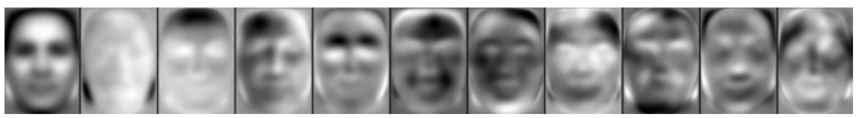
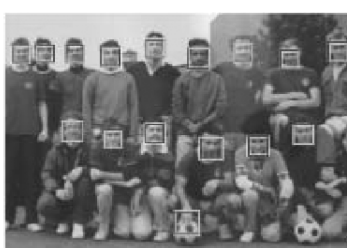
Project I. Face Analysis

face with 87 landmarks | face with 25 landmarks (subset) | face with 12 landmarks (subset)



eigen-faces

Project II: Face Detection



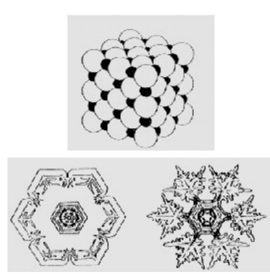
Lecture 1:

Introduction to Pattern Recognition

1. Examples of patterns in nature.
2. Issues in pattern recognition and an example of pattern recognition
3. Schools in pattern recognition
4. Pattern theory

Examples of Patterns

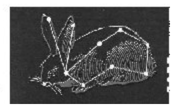
Crystal patterns at atomic and molecular levels



Their structures are represented by 3D graphs and can be described by deterministic grammar or formal language

Examples of Patterns

Constellation patterns in the sky.

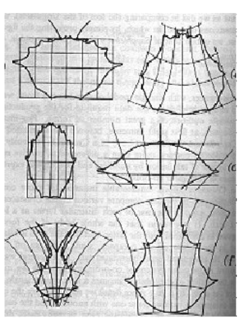


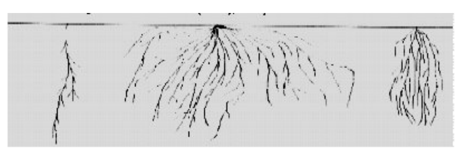
The constellation patterns are represented by 2D (often planar) graphs

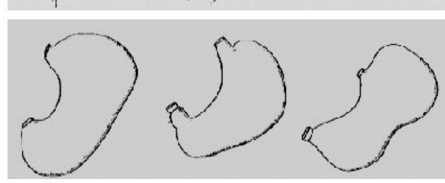
Human perception has strong tendency to find patterns from anything. We see patterns from even random noise --- we are more likely to believe a hidden pattern than denying it when the risk (reward) for missing (discovering) a pattern is often high.

Examples of Patterns

Biology pattern ---morphology





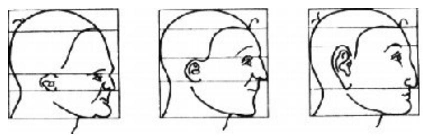


Landmarks are identified from biologic forms and these patterns are then represented by a list of points. But for other forms, like the root of plants, Points cannot be registered crossing instances.

Applications: biometrics, computational anatomy, brain mapping, …

Examples of Patterns

Pattern discovery and association



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.

Examples of Patterns

Patterns of brain activities:

We may understand patterns of brain activity and find relationships between brain activities, cognition, and behaviors

Examples of Patterns

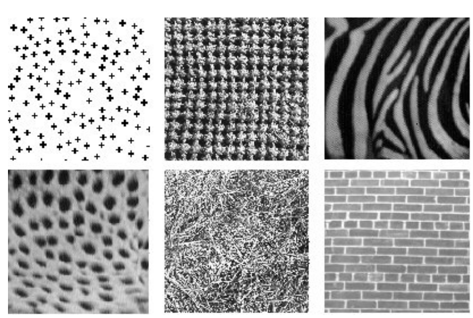
Patterns with variations:

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

Examples of Patterns

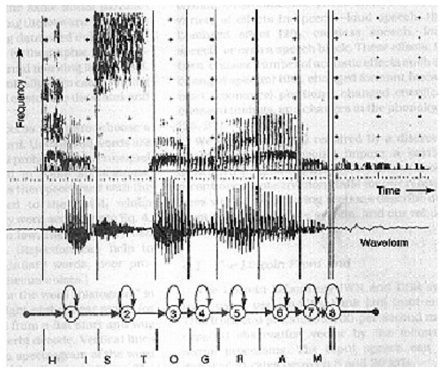
A wide variety of texture patterns are generated by various stochastic processes.

How are these patterns represented in human brain?



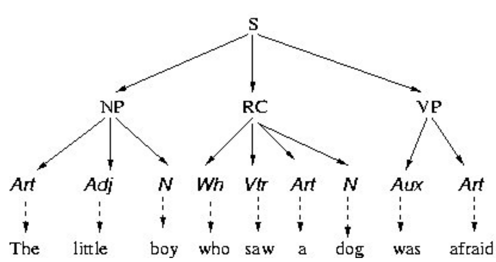
Examples of Patterns

Speech signal and Hidden Markov model



Examples of Patterns

Natural language and stochastic grammar.



Examples of Patterns

A story generated from the rules:

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

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
... ...

Applications

Lie detector,
Handwritten digit/letter recognition
Biometrics: voice, iris, finger print, face, and gait recognition
Speech recognition
Smell recognition (e-nose, sensor networks)
Defect detection in chip manufacturing
Reading DNA sequences
Fruit/vegetable recognition
Medical diagnosis
Network traffic modeling, intrusion detection
… …

Two Schools of Thinking

1. *Generative methods*:
   Bayesian school, pattern theory.
   1). Define patterns and regularities (graph spaces),
   2). Specify likelihood model for how signals are generated
   from hidden structures
   3). Learning probability models from ensembles of signals
   4). Inferences.

2. *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"

Levels of task

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

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

… …

The simple tasks 1-4 may be solved effectively using discriminative methods, but the difficult tasks 5-7 will need generative methods.

Schools and streams

Schools for pattern recognition can be divided in three axes:

Axis I: generative vs discriminative
(Bayesian vs non-Bayesian)
(--- modeling the patterns or just want to tell them apart)

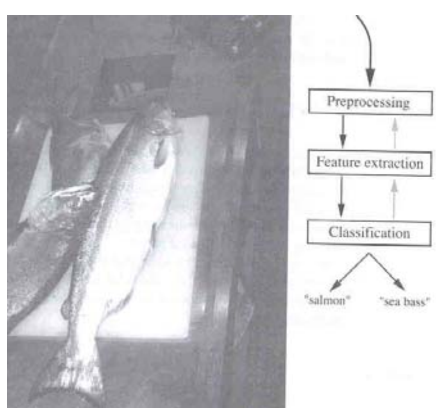
Axis II: deterministic vs stochastic
(logic vs statistics)
(have rigid regularity and hard thresholds or have soft constraints on regularity and soft thresholding)

Axis III: representation---algorithm---implementation

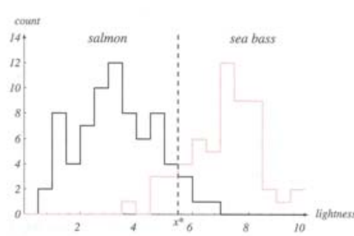
Examples:
Bayesian decision theory, neural networks, syntactical pattern recognition (AI), decision trees, Support vector machines, boosting techniques,

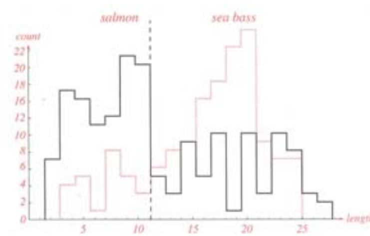
An example of Pattern Recognition

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

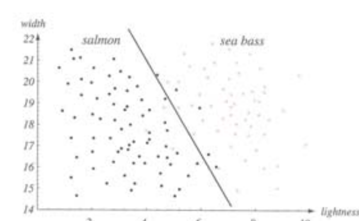


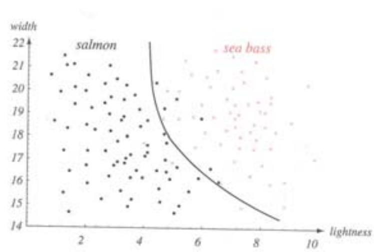
Features and Distributions





Decision/classification Boundaries





Main Issues in Pattern Recognition

1. Feature selection and extraction
   --- 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

What is a pattern?

In plain language, a pattern is a set of instances which share some regularities, and are similar to each other in the set. A pattern should occur repeatedly. A pattern is observable, sometimes partially, by some sensors with noise and distortions.

How do we define "regularity"?
How do we define "similarity"?
How do we define "likelihood" for the repetition of a pattern?
How do we model the sensors?

What is a pattern

In a mathematical language, Grenander proposed to define patterns with the following components (1976-1995)

1. Regularity R=<G, S, ρ, Σ>

G --- a set/space of generators (the basic elements in a pattern), each generator has a number of "bonds" that can be connected to neighbors.

S --- a transformation group (such as similarity transform) for the generators

ρ --- a set of local regularities (rules for the compatibility of generators and their bounds

Σ --- a set of global configurations (graphs with generators being vertices and connected bonds being edges).

What is a pattern

2. An image algebra

I =<C(R), E>

The regularity R defines a class of regular configurations C(R). But such configurations are hidden in signals, when a configuration is projected to a sensor, some information may get lost, and there is an equivalence relationship E. The image algebra is a quotient space of C(R). I.e. some instances are not identifiable by images

In philosophy, patterns are our mental perception of world regularities.

3. A probability p on C(R) and on I

In a Bayesian term, this is a prior model on the configuration and the likelihood model for how the image looks like given a configuration.