“Bag of Words”

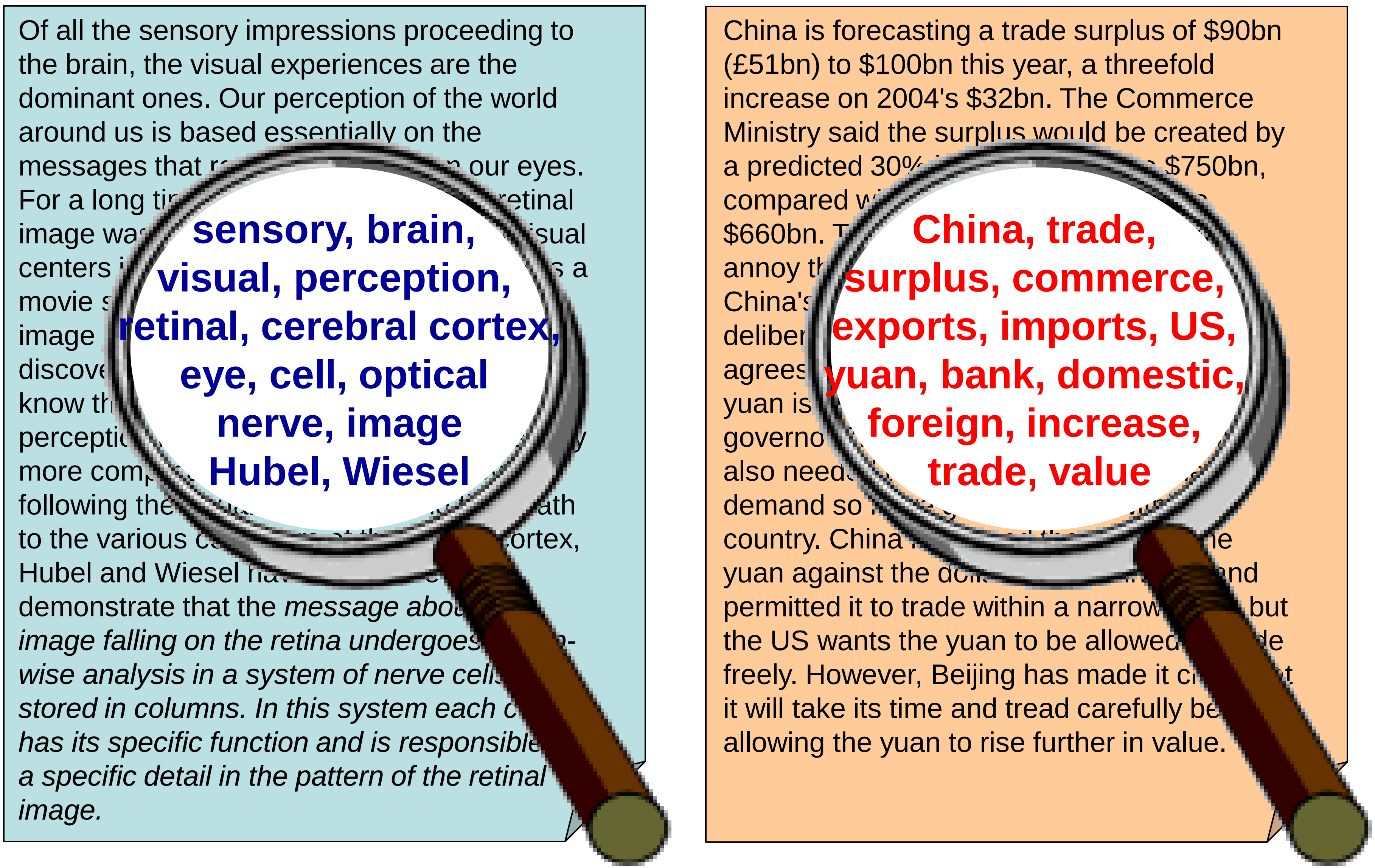
A quiet meditation on the importance of trying simple things first…

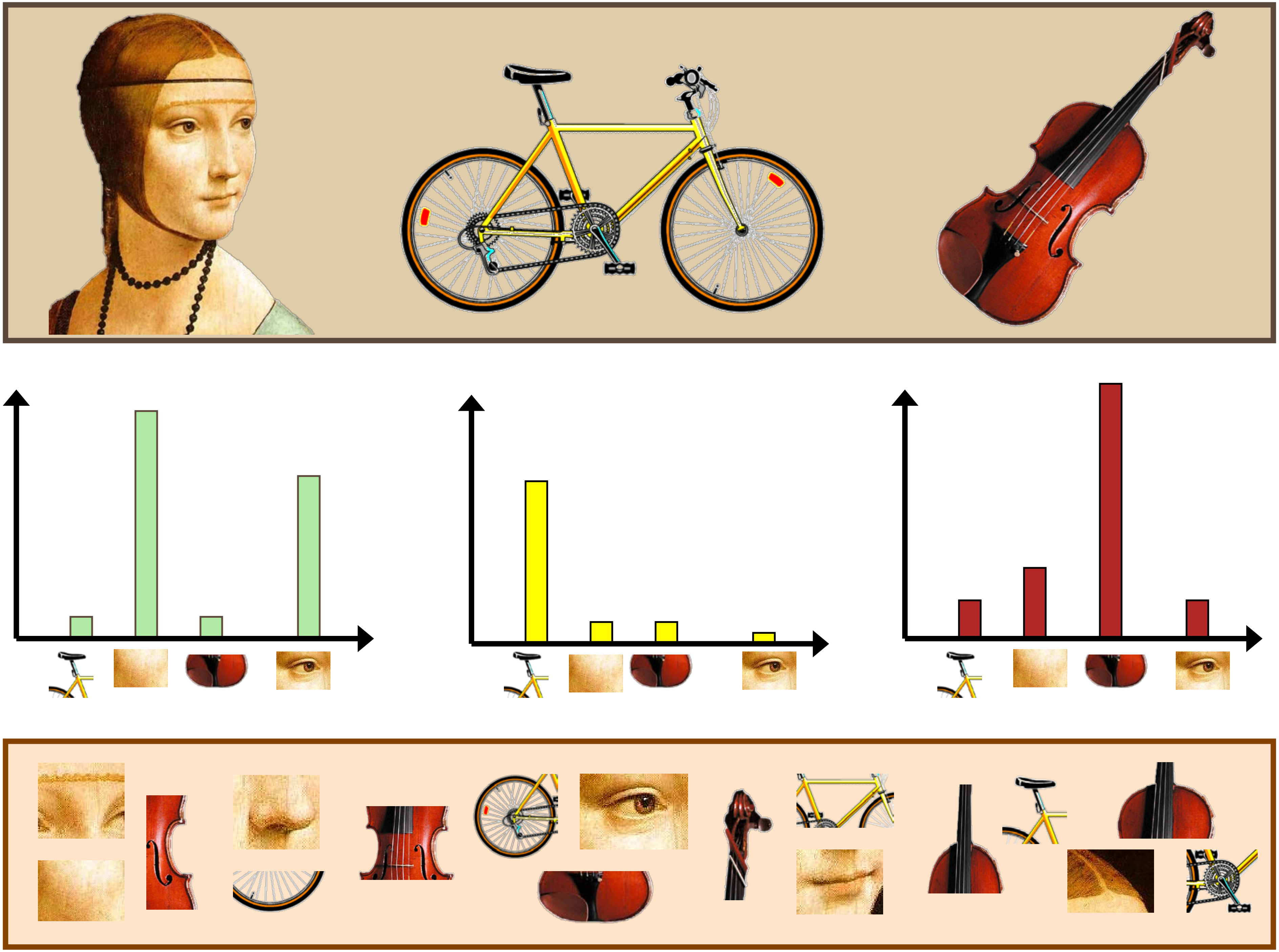
16-721: Advanced Machine Perception
A. Efros, CMU, Spring 2009

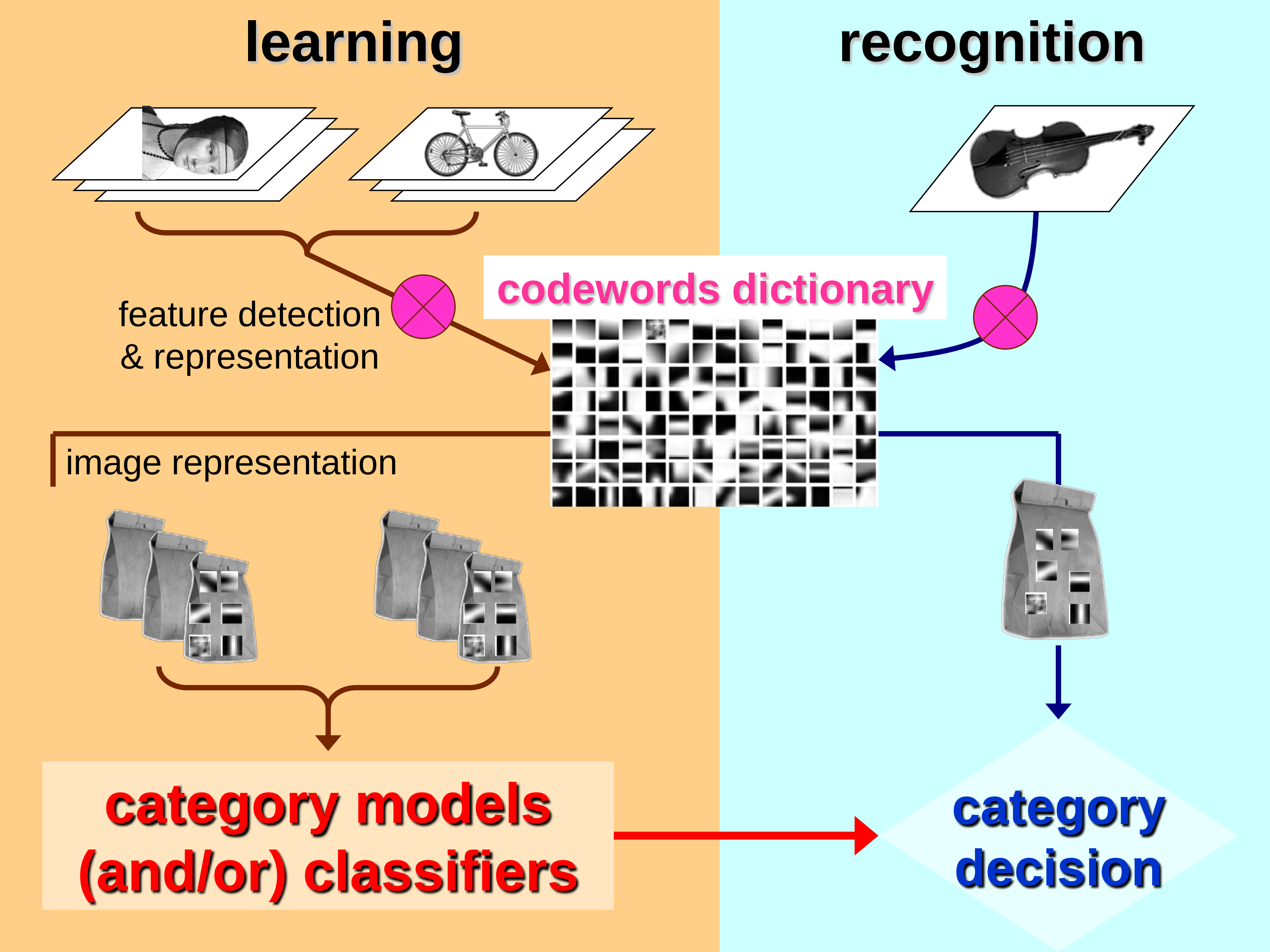
Adopted from Fei-Fei Li, S.c. Zhu, and L.Walker Renninger

Object → **Bag of ‘words’**

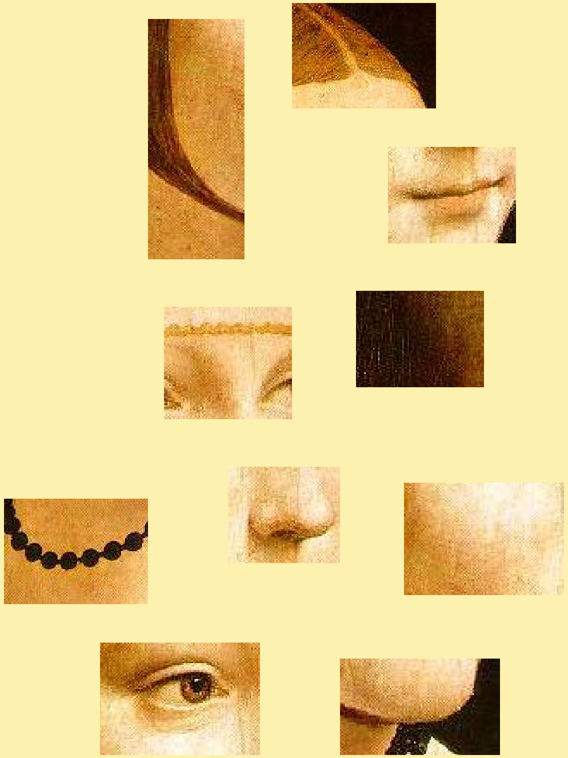
Analogy to documents






learning
recognition
feature detection
& representation
codewords dictionary
image representation
category models
(and/or) classifiers
category
decision

1.Feature detection and representation



Feature detection

- Sliding Window
  - Leung et al, 1999
  - Viola et al, 1999
  - Renninger et al 2002

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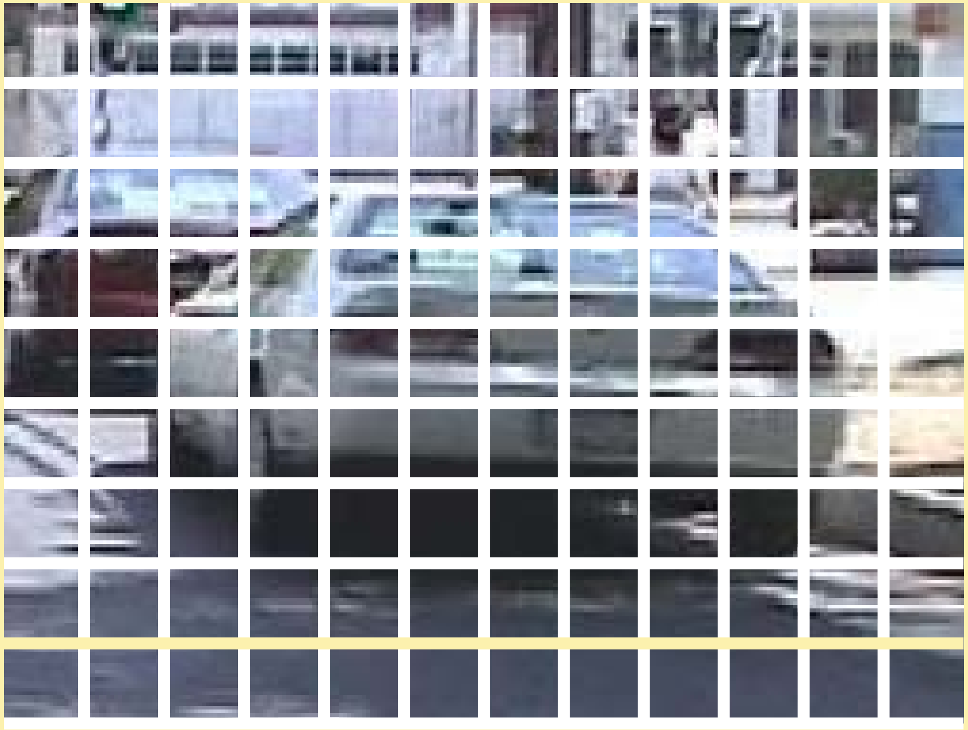

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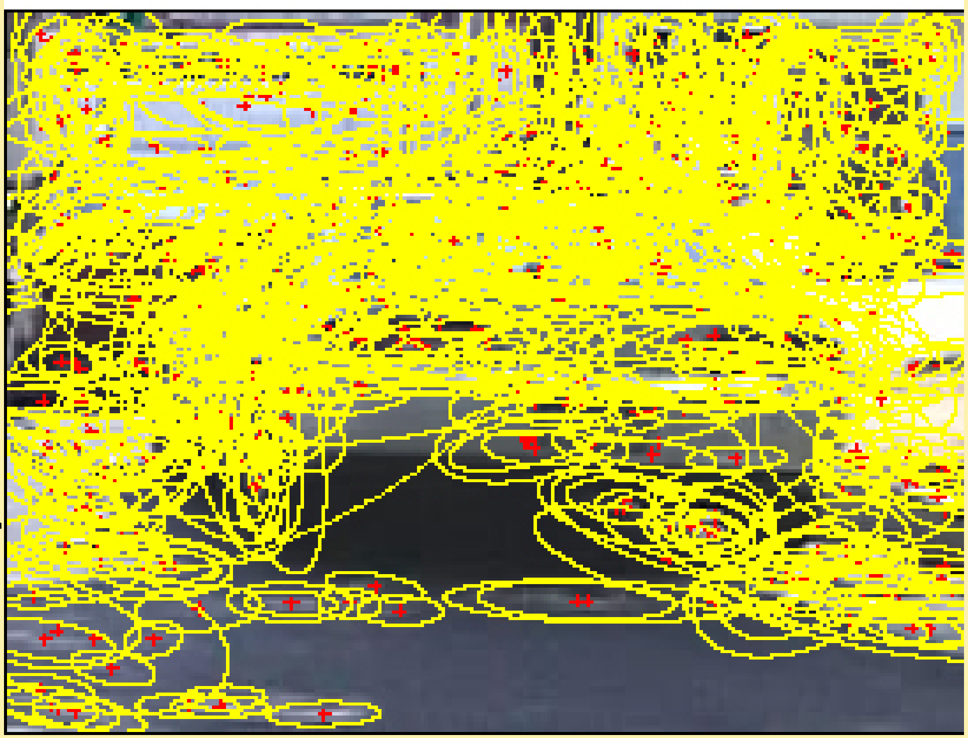

Feature detection

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  - Csurka et al. 2004
  - Fei-Fei et al. 2005
  - Sivic et al. 2005
- Other methods
  - Random sampling (Ullman et al. 2002)
  - Segmentation based patches
    - Barnard et al. 2003, Russell et al 2006, etc.)

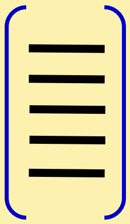
Feature Representation

Visual words, aka textons, aka keypoints:
K-means clustered pieces of the image

- Various Representations:
  - Filter bank responses
  - Image Patches
  - SIFT descriptors

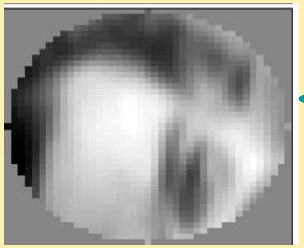
All encode more-or-less the same thing…

Interest Point Features

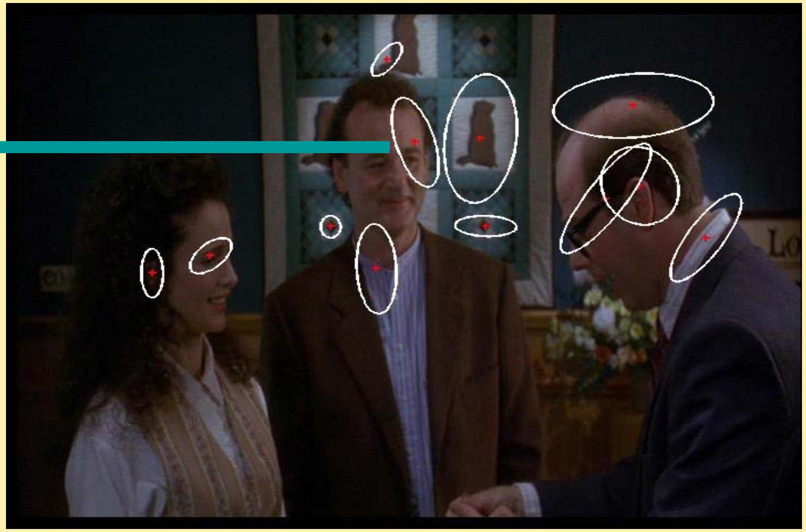


Compute SIFT descriptor

[Lowe'99]



Normalize patch



Detect patches

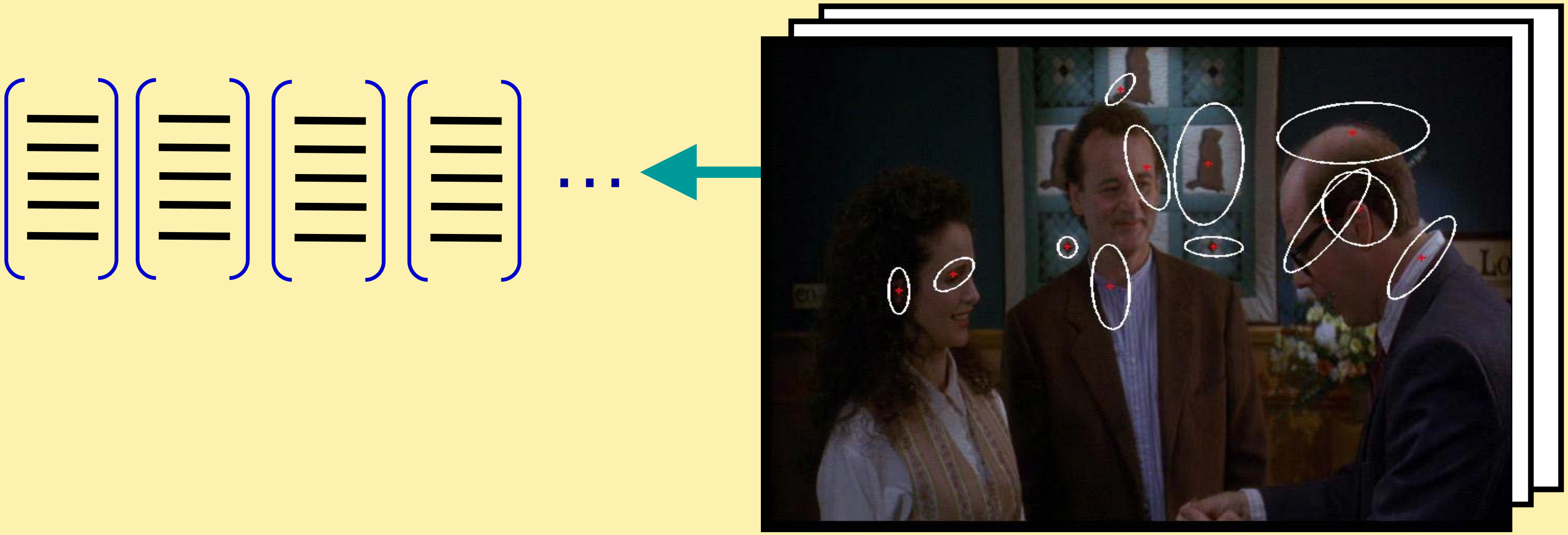
[Mikojaczyk and Schmid '02]

[Matas et al. '02]

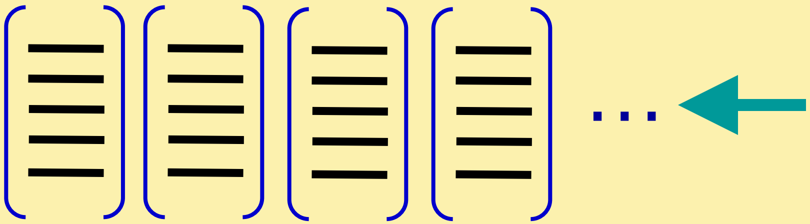
[Sivic et al. '03]

Slide credit: Josef Sivic

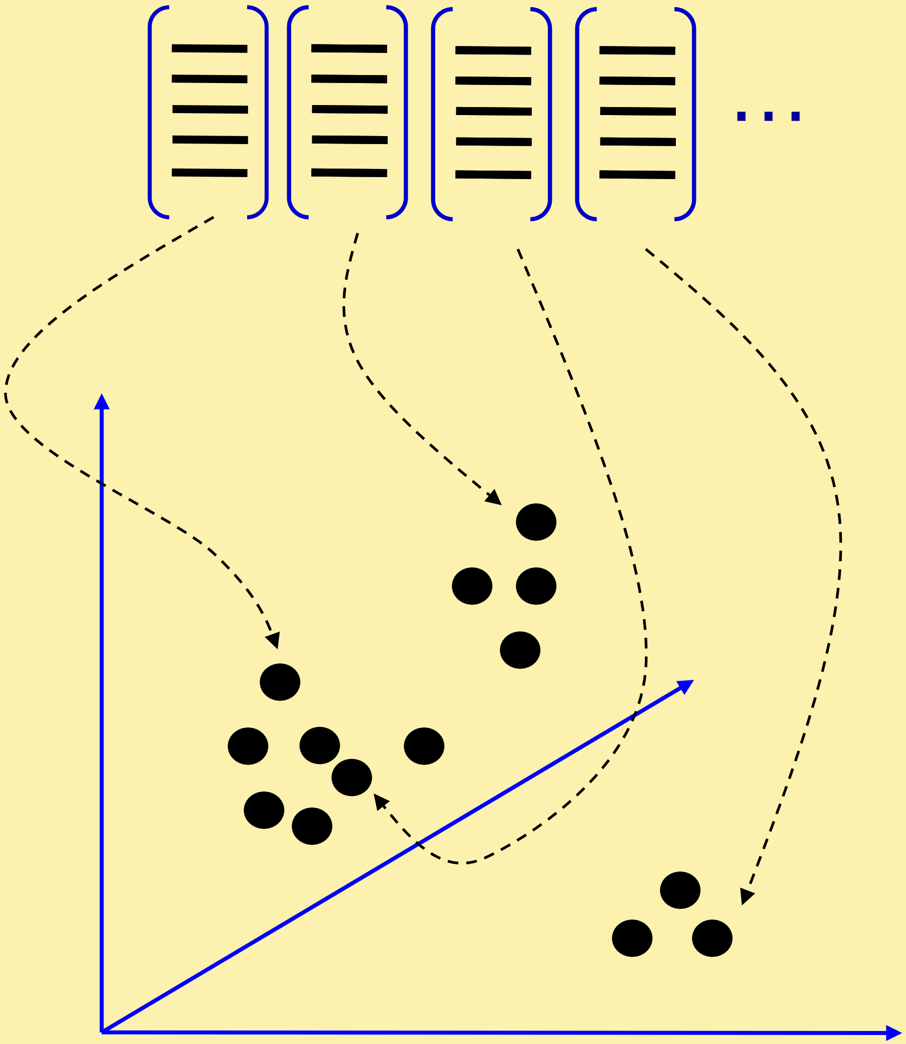
Interest Point Features



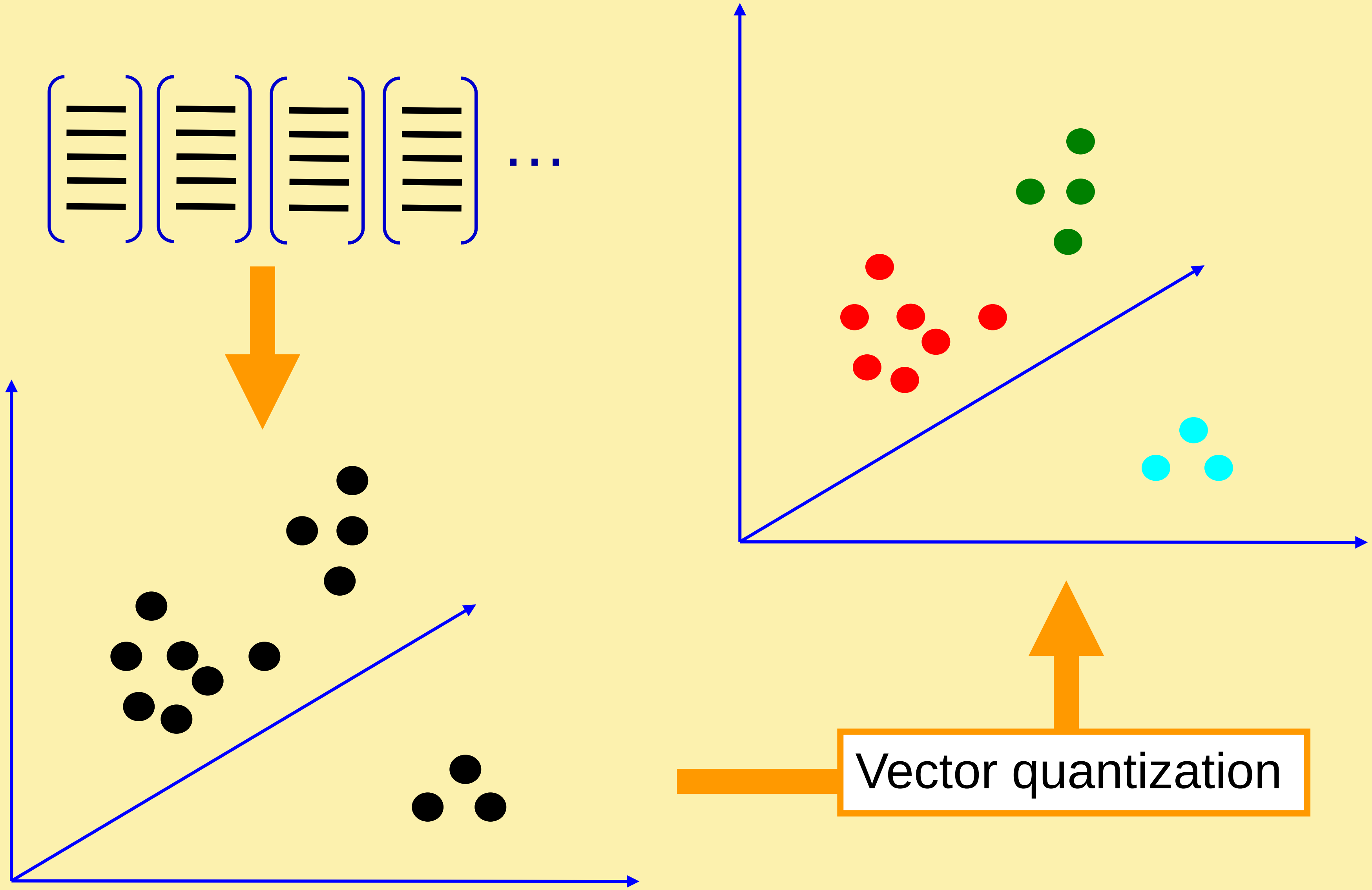
Patch Features



dictionary formation

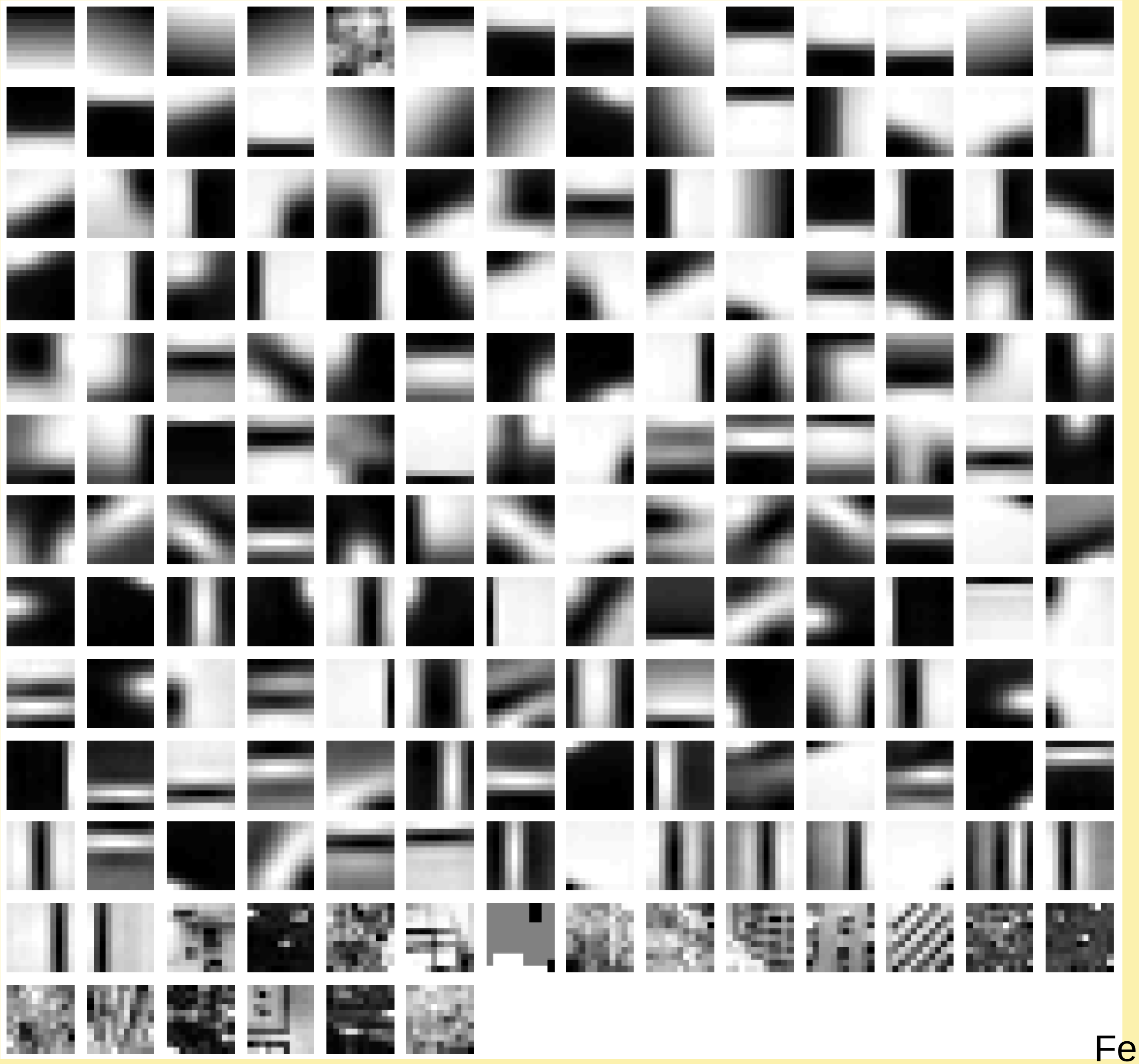


Clustering (usually k-means)



Slide credit: Josef Sivic

Clustered Image Patches



Fei-Fei et al. 2005

Filterbank

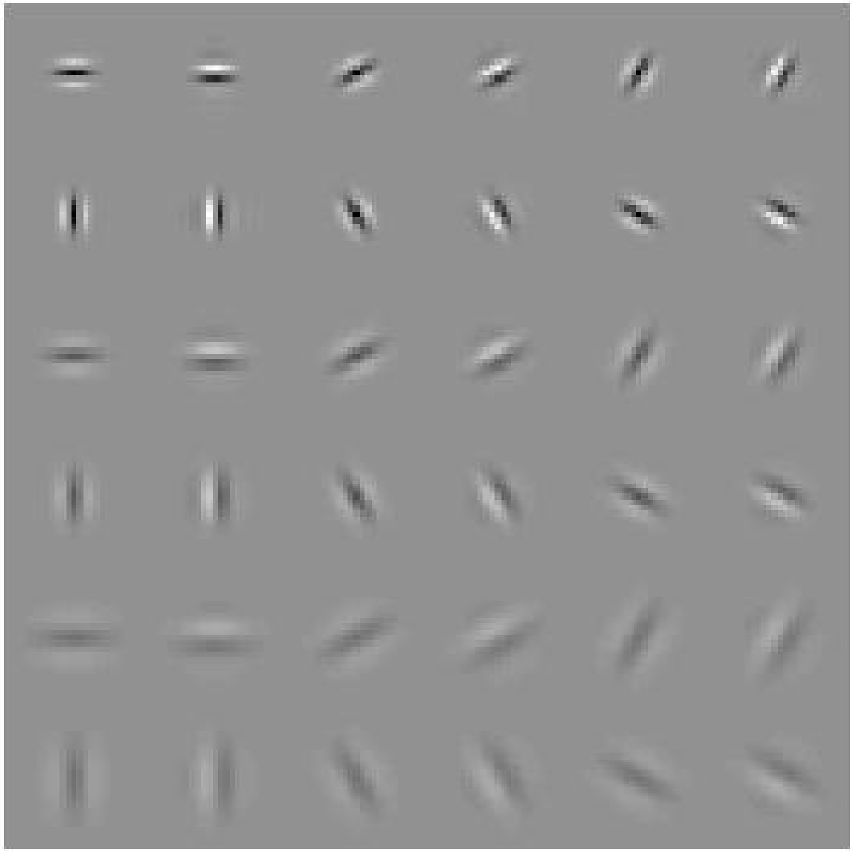
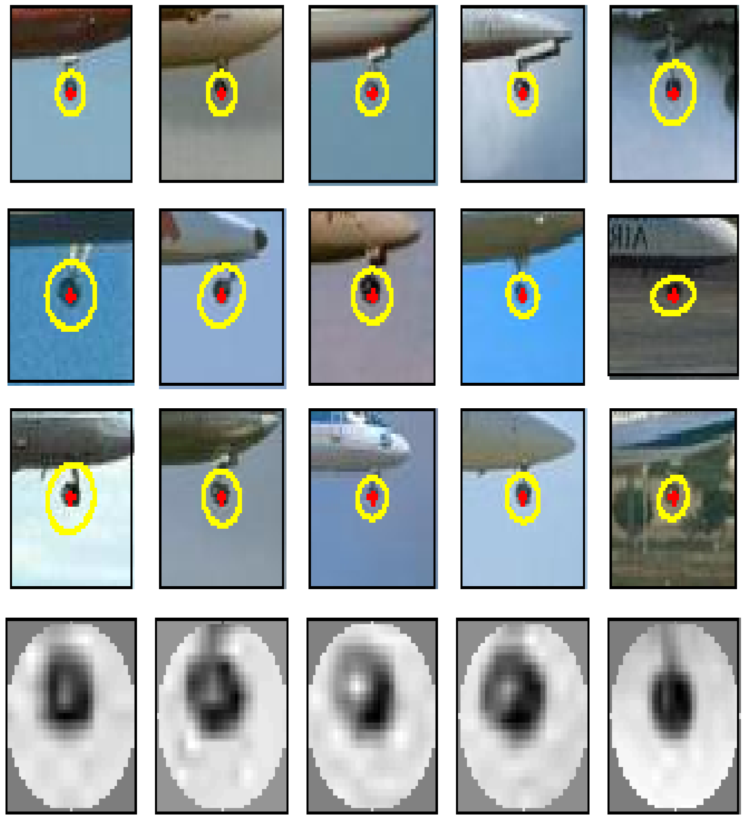
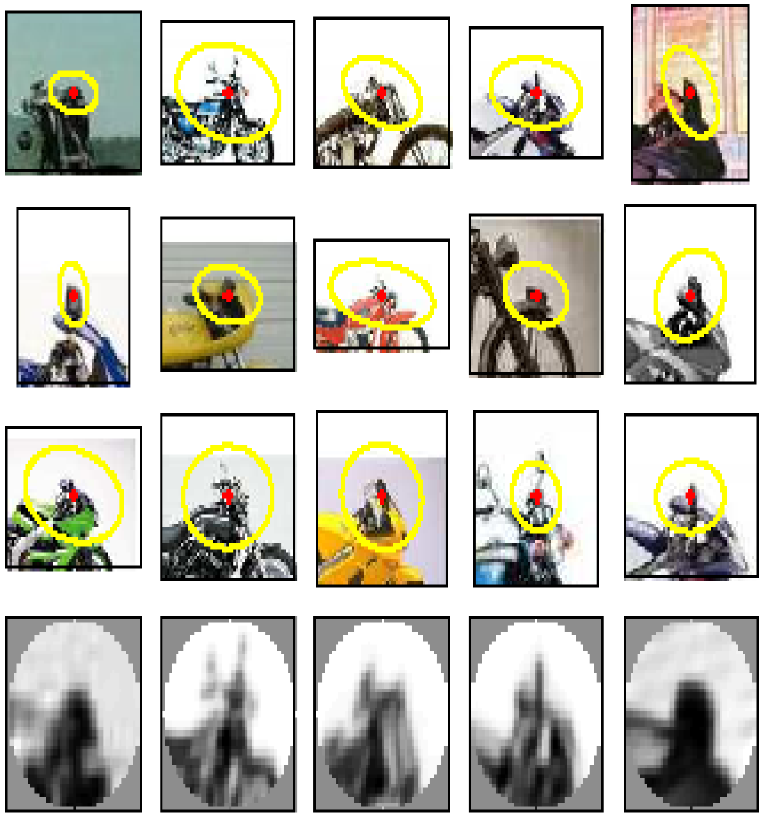


Image patch examples of codewords

(a)

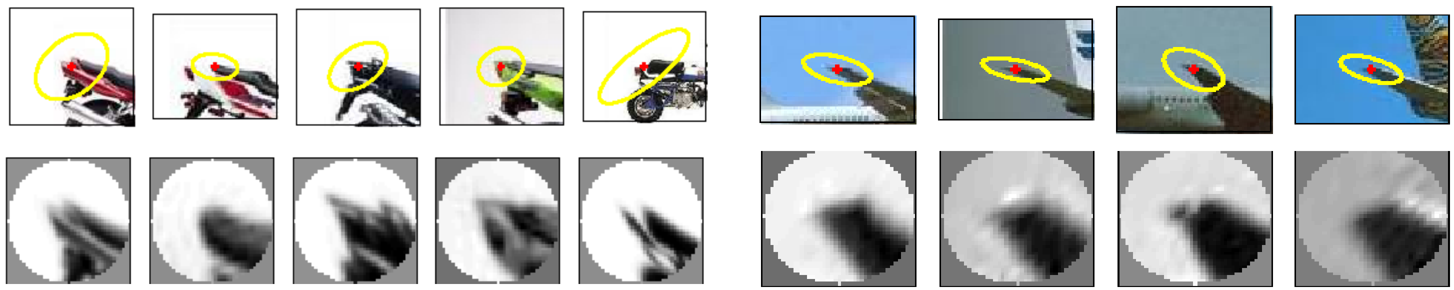


(b)

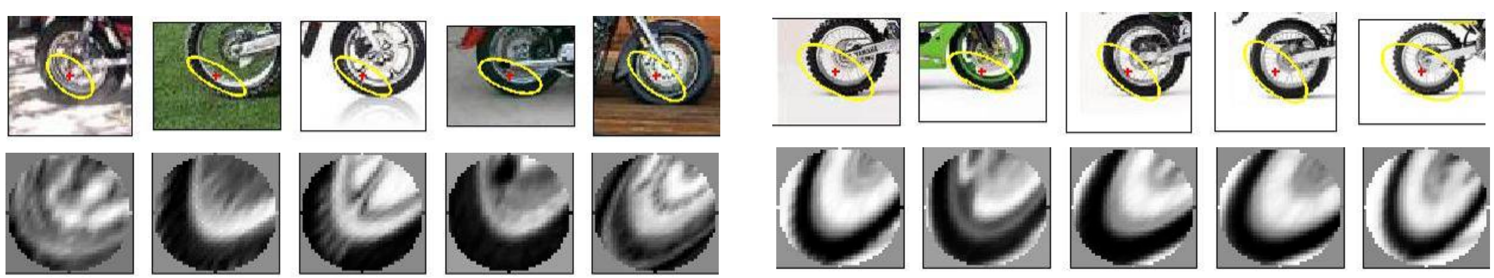


Sivic et al. 2005

Visual synonyms and polysemy



Visual Polysemy. Single visual word occurring on different (but locally similar) parts on different object categories.

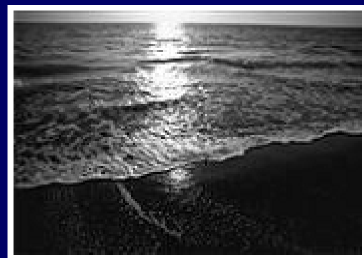


Visual Synonyms. Two different visual words representing a similar part of an object (wheel of a motorbike).

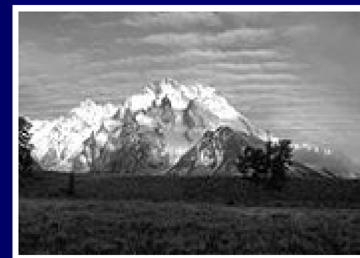
Image representation

Scene Classification (Renninger & Malik)

beach

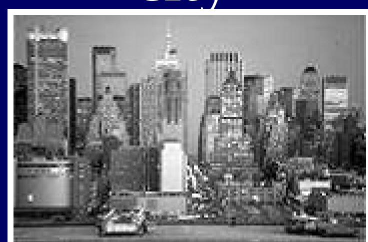


mountain

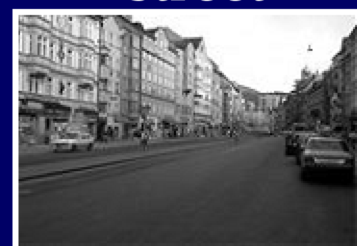


forest

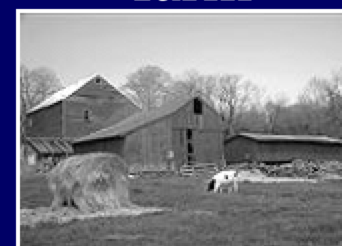
city



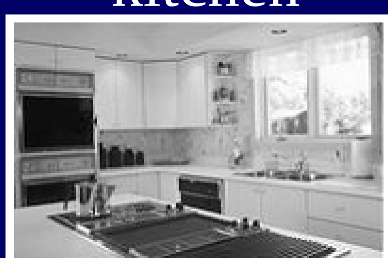
street



farm

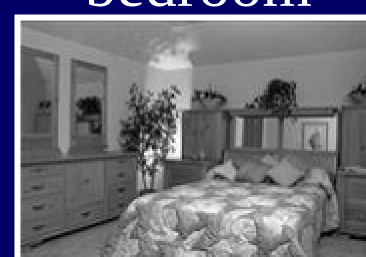


kitchen



livingroom

bedroom



bathroom

1. Bag of visual words model: recognizing object categories

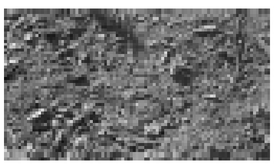
Problem: Image Classification

Given:

- positive training images containing an object class, and



- negative training images that don’t




Classify:

- a test image as to whether it contains the object class or not

?

Weakly-supervised learning

- Learn model from a set of training images containing object instances

- Know if image contains object or not
- But no segmentation of object or manual selection of features

Three stages:

1. Represent each training image by a vector

    - Use a bag of visual words representation

2. Train a classify to discriminate vectors corresponding to positive and negative training images

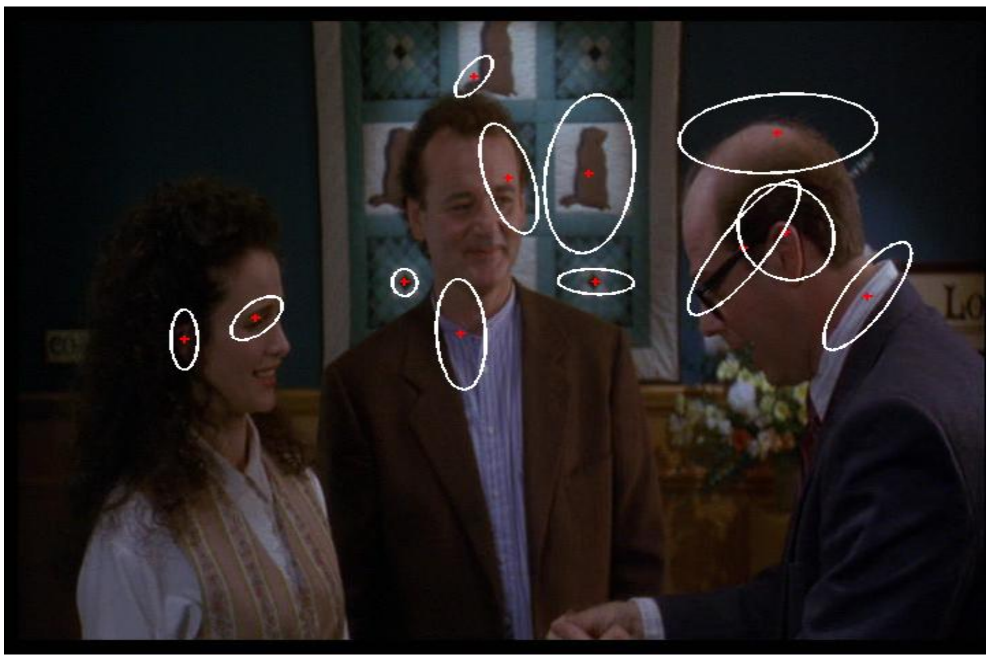
    - Use a Support Vector Machine (SVM) classifier

3. Apply the trained classifier to the test image

Representation: Bag of visual words

Visual words are ‘iconic’ image patches or fragments

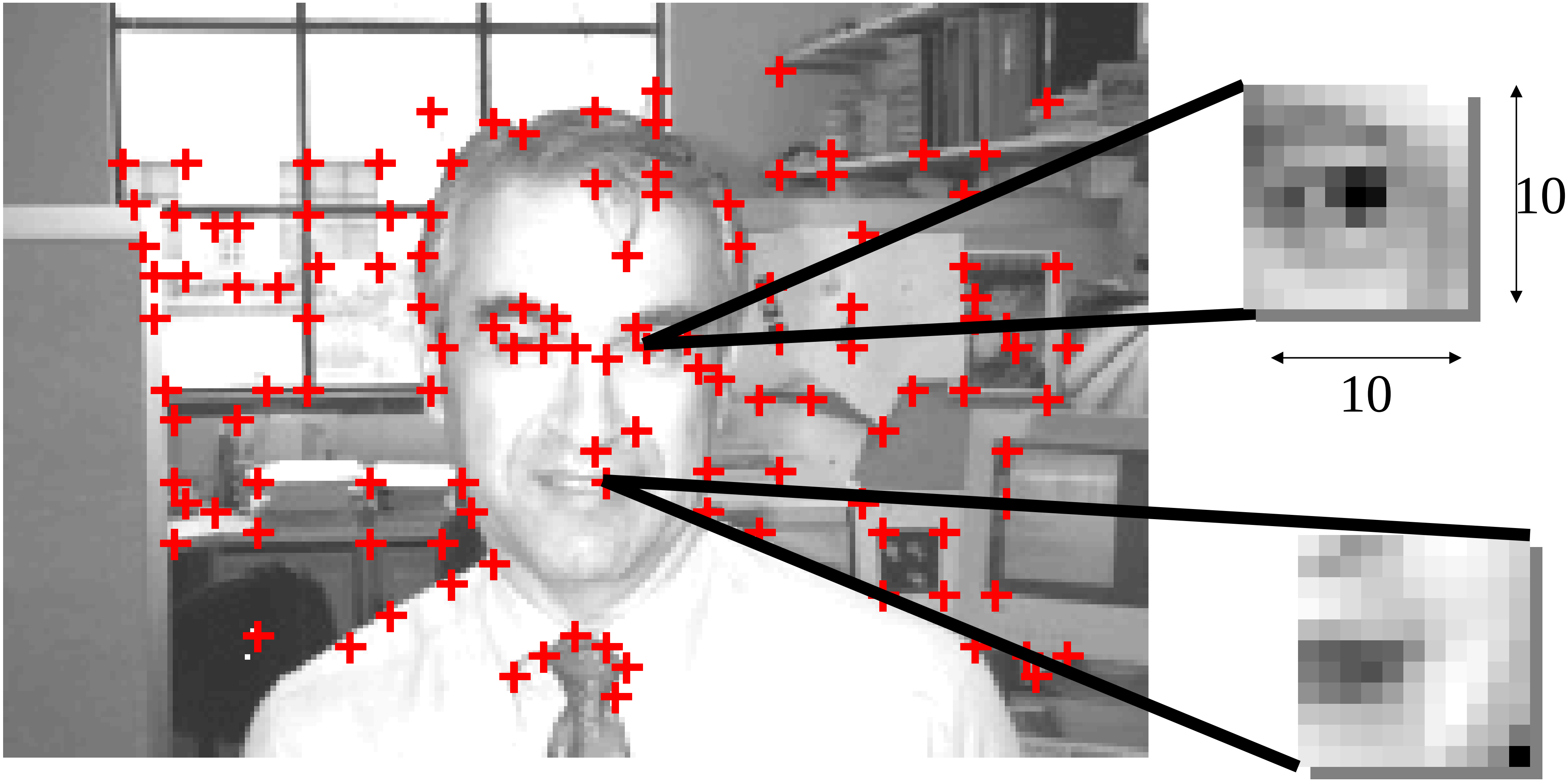
- represent the frequency of word occurrence
- but not their position



Image

Collection of visual words

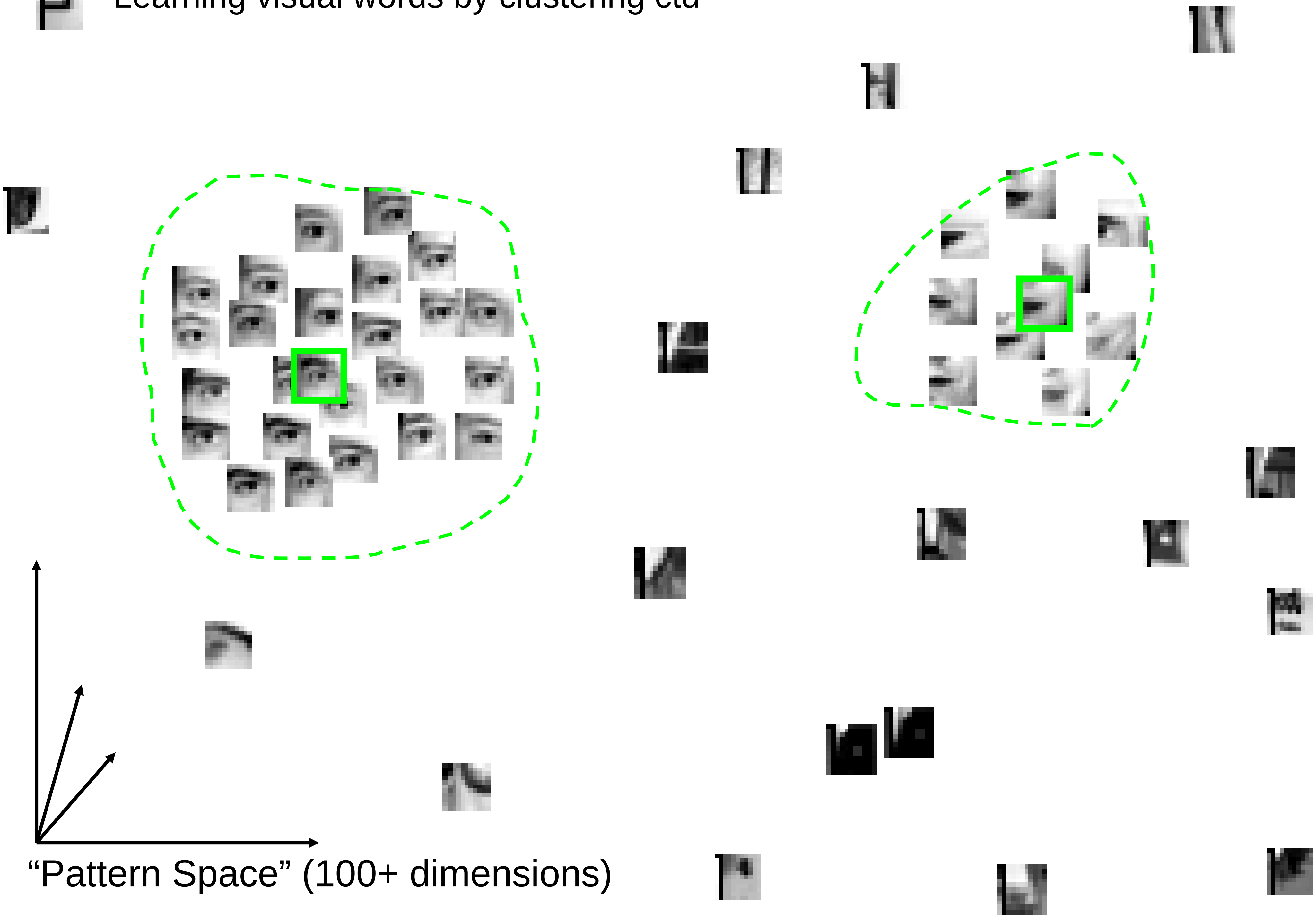
Example: Learn visual words by clustering



- Interest point features: textured neighborhoods are selected
- produces 100-1000 regions per image

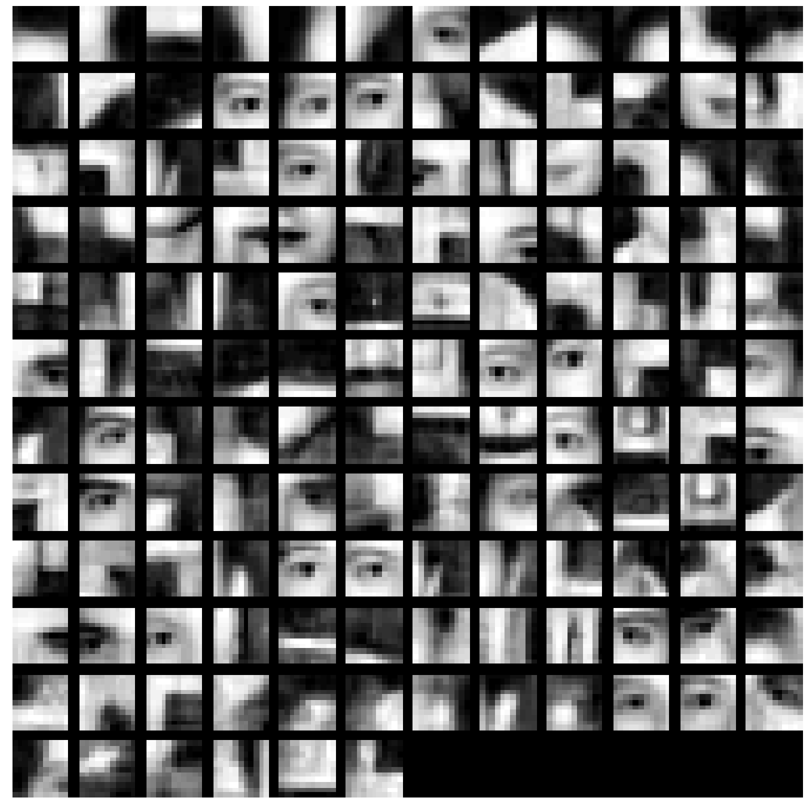
Weber, Welling & Perona 2000

Learning visual words by clustering ctd



Example of visual words learnt by clustering faces

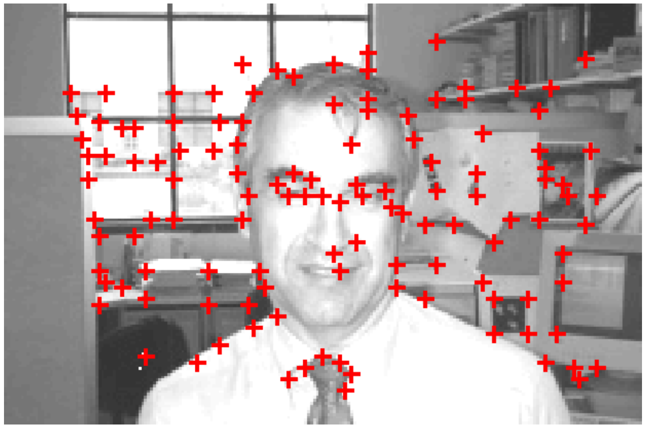
100-1000 images

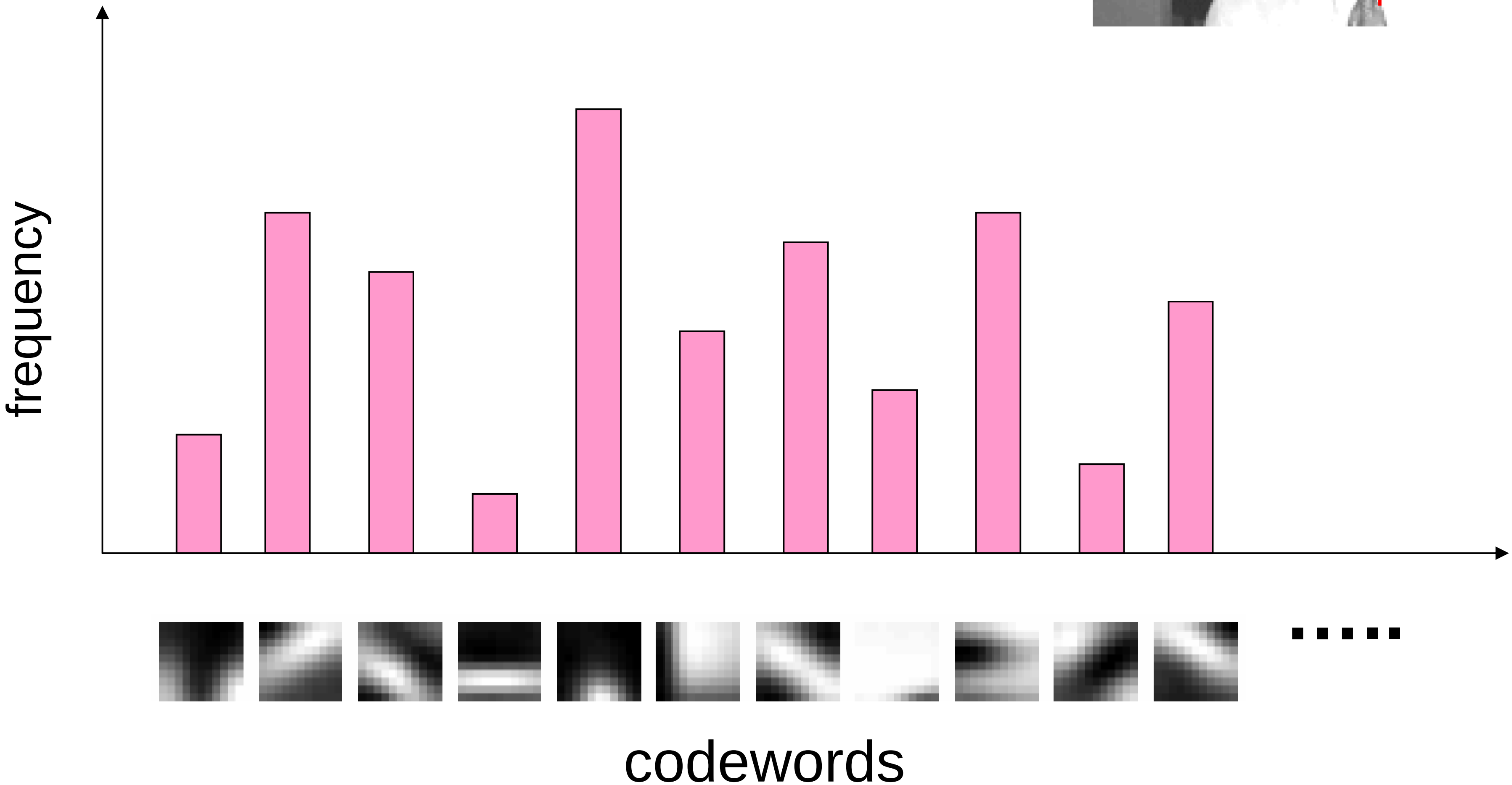


~100 visual words

Image representation – normalized histogram

- detect interest point features
- find closest visual word to region around detected points
- record number of occurrences, but not position



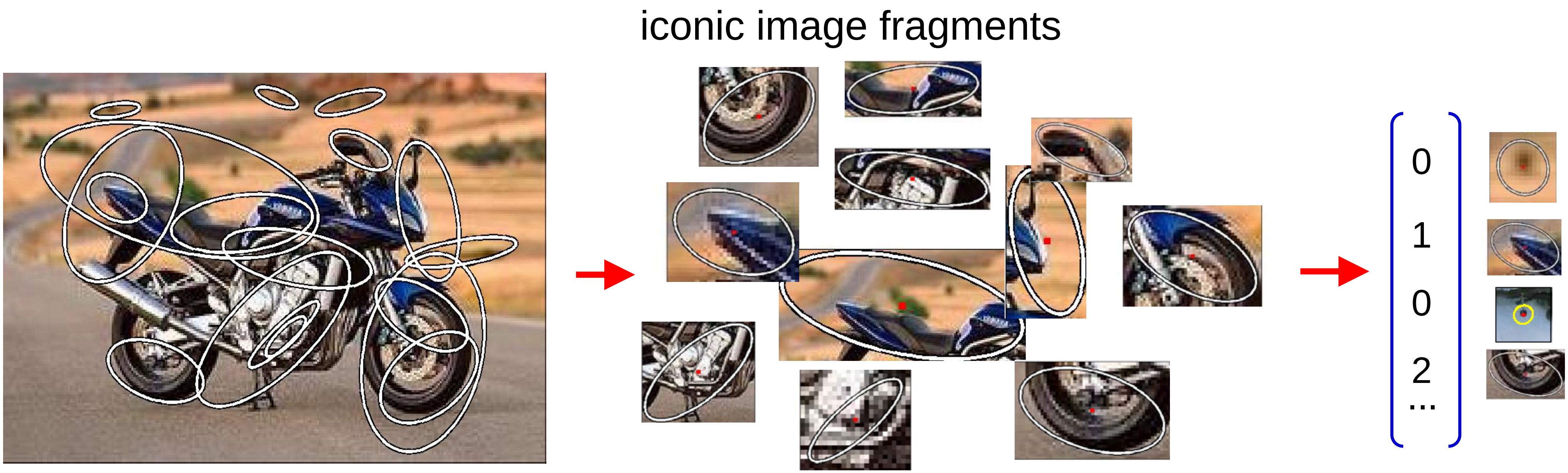


Example Image collection: four object classes + background

Faces	435
Motorbikes	800
Airplanes	800
Cars (rear)	1155
Background	900
Total:	**4090**

The “Caltech 5”

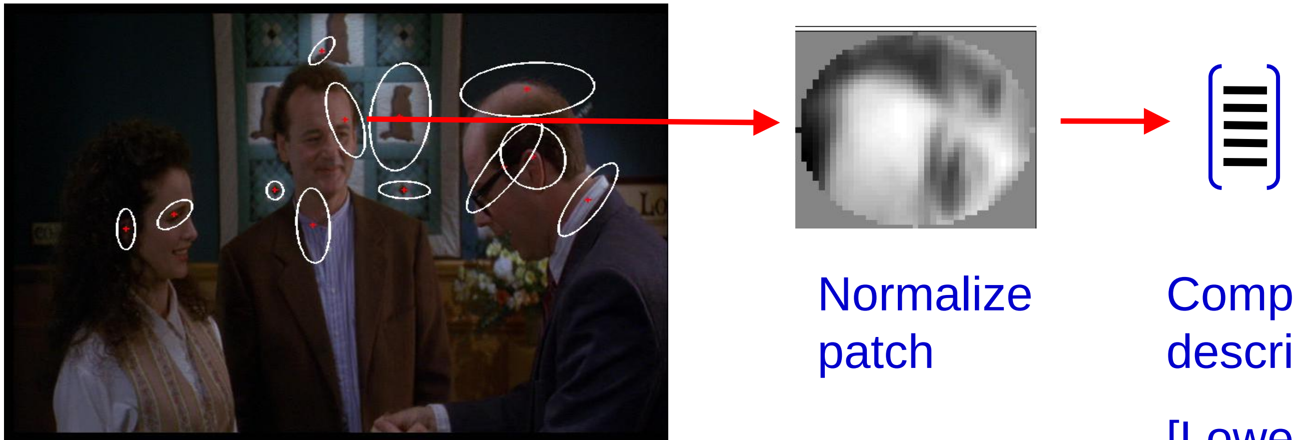
Represent an image as a histogram of visual words



Bag of words model

- Detect affine covariant regions
- Represent each region by a SIFT descriptor
- Build visual vocabulary by k-means clustering (K~1,000)
- Assign each region to the nearest cluster centre

Visual vocabulary for affine covariant patches



Detect patches

[Mikolajczyk and Schmid ’02]

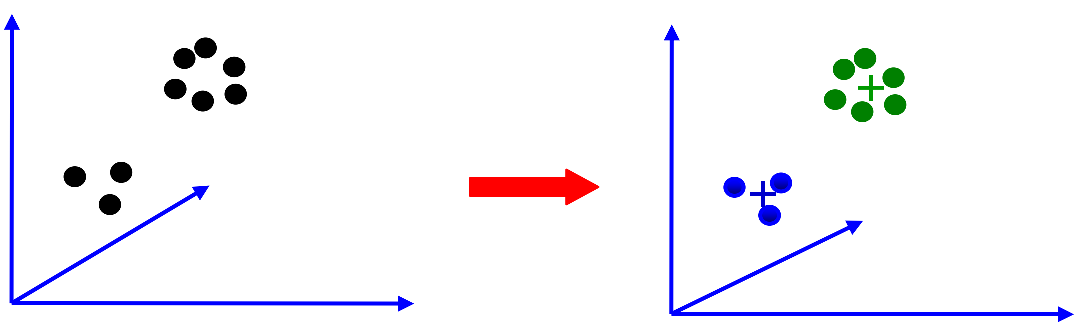
[Matas et al. ’02]

Normalize patch

Compute SIFT descriptor

[Lowe’99]

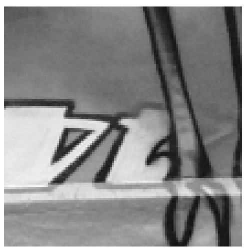
Vector quantize descriptors from a set of training images using k-means



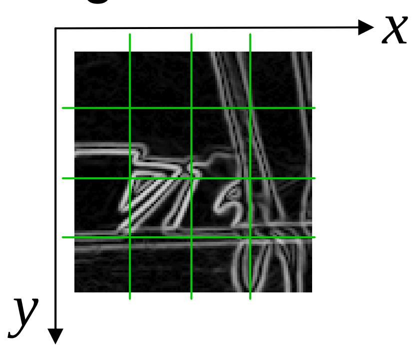
Descriptors – SIFT [Lowe'99]

distribution of the gradient over an image patch

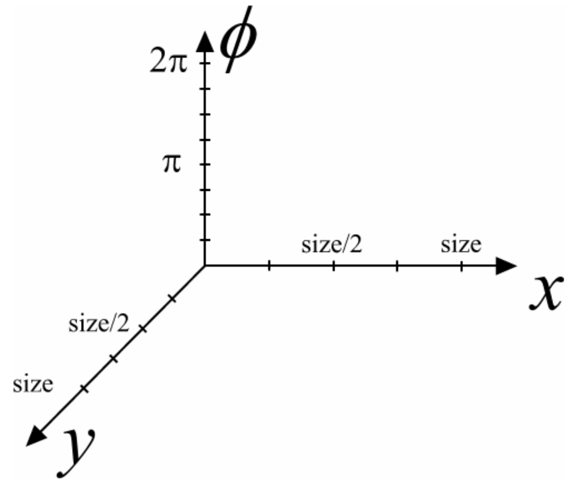
image patch

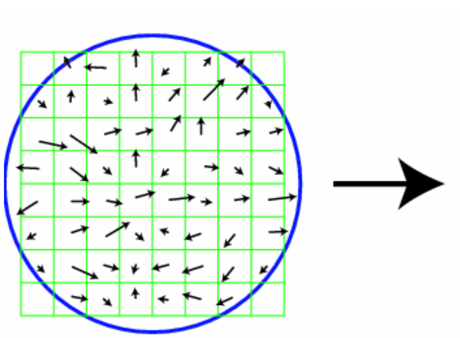


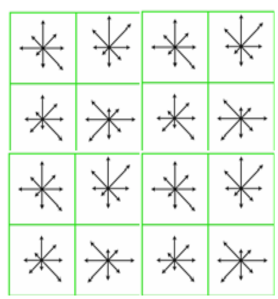
gradient



3D histogram



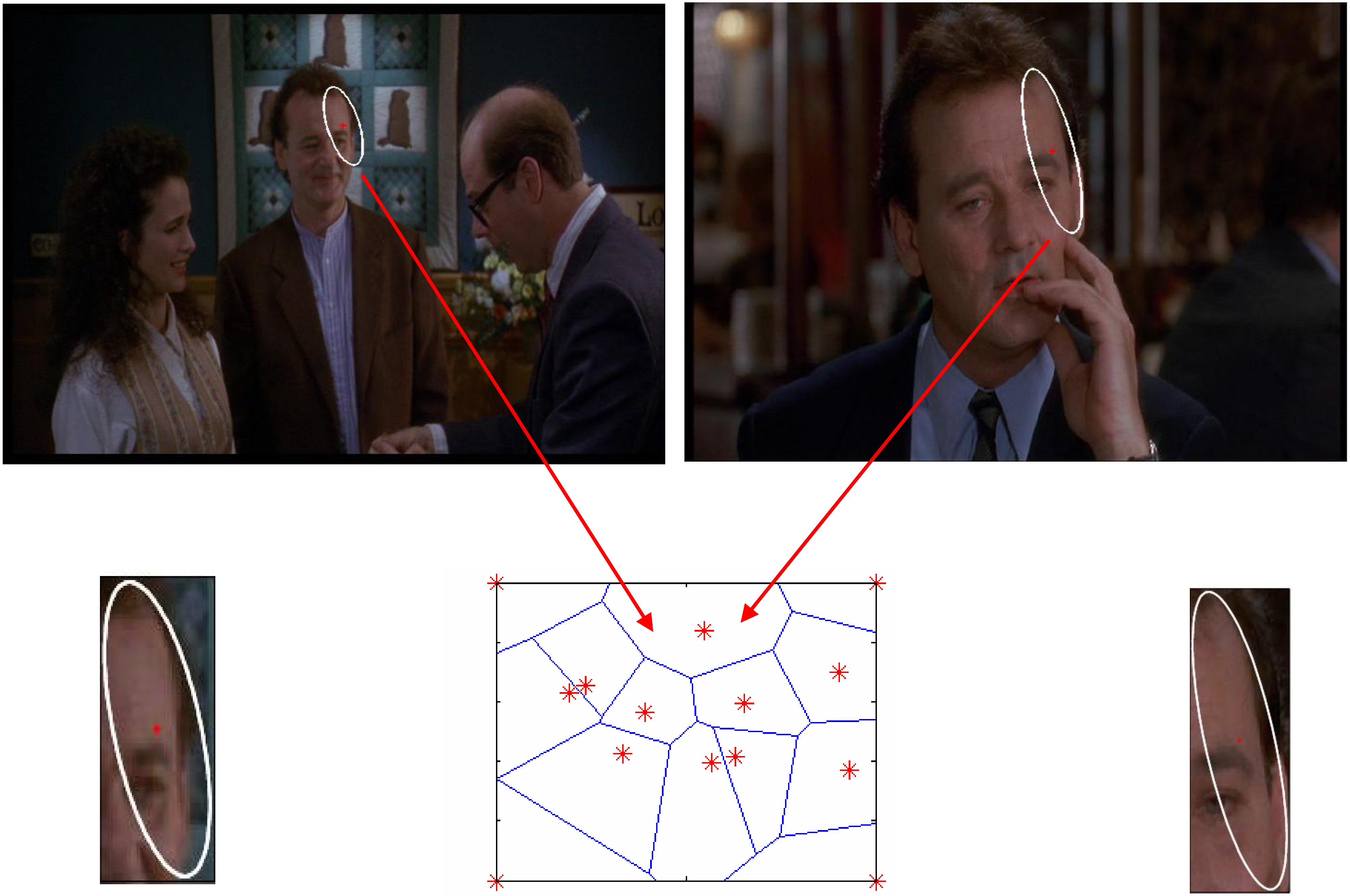




4x4 location grid and 8 orientations (128 dimensions)

very good performance in image matching [Mikolaczyk and Schmid'03]

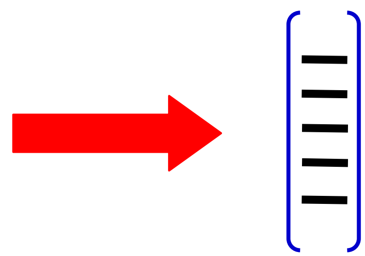
Vector quantize the descriptor space (SIFT)



The same visual word

Each image: assign all detections to their visual words

- gives bag of visual word representation
- normalized histogram of word frequencies
- also called ‘bag of key points’



Visual words from affine covariant patches

Vector quantize SIFT descriptors to a vocabulary of iconic “visual words”.

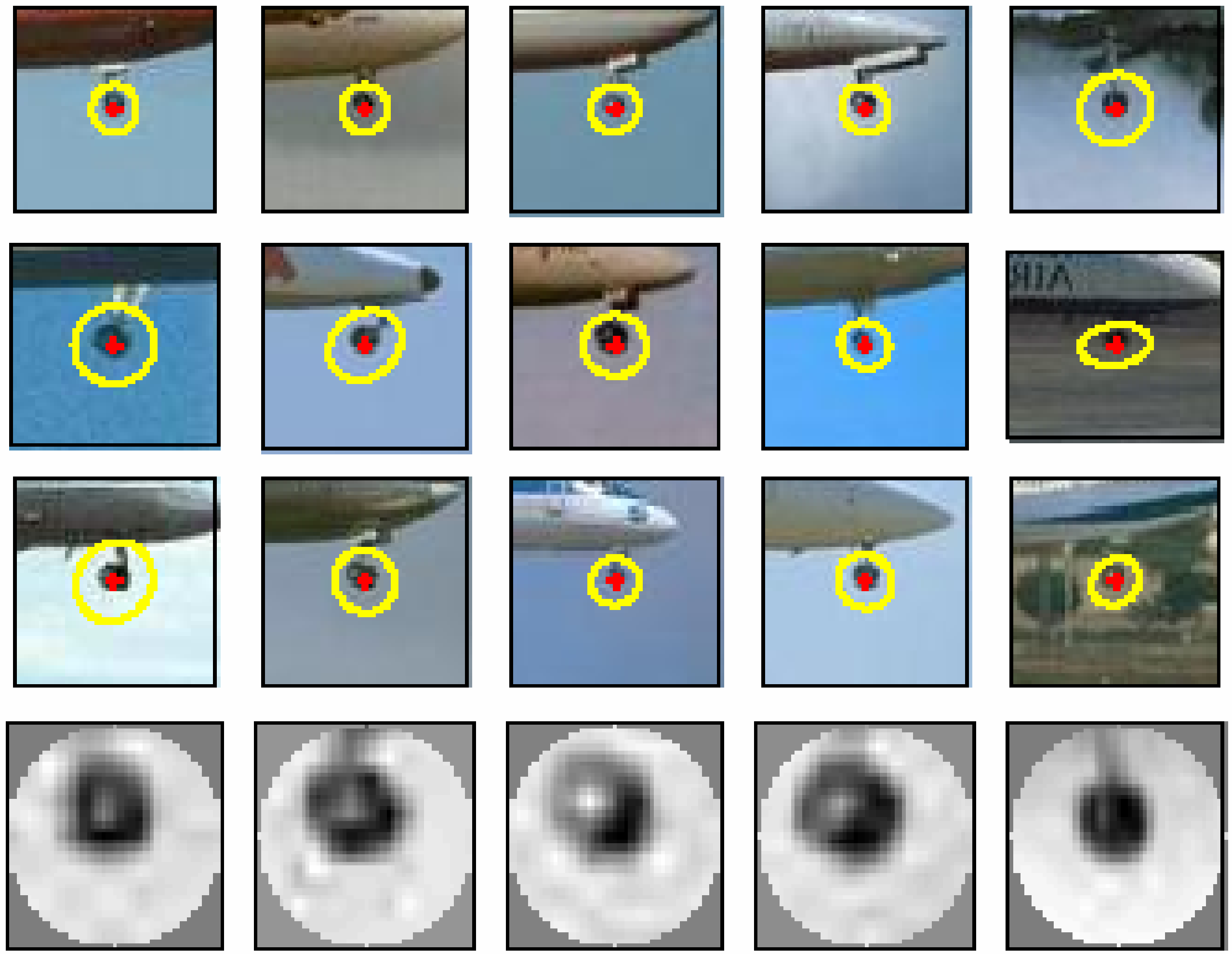
Design of descriptors makes these words invariant to:

- illumination
- affine transformations (viewpoint)

Size (granularity) of vocabulary is an important parameter

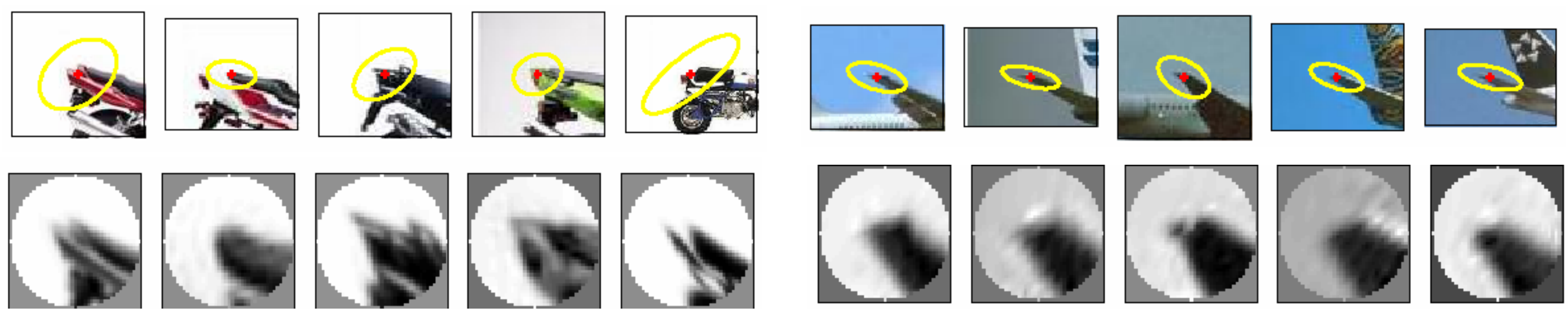
- fine grained – represent model instances
- coarse grained – represent object categories

Examples of visual words



More visual words

Visual synonyms and polysemy



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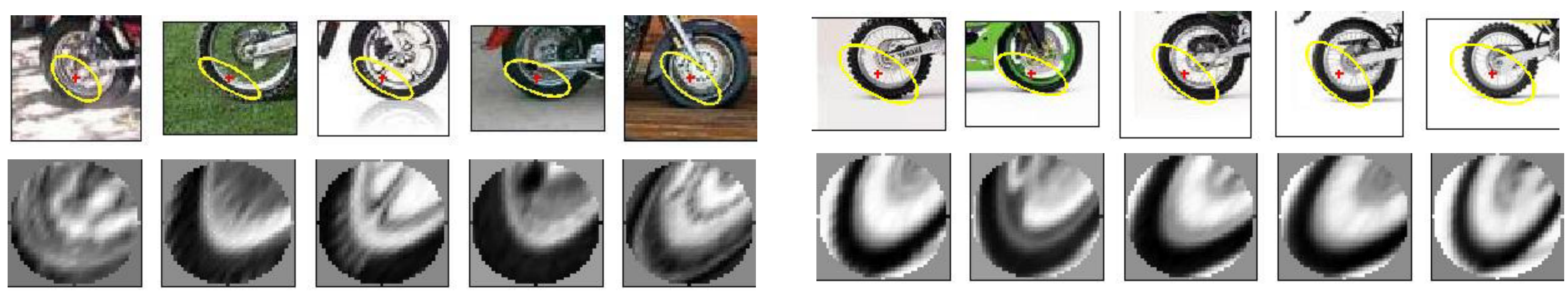
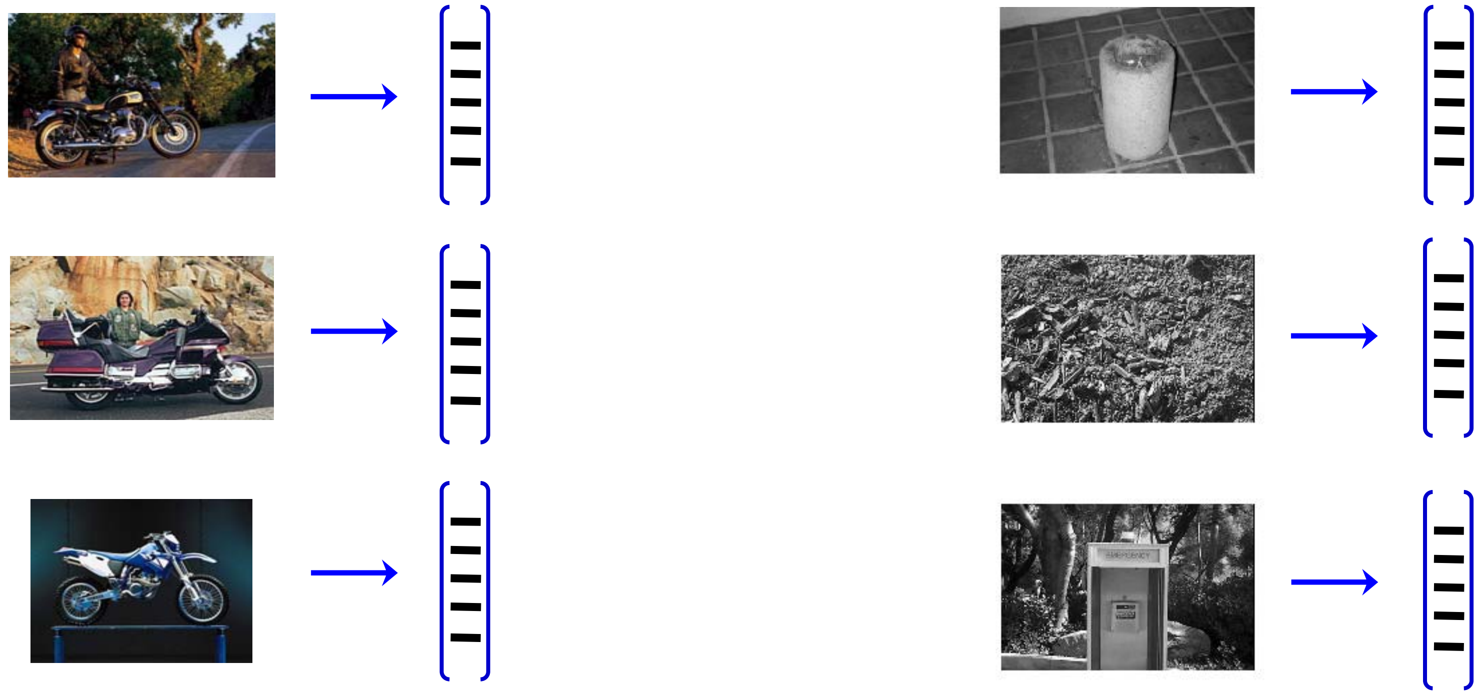


Visual Synonyms: Two different visual words representing a similar part of an object (wheel of a motorbike).

Training data: vectors are histograms, one from each training image

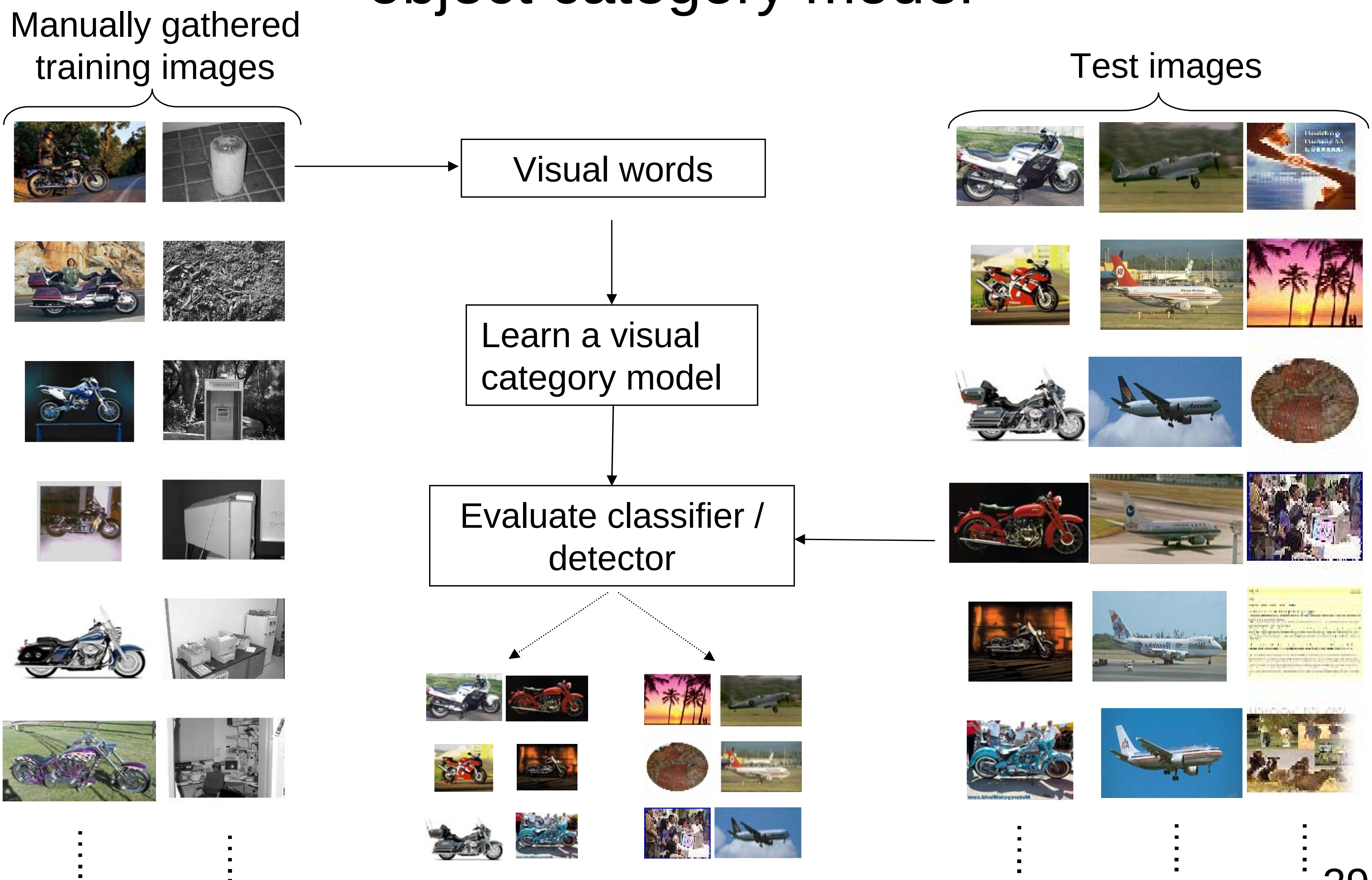
positive

negative



Train classifier,e.g.SVM

Current Paradigm for learning an object category model



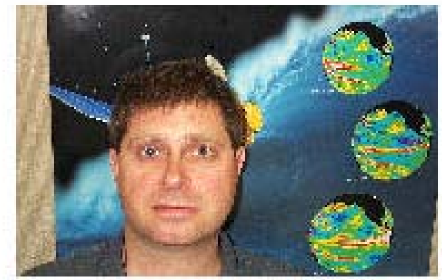
Example: weak supervision

Training
- 50% images
- No identifcation of object within image

Motorbikes

Airplanes

Frontal Faces



Testing
- 50% images
- Simple object present/absent test

Cars (Rear)

Background

Learning
- SVM classifier
- Gaussian kernel using χ^2 as distance between histograms

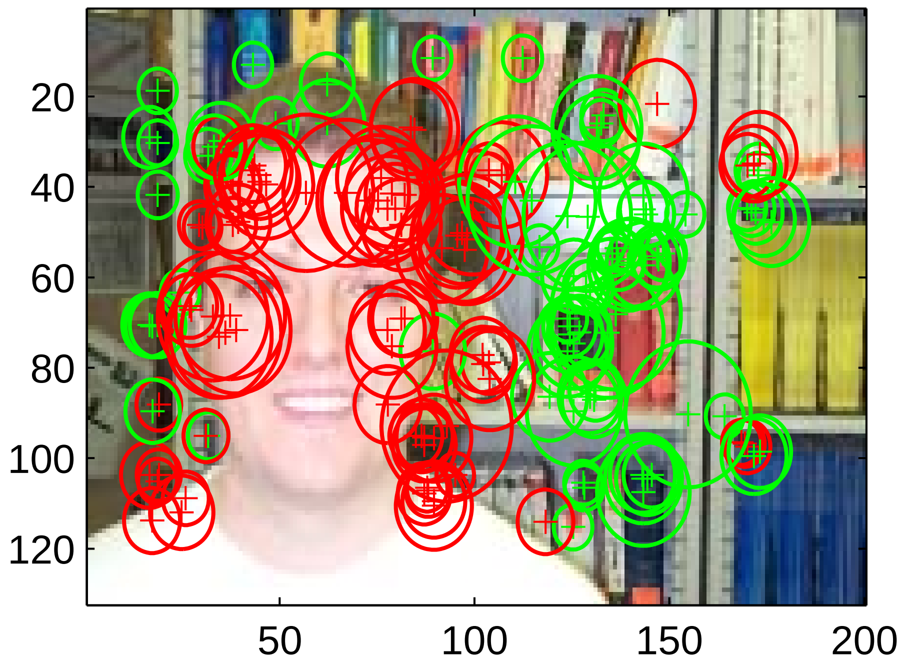
Result
- Between 98.3 – 100% correct, depending on class

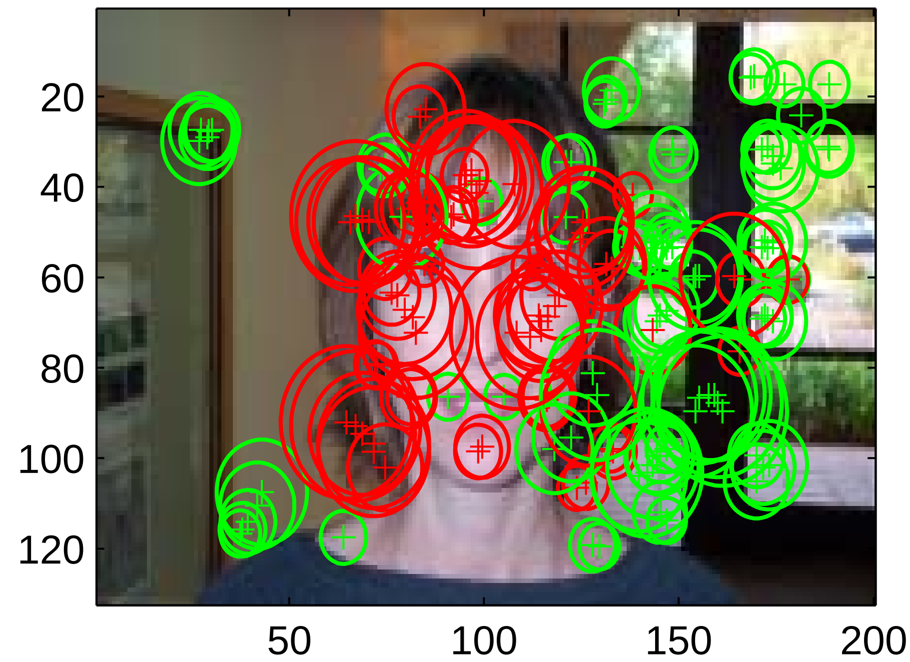
Csurka et al 2004

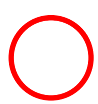
Zhang et al 2005

Localization according to visual word probability

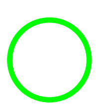
sparse segmentation







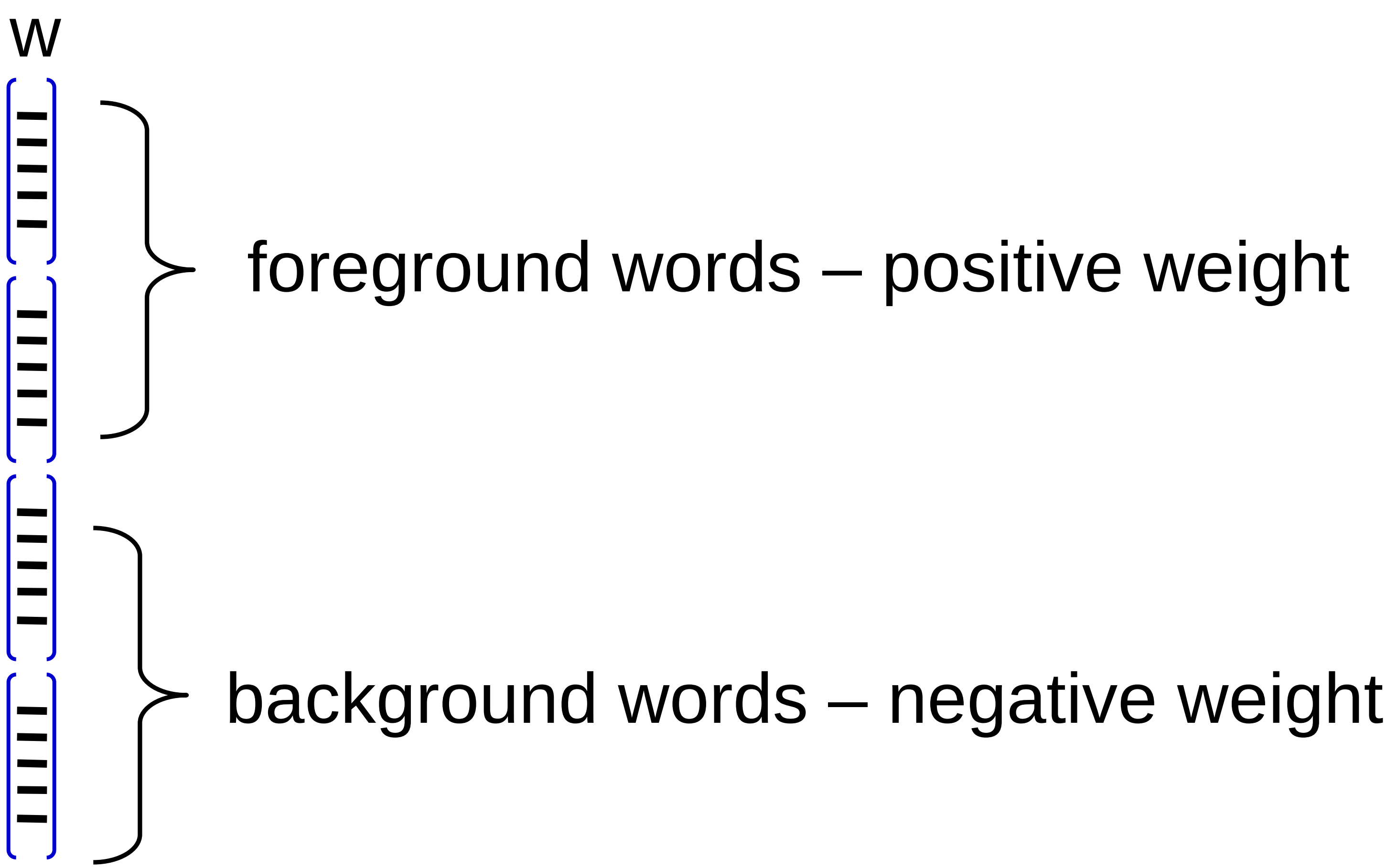
foreground word more probable



background word more probable

Why does SVM learning work?

- Learns foreground and background visual words



Bag of visual words summary

- Advantages:
  - largely unaffected by position and orientation of object in image
  - fixed length vector irrespective of number of detections
  - Very successful in classifying images according to the objects they contain
  - Still requires further testing for large changes in scale and viewpoint

- Disadvantages:
  - No explicit use of configuration of visual word positions
  - Poor at localizing objects within an image