Resources

Books

- *“Deep Learning”* by Ian Goodfellow, Yoshua Bengio and Aaron Courville (MIT Press, 2016)
- *“Neural Networks and Deep Learning”* by Michael Nielsen
- [classical CV] *"Computer Vision: Models, Learning, and Inference”* by Simon J.D. Prince

Courses

- Stanford CS 231n: by Li, Karpathy & Johnson
  http://cs231n.github.io/
- fast.ai online courses (all are free and have no ads)
  https://www.fast.ai/

Goals of the Course

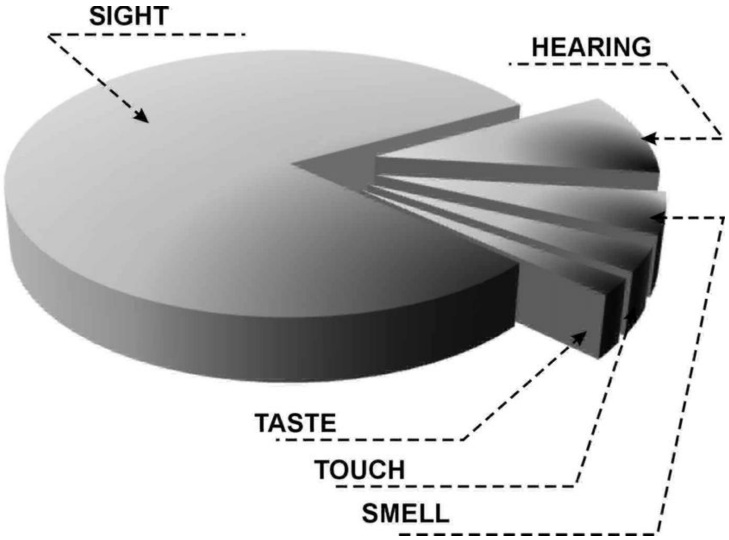
- Get an overview of Convolutional Neural Networks (CNN) with application to Computer Vision;
- Get understanding of various elements/blocks of CNNs and typical network topologies;
- Get deeper with one particular problem (Object Detection);

- Device and train CNN for classification
- Learn useful tools: Pytorch, Colab notebook, TensorBroad

Content of today lecture

- **Intro**
- ML review
- Intro to CNN

Intro



The goal of computer vision is to extract useful information from visual input (images, video)

Intro

- indoor/outdoor? [image classification]
- Where are the objects? [object detection]
- How far is the object ? [depth estimation]
- What people are doing? [activity recognition]
- Is the state of the environment normal? [anomaly detection]
- ...

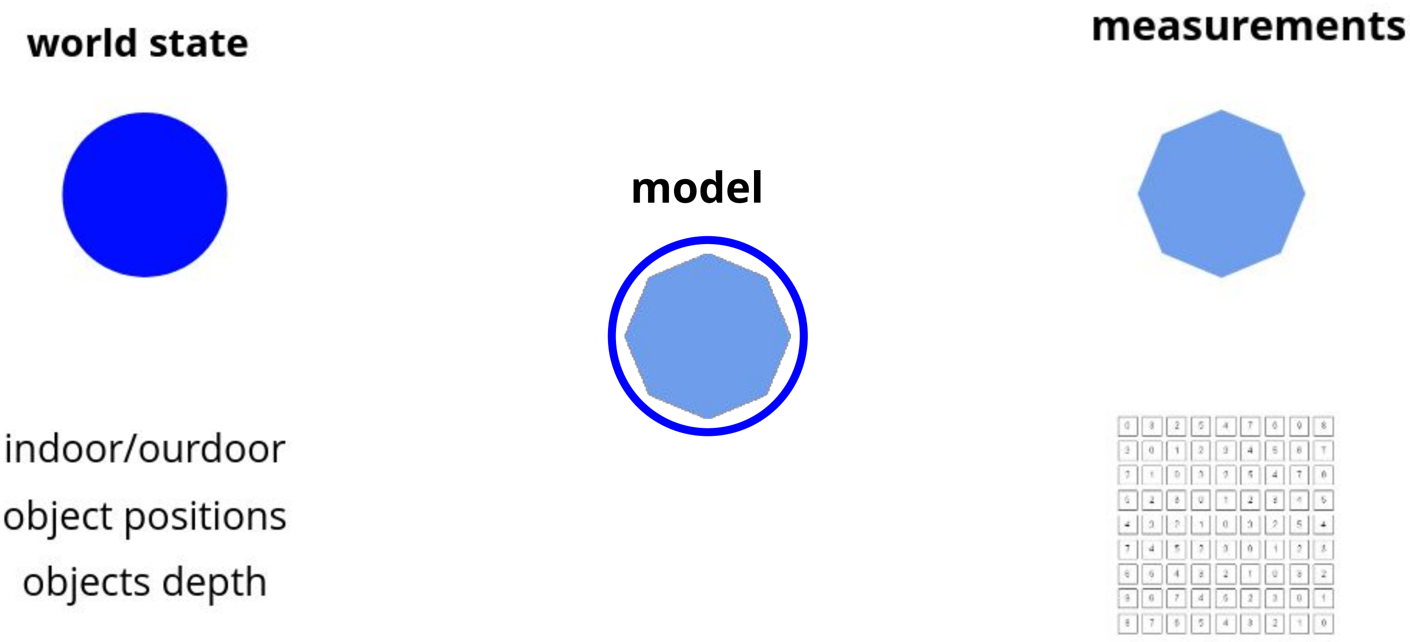
Intro

what humans see

0	3	2	5	4	7	6	9	8
3	0	1	2	3	4	5	6	7
2	1	0	3	2	5	4	7	6
5	2	3	0	1	2	3	4	5
4	3	2	1	0	3	2	5	4
7	4	5	2	3	0	1	2	3
6	5	4	3	2	1	0	3	2
9	6	7	4	5	2	3	0	1
8	7	6	5	4	3	2	1	0

what computers see

Intro

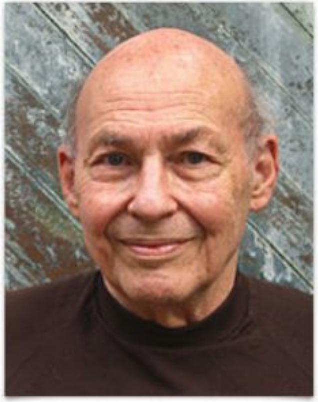


“The vision problem (or goal) is to use the measurements to infer the world state”

Simon J.D. Prince "Computer Vision: Models, Learning, and Inference"

Intro

- **1966:** *Marvin Minsky* posed the development of a computer vision system as an undergraduate summer project.

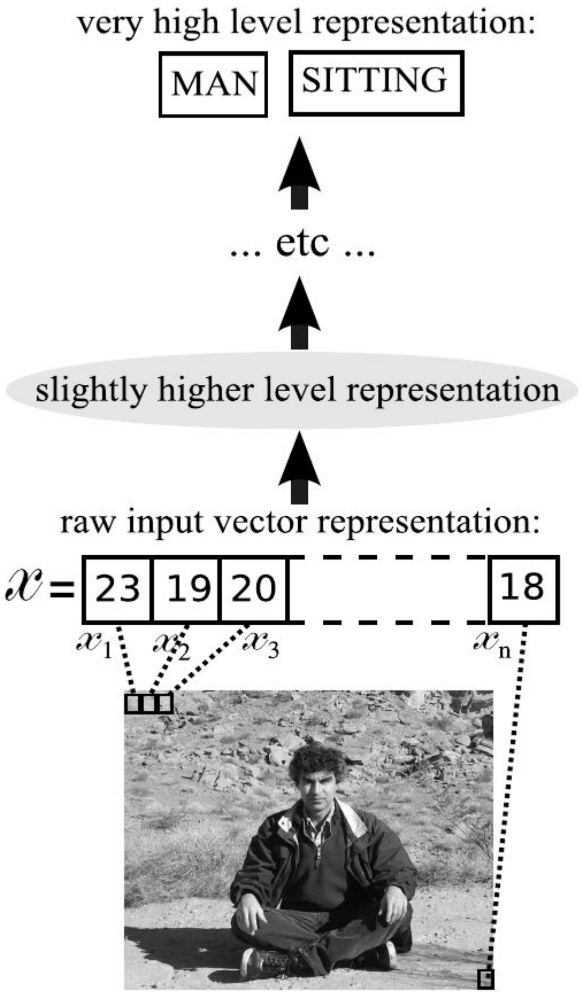


- **1970's:** some progress on interpreting selected images
- **1980's:** NNs come and go; shift toward geometry and increased mathematical rigor
- **1990's:** face recognition;
- **2000's:** broader recognition; large annotated datasets available; video processing
- **2010's:** DNN, convolutional NN

Intro

Visual scene is hierarchically organized

object	trees
↑	↑
object parts	bark, leaves, etc.
↑	↑
primitive features	oriented edges
↑	↑
input image	forest image



https://ttic.uchicago.edu/~shubhendu/Pages/CMSC35246.html

Intro

Visual scene is hierarchically organized

object
↑
object parts
↑
primitive features
↑
input image

trees
↑
bark, leaves, etc.
↑
oriented edges
↑
forest image

Inferotemporal cortex

V4: different textures

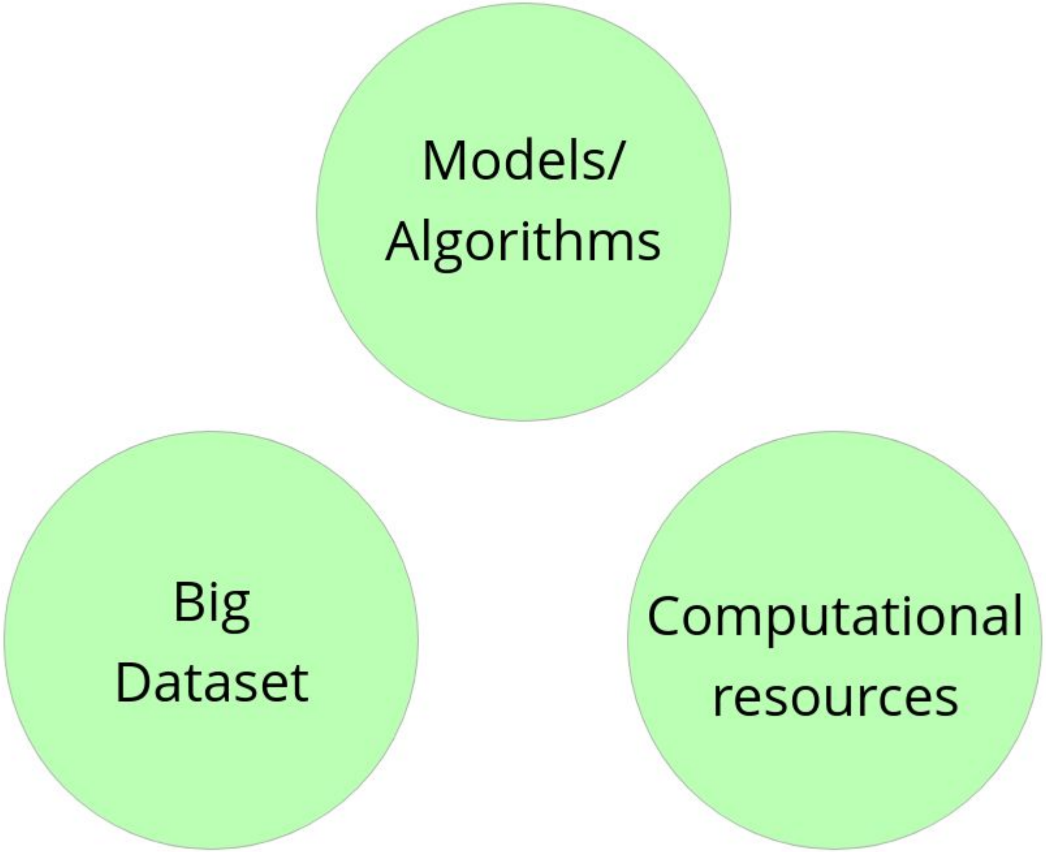
V1: simple and complex cells

photo-receptors retina

Biological vision is hierarchically organized too!

https://ttic.uchicago.edu/~shubhendu/Pages/CMSC35246.html

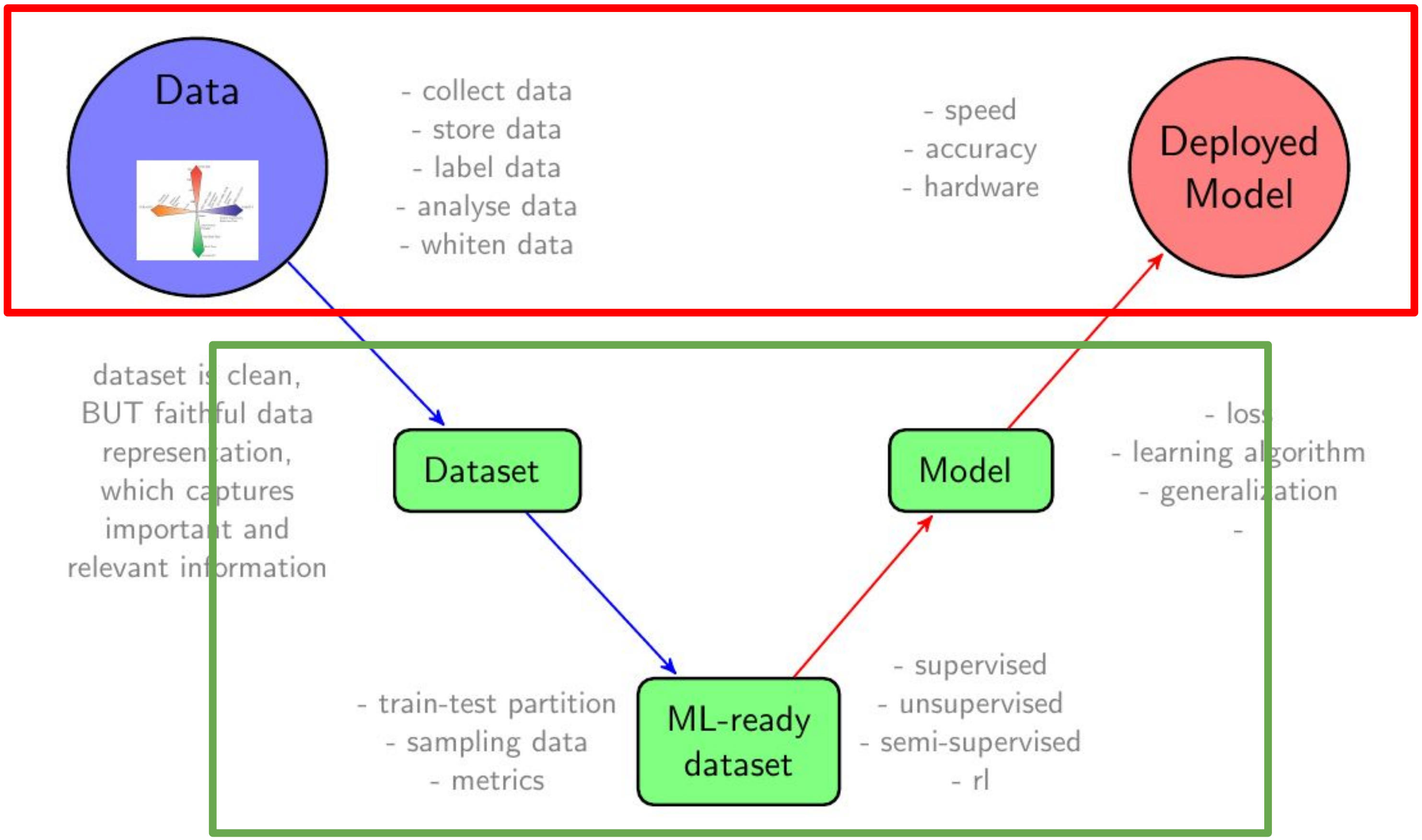
Intro



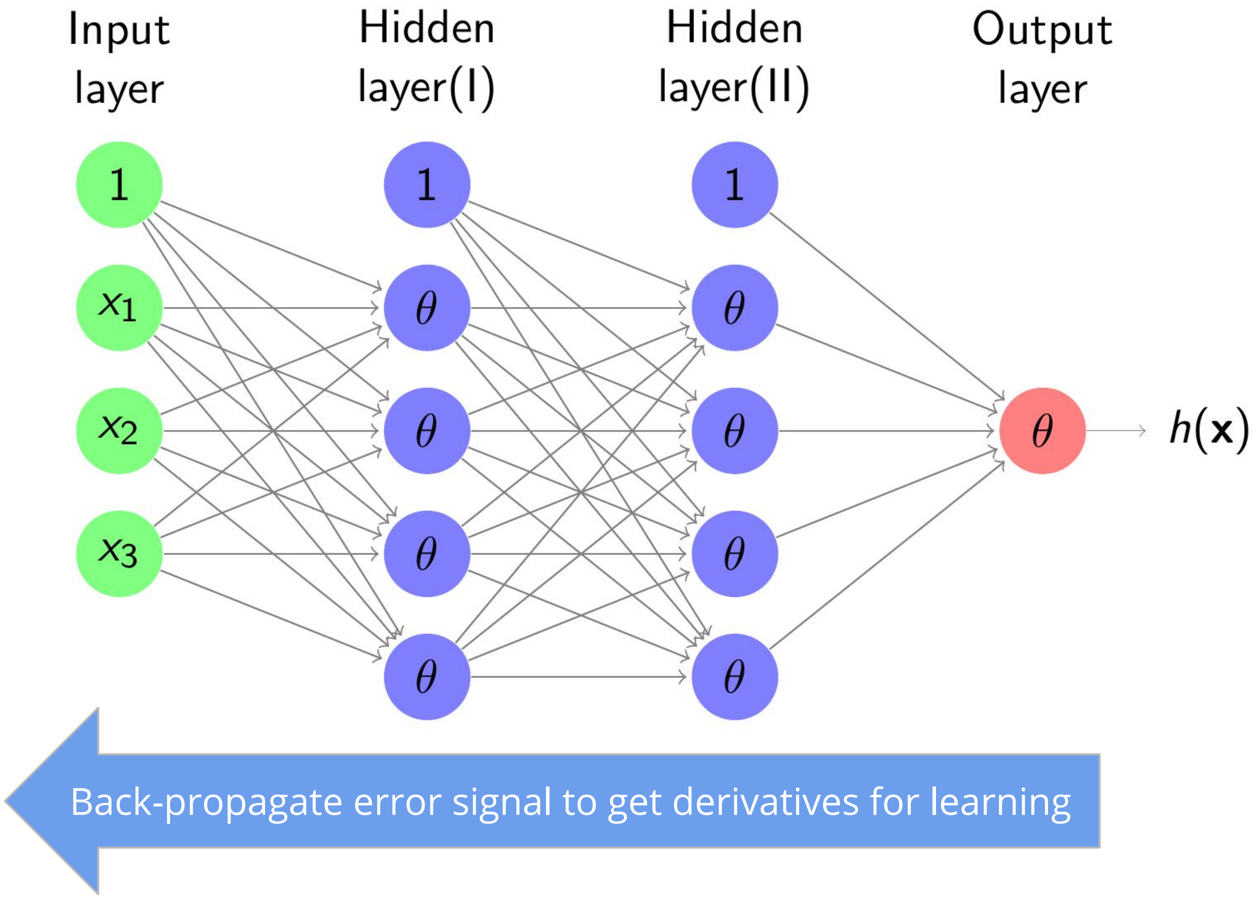
Content

- Intro
- **ML review**
- Intro to CNN

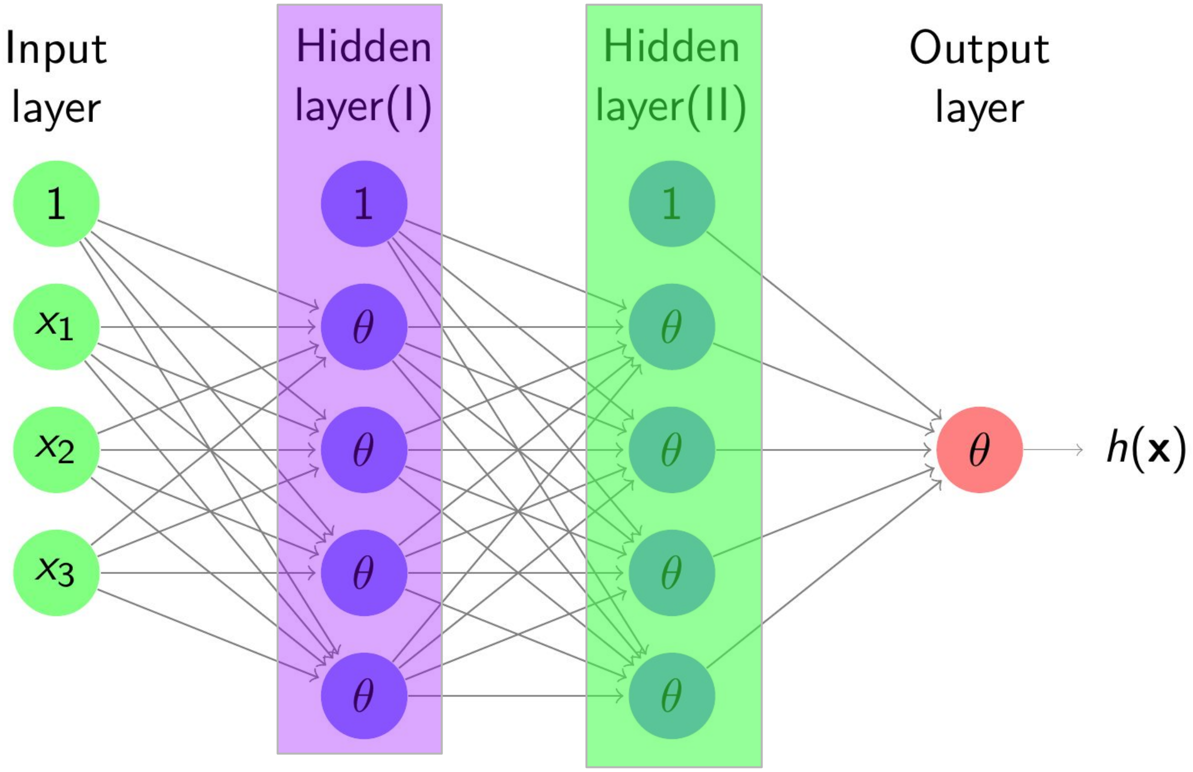
ML review


Data
- collect data
- store data
- label data
- analyse data
- whiten data
- speed
- accuracy
- hardware
Deployed Model
dataset is clean,
BUT faithful data
representation,
which captures
important and
relevant information
Dataset
Model
- loss
- learning algorithm
- generalization
-
- train-test partition
- sampling data
- metrics
ML-ready dataset
- supervised
- unsupervised
- semi-supervised
- rl

ML review (NN)


Input layer
Hidden layer(I)
Hidden layer(II)
Output layer
1
x_1
x_2
x_3
1
θ
1
θ
θ
$h(\mathbf{x})$
Back-propagate error signal to get derivatives for learning

ML review (NN)

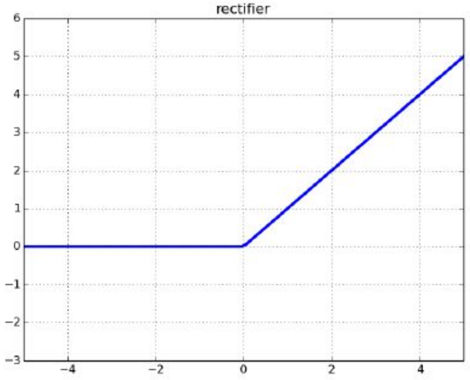


$$\{f(\boldsymbol{x};\boldsymbol{\theta}) = \mathbf{W}_L\boldsymbol{\sigma}_L(\mathbf{W}_{L-1}\cdots\boldsymbol{\sigma}_2(\mathbf{W}_2\boldsymbol{\sigma}_1(\mathbf{W}_1\boldsymbol{x}))) \mid \boldsymbol{\theta} = \{\mathbf{W}_1,\ldots,\mathbf{W}_L\}\}$$

ML review (NN)

parameters in NN:

$$W_l^{ij} = \begin{cases} 1 \le l \le L & \text{layers} \\ 0 \le i \le d^{(l-1)} & \text{inputs} \\ 1 \le j \le d^{(l)} & \text{outputs} \end{cases}$$



activation:

$$x_j^{(l)} = \sigma(s_j^{(l)}) = \sigma\Big(\sum_{i=0}^{d^{(l-1)}} W_l^{ij} x_i^{(l-1)}\Big)$$

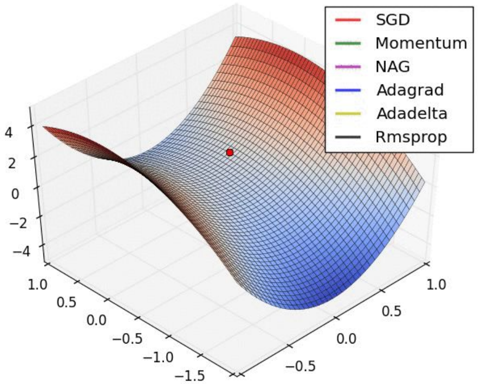
$$\sigma(s) = RELU(s) = max(0, x)$$

ML review (NN)

Define **Loss (or Cost) function**:

$$L_{logloss} = \frac{1}{N}\sum_{n=1}^{N}\sum_{k=1}^{M} y_{nk} \cdot log(p_{nk})$$

$$L_{rmse} = \frac{1}{N}\sum_{n=1}^{N} \parallel F(\mathbf{x_n}) - y_i \parallel_2$$



Gradient Descent (GD) minimizes:

$$L_{train}(\omega) = \frac{1}{N}\sum_{n=1}^{N} e(F(\mathbf{x_n}), y_n)$$

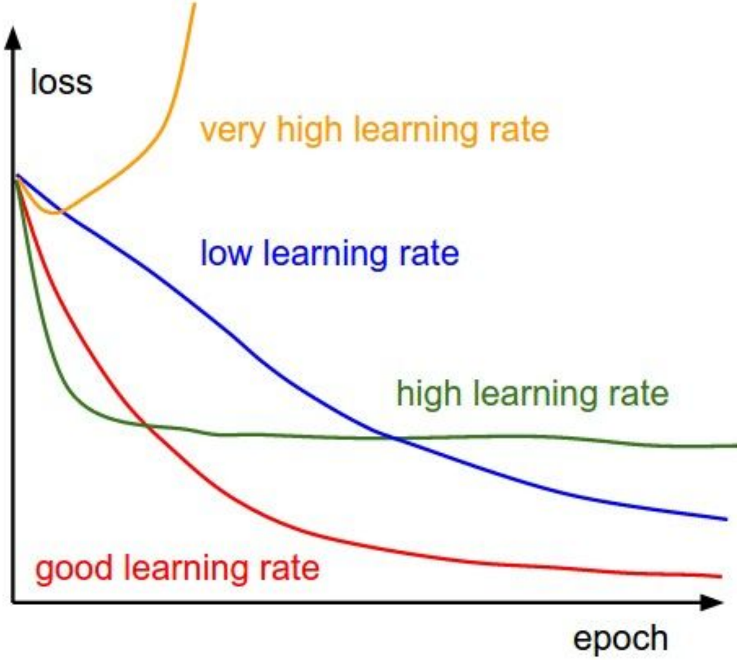
by iterative steps along $-\nabla L_{train}$:

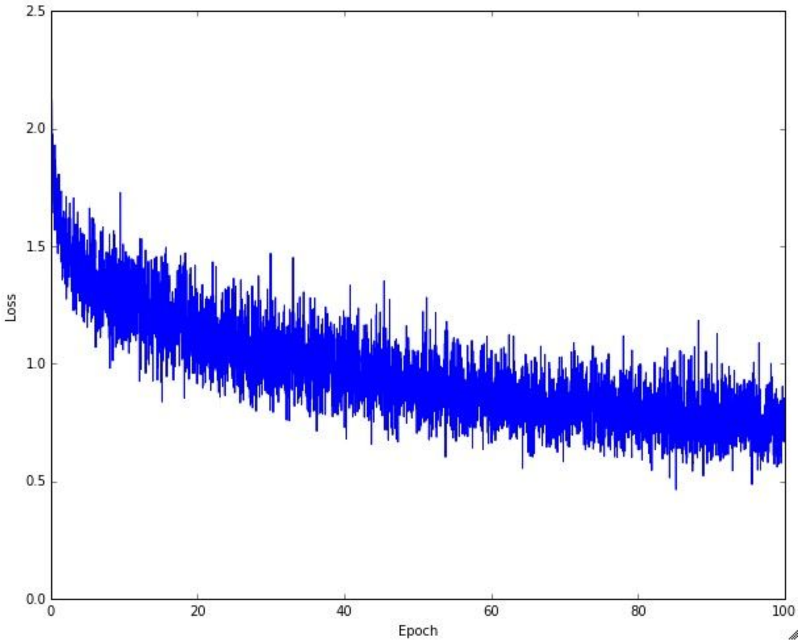
$$\Delta\omega = -\eta\nabla L_{train}(\omega)$$
$$\omega_{prev} = \omega_{next} + \Delta\omega$$

If $\nabla L_{train}(\omega)$ is based on all examples $\{\mathbf{x_n}, y_n\}$ then it is called **batch gradient descent**

images from http://cs231n.stanford.edu/

ML review (NN)





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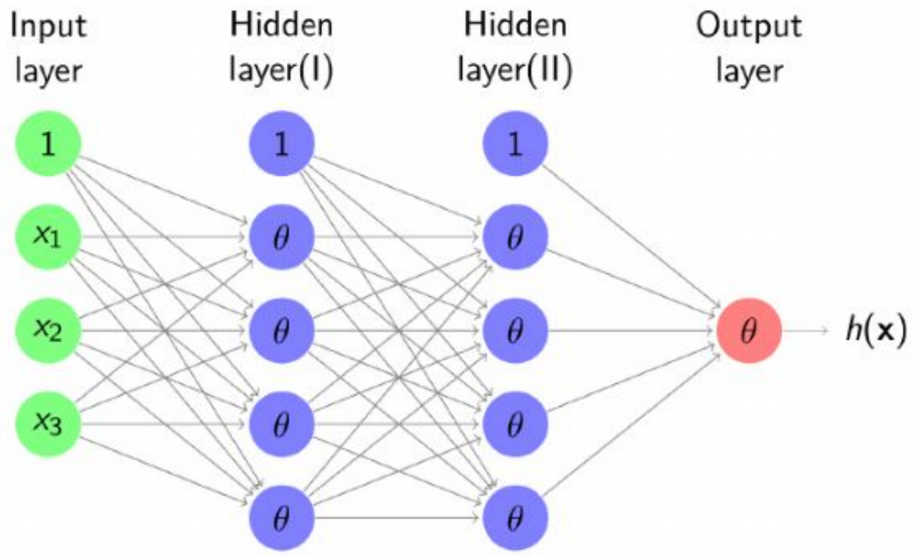
Content

- Intro
- ML review
- **Intro to CNN**

Intro to CNN



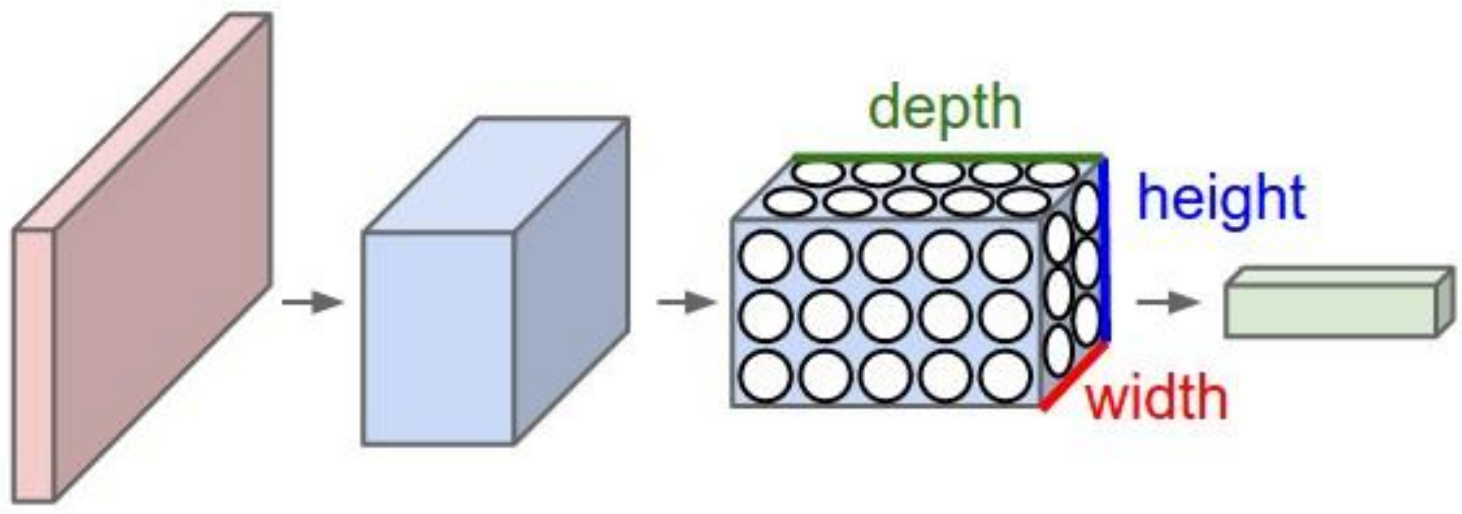
Input layer
$3 \times 256 \times 256 = 200K$

Weights (ω_0):
$200K \times$(size of next layer)

=> millions of parameters
(for just one layer)

Need for alternative architecture

Intro to CNN



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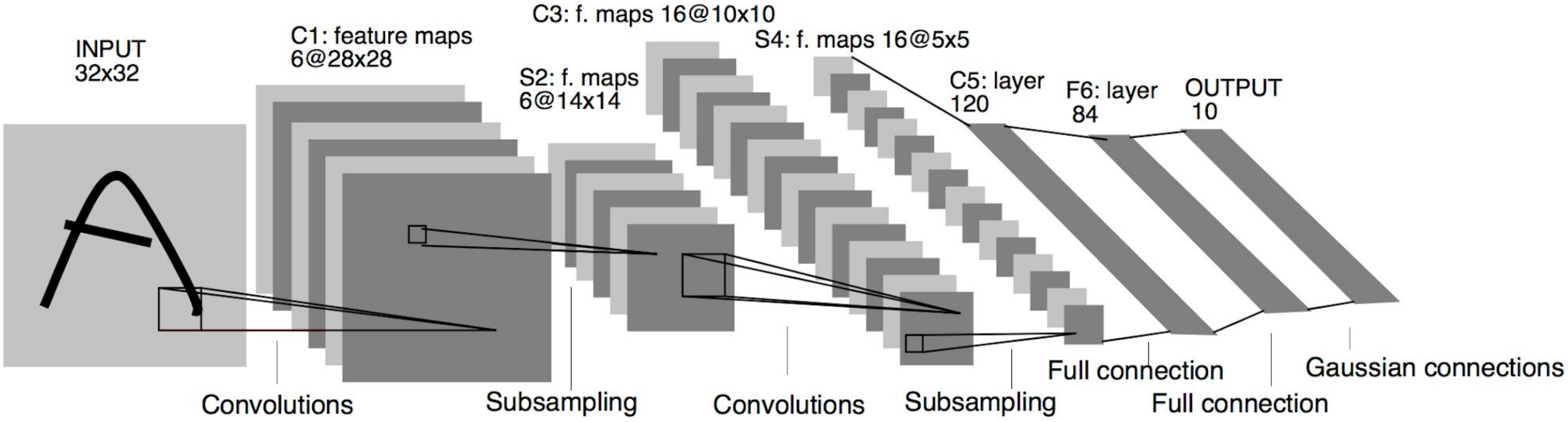
Intro to CNN

LeNet-5 [1998, paper by LeCun et al.]



Intro to CNN

- INPUT holds the raw pixel values of the image.
- $\boxed{\text{CONV layer}}$ computes the output of neurons that are connected to local regions in the input, each computing a dot product between their weights and the region they are connected to in the input volume.
- POOL layer performs a downsampling operation along the spatial dimensions (width, height).
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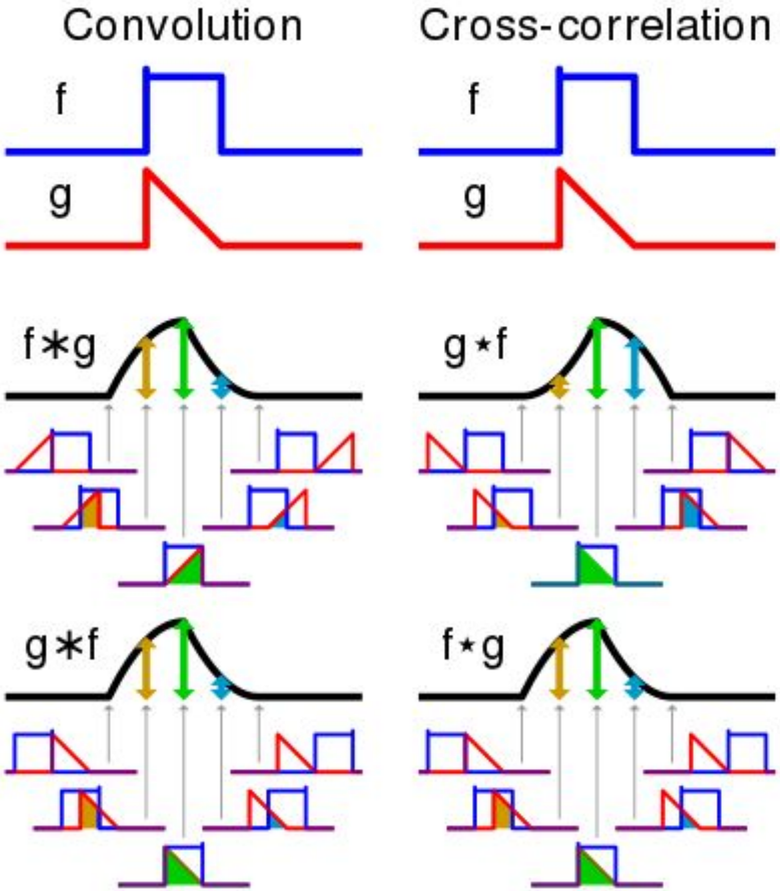
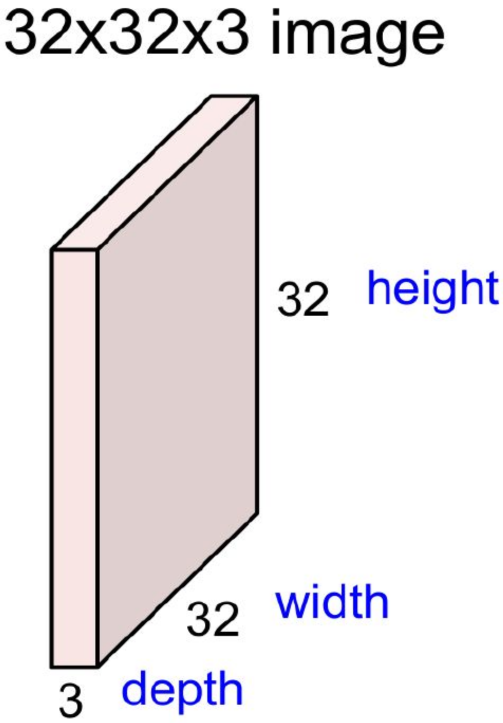
Intro to CNN



https://en.wikipedia.org/wiki/Convolution

Intro to CNN



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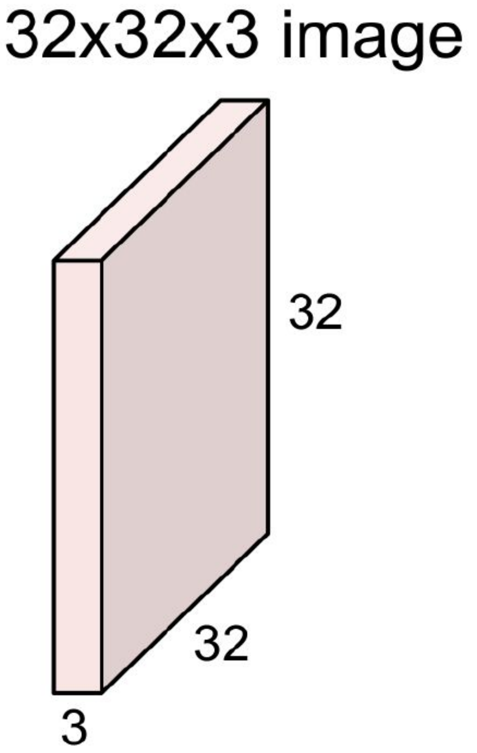
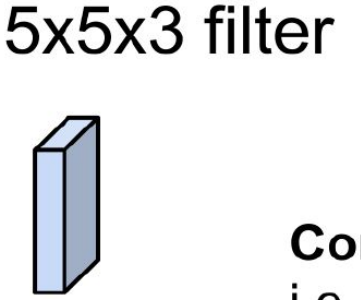
Intro to CNN





Convolve the filter with the image i.e. “slide over the image spatially, computing dot products”

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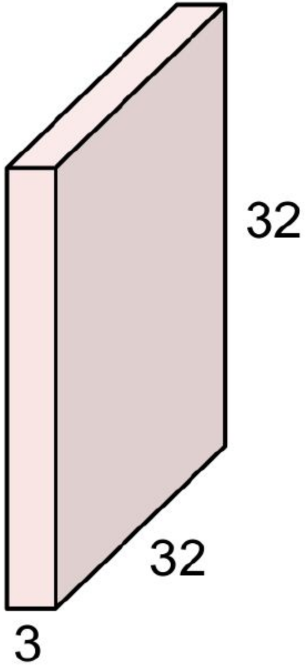
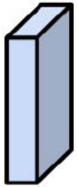
Intro to CNN

32x32x3 image



5x5x3 filter



Convolve the filter with the image
i.e. "slide over the image spatially,
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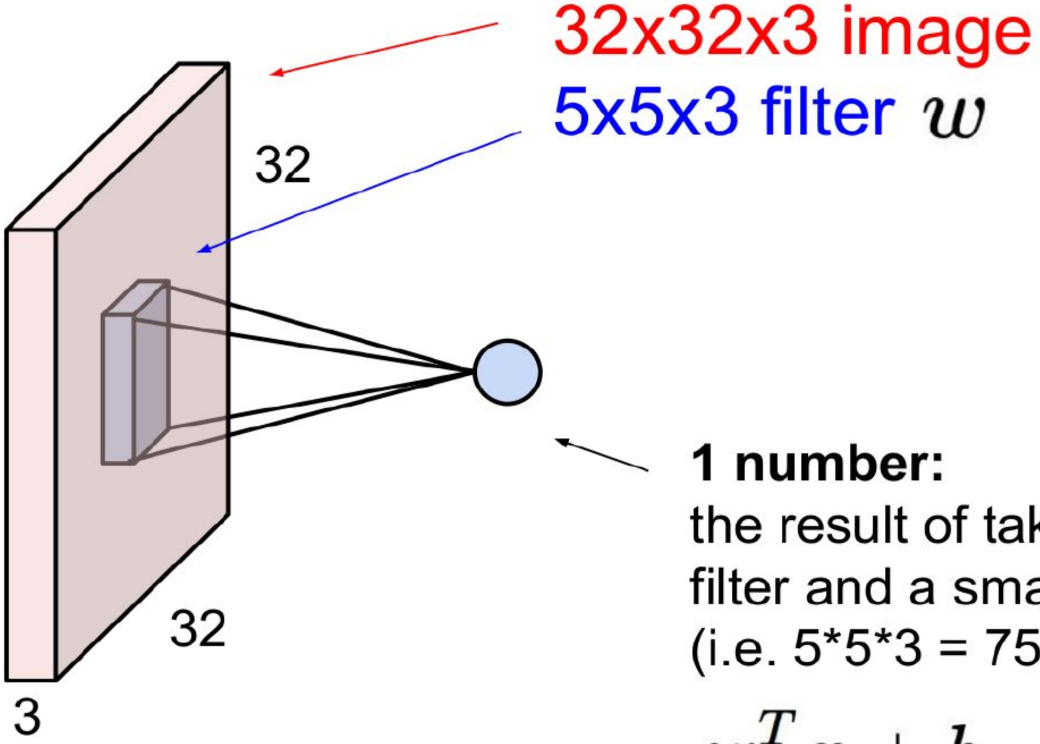
Intro to CNN

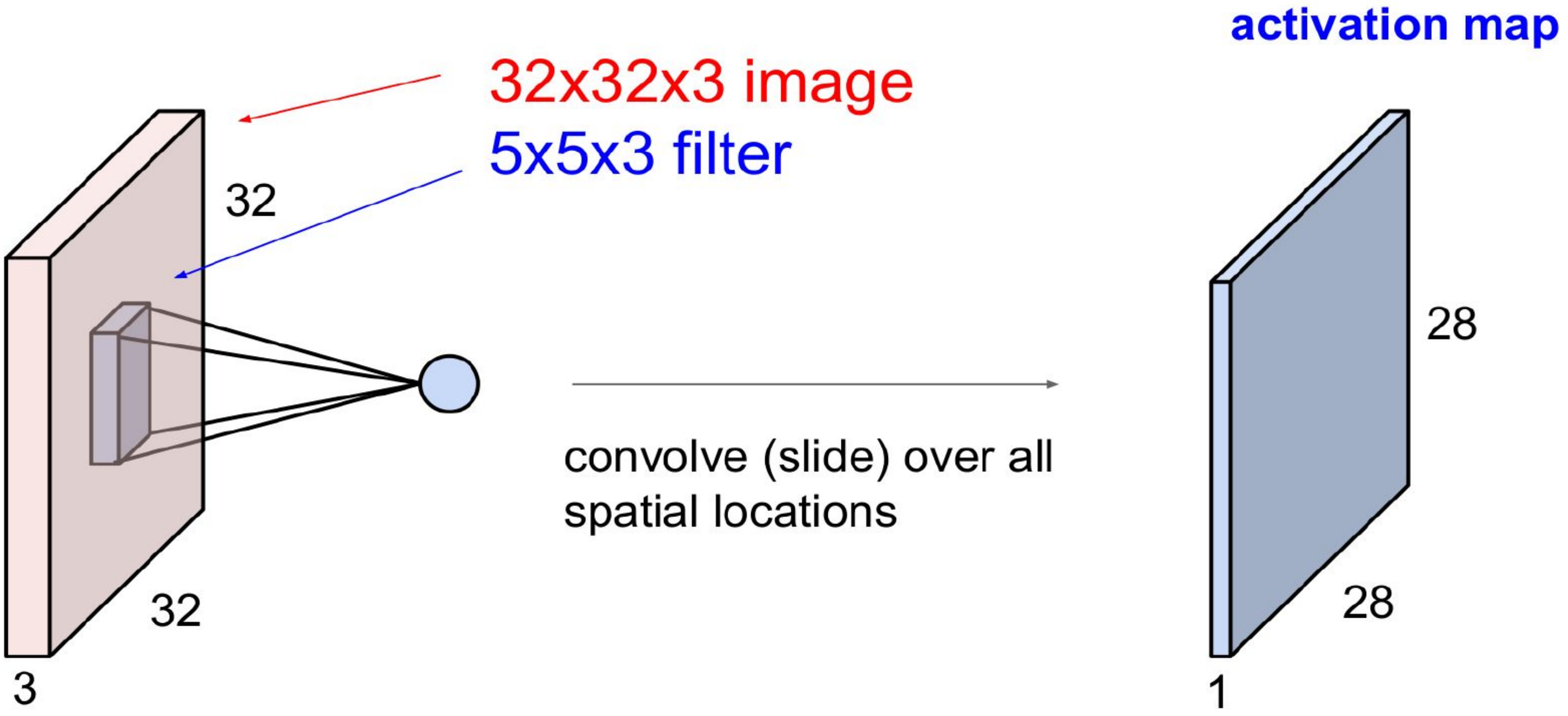


1 number:
the result of taking a dot product between the filter and a small 5x5x3 chunk of the image
(i.e. 5*5*3 = 75-dimensional dot product + bias)

$$w^T x + b$$

images from http://cs231n.stanford.edu/

Intro to CNN



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Intro to CNN

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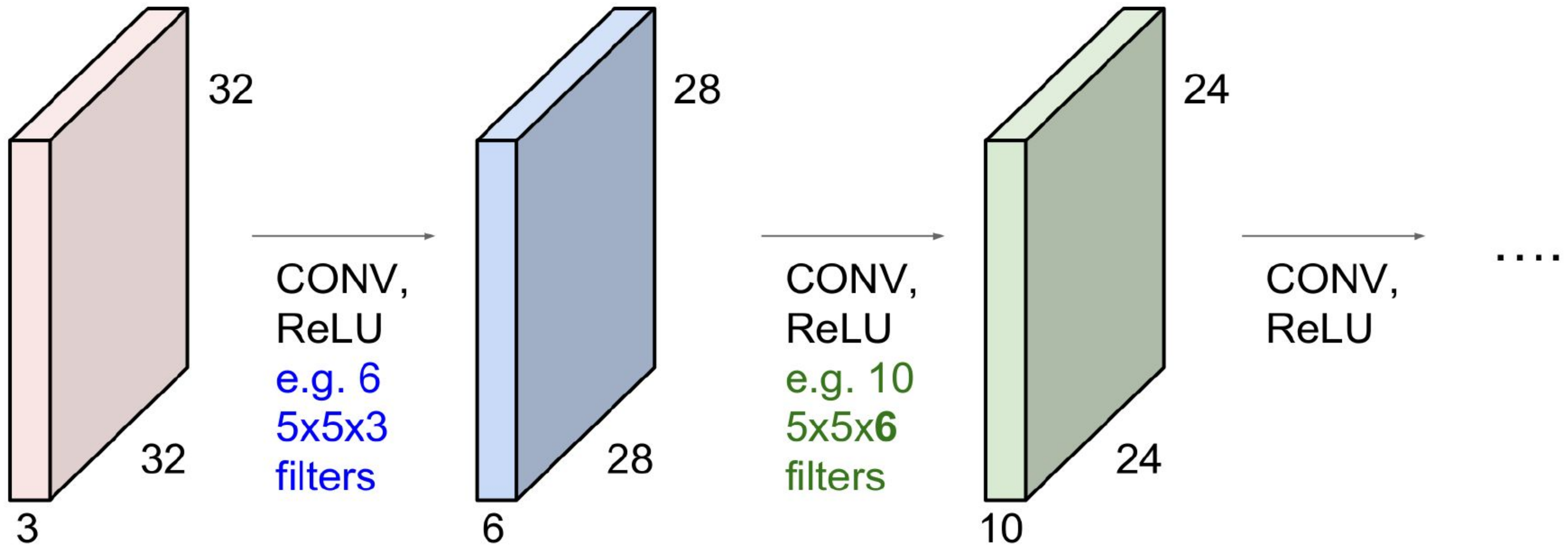

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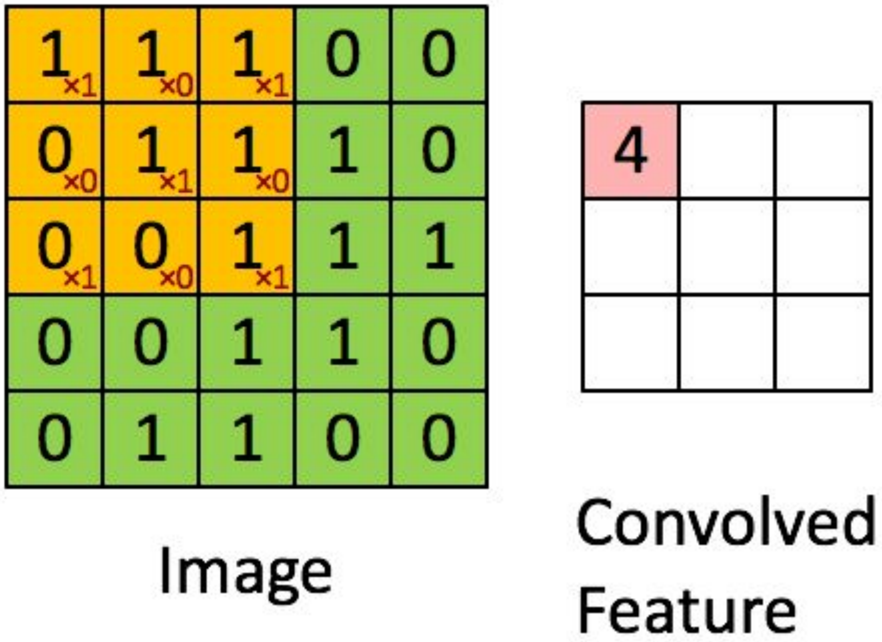

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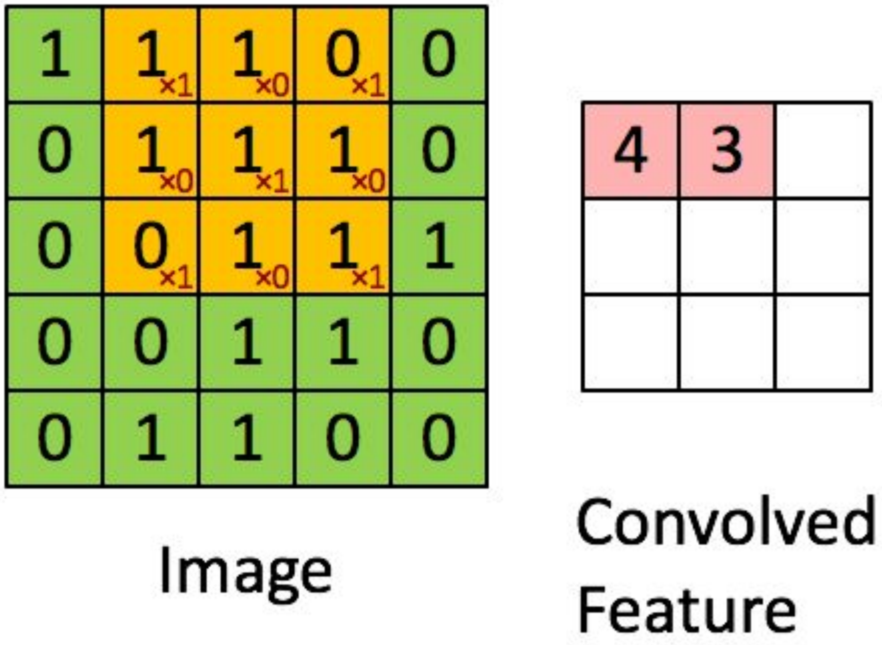

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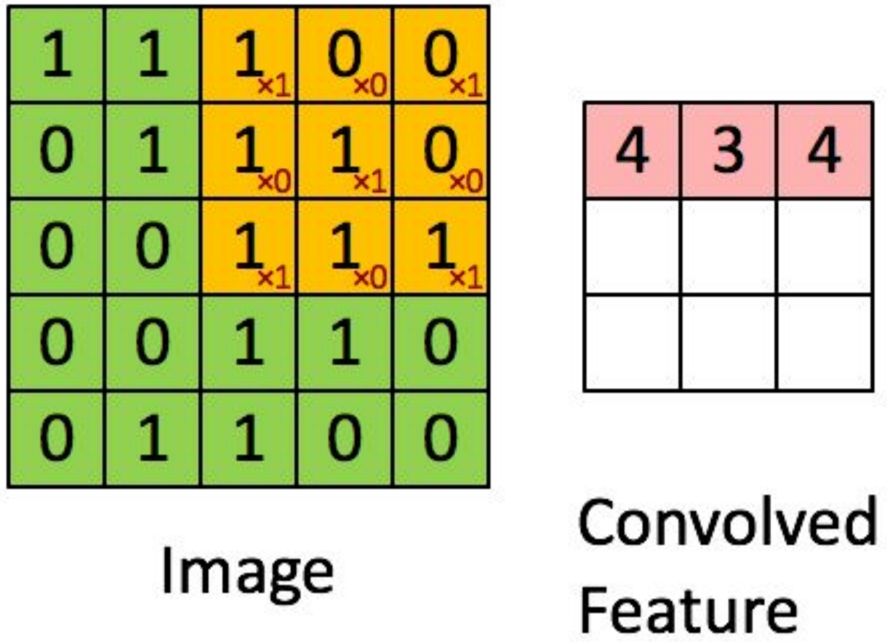

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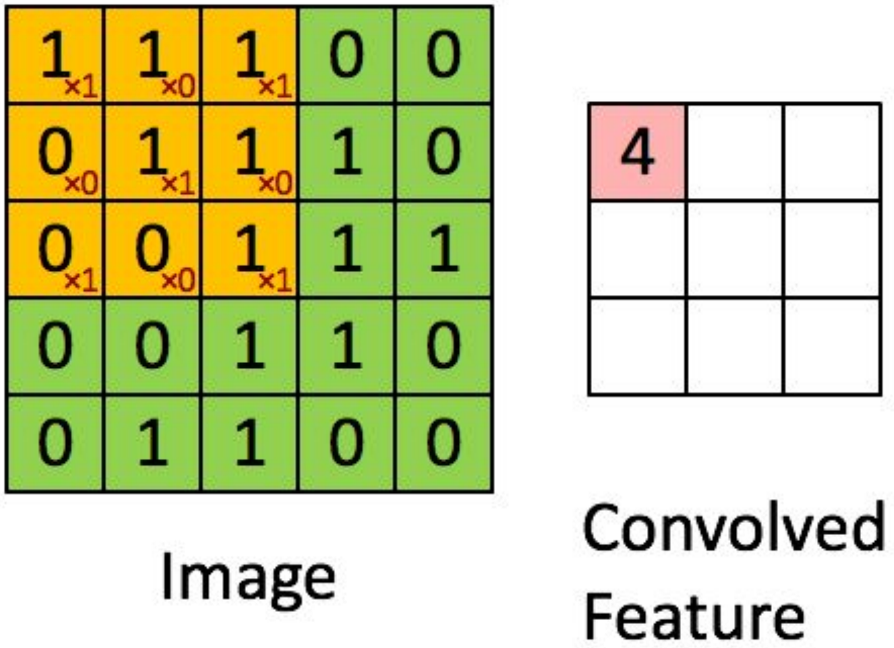
Intro to CNN


1 ×1
1 ×0
1 ×1
0
0
0 ×0
1 ×1
1 ×0
1
0
0 ×1
0 ×0
1 ×1
1
1
0
0
1
1
0
0
1
1
0
0
Image
4
Convolved
Feature

Intro to CNN

We can use one single convolutional layer to modify a certain image

[1. 1. 1.]
[1. 1. 1.]
[1. 1. 1.]

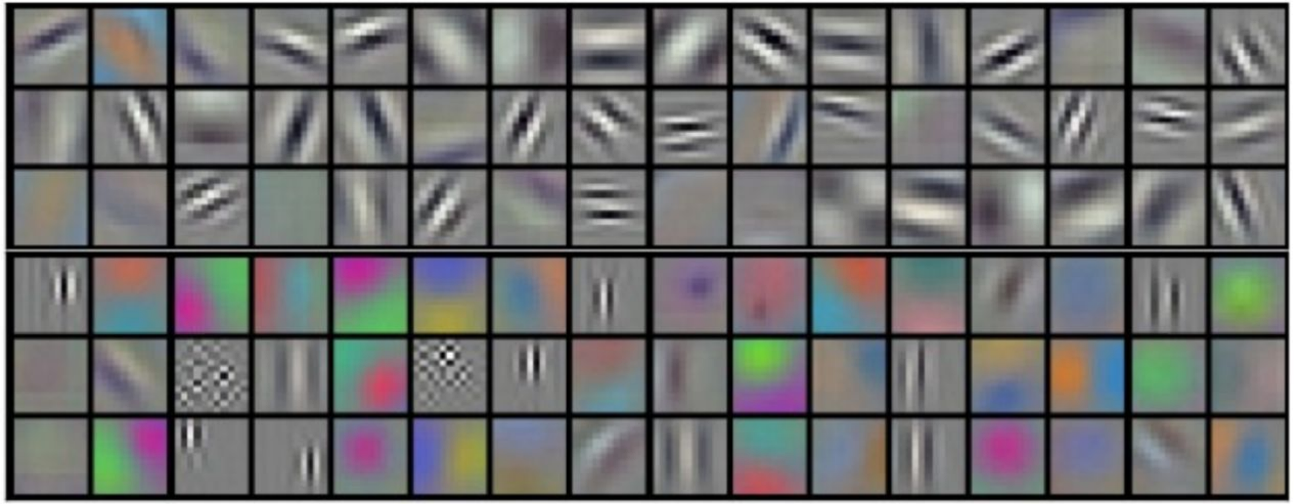
[1. 2. 1.]
[0. 0. 0.]
[-1. -2. -1.]

[0. -1. 0.]
[-1. 5. -1.]
[0. -1. 0.]

based on CS 20SI: Tensorflow for Deep Learning Research

Intro to CNN

In training, we don't specify kernels.
We learn kernels!



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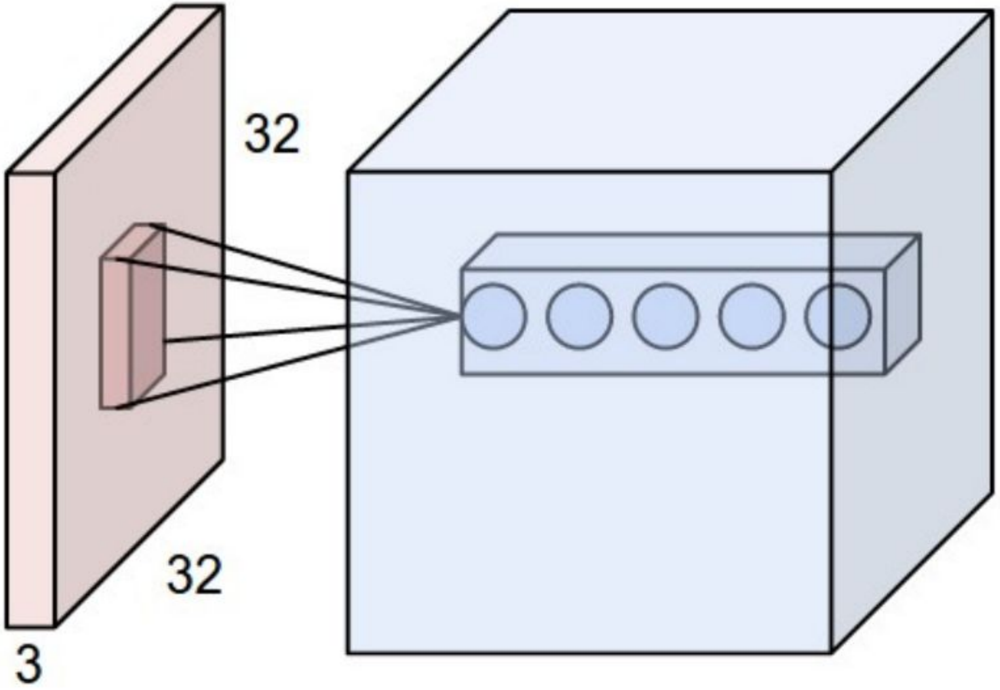

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Intro to CNN

- Accepts a volume of size $W1 \times H1 \times D1$
- Requires four hyperparameters:
  - Number of filters K,
  - their spatial extent F,
  - the stride S,
  - the amount of zero padding P.
- Produces a volume of size $W2 \times H2 \times D2$ where:
  - $W2 = (W1 - F + 2P)/S + 1$,
  - $H2 = (H1 - F + 2P)/S + 1$
  - $D2 = K$
- With parameter sharing, it introduces $F \times F \times D1$ weights per filter, for a total of $(F \times F \times D1) \times K$ weights and K biases.

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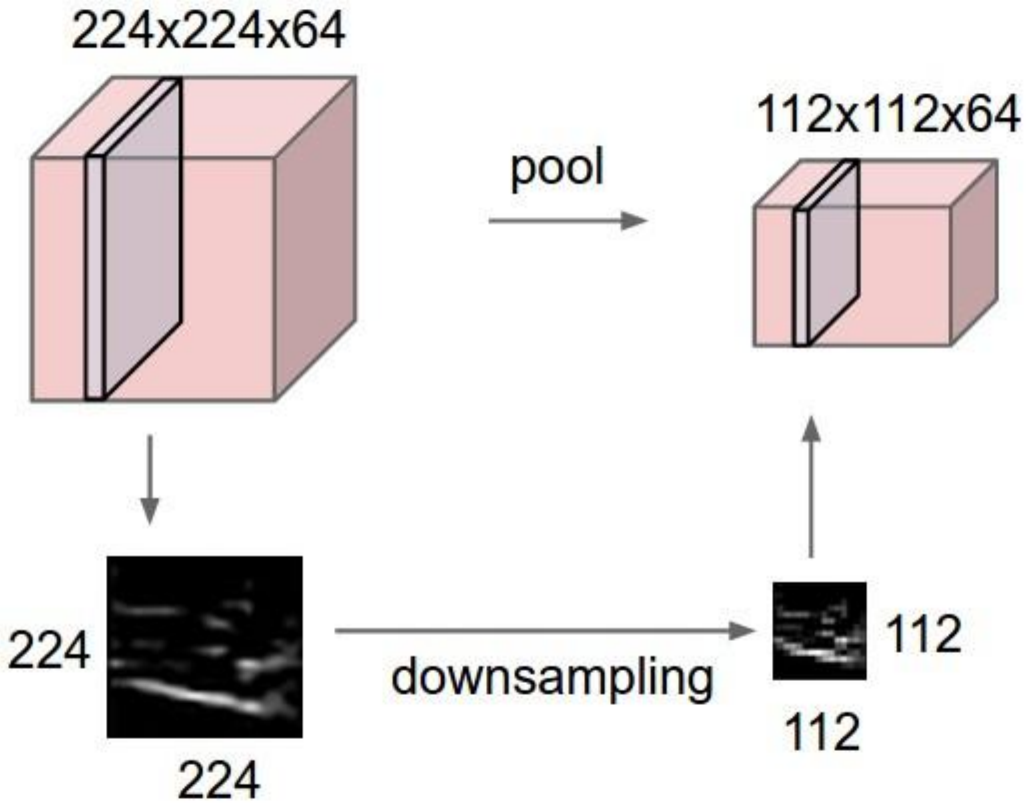

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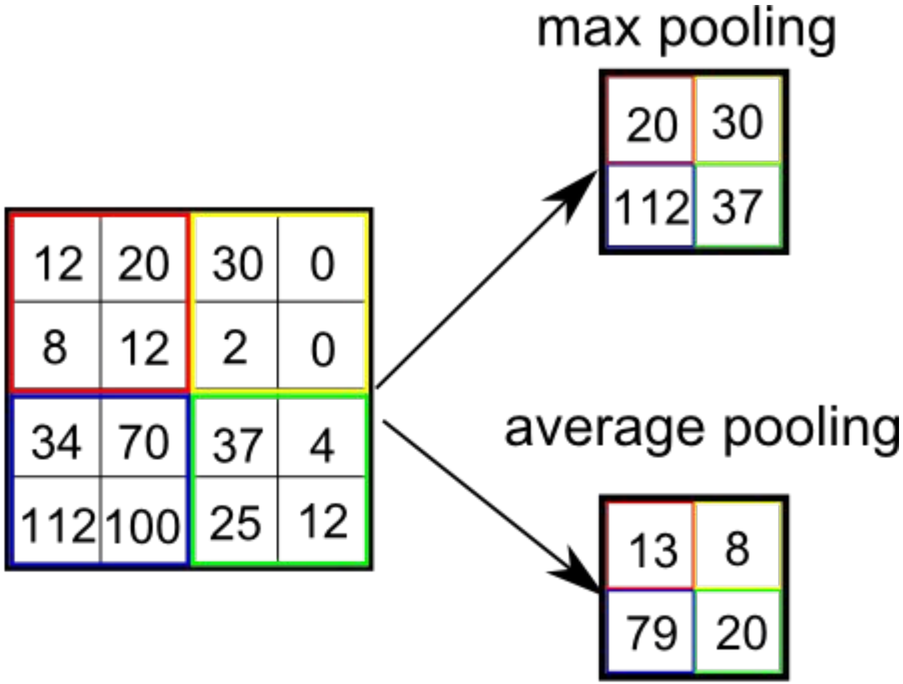

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Intro to CNN

- Accepts a volume of size $W1 \times H1 \times D1$
- Requires three hyperparameters:
  - their spatial extent F,
  - the stride S,
- Produces a volume of size $W2 \times H2 \times D2$ where:
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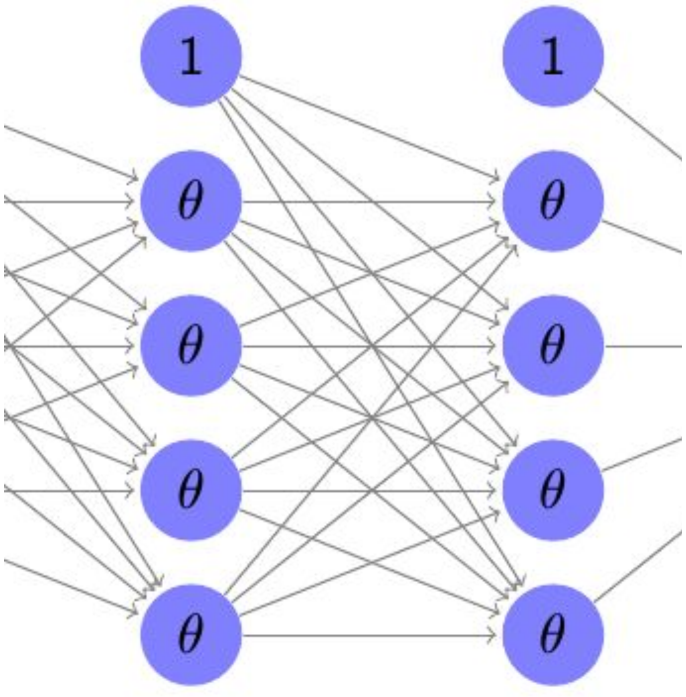
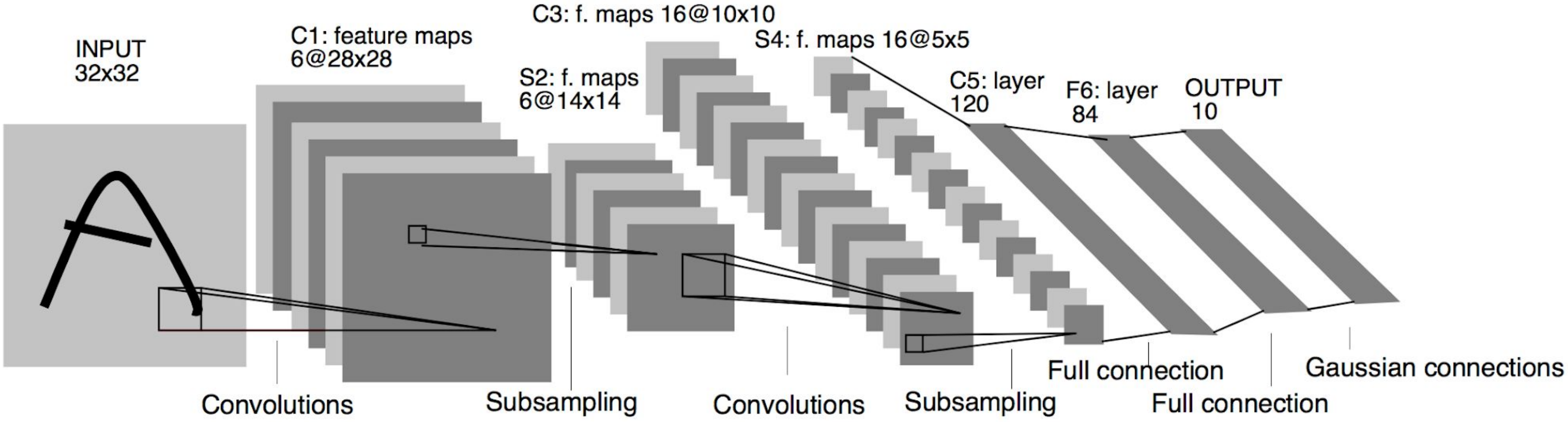


1
1
θ
θ
θ
θ
θ
θ
θ
θ
θ
θ

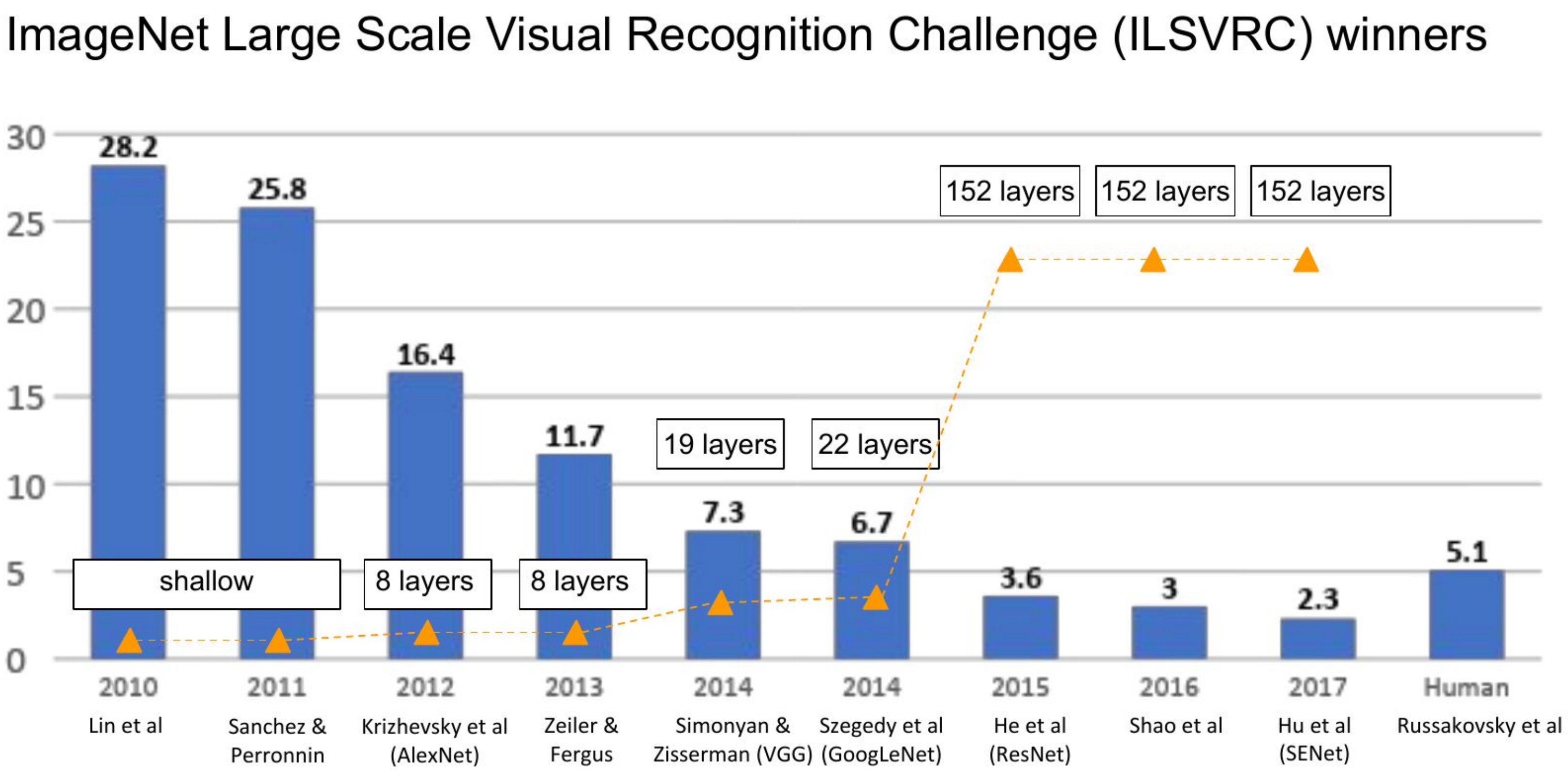
Intro to CNN

LeNet-5 [1998, paper by LeCun et al.]



Intro to CNN

Intro to CNN



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Summary

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