

# Introduction to Deep Learning

## Chapter 4: CNN: Padding

**Bernd Bischl**

Department of Statistics – LMU Munich

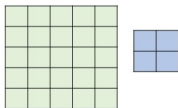
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# PADDING

- “Valid” convolution without padding.

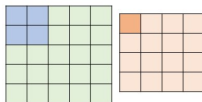
Exactly what we just did is called valid convolution. Suppose we have an input of size  $5 \times 5$  and a filter of size 2.



# PADDING

- “Valid” convolution without padding.

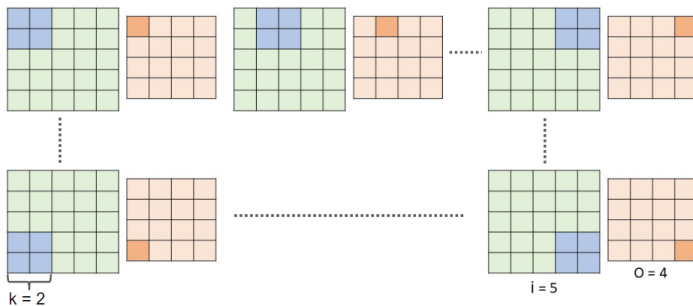
The filter is only allowed to move inside of the input space.



# PADDING

- “Valid” convolution without padding.

That will inevitably reduce the output dimensions.



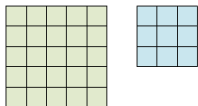
In general, for an input of size  $i (\times i)$  and filter size  $k (\times k)$ , the size of the output feature map  $o (\times o)$  calculated by:

$$o = i - k + 1$$

# PADDING

- Convolution with “same” padding.

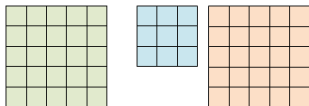
Suppose the following situation: an input with dimensions 5x5 and a filter with size 3.



# PADDING

- Convolution with “same” padding.

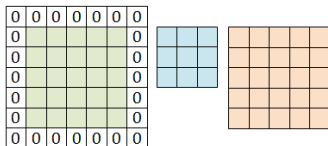
We would like to obtain an output with the same dimensions as the input.



# PADDING

- Convolution with “same” padding.

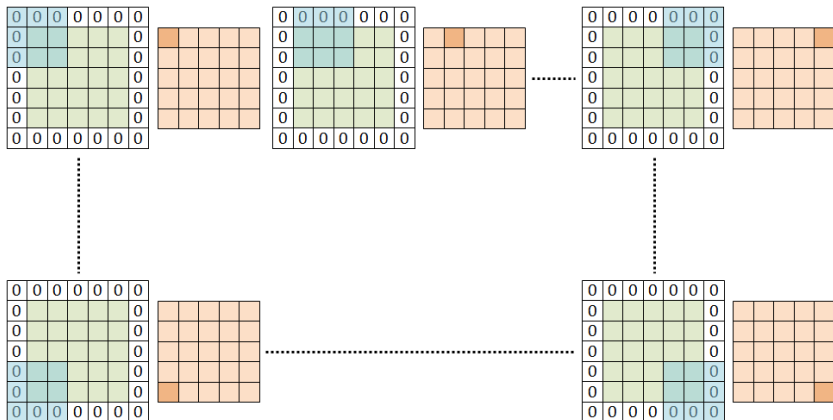
Hence, we apply a technique called zero padding. That is to say “pad” zeros around the input:



# PADDING

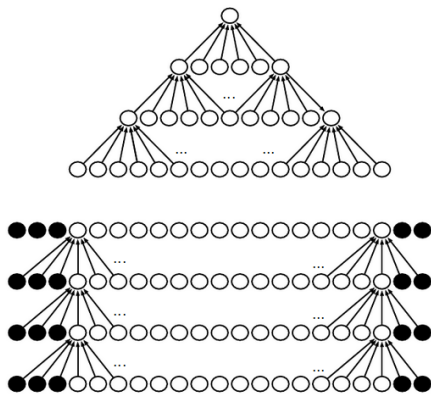
- Convolution with “same” padding.

That always works! We just have to adjust the zeros according to the input dimensions and filter size (ie. one, two or more rows).





# PADDING AND NETWORK DEPTH



**Figure:** “Valid” versus “same” convolution. *Top* : Without padding, the width of the feature map shrinks rapidly to 1 after just three convolutional layers (filter width of 6 shown in each layer). This limits how deep the network can be made. *Bottom* : With zero padding (shown as solid circles), the feature map can remain the same size after each convolution which means the network can be made arbitrarily deep. (Goodfellow, *et al.*, 2016, ch. 9)