11-695: AI Engineering
Convolution I

LTI/SCS

Spring 2020

Outline

Feed-forward NN

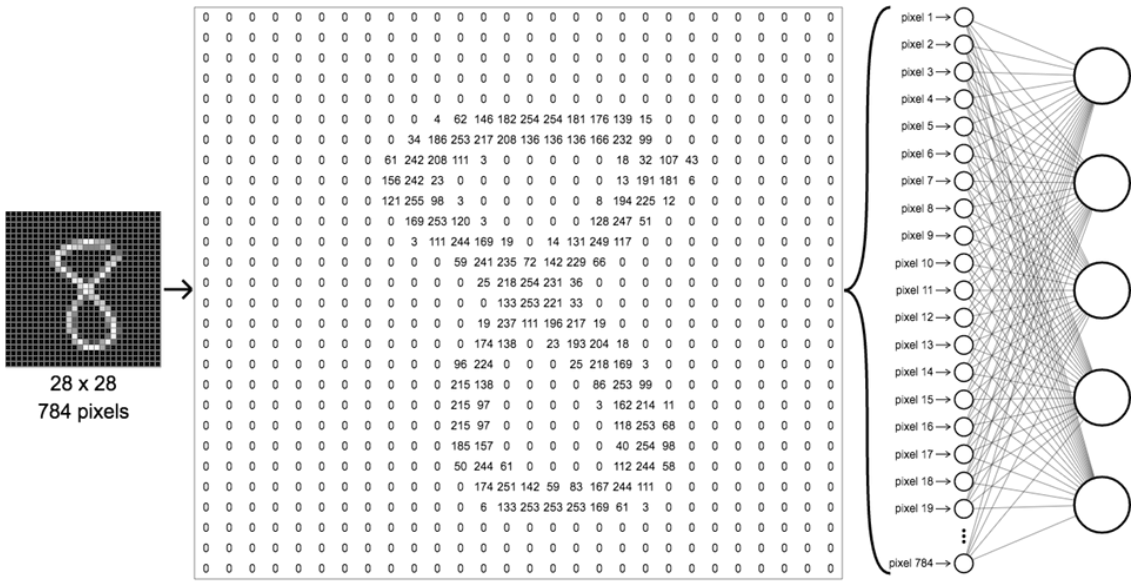
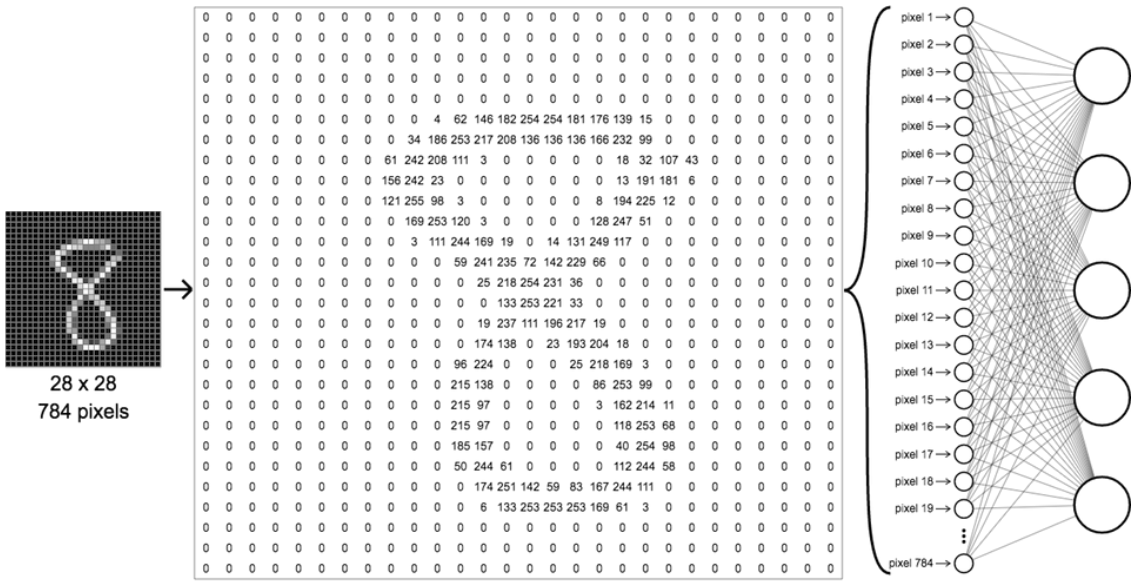


Image credit: https://ml4a.github.io/ml4a/neural_networks/

Feed-forward NN



- The first layer of a NN
- Number of params?

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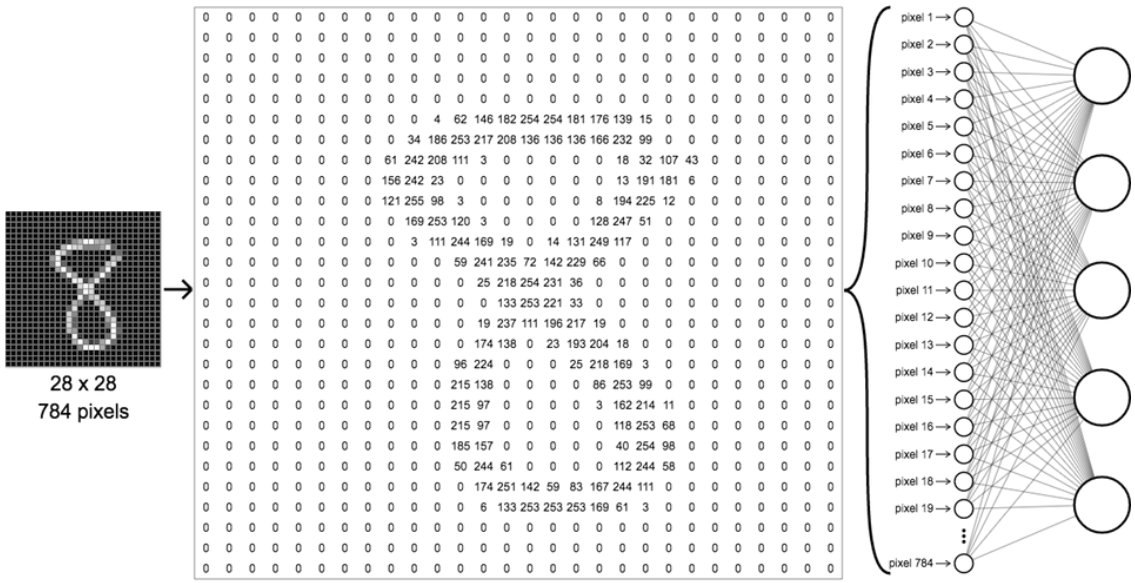

- The first layer of a NN
- Number of params? $28 * 28 * n$

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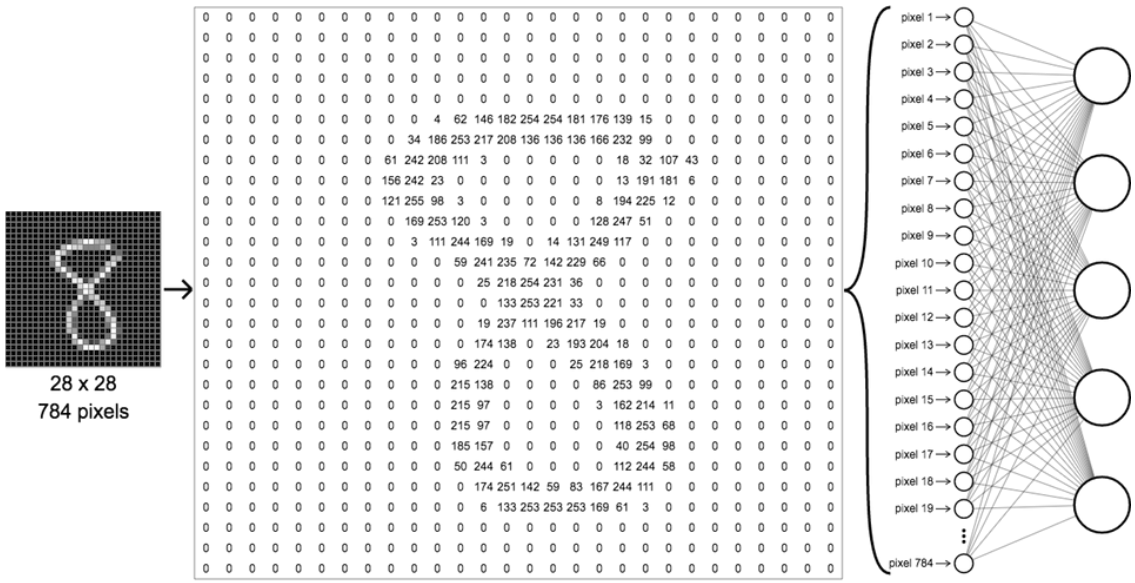
Feed-forward NN

Carnegie Mellon



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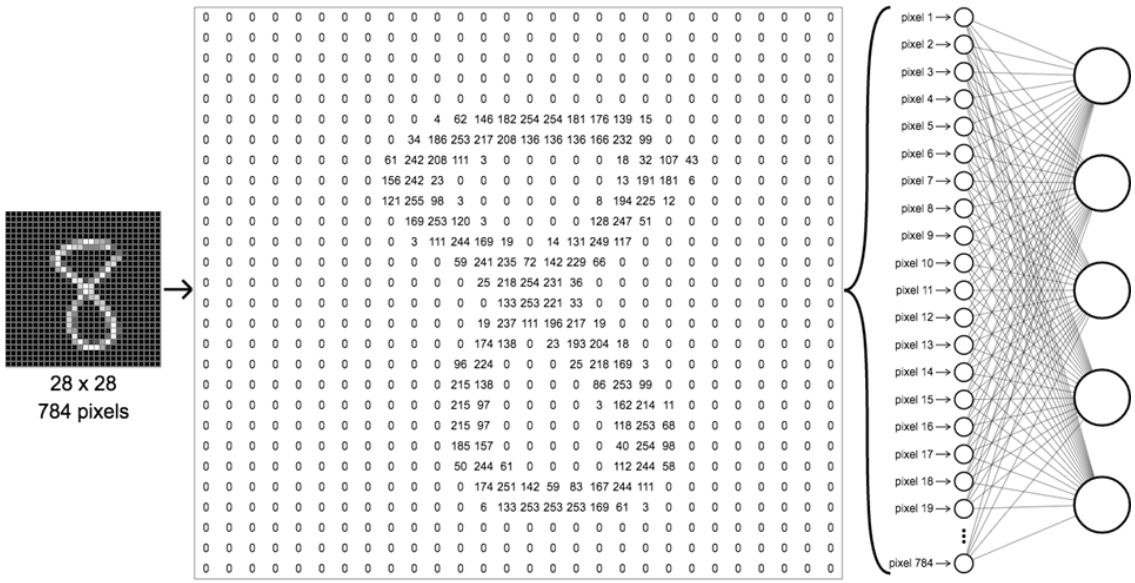

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- What's more?

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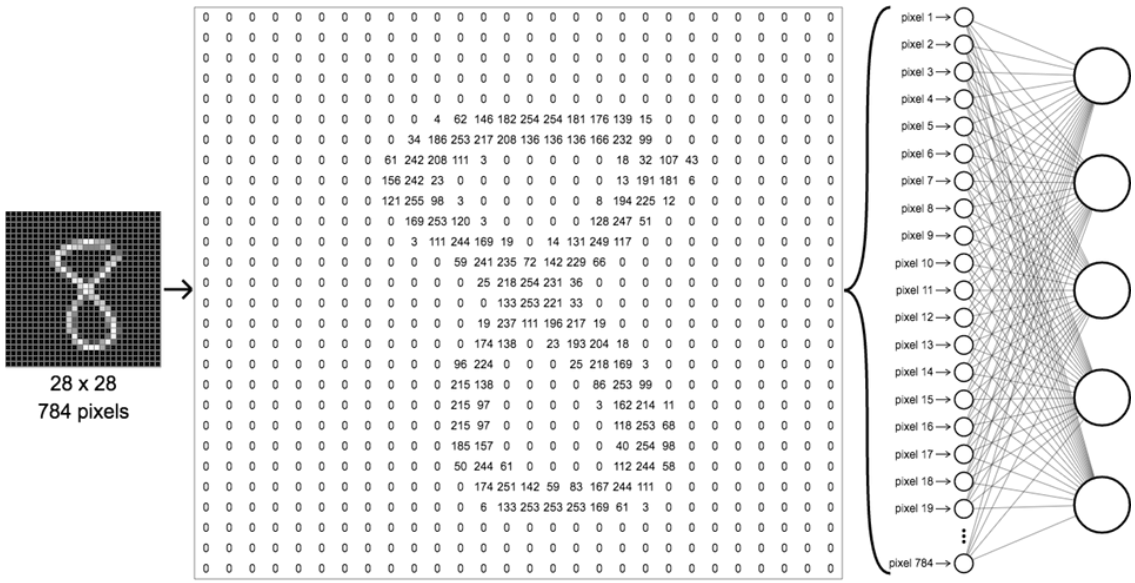

- The first layer of a NN
- Number of params? $28 * 28 * n$
- Real world: $200 * 200 * 3 * 1000 \approx 1e8$ for the first layer
- What's more? How about spatial correlations?

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Spatial Features

- Local spatial features at different locations might be similar

Image credit: Dreamstime.com

Spatial Features

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- Model parts of the image instead of the whole

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Spatial Features

- Local spatial features at different locations might be similar
- Model parts of the image instead of the whole
- Exploit image's redundancy: e.g. edges

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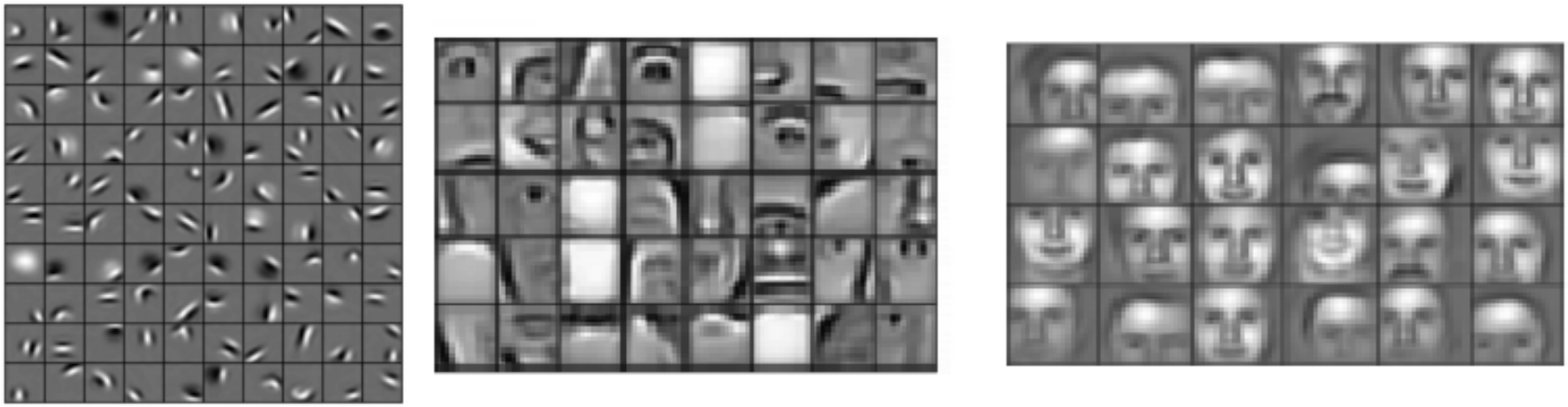
How about Neural Science?



- Human cognition works similarly
  - Eyes detect edges
  - Visual cortex uses Gabor-like filters to recognize objects

[1] Bengio J. et al. Representation Learning: A Review and New Perspectives

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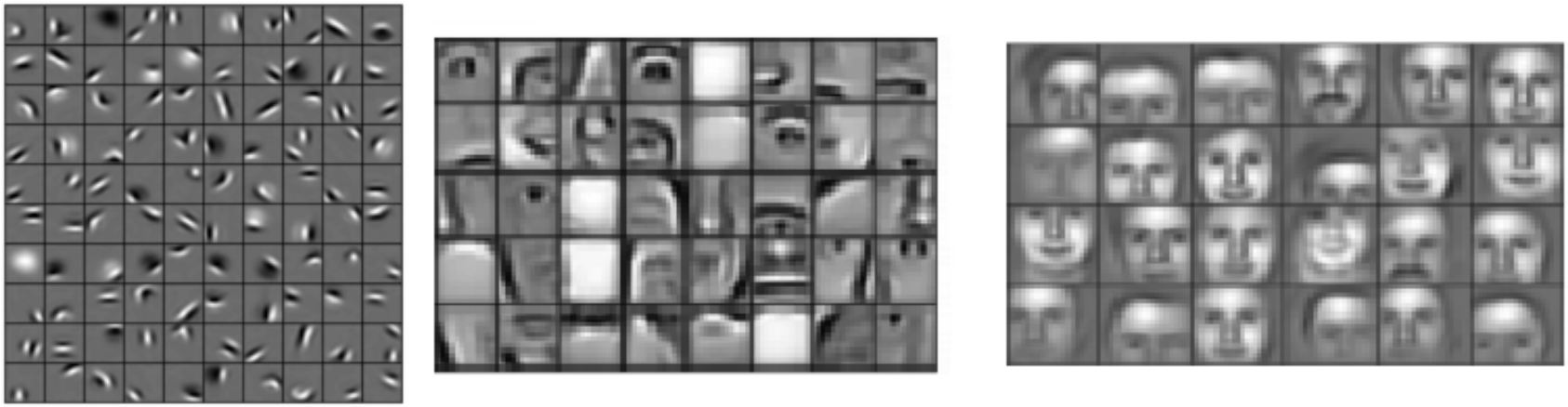

- Human cognition works similarly
  - Eyes detect edges
  - Visual cortex uses Gabor-like filters to recognize objects
- Intention to build hierarchical abstract representation[1]

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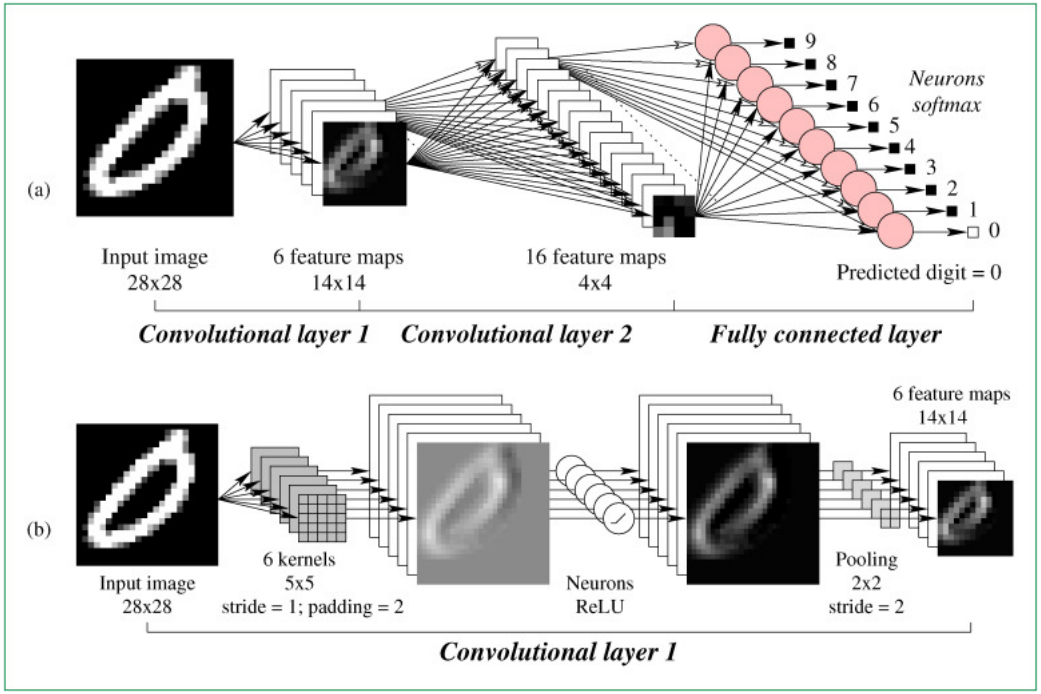
Convolutional Neural Network

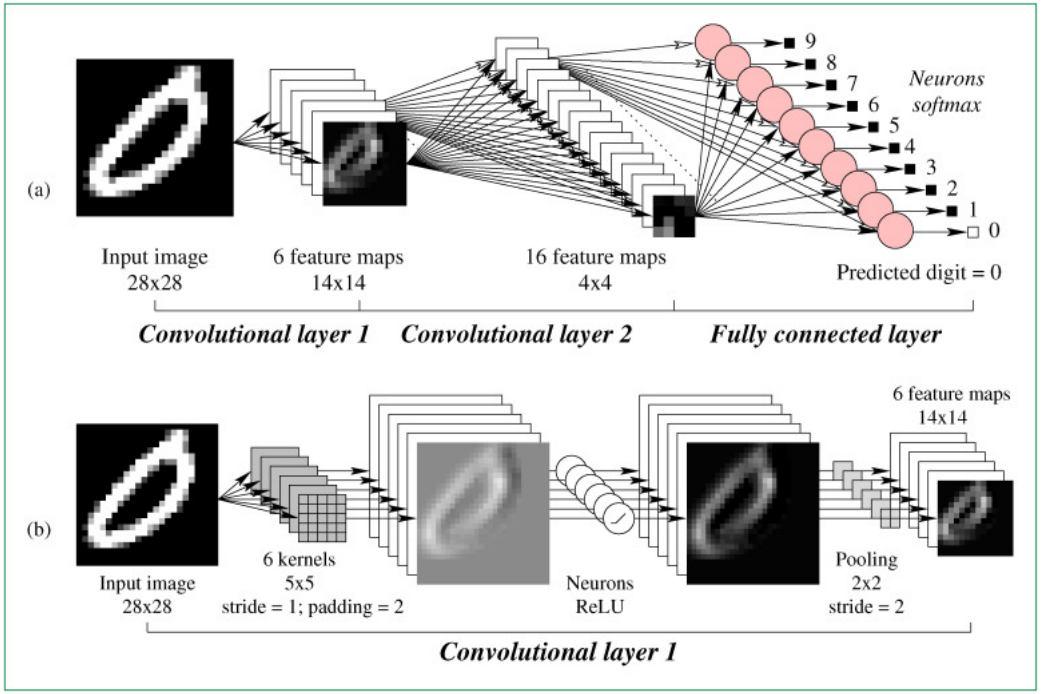


- Similar design to Feedfoward NNs

Image credit: ScienceDirect.com

Convolutional Neural Network

Carnegie Mellon



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- With main components of not FC (or Dense) layers, but:
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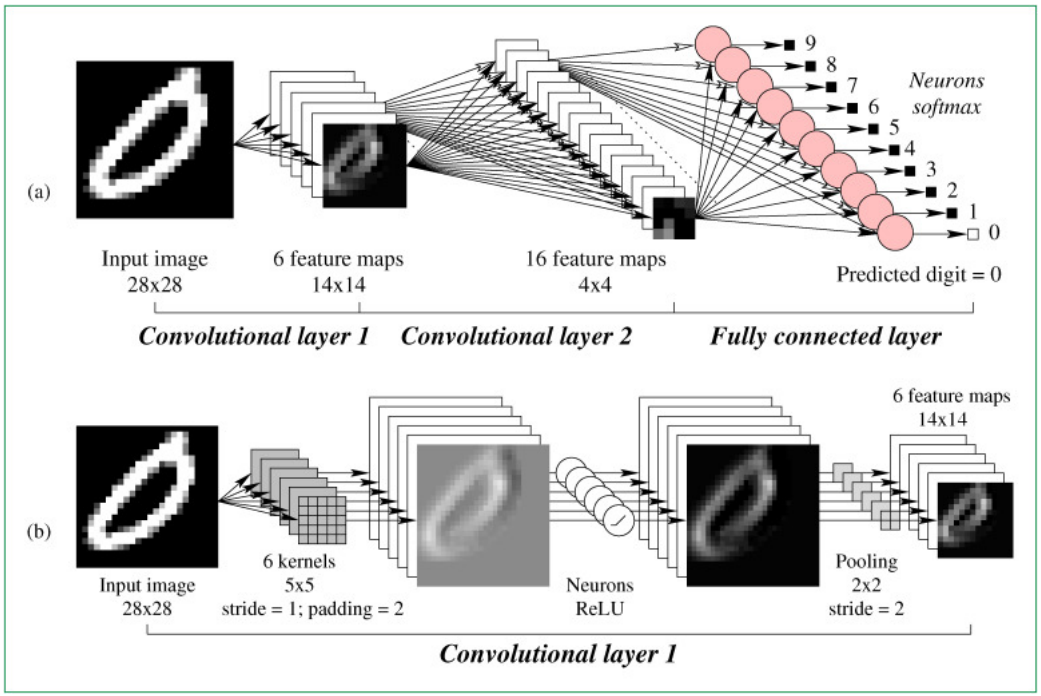

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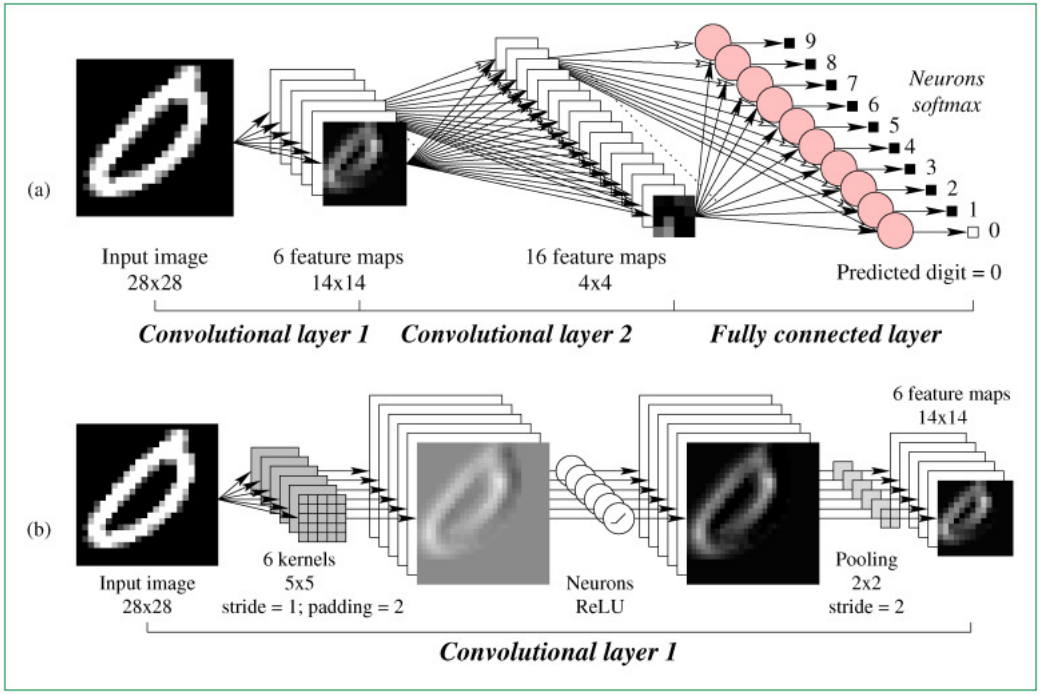

- Similar design to Feedfoward NNs
- With main components of not FC (or Dense) layers, but:
  - Convolutional, and
  - Pooling Layers
- FC usually appears at the end of architectures

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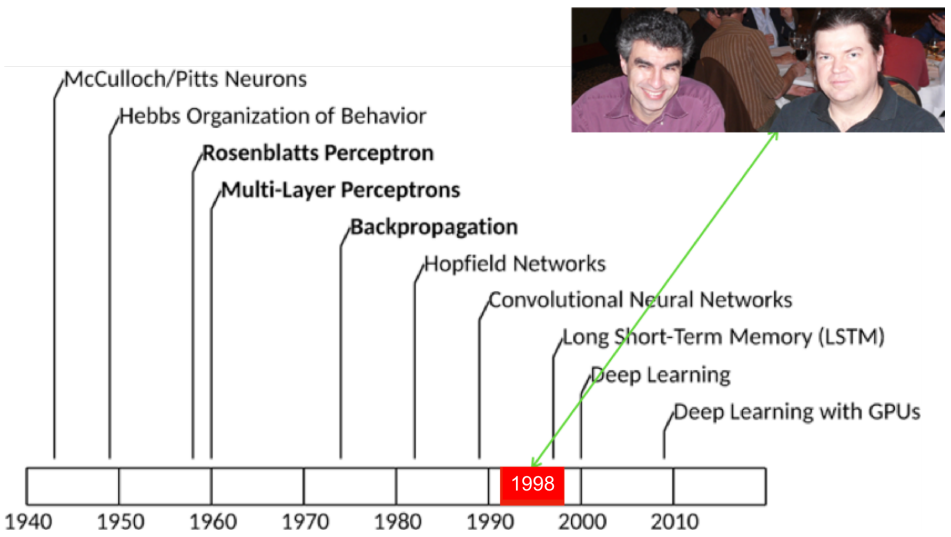
Recap: History of (C)NN



- Be a go-to feature extraction solution for images/videos

[2] Yin W. et al Comparative Study of CNN and RNN for NLP

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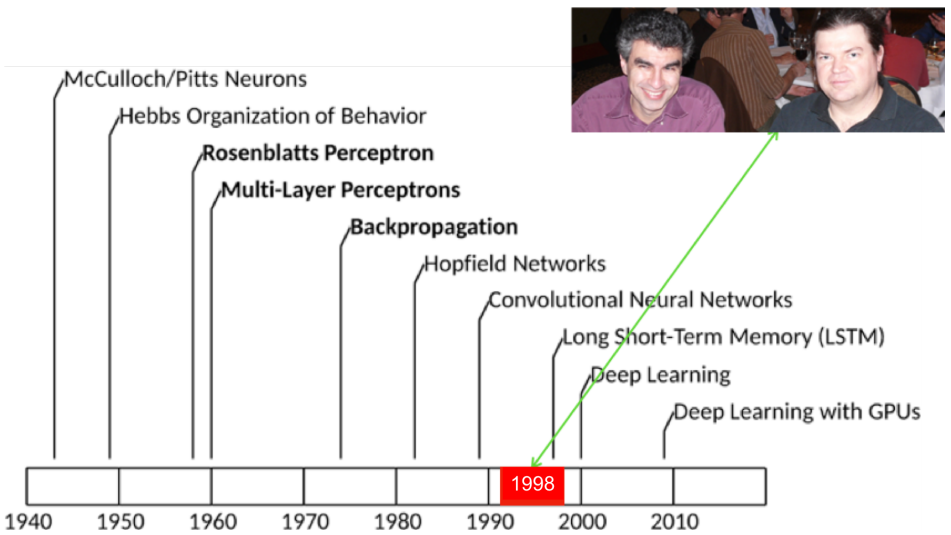

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- Even outperform RNNs in some NLP tasks![2]

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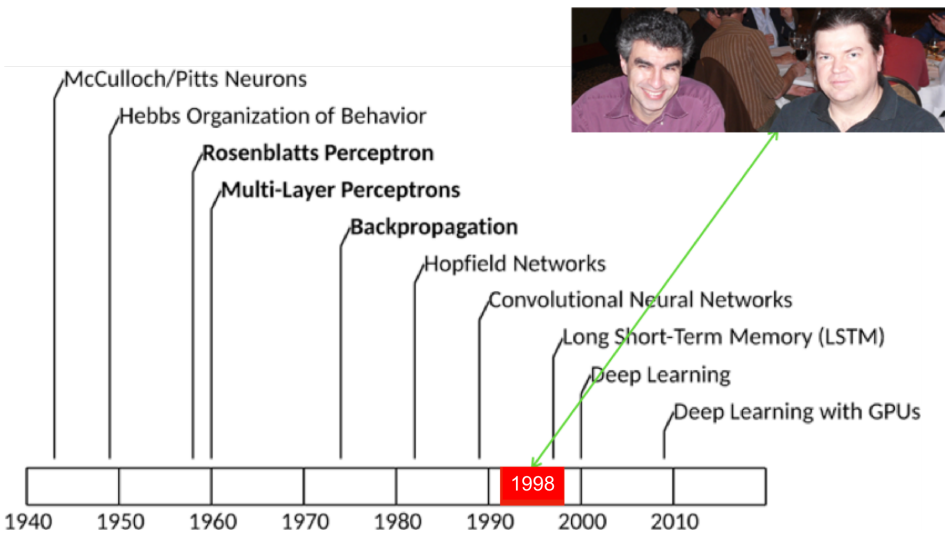

- Be a go-to feature extraction solution for images/videos
- Even outperform RNNs in some NLP tasks![2]
- Be an essential part in many SoTA solutions for classifications, detections, recognition, segmentation, OCR, motion, pose, etc.

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Outline

Convolution

Carnegie Mellon

- A mathematics operation ▸ demo

$$(f * g)(t) = \int_{-\infty}^{\infty} f(u)g(t-u)du = \int_{-\infty}^{\infty} f(t-u)g(u)du$$

Convolution

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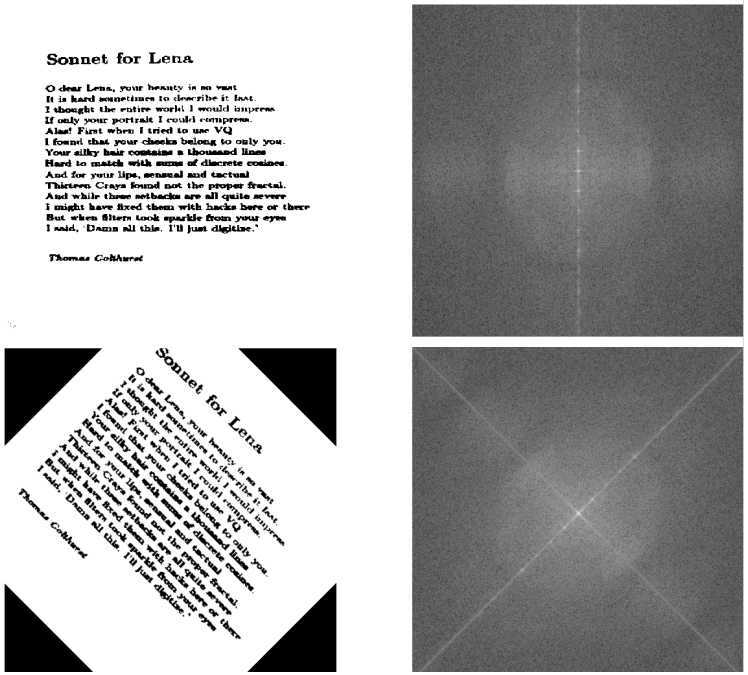
- A linear time invariant (LTI) operation, means that no new frequency components are created, and so output is the pointwise product of input and a transfer function (Wikipedia)
- Relation to Fourier Transformation ▸ demo

$$(f * g)(t) = \mathcal{F}^{-1}(\sqrt{2\pi} \quad \mathcal{F}|f| \cdot \mathcal{F}|g|)$$

Convolution (cont'd)



- Convolution is an operation in Fourier domain

Image credit: Timdettmers.com

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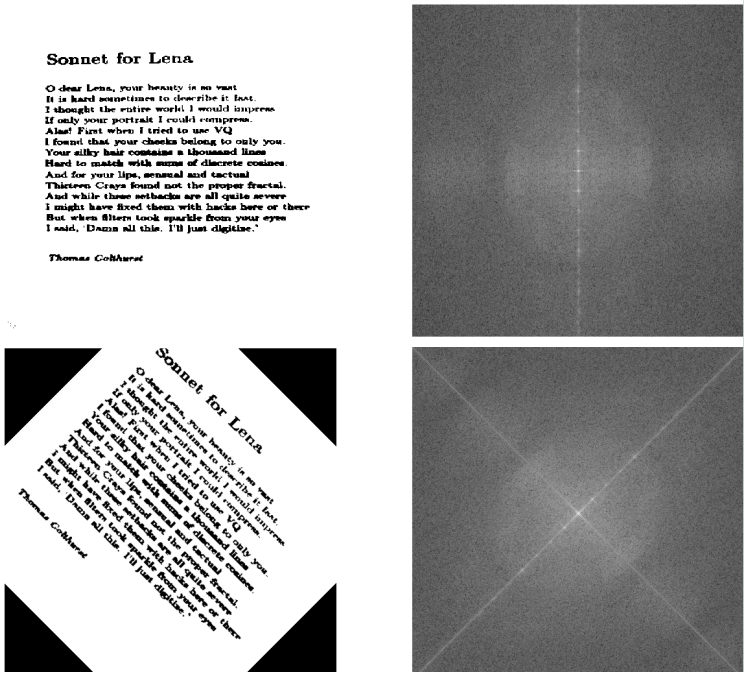

- Convolution is an operation in Fourier domain
- It can capture orientation change

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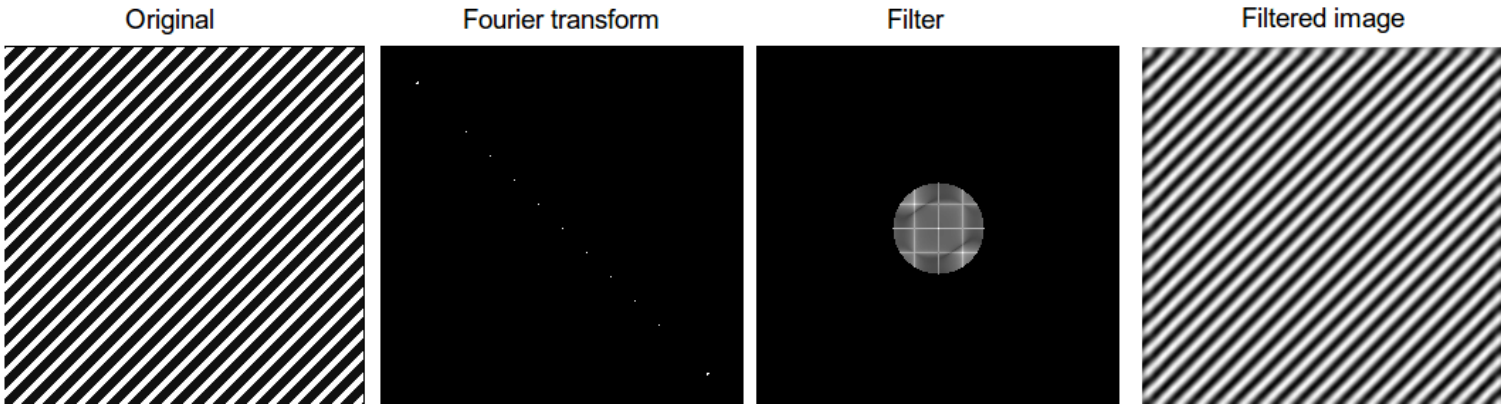
Convolution (cont'd)



- Convolution is often referred to as filtering

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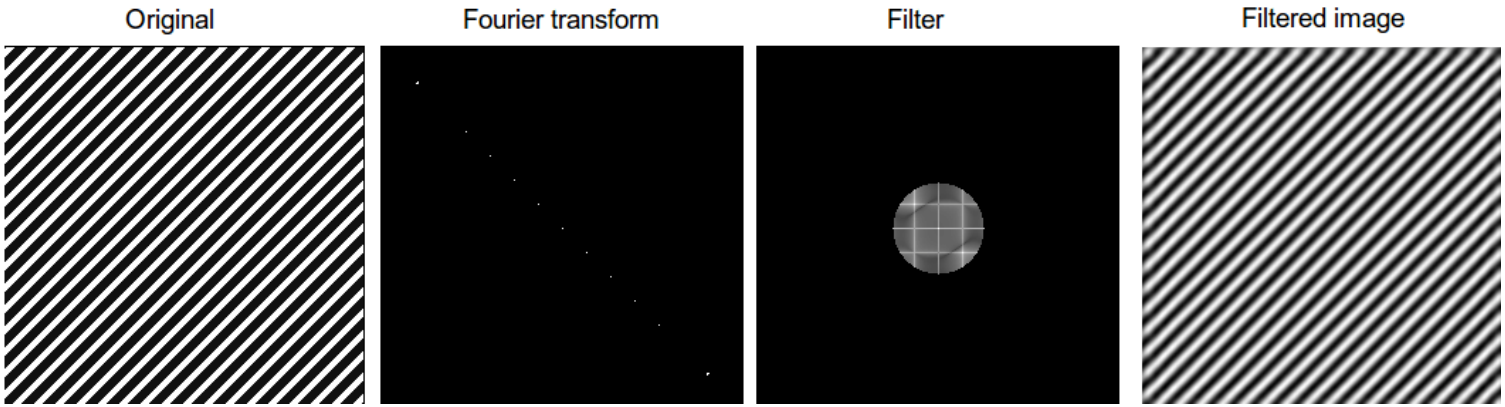

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- Other names: kernel, receptive field

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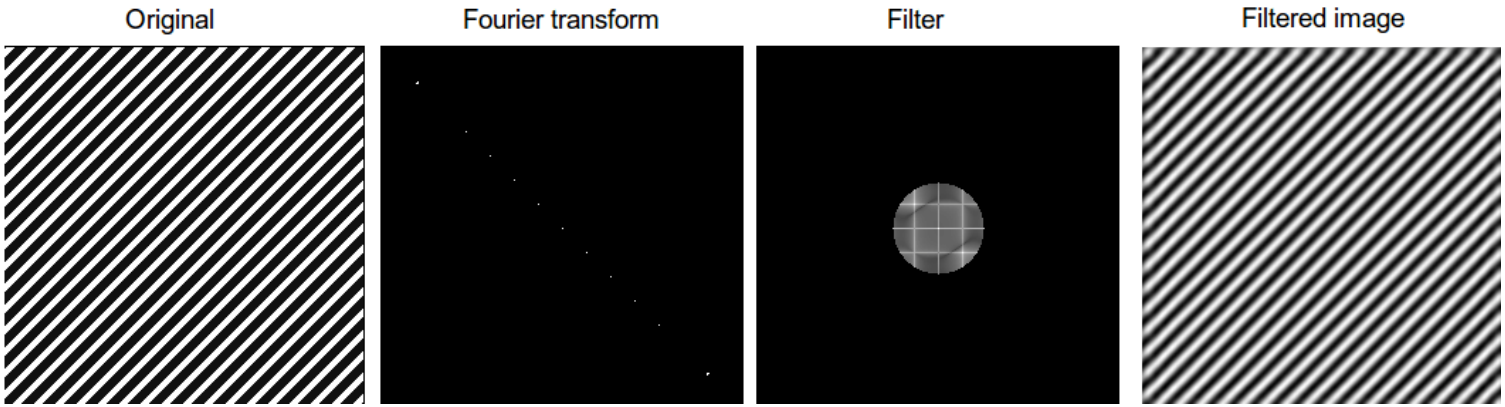

- Convolution is often referred to as filtering
- Other names: kernel, receptive field
- And now:

$$\begin{aligned}\text{feature\_map} &= \text{filter} * \text{input} \\ &= \sum_{y=1}^{\text{n\_cols}} \left(\sum_{x=1}^{\text{n\_rows}} \text{input}(x-a, y-b) * \text{filter}(x, y) \right) \\ &= \mathcal{F}^{-1}(\sqrt{2\pi} \quad \mathcal{F}|\text{input}| \cdot \mathcal{F}|\text{filter}|)\end{aligned}$$

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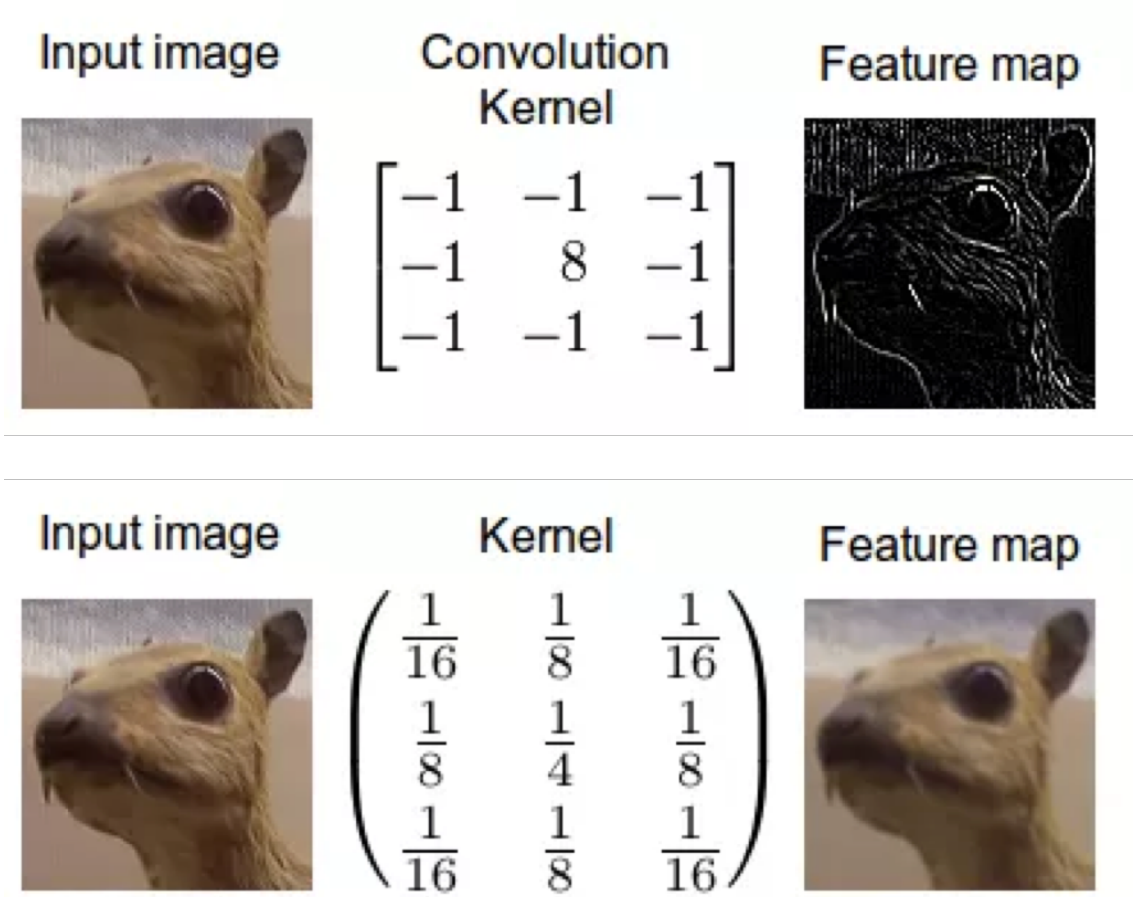

$$\begin{bmatrix} -1 & -1 & -1 \\ -1 & 8 & -1 \\ -1 & -1 & -1 \end{bmatrix}$$

$$\begin{pmatrix} \frac{1}{16} & \frac{1}{8} & \frac{1}{16} \\ \frac{1}{8} & \frac{1}{4} & \frac{1}{8} \\ \frac{1}{16} & \frac{1}{8} & \frac{1}{16} \end{pmatrix}$$

- Similarity: Kernel SVM, PCA?

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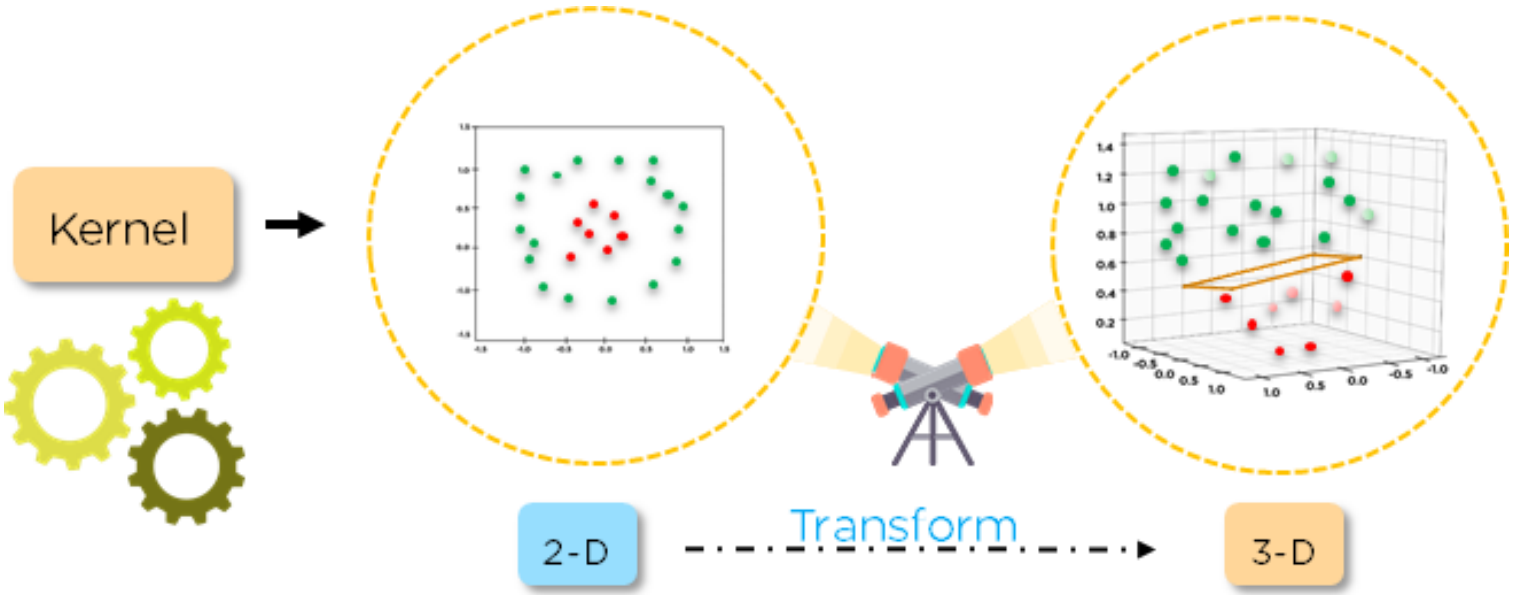
Convolution (cont'd)

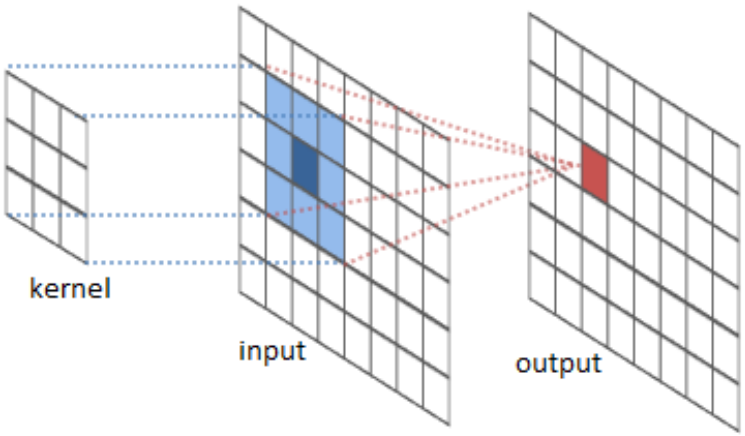


- Key similar intuition: kernel-activated feature space will be helpful.

Image credit: quora.com

Outline

Convolution In Action



- Given a $200 * 200$ image
- A fully-connected layer with n hidden neurons: $200 * 200 * n$ params

Image credit: ricardodeazambuja.com

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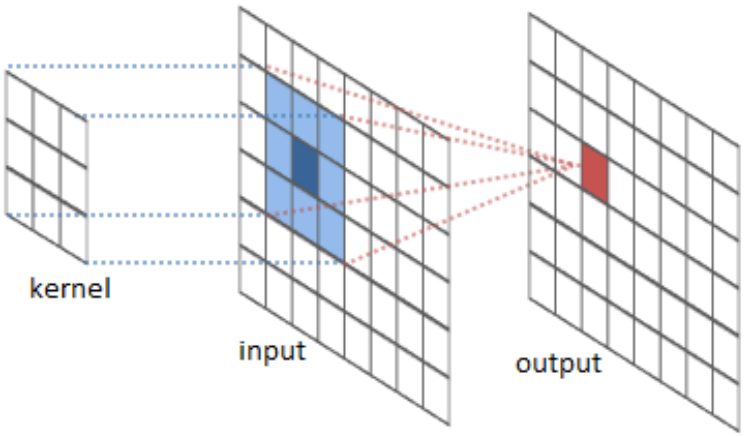

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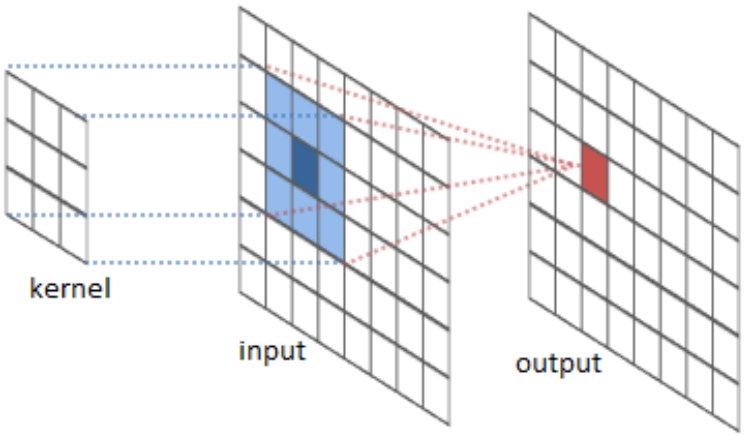

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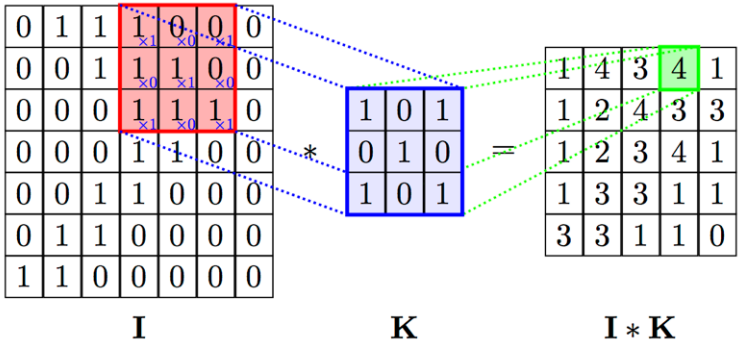

- How it works?

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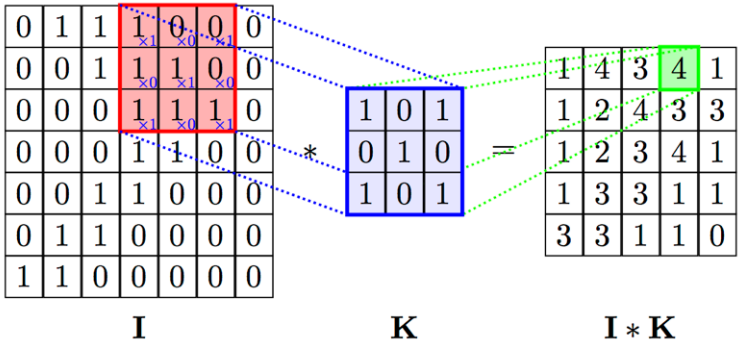

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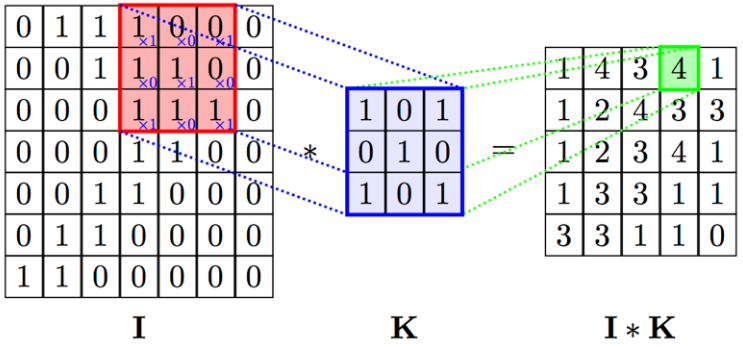

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- A filter scan through the whole image which is convolved by it
- *Important*: a filter has a fixed weight → output is similar if the region is similar

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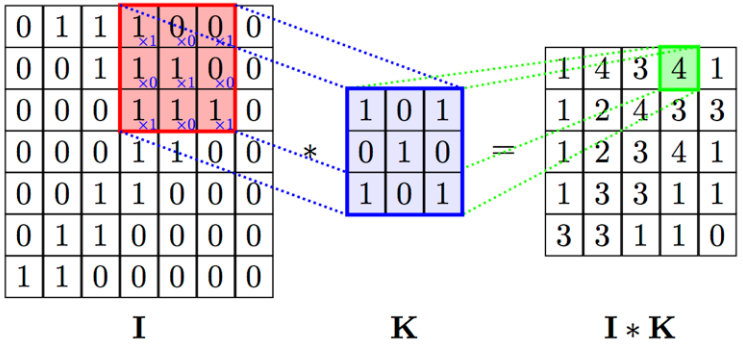

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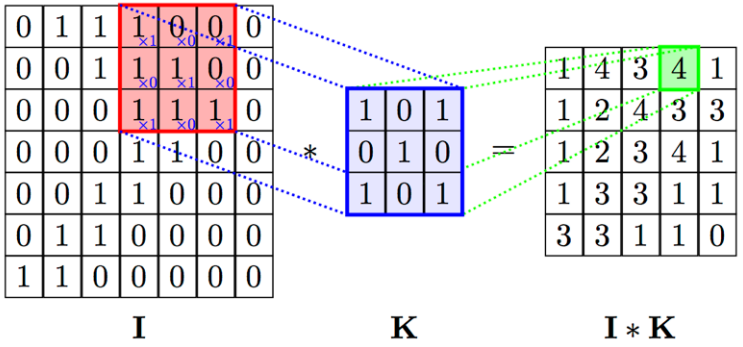

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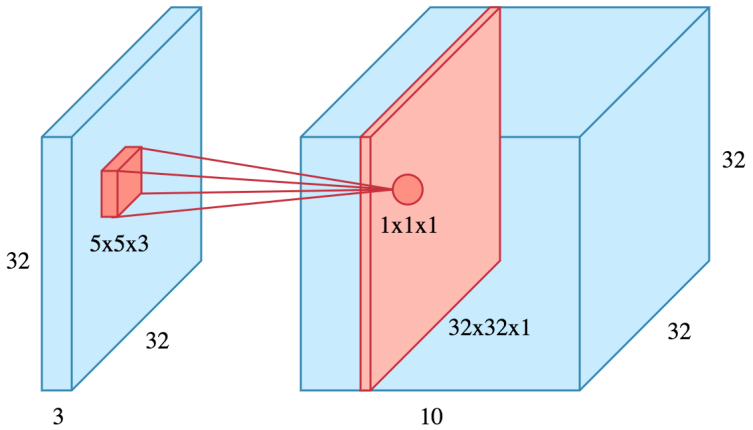
Depth of Convolution



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- If input image has 3 channels: $200 * 200 * 3 \rightarrow$ the filter should be $n * n * 3$

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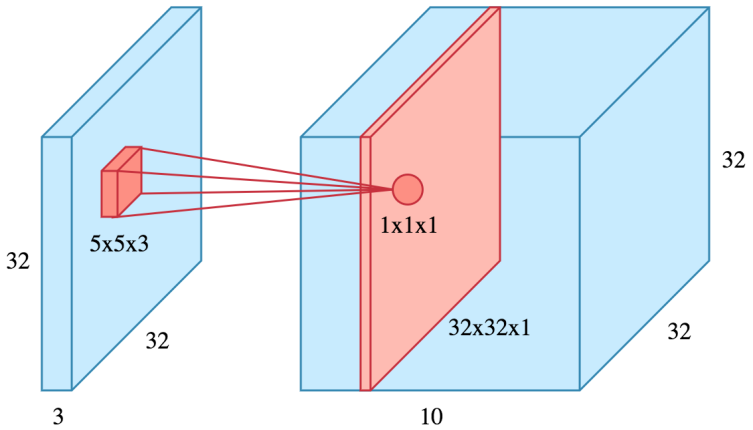

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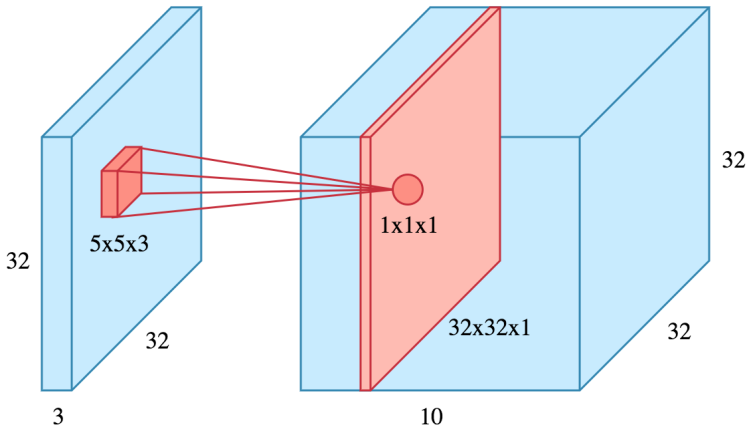

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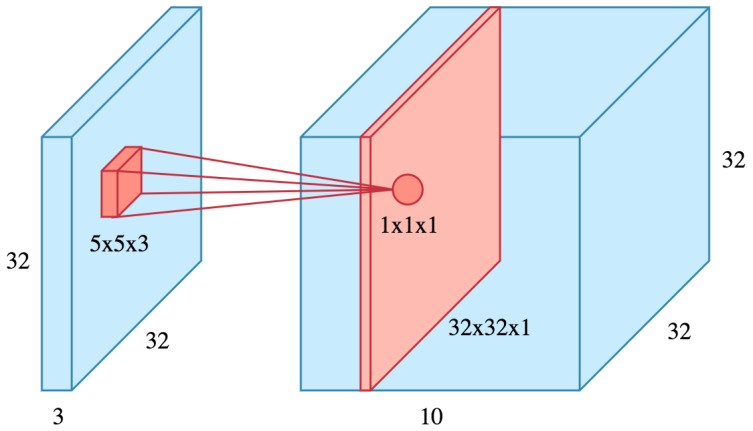

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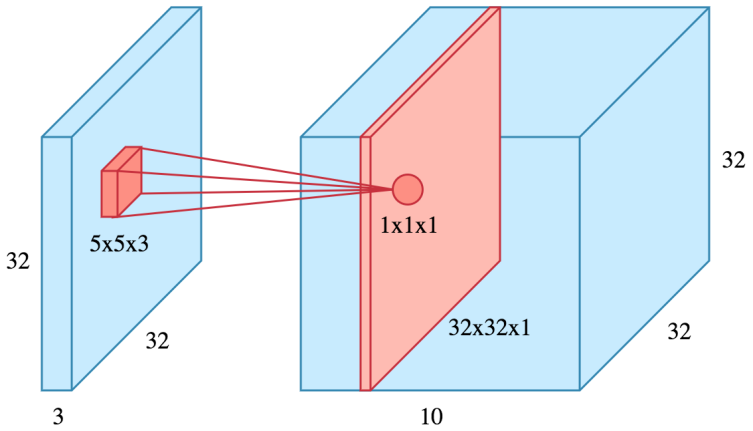

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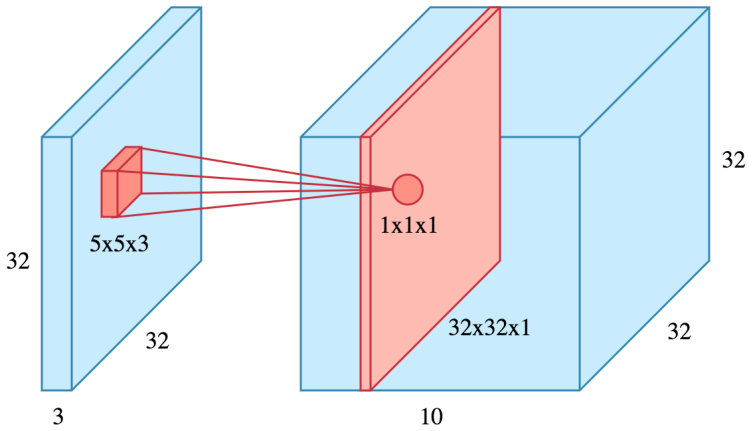

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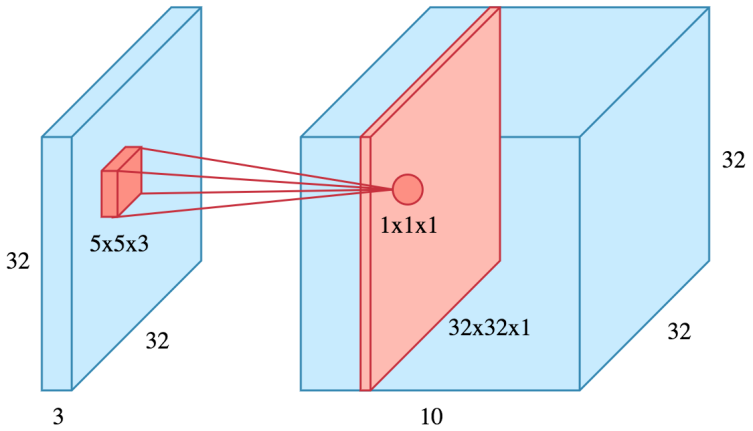

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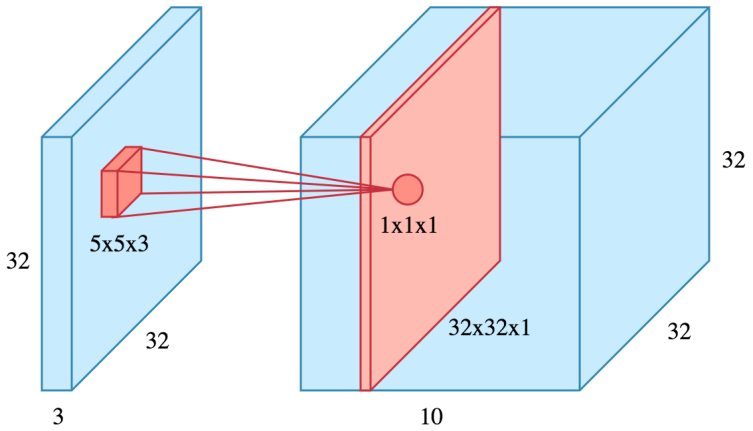

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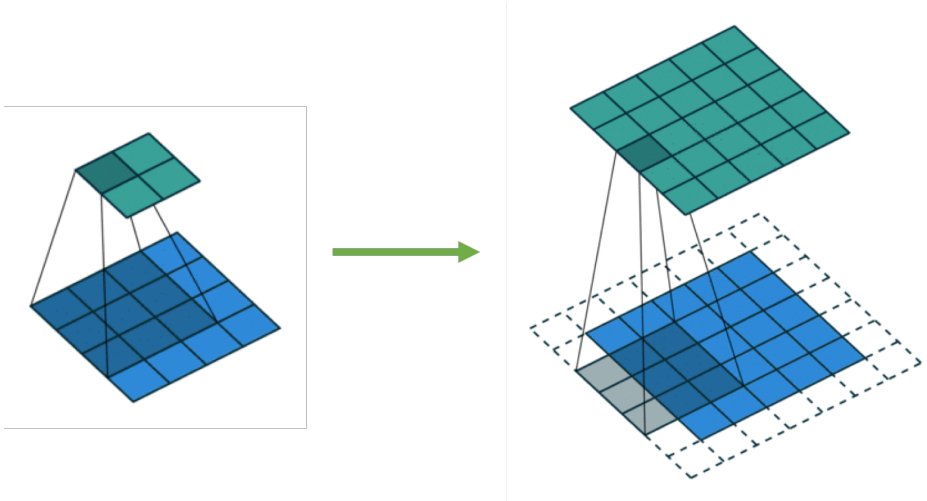
- Practice: If there are 10 filters?

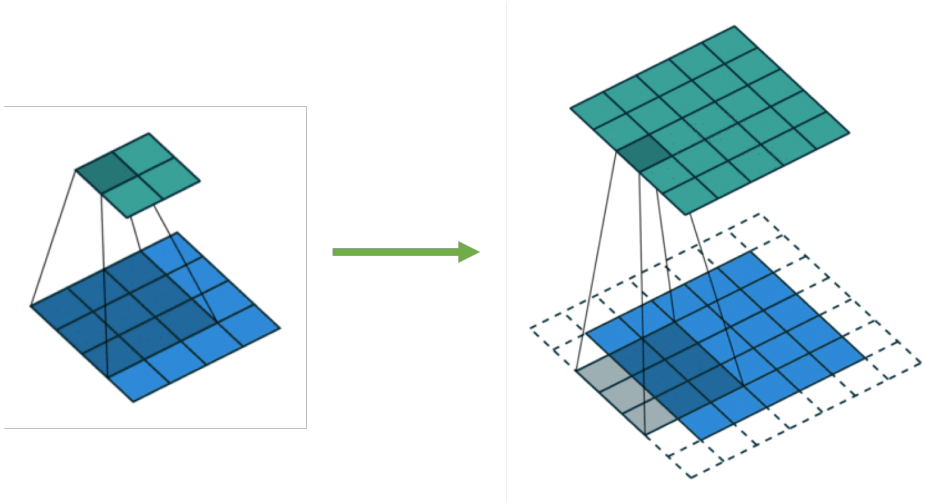
Padding



- Change the size of output, normally with zero ▸ Demo

Image credit: deeplearning.net

Padding



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- There are 2 types of padding
  - *Valid*: no padding

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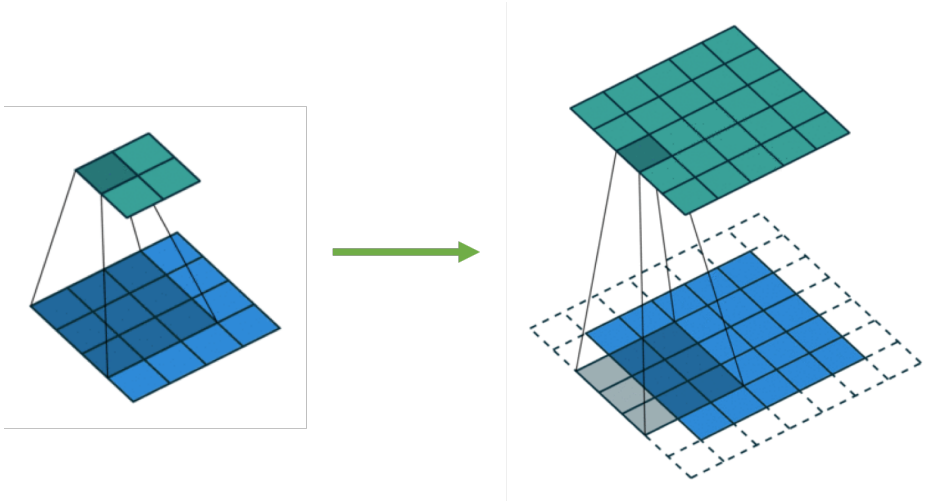
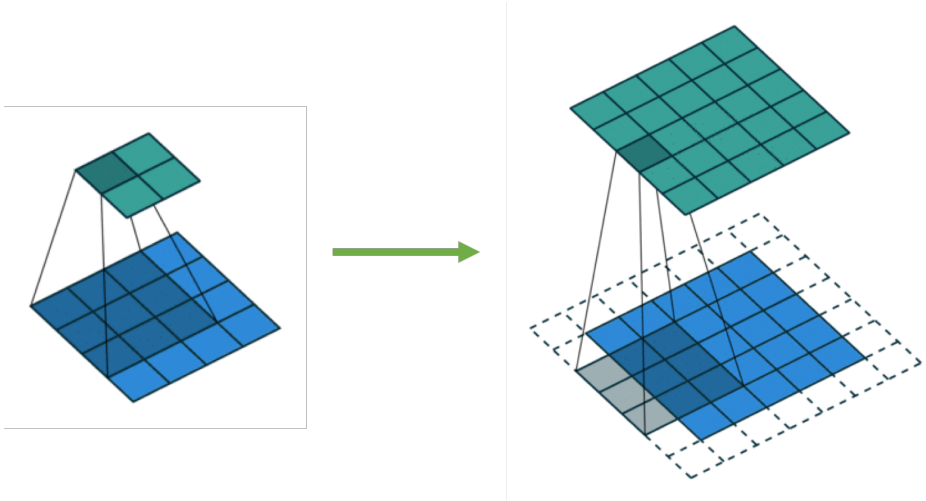


- Change the size of output, normally with zero ▸ Demo
- There are 2 types of padding
  - *Valid*: no padding
  - *Same*: pad so that output size is the same as input's

Image credit: deeplearning.net

Padding



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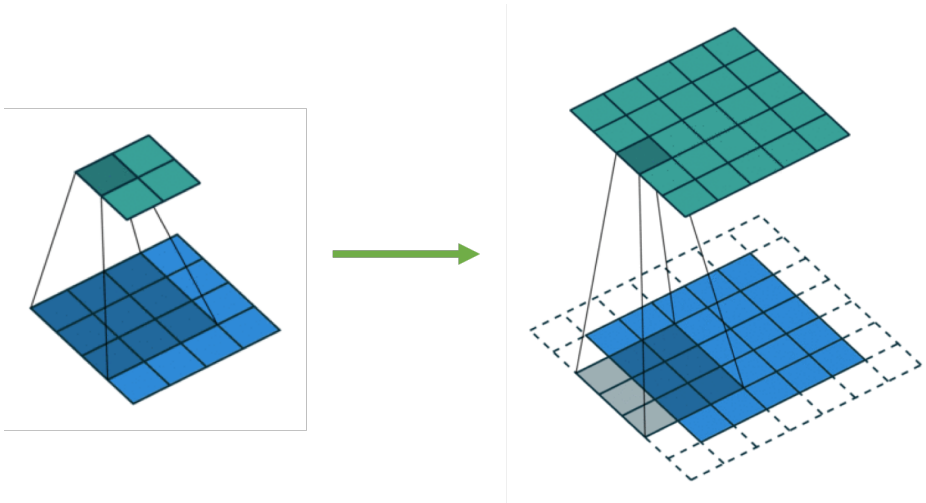
- Practice: $n * n$ convolves $k * k$, padding p, output?

Image credit: deeplearning.net

Padding



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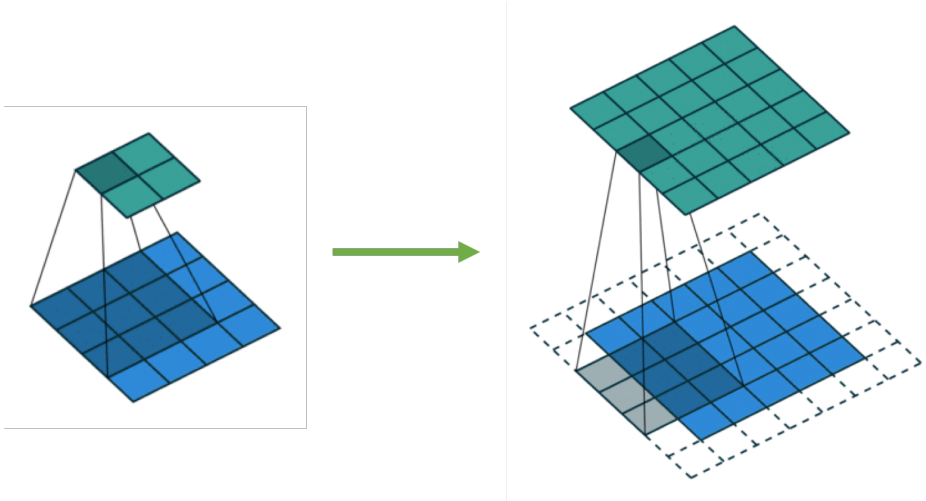
  $(n - k + 1 + 2p) * (n - k + 1 + 2p)$

Image credit: deeplearning.net

Padding



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- There are 2 types of padding
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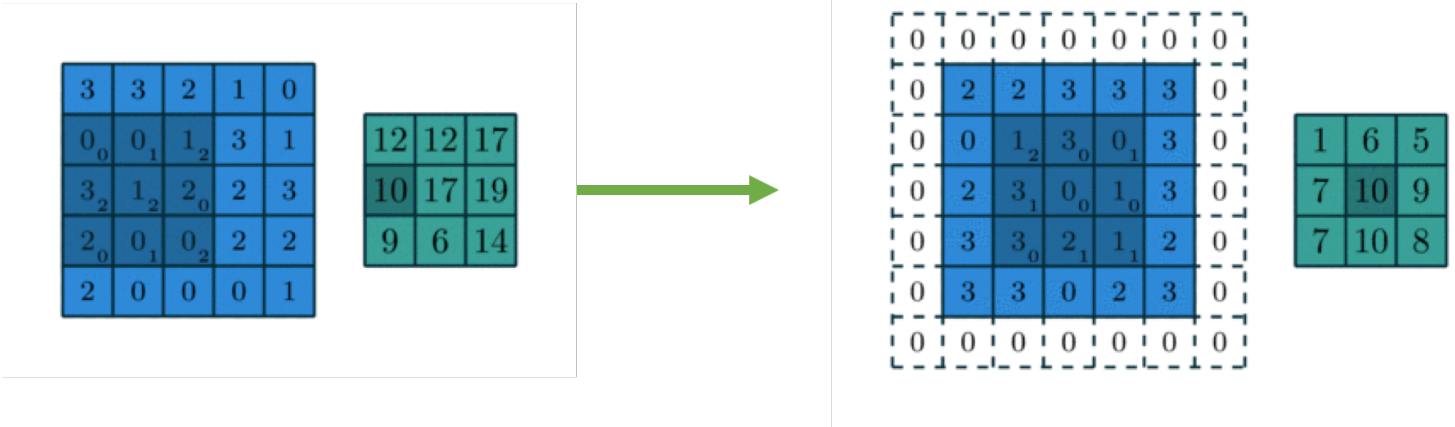
  $(n - k + 1 + 2p) * (n - k + 1 + 2p)$
- Assumption of this formula (and the ones above)?

Image credit: deeplearning.net

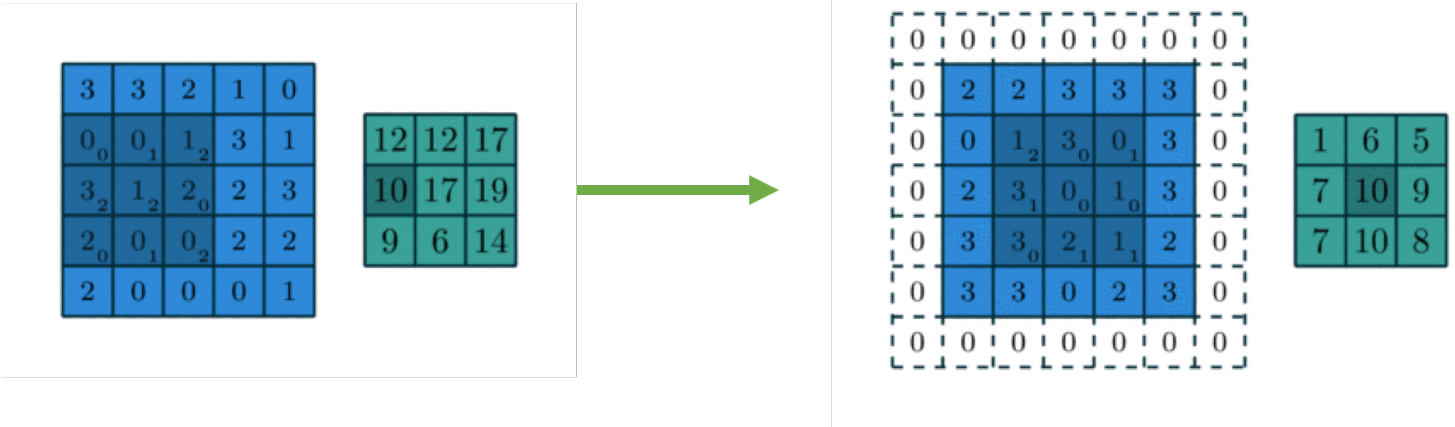
Stride



- Velocity of convolution ▸ Demo
- Practice: 5x5 convolves 3x3
  - Valid padding, stride 1, ouput?

Image credit: deeplearning.net

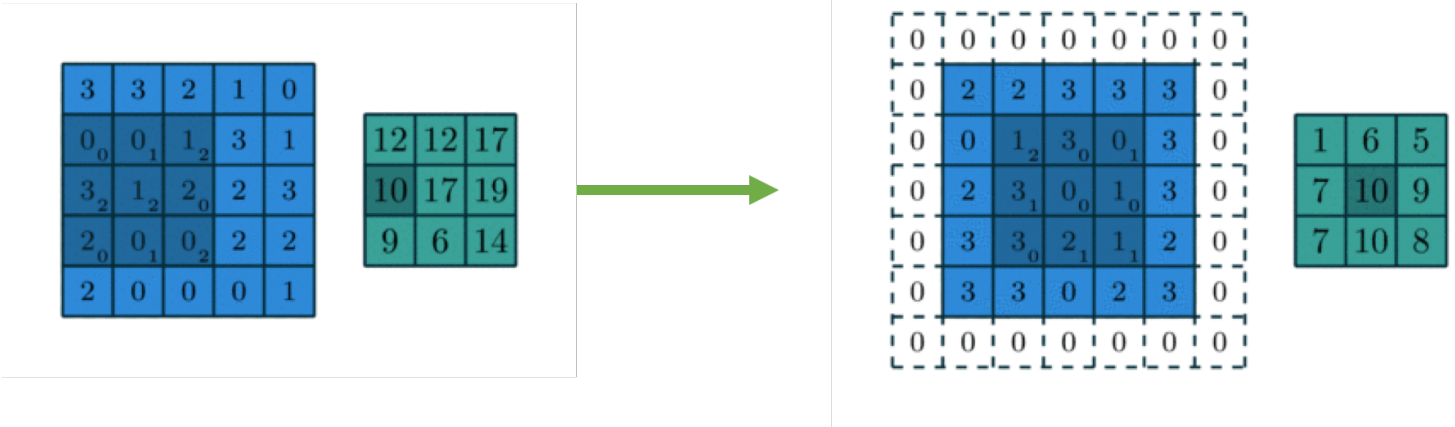
Stride



- Velocity of convolution ▸ Demo
- Practice: 5x5 convolves 3x3
  - Valid padding, stride 1, ouput? $(5-3+1)(5-3+1)$
  - Pad 1, stride 1, output?

Image credit: deeplearning.net

Stride



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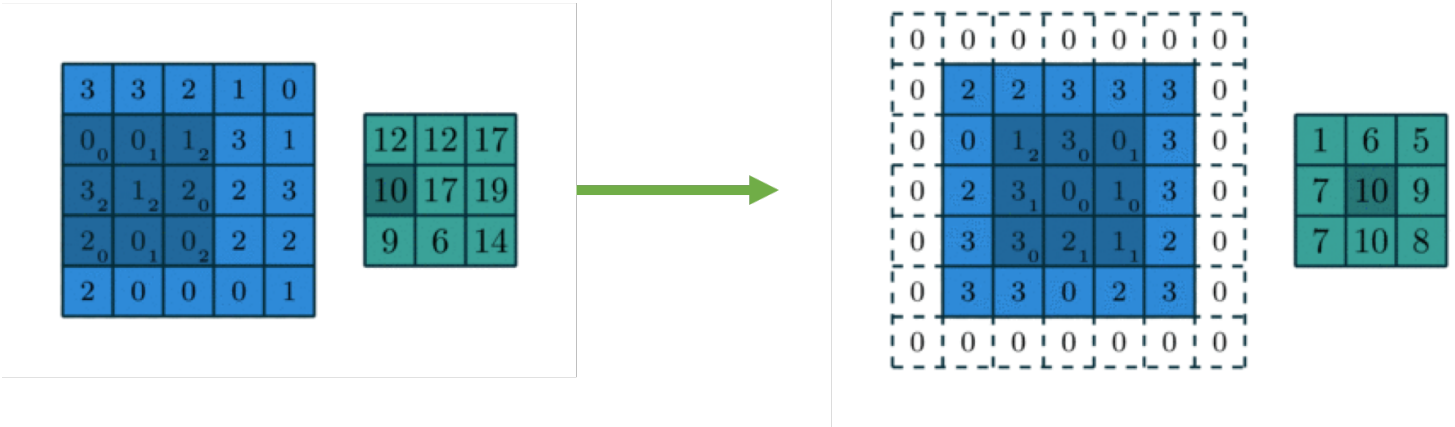
  - Pad 1, stride 2, output?

Image credit: deeplearning.net

Stride



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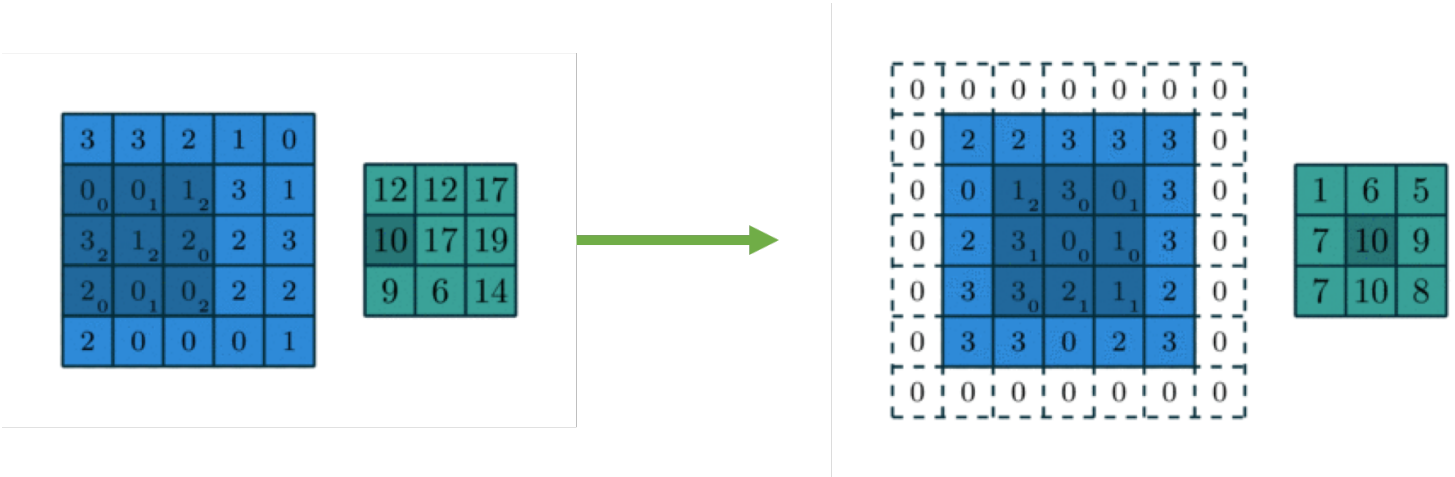
  - Pad 1, stride 2, output? $((5-3+2)/2+1)(((5-3+2)/2+1))$

Image credit: deeplearning.net

Stride



- Velocity of convolution ▸ Demo
- Practice: 5x5 convolves 3x3
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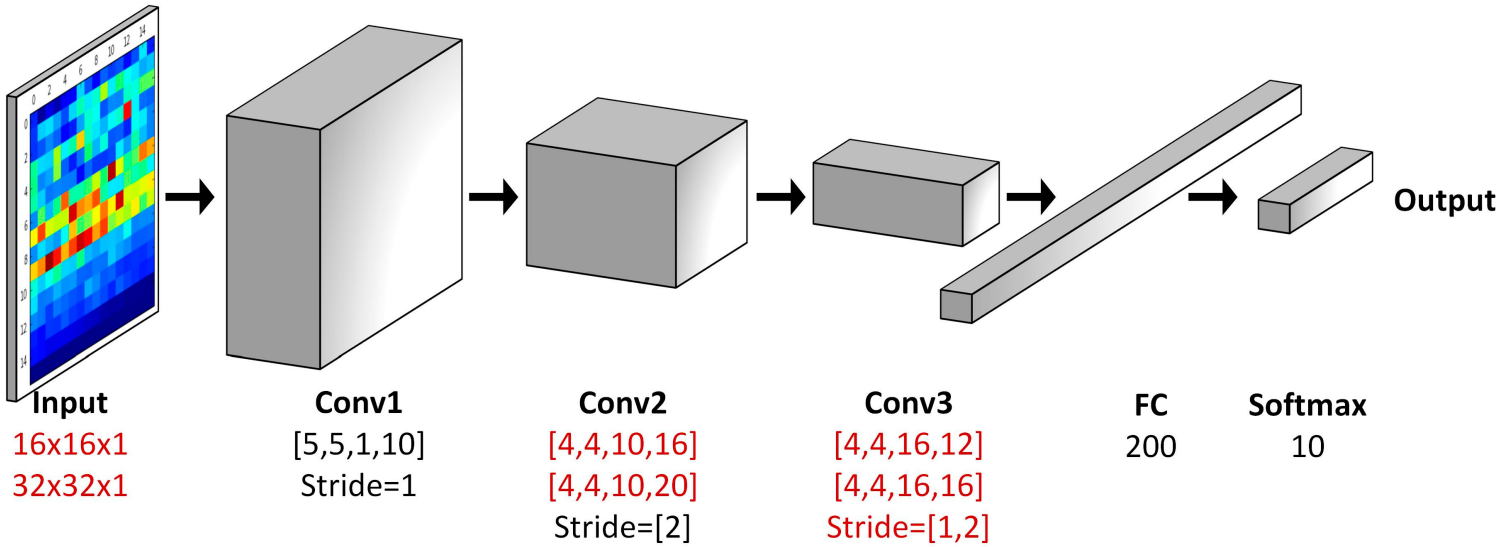
  - Pad 1, stride 1, output? $(5-3+1+2)(5-3+1+2)$
  - Pad 1, stride 2, output? $((5-3+2)/2+1)(((5-3+2)/2+1))$
  - Which one is Same padding?
- So the formula is: $(\frac{n-k+2p}{2}+1)$, Note: n can vary by dimensions
- Practice: *Same* convolution, how p relates to k?

Image credit: deeplearning.net

Outline

Motivation of Pooling

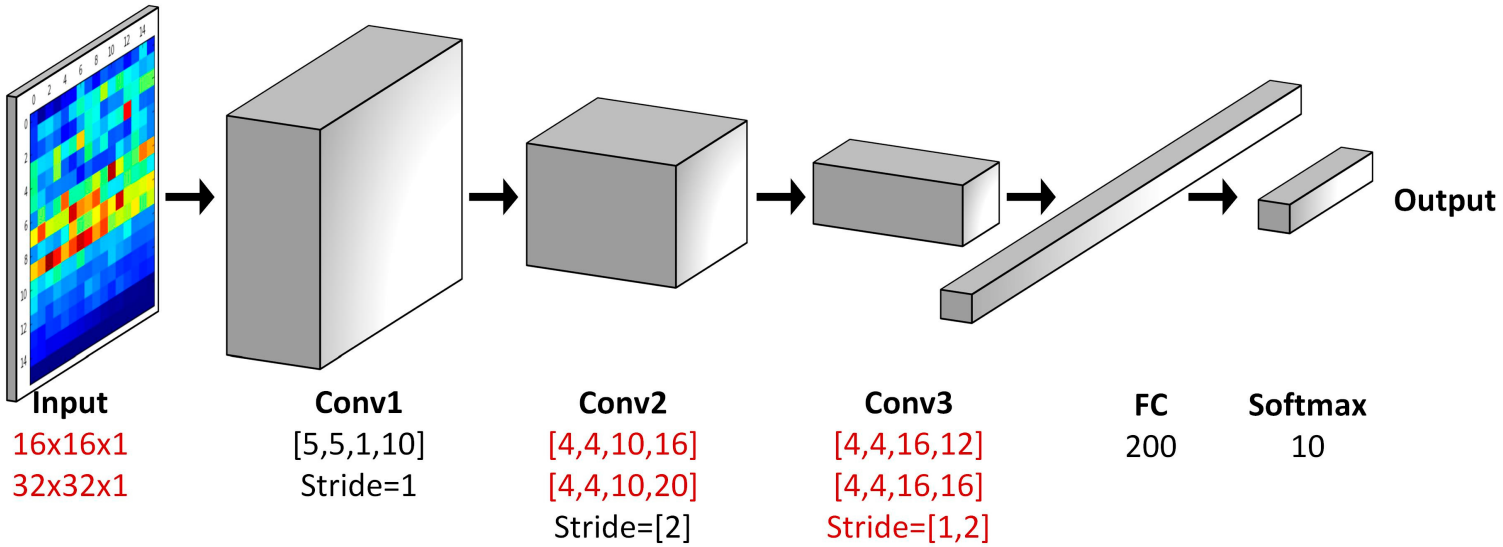


- Practice: given valid conv and zero padding, identify filter size at each step? Then calculate number of parameters at each step?

Image credit: mdpi.com

Motivation of Pooling

Carnegie Mellon



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- Can we go deeper with this? Imagine the real world cases of 200x200, or even 1024x1024.

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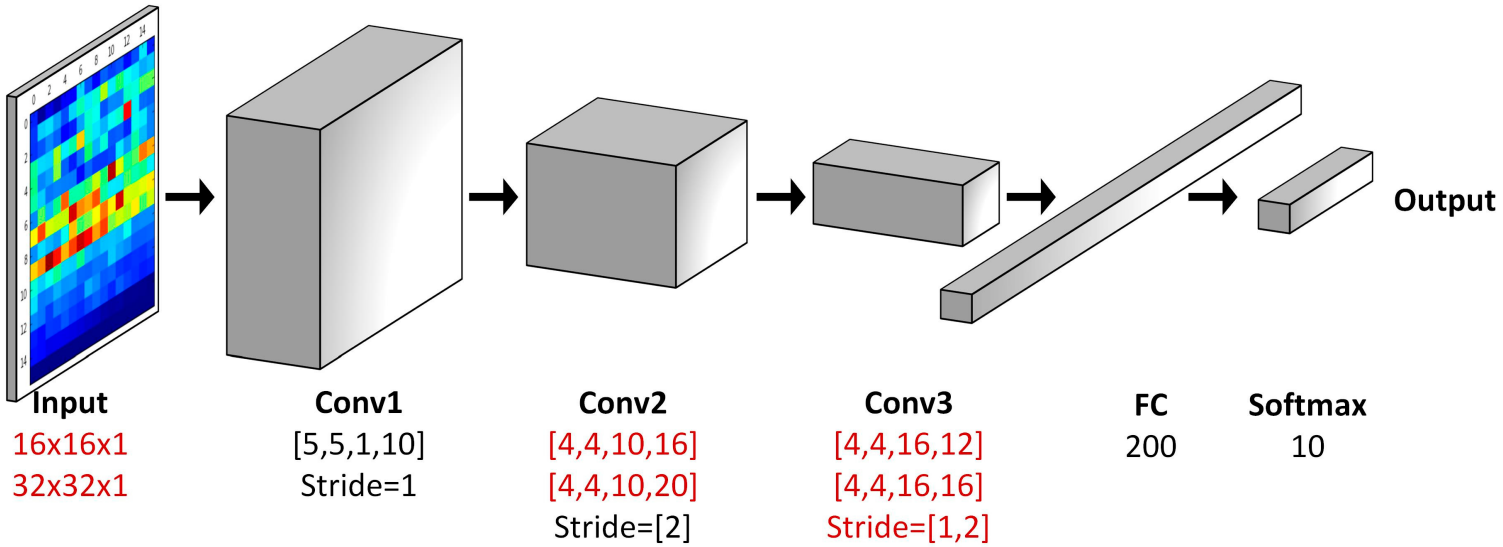
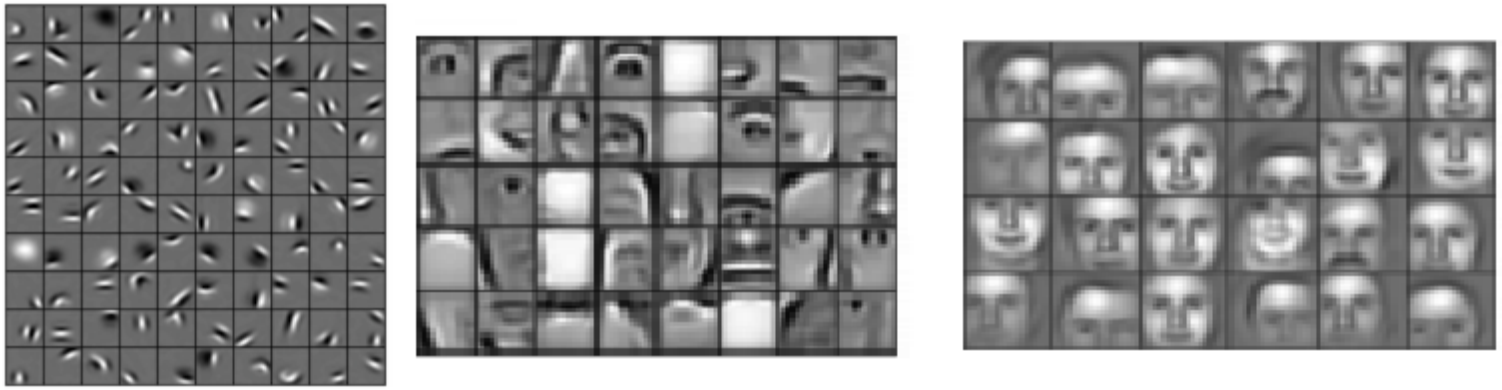


- Practice: given valid conv and zero padding, identify filter size at each step? Then calculate number of parameters at each step?
- Can we go deeper with this? Imagine the real world cases of 200x200, or even 1024x1024.
- We need to reduce dimensionality

Image credit: mdpi.com

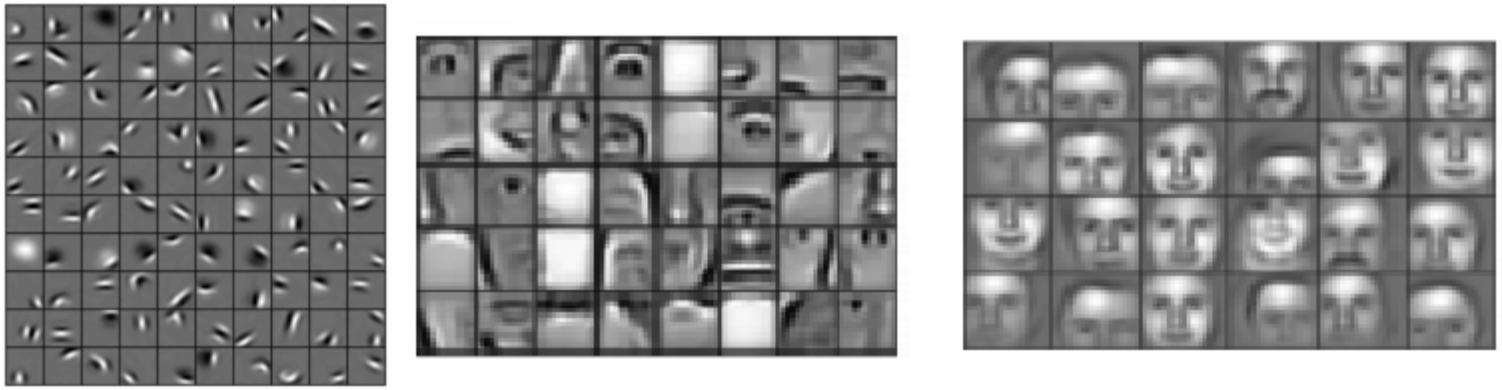
More Motivation of Pooling



- We want to reduce size of feature maps to easily control

Image credit: mdpi.com

More Motivation of Pooling



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- To prevent loss, we *summarize* features:
  - Each node (scalar) in a feature map represents features of a kernel-size region

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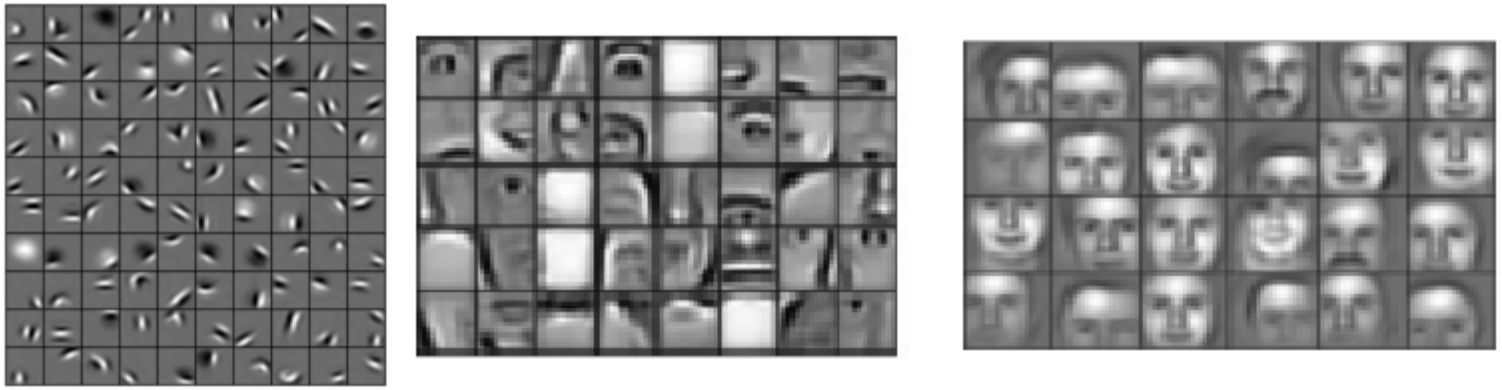
More Motivation of Pooling



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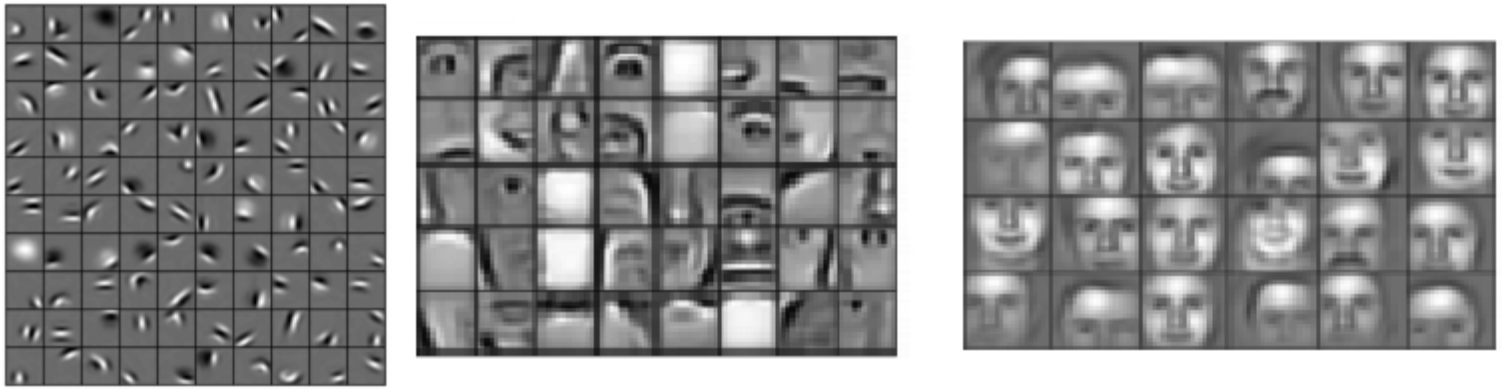

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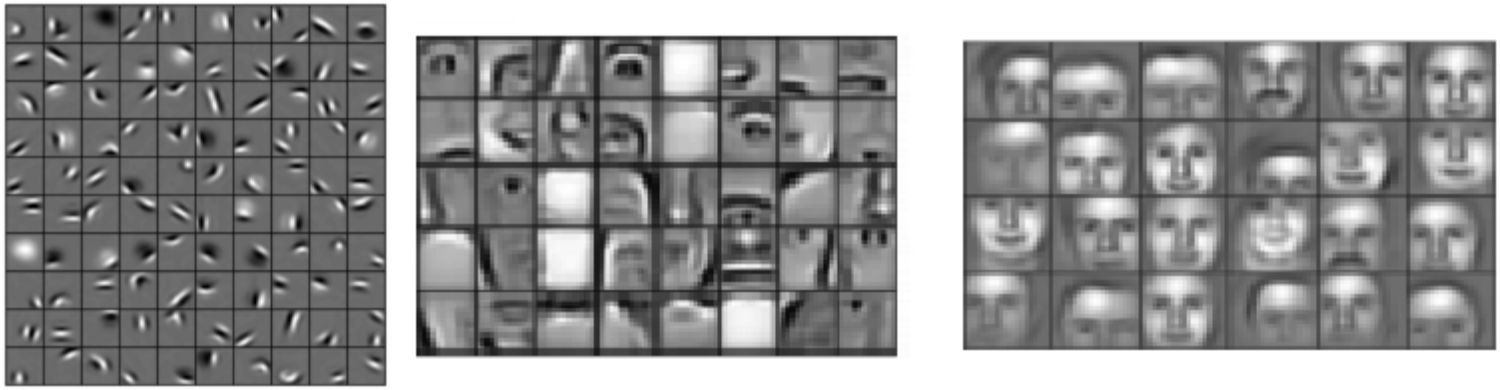

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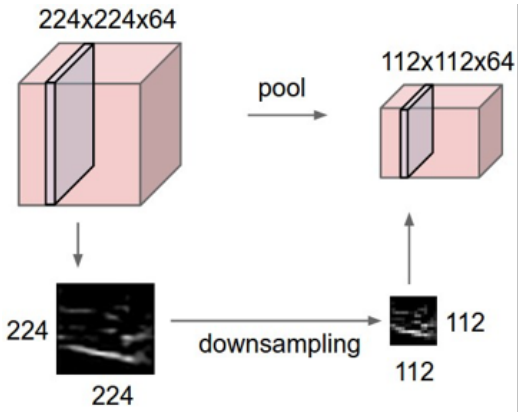
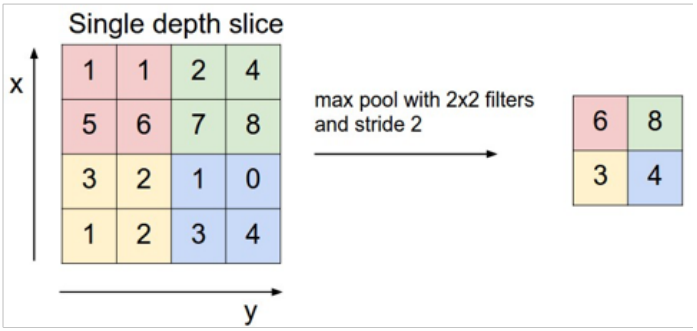
  - Each node (scalar) in a feature map represents features of a kernel-size region
  - Adjacent nodes represent a local region's features
  - Summarize adjacent nodes, we have features of a 'big' local region $\rightarrow$ *hierarchy*
- To get *translation invariance* for higher object levels

Image credit: mdpi.com

How Pooling Works?

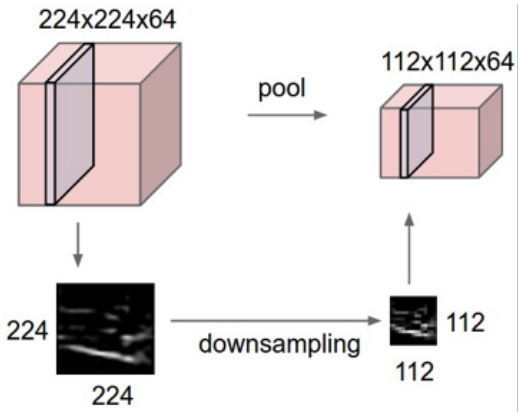


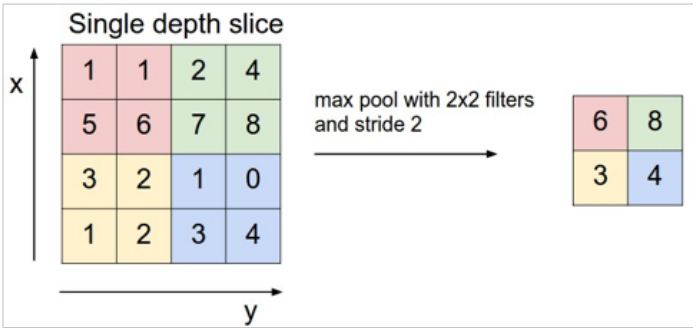


- Process each feature map *independently*
- *a.k.a* subsampling or downsampling process.

Image credit: http://cs231n.github.io/convolutional-networks

How Pooling Works?





- Process each feature map *independently*
- *a.k.a* subsampling or downsampling process.
- The window is also called a kernel/filter
- Popular types: MAX, AVG
- Practice: 5x5 with filter 3x3, stride 1, output?

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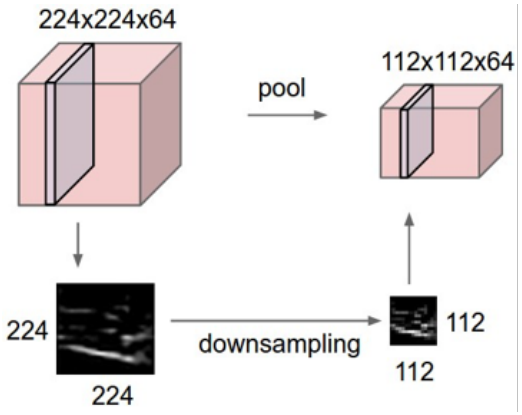

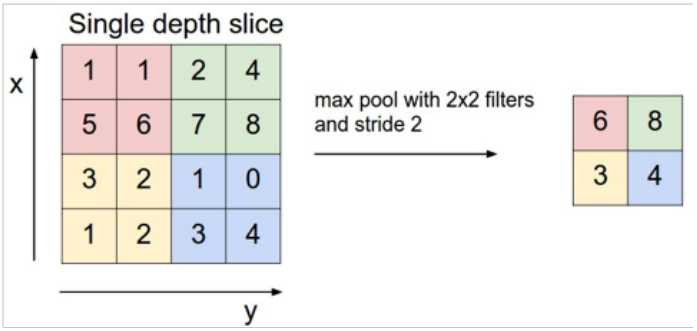

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- Practice: And how many params?

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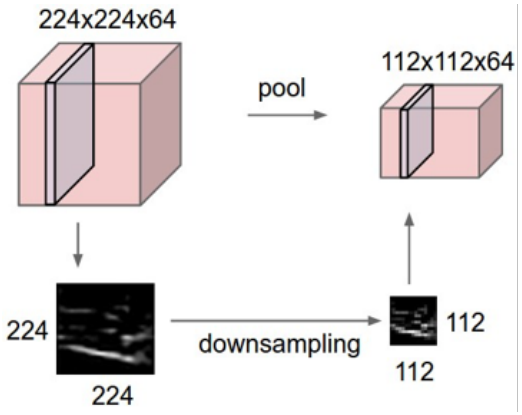

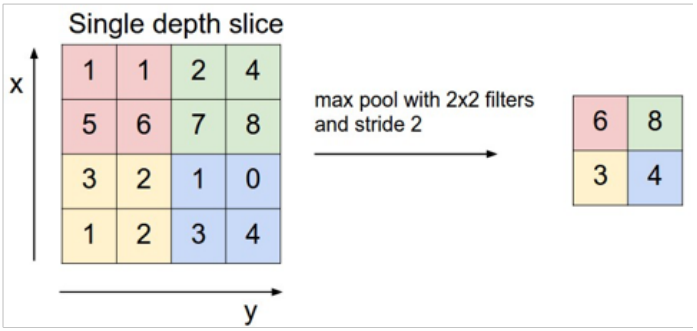

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- Practice: And how many params? Zero

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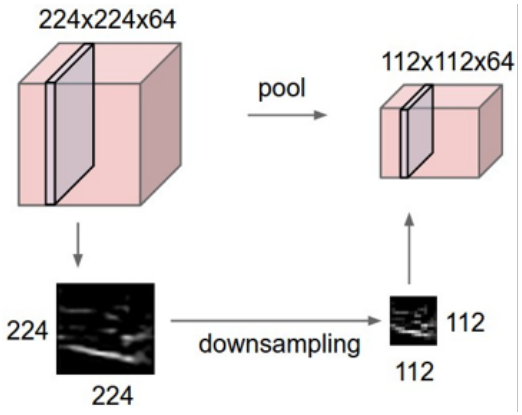

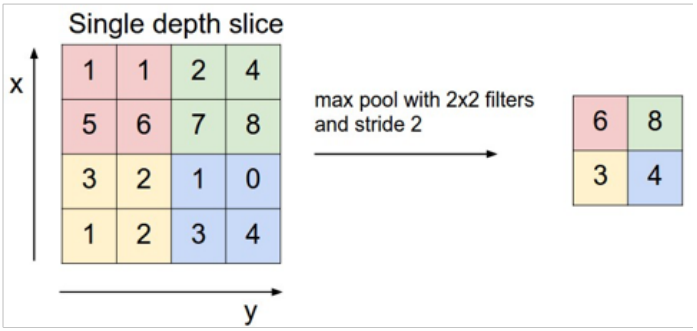

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- The window is also called a kernel/filter
- Popular types: MAX, AVG
- Practice: 5x5 with filter 3x3, stride 1, output? 3x3
- Practice: And how many params? Zero, and None padding.
- Output formula?

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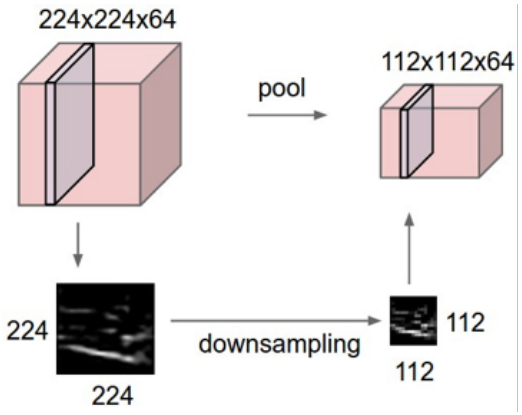
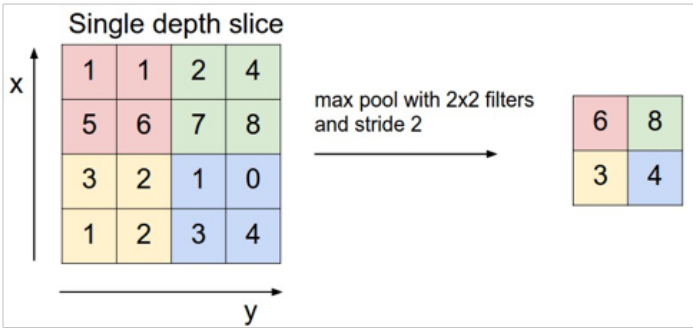
How Pooling Works?





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- Output formula? $(n-k)/s+1$

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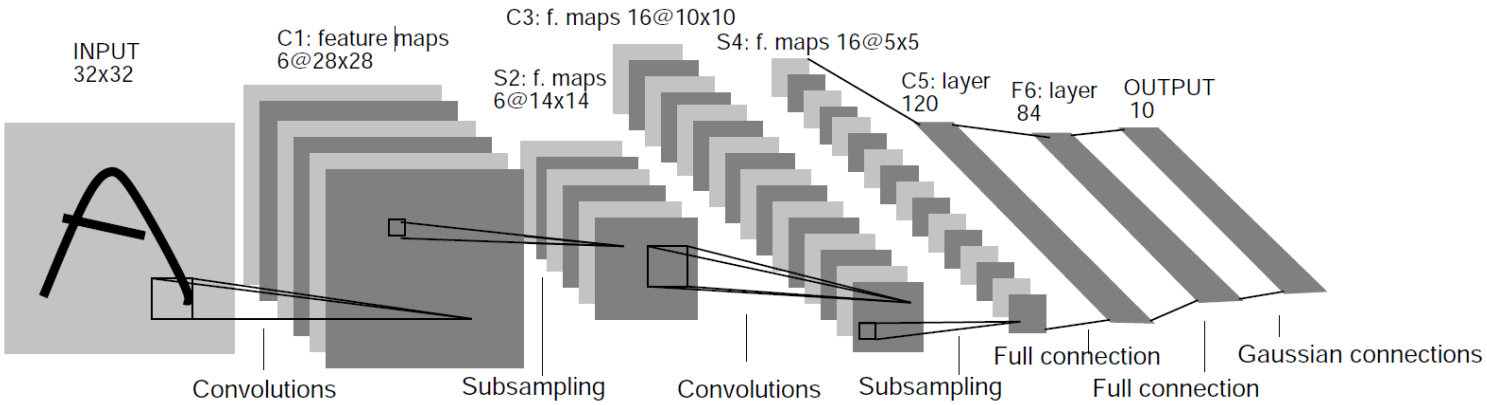
Outline

LeNet-5

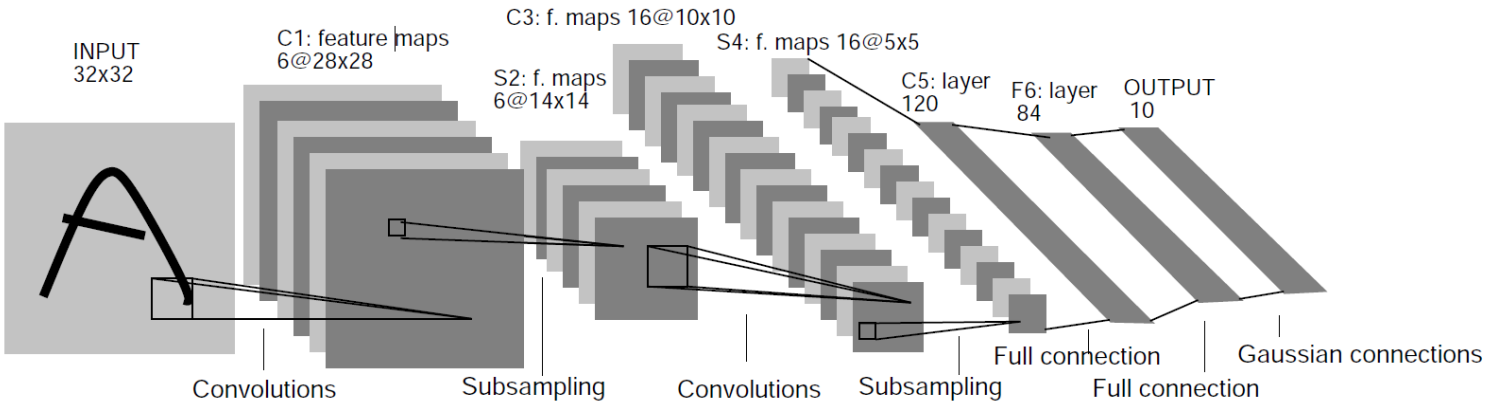
Carnegie Mellon



- Practice: what are the sizes of kernels and strides for Conv, and for Pooling?

Image credit: pythonmachinelearning.pro

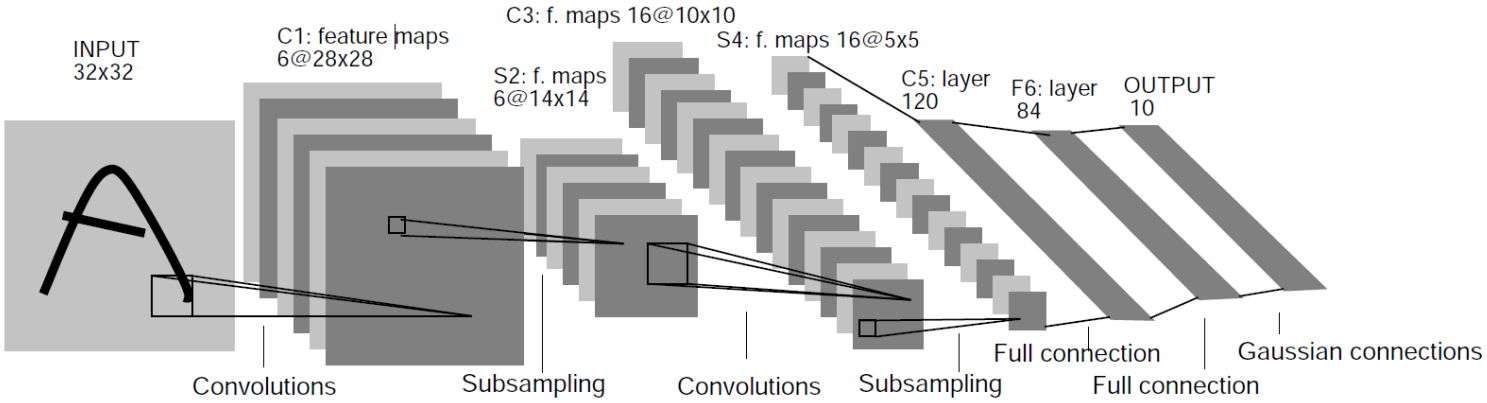
LeNet-5



- Practice: what are the sizes of kernels and strides for Conv, and for Pooling? conv: 5x5 and 1, pool: 2x2 and 2
- Practice: how many params at each step?

Image credit: pythonmachinelearning.pro

LeNet-5

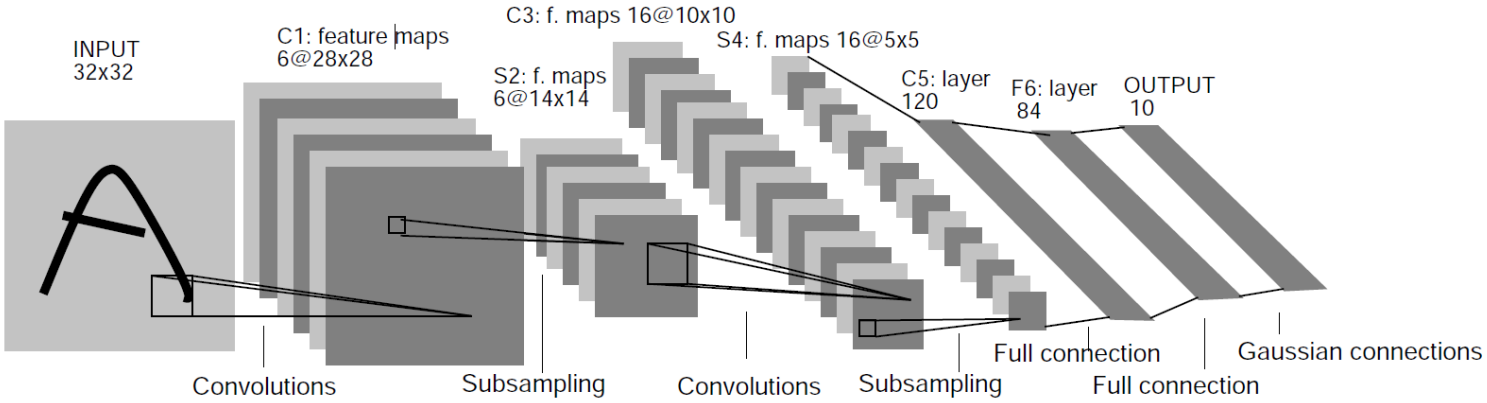


- Arguably the first CNN that *really* works ▸ Demo
- Practice: what are the sizes of kernels and strides for Conv, and for Pooling?

Image credit: Yann Lecun et. al 1998

LeNet-5

Carnegie Mellon



- Arguably the first CNN that *really* works ▸ Demo
- Practice: what are the sizes of kernels and strides for Conv, and for Pooling? conv: $5 * 5$ and 1, pool: $2 * 2$ and 2
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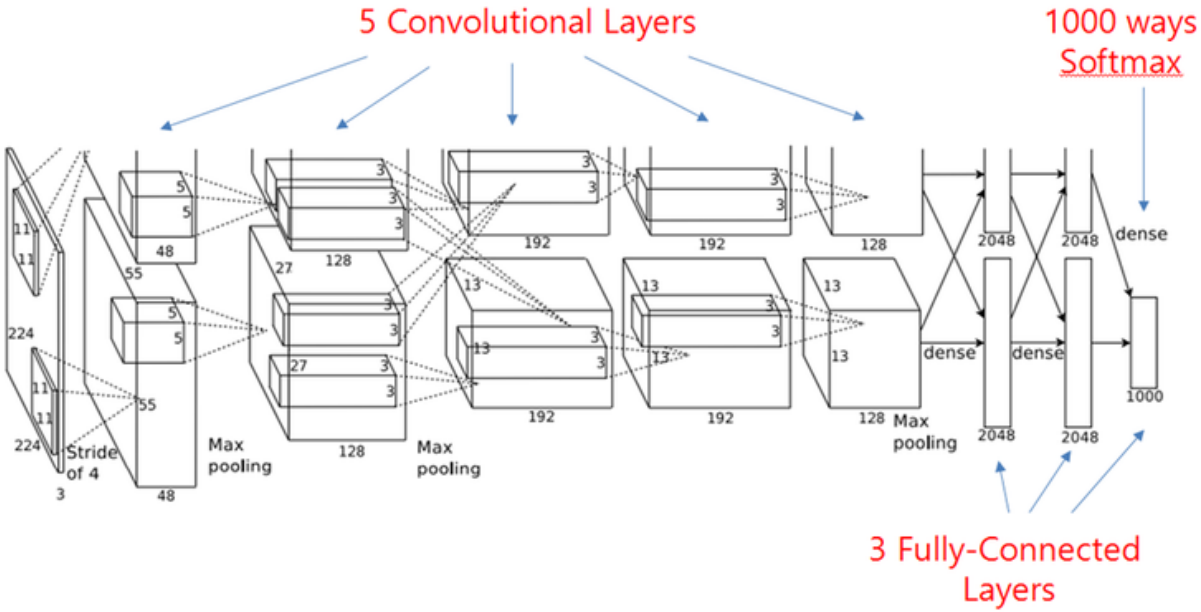
Image credit: Yann Lecun et. al 1998

AlexNet: A Revolution

Carnegie Mellon

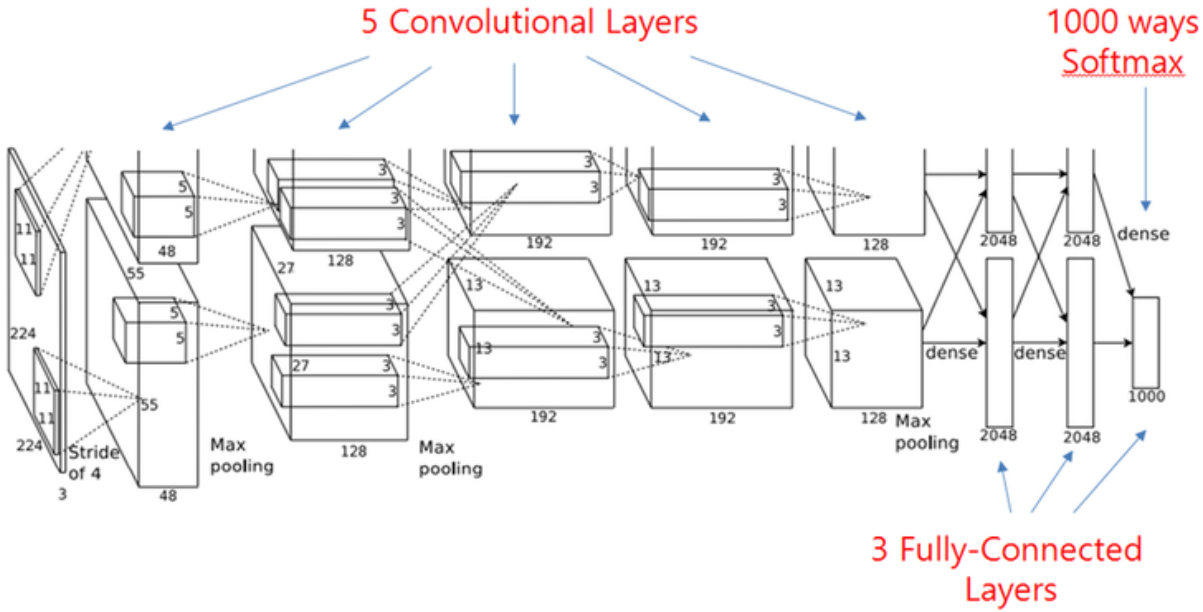


- First use of ReLU, Norm layers, heavy augmentation, dropout, momentum
- Input: $227 * 227 * 3$
- Conv1: 96 of $11 * 11$ filters, stride 4, output?

Image credit: Krizhevsky et. al 2012

AlexNet: A Revolution

Carnegie Mellon



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- Input: $227 * 227 * 3$
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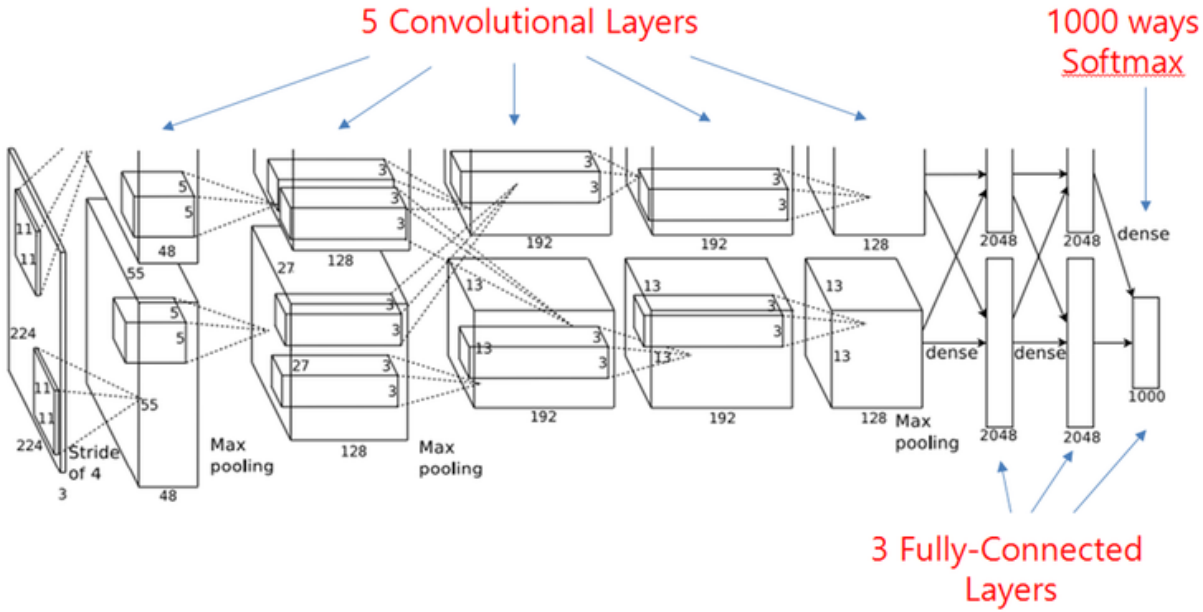
AlexNet: A Revolution

Carnegie Mellon



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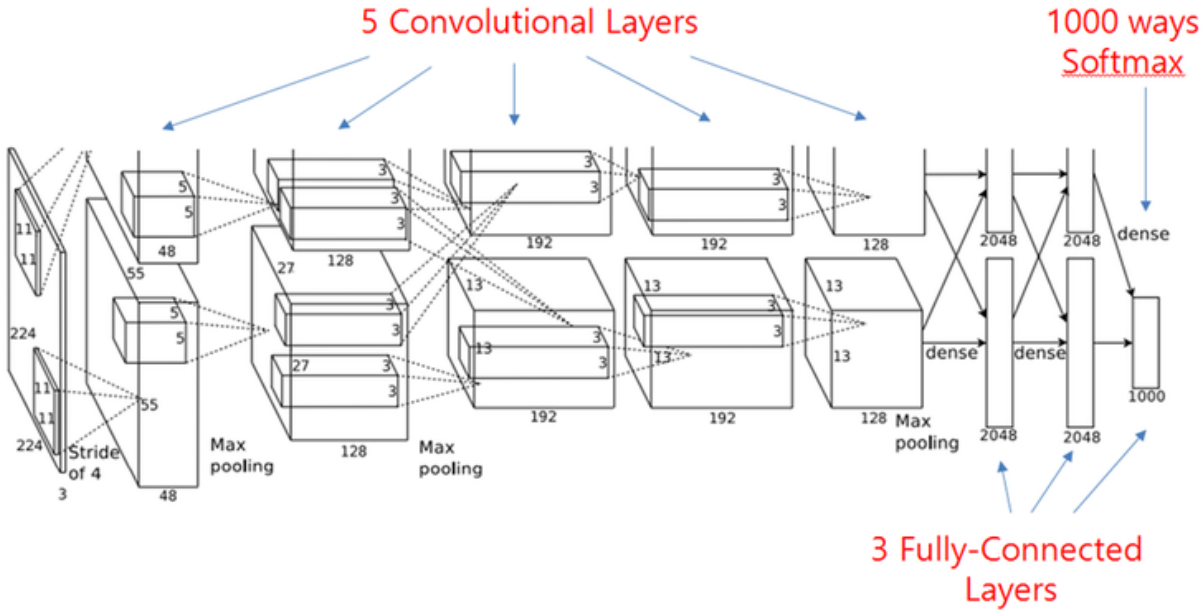
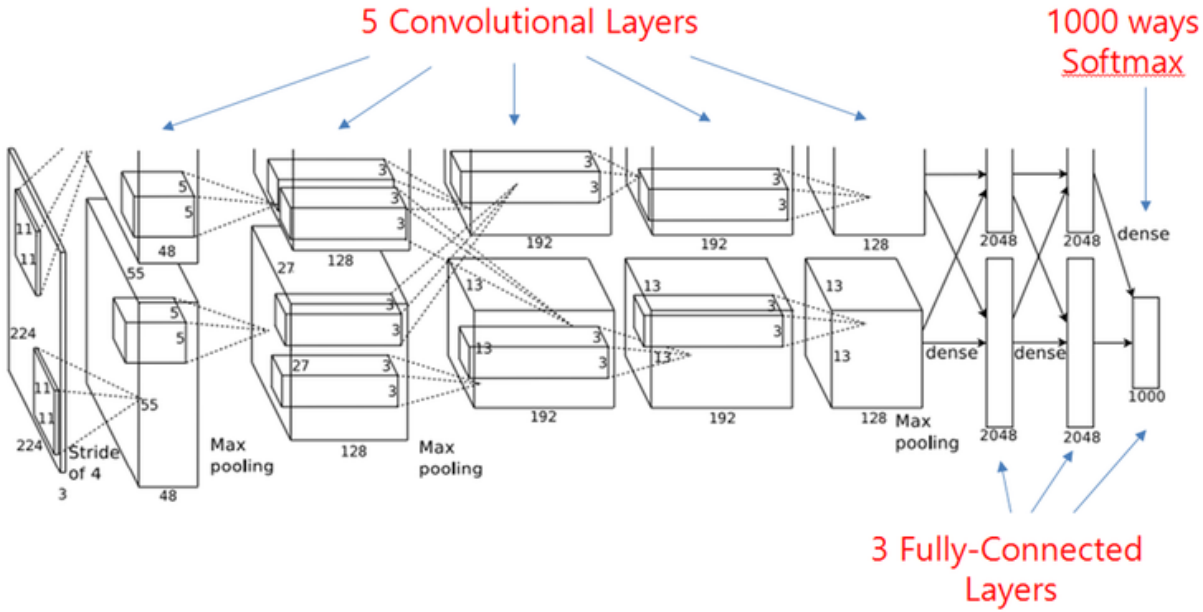


- First use of ReLU, Norm layers, heavy augmentation, dropout, momentum
- Input: $227 * 227 * 3$
- Conv1: 96 of $11 * 11$ filters, stride 4, output? $55 * 55 * 96$, params? $(11 * 11 * 3) * 96$
- Pool1: $3 * 3$ filter, stride 2, output?

Image credit: Krizhevsky et. al 2012

AlexNet: A Revolution

Carnegie Mellon



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- Input: $227 * 227 * 3$
- Conv1: 96 of $11 * 11$ filters, stride 4, output? $55 * 55 * 96$, params? $(11 * 11 * 3) * 96$
- Pool1: $3 * 3$ filter, stride 2, output? $27 * 27 * 96$

Image credit: Krizhevsky et. al 2012

AlexNet (cont'd)

- Conv2: 256 of $5 * 5$ filters, stride 1, padding 2, output?

AlexNet (cont'd)

- Conv2: 256 of $5 * 5$ filters, stride 1, padding 2, output?
  $27 * 27 * 256$ (same padding),

AlexNet (cont'd)

- Conv2: 256 of $5 * 5$ filters, stride 1, padding 2, output?
  $27 * 27 * 256$ (same padding), params?

AlexNet (cont'd)

- Conv2: 256 of $5 * 5$ filters, stride 1, padding 2, output?
  $27 * 27 * 256$ (same padding), params? $(5 * 5 * 96) * 256$
- Pool2: $3 * 3$ filter, stride 2, output?

AlexNet (cont'd)

- Conv2: 256 of $5 * 5$ filters, stride 1, padding 2, output? $27 * 27 * 256$ (same padding), params? $(5 * 5 * 96) * 256$
- Pool2: $3 * 3$ filter, stride 2, output? $13 * 13 * 256$
- Conv3: 384 of $3 * 3$ filters, stride 1, padding 1, output?

AlexNet (cont'd)

Carnegie Mellon

- Conv2: 256 of $5 * 5$ filters, stride 1, padding 2, output? $27 * 27 * 256$ (same padding), params? $(5 * 5 * 96) * 256$
- Pool2: $3 * 3$ filter, stride 2, output? $13 * 13 * 256$
- Conv3: 384 of $3 * 3$ filters, stride 1, padding 1, output? $13 * 13 * 384$ (same padding),

AlexNet (cont'd)

Carnegie Mellon

- Conv2: 256 of $5 * 5$ filters, stride 1, padding 2, output?
  $27 * 27 * 256$ (same padding), params? $(5 * 5 * 96) * 256$
- Pool2: $3 * 3$ filter, stride 2, output? $13 * 13 * 256$
- Conv3: 384 of $3 * 3$ filters, stride 1, padding 1, output?
  $13 * 13 * 384$ (same padding), params?

AlexNet (cont'd)

Carnegie Mellon

- Conv2: 256 of $5 * 5$ filters, stride 1, padding 2, output?
  $27 * 27 * 256$ (same padding), params? $(5 * 5 * 96) * 256$
- Pool2: $3 * 3$ filter, stride 2, output? $13 * 13 * 256$
- Conv3: 384 of $3 * 3$ filters, stride 1, padding 1, output?
  $13 * 13 * 384$ (same padding), params? $(3 * 3 * 256) * 384$
- Conv4: 384 of $3 * 3$ filters, stride 1, padding 1, output?

AlexNet (cont'd)

Carnegie Mellon

- Conv2: 256 of $5 * 5$ filters, stride 1, padding 2, output?
  $27 * 27 * 256$ (same padding), params? $(5 * 5 * 96) * 256$
- Pool2: $3 * 3$ filter, stride 2, output? $13 * 13 * 256$
- Conv3: 384 of $3 * 3$ filters, stride 1, padding 1, output?
  $13 * 13 * 384$ (same padding), params? $(3 * 3 * 256) * 384$
- Conv4: 384 of $3 * 3$ filters, stride 1, padding 1, output?
  $13 * 13 * 384$ (same padding),

AlexNet (cont'd)

Carnegie Mellon

- Conv2: 256 of $5 * 5$ filters, stride 1, padding 2, output?
  $27 * 27 * 256$ (same padding), params? $(5 * 5 * 96) * 256$
- Pool2: $3 * 3$ filter, stride 2, output? $13 * 13 * 256$
- Conv3: 384 of $3 * 3$ filters, stride 1, padding 1, output?
  $13 * 13 * 384$ (same padding), params? $(3 * 3 * 256) * 384$
- Conv4: 384 of $3 * 3$ filters, stride 1, padding 1, output?
  $13 * 13 * 384$ (same padding), params?

AlexNet (cont'd)

Carnegie Mellon

- Conv2: 256 of $5 * 5$ filters, stride 1, padding 2, output?
  $27 * 27 * 256$ (same padding), params? $(5 * 5 * 96) * 256$
- Pool2: $3 * 3$ filter, stride 2, output? $13 * 13 * 256$
- Conv3: 384 of $3 * 3$ filters, stride 1, padding 1, output?
  $13 * 13 * 384$ (same padding), params? $(3 * 3 * 256) * 384$
- Conv4: 384 of $3 * 3$ filters, stride 1, padding 1, output?
  $13 * 13 * 384$ (same padding), params? $(3 * 3 * 384) * 384$
- Conv5: 256 of $3 * 3$ filters, stride 1, padding 1, output?

AlexNet (cont'd)

Carnegie Mellon

- Conv2: 256 of $5 * 5$ filters, stride 1, padding 2, output?
  $27 * 27 * 256$ (same padding), params? $(5 * 5 * 96) * 256$
- Pool2: $3 * 3$ filter, stride 2, output? $13 * 13 * 256$
- Conv3: 384 of $3 * 3$ filters, stride 1, padding 1, output?
  $13 * 13 * 384$ (same padding), params? $(3 * 3 * 256) * 384$
- Conv4: 384 of $3 * 3$ filters, stride 1, padding 1, output?
  $13 * 13 * 384$ (same padding), params? $(3 * 3 * 384) * 384$
- Conv5: 256 of $3 * 3$ filters, stride 1, padding 1, output?
  $13 * 13 * 256$ (same padding),

AlexNet (cont'd)

Carnegie Mellon

- Conv2: 256 of $5 * 5$ filters, stride 1, padding 2, output?
  $27 * 27 * 256$ (same padding), params? $(5 * 5 * 96) * 256$
- Pool2: $3 * 3$ filter, stride 2, output? $13 * 13 * 256$
- Conv3: 384 of $3 * 3$ filters, stride 1, padding 1, output?
  $13 * 13 * 384$ (same padding), params? $(3 * 3 * 256) * 384$
- Conv4: 384 of $3 * 3$ filters, stride 1, padding 1, output?
  $13 * 13 * 384$ (same padding), params? $(3 * 3 * 384) * 384$
- Conv5: 256 of $3 * 3$ filters, stride 1, padding 1, output?
  $13 * 13 * 256$ (same padding), params?

AlexNet (cont'd)

Carnegie Mellon

- Conv2: 256 of $5 * 5$ filters, stride 1, padding 2, output?
  $27 * 27 * 256$ (same padding), params? $(5 * 5 * 96) * 256$
- Pool2: $3 * 3$ filter, stride 2, output? $13 * 13 * 256$
- Conv3: 384 of $3 * 3$ filters, stride 1, padding 1, output?
  $13 * 13 * 384$ (same padding), params? $(3 * 3 * 256) * 384$
- Conv4: 384 of $3 * 3$ filters, stride 1, padding 1, output?
  $13 * 13 * 384$ (same padding), params? $(3 * 3 * 384) * 384$
- Conv5: 256 of $3 * 3$ filters, stride 1, padding 1, output?
  $13 * 13 * 256$ (same padding), params? $(3 * 3 * 384) * 256$
- Pool3: $3 * 3$ filter, stride 2, output?

AlexNet (cont'd)

Carnegie Mellon

- Conv2: 256 of $5 * 5$ filters, stride 1, padding 2, output?
  $27 * 27 * 256$ (same padding), params? $(5 * 5 * 96) * 256$
- Pool2: $3 * 3$ filter, stride 2, output? $13 * 13 * 256$
- Conv3: 384 of $3 * 3$ filters, stride 1, padding 1, output?
  $13 * 13 * 384$ (same padding), params? $(3 * 3 * 256) * 384$
- Conv4: 384 of $3 * 3$ filters, stride 1, padding 1, output?
  $13 * 13 * 384$ (same padding), params? $(3 * 3 * 384) * 384$
- Conv5: 256 of $3 * 3$ filters, stride 1, padding 1, output?
  $13 * 13 * 256$ (same padding), params? $(3 * 3 * 384) * 256$
- Pool3: $3 * 3$ filter, stride 2, output? $6 * 6 * 256$
- FC6: 4096 neurons, output?

AlexNet (cont'd)

Carnegie Mellon

- Conv2: 256 of $5 * 5$ filters, stride 1, padding 2, output? $27 * 27 * 256$ (same padding), params? $(5 * 5 * 96) * 256$
- Pool2: $3 * 3$ filter, stride 2, output? $13 * 13 * 256$
- Conv3: 384 of $3 * 3$ filters, stride 1, padding 1, output? $13 * 13 * 384$ (same padding), params? $(3 * 3 * 256) * 384$
- Conv4: 384 of $3 * 3$ filters, stride 1, padding 1, output? $13 * 13 * 384$ (same padding), params? $(3 * 3 * 384) * 384$
- Conv5: 256 of $3 * 3$ filters, stride 1, padding 1, output? $13 * 13 * 256$ (same padding), params? $(3 * 3 * 384) * 256$
- Pool3: $3 * 3$ filter, stride 2, output? $6 * 6 * 256$
- FC6: 4096 neurons, output? 4096,

AlexNet (cont'd)

Carnegie Mellon

- Conv2: 256 of $5 * 5$ filters, stride 1, padding 2, output? $27 * 27 * 256$ (same padding), params? $(5 * 5 * 96) * 256$
- Pool2: $3 * 3$ filter, stride 2, output? $13 * 13 * 256$
- Conv3: 384 of $3 * 3$ filters, stride 1, padding 1, output? $13 * 13 * 384$ (same padding), params? $(3 * 3 * 256) * 384$
- Conv4: 384 of $3 * 3$ filters, stride 1, padding 1, output? $13 * 13 * 384$ (same padding), params? $(3 * 3 * 384) * 384$
- Conv5: 256 of $3 * 3$ filters, stride 1, padding 1, output? $13 * 13 * 256$ (same padding), params? $(3 * 3 * 384) * 256$
- Pool3: $3 * 3$ filter, stride 2, output? $6 * 6 * 256$
- FC6: 4096 neurons, output? 4096,params?

AlexNet (cont'd)

Carnegie Mellon

- Conv2: 256 of $5 * 5$ filters, stride 1, padding 2, output?
  $27 * 27 * 256$ (same padding), params? $(5 * 5 * 96) * 256$
- Pool2: $3 * 3$ filter, stride 2, output? $13 * 13 * 256$
- Conv3: 384 of $3 * 3$ filters, stride 1, padding 1, output?
  $13 * 13 * 384$ (same padding), params? $(3 * 3 * 256) * 384$
- Conv4: 384 of $3 * 3$ filters, stride 1, padding 1, output?
  $13 * 13 * 384$ (same padding), params? $(3 * 3 * 384) * 384$
- Conv5: 256 of $3 * 3$ filters, stride 1, padding 1, output?
  $13 * 13 * 256$ (same padding), params? $(3 * 3 * 384) * 256$
- Pool3: $3 * 3$ filter, stride 2, output? $6 * 6 * 256$
- FC6: 4096 neurons, output? 4096,params? $6 * 6 * 256 * 4096$
- FC7: 4096 neurons, output?

AlexNet (cont'd)

Carnegie Mellon

- Conv2: 256 of $5 * 5$ filters, stride 1, padding 2, output? $27 * 27 * 256$ (same padding), params? $(5 * 5 * 96) * 256$
- Pool2: $3 * 3$ filter, stride 2, output? $13 * 13 * 256$
- Conv3: 384 of $3 * 3$ filters, stride 1, padding 1, output? $13 * 13 * 384$ (same padding), params? $(3 * 3 * 256) * 384$
- Conv4: 384 of $3 * 3$ filters, stride 1, padding 1, output? $13 * 13 * 384$ (same padding), params? $(3 * 3 * 384) * 384$
- Conv5: 256 of $3 * 3$ filters, stride 1, padding 1, output? $13 * 13 * 256$ (same padding), params? $(3 * 3 * 384) * 256$
- Pool3: $3 * 3$ filter, stride 2, output? $6 * 6 * 256$
- FC6: 4096 neurons, output? 4096,params? $6 * 6 * 256 * 4096$
- FC7: 4096 neurons, output? 4096,

AlexNet (cont'd)

Carnegie Mellon

- Conv2: 256 of $5 * 5$ filters, stride 1, padding 2, output? $27 * 27 * 256$ (same padding), params? $(5 * 5 * 96) * 256$
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- Conv3: 384 of $3 * 3$ filters, stride 1, padding 1, output? $13 * 13 * 384$ (same padding), params? $(3 * 3 * 256) * 384$
- Conv4: 384 of $3 * 3$ filters, stride 1, padding 1, output? $13 * 13 * 384$ (same padding), params? $(3 * 3 * 384) * 384$
- Conv5: 256 of $3 * 3$ filters, stride 1, padding 1, output? $13 * 13 * 256$ (same padding), params? $(3 * 3 * 384) * 256$
- Pool3: $3 * 3$ filter, stride 2, output? $6 * 6 * 256$
- FC6: 4096 neurons, output? 4096,params? $6 * 6 * 256 * 4096$
- FC7: 4096 neurons, output? 4096,params?

AlexNet (cont'd)

Carnegie Mellon

- Conv2: 256 of $5 * 5$ filters, stride 1, padding 2, output?
  $27 * 27 * 256$ (same padding), params? $(5 * 5 * 96) * 256$
- Pool2: $3 * 3$ filter, stride 2, output? $13 * 13 * 256$
- Conv3: 384 of $3 * 3$ filters, stride 1, padding 1, output?
  $13 * 13 * 384$ (same padding), params? $(3 * 3 * 256) * 384$
- Conv4: 384 of $3 * 3$ filters, stride 1, padding 1, output?
  $13 * 13 * 384$ (same padding), params? $(3 * 3 * 384) * 384$
- Conv5: 256 of $3 * 3$ filters, stride 1, padding 1, output?
  $13 * 13 * 256$ (same padding), params? $(3 * 3 * 384) * 256$
- Pool3: $3 * 3$ filter, stride 2, output? $6 * 6 * 256$
- FC6: 4096 neurons, output? 4096,params? $6 * 6 * 256 * 4096$
- FC7: 4096 neurons, output? 4096,params? $4096 * 4096$
- FC8: 1000 neurons, output?

AlexNet (cont'd)

Carnegie Mellon

- Conv2: 256 of $5 * 5$ filters, stride 1, padding 2, output? $27 * 27 * 256$ (same padding), params? $(5 * 5 * 96) * 256$
- Pool2: $3 * 3$ filter, stride 2, output? $13 * 13 * 256$
- Conv3: 384 of $3 * 3$ filters, stride 1, padding 1, output? $13 * 13 * 384$ (same padding), params? $(3 * 3 * 256) * 384$
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- Conv5: 256 of $3 * 3$ filters, stride 1, padding 1, output? $13 * 13 * 256$ (same padding), params? $(3 * 3 * 384) * 256$
- Pool3: $3 * 3$ filter, stride 2, output? $6 * 6 * 256$
- FC6: 4096 neurons, output? 4096,params? $6 * 6 * 256 * 4096$
- FC7: 4096 neurons, output? 4096,params? $4096 * 4096$
- FC8: 1000 neurons, output? 1000,

AlexNet (cont'd)

Carnegie Mellon

- Conv2: 256 of $5 * 5$ filters, stride 1, padding 2, output? $27 * 27 * 256$ (same padding), params? $(5 * 5 * 96) * 256$
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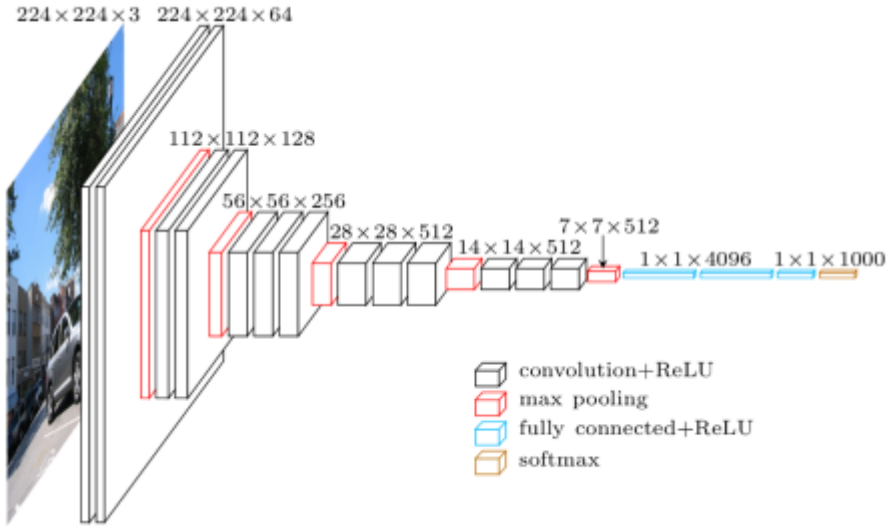
- Conv5: 256 of $3 * 3$ filters, stride 1, padding 1, output? $13 * 13 * 256$ (same padding), params? $(3 * 3 * 384) * 256$
- Pool3: $3 * 3$ filter, stride 2, output? $6 * 6 * 256$
- FC6: 4096 neurons, output? 4096,params? $6 * 6 * 256 * 4096$
- FC7: 4096 neurons, output? 4096,params? $4096 * 4096$
- FC8: 1000 neurons, output? 1000,params?

AlexNet (cont'd)

Carnegie Mellon

- Conv2: 256 of $5 * 5$ filters, stride 1, padding 2, output? $27 * 27 * 256$ (same padding), params? $(5 * 5 * 96) * 256$
- Pool2: $3 * 3$ filter, stride 2, output? $13 * 13 * 256$
- Conv3: 384 of $3 * 3$ filters, stride 1, padding 1, output? $13 * 13 * 384$ (same padding), params? $(3 * 3 * 256) * 384$
- Conv4: 384 of $3 * 3$ filters, stride 1, padding 1, output? $13 * 13 * 384$ (same padding), params? $(3 * 3 * 384) * 384$
- Conv5: 256 of $3 * 3$ filters, stride 1, padding 1, output? $13 * 13 * 256$ (same padding), params? $(3 * 3 * 384) * 256$
- Pool3: $3 * 3$ filter, stride 2, output? $6 * 6 * 256$
- FC6: 4096 neurons, output? 4096,params? $6 * 6 * 256 * 4096$
- FC7: 4096 neurons, output? 4096,params? $4096 * 4096$
- FC8: 1000 neurons, output? 1000,params? $4096 * 1000$

VGG



- Got 11.2% top 5 error at ILSVRC 2013
- Very widely used for its lightweight yet efficient architecture.
- Popular with 16 and 19 layers
- Reduce params: all fixed $3 * 3$ filters, and stride 2 poolings: 138M params (VGG16)

Image credit: David Frossard

Stay Tuned!

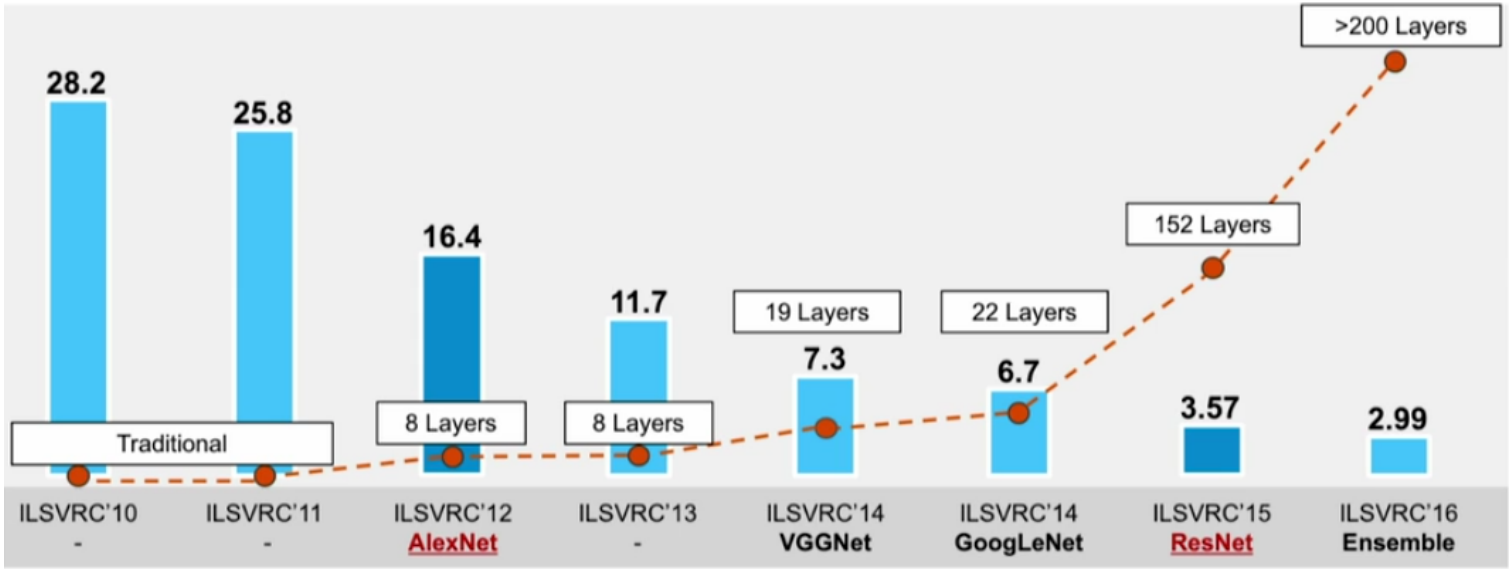


Image credit: SQLML

End of Module I.