Training : Computer Vision

Hackathon CentraleSupélec-ESSEC

14/02/2022

eleven
strategy consultants
London • Paris • Madrid

AGENDA

1. Computer vision approaches
2. An overview of the main Deep Learning algorithms
3. The “open” dataset : our gold mine
4. Measure the performance to improve your algorithm

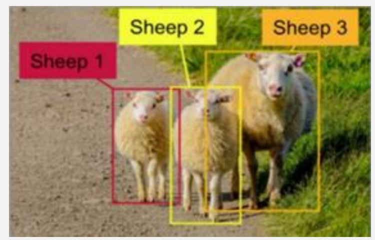
The amount of data available is a critical element to consider in an image-based application

Little data

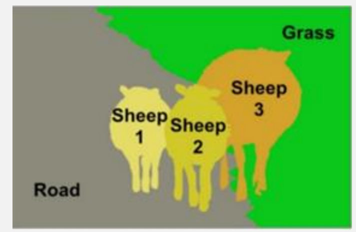
Lots of data

Image recognition

Object detection



Object segmentation



1. More hard engineering (“hacks”)
2. More ad-hoc algorithm
3. Transfer learning

1. More standard algorithms
2. Less hand engineering

Sources of knowledge

1. Labeled data (e.g. image → dog & cat)
2. Hand engineered features, network architecture, etc.

Computer vision can be broken down into a multitude of blocks that can be combined as needed (1/2)

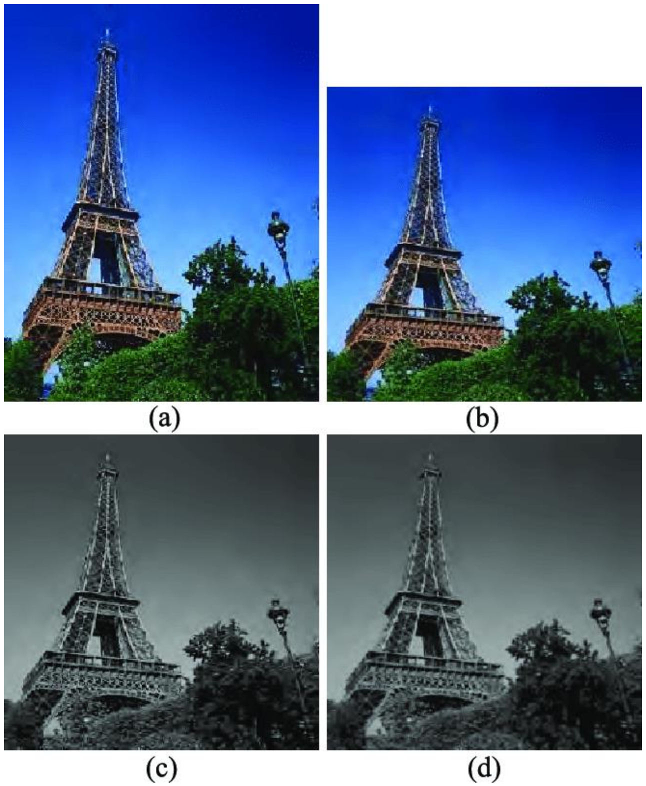
Image Pre-processing

Image scaling

Contrast enhancement

Cropping and padding

Noise reduction



(a)Original image

(b)Resized

(c)Grayed

(d)Blured

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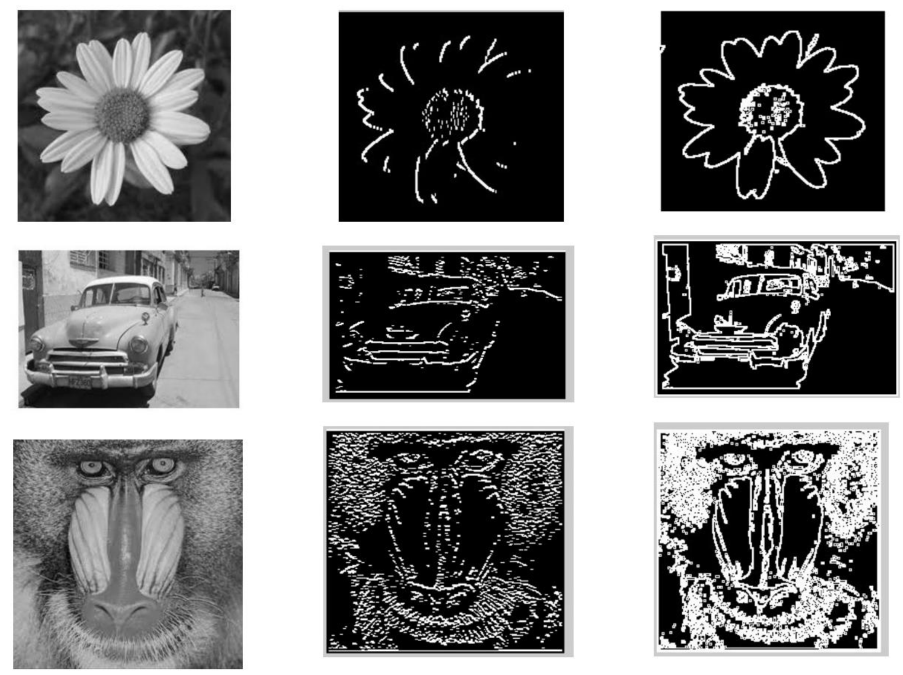
Feature extraction

Lines/Edge detection

Corners/Blobs/Points

(SIFT/SURF, PCA, Watershed)



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Classification algorithm

CNN

Cat

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Image Pre-processing

Image scaling

Contrast enhancement

Cropping and padding

Noise reduction

Feature extraction

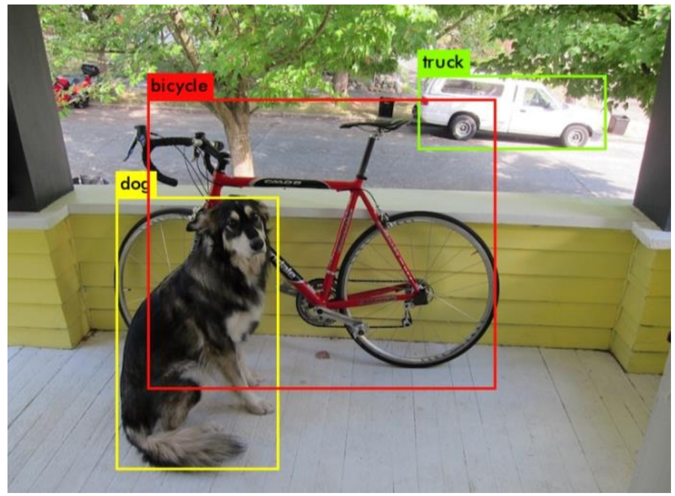
Lines/Edge detection

Corners/Bl

(SIFT/SU

Water

Classification algorithm



Object detection and/or Identification

YOLO

Computer vision can be broken down into a multitude of blocks that can be combined as needed (1/2)

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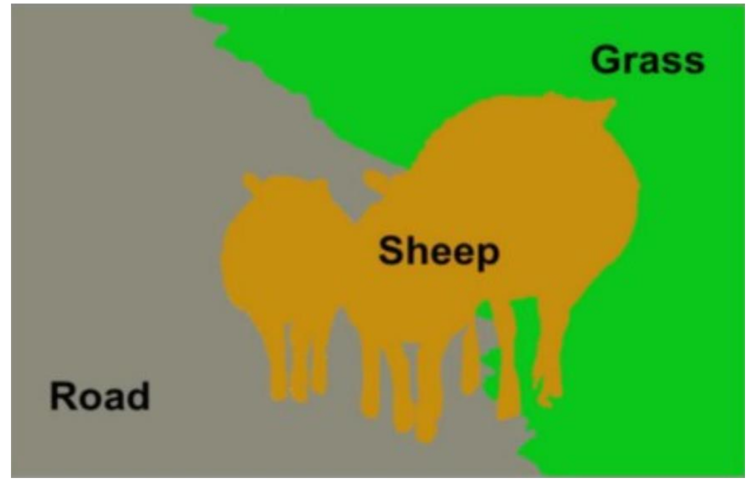
(SIFT/SURF, PCA, Watershed)



Segmentation

Faster R-CNN

Computer vision can be broken down into a multitude of blocks that can be combined as needed (2/2)

Image Pre-processing

Image scaling

Contrast enhancement

Cropping and padding

Noise reduction

Feature extraction

Lines/Edge detection

Corners/Blobs/Points

(SIFT/SURF, PCA, Watershed)

Classification algorithm

CNN

Object detection and/or Identification

YOLO

- We can start our process by applying image pre-processing (for instance if we have few data)
- Later we can use detection algorithm in order to find the object of interest
- Finally we can leverage feature extraction to post process the results to make them more precise of follow some field rules

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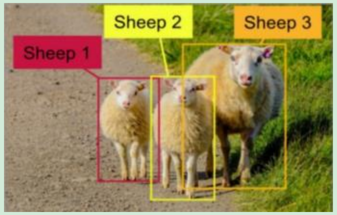
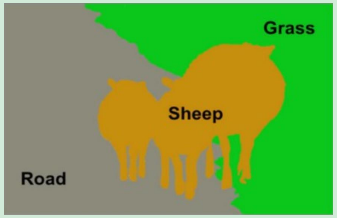
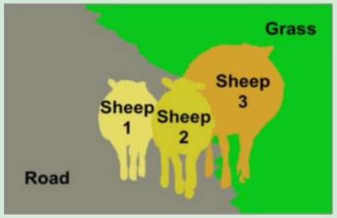
The 3 main approaches to machine learning vision are Classification, Detection and Segmentation

Approach	Objective	Algorithms	Examples
Classification	Associate a class, defining its content, to each image	▪ CNN	
Detection	Spot objects in an image according to predefined categories	▪ YOLO ▪ SSD ▪ Faster R-CNN ▪ RFCN	
Segmentation	**Semantic:** Link a category to each pixel in an image. Recognize a set of pixels that form distinct categories	▪ Unet ▪ PSPNet ▪ ICNet ▪ DeepLab	
	Per instance: Associate each pixel with the instance to which it belongs.	▪ Mask R-CNN ▪ ResNet	

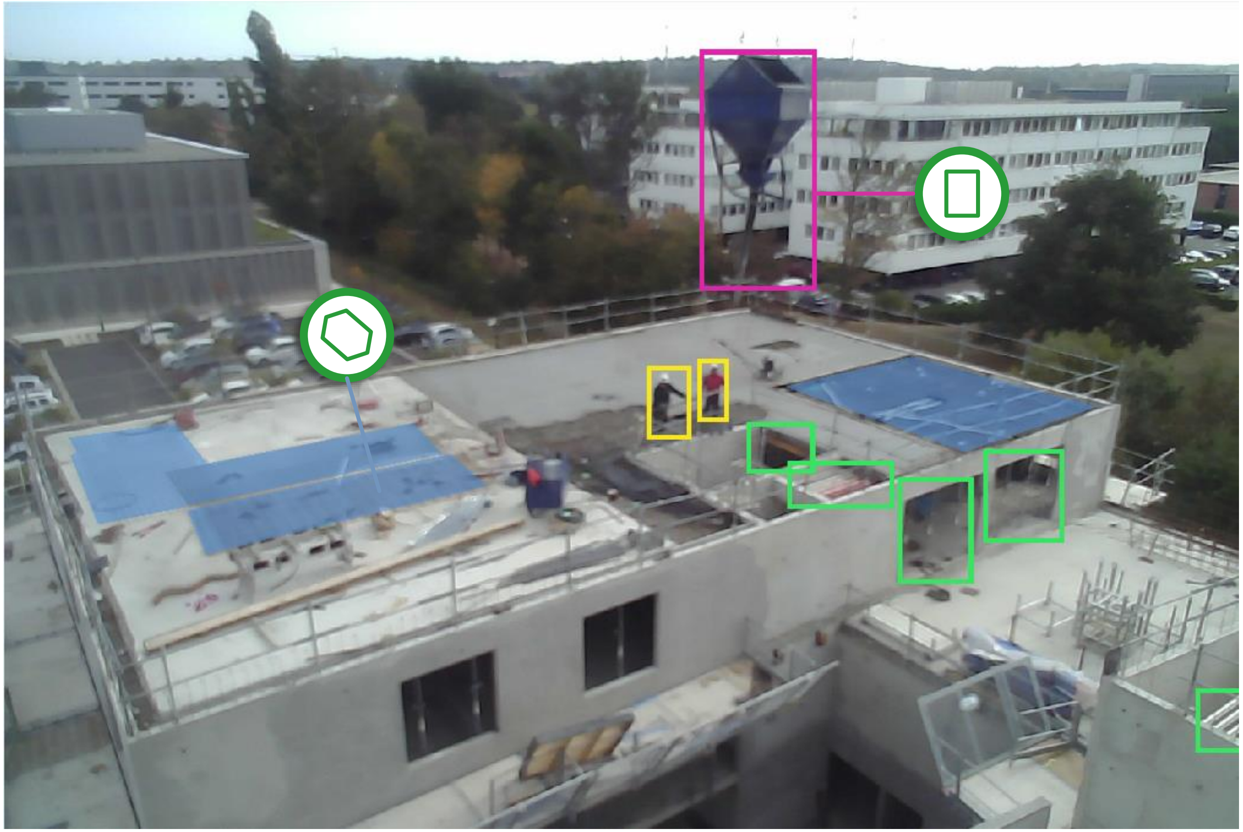
These different approaches are based on two different types of annotation

Polygon

- Polygon annotations select all pixels belonging to an instance. It is used in segmentation

Bounding box

- Bounding box annotations give position, size and type of object contained in a rectangle parallel to the axes: used in detection



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To train these models several datasets are available online

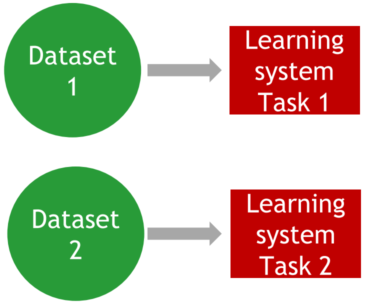
Name	Type	Annotation
COCO	Natural landscapes	Instance segmentation
ADE20K		
SUN		
IMAGE NET		Bounding boxes detection
PASCAL VOC2012		
CITYSCAPES	City landscapes	Instance segmentation

- Is the context of the dataset close to context of my images?
- Does the format of the dataset compatible with my algorithm?
- What classes are labeled in the dataset?
- Is the dataset balanced between classes?

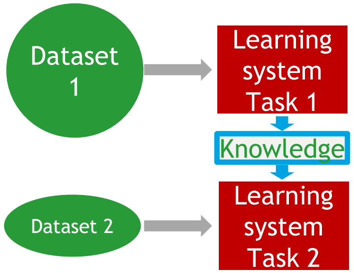
Transfer learning uses knowledge acquired for one task to solve related ones

General overview

- **Isolated**, single task learning:
  - Knowledge is not retained or accumulated
  - Learning is performed without considering past learned knowledge in other tasks



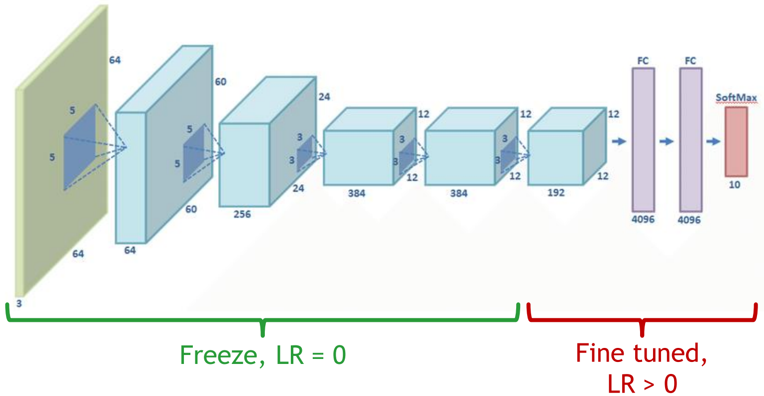
- **Learning** of a new task relies on the **previous learned tasks**:
  - Learning process can be faster, more accurate and/or need less training data



- There are two **variations** of transfer learning:
  - Same domain but different tasks
  - Same task, but different domains

Transfer learning in deep learning

- Use **pre-trained model** and **freeze** most layers of the neural network
  - Freeze layer imply that **weights are not updated** during the backpropagation, the learning rate (LR) is equal to 0
- Apply **fine tuning to lasts layers** in order to adapt the model to the specific task
  - The **weights** of fine-tuned layers are **updated** during the backpropagation



- **Keep** simple and **general features** from shallow layers
- **Retrain complex features** from deep layers

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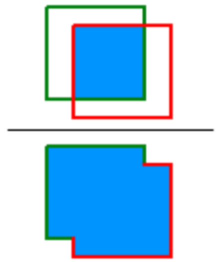
Several metrics can be used in computer vision depending on the objectives to reach

Local Metrics

- **Intersect over Union (IoU)**

Measuring the common cover on an object can be formalized as:

$$\boldsymbol{IoU} = \frac{\mathbf{aire}(\mathbf{Box}_{\mathbf{True}} \cap \mathbf{Box}_{\mathbf{Predicted}})}{\mathbf{aire}(\mathbf{Box}_{\mathbf{True}} \cup \mathbf{Box}_{\mathbf{Predicted}})}$$



We set a threshold $\varepsilon \in [0,1]$

Prediction are considered true if $\boldsymbol{IoU} \geq \boldsymbol{\varepsilon}$.

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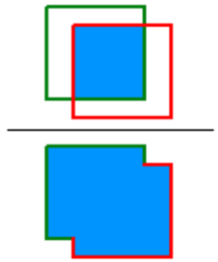

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- **Mean Intersect over Union (mIoU)**

For a **fixed minimum confidence** level, the IoU is calculated for each annotation and then averaged over a class or globally.

- No indication of the type of error: on/under-prediction?
- Depends on a confidence threshold set

- Very "visual" metric, easy to interpret

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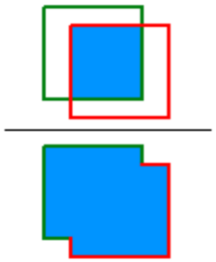

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- **Precision/Recall :**

$$\text{precision} = \frac{TP}{TP + FP}$$

$$\text{recall} = \frac{TP}{TP + FN}$$

Precision answers the question: **What share of the detected objects were the right ones?**

Recall answers the question: **What is the share of the objects that have been detected?**

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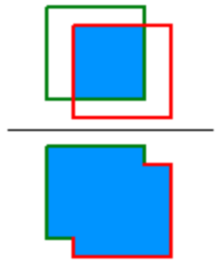

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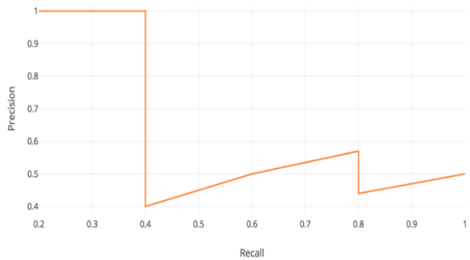
- ### Precision-recall curve :

Precision and recall are calculated for different confidence levels (proba of the class model) in order to obtain the curve:

$$precision = f(recall)$$



Precision-recall curve

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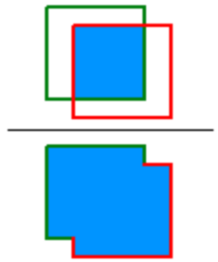

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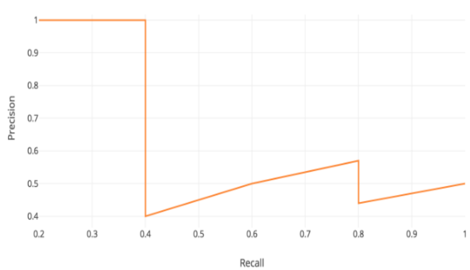

Precision-recall curve

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- **Average Precision (AP)**

Once the IoU threshold is set, the AP of a class can be calculated as a measure of the area below the precision-recall curve.

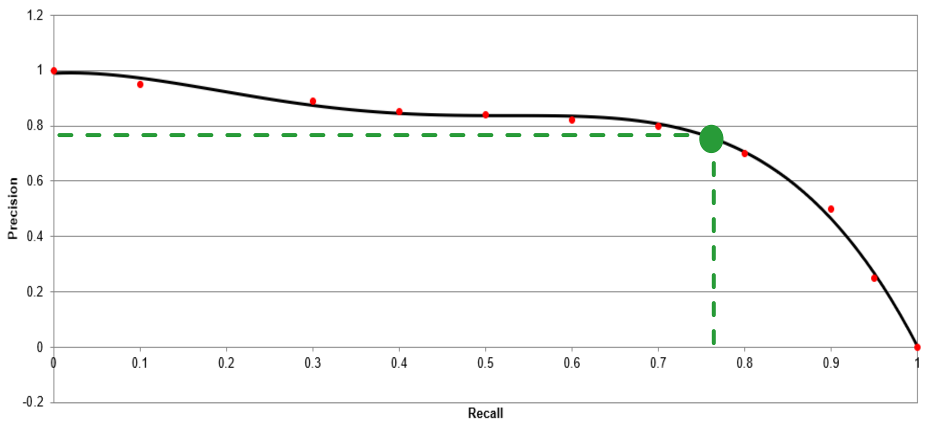
- Difficult to interpret
- Depends on a fixed IoU threshold

- Independent of confidence level
- Gives an indication of the precision/recall trade-off

➢ **The mean Average Precision (mAP)** is the **AP** averaged over all classes

The AP reflects the ability to combine precision and recall for a model

Example n°1



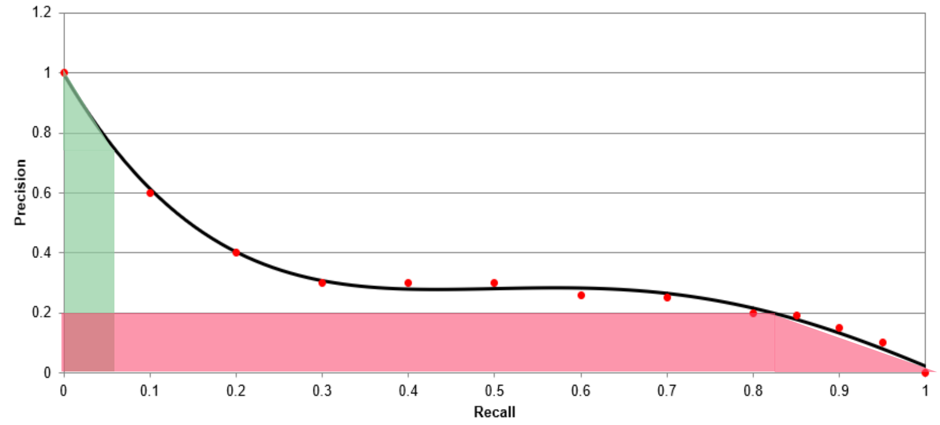
$AP \approx 0.74$

Interpretation :

- We see that we can maintain a good trade-off between the level of precision and the level of recall
- The green dot guarantees an accuracy of about 80% for a 75% recall: most objects are spotted without too many errors

➢ An important AP ensures a certain efficiency of the model that will combine precision and recall

Example n°2



$AP \approx 0.28$

Interpretation :

We see here that we cannot guarantee precision and recall: we must choose to favour one or the other

- The green zone guarantees a precision > 75% accuracy but also a recall $< 20\%$: we don't make much mistake but we spot very few objects
- The pink zone guarantees a recall > 80% but a precision < 5% : We spot almost all the object but most of the objects identified are not the one we want

➢ A low AP means it is difficult to reconcile accuracy and recall: one should be favored

Resources: all classical Machine Learning might come handy and a good understanding of Computer Vision libraries will be helpful

Computer Vision libraries

PyTorch

Standard library for deep learning

OpenCV

Standard library classical computer vision

TensorFlow

An alternative to Pytorch

ML + Viz libraries

scikit learn

To develop a wide range of ML models

pandas

To exploite model's output and aggregate them

Streamlit

To efficiently develop a dashboard / front-end