CNN

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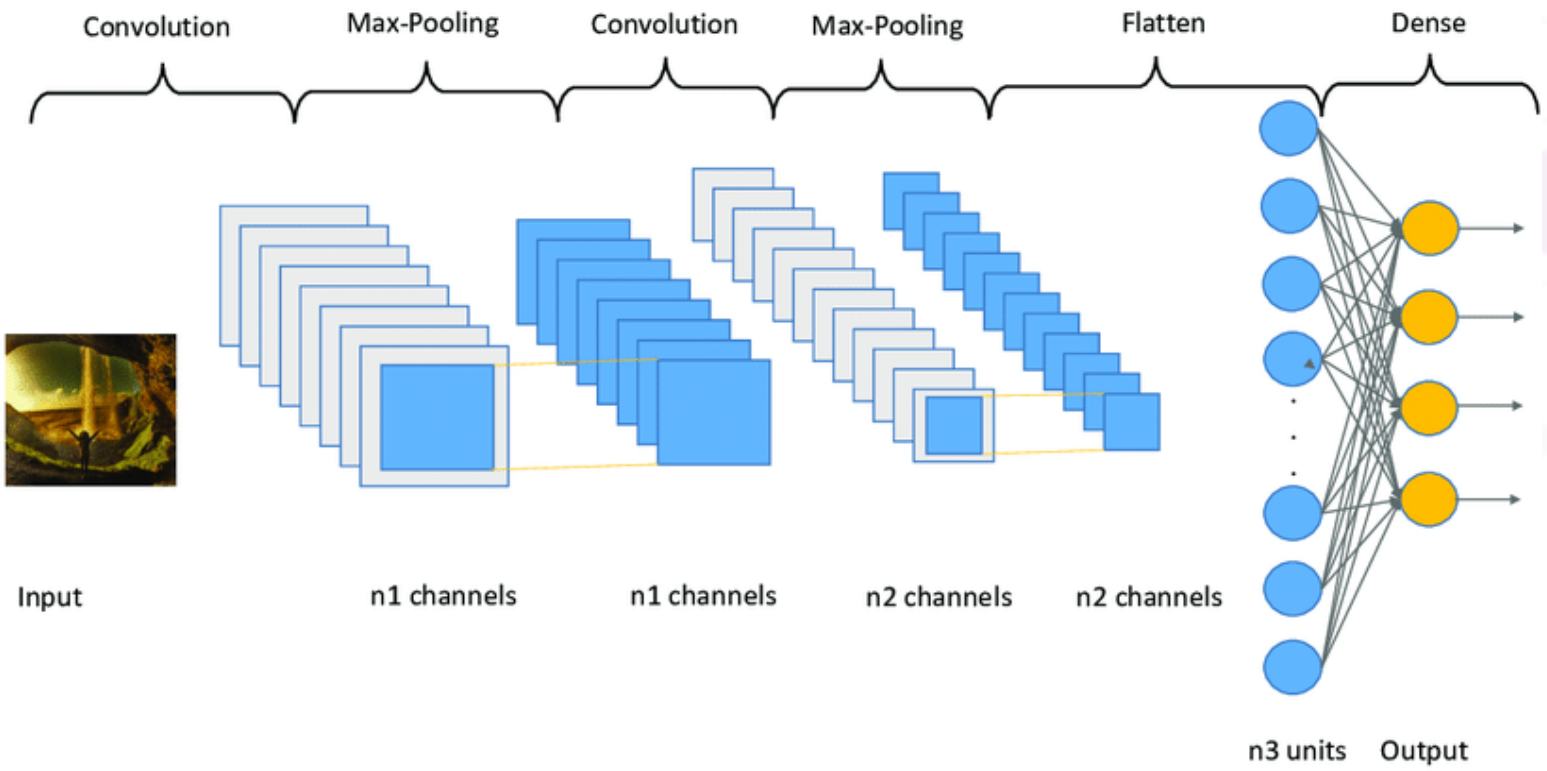
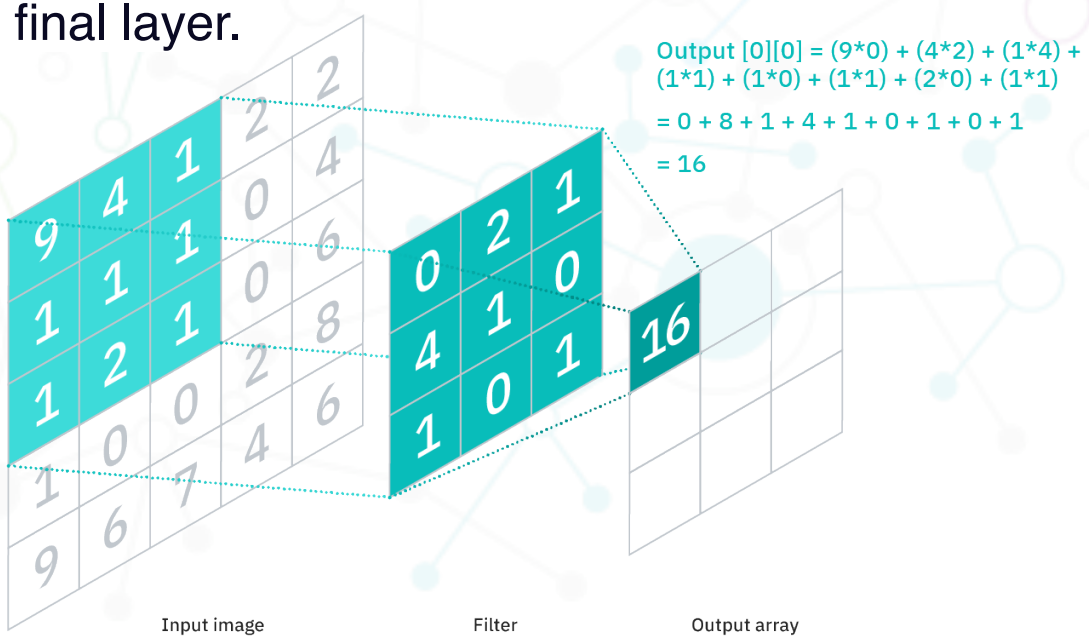
CNN

- A convolutional neural network is a specific kind of neural network with multiple layers.
- It processes data that has a grid-like arrangement then extracts important features.
- One huge advantage of using CNNs is that you don't need to do a lot of pre-processing on images.



CNN

- Convolutional neural networks are distinguished from other neural networks by their superior performance with image, speech, or audio signal inputs
- They have three main types of layers, which are:
  - Convolutional layer
  - Pooling layer
  - Fully-connected (FC) layer
- The convolutional layer is the first layer of a convolutional network.
- While convolutional layers can be followed by additional convolutional layers or pooling layers, the fully-connected layer is the final layer.



CNN

These are the network parameters to be learned.

1	0	0	0	0	1
0	1	0	0	1	0
0	0	1	1	0	0
1	0	0	0	1	0
0	1	0	0	1	0
0	0	1	0	1	0

6 x 6 image

1	-1	-1
-1	1	-1
-1	-1	1

Filter 1

-1	1	-1
-1	1	-1
-1	1	-1

Filter 2

Each filter detects a small pattern (3 x 3).

CNN

1	-1	-1
-1	1	-1
-1	-1	1

Filter 1

stride=1

1	0	0	0	0	1
0	1	0	0	1	0
0	0	1	1	0	0
1	0	0	0	1	0
0	1	0	0	1	0
0	0	1	0	1	0

Dot product

3 -1

6 x 6 image

CNN

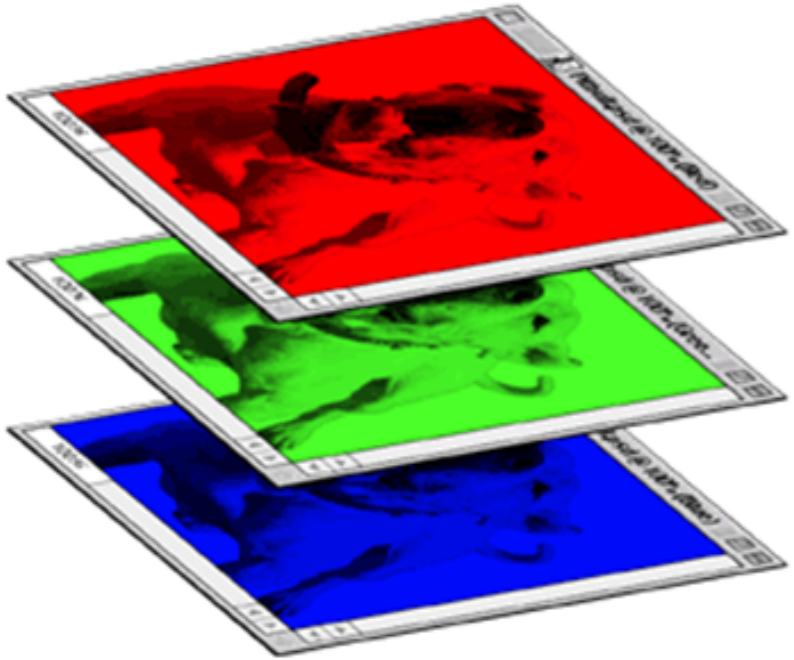
1	-1	-1
-1	1	-1
-1	-1	1

Filter 1

-1	1	-1
-1	1	-1
-1	1	-1

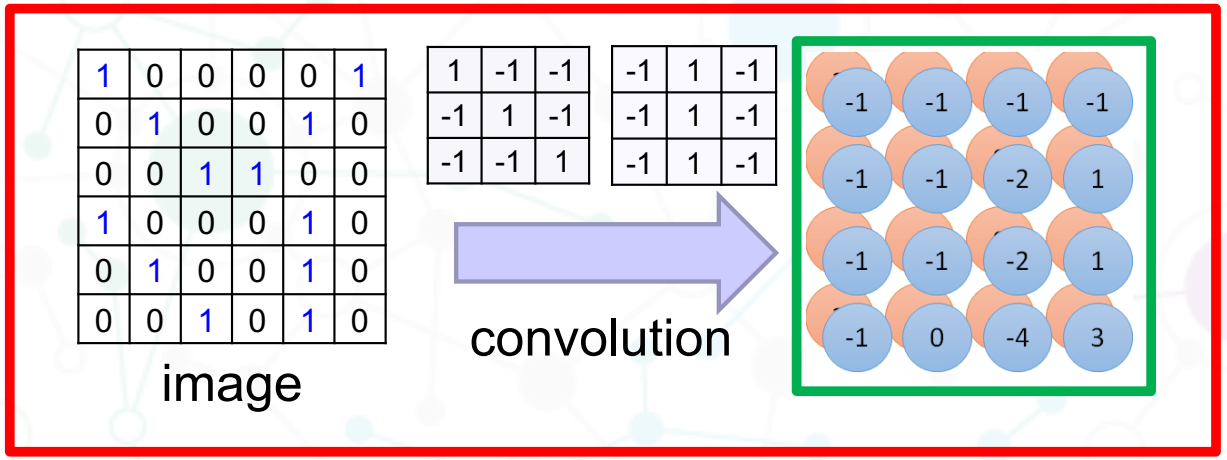
Filter 2

Color image

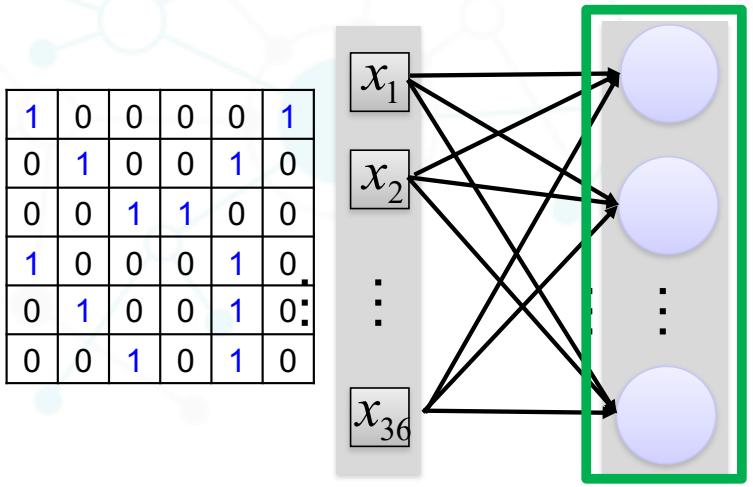


1	0	0	0	0	1
0	1	0	0	1	0
0	0	1	1	0	0
1	0	0	0	1	0
0	1	0	0	1	0
0	0	1	0	1	0

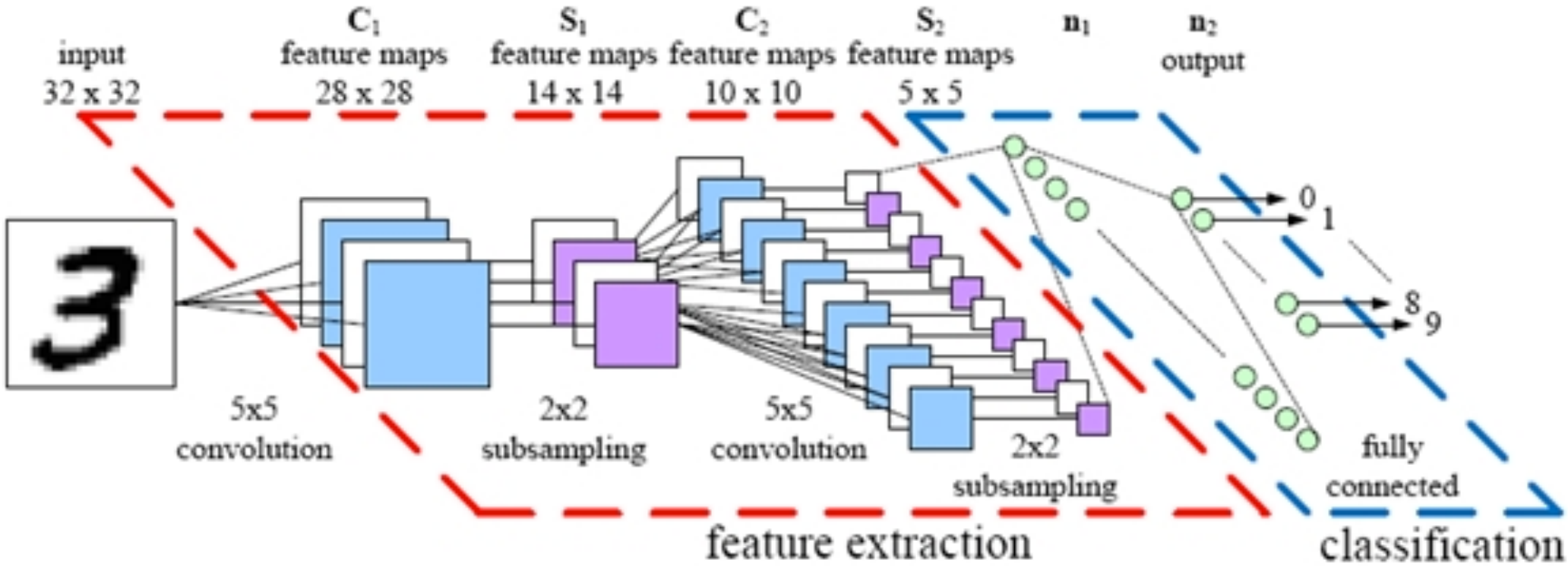
Convolution v.s. Fully Connected



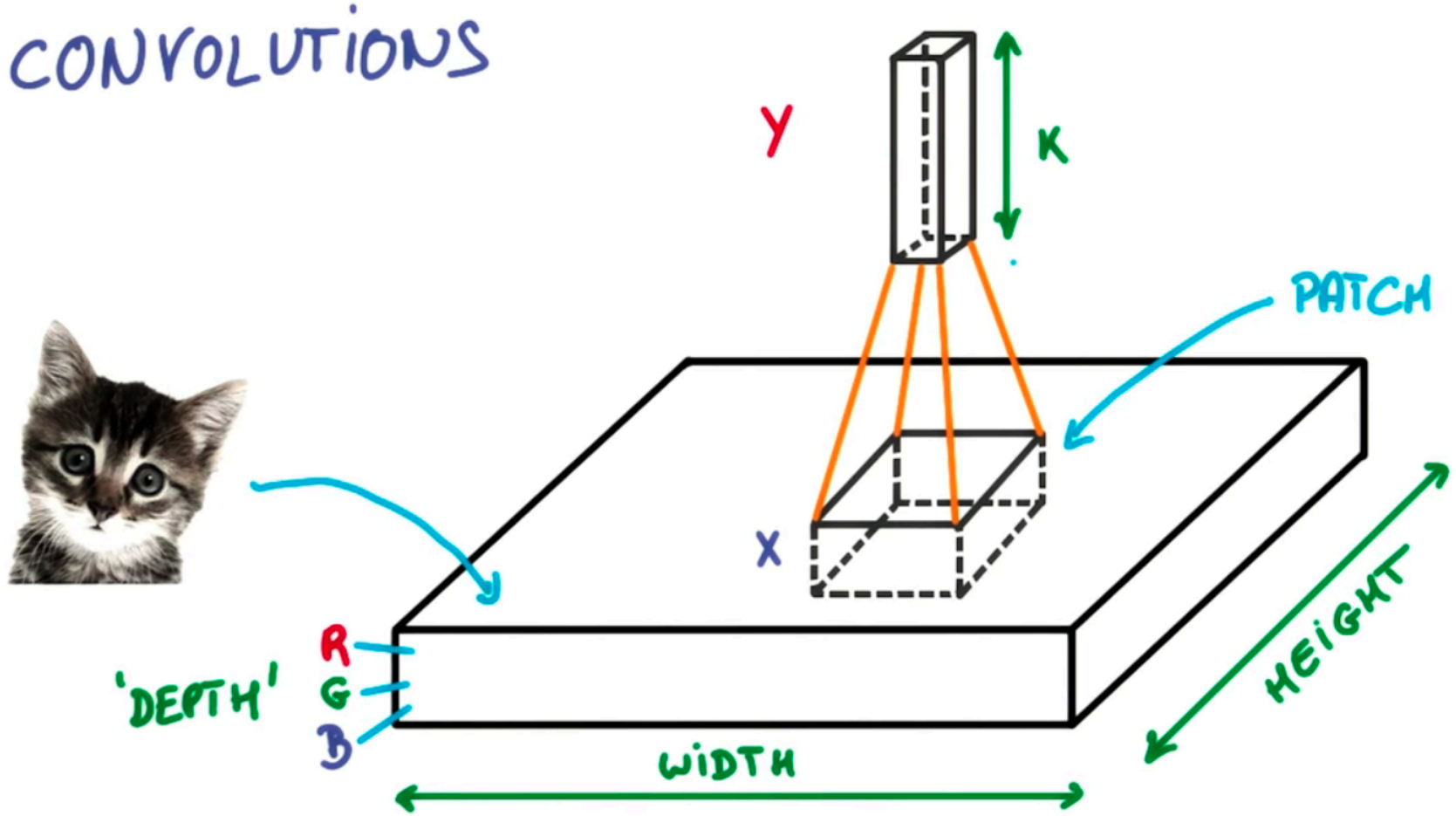
Fully-connected



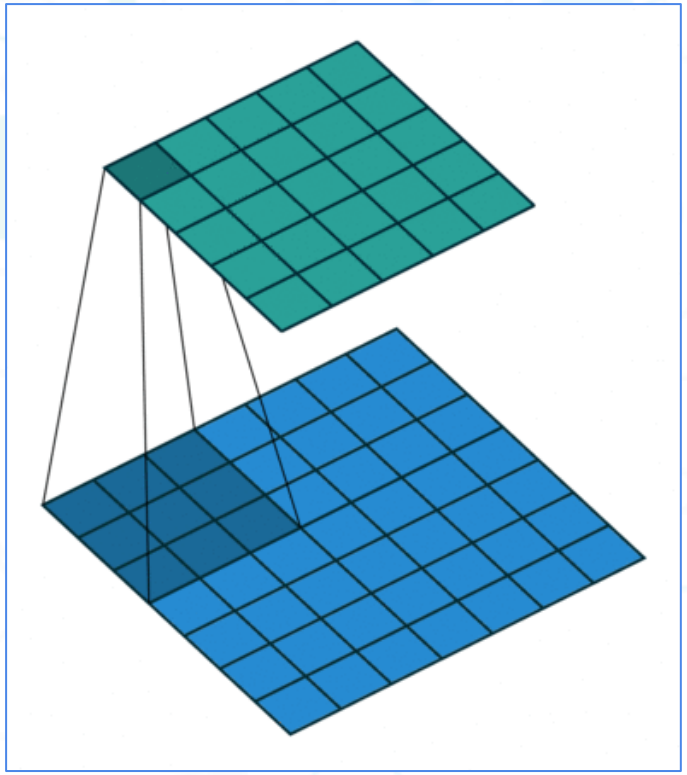
CNN


input
32 x 32
C1
feature maps
28 x 28
S1
feature maps
14 x 14
C2
feature maps
10 x 10
S2
feature maps
5 x 5
n1
n2
output
0
1
8
9
5x5
convolution
2x2
subsampling
5x5
convolution
2x2
subsampling
fully
connected
feature extraction
classification

CNN



CNN

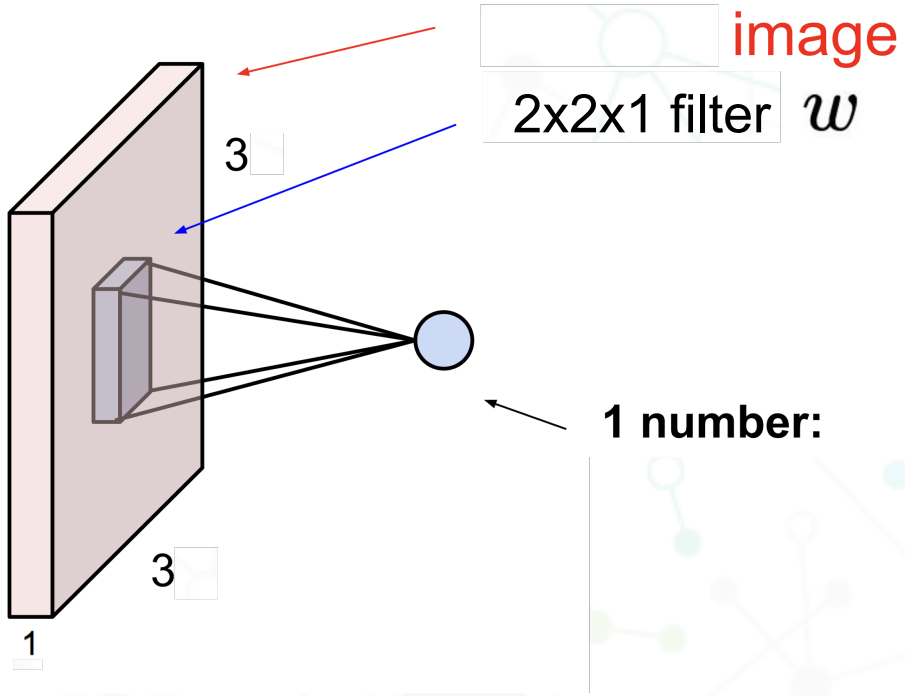


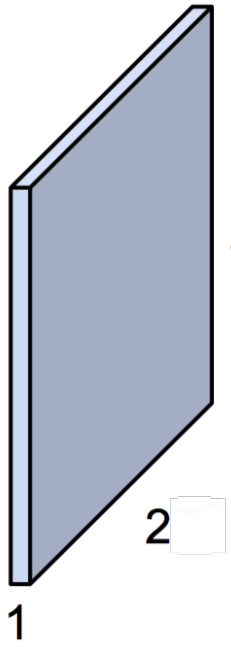
Padding

- If we have been convolving an input of 6 X 6 dimension with a 3 X 3 filter results in 4 X 4 output.
- We can generalize it and say that if the input is $n \times n$ and the filter size is $f \times f$, then the output size will be $(n-f+1) \times (n-f+1)$:
  - **Input:** $n \times n$
  - **Filter size:** $f \times f$
  - **Output:** $(n-f+1) \times (n-f+1)$
- There are primarily two disadvantages here:
  1. Every time we apply a convolutional operation, the size of the image shrinks
  2. Pixels present in the corner of the image are used only a few number of times during convolution as compared to the central pixels. Hence, we do not focus too much on the corners since that can lead to information loss
- To overcome these issues, we can pad the image with an additional border, i.e., we add one pixel all around the edges:
  - **Input:** $n \times n$
  - **Padding:** p
  - **Filter size:** $f \times f$
  - **Output:** $(n+2p-f+1) \times (n+2p-f+1)$

Strided Convolutions

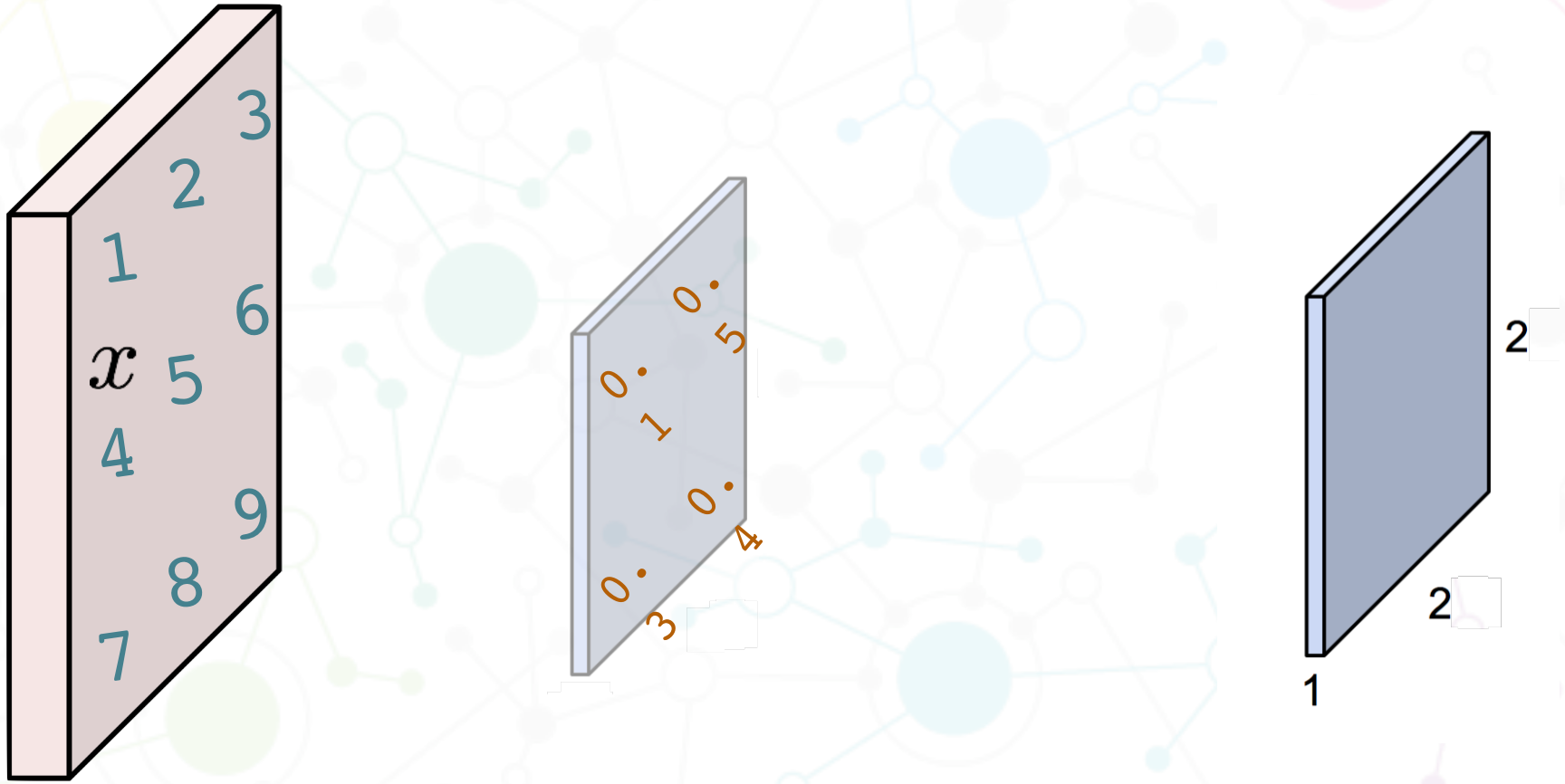
- Suppose we choose a stride of 2. So, while convoluting through the image: we will take two steps – both in the horizontal and vertical directions separately.
- The dimensions for stride s will be:
  - **Input:** $n \times n$
  - **Padding:** p
  - **Stride:** s
  - **Filter size:** $f \times f$
  - **Output:** $[(n + 2p - f)/s + 1] \times [(n + 2p - f)/s + 1]$
- Stride helps to reduce the size of the image, a particularly useful feature.





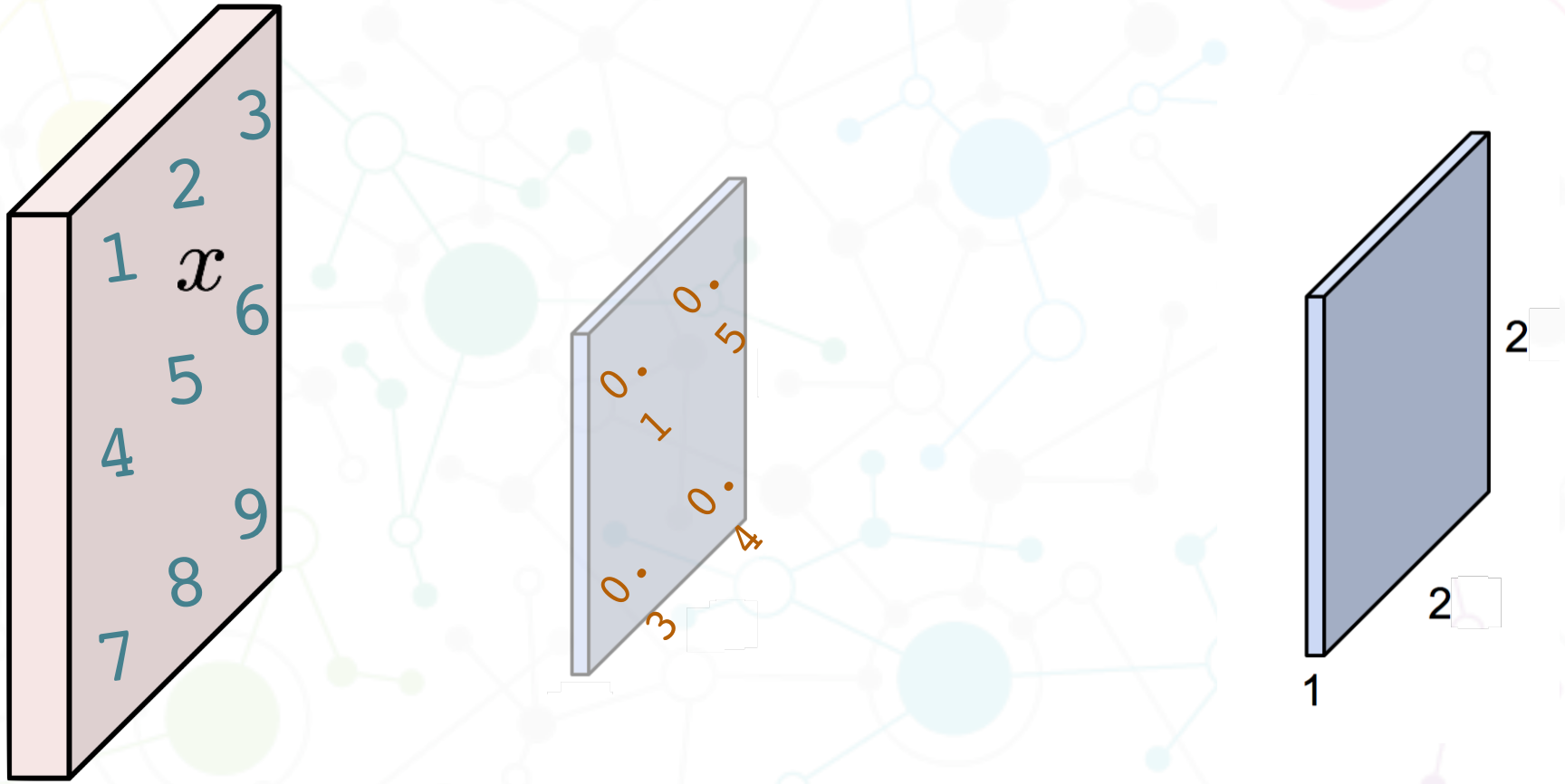
Simple convolution layer

`Stride: 1x1`



Simple convolution layer

Image: 1,3,3,1 image, Filter: 2,2,1,1, Stride: 1x1, No Padding

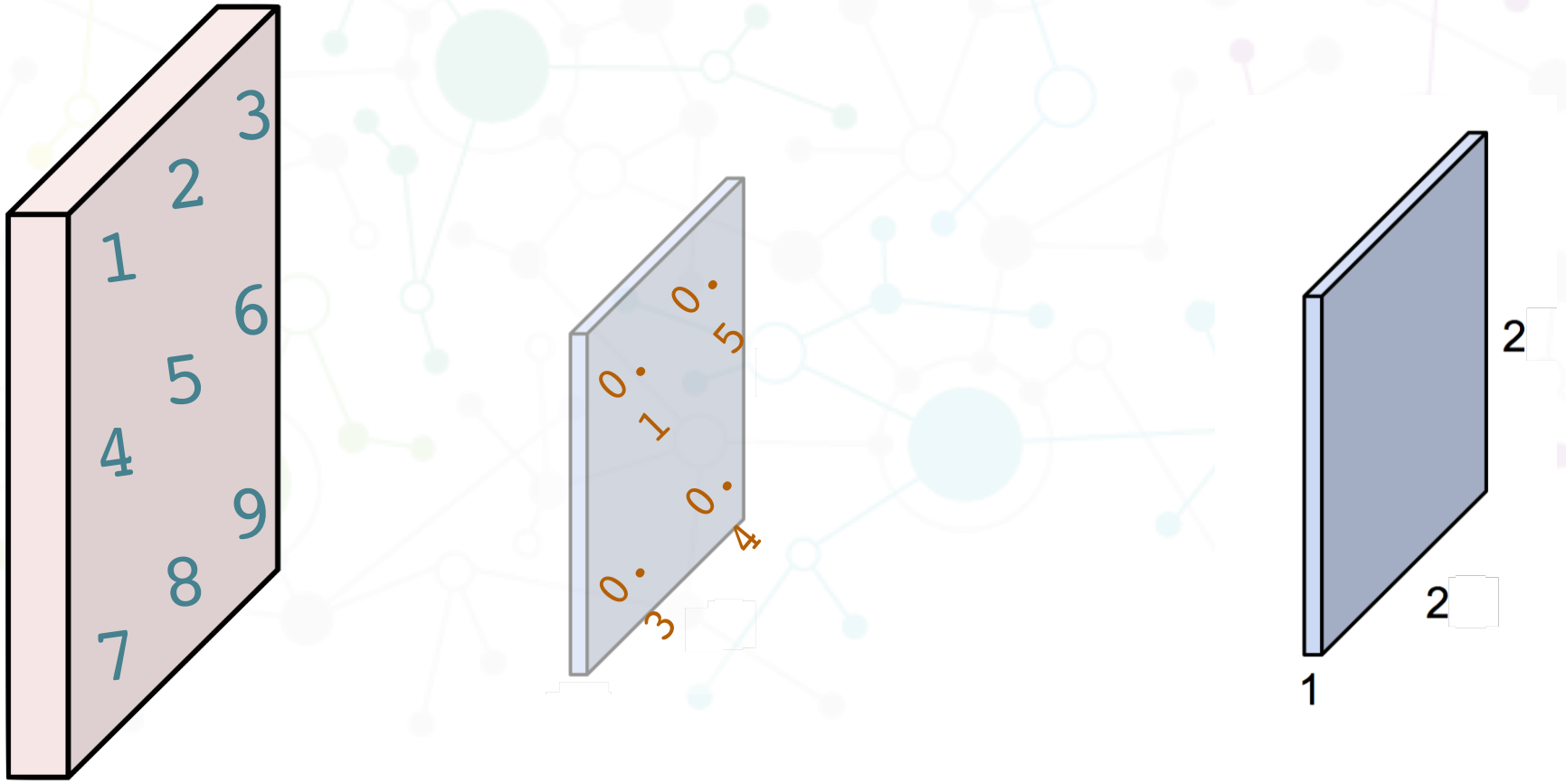


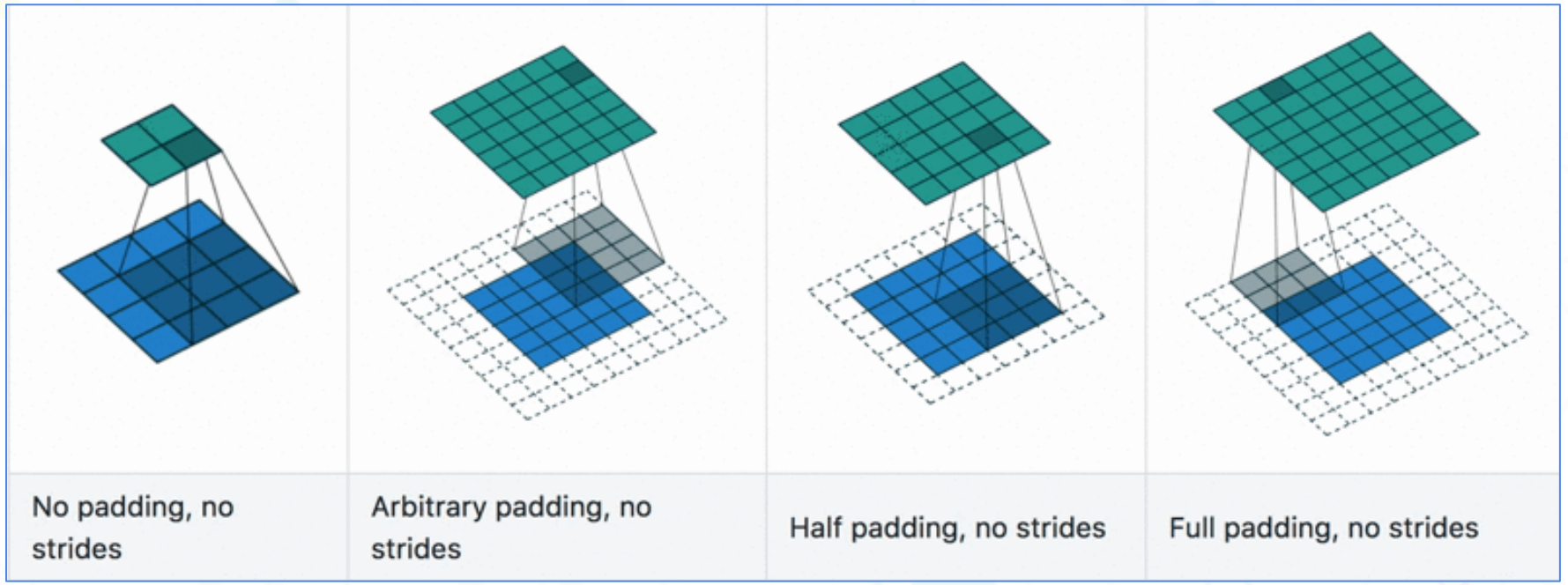
Simple convolution layer

Image: 1,3,3,1 image, Filter: 2,2,1,1, Stride: 1x1, No Padding

Simple convolution layer

Image: 1,3,3,1 image, Filter: 2,2,1,1, Stride: 1x1, With padding





Convolution with padding in Action

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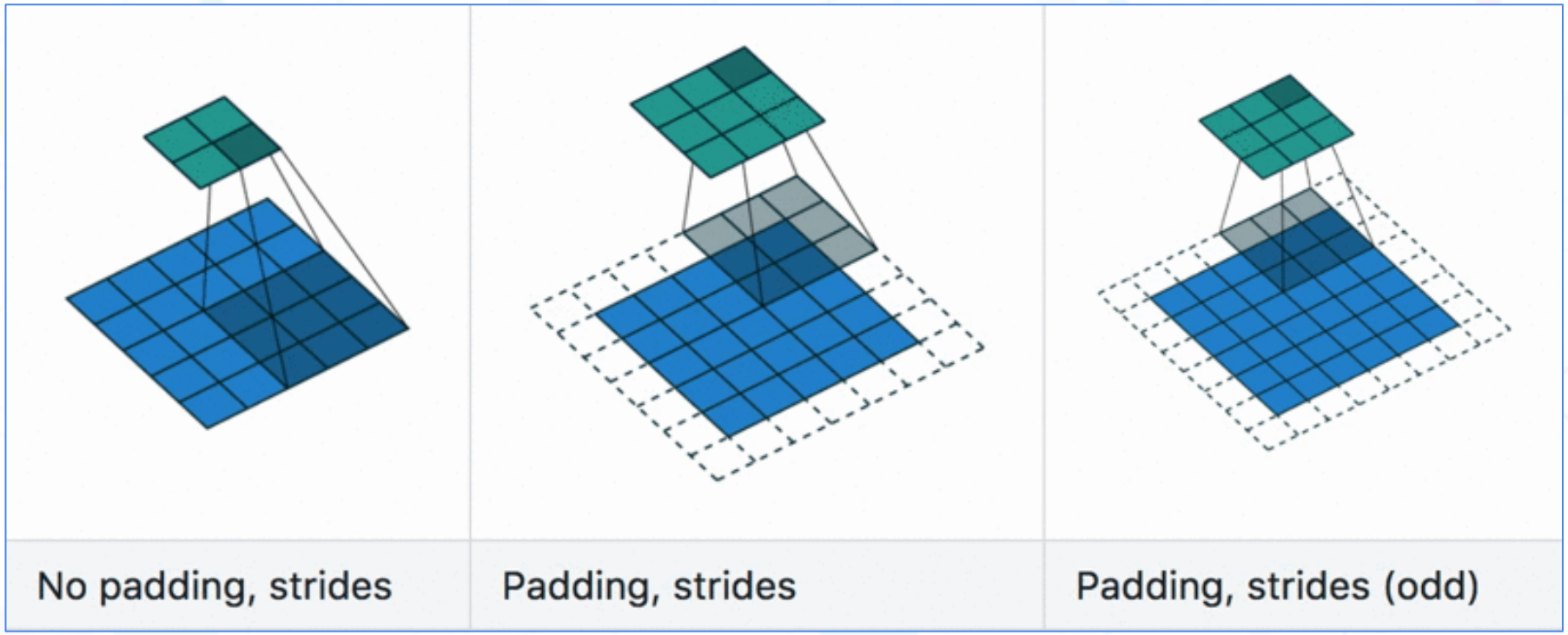
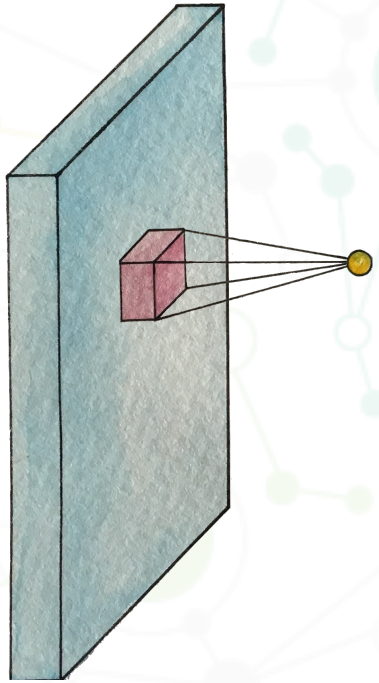


Max pooling

Pooling Layers

Pooling layers are generally used to reduce the size of the inputs and hence speed up the computation.



Single depth slice

1	1	2	4
5	6	7	8
3	2	1	0
1	2	3	4

max pool with 2x2 filters and stride 2 →

6	8
3	4

Why Pooling

- Subsampling pixels will not change the object

bird

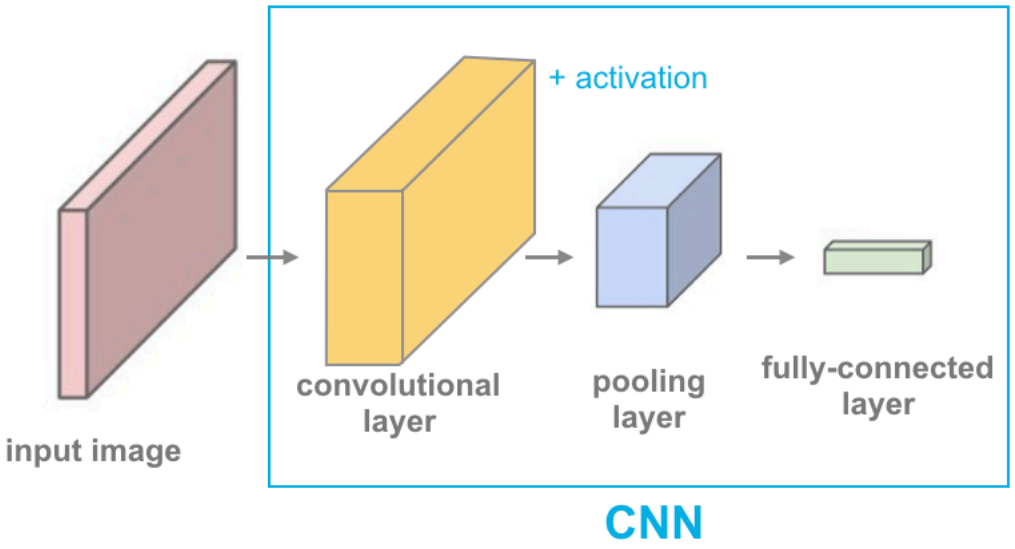
Subsampling

bird

We can subsample the pixels to make image smaller → fewer parameters to characterize the image

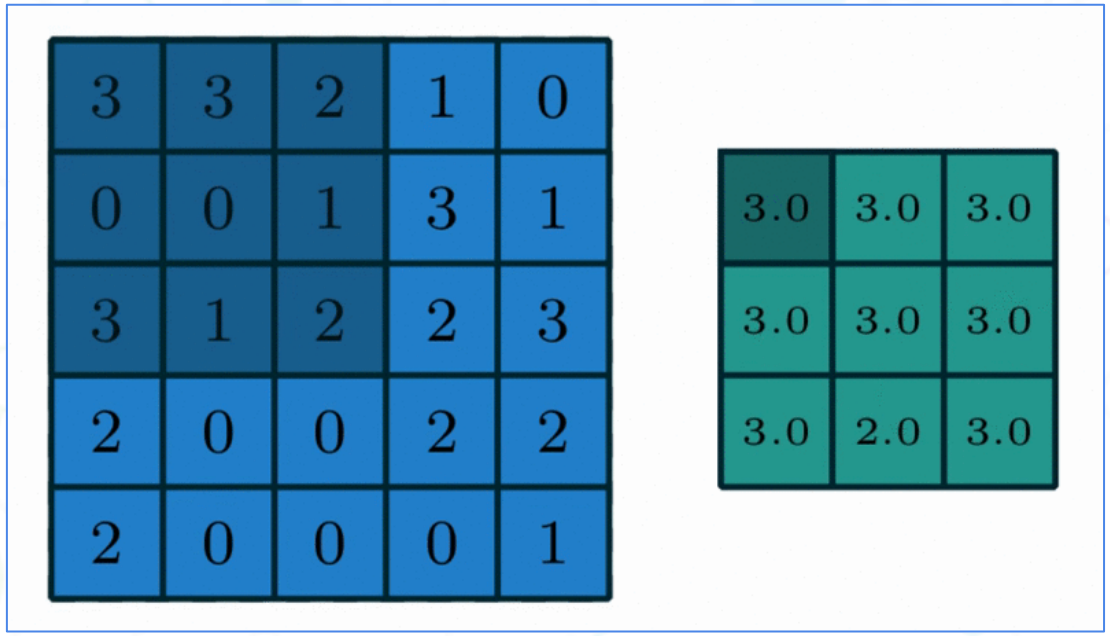
CNN

A convolutional layer + activation function, followed by a pooling layer, and a linear layer (to create a desired output size) make up the basic layers of a CNN.

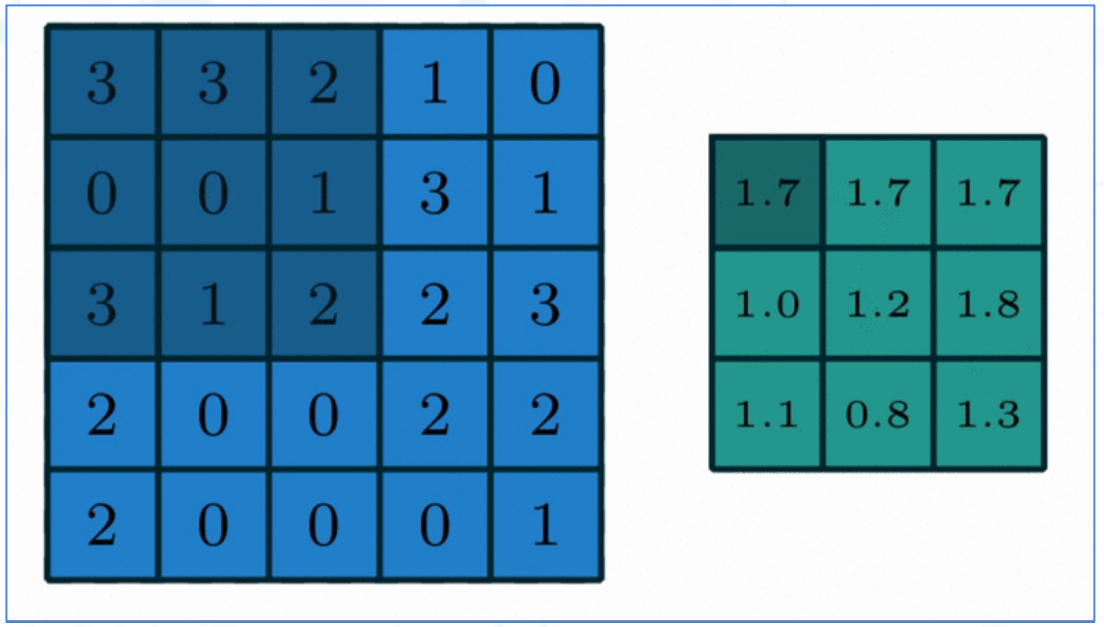


- Pooling layers, also known as downsampling, conducts dimensionality reduction, reducing the number of parameters in the input.
- There are two main types of pooling:
  - **Max pooling:** As the filter moves across the input, it selects the pixel with the maximum value to send to the output array.
  - **Average pooling:** As the filter moves across the input, it calculates the average value within the receptive field to send to the output array.
- Fully-connected layer performs the task of classification based on the features extraction through the previous layers and their different filters.
- While convolutional and pooling layers tend to use ReLu functions, FC layers usually leverage a softmax activation function to classify inputs appropriately, producing a probability from 0 to 1.

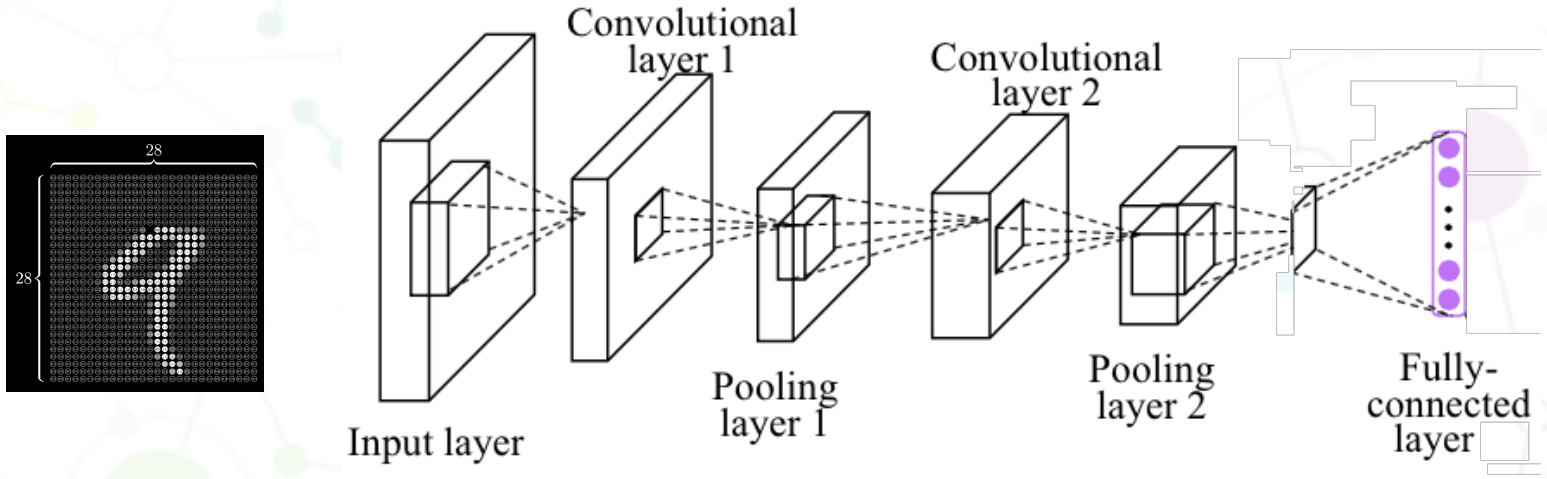
Max Pooling in Action



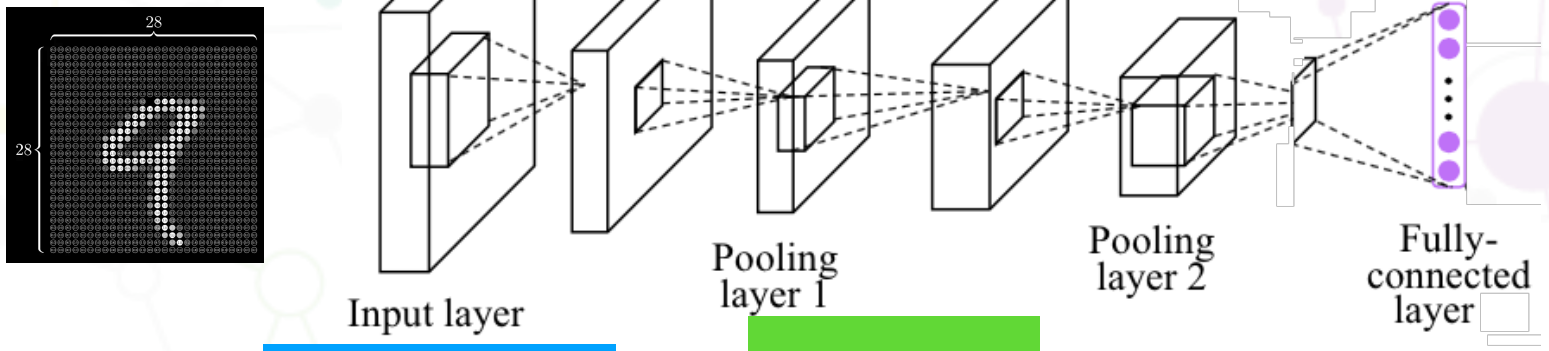
Avg Pooling in Action



Simple CNN


28
28
Convolutional layer 1
Convolutional layer 2
Input layer
Pooling layer 1
Pooling layer 2
Fully-connected layer

Simple CNN



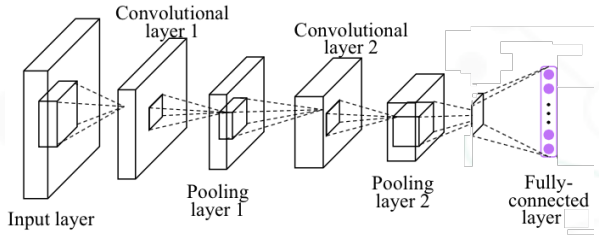

```
self.fc = nn.Linear(320, 10)
```

torch.nn.Conv2d (in_channels, out_channels, kernel_size)

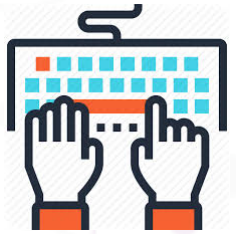
nn.MaxPool2d (kernel_size)

```
self.mp = nn.MaxPool2d(2)
```

```
self.conv1 = nn.Conv2d(1, 10, kernel_size=5)
```



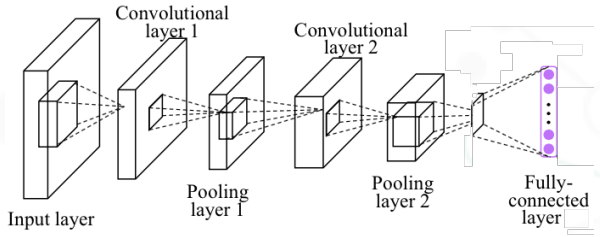
Simple CNN



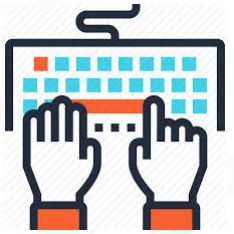
```
class Net(nn.Module):

    def __init__(self):
        super(Net, self).__init__()
        self.conv1 = nn.Conv2d(1, 10, kernel_size=5)
        self.conv2 = nn.Conv2d(10, 20, kernel_size=5)
        self.mp = nn.MaxPool2d(2)
        self.fc = nn.Linear(100???, 10) # ??? -> 10

    def forward(self, x):
        in_size = x.size(0)
        x = F.relu(self.mp(self.conv1(x)))
        x = F.relu(self.mp(self.conv2(x)))
        x = x.view(in_size, -1) # flatten the tensor
        x = self.fc(x)
        return F.log_softmax(x)
```



Simple CNN



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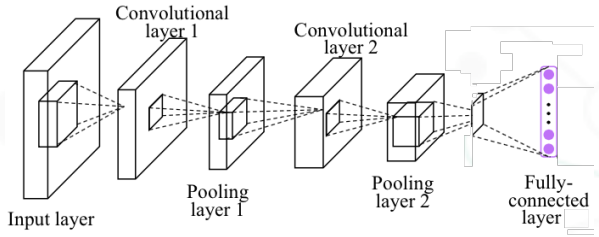
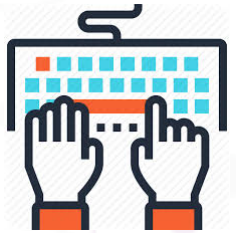
```

RuntimeError: size mismatch, m1: [64 x **320**], m2: [100 x 10]



Simple CNN



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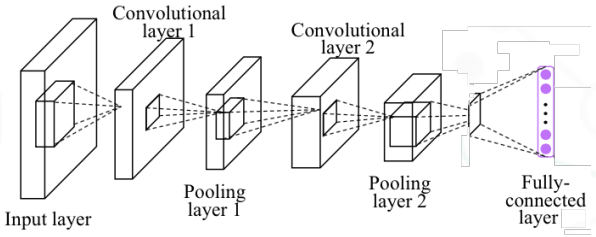
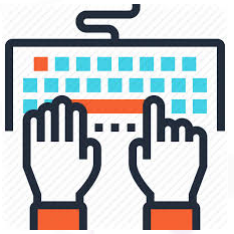


Simple CNN



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        self.conv2 = nn.Conv2d(10, 20, kernel_size=5)
        self.mp = nn.MaxPool2d(2)
        self.fc = nn.Linear(320, 10) # 320 -> 10

    def forward(self, x):
        in_size = x.size(0)
        x = F.relu(self.mp(self.conv1(x)))
        x = F.relu(self.mp(self.conv2(x)))
        x = x.view(in_size, -1) # flatten the tensor
        x = self.fc(x)
        return F.log_softmax(x)
```
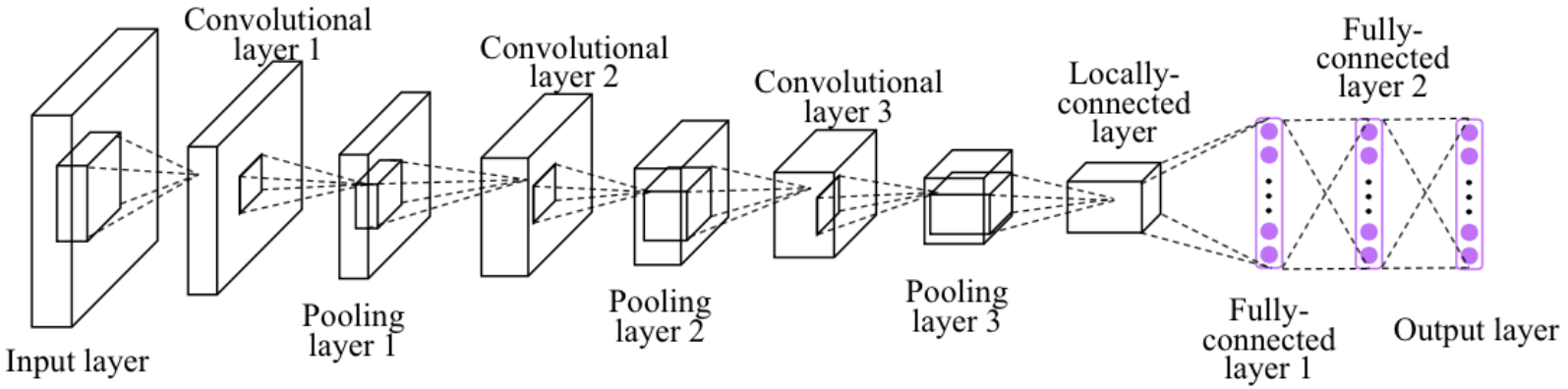

```
Train Epoch: 9 [46080/60000 (77%)]      Loss: 0.108415
Train Epoch: 9 [46720/60000 (78%)]      Loss: 0.140700
Train Epoch: 9 [47360/60000 (79%)]      Loss: 0.090830
Train Epoch: 9 [48000/60000 (80%)]      Loss: 0.031640
Train Epoch: 9 [48640/60000 (81%)]      Loss: 0.014934
Train Epoch: 9 [49280/60000 (82%)]      Loss: 0.090210
Train Epoch: 9 [49920/60000 (83%)]      Loss: 0.074975
Train Epoch: 9 [50560/60000 (84%)]      Loss: 0.058671
Train Epoch: 9 [51200/60000 (85%)]      Loss: 0.023464
Train Epoch: 9 [51840/60000 (86%)]      Loss: 0.018025
Train Epoch: 9 [52480/60000 (87%)]      Loss: 0.098865
Train Epoch: 9 [53120/60000 (88%)]      Loss: 0.013985
Train Epoch: 9 [53760/60000 (90%)]      Loss: 0.070476
Train Epoch: 9 [54400/60000 (91%)]      Loss: 0.065411
Train Epoch: 9 [55040/60000 (92%)]      Loss: 0.028783
Train Epoch: 9 [55680/60000 (93%)]      Loss: 0.008333
Train Epoch: 9 [56320/60000 (94%)]      Loss: 0.020412
Train Epoch: 9 [56960/60000 (95%)]      Loss: 0.036749
Train Epoch: 9 [57600/60000 (96%)]      Loss: 0.163087
Train Epoch: 9 [58240/60000 (97%)]      Loss: 0.117539
Train Epoch: 9 [58880/60000 (98%)]      Loss: 0.032256
Train Epoch: 9 [59520/60000 (99%)]      Loss: 0.026360

Test set: Average loss: 0.0483, Accuracy: 9846/10000 (98%)
```

Exercise 10-1: Implement CNN more layers



THANK YOU!