Fuzzy Set Theory in Computer Vision: **Example 3, Part II**

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Overview

- Resource; CS231n: Convolutional Neural Networks for Visual Recognition
  - https://github.com/tuanavu/Stanford-CS231/tree/master/lectures
- Resource; CNN tutorial
  - http://cs231n.github.io/convolutional-networks/

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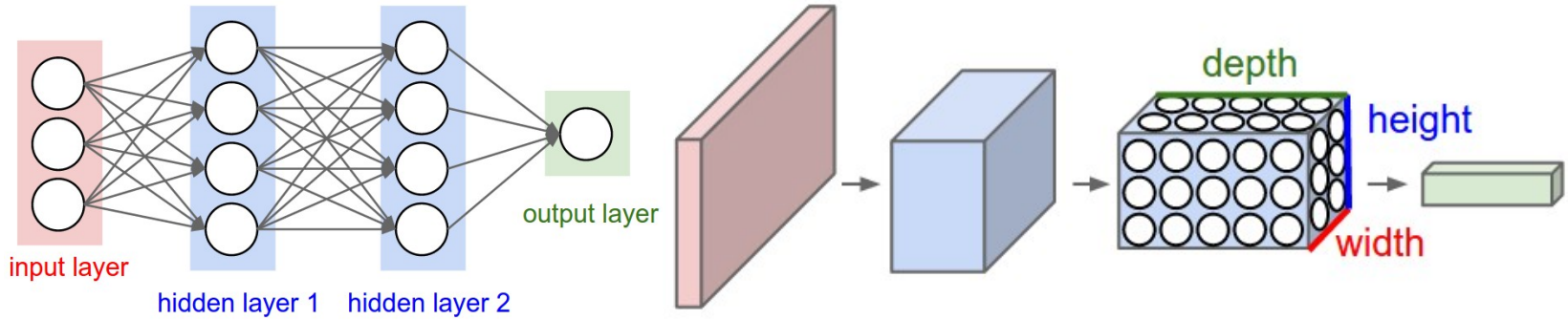
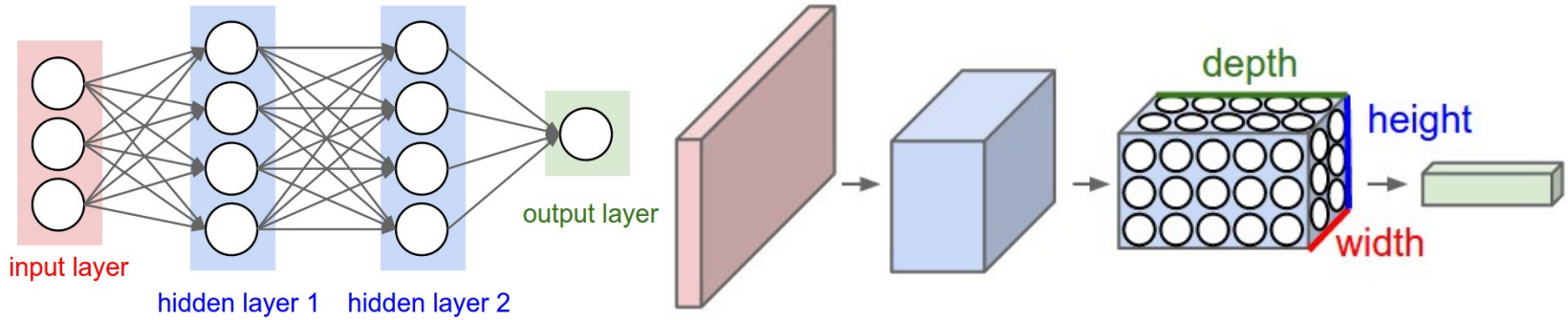
  - For example, on small data sets maybe you just retrain the classifier? However, for medium size data sets maybe you retrain a bigger portion of the network or maybe all of it.



CNN basics

- Neurons typically arranged in width, height and "depth"



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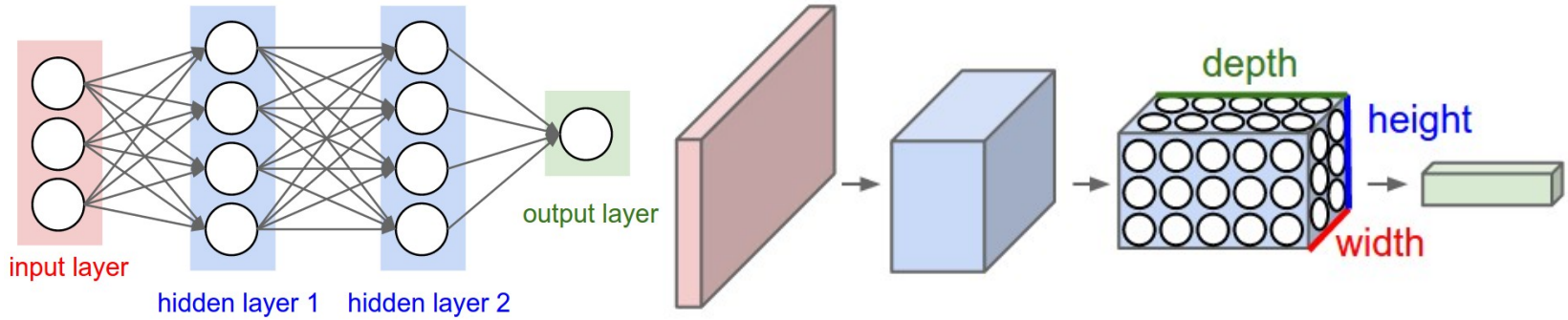

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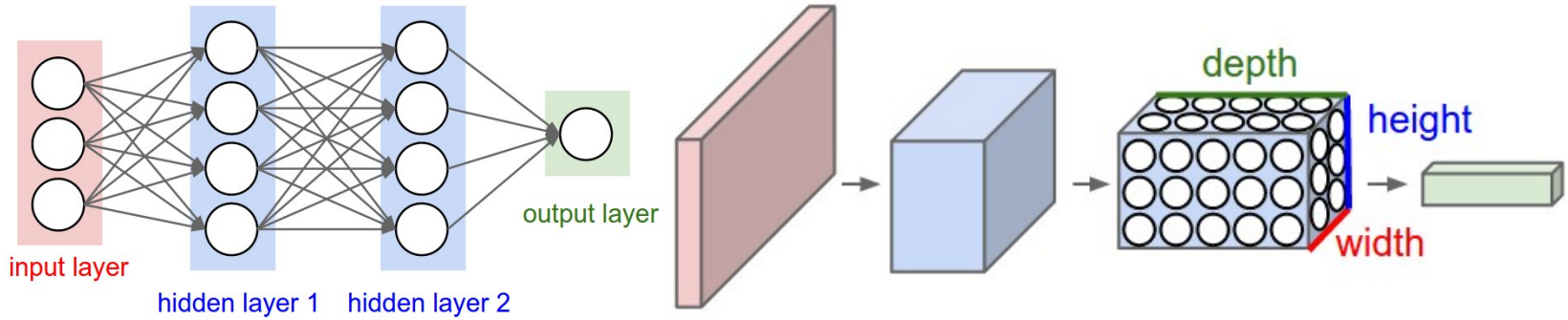

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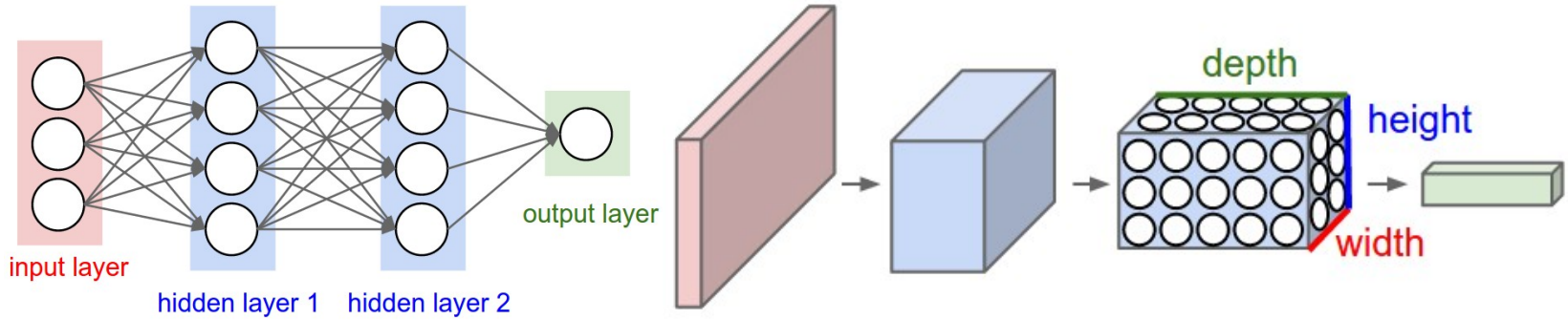

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- Many different types of layers

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- FC layer, MLP, output 5 neurons for 5 classes

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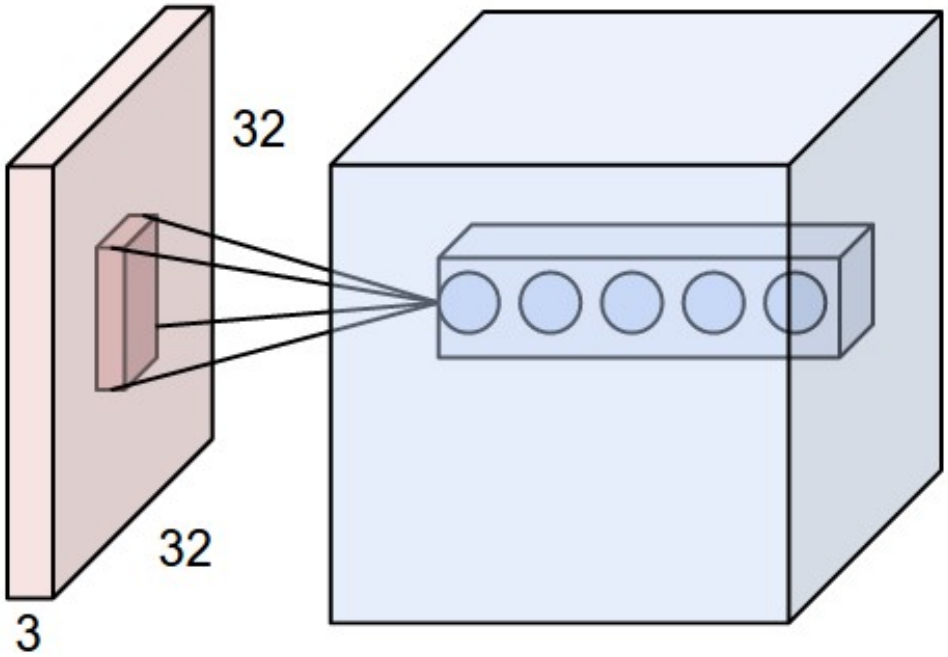
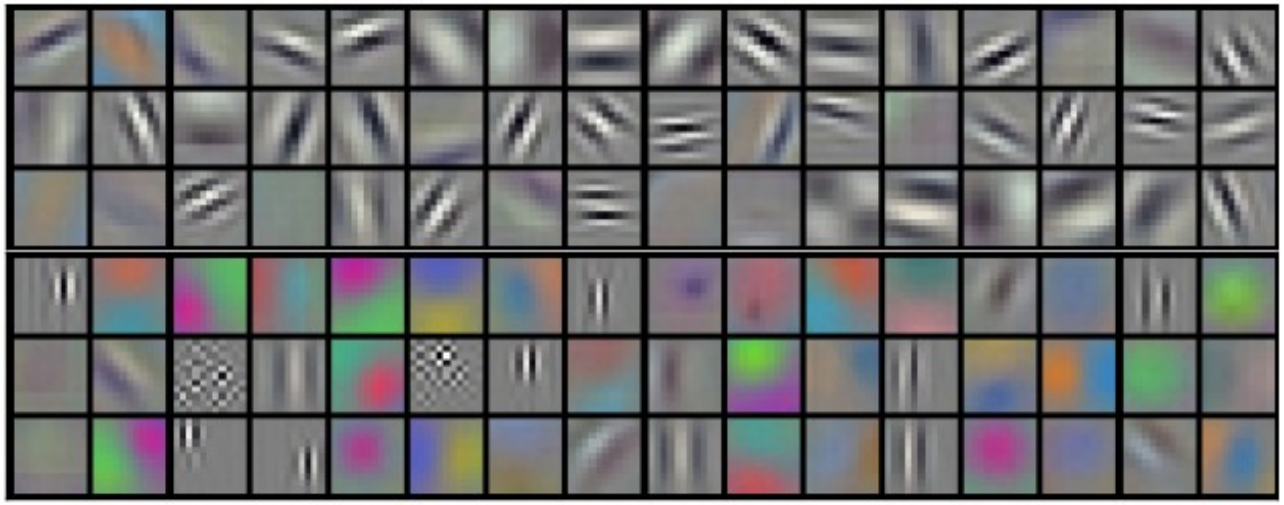
- The deeper you go in the net, typically you move from "micro" to "macro" features, e.g., edges to maybe eyes to maybe faces, and many claim the deeper you go the more "semantic" information you start to mine as well ...

Example of convolution at one spatial location

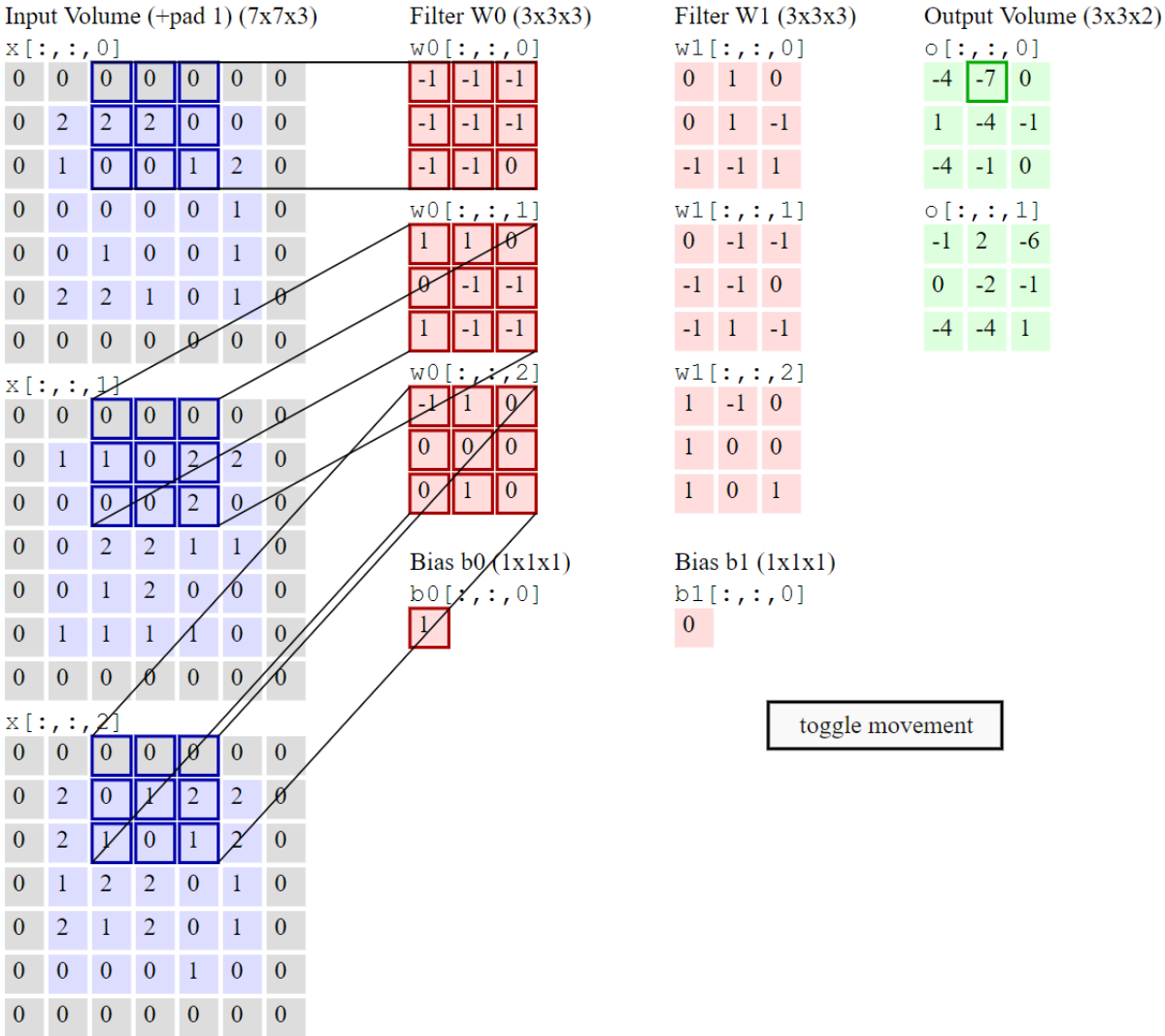


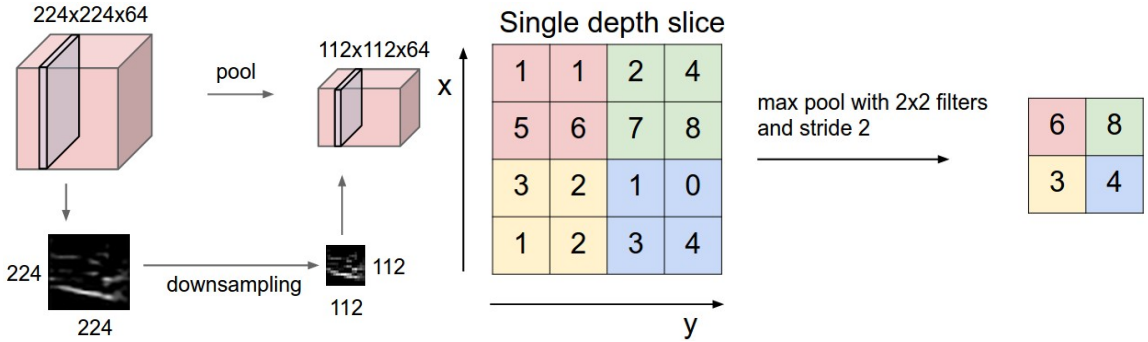
Example filters



Example filters learned by Krizhevsky et al (AlexNet). Each of the 96 filters shown here is of size $[11x11x3]$, and each one is shared by the $55 * 55$ neurons in one depth slice.

Full convolution





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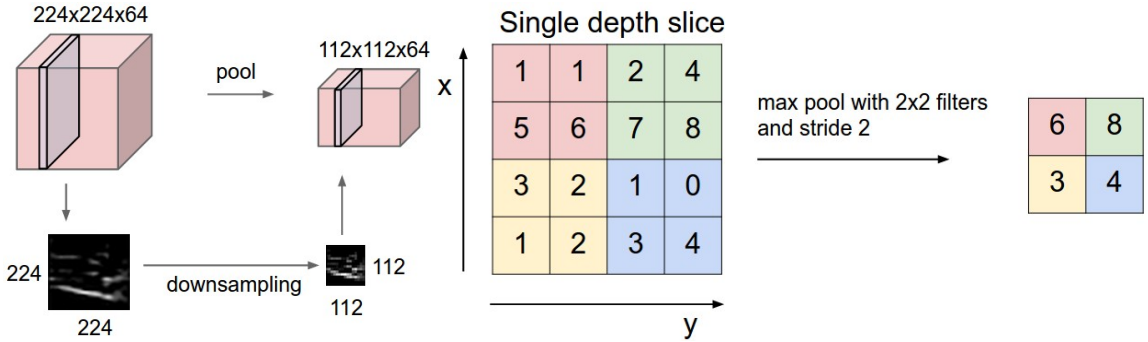

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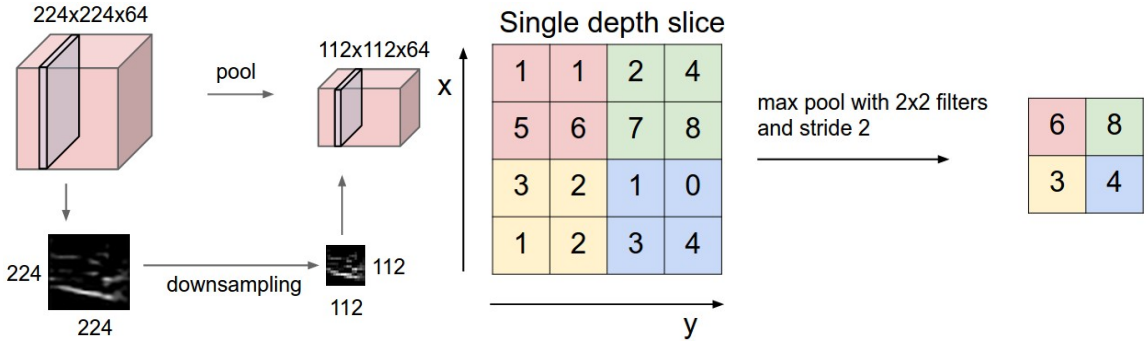

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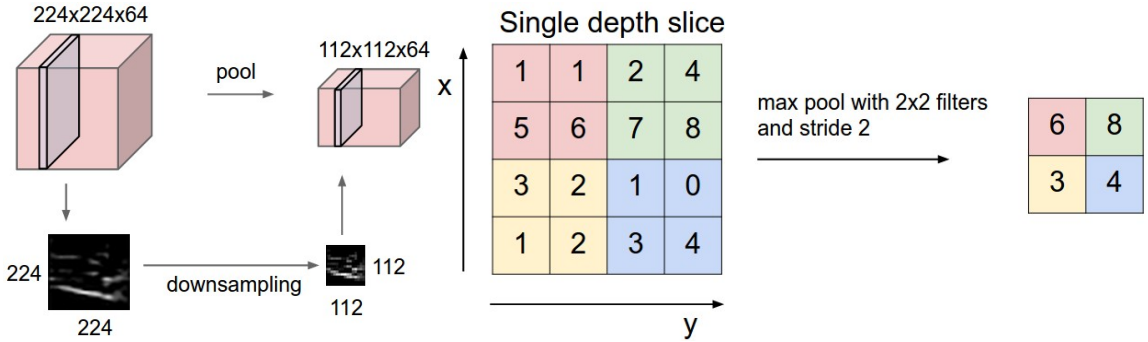

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- Translation and rotation and ...

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- Many use this with deconvolution (a different topic!) to decide how to reverse engineer the filters for purposes like visualization (see Zeiler et al., reverses via the switches, that induces a sparse map and various ways to impute the missing values)

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- ...