

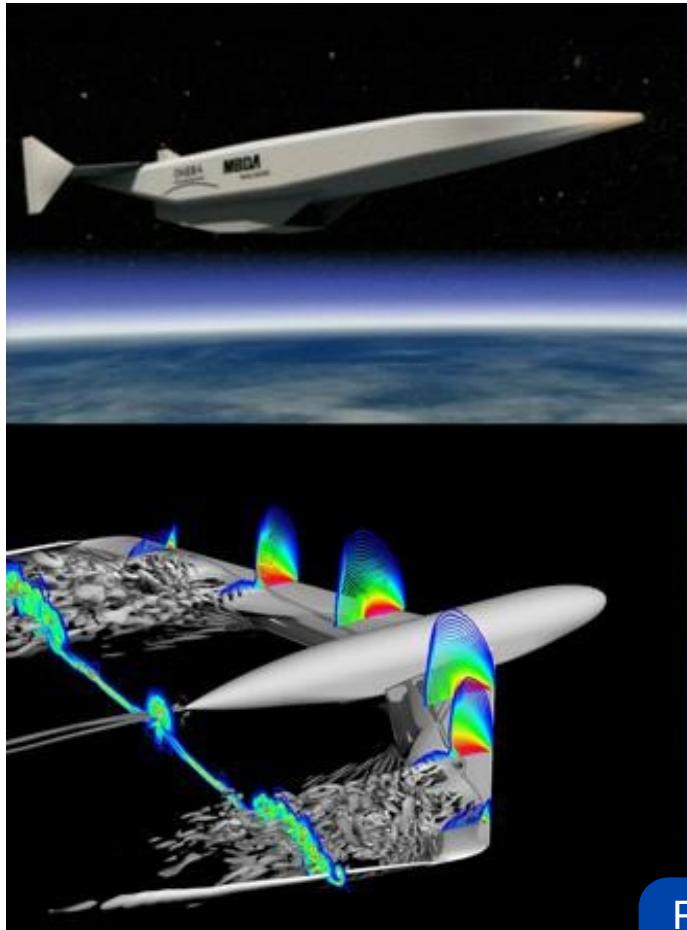
ENPC Data Science Week

Deep Learning for Remote Sensing

Alexandre Boulch



re tour sur innovation



Research, Innovation, expertise and long-term vision
for industry, French government and Europe



Aerodynamics
Flight dynamics

Materials
Propulsion
Optics
Electromagnetism

Information Processing

Aerodynamics
Flight dynamics

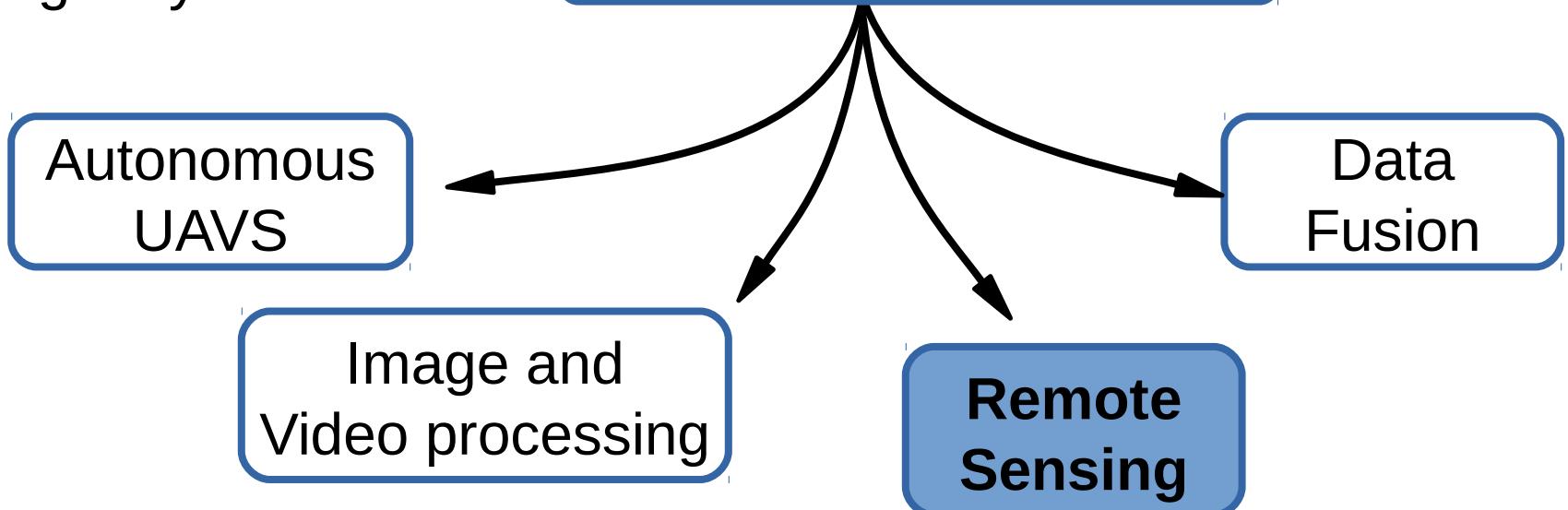
Materials

Propulsion

Optics

Electromagnetism

Information Processing



Remote Sensing

Remote Sensing

Obtaining information about objects without contact

Earth Observation

Gathering information about Earth via Remote Sensors

- aerial
- spatial
- ground



Remote Sensing

Massive data

Satellites constellations covering the earth. e.g. Sentinel (ESA)

Applications examples

- Urban area analysis



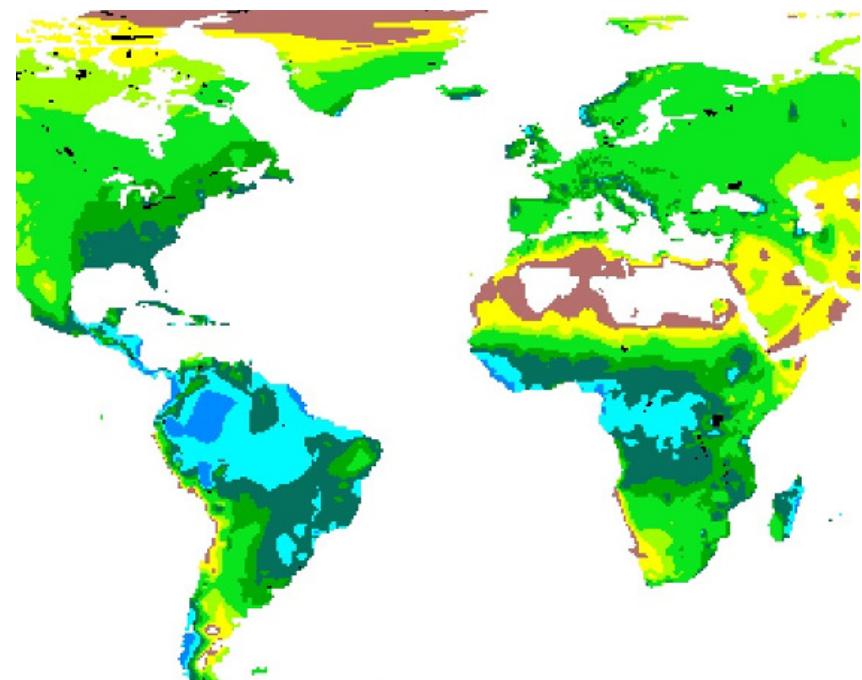
Remote Sensing

Massive data

Satellites constellations covering the earth. e.g. Sentinel (ESA)

Applications examples

- Urban area analysis
- Biomass estimation



Remote Sensing

Massive data

Satellites constellations covering the earth. e.g. Sentinel (ESA)

Applications examples

- Urban area analysis
- Biomass estimation
- Oil spread detection
- MNT estimation
- Building deformation from space



Need for robust, automatic and fast processing

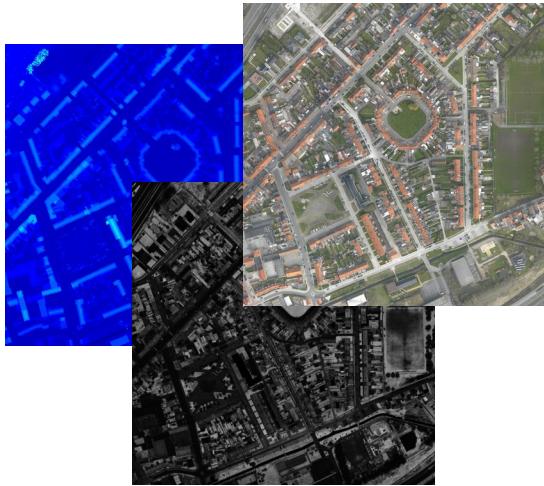
Objective

INPUT DATA

Registered aerial or spatial images

Heterogeneous sources:

- RGB
- Hyperspectral
- LIDAR
- SAR ...

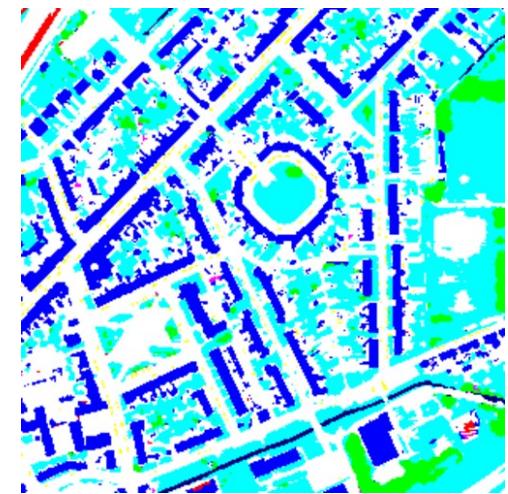


SEMANTIC MAP

1 label per pixel

E.g. Tree, Building, Roads,...

Machine
Learning



Classification problem



Labels:

Car
Dog
House
Plane
Toy
Game
Ball
Cat
Road
Tree
Lego
Ski
Food
Pillow
Sun
Flower
...

Images + Labels

Classification problem

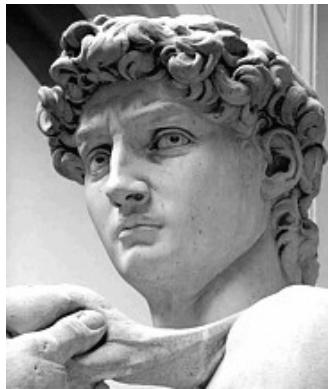


Labels:

Car
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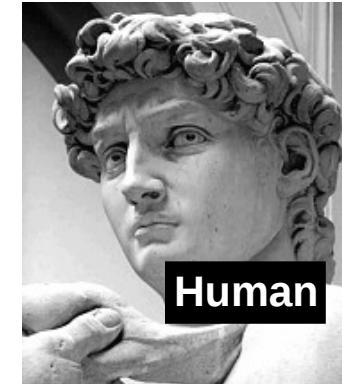
Images + Labels ————— Annotated images

Classification framework



Image

Direct classification is difficult



Annotated
image

Same object, different colors

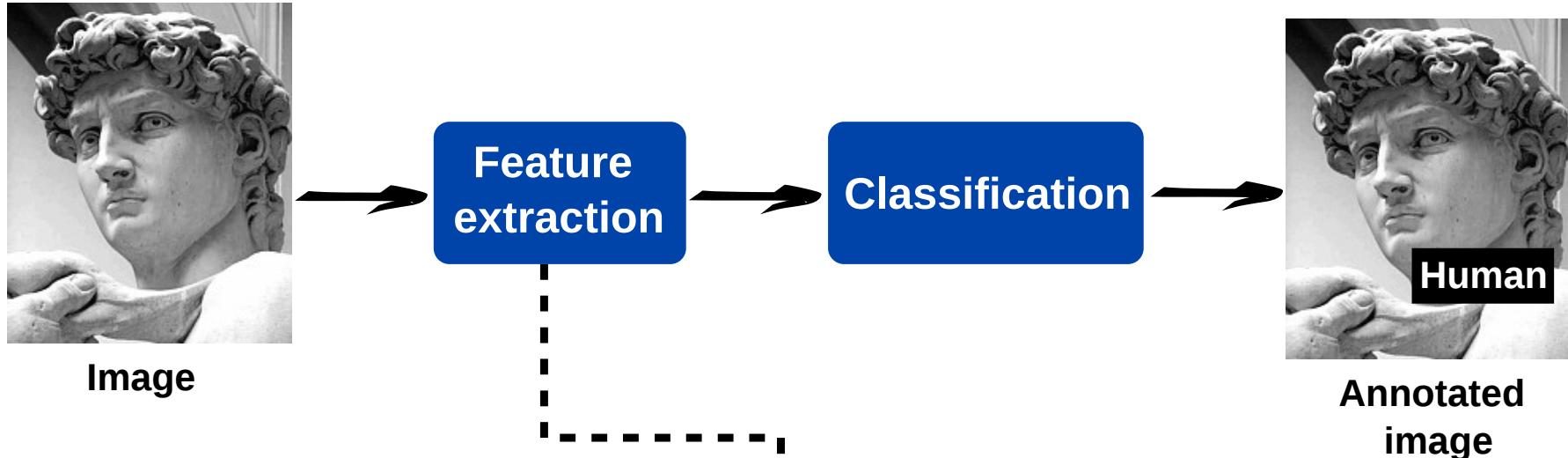


Example

Image space :

- High dimension (Image space)
- No structure of the image
- Not robust to changes

Classification framework



Same object, different colors



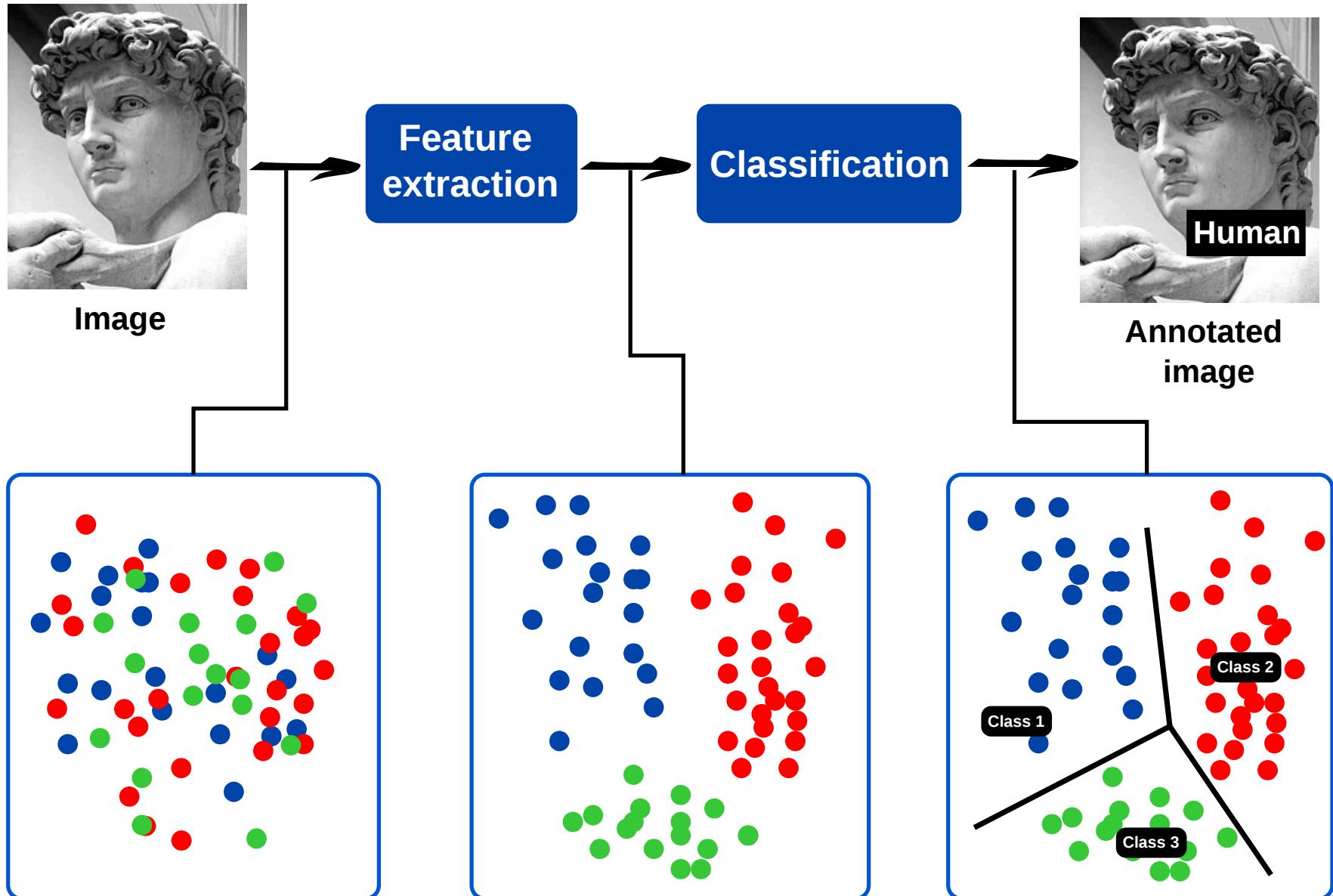
Gradient and threshold

Example

Similar after transformation



Classification framework



How to do it ?

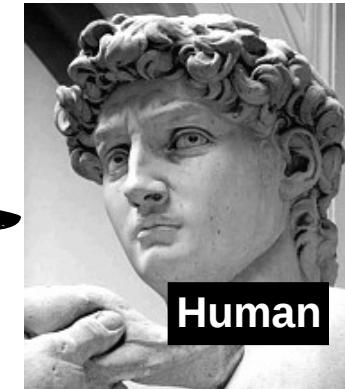
Expert features



Image

Feature
extraction

Classification



Human

Emprical rules

Emprical thresholds
or SVM

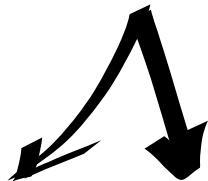
Annotated
image



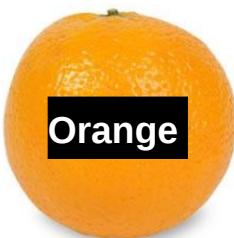
Water is blue
+
blue level > 200
green & red < 100



Designing features is difficult



Binary classification



Designing features is difficult



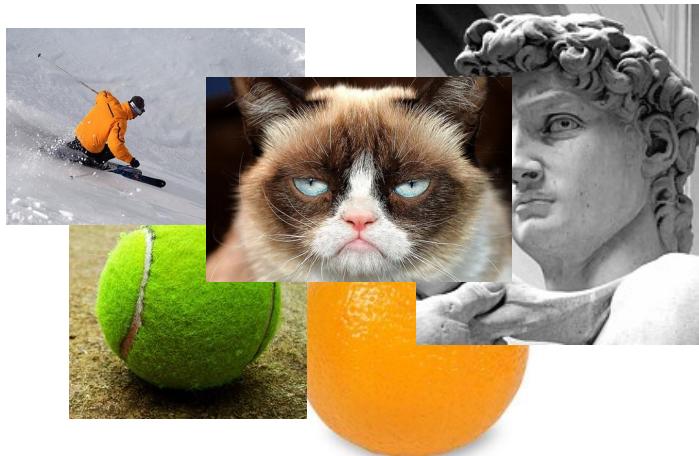
Binary classification



What is a good and generic description of oranges ?



Designing features is difficult



Binary classification

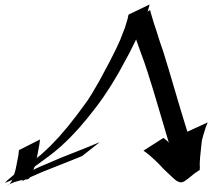


What is a good and generic description of oranges ?

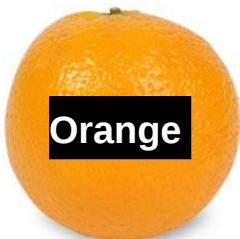


Round

Designing features is difficult



Binary classification



What is a good and generic description of oranges ?



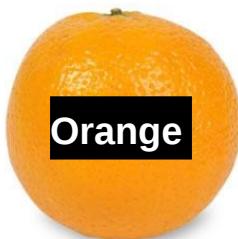
Round



Designing features is difficult

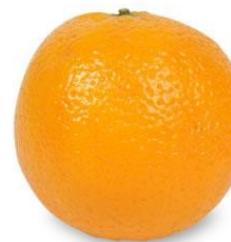


Binary classification



Not orange

What is a good and generic
description of oranges ?



Round
Color: orange



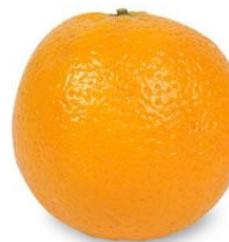
Designing features is difficult



Binary classification



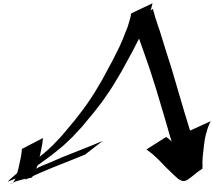
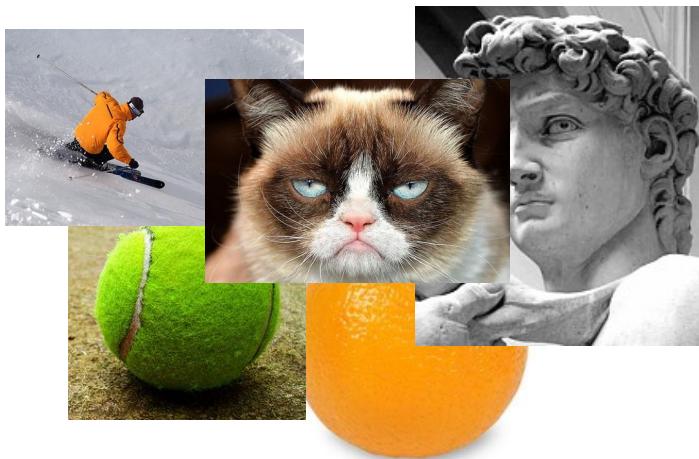
What is a good and generic description of oranges ?



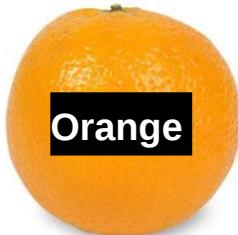
Round
Color: orange
No line



Designing features is difficult



Binary classification



What is a good and generic description of oranges ?



Round
Color: orange
No line

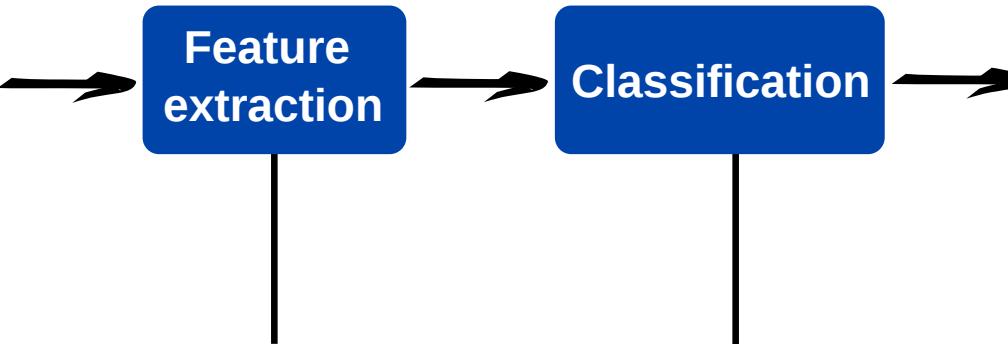


How to do it ?



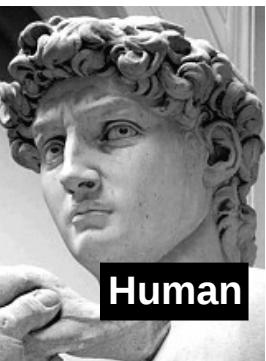
Image

Complex features

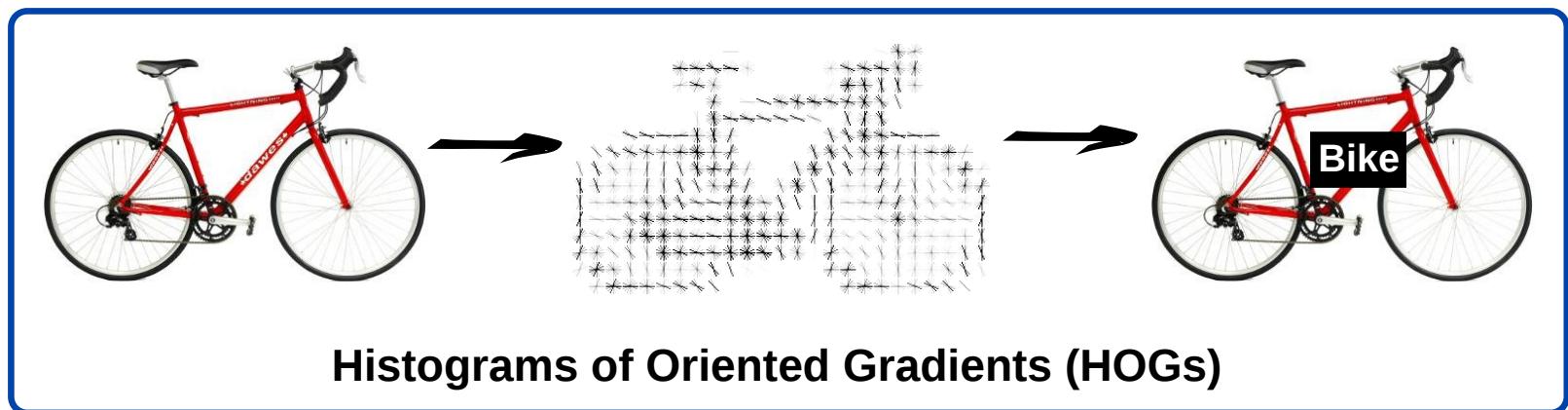


Complex features:
- generic features
- human design

SVM (support vector machines)



Annotated image



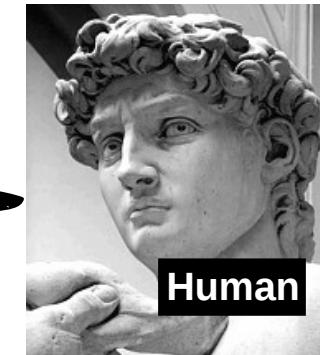
Histograms of Oriented Gradients (HOGs)

How to do it ?

Deep Neural Networks



Image



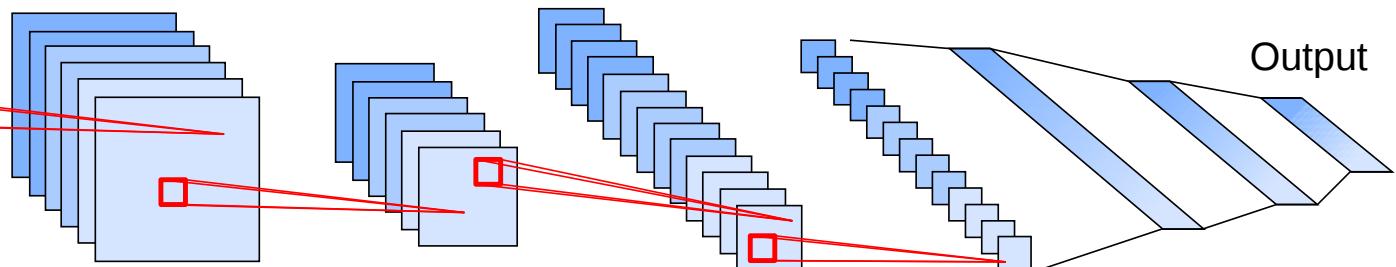
Annotated
image

Convolutions
(First layers)

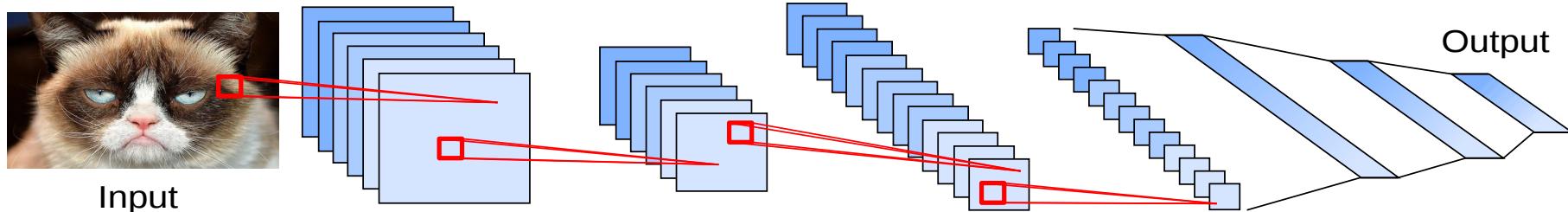
Fully connected
layers



Input

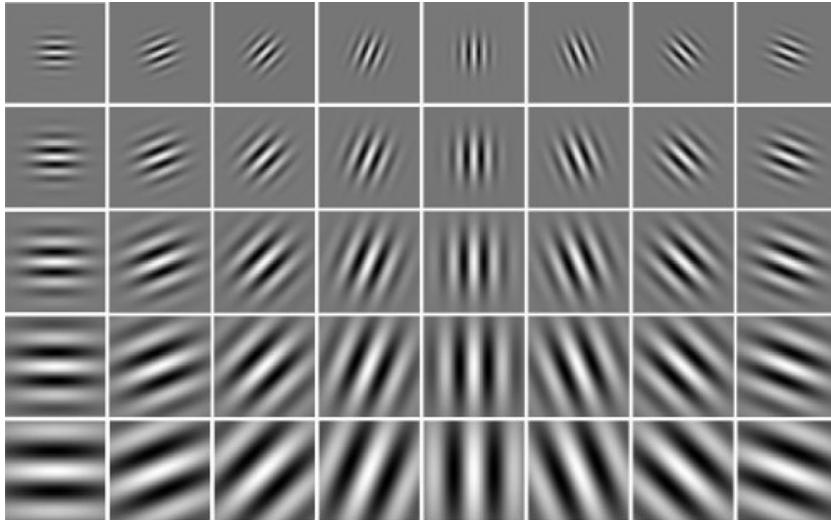


Deep neural networks



- **Two step algorithm:**
 - FORWARD: predict the output given a input
 - BACKWARD: compute the gradient of the loss, update the parameters of the network (back propagation)
- **A lot of parameters to optimize**
- **Efficient computing using GPUs**
- **State of the art**

First convolution layer



Gabor filters
[Daugman 1985]

AlexNet first
convolution layer
[Krizhevsky 2012]



Neural networks are not new

1980's, Artificial Neural Networks

Fukushima, *Neocognitron : A Self-organizing Neural Network Model for a Mechanism of Pattern Recognition Unaffected by Shift in Position*, *Biological Cybernetics* 36-4, 1980

Late 1980's, Backpropagation algorithm applied to deep neural networks

LeCun et al., *Backpropagation Applied to Handwritten Zip Code Recognition*, *Neural Computation*, 1, pp. 541–551, 1989

2000's, GPU implementation, renewed interest in Deep Learning

Ciresan et al., *Deep Big Simple Neural Nets for Handwritten Digit Recognition*, *Neural Computation*, 22, pp. 3207–3220, 2010

Since 2010:

Highly multiclass object recognition (ImageNet challenges),
optical flow, segmentation . . .

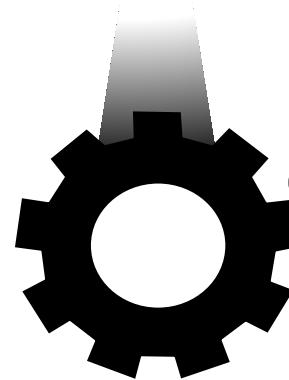
What changed ?



Internet



**Deep
Learning**



**Computing
power**

What about Remote Sensing ?

More data available

Sentinel
Landsat

...

Free data

ESA
NSA / JPL

Platforms

PEPS
Google Earth Engine

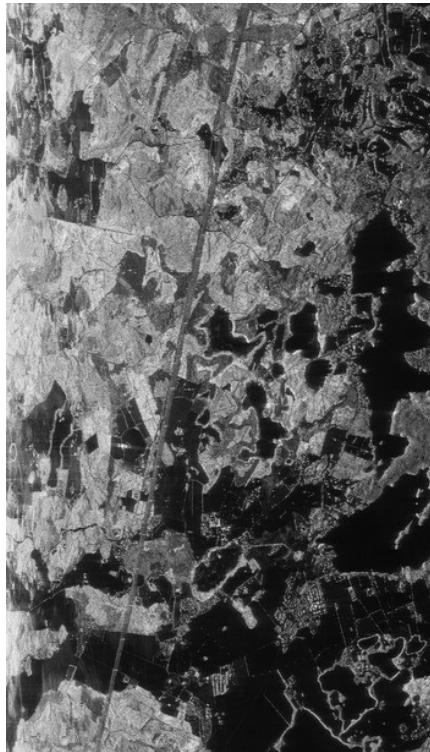


www.esa.int

ONERA

THE FRENCH AEROSPACE LAB

Application examples



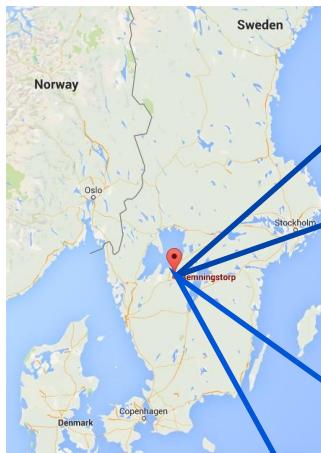
RADAR
Tree Species
recognition

Optical
Urban
semantics

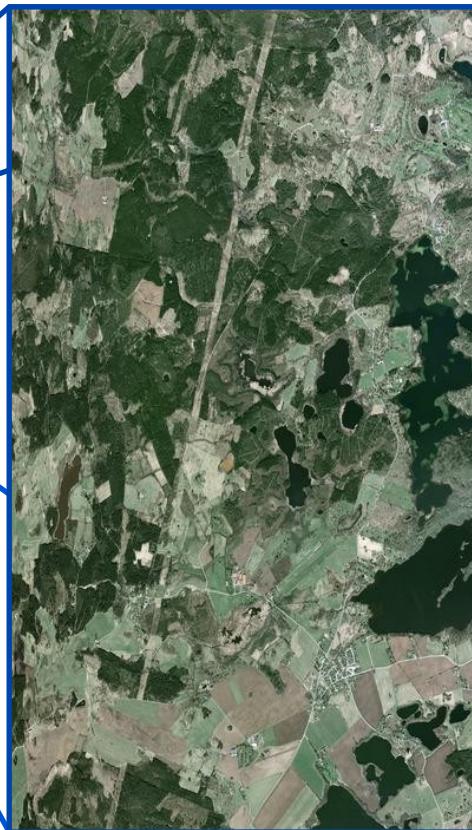


3D data
Urban
semantics

Tree species recognition



Remnningstorp
(Sweden)



Objective

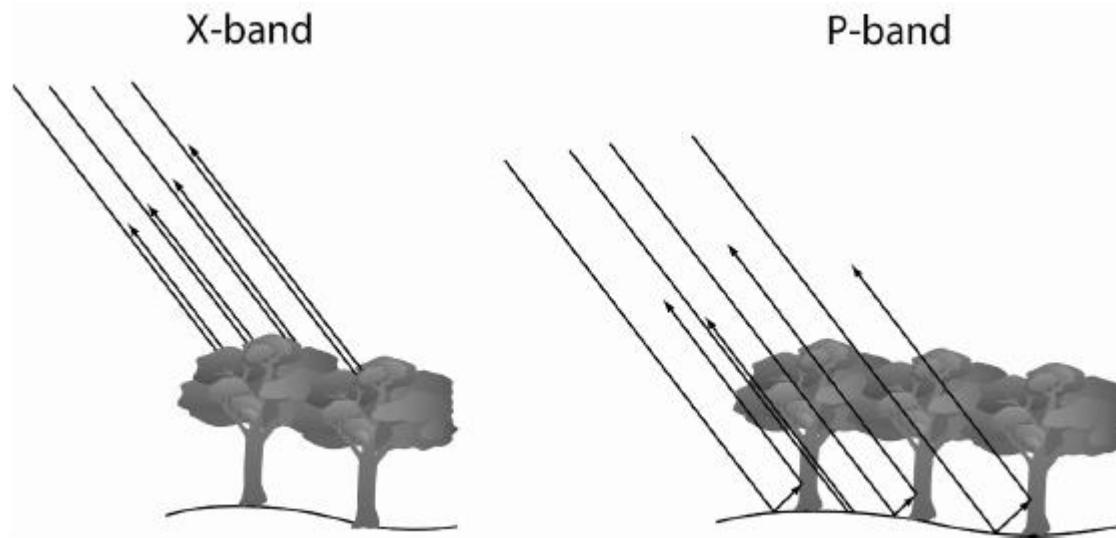
Semantic labeling of forest areas up to the species level

Challenge

Doing better than human eye.

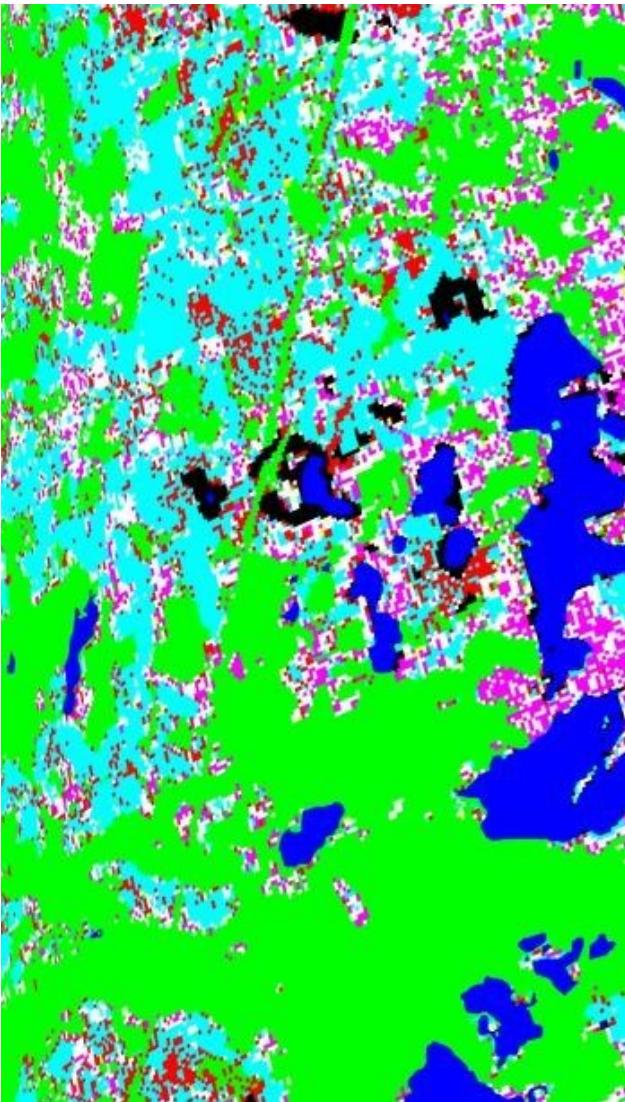
Tree species recognition with SAR data

Radar penetrates vegetation, it reflects on object with size similar to wave length.



Radar data gives information on the structure of the forest.

Tree species recognition



Generated from open data:

Dept. of Forest Resource
Management,
*Swedish University of
Agricultural Sciences*

7 classes:

Water



No tree



Trees:

Birch



Oak



Pine



Spruce



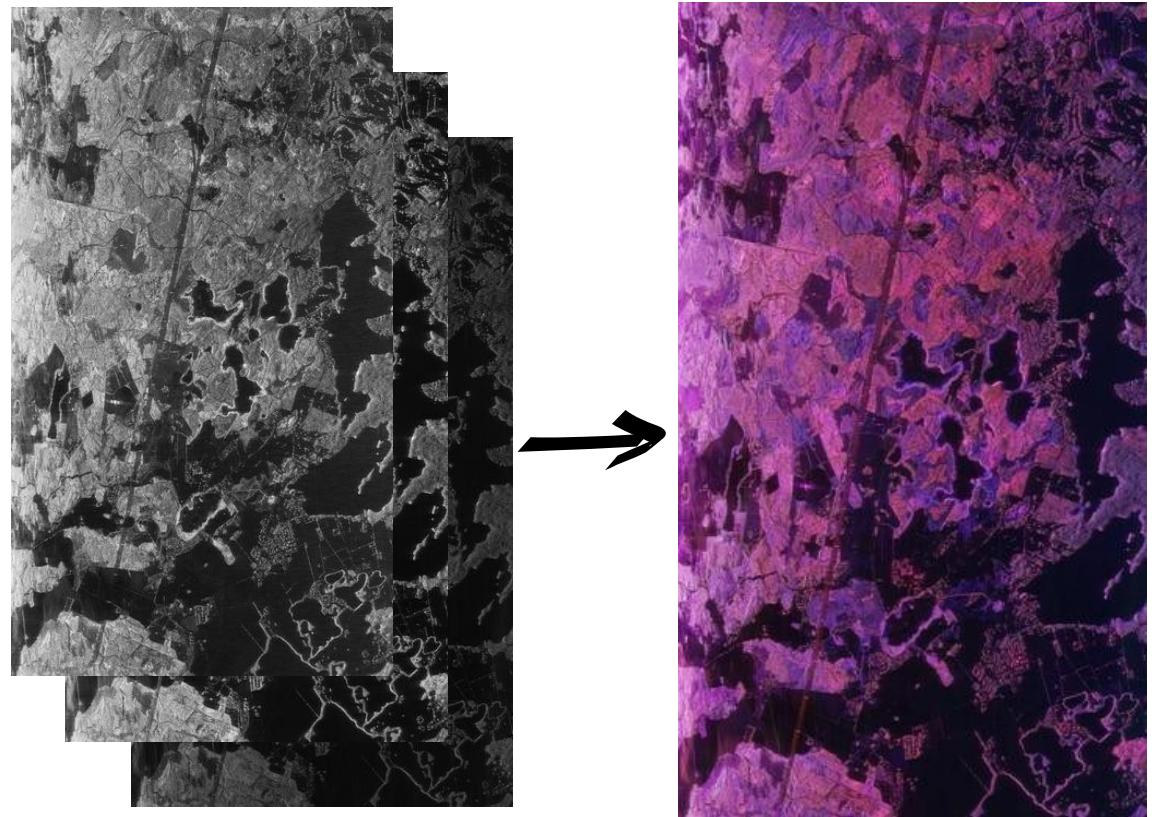
Misc.



Tree species recognition

SAR data

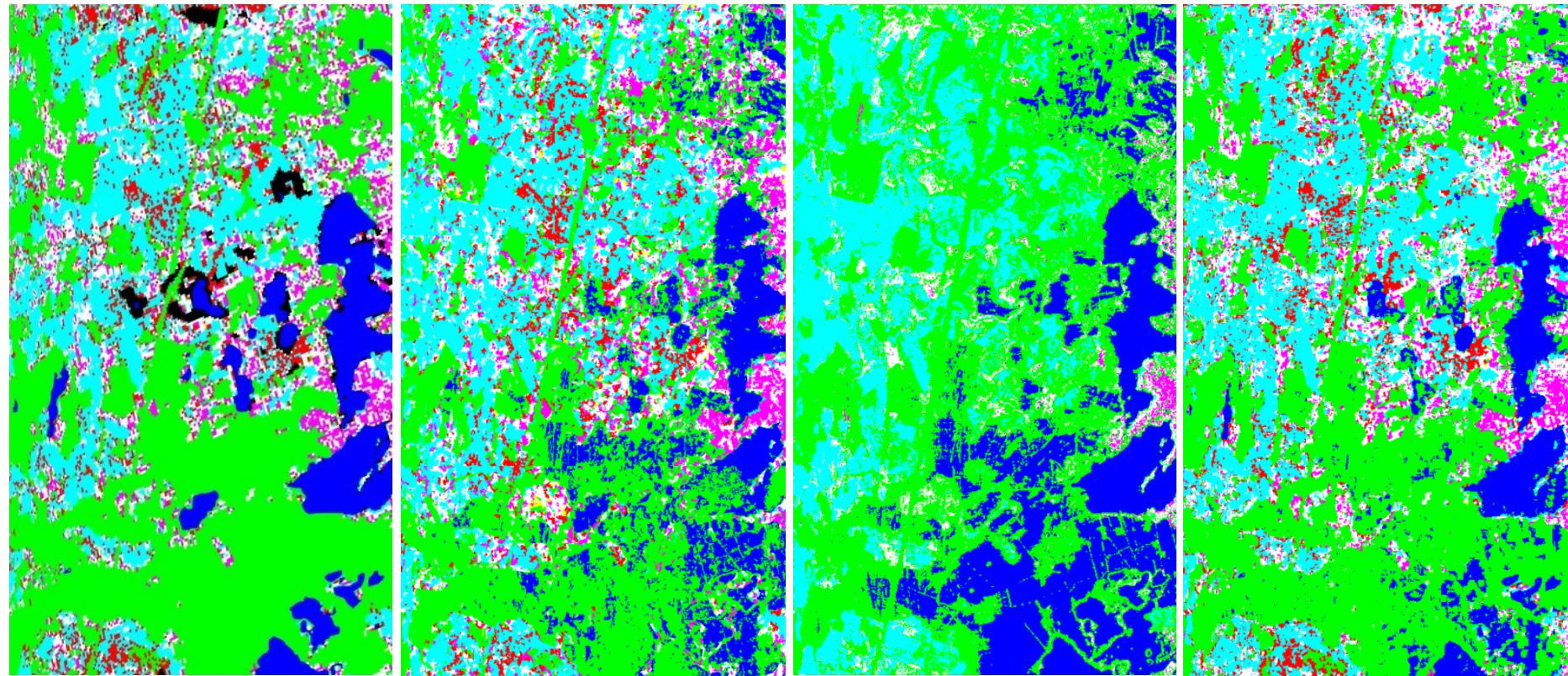
- Band P
- Polarized
- Vegetation penetration



HH HV VV channels

RGB Color composition

Tree species recognition



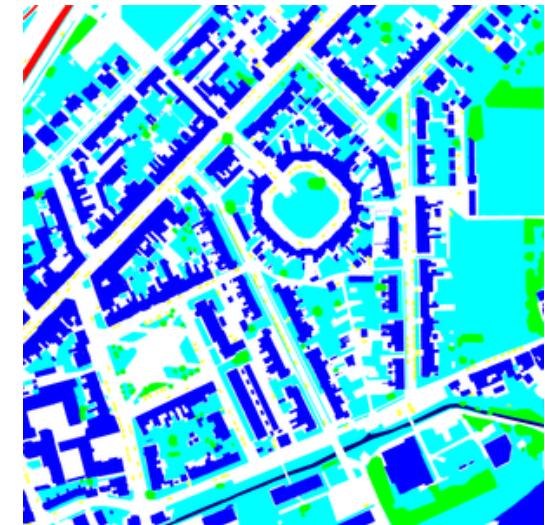
Ground Truth

Histograms
and SVM

LeNet
Small neural
network

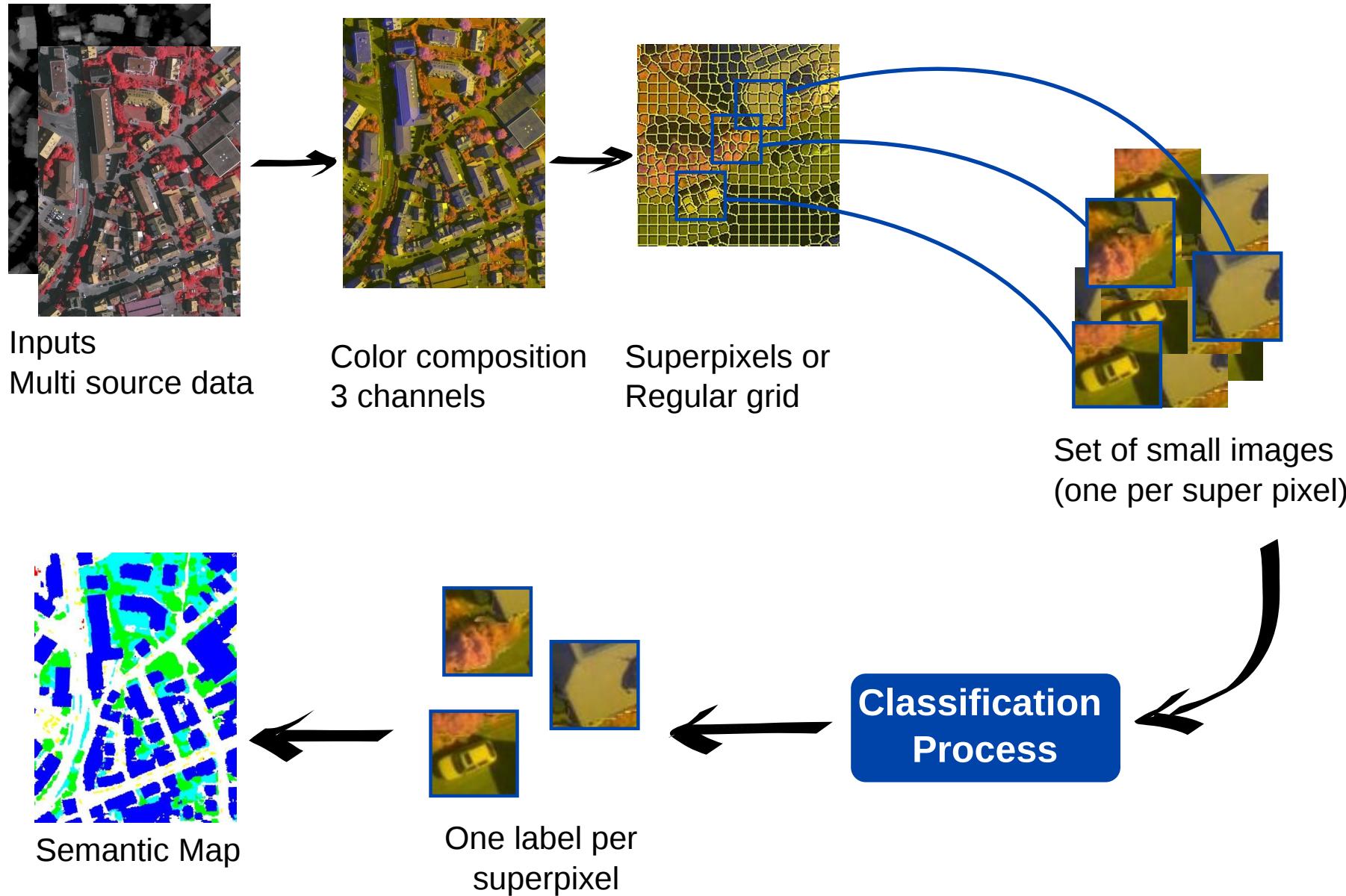
AlexNet
Large neural
network

Urban semantics

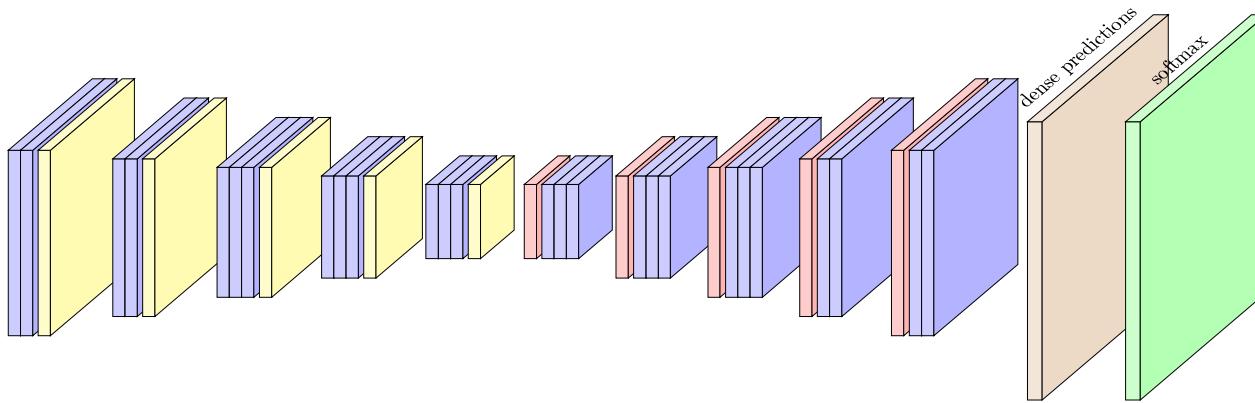


- Car park optimization
- Road mapping
- Urban extension

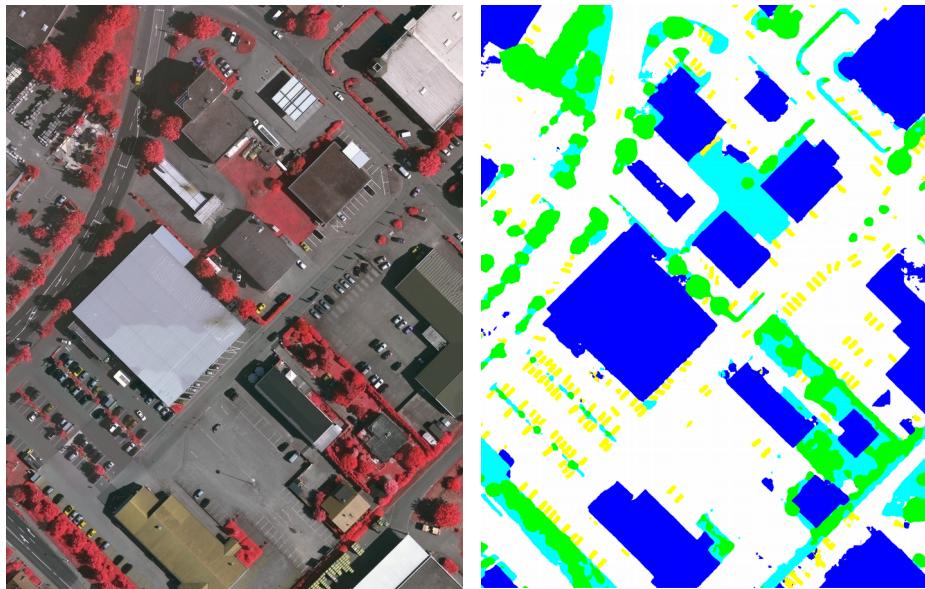
Using a classification framework



Using segmentation networks



Dense prediction

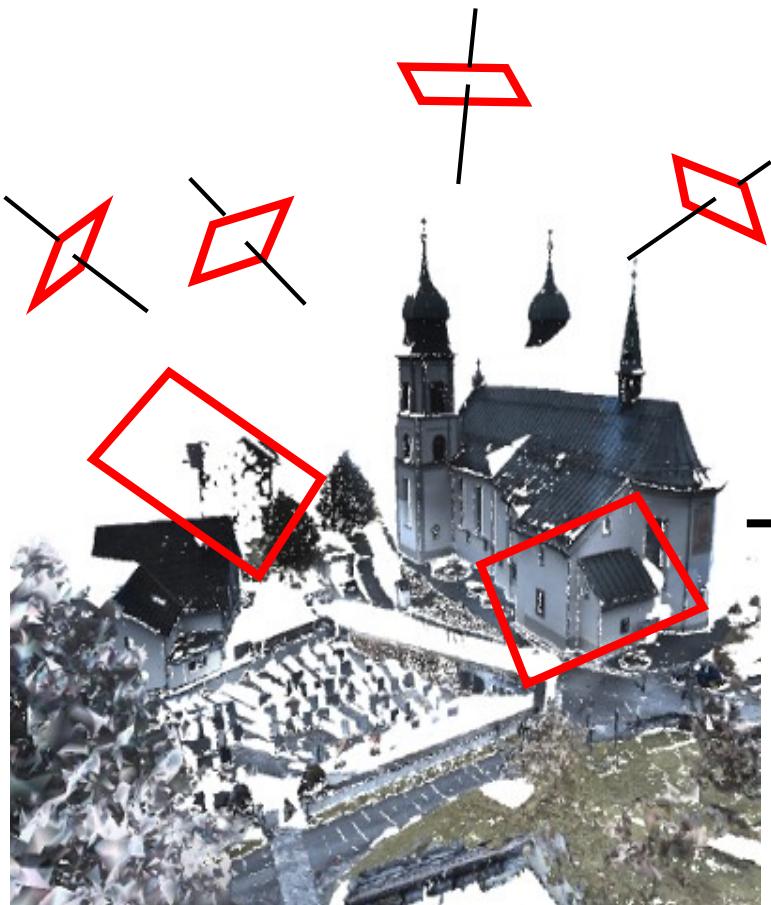


**Semantic Segmentation of Earth
Observation Data Using Multimodal and
Multi-scale Deep Networks**

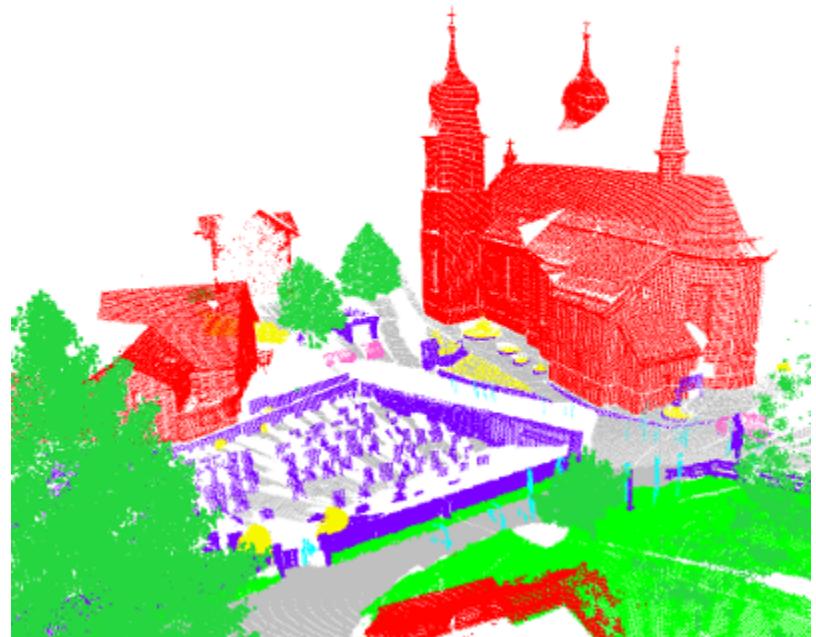
Nicolas Audebert, B. Le Saux, Sébastien Lefèvre

ACCV 2016

3D data semantics using segmentation networks



Pick snap shots of the Point cloud



Project back from 2d predictions to point cloud

First place on the Semantic 3D dataset

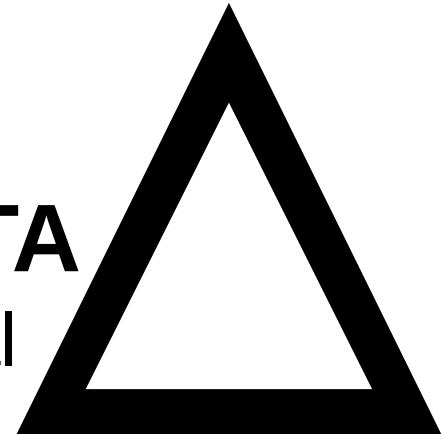
On going projects at ONERA



Multidate Earth Observation Datamass for Urban Sprawl Aftercare

Big data for
Remote Sensing
w3.onera.fr/medusa

DeLTA
Deep learning for aerospatial
delta-onera.github.io



Intern and PhD positions

Internship opportunities

From October to January

PhD positions 2017

A joint geometrical and semantic approach to reconstructing digital model (*ENPC / ONERA*)

Remote sensing images registration using a deep framework (*ONERA*)

Deep learning for multi-temporal activity analysis in remote sensing
(*ONERA / ENST*)

All opportunities on www.onera.fr

Conclusion

“We chose it because we deal with huge amounts of data. Besides, it sounds really cool.”

Larry Page - Google

RS in Information Processing team: Alexandre Boulch, Nicolas Audebert, Guillaume Brigot, Fabrice Janez, Elise Koeniguer, Bertrand Le Saux

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