



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

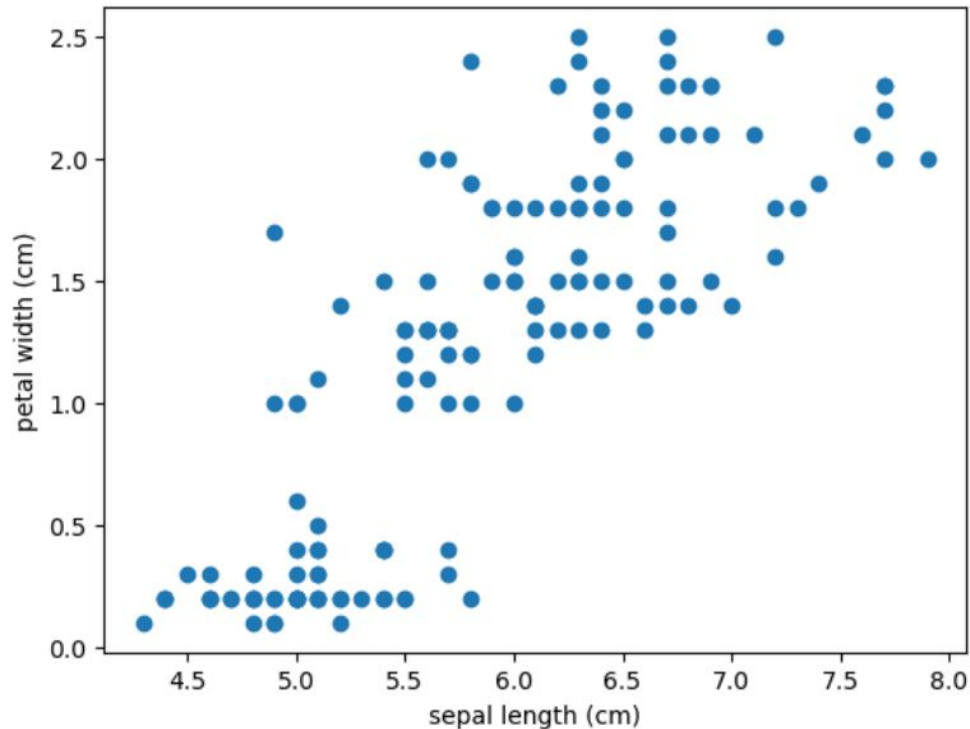
Separate individuals into
homogeneous groups



Clustering: presentation

Separate individuals into homogeneous groups

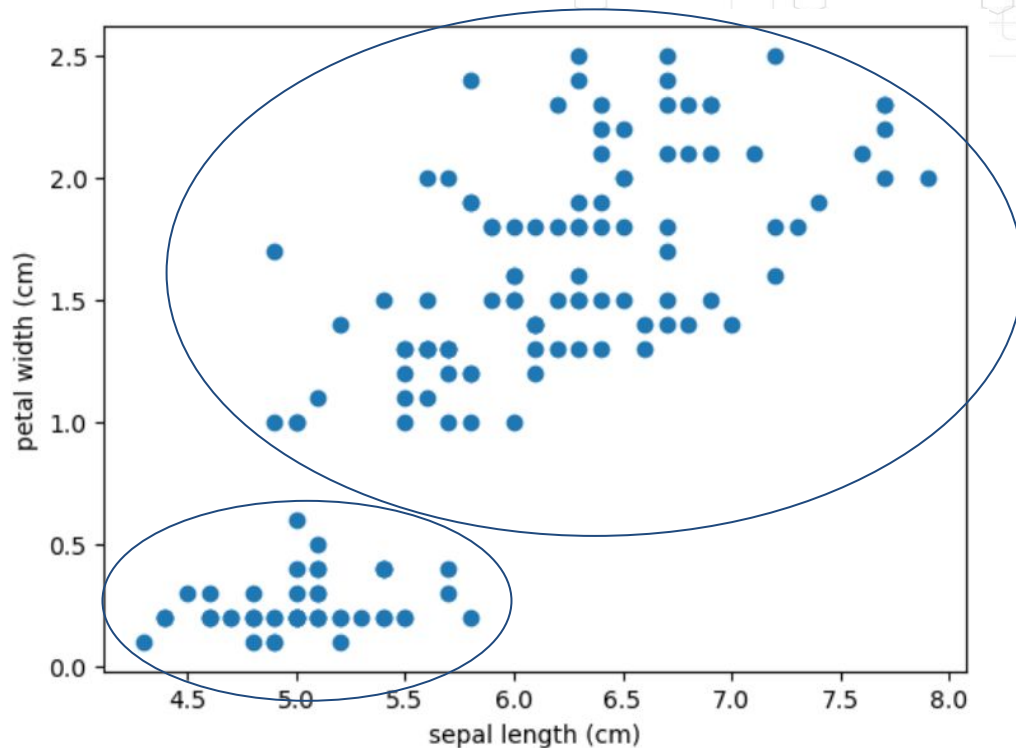
	sepal length (cm)	sepal width (cm)	petal length (cm)	petal width (cm)
0	5.1	3.5	1.4	0.2
1	4.9	3.0	1.4	0.2
2	4.7	3.2	1.3	0.2
3	4.6	3.1	1.5	0.2
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...
145	6.7	3.0	5.2	2.3
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Clustering: presentation

Separate individuals into homogeneous groups

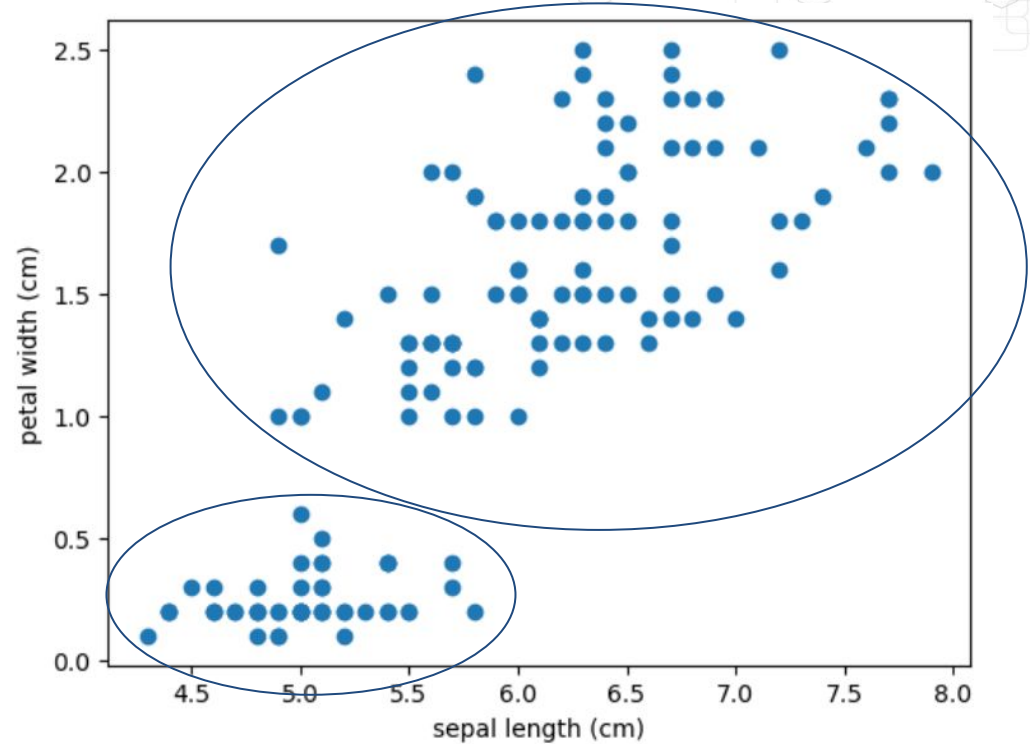
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Clustering: challenges

Separate individuals into homogeneous groups :

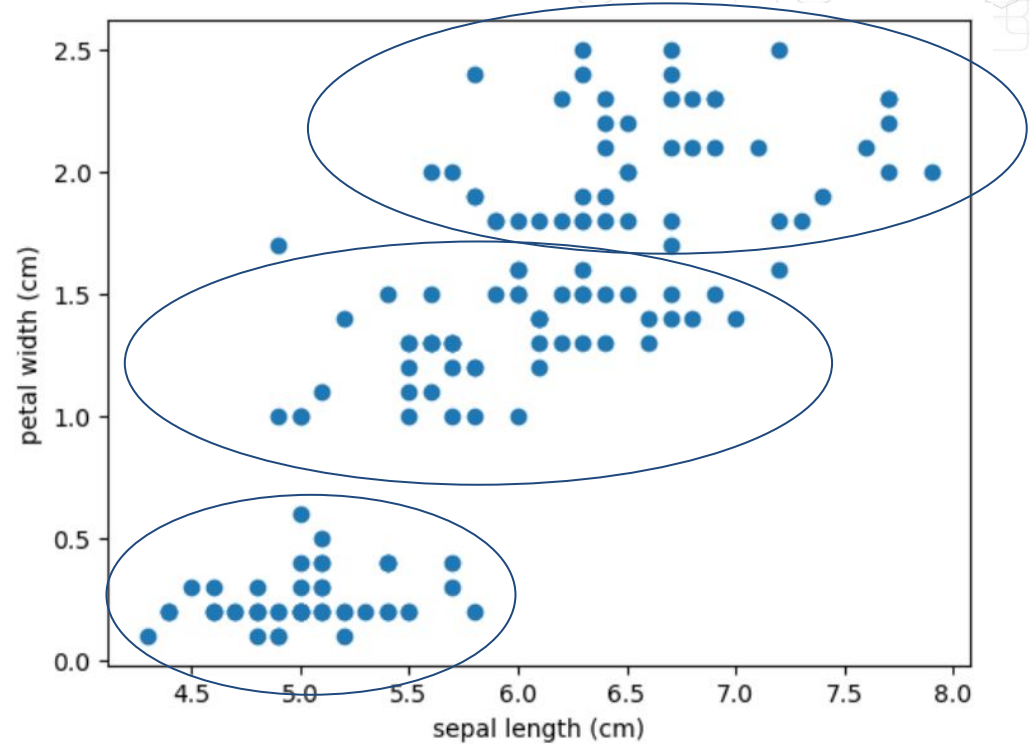
- how many groups ?



Clustering: challenges

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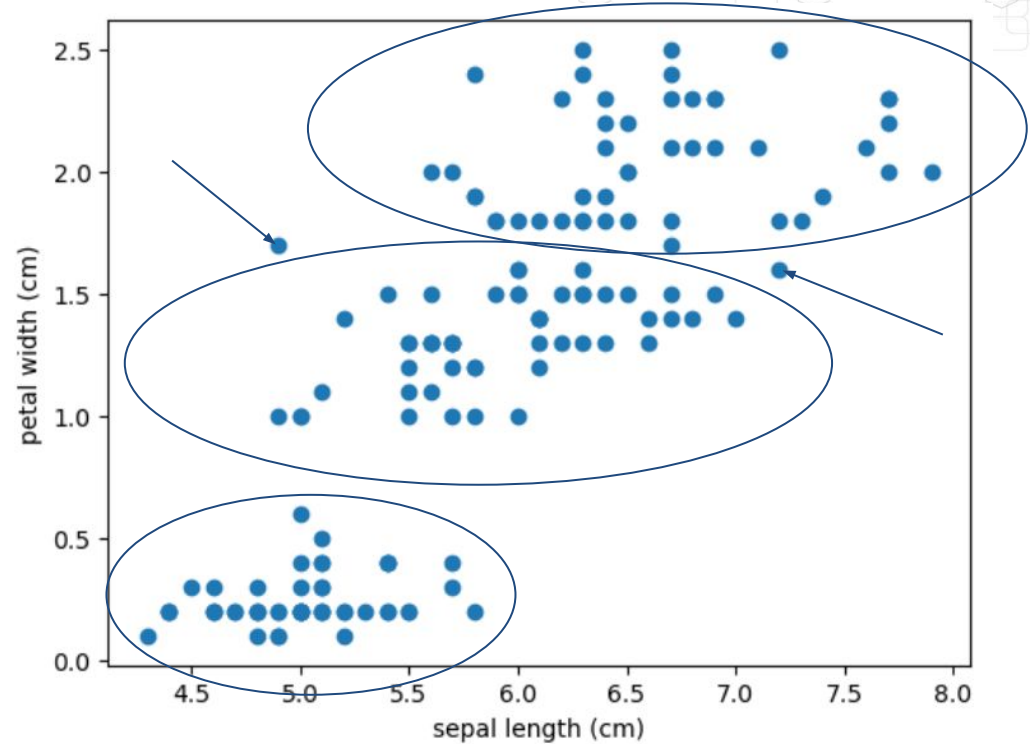
- how many groups ?



Clustering: challenges

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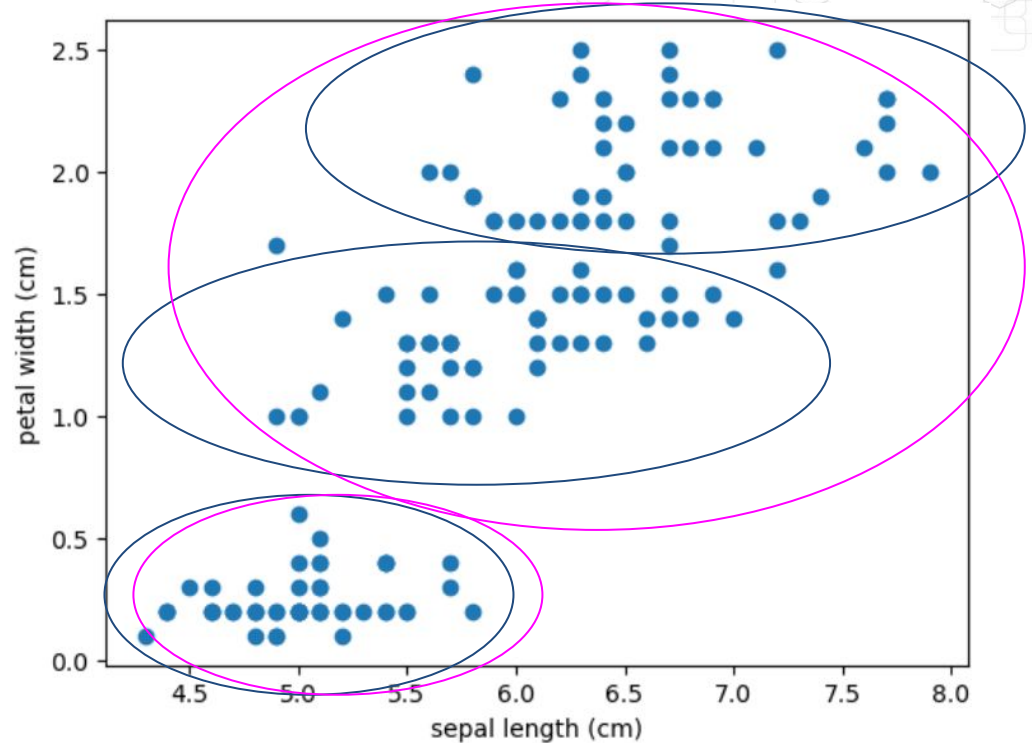
- how many groups ?
- with outliers ?



Clustering: challenges

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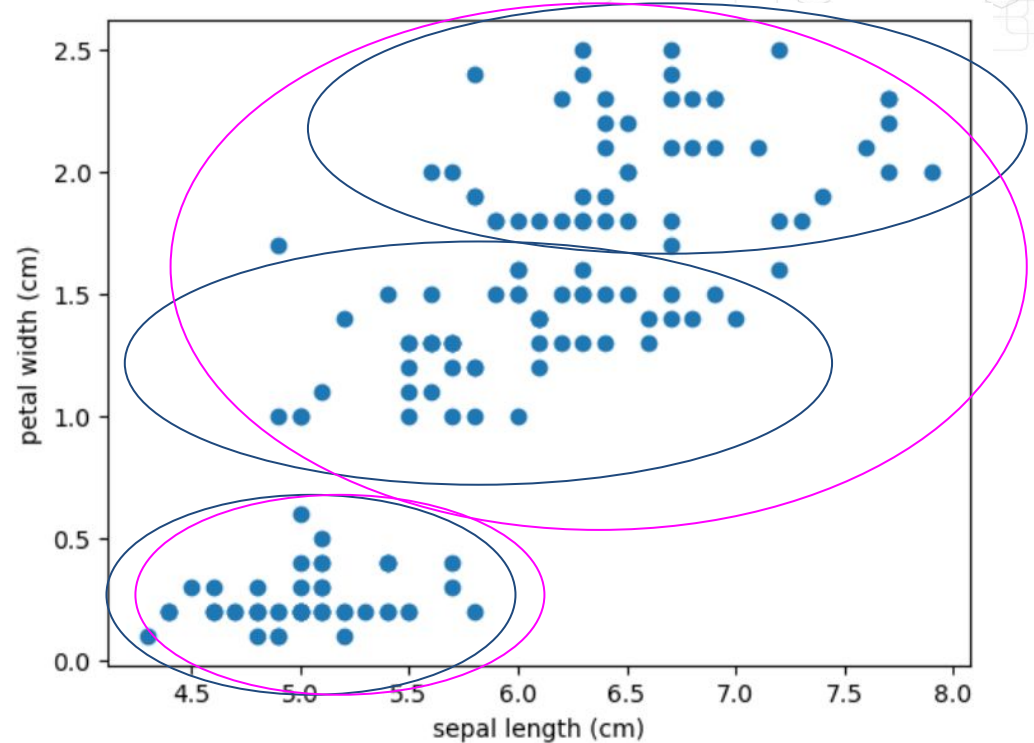
- how many groups ?
- with outliers ?
- how to:
 - evaluate one clustering
 - choose between two clusterings ?



Clustering: challenges

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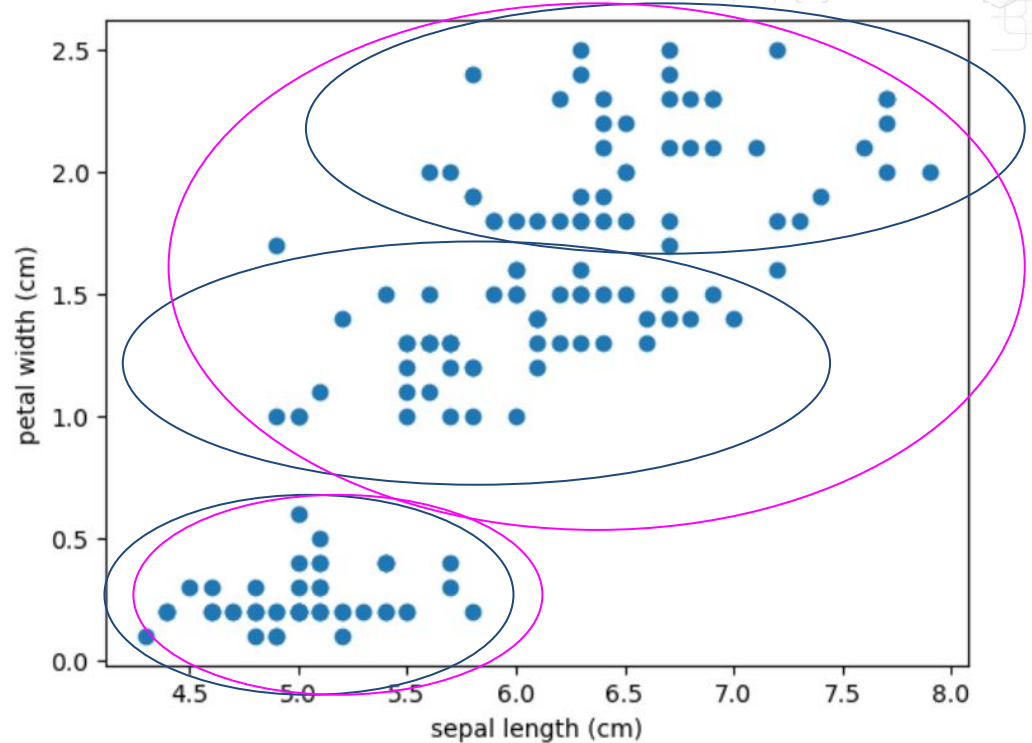
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 - choose between two clusterings ?
- Which method to use, with which parameters?



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...)



Classification: presentation

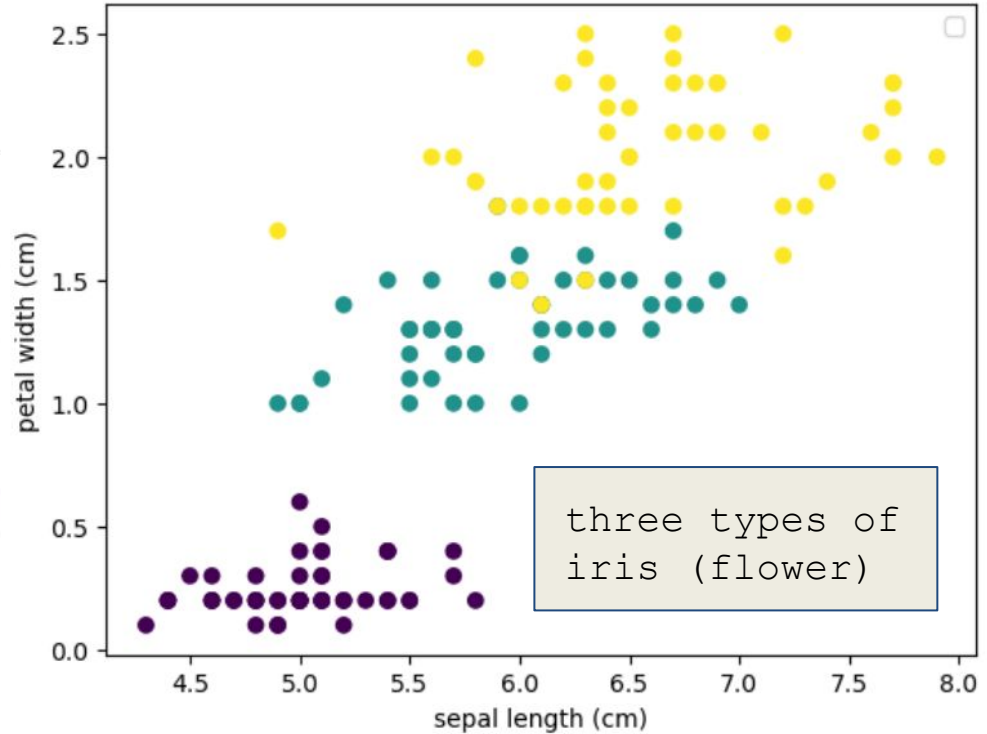
Predict a class from
features



Classification: presentation

Predict a class from features

	sepal length (cm)	sepal width (cm)	petal length (cm)	petal width (cm)	Iris
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3	4.6	3.1	1.5	0.2	setosa
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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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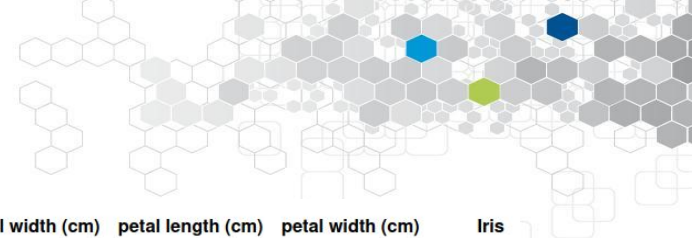
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What is the Iris type of an unknown flower with sepal length of 5.6, sepal width of 2.9, petal length of 4.7, and petal width of 1.7 ?

OBJECTIVE: learn the link between X and y, and

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Clustering versus classification



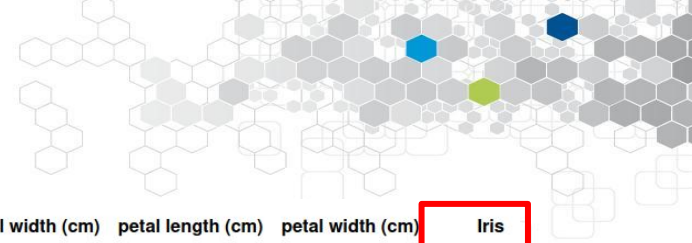
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Classification

Classification versus clustering



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...	...	X
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Clustering

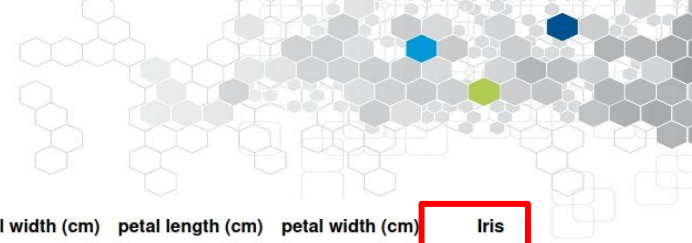
We want to find groups/clusters

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Classification

We want to learn/predict the class y

Classification versus clustering



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Clustering

*We want to find groups/clusters
=> unsupervised learning*

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Classification

*We want to learn/predict the class y
=> supervised learning*

Classification versus regression



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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	X 271.950000	63.000000	Y 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

Regression

We want to learn/predict the number y
=> y is a **number** (float, int...)

Classification versus regression



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Classification

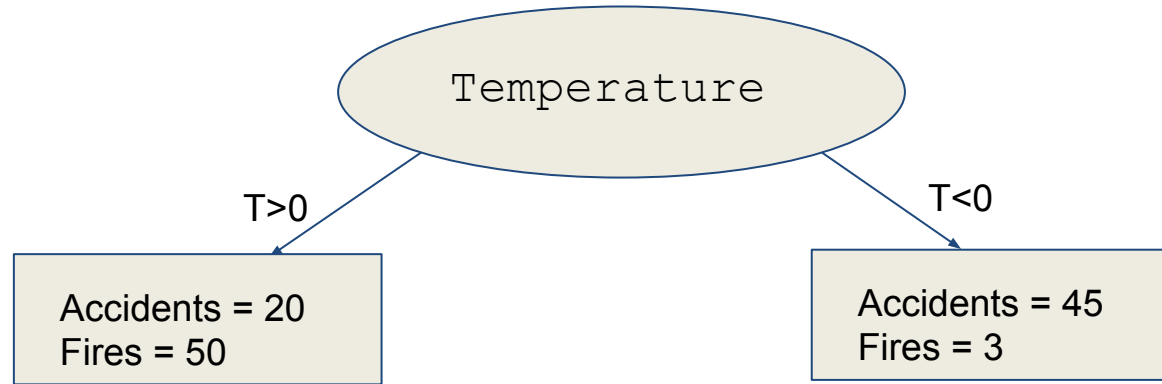
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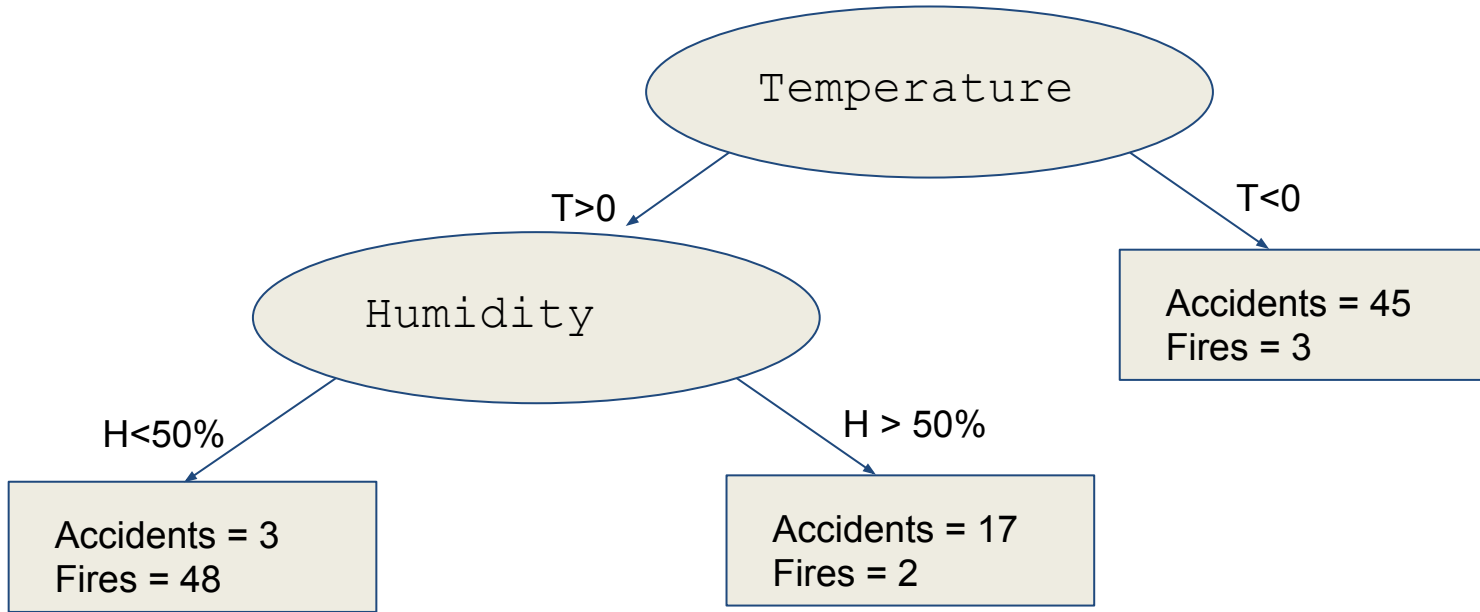
Regression

We want to learn/predict the number y
=> y is a **number** (float, int...)

Decision trees for regression



Decision trees for regression





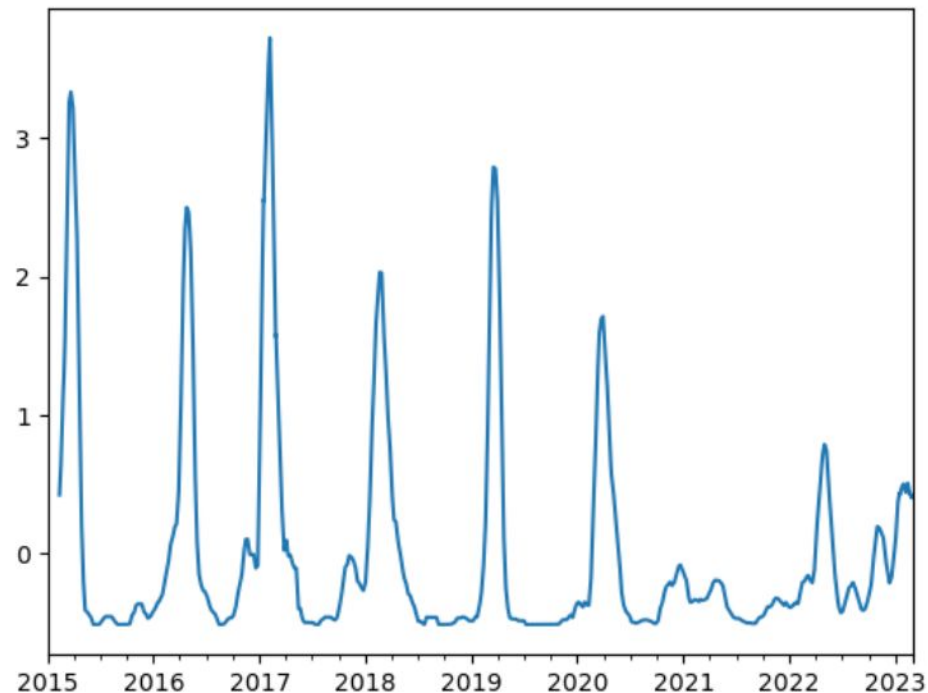
A.I. on time series

Time series



A set of dates+values

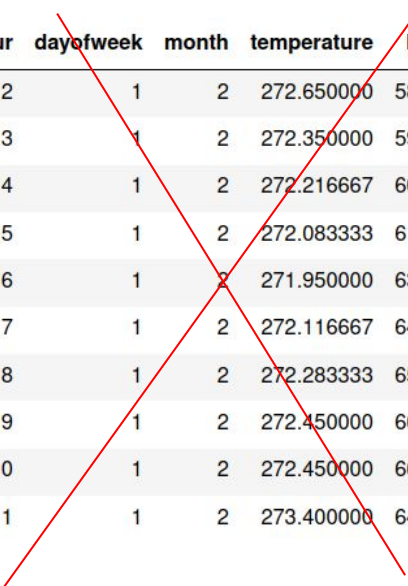
2015-02-11 16:00:00	1.088060
2015-02-11 17:00:00	1.062649
2015-02-11 18:00:00	1.036881
2015-02-11 19:00:00	1.010756
2015-02-11 20:00:00	0.984272
2015-02-11 21:00:00	0.957430
2015-02-11 22:00:00	0.930231
2015-02-11 23:00:00	0.902673
2015-02-12 00:00:00	0.874758
2015-02-12 01:00:00	0.847491



No feature in time series

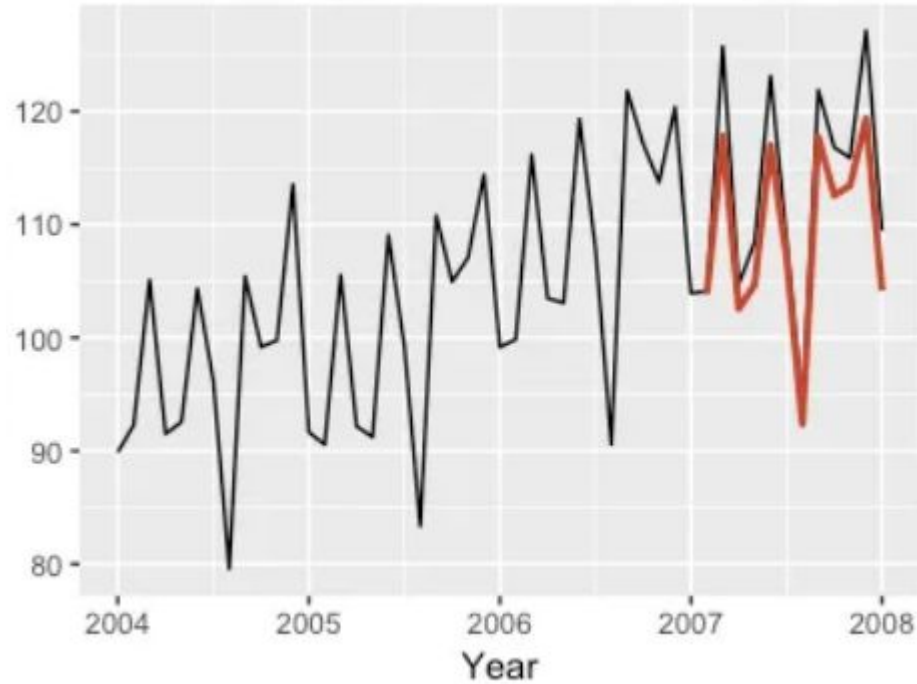


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y

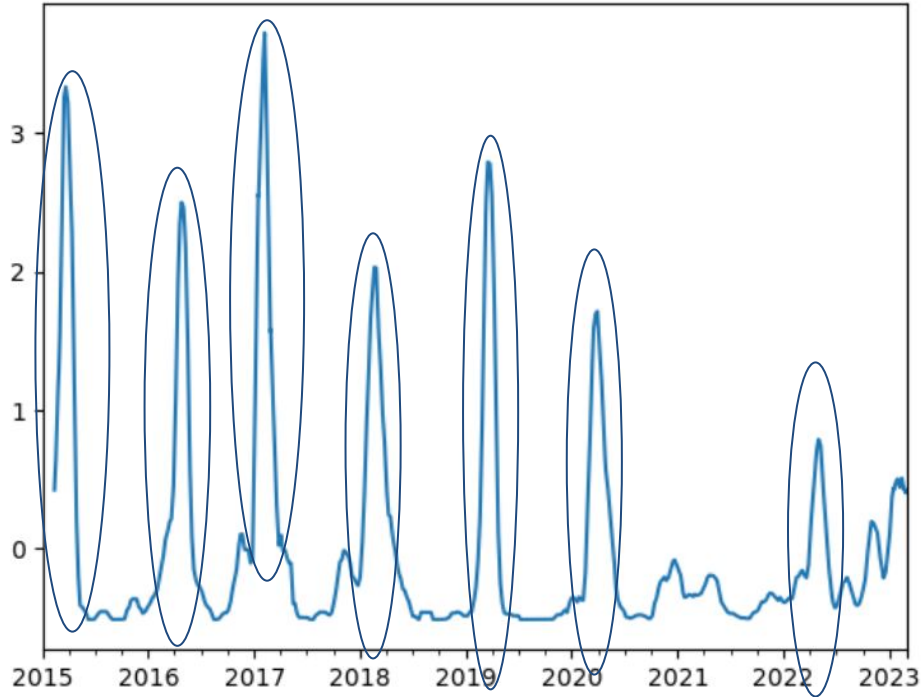
Time series forecasting



Time series forecasting how to...



influenza

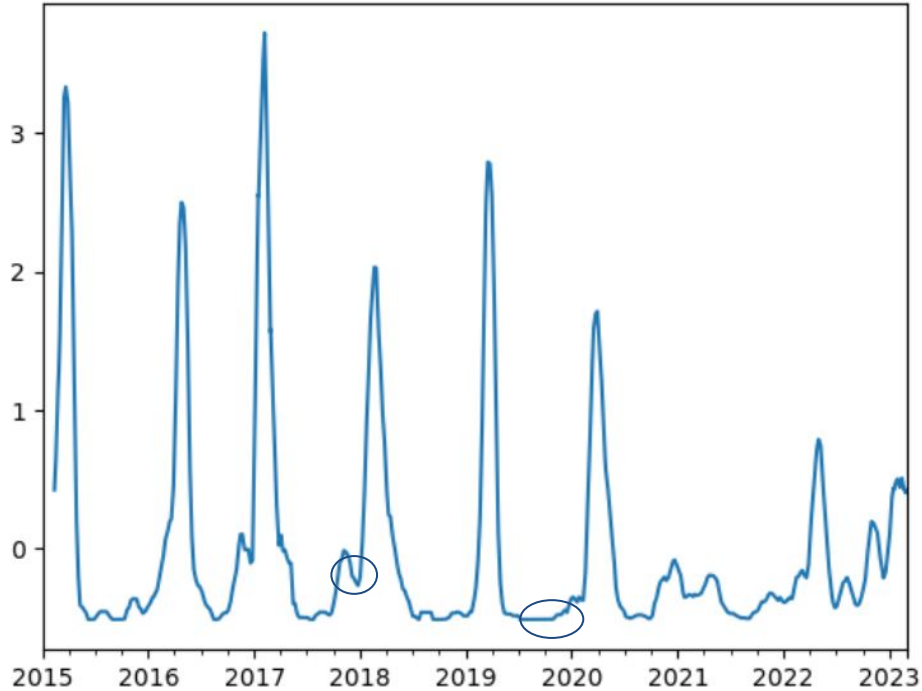


Use of:
- seasonality

Time series forecasting how to...



influenza



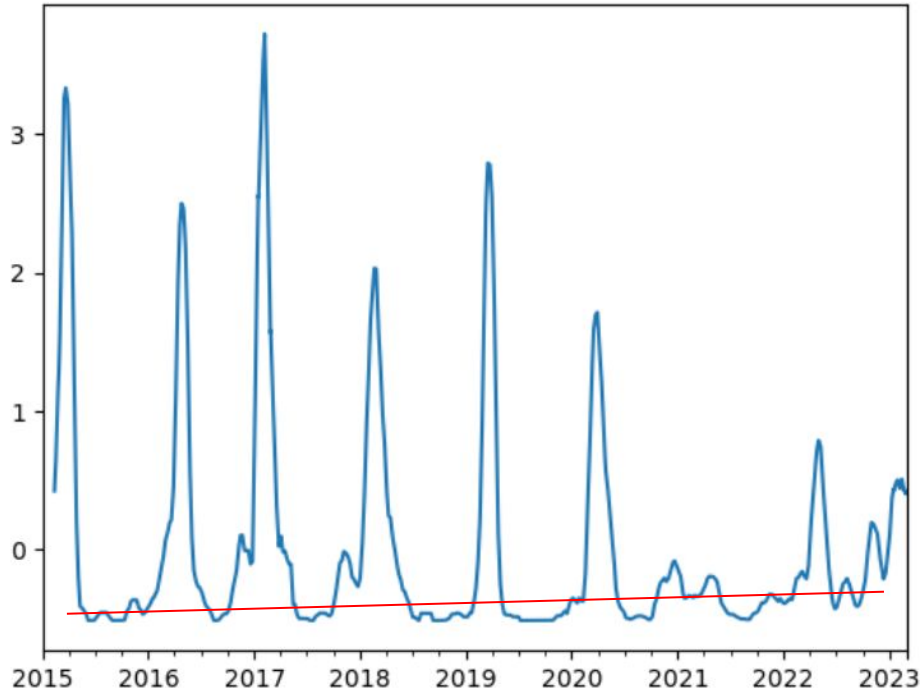
Use of:

- seasonality
- auto-regressive part

Time series forecasting how to...



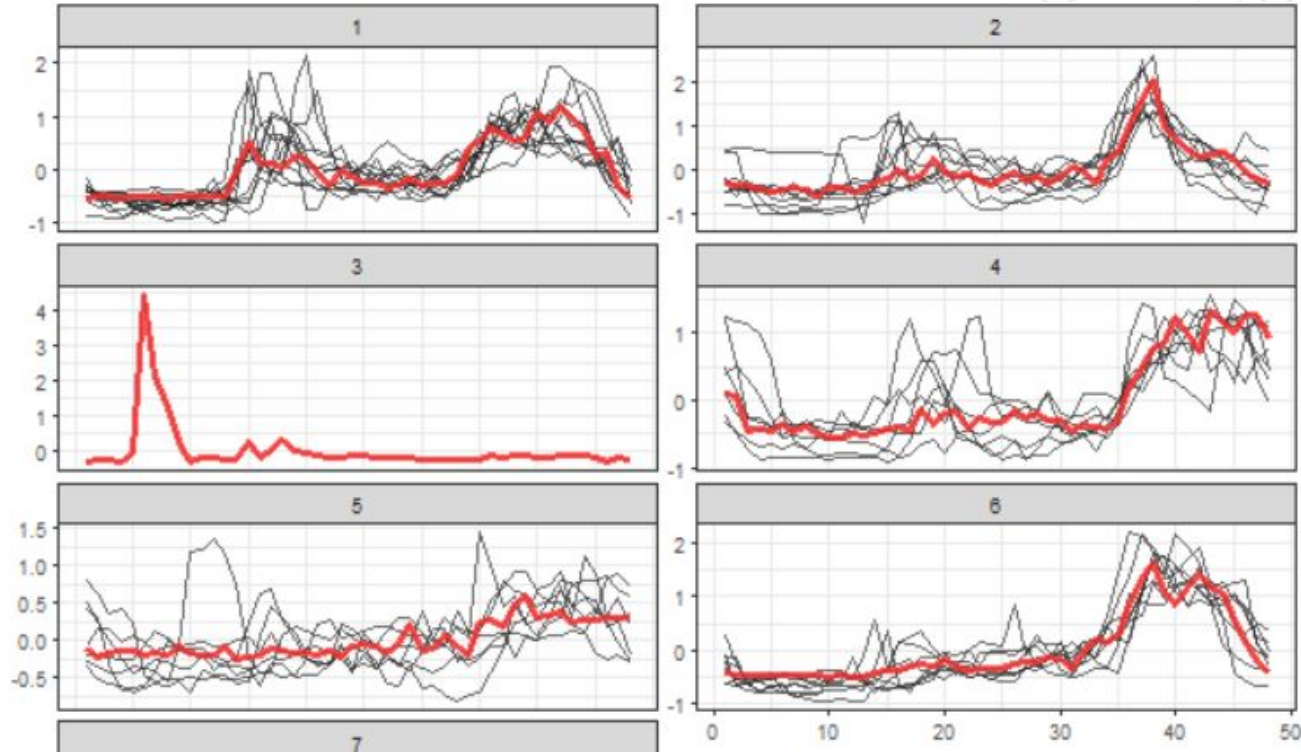
influenza



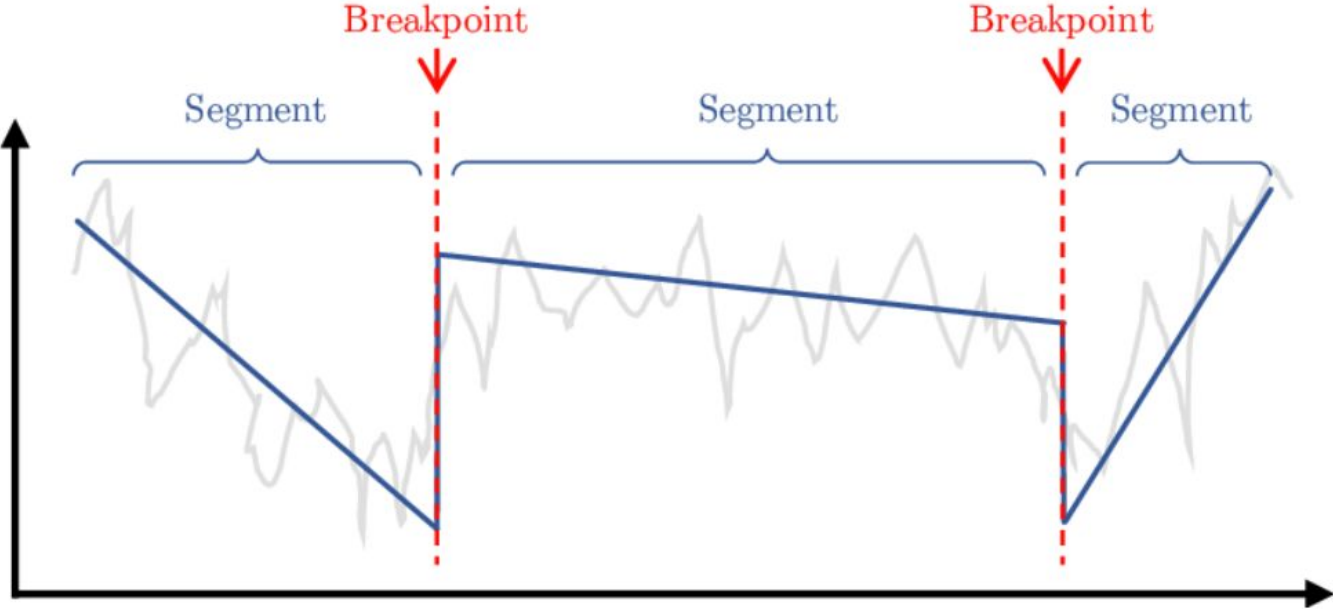
Use of:

- 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)



cat



cat



cat



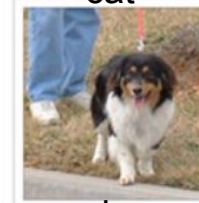
cat



dog



dog



dog



dog

Image enhancement



Input

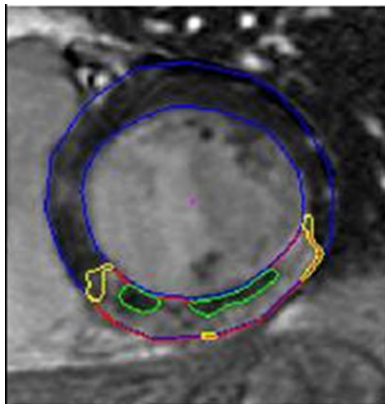


Output



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

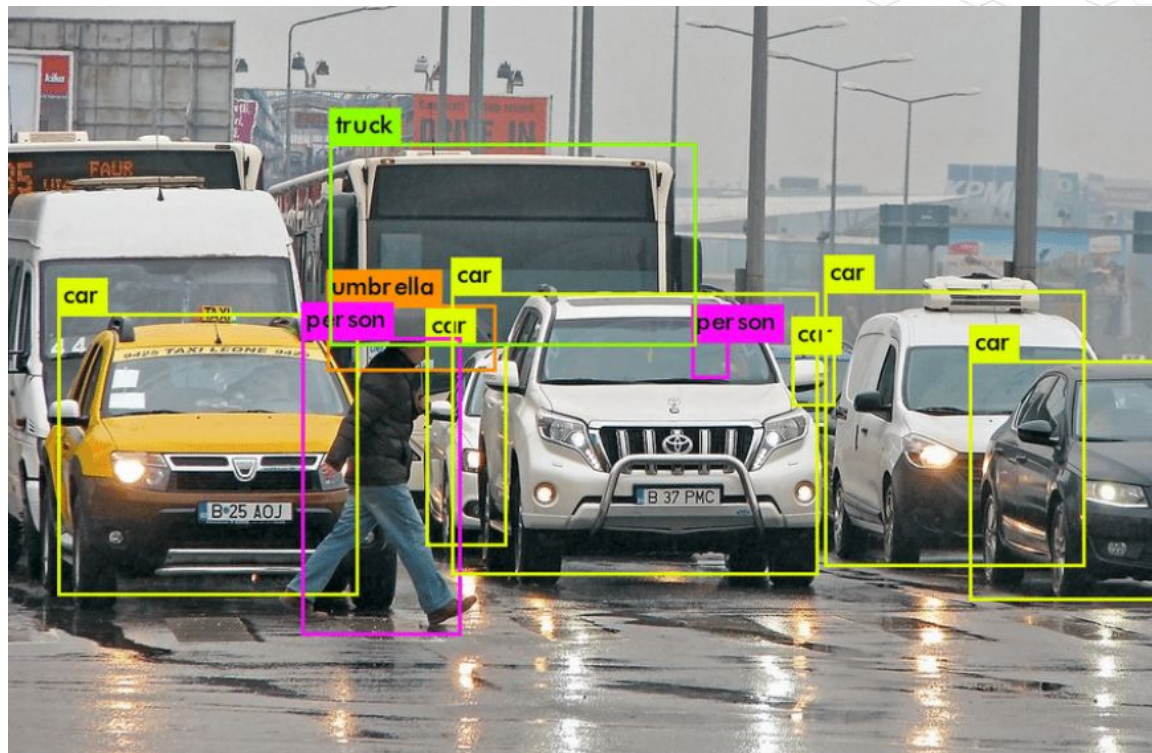


Image generation



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

Output

Input

Image description



a man sitting at a table with a laptop

Input



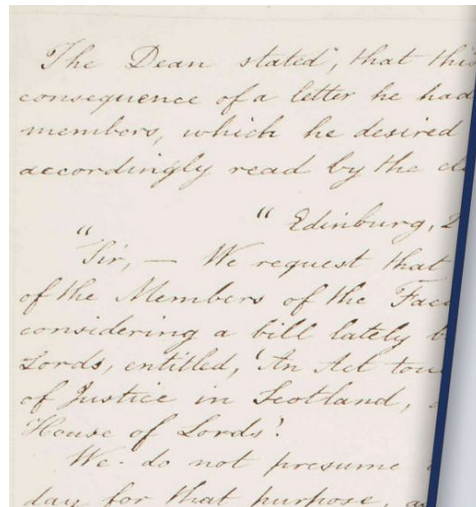
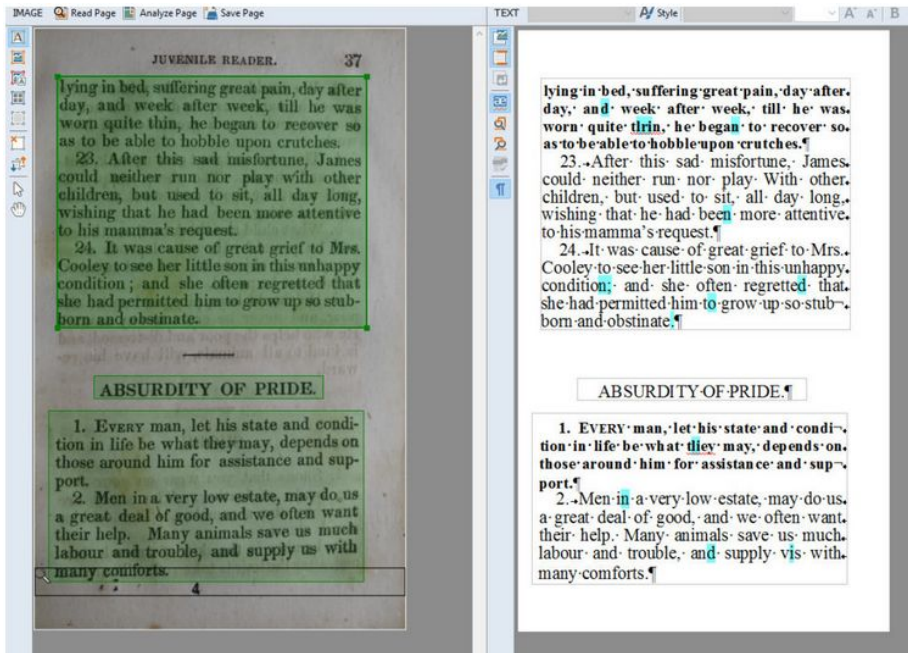
a street sign on a pole in front of a building



a plate with a sandwich and a salad

Output

Text recognition (OCR)



The Dean stated, that this meeting was called in consequence of a letter he had received from seven members, which he desired might be read. It was accordingly read by the clerh and is as follows.

"Edinburg, 25th Nov. 1807

We request that you will call a meeting of the Members of the Faculty, for the purpose of considering a bill lately brought into the House of Lords, entitled, An Act touching the Administration of Justice in Scotland, and touching Appeals to the House of Lords.

We do not presume to suggest any particular

Typed or handwritten



A.I. on texts

Text classification



Example: sentiment analysis on tweets

The image shows two tweets from a user named 'twitter__zendesk__is_'. The first tweet, created 11 minutes ago, contains the text: 'Hey @MaestroQA @lessonly @StellaConnect @Statuspage @tymeshift @geckoboard @adasupport are you ready? Sweet! I know that @Zendesk is! #ZendeskShowcase #SuiteReady https://t.co/un8CnZt1cl'. A blue 'Positive' sentiment label is visible in the top right corner of the tweet. The second tweet, created 12 minutes ago, contains the text: 'Our new integration with @Zendesk is improving #customerexperience by making support even easier. https://t.co/z8YXpkPw3I @Forbes https://t.co/NMLJzX4eQr'. A blue 'Positive' sentiment label is also visible in the top right corner of this tweet.

But also: spam detection, language detection...

Seq 2 seq mapping



Automatic translation (deepL)

Français (langue détectée) ▾

↔ Anglais (USA) ▾

Utilisation de deep learning pour de la traduction automatique

×

Using deep learning for machine translation

Automatic paraphrasing (QuillBot)

Modes: **Standard** Fluency Formal Simple Creative Expand Shorten

Synonyms: 

Using deep learning for machine translation

Deep learning **is being used** for machine translation

And also...



- From text...
 - ... to summary
 - ... to keywords
 - ... to code
 - ... to speech
- Automatic correction, simplification, disambiguation
- Text generation: ChatGPT, Google Bard...

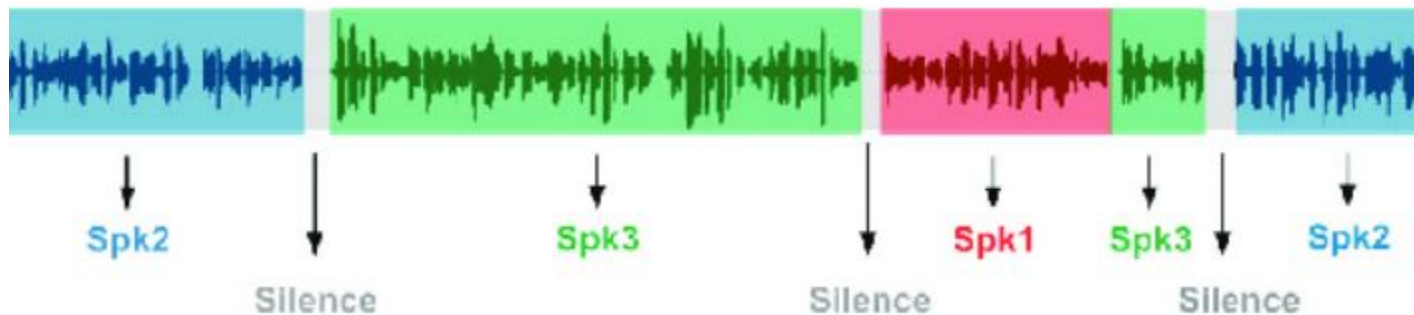


A.I. on speech

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>