# Driving Style Recognition for Co-operative Driving: A survey

Anastasia Bolovinou, ISENSE group, ICCS

* joint work with A. Amditis (ICCS), F.Belloti (UoG) and M.Tarkiainen (VTT) during TEAM IP

# Outline

- Intro:  why automatic driving style recognition?
- Problem formulation: from raw vehicle data to maneuver recognition

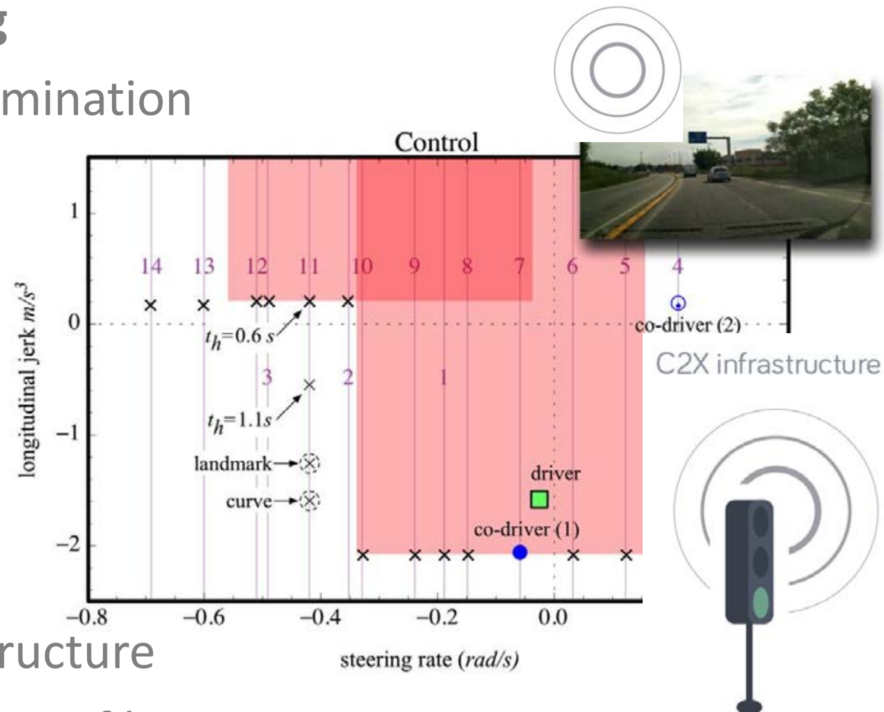
- Related work overview:
  - Sorted by observables
  - Sorted by recognized classes of driving style
  - Methods

- Reduced time series data representation: a promising research direction

- TEAM application: A case study
- Future work
- Conclusions

# Introduction | why automatic driving style recognition?

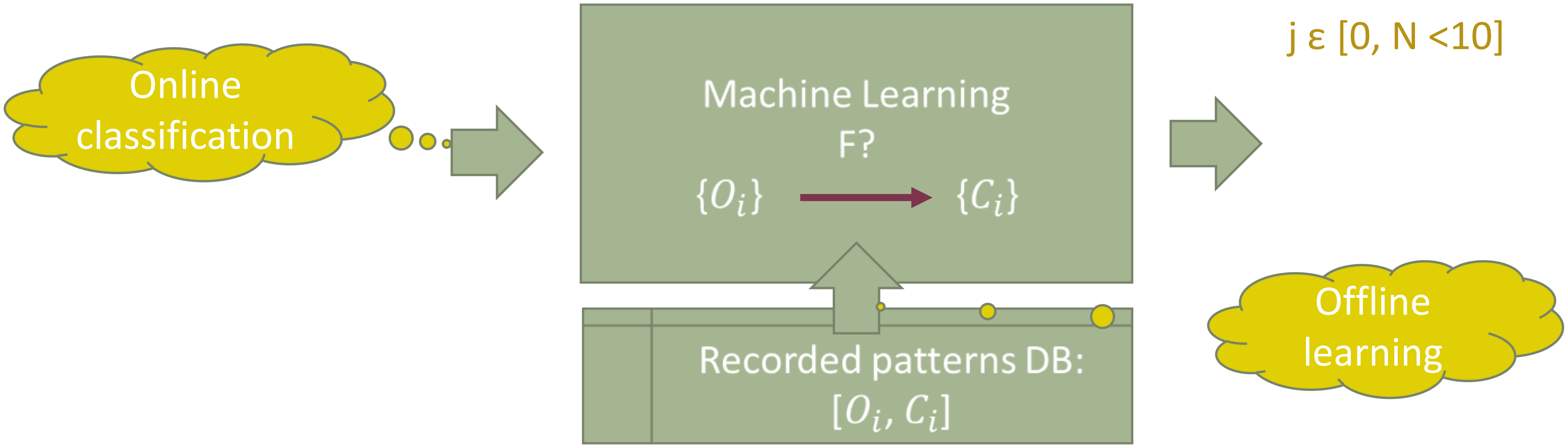
- In-vehicle semi-automatic functions:
  - "Seamless" **workload monitoring**
  - Control algorithms for path determination become more **user-aware**
  - ADAS acceptability will increase
  - **Coaching**: feedback to the driver while driving




- Infrastructure:
  - Safety assessment of road infrastructure
  - Promote eco-safe driving through profile sharing → **collaborative driving**

# Problem formulation

- Observables: $\{O_i\}$  i ε [0, T >> 1k]
- Classes: $\{C_i\}$  j ε [0, N <10]




- Assumptions of labelled maneuvers: Supervised setting (classes are known)
- Assumption of no labels available: Unsupervised setting (classes have to be discovered)

# Related work | Observables

| Feature | Sensor needed |
|---|---|
| Distance travelled (m) | CAN (odometer) |
| Longitudinal velocity (m/sec)<br>Lateral velocity (m/sec)<br>Angular velocity around vertical axis (yawrate) | CAN + inertial navigation unit: gps receiver and gyroscope |
| Longitudinal acceleration (m/sec2)<br>Lateral acceleration(m/sec2) | Accelerometer or Velocity filtering |
| Brake position | CAN |
| Steering wheel angle<br>Steering wheel velocity | CAN |
| Heading: distance and angle from the vehicle in front | Radar |
| lateral displacement in the lane | Lane recognition camera |
| Geo-data: weather info, avg speed, number of lanes, traffic info, road rype, time of the day | Local dynamic map cloud component (Wifi connection) |

# Related work | Classes of driving style

| Classes | …based on Driving patterns | Data |
|---|---|---|
| {aggressive, non-aggresive} | Speeding, failure to stop, lane violations | ✓ |
| {Flow conformist, extremist, tailgater, planner, ultraconservative} | Speed, heading profile | ✓ |
| {aggressive, non-aggressive in roundabouts}<br>{emission hotspots in roundabouts} | Mean circulating speed, acceleration maxima profile | Sim<br>(4 users) |
| {driver A, driver B} | Brake, acceleration, turn event | ✓ |
| {Emergency braking<br>Obstacle avoidance<br>Hill-starting<br>Braking in a turn} | Short term steering maneuvers<br>Short term braking/accelaration events | ✓<br>(10 subjects) |
| {steer, ease up on the accelerator, brake}<br>On 9 intersection classes | Past velocity, acceleration | ✓ |
| {economical, normal, sporting} | Gasoline consumption rate from speed, acceleration and heading degree | Sim |
| {economical, normal, sporting} | Electric energy consumption based on SoC, weather info, avg speed, traffic info, road rype, time of the day | - |

# Related work | Methods

Context is modelled as hidden layers in HMM network

double layer HMM

sticky HDP-HMM

- Classification methods


Context is either inserted if known or ignored

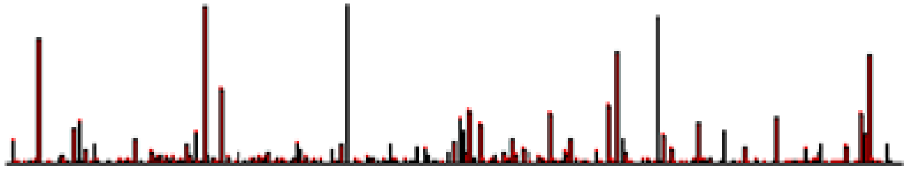
- Regression methods

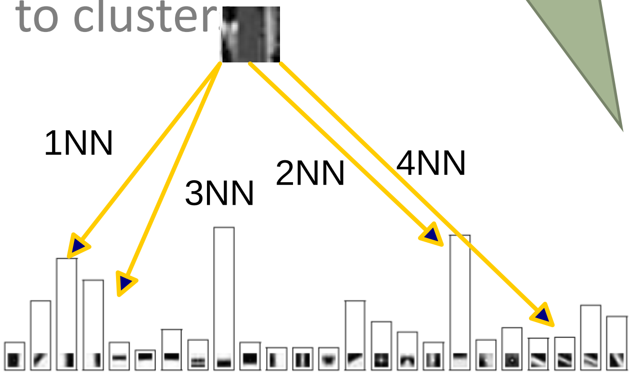
# Related work | Time series data representation

- Discretization to create a vocabulary of time strings :
  - Discretize into time strings (SAX symbolic repr.)
  - Map each new data sequence to a SAX vocabulary
  - Select a suitable simillarity metric for SAX histogram repr.

BOP produces very good results even without knowing the ordering of the patterns.

- BOP Representation: Histogram of membership to cluster

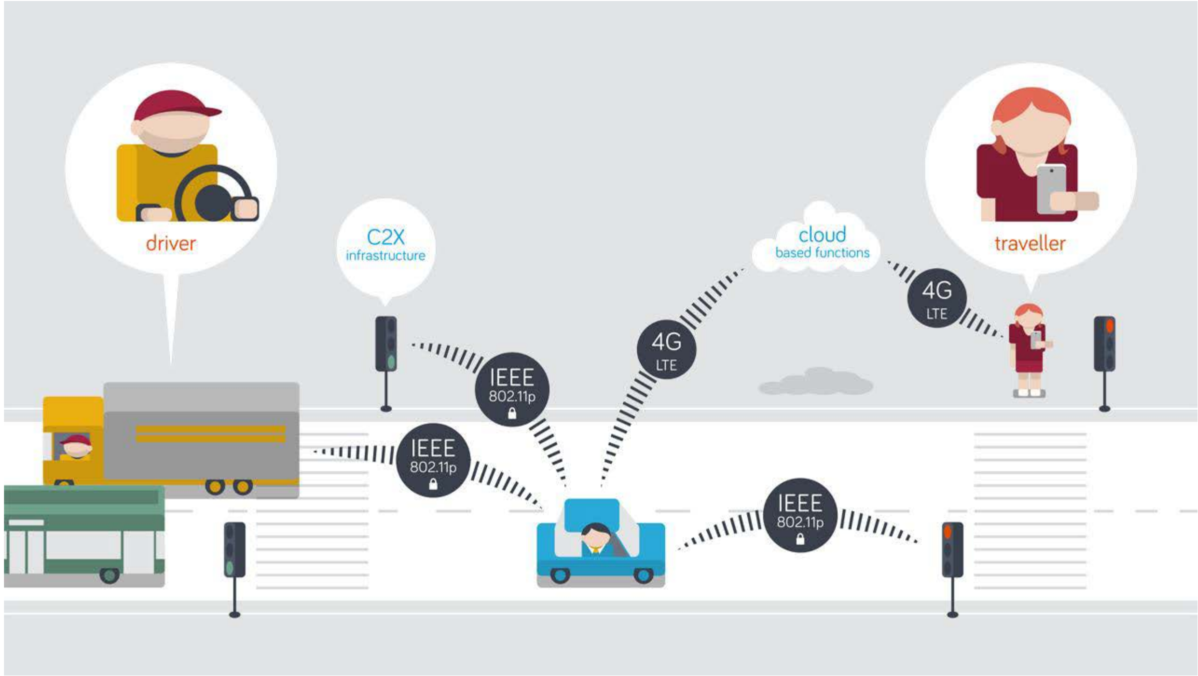





- Visual analog

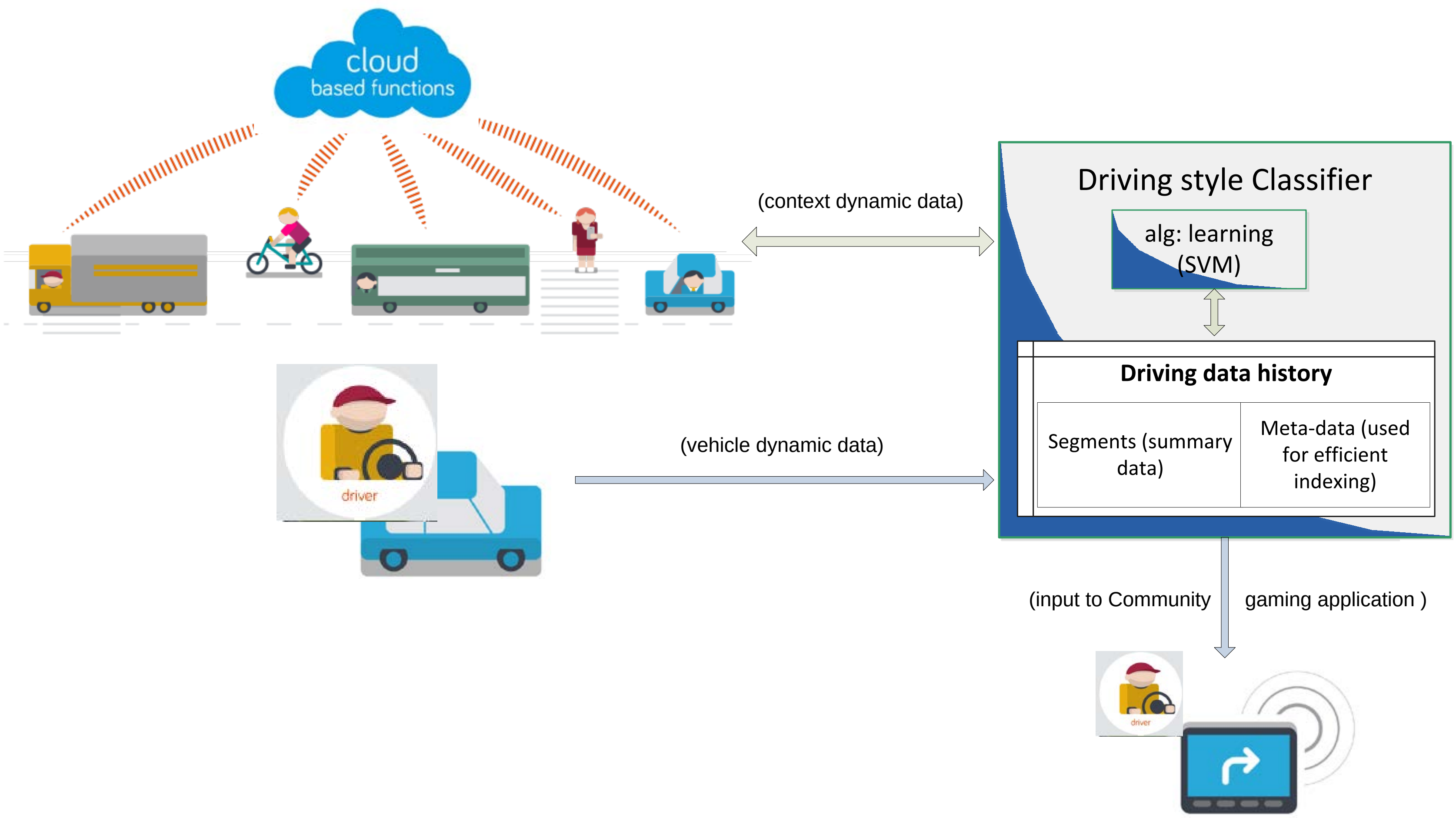
# Case Study: Driver profile enabler in TEAM

- Encouraging collaborative behaviour of travellers and drivers.
- Making infrastructures adapt pro-actively and in real-time based on user needs.
- Combining automotive communication systems with cloud technologies.



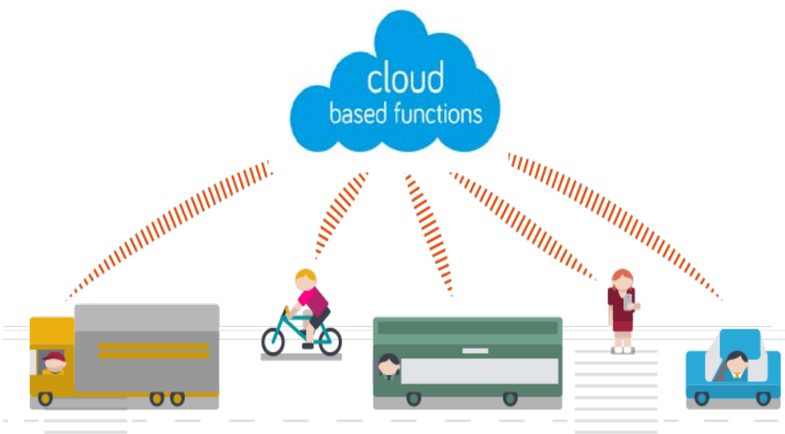
# Case Study: Functional architecture (1/3)

- Online driving style classification for collaborative driving



# Case Study: Functional architecture (2/3)

- Dynamic data feed




(context dynamic data)

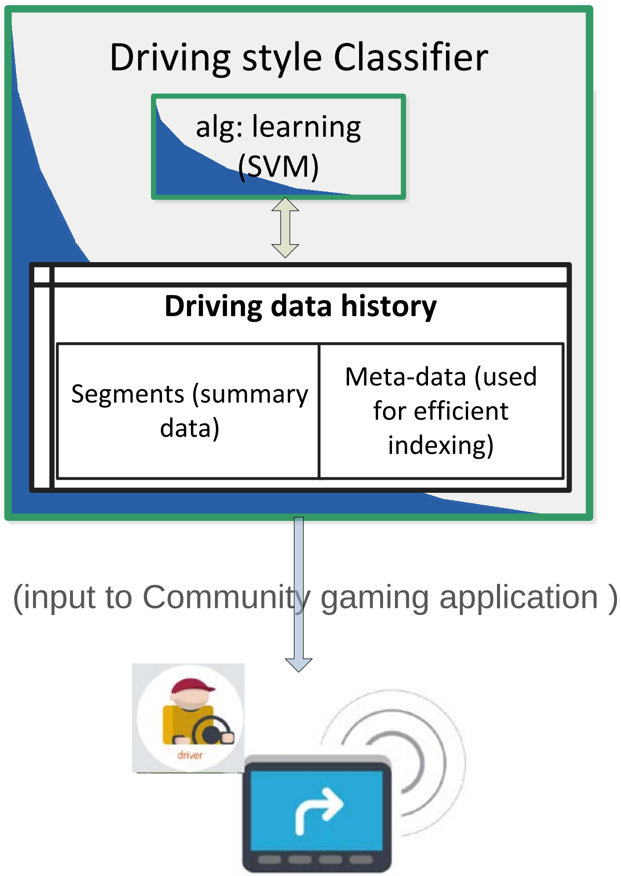
| | |
|---|---|
| **GeoTrip DB** | Personal trip geo-referenced data: e.g.<br>o ego-vehicle **location** in the map<br>o **avg speed** in the road segment being traversed. |
| DrivProfile DB | Personal driving indicators' aggregated data:, e.g:<br>o lane violations per km,<br>o overspeeding per km. |


(vehicle dynamic data)

| | |
|---|---|
| **CAN** | o Long/lat velocity<br>o Acceleration<br>o Brake activity<br>o Gear selection |
| ADAS OBU | o ACC heading distance |
| ADAS cloud | o Lane violations counted by LR camera per km |

# Case Study: Functional architecture (3/3)

- **Users:** Encouraging collaborative behaviour of travellers and drivers.




| | |
|---|---|
| **Long/Lat acceleration profile** | ? |
| **Headway profile** | ? |
| **Stopping profile** | ? |

| | |
|---|---|
| **Headway profile** | fluid-friendly<br>fluid-neutral<br>not fluid-friendly |
| **Eco-safe profile** | eco<br>normal driving<br>aggressive driving |

# Future work

- Logging sessions for TEAM use cases (difficult use cases are included: intersections, highway lane exits/mergings)
- Define levels of maneuvering activity to be recognized.
- Clustering of vehicle time series data to discover subsets of different profiles.
- Apply feature space quantization in order to use histogram-based low-dimensional representation and compare it against row data representation using SVM

# Conclusions

- Automatic driving pattern recognition can make modern ITS systems more efficient

- Advances in time series data mining and classification make this possible
  - REGRESSION can be used to explore the importance of different signal activity in a specific problem ()
  - CLASSIFICATION can be used to recognize higher level events from low-level observations
  - Dimensionality reduction techniques like bag of features seem appropriate for time series data and deserve further investigation

Key message: Personalization and context adaptivity can be learned

Find out more in TEAM website:

Tomorrow's Elastic Adaptive Mobility

http://www.collaborative-team.eu/

This project is co-funded by the European Commission DG CONNECT in FP7

# Selected references


- D. Zhang, Q. Xiao, J,Wang and K. Li, “Driver curve speed model and its application to ACC,” International Journal of Automotive Technology, 2013, vol. 14, no. 2, pp. 241−247.
- A. Amditis, P. Lytrivis, I. Karaseitanidis, M. Prandtstädter, and I. Radusch, “Tomorrow´s Transport Infrastructure: from Static to Elastic Mobility,” Proc. of the 20th ITS World Congress 2013, Tokyo, 14-18 October 2013.
- Mudgal, S. Hallmark, A. Carriquiry, and K. Gkritza,“Driving behavior at a roundabout: A hierarchical Bayesian regression analysis,” Transportation Research Part D: Transport and Environment, vol. 26, January 2014
- M. V. Ly, S. Martin, and M. M. Trivedi, “Driver Classification and Driving Style Recognition using Inertial Sensors,” IEEE IV2013
- L. He, C. Zong, and C. Wang, “Driving intention recognition and behaviour prediction based on a double-layer hidden Markov model,” Journal of Zhejiang University Science C, Issue 13, 2013
- R. Wang and S.M. Lukic, “Review of driving conditions prediction and driving style recognition based control algorithms for hybrid electric vehicles,” IEEE Vehicle Power and Propulsion Conference (VPPC) , 6-9 Sept. 2011
- J. Lin and Y. Li, Finding Structural Similarity in Time Series Data Using Bag-of-Patterns Representation.

Thank you!


Anastasia Bolovinou
Research engineer


Follow our work:
abolov@iccs.gr
http://i-sense.iccs.ntua.gr/