172, 173, 175],
        [166, 164, 167, 169, 169, 171, 172, 174],
        [169, 167, 170, 171, 171, 173, 174, 176],
        [170, 169, 172, 173, 175, 176, 177, 178]],
      [[198, 196, 199, 200, 200, 202, 203, 204],
        [195, 194, 197, 197, 197, 199, 200, 201],
        [197, 195, 198, 198, 198, 199, 201, 202],
        [197, 196, 199, 198, 198, 199, 200, 201]], dtype=torch.uint8)
```
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Deep learning encompasses software technologies to scale-up to billions of model parameters and as many training examples.
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“Artificial neural networks” pre-dated these approaches, and do not follow this dichotomy. They consist of “deep” stacks of parametrized processing.
From artificial neural networks to “Deep Learning”
Networks of “Threshold Logic Unit”

(McCulloch and Pitts, 1943)
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1959 – David H. Hubel and Torsten Wiesel demonstrate orientation selectivity and columnar organization in the cat’s visual cortex.
1982 – Paul Werbos proposes back-propagation for ANNs.
Neocognitron

Follows Hubel and Wiesel's results.

(Fukushima, 1980)
Network for the T-C problem

Trained with back-prop.

(Rumelhart et al., 1988)
LeNet family

10 output units

**layer H3**
30 hidden units

**layer H2**
12 x 16 = 192 hidden units

**layer H1**
12 x 64 = 768 hidden units

256 input units

fully connected
~ 300 links

fully connected
~ 6000 links

~ 40,000 links from 12 kernels
5 x 5 x 8

~ 20,000 links from 12 kernels
5 x 5

(LeCun et al., 1989)
Figure 2: An illustration of the architecture of our CNN, explicitly showing the delineation of responsibilities between the two GPUs. One GPU runs the layer-parts at the top of the figure while the other runs the layer-parts at the bottom. The GPUs communicate only at certain layers. The network’s input is 150,528-dimensional, and the number of neurons in the network’s remaining layers is given by 253,440–186,624–64,896–64,896–43,264–4096–4096–1000.

The second convolutional layer takes as input the (response-normalized and pooled) output of the first convolutional layer and filters it with 256 kernels of size $5 \times 48$. The third, fourth, and fifth convolutional layers are connected to one another without any intervening pooling or normalization layers. The third convolutional layer has 384 kernels of size $3 \times 256$ connected to the (normalized, pooled) outputs of the second convolutional layer. The fourth convolutional layer has 384 kernels of size $3 \times 192$, and the fifth convolutional layer has 256 kernels of size $3 \times 192$. The fully-connected layers have 4096 neurons each.

4 Reducing Overfitting

Our neural network architecture has 60 million parameters. Although the 1000 classes of ILSVRC make each training example impose 10 bits of constraint on the mapping from image to label, this turns out to be insufficient to learn so many parameters without considerable overfitting. Below, we describe the two primary ways in which we combat overfitting.

4.1 Data Augmentation

The easiest and most common method to reduce overfitting on image data is to artificially enlarge the dataset using label-preserving transformations (e.g., [25, 4, 5]). We employ two distinct forms of data augmentation, both of which allow transformed images to be produced from the original images with very little computation, so the transformed images do not need to be stored on disk. In our implementation, the transformed images are generated in Python code on the CPU while the GPU is training on the previous batch of images. So these data augmentation schemes are, in effect, computationally free.

The first form of data augmentation consists of generating image translations and horizontal reflections. We do this by extracting random $224 \times 224$ patches (and their horizontal reflections) from the $256 \times 256$ images and training our network on these extracted patches. This increases the size of our training set by a factor of 2048, though the resulting training examples are, of course, highly interdependent. Without this scheme, our network suffers from substantial overfitting, which would have forced us to use much smaller networks. At test time, the network makes a prediction by extracting five $224 \times 224$ patches (the four corner patches and the center patch) as well as their horizontal reflections (hence ten patches in all), and averaging the predictions made by the network’s softmax layer on the ten patches.

The second form of data augmentation consists of altering the intensities of the RGB channels in training images. Specifically, we perform PCA on the set of RGB pixel values throughout the ImageNet training set. To each training image, we add multiples of the found principal components, 4This is the reason why the input images in Figure 2 are $224 \times 224 \times 3$-dimensional. 5

(Krizhevsky et al., 2012)
Figure 3: GoogLeNet network with all the bells and whistles

(Szegedy et al., 2015)
Resnet

(He et al., 2015)
Deep learning is built on a natural generalization of a neural network: a graph of tensor operators, taking advantage of

- the chain rule (aka “back-propagation”),
- stochastic gradient decent,
- convolutions,
- parallel operations on GPUs.

This does not differ much from networks from the 90s
This generalization allows to design complex networks of operators dealing with images, sound, text, sequences, etc. and to train them end-to-end.

(Yeung et al., 2015)
ImageNet Large Scale Visual Recognition Challenge.

1000 categories, > 1M images

(http://image-net.org/challenges/LSVRC/2014/browse-synsets)
Error
Human performance

(Gershgorn, 2017)
The end
References


D. Gershgorn. The data that transformed AI research—and possibly the world, July 2017.


