VC 18/19 – TP14
Pattern Recognition

Mestrado em Ciência de Computadores

Mestrado Integrado em Engenharia de Redes e Sistemas Informáticos

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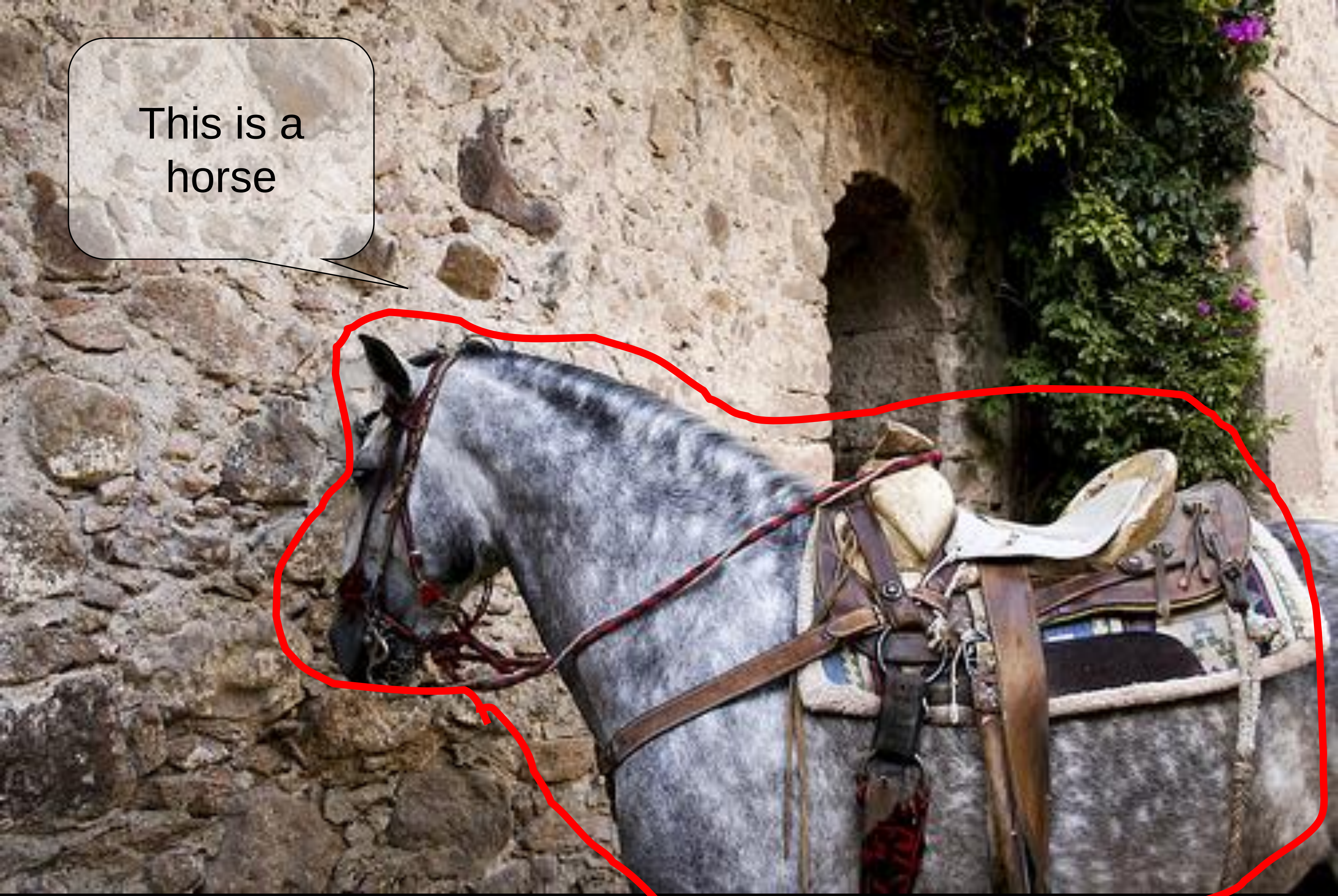
Outline

- Introduction to Pattern Recognition
- Statistical Pattern Recognition
- Classifiers

Topic: Introduction to Pattern Recognition

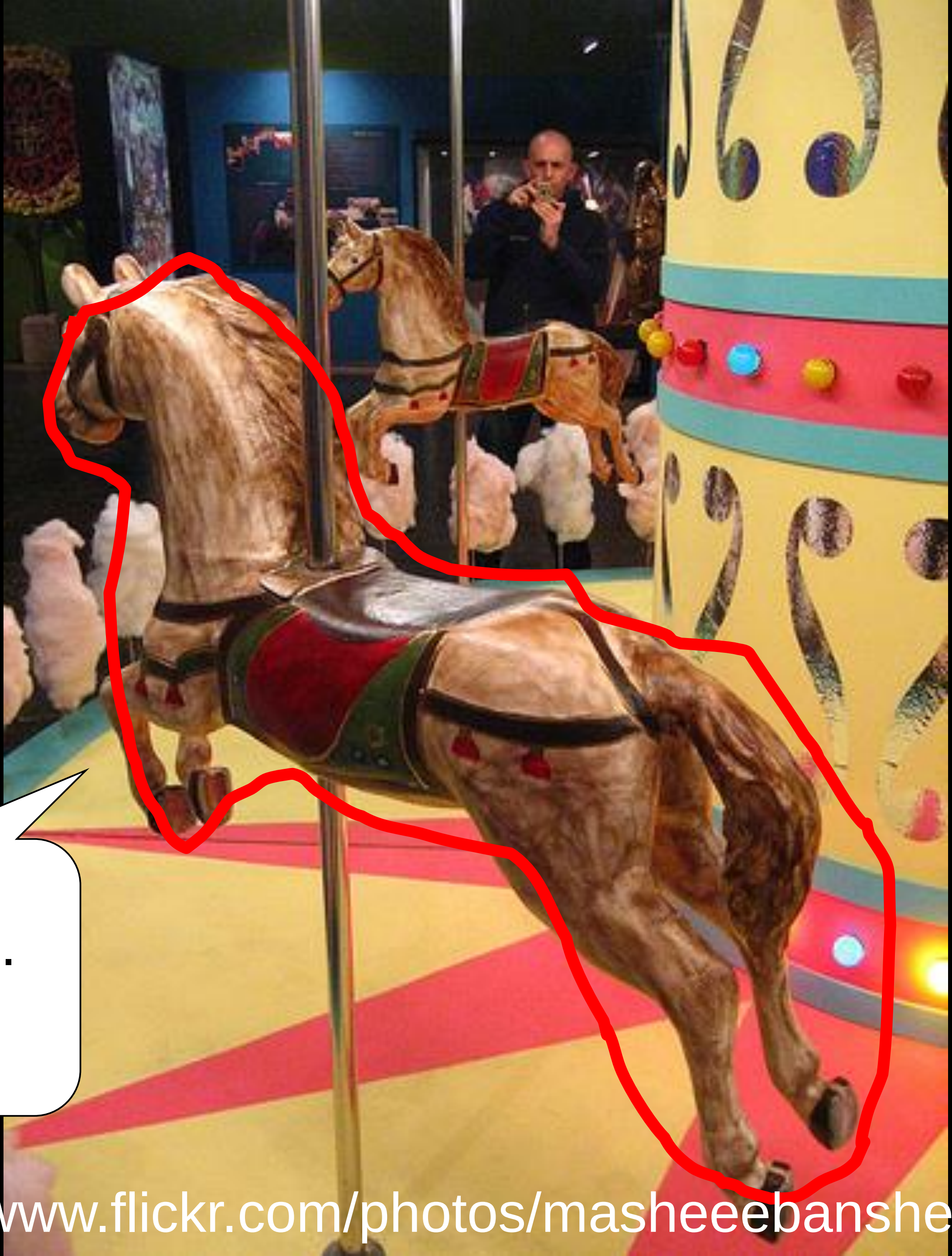
- Introduction to Pattern Recognition
- Statistical Pattern Recognition
- Classifiers



http://www.flickr.com/photos/kimbar/2027234083/

This is a horse

http://www.flickr.com/photos/genewolf/2031802050/



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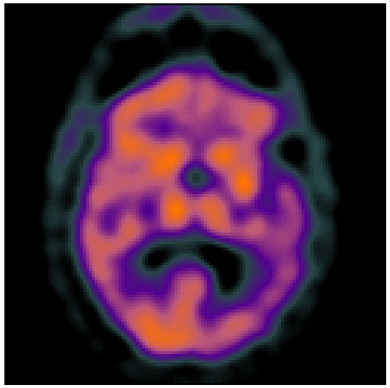
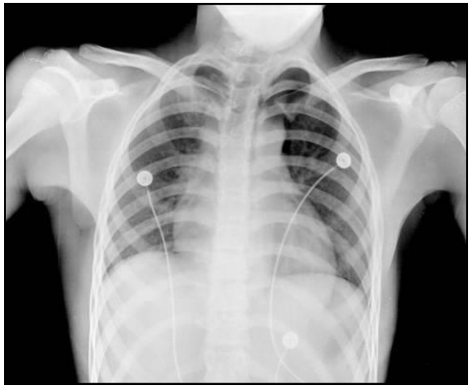
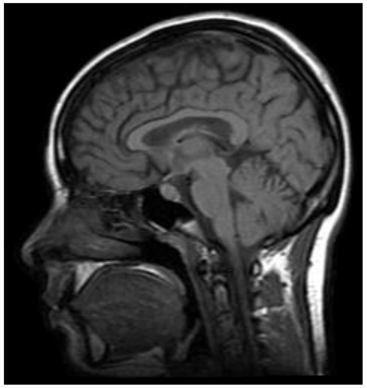
Decisions

- I can **manipulate** images.
- I want to make **decisions**!

- Classify / Identify **features**.
- Recognize **patterns**.

One definition

- Pattern recognition

  "the act of taking in raw data and taking an action based on the category of the data".

  Wikipedia

- How do I do this so well?
- How can I make machines do this?

The problem

0	3	2	5	4	7	6	9	8
3	0	1	2	3	4	5	6	7
2	1	0	3	2	5	4	7	6
5	2	3	0	1	2	3	4	5
4	3	2	1	0	3	2	5	4
7	4	5	2	3	0	1	2	3
6	5	4	3	2	1	0	3	2
9	6	7	4	5	2	3	0	1
8	7	6	5	4	3	2	1	0

Do you ‘see’ a horse?

What a computer sees

Mathematics

- We only deal with numbers.
  - How do we represent knowledge?
  - How do we represent visual features?
  - How do we classify them?
- Very complex problem!!
  - Let’s break it into smaller ones...

Typical PR system

Sensor

Gathers the observations to be classified or described

Feature Extraction

Computes numeric or symbolic information from the observations;

Classifier

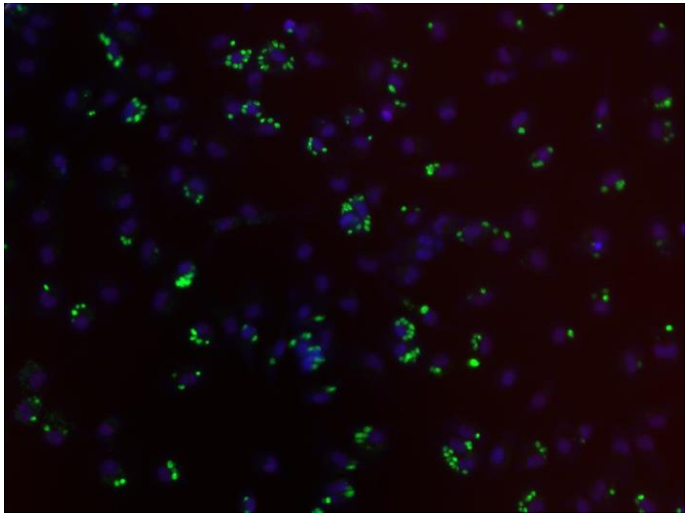
Does the actual job of classifying or describing observations, relying on the extracted features.

Sensor

- In our specific case:
  - Image acquiring mechanism.
  - Let’s assume we don’t control it.

One observation = One Image

Video = Multiple Observations



Feature Extraction

- What exactly are features?
  - – Colour, texture, shape, etc.
  - – Animal with 4 legs.
  - – Horse.
  - – Horse jumping.
- These vary a lot!
- Some imply some sort of ‘recognition’

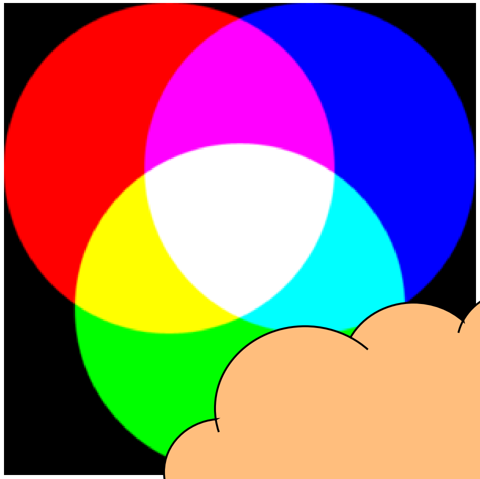
  e.g. How do I know the horse is jumping?

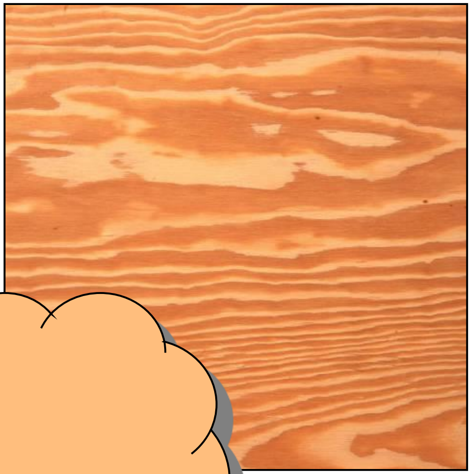
Broad classification of features

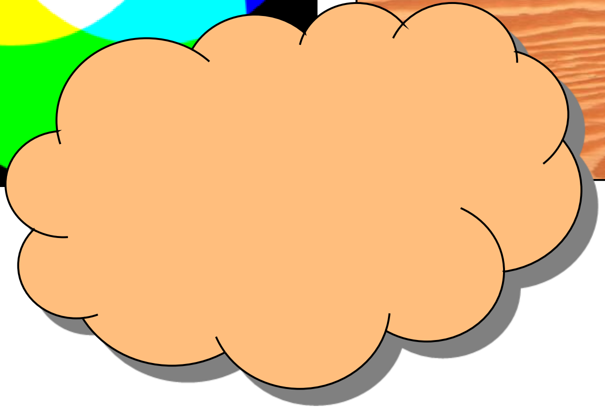
- Low-level
  - Colour, texture
- Middle-level
  - Object with head and four legs.
  - Object moving up.
  - Horse
- High-level
  - Horse jumping.
  - Horse competition.

Low-level features

- Objective
- Directly reflect specific image and video features.
  - Colour
  - Texture
  - Shape
  - Motion
  - Etc.

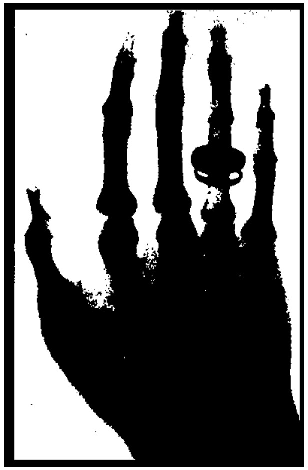






Middle-level features

- Some degree of subjectivity
- They are typically one solution of a problem with multiple solutions.
- Examples:
  – Segmentation
  – Optical Flow
  – Identification
  – Etc.



High-level features

- Semantic Interpretation
- Knowledge
- Context
- Examples:
  – This person suffers from epilepsy.
  – The virus attacks the cell with some degree of intelligence.
  – This person is running from that one.

How do humans do this so well?

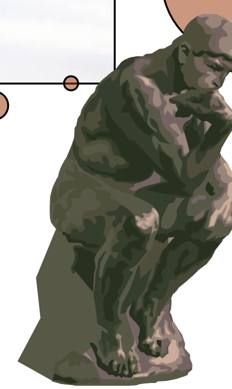
The semantic gap

- Fundamental problem of current research!

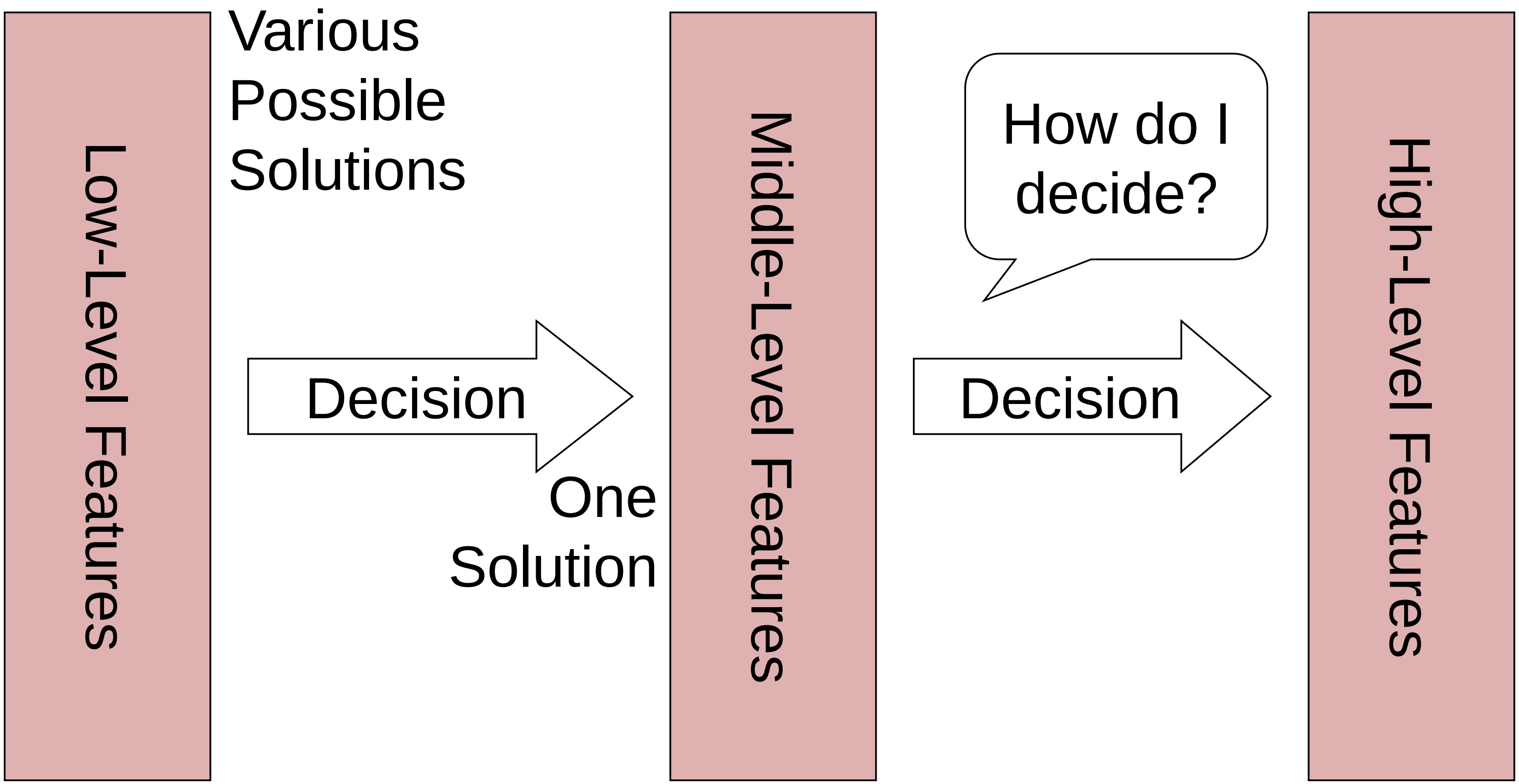
Low-level:
-Colour
-Texture
-Shape
-…

High-level:
-Interpretation
-Decision
-Understanding
-…

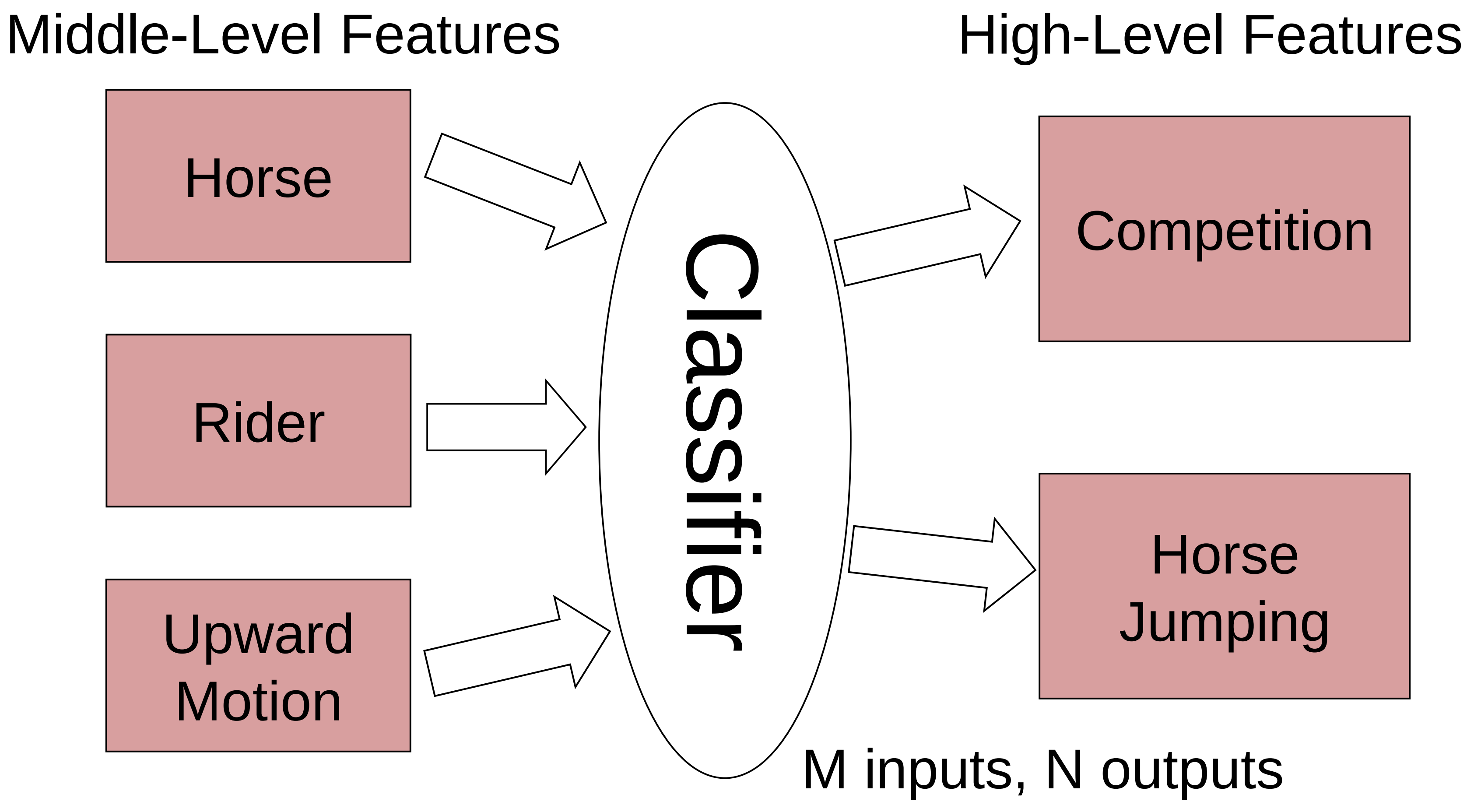
Now what??
How do i cross this bridge?



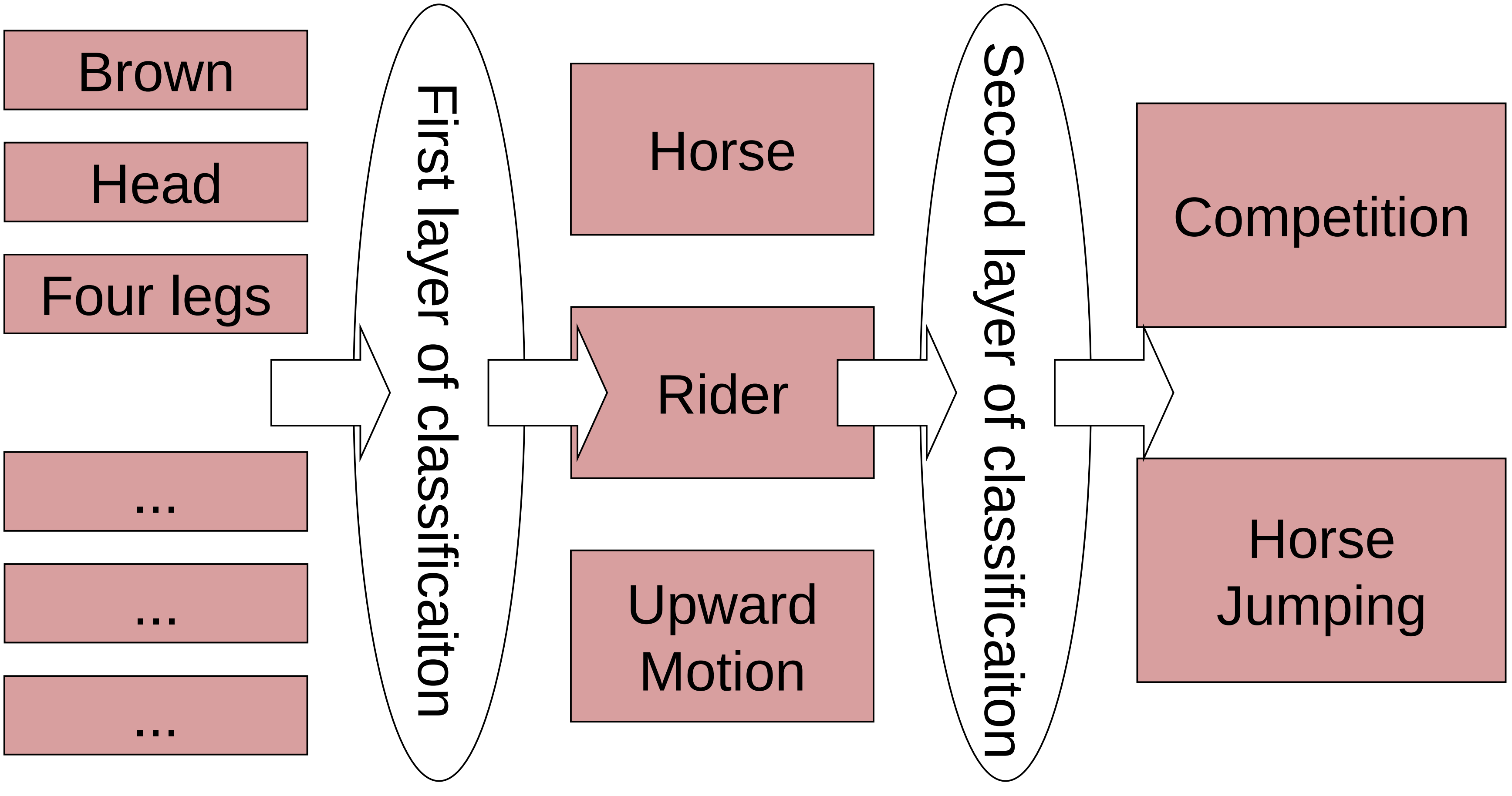
Features & Decisions



Classification



Layers of classification



Classifiers

- How do I map my M inputs to my N outputs?
- Mathematical tools:
  - Distance-based classifiers.
  - Rule-based classifiers.
  - Neural Networks.
  - Support Vector Machines
  - ...

Types of PR methods

- Statistical pattern recognition
  - based on statistical characterizations of patterns, assuming that the patterns are generated by a probabilistic system.
- Syntactical (or structural) pattern recognition
  - based on the structural interrelationships of features.

Topic: Statistical Pattern Recognition

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Is Porto in Portugal?

Porto is in Portugal

- I want to make decisions.
  - Is Porto in Portugal?
- I know certain things.
  - A world map including cities and countries.
- I can make this decision!
  - Porto **is** in Portugal.
- I had enough ***a priori*** knowledge to make this decision.

What if I don't have a map?

- I still want to make this decision.
- I observe:
  - Amarante has coordinates x_1,y_1 and is in Portugal.
  - Viseu has coordinates x_2, y_2 and is in Portugal.
  - Vigo has coordinates x_3, y_3 and is in Spain.
- I classify:
  - Porto is close to Amarante and Viseu so **Porto <u>is</u> in Portugal**.
- What if I try to classify *Valença*?

Statistical PR

- I used **statistics** to make a decision.
  – I can make **decisions** even when I don't have full a priori knowledge of the whole process.
  – I can make **mistakes**.
- How did I **recognize** this pattern?

What pattern?

  – I **learned** from previous observations where I knew the classification result.
  – I **classified** a new observation.

Back to the Features

- Feature $\boldsymbol{F_i}$ $F_i = [f_i]$
- Feature $\boldsymbol{F_i}$ with $\boldsymbol{N}$ values.

$$F_i = [f_{i1}, f_{i2}, \ldots, f_{iN}]$$

- Feature vector F with M features.

$$F = [F_1 \mid F_2 \mid \ldots \mid F_M]$$

- Naming conventions:
  - Elements of a **feature vector** are called **coefficients**.
  - **Features** may have one or more **coefficients**.
  - **Feature vectors** may have one or more **features**.

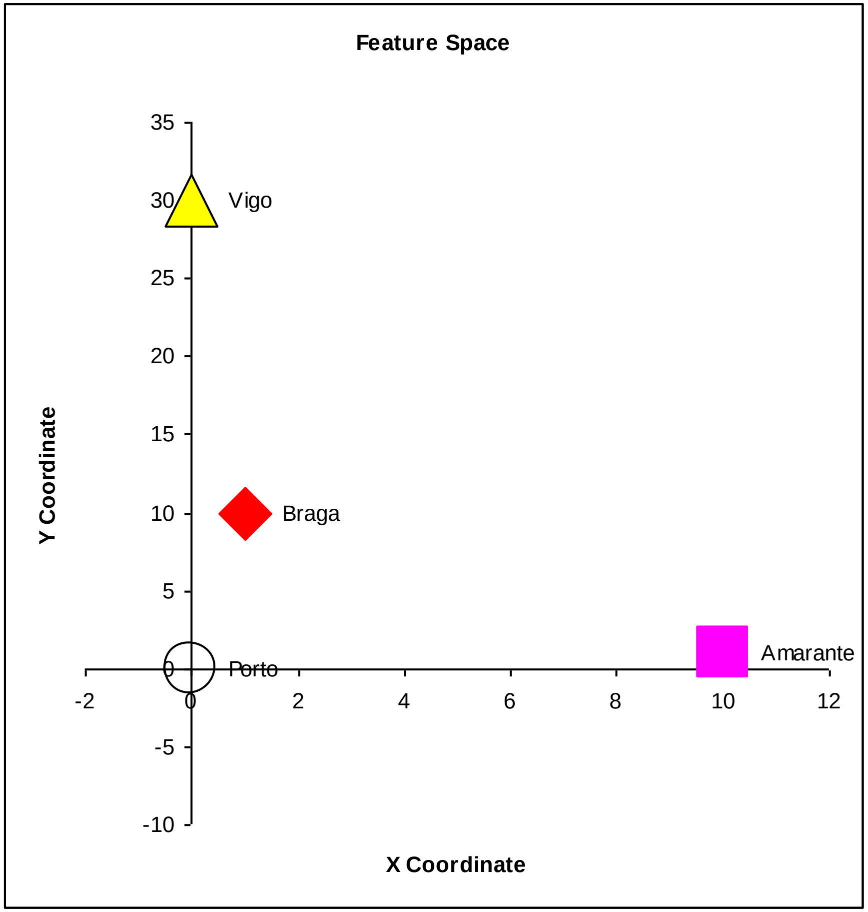
Back to our Porto example

- I've classified that Porto is in Portugal.
- What feature did I use?
  - Spatial location
- Let's get more formal
  - I've defined a feature vector ***F*** with one feature $\boldsymbol{F_1}$, which has two coefficients $\boldsymbol{f_{1x}}$, $\boldsymbol{f_{1y}}$.

$$F = [F_1] = [f_{1x}, f_{1y}]$$

Feature Space

- Feature Vector
  - Two total coefficients.
  - Can be seen as a feature 'space' with two orthogonal axis.
- Feature Space
  - Hyper-space with N dimensions where N is the total number of coefficients of my feature vector.



A Priori Knowledge

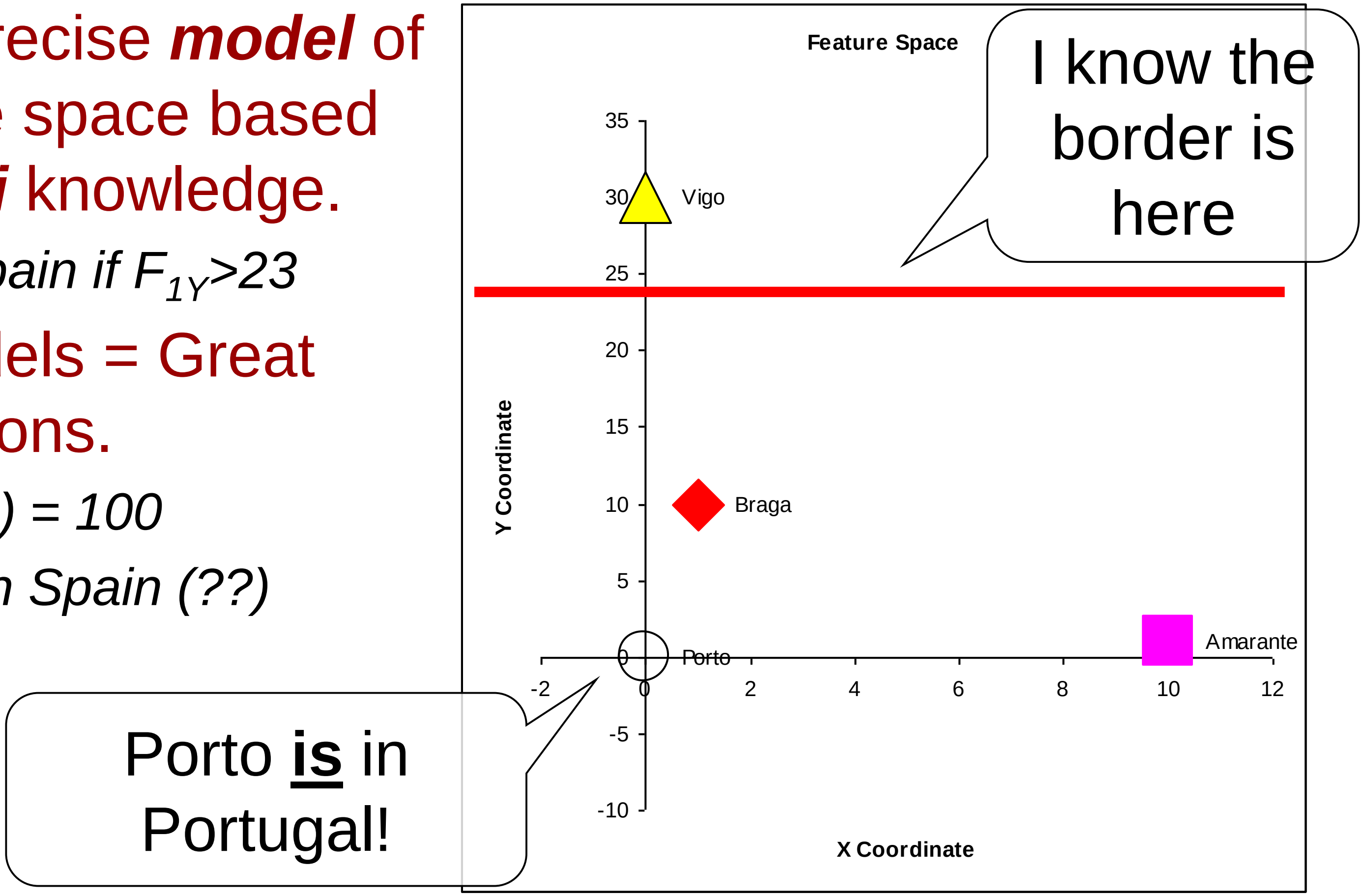
- I have a precise ***model*** of my feature space based on ***a priori*** knowledge.

  City is in Spain if F_{1Y}>23

- Great models = Great classifications.

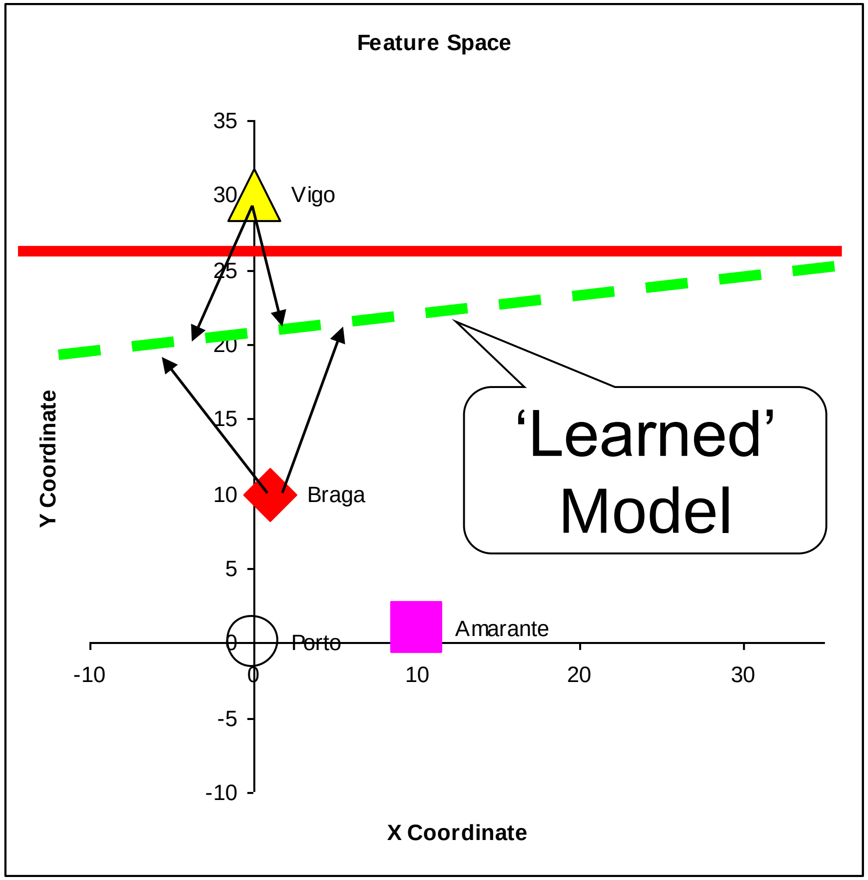
  F_{1Y}(London) = 100

  London is in Spain (??)



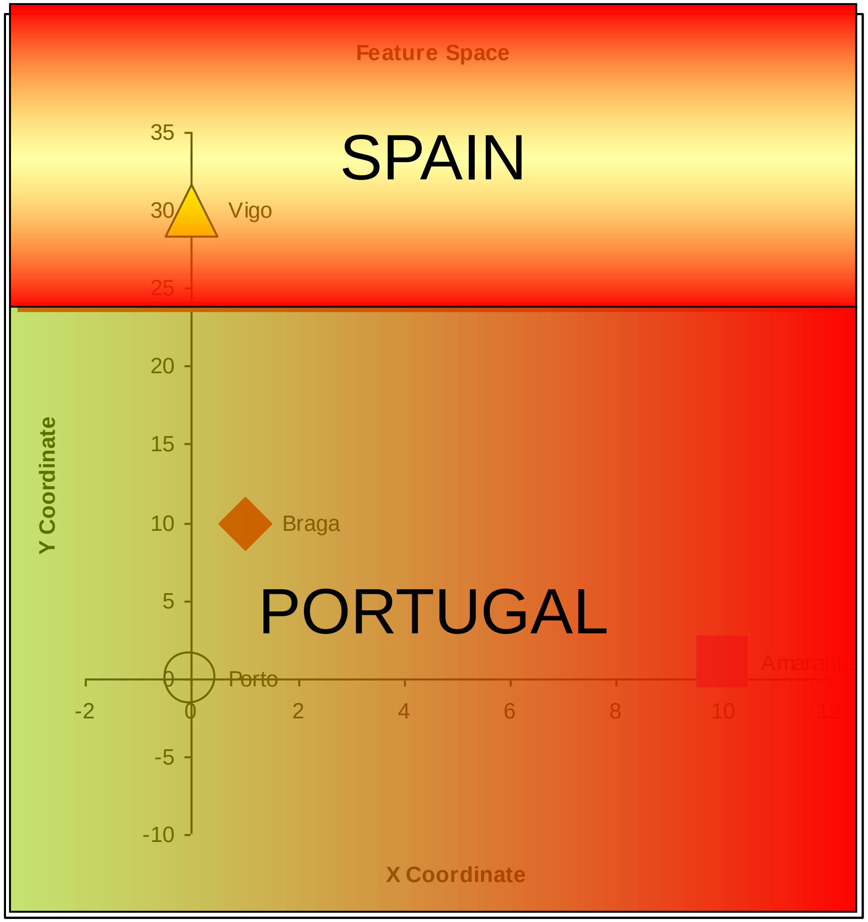
What if I don't have a model?

- I need to **learn** from observations.
  - Derive a model.
  - Direct classification.
- Training stage.
  - Learn model parameters.
- Classification



Classes

- In our example, cities can belong to:
  - Portugal
  - Spain
- I have two ***classes*** of cities.
- A ***class*** represents a sub-space of my feature space.



Classifiers

- A **Classifier C** maps a class into the feature space.

$$C_{\text{Spain}}(x, y) = \begin{cases} true & , y > K \\ false & , otherwise \end{cases}$$

- Various types of classifiers.
  - Nearest-Neighbours.
  - Bayesian.
  - Soft-computing machines.
  - Etc...

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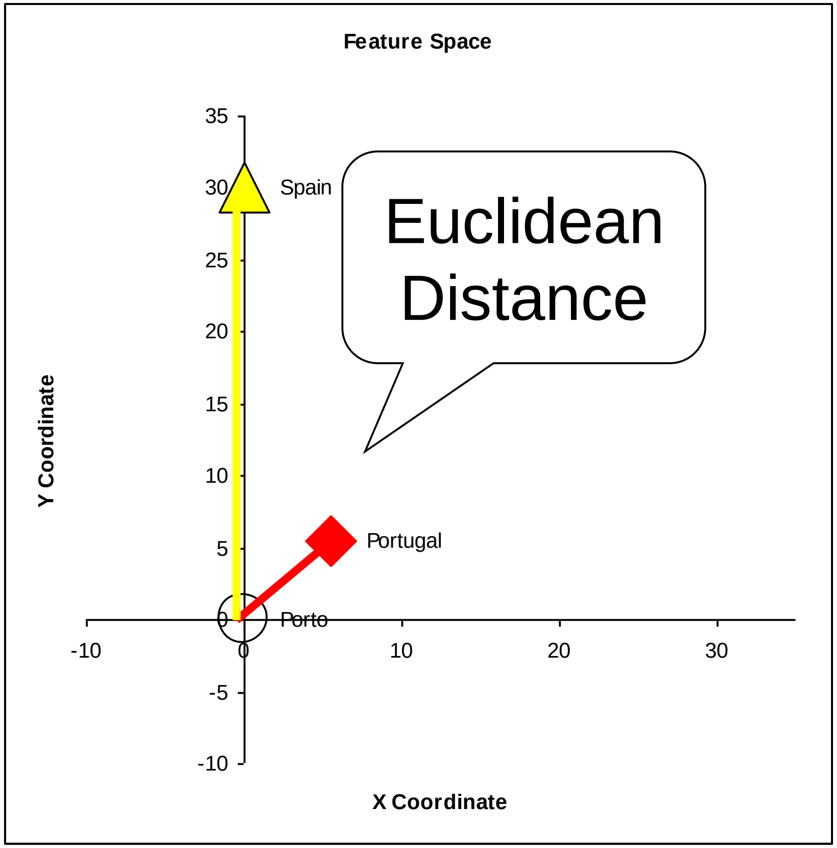
Distance to Mean

- I can represent a class by its mean feature vector.

$$C = \overline{F}$$

- To classify a new object, I choose the class with the closest mean feature vector.
- Different distance measures!



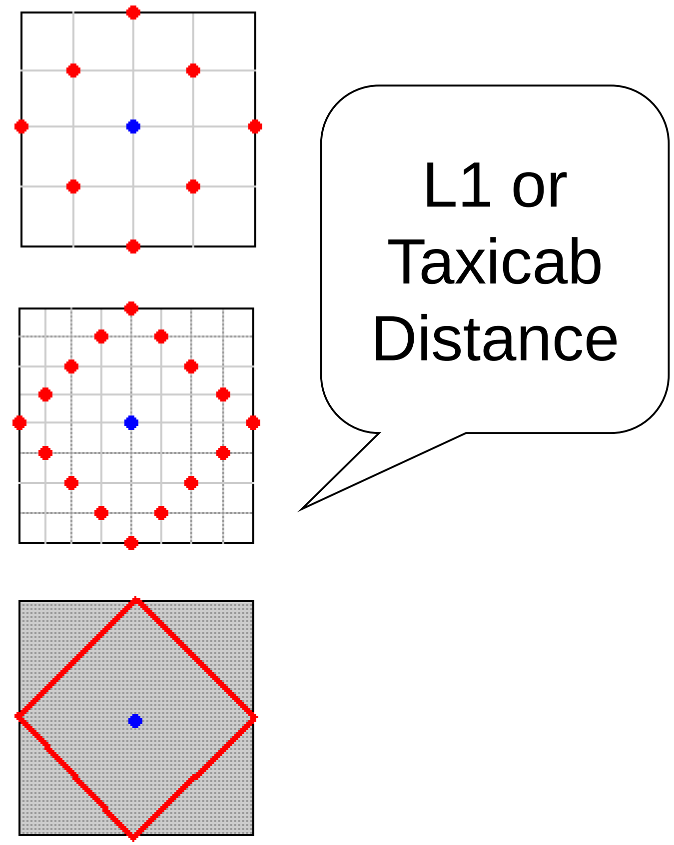
Possible Distance Measures

- L1 Distance

$$L1 = \frac{1}{N} \sum_{x=1}^{N} \left| S(x) - v(x) \right|$$

- Euclidean Distance (L2 Distance)

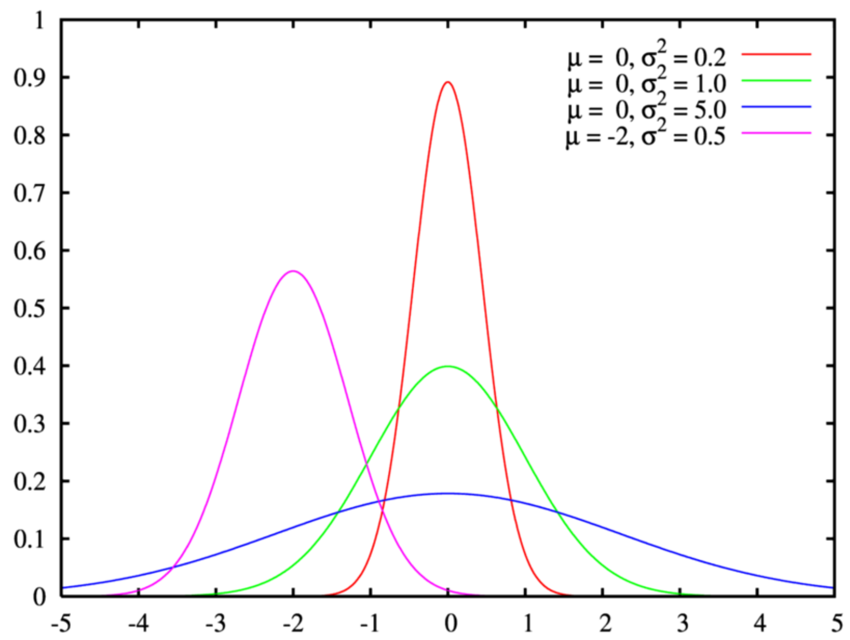
$$L2 = \frac{1}{N} \sum_{x=1}^{N} \left(S(x) - v(x) \right)^2$$



Gaussian Distribution

- Defined by two parameters:
  - Mean: μ
  - Variance: σ^2
- Great approximation to the distribution of many phenomena.
  - *Central Limit Theorem*

$$f(x) = \frac{1}{\sigma\sqrt{2\pi}} \exp\left(-\frac{(x-u)^2}{2\sigma^2}\right)$$



Multivariate Distribution

- For N dimensions:

$$f_X(x_1,\ldots,x_N) = \frac{1}{(2\pi)^{N/2}\,|\Sigma|^{1/2}} \exp\left(-\frac{1}{2}(x-\mu)^\top \Sigma^{-1}(x-\mu)\right)$$

- Mean feature vector:

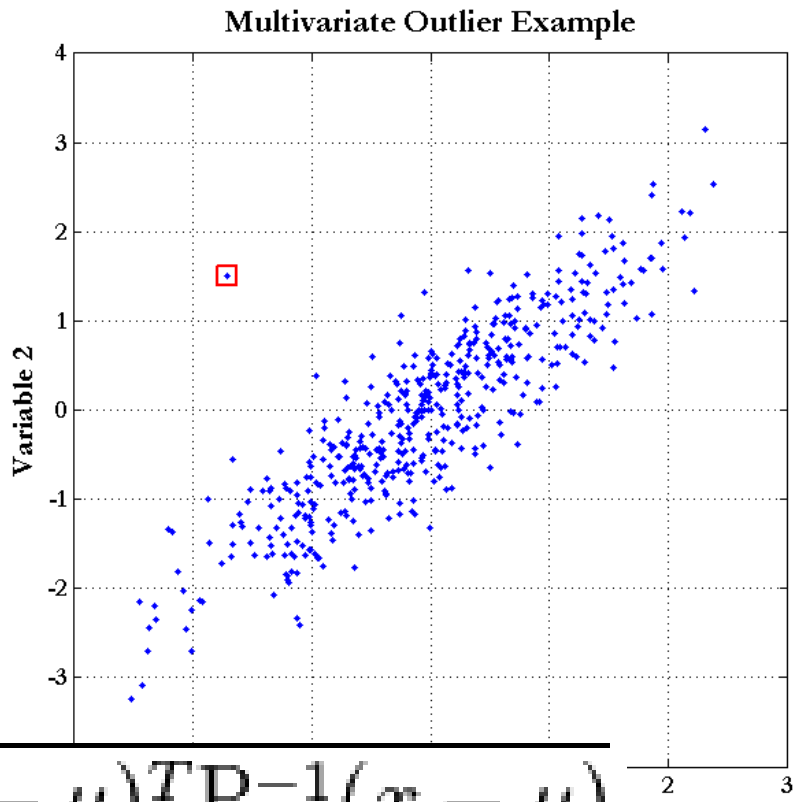
$$\mu = \overline{F}$$

- Covariance Matrix:

$$X = \begin{bmatrix} X_1 \\ \vdots \\ X_n \end{bmatrix} \qquad \mu_i = \mathrm{E}(X_i) \qquad \Sigma_{ij} = \mathrm{E}\left[(X_i-\mu_i)(X_j-\mu_j)\right]$$

Mahalanobis Distance

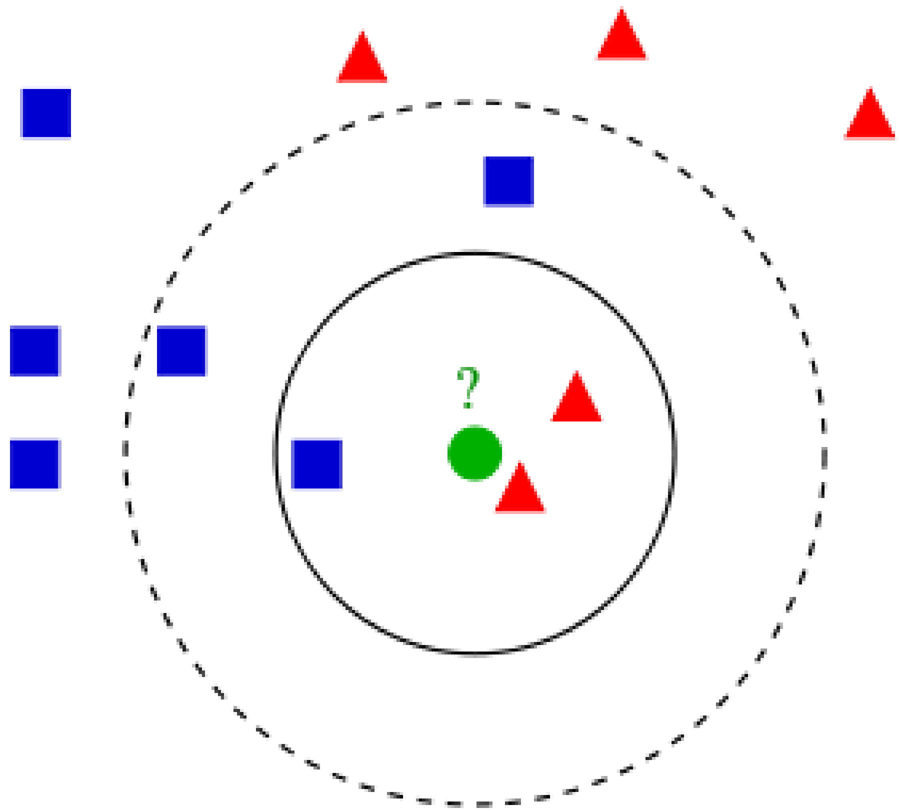
- Based on the covariance of coefficients.
- Superior to the Euclidean distance.



$$D_M(x) = \sqrt{(x-\mu)^T P^{-1} (x-\mu)}.$$

K-Nearest Neighbours

- Algorithm
  - Choose the closest K neighbours to a new observation.
  - Classify the new object based on the **class** of these K objects.
- Characteristics
  - Assumes no model.
  - Does not scale very well...



Resources

- Gonzalez & Woods, 3rd Ed, Chapter 12.
- Andrew Moore, Statistic Data Mining Tutorial, http://www.autonlab.org/tutorials/