Object & scene classification for large image collections

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University of Oxford

INTRODUCTION

Introduction

Low-level processing

Sensing

Preprocessing

Segmentation

Description

Object Recognition

High-level processing

Scene Classification

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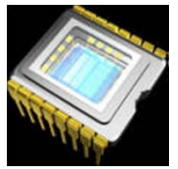
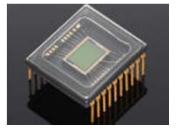
High-level processing

Lens focus

shutter





CCD

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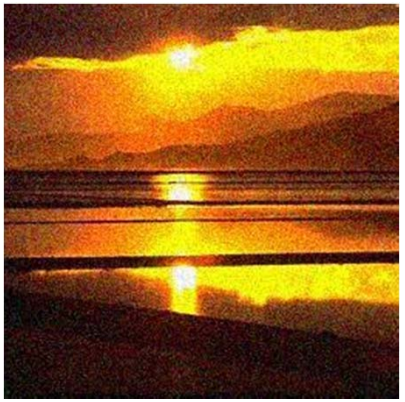

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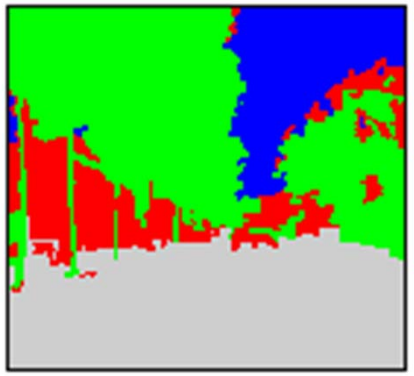

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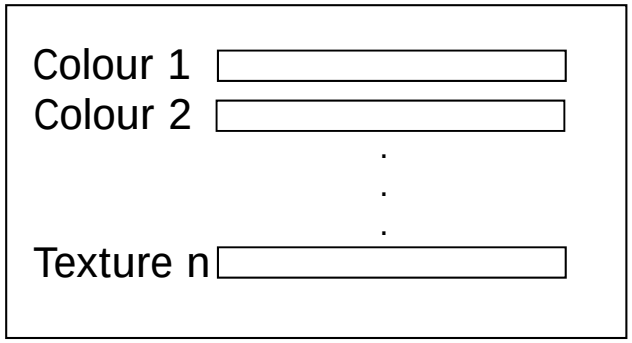

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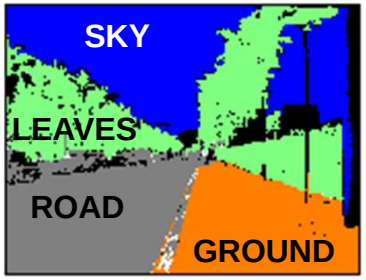
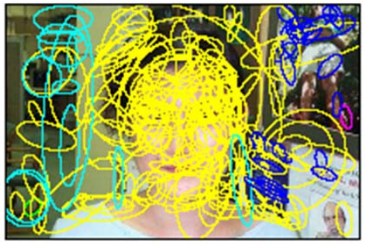


Segmentation

Description



Object Recognition

High-level processing

Scene Classification

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Scene Classification

High-level processing

This scene contains: sea and sky → Coast scene

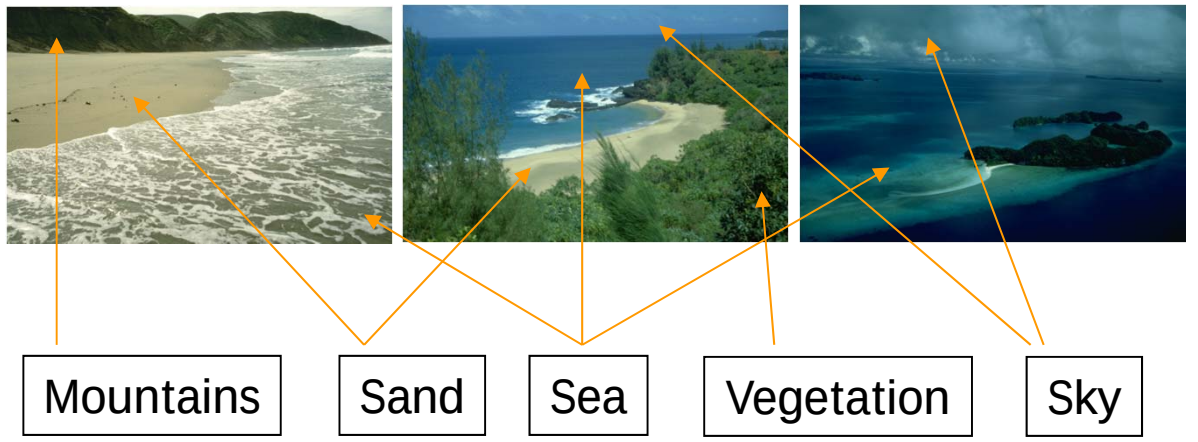
This scene contains: sea, sky, sand and mountains → Coast scene

Goals

GOAL Scene classification using *topic* distribution
Discover *topics* in images.

TOPIC DISCOVERY pLSA over bag-of-words

SCENE CLASSIFICATION KNN or SVM

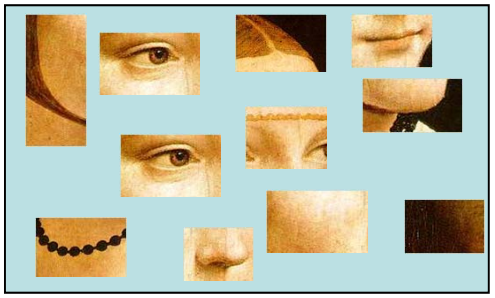


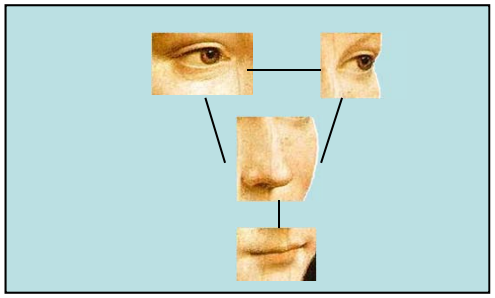
Key Points

- **Representation**
  - How to represent an object category
- **Learning**
  - How to form the classifier, given training data
- **Recognition**
  - How the classifier is to be used on novel data

Representation

- **Appearance** only or **location** and appearance



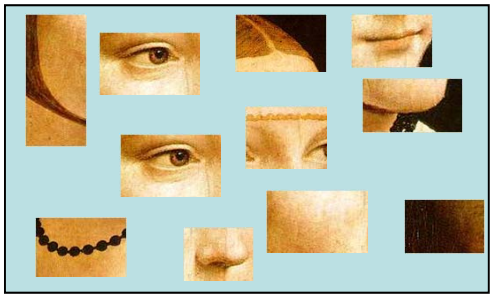


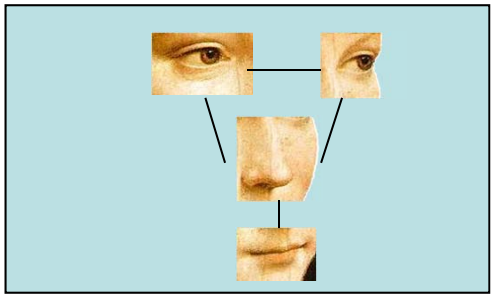
- **Invariances**

View point
Illumination
Occlusion
Scale
Intra-class variation
etc.

Representation

- **Appearance** only or **location** and appearance





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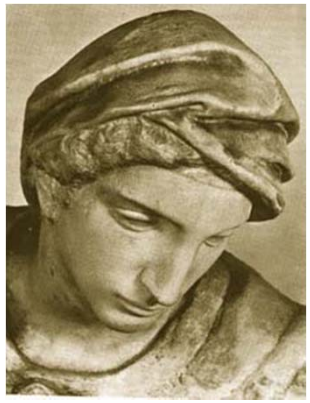

Michelangelo 1475-1564

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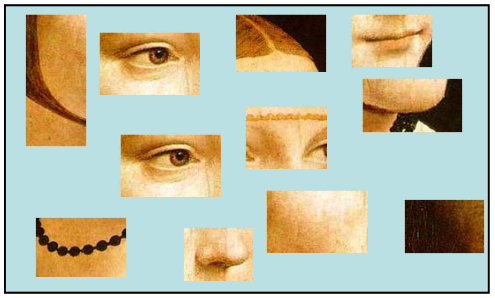

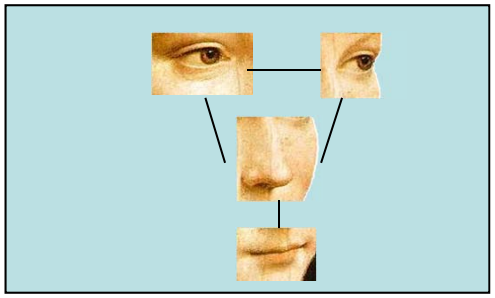

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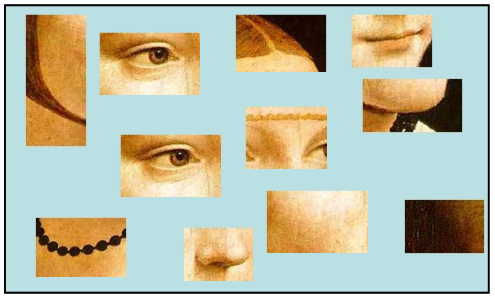

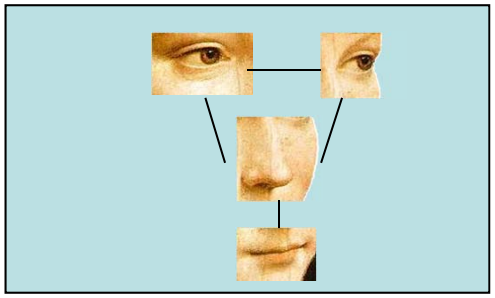

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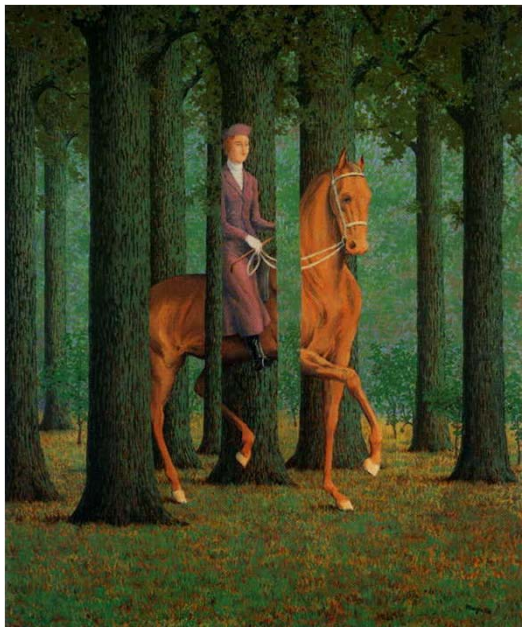

Magritte, 1957

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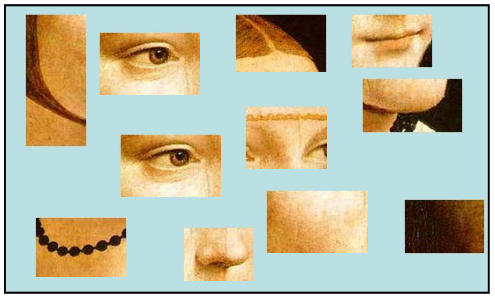

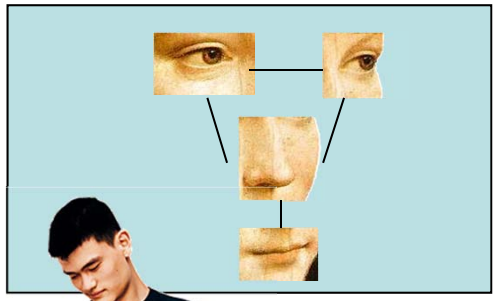

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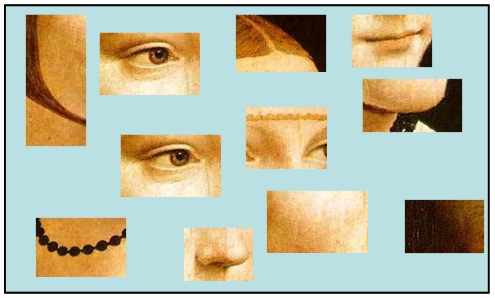

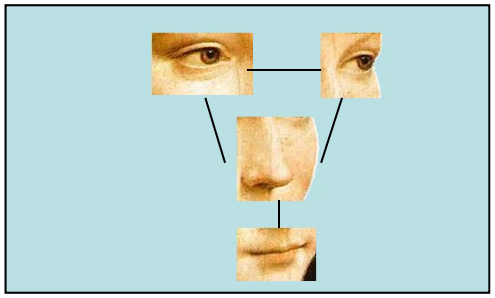

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etc.

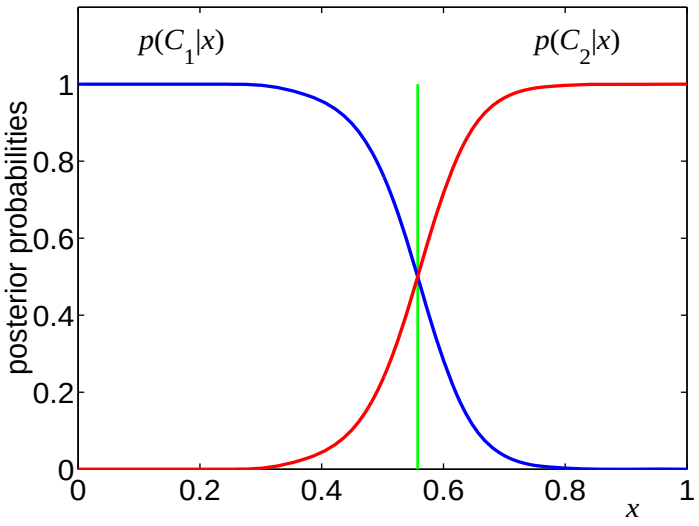
Learning: statistical viewpoint

$$\underbrace{\frac{p(zebra \mid image)}{p(no\ zebra \mid image)}}_{\text{posterior ratio}} = \underbrace{\frac{p(image \mid zebra)}{p(image \mid no\ zebra)}}_{\text{likelihood ratio}} \cdot \underbrace{\frac{p(zebra)}{p(no\ zebra)}}_{\text{prior ratio}}$$

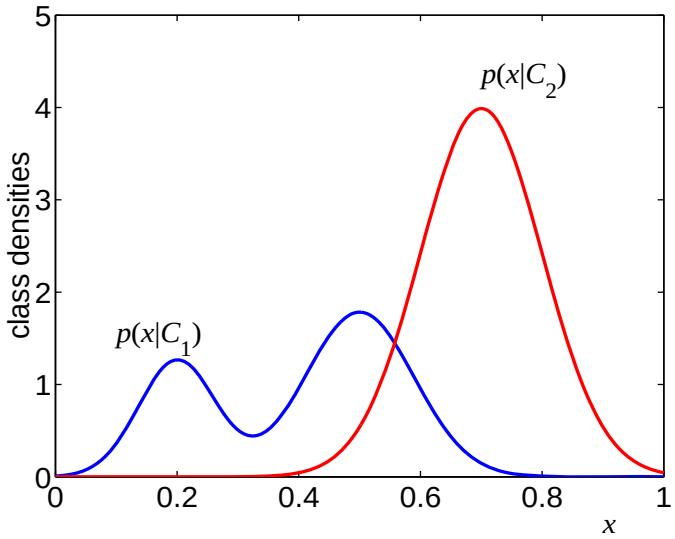
- **Discriminative methods** model posterior
- **Generative methods** model likelihood and prior

Learning: statistical viewpoint

- **Discriminative methods** model posterior
- **Generative methods** model likelihood and prior



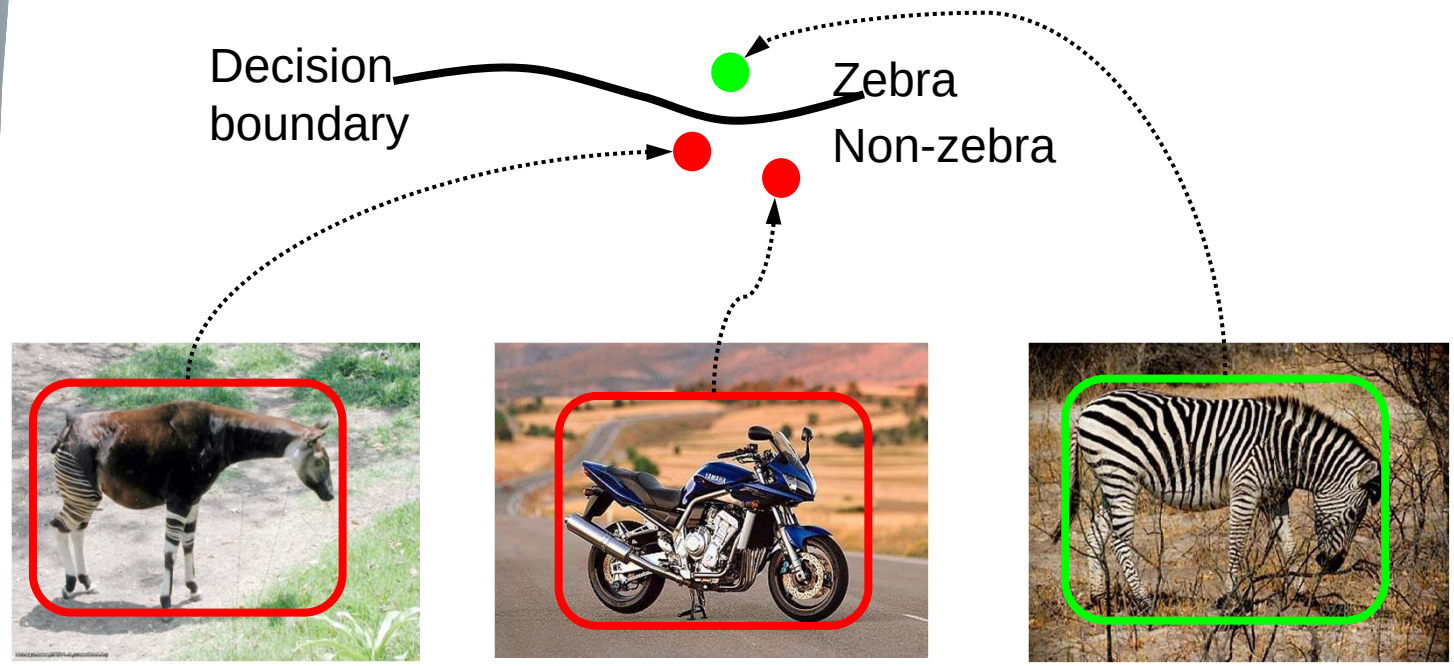
Discriminative methods



Generative methods

Learning: Discriminative

Direct modeling of $\frac{p(zebra \mid image)}{p(no\ zebra \mid image)}$

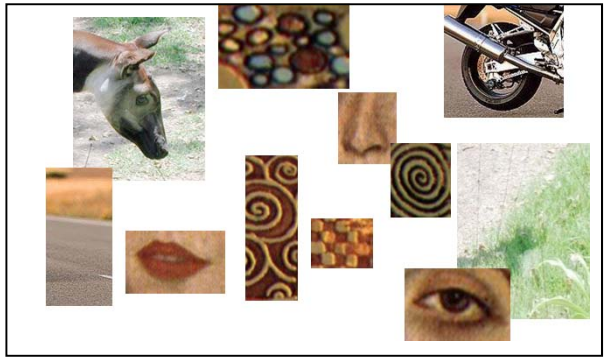


Learning: Generative

Model

$p(image \mid zebra)$

$p(image \mid no\ zebra)$



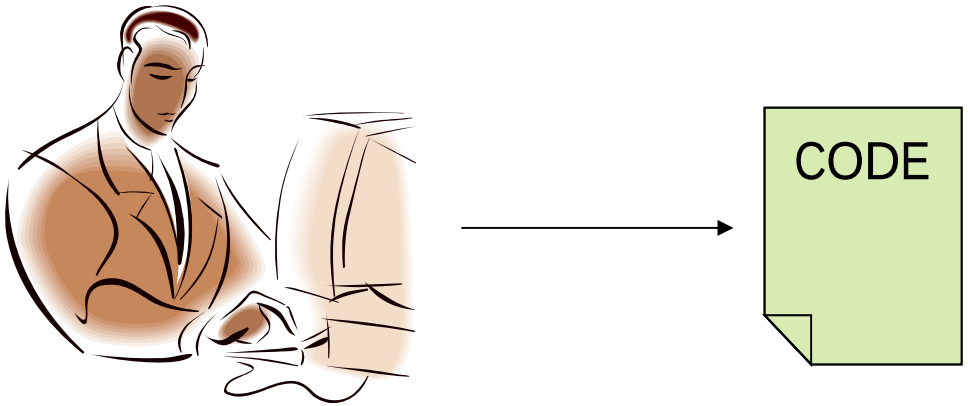
$p(image \mid zebra)$	$p(image \mid no\ zebra)$
Low	Middle
High	Middle→Low

Learning

Hand and code encapsulated data

Supervised Learning

Unsupervised Learning



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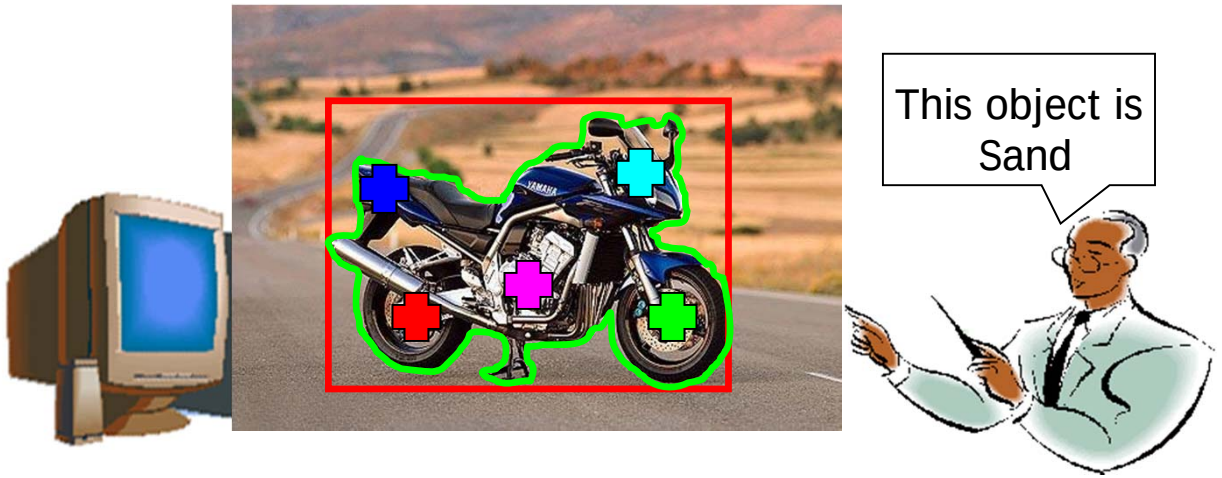
Unsupervised Learning



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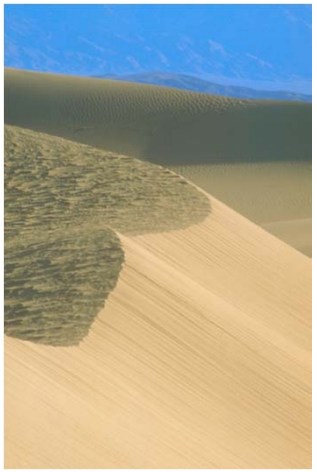
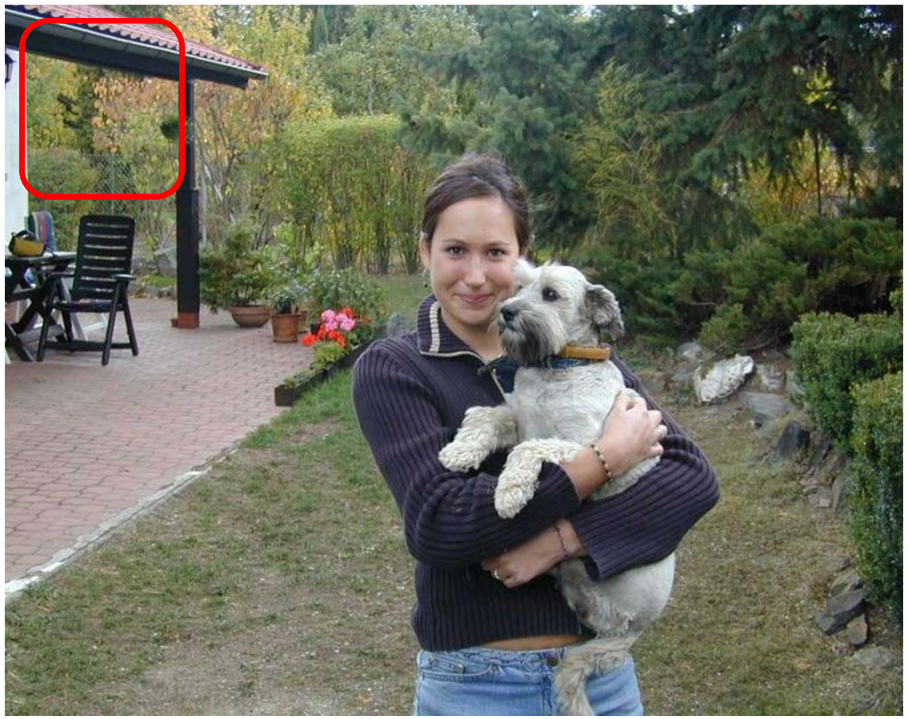


Recognition

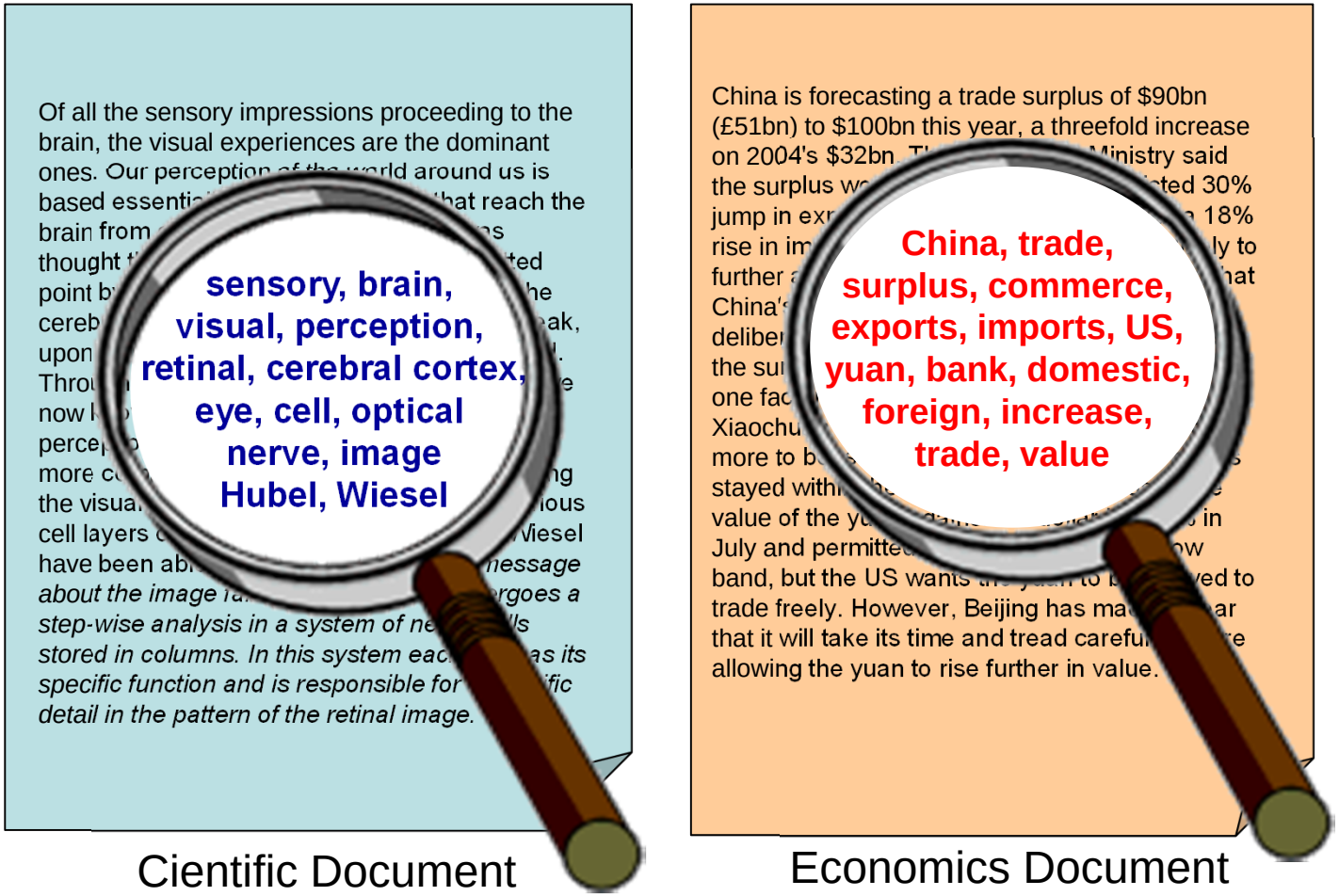
– Scale / orientation range to search over

– Speed



Bag-of-words

Origin: document retrieval



Cientific Document

Economics Document

From documents to images

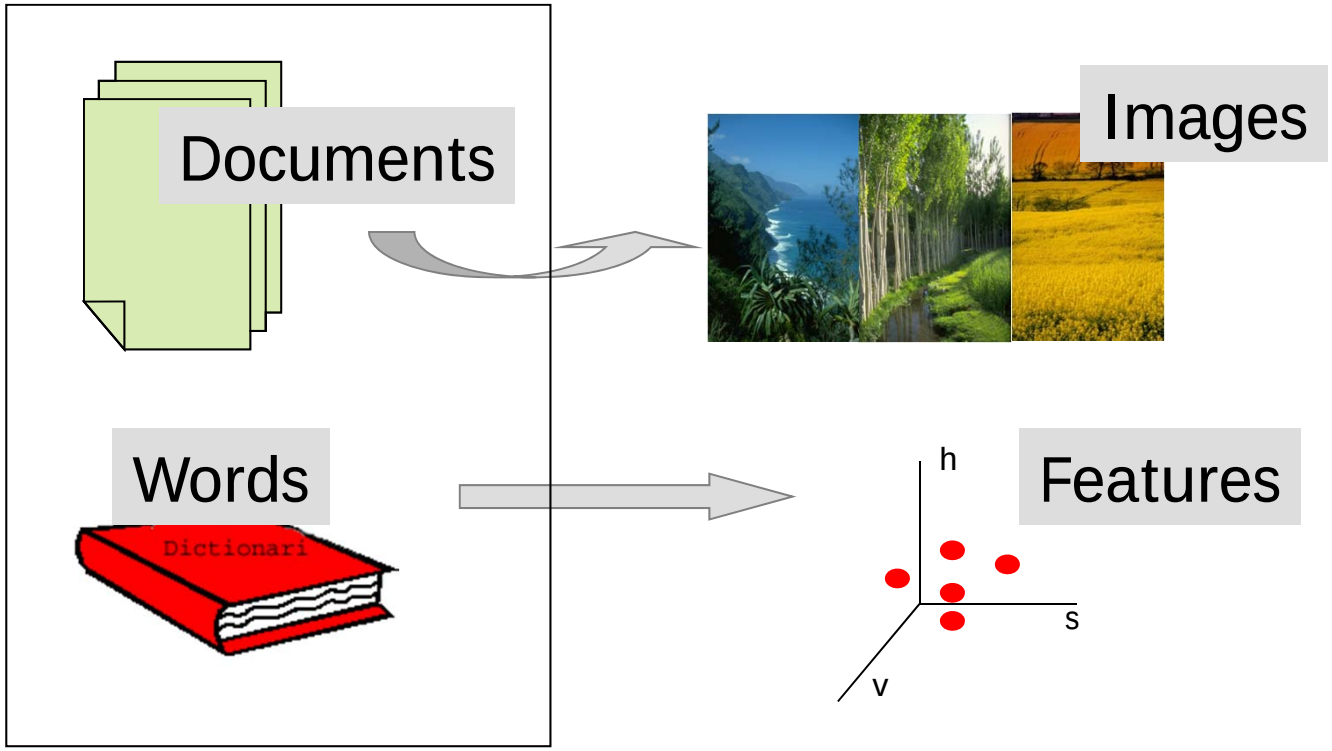
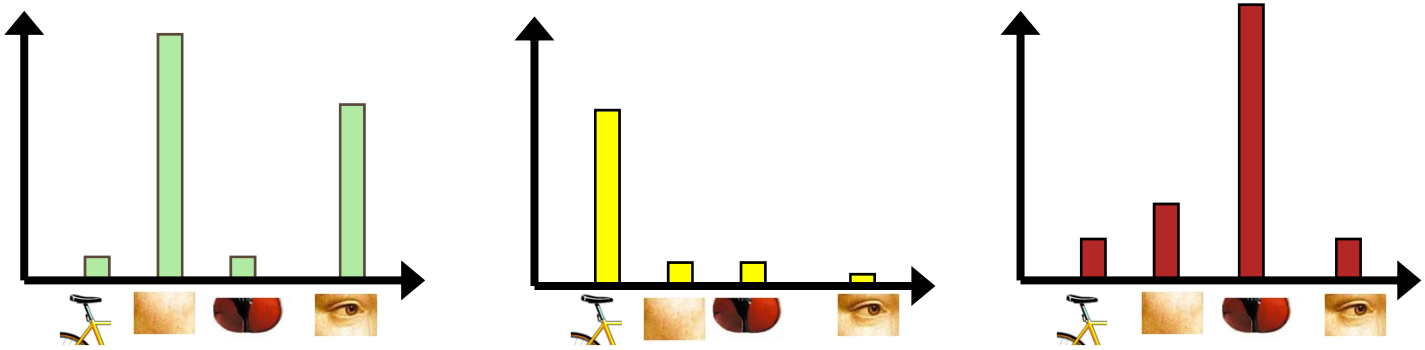
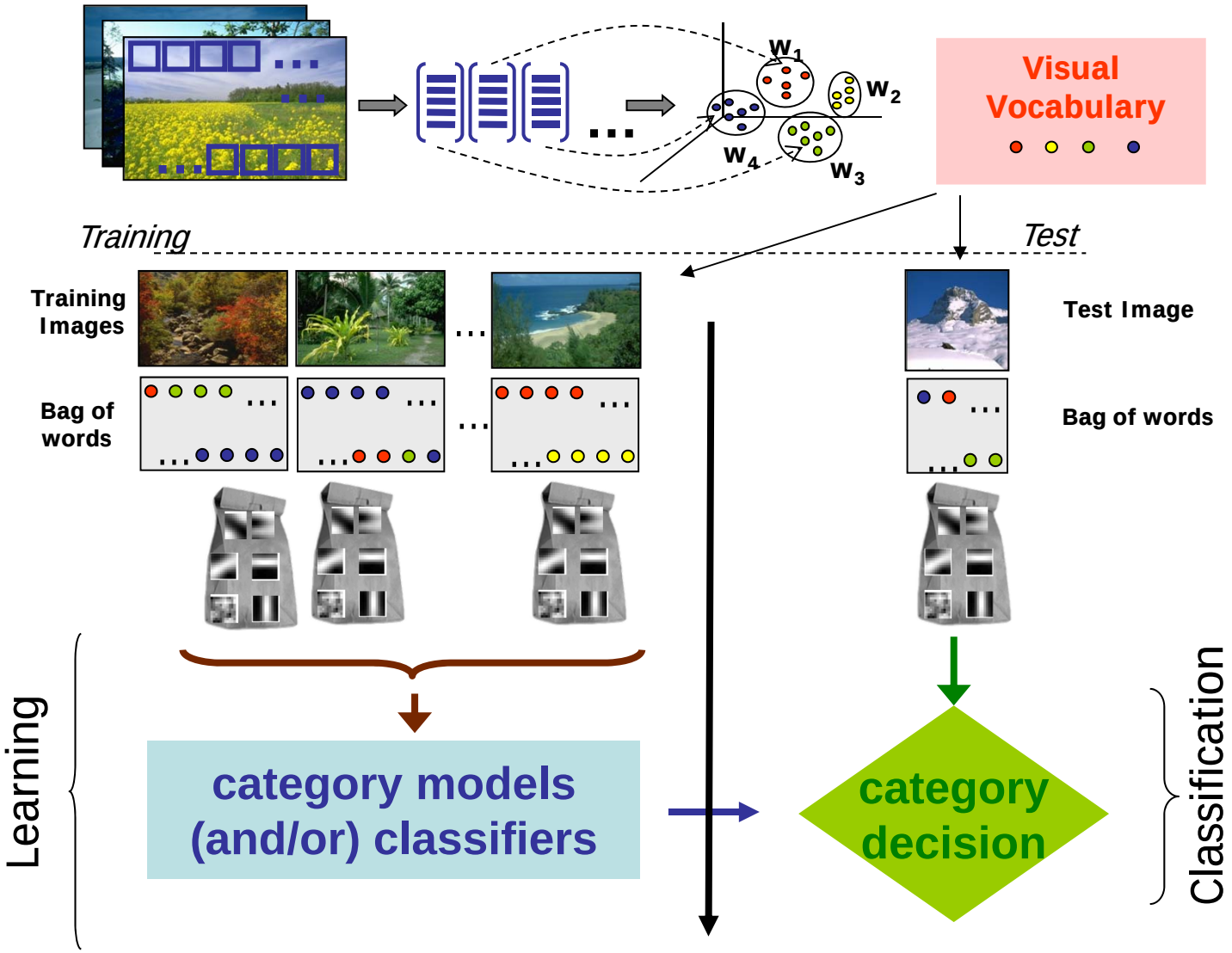


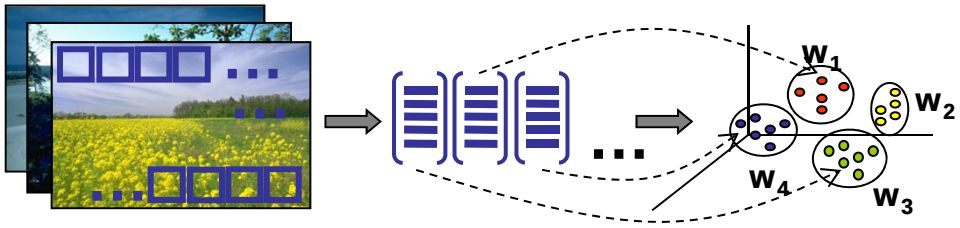
Image representation



Overview

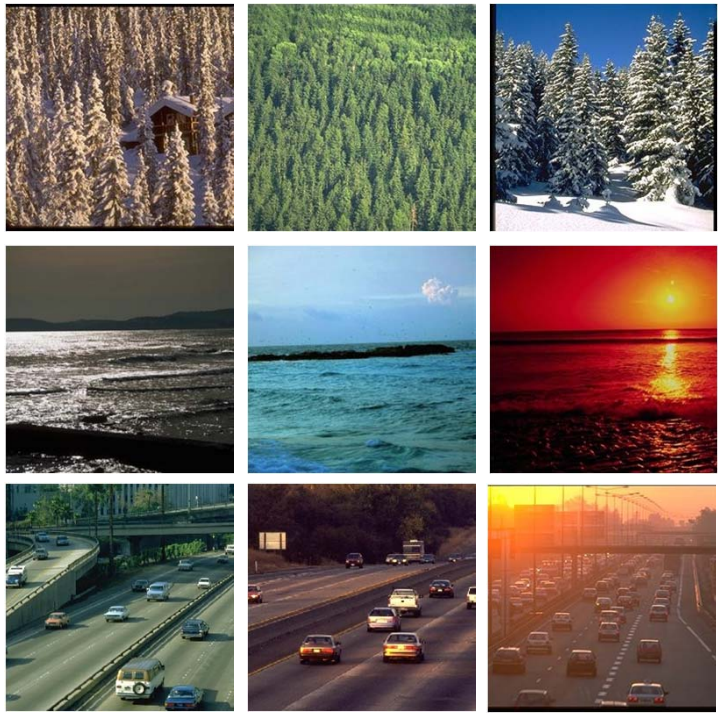


Visual Vocabulary



Visual Vocabulary

Feature detection & representation



Middle 90' until now:

-Textons: good performance in texture classification [Varma'03]

-Features invariant to affine geometric and photometric Transformantions [ICCV'01]

-Scale Invariant Feature Transform (SIFT) [IJCV'04]

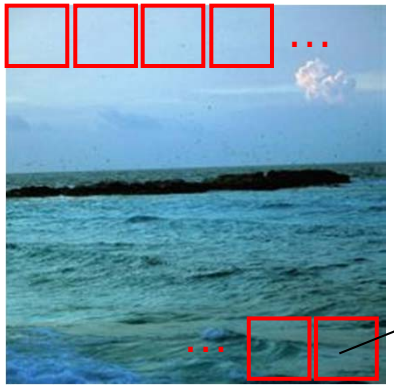
Feature detection & representation

SPARSE PATCHES – Affine covariant regions (harris & hessian)

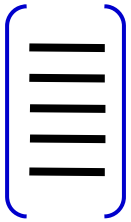
Feature detection & representation

DENSE PATCHES

Textons



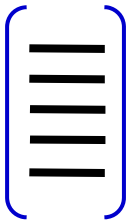
Parameters: N – size of patch
M – distance between patches



Row reorder gray values
And form a vector of
Size N^2

SIFT

Parameters: r – radi of patch
M – distance between patches



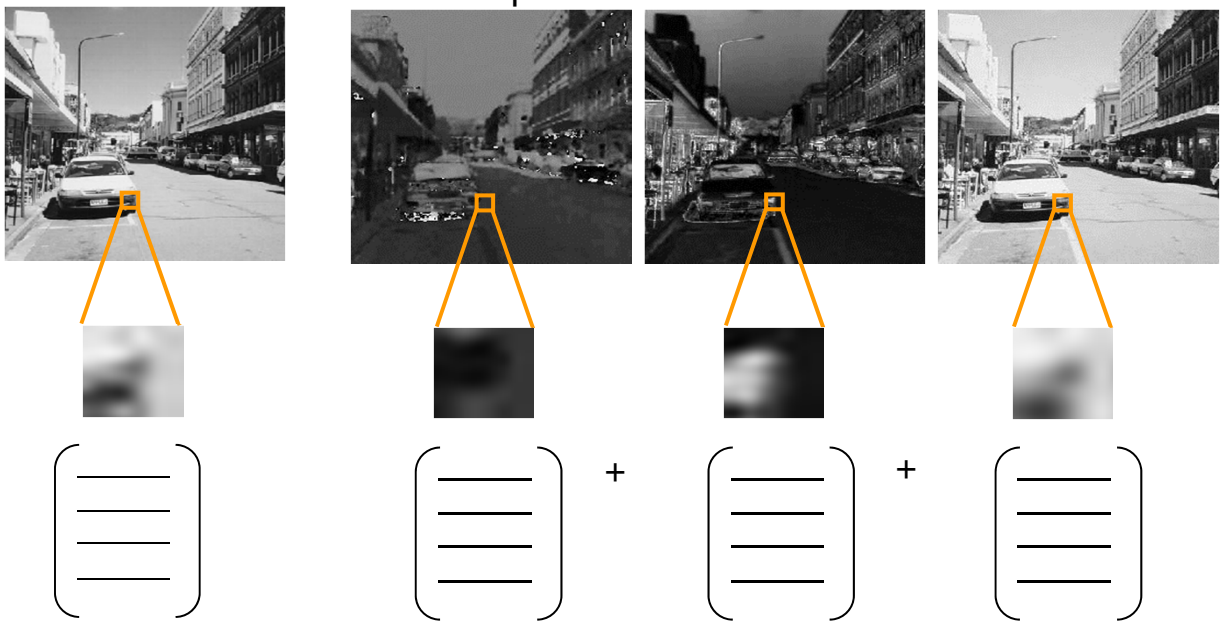
128- SIFT descriptor

Feature detection & representation

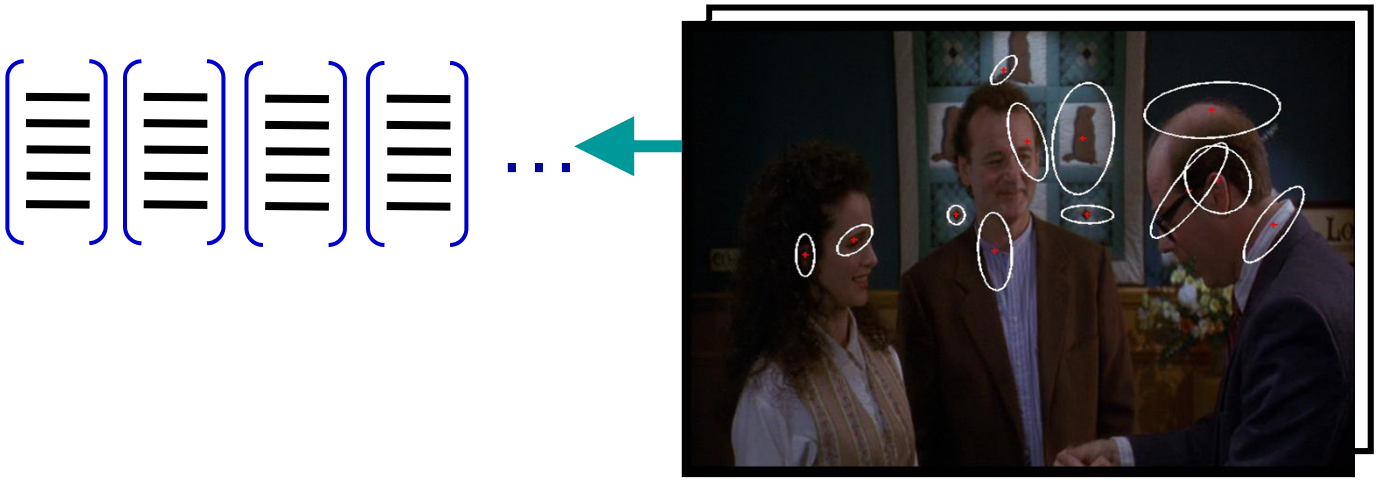
USING COLOUR

Gray

Colour (HSV) → descriptors are computed for each component



Visual vocabulary formation



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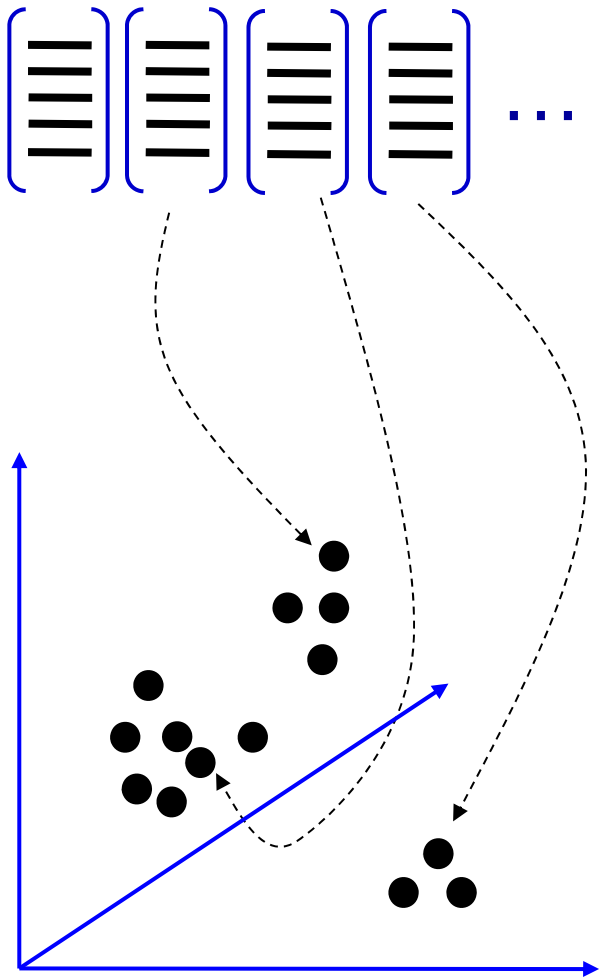

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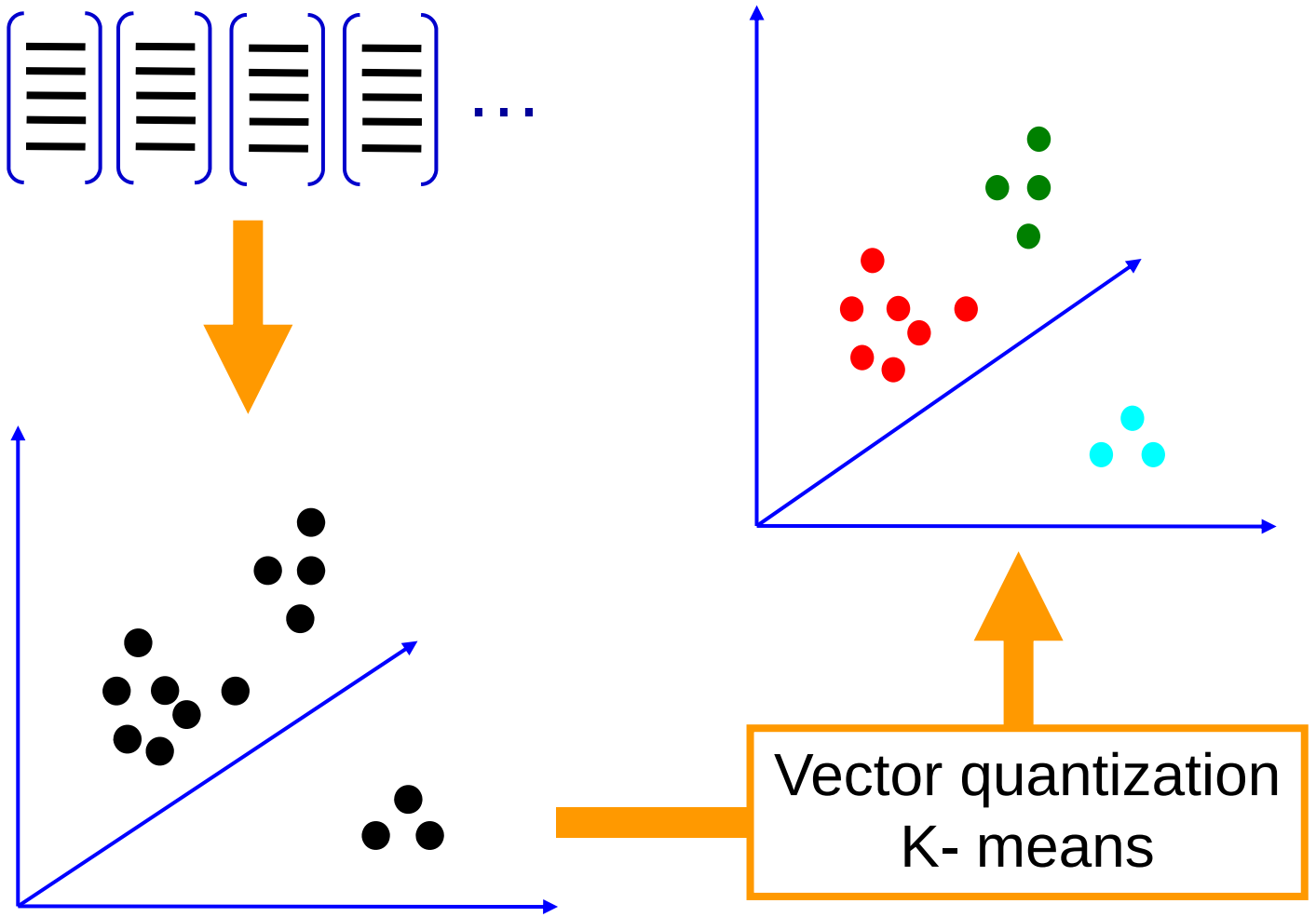
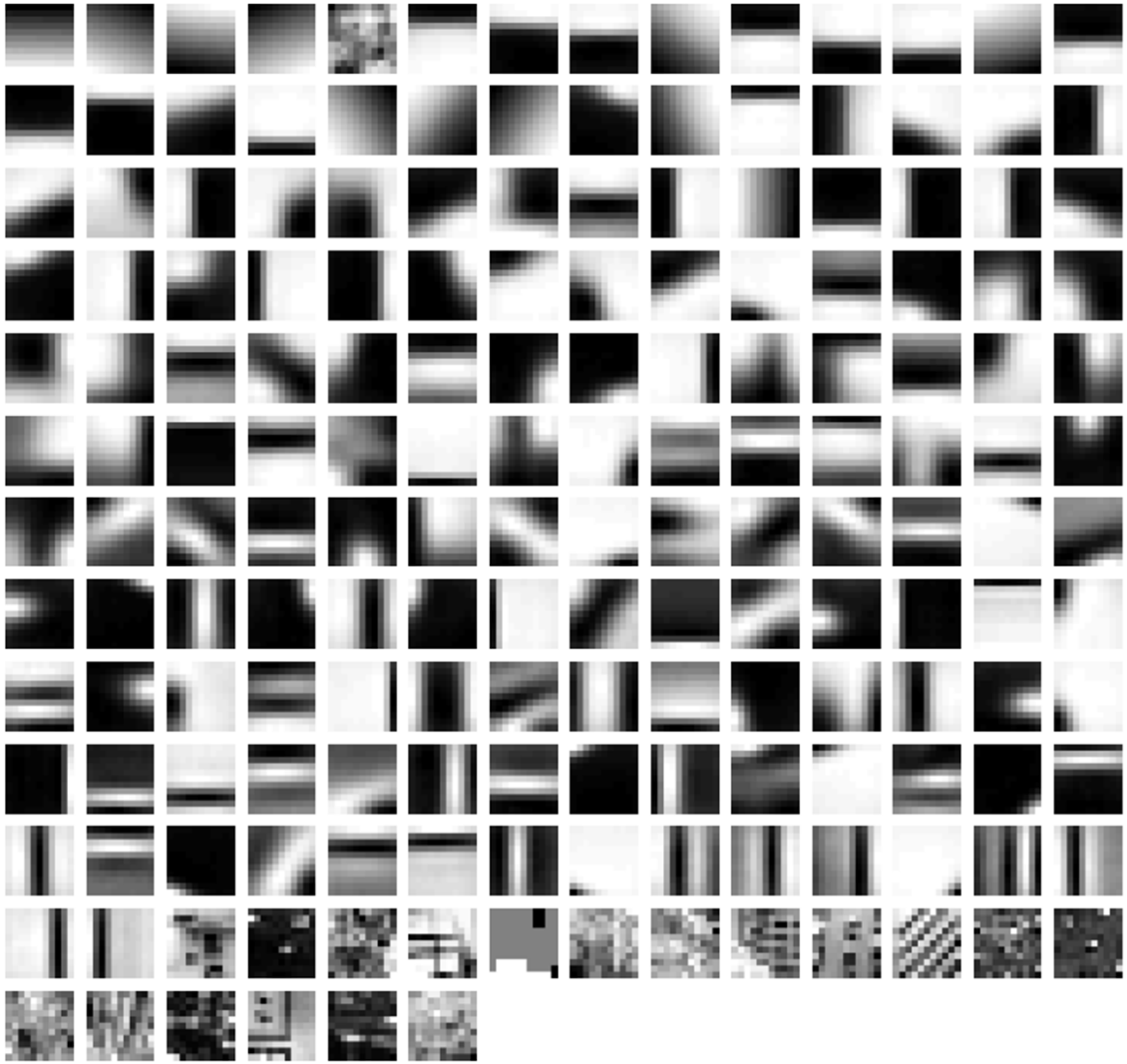


Examples of visual words



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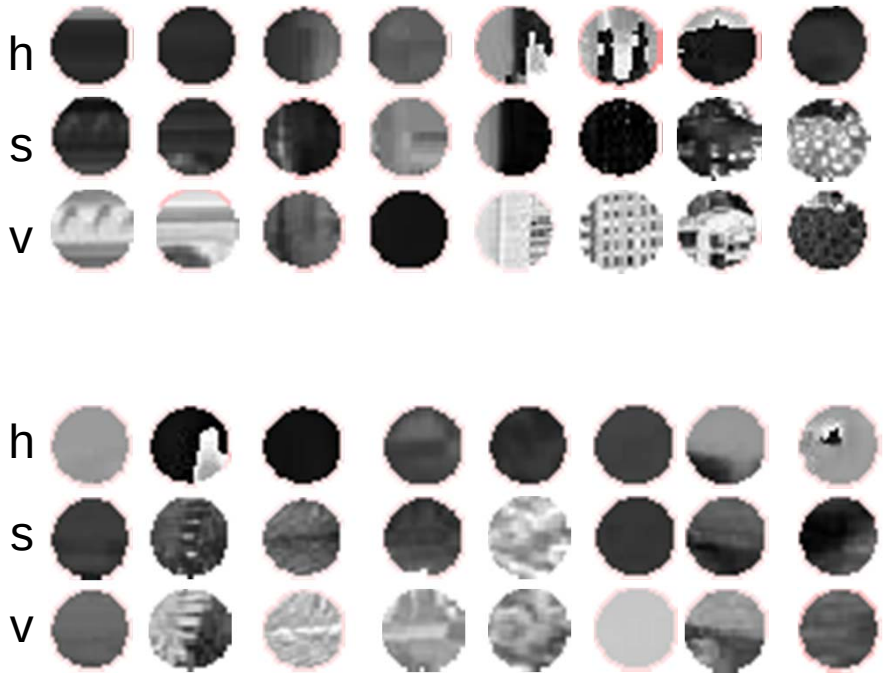
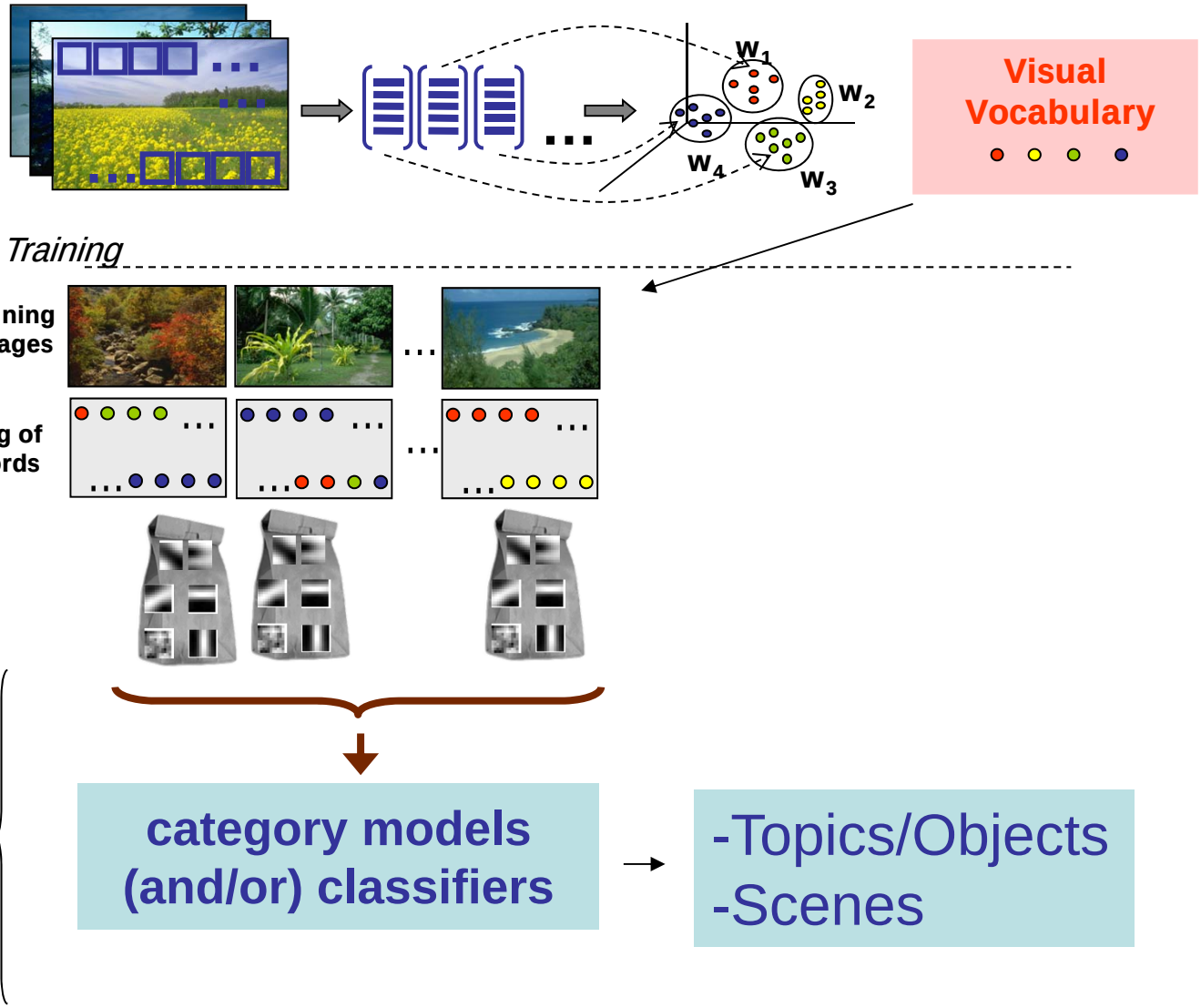
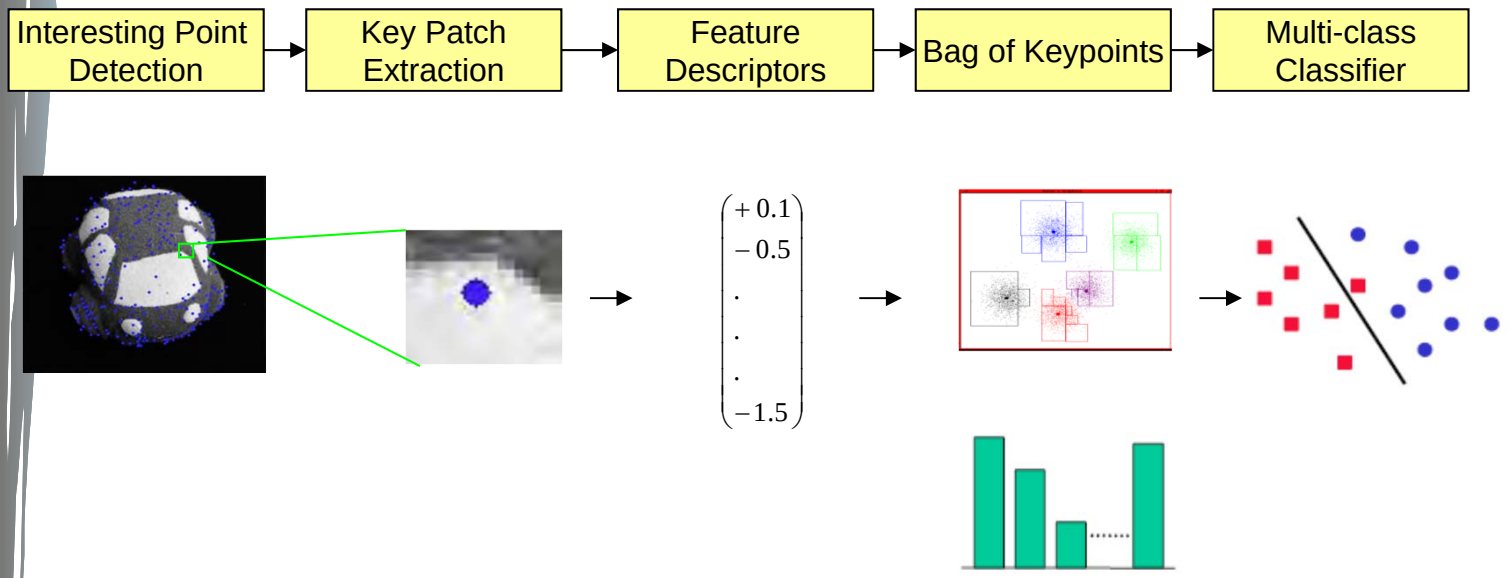


Learning



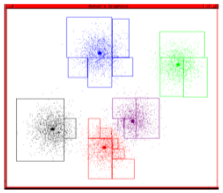
Learning

SPARSE BAG OF WORDS APPROACH



Learning

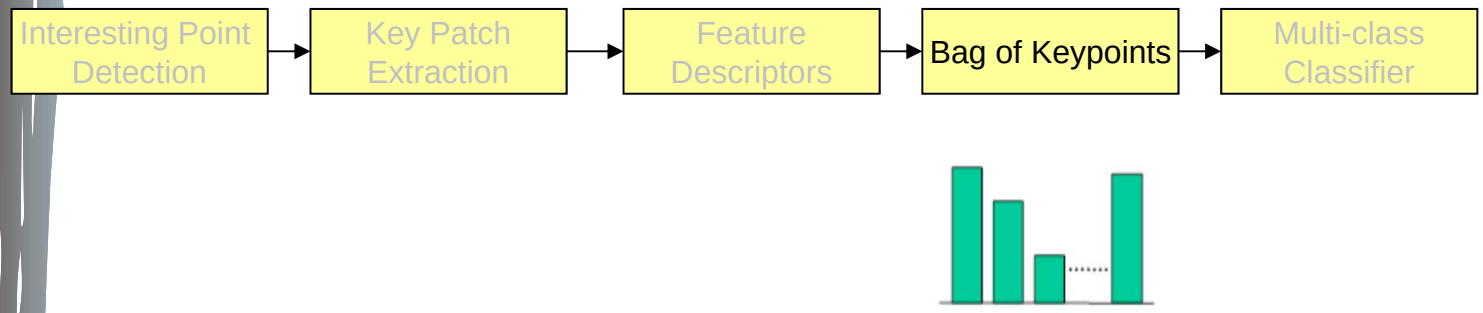
SPARSE BAG OF WORDS APPROACH



- Construction of a vocabulary
  - Kmeans clustering → find “centroids”
    (on all the descriptors we find from a set of training images)
  - Define a “vocabulary” as a set of “centroids”, where every centroid represents a “word”

Learning

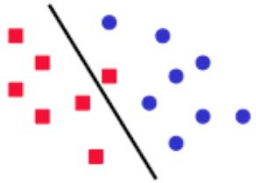
SPARSE BAG OF WORDS APPROACH



- Histogram
  - Counts the number of occurrences of different *visual words* in each image

Learning

SPARSE BAG OF WORDS APPROACH



- The classification using different classifiers
  - NN, K-NN
  - Support Vector Machine (SVM)
  - Adaboost
- What happens with a dense approach?

Generative Learning

1. Naïve Bayes classifier
   - Csurka et al. 2004

2. Hierarchical Bayesian text models
   - pLSA Hoffman 2001
   - LDA Blei et al. 2004

Weakness of the model

- No context information about the **scenes**
- No rigorous geometric information of the **object** components
- It's intuitive to most of us that **objects** are made of parts – no such information

Properties of an ideal recognition system

- Representation
  - 1000's categories,
  - Handle all invariances (occlusions, view point,…)
  - Explain as many pixels as possible (or answer as many questions as you can about the object)
  - fast, robust
- Learning
  - Handle all degrees of supervision
  - Incremental learning
  - Few training images

Bibliography

- [PAMI 2008] A. Bosch, A. Zisserman, X. Muñoz. *Scene classification using a hybrid generative / discriminative approach*. IEEE Transactions on Pattern Analysis and Machine Intelligence

- [Hofman 2001] Probabilistic Latent Semantic Analysis (pLSA)

- [Tutorial 2007] Some of the slides are extracted from the following link, where you can also find available code:

http://people.csail.mit.edu/torralba/shortCourseRLOC/