CS688: Web-Scale Image Retrieval

# Bag-of-Words (BoW) Models for Local Descriptors


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(윤성의)


Course URL:
http://sgvr.kaist.ac.kr/~sungeui/IR

# Class Objectives

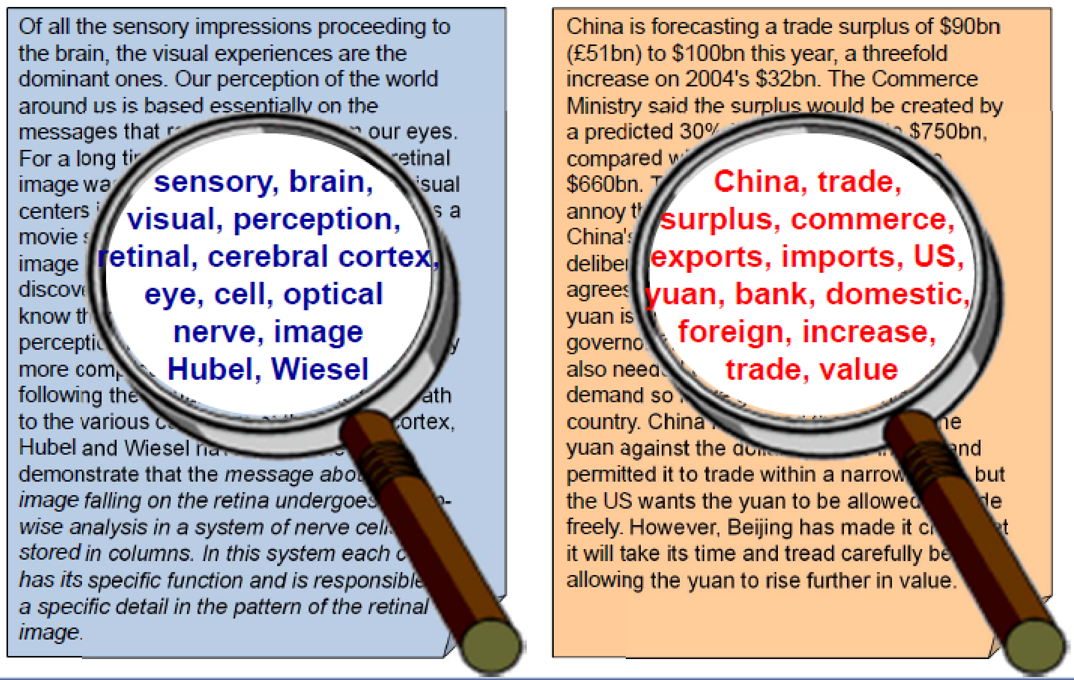
- Bag-of-visual-Word (BoW) model
  - Pooling operation
- Ranking loss for CNN features

- At the prior class:
  - Went over main components of CNNs: local connectivity and pooling

**Object** → **Bag of 'words'**

# Inspired by text search

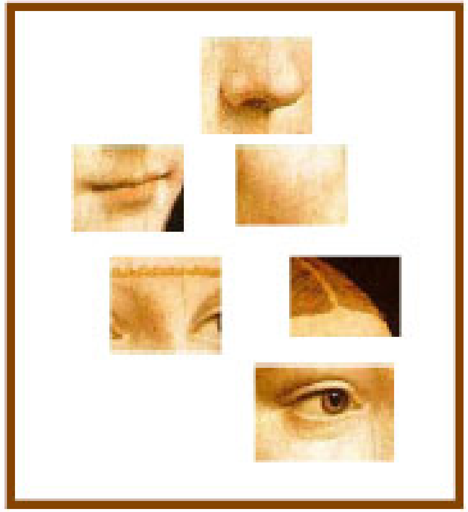
# Represent an image with a histogram of words



# definition of "BoW"

– Independent features

face

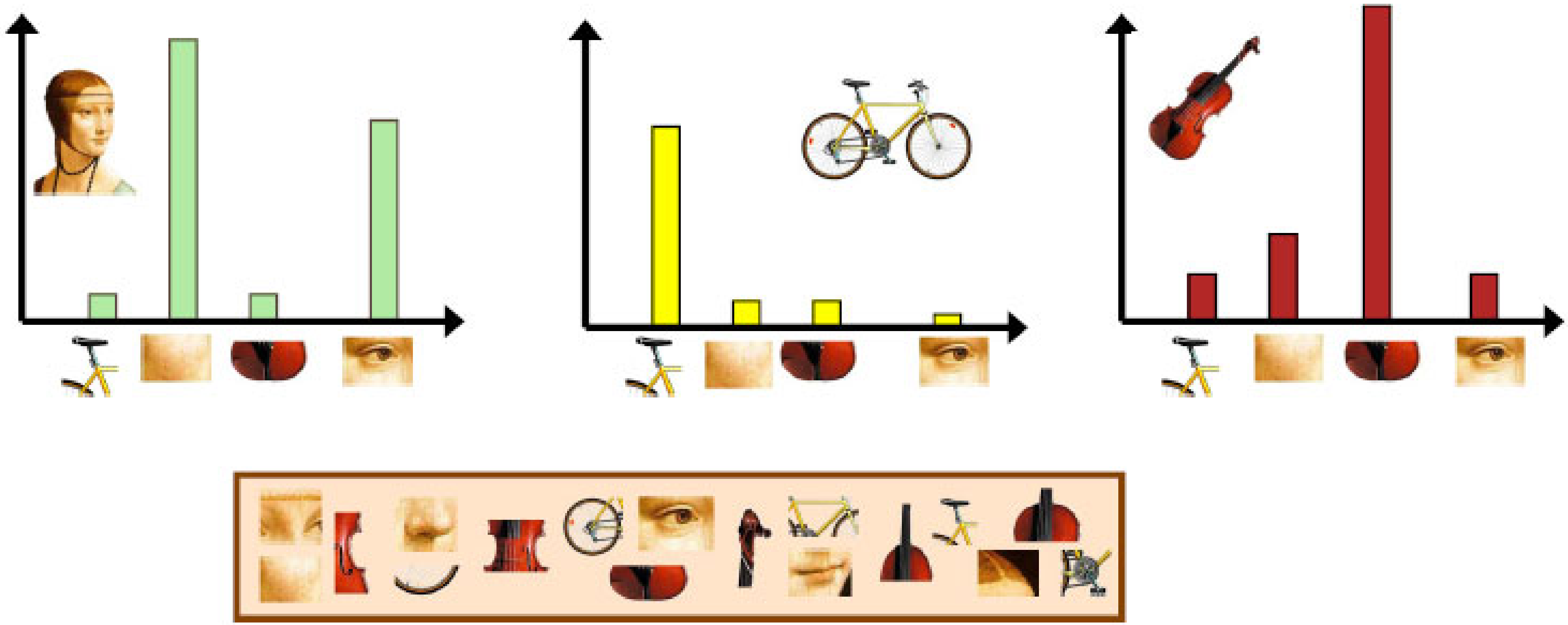


bike

violin

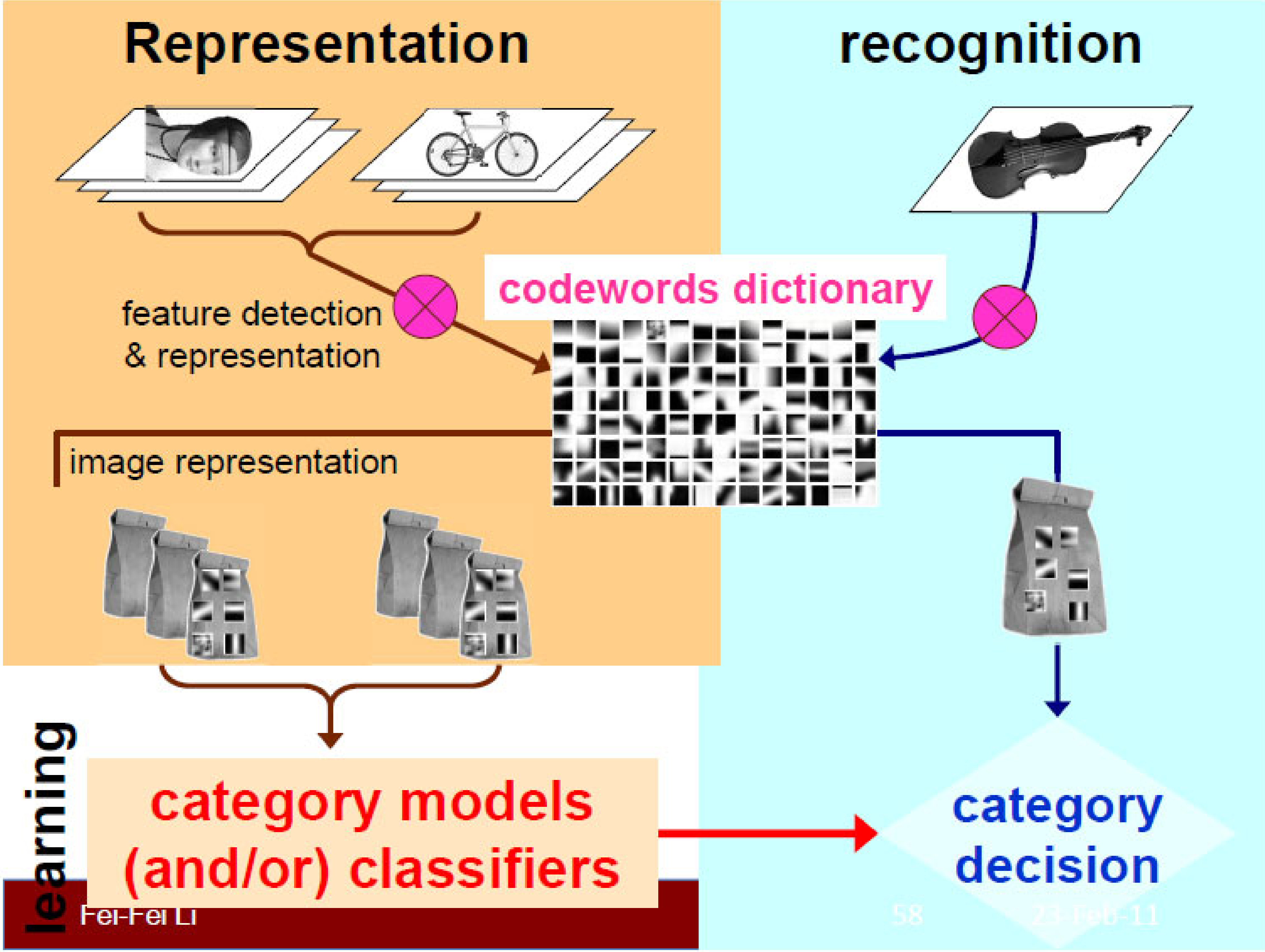
# definition of "BoW"

- Independent features
- histogram representation



codewords dictionary

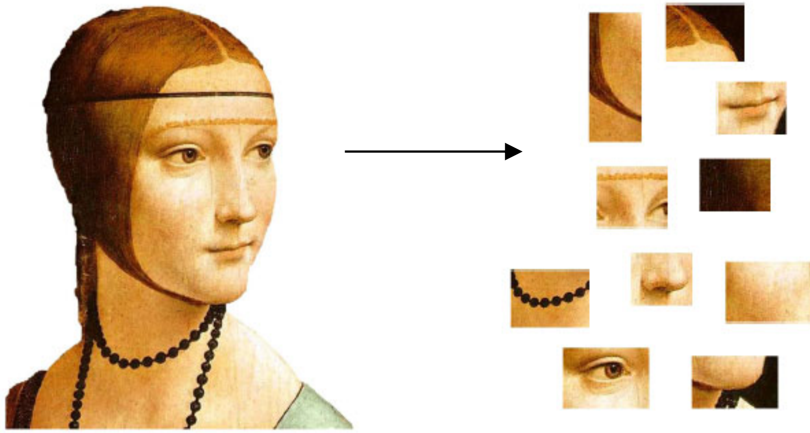
Fei-Fei Li



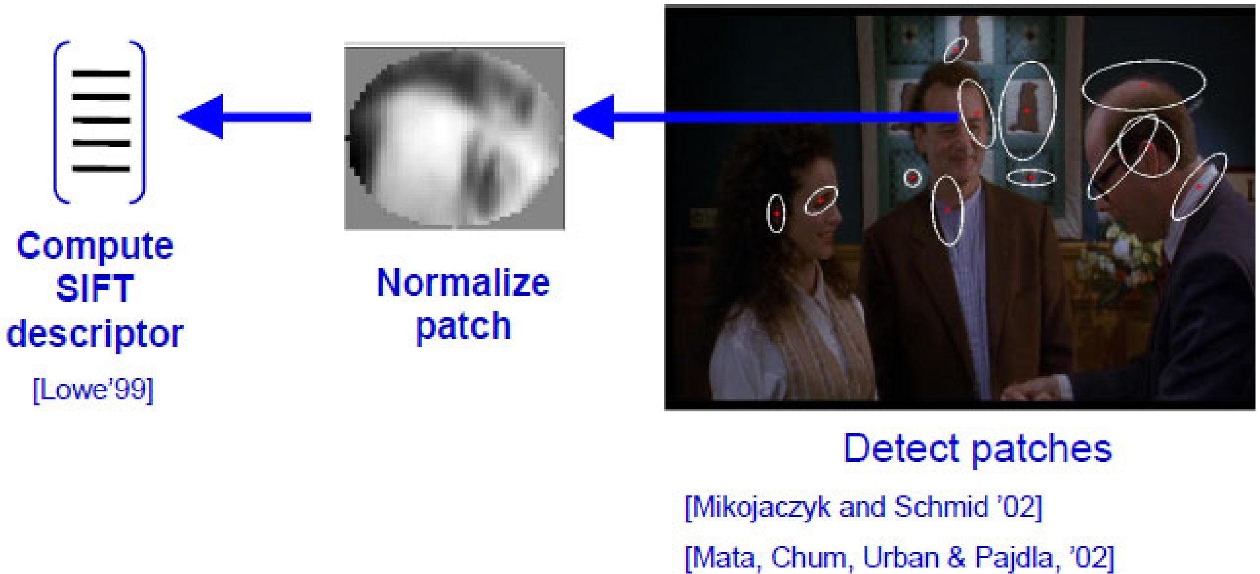
Representation
recognition
codewords dictionary
feature detection
& representation
image representation
learning
category models
(and/or) classifiers
category
decision

# 1. Feature Detection and Representations

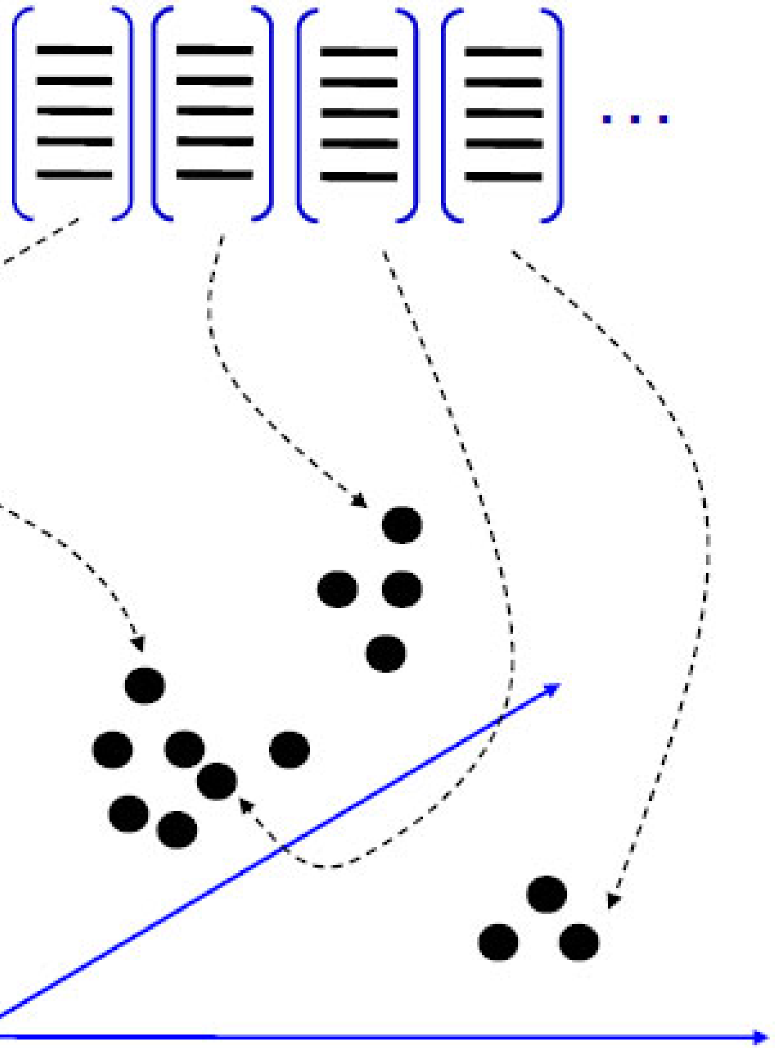
- **Assume many local features as an aggregation model**
  - **Global feature is not used in this context**
- **Densely sampled or sampled only at key points**
  - **Detect patches a extract features from them**



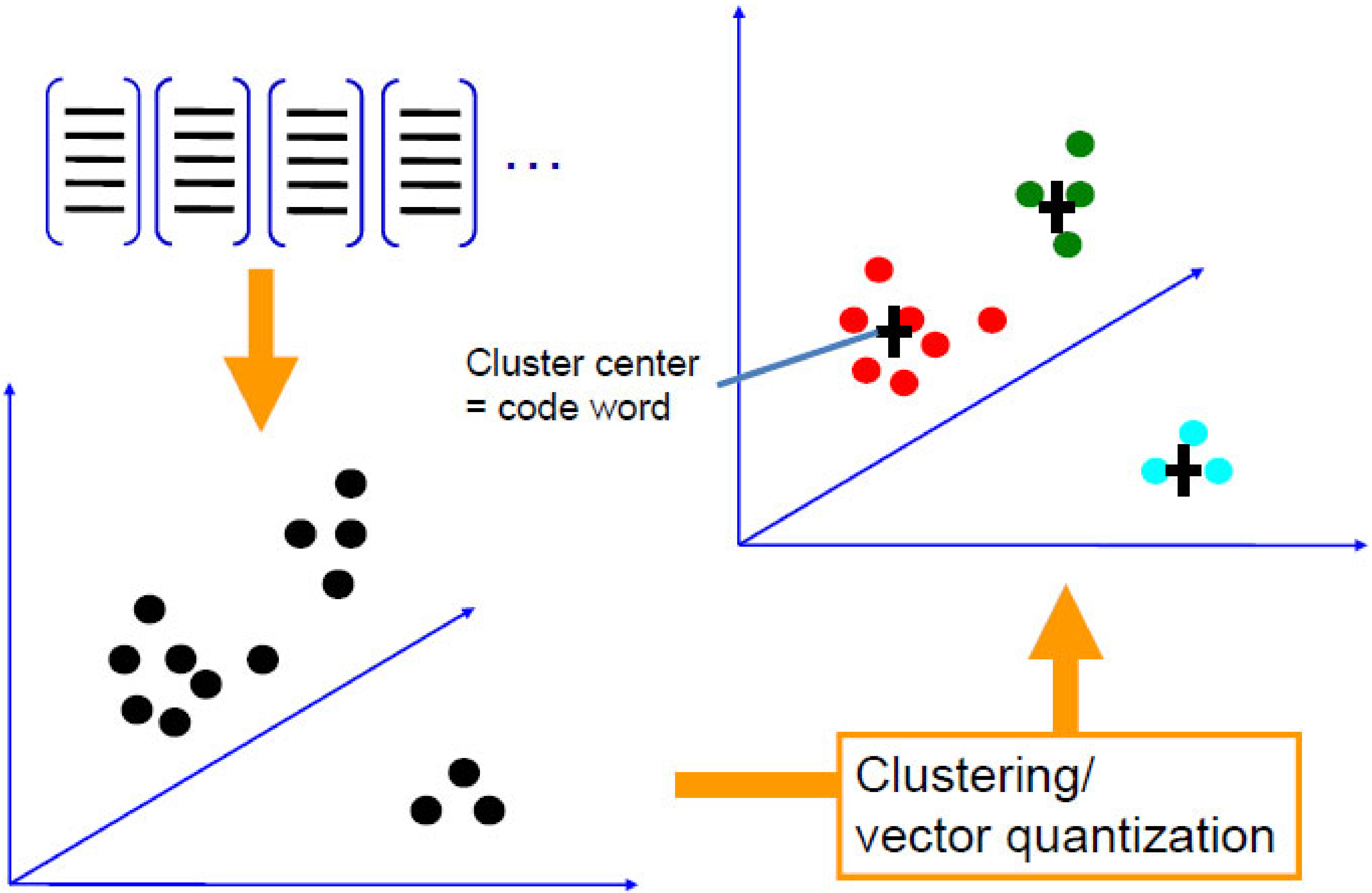
Ack.: Josef Sivic and Li Fei-Fei



# 2. Codewords dictionary formation



# 2. Codewords dictionary formation

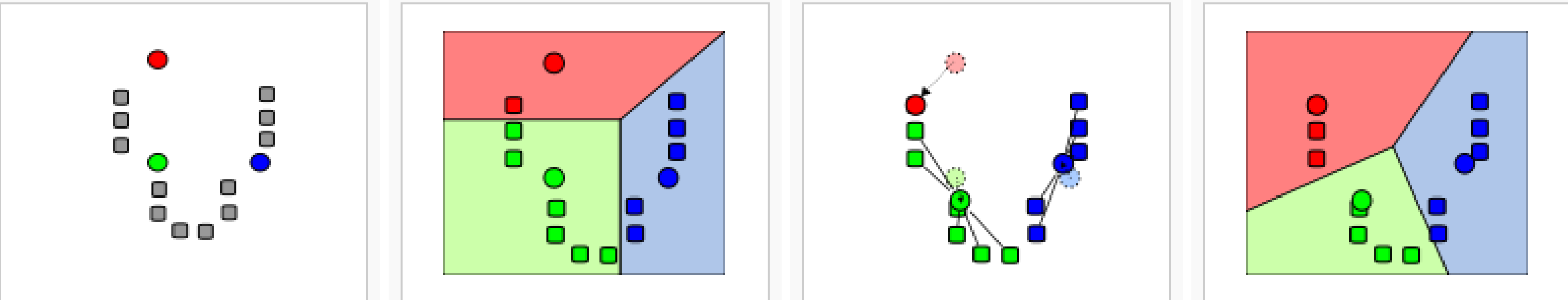


# K-Means Clustering

- **An unsupervised learning**
- **Minimize the within-cluster sum of squares**

$$\underset{\mathbf{S}}{\arg\min} \sum_{i=1}^{k} \sum_{\mathbf{x}_j \in S_i} \left\| \mathbf{x}_j - \boldsymbol{\mu}_i \right\|^2$$

Demonstration of the standard algorithm



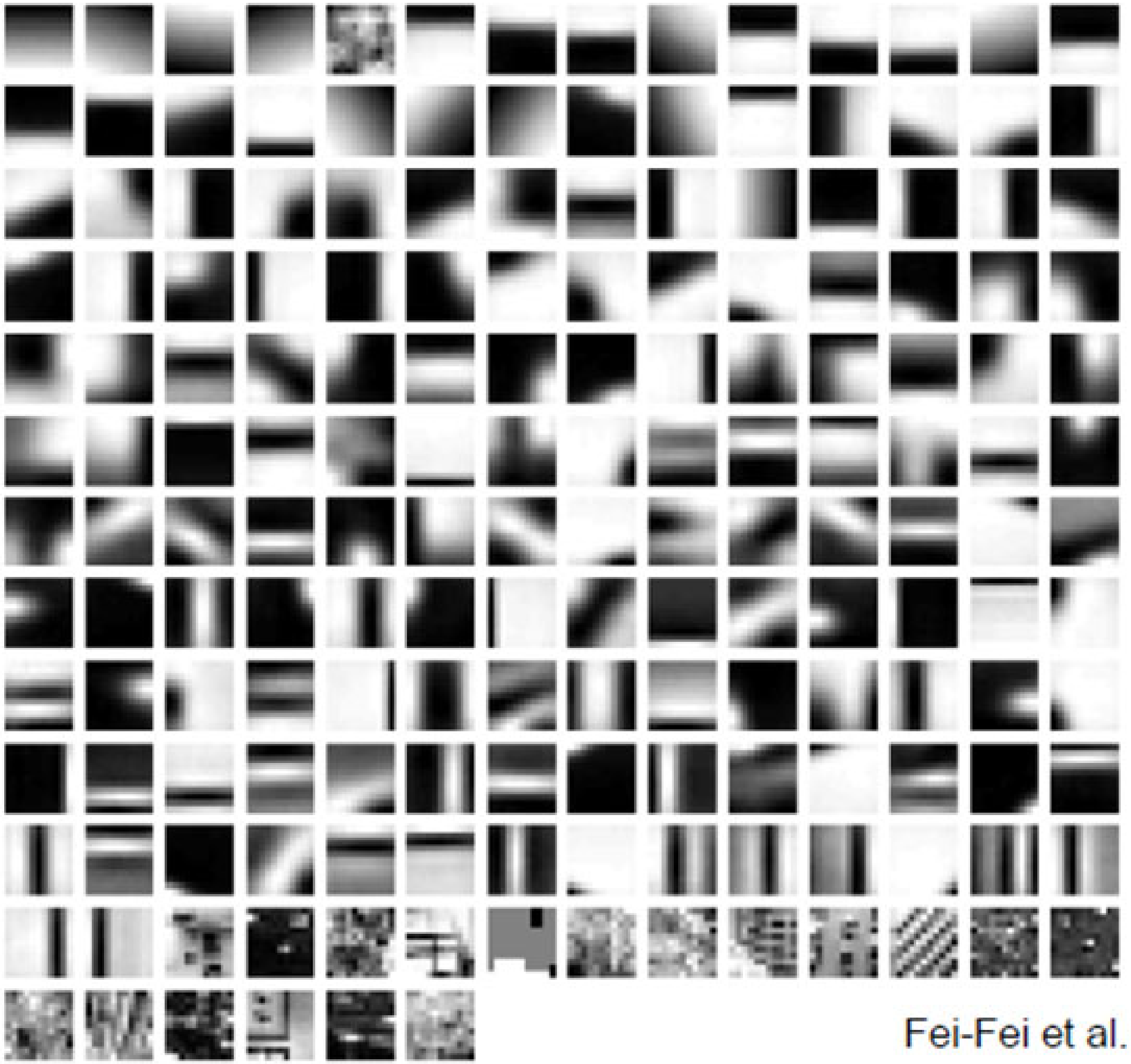
1) *k* initial "means" (in this case *k*=3) are randomly selected from the data set (shown in color).

2) *k* clusters are created by associating every observation with the nearest mean. The partitions here represent the Voronoi diagram generated by the means.

3) The centroid of each of the *k* clusters becomes the new means.

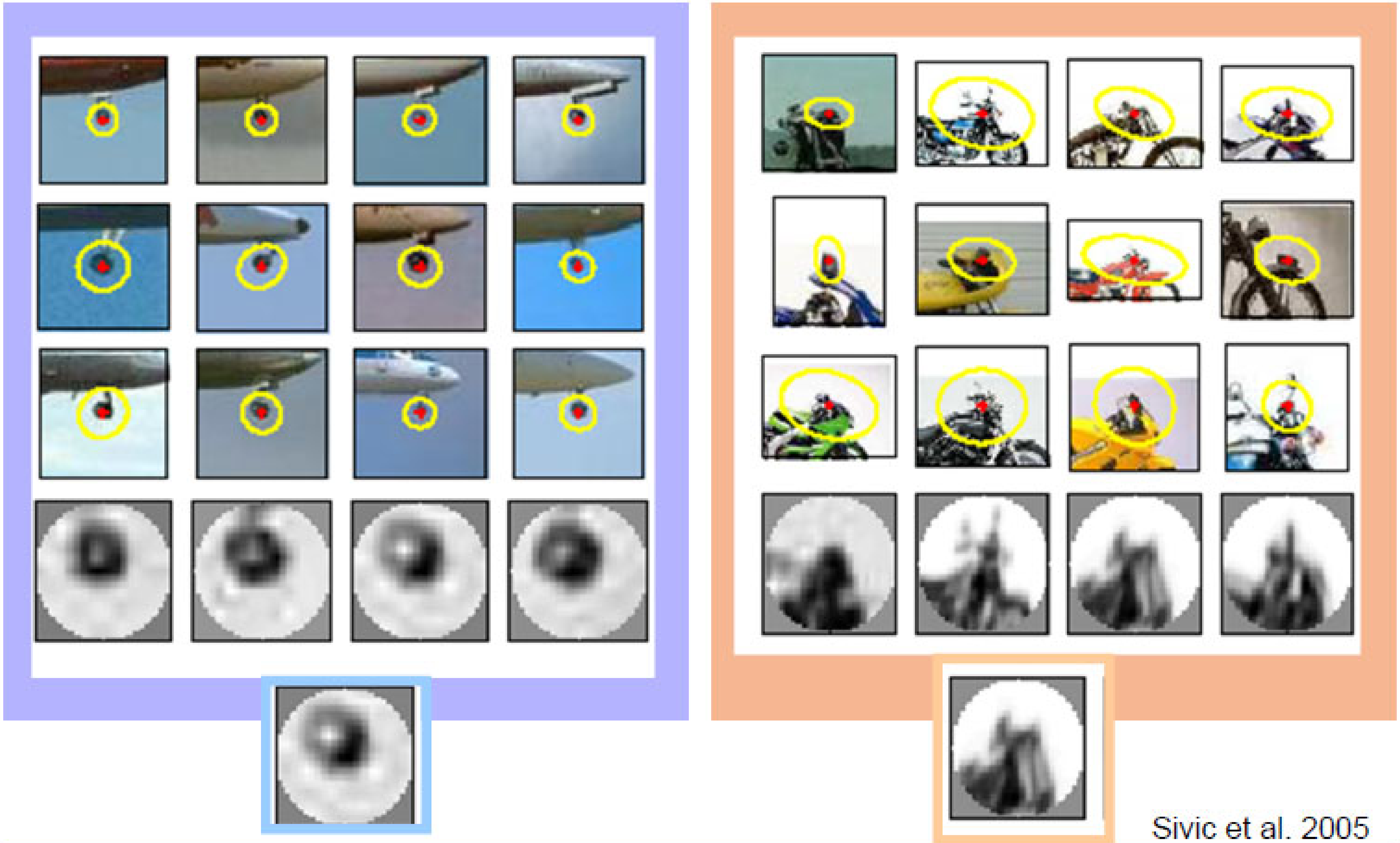
4) Steps 2 and 3 are repeated until convergence has been reached.

# Codewords Dictionary Formation



Fei-Fei et al. 2005

# Image patch examples of codewords

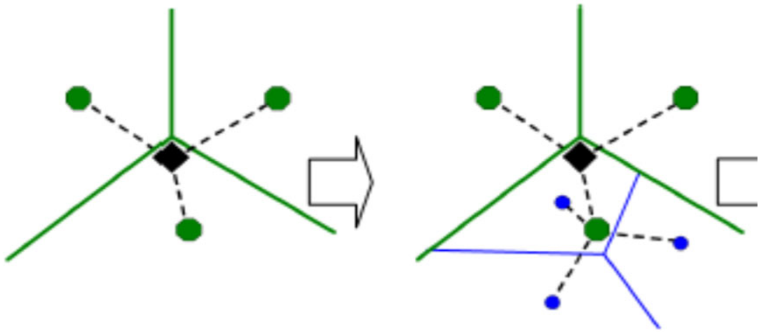


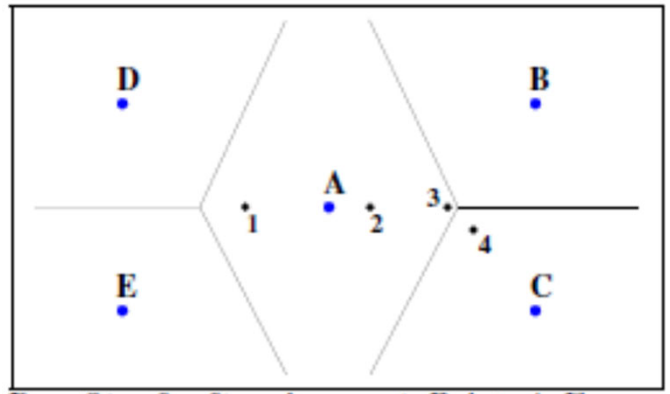
Sivic et al. 2005

# Issues of Visual Vocabulary

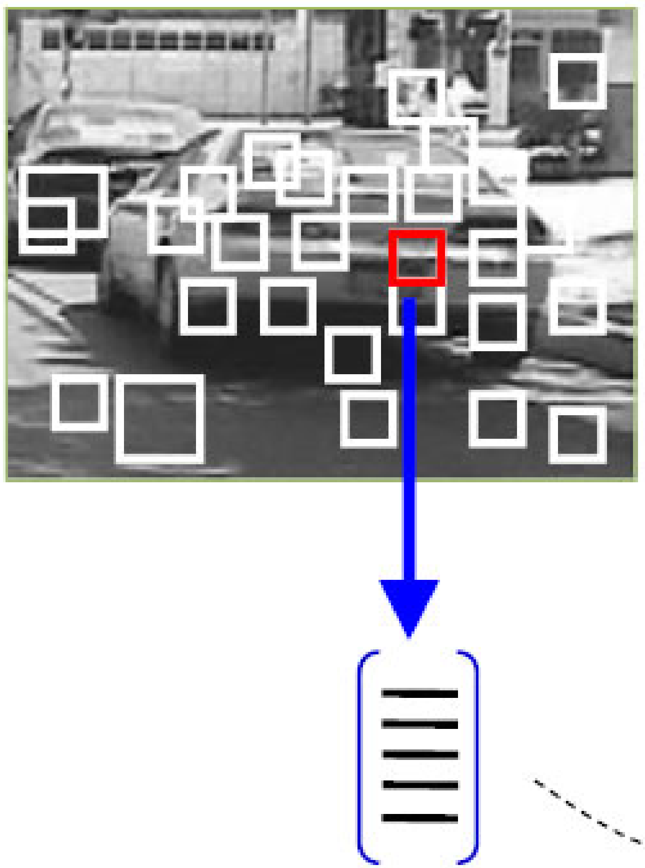
- **Related to quantization**
  - **Too many words: quantization artifacts**
  - **Too small words: not representative**
- **K-means also takes long computation times**

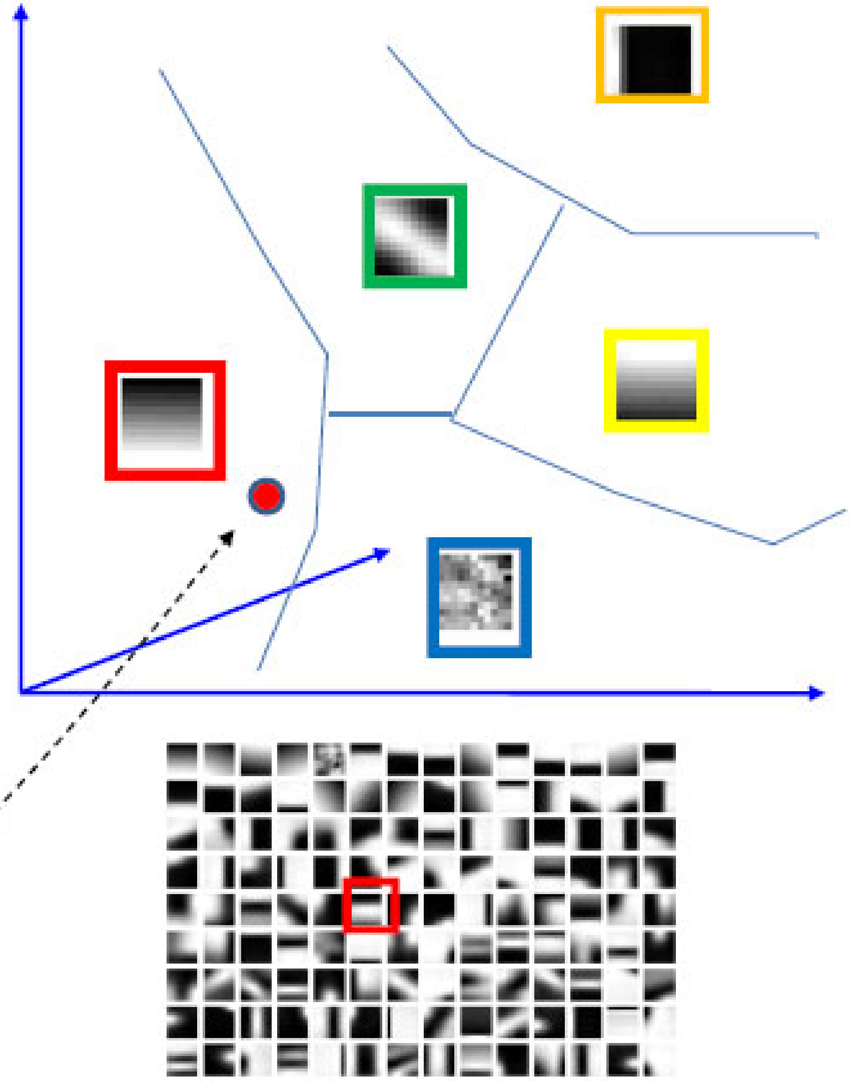
- **Alternatives**
  - **Faster performance:**
    **vocabulary tree, Nister et al.**
  - **Low quantization artifacts:**
    **soft quantization, Philbin et al.**





# 3. Bag of word representation

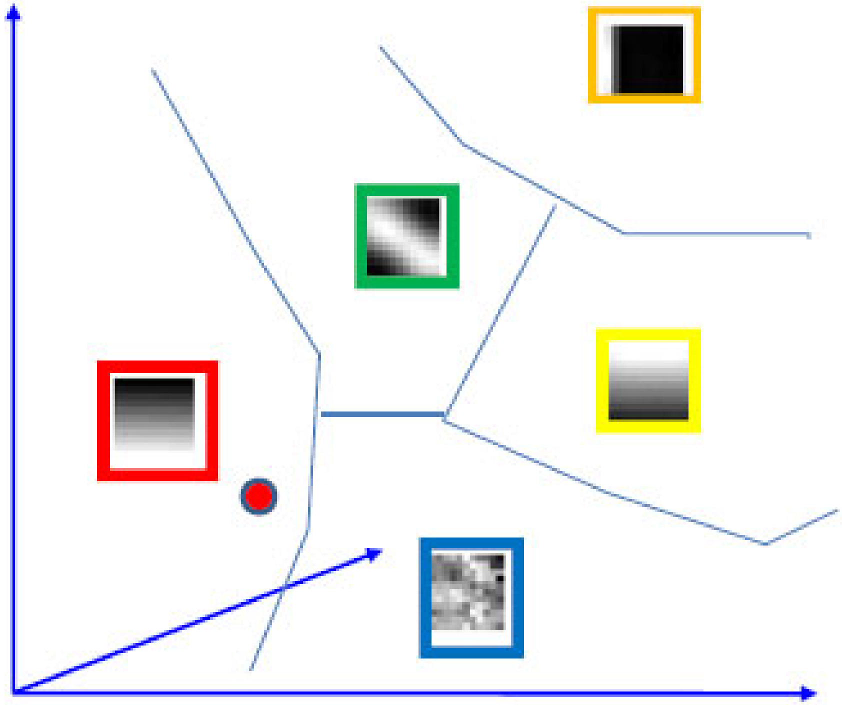


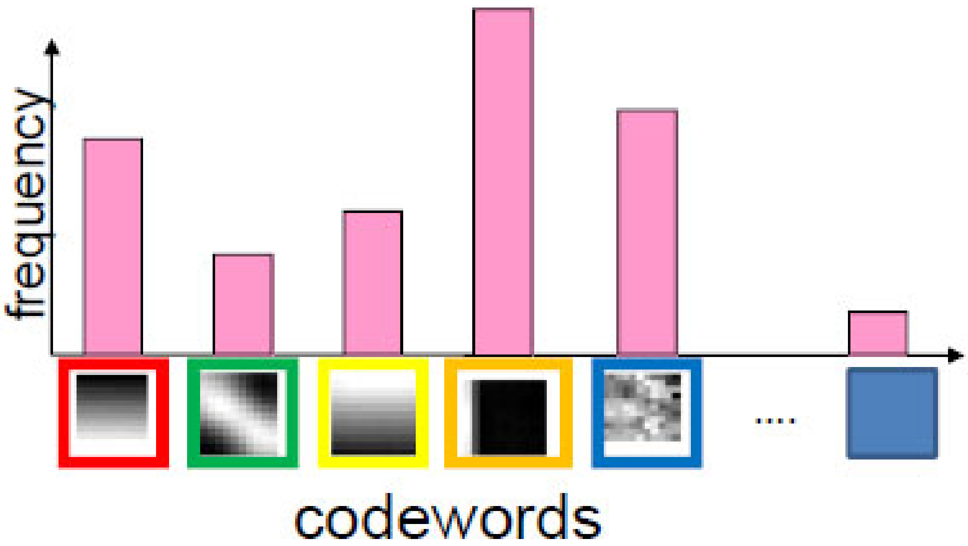


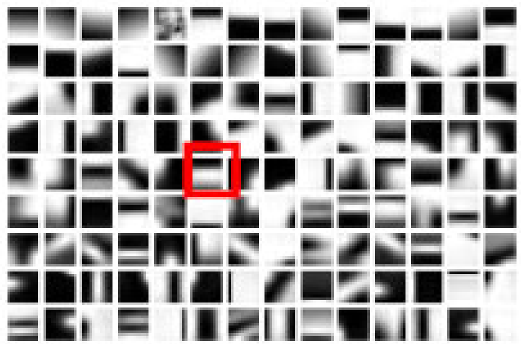
Codewords dictionary

- Nearest neighbors assignment
- K-D tree search strategy

# 3. Bag of word representation

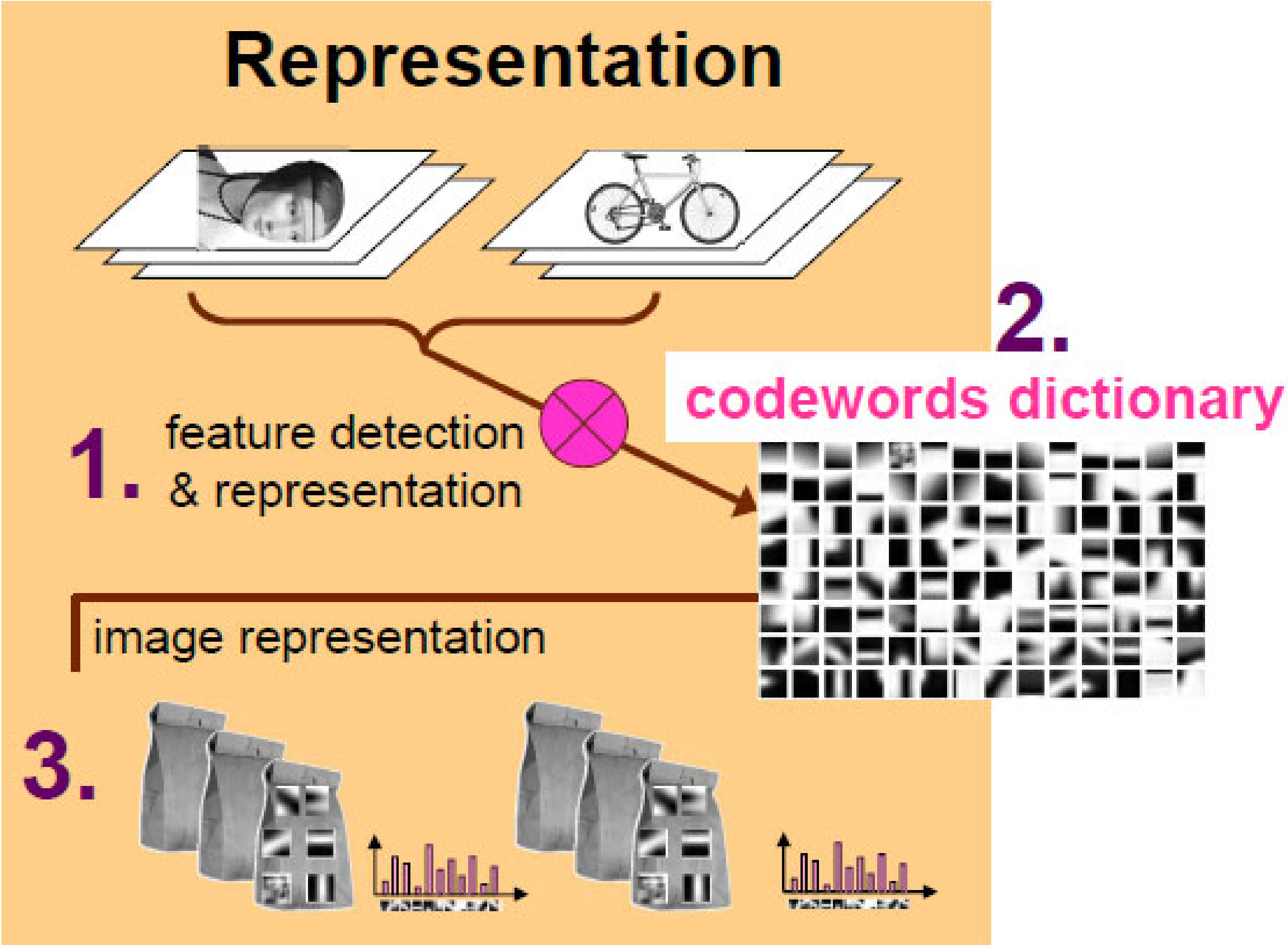




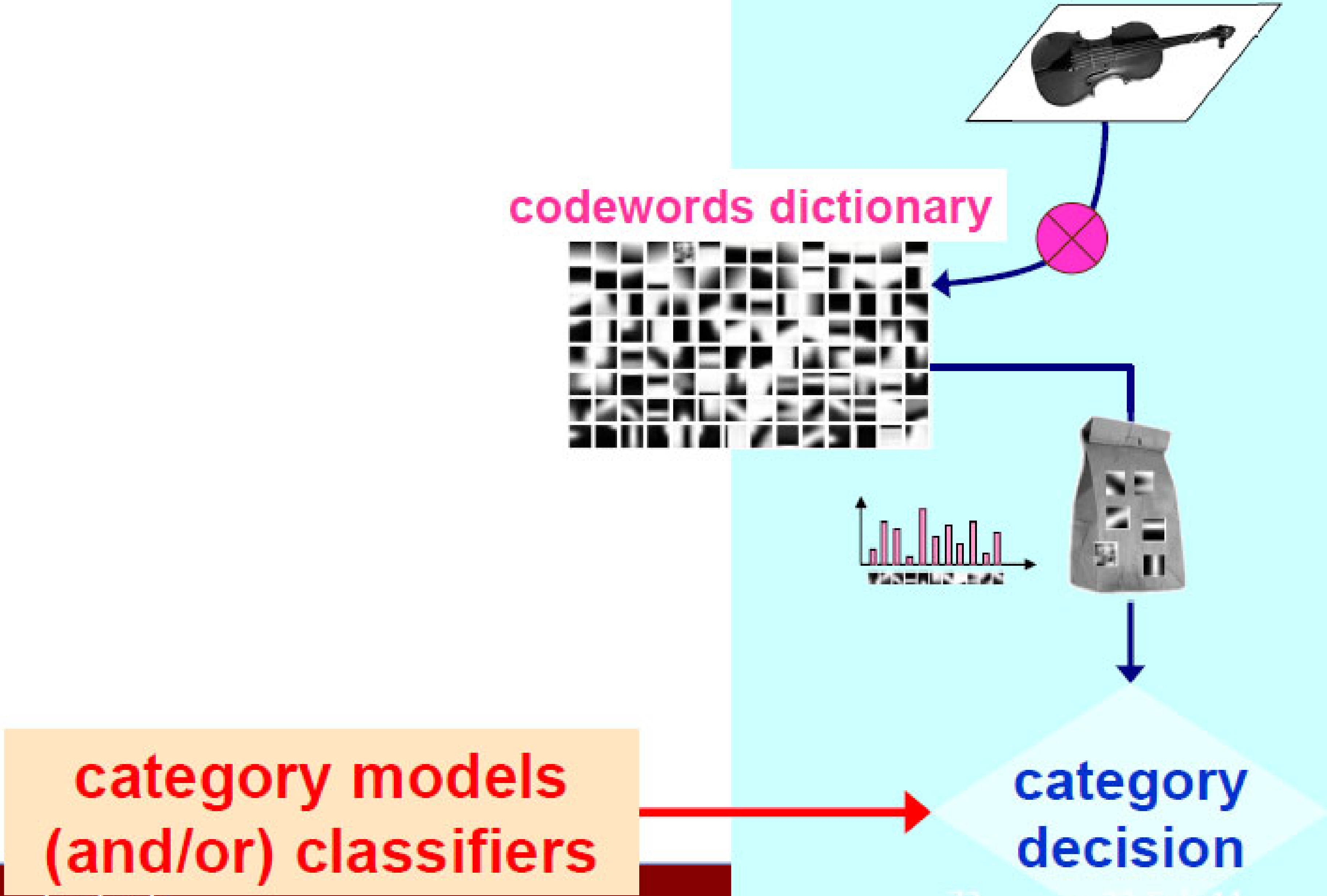



Codewords dictionary

**A kind of pooling operations**


Representation
2.
codewords dictionary
1.
feature detection
& representation
image representation
3.

# Learning and Recognition



# TF-IDF

- **Adopted from text search**
  - **A kind of weighting and normalization process**
- **Assume a document to be represented by** $(t_1, ..., t_i, ..., t_k)^\top$
- **Weighted by TF (Term frequency) * log (IDF (Inverse Document Frequency))**

$$t_i = \frac{n_{id}}{n_d} \log \frac{N}{n_i}$$

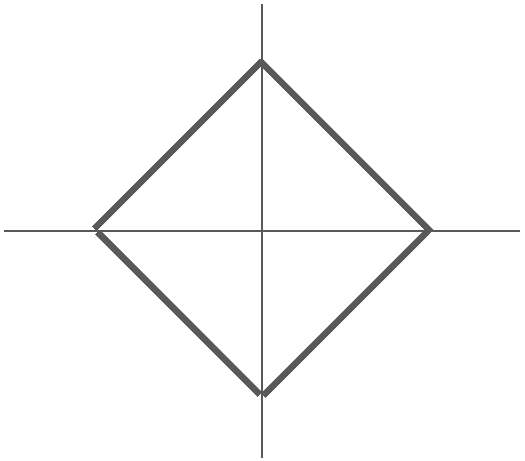
  - **$n_{id}$ : # of occurrences of word i in document d**
  - **$n_d$ : total # of words in the document d**
  - **$n_i$ : # of occurrences of term i in the whole database**
  - **N: # of documents in the whole database**

# Similarity and Distance Functions

- **Dot product measuring the angle between two vectors**

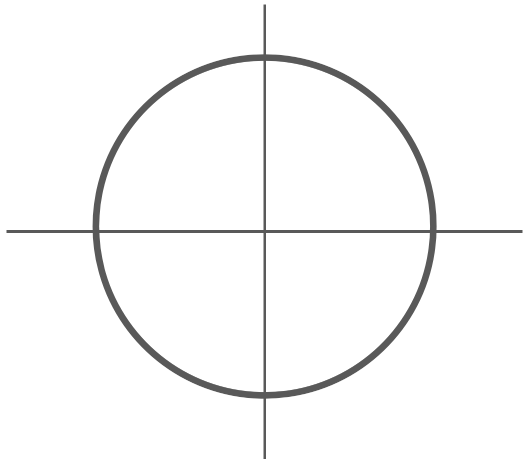
**L1 (Manhattan) distance**

$$d_1(I_1, I_2) = \sum_p \left| I_1^p - I_2^p \right|$$



**L2 (Euclidean) distance**

$$d_2(I_1, I_2) = \sqrt{\sum_p \left( I_1^p - I_2^p \right)^2}$$



# Mahalanobis Distance

- **Mahalanobis weighs L2 distance between two points, by the standard deviation of the data**

  $f(x, y) = (x - y)^T \sum^{-1} (x - y)$,

  **where $\sum$ is the mean-subtracted covariance matrix of all data points.**

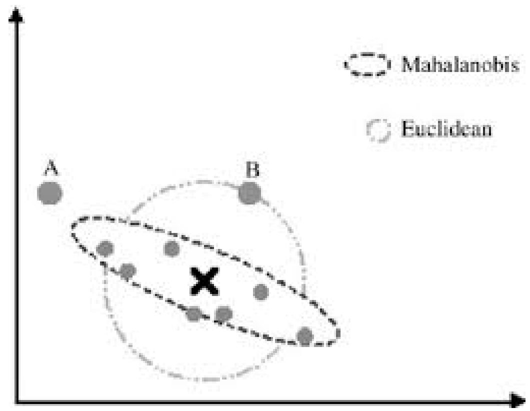
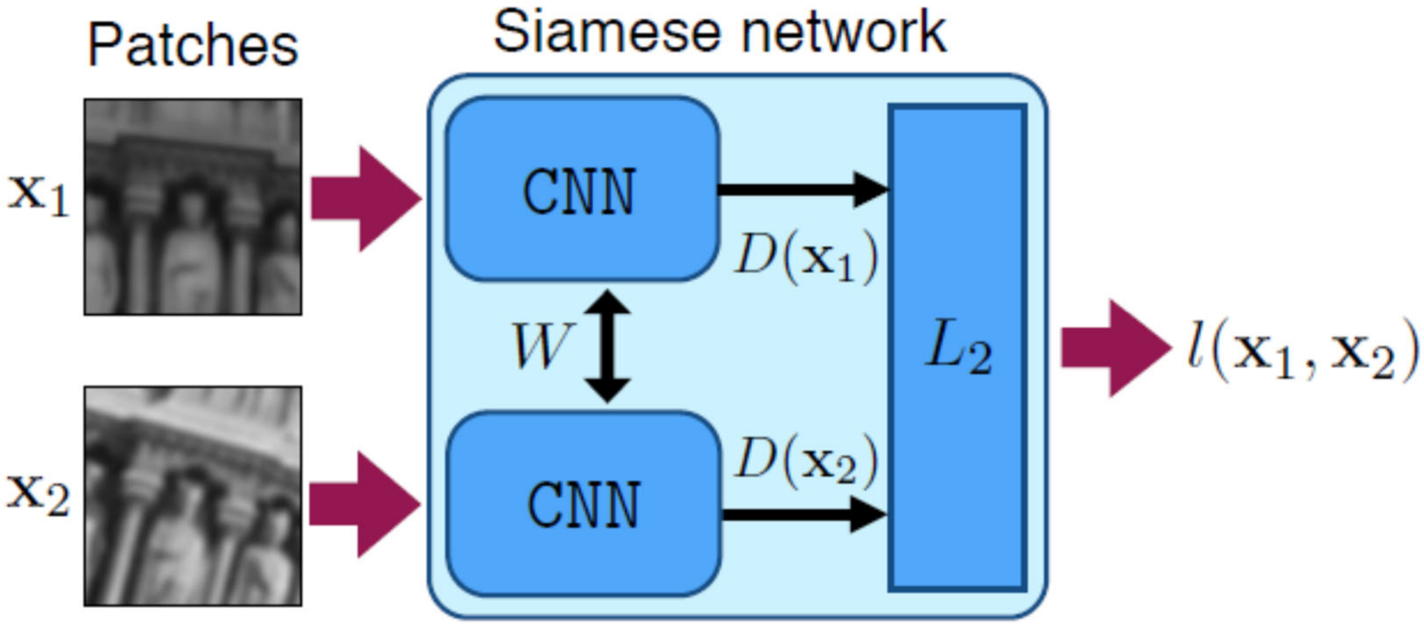



Image Source: Google

Chandra, M.P., 1936. On the generalised distance in statistics. In *Proceedings of the National Institute of Sciences of India* (Vol. 2, No. 1, pp. 49-55).

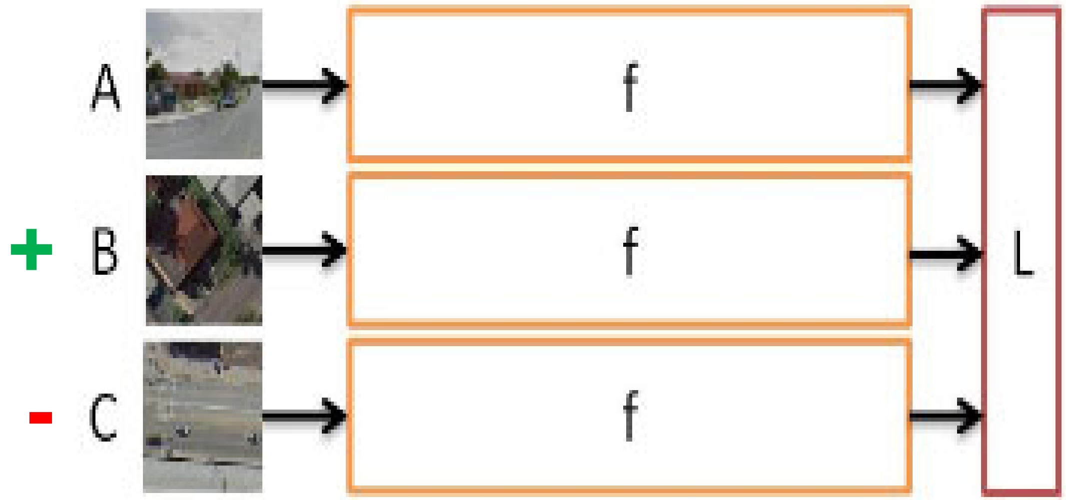
# Similarity Learning: Siamese CNN

- **Learn a feature representation mapping the sample patches with the L2 distance**




**Simo-Serra, E., Trulls, E., Ferraz, L., Kokkinos, I., Fua, P. and Moreno-Noguer, F., 2015. Discriminative learning of deep convolutional feature point descriptors. In *Proceedings of the IEEE International Conference on Computer Vision* (pp. 118-126).**

# Siamese CNN Variants: Triplet Network or Loss



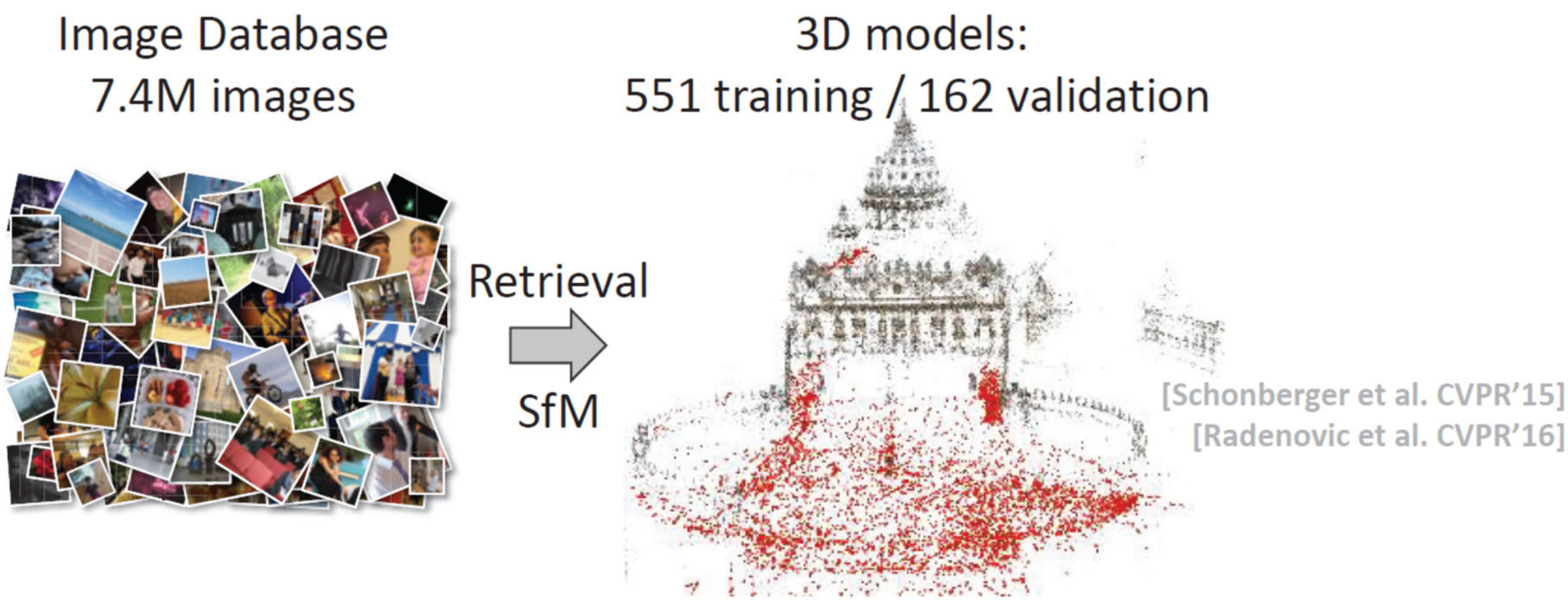

D(f(A), f(B)) < D(f(A), f(C))

- Allows us to learn ranking between samples
  - Known as a ranking loss

Vo, N.N. and Hays, J., 2016, October. Localizing and orienting street views using overhead imagery. In European Conference on Computer Vision (pp. 494-509).

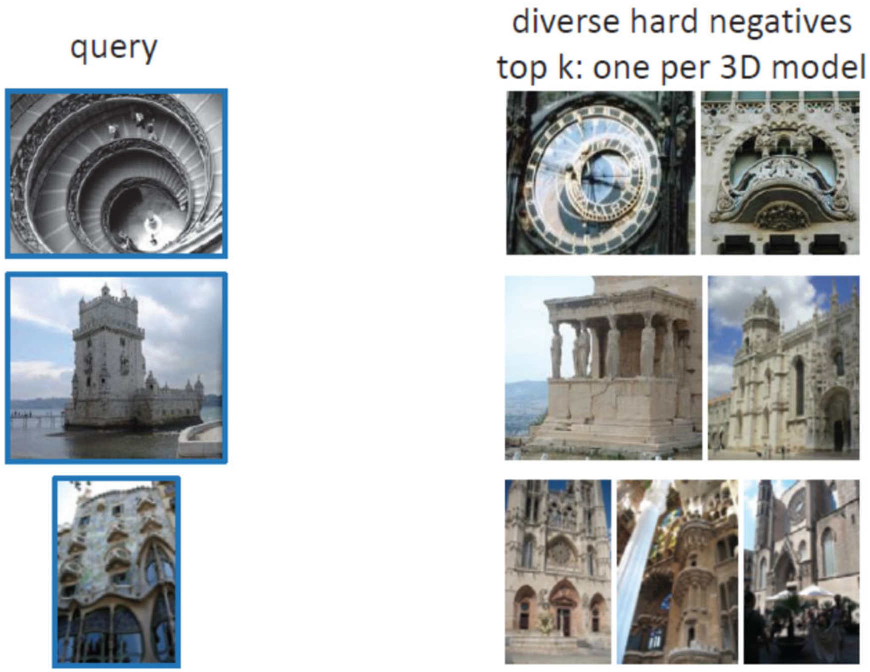
# Utilize BoW for CNN Image Retrieval

- **Construct 3D models from BoW based image retrieval**
  - **Refine CNN features by mimicking BoW-based retrieval**
  - **Unsupervised groups of photos with different landmarks**

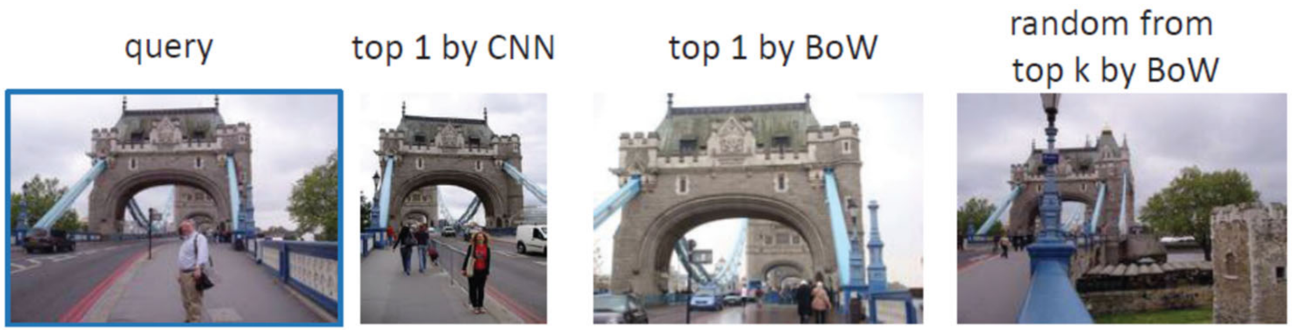


# Given a query, identify its positive (same cluster or city) and its negative image

## Negative images



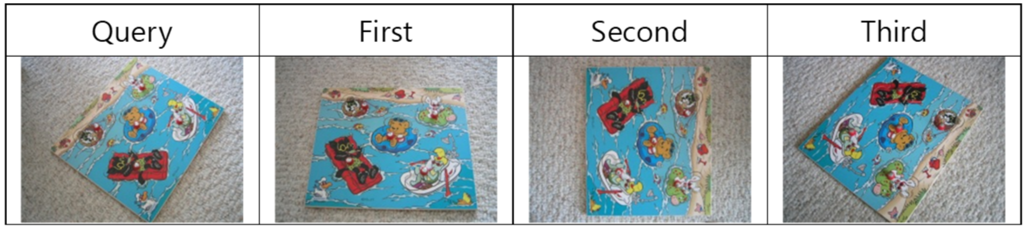

## Positive images




CNN Image Retrieval Learns from BoW:
Unsupervised Fine-Tuning with Hard Examples, ECCV

# PA2

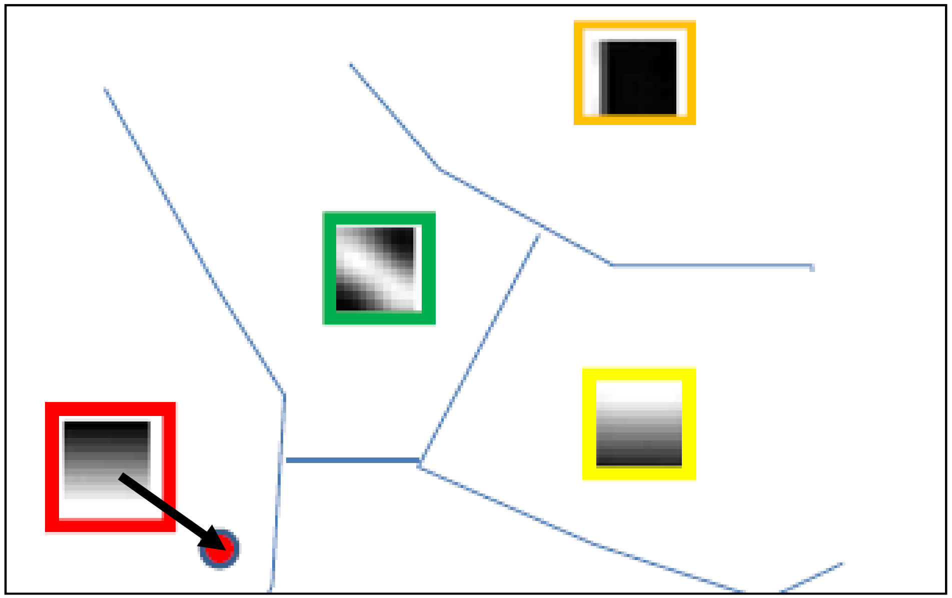
- Understand and implement a basic image retrieval system
- Use the original UKBenchmark
- Measure its accuracy



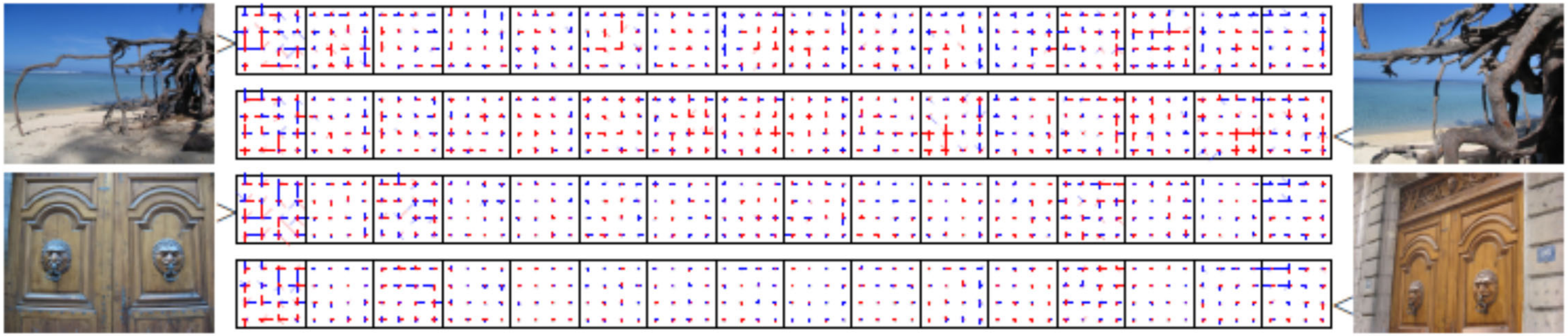

# VLAD (Vector of Locally Aggregated Descriptors)

- BoW
  - Count the number of SIFTs assigned to each cluster
- VLAD
  - Compute the difference between a feature and its cluster center

$$v_{i,j} = \sum_{x \text{ such that } \mathrm{NN}(x)=c_i} x_j - c_{i,j}$$



# VLAD



- **VLAD descriptors w/ 16 clusters**
- **Show better accuracy than BoW**

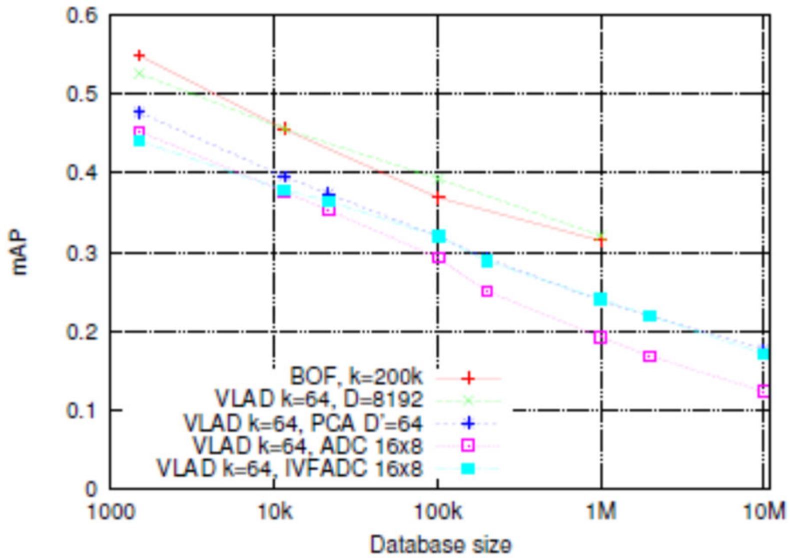



Figure 5. Search accuracy as a function of the database size.

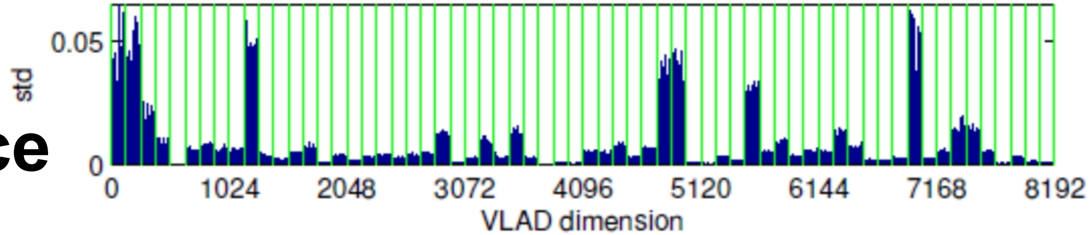


Ack. Aggregating local descriptors ..

# Normalization for VLAD

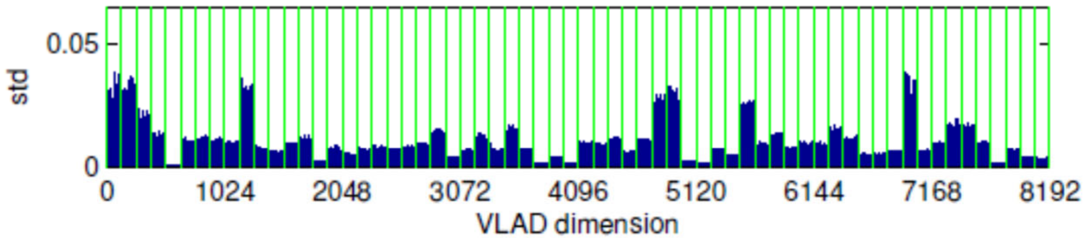
- **Results in better accuracy**

**Variance**



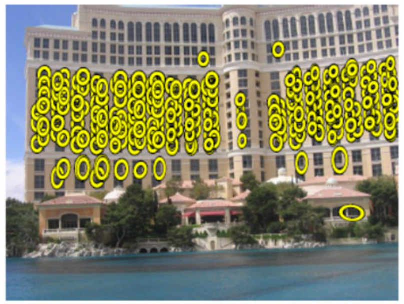

(a) Original VLAD normalization (L2)

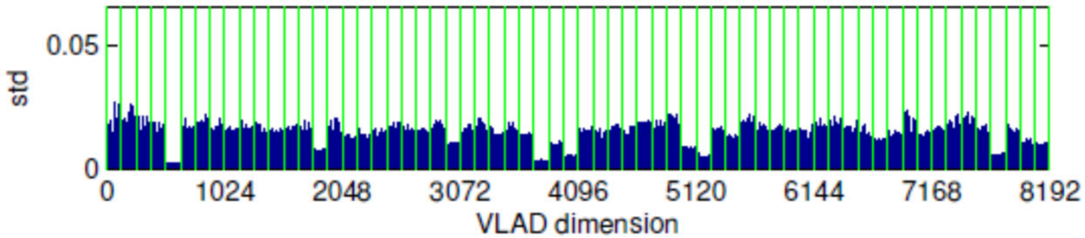
**L2 normalization,**
**i.e., $\frac{v}{|v|^2}$**




(b) Signed square rooting (SSR) followed by L2

**Square rooting for burstiness**






(c) Intra-normalization (innorm) followed by L2

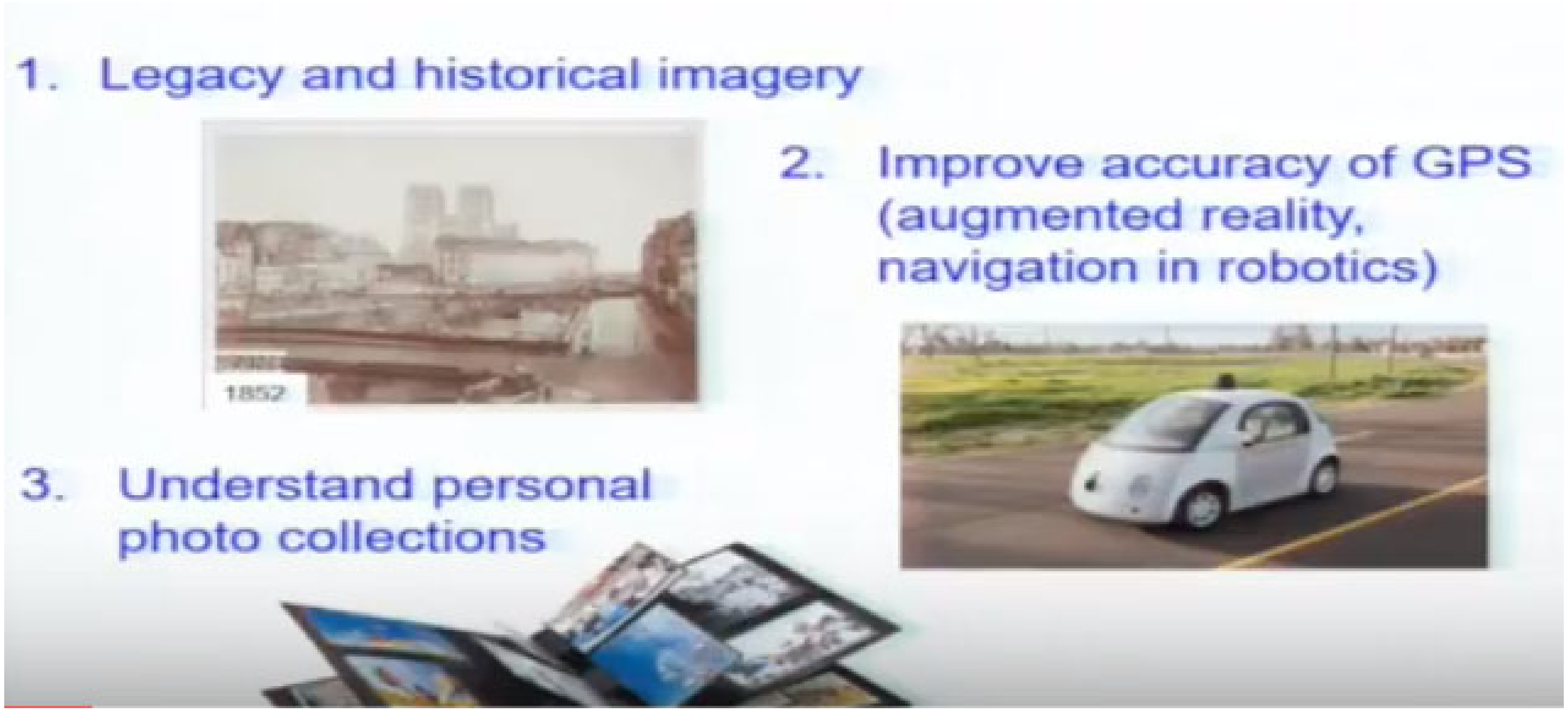
**L2 normalization within each VLAD block**



Ack. All about VLAD

# NetVLAD: CNN architecture for weakly supervised place recognition

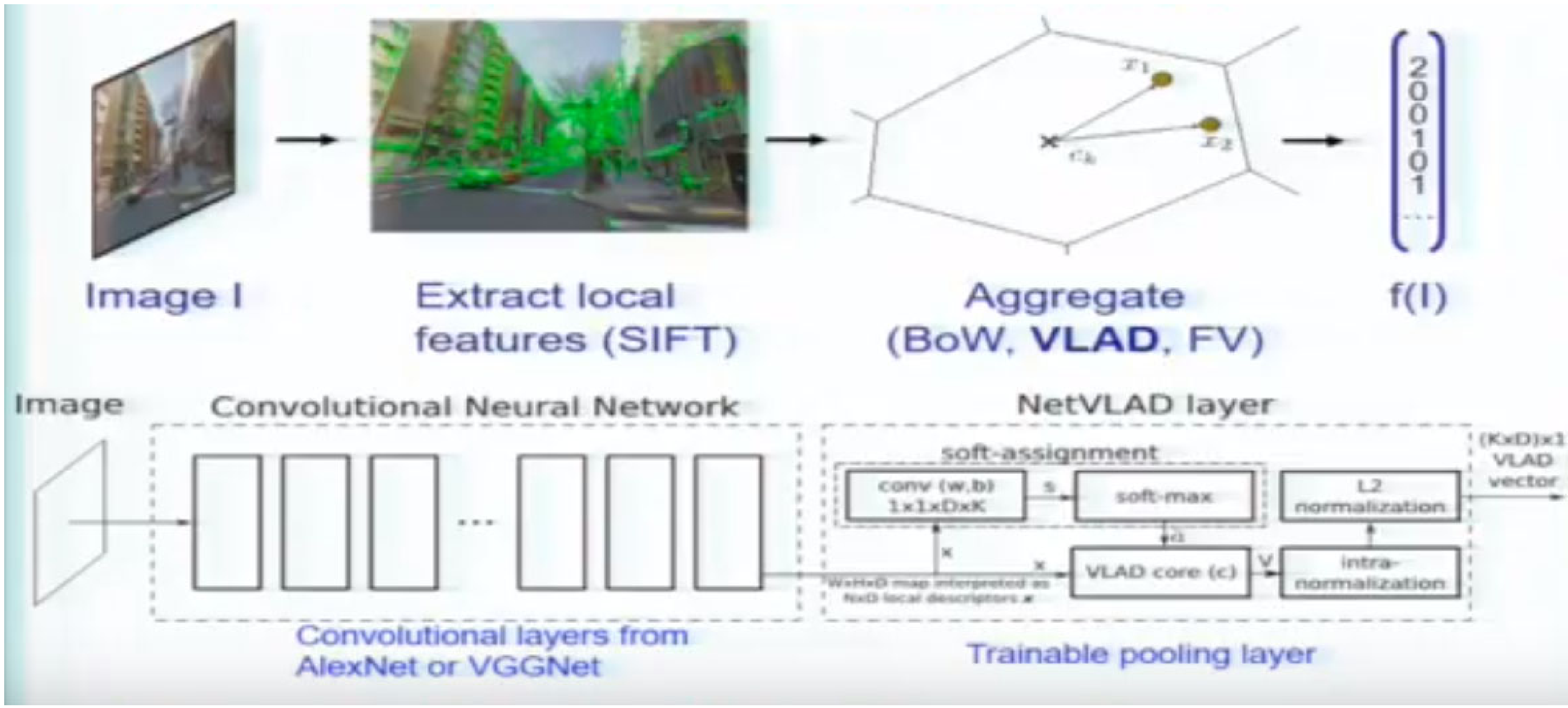
- **Identify its location given an query image**
  - **Application of place recognition**




From the author talk

# Mimic the classical approach

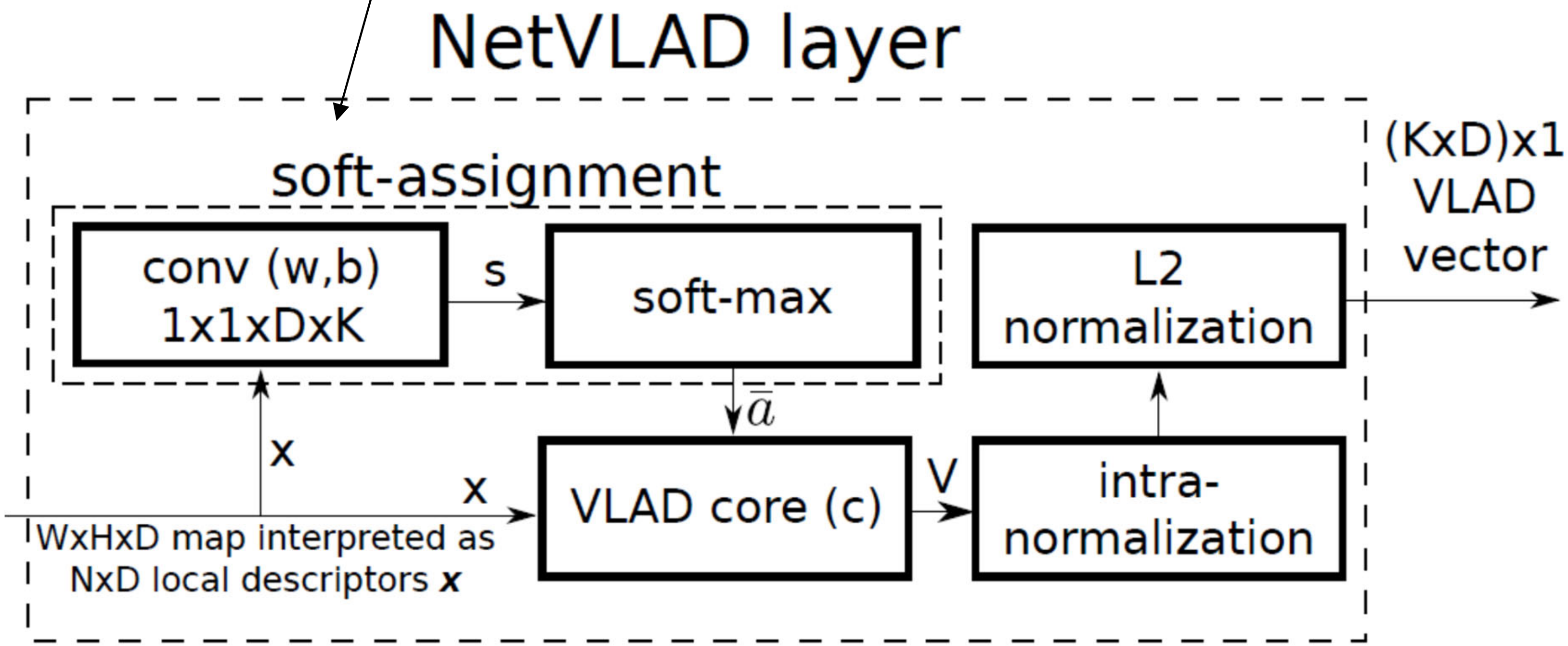
- **Make it end-to-end trainable for achieving better accuracy**



# Trainable VLAD

- **Hard assignment to soft assignment using the soft-max, to make it differentiable**

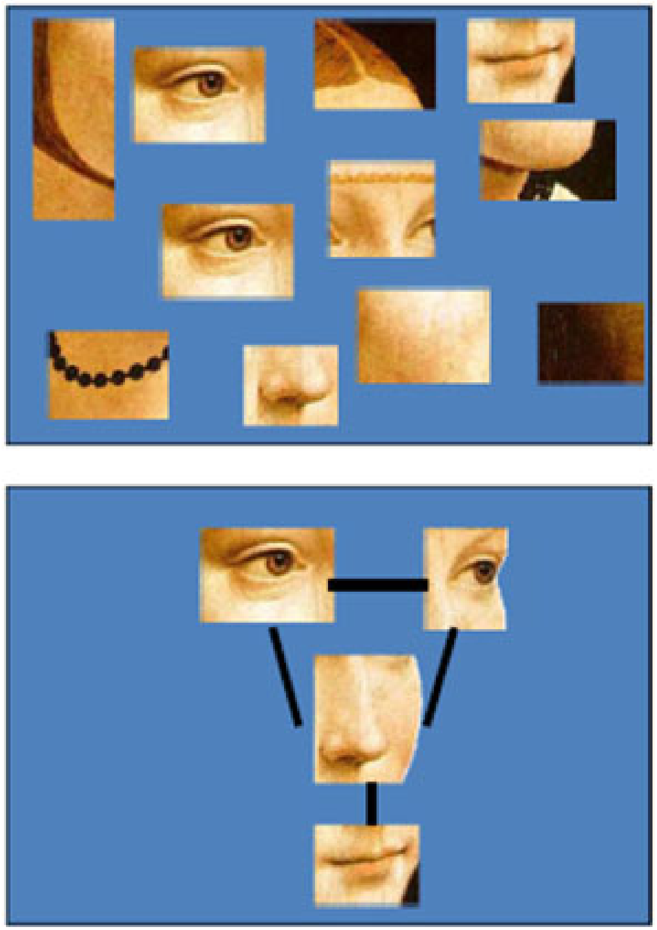
$$V(j,k) = \sum_{i=1}^{N} a_k(\mathbf{x}_i)\left(x_i(j) - c_k(j)\right), \qquad \bar{a}_k(\mathbf{x}_i) = \frac{e^{-\alpha\|\mathbf{x}_i - \mathbf{c}_k\|^2}}{\sum_{k'} e^{-\alpha\|\mathbf{x}_i - \mathbf{c}_{k'}\|^2}},$$



# Problems of BoW Model

- **No spatial relationship between words**

- **How can we perform segmentation and localization?**



Ack.: Fei-Fei Li

# Class Objectives were:

- **Bag-of-visual-Word (BoW) model**
  - **Pooling operation**
- **Ranking loss for CNN features**

# Next Time…

- **Inverted index**

# Homework for Every Class

- Go over the next lecture slides
- Come up with one question on what we have discussed today
  - Write questions three times
- Go over recent papers on image search, and submit their summary before Tue. class

# Figs