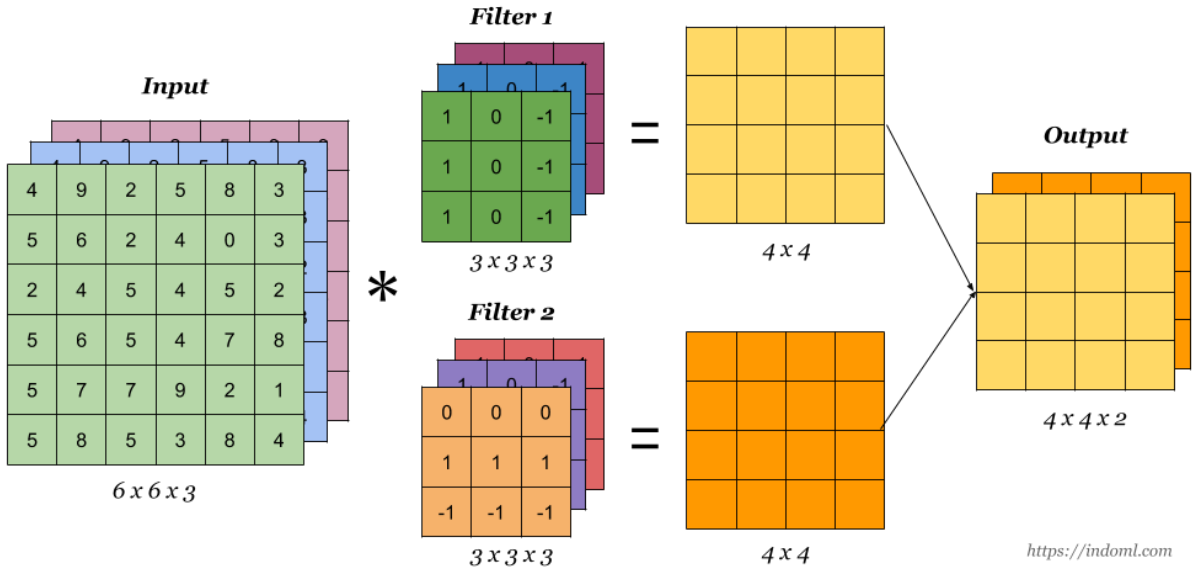
# Student Notes: Convolutional Neural Networks (CNN) Introduction




These notes are taken from the first two weeks of Convolutional Neural Networks course (part of Deep Learning specialization) by Andrew Ng on Coursera. The course is actually four weeks long, but I didn't take the note for the last two weeks which discuss about object localization/detection, face recognition, and neural style transfer.

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# Why Convolutions

- **Parameter sharing**: a feature detector (such as a vertical edge detector) that's useful in one part of the image is probably useful in another part of the image.
- **Sparsity of connections**: in each layer, each output value depends only on small number of inputs.

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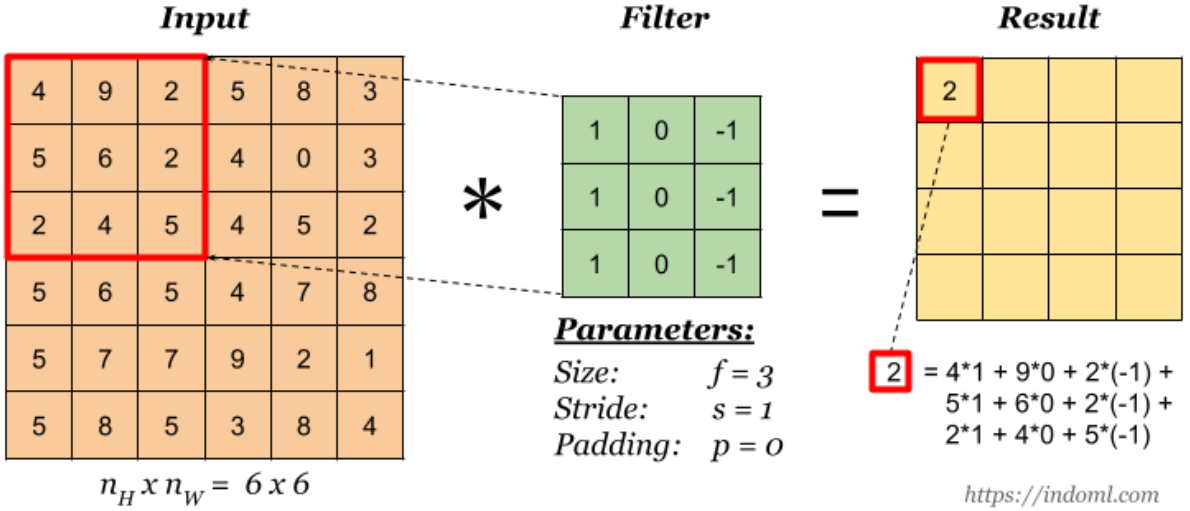
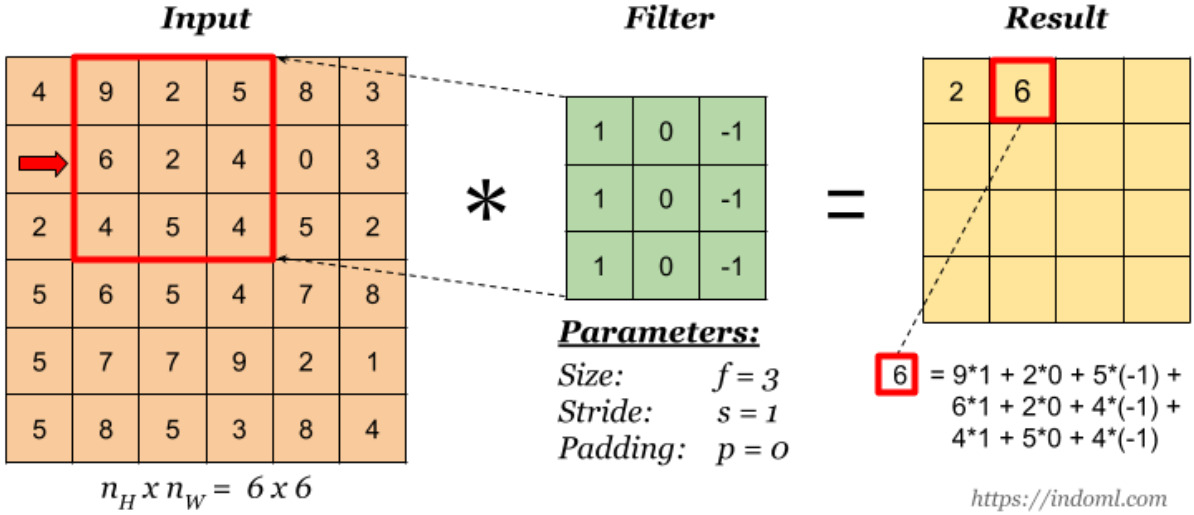
# Convolution Operation

## Basic Convolution Operation

**Step 1**: overlay the filter to the input, perform element wise multiplication, and add the result.



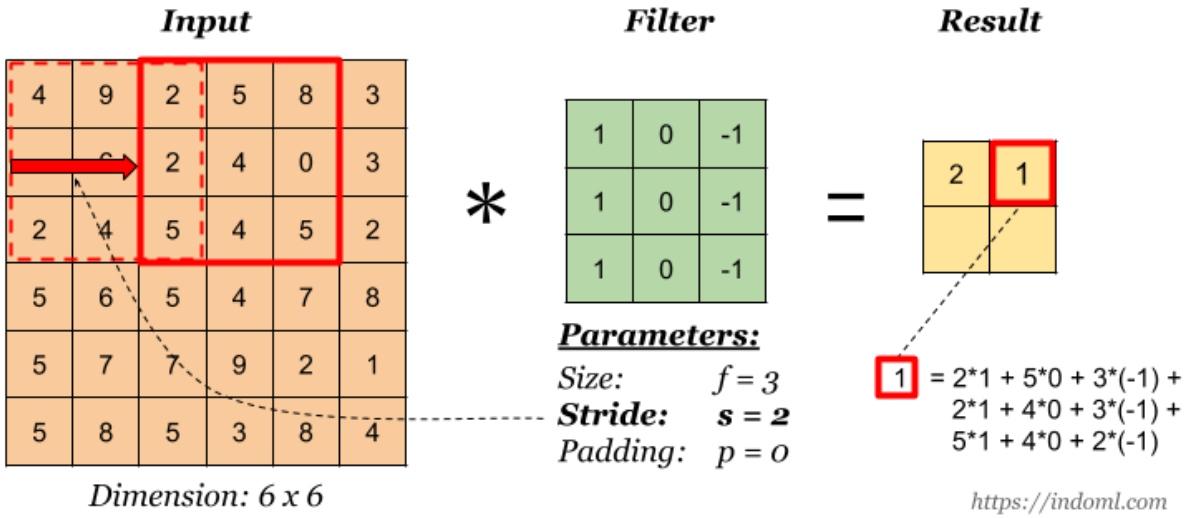

**Step 2**: move the overlay right one position (or according to the **stride** setting), and do the same calculation above to get the next result. And so on.



The total number of multiplications to calculate the result above is (4 x 4) x (3 x 3) = 144.

# Stride

Stride governs how many cells the filter is moved in the input to calculate the next cell in the result.




Filter with stride (s) = 2

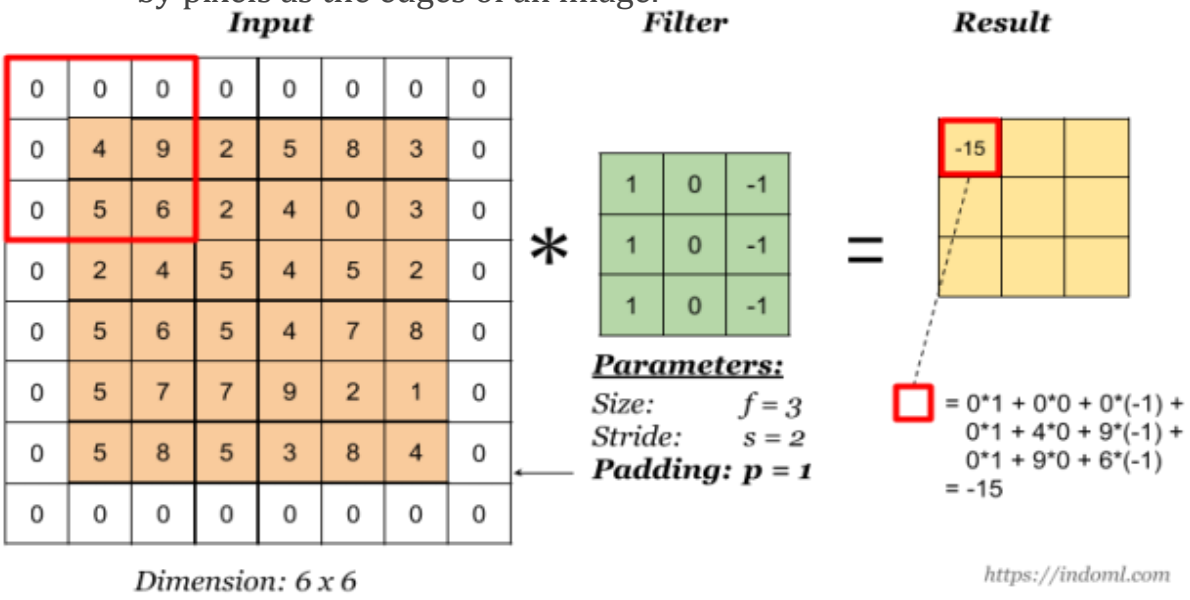
The total number of multiplications to calculate the result above is (2 x 2) x (3 x 3) = 36.

# Padding

Padding has the following benefits:

1. It allows us to use a CONV layer without necessarily shrinking the height and width of the volumes. This is important for building deeper networks, since otherwise the height/width would shrink as we go to deeper layers.

2. It helps us keep more of the information at the border of an image. Without padding, very few values at the next layer would be affected by pixels as the edges of an image.




Notice the the dimension of the result has changed due to padding. See the following section on how to calculate output dimension.

Some padding terminologies:

- "**valid**" padding: no padding
- "**same**" padding: padding so that the output dimension is the same as the input

# Calculating the Output Dimension

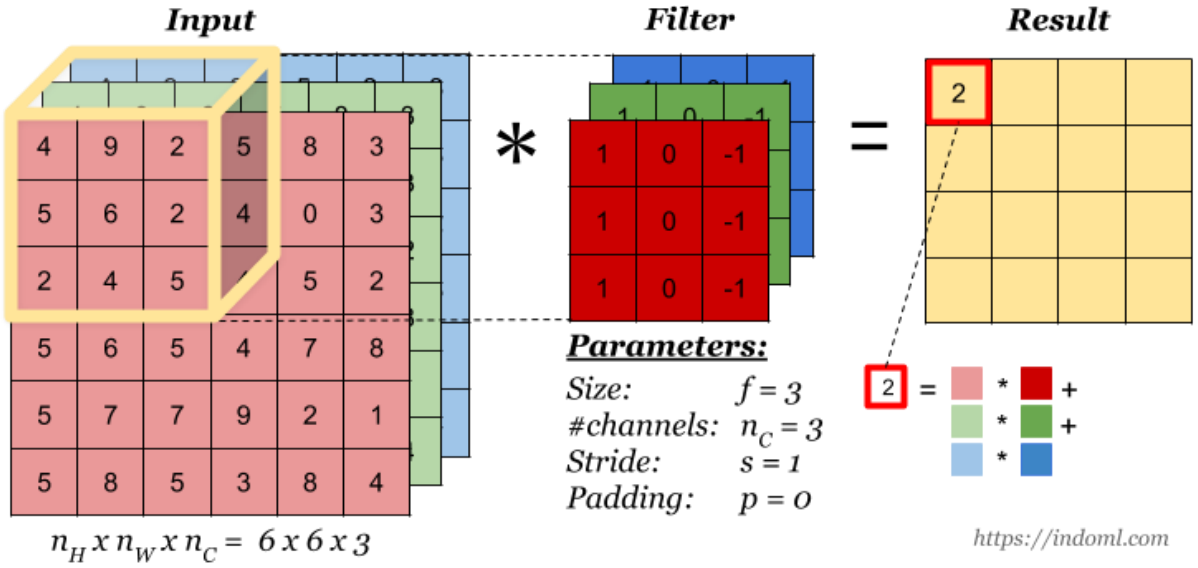
The output dimension is calculated with the following formula:

$$n^{[l]} = \lfloor \frac{n^{[l-1]} + 2p^{[l-1]} - f^{[l]}}{s^{[l]}} + 1 \rfloor$$

where the $\lfloor \rfloor$ symbols denote *math.floor()* operation.

# Convolution Operation on Volume

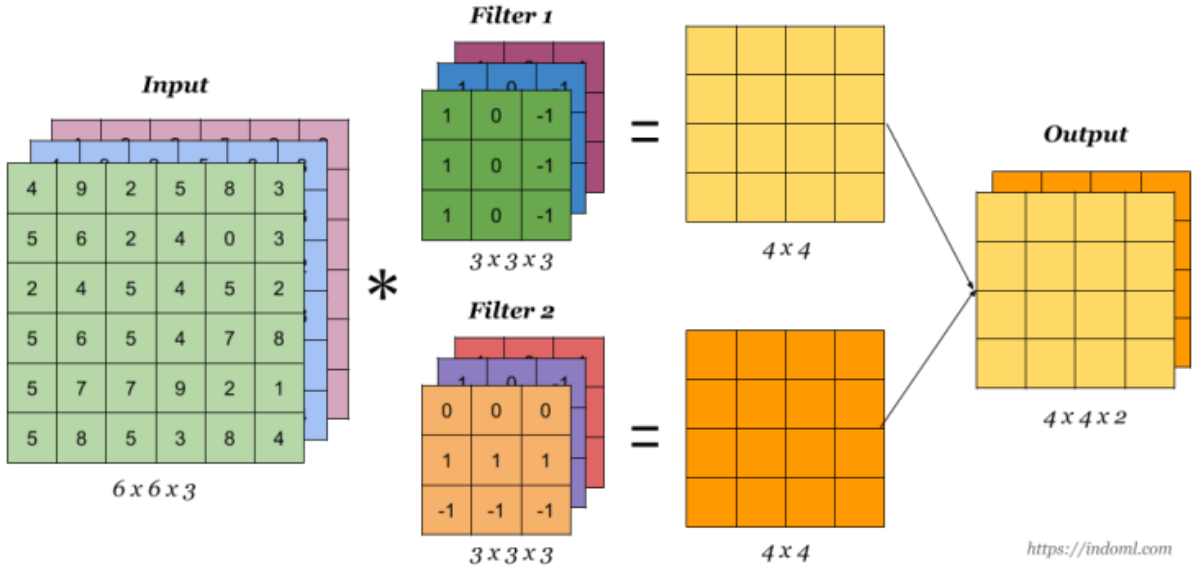
When the input has more than one channels (e.g. an RGB image), the filter should have matching number of channels. To calculate one output cell, perform convolution on each matching channel, then add the result together.




The total number of multiplications to calculate the result is (4 x 4) x (3 x 3 x 3) = 432.

# Convolution Operation with Multiple Filters

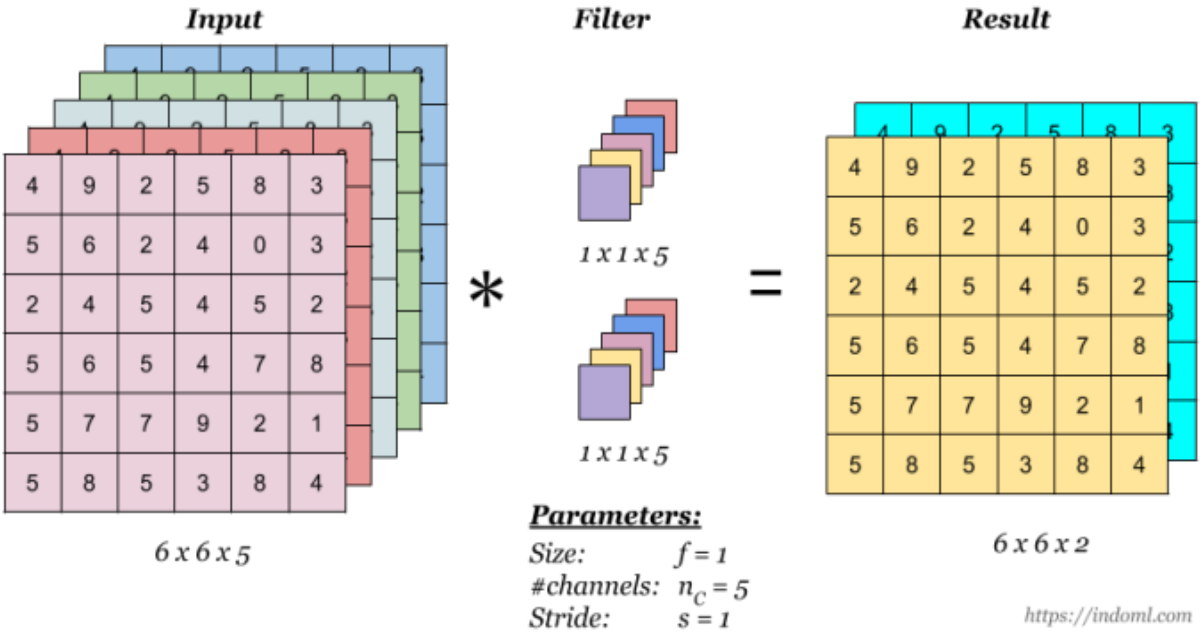
Multiple filters can be used in a convolution layer to detect multiple features. The output of the layer then will have the same number of channels as the number of filters in the layer.




The total number of multiplications to calculate the result is (4 x 4 x 2) x (3 x 3 x 3) = 864.

# 1 x 1 Convolution

This is convolution with 1 x 1 filter. The effect is to flatten or “merge” channels together, which can save computations later in the network:



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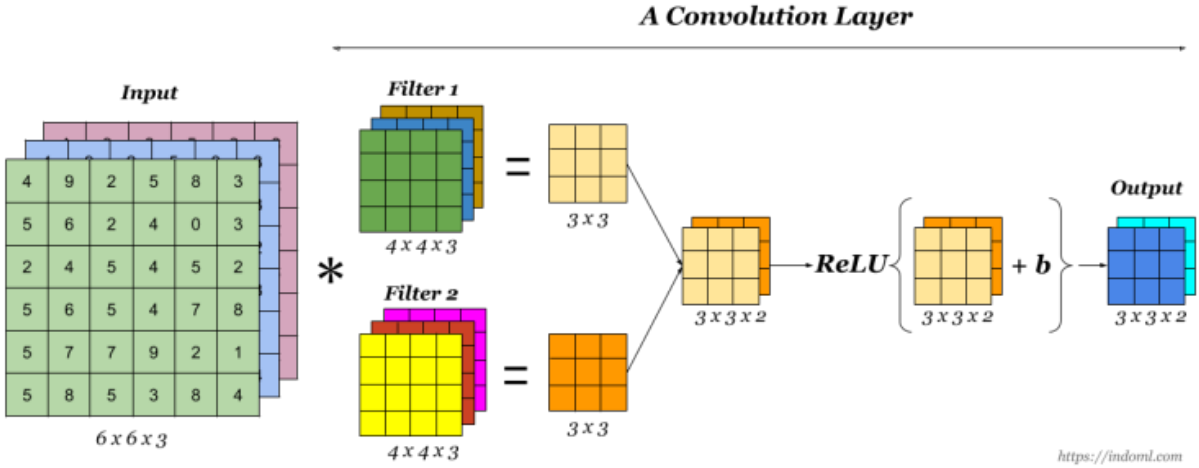
# One Convolution Layer

Finally to make up a convolution layer, a bias (ϵ R) is added and an activation function such as **ReLU** or **tanh** is applied.

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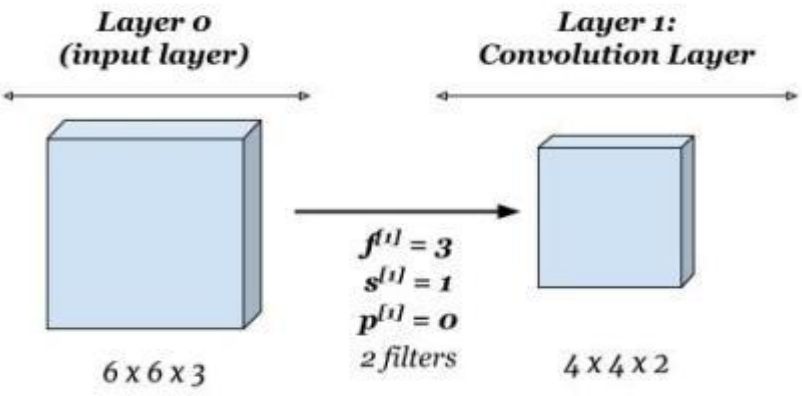
# Shorthand Representation

This simpler representation will be used from now on to represent one convolutional layer:



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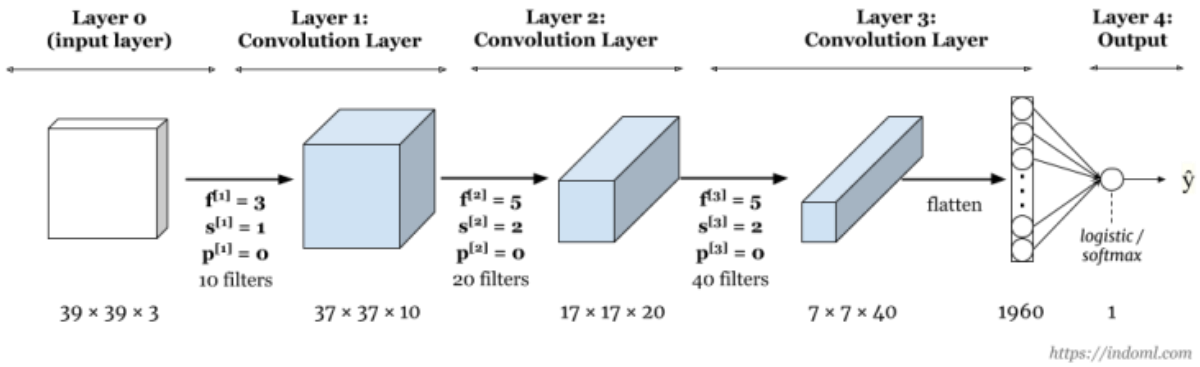
# Sample Complete Network

This is a sample network with three convolution layers. At the end of the network, the output of the convolution layer is flattened and is connected to a logistic regression or a softmax output layer.

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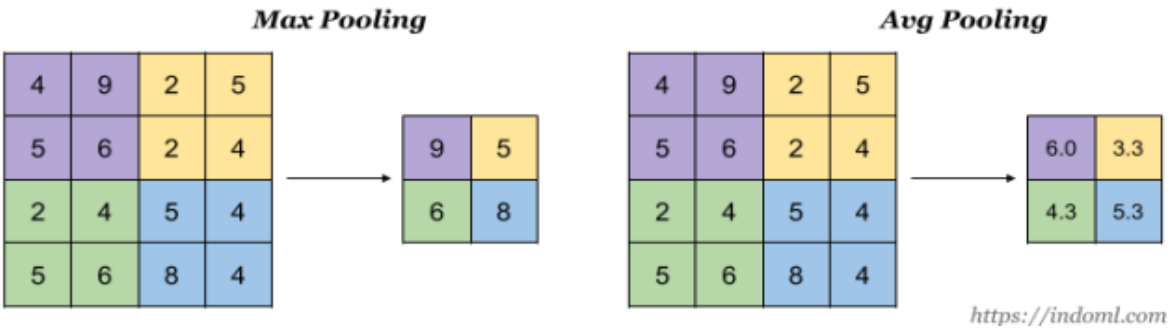
# Pooling Layer

Pooling layer is used to reduce the size of the representations and to speed up calculations, as well as to make some of the features it detects a bit more robust.

Sample types of pooling are **max pooling** and **avg pooling**, but these days max pooling is more common.




Interesting properties of pooling layer:

- it has hyper-parameters:
    - **size** (***f***)
    - **stride** (***s***)
    - **type** (max or avg)
- but it doesn't have parameter; there's nothing for gradient descent to learn

When done on input with multiple channels, pooling reduces the height and width (nW and nH) but keeps nC unchanged: