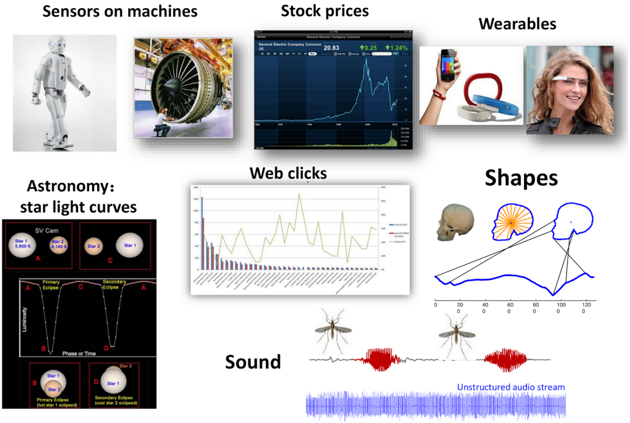
Content

Time Series

Time series

- describe the evolution of a process over time
- are everywhere and ubiquitous: daily life, medical, food security, financial, environmental...
- increase in quantity

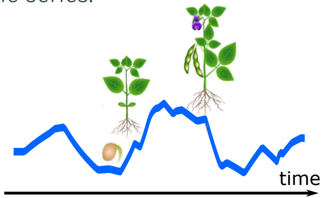


Formally, a time series

- is a sequence of values ordered in time
- either univariate or multivariate
- possibly of different lengths

An example univariate time series:

time	value
t1	0.236
t2	0.563
t3	0.748
t4	0.692
...	
tL	0.167



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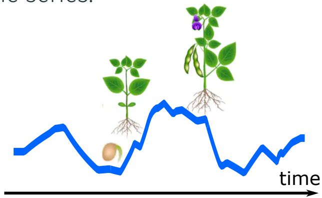
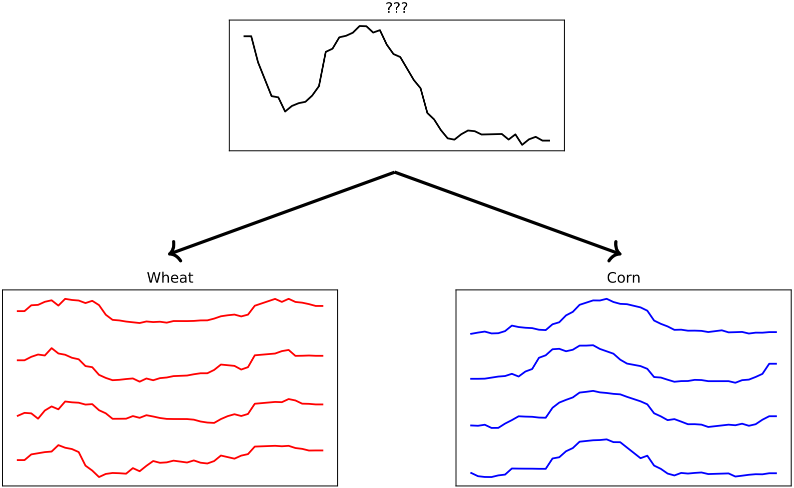


Time series analysis include

- forecasting: predicting future values
- regression: predicting a continuous scalar variable
- retrieval: finding similar time series
- segmentation: dividing a time series into ”homogeneous” subseries
- classification: today’s tutorial

The goal is to associate an unlabelled time series with a class with the help of some labelled time series (supervised learning).



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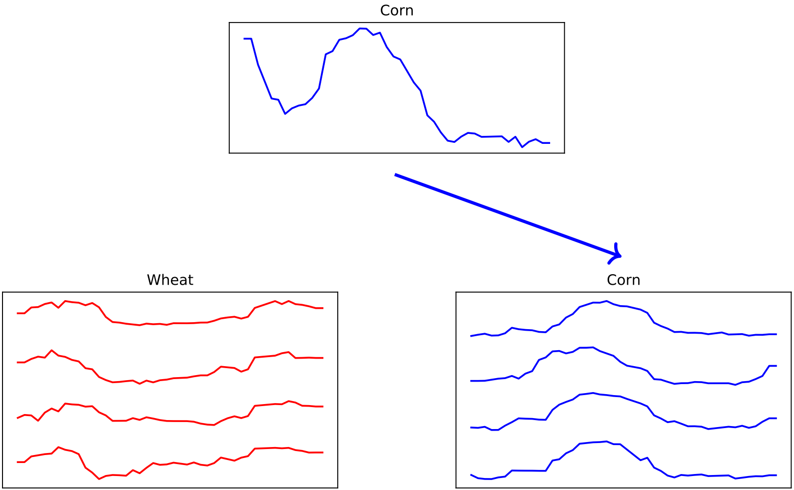

An example satellite image time series

- Sentinel-2 images over Brittany, France

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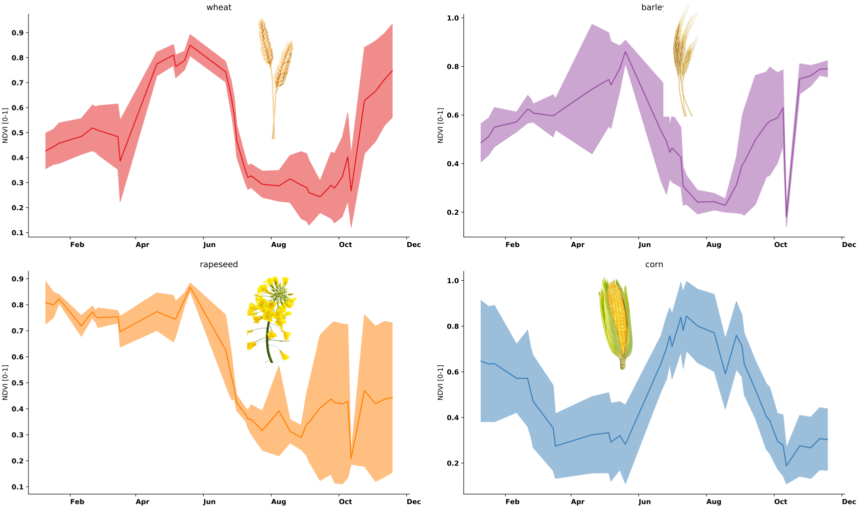
Applications

- vegetation monitoring
- landscape changes
- large scale study

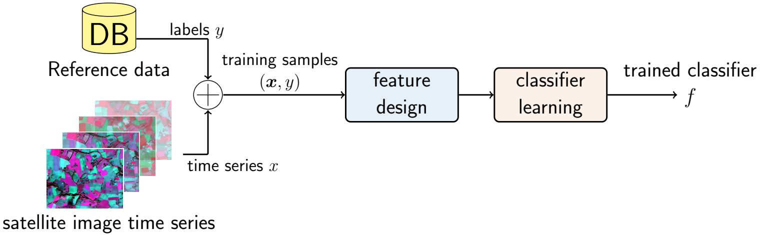
An example application: crop type mapping at large scale



Supervised classification framework

Two main steps:

1. Learning a model f such that $f(\mathbf{x}) \approx y$



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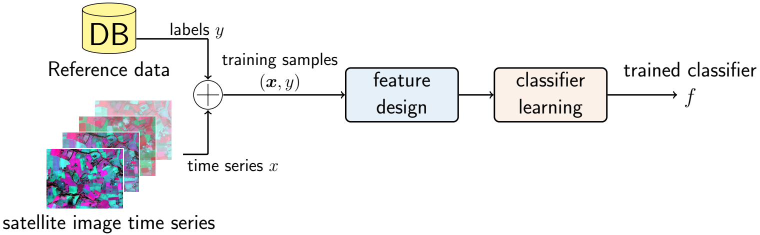
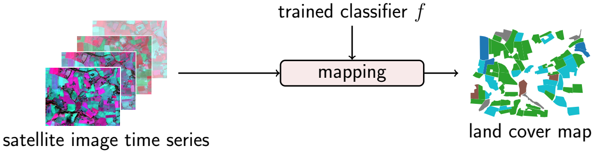


2. Using the model f to map the study area



Inputs for learning

Satellite data, *e.g.*, Sentinel-2 images

- Where to download images?
  - Sentinels Scientific Data Hub
  - Copernicus DIAS
  - cloud platforms: GEE, Amazon, Microsoft Planetary Computer
  - THEIA, USGSS, *etc.*
- Common pre-processing steps:
  - coregistration
  - atmospheric correction
  - gapfilling
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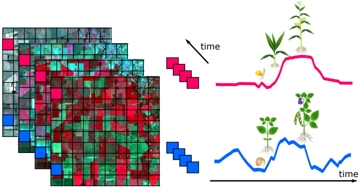
From satellite images to time series

Pixel-based analysis



Object-based analysis, *e.g.*, averaging the reflectance values within an agricultural parcel

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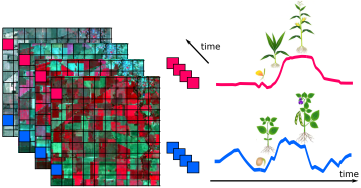

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Reference data

Usually vector files

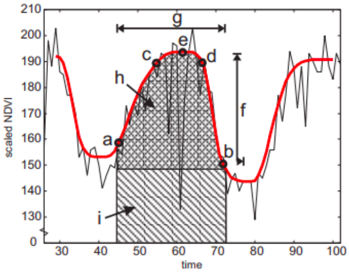
↳ label $y \in \{1, \cdots, \mathcal{C}\}$

- photo-interpretation
- field campaigns
- governmental data (*e.g.* Corine Land Cover)
- collaborative data (*e.g.* Open Street Map)

From time series to feature vectors

Feature design is a key step when using traditional machine learning algorithms
- ◇ flatten reflectance time series
- ◇ compute spectral features, *e.g.*, Normalized Difference Vegetation Index
- ◇ extract temporal features: statistical and phenological features
- ◇ and even compute spatial features, *e.g.* Haralick or attribute profiles

TIMESAT example: extraction of key phenological stages [1]



[1] Jönsson, P., & Eklundh, L. (2004). TIMESAT—a program for analyzing time-series of satellite sensor data. *Computers & Geosciences*, 30(8), 833-845.

Evaluation

Types of evaluation: quantitative (accuracy, computational complexity, explainability), visual, evaluation on a downstream task

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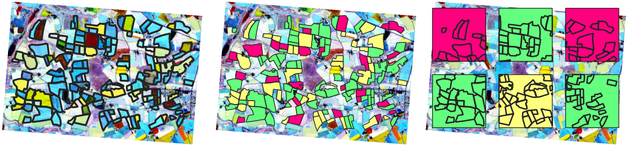
Quantitative evaluation: split the labeled data into 3 spatially independent sets

- a train set to learn the model's parameters
- a validation set to tune the hyperparameter values of the model
- a test set to obtain a non-biased estimation of the model's performance

Labeled data | Polygon-split | Grid-split



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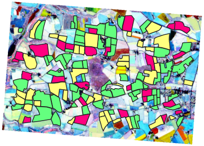
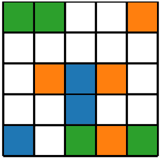


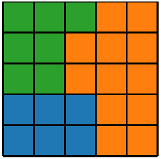
Grid-split

The confusion matrix:

Ground truth



Dense predictions



predicted

real			
	2	1	0
	0	3	1
	1	1	2

How to implement this framework?

- develop your own Python code
- use dedicated libraries, *e.g.*, snap, OTB
- use existing frameworks, *e.g.*, ***`iota2`***

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Let us now move to our first practical activity!

Notebook 1: Feature Engineering

	pre-processing		feature design		classification	
feat. engineering	raw data X $\longrightarrow$	processed data	$\longrightarrow$	features	$\longrightarrow$	labels y
realization	Sentinel-2 Series $\longrightarrow$	cloud filtering	$\longrightarrow$	NDVI-statistics	$\longrightarrow$	crop type y

Link for the notebooks: ***`https://tinyurl.com/isprs2022`***