Deep Learning and Optimization

Unpacking Transformers, LLMs and Diffusion

Session 5

olivier.koch@ensae.fr

slack #ensae-dl-2025

Summary of Session 4

The architecture of Transformers and GPT.

Encoder and decoder architectures, masked-attention, self- and cross-attention.

We built a mini GPT from scratch.

Session	Date	Topic
1	05-02-2025	Intro to Deep Learning Practical: micrograd
2	12-02-2025	DL fundamentals • Backprop • Loss functions Practical: bigram, MLP for next character prediction
3	19-02-2025	DL Fundamentals II • Activation functions • Regularization • Initialization • Residual networks • Normalization Practical: tensor-based models
	26-02-2025	Pas de cours
4	05-03-2025	Attention & Transformers Practical: GPT from scratch
5	12-03-2025	DL for computer vision Practical: Convnets for CIFAR-10
6	19-03-2025	VAE & Diffusion models Practical: diffusion from scratch Quiz/Exam

More depth is not always better

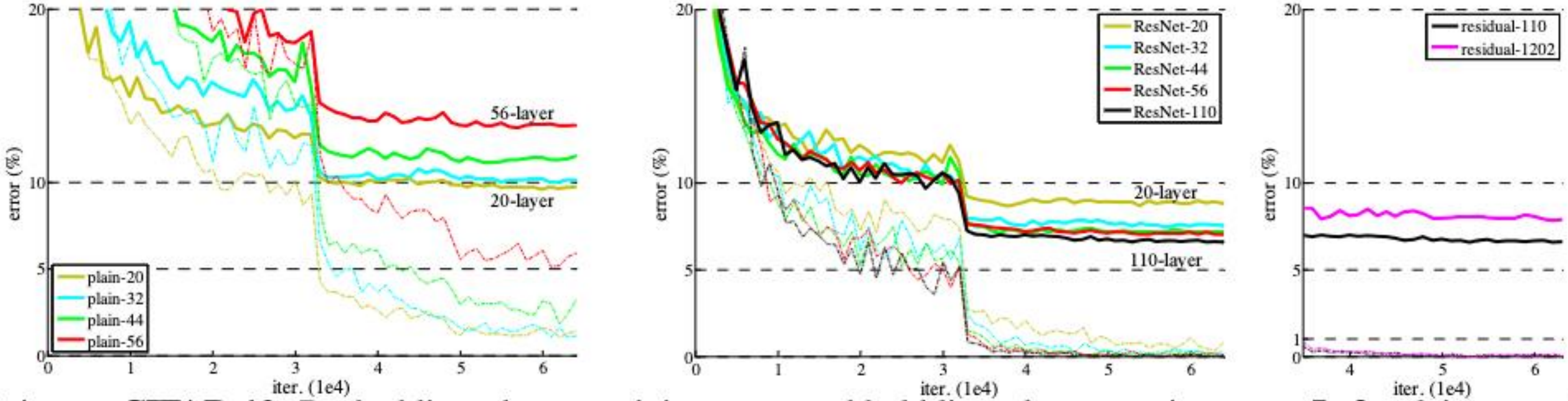


Figure 6. Training on **CIFAR-10**. Dashed lines denote training error, and bold lines denote testing error. **Left**: plain networks. The error of plain-110 is higher than 60% and not displayed. **Middle**: ResNets. **Right**: ResNets with 110 and 1202 layers.

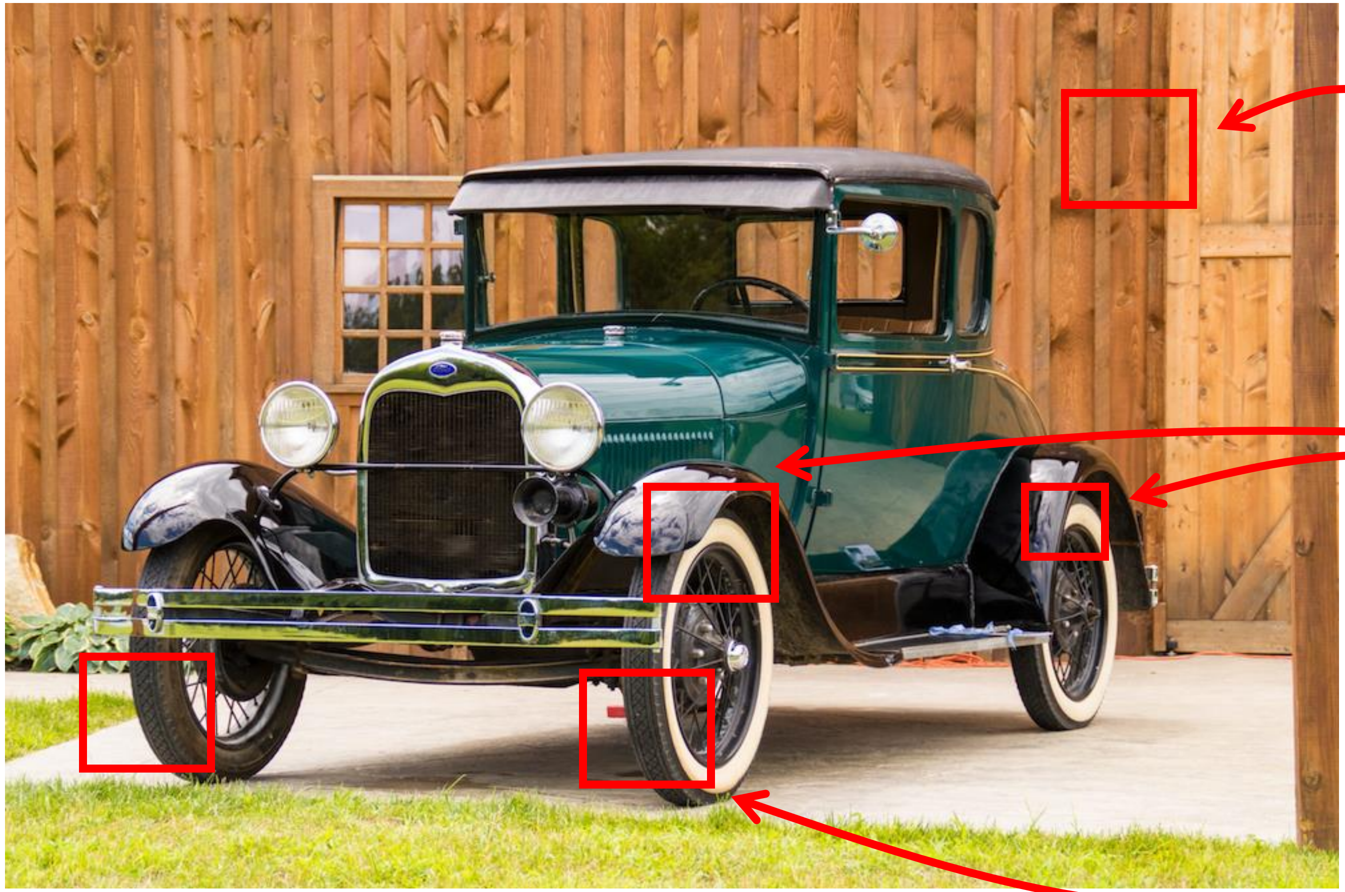
Deep Residual Learning for Image Recognition, Kaiming He et al., 2015

Residual networks

Do better architectures learn better than deeper models?

Deep Residual Learning for Image Recognition, Kaiming He et al., 2015

Inductive bias for computer vision

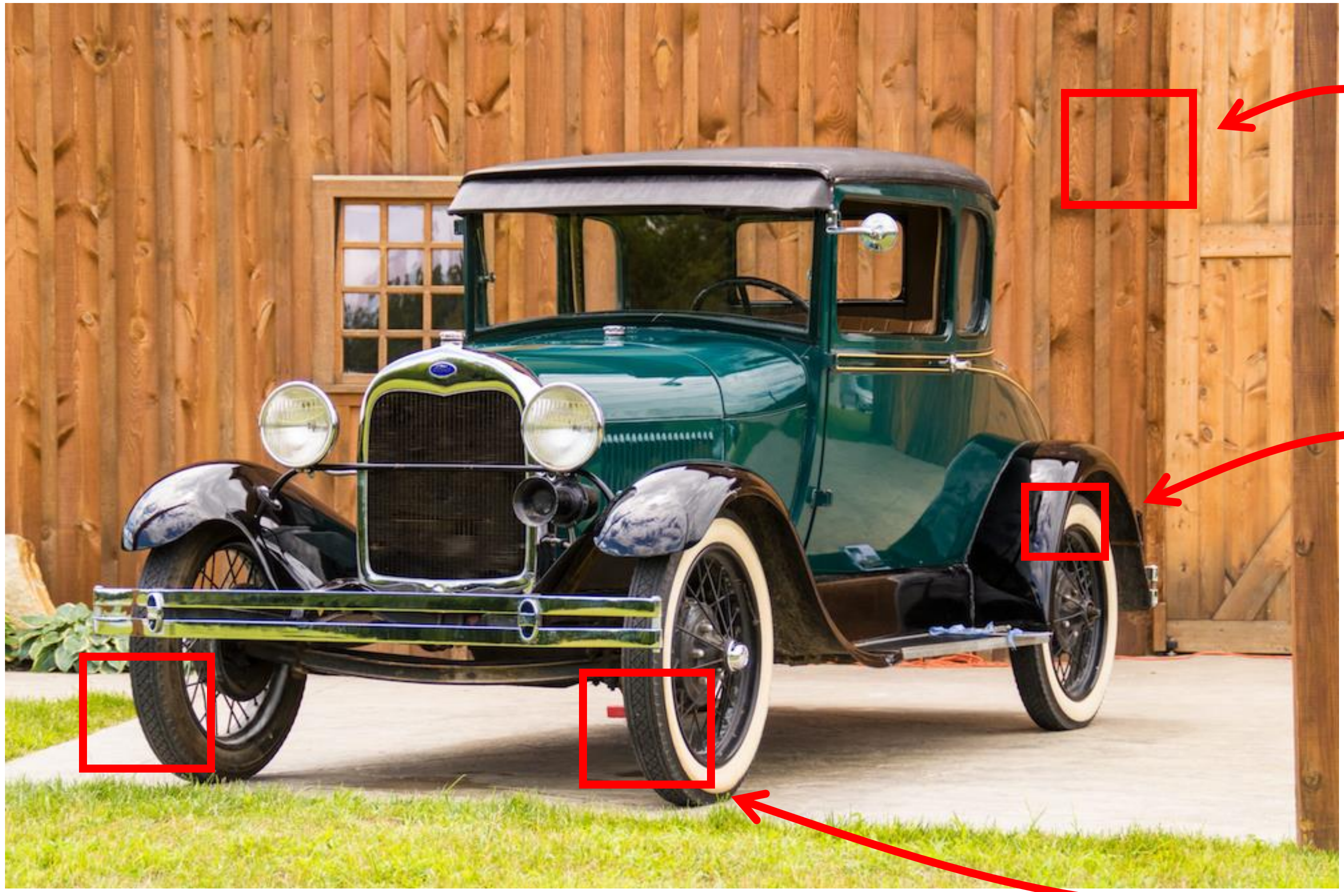


Locality — Neurons interact locally only

Scale — Operate at multiple scales

Globality — Learn the same features across the whole image

Inductive bias for computer vision: convolutional networks

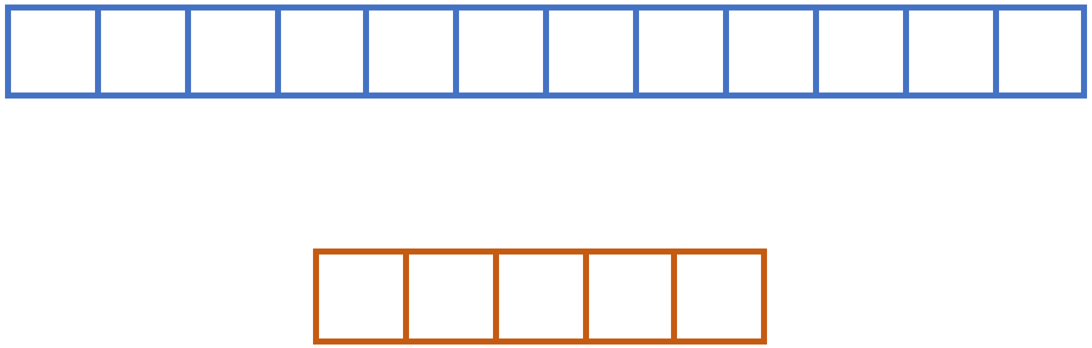


Unique operator/kernel (convolution)

Applied at multiple scales

Reused across the image (feature maps)

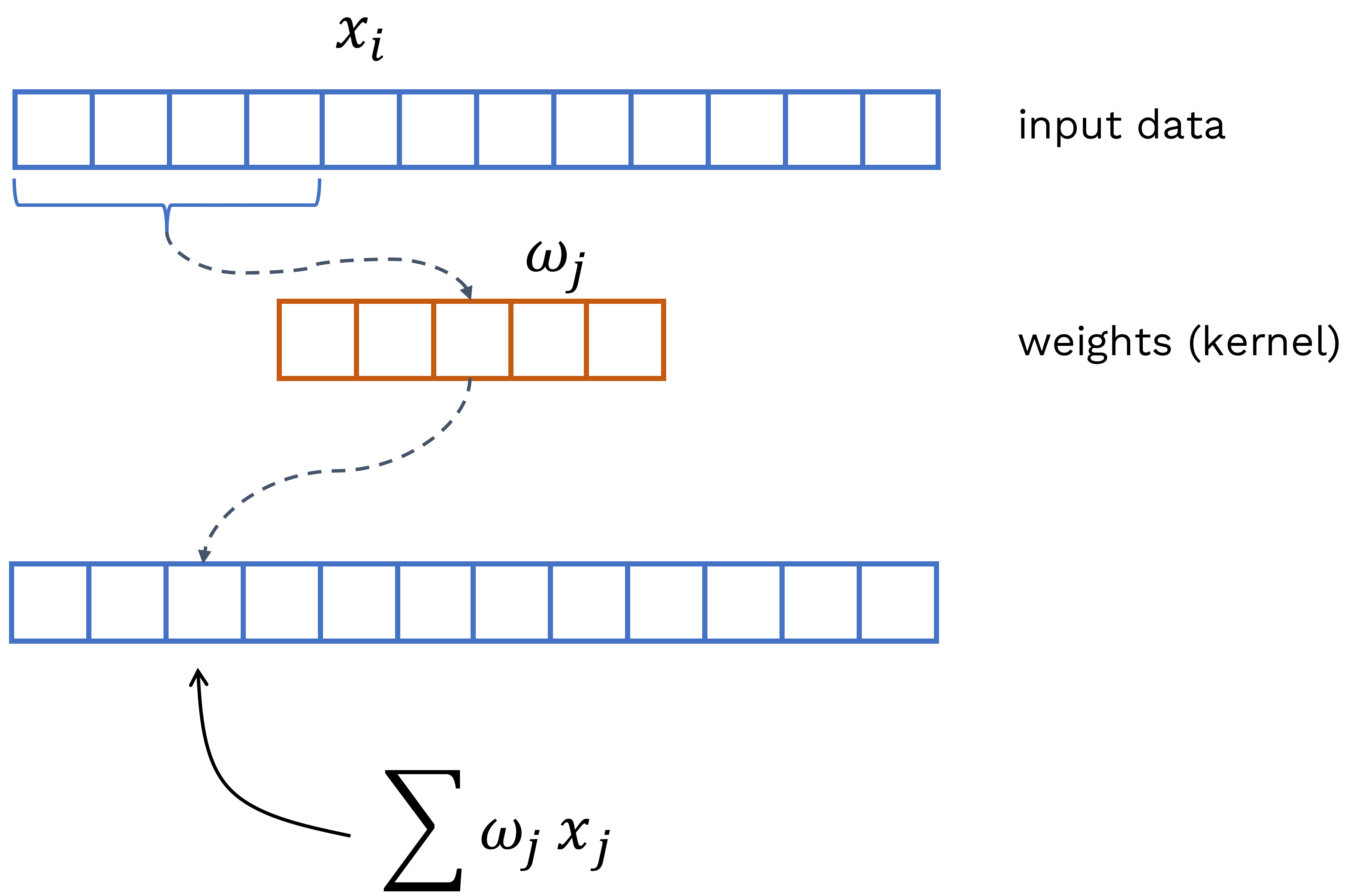
Convolutions



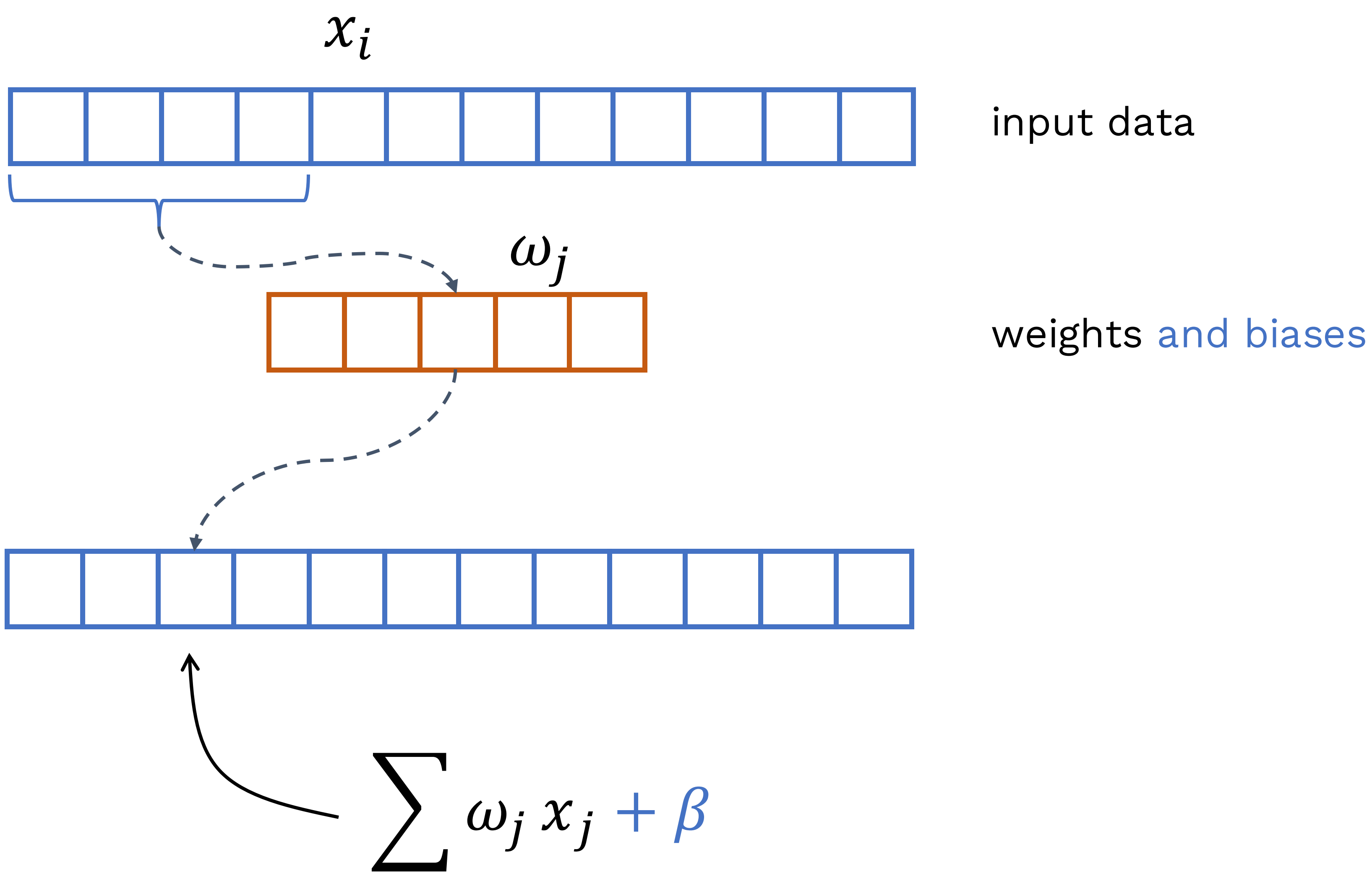
input data

weights

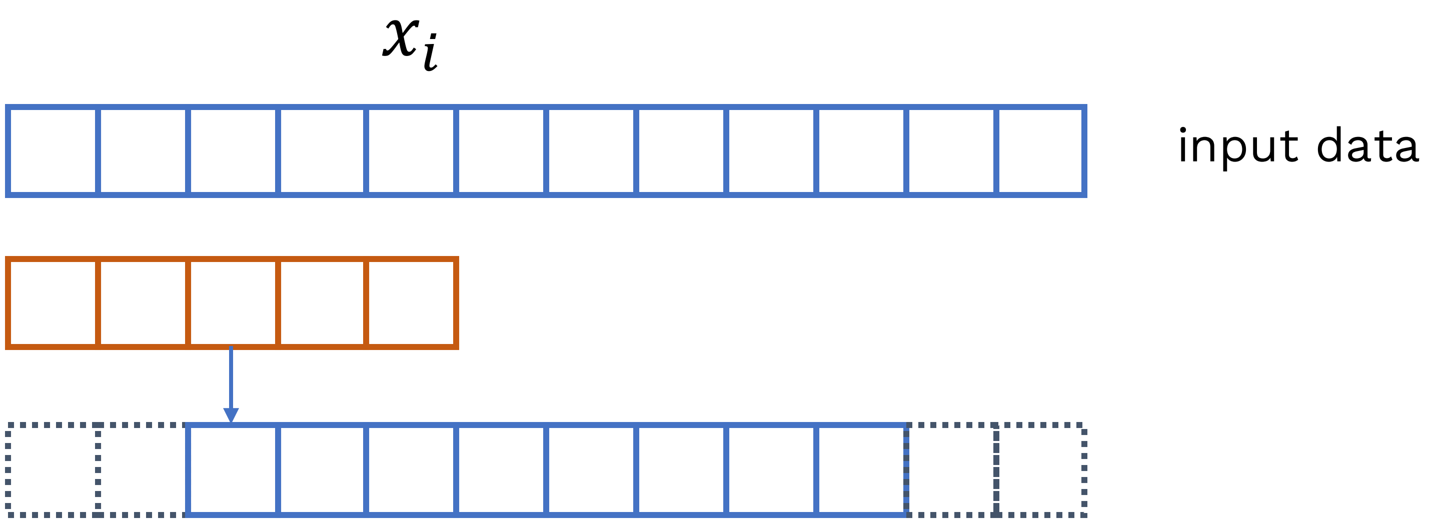
Convolutions

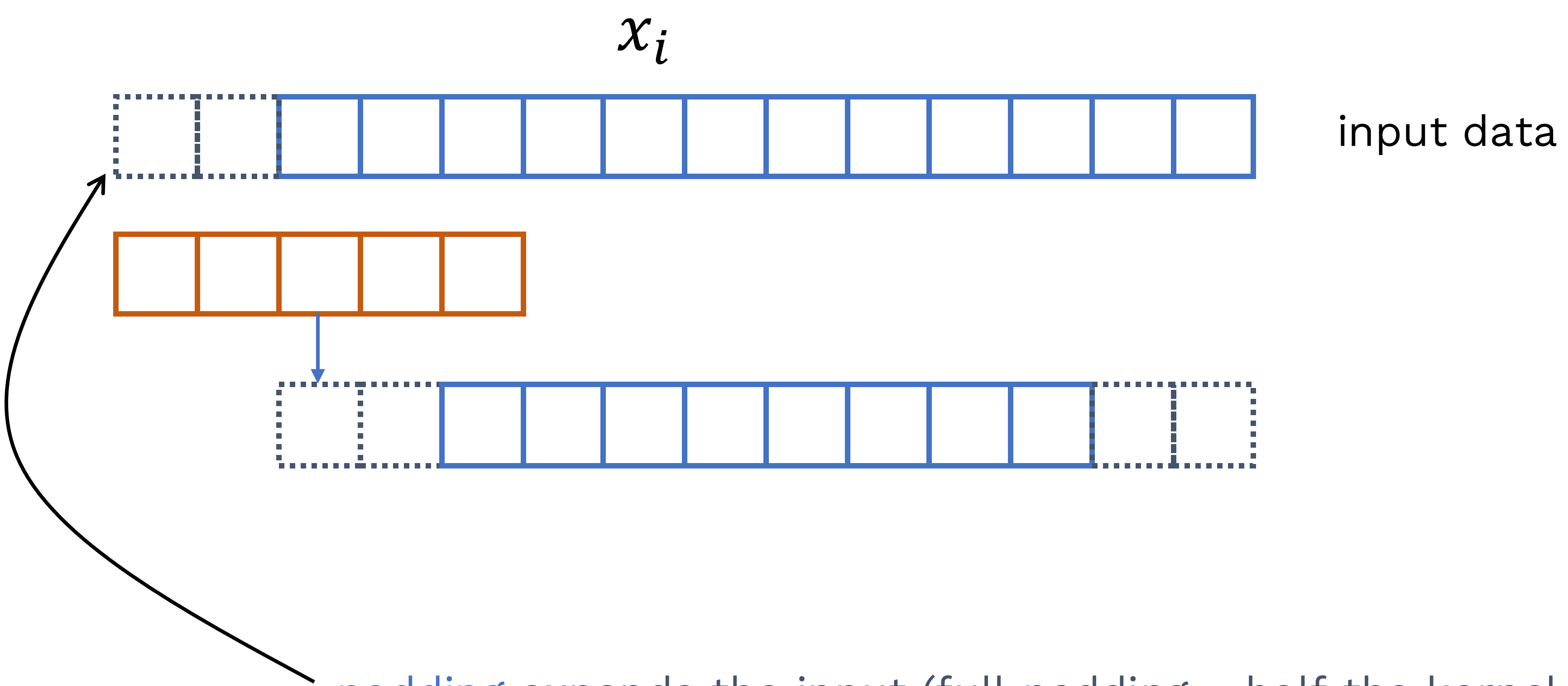


Convolutions



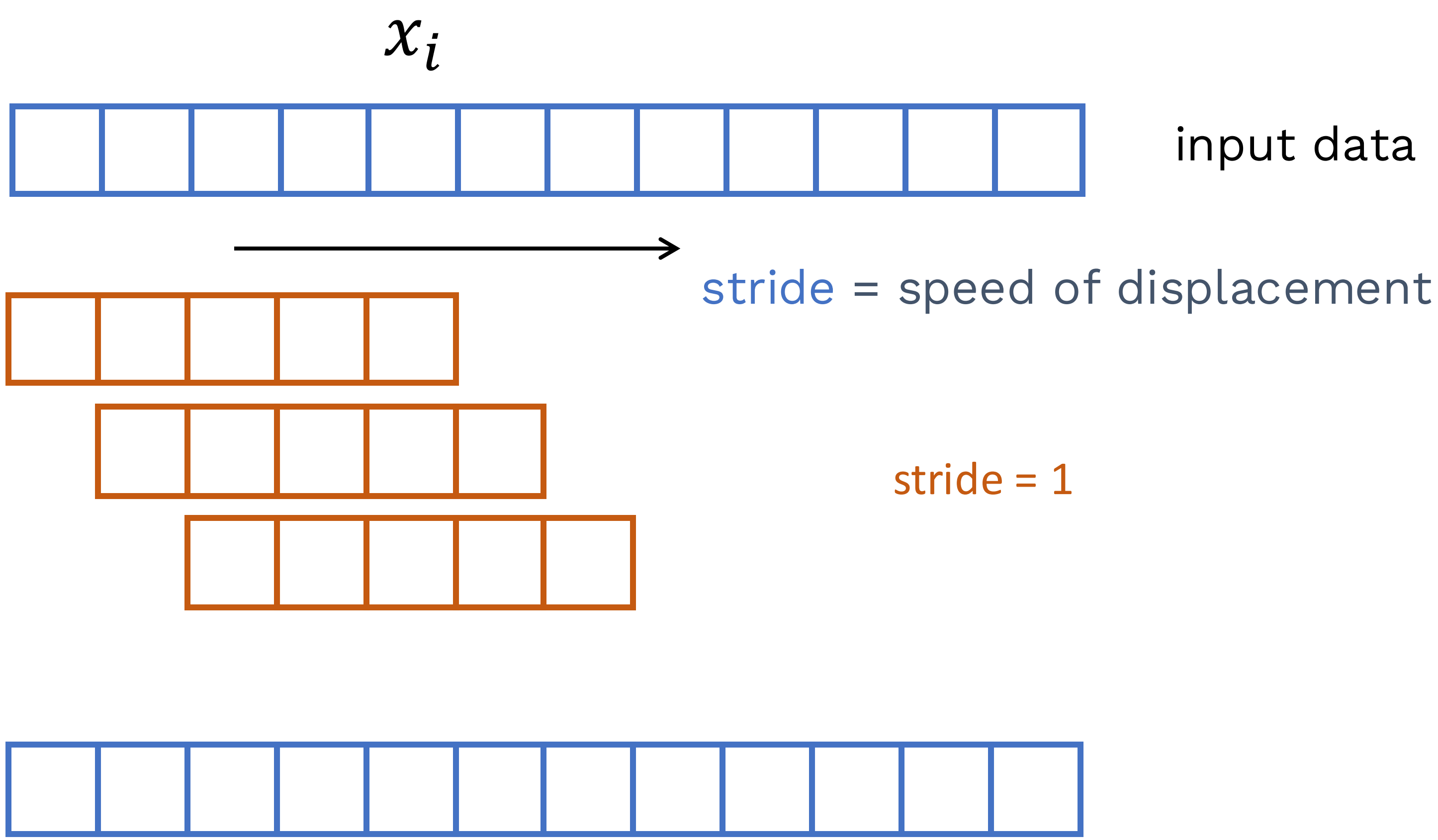
Convolutions



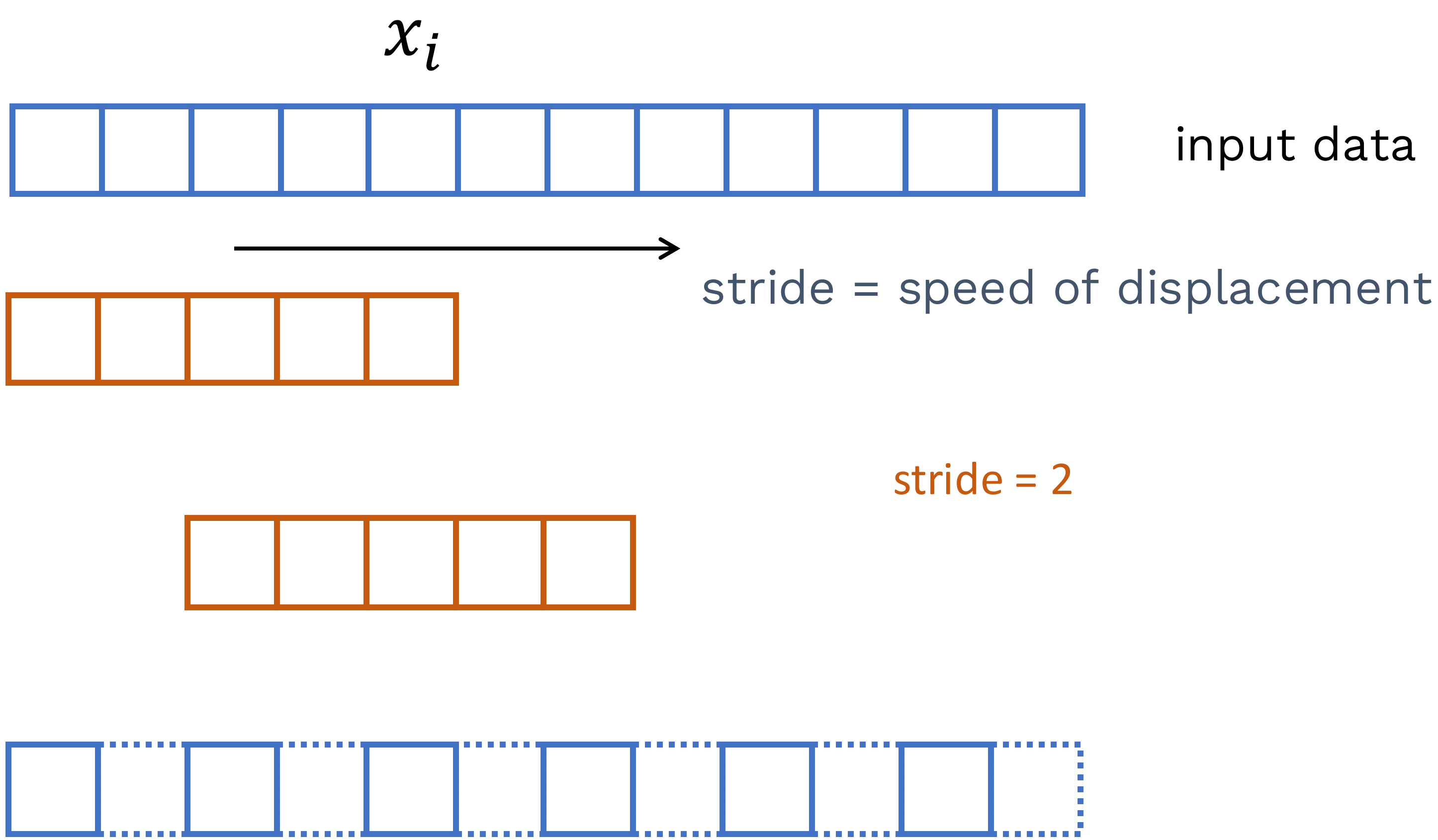


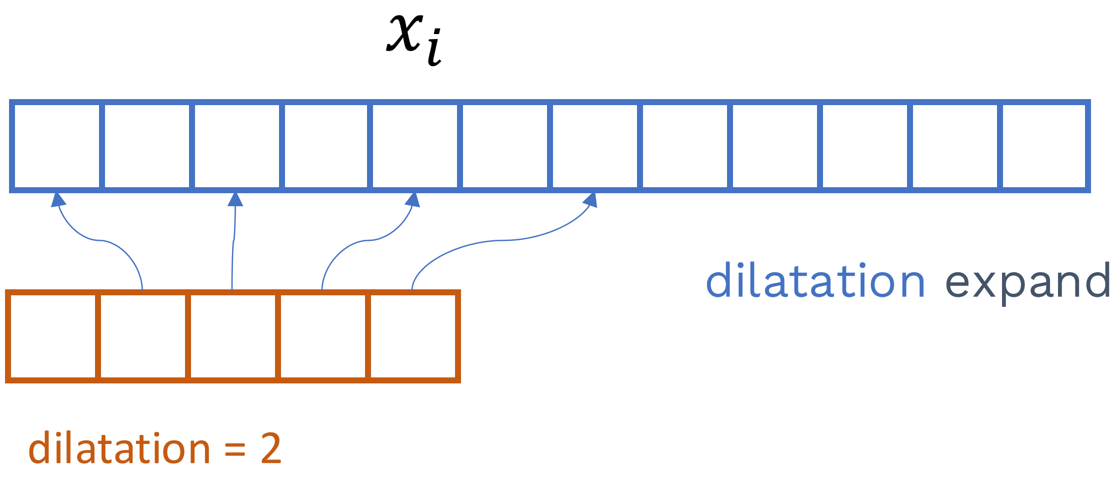
padding expands the input (full padding = half the kernel size)

Convolutions



Convolutions

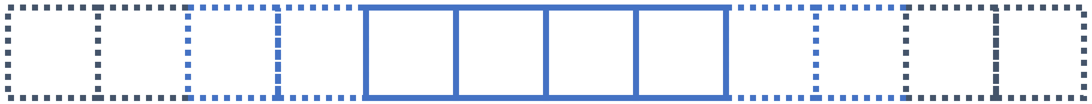




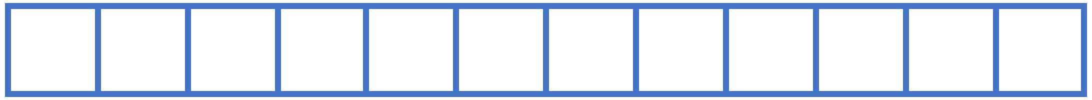
input data

dilatation expands the kernel...

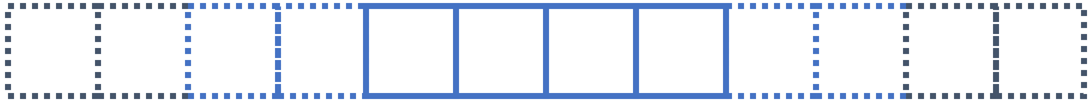
... and effectively requires further padding



Convolutions



$$L_{out} = \left\lfloor \frac{L_{in} + 2 \times \text{padding} - \text{dilation} \times (\text{kernel\_size} - 1) - 1}{\text{stride}} + 1 \right\rfloor$$



Convolutions

input dimension

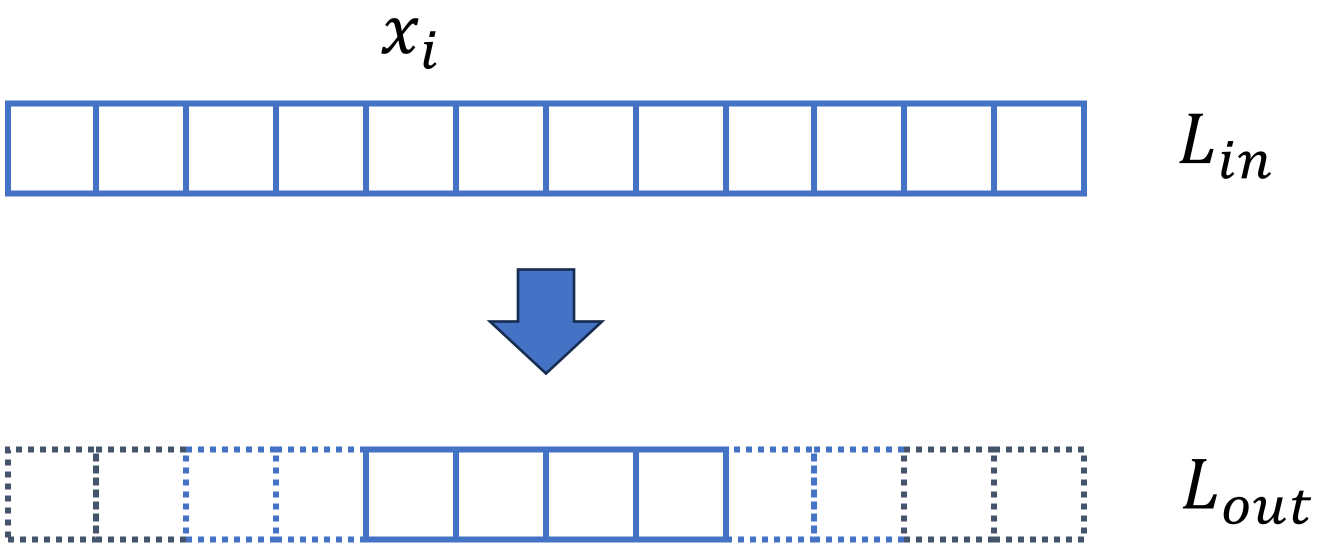
output dimension

```
m = nn.Conv1d(1, 1, kernel_size=5, stride=1, dilation=1, bias=False)

input = torch.ones((1,16))

m(input).shape


torch.Size([1, 12])
```

input dimension

output dimension

```
m = nn.Conv1d(1, 1, kernel_size=5, stride=1, dilation=1, bias=False)
```

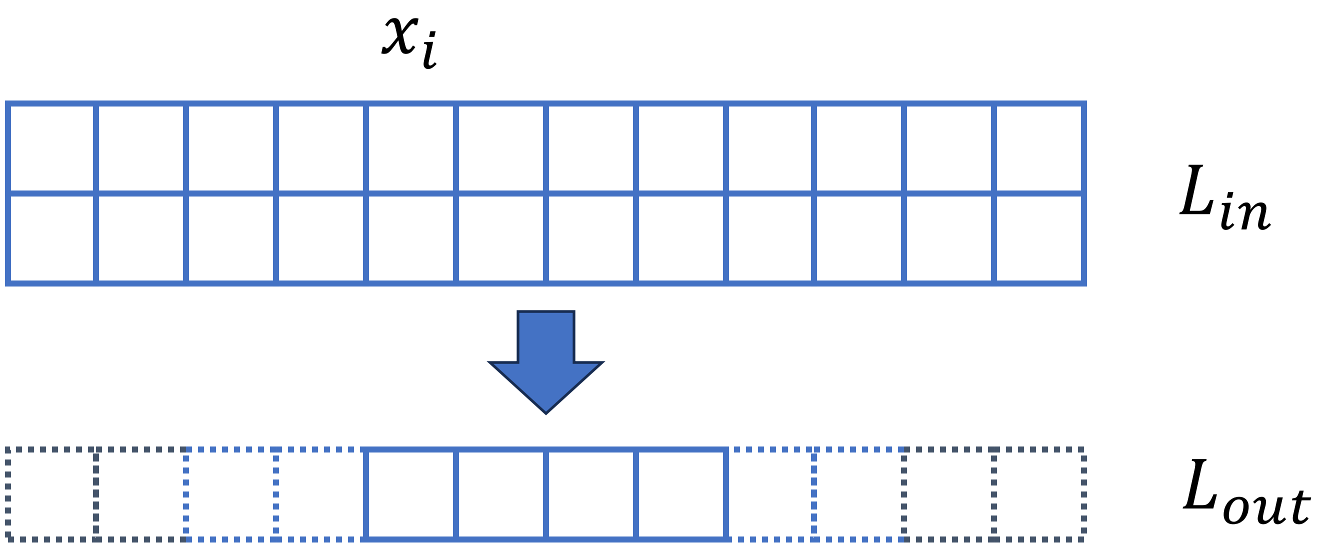


1D Convolutions

input dimension

output dimension

```
m = nn.Conv1d(2, 1, kernel_size=5, bias=False)
```



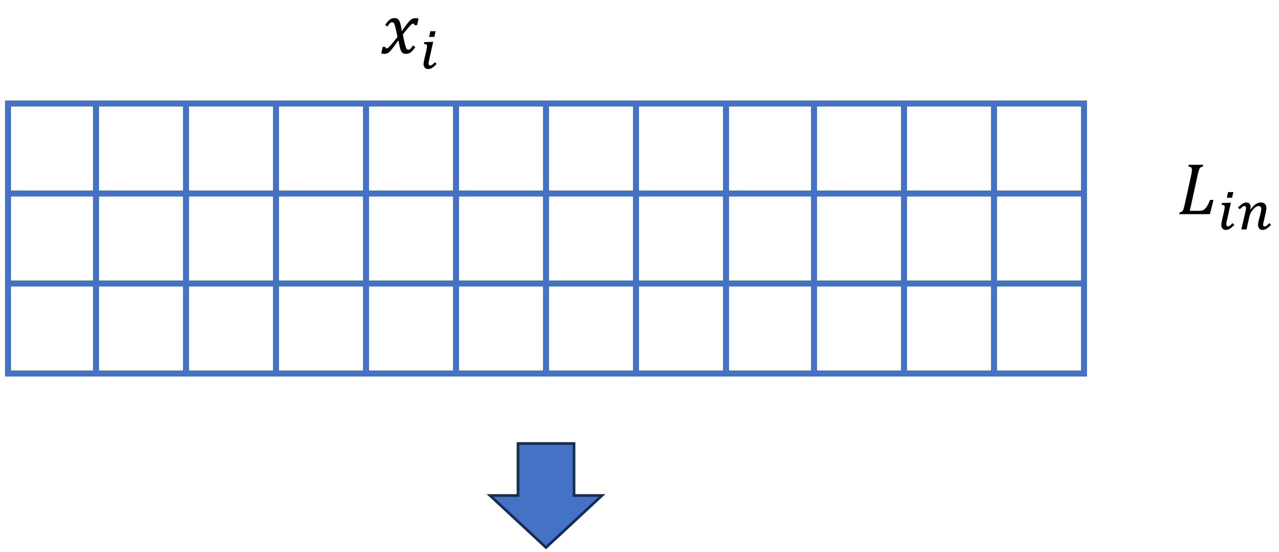

```
m.weight.shape
> [1, 2, 5]
```

1D Convolutions

input dimension

output dimension

```
m = nn.Conv1d(2, 1, kernel_size=5, bias=False)
```




```
m.weight.shape
> [1, 2, 5]
```

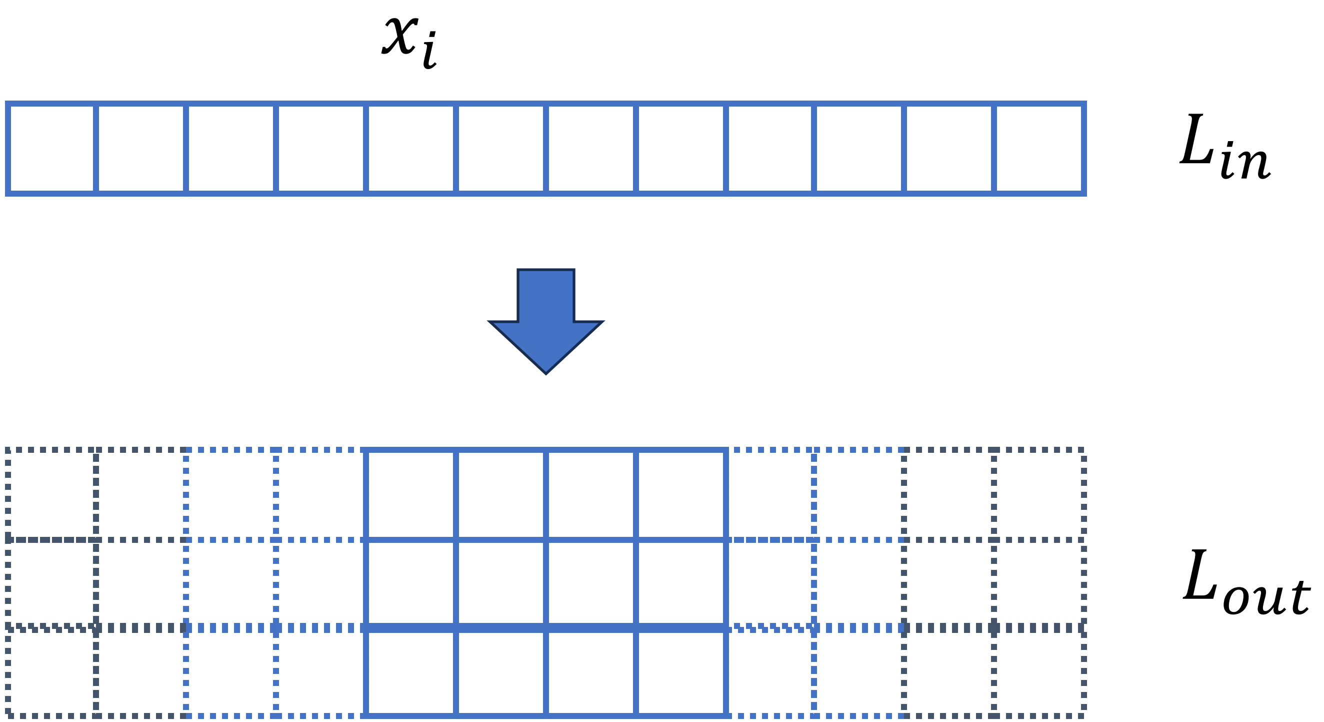
RuntimeError: weight of size [1, 2, 5], expected input[1, 3, 7] to have 2 channels, but got 3 channels instead

1D Convolutions

input dimension

output dimension

```
m = nn.Conv1d(1, 3, kernel_size=5, stride=1, dilation=1, bias=False)
```



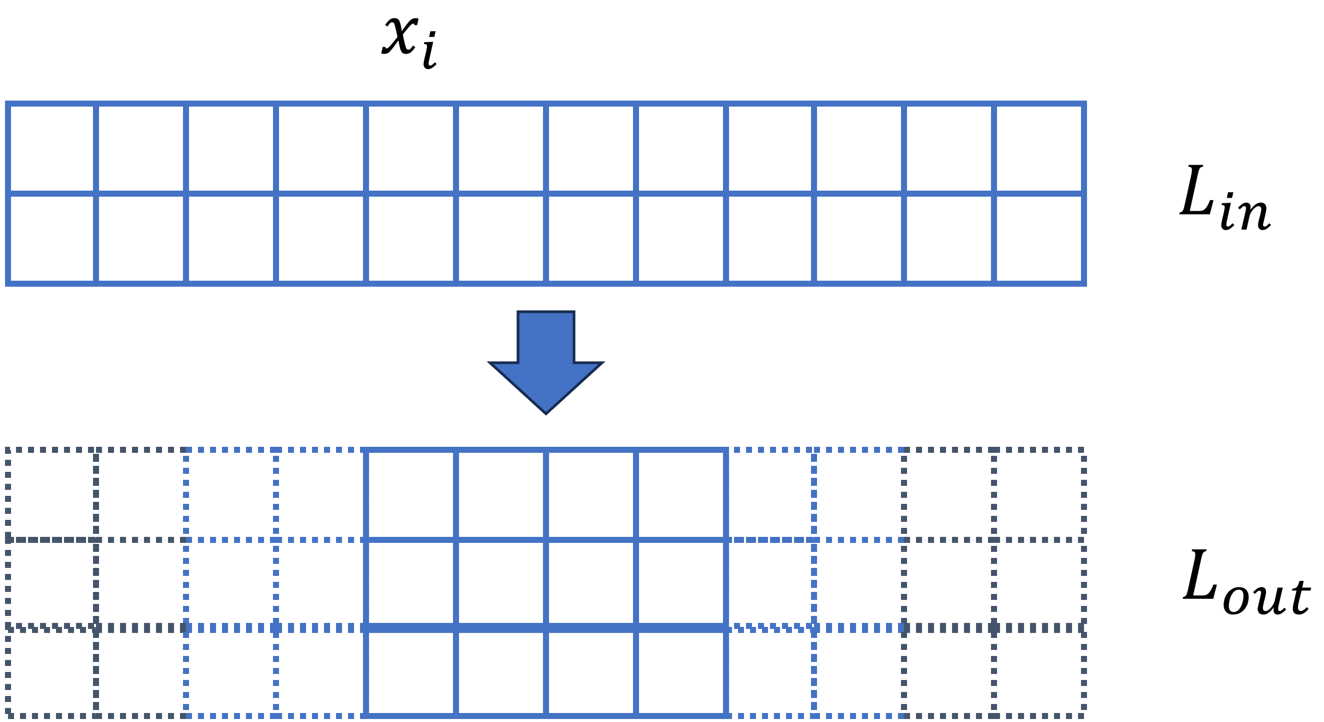

```
m.weight.shape
> [3, 1, 5]
```

1D Convolutions

input dimension

output dimension

```
m = nn.Conv1d(2, 3, kernel_size=5, bias=False)
```




```
m.weight.shape
> [3, 2, 5]
```

2D Convolutions

input dimension

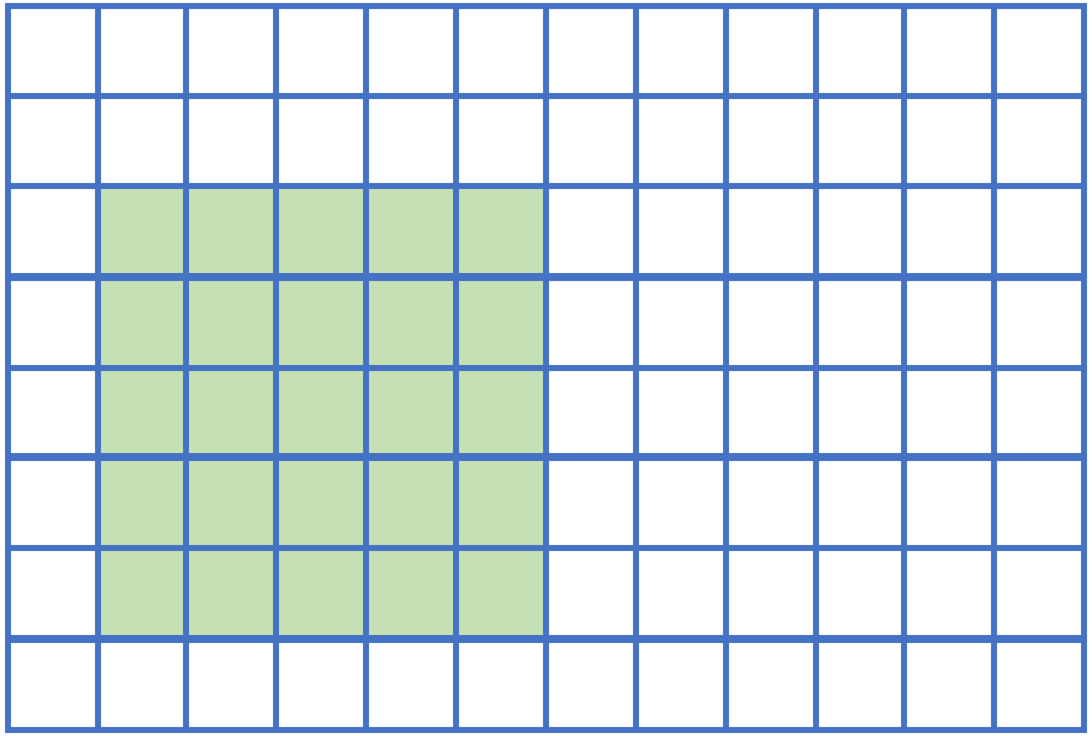
output dimension

```
m = nn.Conv2d(1, 1, kernel_size=5, bias=False)
```

input.shape
> [N, Cin, H, W]

m.weight.shape
> [1, 1, 5, 5]

x_i



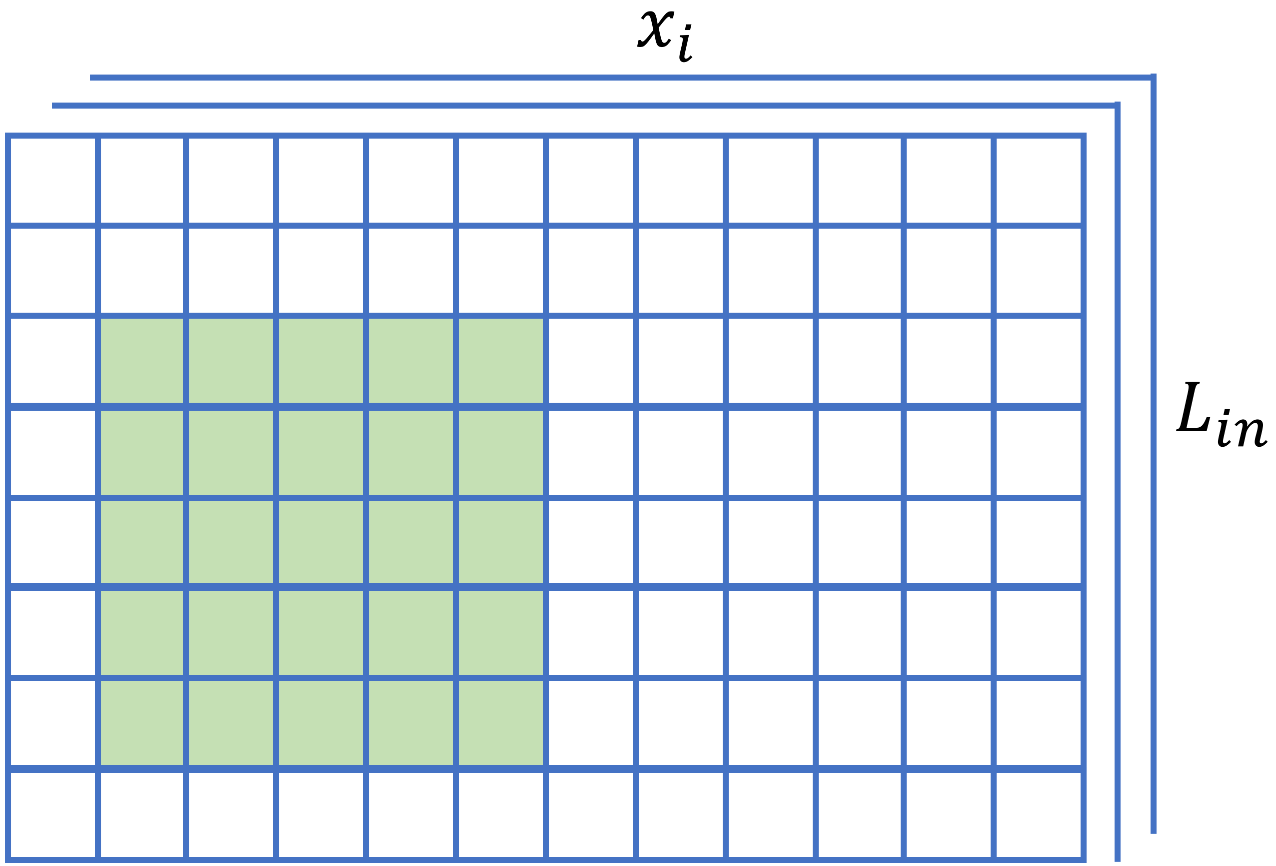
L_{in}

2D Convolutions

input dimension

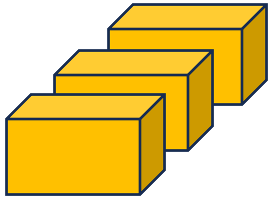
output dimension

```
m = nn.Conv2d(3, 3, kernel_size=5, bias=False)
```



input.shape
> [N, Cin, H, W]

m.weight.shape
> [3, 3, 5, 5]



2D Convolutions

```
m = nn.Conv2d(C_in, C_out, kernel_size=5, stride=2, padding=2)
```

```
input = torch.ones(N, C_in, H, W)
```

batch size

number of channels = input dimension

Image size (HxW)

```
output = torch.ones(N, C_out, H_out, W_out)
```

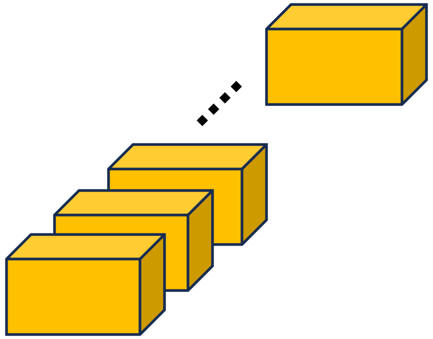
$$L_{out} = \left\lfloor \frac{L_{in} + 2 \times \text{padding} - \text{dilation} \times (\text{kernel\_size} - 1) - 1}{\text{stride}} + 1 \right\rfloor$$

2D Convolutions

input dimension

output dimension

```
m = nn.Conv2d(3, 64, kernel_size=5, padding=2, stride=2)
```

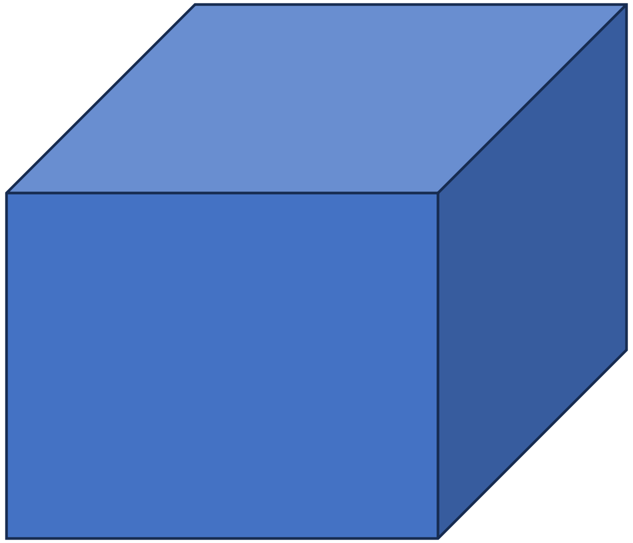


m.weight.shape

> [64, 3, 5, 5]

input.shape

> [12, 3, 224, 224]

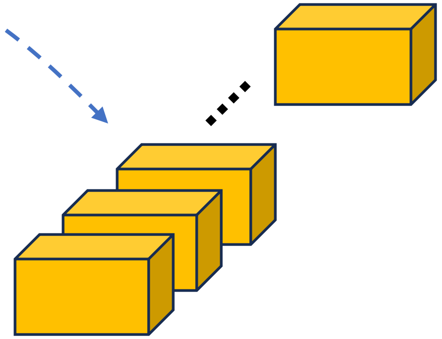


output.shape

> [12, 64, 112, 112]

2D Convolutions

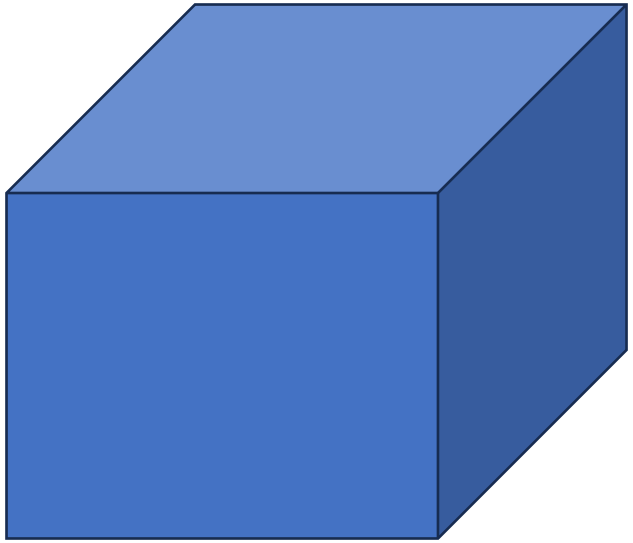
Kernels are the same across the image (inductive bias). Shape is independent of image size.



```
m = nn.Conv2d(3, 64, kernel_size=5, padding=2, stride=2)
```

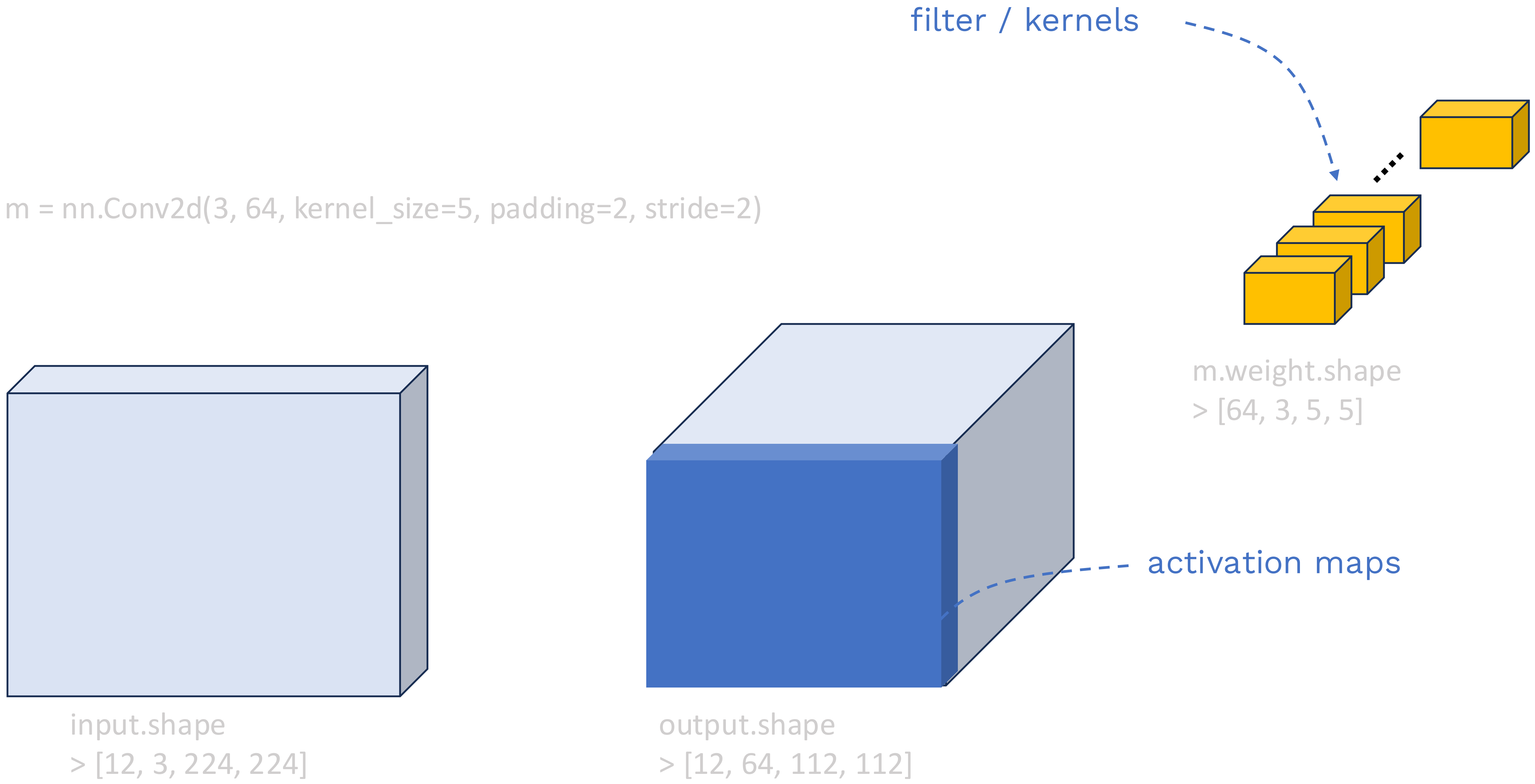
m.weight.shape
> [64, 3, 5, 5]

input.shape
> [12, 3, 224, 224]



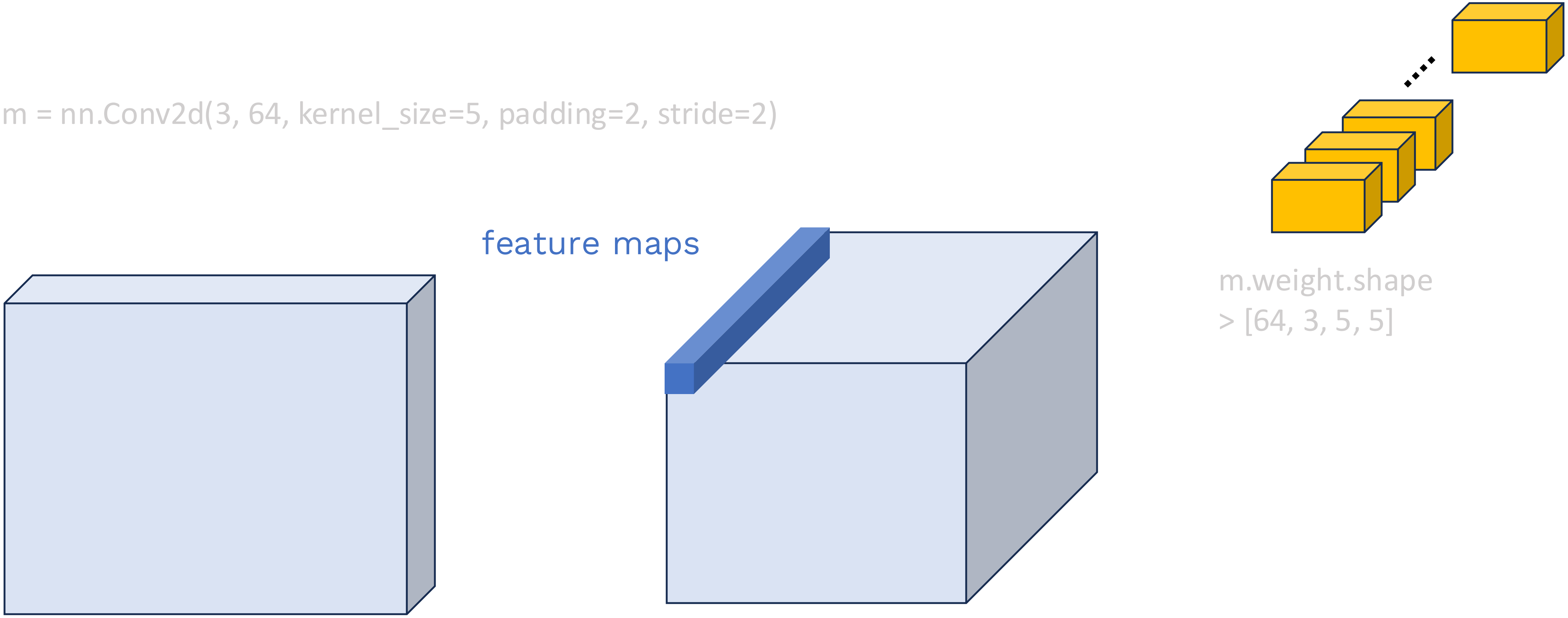
output.shape
> [12, 64, 112, 112]

2D Convolutions

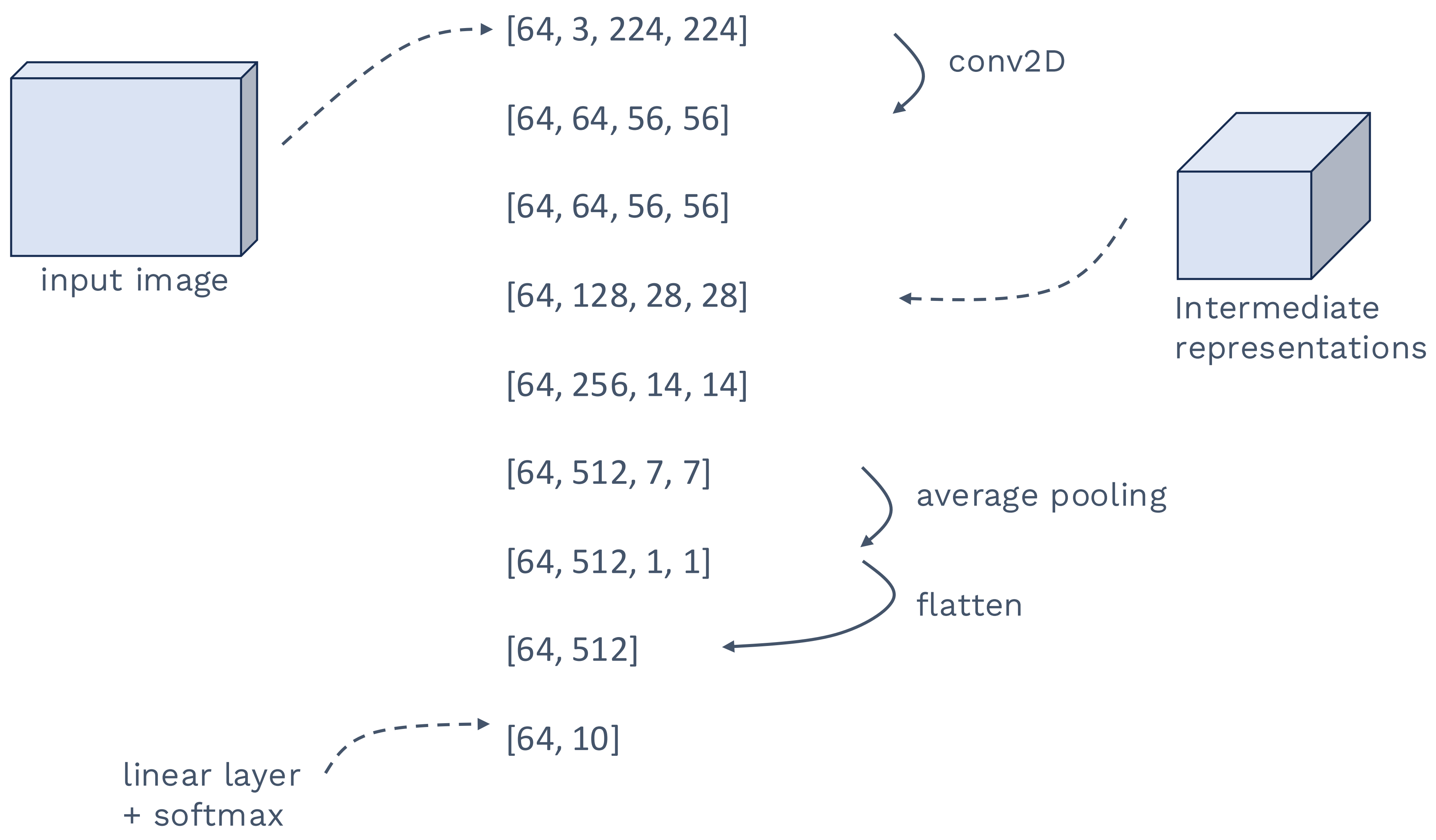


2D Convolutions

```
m = nn.Conv2d(3, 64, kernel_size=5, padding=2, stride=2)
```



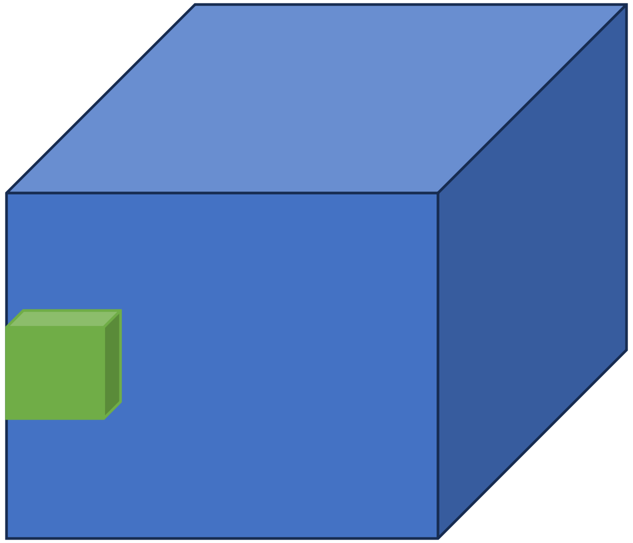
2D Convolutions



Max Pooling

```
m = nn.MaxPool2d(kernel_size = 3)
input = torch.ones((11, 3, 112, 112))

output.shape
> [11, 3, 37, 37]
```

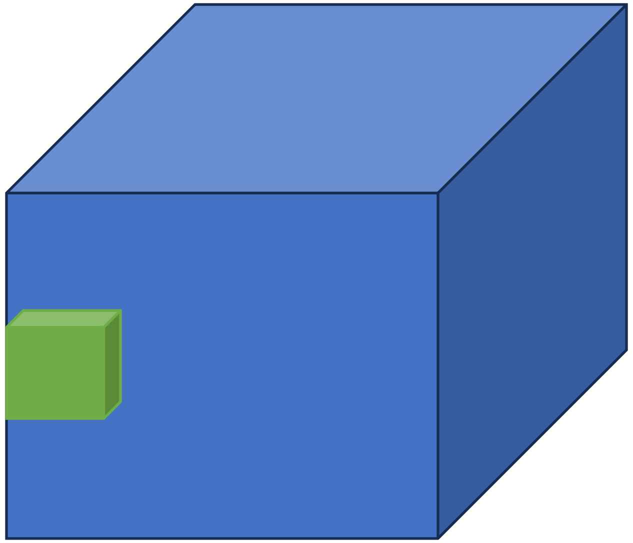
⚠ default stride = kernel size



Average Pooling

```
m = nn.AvgPool2D(kernel_size = 3)
input = torch.ones((11, 3, 112, 112))

output.shape
> [11, 3, 37, 37]
```

default stride = kernel size



ResNet architecture

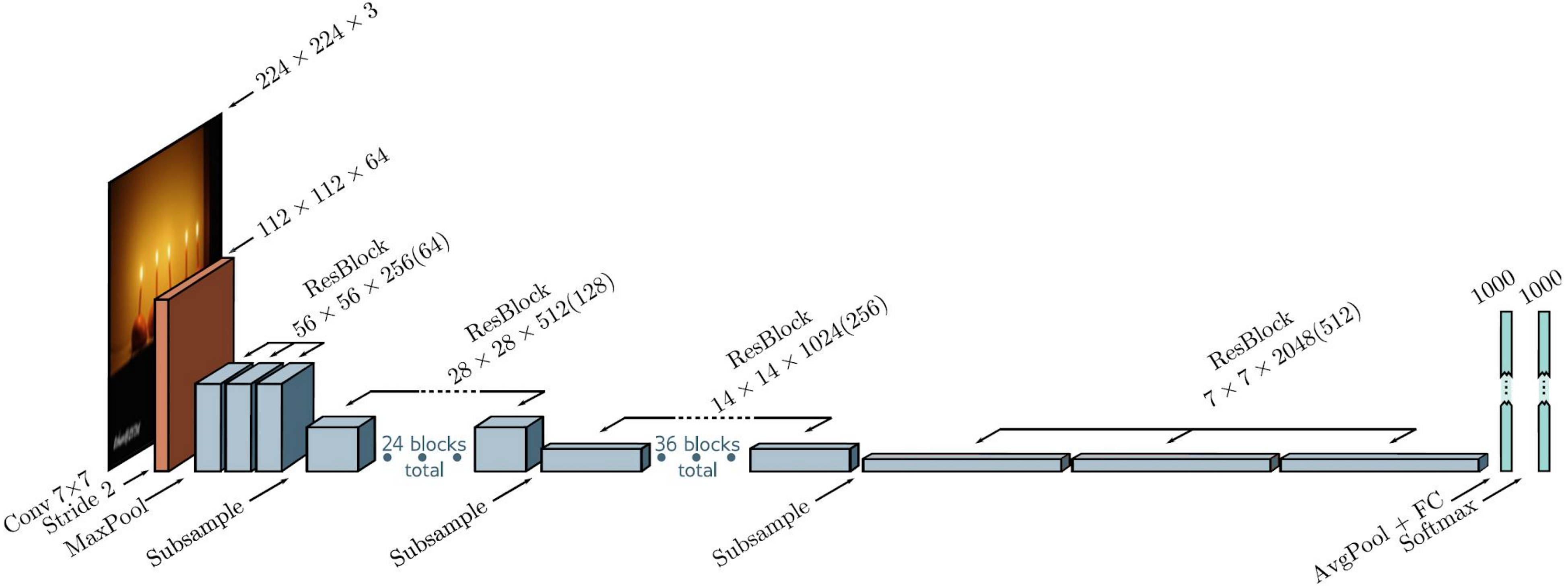


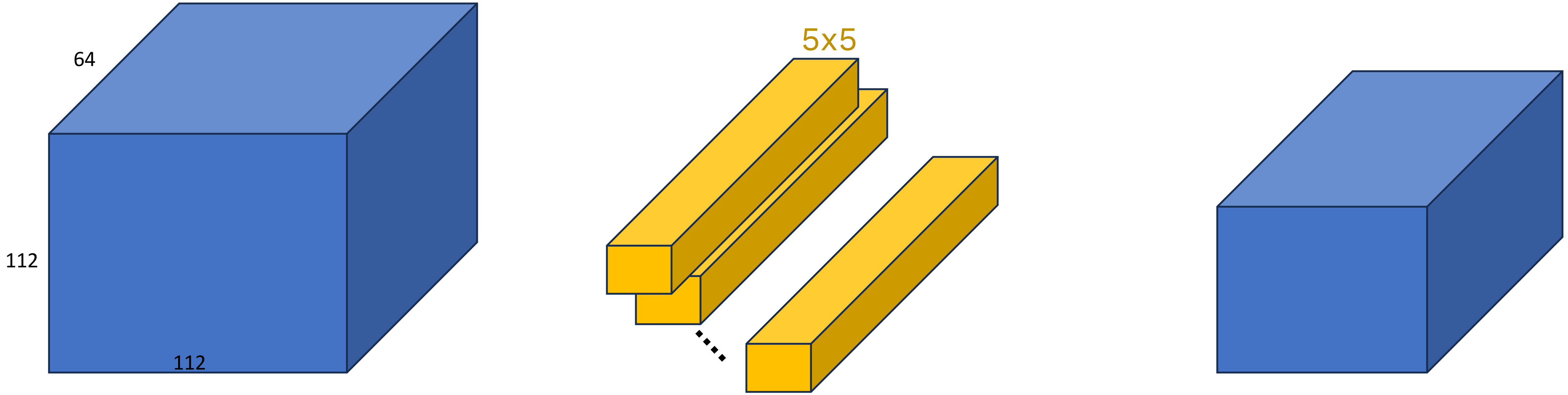
Figure 11.8 ResNet-200 model. A standard 7×7 convolutional layer with stride two is applied, followed by a MaxPool operation. A series of bottleneck residual blocks follow (number in brackets is channels after first 1×1 convolution), with periodic downsampling and accompanying increases in the number of channels. The network concludes with average pooling across all spatial positions and a fully connected layer that maps to pre-softmax activations.

Source: Understanding Deep Learning, S. Prince, 2023

Convolutions are expensive!

204,800 parameters!

128 x 64 x 5 x 5 x (112 x 112) = 2,569,011,200 operations!

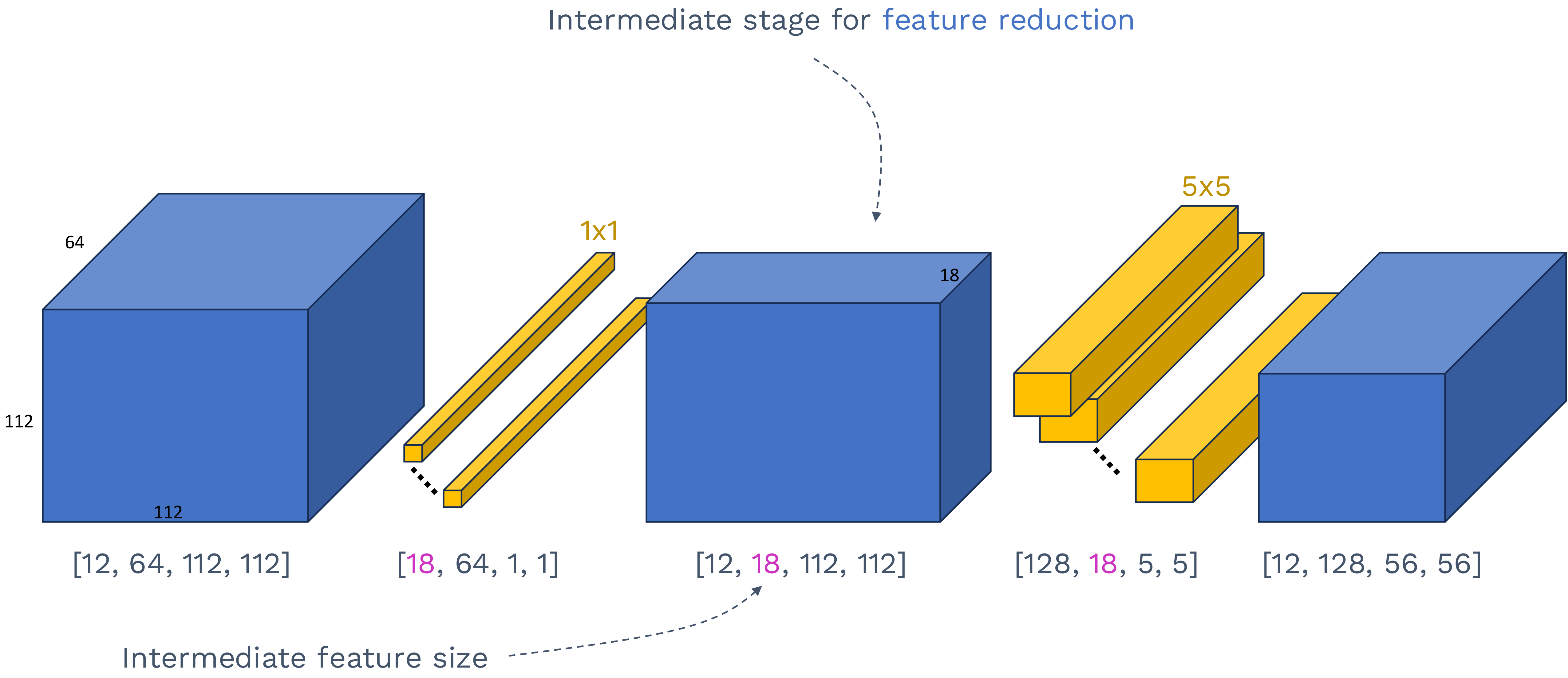


[12, 64, 112, 112]

[128, 64, 5, 5]

[12, 128, 56, 56]

The 1x1 convolution trick



The 1x1 convolution trick

58,752 parameters

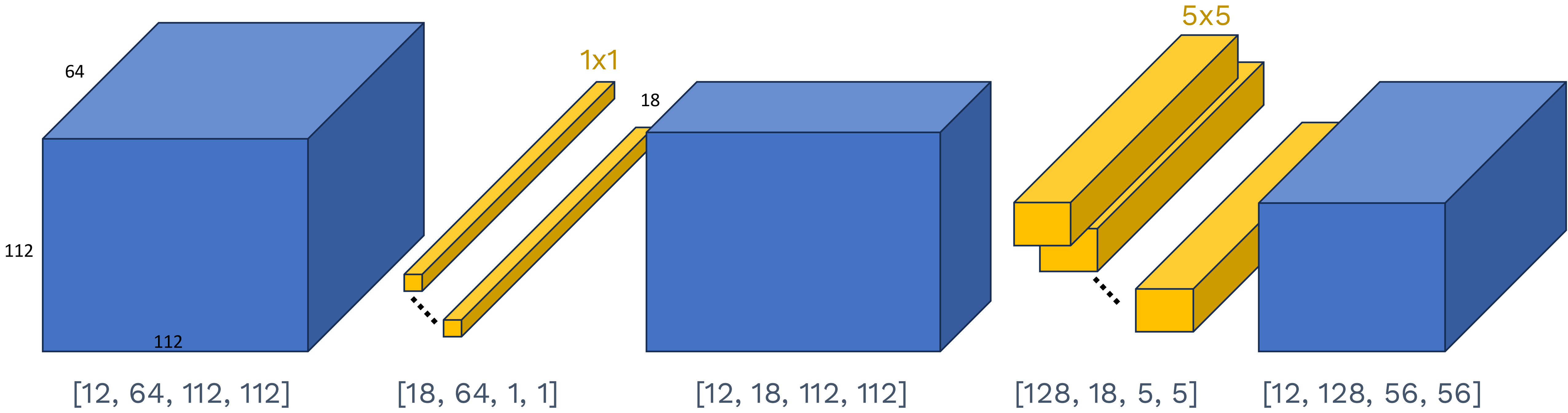
3x less parameters!

18 x 64 x 1 x 1 x 112 x 112 = 14,450,688 operations

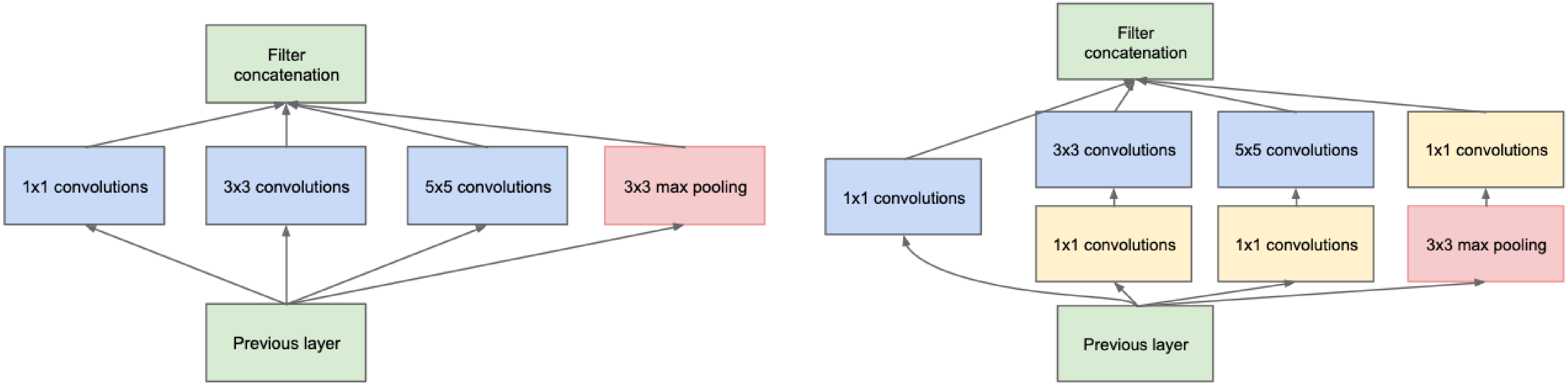
128 x 18 x 5 x 5 x 112 x 112 = 722,534,400 operations

3x faster!

736,985,088 operations in total



The Inception architecture

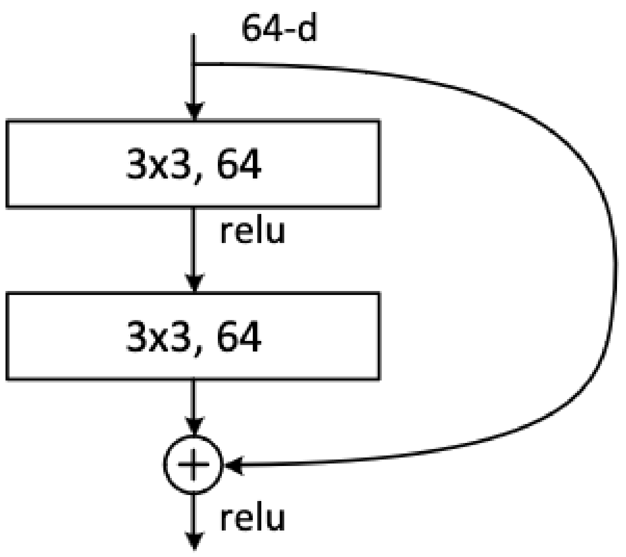


(a) Inception module, naïve version (b) Inception module with dimension reductions

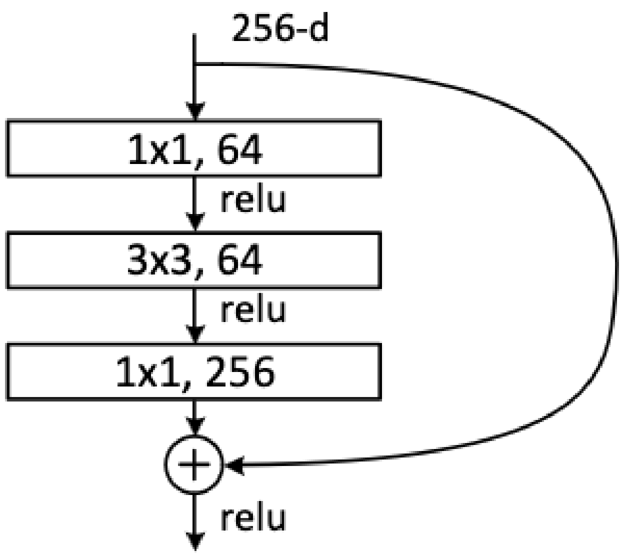
Figure 2: Inception module

Going deeper with convolutions, 2014

The ResNet architecture



Naïve block



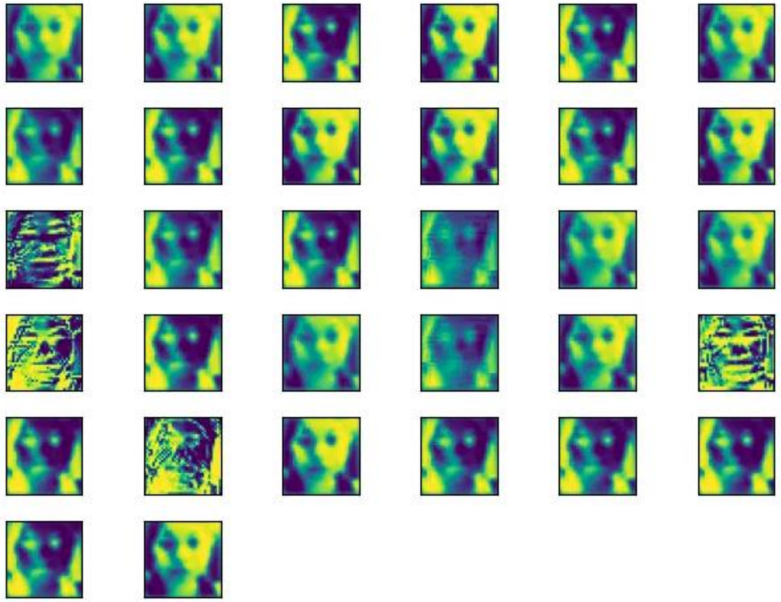
Bottleneck block

Deep Residual Learning for Image Recognition, 2015

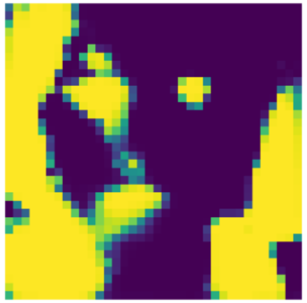
The 1x1 convolution trick: do we maintain information?

Task: skin detector

Source image



Activation maps in 32D



Activation maps with 1D pooling

The 1x1 convolution trick

1x1 convolution layers are useful to:

1. Reduce the computational load
2. Reduce feature maps dimensionality
3. Add non-linearity along the channel dimension
4. Create smaller models with the same level of accuracy

The ResNet blocks

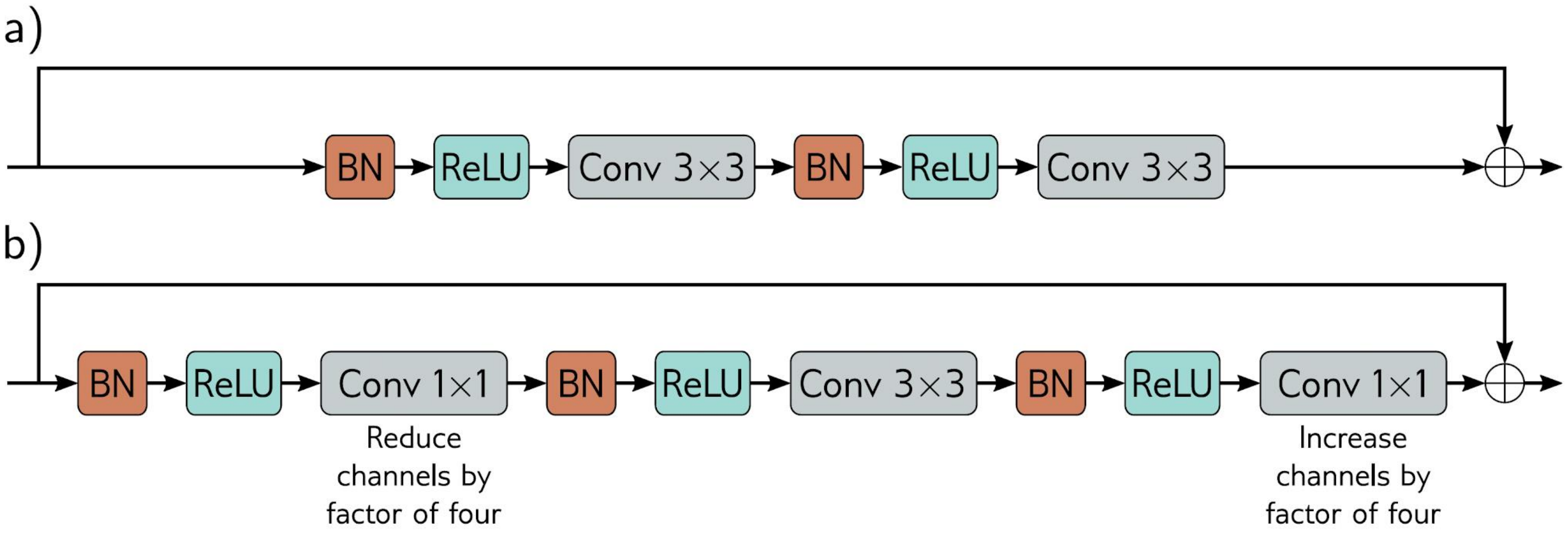
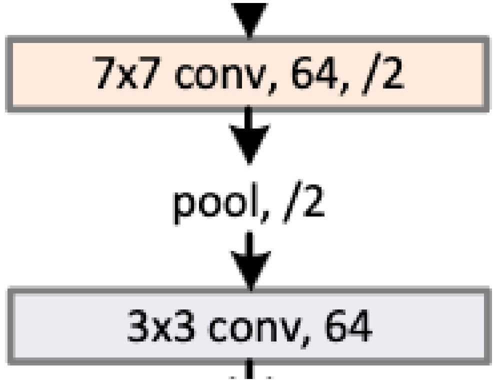


Figure 11.7 ResNet blocks. a) A standard block in the ResNet architecture contains a batch normalization operation, followed by an activation function, and a 3×3 convolutional layer. Then, this sequence is repeated. b). A bottleneck ResNet block still integrates information over a 3×3 region but uses fewer parameters. It contains three convolutions. The first 1×1 convolution reduces the number of channels. The second 3×3 convolution is applied to the smaller representation. A final 1×1 convolution increases the number of channels again so that it can be added back to the input.

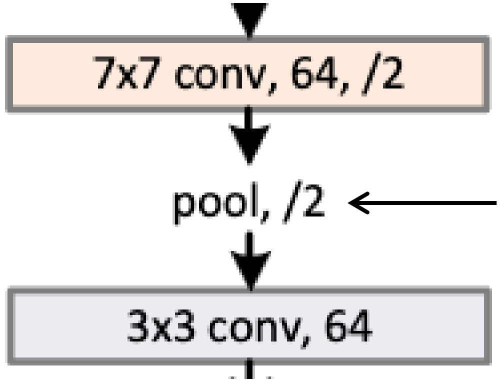
Source: Understanding Deep Learning, S. Prince, 2023

The ResNet blocks




```
nn.Conv2d(..., 64, kernel_size=7, stride=2, padding=3)
nn.BatchNorm2d(64)
nn.ReLU()
```

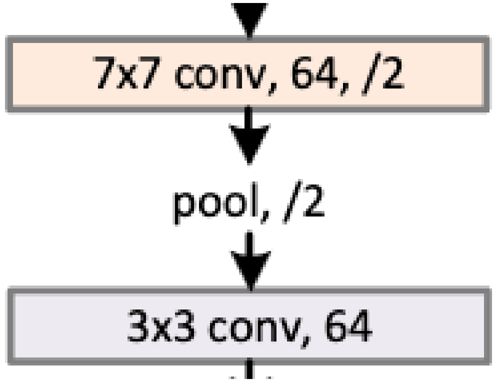
The ResNet blocks



nn.MaxPool2d(kernel_size=7, stride=2, padding=3)

Deep Residual Learning for Image Recognition, 2015

The ResNet blocks




```
nn.Conv2d(64, 64, kernel_size=3, stride=1, padding=1)
nn.BatchNorm2d(64)
nn.ReLU()
```

Tips

You can stack modules in a layer with nn.Sequential()

```
net = [nn.Conv2d(12, 14, kernel_size=3), nn.Conv2d(12, 14, kernel_size=3)]
m = nn.Sequential(*net)
sum([p.numel() for p in m.parameters()])
```

```
3052
```

Tips

But beware, the following does not work!

```
net = [nn.Conv2d(12, 14, kernel_size=3)] * 2
m = nn.Sequential(*net)
sum([p.numel() for p in m.parameters()])

1526
```

You would expect 3052 here!

Instead, use a for loop

```
net = []
for _ in range(2):
        net += [nn.Conv2d(12, 14, kernel_size=3)]
m = nn.Sequential(*net)
sum([p.numel() for p in m.parameters()])

3052
```

Practical 5: ResNet from scratch

Step 1: a stack of convnets (PlainNet)

Step 2: a standard ResNet

Step 3: a ResNet with bottlenecks

Learning:

With standard convnets, more depth does not mean better performance.

With ResNet, better performance with as many parameters.

With bottlenecks, better performance with more depth.

Practical 5: ResNet from scratch

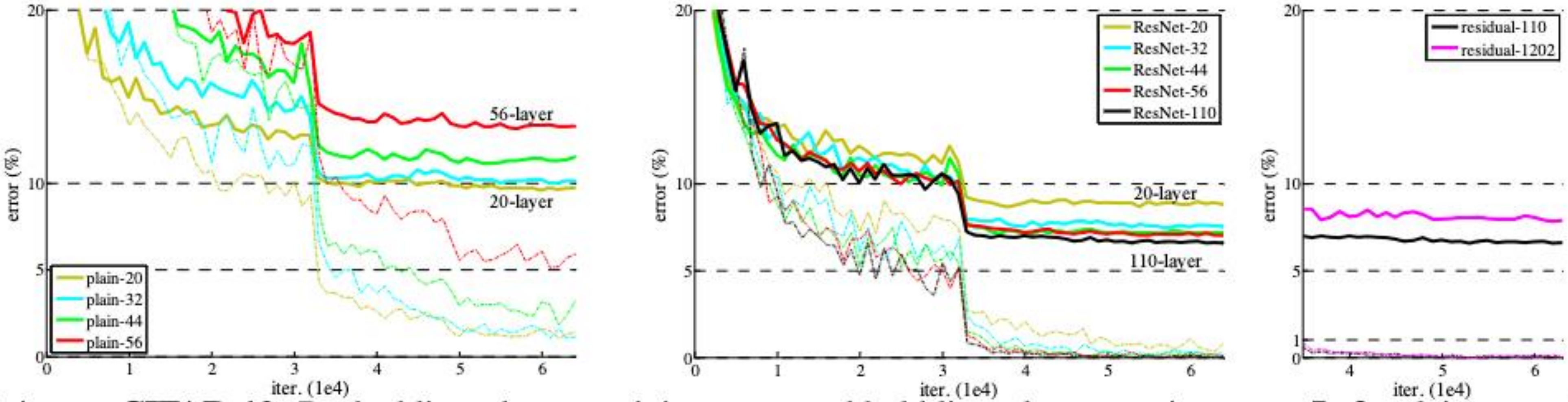


Figure 6. Training on **CIFAR-10**. Dashed lines denote training error, and bold lines denote testing error. **Left**: plain networks. The error of plain-110 is higher than 60% and not displayed. **Middle**: ResNets. **Right**: ResNets with 110 and 1202 layers.

Deep Residual Learning for Image Recognition, Kaiming He et al., 2015

DenseNet

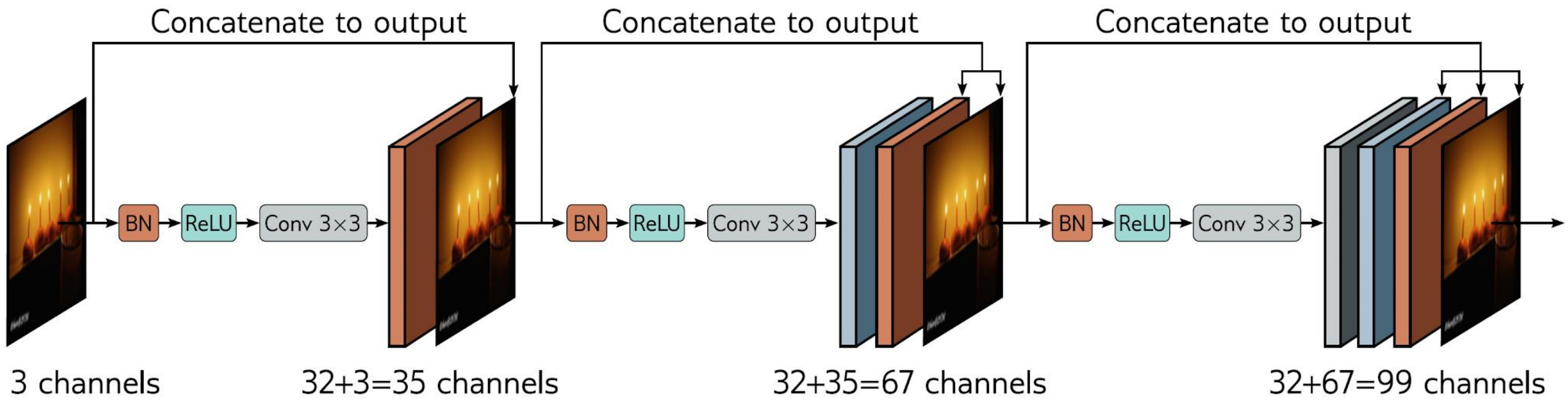


Figure 11.9 DenseNet. This architecture uses residual connections to concatenate the outputs of earlier layers to later ones. Here, the three-channel input image is processed to form a 32-channel representation. The input image is concatenated to this to give a total of 35 channels. This combined representation is processed to create another 32-channel representation, and both earlier representations are concatenated to this to create a total of 67 channels and so on.

Source: Understanding Deep Learning, S. Prince, 2023

U-Net

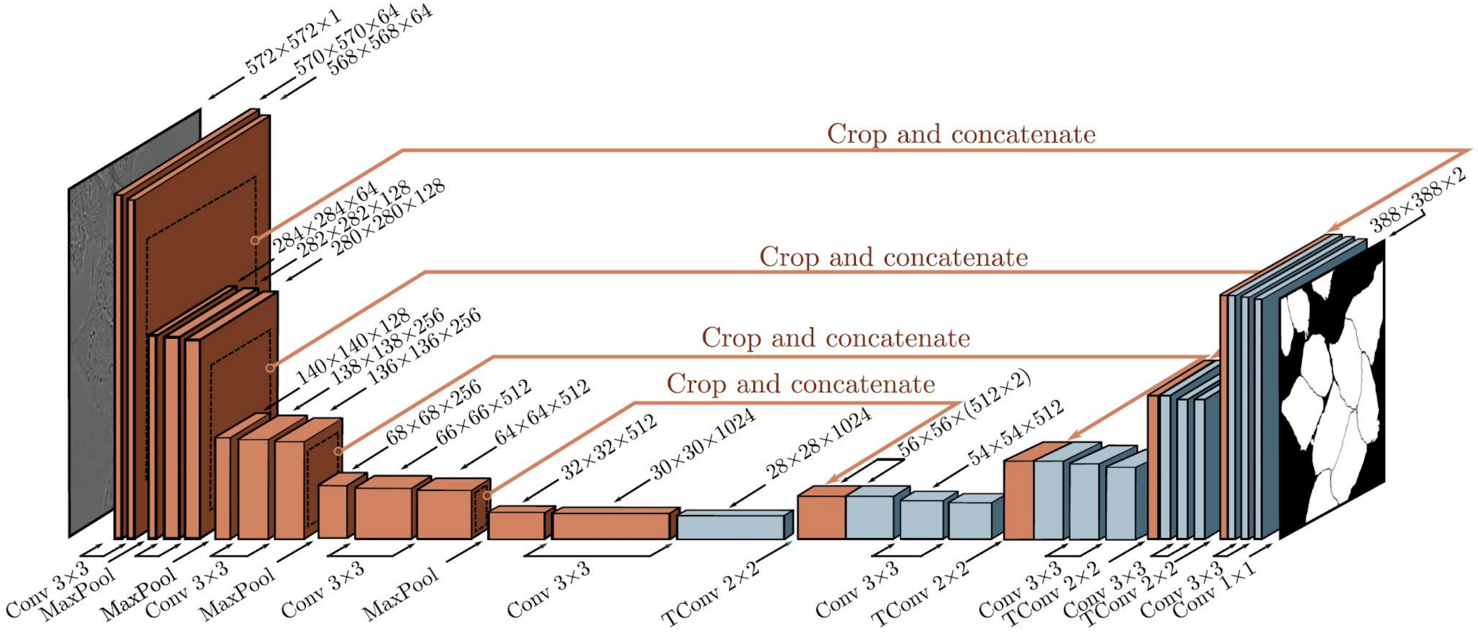


Figure 11.10 U-Net for segmenting HeLa cells. The U-Net has an encoder-decoder structure, in which the representation is downsampled (orange blocks) and then re-upsampled (blue blocks). The encoder uses regular convolutions, and the decoder uses transposed convolutions. Residual connections append the last representation at each scale in the encoder to the first representation at the same scale in the decoder (orange arrows). The original U-Net used "valid" convolutions, so the size decreased slightly with each layer, even without downsampling. Hence, the representations from the encoder were cropped (dashed squares) before appending to the decoder. Adapted from Ronneberger et al. (2015).

U-Net for segmentation

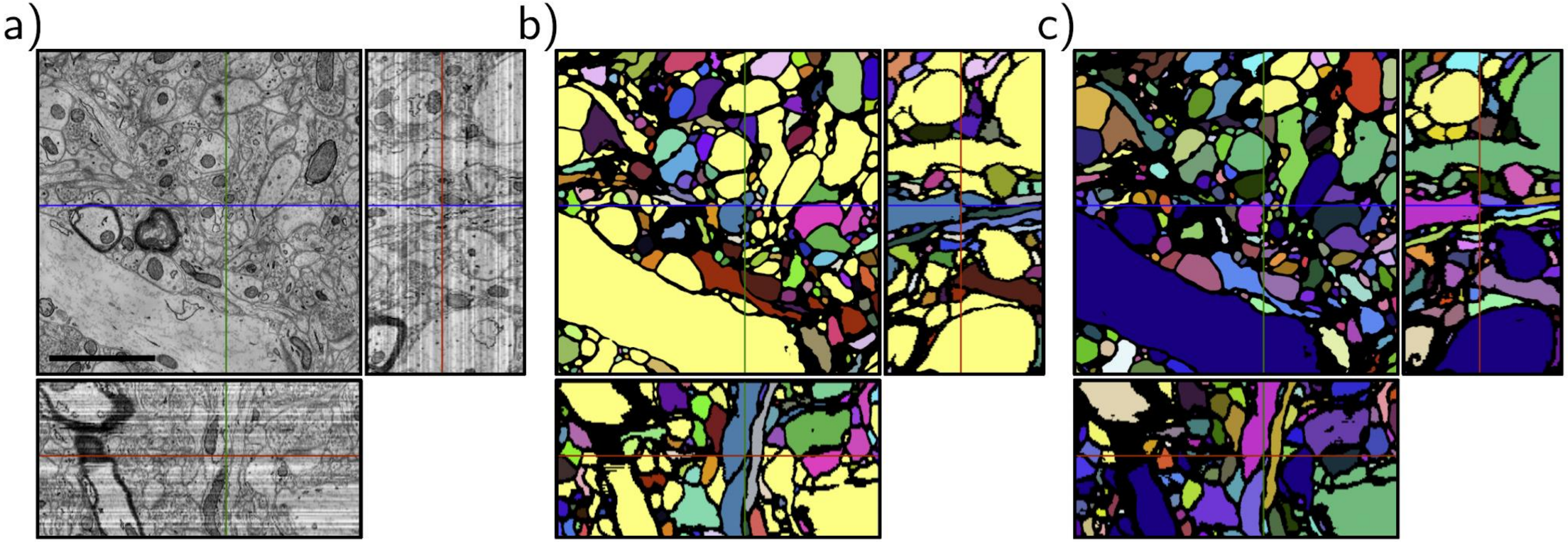


Figure 11.11 Segmentation using U-Net in 3D. a) Three slices through a 3D volume of mouse cortex taken by scanning electron microscope. b) A single U-Net is used to classify voxels as being inside or outside neurites. Connected regions are identified with different colors. c) For a better result, an ensemble of five U-Nets is trained, and a voxel is only classified as belonging to the cell if all five networks agree. Adapted from Falk et al. (2019).

U-Net for pose estimation

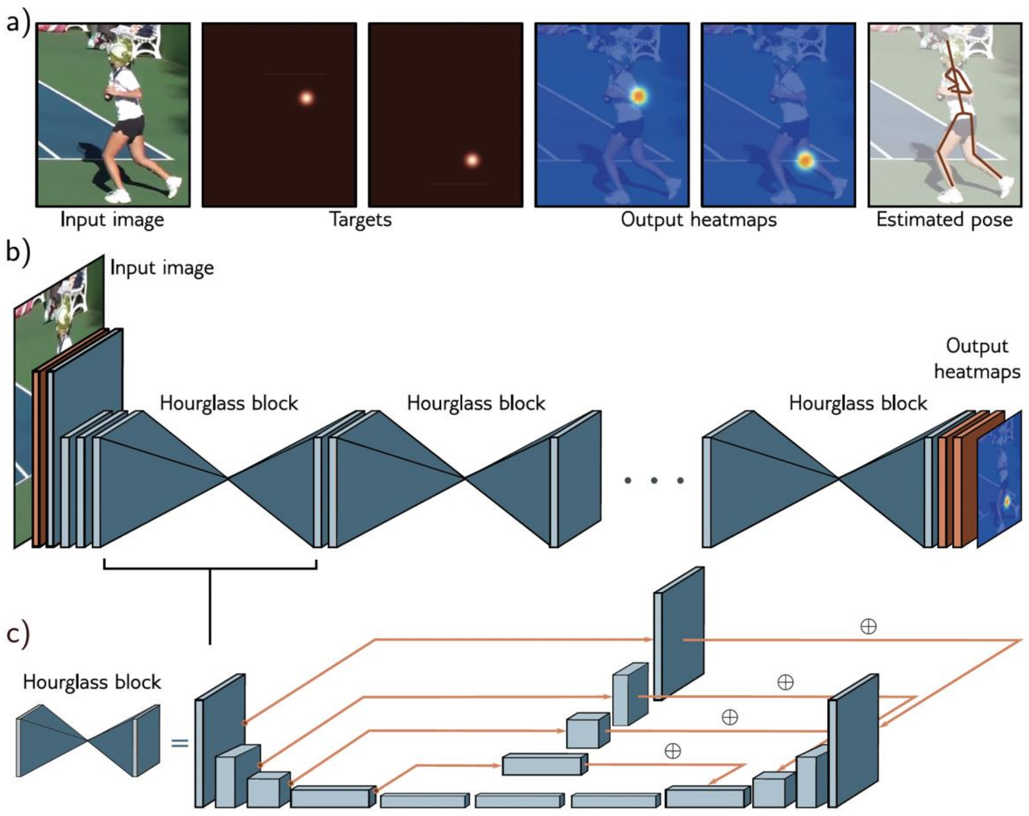


Figure 11.12 Stacked hourglass networks for pose estimation. a) The network input is an image containing a person, and the output is a set of heatmaps, with one heatmap for each joint. This is formulated as a regression problem where the targets are heatmap images with small, highlighted regions at the ground-truth joint positions. The peak of the estimated heatmap is used to establish each final joint position. b) The architecture consists of initial convolutional and residual layers followed by a series of hourglass blocks. c) Each hourglass block consists of an encoder-decoder network similar to the U-Net except that the convolutions use zero padding, some further processing is done in the residual links, and these links add this processed representation rather than concatenate it. Each blue cuboid is itself a bottleneck residual block (figure 11.7b). Adapted from Newell et al. (2016).

Source: Understanding Deep Learning, S. Prince, 2023

Summary

Convnets as inductive bias for computer vision tasks.

Convnets are very expensive from a compute/memory perspective (1x1 trick)

More depth does not mean better performance.

ResNets and bottlenecks unlock performance and efficiency.