Lectern Session 841
Machine Learning Methods for Crash Prediction and Safety Analysis
Sponsored by ABJ70

Mobile Sensing and Machine Learning for Identifying Driving Safety Profiles

#18-01416

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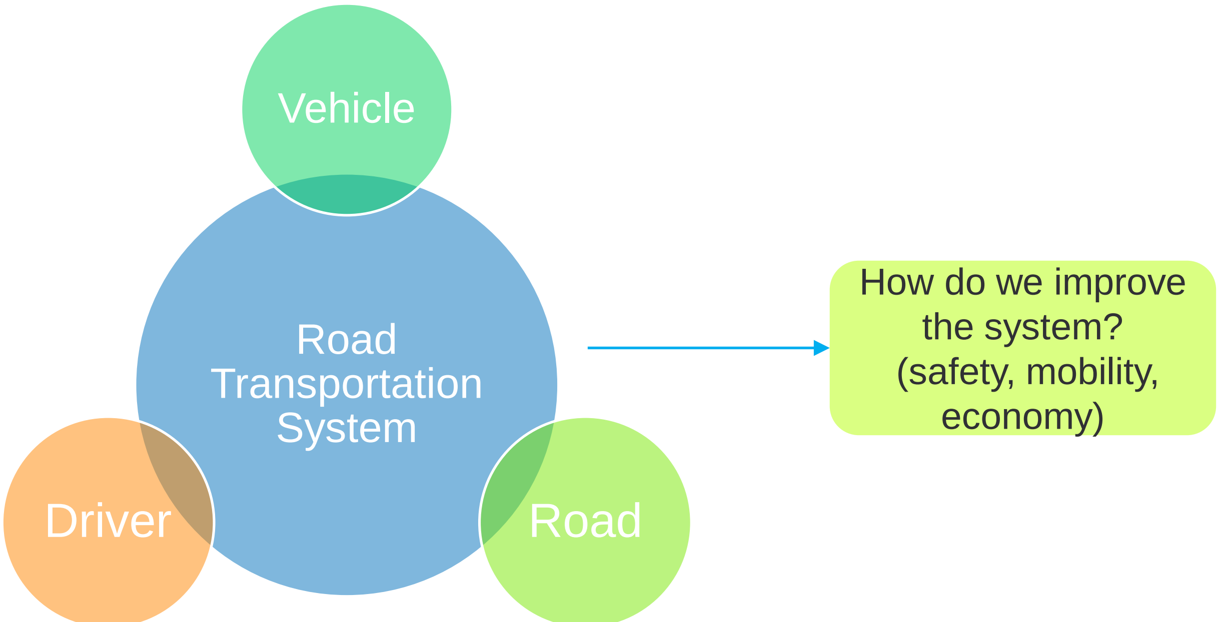
Data driven Era in Transportation

Data

Improve the understanding and solutions of existing problems

Create new research questions.

The Problem



Monitor, Identify and control driving behavior

The Potential

Smartphone sensors and communications features, allow for continuous, inexpensive, multipurpose and non intrusive data collection.

The data collected can be used for monitoring driving behavior.

Research questions:

> *Is it possible to produce a meaningful characterization for every trip in relation to the driving behavior?*
>
> *Is it possible to extend trip characterization to driver characterization and produce a consistent manner to distinguish different drivers on the road?*

Scope

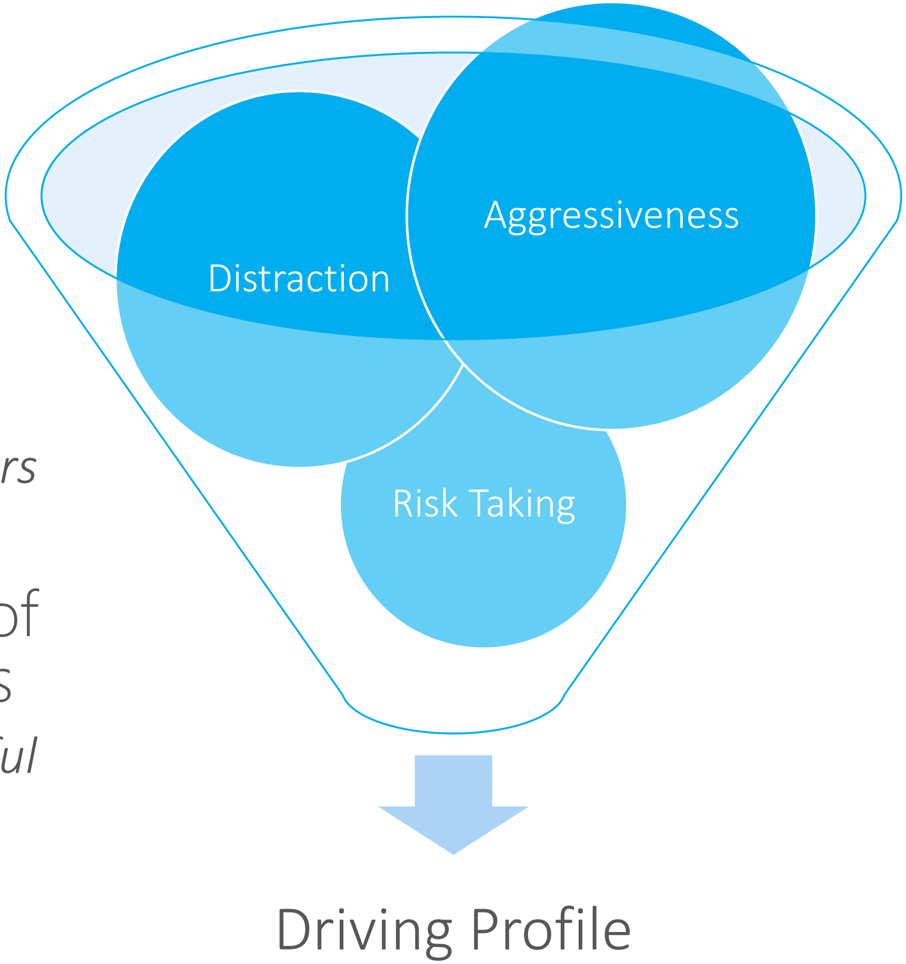
Identify different driving profiles

Data are being collected a smartphone application

Unsupervised learning techniques are applied to identify comprehensive clusters of driving behaviors per trip

Define an indicator of the volatility of driving behavior for different drivers

Extend the trip information to meaningful information for the driver



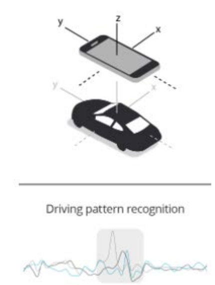
Methodology:
Data collection

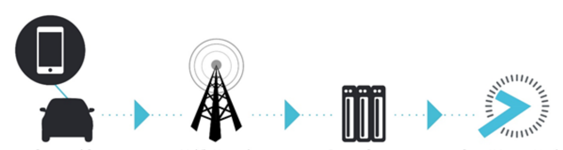
Cloud-based service + mobile app

- *automatic detection of the end of the trip*
- *data recording with no user involvement from accelerometer, gyroscope and GPS sensors*
- *data uploaded and stored in an anonymized way for further processing*
- *Machine learning and computational intelligence to provide driving analytics*

10212 trips made by 129 unique drivers from June 2016 to April 2017

- *The data are continuously growing*
- *External information and smartphone data are also fused*





Methodology:
Variables

Aggressiveness

- Harsh accelerations/brakes per km
  - The number of harsh accelerations/brakes per kilometer traveled
- Smoothness indicator
  - Kinetic energy during acceleration
- Standard deviation of acceleration
  - The standard deviation of acceleration in each trip

Distraction

- Percent of mobile usage
  - The percentage of trip duration in which the driver interacts with the mobile phone

Risk taking

- Percent of speeding
  - The percentage of trip duration in which the vehicle travels over the speed limit

Methodology:
Trips’ characterization

Ranked by importance to driving safety:

Safe behavior

Aggressive behavior (harsh accelerate and harsh brake)

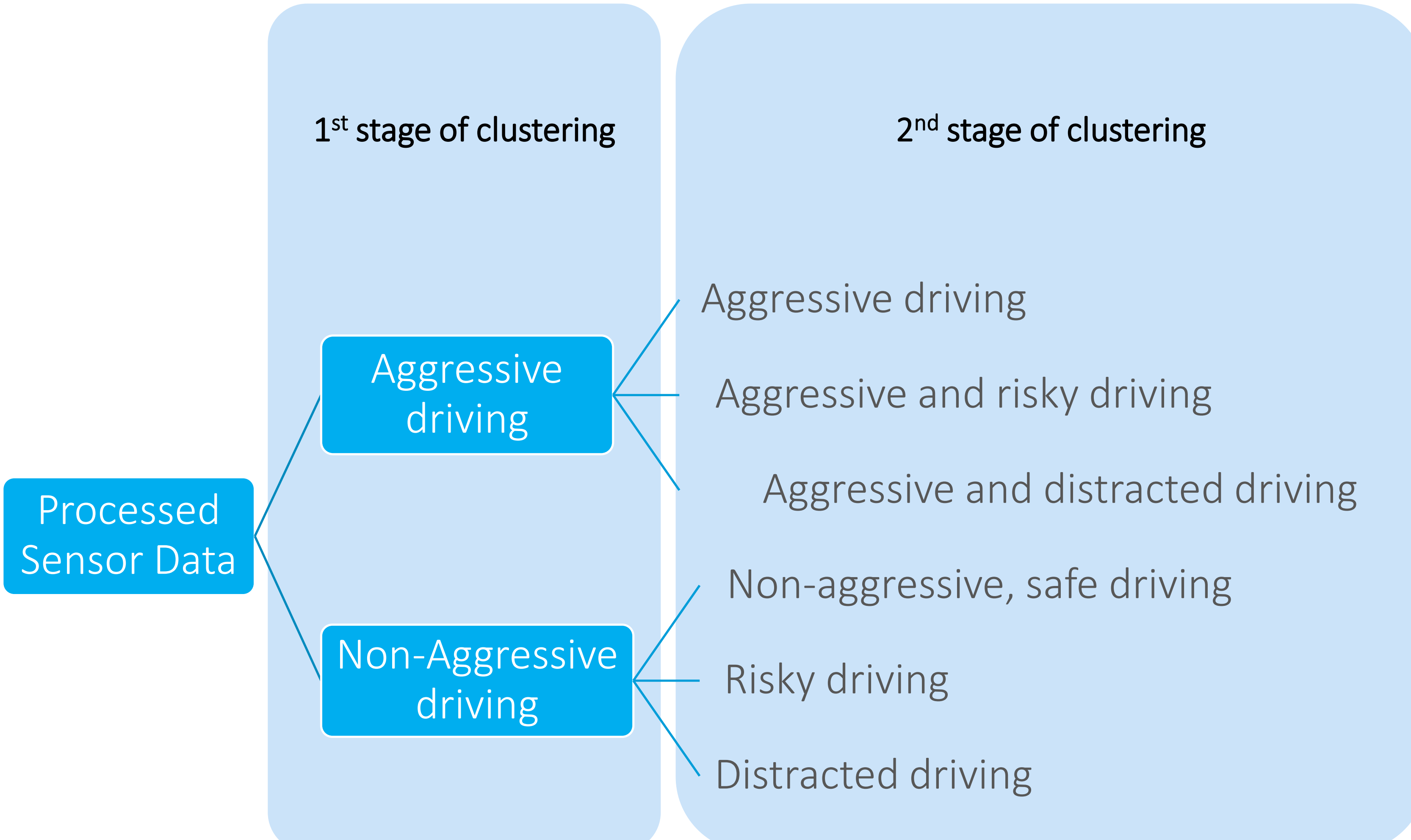
Risky behavior (speed limit violations)

Distracted Behavior (mobile phone usage)

Aggressive and Risky behavior

Aggressive and Distracted behavior

Methodology:
Unsafe driving detection procedure



Methodology:
K-means clustering

Divide a set of samples N into several groups (k) so that the samples within the same group are similar by minimizing an objective function:

$$J = \sum_{n=1}^{N} \sum_{k=1}^{K} r_{nk} \left\| x_n - \mu_k \right\|^2$$

The silhouette index is used to find the optimum value of k.

it measures how similar an object is to its own cluster (cohesion) compared to other clusters (separation).

Results:
1st stage clustering

Variable/ Driving cluster	Harsh Acceleration/km	Harsh Brake/km	Smoothness Indicator	Standard Deviation of Acceleration	Number of trips
Non–aggressive	0.13	0.07	0.32	1.15	7534
Aggressive	0.72	0.19	0.45	1.62	2678

Some interesting results:
74% of trips are not featured by aggressiveness

Although average acceleration is almost equal, in case of aggressive trips the number of harsh acceleration events is almost 6 times more than in case of non-aggressive trips

Results:
2^{nd} stage clustering

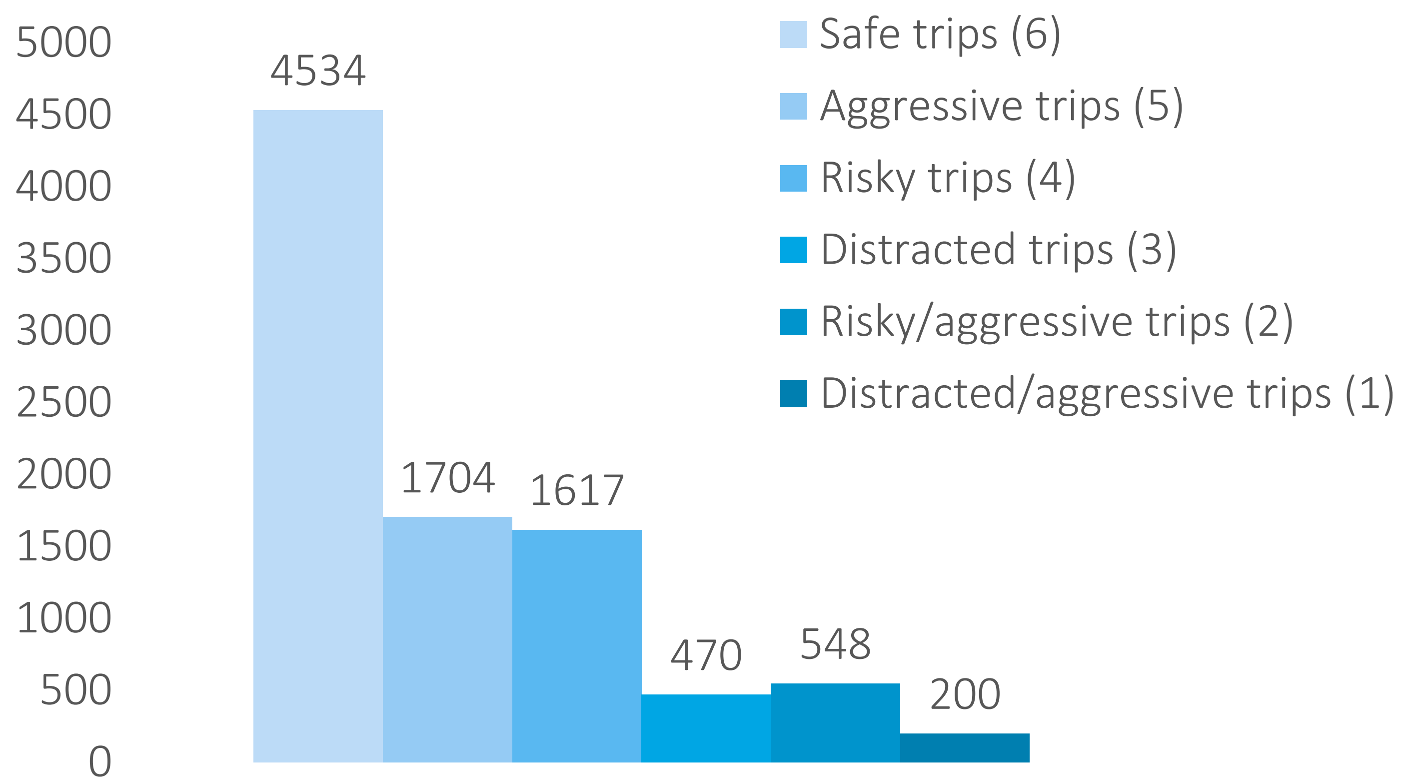
Variable/ Driving cluster	Percent of mobile usage	Percent of speeding	Number of trips
		Aggressive	
Aggressive	0.03	0.07	1837
Distracted	0.44	0.11	226
Risky	0.02	0.41	615
		Non–aggressive	
Safe	0.02	0.07	5183
Distracted	0.52	0.06	566
Risky	0.02	0.29	1785

Some interesting results:
In 69% of aggressive trips, the driver exhibits no other unsafe behavior (risk taking or distracted driving)

In both aggressive and non-aggressive trips only 8% of the trips are characterized as "distracted trips"

Results:

Distribution driving states



Results:
Driver's behavior volatility

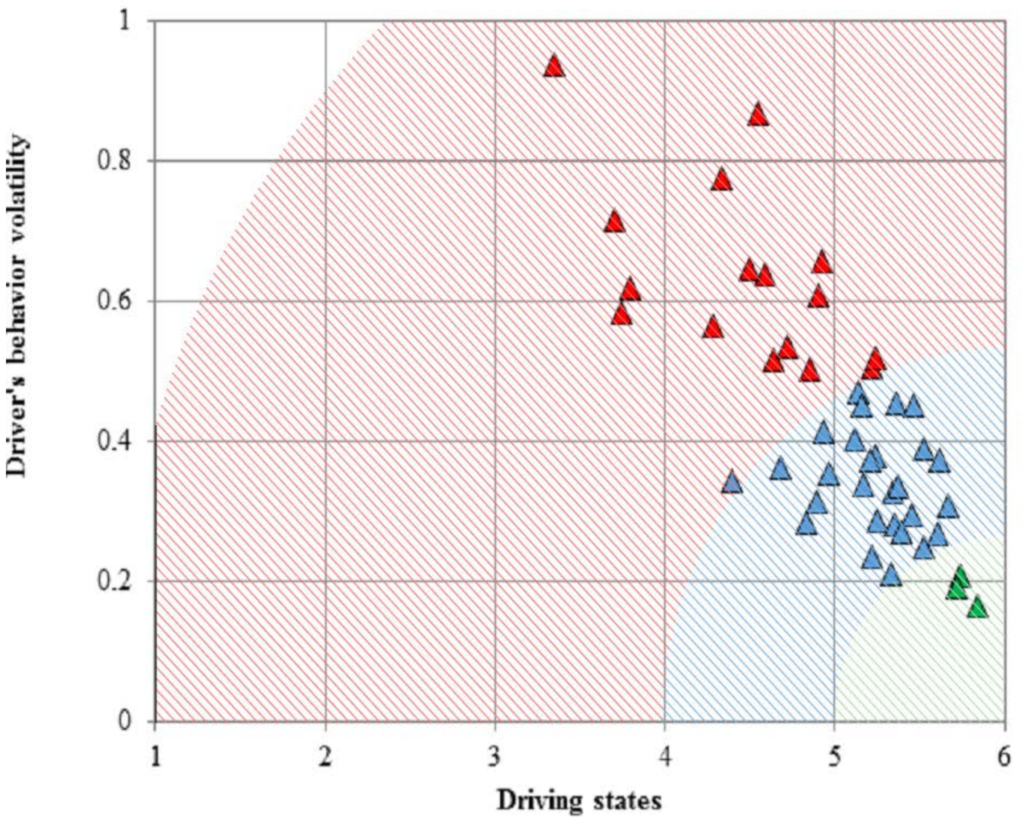
Gain/loss ratio per trip is estimated, indicating gain or loss driver receives between successive trips:

$$r_{t,i} = \ln\left(\frac{S_{t,i}}{S_{t-1,i}}\right)$$

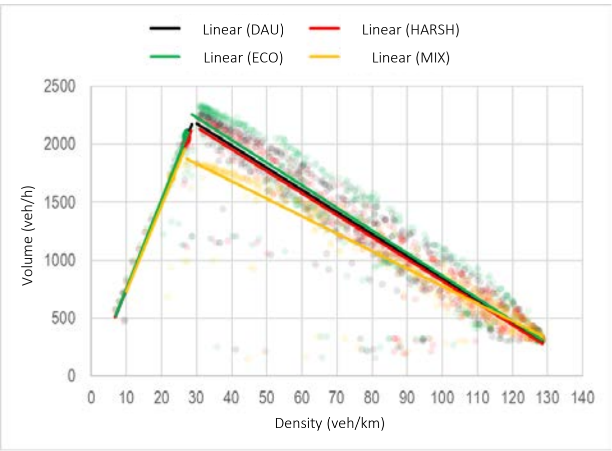
$\boldsymbol{S_{t,i}}$: driving state of trip t

The standard deviation of the gain/loss ratio is the driver's behavior **volatility** :

$$Volatility = \sqrt{\frac{\sum_{t=1}^{n}\left(r_{t,i} - \bar{r}_i\right)^2}{n-1}}$$

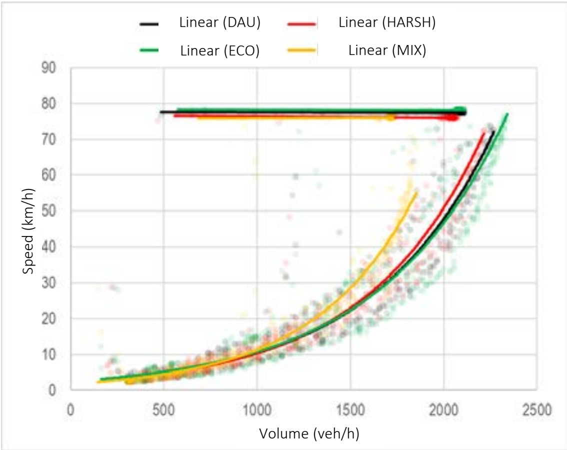


Results:
Network Level Impacts (preliminary findings)



HARSH and **ECO** model perform better than **MIX** in terms of mobility

- Homogeneity of traffic
- Reduced micro-variations of speed
- Increase of road capacity and reduce of pollutants



Project Luxembourg SUMO Traffic Scenario 2.0 (LuST)

- 24h Simulation
- 5959 edges, 929.5 km
- 4477 junctions
- 203 traffic lights
- 3155 Induction Loops
- Demand Peak: max.5000 vehicles/h

Conclusions

2-stage unsupervised learning models to extract driving profiles from real world naturalistic data

6 driving profiles are identified

Aggressiveness does not mean risk taking or distracted driving

Drivers exhibit risk taking driving behavior, either more often or rarely!

Drivers do not have a stable driving profile, but they change the way they drive on every trip

Future research

Impact of external factors (traffic, road conditions, adverse weather)

Identification of additional unsafe behavior while driving (Inappropriate lane changing, Overtaking, Abnormal steering)

Linking trip characterization to driver characterization

Driving profiles can be used to develop personalized recommendation systems

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