Lecture #8

"ConvNet" architecture originally proposed for images

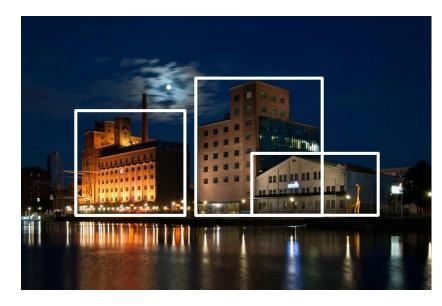
"ConvNet" architecture originally proposed for images

The assumption was that spatially local information is very important in images



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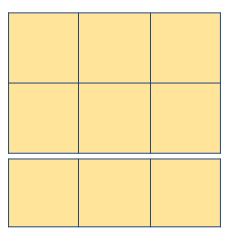
Objects are "groups" of pixels that are nearby

ConvNet's propose the concept of a *filter* (also known as a *kernel*) - which acts like a **feature detector**

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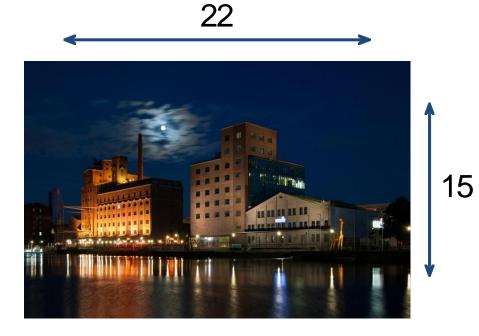
It does the same job as a *neuron* in the networks we've seen so far - each *filter* considers some aspect of the input and its outputs are a measure of how much the filter supports the particular aspect/feature

Filters are defined by some width and height, and are usually square



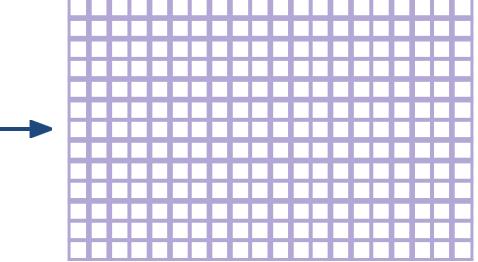
We slide a filter over the entire image, and therefore produce a corresponding second image from the activations of the filter

Let's look at a concrete example Consider an image of size 15x22 pixels

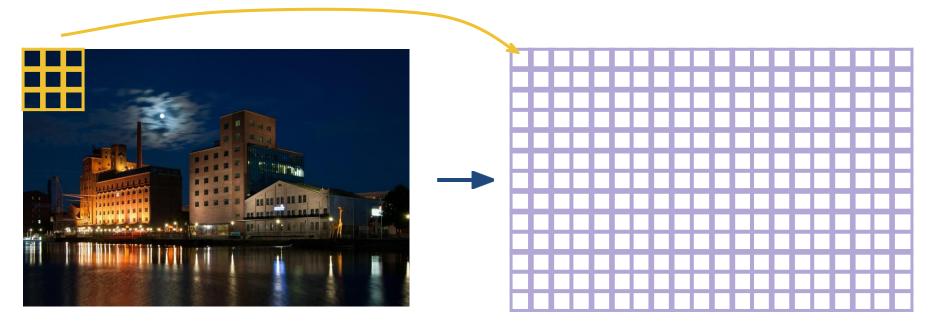


Consider a small 3x3 filter that has learned to detect buildings

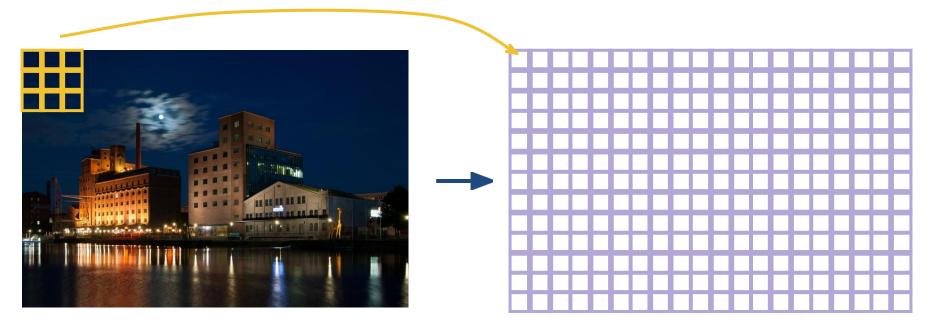




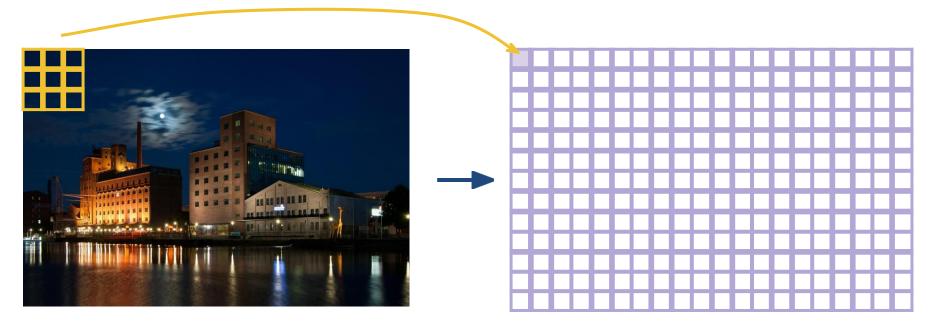
The filter will look at the 9 pixels underneath it, and output **one** value



This value can be considered as its "support" for the feature it is learning, in this case "buildings"



Since there is no building underneath the filter, it will output a low value in this case

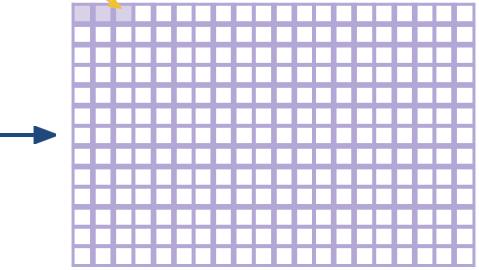


We then slide the window by a pixel to the right, and repeat the process



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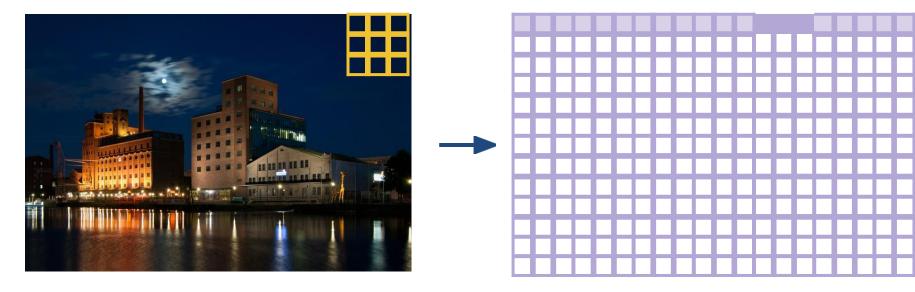
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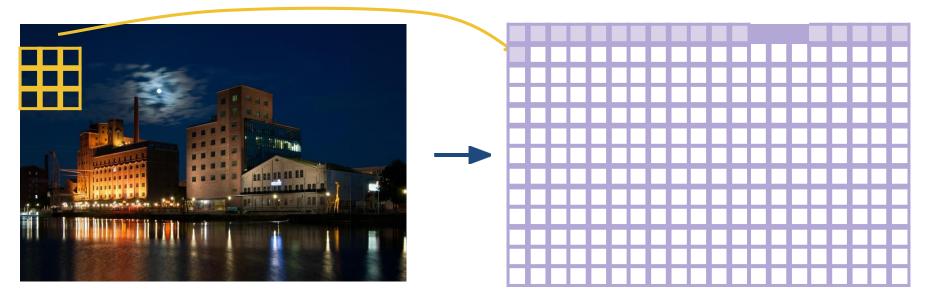
In this case, the filter finally sees some portion of some building, so its output will be slightly higher



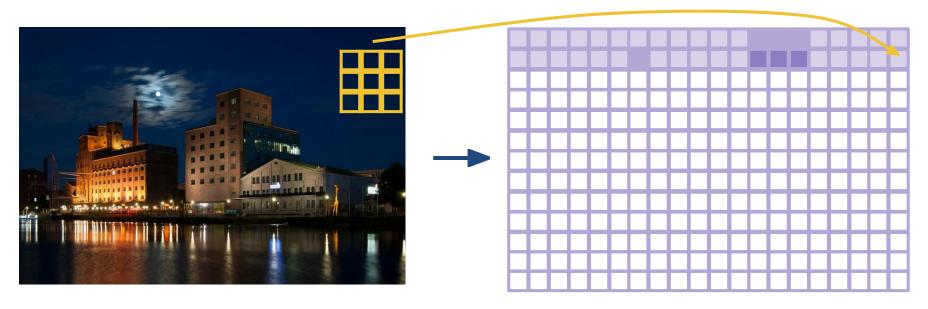
We repeat the process until we reach the end of the row



We shift **one pixel down** and repeat the entire process, filling in the second row of the "activation map"

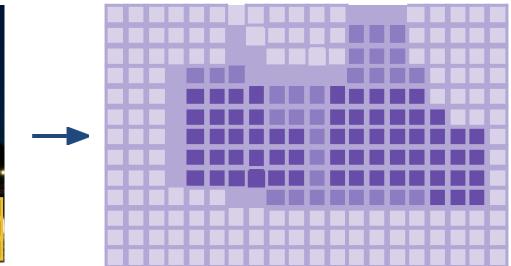


We continue until the end of the row

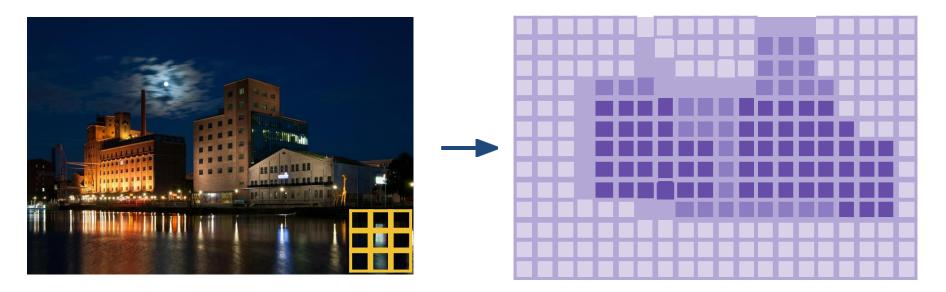


And repeat the entire process for the whole image

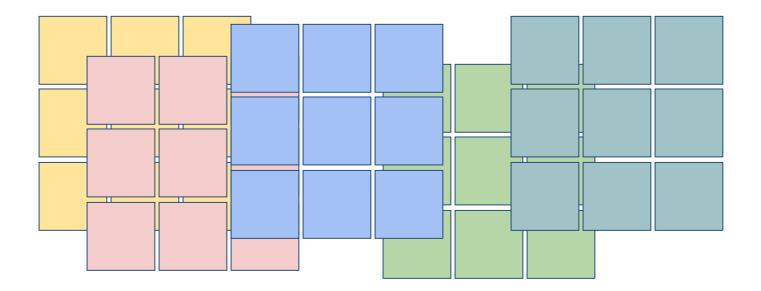




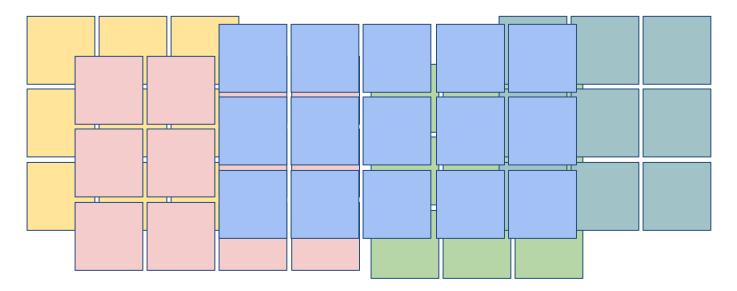
The higher layers can now use this activation map to create richer features based on "buildings information"



Usually, we have a lot of filters, so each of them can learn different features from the input image



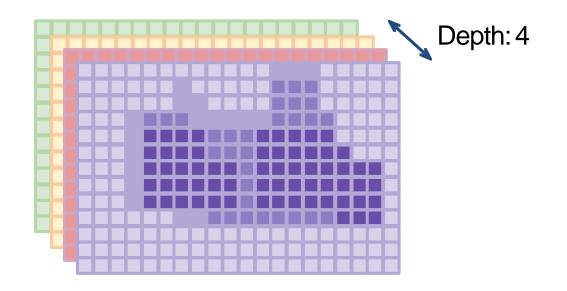
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Although not common in images, for text, we can also have filters of different sizes!

- Stride: The number of pixels to shift at each step
- **Depth:** The depth of a Conv layer is the number of filters in it If we have *N* filters, we will have *N* activation maps

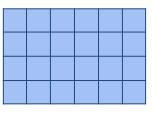
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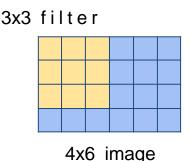
Some terminologies:

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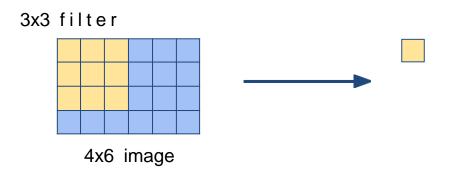


4x6 image

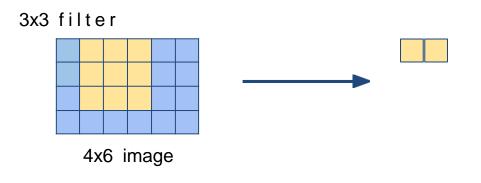
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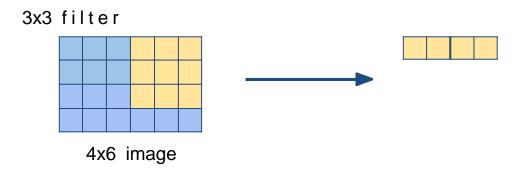
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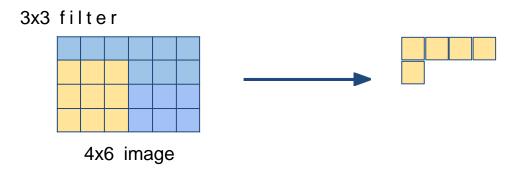
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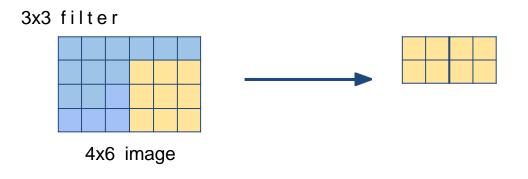
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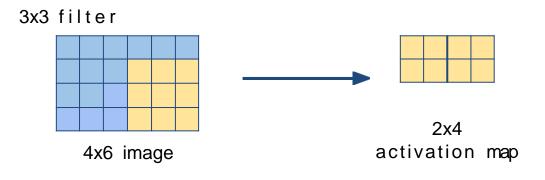
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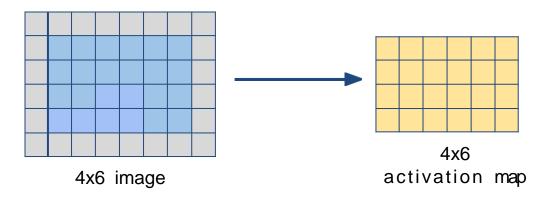
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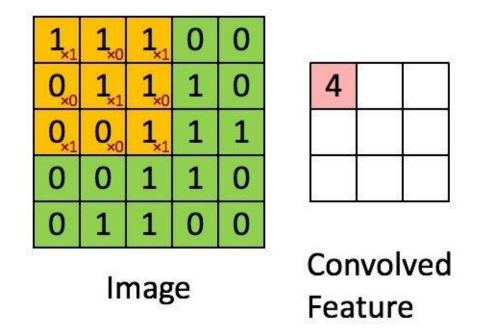
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- **Padding:** Each image is padded with "zero" pixels to maintain the image size in the map



• Example of an actual computation



http://deeplearning.stanford.edu/wiki/index.php/Feature_extraction_using_convolution

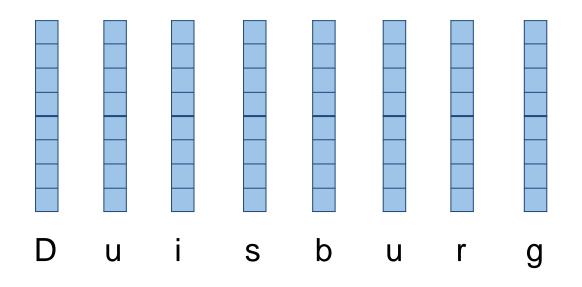
Convolutional layers in text are quitesimilar to the ones in images, but we work only in one dimension!

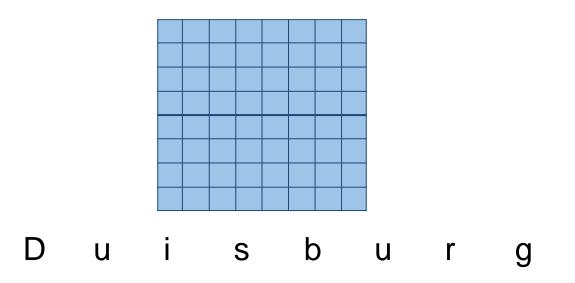


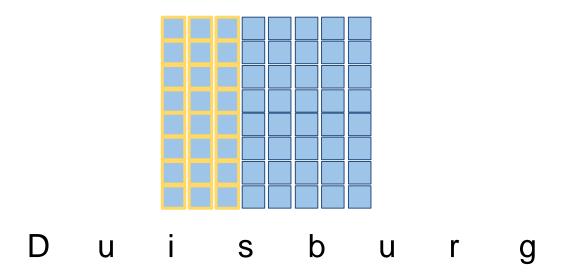
2 Dimensions

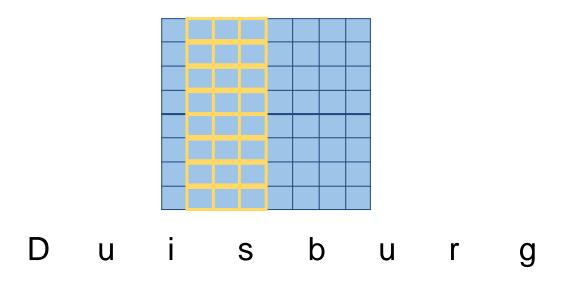
John is driving a car

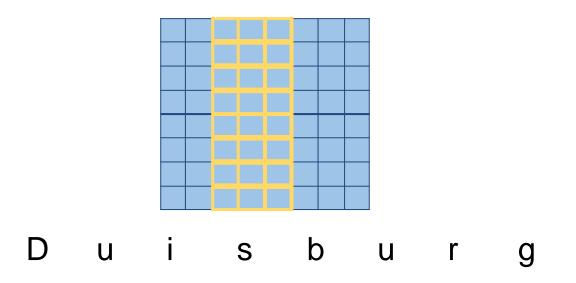
1 Dimension

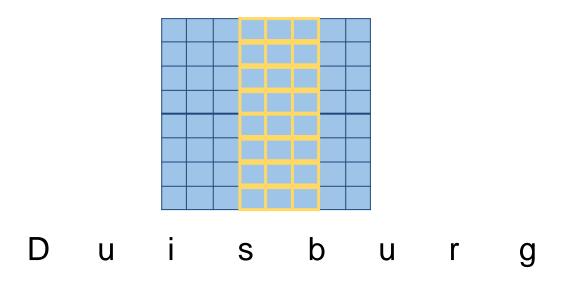


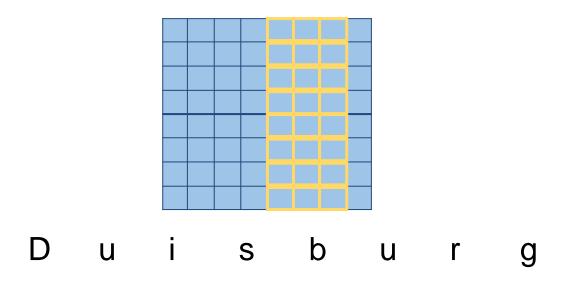


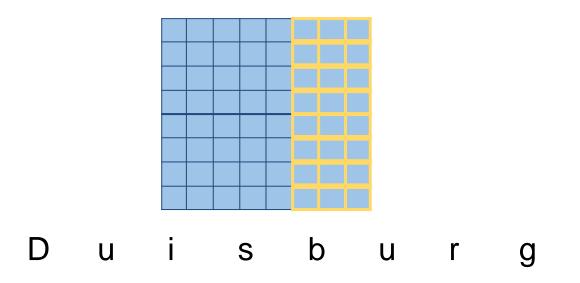




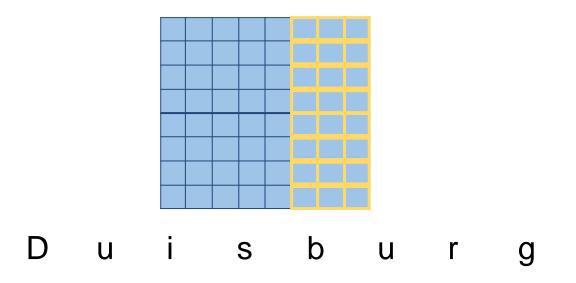




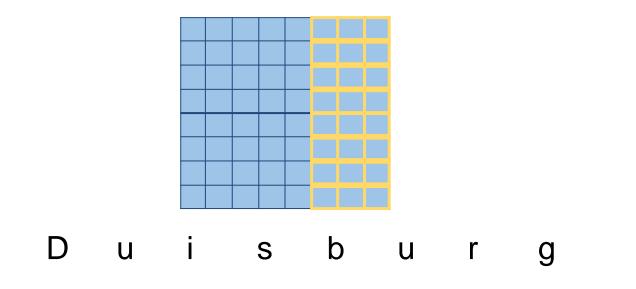




Filters are usually as tall as the embedding layer, and sliding is in one dimension only

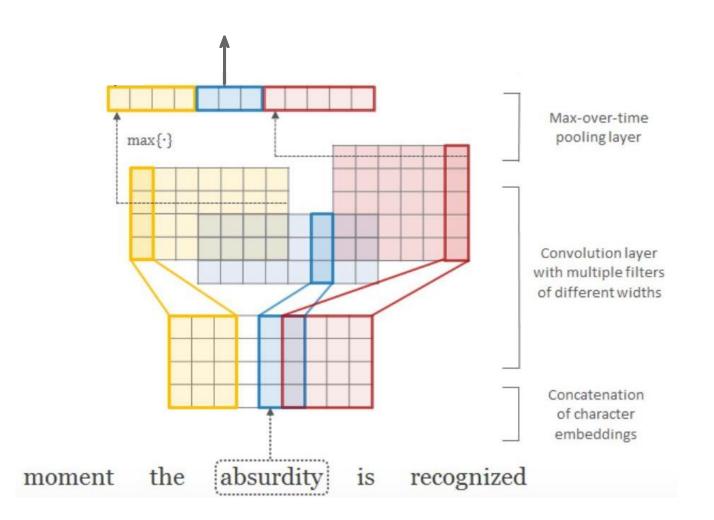


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The output in this case will be a6-vector

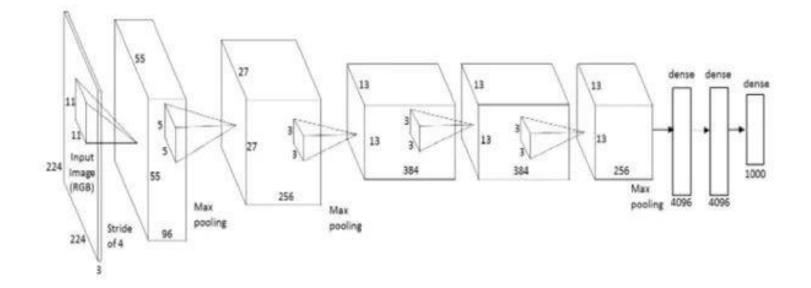
Character CNN



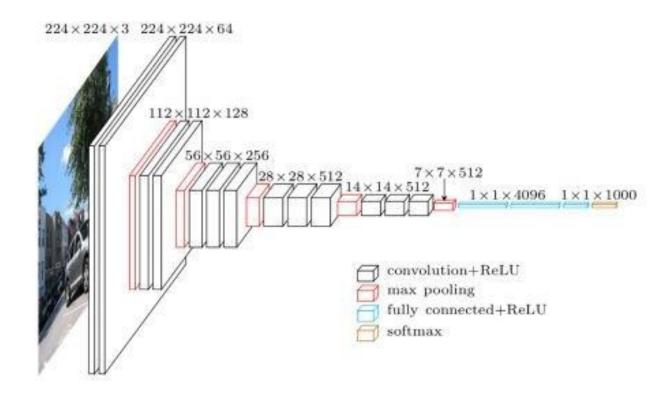
Kim, Jernite, Sontag, Rush, Character-Aware Neural Language Model, AAAI 2016

- ConvNets are quite popular in text at character level
- Used to build word embeddings for a larger network

Atleast in vision, some of the deepest architectures involve ConvNets



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