Convolutional Neural Networks

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Reference: *Hands-On Machine Learning with Scikit-Learn and TensorFlow* by Aurélien Géron (O'Reilly), 2017, 978-1-491-96229-9.

Introduction

- YouTube Video: *Convolutional Neural Networks (CNNs) explained* from deeplizard

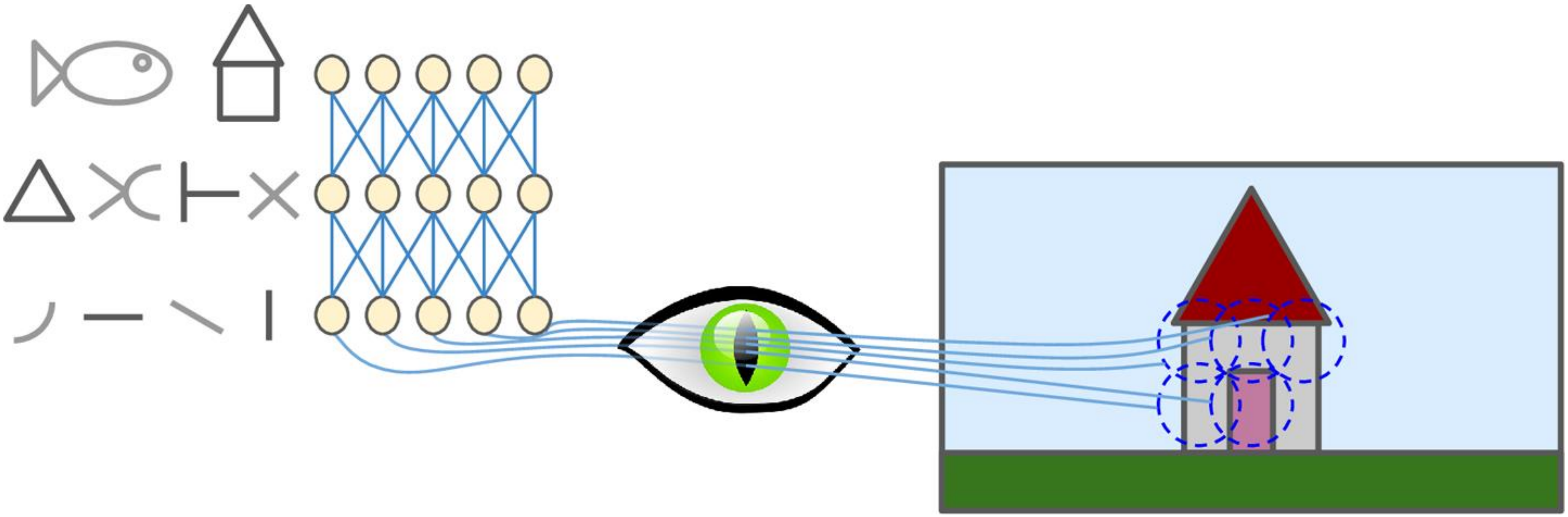
https://youtu.be/YRhxdVk_sIs

Outline

1. Introduction
2. Convolutional layer
    1. Filters
    2. Stacking feature maps
    3. Mathematical summary
    4. TensorFlow implementation
3. Pooling layer
4. CNN architectures
5. Exercises

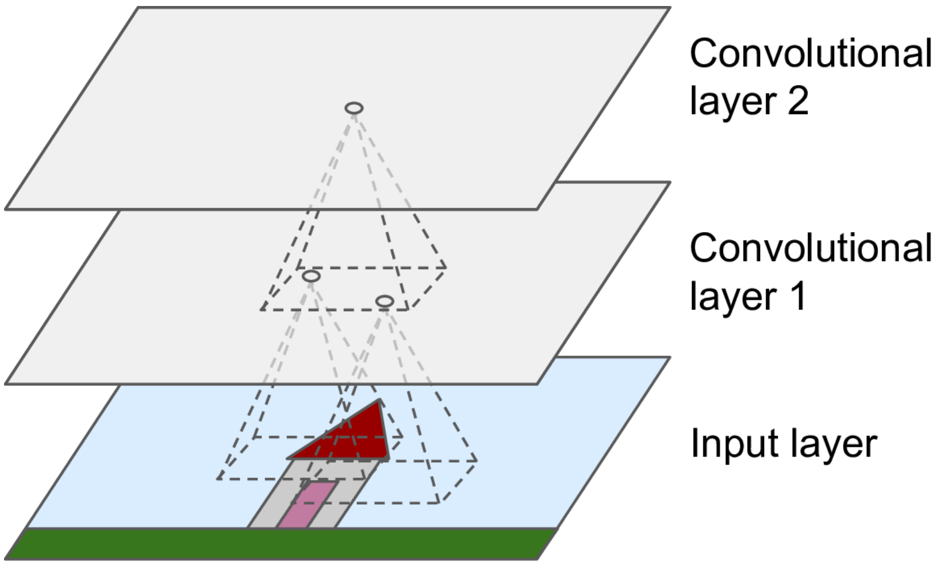
1. Introduction

- *Convolutional neural networks (CNNs)* emerged from the study of the brain's visual cortex.
- Many neurons in the visual cortex have a small *local receptive field.*



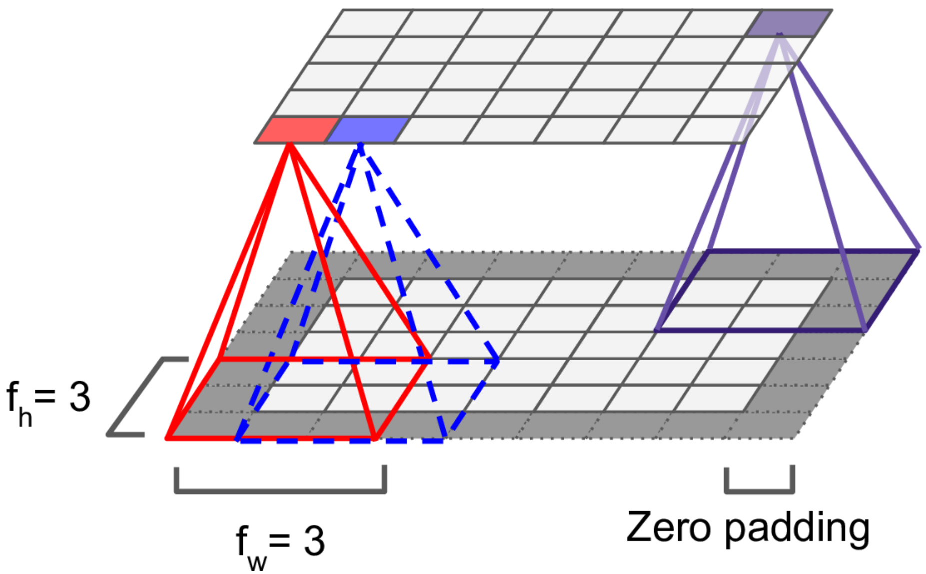
2. Convolutional Layer

- Neurons in one layer are not connected to every single pixel/neuron in the previous layer, but only to pixels/neurons in their receptive fields.
- This architecture allows the network to concentrate on low-level features in one layer, then assemble them into higher-level features in the next layer.
- Each layer is represented in 2D.



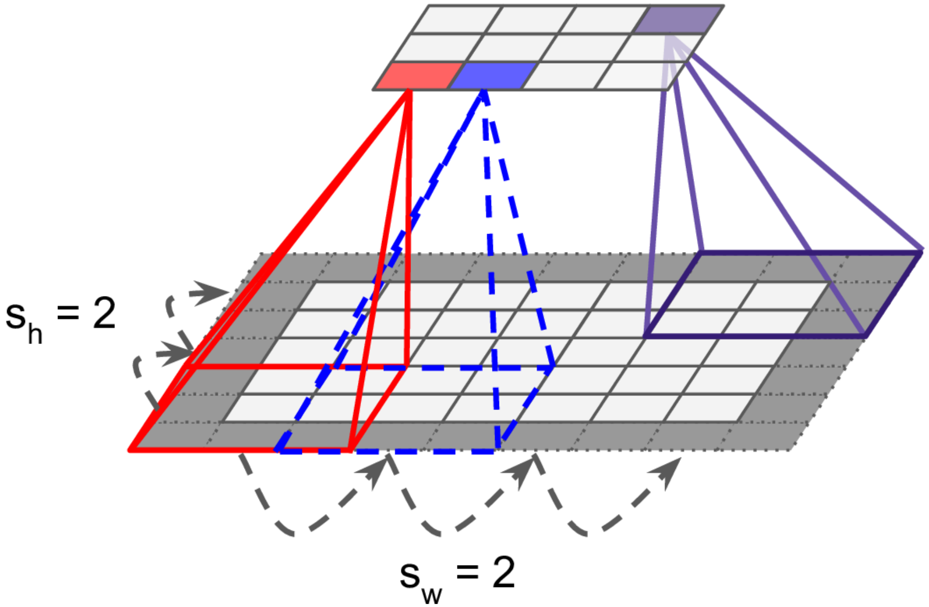
2. Convolutional Layer

- f_h and f_w are the height and width of the receptive field.
- *Zero padding:* In order for a layer to have the same height and width as the previous layer, it is common to add zeros around the inputs.



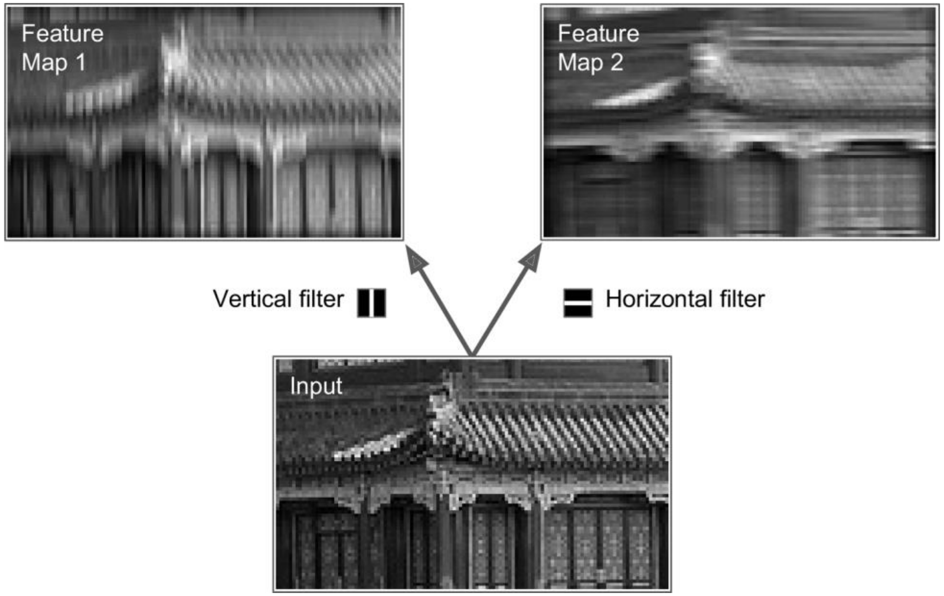
2. Convolutional Layer

- It is also possible to connect a large input layer to a smaller layer by spacing out the receptive fields.
- The distance between two consecutive receptive fields is called the *stride.*
- A neuron located in row *i*, column *j* is connected to the neurons in the previous layer located in rows $i \times s_h$ to $i \times s_h + f_h - 1$, columns $j \times s_w$ to $j \times s_w + f_w - 1$.



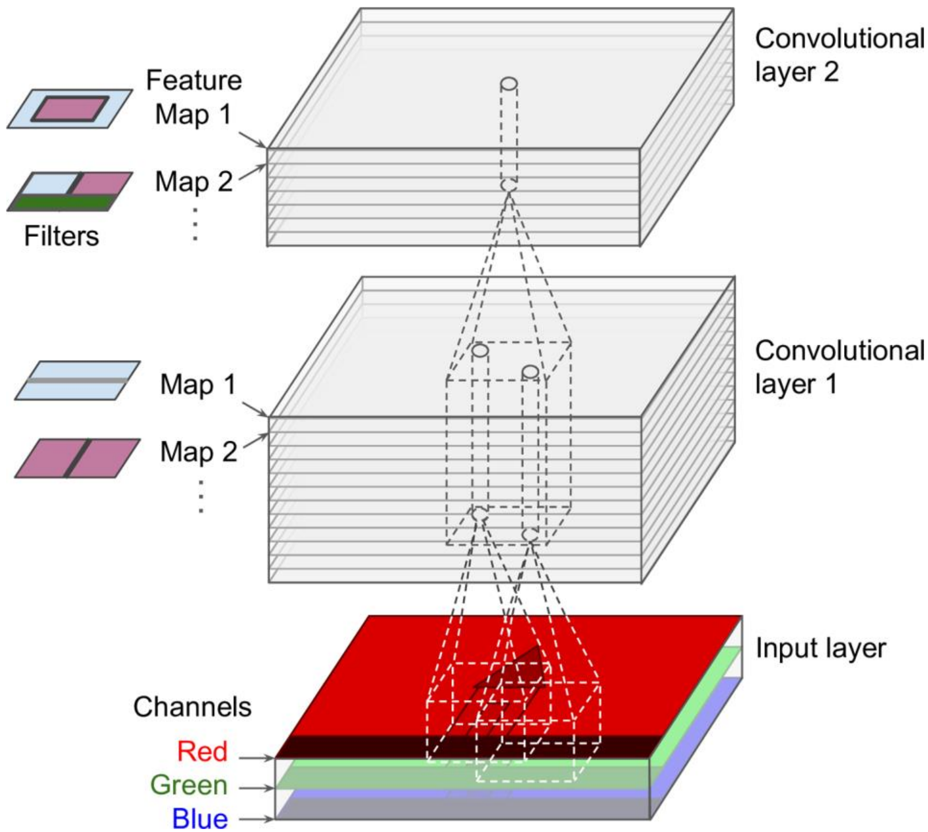
2.1. Filters

- A neuron's weights can be represented as a small image the size of the receptive field, called *filters*.
- When all neurons in a layer use the same line filters, we get the *feature maps* on the top.



2.2. Stacking Feature Maps

- In reality, each layer is *3D* composed of several feature maps of equal sizes.
- Within one feature map, all neurons share the same parameters, but different feature maps may have different parameters.
- Once the CNN has learned to recognize a pattern in one location, it can recognize it in any other location.



2.3. Mathematical Summary

Equation 13-1. Computing the output of a neuron in a convolutional layer

$$z_{i,j,k} = b_k + \sum_{u=1}^{f_h} \sum_{v=1}^{f_w} \sum_{k'=1}^{f_{n'}} x_{i',j',k'} \cdot w_{u,v,k',k} \quad \text{with} \begin{cases} i' = u \cdot s_h + f_h - 1 \\ j' = v \cdot s_w + f_w - 1 \end{cases}$$

- $z_{i,j,k}$ is the output of the neuron located in row *i*, column *j* in feature map *k*
- $f_{n'}$ is the number of feature maps in the previous layer

2.4 TensorFlow Implementation

```
import numpy as np
from sklearn.datasets import load_sample_images

# Load sample images
dataset = np.array(load_sample_images().images, dtype=np.float32)
batch_size, height, width, channels = dataset.shape

# Create 2 filters
filters_test = np.zeros(shape=(7, 7, channels, 2), dtype=np.float32)
filters_test[:, 3, :, 0] = 1  # vertical line
filters_test[3, :, :, 1] = 1  # horizontal line

# Create a graph with input X plus a convolutional layer applying the 2 filters
X = tf.placeholder(tf.float32, shape=(None, height, width, channels))
convolution = tf.nn.conv2d(X, filters, strides=[1,2,2,1], padding="SAME")

with tf.Session() as sess:
    output = sess.run(convolution, feed_dict={X: dataset})
```

(s_h and s_w)

SAME: Zero padding
VALID: No padding

2.4 TensorFlow Implementation

```
plt.imshow(output[0, :, :, 1])  # plot 1st image's 2nd feature map
plt.show()
```

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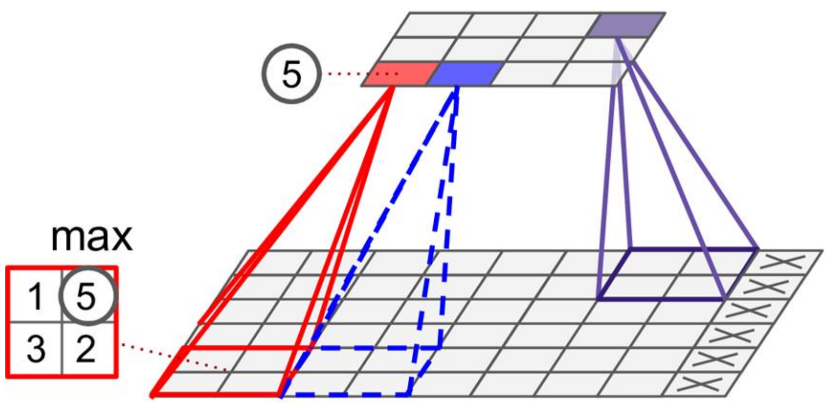
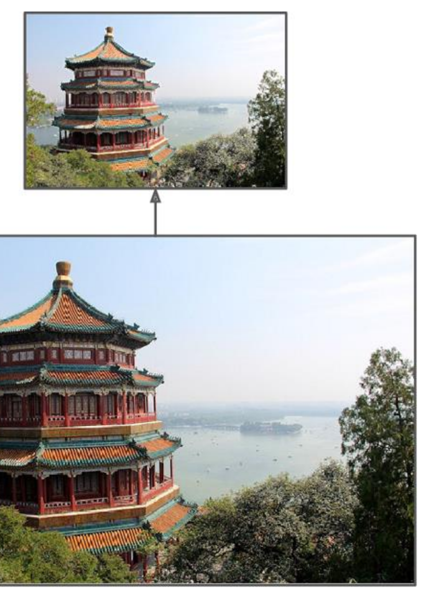
3. Pooling Layer

- Its goal is to *subsample* (i.e., shrink) the input image in order to reduce the computational load, the memory usage, and the number of parameters.
- It aggregates the inputs using max or mean.





3. Pooling Layer

- The following code creates a max pooling layer using a 2 × 2 kernel, stride 2, and no padding, then applies it to all the images in the dataset.

```
[...] # load the image dataset, just like above

# Create a graph with input X plus a max pooling layer
X = tf.placeholder(tf.float32, shape=(None, height, width, channels))
max_pool = tf.nn.max_pool(X, ksize=[1,2,2,1], strides=[1,2,2,1],padding="VALID")

with tf.Session() as sess:
    output = sess.run(max_pool, feed_dict={X: dataset})
```

[batch size, height, width, channels]

There is also avg_pool()

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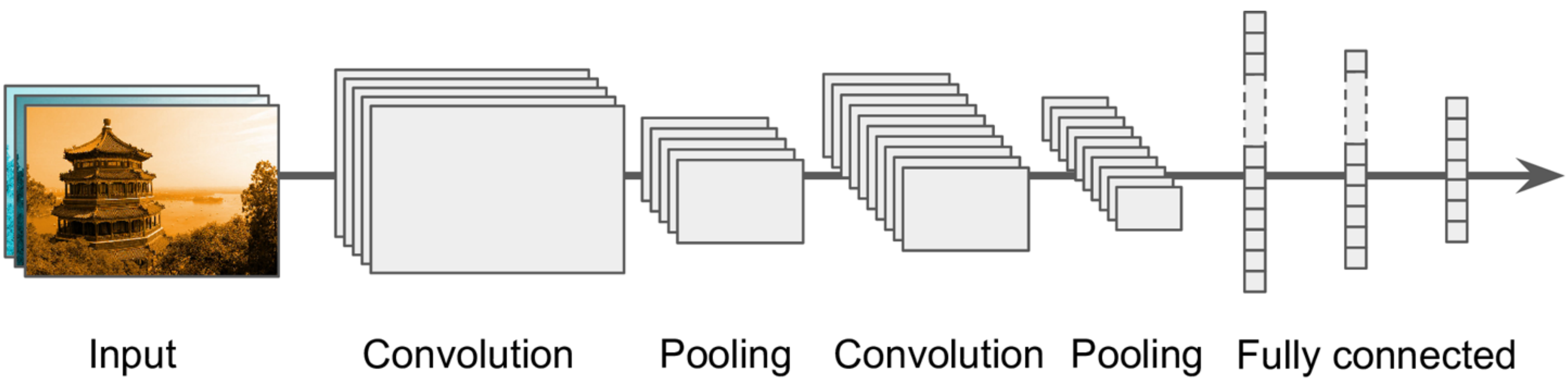
4. CNN Architectures

- Stack few convolutional layers (each one generally followed by a ReLU layer), then a pooling layer, then another few convolutional layers, then another pooling layer, and so on. The image gets smaller and smaller, but it also gets deeper and deeper. At the end, a regular NN is added.



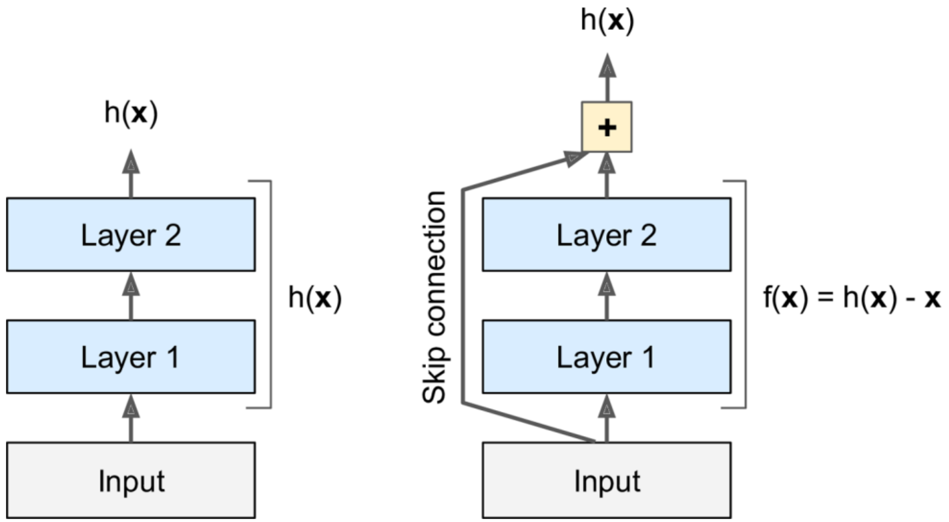
4.1. LeNet-5 (LENET Section)

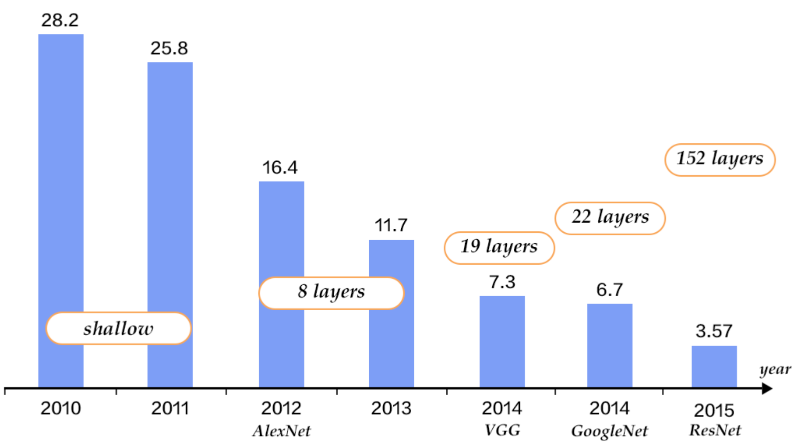
- It was created by Yann LeCun in 1998 and widely used for handwritten digit recognition (MNIST).

Layer	Type	Maps	Size	Kernel size	Stride	Activation
Out	Fully Connected	–	10	–	–	RBF
F6	Fully Connected	–	84	–	–	tanh
C5	Convolution	120	1×1	5×5	1	tanh
S4	Avg Pooling	16	5×5	2×2	2	tanh
C3	Convolution	16	10×10	5×5	1	tanh
S2	Avg Pooling	6	14×14	2×2	2	tanh
C1	Convolution	6	28×28	5×5	1	tanh
In	Input	1	32×32	–	–	–

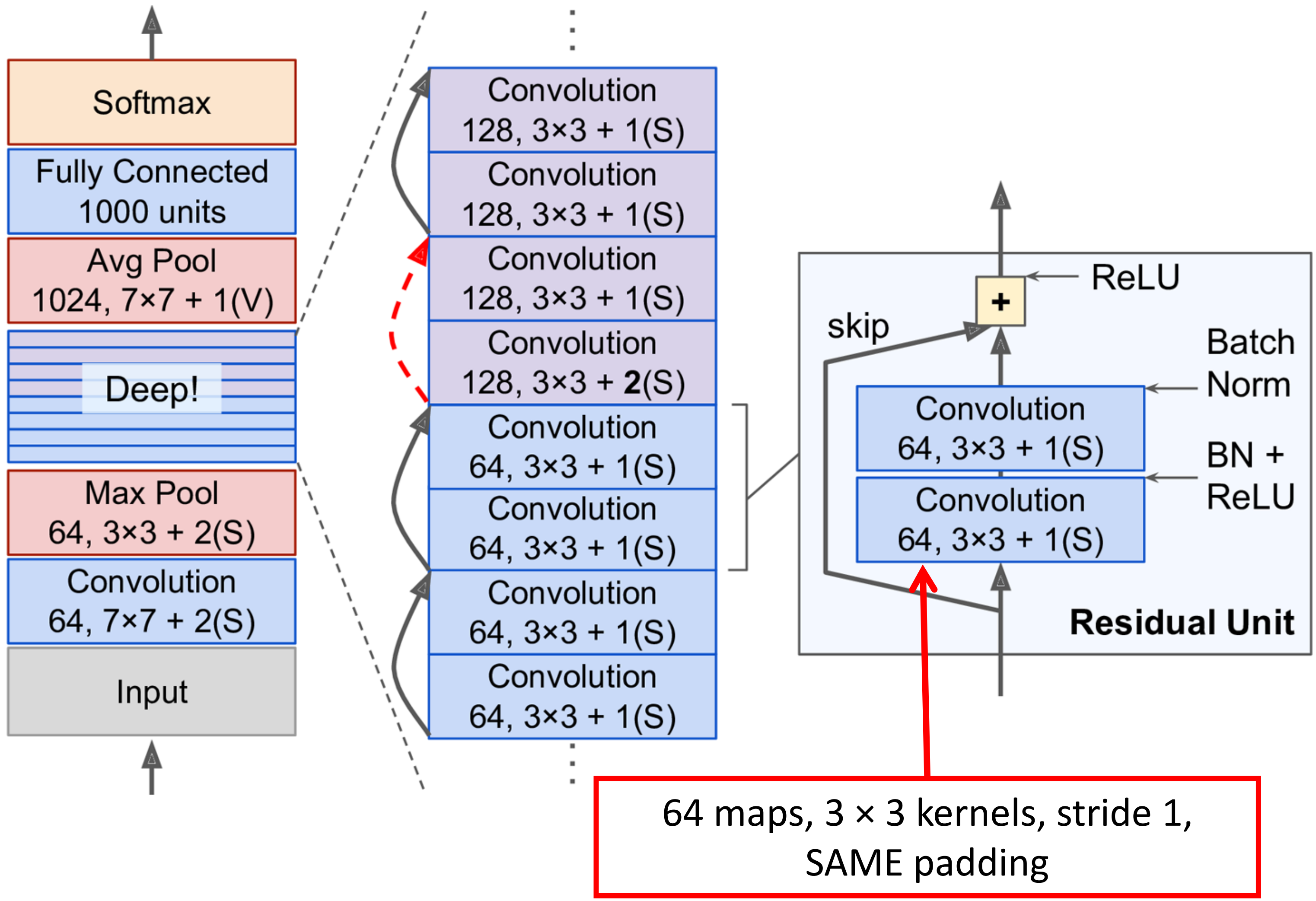
4.2. ResNet: Residual Network

- The winner of ILSVRC 2015, developed by Kaiming He et al., delivered top-5 error rate under 3.6%, using an extremely deep CNN of 152 layers.
- Uses *skip connections* (*shortcut connections*)
- *ILSVRC*: ImageNet Large Scale Visual Recognition Challenge





4.2. ResNet: Residual Network



Summary

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Exercises

From Chapter 13, solve exercises:

- 2
- 7