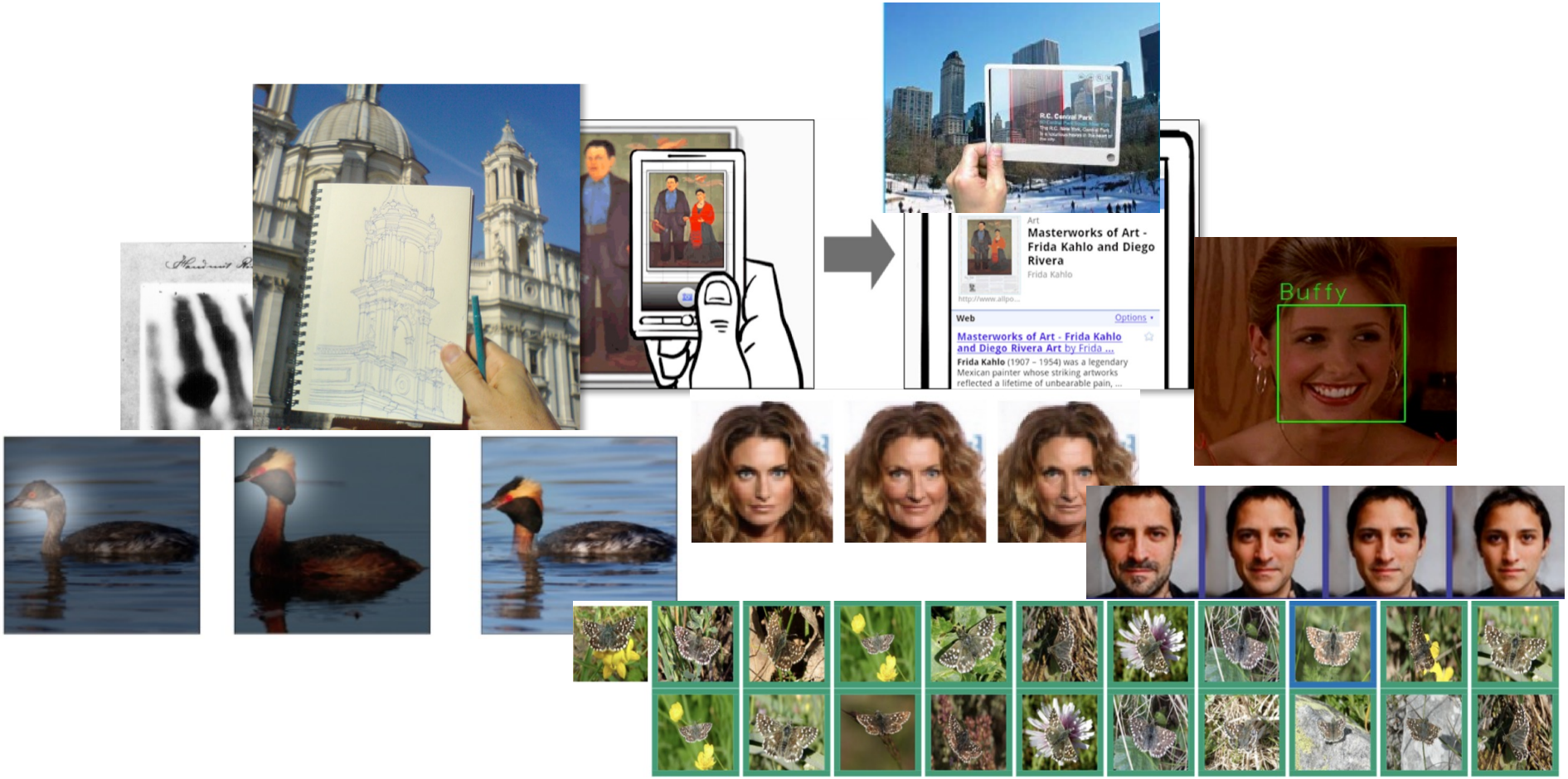


COURS RDFIA deep Image

https://cord.isir.upmc.fr/teaching-rdfia/

Matthieu Cord

Sorbonne University

Course Outline

1. Computer Vision basics: Visual (local) feature detection and description, Bag of Word Image representation
2. Introduction to Neural Networks (NNs)
3. Machine Learning basics: Risk, Classification, Datasets, benchmarks and evaluation, Linear classification (SVM)
4. Neural Nets for Image Classification
5. Large scale convolutional neural nets
6. Vision Transformers
7. Transfer learning and domain adaptation
8. Segmentation and Detection
9. Generative models with GANs
10. Control – AI Challenges
11. Explainable AI, Applications

12/13 Bayesian deep learning

14 Robustness

Info about practicals

Course 1
Visual Representation of images Bag of Features and Bag of Words

Course 2
Supervised Learning: Neural Net architectures

Course 3
Supervised Learning: theory and practices
Supervised Learning: SVM algorithm

Weakly updated

Course 4
Supervised Learning: Dataset evaluation and Extra on BoW
Neural Nets for Image Classification

Course 5
Large scale convolutional neural nets

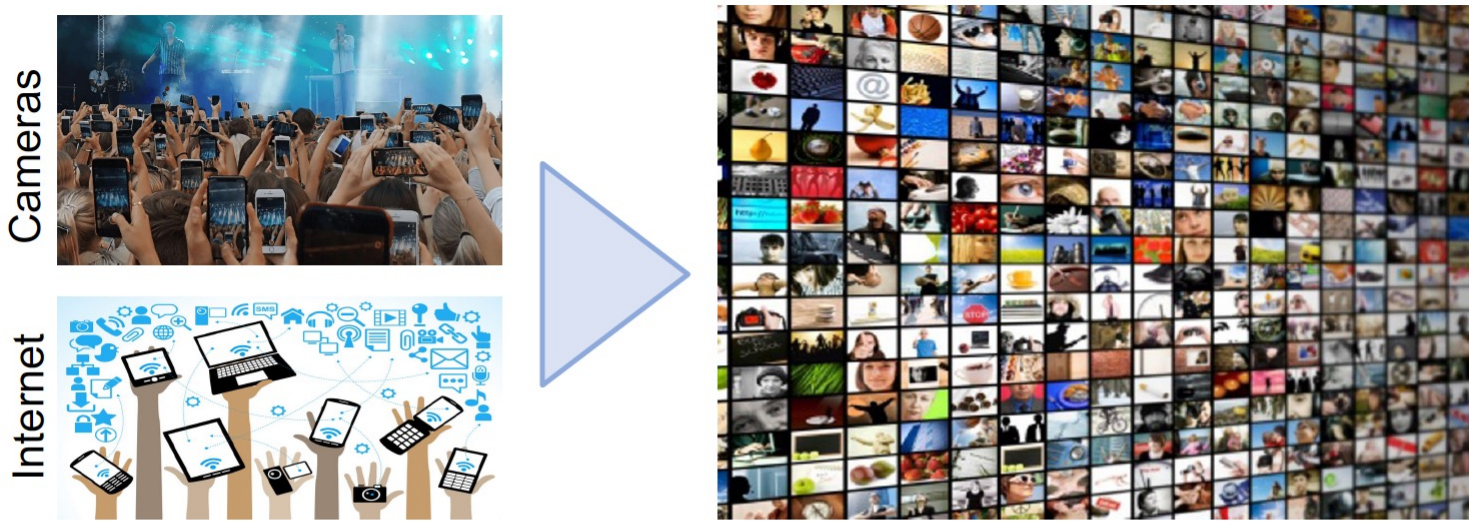
Course 6
VERY Large scale convolutional neural nets and Beyond ImageNet

Course 7 Transformers for Images

Course 8
Visual Transfer Learning: transfer and domain adaptation

Course 9
Generative models for Vision – GAN (1)

Course 10
GAN (2)++



- Facts: Exponential increase in quantity of images/videos taken across the world
  - YouTube: 500h of video / min
  - Facebook: 300M photos / day

COMPUTER VISION:

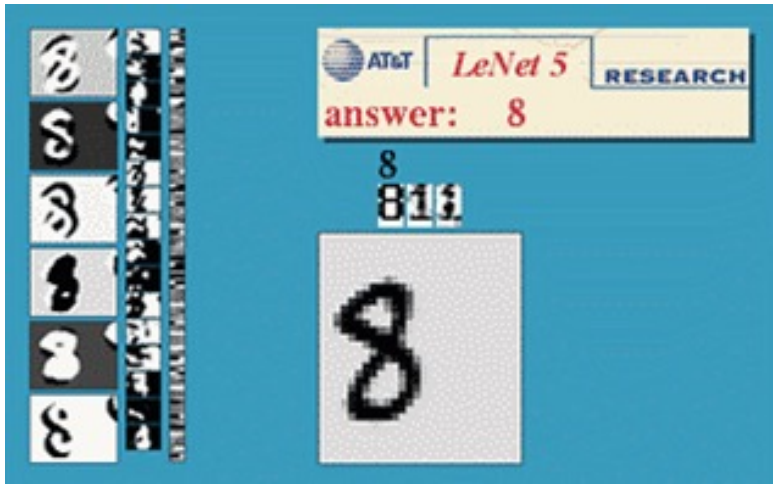
(Processing, analyzing and) **understanding visual data**

=>WHERE ARE WE NOW?

Source (many slides): Cornell CV course

Deployed: Optical character recognition (OCR)

- If you have a scanner, it probably came with OCR software



Digit recognition, AT&T labs
http://www.research.att.com/~yann/

License plate readers
http://en.wikipedia.org/wiki/Automatic_number_plate_recognition

Automatic check processing

Source: S. Seitz

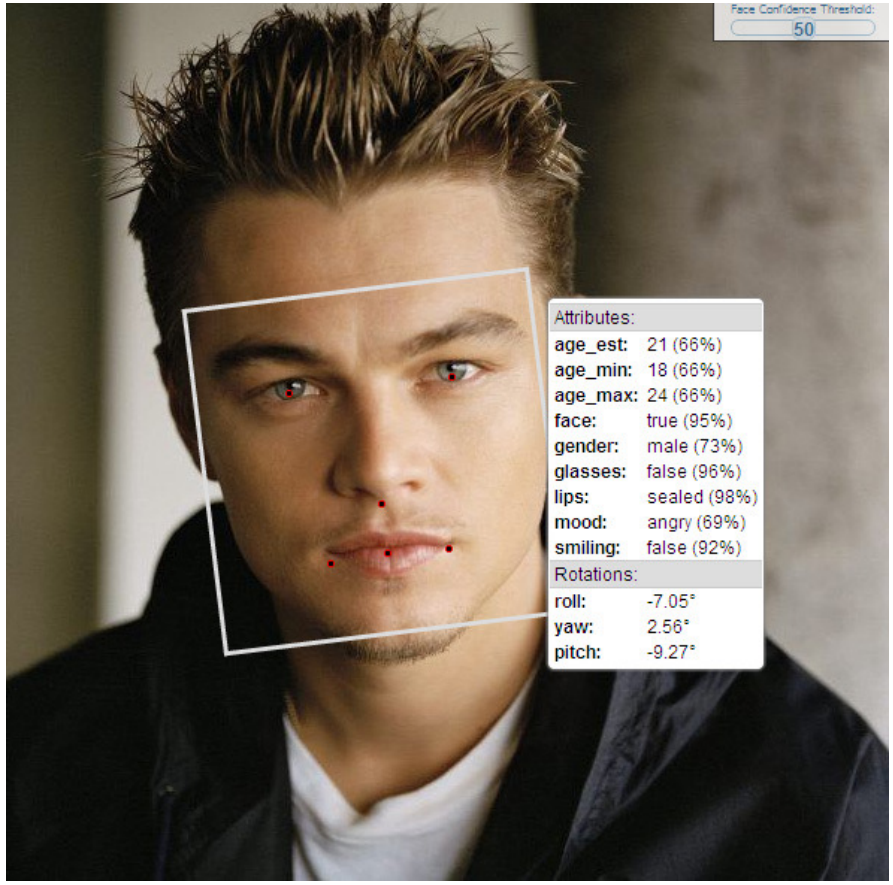
Deployed: Face detection

- Cameras now detect faces
  - Canon, Sony, Fuji, …

Source: S. Seitz

Deployed&Significant progress: Face Recognition

FACE++



Significant progress: Recognizing objects

Mask R-CNN. Kaiming He, Georgia Gkioxari, Piotr Dollar, Ross Girshick. ICCV 2017

Ex: Recognition-based product search

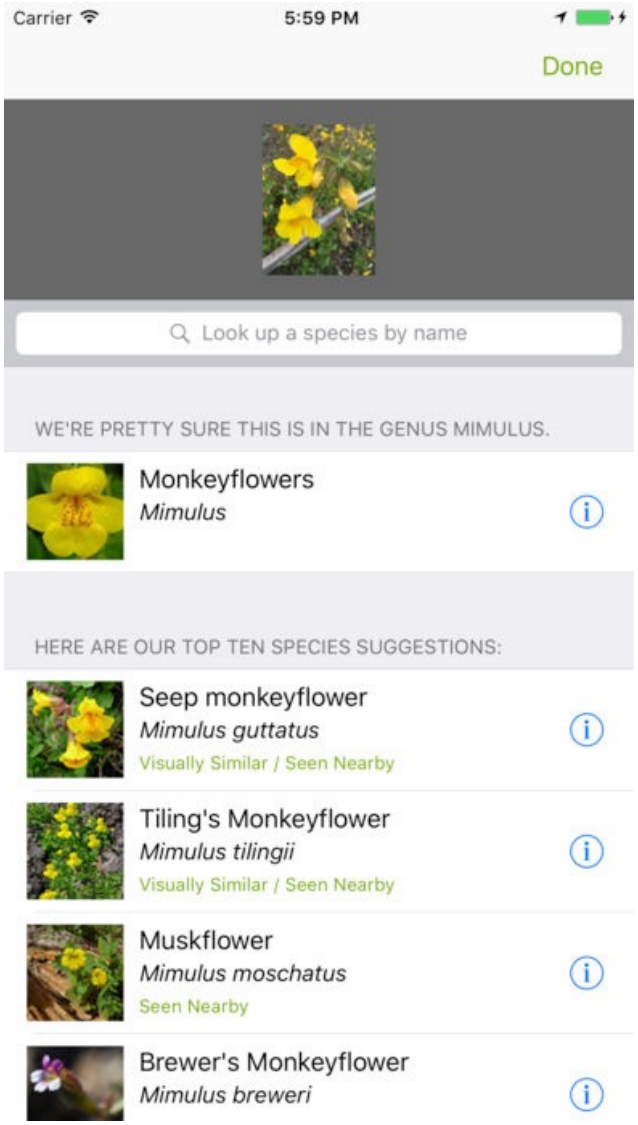
Recognition-based product search

Recognition-based product search






Significant progress: Species recognition



iNaturalist dataset

Challenges:

- fine-grained recognition
- Detecting rare concepts

Challenges: Fully autonomous driving

Challenges: Medical Imaging, Health

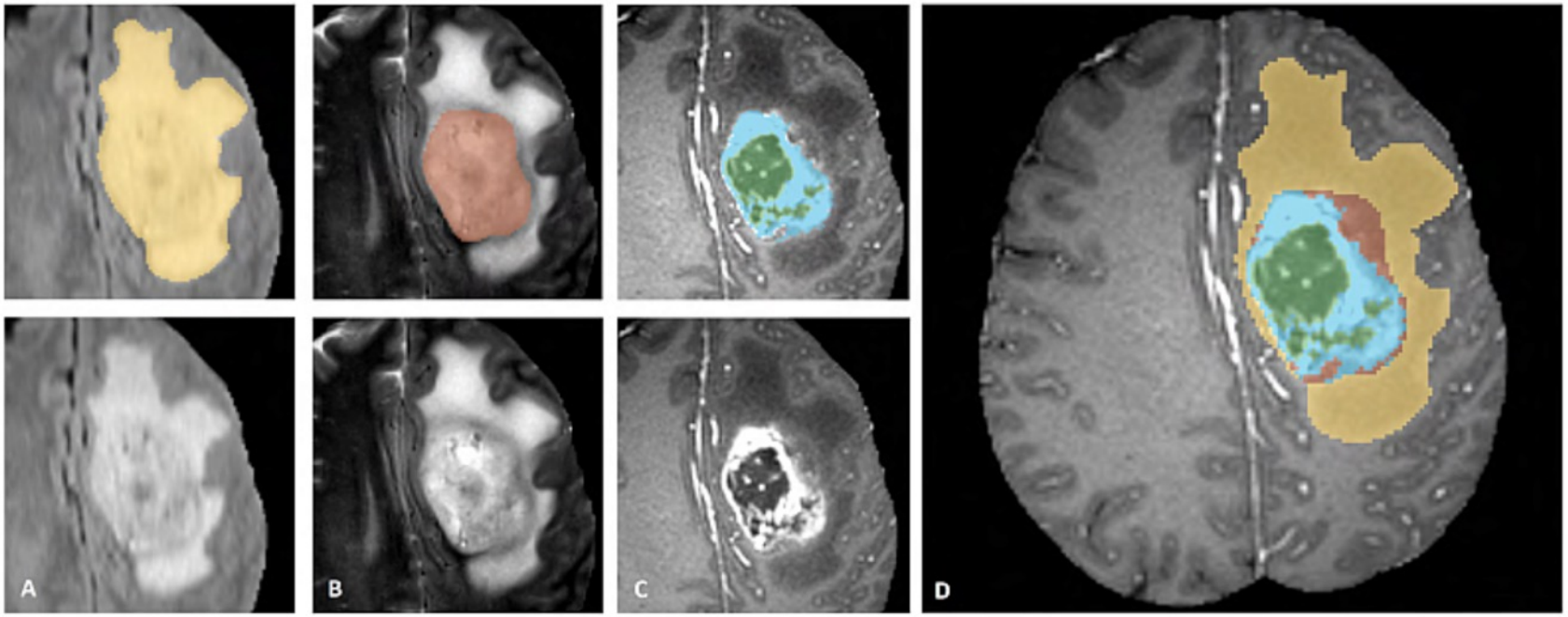
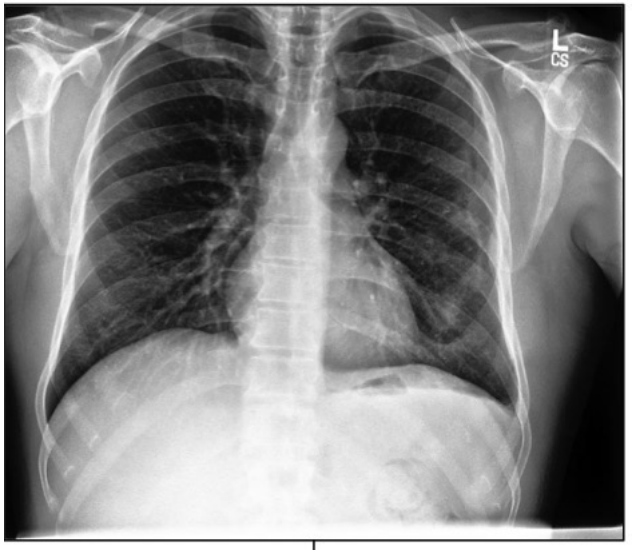


Fig.1: Glioma sub-regions. Shown are image patches with the tumor sub-regions that are annotated in the different modalities (top left) and the final labels for the whole dataset (right). The image patches show from left to right: the whole tumor (yellow) visible in T2-FLAIR (Fig.A), the tumor core (red) visible in T2 (Fig.B), the enhancing tumor structures (light blue) visible in T1Gd, surrounding the cystic/necrotic components of the core (green) (Fig. C). The segmentations are combined to generate the final labels of the tumor sub-regions (Fig.D): edema (yellow), non-enhancing solid core (red), necrotic/cystic core (green), enhancing core (blue). (Figure taken from the BraTS IEEE TMI paper.)

Challenges: Medical Imaging, Health

Building system to detect Covid in chest x rays
What should a metric measure?
Accuracy = P(pred. label == true label)
Accuracy of candidate system = 95%
Is this good? Did it actually help / work?



Artificial intelligence / Machine learning

Hundreds of AI tools have been built to catch covid. None of them helped.

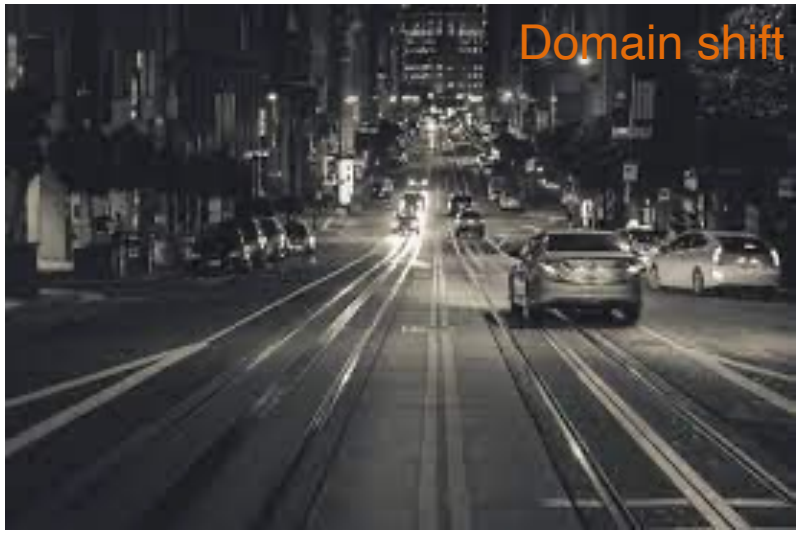
Some have been used in hospitals, despite not being properly tested. But the pandemic could help make medical AI better.

by **Will Douglas Heaven** July 30, 2021

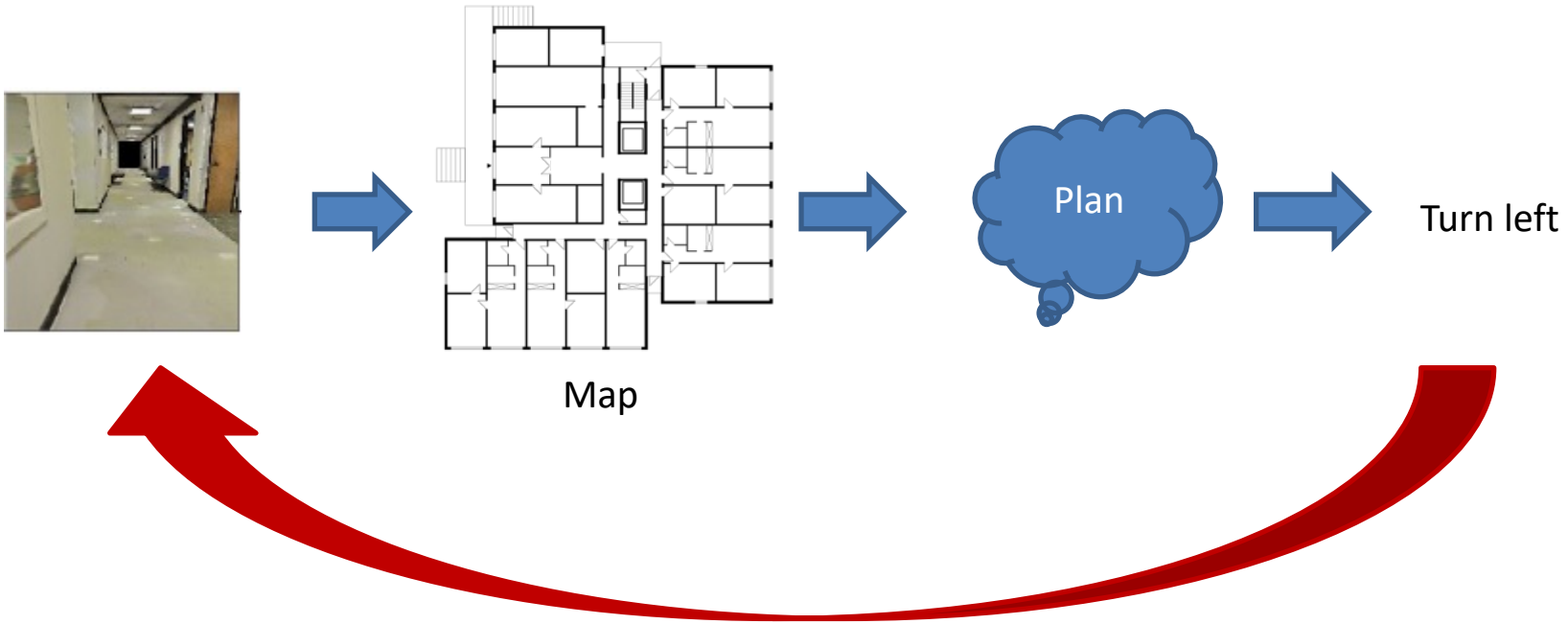
Why?

Typical issues that plague deployment

- Images seen during deployment are very different: domain shift
- Meaning of classes etc. change: concept drift
- Unforeseen circumstances, e.g., new classes: open world



Challenges: Integrating Vision and Action, Robotics



Cognitive Mapping and Planning for Visual Navigation
Saurabh Gupta, James Davidson, Sergey Levine, Rahul Sukthankar, Jitendra Malik
CVPR 2017

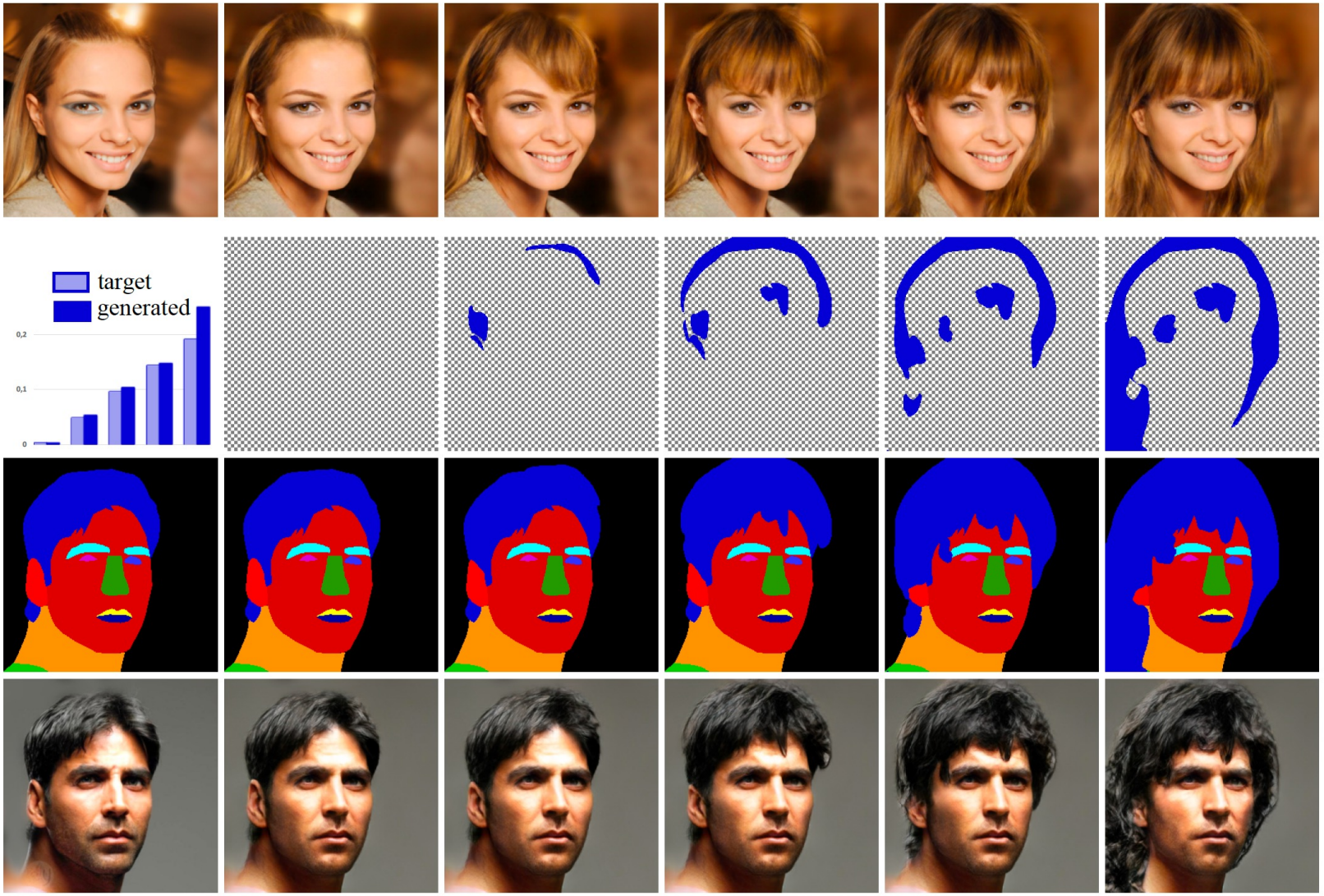
Challenges: Understanding complex situations / Reasoning

Challenges: Visual Reasoning
VQA task: Why is this funny?

The picture above is funny.

Andrej Karpathy

Challenges: Generative models for images-edition, manipulation



Course Outline

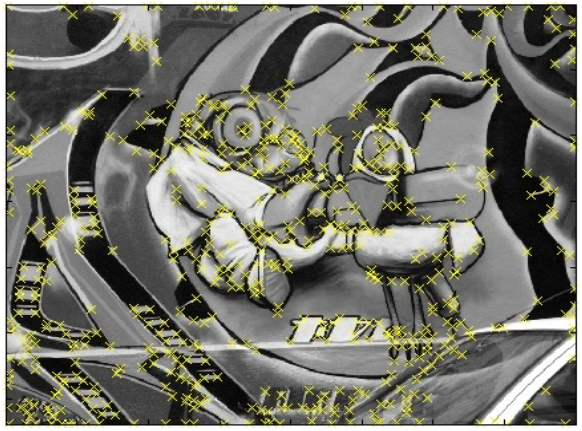
1. Computer Vision:

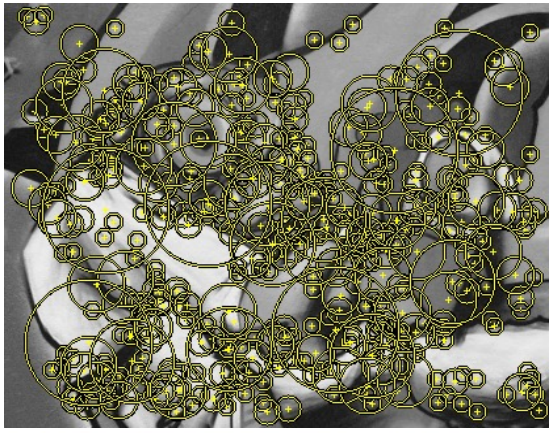
   Visual (local) feature detection and description,

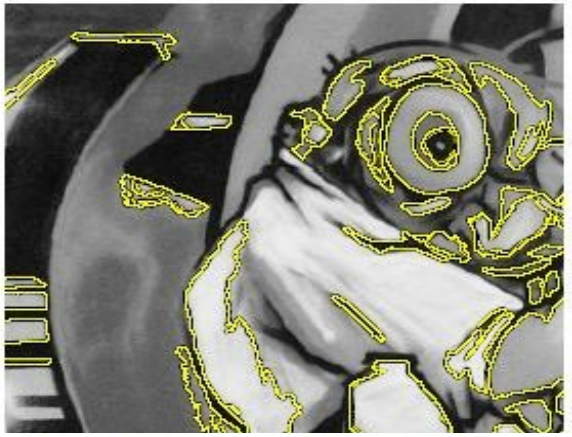
   Bag of Word Image representation

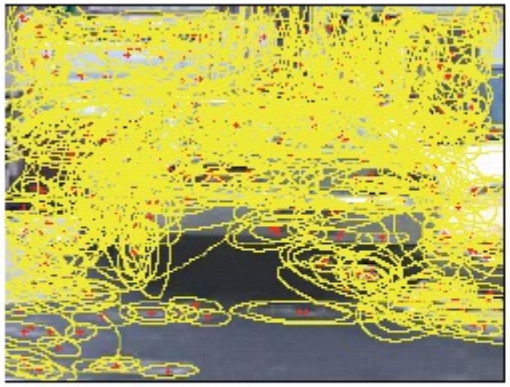
Local feature detection and description

Points/Regions of Interest detection









Sparse, at interest points

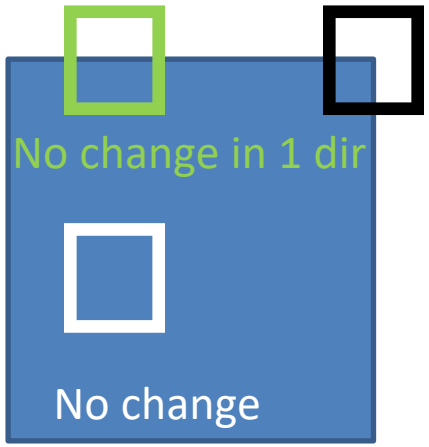
Dense, uniformly

Randomly

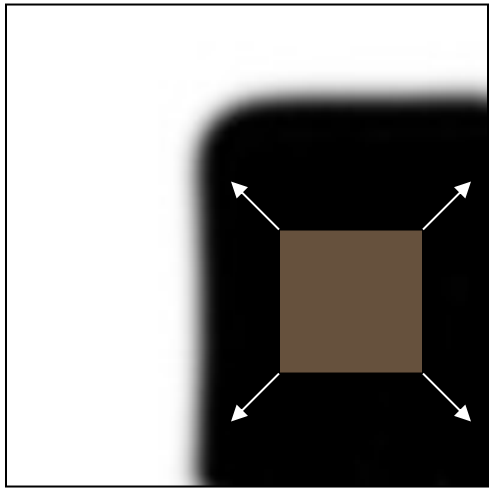
One example: Corner detection (Harris corner detector)

Corner detection

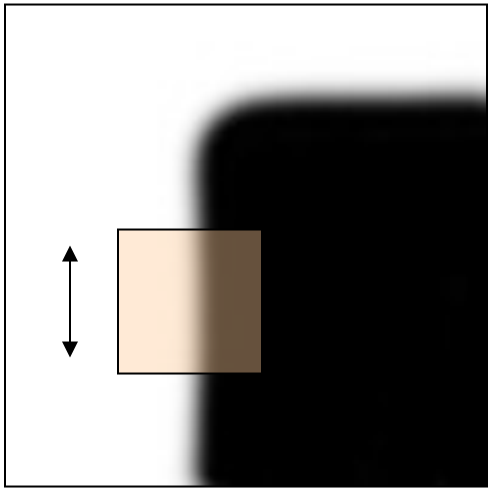
- Corner point: singular point highly informative, rare, …
- Basic idea for Algo: For each pixel (x,y) from image I, *translating* a centered window: Iff (x,y) is a corner, it should cause large differences in patch appearance (whatever the translation)



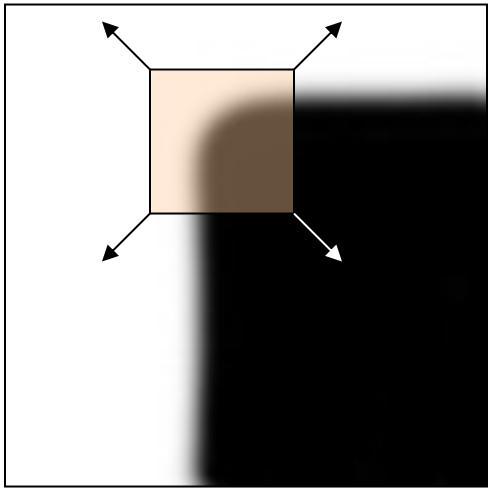
Corner Detection: Basic Idea



"flat" region:
no change in
all directions



"edge":
no change
along the edge
direction

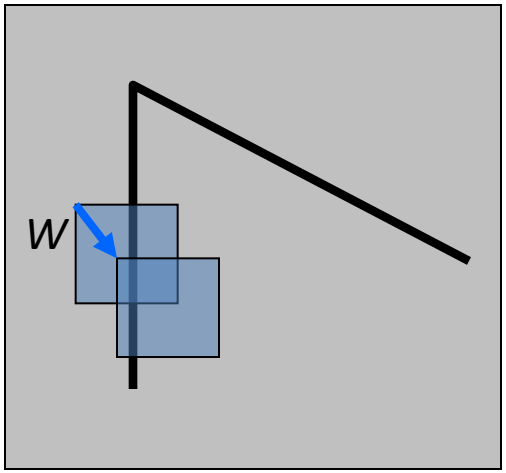


"corner":
significant
change in all
directions

Corner detection op == For all pix, shift a window in *any direction*, keep the ones that give *a large change* in intensity

Harris corner detection: algo1

Consider a pix (x,y), a small window W, a shifting vector (*u,v*):



- how do the pixels in W change?
- compare each pixel before and after by summing up the squared differences (SSD)
- this defines an SSD "error" *E*(*u,v*):

$$E(u,v) = \sum_{(x,y)\in W} [I(x+u, y+v) - I(x,y)]^2$$

- To select (x,y) as corner, E(u,v) has to be *as high as possible for all shifting dir (u,v)!*

ALGO 1: very computationally expensive

Simplify E(u,v)? Small motion assumption

Taylor Series expansion of *I*:

$$I(x+u, y+v) = I(x,y) + \frac{\partial I}{\partial x}u + \frac{\partial I}{\partial y}v + \text{higher order terms}$$

If the motion (u,v) is small, then first order approximation is good

$$\begin{aligned} I(x+u, y+v) &\approx I(x,y) + \frac{\partial I}{\partial x}u + \frac{\partial I}{\partial y}v \\ &\approx I(x,y) + \begin{bmatrix} I_x & I_y \end{bmatrix} \begin{bmatrix} u \\ v \end{bmatrix} \end{aligned}$$

$$\text{shorthand: } I_x = \frac{\partial I}{\partial x}$$

Plugging this into the formula on the previous slide…

Simplify E(u,v)? Small motion assumption

$$E(u,v) = \sum_{(x,y)\in W} [I(x+u, y+v) - I(x,y)]^2$$

$$\approx \sum_{(x,y)\in W} [I(x,y) + I_x u + I_y v - I(x,y)]^2$$

$$E(u,v) \approx \sum_{(x,y)\in W} [I_x u + I_y v]^2$$

$$\approx Au^2 + 2Buv + Cv^2$$

$$A = \sum_{(x,y)\in W} I_x^2 \qquad B = \sum_{(x,y)\in W} I_x I_y \qquad C = \sum_{(x,y)\in W} I_y^2$$

E(*u*,*v*) is locally approximated as a quadratic error function =>Once A, B and C computed, very fast to compute E(u,v) for many (u,v)!

ALGO 2!

Interpreting the second moment matrix

$$M = \sum_{x,y} \begin{bmatrix} I_x^2 & I_x I_y \\ I_x I_y & I_y^2 \end{bmatrix} = \begin{bmatrix} A & B \\ B & C \end{bmatrix}$$

$$E(u,v) \approx \begin{bmatrix} u & v \end{bmatrix} M \begin{bmatrix} u \\ v \end{bmatrix}$$

Recall that we want E(u,v) to be as large as possible for all u,v

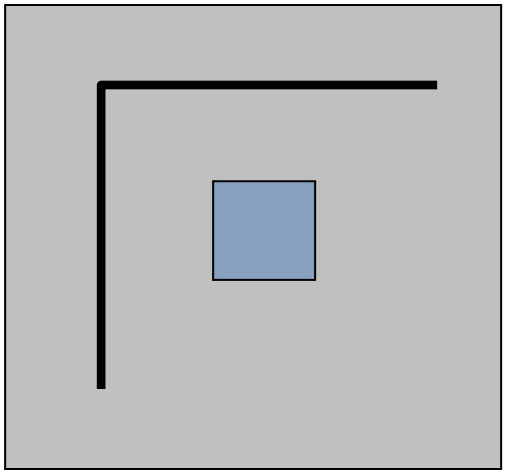
What does this mean in terms of M?

$$E(u,v) \approx \begin{bmatrix} u & v \end{bmatrix} \underbrace{\begin{bmatrix} A & B \\ B & C \end{bmatrix}}_{M} \begin{bmatrix} u \\ v \end{bmatrix}$$

$$A = \sum_{(x,y)\in W} I_x^2$$

$$B = \sum_{(x,y)\in W} I_x I_y$$

$$C = \sum_{(x,y)\in W} I_y^2$$



$$M = \begin{bmatrix} 0 & 0 \\ 0 & 0 \end{bmatrix}$$

$$M \begin{bmatrix} u \\ v \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \end{bmatrix}$$

$$E(u,v) = 0 \quad \forall u, v$$

Flat patch: $I_x = 0$

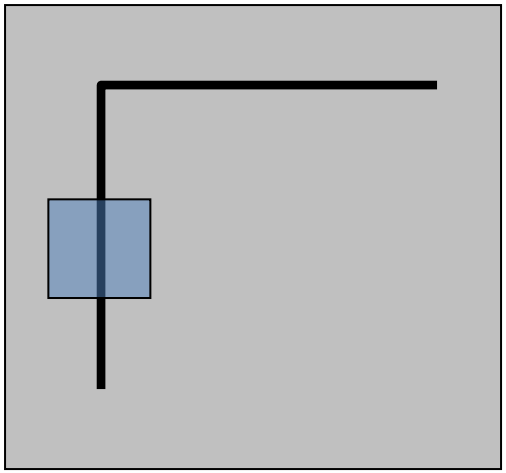
$I_y = 0$

$$E(u,v) \approx \begin{bmatrix} u & v \end{bmatrix} \underbrace{\begin{bmatrix} A & B \\ B & C \end{bmatrix}}_{M} \begin{bmatrix} u \\ v \end{bmatrix}$$

$$A = \sum_{(x,y)\in W} I_x^2$$

$$B = \sum_{(x,y)\in W} I_x I_y$$

$$C = \sum_{(x,y)\in W} I_y^2$$



Vertical edge: $I_y = 0$

$$M = \begin{bmatrix} A & 0 \\ 0 & 0 \end{bmatrix}$$

$$M \begin{bmatrix} 0 \\ v \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \end{bmatrix}$$

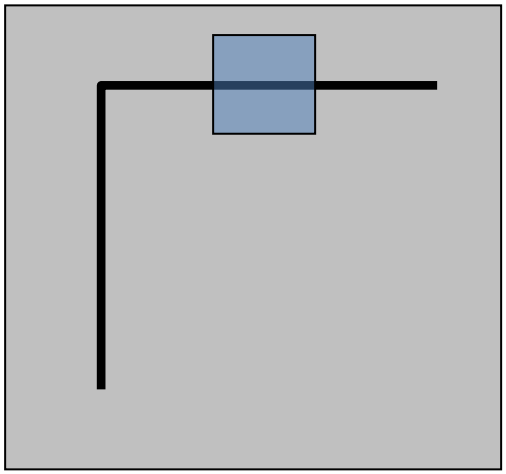
$$E(0,v) = 0 \quad \forall v$$

$$E(u,v) \approx \begin{bmatrix} u & v \end{bmatrix} \underbrace{\begin{bmatrix} A & B \\ B & C \end{bmatrix}}_{M} \begin{bmatrix} u \\ v \end{bmatrix}$$

$$A = \sum_{(x,y)\in W} I_x^2$$

$$B = \sum_{(x,y)\in W} I_x I_y$$

$$C = \sum_{(x,y)\in W} I_y^2$$



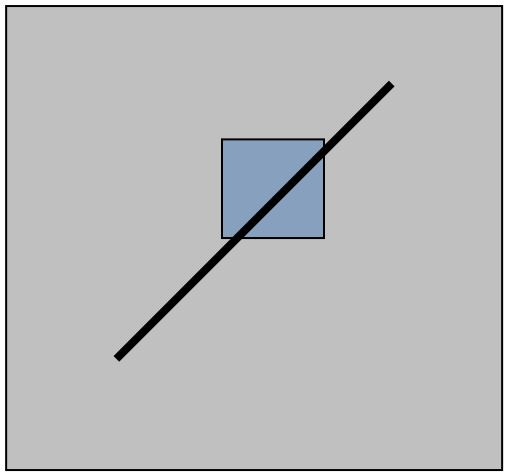
Horizontal edge: $I_x = 0$

$$M = \begin{bmatrix} 0 & 0 \\ 0 & C \end{bmatrix}$$

$$M \begin{bmatrix} u \\ 0 \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \end{bmatrix}$$

$$E(u,0) = 0 \; \forall u$$

What about edges in arbitrary orientation?



$$E(u,v) \approx \begin{bmatrix} u & v \end{bmatrix} M \begin{bmatrix} u \\ v \end{bmatrix}$$

$$M \begin{bmatrix} u \\ v \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \end{bmatrix} \Rightarrow E(u,v) = 0$$

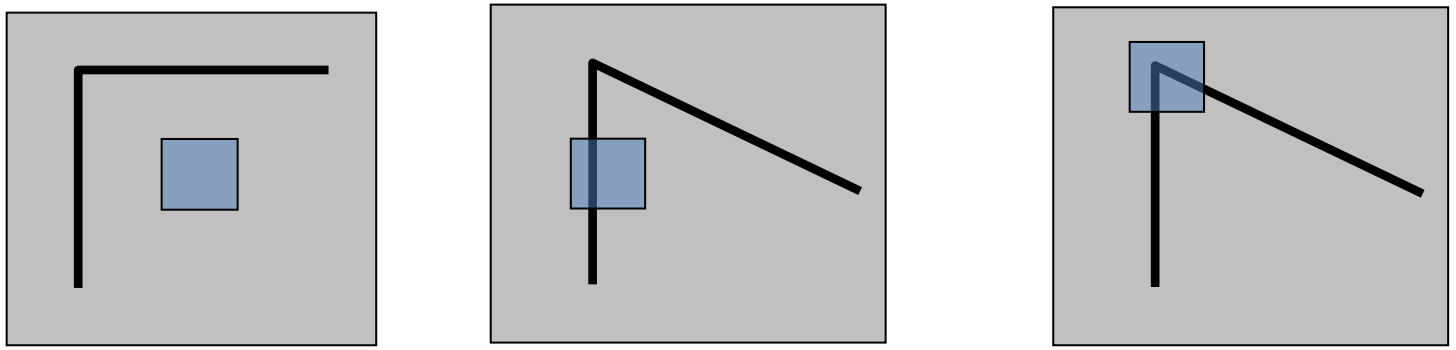
$$M \begin{bmatrix} u \\ v \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \end{bmatrix} \Leftrightarrow E(u,v) = 0$$

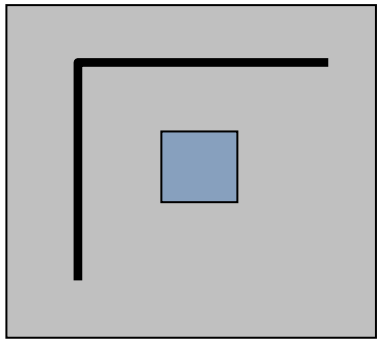
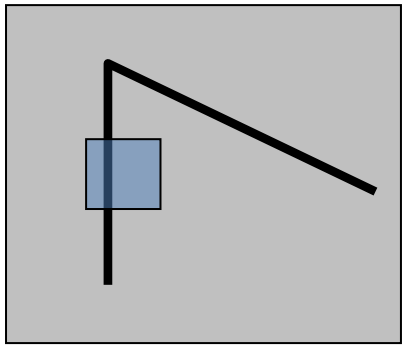
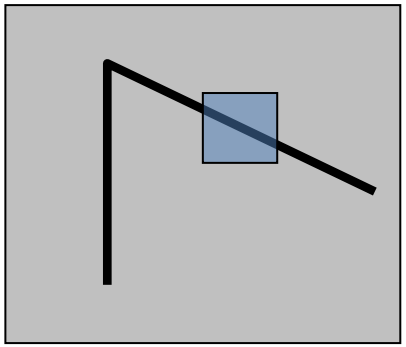
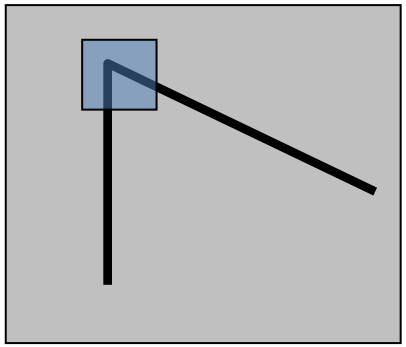
Solutions to Mx = 0 are directions for which E is 0: window can slide in this direction without changing appearance

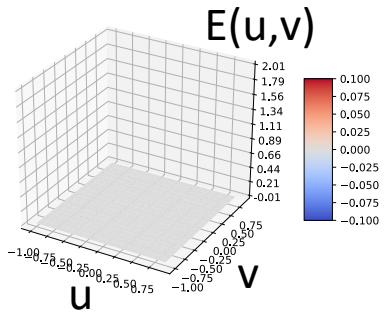
$$E(u,v) \approx \begin{bmatrix} u & v \end{bmatrix} M \begin{bmatrix} u \\ v \end{bmatrix}$$

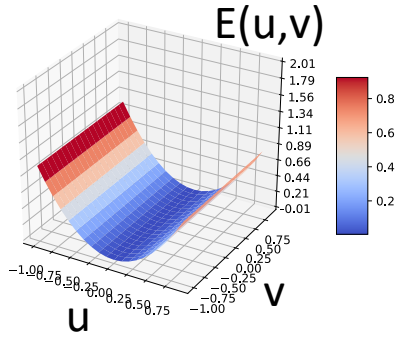
Solutions to Mx = 0 are directions for which E is 0: window can slide in this direction without changing appearance

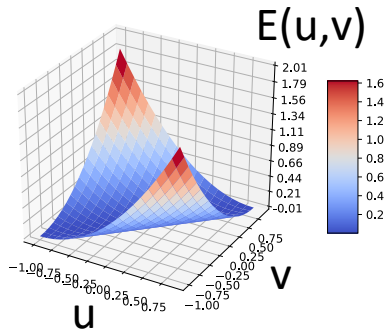
For corners, no such directions exist

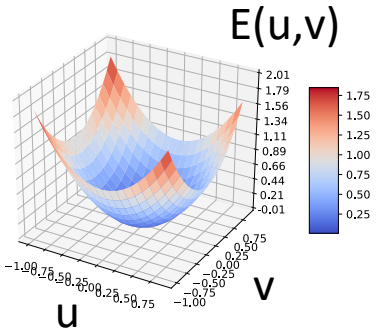



E(u,v)
u
v


E(u,v)
u
v


E(u,v)
u
v

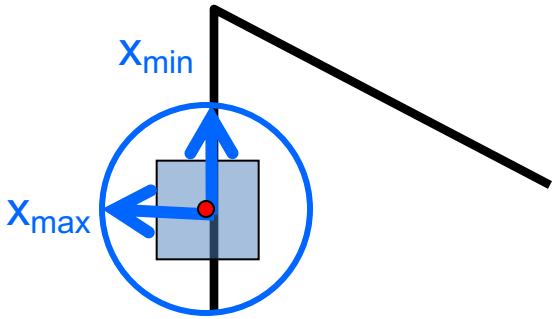

E(u,v)
u
v

Eigenvalues and eigenvectors of M

- $Mx = 0 \Rightarrow Mx = \lambda x$: x is an eigenvector of M with eigenvalue 0
- M is 2 x 2, so it has 2 eigenvalues $(\lambda_{max}, \lambda_{min})$ with eigenvectors (x_{max}, x_{min})
- $E(x_{max}) = \ x_{max}^T M x_{max} = \lambda_{max} ||x_{max}||^2 = \lambda_{max}$ (eigenvectors have unit norm)
- $E(x_{min}) = x_{min}^T M x_{min} = \lambda_{min} ||x_{min}||^2 = \lambda_{min}$

Eigenvalues and eigenvectors of M

$$E(u,v) \approx \begin{bmatrix} u & v \end{bmatrix} M \begin{bmatrix} u \\ v \end{bmatrix}$$



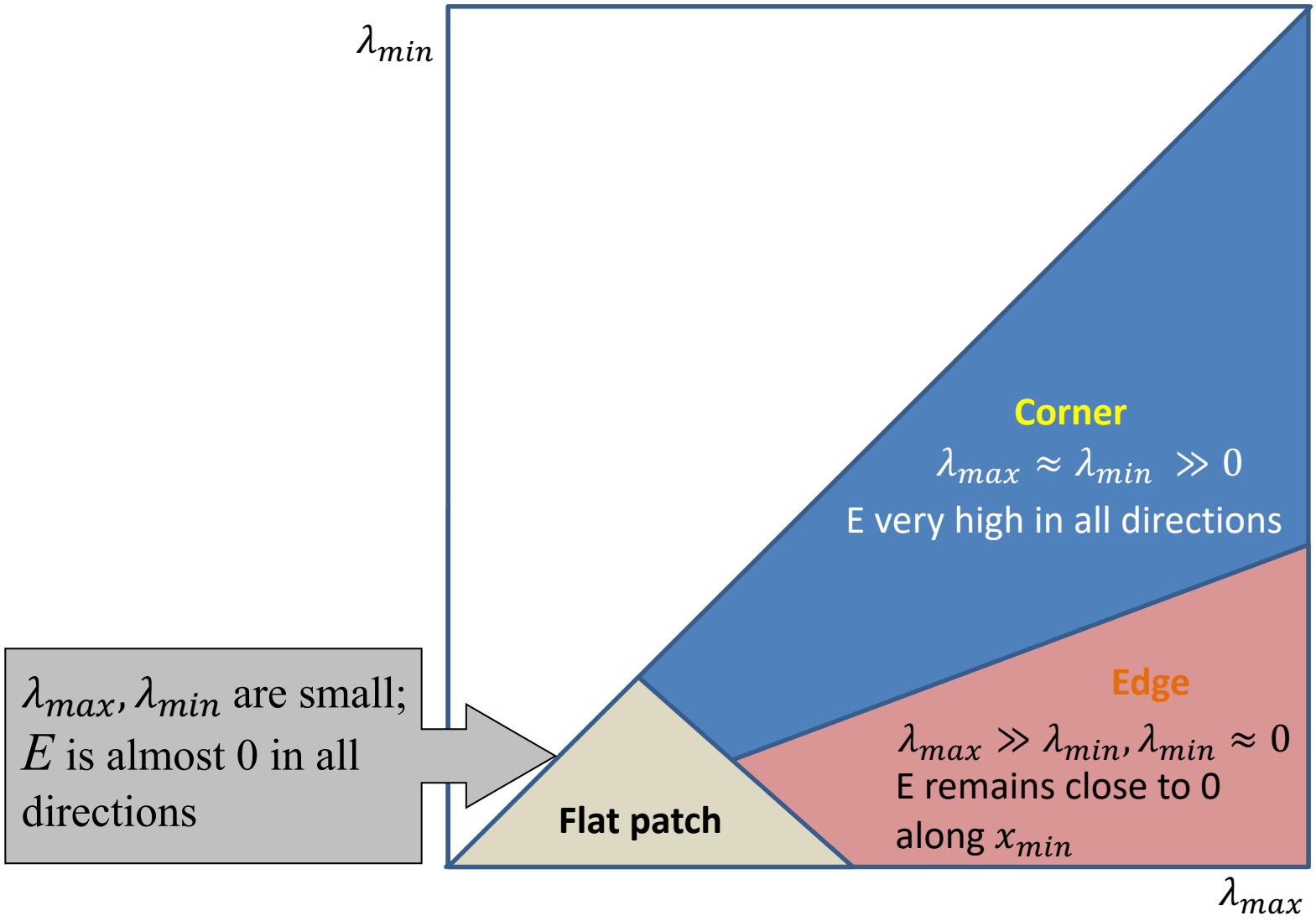
$$M\ x_{\max} = \lambda_{\max} x_{\max}$$

$$M\ x_{\min} = \lambda_{\min} x_{\min}$$

Eigenvalues and eigenvectors of M

- Define shift directions with the smallest and largest change in error
- x_{max} = direction of largest increase in *E*
- λ_{max} = amount of increase in direction x_{max}
- x_{min} = direction of smallest increase in *E*
- λ_{min} = amount of increase in direction x_{min}

Interpreting the eigenvalues



Corner detection: M-based algo

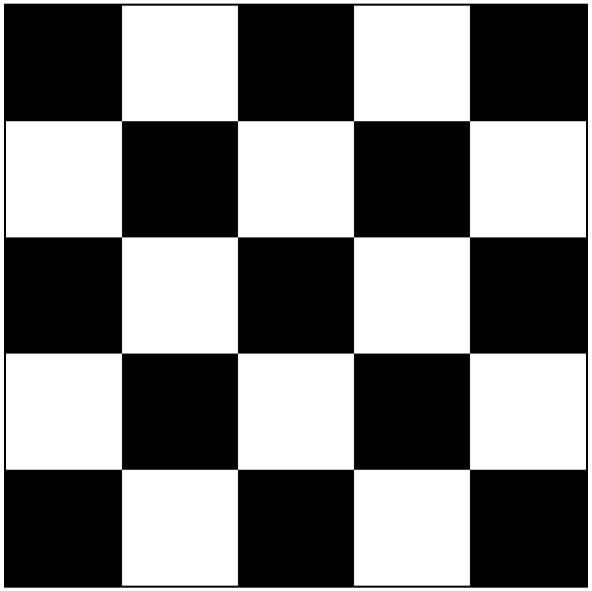
How are λ_{max}, x_{max}, λ_{min}, and x_{min} relevant for feature detection?

- Need a feature scoring function

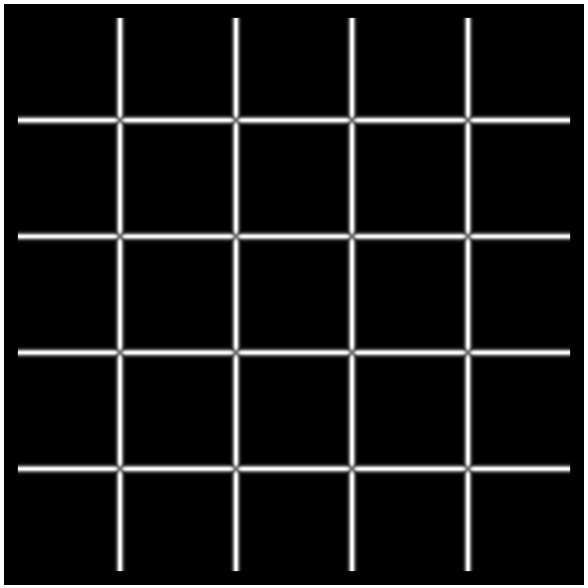
Want $E(u,v)$ to be large for small shifts in all directions

- the minimum of $E(u,v)$ should be large, over all unit vectors $[u\ v]$
- this minimum is given by the smaller eigenvalue (λ_{min}) of M

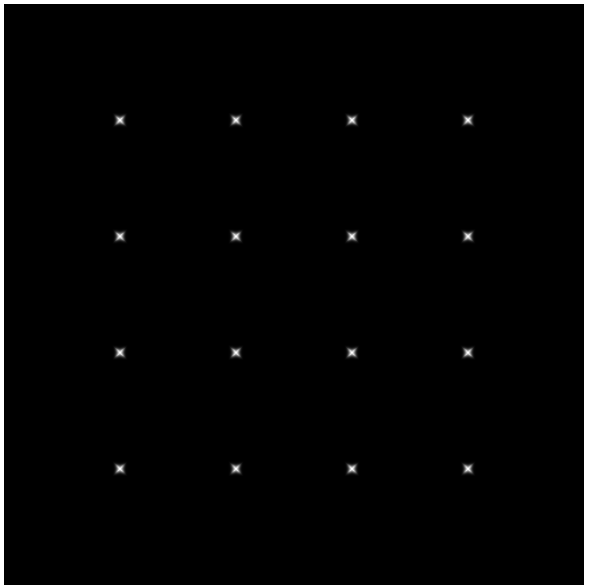
Good detector: λ_{min} > threshold



I



λ_{max}

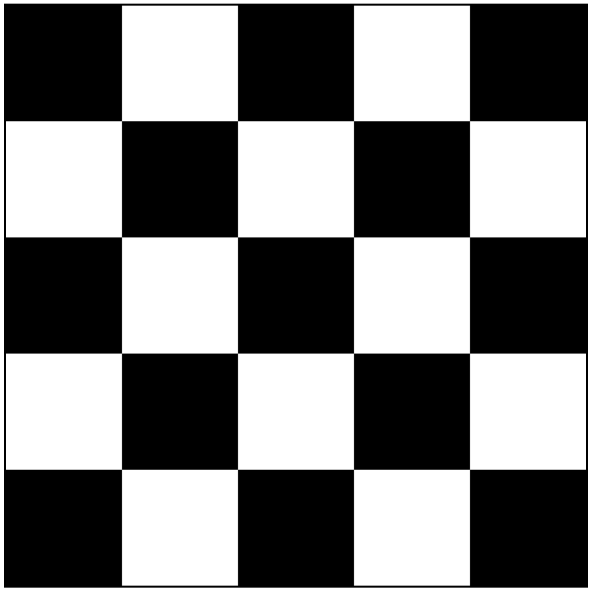


λ_{min}

Corner detection summary

Algo3 (M-based)

- Compute the gradient at each point in the image
- Create the *M* matrix from the entries in the gradient
- Compute the eigenvalues of *M*
- Find points with large response (λ_{min} > threshold)
- Choose those points where λ_{min} is a local maximum as features



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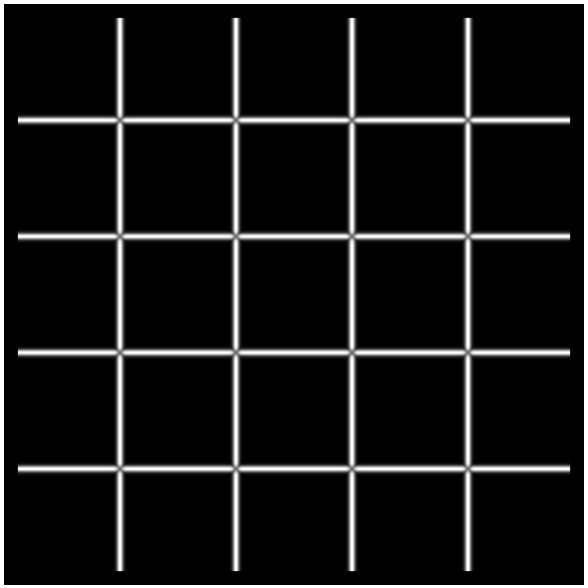
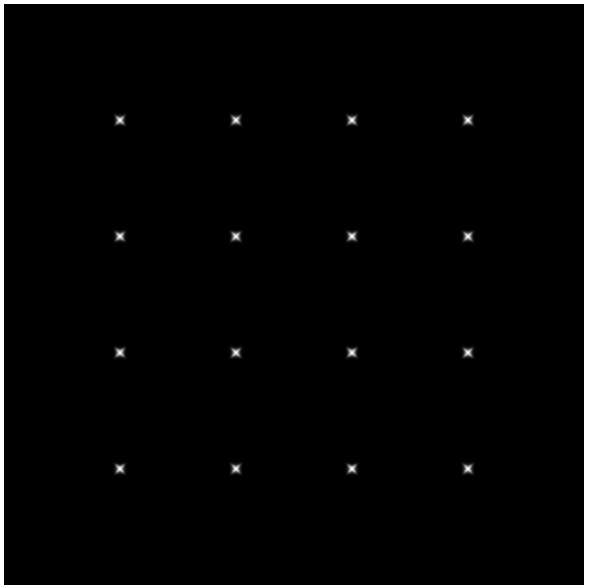


$\lambda_{\max}$

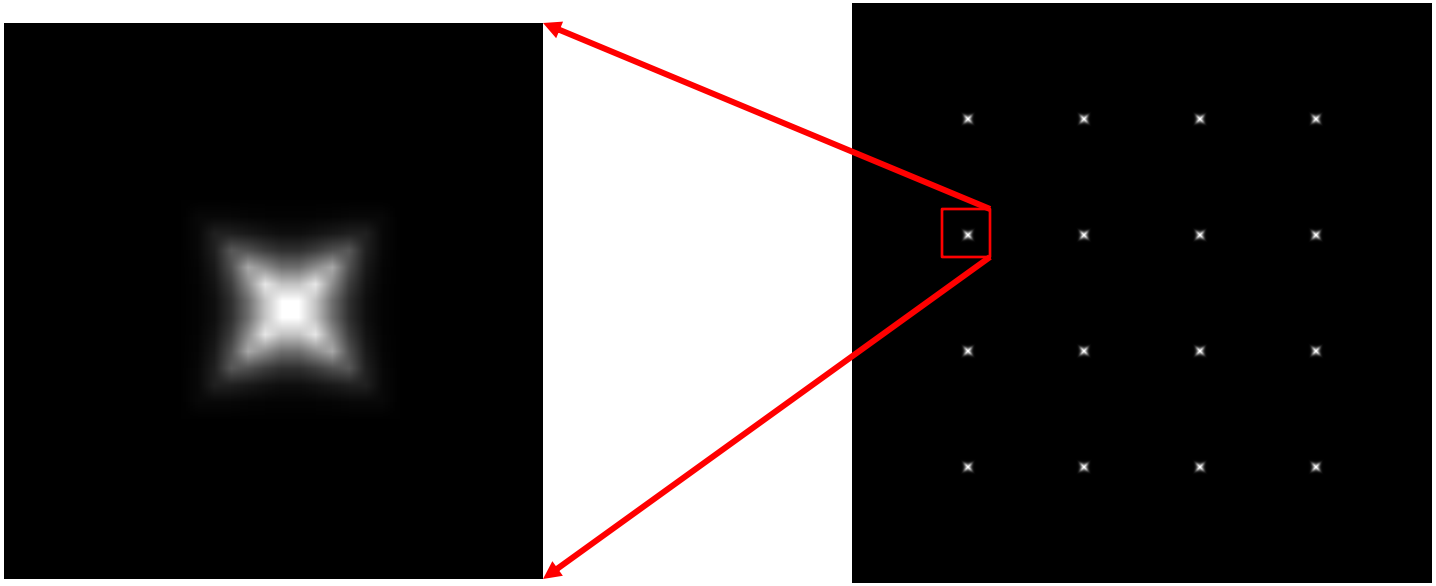


$\lambda_{\min}$

Corner detection summary

Algo3 (M-based)

- Compute the gradient at each point in the image
- Create the *H* matrix from the entries in the gradient
- Compute the eigenvalues
- Find points with large response (λ_{min} > threshold)
- Choose those points where λ_{min} is a local maximum as features



λ_{min}

Algo4: The Harris operator

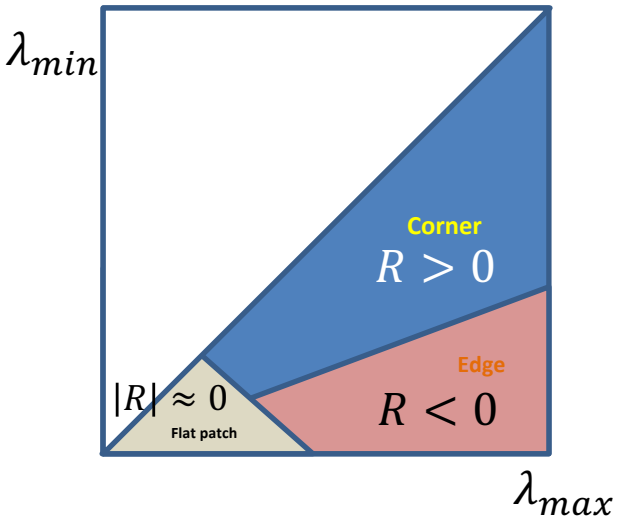
Algo3 still expensive because explicit eigen-decomposition of M.

"Harris operator" for corner detection is is a variant of the Algo3 (λ_{min}based)

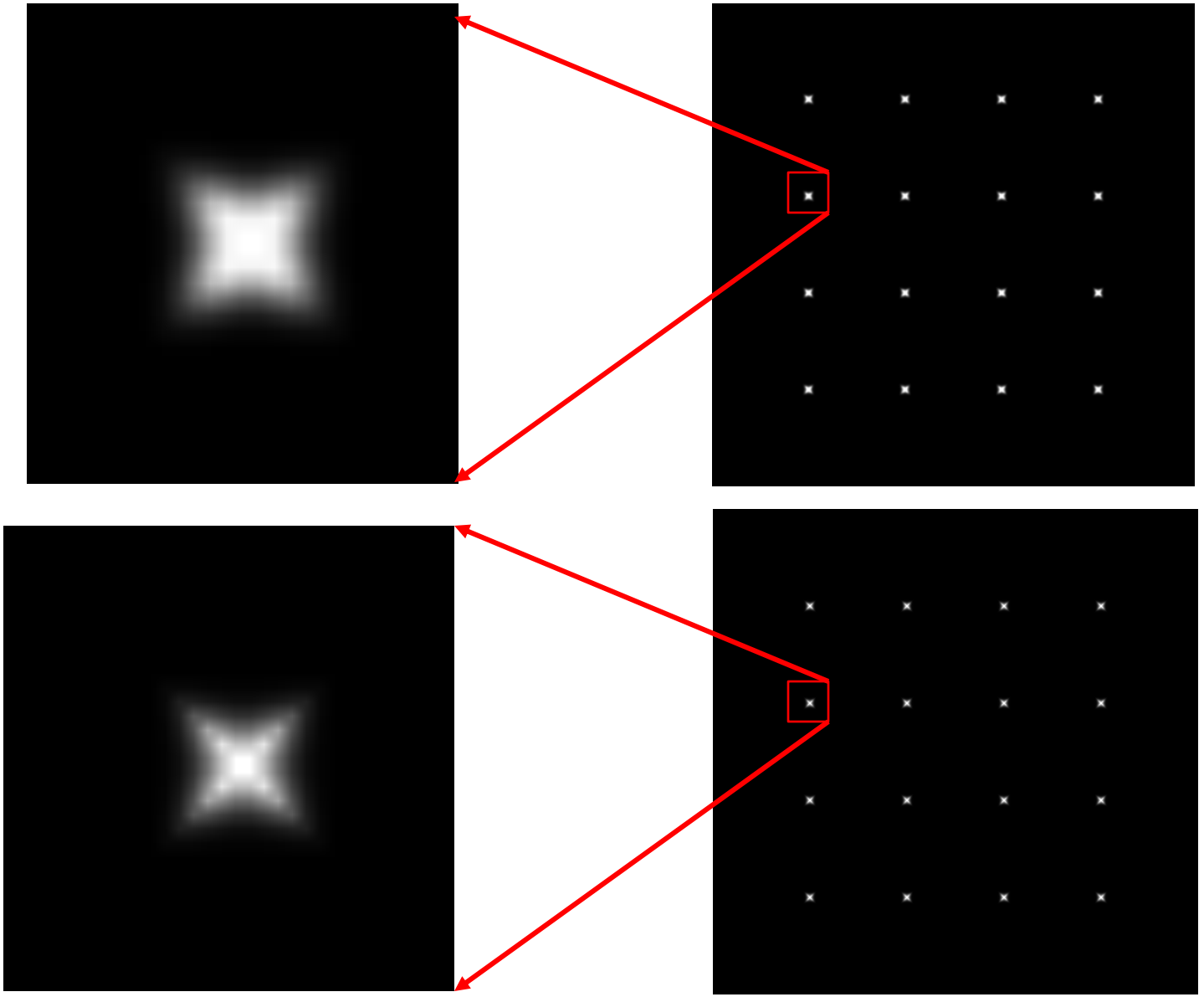
Heuristic criterion R using matrix ppties but not explicit decomposition:

$$R = \det(M) - \alpha \,\mathrm{trace}(M)^2 = \lambda_1\lambda_2 - \alpha(\lambda_1 + \lambda_2)^2$$

- The *trace* is the sum of the diagonals, i.e., *trace(H) = h_{11} + h_{22}*
- Very similar to λ_{min} but less expensive (no square root)
- Called the "Harris Corner Detector" or "Harris Operator"
- Simple threshold R>0:

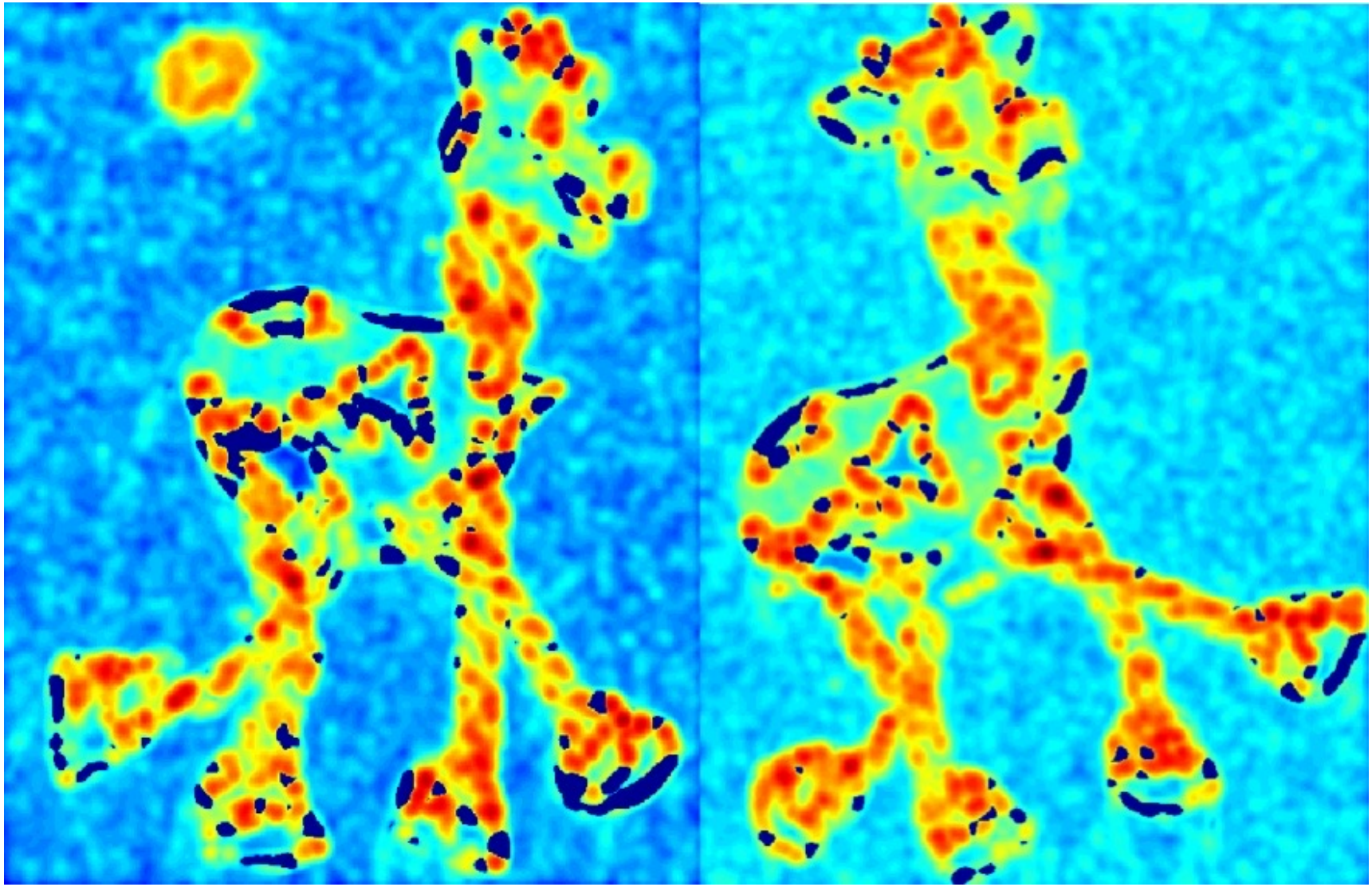


The Harris operator

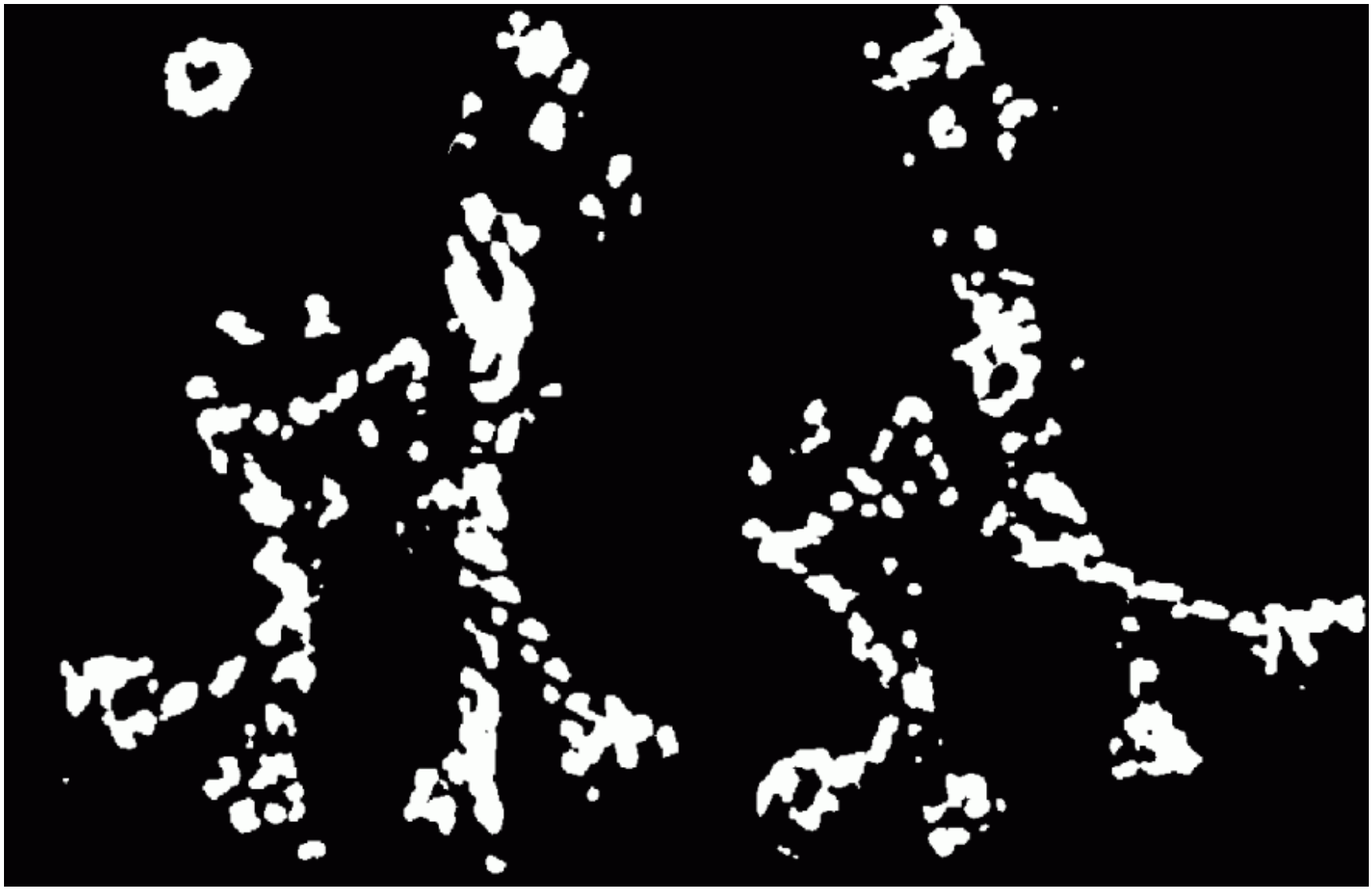


Harris detector example

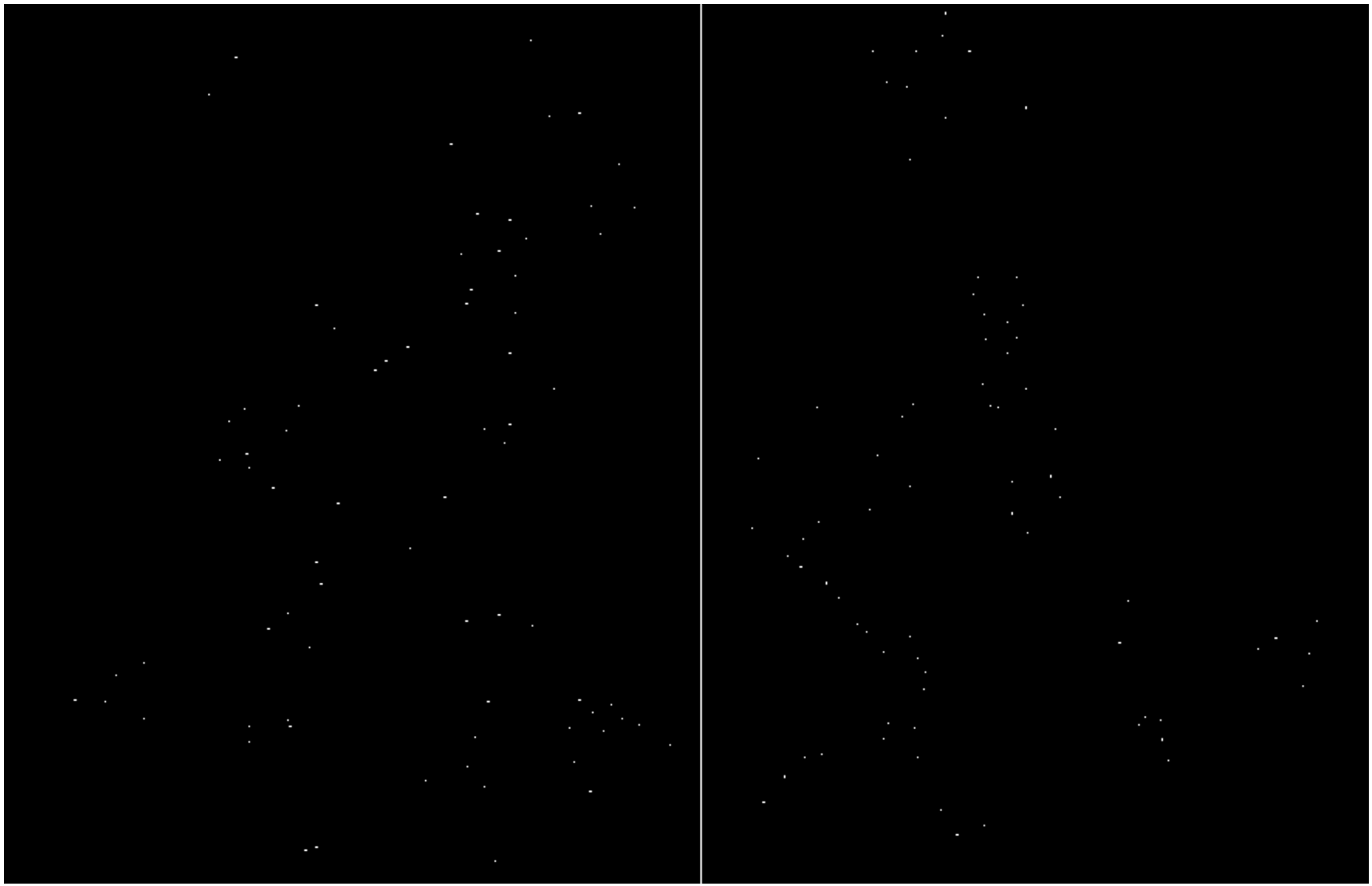
f value (red high, blue low)



Threshold (f > value)



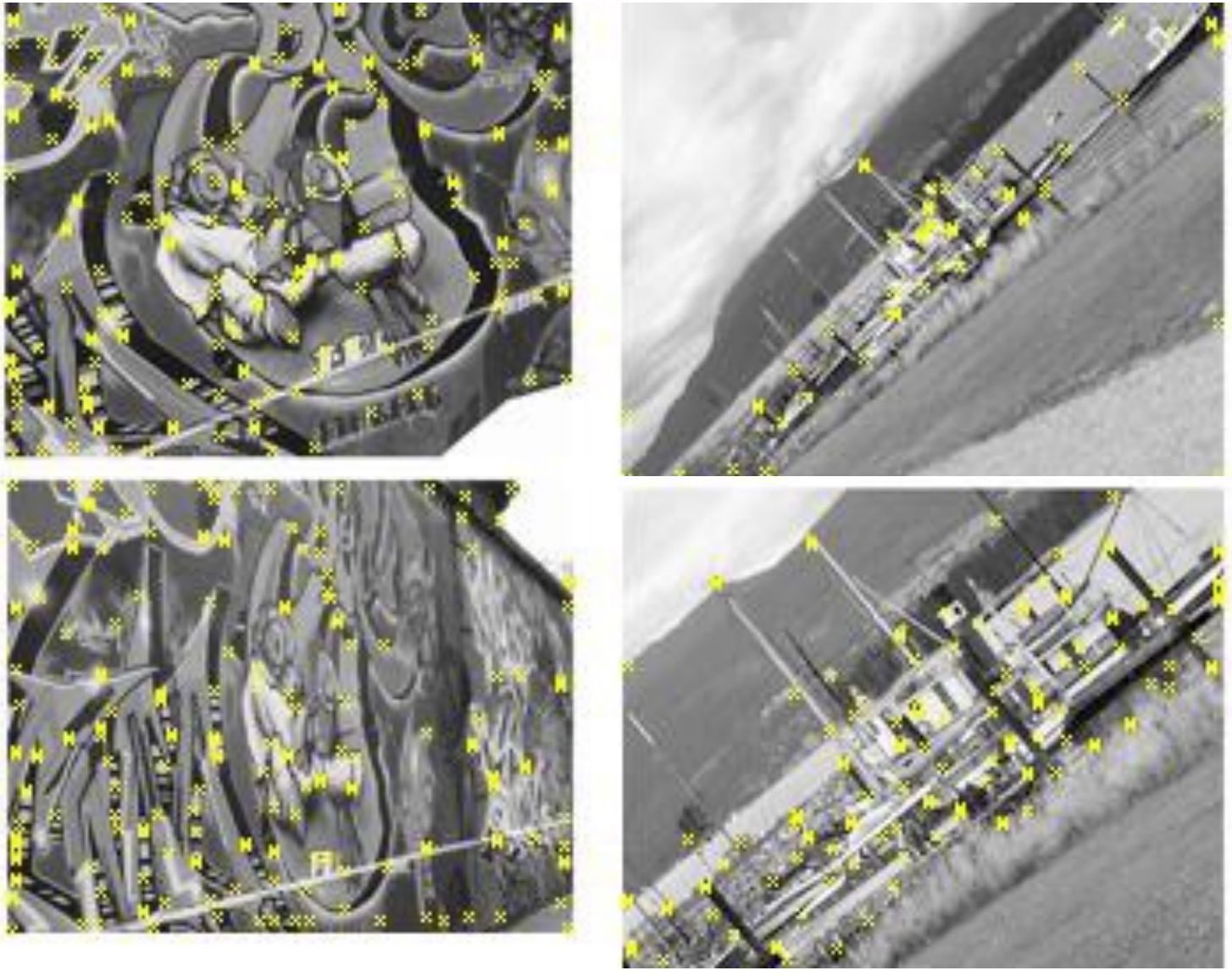
Find local maxima of f



Harris features (in red)

Local feature detection

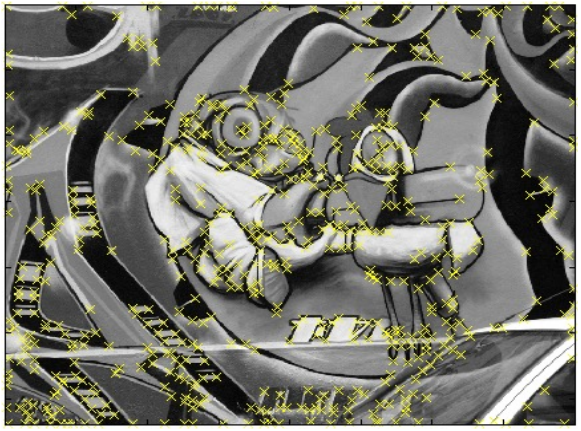
Looking for repeatability

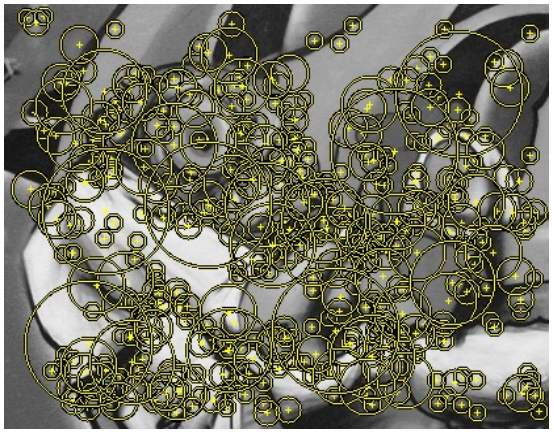


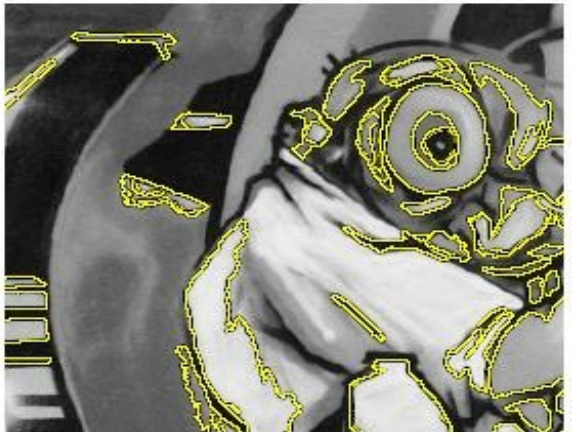
Local feature detection

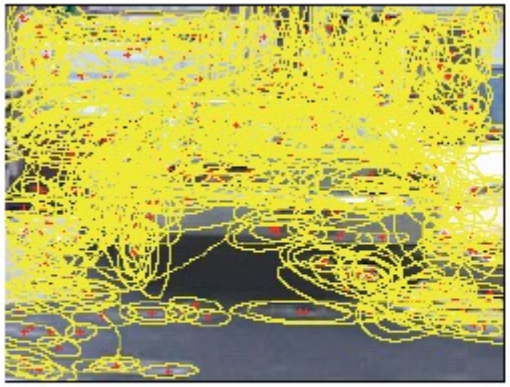
One example: Corner detection (Harris corner detector)

Many other Points/Regions of Interest detectors

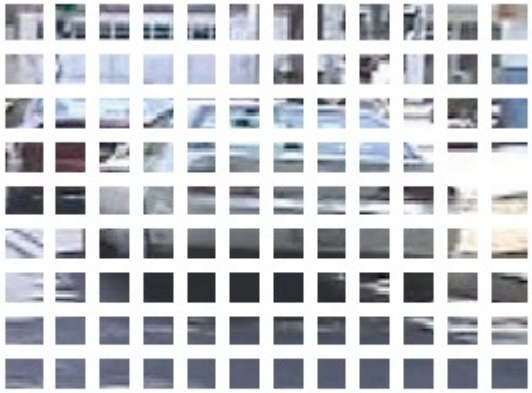








Sparse, at interest points



Dense, uniformly

Randomly

Course Outline

1. Computer Vision Introduction:

   Visual (local) feature detection,

   Visual (local) feature description,

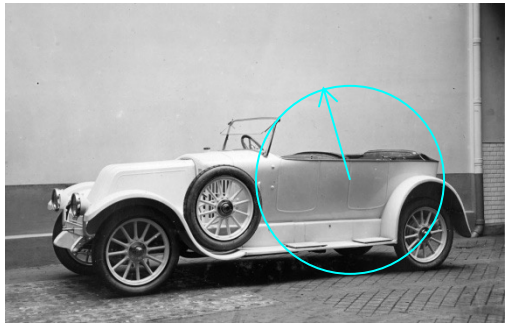
   Bag of Word Image representation

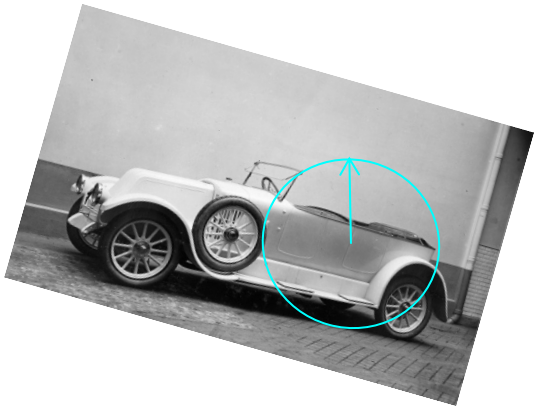
Local feature description

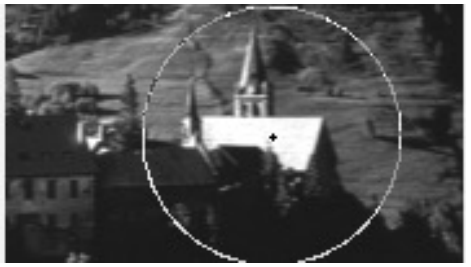
Many Points/Regions of Interest descriptors

One example: SIFT descriptor

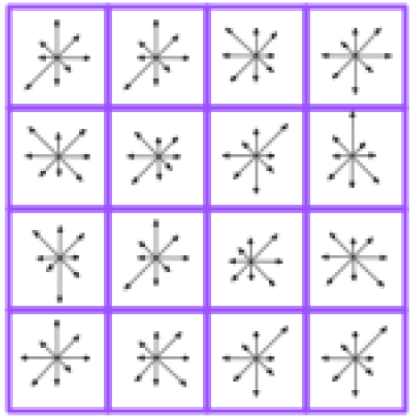
Local description (always looking for invariance)







SIFT descriptors/features

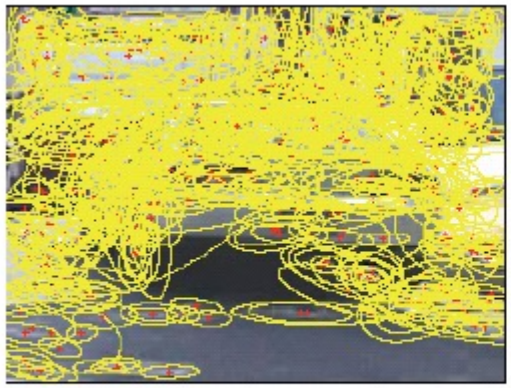


10
17
35
77
35
8
44
3
27
3
0
...

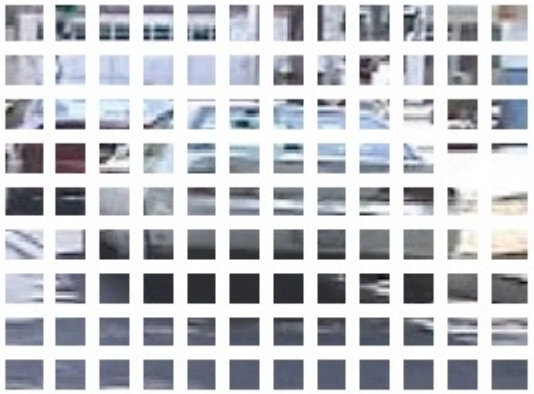
Feature descriptors

- Expected properties?
  - Similar patches => close descriptors
  - Invariance (robustness) to geom. transformation : rotation, scale, view point, luminance, semantics ? …

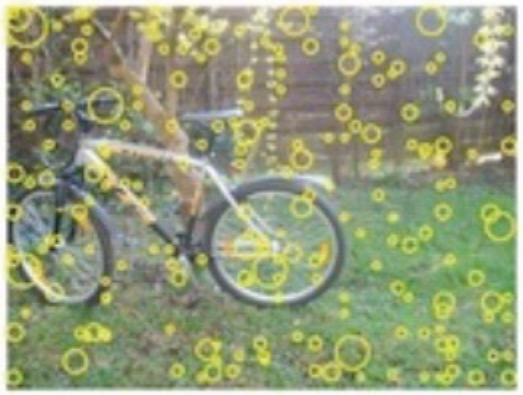
BoF: (First) Image representation



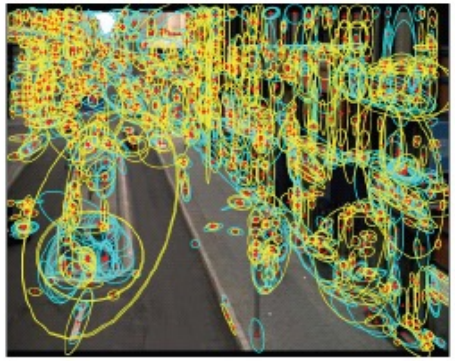
Sparse, at interest points



Dense, uniformly

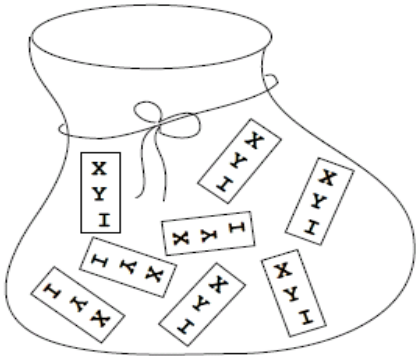


Randomly



Multiple interest operators

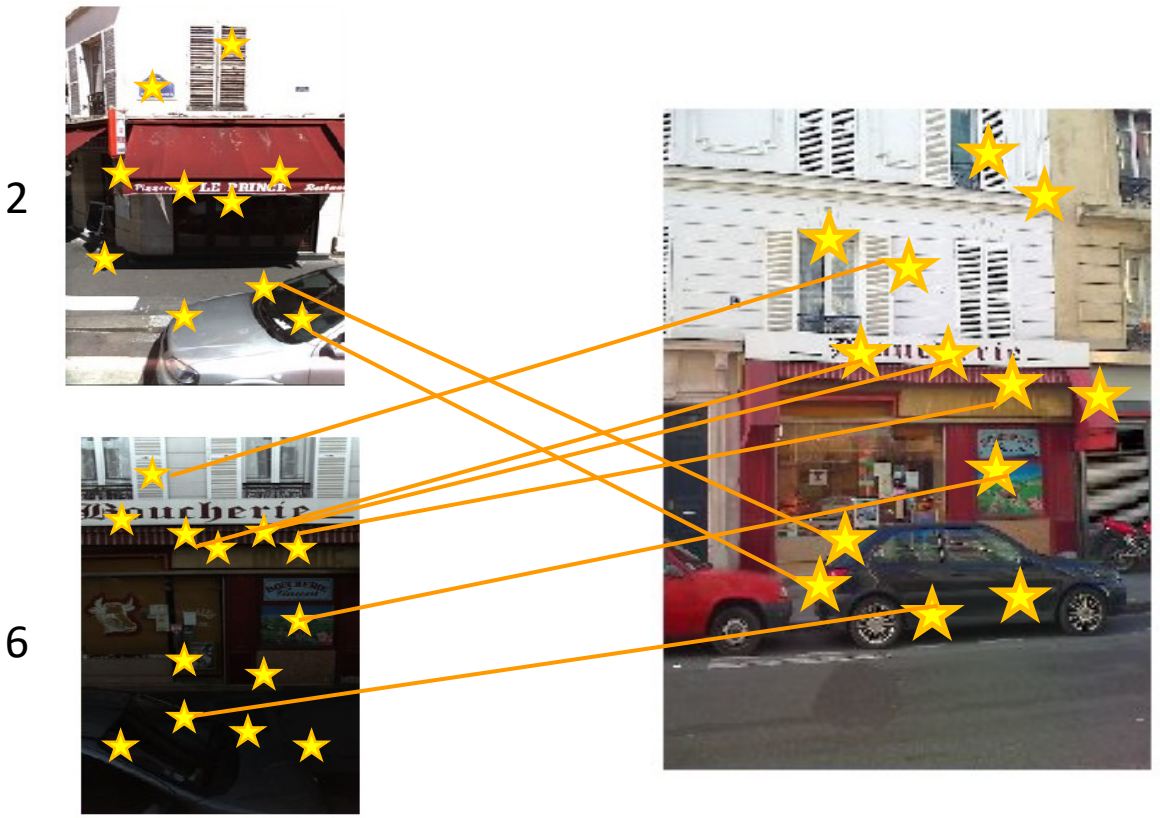
Feature extraction



A bag of features
BoF

BoF -- Image representation

- Image similarity based on matching of local features + voting

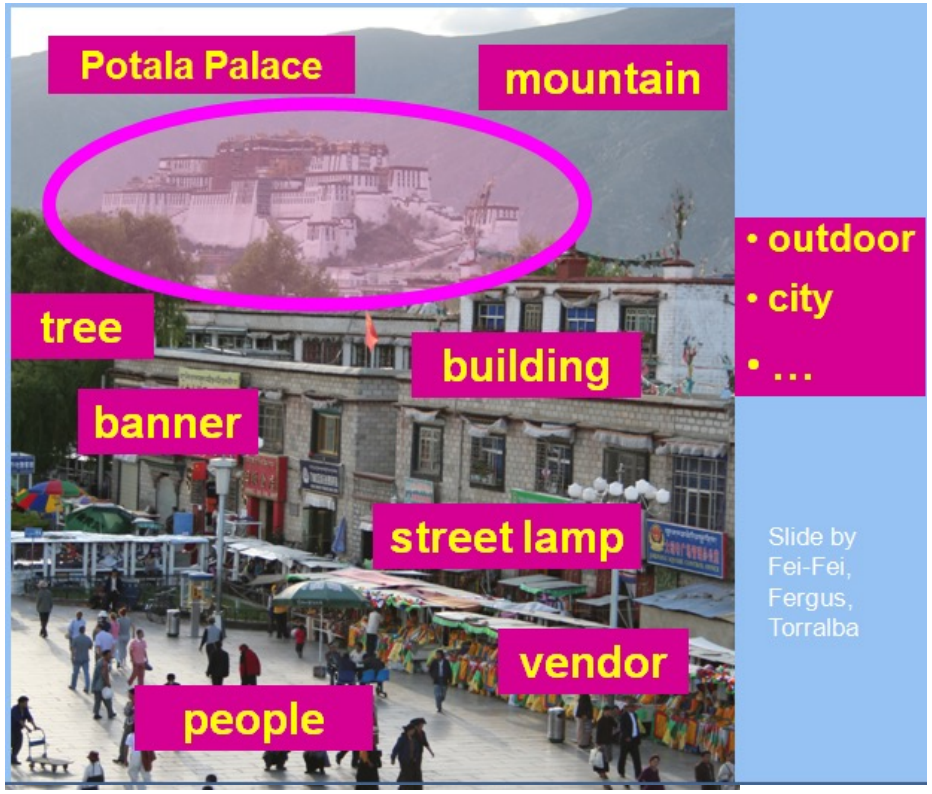


Applications to Image Retrieval

Image Retrieval

- Context: Instance search (second example)

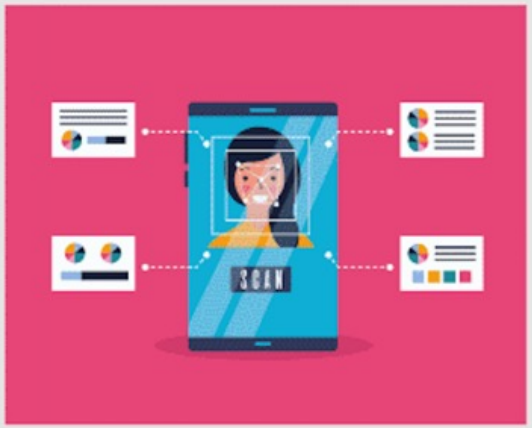
Advanced Visual Understanding

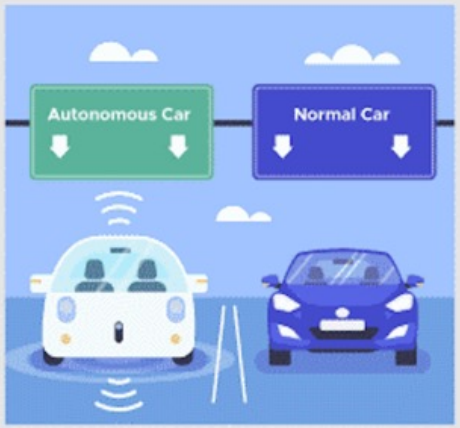


Two pizzas sitting on top of a stove top oven

Image Understanding

- Focus of this course: recognition, classification and understanding
- Fundamental Pbs:
  - Image representation,
  - Data similarity,
  - Decision function
- Examples of applications:
  - (Health) Medical imagery
  - (Mobility) Autonomous driving/Robotics
  - (Security/entertainment) Face/ Human action recognition
  - (Physics, Astronomy, Bio …) Pattern recognition





Course Outline

1. Computer Vision Introduction:

   Visual (local) feature detection and description,

   Bag of Word Image representation

   1. **Introduction to Bag of Words**
   2. Visual Dictionary
   3. Image signature
   4. Whole recognition pipeline

Bag of Feature (BoF) Model

Image

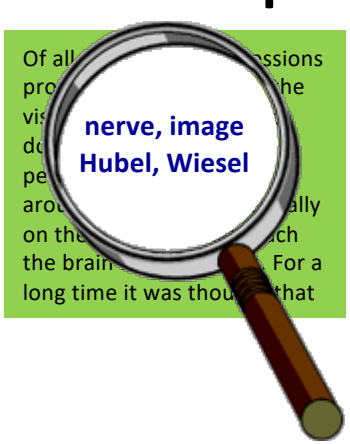
(features)

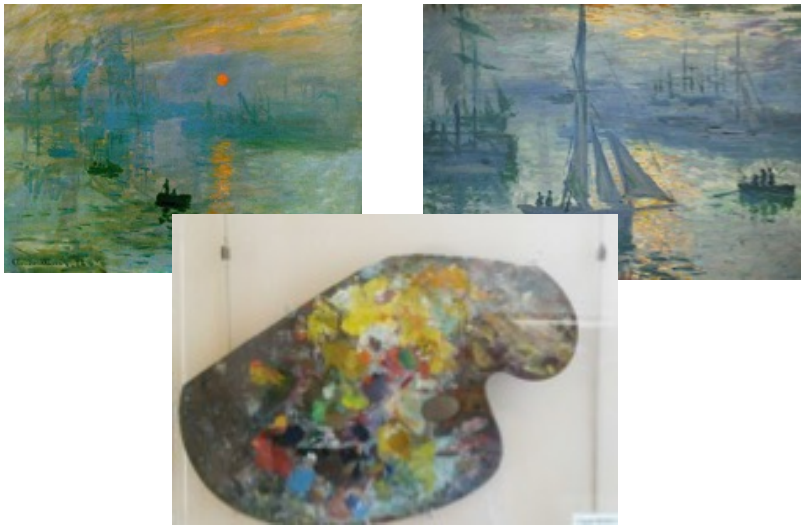
Bag of Words repsentation

- BoF
  - Local signatures: not a scalable representation
  - Not a *semantic* representation

- Model to represent images for categorization: « **Bag of Words BoW** »
- BoW model computed from BoF (Bag of features)

Bag of Words (BoW) model: basic explication with textual representation and color indexing



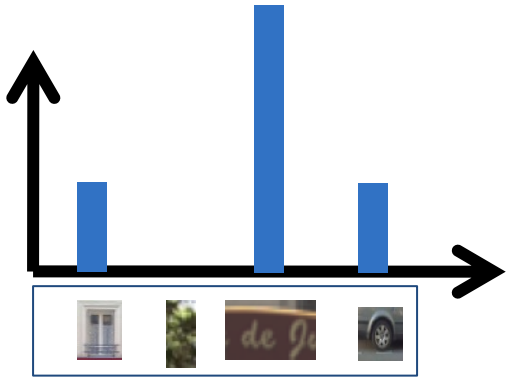


Comparing 2 docs using visual/color/word occurrences

Bag of Visual Words (BoW)

(features)

BoW : histogram on visual dictionary



Questions:

1. Which dictionary ?
2. How to project the BoF onto the dico
3. How to compute the histogram?

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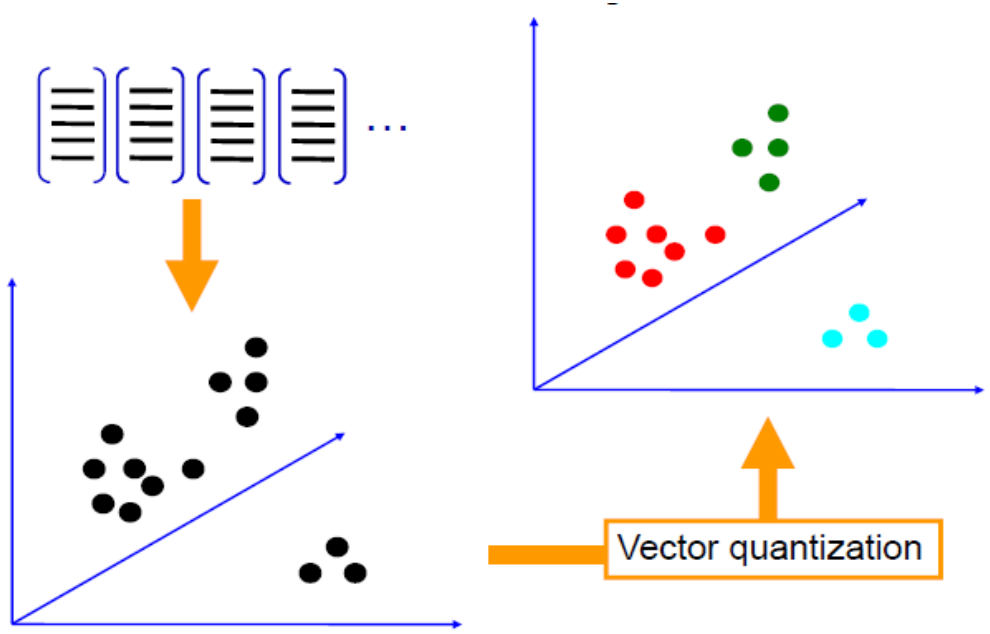
Visual space clustering

1. Extraction of local features (pattern/visual words) in images
   - Training dataset in classification
   - Image dataset in retrieval
2. Clustering of feature space

Training set but no labels => UNSUPERVISED Learning

Visual space clustering

- Many algorithms for clustering :
  - K-Means
  - Vectorial Quantization
  - Gaussian Mixture Models
  - …



Clustering with K clusters

Input: set of n points $\{x_j\}_n$ in R^d

Goal: find a set of K (K<<n) points $w=\{w_k\}_K$

that gives an approximation of the n input points,

ie. minimizing mean square error C(w):

$$C(w) = \sum_{i=1}^{n} \min_k \|x_i - w_k\|^2 \quad :$$

At k fixed, complexity is $O(n^{(Kd+1)}\log(n))$

A lot of strategies to approximate the global optimization problem

Clustering with K clusters

$$C(w) = \sum_{i=1}^{n} \min_{k} \|x_i - w_k\|^2$$

***K-means* Algorithm:**

Init K centers (c_k) by sampling K points w_k in R^d

$$\min_{k} \|x_i - w_k\|^2$$

1. (Re)assign each point x_i to the cluster s_i with the center w_{si} so that dist(x_i, w_{si}) is less than dist from x_i to any other clusters
2. Move all w_k inside each cluster as the new barycenter from all the points assigned to the cluster k (equ. to minimize the corresponding mean square error)

$$\sum_{i=1}^{n} \|x_i - w_{s_i}\|^2$$

3. Go to step 1 if some points changed clusters during the last iteration

Output: the set of the final K cluster centers $\{c_k = w_k\}$

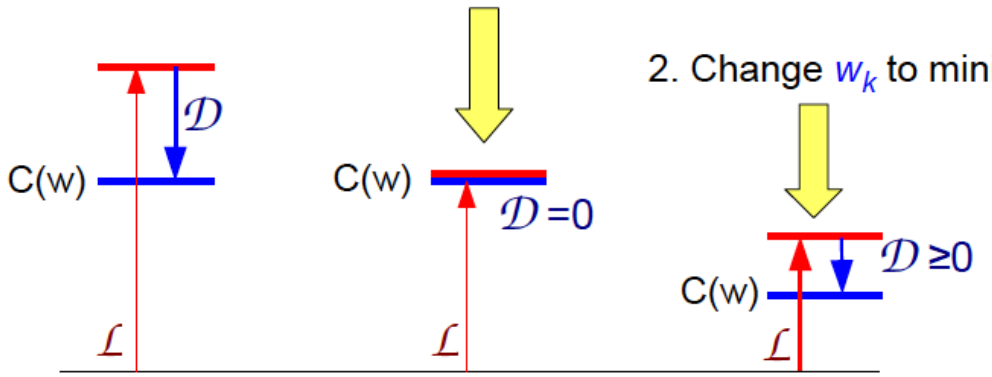
K-means : why it is successful ?

Consider an arbitrary cluster assignment s_i.

$$C(w) = \sum_{i=1}^{n} \min_k \|x_i - w_k\|^2 = \underbrace{\sum_{i=1}^{n} \|x_i - w_{s_i}\|^2}_{\mathcal{L}(s,w)} - \underbrace{\sum_{i=1}^{n} \|x_i - w_{s_i}\|^2 - \min_k \|x_i - w_k\|^2}_{\mathcal{D}(s,w) \geq 0}$$

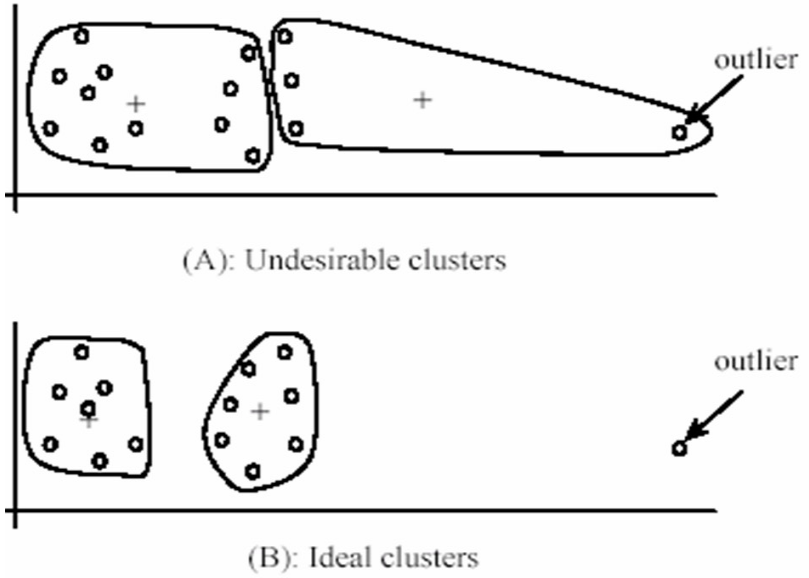
1. Change s_i to minimize $\mathcal{D}$ leaving C(w) unchanged.

2. Change w_k to minimize $\mathcal{L}$. Meanwhile $\mathcal{D}$ can only increase.



Clustering

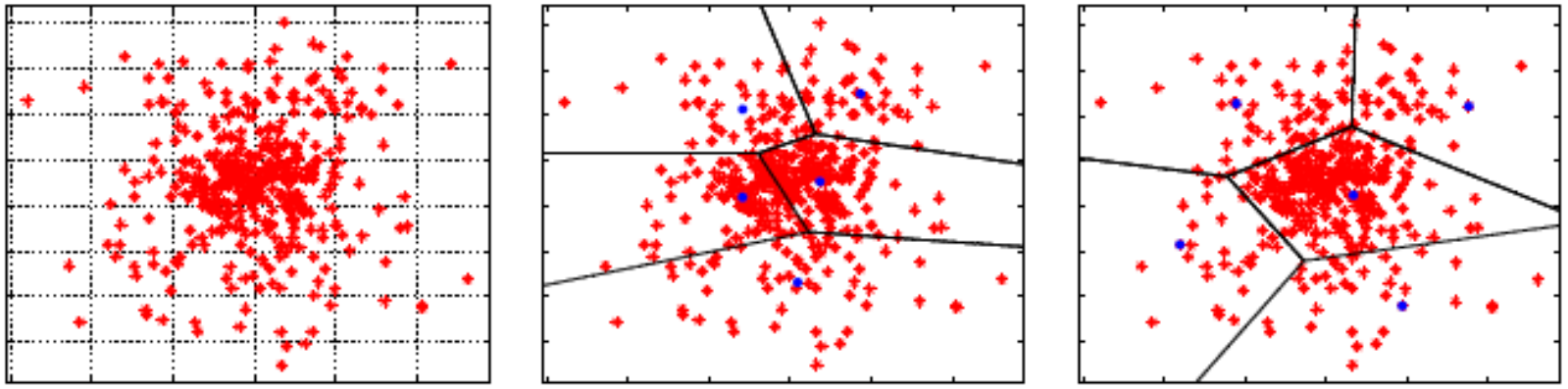
- K-means :
  - Pros
    - Simplicity
    - Convergence (local min)
  - Cons
    - Memory-intensive
    - Depending on K
    - Sensitive to initialization
    - Sensitive to artifacts
    - Limited to spherical clusters
    - Concentration of clusters to areas with high densities of points (Alternatives : radial based methods)



- K-Means deeply used in practice

Clustering

- Uniform / K-means / radius-based :



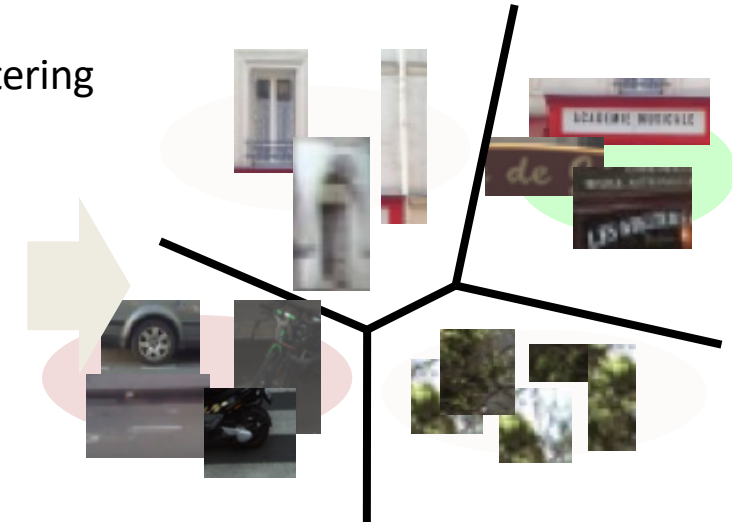
(a) Histogram (b) K-means (c) Radius-based

- *Radius-based clustering assigns all features within a fixed radius of similarity r to one cluster.*

Dictionary = K Visual words

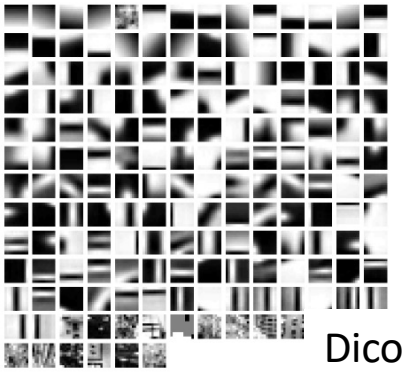
Extraction

Clustering



Dico extraction

Centers = dico. Visual words



Dico examples

Course Outline

1. Computer Vision Introduction:

   Visual (local) feature detection and description,

   Bag of Word Image representation

   1. Introduction to Bag of Words
   2. Visual Dictionary
   3. **Image signature**
   4. Whole recognition pipeline

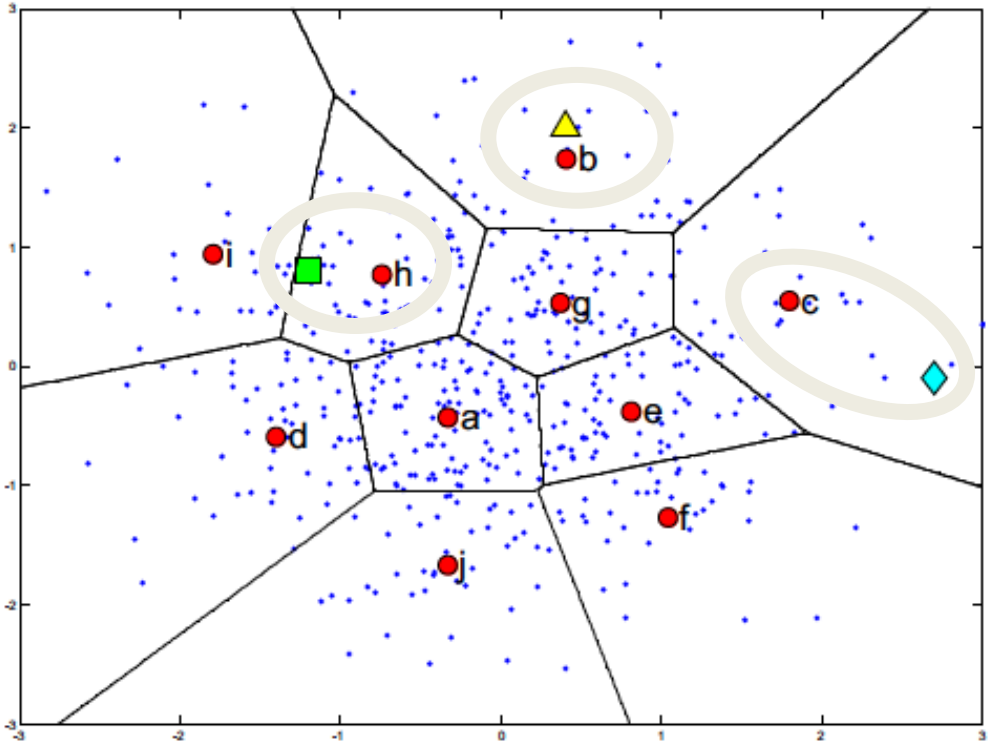
Bag-of-Words (BoW) image signature

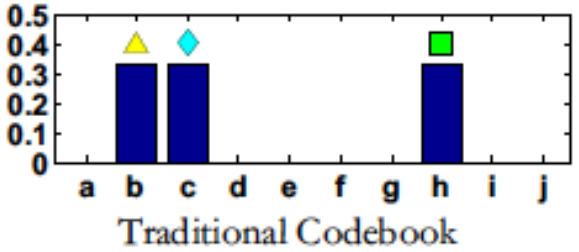
- For each image:
  - For each local feature: find the closest visual word
  - Increase the corresponding bin in histogram of visual dico

- Image signature (global Index):
  - Vector (histogram of M bins)
  - M= dimension K = dico size
  - Each term represents a Likelihood to get this visual word

Bag-of-Words (BoW) image signature

- Original BoW strategy: **hard assignement/coding**
  - Find the closest cluster for each feature
  - Assign a fix weight (*e.g.* 1)



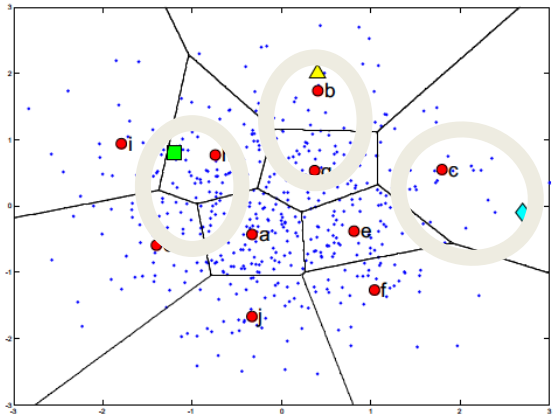


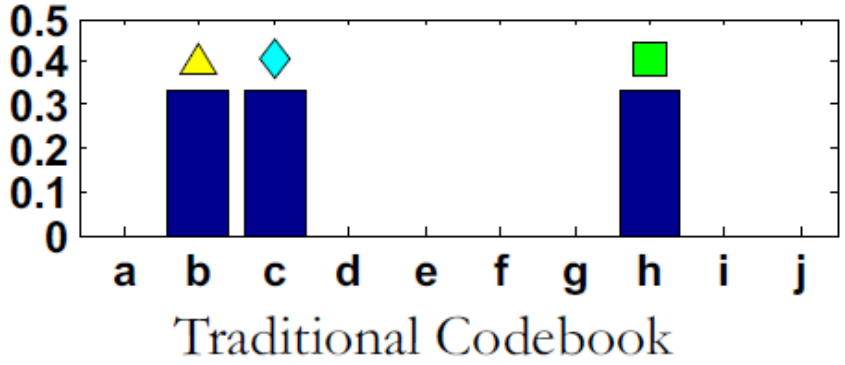
Bag-of-Words (BoW) image signature

Sum pooling : initial BoW strategy (just counting occurrences of words in the document)

Classical BoW = **hard coding + sum pooling**

1. Find the closest cluster for each feature
2. Assign a fix weight (*e.g.* 1) to this cluster





BoW: the math

Image features: $\mathbf{X} = \left\{ x_j \in \mathbb{R}^d \right\}, j \in \{1; N\}$

Centers: $\mathbf{C} = \{C_m\},\ m \in \{1; M\}$

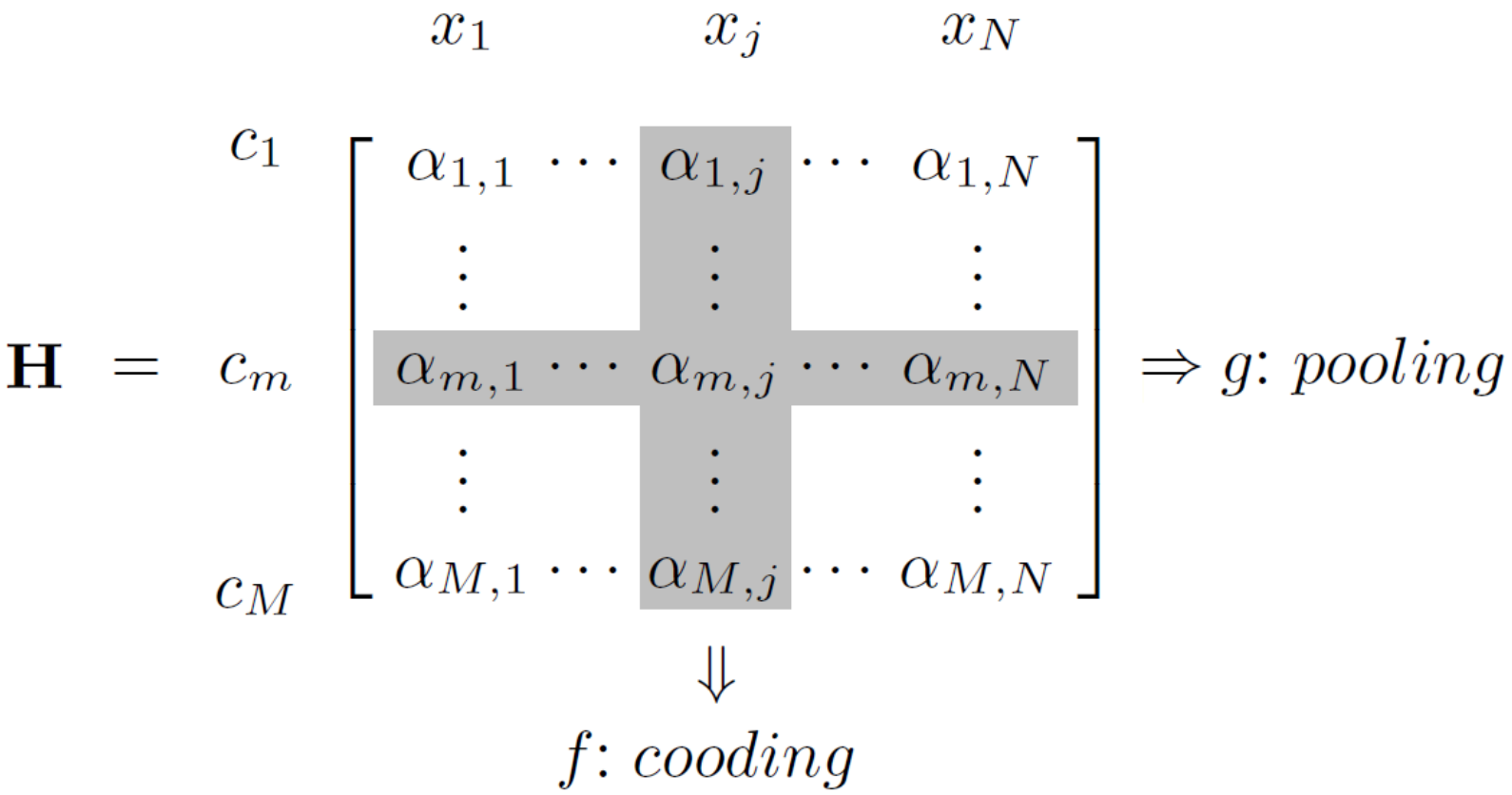
Coding:

$$\begin{aligned} f : \mathbb{R}^d &\longrightarrow \mathbb{R}^M \\ x_j &\longrightarrow f(x_j) = \alpha_{\mathbf{j}} = \{\alpha_{m,j}\}, \quad m \in \{1; M\} \end{aligned}$$

Hard coding: $f = f_Q$ assigns a constant weight to its closest center:

$$f_Q(x_j)[m] = \begin{cases} 1 & \text{if } m = \underset{k \in \{1;M\}}{\operatorname{argmin}} \|x_j - c_k\|^2 \\ 0 & \text{otherwise} \end{cases}$$

BoW: the math

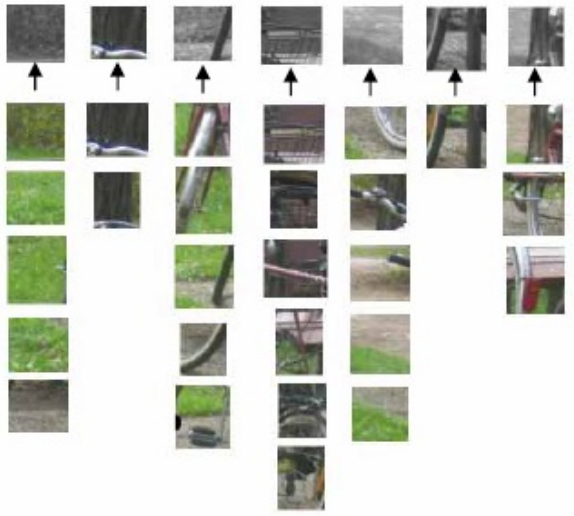

x_1 x_j x_N
c_1
c_m
c_M
$\mathbf{H} = \begin{bmatrix} \alpha_{1,1} & \cdots & \alpha_{1,j} & \cdots & \alpha_{1,N} \\ \vdots & & \vdots & & \vdots \\ \alpha_{m,1} & \cdots & \alpha_{m,j} & \cdots & \alpha_{m,N} \\ \vdots & & \vdots & & \vdots \\ \alpha_{M,1} & \cdots & \alpha_{M,j} & \cdots & \alpha_{M,N} \end{bmatrix}$
$\Rightarrow g$: pooling
$\Downarrow$
f: cooding

BoW: the math

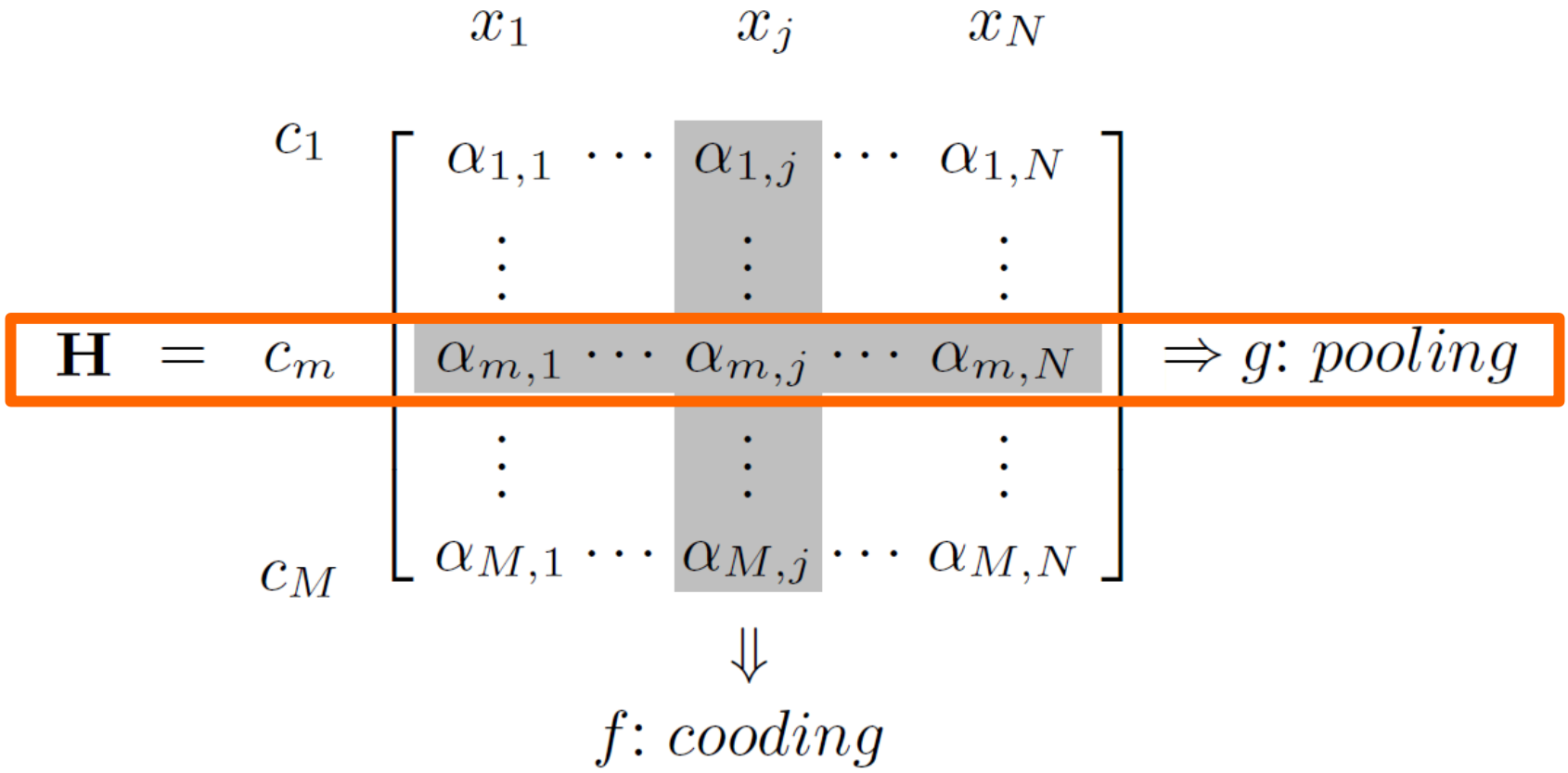
- Global Index: image likelihood to get each visual word
- Several strategies to aggregate the projections: **pooling**

$$g : \mathbb{R}^N \longrightarrow \mathbb{R}$$

$$\alpha_{\mathbf{m}} = \{\alpha_{m,j}\}, j \in \{1; N\} \longrightarrow g(\alpha_m) = z_m$$



BoW: the math


x_1 x_j x_N
c_1
c_m
c_M
$\mathbf{H} = \begin{bmatrix} \alpha_{1,1} & \cdots & \alpha_{1,j} & \cdots & \alpha_{1,N} \\ \vdots & & \vdots & & \vdots \\ \alpha_{m,1} & \cdots & \alpha_{m,j} & \cdots & \alpha_{m,N} \\ \vdots & & \vdots & & \vdots \\ \alpha_{M,1} & \cdots & \alpha_{M,j} & \cdots & \alpha_{M,N} \end{bmatrix}$
$\Rightarrow g$: pooling
$\Downarrow$
f: cooding

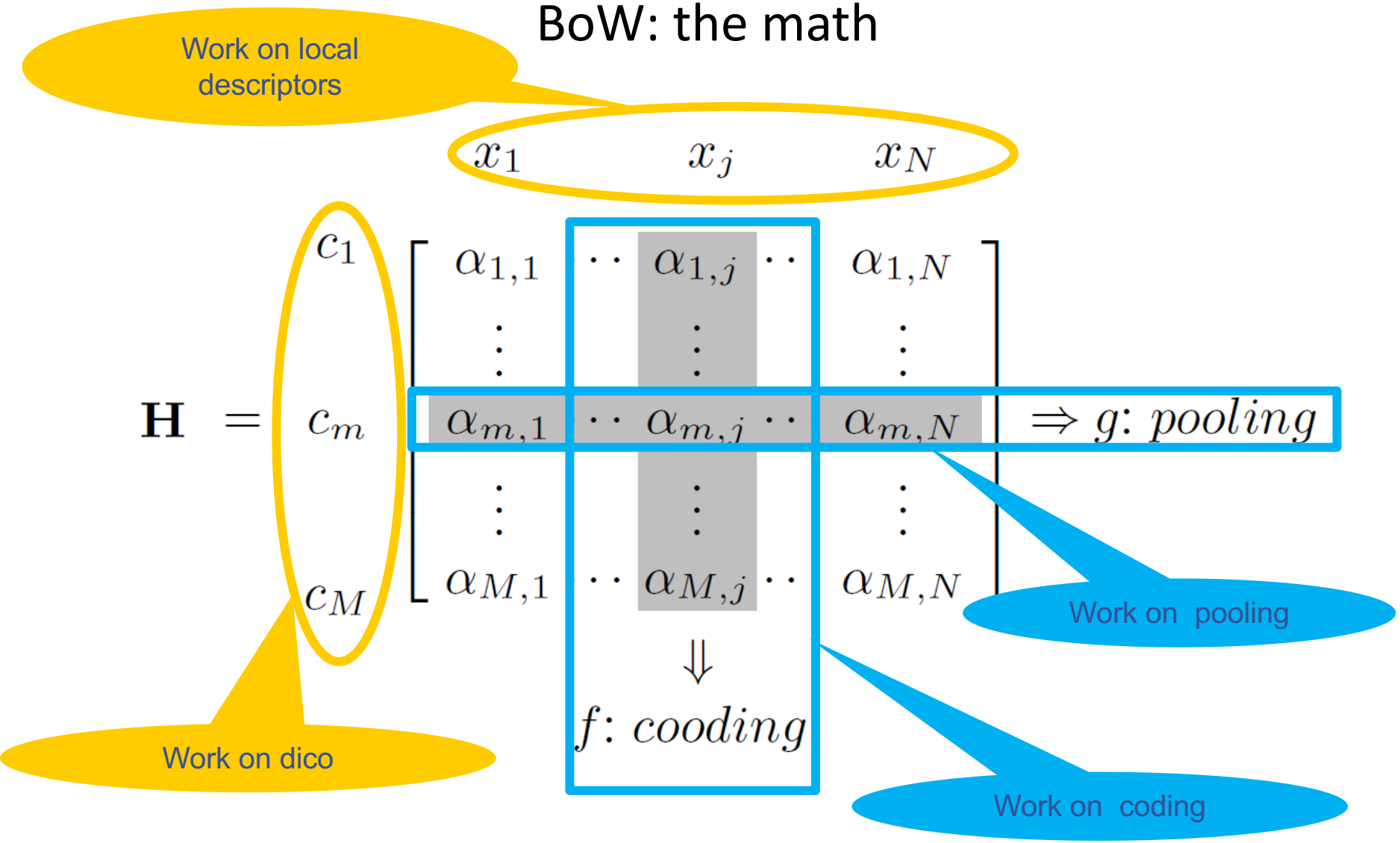
BoW: the math

BoW Sum pooling:

$$z_m = g(\alpha_m) = \sum_{j=1}^{N} \alpha_{m,j} = \sum_{j=1}^{N} f_Q(x_j)[m]$$

$$z_m = \sum_{j=1}^{N} \begin{cases} 1 & \text{if } m = \underset{k \in \{1;M\}}{\operatorname{argmin}} \|x_j - c_k\|^2 \\ 0 & \text{otherwise} \end{cases}$$

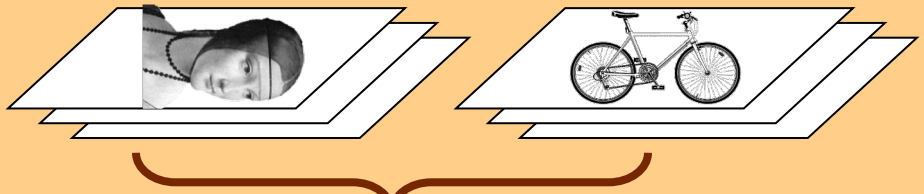
BoW: the math


Work on local descriptors
x_1 x_j x_N
$\mathbf{H} = \begin{bmatrix} \alpha_{1,1} & \cdots & \alpha_{1,j} & \cdots & \alpha_{1,N} \\ \vdots & & \vdots & & \vdots \\ \alpha_{m,1} & \cdots & \alpha_{m,j} & \cdots & \alpha_{m,N} \\ \vdots & & \vdots & & \vdots \\ \alpha_{M,1} & \cdots & \alpha_{M,j} & \cdots & \alpha_{M,N} \end{bmatrix}$
c_1
c_m
c_M
$\Rightarrow g$: pooling
$\Downarrow$
f: cooding
Work on dico
Work on pooling
Work on coding

Bag of Word Image representation

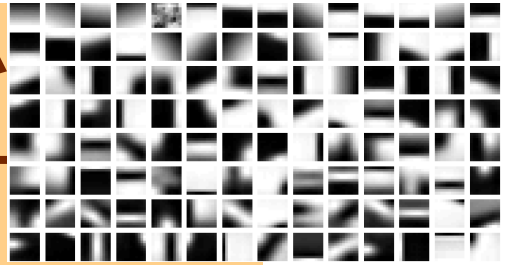
1. Introduction to Bag of Words
2. Dictionary computation
3. Coding of local descriptors
4. Image signature computation: pooling
5. **Whole recognition pipeline**

Representation



2.

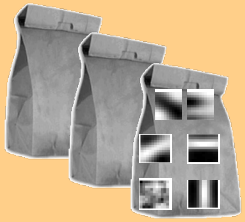
codewords dictionary

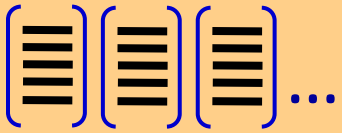


1. feature detection & representation

image representation

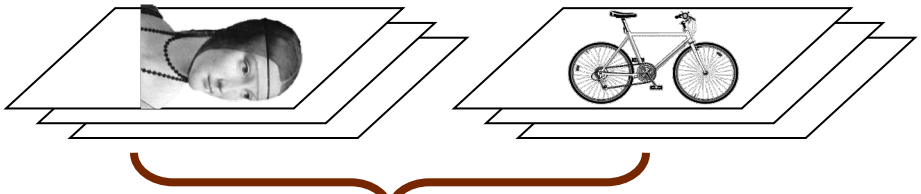
3.





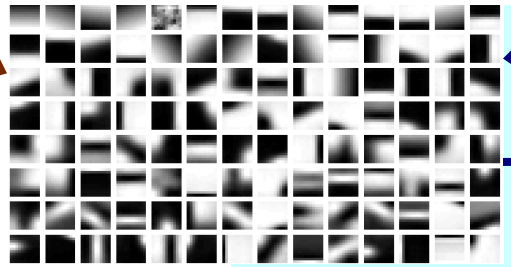
Representation

Learning and Recognition



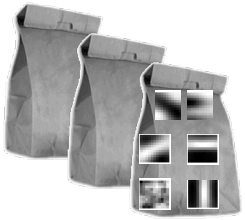
2.

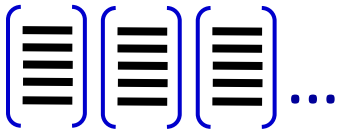
codewords dictionary

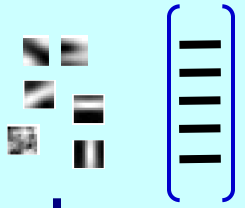


1. feature detection & representation

3.



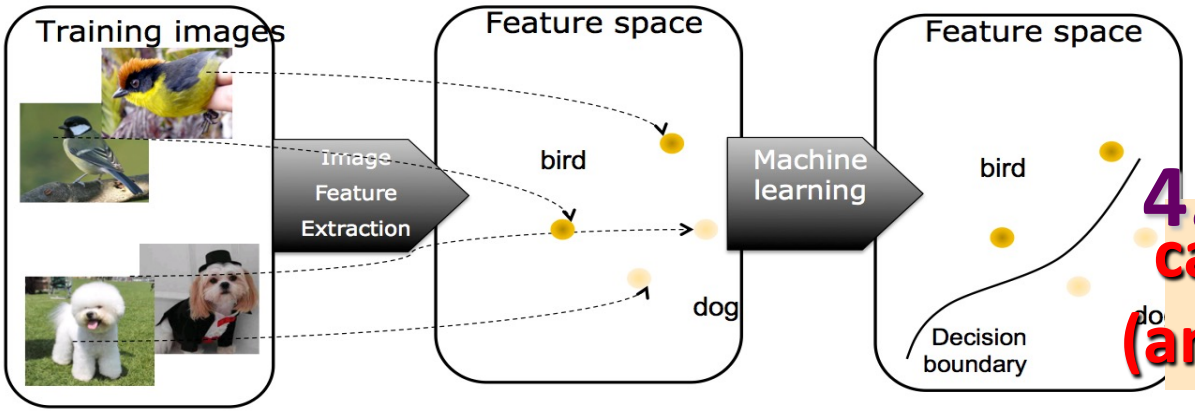




4.

category models (and/or) classifiers

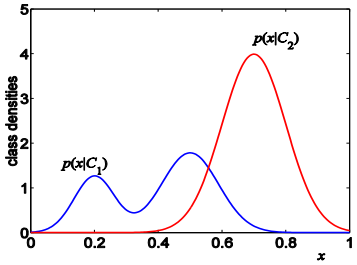
category decision



4. category models (and/or) classifiers

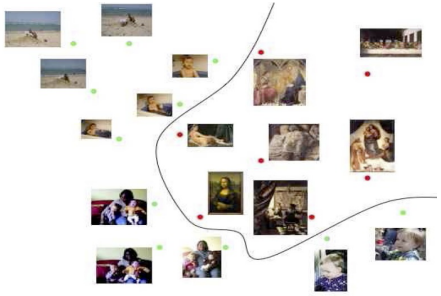
Generative method:

- graphical models



Discriminative methods:

- SVM, NNs



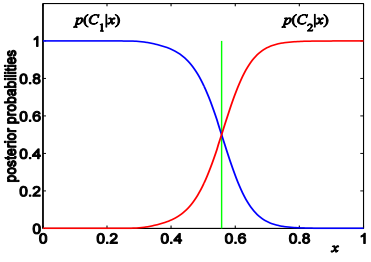
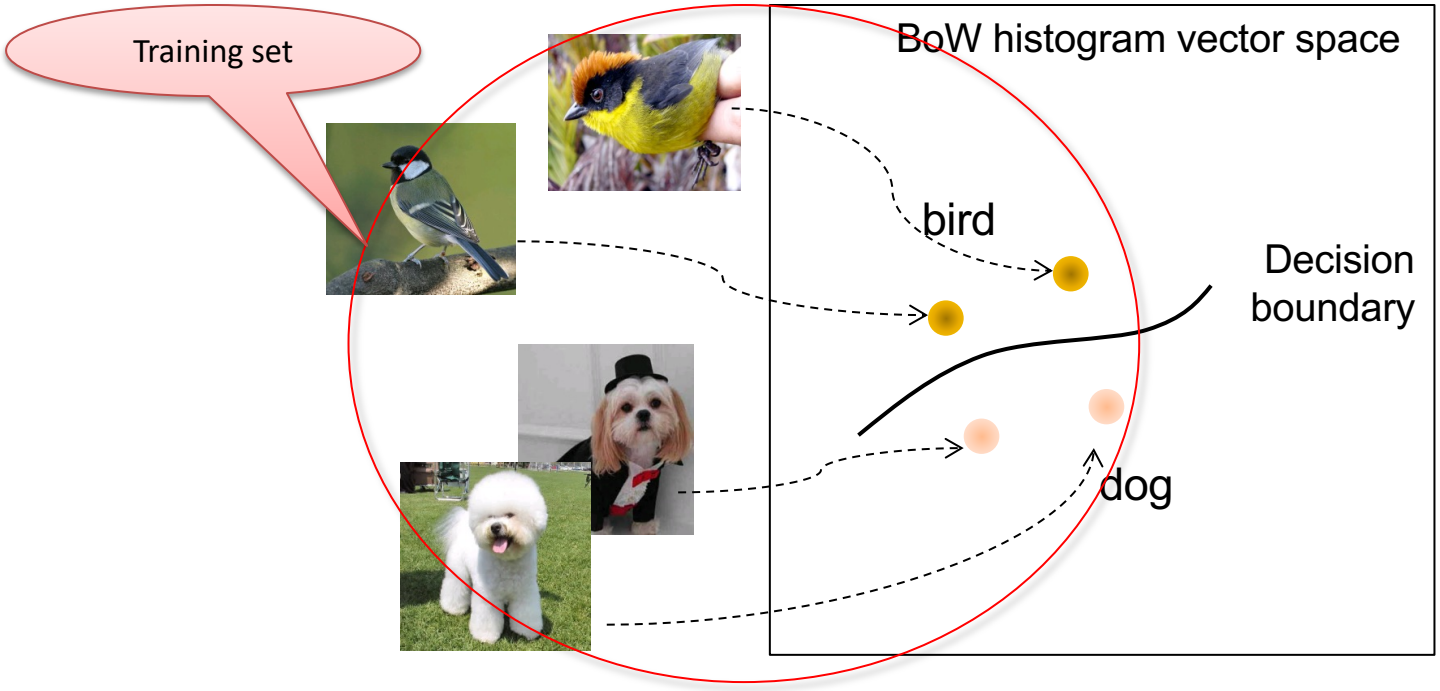


Image classification based on BoW



Learn a classification model to determine the decision boundary