Computer Vision – TP7
Pattern Recognition

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Outline

- Introduction to Pattern Recognition
- Statistical Pattern Recognition
- Visual Features
- Detection of interest points
- Local invariant descriptors

Topic: Introduction to Pattern Recognition

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- Statistical Pattern Recognition
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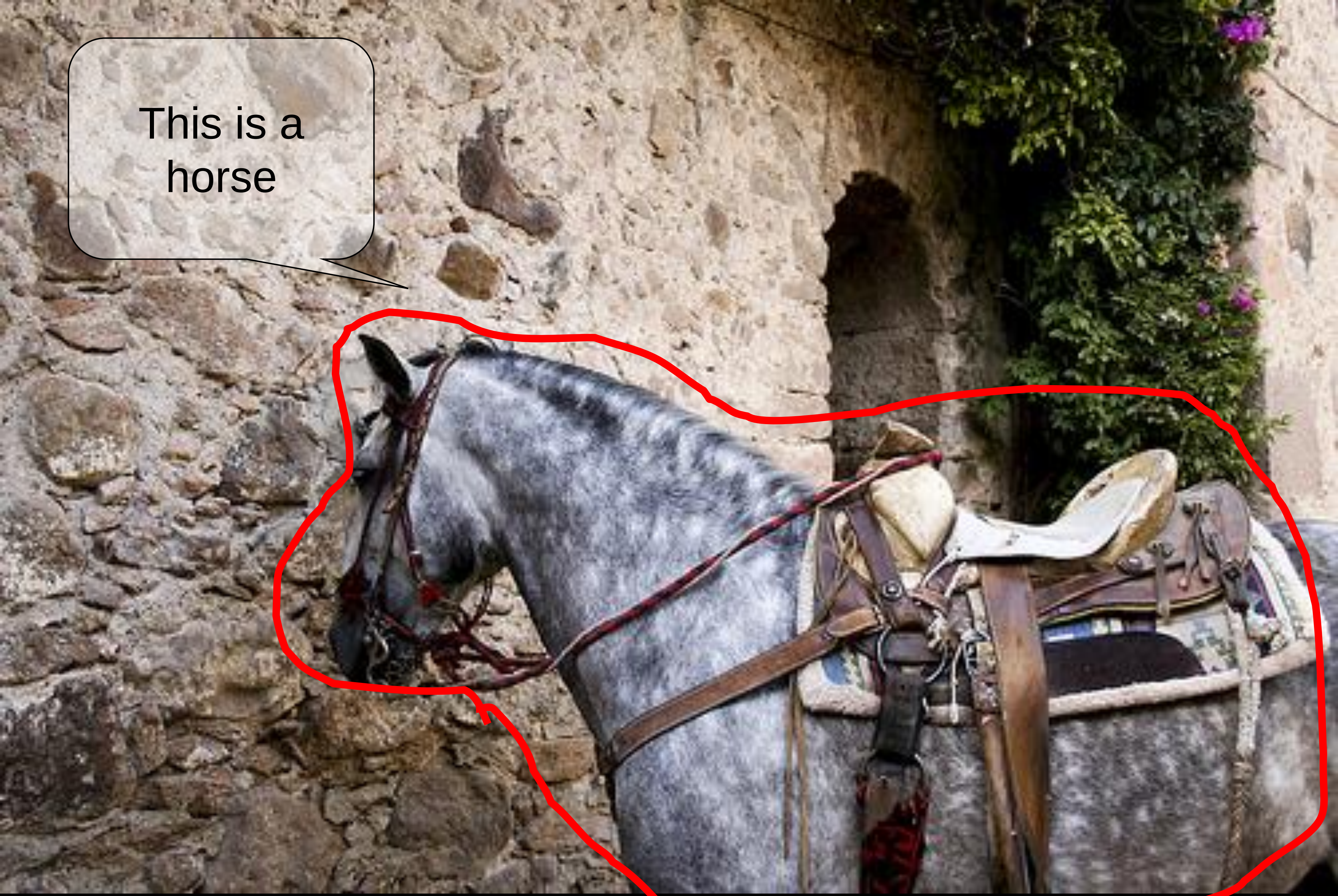
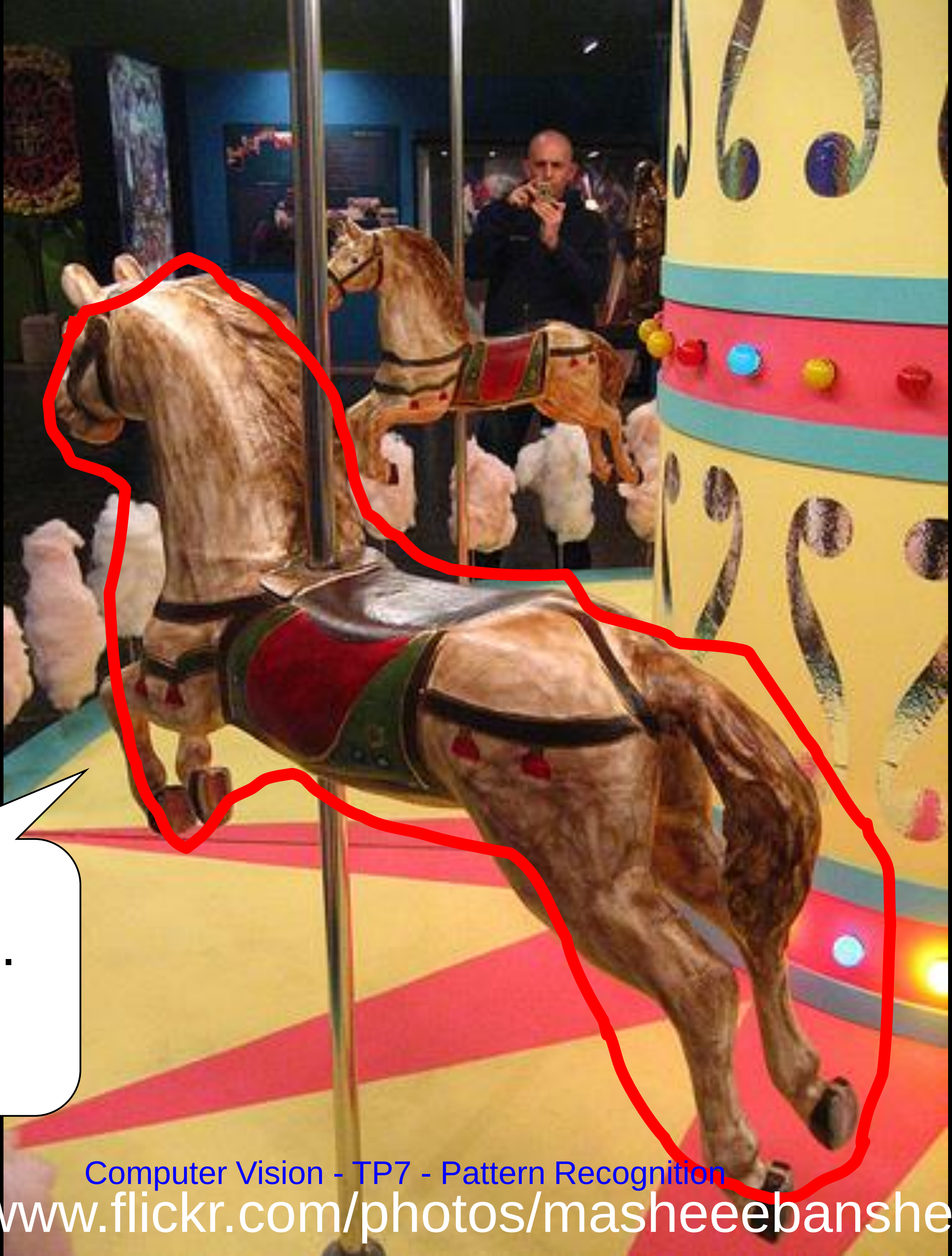


http://www.flickr.com/photos/kimbar/2027234083/

This is a horse

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



This is a...
Horse?

http://www.flickr.com/photos/masheeebanshee/413465808/

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

Do you ‘see’ a horse?

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

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

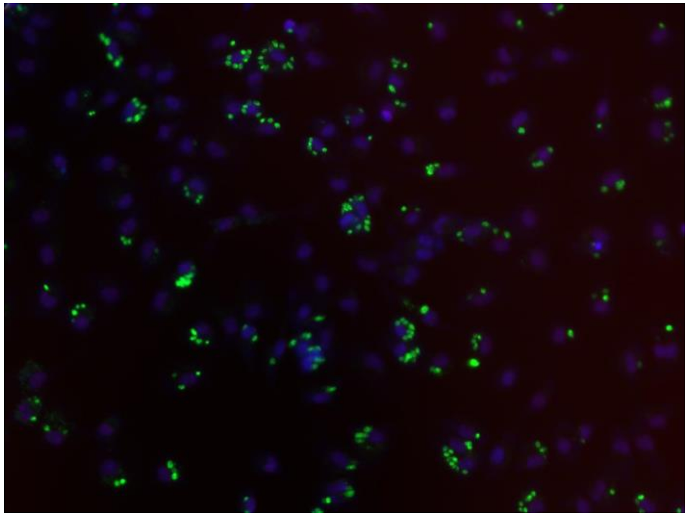
Does the actual job of classifying or describing observations, relying on the extracted features.

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

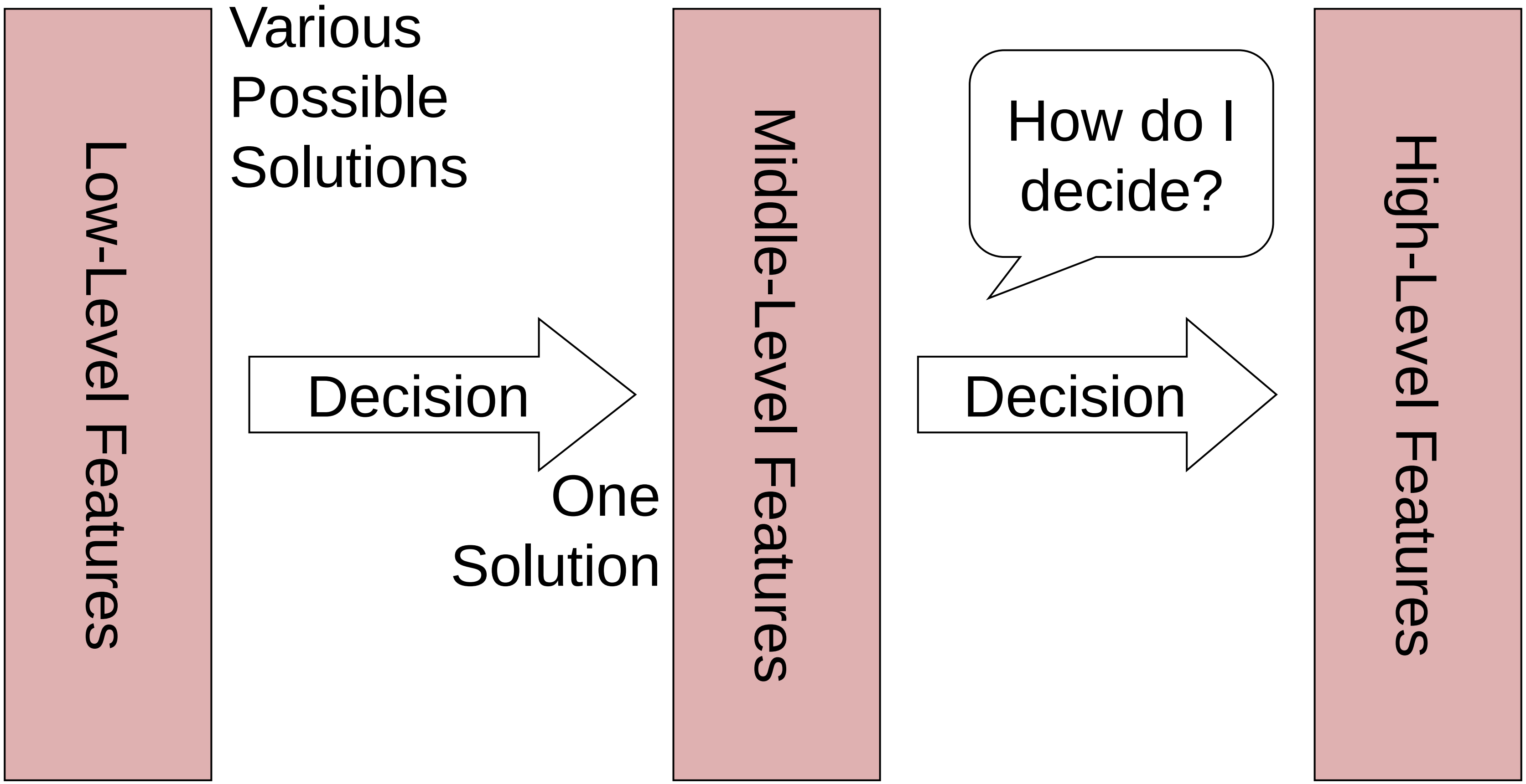
- What exactly are features?
  - Colour, texture, shape, etc
  - Animal with 4 legs
  - Horse
  - Horse jumping
- These vary a lot!
- Some imply some sort of 'recognition'

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

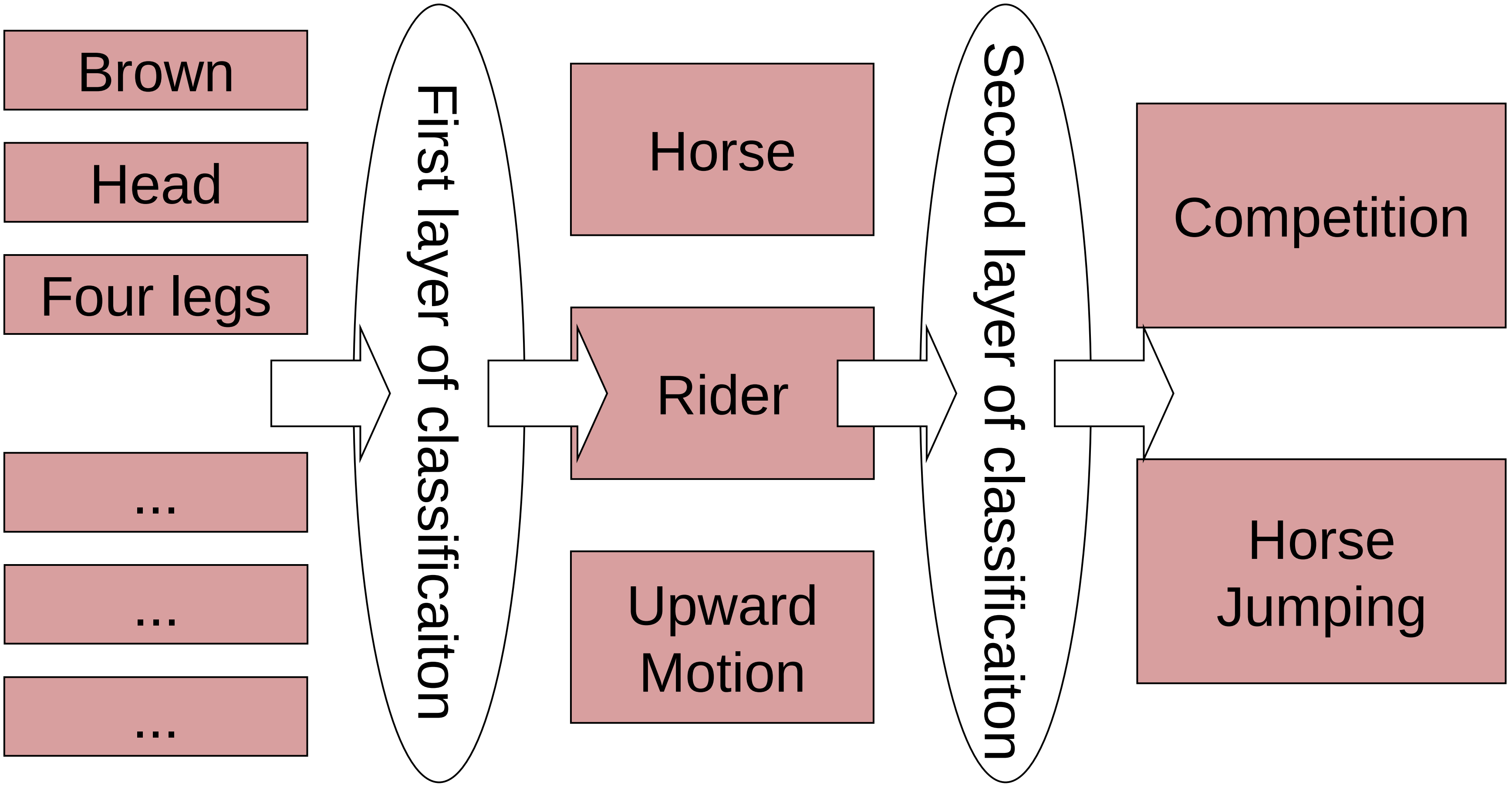
Broad classification of features

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

Features & Decisions



Layers of classification



Classifiers

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

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

- Introduction to Pattern Recognition
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- Visual Features
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- Local invariant descriptors

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 **<u>is</u>** 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 F_i $F_i = [f_i]$
- Feature F_i with N values.

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

- Feature vector F with M features.

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

- 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**

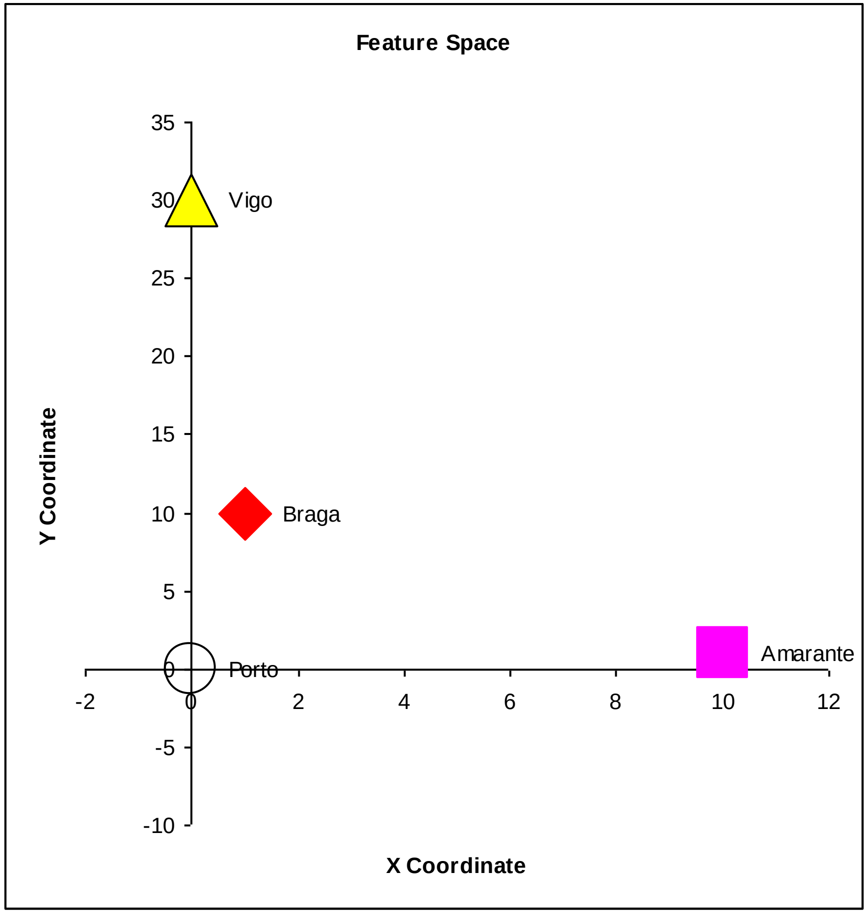
Back to our Porto example

- 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 $\boldsymbol{F}$ 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

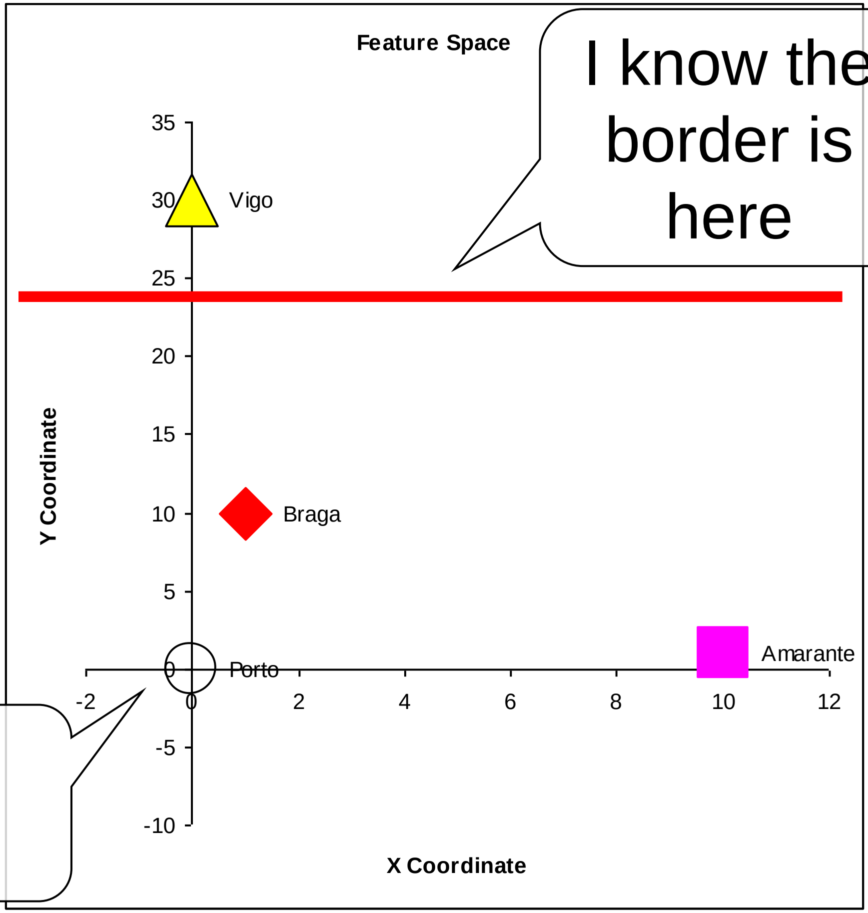
- I have a precise ***model*** of my feature space based on ***a priori*** knowledge

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

- Great models = Great classifications

  $F_{1Y}(London) = 100$

  London is in Spain (??)

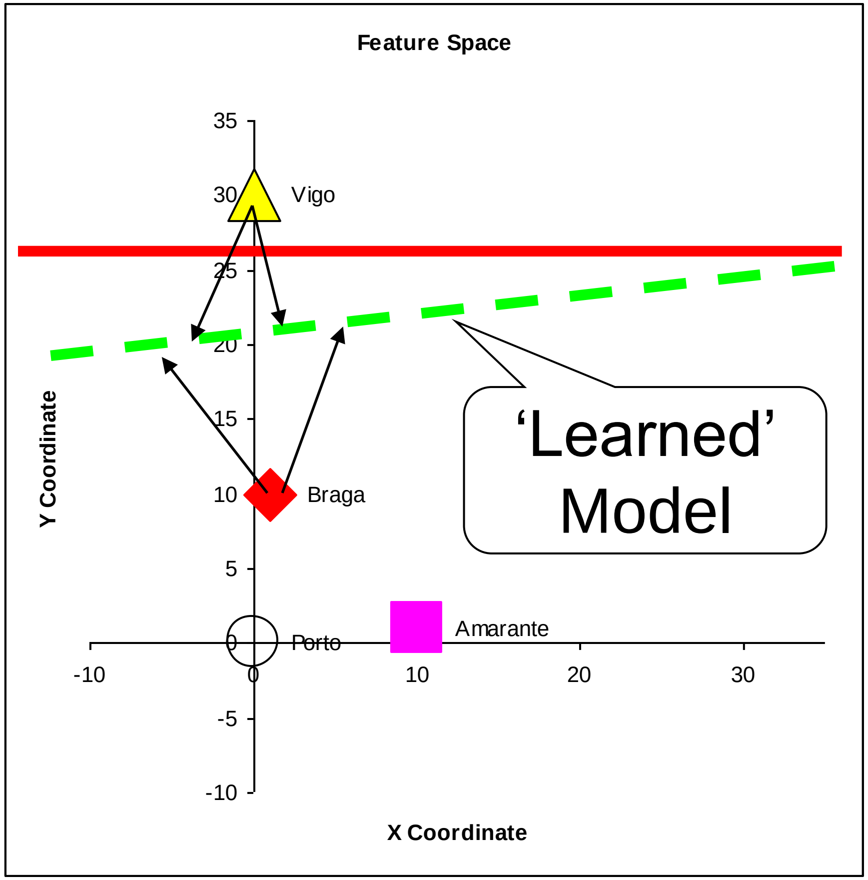


I know the border is here

Porto **<u>is</u>** in Portugal!

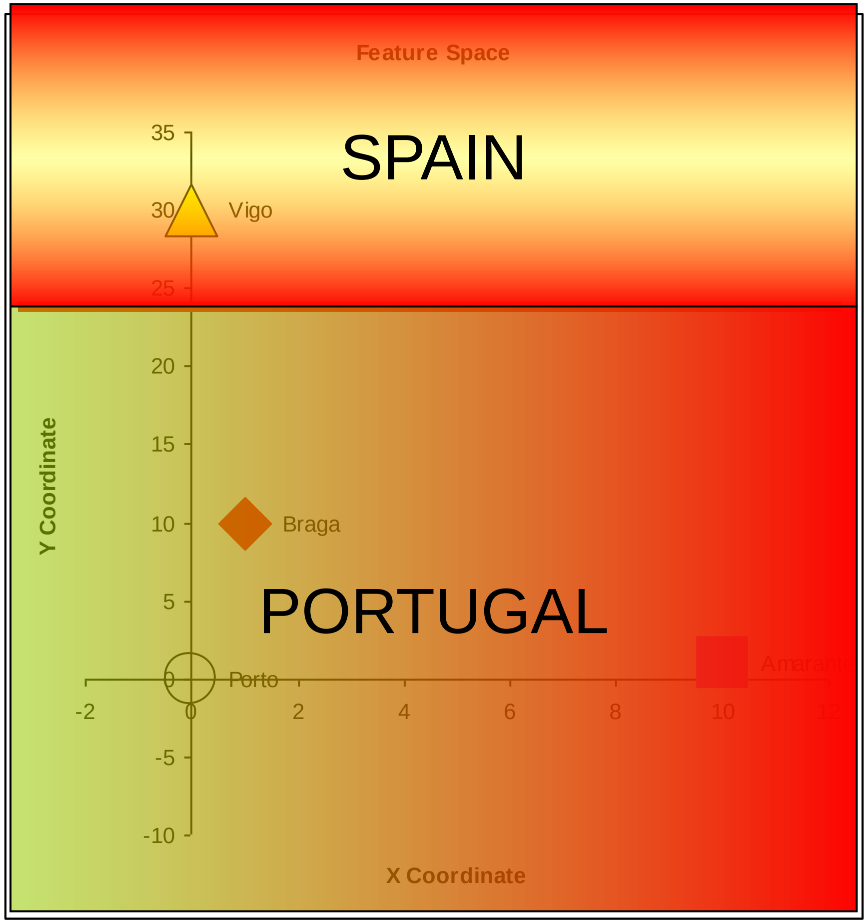
What if I don't have a model?

- 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...

Topic: Visual Features

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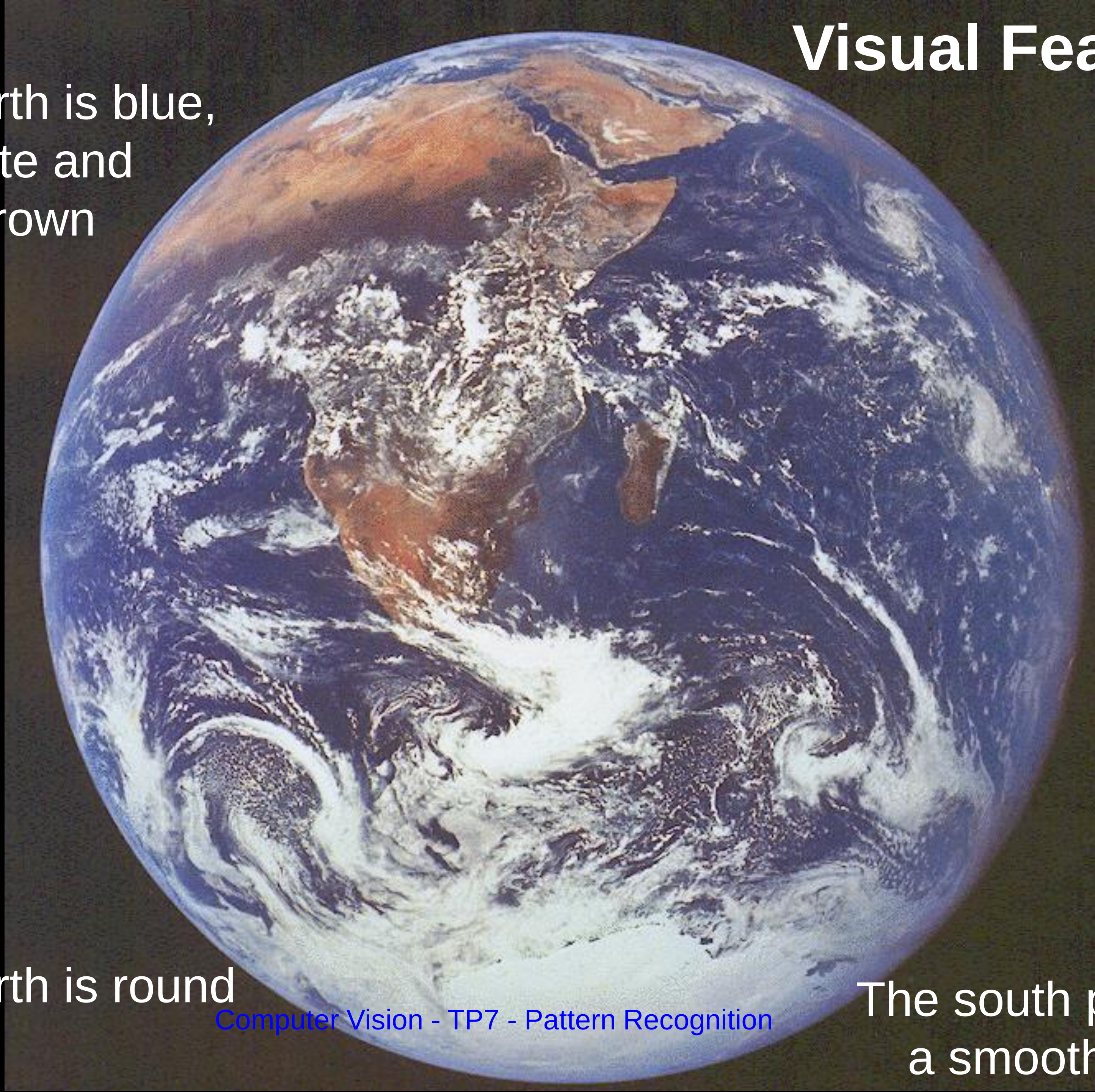
Visual Features

The earth is blue, white and brown



The earth is round

The south pole has a smooth texture

Visual Features

- Features
  - Measure specific characteristics
  - Numerical values
  - May have multiple values
- Visual Features
  - Quantify visual characteristics of an image
  - Popular features
    - Colour, Texture, Shape

Feature vector

- Feature $\boldsymbol{F_i}$ $$F_i = [f_i]$$
- Feature $\boldsymbol{F_i}$ with $\boldsymbol{N}$ values.
$$F_i = [f_{i1}, f_{i2}, \dots, f_{iN}]$$
- Feature vector F with M features.
$$F = [F_1 \mid F_2 \mid \dots \mid F_M]$$

- Naming conventions for this module:
  - Elements of a **feature vector** are called **coefficients**
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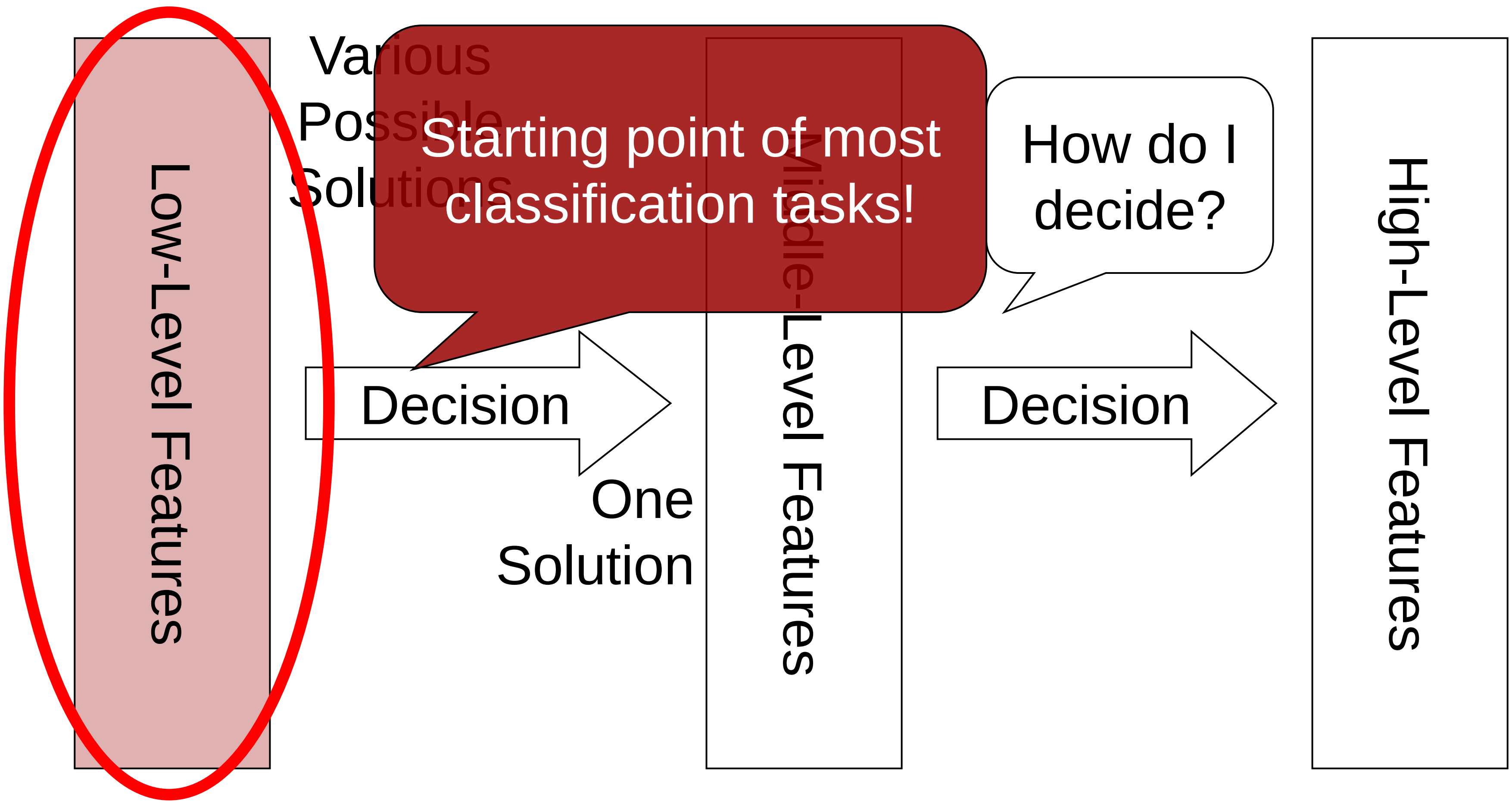
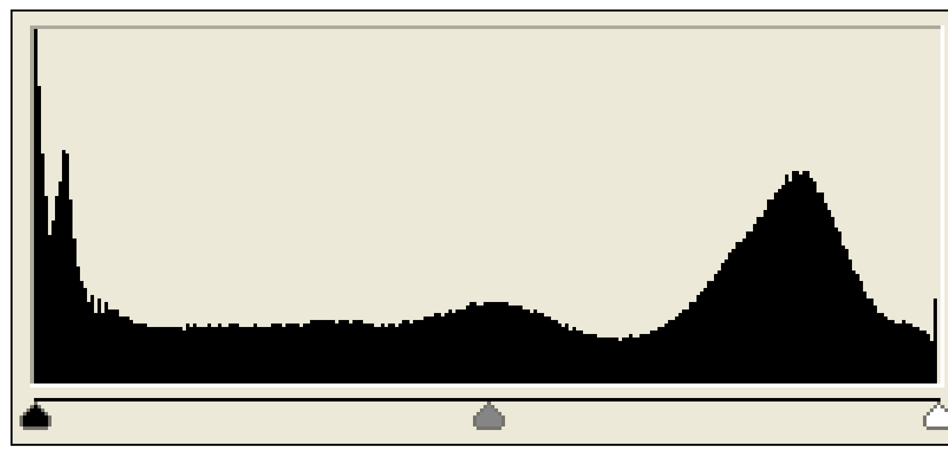
Features & Decisions



Gray-Level Histogram

- Intensity distribution (HSI)
- We can define the number of histogram bins
- Histogram bins = Feature coefficients

$$F = [f_0, \ldots, f_{255}]$$



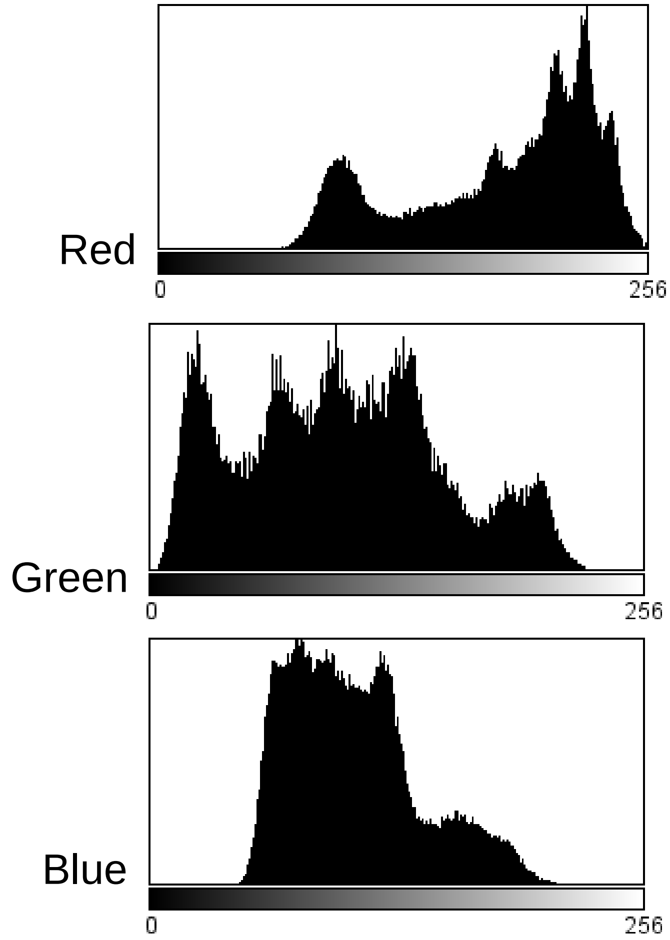
Colour Histogram

- We typically have three histograms

  Ex: RGB Colour space

  - Red Histogram
  - Green Histogram
  - Blue Histogram

- How do we build a feature vector?
  - Concatenate vectors
  - Multi-dimensional quantization of colour space

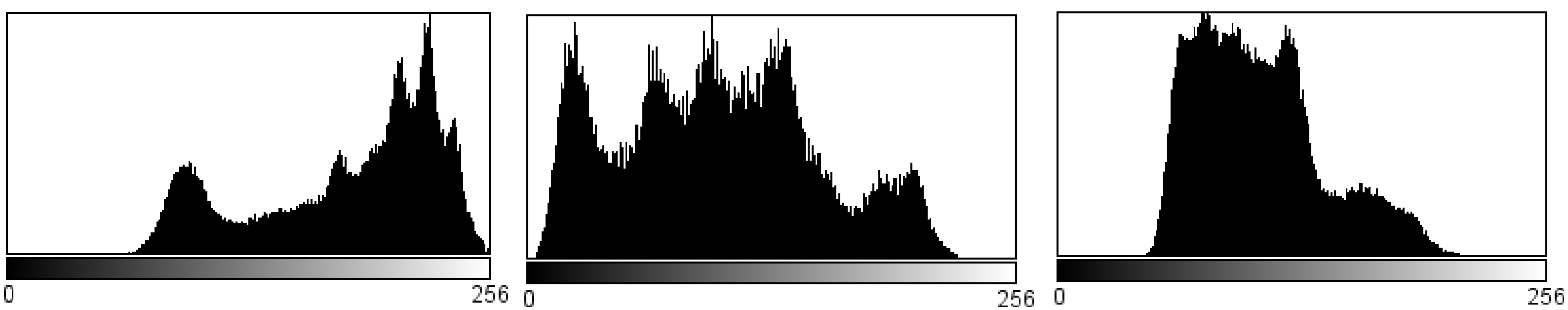


RGB Histogram

- Simply concatenate vectors
- Not very smart... (why?)

$$F_R = [\, f_{R0}, \ldots, f_{R255} \,]$$
$$F_G = [\, f_{G0}, \ldots, f_{G255} \,]$$
$$F_B = [\, f_{B0}, \ldots, f_{B255} \,]$$

$$F_{RGB} = \left[F_R \mid F_G \mid F_B \right]$$

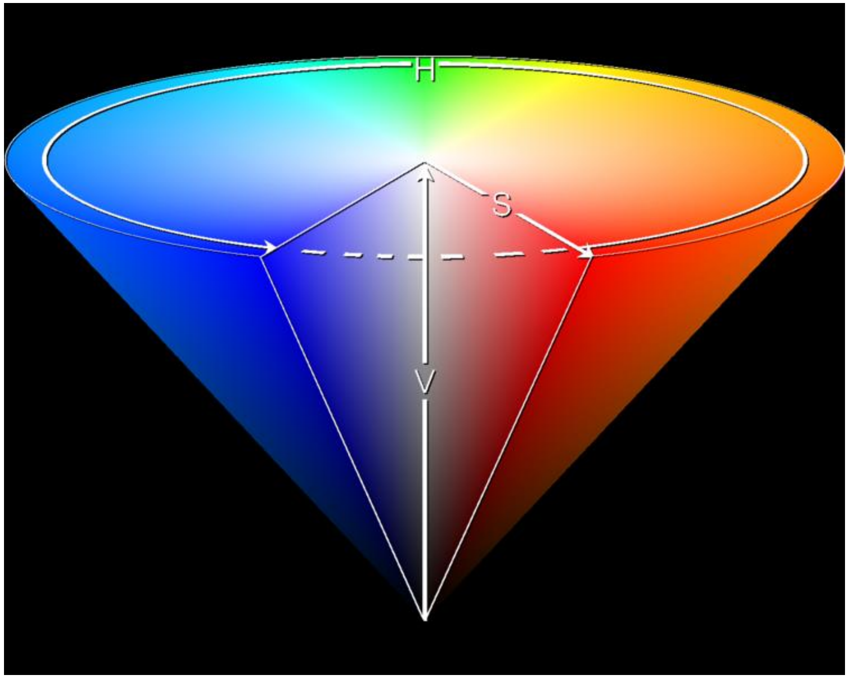


HSV Histogram

- Quantize HSV space
  - Define number of bins N.
  - Feature vector

$$F_{HSV} = [f_0, \ldots, f_N]$$

- Typically better for object description



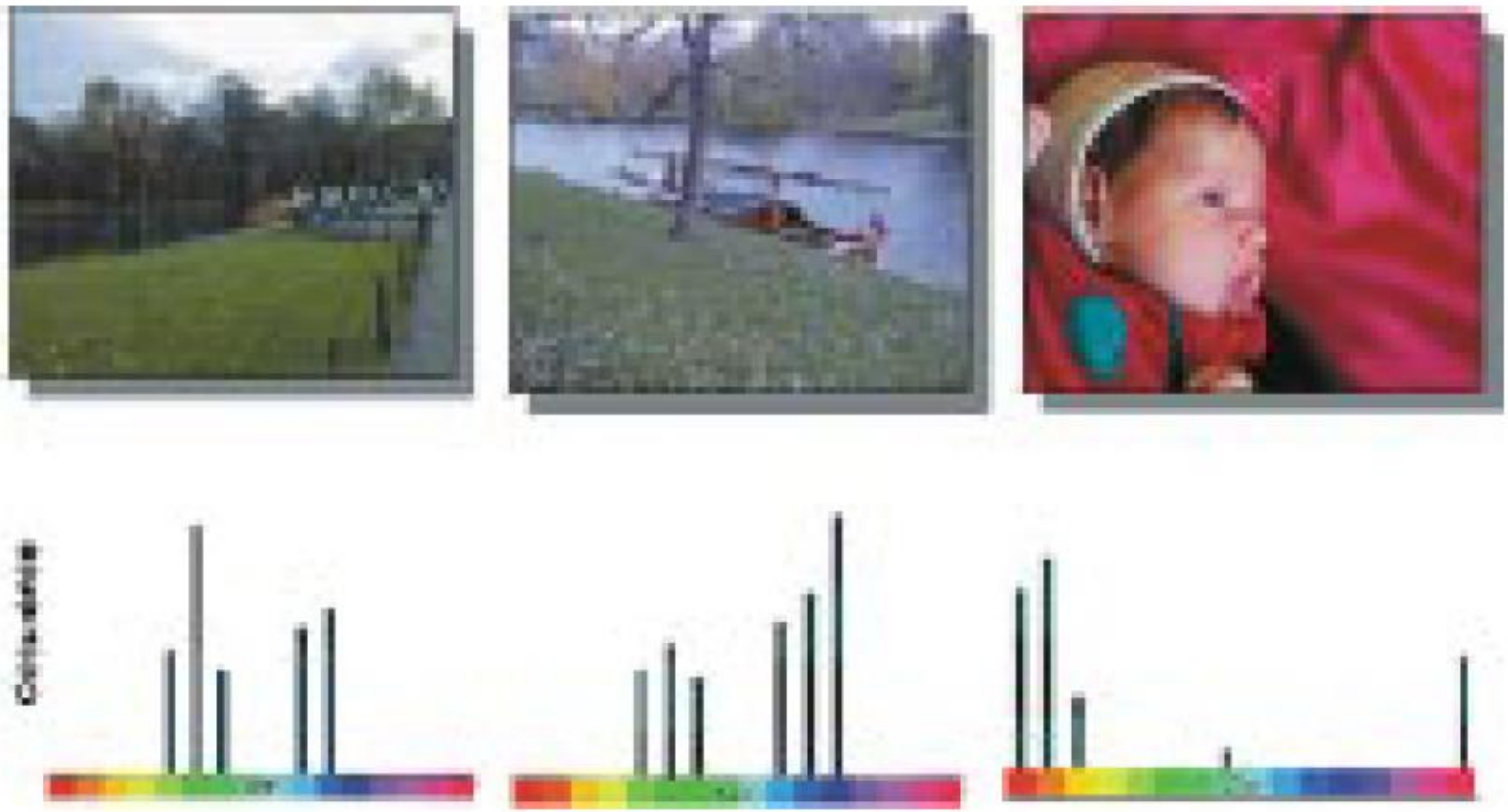


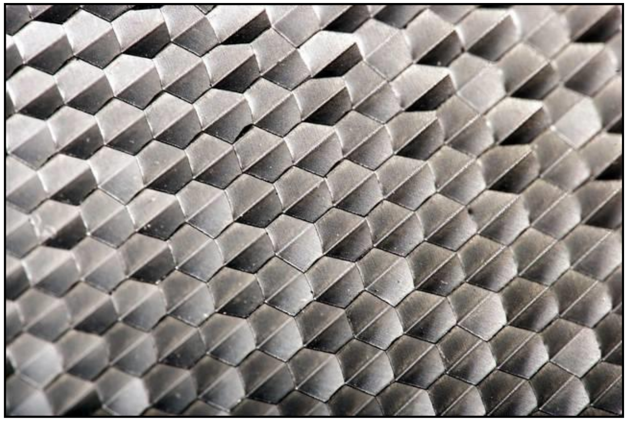
Fig. 2. Three color images and their MPEG-7 histogram color distribution, depicted using a simplified color histogram. Based on the color distribution, the two left images would be recognized as more similar compared to the one on the right.

[Sikora 2001]

What is texture?

"Texture gives us information about the spatial arrangement of the colours or intensities in an image"

[L. Shapiro]



Two approaches to texture

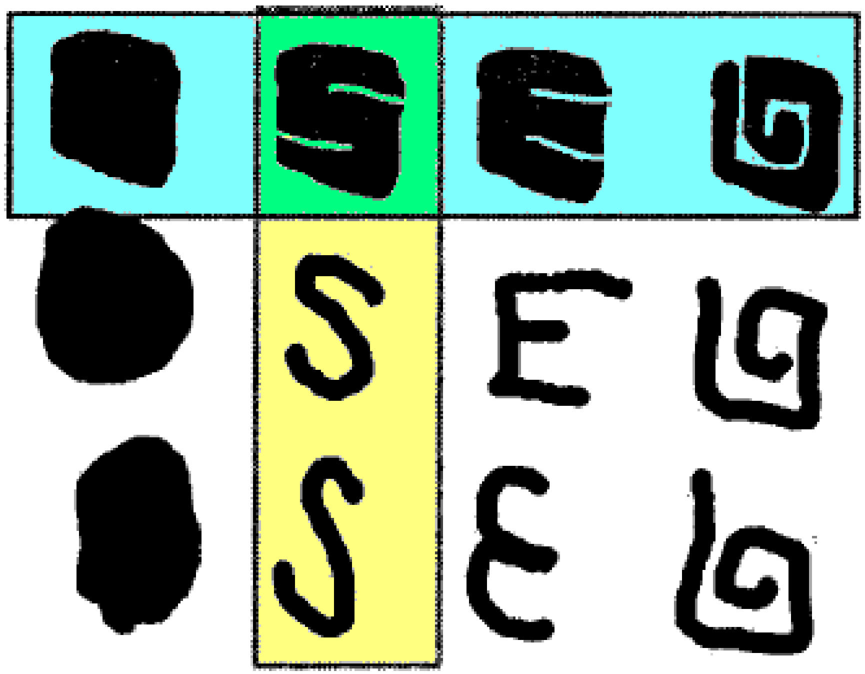
- Structural approach
  - Texture is a set of primitive *texels* in some regular or repeated relationship
  - Good for regular, ‘man-made’ textures
- Statistical approach
  - Texture is a quantitative measure of the arrangement of intensities in a region
  - More general and easier to compute

Statistical approaches

- Grey level of central pixels
- Average of grey levels in window
- Median
- Standard deviation of grey levels
- Difference of maximum and minimum grey levels
- Difference between average grey level in small and large windows
- Sobel feature
- Kirsch feature
- Derivative in x window
- Derivative in y window
- Diagonal derivatives
- Combine features

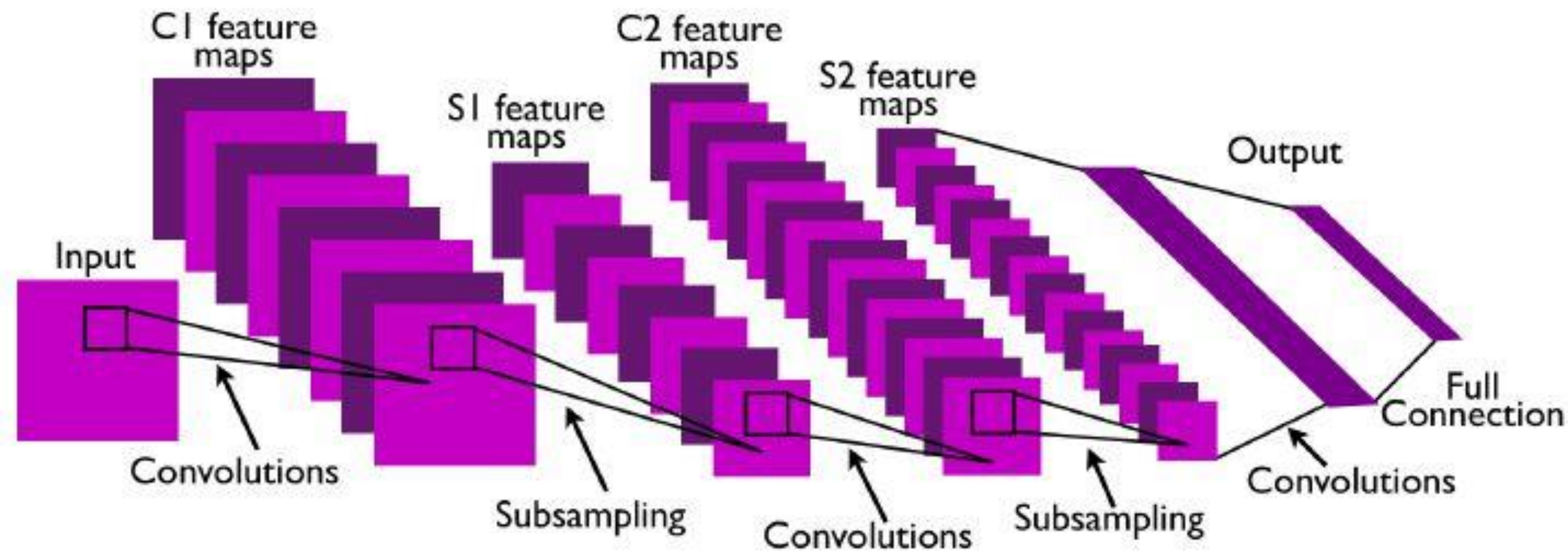
How do I pick one??

Shape Descriptors



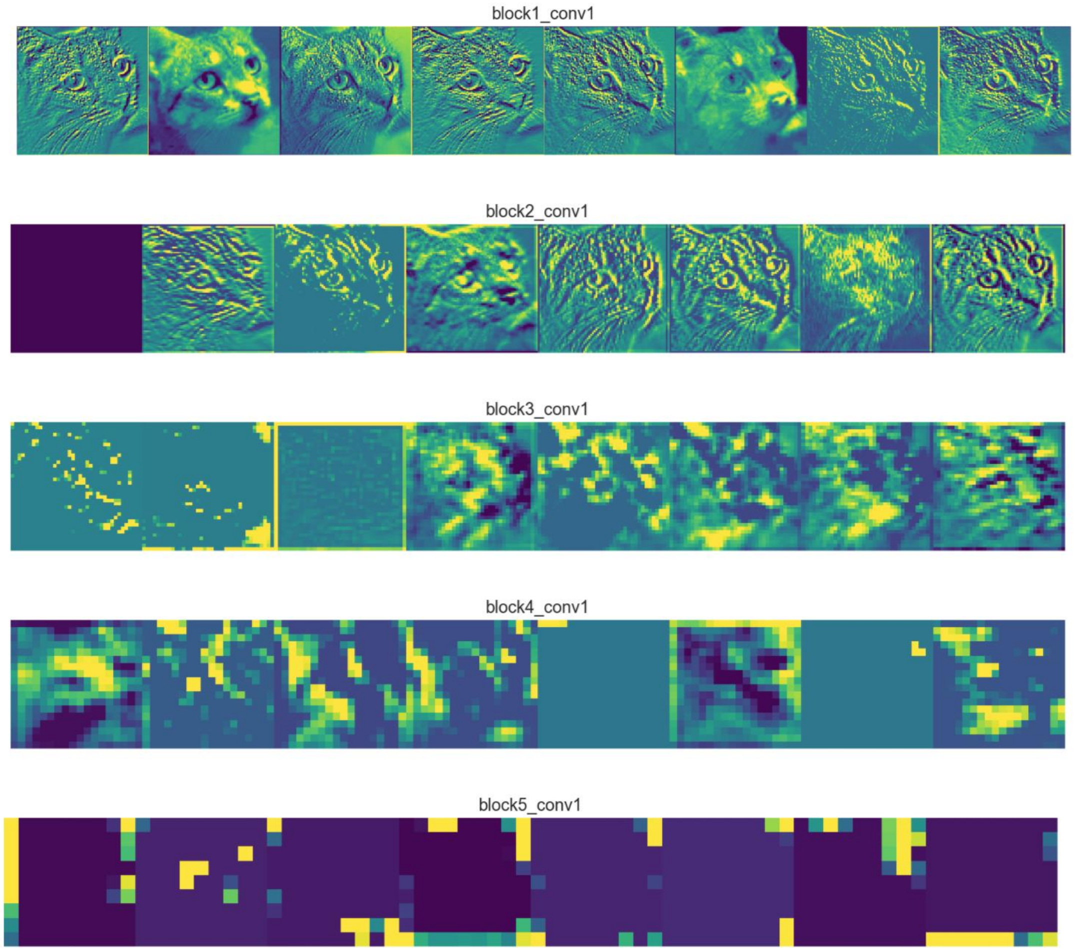
- Blue: Similar shapes by Region-Based
- Yellow: Similar shapes by Contour-Based

Deep Learning: Learnt Features



- Convolutional layers, followed by nonlinear activation and subsampling
- Output of hidden layers (feature maps) = features learnt by the CNN
- Before classification, fully connected layers (as in “standard” NN)

Automatically learnt features



Retain most information (edge detectors)

Towards more abstract representation

Encode high level concepts

Sparser representations:
Detect less (more abstract) features

https://towardsdatascience.com/applied-deep-learning-part-4-convolutional-neural-networks-584bc134c1e2

Topic: Detection of interest points

- Introduction to Pattern Recognition
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- Local invariant descriptors

Motivation: Same interest points

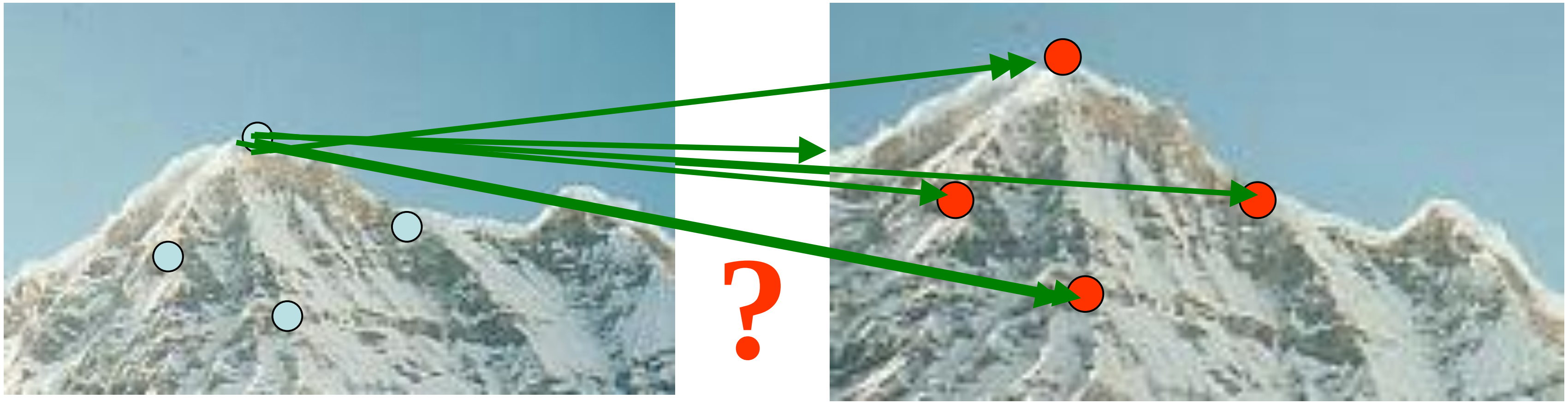
- We want to detect the same points in both images

No chance to find true matches!

Motivation: ‘Unique’ descriptor per interest point

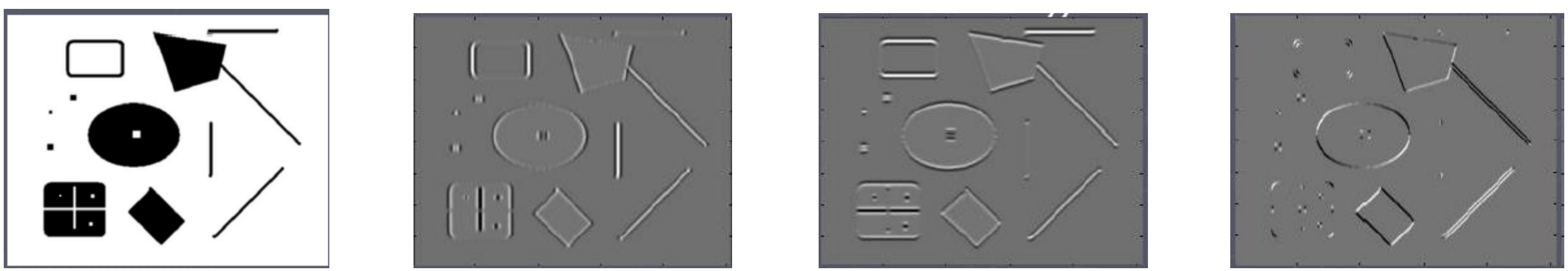
- We want to match the same interest points
- Need a descriptor invariant to geometric and photometric differences



Corners are distinctive interest points

$$M = \sum w(x,y) \begin{bmatrix} I_x I_x & I_x I_y \\ I_x I_y & I_y I_y \end{bmatrix}$$

2 x 2 matrix of image derivatives (averaged in neighborhood of a point)

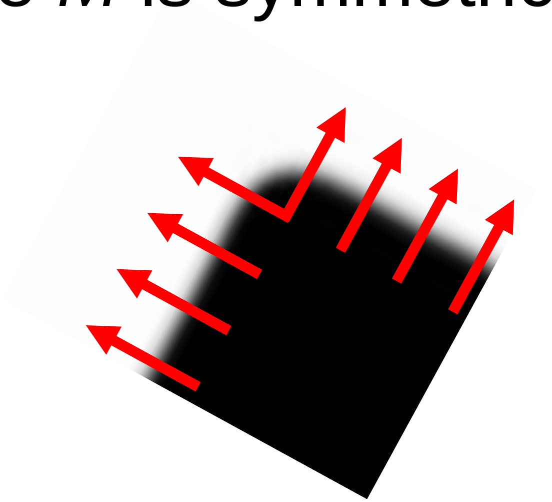


Notation: $I_x \Leftrightarrow \frac{\partial I}{\partial x}$ $I_y \Leftrightarrow \frac{\partial I}{\partial y}$ $I_x I_y \Leftrightarrow \frac{\partial I}{\partial x}\frac{\partial I}{\partial y}$

Gradient strength

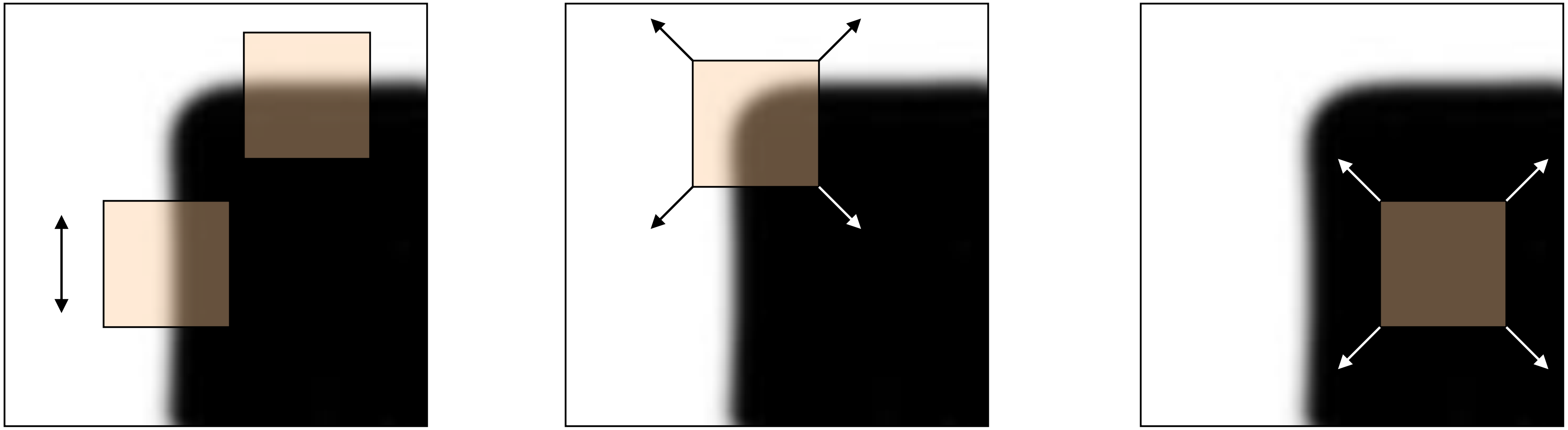
Since *M* is symmetric, we have $M = X \begin{bmatrix} \lambda_1 & 0 \\ 0 & \lambda_2 \end{bmatrix} X^T$

$$Mx_i = \lambda_i x_i$$



The *eigenvalues* of *M* reveal the amount of intensity change in the two principal orthogonal gradient directions in the window

Scoring 'cornerness'



"edge":

$\lambda_1 >> \lambda_2$

$\lambda_2 >> \lambda_1$

"corner":

λ_1 and λ_2 are large,
$\lambda_1 \sim \lambda_2$;

"flat" region

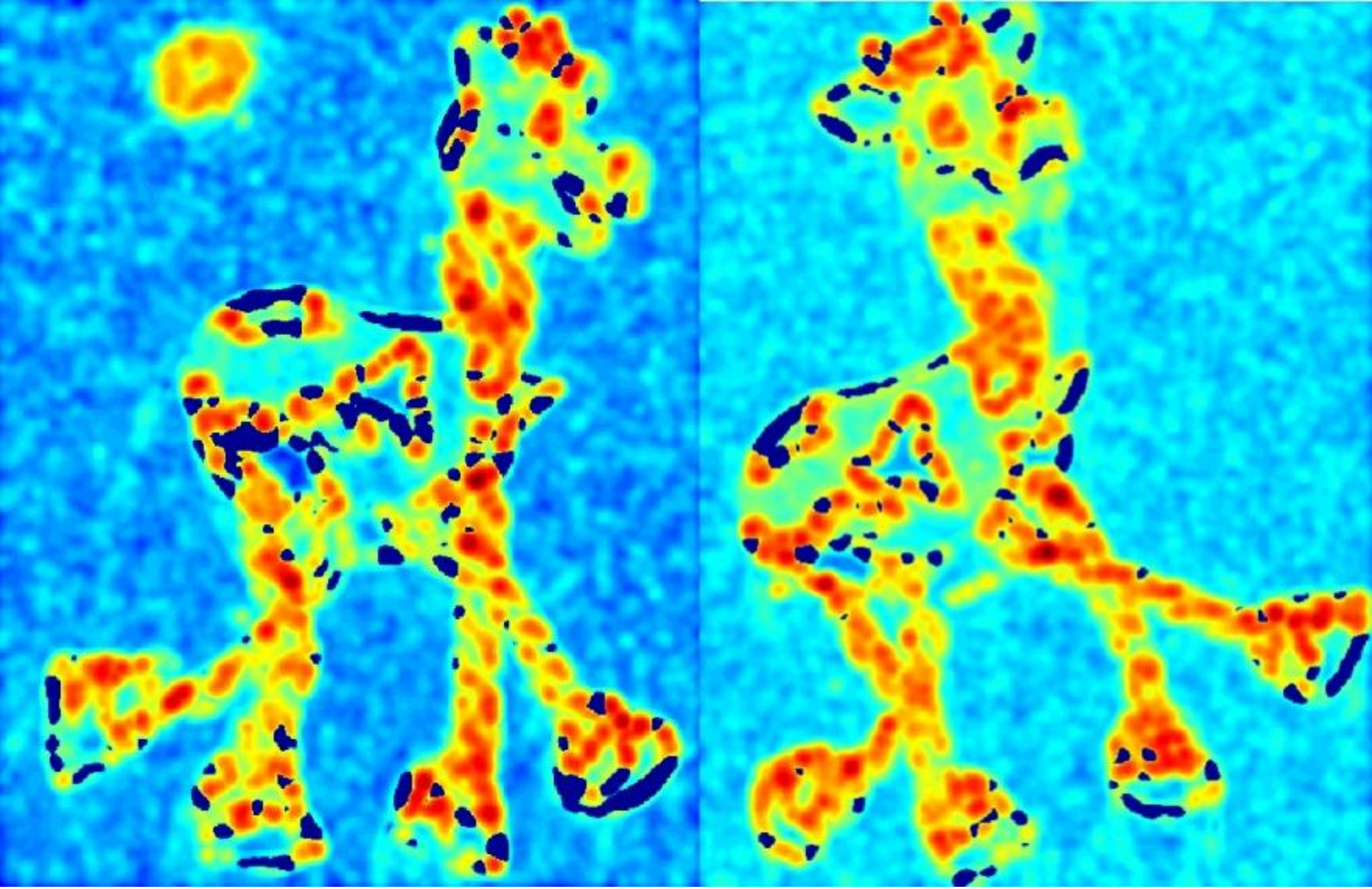
λ_1 and λ_2 are small;

One way to score the cornerness:

$$f = \frac{\lambda_1 \lambda_2}{\lambda_1 + \lambda_2}$$

Harris corner detector

1) Compute *M* matrix for image window surrounding each pixel to get its *cornerness* score.
2) Find points with large corner response (f > threshold)
3) Take the points of local maxima, i.e., perform non-maximum suppression



Properties of the Harris corner detector

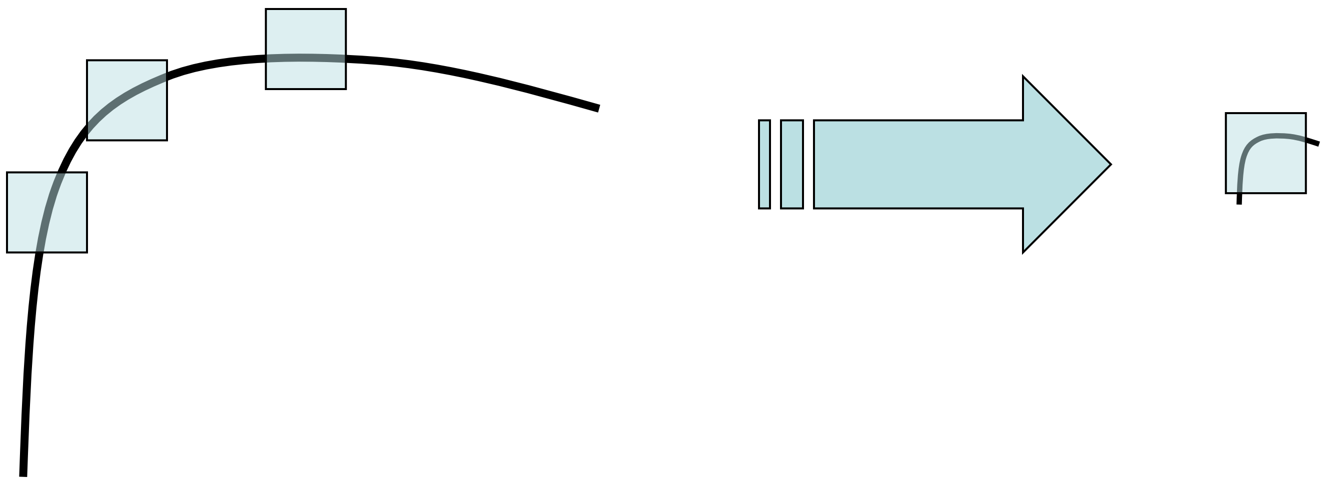
- Rotation invariant? Yes

$$M = X \begin{bmatrix} \lambda_1 & 0 \\ 0 & \lambda_2 \end{bmatrix} X^T$$

- Scale invariant?

Properties of the Harris corner detector

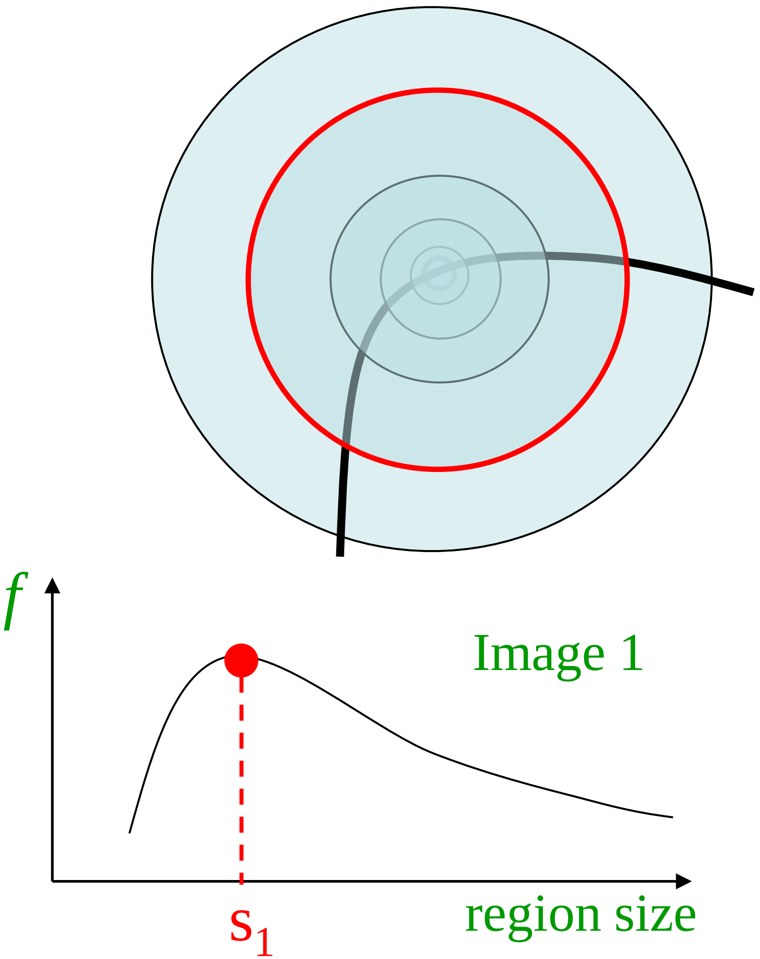
- Rotation invariant? Yes
- Scale invariant? No

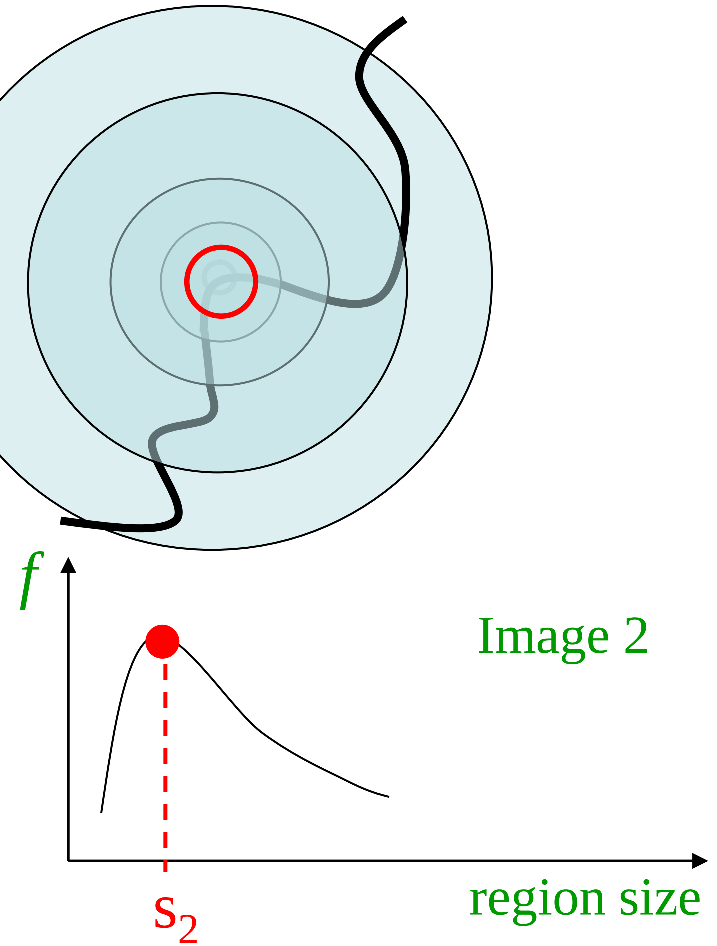


All points will be classified as edges

Corner !

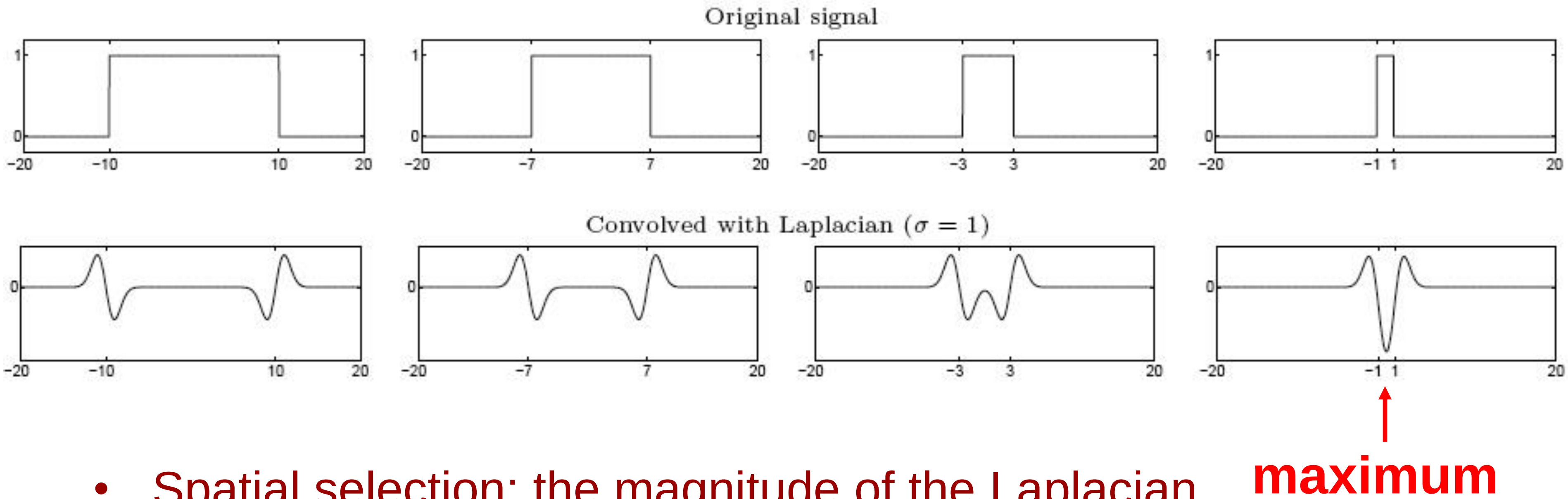
Automatic scale selection





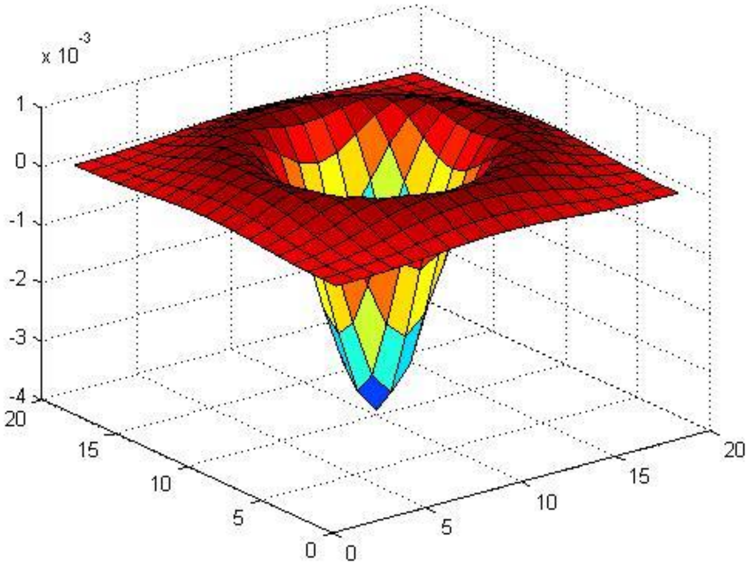
From edges to blobs

- Edge = ripple
- Blob = superposition of two ripples



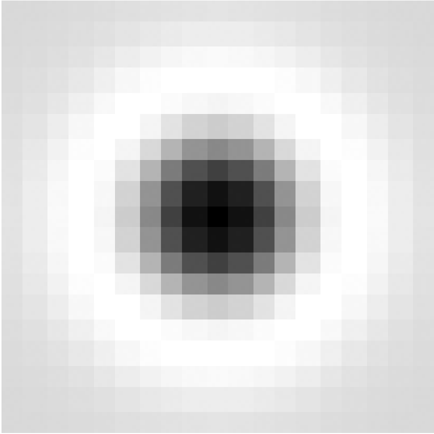
- Spatial selection: the magnitude of the Laplacian response will achieve a maximum at the center of the blob, provided the scale of the Laplacian is "matched" to the scale of the blob

Blob detection in 2D



- Laplacian of Gaussian: Circularly symmetric operator for blob detection in 2D

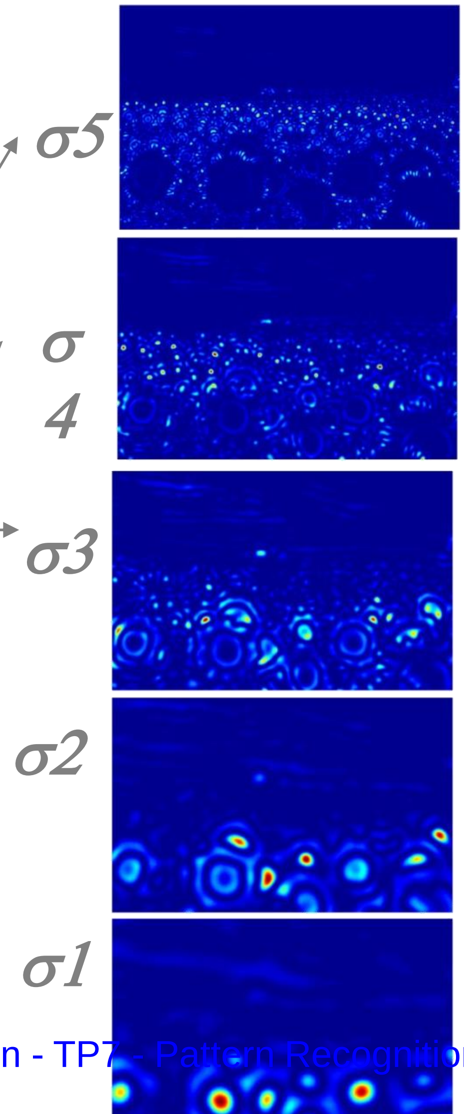
$$\nabla^2 g = \frac{\partial^2 g}{\partial x^2} + \frac{\partial^2 g}{\partial y^2}$$

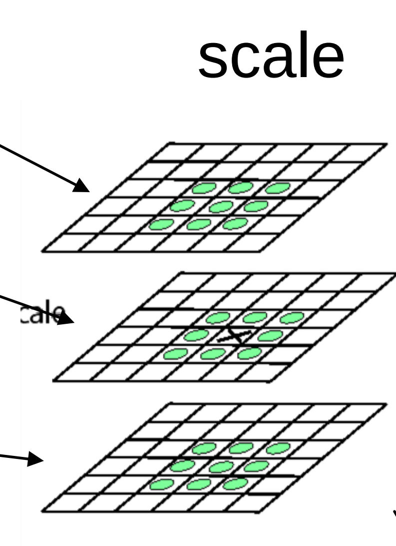


Scale invariant interest points

Interest points are local maxima in both position and scale

$$L_{xx}(\sigma) + L_{yy}(\sigma)$$





Squared filter response maps

$\Rightarrow$ **List of *(x, y, σ)***

Topic: Local invariant descriptors

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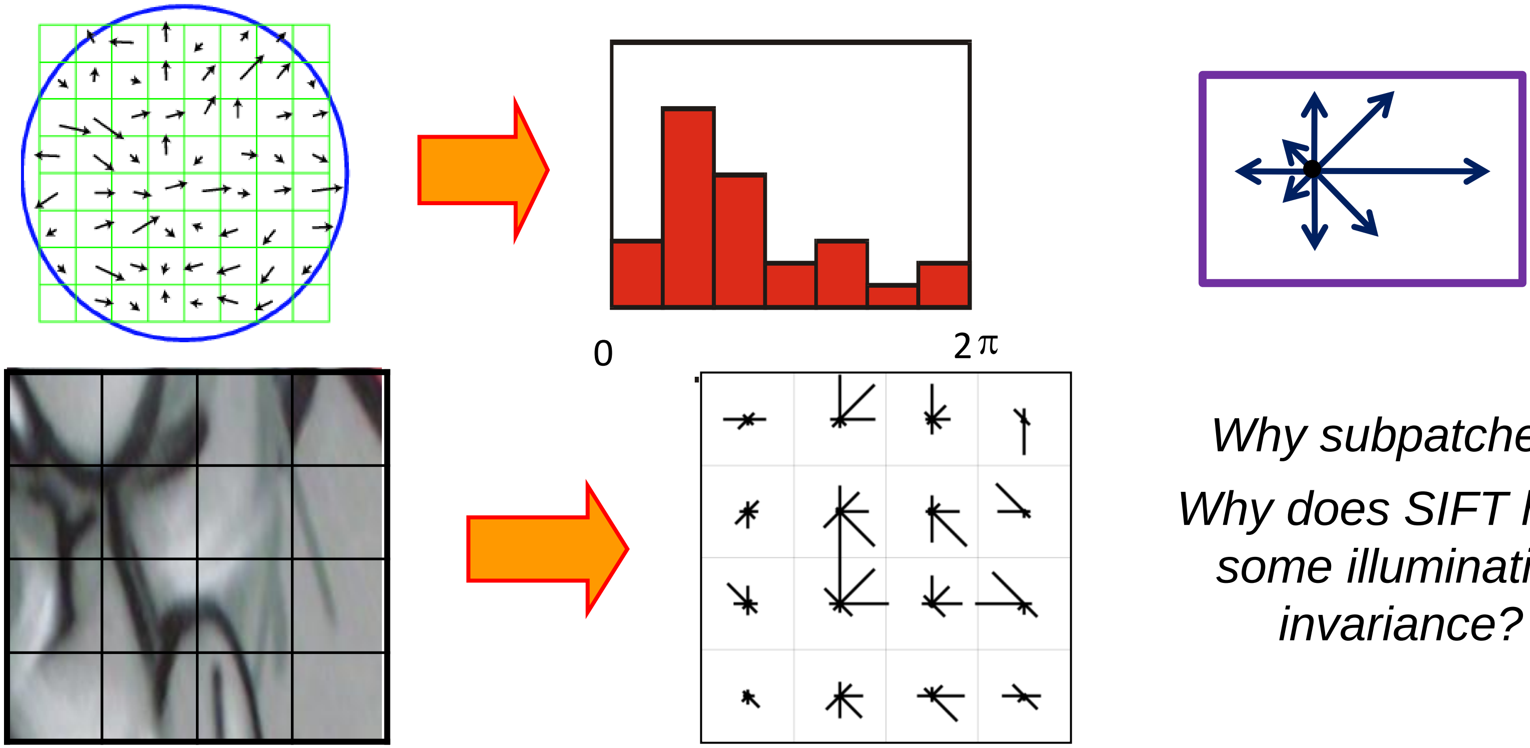
Geometric transformations

e.g. scale,
translation,
rotation

SIFT descriptor [Lowe 2004]

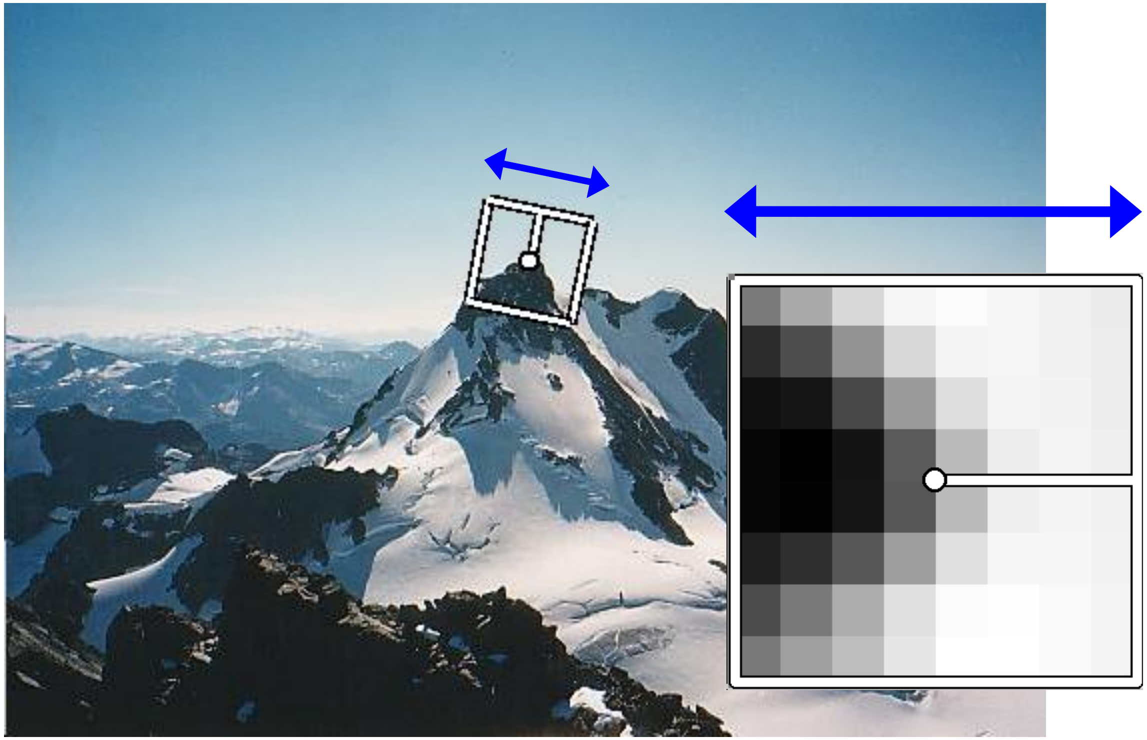
- Use histograms to bin pixels within sub-patches according to their orientation



Why subpatches?

Why does SIFT have some illumination invariance?

Making descriptor rotation invariant

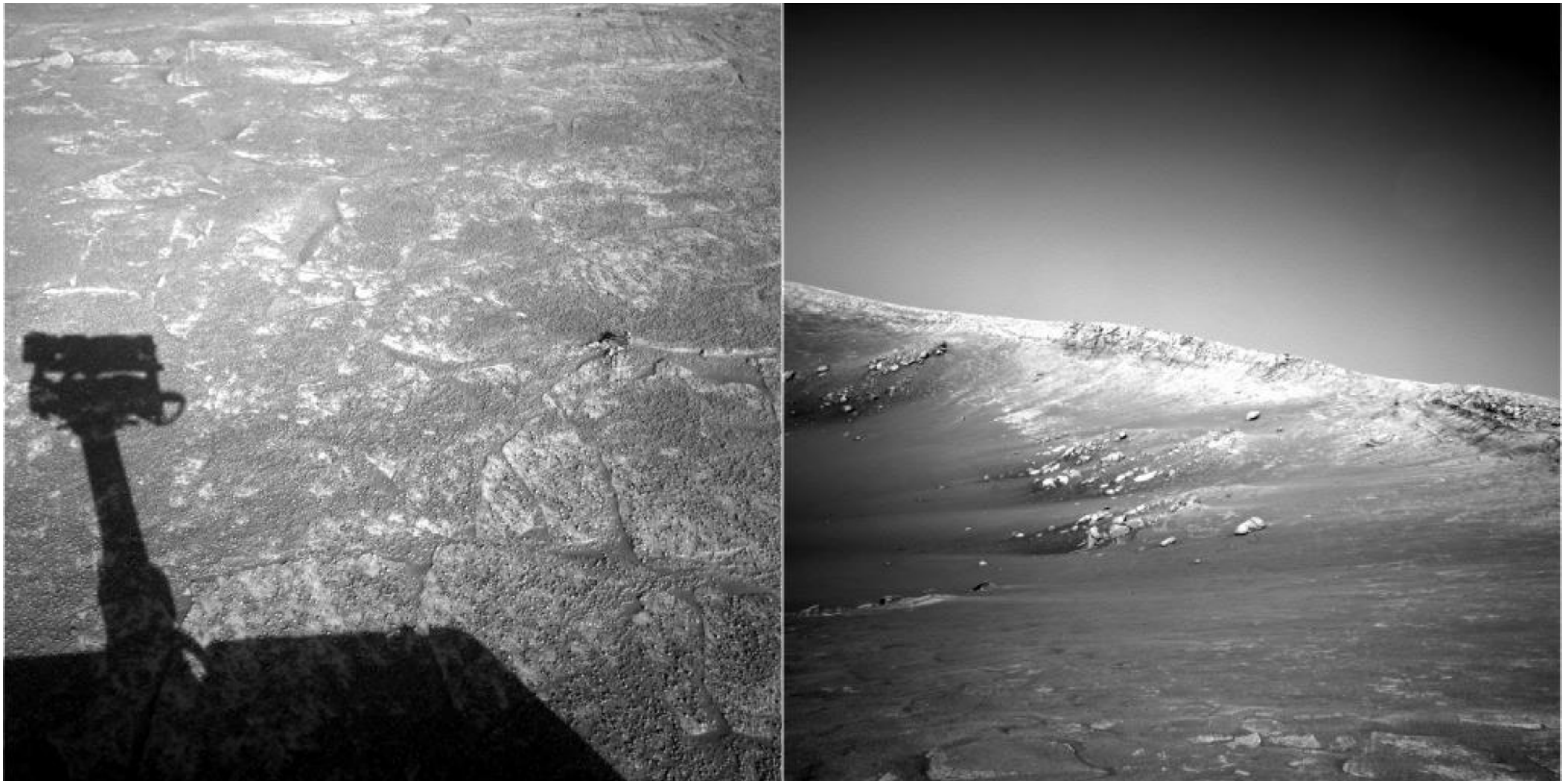


- Rotate patch according to its dominant gradient orientation
- This puts the patches into a canonical orientation

SIFT descriptor [Lowe 2004]

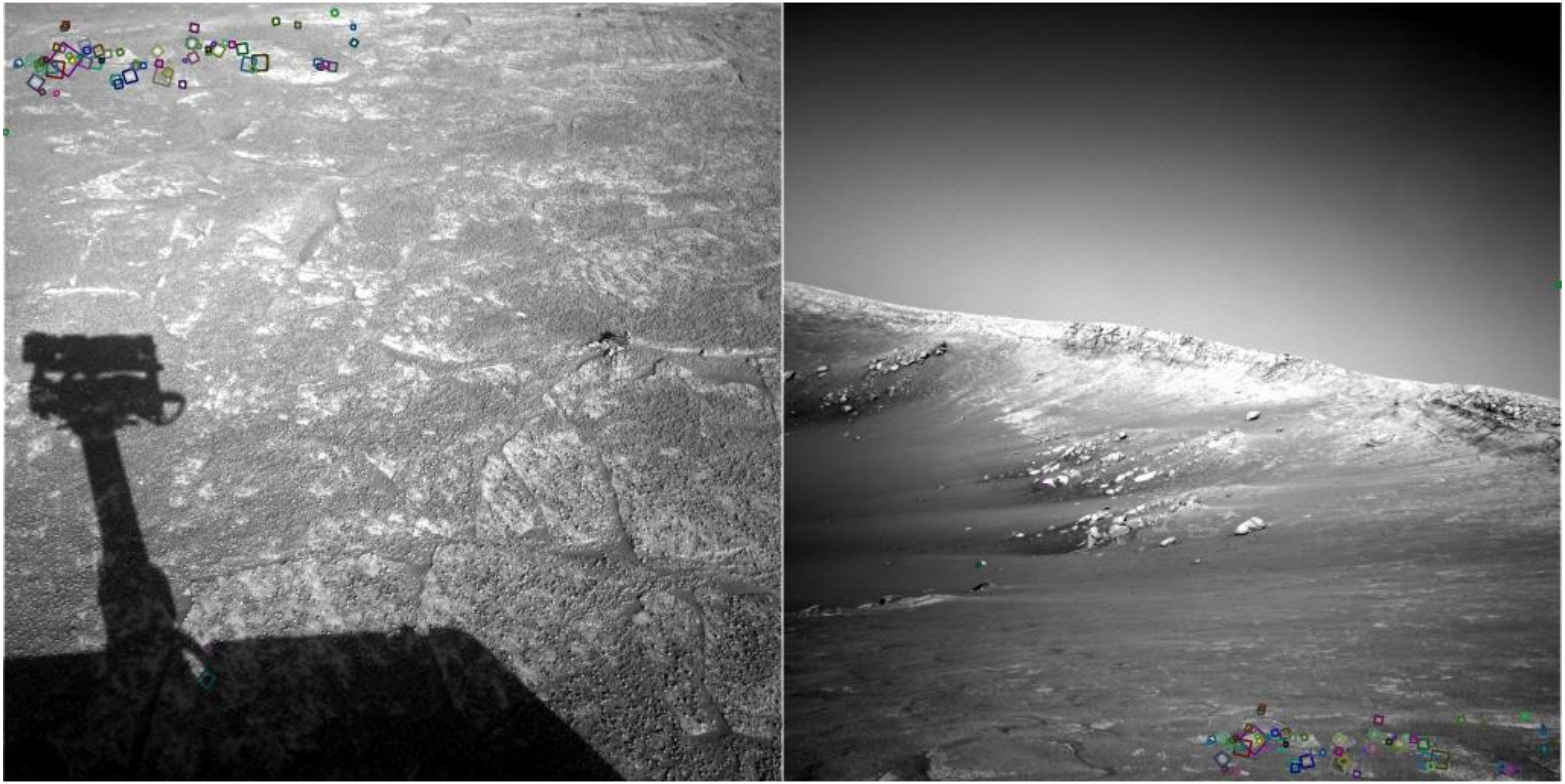
- Extraordinarily robust matching technique
  - Can handle changes in viewpoint
  - Can handle significant changes in illumination
  - Fast and efficient—can run in real time
  - Lots of code available

Example



NASA Mars Rover images

Example



NASA Mars Rover images

SIFT properties

- Invariant to
  - Scale
  - Rotation

- Partially invariant to
  - Illumination changes
  - Camera viewpoint
  - Occlusion, clutter

Resources

- Szeliski, "Computer Vision: Algorithms and Applications", Springer, 2011
  - Chapter 14 – "Recognition"
  - Chapter 4 – "Feature Detection and Matching"