

### A non-exhaustive overview of the possibilities of AI

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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





# Clustering: presentation



	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
145	6.7	3.0	5.2	2.3
1 <b>4</b> 6	6.3	2.5	5.0	1.9
147	6.5	3.0	5.2	2.0
148	6.2	3.4	5.4	2.3
149	5.9	3.0	5.1	1.8



# Clustering: presentation

	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
145	6.7	3.0	5.2	2.3
<mark>146</mark>	6.3	2.5	5.0	1.9
147	6.5	3.0	5.2	2.0
148	6.2	3.4	5.4	2.3
149	5.9	3.0	5.1	1.8





Separate individuals into homogeneous groups :

- how many groups ?





Separate individuals into homogeneous groups :

- how many groups ?





- how many groups ?
- with outliers ?





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





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





- 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...)





Predict a class from features







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	Ê
3	4.6	3.1	1.5	0.2	setosa	c) (c
4	5.0	3.6	1.4	0.2	setosa	dth
						N
145	6.7	3.0	5.2	2.3	virginica	eta
146	6.3	2.5	5.0	1.9	virginica	à
147	6.5	3.0	5. <mark>2</mark>	2.0	virginica	
148	6.2	3.4	5.4	2.3	virginica	
149	5.9	3.0	5.1	1.8	virginica	





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Iris	petal width (cm)	petal length (cm)	sepal width (cm)	sepal length (cm)	
setosa	0.2	1.4	3.5	5. <mark>1</mark>	0
setosa	0.2	1.4	3.0	4.9	1
setosa	0.2	1.3	3.2	4.7	2
setosa	0.2	1.5	3.1	4.6	3
setosa	0.2	1.4	3.6	5.0	4
virginica	2.3	5.2	3.0	6.7	145
virginica	1.9	5.0	2.5	6.3	146
virginica	2.0	5.2	3.0	6.5	147
virginica	2.3	5.4	3.4	6.2	148
virginica	1.8	5.1	3.0	5.9	149

INPUT: a basis of knowledge





		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
INFUI. a	4	5.0	3.6	1.4	0.2	setosa
basis of						
knowledge	145	6.7	3.0	5.2	2.3	virginica
	146	6.3	2.5	5.0	1.9	virginica
	147	6.5	3.0	5.2	2.0	virginica
	148	6.2	3.4	5.4	2.3	virginica
	149	5.9	3.0	5.1	1.8	virginica
	<					
Features	5 ()	X)				Targ
						a cl





Iris	petal width (cm)	petal length (cm)	sepal width (cm)	sepal length (cm)	
setosa	0.2	1.4	3.5	5.1	0
setosa	0.2	1.4	3.0	4.9	1
setosa	0.2	1.3	3.2	4.7	2
setosa	0.2	1.5	3.1	4.6	3
setosa	0.2	1.4	3.6	5.0	4
virginica	2.3	5.2	3.0	6.7	145
virginica	1.9	5.0	2.5	6.3	146
virginica	2.0	5.2	3.0	6.5	147
virginica	2.3	5.4	3.4	6.2	148
virginica	1.8	5.1	3.0	5.9	149

INPUT: a basis of knowledge

OBJECTIVE: learn the link between X and y, and

given a new X row, predict its class y





Iris	petal width (cm)	petal length (cm)	sepal width (cm)	sepal length (cm)	
setosa	0.2	1.4	3.5	5.1	0
setosa	0.2	1.4	3.0	4.9	1
setosa	0.2	1.3	3.2	4.7	2
setosa	0.2	1.5	3.1	4.6	3
setosa	0.2	1.4	3.6	5.0	4
virginica	2.3	5.2	3.0	6.7	145
virginica	1.9	5.0	2.5	6.3	146
virginica	2.0	5.2	3.0	6.5	147
virginica	2.3	5.4	3.4	6.2	148
virginica	1.8	5.1	3.0	5.9	149

INPUT: a basis of knowledge

OBJECTIVE: learn the link between X and y, and

given a new X row, predict its class y



145

146

	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

INPUT: a basis of knowledge

What is the Iris type of an <u>unknown</u> flower with sepal length of 5.6, sepal width of 2.9, petal length of 4.7, and petal width of 1.7 ?

147	6.5	3.0	5.2	2.0 virginica
148	6.2	3.4	5.4	2.3 virginica
149	5.9	3.0	5.1	1.8 virginica

OBJECTIVE: learn the link between X and y, and

given a new X row, predict its class y



# **Clustering versus classification**

1.4

1.4

1.3

1.5

1.4

...

5.2

5.0

5.2

5.4

5.1

0.2

0.2

0.2

0.2

0.2

...

2.3

1.9

2.0

2.3

1.8

sepal length (cm) sepal width (cm) petal length (cm) petal width (cm)

3.5

3.0

3.2

3.1

3.6

...

3.0

2.5

3.0

3.4

3.0

5.1

4.9

4.7

4.6

5.0

...

6.7

6.3

6.5

6.2

5.9

Iris	petal width (cm)	petal length (cm)	sepal width (cm)	sepal length (cm)	
setosa	0.2	1.4	3.5	5.1	0
setosa	0.2	1.4	3.0	4.9	1
setosa	0.2	1.3	3.2	4.7	2
setosa	0.2	1.5	3.1	4.6	3
setosa	0.2	1.4	3.6	5.0	4
virginica	2.3	5.2	3.0	6.7	145
virginica	1.9	5.0	2.5	6.3	146
virginica	2.0	5.2	3.0	6.5	147
virginica	2.3	5.4	3.4	6.2	148
virginica	1.8	5.1	3.0	5.9	149

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#### Classification



0

1

2

3

4

145

146

147

148

149

# **Classification versus clustering**

	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
		X			Y
45	6.7	3.0	5.2	2.3	virginica
46	6.3	2.5	5.0	1.9	virginica
47	6.5	3.0	5.2	2.0	virginica
48	6.2	3.4	5.4	2.3	virginica
49	5.9	3.0	5.1	1.8	virginica

	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
		X		
145	6.7	3.0	5.2	2.3
146	6.3	2.5	5.0	1.9
147	6.5	3.0	5.2	2.0
148	6.2	3.4	5.4	2.3
140	5.0	20	5.1	1.9

Clustering

### Classification



# **Classification versus clustering**

1.4

1.4

1.3

1.5

1.4

...

5.2

5.0

5.2

5.4

5.1

0.2

0.2

0.2

0.2

0.2

....

2.3

1.9

2.0

23

1.8

sepal length (cm) sepal width (cm) petal length (cm) petal width (cm)

3.5

3.0

3.2

3.1

3.6

...

3.0

2.5

3.0

3.4

3.0

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5.1

4.9

4.7

4.6

5.0

...

6.7

6.3

6.5

6.2

5.9

	sepal length (cm)	sepal width (cm)	petal length (cm)	petal width (cm)	Iris
0	5. <mark>1</mark>	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
		Χ			V
45	6.7	3.0	5.2	2.3	virginica
46	6.3	2.5	5.0	1.9	virginica
47	6.5	3.0	5.2	2.0	virginica
48	6.2	3.4	5.4	2.3	virginica
49	5.9	3.0	5.1	1.8	virginica

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We want to find groups/clusters

Classification

We want to learn/predict the class y



0

2

3

4

....

145

146

147

148

149

# **Classification versus clustering**

1.4

1.4

1.3

1.5

1.4

...

5.2

5.0

5.2

5.4

5.1

0.2

0.2

0.2

0.2

0.2

....

2.3

1.9

2.0

2.3

1.8

sepal length (cm) sepal width (cm) petal length (cm) petal width (cm)

3.5

3.0

3.2

3.1

3.6

...

3.0

2.5

3.0

3.4

3.0

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5.1

4.9

4.7

4.6

5.0

...

6.7

6.3

6.5

6.2

5.9

	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
4	5.0	3.6	1.4	0.2	setosa
		Χ			Y
45	6.7	3.0	5.2	2.3	virginica
46	6.3	2.5	5.0	1.9	virginica
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48	6.2	3.4	5.4	2.3	virginica
49	5.9	3.0	5.1	1.8	virginica

Clustering	
J	

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

#### Classification

We	want	to	learn	/predict	the	class	У
	=> sı	ipei	rvised	learnind	7		



0

2

3

4

....

145

146

147

148

149

# **Classification versus regression**

1.4

1.4

1.3

1.5

1.4

...

5.2

5.0

5.2

5.4

5.1

Iris

setosa

setosa

setosa

setosa

setosa

V...

virginica

virginica 2.0 virginica

2.3 virginica

1.8 virginica

0.2

0.2

0.2

0.2

0.2

2.3

1.9

sepal length (cm) sepal width (cm) petal length (cm) petal width (cm)

3.5

3.0

3.2

3.1

3.6

....

3.0

2.5

3.0

3.4

3.0

Х

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	у <sup>7</sup>
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

=> y is a category

Classification





0

2

3

4

....

145 146

147

148

149

5.1

4.9

4.7

4.6

5.0

...

6.7

6.3

6.5

6.2

5.9

# **Classification versus regression**

1.4

1.4

1.3

1.5

1.4

...

5.2

5.0

5.2

5.4

5.1

Iris

setosa

setosa

setosa

setosa

setosa V...

virginica

virginica

2.0 virginica 2.3 virginica

1.8 virginica

0.2

0.2

0.2

0.2

0.2

2.3

1.9

sepal length (cm) sepal width (cm) petal length (cm) petal width (cm)

3.5

3.0

3.2

3.1

3.6

...

3.0

2.5

3.0

3.4

3.0

Classification

Х

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	у 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

war	пt	to	16	earn/predict	the	class	У	
=>	У	is	а	category				





0

1

2

3

4

...

145

146

147

148

149

We

5.1

4.9

4.7

4.6

5.0

...

6.7

6.3

6.5

6.2

5.9

supervised learning (both)











# 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

	( )				
nour	dayofweek	month	temperature	numidity	nb. of Intervention
2	1	2	272.650000	58.333333	7
3	X	2	272.350000	59.000000	4
4	1	2	272.216667	60.333333	12
5	1	2	272.083333	61.666667	4
6	1	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
/				$\backslash$	



### Time series forecasting







# 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



Input

Output



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 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)



lying in bed, suffering great pain, day after. day, and week after week, till he was. worn · quite · tlrin, · he · began · to · recover · so. as to be able to hobble upon crutches.

23. After this sad misfortune, James, could neither run nor play With other, children, but used to sit, all day long, wishing that he had been more attentive, to his mamma's request.

24.-It was cause of great grief to Mrs.-Cooley to see her little son in this unhappy, condition, and she often regretted that, she had permitted him to grow up so stubbom and obstinate.

#### ABSURDITY OF PRIDE.

1. EVERY'man, 'let'his state and condi-, tion in life be what they may, depends on, those around him for assistance and sup-, port.

2. Men in a very low estate, may do us, a great deal of good, and we often want their help. Many animals save us much labour and trouble, and supply vis with many comforts. The Dean stated, that this consequence of a letter he had members, which he desired accordingly read by the de " Edinburg, 2

"Jir, - We request that of the Members of the Face considering a bill lately to Lords, entitled, "In Act tou of Justice in Scotland, . House of Lords ?. We do not presume day for that purpose,

The Dean stated, that this meeting was called in consequence of a letter he had received from sew members, which he desired might be read. It wa 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 c considering a bill lately brought into the House c Lords, entitled, An Act touching the Administr of Justice in Scotland, and touching Appeals to House of Lords.

W do not presume to suggest any particular-

Typed or handwritten

- A' A' B



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



### A.I. on texts





#### Example: sentiment analysis on tweets

Hey @MaestroQA @lessonly @StellaConnect @Statuspage @tymeshift @geckoboard @adasupport are you ready? Sweet! I know that @Zendesk is! #ZendeskShowcase #SuiteReady https://t.co/un8CnZt1cl	Positive
Created 11 minutes ago 🔲 twitterzendesk_is_	
Our new integration with @Zendesk is improving #customerexperience by making support even easier. https://t.co/z8YXpkPw3I @Forbes https://t.co/NMLJzX4eQr 🥑	Positive
Created 12 minutes ago 📓 twitterzendeskis	

But also: spam detection, language detection ...



# Seq 2 seq mapping



Français (langue détectée) 🗸	¢	Anglais (USA) 🗸
Utilisation de <u>deep learning</u> pour de la traduction automatique	×	Using deep learning for machine translation

### Automatic paraphrasing (QuillBot)

Modes:	Standard	Fluency	Formal	Simple	Creative	Expand	Shorten	Synonyms: ————————————————————————————————————
Using de	ep learning	for machir	ne transla	tion				Deep learning is being used for machine translation







- 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





- ➤ 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 : <u>http://bit.ly/3ENkQgl</u>

