Bag of Visual Words

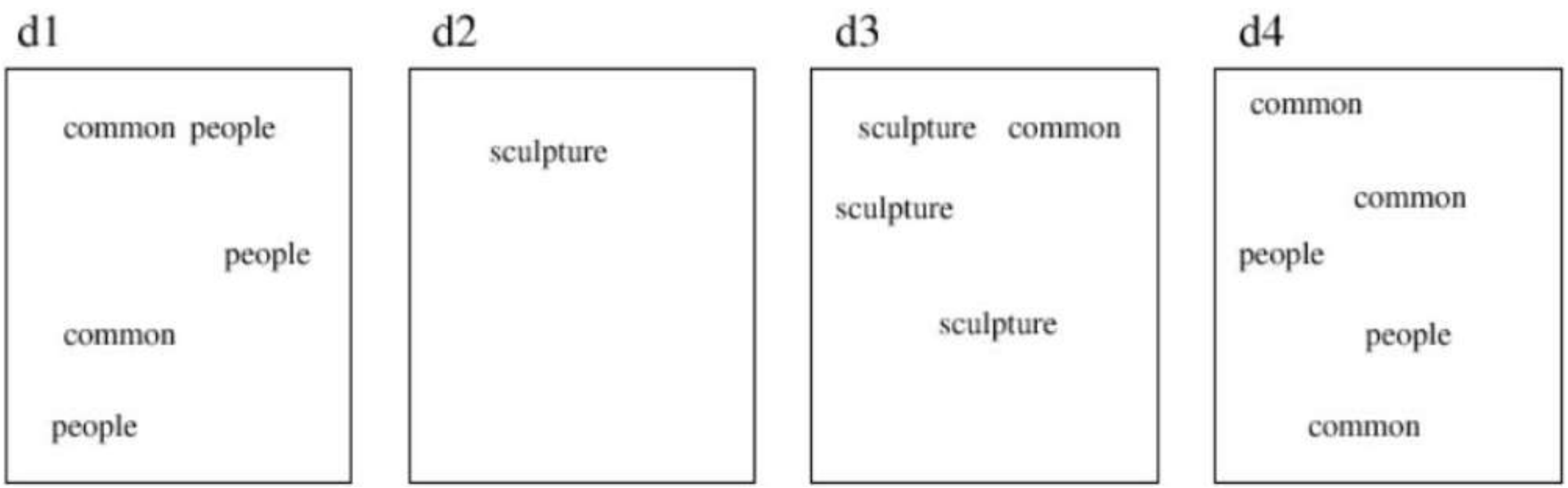
Outline

- Bag-of-features – Origin
- Bag-of-features steps
- Indexing local features

Bag-of-features

Bag-of-features – Origin: bag-of-words (text)

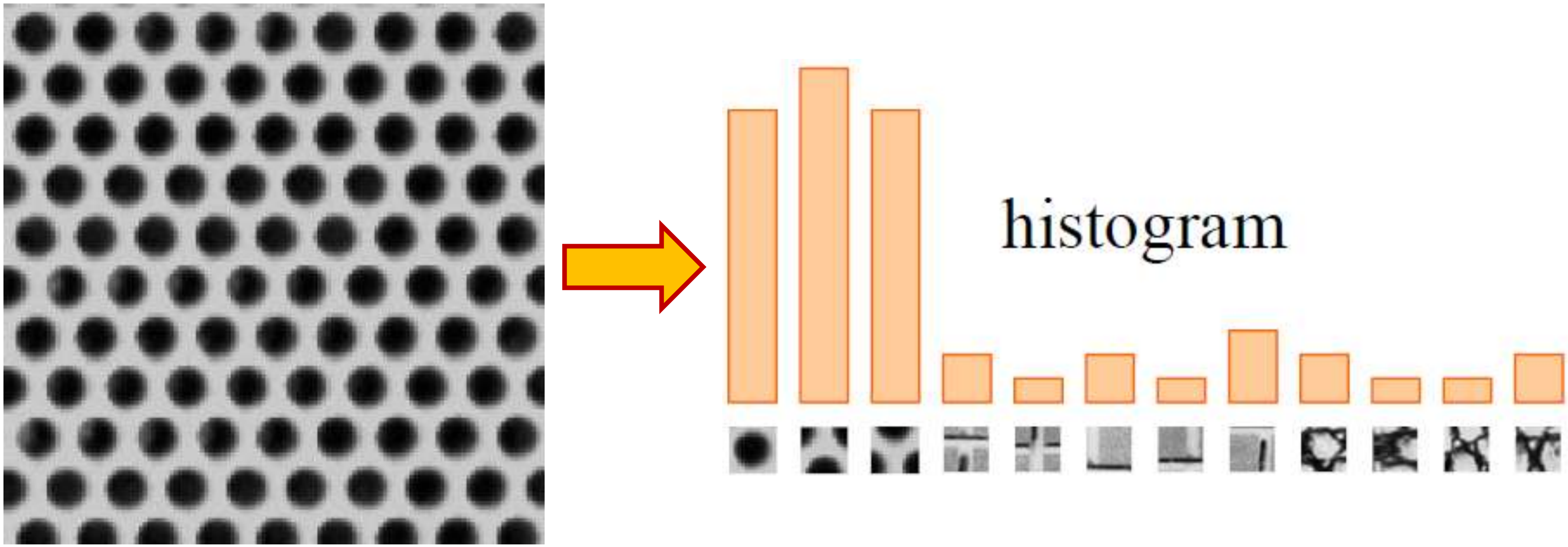
- Order less document representation: frequencies of words from a dictionary
- Classification to determine document categories



Bag-of-words:

Common	2	0	1	3
People	3	0	0	2
Sculpture	0	1	3	0

Bag-of-features – Origin: texture recognition

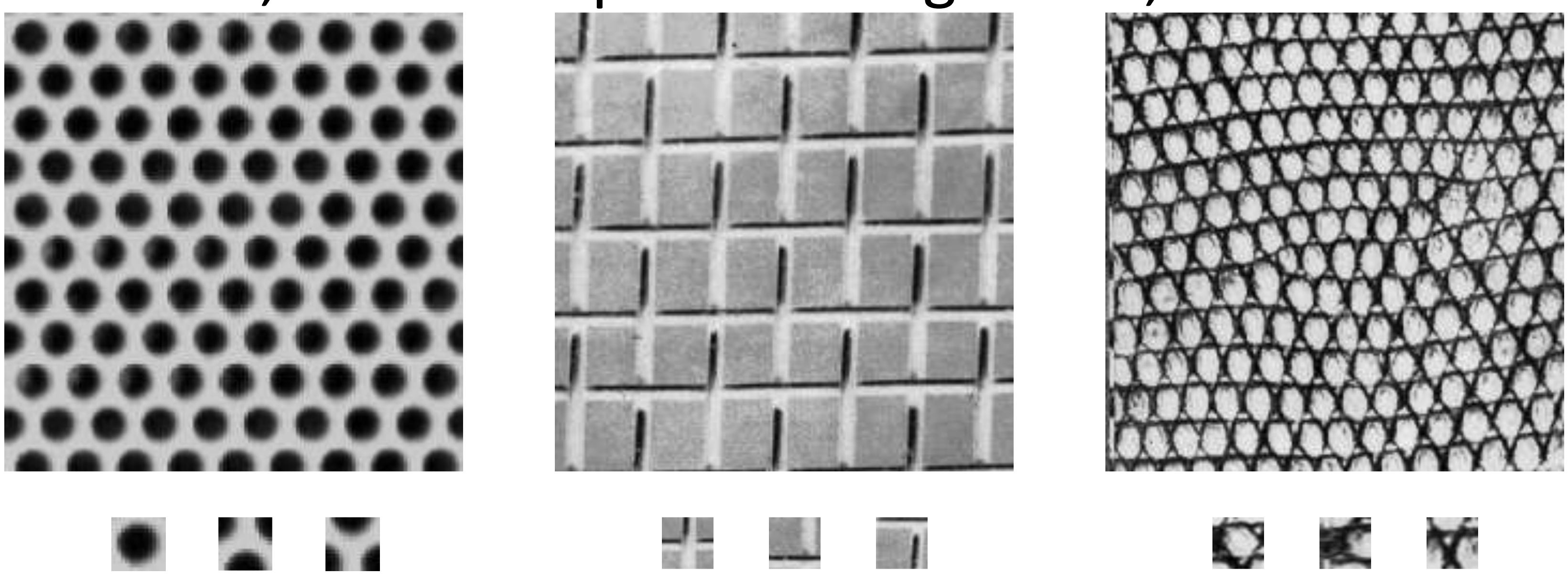


- Texture is characterized by the repetition of basic elements or *textons*

Bags of features

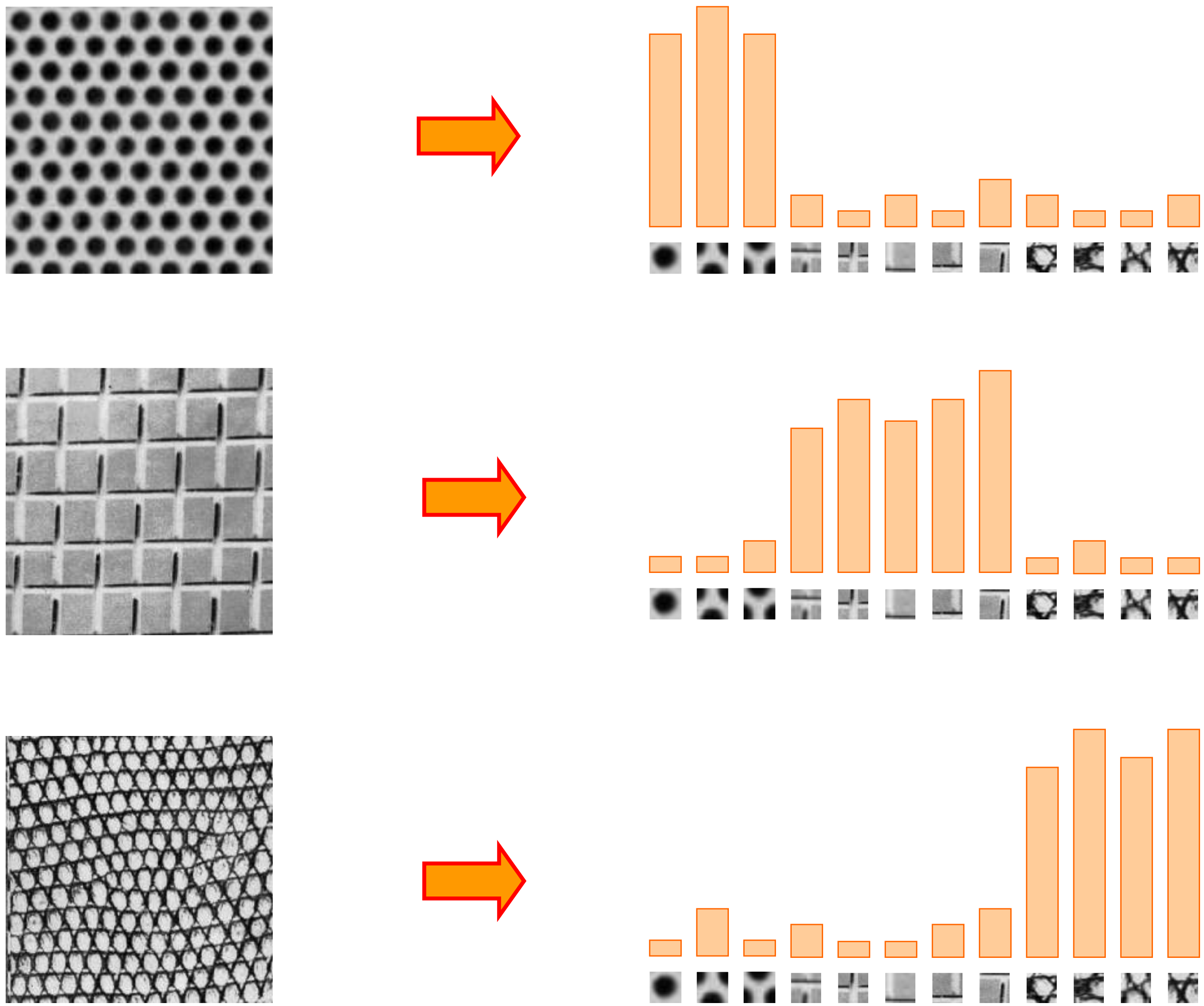
Origin 1: Texture recognition

- Texture is characterized by the repetition of basic elements or *textons*
- For stochastic textures, it is the identity of the textons, not their spatial arrangement, that matters



Julesz, 1981; Cula & Dana, 2001; Leung & Malik 2001; Mori, Belongie & Malik, 2001; Schmid 2001; Varma & Zisserman, 2002, 2003; Lazebnik, Schmid & Ponce, 2003

Origin 1: Texture recognition



Origin 2: Bag-of-words models

- Orderless document representation: frequencies of words from a dictionary Salton & McGill (1983)

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- Orderless document representation: frequencies of words from a dictionary Salton & McGill (1983)

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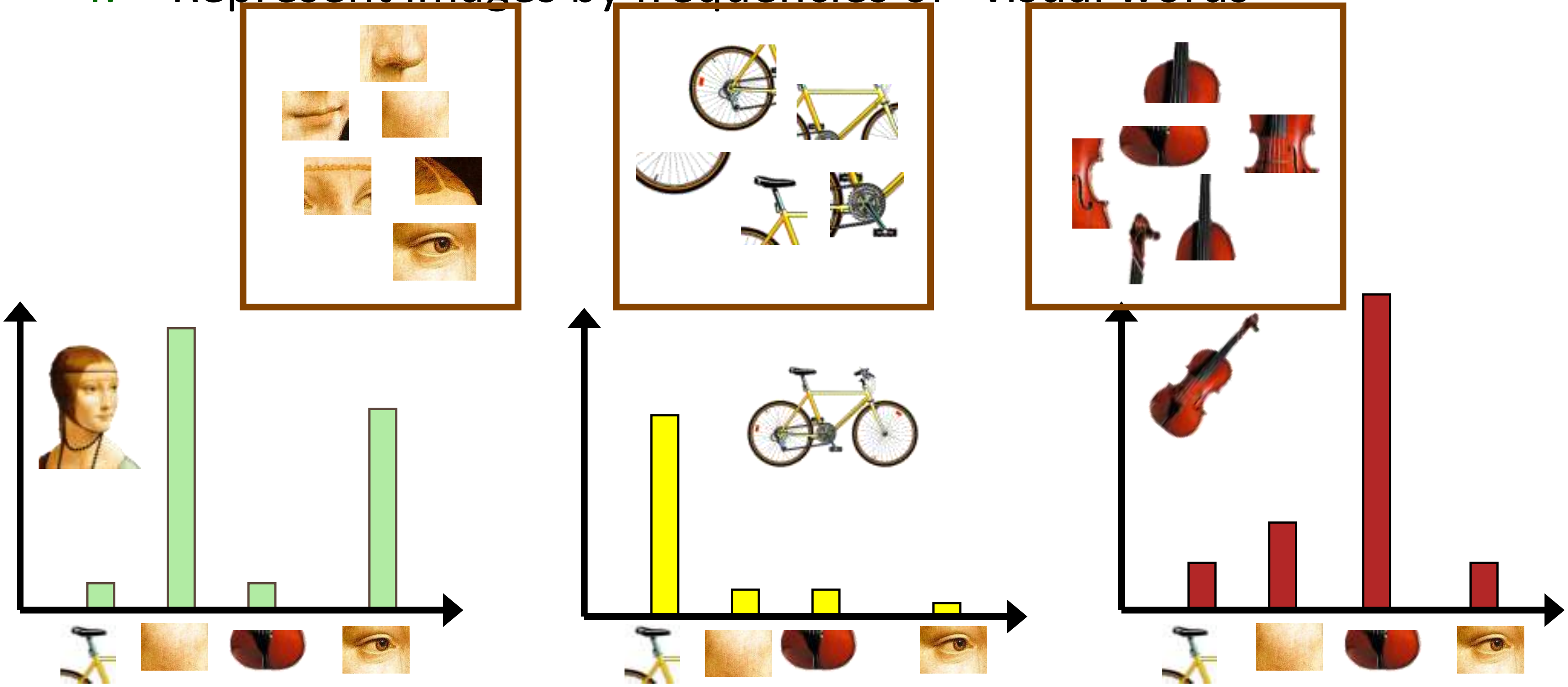
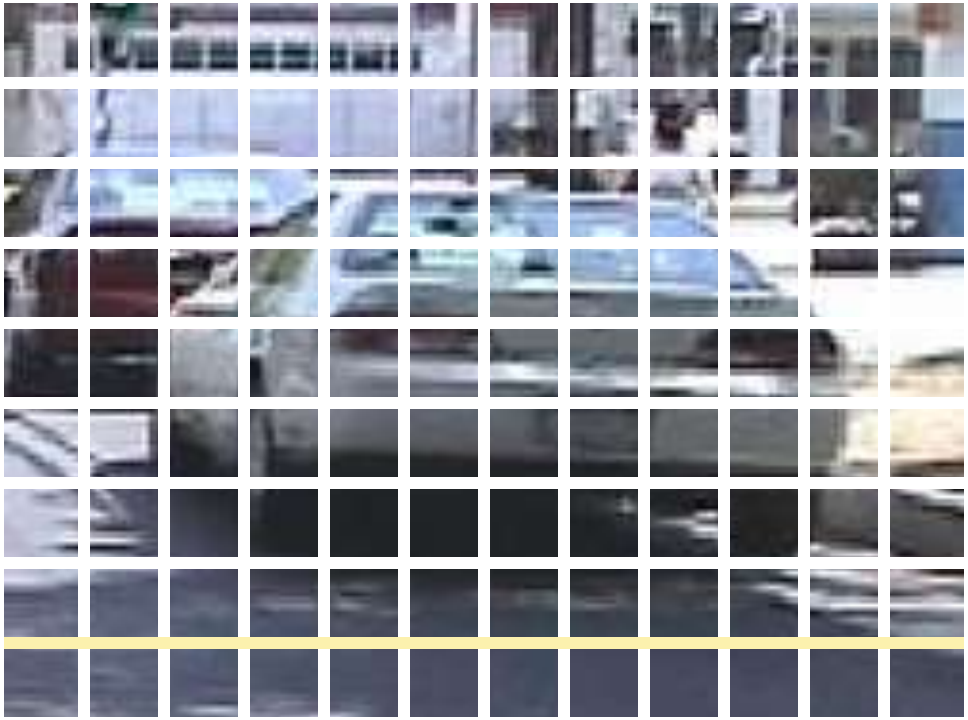
Bag-of-features steps

1. Extract local features
2. Learn "visual vocabulary"
3. Quantize local features using visual vocabulary
4. Represent images by frequencies of "visual words"



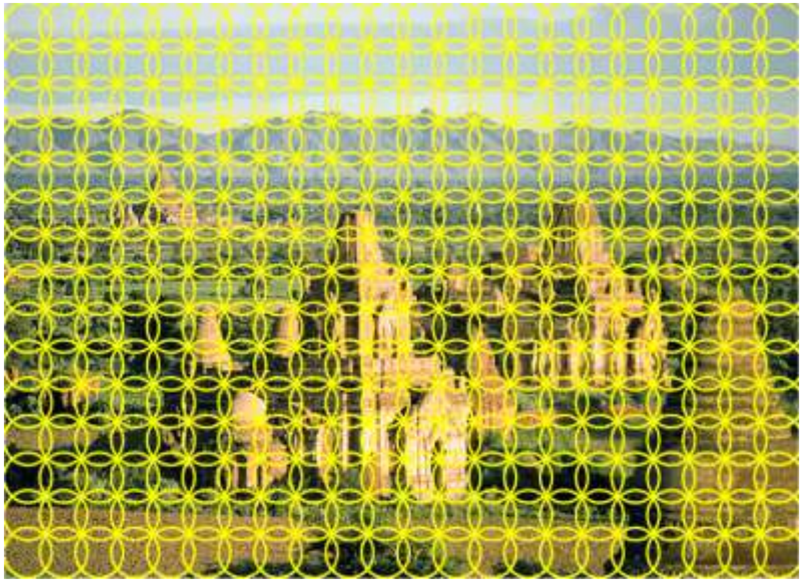
1. Local feature extraction

- Regular grid

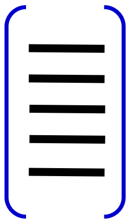


1. Local feature extraction

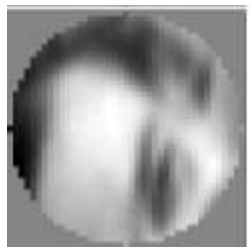
- Regular grid or interest regions



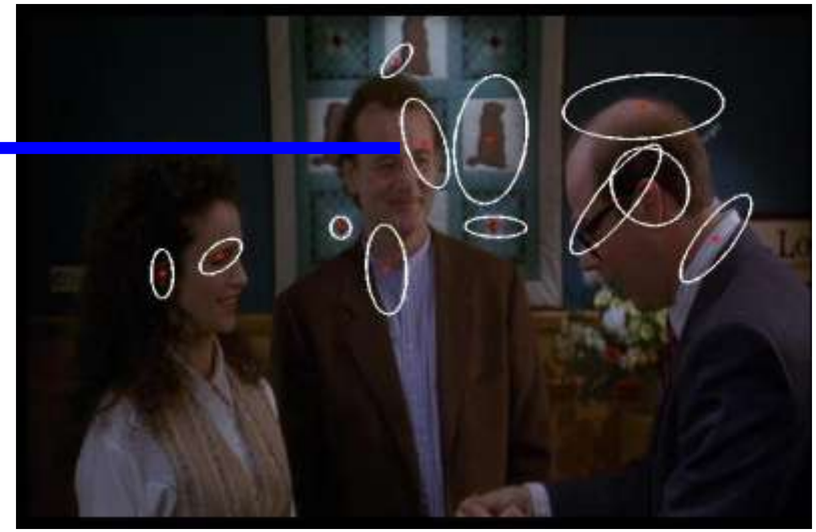
1. Local feature extraction



Compute descriptor



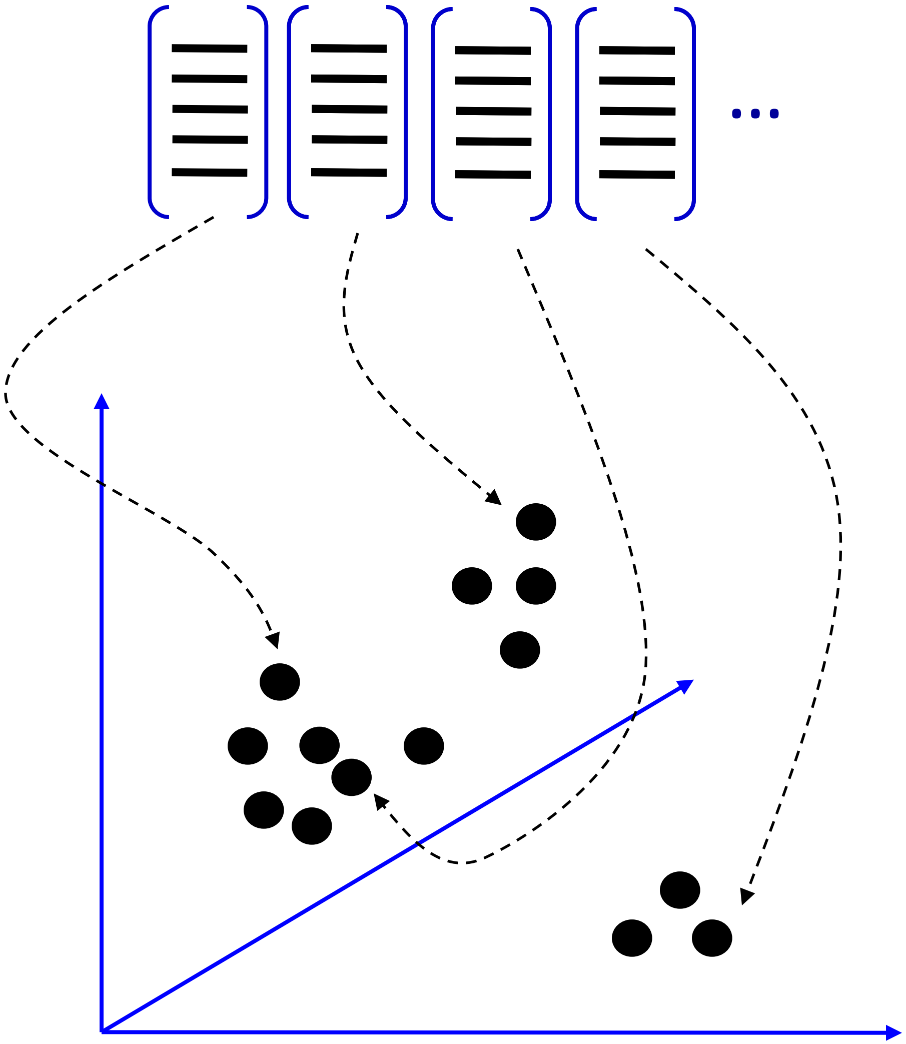
Normalize patch



Detect patches

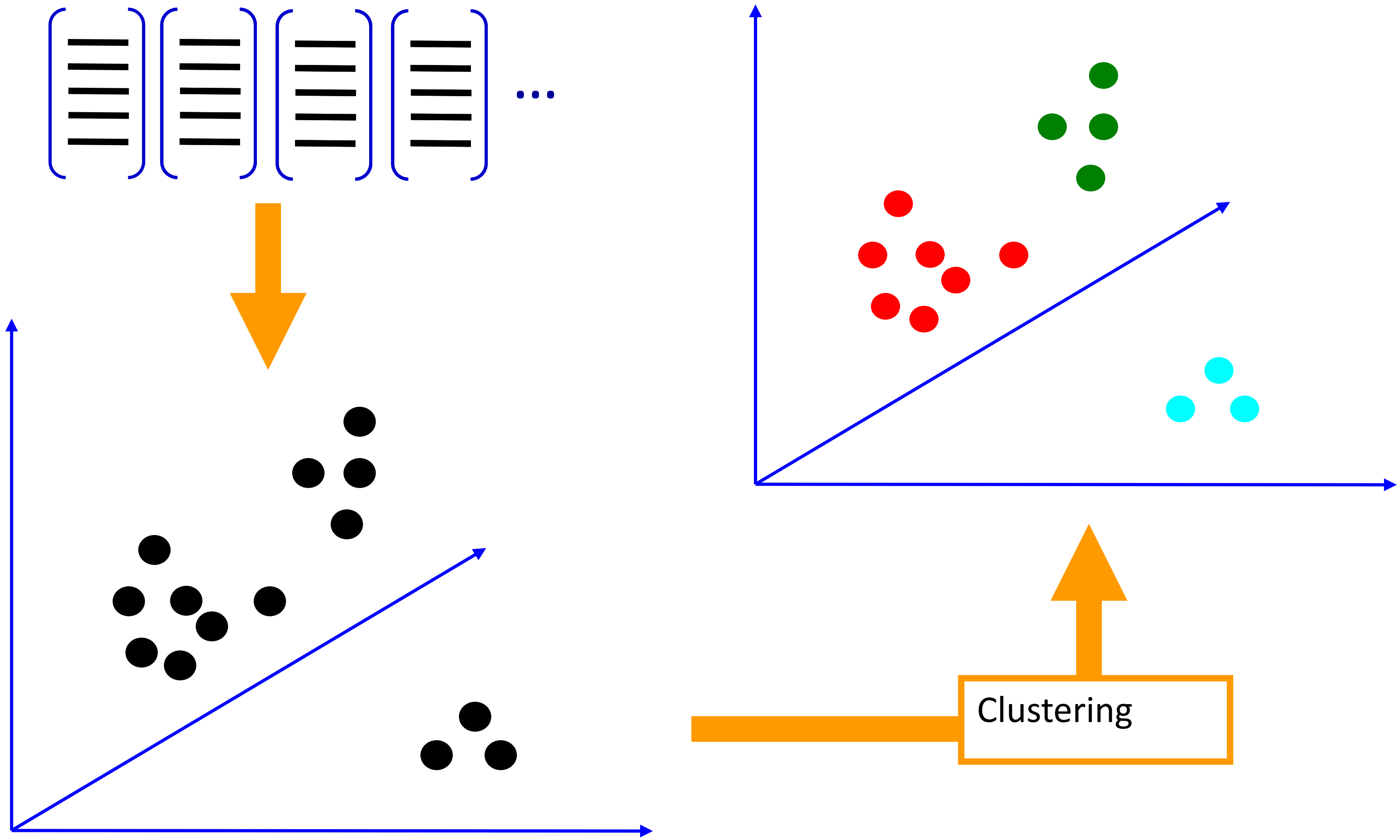
Slide credit: Josef Sivic

2. Learning the visual vocabulary



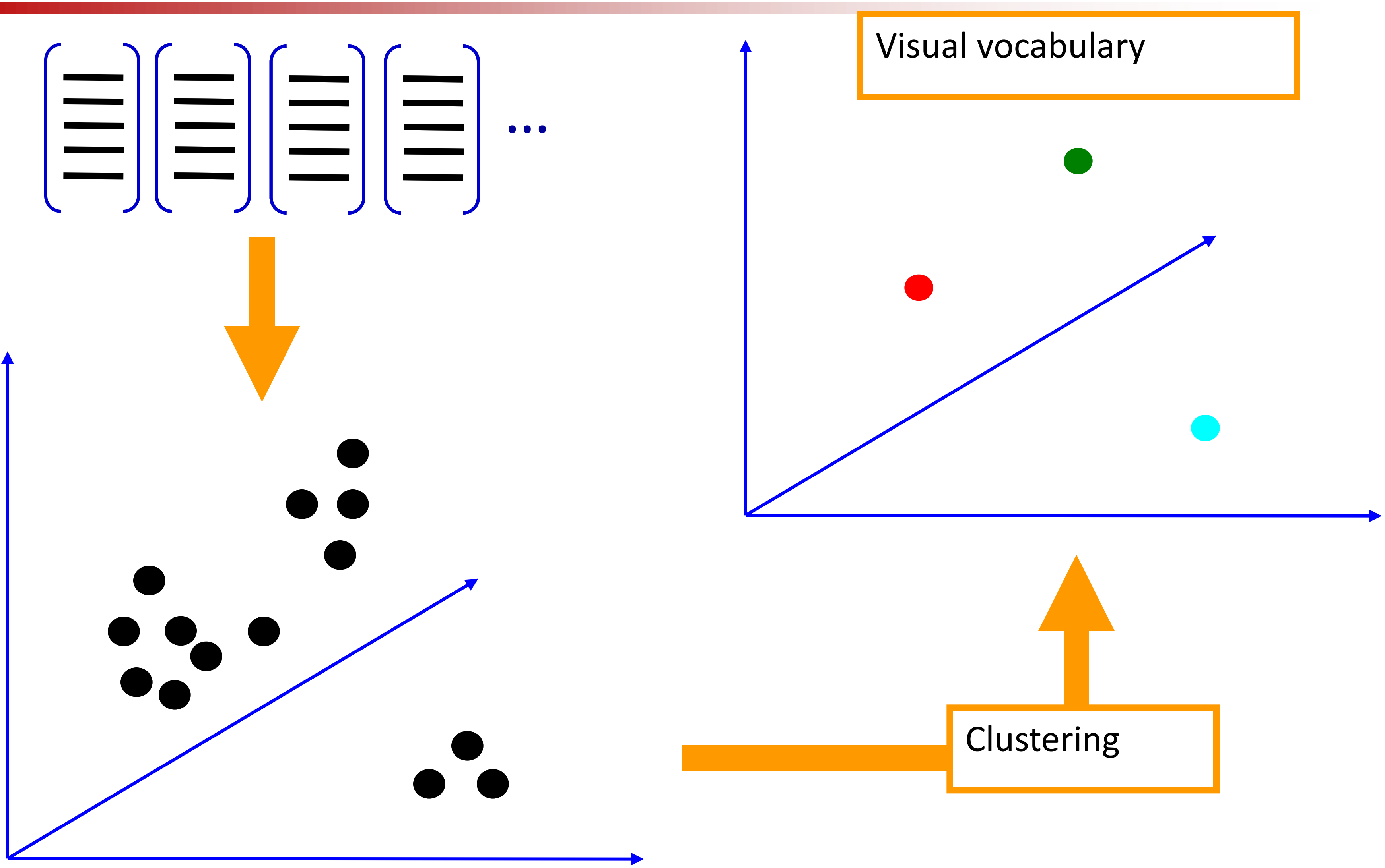
Slide credit: Josef Sivic

2. Learning the visual vocabulary



Slide credit: Josef Sivic

2. Learning the visual vocabulary



Slide credit: Josef Sivic

Review: K-means clustering

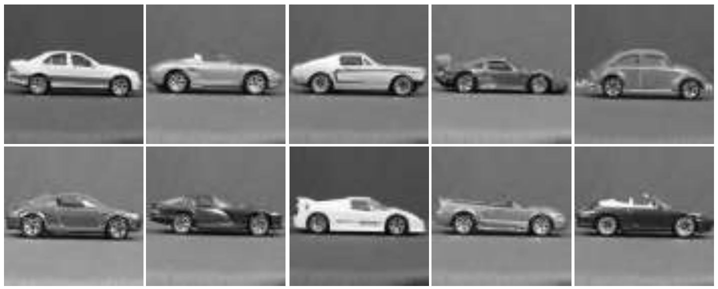
- Want to minimize sum of squared Euclidean distances between features $\mathbf{x}_i$ and their nearest cluster centers $\mathbf{m}_k$

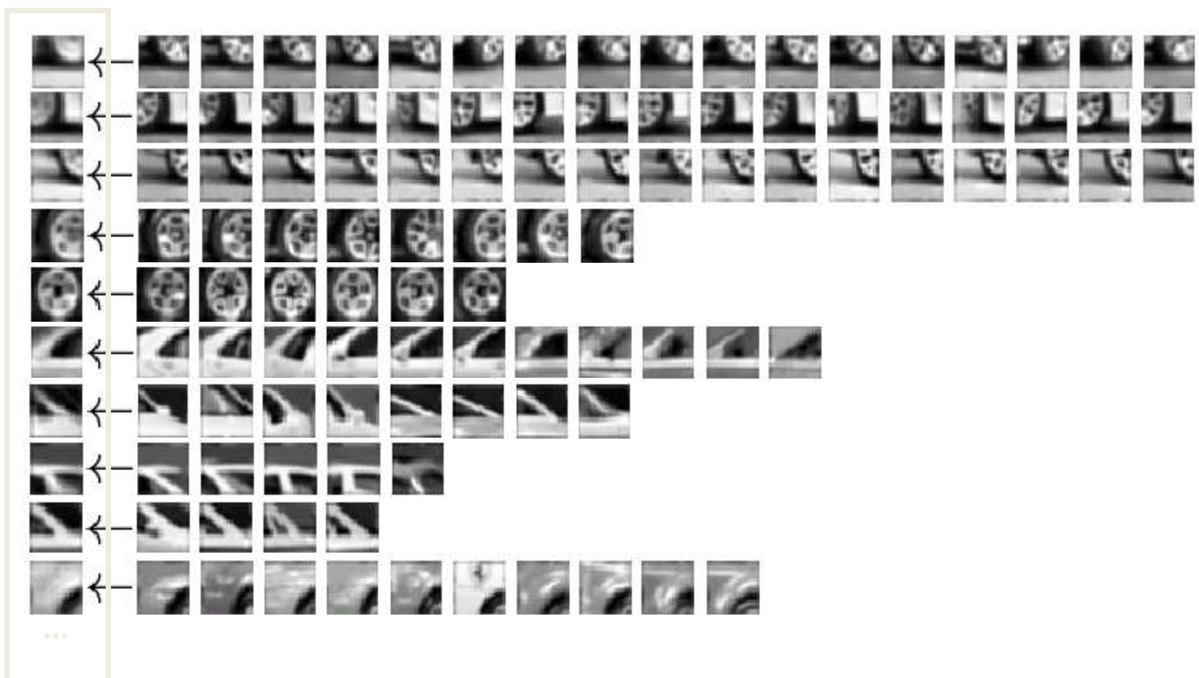
$$D(X,M) = \sum_{\text{cluster } k} \sum_{\substack{\text{point } i \text{ in} \\ \text{cluster } k}} (\mathbf{x}_i - \mathbf{m}_k)^2$$

Algorithm:

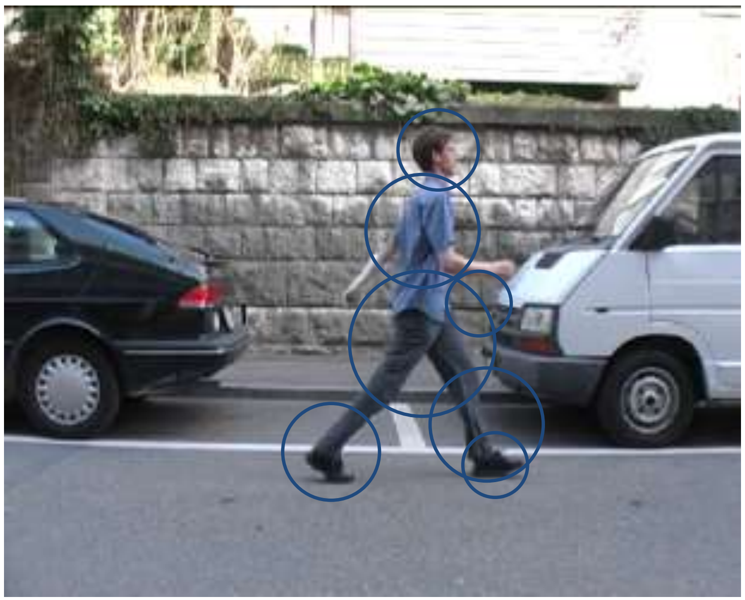
- Randomly initialize K cluster centers
- Iterate until convergence:
  - Assign each feature to the nearest center
  - Recompute each cluster center as the mean of all features assigned to it

Example codebook



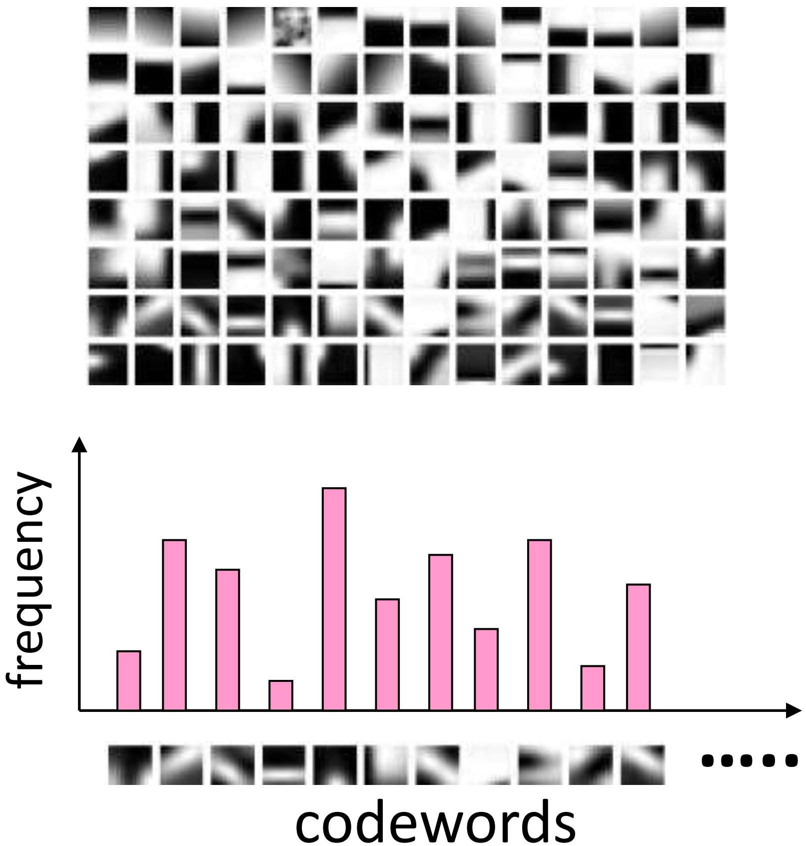


Another codebook

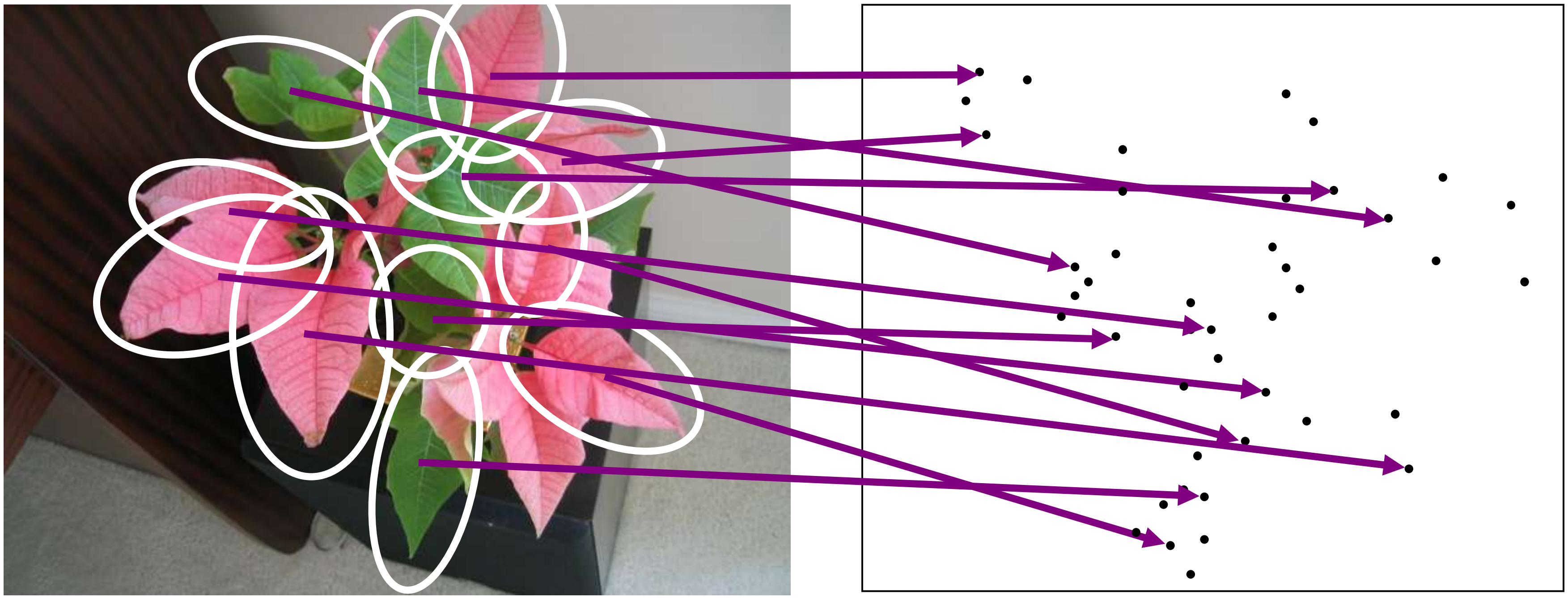


Bag-of-words

visual vocabulary

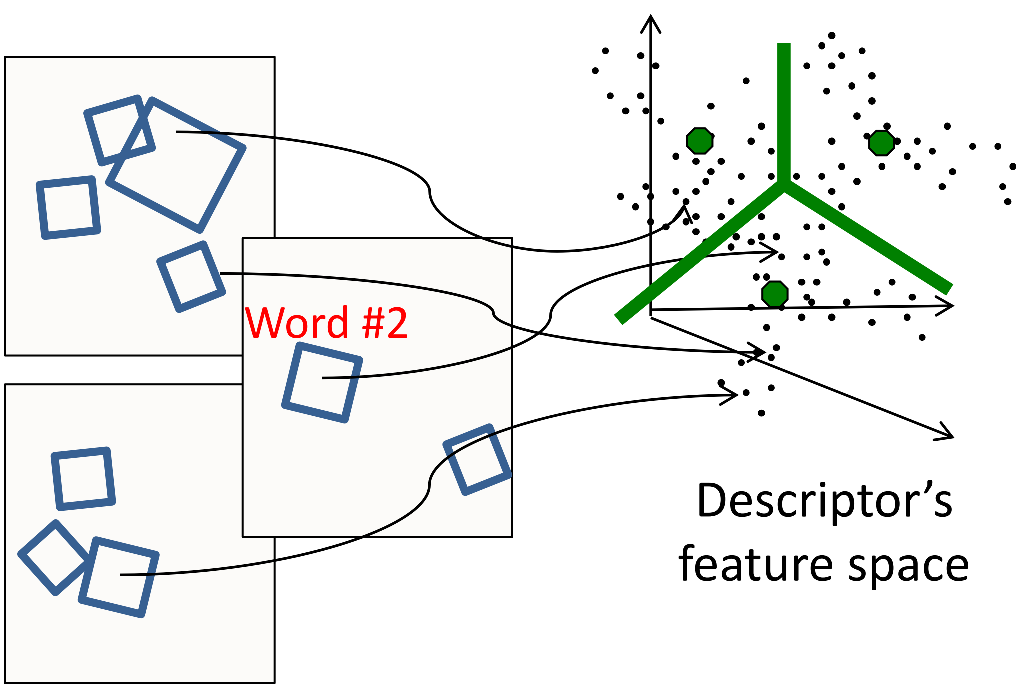


Visual words



Visual words (quantizing the feature space)

- Map high-dimensional descriptors to tokens/words by quantizing the feature space

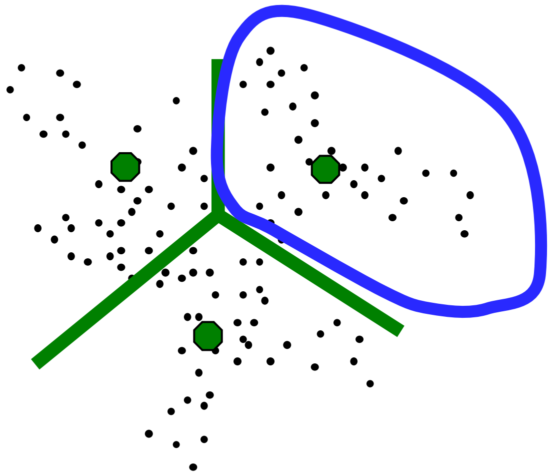


- Quantize via clustering, let cluster centers be the prototype "words"

- Determine which word to assign to each new image region by finding the closest cluster center.

Visual words

- Each group of patches belongs to the same visual word!



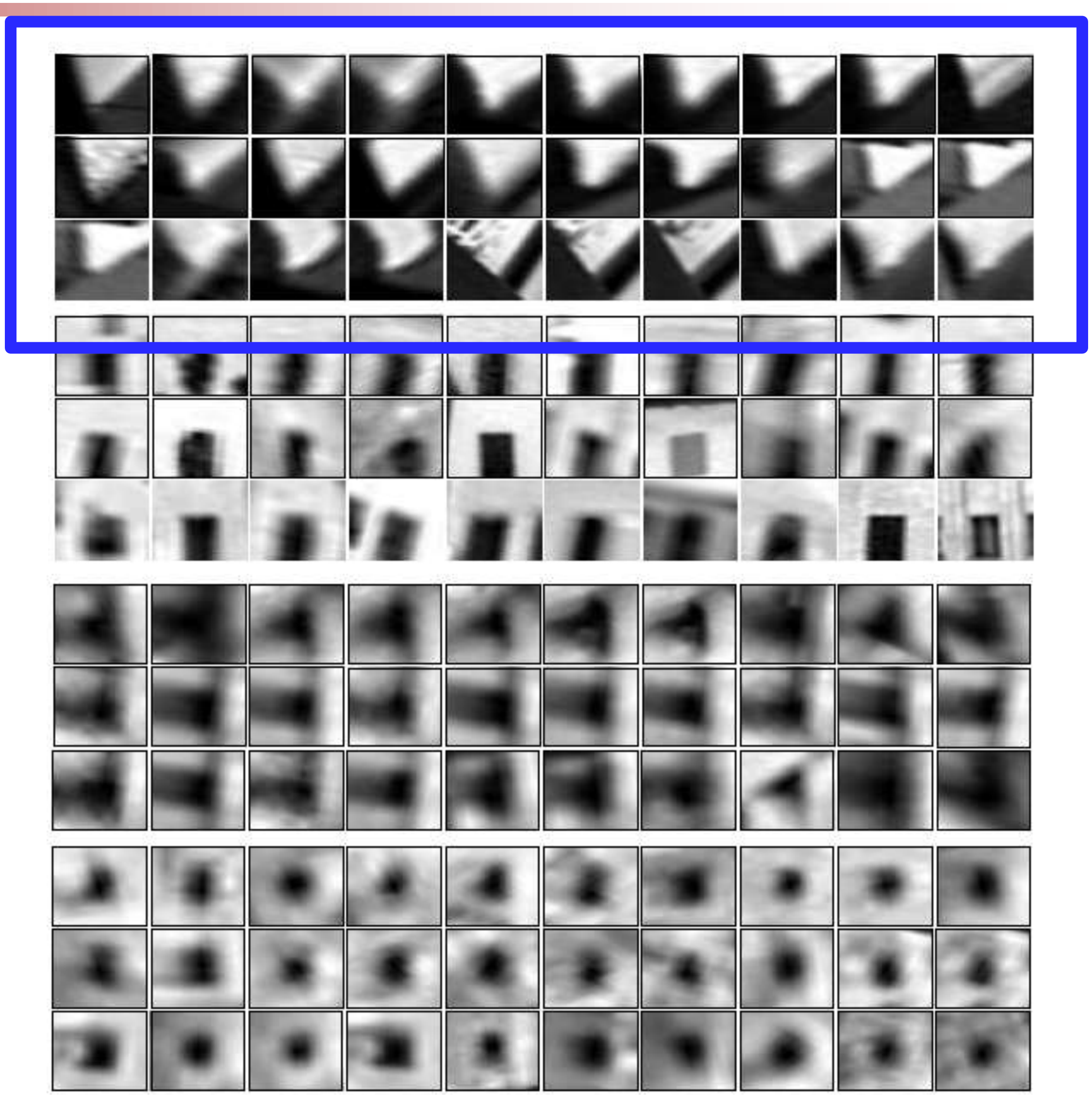


Figure from Sivic & Zisserman, ICCV 2003

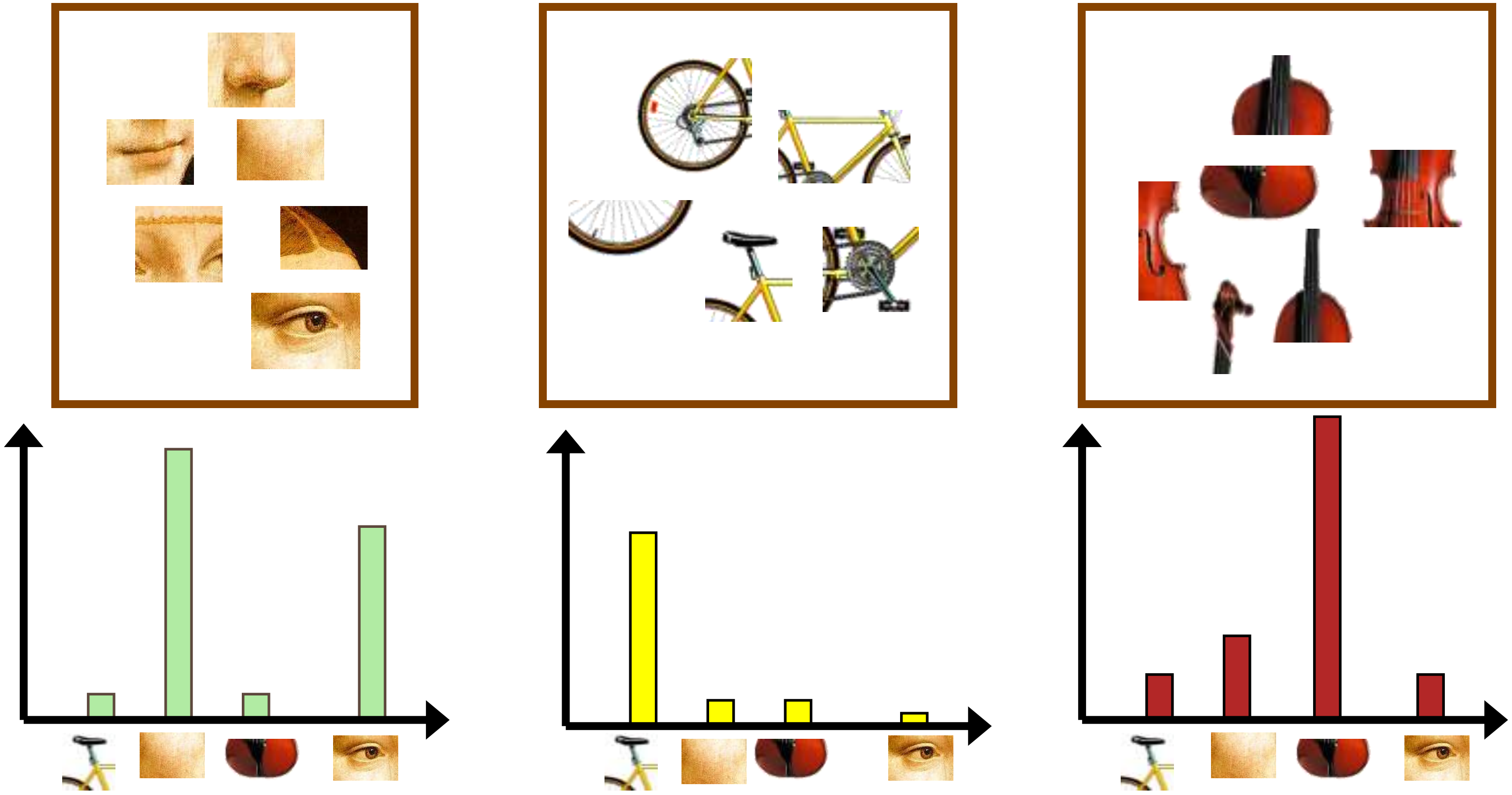
Visual vocabulary formation

Issues:

- Sampling strategy: where to extract features? Fixed locations or interest points?
- Clustering / quantization algorithm
- What corpus provides features (universal vocabulary?)
- Vocabulary size, number of words
- Weight of each word?

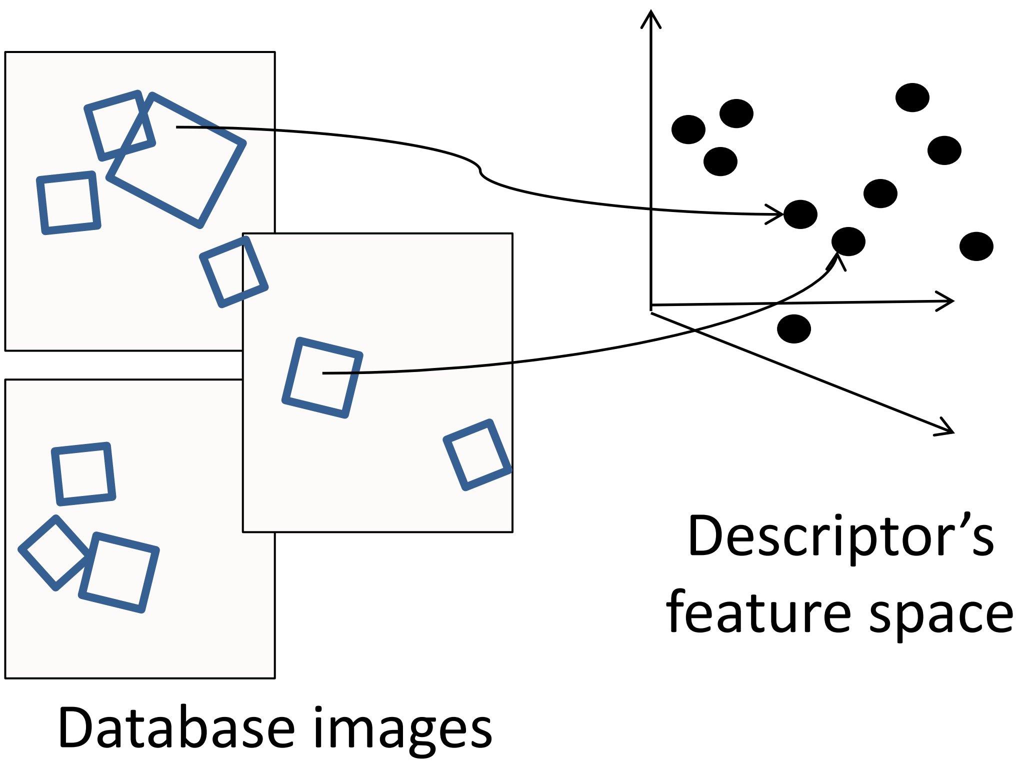
Bag-of-features steps

1. Extract local features
2. Learn "visual vocabulary"
3. **Quantize local features using visual vocabulary**
4. **Represent images by frequencies of "visual words"**



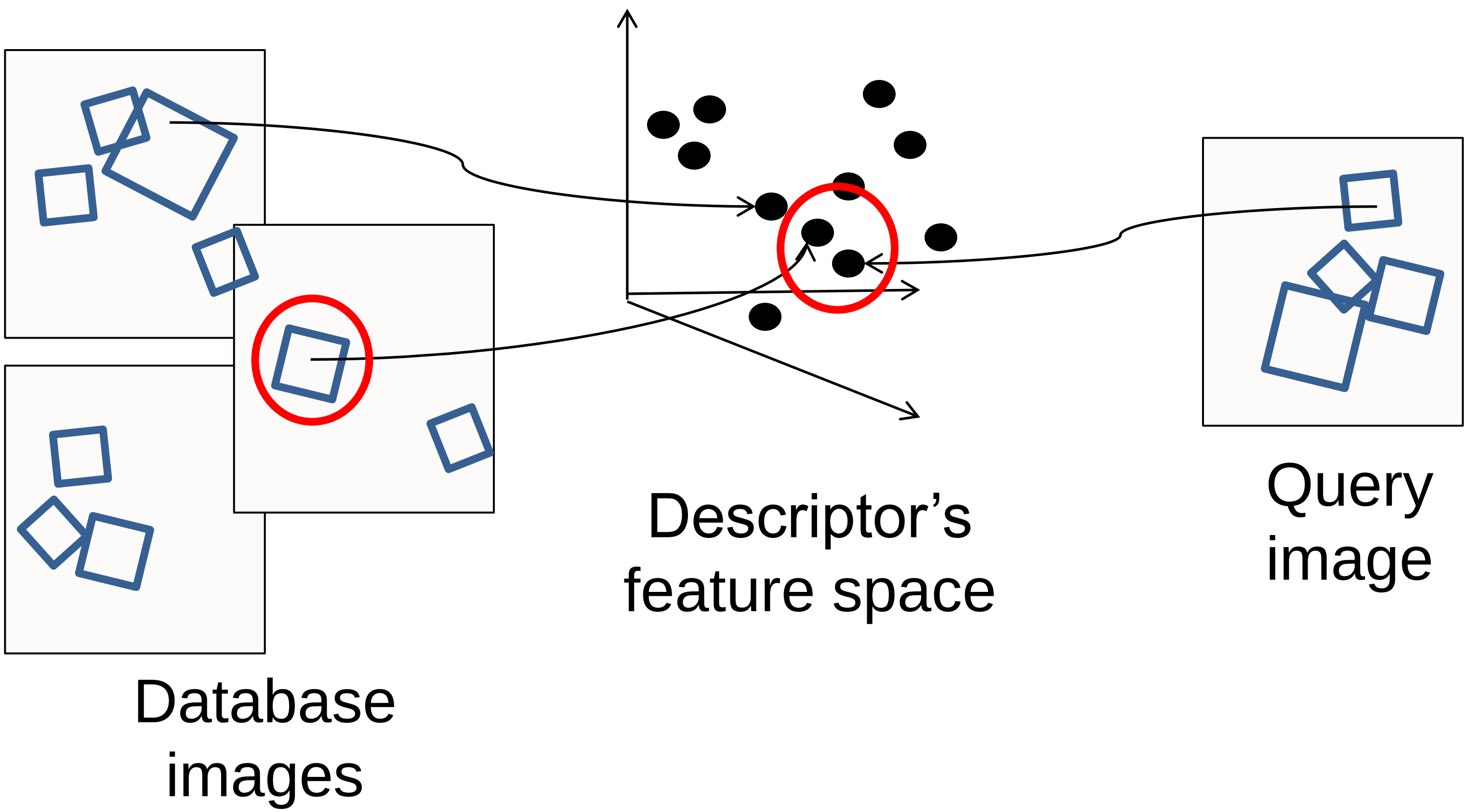
Indexing local features

- Each patch / region has a descriptor, which is a point in some high-dimensional feature space (e.g., SIFT)



Indexing local features

- When we see *close* points in feature space, we have *similar* descriptors, which indicates *similar* local content.



Indexing local features: **inverted file**

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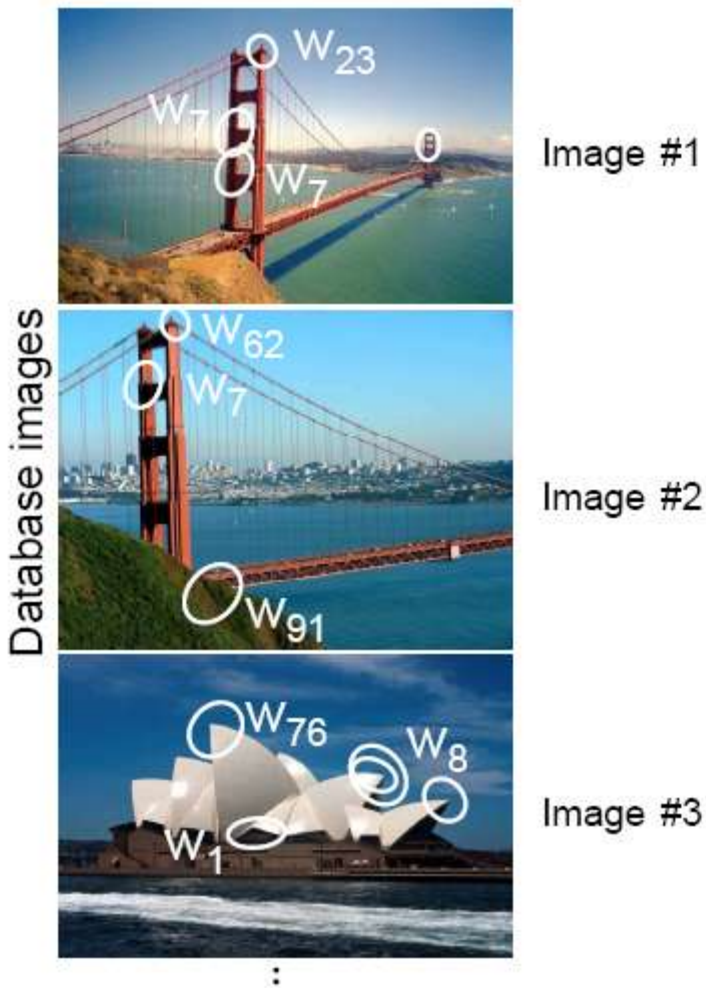
Indexing local features: Inverted index

- For text documents, an efficient way to find all *pages* on which a *word* occurs is to use an index.
- We want to find all *images* in which a *feature* occurs.
  - page $\sim$ image
  - word $\sim$ feature
- To use this idea, we'll need to map our features to "visual words".

Inverted file index



Word #	Image #
1	3
2 …	
7	1, 2
8	3
9	
10 …	
91	2
⋮	⋮

…

Why the index give us a significant gain in efficiency?

database images are loaded into the index mapping words to image numbers

Inverted file index

New query image

Word #	Image #
1	3
2 ...	
7	1, 2
8	3
9	
10 ...	
91	2
⋮	⋮

...

A query image is matched to database images that share visual words.

tf-idf weighting

- ***t**erm **f**requency – **i**nverse **d**ocument **f**requency*
- Describe the *frequency* of each word within an image, decrease the weights of the words that appear often in the database
  - economic, trade, … $w \nearrow$ discriminative regions
  - the, most, we, … $w \searrow$ common regions

tf-idf weighting

- ***t**erm **f**requency – **i**nverse **d**ocument **f**requency*
- Describe the *frequency* of each word within an image, decrease the weights of the words that appear often in the database

Number of occurrences of word *i* in document *d*

Number of words in document *d*

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

Total number of documents in database

Number of documents containing word *i*, in whole database

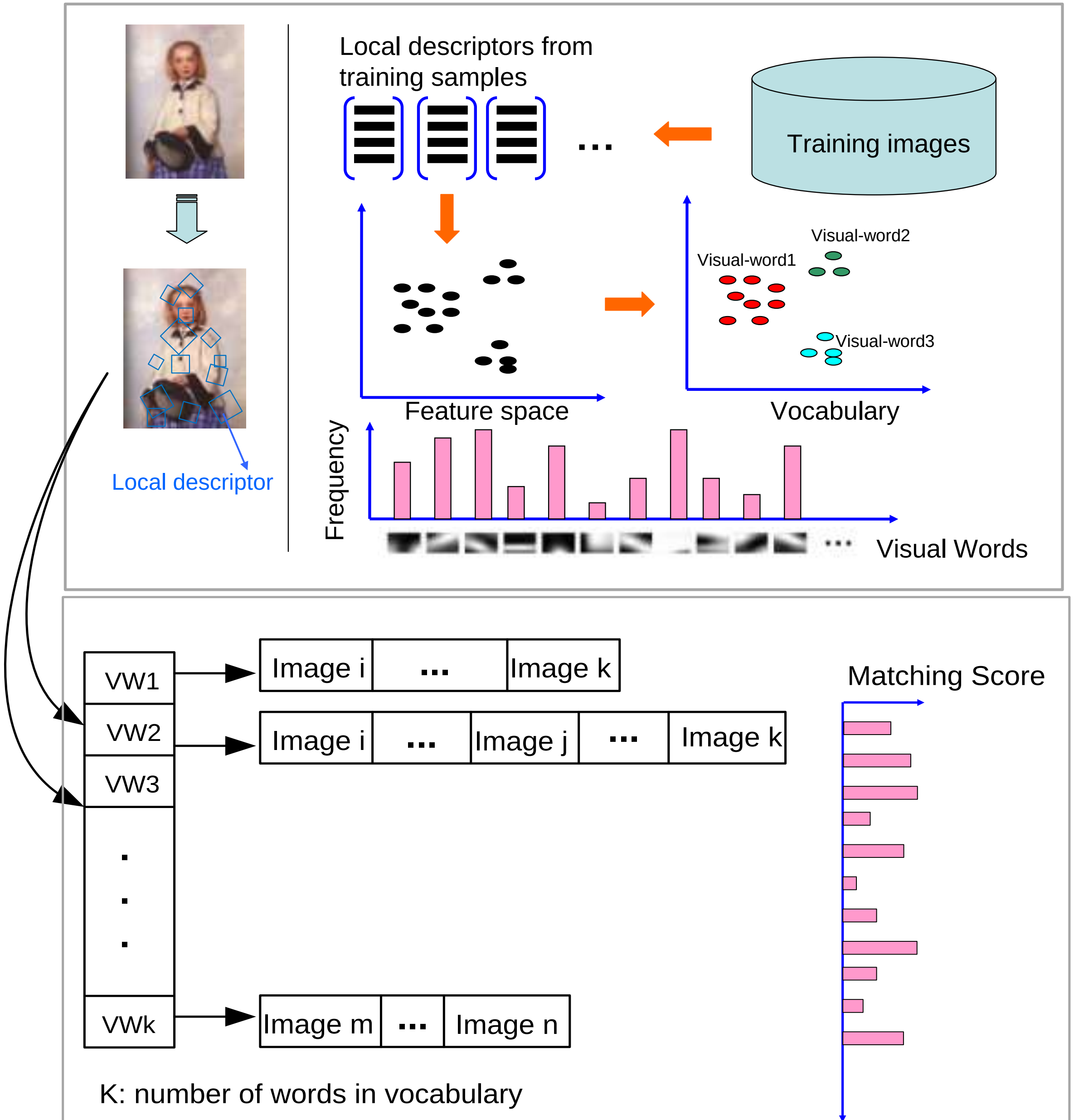
tf-idf weighting: matching

- At match time, each document (or query region) is represented by its tf-idf vector,

  $\boldsymbol{t} = (t_1, \ldots, t_i, \ldots t_m)$.

- The similarity between two documents is measured by the dot product between their corresponding normalized vectors $\hat{\mathbf{t}} = \mathbf{t}/\|\mathbf{t}\|$

Bag-of-Words + Inverted file



Bag-of-words representation

Inverted file

Visual vocabularies: Details

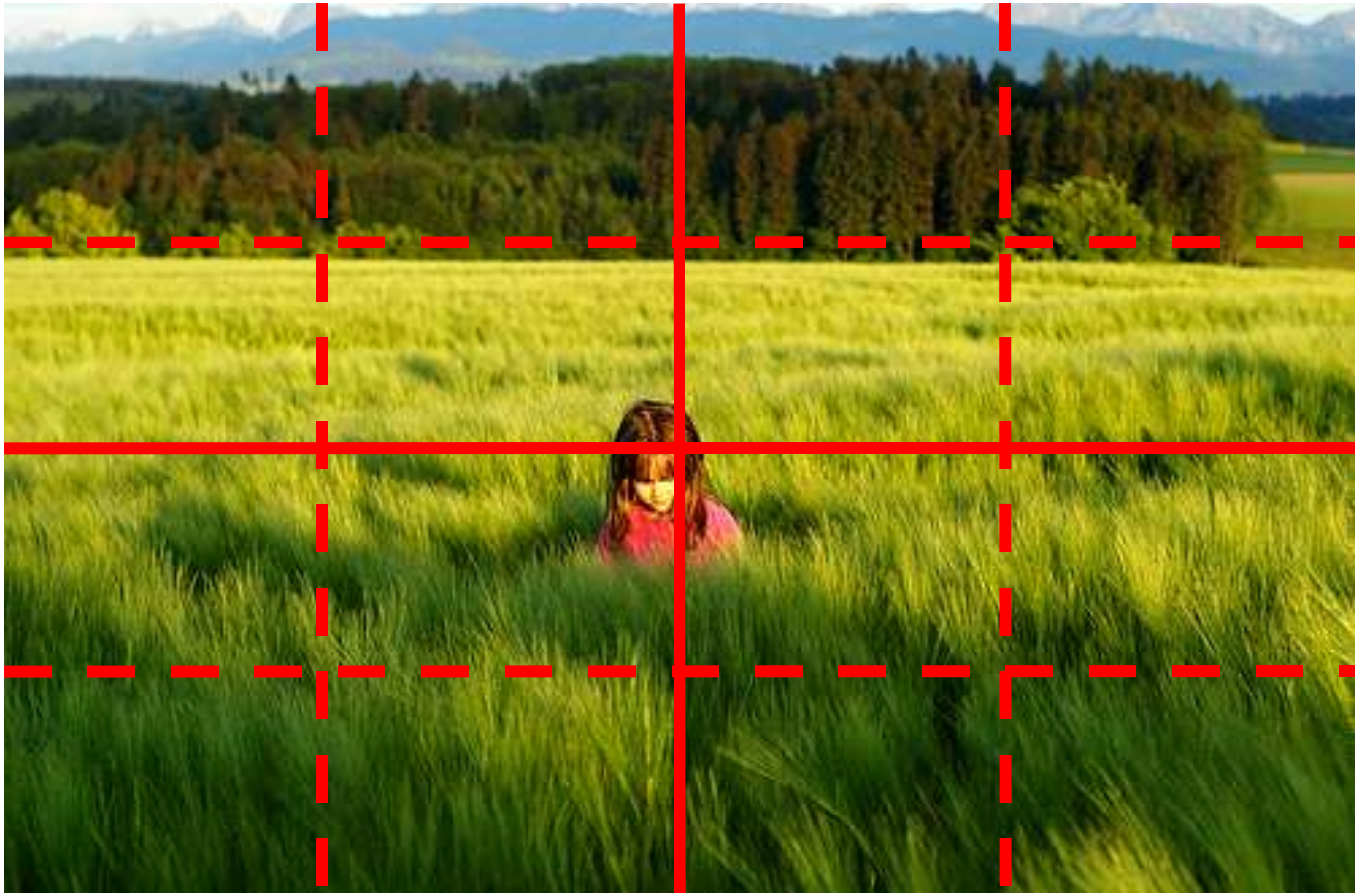
- How to choose vocabulary size?
  - Too small: visual words not representative of all patches
  - Too large: quantization artifacts, overfitting
  - Right size is application-dependent

- Improving vocabulary quality
  - Discriminative/supervised training of codebooks
  - Sparse coding, non-exclusive assignment to codewords

The lack of geometry in BoW (spatial information)

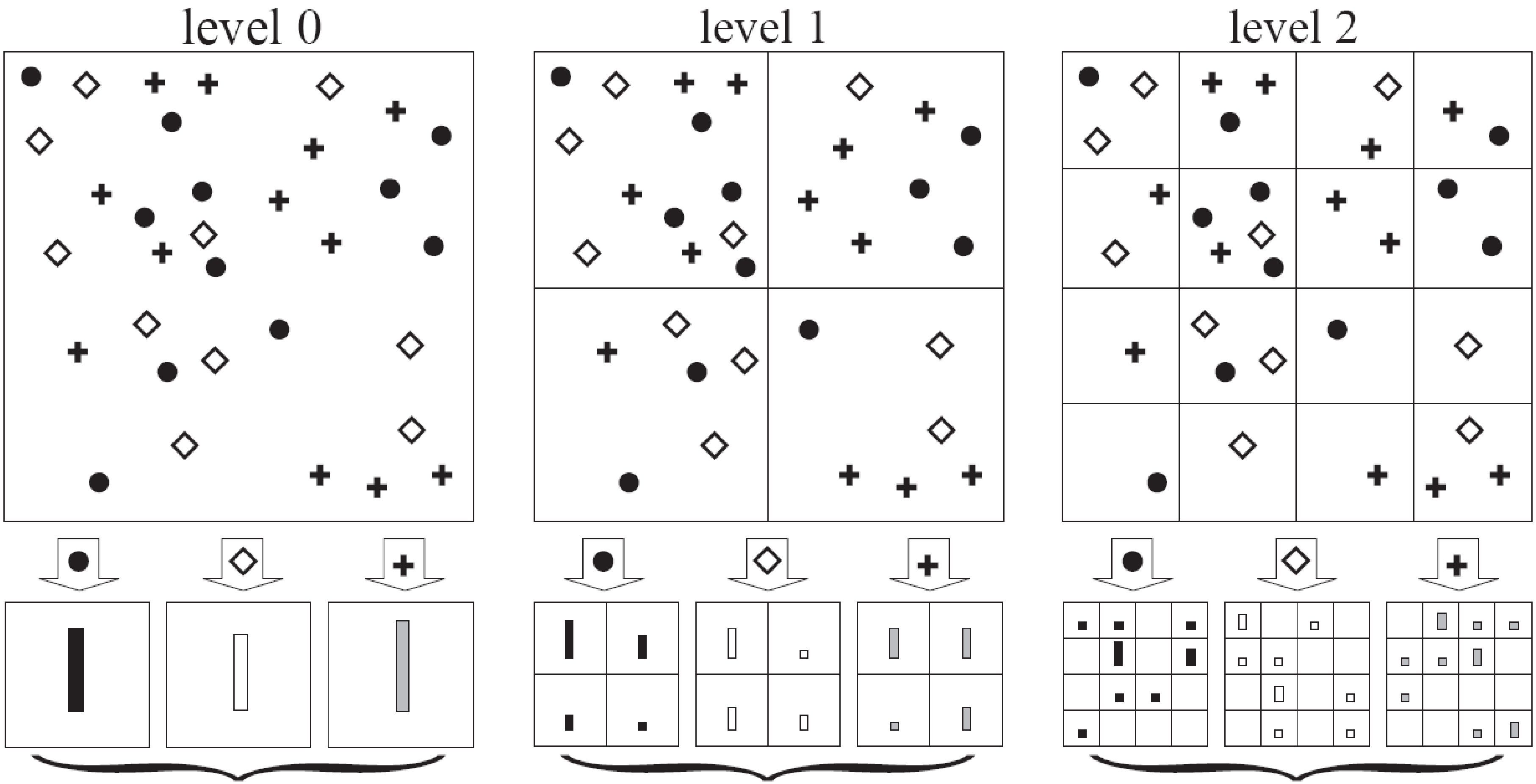
- The lack of geometry in the bag-of-words representation (BoW) can be either an advantage or a disadvantage.
- By encoding only the occurrence of the appearance of the local patches, not their relative geometry, we get significant flexibility to viewpoint and pose changes.
- Geometry between features can itself be an important discriminating factor, which a BoW will miss.

Spatial pyramid



- Compute histogram in each spatial bin

Spatial pyramid



- One critism high dimensionality and you can deal with by doing PCA dimension reduction