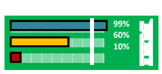
Stat231--CS276A

Pattern Recognition and Machine Learning

Recent advances in PRML

IBM Watson for Jeopardy

1, Understand human speech
2, Search and evaluates hypotheses



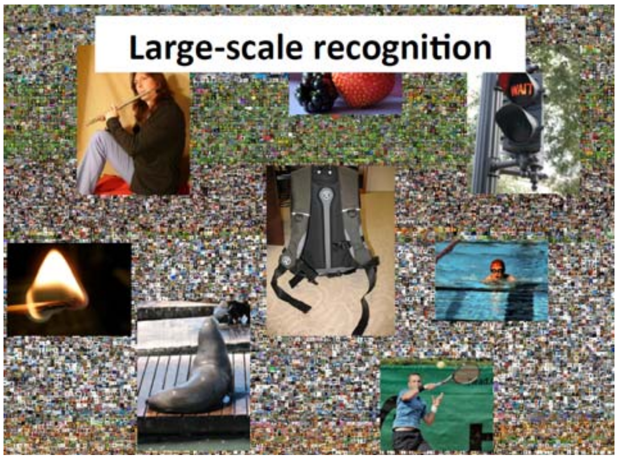
3, Learns from user selections

Google driverless car

Still many obstacles remain in high level cognition.

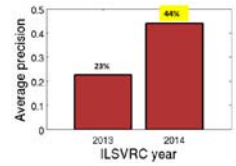
In 2012, we piloted project 3 with IBM Watson.
The main method behind is Logistic regression.

Recent advances in PRML

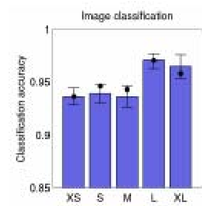


ImageNet Challenges:
(Russakovsky and Deng IJCV 2015)

200 object classes for detection



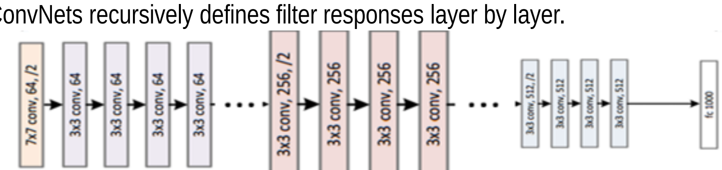
1000 classes for classification
(top five accuracy plotted
for object sizes in real world)



This dataset rejuvenated interests on the multi-layer Neural Network (Deep Learning).

Recent advances in PRML

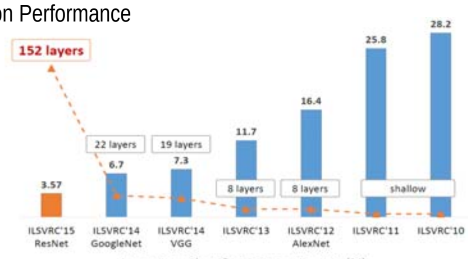
ConvNets recursively defines filter responses layer by layer.



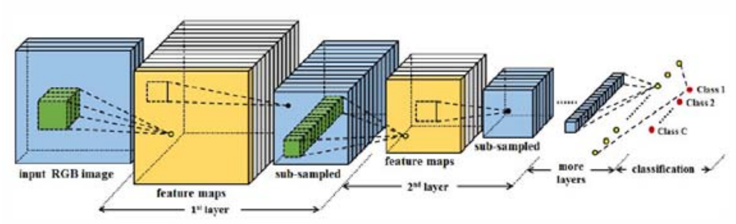
152-Layer ResNet and model is 0.5~1GB !

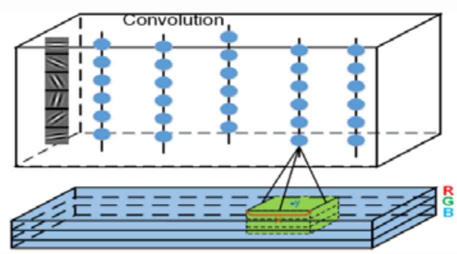
K. He, X. Zhang, S. Ren, J. Sun, Microsoft Research Asia, CVPR 2016.

Classification Performance

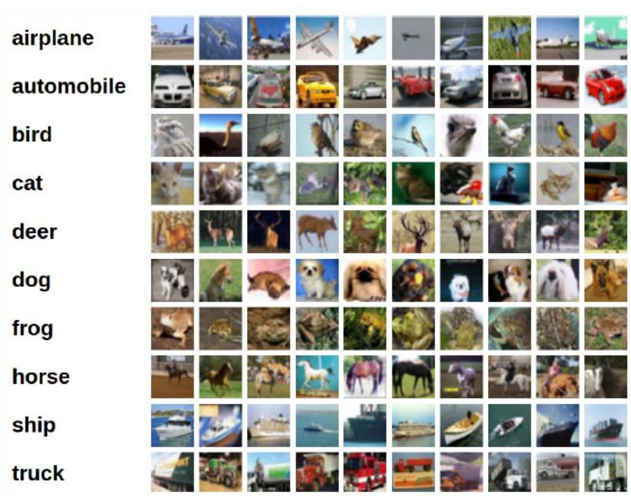


Project 0. Classification by Deep Learning

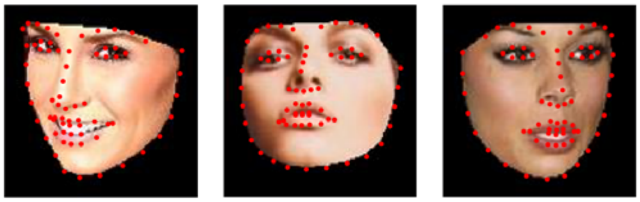


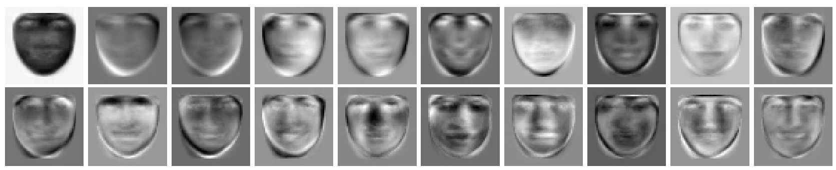


Project 0. Classification by Deep Learning



Project I. Human face modeling



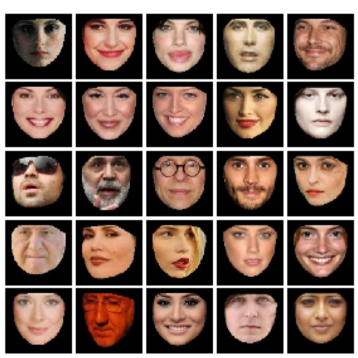


First 20 eigen-faces without alignment

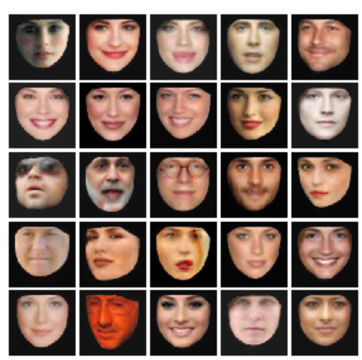
Project I. Human face modeling

Results from previous student:

Face examples in the dataset



Face (lossy) reconstructed by 50+10 numbers



Generated faces by geometric and appearance changes

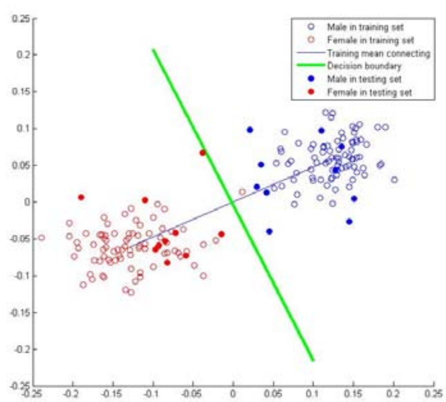
(a) Training faces with 68 landmarks

(b) Sliding in an axis for geometric changes

(c) Sliding in an axis for appearance changes

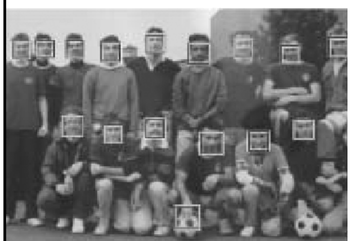
Project I. Human face analysis

Classifying male and female using Fisher's Linear Discriminants



Project II: Face detection by Boosting

Example: Human face

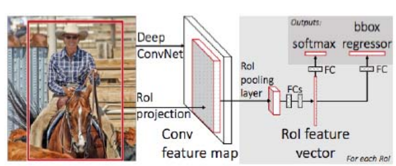


Viola and Jones, 2000

A 231 project by a student whose face was not detected here.

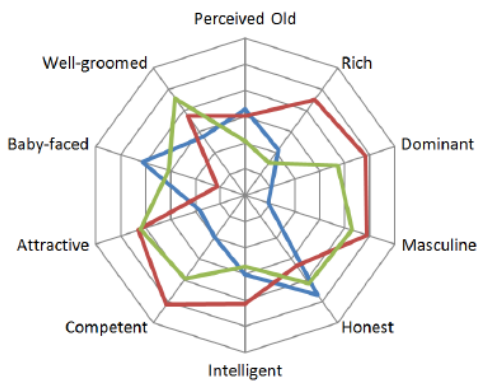
Project III: Face Detection by Faster R-CNN

Recently, the results have been much improved through engineering the neural networks.



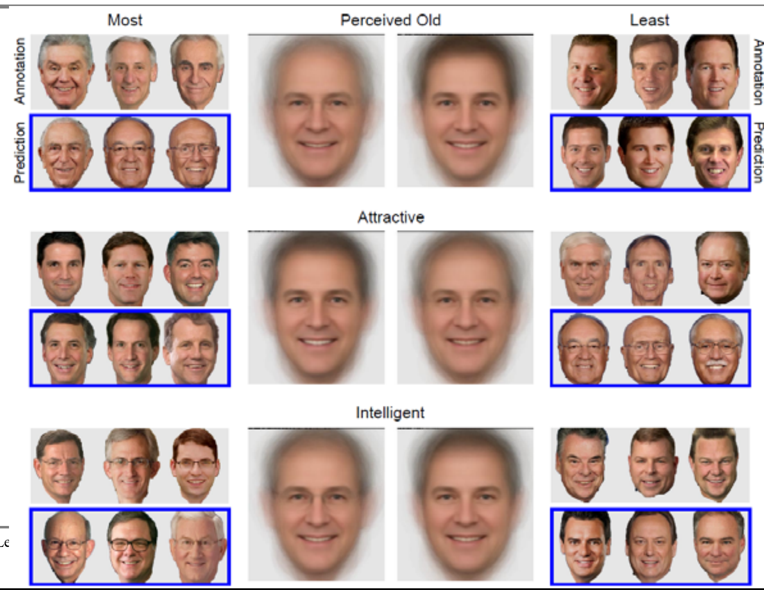
Project IV: Face social attributes

Social dimensions of faces by machine learning

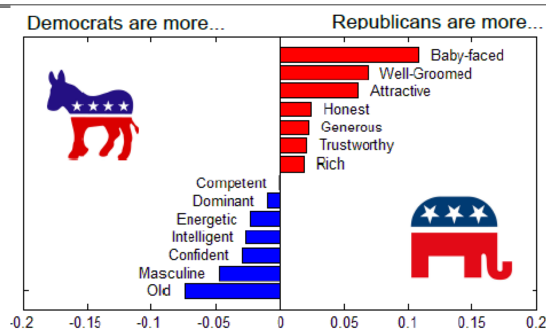


This result is from Jungseock Joo, Ph.D 2015. We are tracking the US 2016 elections.

Training SVM scoring for each dimensions on US politicians



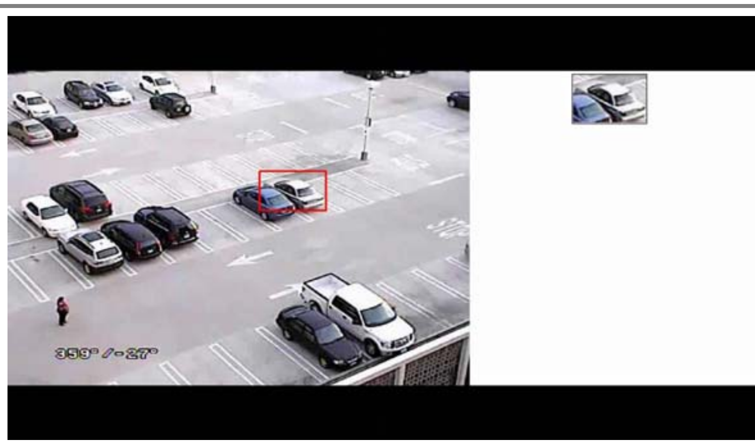
Some relative scores found by machine learning



	Prediction rate	Number of pairs
Congress election	56.3%	32
Senator election	65.0%	40
Governor election	91.7%	12

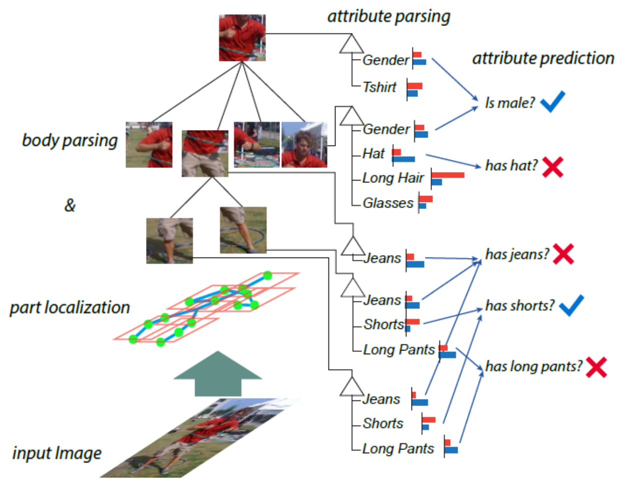
results from Joo, Steen and Zhu, ICCV 2015.

Demos of automatic PTZ camera for reading license



video files are from Tianfu Wu and Brandon Rothrock

Recognizing human pose and attributes by attribute grammar



 S. Park and S. Zhu, ICCV 2015

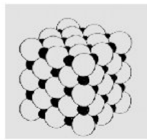
Lecture 1: Introduction

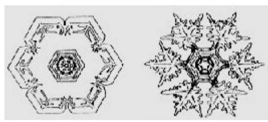
Outline:

1. Patterns in nature: a continuous spectrum.
   --- Overview of the terminologies: concepts, models, and theories.
2. Applications of pattern recognition
3. Schools of thought in pattern recognition and machine learning
4. A simplistic example of pattern recognition
5. Overview of the four course projects

Examples of Patterns

Crystal patterns at atomic and molecular levels





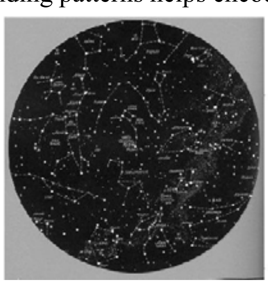
Pattern, in English usually, refers to regular repeated structures. But in pattern recognition, anything that you can perceive is a pattern.

These structures can be represented by graphs or by grammars.
This is often called **syntactic pattern recognition** with **generative** models.

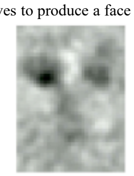
One may view a compiler for a programming language (e.g. matlab, c) as a syntactic pattern recognition system. A syntactic pattern recognition system not only classifies the input, but also extracts **hierarchical (compositional) structures**.

Examples of Patterns

Constellation patterns in the sky are represented by 2D (often planar) graphs.
Finding patterns helps encoding the signals.



random noise images are reported as positives or negatives, then sum Of positives minus the sum of negatives to produce a face pattern.

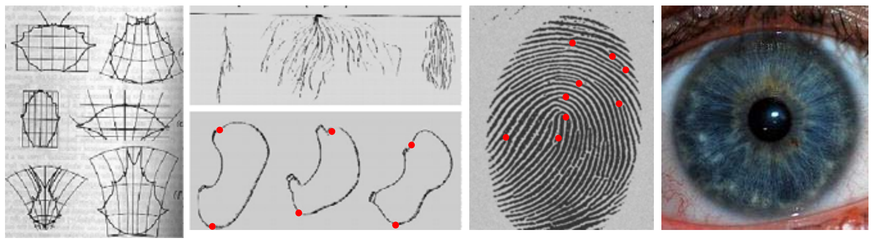


From Philippe Schyns and Nicola van Rijsbergen, 2014

Human perception has a strong tendency to find patterns from almost anything.
We see (hallucinate) patterns from even random noise (psychology evidence) --- we are more likely to believe a hidden pattern than denying it when the **risk (reward)** for missing (discovering) a pattern is often high. This is an important aspect in **pattern discovery**.
It is formulated in the **Bayesian decision theory ---** considering the risk of classification.

Examples of Patterns

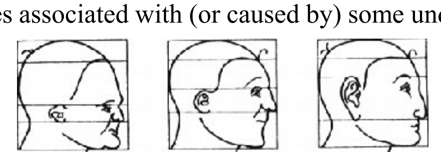
Biology patterns --- study in morphology and **biometrics** (Human ID is now an industry)



Landmarks (key points) are identified and **matched** between instances.
Applications include biometrics, computational anatomy, brain mapping, forensics (fingerprint was first used in 1905 for solving a murder case, now it is used for all kinds of ID systems and smart phone login).
But for other forms, like the root of plants, points cannot be registered crossing instances. They are described by **stochastic models**.

Examples of Patterns

Pattern discovery and association: In plain language, a pattern often mean a set of instances associated with (or caused by) some underlying factors.



Statistics show connections between the shape of one's face (adults) and his/her Character. There is also evidence that the outline of children's face is related to alcohol abuse during pregnancy.

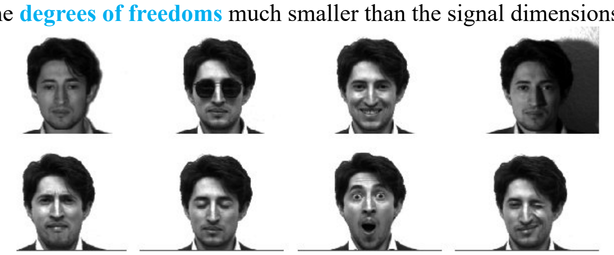
With fMRI, we now can look the internal patterns of brain activity and find relationships between brain activities, cognition, and behaviors.

Examples of Patterns

A pattern often exhibits a wide range of variations with **nuisance factors** : e.g. faces

1. Expression –geometric deformation
2. lighting --- photometric deformation
3. 3D pose transform
4. Noise and occlusion

Each pattern corresponds to a set (sometimes a **manifold**) in the signal space (spanned by the **degrees of freedoms** much smaller than the signal dimensions).

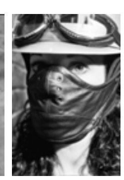


The nuisance factors are called **attributes** when they are “useful”, e.g. as social traits.

Examples of Patterns

Detecting or recognizing human faces in the real world is challenging.

We need to consider many factors to build a robust system.

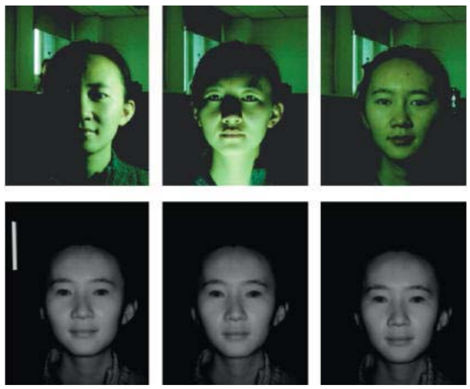




1, Face detection with cooperative subjects has found wide commercial applications. e.g. face detection in camera and iphones.

2, Face recognition is getting more promising this year, after failing many companies.

Examples of Patterns

Face recognition becomes more tractable in **constrained environments**.



Outdoor lighting variation is the main obstacle for face recognition.

infrared camera from Stan Li's lab/com

Neurons in our Brain are detecting all kinds of patterns.

This example is a recorded neuron at the human medial temporal lobe (MTL).

"Invariant visual representation by single neurons in the human brain," Nature, Vol 435, June 2005. From Dr. Izthak Fried's lab at UCLA.

Examples of Patterns

Classifying human actions, activities, and events in video. Other activities include city level (your mobile pattern recorded by GPS, Phone, e.g. Intelligent City)

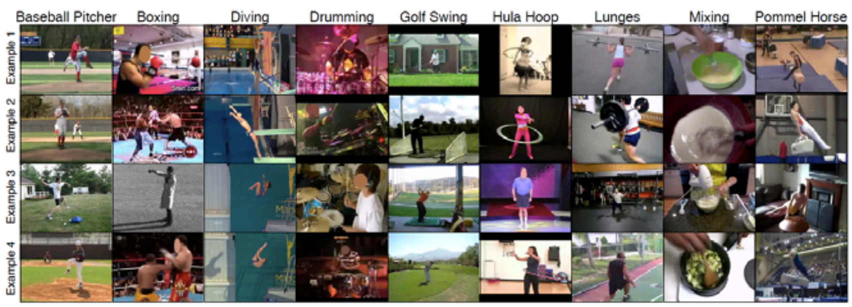
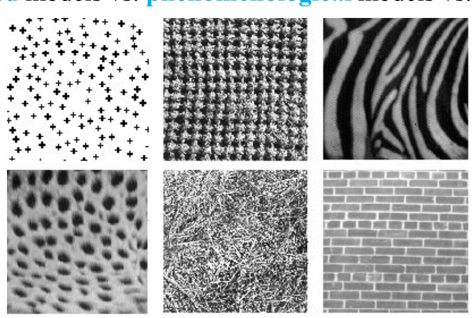


Image from Jason Corso, Action Bank.

Some neurons in the pre-motor area of our brain respond to various actions, and how do we encode actions in our brain? Mirror neurons and origin of language.

Types of models for patterns

How are these texture patterns represented in a human brain or a computer?
physics-based models vs. **phenomenological** models vs. **example-based** models

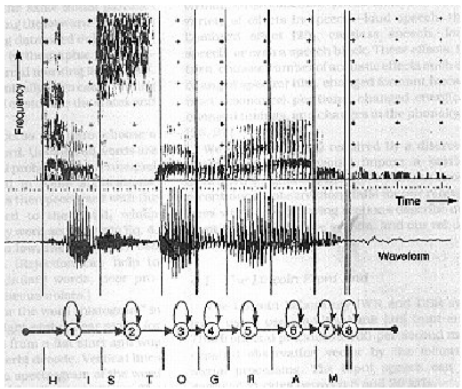


A wide variety of texture patterns are generated by various stochastic processes (chemical or physical, biologic), do we need to simulate these processes for representing the patterns?
A pattern could be represented by many ways for different **purposes**.

Lecture note, Stat231-CS276A, © S.C.Zhu

Examples of Patterns

Speech signal and hidden Markov model (level I)

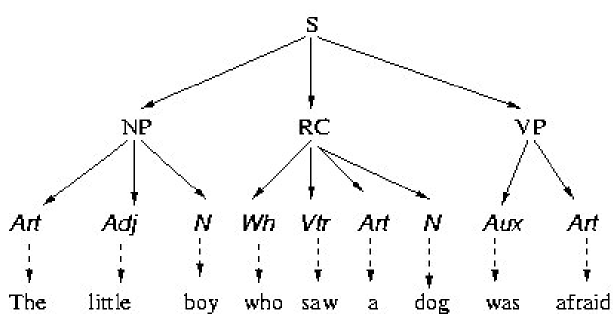


An example is the model for speech recognition:
People built **physical models** to simulate the uttering of phonemes.

Now this problem is solved more effectively by collecting large **examples** of speech to combat accents and variations.

Examples of Patterns

Natural language and **stochastic grammar** (level II).



Syntactic pattern recognition methods were developed in the 1970s for recognizing patterns which have wide structural variations (i.e. signals have varying dimensions).

Examples of Patterns

A story generated from the rules: (level III)

$$\alpha\beta^3\delta^1 A^1 B^2 C \uparrow H^1 - I^2 K^4 \downarrow w^c$$

A tsar (emperor in Russian), three daughters (α). The daughters go walking (β^3), overstay in the garden (δ^1). A dragon kidnaps them (A^1). A call for rescue (B^2). Quest for three heros ($C \uparrow$). Three battles with the dragon ($H^1 - I^2$), rescue of the maidens (K^4). Return ($\downarrow$), and reward (w^c).

α = initial situation
β_1 = departure of elders
β_2 = death of parents
… …
A^1 = kidnapping of a person
A^2 = seizure of a magical agent
… …
B^1 = call for help
D^1 = test of hero
E^1 = sustained ordeal
… …

I didn't update this slice. Nowadays, games are designed by stochastic grammatical odels.

Applications of Pattern Recognition

Lie detector,

Handwritten Zip code/digit/letter recognition

Biometrics: voice, iris, finger print, face, and gait recognition

Speech/voice recognition

Smell recognition (e-nose, sensor networks)

Defect detection in chip manufacturing

Reading DNA sequences, Medical diagnosis

Detecting spam mails, …

Levels of difficulties in Pattern Recognition Tasks

For example, there are many levels of tasks related to human face patterns

1. Face authentication (hypothesis test for one class)
2. Face detection (yes/no for many instances).
3. Face recognition (classification)
4. Expression recognition (smile, disgust, surprise, angry)
   identifiability problem.
5. Gender and age recognition

----

6. Face sketch and from images to cartoon
   --- needs generative models.
7. Face caricature

… …

The simpler tasks 1-4 may be solved effectively using discriminative methods, but the tasks 5-7 will need generative methods that model faces explicitly.

From this example, we can see a problem of generalization in discriminative methods.

Some hard example: art and antique authentication

In many cases, we only have small data.

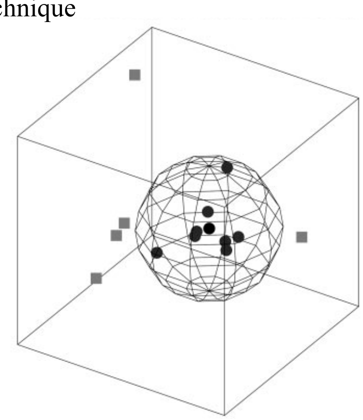
Is a picture drawn by a master or an amateur?

Example: Art Authentication

A **multi-dimensional scaling (MDS)** technique

Project a high-dimensional feature vector to 3D space so as to preserve the similarity (distance).

The circular and rectangular dots correspond to two types of styles.



（from S. Lyu, D. Rockmore, Hany Farid 2004）

Two Schools of Thoughts

1. ***Discriminative methods***:

The goal is to tell apart a number of patterns, say 100 people in a company, 10 digits for zip-code reading. These methods hit the discriminative target directly, without having to understand the patterns (their structures) or to develop a full mathematical description.

For example, we may tell someone is speaking English or Chinese in the hallway without understanding the words he is speaking.

"You should not solve a problem to an extent more than what you need" –Vapnik.

2. Generative methods:

Bayesian school, pattern theory.
1). Define patterns and regularities (in graphical representations),
2). Specify likelihood model for how signals are generated from hidden structures
3). Learning probability models from ensembles of signals
4). Inferences.

"If you cannot solve a simple problem in vision, you may have to solve for a complex one"

Recently, the two schools are increasingly integrated, leads to lifelong continuous learning.

Methods and research streams

Methods for pattern recognition:

Axis I: **Denerative** vs. **discriminative**
(Bayesian vs. non-Bayesian)

Axis II: **Deterministic** vs. **stochastic**
(logic/syntactic/rule-based vs. statistics)

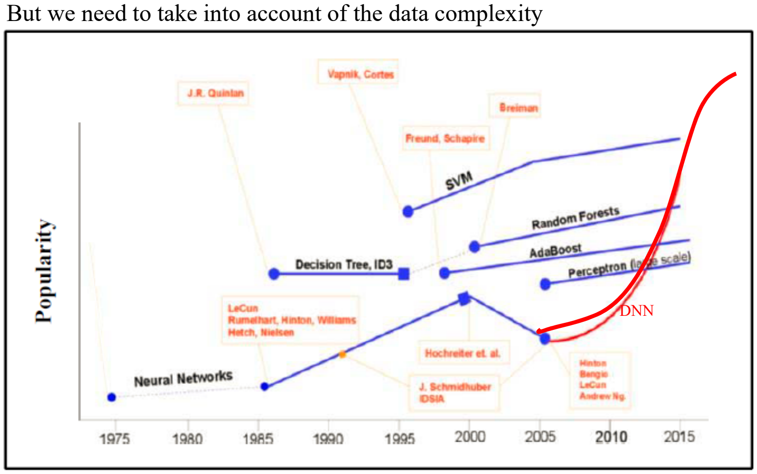
Axis III: **Parametric** vs. **semi-parametric** vs. **non-parametric**
(the number of parameters vs. the size of training examples)

Axis IV: **Supervised** vs. **Weakly supervised** vs. **unsupervised**

Examples:
Bayesian decision theory, neural networks, syntactical pattern recognition (AI), decision trees, support vector machines, boosting techniques, Deep Learning.

Some popular methods over the years

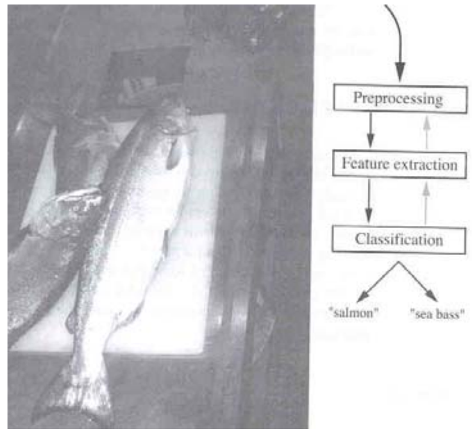
But we need to take into account of the data complexity



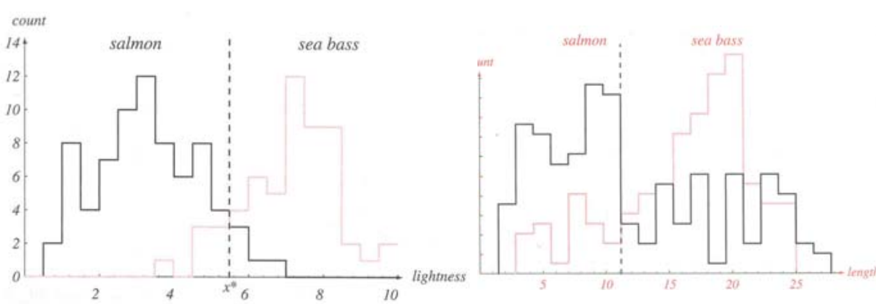
This is a slide borrowed from a DARPA manager.

A simple example of pattern recognition

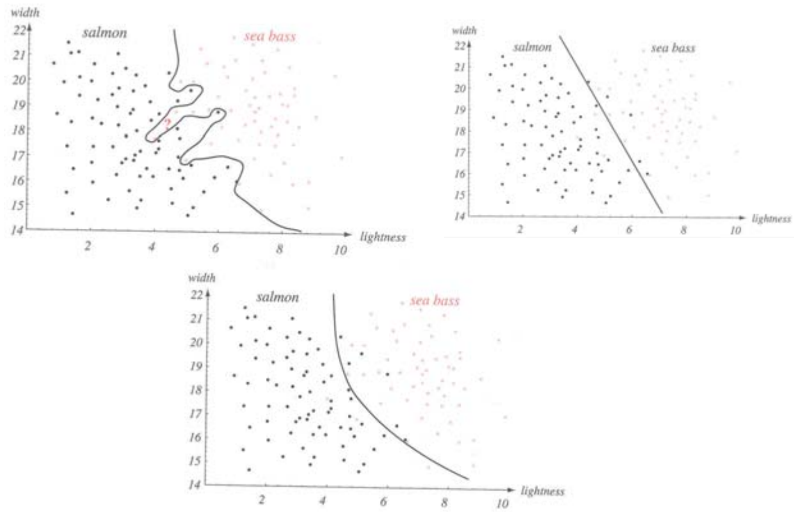
Classifying fish into two classes: salmon and Sea Bass by discriminative method



Features and Distributions



Decision/classification Boundaries



Main Issues in Pattern Recognition

1. Feature selection and learning.
   --- What are good discriminative features?
2. Modeling and learning
3. Dimension reduction, model complexity
4. Decisions and risks
5. Error analysis and validation.
6. Performance bounds and capacity.
7. Algorithms