A non-exhaustive overview of the possibilities of AI

C. Guyeux

Master IoT

Purpose of this course

- Know what you can do with A.I.
- Have a list of applications in mind
- Know some categories of algorithms
- At this level, nothing technical: general public introduction

A.I. on (matrices of) numbers

Clustering: presentation

Separate individuals into homogeneous groups

Clustering: presentation

Separate individuals into homogeneous groups

	sepal length (cm)	sepal width (cm)	petal length (cm)	petal width (cm)
0	5.1	3.5	1.4	0.2
1	4.9	3.0	1.4	0.2
2	4.7	3.2	1.3	0.2
3	4.6	3.1	1.5	0.2
4	5.0	3.6	1.4	0.2
...	...	...	...	...
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148	6.2	3.4	5.4	2.3
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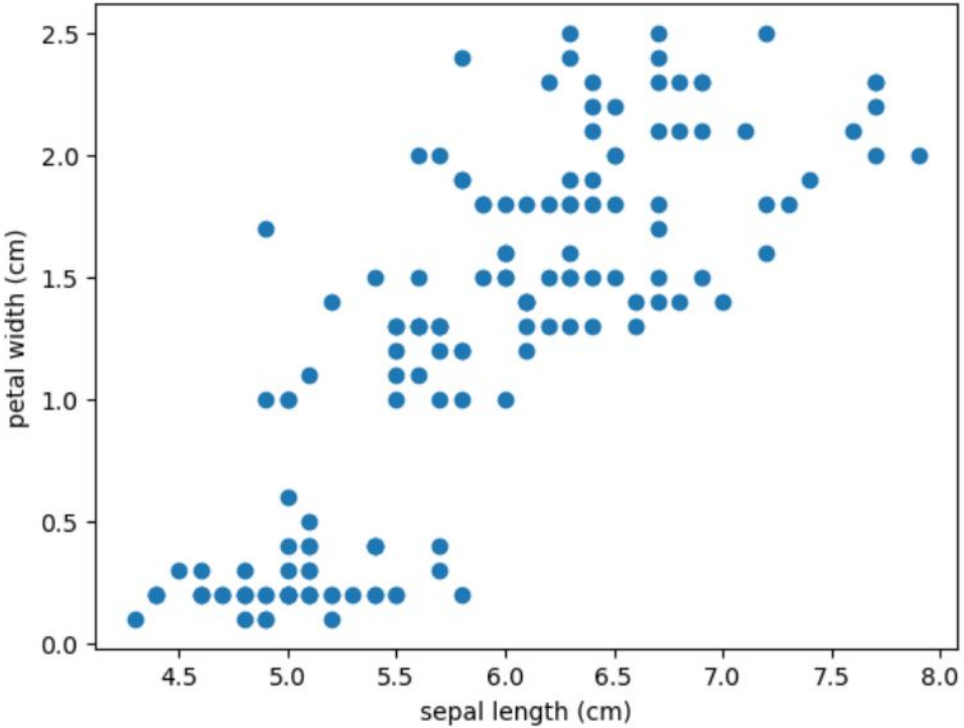

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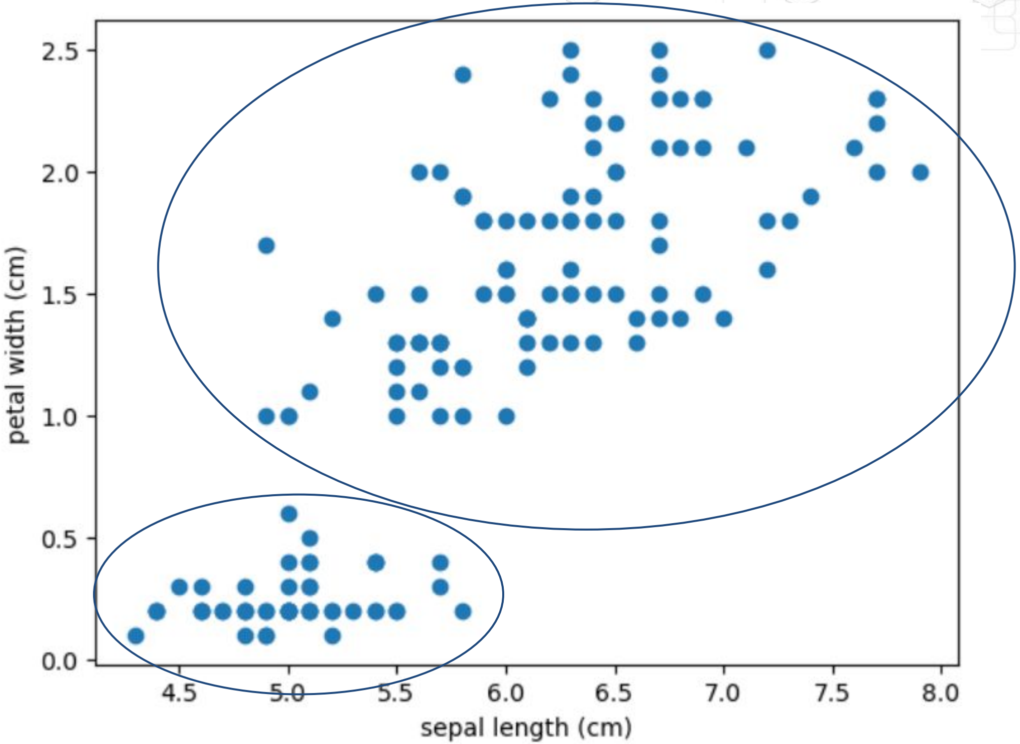
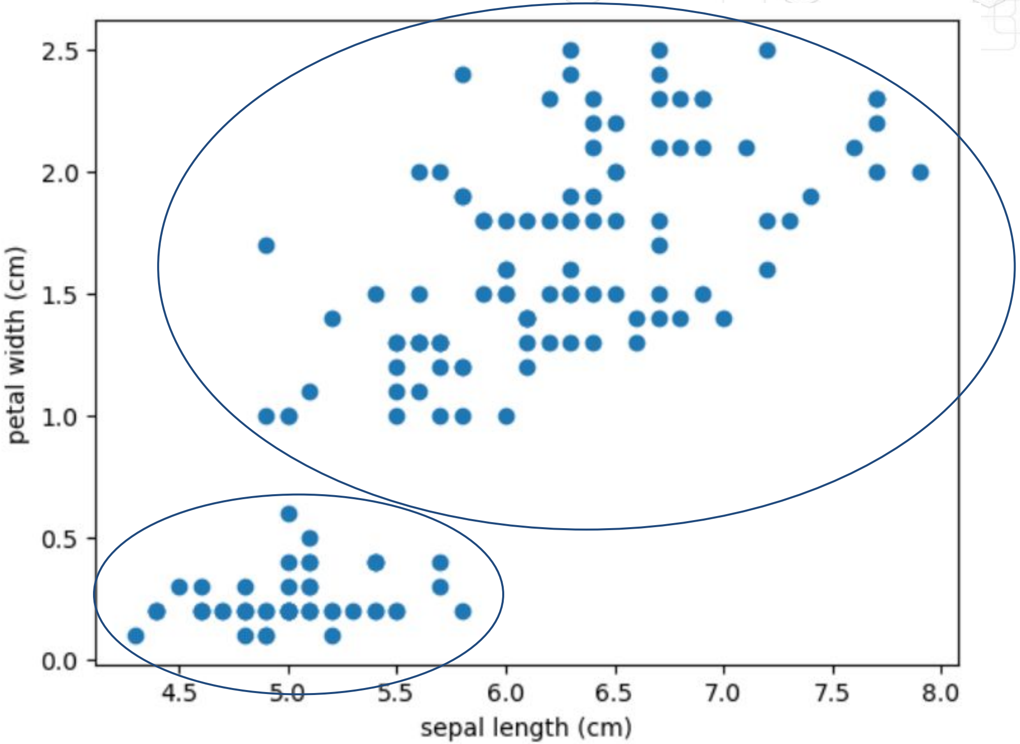


Clustering: challenges

Separate individuals into homogeneous groups :

- how many groups ?



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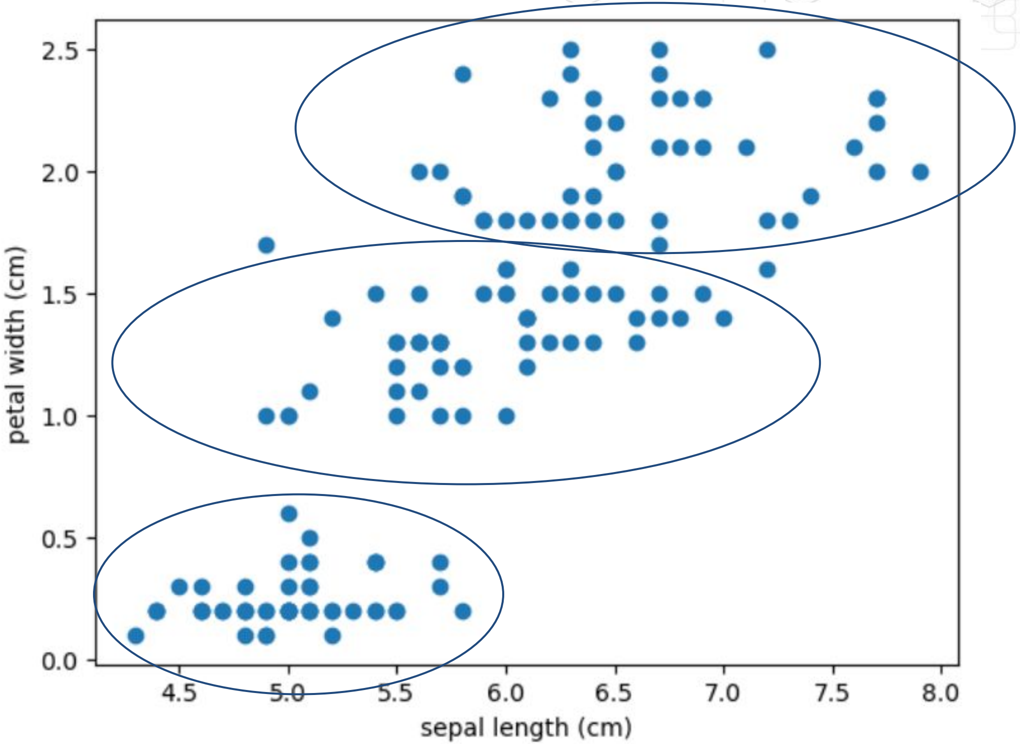
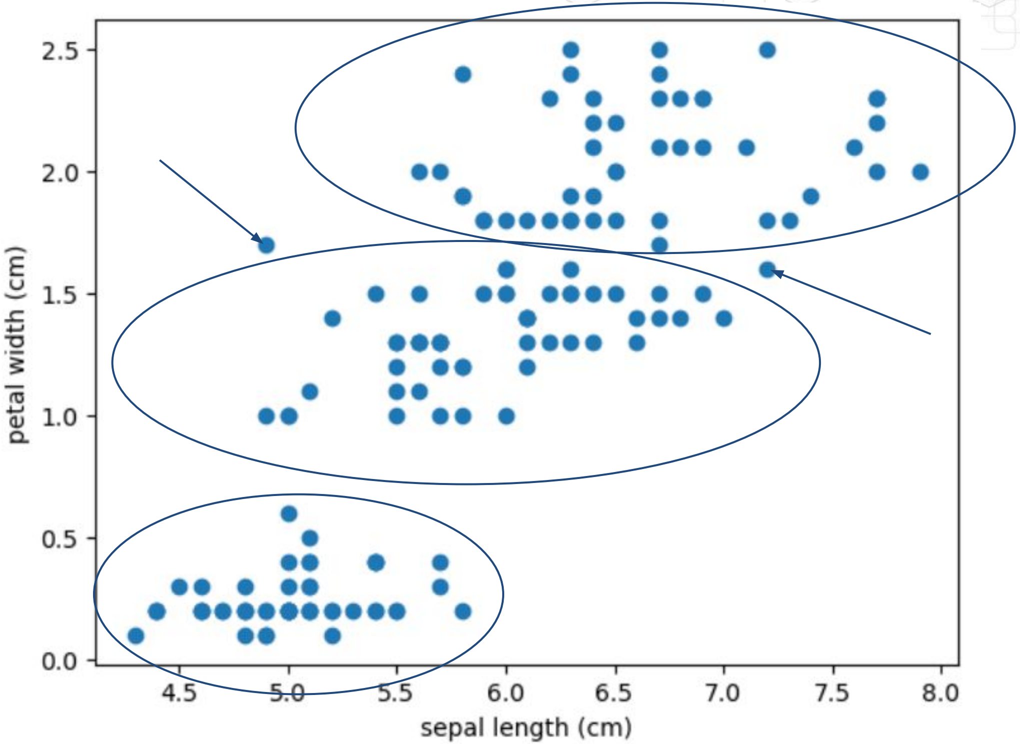


Clustering: challenges

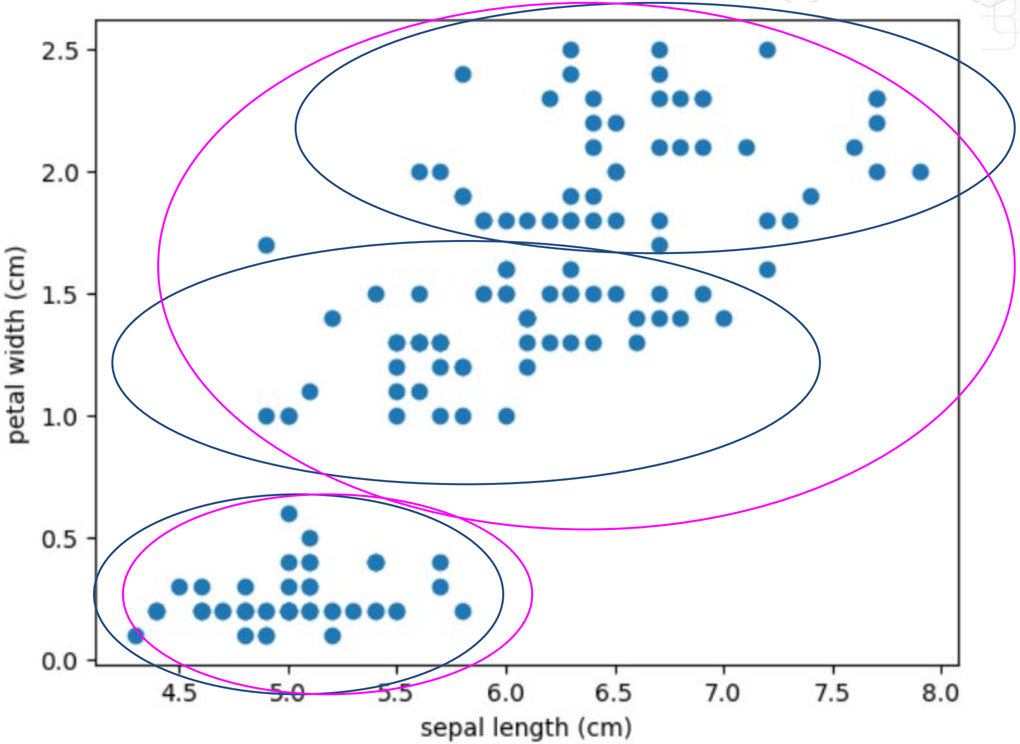
Separate individuals into homogeneous groups :
- how many groups ?
- with outliers ?



Clustering: challenges

Separate individuals into homogeneous groups :

- how many groups ?
- with outliers ?
- how to:
  - evaluate one clustering
  - choose between two clusterings ?



Clustering: challenges

Separate individuals into homogeneous groups :

- how many groups ?
- with outliers ?
- how to:
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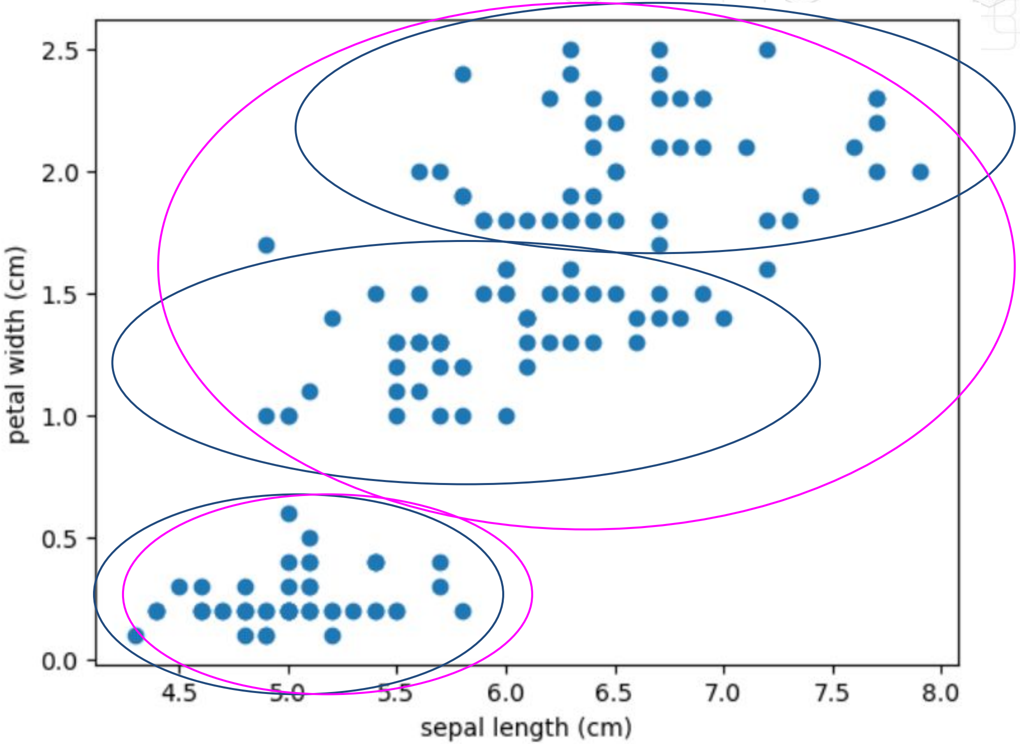
  - choose between two clusterings ?
- Which method to use, with which parameters?

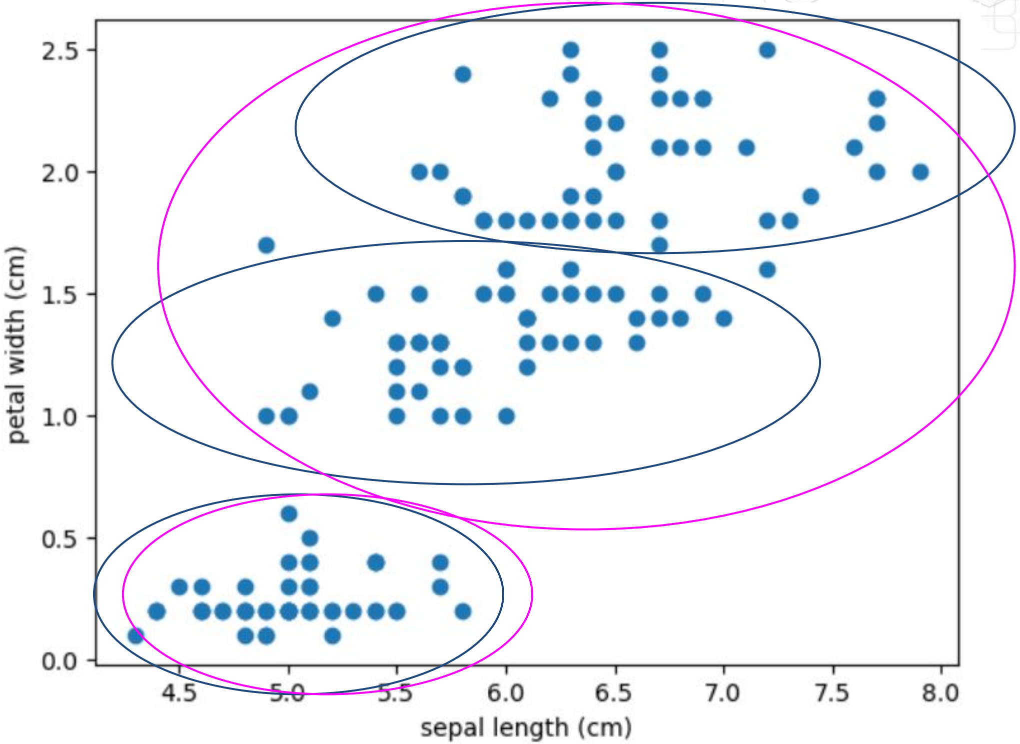


Clustering: challenges

Separate individuals into homogeneous groups :

- how many groups ?
- with outliers ?
- how to:
  - evaluate one clustering
  - choose between two clusterings ?
- Which method to use, with which parameters?

(k-means, mean shift, DBscan, hierarchical clustering…)



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Classification: presentation

Predict a class from features

Classification: presentation

Predict a class from features

	sepal length (cm)	sepal width (cm)	petal length (cm)	petal width (cm)	Iris
0	5.1	3.5	1.4	0.2	setosa
1	4.9	3.0	1.4	0.2	setosa
2	4.7	3.2	1.3	0.2	setosa
3	4.6	3.1	1.5	0.2	setosa
4	5.0	3.6	1.4	0.2	setosa
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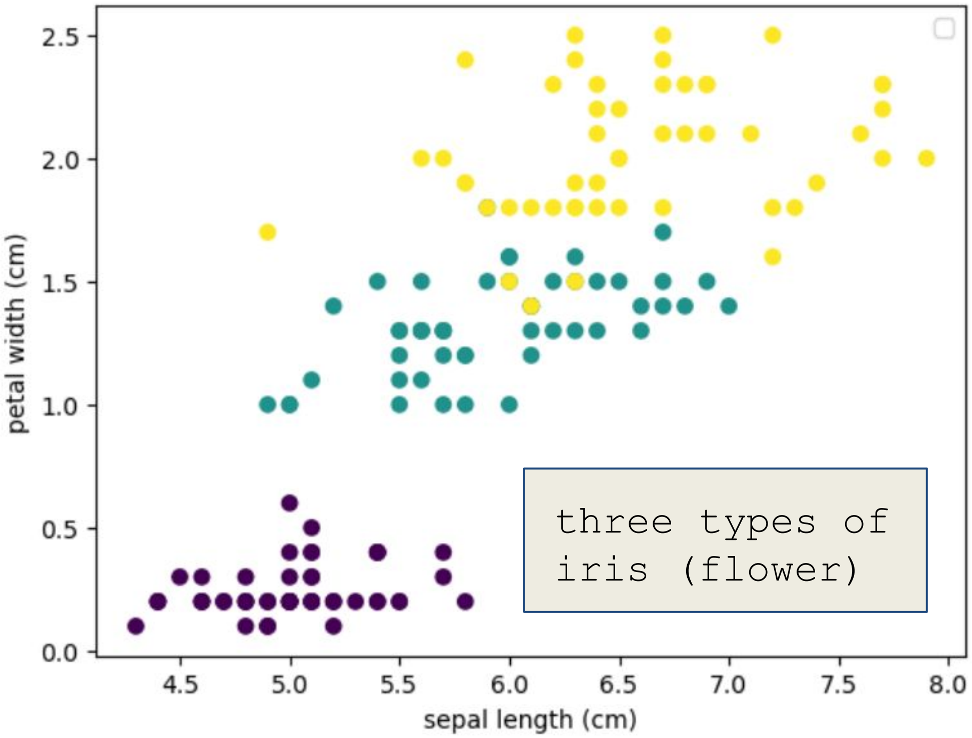

three types of iris (flower)

Classification: presentation

INPUT: a basis of knowledge

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Features (X)

Target (y):
a class (**category**)

Classification: presentation

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OBJECTIVE: learn the link between X and y, and

given a new X row, predict its class y

Classification: presentation

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4					
...					
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146					
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What is the Iris type of an unknown flower with sepal length of 5.6, sepal width of 2.9, petal length of 4.7, and petal width of 1.7 ?

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Clustering versus classification

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Clustering

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Classification

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X

Clustering

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X y

Classification

Classification versus clustering

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X

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X y

Clustering

We want to find groups/clusters

Classification

We want to learn/predict the class y

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Classification versus clustering

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X

Clustering

We want to find groups/clusters

=> unsupervised learning

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X y

Classification

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=> supervised learning

Classification versus regression

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X y

Classification

We want to learn/predict the class y

=> y is a ***category***

hour	dayofweek	month	temperature	humidity	nb. of intervention
2	1	2	272.650000	58.333333	7
3	1	2	272.350000	59.000000	4
4	1	2	272.216667	60.333333	12
5	1	2	272.083333	61.666667	4
6	1	2	271.950000	63.000000	7
7	1	2	272.116667	64.000000	10
8	1	2	272.283333	65.000000	1
9	1	2	272.450000	66.000000	7
10	1	2	272.450000	66.000000	10
11	1	2	273.400000	64.000000	6

X y

Regression

We want to learn/predict the number y

=> y is a ***number*** *(float, int…)*

Classification versus regression

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X y

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X y

Regression

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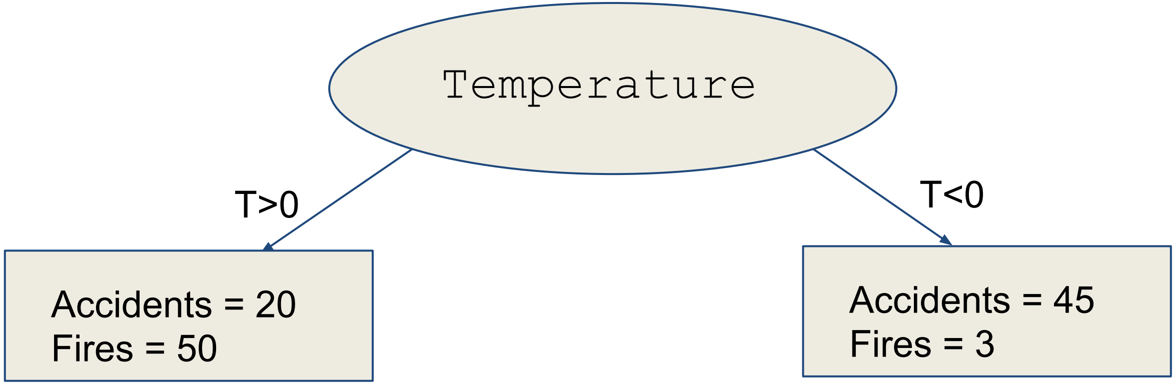
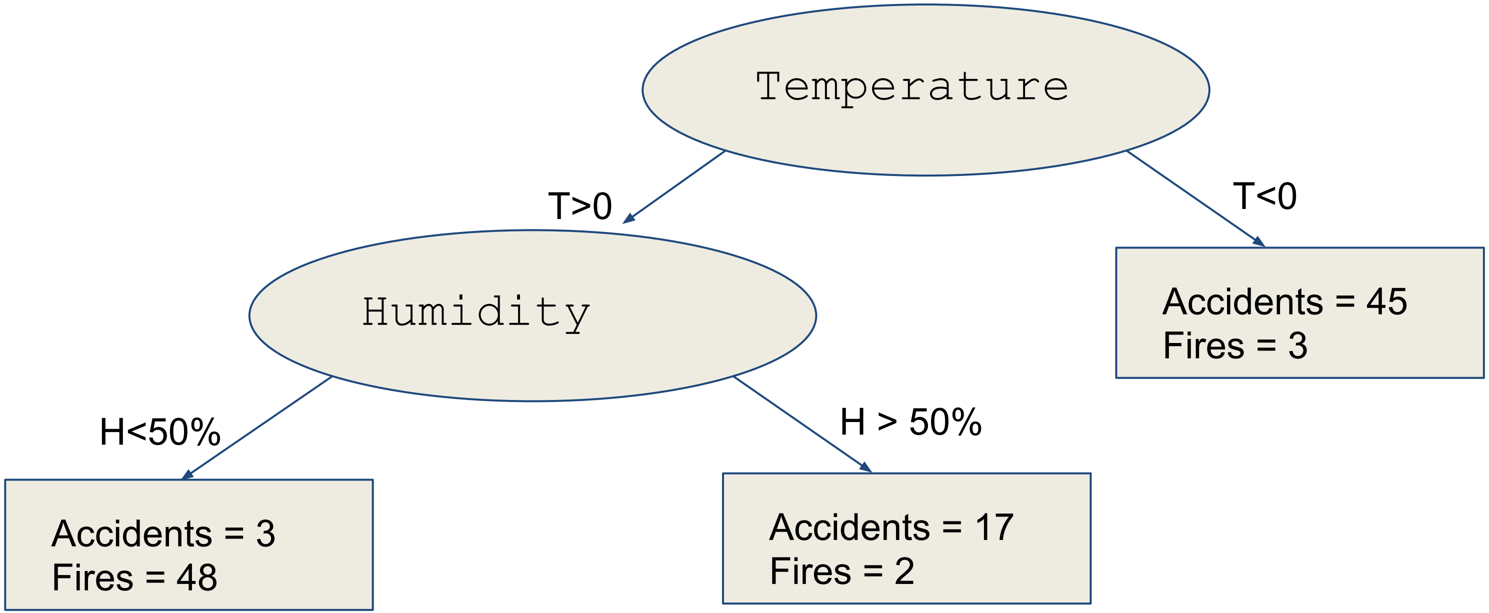
supervised learning (both)

Decision trees for regression



Decision trees for regression

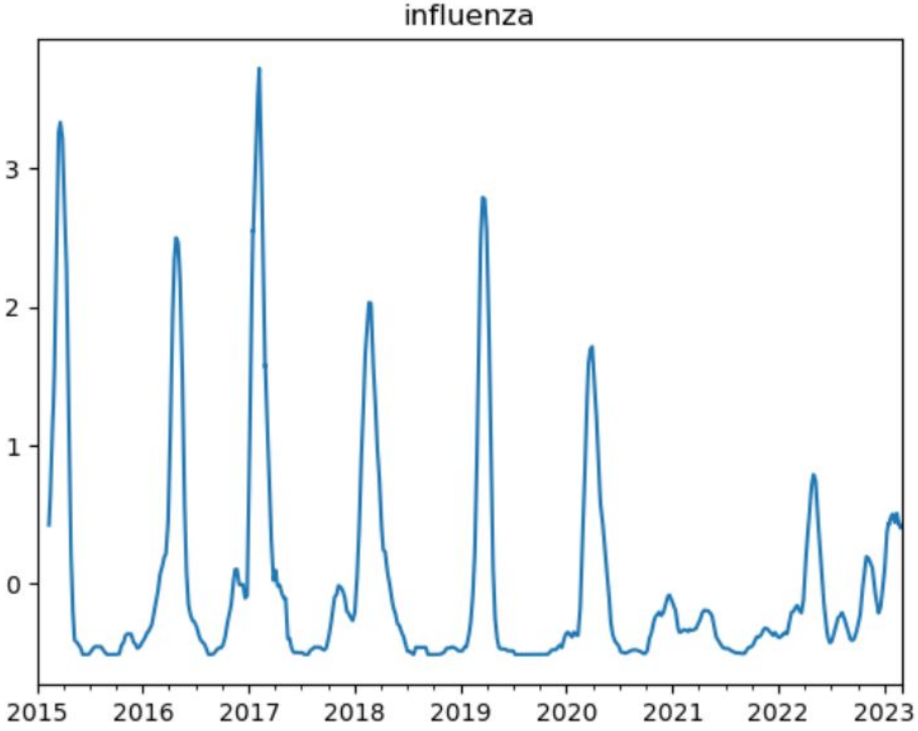


A.I. on time series

Time series

A set of dates+values

2015-02-11 16:00:00	1.088060
2015-02-11 17:00:00	1.062649
2015-02-11 18:00:00	1.036881
2015-02-11 19:00:00	1.010756
2015-02-11 20:00:00	0.984272
2015-02-11 21:00:00	0.957430
2015-02-11 22:00:00	0.930231
2015-02-11 23:00:00	0.902673
2015-02-12 00:00:00	0.874758
2015-02-12 01:00:00	0.847491



No feature in time series

hour	dayofweek	month	temperature	humidity	nb. of intervention
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y

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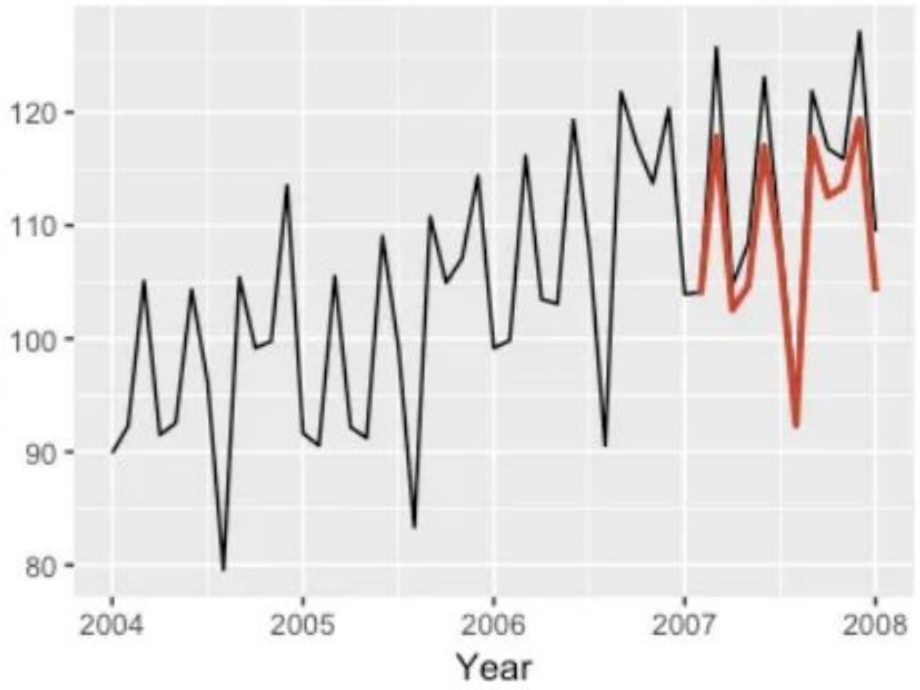
Time series forecasting



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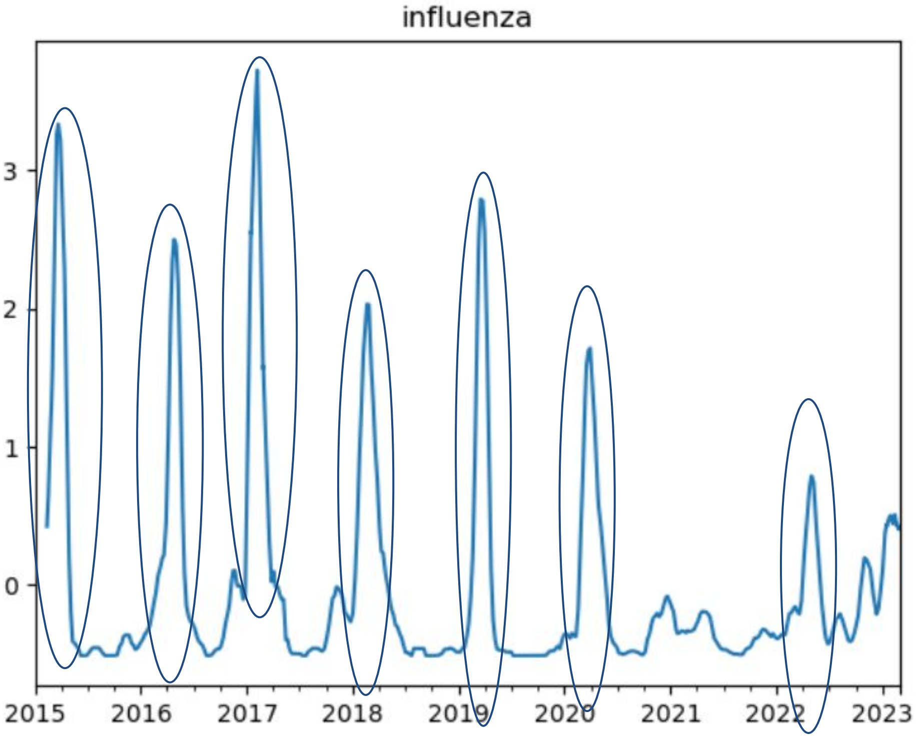
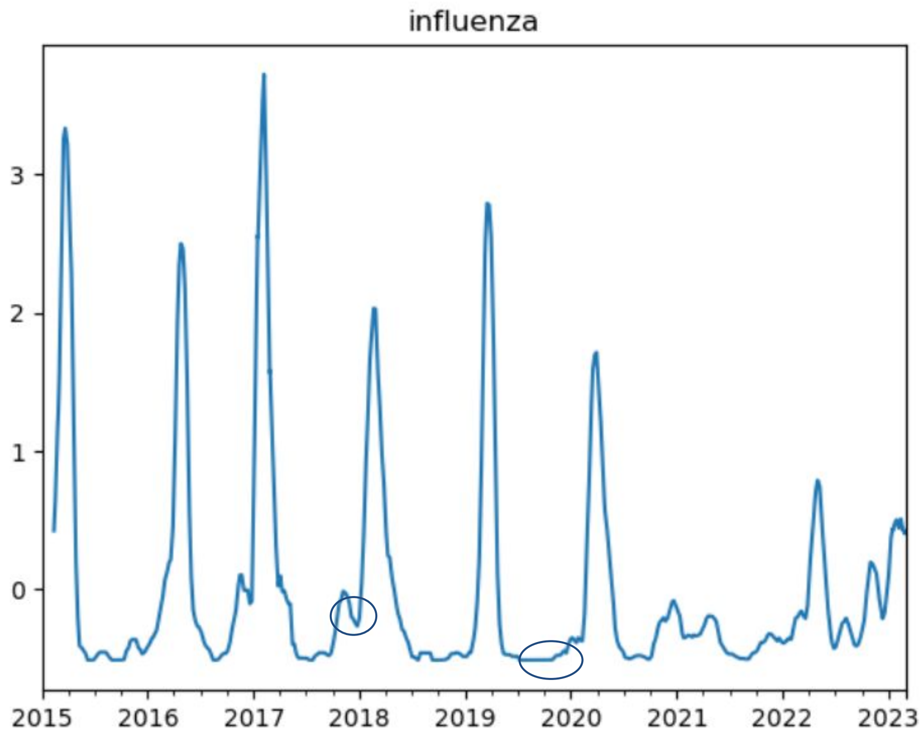
Time series forecasting how to…



Use of:

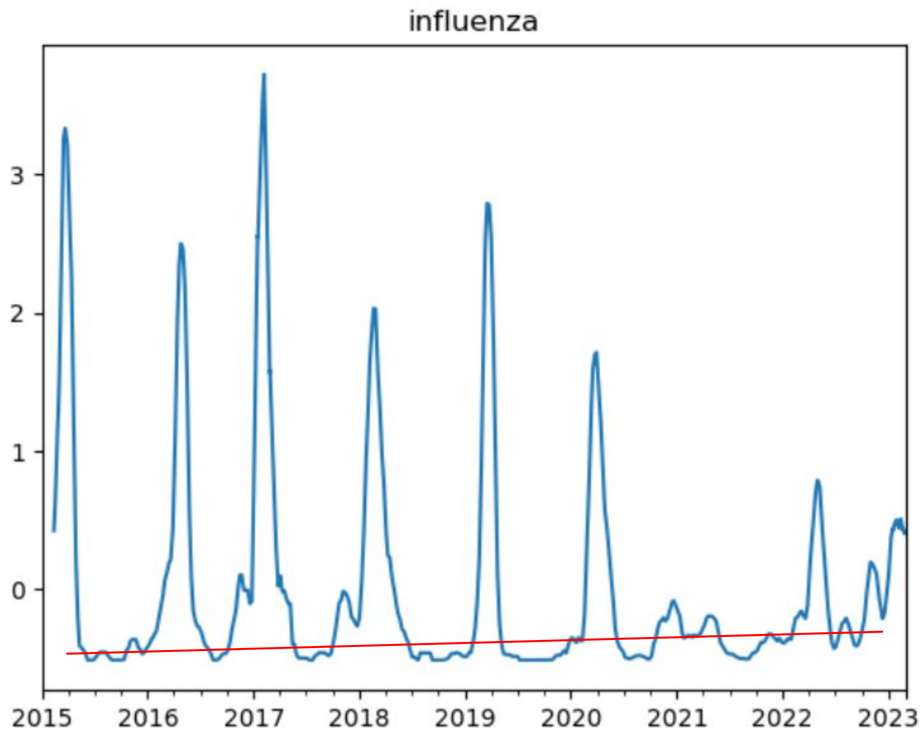
- seasonality

Time series forecasting how to…



Use of:
- seasonality
- auto-regressive part

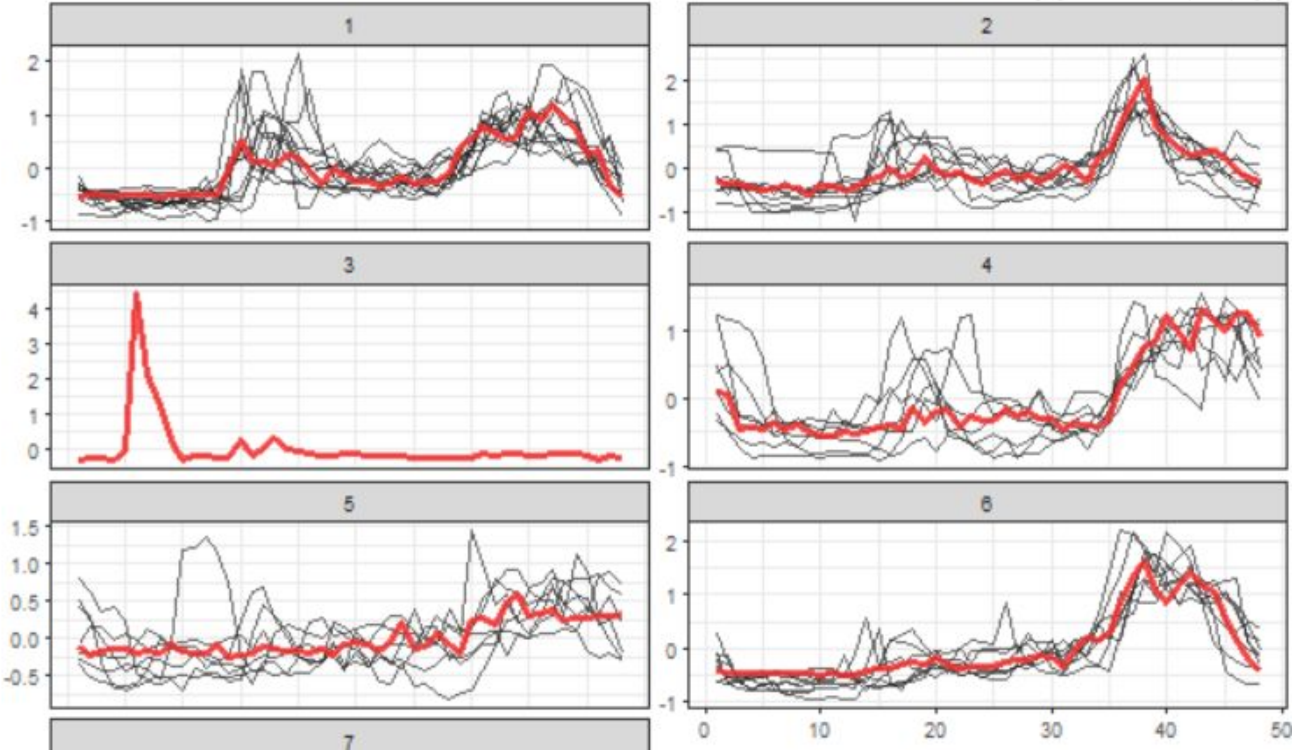
Time series forecasting how to…



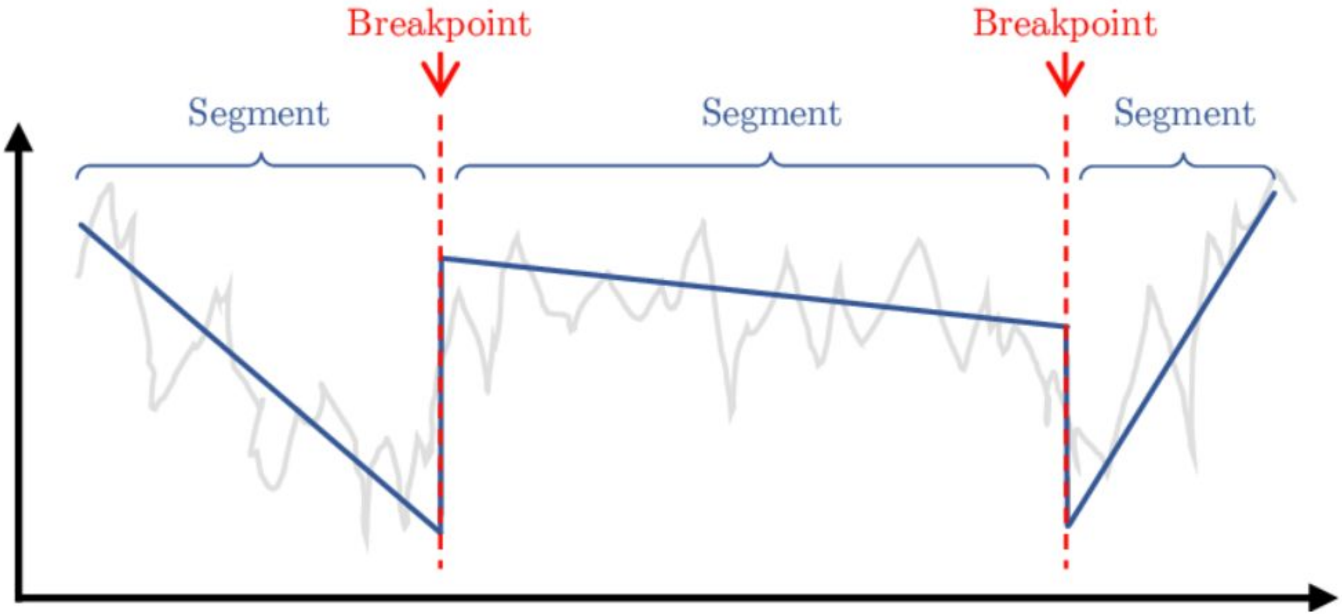
Use of:

- seasonality
- auto-regressive part
- general trend
- etc.

Time series clustering



Breakpoint detection



A.I. on images

Image classification

```
Learn to classify images
```

Image classification

Learn to classify images

Input: a basis of knowledge
(set of image + class)

Method: neural network (CNN)

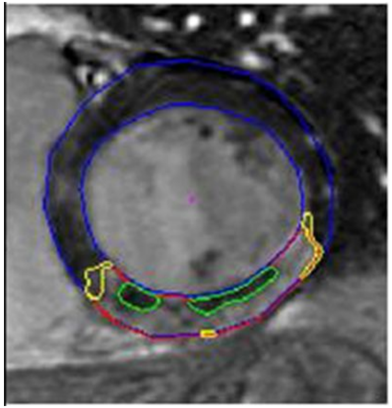
Image enhancement

Input

Output

Example: image denoising

Image segmentation



Example: *myocardial infarction*
- Learning to recognize the area of the myocardium
- Learn to find the damaged part of the heart muscle

Knowledge base: manually annotated MRIs

Object detection

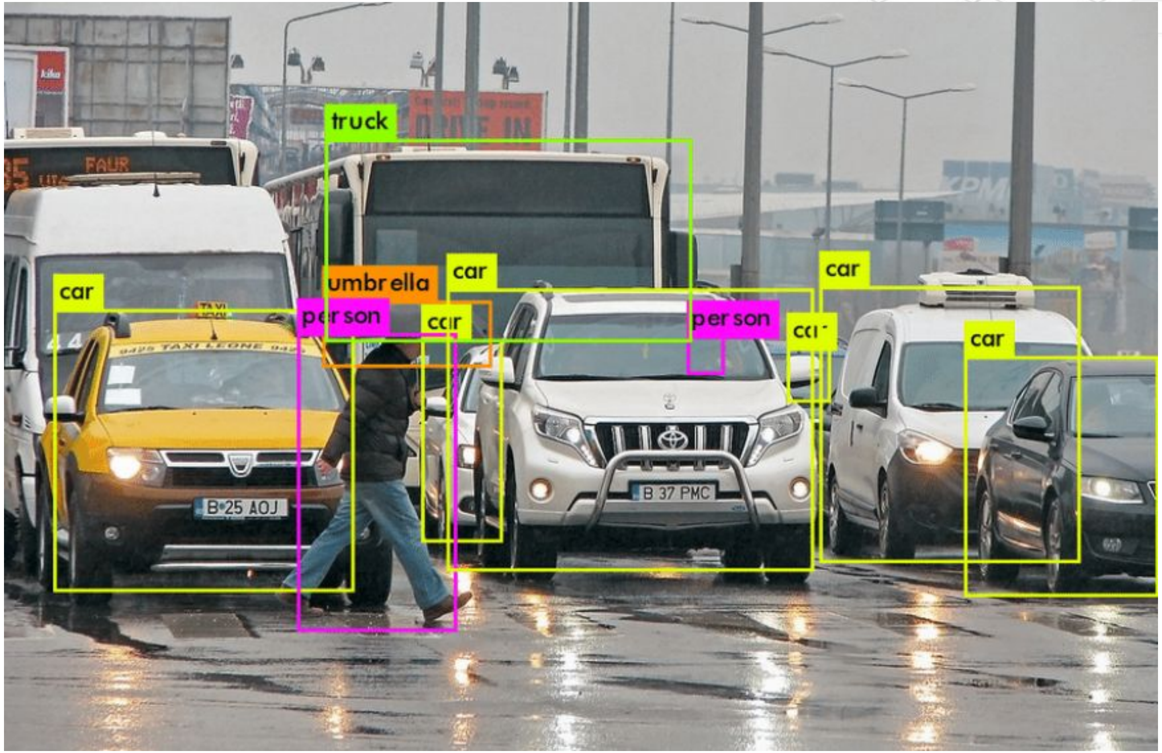


Image generation

Output

Input

a man sitting at a table with a laptop

a street sign on a pole in front of a building

a plate with a sandwich and a salad

https://github.com/karpathy/neuraltalk2

Image description

Input

Output

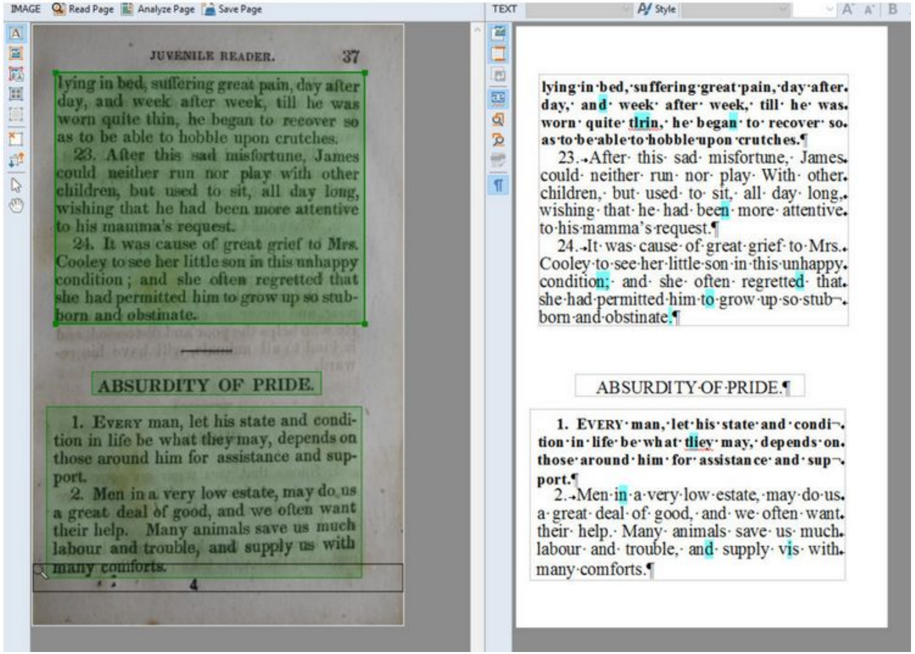
a man sitting at a table with a laptop

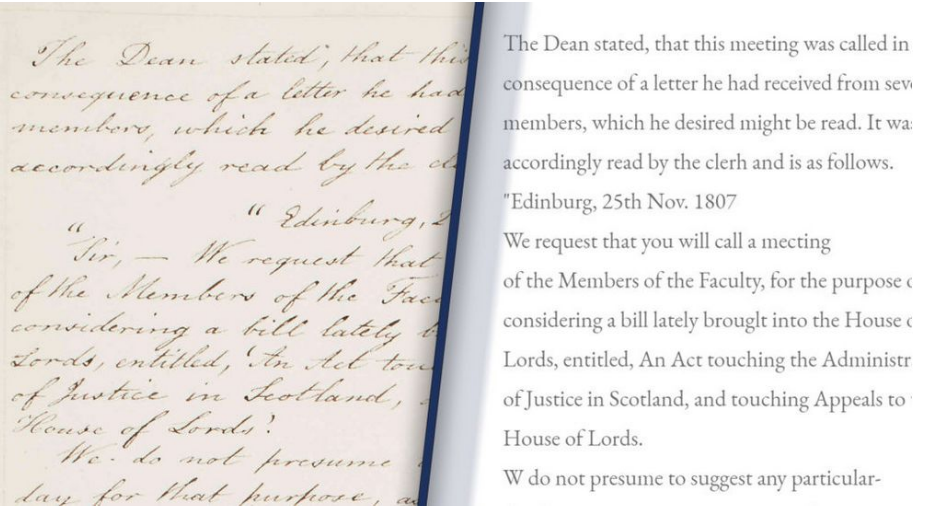
a street sign on a pole in front of a building

a plate with a sandwich and a salad

https://github.com/karpathy/neuraltalk2

Text recognition (OCR)





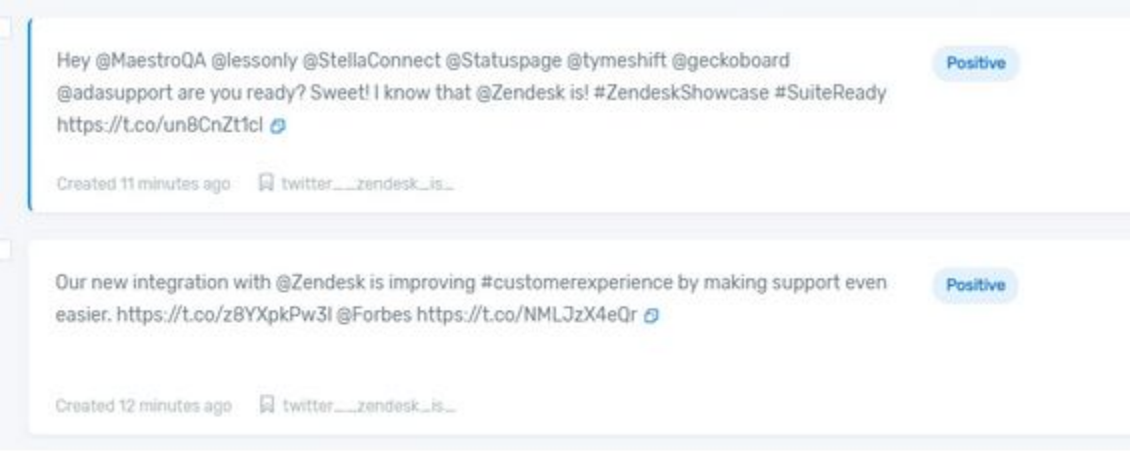
Typed or handwritten

https://huggingface.co/microsoft/trocr-large-handwritten

A.I. on texts

Text classification

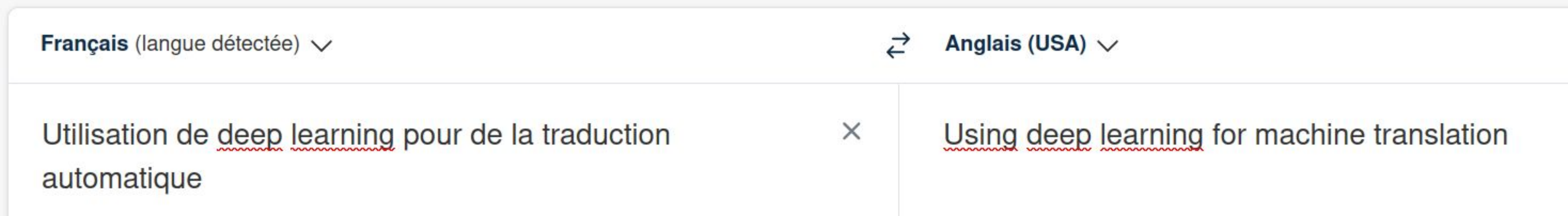
Example: sentiment analysis on tweets



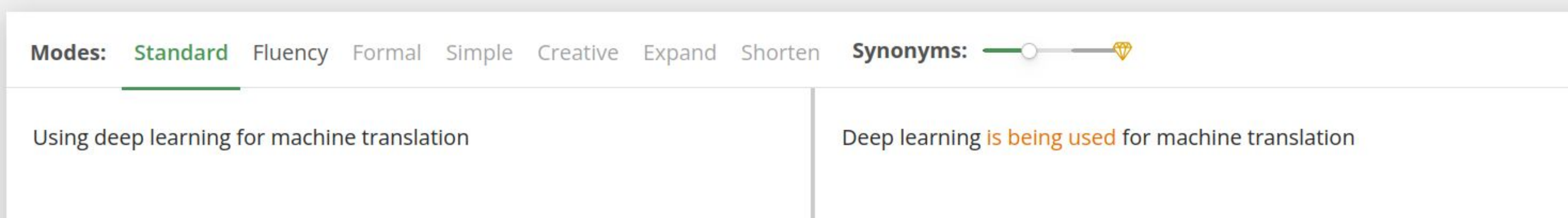
But also: spam detection, language detection…

Seq 2 seq mapping

Automatic translation (deepL)



Automatic paraphrasing (QuillBot)



And also…

- From text…
  … to summary
  … to keywords
  … to code
  … to speech

- Automatic correction, simplification, disambiguation

- Text generation: ChatGPT, Google Bard…

A.I. on speech

A.I. on speech

- Sentiment analysis
- Speech to text
- Diarization :

A.I. course: next step

Next step of this course

- Most A.I. libraries are in Python
  - Pytorch or tensorflow for neural networks
  - scikit-learn for machine learning
  - XGBoost, LightGBM, Prophet…

- Massive data manipulation is done with Pandas

=> Learn or revise Python, discover Pandas

wikimath : http://bit.ly/3ENkQgl