

# lecture 1: introduction

## deep learning for vision

Yannis Avrithis

Inria Rennes-Bretagne Atlantique

Rennes, Nov. 2017 – Jan. 2018



# outline

**research field**

**psychology and neuroscience background**

**computer vision background**

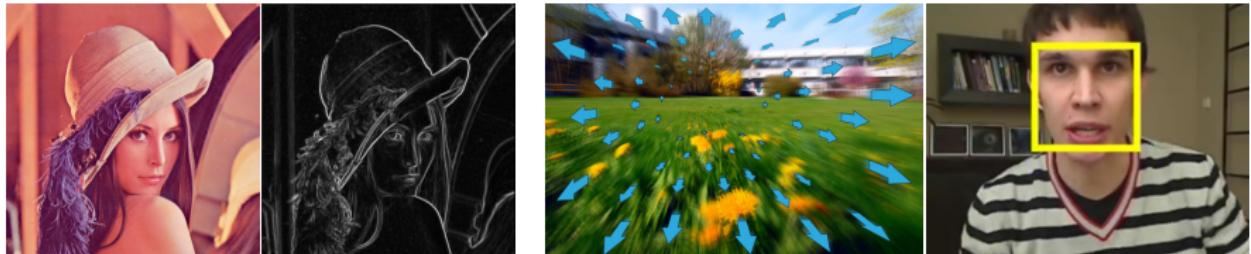
**machine learning background**

**modern deep learning**

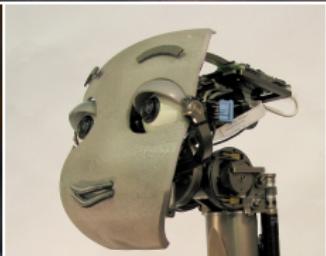
**about this course**

# research field

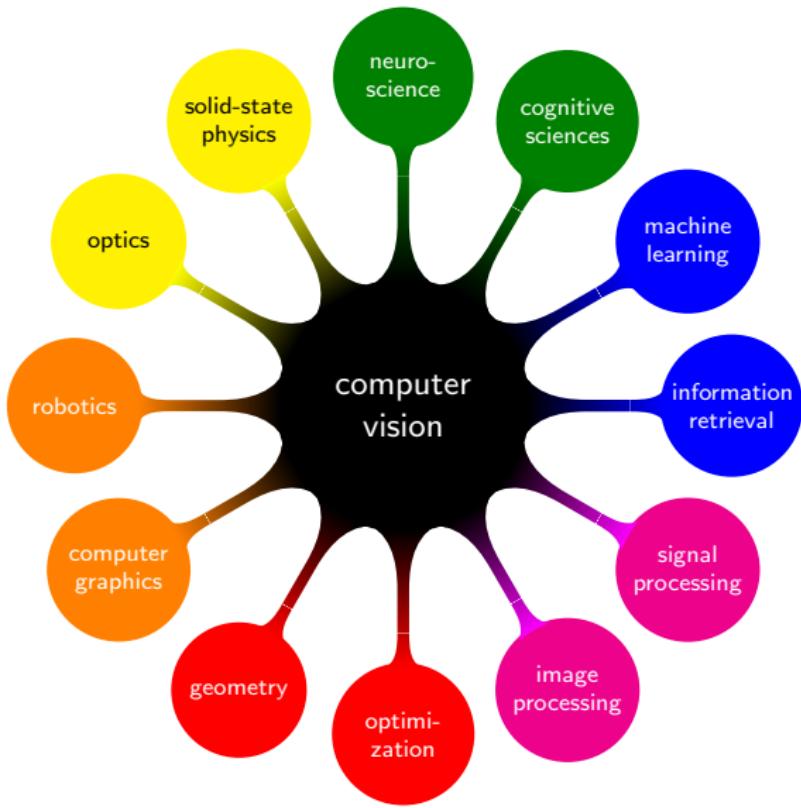
# computer vision in images



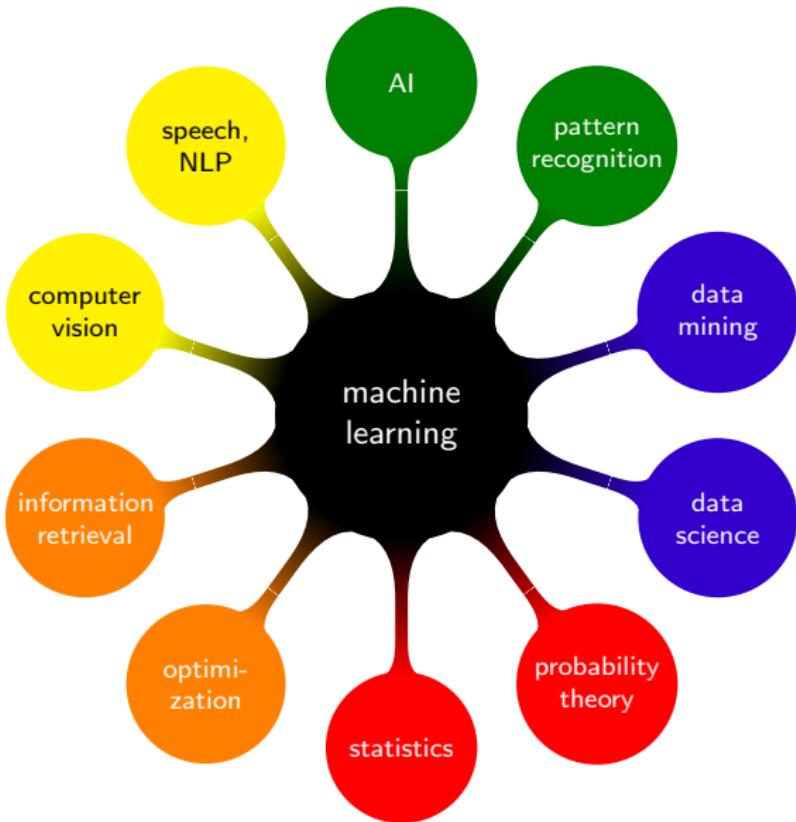
# computer vision in images



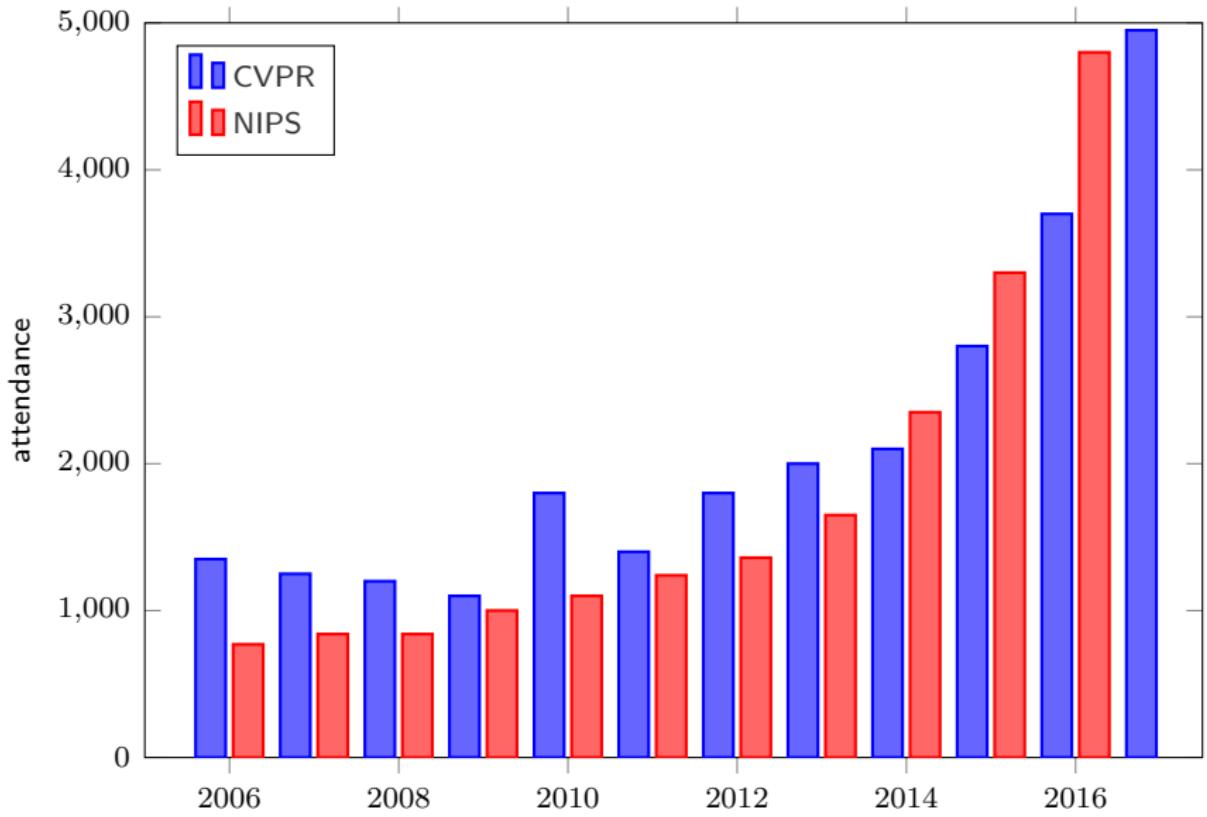
# computer vision—related fields



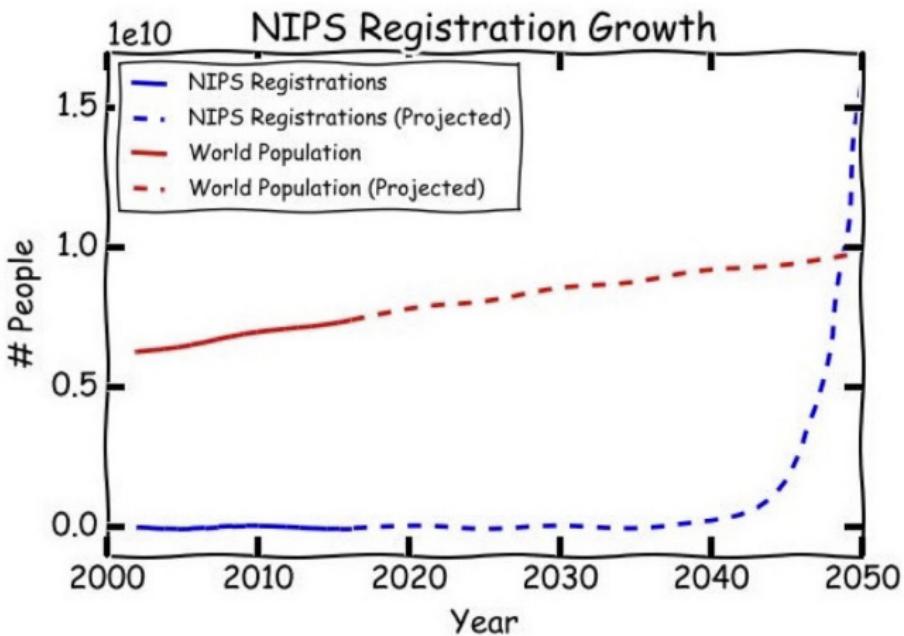
# machine learning—related fields



# conference attendance growth



really?



# CVPR 2017 sponsors



DEEPLINT  
格灵深瞳



Tencent 腾讯

NAVER | LINE



SAMSUNG



Dream-Future  
视源股份



码隆



UBER ATG



AIMATTER

SIEMENS  
Healthineers



Honda  
Research  
Institute USA



ALL PROGRAMMABLE™



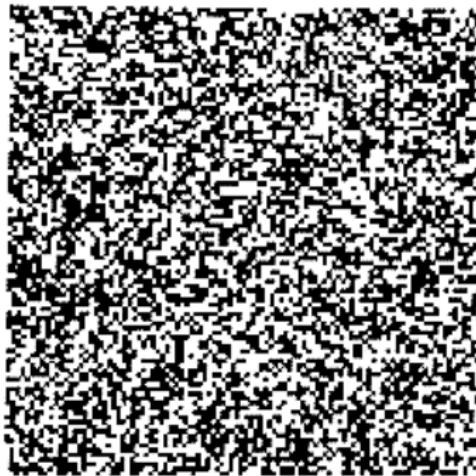
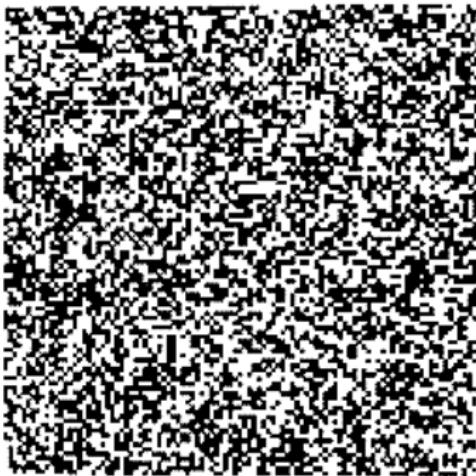
# hype cycle



Source: Gartner (July 2016)

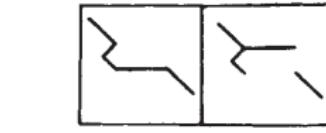
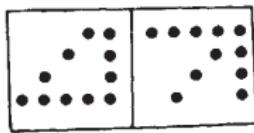
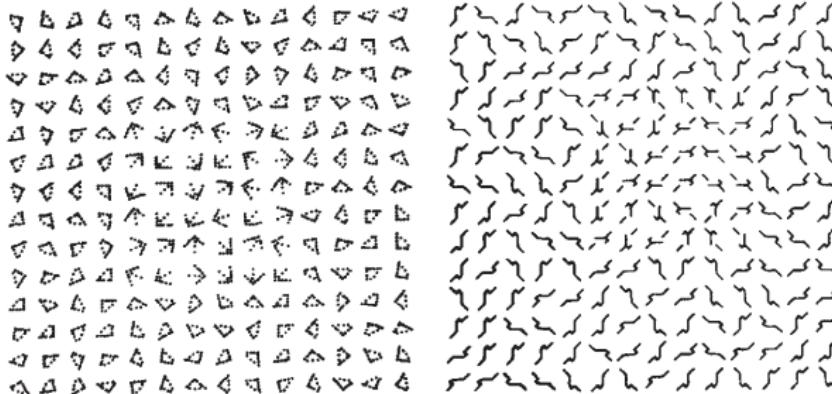
# psychology and neuroscience background

## non-invasive: Béla Julesz



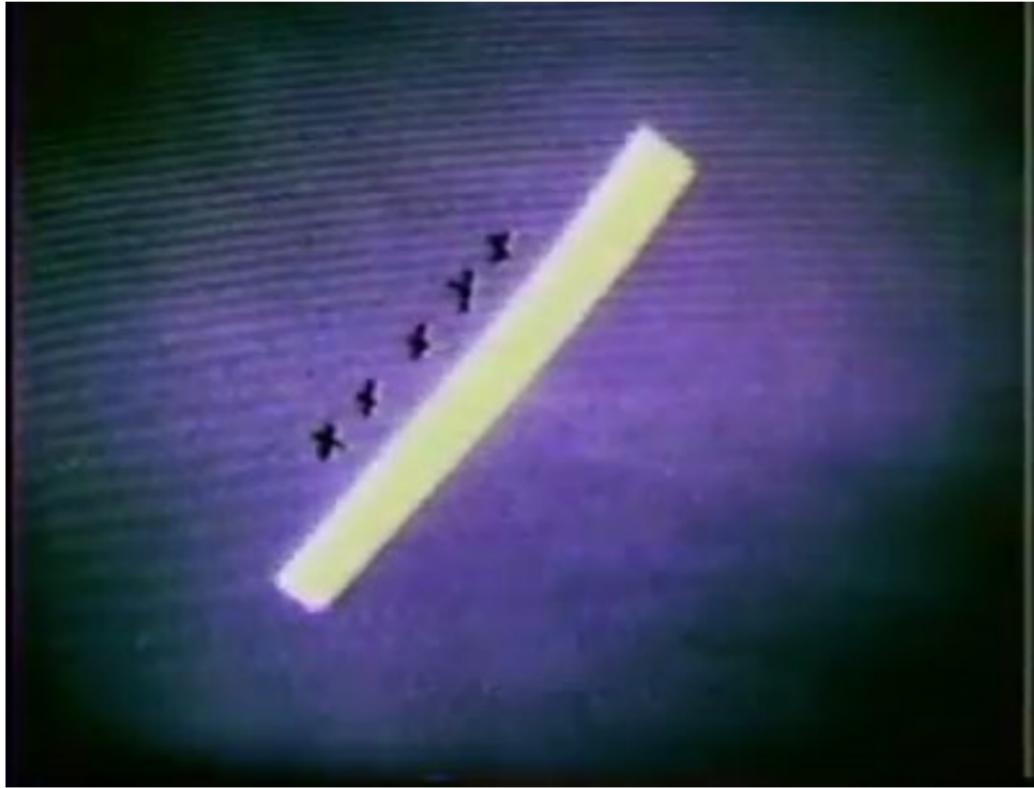
- which happens first? stereopsis or recognition?
- **random dot stereogram:** two identical images, except for a central square region that is displaced randomly in one image
- yields the impression of the square floating over the background

# non-invasive: Béla Julesz



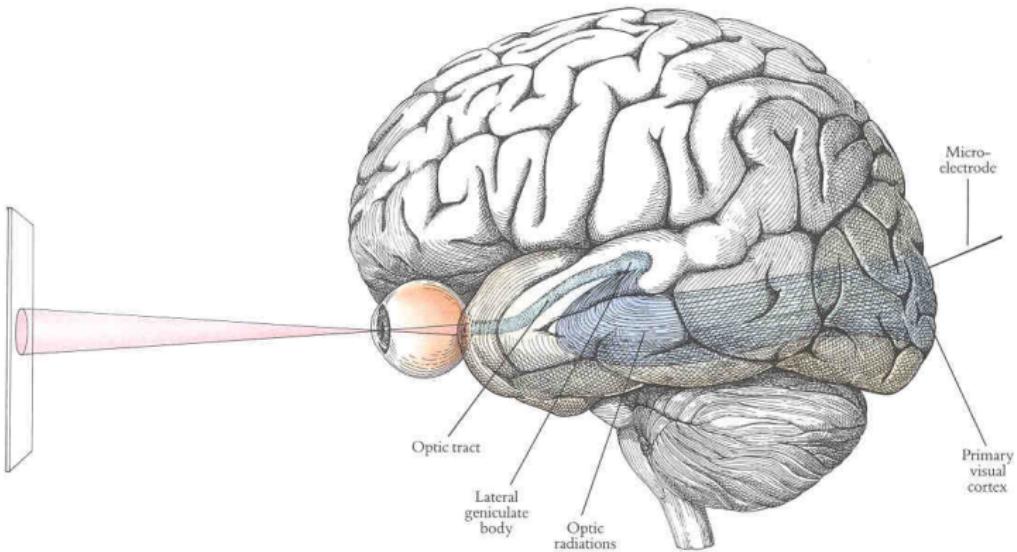
- study of pre-attentive (effortless, instantaneous) texture discrimination
- texture pairs with identical second order statistics
- **textons**: “basic elements of pre-attentive human texture perception”

# invasive: Hubel & Wiesel

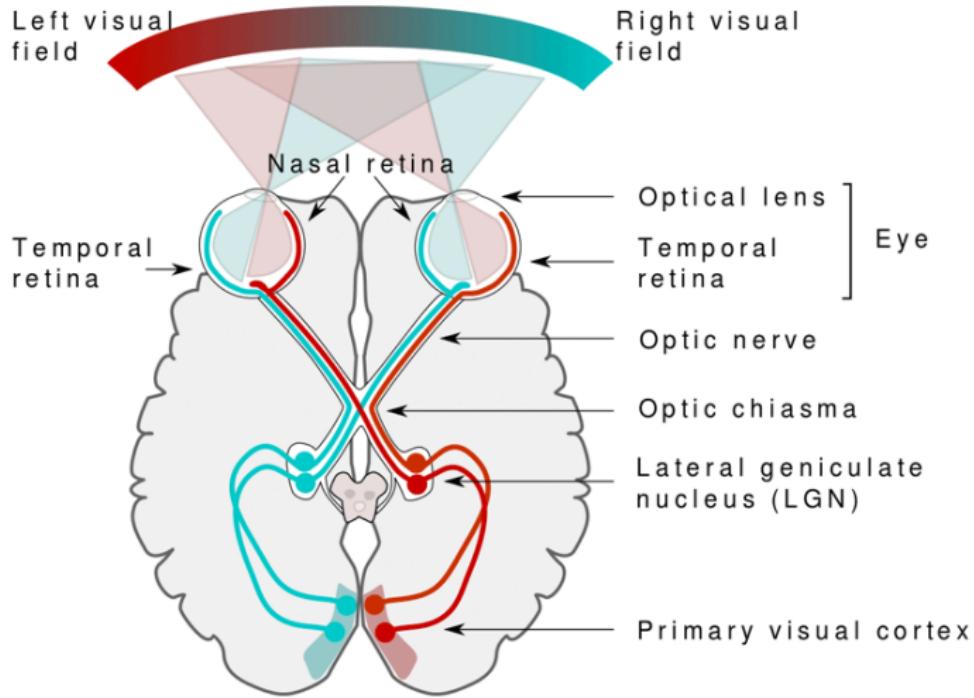


Hubel and Wiesel. JP 1959. Receptive Fields of Single Neurones in the Cat's Striate Cortex.

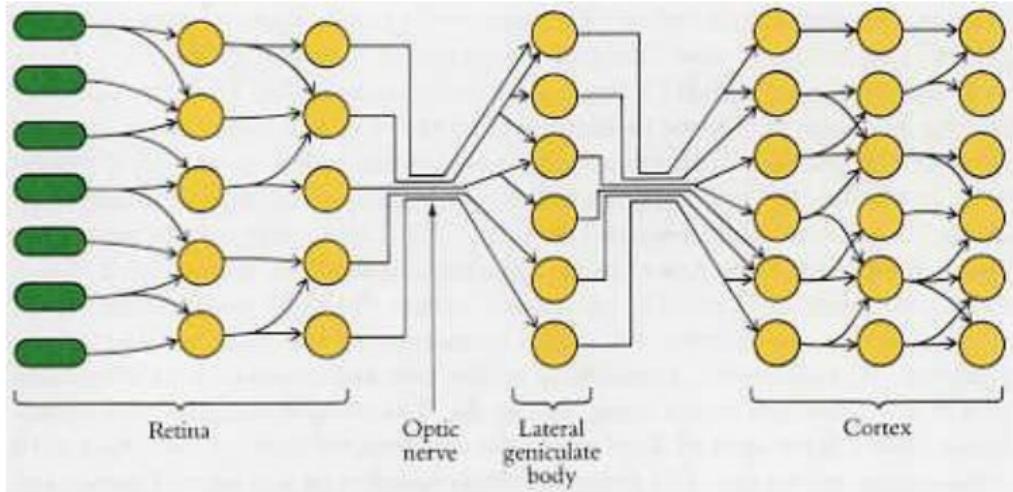
## **visual system of mammals**



# visual pathway

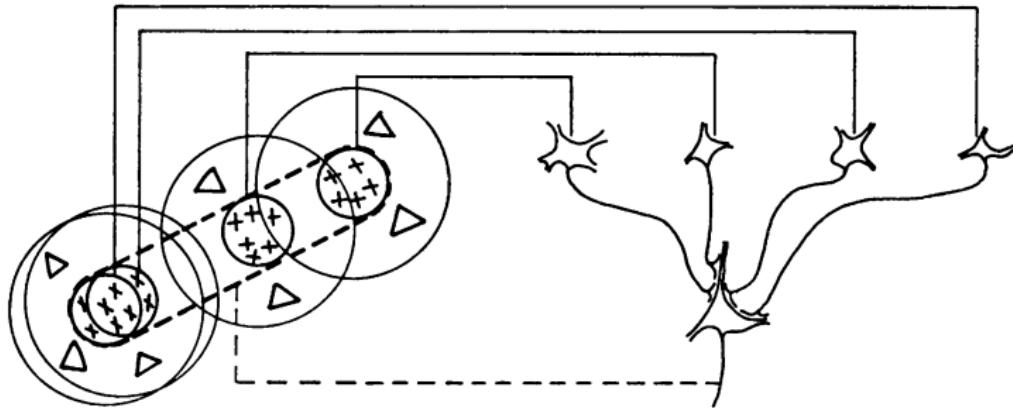


## topographic representation



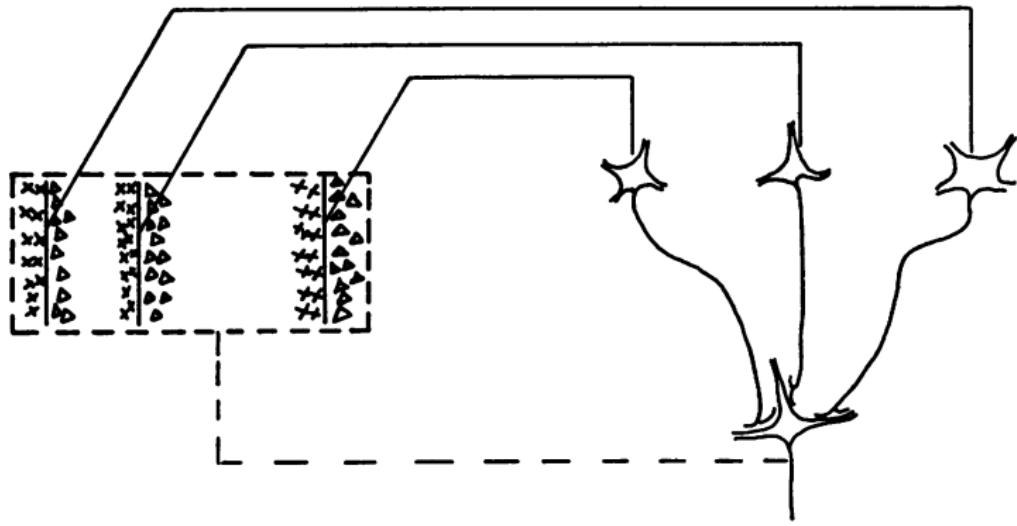
- as you move along the retina, the corresponding points in the cortex trace a continuous path
  - each column represents a two-dimensional array of cells

## simple cells



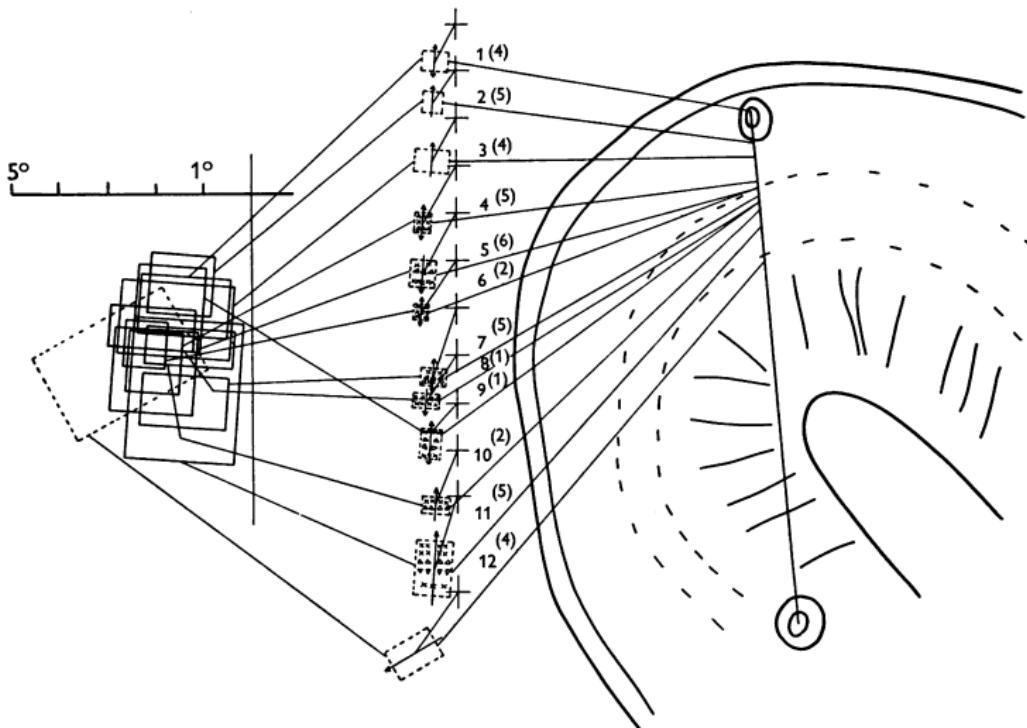
- lower-order cells with radially symmetric receptive field with on-center and off-surround
- cells centered along a line with excitatory synaptic connections to a cell of higher order

## complex cells



- simple cells respond to a vertically oriented edge
- cells scattered throughout a rectangle with excitatory synaptic connections to a complex cell

# electrode recordings



# computer vision background

# the summer vision project

[Papert 1966]

“The summer vision project is an attempt to use our summer workers effectively in the construction of a significant part of a visual system. The particular task was chosen partly because it can be segmented into sub-problems which allow individuals to work independently and yet participate in the construction of a system complex enough to be a real landmark in the development of "pattern recognition".”

# general goals

## FIGURE-GROUND

“divide a picture into regions such as likely objects, likely background areas and chaos”

## REGION DESCRIPTION

“analysis of shape and surface properties”

## OBJECT IDENTIFICATION

“name objects by matching them with a vocabulary of known objects”

# specific goals

## July

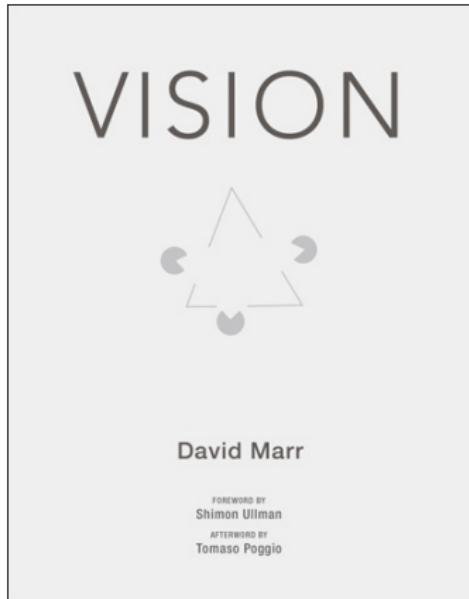
- “non-overlapping objects like balls, bricks, cylinders”
- “each face will be of uniform and distinct color and/or texture”
- “background will be homogeneous”

## August

- “complex surfaces and background, e.g. cigarette pack with writing, or a cylindrical battery”
- “objects like tools, cups, etc.”

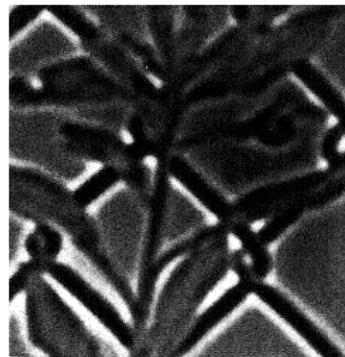
# David Marr, “Vision”

[Marr 1982]

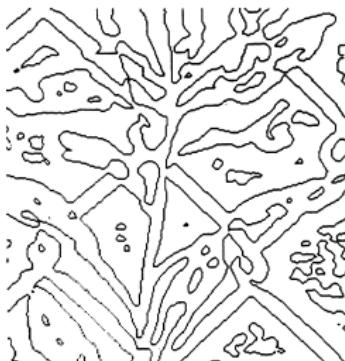


- **biological plausibility**: turning psychology and neuroscience results into models of visual information processing
- **inverse graphics**: from images to surfaces through geometric and photometric models
- **philosophy**: levels of analysis, processing stages, generic principles

# edge detection

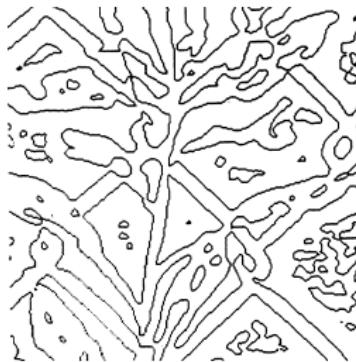


sign



zero crossings

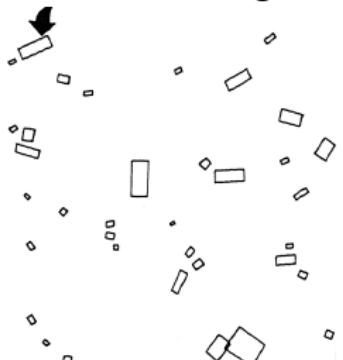
## raw primal sketch



zero crossings



edge segments

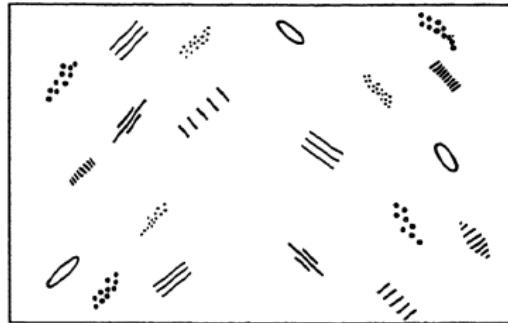


blobs

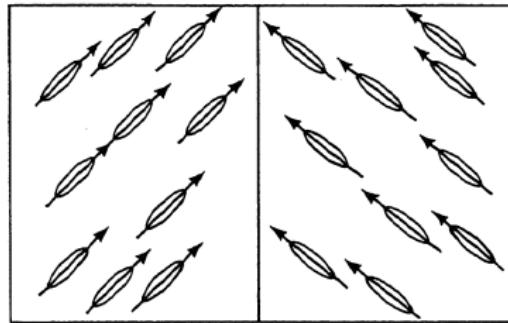


bars

# full primal sketch

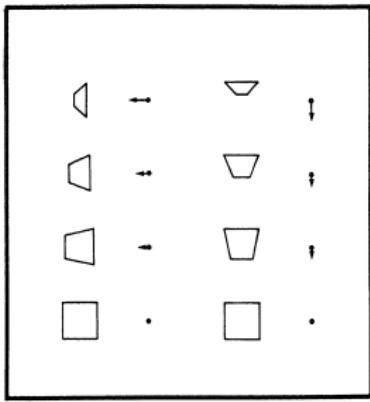


image

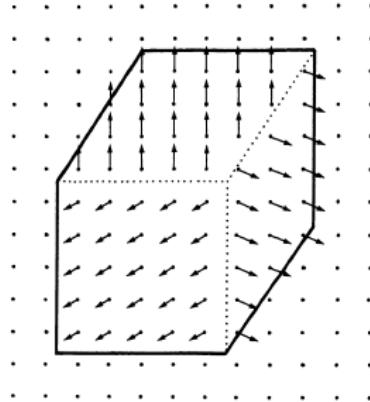


hierarchical grouping of tokens

## 2.5d sketch



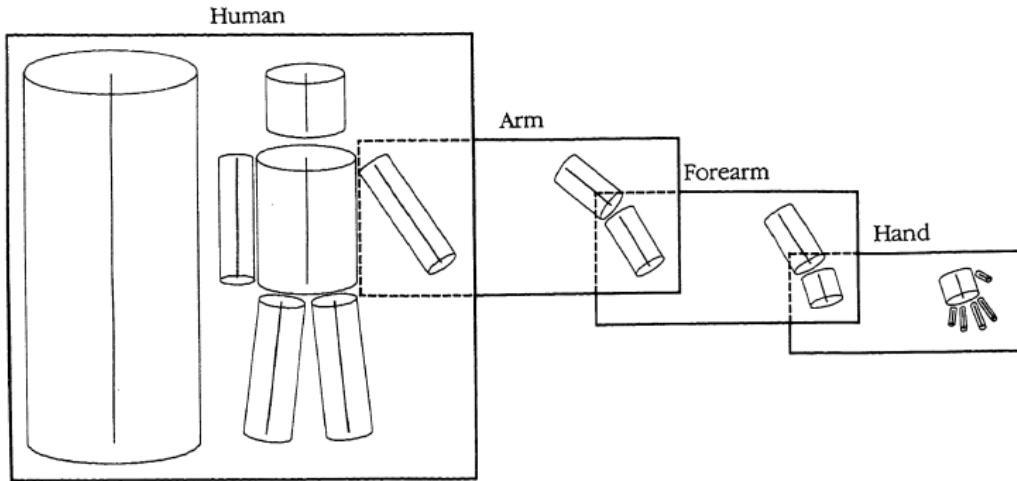
surface orientation



2.5d sketch

- surface orientation (vector field), surface orientation discontinuities (dotted lines), depth discontinuities (continuous lines)
- obtained via stereopsis, optical flow, motion parallax, photometric stereo

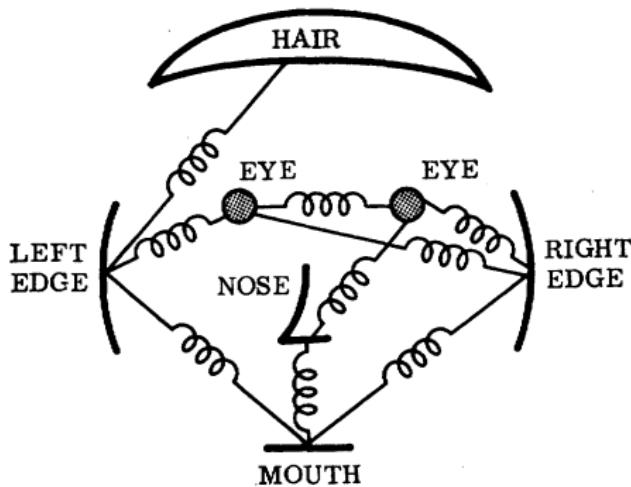
# 3d model representation



- hierarchical 3d model description
- parts of limited complexity, specified in local coordinate systems
- flexible, allowing for relative part transformation

# pictorial structures

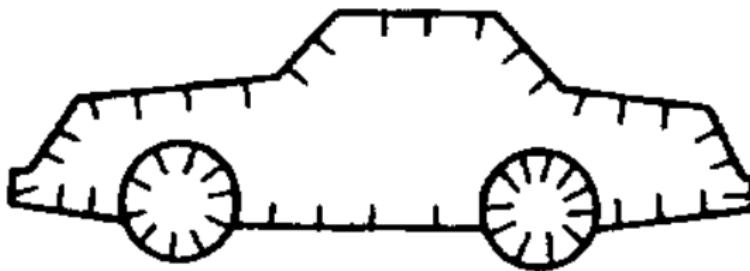
[Fischler and Elschlager 1973]



- manually specified object description
- parts-based model: part attributes and pairwise spatial relations
- efficient dynamic programming implementation

# generalized Hough transform

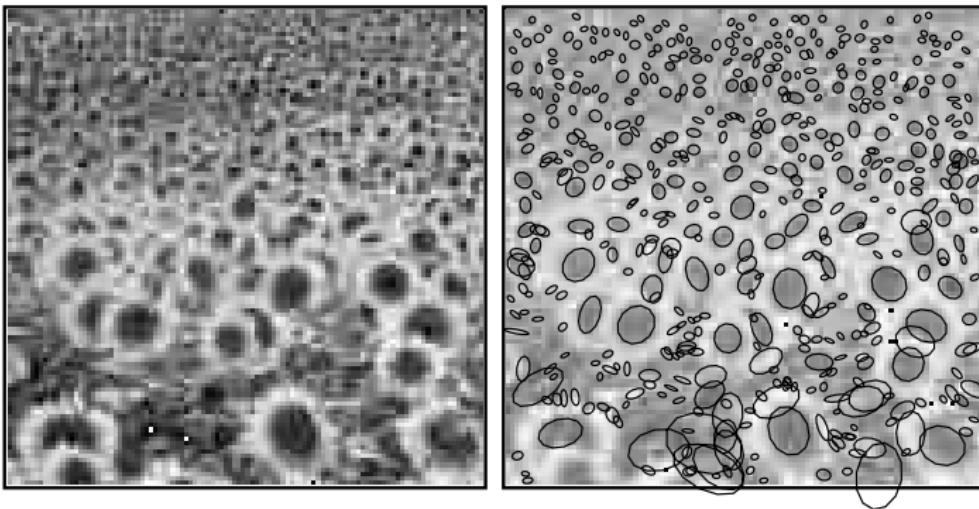
[Ballard 1981]



- Hough transform detects analytic curves in parameter space
- generalized version detects arbitrary non-analytic curves
- detection based on a voting process

# scale selection

[Lindeberg 1993]



- scale-space and scale-normalized derivatives
- automatic scale selection at local maxima over scale
- applies to blobs, junctions, corners, edges or ridges

# scale-invariant feature transform (SIFT)

[Lowe 1999]



- scale selection by difference of Gaussians (DoG)
- orientation assignment, local descriptor
- Hough transform on affine space

# textons

[Malik et al. 1999]



oriented filter bank



image



texture segmentation

- textons defined as clusters of filter responses
- regions described by texton histograms

# real-time face detection

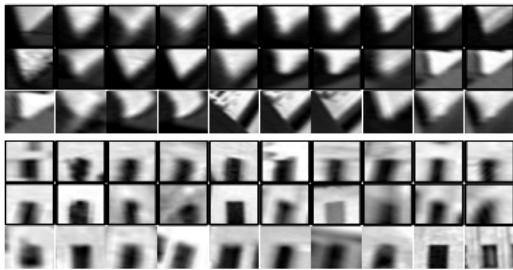
[Viola and Jones 2001]



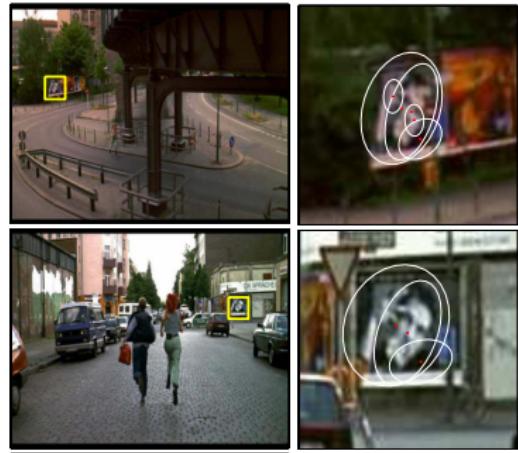
- simple rectangle features in constant time on integral images
- learning weak classifiers by boosting
- classifier cascade provides a focus-of-attention mechanism

# bag of words

[Sivic and Zisserman 2003]



visual vocabulary

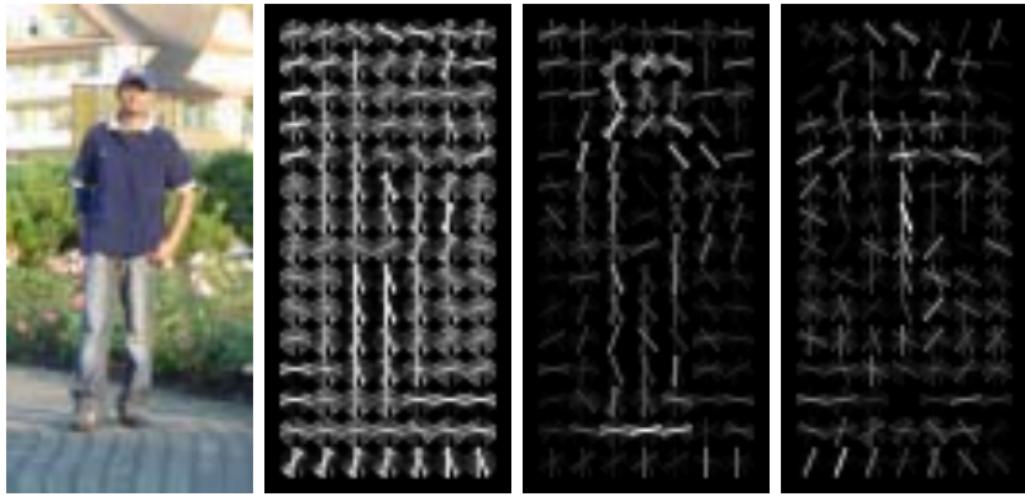


video retrieval

- “visual words” defined as clusters of SIFT descriptors
- images described by visual word histograms
- text retrieval methods applied to video retrieval

# histogram of oriented gradients (HOG)

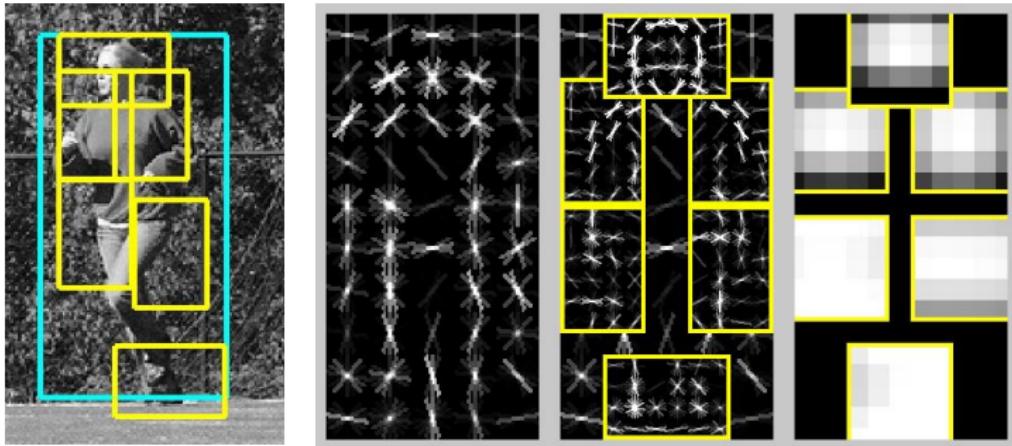
[Dalal and Triggs 2005]



- dense, SIFT-like descriptors
- SVM classifier
- sliding window detection at all positions and scales

# deformable part model (DPM)

[Felzenszwalb et al. 2008]

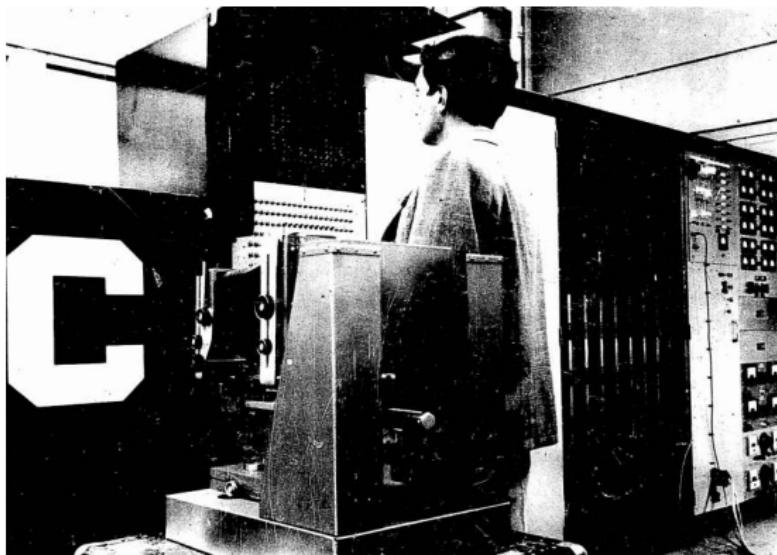


- appearance represented by HOG
- spatial configuration inspired by “pictorial structures”
- part locations treated as latent variables

# machine learning background

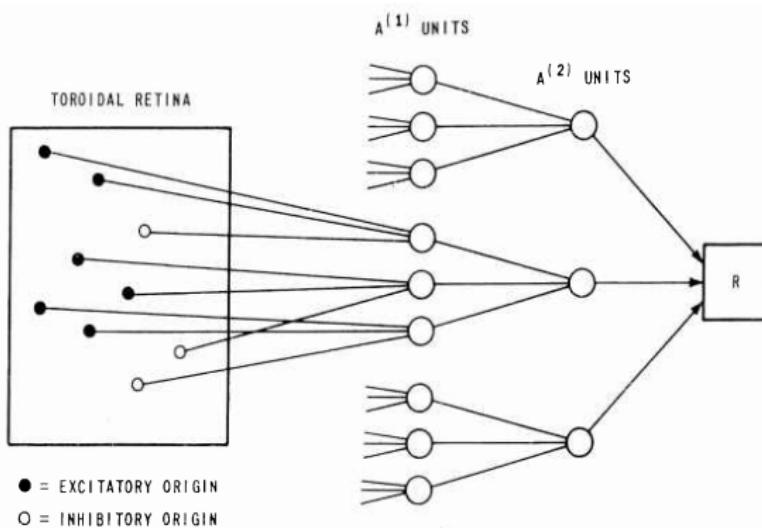
# perceptron

[Rosenblatt 1962]



- Mark-I perceptron
- analog circuit implementation; parameters as potentiometers

# perceptron



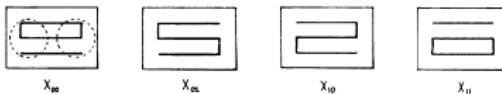
- early forms of multi-layer networks, continuous activation functions, back-propagating errors, convolution, skip connections, recurrent networks, selective attention, program learning, and multi-modality

# perceptron

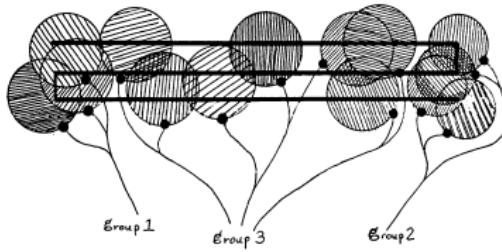
[Minsky and Papert 1969]

Theorem 0.8: No diameter-limited perceptron can determine whether or not all the parts of any geometric figure are connected to one another! That is, no such perceptron computes  $\psi_{\text{CONNECTED}}$ .

The proof requires us to consider just four figures



and a diameter-limited perceptron  $\psi$  whose support sets have diameters like those indicated by the circles below:



- (re-)define perceptron as a linear classifier
- then prove a series of negative results
- “AI winter” follows; misconception remains until today

# automatic differentiation

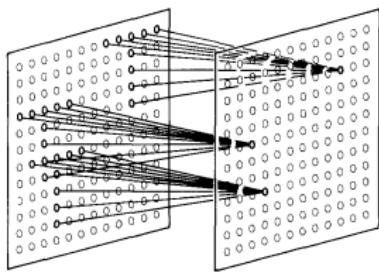
[Werbos 1974]

Actual Variable	Variable Number	Operation Category	Major Source	Minor Source
$(b(2))^2$	20	product	19	19
$b(2) = C(2) - k_1 Y_p(2)$	19	difference	18	17
$C(2)$	18	input	-	-
$k_1 Y_p(2)$	17	product	16	1
$Y_p(2)$	16	sum	15	13
$k_2 Y_A(2)$	15	product	14	2
$Y_A(2)$	14	input	-	-
$(1-k_2)Y_p(1)$	13	product	12	4
$(b(1))^2$	12	product	11	11
$b(1) = C(1) - k_1 Y_p(1)$	11	difference	10	9
$C(1)$	10	input	-	-
$k_1 Y_p(1)$	9	product	8	1

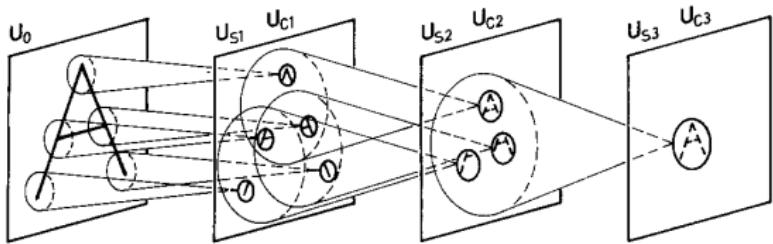
- formulate an arbitrary function as a computational graph
- **dynamic feedback**: compute symbolic derivatives by dynamic programming

# neocognitron

[Fukushima 1980]



convolution



feature hierarchy

- biologically-inspired convolutional network
- unsupervised learning

# back-propagation

[Rumelhart et al. 1986]

The backward pass starts by computing  $\partial E / \partial y$  for each of the output units. Differentiating equation (3) for a particular case,  $c$ , and suppressing the index  $c$  gives

$$\frac{\partial E}{\partial y_j} = y_j - d_j \quad (4)$$

We can then apply the chain rule to compute  $\partial E / \partial x_j$

$$\frac{\partial E}{\partial x_j} = \frac{\partial E}{\partial y_j} \cdot \frac{dy_j}{dx_j}$$

Differentiating equation (2) to get the value of  $dy_j / dx_j$  and substituting gives

$$\frac{\partial E}{\partial x_j} = \frac{\partial E}{\partial y_j} \cdot y_j(1 - y_j) \quad (5)$$

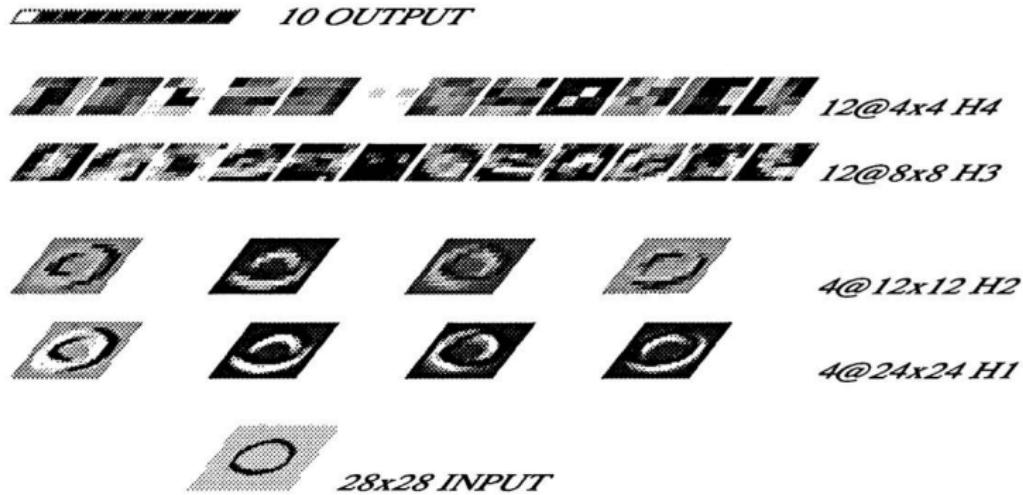
This means that we know how a change in the total input  $x$  to an output unit will affect the error. But this total input is just a linear function of the states of the lower level units and it is also a linear function of the weights on the connections, so it is easy to compute how the error will be affected by changing these states and weights. For a weight  $w_{ji}$ , from  $i$  to  $j$  the derivative is

$$\begin{aligned} \frac{\partial E}{\partial w_{ji}} &= \frac{\partial E}{\partial x_j} \cdot \frac{\partial x_j}{\partial w_{ji}} \\ &= \frac{\partial E}{\partial x_j} \cdot y_i \end{aligned} \quad (6)$$

- introduce back-propagation in multi-layer networks with sigmoid nonlinearities and sum of squares loss function
- advocate batch gradient descent for supervised learning
- discuss online gradient descent, momentum and random initialization

# convolutional networks

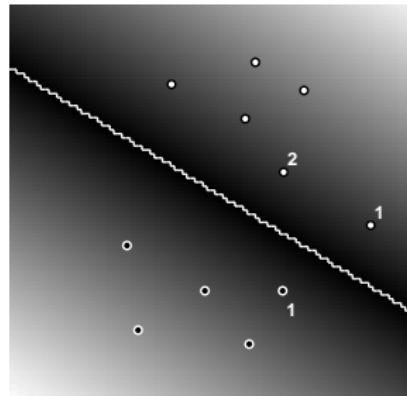
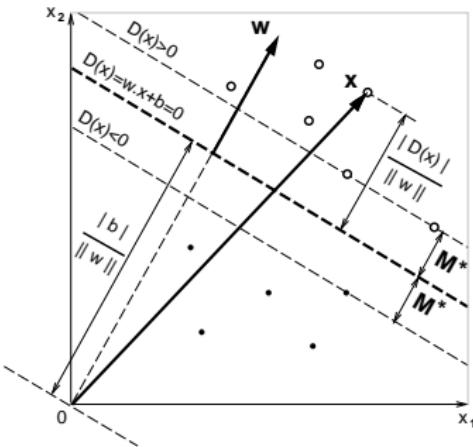
[LeCun et al. 1990]



- train a convolutional network by back-propagation
- advocate end-to-end feature learning for image classification

# support vector machines

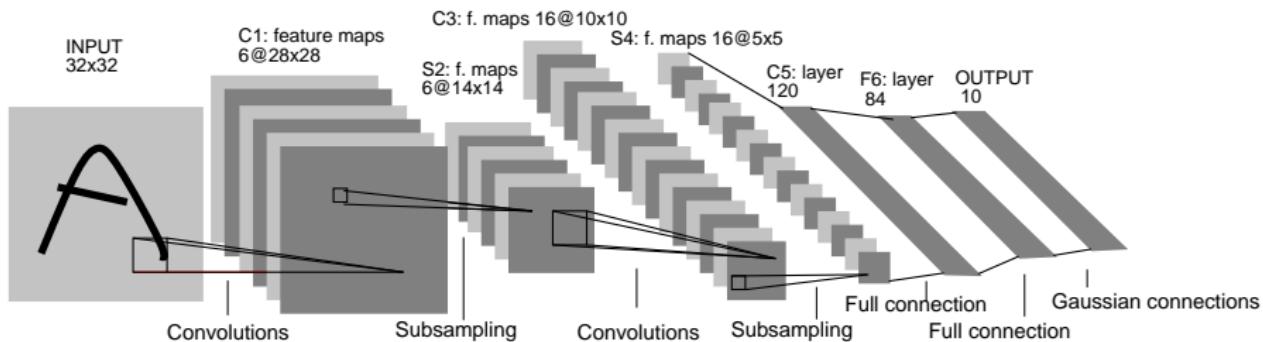
[Boser et al. 1992]



- linear classifier, made nonlinear via kernel trick
- convex optimization
- back to raw inputs; hand-crafted kernel functions
- shift focus from neural networks to kernel methods

# LeNet-5

[LeCun et al. 1998]



- sub-sampling gradually introduces translation, scale and distortion invariance
- non-linearity included in sub-sampling layers as feature maps are increasing in dimension

# modern deep learning

# ImageNet

[Russakovsky et al. 2014]

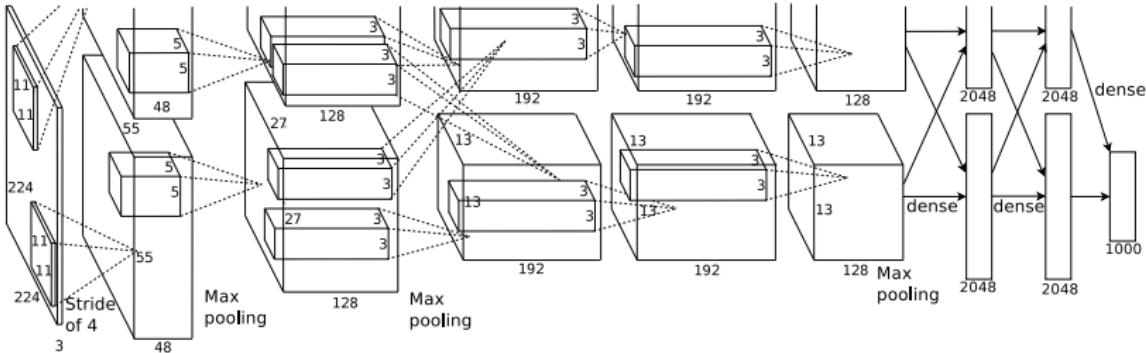


- 22k classes, 15M samples
- ImageNet Large-Scale Visual Recognition Challenge (ILSVRC): 1000 classes, 1.2M training images, 50k validation images, 150k test images

Russakovsky, Deng, Su, Krause, et al. 2014. Imagenet Large Scale Visual Recognition Challenge.

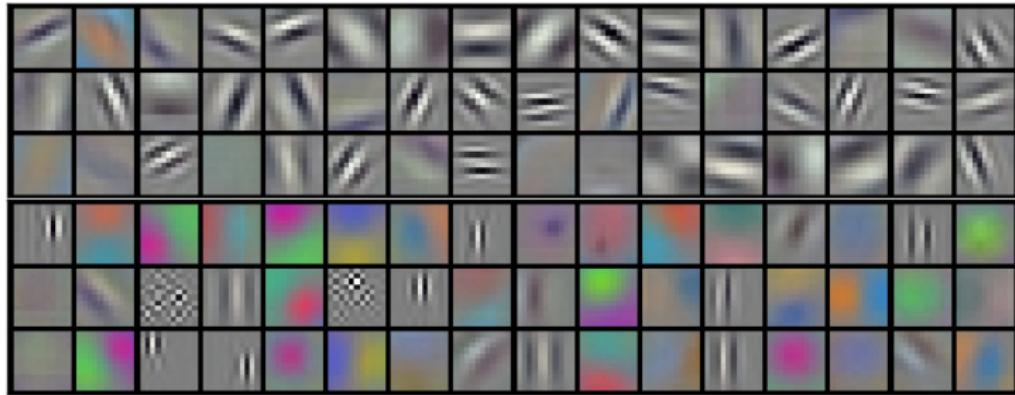
# AlexNet

[Krizhevsky et al. 2012]



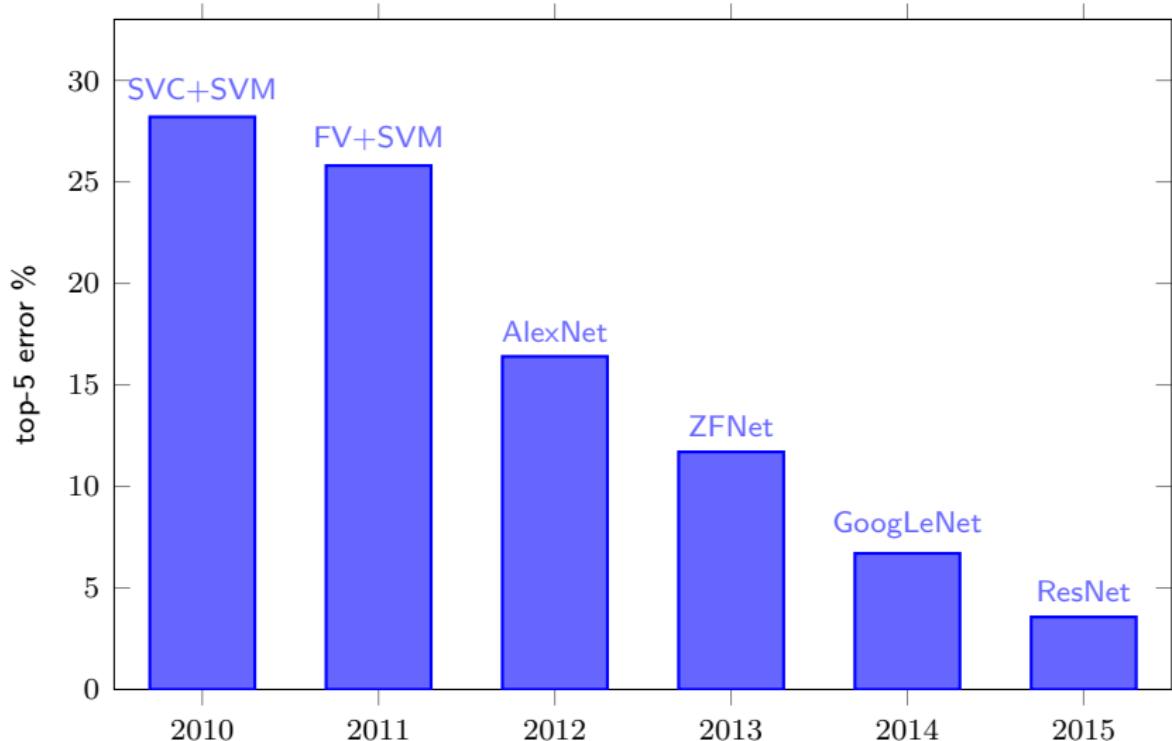
- implementation on two GPUs; connectivity between the two subnetworks is limited
  - ReLU, data augmentation, local response normalization, dropout
  - outperformed all previous models on ILSVRC by 10%

## learned layer 1 kernels



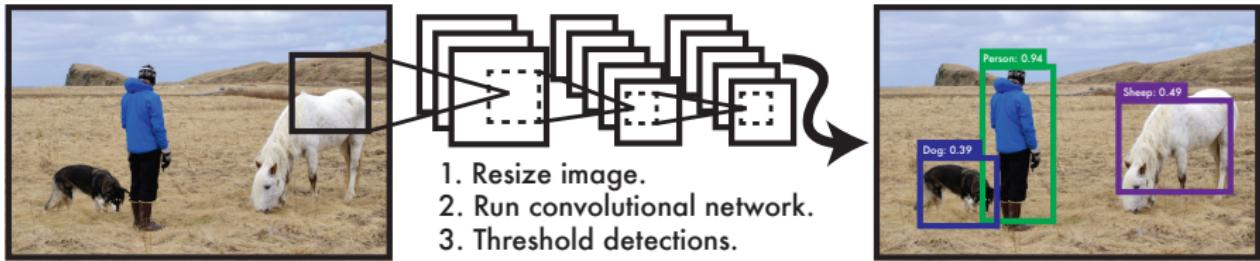
- 96 kernels of size  $11 \times 11 \times 3$
- top: 48 GPU 1 kernels; bottom: 48 GPU 2 kernels

# ImageNet classification performance



# object detection

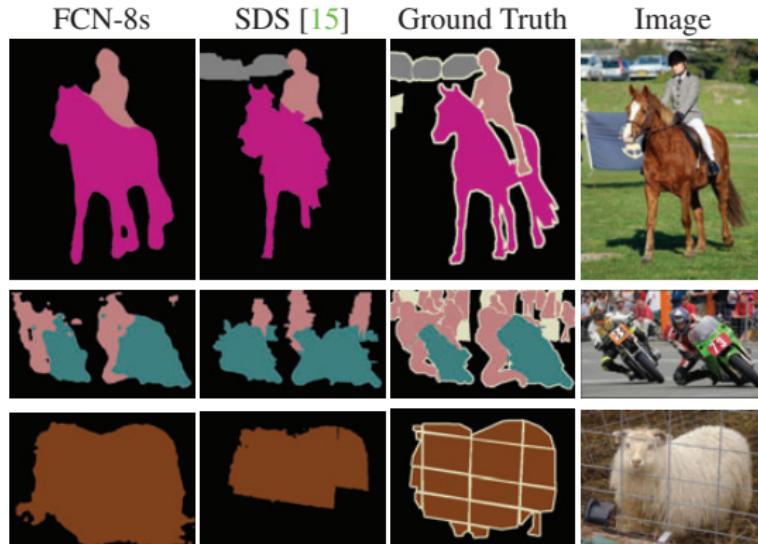
[Redmon et al. 2016]



- learn to detect objects as a single classification and regression task, without scanning the image or detecting candidate regions
- first object detector to operate at 45fps

# semantic segmentation

[Long et al. 2015]



- learn to upsample
- apply to pixel-dense prediction tasks

# instance segmentation and pose estimation

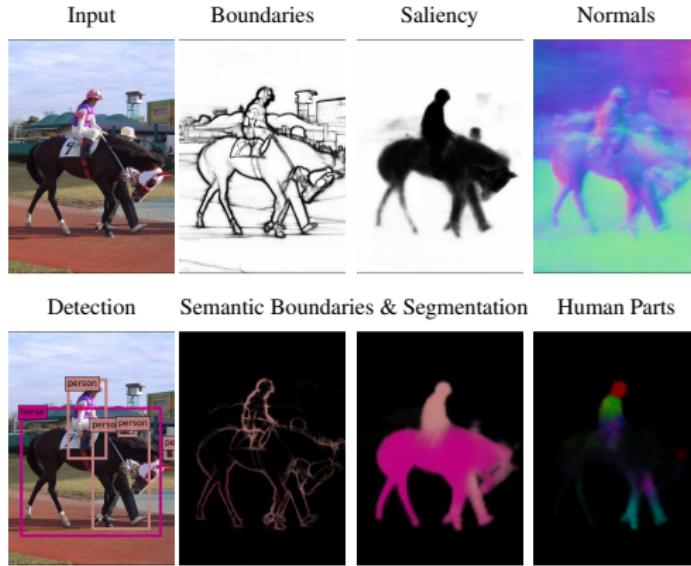
[He et al. 2017]



- semantic segmentation per detected region
- pose estimation as regression

# multi-task learning

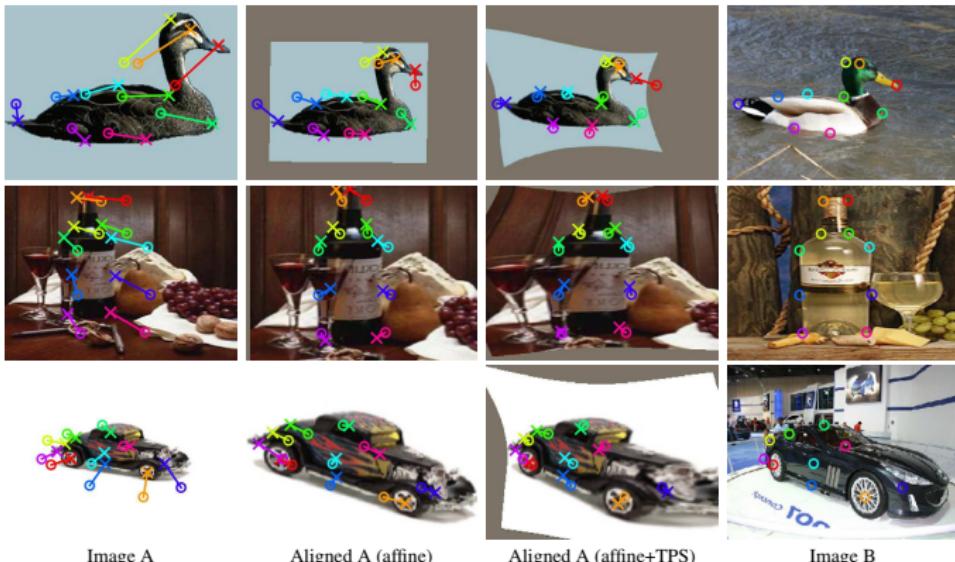
[Kokkinos 2017]



- learn several vision tasks with a joint network architecture including task-specific skip layers

## geometric matching

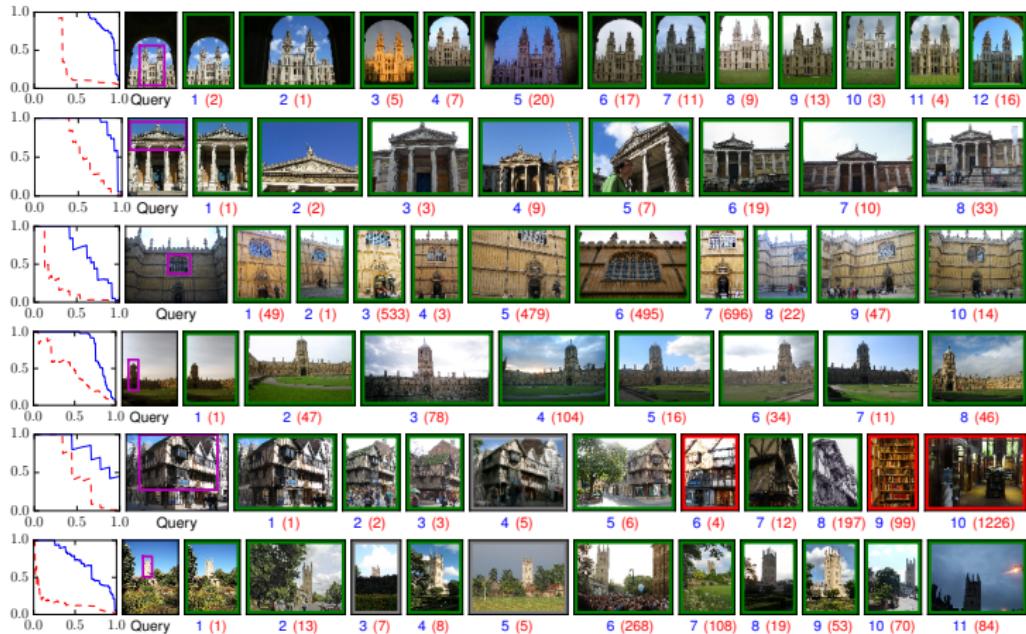
[Rocco et al. 2017]



- mimic the standard steps of feature extraction, matching and simultaneous inlier detection and model parameter estimation
  - still trainable end-to-end

# image retrieval

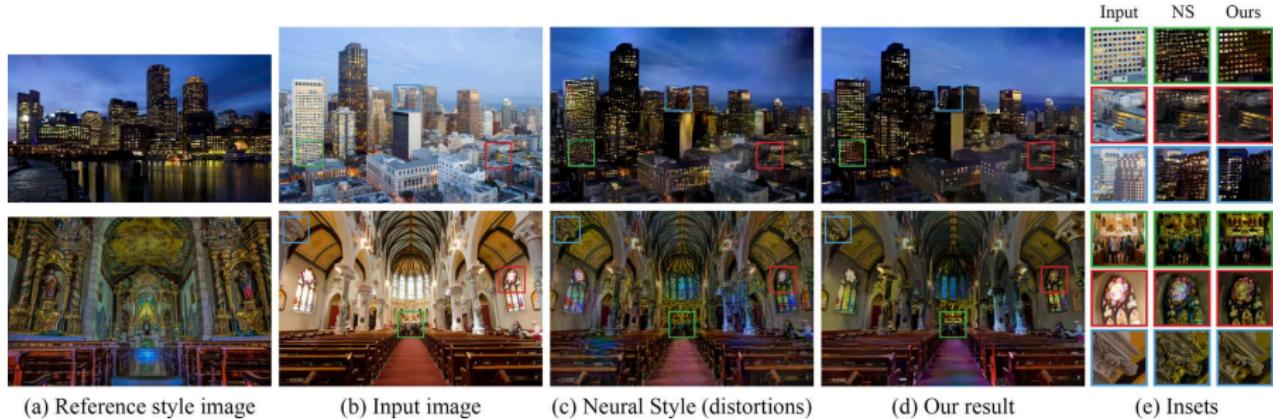
[Gordo et al. 2016]



- learn to match
- apply as generic feature extractor

## photorealistic style transfer

[Luan et al. 2017]



- generate same scene as input image
  - transfer style from reference image
  - photorealism regularization

# image captioning

[Vinyals et al. 2017]



Describes without errors

Describes with minor errors

Somewhat related to the image

Unrelated to the image

- image description by deep CNN
- language generation by RNN

Vinyals, Toshev, Bengio and Erhan. PAMI 2017. Show and Tell: Lessons Learned From the 2015 MSCOCO Image Captioning Challenge.

# about this course

# logistics

- **course website:** <https://sif-dlv.github.io/>
- **piazza:** <https://piazza.com/inria.fr/fall2017/dlv>

# prerequisites

basic knowledge of

- linear algebra
- calculus
- probabilities
- machine learning
- python
- C++

# goals

- discuss well-known methods from low-level description to intermediate representation, and their dependence on the end task
- study a data-driven approach where the entire pipeline is optimized jointly in a supervised fashion, according to a task-dependent objective
- study deep learning models in detail
- interpret them in connection to conventional models
- focus on recent, state of the art methods and large scale applications

# conventional methods

- **representation**: global/local visual descriptors, dense/sparse representation, feature detectors; encoding/pooling, vocabularies, bag-of-words; match kernels, embedding, Fisher vectors, VLAD
- **matching**: spatial matching, geometric models, RANSAC, Hough transform; pyramid matching, spatial and Hough pyramids; object detection, subwindow search, Hough model, deformable part model
- **indexing**: clustering, dimensionality reduction, density estimation, nearest neighbor search; tree-based methods, hashing, product quantization; inverted index and multi-index
- **learning**: naive Bayes, nearest neighbor classification; regression, classification; logistic regression, support vector machines, neural networks; activation functions, loss functions, gradient descent

# deep learning approach

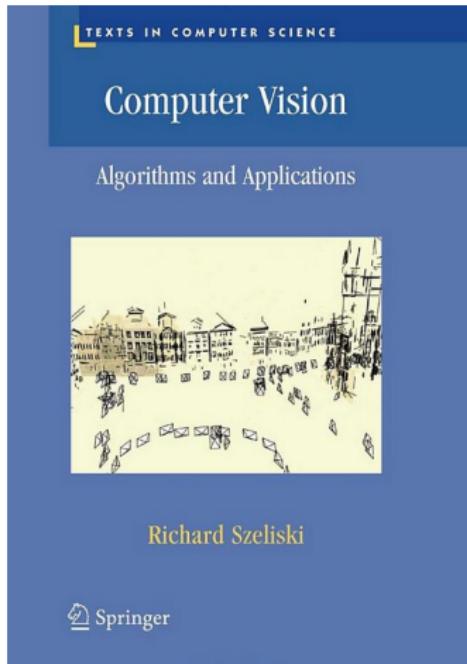
- **differentiation**: computational graphs, back-propagation, automatic differentiation
- **convolution**: pooling, strided convolution, dilated convolution; convolutional networks; deconvolution, fully convolutional networks
- **optimization**: parameter initialization, data-dependent initialization, normalization, regularization; optimization methods, second-order methods, Hessian-free methods
- **detection**: class-agnostic region proposals, bounding box regression, non-maxima suppression, part-based models, spatial transformers, attention networks
- **retrieval**: siamese, triplet, and batch-wise loss functions; embedding, pooling, dimensionality reduction and manifold learning; partial matching, spatial matching, quantization, diffusion

## related courses at sif

- **ADM** Advanced Probabilistic Data Analysis and Modeling (Guillaume Gravier)
- **BSI** Big Data Storage and Processing Infrastructures (Gabriel Antoniu)
- **CG** Computer Graphics: Rendering and Modeling 3D Scenes (Rémi Cozot)
- **CV** Computer Vision (Eric Marchand)
- **DMV** Data Mining and Visualization (Alexandre Termier)
- **GDP** Graph Data Processing (Pierre Vandergheynst)
- **HDL** High-Dimensional Statistical Learning (Rémi Gribonval)
- **REP** Image Representation, Editing and Perception (Olivier Le Meur)
- **SML** Supervised Machine Learning (François Coste)

# computer vision: algorithms and applications

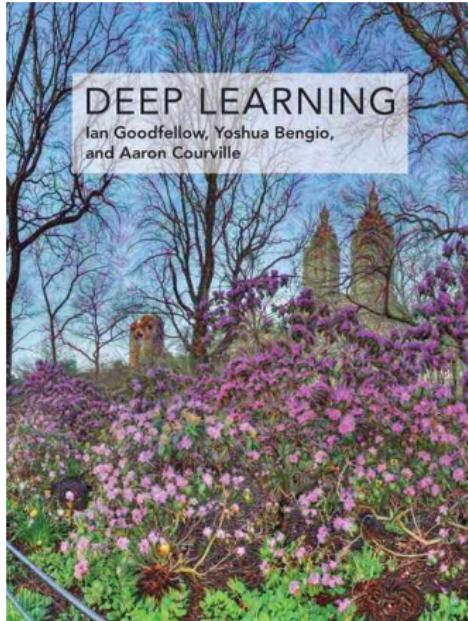
<http://szeliski.org/Book/>



- 1 introduction
- 3 image processing
- 4 feature detection and matching
- 6 feature-based alignment
- 14 recognition

# deep learning book

<http://www.deeplearningbook.org/>



- 1 introduction
- 5 machine learning basics
- 6 deep feedforward networks
- 7 regularization for deep learning
- 8 optimization for training deep models
- 9 convolutional networks
- 11 practical methodology

# evaluation

- oral presentation: 50%
- written exam: 50%

**good luck!**