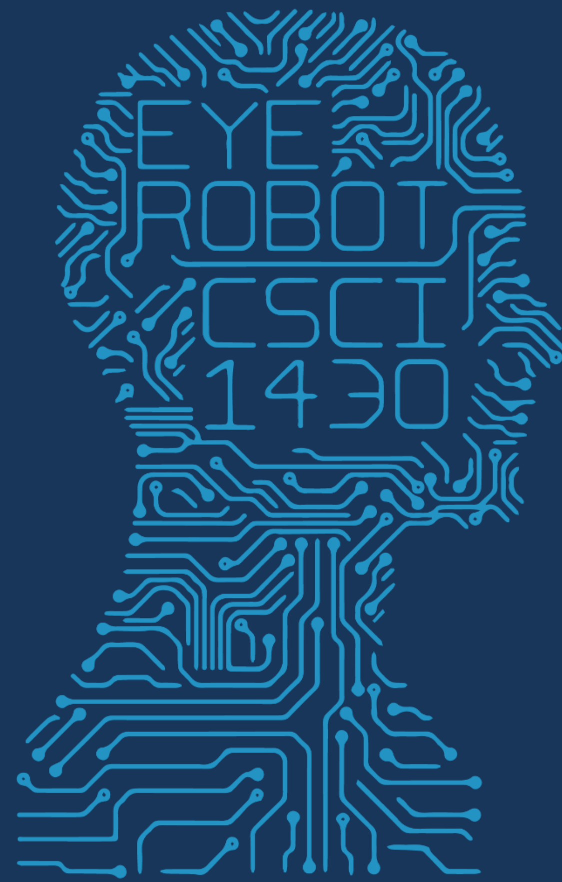
1950

Future Vision



2020

Computer Vision

Facial-Recognition Company That Works With Law Enforcement Says Entire Client List Was Stolen

BREACH

Clearview AI, which contracts with law enforcement after reportedly scraping 3 billion images from the web, now says someone got "unauthorized access" to its list of customers.

Betsy Swan
Political Reporter
Published Feb. 26, 2020 9:55AM ET

REUTERS/Thomas Peter

A facial-recognition company that contracts with powerful law-enforcement agencies just reported that an intruder stole its entire client list, according to a notification the company sent to its customers.

READ THIS LIST

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SAM BRODEY, SAM STEIN

Klobuchar to End Her Presidential Bid and Back Biden
HUNTER WOODALL, HANNA TRUDO

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EMMA TUCKER

The Coronavirus Is a Pandemic, and We're Not Prepared
IRWIN REDLENER

McCain: Bernie Bros 'Are the Dirtiest Thugs I've Ever Seen'
JUSTIN BARAGONA

!!! Warning !!!

Learning jargon is always painful…

…even if the concepts behind the jargon are not hard.

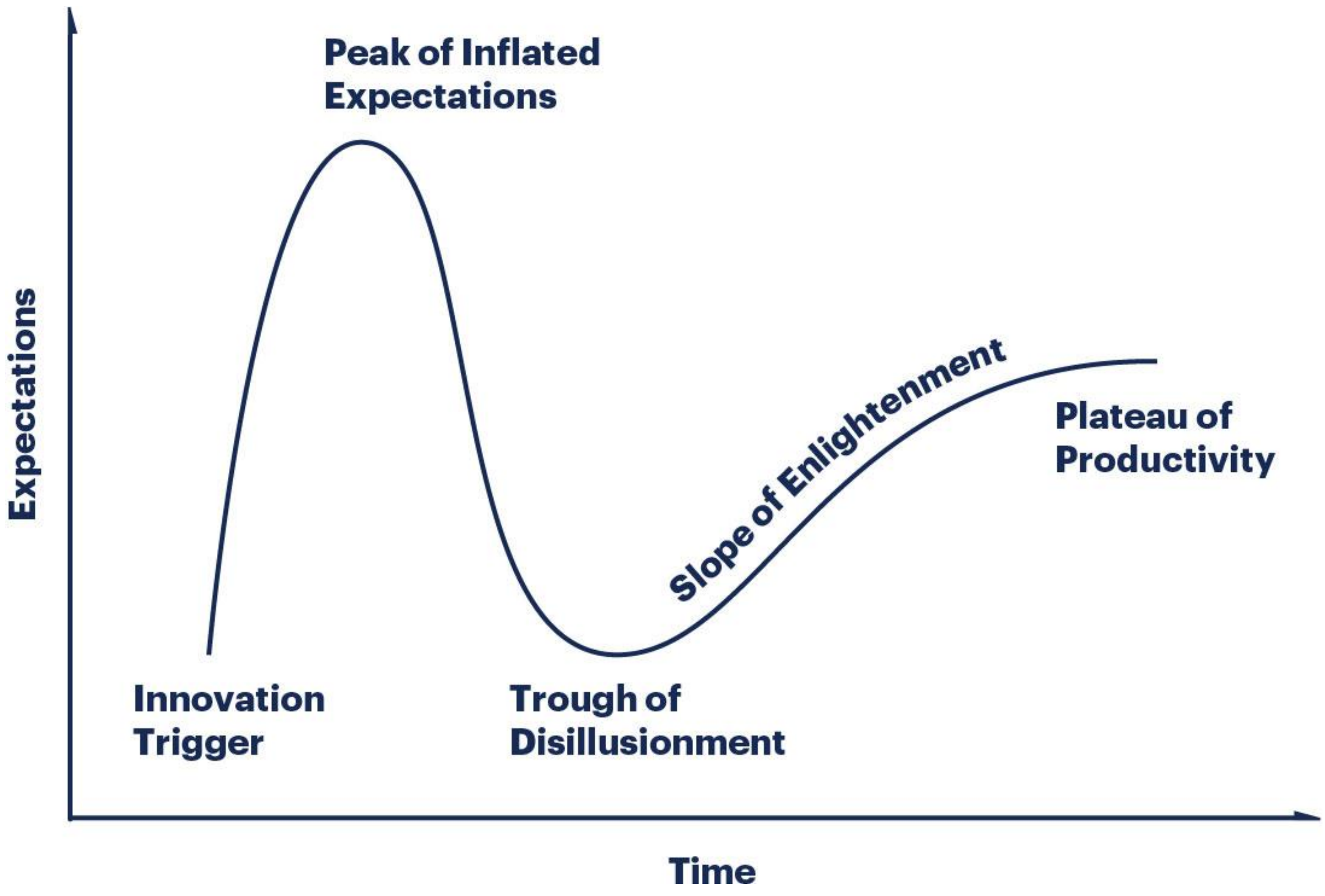
So, let’s get used to it.

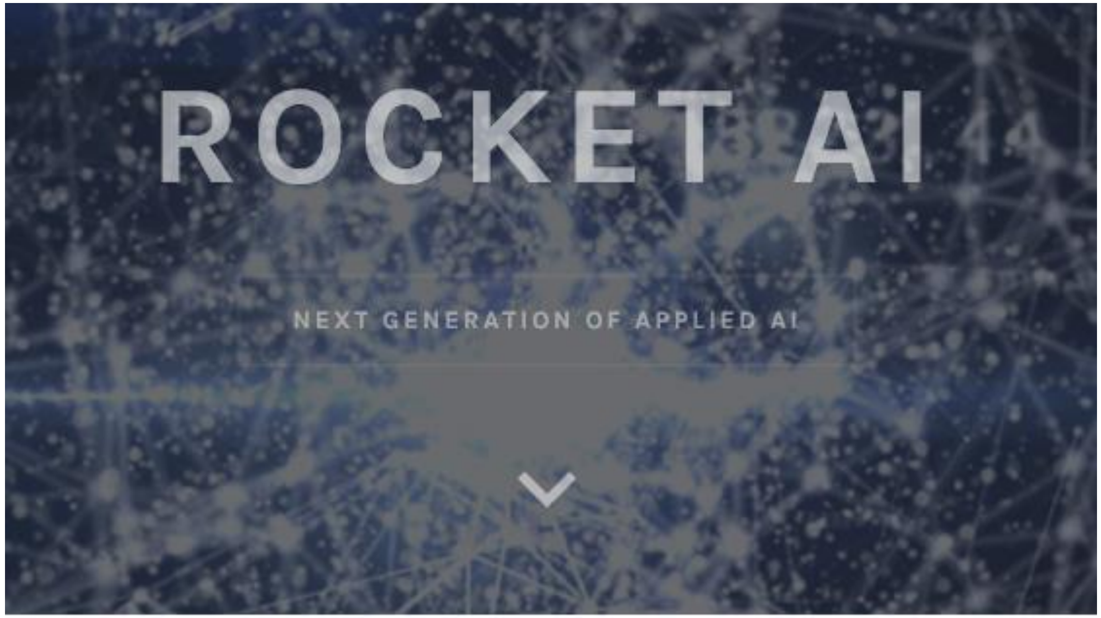
“In mathematics you don't understand things.
You just get used to them.”

von Neumann

(telling a joke)

Gartner Hype Cycle





Launching in 2017, Rocket AI will be the global leader in neurologically-inspired applied machine learning.

We build our systems around our patent-pending technology

Temporally Recurrent Optimal Learning™

We Are Hiring

launch@rocketai.org

Rocket AI

- Launch party @ NIPS 2016 *[now NeurIPS]*
- Neural Information Processing Systems
- Academic conference

Markus Wulfmeier
December 8 at 5:15pm · Barcelona, Spain ·

#rocketai s launch party at #nips2016 clearly the best. Including the police involvement.

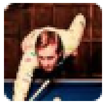
Rocket AI

Pôle #AI au #Québec and 22 others liked

Andrej Karpathy @karpathy · Dec 9

Best party of #nips2016 award goes to **#rocketai** (rocketai.org). Definitely a company to watch closely.

5 44 130



Karl Moritz Hermann @karlmoritz · Dec 9

One day we will look back and realise that the **#rocketai** launch was the day when things in our field changed forever.

2 3 20

Ian Goodfellow @goodfellow_ian · Dec 11

#rocketai definitely has the most popular Jacobian-Optimized Kernel Expansion of NIPS 2016

6 42 214

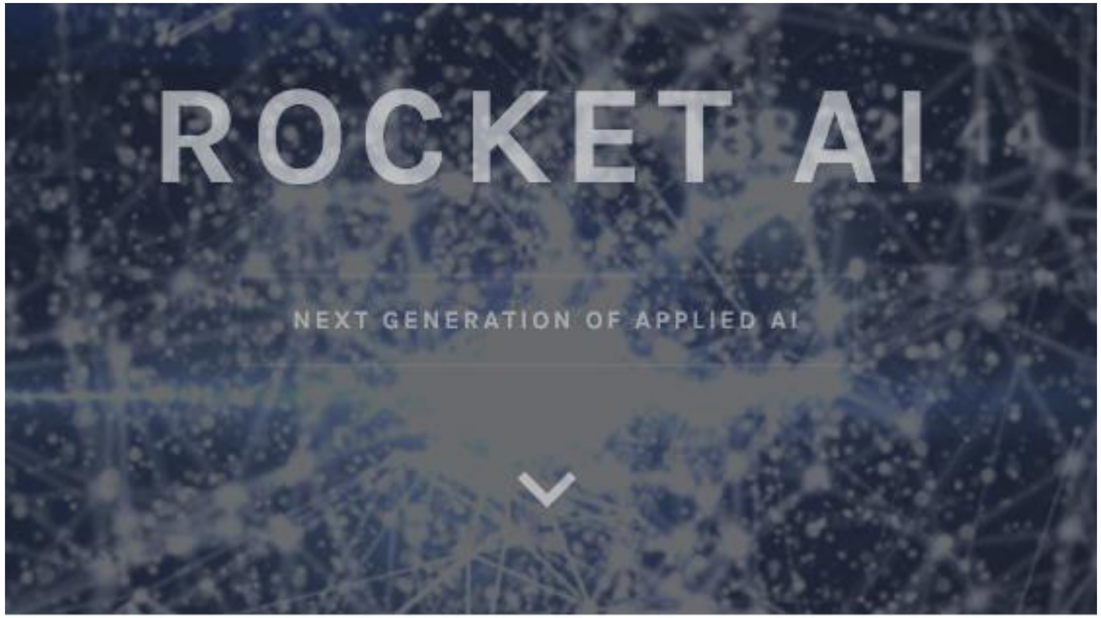
Rocket AI

Metrics for the Rocket AI launch party

Email RSVPs to party: 316
People who emailed in their resume: 46
Large name brand funds who contacted us about investing: 5
Media: Twitter, Facebook, HackerNews, Reddit, Quora, Medium etc
Time Planning: < 8 hours
Money Spent: $79 on the domain, $417 on alcohol and snacks + (police fine)
For reference, NIPS sponsorship starts at $10k.

Estimated value of Rocket AI: *in the tens of millions.*

Article by Riva-Melissa Tez



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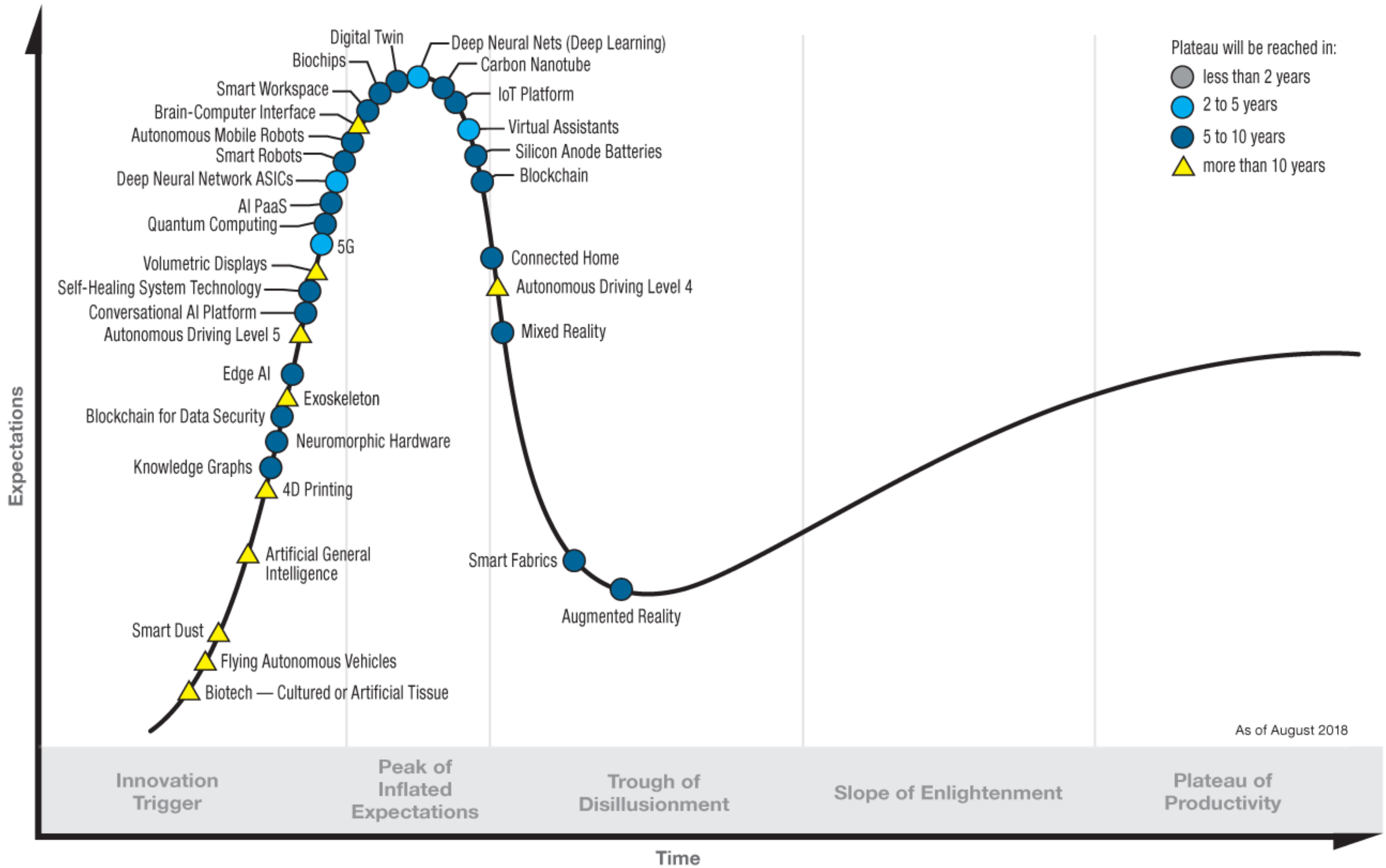
Hype Cycle for Emerging Technologies, 2018



gartner.com/SmarterWithGartner

Source: Gartner (August 2018)

Gartner

Gartner Hype Cycle for Emerging Technologies, 2019

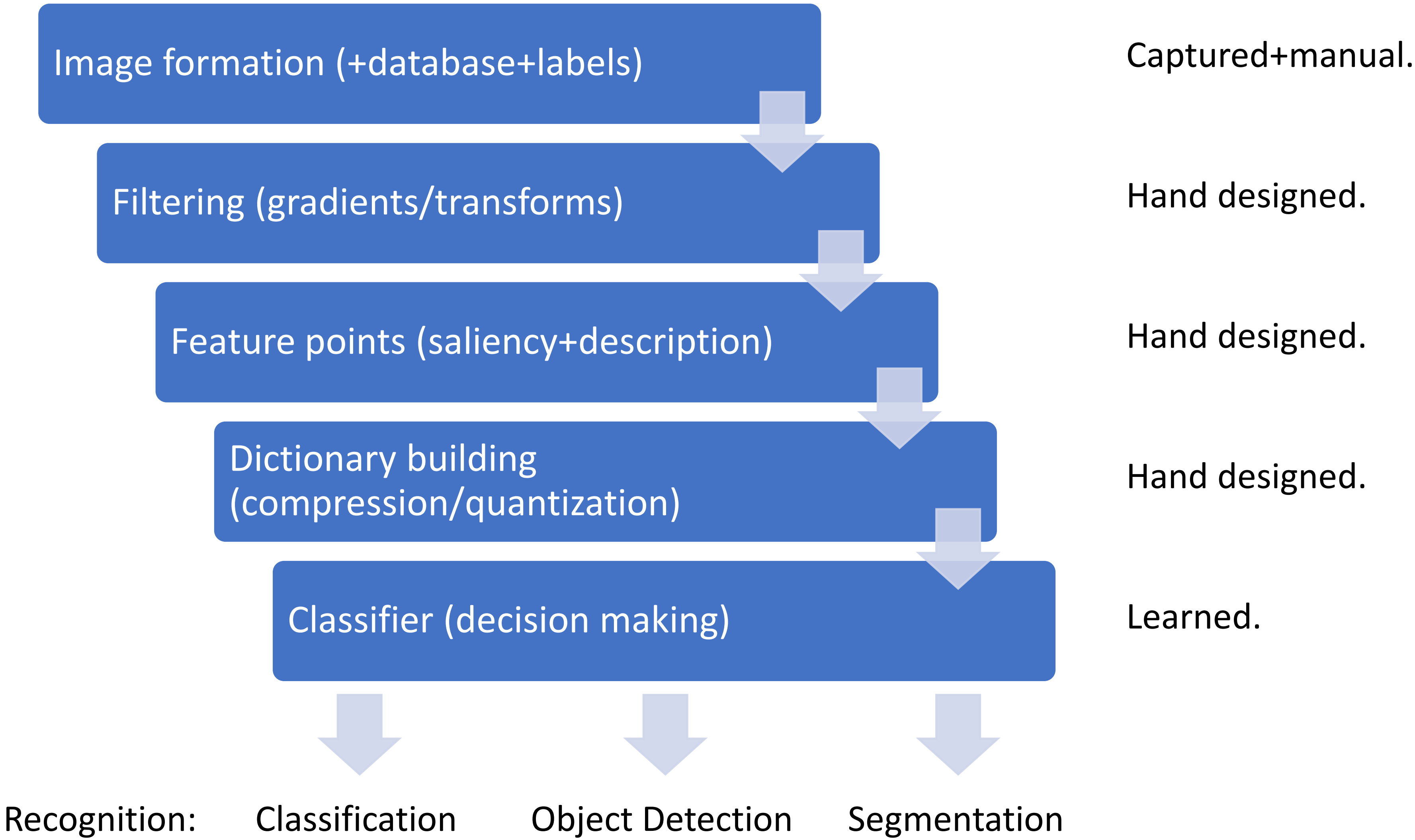
gartner.com/SmarterWithGartner

Source: Gartner

So far…

PASCAL VOC	= ~75%	20-class
ImageNet	= ~75%	1000-class, top 5

Human brains used intuition and understanding of how we think vision works to develop computer vision systems, and it’s pretty good.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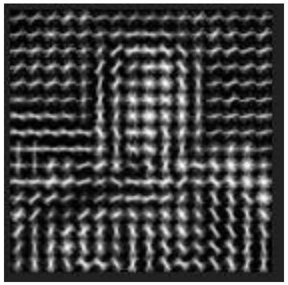
Feature points (saliency+description)
Hand designed.
Dictionary building (compression/quantization)
Hand designed.
Classifier (decision making)
Learned.
Recognition:
Classification
Object Detection
Segmentation

Well, what do we have?

Best performing visions systems have commonality:

Hand designed features

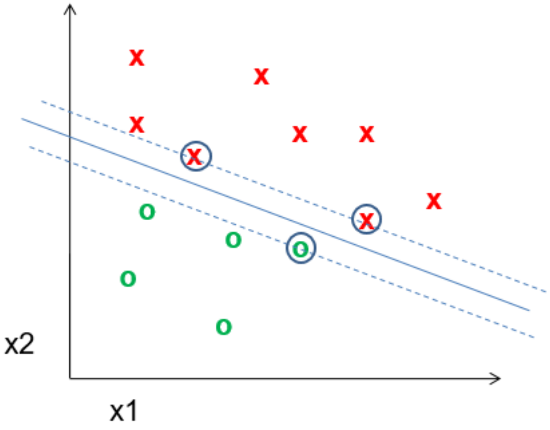
- Gradients + non-linear operations (exponentiation, clamping, binning)
- Features in combination (parts-based models)
- Multi-scale representations



Machine learning from databases

Linear classifiers (SVM)

- Some non-linear kernel tricks



But it’s still not that good…

PASCAL VOC	= ~75%	20-class
ImageNet	= ~75%	1000-class, top 5
ImageNet (human)	= ~95%	

Problems:

- Lossy features
- Lossy quantization
- ‘Imperfect’ classifier

But it’s still not that good…

PASCAL VOC	= ~75%	20-class
ImageNet	= ~75%	1000-class, top 5
ImageNet (human) = ~95%		

How to solve?

- *Features: More principled modeling?*
  We *know* why the world looks (it’s physics!);
  Let’s build better physically-meaningful models.
- *Quantization: More data and more compute?*
  It’s just an interpolation problem; let’s represent the space with fewer data approximations.
- *Classifier: …*

The limits of learning?

Where should we put our effort?

Previous claim:

It is more important to have
more or better labeled data than to use
a different supervised learning technique.

“The Unreasonable Effectiveness of Data” - Norvig

No free lunch theorem

Hume (c.1739):

“Even after the observation of the frequent or constant conjunction of objects, we have no reason to draw any inference concerning any object beyond those of which we have had experience.”

-> Learning beyond our experience is impossible.

No free lunch theorem for ML

Wolpert (1996):

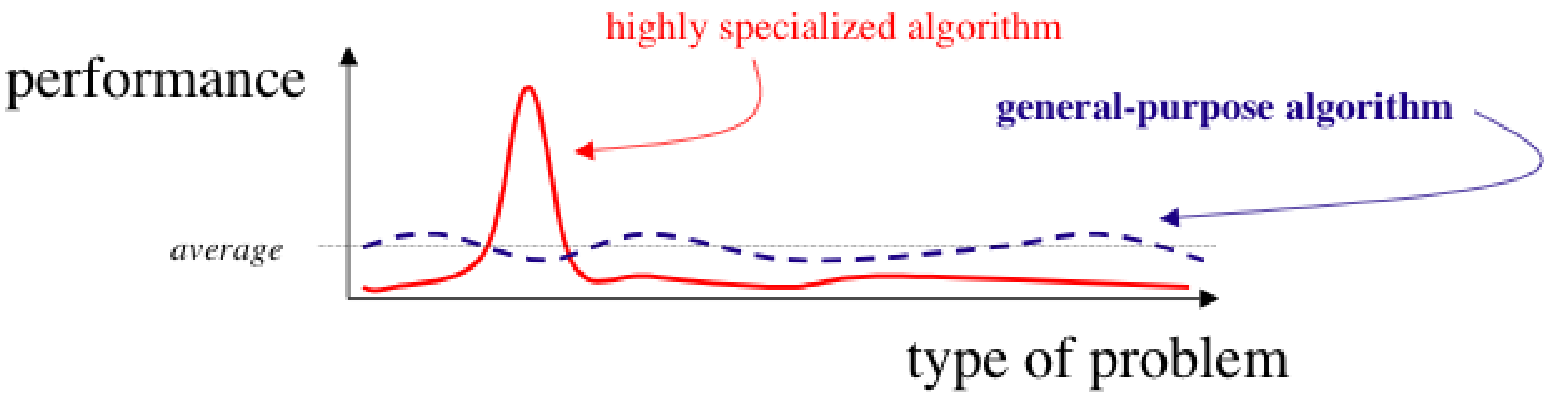
'No free lunch' for supervised learning:

"In a noise-free scenario where the loss function is the misclassification rate, if one is interested in off-training-set error, then there are no *a priori* distinctions between learning algorithms."

-> Averaged over all possible datasets,
   no learning algorithm is better than any other.

OK, well, let's give up. Class over.

No, no, no!



We can build a classifier which better matches the characteristics of the problem!

But…didn't we just do that?

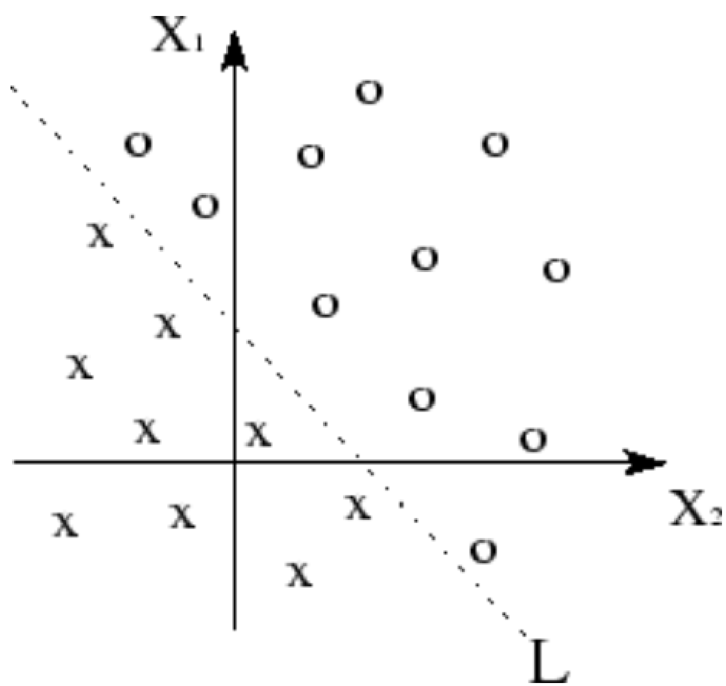
- PASCAL VOC = ~75%
- ImageNet = ~75%; human performance = ~95%

We used intuition and understanding of how we think vision works, but it still has limitations.

Why?

Linear spaces - separability

- + kernel trick to transform space.



Linearly separable data
+ linear classifer = good.

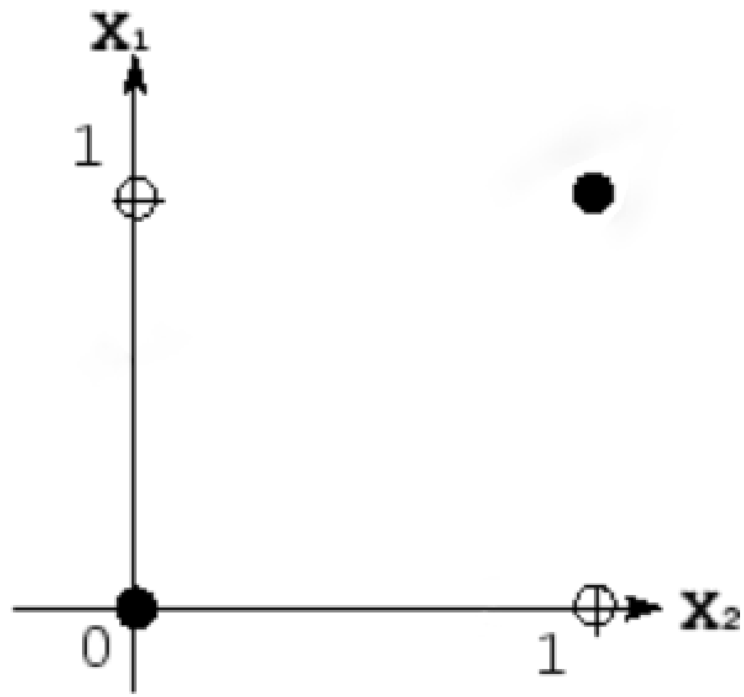
Non-linear spaces - separability

Take XOR – exclusive OR

E.G., human face has two eyes XOR sunglasses

X_1	X_2	Y
0	0	0
0	1	1
1	0	1
1	1	0

$$Y = X_1 \oplus X_2$$

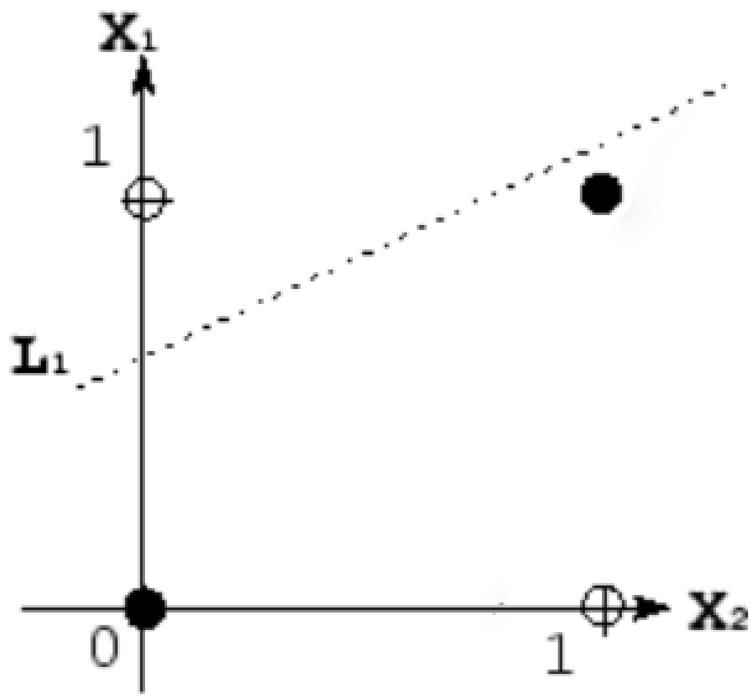


Non-linear spaces - separability

Linear functions are insufficient on their own.

X_1	X_2	Y
0	0	0
0	1	1
1	0	1
1	1	0

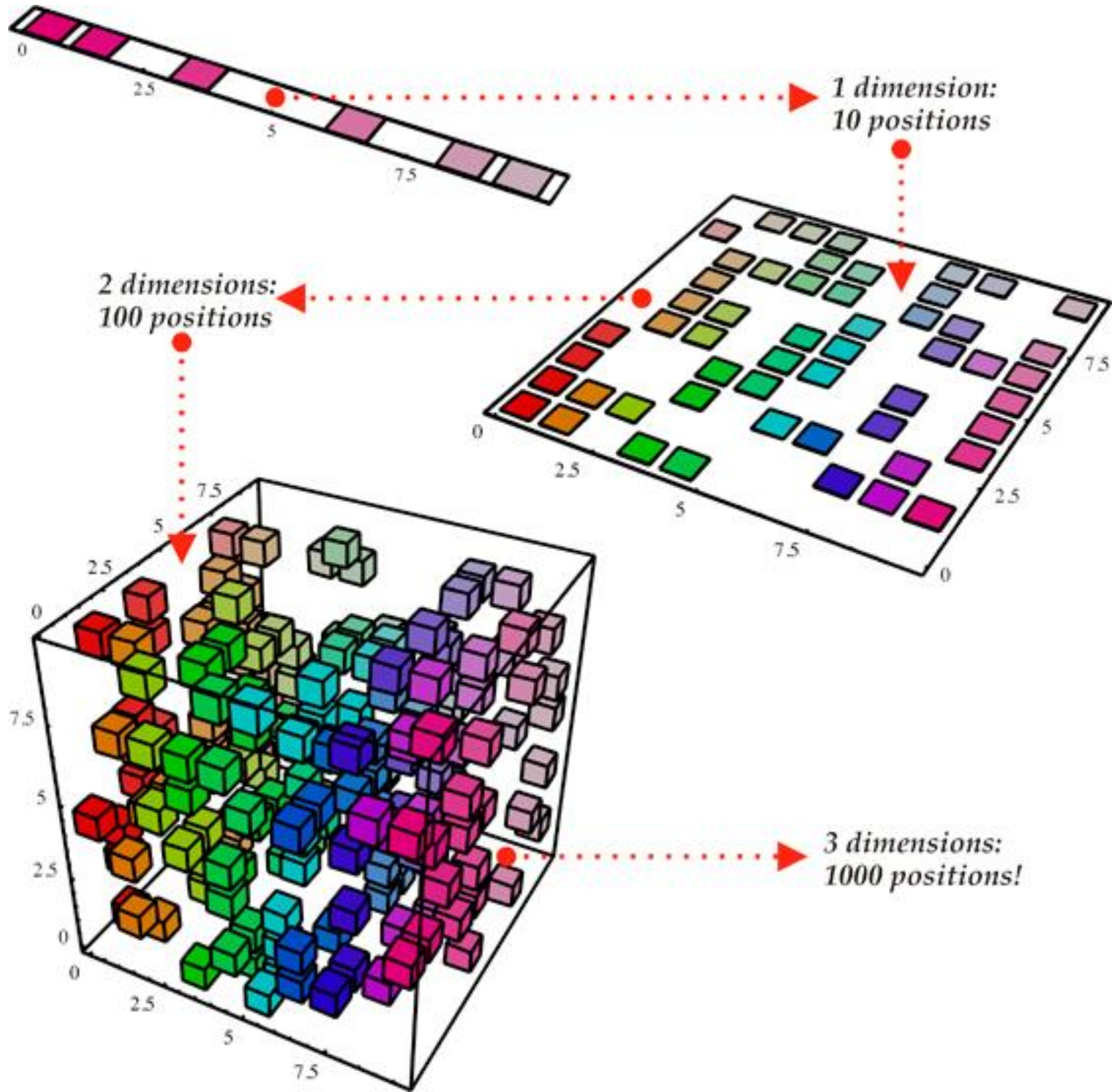
$Y = X_1 \oplus X_2$



Curse of Dimensionality

Every feature that we add requires us to learn the useful regions in a much larger volume.

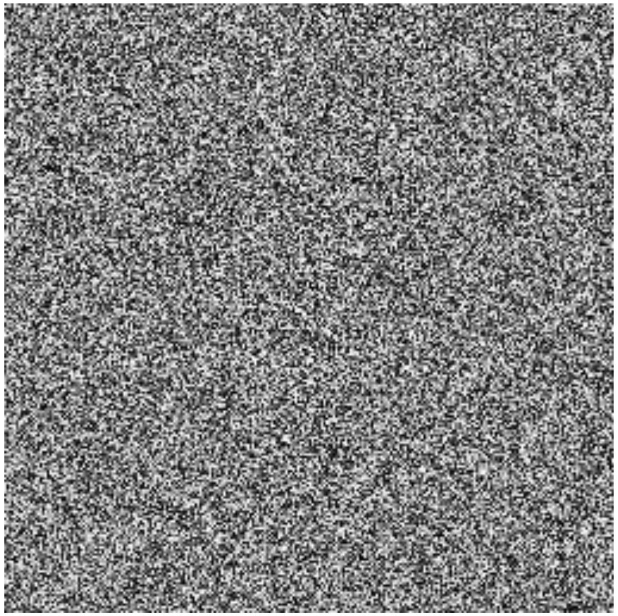
d binary variables = $O(2^d)$ combinations



Curse of Dimensionality

Not all regions of this high-dimensional space are meaningful.

```
>> I = rand(256,256);
>> imshow(I);
```



@ 8bit = 256 values ^ 65,536

Local constancy / smoothness of feature space

All existing learning algorithms we have seen assume **smoothness** or **local constancy.**

-> New example will be near existing examples

-> Each region in feature space requires an example

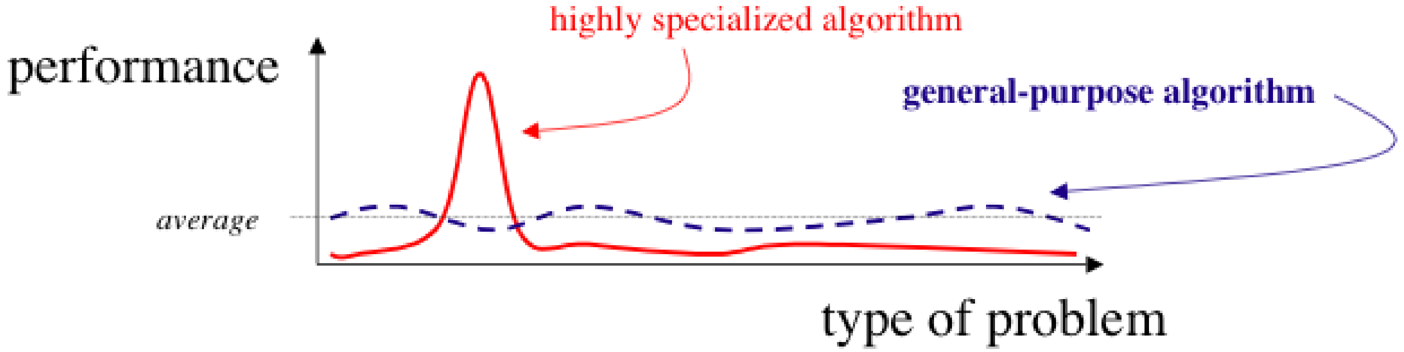
-> Cannot generalize beyond examples

Extreme example: k-NN classifier. The number of regions cannot be more than the number of examples.

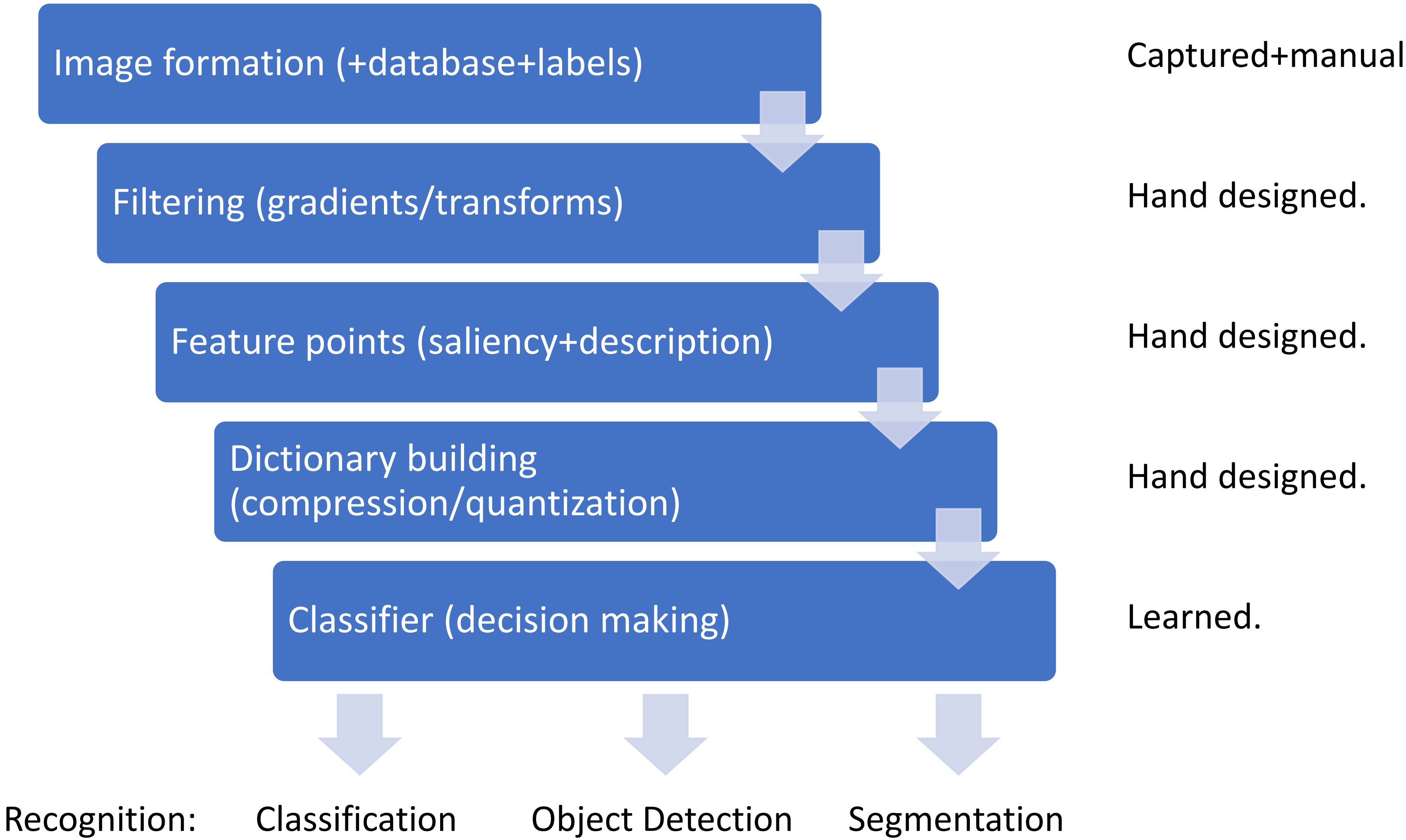
How to try and represent this high-dimensional space in a way which maximizes generalization?

More specialization?

- PASCAL VOC = ~75%
- ImageNet = ~75%; human performance = ~95%



Is there a way to make our system better suited to the problem?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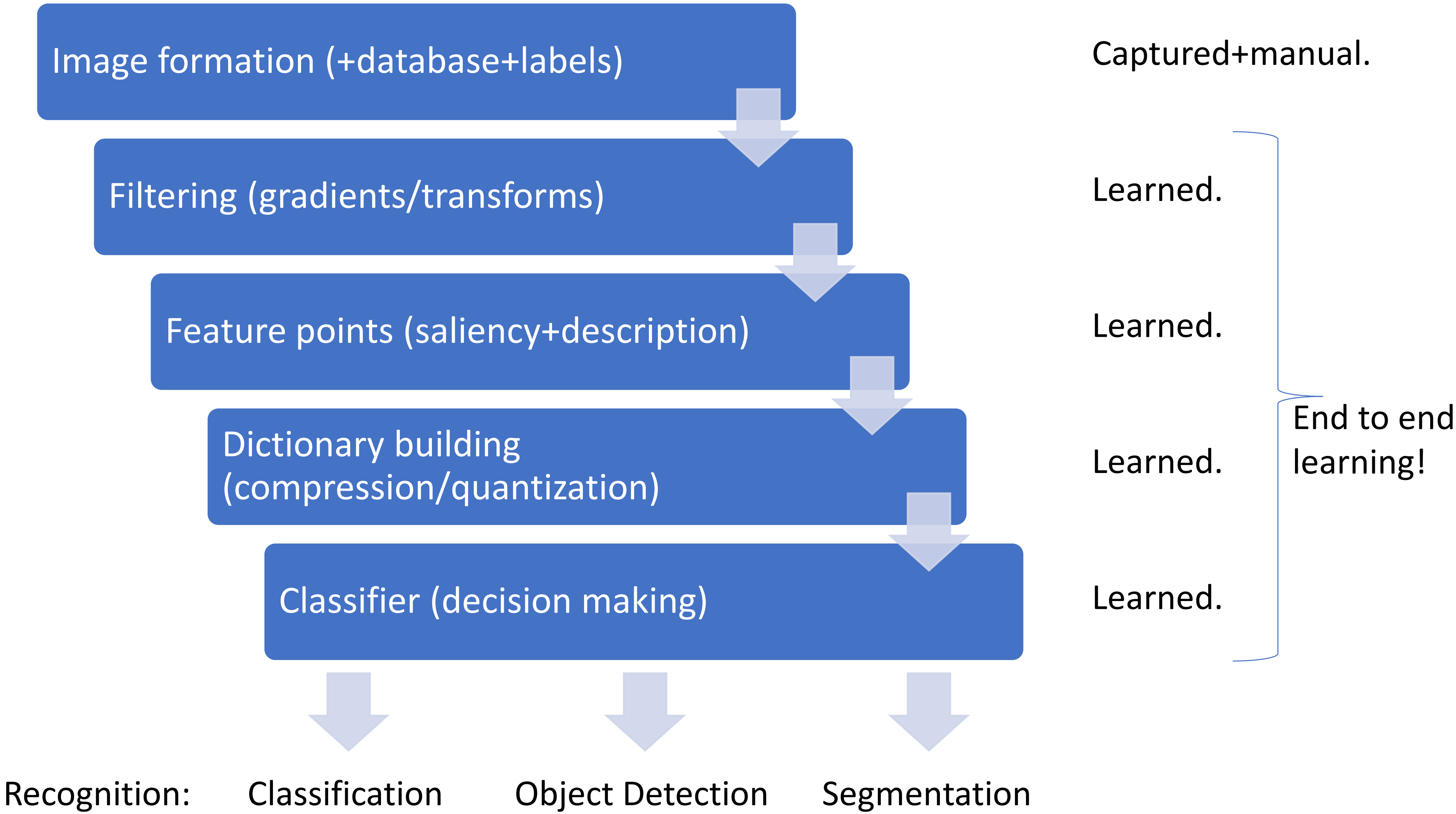
Hand designed.
Dictionary building (compression/quantization)
Hand designed.
Classifier (decision making)
Learned.
Recognition:
Classification
Object Detection
Segmentation

Wouldn’t it be great if we could…



Goals

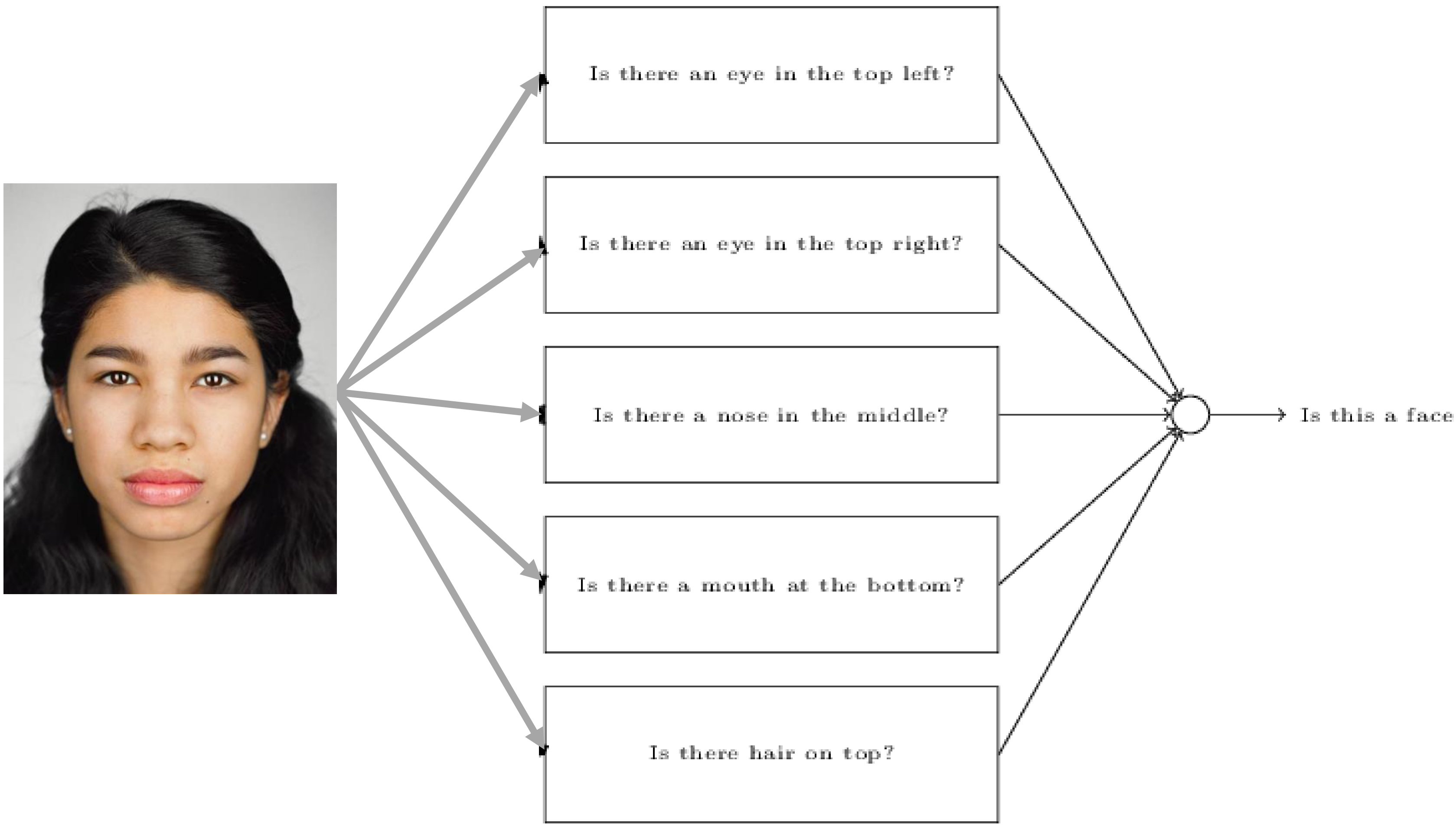
Build a classifier which is more powerful
at representing complex functions
and more suited to the learning problem.

What does this mean?

1. Assume that the *underlying data generating function* relies on a composition of factors in a hierarchy.

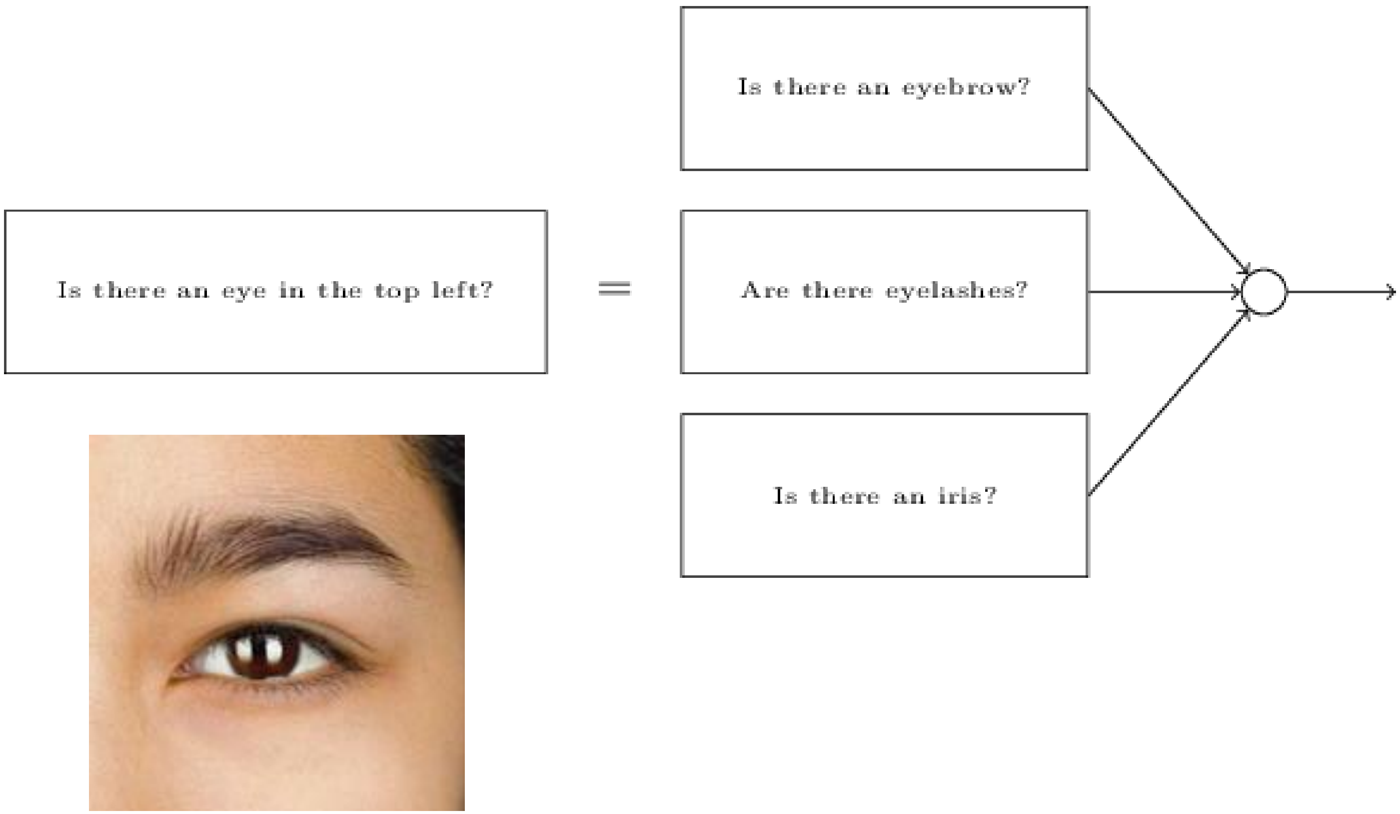
Dependencies between regions in feature space
= factor composition

Example



Nielsen, National Geographic

Example



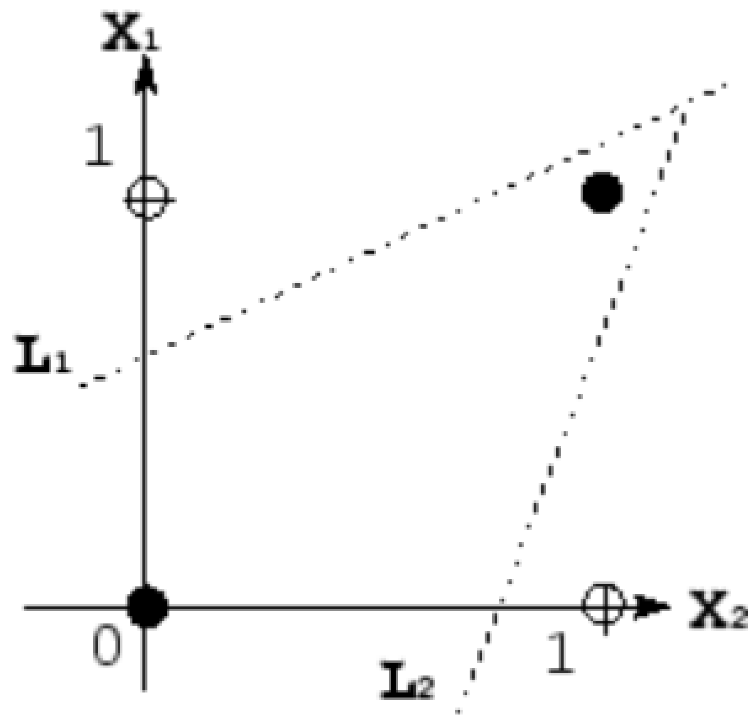
Nielsen, National Geographic

Non-linear spaces - separability

Composition of linear functions can represent more complex functions.

X_1	X_2	Y
0	0	0
0	1	1
1	0	1
1	1	0

$$Y = X_1 \oplus X_2$$



Kawaguchi

Goals

Build a classifier which is more powerful
at representing complex functions
and more suited to the learning problem.

What does this mean?

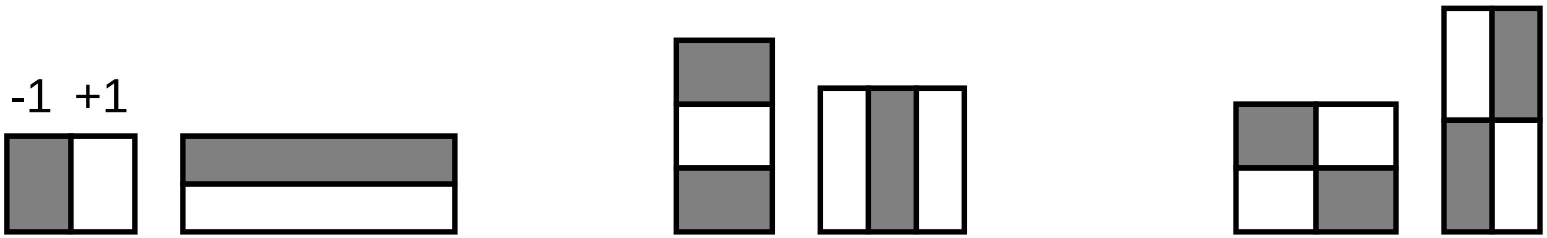
1. Assume that the *underlying data generating function* relies on a composition of factors in a hierarchy.

2. Learn a feature representation specific to the dataset.

10k/100k + data points + factor composition
= sophisticated representation.

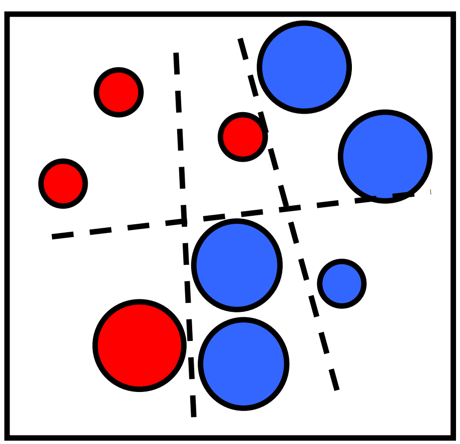
Reminder: Viola Jones Face Detector

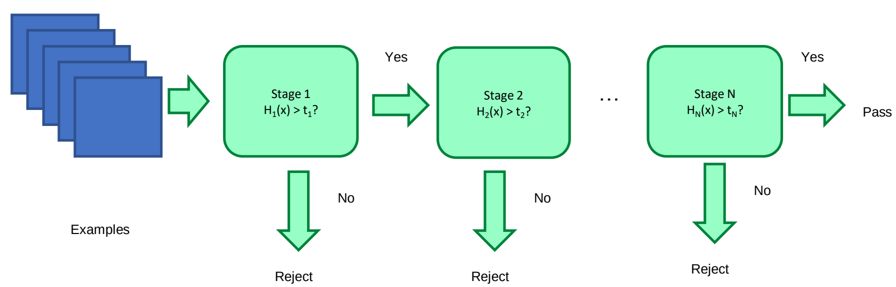
Combine *thousands* of ‘weak classifiers’



Two-rectangle features Three-rectangle features Etc.

Learn how to combine in cascade with boosting





Viola Jones

Image formation (+database+labels)

Captured+manual.

Features (saliency+description)

Specified space, but selected automatically.

Classifier

(decision making)

Learned combination.

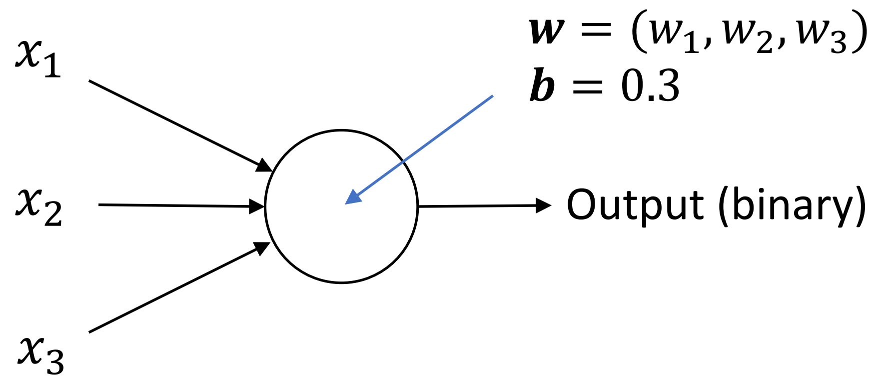
Recognition: Object Detection

Neural Networks

Neural Networks

Basic building block for composition is a *perceptron* (Rosenblatt c.1960)

Linear classifier – vector of weights *w* and a 'bias' *b*



$$\text{output} = \begin{cases} 0 & \text{if } w \cdot x + b \leq 0 \\ 1 & \text{if } w \cdot x + b > 0 \end{cases}$$

$$w \cdot x \equiv \sum_j w_j x_j$$

Binary classifying an image

Each pixel of the image would be an input.

So, for a 28 x 28 image, we vectorize:

$$\mathbf{x} = 1 \times 784$$

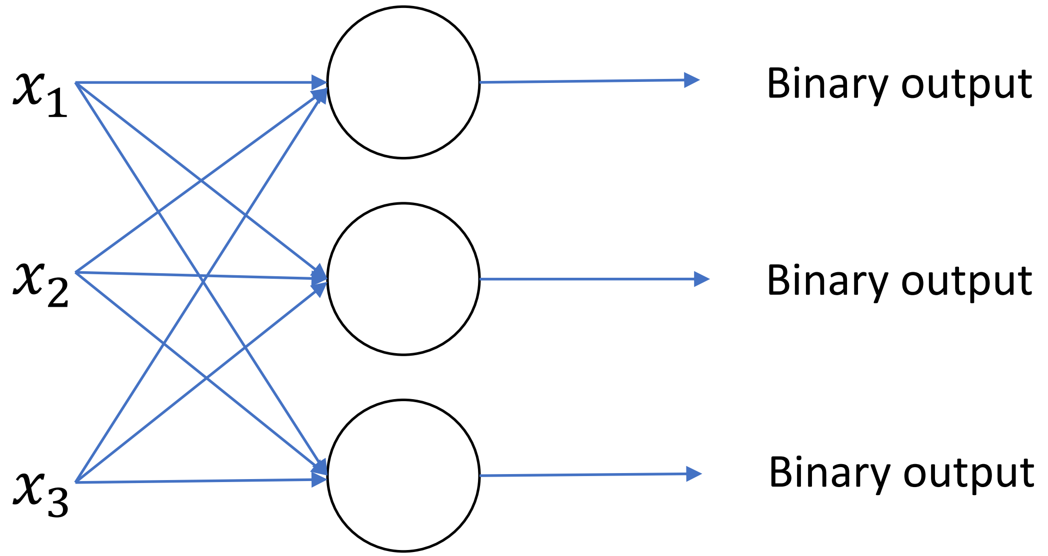
w is a vector of weights for each pixel, 784 x 1

b is a scalar bias per perceptron

Result = **xw** + b -> (1x784) x (784x1) + b = (1x1)+b

Neural Networks - multiclass

Add more perceptrons



Multi-class classifying an image

Each pixel of the image would be an input.

So, for a 28 x 28 image, we vectorize.

x = 1 x 784

W is a matrix of weights for each pixel/each perceptron

W = 10 x 784 (10-class classification)

b is a bias *per perceptron* (vector of biases); (1 x 10)

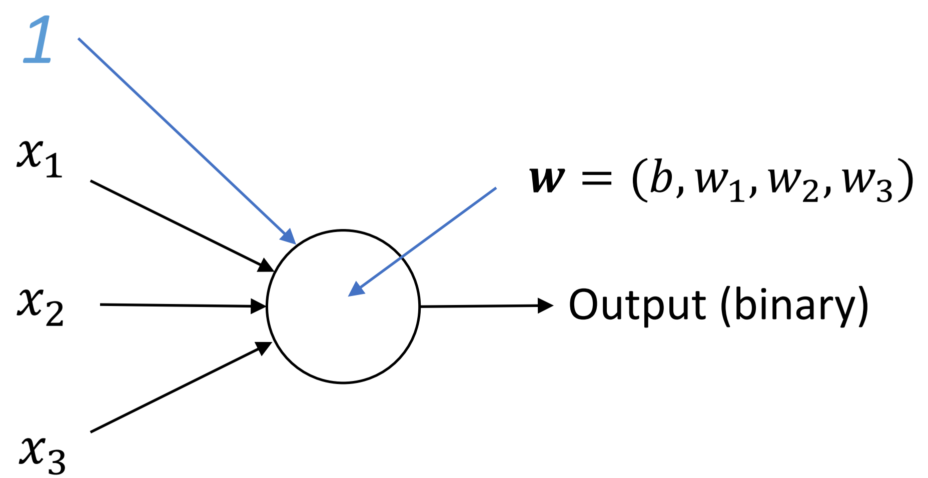
Result = **xW** + **b** -> (1x784) x (784 x 10) + **b**

-> (1 x 10) + (1 x 10) = output vector

Bias convenience

Let’s turn this operation into a multiplication only:

- Create a ‘fake’ feature with value 1 to represent the bias
- Add an extra weight that can vary



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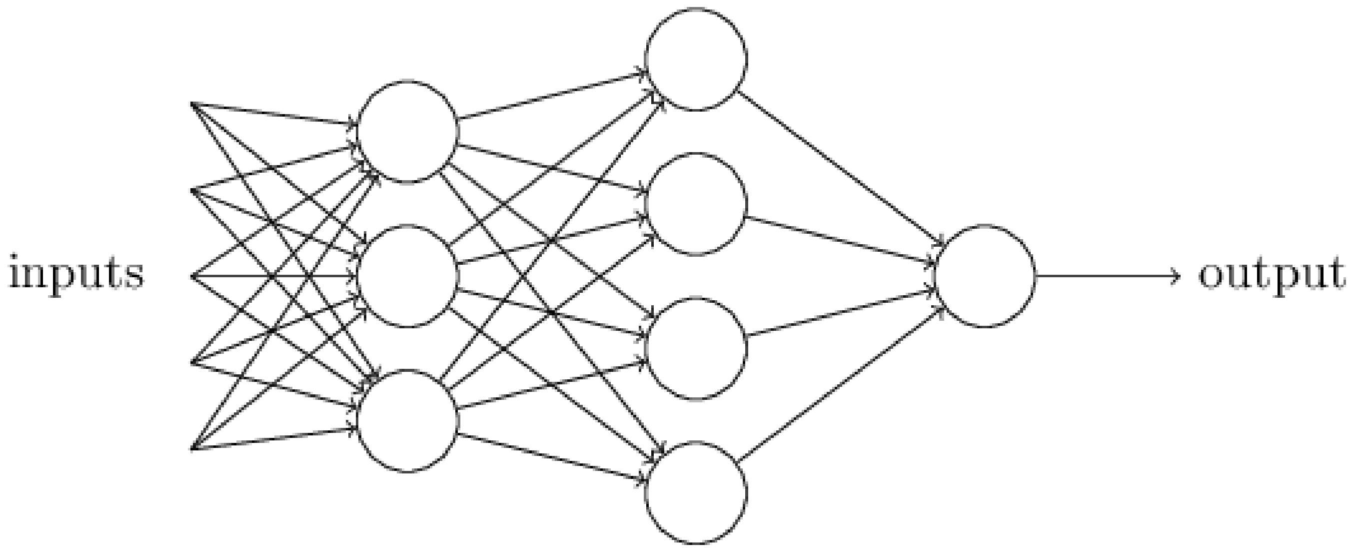
$$w \cdot x \equiv \sum_j w_j x_j$$

Composition

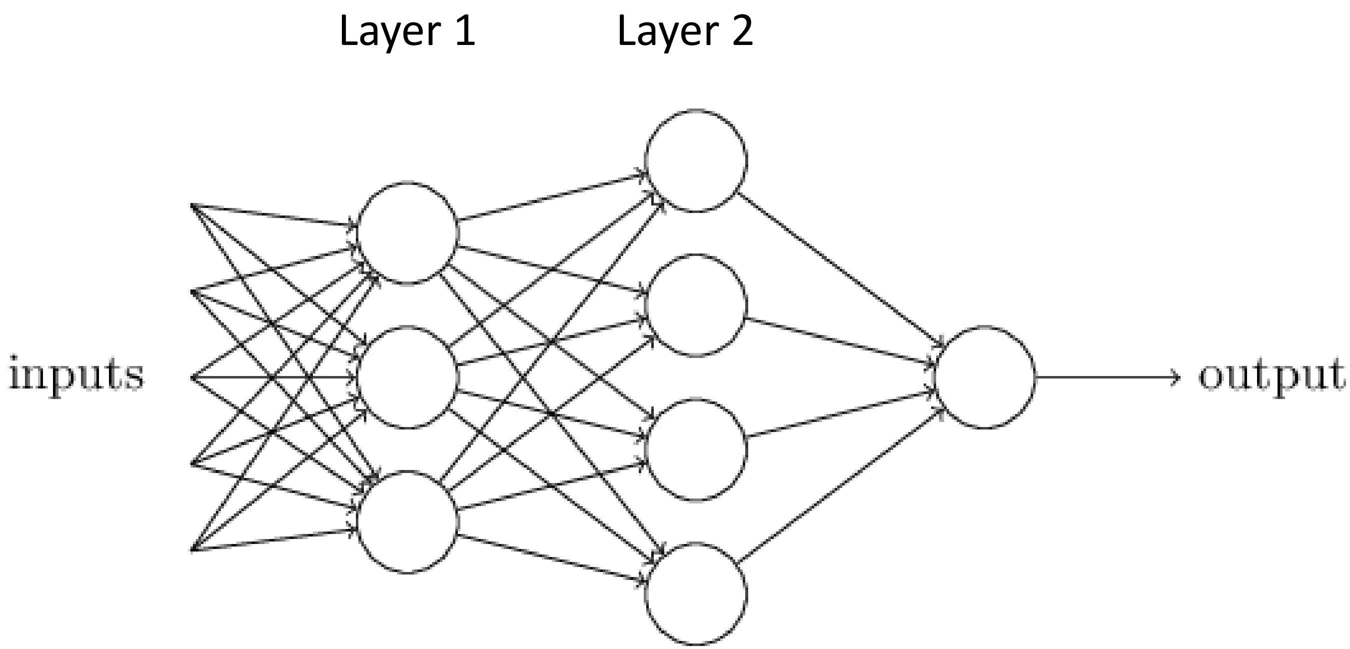


Attempt to represent complex functions as compositions of smaller functions.

Outputs from one perception are fed into inputs of another perceptron.

Nielsen

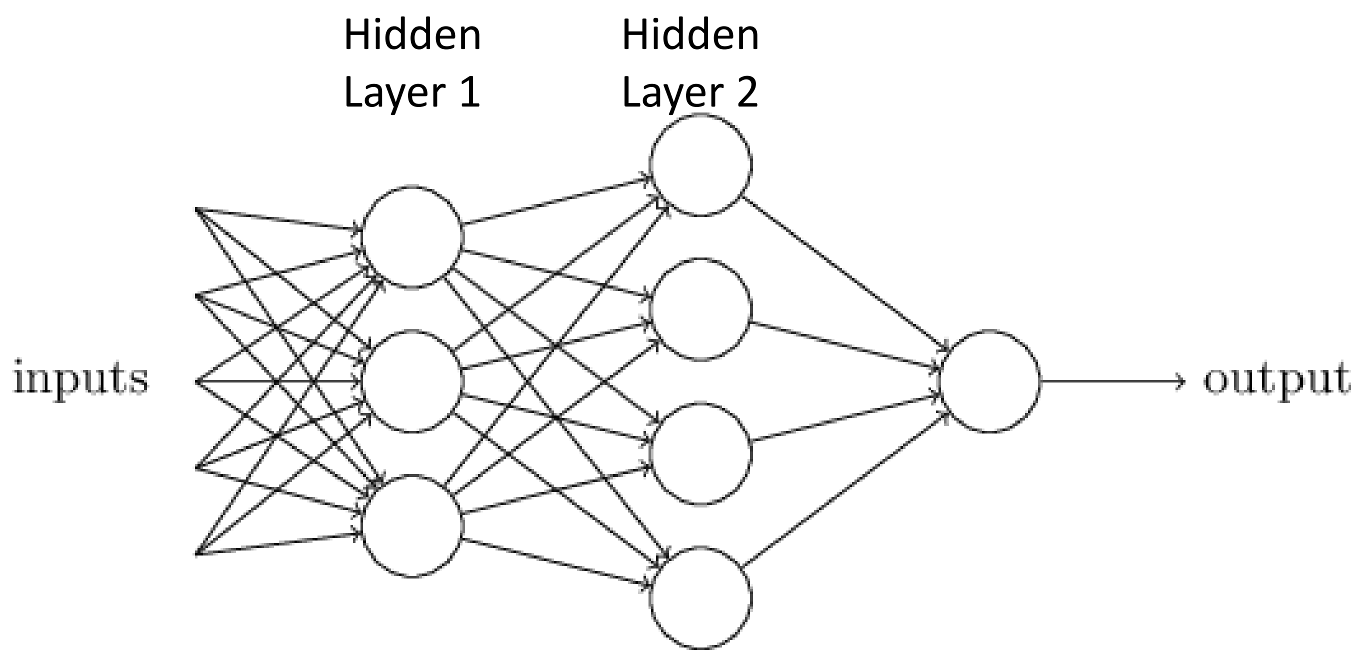
Composition



Sets of layers and the connections (weights) between them define the *network architecture.*

Nielsen

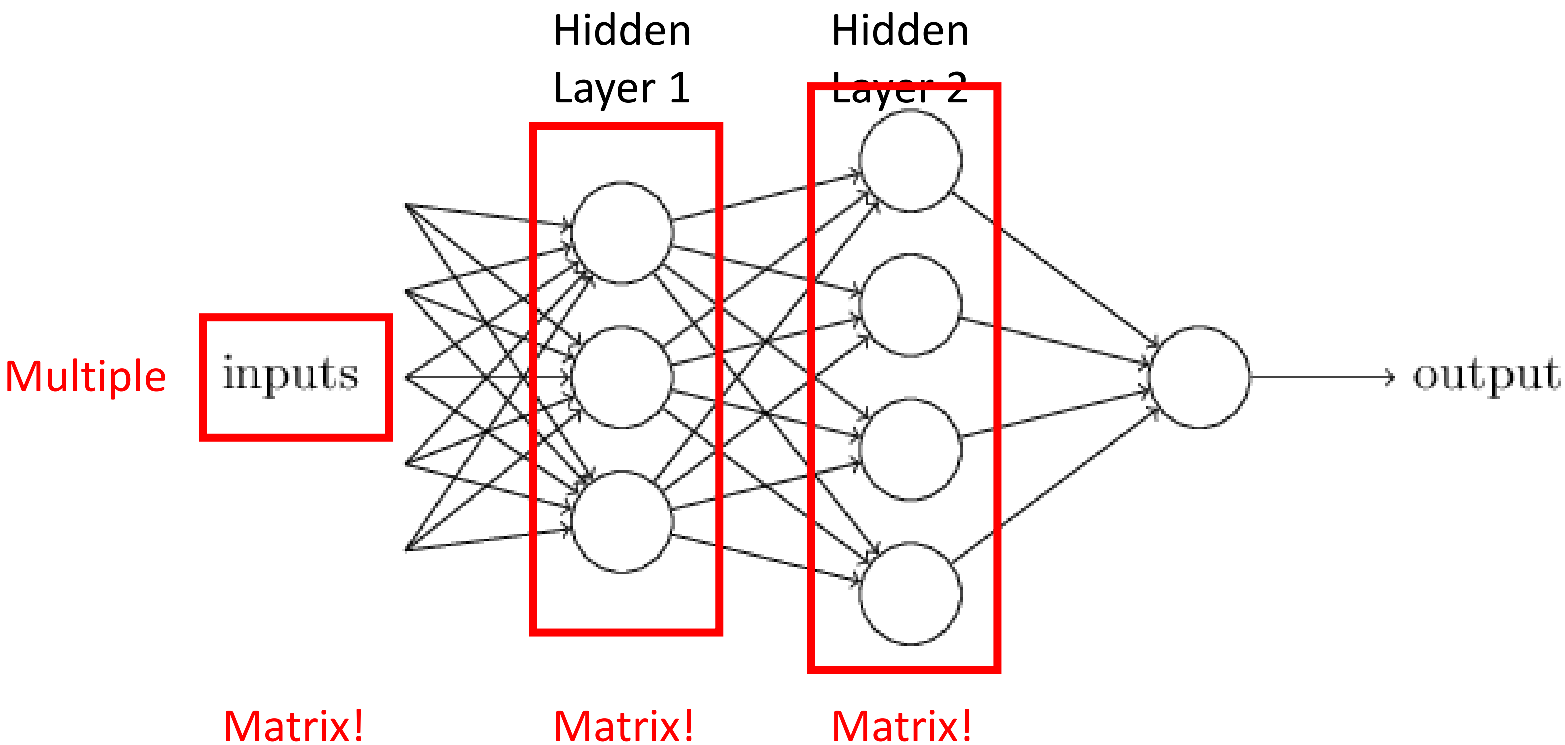
Composition



Layers that are in between the input and the output are called *hidden layers*, because we are going to *learn* their weights via an optimization process.

Nielsen

Composition



It's all just matrix multiplication!

GPUs -> special hardware for fast/large matrix multiplication.

Nielsen

Problem 1 with all linear functions

We have formed chains of linear functions.

We know that linear functions can be reduced

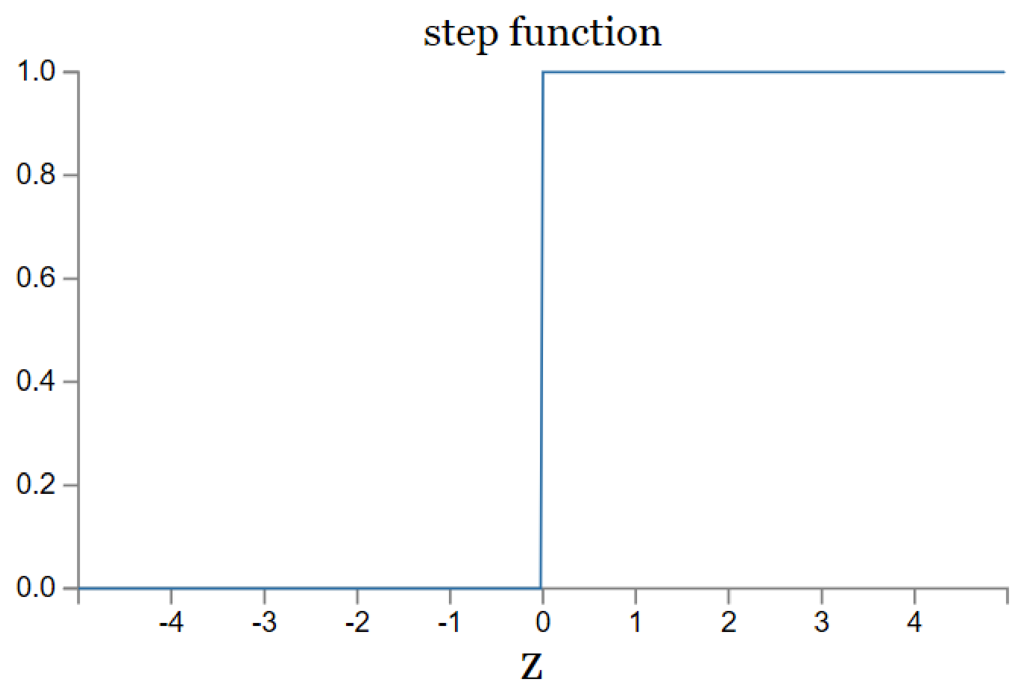
- $g = f(h(x))$

Our composition of functions is really
just a single function : (

Problem 2 with all linear functions

Linear classifiers: small change in input can cause large change in binary output
= problem for composition of functions

Activation function for a perceptron: Heaviside function

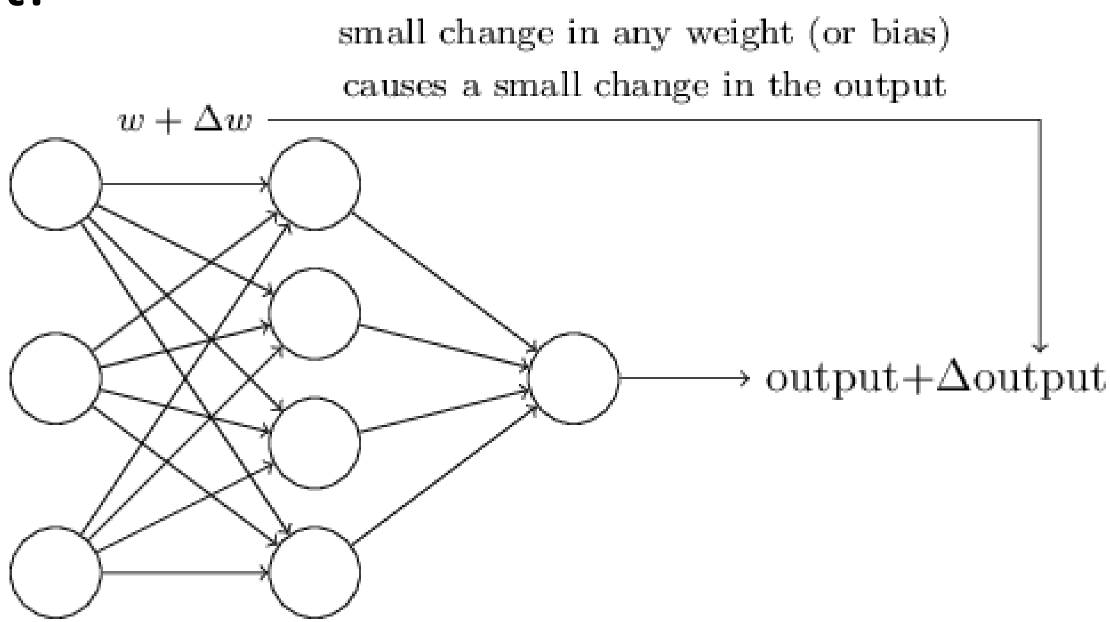


Nielsen

Problem 2 with all linear functions

Linear classifiers: small change in input can cause large change in binary output.

We want:



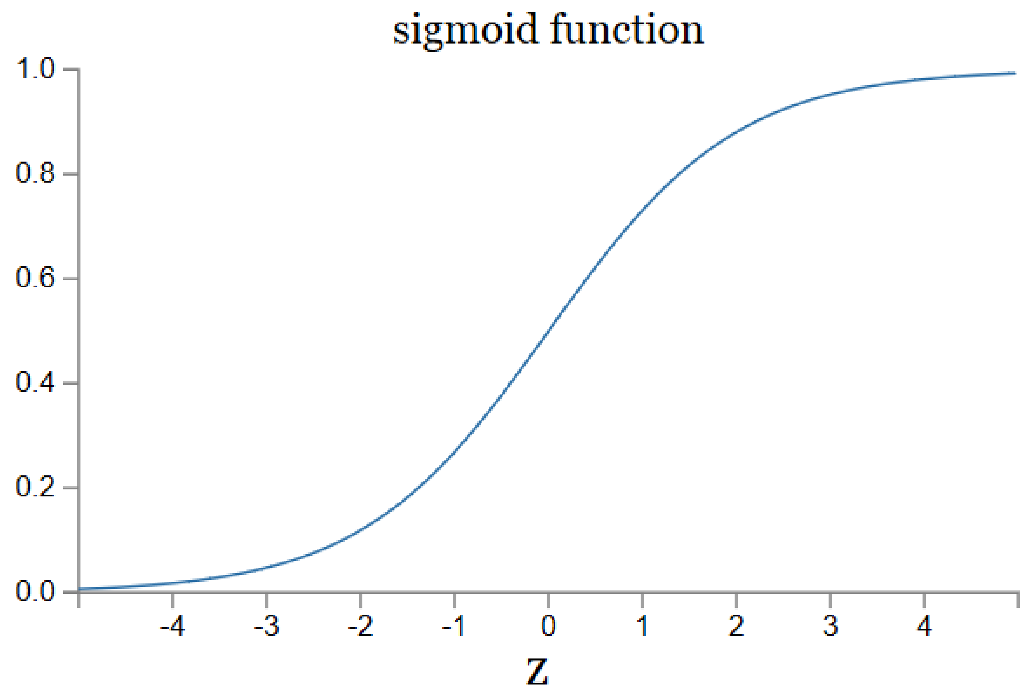
Nielsen

Let’s introduce non-linearities

We’re going to introduce non-linear functions to transform the features.

$$\sigma(w \cdot x + b)$$

$$\sigma(z) \equiv \frac{1}{1+e^{-z}}.$$



Nielsen

Universality

A single-layer of perceptrons can learn any univariate function:

- Combination of many step functions
- So long as it is differentiable
- To some approximation;
  More perceptrons = a better approximation

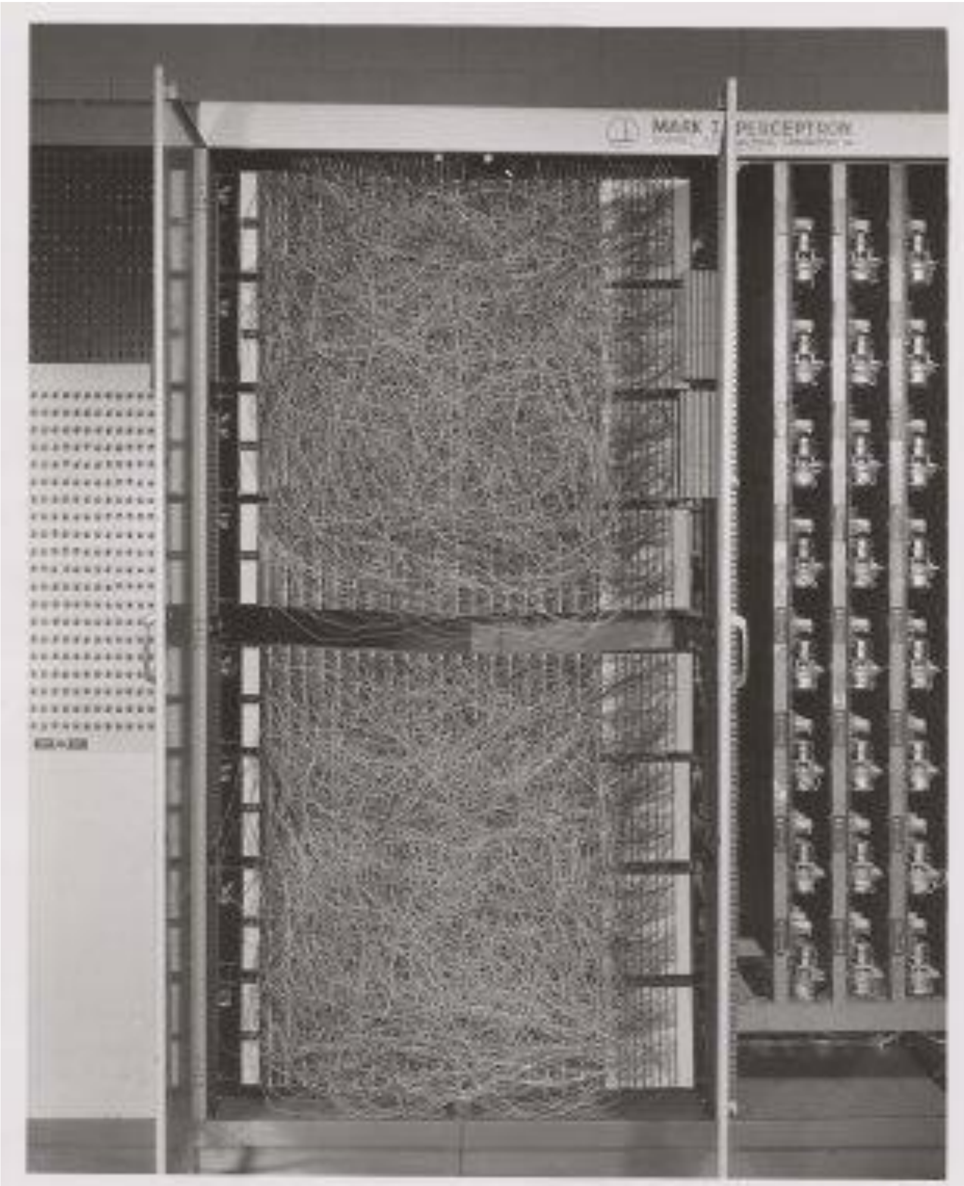
Visual proof (Michael Nielson):

http://neuralnetworksanddeeplearning.com/chap4.html

- using non-linear activation functions

Perceptron model

- Use is grounded in theory
  - Universal approximation theorem (Goodfellow 6.4.1)
- Can represent a NAND circuit, from which any binary function can be built by compositions of NANDs
- With enough parameters, it can approximate any function.



Mark 1 Perceptron
c.1960

20x20 pixel
camera feed

Wikipedia

If a single-layer network can learn any function…
…given enough parameters…

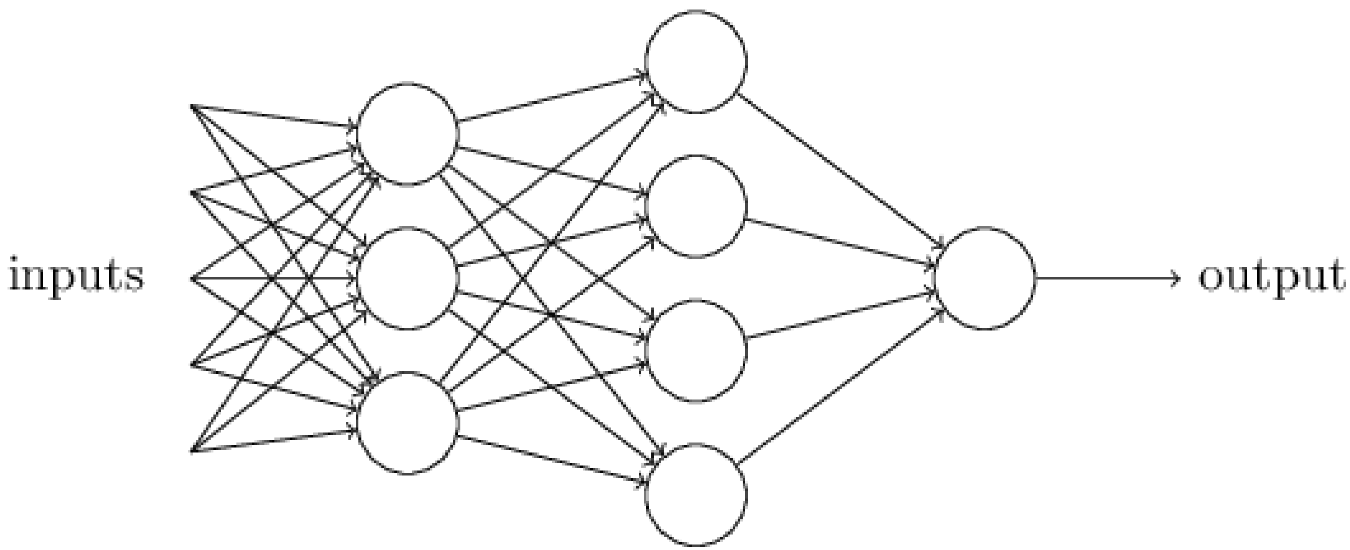
…then why do we go deeper?

Intuitively, composition is efficient because it allows *reuse*.

Empirically, deep networks do a better job than shallow networks at learning such hierarchies of knowledge.

Multi-layer perceptron (MLP)

- …is a ‘*fully connected*’ neural network with non-linear activation functions.

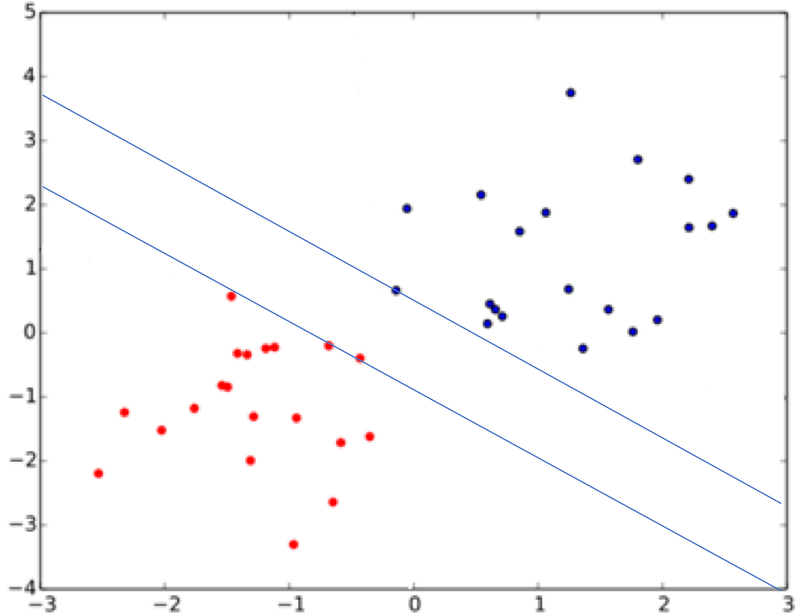


- ‘*Feed-forward*’ neural network

Nielson

What is the relationship between SVMs and perceptrons?

SVMs attempt to learn the support vectors which maximize the margin between classes.



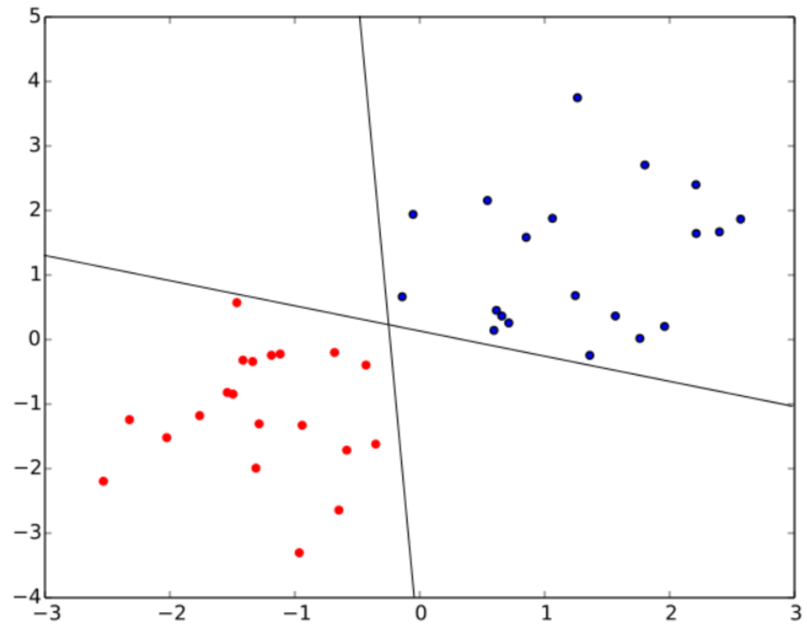
What is the relationship between SVMs and perceptrons?

SVMs attempt to learn the support vectors which maximize the margin between classes.

A perceptron does not.
Both of these perceptron classifiers are equivalent.

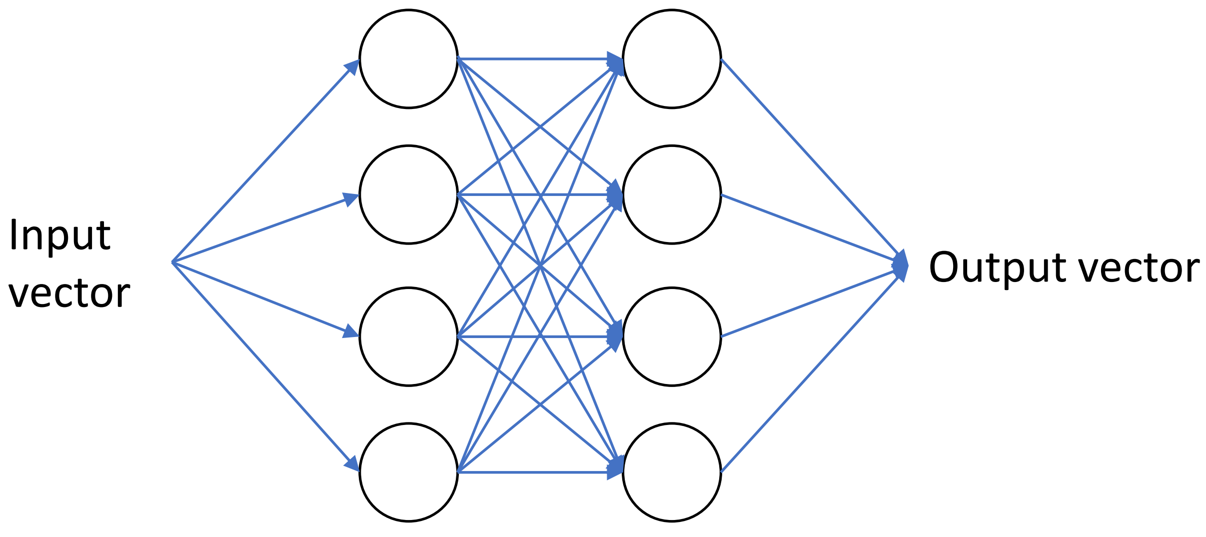
'Perceptron of optimal stability' is used in SVM:

Perceptron
+ optimal stability
+ kernel trick
= foundations of SVM



Does anyone pass along the weight without an activation function?

No – this is linear chaining.



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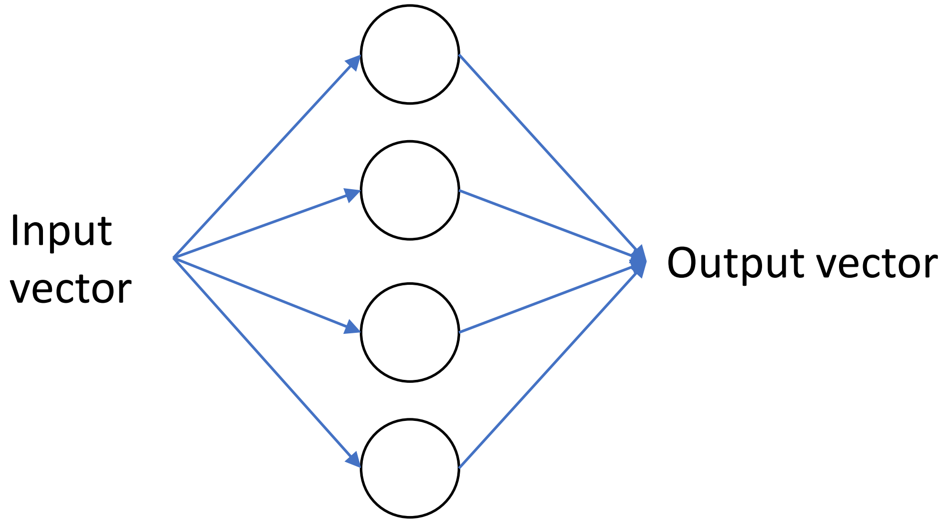


Are there other activation functions?

Yes, many.

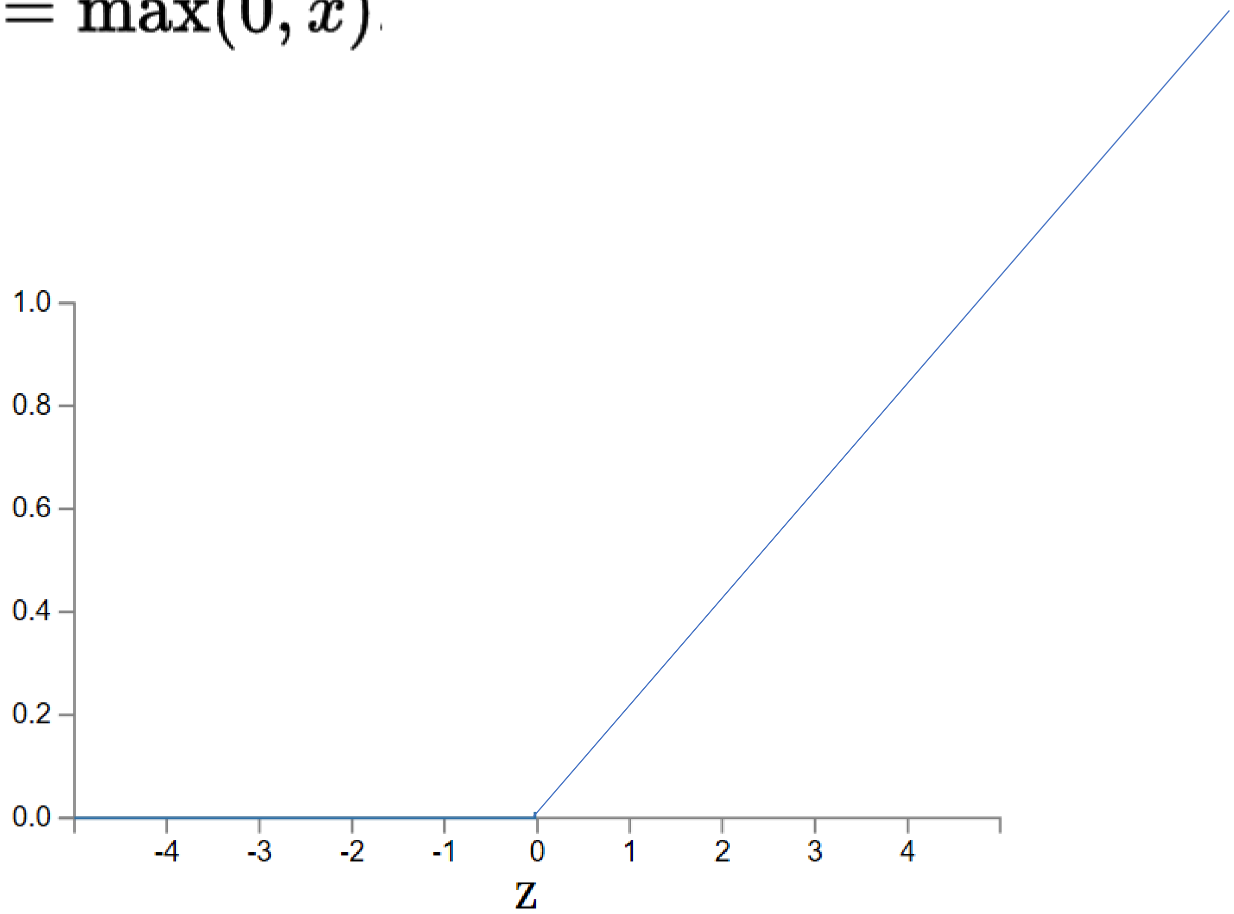
As long as:

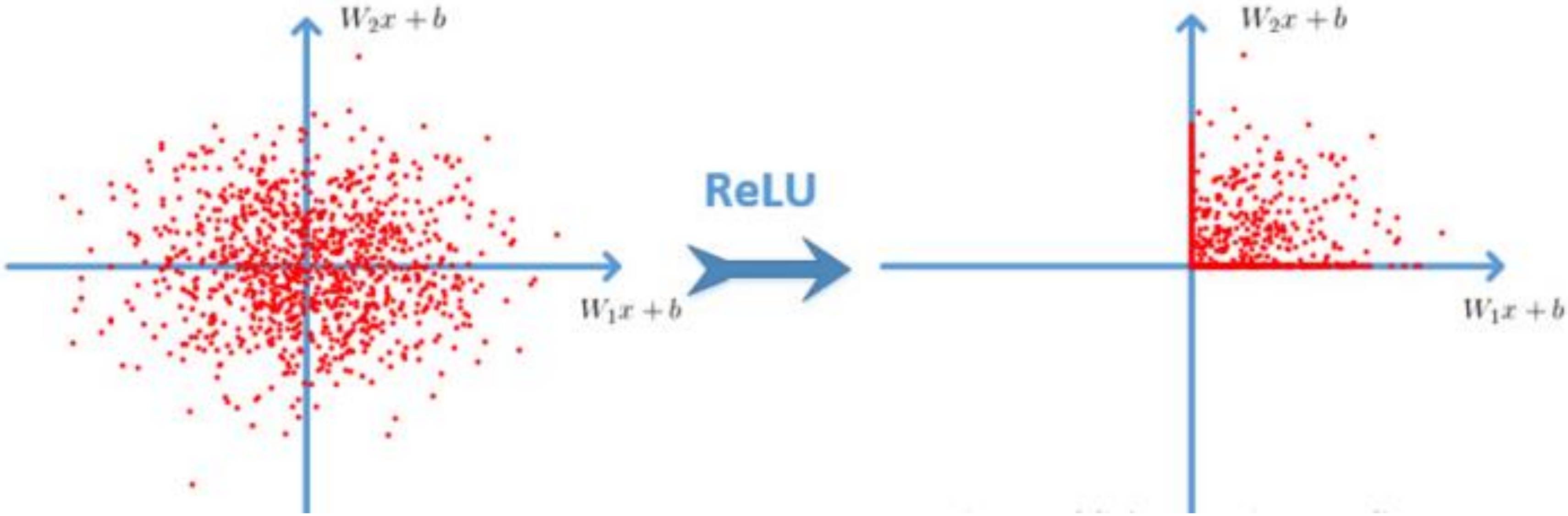
- Activation function s(z) is well-defined
  as z -> -∞ and z -> ∞
- These limits are different

Then w*e can make a step!* [Think visual proof]
It can be shown that it is universal for function approximation.

Activation functions: Rectified Linear Unit

- ReLU $f(x) = \max(0, x)$



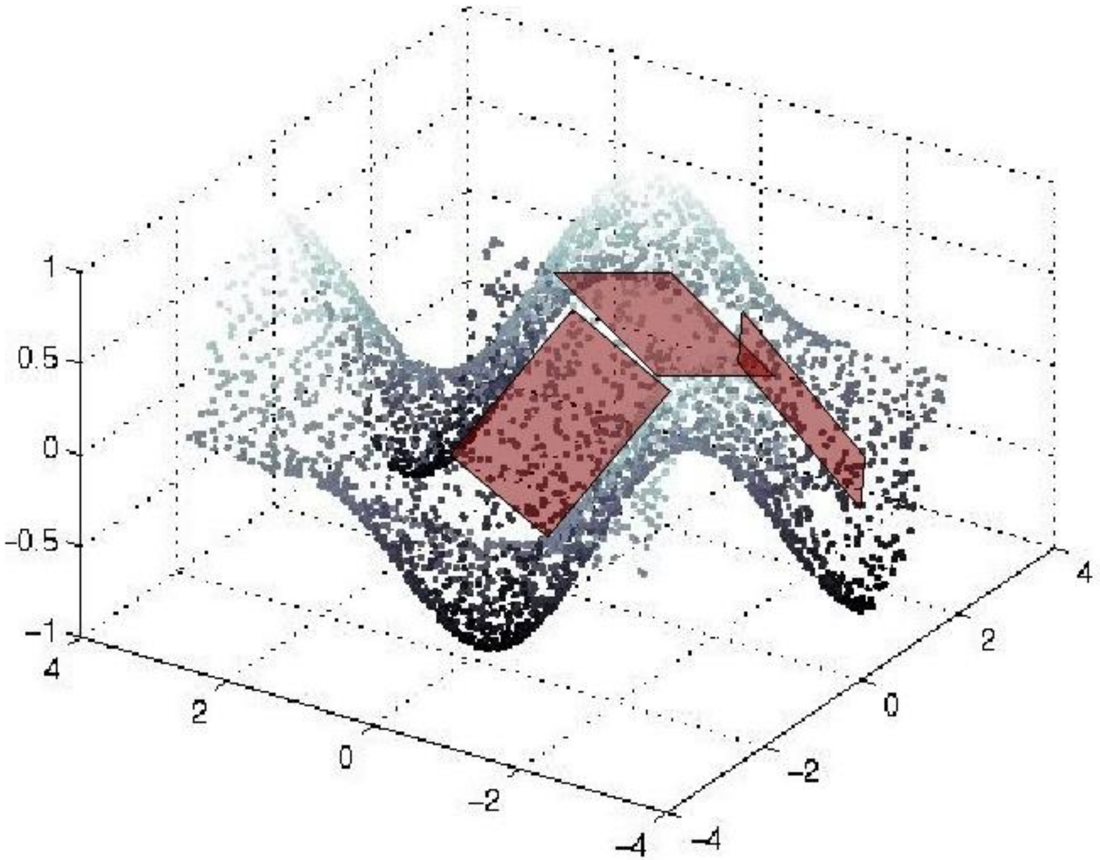


$W_2x + b$
$W_1x + b$
ReLU
$W_2x + b$
$W_1x + b$

Rectified Linear Unit

Question: What do ReLU layers accomplish?

Answer: Piece-wise linear tiling: mapping is locally linear.



Ranzato

Goals

Build a classifier which is more powerful at representing complex functions *and* more suited to the learning problem.

What does this mean?

1. Assume that the *underlying data generating function* relies on a composition of factors.

2. Learn a feature representation that is specific to the dataset.

Supervised Learning

$\left\{ (\boldsymbol{x}^i, y^i), i = 1 \ldots P \right\}$ training dataset

$\boldsymbol{x}^i$ i-th input training example

y^i i-th target label

P number of training examples

Goal: predict the target label of unseen inputs.

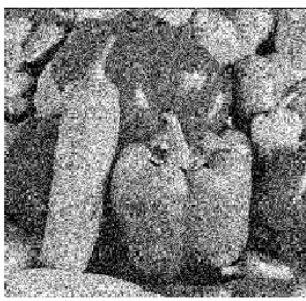
Supervised Learning: Examples

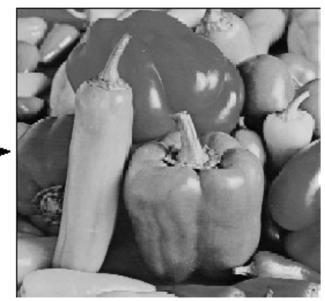
Classification

"dog"

classification

Denoising





regression

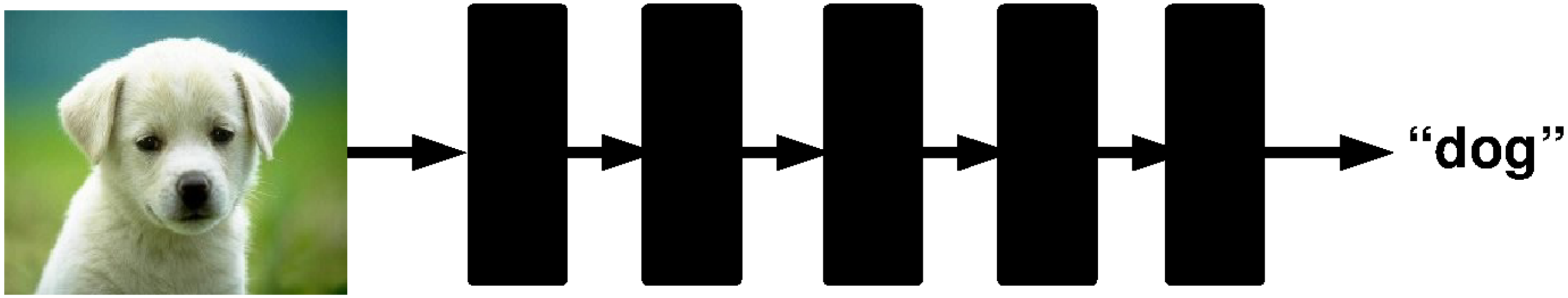
OCR

"2 3 4 5"

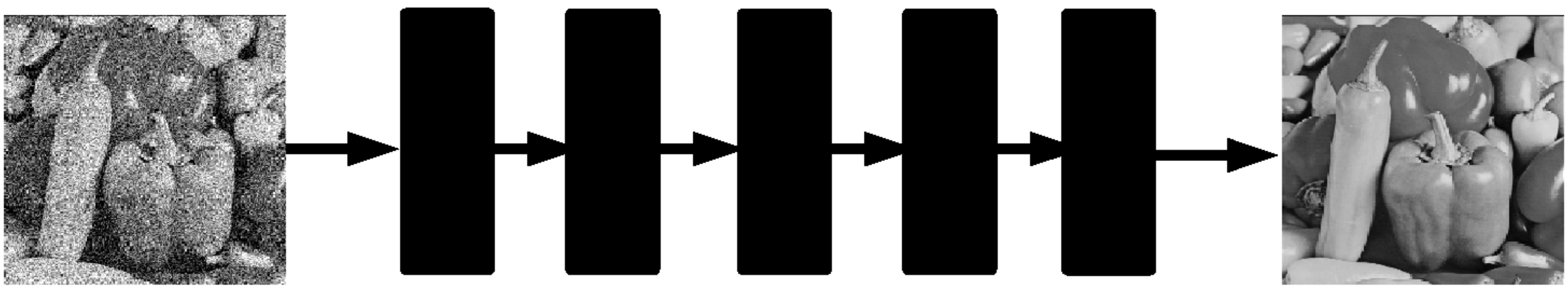
structured prediction

Supervised Deep Learning

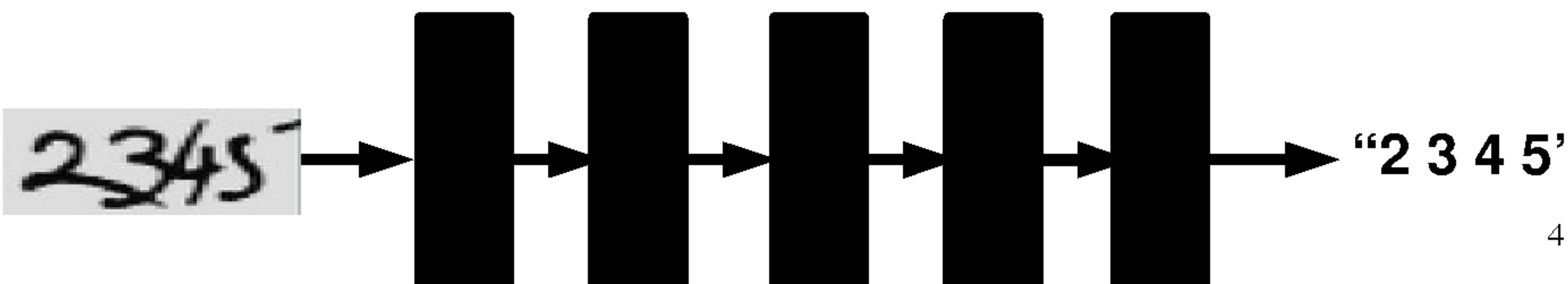
Classification



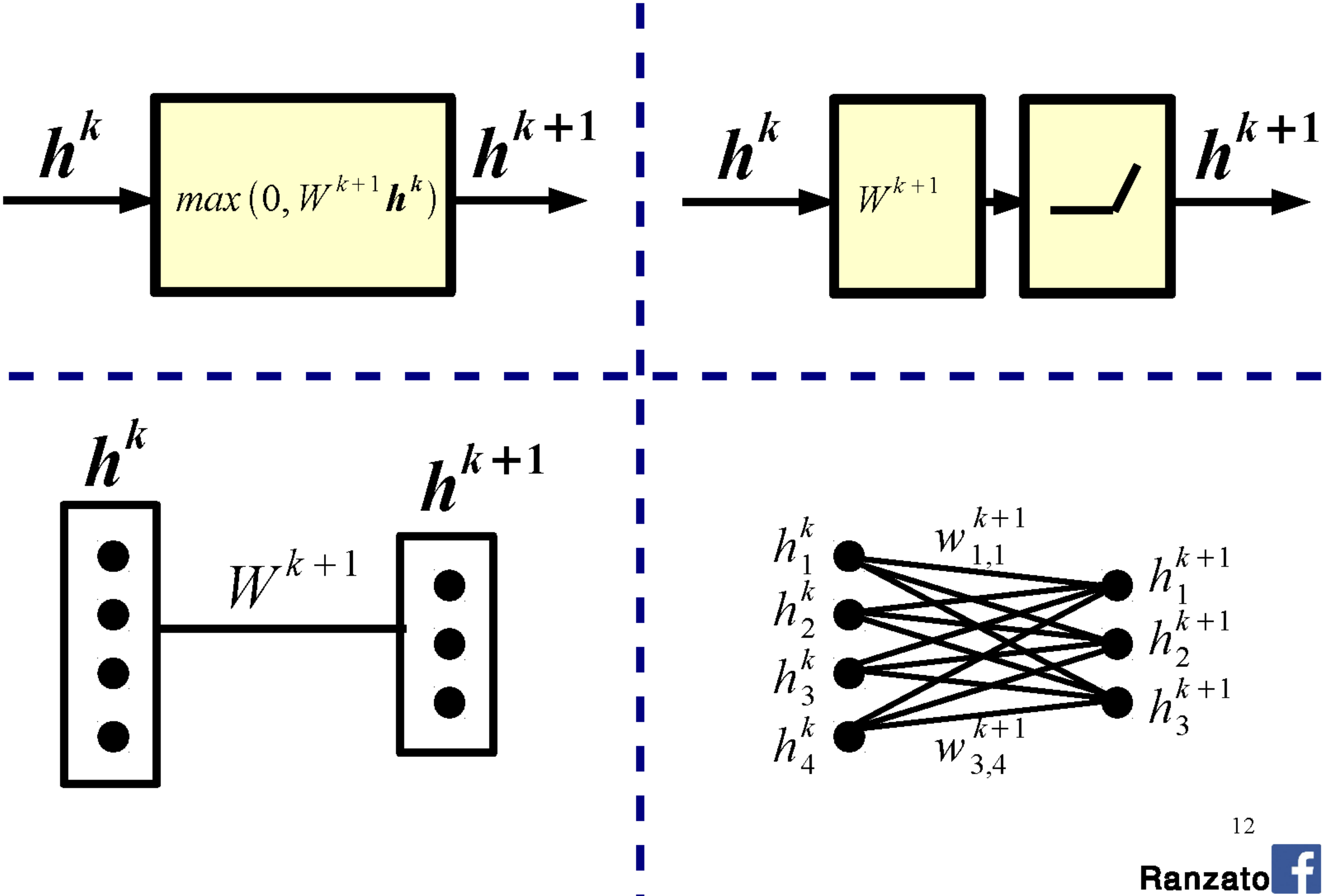
Denoising



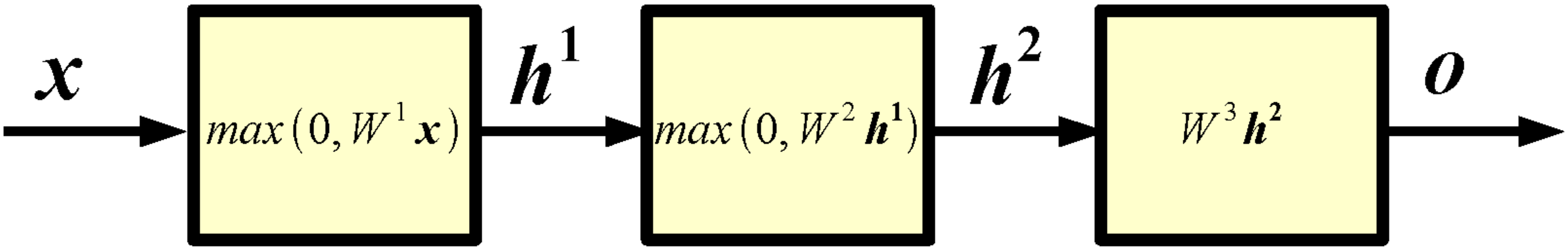
OCR



Alternative Graphical Representation



Neural Networks: example



x input

h^1 1-st layer hidden units

h^2 2-nd layer hidden units

o output

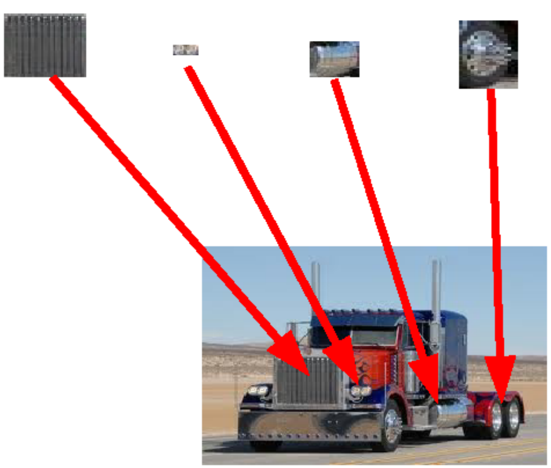
Example of a 2 hidden layer neural network (or 4 layer network, counting also input and output).

Why do we need many layers?

- A hierarchical structure is potentially more efficient because we can reuse intermediate computations.

- Different representations can be distributed across classes.

[0 0 1 0 0 0 0 1 0 0 1 1 0 0 1 0 ...] truck feature



Exponentially more efficient than a 1-of-N representation (a la k-means)

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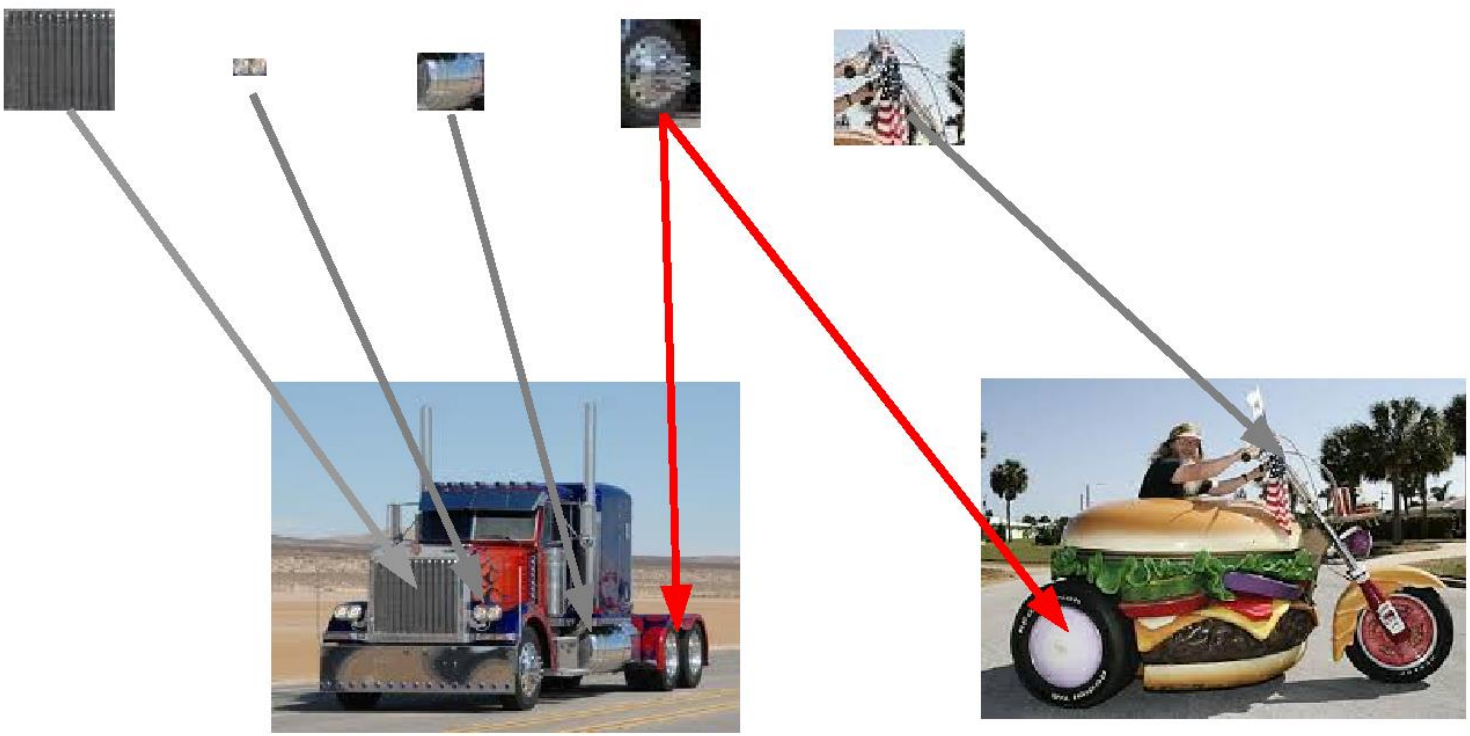
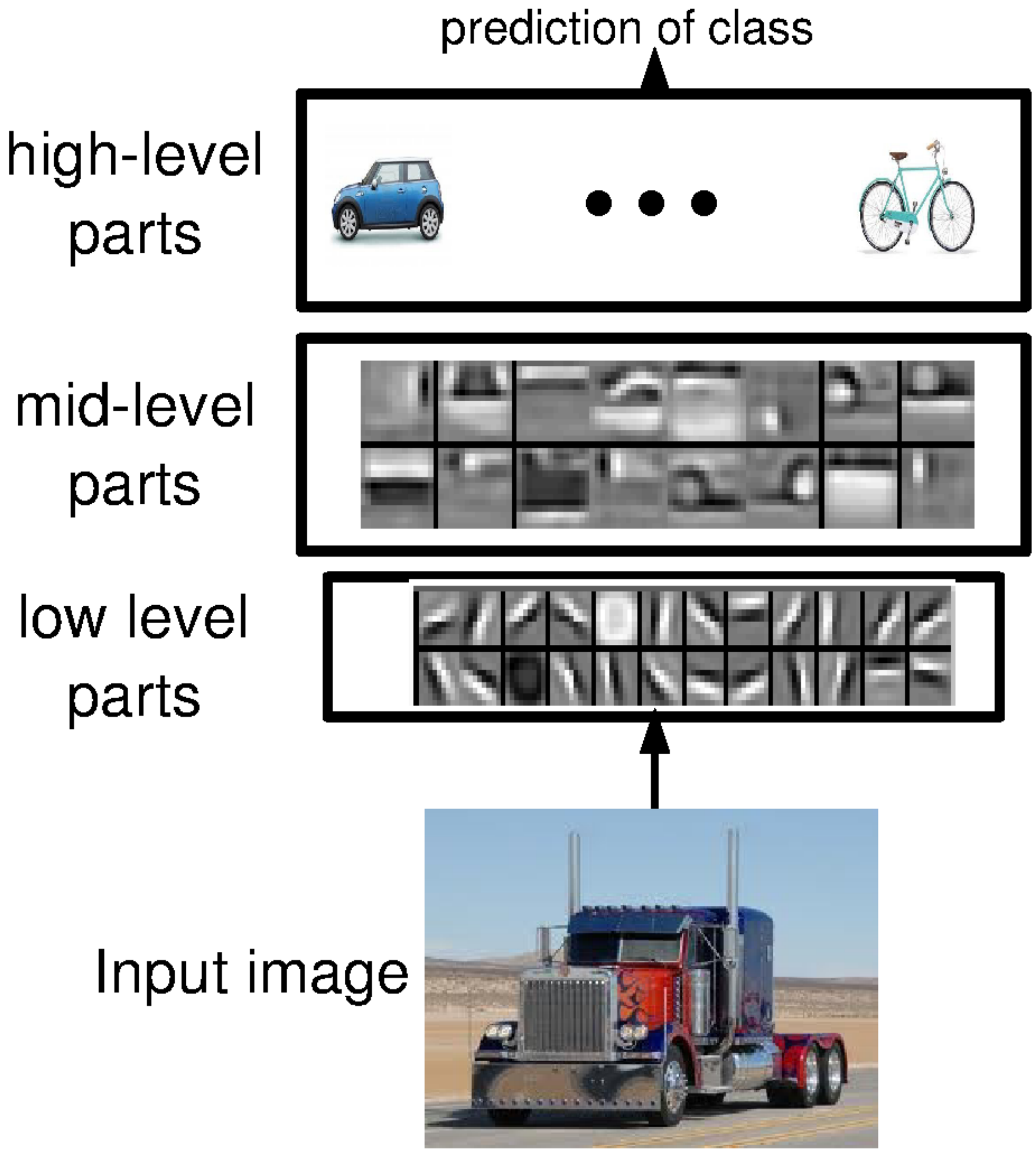
Interpretation

[1 1 0 0 0 1 0 1 0 0 0 0 1 1 0 1…] motorbike

[0 0 1 0 0 0 0 1 0 0 1 1 0 0 1 0 …] truck



Interpretation



- distributed representations
- feature sharing
- compositionality

Lee et al. "Convolutional DBN's ..." ICML 2009

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Interpretation

Question: What does a hidden unit do?

Answer: It can be thought of as a classifier or feature detector.

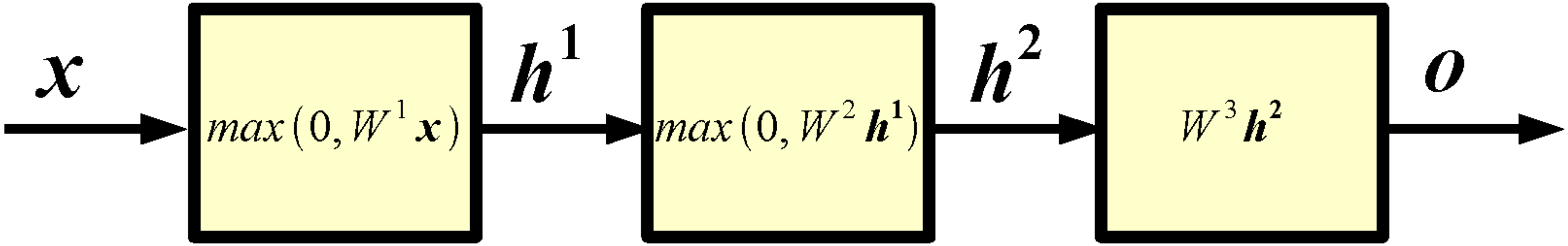
Question: How many layers? How many hidden units?

Answer: Cross-validation or hyper-parameter search methods are the answer. In general, the wider and the deeper the network the more complicated the mapping.

Question: How do I set the weight matrices?

Answer: Weight matrices and biases are learned.
First, we need to define a measure of quality of the current mapping.
Then, we need to define a procedure to adjust the parameters.

Neural Networks: example



$\boldsymbol{x}$ input

$\boldsymbol{h}^1$ 1-st layer hidden units

$\boldsymbol{h}^2$ 2-nd layer hidden units

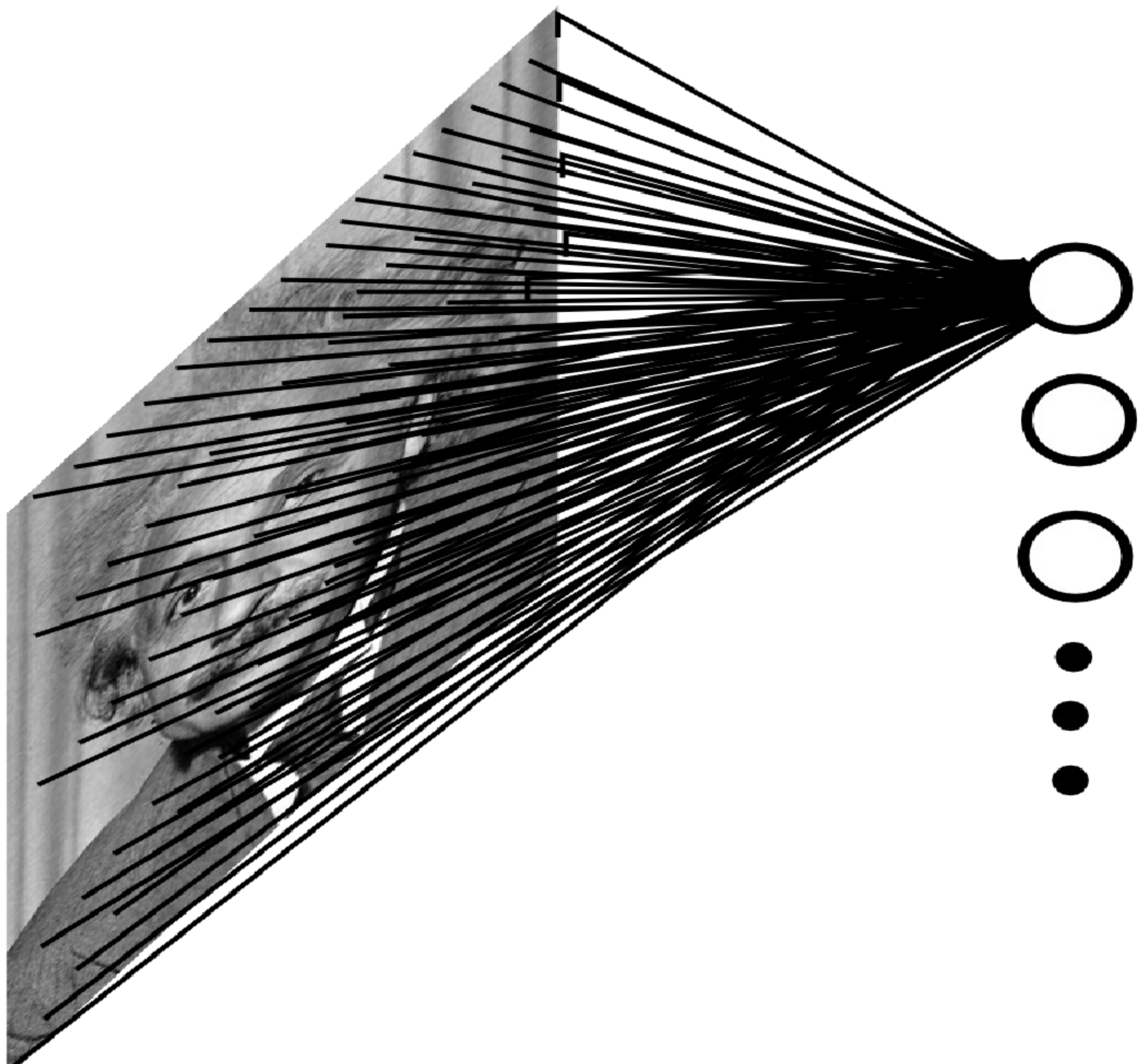
$\boldsymbol{o}$ output

Example of a 2 hidden layer neural network (or 4 layer network, counting also input and output).

Outline

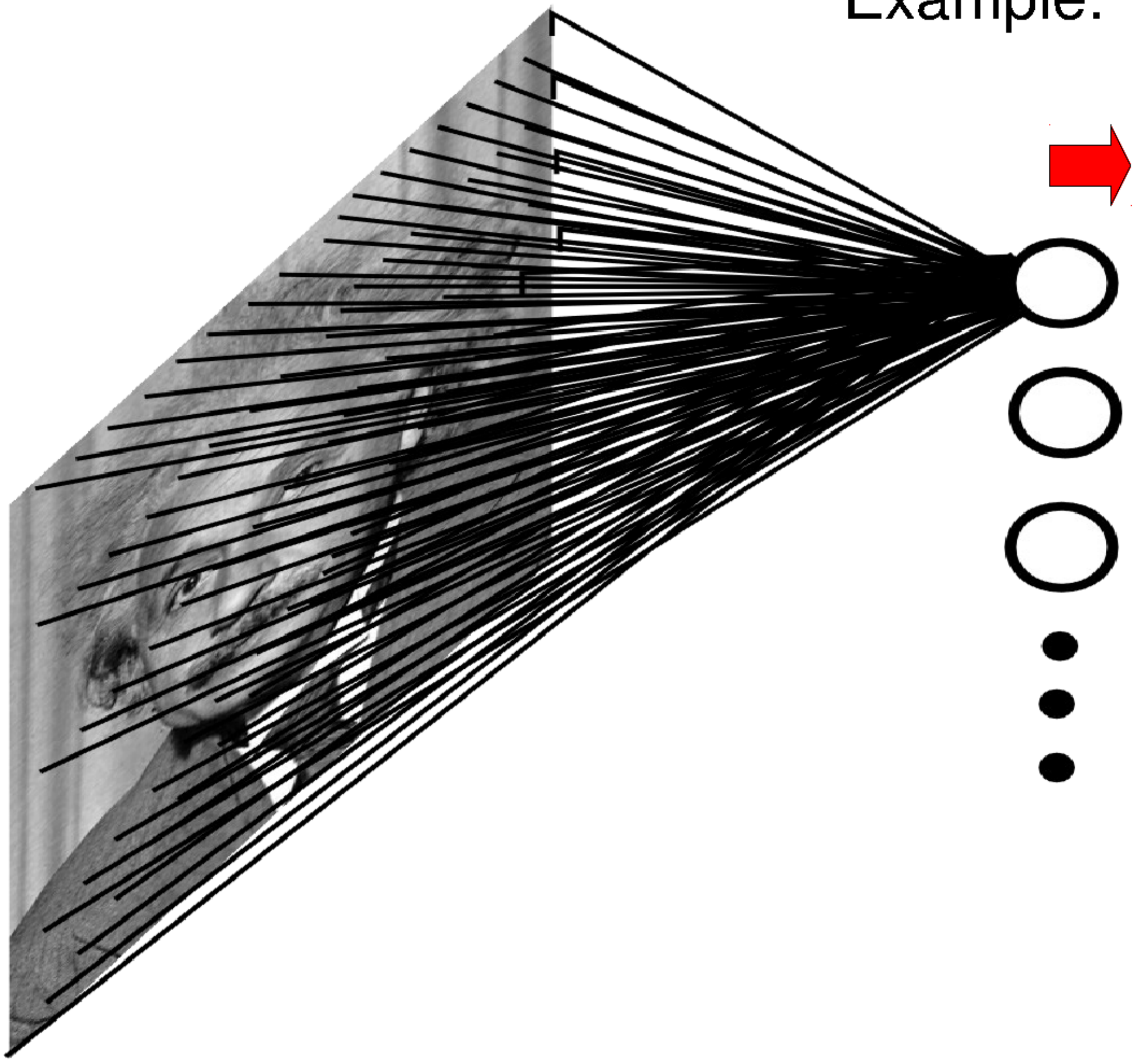
- Supervised Neural Networks
- Convolutional Neural Networks
- Examples
- Tips

Images as input to neural networks



Images as input to neural networks

Example: 200x200 image
40K hidden units
~2B parameters!!!



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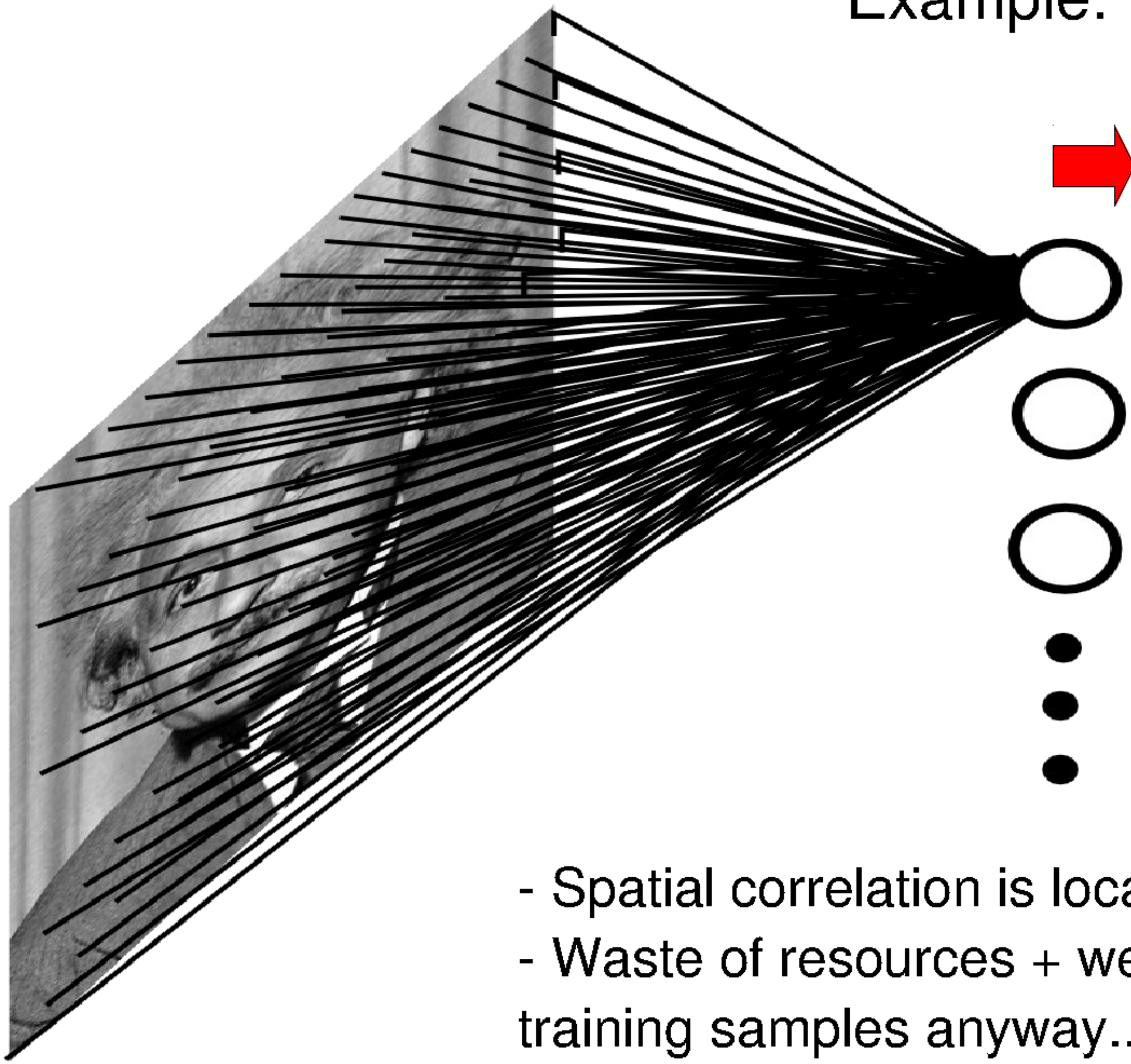
Images as input to neural networks



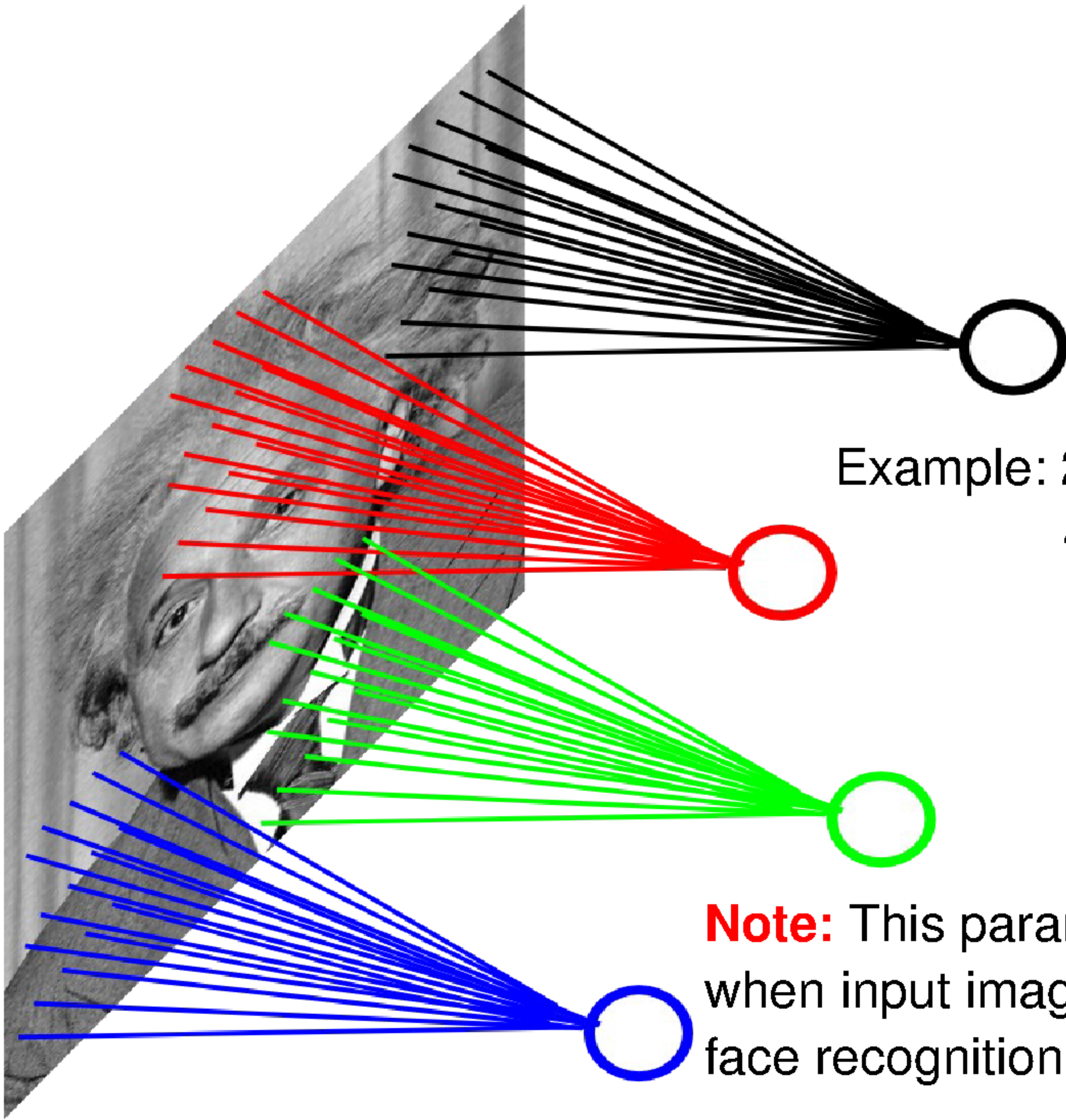
Example: 200x200 image
40K hidden units
~2B parameters!!!

- Spatial correlation is local
- Waste of resources + we have not enough training samples anyway..

Ranzato

Motivation

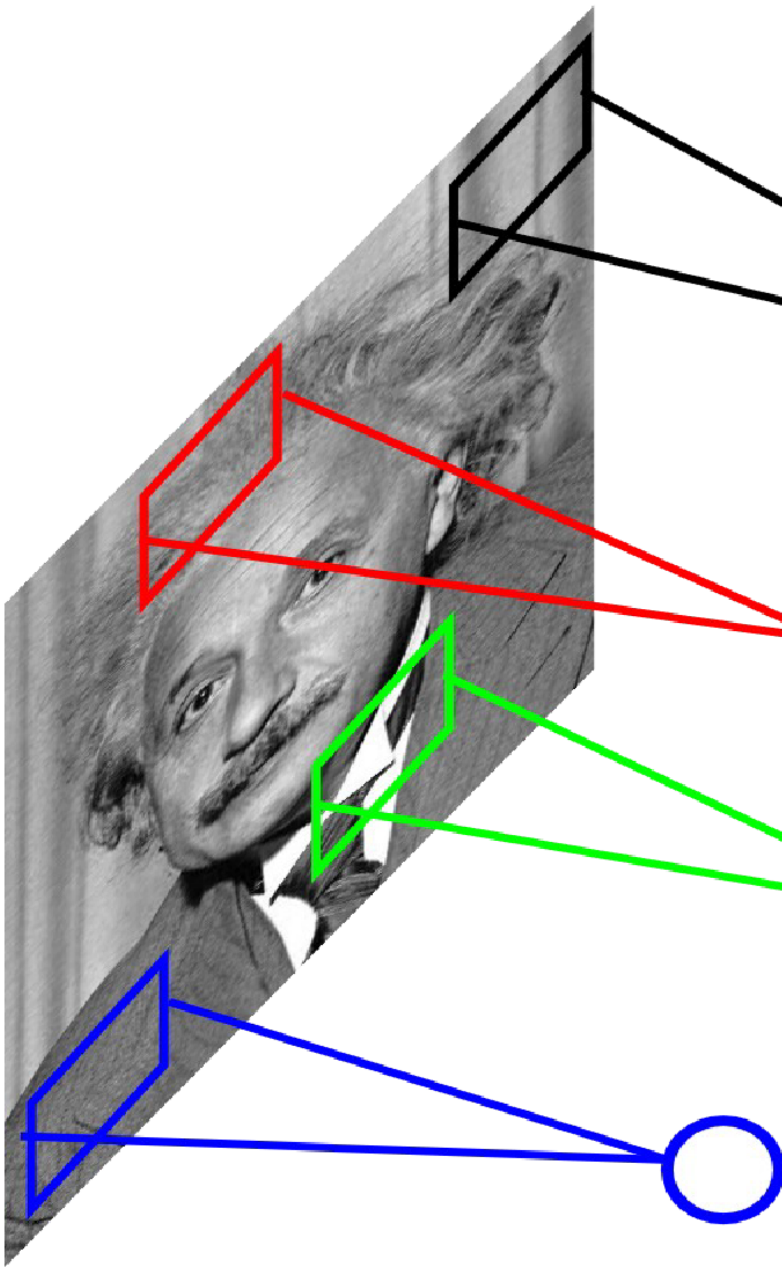
- Sparse interactions – *receptive fields*
  - Assume that in an image, we care about ‘local neighborhoods’ only for a given neural network layer.
  - Composition of layers will expand local -> global.



Example: 200x200 image
40K hidden units
Filter size: 10x10
4M parameters

Note: This parameterization is good when input image is registered (e.g., face recognition).

Ranzato



STATIONARITY? Statistics is similar at different locations

Example: 200x200 image
40K hidden units
Filter size: 10x10
4M parameters

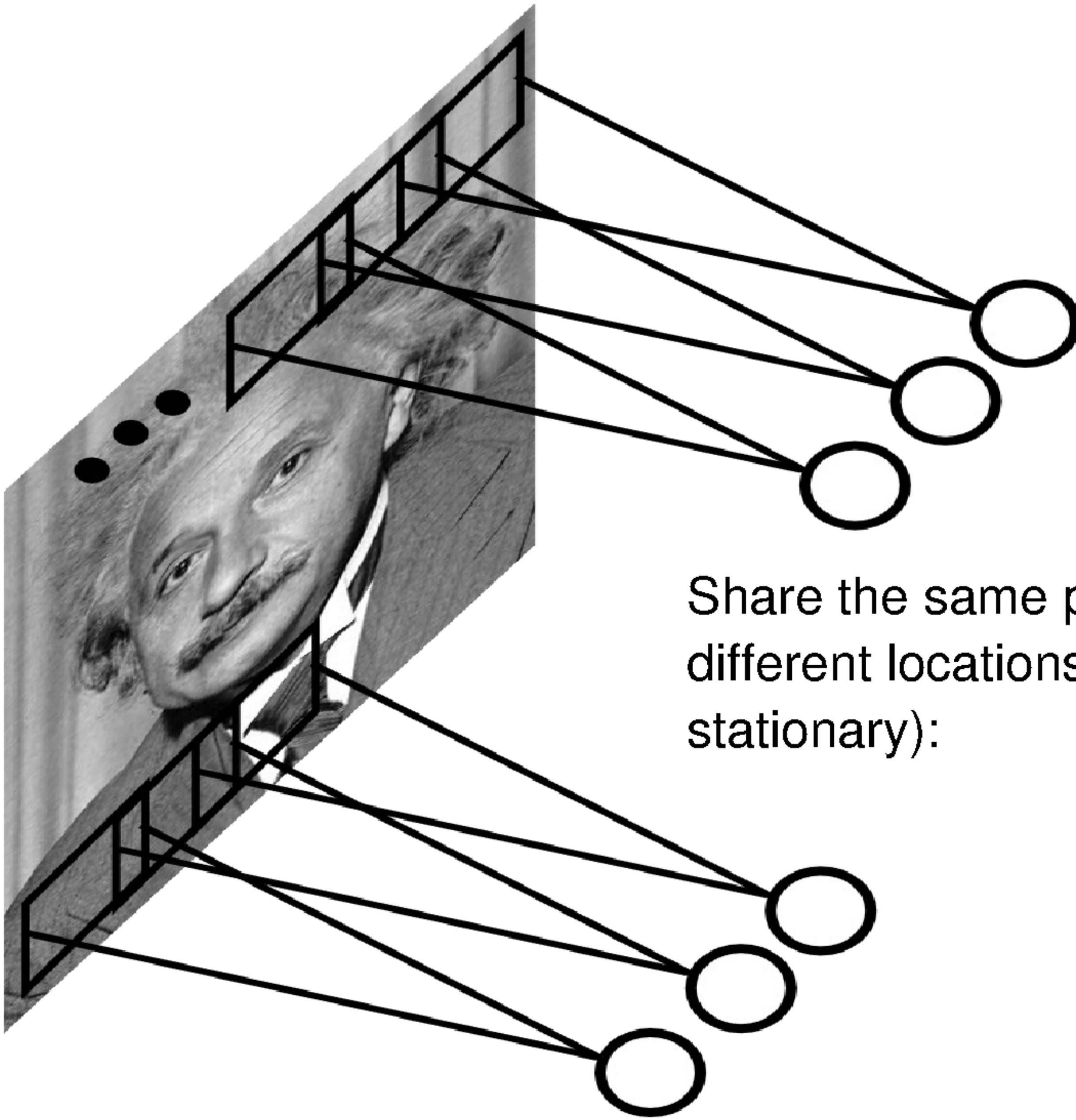
Note: This parameterization is good when input image is registered (e.g., face recognition).

Ranzato

Motivation

- Sparse interactions – *receptive fields*
  - Assume that in an image, we care about 'local neighborhoods' only for a given neural network layer.
  - Composition of layers will expand local -> global.

- Parameter sharing
  - 'Tied weights' – use same weights for more than one perceptron in the neural network.
  - Leads to *equivariant representation*
    - If input changes (e.g., translates), then output changes similarly



Share the same parameters across different locations (assuming input is stationary):

Filtering reminder:
Correlation (rotated convolution)

$$f[\cdot\,,\cdot\,] \quad \frac{1}{9}\begin{bmatrix} 1 & 1 & 1 \\ 1 & 1 & 1 \\ 1 & 1 & 1 \end{bmatrix}$$

$$I[.,.]$$

0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0
0	0	0	90	90	90	90	90	0	0
0	0	0	90	90	90	90	90	0	0
0	0	0	90	90	90	90	90	0	0
0	0	0	90	0	90	90	90	0	0
0	0	0	90	90	90	90	90	0	0
0	0	0	0	0	0	0	0	0	0
0	0	90	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0

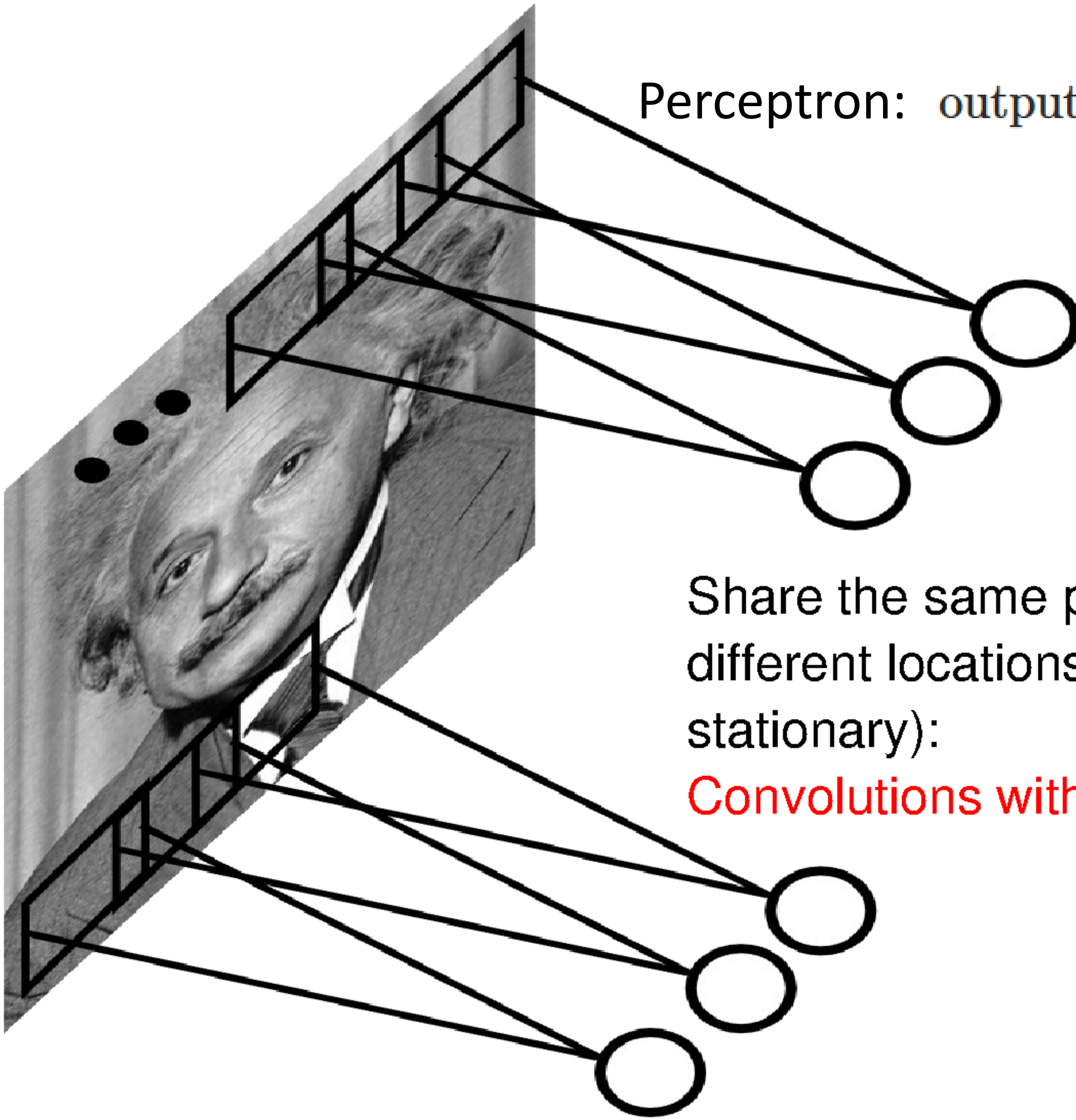
$$h[.,.]$$

	0	10	20	30	30	30	20	10	
	0	20	40	60	60	60	40	20	
	0	30	60	90	90	90	60	30	
	0	30	50	80	80	90	60	30	
	0	30	50	80	80	90	60	30	
	0	20	30	50	50	60	40	20	
	10	20	30	30	30	30	20	10	
	10	10	10	0	0	0	0	0	

$$h[m,n] = \sum_{k,l} f[k,l]\, I[m+k, n+l]$$

Credit: S. Seitz

Convolutional Layer



Perceptron: $\text{output} = \begin{cases} 0 & \text{if } w \cdot x + b \leq 0 \\ 1 & \text{if } w \cdot x + b > 0 \end{cases}$

$w \cdot x \equiv \sum_j w_j x_j,$

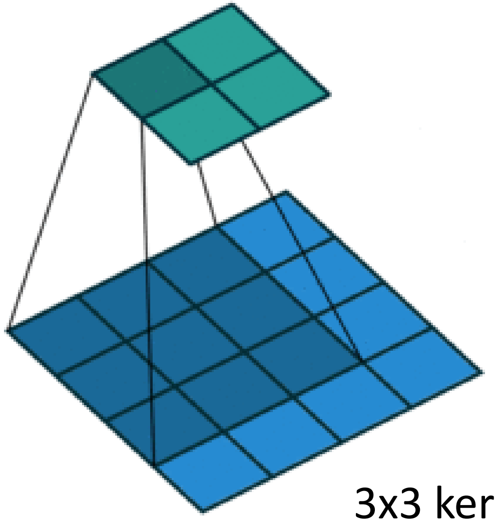
This is convolution!

Share the same parameters across different locations (assuming input is stationary):

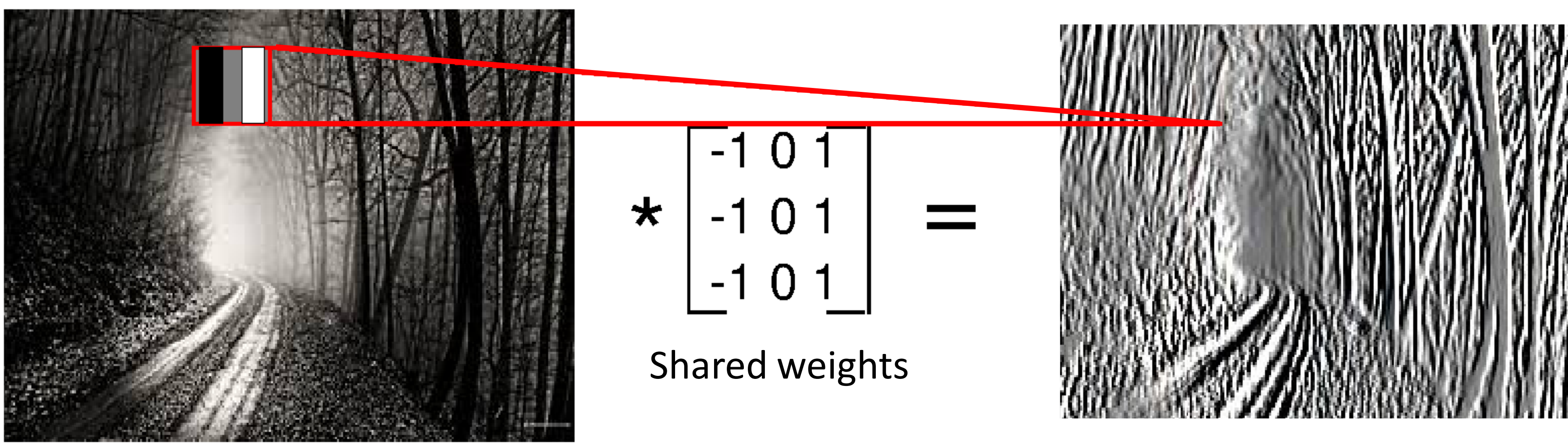
Convolutions with learned kernels

Ranzato

Convolution



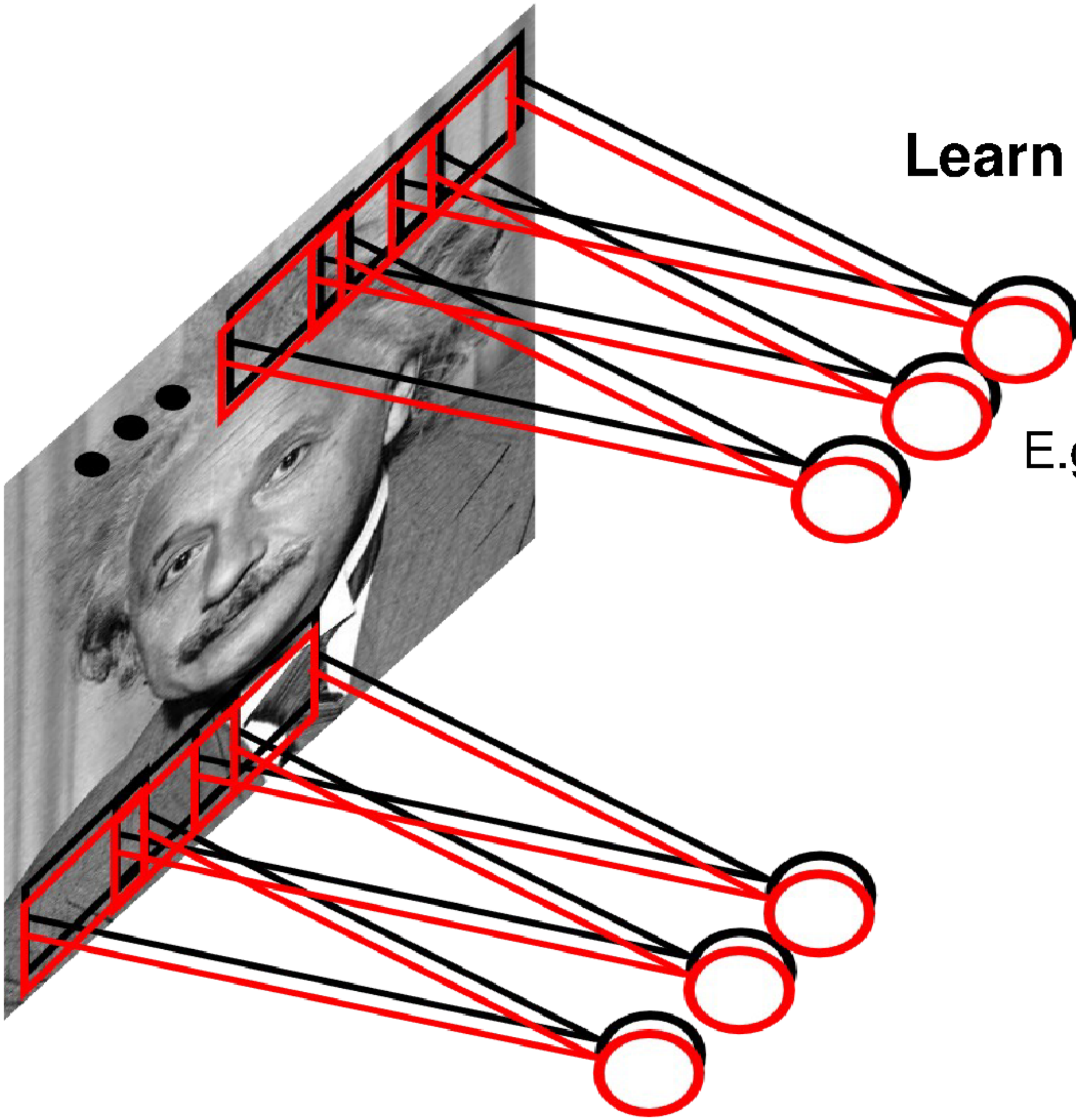
3x3 kernel



$$* \begin{bmatrix} -1 & 0 & 1 \\ -1 & 0 & 1 \\ -1 & 0 & 1 \end{bmatrix} =$$

Shared weights

Convolutional Layer

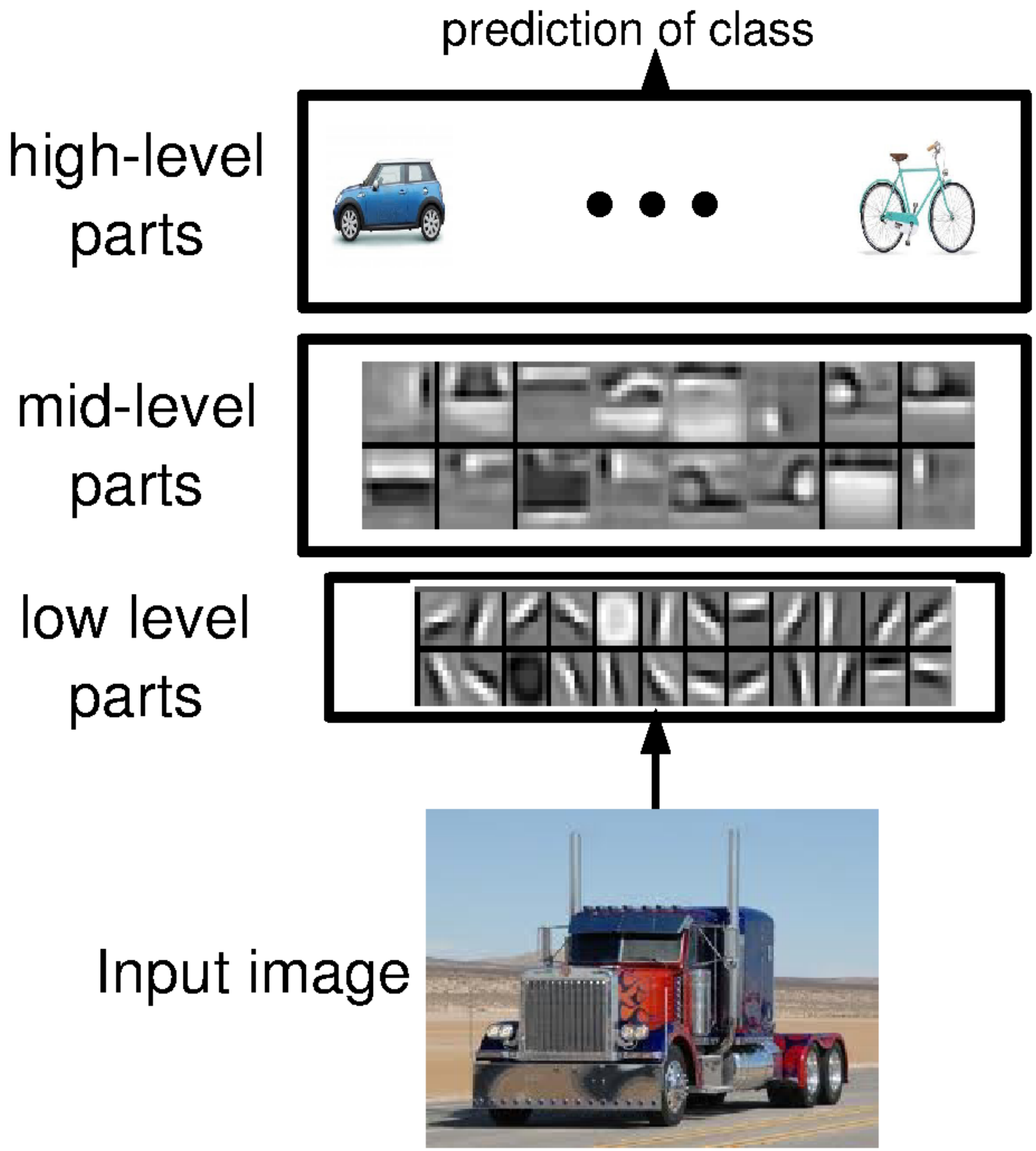


Learn multiple filters.

Filter = ‘local’ perceptron.
Also called *kernel.*

E.g.: 200x200 image
100 Filters
Filter size: 10x10
10K parameters

Interpretation



- distributed representations
- feature sharing
- compositionality

Lee et al. "Convolutional DBN's ..." ICML 2009

Convolutional Layer

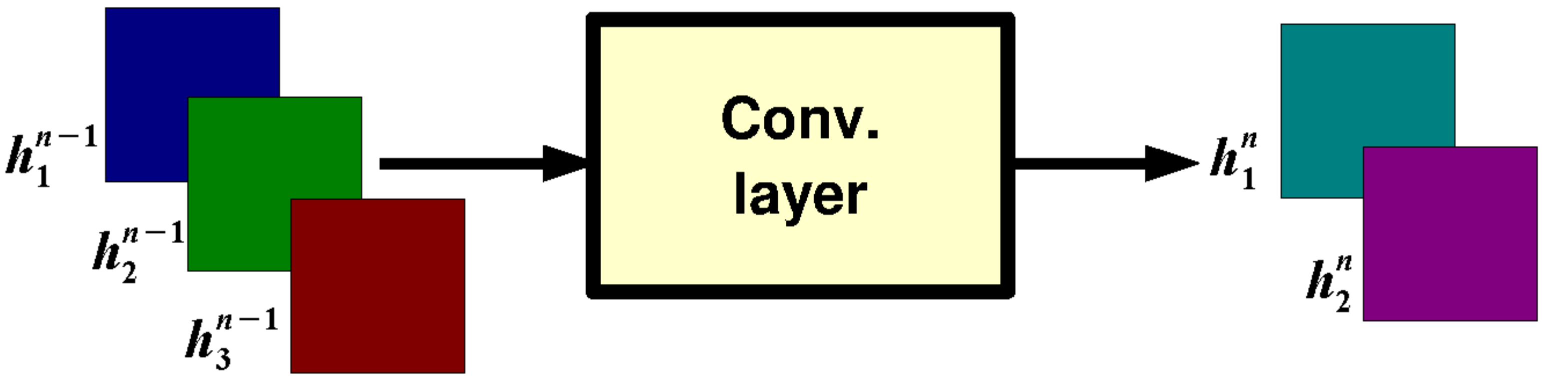
$$h_j^n = max\left(0, \sum_{k=1}^{K} h_k^{n-1} * w_{kj}^n\right)$$

n = layer number
K = kernel size
j = # channels (input) or # filters (depth)

output feature map

input feature map

kernel



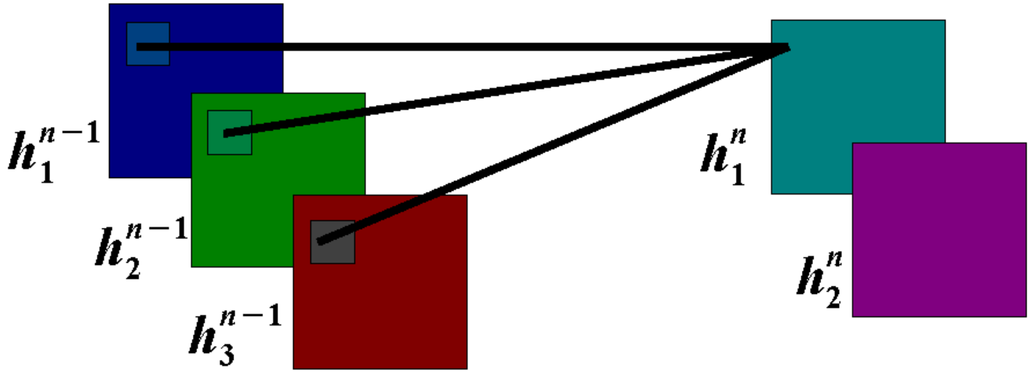
Convolutional Layer

$$h_j^n = max\left(0, \sum_{k=1}^{K} h_k^{n-1} * w_{kj}^n\right)$$

output feature map

input feature map

kernel



Ranzato

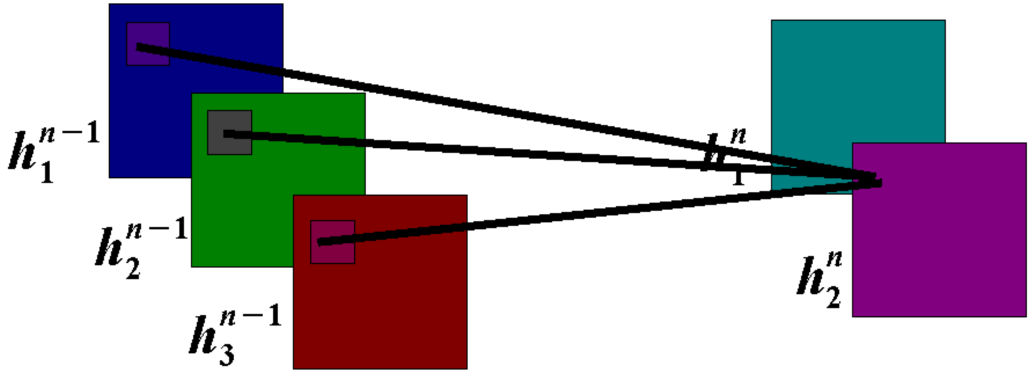
Convolutional Layer

$$h_j^n = max\left(0, \sum_{k=1}^{K} h_k^{n-1} * w_{kj}^n\right)$$

output feature map

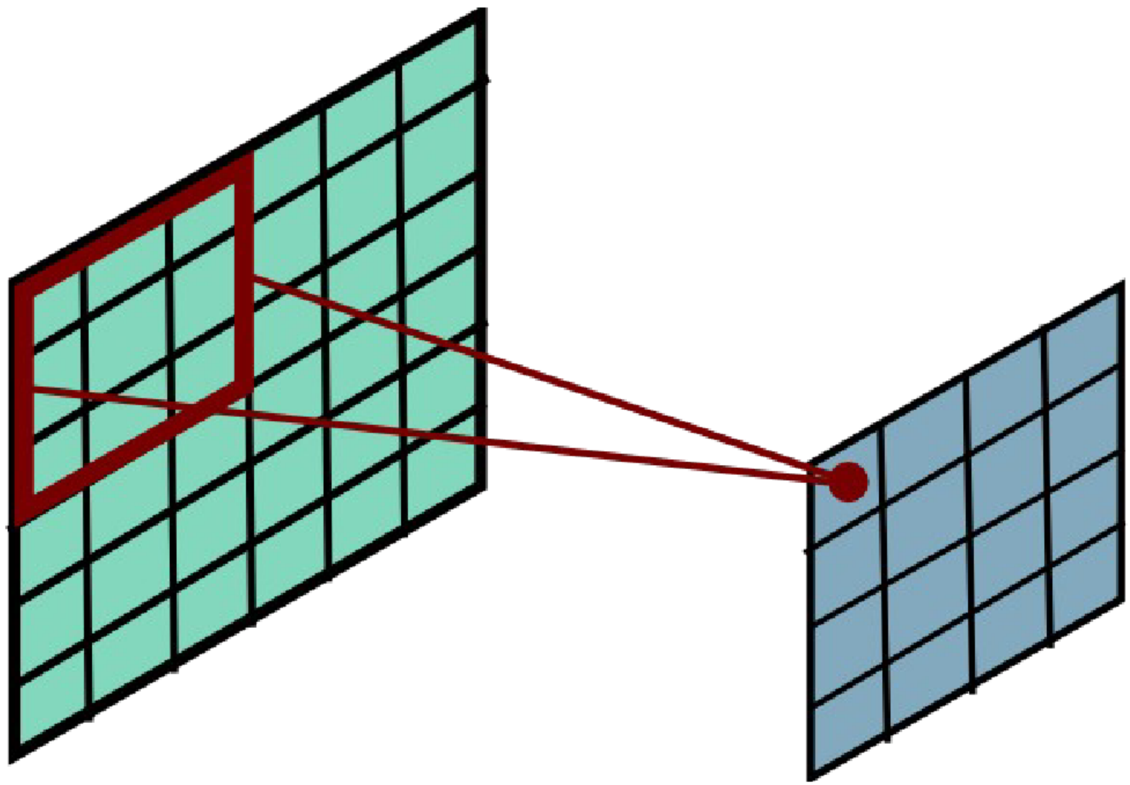
input feature map

kernel

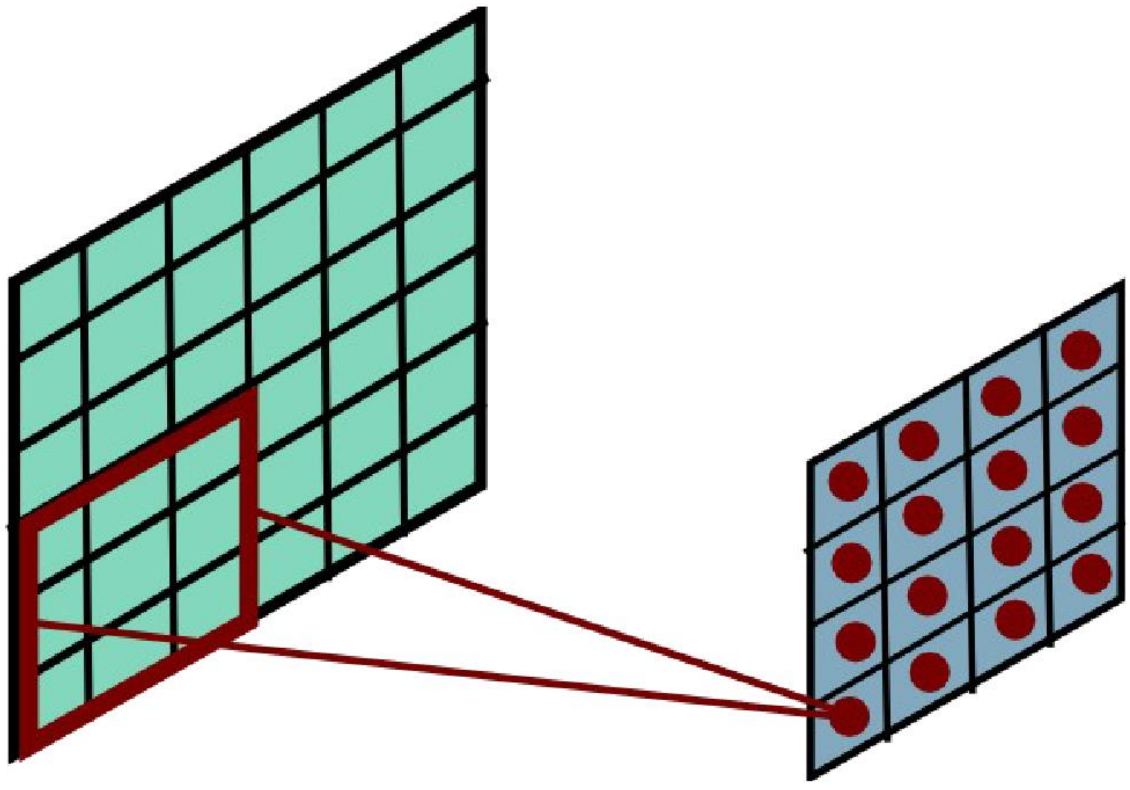


Ranzato

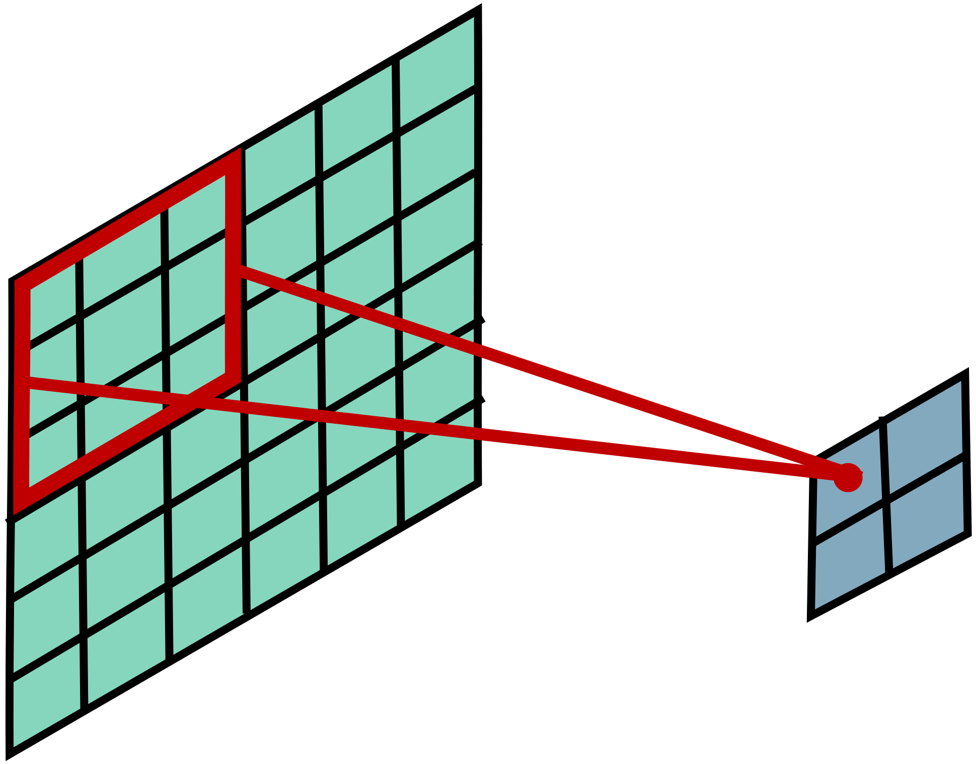
Stride = 1



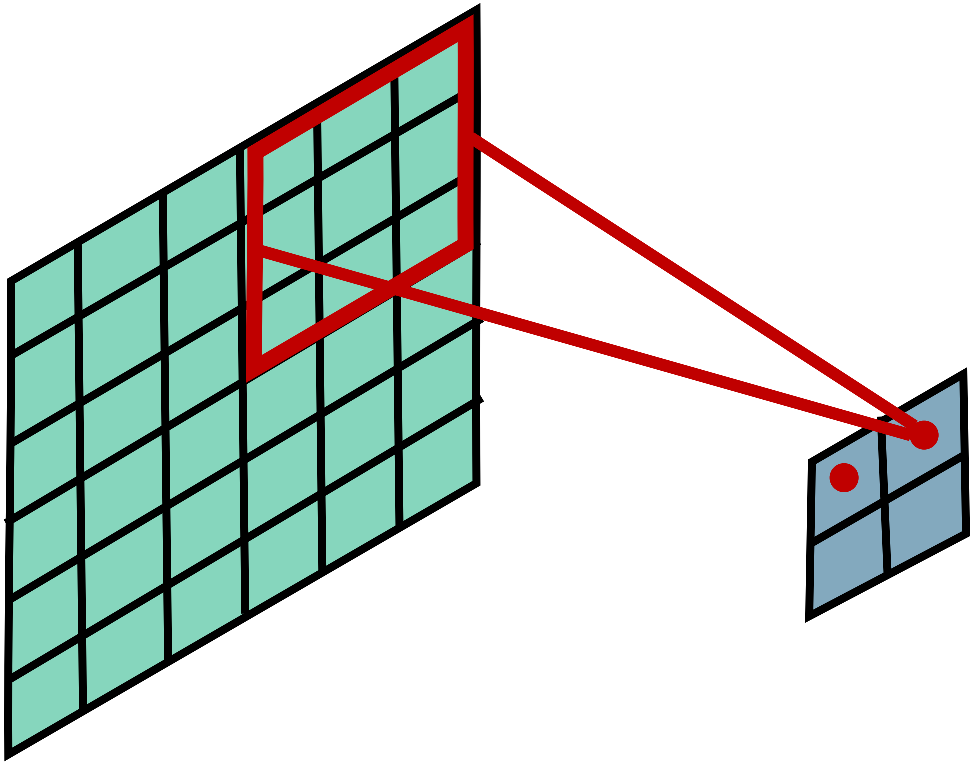
Stride = 1



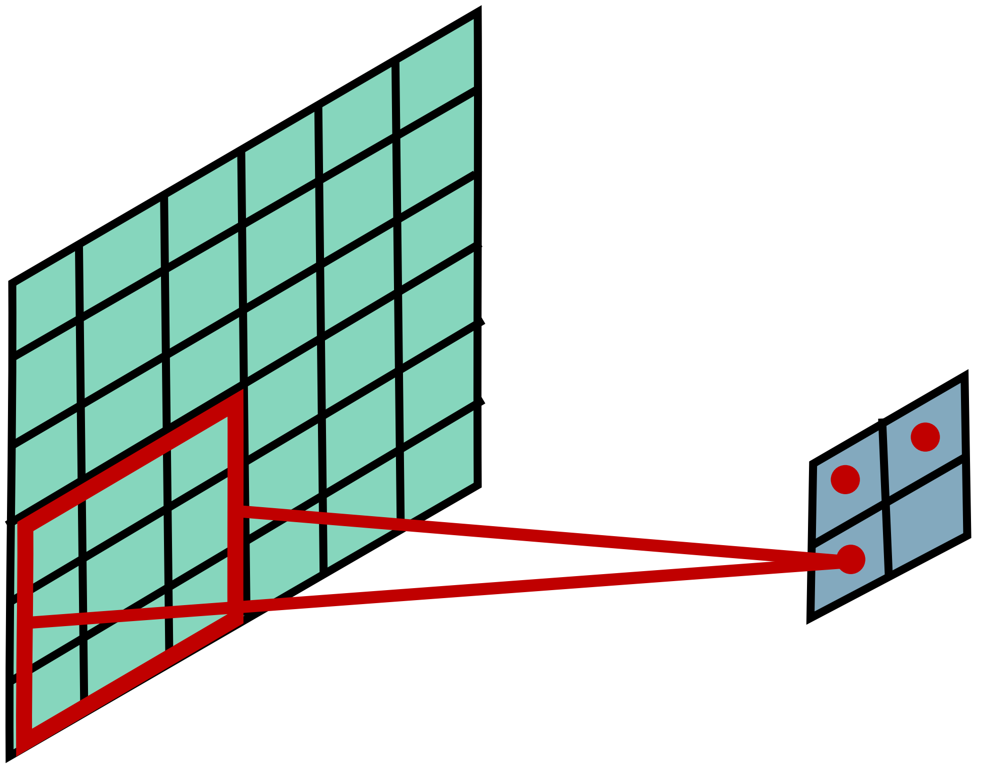
Stride = 3



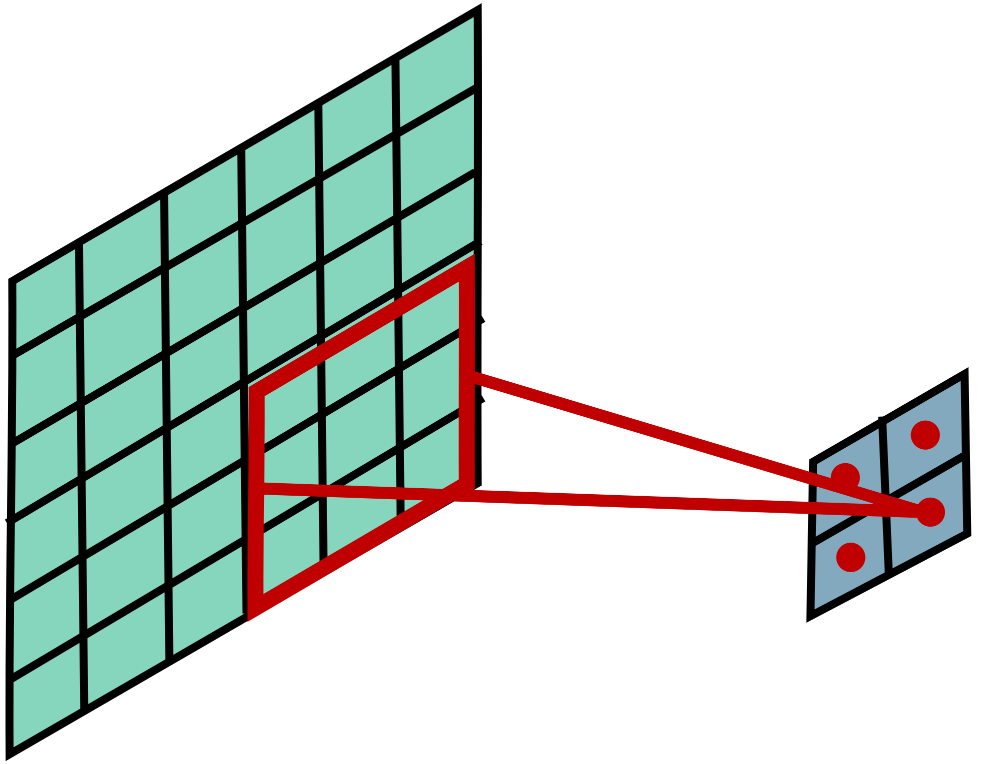
Stride = 3



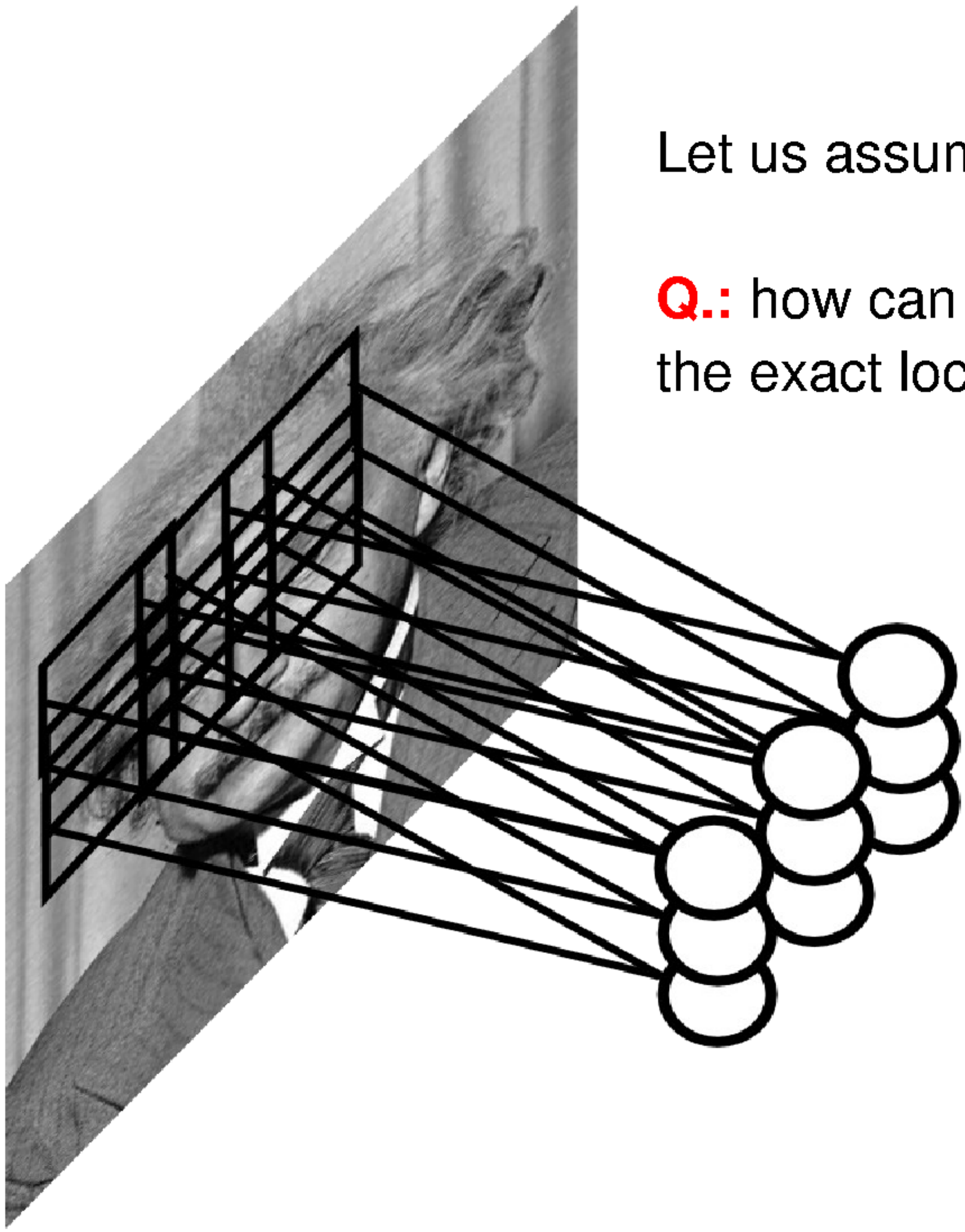
Stride = 3



Stride = 3



Pooling Layer



Let us assume filter is an “eye” detector.

Q.: how can we make the detection robust to the exact location of the eye?

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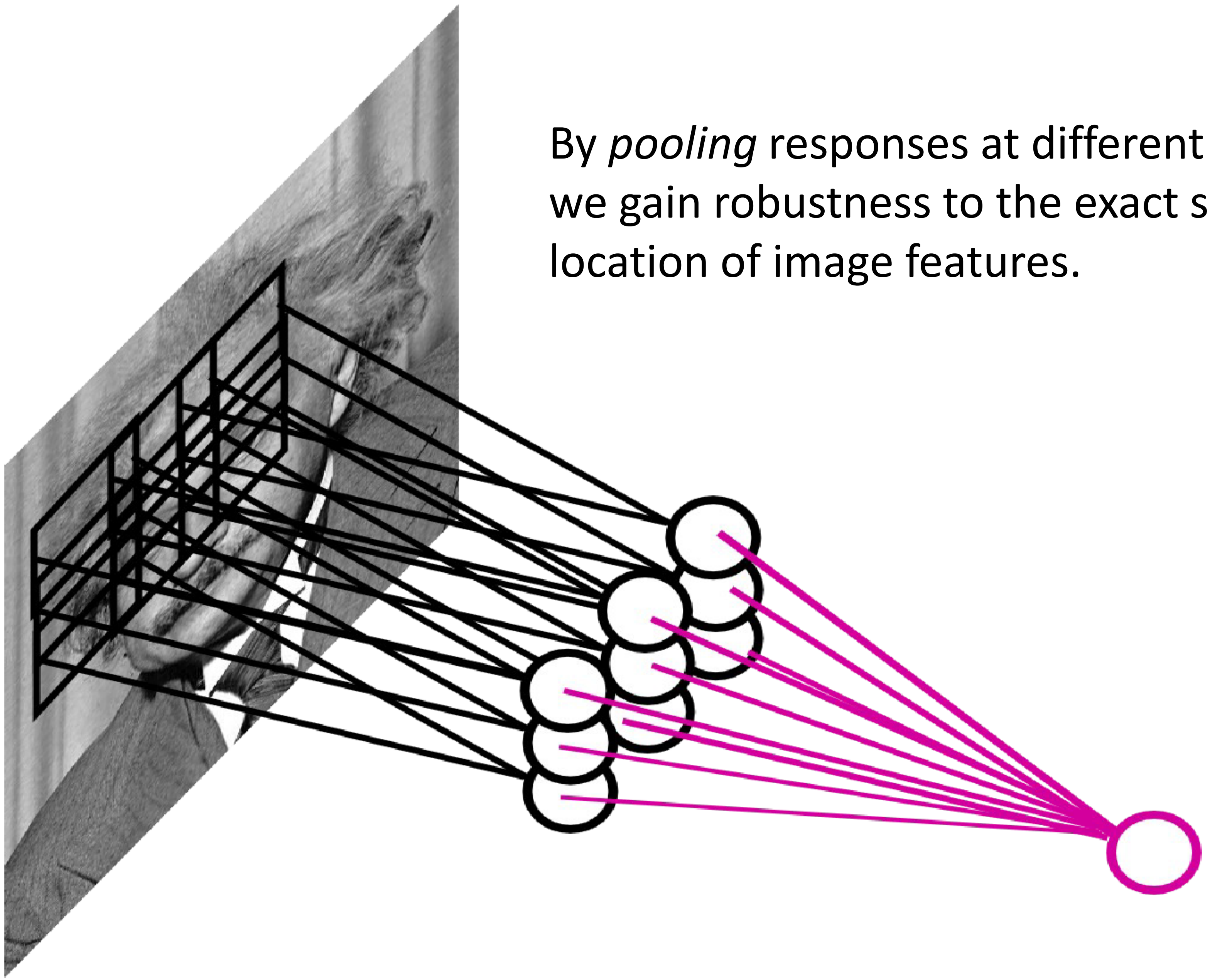
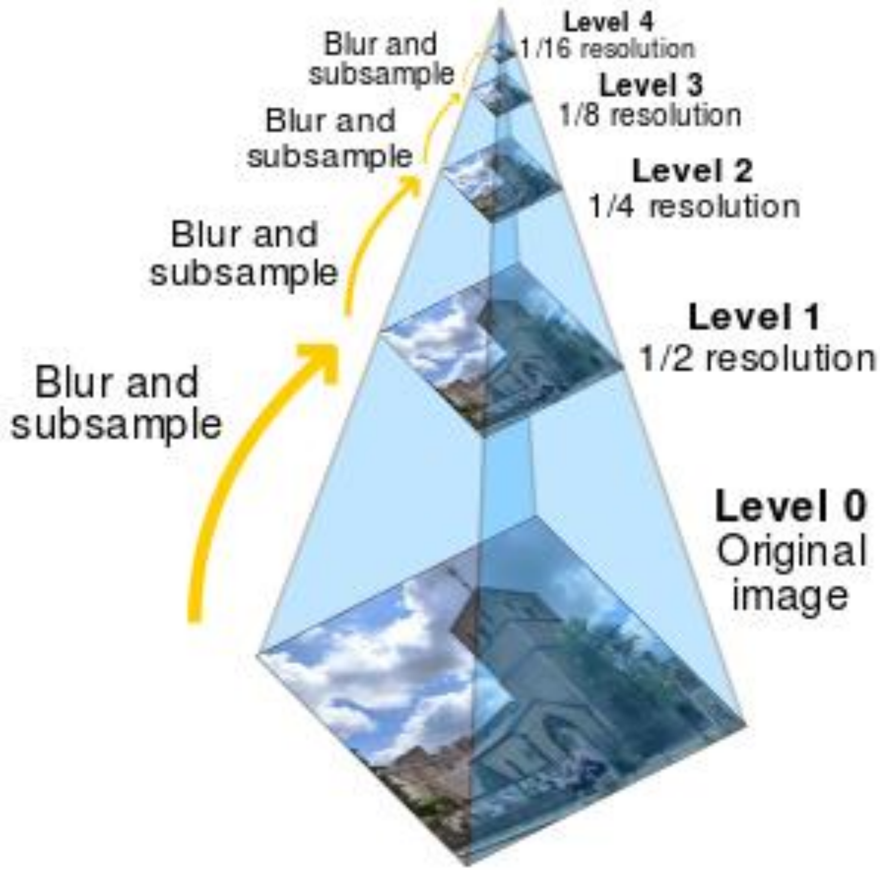
Pooling Layer



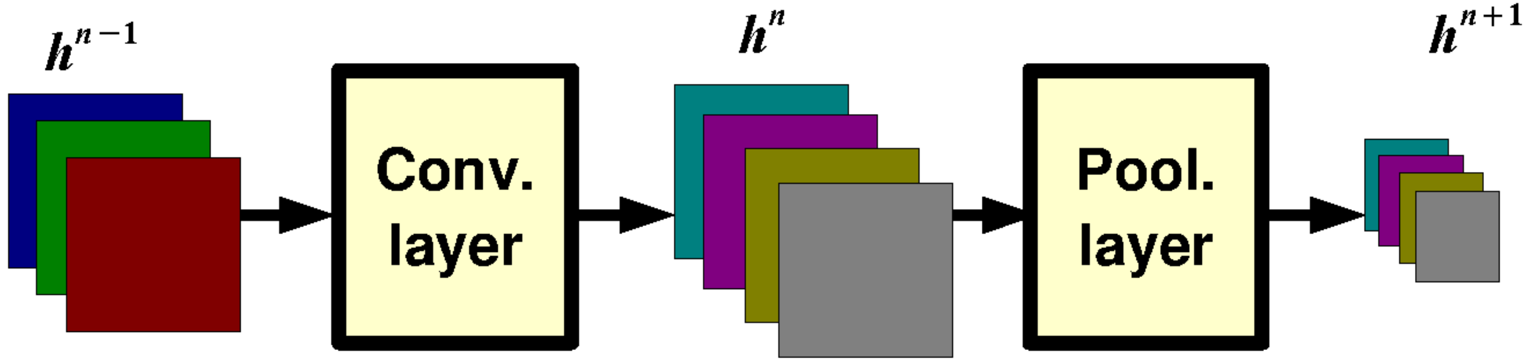
By *pooling* responses at different locations, we gain robustness to the exact spatial location of image features.

Pooling is similar to downsampling



…except sometimes we don't want to blur,
as other functions might be better for classification.

Pooling Layer: Receptive Field Size



Pooling Layer: Examples

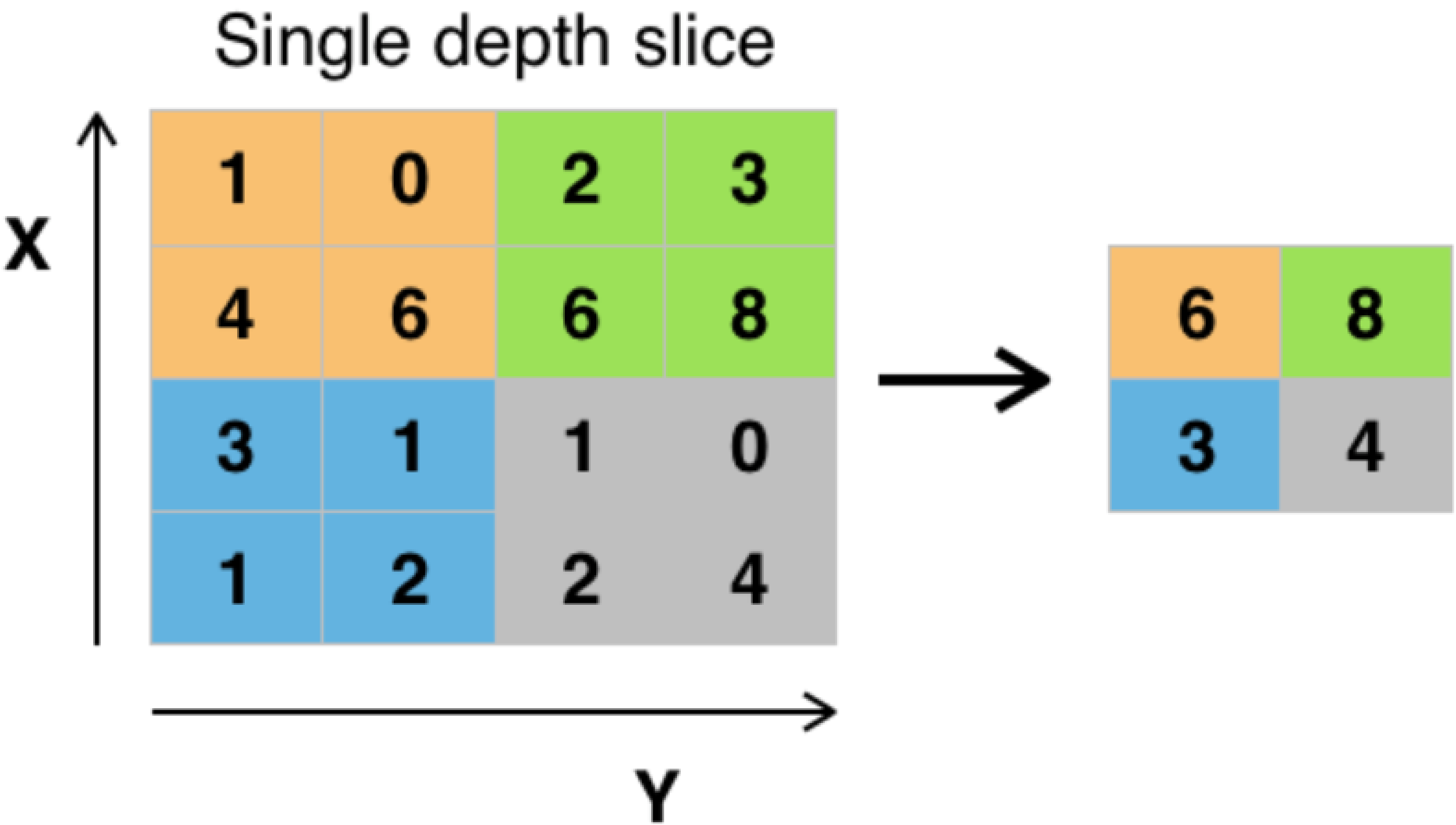
Max-pooling:

$$h_j^n(x, y) = max_{\bar{x} \in N(x),\, \bar{y} \in N(y)} h_j^{n-1}(\bar{x}, \bar{y})$$

Average-pooling:

$$h_j^n(x, y) = 1/K \sum_{\bar{x} \in N(x),\, \bar{y} \in N(y)} h_j^{n-1}(\bar{x}, \bar{y})$$

Max pooling



Wikipedia

Pooling Layer: Examples

Max-pooling:

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Average-pooling:

$$h_j^n(x, y) = 1/K \sum_{\bar{x} \in N(x), \bar{y} \in N(y)} h_j^{n-1}(\bar{x}, \bar{y})$$

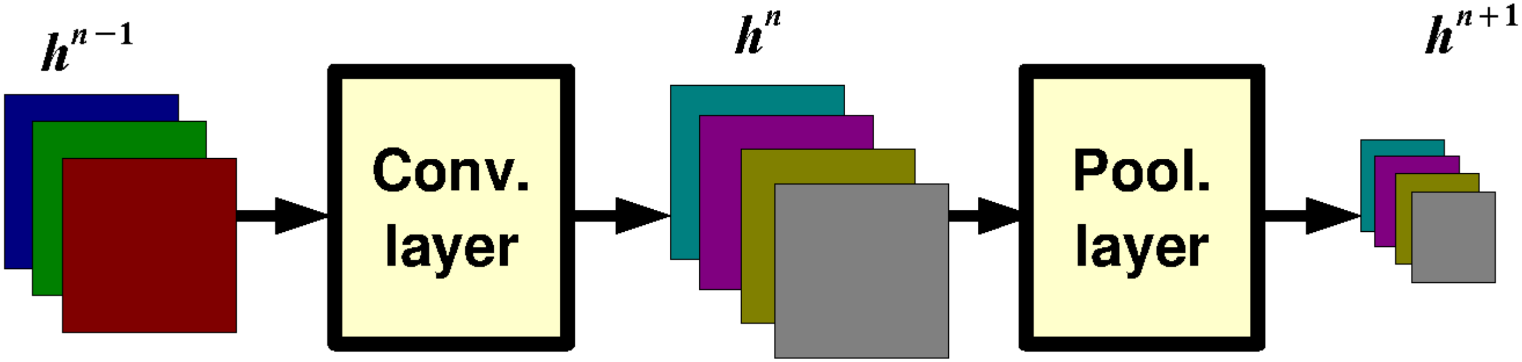
L2-pooling:

$$h_j^n(x, y) = \sqrt{\sum_{\bar{x} \in N(x), \bar{y} \in N(y)} h_j^{n-1}(\bar{x}, \bar{y})^2}$$

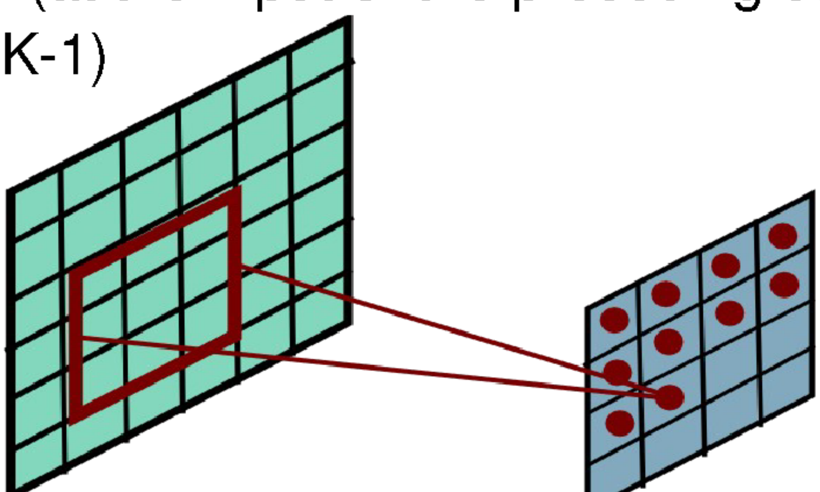
L2-pooling over features:

$$h_j^n(x, y) = \sqrt{\sum_{k \in N(j)} h_k^{n-1}(x, y)^2}$$

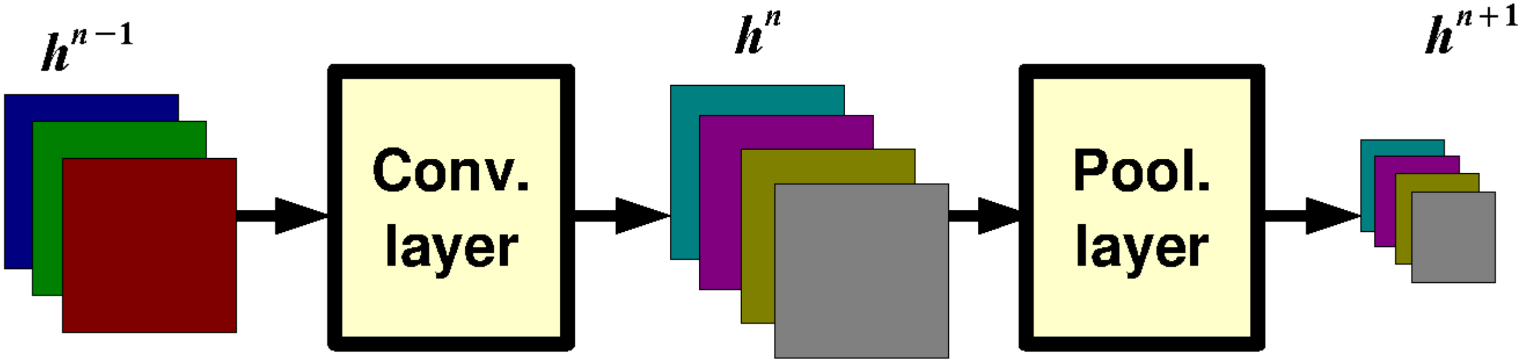
Pooling Layer: Receptive Field Size



If convolutional filters have size KxK and stride 1, and pooling layer has pools of size PxP, then each unit in the pooling layer depends upon a patch (at the input of the preceding conv. layer) of size: (P+K-1)x(P+K-1)



Pooling Layer: Receptive Field Size



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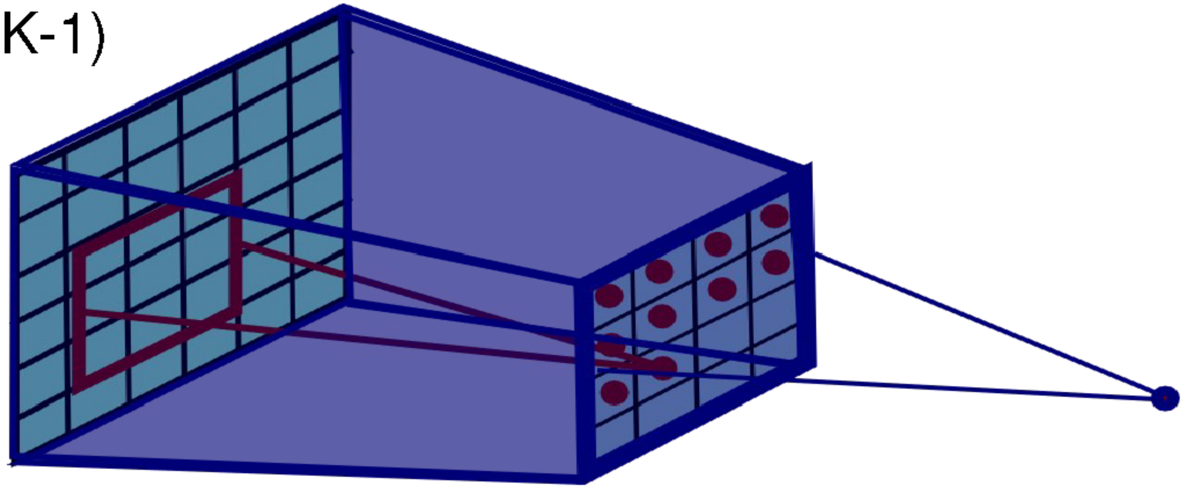

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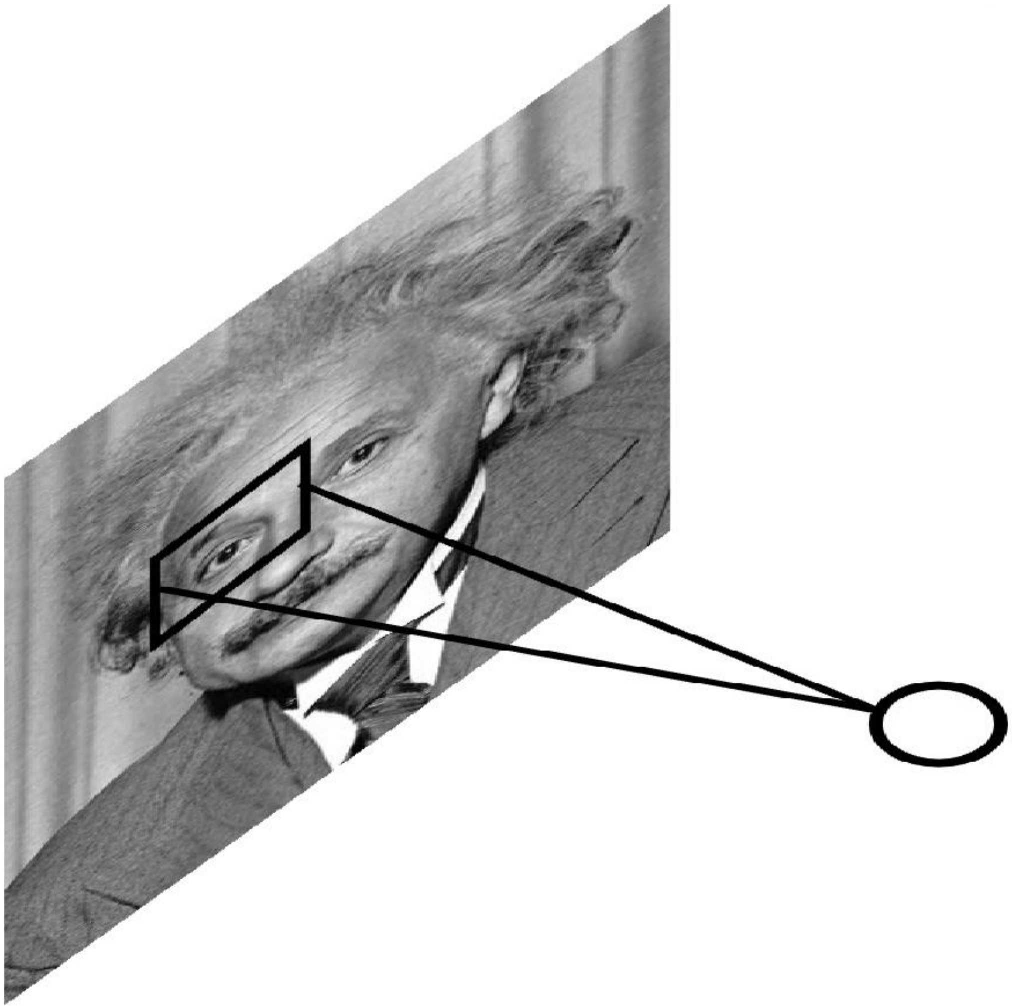
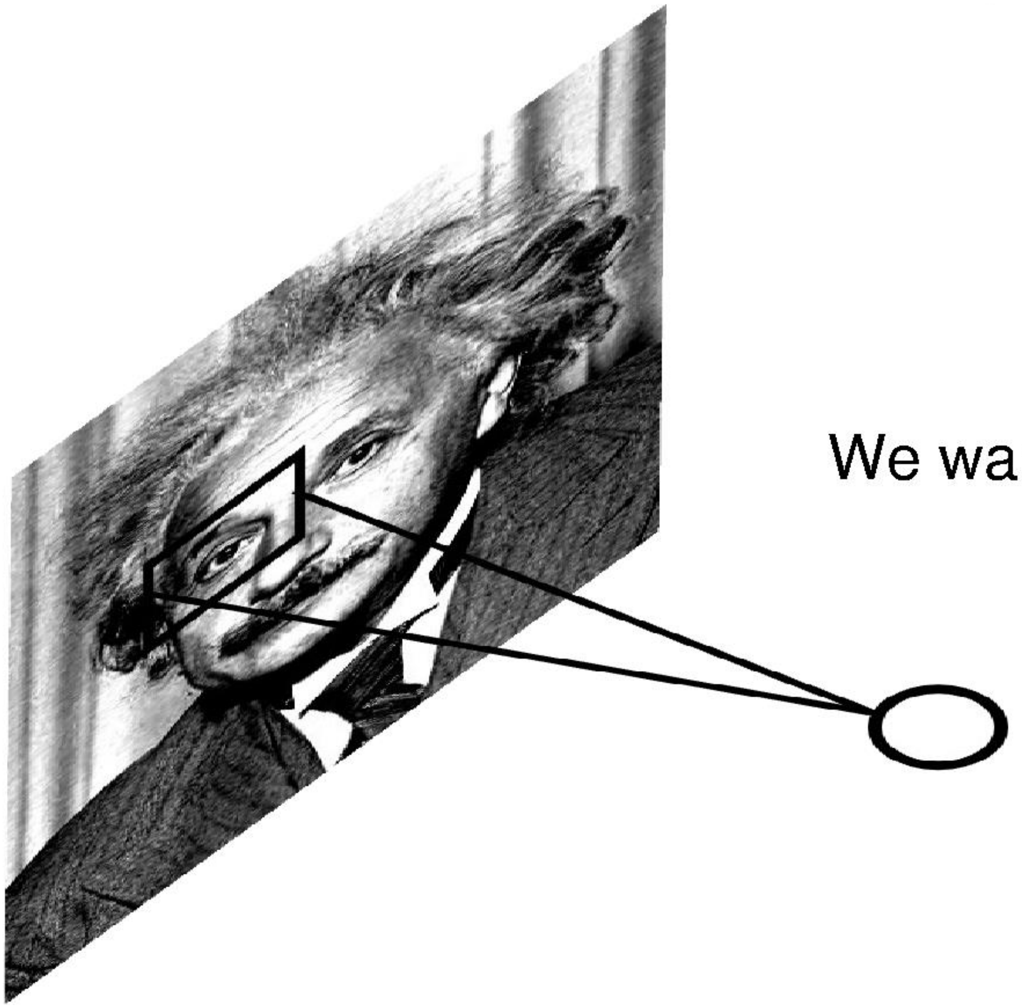
Local Contrast Normalization



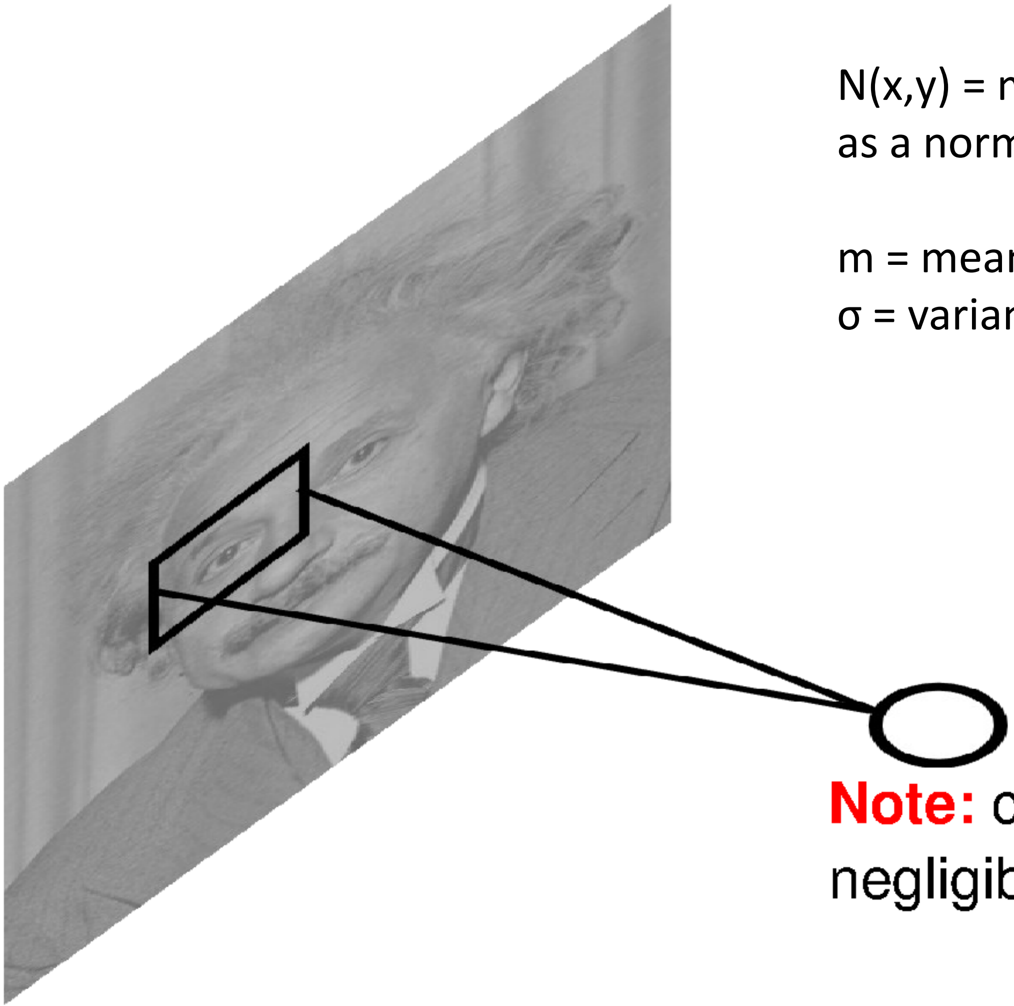
Local Contrast Normalization



We want the same response.

Local Contrast Normalization

$$h^{i+1}(x,y)=\frac{h^i(x,y)-m^i(N(x,y))}{\sigma^i(N(x,y))}$$



N(x,y) = model pixel values in window as a normal distribution

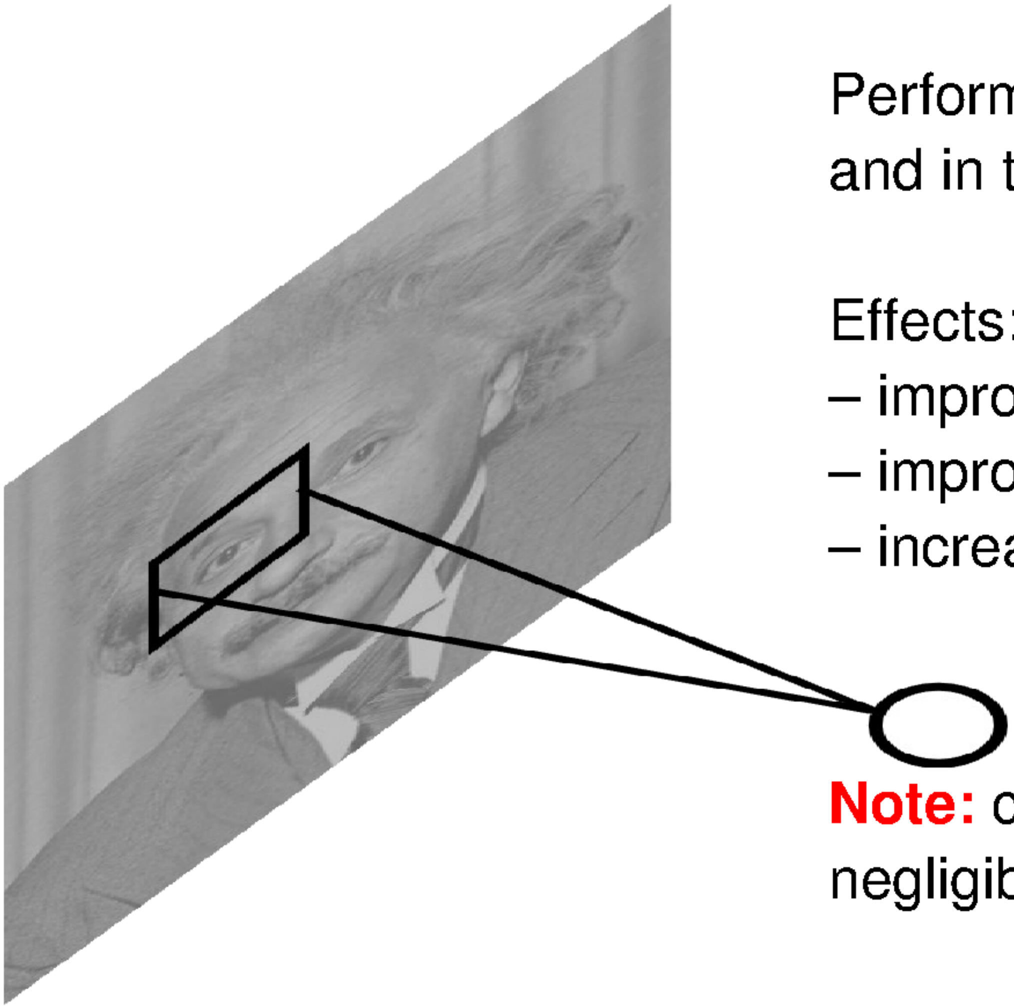
m = mean
σ = variance

Note: computational cost is negligible w.r.t. conv. layer.

Ranzato

Local Contrast Normalization

$$h^{i+1}(x,y) = \frac{h^i(x,y) - m^i(N(x,y))}{\sigma^i(N(x,y))}$$

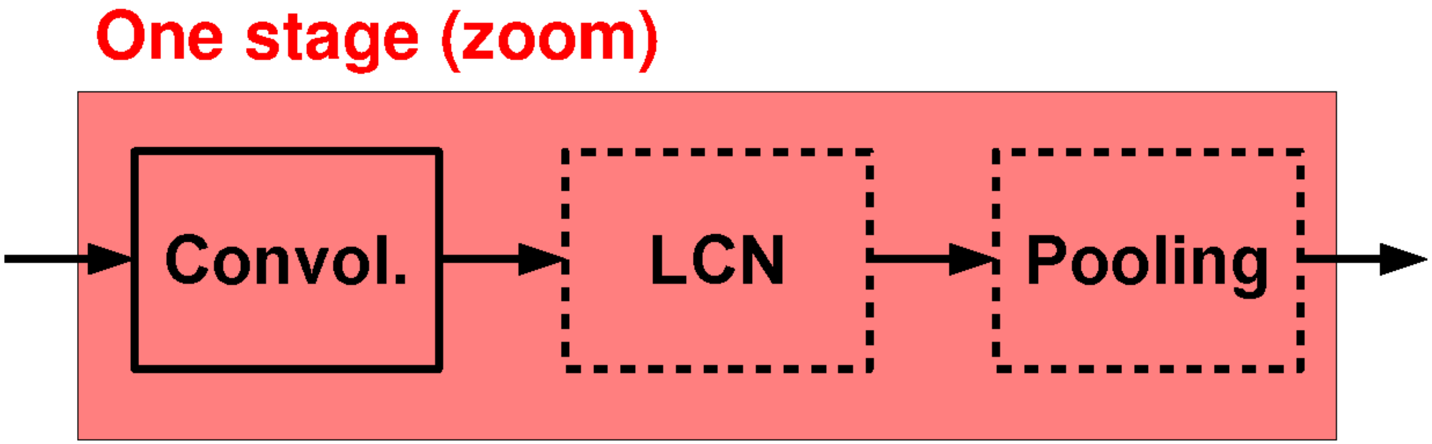


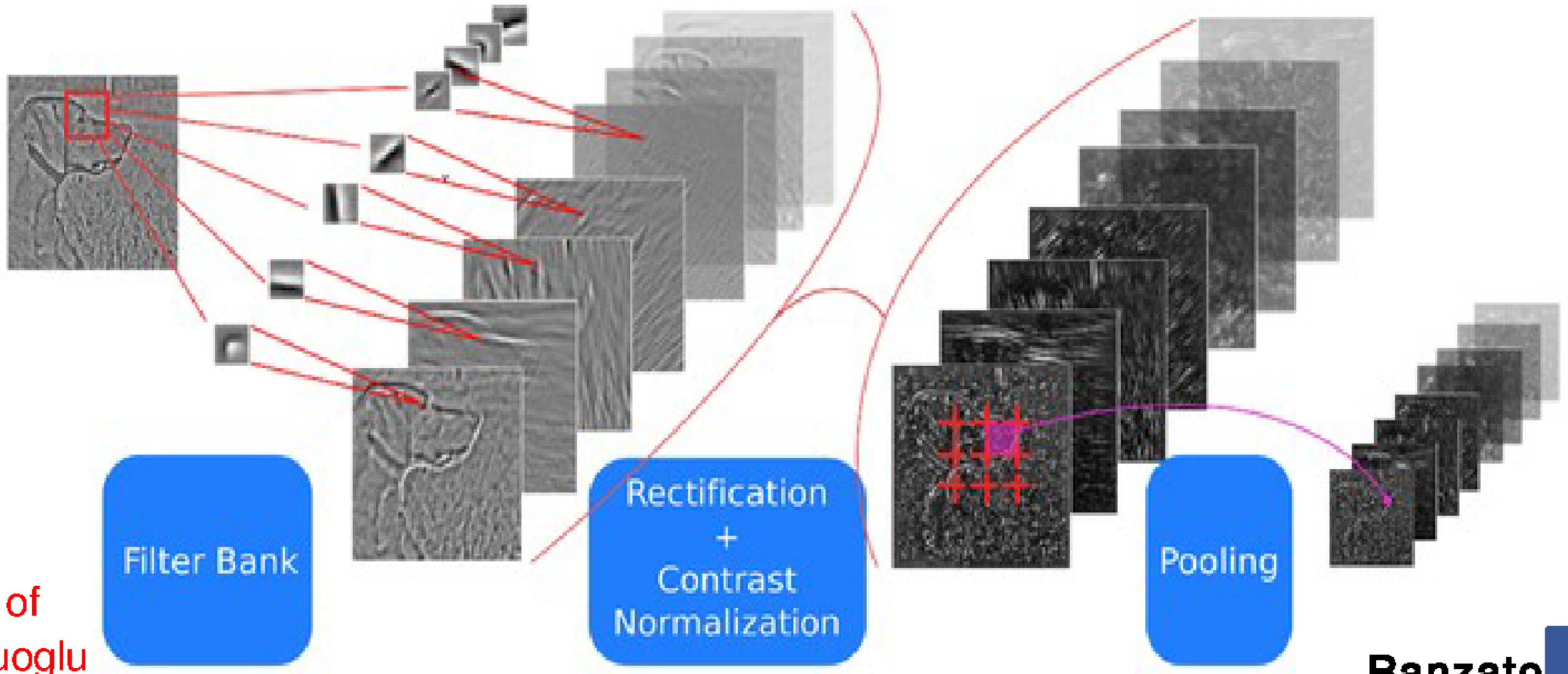
Performed also across features and in the higher layers..

Effects:
– improves invariance
– improves optimization
– increases sparsity

Note: computational cost is negligible w.r.t. conv. layer.

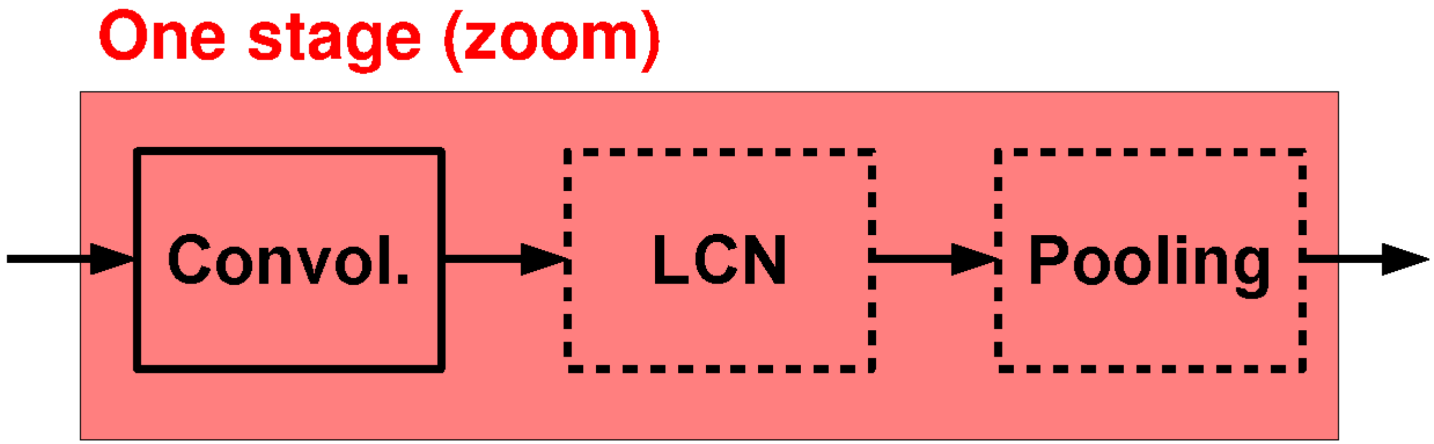
ConvNets: Typical Stage

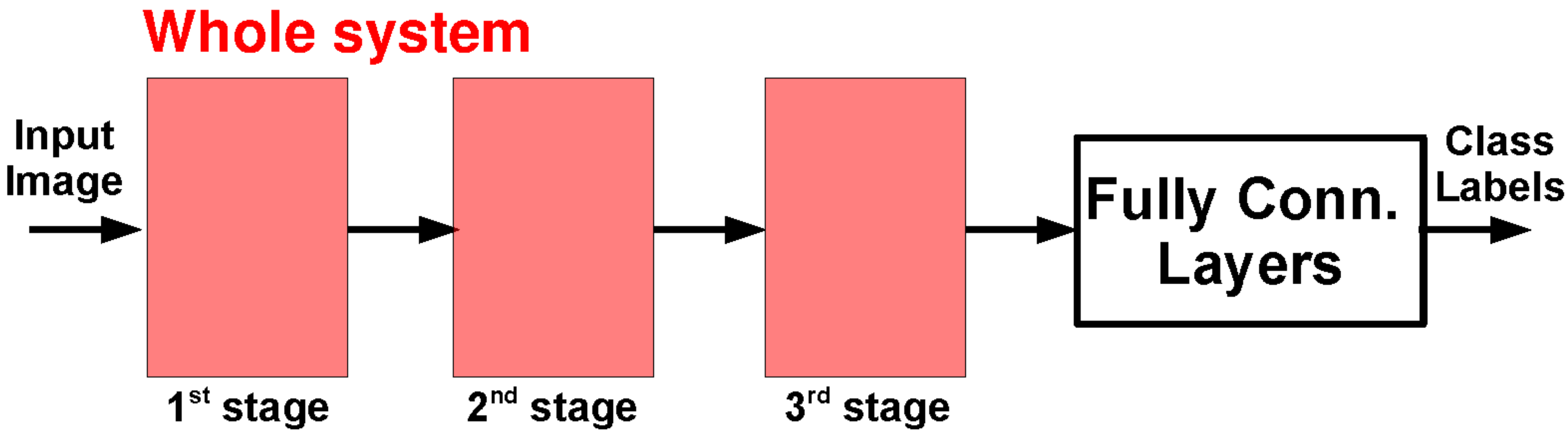




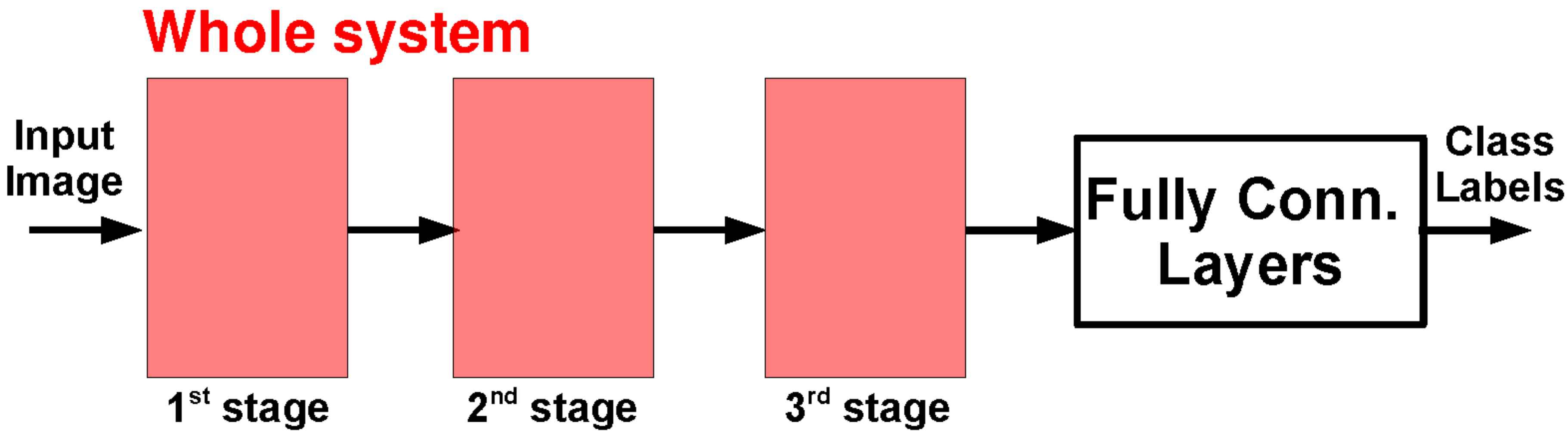
courtesy of
K. Kavukcuoglu

ConvNets: Typical Architecture





ConvNets: Typical Architecture



Conceptually similar to:

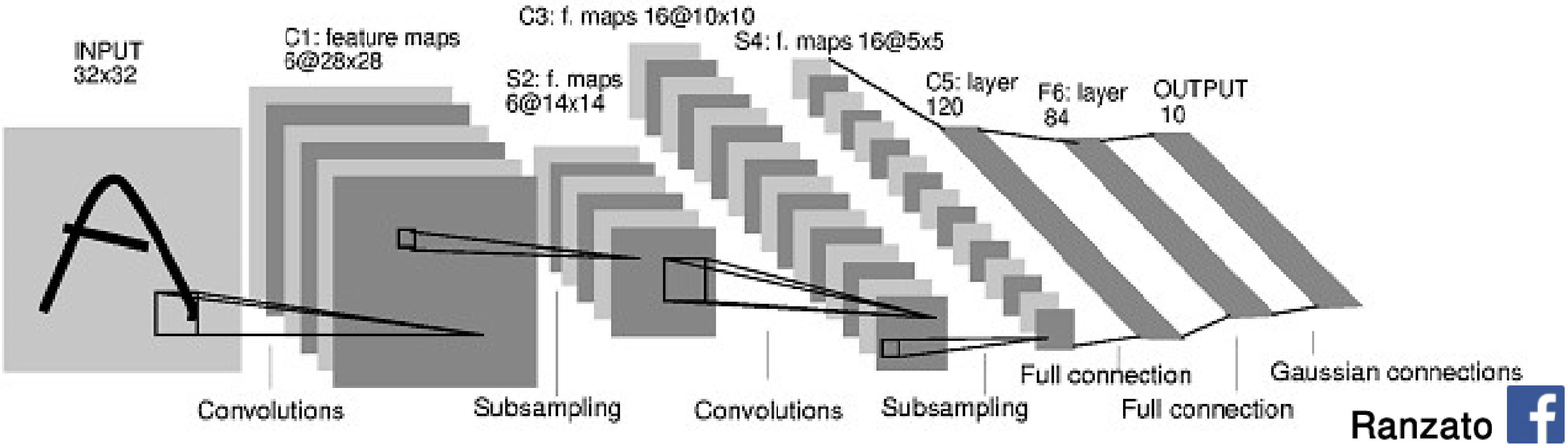
SIFT → K-Means → Pyramid Pooling → SVM

Lazebnik et al. "...Spatial Pyramid Matching..." CVPR 2006

SIFT → Fisher Vect. → Pooling → SVM

Sanchez et al. "Image classifcation with F.V.: Theory and practice" IJCV 2012

Yann LeCun's MNIST CNN architecture



DEMO

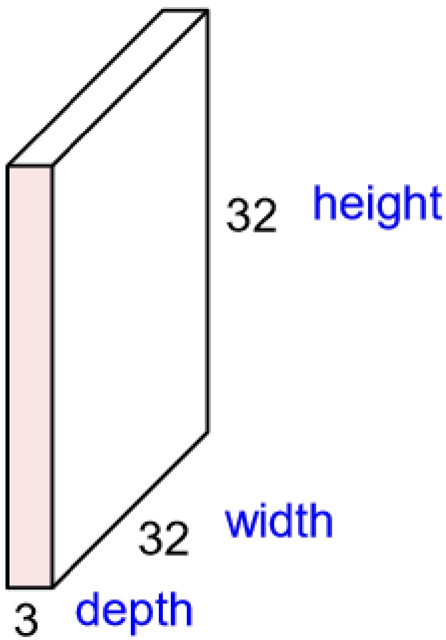
http://scs.ryerson.ca/~aharley/vis/conv/

Thanks to Adam Harley for making this.

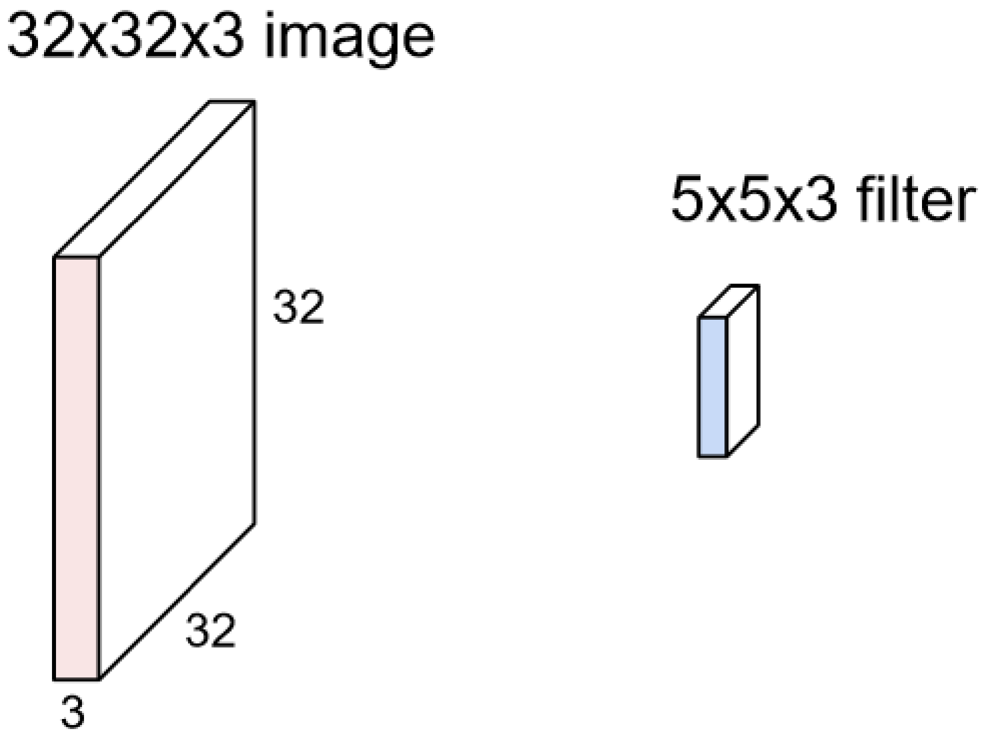
More here: http://scs.ryerson.ca/~aharley/vis

Convolutions: More detail

32x32x3 image



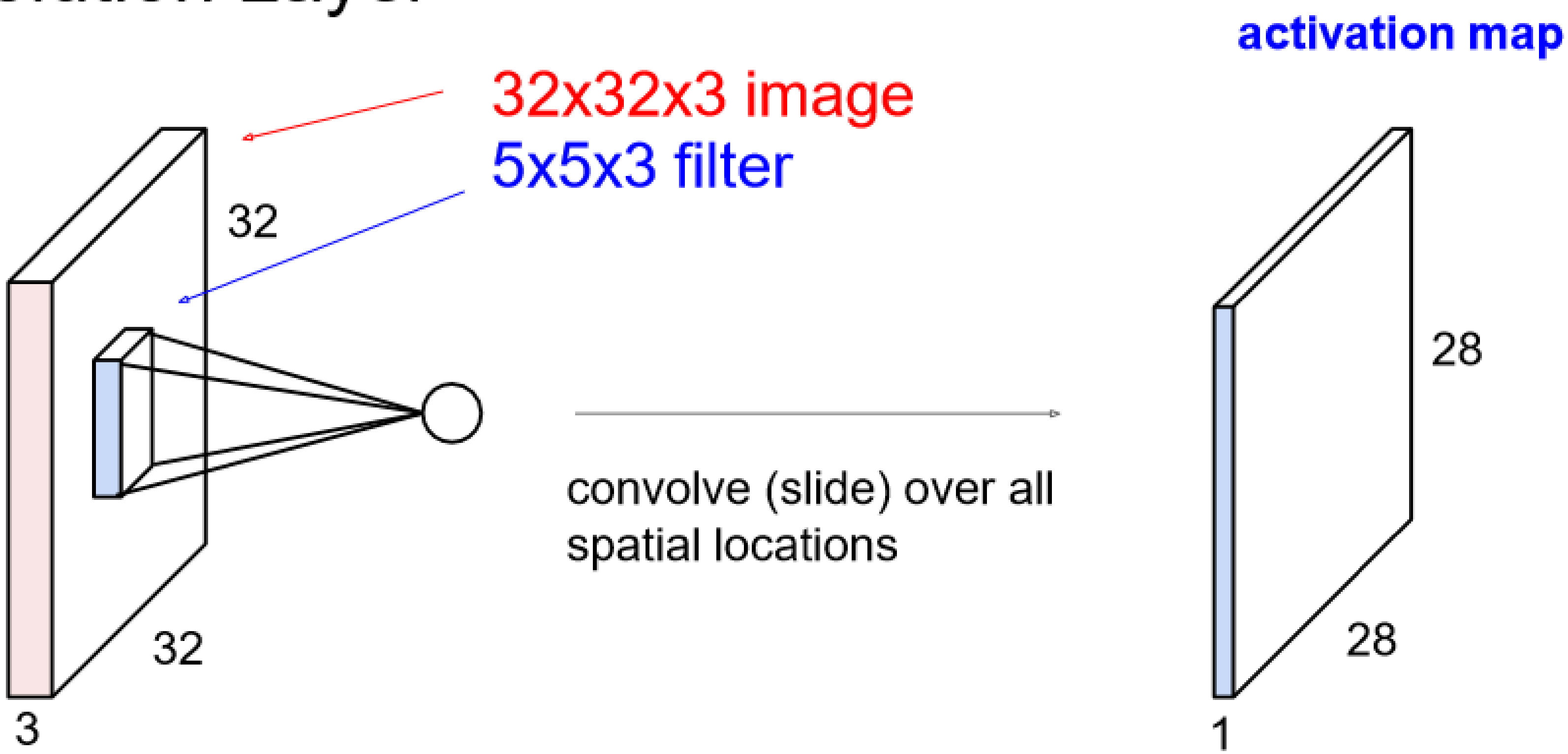
Convolutions: More detail



Andrej Karpathy

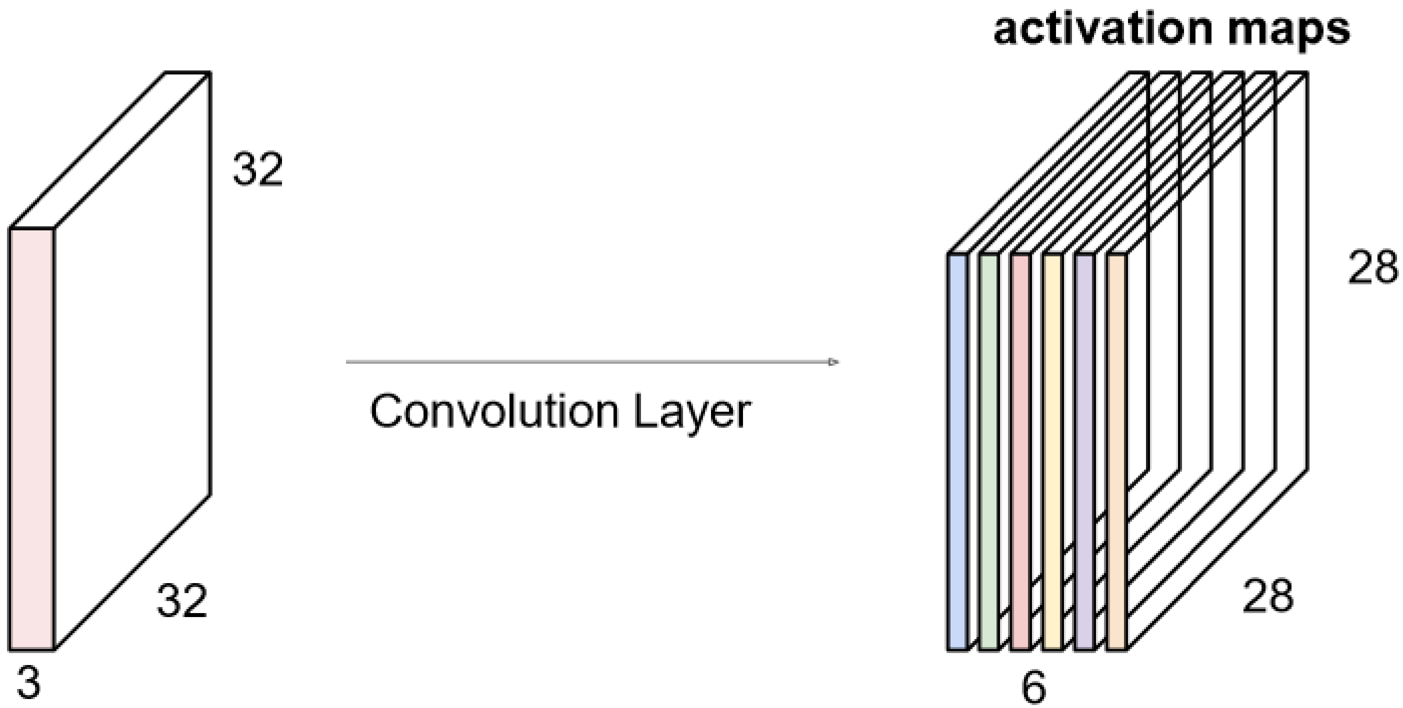
Convolutions: More detail

Convolution Layer



Convolutions: More detail

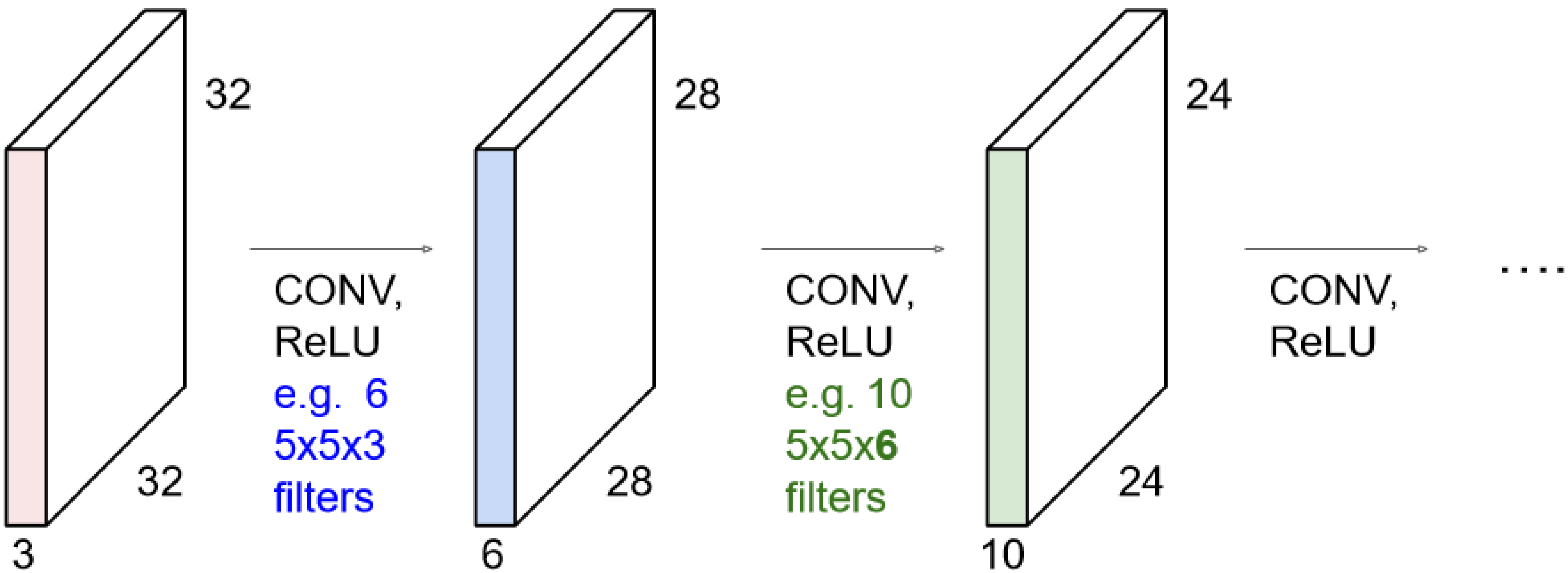
For example, if we had 6 5x5 filters, we'll get 6 separate activation maps:



We stack these up to get a "new image" of size 28x28x6!

Andrej Karpathy

Convolutions: More detail



Andrej Karpathy

Think-Pair-Share

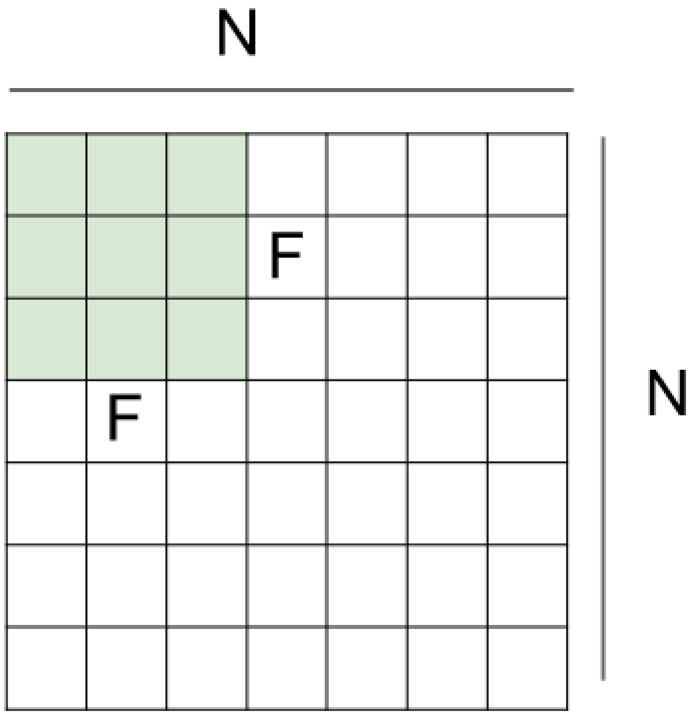
Input size: 96 x 96 x 3
Kernel size: 5 x 5 x 3
Stride: 1
Max pooling layer: 4 x 4

Output feature map size?
a) 5 x 5
b) 22 x 22
c) 23 x 23
d) 24 x 24
e) 25 x 25

Input size: 96 x 96 x 3
Kernel size: 3 x 3 x 3
Stride: 3
Max pooling layer: 8 x 8

Output feature map size?
a) 2 x 2
b) 3 x 3
c) 4 x 4
d) 5 x 5
e) 12 x 12

Convolutions: More detail



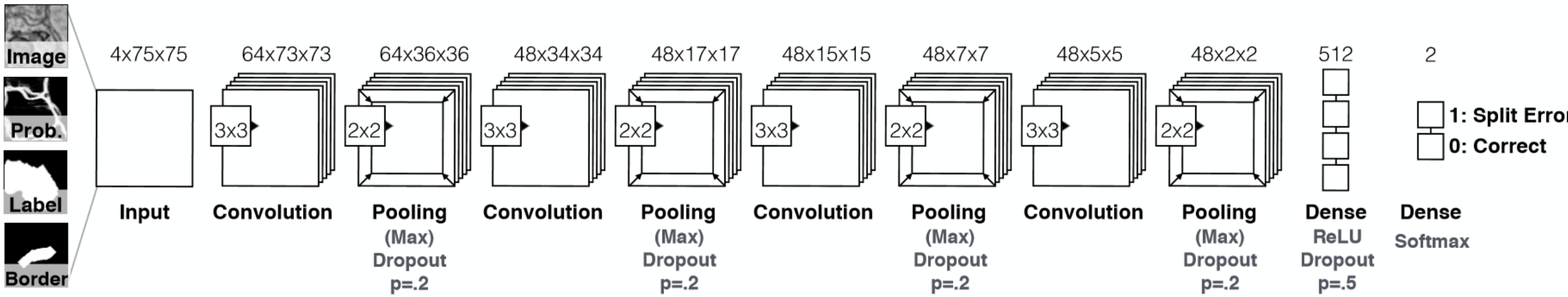
Output size:
(N - F) / stride + 1

Andrej Karpathy

Our connectomics diagram

Auto-generated from network declaration by *nolearn* (for Lasagne / Theano)

Input
75x75x4

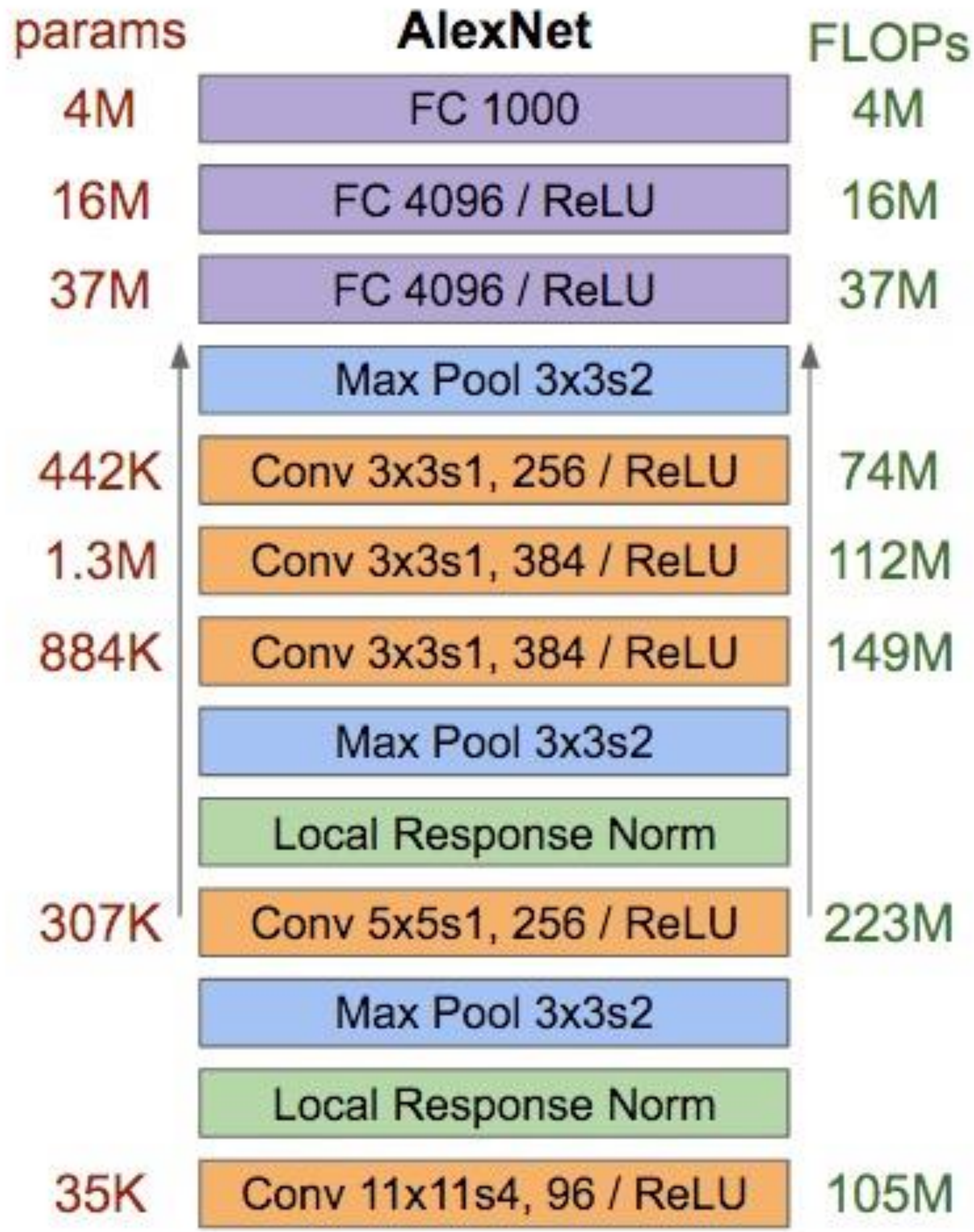


Conv 1	Conv 2	Conv 3	Conv 4
3x3x4	3x3x64	3x3x48	3x3x48
64 filters	48 filters	48 filters	48 filters

Max pooling	Max pooling	Max pooling	Max pooling
2x2 per filter	2x2 per filter	2x2 per filter	2x2 per filter

Reading architecture diagrams

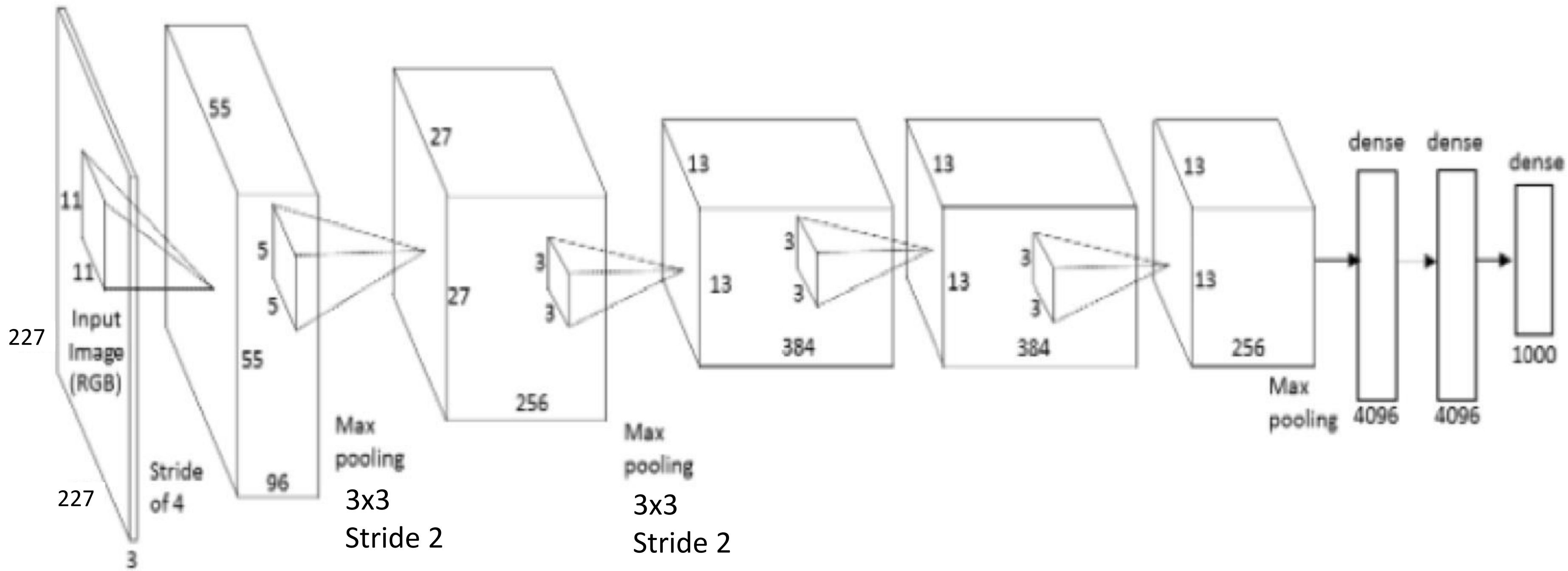
Layers
- Kernel sizes
- Strides
- # channels
- # kernels
- Max pooling



[Krizhevsky et al. 2012]

AlexNet diagram (simplified)

Input size
227 x 227 x 3



Conv 1
11 x 11 x 3
Stride 4
96 filters

Conv 2
5 x 5 x 96
Stride 1
256 filters

Conv 3
3 x 3 x 256
Stride 1
384 filters

Conv 4
3 x 3 x 192
Stride 1
384 filters

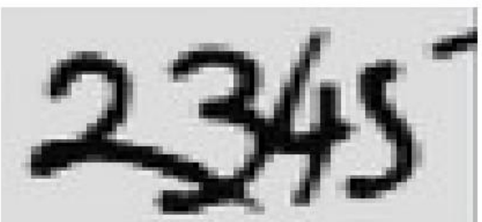
Conv 4
3 x 3 x 192
Stride 1
256 filters

Outline

- Supervised Neural Networks
- Convolutional Neural Networks
- Examples
- Tips

CONV NETS: EXAMPLES

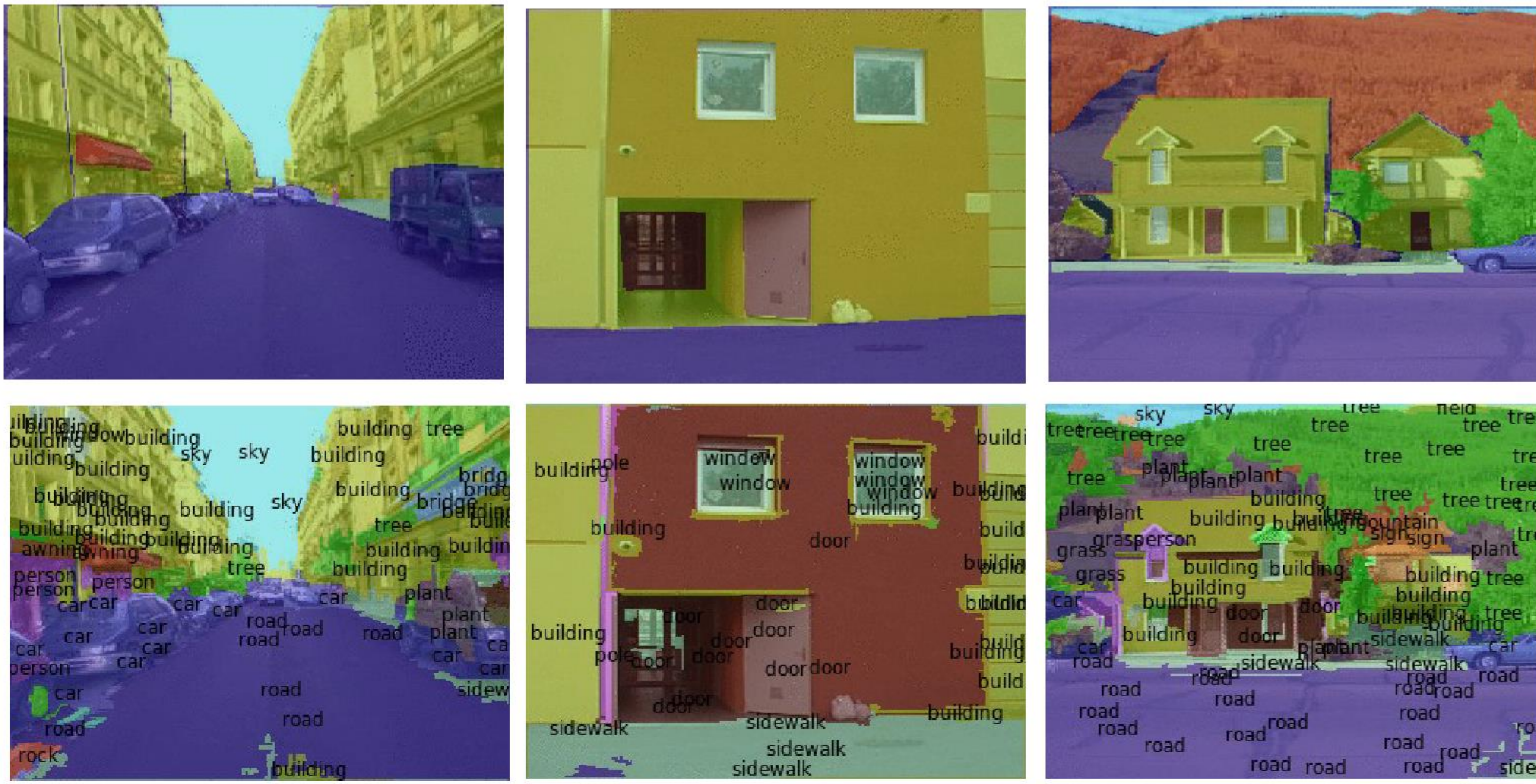
- **OCR / House number & Traffic sign classification**



Ciresan et al. "MCDNN for image classification" CVPR 2012
Wan et al. "Regularization of neural networks using dropconnect" ICML 2013
Jaderberg et al. "Synthetic data and ANN for natural scene text recognition" arXiv 2014

CONV NETS: EXAMPLES

- **Scene Parsing**



Farabet et al. "Learning hierarchical features for scene labeling" PAMI 2013
Pinheiro et al. "Recurrent CNN for scene parsing" arxiv 2013

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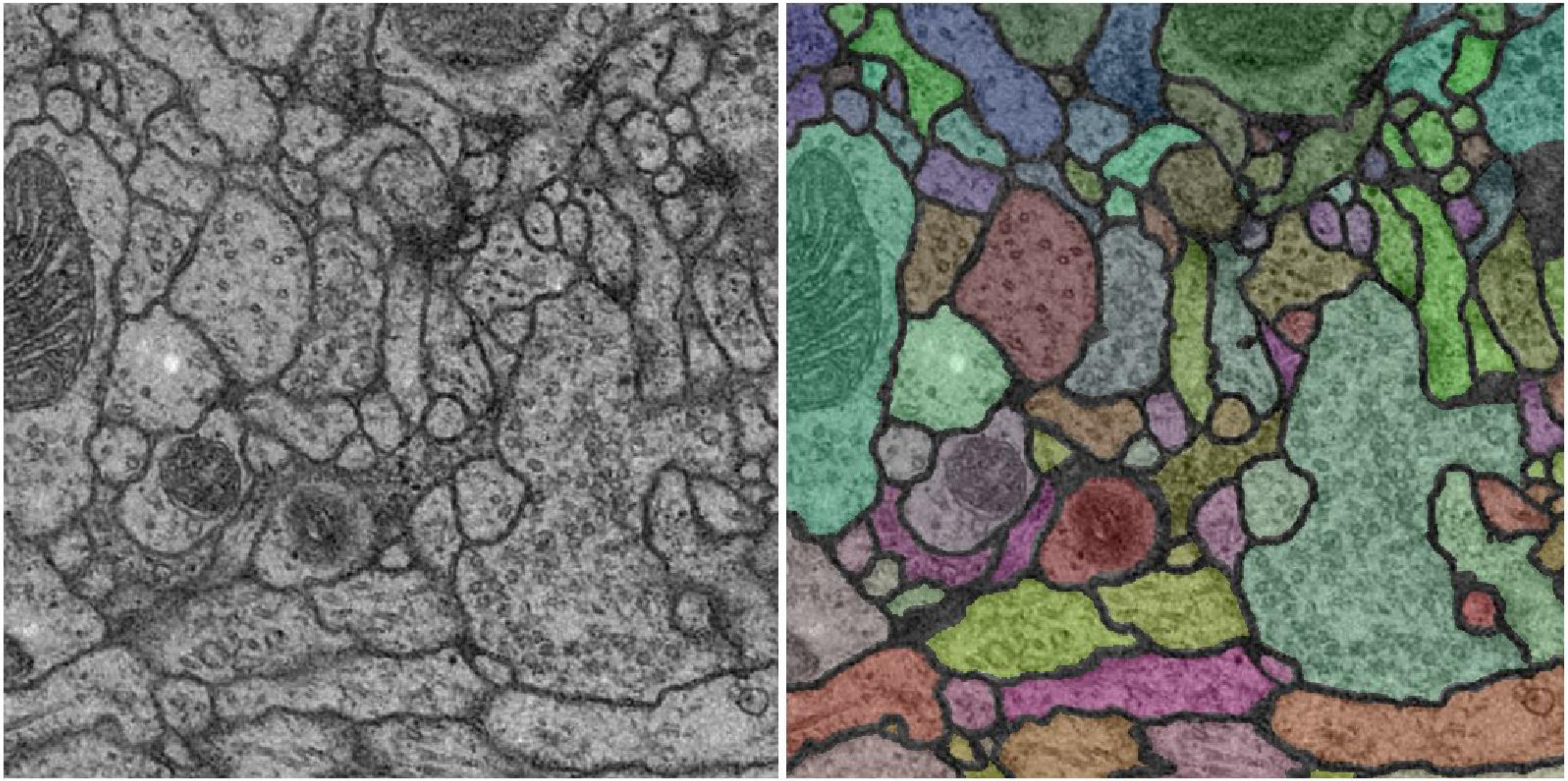
CONV NETS: EXAMPLES

- **Segmentation 3D volumetric images**



Ciresan et al. “DNN segment neuronal membranes...” NIPS 2012
Turaga et al. “Maximin learning of image segmentation” NIPS 2009

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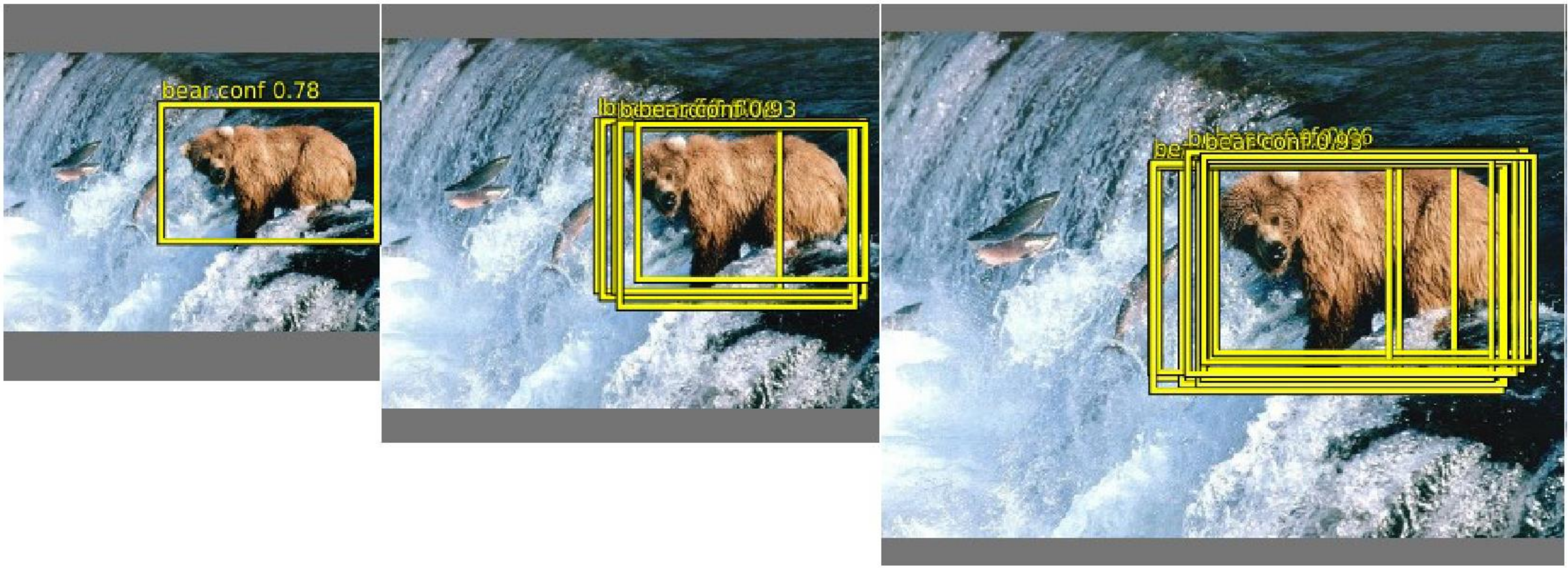
CONV NETS: EXAMPLES

- **Object detection**



Sermanet et al. “OverFeat: Integrated recognition, localization, ...” arxiv 2013
Girshick et al. “Rich feature hierarchies for accurate object detection...” arxiv 2013
Szegedy et al. “DNN for object detection” NIPS 2013

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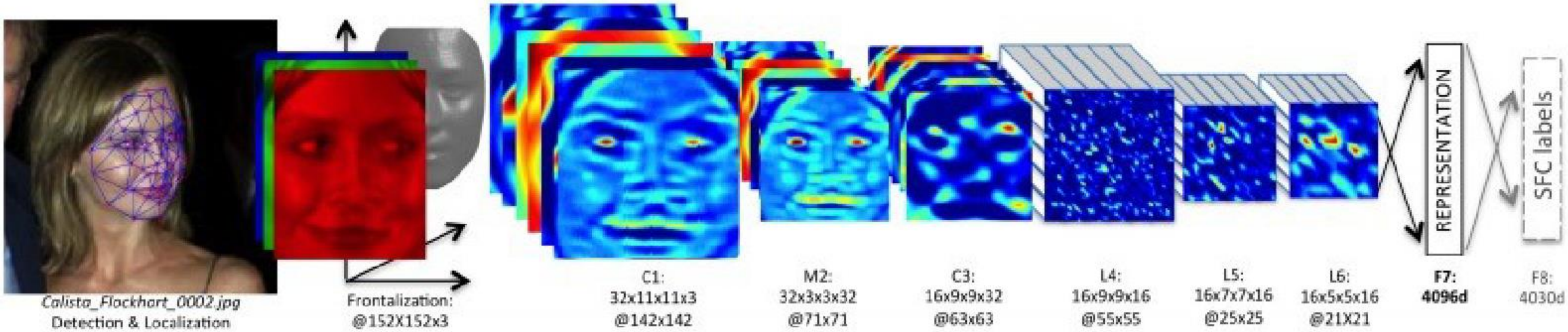
CONV NETS: EXAMPLES

- **Face Verification & Identification**



Taigman et al. "DeepFace..." CVPR 2014

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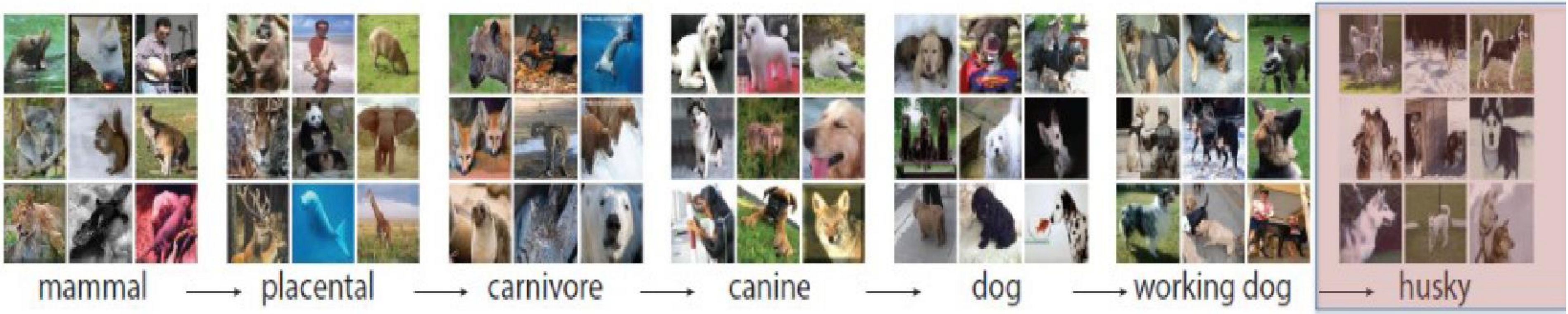
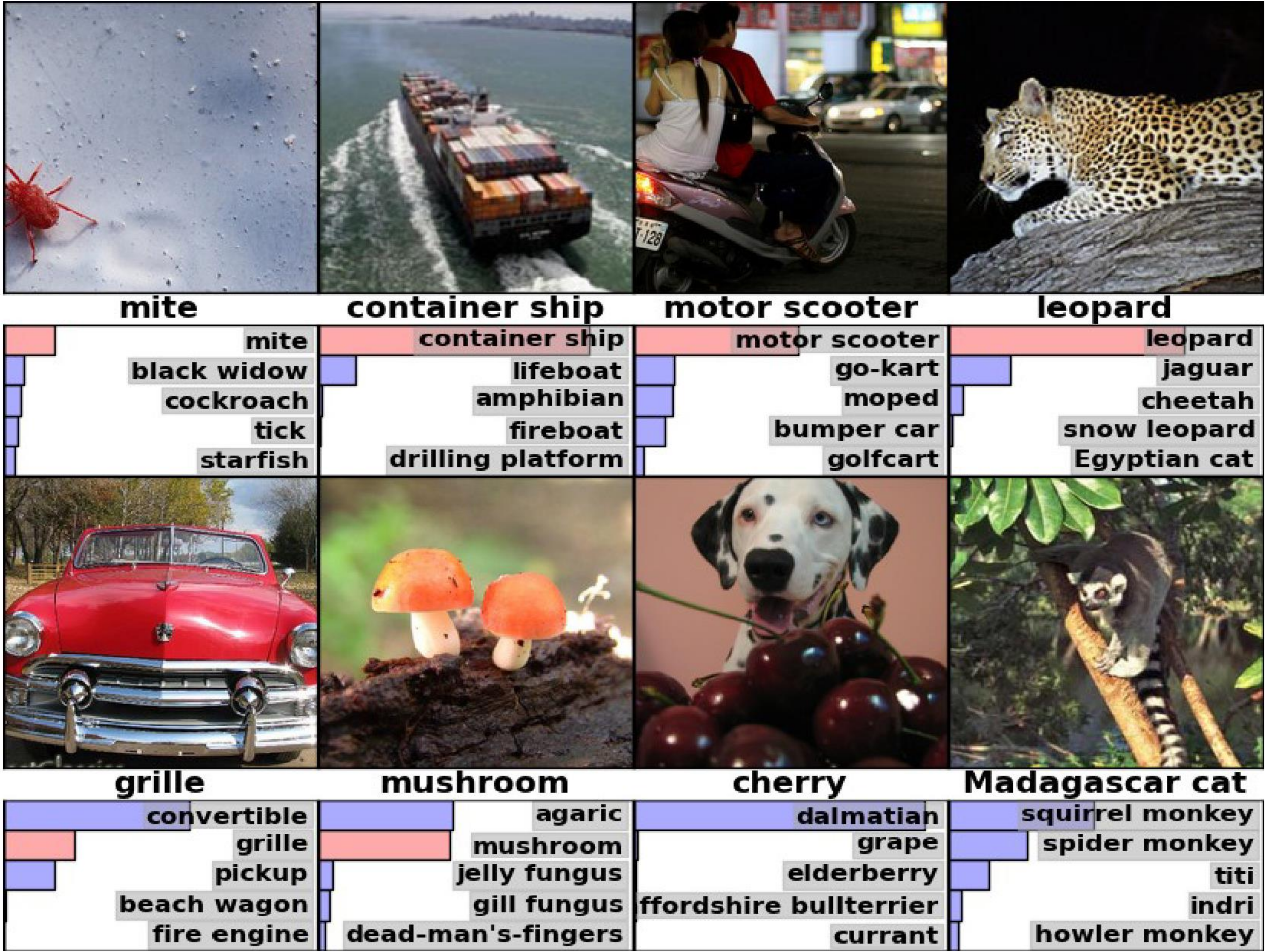
Dataset: ImageNet 2012

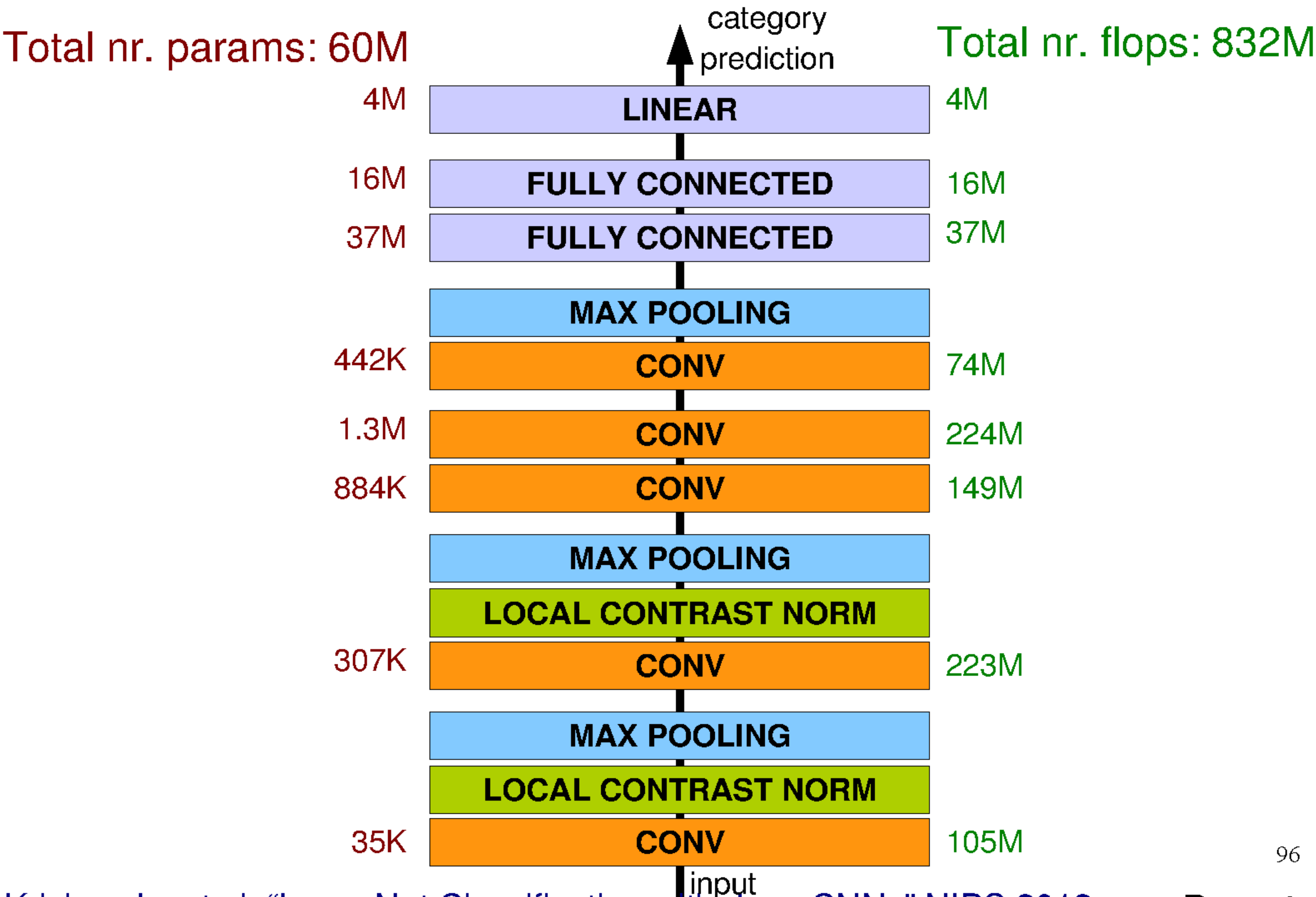


- S: (n) Eskimo dog, **husky** (breed of heavy-coated Arctic sled dog)
  - *direct hypernym* / ***inherited hypernym*** / *sister term*
    - S: (n) working dog (any of several breeds of usually large powerful dogs bred to work as draft animals and guard and guide dogs)
      - S: (n) dog, domestic dog, Canis familiaris (a member of the genus Canis (probably descended from the common wolf) that has been domesticated by man since prehistoric times; occurs in many breeds) *"the dog barked all night"*
        - S: (n) canine, canid (any of various fissiped mammals with nonretractile claws and typically long muzzles)
          - S: (n) carnivore (a terrestrial or aquatic flesh-eating mammal) *"terrestrial carnivores have four or five clawed digits on each limb"*
            - S: (n) placental, placental mammal, eutherian, eutherian mammal (mammals having a placenta; all mammals except monotremes and marsupials)
              - S: (n) mammal, mammalian (any warm-blooded vertebrate having the skin more or less covered with hair; young are born alive except for the small subclass of monotremes and nourished with milk)
                - S: (n) vertebrate, craniate (animals having a bony or cartilaginous skeleton with a segmented spinal column and a large brain enclosed in a skull or cranium)
                  - S: (n) chordate (any animal of the phylum Chordata having a notochord or spinal column)
                    - S: (n) animal, animate being, beast, brute, creature, fauna (a living organism characterized by voluntary movement)
                      - S: (n) organism, being (a living thing that has (or can develop) the ability to act or function independently)
                        - S: (n) living thing, animate thing (a living (or once living) entity)
                          - S: (n) whole, unit (an assemblage of parts that is regarded as a single entity) *"how big is that part compared to the whole?"; "the team is a unit"*
                            - S: (n) object, physical object (a tangible and visible entity; an entity that can cast a shadow) *"it was full of rackets, balls and other objects"*
                              - S: (n) physical entity (an entity that has physical existence)
                                - S: (n) entity (that which is perceived or known or inferred to have its own distinct existence (living or nonliving))

Deng et al. "Imagenet: a large scale hierarchical image database" CVPR 2009


mite
mite
black widow
cockroach
tick
starfish
container ship
container ship
lifeboat
amphibian
fireboat
drilling platform
motor scooter
motor scooter
go-kart
moped
bumper car
golfcart
leopard
leopard
jaguar
cheetah
snow leopard
Egyptian cat
grille
convertible
grille
pickup
beach wagon
fire engine
mushroom
agaric
mushroom
jelly fungus
gill fungus
dead-man's-fingers
cherry
dalmatian
grape
elderberry
ffordshire bullterrier
currant
Madagascar cat
squirrel monkey
spider monkey
titi
indri
howler monkey

Architecture for Classification



Krizhevsky et al. "ImageNet Classification with deep CNNs" NIPS 2012

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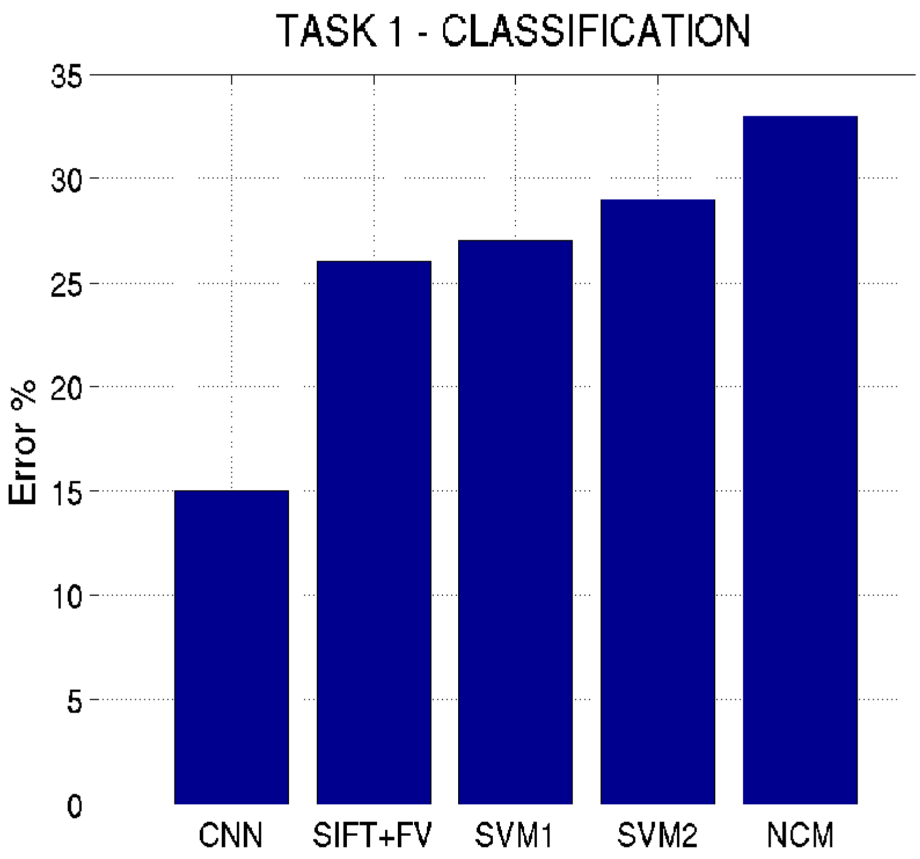
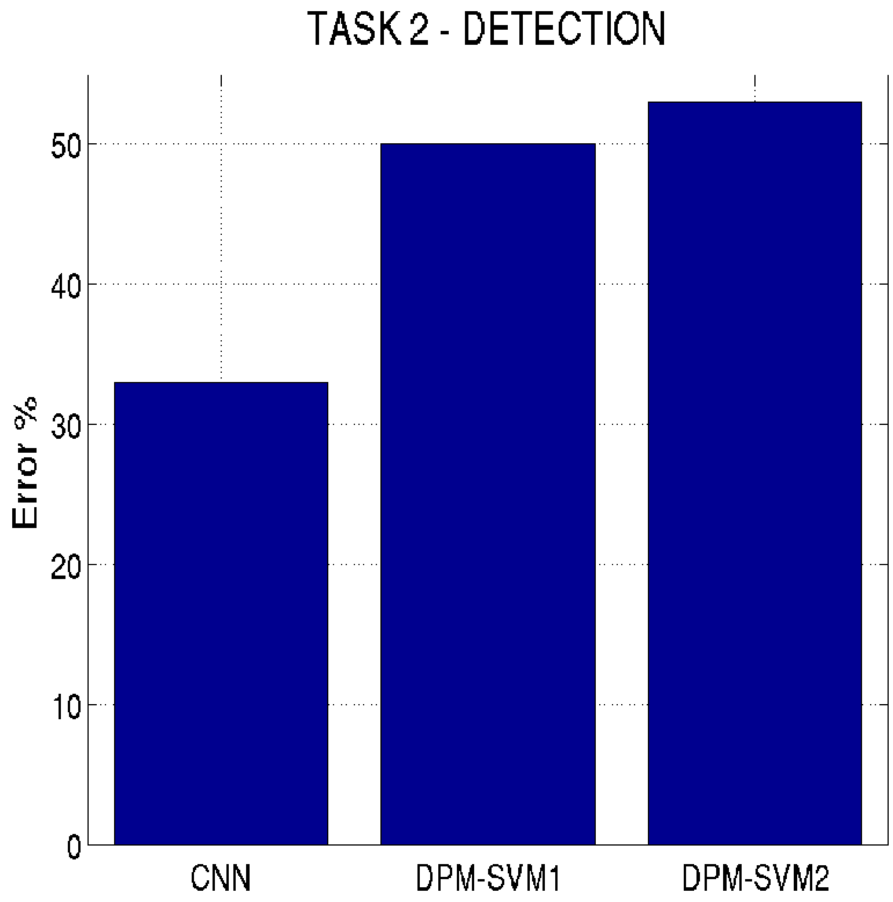
Results: ILSVRC 2012





Krizhevsky et al. “ImageNet Classification with deep CNNs” NIPS 2012

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Wait, why isn't it called a correlation neural network?

It could be.

Deep learning libraries actually implement correlation.

Correlation relates to convolution via a 180deg rotation of the kernel. When we *learn* kernels, we could easily learn them flipped.

Associative property of convolution ends up not being important to our application, so we just ignore it.

[p.323, Goodfellow]

Phew!

Monday:

How to Train your ~~Dragon~~ Network

Project 4: Out Friday

- Questions
- Code part 1

Due 15^{th}.

More ConvNet explanations

- https://ujjwalkarn.me/2016/08/11/intuitive-explanation-convnets/