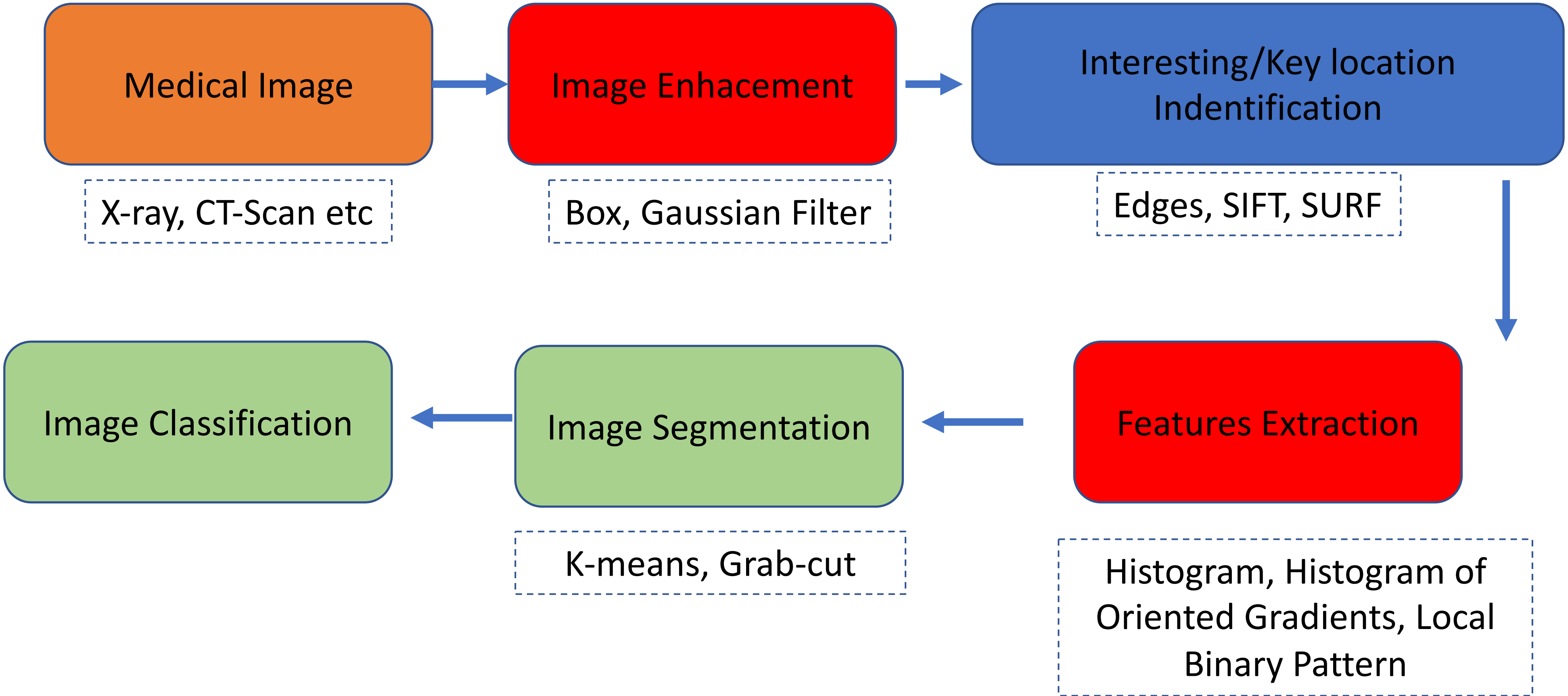
Medical Images Computing

Lecture 9 – Medical Image Classification

Waqas Sultani
Information Technology University


Medical Image
X-ray, CT-Scan etc
Image Enhacement
Box, Gaussian Filter
Interesting/Key location Indentification
Edges, SIFT, SURF
Features Extraction
Histogram, Histogram of Oriented Gradients, Local Binary Pattern
Image Segmentation
K-means, Grab-cut
Image Classification

Vector Space Model

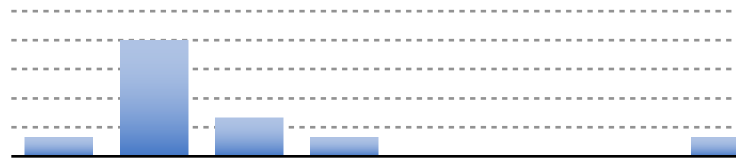
G. Salton. ‘Mathematics and Information Retrieval’ Journal of Documentation,1979

The Newsp

Sunday, December 22, 2013

DARPA Selects Carnegie Me

The Tartan Rescue Team from Carnegie Mellon University's National Robotics Engineering Center ranked third among teams competing in the Defense Advanced Research Projects Agency (DARPA) Robotics Challenge Trials this weekend in Homestead, Fla., and was selected by the agency as one of eight teams eligible for DARPA funding to prepare for next December's finals. The team's four-limbed CMU Highly Intelligent Mobile Platform, or CHIMP, robot scored 18 out of a possible 32 points during the two-day trials. It demonstrated its ability to perform such tasks as removing debris, cutting a hole through a wall and closing a series of valves.



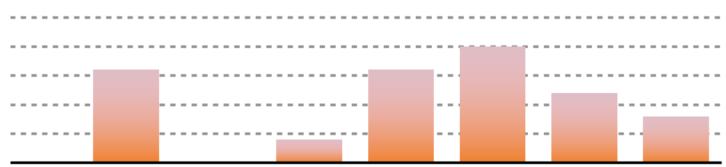
1	6	2	1	0	0	0	1
Tartan	robot	CHIMP	CMU	bio	soft	ankle	sensor

Tartan Tim

Monday, January 20, 2014

Bio-Inspired Robotic Device

PITTSBURGH—A soft, wearable device that mimics the muscles, tendons and ligaments of the lower leg could aid in the rehabilitation of patients with ankle-foot disorders such as drop foot, said Yong-Lae Park, an assistant professor of robotics at Carnegie Mellon University. Park, working with collaborators at Harvard University, the University of Southern California, MIT and BioSensics, developed an active orthotic device using soft plastics and composite materials, instead of a rigid exoskeleton. The soft materials, combined with pneumatic artificial muscles (PAMs), lightweight sensors and advanced control software, made it possible for the robotic device to achieve natural motions in the ankle.



0	4	0	1	4	5	3	2
Tartan	robot	CHIMP	CMU	bio	soft	ankle	sensor

http://www.fodey.com/generators/newspaper/snippet.asp

A document (datapoint) is a vector of counts over each word (feature)

$$\boldsymbol{v}_d = [n(w_{1,d}) \quad n(w_{2,d}) \quad \cdots \quad n(w_{T,d})]$$

$n(\cdot)$ counts the number of occurrences

just a histogram over words

What is the similarity between two documents?

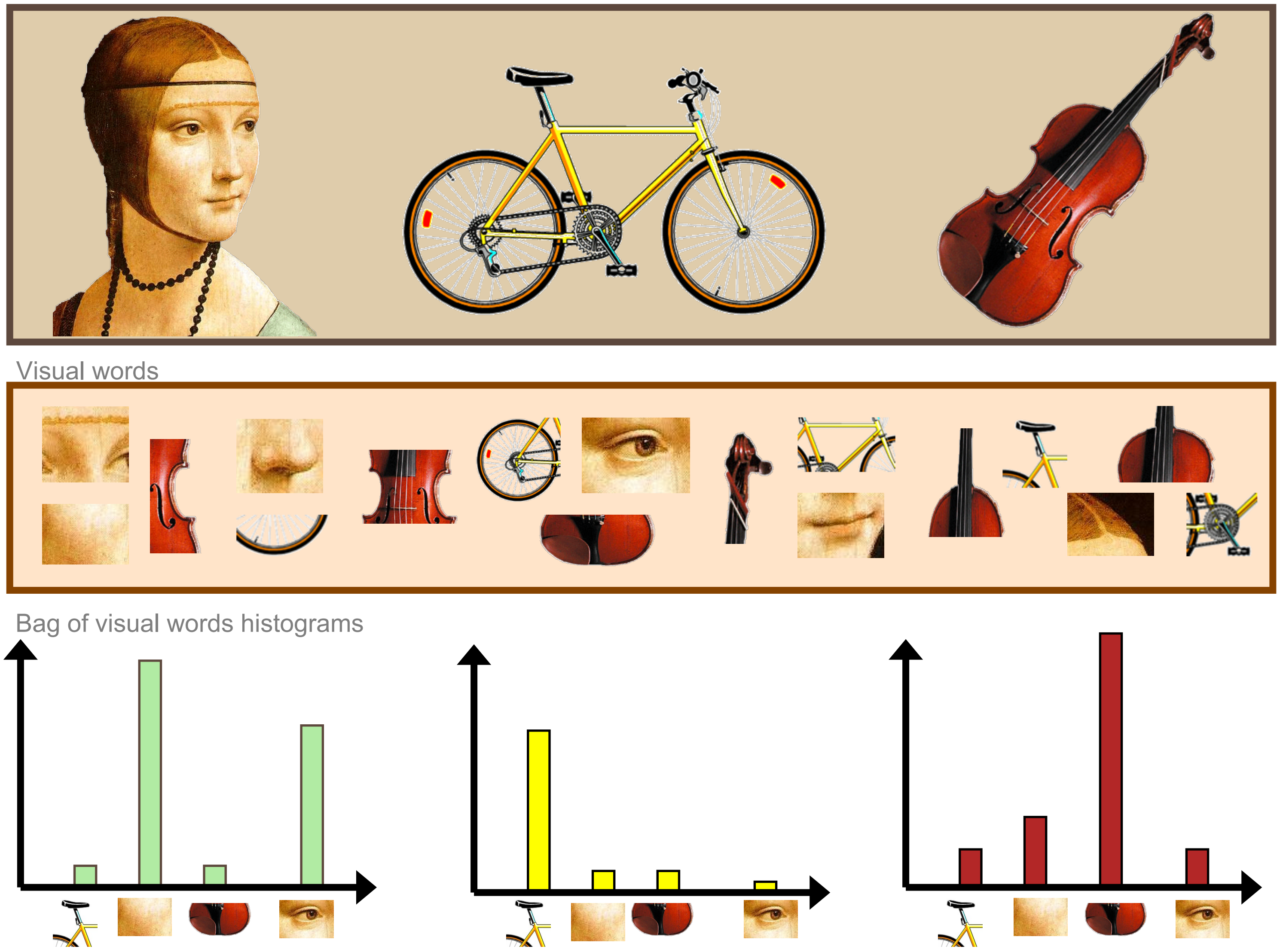

The Newspa
DARPA Selects Carnegie Me


Tartan Tim
Bio-Inspired Robotic Device

Bag-of-features models

Object → Bag of 'words'

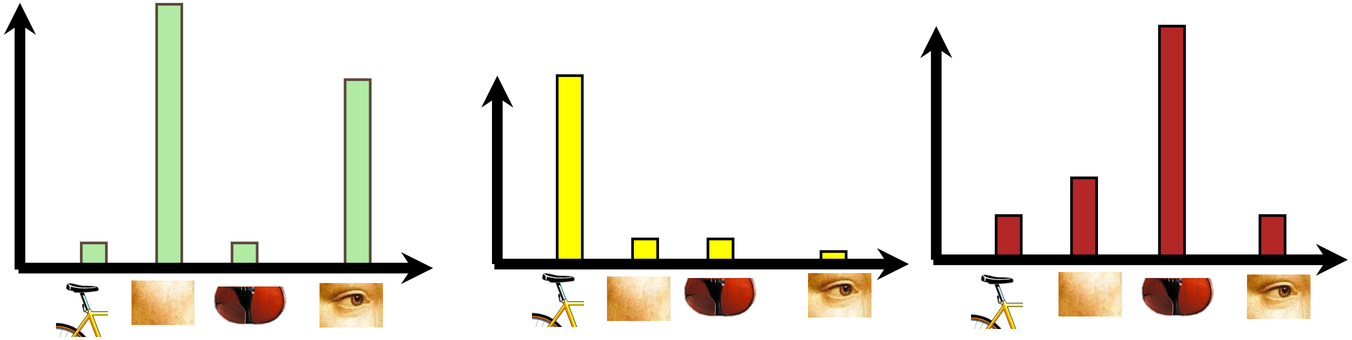
Svetlana Lazebnik


Visual words
Bag of visual words histograms

Encode:

build Bags-of-Words (BOW) vectors for each image

2. Histogram: count the number of visual word occurrences

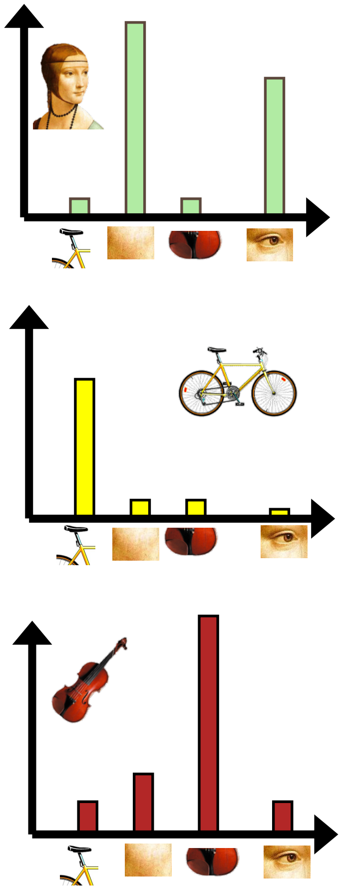


Bags of visual words

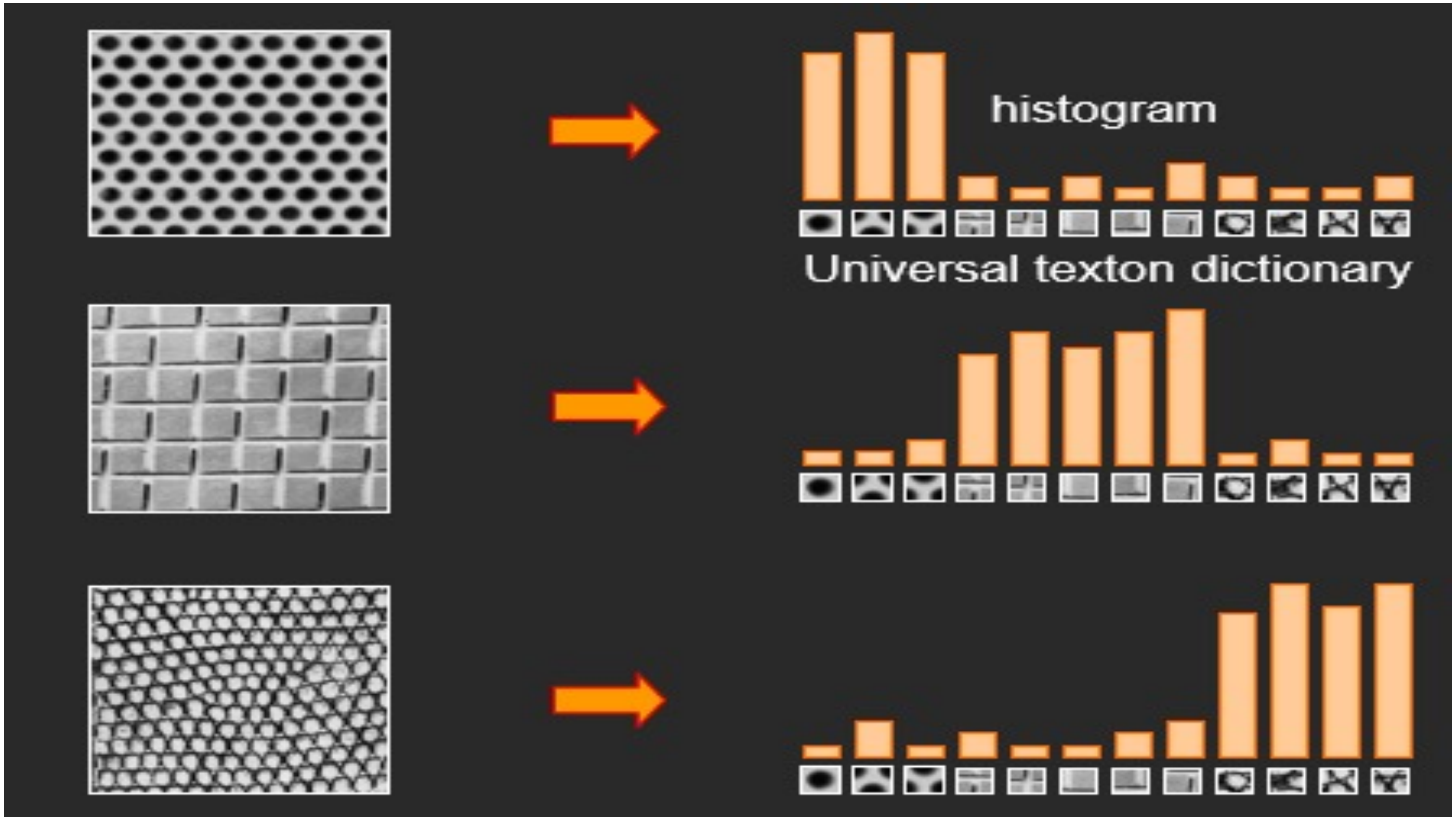
- Summarize entire image based on its distribution (histogram) of word occurrences.
- Analogous to bag of words representation commonly used for documents.

Visual words

Bag of visual words histograms



Origin 2: Texture recognition



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

Image Categorization/Classification

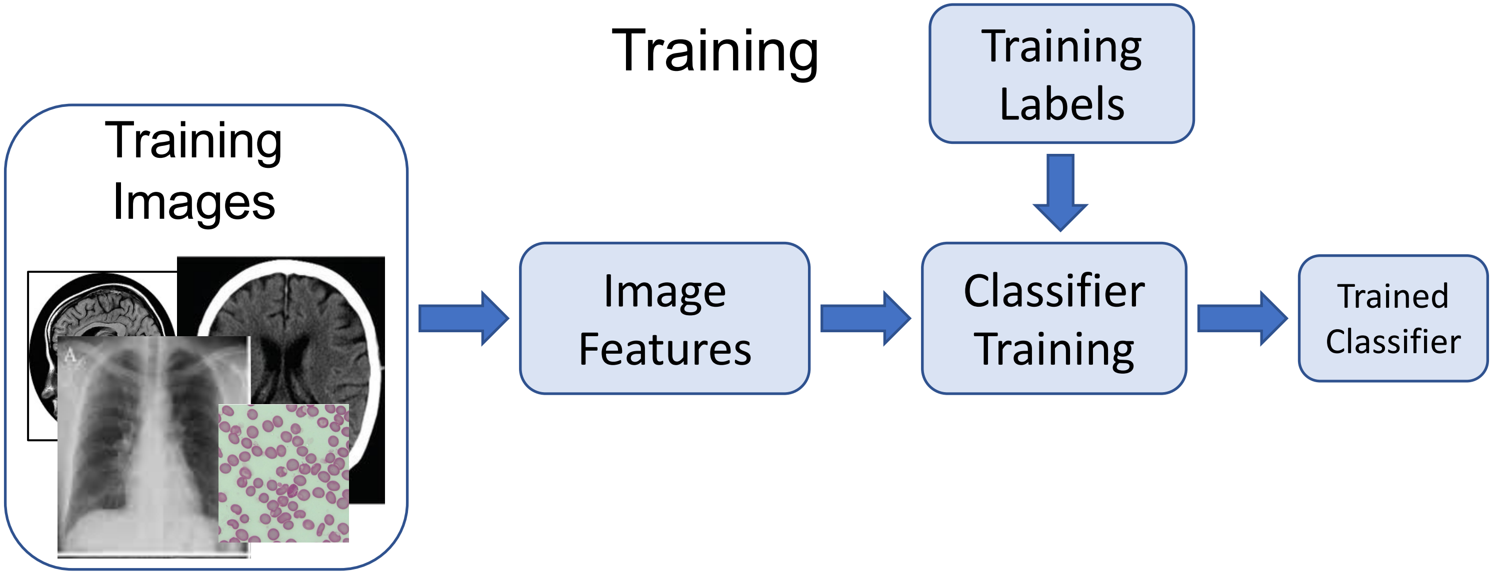


Image Categorization/Classification

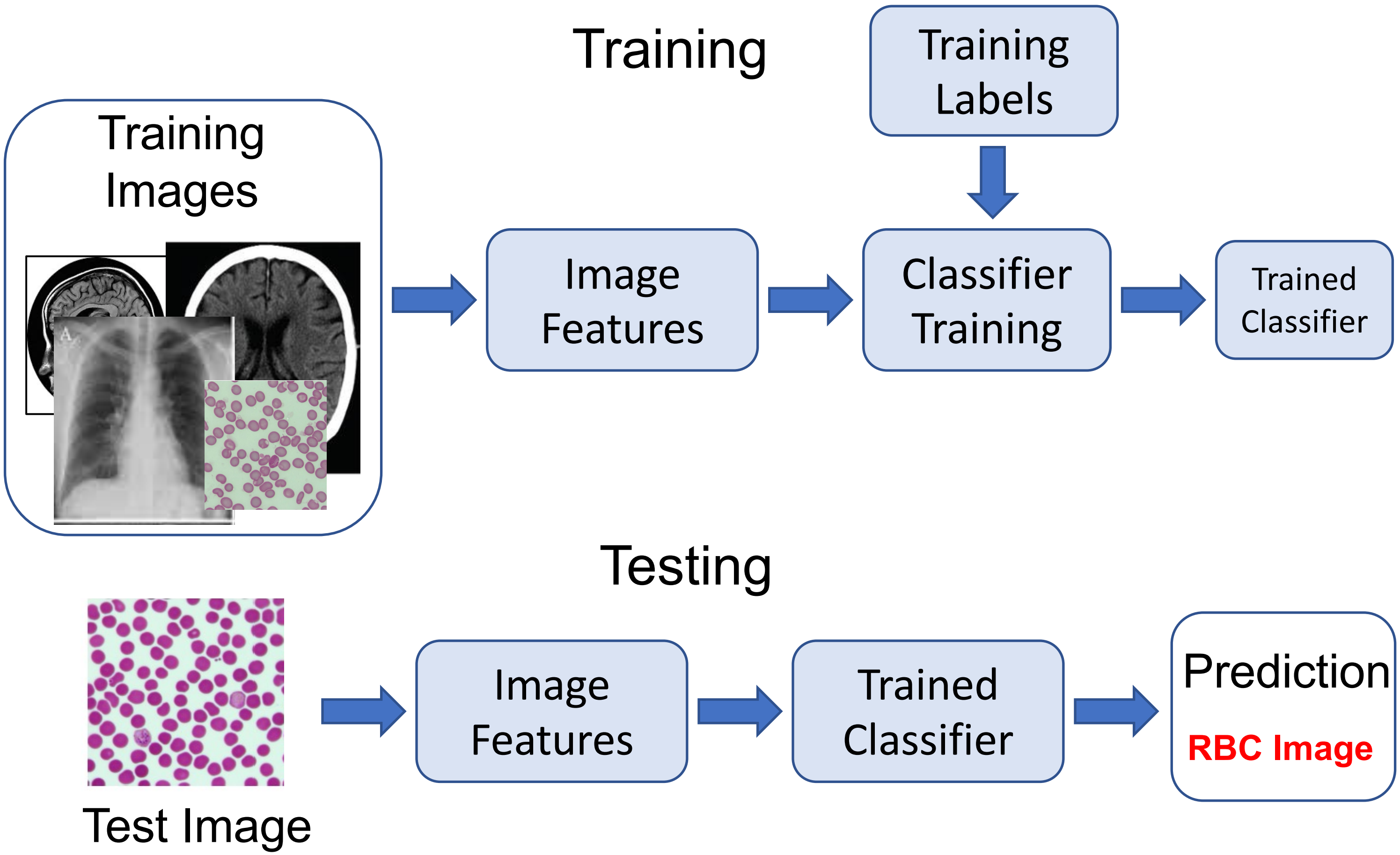
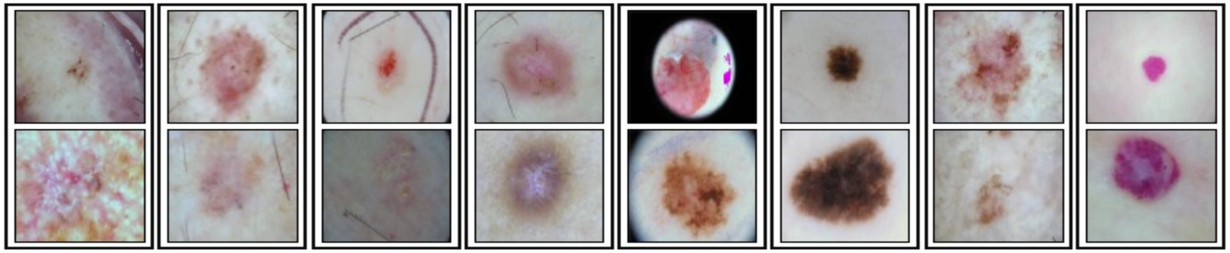


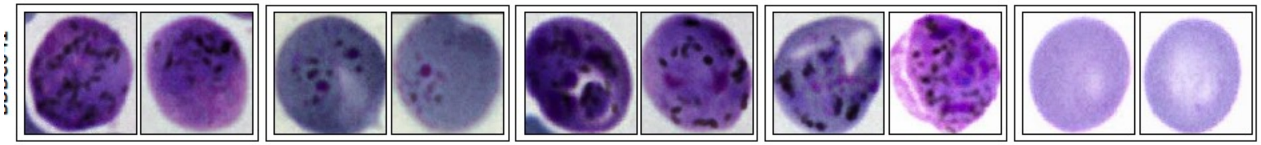
Image classification

- 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

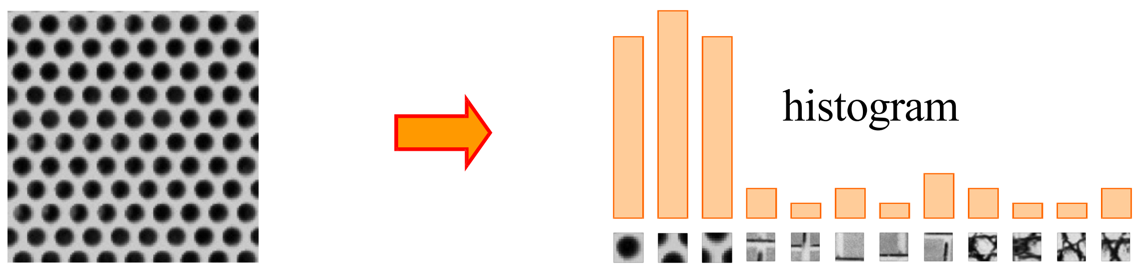
?

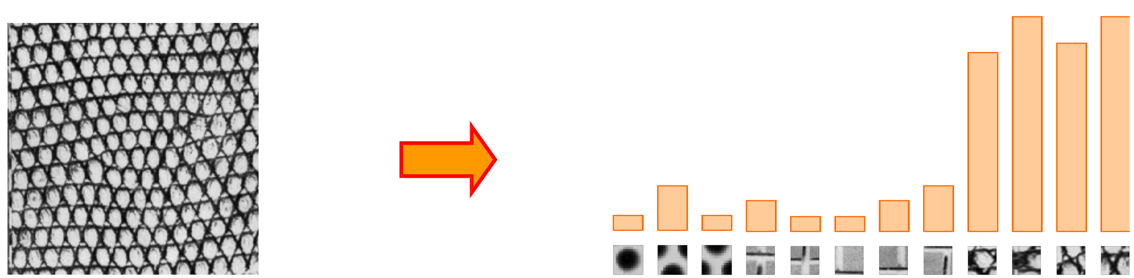
Bag-of-features – Origin: texture recognition

- 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

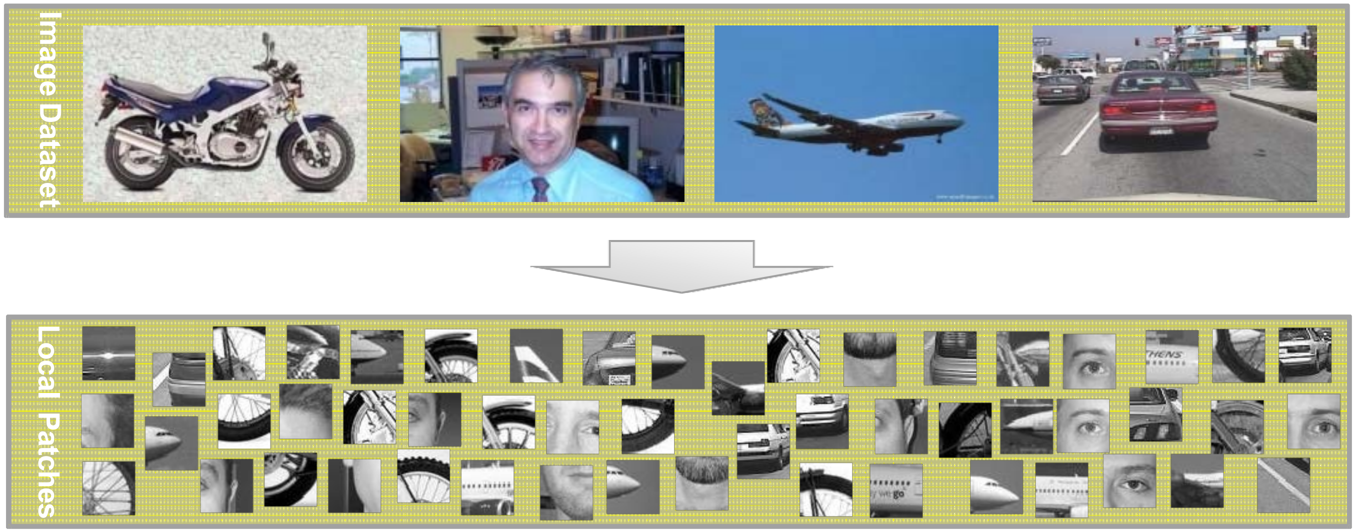




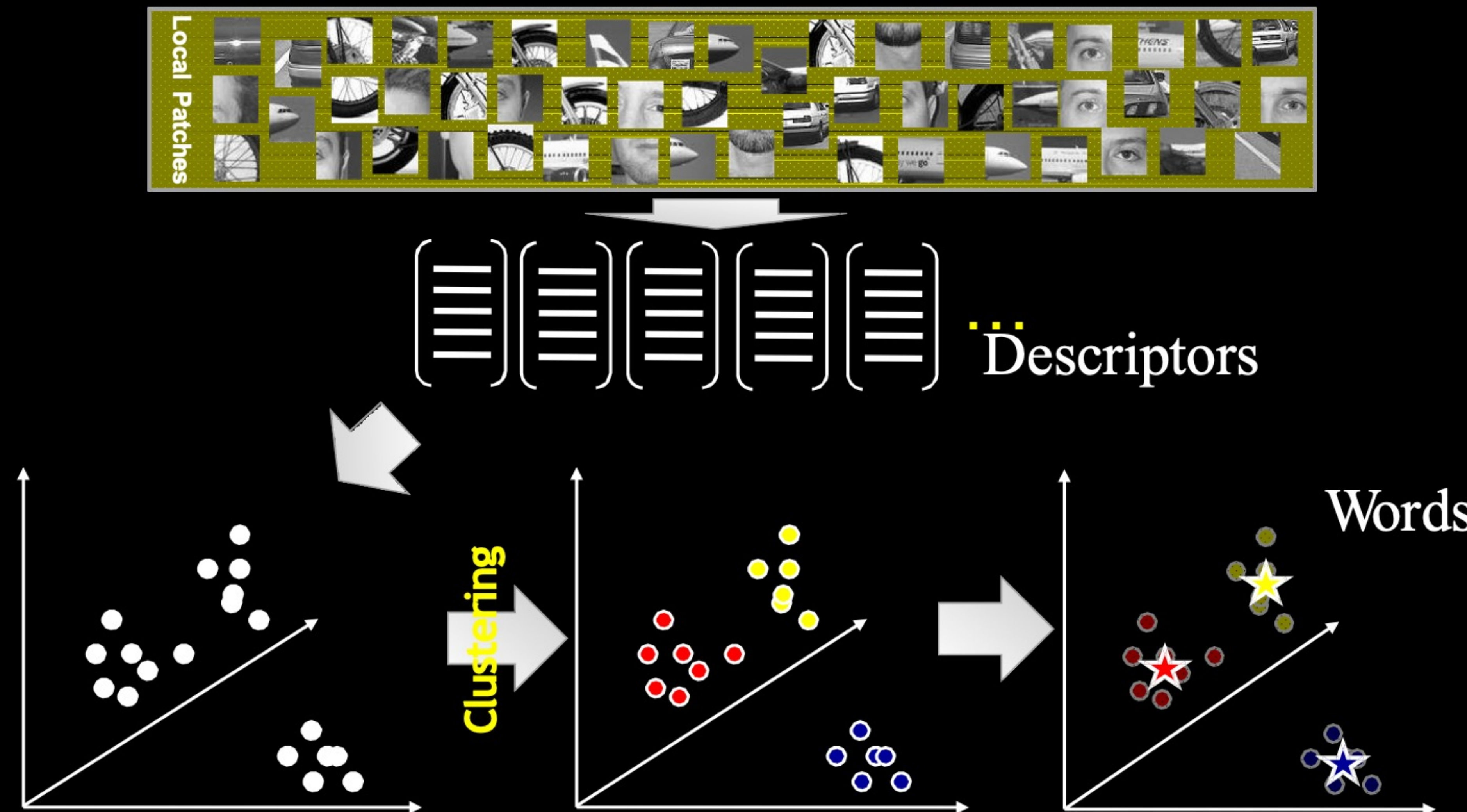
Cula & Dana, 2001; Varma &

Malik 2001; Mori, Belongie & 2003; Lazebnik, & Ponce,

Bag of Visual Words model

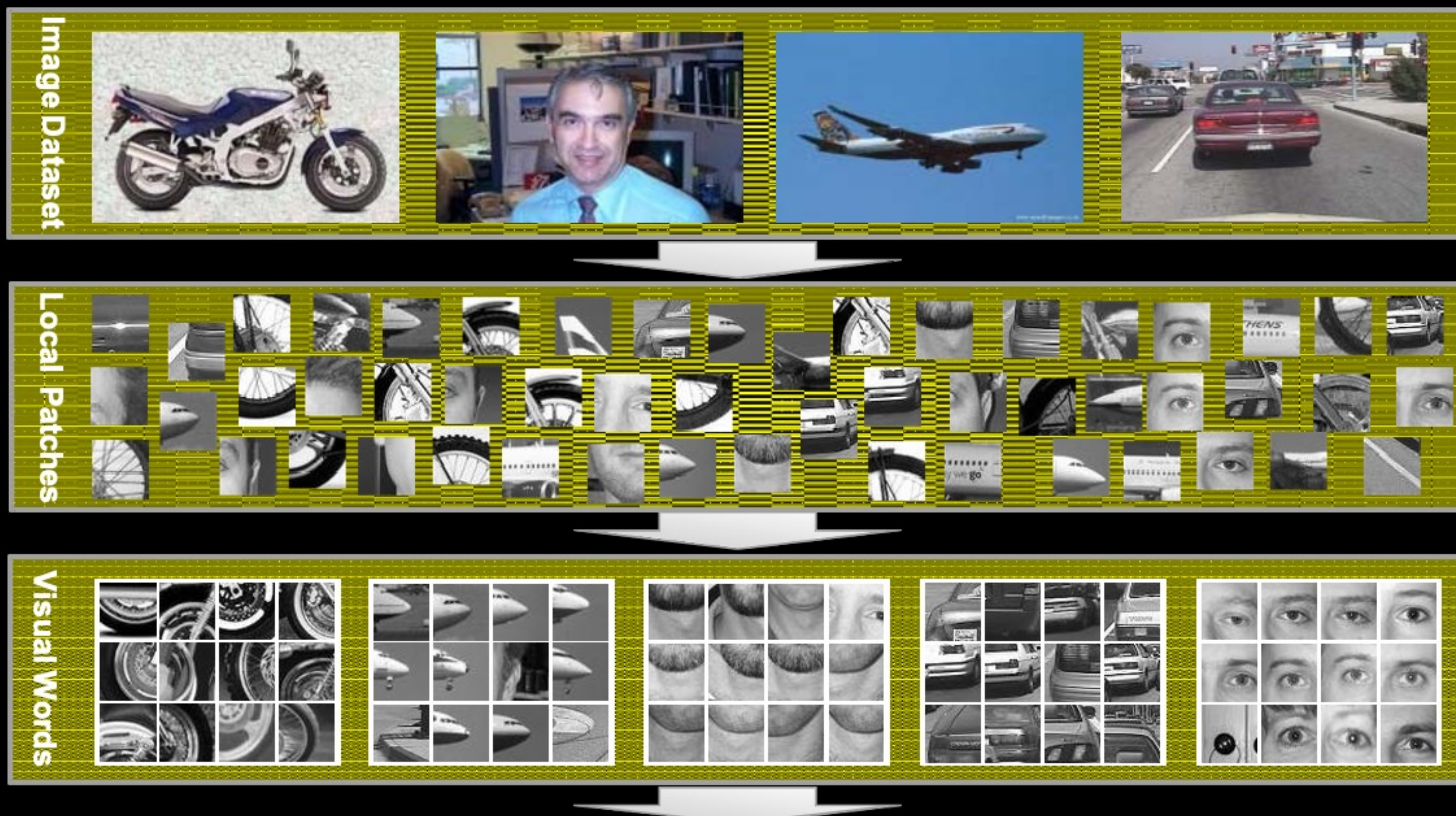


Bag of Visual Words model

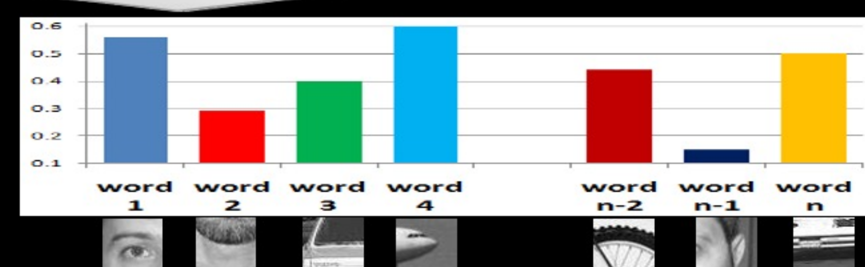


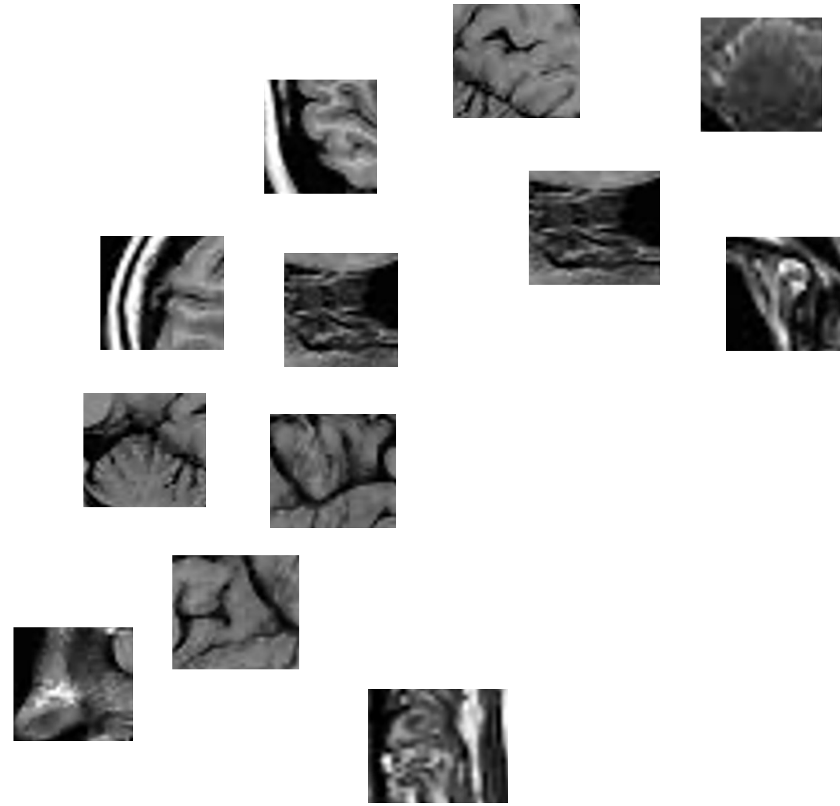
Generate the visualvocabulary

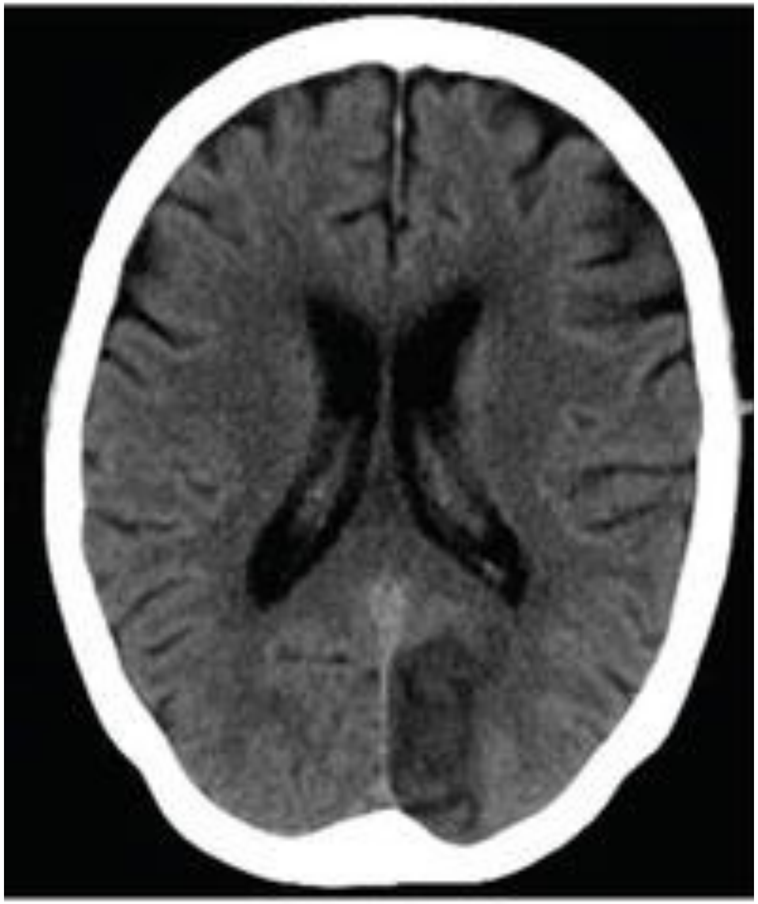
Bag of Visual Words model

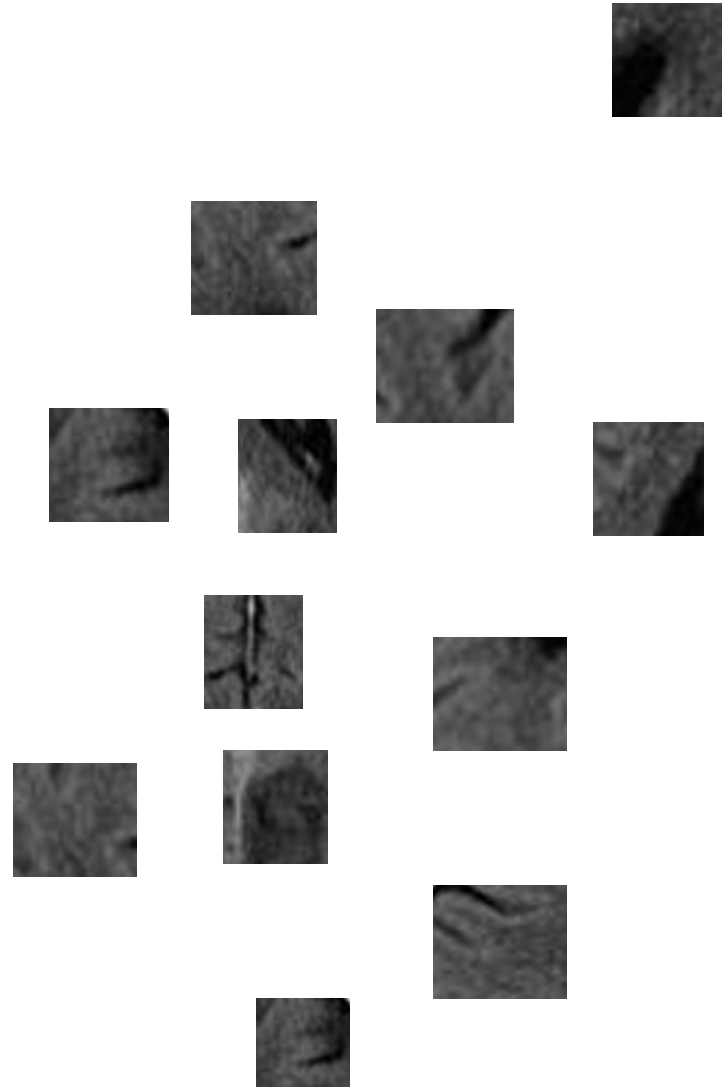


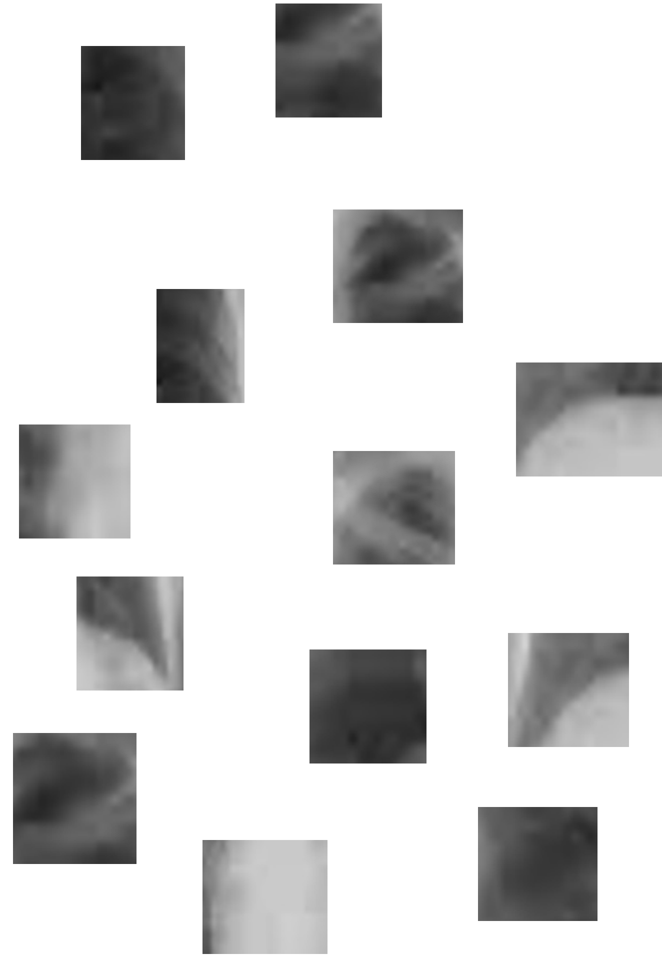
Represent an image as a histogram or bag of words

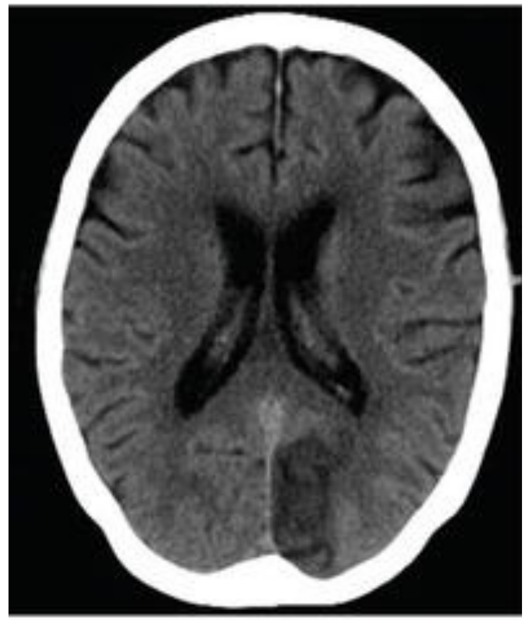


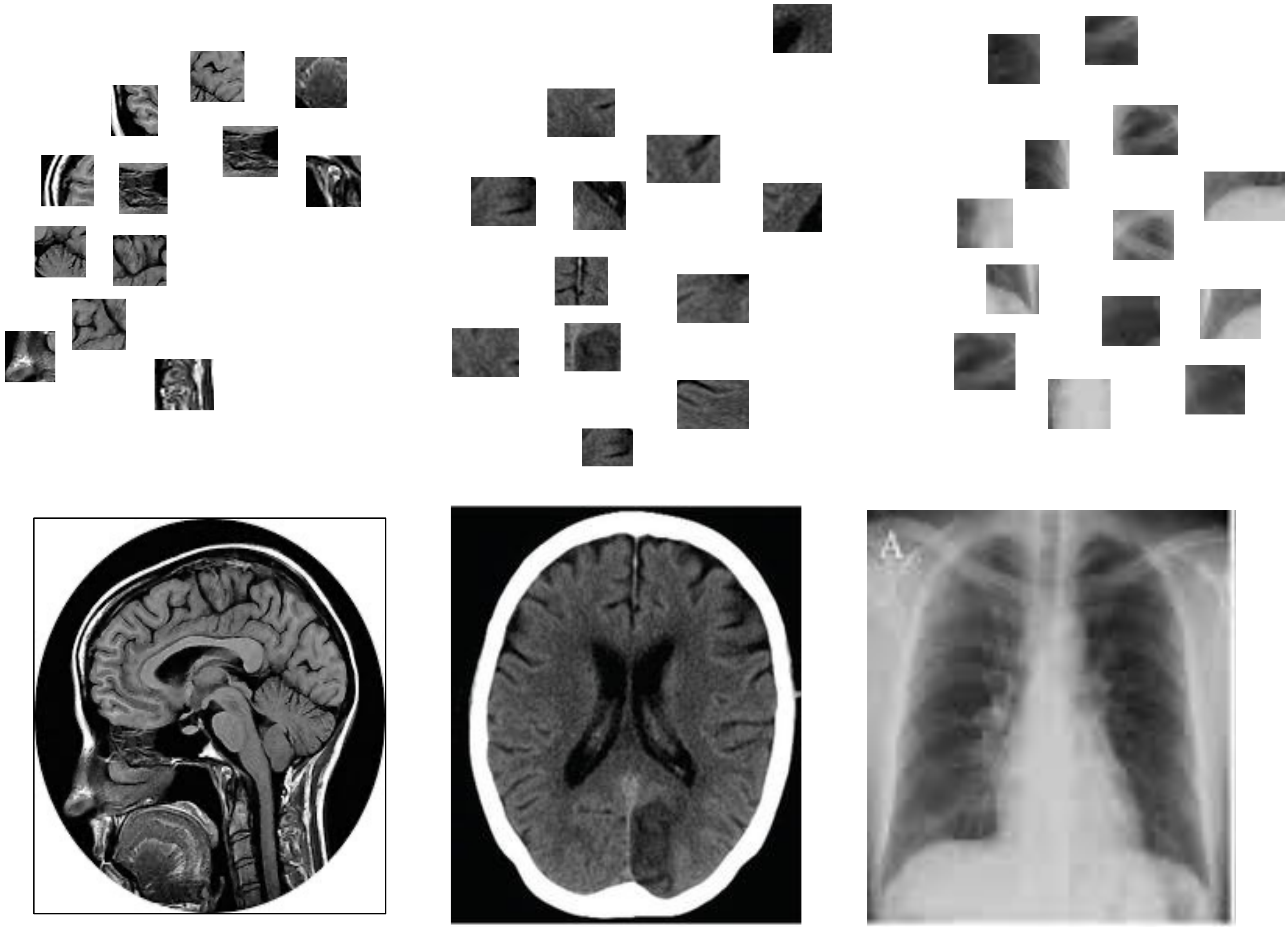




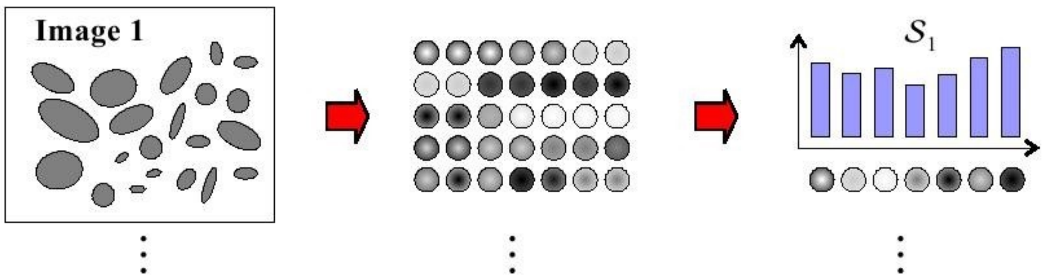



A





A

Bag-of-features for image classification

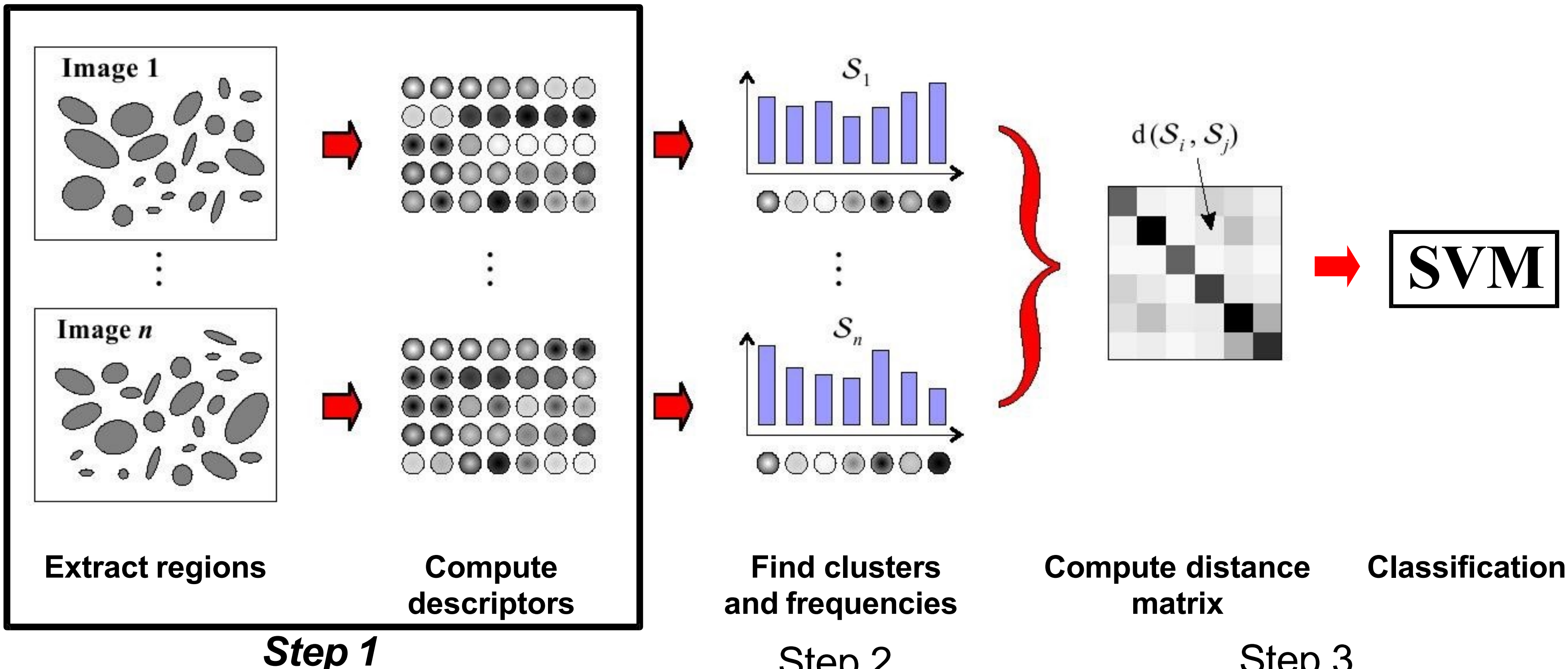


Extract regions
or
Interest Points

Compute descriptors

Find clusters and frequencies

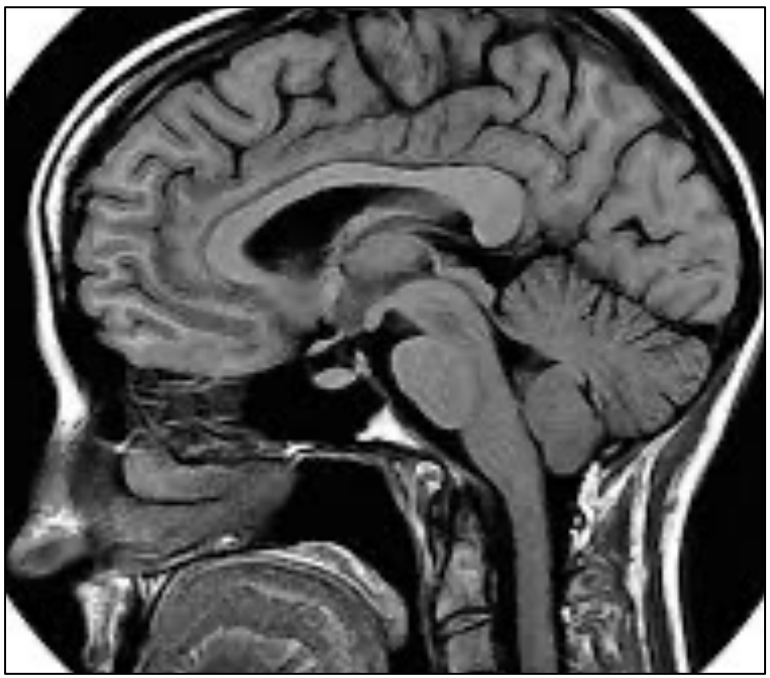
Bag-of-features for image classification

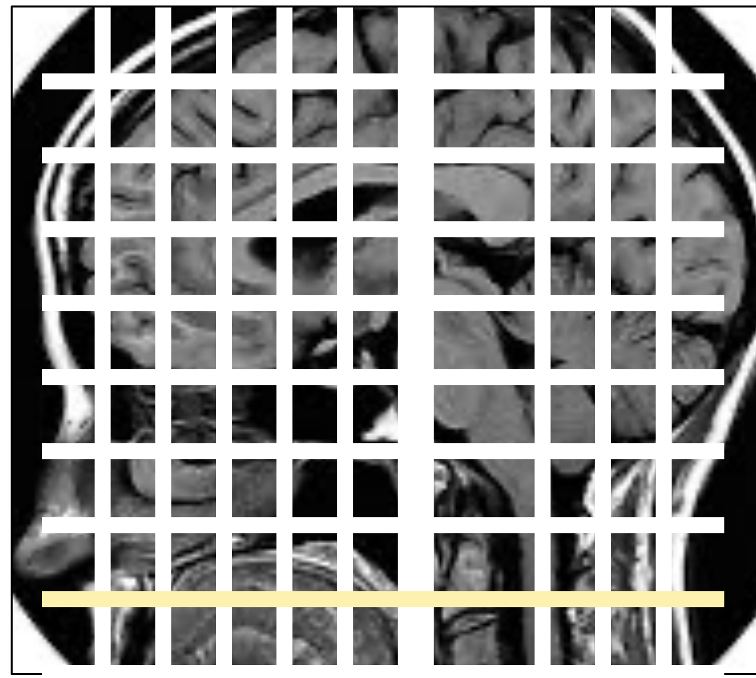


Step 1: feature extraction

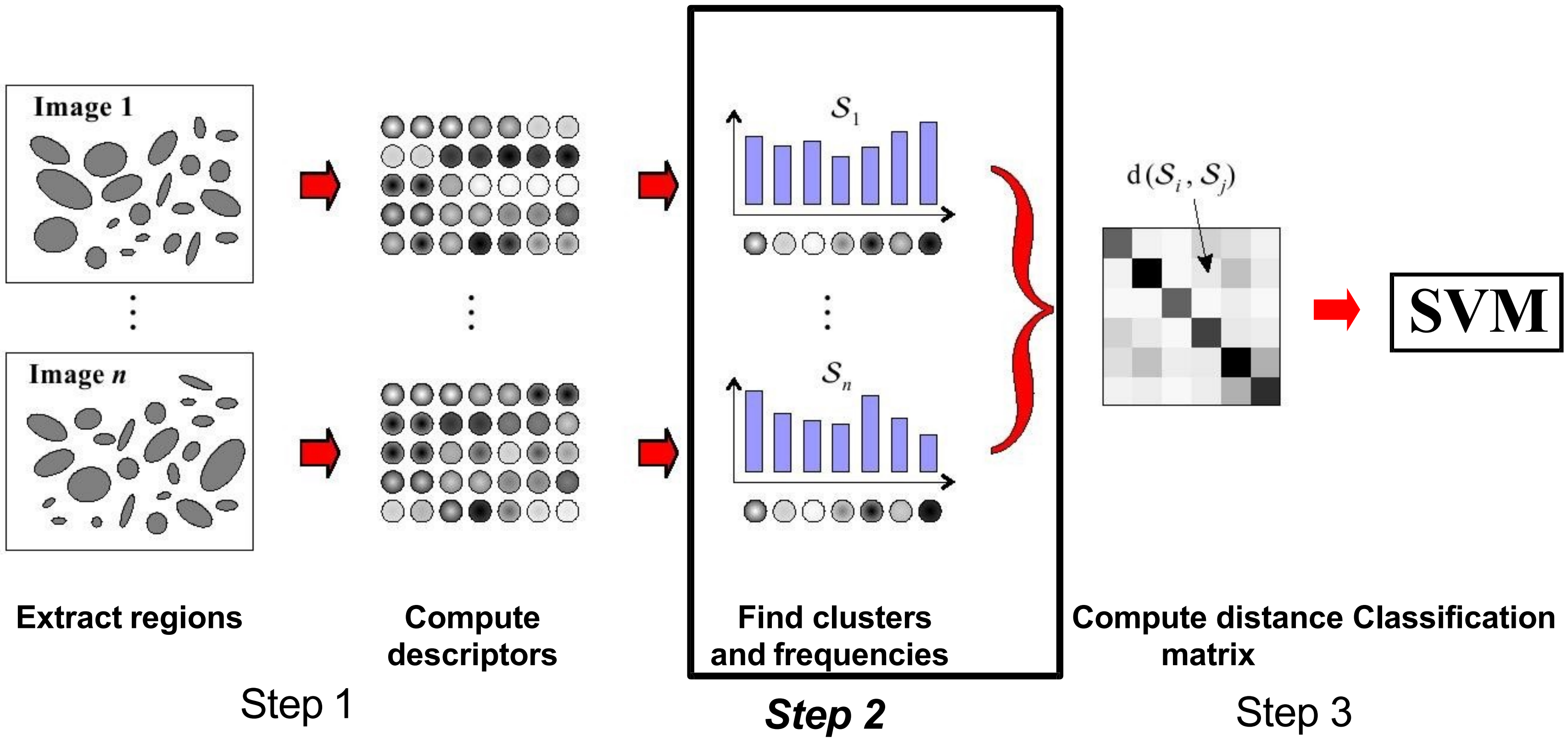
- Detect Interest Points
  - SIFT
  - Harris
  - Dense (take every nth pixel as interest point)
- Compute Descriptor around each interest point
  - SIFT
  - HOG

Dense features

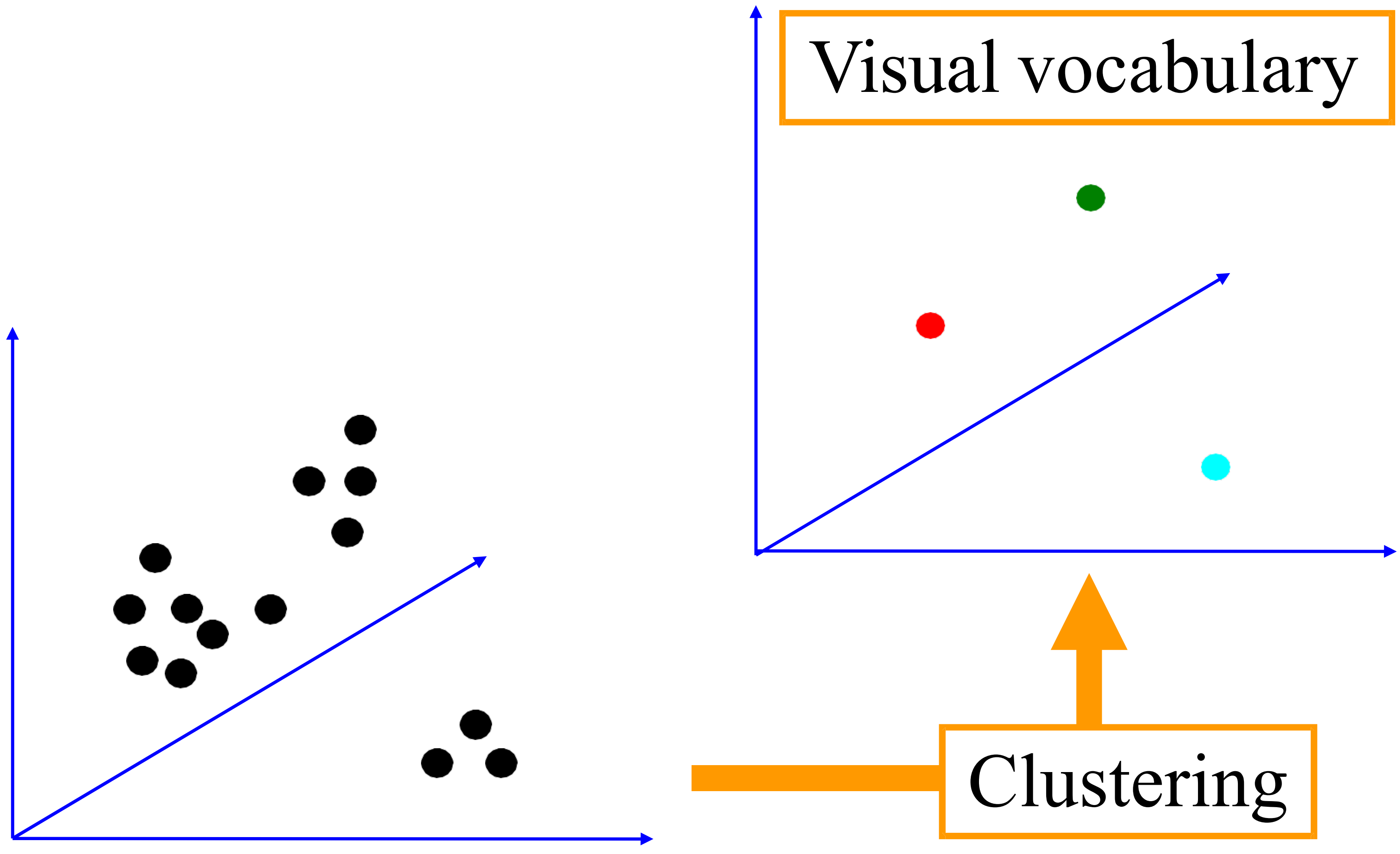




Bag-of-features for image classification



Step 2: Quantization



Step 2: Quantization

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

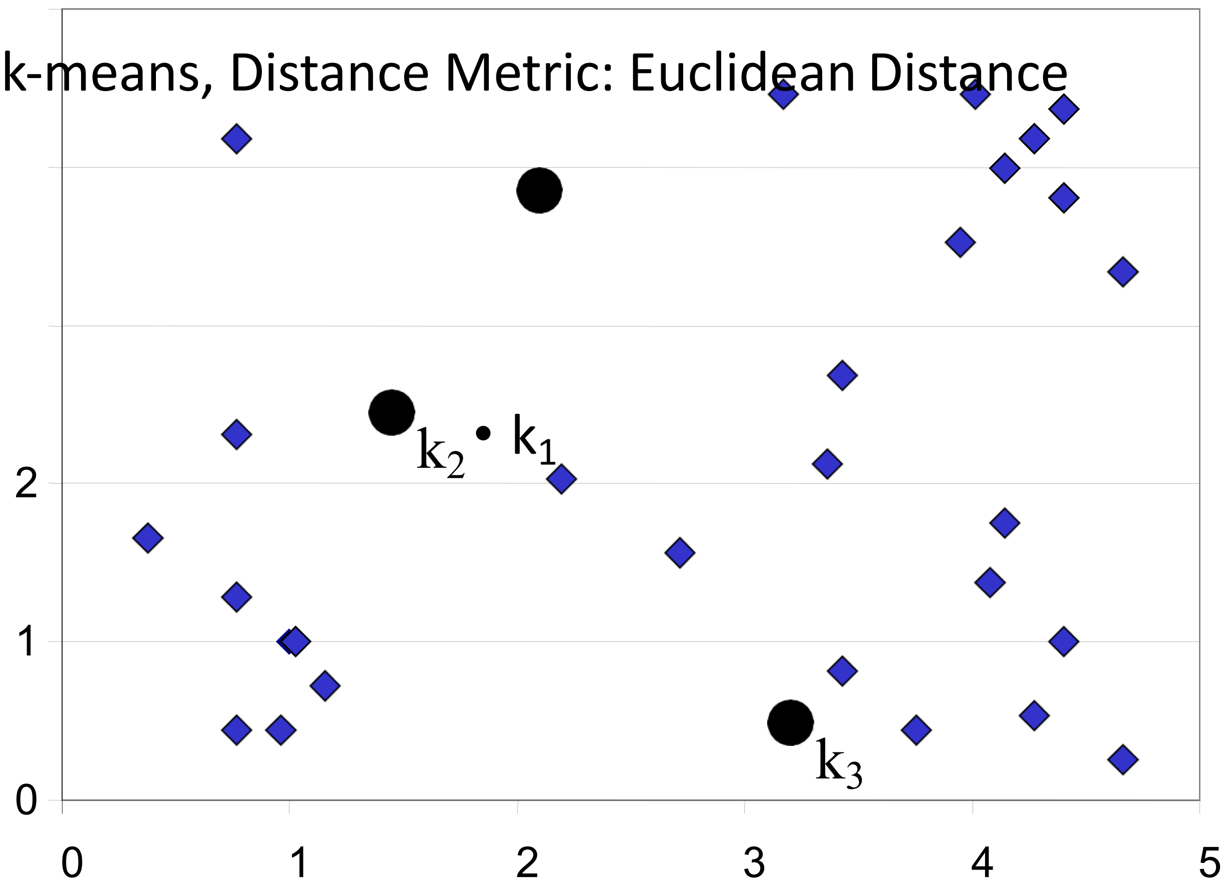
K-Means

```
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*

K-means Clustering: Step 1

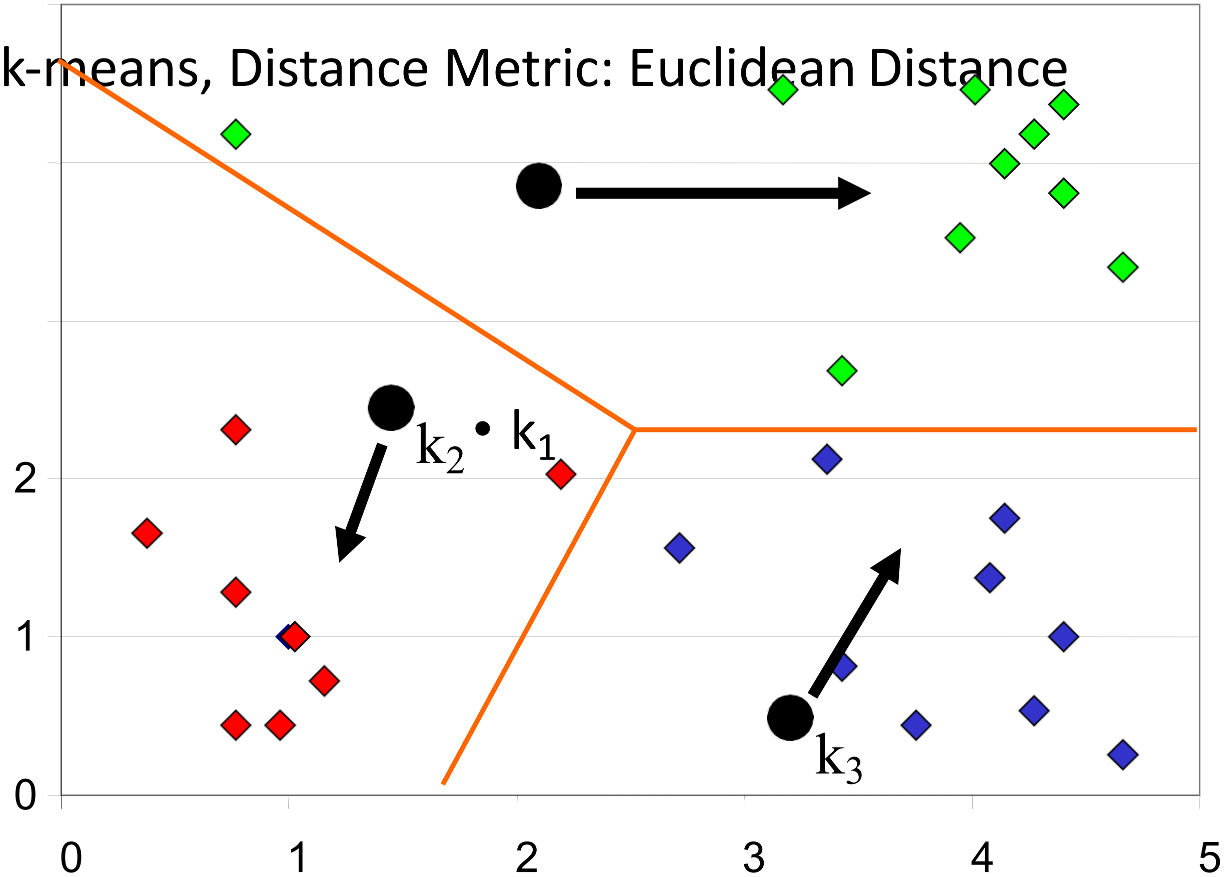
- Algorithm: k-means, Distance Metric: Euclidean Distance
    - 5
    - 4
    - 3



From unknown source on internet

K-means Clustering: Step 2

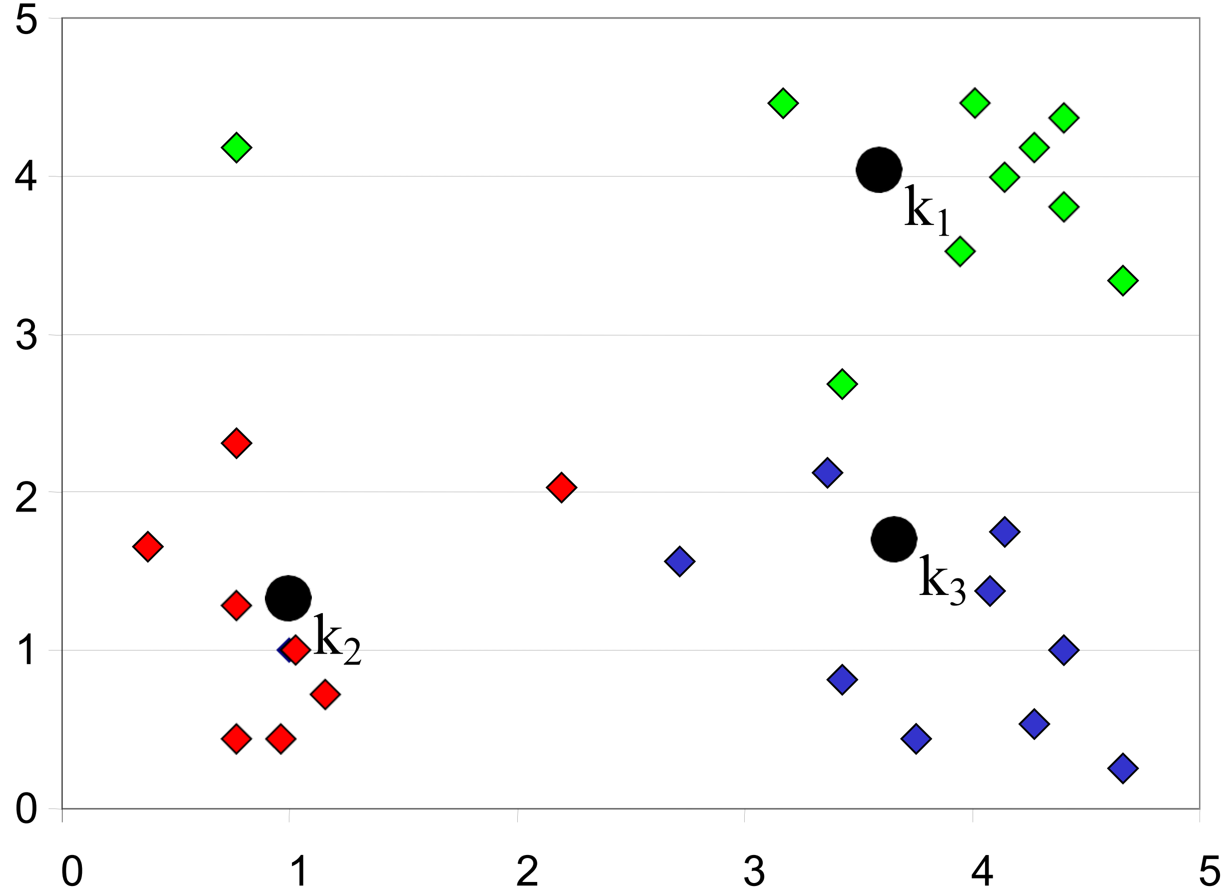
- Algorithm: k-means, Distance Metric: Euclidean Distance
  - 5
  - 4
  - 3



From unknown source on internet

K-means Clustering: Step 3

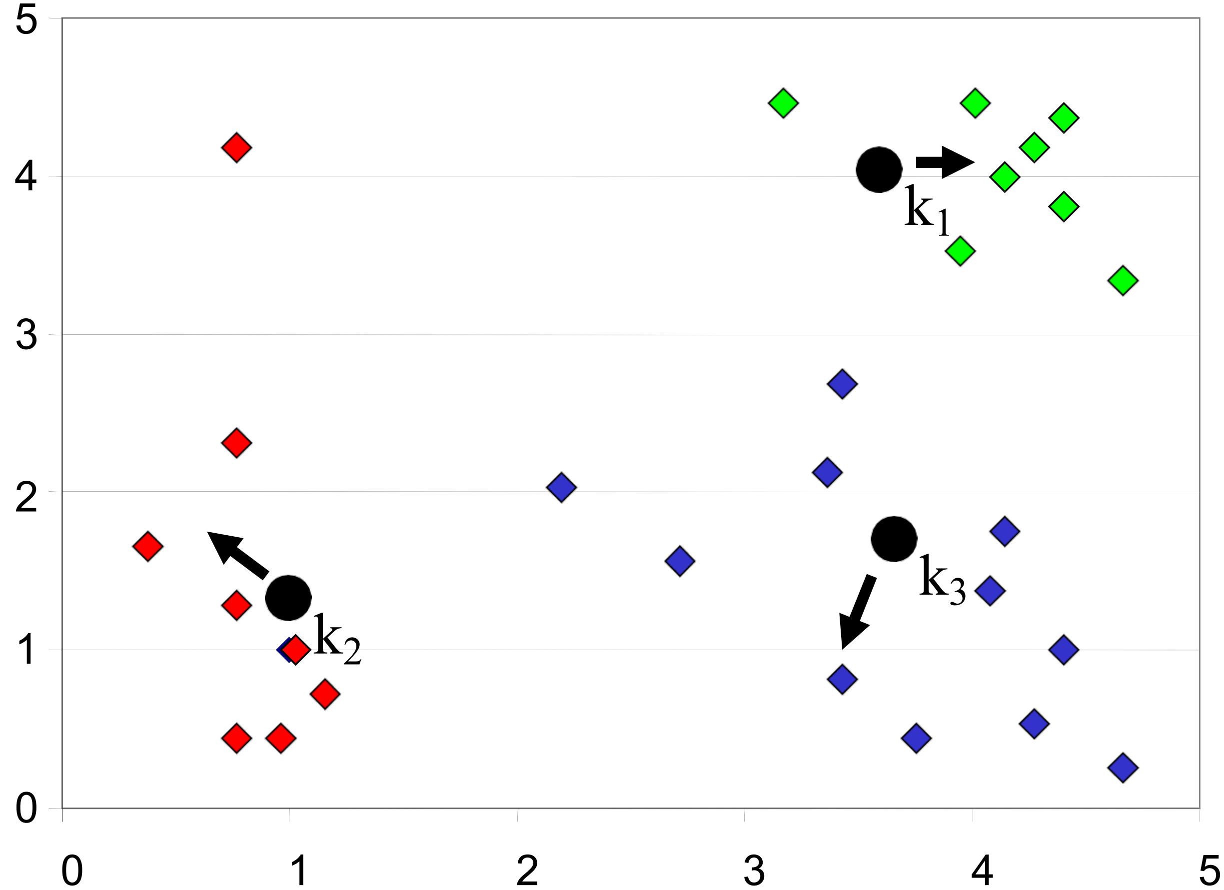
Algorithm: k-means, Distance Metric: Euclidean Distance



From unknown source on internet

K-means Clustering: Step 4

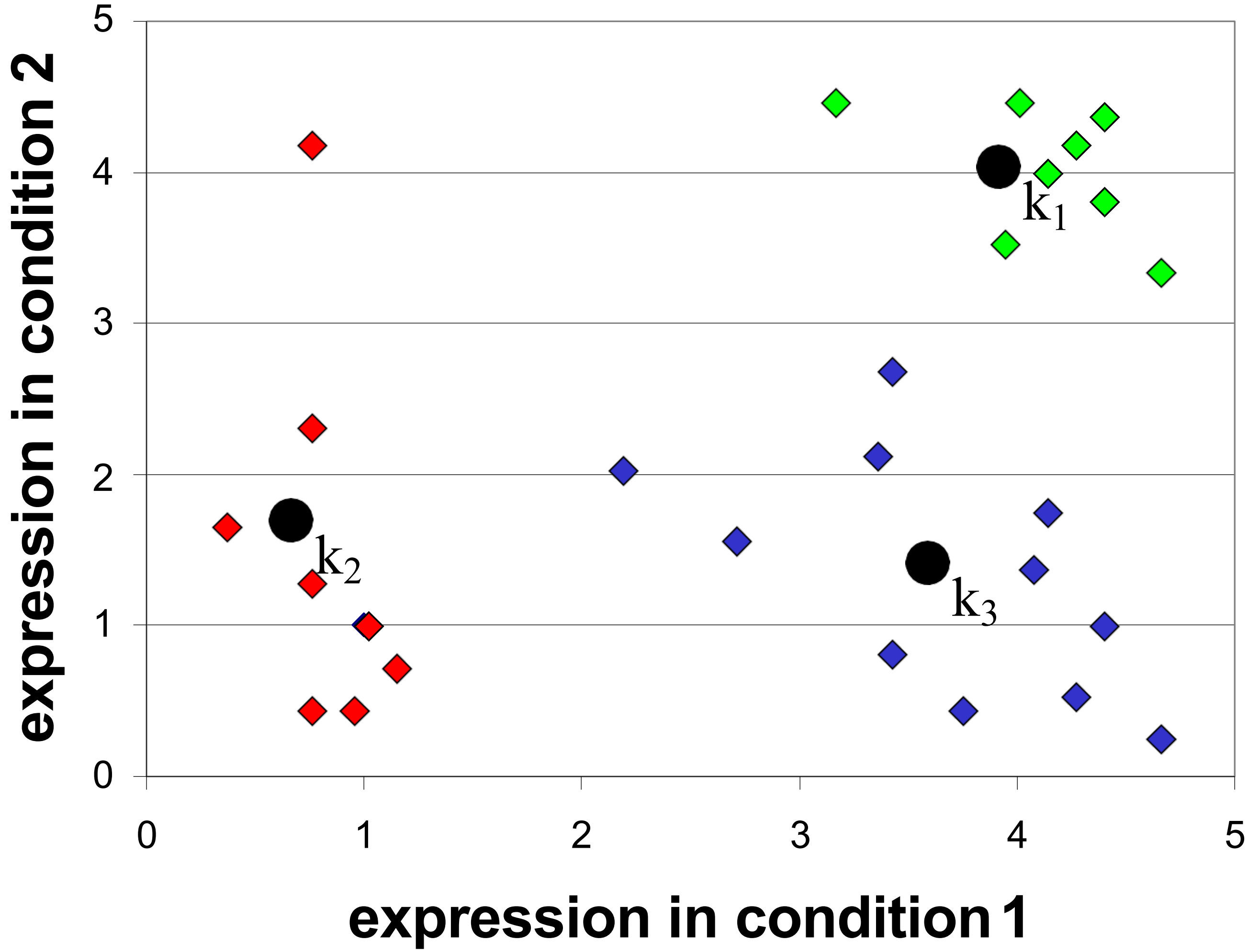
Algorithm: k-means, Distance Metric: Euclidean Distance



From unknown source on internet

K-means Clustering: Step 5

Algorithm: k-means, Distance Metric: Euclidean Distance



From unknown source on internet

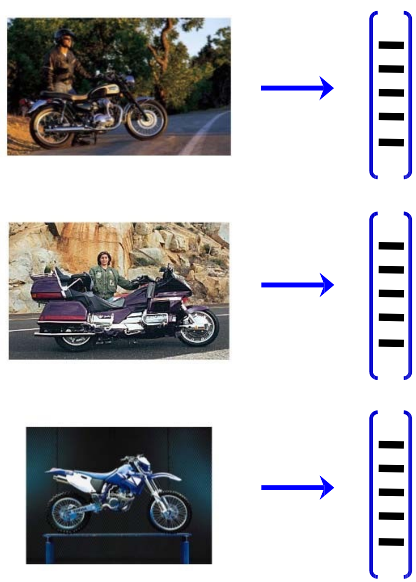
Step 3: Classification

- 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

Supervised learning

$$y = f(\mathbf{x})$$

output

prediction function

Image feature

- **Training:** given a *training set* of labeled examples $\{(\mathbf{x}_1,y_1), \ldots, (\mathbf{x}_N,y_N)\}$, estimate the prediction function f by minimizing the prediction error on the training set
- **Testing:** apply f to a never before seen *test example* $\mathbf{x}$ and output the predicted value $y = f(\mathbf{x})$

Slide credit: L. Lazebnik

Support Vector Machines (SVM)

Application

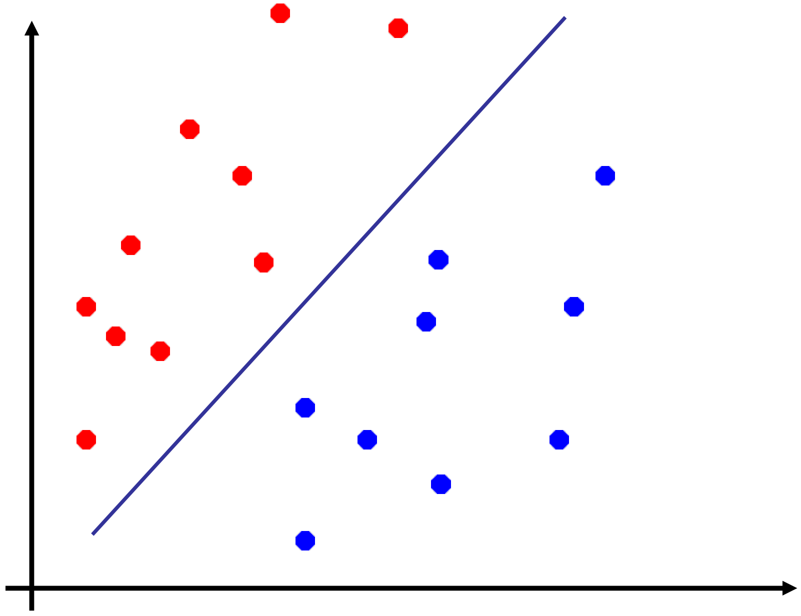
- Pattern recognition
- Object classification/detection

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.

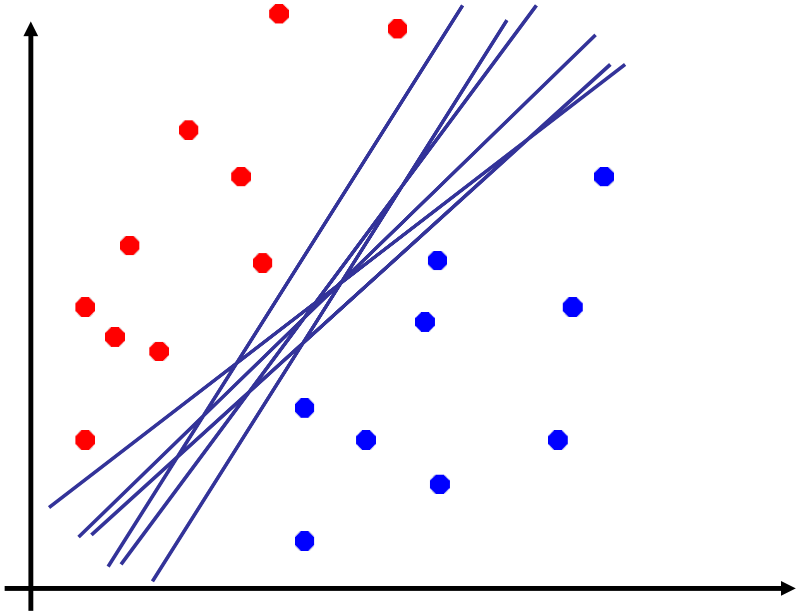
Linear Classifier

- Binary classifier → Task of separating classes in feature space



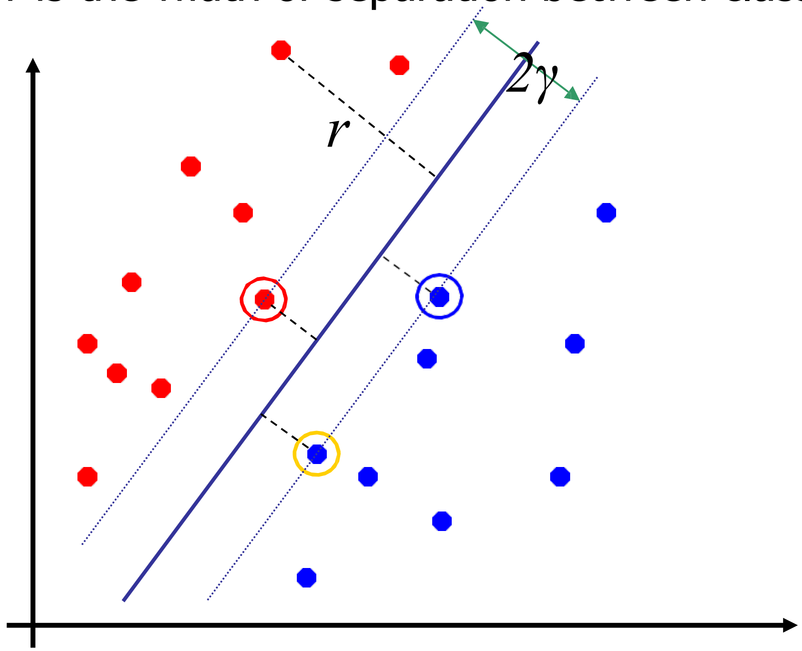
Linear Classifier cont'd

- Which of the linear separators is optimal?



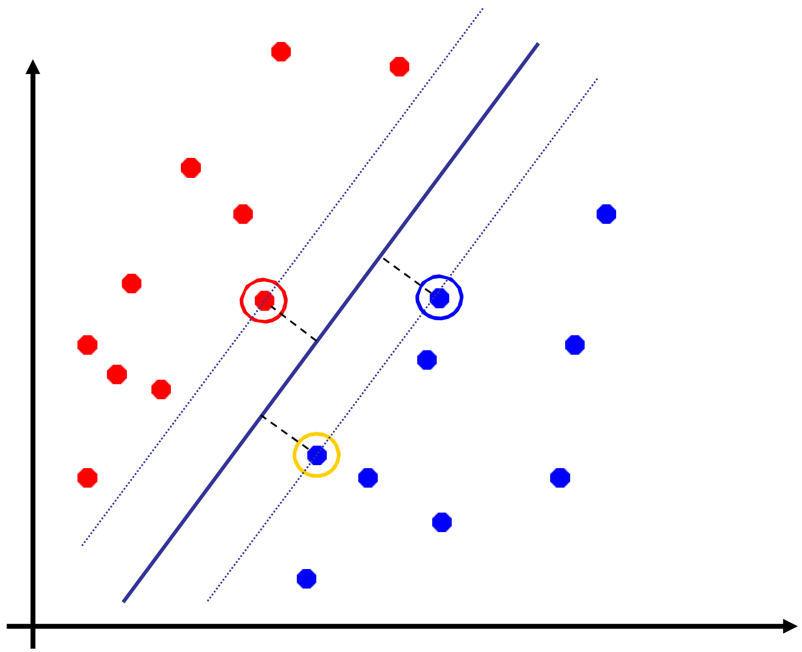
Margin

- Distance from example to the separator is (Point to Plane Distance Equation)
- 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/

Kernels for bags of features

- Histogram intersection kernel: $I(h_1, h_2) = \sum_{i=1}^{N} \min(h_1(i), h_2(i))$

- Generalized Gaussian kernel:

$$K(h_1, h_2) = \exp\left(-\frac{1}{A} D(h_1, h_2)^2 \right)$$

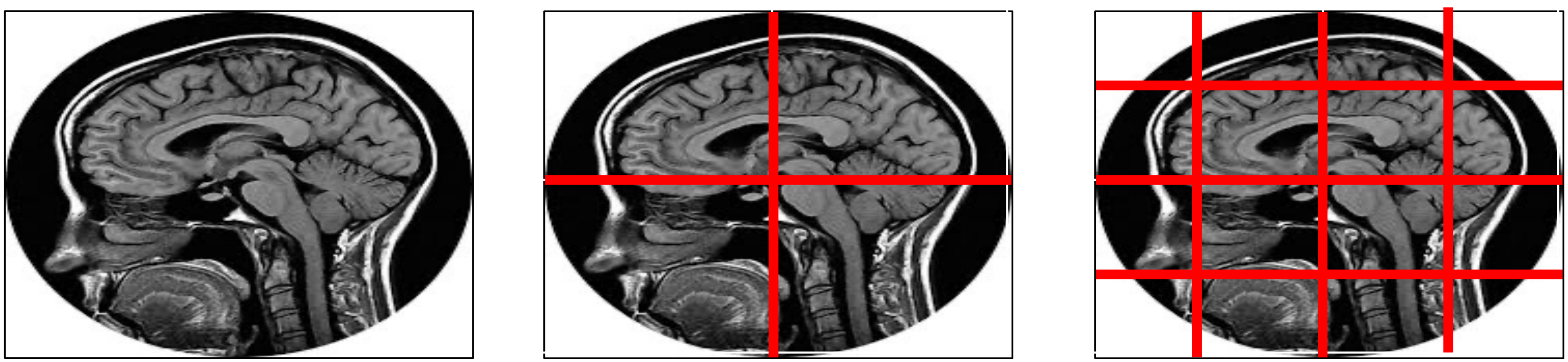
- *D* can be Euclidean distance → RBF kernel

- D can be χ^2 distance $D(h_1, h_2) = \sum_{i=1}^{N} \frac{\left(h_1(i) - h_2(i)\right)^2}{h_1(i) + h_2(i)}$

- Earth mover's distance

Spatial pyramid matching

- Add spatial information to the bag-of-features
- Perform matching in 2D image space

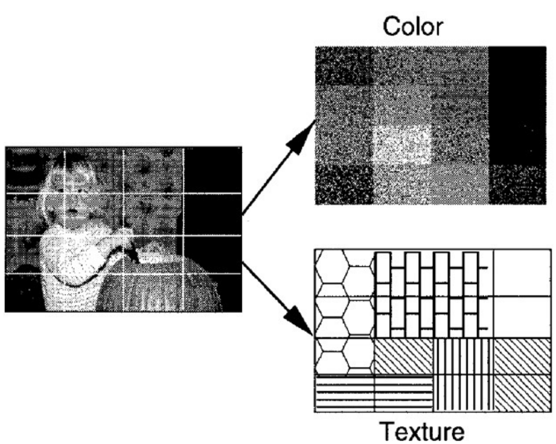


[Lazebnik, Schmid & Ponce, CVPR 2006]

Related work

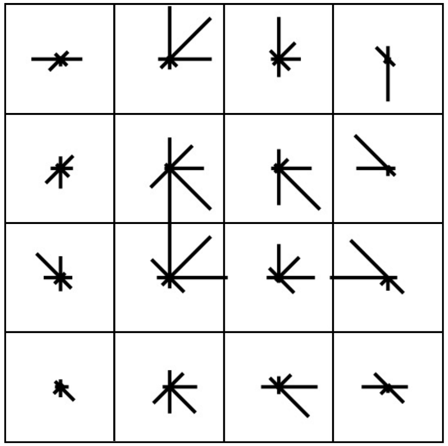
Similar approaches:

- Subblock description [Szummer & Picard, 1997]
- SIFT [Lowe, 1999]
- GIST [Torralba et al., 2003]



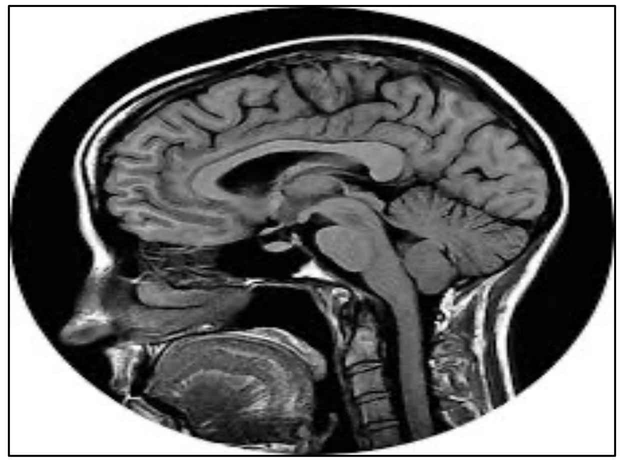
Szummer & Picard (1997)

SIFT

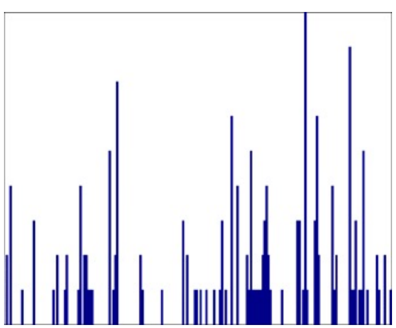


Lowe (1999, 2004)

Spatial pyramid representation

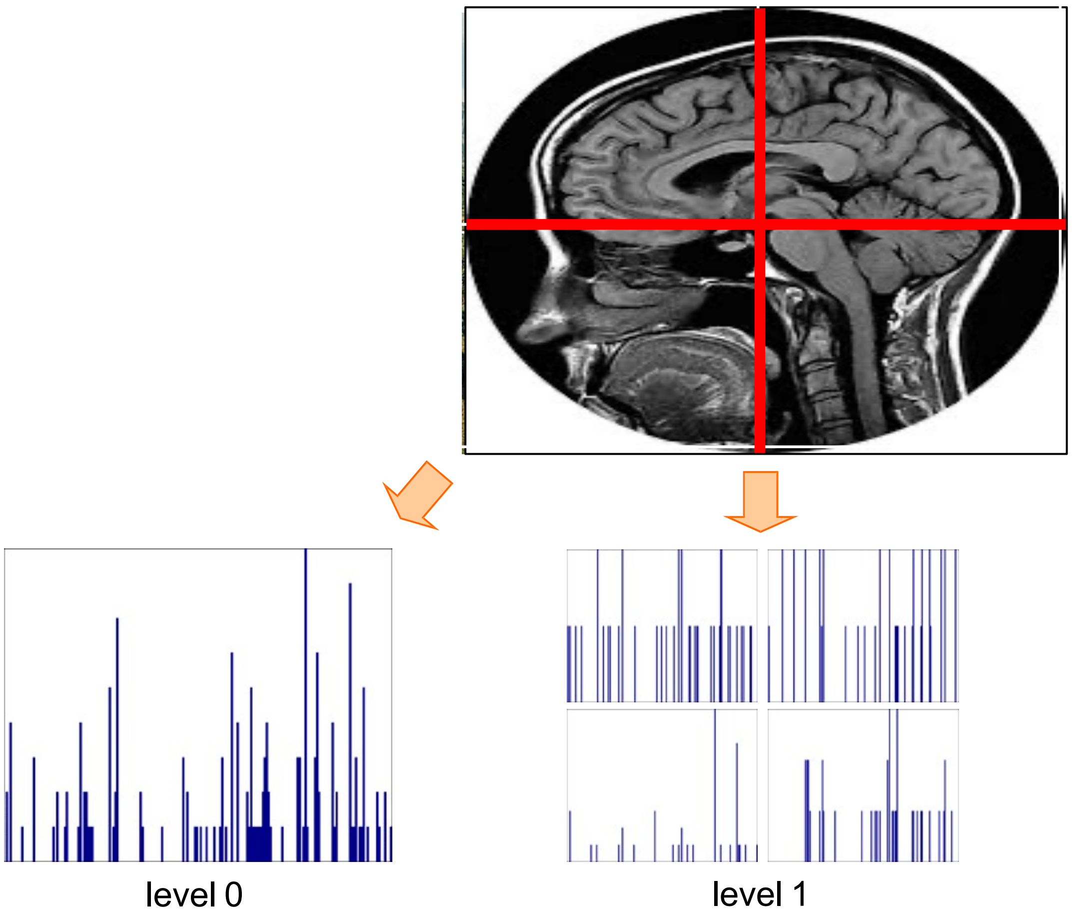


Locally orderless representation at several levels of spatial resolution



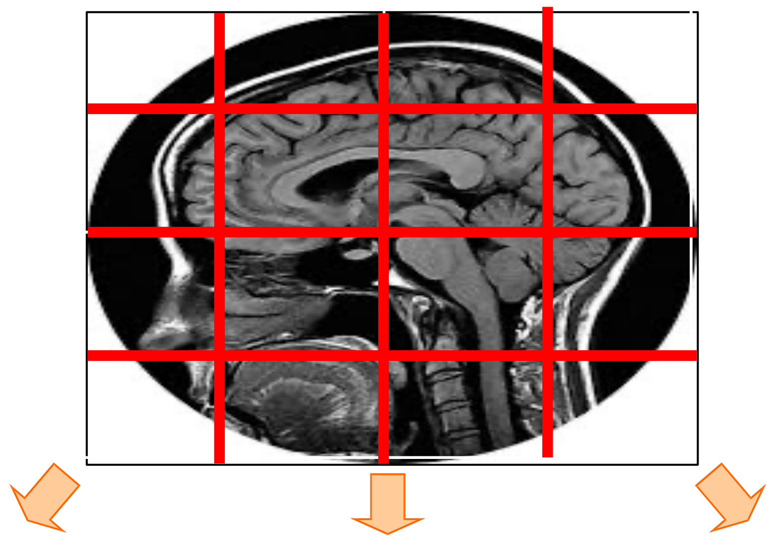
level 0

Spatial pyramid representation

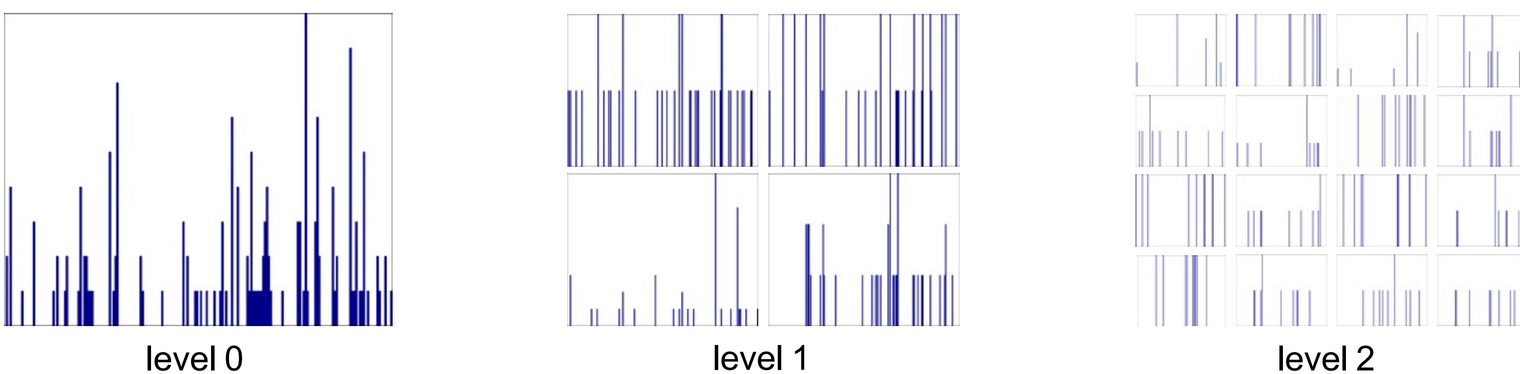


Locally orderless representation at several levels of spatial resolution

Spatial pyramid representation

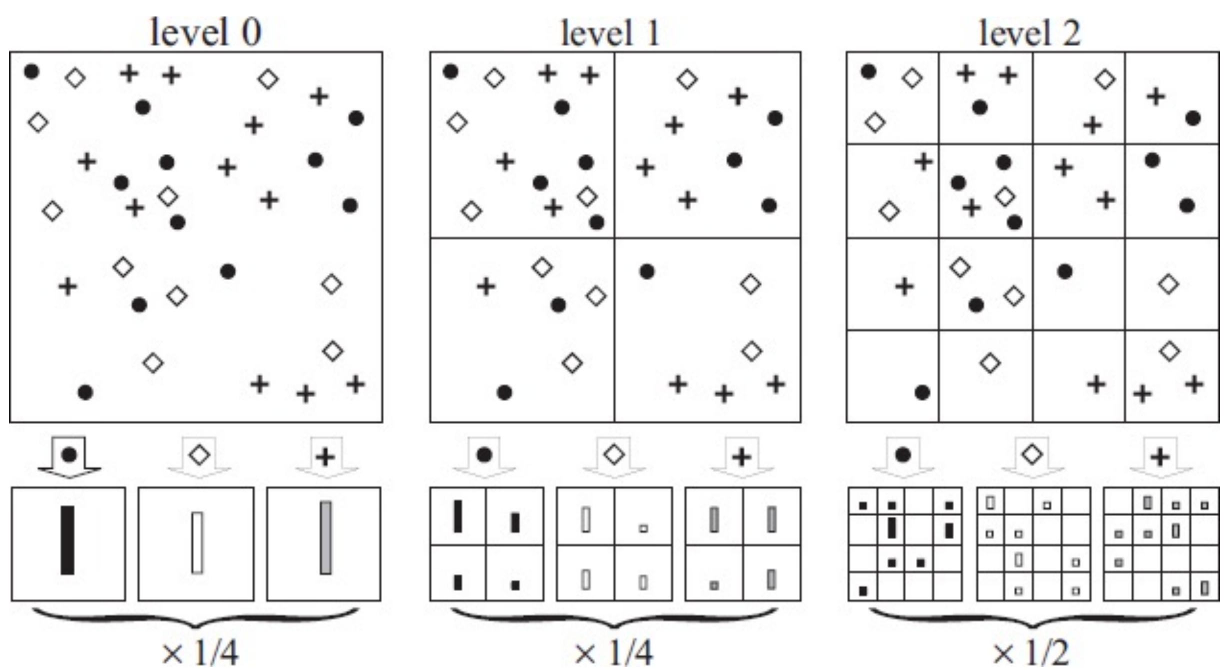


Locally orderless representation at several levels of spatial resolution



Spatial pyramid matching

- Combination of spatial levels with pyramid match kernel
  [Grauman & Darell'05]
- Intersect histograms, more weight to finer grids



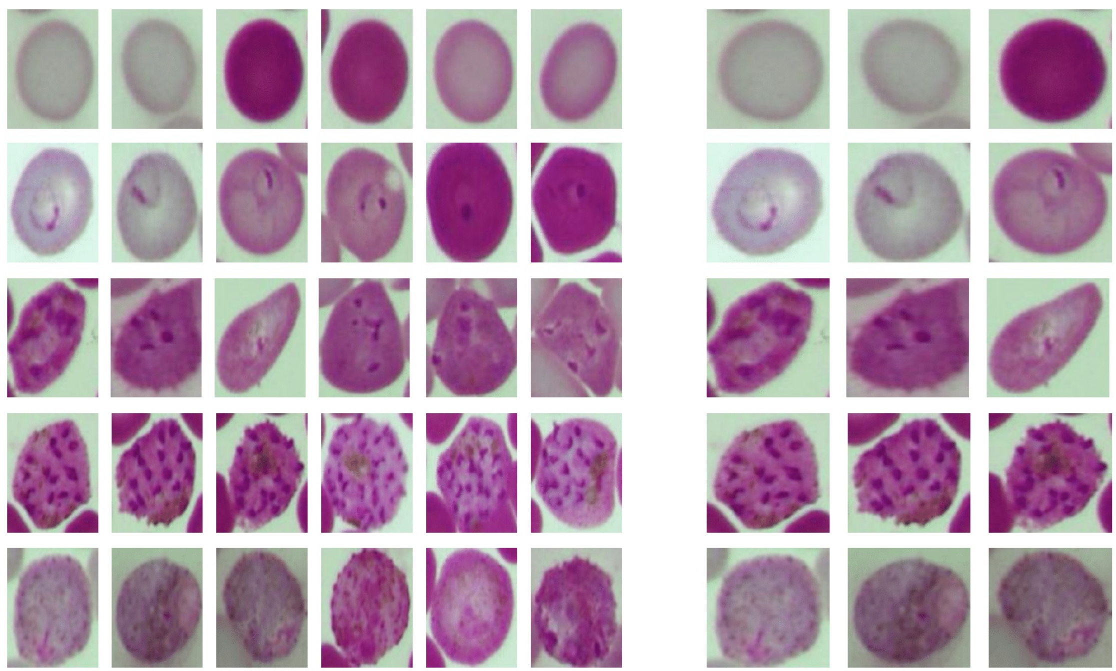
Machine Learning Approaches

• Supervised Appoaches	All Labels available
• Unsupervised Appoaches	No Labels available
• Weakly Supervised Appoaches	No Complete Labels available
• Few shot approaches	A few Labels available
• Single shot approaches	Only One Labels available
• Semi Supervised approaches	Label and Unlabeled data available

- # Self Supervised approaches

  Unsupervised learning concentrates on clustering, grouping, and dimensionality reduction, while self-supervised learning aims to draw conclusions for regression and classification tasks.

<u>Pretext Task</u>



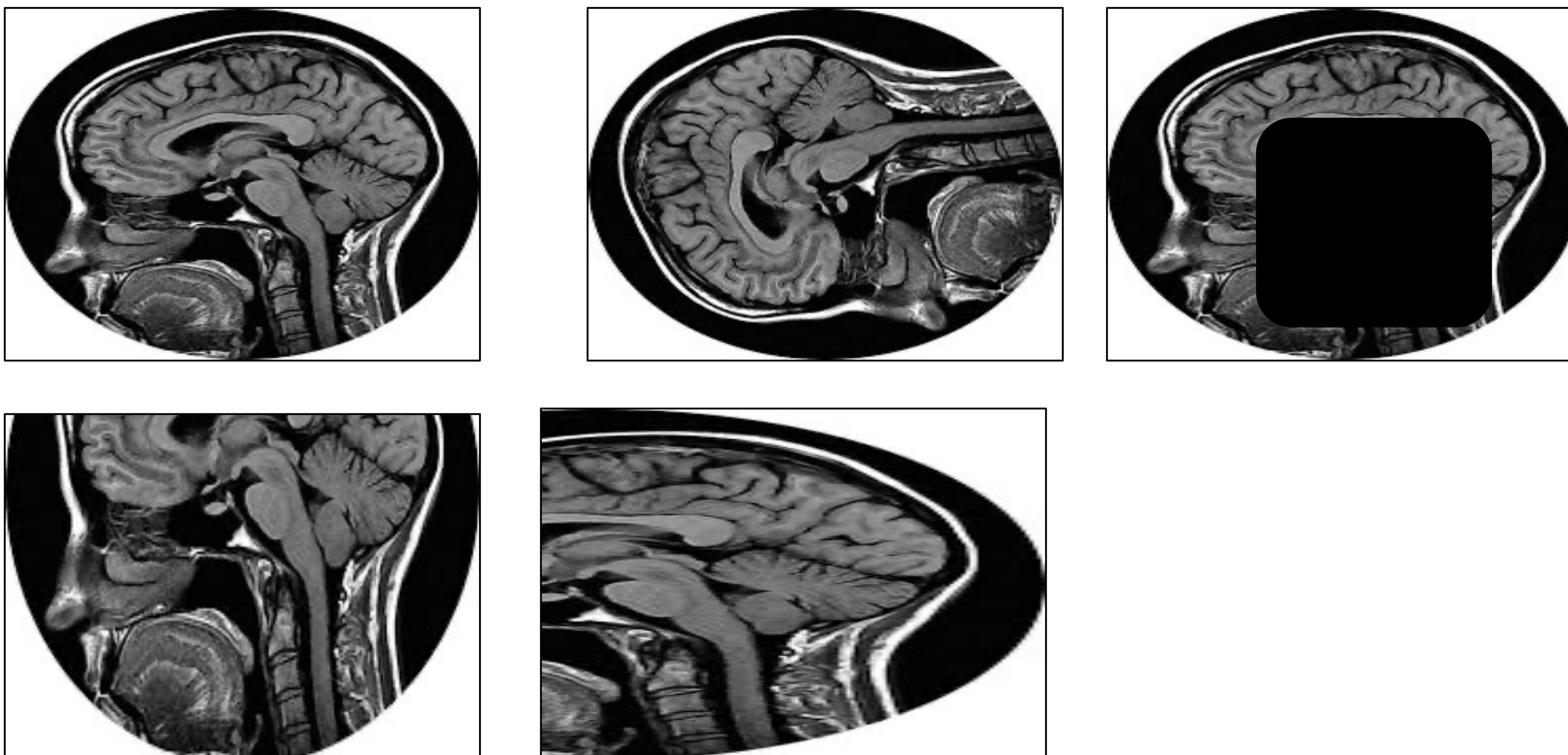
(a) (b)

Number of cells in (a) are greater than number of cells in (b)

- Self Supervised approaches

  Unsupervised learning concentrates on clustering, grouping, and dimensionality reduction, while self-supervised learning aims to draw conclusions for regression and classification tasks.

Pretext Task



References and Slide Credits

- Jayaram K. Udupa, MIPG of University of Pennsylvania, PA.
- P. Suetens, Fundamentals of Medical Imaging, Cambridge Univ. Press.
- N. Bryan, Intro. to the science of medical imaging, Cambridge Univ. Press.
- CAP 5415 Computer Vision (Fall 2016) Lecture Presentations
- Computer Vision (Lecture Presentations) by Dr. Mohsen Ali