
# Deep Learning and Optimization

## Unpacking Transformers, LLMs and Diffusion

## Session 5

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# 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 | Content |
|---|---|---|---|
| Foundations | 1 | Jan, 28 | Intro to DL<br>TP: micrograd |
| | 2 | Feb, 4 | Fundamentals I: inductive bias, loss functions<br>TP: bigram, MLP for next character prediction |
| | 3 | Feb, 11 | Fundamentals II: DL architectures<br>TP: tensor-based models |
| Applications | 4 | Feb, 18 | Attention & Transformers<br>TP: GPT from scratch |
| | 5 | Feb, 25 | DL for Computer vision<br>TP: convnets on CIFAR-10 |
| | 6 | Mar, 11 | VAE and Diffusion<br>TP: diffusion from scratch<br>Quiz / Exam |

# More depth is not always better

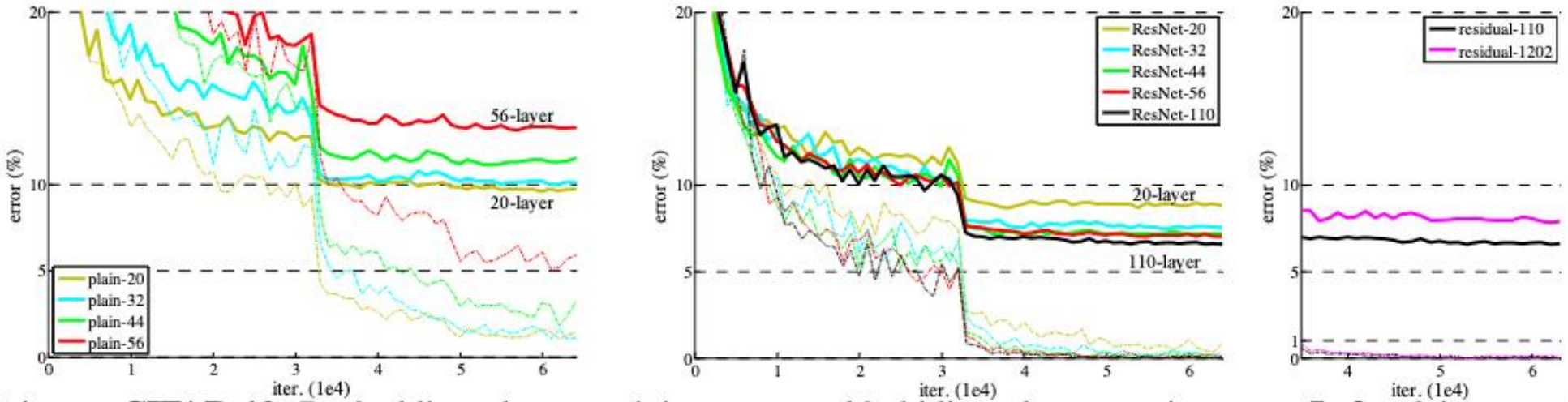



Figure 6. Training on **CIFAR-10**. Dashed lines denote training error, and bold lines denote testing error. **Left**: plain networks. The error of plain-110 is higher than 60% and not displayed. **Middle**: ResNets. **Right**: ResNets with 110 and 1202 layers.

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

# The timeline of vision models

2013 – Network in network (Lin et al.) introduced 1x1 convs

2014 – Google LeNet/Inception 1x1 for channel reduction

2015 – ResNet: 1x1 bottlenecks

2016 – Xception: depthwise separable convolutions

2017 – MobileNet: depthwise for mobile/efficient models

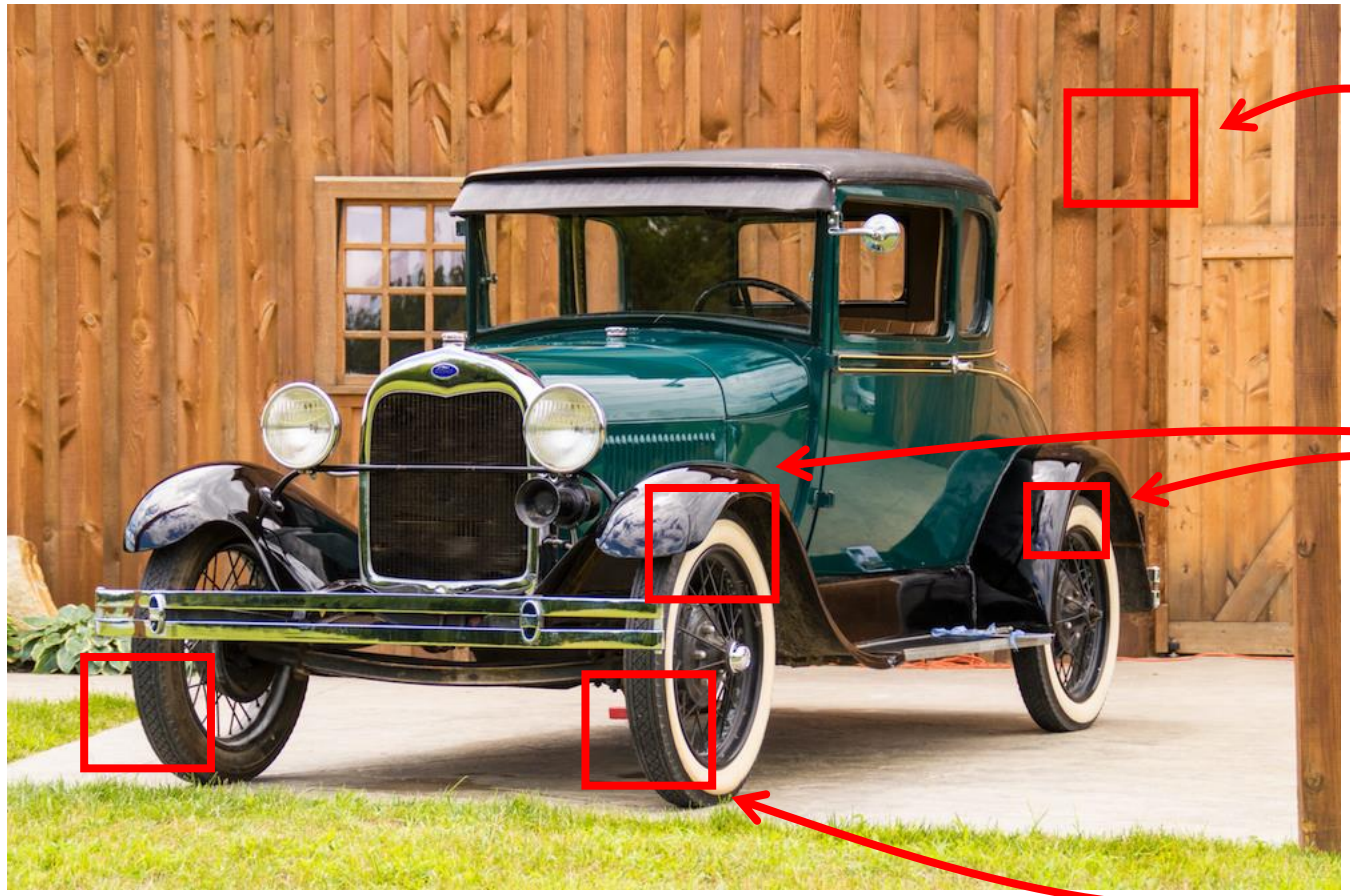
2019 – EfficientNet

2020 – Vision Transformer (ViT): attention > convolutions?

2022 – ConvNext -> convolutions are not dead!

Today – the gap has closed. Choice depends on the task.

# Inductive bias for computer vision

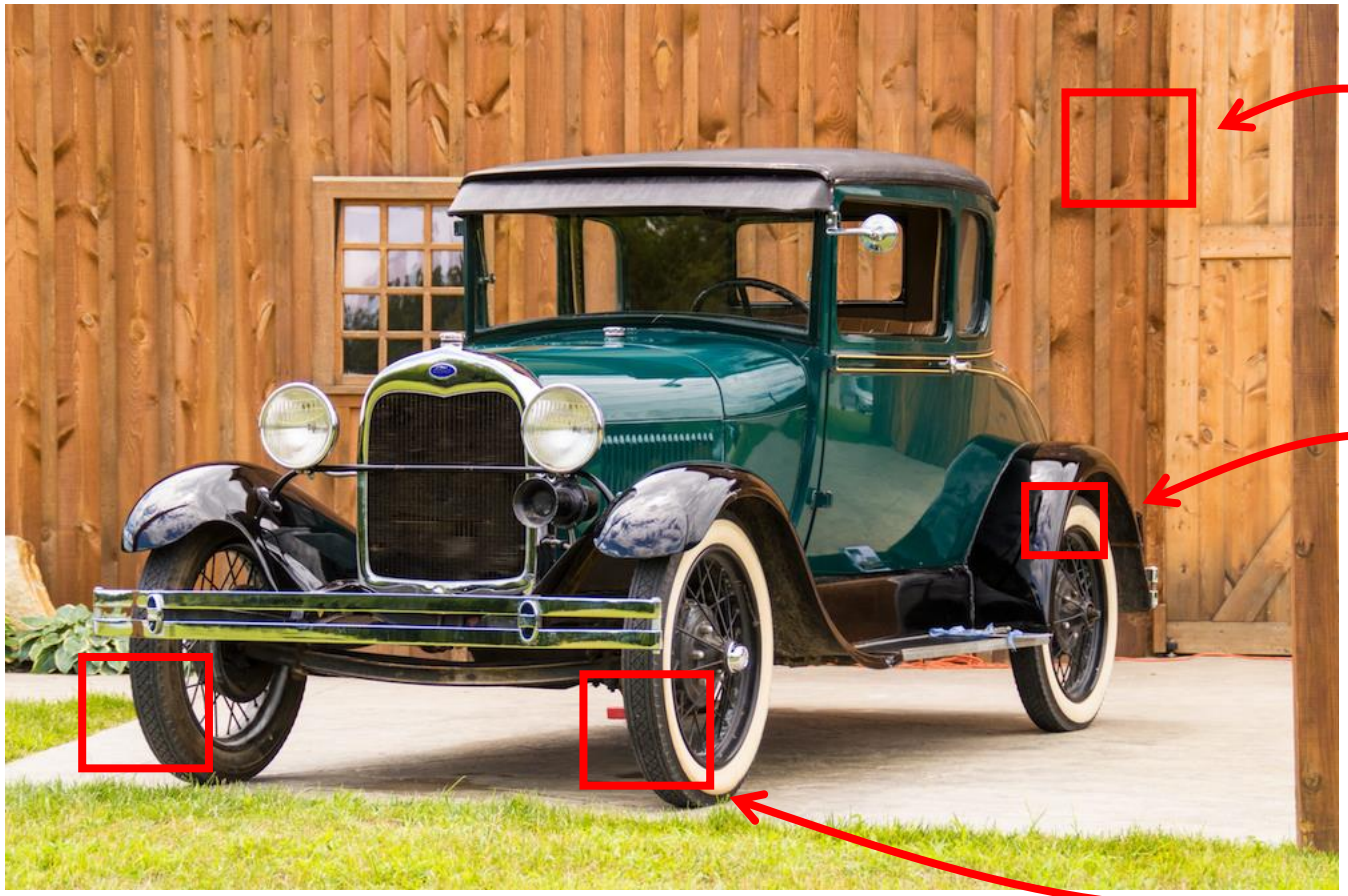


**Locality** Neurons interact locally only

**Scale** Operate at multiple scales

**Globality** Learn the same features across the whole image

# Inductive bias for computer vision: convolutional networks

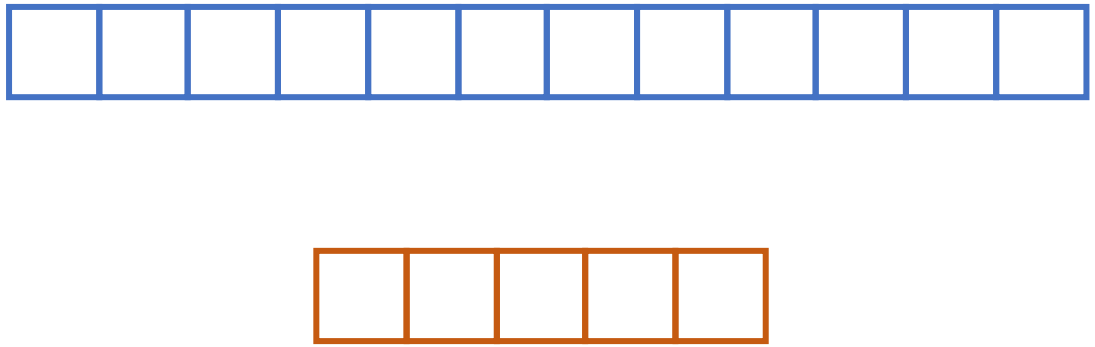


Unique operator/kernel (convolution)

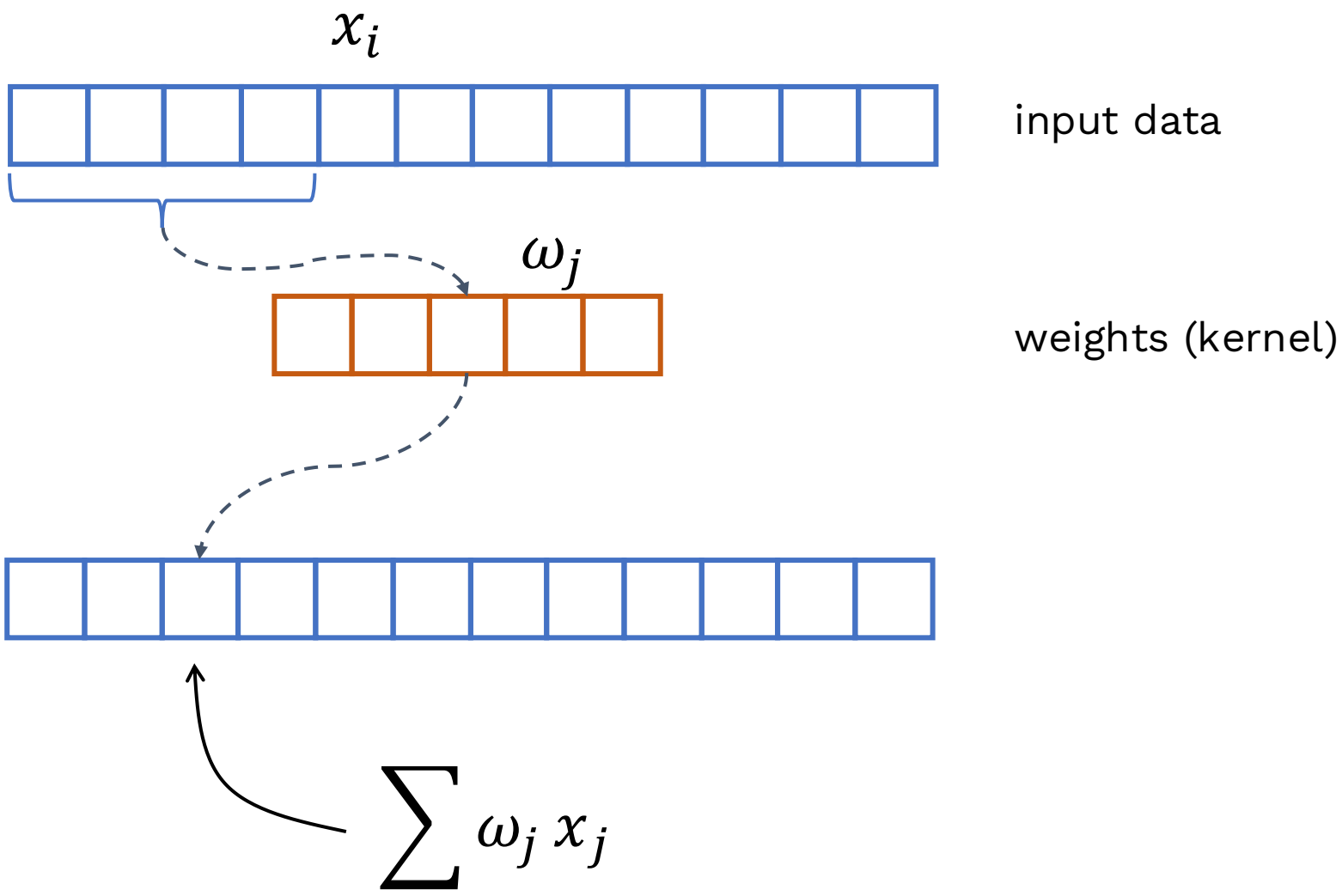
Applied at multiple scales

Reused across the image (feature maps)

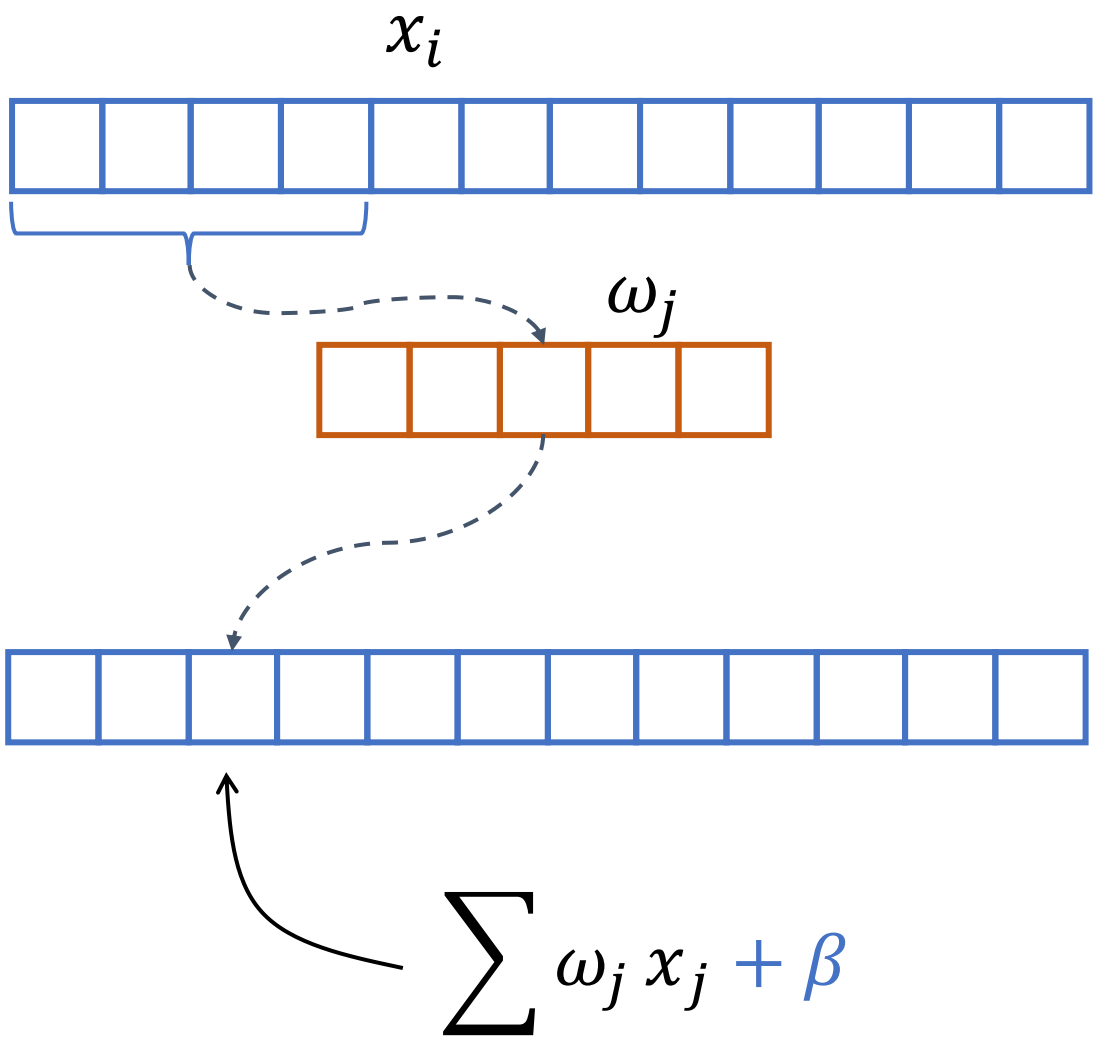
# Convolutions



# Convolutions



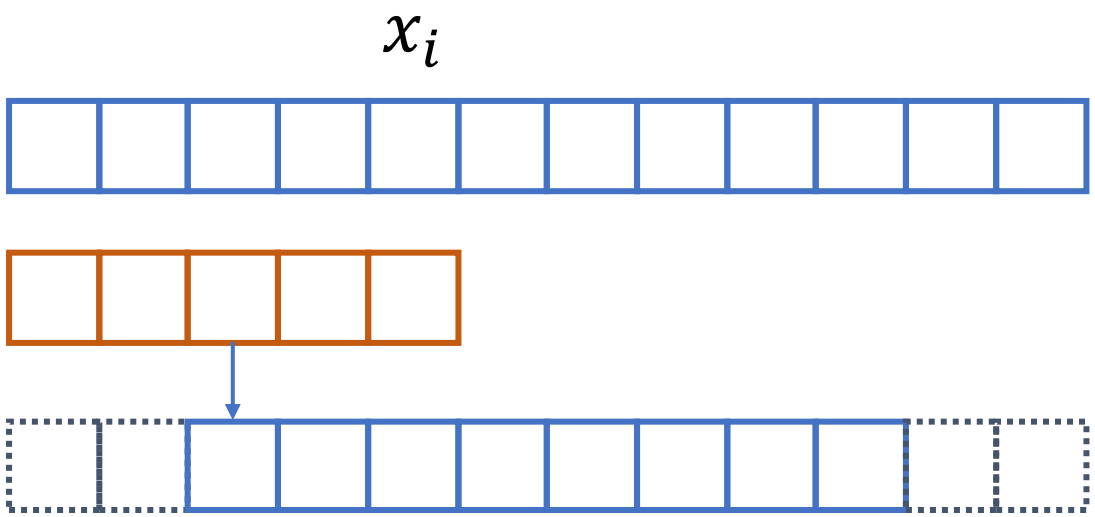
# Convolutions




input data

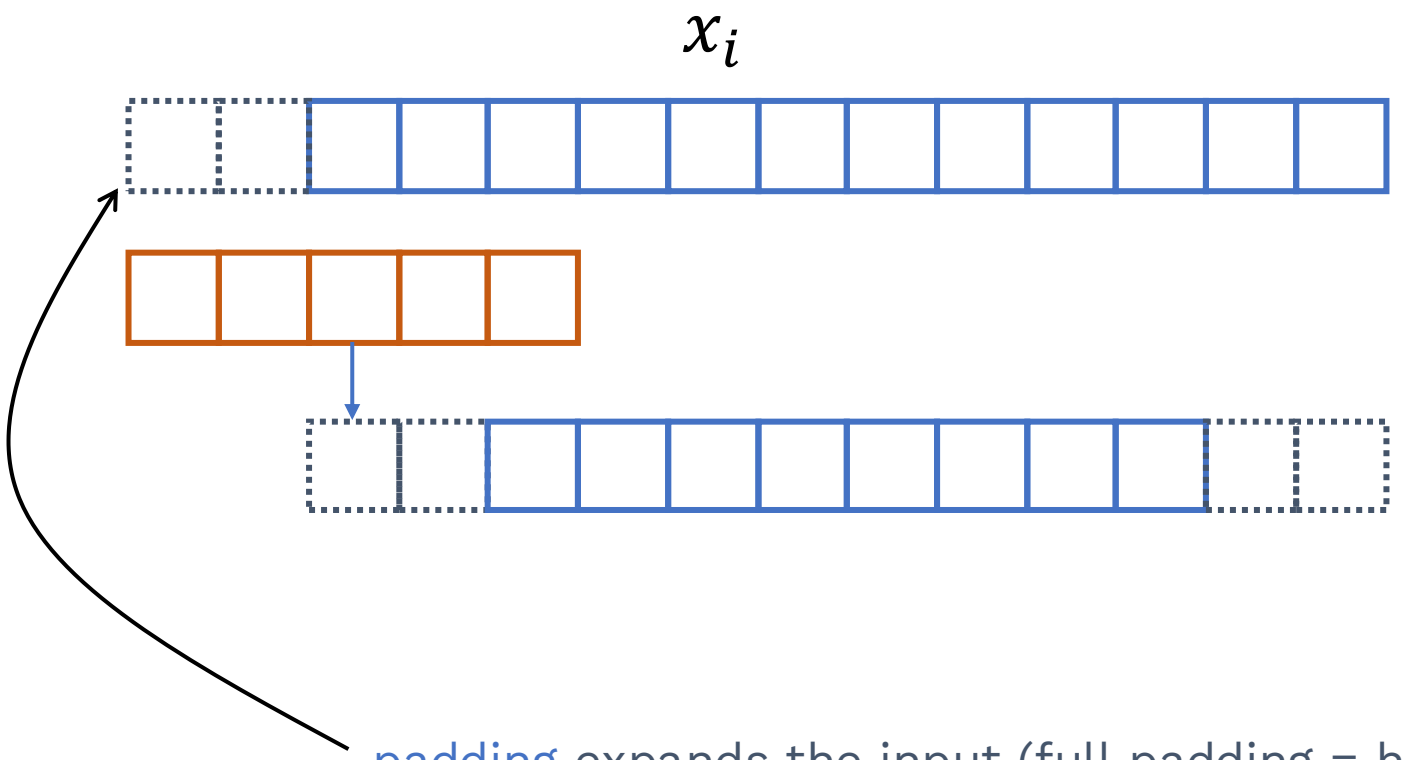
weights and biases

# Convolutions



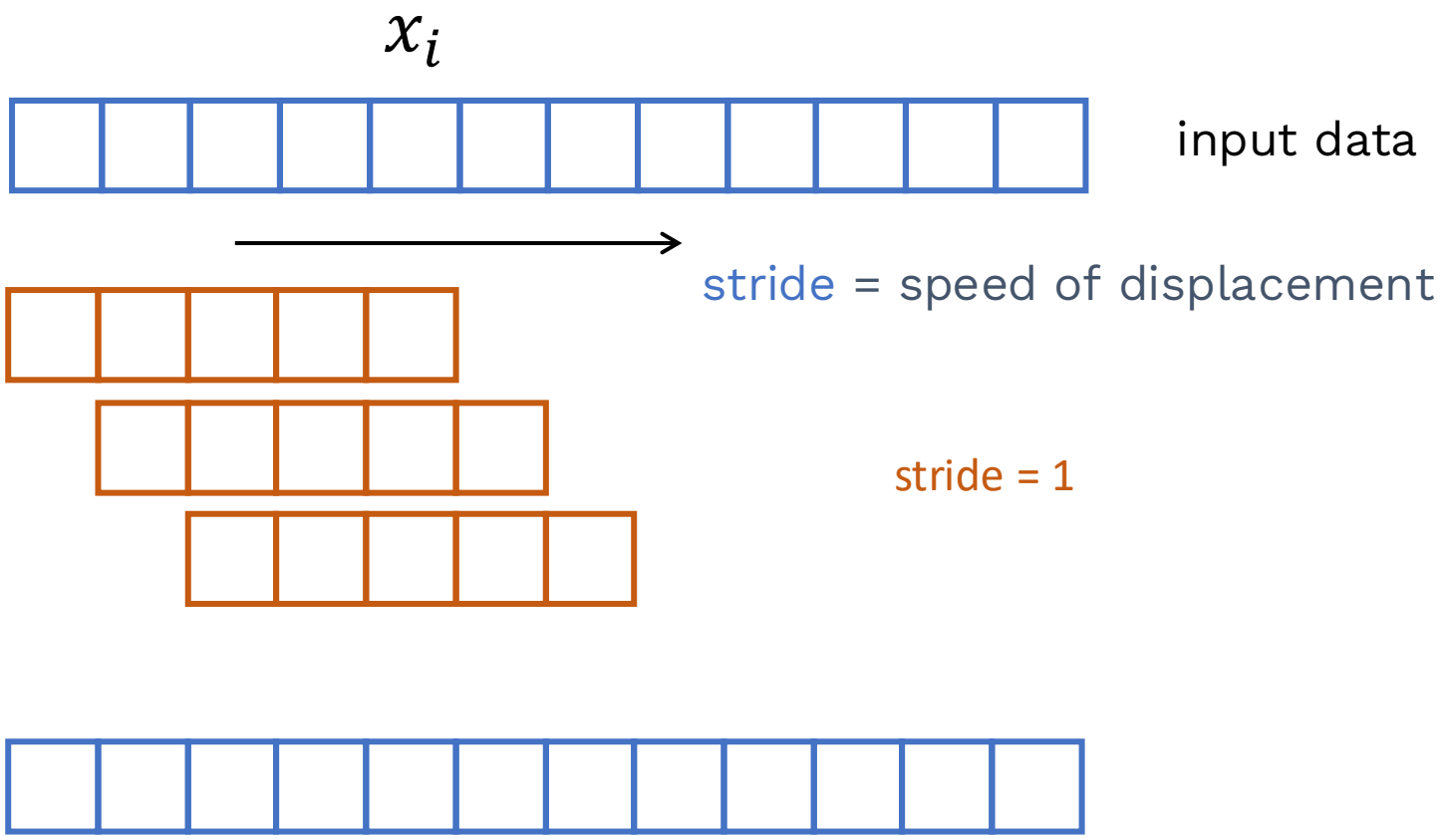

input data

# Convolutions

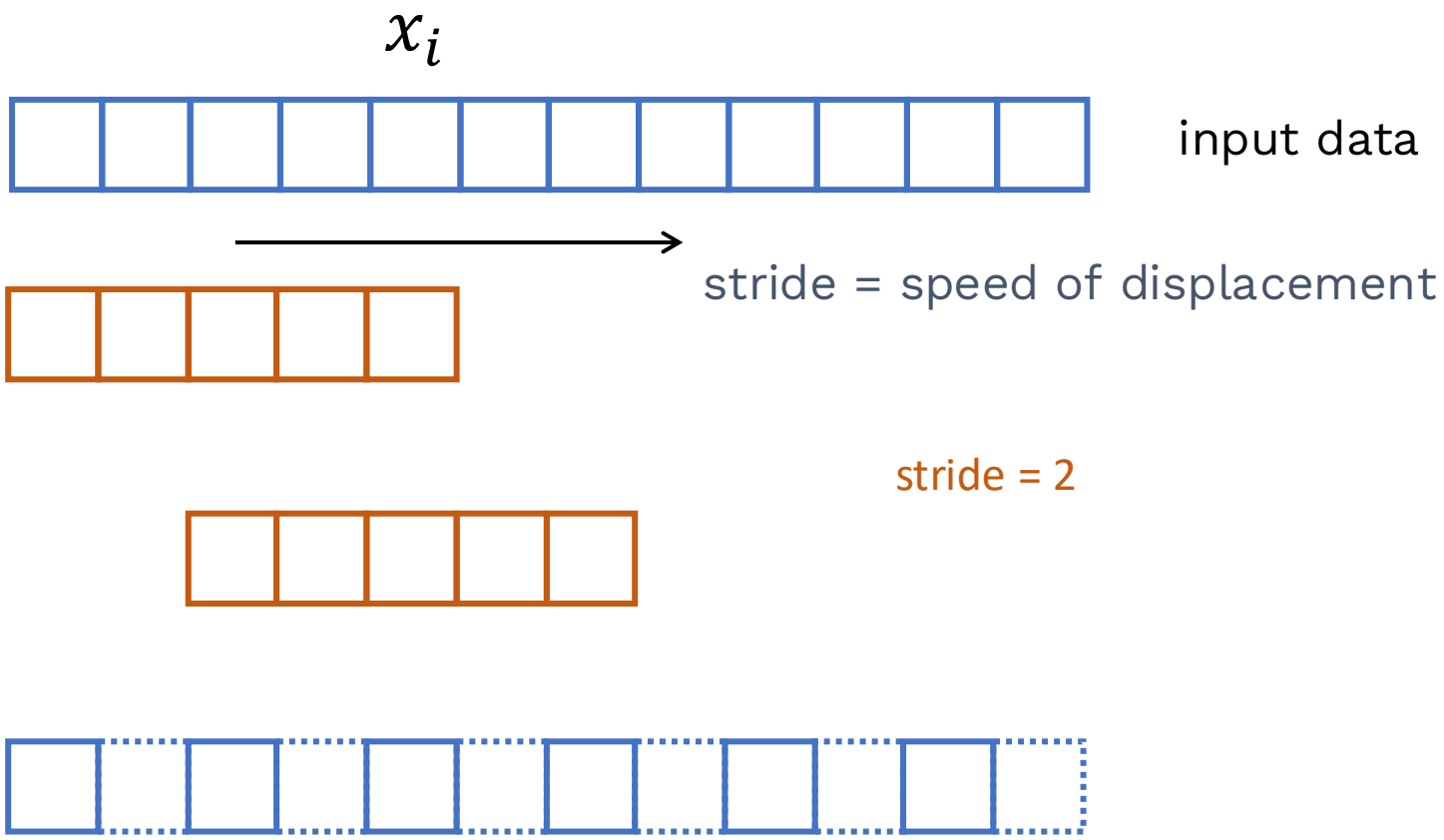



padding expands the input (full padding = half the kernel size)

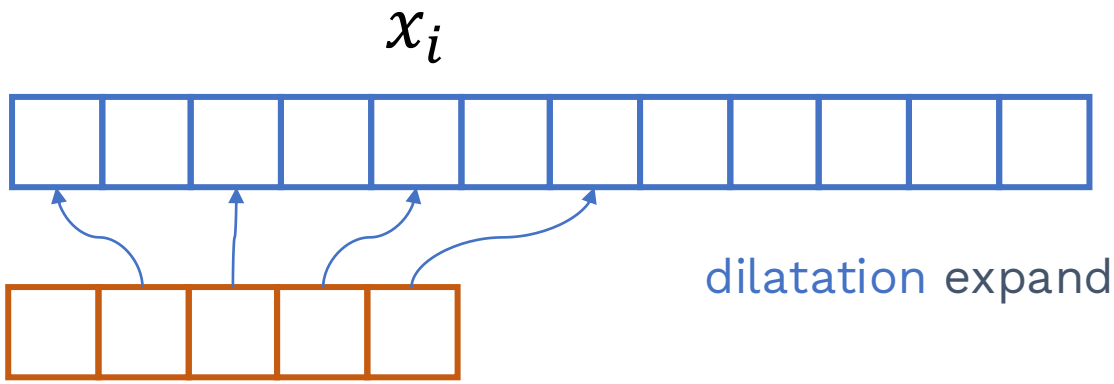
# Convolutions



# Convolutions

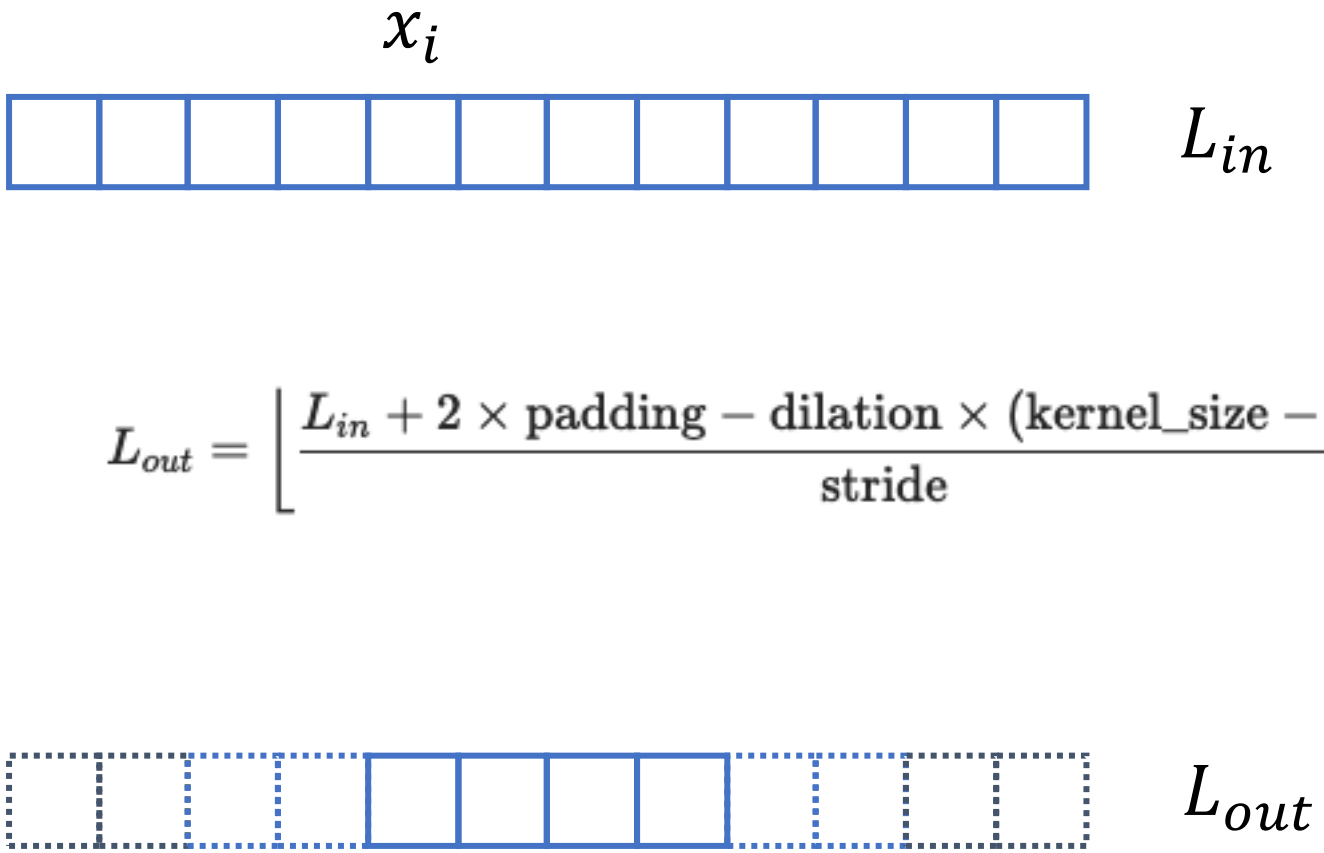


# Convolutions

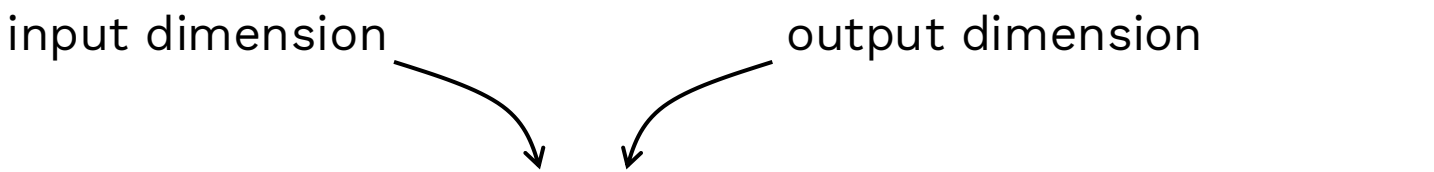



... and effectively requires further padding

# Convolutions



# Convolutions




```
m = nn.Conv1d(1, 1, kernel_size=5, stride=1, dilation=1, bias=False)
input = torch.ones((1,16))
m(input).shape
```

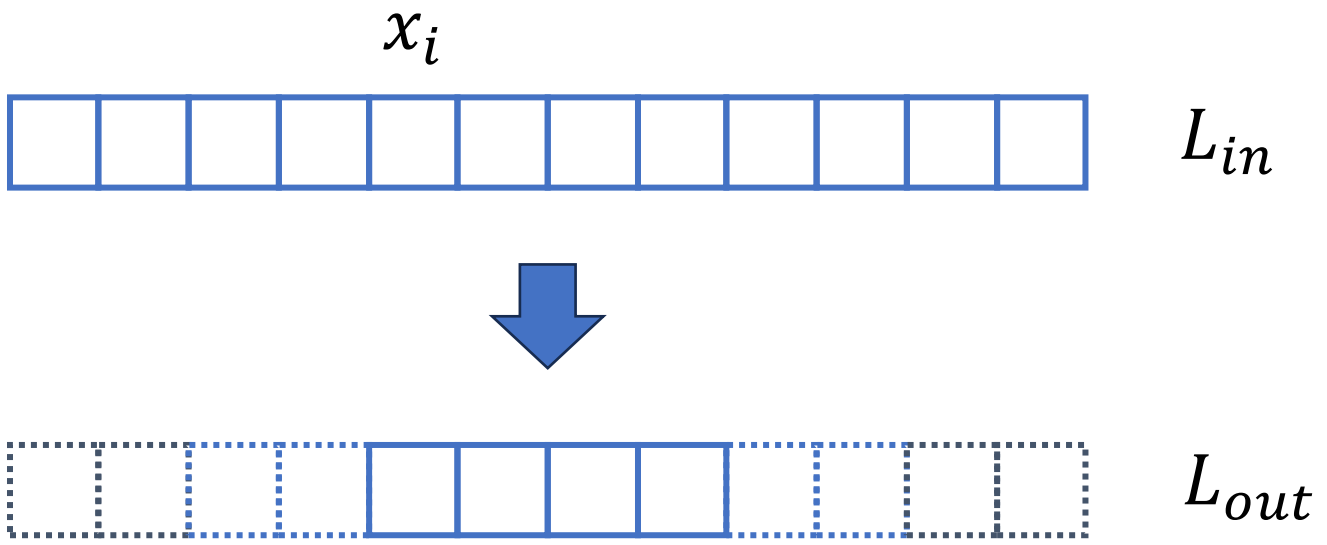
```
torch.Size([1, 12])
```

# 1D Convolutions

input dimension

output dimension

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

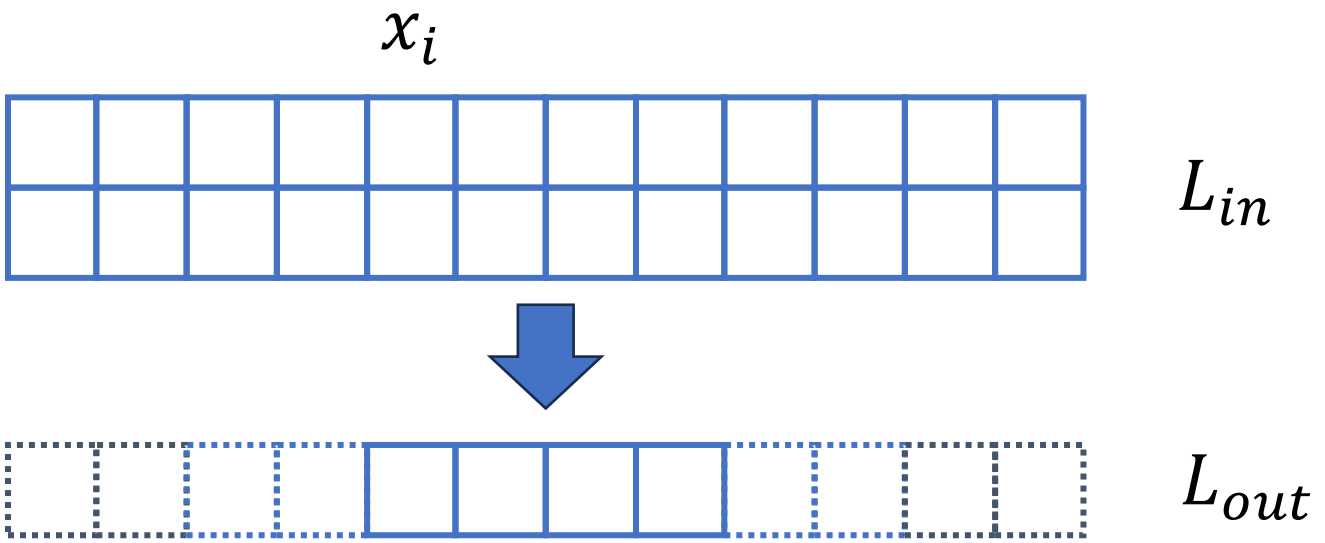


# 1D Convolutions

input dimension

output dimension

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



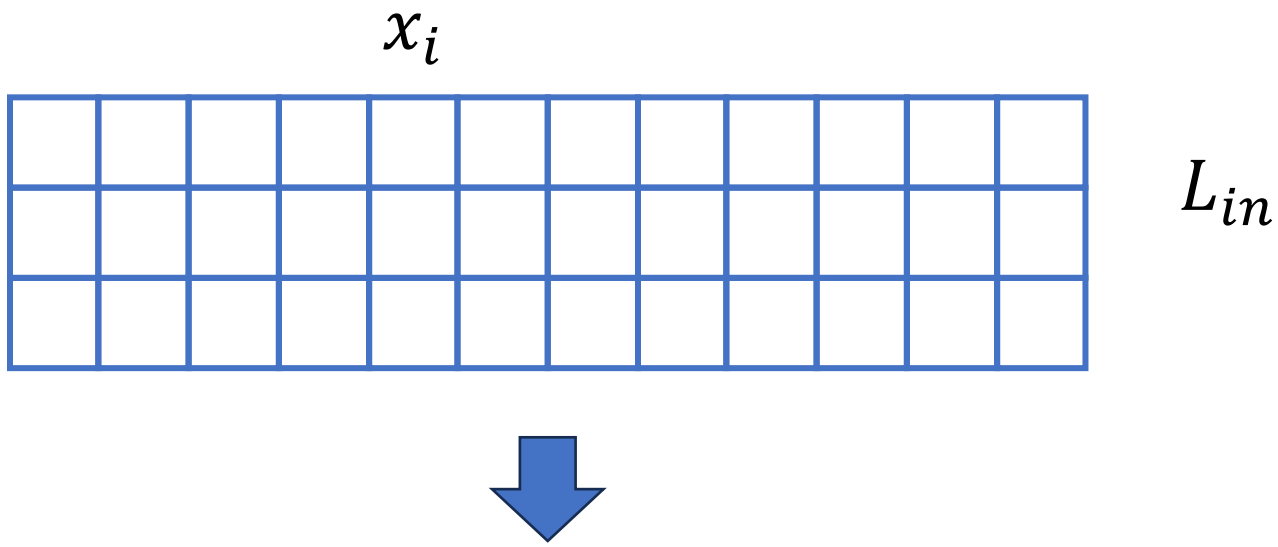

```
m.weight.shape
> [1, 2, 5]
```

# 1D Convolutions

input dimension

output dimension

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




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

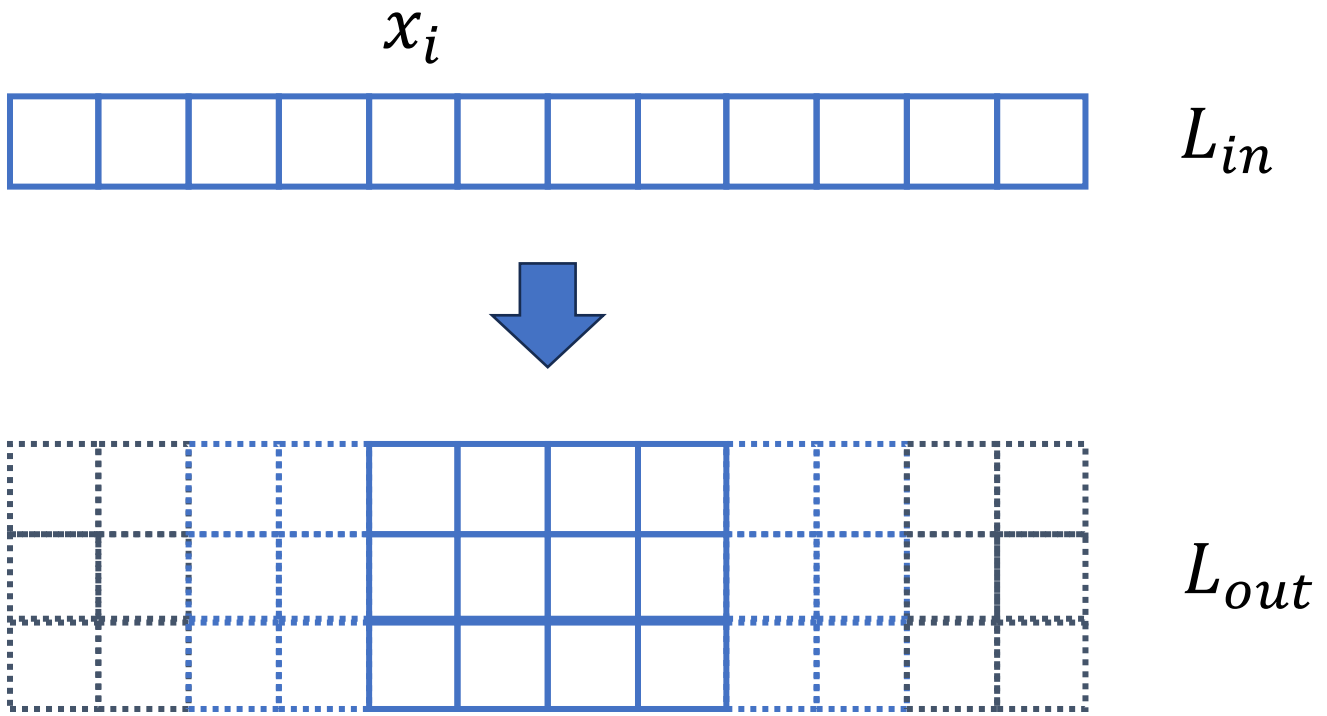
RuntimeError: weight of size [1, 2, 5], expected input[1, 3, 7] to have 2 channels, but got 3 channels instead

# 1D Convolutions

input dimension

output dimension

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



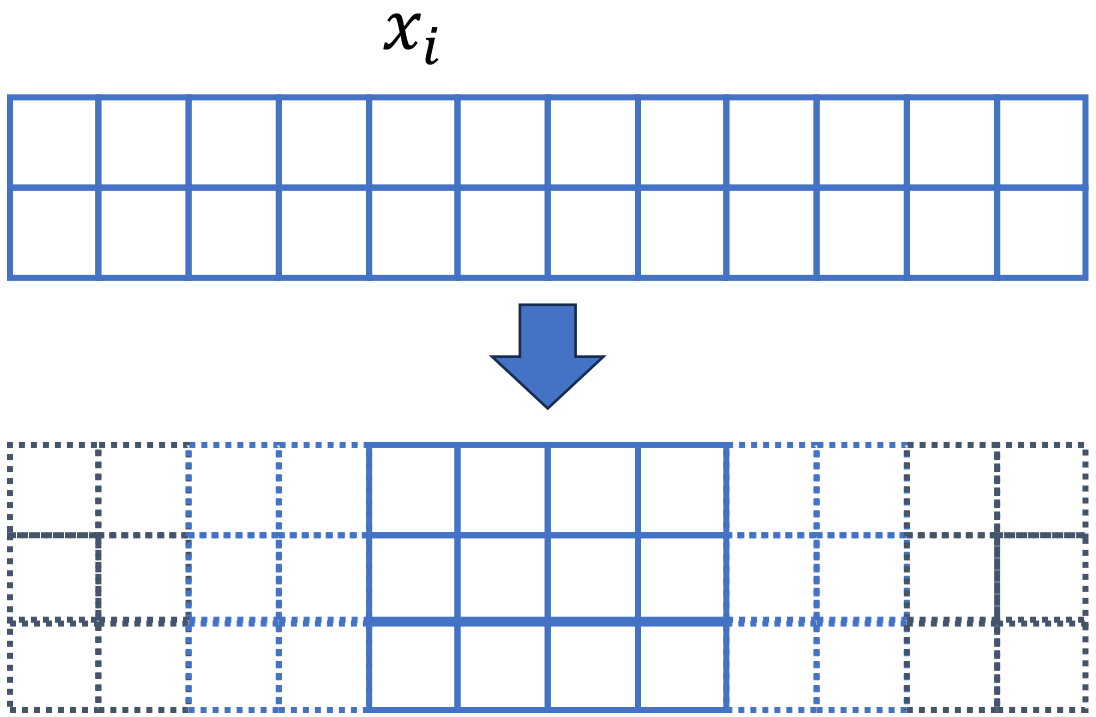

```
m.weight.shape
> [3, 1, 5]
```

# 1D Convolutions

input dimension

output dimension

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




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

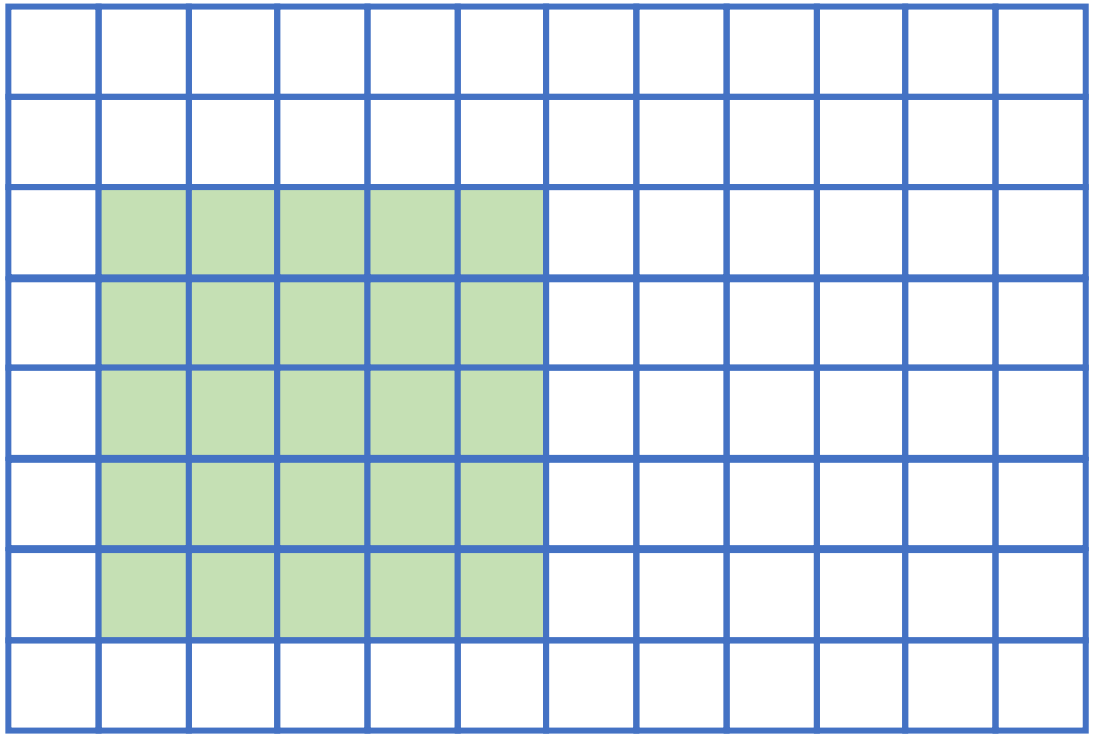
# 2D Convolutions

input dimension

output dimension

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

$x_i$



$L_{in}$

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

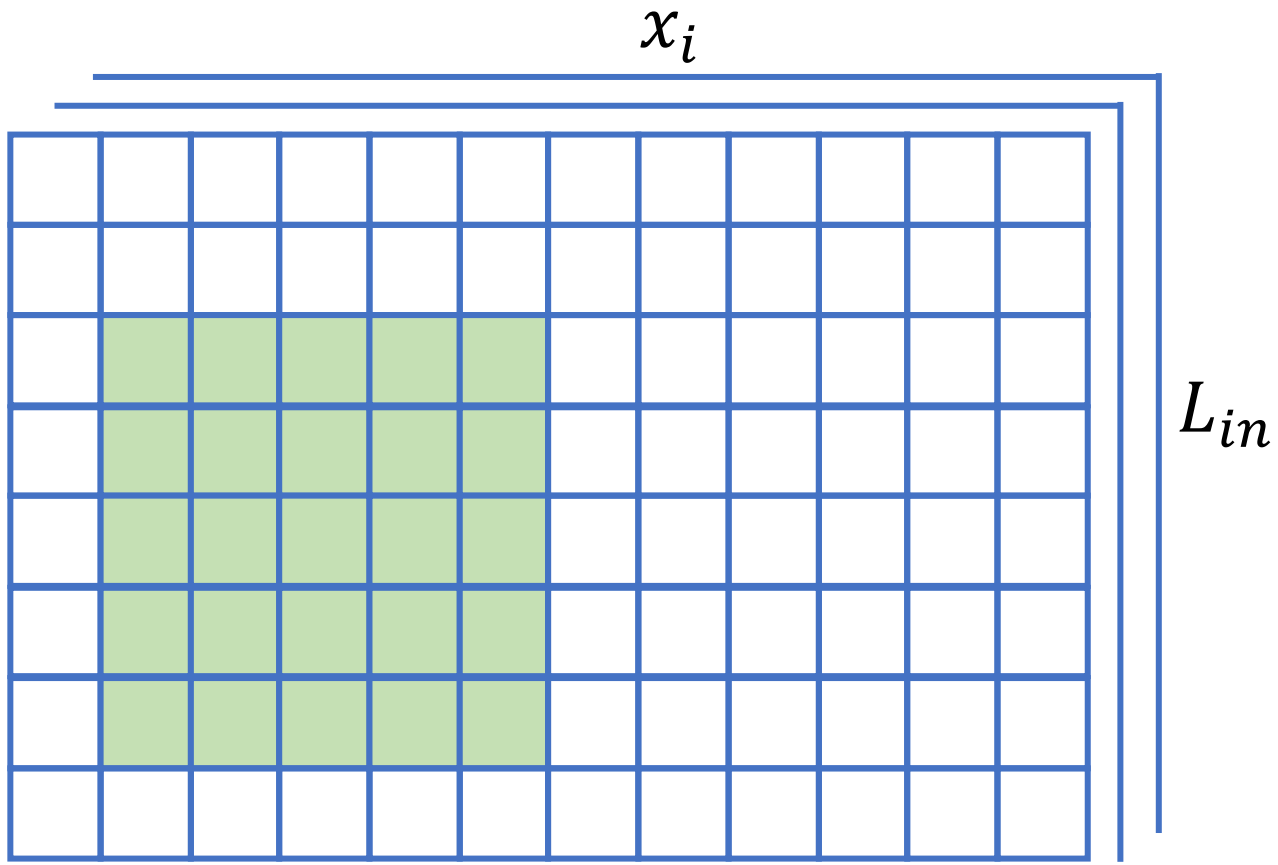
m.weight.shape
> [1, 1, 5, 5]

# 2D Convolutions

input dimension

output dimension

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

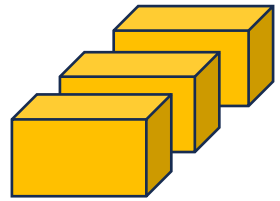



input.shape

> [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

Image size (HxW)

number of channels = input dimension

output = torch.ones(N, $C_{out}$, $H_{out}$, $W_{out}$)

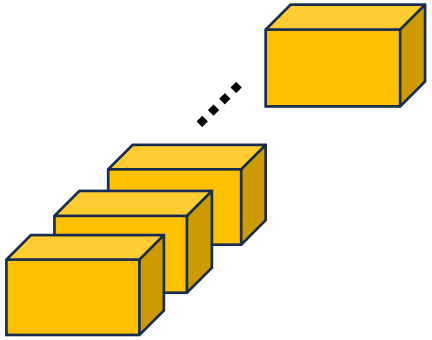
$$L_{out} = \left\lfloor \frac{L_{in} + 2 \times \text{padding} - \text{dilation} \times (\text{kernel\_size} - 1) - 1}{\text{stride}} + 1 \right\rfloor$$

# 2D Convolutions

input dimension

output dimension

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

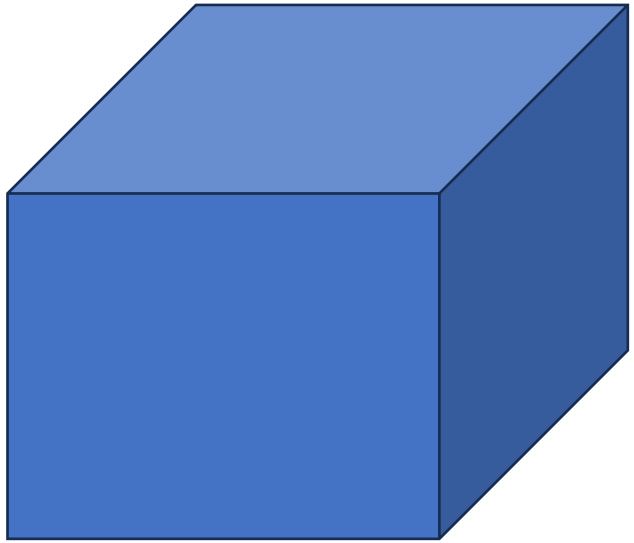


m.weight.shape

> [64, 3, 5, 5]

input.shape

> [12, 3, 224, 224]



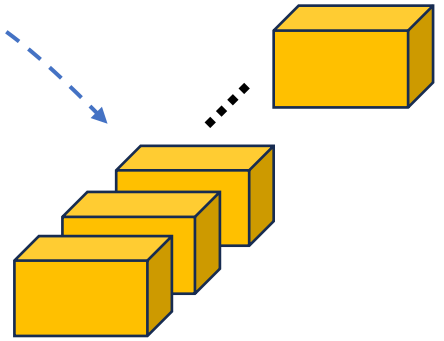
output.shape

> [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)
```

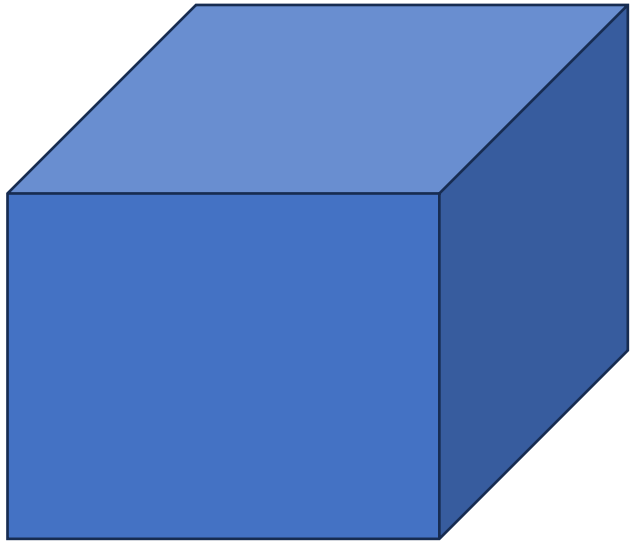


m.weight.shape

> [64, 3, 5, 5]

input.shape

> [12, 3, 224, 224]

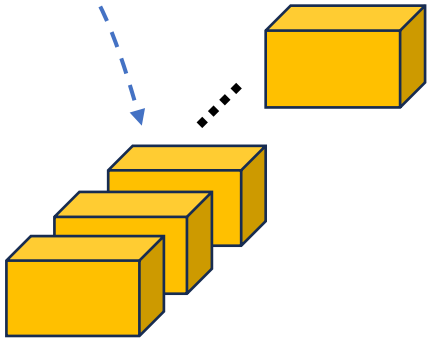


output.shape

> [12, 64, 112, 112]

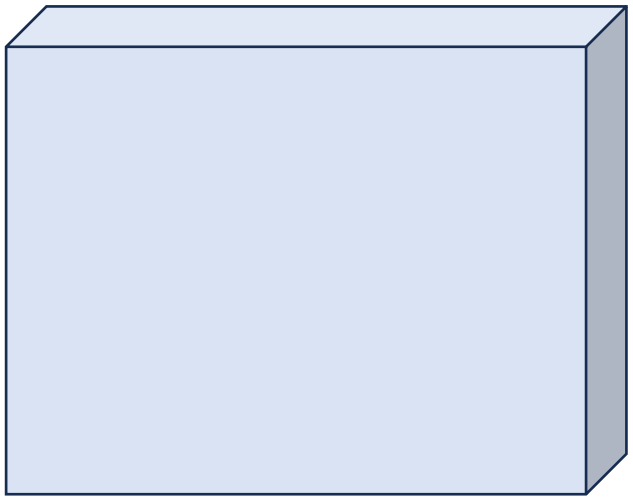
# 2D Convolutions

filter / kernels

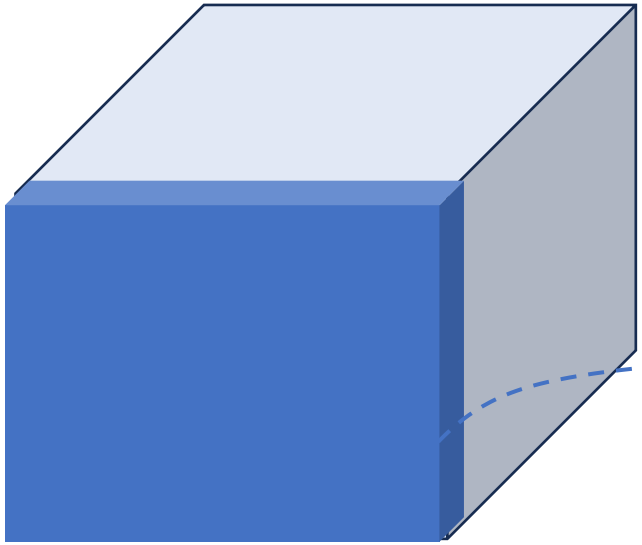


m = nn.Conv2d(3, 64, kernel_size=5, padding=2, stride=2)

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



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

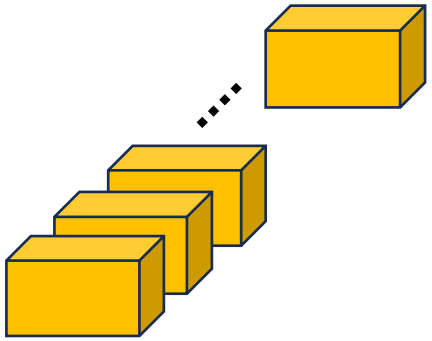


activation maps

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

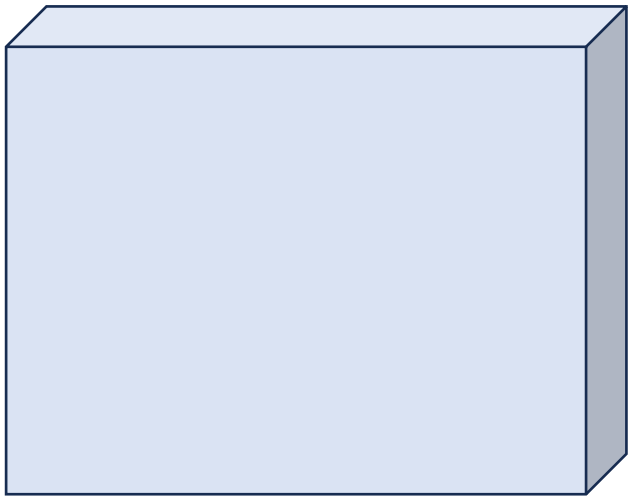
# 2D Convolutions

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

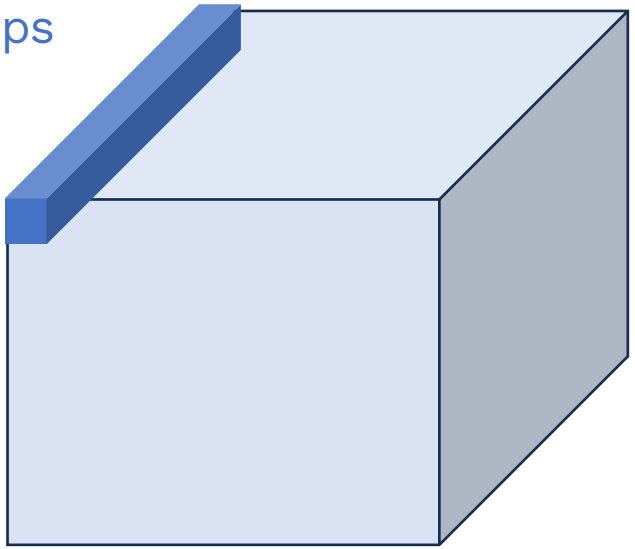


m.weight.shape
> [64, 3, 5, 5]

feature maps

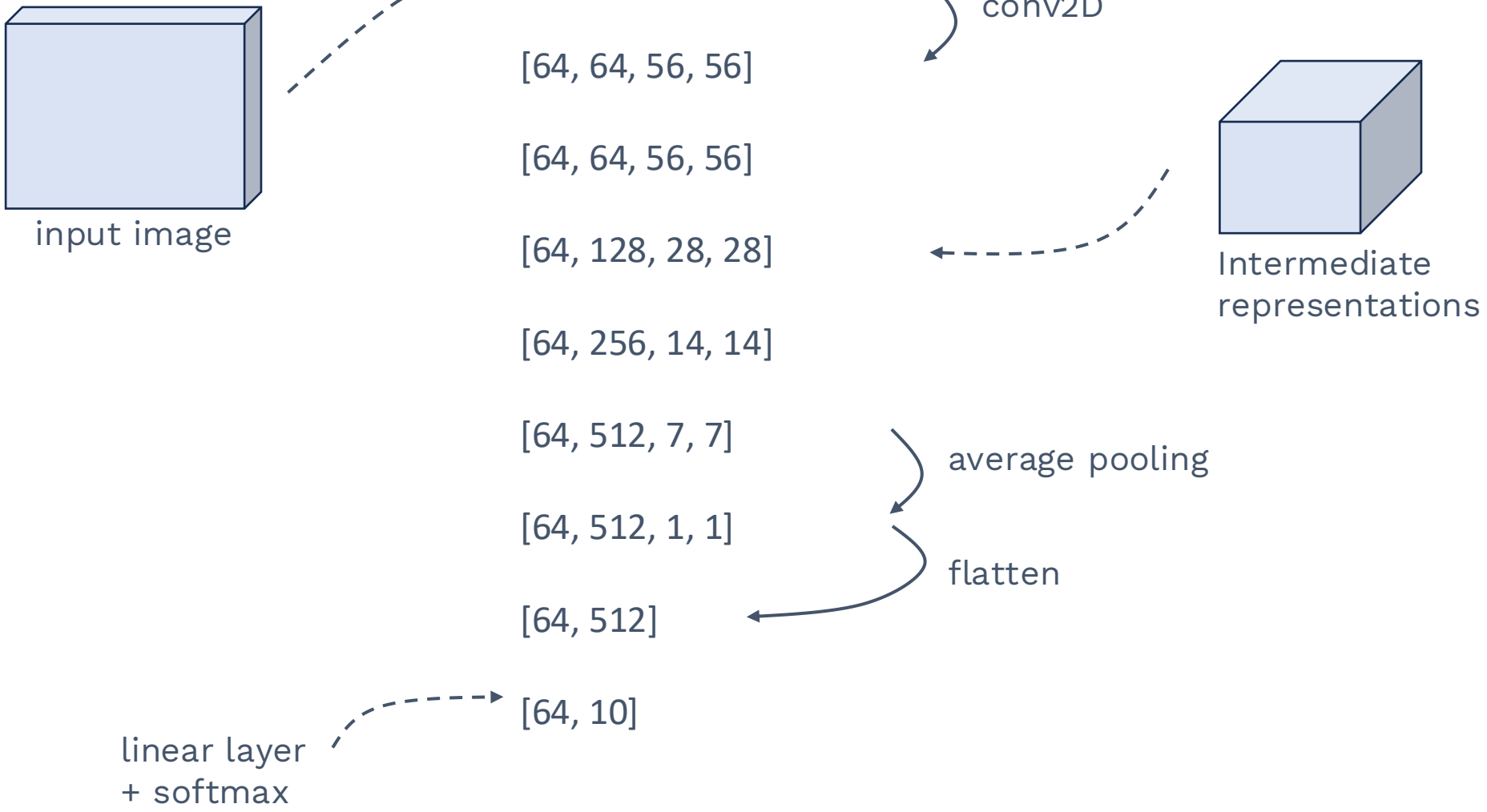


input.shape
> [12, 3, 224, 224]



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

# 2D Convolutions



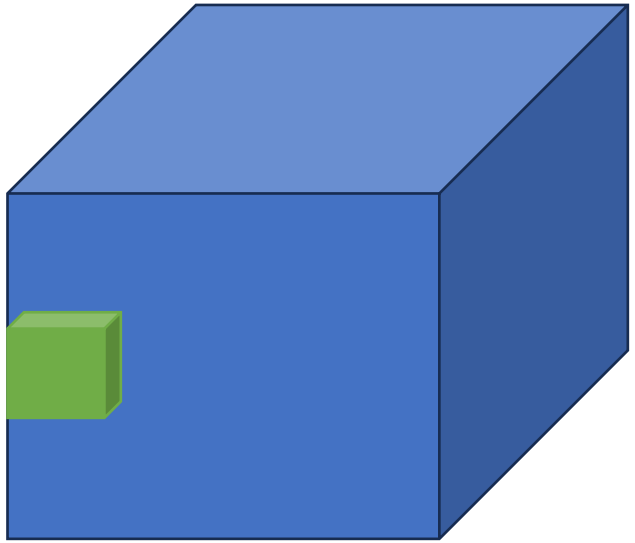
# Max Pooling

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

```
output.shape
```

> [11, 3, 37, 37]

default stride = kernel size

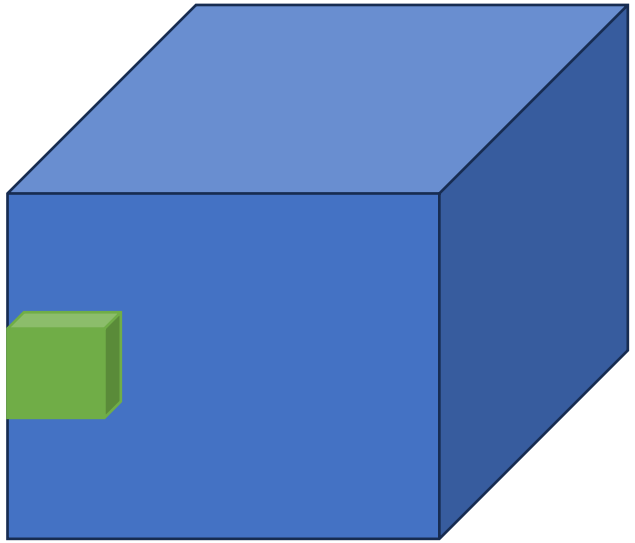


# Average Pooling

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

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

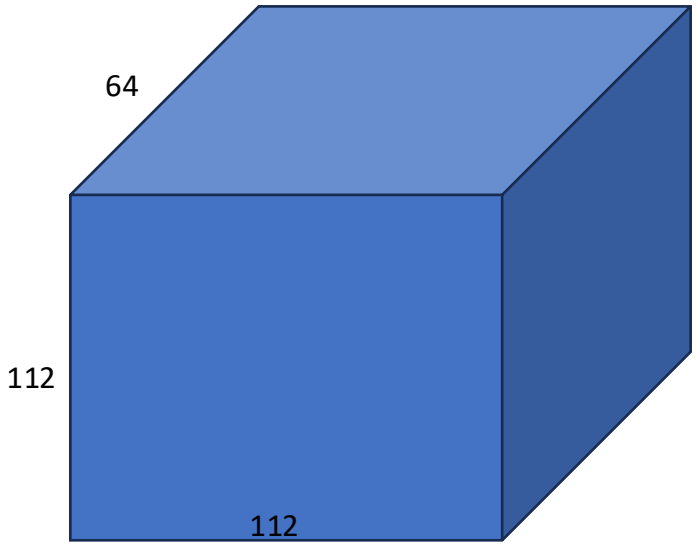
default stride = kernel size



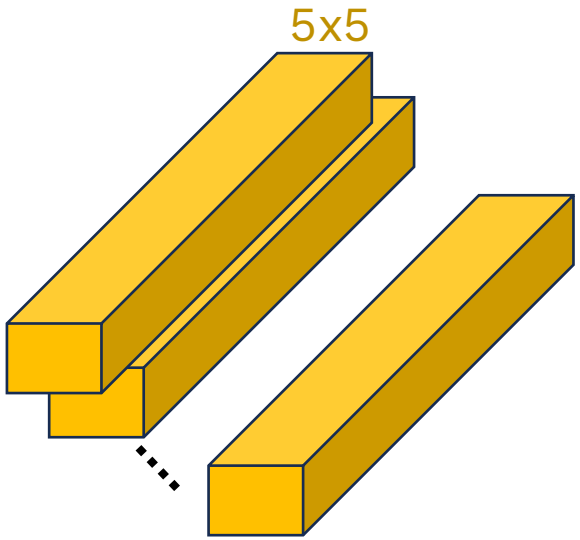
# Convolutions are expensive!

64 x 128 x 5 x 5 = 204,800 parameters!

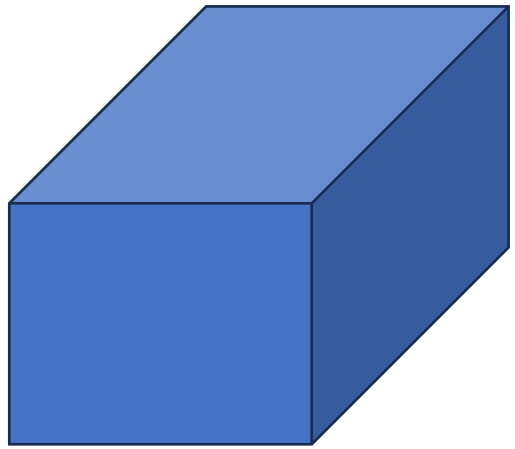
128 x 64 x 5 x 5 x (56 x 56) = 642,252,800 operations!




[12, 64, 112, 112]

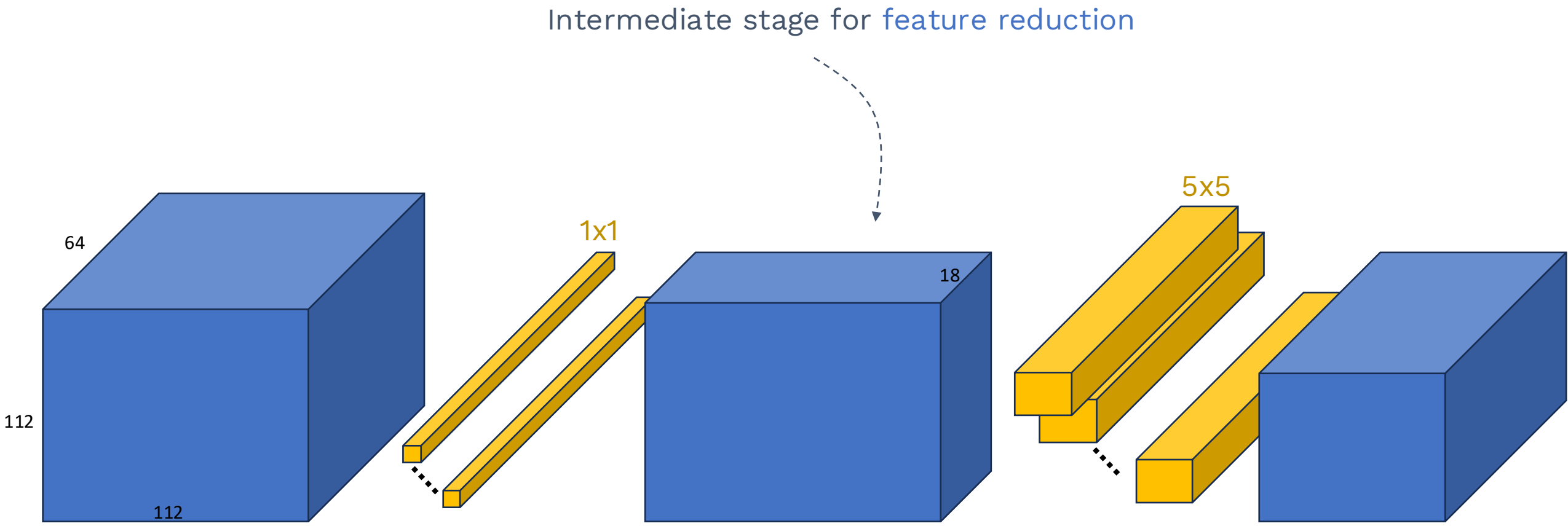



128 x 64 x 5 x 5



[12, 128, 56, 56]

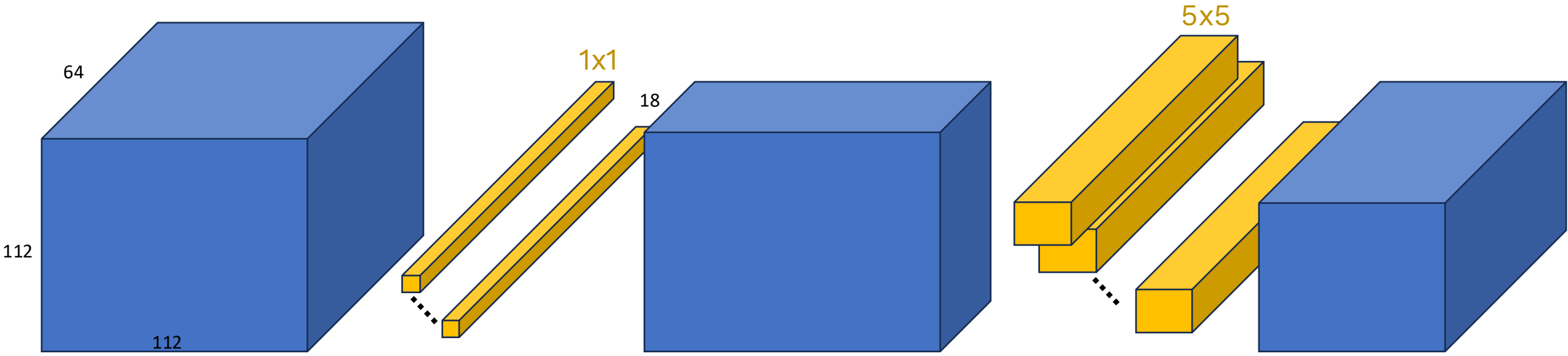
# Feature reduction with 1x1 convolutions



# Feature reduction with 1x1 convolutions

# params: C_in x C_out x K x K -> C_out x C_med + C_out x C_med x K x K

e.g. 204,800 -> 58,752 parameters



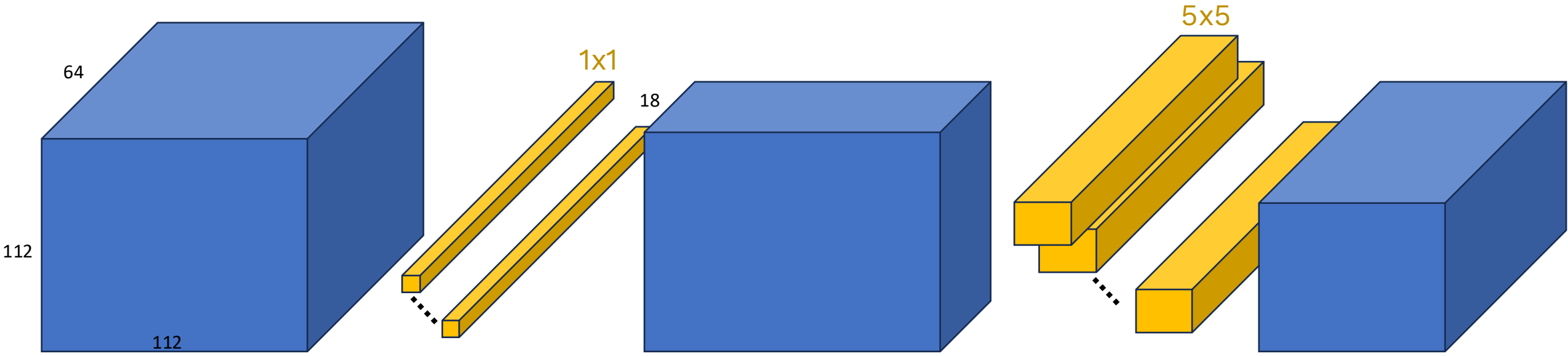

[12, 64, 112, 112] [18, 64, 1, 1] [12, 18, 112, 112] [128, 18, 5, 5] [12, 128, 56, 56]

# Feature reduction with 1x1 convolutions

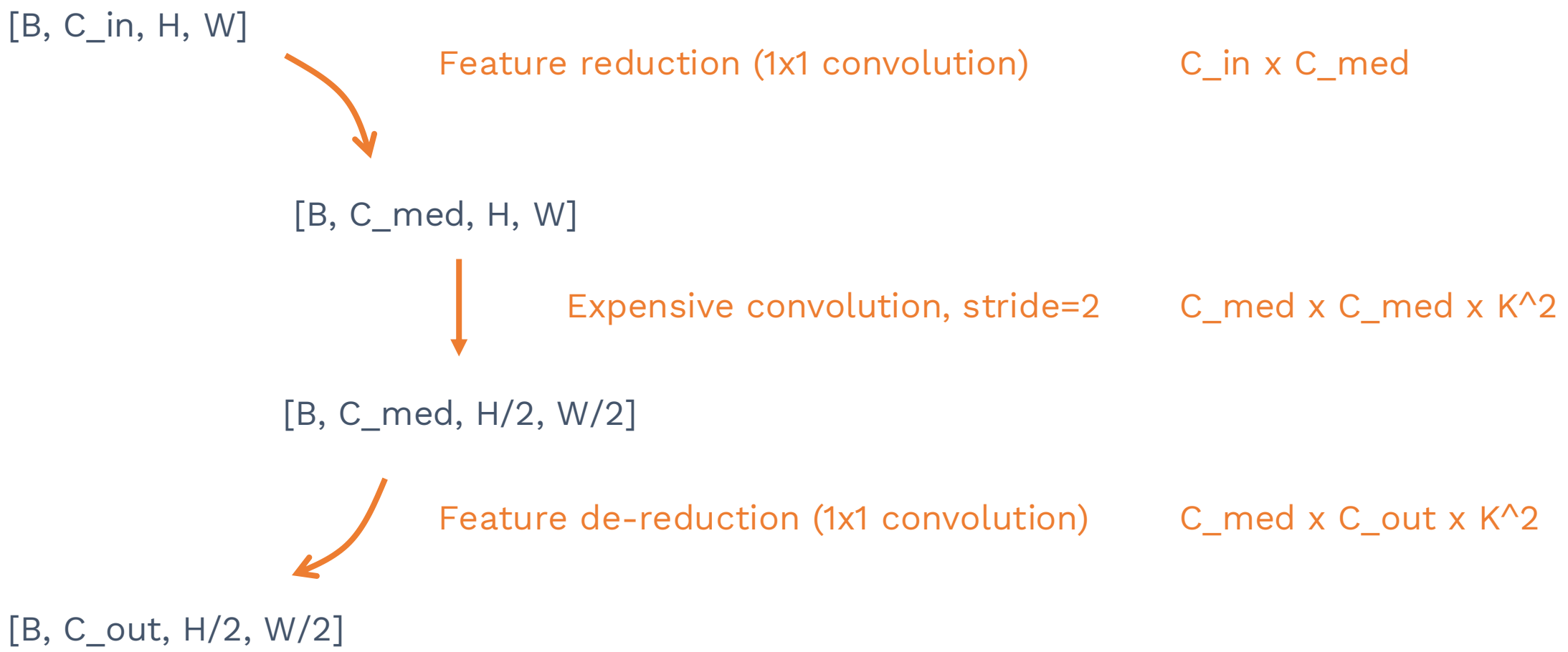
# ops: C_in x C_out x K x K x H' x W' ->

C_out x C_med x H x W + C_out x C_med x K x K x H' x W'

e.g. 642,252,800 -> 195,084,288 operations



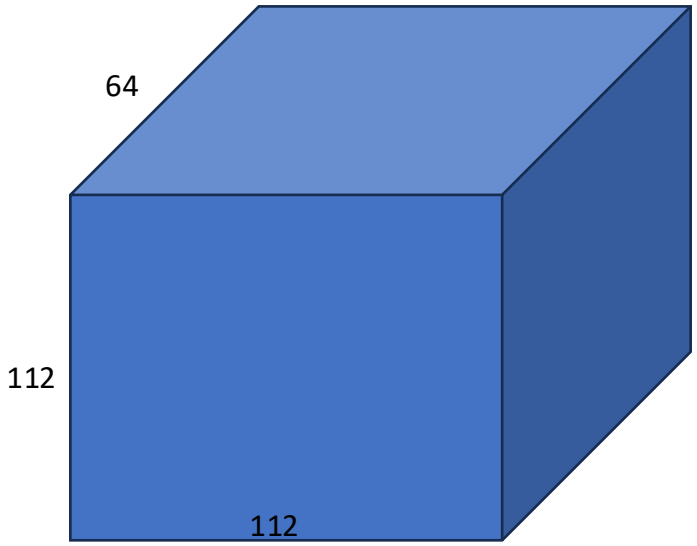
# Bottlenecks with 1x1 convolutions



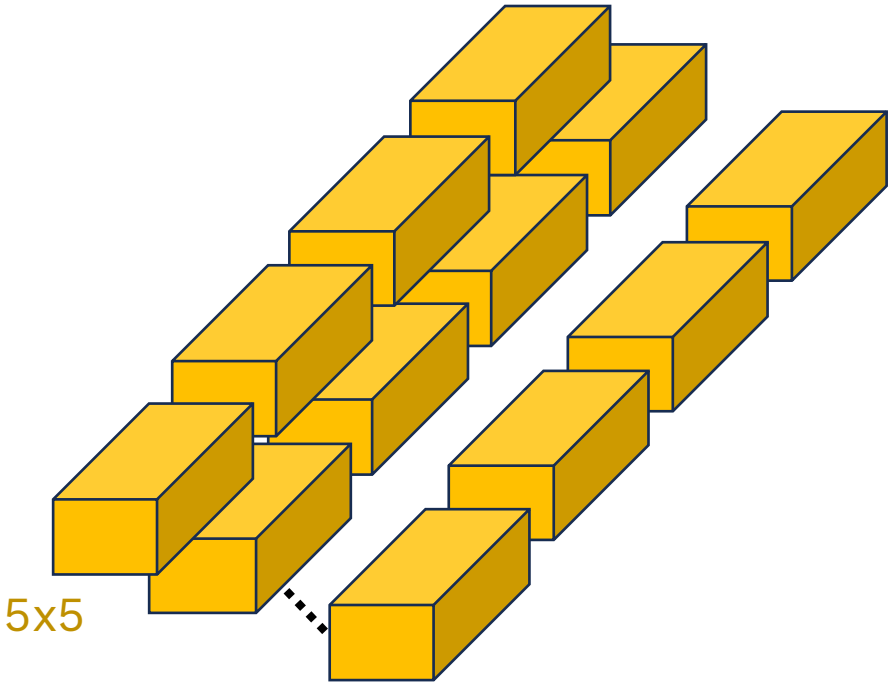
# Group convolutions

204,800 parameters -> 4 x 32 x 16 x 5 x 5 = 51,200 parameters

128 x 16 x 5 x 5 x (112 x 112) -> 4X less operations!

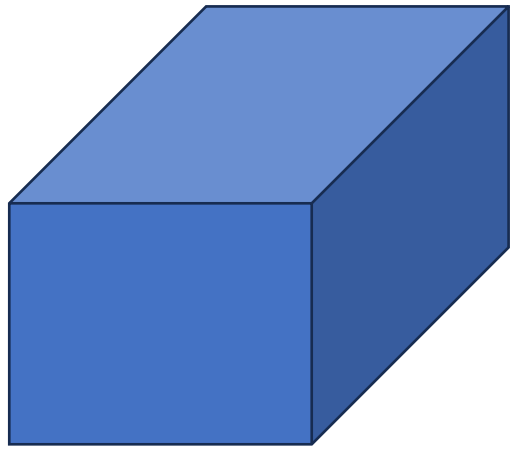



[12, 64, 112, 112]




4 x 32 x 16 x 5 x 5

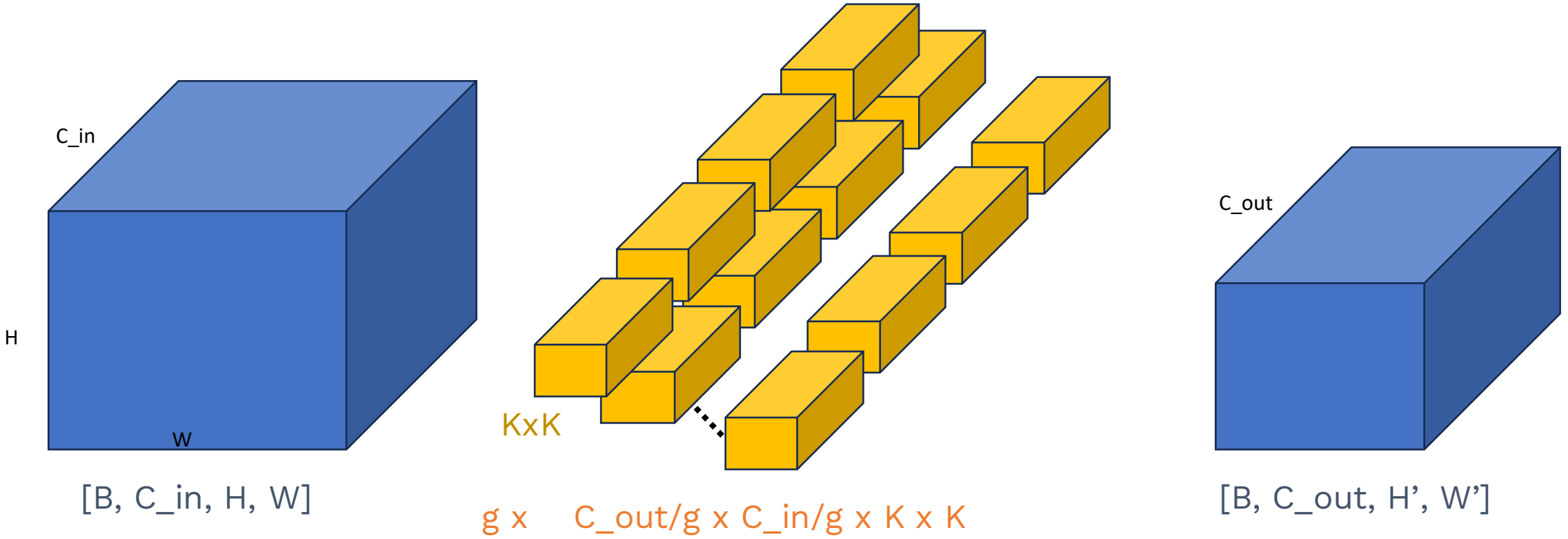
128 x 64 x 5 x 5



[12, 128, 56, 56]

# Group convolutions

For g groups: g X less memory, g X less compute




[B, C_in, H, W]

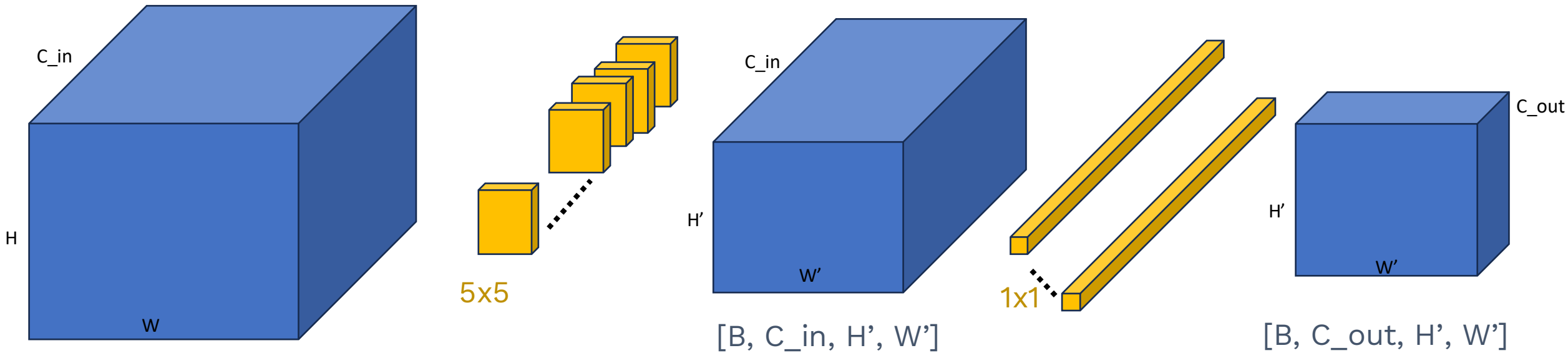
g x C_out/g x C_in/g x K x K

[B, C_out, H', W']

# Depthwise Separable Convolutions

Step 1 (spatial mixing): one filter per input channel (groups = in_channels)

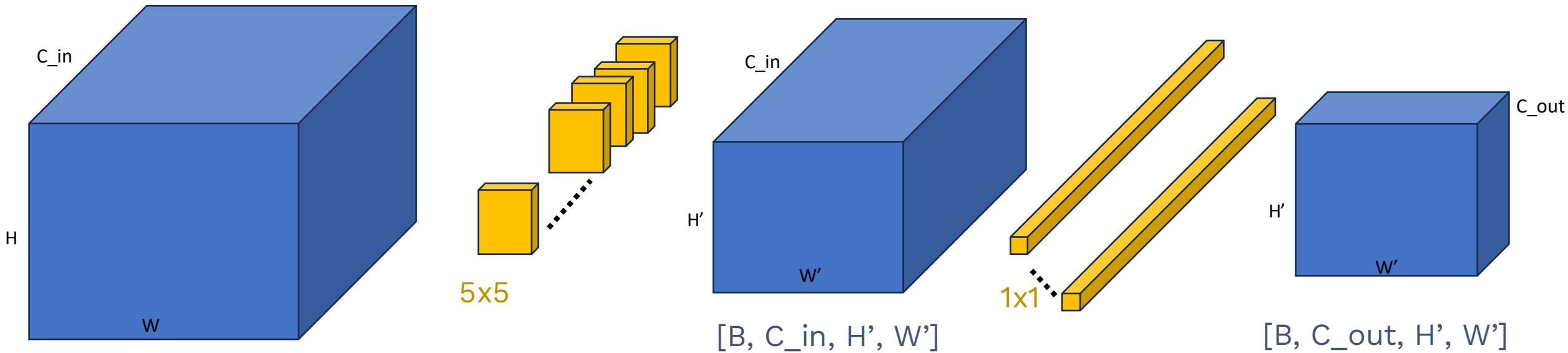
Step 2 (channel mixing): 1x1 convolutions to mix channels



# Depthwise Separable Convolutions

C_in x C_out x K x K -> C_in x K x K + C_out x C_in

C_in = 224, C_out=112, K=5: 627,000 -> 8,288 (75X less params!)



# ResNet architecture

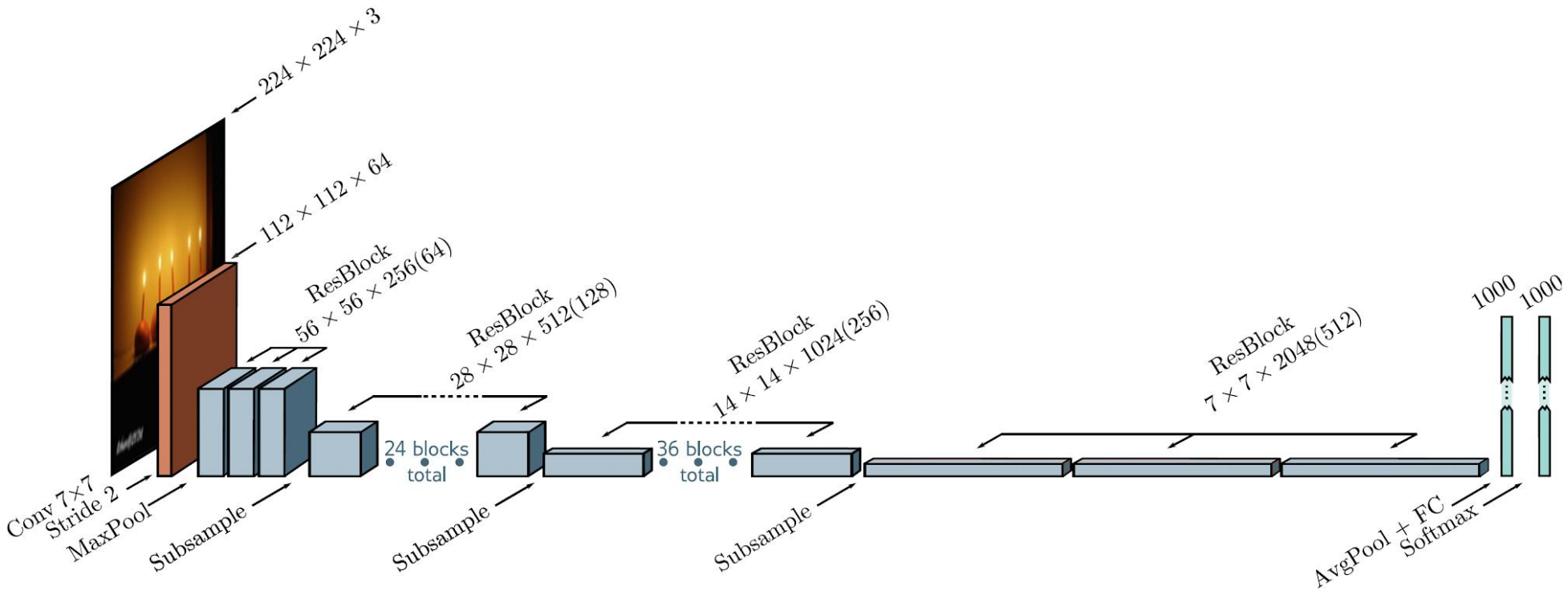
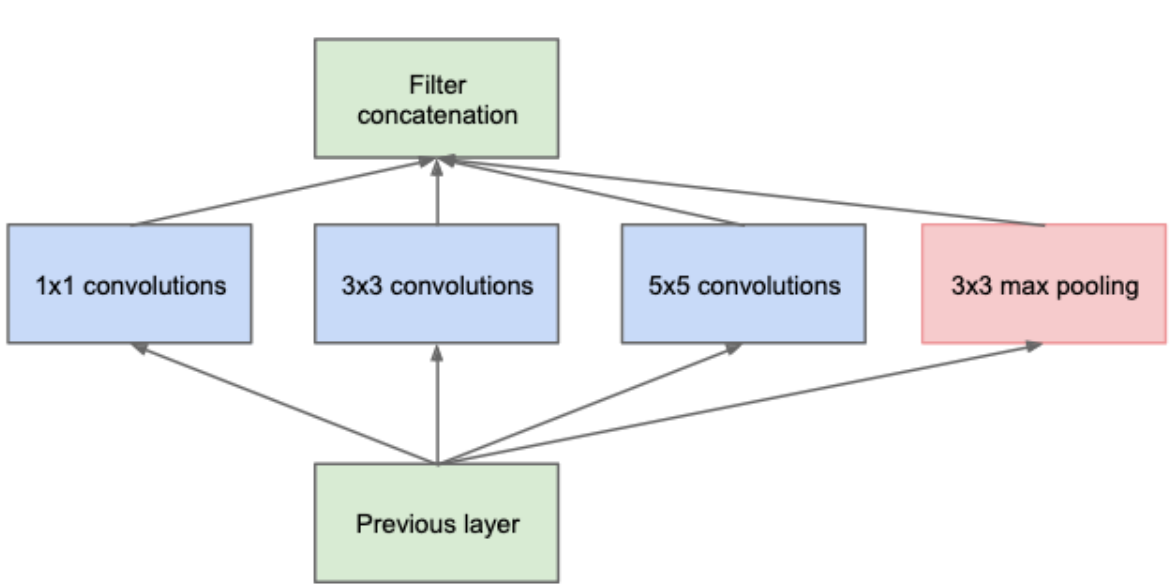


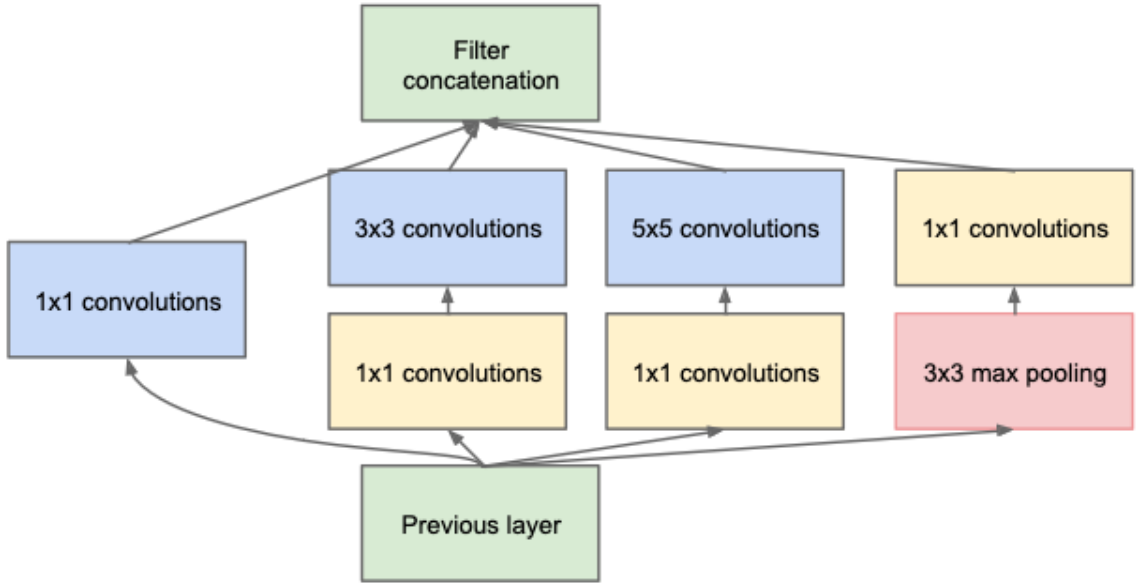

**Figure 11.8** ResNet-200 model. A standard 7×7 convolutional layer with stride two is applied, followed by a MaxPool operation. A series of bottleneck residual blocks follow (number in brackets is channels after first 1×1 convolution), with periodic downsampling and accompanying increases in the number 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

# The Inception architecture




(a) Inception module, naïve version

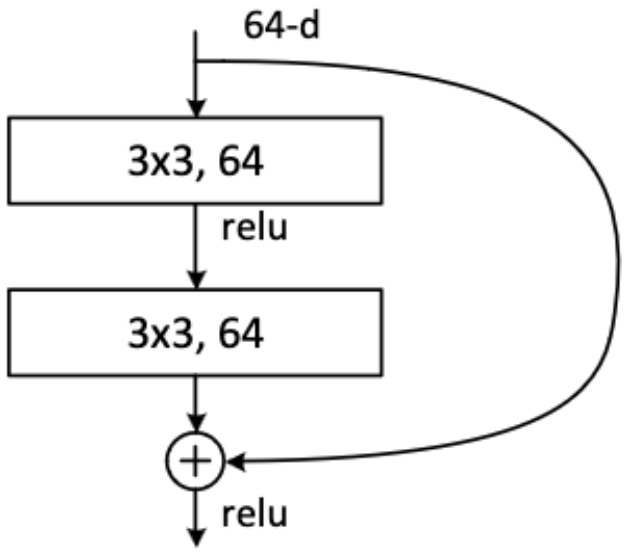



(b) Inception module with dimension reductions

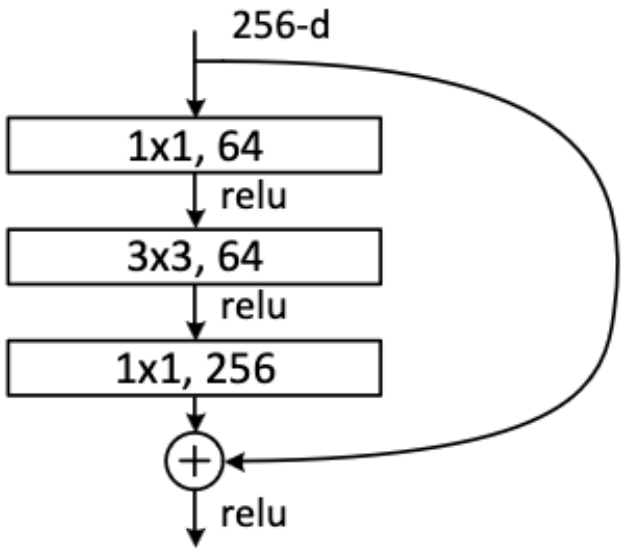
Figure 2: Inception module

Going deeper with convolutions, 2014

# The ResNet architecture




Naïve block



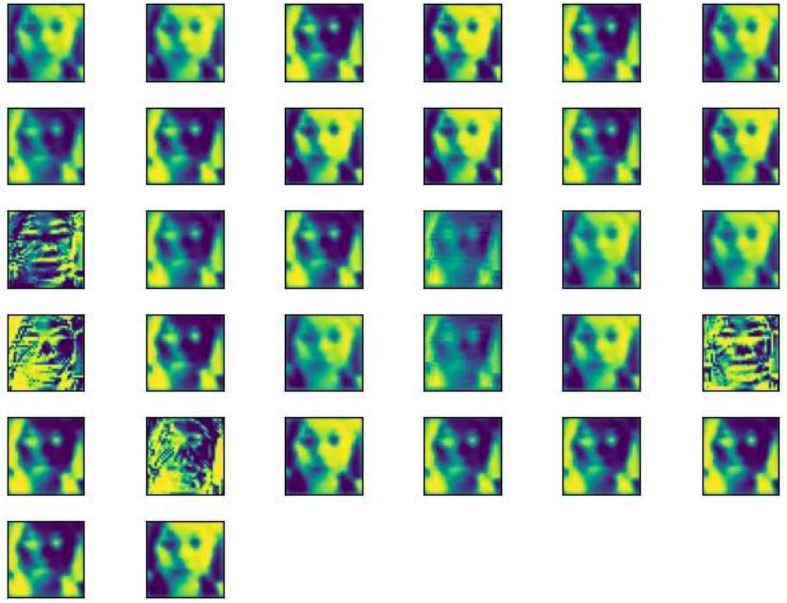

Bottleneck block

Deep Residual Learning for Image Recognition, 2015

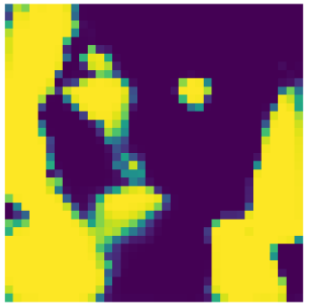
# The 1x1 convolution trick: do we maintain information?

Task: skin detector

Source image



Activation maps in 32D



Activation maps with 1D pooling

Source: 1x1 convolutions demystified, Anwesh Marwade, 2021

# 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

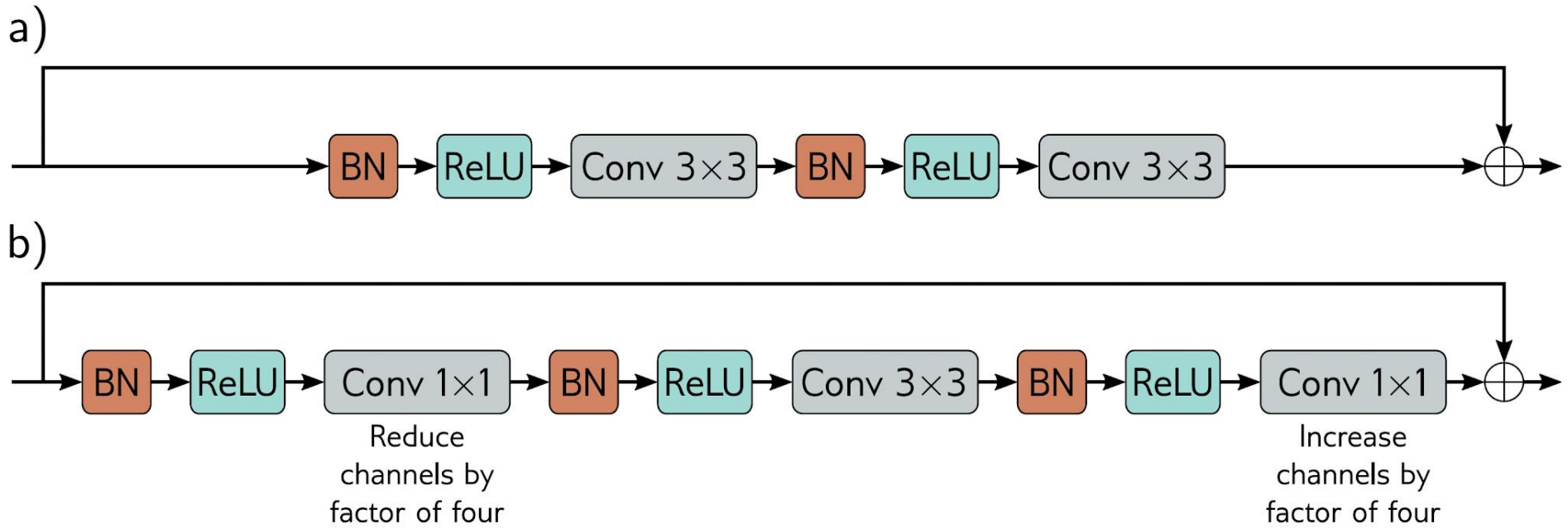
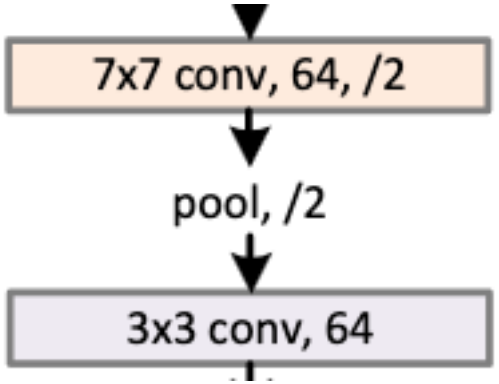



**Figure 11.7** ResNet blocks. a) A standard block in the ResNet architecture contains a batch normalization operation, followed by an activation function, and a 3×3 convolutional layer. Then, this sequence is repeated. b). A bottleneck ResNet block still integrates information over a 3×3 region but 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

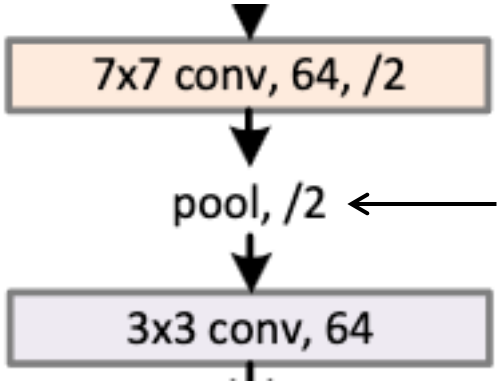
# The ResNet blocks




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

Deep Residual Learning for Image Recognition, 2015

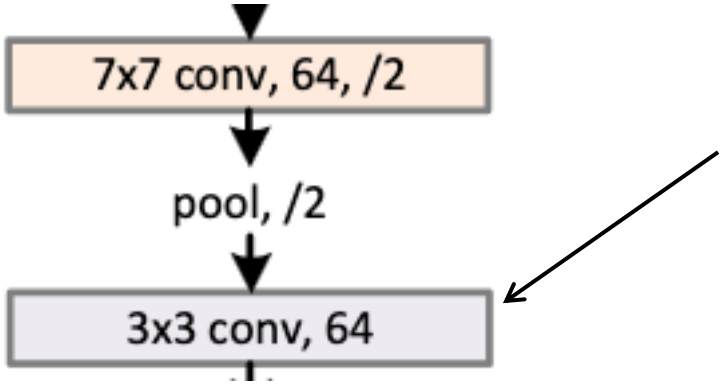
# The ResNet blocks




```
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()
```

Deep Residual Learning for Image Recognition, 2015

# 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()])
```

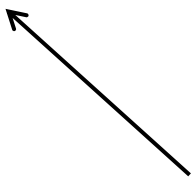
```
3052
```

# 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!

# Tips

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

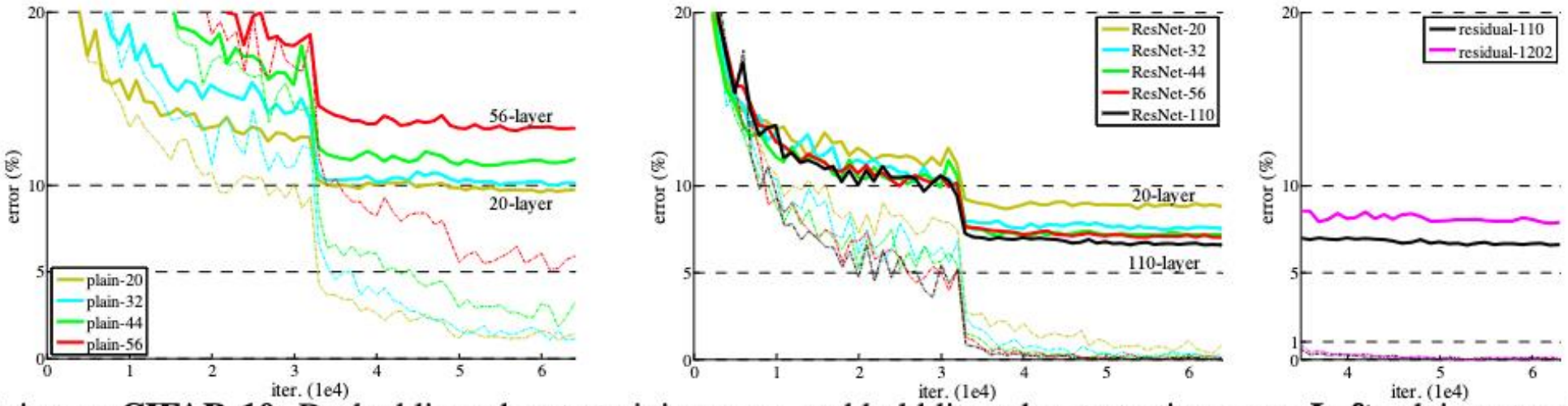



Figure 6. Training on **CIFAR-10**. Dashed lines denote training error, and bold lines denote testing error. **Left**: plain networks. The error of plain-110 is higher than 60% and not displayed. **Middle**: ResNets. **Right**: ResNets with 110 and 1202 layers.

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

# The timeline of vision models

2013 – Network in network (Lin et al.) introduced 1x1 convs

2014 – Google LeNet/Inception 1x1 for channel reduction

2015 – ResNet: 1x1 bottlenecks

2016 – Xception: depthwise separable convolutions

2017 – MobileNet: depthwise for mobile/efficient models

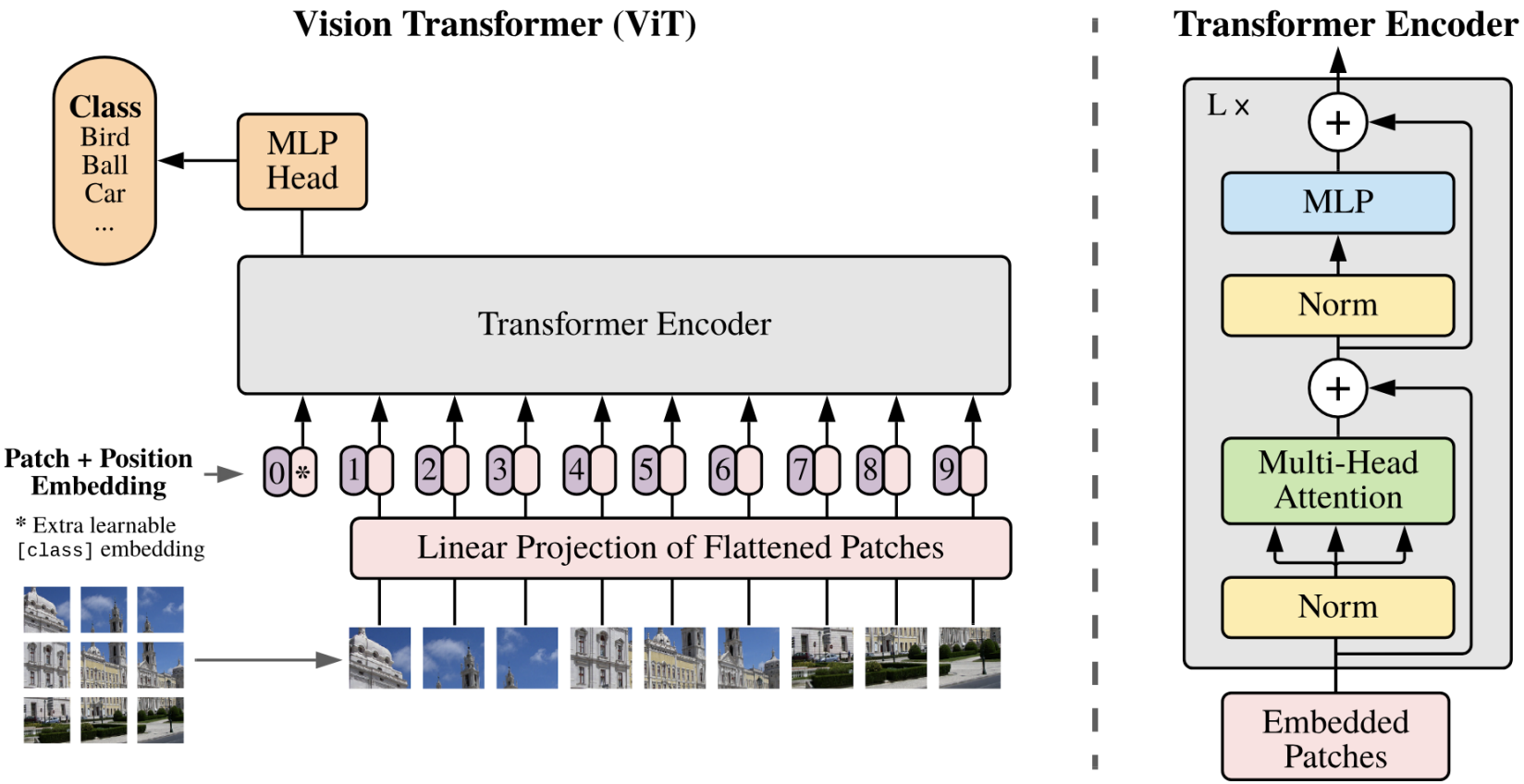
2019 – EfficientNet

2020 – Vision Transformer (ViT): attention > convolutions?

2022 – ConvNext (convs are not dead!)

Today – the gap has closed. Choice depends on the task.

# Vision Transformers

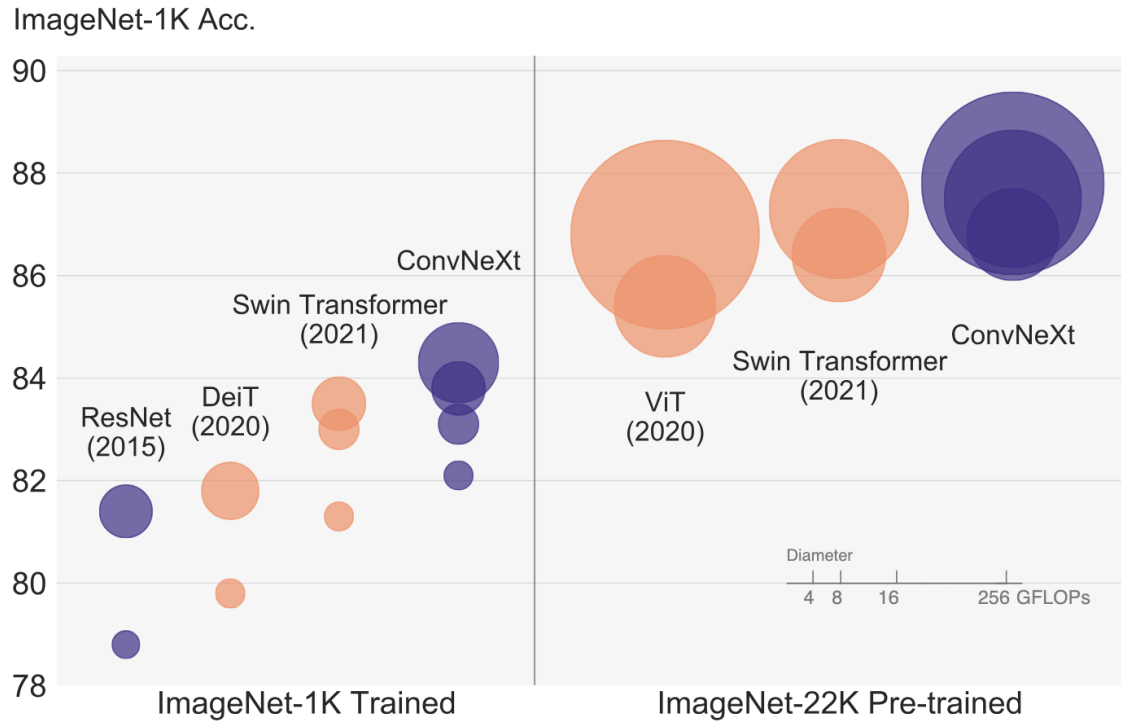



[1] An image is worth 16x16 words: Transformers for Image Recognition at Scale, ICLR 2021, arxiv

# Convnext

Borrow ideas from ViT and bring them back to convnets:

- Larger kernel sizes (bigger attention span)
- Reversed bottlenecks (small -> big -> small)
- LayerNorm vs BatchNorm




[1] A Convnext for the 2020s, CVPR 2022, arxiv

# DenseNet

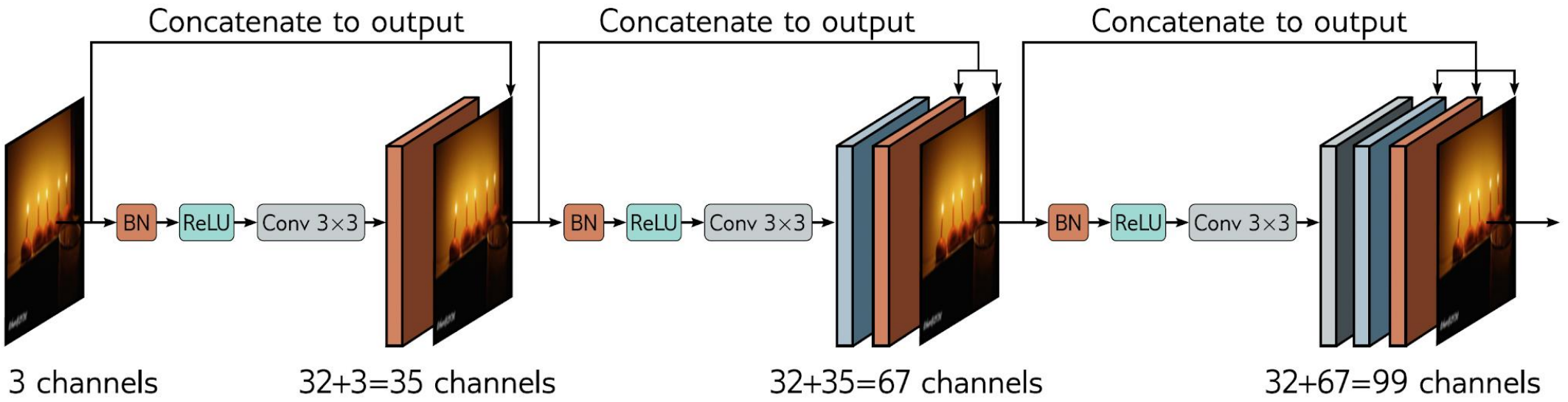



**Figure 11.9** DenseNet. This architecture uses residual connections to concatenate the outputs of earlier layers to later ones. Here, the three-channel input image is processed to form a 32-channel representation. The input image is concatenated to this to give a total of 35 channels. This combined 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

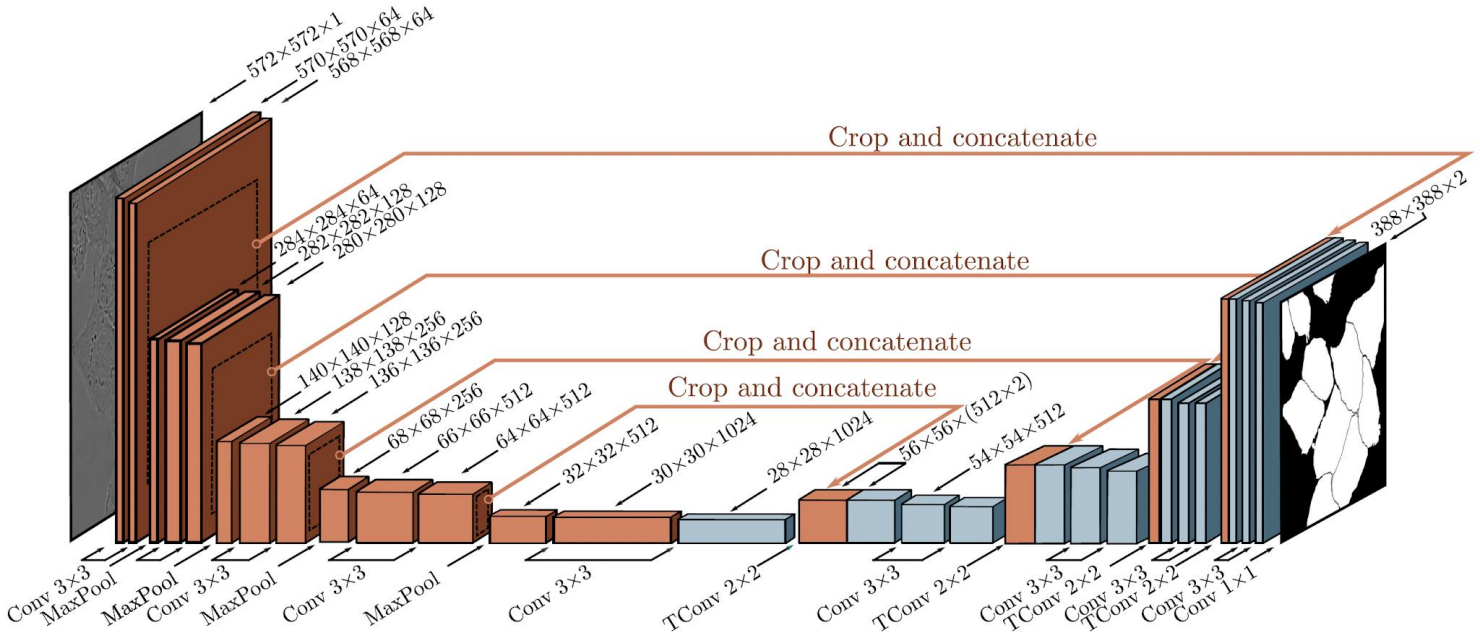



**Figure 11.10** U-Net for segmenting HeLa cells. The U-Net has an encoder-decoder structure, in which the representation is downsampled (orange blocks) and then re-upsampled (blue blocks). The encoder uses regular convolutions, and the decoder uses transposed convolutions. Residual connections append 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).

Source: Understanding Deep Learning, S. Prince, 2023

# U-Net for segmentation

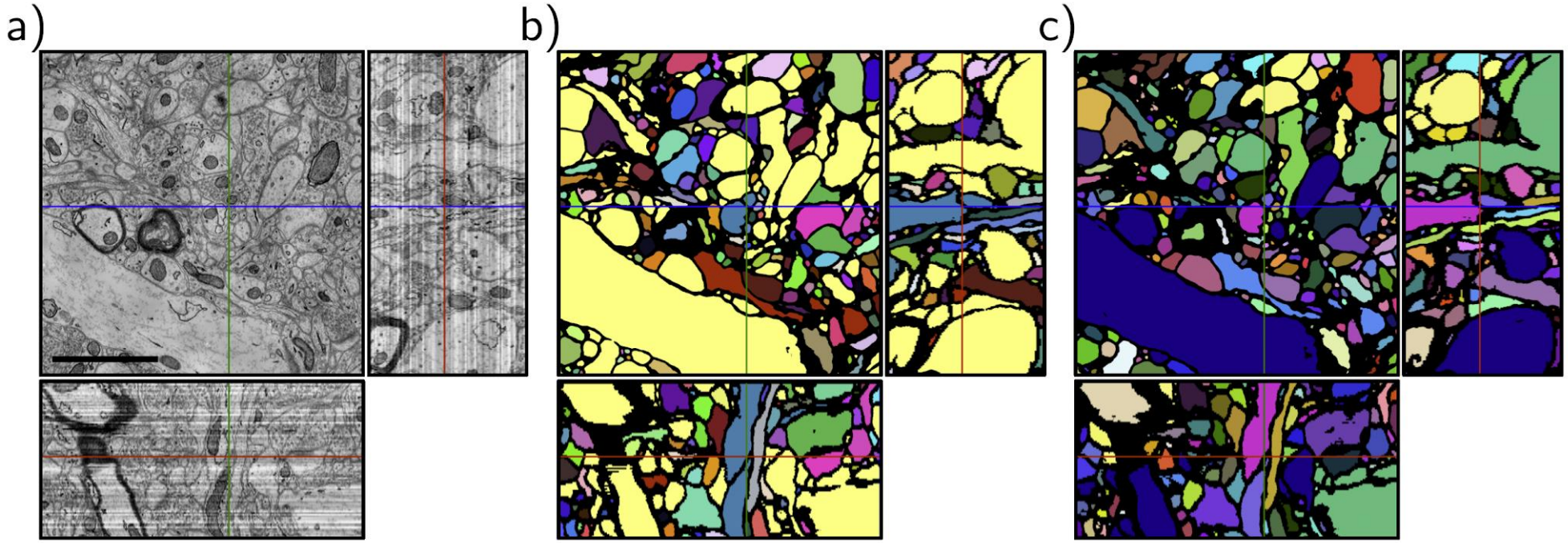



**Figure 11.11** Segmentation using U-Net in 3D. a) Three slices through a 3D volume of mouse cortex taken by scanning electron microscope. b) A single U-Net is used to classify voxels as being inside or outside neurites. Connected regions are identified with different colors. c) For a better result, 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).

Source: Understanding Deep Learning, S. Prince, 2023

# U-Net for pose estimation

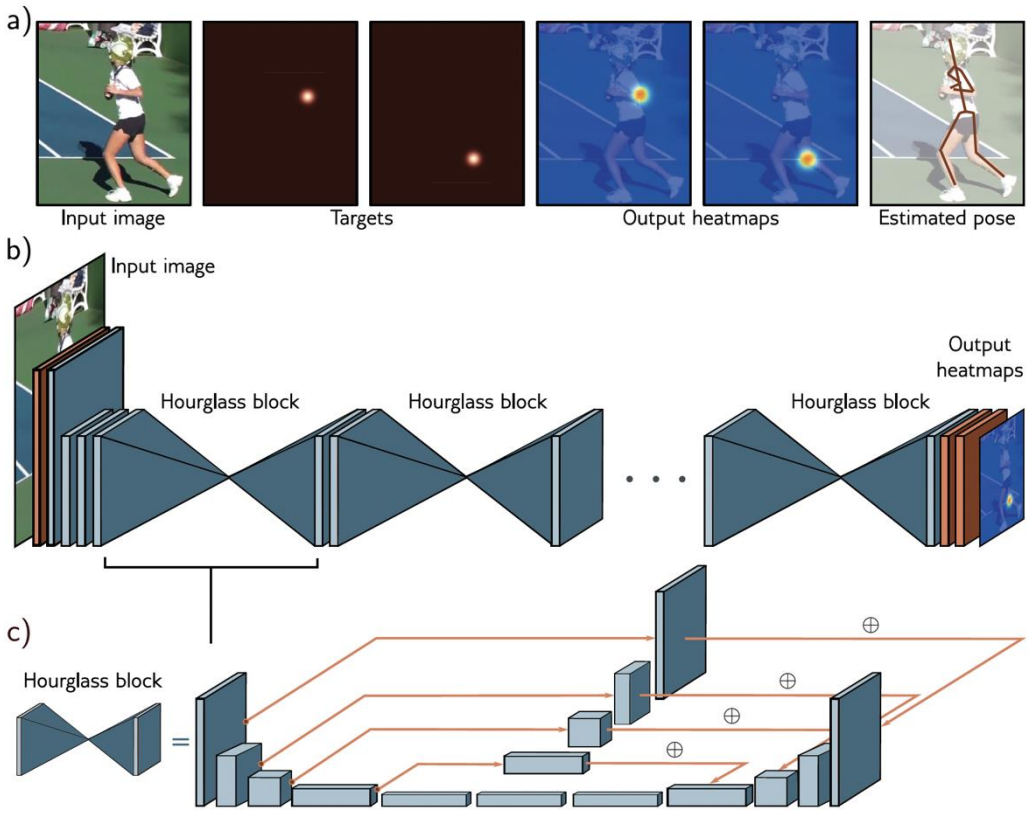



**Figure 11.12** Stacked hourglass networks for pose estimation. a) The network input is an image containing a person, and the output is a set of heatmaps, with one heatmap for each joint. This is formulated as a regression problem where the targets are heatmap images with small, highlighted regions 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

Convolutions offer strong inductive bias for computer vision tasks.

Convnets are very expensive from a compute/memory perspective

Lots of architecture evolutions over the past decade.

More depth does not mean better performance unless better architecture.