



Master in Computer Vision *Barcelona*

Module 3: Machine learning for computer vision

Project: Bag of Visual Words Image Classification

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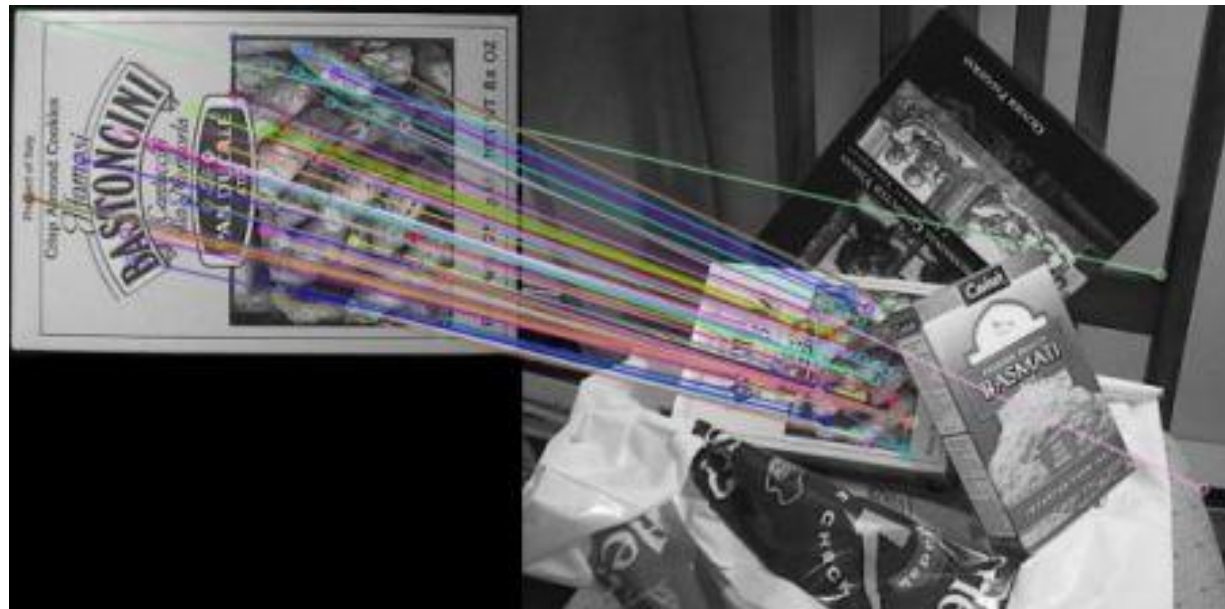
Preamble: Local descriptors

Local descriptors

- keypoint detection
- local description with strong invariance

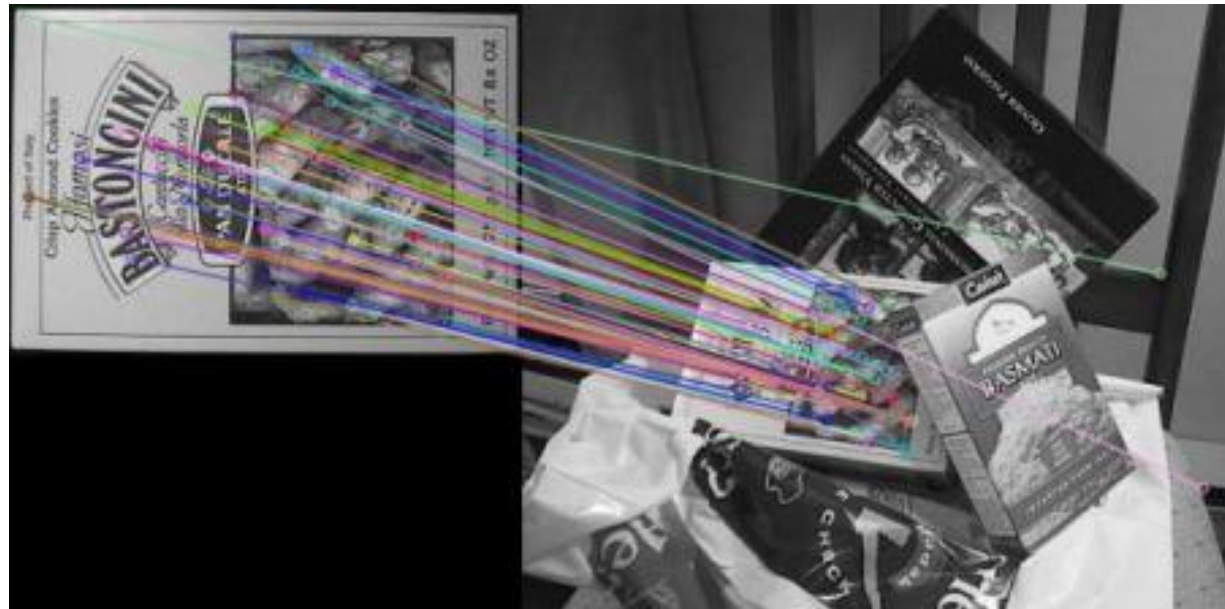
Object detection, localization, recognition, matching...

- Pair template objects within clutter environments



Preamble: Local descriptors

- SIFT (D. Lowe ICCV99, IJCV04)
- SURF,
- KAZE,
- BRIEF,
- BRISK,
- ORB...



Preamble: Local descriptors

Can we use such local features for image categorization?



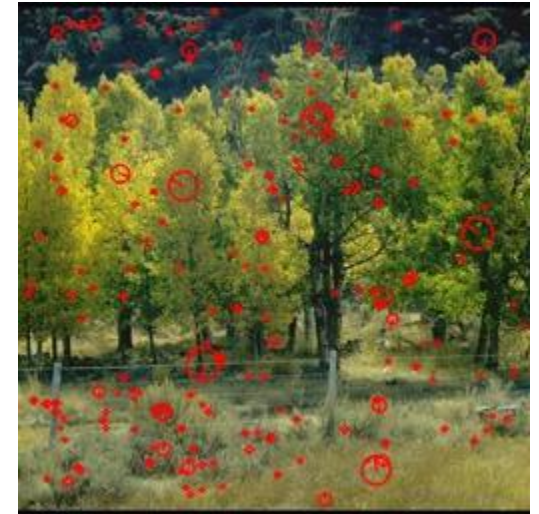
Preamble: Local descriptors

Use of local features (e.g. SIFT) for image categorization



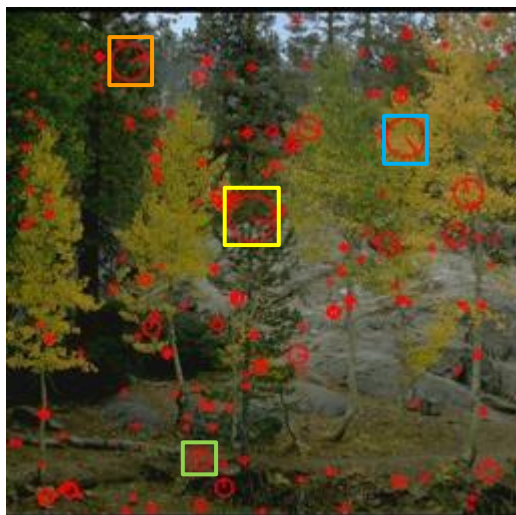
Robust local features:

- Scale
- Viewpoint
- Partial occlusions
- Noise



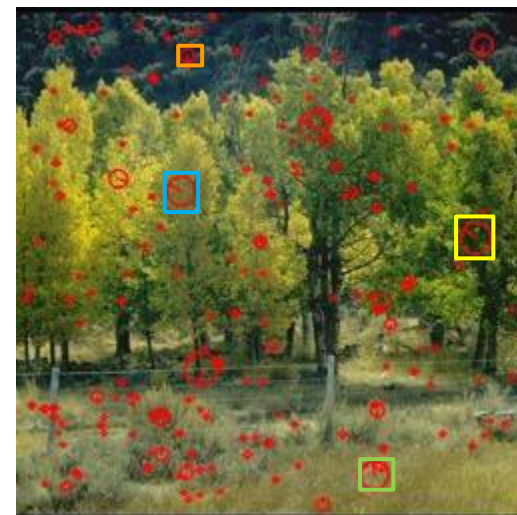
Preamble: Local descriptors

Use of local features for image categorization



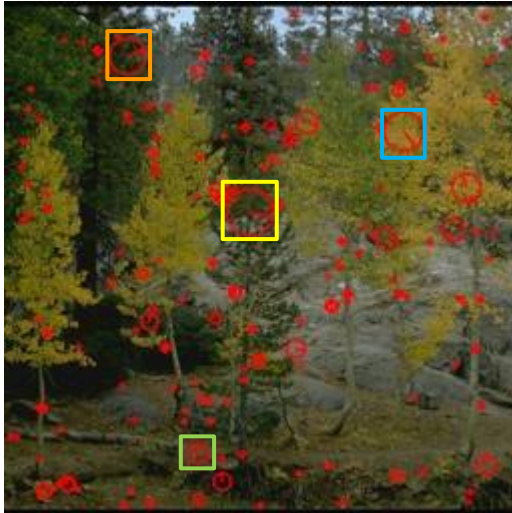
Basic assumption:

- Images of the same class have similar local descriptors



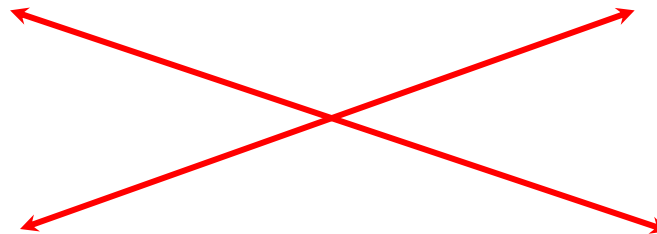
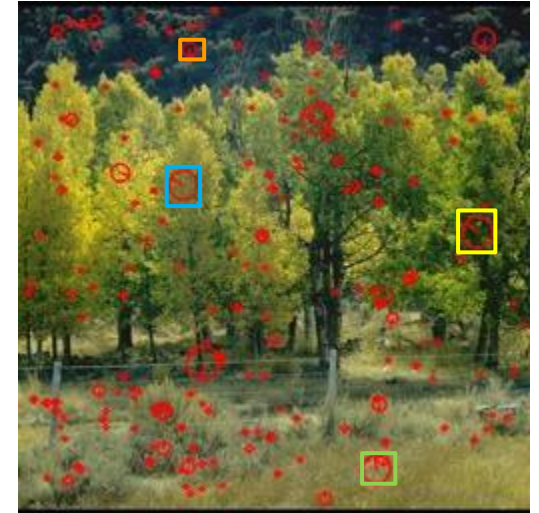
Preamble: Local descriptors

Use of local features for image categorization



Basic assumption:

- Images of the same class have similar local descriptors
- Images of different classes have different local descriptors

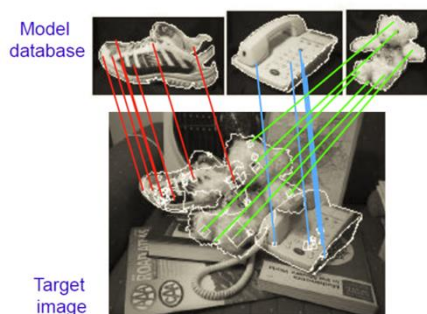


Motivation

Local features are well suited for image categorization

A generic approach could be:

1. Local feature extraction and description (ex. SIFT)
2. Matching local features based on similarity of local appearance
 - For every keypoint in one image find the closest keypoint (in the feature space) in the other image
 - Verify matches based on semi-local/global geometric relations



[D. Lowe, 1999]

D. Lowe. *Object Recognition from Local Scale-Invariant Features*. ICCV 1999

Motivation

Local features are well suited for image categorization

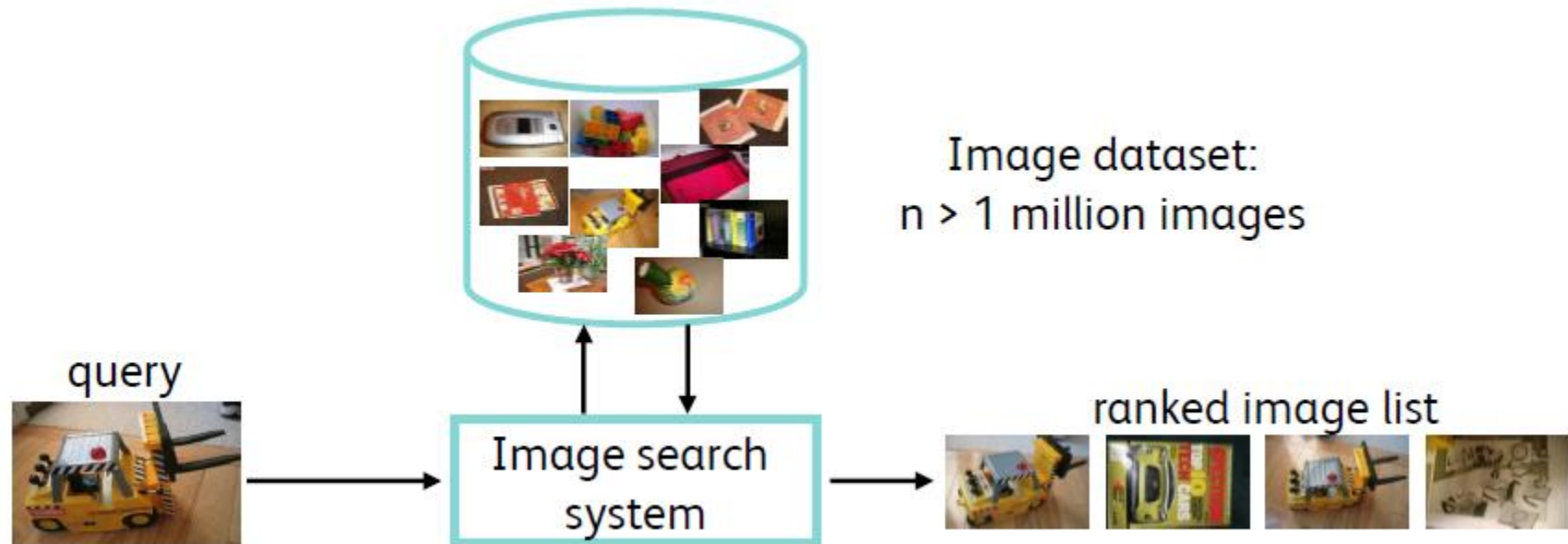
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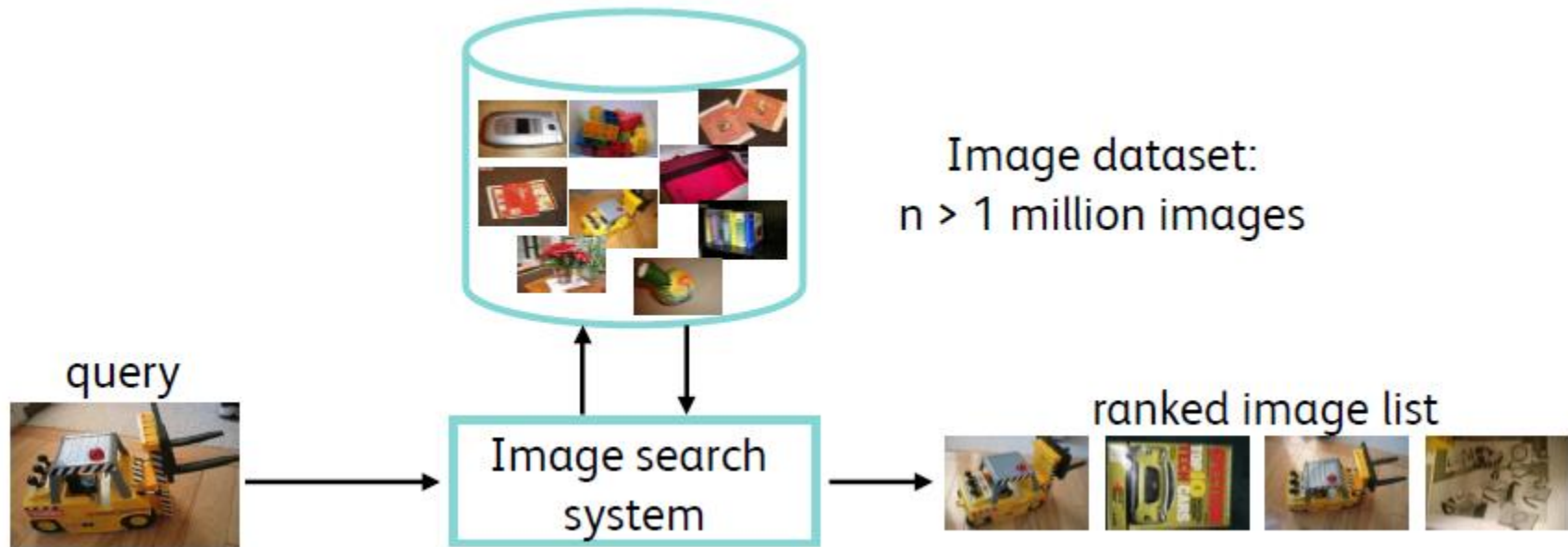
but...

- Difficult to scale with the number of classes
- Computationally expensive
- Not well suited for applying machine learning

Let's do some numbers...



Let's do some numbers...



- An image is described by $m=1000$ SIFT descriptors ($d=128$)
 - $n*m=1$ billion descriptors to index
- Database representation: 128 GB RAM
- Search $m^2 \times n \times d$ elementary operations!

Motivation

Local features are well suited for image categorization

A **generic approach** could be:

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... therefore, **better** if we can obtain a **global image representation** from the set of local features

Any thoughts??

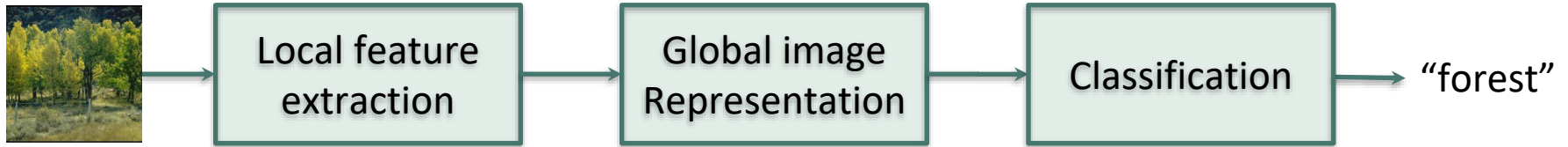
Can we use such local features for image categorization?

So that:

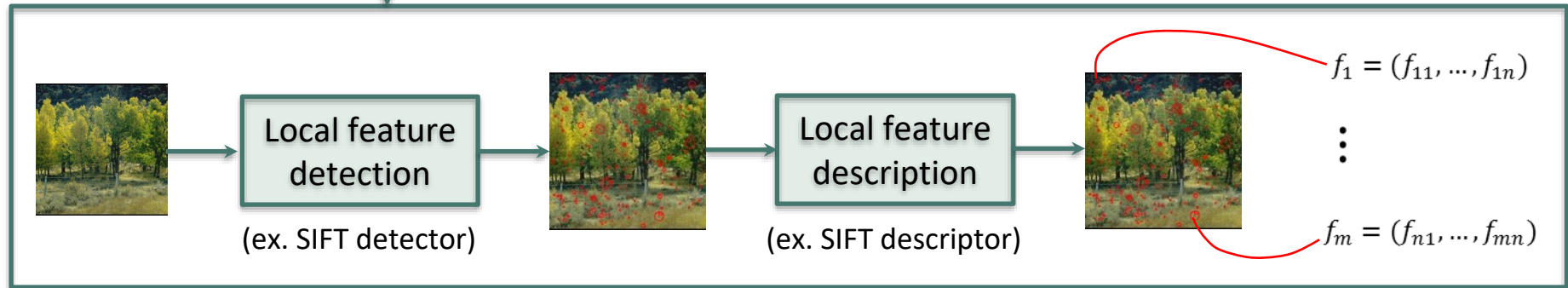
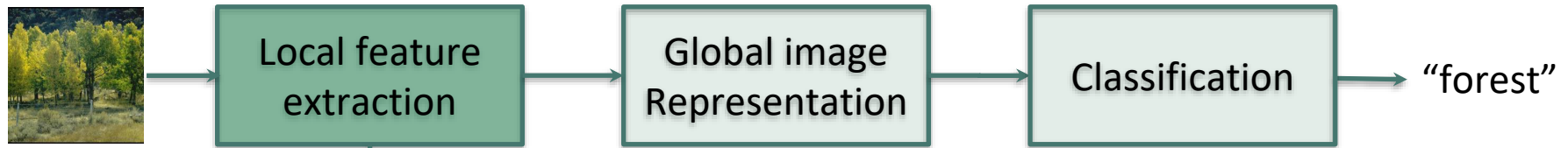
- keep discriminative power,
- we can scale,
- can apply statistical classifiers,
- ...

How can we go from a set of local descriptors to a single fixed-length global representation for each image?

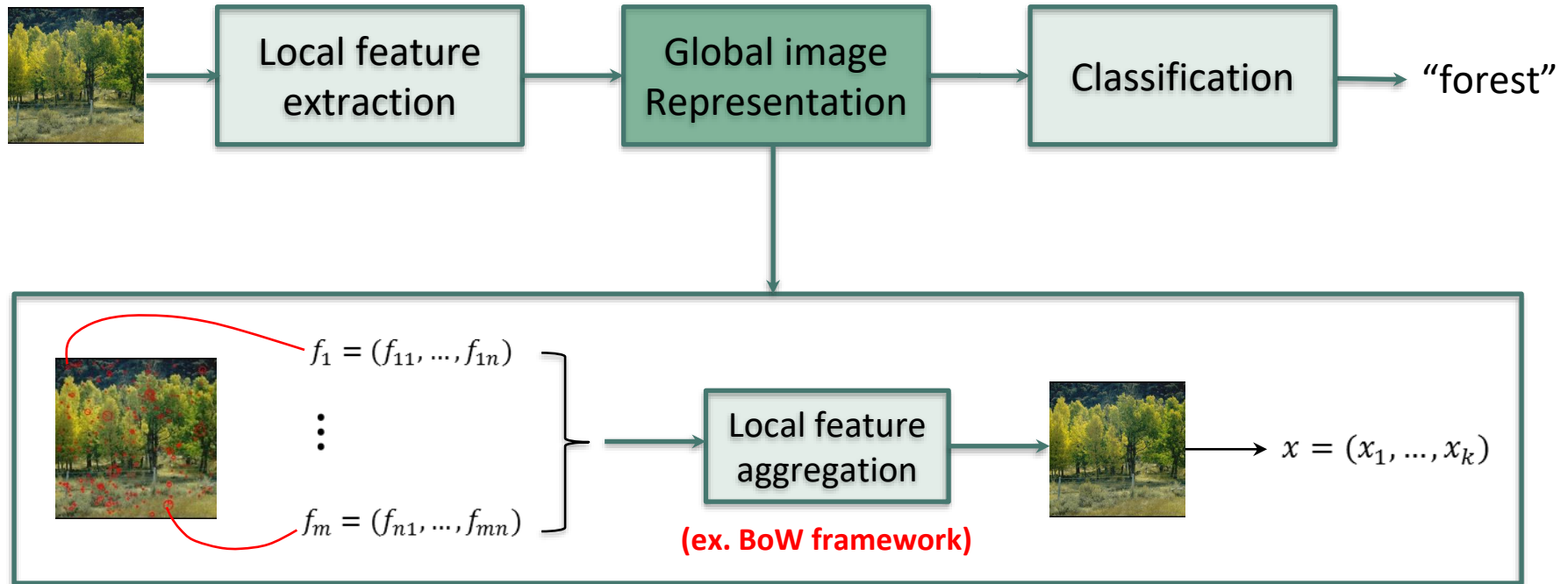
Pipeline for Image Categorization



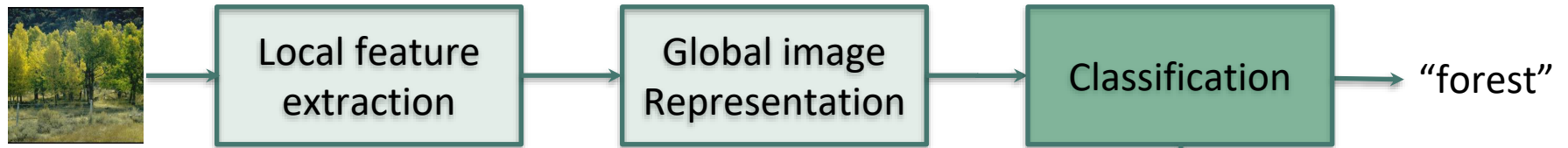
Pipeline for Image Categorization



Pipeline for Image Categorization

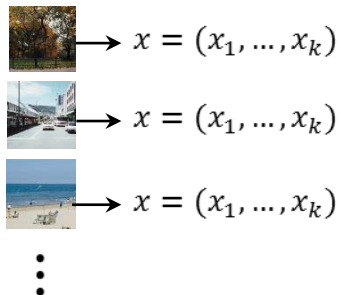


Pipeline for Image Categorization

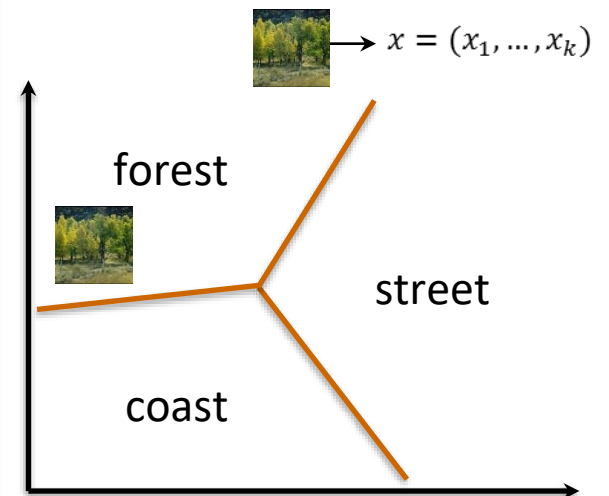


Training

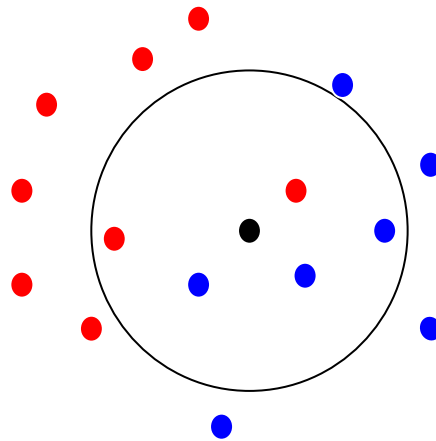
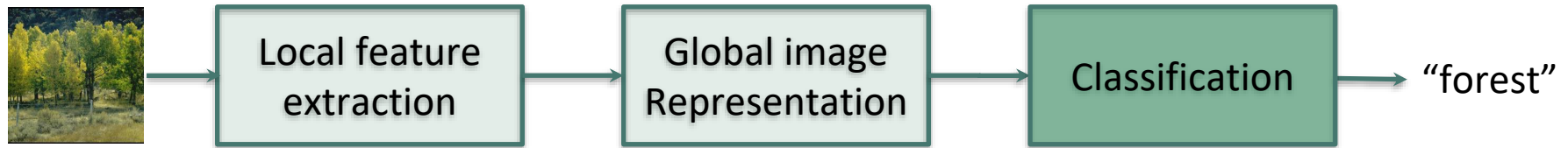
Training set



Test

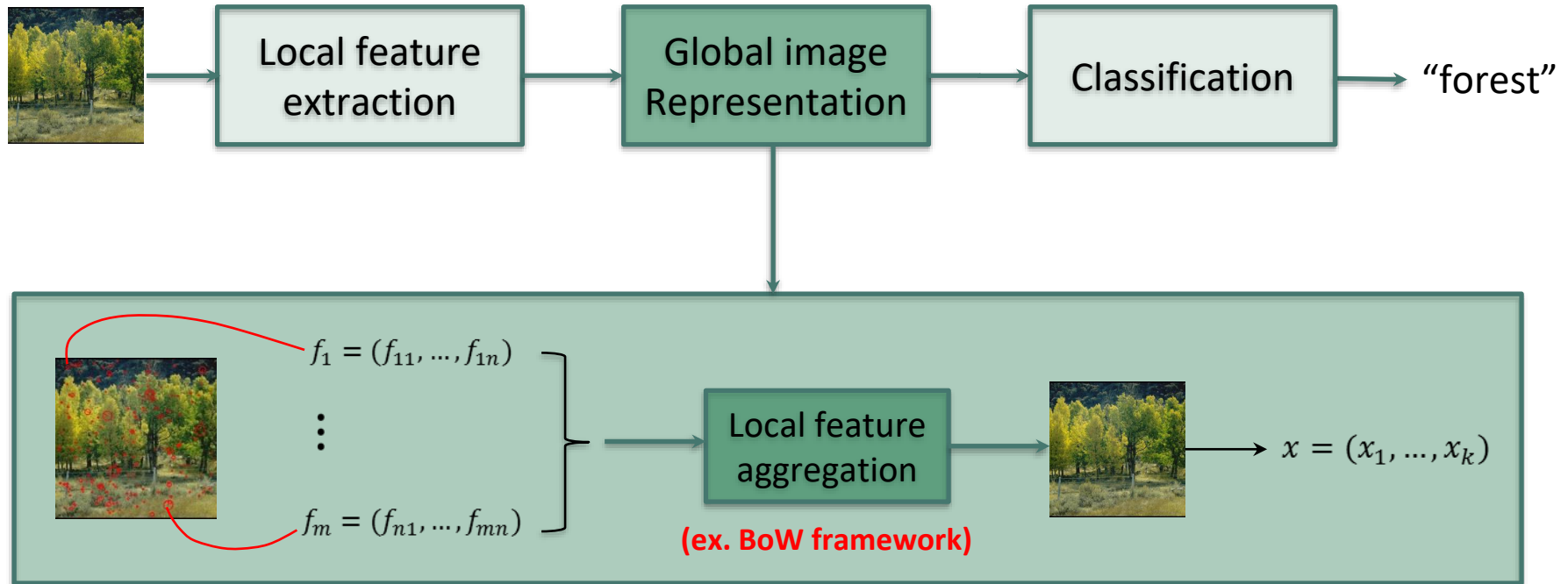


Pipeline for Image Categorization



k-NN classifier (for this first session), later on we will move to more powerful statistical classifiers (e.g. SVMs)

Image representation: The Bag of Words model



The Bag of Words model

Inspiration: document categorization

Just as humans use our eyes and brains to understand the world around us, computer vision tries to produce the same effect so that computers can perceive and understand an image or sequence of images and act as appropriate in a given situation. Data acquisition is achieved by various means such as image sequences, viewed from various video cameras, or multidimensional data from a medical scanner.

The sense of sight or vision is ensured by a receptor organ, the eye; a membrane, the retina, these receive the light impressions and transmit them to the brain through the optic pathways. The eye is a paired organ located in the orbital cavity. It is protected by the eyelids and by the secretion of the lacrimal gland. It is mobilized by a group of extrinsic muscles commanded by the motor nerves of the eye.

- Biology
- Computing

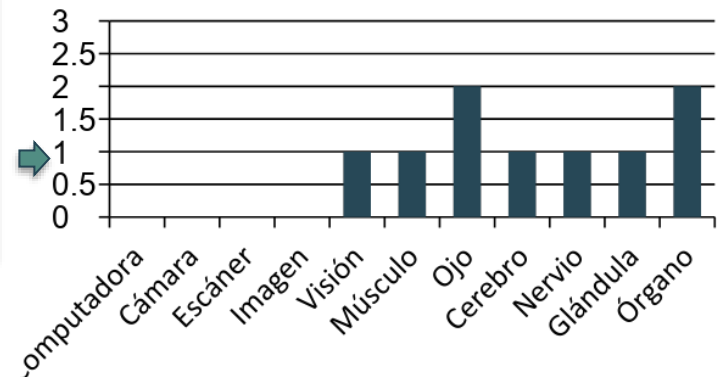
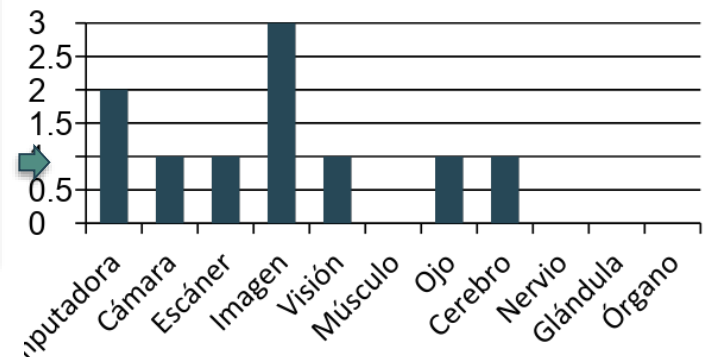
The Bag-of-Words model

Inspiration: document categorization

Tal y como los humanos usamos nuestros **ojos** y **cerebros** para comprender el mundo que nos rodea, la **visión por computador** trata de producir el mismo efecto para que las **computadoras** puedan percibir y comprender una **imagen** o secuencia de **imágenes** y actuar según convenga en una determinada situación. La adquisición de los datos se consigue por varios medios como secuencias de **imágenes**, vistas desde varias **cámaras** de video o datos multidimensionales desde un **escáner** médico.

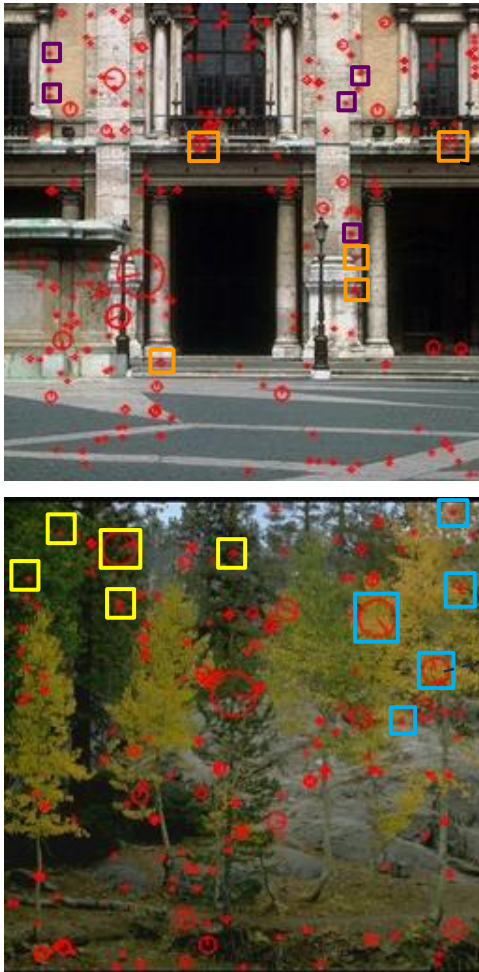
El sentido de la vista o **visión** está asegurado por un **órgano** receptor, el **ojo**; una membrana, la retina, estos reciben las impresiones luminosas y las transmite al **cerebro** por las vías ópticas. El **ojo** es un **órgano** par situado en la cavidad orbitaria. Está protegido por los párpados y por la secreción de la **glándula** lagrimal. Es movilizado por un grupo de **músculos** extrínsecos comandados por los **nervios** motores del ojo.

Histogram of representative words (Bag of Words)



The Bag of Words model

Adapting the model to visual recognition: *Bag of Visual Words*

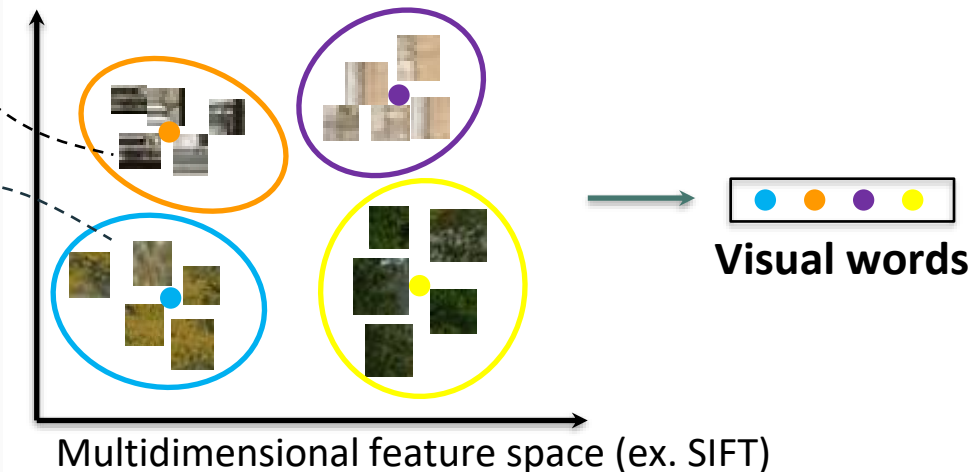


Training
data

- We do not have a predefined set of relevant visual features
- We must Identify relevant common visual features: *visual words*

Vocabulary learning

Unsupervised learning: *clustering*

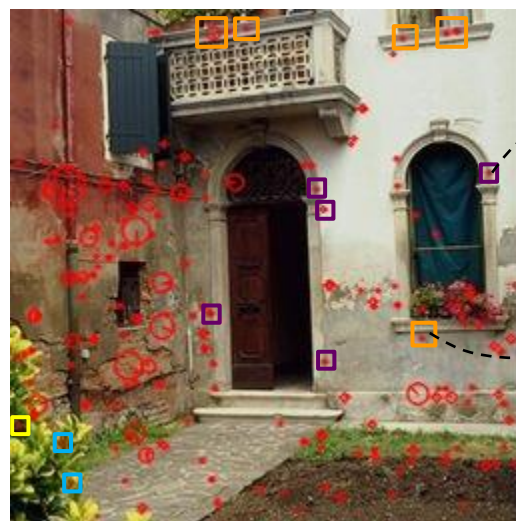


The Bag of Words model

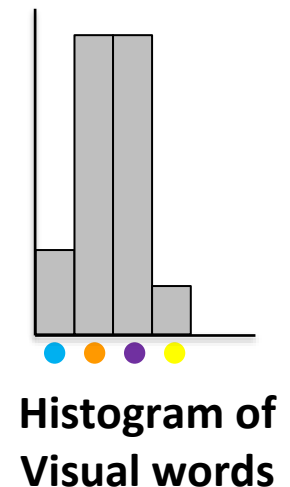
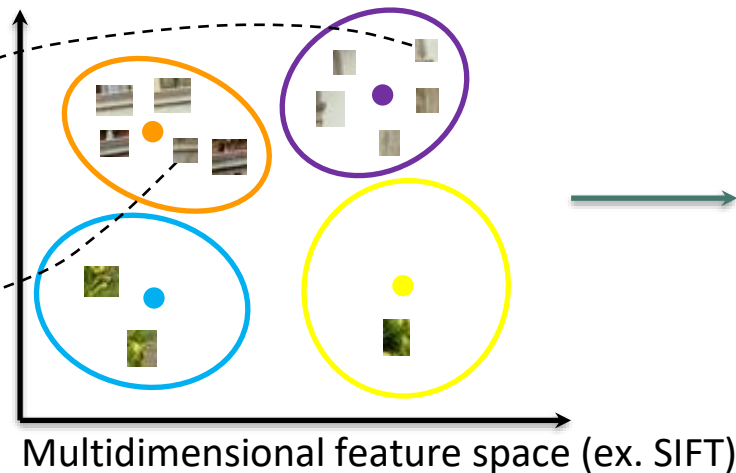
Adapting the model to visual recognition: *Bag of Visual Words*

- Every local feature in the image can be assigned to one visual word
- Image representation: histogram of *visual words*

Image representation



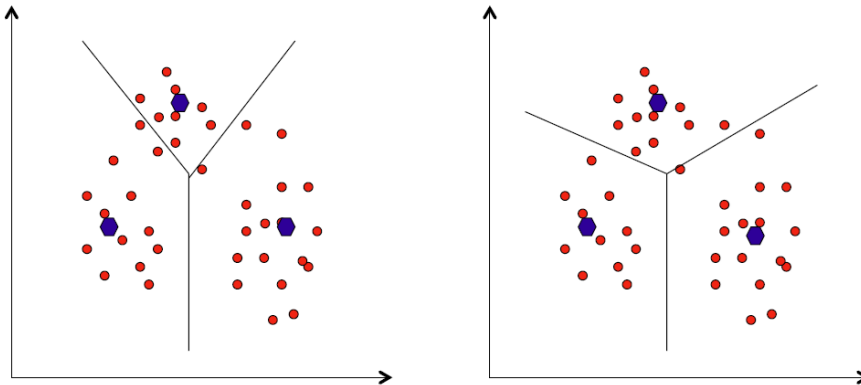
Feature encoding



Vocabulary learning

k-means algorithm (M 1 – Lecture 10)

■ K-means algorithm: example (II)

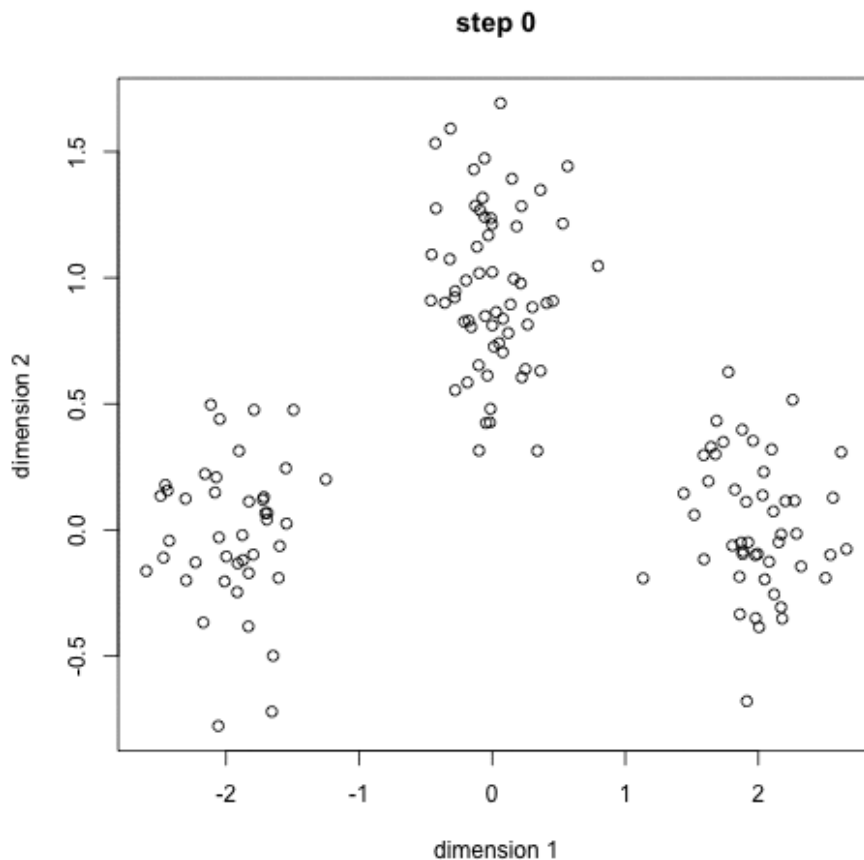


1. Initialize K classes. Compute the centers of each class
2. For each point:
 - a. Compute the distances between the point and the class centers
 - b. Assign the point to the closest class
3. Update the class centers
4. Repeat 2 & 3 until no change (in assignments or center values) is observed.

Max Lloyd algorithm

Vocabulary learning

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Max Lloyd algorithm

BoVW recap

group image
samples



BoVW recap

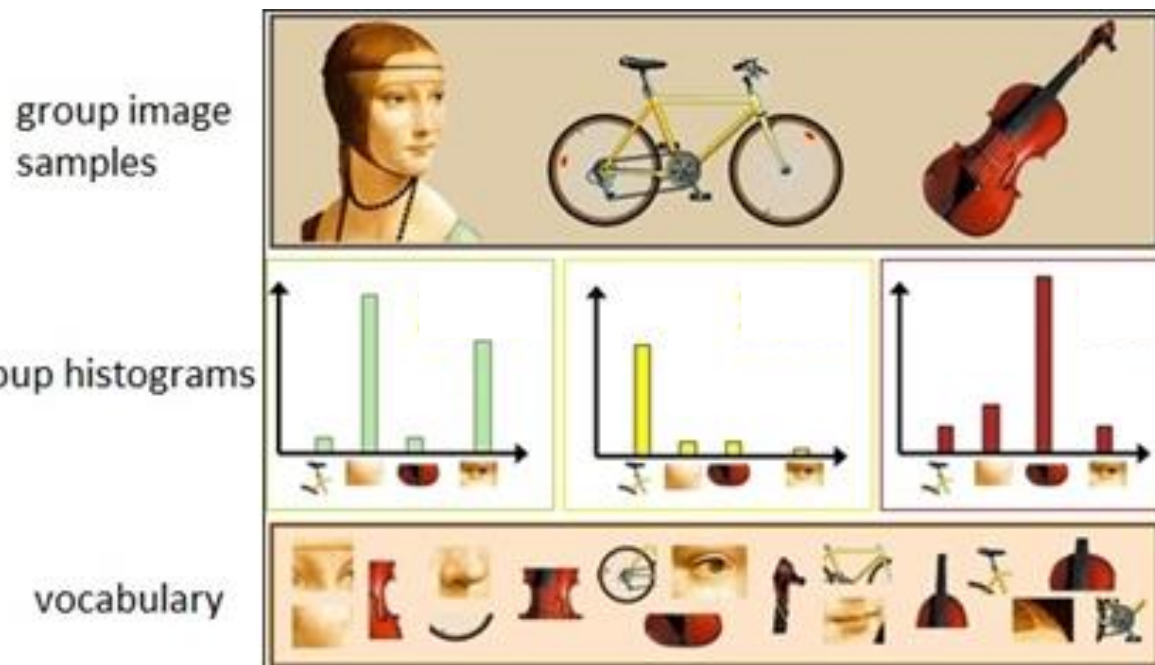
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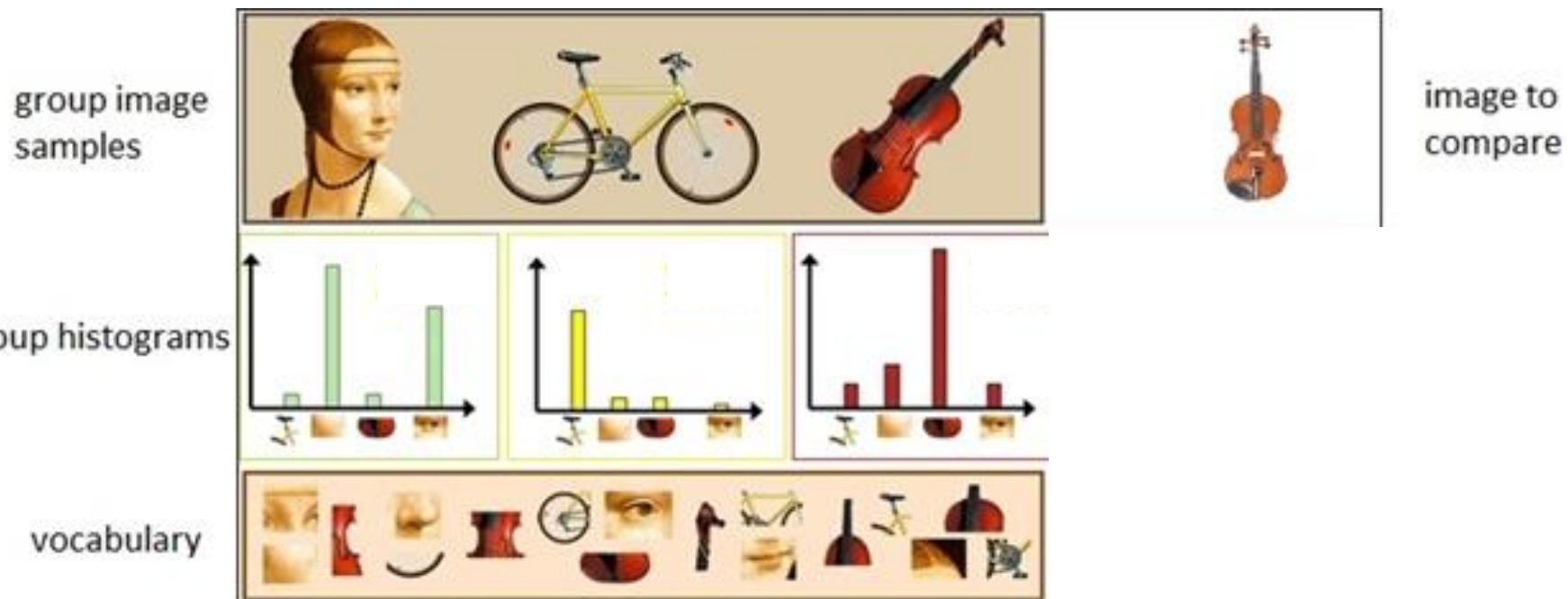
vocabulary



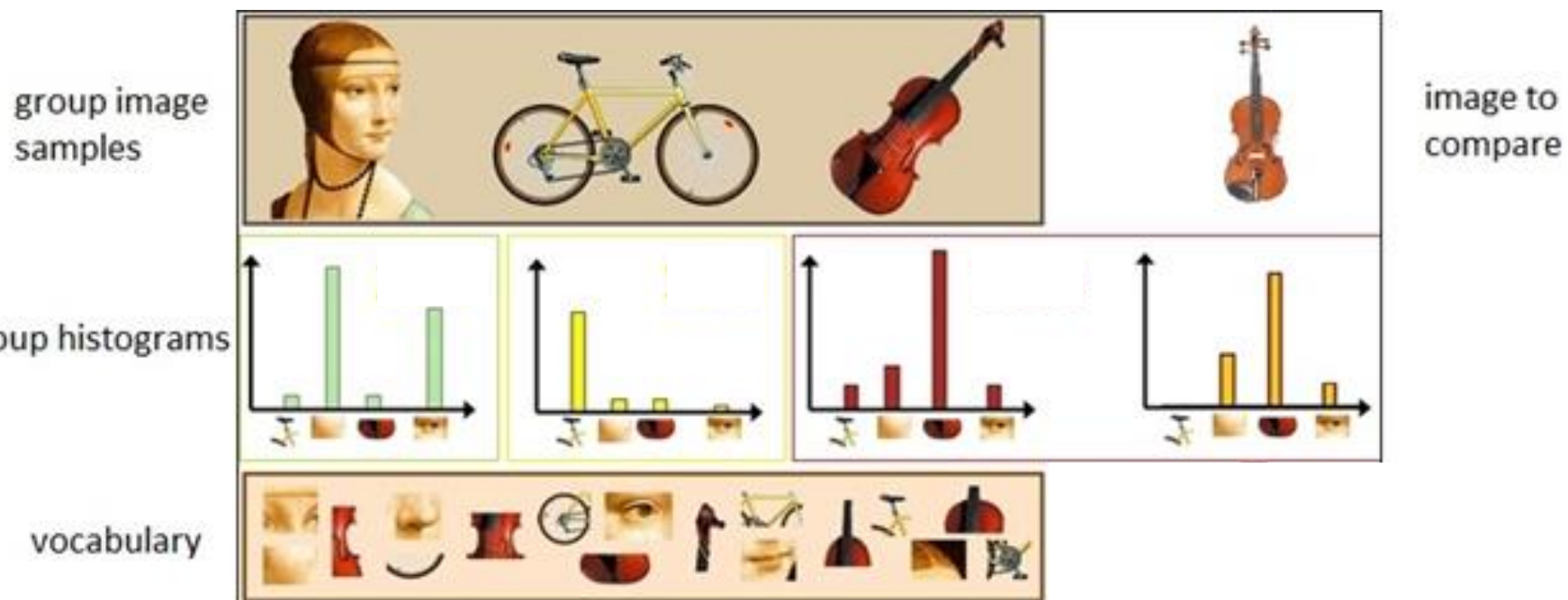
BoVW recap



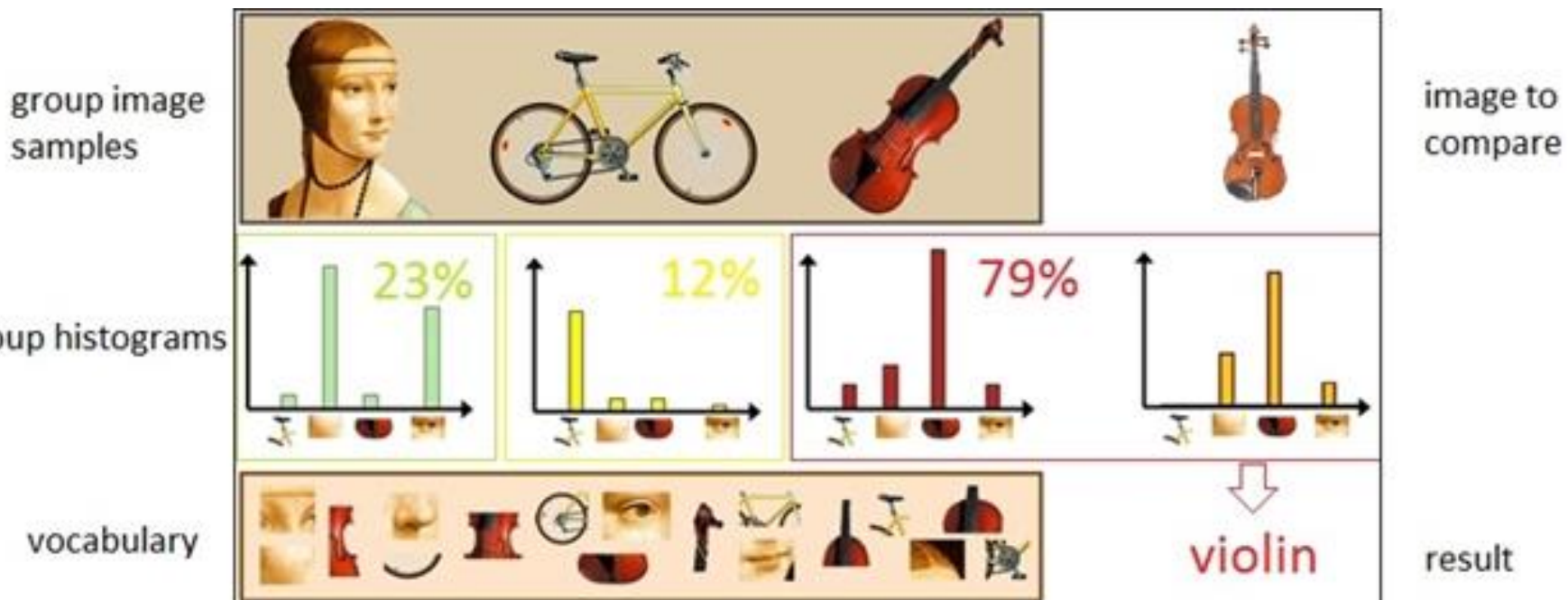
BoVW recap



BoVW recap



BoVW recap



WAKE UP!! Surprise test!!

- Would it be a good idea to use the BoVW framework as explained using the ORB local descriptors? Why?

WAKE UP!! Surprise test!!

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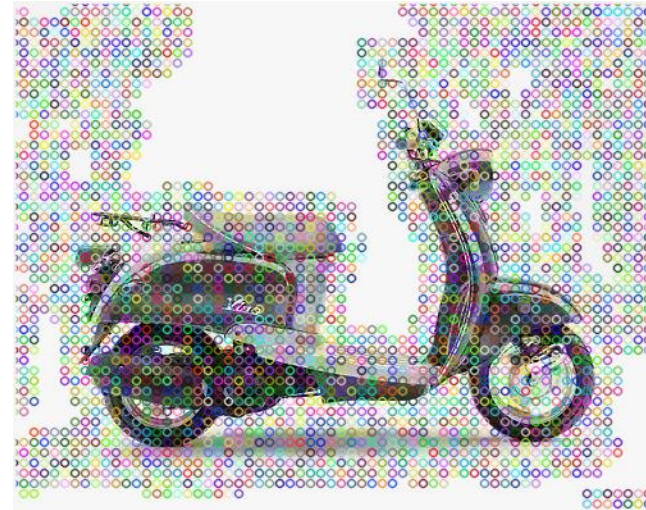
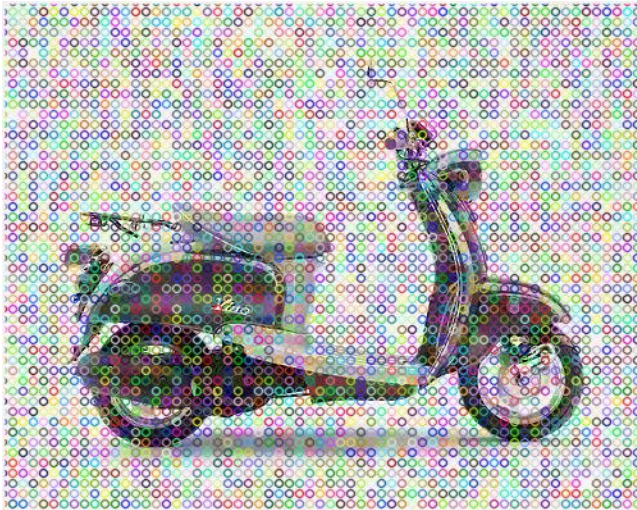
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- Is there any way of performing well (i.e. have a good description) in images where the keypoint detector step tend to perform poorly (e.g. low textures, or repetitive patterns)?

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- What kind of information is lost when using the BoVW framework compared to local keypoint matching? is there any way of include it in a coarse manner?

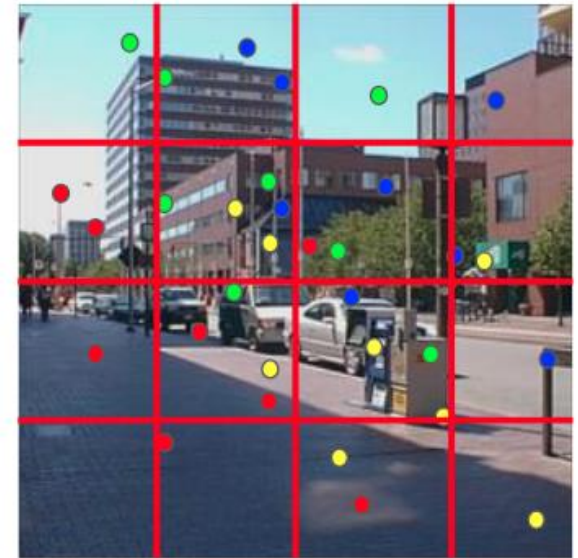
Beyond BoVW: Dense SIFT

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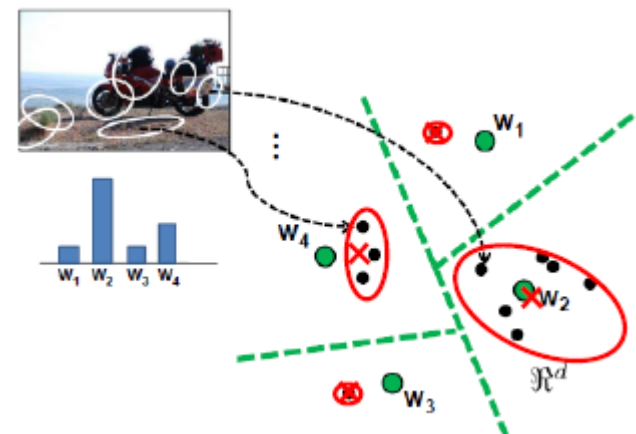
Beyond BoVW: Spatial Pyramids

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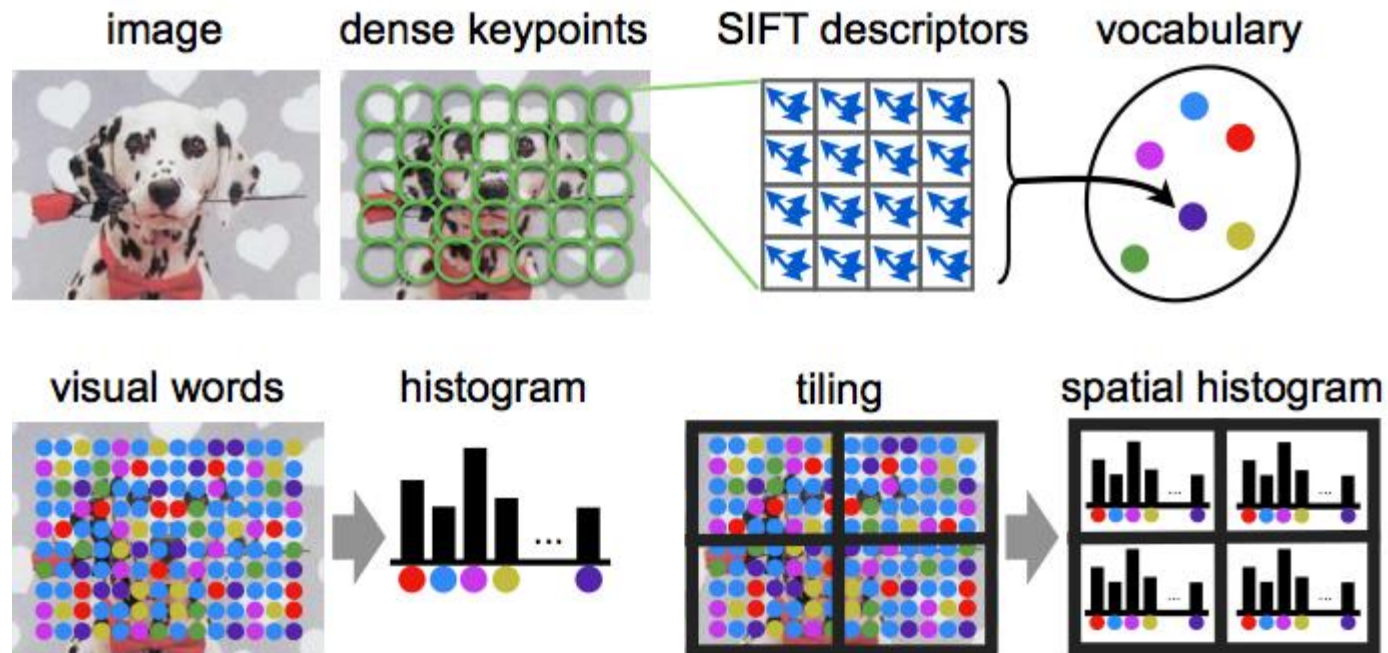
Beyond BoVW: Fisher Vectors

- BoVW is only counting the number of local descriptors assigned to each Voronoi cell
- Why not including higher order statistics?
 - Mean of local descriptors
 - Co-variance of local descriptors
- FV is typically $2 \times D \times k$ dimensional

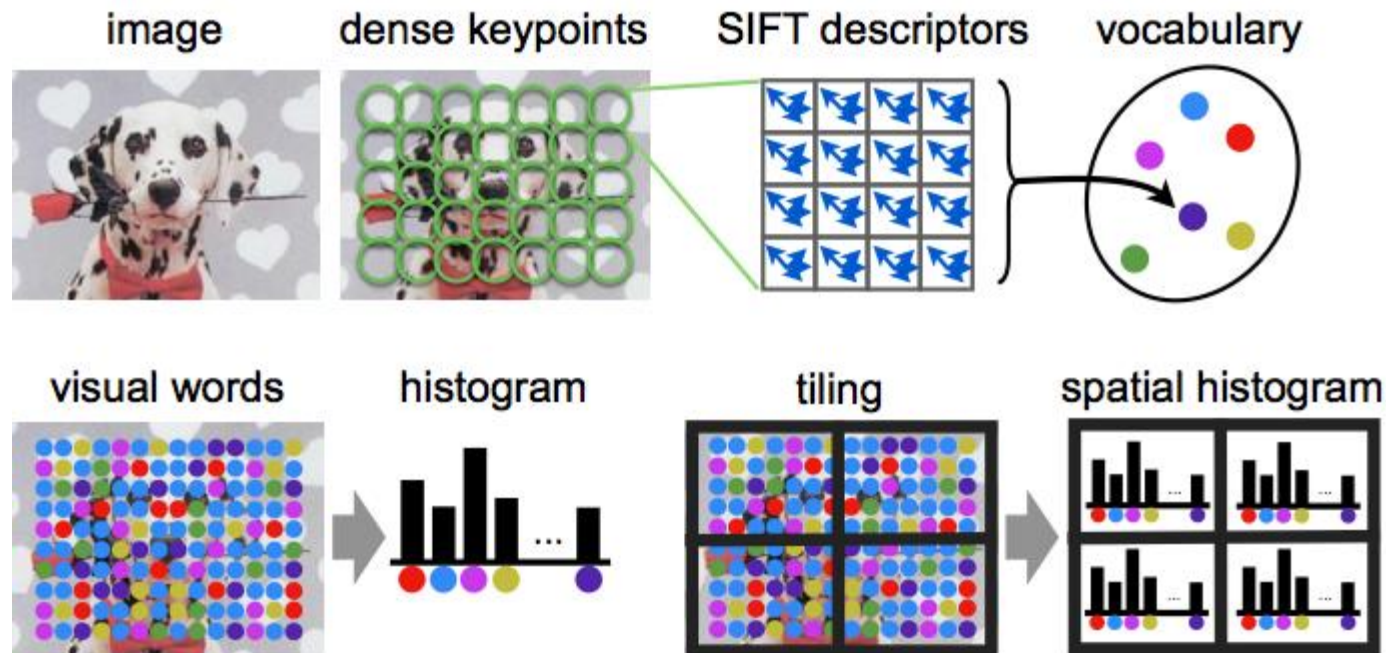


Slide credit: F. Perronnin. Features for Large-Scale Visual Recognition

Everything together

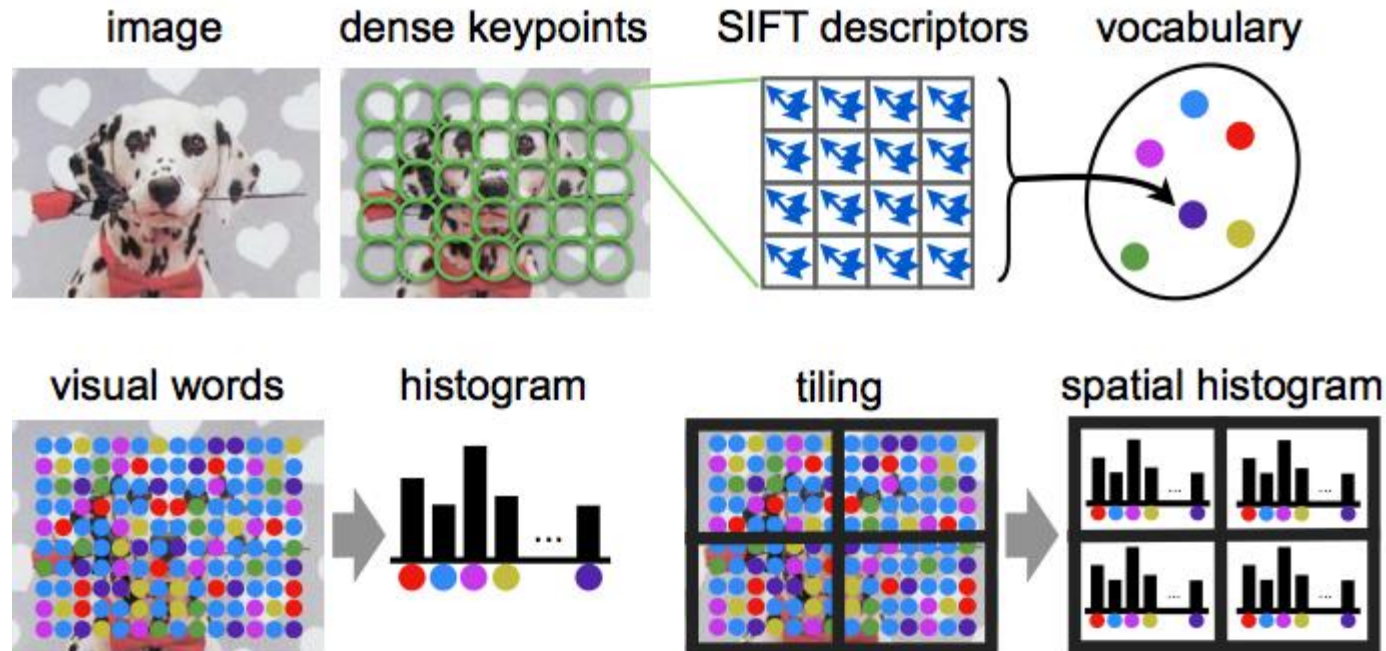


Everything together



- Image 512 x 512
- Dense SIFT extracted every 2 pixels, at 4 different scales
 - $256 \times 256 \times 4 = 262.144$ descriptors per image...
- If we have 1M images in the dataset, how to compute the vocabulary?

Everything together



- $k = 2048$
- 1 level Spatial Pyramid
- BoVW dimension: $2048 \times 5 = 10.240$
- FV dimension:

$2 \times 128 \times 2048 \times 5$	$= 2.621.440$
$2 \times 128 \times 32 \times 5$	$= 40.960$ (reducing k)
$2 \times 64 \times 32 \times 5$	$= 20.480$ (reducing SIFT dims)

Dimensionality Reduction

Goal: represent samples with fewer features

- Try to preserve as much **structure** in the data as possible

Feature selection

- Pick a subset of the original dimensions
- E.g. using information gain to decide which features to pick
- You are throwing out some of the features

Feature extraction

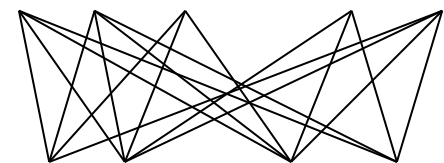
- Construct a new set of k features (with $k < n$) combining existing ones
- The i^{th} feature given by: $z_i = f(x_1, x_2, \dots, x_n)$
- The easiest way is by linearly combining the original features

$x_1, x_2, x_3, \dots, x_{n-1}, x_n$



$x_1, \mathbf{x}_2, x_3, \dots, x_{n-1}, \mathbf{x}_n$

$x_1, x_2, x_3, \dots, x_{n-1}, x_n$

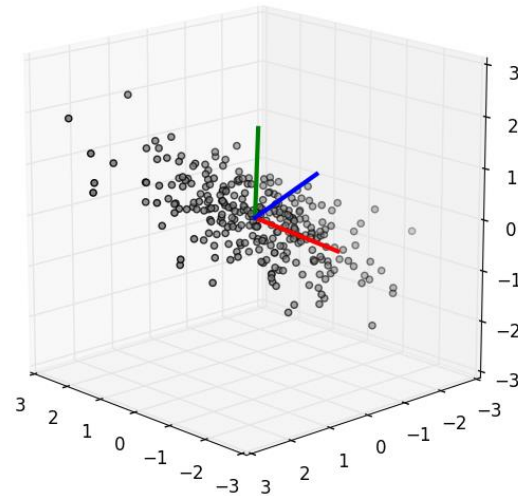
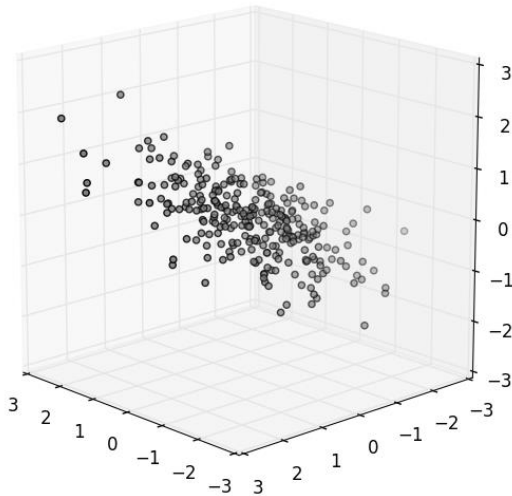


$z_1, z_2, \dots, z_{k-1}, z_k$

Principal Component Analysis

PCA defines a set of principal components (a new set of dimensions, a new set of features)

- 1st dimension: direction of the greatest variability in the data
- 2nd dimension: perpendicular to the 1st, greatest variability of what's left to explain
- 3rd dimension: perpendicular to all the previous ones, greatest variability of what's left to explain
- ... and so on until n (the original dimensionality)



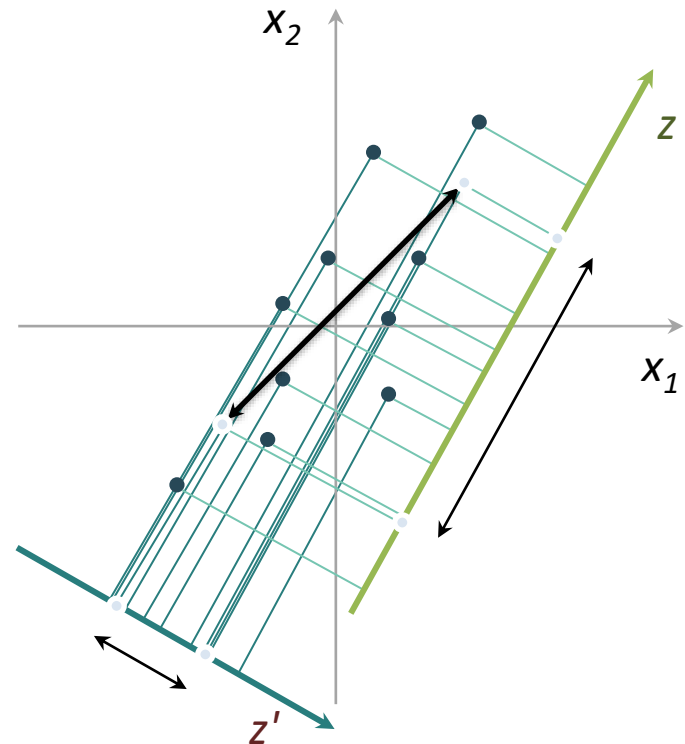
Why maximum variability

An example, reducing from \mathbb{R}^2 to \mathbb{R}^1

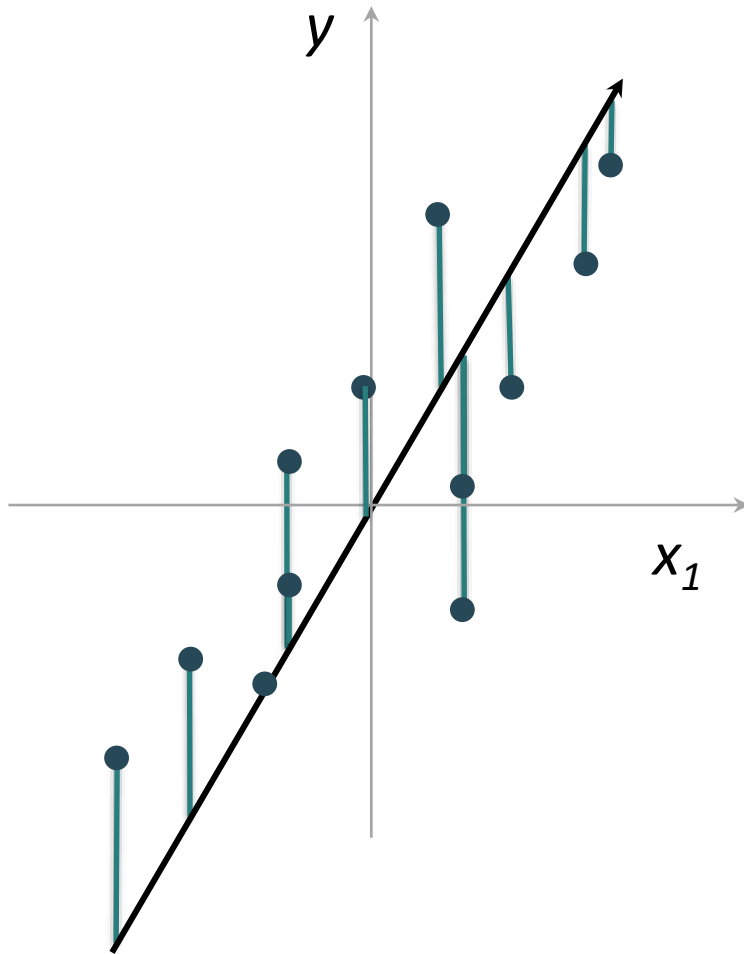
If we pick a direction z that maximises variability (green in the plot), it will maintain to a certain degree the relative distance between points in the original space:

If two points are far in the original (x_1, x_2) -space, they will most probably be far in the new (z) -space

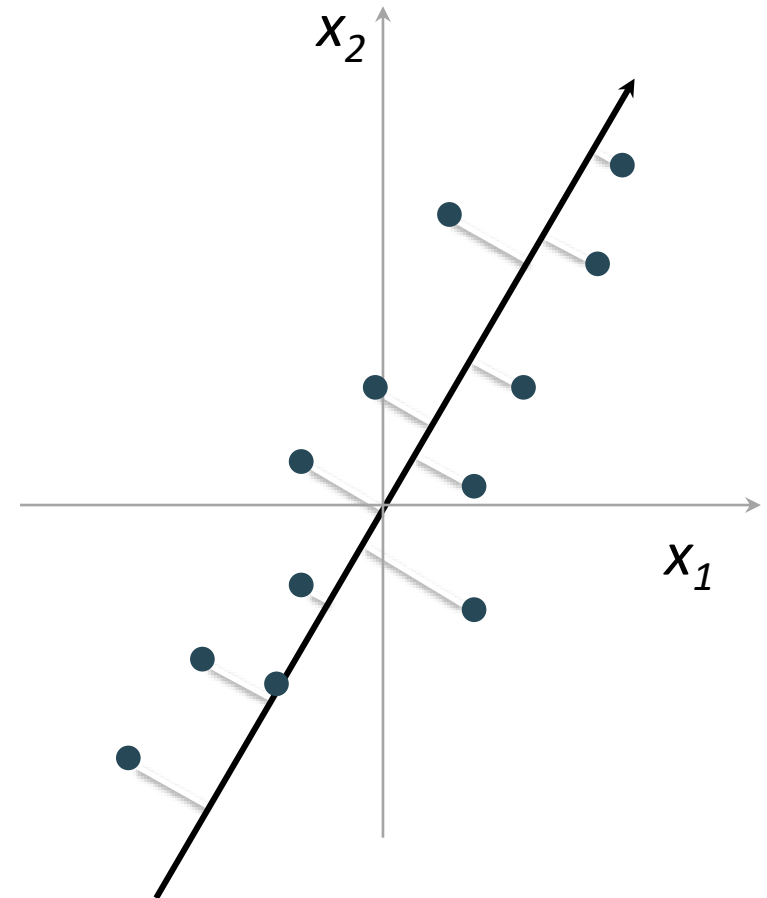
If we pick any other direction z' the relative distance between points in the original space is not preserved so well.



PCA is not linear regression



Linear regression



PCA

PCA algorithm summary

1. We start with correlated, high-dimensional data, $x \in \mathbb{R}^n$
2. Centre the points (optionally scale the features)
3. Compute the covariance matrix
4. Find the eigenvectors and the eigenvalues of the covariance matrix (e.g. using SVD)
5. Pick the $k \ll n$ eigenvectors with the highest eigenvalues
6. Project data points to the selected eigenvectors
7. Obtain uncorrelated low-dimensional data, $z \in \mathbb{R}^k$

PCA and classification

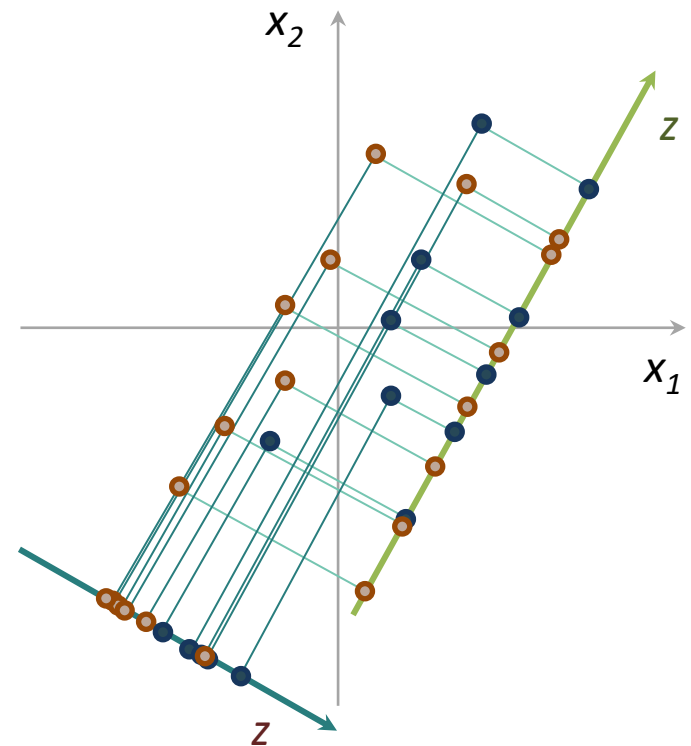
PCA can sometimes hurt instead of help, as it does not take into account the class labels

PCA is unsupervised

- Maximises overall variance along a small set of directions
- Does not know anything about class labels

Discriminative approach

- Look for a dimension that makes it easy to separate classes



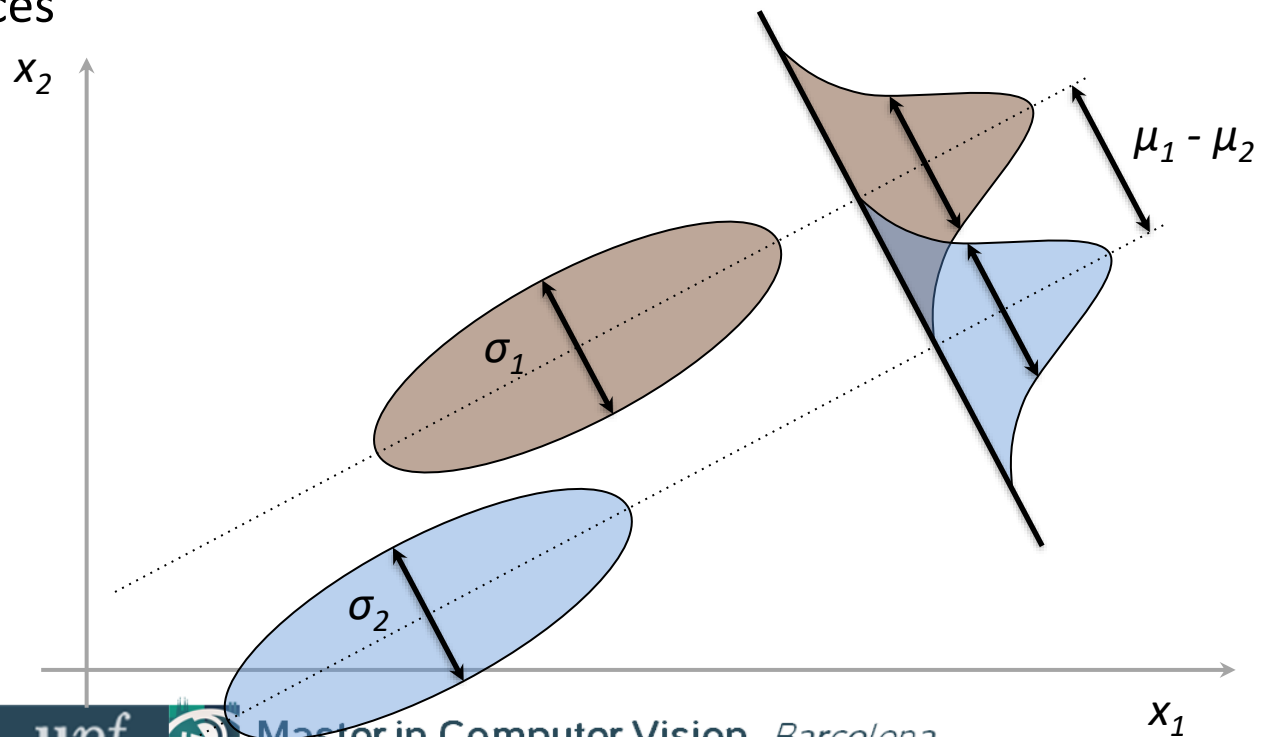
Linear Discriminant Analysis

LDA picks a new dimension that gives:

- Maximum separation between means of projected classes
- Minimum variance within each projected class

Solution: eigenvectors based on between-class and within-class covariance matrices

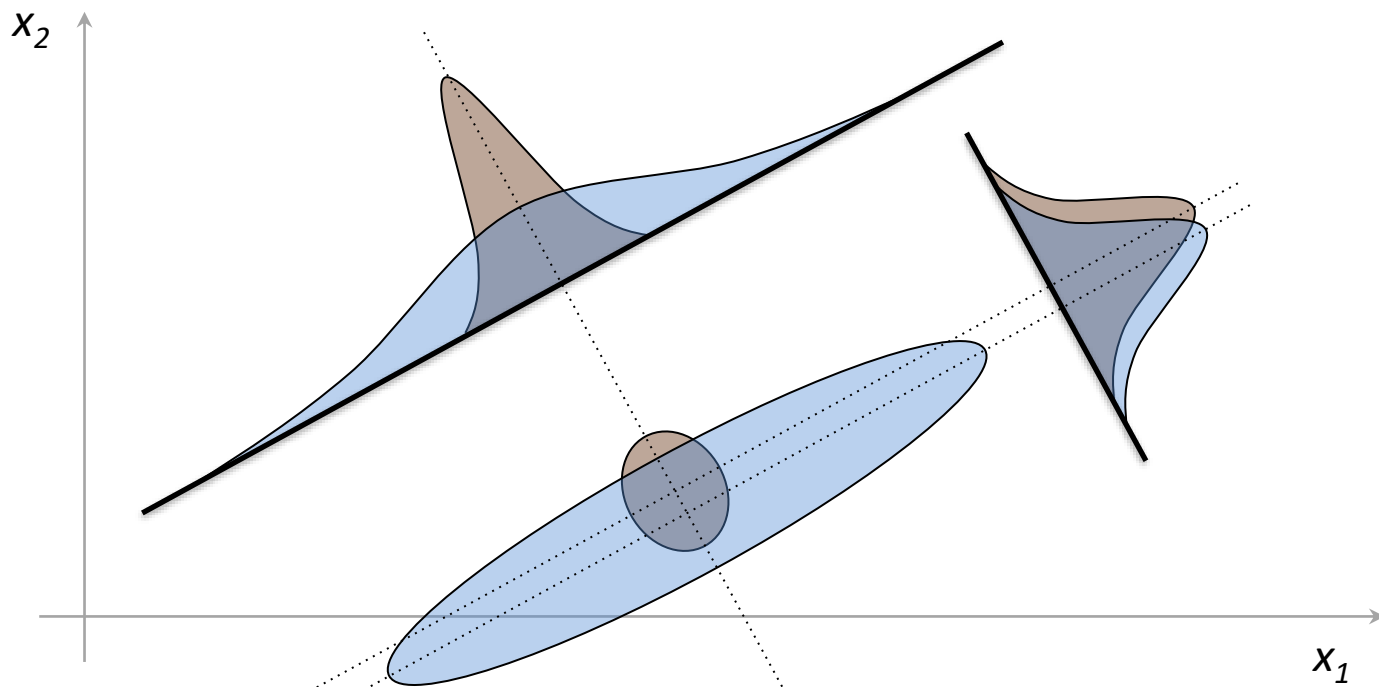
$$\max \frac{(\mu_1 - \mu_2)^2}{\sigma_1^2 + \sigma_2^2}$$



Linear Discriminant Analysis

LDA is not guaranteed to be better for classification

- Assumes that distributions are unimodal Gaussians
- Assumes that they are separable
- Fails when the discriminatory information is not in the mean but in the variance of the data



References

- D. Lowe. *Object Recognition from Local Scale-Invariant Features*. ICCV 1999
- D. Lowe. *Distinctive Image Features from Scale-Invariant Keypoints*. IJCV 2004
- E. Nowak, F. Jurie, B. Triggs. *Sampling Strategies for Bag-of-Features Image Classification*. ECCV'06
- J. Sivic and A. Zisserman. *Video Google: A Text Retrieval Approach to Object Matching in Videos*. ICCV 2003.
- F. Perronnin, C. Dance, G. Csurka, M. Bressan. *Adapted Vocabularies for Generic Visual Categorization*, ECCV 2006.
- J. Vogel, B. Schiele. *Semantic Modeling of Natural Scenes for Content-Based Image Retrieval*. International Journal of Computer Vision, 2006.
- L. Fei-Fei and P. Perona. *A Bayesian hierarchical model for learning natural scene categories*. Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, 2005.
- G. Csurka, C. R. Dance, L. Fan, J. Willamowski, C. Bray. *Visual Categorization with Bags of Keypoints*. ECCV 2004

References

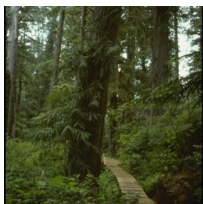
- J. Sivic, B. Russell, A. Efros, A. Zisserman, and W. Freeman. *Discovering object categories in image collections*. Technical Report A. I. Memo 2005-005, Massachusetts Institute of Technology, 2005.
- J. Savarese, A. Winn and T. Criminisi, *Object Categorization by Learned Universal Visual Dictionary*. CVPR 2006
- A. Vedaldi, A. Zisserman. *Efficient additive kernels via explicit feature maps*. PAMI 2011
- S. Lazebnik, C. Schmid, J. Ponce. *Beyond Bags of Features: Spatial Pyramid Matching for Recognizing Natural Scene Categories*. CVPR 2006.
- K. Grauman, T. Darrell. *The Pyramid Match Kernel: Efficient Learning with Sets of Features*. Journal of Machine Learning Research, 2008
- N. Elfiky, F. Khan, J. Van de Weijer, J. González. *Discriminative Compact Pyramids for Object and Scene Categorization*. PR, 2011
- F. Perronin, J. Sánchez, T. Mensink. *Improving the Fisher Kernel for large-scale image classification*. ECCV 2010
- F. Perronin, C. Dance. *Fisher Kernels on Visual Vocabularies for Image Categorization*. CVPR 2007
- K. Chatfield, V. Lempitsky, A. Vedaldi, A. Zisserman. *The devil is in the details: an evaluation of recent feature encoding methods*. BMVC 2011

Toy Dataset

8 classes



Coast
244 train
116 test



Forest
227 train
101 test



Highway
184 train
76 test



Inside city
214 train
94 test



Mountain
260 train
114 test



Open country
292 train
118 test



Street
212 train
80 test



Tall building
248 train
108 test

To Do...

Improve the BoVW code with:

- Test different amounts of local features. What performs best?
- Use dense SIFT instead of detected keypoints. Conclusions?
- Test different amounts of codebook sizes k . What performs best?
- Test different values of k for the k-nn classifier. What performs best?
- Test other distances in k-nn classifier. Does that make a difference? Why?
- Play with reducing dimensionality. Conclusions?
- Cross-validate everything (topic covered on Wednesday)

Next session:

- SVM classifier.
- Linear, RBF and histogram intersection kernels.
- Spatial Pyramid.
- Fisher Vectors (OPTIONAL, check out yael library...)

Warning: provided code might not work out of the box depending on the used versions (OpenCV, numpy, sklearn...) do not panic, and ~~RTFM~~ read the documentation

Deliverable

- A **single Python notebook file per group** reporting all the work done,
 - with the different experiments,
 - code,
 - plots,
 - explanations, etc.
 - **EVERYTHING EXECUTED!**
- To deliver by Friday, january, 7th @ 10 A.M. at MS-Teams