

Bag of Words

or

Bag of Features

Lecture-17

**(Slides Credit: Cordelia Schmid
LEAR – INRIA Grenoble)**

Contents

- Interest Point Detector
- Interest Point Descriptor
- K-means clustering
- Support Vector Machine (SVM) classifier
- Evaluation Metrics: Precision & Recall

Image classification

- Image classification: assigning a class label to the image



Car: present
Cow: present
Bike: not present
Horse: not present
...

Image classification

- Image classification: assigning a class label to the image



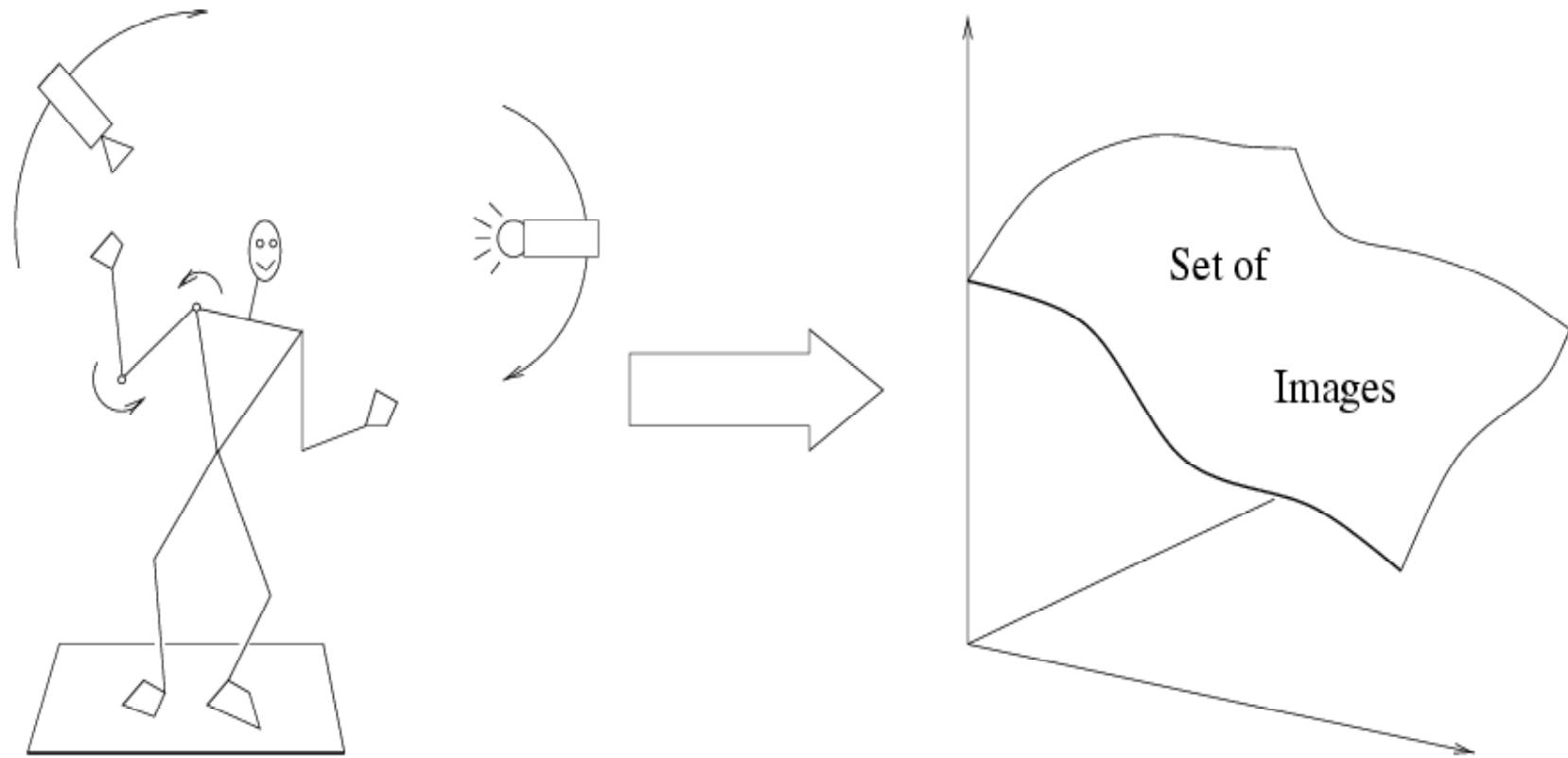
Car: present
Cow: present
Bike: not present
Horse: not present
...

- Object localization: define the location and the category

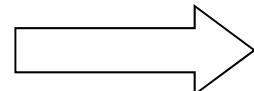


Location
Category

Difficulties: within object variations



Variability: Camera position, Illumination, Internal parameters



Within-object variations

Difficulties: within class variations



Image classification

- Given

Positive training images containing an object class



Negative training images that don't



- Classify

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



?

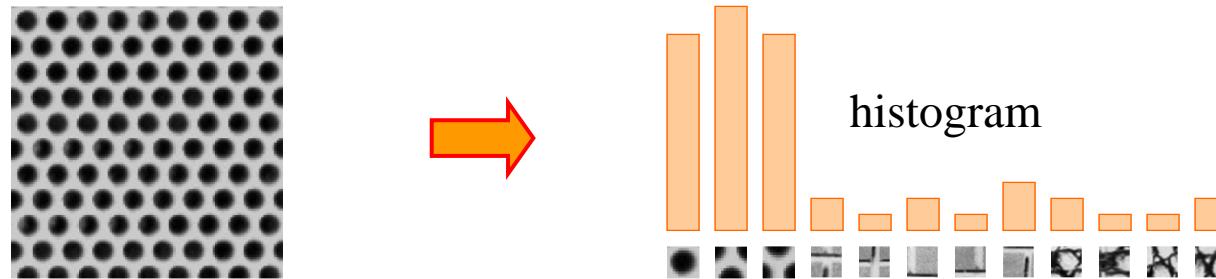
Bag-of-features – Origin: texture recognition

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

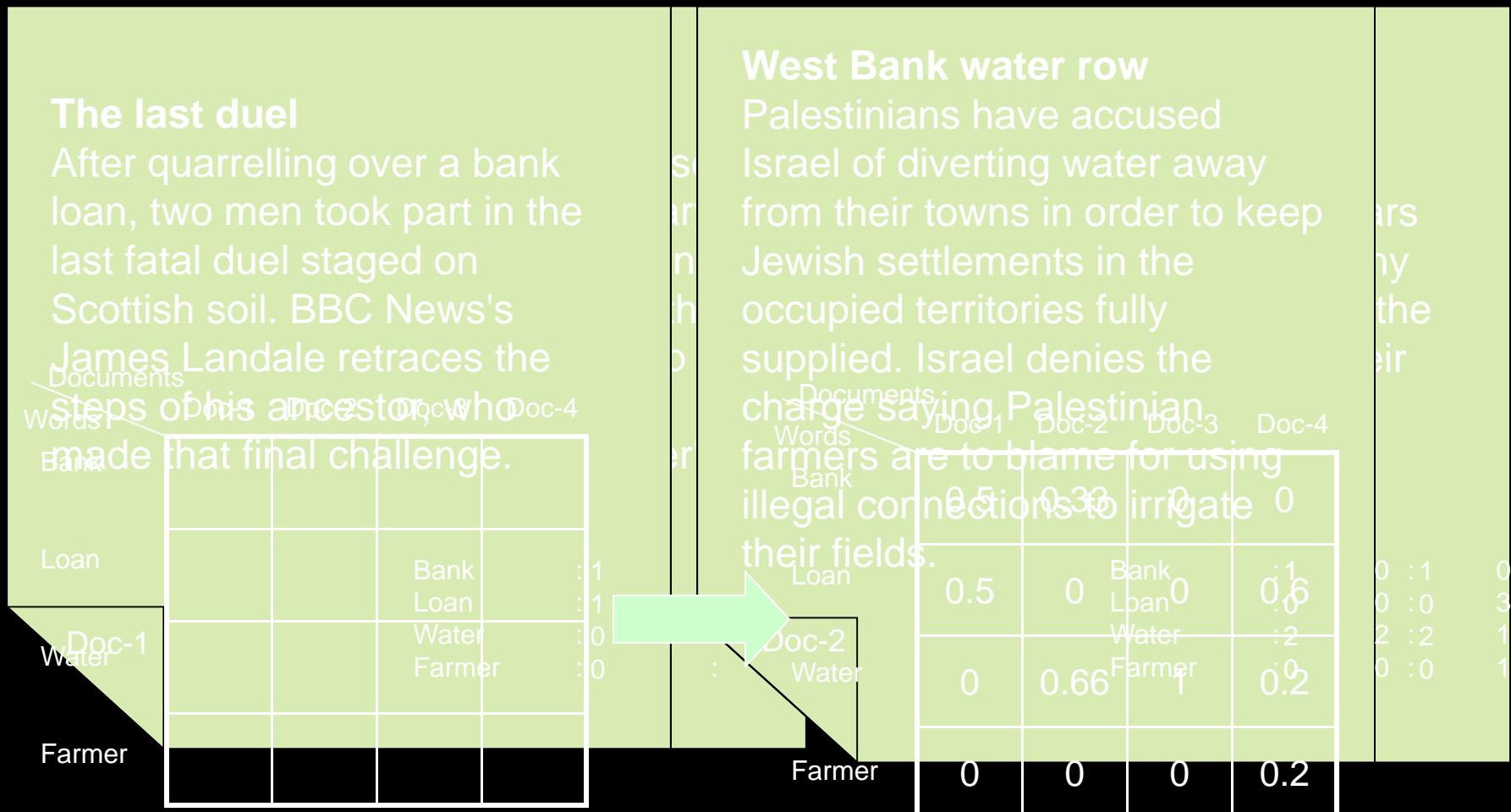
Julesz, 1981; Cula & Dana, 2001; Leung & Malik 2001; Mori, Belongie & Malik, 2001

Schmid 2001; Varma & Zisserman, 2002, 2003; Lazebnik, Schmid & Ponce, 2003

Bag-of-features – Origin: texture recognition



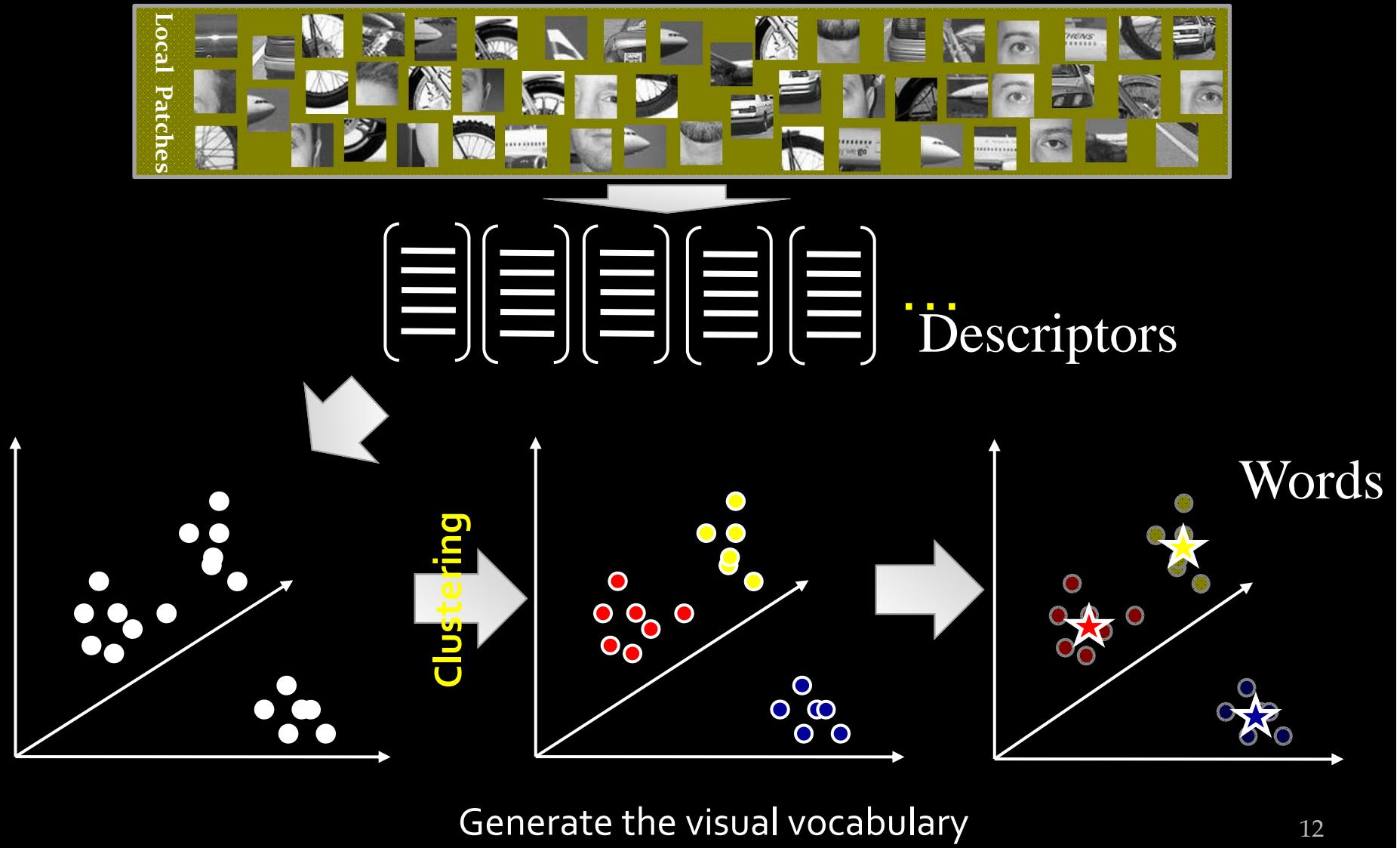
Bag of Words Model



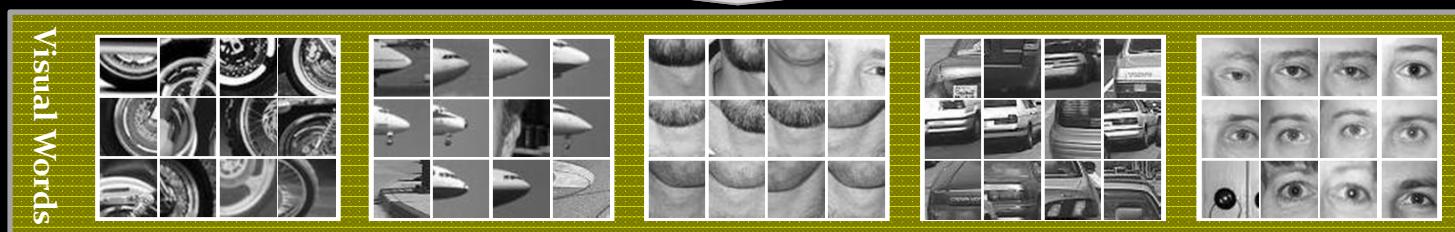
Bag of Visual Words model



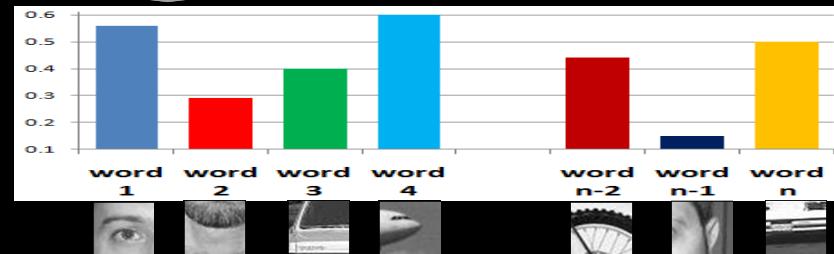
Bag of Visual Words model



Bag of Visual Words model

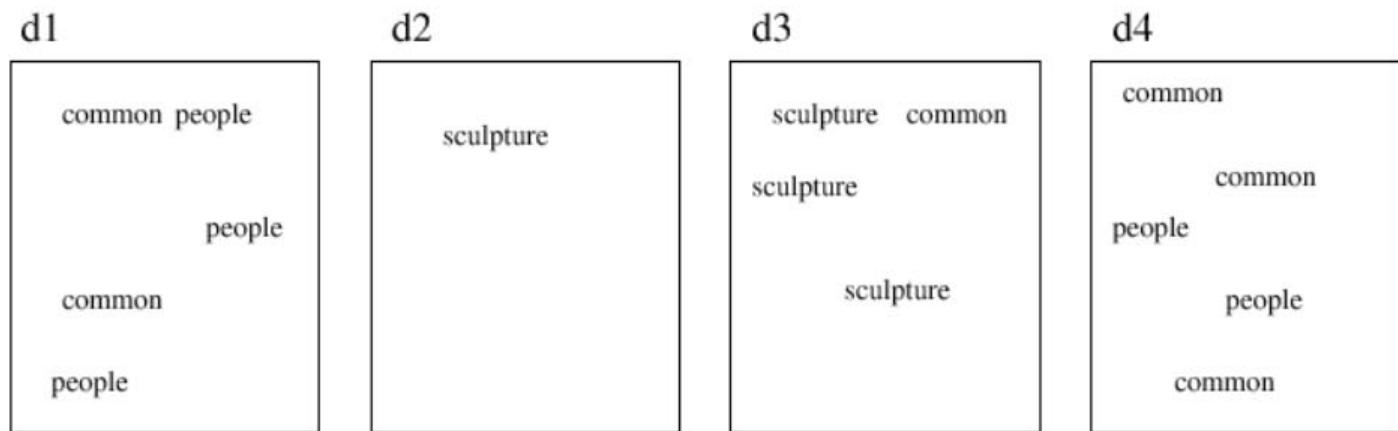


Represent an image as a histogram or bag of words



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

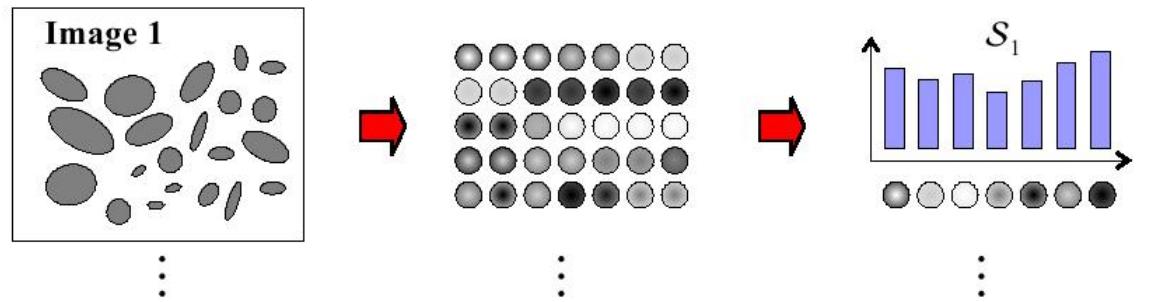
- Orderless document representation: frequencies of words from a dictionary
- Classification to determine document categories



Bag-of-words

| | | | | |
|-----------|-----|-----|-----|-----|
| Common | 2 | 0 | 1 | 3 |
| People | 3 | 0 | 0 | 2 |
| Sculpture | 0 | 1 | 3 | 0 |
| ... | ... | ... | ... | ... |

Bag-of-features for image classification

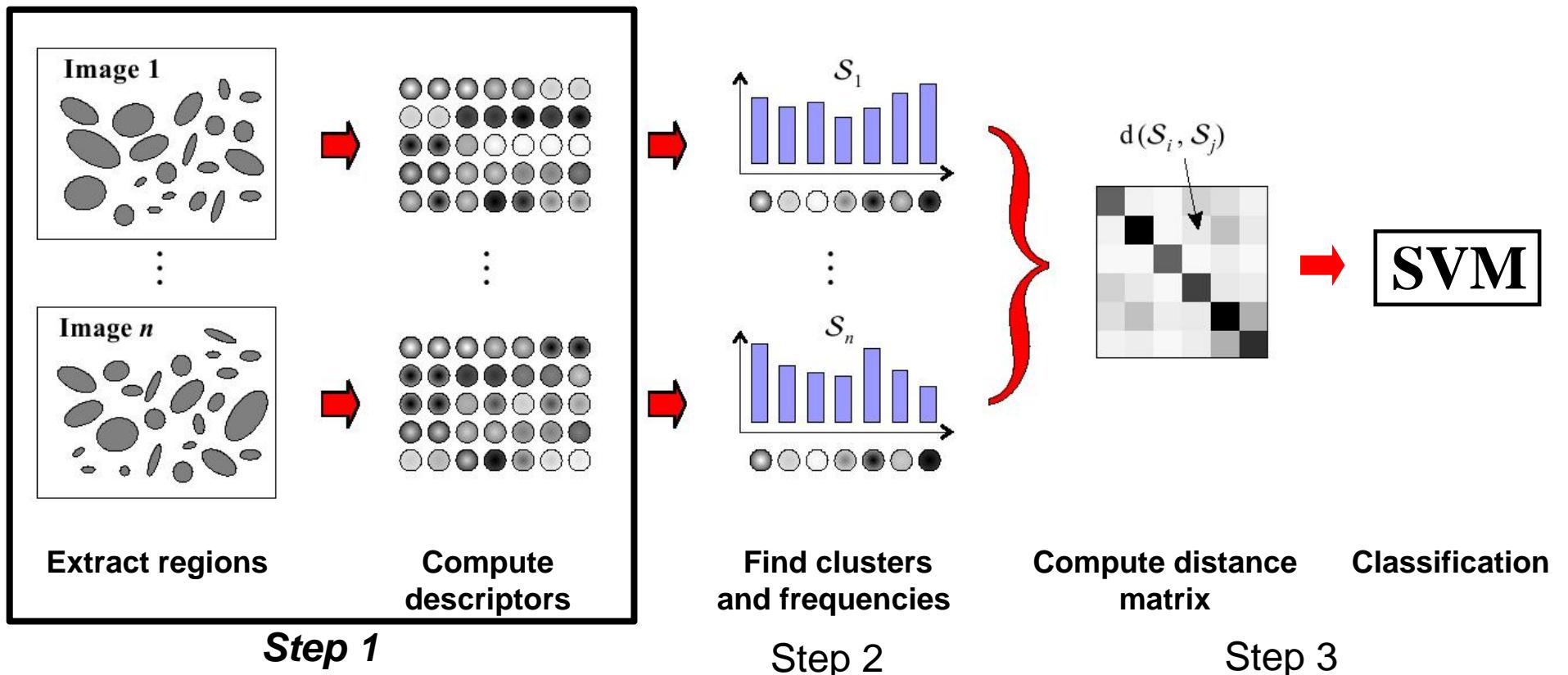


Extract regions
or
Interest Points

Compute
descriptors

Find clusters
and frequencies

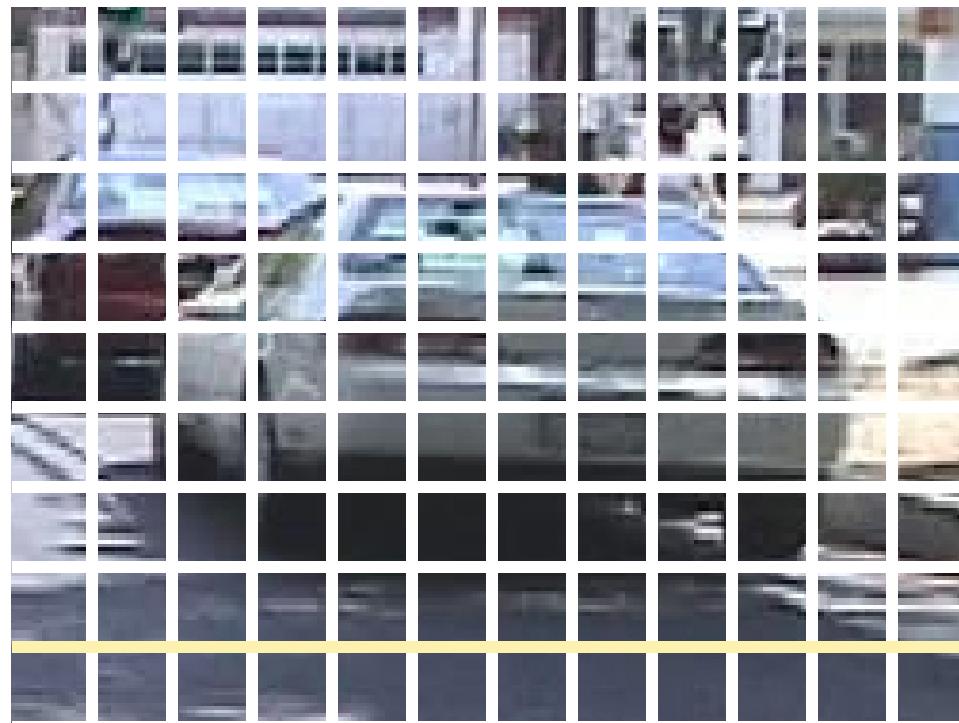
Bag-of-features for image classification



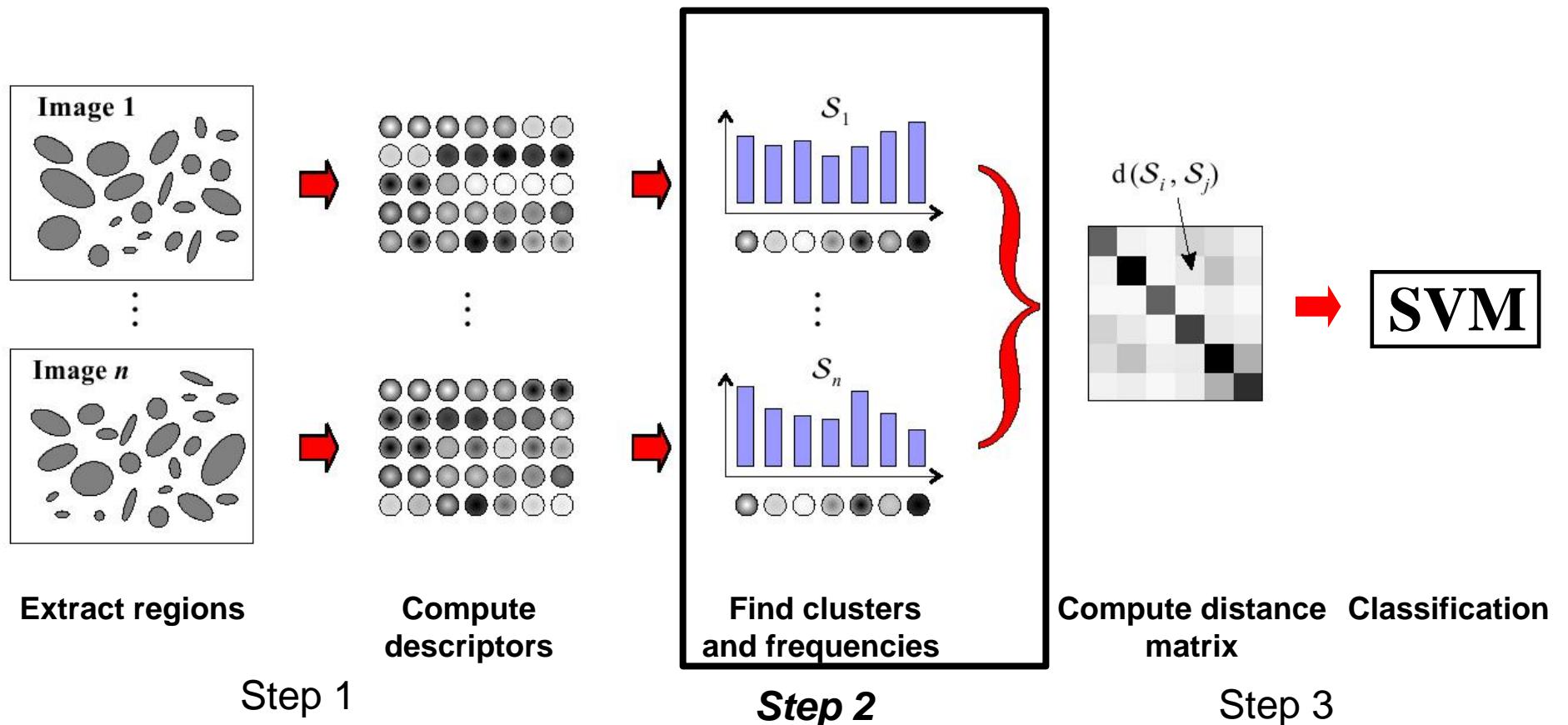
Step 1: feature extraction

- Detect Interest Points
 - SIFT
 - Harris
 - Dense (take every nth pixel as interest point)
- Compute Descriptor around each interest point
 - SIFT
 - HOG

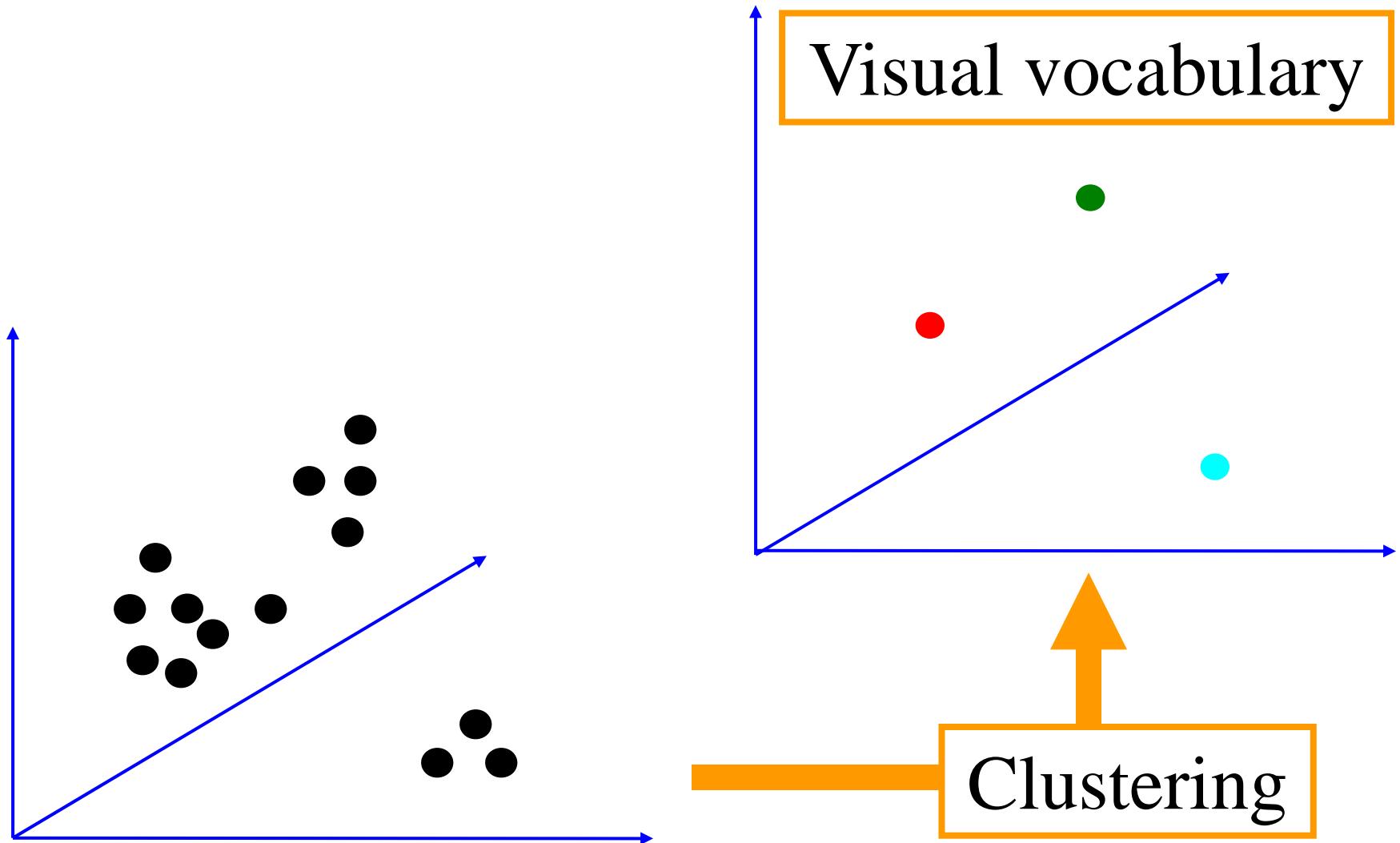
Dense features



Bag-of-features for image classification



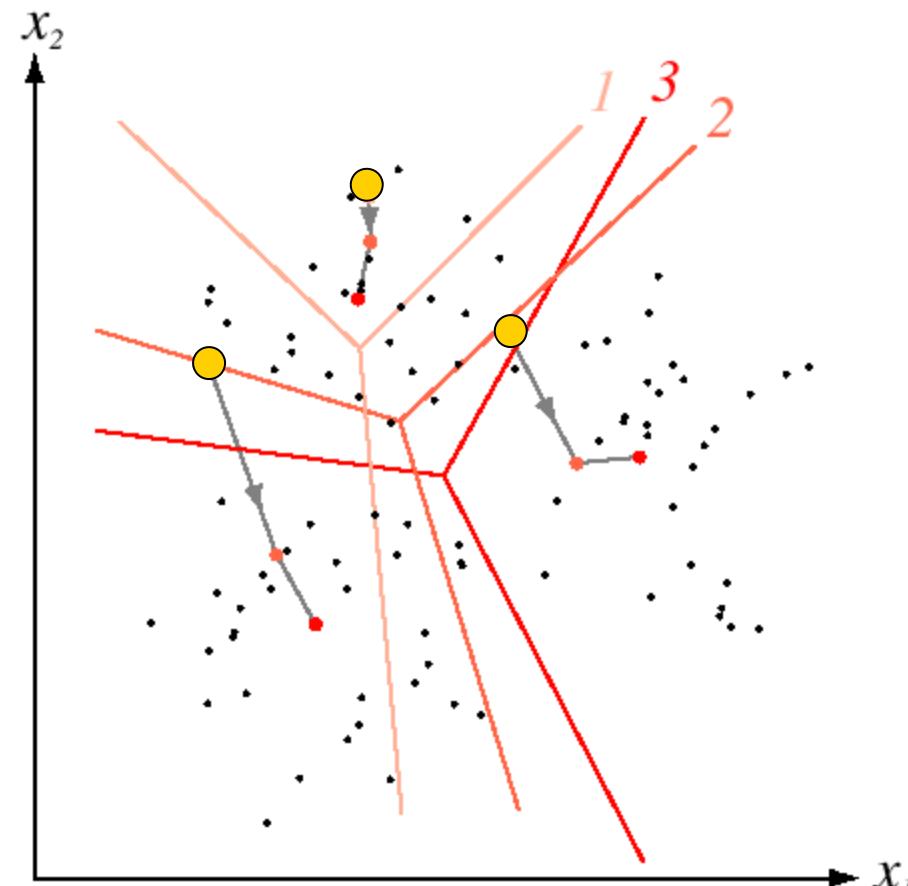
Step 2: Quantization



Step 2: Quantization

- Cluster descriptors
 - K-means
- Assign each visual word to a cluster
- Build frequency histogram

Example: 3-means Clustering



Convergence in 3 steps

from
Duda et al.

K-Means

```
Choose  $k$  data points to act as cluster centers
```

```
Until the cluster centers are unchanged
```

```
    Allocate each data point to cluster whose center is nearest
```

```
    Replace the cluster centers with the mean of the elements  
    in their clusters.
```

```
end
```

Algorithm 16.5: *Clustering by K-Means*

Examples for visual words

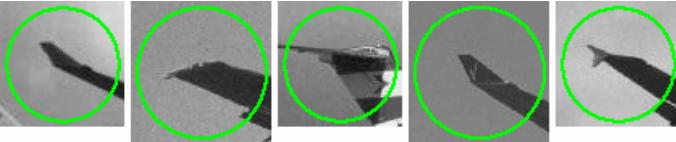
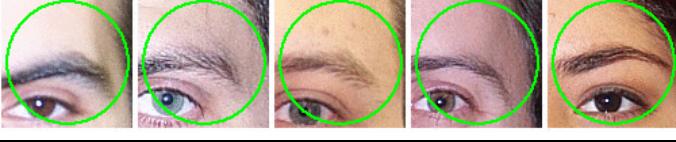
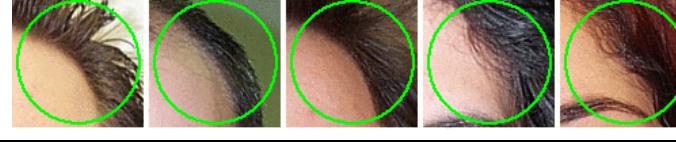
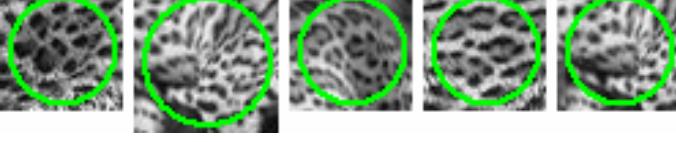
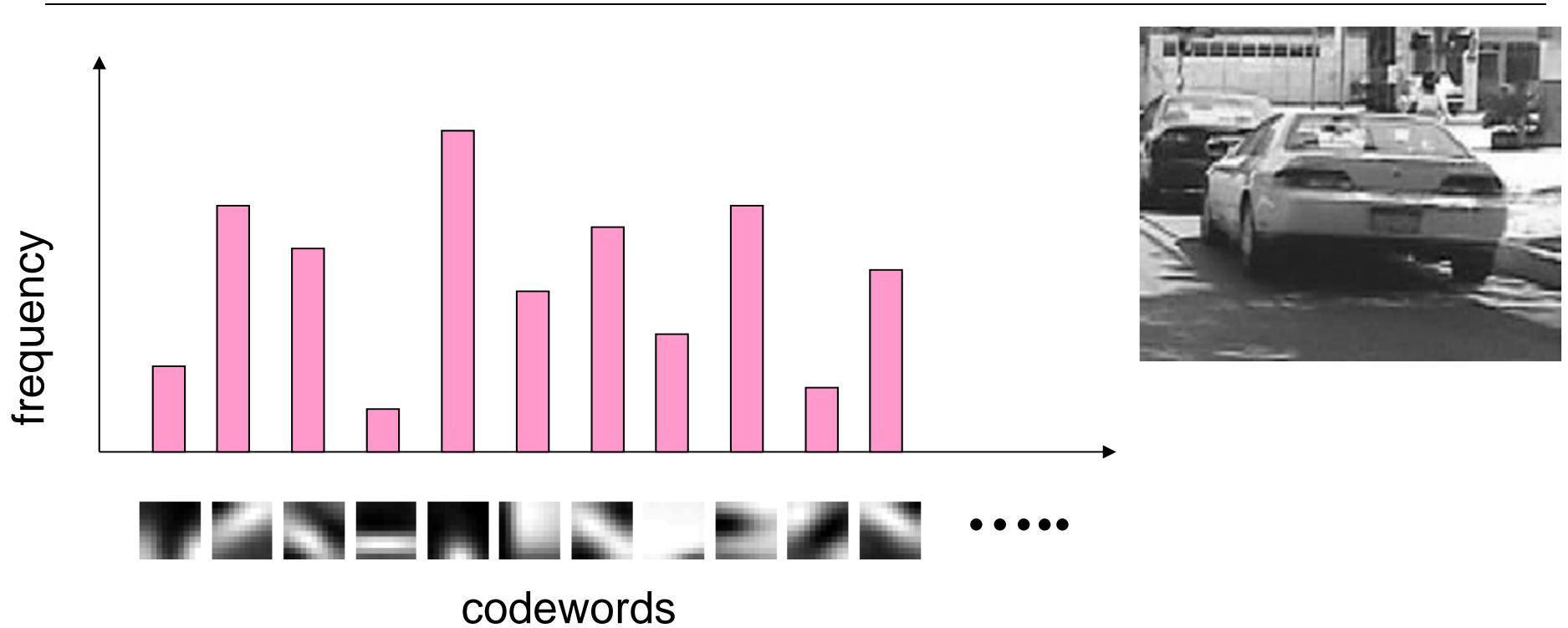
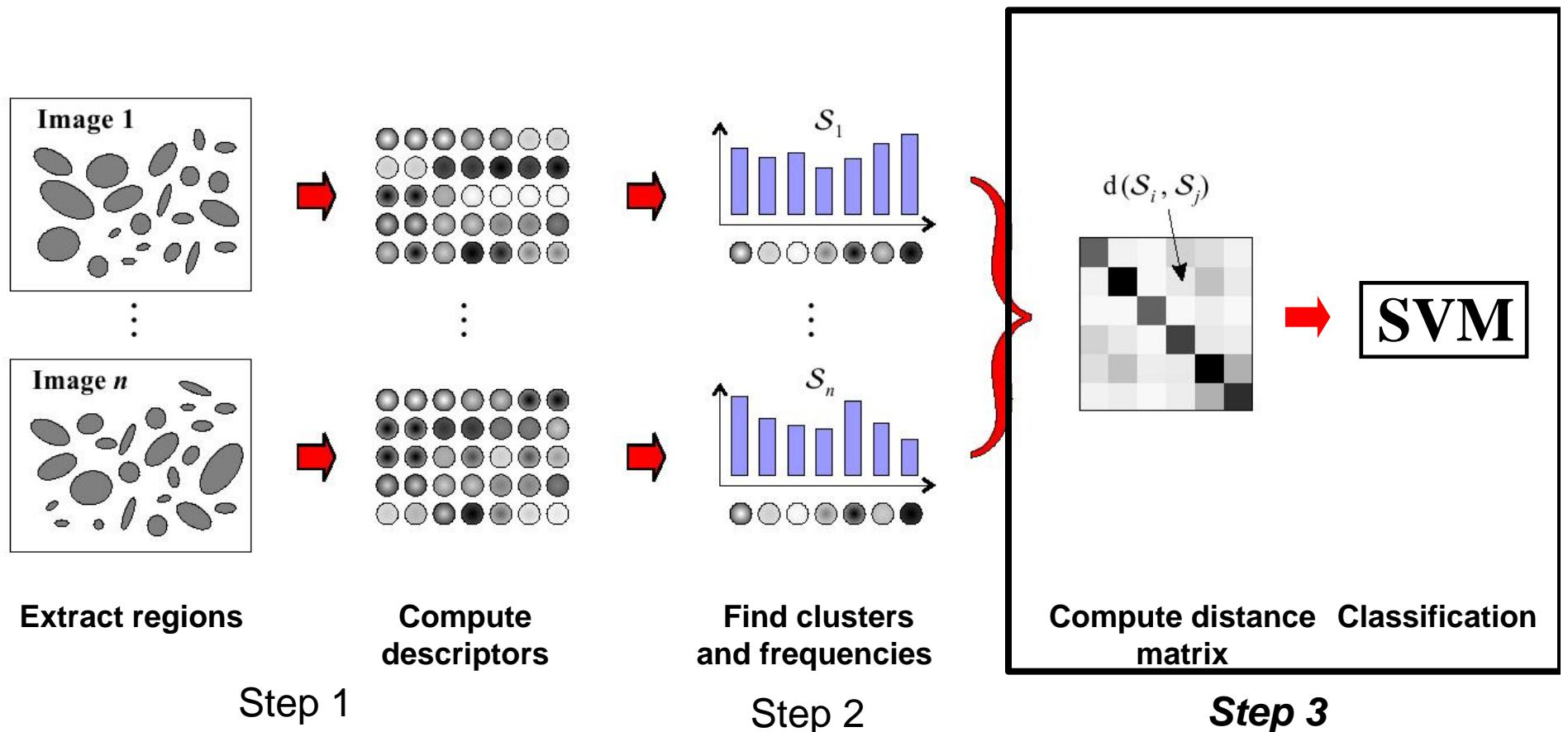
| | |
|------------|--|
| Airplanes |   |
| Motorbikes |   |
| Faces |   |
| Wild Cats |   |
| Leaves |   |
| People |   |
| Bikes |   |

Image representation



- each image is represented by a vector, typically 1000-4000 dimension,

Bag-of-features for image classification



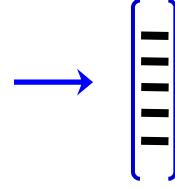
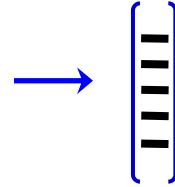
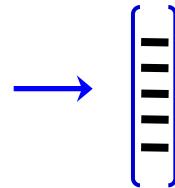
Step 3: Classification

- Learn a decision rule (classifier) assigning bag-of-features representations of images to different classes

Training data

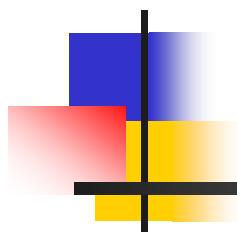
Vectors are histograms, one from each training image

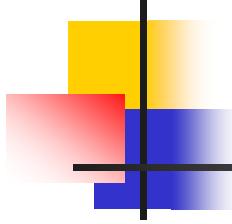
positive



Train classifier, e.g. SVM

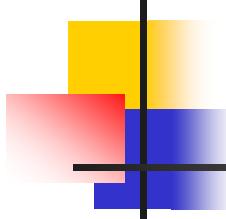
Support Vector Machines (SVM)





Application

- Pattern recognition
- Object classification/detection

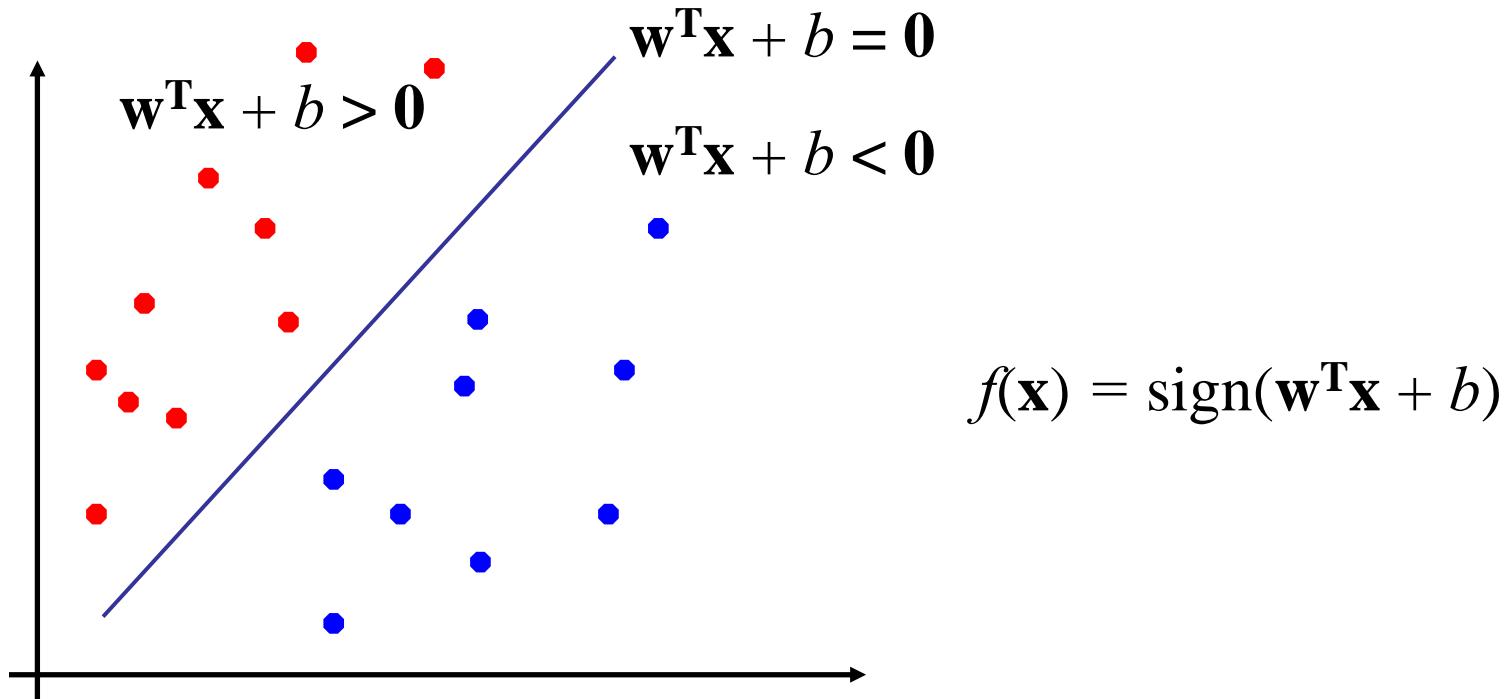


Usage

- The classifier must be trained using a set of negative and positive examples.
- The classifier “learns” the regularities in the data
- If training was successful classifier is capable of classifying an unknown example with a high degree of accuracy.

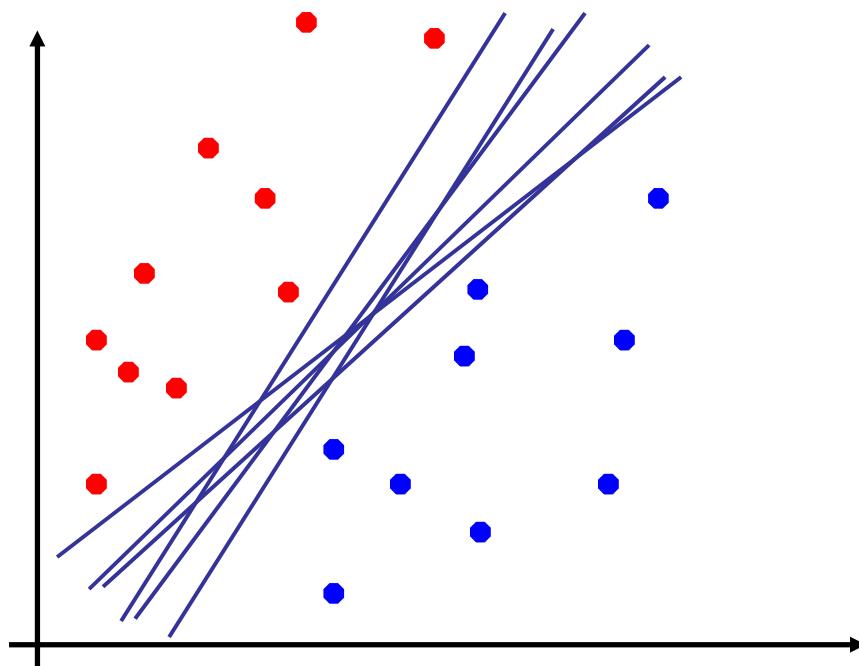
Linear Classifier

- Binary classifier → Task of separating classes in feature space



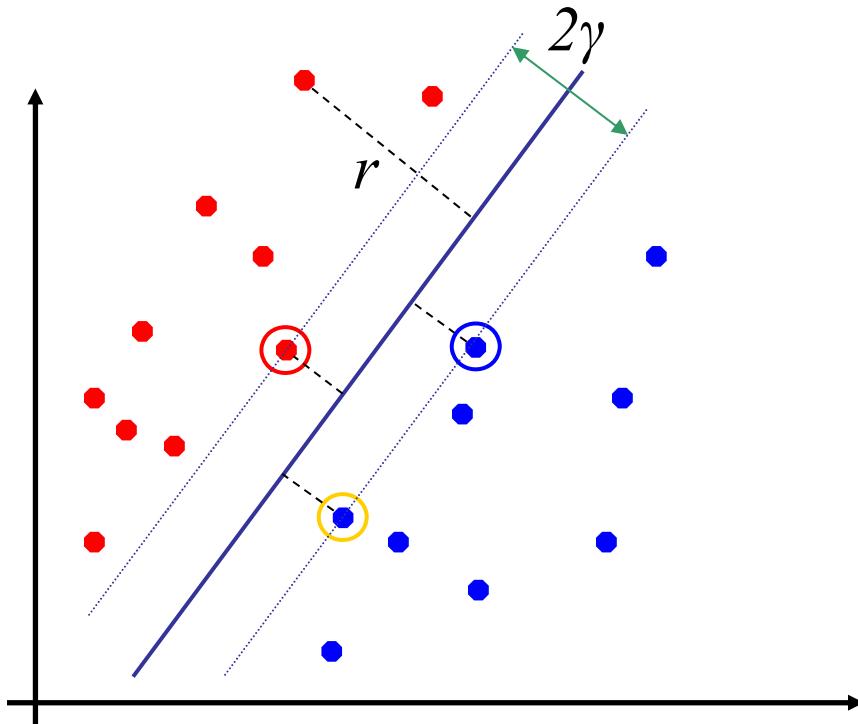
Linear Classifier cont'd

- Which of the linear separators is optimal?



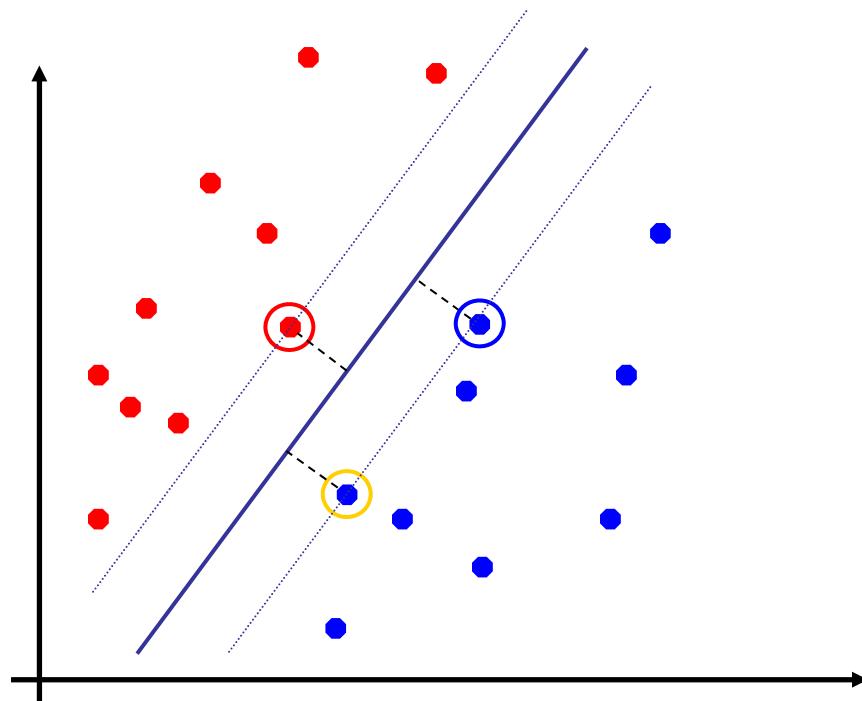
Margin

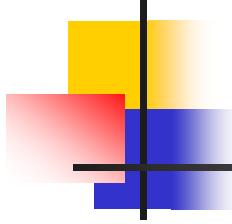
- Distance from example to the separator is (Point to Plane Distance Equation) $r = \frac{\mathbf{w}^T \mathbf{x} + b}{\|\mathbf{w}\|}$
- Examples closest to the hyperplane are ***support vectors***.
- ***Margin*** 2γ of the separator is the width of separation between classes.



Maximum Margin Classification

- Maximizing the margin is good according to intuition.
- Implies that only support vectors are important; other training examples are ignorable.





LibSVM

SVM implementation

- <http://www.csie.ntu.edu.tw/~cjlin/libsvm/>
- <http://www.cs.wisc.edu/dmi/svm/>

Bag-of-features for image classification

- Excellent results in the presence of background clutter



bikes

books

building

cars

people

phones

trees

Examples for misclassified images



Books- misclassified into faces, faces, buildings



Buildings- misclassified into faces, trees, trees



Cars- misclassified into buildings, phones, phones

Evaluation of image classification

- PASCAL VOC [05-10] datasets
- PASCAL VOC 2007
 - Training *and* test dataset available
 - Used to report state-of-the-art results
 - Collected January 2007 from Flickr
 - 500 000 images downloaded and random subset selected
 - 20 classes
 - Class labels per image + bounding boxes
 - 5011 training images, 4952 test images
- Evaluation measure: average precision

PASCAL 2007 dataset

Aeroplane



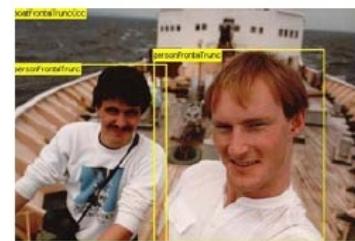
Bicycle



Bird



Boat



Bottle



Bus



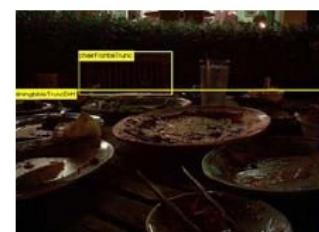
Car



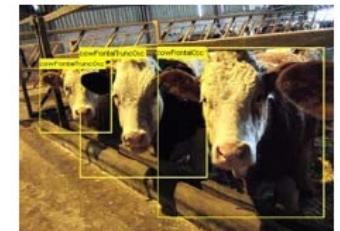
Cat



Chair



Cow



PASCAL 2007 dataset

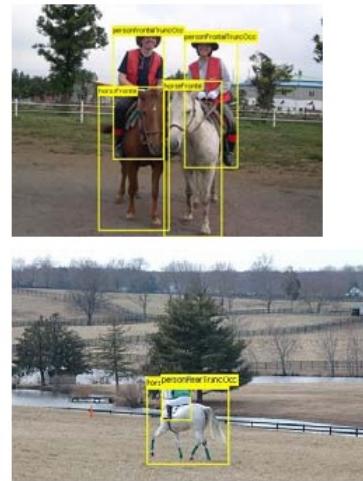
Dining Table



Dog



Horse



Motorbike



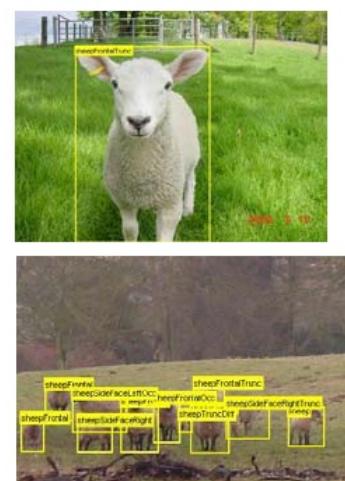
Person



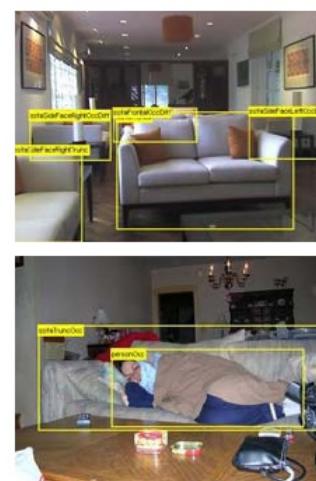
Potted Plant



Sheep



Sofa



Train



TV/Monitor



Evaluation Metrics

$$\text{precision} = \frac{\text{GT} \cap \text{RM}}{\text{RM}} = \frac{\text{TP}}{\text{RM}}$$

$$\text{recall} = \frac{\text{GT} \cap \text{RM}}{\text{GT}} = \frac{\text{TP}}{\text{GT}}$$

