ELEC5307

Advanced Signal Processing with Deep Learning

Lecturer: Dr Luping Zhou

School of Electrical and Information Engineering

UoS Outline

- Course materials (Lecture Notes, Tutorial/Lab Notes) for ELEC5307 available via Canvas

–https://canvas.sydney.edu.au/

- Look for ELEC5307

- Please check this website regularly!

Lecturer

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- Contact

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Timetable

- 2-hour Lecture per week

  Friday 17:00-19:00, Room F07.01.175
- 1-hour Lab **or** Tutorial per week

  Lab 01: Thursday 17:00-18:00, Room J15.01.101

  Lab 02: Friday 19:00–20:00, Room J15.01.101, or

  Lab 02: Friday 20:00-21:00, Room J15.01.101

- ~ 5-hour independent study

- Note 1: Tutorials/Labs start on week 2.

Assessment

- Project 1 (20%), deadline: Week 8 (Sunday)
- Project 2 (20%), deadline: Week 12 (Sunday)
- Final Exam (60%)

[1] Text-based similarity detecting software (Turnitin) will be used for all text-based written assignments.

[2]Late submission for lab reports: 1) There is no penalty for submissions until 11:59pm of the due day; 2) For submissions that are late than 11:59pm of the due day, 5% penalty will be applied for each day. Submissions that are late for 10 calendar days will be given ZERO marks.

Text Books

- Course Recommended Text
  - *Deep learning*
    I. Goodfellow, Y. Bengio and A. Courville, MIT Press 2016
  - *Pattern Classification*
    R. Duda, P. Hart & D. Stork, Wiley 2000
- Good Reference
  - *Pattern Recognition and Machine Learning*
    Christopher M. Bishop, Springer 2006

Note: Deep learning technologies evolve very quickly in recent years. Part of the course materials will come from the recently published papers in related conferences like CVPR, ICCV and ECCV.

Course Topics

Week 1: Introduction

Week 2: Basics of Neural Networks

Week 3: CNN architectures

Week 4: CNN applications (I)

Week 5: Practical in Neural Network

Week 6: Graphical model and RNN

Week 7: Deep generative models

Week 8: Invited guest lecture

Week 9: Applications (II)

Week 10: Attention and transformer

Week 11: Learning with few labels

Week 12: Invited guest lecture

Week 13: Review

Outcomes

- To be able to use appropriate software platforms for a given multi-dimensional signal processing task
- To be able to understand and apply the machine/deep learning methods for multi-dimensional signal processing applications
- To be able to use the existing machine/deep learning toolboxes
- To be able to report results in a professional manner
- To be able to develop some basic teamwork and project management skills through a group project

Lecture Notes

- Materials for this unit of study are taken from several textbooks and are organized so that they provide a complete introductory course on machine learning and deep learning.

- A set of slides used by the lecturer will be provided to you. Slides used during lectures may have more information than those you find on the web. So you may need to complete your copy during lectures.

- It is always a good idea to add your personal comments to the lecture notes during lecture sessions.

- You may read other references provided in this note if you feel that you understand their method better. Students should find their most appropriate way and text in learning the topics discussed in this unit.

How to be successful in this course?

- Regularly attend the lectures and tutorials/labs
- Try to answer tutorial questions by yourself
- Lectures give you fundamental theories; to pass this unit you need to improve your problem solving skill by
    - Attempting as many problems and questions as you can (from your text books and other reading materials)
    - Trying to connect the theory and the mathematics required to solve real world problems

What is Machine Learning?

- Principles, methods and algorithms for learning and prediction on the basis of past experience
  - Learn existing and known structures and rules or discover new findings and structures.
  - Already everywhere: speech recognition, hand-written character recognition, face recognition, information retrieval, operating systems, fraud detection, security, defense application.

Types of Learning Problems

- Supervised learning: where we get a set of training inputs and outputs
  - Regression
  - Classification
- Unsupervised learning: where we are interested in capturing inherent organization in the data
  - Clustering
  - Density estimation
- Semi-supervised learning: where we get part of training inputs and outputs, and part of data without label information

Preprocessing: Feature extraction for document classification

Label	Titles
B1	A Course on Integral Equations
B2	Attractors for Semigroups and Evolution Equations
B3	Automatic Differentiation of Algorithms: Theory, Implementation, and Application
B4	Geometrical Aspects of Partial Differential Equations
B5	Ideals, Varieties, and Algorithms – An Introduction to Computational Algebraic Geometry and Commutative Algebra
B6	Introduction to Hamiltonian Dynamical Systems and the N-Body Problem
B7	Knapsack Problems: Algorithms and Computer Implementations
B8	Methods of Solving Singular Systems of Ordinary Differential Equations
B9	Nonlinear Systems
B10	Ordinary Differential Equations
B11	Oscillation Theory for Neutral Differential Equations with Delay
B12	Oscillation Theory of Delay Differential Equations
B13	Pseudodifferential Operators and Nonlinear Partial Differential Equations
B14	Sinc Methods for Quadrature and Differential Equations
B15	Stability of Stochastic Differential Equations with Respect to Semi-Martingales
B16	The Boundary Integral Approach to Static and Dynamic Contact Problems
B17	The Double Mellin-Barnes Type Integrals and Their Applications to Convolution Theory

Task: Classify the documents into predefined categories (*i.e.*, classes)

Preprocessing: Feature extraction for document classification

TABLE 3

The 16 × 17 term-document matrix corresponding to the book titles in Table 2.

Terms	Documents																
	B1	B2	B3	B4	B5	B6	B7	B8	B9	B10	B11	B12	B13	B14	B15	B16	B17
algorithms	0	0	1	0	1	0	1	0	0	0	0	0	0	0	0	0	0
application	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	1
delay	0	0	0	0	0	0	0	0	0	0	1	1	0	0	0	0	0
differential	0	0	0	1	0	0	0	1	0	1	1	1	1	1	1	0	0
equations	1	1	0	1	0	0	0	1	0	1	1	1	1	1	1	0	0
implementation	0	0	1	0	0	0	1	0	0	0	0	0	0	0	0	0	0
integral	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1
introduction	0	0	0	0	1	1	0	0	0	0	0	0	0	0	0	0	0
methods	0	0	0	0	0	0	0	1	0	0	0	0	0	1	0	0	0
nonlinear	0	0	0	0	0	0	0	0	1	0	0	0	1	0	0	0	0
ordinary	0	0	0	0	0	0	0	1	0	1	0	0	0	0	0	0	0
oscillation	0	0	0	0	0	0	0	0	0	0	1	1	0	0	0	0	0
partial	0	0	0	1	0	0	0	0	0	0	0	0	1	0	0	0	0
problem	0	0	0	0	0	1	1	0	0	0	0	0	0	0	0	1	0
systems	0	0	0	0	0	1	0	1	1	0	0	0	0	0	0	0	0
theory	0	0	1	0	0	0	0	0	0	0	1	1	0	0	0	0	1

After the preprocessing step, each document is represented as one data point in the 16-D feature space.

Image Representation

Definition of Image

- Image: An image of dimensions $M \times N$ is defined by the function *b* with: $b : D_M \times D_N \rightarrow I^n$

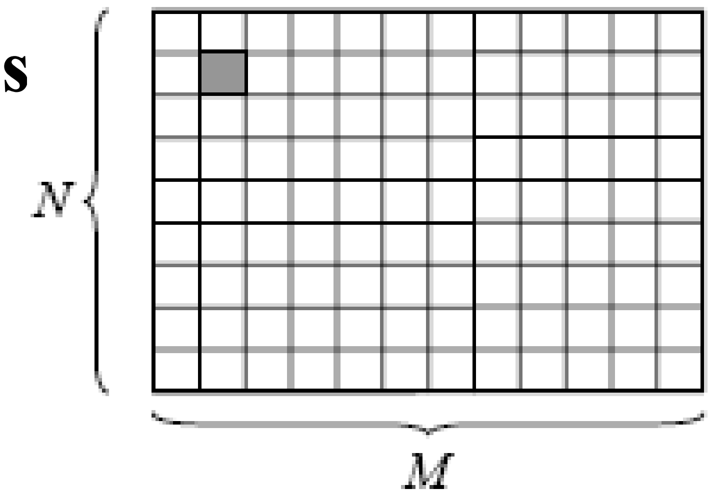
  where $D_M=\{1,\ldots,M\}$, $D_N=\{1,\ldots,N\}$ and $n=1,2,3,\ldots$.
- Pixel: The smallest part of an image is the pixel (*picture element*). It is characterized by its position (i,j) and the intensity vector $g(i,j)$.

  ⇒ Discretisation of spatial coordinates and intensity

Intensity Image Representation

Grey-scale / intensity image:

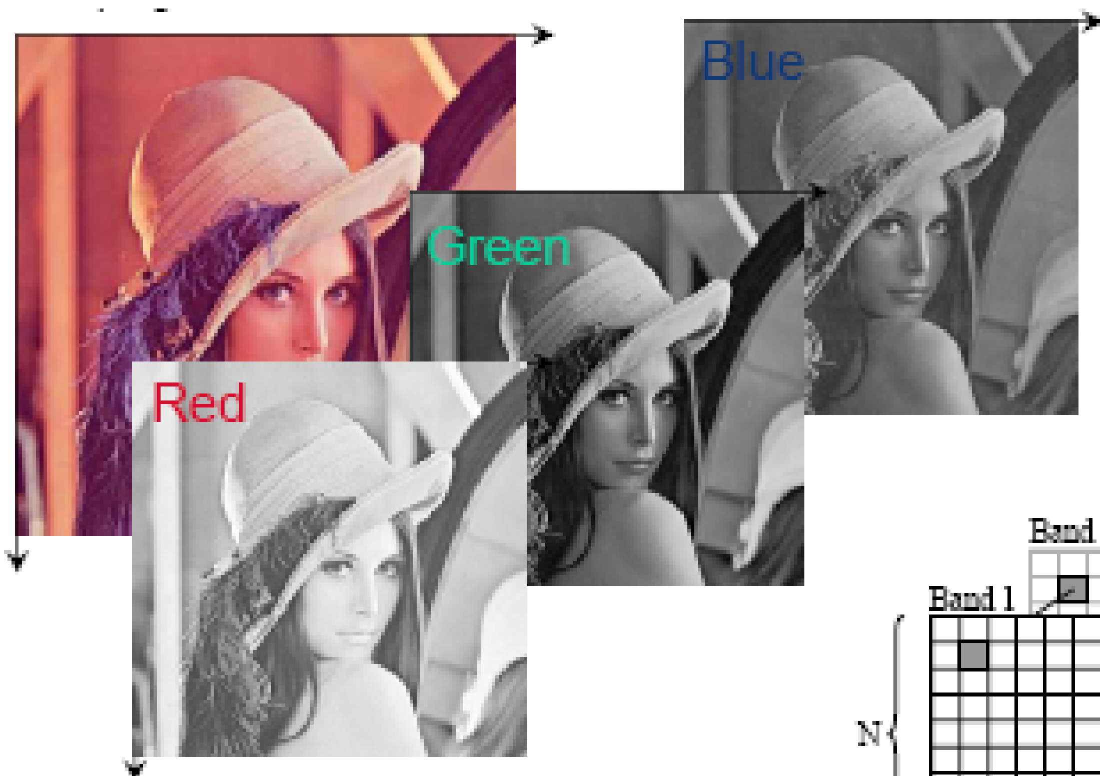
- ***N* rows × *M* columns**



$$g(n,m)=\begin{bmatrix} g(1,1) & g(1,2) & \cdots & g(1,M) \\ g(2,1) & g(2,2) & \cdots & g(2,M) \\ \vdots & \vdots & \ddots & \vdots \\ g(N,1) & g(N,2) & \cdots & g(N,M) \end{bmatrix}$$

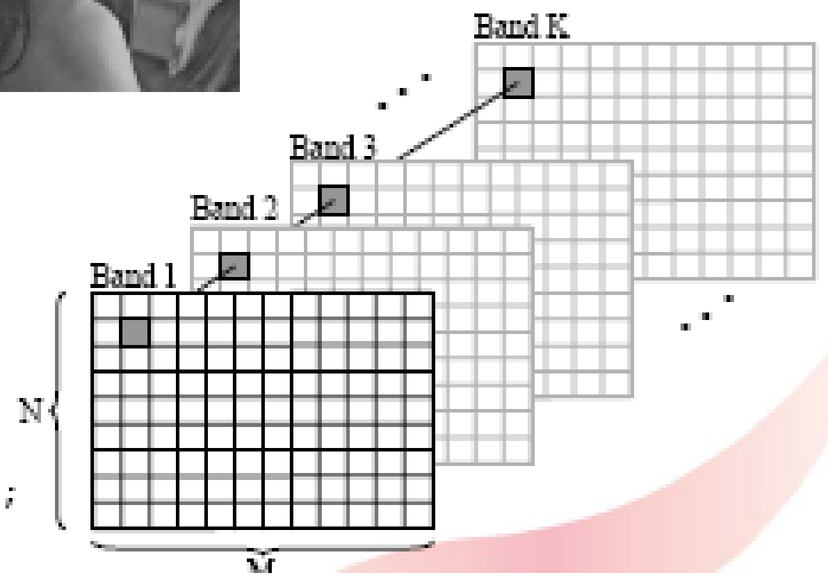
One intensity image is represented as *NM* data points (*i.e.*, pixels) in the 1-D feature space.

Color Image and Multi-spectral Image




```
a = double(imread('lena (colour).jpg'));
imshow(a(:, :, 1) / 256);
```

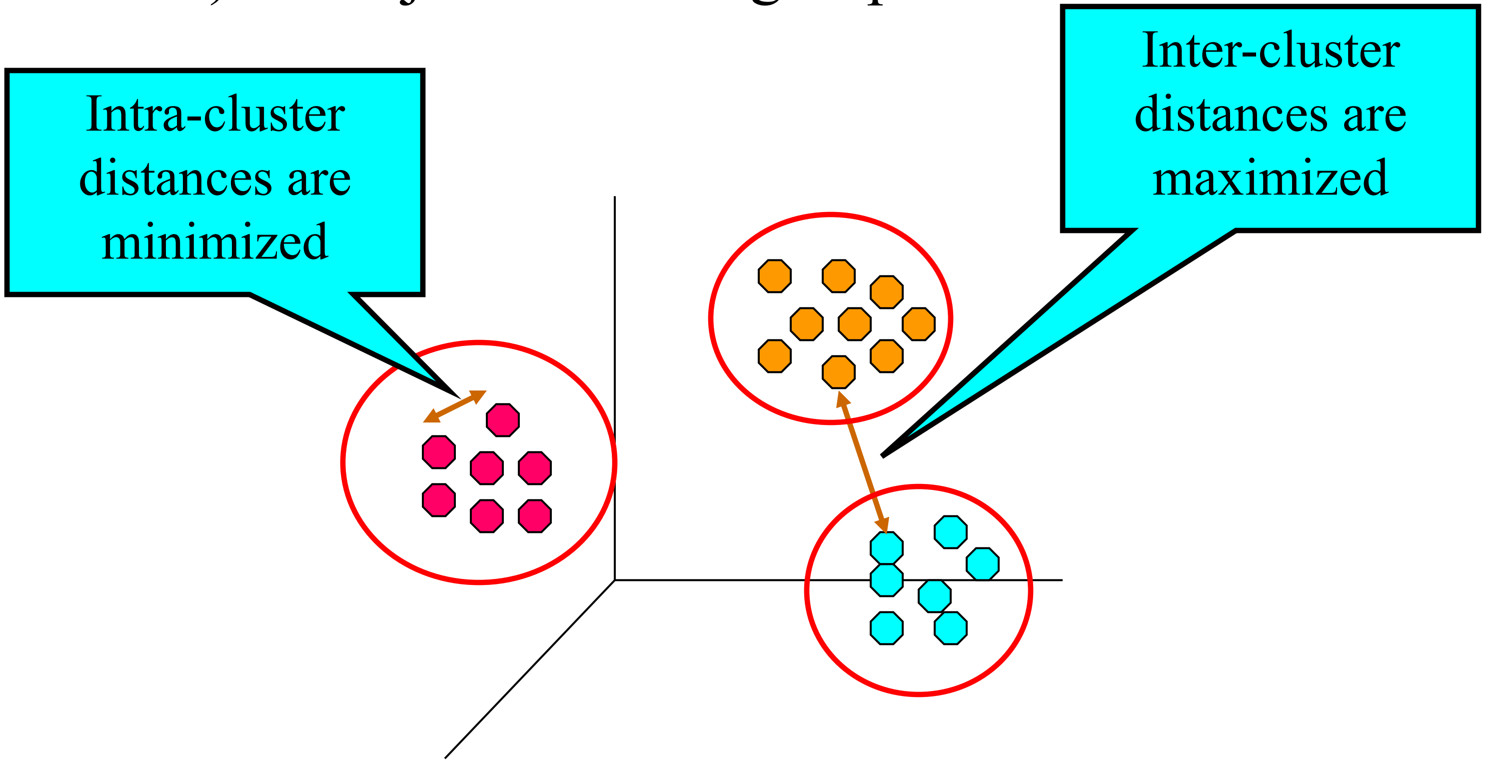
Multispectral image:
M columns
N rows
K bands



One color (*resp.* multi-spectral) image is represented as *NM* data points (*i.e.*, pixels) in the 3-D (*resp.* *K*-D) feature space.

Clustering

Finding groups of objects such that the objects in a group will be similar (or related) to one another and different from (or unrelated to) the objects in other groups

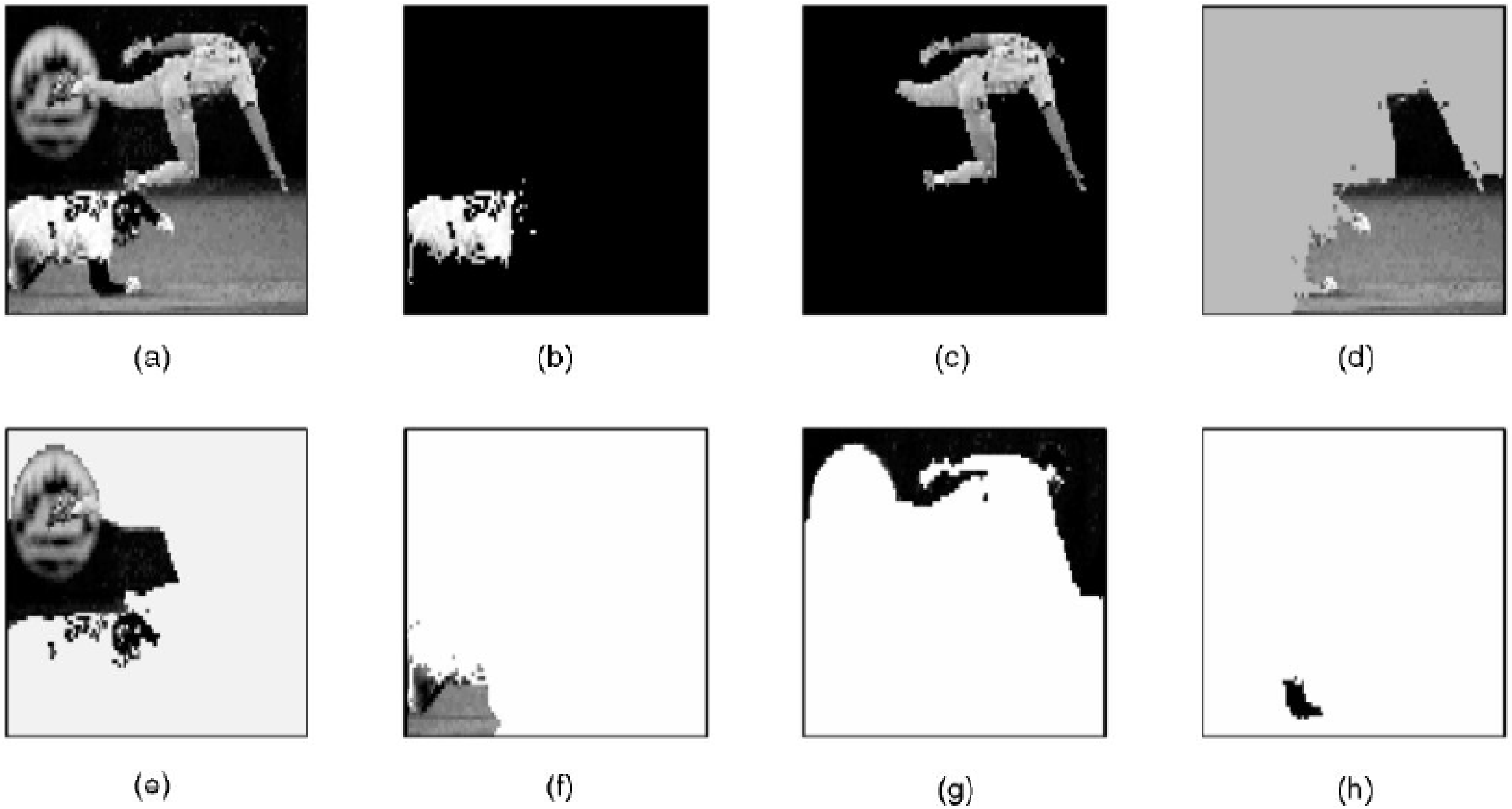


Clustering in Image Segmentation

Task: Partition an intensity/color image into a few groups. This task is called image segmentation.

- Data reduction - obtain a compact representation for *interesting* image data in terms of a set of components
- Find components that belong together (form clusters)

Clustering in Image Segmentation (Cont'd)



From: *Normalize Cut: Normalized Cuts and Image Segmentation*, Jianbo Shi and Jitendra Malik, T-PAMI 2000

Classification

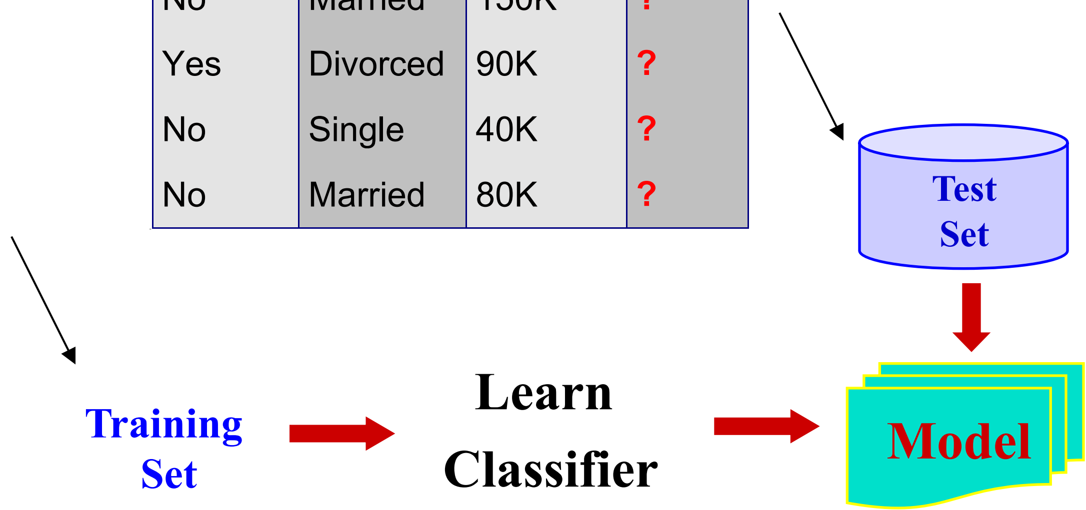
- Given a collection of records (*training set*)
  - Each record contains a set of *attributes*, one of the attributes is the *class*.
- Find a *model* for class attribute as a function of the values of other attributes.
- Goal: <u>previously unseen</u> records should be assigned a class as accurately as possible.
  - A *test set* is used to determine the accuracy of the model. Usually, the given data set is divided into training and test sets, with training set used to build the model and test set used to validate it.

Classification Example

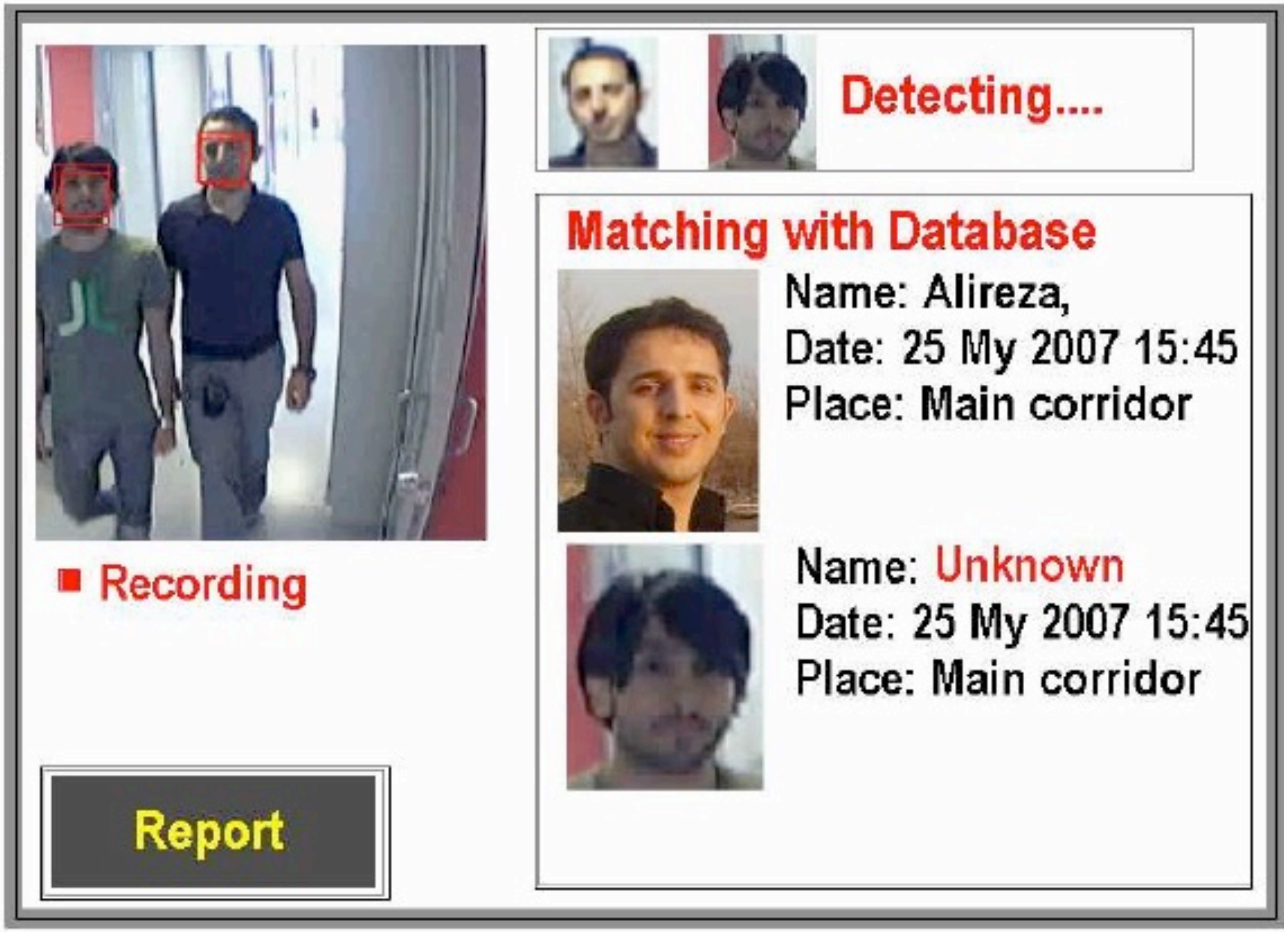
categorical categorical continuous class

Tid	Refund	Marital Status	Taxable Income	Cheat
1	Yes	Single	125K	No
2	No	Married	100K	No
3	No	Single	70K	No
4	Yes	Married	120K	No
5	No	Divorced	95K	Yes
6	No	Married	60K	No
7	Yes	Divorced	220K	No
8	No	Single	85K	Yes
9	No	Married	75K	No
10	No	Single	90K	Yes

Refund	Marital Status	Taxable Income	Cheat
No	Single	75K	?
Yes	Married	50K	?
No	Married	150K	?
Yes	Divorced	90K	?
No	Single	40K	?
No	Married	80K	?

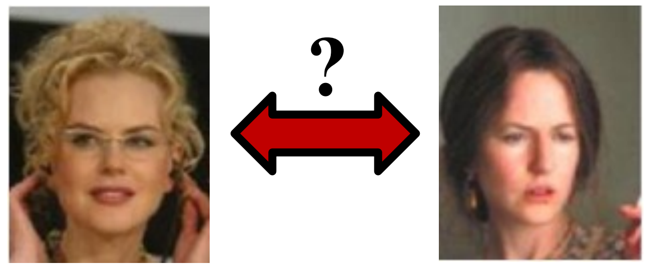


Face Recognition in Surveillance

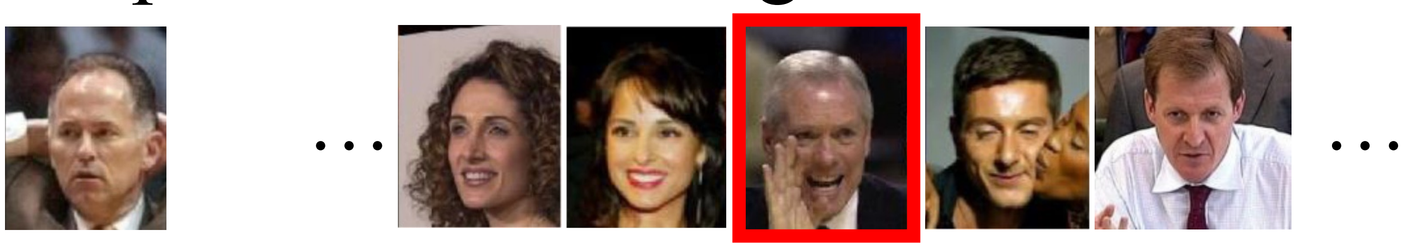


Typical face recognition scenarios

- Verification: a person is claiming a particular identity; verify whether that is true



- Closed-world identification: assign a face to one person from among a known set



- General identification: assign a face to a known person or to "unknown"

What makes face recognition hard?

Expression

What makes face recognition hard?

Lighting

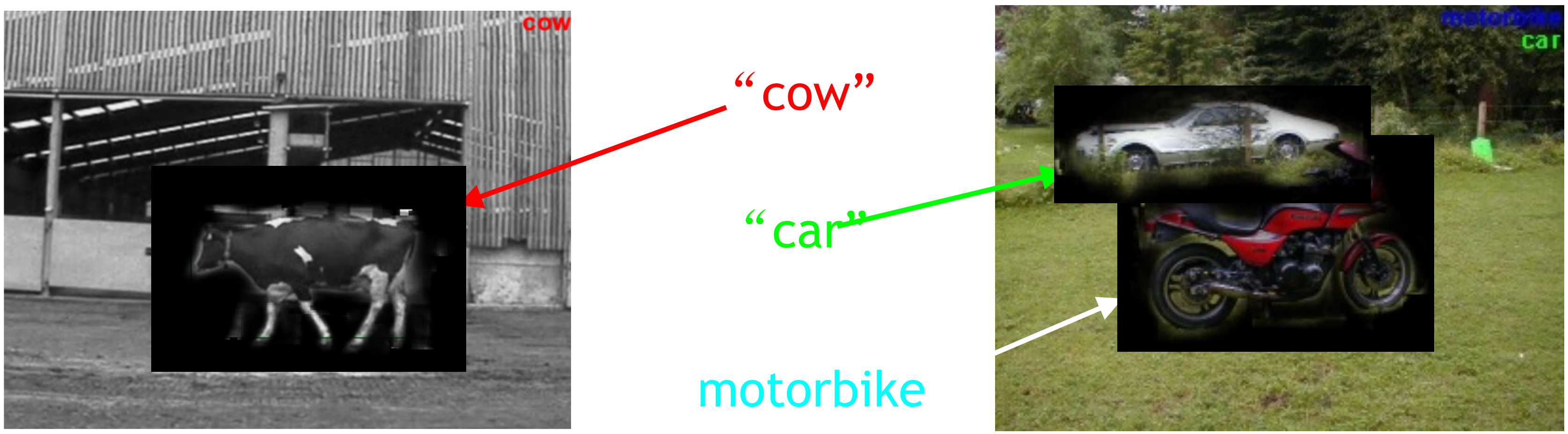
What makes face recognition hard?

Occlusion

What makes face recognition hard?

Viewpoint

Object Recognition



- Different levels of recognition
  - *Which* object class is in the image? ⇒ Obj/Img categorization
  - *Where* is it in the image? ⇒ Detection/Localization
  - *Where exactly* — which pixels? ⇒ F/G segmentation

Challenges 1: view point variation

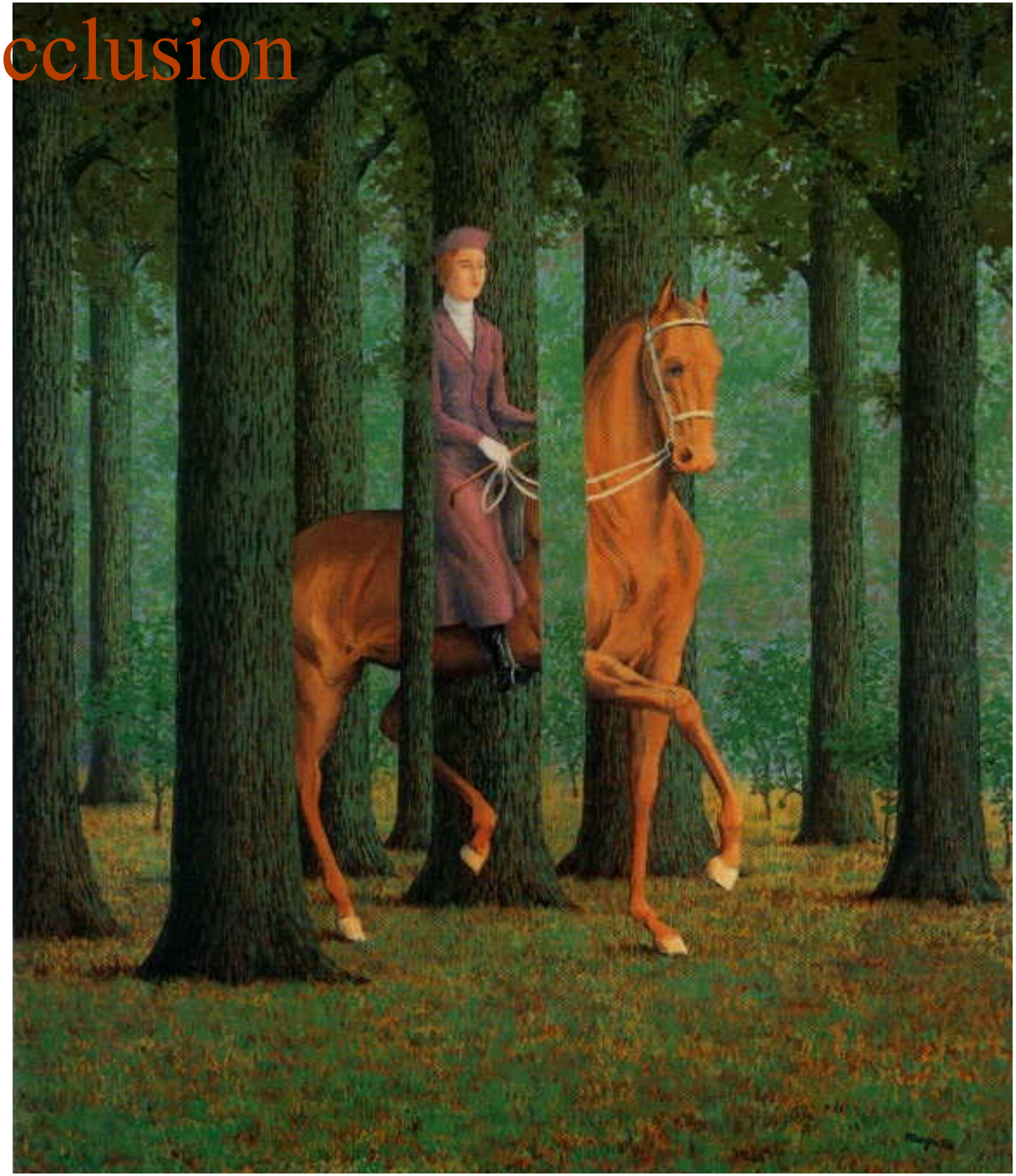
Michelangelo Italy
1475-1564

Challenges 2: illumination

slide credit: S. Ullman

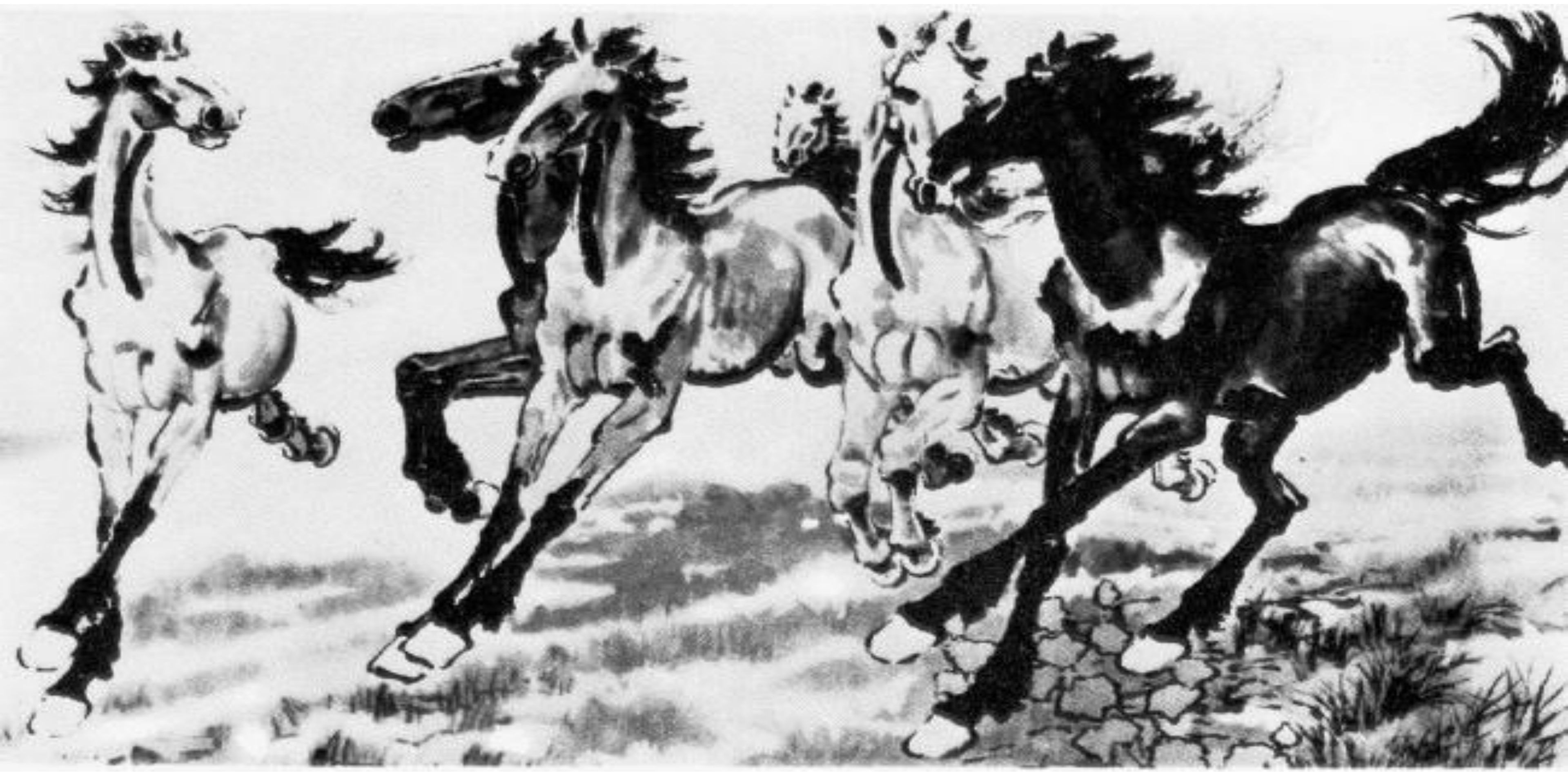
Challenges 3: occlusion



Magritte, 1957

Challenges 4: scale

Challenges 5: deformation



Xu, Beihong 1943

Challenges 6: background clutter

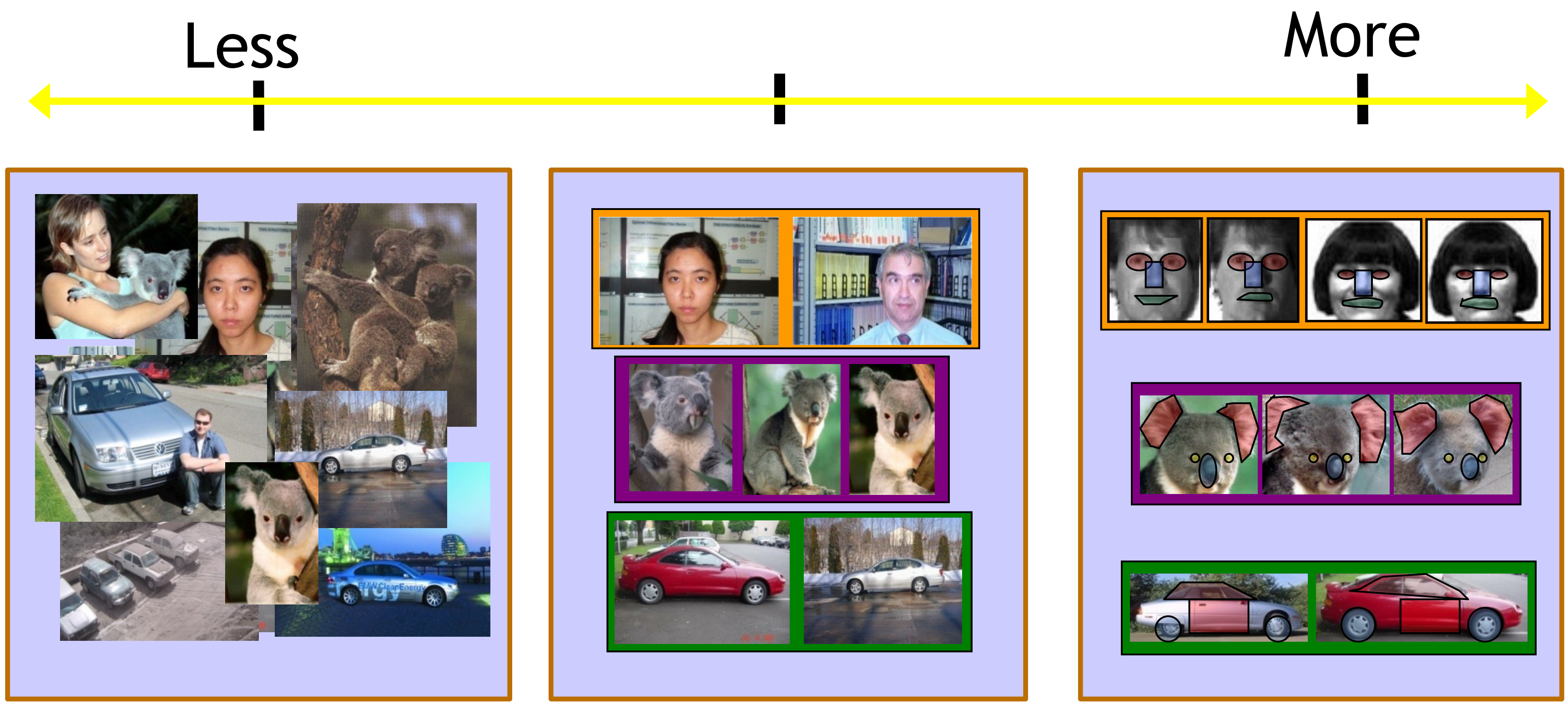
Klimt, 1913

Challenges 7: intra-class variation






learning with minimal supervision



Unlabeled, multiple objects

Classes labeled, some clutter

Cropped to object, parts and classes labeled

History: early object categorization


~10,000 to 30,000

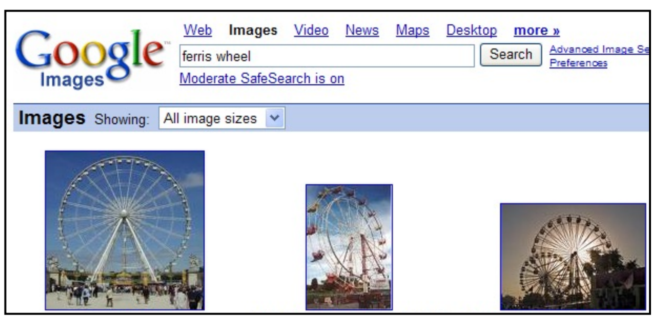
What could be done with recognition algorithms?

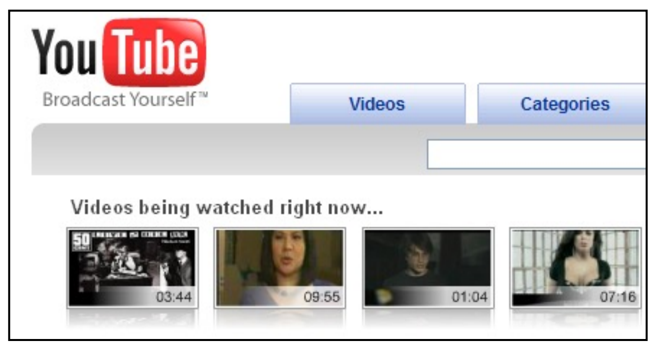
There is a wide range of applications, including…

Autonomous robots

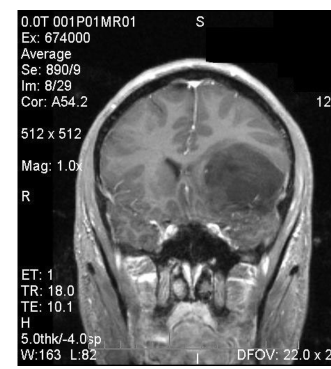
Navigation, driver safety

Landmark search



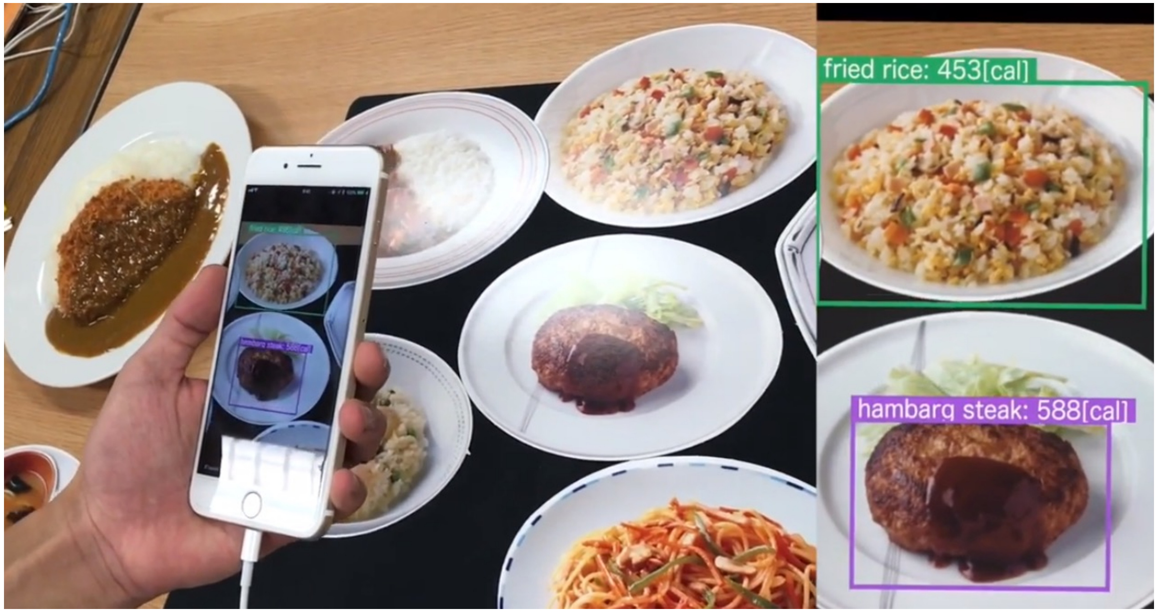


Content-based retrieval and analysis for images and videos

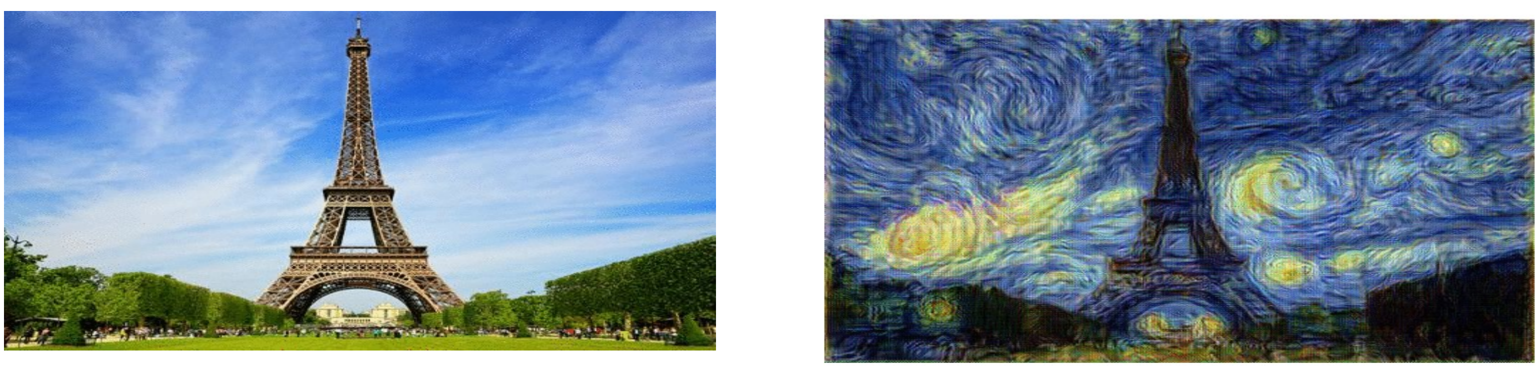


Medical image analysis

What could be done with recognition algorithms?



Calories estimation from food images



Paint Generation

CalTech101 Dataset

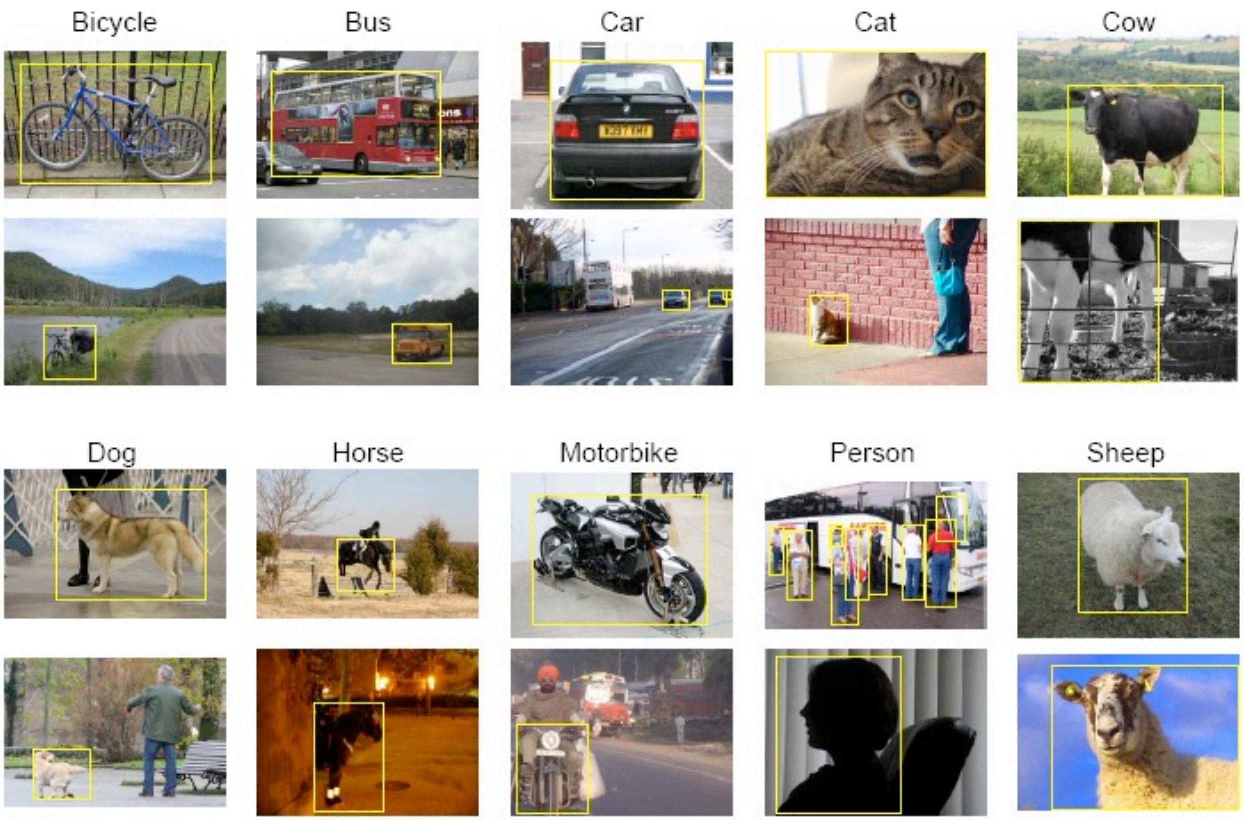
www.vision.caltech.edu/Image_Datasets/Caltech101/Caltech101.html

- The **CalTech101** dataset (Fei-Fei et al., 2004) contains 101 object categories with 40 to 800 images per category.

CalTech256 dataset: http://www.vision.caltech.edu/Image_Datasets/Caltech256/

PASCAL 2006 Dataset

- **Ten object classes:** bicycle, bus, car, cat, cow, dog, horse, motorbike, person, sheep
- **Images taken from three sources:** 1)Personal photos contributed by Edinburgh /Oxford; 2) Microsoft Research Cambridge images; 3) Images taken from “flickr” photo-sharing website.



PASCAL 2012 dataset:
http://pascallin.ecs.soton.ac.uk/challenges/VOC/voc2012/index.html

More Datasets

- ImageNet dataset: IMAGENET

  Download: http://www.image-net.org/

  - Total number of non-empty synsets: 21841
  - Total number of images: 14,197,122
  - Number of images with bounding box annotations: 1,034,908

- SUN dataset: SUN

  Download: http://groups.csail.mit.edu/vision/SUN/

  - Total number of scene categories: 908
  - Total number of images: 131,072
  - Total number of object categories: 3819
  - Number of segmented objects: 249,522

Examples from ImageNet

More challenging recognition tasks

[Caltech UCSD Birds-200-2011 Dataset]

[FGVC-Aircraft dataset]

Fine-grained Visual Recognition

More challenging recognition tasks

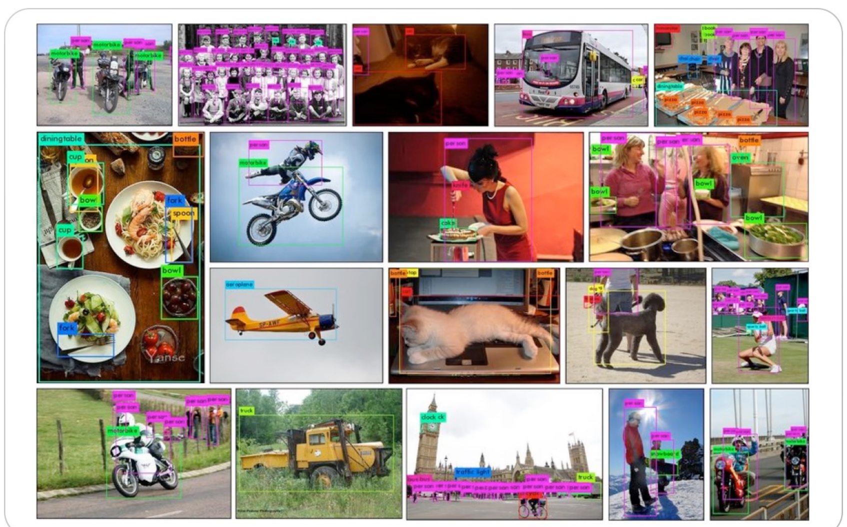
Scene Recognition : Places2 Dataset

More challenging recognition tasks

- MS COCO dataset:

The COCO (Common Objects in Context) dataset is a large-scale object detection, segmentation, and captioning dataset.

- 330K images; 80 object categories; 5 captions per image



Performance evaluation for object recognition

Precision, Recall, and F-measure (1)

- Suppose the cutoff threshold is chosen to be 0.8. In other words, any instance with posterior probability greater than 0.8 is classified as positive.

- Compute the precision, recall, and F-measure for the model at this threshold value.

Instance	P(+|A)	True Class
1	0.95	+
2	0.93	+
3	0.87	-
4	0.85	-
5	0.85	-
6	0.85	+
7	0.76	-
8	0.53	+
9	0.43	-
10	0.25	+

Precision, Recall, and F-measure (2)

	PREDICTED CLASS	
	Class =Yes	Class= No
ACTUAL CLASS Class =Yes	(TP) 3	(FN) 2
ACTUAL CLASS Class =No	(FP) 3	(TN) 2

Instance	P(+|A)	True Class
1	0.95	+
2	0.93	+
3	0.87	-
4	0.85	-
5	0.85	-
6	0.85	+
7	0.76	-
8	0.53	+
9	0.43	-
10	0.25	+

Precision, Recall, and F-measure (3)

	PREDICTED CLASS		
		Class =Yes	Class= No
ACTUAL CLASS	Class =Yes	(TP) 3	(FN) 2
	Class =No	(FP) 3	(TN) 2

p = TP/(TP+FP)= 3/(3+3) = ½

r = TP/(TP+FN) =3/(3+2) = 3/5

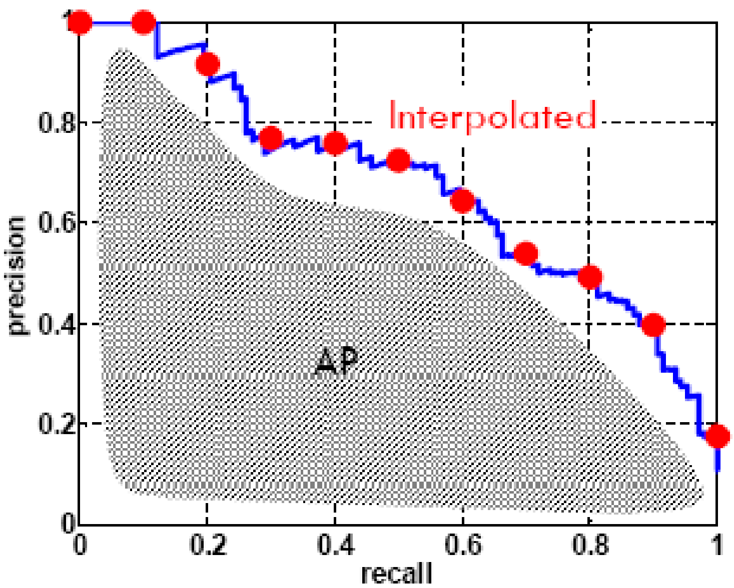
F-measure = 2pr/(p+r)=6/11

TP+FN: the total number of positive samples

FP + TN: the total number of negative samples

Average Precision (1)

- Average Precision (AP):
  –Averages precision over the entire range of recall
  – A good score requires both high recall and high precision
  – Application-independent



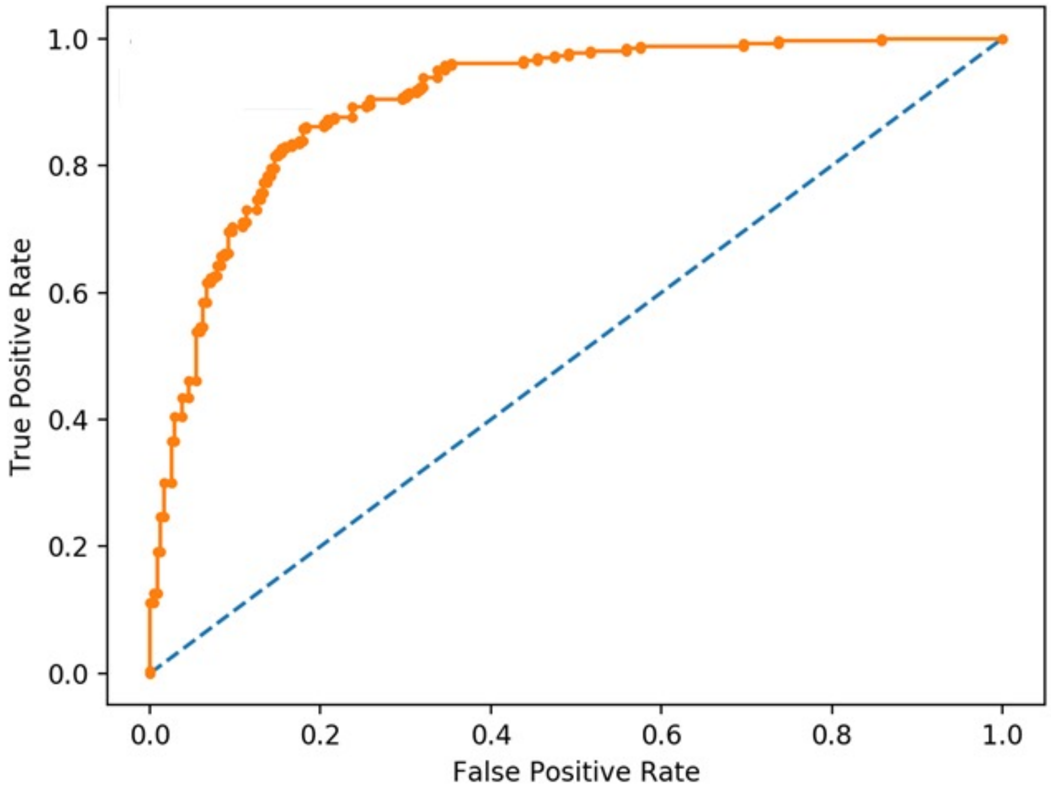
Average Precision (2)

Instance	P(+|A)	True Class
1	0.95	+
2	0.93	+
3	0.87	-
4	0.85	-
5	0.85	-
6	0.85	+
7	0.76	-
8	0.53	+
9	0.43	-
10	0.25	+

How to compute:

$$\frac{1}{5}\left(1+\frac{2}{2}+\frac{3}{6}+\frac{4}{8}+\frac{5}{10}\right)=0.7$$

Receiver Operating Characteristic (ROC) Curve



How to Construct an ROC curve

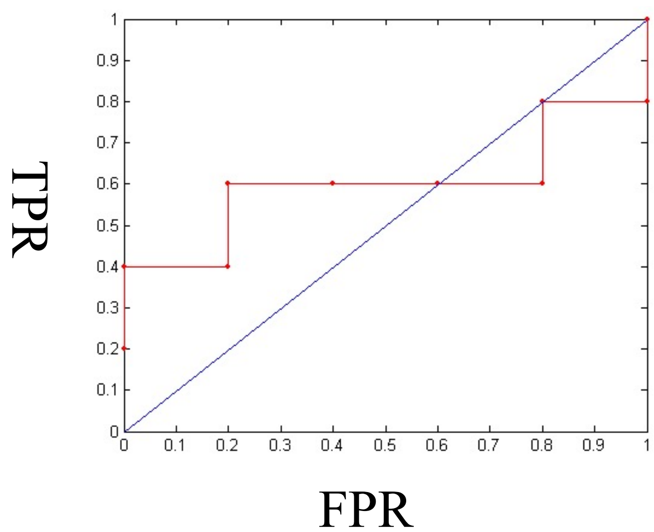
Instance	P(+|A)	True Class
1	0.95	+
2	0.93	+
3	0.87	-
4	0.852	+
5	0.851	-
6	0.85	-
7	0.76	-
8	0.53	+
9	0.43	-
10	0.25	+

- Use classifier that produces posterior probability for each test instance P(+|A)
- Sort the instances according to P(+|A) in decreasing order
- Apply threshold at each unique value of P(+|A)
- Count the number of TP, FP, TN, FN at each threshold
- TP rate, TPR = TP/(TP+FN)
- FP rate, FPR = FP/(FP + TN)

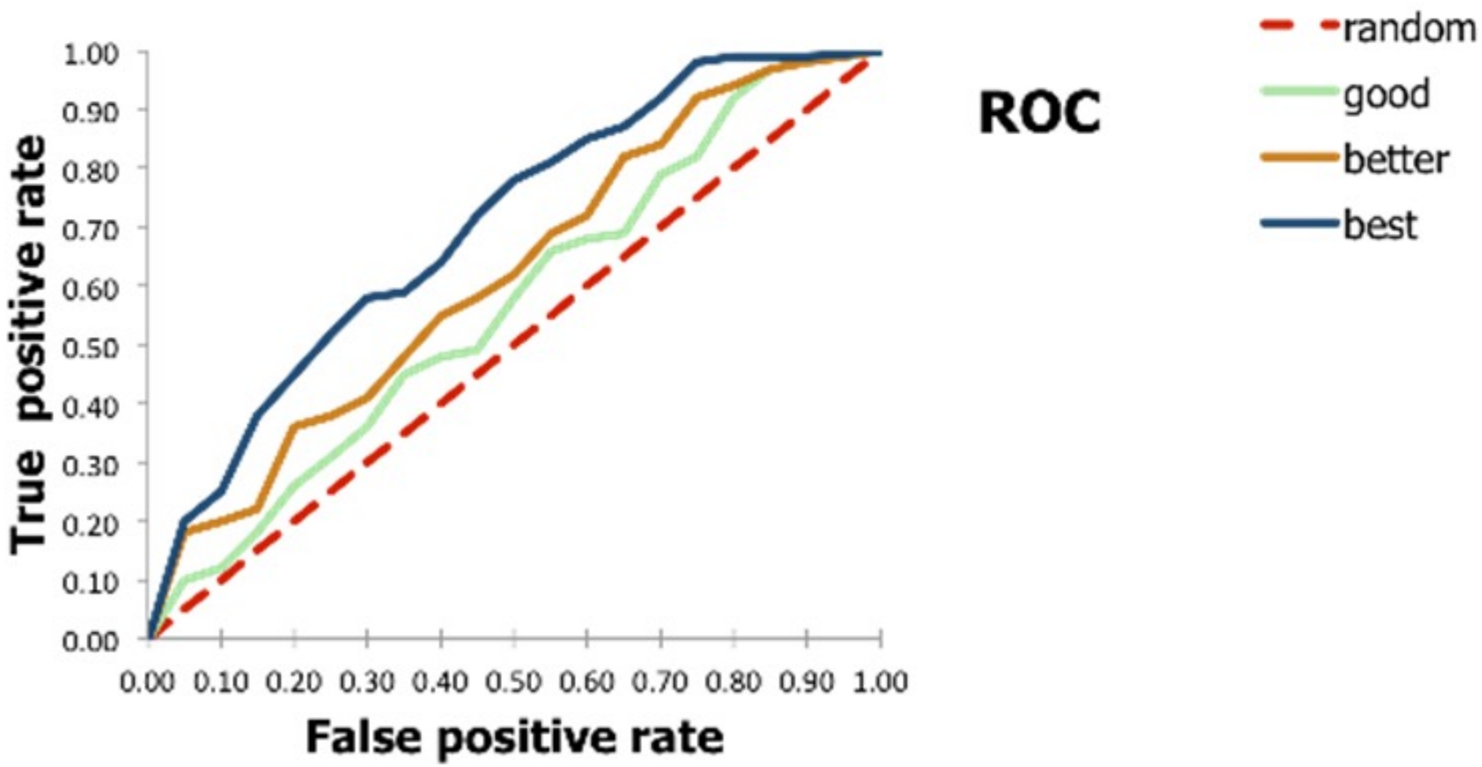
How to construct an ROC curve

Class	+	-	+	-	-	-	+	-	+	+	
Threshold >=	0.25	0.43	0.53	0.76	0.85	0.851	0.852	0.87	0.93	0.95	1.00
TP	5	4	4	3	3	3	3	2	2	1	0
FP	5	5	4	4	3	2	1	1	0	0	0
TN	0	0	1	1	2	3	4	4	5	5	5
FN	0	1	1	2	2	2	2	3	3	4	5
TPR	1	0.8	0.8	0.6	0.6	0.6	0.6	0.4	0.4	0.2	0
FPR	1	1	0.8	0.8	0.6	0.4	0.2	0.2	0	0	0

ROC Curve:



How to construct an ROC curve



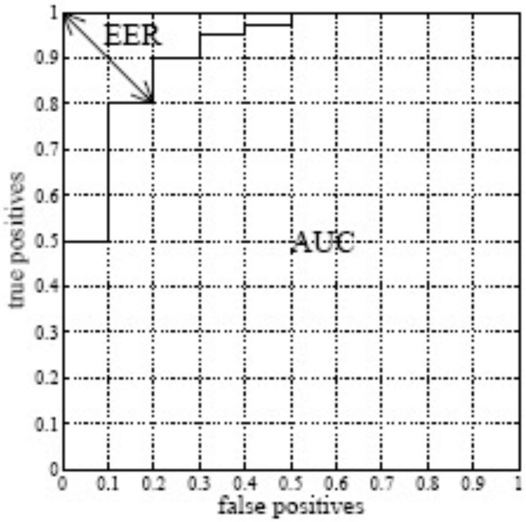
EER and AUC

- **Equal Error Rate (EER)** measures the **accuracy** at which the number of false positives and false negatives are equal.

  Somewhat emphasizes the behaviour of a method at low false positive rates which might be reasonable for a real-world application

- **Area Under Curve (AUC)** measures the total area under the ROC curve.

  Penalizes failures across the whole range of false positives, e.g. a method which recognizes some large proportion of instance with zero error but fails on the remaining portion of the data.



We are in the new era of AI 2.0

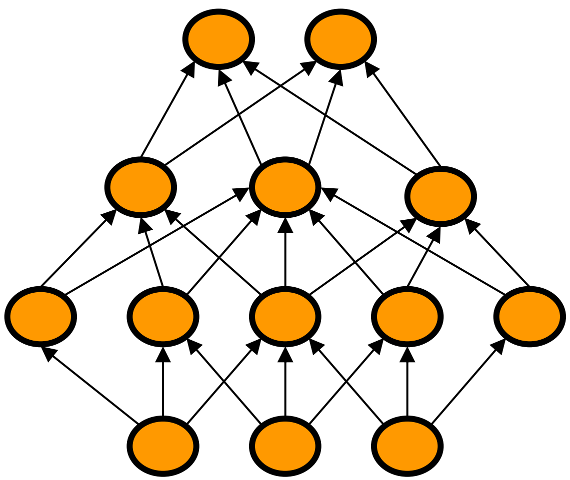
Deep learning is the key innovation in AlphaGo/Master

Neural network
Back propagation

Nature

1986

Geoffrey E. Hinton



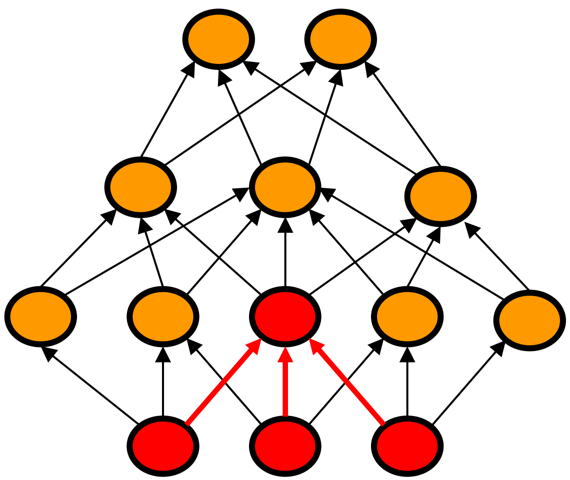
- Solve general learning problems
- Tied with biological system

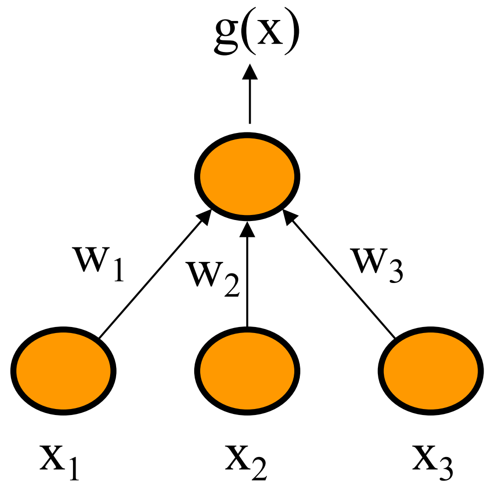
Rumelhart, D. E., Hinton, G. E., and Williams, R. J. (1986), Learning representations by back-propagating errors, Nature, 323, 533—536

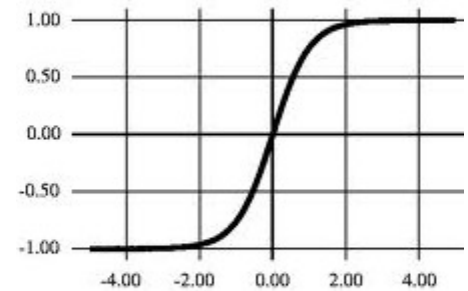
Neural network
Back propagation

Nature

1986







$f(net)$
activation function

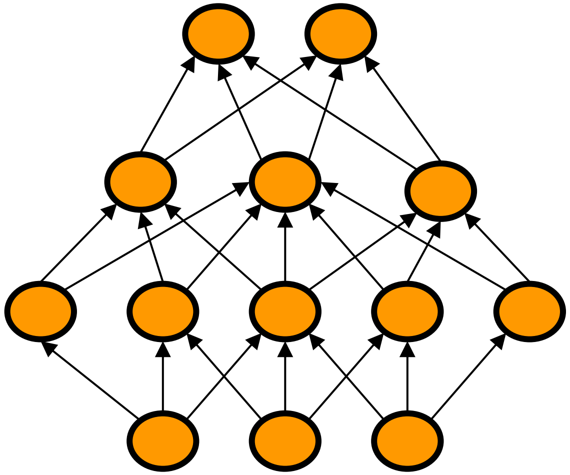
$$g(\mathbf{x}) = f(\sum_{i=1}^{d} x_i w_i + w_0) = f(\mathbf{w}^t \mathbf{x})$$

A set of nodes in their model -> a set of neurons in our brain

Neural network
Back propagation

Nature

1986



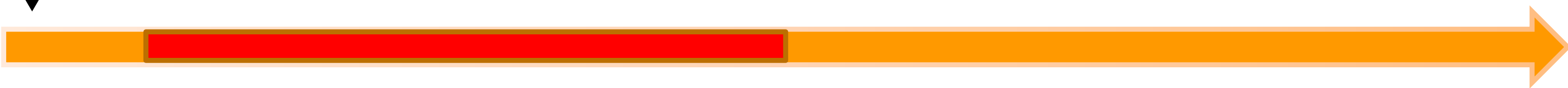
- Solve general learning problems
- Tied with biological system

But it is given up…

- Hard to train
- Insufficient computational resources
- Small training sets
- Does not work well

Neural network
Back propagation

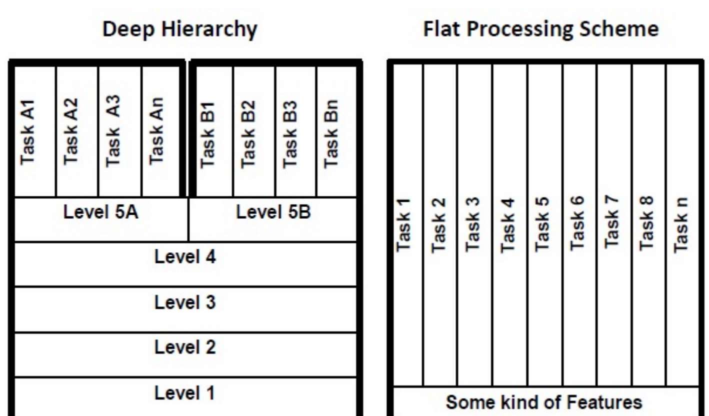
Nature



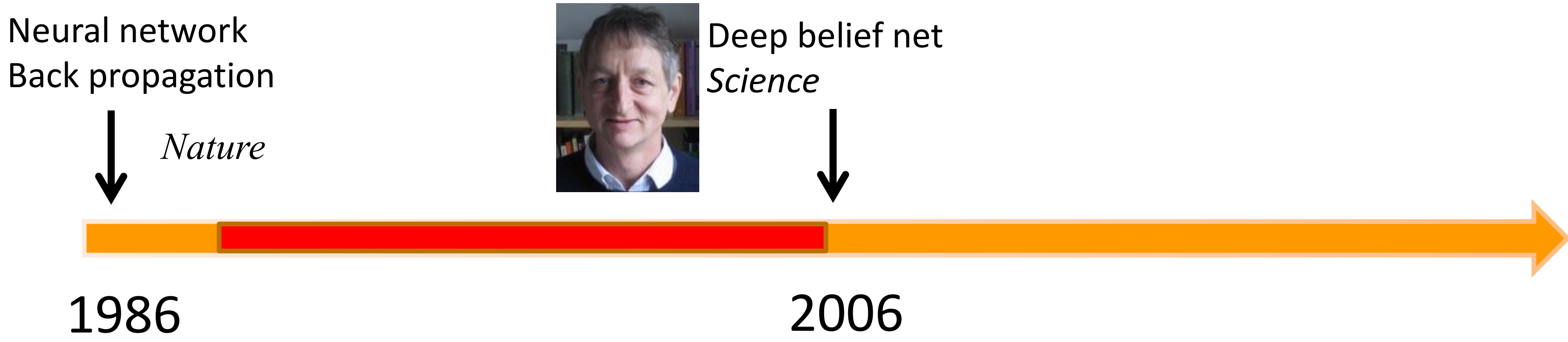
1986 2006

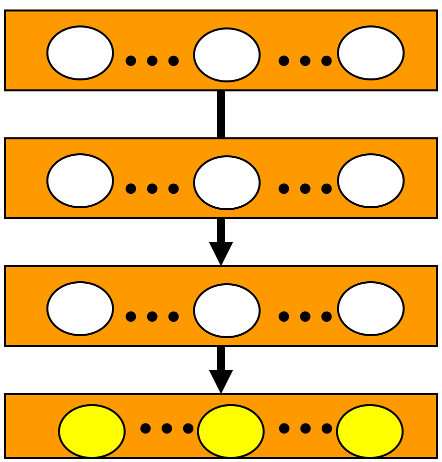
- Flat structures
- Loose tie with biological systems
- Specific methods for specific tasks
  - Hand crafted features (GMM-HMM, SIFT, LBP, HOG)

- SVM
- Boosting
- Decision tree
- KNN
- …



Kruger et al. TPAMI'13





deep autoencoder networks

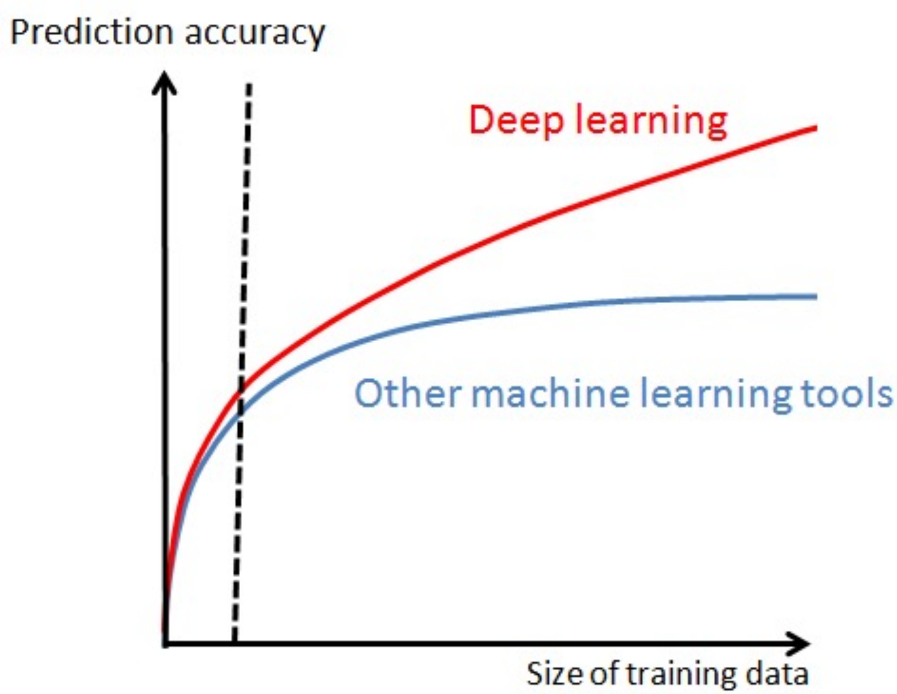
- Unsupervised & Layer-wised pre-training
- Better designs for modeling and training (normalization, nonlinearity, dropout)
- New development of computer architectures
  - GPU
  - Multi-core computer systems
- Large scale databases

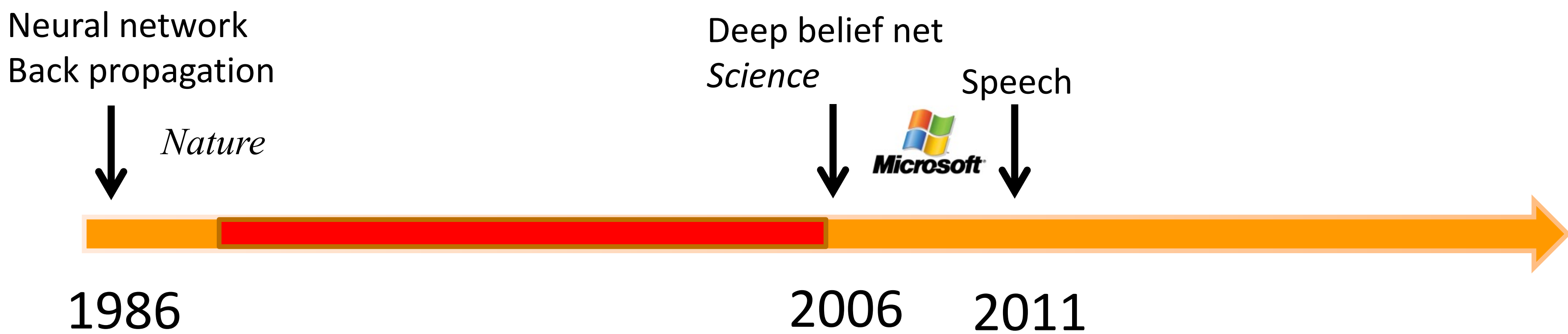
Big Data !

Hinton, G. E. and Salakhutdinov R.R. (2006), Reducing the dimensionality of data with neural networks, Science, 313(5786), July 2006.

Machine Learning with Big Data

- Machine learning with small data: overfitting, reducing model complexity (capacity), adding regularization
- Machine learning with big data: underfitting, increasing model complexity, optimization, computation resource





DNN: Deep Neural network

HMM: Hidden Markov Model

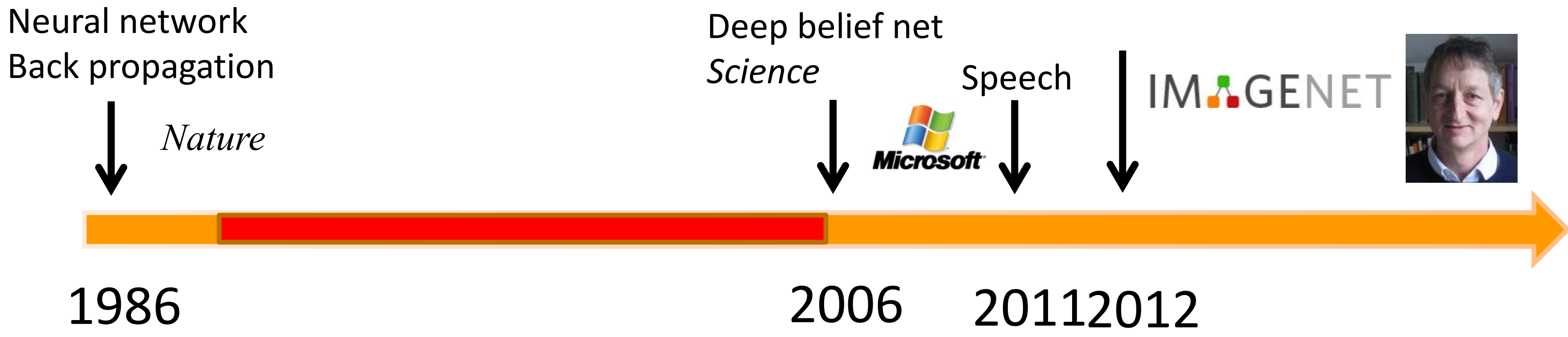
GMM: Gaussian Mixture Model

deep learning results

task	hours of training data	DNN-HMM	GMM-HMM with same data
Switchboard (test set 1)	309	18.5	27.4
Switchboard (test set 2)	309	16.1	23.6
English Broadcast News	50	17.5	18.8
Bing Voice Search (Sentence error rates)	24	30.4	36.2
Google Voice Input	5,870	12.3	
Youtube	1,400	47.6	52.3

Deep Networks Advance State of Art in Speech

Deep Learning leads to breakthrough in speech recognition at MSR.



Rank	Name	Error rate	Description
1	**U. Toronto**	0.15315	Deep learning
2	U. Tokyo	0.26172	Hand-crafted features and learning models. Bottleneck.
3	U. Oxford	0.26979	
4	Xerox/INRIA	0.27058	

Object recognition over 1,000,000 images and 1,000 categories (2 GPUs)

A. Krizhevsky, L. Sutskever, and G. E. Hinton, “ImageNet Classification with Deep Convolutional Neural Networks,” NIPS, 2012.

What makes deep learning successful in computer vision?

Li Fei-Fei

IMAGENET

Geoffrey Hinton

Data collection

Evaluation task

Deep learning

One million images with labels

Predict 1,000 image categories

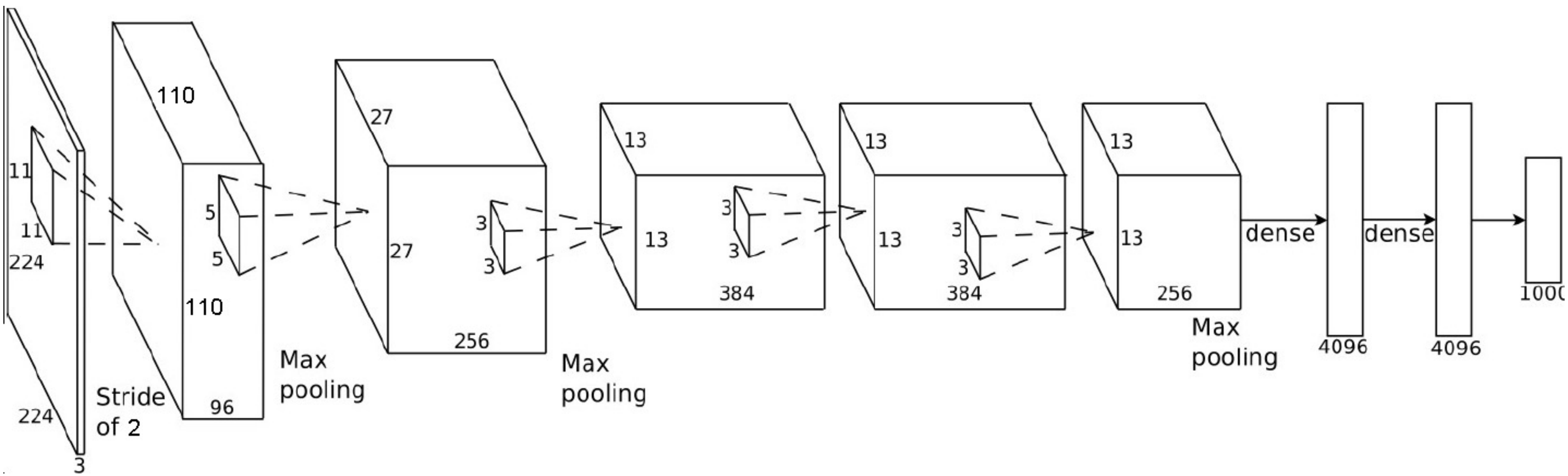
CNN is not new

Design network structure

New training strategies (e.g. dropout)

Feature learned from ImageNet can be well generalized to other tasks and datasets

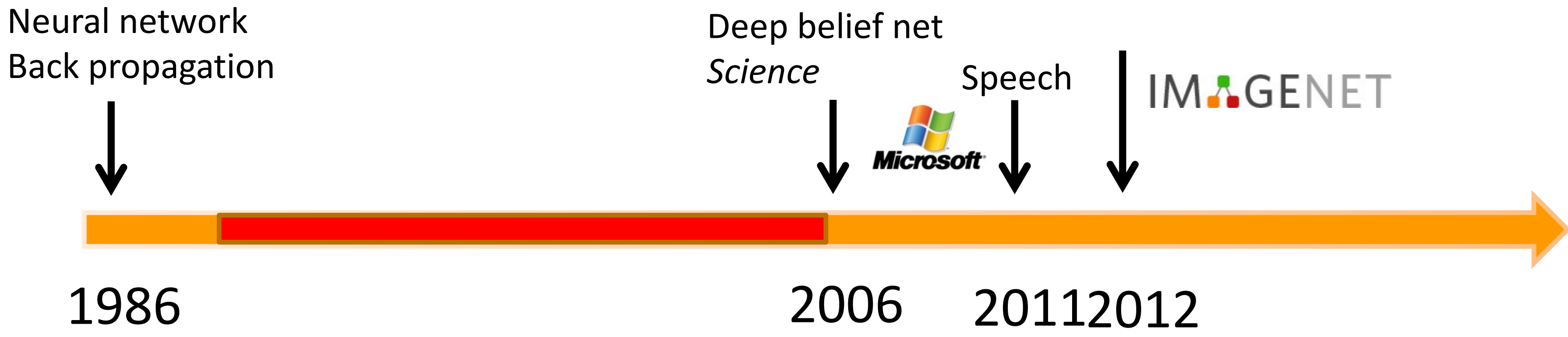
AlexNet, VGG, GoogleNet and ResNet DenseNet



YannLeCun’s paper on deep learning for scene labelling got rejected by CVPR 2012 (https://plus.google.com/+YannLeCunPhD/posts/gurGyczzsJ7)

Plenary talk at CVPR 2015, What's Wrong with Deep Learning?

[1]Krizhevsky, L. Sutskever, and G. E. Hinton, “ImageNet Classification with Deep Convolutional Neural Networks,” NIPS, 2012.
[2] K. Simonyan, A. Zisserman, Very Deep Convolutional Networks for Large-Scale Image Recognition, ICLR, 2015.
[3]C. Szegedy, W. Liu, Y. Jia, P. Sermanet, S. Reed, D. Anguelov, D Erhan, V. Vanhoucke and A. Rabinovich, Going Deeper With Convolutions, CVPR 2015.
[4]K. He, X. Zhang, S. Ren and J. Sun, Deep Residual Learning for Image Recognition, CVPR 2016.
[5]G. Huang et all, “Densely Connected Convolutional Networks,” CVPR 2017.



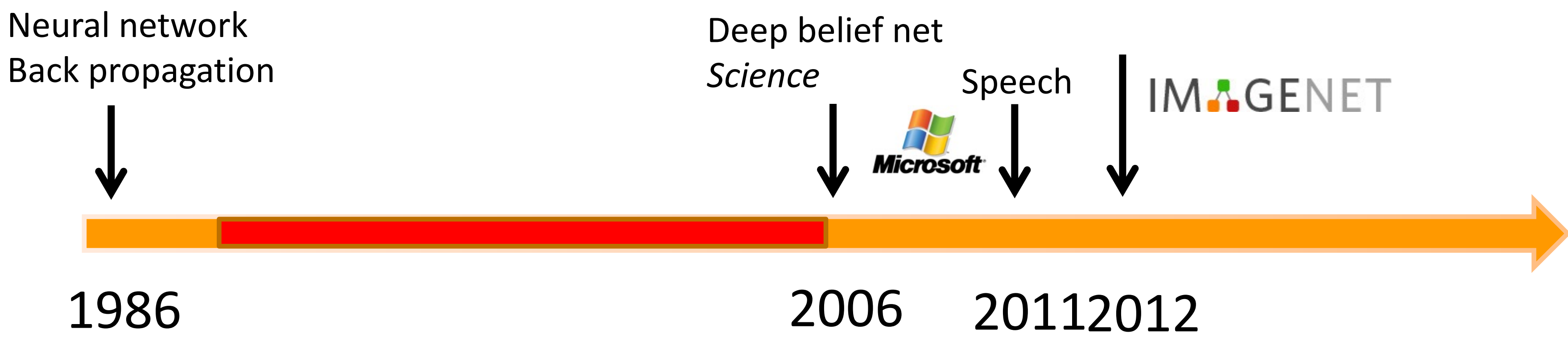
- ImageNet 2013 – image classification challenge

Rank	Name	Error rate	Description
1	NYU	0.11197	Deep learning
2	NUS	0.12535	Deep learning
3	Oxford	0.13555	Deep learning

MSRA, IBM, Adobe, NEC, Clarifai, Berkley, U. Tokyo, UCLA, UIUC, Toronto …. Top 20 groups all used deep learning

- ImageNet 2013 – object detection challenge

Rank	Name	Mean Average Precision	Description
1	UvA-Euvision	0.22581	Hand-crafted features
2	NEC-MU	0.20895	Hand-crafted features
3	NYU	0.19400	Deep learning



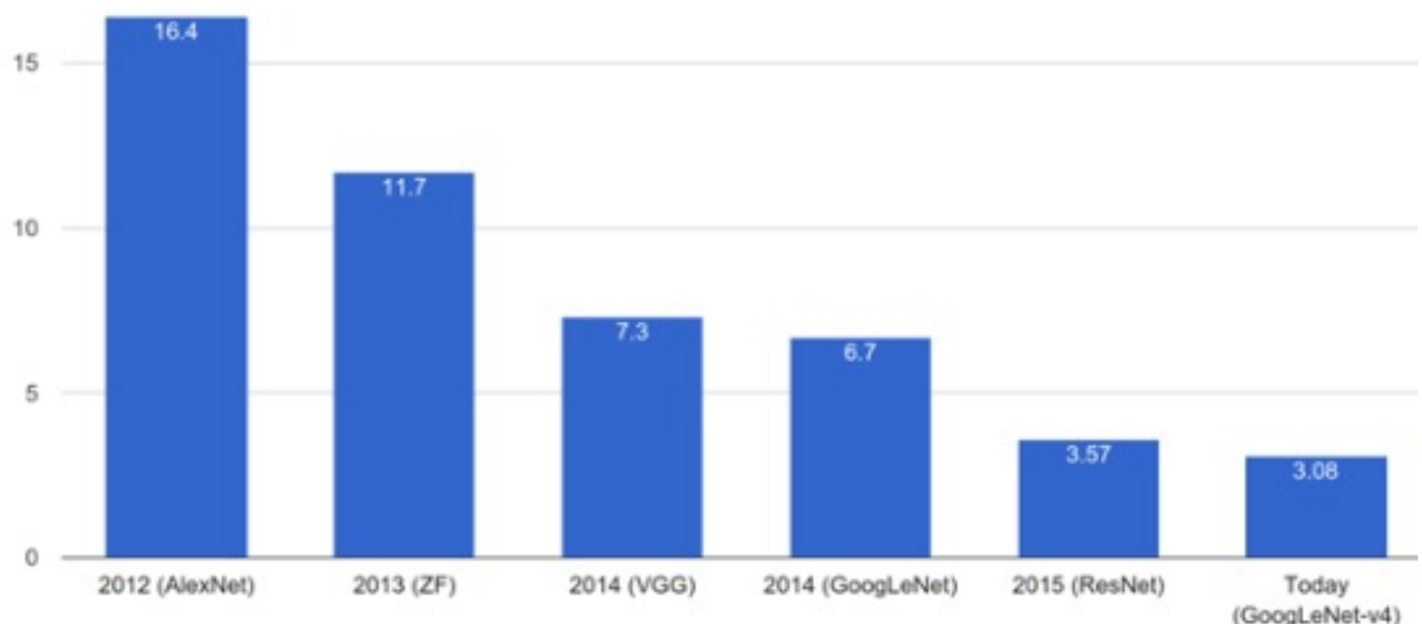
- ImageNet 2014 – Image classification challenge

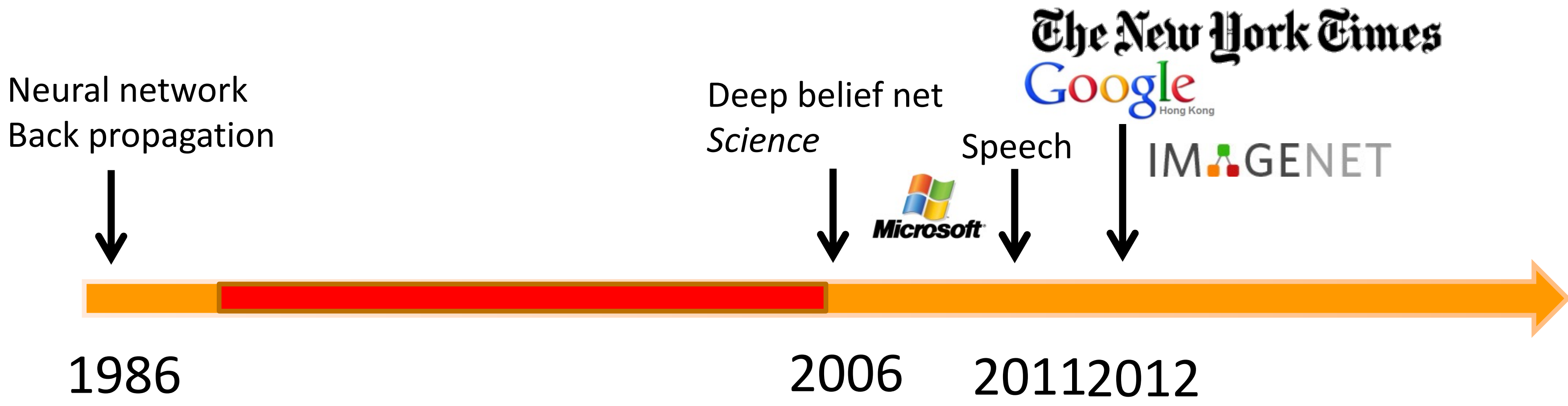
Rank	Name	Error rate	Description
1	Google	0.06656	Deep learning
2	Oxford	0.07325	Deep learning
3	MSRA	0.08062	Deep learning

- ImageNet 2014 – object detection challenge

Rank	Name	Mean Average Precision	Description
1	Google	0.43933	Deep learning
2	CUHK	0.40656	Deep learning
3	DeepInsight	0.40452	Deep learning
4	UvA-Euvision	0.35421	Deep learning
5	Berkley Vision	0.34521	Deep learning

ImageNet Competition Results





- Google and Baidu announced their deep learning based visual search engines (2013)
  - Google
    - "on our test set we saw **double the average precision** when compared to other approaches we had tried. We acquired the rights to the technology and went full speed ahead adapting it to run at large scale on Google's computers. We took cutting edge research straight out of an academic research lab and launched it, in just a little over six months."
  - Baidu

MIT Technology Review

10 BREAKTHROUGH TECHNOLOGIES 2013

Deep Learning

With massive amounts of computational power, machines can now recognize objects and translate speech in real time. Artificial intelligence is finally getting smart. →

Temporary Social Media

Messages that quickly self-destruct could enhance the privacy of online communications and make people freer to be spontaneous. →

Prenatal DNA Sequencing

Reading the DNA of fetuses will be the next frontier of the genomic revolution. But do you really want to know about the genetic problems or musical aptitude of your unborn child? →

Additive Manufacturing

Skeptical about 3-D printing? GE, the world's largest manufacturer, is on the verge of using the technology to make jet parts. →

Baxter: The Blue-Collar Robot

Rodney Brooks's newest creation is easy to interact with, but the complex innovations behind the robot show just how hard it is to get along with people. →

Memory Implants

A maverick neuroscientist believes he has deciphered the code by which the brain forms long-term memories. Next: testing a prosthetic implant for people suffering from long-term memory loss.

Smart Watches

The designers of the Pebble watch realized that a mobile phone is more useful if you don't have to take it out of your pocket.

Ultra-Efficient Solar Power

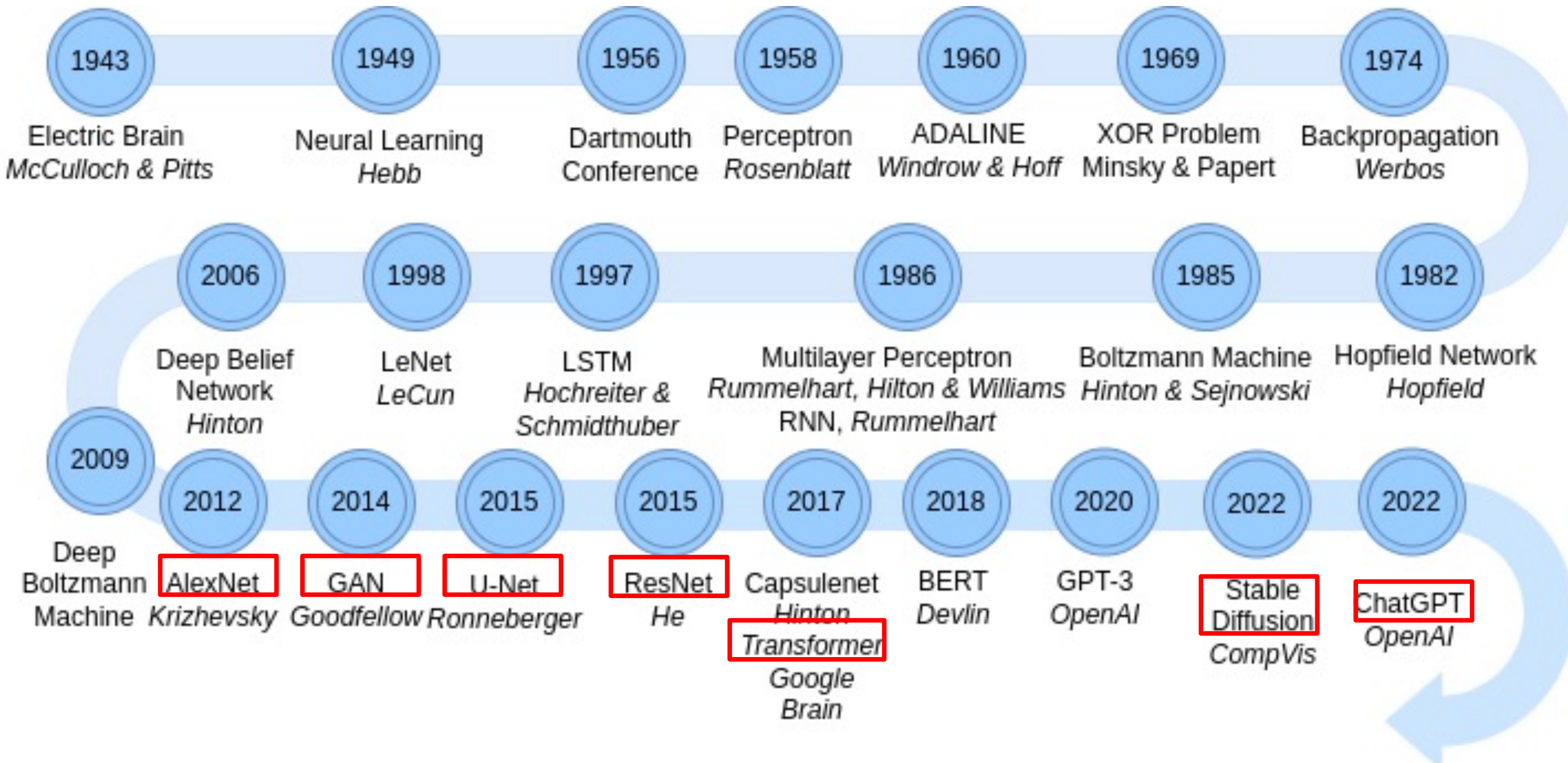
Doubling the efficiency of a solar cell would completely change the economics of renewable energy. Nanotechnology just might make it possible.

Big Data from Cheap Phones

Collecting and analyzing information from simple cell phones can provide surprising insights into how people move about and behave – and even help us understand the spread of diseases.

Supergrids

A new high-power circuit breaker could finally make highly efficient DC power grids practical.



1943
Electric Brain
McCulloch & Pitts
1949
Neural Learning
Hebb
1956
Dartmouth Conference
1958
Perceptron
Rosenblatt
1960
ADALINE
Windrow & Hoff
1969
XOR Problem
Minsky & Papert
1974
Backpropagation
Werbos
1982
Hopfield Network
Hopfield
1985
Boltzmann Machine
Hinton & Sejnowski
1986
Multilayer Perceptron
Rummelhart, Hilton & Williams
RNN, Rummelhart
1997
LSTM
Hochreiter & Schmidthuber
1998
LeNet
LeCun
2006
Deep Belief Network
Hinton
2009
Deep Boltzmann Machine
2012
AlexNet
Krizhevsky
2014
GAN
Goodfellow
2015
U-Net
Ronneberger
2015
ResNet
He
2017
Capsulenet
Hinton
Transformer
Google Brain
2018
BERT
Devlin
2020
GPT-3
OpenAI
2022
Stable Diffusion
CompVis
2022
ChatGPT
OpenAI