



CNES Initiatives on AI

WGISS

Pierre Lassalle

Thursday, May 2, 2019



- ① Contents
- ② Automatic car counting
- ③ Automatic building detection from 3D data
- ④ Transfer learning

- ① Contents
- ② Automatic car counting
 - Motivations
 - Challenges
 - Training
 - Current performance
 - Use cases
- ③ Automatic building detection from 3D data
 - Context
 - Objectives & Challenges
 - Training
 - Current performance
 - Perspectives
- ④ Transfer learning
 - Motivations
 - Challenges
 - State of art
 - First test
 - Perspectives

- ① Contents
- ② Automatic car counting
 - Motivations
 - Challenges
 - Training
 - Current performance
 - Use cases
- ③ Automatic building detection from 3D data
- ④ Transfer learning

Motivations

- Help companies to develop new applications using satellite images
- Elaborate remote sensing indicators to cross with other type of indicators to estimate economic health in different fields:
 - Car industry
 - Tourism
 - Mineral exploitation
 - ...
- Current work in collaboration with the company QUANTCUBE and the research lab IRISA.



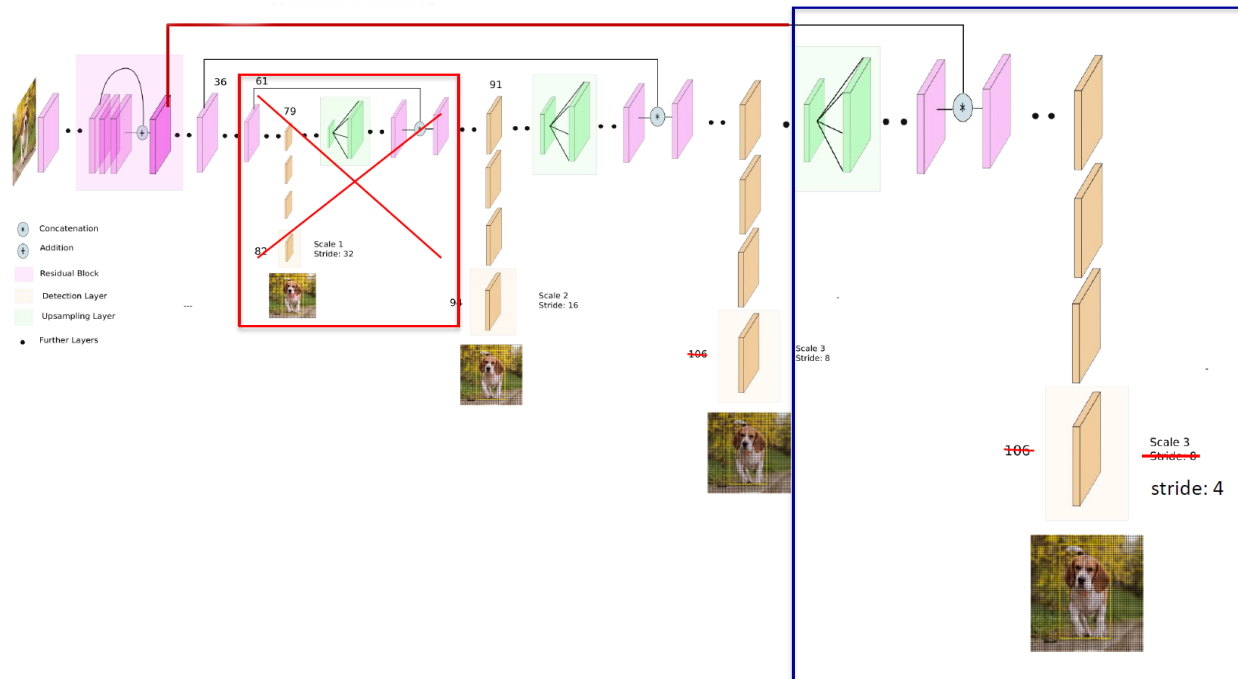
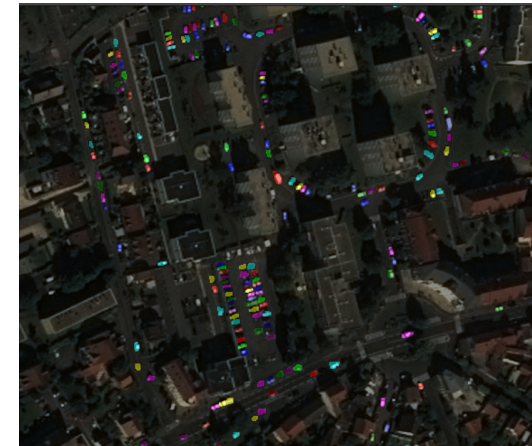
Challenges

- Build a predictive model able to detect cars on VHR Pleiades satellite images:
 - Cars are represented by small areas in the images (around 30 pixels on average)
 - Build training and test datasets from a set of orthorectified pansharpened orthorectified images over Paris.
- Cross the car number over interest areas with other indicators to predict economic trends in field of interest:
 - Define application and its need to have one-time or frequent observations of the interest areas
 - Data science methods to cross various indicators with the car numbers



Training

- Use of labelling tools based on segmentation algorithms to help building training and test datasets.



Current performance

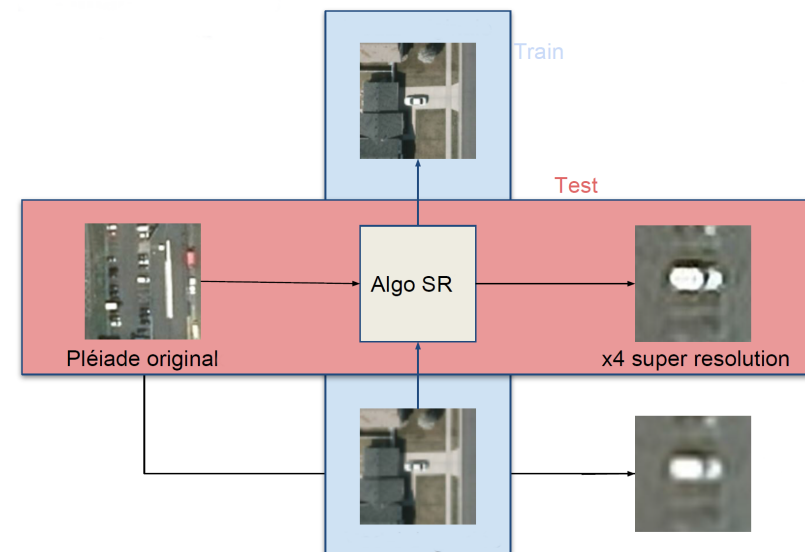
Area Type	Accuracy
Downtown	58%
Area with large parkings and roads	75%
Countryside area	77%

- Difficulty to detect black cars
- Use post-processing to filter false positive detections by looking at local NDVI mean.



Improvement: Use super-resolution AI

- Enhance the car contours



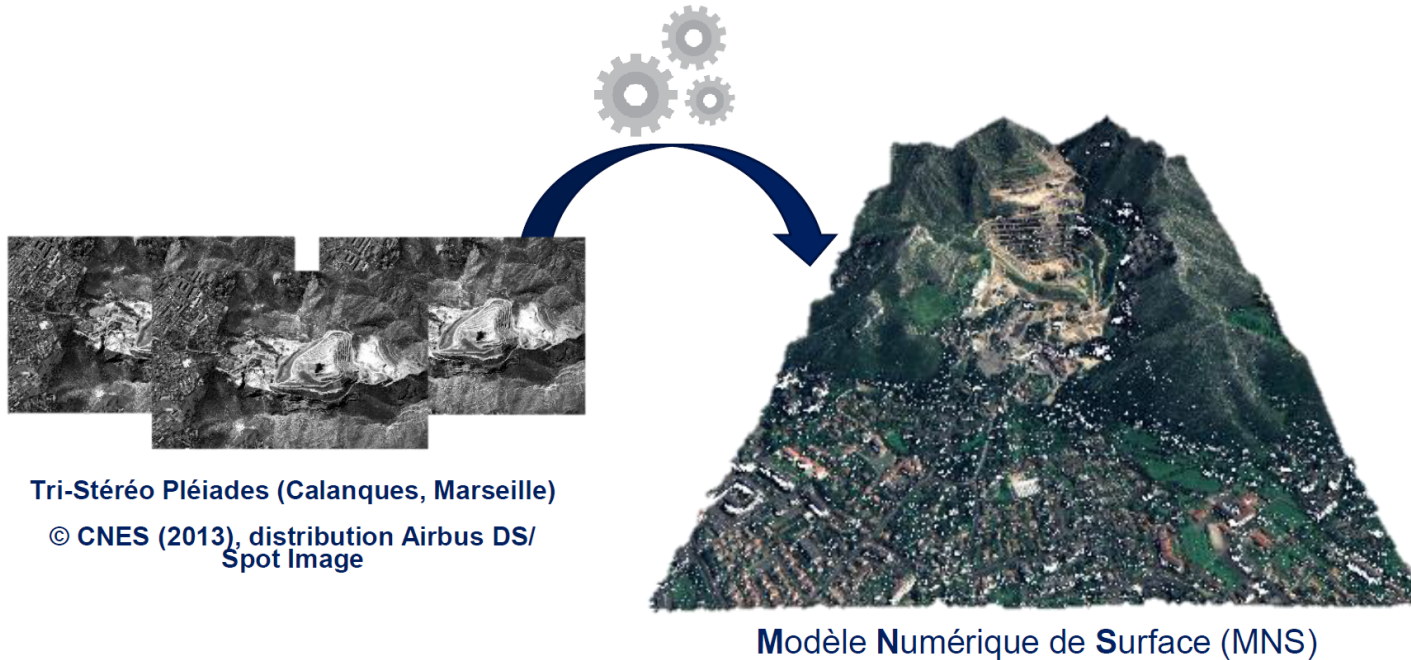
Use cases proposed

- Detection of deserted urban areas.
- Monitor mining operations
- Monitor activities of commercial centers
- Estimation of hotel incomes with the following information:
 - Satellite images
 - Room prices
 - Job offers
 - Other alternative data

- ① Contents
- ② Automatic car counting
- ③ Automatic building detection from 3D data
 - Context
 - Objectives & Challenges
 - Training
 - Current performance
 - Perspectives
- ④ Transfer learning

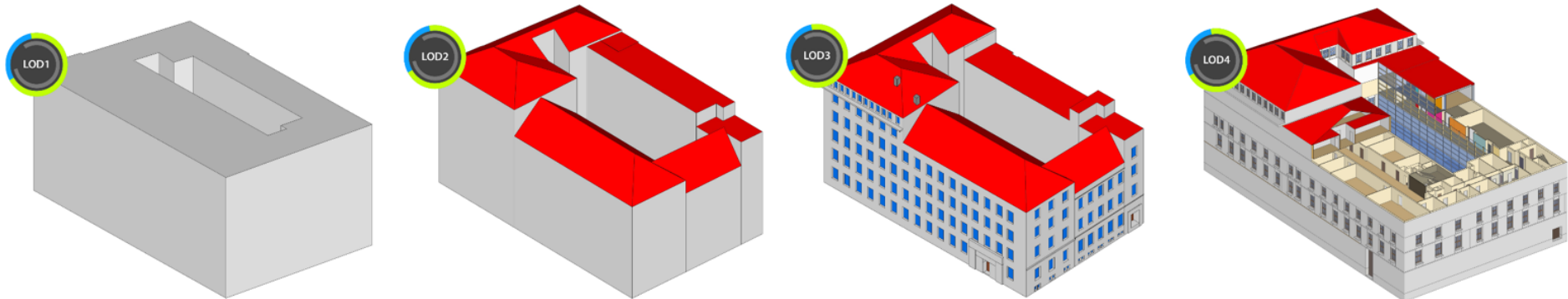
Context

- Preparing the applications of the 3D data provided by the future mission CO3D:
 - Constellation of 2 or 4 VHR optical satellites looking at the same landscape at the same time
 - World DEM (Digital Elevation model) cover every year
 - S2P software used by CNES to generate DEM and cloud points from those stereo-images
 - Set of ortho images registered with DEM available: gain of the height information



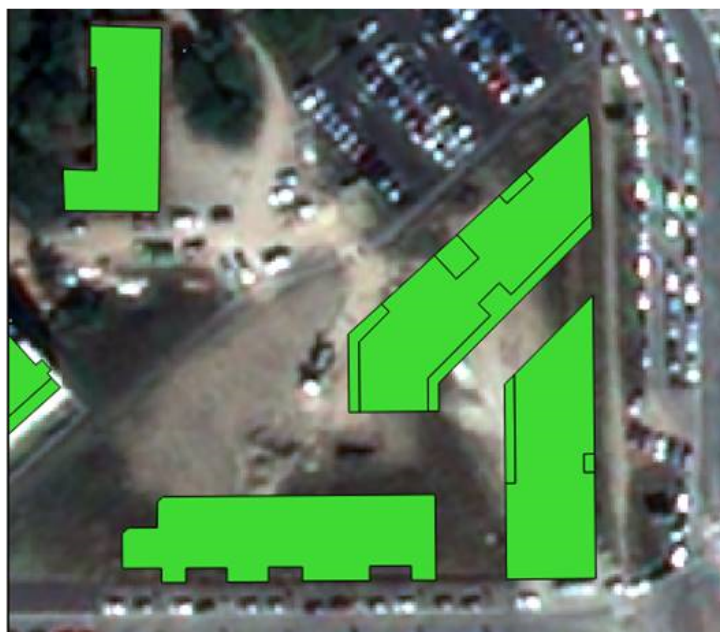
Objectives & Challenges

- Objectives
 - Monitor the urban areas (building changes) of cities
 - Elaborate high quality 3D products (Level of Details $\in [1; 3]$) by extrusion
- Challenges
 - Apply and adapt classical 2D machine learning algorithms on 3D point clouds (irregular data structures).
 - Creation of 3D training and test datasets

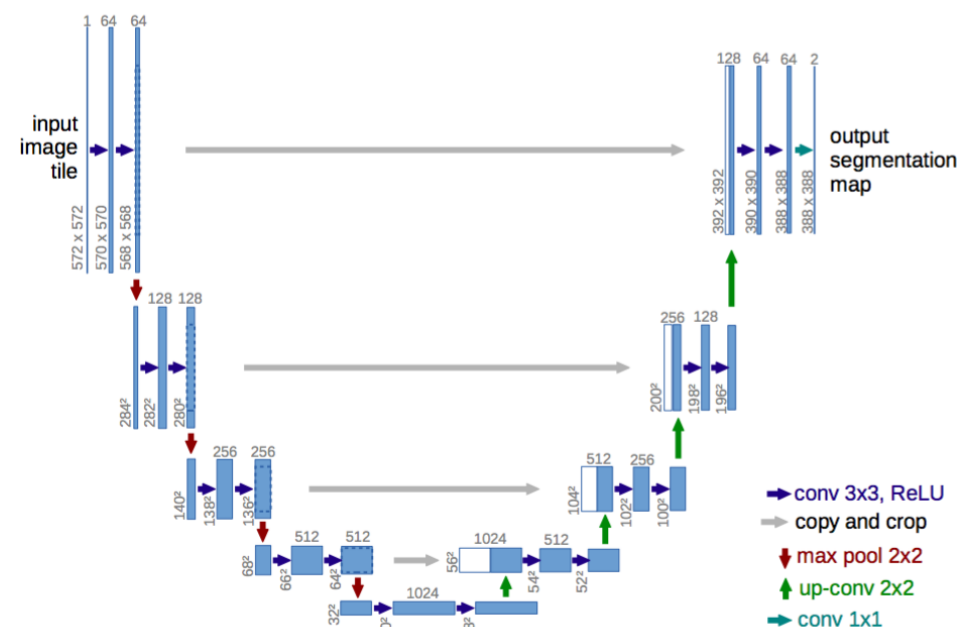


Training

- Ortho + DEM on Toulouse city area
- 14157 tiles for training dataset
- 6067 tiles for test dataset
- 2 classes: no-building (0) and building (1)
- Labelization made with OpenStreetMap
- 3-Fold stratified splitting strategy

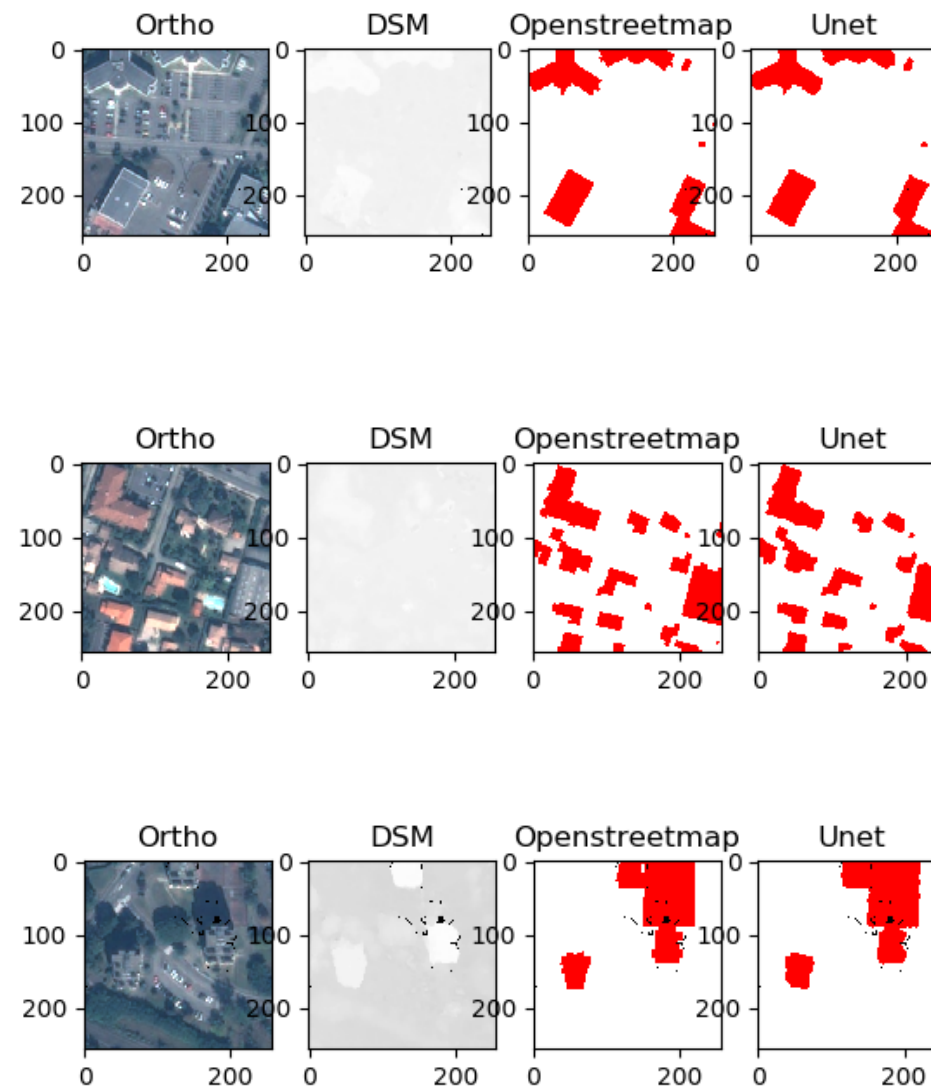
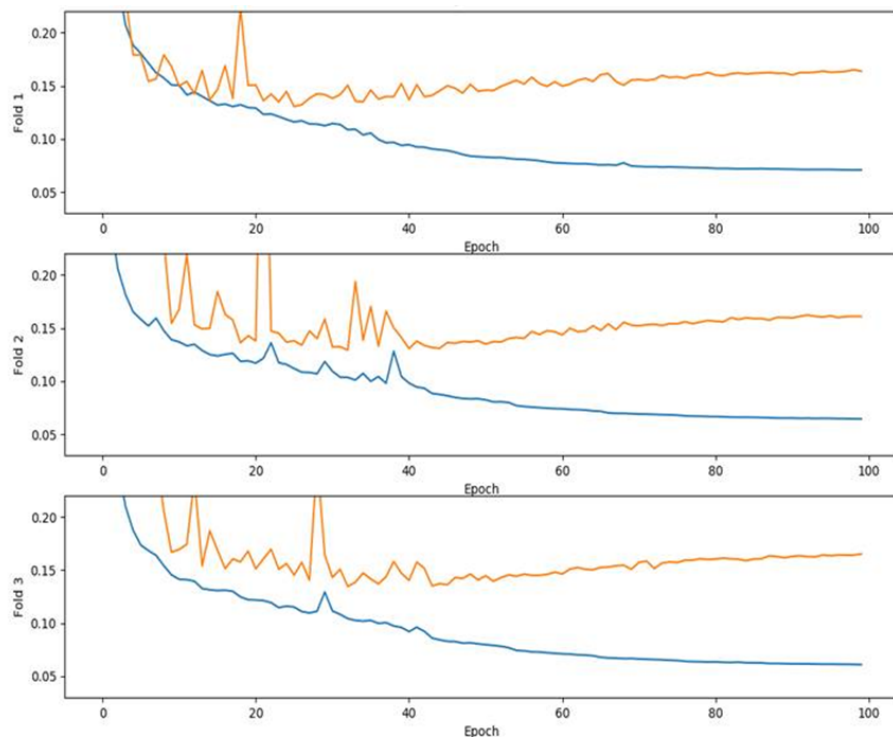


- Classical U-Net



Current performance

- Need to correct manually temporal incoherences between OSM and the ortho.



truth / predicted	building	no building
building	0.97	0.02
no building	0.03	0.98

Perspectives to reach high quality LOD products

- Improve the correlation methods to find corresponding points between stereo images.
 - Existing deep learning methods to find corresponding points
- Noisy DEM products
 - Denoising AI algorithms to remove noise from the optical instrument, atmospheric perturbations.
- Extrusion of building from classification results
 - Extrusion methods with no artefacts
 - Determination of the average height of detected buildings compared to ground height (DEM vs DTM)
 - Towards the modelization of the roofs (LOD2)
- Determine useful indicators for urban policy

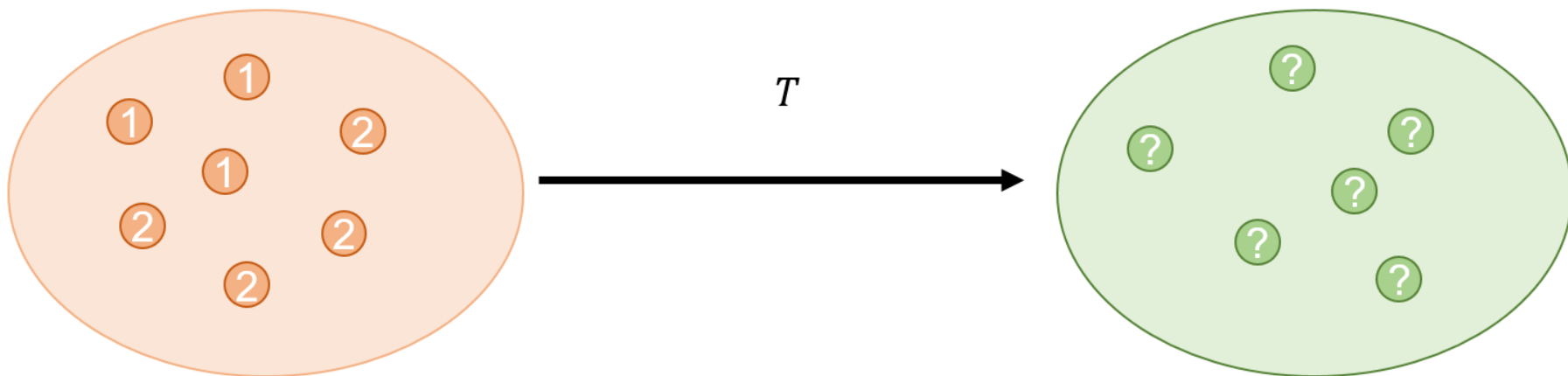
- ① Contents
- ② Automatic car counting
- ③ Automatic building detection from 3D data
- ④ **Transfer learning**
 - Motivations
 - Challenges
 - State of art
 - First test
 - Perspectives

Motivations

- Build predictive model on unlabeled dataset:
 - Historical dataset without ground truth (Spot World Heritage)
 - unlabeled dataset for specific classes (car ground truth available for Pleiades but not for Spot 6)
 - upcoming dataset of a new Earth Observation mission (CO3D)
- Taking full advantage of trained models on a specific dataset:
 - Trained model to detect clouds on Sentinel-2 satellite images
 - Trained model to detect building on 3D data obtained from the processing of S2P to Pleiades satellite images.

Challenges

- PH.D research lead with the research lab IRISA with Claire Voreiter, the company Thales Alenia Space and CNES with the following goals:
 - Labelization of a unlabeled dataset Ω_t from a labeled dataset Ω_s
 - Study the adaptation and the application of optimal transport methods between heterogeneous datasets.
 - Study the performance of a predictive model trained from a transported labeled data
 - Study different use cases of transfer learning for Earth Observation:
 - Car detection
 - 3D building detection
 - Cloud detection

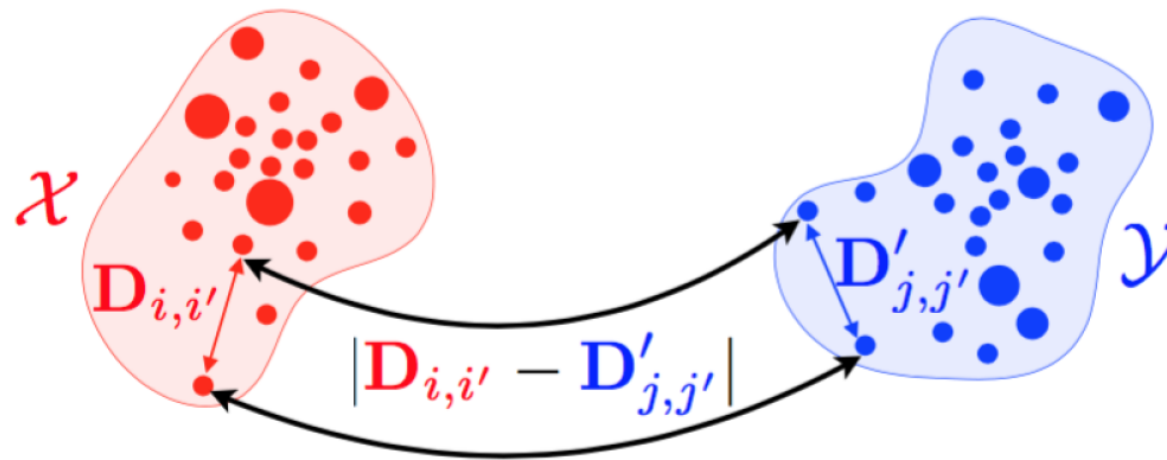


State of art

- Optimal transport method:

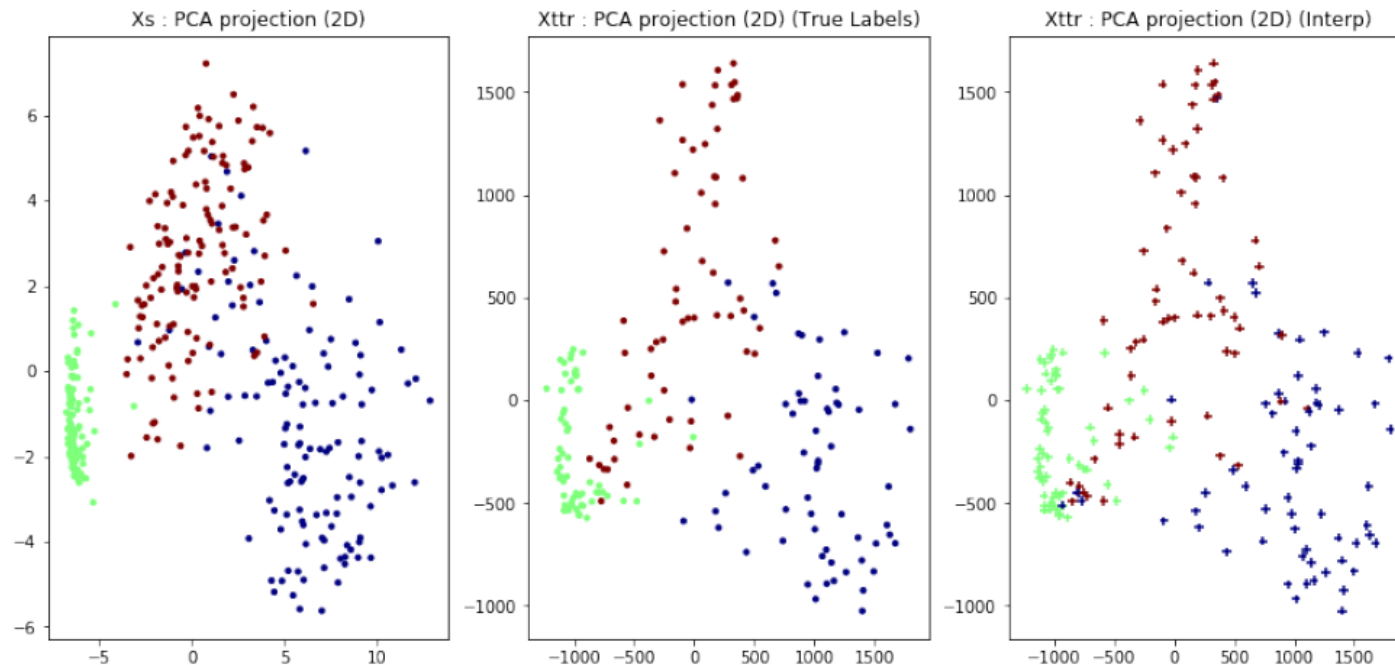
$$\min C(T) = \int_{\Omega_s} c(x, T(x))\mu(x)dx$$

- Use of Gromov Wassertein distance



First test

- Ω_s : USPC dataset (16 x 16 pixels) with ground truth (classes $\in [0, 2]$)
- Ω_t : MNIST dataset (28 x 28 pixels)
- Experience:
 - ① Use of Gromov Wassertein distance to label MNIST dataset from USPC dataset
 - ② Visualize the tranported labeled dataset



Perspectives

- Solve the scalability issue when using Gromov Wassertein since it is a quadratic algorithm
- Currently, this method is not relevant for Earth Observation data:
 - Find a way to reduce the dimension and use the Gromov Wassertein in the latent space (AutoEncoder)
- Explore alternative solutions for optimal transport (Generative and Discriminative models)

Thank you for your attention

pierre.lassalle@cnes.fr