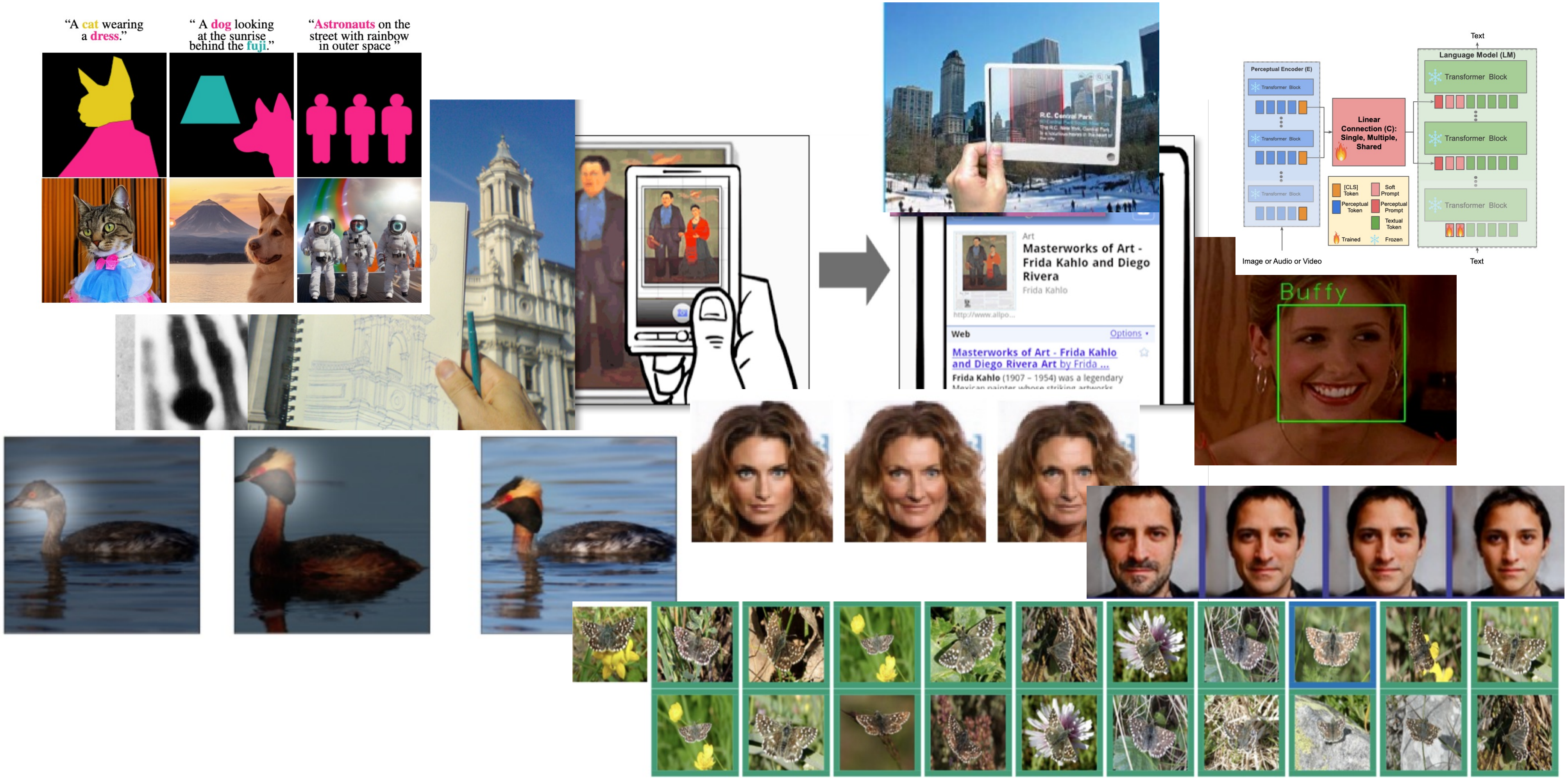


COURS RDFIA deep Image

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

Matthieu Cord
Sorbonne University

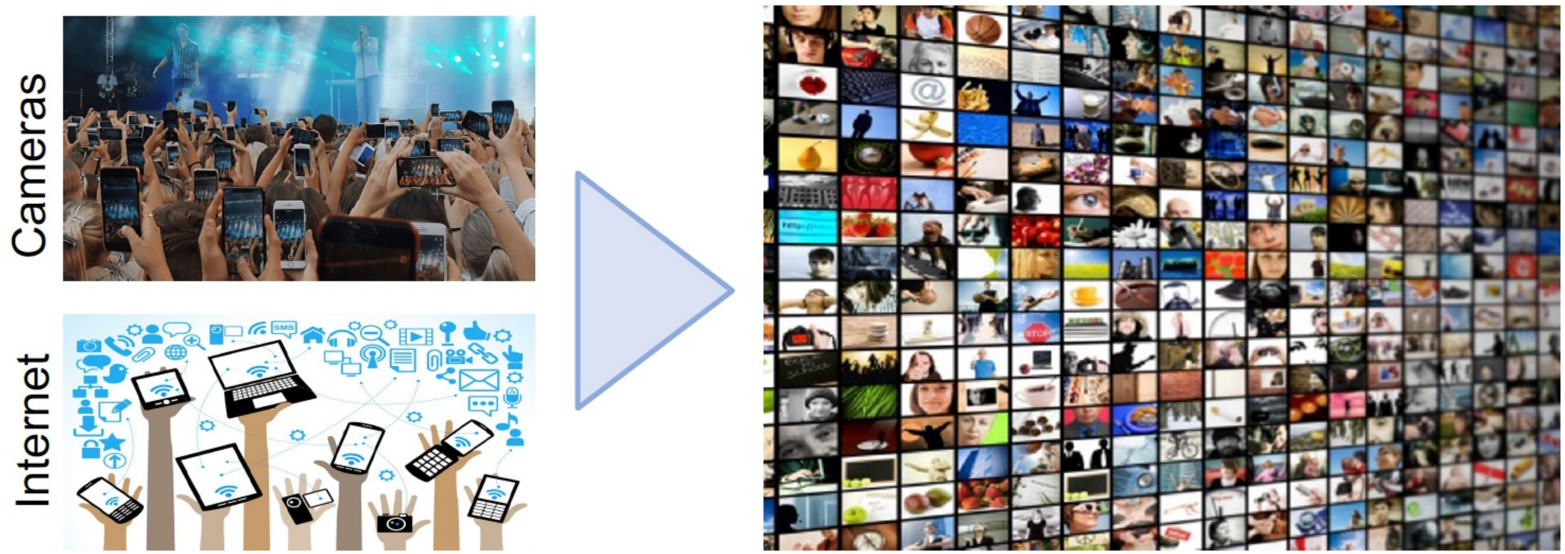
Course Outline

1. Computer Vision and ML basics: Visual (local) feature detection and description, Bag of Word Image representation, Linear classification (SVM)
2. Introduction to Neural Networks (NNs)
3. Machine Learning basics (2): Risk, Classification, Datasets, benchmarks and evaluation
4. Neural Nets for Image Classification
5. Vision Transformers
6. Transfer learning and domain adaptation
7. Segmentation and Detection
8. Generative models with GANs
9. Generative models with diffusion
10. Large VL models: CLIP, StableDiffusion, Flamingo
11. Control (to be checked) -- Explainable AI, Fairness

12/13 Bayesian deep learning

14 Robustness

Evaluations: Control (30%) + Practicals (3 reports; 70%)
can be modified by 10% between the 2 evaluations



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

COMPUTER VISION:

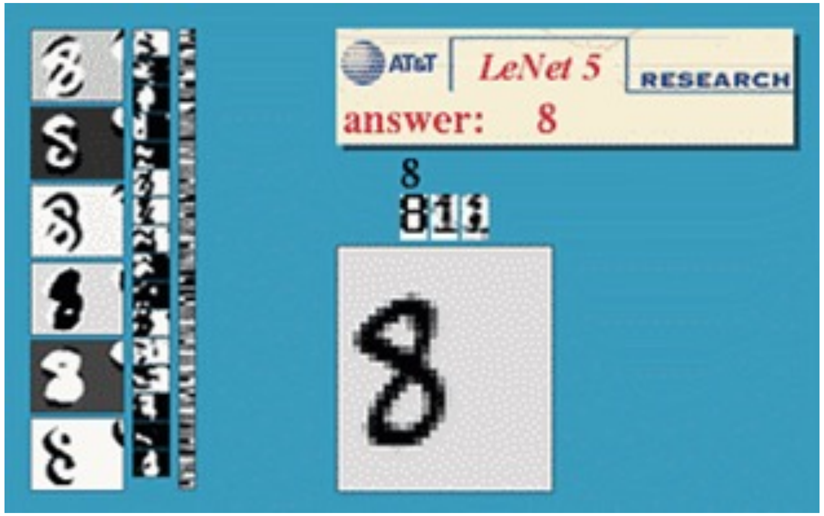
(Processing, analyzing and) **understanding visual data**

=>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

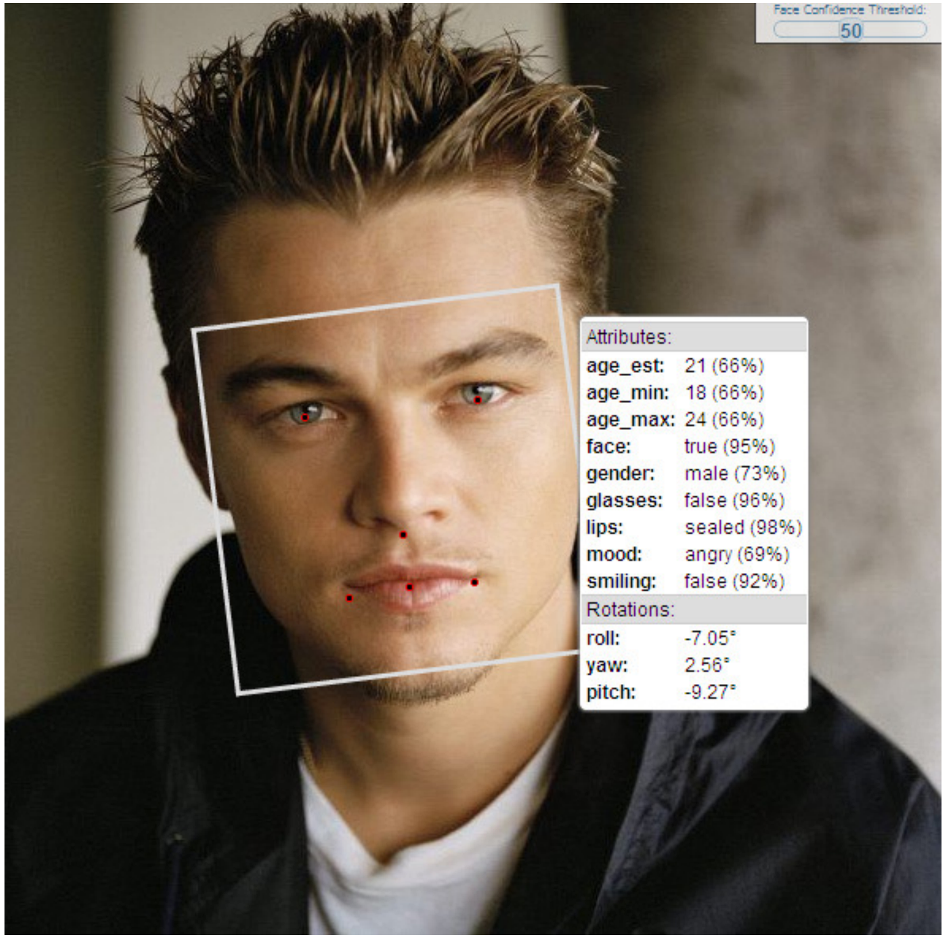
Deployed: Face detection

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

Source: S. Seitz

Deployed&Significant progress: Face Recognition

FACE++



Significant progress: Recognizing objects

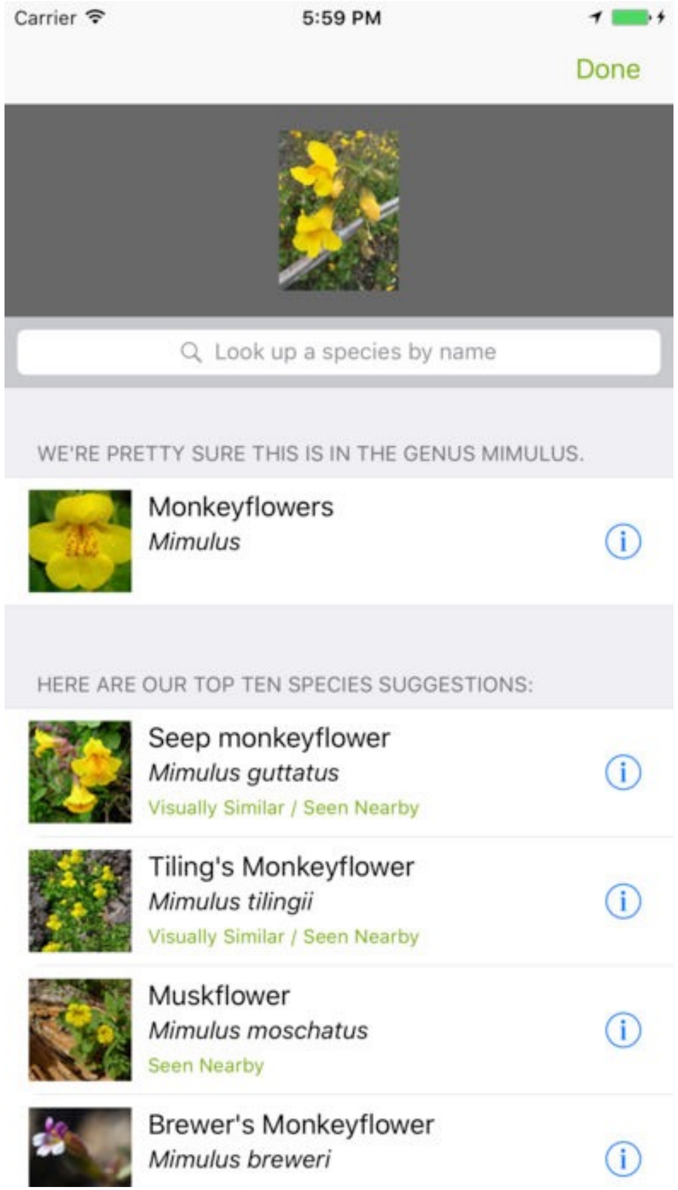
Mask R-CNN. Kaiming He, Georgia Gkioxari, Piotr Dollar, Ross Girshick. ICCV 2017

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

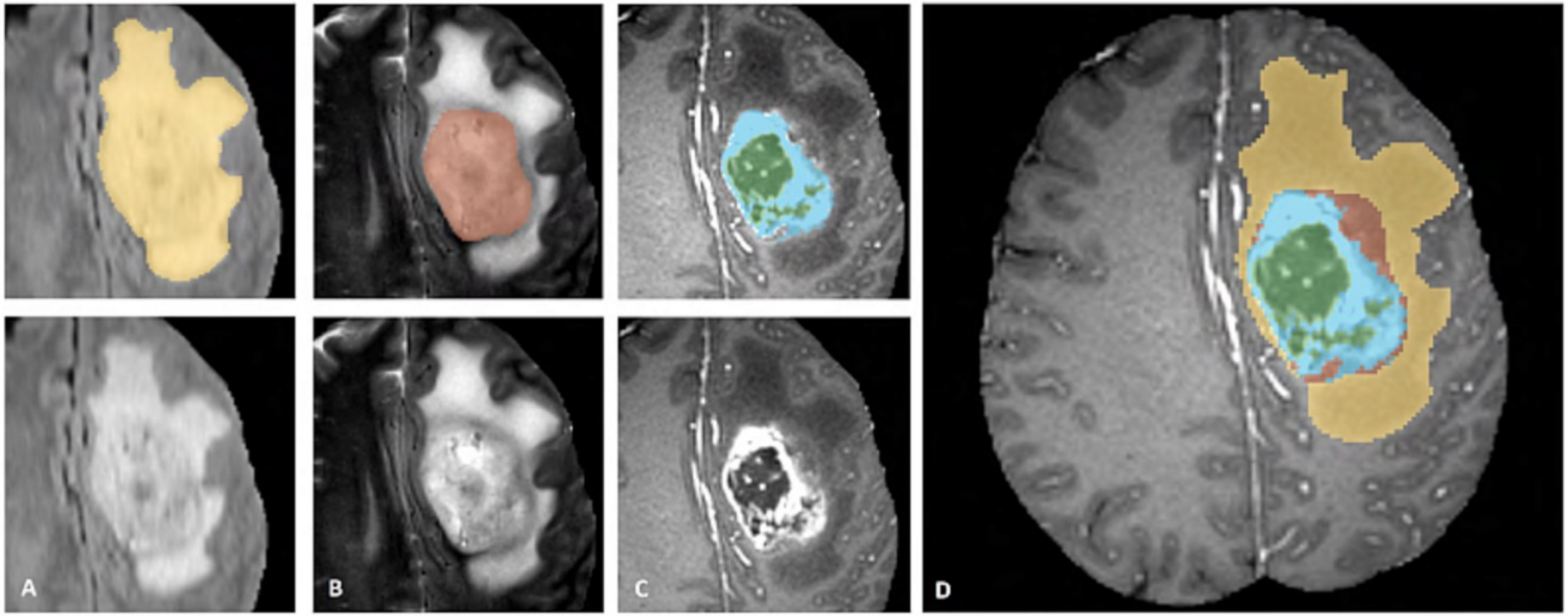


Fig.1: Glioma sub-regions. Shown are image patches with the tumor sub-regions that are annotated in the different modalities (top left) and the final labels for the whole dataset (right). The image patches show from left to right: the whole tumor (yellow) visible in T2-FLAIR (Fig.A), the tumor core (red) 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.

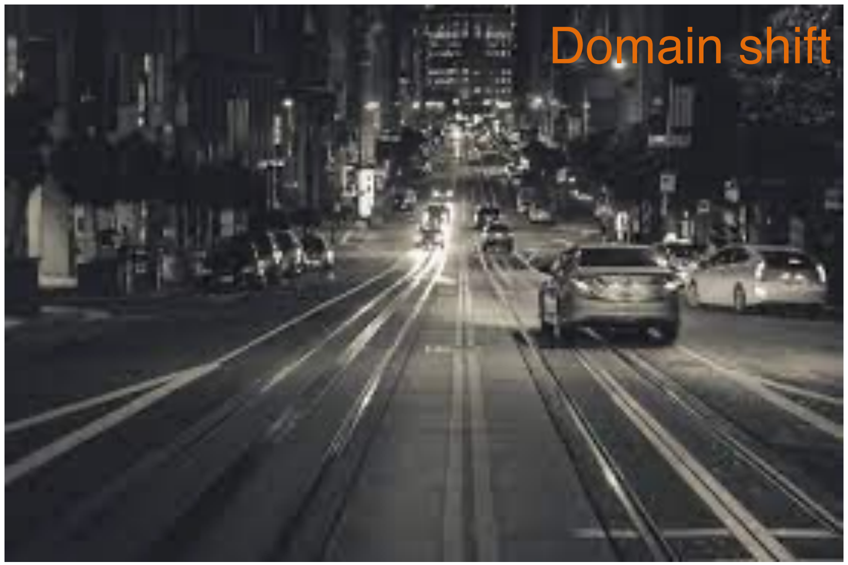
Some have been used in hospitals, despite not being properly tested. But the pandemic could help make medical AI better.

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

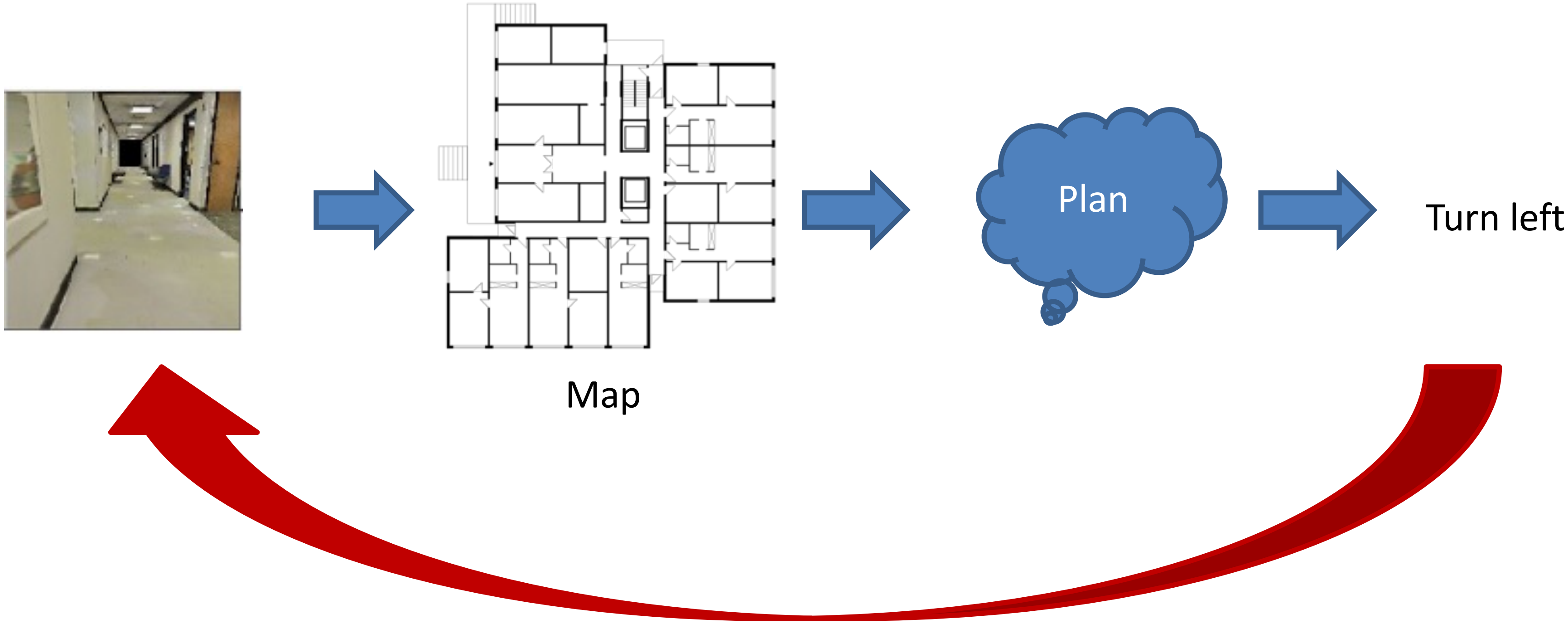
Why?

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

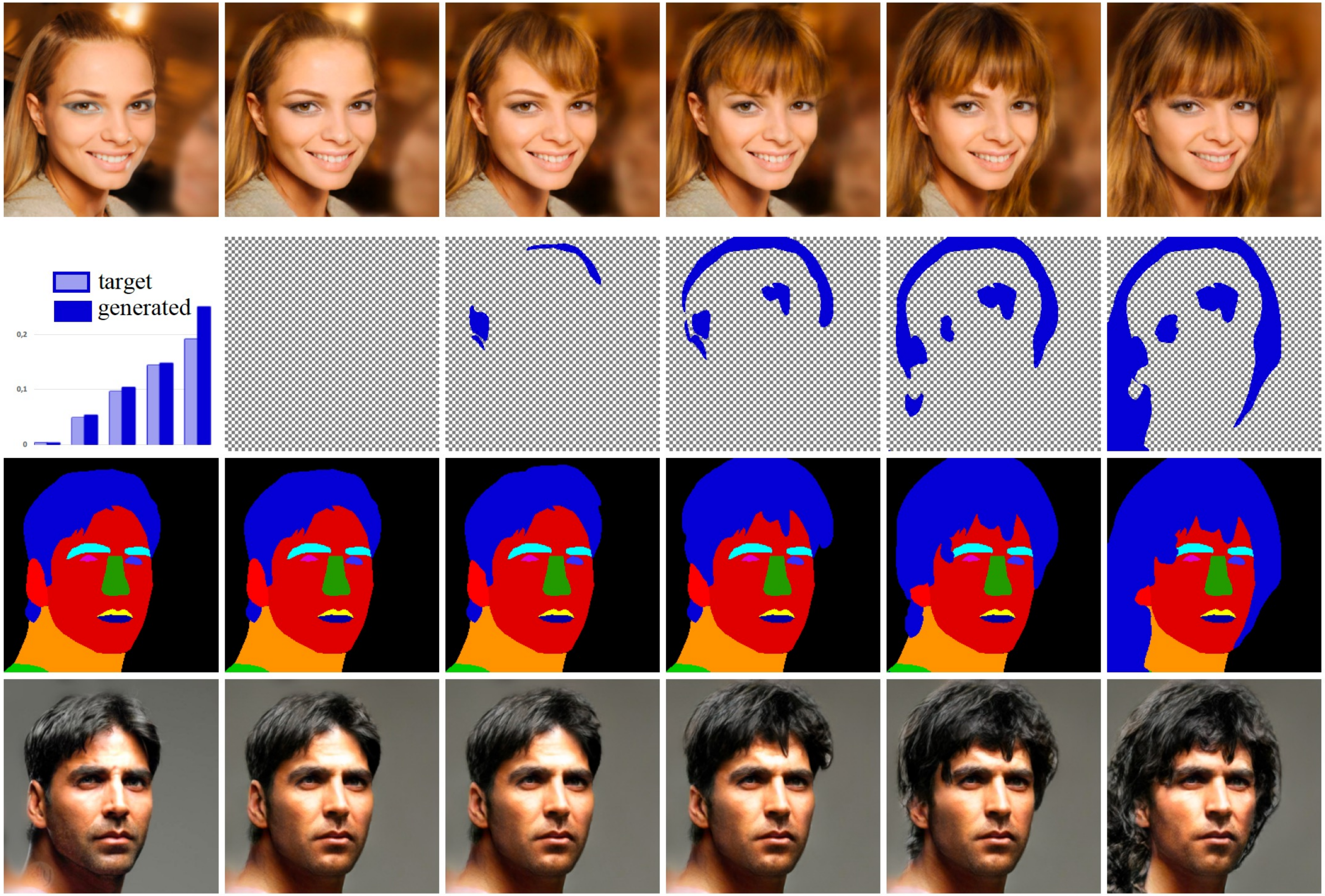
Challenges: Understanding complex situations / Reasoning

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

The picture above is funny.

Andrej Karpathy

Challenges: Generative models for images-edition, manipulation (with GANs)



Challenges: Image Generation in 2023 (Diffusion Models) **from Text**

Sprouts in the shape of text 'Imagen' coming out of a fairytale book

A photo of a Shiba Inu dog with a backpack riding a bike. It is wearing sunglasses and a beach hat.

A high contrast portrait of a very happy fuzzy panda dressed as a chef in a high end kitchen making dough. There is a painting of flowers on the wall behind him.

Course Outline

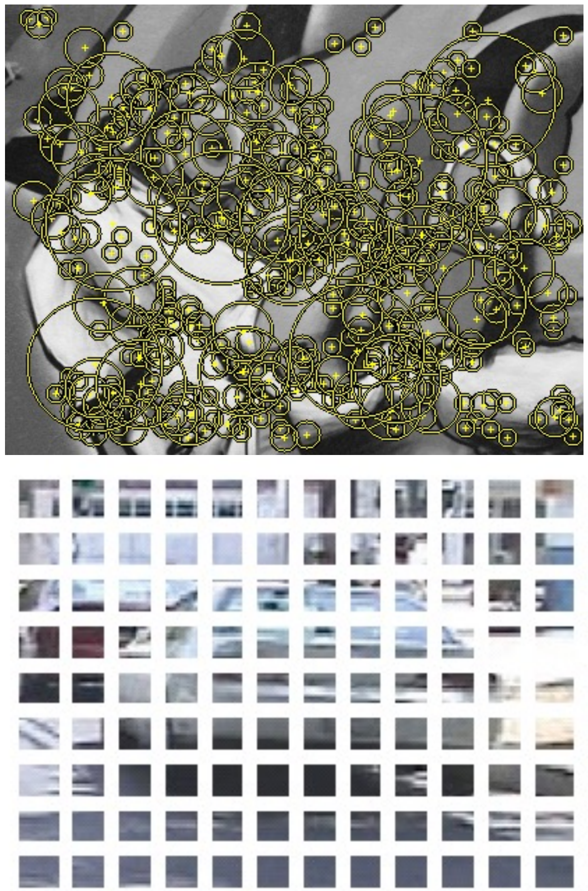
1. Computer Vision and Machine Learning basics

    Visual (local) feature detection

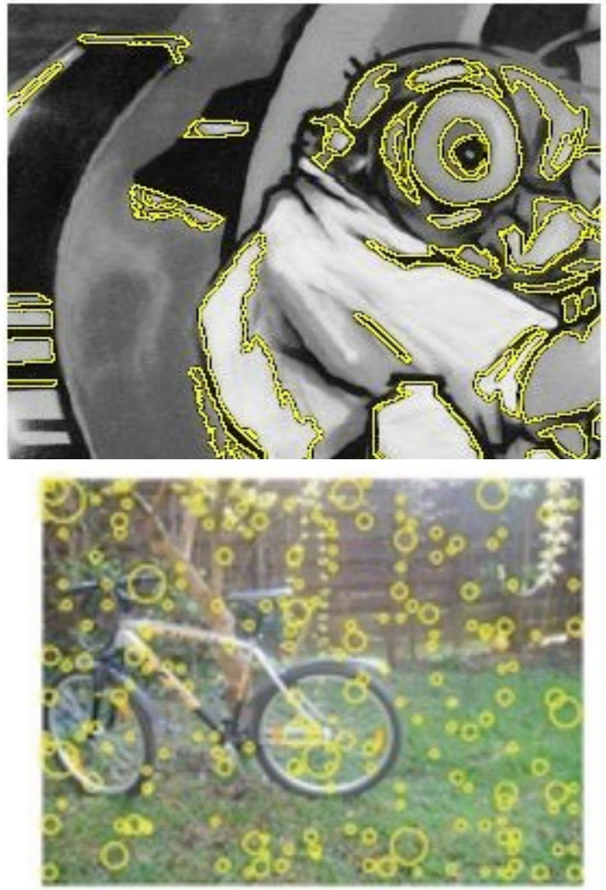
Local feature detection and description

Points/Regions of Interest detection

Sparse, at interest points



Dense, uniformly

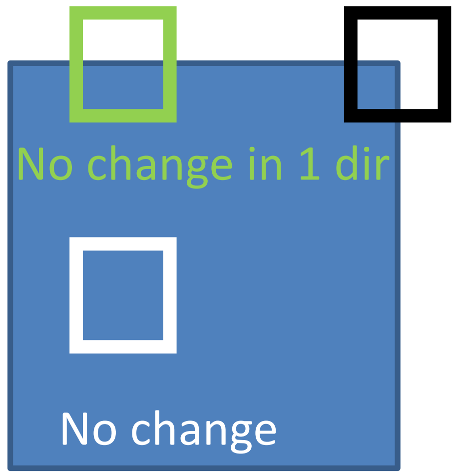


Randomly

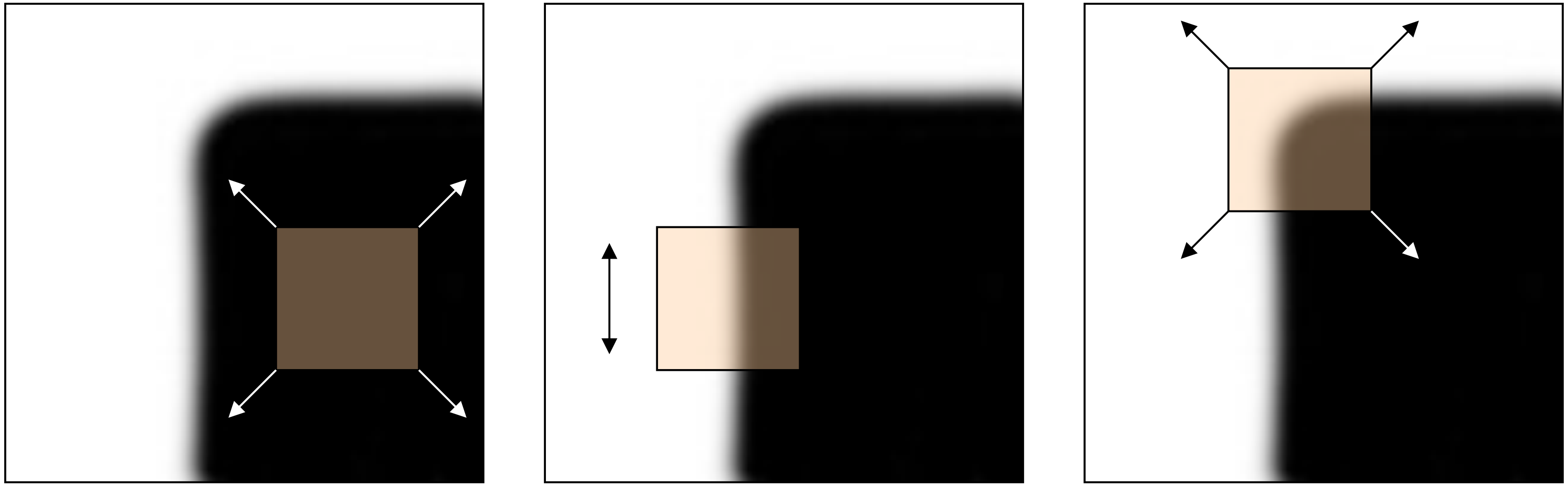
One example: Corner detection (Harris corner detector)

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

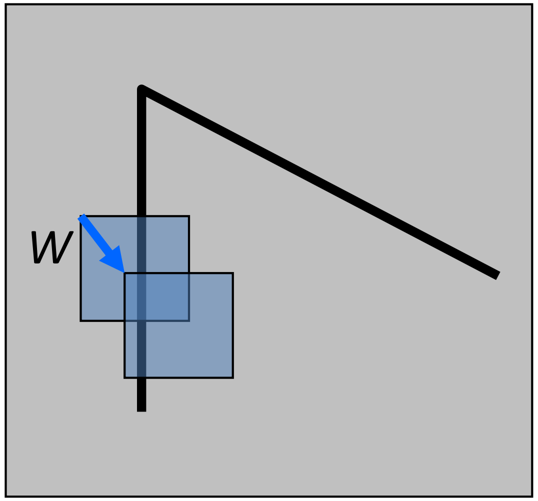
"edge":
no change
along the edge
direction

"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*):

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

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

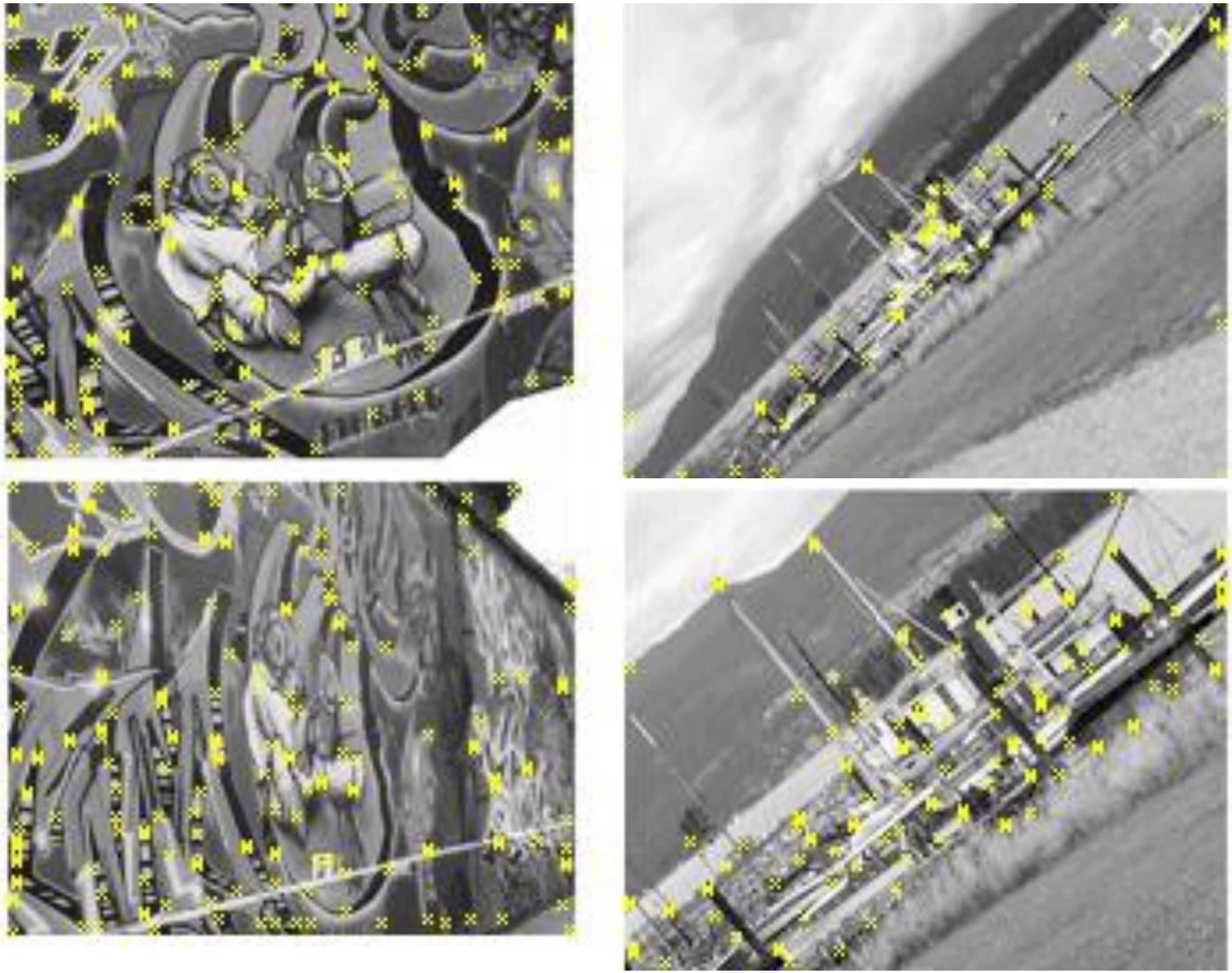
ALGO 1: very computationally expensive

Harris detector example

Harris features (in red)

Local feature detection

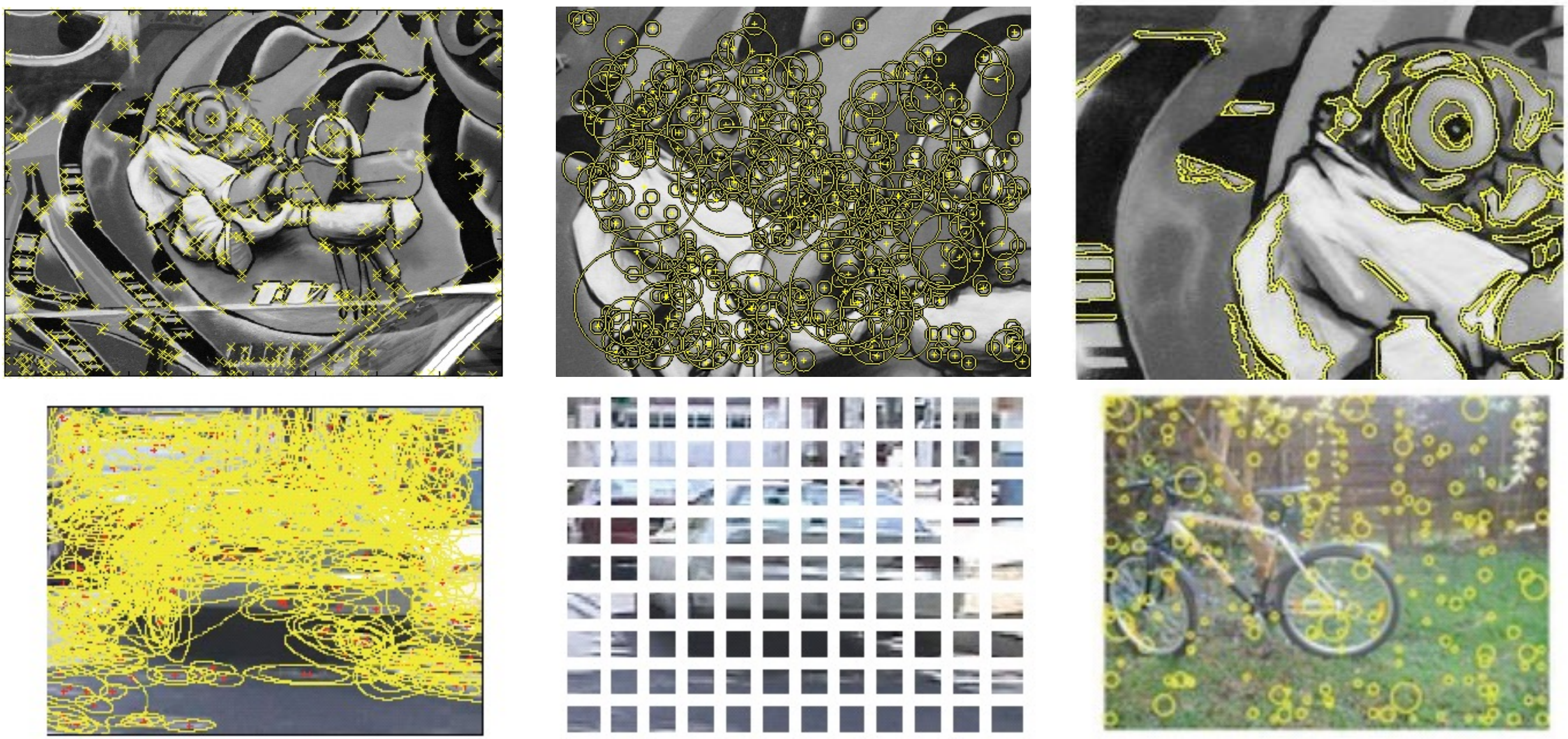
Looking for repeatability



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 and Machine Learning basics

    Visual (local) feature detection

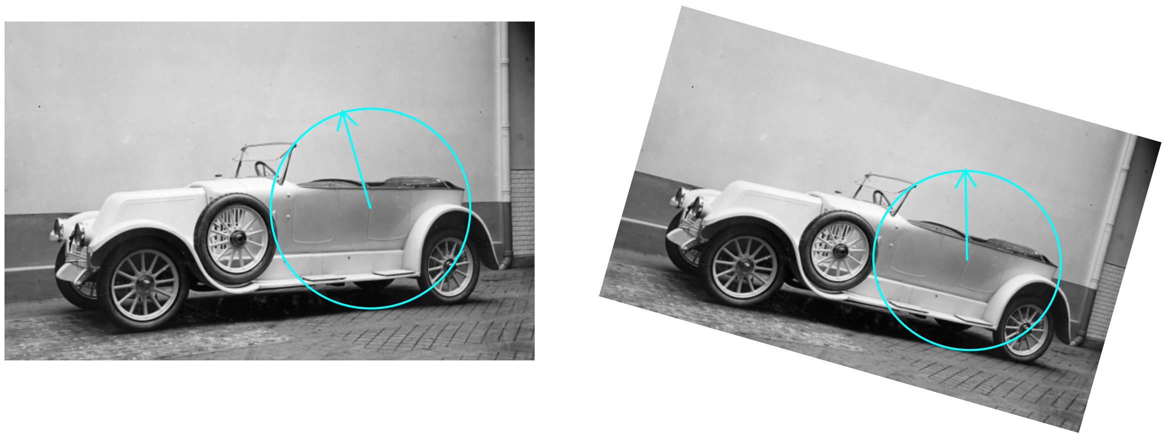
    Visual (local) feature description

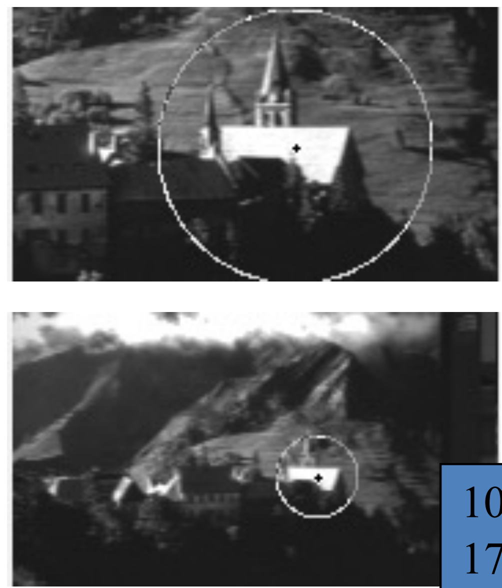
Local feature description

Many Points/Regions of Interest descriptors

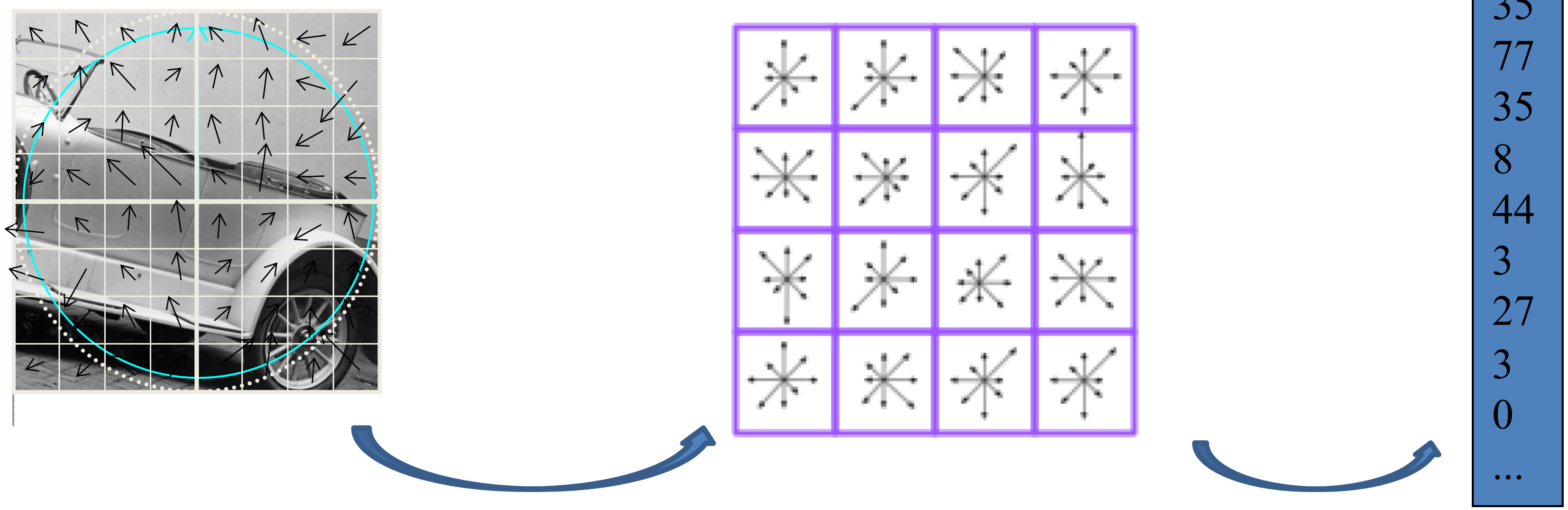
One example: SIFT descriptor

Local description (always looking for invariance)





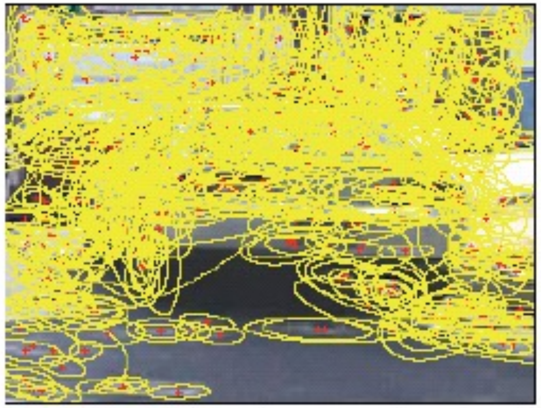
SIFT descriptors/features



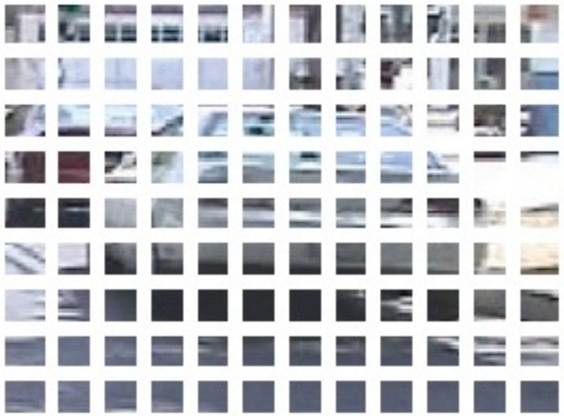
Feature descriptors

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

BoF: (First) Image representation

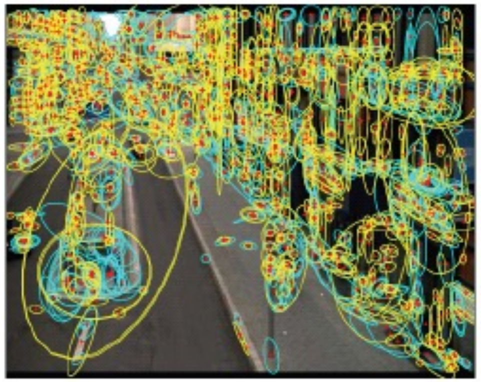


Sparse, at interest points



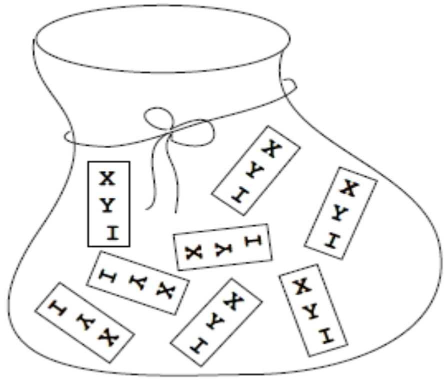
Dense, uniformly

Randomly



Multiple interest operators

Feature extraction



A bag of features
BoF

Bag of Feature (BoF) Model

Image

(features)

Image repsentation

- BoF (Bag of features)

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

- The missing bits: **the visual word**
- From BoF to Bag of (Visual) words

Course Outline

1. Computer Vision and Machine Learning basics

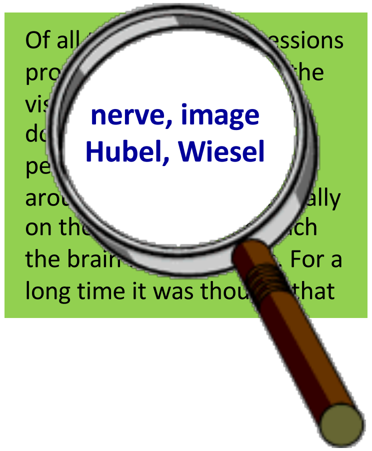
    Visual (local) feature detection

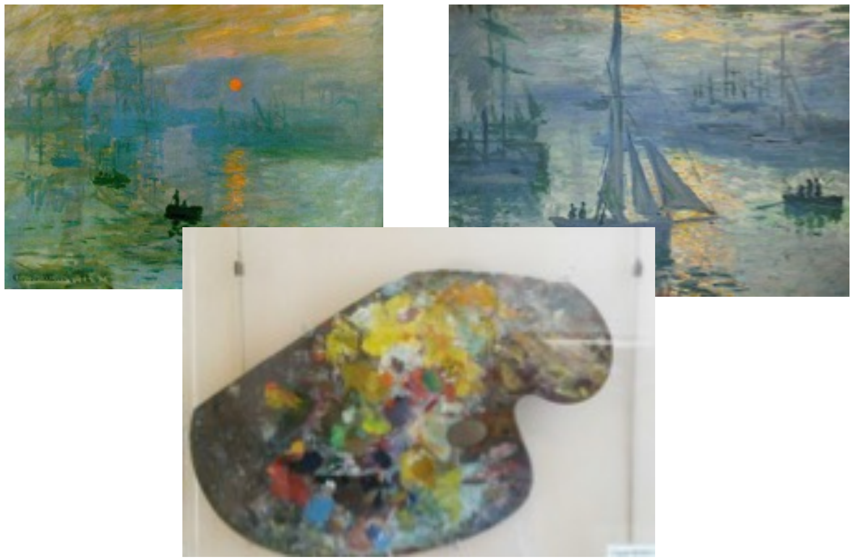
    Visual (local) feature description

    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) model: basic explication with textual representation and color indexing





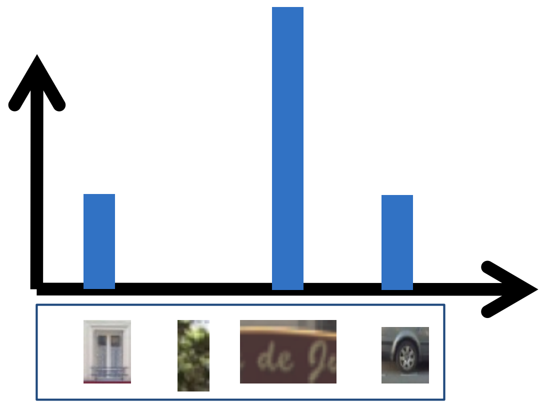
Comparing 2 docs using visual/color/word occurrences

Slide credit L. Fei-Fei

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?

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

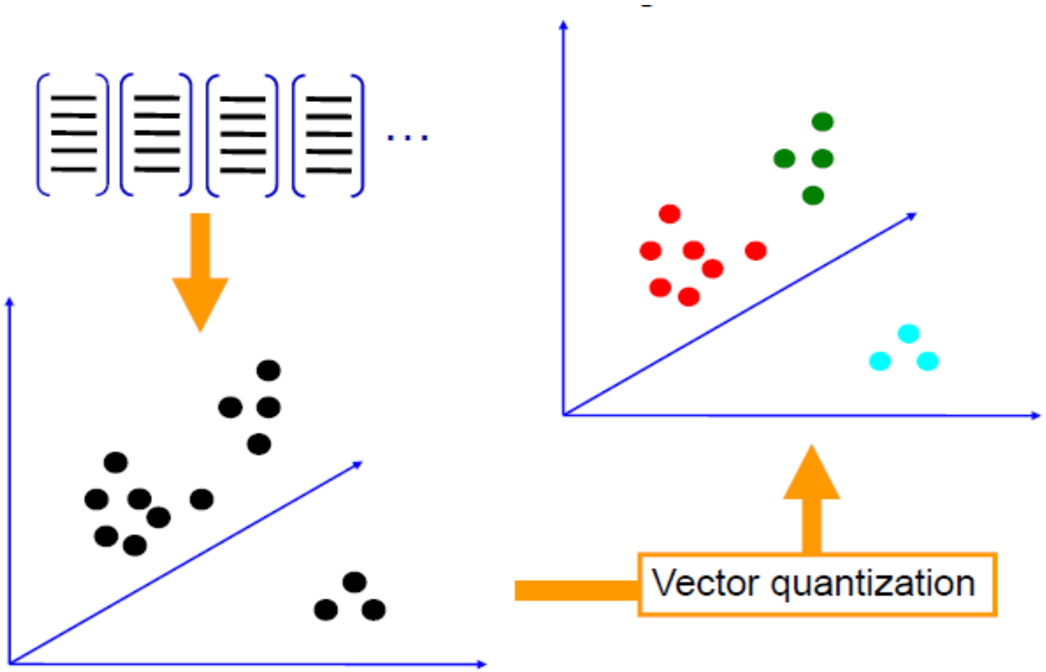
Visual space clustering

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):

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

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

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

$$\min_k \|x_i - w_k\|^2$$

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 $\{c_{k} = w_k\}$

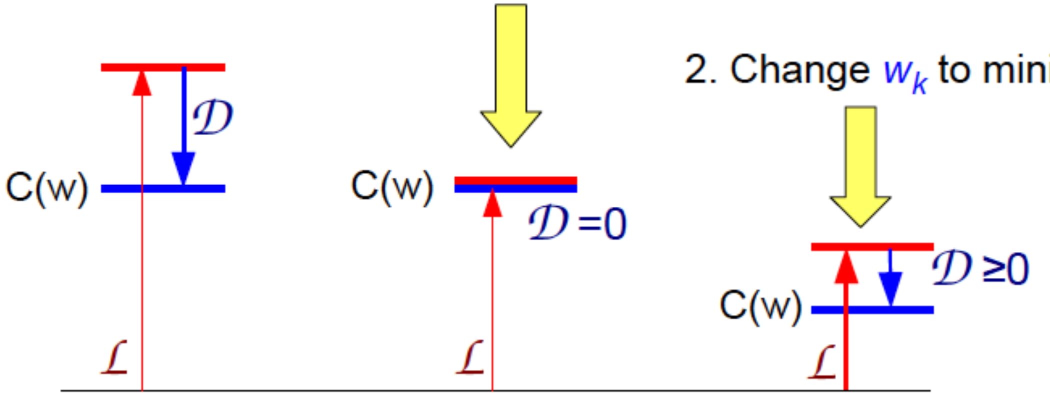
K-means : why it is successful ?

Consider an arbitrary cluster assignment s_i.

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

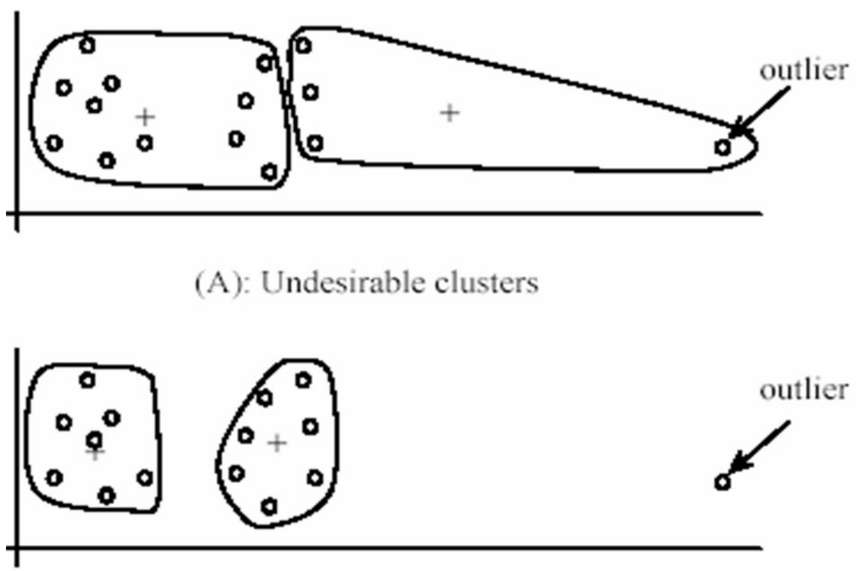
1. Change s_i to minimize $\mathcal{D}$ leaving C(w) unchanged.

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)



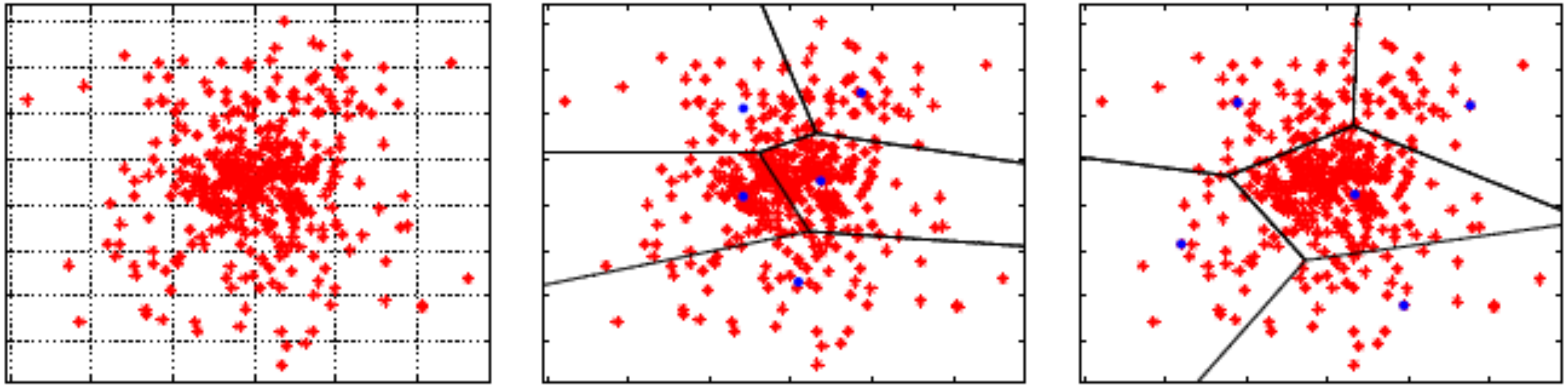
(A): Undesirable clusters

(B): Ideal clusters

- K-Means deeply used in practice

Clustering

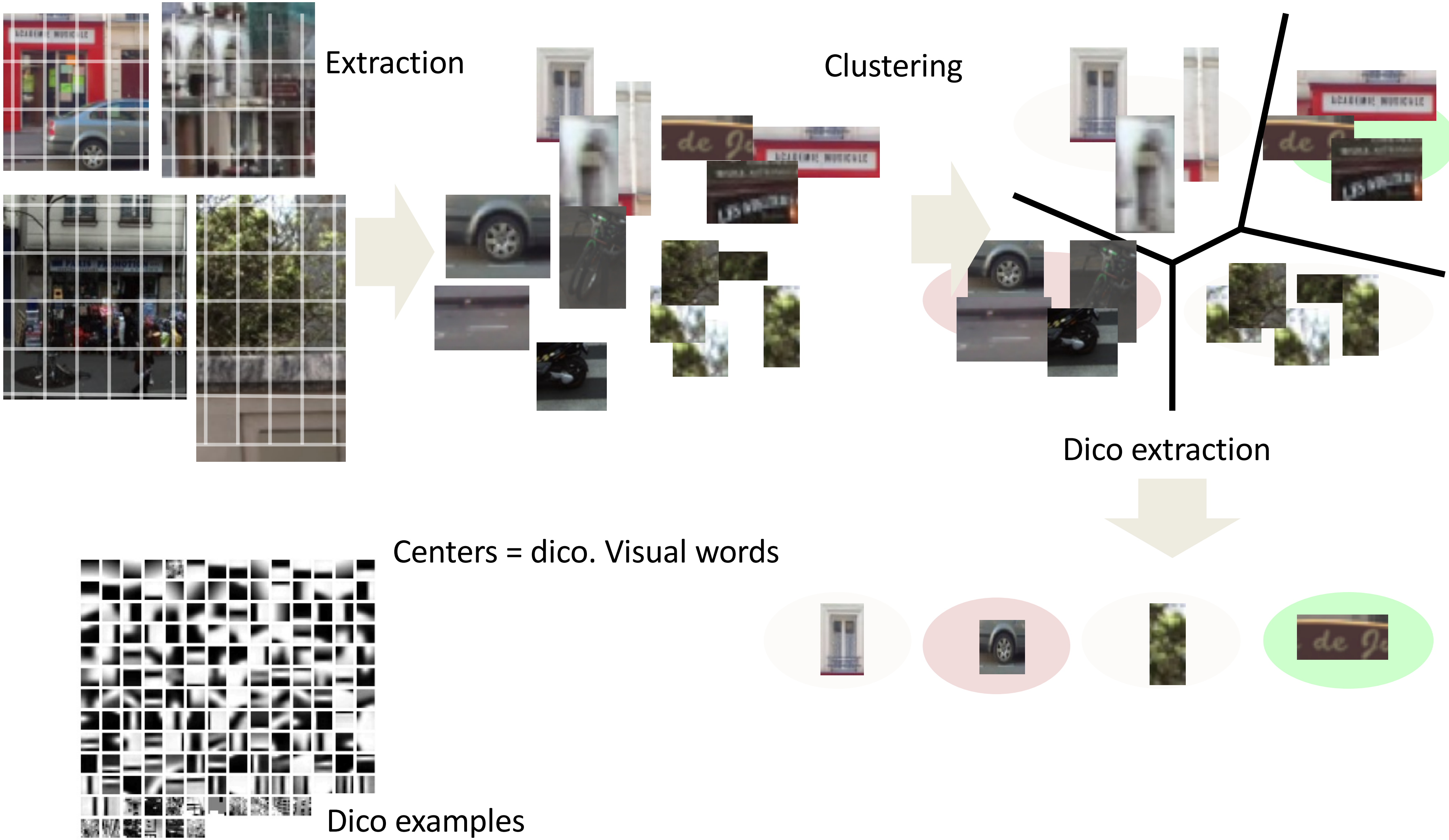
- Uniform / K-means / radius-based :



(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



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

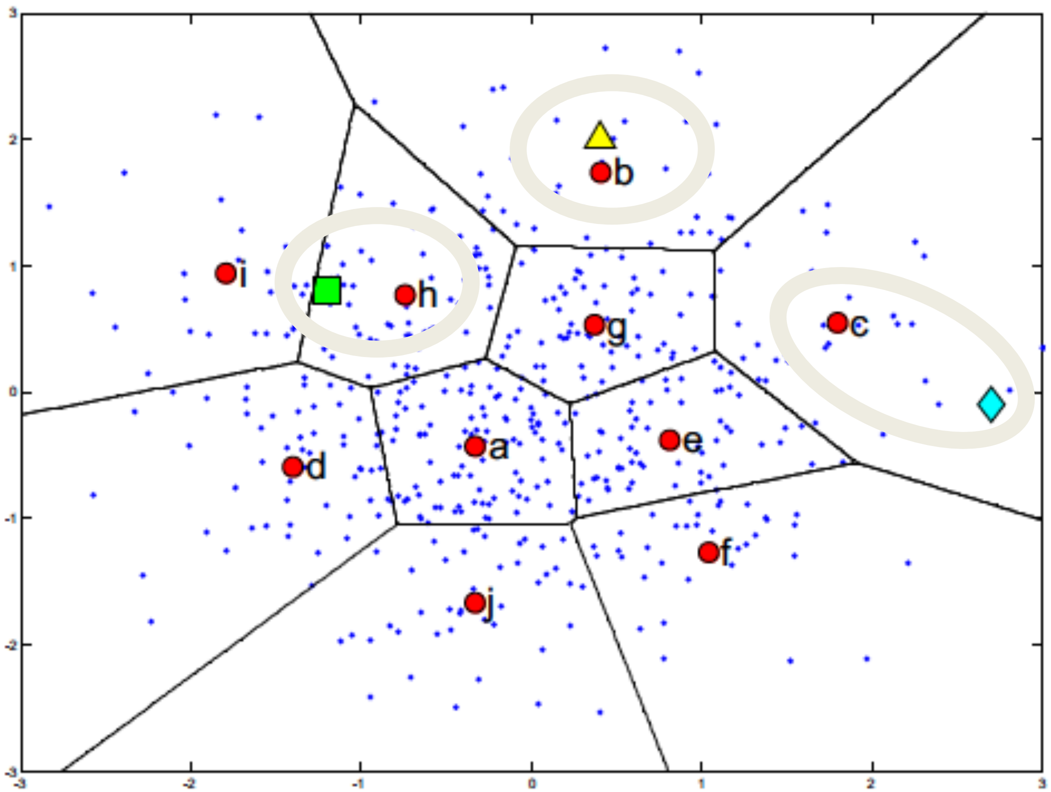
Bag-of-Words (BoW) image signature

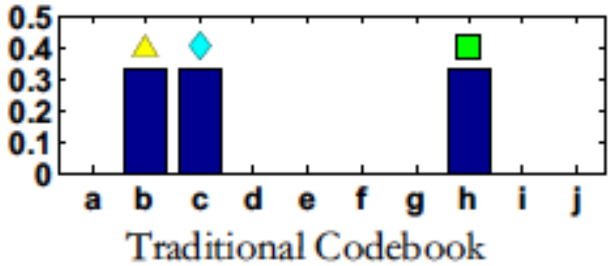
- For each image:
  - For each local feature: find the closest visual word
  - Increase the corresponding bin in histogram of visual dico

- 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)



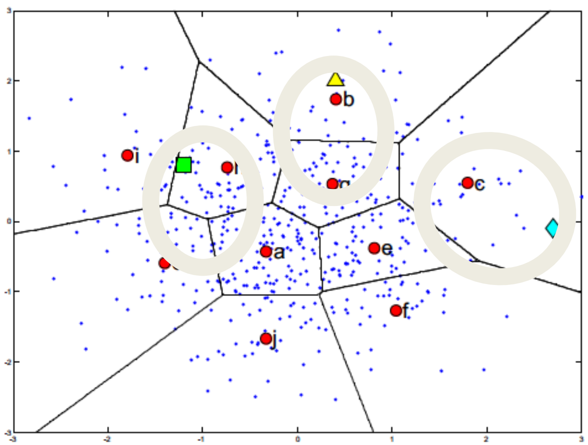


Bag-of-Words (BoW) image signature

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



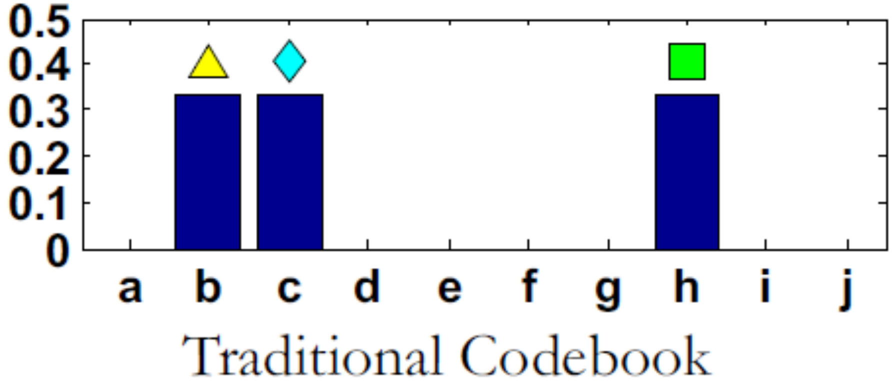
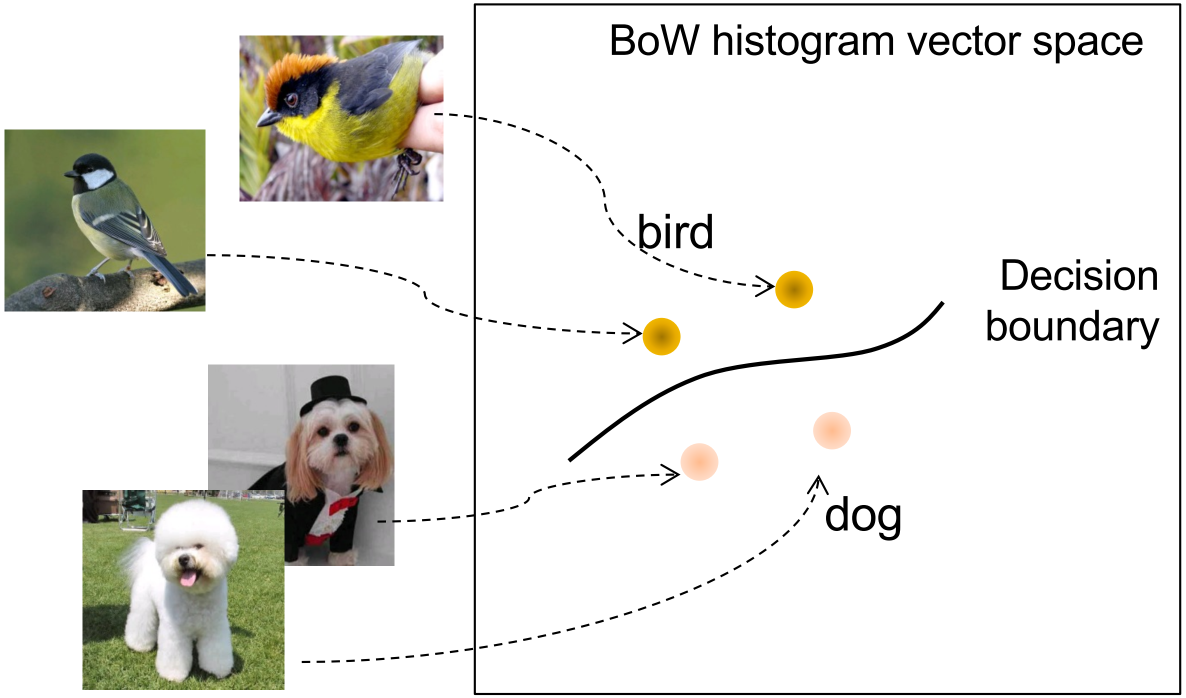


Image classification based on BoW



Learn a classification model to determine the decision boundary

Classification model to determine the decision boundary

SVM classifiers

SVM

Notations:

- Image/Patterns $\mathbf{x} \in \mathbf{X}$
- Φ: function transforming the patterns into feature vectors $\Phi(x)$
- $< \cdot, \cdot >$ dot product in the feature space endowed by $\Phi(\cdot)$
- Classes $y = \pm 1$

Early kernel classifiers derived from the perceptron [Rosenblatt58]:

- taking the sign of a linear discriminant function:

$$f(\mathbf{x}) =< \mathbf{w}, \Phi(\mathbf{x}) > +b$$

- Classifiers called Φ-machines

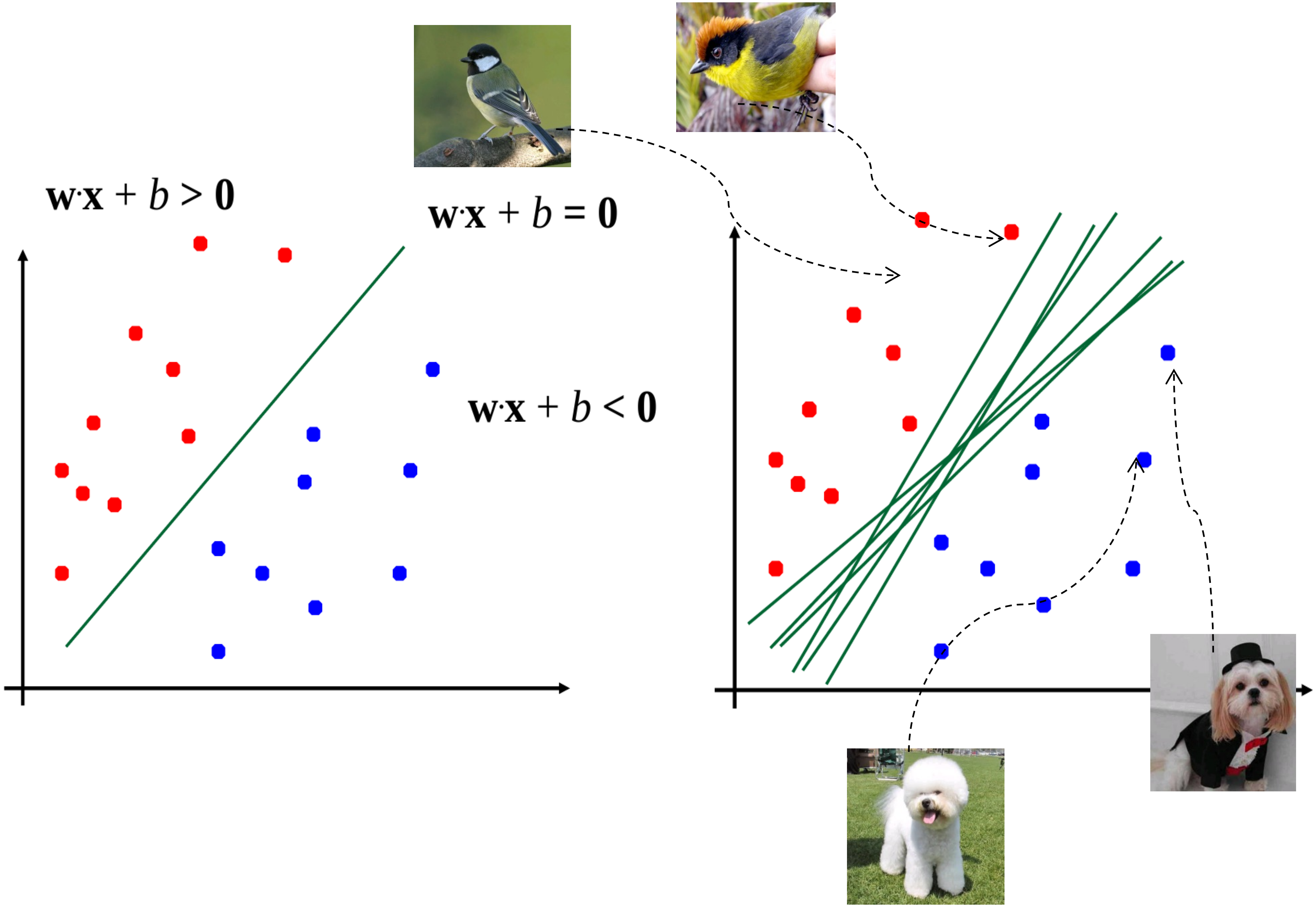
SVM

- Question: how to find/estimate f ?
  - Feature function Φ usually hand-chosen for each problem
  - Several Φ for image processing like BoW
  - w and b: parameters to be determined

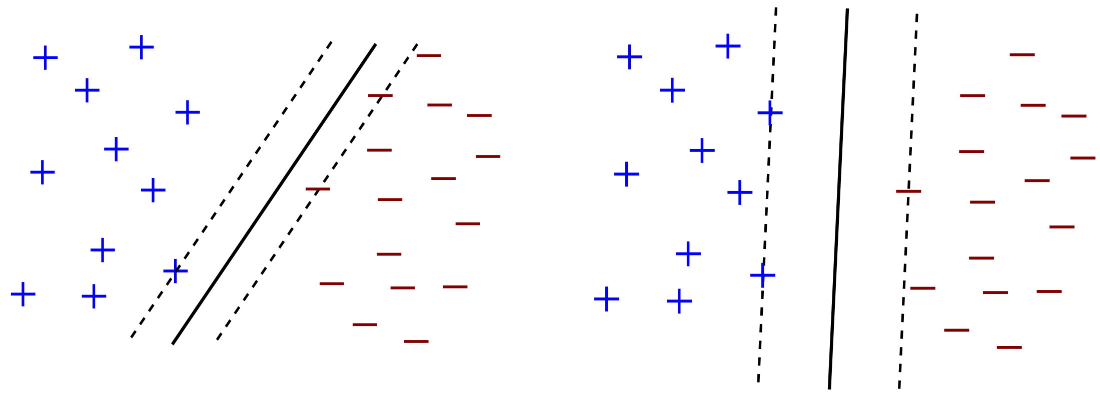
$$f(x) = \langle w, \Phi(x) \rangle + b$$

- Learning algorithm on a set of training examples:
  $\mathcal{A} = (x_1, y_1) \cdots (x_n, y_n)$

Which hyperplane ? w? b?



SVM



SVM optimization: maximizing the margin between + and -

Def.: Margin = distance between the hyperplanes $f(x) = 1$and $f(x) = -1$ (dashed lines in Figure).

Intuitively, a classifier with a larger margin is more robust to fluctuations

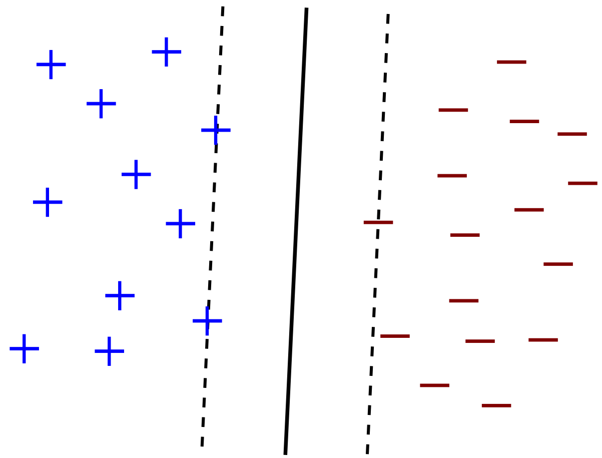
Hard Margin

Final expression for the Hard Margin SVM optimization:

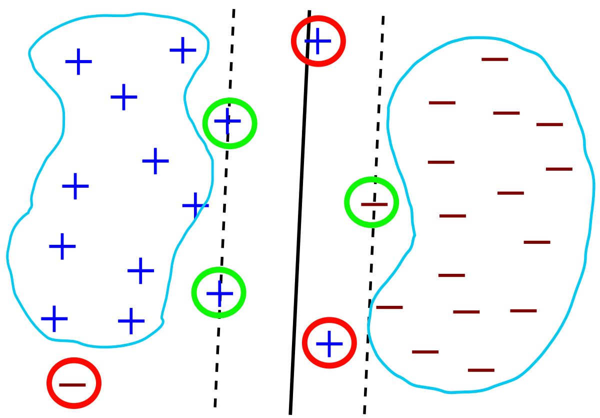
$$\min_{w,b} \; P(w,b) = \frac{1}{2}\|w\|^2 \quad \text{with} \quad \forall\, i \quad y_i\, f(x_i) \geq 1$$

SVM

- Hard Margin: OK if data are linearly separated



- Otherwise: noisy data (in red) disrupt the optim.
- Solution: Soft SVM



SVM: Soft Margin

Introducing the slack variables ξ_i, one usually gets rid of the inconvenient max of the loss and rewrite the problem as

$$\min_{w,b} P(w,b) = \frac{1}{2}\|w\|^2 + C\sum_{i=1}^{n}\xi_i \quad \text{with} \quad \begin{cases} \forall\, i & y_i\, f(x_i) \geq 1 - \xi_i \\ \forall\, i & \xi_i \geq 0 \end{cases}$$

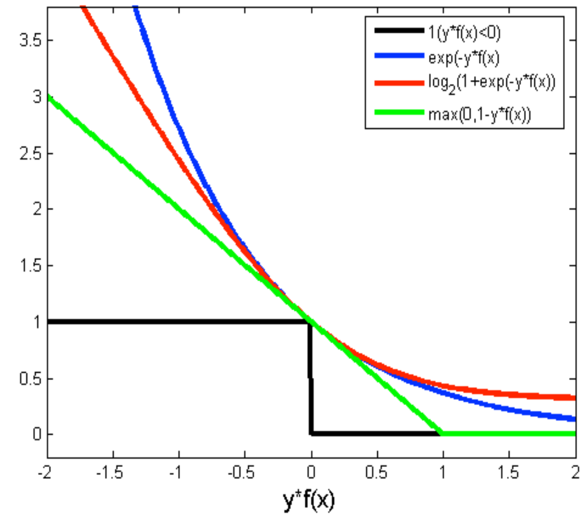
For very large values of the hyper-parameter C, **Hard Margin** case:

- Minimization of ||w|| (ie margin maximization) under the constraint that all training examples are correctly classified with a loss equal to zero.

Smaller values of C relax this constraint: **Soft Margin** case

- SVMs that produces markedly better results on noisy problems.

SVM learning scheme



Equivalently, minimizing the following objective function in feature space with the hinge loss function:

$$\ell(y_i\, f(x_i)) = \max\left(0, 1 - y_i\, f(x_i)\right)$$

$$\min_{w,b}\ P(w,b) = \frac{1}{2}\|w\|^2 + C\sum_{i=1}^{n}\ell(y_i\, f(x_i))$$

Regularization

Margin Maximization

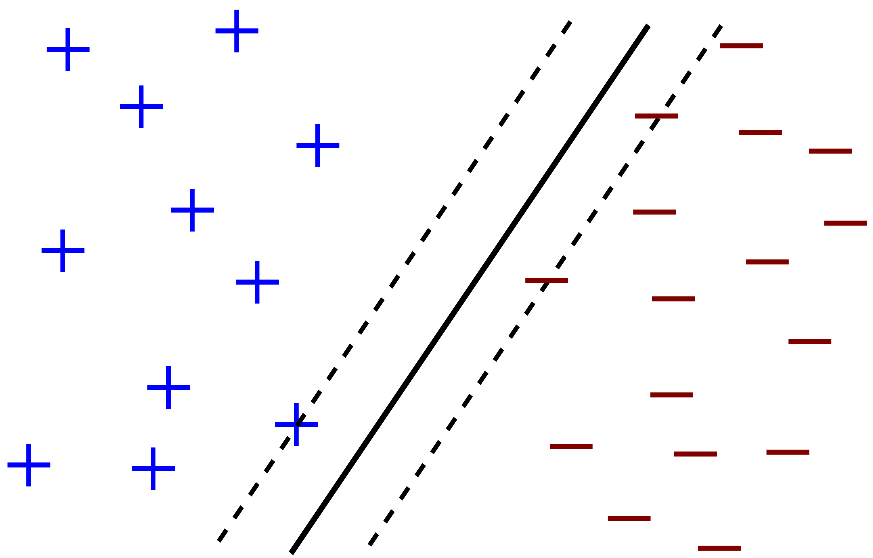
Data fitting

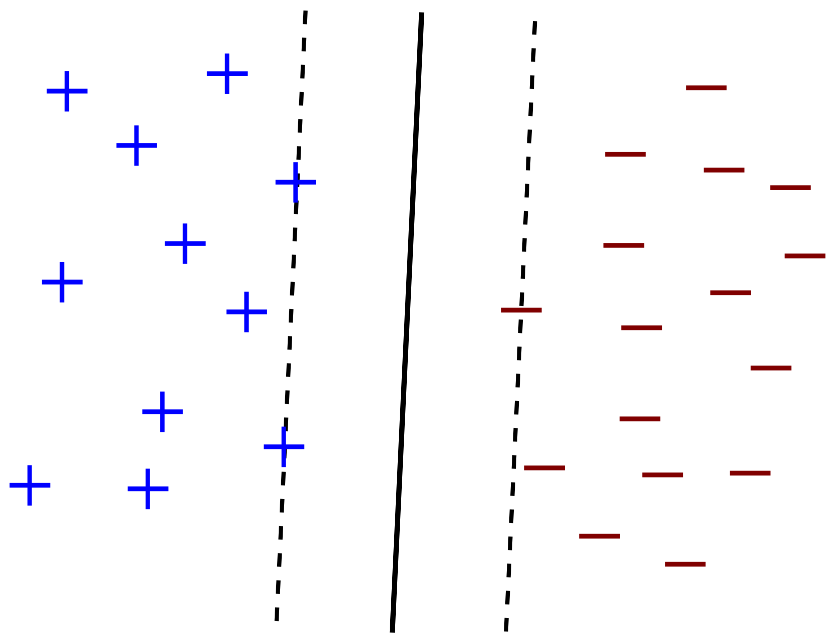
Constraint satisfaction

Solving equation: SVM

Support Vector Machines (SVM) defined by three incremental steps:

1. [Vapnik63]: linear classifier / separates the training examples with the **widest margin** => Optimal Hyperplane



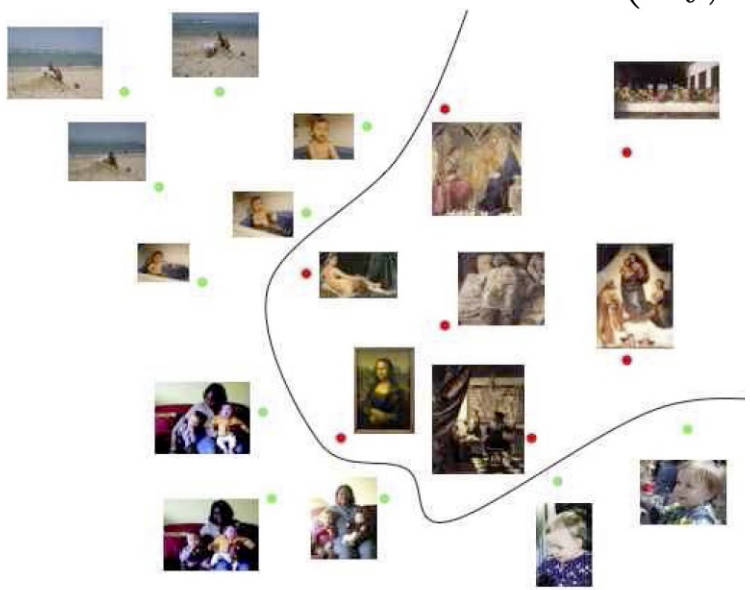


Solving equation: SVM

Support Vector Machines (SVM) defined by three incremental steps:

1. [Vapnik63]: linear classifier / separates the training examples with the widest margin =>Optimal Hyperplane
2. **[Guyon93] Optimal Hyperplane built in the feature space induced by a kernel function**

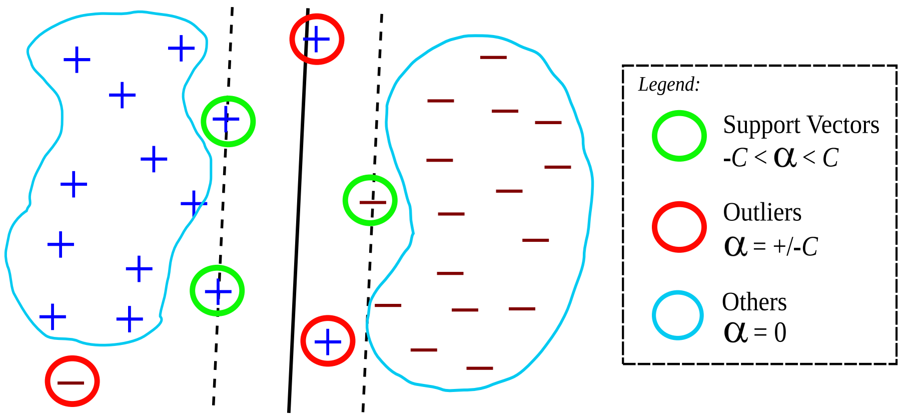
$$k(x_i, x_j) = \langle \Phi(x_i), \Phi(x_j) \rangle$$



Solving equation: SVM

Support Vector Machines (SVM) defined by three incremental steps:

1. [Vapnik63]: linear classifier / separates the training examples with the widest margin =>Optimal Hyperplane
2. [Guyon93] Optimal Hyperplane built in the feature space induced by a kernel function
3. **[Cortes95] soft version: noisy problems addressed by allowing some examples to violate the margin constraint**



Classification pipeline

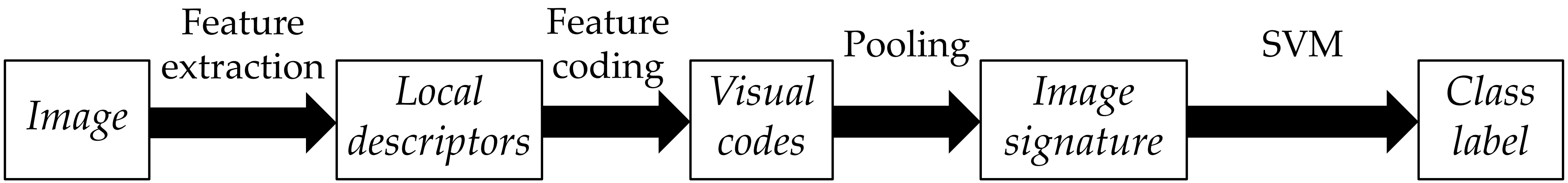
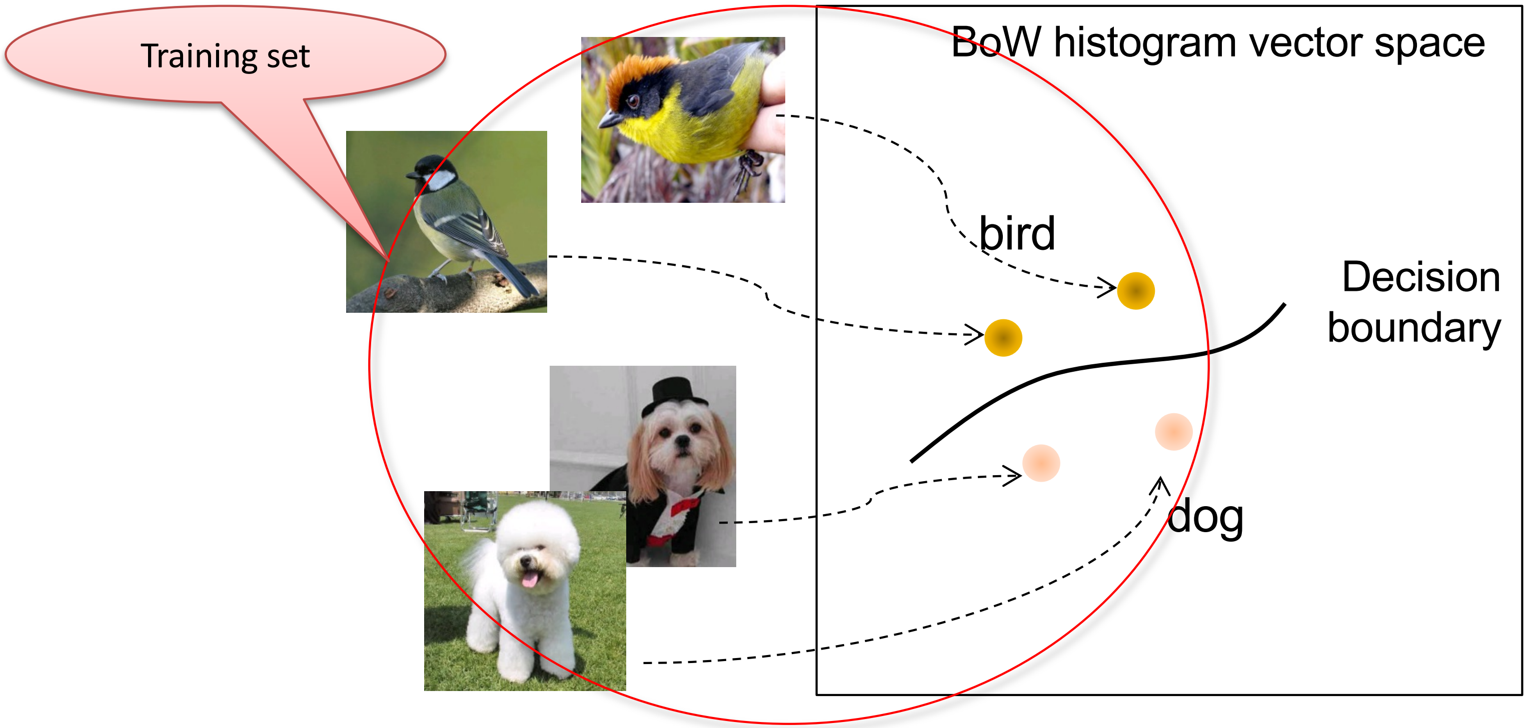


Image classification based on BoW



Learn a classification model to determine the decision boundary

Datasets for learning/testing

- How to define a category ?
  - Bicycle
  - Paintings with women
  - Portraits

  …

  Concepts, semantics, ontologies …

Image/video datasets for training/testing

CalTech 101

TRECVID

- Choice of the categories (objects, concepts)
  - Number of categories
  - Number of images per category
  - Hierarchical structure ?
- Mono-label/multi-labels
- Pre-processing
  - Color, resolution, centered …

Example: ImageNet dataset

- Large Scale Visual Recognition Challenge (ILSVRC)
  - 1,2 Million images, 1000 classes
- Paper:
  - ImageNet: A Large-Scale Hierarchical Image Database, Jia Deng, Wei Dong, Richard Socher, Li-Jia Li, Kai Li and Li Fei-Fei, CVPR 2009

Classes of ImageNet

- Based on WordNet
  - Each node is depicted by images
- A knowledge ontology
  - Taxonomy
  - Partonomy

- Website:

IMAGENET

14,197,122 images, 2 841 synsets indexed

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ImageNet is an image database organized according to the WordNet hierarchy (currently only the nouns), in which each node of the hierarchy is depicted by hundreds and thousands of images. Currently we have an average of over five hundred images per node. We hope ImageNet will become a useful resource for researchers, educators, students and all of you who share our passion for pictures.
Click here to learn more about ImageNet, Click here to join the ImageNet mailing list.

Constructing ImageNet

- 2-step process

Step 1 :
Collect candidate
images Via the Internet

→

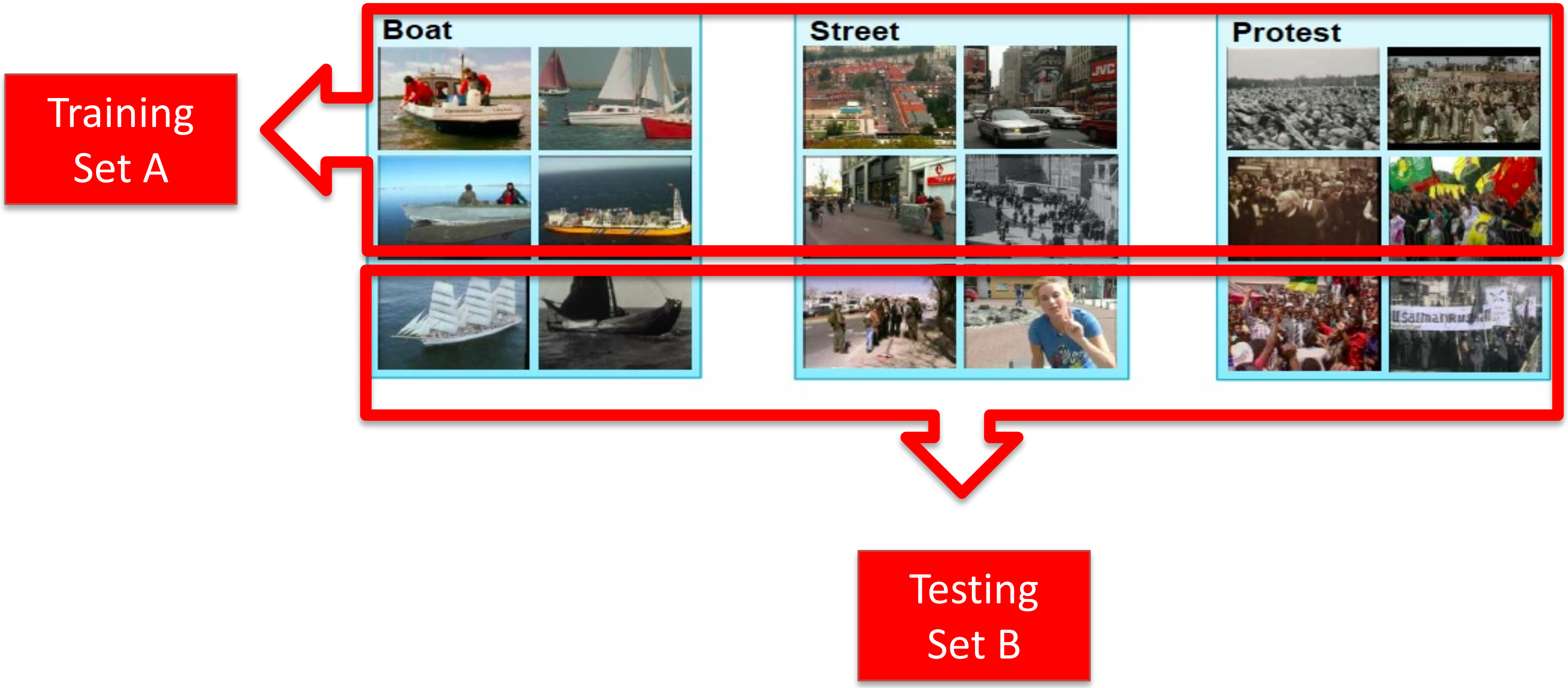
Step 2 :
Clean up candidate
Images by humans

- Still a lot of pbs, biases => ImageNetv2, …

Benchmarks and evaluation

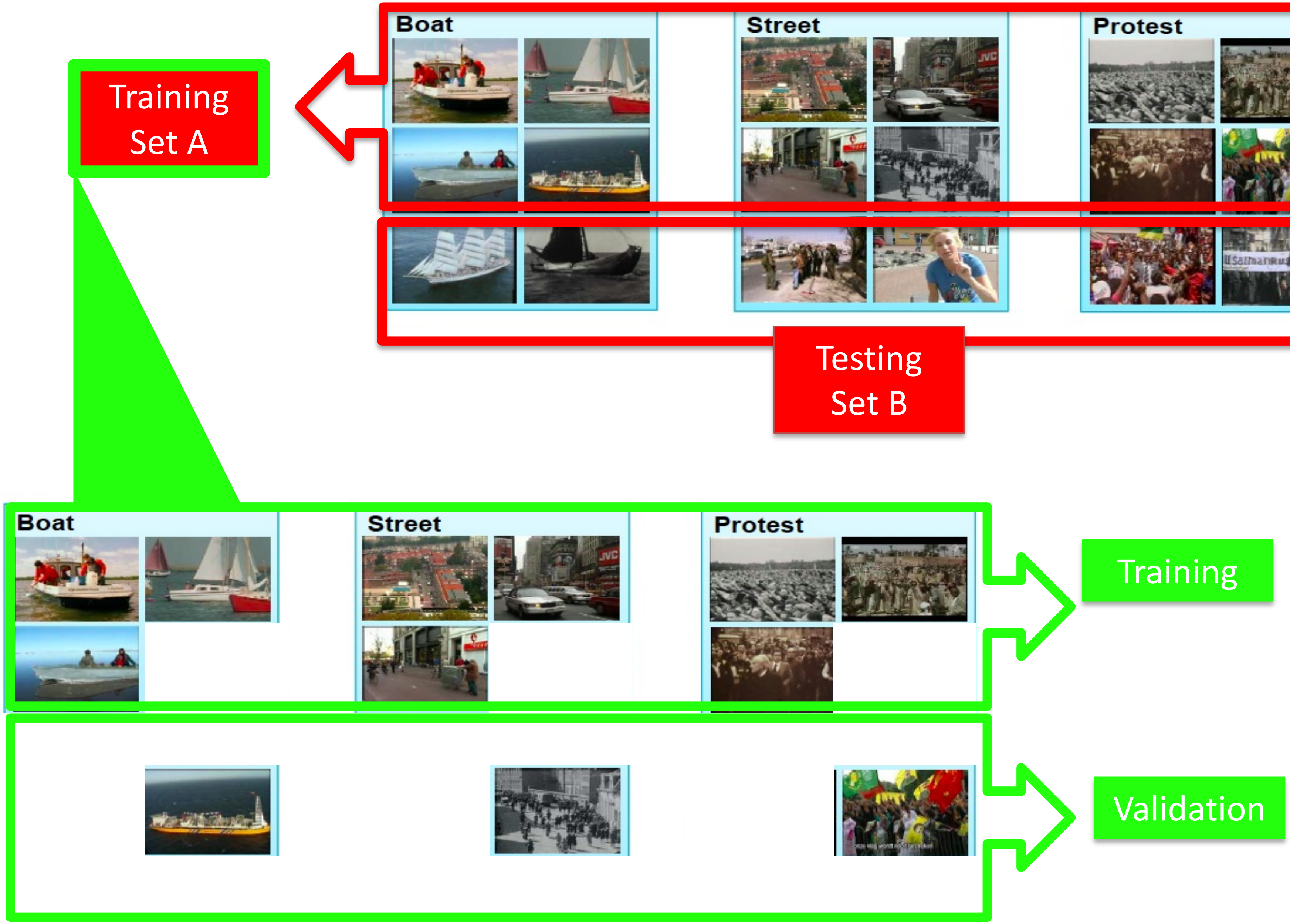
- Train / test / validation sets
    - Cross-validation
    - Learning hyper parameters
- Evaluation
    - Test Error
    - Accuracy, MAP, confusion matrix, Per-class averaging
    - Significance of the comparison, statistical tests, …
- Dataset building, concepts and semantics
    - Data pre-processing, data augmentation

Image/video datasets for training/testing



- Training classifiers on A
- Testing on B: error evaluation
- A and B disjoints!

Training: Cross-validation

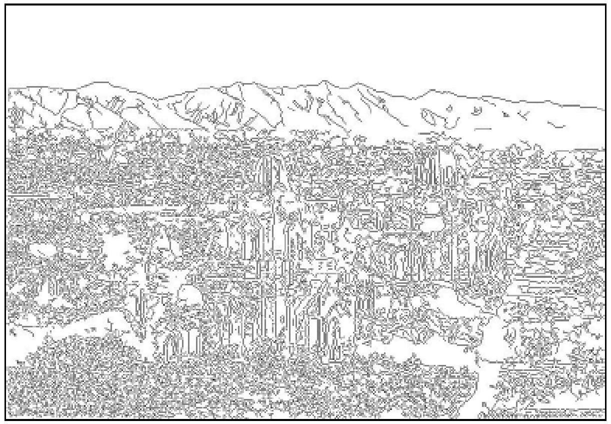


One example

SPM algorithm

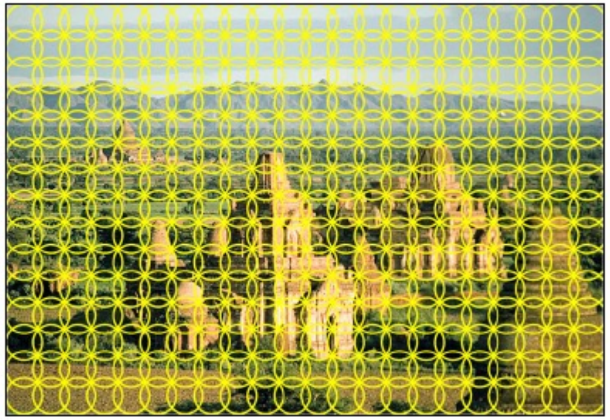
SPM Algorithm

1. Extract interest point descriptors (dense scan)
2. Construct visual word dictionary
3. Build spatial histograms
4. Train an SVM



Weak (edge orientations)

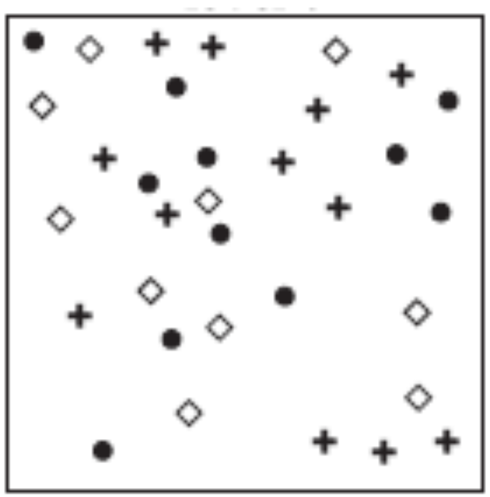
OR



Strong (SIFT)

Algorithm

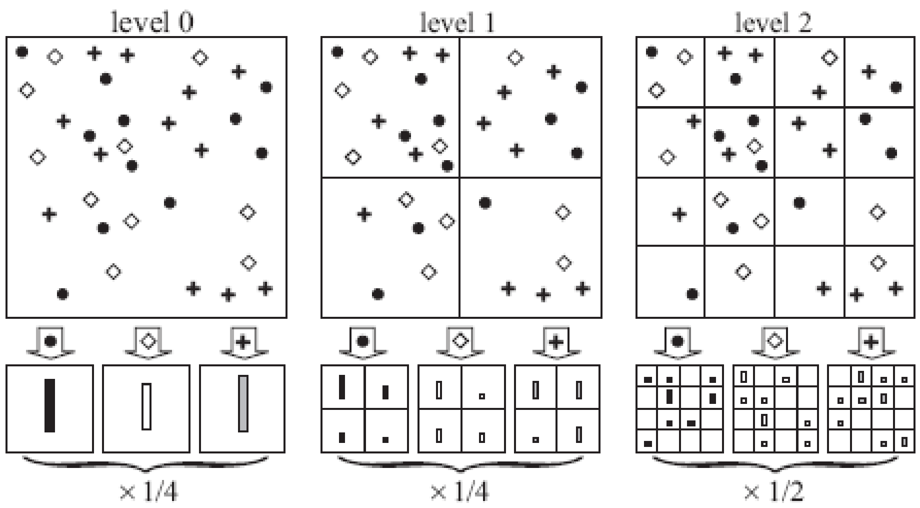
1. Extract interest point descriptors (dense scan)
2. Construct visual word dictionary
3. Build spatial histograms
4. Train an SVM

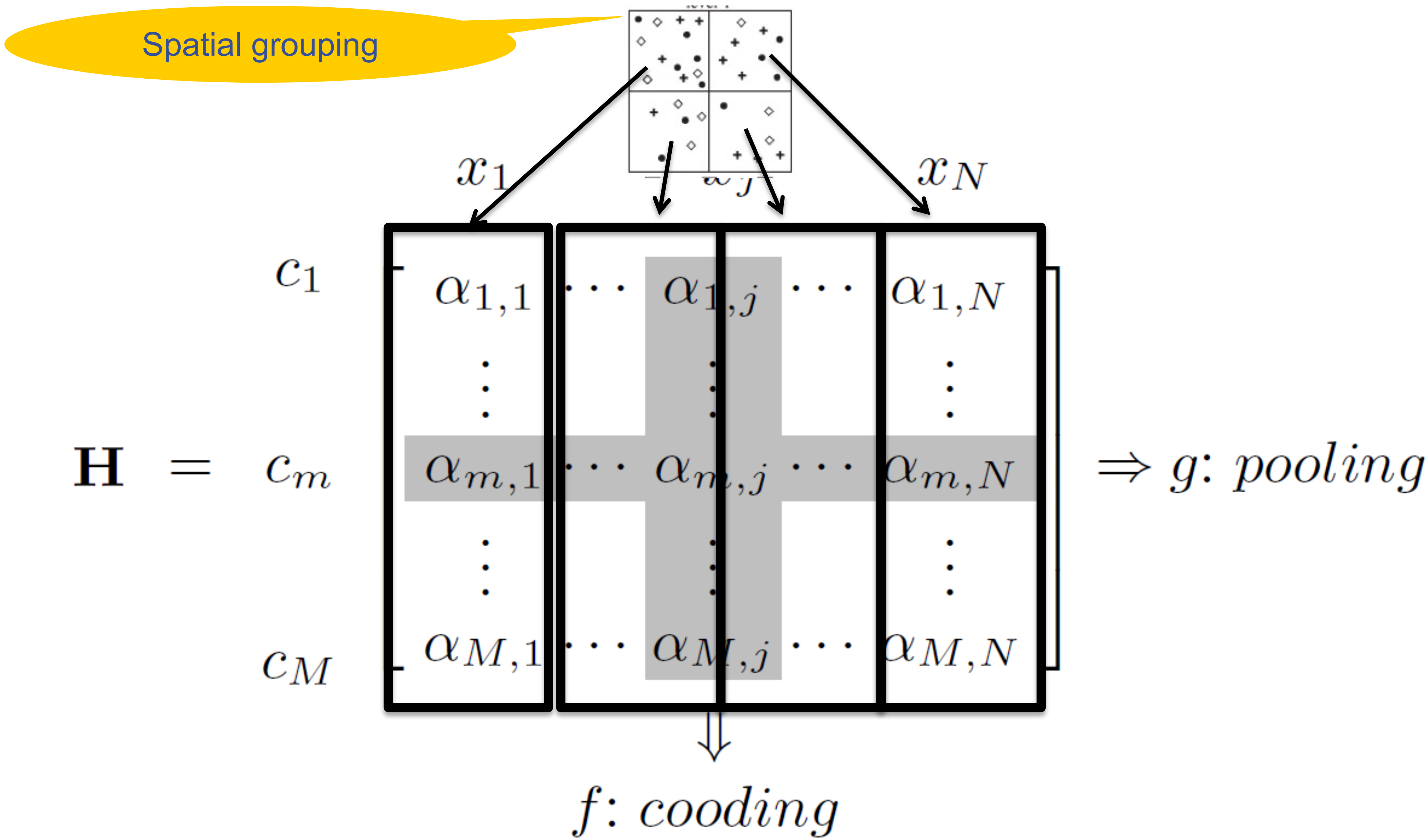


- Vector quantization
- Usually K-means clustering
- Vocabulary size (16 to 400)

Algorithm

1. Extract interest point descriptors (dense scan)
2. Construct visual word dictionary
3. Build spatial histograms
4. Train an SVM (with specific kernels)



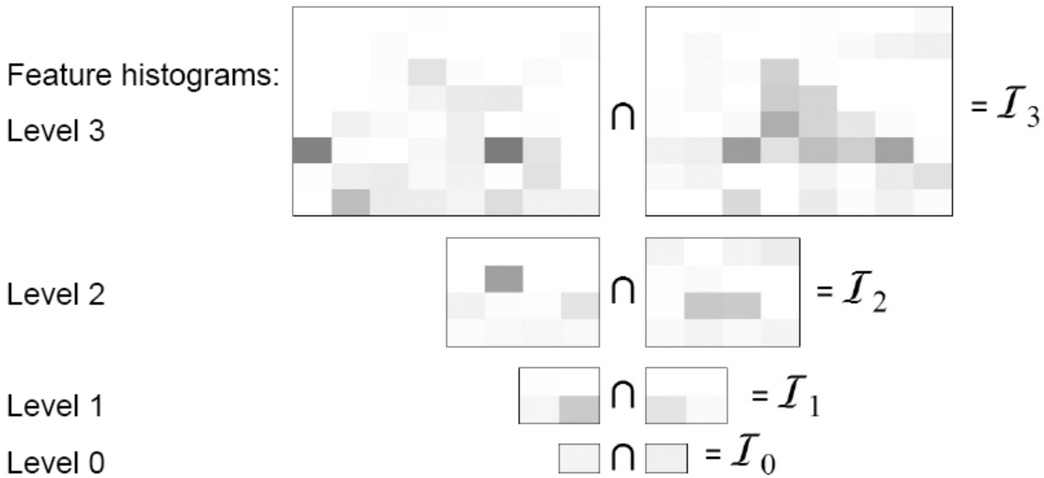


=> Break global invariance because of fixed pyramid

Algorithm

1. Extract interest point descriptors (dense scan)
2. Construct visual word dictionary
3. Build spatial histograms
4. Train an SVM

Similarity



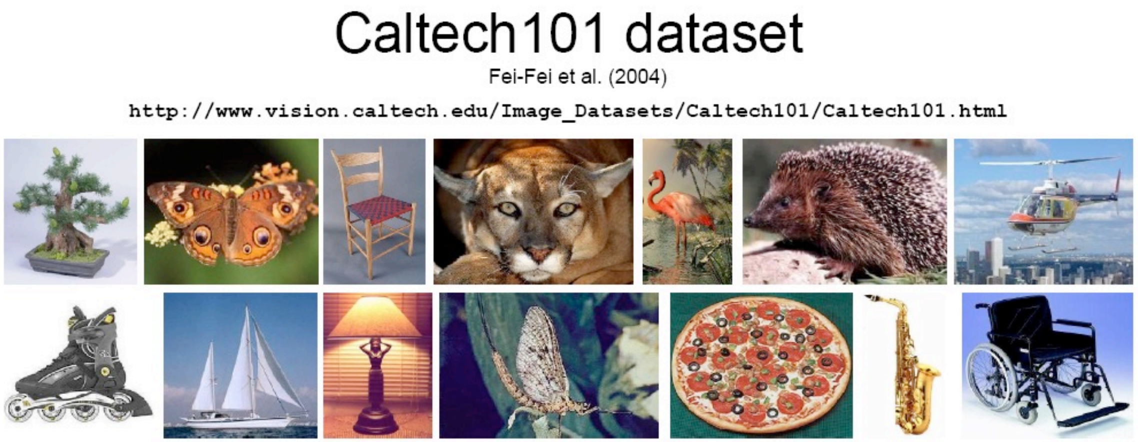
Total weight (value of *pyramid match kernel*): $\mathcal{I}_3 + \frac{1}{2}(\mathcal{I}_2 - \mathcal{I}_3) + \frac{1}{4}(\mathcal{I}_1 - \mathcal{I}_2) + \frac{1}{8}(\mathcal{I}_0 - \mathcal{I}_1)$

Algorithm

1. Extract interest point descriptors (dense scan)
2. Construct visual word dictionary
3. Build spatial histograms
4. **Train an SVM**

… Based on the kernel Similarity PMK

SPM Article: Results



- 3 Datasets
  - Nb images
  - Nb classes
- SVM multiclass !?!
- Eval protocol:
  - Train/test/val
    - 10 folds => average+standard deviation
    - Average per class
  - Nb of images per class in train (from 5 to 30)
- Parameter optimization
- Comparison to others

Multi-class SVM

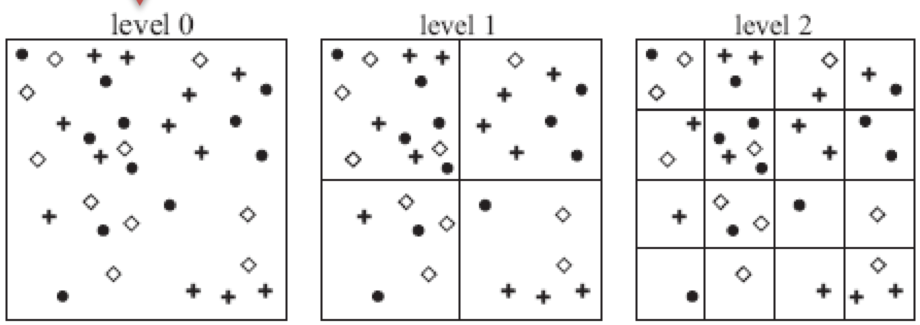
… By combining multiple two-class SVMs!

- One vs. All
  - Training: learn an SVM for each class vs. all others grouped in 1 class
  - Testing: apply each SVM to test example and assign to it the class of the SVM that returns the highest decision value
- One vs. One
  - Training: learn an SVM for each pair of classes
  - Testing: each learned SVM “votes” for a class to assign to the test example

SPM Article: Results on Caltech101

Multi-class classification results (30 training images per class)

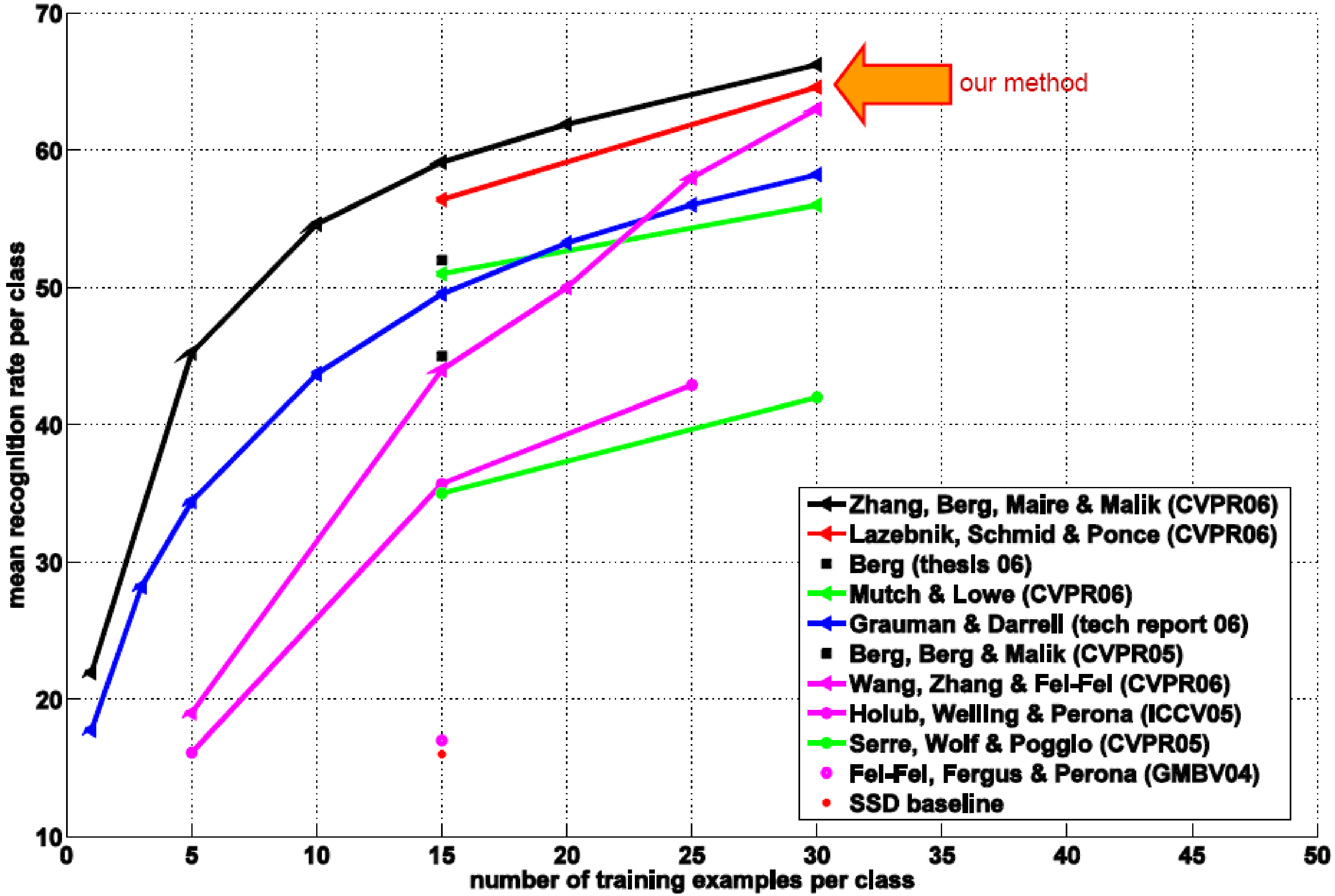
	Weak features (16)		Strong features (200)	
Level	Single-level	Pyramid	Single-level	Pyramid
0	15.5 $\pm$0.9		41.2 $\pm$1.2	
1	31.4 $\pm$1.2	32.8 $\pm$1.3	55.9 $\pm$0.9	57.0 $\pm$0.8
2	47.2 $\pm$1.1	49.3 $\pm$1.4	63.6 $\pm$0.9	**64.6** $\pm$0.8
3	52.2 $\pm$0.8	**54.0** $\pm$1.1	60.3 $\pm$0.9	64.6 $\pm$0.7



SPM Article

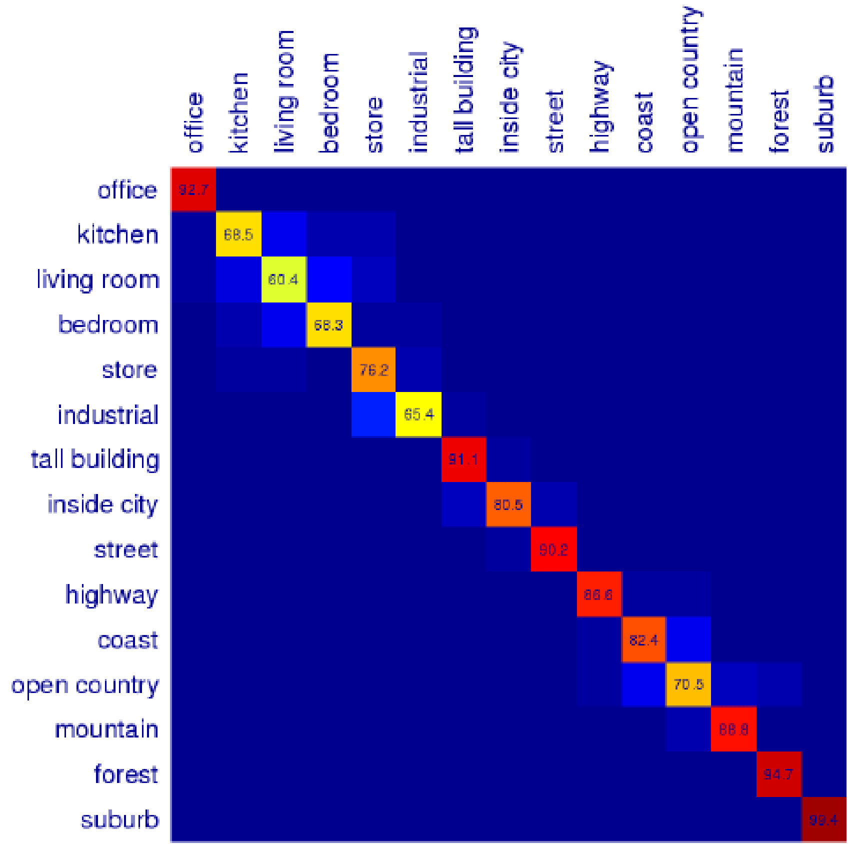
Caltech101 comparison

Zhang, Berg, Maire & Malik, 2006



SPM Article

Scene category confusions



Difficult indoor images


kitchen


living room


bedroom

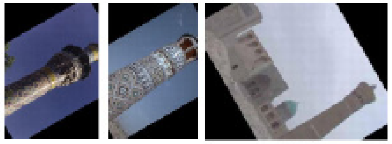
SPM Article

Caltech101 challenges

Top five confusions

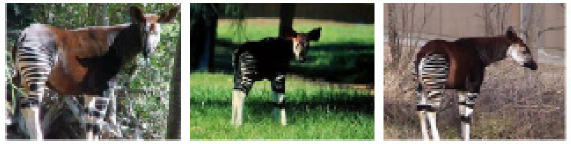
class 1 / class 2	class 1 mis-classified as class 2	class 2 mis-classified as class 1
ketch / schooner	21.6	14.8
lotus / water lily	15.3	20.0
crocodile / crocodile head	10.5	10.0
crayfish / lobster	11.3	9.1
flamingo / ibis	9.5	10.4

Easiest and hardest classes


minaret (97.6%)


windsor chair (94.6%)


joshua tree (87.9%)


okapi (87.8%)


cougar body (27.6%)


beaver (27.5%)


crocodile (25.0%)


ant (25.0%)

- Sources of difficulty: lack of texture, camouflage, “thin” objects, highly deformable shape

SPM Article

PMK/SIFT Best Categories (1-5)

100%

100%

99.7%

99.1%

98.2%

SPM Article

PMK/SIFT Best Categories (6-10)

97.7%

97.4%

95.7%

95.3%

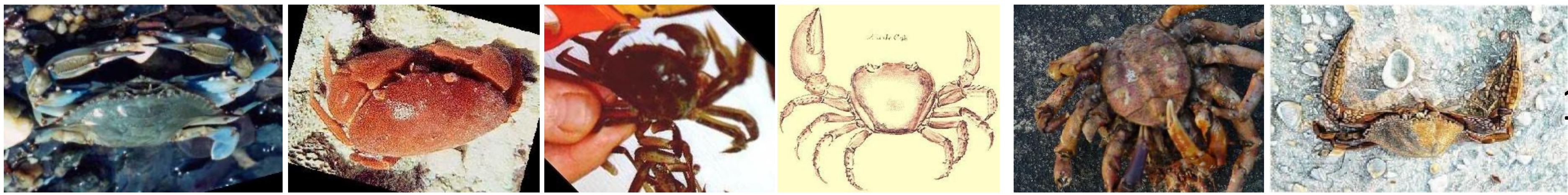
95.2%

SPM Article

PMK/SIFT 5 Worst Categories

7.7%

11.2%



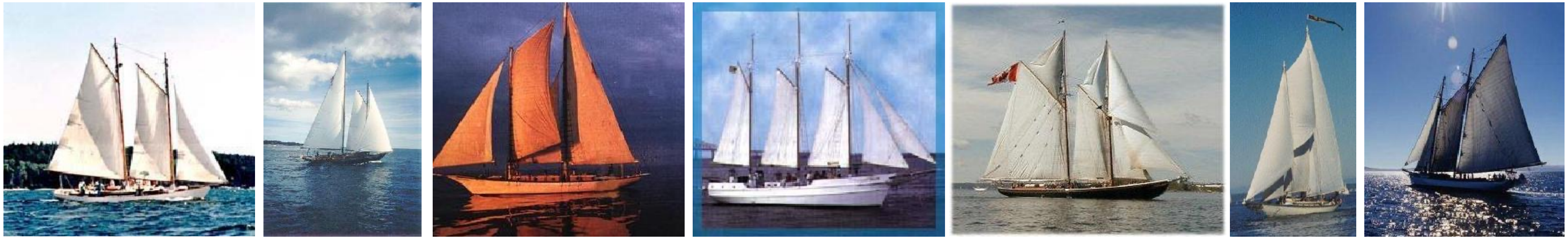
11.5%

11.8%

12.3%

SPM Article

PMK/SIFT Most Confused Category Pairs



schooner

A fore-and-aft rigged sailing vessel having at least two masts, with a foremast that is usually smaller than the other masts.

ketch

A two-masted fore-and-aft-rigged sailing vessel with a mizzenmast stepped aft of a taller mainmast but forward of the rudder.

SPM Article

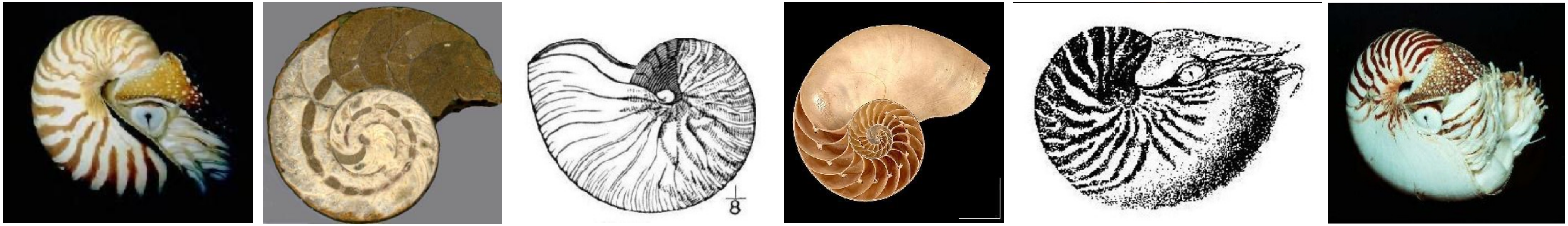
PMK/SIFT Most Confused Category Pairs

Gerenuk (**antilope girafe** ou **gérénuk)**

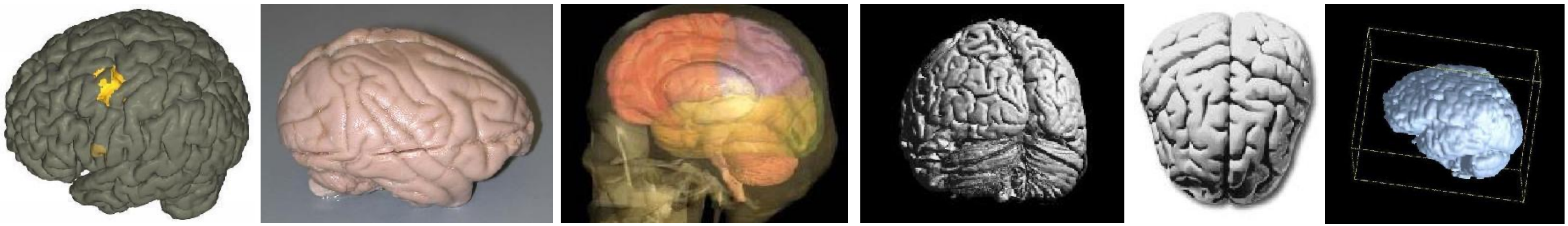
kangaroo

SPM Article

PMK/SIFT Most Confused Category Pairs



nautilus



brain