Random Forest in remote sensing

GDP - Luca Ferrari, 2021

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Random Forest

The model

The model

- RF is an ensamble classifier where classifications are made by combining the output of multiple decision trees
- The model has become popular in the Remote Sensing world due to the accuracy of the classifications and due to the multidimensional data handling capability

Random Forest Training (theory)

- A bootstrapped dataset is created from an original dataset and then used to train a decision tree with a subset of features at each step
- The procedure is repeated *nTree* times so that a number of decision trees are trained on multiple bootstrapped datasets

Random Forest Training (theory)

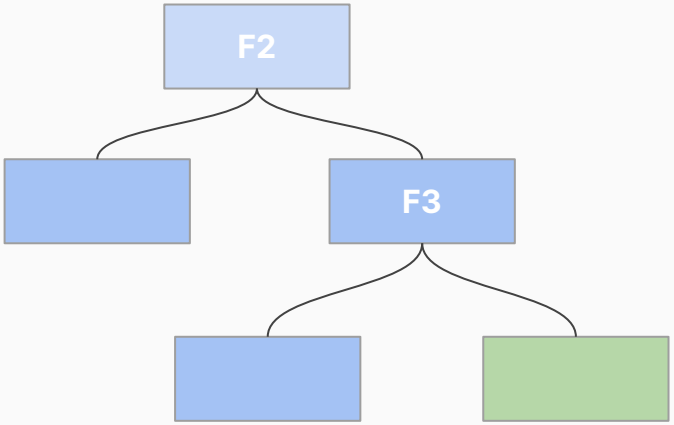
Original Dataset

F1	F2	F3	CLASS
1	2	3	A
5	2	5	B
3	3	2	C
1	2	5	B

Bootstrapped Dataset

F1	F2	F3	CLASS
1	2	3	A
5	2	5	B
1	2	3	A

Random Forest Training (theory)



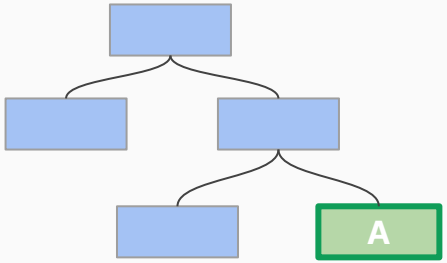
Bootstrapped Dataset

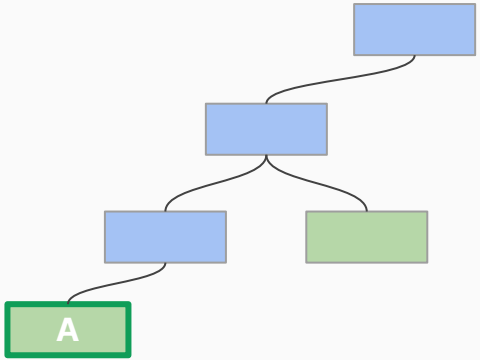
F1	F2	F3	CLASS
1	2	3	A
5	2	5	B
1	2	3	A
1	2	5	B

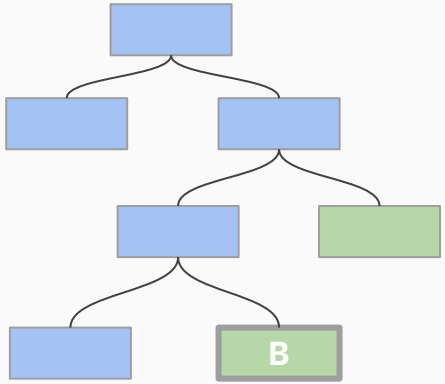
Random Forest Classification

F1	F2	F3	CLASS
1	2	3	**A**

A	B
2	1







Random Forest performance evaluation

- To evaluate the RF's accuracy we can exploit two different methods:
  - Out Of Bag validation set
  - external validation set
- nTree is the number of trees used in the RF
- mTry is the number of subset features used to train the decision trees

Remote sensing applications

Random Forest: Remote Sensing applications

- Random Forest has been used in different applications related to remote sensing:
  - Land Cover classes mapping
  - Urban buildings detection
  - Urban object classification from airborn LiDAR data

Random Forest: Pros and cons

+ Doesn’t assume Normal distribution
+ Doesn’t overfit
+ Correct for decision tree variance (by ensambling)
+ Not sensitive to outliers
- Memory intensive → Hyperspectral images problem → Rotation forests

Random Forest: Sensitivity to data

- Training and validation sets must be statistically indipendent
- Training samples must be class balanced
  - Unbalanced dataset problem and strength
- Spatial autocorrelation
- Training set dimension

Random Forest applications

First approach: Landsat8 + CORINE LC

First approach: Landsat8 + CORINE LC

- As a first approach I decided to use two different data sources to tackle the classification problem
- The idea is to use an already classified raster image as a dataset and then sample points from it to create a new training set for the RF model
- All the operations were carried out in Python interfacing with GEE through a library called *geemap*

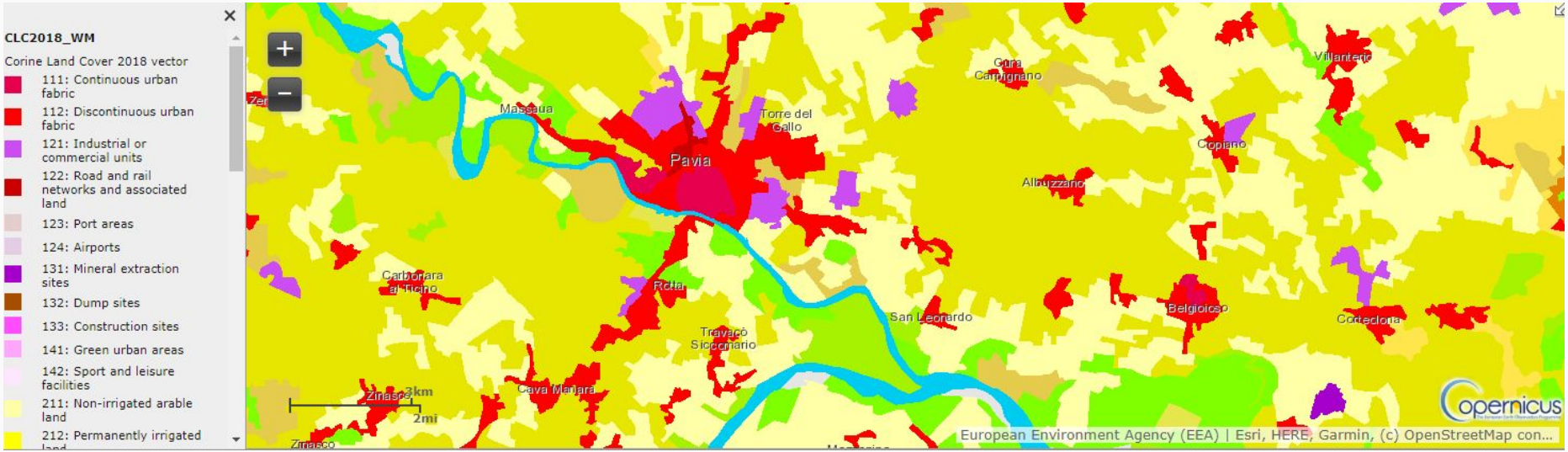
First approach: Landsat8 + CORINE LC

+ Accurate classes (specific and verified labels)
+ Flexible control on the number of samples
+ Easy model evaluation
- Scarse control on the sampling zones

First approach: Landsat8 + CORINE LC

- Satellite data comes from the Landsat 8 satellite program
- Landsat 8 was chosen because the spatial resolution of images was suitable for the application (30m)
- Classification data comes from the Copernicus CORINE Land Cover which provides a standardized data collection on land in Europe
- Data from 2017 was taken into account so that both the Landsat8 and CORINE Land Cover images were referring to the same exact time period

Copernicus CORINE Land Cover



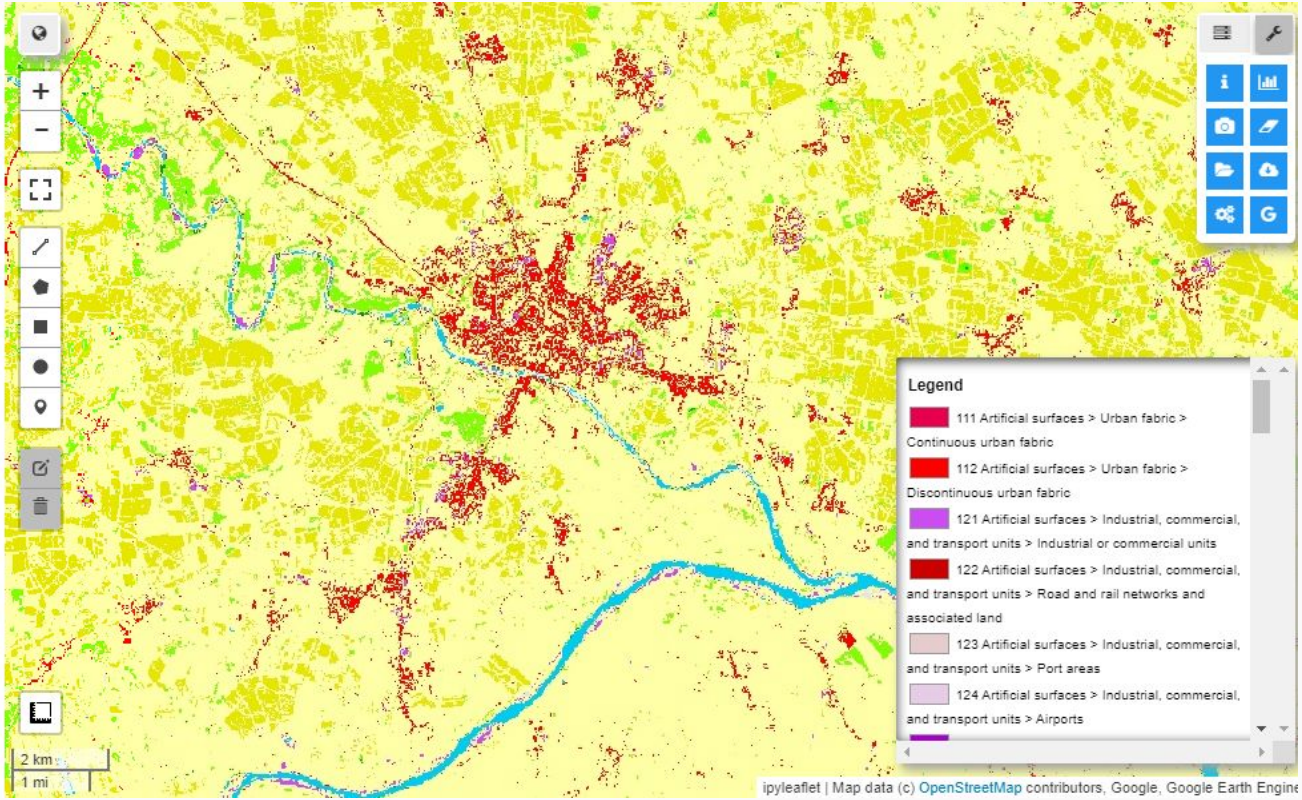
Data exploration and TrSet creation

- Data exploration was performed to verify that the image was suitable for being used as a proper dataset (cloud cover, basic corrections)
- 10k points were sampled from the Corine dataset and then used as regions in the Landsat8 satellite image to create a Training set for the RF model

Random Forest Training

- As a first experiment the RF model was trained with 10k samples points, using 100 decision trees and the default number of variables per split (*sqrt(p)*)
- The classification is then plotted on top of the map in a new layer

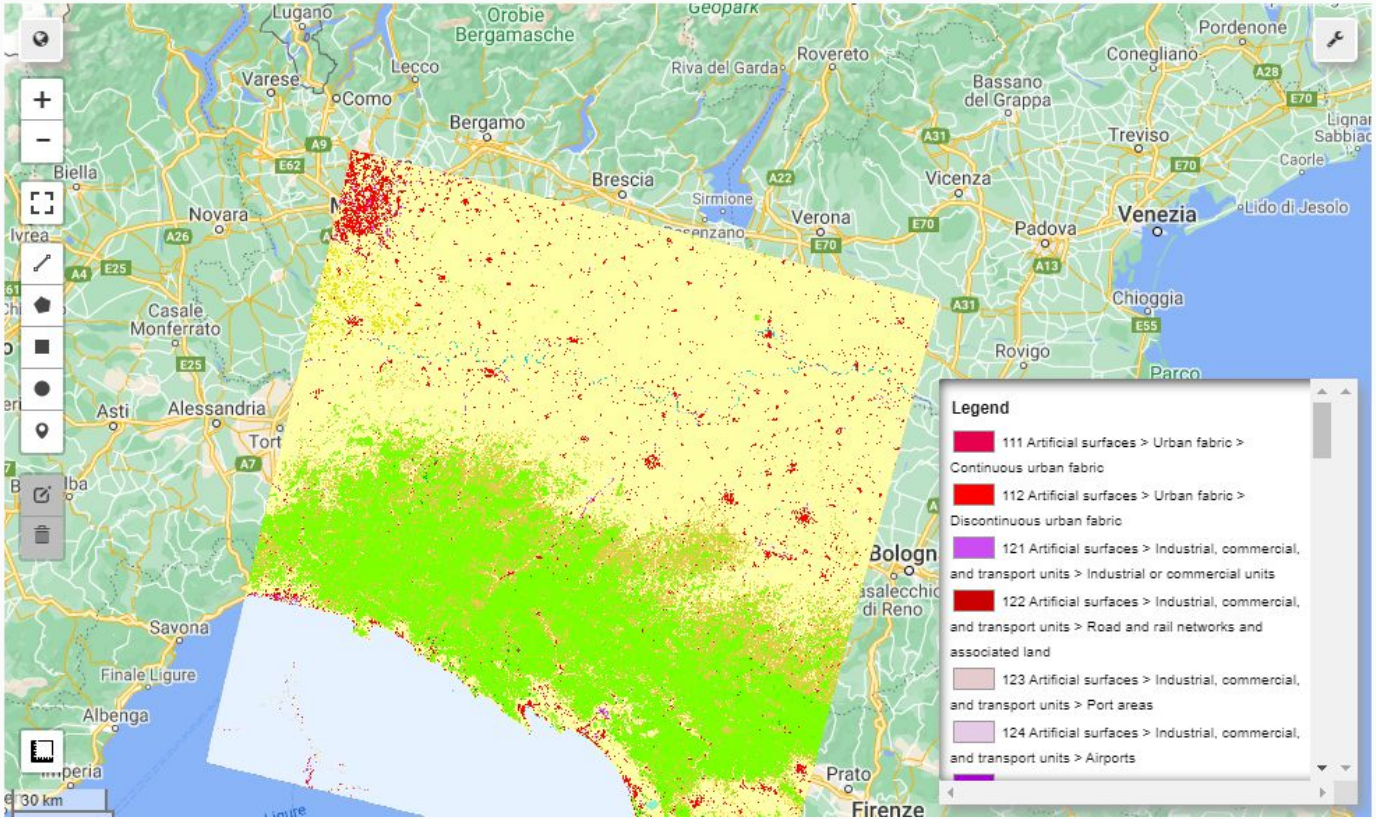
Random Forest visual inspection



Random Forest visual inspection

- By visually inspecting the classification plot we can see that in general the classifier does a pretty good job classifying pixels correctly, however we can notice that most of the misclassifications happen to be in the urban areas
- Probably we can observe this behaviour because the majority of the data points are taken from the Pianura Padana region

Random Forest visual inspection



Random Forest, fewer samples

- By reducing the number of samples a even worse result was produced because having no control on the way points are sampled, doesn’t let us compensate for fewer represented classes

Second approach:
Landsat8 + Custom classes

Second approach: Landsat8 + Custom classes

- Since the first approach didn’t work well, I decided to move to the JS Google Earth Engine platform which provides a more friendly interface to interact with the map
- In this case I decided to limit the number of classes to 4 (water, vegetation, soil, urban) so that the sampling procedure was easier and a balanced dataset could be created

Dataset creation

- 100 points for each class were collected by sampling on the map so that the final dataset contained 400 points
- The dataset was then filtered to reduce possible spatial correlation (200m distance)
- The dataset can finally be divided into a training set and into a test (or validation) set

Random Forest: Training and evaluation procedure

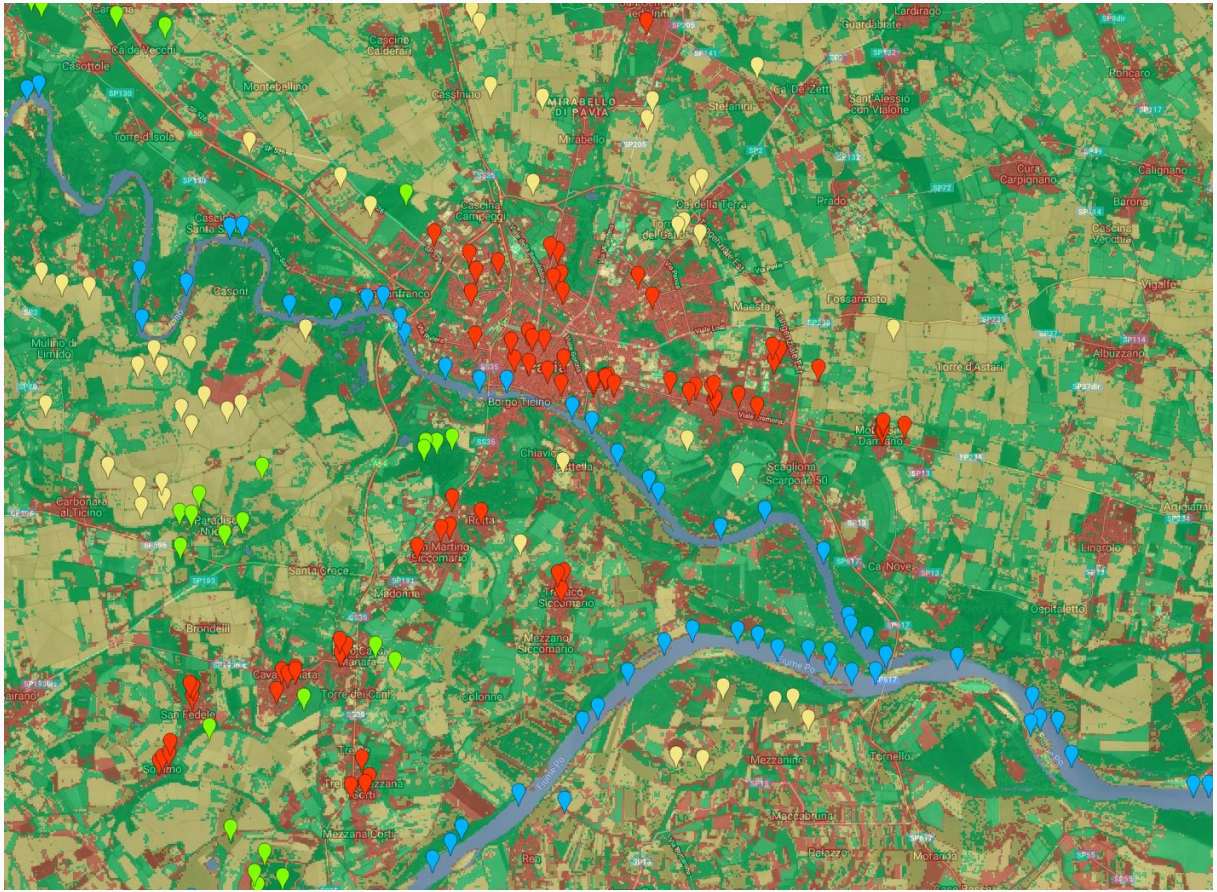
- To assess the model's performance, I set up a grid search method to systematically verify the effect of the parameters' tuning
- For every set of parameters a RF model is trained and evaluated
- Training Accuracy, Test Accuracy and error matrices are recorded for every single model
- The model's parameters we are going to change in the training phase are: *number of decision trees* (nTree), *number of variables per split* (mTry), *percentage of dataset that will be dedicated to Tr and Ts*

nTree	**mTry**	**Split** (Ts)	**trAcc**	**tsAcc**
100	3	**0.4**	1	0.768
100	3	**0.3**	1	0.785
100	3	**0.2**	0.995	0.8255
100	3	**0.1**	0.994	**0.829**
10	3	0.2	0.97	0.767
50	3	0.2	0.996	0.802
100	3	0.2	1	**0.825**
500	3	0.2	1	0.825
1000	3	0.2	1	0.825
100	**3**	0.2	0.98	0.825
100	**5**	0.2	0.978	0.814
100	**6**	0.2	1	**0.827**
100	**8**	0.2	1	0.823

Random Forest: best parameter combination

- **tsAcc**: **0.853**
- trAcc: 0.994
- split: 0.9tr, **0.1**ts
- mTry: **6**
- nTree: **100**

Random Forest final classification



Conclusions

- The model needs to be refined maybe by applying some basic computer vision corrections to get a more precise classification
- More points (sampled in a balanced way) should be used to achieve higher classification performance