# CuttinEdge

## The underlying technology

Lucas Saban

ENSAE Paris, Institut Polytechnique de Paris
MVA, ENS Paris-Saclay

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# Problem

We seek to identify and count the number of customers in a hair salon
Our constraints :

- The unpredictable events (People waiting in chair, child with parents, movements of hairdressers)
- Visual obstructions (hairdressers blocking the view, etc.)
- The less salon-dependant parameters the better, for scalability
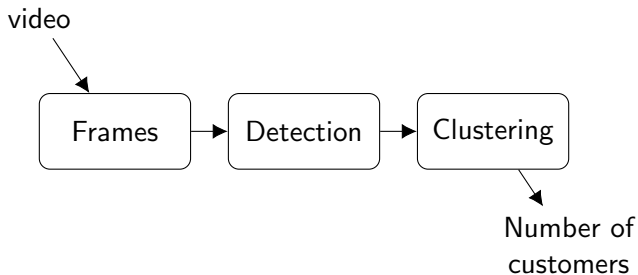- We rely on video feeds, the less hardware the better

# Overview

1. **Overall Pipeline**

2. **Human Detection**

3. **Pattern Recognition with** `c4der`

# Overall Pipeline

# Global Pipeline

video

Frames → Detection → Clustering

Number of customers

# Human Detection

# pre-detection

# post-detection

# data fetched

From the frame, we extract temporally indexed vectors for each person detected



In particular, we get :

- The bounding boxes centroid, width and length
- the timestamp

# How ?

We use a convolutionnal neural network using the YoloV4[1] architecture.
The model is pre-trained on COCO[2] Dataset (>300K images)

Why YoloV4 ?

- You Only Look Once : single stage object detector $\rightarrow$ fast detection
- Relatively lightweight $\rightarrow$ easier to distribute
- Accurate enough
- Compatible with opencv[3] built-in neural network implementation

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[1]Bochkovskiy et al.
[2]Lin et al. [2014]
[3]Bradski

# Pattern Recognition with `c4der`

# First glance

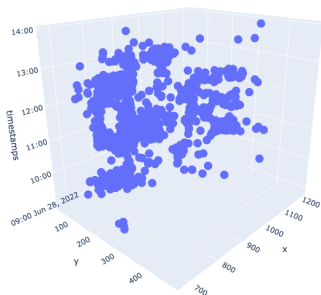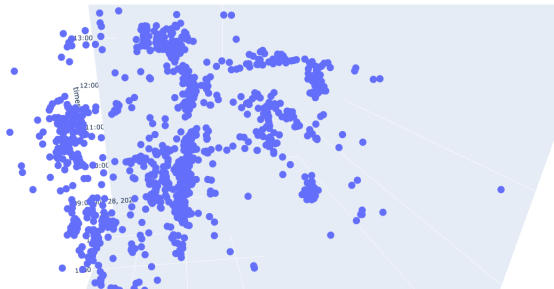If we plot the centroids found with respect to time :



Centroids position

Figure: raw_points.html

# Zoom in

Some patterns seems to appear, it is not random noise.



Centroids position

If we can regroup points together[4] and get rid of the noise[5], we can retrieve the underlying distribution.

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[4]e.g. count customers
[5]+1 robustness

# Clustering

## Goal of clustering

Create clusters that minimizes intra-cluster differences while maximizing inter-cluster differences.

Yet, we have more constraints compared to usual clustering setups :

1. We have 1 temporal , 2 spatial and k other dimensions[6].
2. Variations along the Y axis are more meaningful to distinguish clusters than along the X axis [7]
3. We need adaptability because clusters don't share the same intra-variance because of perspective[8]
4. We need to distinguish a customer waiting from a customer being processed.

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[6]width, lengths of bounding and any transformation of those
[7]Seats can be separated with horizontal lines, not vertical
[8]2D representation of 3D space

# Proposed solution

## c4der

c4der for Clustering for Dynamical Event Recognition is a clustering algorithm that answers the attention points from the last slide.

Based on the DBSCAN/ST_DBSCAN algorithms[9], it is :

- Agnostic w.r.t. data distribution
- compatible with non-spatial data

That's not all, it :

- is semi-stochastic using gaussian-based kernels for neighborhoods.
- uses tweaked Mahalanobis-distance for spatial distances
- detects seats and pre-clusterizes points according to them
- filters clusters by timespan and intra-variance

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[9]https://www.youtube.com/watch?v=RDZUdRSDOok
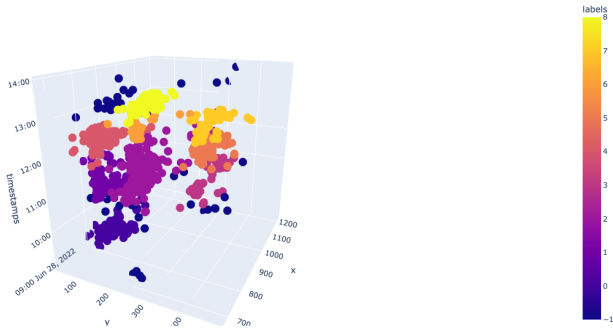
# c4der **in practice**

Centroids position



Figure: clusters.html

# Post-processing

The clusters left are the customers we sought to identify. -1 label correspond to noise.
With little post-processing, we can get from the previous graphs :

```
################# c4der #################

[c4der]     Cluster 0 rejected => [size = 5] [TimeSpan = 0:02:40] [Variance = 13.043772460450237]
[c4der]     Cluster 1 rejected => [size = 6] [TimeSpan = 0:02:00] [Variance = 4.667561298175124]
[c4der]    Cluster 11 rejected => [size = 6] [TimeSpan = 0:08:20] [Variance = 12.266711956438133]
                        Nombre de clients détectés :9
                              09:09 —-> 09:37
                              10:35 —-> 11:38
                              10:48 —-> 12:18
                              11:10 —-> 11:25
                              11:46 —-> 12:34
                              11:53 —-> 12:09
                              12:29 —-> 12:54
                              12:33 —-> 12:54
                              12:57 —-> 13:20
                            Execution time : 967 ms

                 #########################################
```

By having a macro point of view, the process is more **robust** to noise and unpredictable events.
Coupled with human verification in case of fraud suspicion, it can handle most of the situations **accurately**.

# References

D. Birant and A. Kut. ST-DBSCAN: An algorithm for clustering spatial–temporal data. 60(1):208–221. ISSN 0169-023X. doi: 10.1016/j.datak.2006.01.013.

A. Bochkovskiy, C.-Y. Wang, and H.-Y. M. Liao. YOLOv4: Optimal speed and accuracy of object detection. URL http://arxiv.org/abs/2004.10934.

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M. Ester, H.-P. Kriegel, and X. Xu. A density-based algorithm for discovering clusters in large spatial databases with noise. page 6.

T.-Y. Lin, M. Maire, S. Belongie, L. Bourdev, R. Girshick, J. Hays, P. Perona, D. Ramanan, C. L. Zitnick, and P. Dollár. Microsoft coco: Common objects in context, 2014. URL https://arxiv.org/abs/1405.0312.

# The End