Jaime S. Cardoso jaime.cardoso@inescporto INESC Porto, Faculdade de Engenharia, Universidade do Porto December 12, 2011

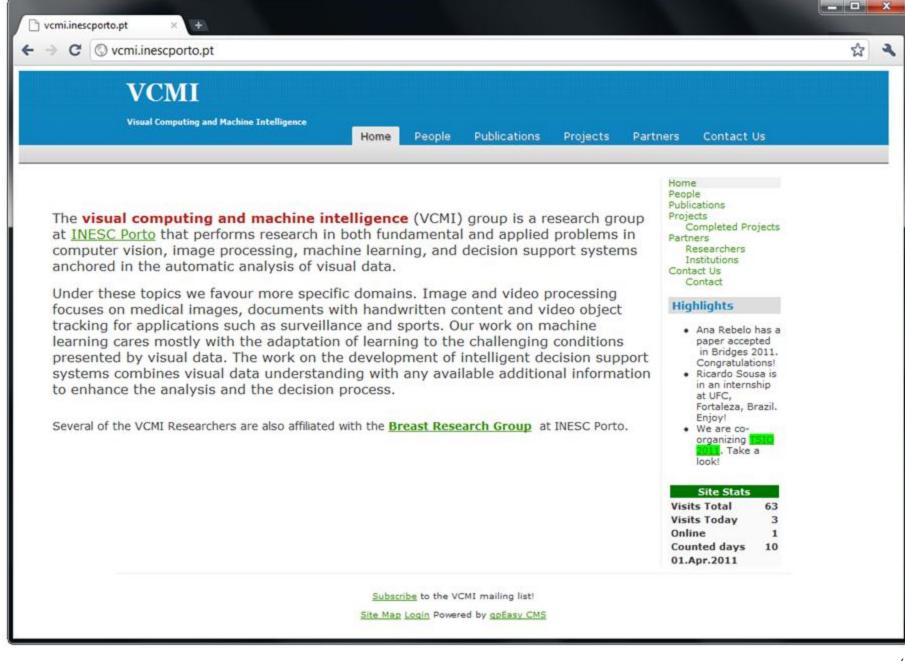
### MAPi – Computer Vision 2011/12 Lecture 1a – Pattern Recognition Concepts

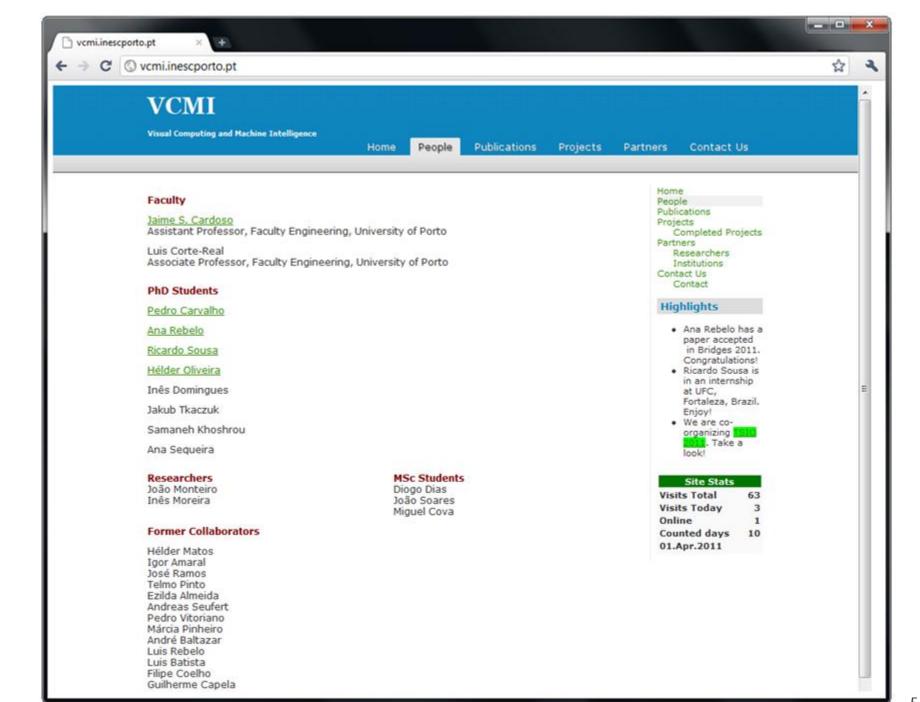
# INESC Porto & Speaker



### INESC Porto > UTM > Multimedia

- 1. Information Processing and Pattern Recognition
  - i. Computer vision
  - ii. Sound and music computing
  - iii. Network information processing
- 2. Digital Media Technologies
  - i. Management and distribution of multimedia content
  - ii. Context-aware multimedia services
  - iii. Multimedia content recommendation systems
  - iv. Adaptable mobile multimedia applications





### Visual Computing and Machine Intelligence http://vcmi.inescporto.pt/

- Our Team
  - Jaime S. Cardoso, PhD, Assistant Professor DEEC/FEUP
  - Pedro Carvalho, PhD Std.
  - Ana Rebelo, PhD Std.
  - Ricardo Sousa, PhD Std.
  - Hélder Oliveira, PhD Std.
  - Inês Domingues, PhD Std.
  - Samaneh Khoshrou, PhD Std.
  - Ana F. Sequeira, PhD Std.
  - Inês Moreira, Researcher
  - João Moreira, Researcher
  - etc.

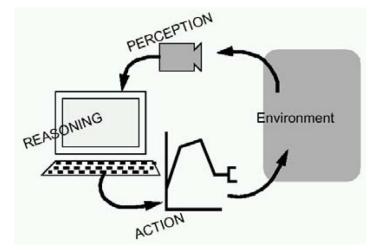
- Our Projects
  - 3d BCT
  - Semantic PACS
    - Picture Archiving and Communication System with Semantic Search Engine
  - BCCT
    - Advanced Objective Method for the Evaluation of the Aesthetical Result of Breast Interventions
  - OMR
    - Optical Recognition System for Handwritten Music Scores
  - NeTS
    - Next Generation Network Operations and Management
  - INCT-MACC
  - SINPATCO
  - etc

## Pattern Recognition Concepts

### **Goal of computer vision**

- Provide computers with human-like perception capabilities so that they can sense the environment, understand the sensed data, take appropriate actions (make decisions), learn from this experience in order to enhance future performance
  - Understand the visual information with no accompanying structural, administrative or descriptive text information

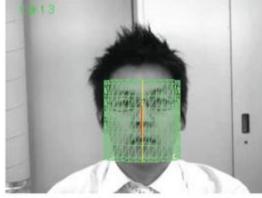
- Sources of difficulties:
  - Sensory gap
  - Semantic gap



### **From Pixels to Perception**



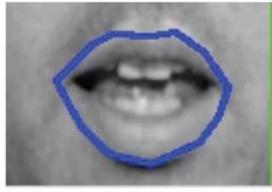
"Face Recognition"



"Pose Estimation"



"Body Tracking"



"Speech Reading"



"Object detection"



"Car Tracking"

### **Object Recognition**

 Perception of function: We can perceive the 3D shape, texture, material properties, without knowing about objects. But, the concept of category encapsulates also information about what can we do with those objects.

### **Object recognition: Is it really so hard?**

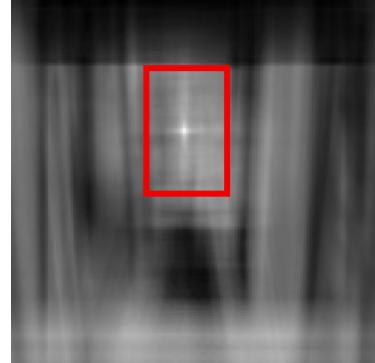
#### This is a chair



#### Find the chair in this image



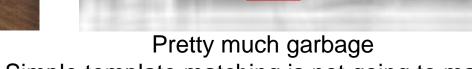
#### Output of normalized correlation



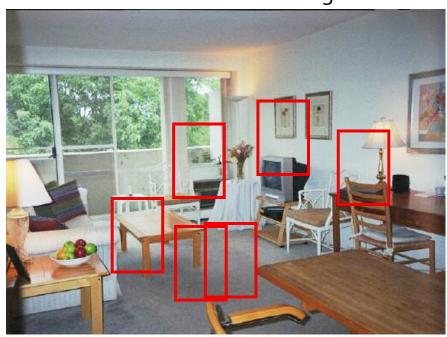


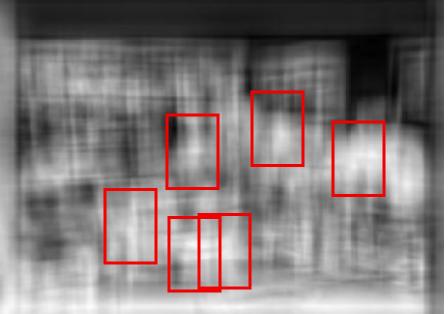
### Object recognition: Is it really so hard?

#### Find the chair in this image



Simple template matching is not going to make it







### **Object recognition: Is it really so hard?**



#### Find the chair in this image



A "popular method is that of template matching, by point to point correlation of a model pattern with the image pattern. These techniques are inadequate for three-dimensional scene analysis for many reasons, such as occlusion, changes in viewing angle, and articulation of parts." Nivatia & Binford, 1977.

Why is vision hard?

Grayscale Image

		x = 58	59	60	61	62	63	64	65	66	67	68	69	70	1	
- 4		210	209	204	_	-	247		71	64	80	84	54	54	57	V33
	2	206	196	203	197	195	210	207	56	63	58	53	53	61	62	51
	3	201	207	192	201	198	213	156	69	65	57	55	52	53	100	124
	4	216	206	211	193	202	207	208	57	69	60	55	77	49	152	-
4	5	221	206	211	194	196	197	220	56	63	60	55	46	97	58	106
4	6	209	214	224	199	194	193	204	173	64	60	59	51	62	56	48
4	7	204	212	213	208	191	190	191	214	60	62	66	76	51	49	55
4	8	214	215	215	207	208	180	172	188	69	72	55	49	56	52	56
4	9	209	205	214	205	204	196	187	196	86	62	66	87	57	60	48
5	0	208	209	205	203	202	186	174	185	149	71	63	55	55	45	56
5	1	207	210	211	199	217	194	183	177	209	90	62	64	52	93	52
5	2	208	205	209	209	197	194	183	187	187	239	58	68	61	51	56
5	3	204	206	203	209	195	203	188	185	183	221	75	61	58	60	60
5	4	200	203	199	236	188	197	183	190	183	196	122	63	58	64	66
5	5	205	210	202	203	199	197	196	181	173	186	105	62	57	64	63

How do we go from an array of numbers to recognizing fruit?

#### viewpoint variation



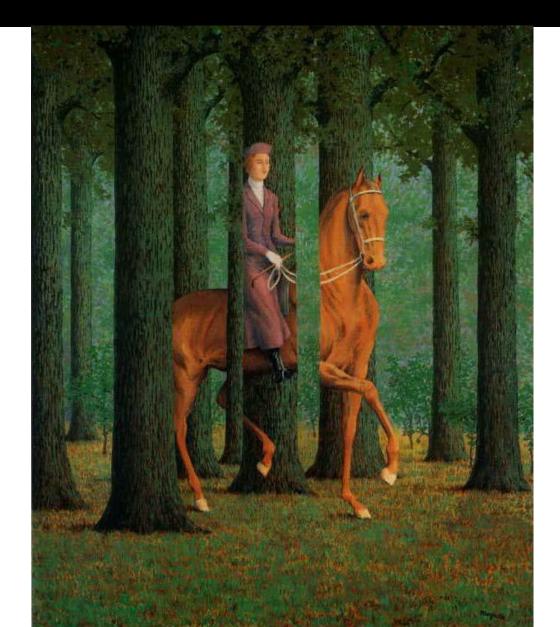




#### Illumination



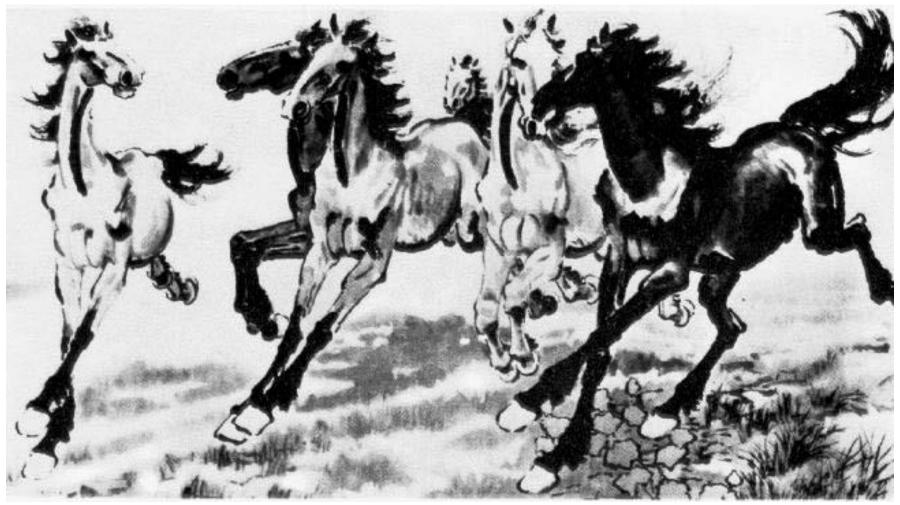
#### Occlusion



#### scale



#### deformation



### background clutter



### An Example

- Problem: sorting incoming fish on a conveyor belt according to species
- Assume that we have only two kinds of fish:
  - Salmon
  - Sea bass

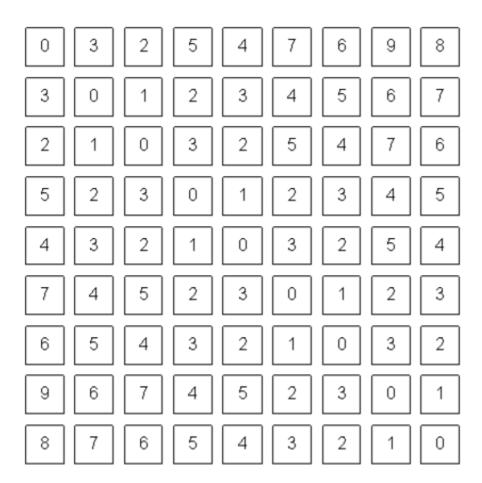


Picture taken with a camera

### An Example: the problem



What we see

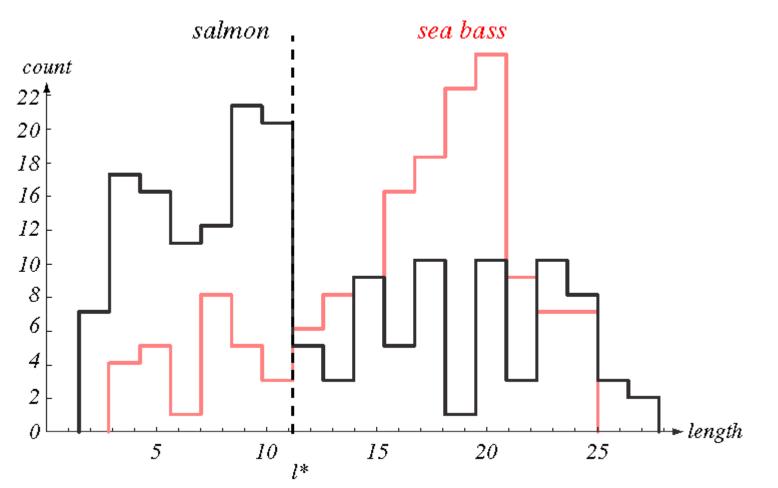


What a *computer* sees

### **An Example: Decision Process**

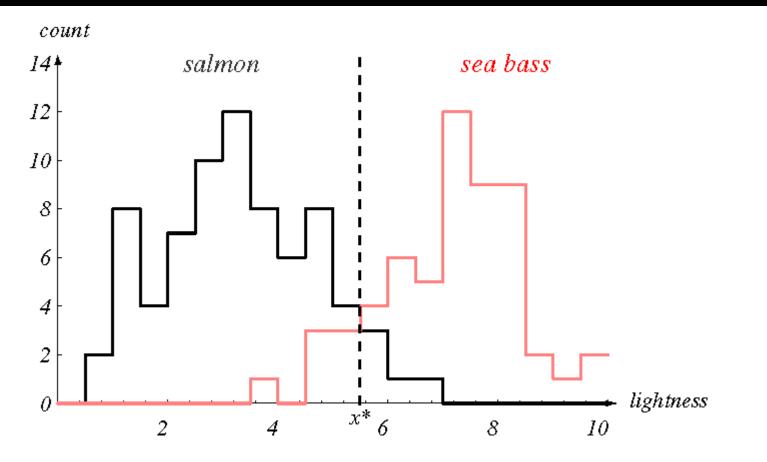
- What kind of information can distinguish one species from the other?
  - Length, width, weight, number and shape of fins, tail shape, etc.
- What can cause problems during sensing?
  - Lighting conditions, position of fish on the conveyor belt, camera noise, etc.
- What are the steps in the process?
  - Capture image -> isolate fish -> take measurements -> make decision

- Assume a fisherman told us that a sea bass is generally longer than a salmon.
  - We can use *length* as a feature and decide between sea bass and salmon according to a threshold on length.
  - I How can we choose this threshold?



Histogram of the length feature for two types of fish in training samples. How can we choose the threshold  $\ell^*$  to make a reliable decision?

- Even though sea bass is longer than salmon on the average, there are many examples of fish where this observation does not hold.
- Try another feature: average lightness of the fish scales.



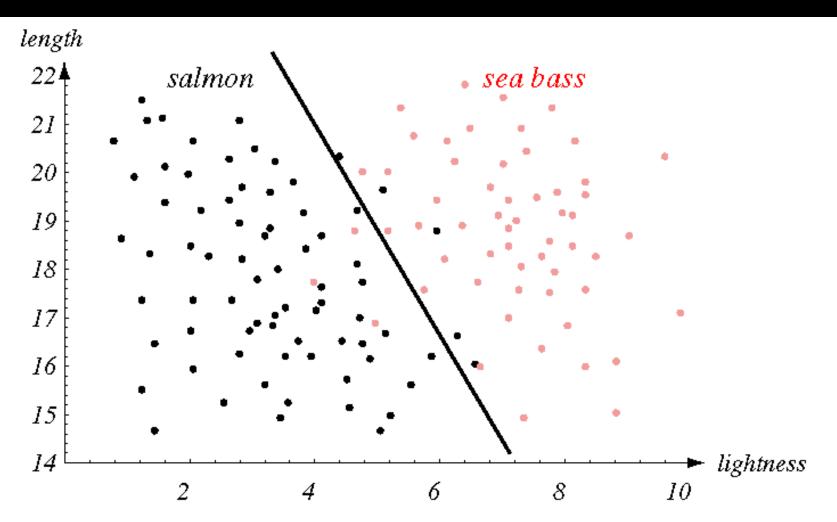
Histogram of the lightness feature for two types of fish in training samples. It looks easier to choose the threshold  $x^*$  but we still cannot make a perfect decision.

### **An Example: Multiple Features**

- We can use two features in our decision:
  - lightness: x<sub>1</sub>
  - length:  $x_2$

• Each fish image is now represented as a point (feature vector)  $\mathbf{x} = \begin{bmatrix} x_1 \\ x_2 \end{bmatrix}$  in a two-dimensional feature space.

### **An Example: Multiple Features**

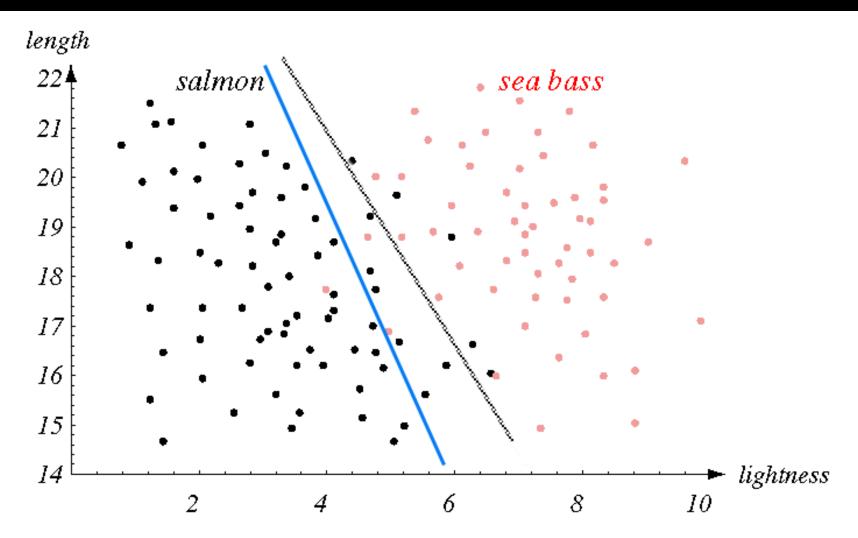


Scatter plot of lightness and length features for training samples. We can draw a decision boundary to divide the feature space into two regions.

### **An Example: Cost of Error**

- We should also consider costs of different errors we make in our decisions.
- For example, if the fish packing company knows that:
  - Customers who buy salmon will object vigorously if they see sea bass in their cans.
  - Customers who buy sea bass will not be unhappy if they occasionally see some expensive salmon in their cans.
- How does this knowledge affect our decision?

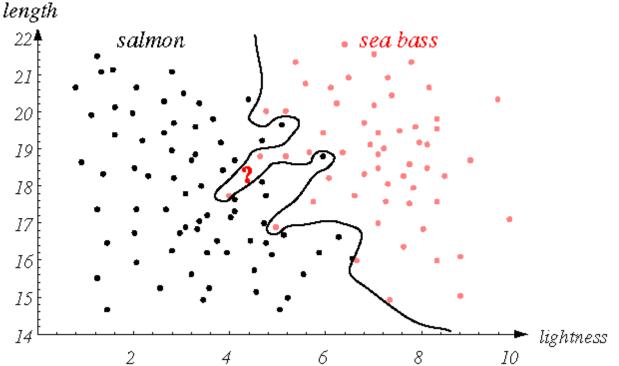
### **An Example: Multiple Features**



Scatter plot of lightness and length features for training samples with distinct costs.

### **An Example: Decision Boundaries**

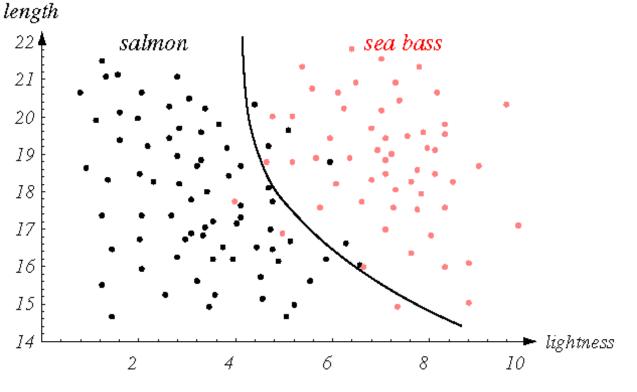
- Can we do better with another decision rule?
- More complex models result in more complex boundaries.



We may distinguish training samples perfectly but how can we predict how well we can generalize to unknown samples?

### **An Example: Decision Boundaries**

 How can we manage the tradeoff between complexity of decision rules and their performance to unknown samples?



Different criteria lead to different decision boundaries.



### Data collection:

- Data acquisition and sensing
  - Measurements of physical variables
  - Important issues: bandwidth, resolution, sensitivity, distortion, SNR, latency, etc.
- Collecting training and testing data
- How can we know when we have adequately large and representative set of samples?

- Feature extraction and selection:
  - Finding a new representation in terms of features
  - Domain dependence and prior information
  - Computational cost and feasibility
  - Discriminative features
    - Similar values for similar patterns
    - Different values for different patterns
  - Invariant features with respect to translation, rotation and scale
  - Robust features with respect to occlusion, distortion, deformation, and variations in environment

- Model learning and estimation
  - Learning a mapping between features and pattern groups and categories
- Model selection & training:
  - Domain dependence and prior information
  - Definition of design criteria
  - Parametric vs. non-parametric models
  - Computational complexity
  - Types of models: templates, decision-theoretic or statistical, syntactic or structural, neural, and hybrid
  - How can we know how close we are to the true model underlying the patterns?
  - How can we learn the rule from data?

### Predicting:

- Using features and learned models to assign a pattern to a category
- Evaluation:
  - How can we estimate the performance with training samples?
  - How can we predict the performance with future data?
  - Problems of overfitting and generalization

### References

- Selim Aksoy, Introduction to Pattern Recognition, Part I, http://retina.cs.bilkent.edu.tr/papers/patrec\_tutorial1.pdf
- Christopher M. Bishop, Pattern recognition and machine learning, Springer, 2006.
- Richard O. Duda, Peter E. Hart, David G. Stork, Pattern Classification, John Wiley & Sons, 2001