

# MLRF Lecture 01

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# More definitions

Lecture 01 part 02

# Computer Vision

# Computer Vision: a definition

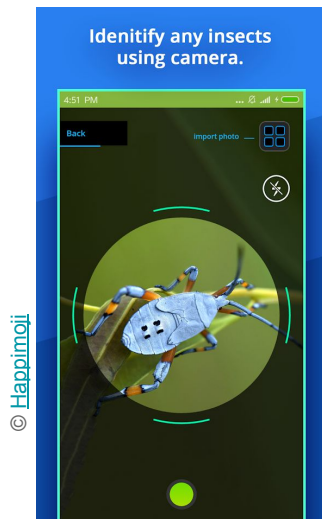
***Computer Vision:*** *the automation of visual tasks with the goal of producing results directly or indirectly usable by humans.*  $\Leftarrow$  *Engineer definition*

**Input:** image(s) in machine format (image acquisition is a subpart of CV)

**Output:** some pieces of information about the image, new image(s)...

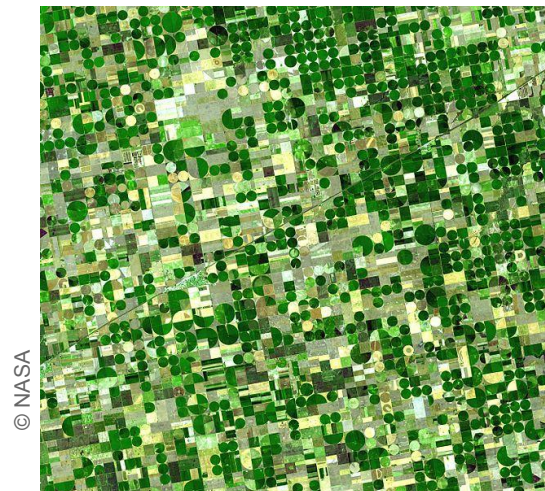
# Computer Vision: some examples (1/4)

*How would you process image pixels to get those results?*



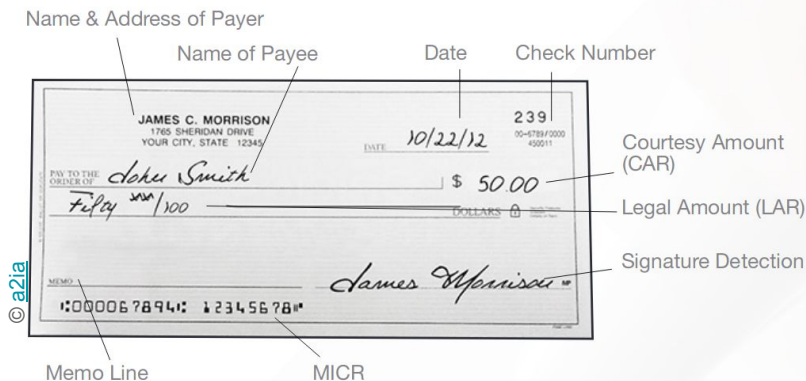
**Input:** still picture of insect  
**Output:** insect name  
**Application:** farming, ...

*Classification*



**Input:** satellite image (near visible range)  
**Output:** crop maturity  
**Application:** farming, trading...

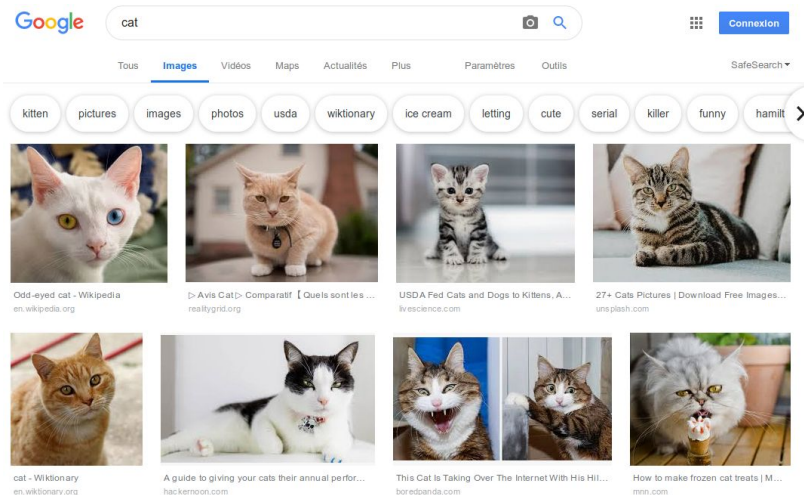
*Regression*



**Input:** bank check image (greylevel)  
**Output:** account number, amount...  
**Application:** banks

*Detection,  
Classification, ...*

# Computer Vision: some examples (2/4)

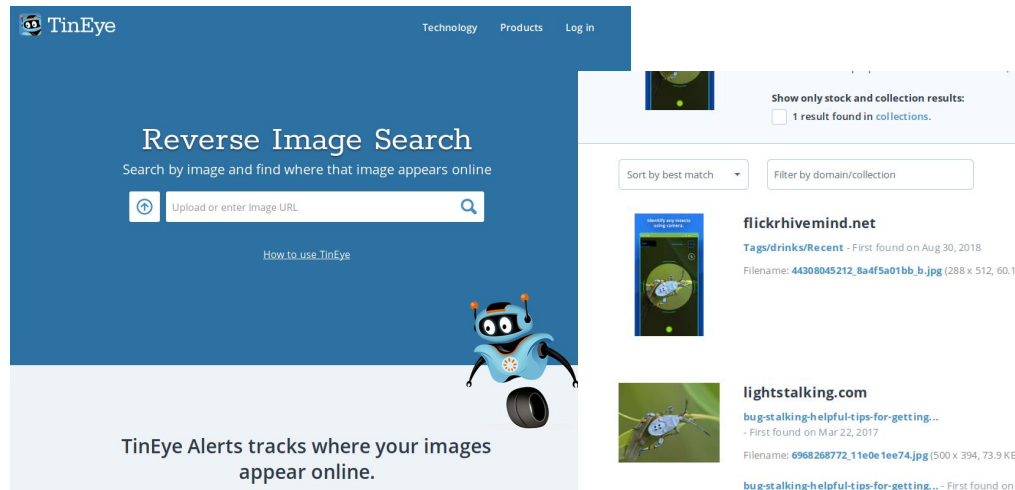


**Input:** text

**Output:** list of relevant images

**Application:** look for cats, ...

Indexing, ...



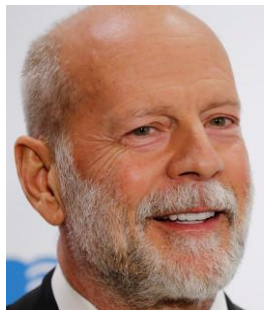
**Input:** image

**Output:** similar images

**Application:** duplicate detection, copyright, ...

Content-based  
Image retrieval, ...

# Computer Vision: some examples (3/4)



VS

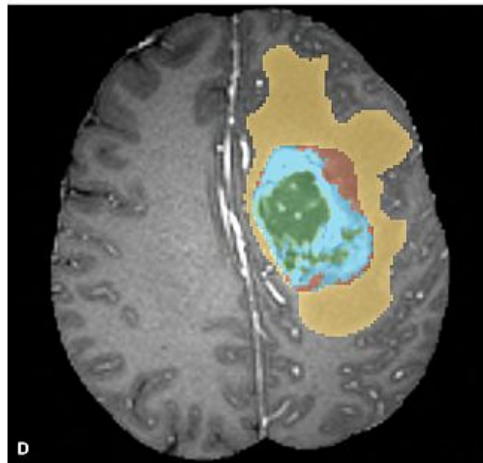


**Input:** two images of face

**Output:** same/different person

**Application:** authentication, ...

*Distance/similarity  
learning, ...*



**Input:** brain 3D scan

**Output:** regions with high tumor probability

**Application:** assisted diagnosis, ...

*Segmentation,  
classification, ...*

# Computer Vision: some examples (4/4)

Some applications are direct (like the insect recognition app):  
a human reads and uses the output

Some applications are indirect (like bank check reading):  
the output is fed to a business system

Some applications extend what humans can naturally do:  
either by extending our range of visible colors (satellite example)  
or by simply being more efficient (face verification)

And there are many many many more examples...



# Pattern Recognition

# Pattern Recognition: a definition

***Pattern Recognition:** The field of pattern recognition is concerned with the automatic discovery of regularities in data through the use of computer algorithms and with the use of these regularities to take actions such as classifying the data into different categories. — Bishop 2006*



The International Association for Pattern Recognition (IAPR) is an international association [...] concerned with pattern recognition, computer vision, and image processing in a broad sense.

# Pattern Recognition: examples

OCR *Computer Vision*

Pedestrian detection *Computer Vision*

Credit card fraud detection *NOT  
Computer Vision*

...

$\Rightarrow CV \cap PR \neq \emptyset$ , “recognition” used to mean “classification”

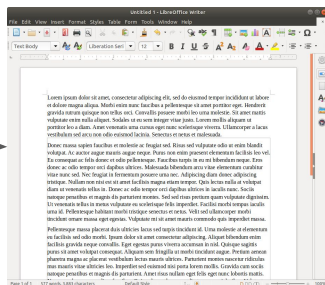
# Pattern Recognition is an inverse problem

## OCR example – Why Pattern Recognition is hard

Lorem ipsum dolor  
sit amet,  
consectetur  
adipiscing elit.  
Phasellus nulla ...

Forward

Type some text



Print it

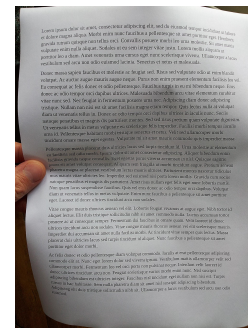


...



“Scan” it

Reverse



Loren gypsum  
dolor sit mate,  
consecrate  
disciplining lit.  
Phallus nulls ...

Try to guess  
was the original  
text was

“Shapes”

# “Shapes”

Sometimes used to describe “visual percepts” (image patterns) which exhibit a “large [deviation] from randomness”. See *Cao et al. 2008*.

A way to designate meaningful visual patterns.

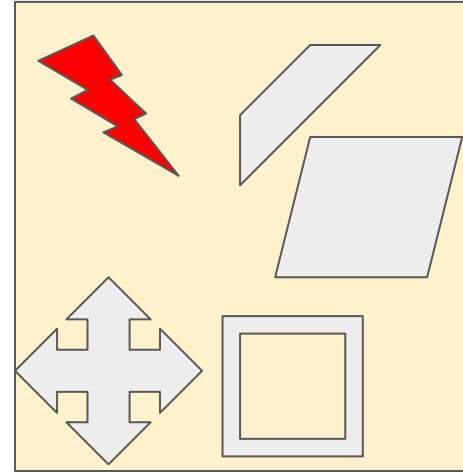
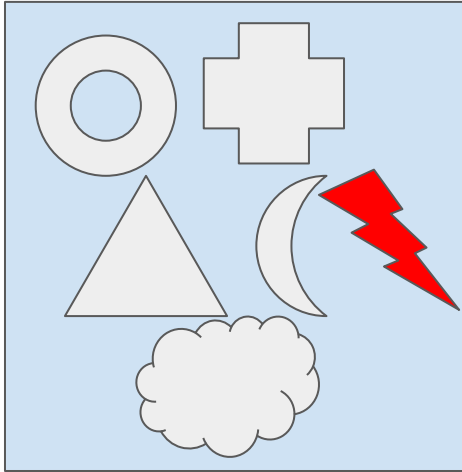
An interesting mathematical foundation to compare them:

*Let  $S$  and  $S'$  be two shapes observed in two different images and which happen to be similar. Denote their (small) Hausdorff distance after registration by  $\delta = d(S, S')$ . Assume we know enough of the background model to compute the probability  $\Pr(S, \delta) = \Pr(d(S, \Sigma) \leq \delta)$  that some shape in the background,  $\Sigma$  be as similar to  $S$  as  $S'$  is. If this probability is very small one can deduce that  $S'$  does not look like  $S$  just by chance. Then  $S$  and  $S'$  will be identified as the same shape.*

We can check whether two shapes are significantly close.

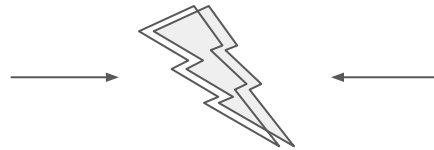
# “Shapes”

Let  $S$  and  $S'$  be two shapes observed in two different images and which happen to be similar.



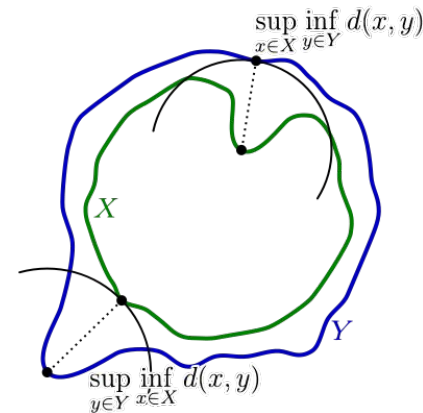
# “Shapes”

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Hausdorff distance = max of min distances between points on the contours of two shapes.

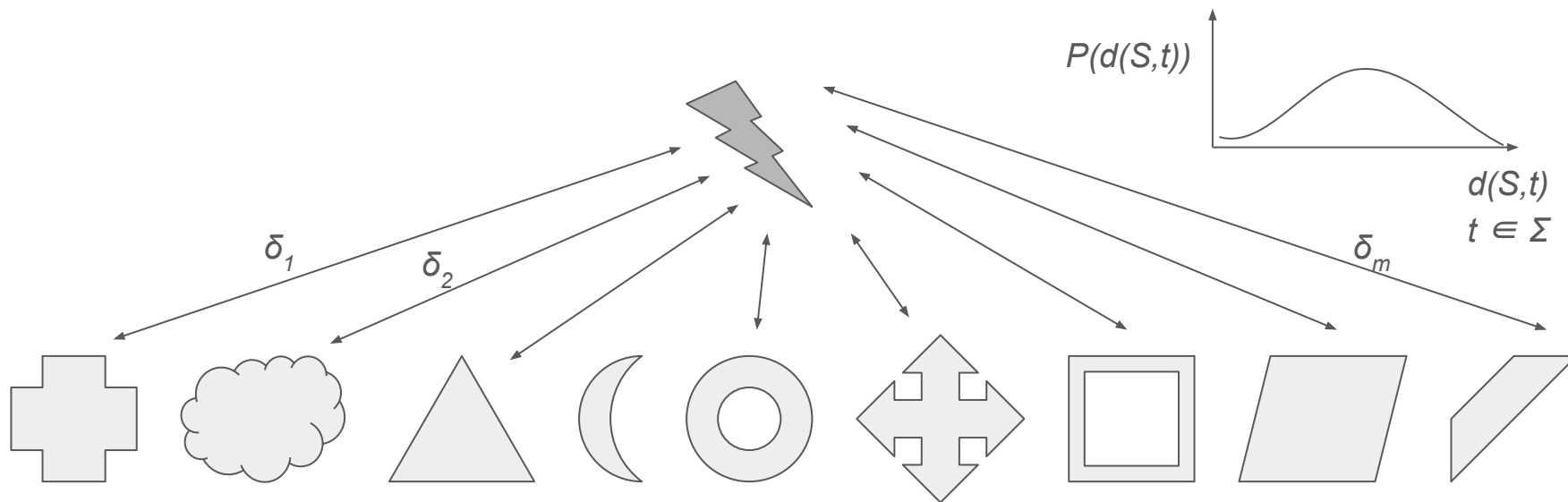
$$d_H(X, Y) = \max\left\{ \sup_{x \in X} \inf_{y \in Y} d(x, y), \sup_{y \in Y} \inf_{x \in X} d(x, y) \right\}.$$





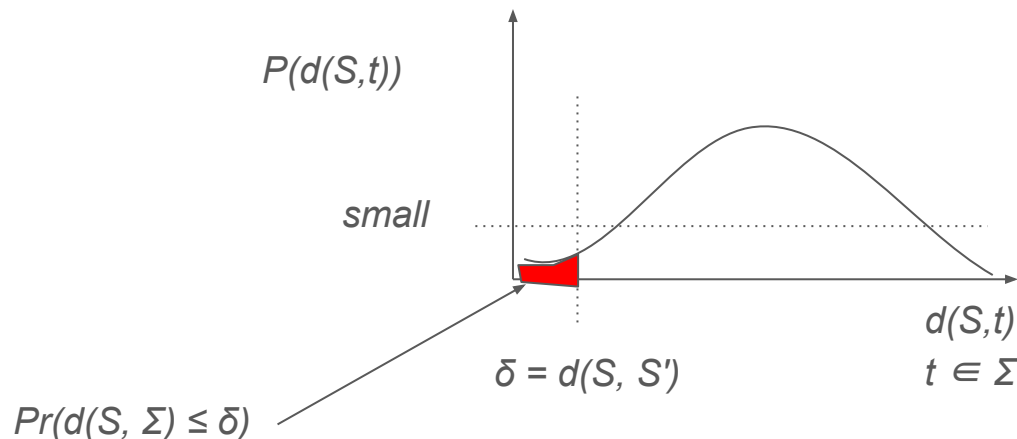
# “Shapes”

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# “Shapes”

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So, some **statistics** can help us making better decisions...

Idea: **learn** the distance threshold under which shapes can be deemed identical.

**A contrario** approach.

# Benefits of ML for CV/PR

# A duck example

How to filter the grass to keep only the duck shape, using thresholds in the color domain?



**Try it during practice session!**  
*How boring is it to tune the parameters by hand?*

# Why using Machine Learning in Computer Vision?

To avoid knob tuning. It's complex. It's unsafe.



Photo by [jc.winkler](#)



# Computer Vision / Pattern Recognition

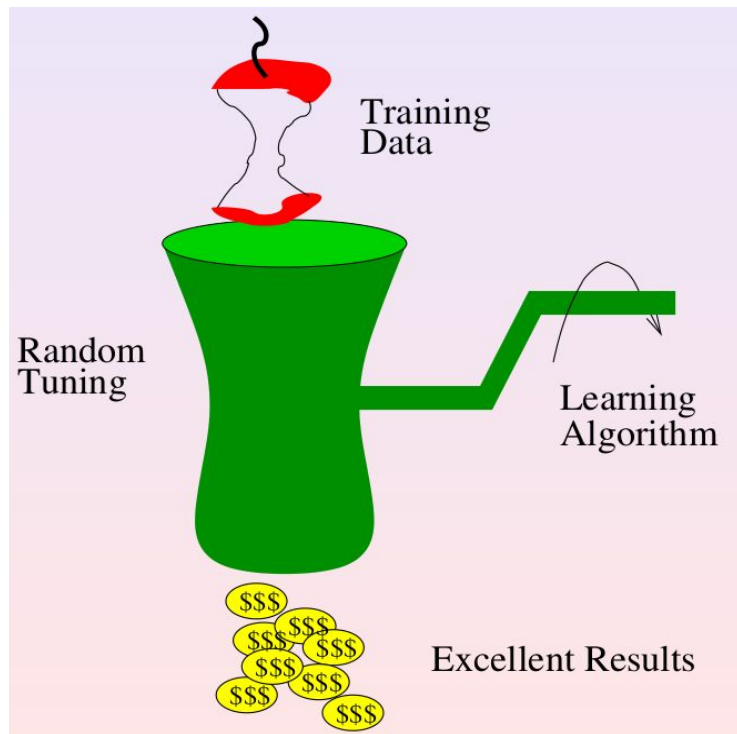


**With  
ML**

**Without  
ML**

# But Beware of the Machine Learning Magic

What they sell you...



But most often...

