Image processing for Earth Observation

Image transformations

2. Spatial indices

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Reminder: In the next two weeks

- We will study a number of information extraction techniques
  - spectral indices: enhance spectral relations between the bands of a pixel
  - spatial indices: extract information about spatial relationships
- We will also discuss how to deal with the increase in number of variables and see some data reduction techniques

More precisely

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We will talk about how to describe local image appearance

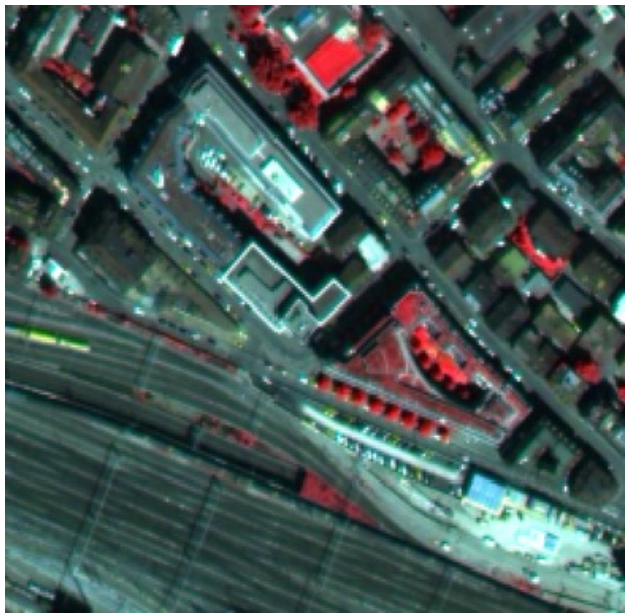
- Spatial supports
- Families of descriptors

What is appearance description?

- Images show ambiguous appearance, especially at pixel level.
- Color / spectra is often not discriminative.
- E.g. in RGB images.
- Can you tell me which land coverage are these?

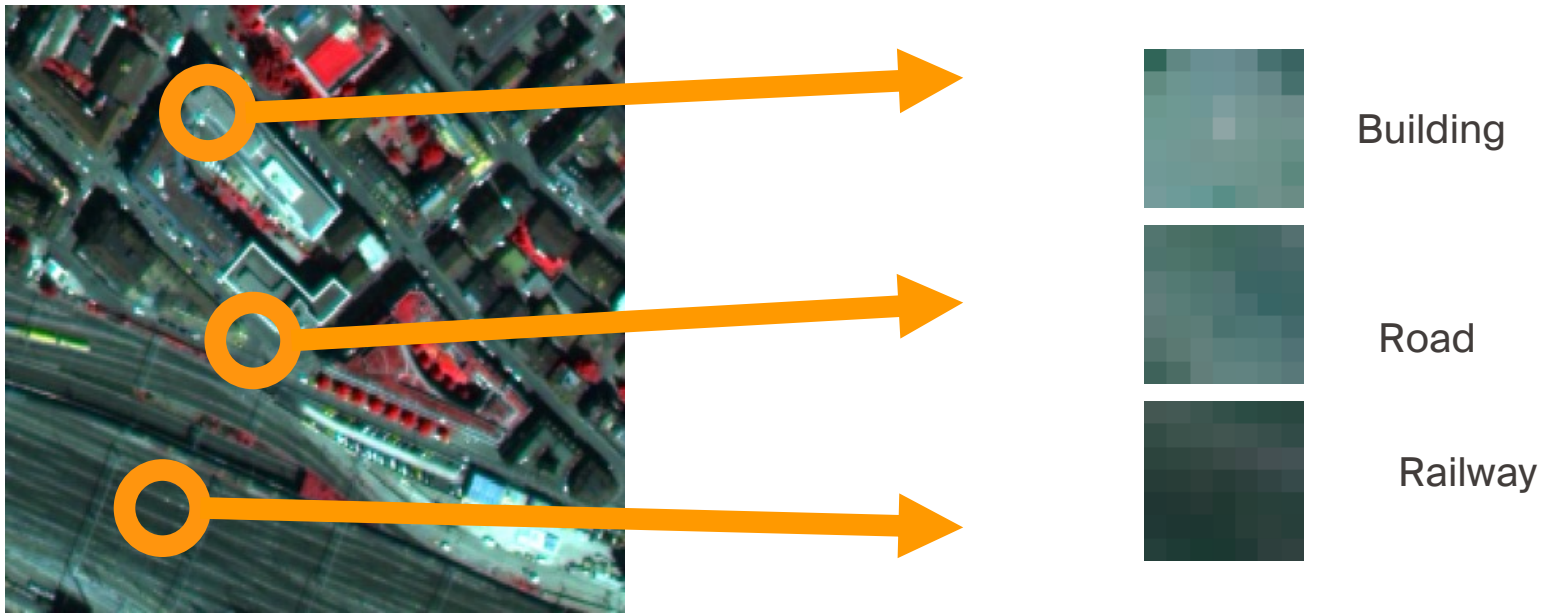
What is appearance description?

- This is particularly true at very high spatial resolution.
- Seeing the full image, you start to have an idea.



What is appearance description?

- But if you add spatial context and localisation, ambiguity is resolved!



Why?

- Let's consider the input pixel space
- Aerial / sat VHR imagery holds often little spectral information
- Same color /spectral signature is observed for different classes

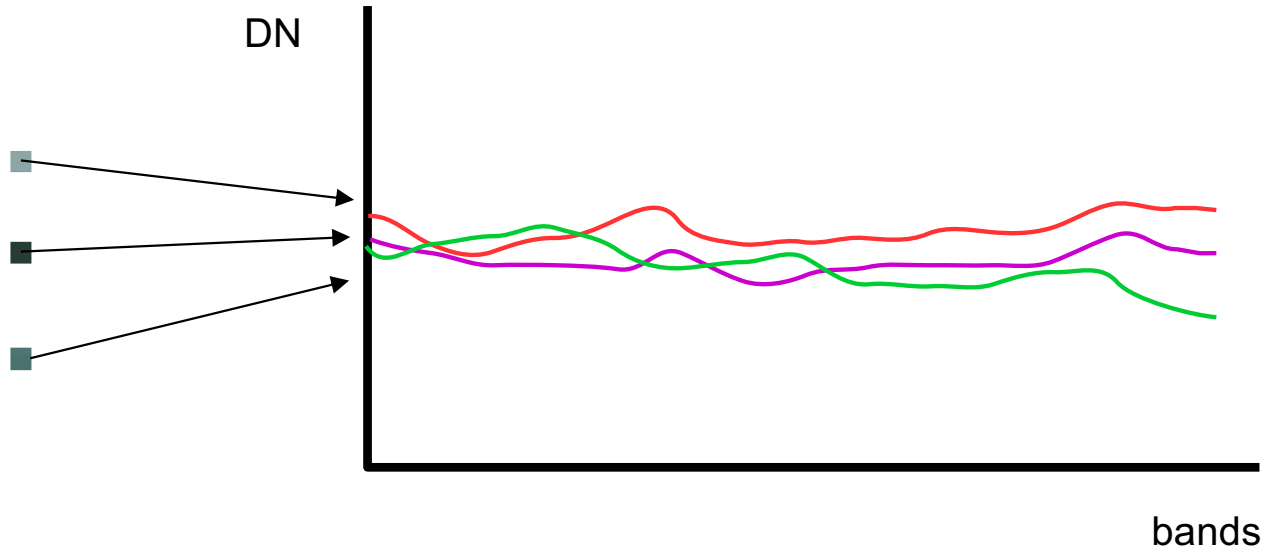


Image processing pipeline

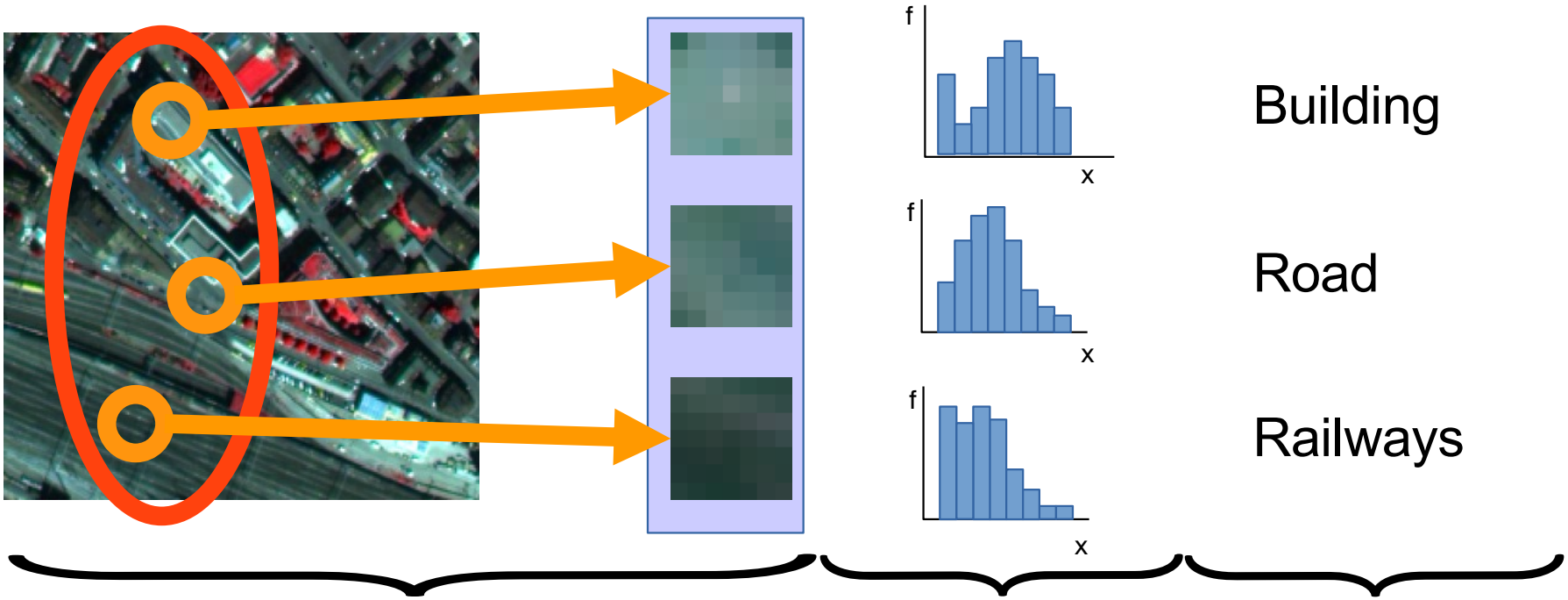
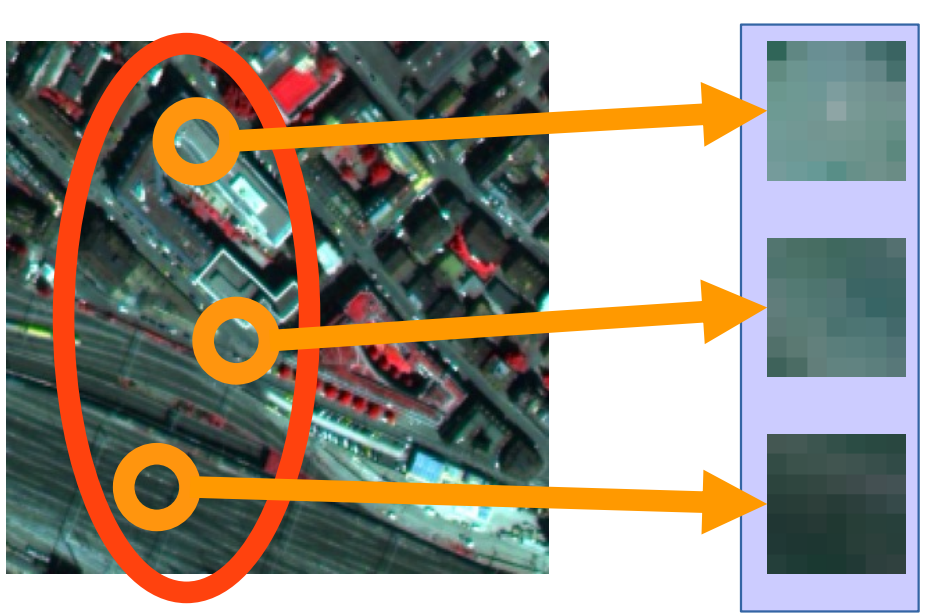
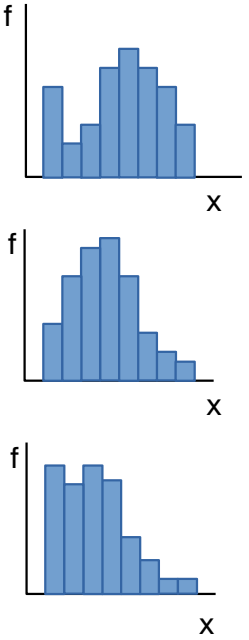


Image processing pipeline





Building

Road

Railways

Image representation
→ SPATIAL SUPPORT

Image representation
→ APPEARANCE DESCRIPTOR

Semantic class
→ CLASSIFIER
→ INFERENCE

THIS COURSE

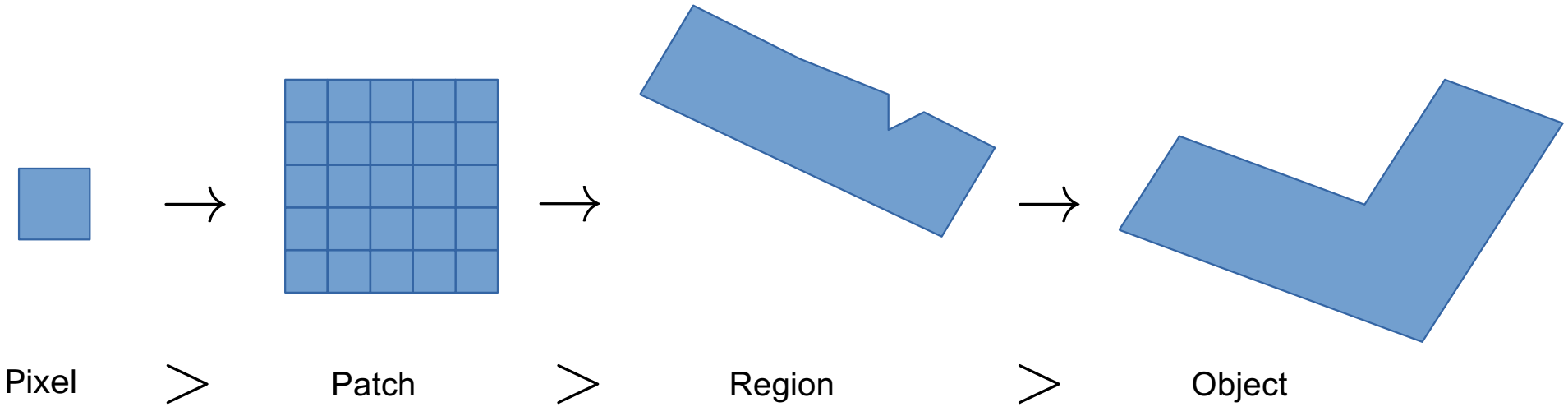
NEXT COURSES

EPFL

Spatial supports

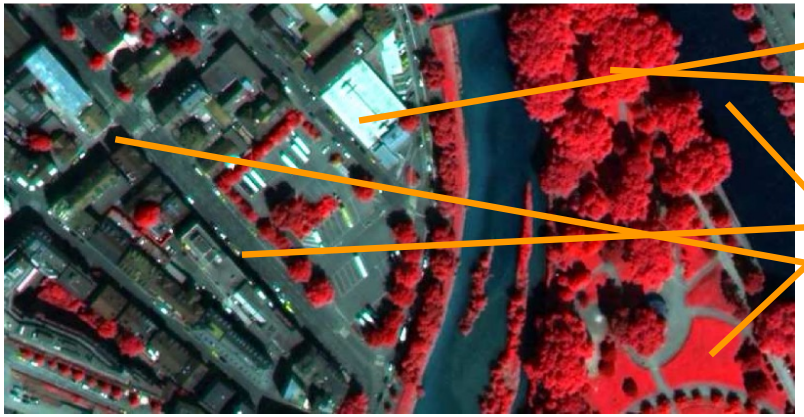
Spatial support types

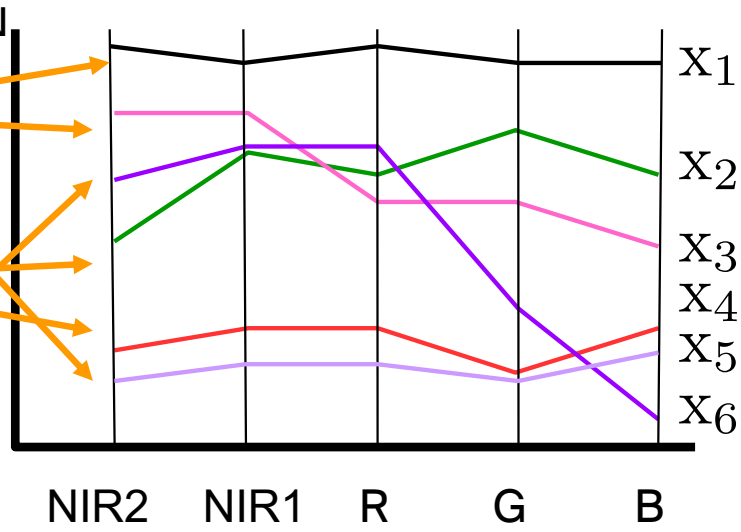
- Defines *spatial boundaries* on which to compute descriptors
- Ideally, provide spatial boundaries *as close as possible to those of the objects*
- *Large enough* to contain relevant info, *tight enough* to preserve image resolution



1. Pixel

- Smallest possible mapping unit
- No spatial information
- Low(est)-level descriptor
- “Vector” of spectral information





$$\mathbf{X} = [\mathbf{x}_1^\top \dots \mathbf{x}_N^\top]^\top$$

$$\mathbf{X} \in \mathbb{R}^{N \times d}$$

$$\mathbf{x}_i = [x^{\mathrm{NIR2}} \quad x^{\mathrm{NIR1}} \quad x^{\mathrm{R}} \quad x^{\mathrm{G}} \quad x^{\mathrm{B}}]$$

1. Pixel  pros and cons

✓ Very simple to implement and run

✓ When the spectral information is rich, results can be good

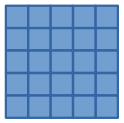
→ e.g. image spectroscopy channels + normalized band ratios

✖ No higher level semantic concepts

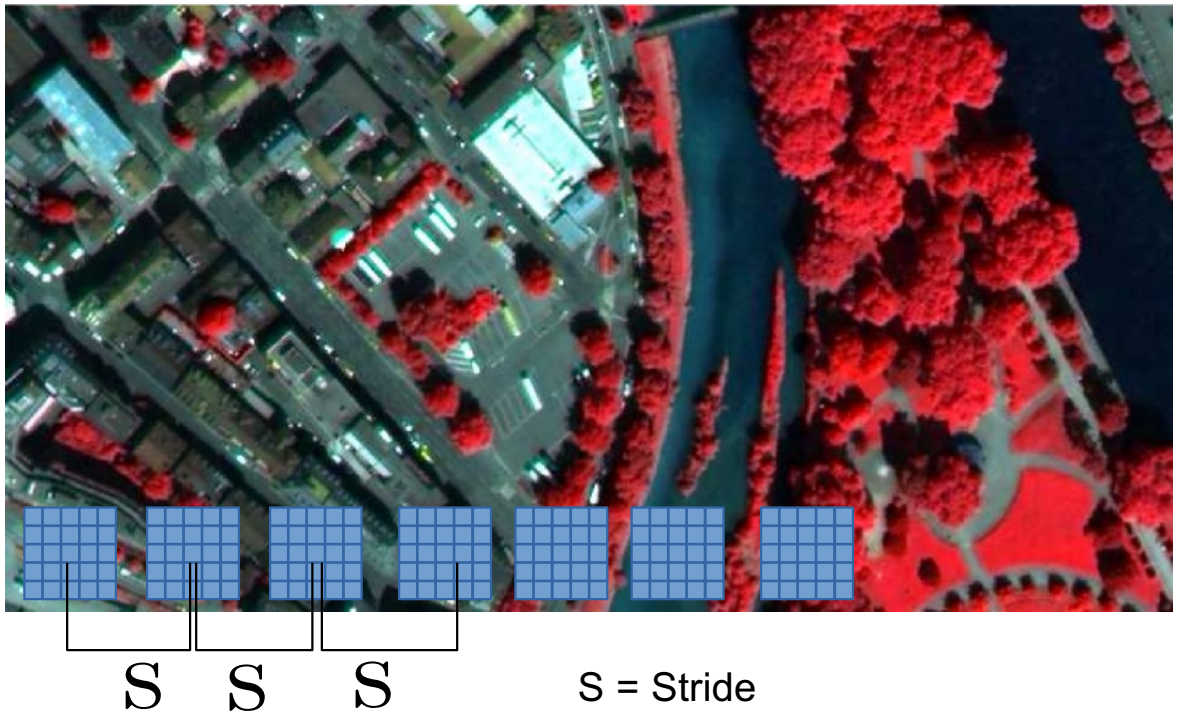
→ parking, highway, tar rooftop, railway banks = “asphalt”

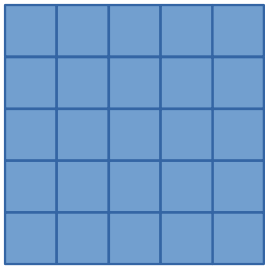
✖ Lots of data samples to be processed

→ e.g. 2000 x 2000 x 5 image = $4*10^6$ samples and $2*10^7$ floats

2. Patch 

- Square “windows”, simplest possible spatial information
- For each patch, a set of descriptors (e.g. spatial statistics) is extracted
- 2 hyperparameters: stride and size





$P \times P$

Size

2. Patch

The filter is defined by a *function* taking as input all the pixels contained in the image

$$\mathbf{x} \mapsto f(\mathbf{x}) = \mathbf{x}'$$
$$f : \mathbb{R}^{P \times P} \rightarrow \mathbb{R}$$

E.g. the spatial average

$$f(\mathbf{x}) = \frac{1}{P^2} \sum_{p=1}^{P^2} \mathbf{x}_p$$

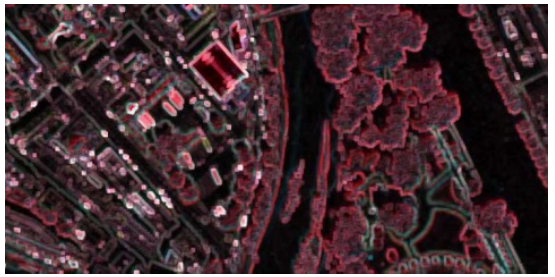
(or expressed as a convolution:

$$f(\mathbf{x}) = \mathbf{W}_p \star \mathbf{x}$$
$$\mathbf{W}_p = \frac{1}{P^2}$$

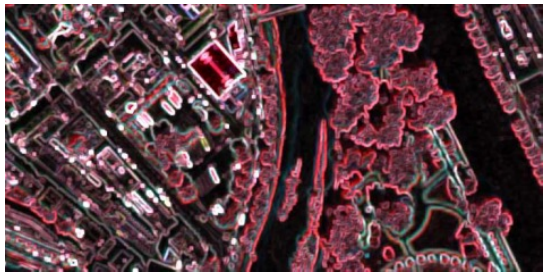
Spatial statistics on patches

- By using $S = 1$, we create an image with the same spatial size of the original but with “new” signals
- Each pixel is now explicitly dependent on neighbors
- Compute descriptors related to local moments
- Family of descriptors to use usually problem / domain specific

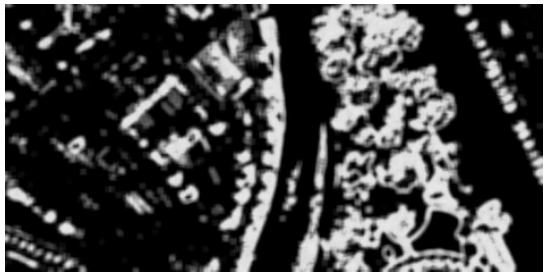
$$\mathbf{X} = [\mathbf{x}_1^\top \dots \mathbf{x}_N^\top]^\top$$



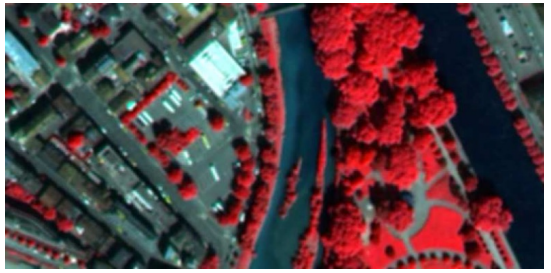
St. dev



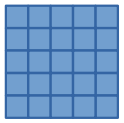
Range



Energy



Average

2. Patch  pros and cons

- ✔ Very simple to implement functions taking as inputs square patches
- ✔ Lots of descriptors can be stacked (in *d*-dimensional arrays) and processed as *standard images*
- ✔ Off the shelf implementations in many software
- ✖ Object boundaries not preserved by spatial statistics
- ✖ The spatial extent of the filtered image is the same (stride = 1), or the resolution degraded (stride > 1)

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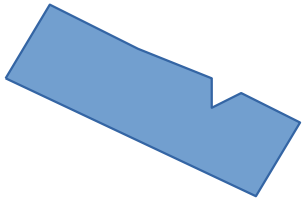
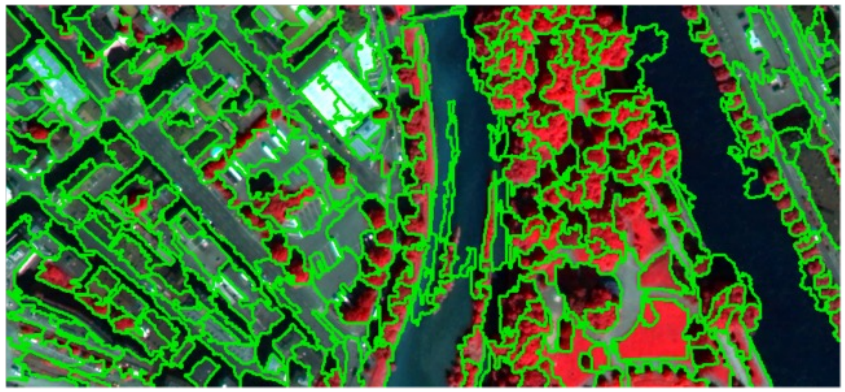
3. Regions / superpixels



- Edges of regions correspond to gradients in image
- For each region, a set of descriptor is extracted
- Many hyperparameters, depending on method to be used (thresholds, min size, smoothing, etc)

Each region contains *similar* pixels

Decompose the image into *nonoverlapping* regions



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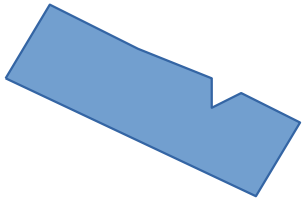
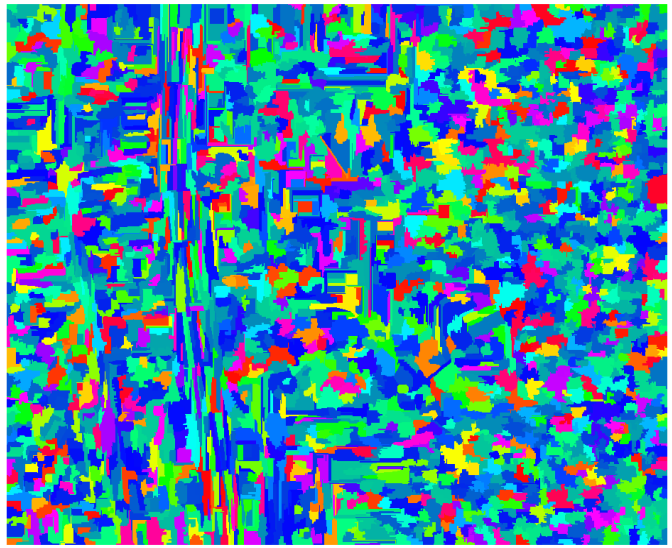
3. Regions / superpixels

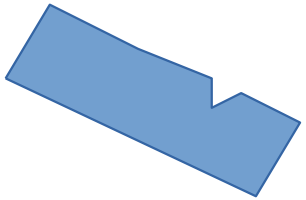


- Cluster pixels in groups that are
  - Nearby
  - Of similar spectral properties

Superpixels (each color is a SP)



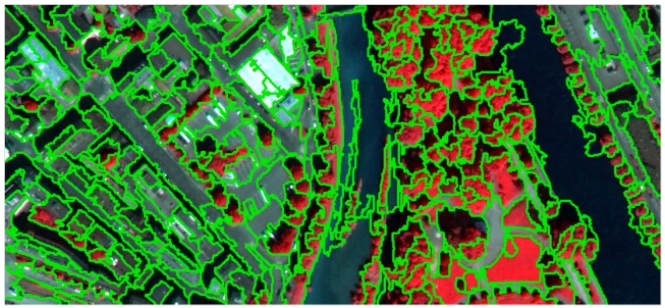
3. Regions / superpixels



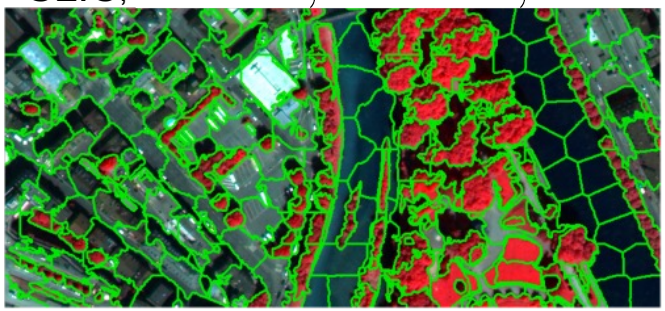
- Different systems producing such decompositions exist
- Each region is uniform under some criteria (color variance, texture, homogeneity, etc.)
- Compute discriminative / informative descriptors from each region
- Problem decomposed in N^r regions, and $N^r << N$

(here ~200 to 500 instead of 10E6)

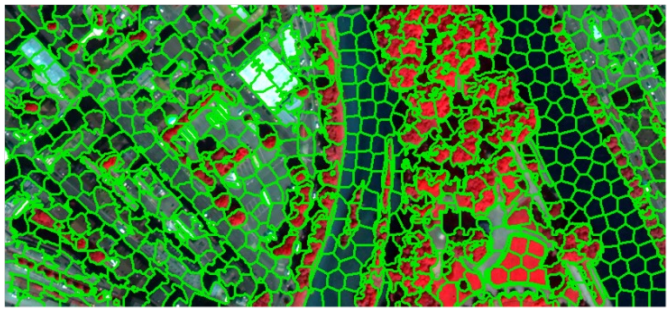
Felzenszwalb and Huttenlocher



SLIC, $\sigma = 0.5$, $\tau = 500$, $m = 20$



SLIC, $\sigma = 0.5$, $\tau = 500$, $m = 40$



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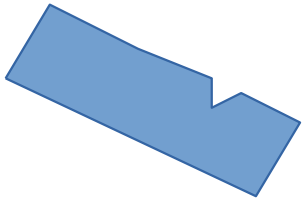
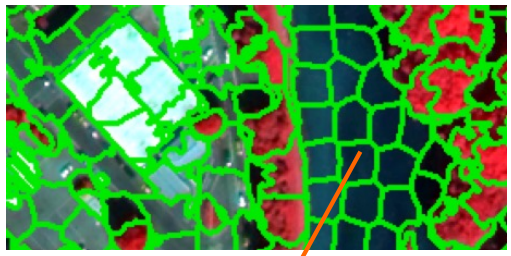
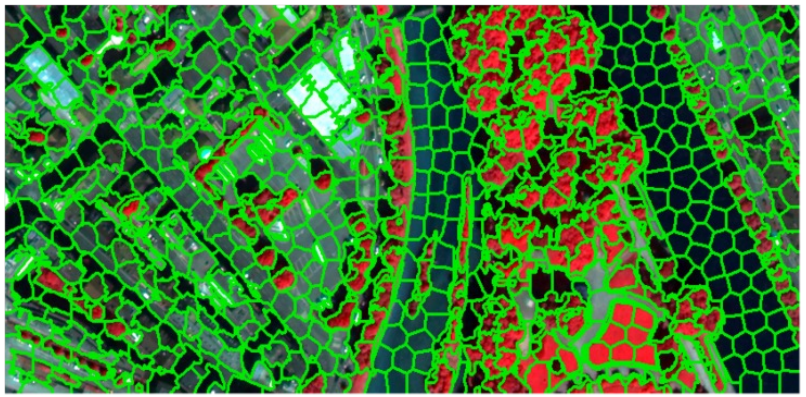
3. Regions / superpixels

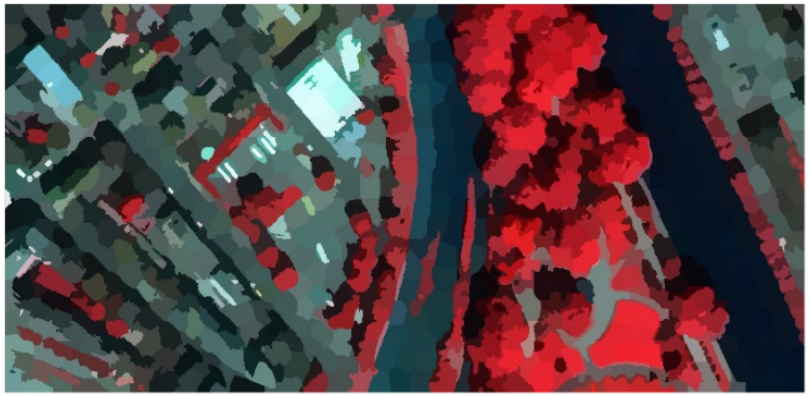


- Same reasoning as for “patch” descriptors, but the size of each region $|R|$ is different!

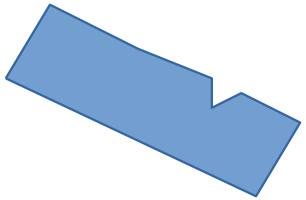


$$f(\mathbf{x}) = \frac{1}{|R|} \sum_{p=1}^{|R|} \mathbf{x}_p$$



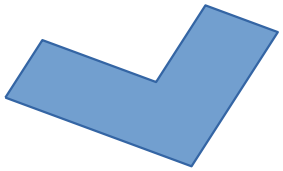


3. Regions /spix pros and cons



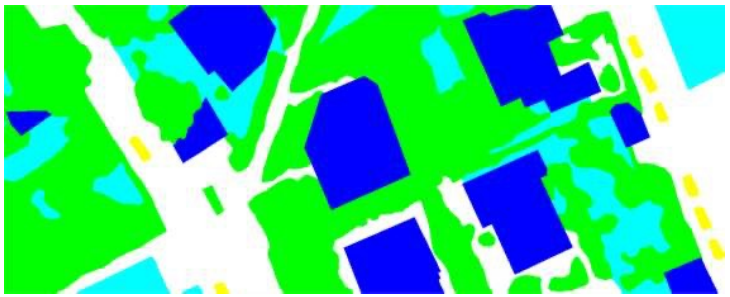
- ✔ Natural border of the objects composing the image are preserved
- ✔ Size of the problem greatly reduced without loss of resolution (label assumed to be homogeneous in each region)
- ✔ Off the shelf libraries to compute regions
- ✖ Regions are not representative for real *objects* (1 object = 1 or + regions)
- ✖ Errors in region computation cannot be recovered in later steps → regions become the image “atomic regions”

4. Objects

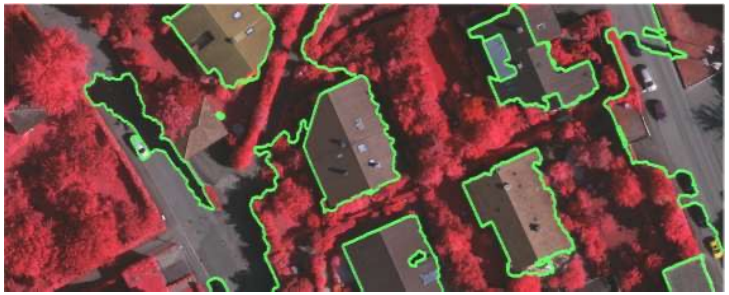


- Edges correspond to *real* object boundaries
- Each object has fully described appearance
- Object segmentation is usually harder than classifying all pixels!

+



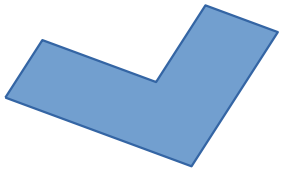
Objects reference



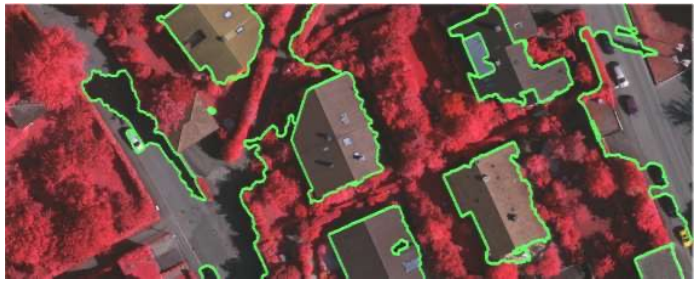
"Building" proposals

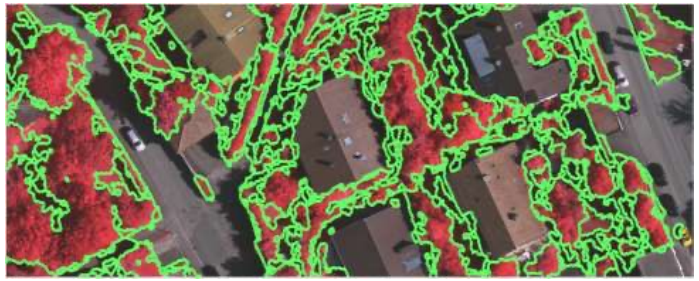
"Car" proposals

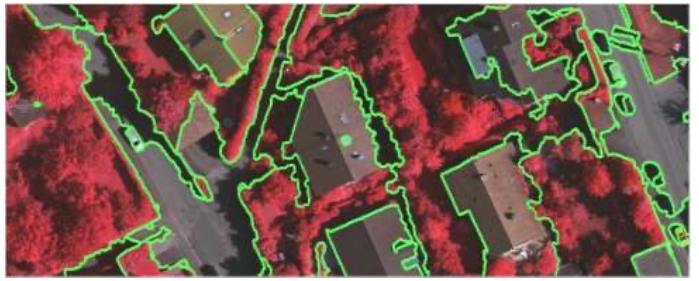
4. Objects



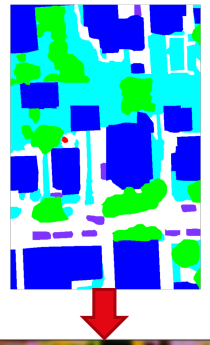
- Usually obtained by merging regions
- Ideally, an image image decomposed perfectly has O < R << N
- It is common to work on *object proposals* O^p, and to select among them the ones best scored by our models
- Problem decomposed in O^p objects, and $R < O^p << N$
- *Information contained in O is semantically meaningful, while on pixel or regions it is not!*







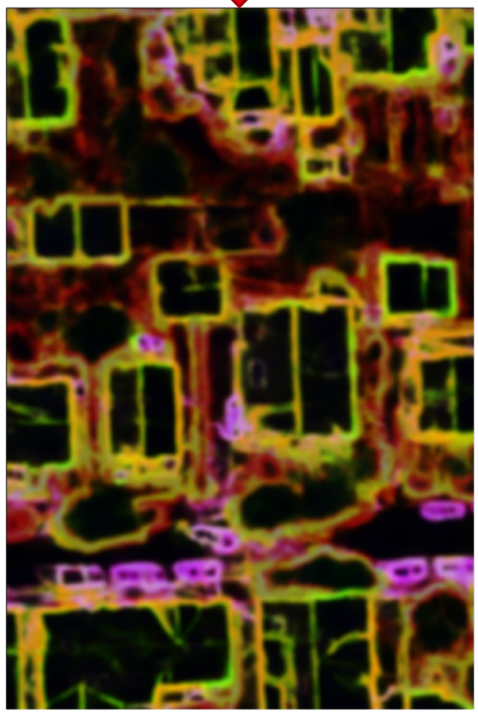
Creating object proposals



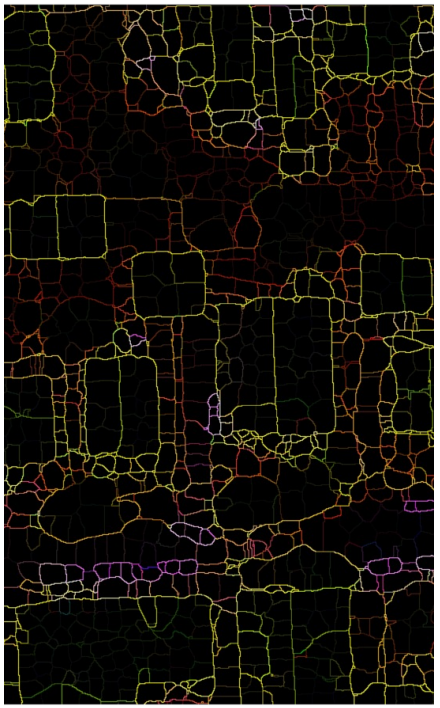
Object proposals

Image

Superpixels

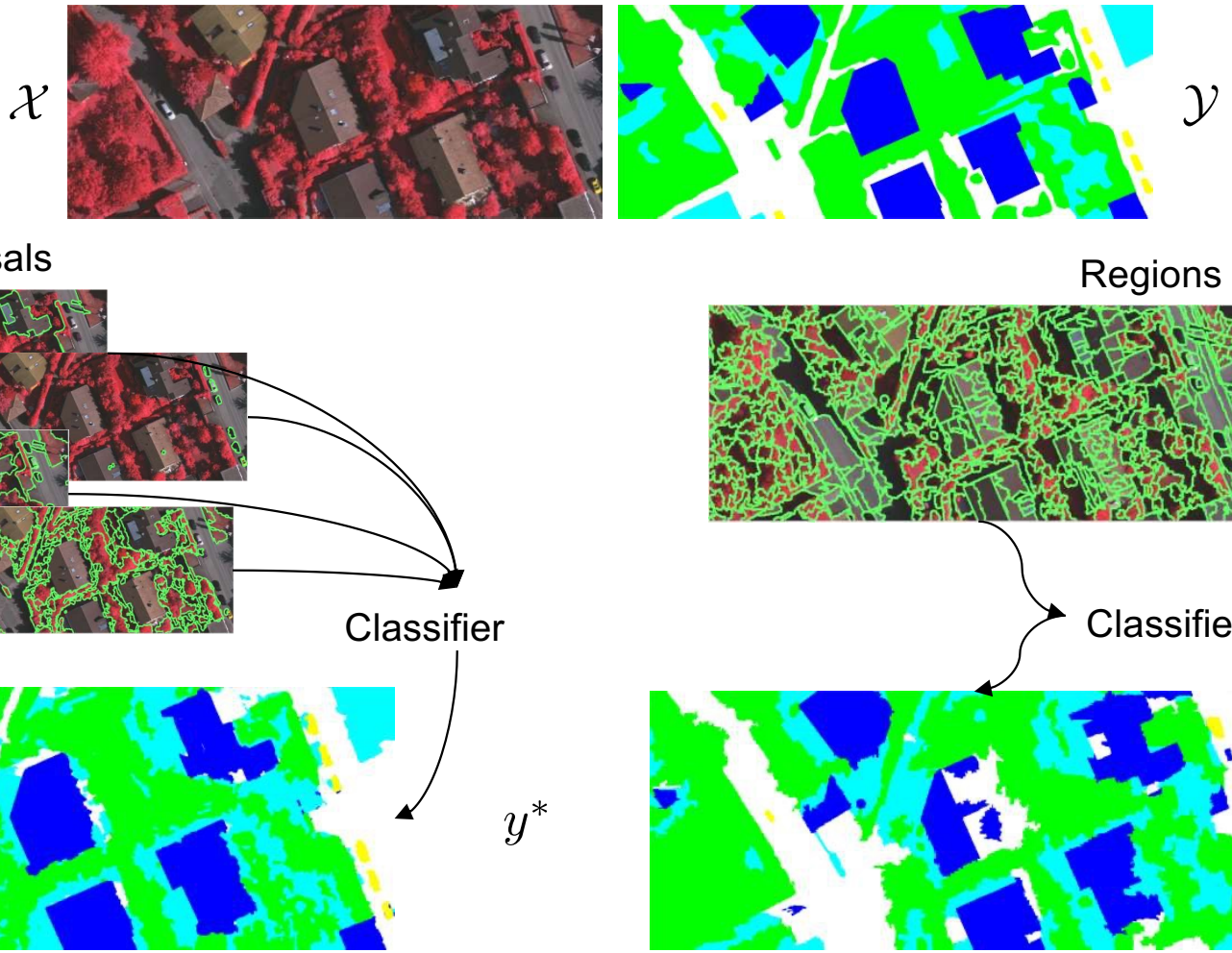


Class-specific borders
(learned with machine learning model)

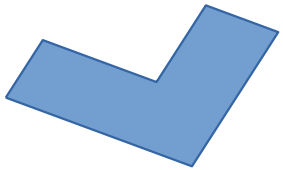


M. Volpi and D. Tuia. Deep multi-task learning for a geographically-regularized semantic segmentation of aerial images. *ISPRS J. Int. Soc. Photo. Remote Sens.*, 144:48–60, 2018.

Regions vs objects



4. Objects pros and cons



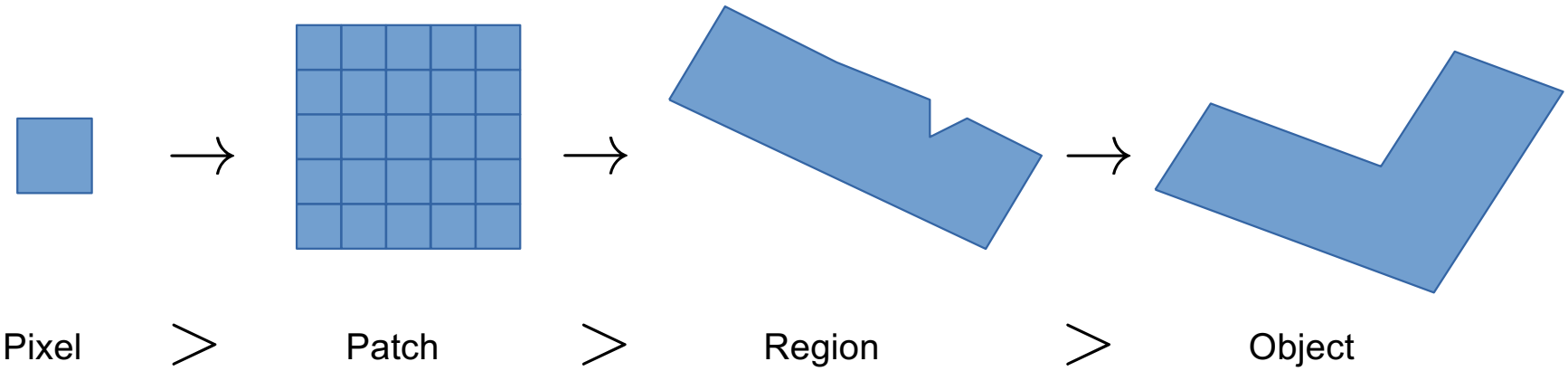
- ✔ Natural edges AND “semantic edges” are preserved, if they correspond
- ✔ Objects are not homogeneous in color, but their label is! (semantic + sensory gap)
- ✔ Allows to learn exhaustive and informative aspects of our data

  → e.g. rooftops are composed by tar, concrete, chimneys, windows, veg.
- ✖ Objects can be trivially decomposed in regions, the opposite is hard
- ✖ Most of the time, finding objects is a very difficult task since size and shape is varying significantly across classes

Which one to chose?

Always study the problem:

- If spectral information is sufficient → go pixel
- If spatial resolution is not a concern → patches
- If unsure → regions
- If good geometry and you're good with statistical models → object



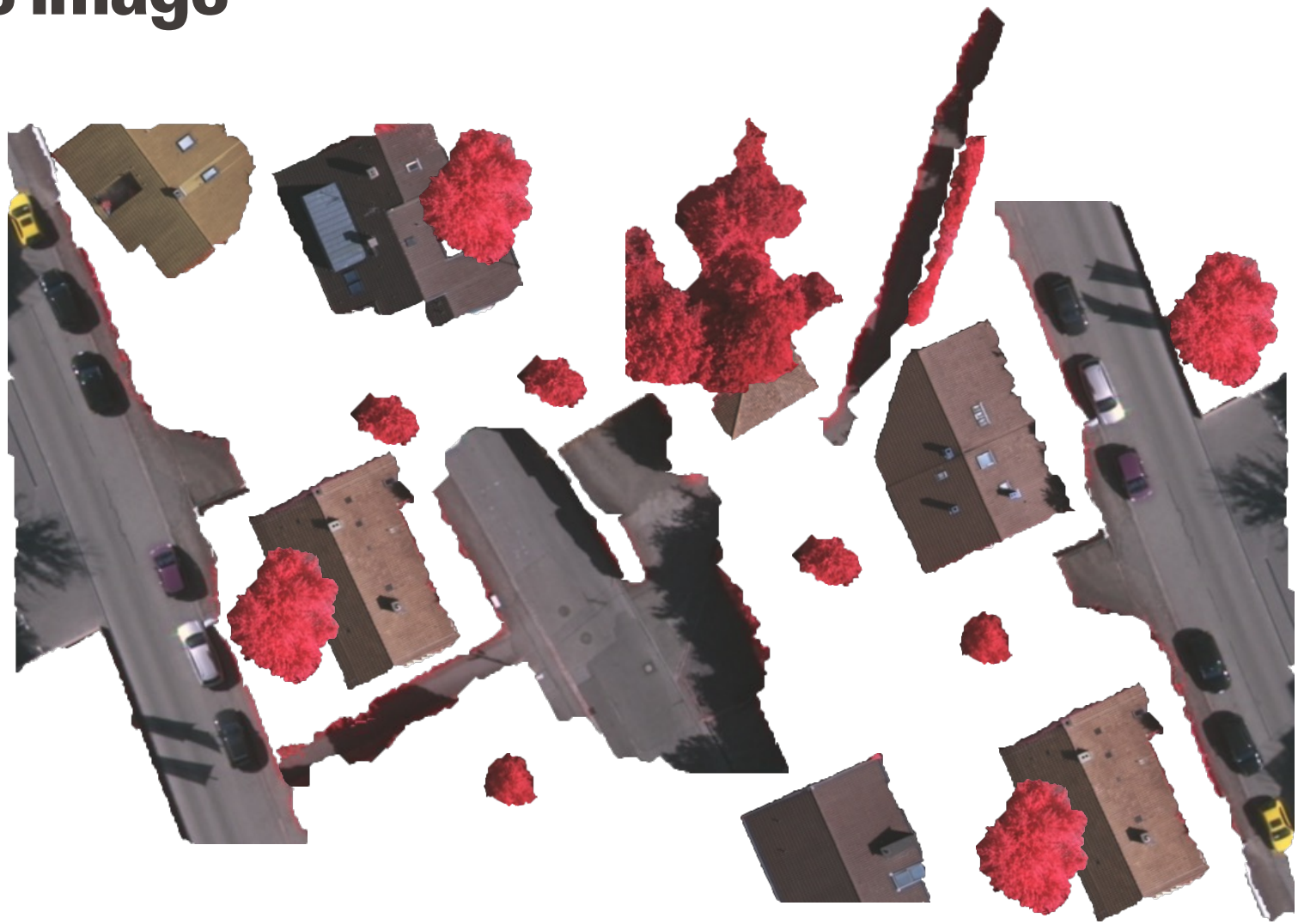
Appearance descriptors

What to extract? And why?

Images are spatial entities, and so is their content

- Color and spatial arrangement of colors (e.g. texture, gradients, orientations) are equally important to label and detect things
- Important aspects can be approximated by simple statistics (generally first [e.g. mean, histogram] and second moments [e.g. standard deviation, variance])

From the image space...



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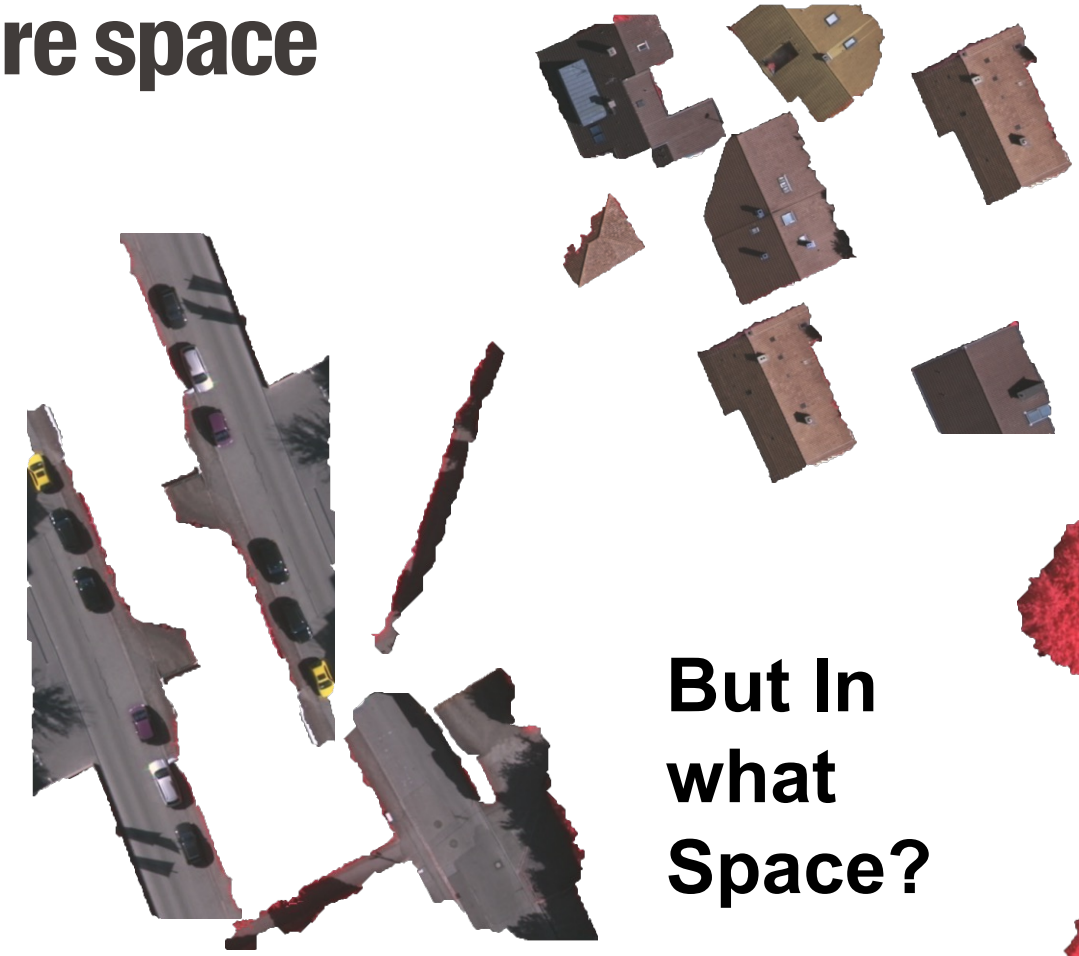
To a meaningful feature space



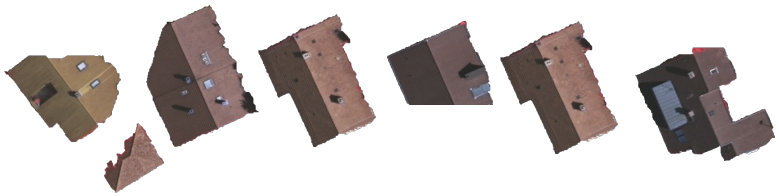
But In what Space?

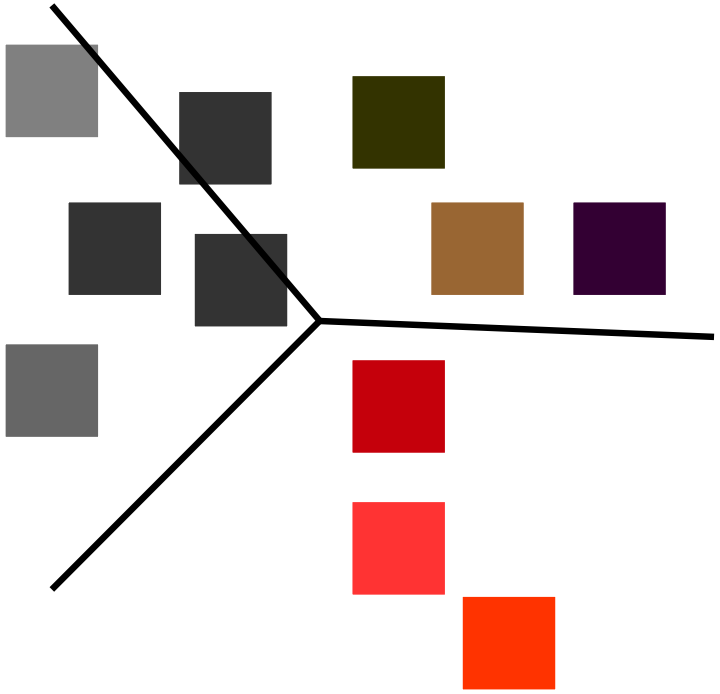
Example 1: Average color per region

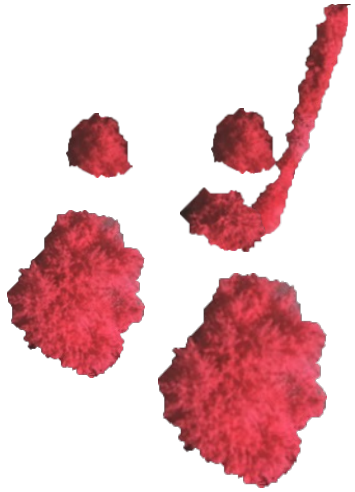
R is the set containing all the pixels *p* in R

$$\bar{\mathbf{x}} = \frac{1}{|R|} \sum_{p=1}^{|R|} \mathbf{x}_p$$

$$\bar{\mathbf{x}} = [\bar{R} \quad \bar{G} \quad \bar{B}]$$





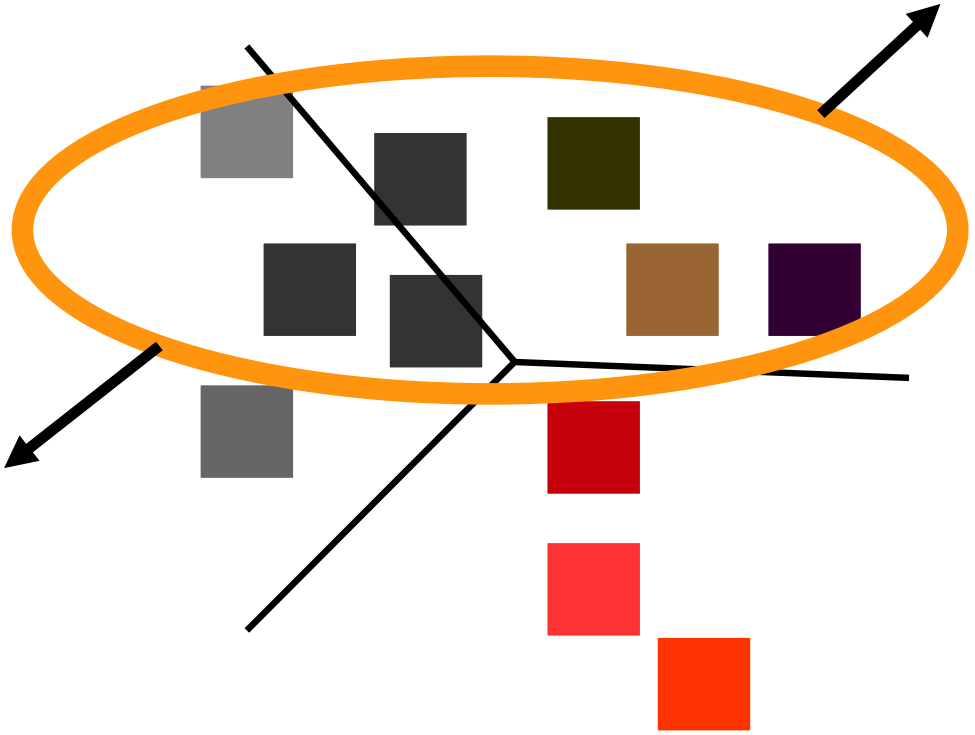


Example 1: Average color per region

$$\bar{\mathbf{x}} = \frac{1}{|R|} \sum_{p=1}^{|R|} \mathbf{x}_p$$

$$\bar{\mathbf{x}} = [\bar{R} \quad \bar{G} \quad \bar{B}]$$

The average color is not discriminative enough between objects with similar colors!



It tells little about texture or spatial arrangement!

Appearance descriptors

- Encode *discriminative* statistical properties of the patch / regions / objects
- Try to encode what you see, what makes a road a “road” and a rooftop a “rooftop” ?
- Most of the time, stack together all the information you can!

$$\mathbf{x}_i = [\mathbf{x}_i^{\text{av}} \quad \mathbf{x}_i^{\text{std}} \quad \mathbf{x}_i^{\text{entr}} \quad \mathbf{x}_i^{\text{hist}} \quad \dots]$$

i is the index of the patch / region / object.

Example descriptors: average color in the region

$$\mathbf{x}_i = [\mathbf{x}_i^{\text{av}} \quad \mathbf{x}_i^{\text{std}} \quad \mathbf{x}_i^{\text{entr}} \quad \mathbf{x}_i^{\text{hist}} \quad \dots]$$

(information about average spectral signature / color)

$$\bar{\mathbf{x}} = \frac{1}{|R|} \sum_{j=1}^{j \in R} \mathbf{x}_j$$

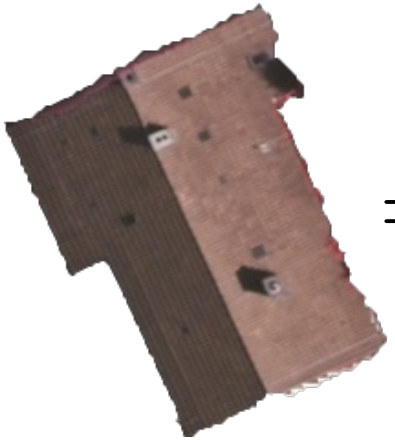
$$= [x_i^{\text{av,R}} \quad x_i^{\text{av,G}} \quad x_i^{\text{av,B}}]$$

Example descriptors: standard deviation in the region

$$\mathbf{x}_i = [\mathbf{x}_i^{\text{av}} \quad \mathbf{x}_i^{\text{std}} \quad \mathbf{x}_i^{\text{entr}} \quad \mathbf{x}_i^{\text{hist}} \quad \dots]$$

(information about variance of the color, in each object)

$$\mathbf{x}_i^{\text{std}} = \sqrt{\frac{1}{|R|}\sum_{j \in R}(\mathbf{x}_j - \bar{\mathbf{x}})^2}$$



$$= [x_i^{\text{std,R}} \quad x_i^{\text{std,G}} \quad x_i^{\text{std,B}}]$$

Example descriptors: entropy in the region

$$\mathbf{x}_i = [\mathbf{x}_i^{\text{av}} \quad \mathbf{x}_i^{\text{std}} \quad \mathbf{x}_i^{\text{entr}} \quad \mathbf{x}_i^{\text{hist}} \quad \dots]$$

(information about variance and "disorder" of color values, spatially)

$$\mathbf{x}_i^{\text{entr}} = -\sum_{j=1}^{\text{nbins}} p_j \log(p_j)$$

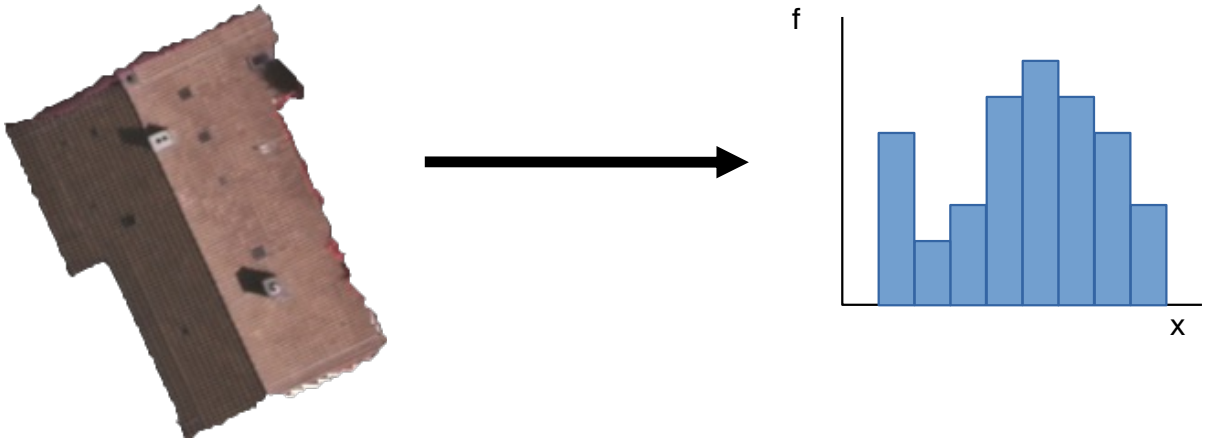
p_j is the histogram of the region, with colors divided in bins

$$= [x_i^{\text{entr,R}} \quad x_i^{\text{entr,G}} \quad x_i^{\text{entr,B}}]$$

Example descriptors: histogram of colors in the region

$$\mathbf{x}_i = [\mathbf{x}_i^{\text{av}} \quad \mathbf{x}_i^{\text{std}} \quad \mathbf{x}_i^{\text{entr}} \quad \mathbf{x}_i^{\text{hist}} \quad \dots]$$

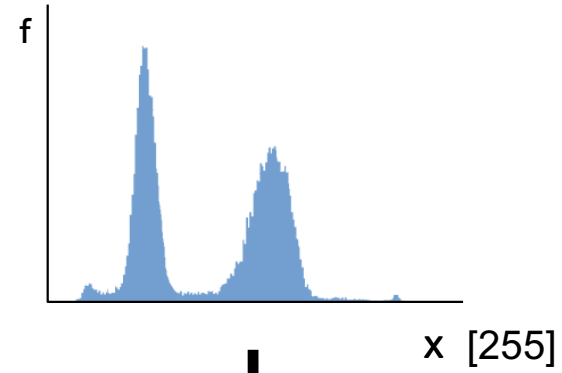
Distribution of the color (information frequency of given color ranges)



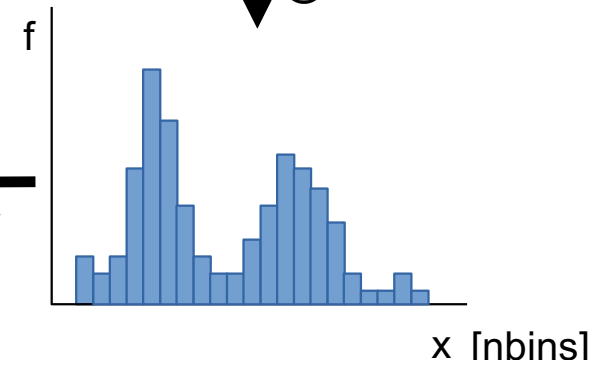
Building the histogram

Count DN occurrences

Per each channel



Binning (resampling)



Vectorization

(1 such vector per color channel !)

$$\mathbf{x}_i^{\text{hist}} = [\mathbf{x}_i^{\text{hist,R}} \quad \mathbf{x}_i^{\text{hist,G}} \quad \mathbf{x}_i^{\text{hist,B}}]$$

$$\mathbf{x}_i^{\text{hist,C}} = [f_i^1 \quad f_i^2 \quad \dots \quad f_i^{\text{nbins}}]$$

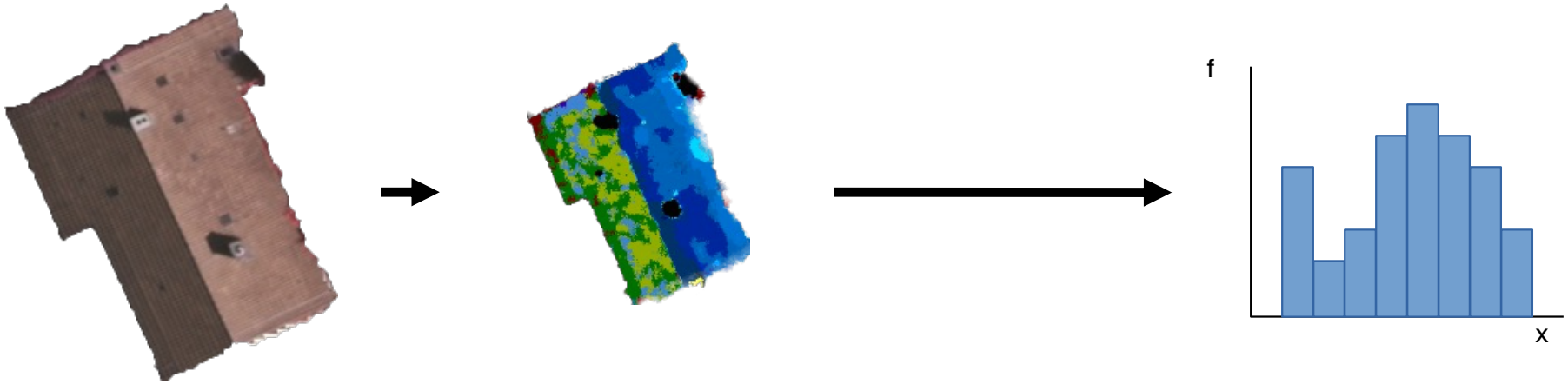
$$\mathbf{x}_i^{\text{hist,C}} \leftarrow \sum f = 1$$

e.g. $[0.01 \quad 0.04 \quad \dots \quad 0.1]$

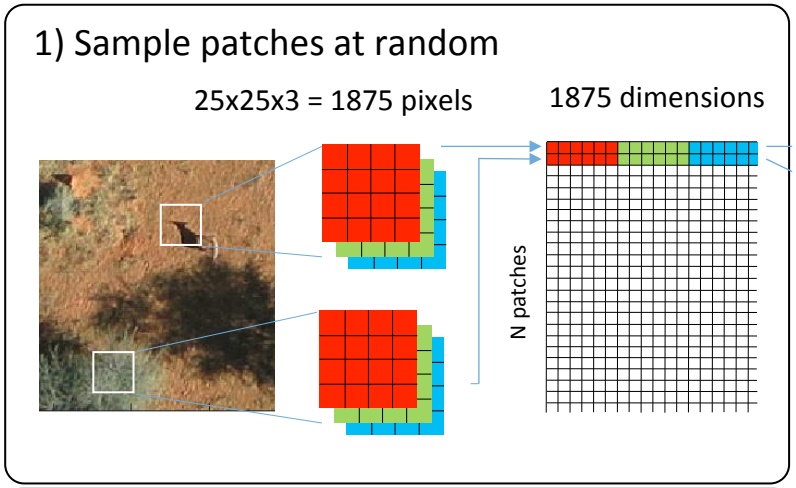
Example descriptors: bag of visual words (BOW)

$$\mathbf{x}_i = [\mathbf{x}_i^{\text{av}} \quad \mathbf{x}_i^{\text{std}} \quad \mathbf{x}_i^{\text{entr}} \quad \mathbf{x}_i^{\text{hist}} \quad \mathbf{x}_i^{\text{bow}} \quad \dots]$$

Distribution of *features*
Or spatial prototypes



Building the BOW (1)



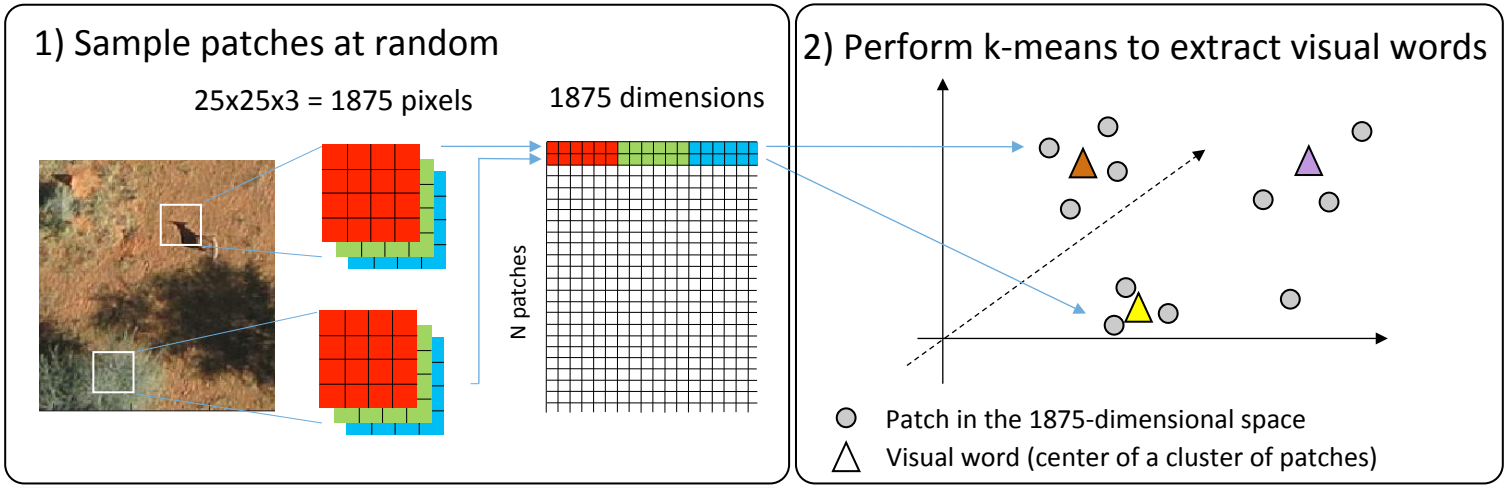
- extract random patches from the image,
- enough to have all representative structures
- Every patch is a 1875 dim vector, 1 dimension per pixel composing it

We want to use this 1875-dimensional space as a space to extract the descriptors from

But how?

N. Rey, M. Volpi, S. Joost, and D. Tuia. Detecting animals in african savanna with UAVs and the crowds. *Remote Sens. Environ.*, 200C:341–351, 2017.

Building the BOW (2)



- Run a k-means, i.e. cluster the patches into a number of representative types
- Each cluster center is a typical pattern seen in the images
- We call them **visual words**

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A brief explanation of k-means

D. Tuia. ECEO

- It's a method to partition the data into groups, in an unsupervised way
- Aims at finding compact clusters

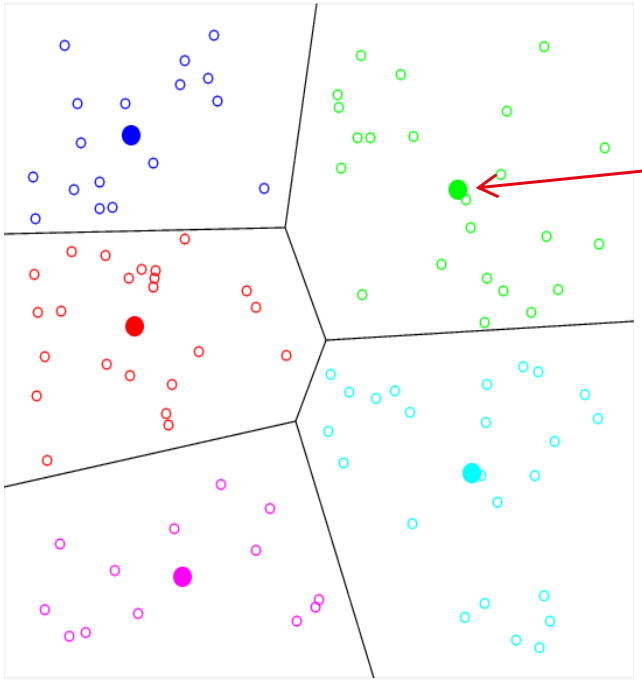
  → minimize variance within the clusters!

- Variance? (statistics course)

$$\mathrm{var}(x) = \sum_i (x_i - \mu)^2$$

Mean of x

Example of k-means (k = 5)



Mean of data assigned
to the green cluster
= Centroid of the cluster μ

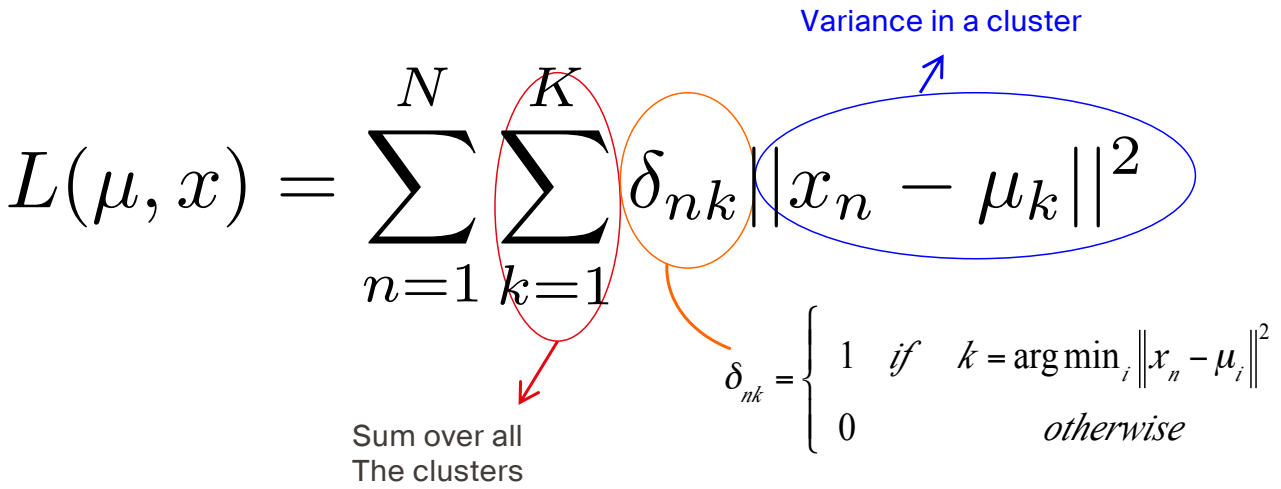
The centroids is
What we are interestd in!

Because they “represent well”
Common patterns in the data!

D. Tuia. ECEO

k-means objective function

- We define a cost function L(m,x) in this sense:



- The smaller L(m,x) is, the more desirable the solution.

D. Tuia. ECEO

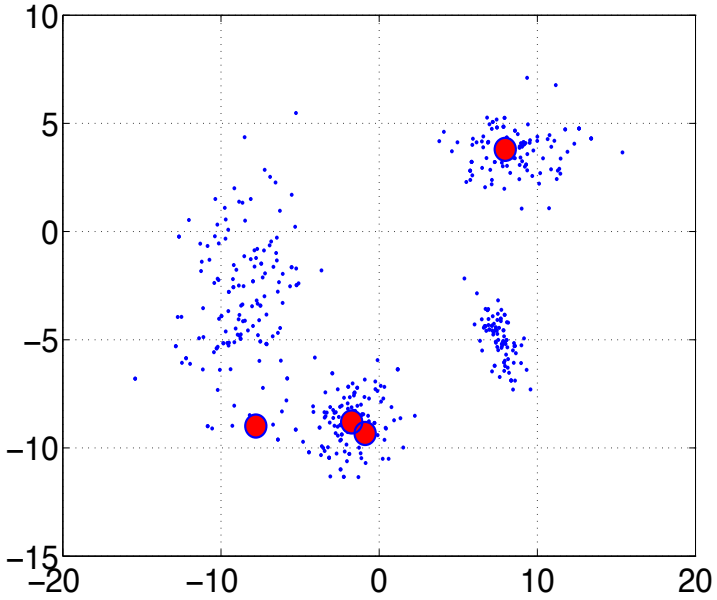
k-means in a nutshell

- K-means is an iterative method
- It starts with a guess of the cluster centers (often random)
- Computes the assignment by minimizing L
- Updates the centers as the means of the samples assigned to each center
- Repeats 2.-3. until stability is reached.

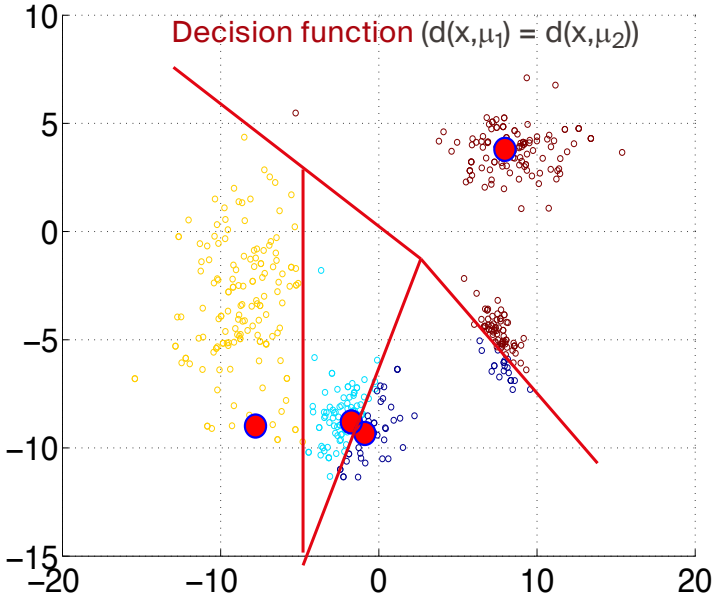
- Stability can be: - a fixed number of iterations
- - when the centroids do not move anymore

D. Tuia. ECEO

Example



Data and initial (random) centroids



Initial cluster assignment

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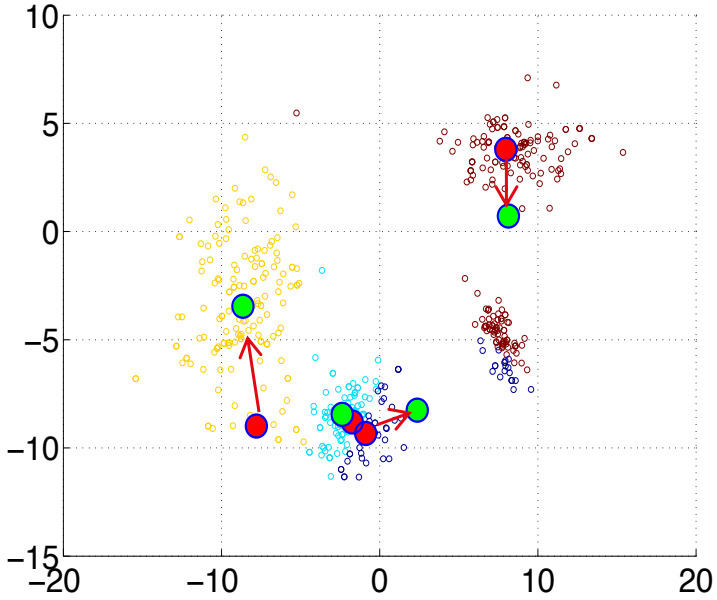
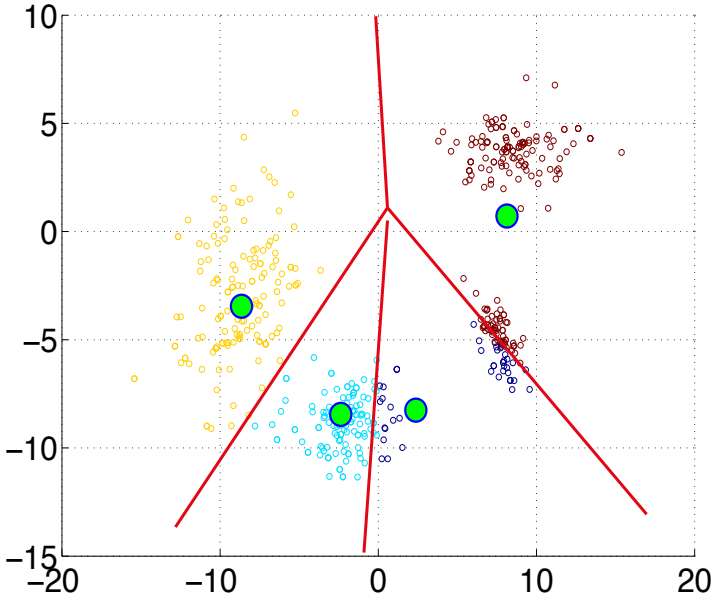
Iteration 1: solving 3 clusters





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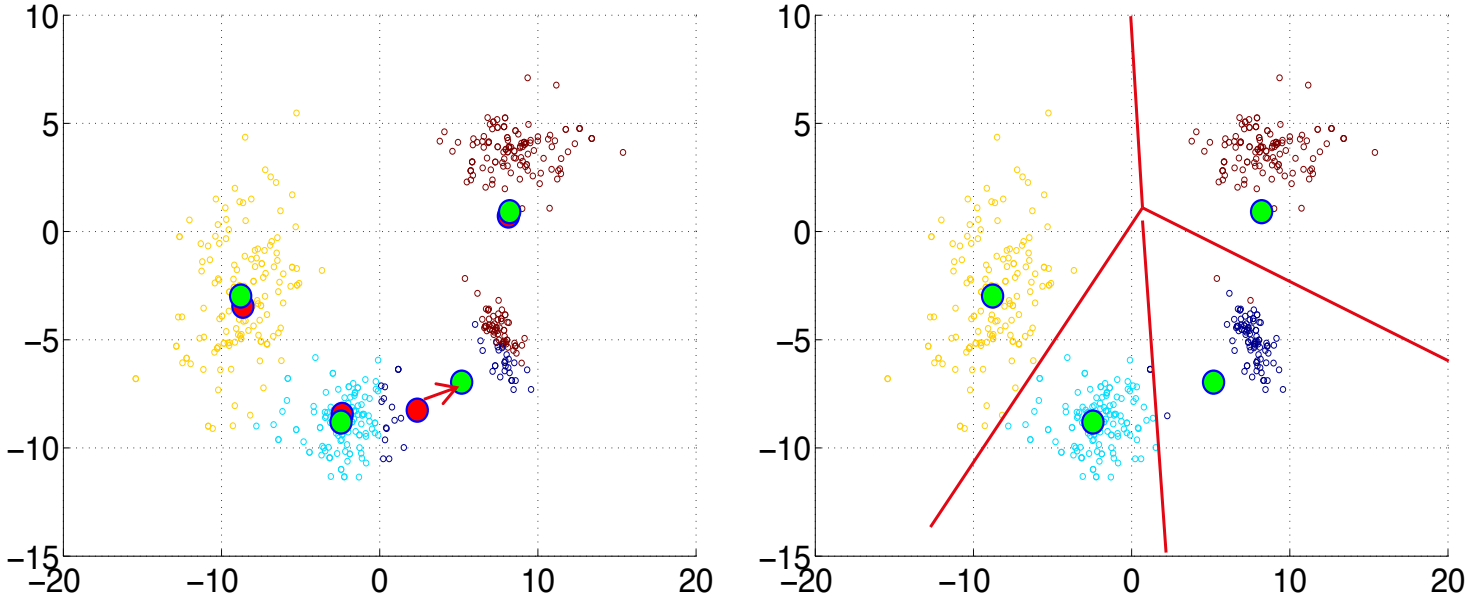
Iteration 2: solving the blue cluster



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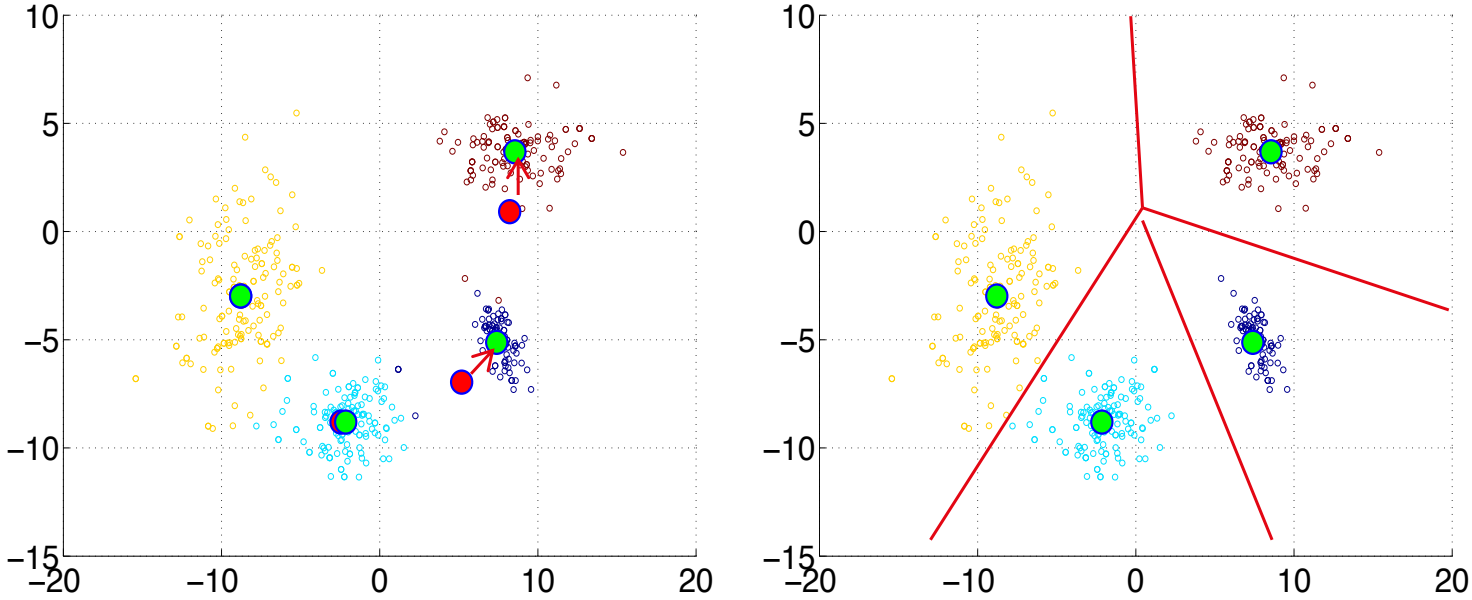
Iteration 3: convergence!



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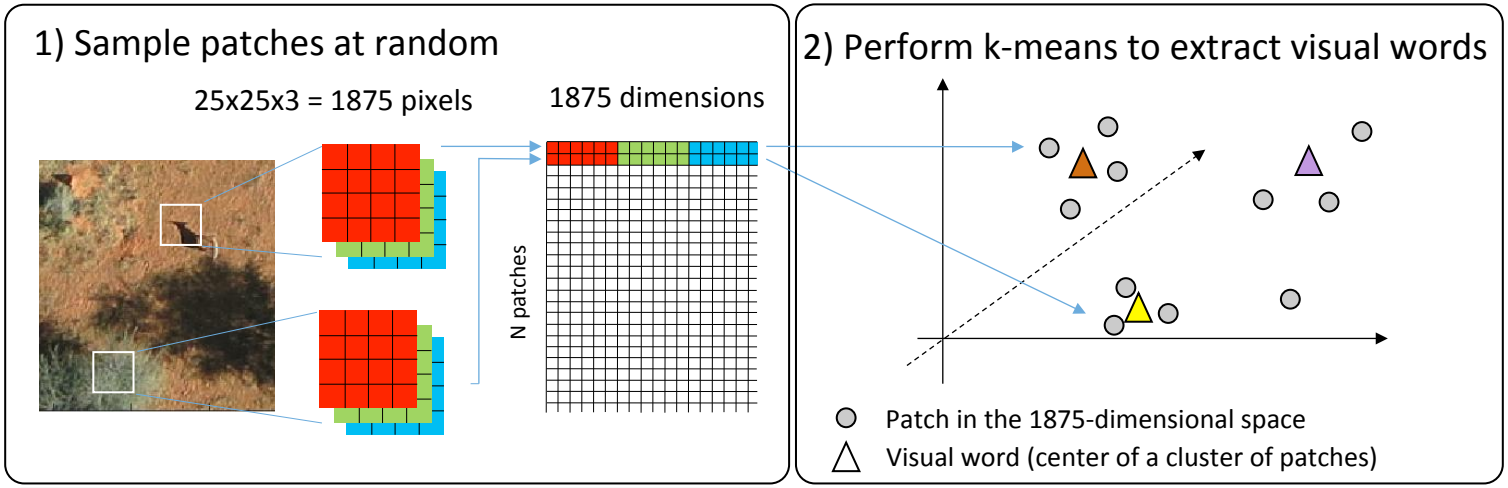
Building the BOW



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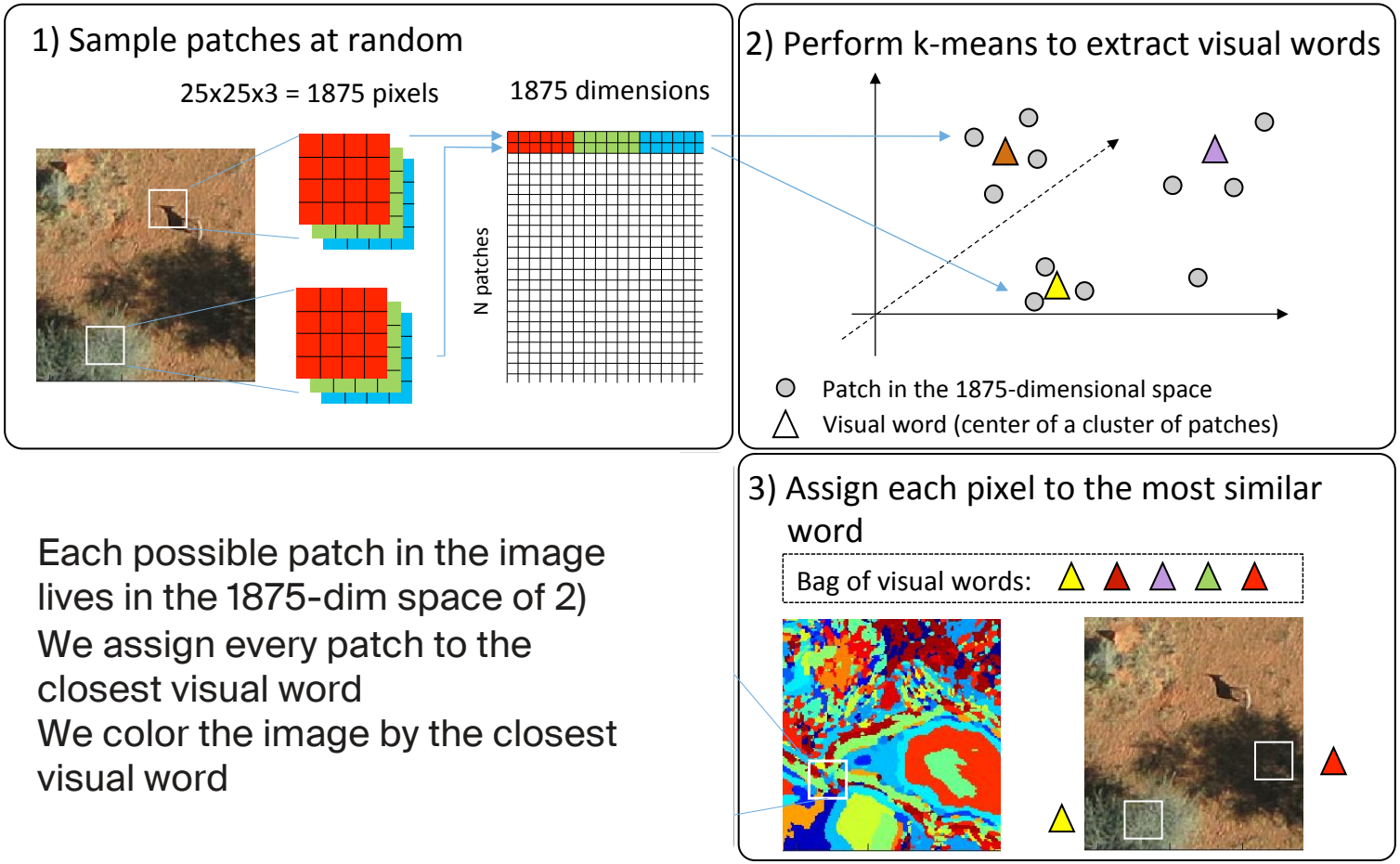
Building the BOW



- Each possible patch in the image lives in the 1875-dim space of 2)
- We assign every patch to the closest visual word
- We color the image by the closest visual word

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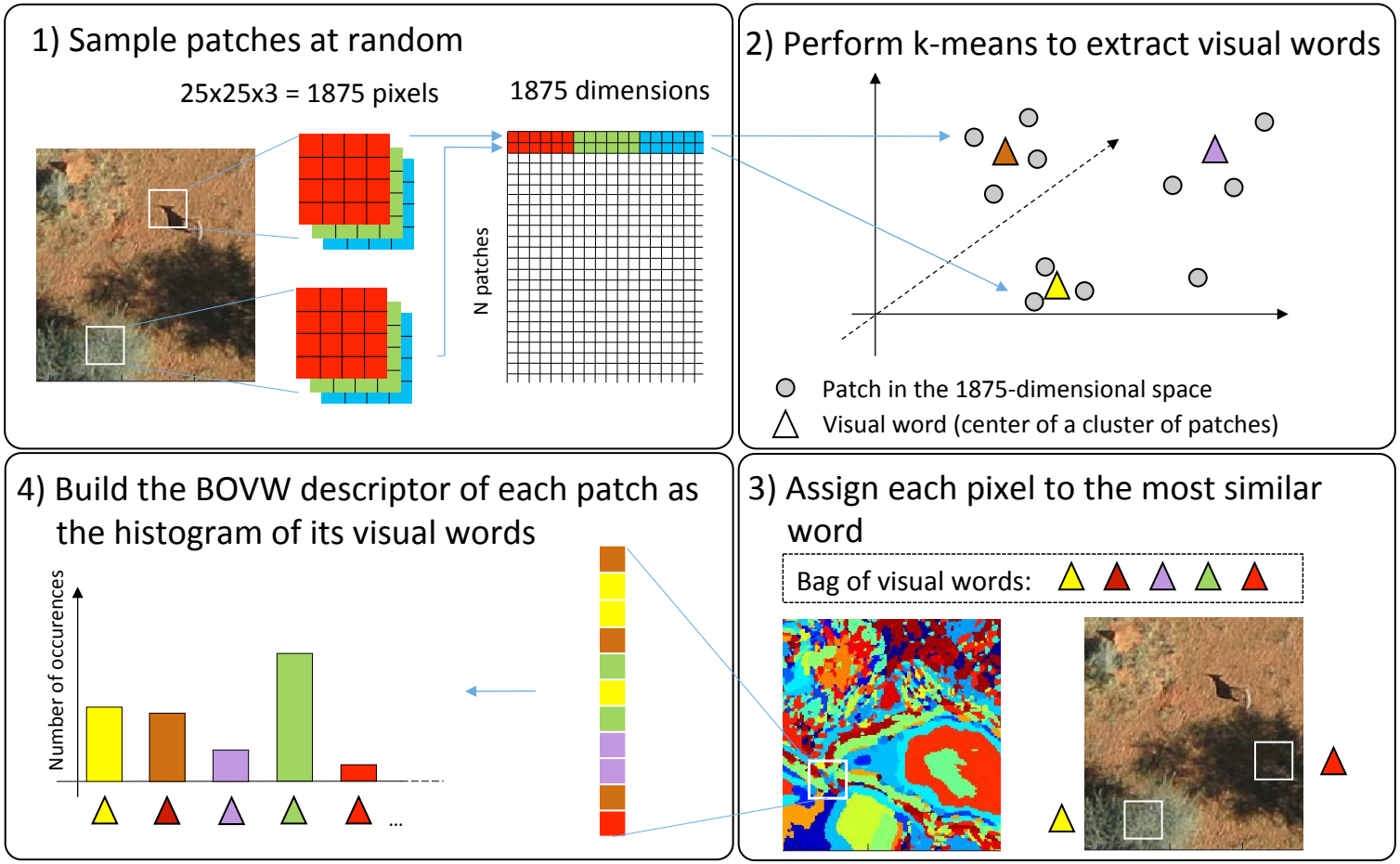
Building the BOW



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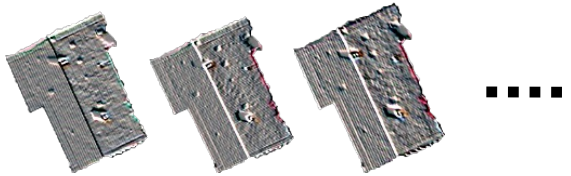
Summing up the BOW

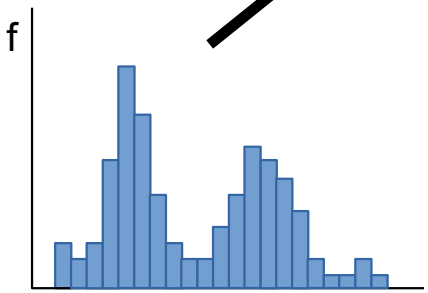
Compute filters on all channels

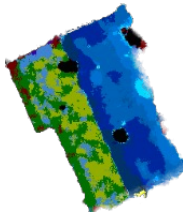
e.g. oriented filters, gradients, etc.



Visual word extraction

$$\mathbf{x}_i^{\text{bow}} = [f_i^1 \quad f_i^2 \quad \dots \quad f_i^k]$$

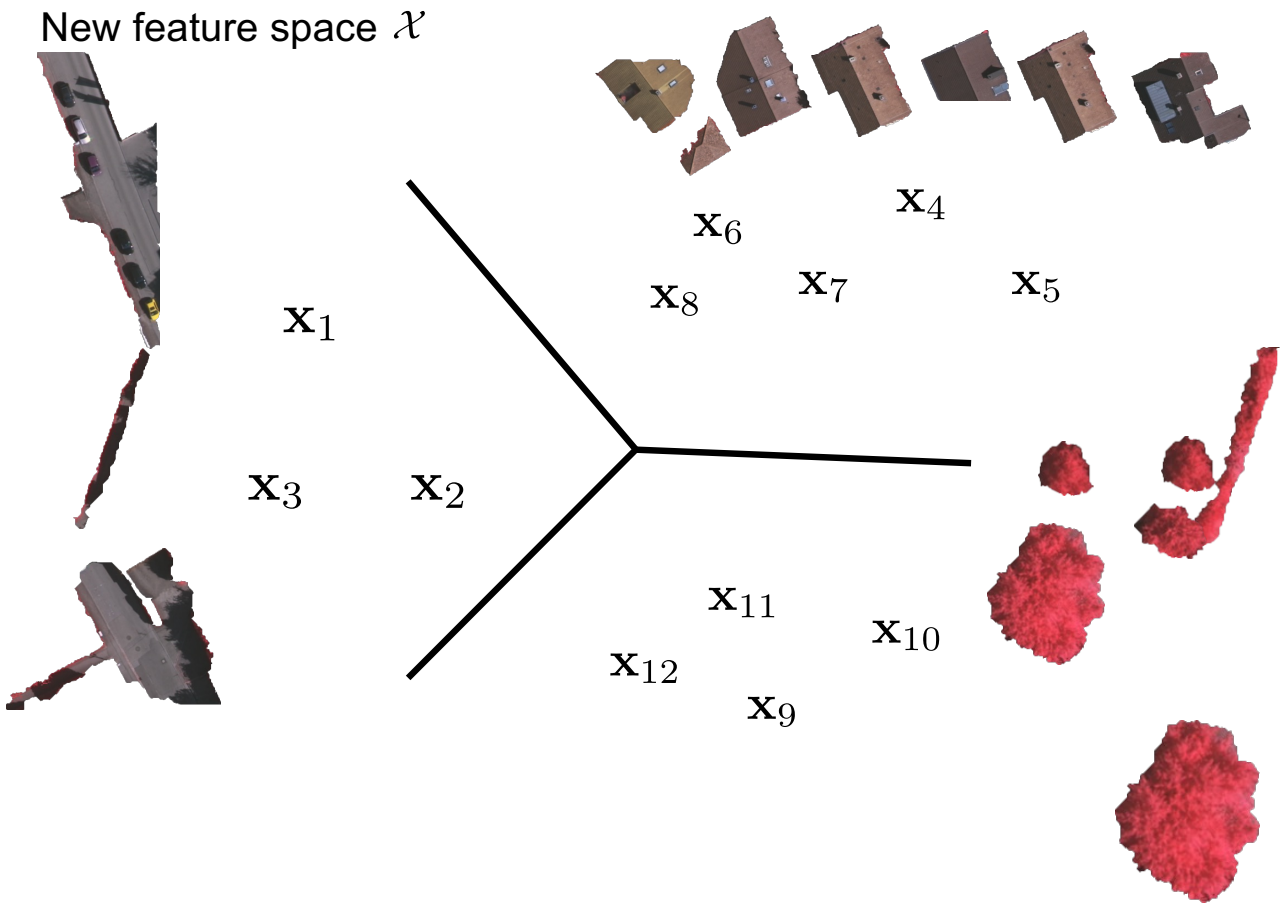




Word counts per object (binning)

- Stack filter responses (*D*-dimensional image)
- Run *k*means clustering over *all* pixels with many centers (*k*)
- Assign to each pixel the label of the closes centroid

From colors to feature space



In summary

- The appearance of patches / regions / objects requires a careful extraction of information:
  - The **spatial support** must be as precise as possible
  - The **descriptors** must cover all the possible data variability
  - The descriptors must be related to the problem to be solved

    e.g. classifying

    - vegetated areas vs non-vegetated areas requires spectral information / spectral indexes;

    - buildings vs roads requires texture and “shape” information; etc.