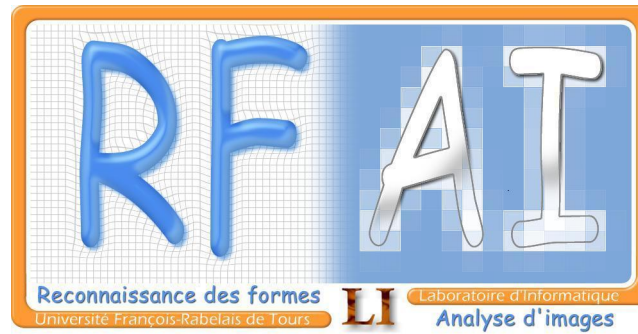


Computer Vision and Graph-Based Representation

Presented by:
Romain Raveaux



Jean-Yves Ramel – Romain Raveaux
Laboratoire Informatique de Tours - FRANCE

About me I

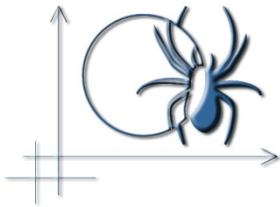
- Romain Raveaux
- Teacher at the university of Tours. Polytech'Tours
- Researcher at the Computer Science Laboratory
- Researcher Activity:
 - Graph-Based representation
 - Graph classification
 - Graph comparison
 - Image analysis

About me II

- Main publications : Referenced International Journal
 - Romain Raveaux et al. Structured representations in a content based image retrieval context. Journal of Visual Communication and Image Representation, Volume 24, Issue 8, November 2013, Pages 1252-1268.
 - Romain Raveaux et al. A local evaluation of vectorized documents by means of polygon assignments and matching. IJDAR 15(1): 21-43 (2012)
 - Romain Raveaux et al. Learning graph prototypes for shape recognition. Computer Vision and Image Understanding 115(7): 905-918 (2011)
 - Romain Raveaux et al. A graph matching method and a graph matching distance based on subgraph assignments. Pattern Recognition Letters 31(5): 394-406 (2010)

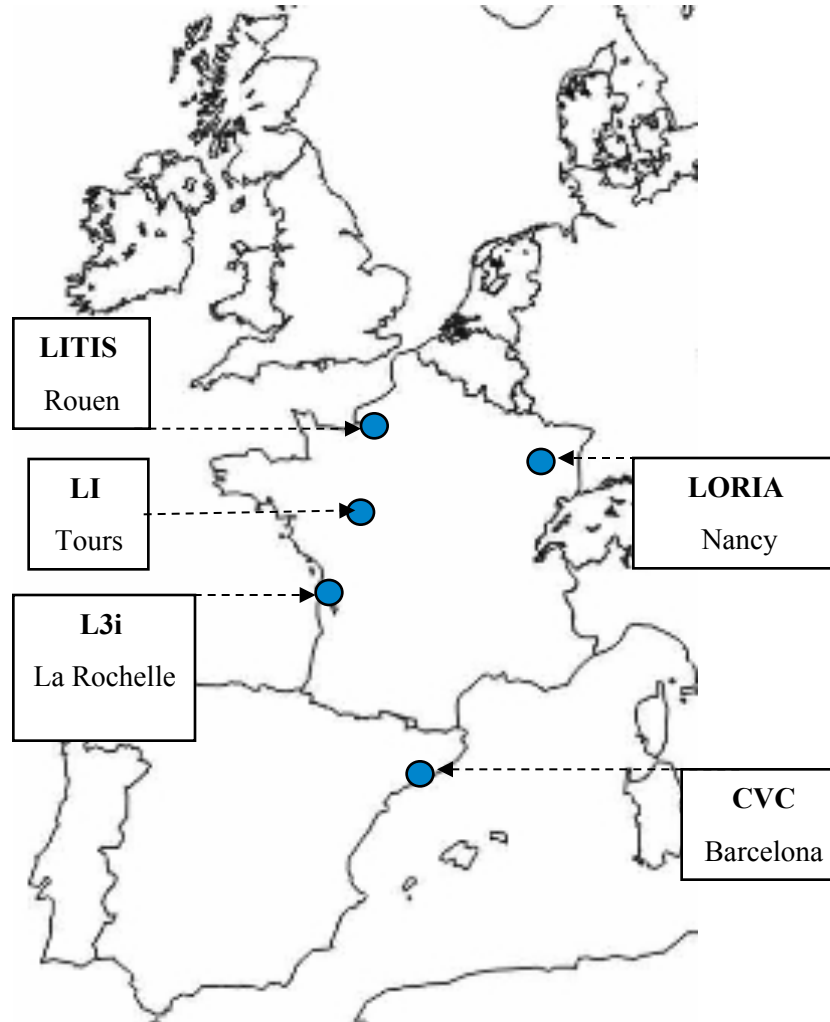
Recherche Partners

ISRC' 2011



Relations inter-laboratoires

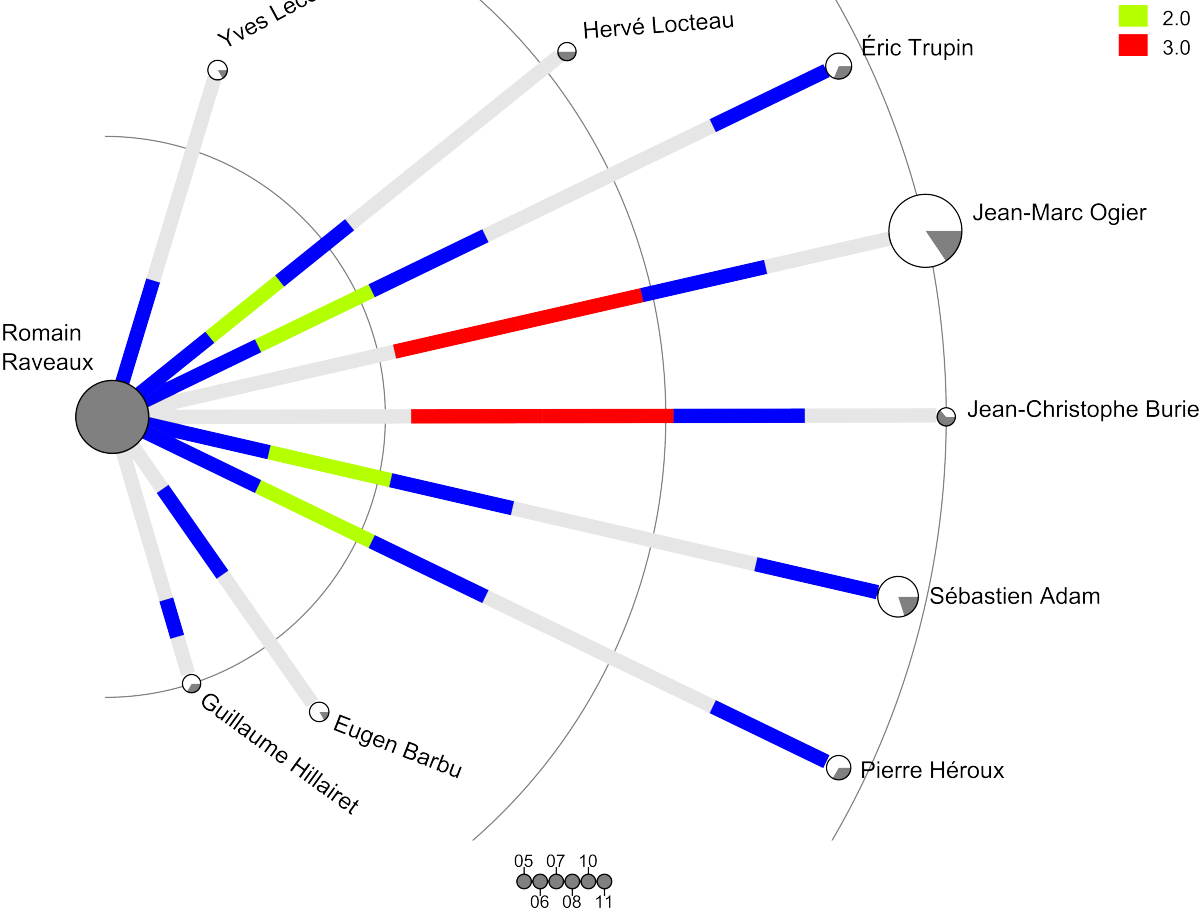
- 3 séjours recherche
- 8 séminaires extérieurs
- Co-rédactions de projets ANR
- Co-encadrements de stagiaires
- Co-écritures d'articles



Some colleagues

Romain Raveaux [2005 - 2011]
Person -> Person

[help](#)



Content

1. Computer Vision and Graph-Based Representation
 1. {pixel, interest point, region, primitive, shape} graph
 2. Spatial relationship graph
2. Pattern Recognition problems
 1. Classification
 2. Indexing
 3. Clustering

Aim of the talk

- We want to illustrate the very particular graphs issued from computer vision techniques.
 - Noisy
 - Complex Attributes (continuous, numerical, symbolic, semantic, ...)
 - Graph Size
- What we won't talk about :
 - Graph for image segmentation (Normalized Cut Graph, ...)
 - Graph for knowledge representation (Ontology, RDF, ...)

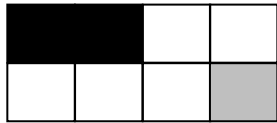
Part 1

- Computer Vision and Graph-Based Representation

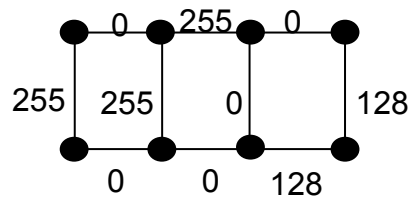
Graph of pixels

Pixels → The nodes of the graph
Edges → The values (RGB, grey shades)

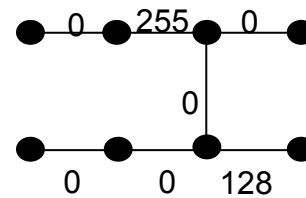
[Morris, 1986]



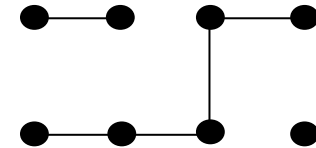
Image



Attributed graph

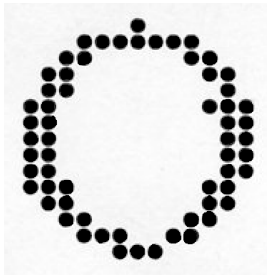


Maximum spanning tree



Expensive edge deletion

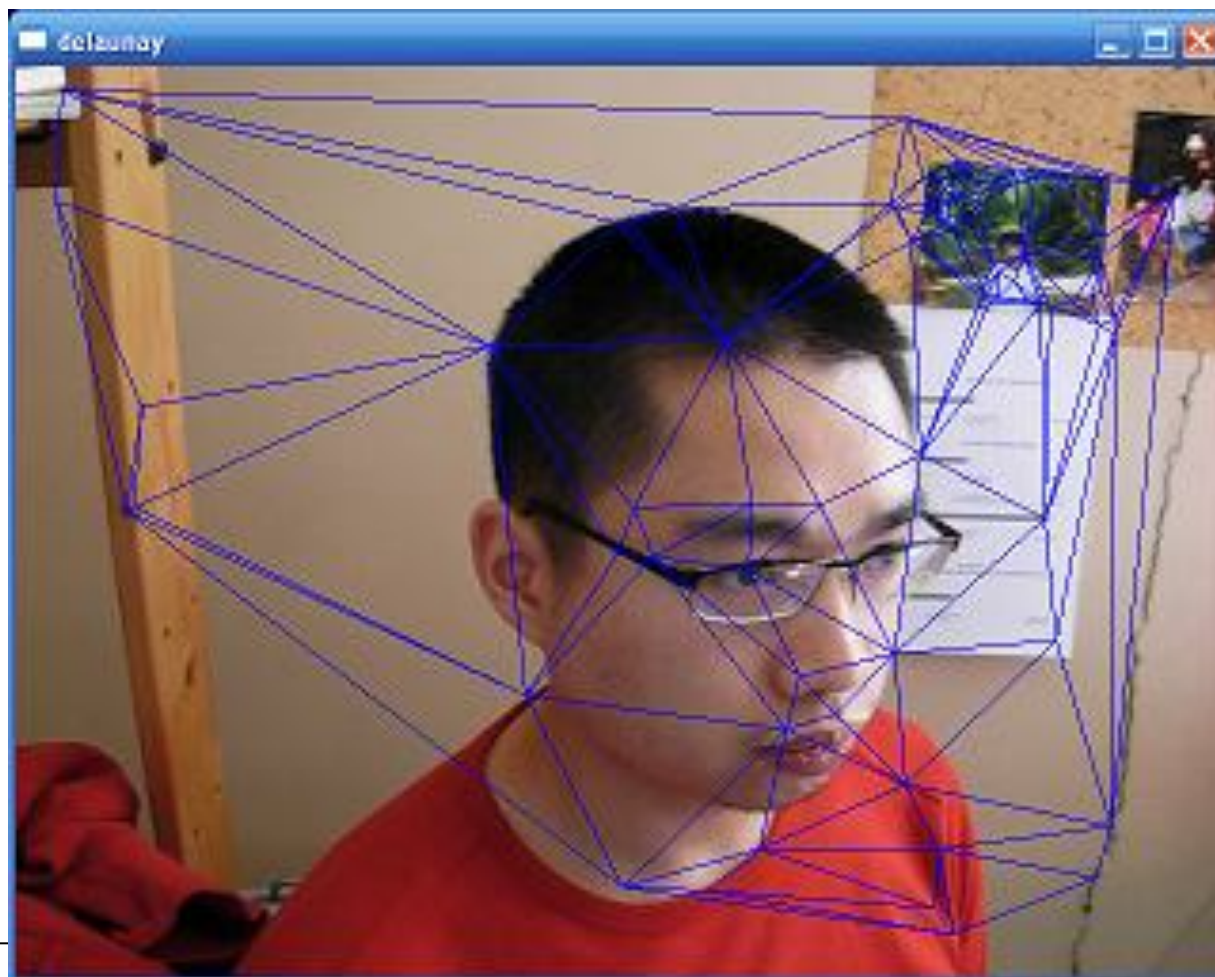
[Franco, 2003]



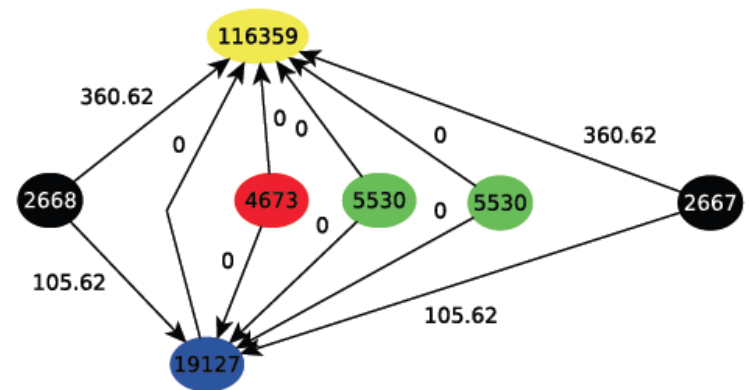
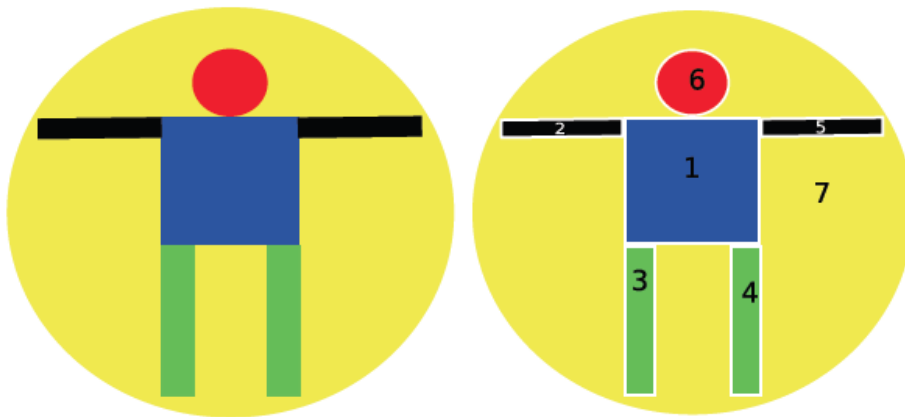
Problem

Graphs made of pixels are often too big to be analysed

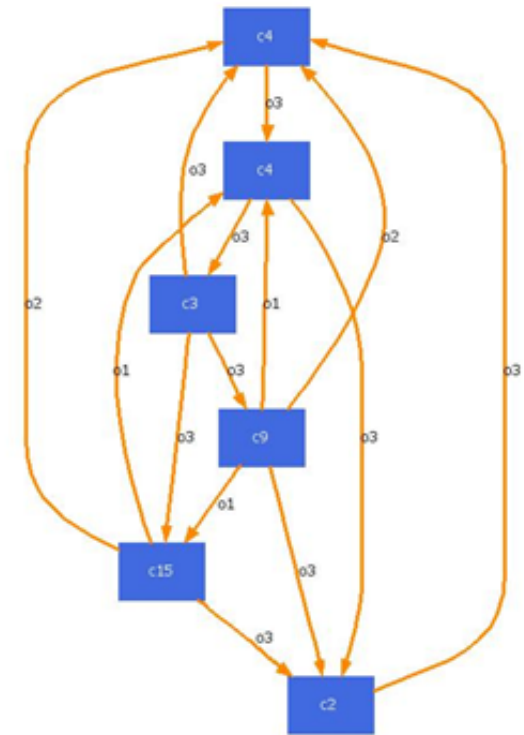
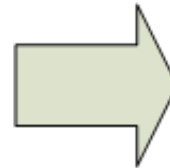
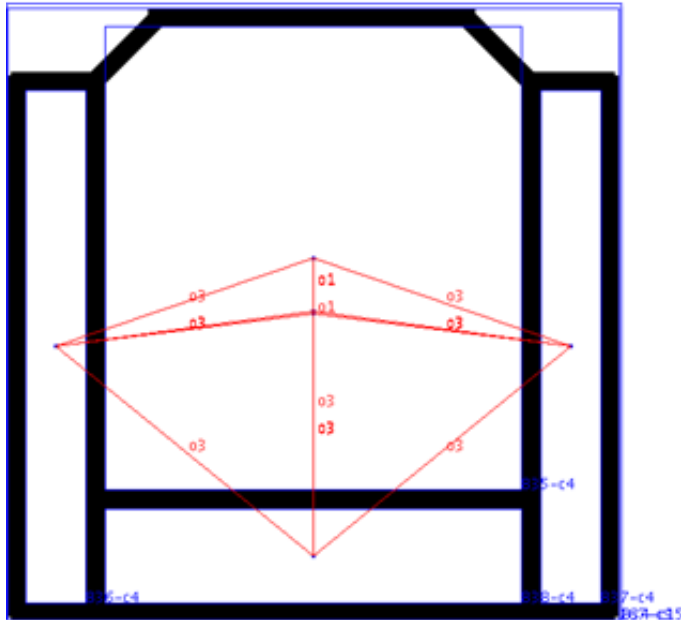
Interest Point Graph



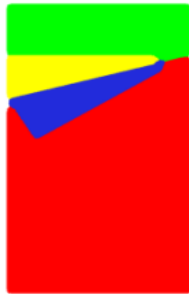
Region Adjacency Graph



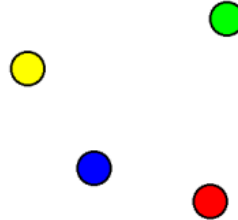
Neighbourhood graph



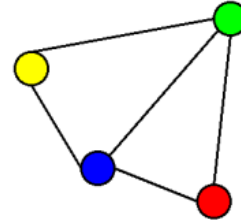
Region Adjacency Graph



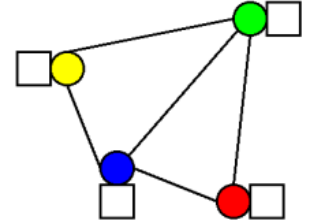
⇒ Segmentation
« région »



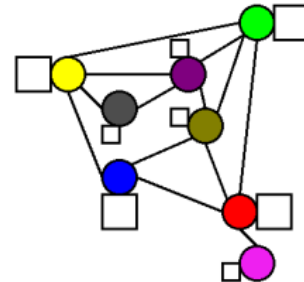
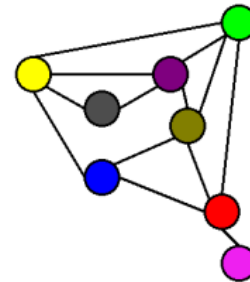
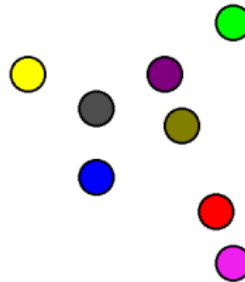
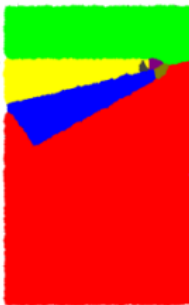
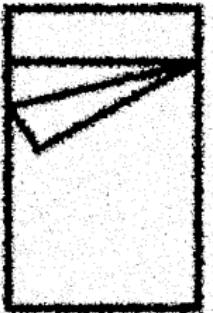
région ⇔ nœud



adjacence ⇔ arc

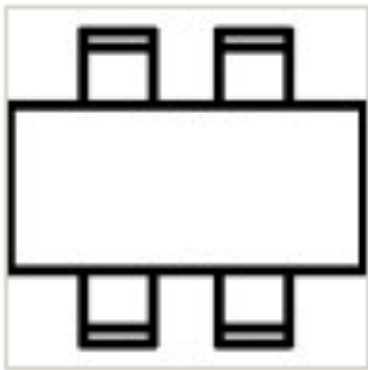


⇒ Description



Impact of noise on Graph-Based Representation

Impact of noise on Graph-Based Representation



ArchitecturalH.BMP

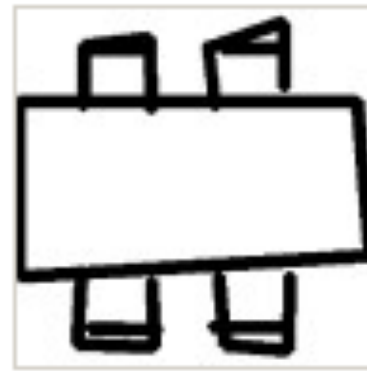
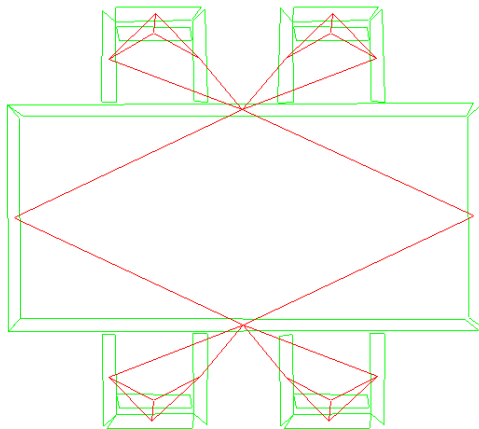
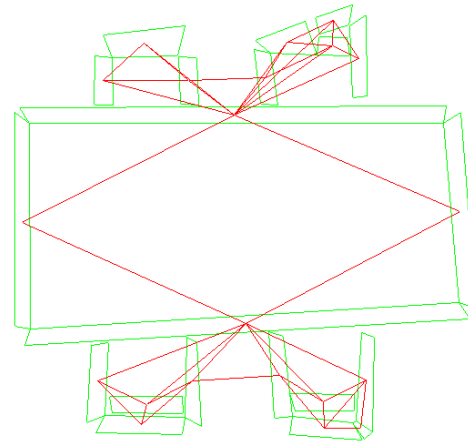


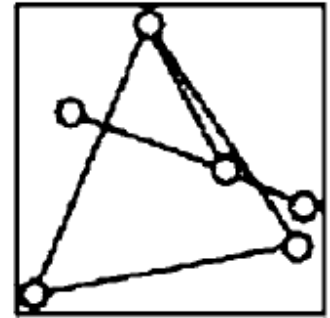
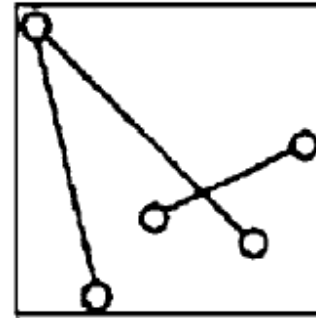
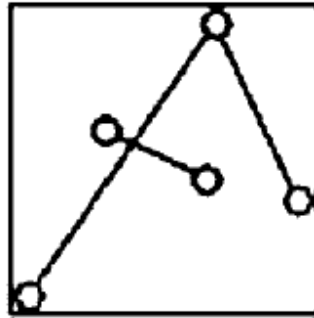
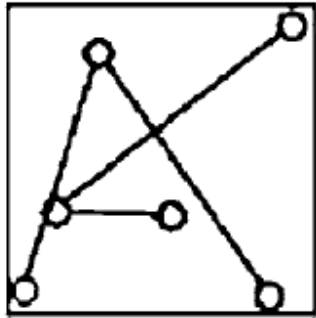
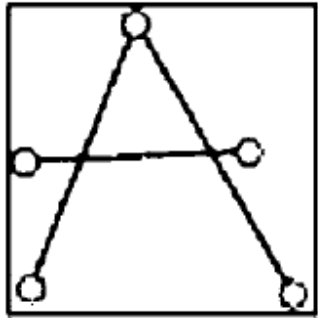
Image98.bmp



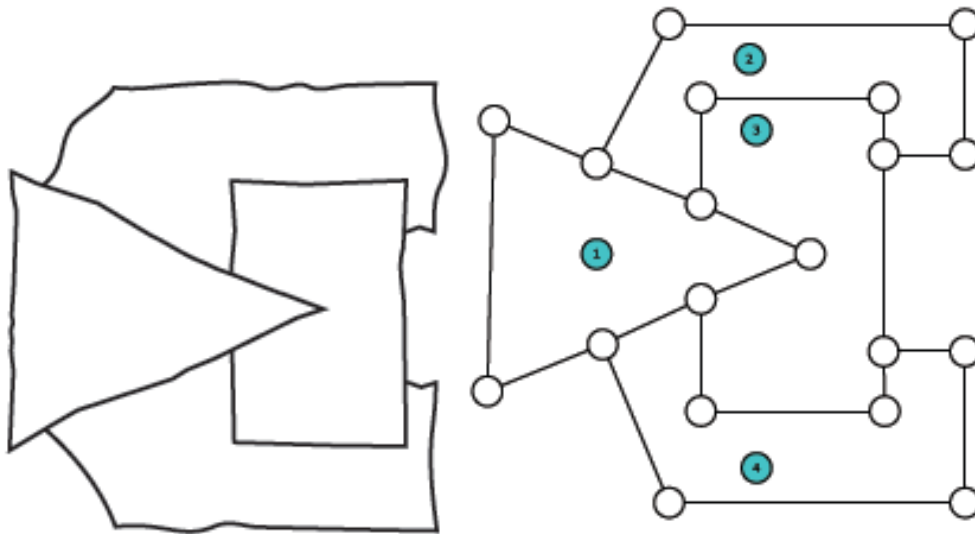
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Impact of noise on Graph-Based Representation

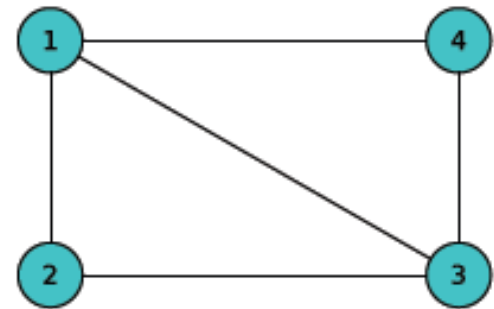


Region Adjacency Graph



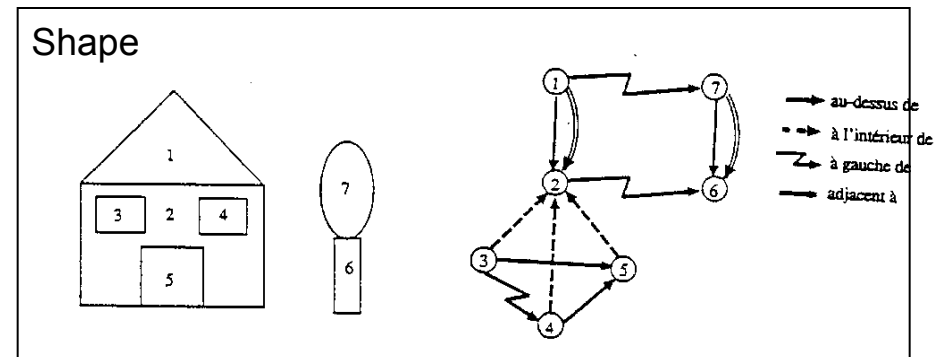
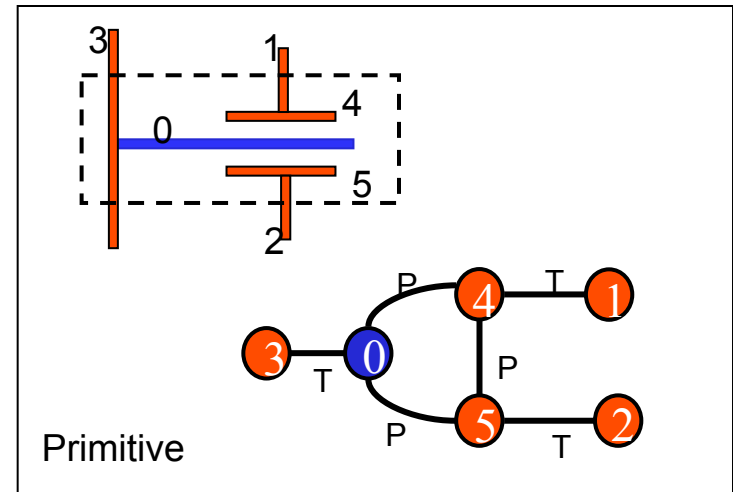
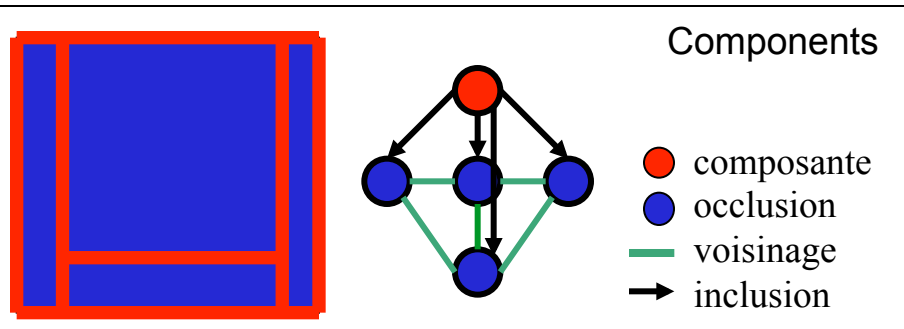
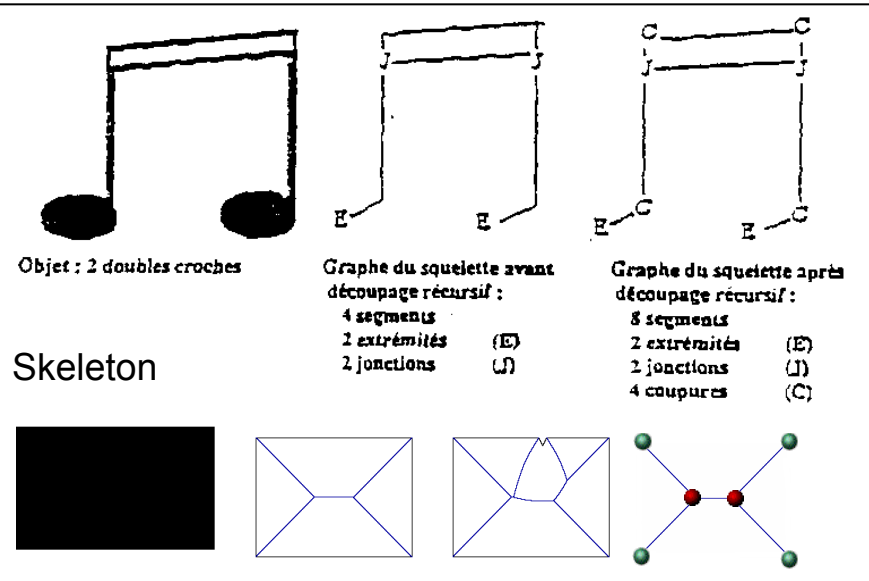
(a) Symbole original

(b) Graphe correspondant



(c) Graphe d'adjacence des régions

Primitive, shape graphs



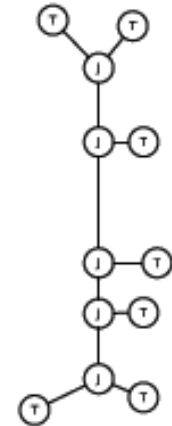
Skeleton Graph



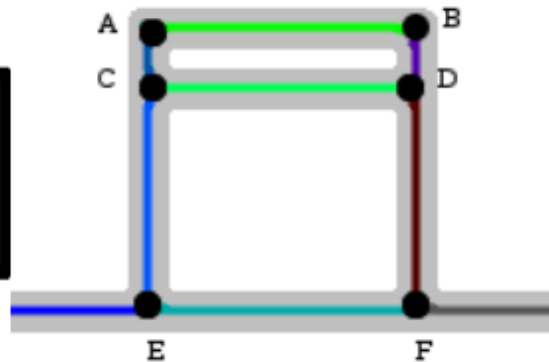
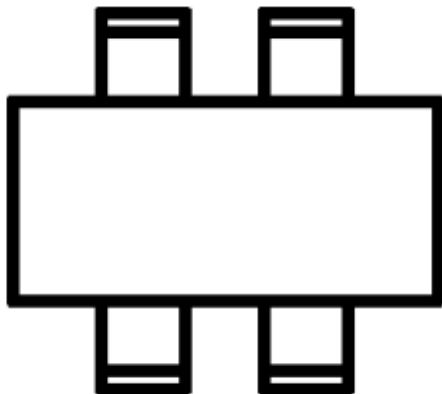
(a) Image d'une forme



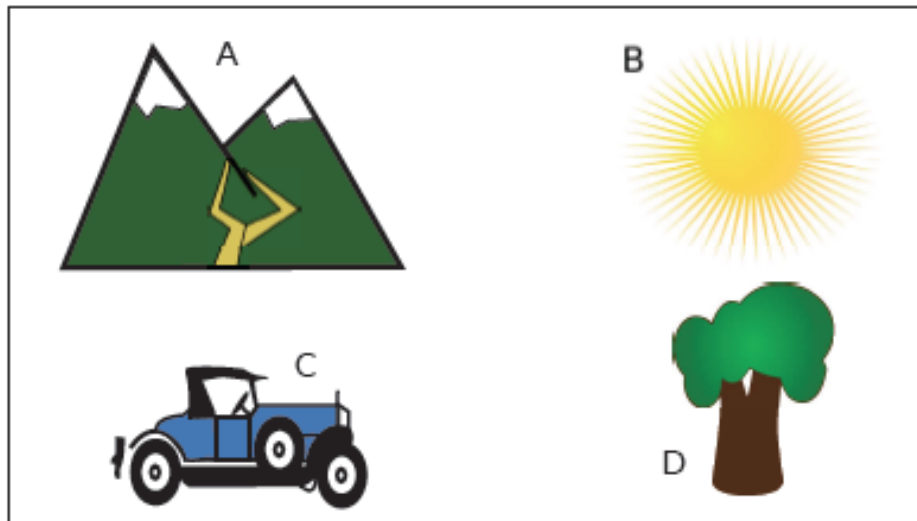
(b) Le squelette de la forme



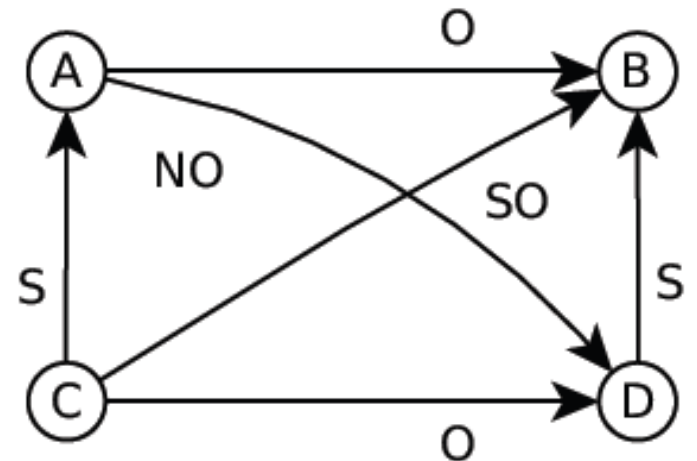
(c) Représentation sous forme de graphe du squelette



Spatial relationship graph

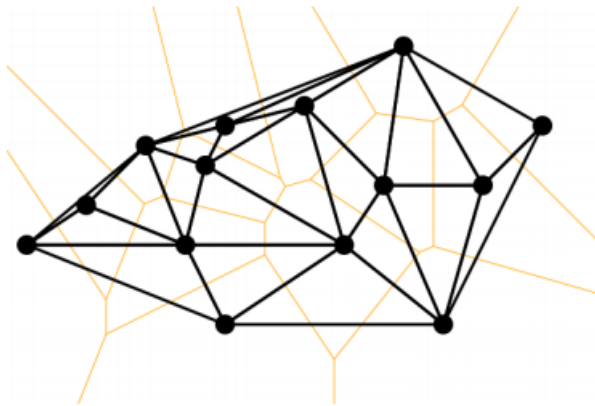


(a) Image *symbolique*

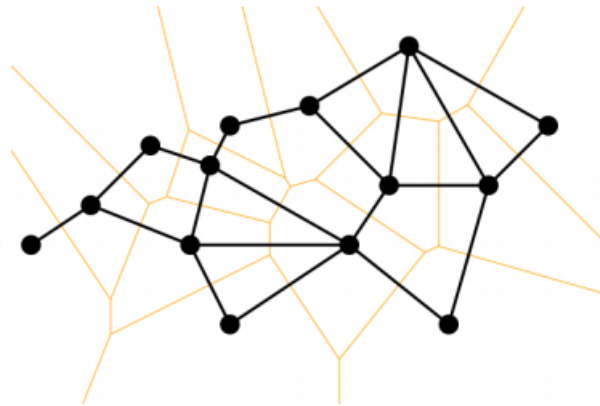


(b) Représentation sous forme de graphe de relation spatiale

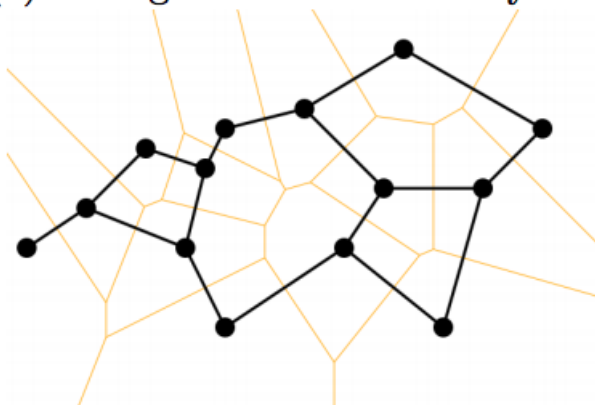
Spatial relationship graph



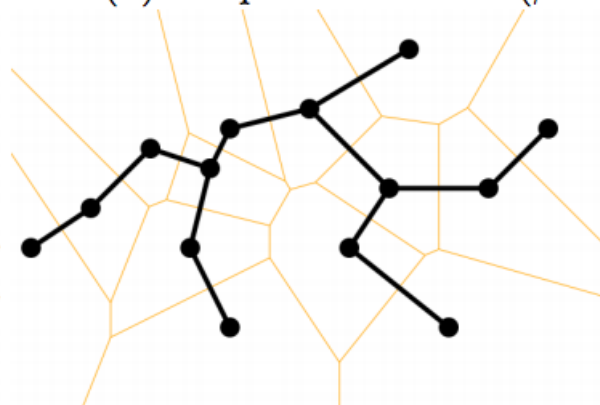
(a) Triangulation de Delaunay



(b) Graphe de Gabriel ($\beta=1$)



(c) Graphe de voisinage



(d) Arbre de recouvrement minimal

Spatial relationship graph

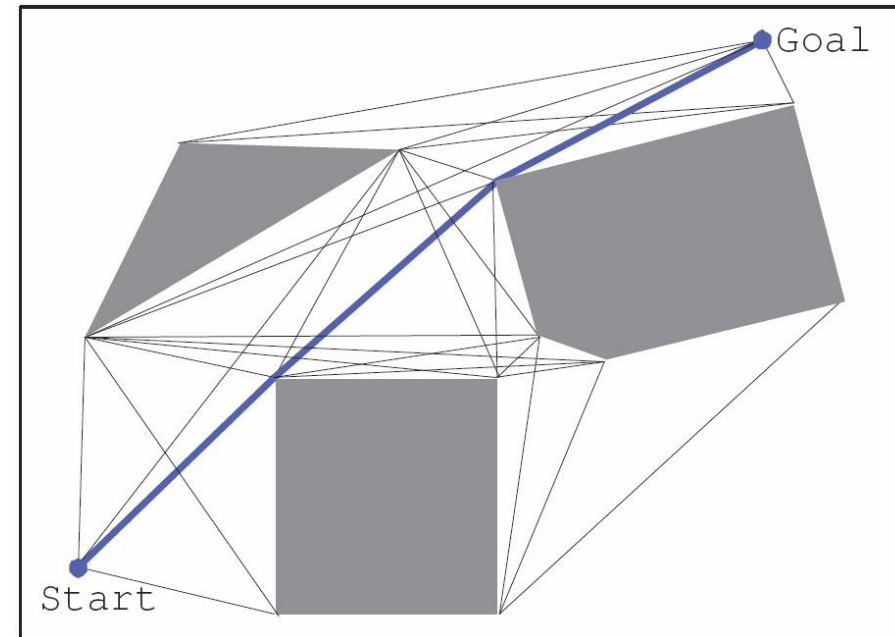
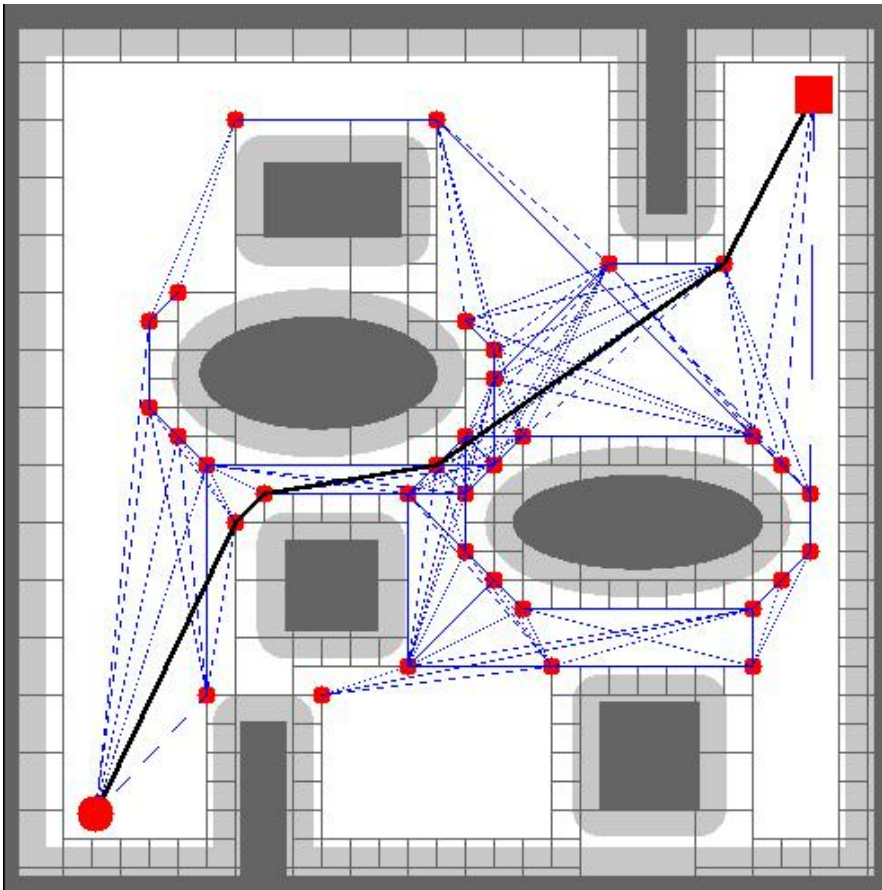
- Bi dimensional Allen Algebra
- Egenhofer algebra



Fig. 1.12. Relations topologiques entre deux objets telles que définies par Egenhofer

Spatial relationship graph

- Visibility Graph



Spatial relationship graph

Visibility Graph

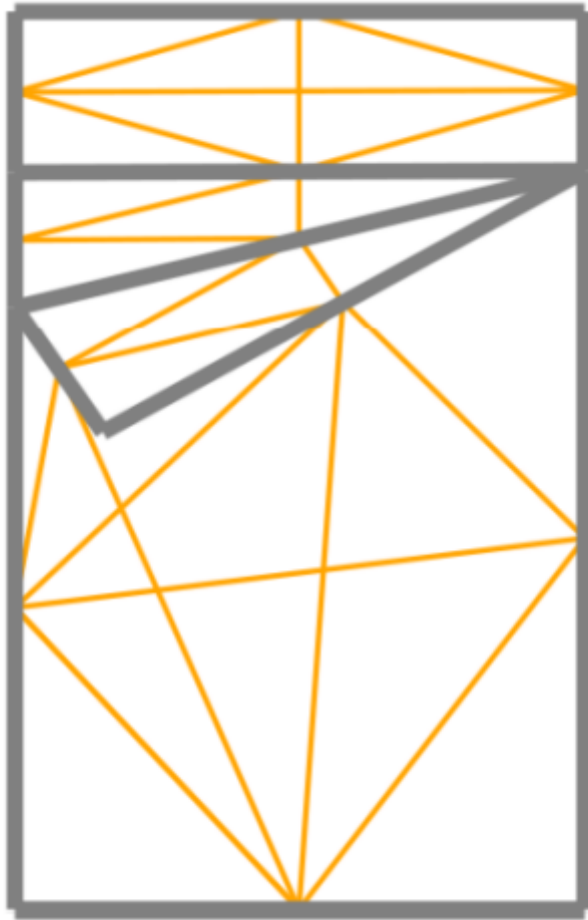


Image : Graph based representation

- Strongly attributed graphs
 - Numerical vectors
 - Symbolic information
- Complex structures
 - From planar graph to complete graph
- Graph size
 - From large to small : It depends on the description level
 - Low level : One node = one pixel
 - High level: One node = one object
- Graph corpus
 - Large data set :
 - one graph equal one image

IAM DB

- Please read the following paper :
 - IAM Graph Database Repository for Graph Based Pattern Recognition and Machine Learning

Table 1. Summary of graph data set characteristics, viz. the size of the training (*tr*), the validation (*va*) and the test set (*te*), the number of classes (#classes), the label alphabet of both nodes and edges, the average and maximum number of nodes and edges (\emptyset /max nodes/edges), whether the graphs are uniformly distributed over the classes or not (balanced), and the recognition rate of the *k*-NN classifier (RR).

Database	size (<i>tr</i> , <i>va</i> , <i>te</i>)	#classes	node labels	edge labels	\emptyset nodes	\emptyset edges	max nodes	max edges	balanced	RR
Letter (<i>low</i>)	750, 750, 750	15	<i>x, y</i> coordinates	none	4.7	3.1	8	6	Y	99.6%
Letter (<i>medium</i>)	750, 750, 750	15	<i>x, y</i> coordinates	none	4.7	3.2	9	7	Y	94.0%
Letter (<i>high</i>)	750, 750, 750	15	<i>x, y</i> coordinates	none	4.7	4.5	9	9	Y	90.0%
Digit	1,000, 500, 2,000	10	<i>x, y</i> coordinates	Angle	11.8	13.1	32	30	Y	91.0%
GREC	286, 286, 528	22	<i>x, y</i> coordinates	Line type	11.5	12.2	25	30	Y	95.5%
Fingerprint	500, 300, 2,000	4	<i>x, y</i> coordinates	Angle	5.42	4.42	26	24	N	76.6%
COIL-RAG	2,400, 500, 1,000	100	RGB histogram	Boundary length	3.0	3.0	11	13	Y	92.5%
COIL-DEL	2,400, 500, 1,000	100	<i>x, y</i> coordinates	none	21.5	54.2	77	222	Y	93.3%
Web	780, 780, 780	20	Word and its frequency	Section(s) type	186.1	104.6	834	596	N	80.3%
AIDS	250, 250, 1,500	2	Chemical symbol	Valence	15.7	16.2	95	103	N	97.3%
Mutagenicity	1,500, 500, 2,337	2	Chemical symbol	Valence	30.3	30.8	417	112	N	71.5%
Protein	200, 200, 200	6	Type and aa-sequence	Type and distance	32.6	62.1	126	149	Y	65.5%

Pattern Recognition

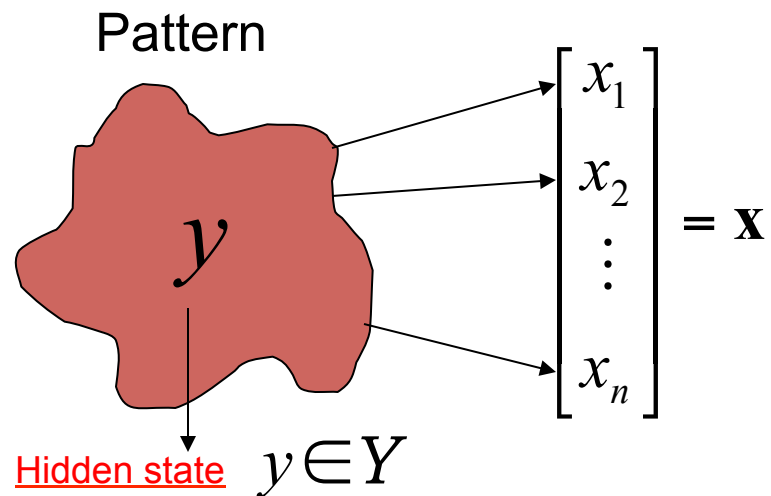
- Classification (supervised)
 - Clustering (Unsupervised)
 - Indexing
-
- All these notions will be deeply explained by Nicolas Ragot in details.

What is pattern recognition?

"The assignment of a physical object or event to one of several prespecified categories" -- Duda & Hart

- A **pattern** is an object, process or event that can be given a name.
- A **pattern class** (or category) is a set of patterns sharing common attributes and usually originating from the same source.
- During **recognition** (or **classification**) given objects are assigned to prescribed classes.
- A **classifier** is a machine which performs classification.

Basic concepts



Feature vector

$$\mathbf{x} \in X$$

- A vector of observations (measurements).

- \mathbf{x} is a point in feature space X .

- Cannot be directly measured.

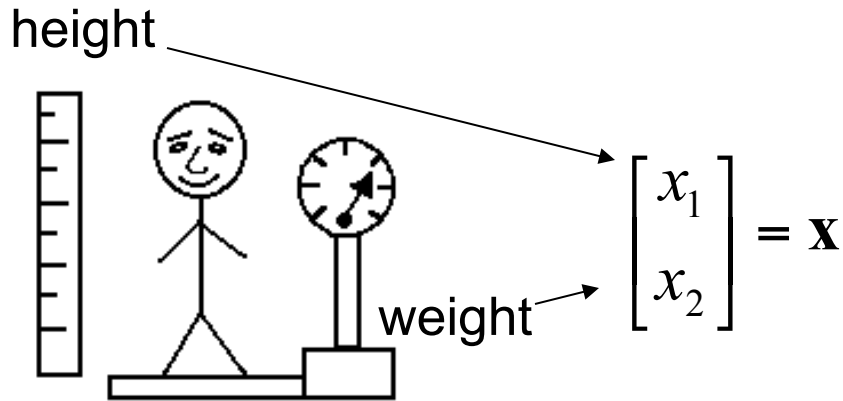
- Patterns with equal hidden state belong to the same class.

Task

- To design a classifier (decision rule) $q : X \rightarrow Y$

which decides about a hidden state based on an onbserveation.

Example



Task: jockey-hoopster recognition.

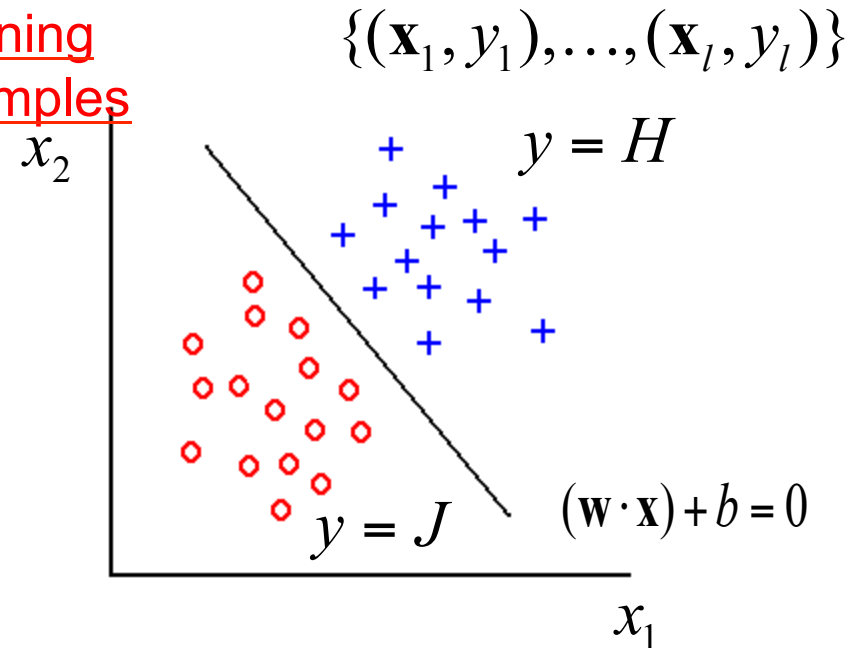
The set of hidden state is $Y = \{H, J\}$

The feature space is $X = \mathbb{R}^2$

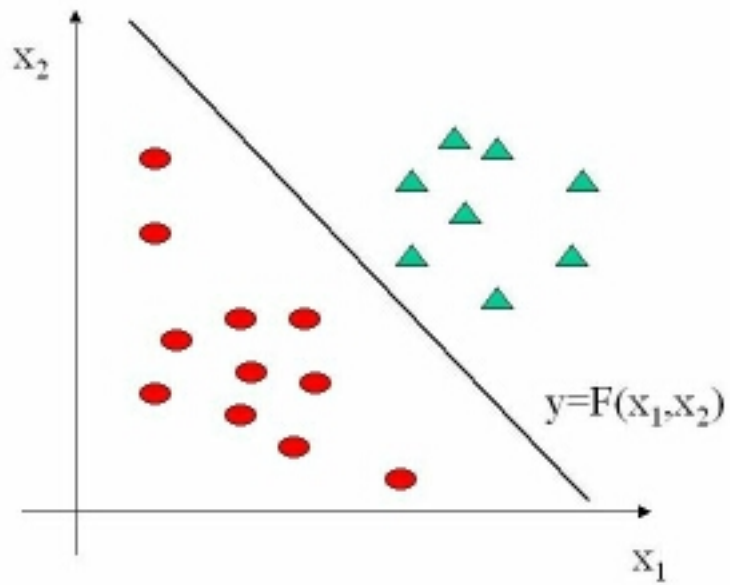
Linear classifier:

$$q(\mathbf{x}) = \begin{cases} H & \text{if } (\mathbf{w} \cdot \mathbf{x}) + b \geq 0 \\ J & \text{if } (\mathbf{w} \cdot \mathbf{x}) + b < 0 \end{cases}$$

Training examples

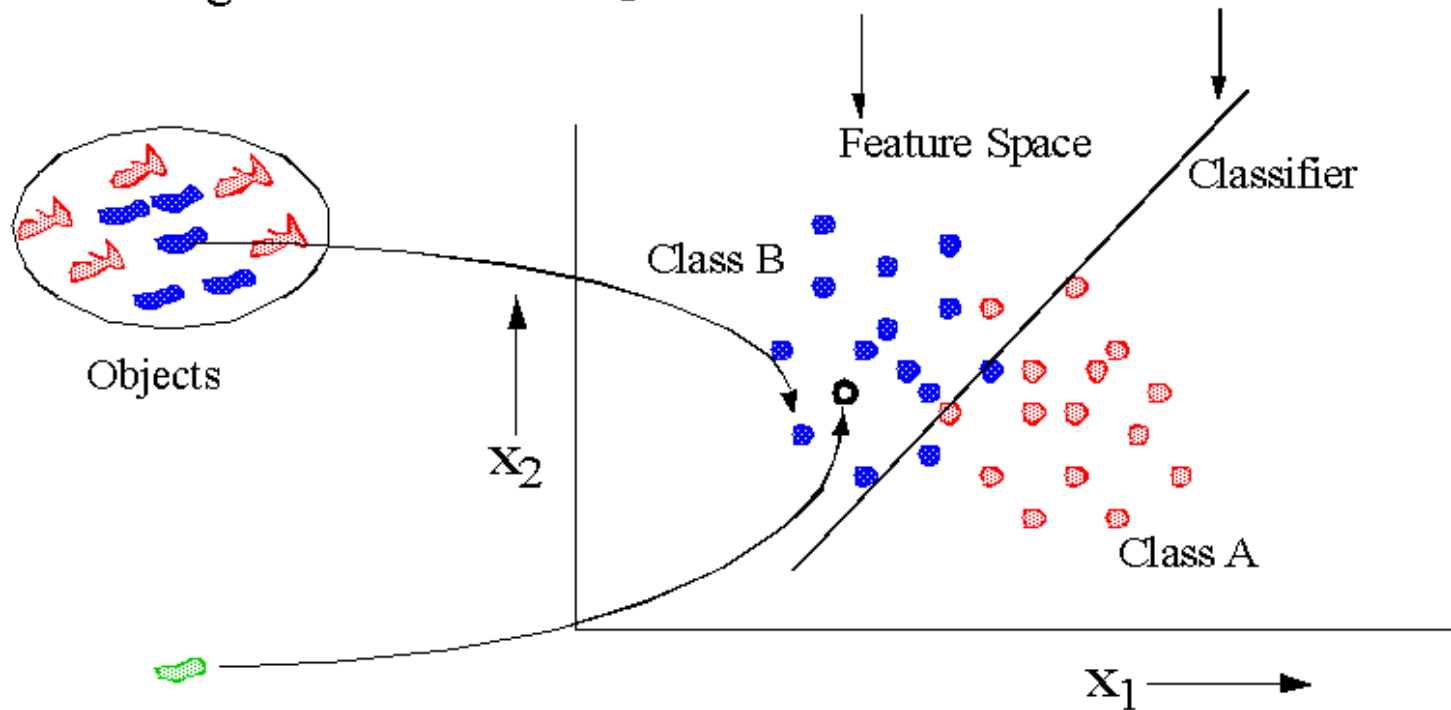


Pattern Recognition

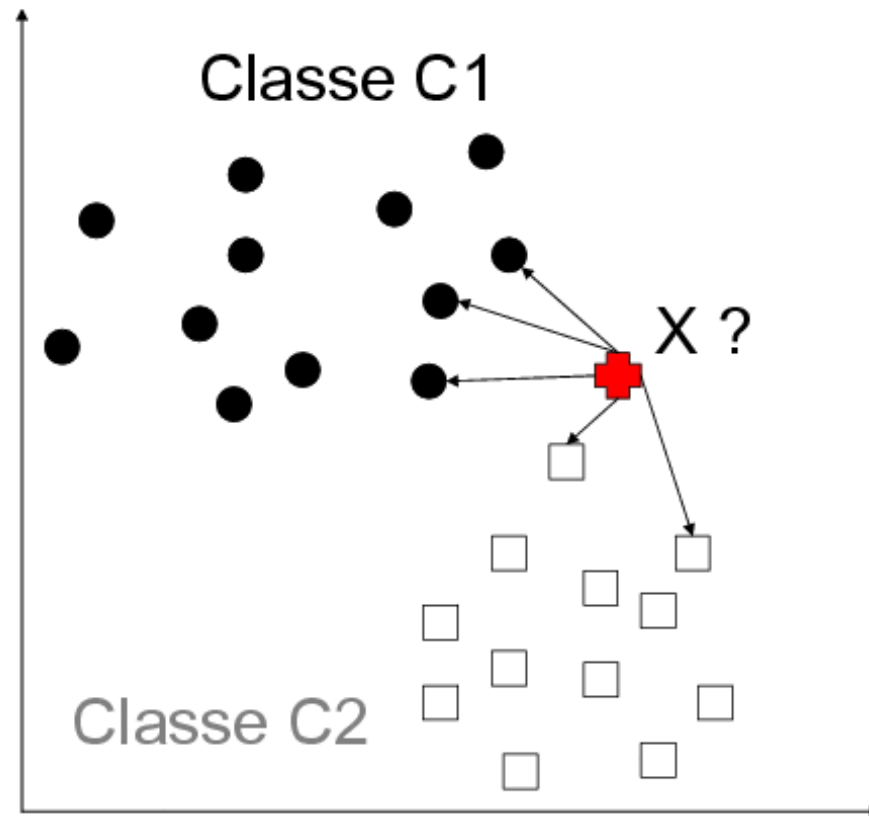


Pattern Recognition

Training Set \longrightarrow Representation \longrightarrow Generalization



Nearest Neighbor Search



Vector vs Graph

	Pattern Recognition	
	Structural	Statistical
Data structure	symbolic data structure	numeric feature vector
Representational strength	Yes	No
Fixed dimensionality	No	Yes
Sensitivity to noise	Yes	No
Efficient computational tools	No	Yes

Graph recognition

- ① Given a graph database consisting of n graphs, $D = g_1, g_2, \dots, g_n$, and a query graph q , almost all existing algorithms of processing graph search can be classified into the following four categories: Full graph search, Subgraph search, Similarity search and Graph mining.
- ② **Full graph search.** Find all graphs g_i in D s.t. g_i is the same as q .
- ③ **Subgraph search.** Find all graphs g_i in D containing q or contained by q .
- ④ **Similarity search.** Find all graphs g_i in D s.t. g_i is similar to q within a user-specified threshold based on some similarity measures.
- ⑤ **Graph mining** Graph mining problem gathers similar graph or subgraph of D in order to find clusters or prototypes. No query is provided by the user.

Pattern Recognition

- When using graphs in pattern recognition the question turns often in a graph comparison problem ?
 - Are two graphs similar or not?
- How to compute a similarity measure for graphs ?
- Any ideas ?

Graph Comparison

A dissimilarity measure is a function:

$$d : X \times X \rightarrow \mathfrak{R},$$

where X is the representation space for the object description. It has the following properties:

- non-negativity

$$d(x, y) \geq 0, \tag{1}$$

- uniqueness

$$d(x, y) = 0 \Rightarrow x = y, \tag{2}$$

- symmetry

$$d(x, y) = d(y, x). \tag{3}$$

- Triangle inequality :

$$d(x, y) \leq d(x, z) + d(z, y). \tag{4}$$

Graph Comparison

- Distance (metric) : 1-2-3-4
- Pseudo metric : 1-3-4
- Similarity measure : $s(x,y) = k - d(x,y)$
- Dissimilarity measure

Pattern Recognition

- When using graphs in pattern recognition the question turns often in a graph comparison problem ?
 - Are two graphs similar or not?
- How to compute a similarity measure for graphs ?
- Any ideas ?
- At least 2 solutions :
 - Graph matching
 - Graph embedding

Some clues : Graph Matching

the measure on the quantity of shared terms. The simplest similarity measure between two complex objects o_1 and o_2 is the matching coefficient mc , which is based on the number of shared terms.

$$mc = \frac{o_1 \wedge o_2}{o_1 \vee o_2}, \quad (5)$$

where $o_1 \wedge o_2$ denotes the intersection of o_1, o_2 and $o_1 \vee o_2$ stands for the union between the two objects.

Some clues : Graph Matching

- MCS : Stands for Maximum common subgraph

$$d(G_1, G_2) = 1 - \frac{mcs(G_1, G_2)}{\max(|G_1|, |G_2|)}$$

Bibliography

- Bibliography :
 - IAM Graph Database Repository for Graph Based Pattern Recognition and Machine Learning