Computer vision algorithms for detecting secondary tasks in naturalistic driving studies

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Motivations

- **Driver distraction** (in particular use of **mobile phones**): main concern for road safety studies.
- Importance of **NDS (Naturalistic Driving Studies)**: high amount of data but need to be annotated.
  - Manual annotation: expensive and **time-consuming**.
  - Alternative: **automatic detection based on computer vision** methods.
    - Helpful for manual annotators.

Data and challenges

Cockpit camera

Driver camera

Top view camera

Pedal camera

+

CAN files
(speed, wheel rotation, seat belts…)

Data and challenges

Passenger?

Cockpit camera

Driver camera

Top view camera

Pedal camera

+

CAN files
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Data and challenges

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Hands on wheel?

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Data and challenges

Passenger?

Hands on wheel?

Texting?

+

CAN files
(speed, wheel rotation, seat belts…)

Data and challenges

Cockpit camera

Driver camera

Passenger?

Phone-to-the-ear use?

Hands on wheel?

Texting?

Top view camera

Pedal camera

+

CAN files
(speed, wheel rotation, seat belts…)

Data and challenges

Cockpit camera

Driver camera

Passenger?

Phone-to-the-ear use?

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Foot on gas/ clutch/brake?

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Data and challenges

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Texting?

\+

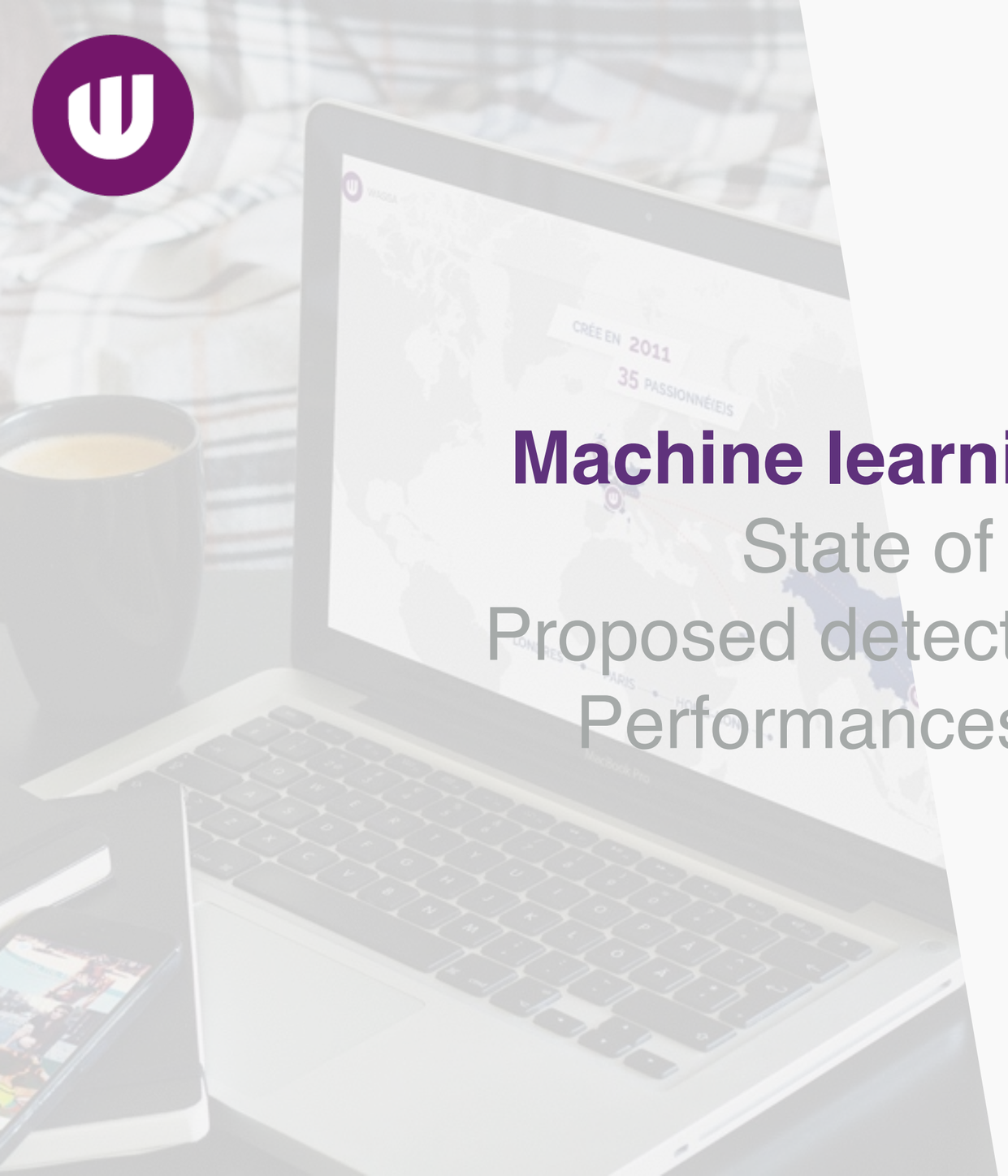
CAN files (speed, wheel rotation, seat belts…)

Foot on gas/ clutch/brake?

Top view camera

Pedal camera

Difficulties: - Low resolution data, gray level, strong illuminations…
- High amount of data (computing time).



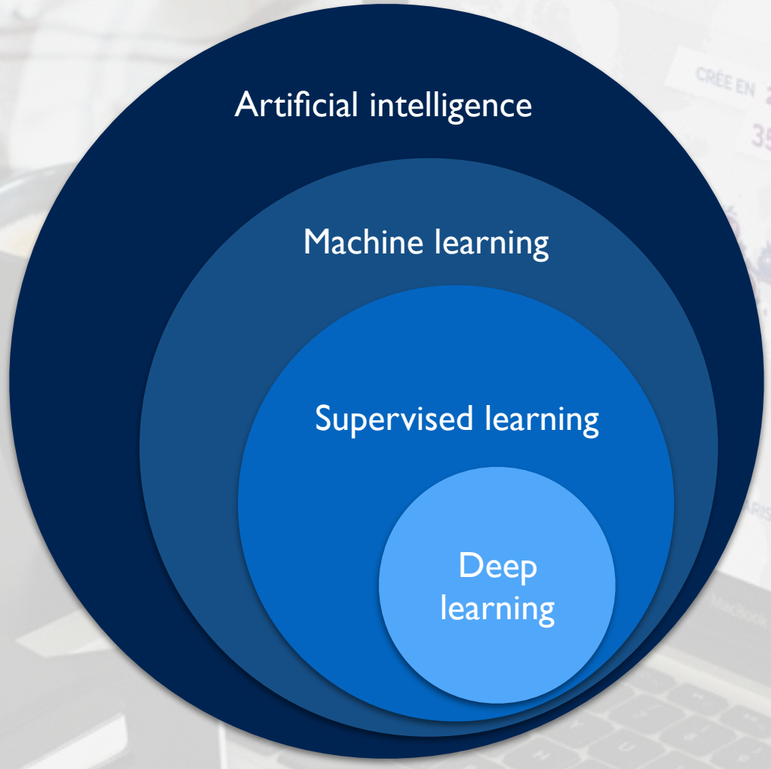
Machine learning concepts

State of the art

Proposed detection algorithms

Performances evaluation

Machine learning concepts



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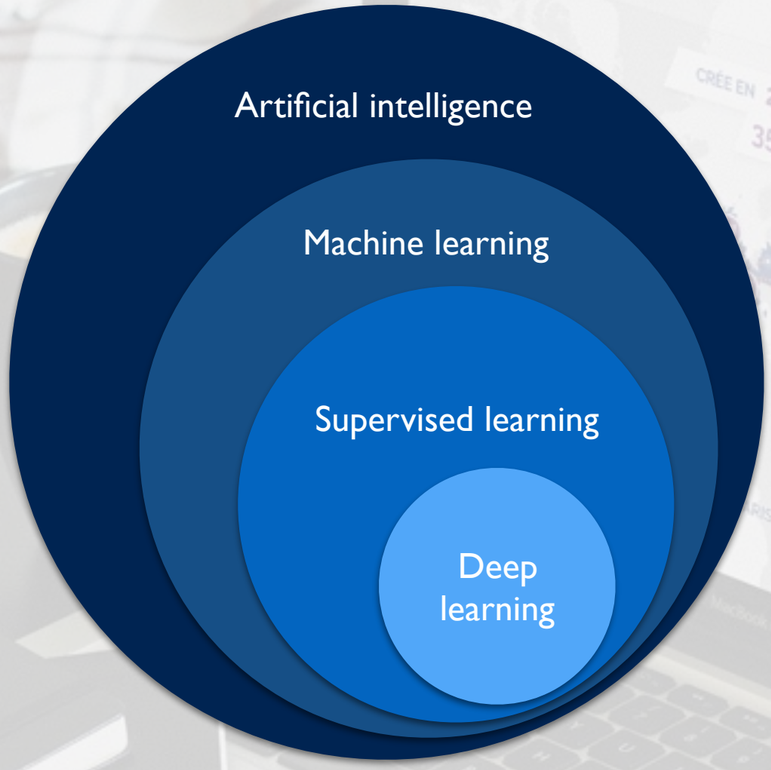
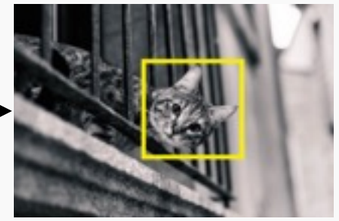


Traditional Machine learning

Feature extraction

Classifier



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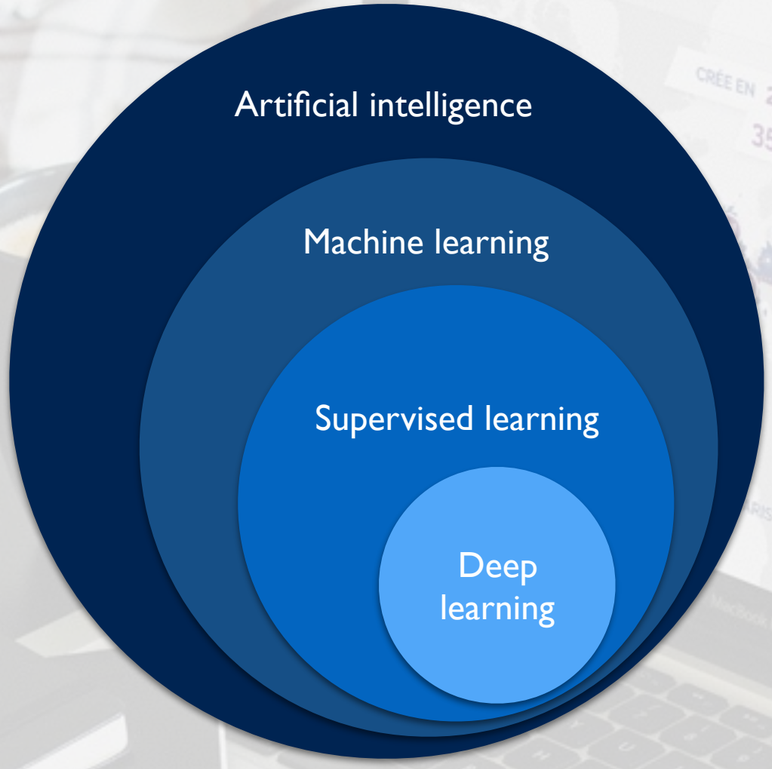
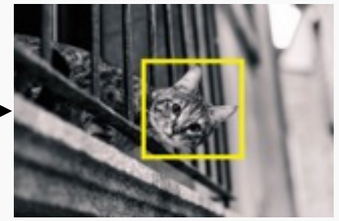


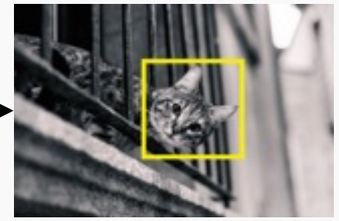
Traditional Machine learning

Feature extraction → Classifier →



Deep learning

Trains detector model →



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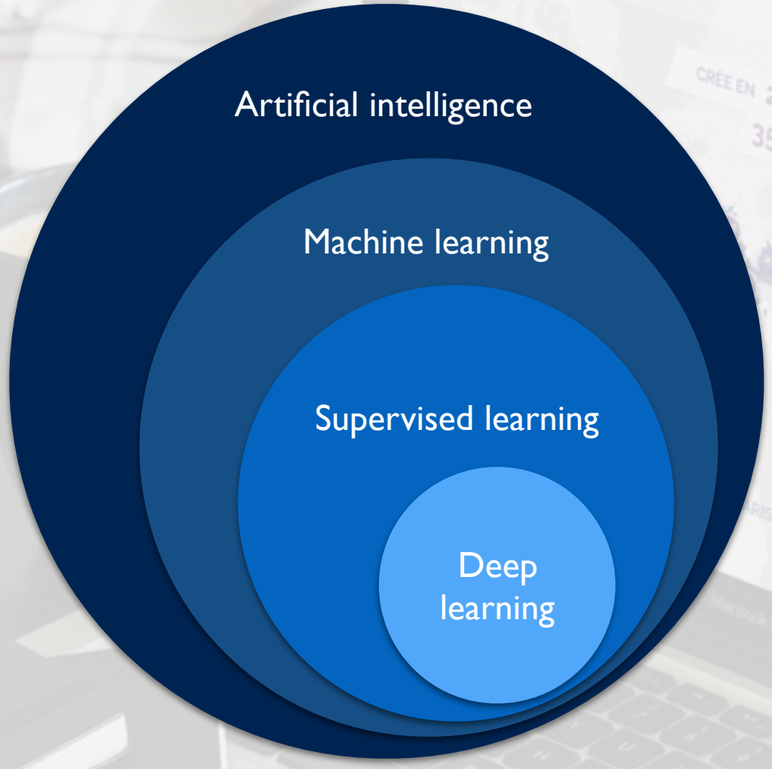
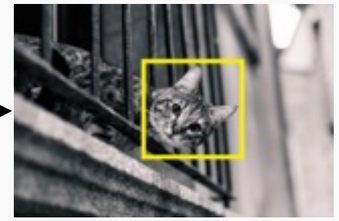


Traditional Machine learning

- Fast to train and test
- Light architecture

Feature extraction → Classifier →



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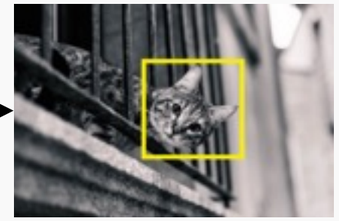

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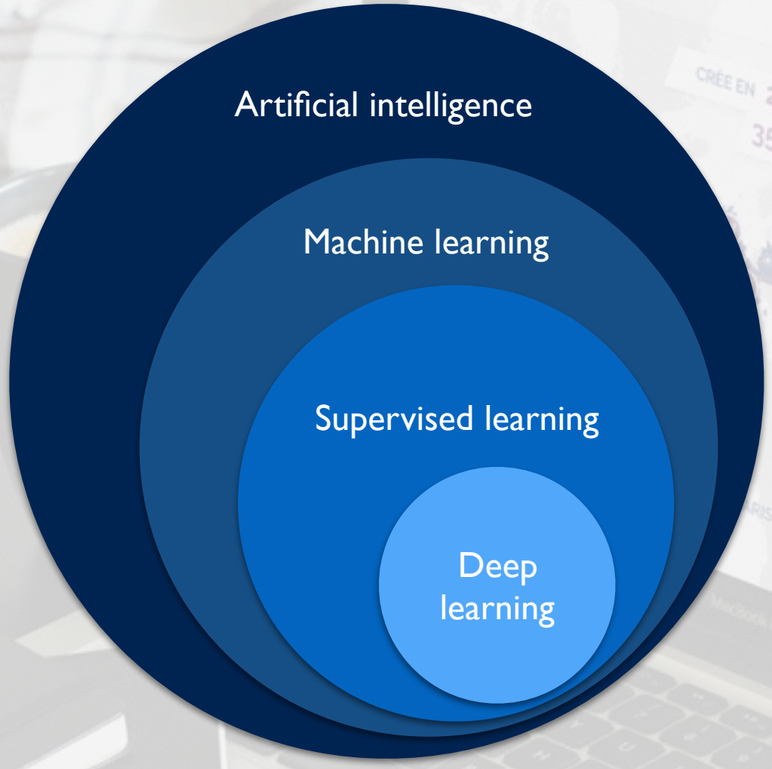
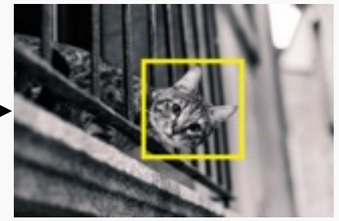


Traditional Machine learning

- Fast to train and test
- Light architecture

- Performances limited for complex objects
- Difficulty to find distinctive features
- Tuning of parameters

Feature extraction → Classifier →



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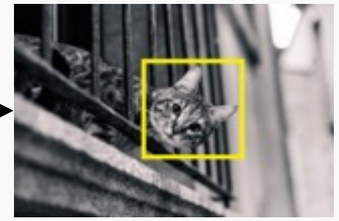

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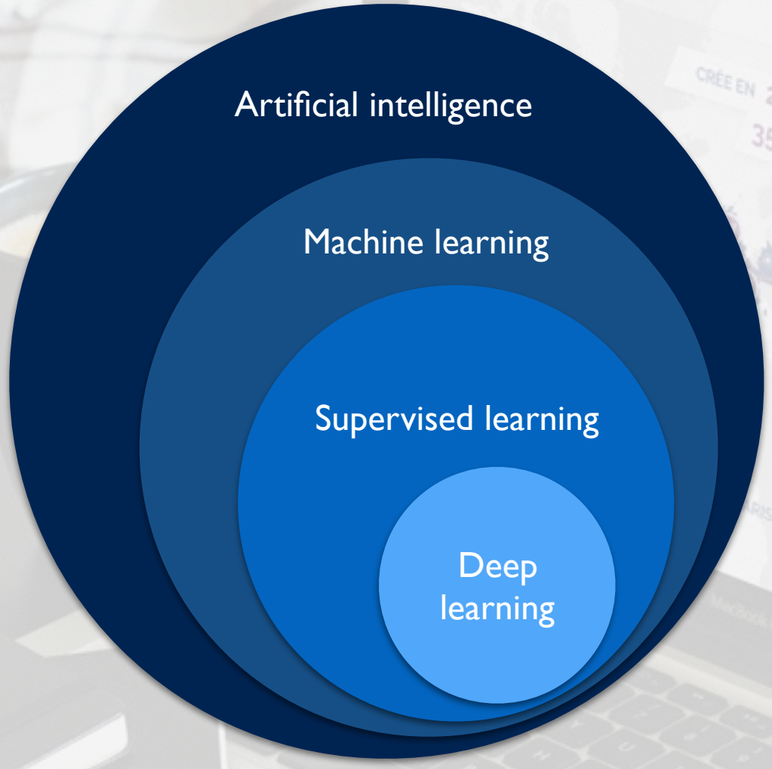

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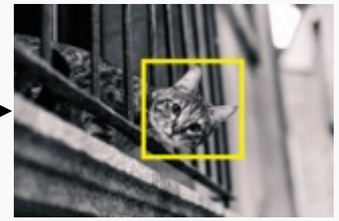
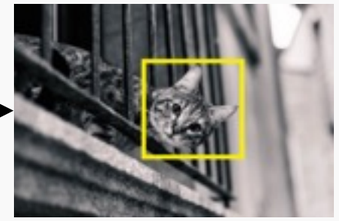


Deep learning

- Can model complex objects
- Computer selects itself distinctive features

Trains detector model →



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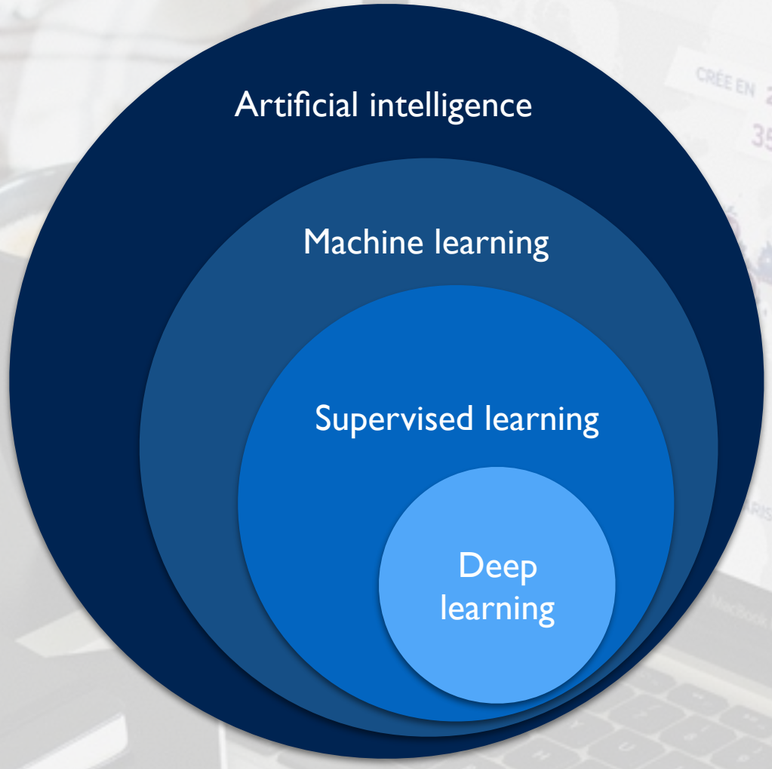

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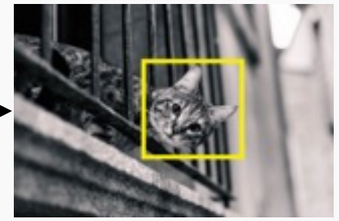
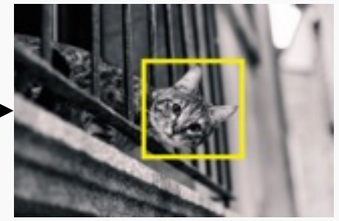


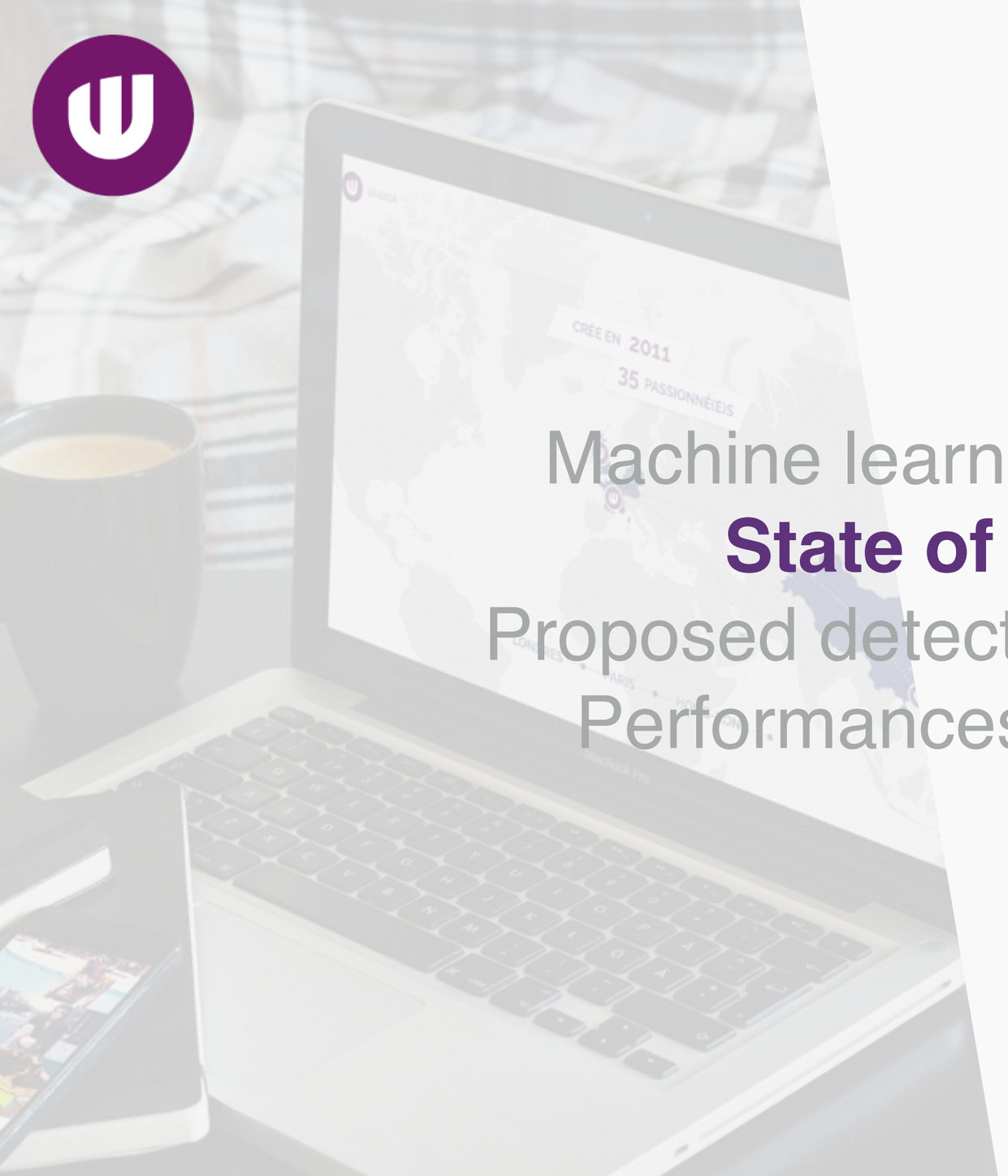
Deep learning

- Can model complex objects
- Computer selects itself distinctive features

- Strong requirements: high amount of training data, GPU
- Long training and computing

Trains detector model →





Machine learning concepts

State of the art

Proposed detection algorithms

Performances evaluation

State of the art

- **Traditional machine learning techniques**
  - **Hand detection**
    - Aggregated Channel Features (based on color and shape informations) [Das et al., 2015] [Rangesh et al., 2016]
    - Histogram of Oriented Gradient (HoG) + Support Vector Machine (SVM) [Ohn-Bar, 2014]
  - **Phone-to-the-ear detection**
    - Detection of ear area based on face detection and landmarks, followed by HoG + SVM [Seshadriv et al., 2016]
- **Deep learning techniques**
  - **Hand and phone-to-the-ear detections**
    - Detect face, hand, cell-phone and steering wheel based on approach called Multiple Scale Faster-RCNN [Hoang Ngan Le et al., 2016]

Machine learning concepts

State of the art

Proposed detection algorithms

Performances evaluation

Proposed detection algorithms: Framework

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Small objects, with moderate complexity and fixed localization

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Small objects, with moderate complexity and fixed localization

Traditional machine learning

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Small objects, with moderate complexity and fixed localization

Traditional machine learning

Objects with strong complexity and variability, fast and unpredictable movements

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Deep learning

Proposed detection algorithms: Traditional Machine learning

Crop an image region

Proposed detection algorithms: Traditional Machine learning

Crop an image region → Compute feature image descriptor HoG (Histogram of Oriented Gradient)

Proposed detection algorithms: Traditional Machine learning

Crop an image region

Compute feature image descriptor HoG
(Histogram of Oriented Gradient)

SVM model pre-trained with labeled videos

Apply a classifier called SVM
(Support Vector Machine)

3 SVM models pre-trained with CAN files

Proposed detection algorithms: Traditional Machine learning

Crop an image region

Compute feature image descriptor HoG
(Histogram of Oriented Gradient)

SVM model pre-trained with labeled videos

3 SVM models pre-trained with CAN files

Apply a classifier called SVM
(Support Vector Machine)

Decision

Passenger presence

Yes

No

Foot on pedal

Yes

No

Proposed detection algorithms: Deep learning

Training step

Proposed detection algorithms: Deep learning

Training step

Standard Architecture

Proposed detection algorithms: Deep learning

Training step

Standard Architecture

Labeled samples

Proposed detection algorithms: Deep learning

Training step

Standard Architecture

Labeled samples

Training step

Proposed detection algorithms: Deep learning

Training step

Standard Architecture

Labeled samples

Training step

Object detector

Proposed detection algorithms: Deep learning

Training step

Standard Architecture

Labeled samples

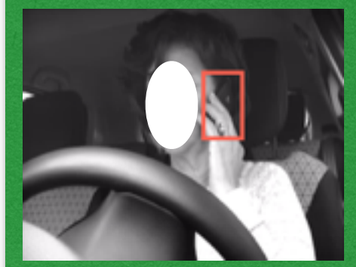
Training step

Object detector

Phone-to-the-ear

Texting

Hands on wheel



Proposed detection algorithms: Deep learning

Testing step

Proposed detection algorithms: Deep learning

Testing step

Object detector

Proposed detection algorithms: Deep learning

Testing step

Object detector

Input image

Proposed detection algorithms: Deep learning

Testing step

Object detector

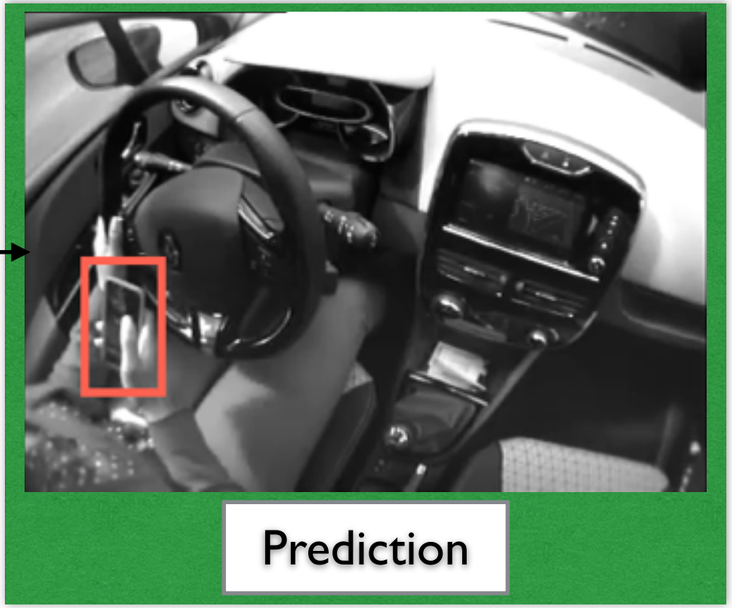
Testing step

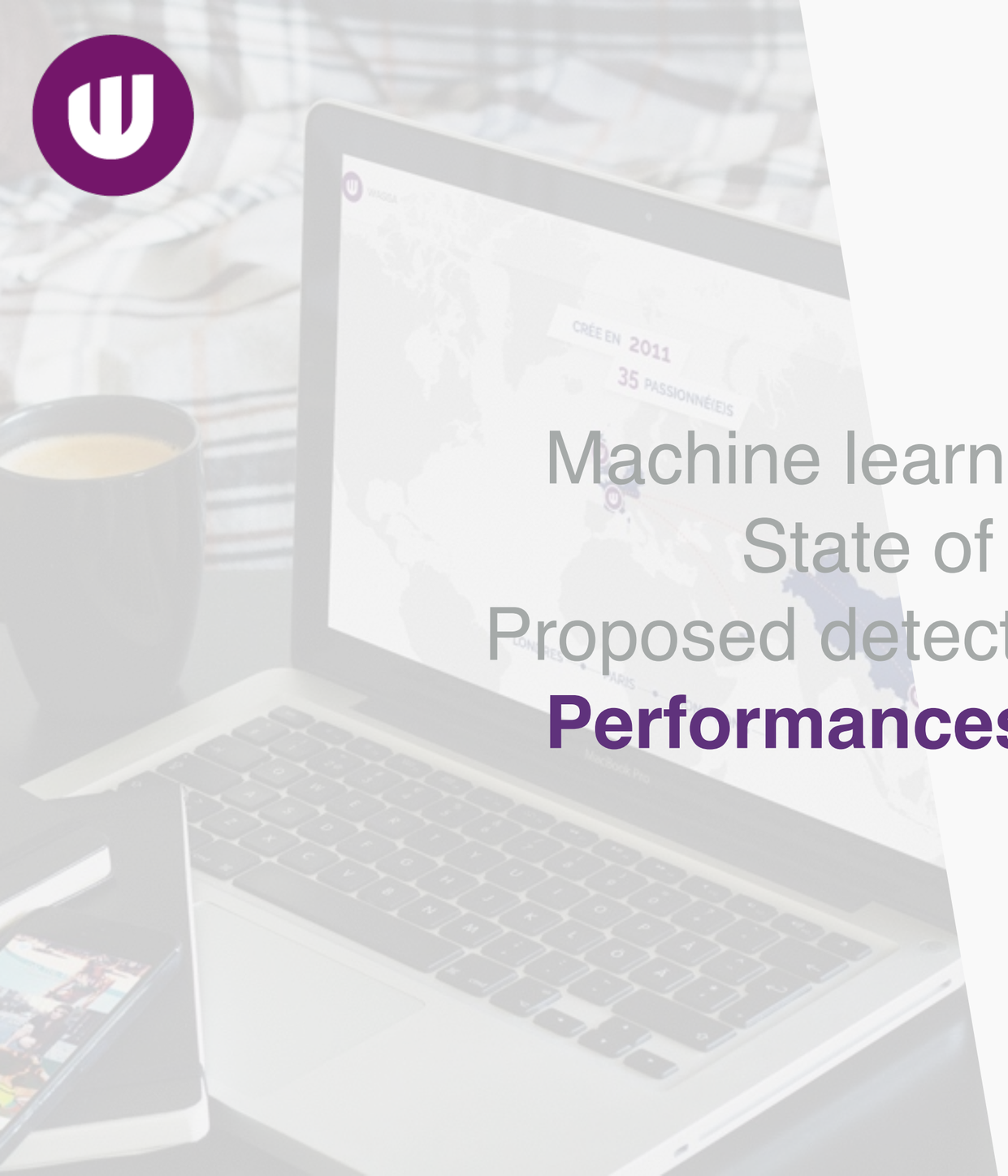
Proposed detection algorithms: Deep learning

Testing step

Object detector

Testing step





Machine learning concepts
State of the art
Proposed detection algorithms
Performances evaluation

Performances evaluation: Frame-by-frame

Secondary tasks	Testing data	Precision rate	Recall rate
Passenger	21 videos of 51 minutes in total (balanced set)	95,6 %	99,8 %
Feet on pedals	4 videos of 55 minutes in total (balanced set)	Close to 100 %	94 to 98%
Hands on wheel	6 vidéos of 81 minutes in total (80% with hands)	99,5 %	85,4 %
Texting	11 videos of 155 minutes in total (7.5% of phone)	17 %	67 %
Phone-to-the-ear	12 videos of 122 minutes in total (3.2% of phone)	13 %	67 %

Performances evaluation: Frame-by-frame

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+ Algorithm rarely misses passenger presence
- Some false detections.

Performances evaluation: Frame-by-frame

Secondary tasks	Testing data	Precision rate	Recall rate	
Passenger	21 videos of 51 minutes in total (balanced set)	95,6 %	99,8 %	+ Algorithm rarely misses passenger presence - Some false detections.
Feet on pedals	4 videos of 55 minutes in total (balanced set)	Close to 100 %	94 to 98%	+ Algorithm is rarely wrong - Misses some detections.
Hands on wheel	6 vidéos of 81 minutes in total (80% with hands)	99,5 %	85,4 %	
Texting	11 videos of 155 minutes in total (7.5% of phone)	17 %	67 %	
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Performances evaluation: Frame-by-frame

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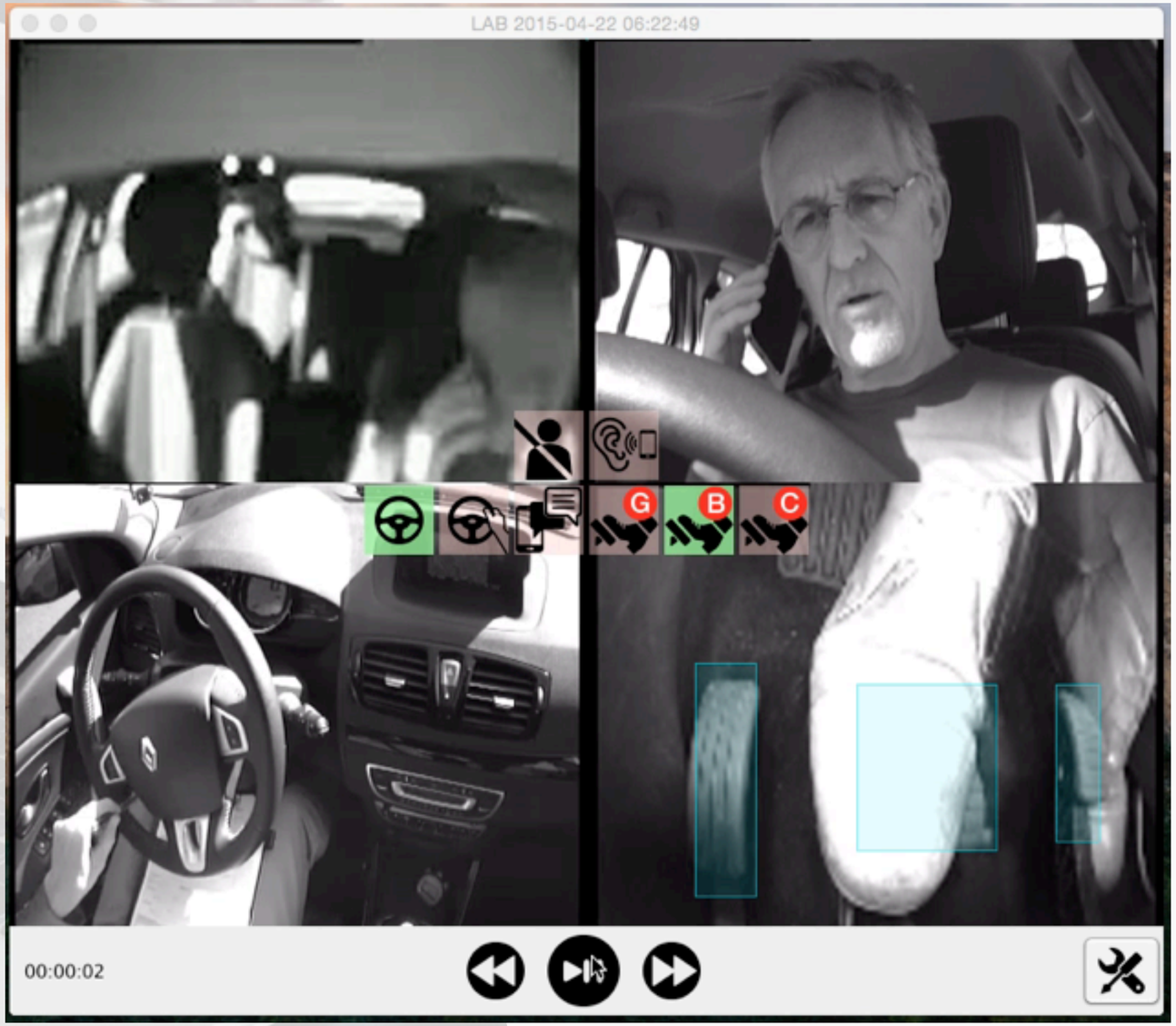
Hands on wheel	6 vidéos of 81 minutes in total (80% with hands)	99,5 %	85,4 %	
Texting	11 videos of 155 minutes in total (7.5% of phone)	17 %	67 %	+ Algorithm correctly detects 2 out 3 frames with phone presence - A lot of false detections.
Phone-to-the-ear	12 videos of 122 minutes in total (3.2% of phone)	13 %	67 %	

Performances evaluation: Example



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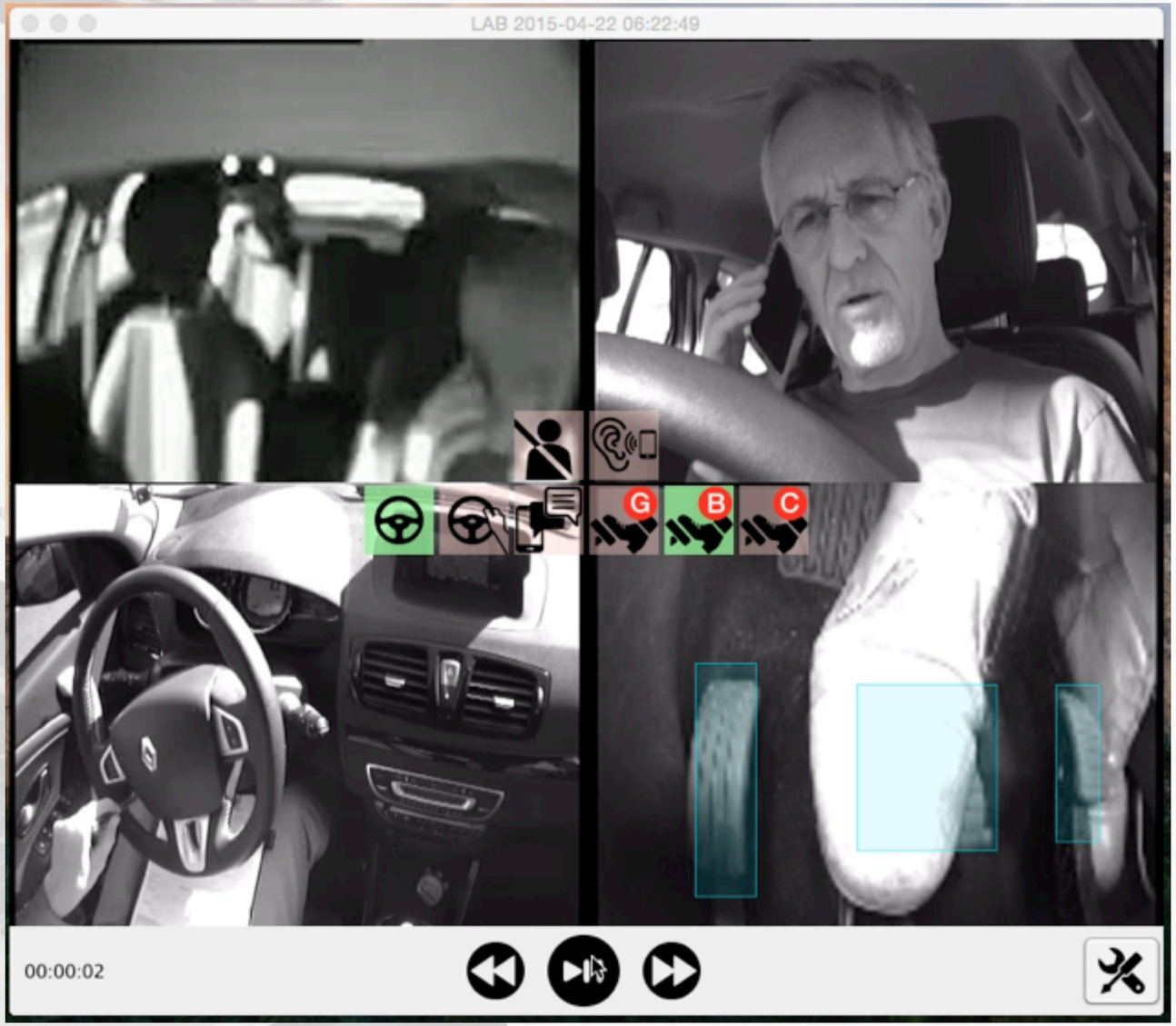

Conclusions

- **Use of machine learning approaches for NDS**
  - Promising results for secondary tasks detection.
  - Allows to strongly reduce manual annotations computing time.
  - False detections still need to be lowered.
- **Improvements**
  - Post-processing filtering, add object tracking.
  - Add more training samples.
  - Try other frameworks or network architectures.

Thank you for your attention.

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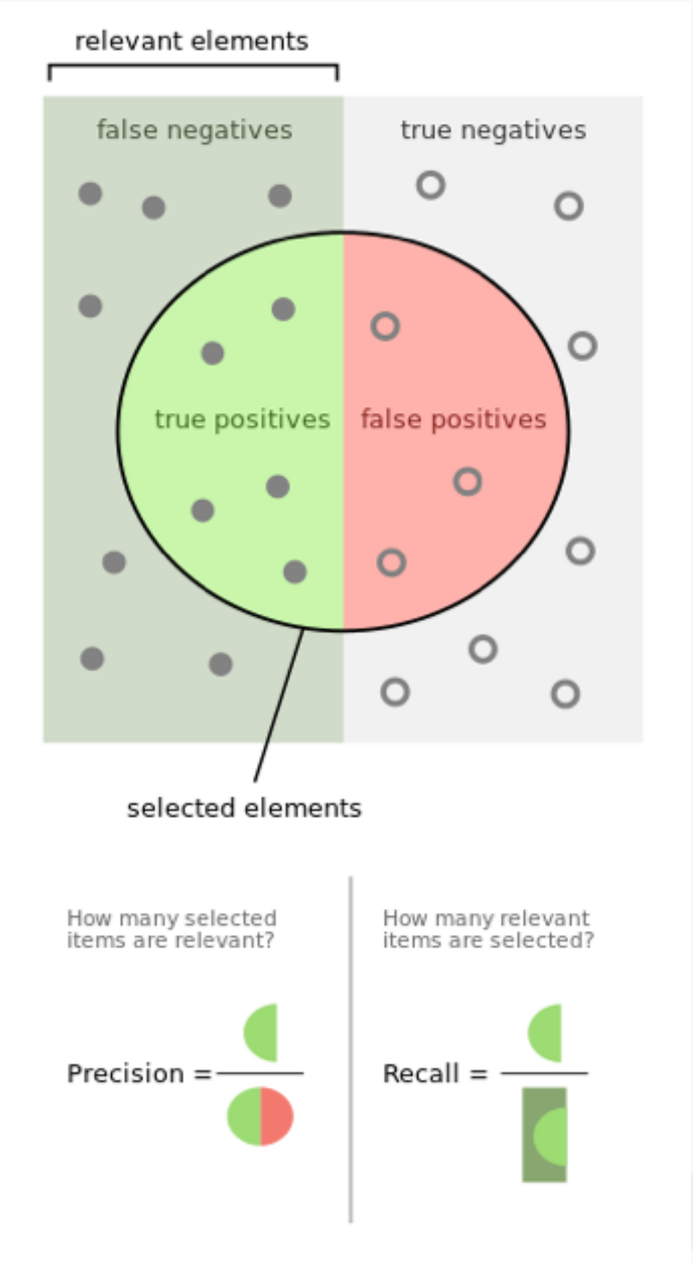
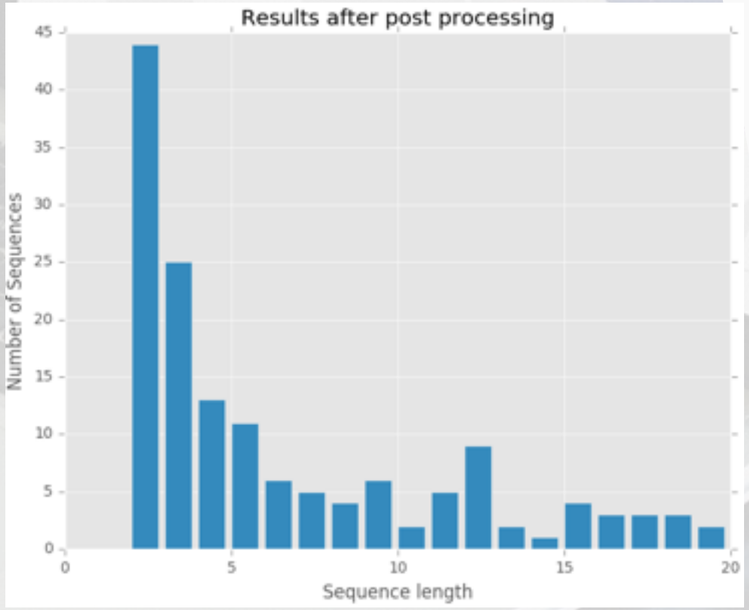
Performances evaluation: Protocol and metrics

- **Videos labeled manually** through sequences for each feature:
  - **Positive and negative** sequences.
  - **Several videos with different conditions:** day/night situations, different drivers, wearing gloves or not, different types of cellphones etc.
- **Studied metrics:**
  - Evaluation frame-by-frame: Recall and Precision
  - Evaluation by sequence (Texting and phone-to-the-ear).

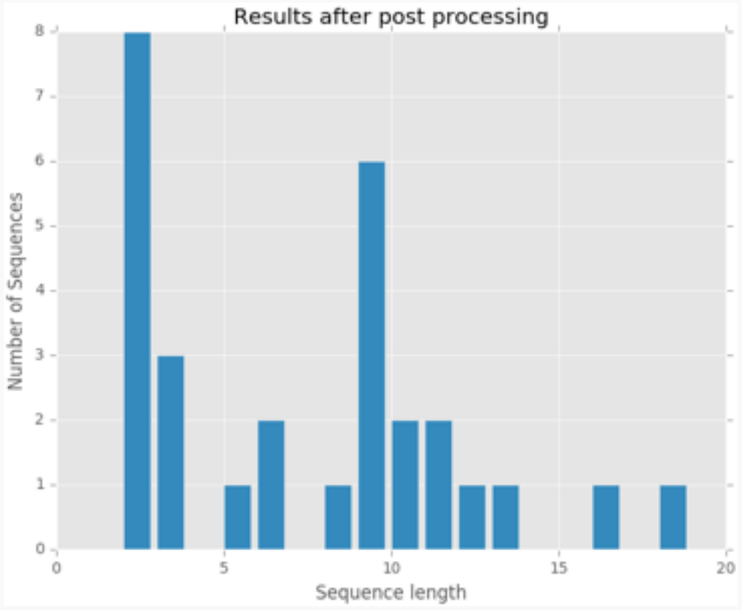


Performances evaluation: Sequences

Metrics	Positive sequences correctly detected	False positive sequences detected
Texting	25 out of 32	352 out of 377
Phone-to-the-ear	12 out of 14	103 out of 115



Histogram of sequence length for Texting



Histogram of sequence length for Phone-to-the-ear