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Introduction to Deep Convolutional Neural Networks

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Introduction to Deep Convolutional Neural Networks

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Professor,

DCIS, PIEAS, Islamabad, Pakistan

Outline

- Artificial Neurons and Perceptron
- Building blocks of CNN
  - Convolution
  - Pooling
- Motivations for CNN
- Working of a CNN
- Why use Hierarchical Learning
- Visualizing CNN Activations (features)
- Deep CNN architectures: case studies
- Transfer Learning

Biological neuron

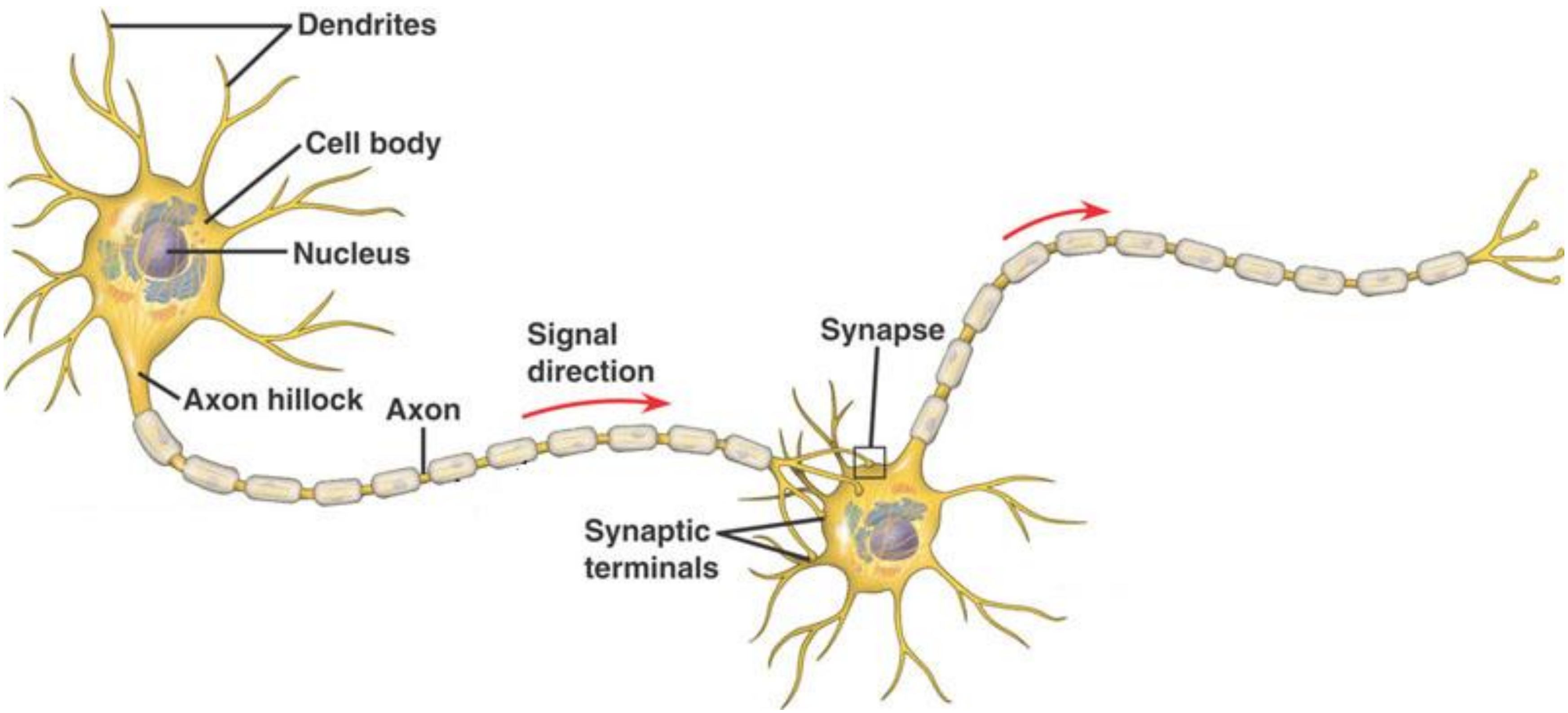
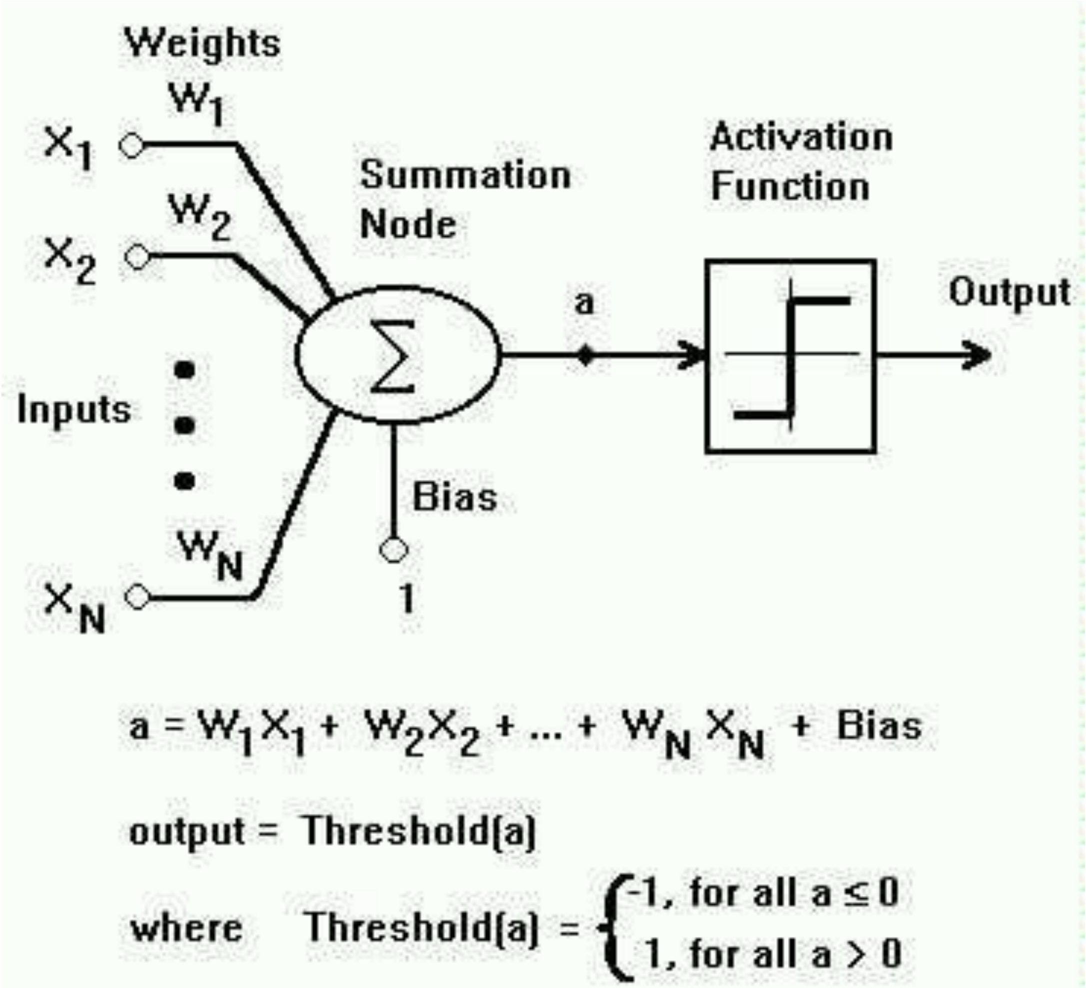


Image from: http://hplusmagazine.com/2012/10/17/four-statements-about-the-future

Single layer perceptron



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Multi-layered Neural Net

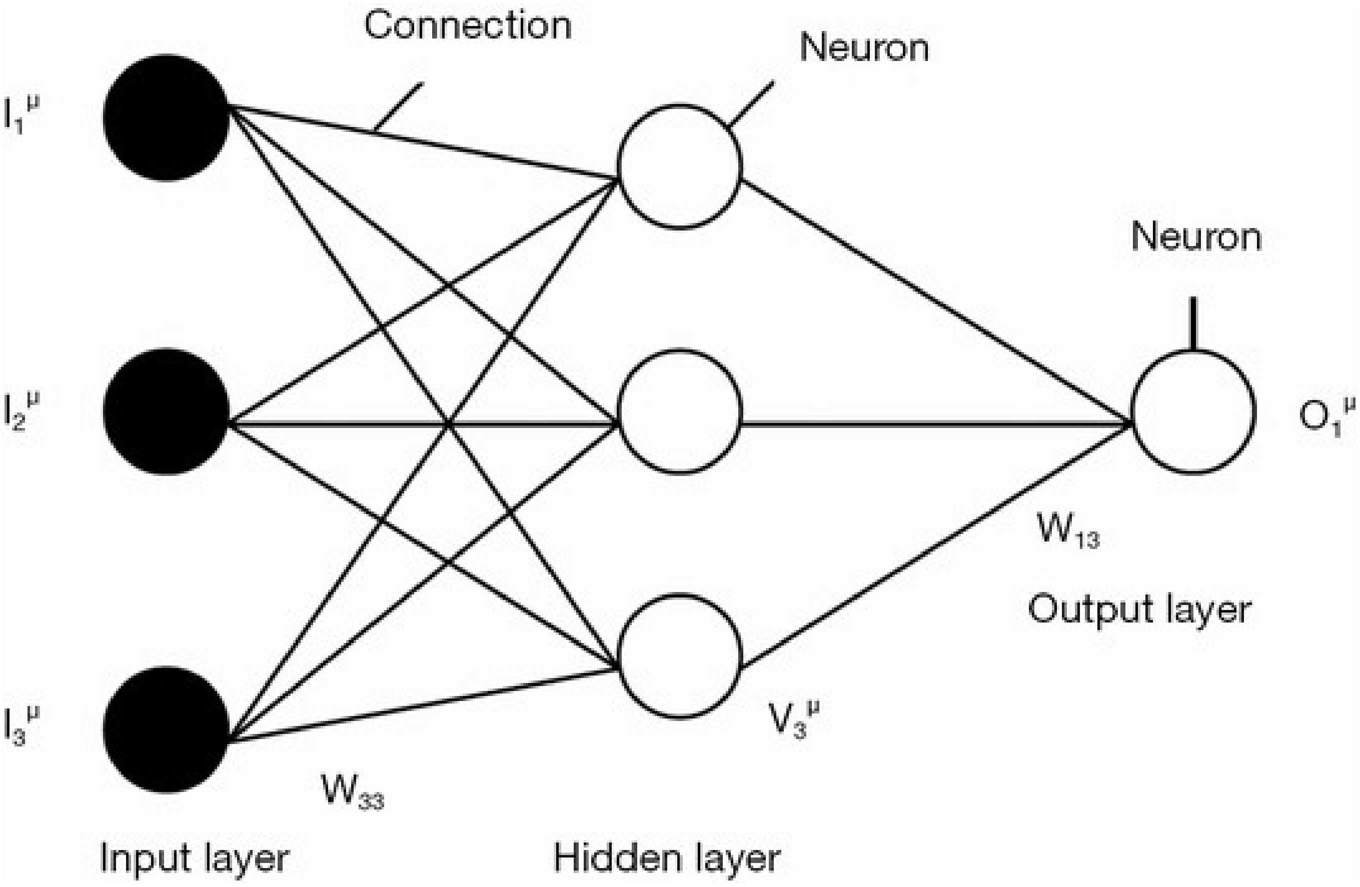


Image from: Pasini, Antonello. "Artificial neural networks for small dataset analysis."*Journal of thoracic disease* 7.5 (2015): 953.

Convolution

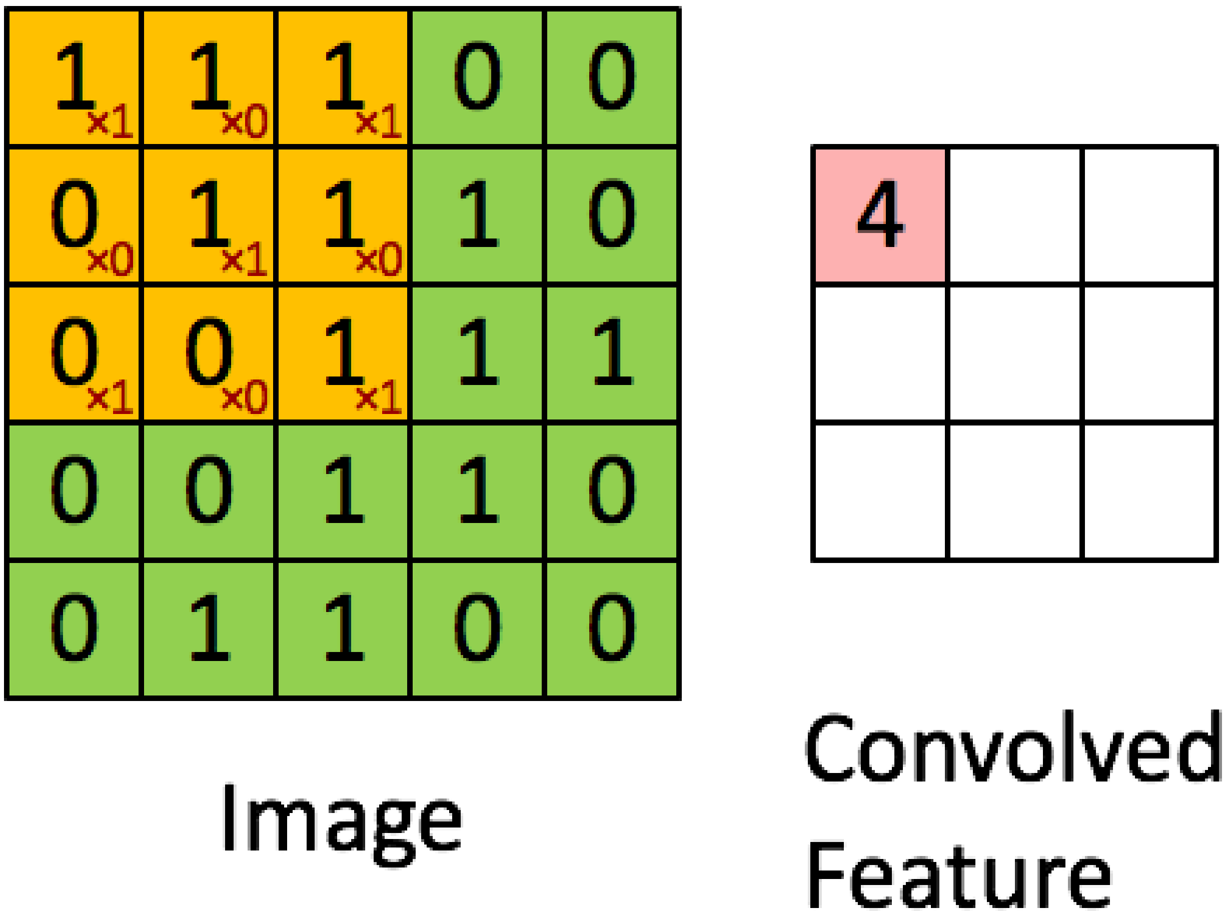
1	1	1	0	0
0	1	1	1	0
0	0	1	1	1
0	0	1	1	0
0	1	1	0	0

Image

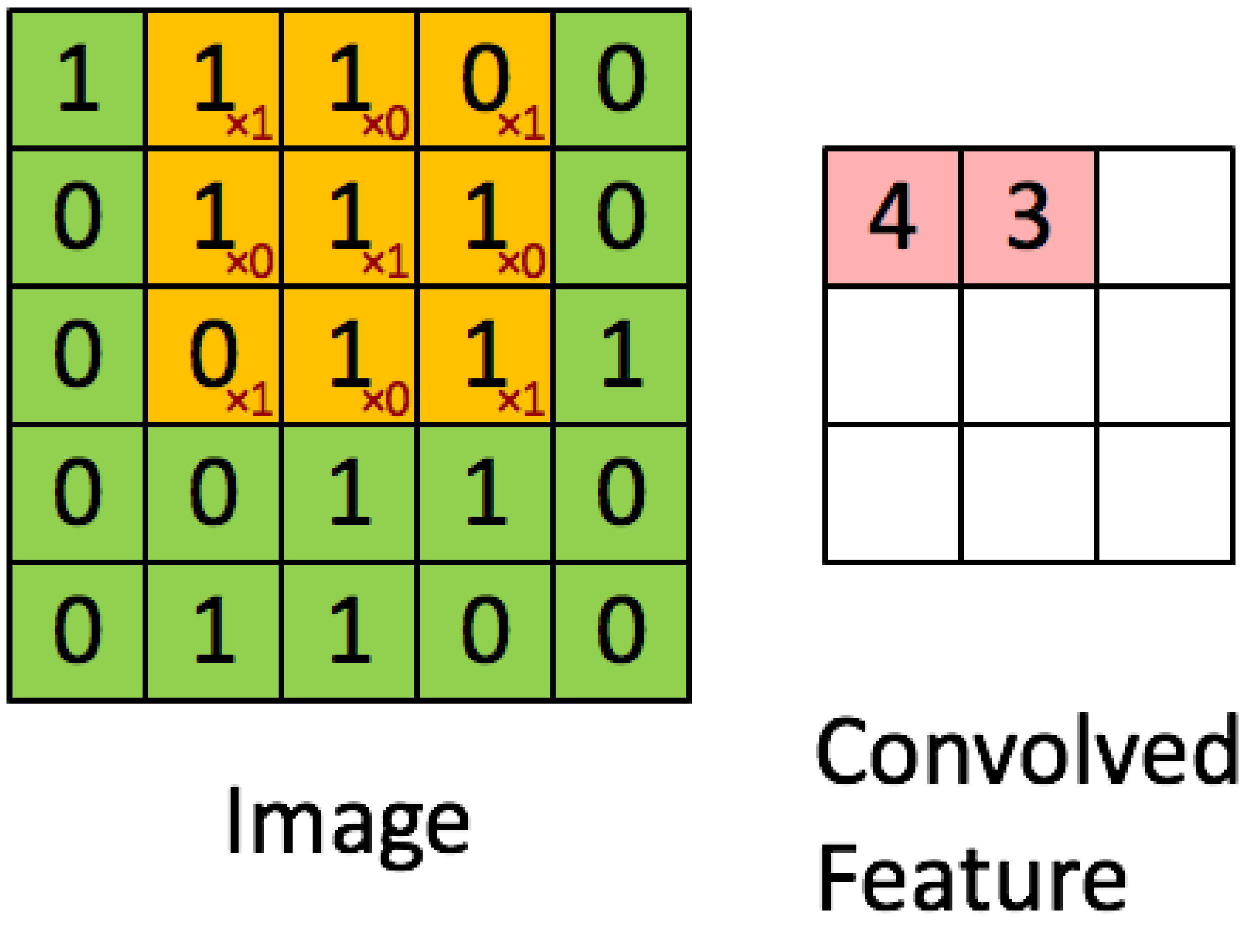
1	0	1
0	1	0
1	0	1

Filter/kernel

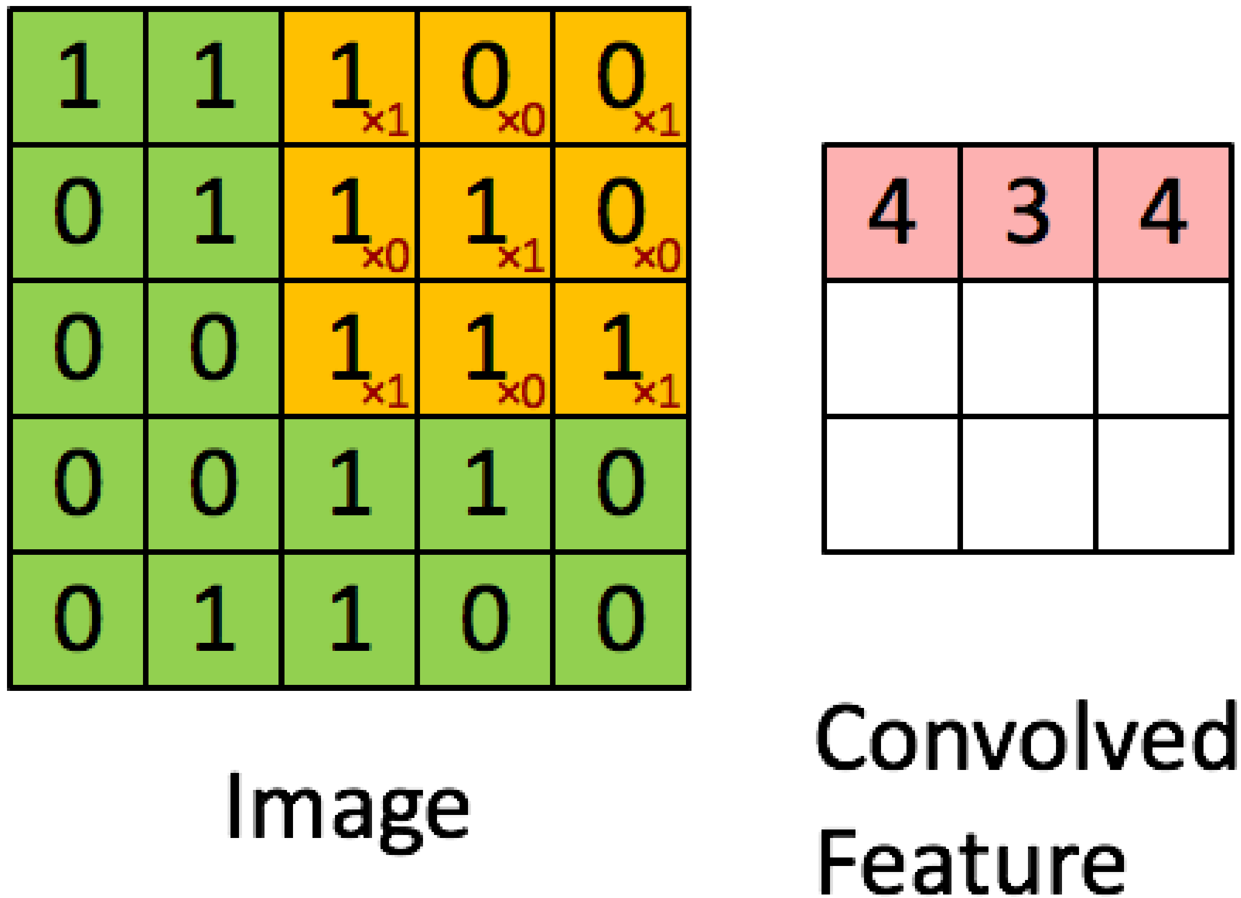
Convolution



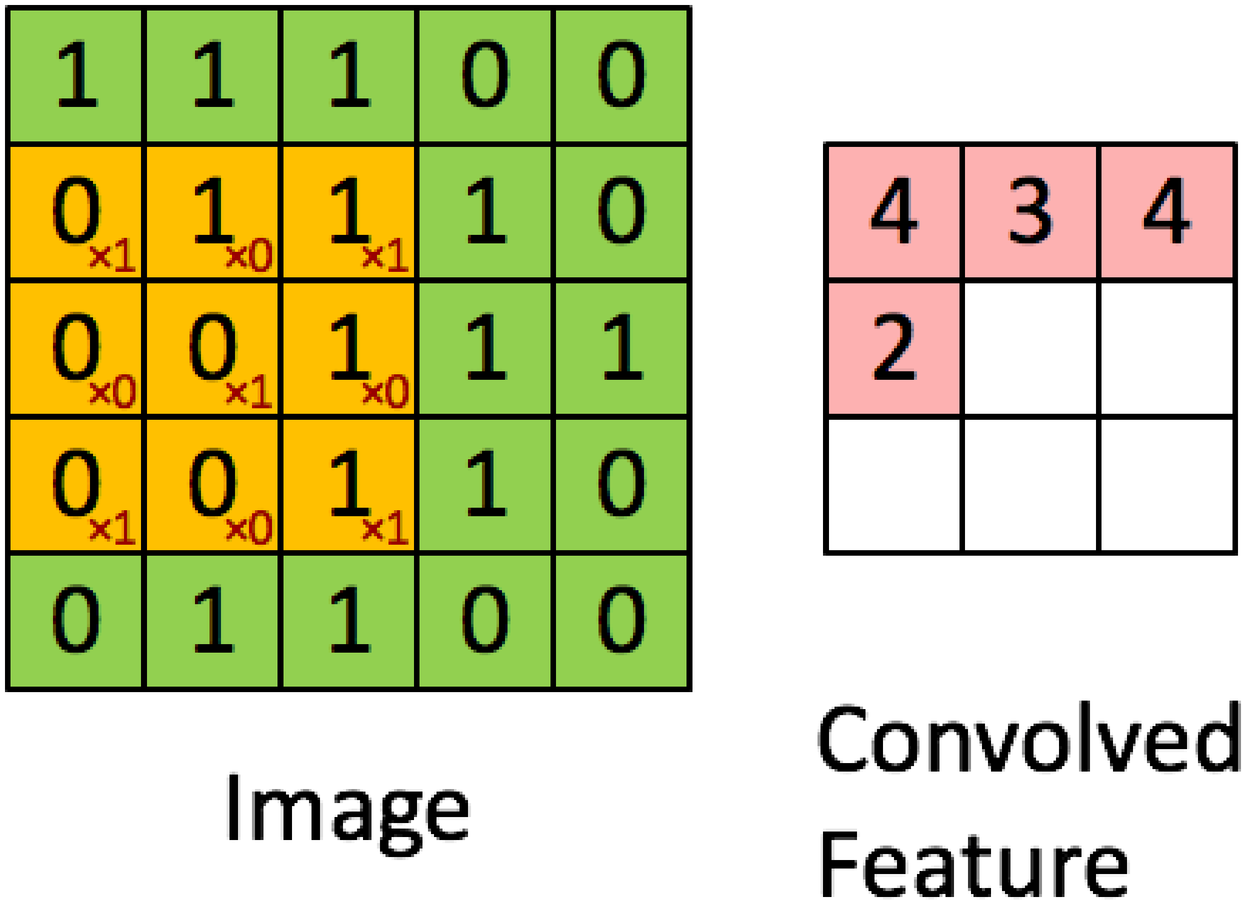
Convolution



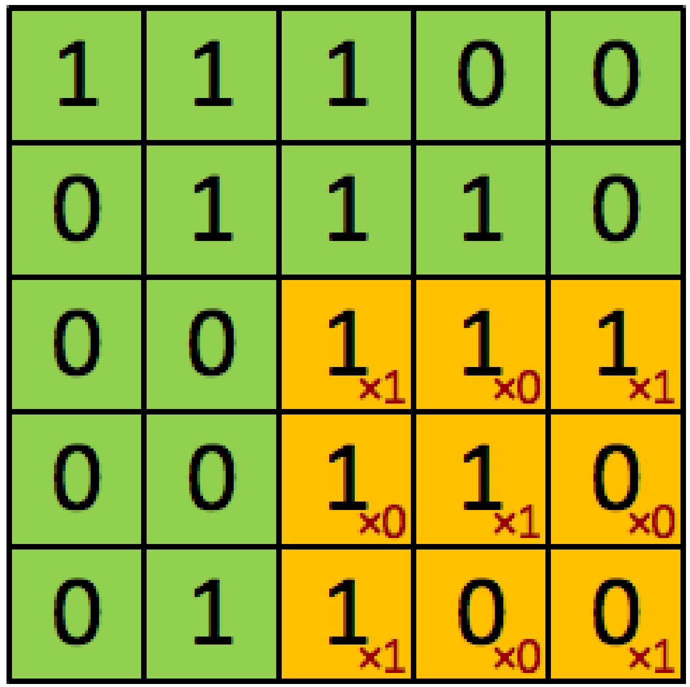
Convolution



Convolution



Convolution



Image

$W_{conv} = W_{img} - W_{filt} + 1$

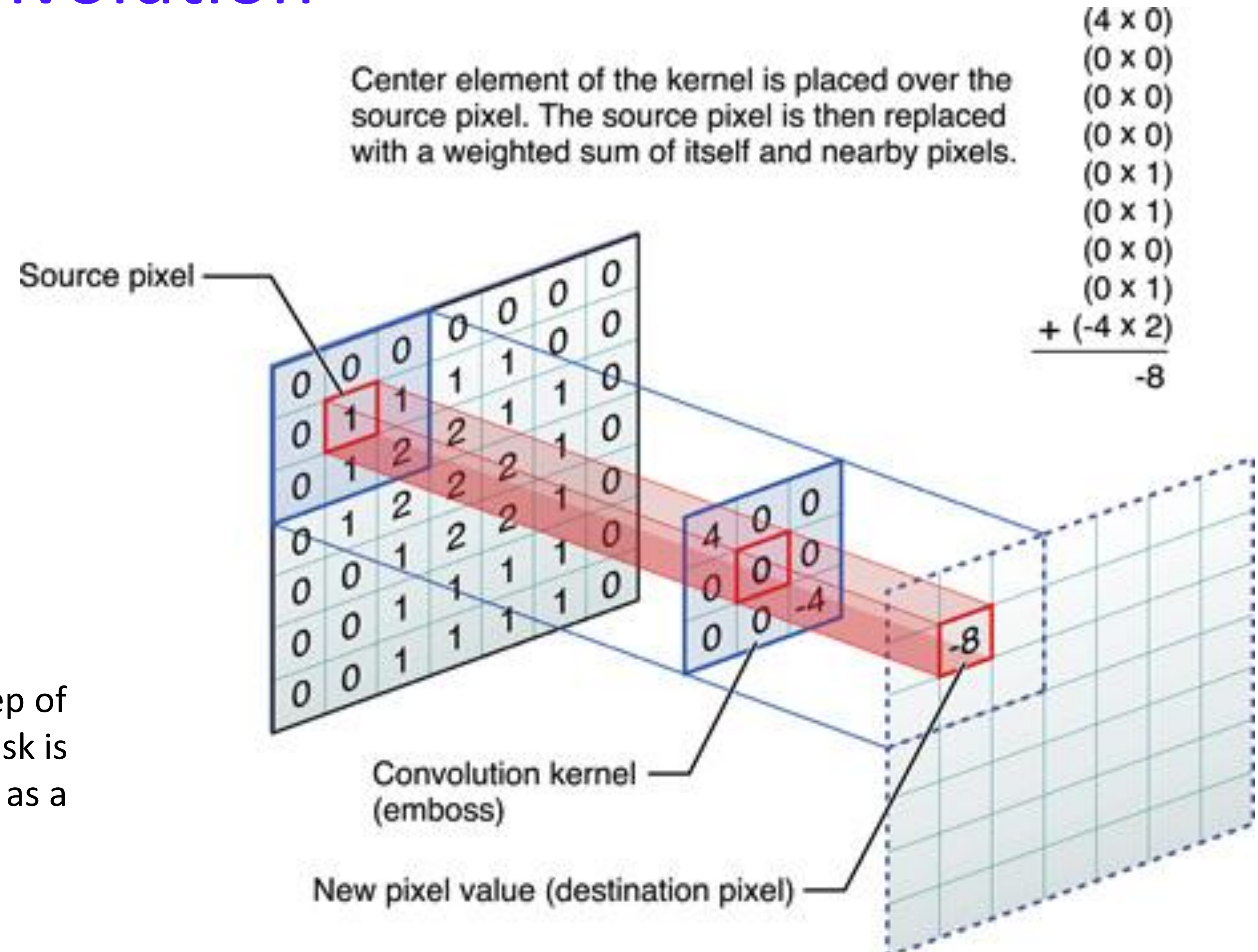
$H_{conv} = H_{img} - H_{filt} + 1$

4	3	4
2	4	3
2	3	4

Convolved Feature

Convolution and Correlation becomes the same if the Kernel is symmetric; no effect from flipping.
In Machine Learning community, mostly correlation Kernels are used.

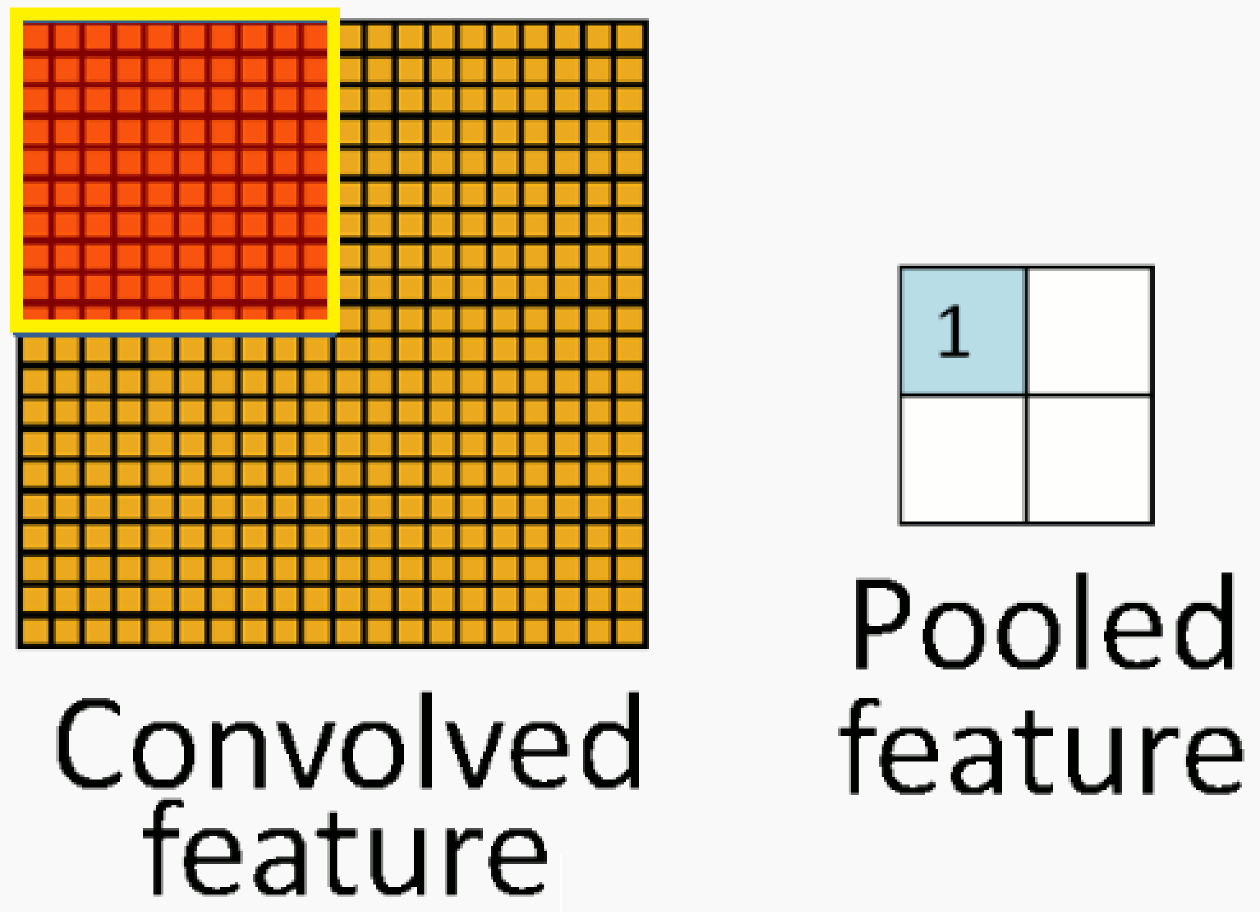
Convolution



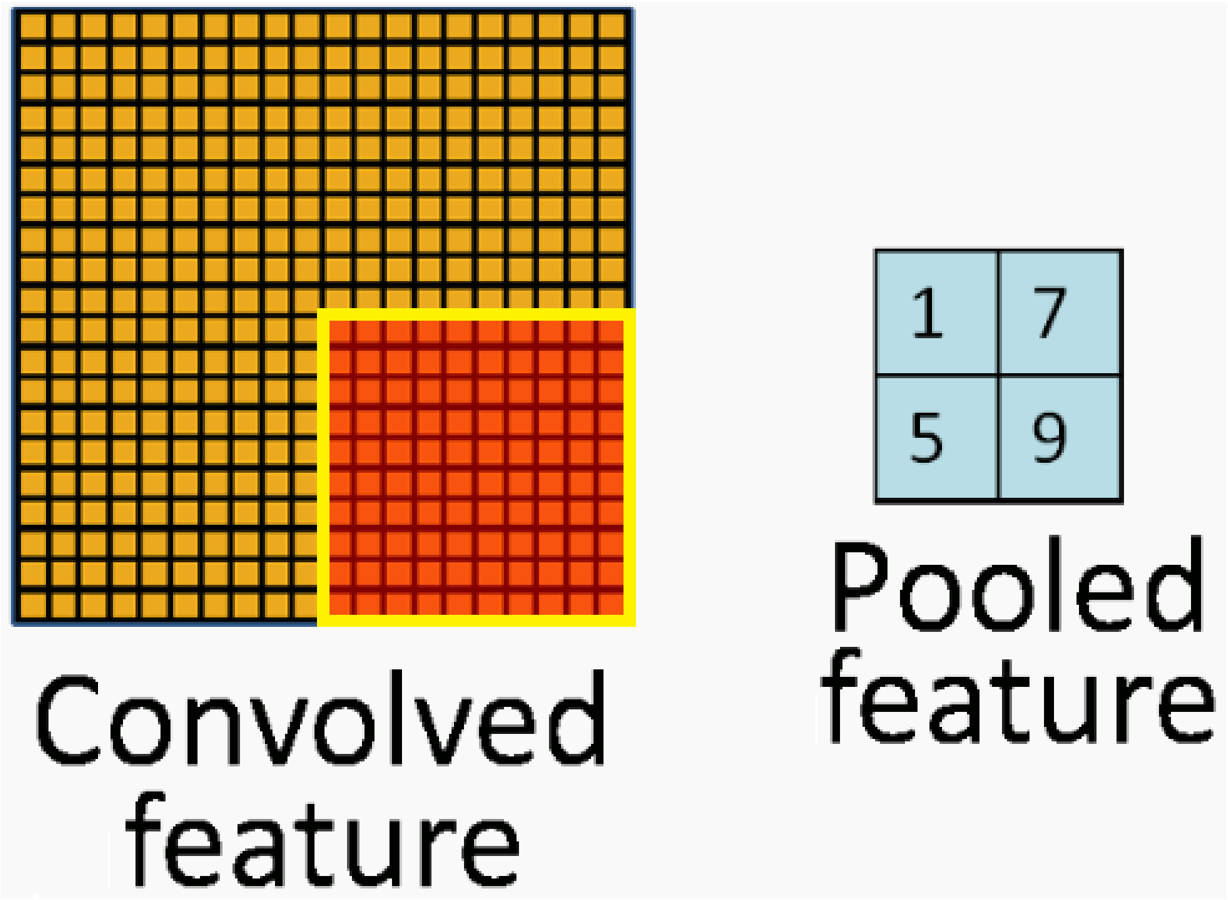
The step of the mask is known as a **stride**

Image from: http://www.slideshare.net/uspace/ujavaorg-deep-learning-with-convolutional-neural-network

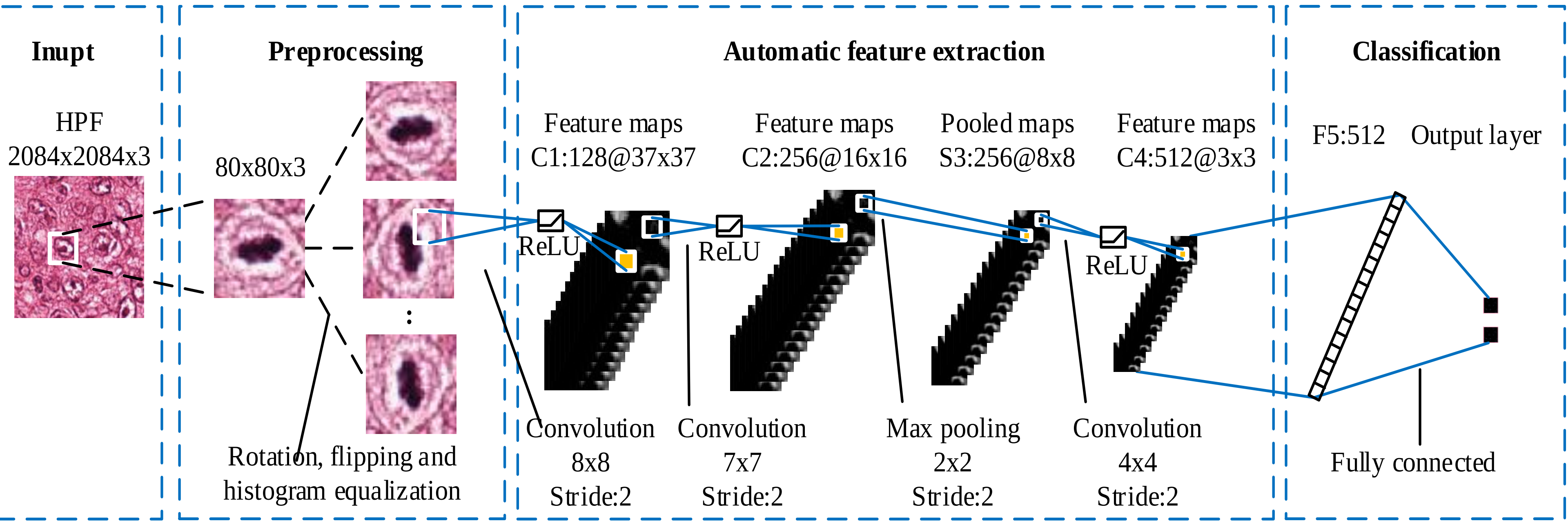
Pooling



Pooling



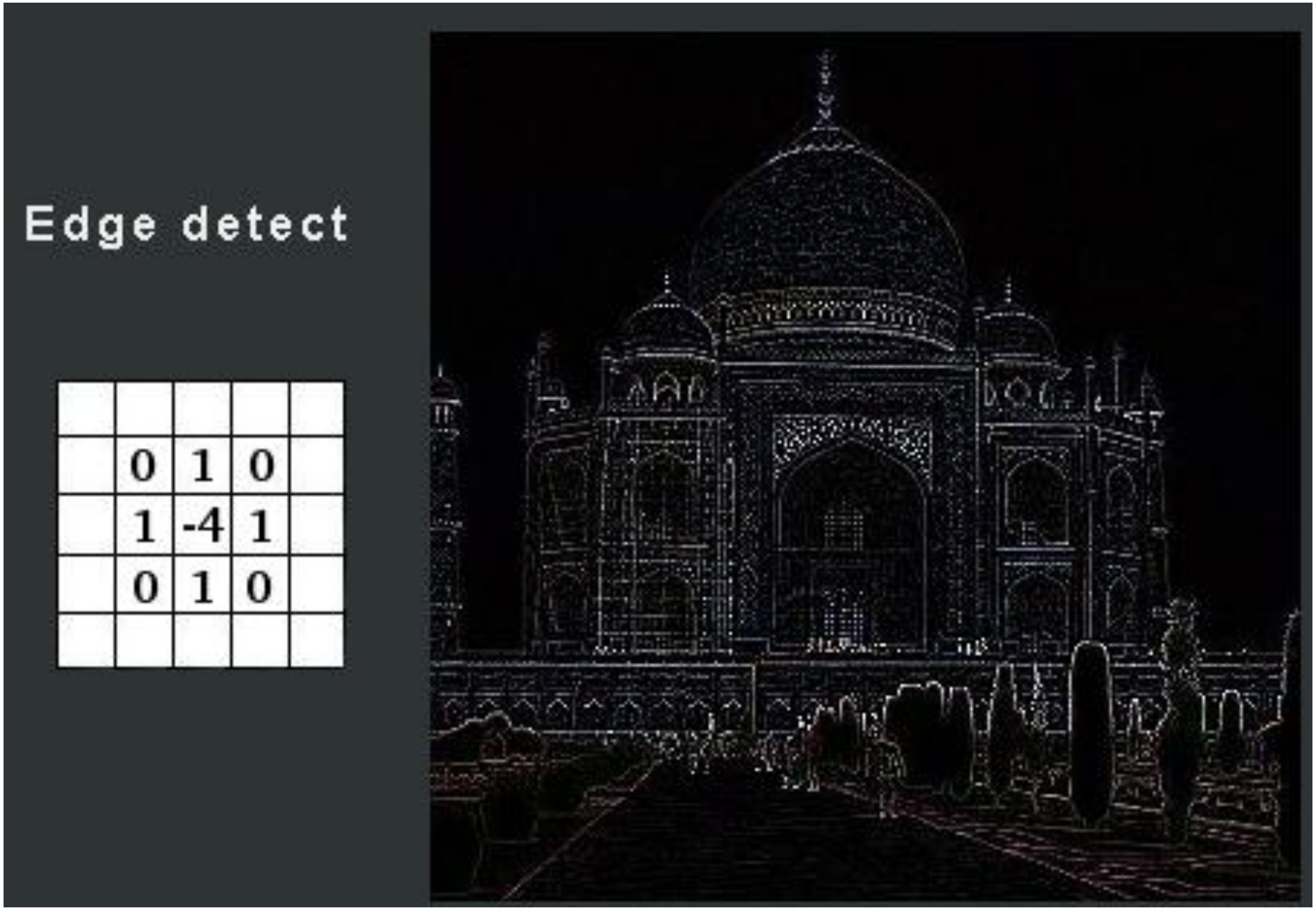
One of our Proposed CNN Architecture;



featureMapSize = [(inputsize – filtersize + 2xzeropadding)/stride]+1

pooledMapSize = [(inputsize – filtersize)/stride]+1

Filters/Kernels/Mask/Feature-extractor



Static/hand-made Filters

Motivation for CNN

- Invariant Features: Detection and classification independent of pose, scale, illumination, occlusion and clutter
- Dynamic Feature Extraction: how could an artificial vision system learn appropriate internal representations automatically, the way humans seem to by simply looking at the world?
- Reduced Learnable Parameters compared to a BackPropagator.
- Hierarchical Learning

Motivation for CNN; Invariance

Goal

- Detection and classification independent of pose, scale, illumination, occlusion and clutter

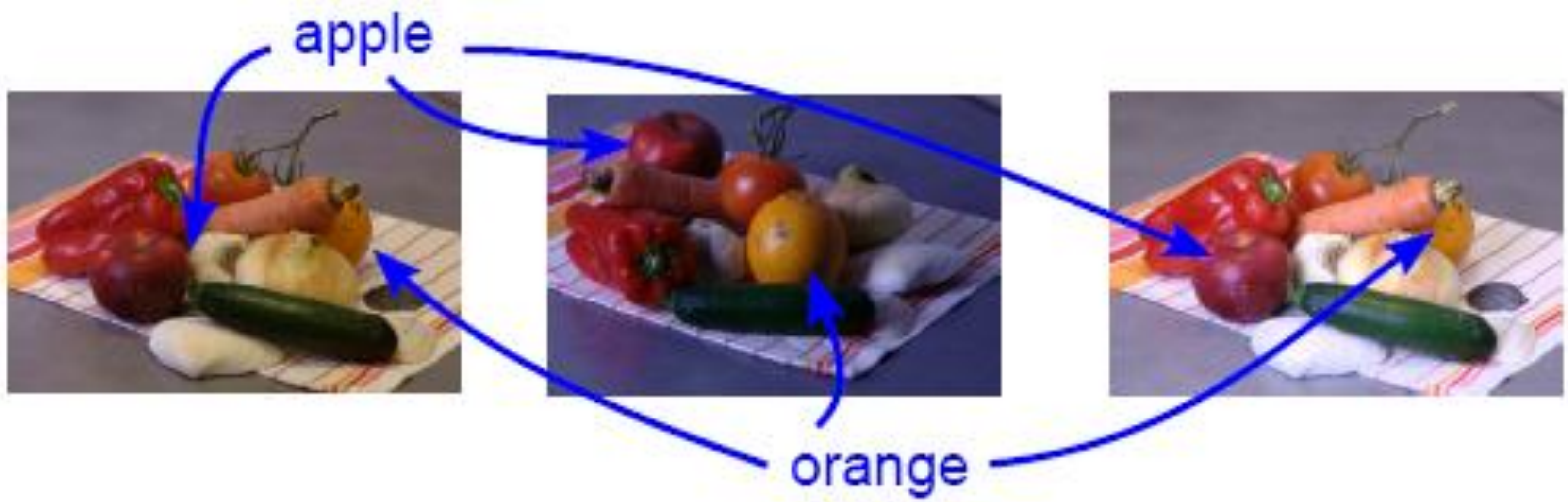


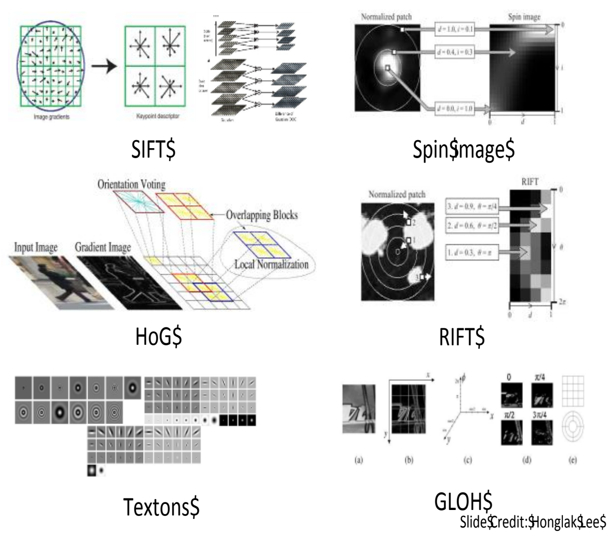
Image from: Dr. Richard E. Turner presentation (2014)

Static Feature Extraction: Standard image classification approach

Input

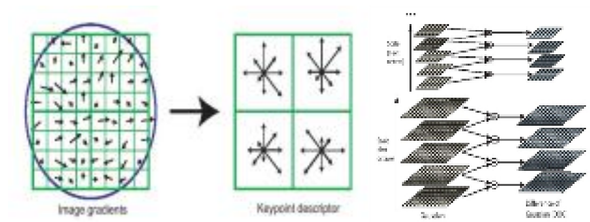
Extract features

Use simple classifier e.g., logistic regression, SVMs

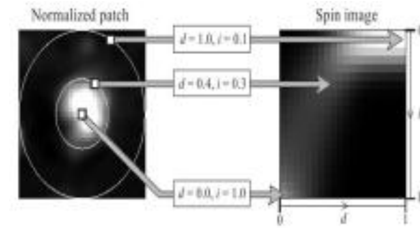


Face

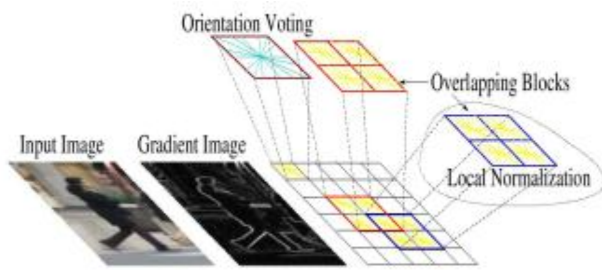
Static Feature Extraction: many hand crafted Features exist...



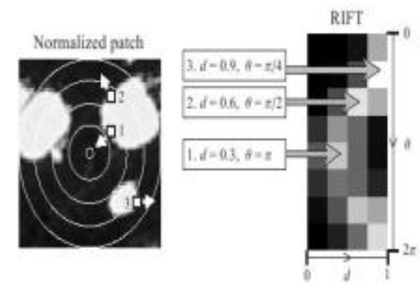
SIFT$



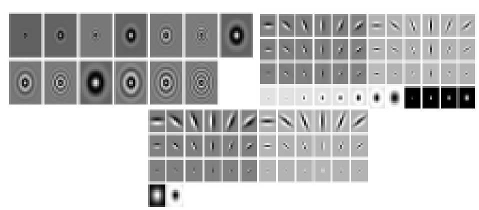
Spin$mage$



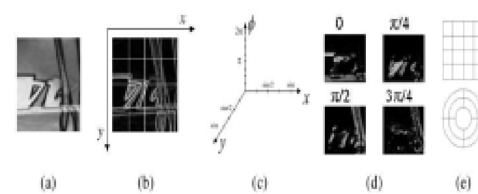
HoG$



RIFT$



Textons$



GLOH$

Slide$Credit:$HonglakLee

… but very painful to design

Dynamic Feature Extraction: Change Image Classification Approach?

Input

Extract features dynamically

Use simple classifier e.g., SVM, etc.

Can we automatically learn features from data?

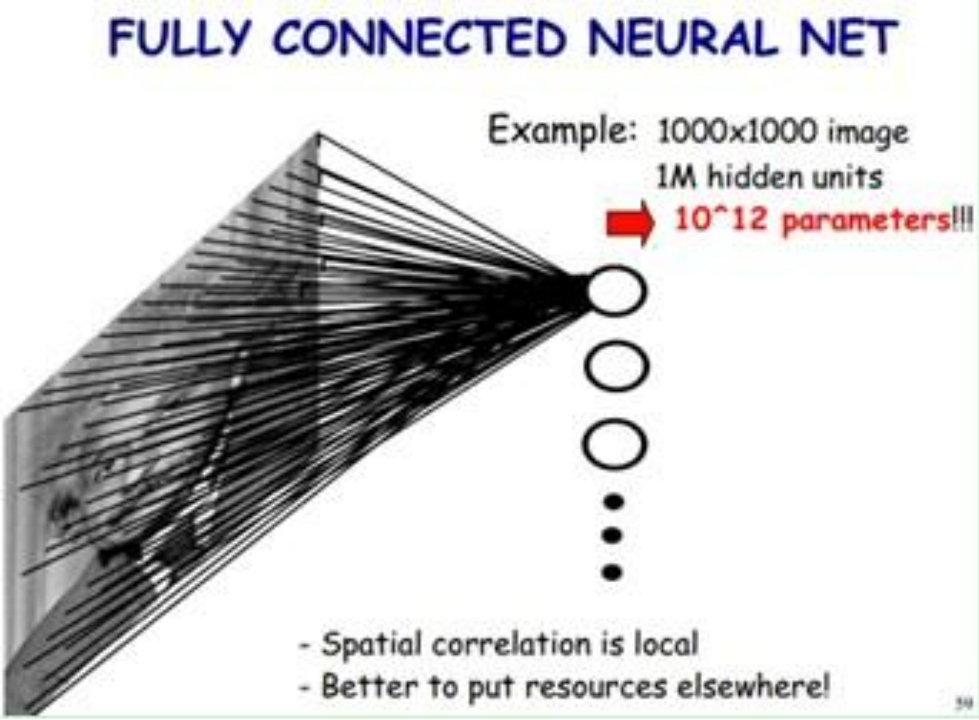
Face

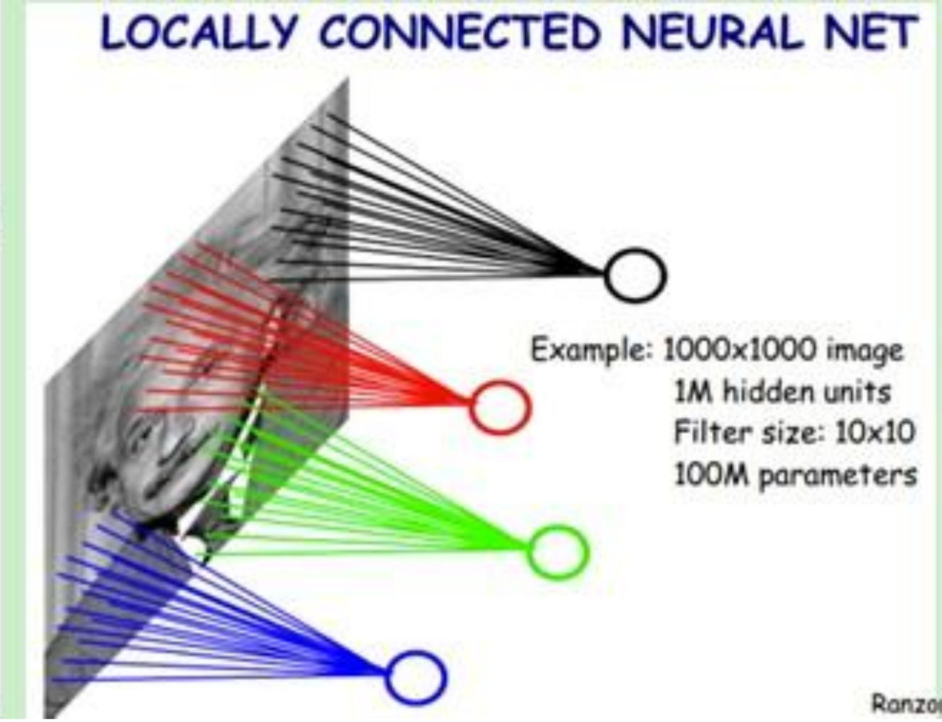
Motivation for CNN; Less Parameters

Cons of multilayer perceptron

- The number of trainable parameters becomes extremely large. For example, a 24×24 input layer would already have 576 connections per single neuron in the hidden layer
- Secondly, it offers little or no invariance to shifting, scaling, and other forms of distortion
- Hand-crafted feature extraction requires a great deal of time

Motivation for CNN; Less Parameters





Motivation for CNN; Hierarchical Learning

- Hubel/Wiesel Architecture
- D. Hubel and T. Wiesel (Nobel Prize 1981)
- Visual cortex consists of a hierarchy of *simple*, *complex*, and *hyper-complex* cells

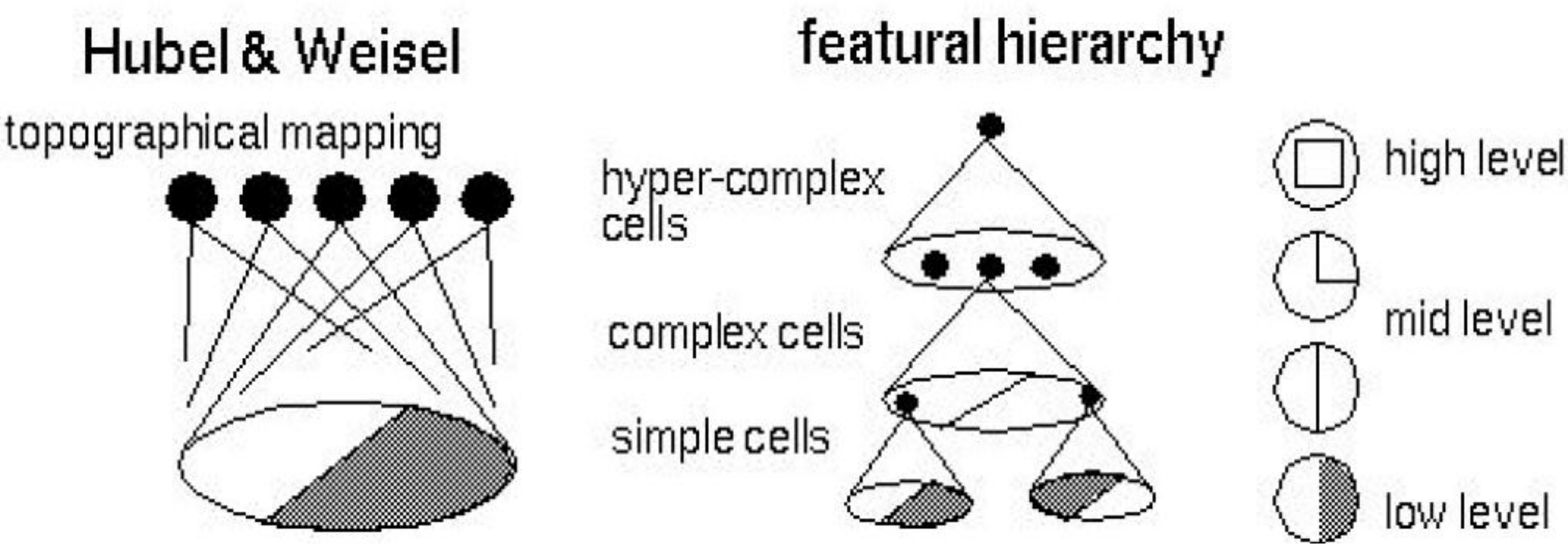


Image from: http://cns-alumni.bu.edu/~slehar/webstuff/pcave/hubel.html

Motivation for CNN: Hierarchical Learning

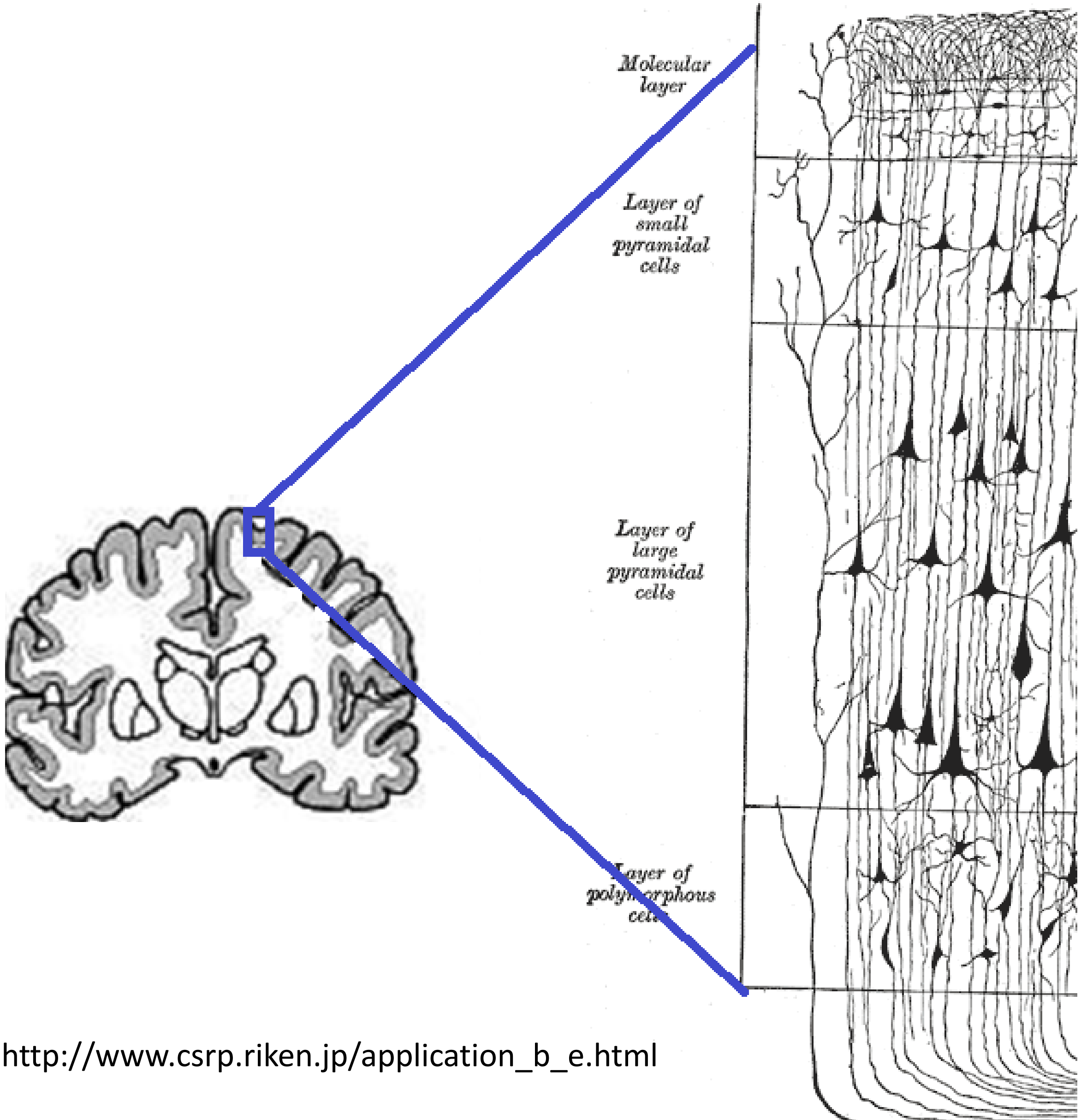


Image from: http://www.csrp.riken.jp/application_b_e.html

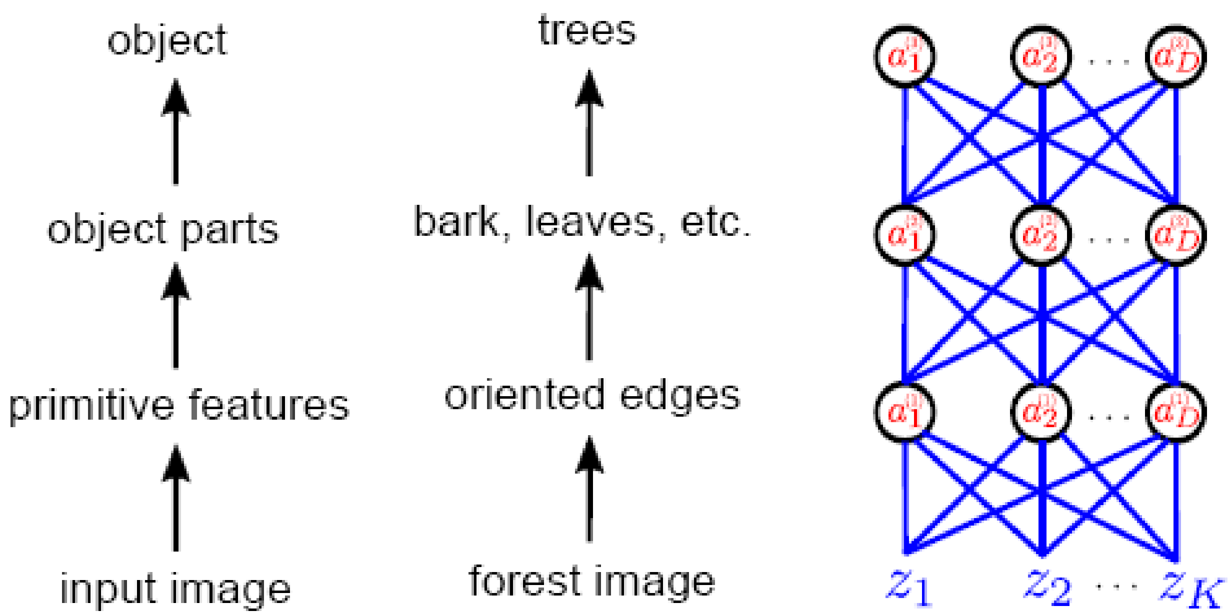
Motivation for CNN; Hierarchical Learning

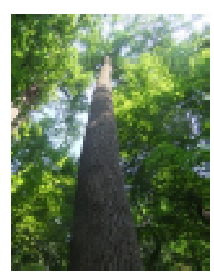
- In 1995, Yann LeCun and Yoshua Bengio introduced the concept of CNN

- Neurobiologically motivated by the findings of locally sensitive and orientation-selective nerve cells in the visual cortex of the cat

Motivation for CNN; Why use hierarchical multi-layered models?

- visual scenes are hierarchically organized



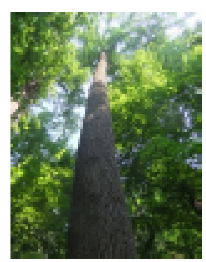


Slide credit: Dr. Richard E. Turner presentation (2014)

Motivation for CNN; Why use hierarchical multi-layered models?

- biological vision is hierarchically organized

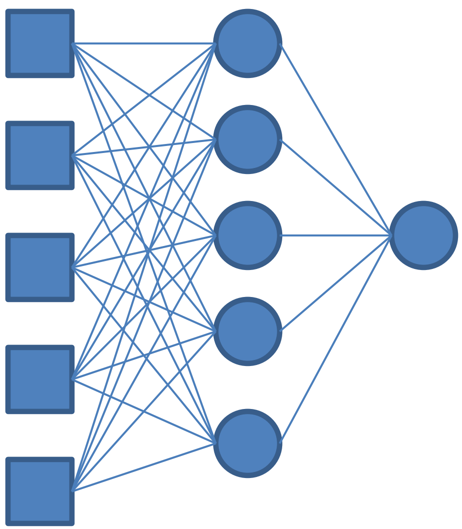
object	trees	Inferotemporal cortex
object parts	bark, leaves, etc.	V4: different textures
primitive features	oriented edges	V1: simple and complex cells
input image	forest image	photo-receptors retina



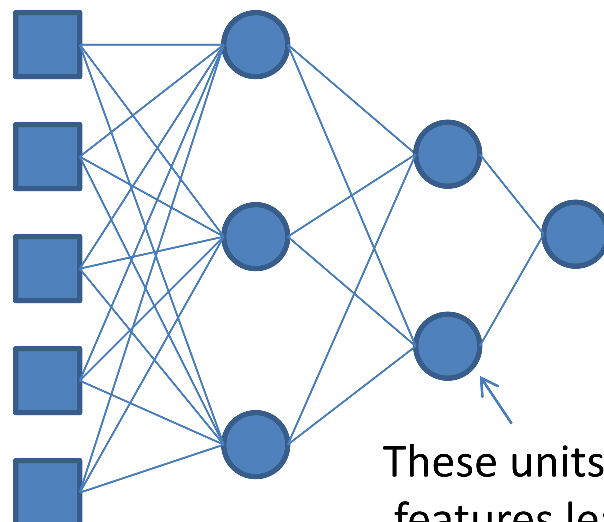
Slide credit: Dr. Richard E. Turner presentation (2014)

Motivation for CNN; Why use hierarchical multi-layered models?

- Shallow architectures are inefficient at representing deep functions
- Deep net, deep (enriched) features



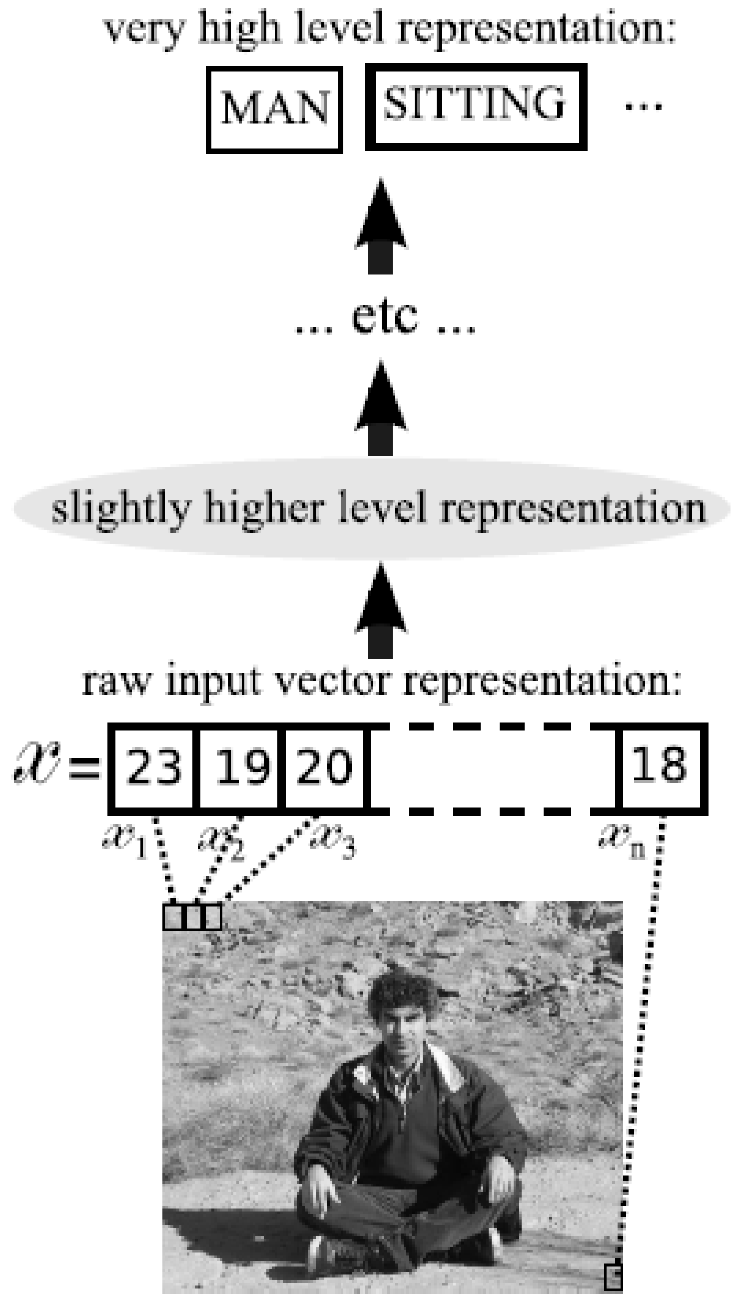
Params: 5x5+5=30



These units fine-tune the features learned by those in the previous layer

Params: 5x3+6+2=23

Motivation for CNN; Hierarchical Representation Example



Yoshua Bengio (2009)

Working of Convolutional Neural Networks

- Neural network with specialized connectivity structure
- Stack multiple stages of feature extractors
- Higher stages compute more global, more invariant features
- Classification layer at the end

Working of Convolutional Neural Network

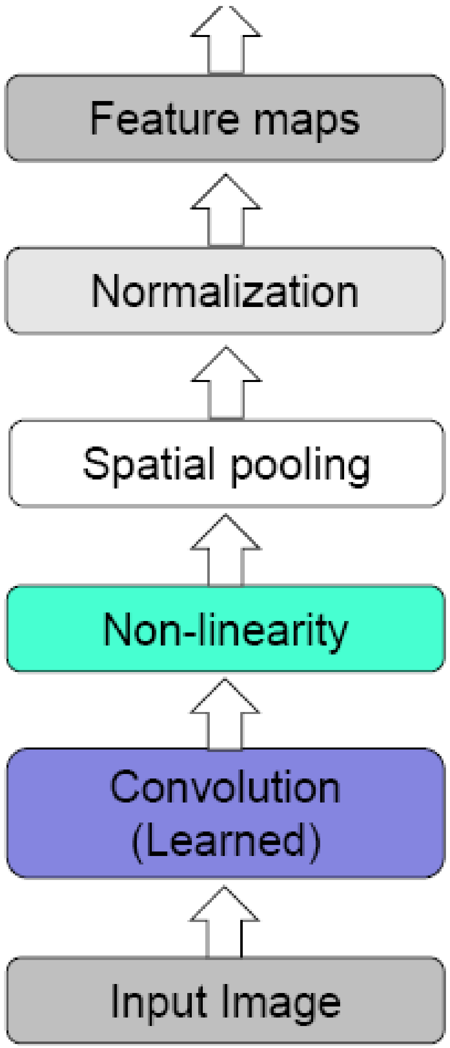
- Feed-forward feature extraction:
- 1. Convolve input with filters
- 2. Non-linearity (ReLU)
- 3. Spatial pooling
- 4. Normalization

Supervised training of convolutional filters by back-propagating classification error.

A CNN can be both Generative and Discriminative Learning Mechanism

Working of Convolutional Neural Network

- Feed-forward feature extraction:



Working of Convolutional Neural Network

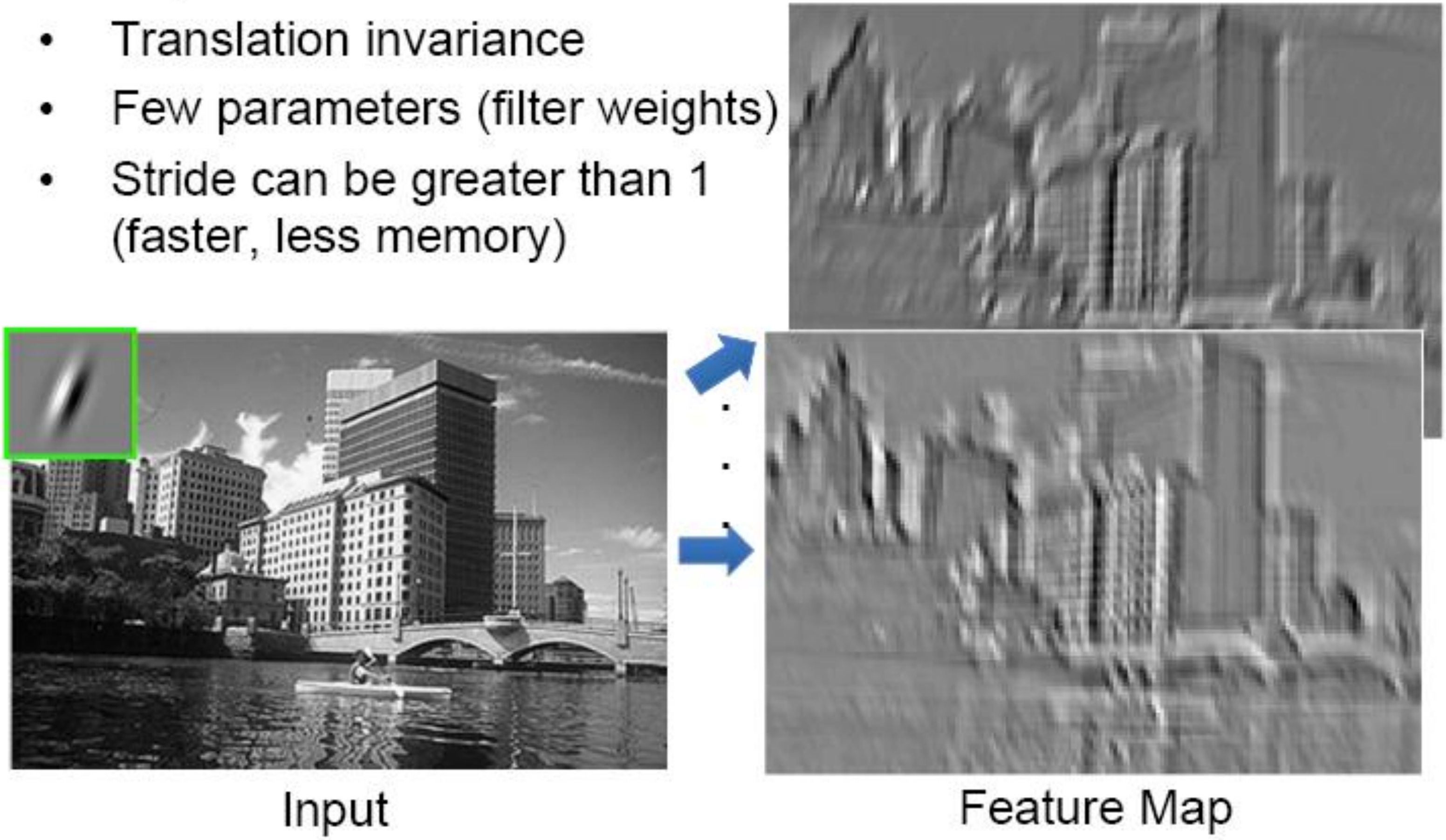
- CNN is a type of feed-forward artificial neural network.
- Individual neurons are tiled in such a way that they respond to overlapping regions in the visual field
- The lower layers obtain low-level features (like pixels, edges, lines and corners) while the higher layers obtain high-level features (like shapes)
- The more layers the network has, the higher-level features it will get

Working of Convolutional Neural Network; **Convolutional layer**

- Unlike a hand-coded convolution kernel (Sobel, Prewitt, Roberts), in a CNN, the parameters of each convolution kernel are trained by the backpropagation algorithm
- Convolution operators extract different features of the input
- There are many convolution kernels in each layer, and each kernel is replicated over the entire image with the same parameters (weights and bias)

Working of Convolutional Neural Network: **Convolutional layer**

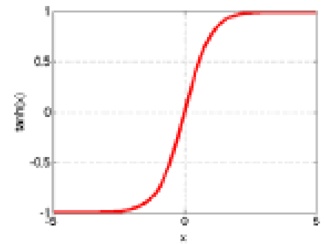
- Dependencies are local
- Translation invariance
- Few parameters (filter weights)
- Stride can be greater than 1 (faster, less memory)

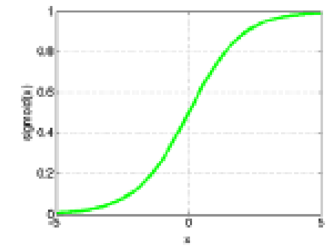


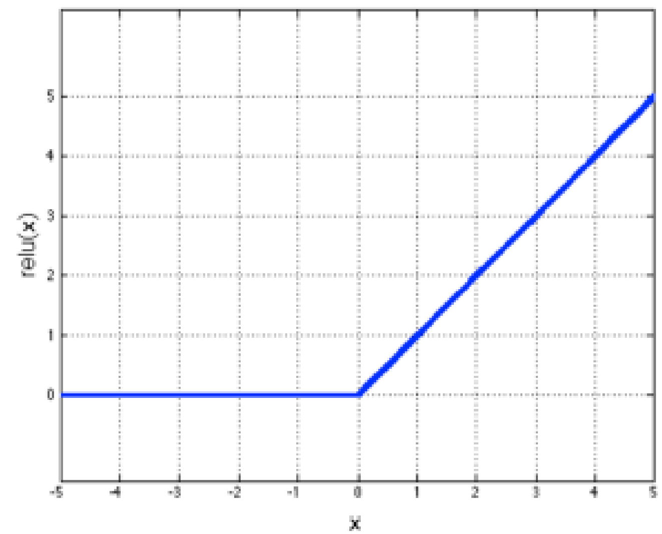
Slide credit: Rob Fergus (NIPS 2013 tutorial)
http://cs.nyu.edu/~fergus/presentations/nips2013_final.pdf

Working of Convolutional Neural Network: **Non-linearity**

- Per-element (independent)
- Options:
  - Tanh
  - Sigmoid: 1/(1+exp(-x))
  - Rectified linear unit (ReLU)
    - Simplifies backpropagation
    - Makes learning faster
    - Avoids saturation issues
      → Preferred option







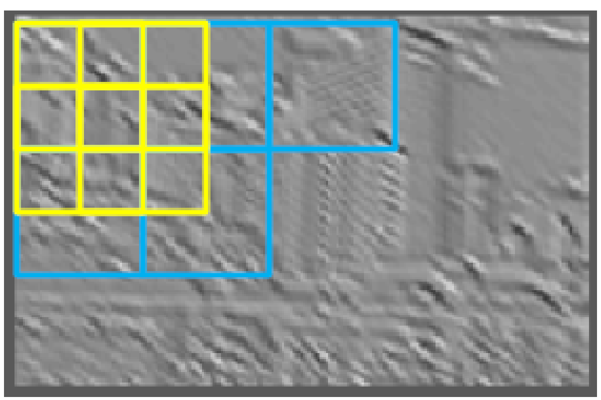
Slide credit: Rob Fergus (NIPS 2013 tutorial)
http://cs.nyu.edu/~fergus/presentations/nips2013_final.pdf

Working of Convolutional Neural Network: Pooling Layer

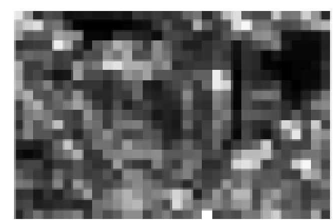
- In order to reduce variance, pooling layers compute the max or average value of a particular feature over a region of the image
- This will ensure that the same result will be obtained, even when image features have small translations
- This is an important operation for object classification and detection

Working of Convolutional Neural Network: Pooling Layer

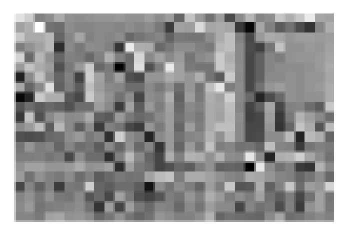
- Sum or max
- Non-overlapping / overlapping regions
- Role of pooling:
  - Invariance to small transformations
  - Larger receptive fields (see more of input)



Max



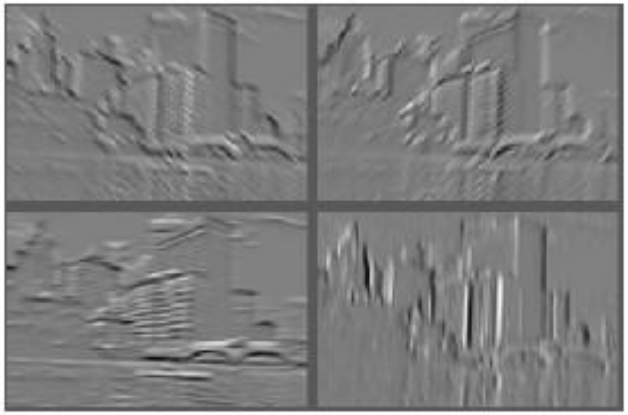
Sum



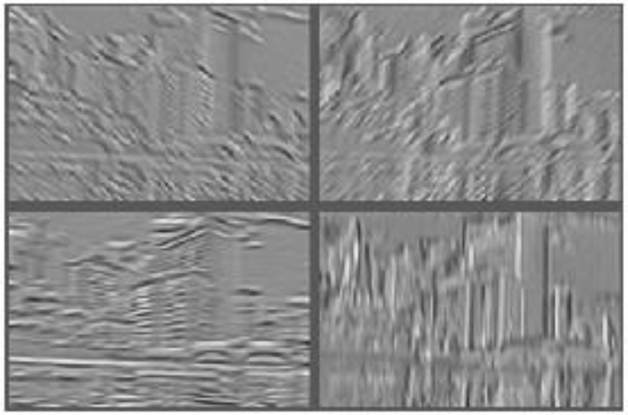
Slide credit: Rob Fergus (NIPS 2013 tutorial)
http://cs.nyu.edu/~fergus/presentations/nips2013_final.pdf

Working of Convolutional Neural Network: Normalization

- Within or across feature maps
- Before or after spatial pooling



Feature Maps

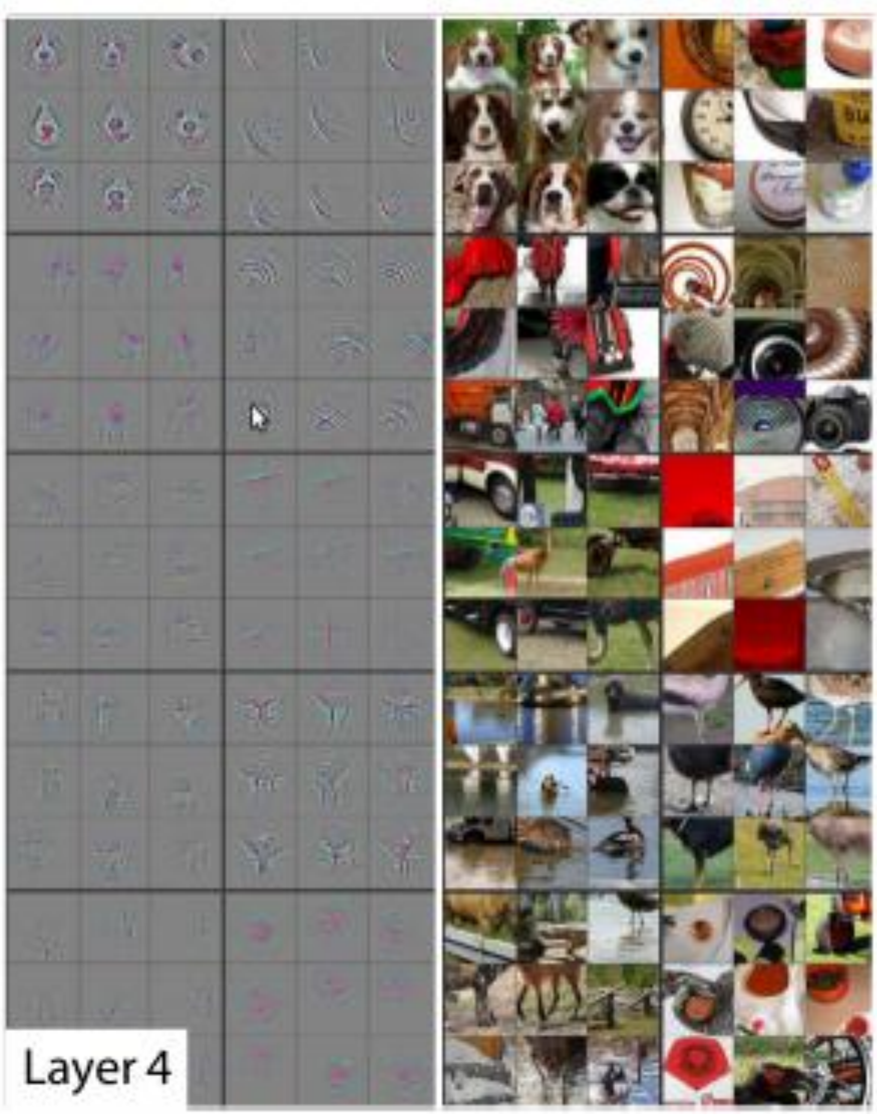


Feature Maps
After Contrast Normalization

Slide credit: Rob Fergus (NIPS 2013 tutorial)
http://cs.nyu.edu/~fergus/presentations/nips2013_final.pdf

Visualizing activations in CNN

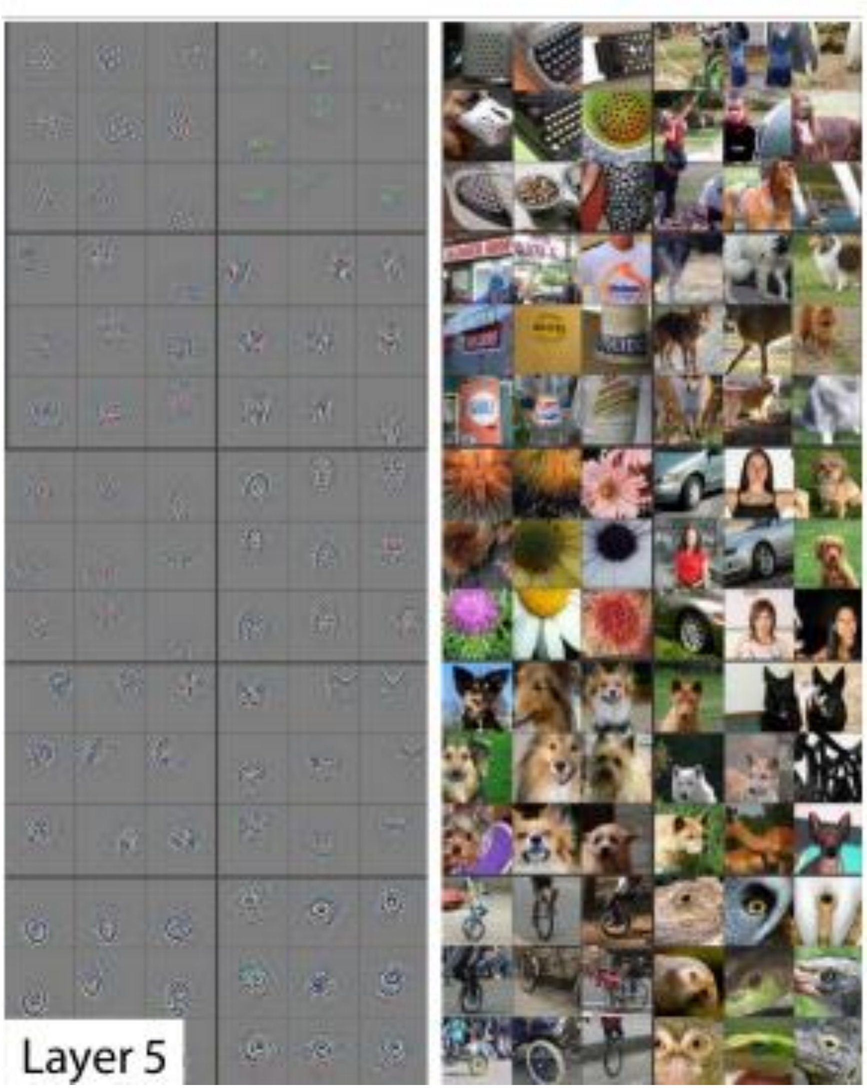
Visualizing activations



Zeiler, Matthew (2014)

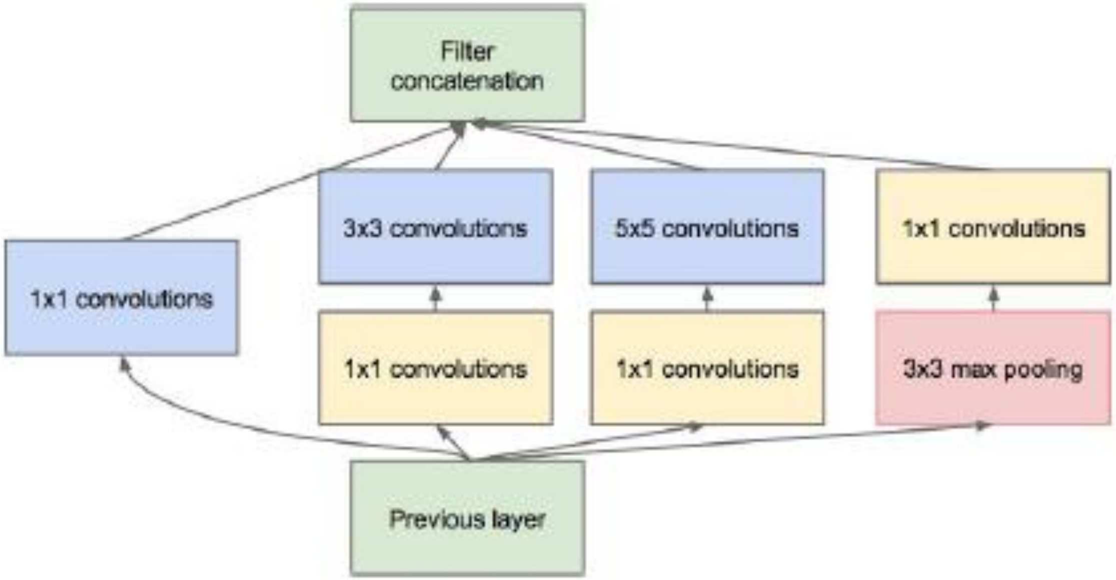
Visualizing activations in CN cont..

Visualizing activations

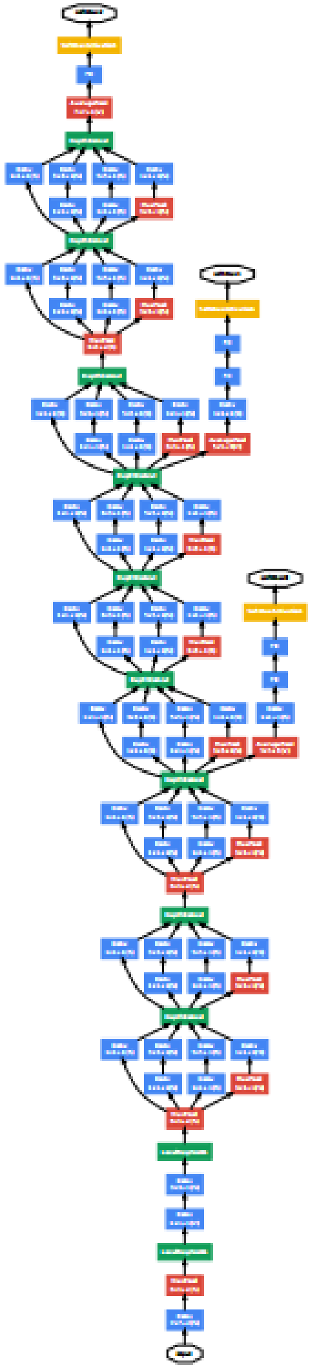


Zeiler, Matthew (2014)

Deep CNN recent examples: GoogLeNet (ILSVRC 2014 winner)

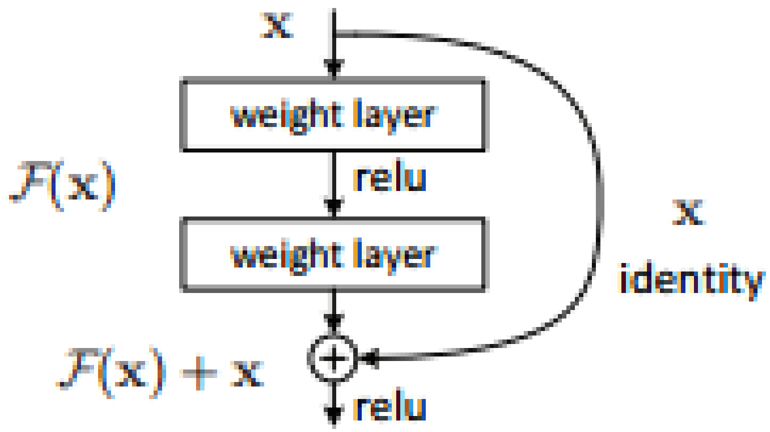


Inception module



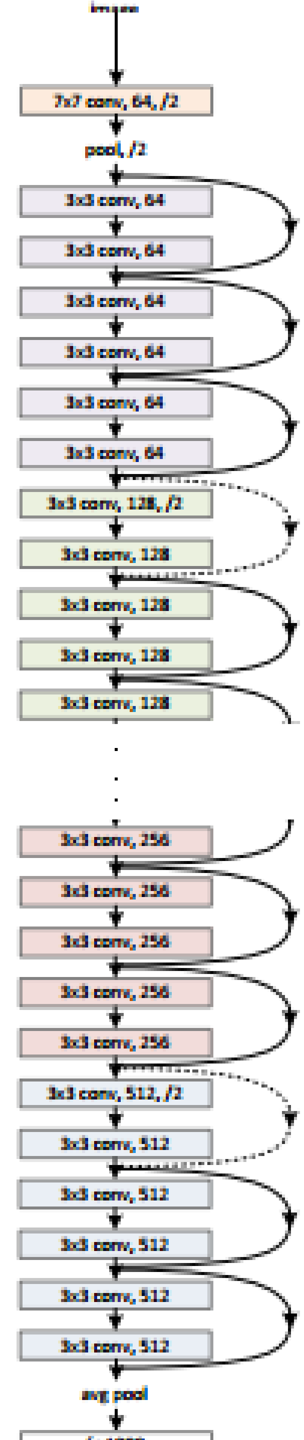
Szegedy, et al (2015)

Deep CNN recent examples: ResNet (ILSVRC 2015 winner)

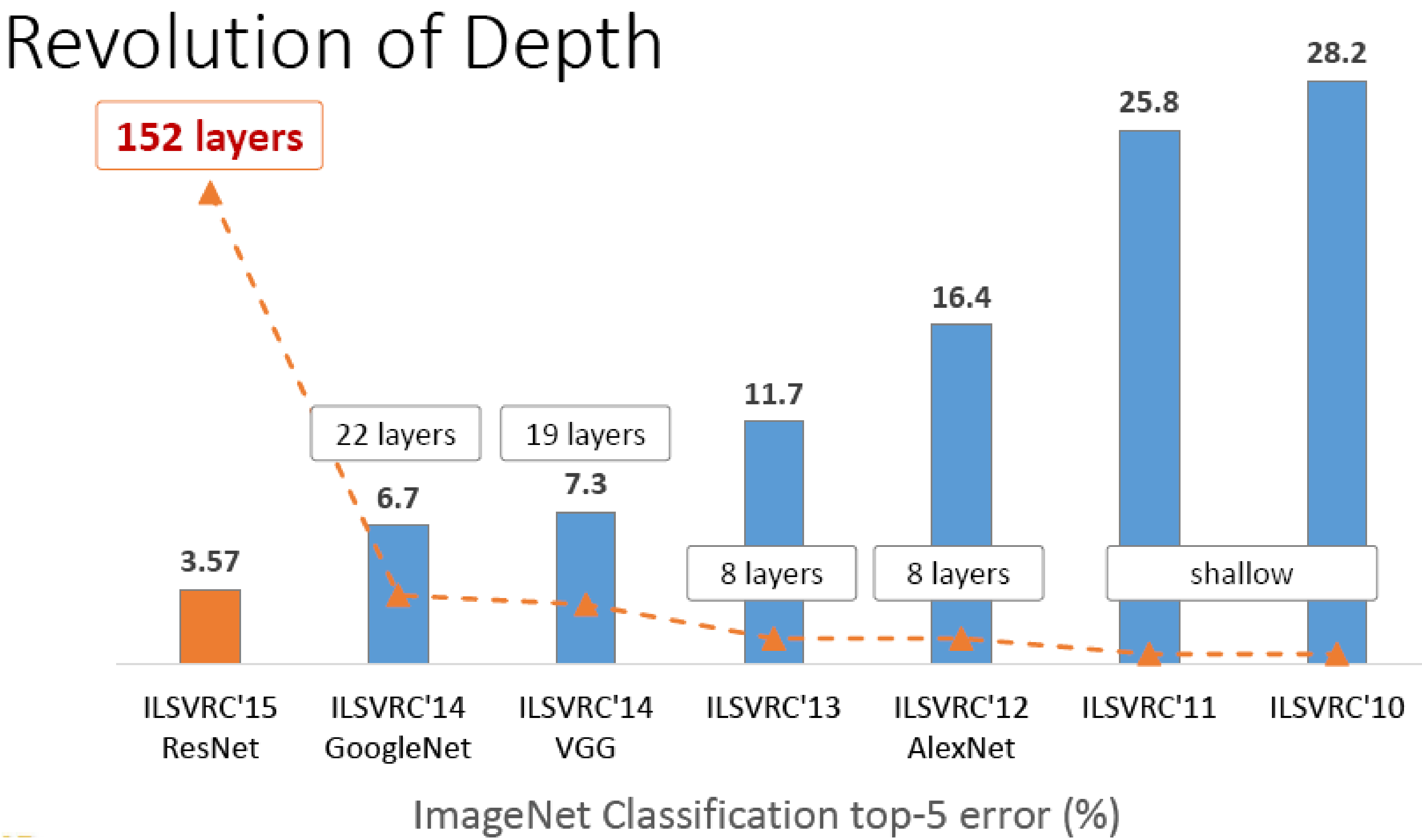


Residual learning: a building block

152 layers; 3.57 top 5% error
ImageNet 2012 dataset;
1000 classes, 1.28 million
training Images,
50K validation images, 100 K
test images;
millions of parameters;
Kaiming He, et al. (2015)

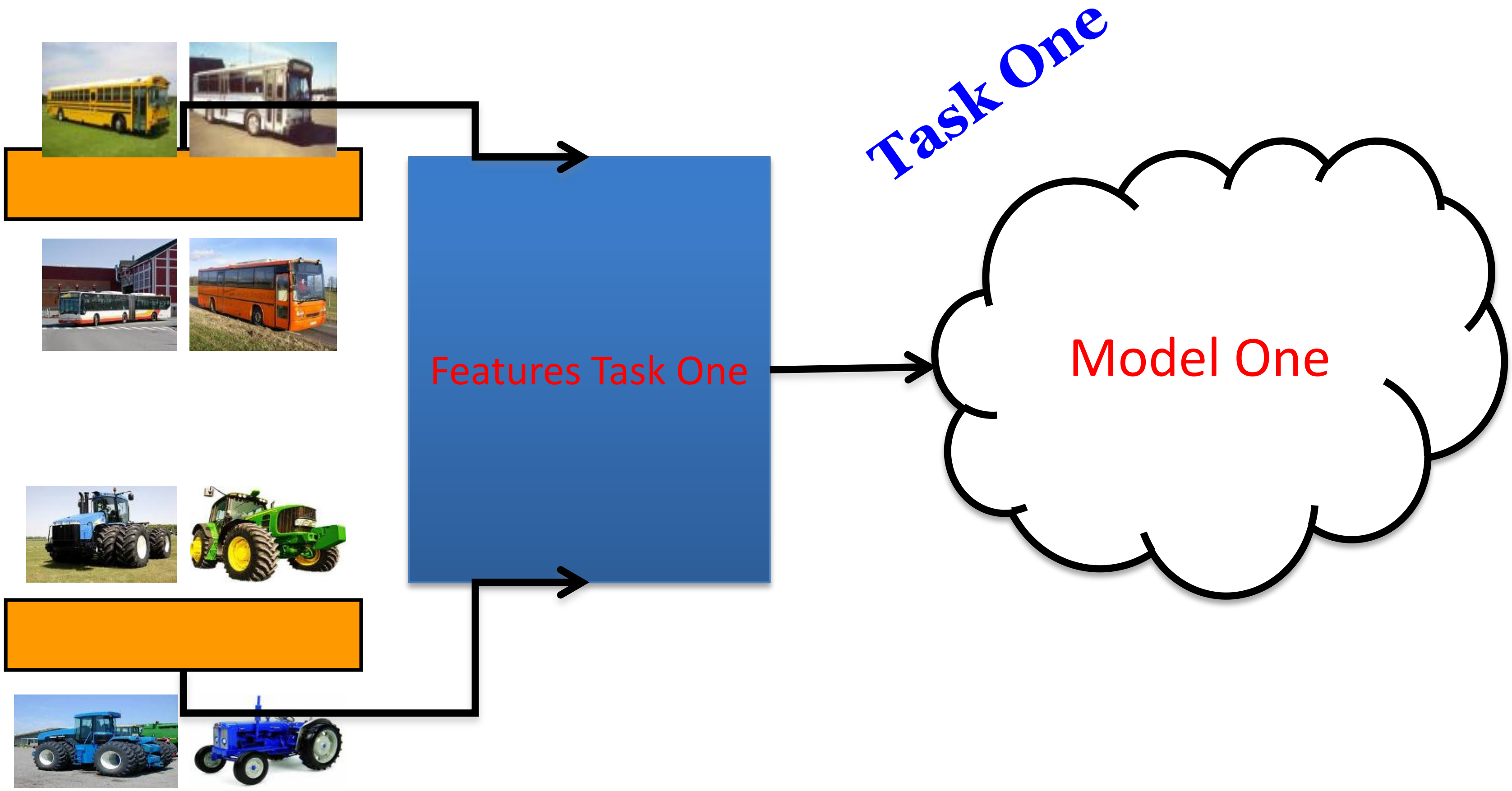


CNN; Competition in Depth

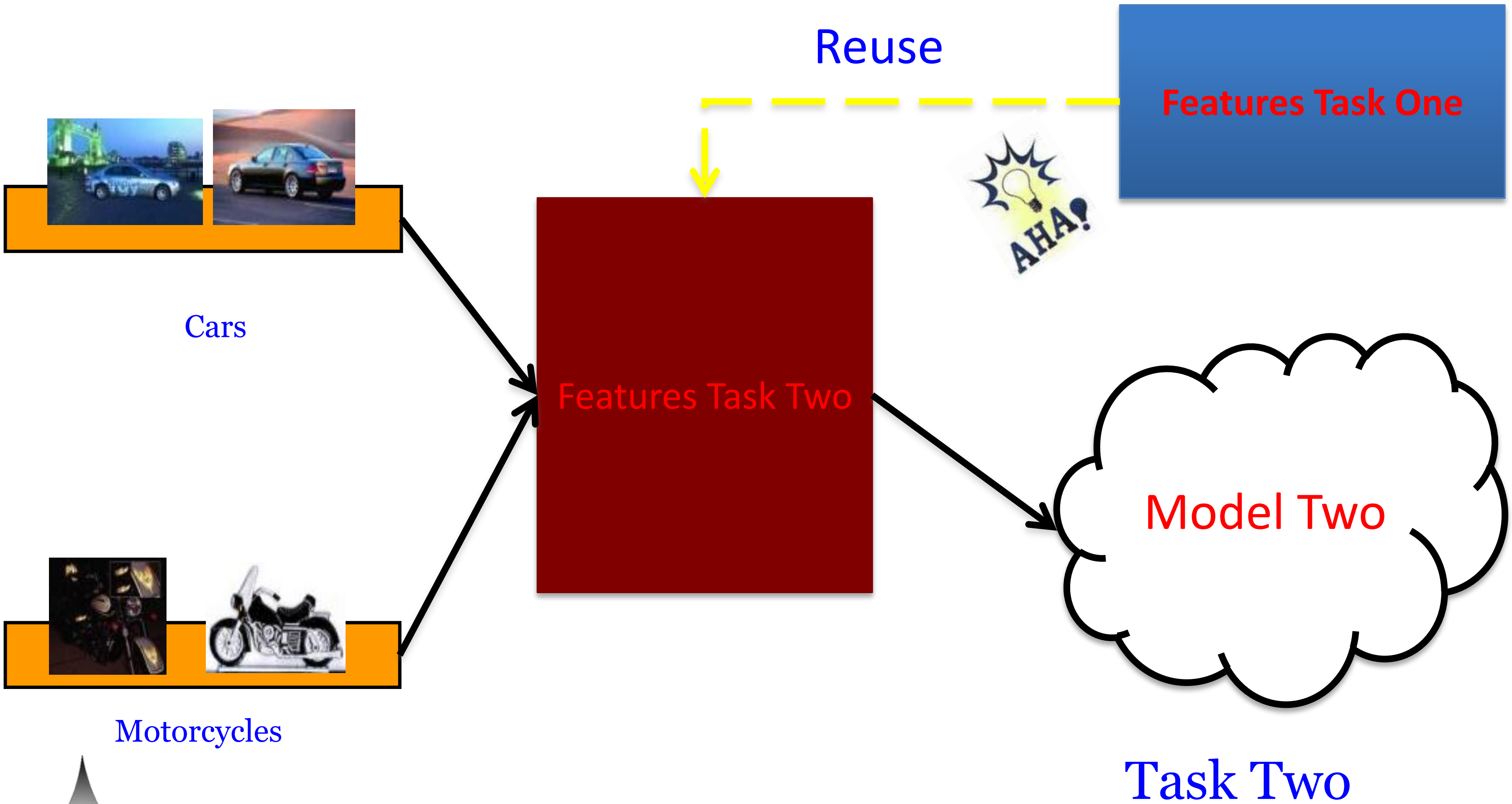


Slide from Kaiming He et al.,

Transfer Learning; Image Classification example



Transfer Learning; Image Classification example



Convolutional Neural Networks

To ponder on:

- Computational cost vs. performance/results
- What should be the filter sizes at different layers?
- How much pooling?
- How many neurons to keep in different layers?
- How many layers to employ?
- How to increase generalization of a CNN?
  - Use a good cross-validation startegy
  - Use pruning (Dropout, Swapout, etc.)
  - Use unsupervised pre-training

References

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