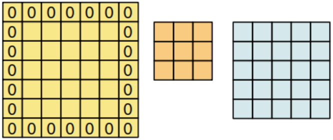
Deep Learning

CNN: Padding

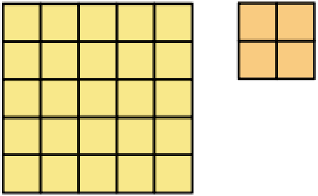


Learning goals

- Valid Padding
- Same Padding

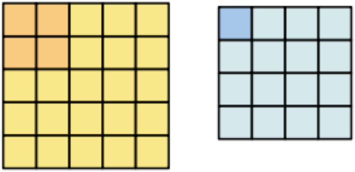
VALID PADDING

Suppose we have an input of size 5×5 and a filter of size 2×2.



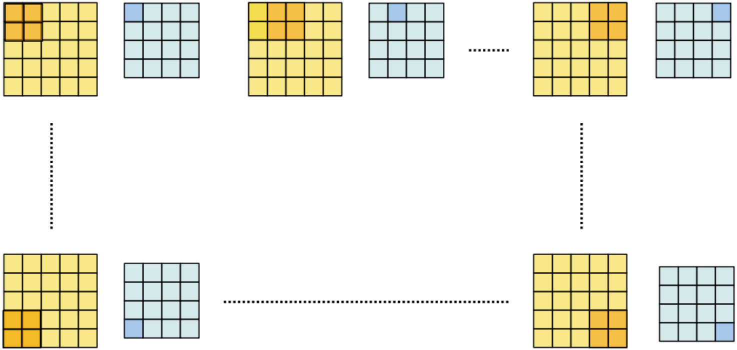
VALID PADDING

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



VALID PADDING

That will inevitably reduce the output dimensions.

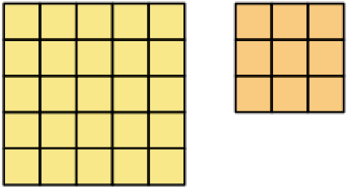


In general, for an input of size i ($\times$ i) and filter size k ($\times$ k), the size of the output feature map o ($\times$ o) claculated by:

$$o = i - k + 1$$

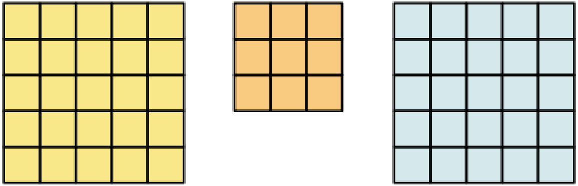
SAME PADDING

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



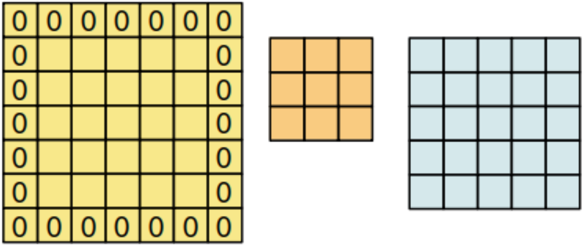
SAME PADDING

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



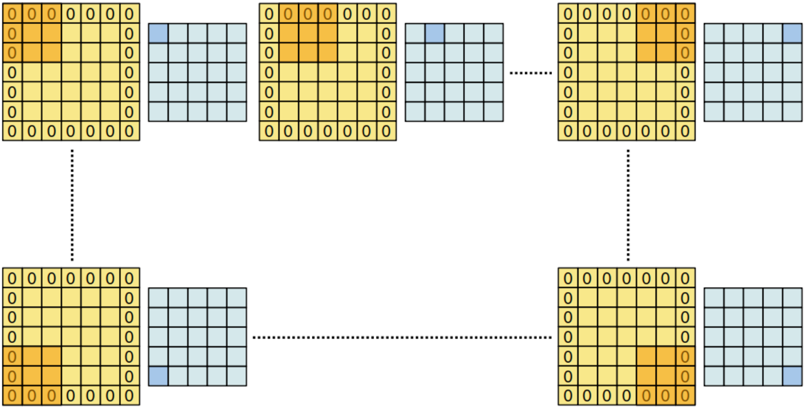
SAME PADDING

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



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

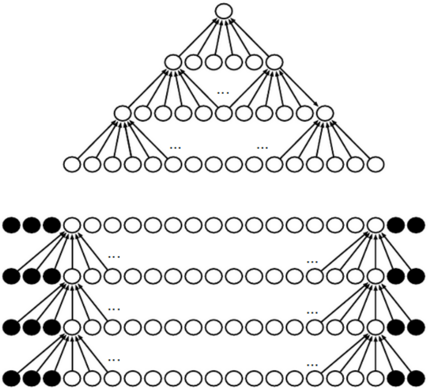


Figure: “Valid” versus “same” convolution. *Top* : Without padding, the width of the feature map shrinks rapidly to 1 after just three convolutional layers (filter width of 6 shown in each layer). This limits how deep the network can be made. Bottom : With zero padding (shown as solid circles), the feature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