Elaborazione di immagini satellitari tramite tecniche di deep learning per il monitoraggio di aree ambientali

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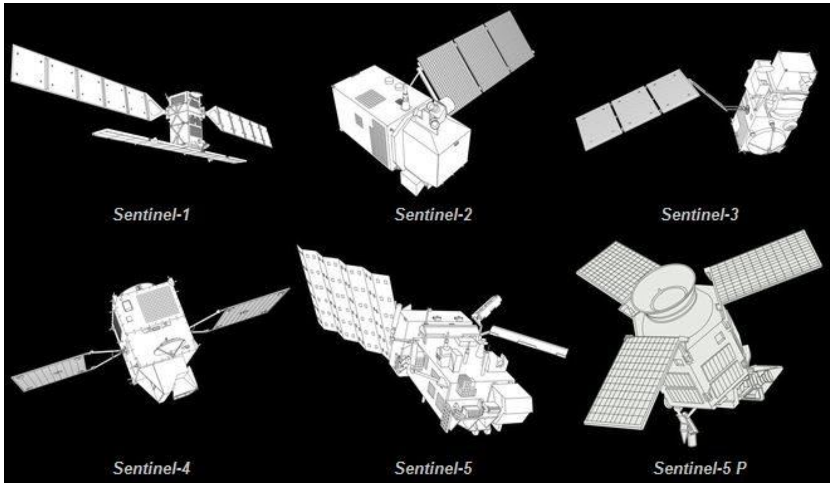
Summary

1. Machine Learning for Remote Sensing Applications
2. Sentinel-2 Image Segmentation
3. The Analysis Framework
4. Experimental Results for Cloud detection
5. Conclusions and Perspectives

Machine Learning for Remote Sensing Applications



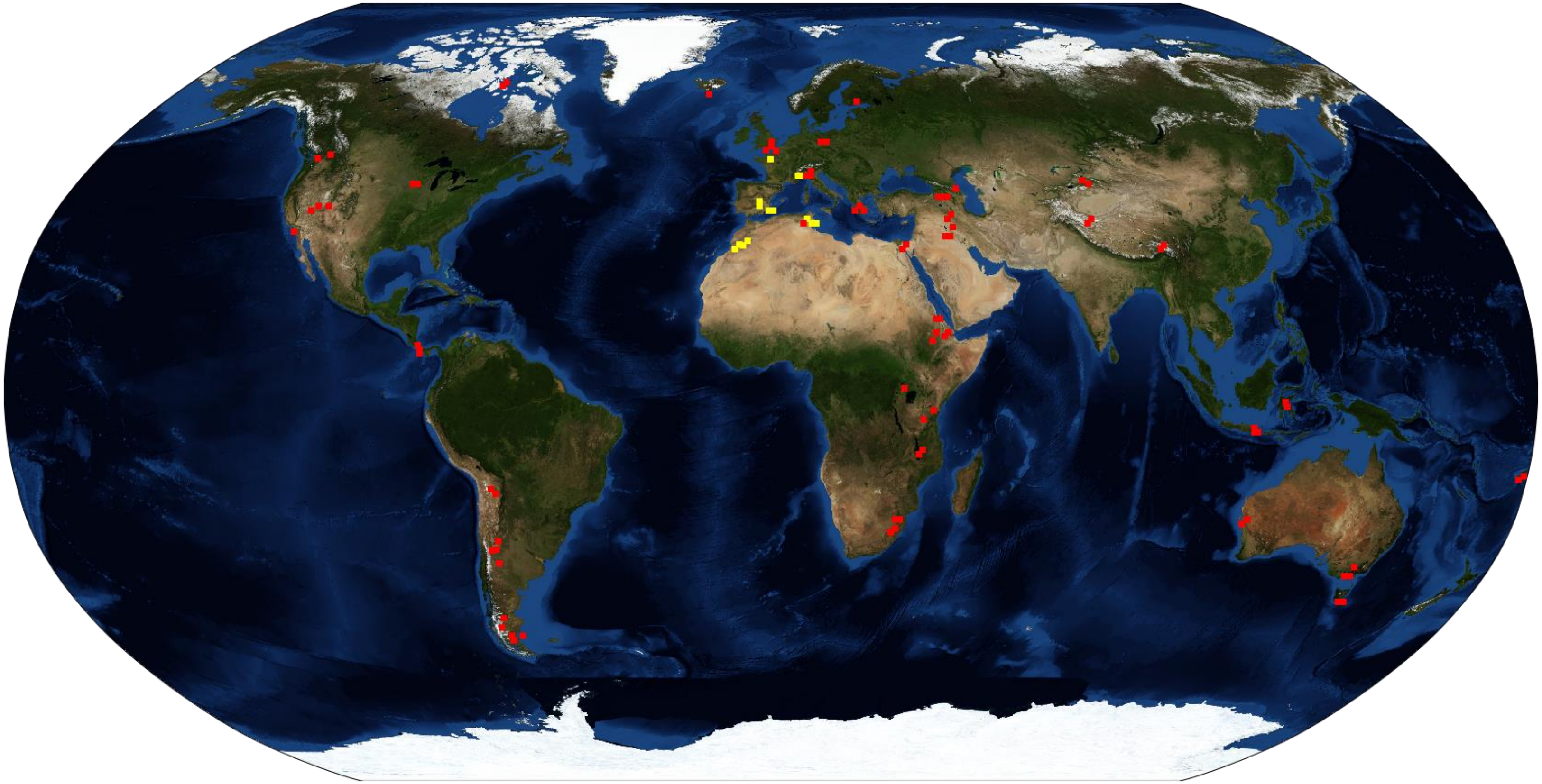
Remote Sensing for Earth Observation is the acquisition of a region of interest by means of air-borne and space-borne sensors.

We analyse Sentinel Images with Machine Learning and Deep learning techniques for several applications:

1. Image **segmentation** (Cloud Detection);
2. Image **classification** (Land Cover/Use);
3. Terrain **monitoring** (Subsidence).

Sentinel-2 Image Segmentation

We compared several state-of-the-art cloud detection methods including those based on machine learning with an open dataset D[1] of labeled Sentinel-2 (S2) images for **training** and an independent dataset D[2] of labeled Sentinel-2 (S2) images for **test**.



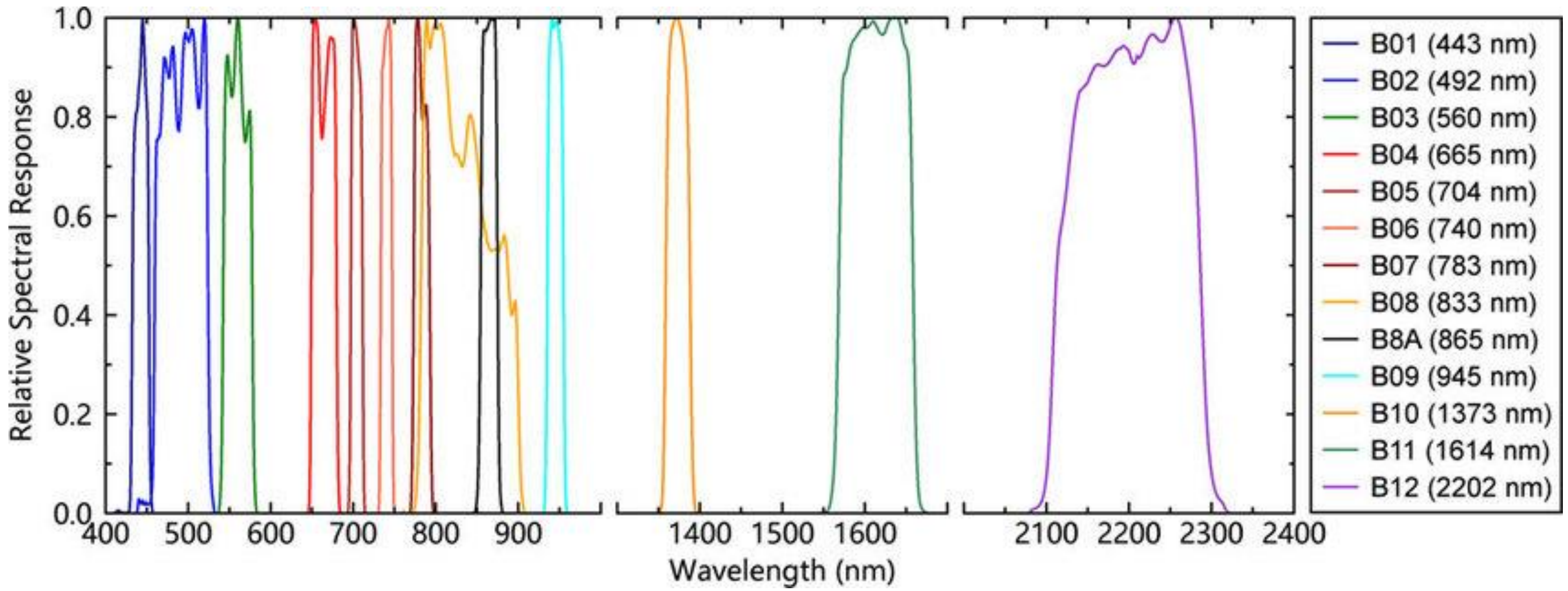
[1] Hollstein A, et al. M. *Remote Sens.* **2016**, *8*(8), 666;

[2] Baetens L, et al. *Remote Sens.* **2019**, *11*(4), 433;

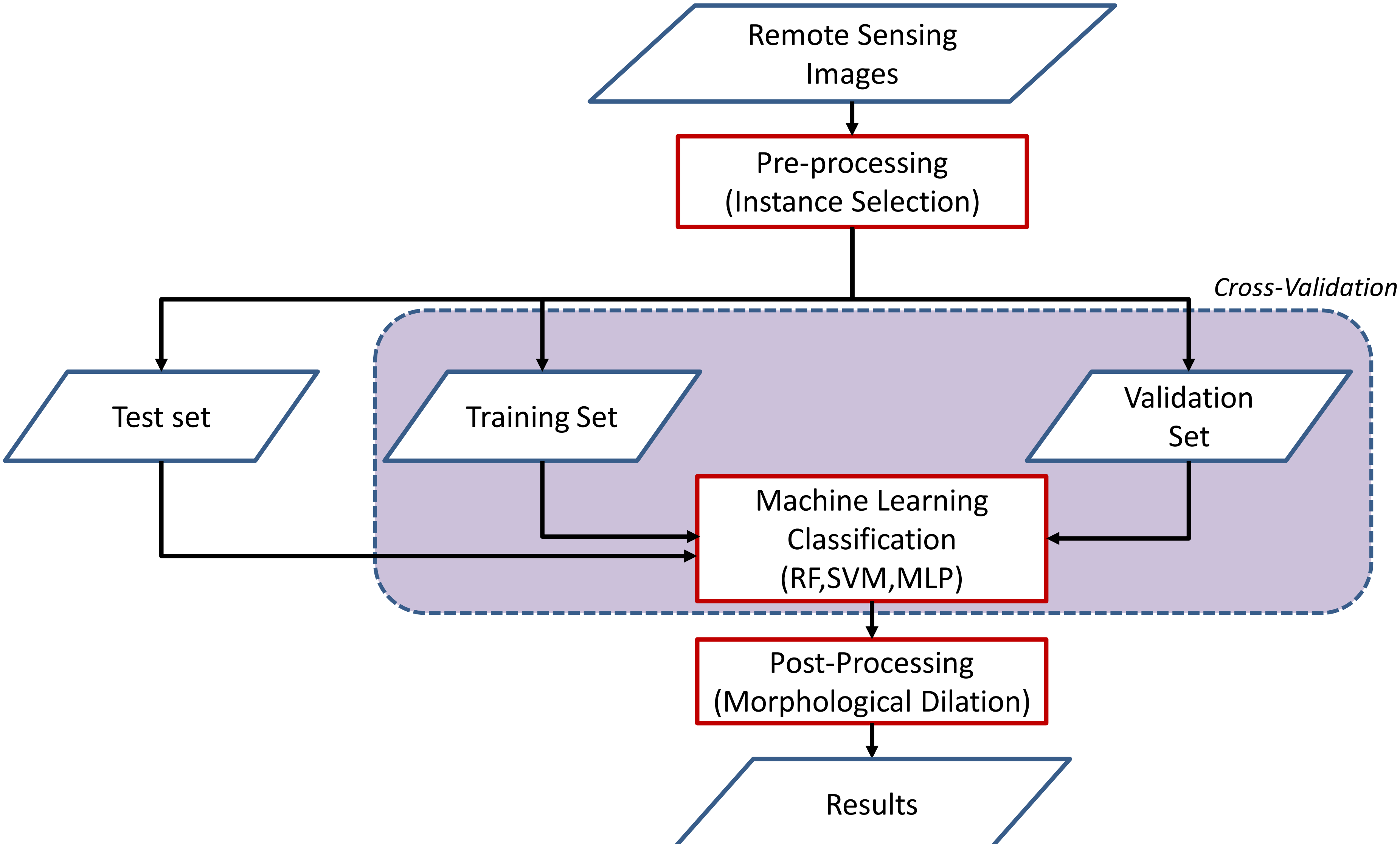
The Physical Properties

Dataset	# Pixels	# Images	# Sites
D^1	~ 5×10^6	97	41
D^2	~ 10^8	29	10

Each pixel is described by **13 features** which correspond to different reflectance ranges.



The analysis framework



Experimental Results for Cloud detection

We performed a 5-fold cross-validation procedure on D[1] in order to assess the performance of RF, SVM and MLPs when dealing with classification tasks (cloud detection) in Sentinel-2 images.

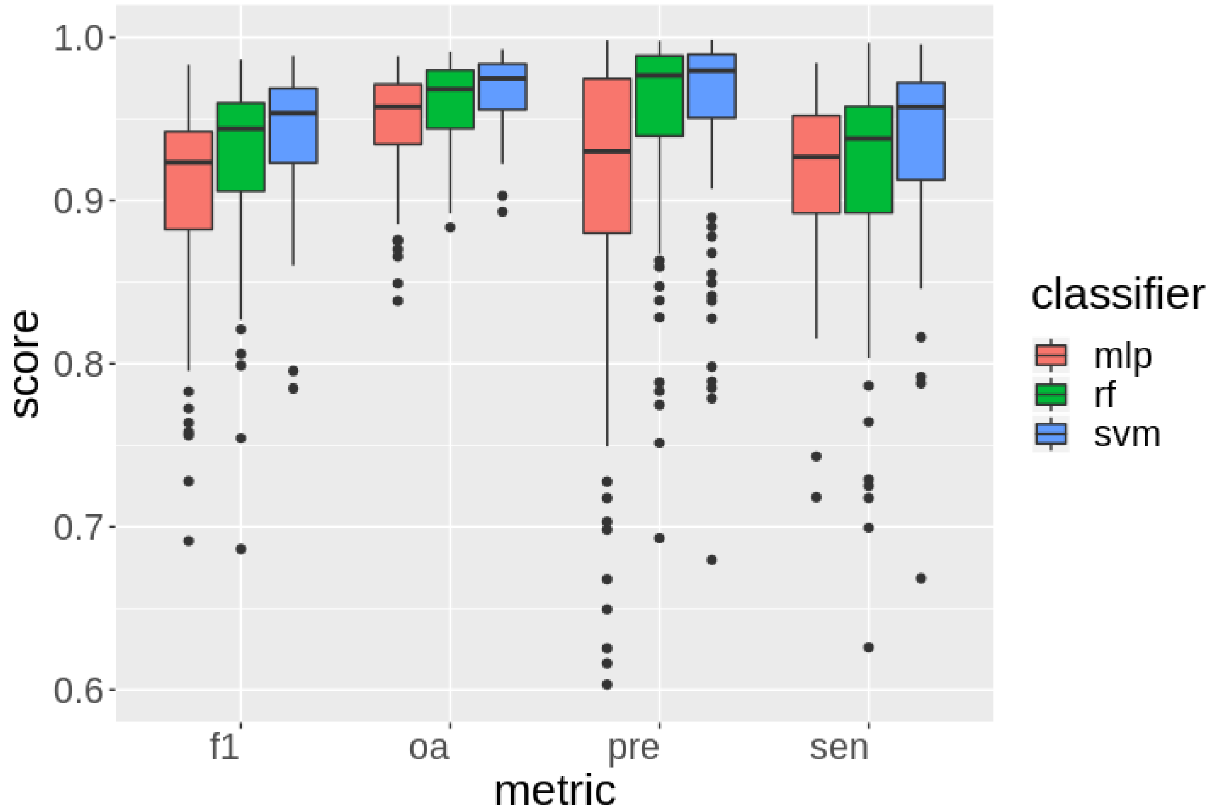
The classification performance is evaluated by the OA, SEN, PRE and F1 metrics:

$$ACC = \frac{TP + TN}{TP + TN + FP + FN}$$

$$SEN = \frac{TP}{TP + FN}$$

$$PRE = \frac{TP}{TP + FP}$$

$$F1 = \frac{2\ SEN\ PRE}{SEN + PRE}$$



As can be seen, **SVM** shows the best performance.

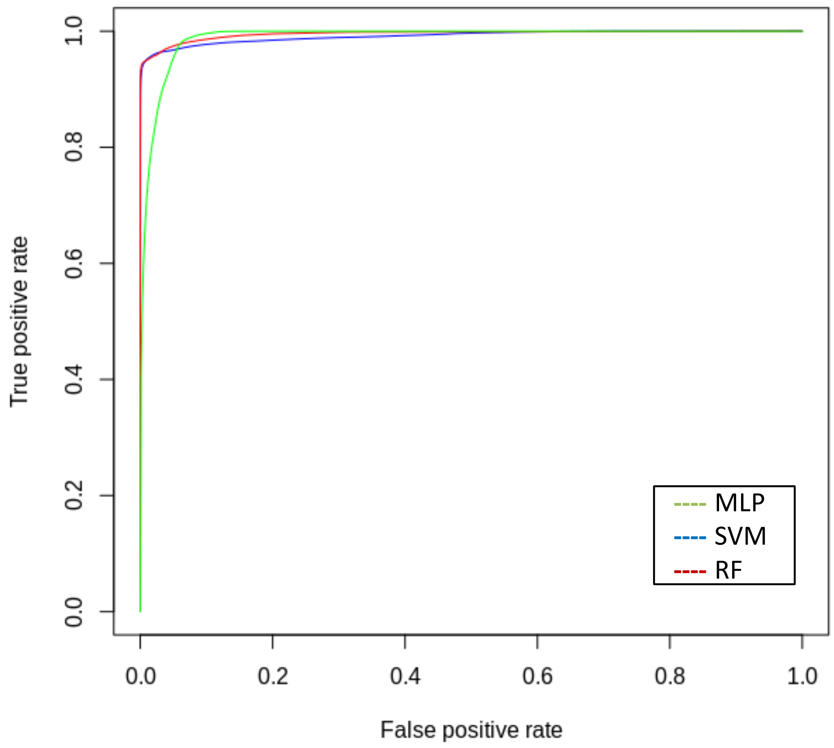
Experimental Results for Cloud detection

We performed a 5-fold cross-validation procedure on D^1 in order to assess the performance of RF, SVM and MLPs when dealing with classification tasks (cloud detection) in Sentinel-2 images.

Receiver operating characteristic (ROC) curve

The classification performance is evaluated in terms of the area under the ROC curve (AUC):

-MLP : 0.990 ± 0.10
-SVM : 0.995 ± 0.005
-RF : 0.995 ± 0.005



As can be seen, both **SVM and RF** shows the best performance in terms of AUC.

The indepedent test set D2

We compared the performance of both SVM and the **state-of-the-art** methodologies in terms of ACC, PRE, SEN and F1 scores on D^2.

The classification performance is evaluated by the OA, SEN, PRE and F1 metrics:

$$ACC = \frac{TP + TN}{TP + TN + FP + FN}$$

$$SEN = \frac{TP}{TP + FN}$$

$$PRE = \frac{TP}{TP + FP}$$

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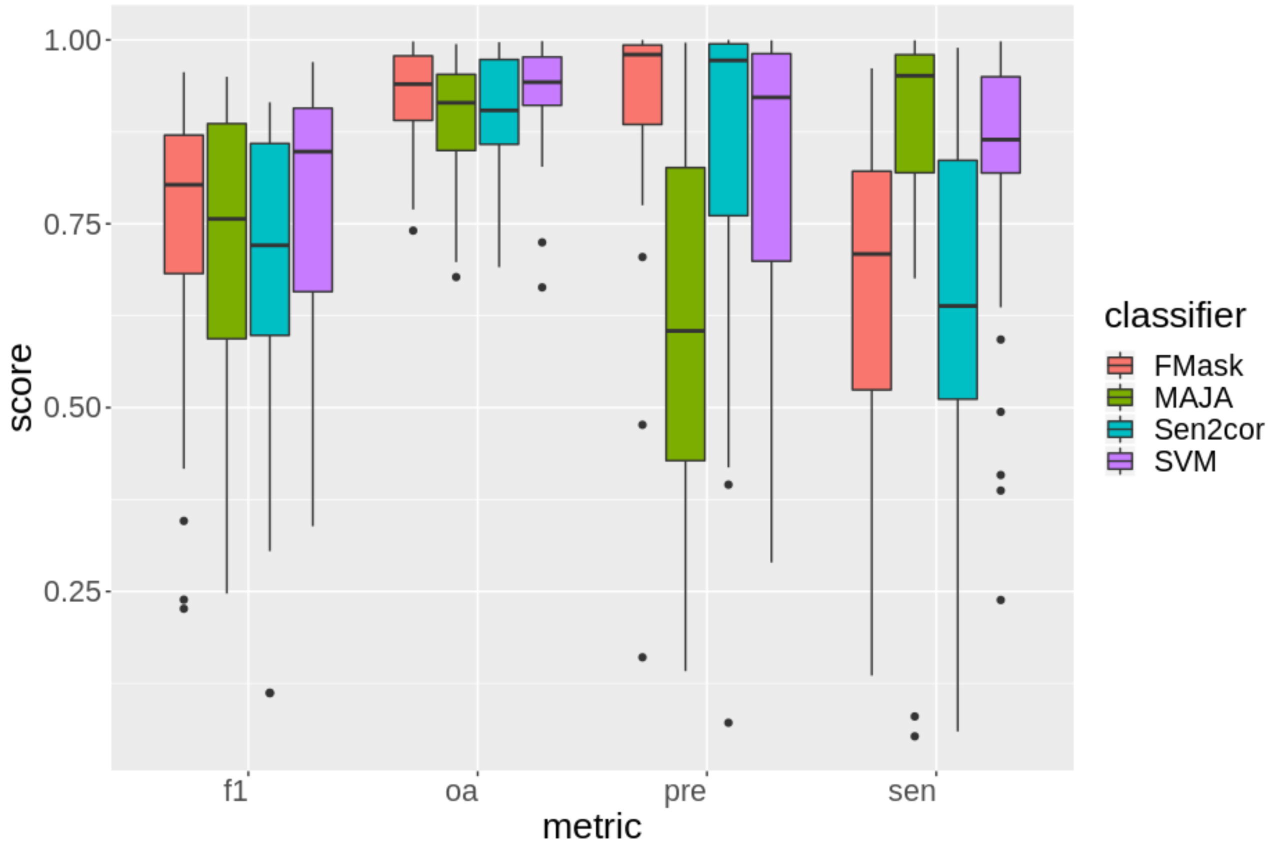
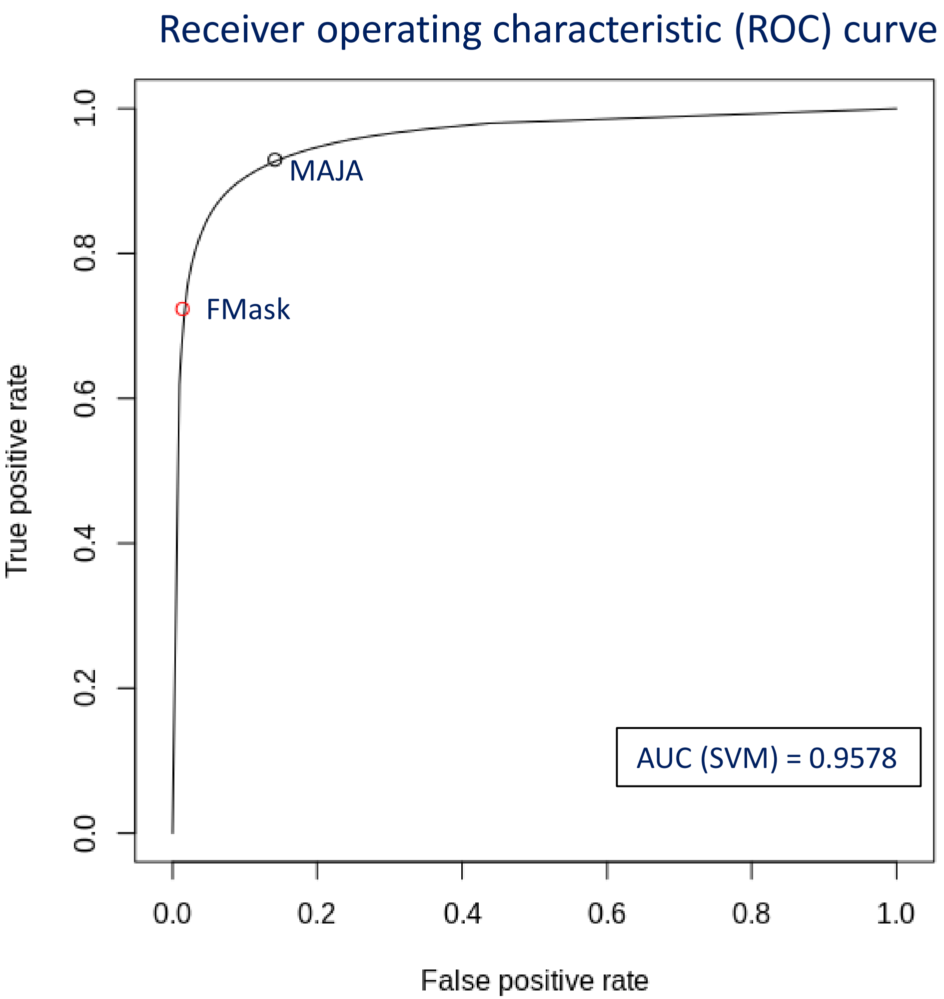


SVM performance in terms of OA and F1 is significantly higher than those obtained by other methods.

The indepedent test set D2

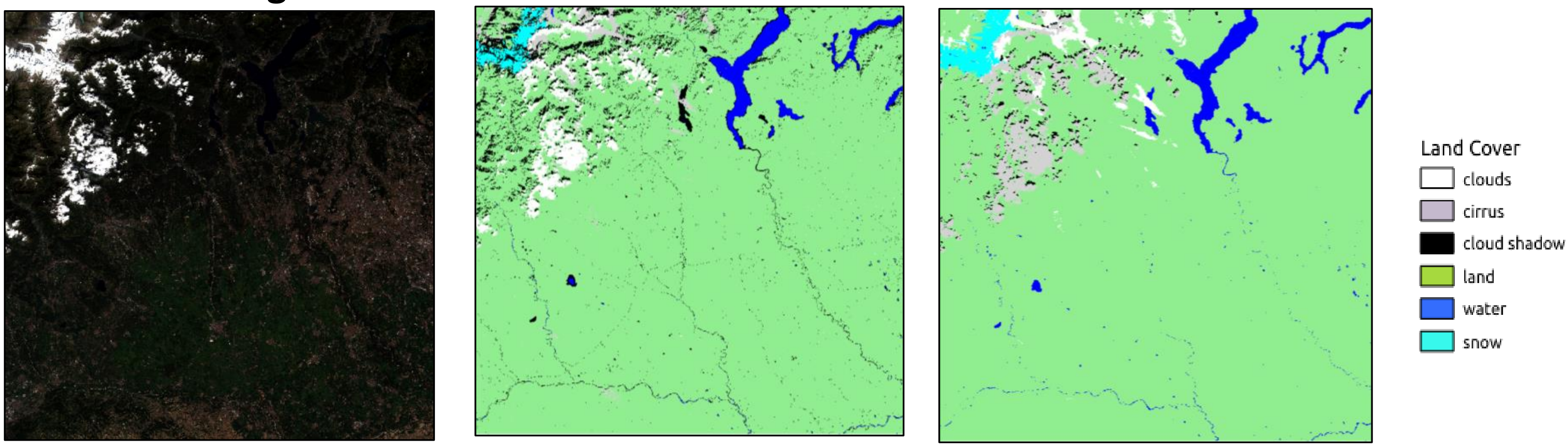
We compared the performance of both SVM and the **state-of-the-art** methodologies on D^2 in terms of the area under the ROC curve (AUC).



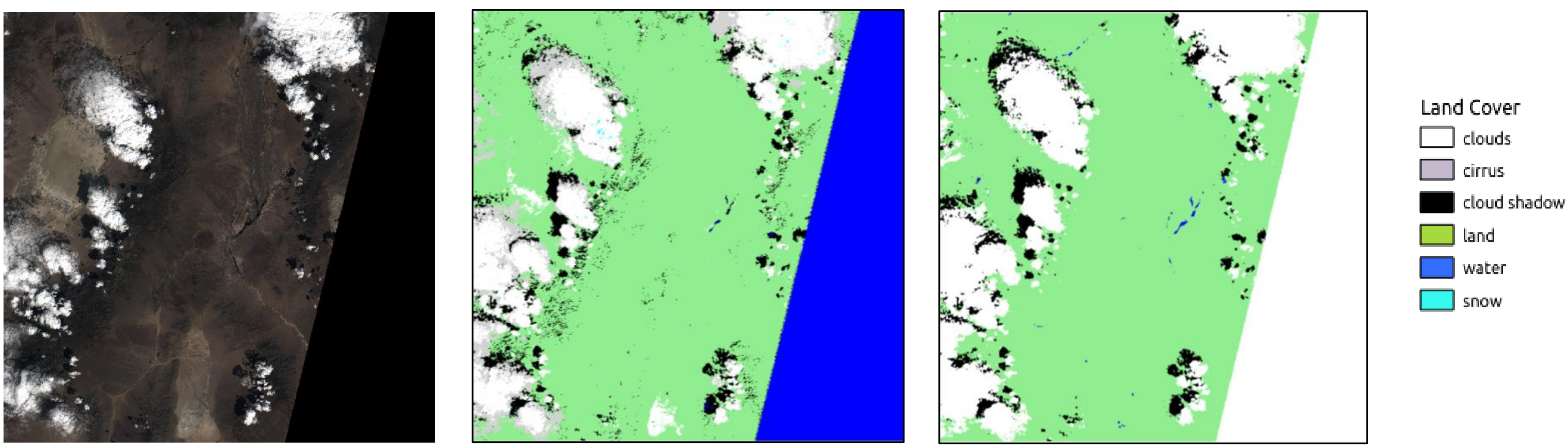
SVM performance is significantly higher than those obtained by other methods.

Ongoing work

RGB Image | **SVM** | **Reference Map**



Ispra, Italy 15/08/2017



Railroad Valley, Nevada, 27/08/2017

Conclusions and perspectives

We have developed an analysis framework that can accomplish several tasks related to remote sensing

Classification procedures based on ML and DL techniques can outperform the existing state-of-the-art solutions

Events

- The ESA Earth Observation ϕ-week Open Science and Future EO, Frascati, ESRIN, 12-16/11/2018
- Copernicus Hackathon, Bari, 11-13/10/2019
- Copernicus Hackathon in Athens 2019, Marousi, 8-9/11/2019.
- Riunione generale RPASinAir - Integrazione dei Sistemi Aeromobili a Pilotaggio Remoto nello spazio aereo non segregato per servizi. Brindisi, 5-6/02/2020

Seminaries

- ”United Nations eGovernement Survey 2018: Gearing eGovernement to Support Transformation toward Sustainabl and Resilient Societies”, Ing. Aquaro - Direttore del Digital Governement Branch presso il Dipartimento degli Affari Economici e Sociali delle Nazioni Unite. 8/10/2018
- ”La prima immagine di un buco nero”. Bari, Dipartimento Interateneo di Fisica, Prof. Luciano Rezzolla - Director at the Institute for Theoretical Physics (ITP) of the Goethe University of Frankfurt, Germany.
- ”Riuso delle acque reflue: innovazioni tecnologiche e condizionamenti sociali e gestionali”. Bari, Politecnico di Bari, 30/01/2020

Thank you for your attention!

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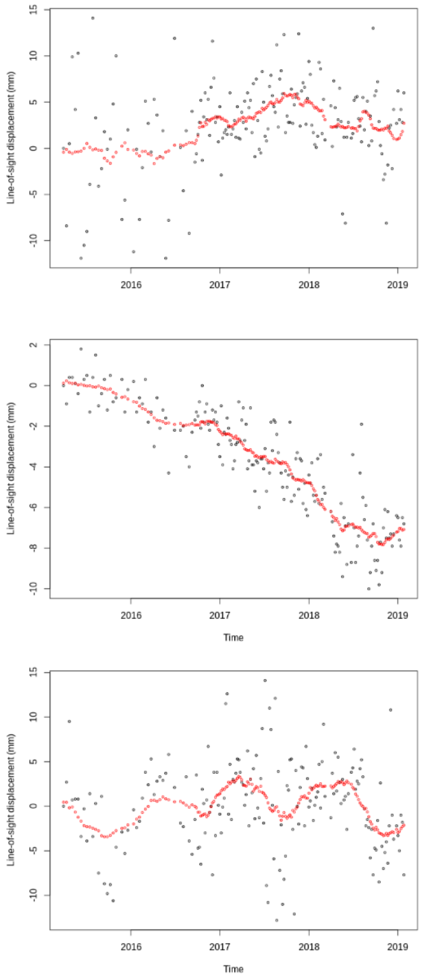
Pre-processing strategies

- Instance selection strategies
- Moving average filter (for time series):

$$(x_i)_{i=1,2,\ldots N} \rightarrow (y_i)_{i=1,2,\ldots N}$$

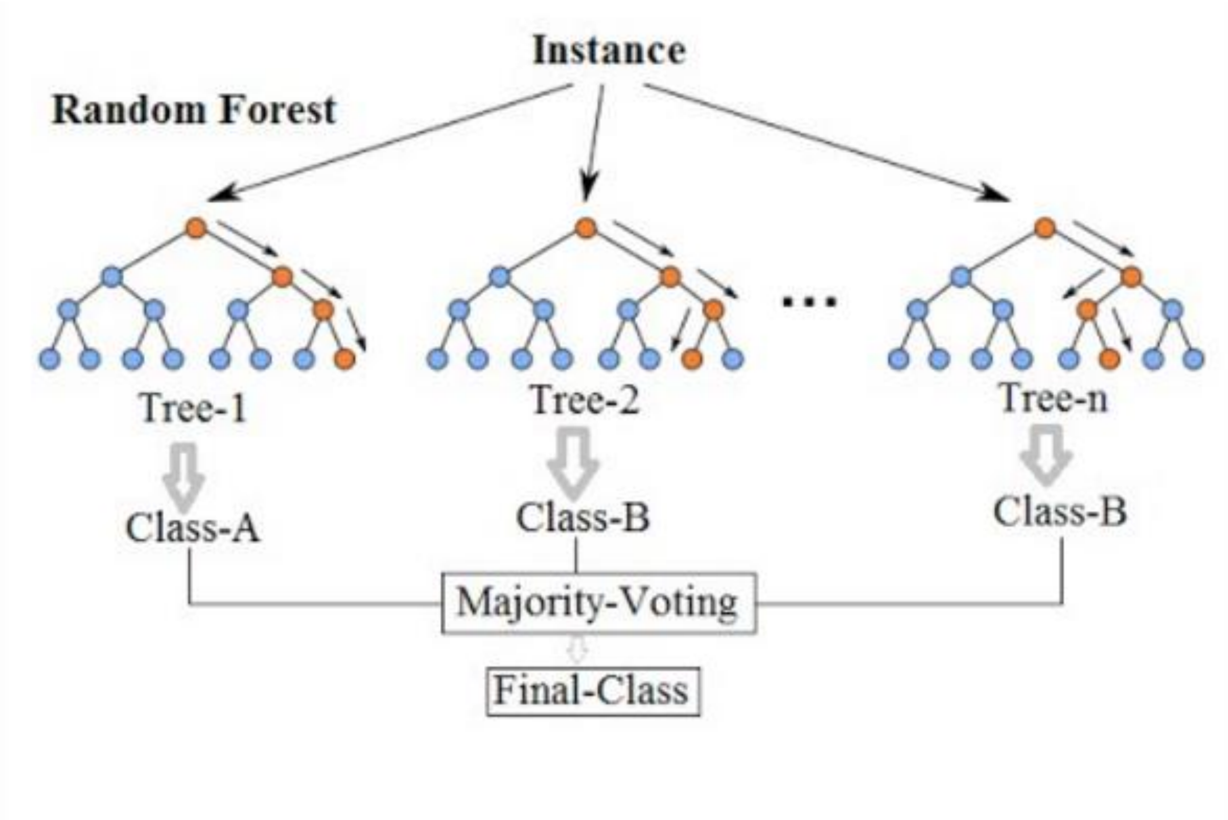
$$y_i = \frac{1}{n}\sum_{i=0}^{n-1} x_i$$

- Feature Engineering:
    - Feature Selection strategies
    - Principal Component Analysis



Classification methods: Random Forest

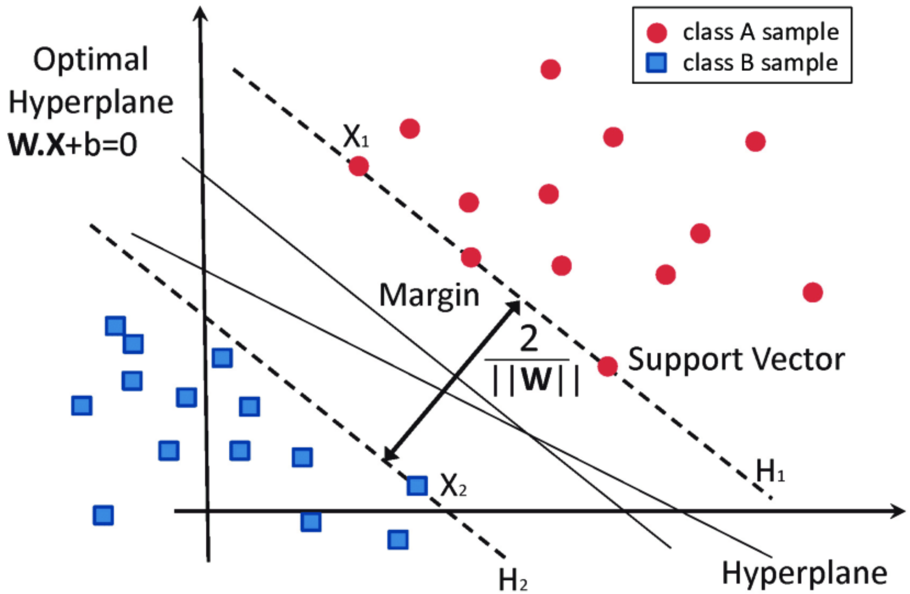
Random forests are an ensemble learning method for classification that operates by constructing a multitude of decision trees at training time and outputting the class that is the mode of the classes

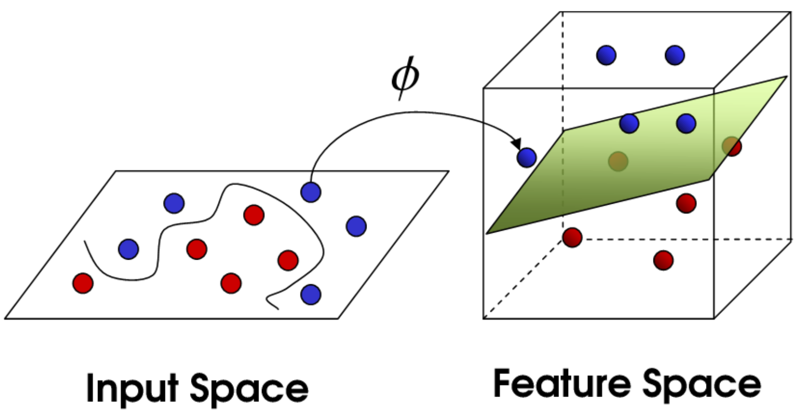


Classification methods: Support Vector Machines

Support Vector Machines are a discriminative classifier defined by a separating hyperplane in a transformed feature space .

Given labeled training data, SVMs output an optimal hyperplane which classifies new examples

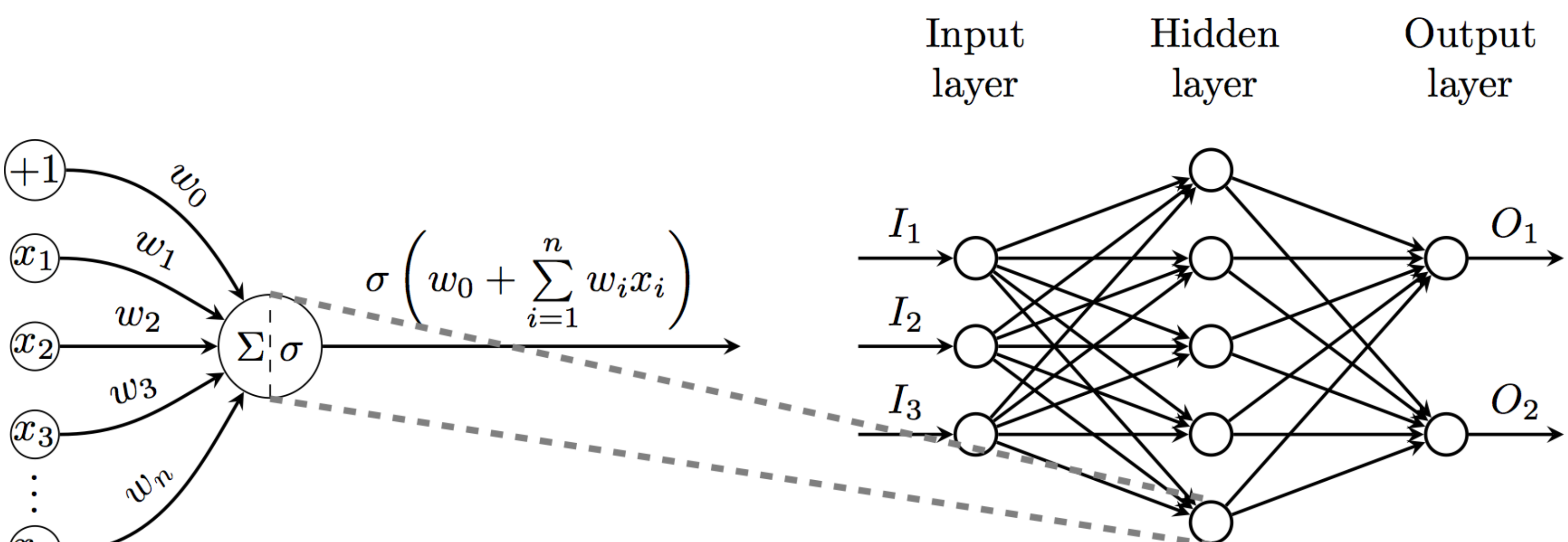




Classification methods: Multi-Layer Perceptrons

A **multi-layer perceptron** is a class of feed-forward neural network which consists of multiple layers of perceptrons (or nodes)

Except for the input nodes, each node is a neuron that uses non-linear activation function.



Perceptron

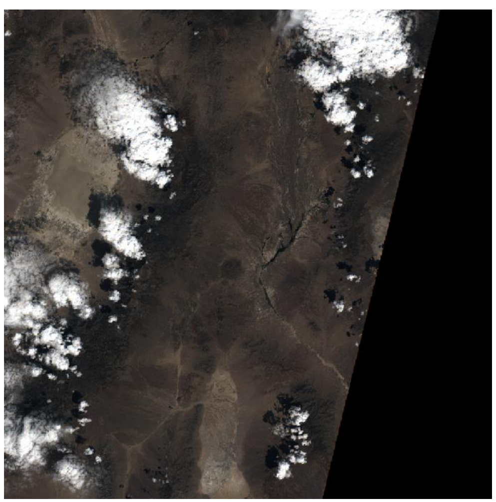
MLP

Post-processing techniques

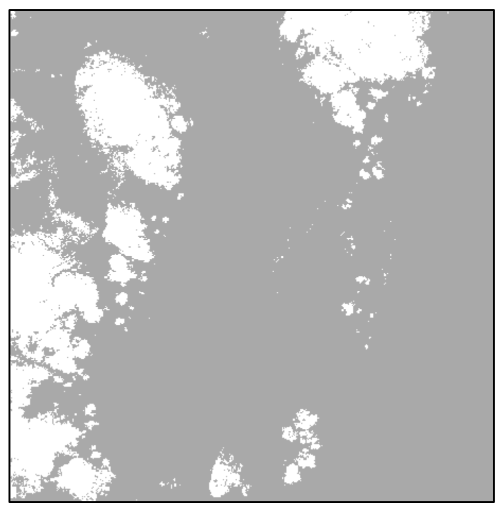
Morphological operations:

- Dilation
- Erosion
- Edge filters (Sobel filters)

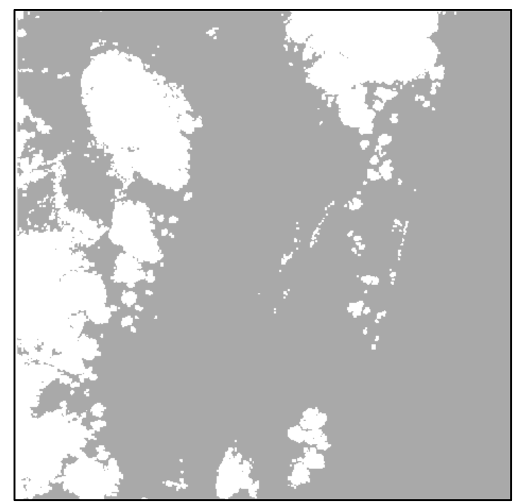
RGB



Original Mask



Dilated Mask



Definition of Machine Learning (ML)

«Machine Learning is a method of data analysis that automates analytical model building. It is a branch of artificial intelligence based on the idea that systems can learn from data, identify patterns and make decision with minimal human intervention»

When do we need to ML to solve a problem

- We know a pattern exists
- We cannot pin it down analytically
- We have data on it

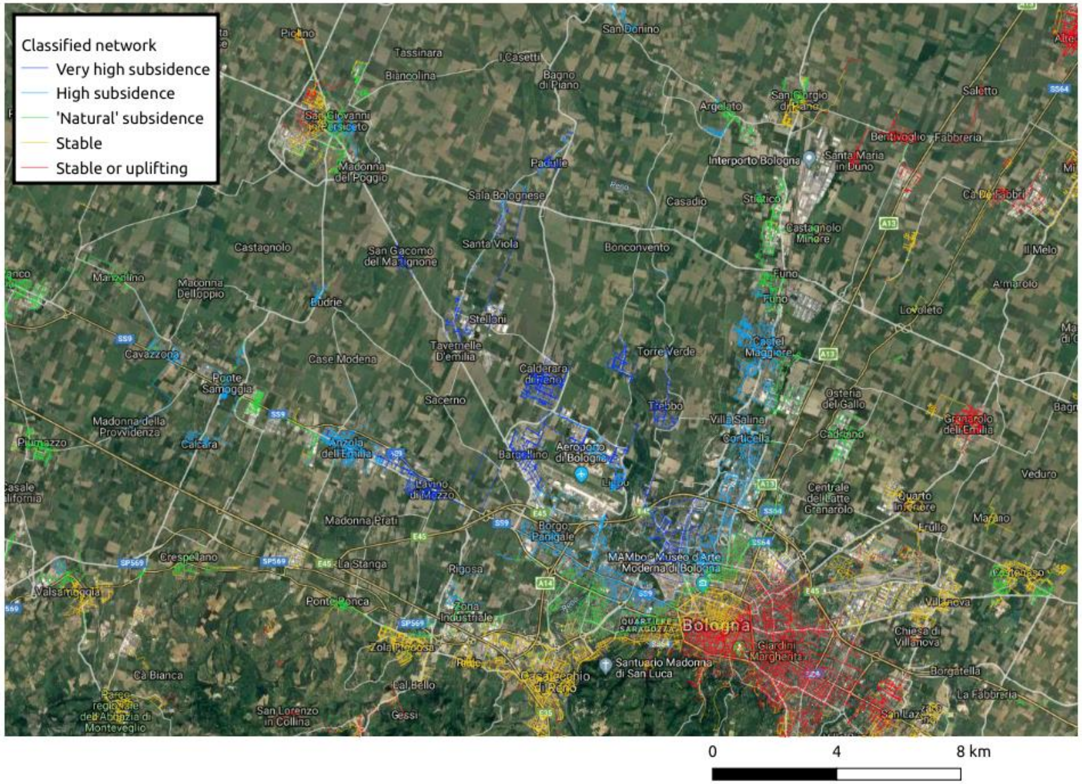
DECISION

Our contribution to DeCiSion project is the development of a processing chain of early warning for damages of a water-sewage network due to subsidence and landslide phenomena.

The procesing chain relies on:

- the **SPINUA® PSInSAR** processing algorithm to recover the terrain deformations of the region of interest
- **kmeans clustering algorithm** to group together measurement points characterized by similar time series of terrain deformation
- An **early warning step** that detects pipes of the network near to a region of high spatial gradient of terrain deformation

Output of kmeans clustering algorithm

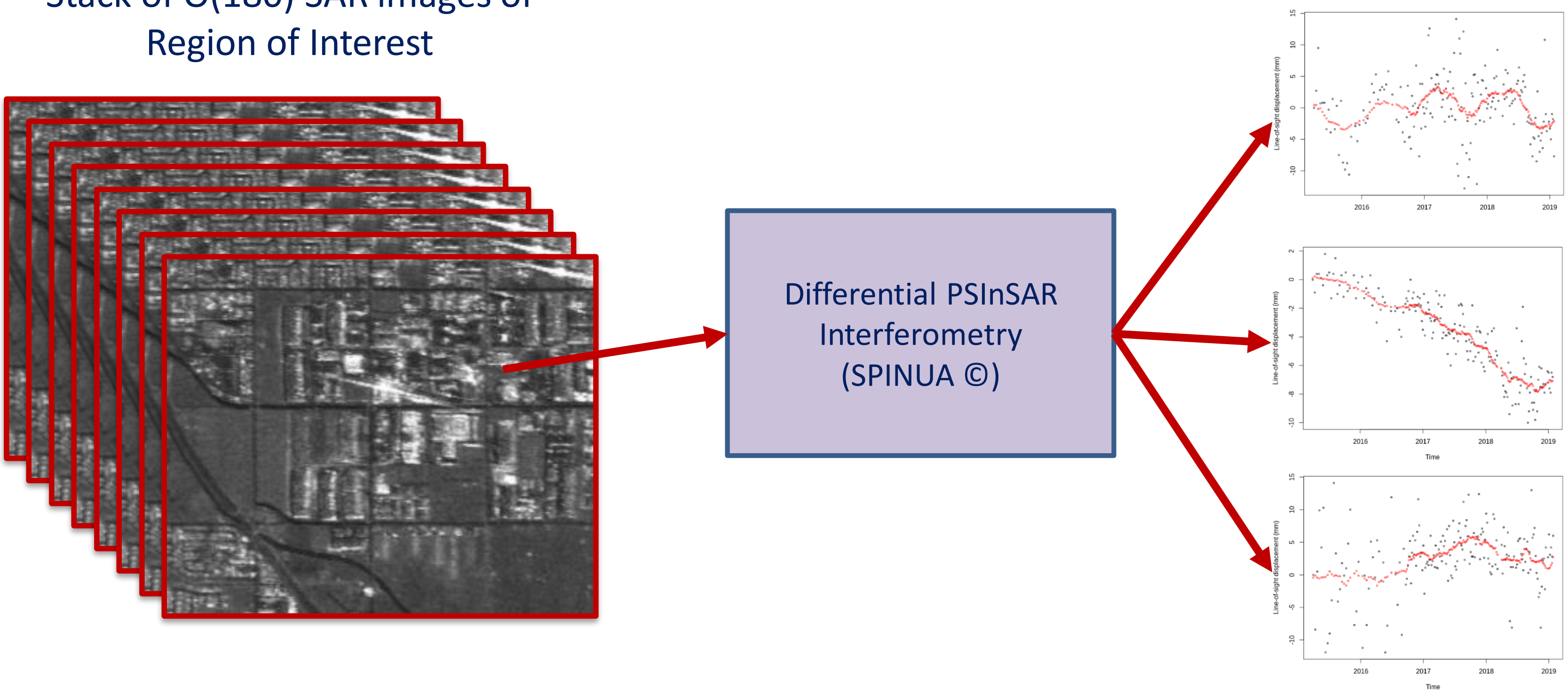


SPINUA® PSInSAR processing algorithm

PSInSAR (Persistent scatterer Interferometry of SAR images)

Time Series of terrain deformation of PSs (Persistent Scatters)

Stack of O(180) SAR images of Region of Interest



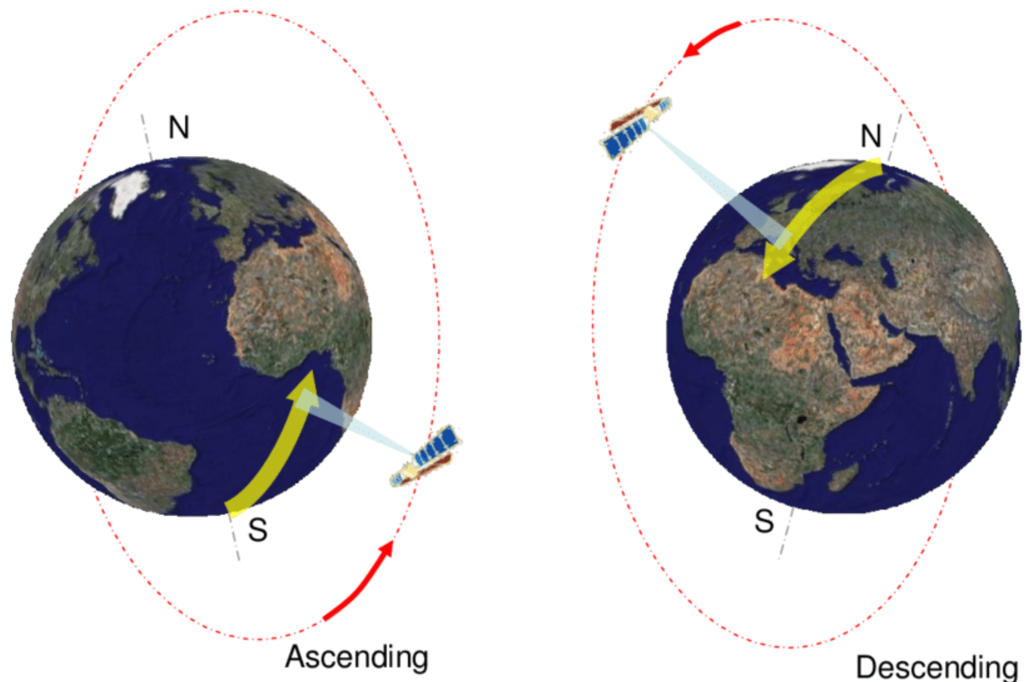
Ascending and Descending Datasets

Ogni PS è descritto dalle seguenti feature:

- Latitudine e Longitudine
- DEM (stima della quota)
- Angolo Incidenza
- Angolo Azimut
- Coerenza
- Velocità media nell'intervallo (Novembre 2014 – Gennaio 2019)
- Circa 180 misure di deformazione ricostruite mediante SPINUA

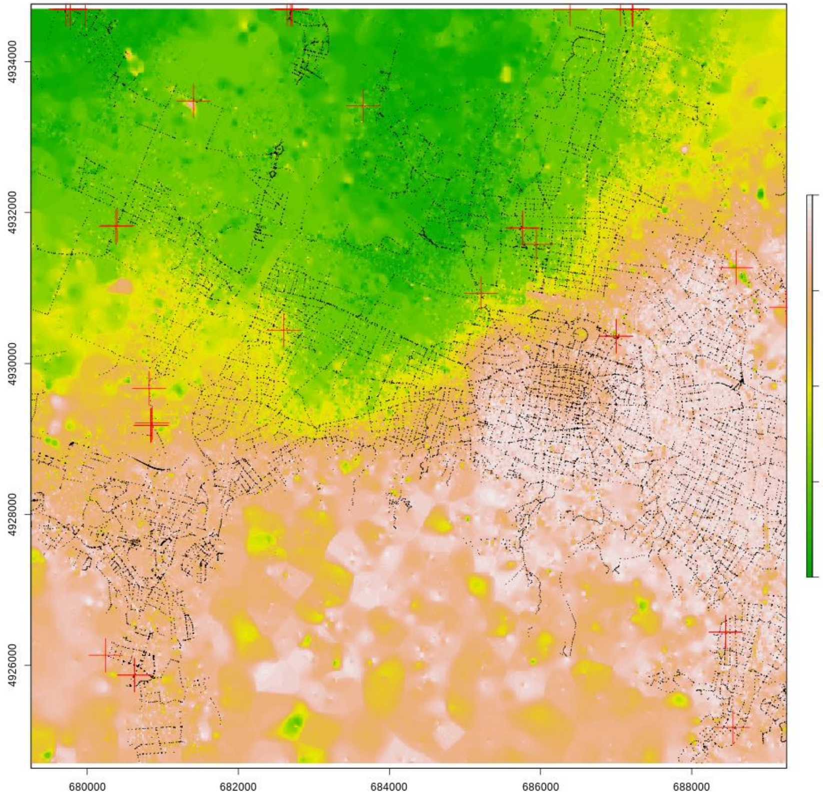
Numero di Persistent Scatterer ritenuti validi per l'analisi:

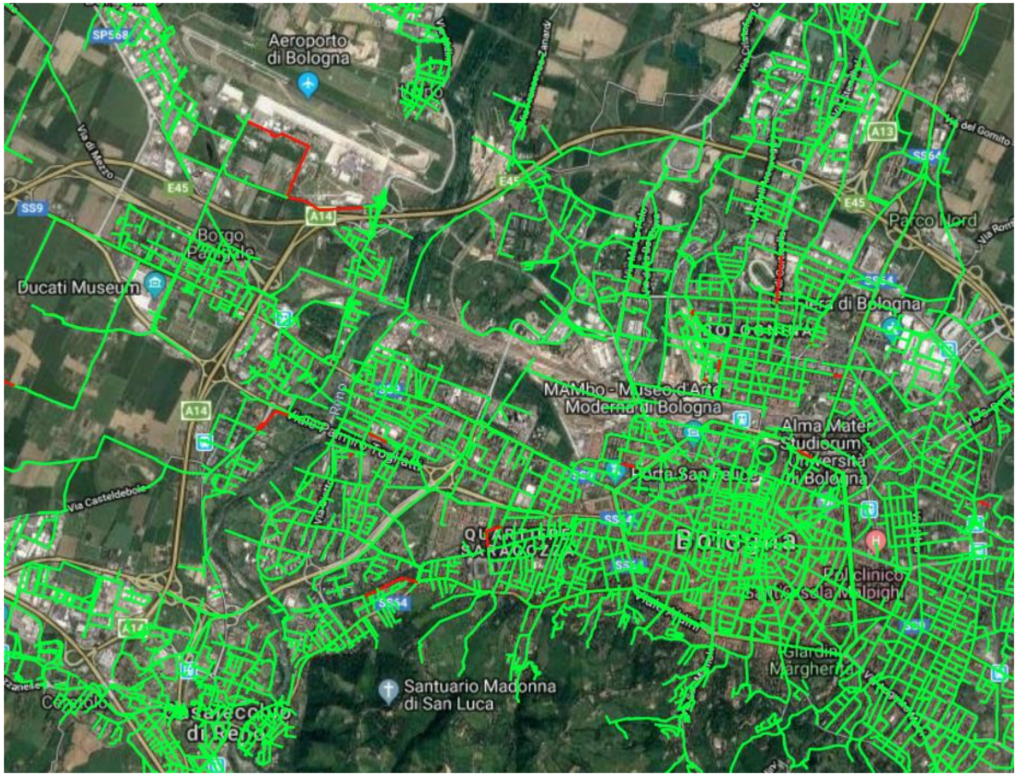
- Circa 3 milioni per orbita ascendente
- Circa 4 milioni per orbita discendente



DECISION – Early Warning Step

Our contribution to DeCiSion project is the development of a processing chain of early warning for damages of a water-sewage network due to subsidence and landslide phenomena.

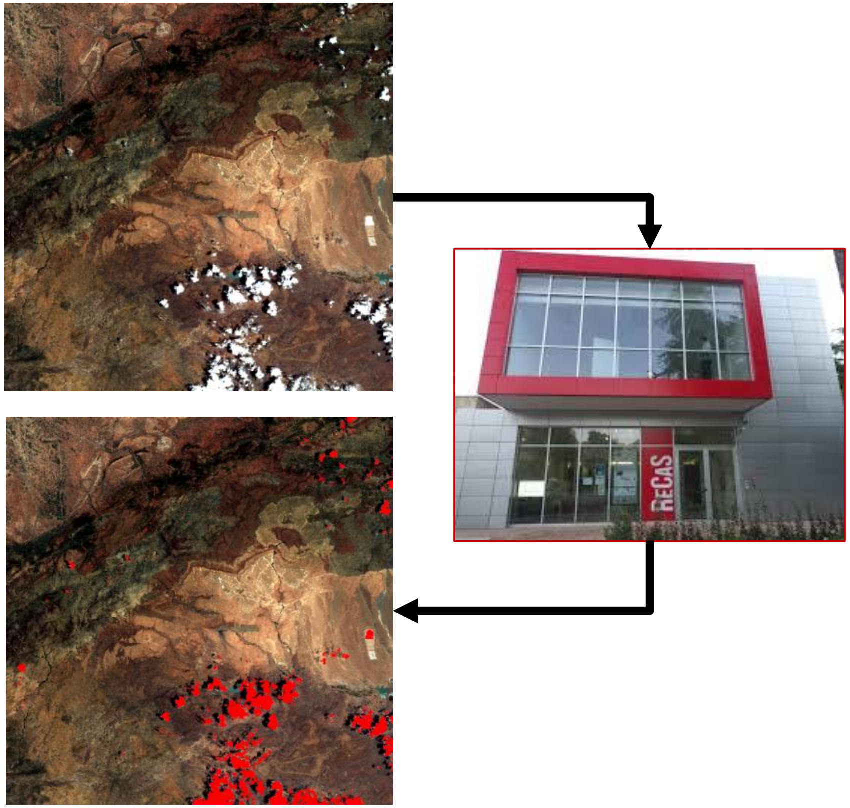




Computational Requirements

Data dimensionality (up-to-date)
- Size: 5 GB

Sentinel-2 L1C Raster files
- # images ~10^2
- # pixels: 3.6×10^6
- Area: 110 Km x 110 Km
- Size per image: 330 MB



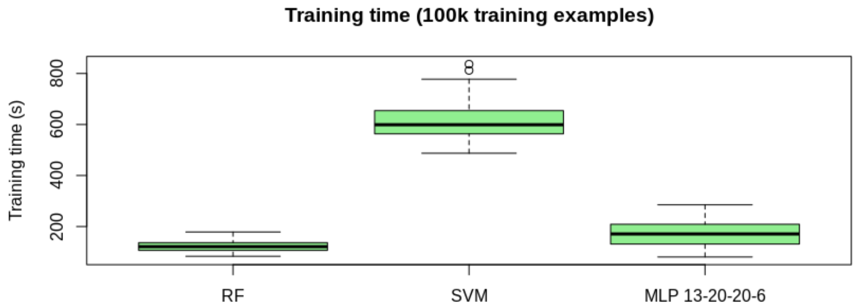
Processing (job submission to Htcondor)
- 100 jobs (100 rounds of 5-fold CV)
- CPUs per job: 1
- RAM per job: 8 - 100 GB*

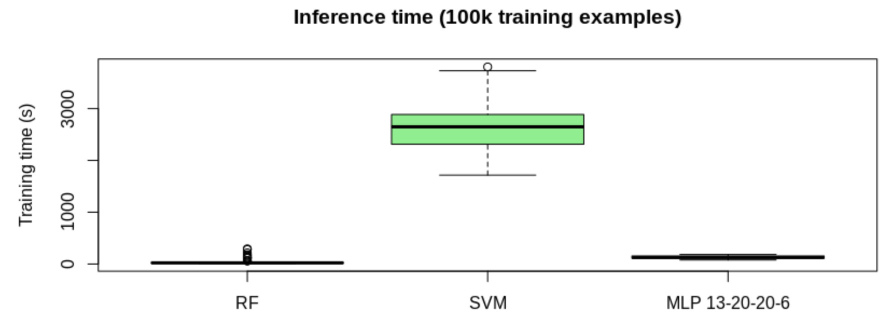
Output

*Depending on the analysis to perform

Training and Inference Time of State-of-the-art Classifiers

We compared training and inference times of Random Forest (RF), Support Vector Machine (SVM) and Multi-Layer Perceptron classifiers trained with an increasing number of training examples. The computing times were assessed on dataset.





Training time τ vs number N of training pixels

- $\tau_{RF} \propto ln(N)$
- $\tau_{SVM} \propto N$
- $\tau_{MLP} \sim const$

Inference time τ vs number N of training pixels

- $\tau_{RF} \sim const$
- $\tau_{SVM} \propto N$ (*)
- $\tau_{MLP} \sim const$

*The computational burden for SVM is proportional to the number of support vectors.

Random Forest Algorithm

Random forests are an ensemble learning method for classification that operates by constructing a multitude of decision trees at training time and outputting the class that is the mode of the classes

Each tree is constructed using the following algorithm:

1. Let the number of training cases be *N*, and the number of variables in the classifier be *M*.
2. We are told the number *m* of input variables to be used to determine the decision at a node of the tree; *m* should be much less than *M*.
3. Choose a training set for this tree by choosing *n* times with replacement from all *N* available training cases (i.e. take a bootstrap sample). Use the rest of the cases to estimate the error of the tree, by predicting their classes.
4. For each node of the tree, randomly choose *m* variables on which to base the decision at that node. Calculate the best split based on these *m* variables in the training set.
5. Each tree is fully grown and not pruned (as may be done in constructing a normal tree classifier).

For prediction a new sample is pushed down the tree. It is assigned the label of the training sample in the terminal node it ends up in. This procedure is iterated over all trees in the ensemble, and the average vote of all trees is reported as random forest prediction.