DE LA RECHERCHE À L'INDUSTRIE

Co-clustering de séries temporelles multivariées pour la validation du véhicule autonome

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Industrial context

AD / ADAS: Huge increase of the number of systems

2015 2022

ADAS SYSTEMS

2015 2022

VEHICLE APPLICATIONS

2015 2022

PLANTS & MARKETS

AD / ADAS: Huge increase of car complexity

ADAS ECU

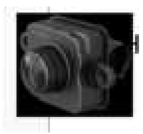
Front camera

Radar

HD Map

Lidar

Around view camera



Ultrasound barrier

Flight recorder

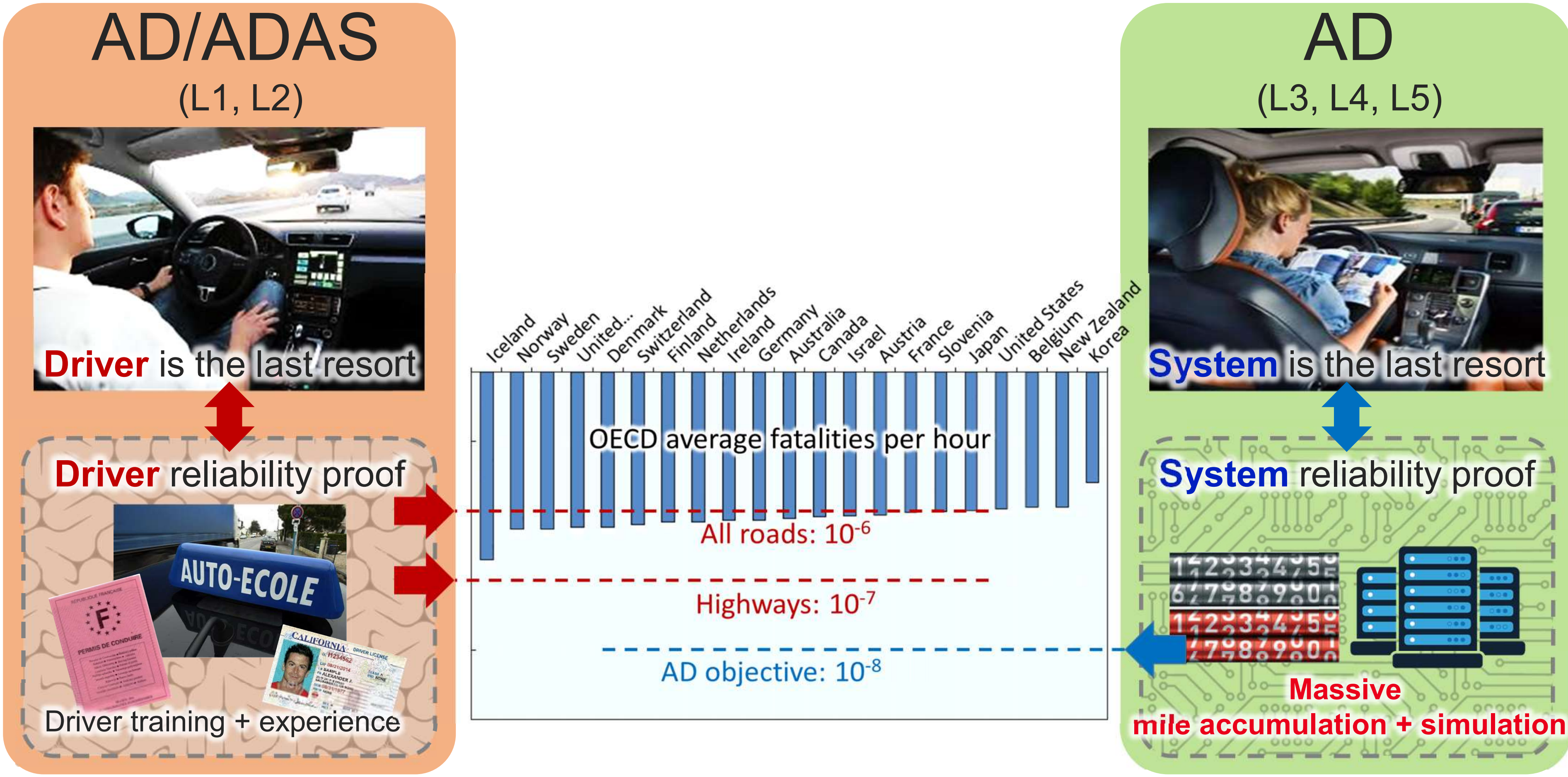
Redundant steering

Redundant braking

AD / ADAS: Huge increase of car complexity

2015: https://informationisbeautiful.net/visualizations/million-lines-of-code/

AD / ADAS: High reliability requirements



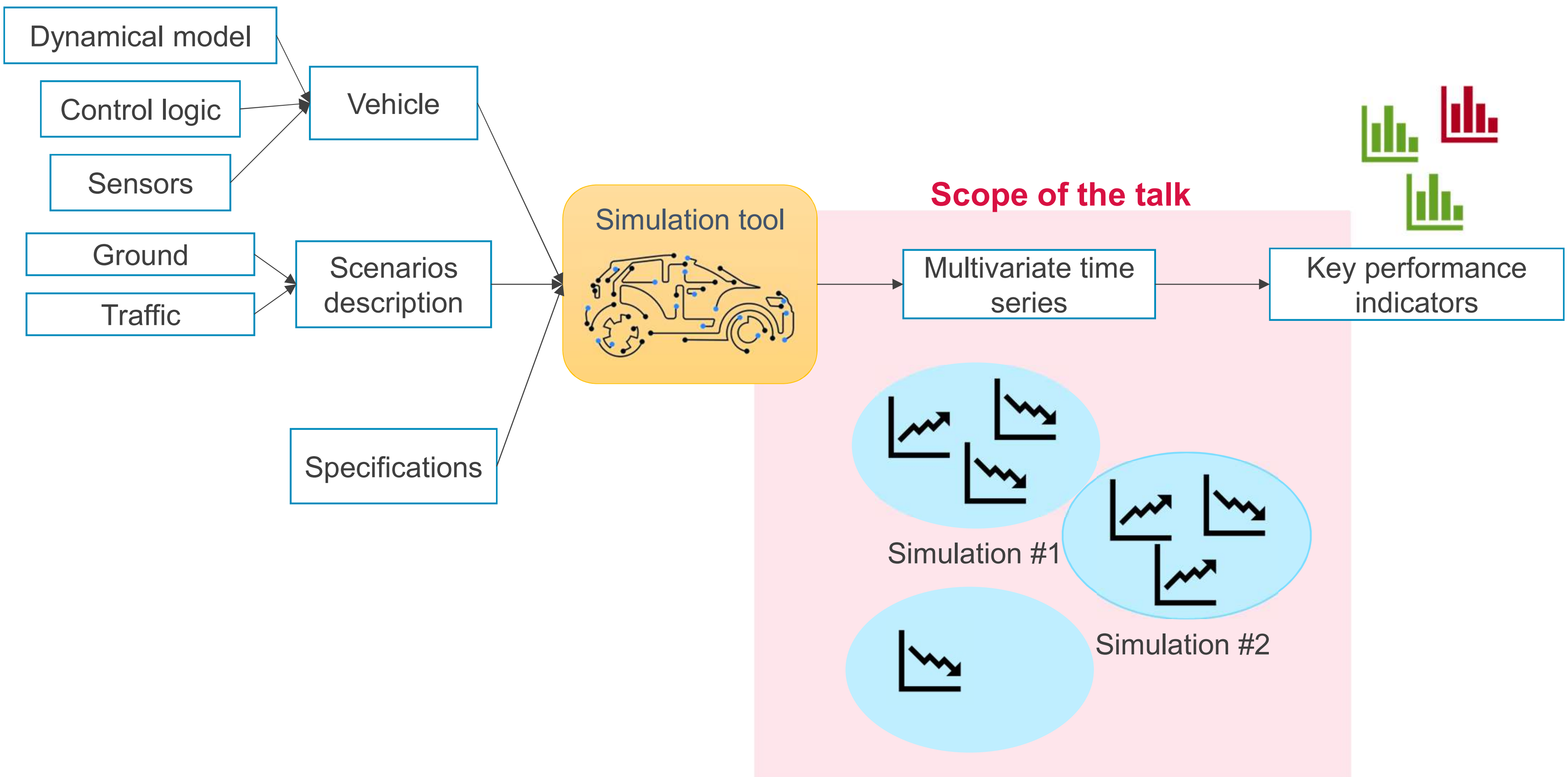
Naive estimation of the required number of cars for validation

- For a reliability of 10^{-8} and a confidence of 95%, using a Poisson distribution we find
  - Required driving time $= 3 \times 10^8$ hours
  - Number of kilometers at 50kph $= 1.5 \times 10^{10}$ km

$\approx 10^5$ cars should be dedicated to AD/ADAS validation

- A (partial) solution: numerical validation

Typical design of experiment for AD/ADAS validation



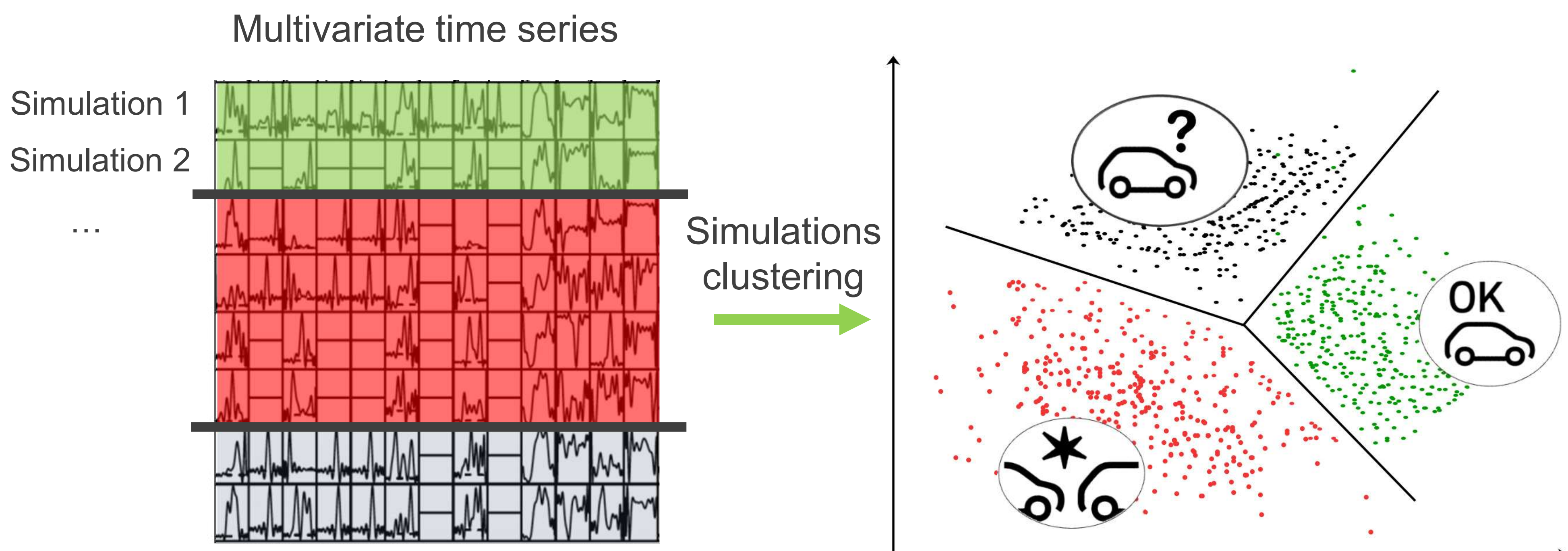
Opportunities and challenges

- **Business opportunities from time series mining:**
  - Identify operating modes of the vehicle – multivariate time series (co-)clustering problem
  - Identify anomalies

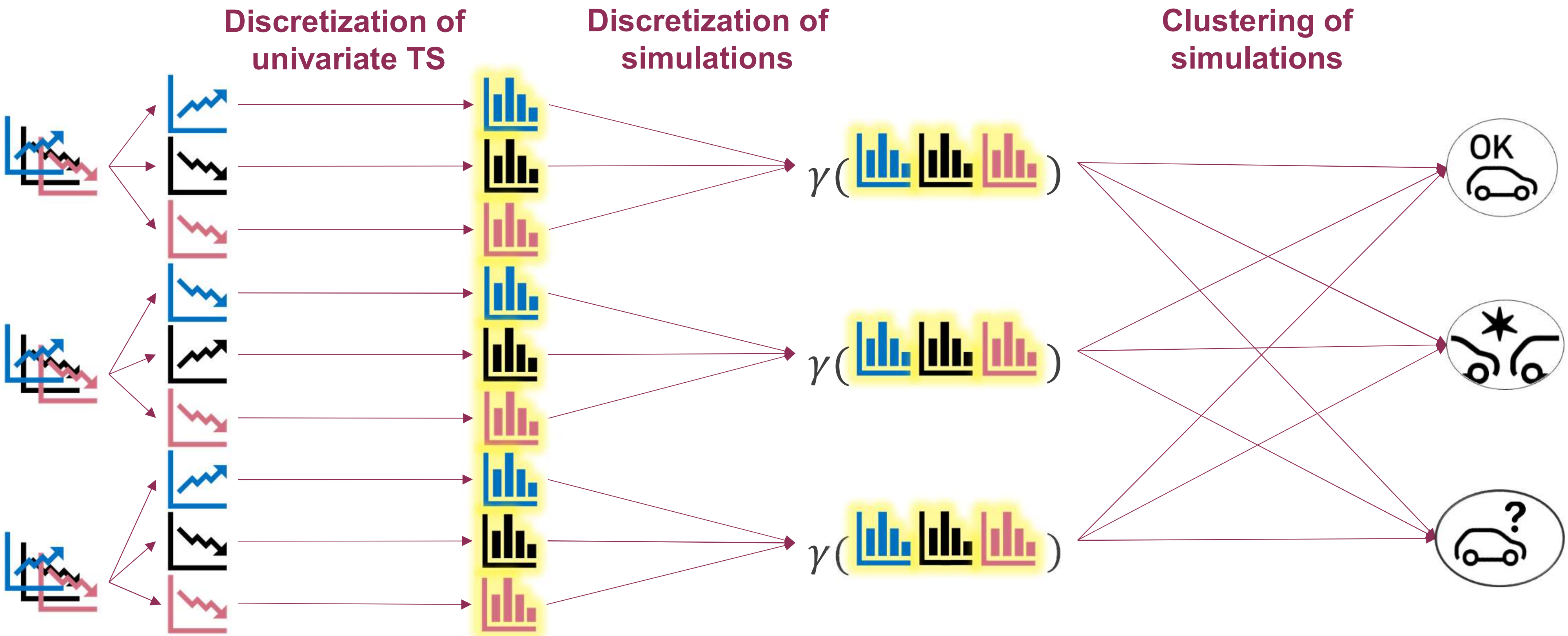
- **Scientific challenges**
  - **Many simulations** (e.g. 10k)
  - **Many signals** (e.g. 300)
  - **Many timesteps** (signal sampling @ 20Hz)
  - Dataset size **up to 1Tb**
  - **Different time series lengths** per simulation

Clustering of AD / ADAS simulations

Clustering of simulations via multivariate time series analysis

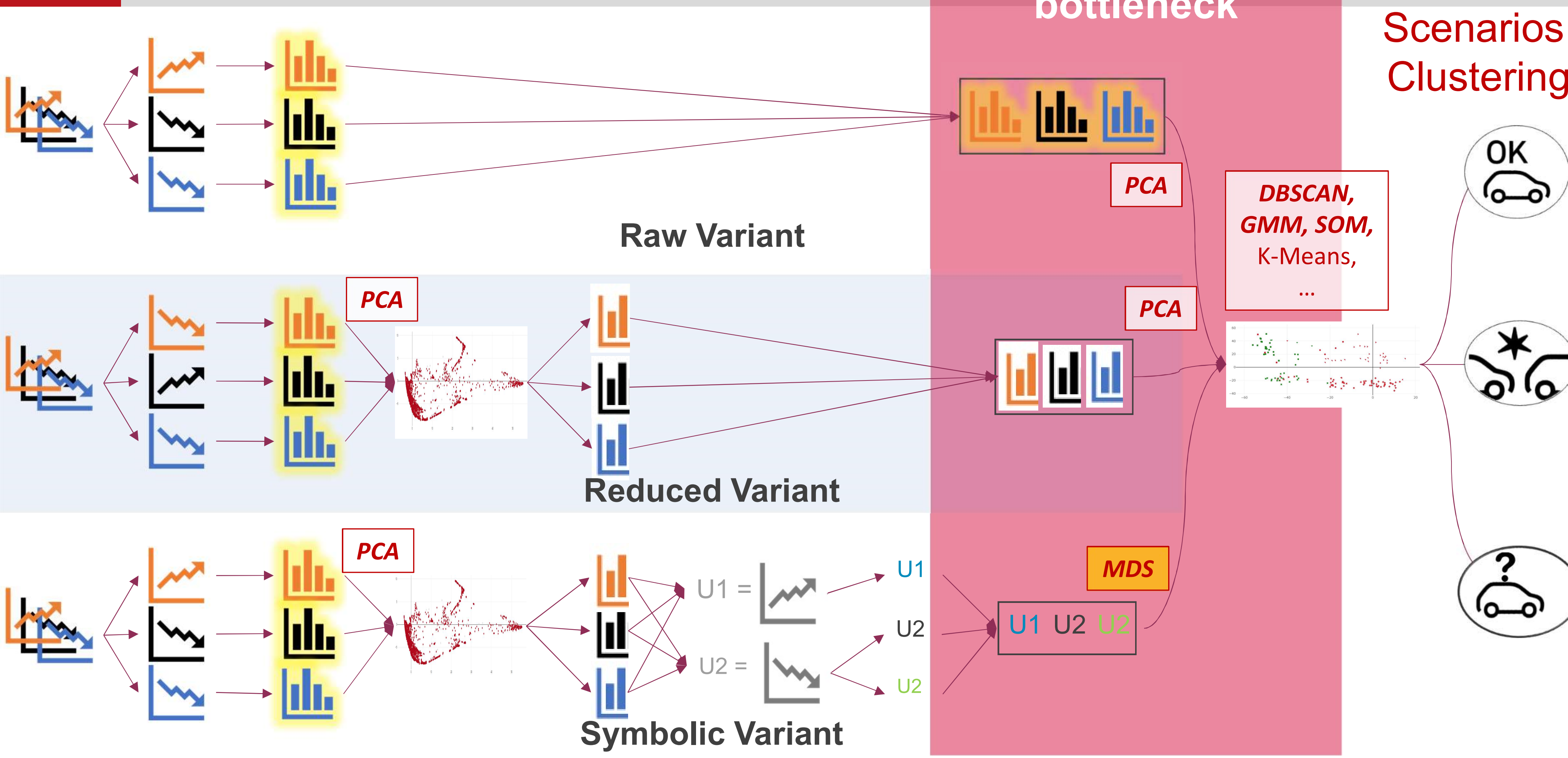


From raw time series to simulation clustering

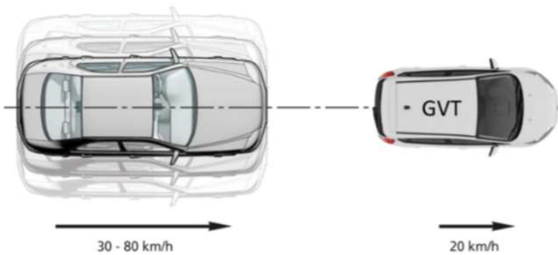


FFT + log-periodogram interpolation
Caiado, J., Crato, N., & Peña, D. (2009). Comparison of times series with unequal length in the frequency domain. *Communications in Statistics—Simulation and Computation*

From raw time series to simulation clustering

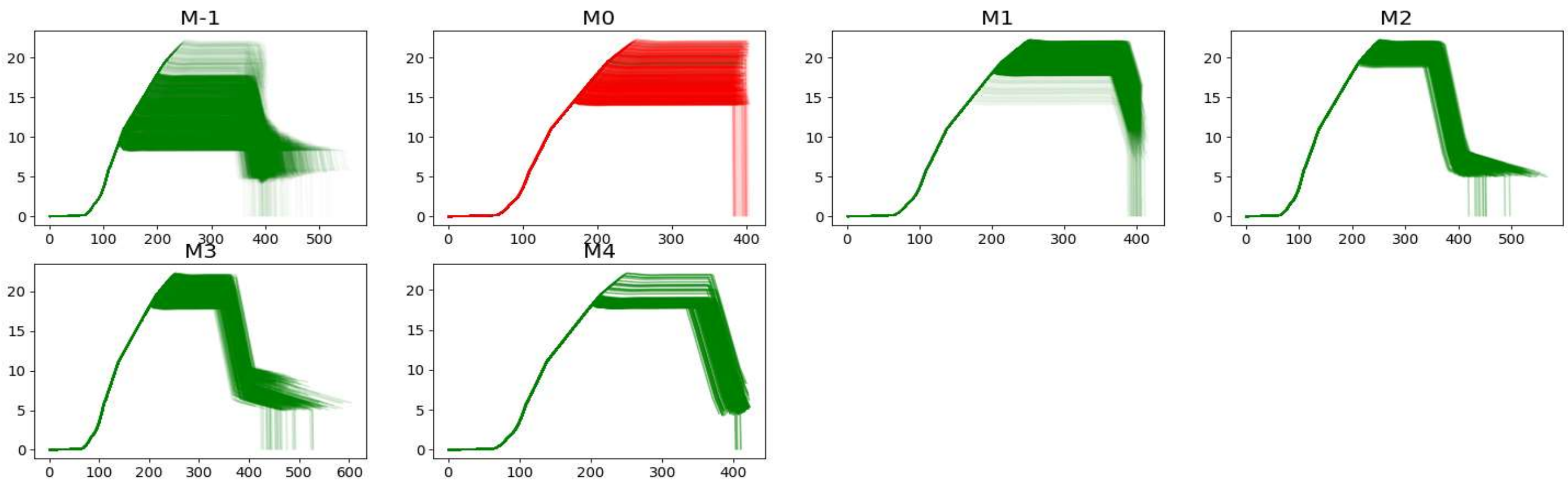


- **Advanced Emergency Braking – Car to Car Rear Moving (AEB-CCRm)**
  - 20000 simulations
  - Varying speeds
  - Varying overlaps
  - Analysis based on 30 signals

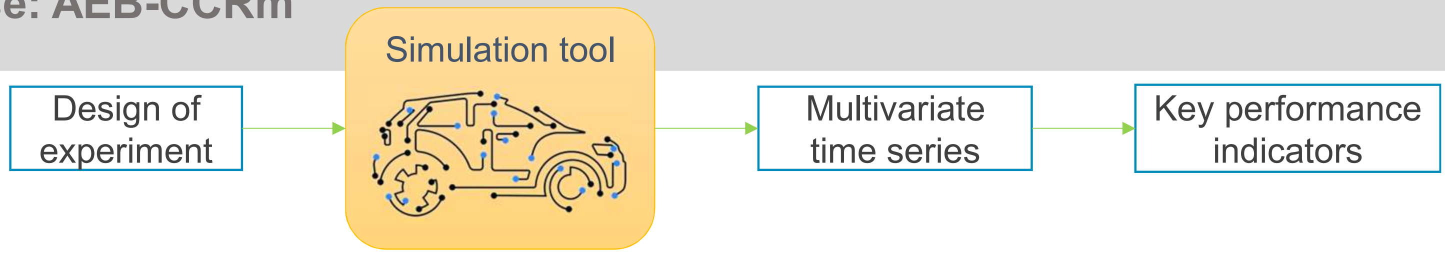


- **Analysis performed with the reduced variant of the pipeline**

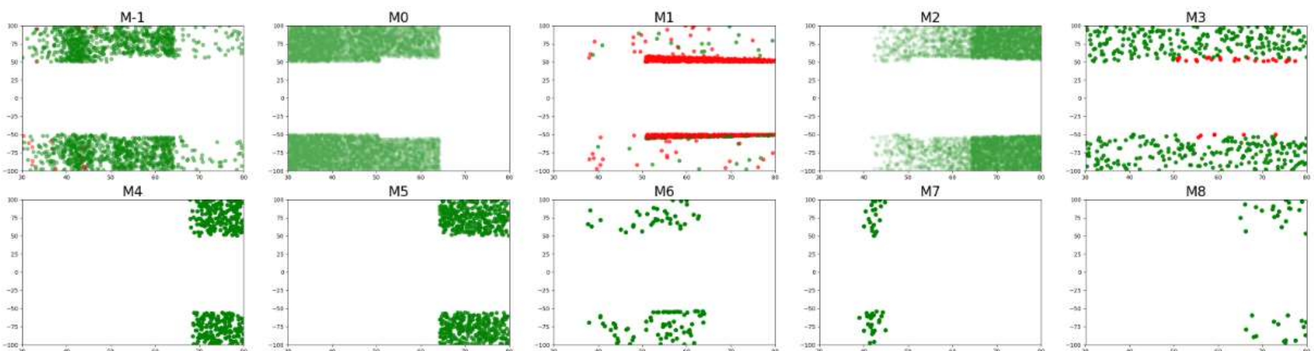
Car speed w.r.t. time



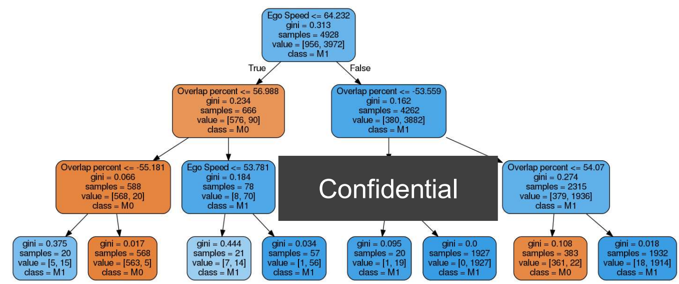
Use case: AEB-CCRm



- **Focus on multivariate time series: can we extract more informations?**
- **Yes: combine clustering with classification methods:**
  - feature: design of experiment / input simulation parameters
  - label: assigned cluster



Car speed vs Overlap vs Cluster



Decision tree:
DOE classification
predicting cluster labels

Co-clustering of AD / ADAS simulations

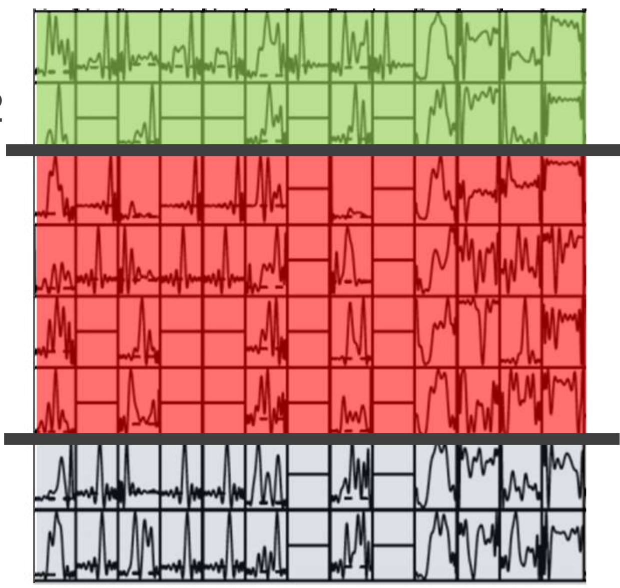
Simulation clustering

Multivariate Time series

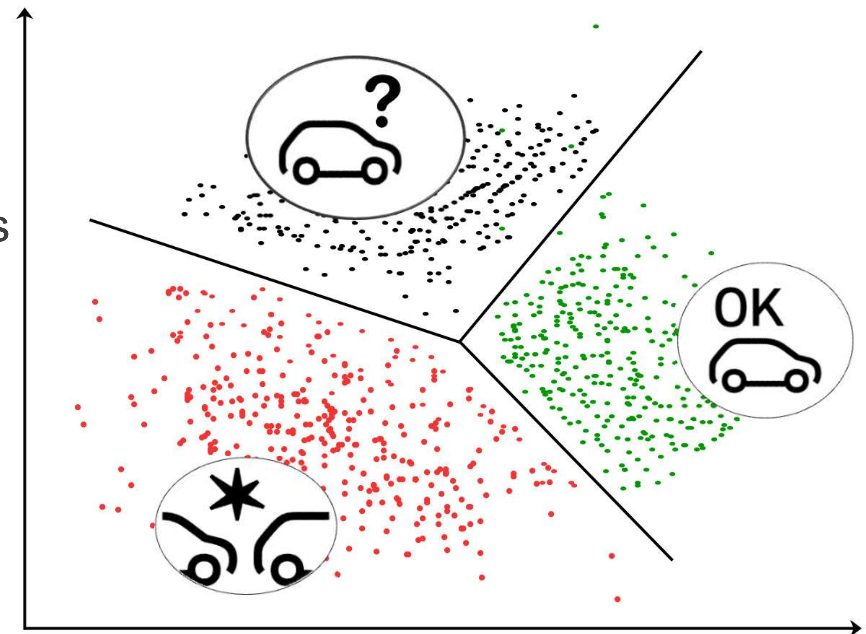
Simulation 1

Simulation 2

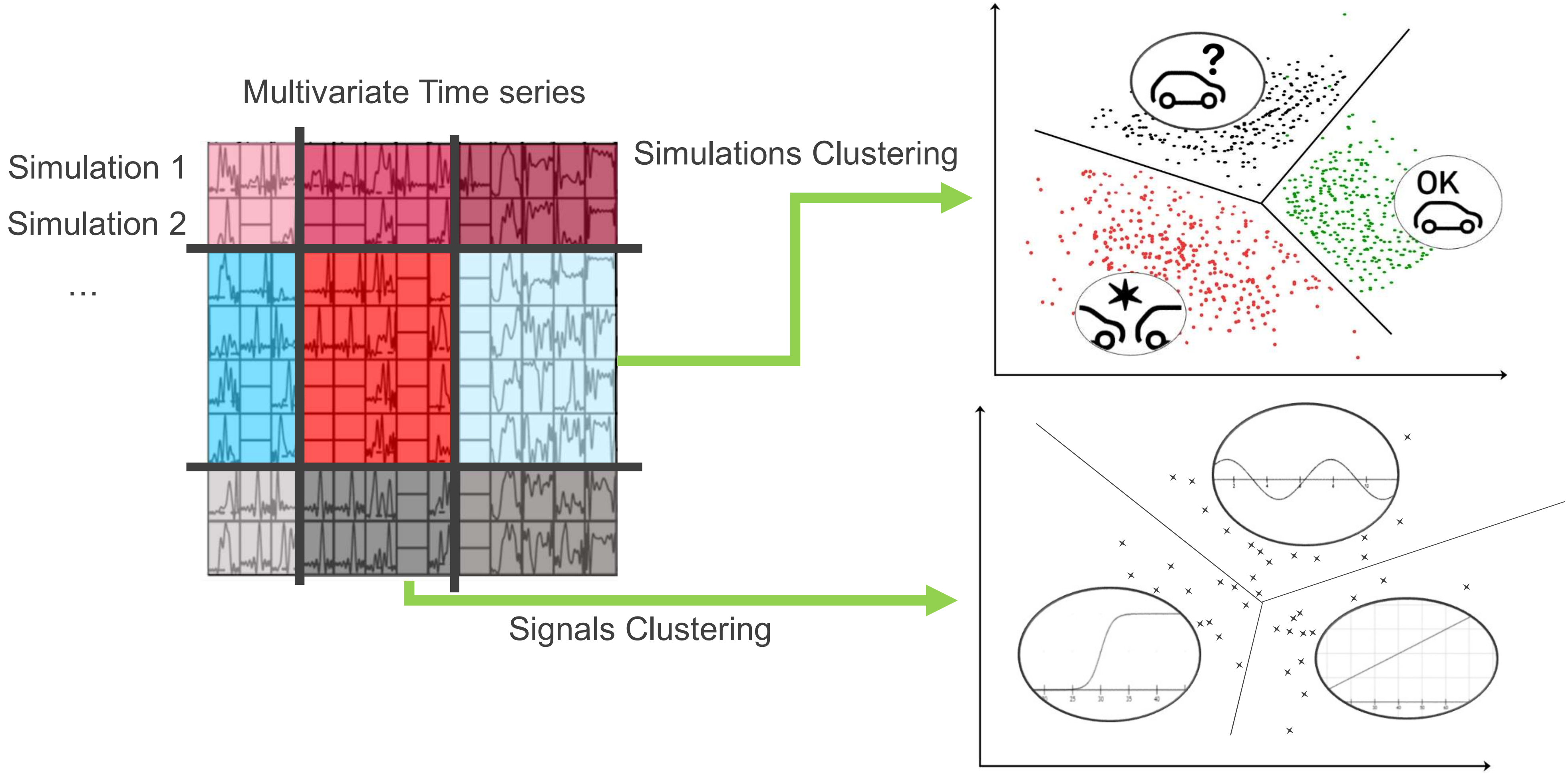
…



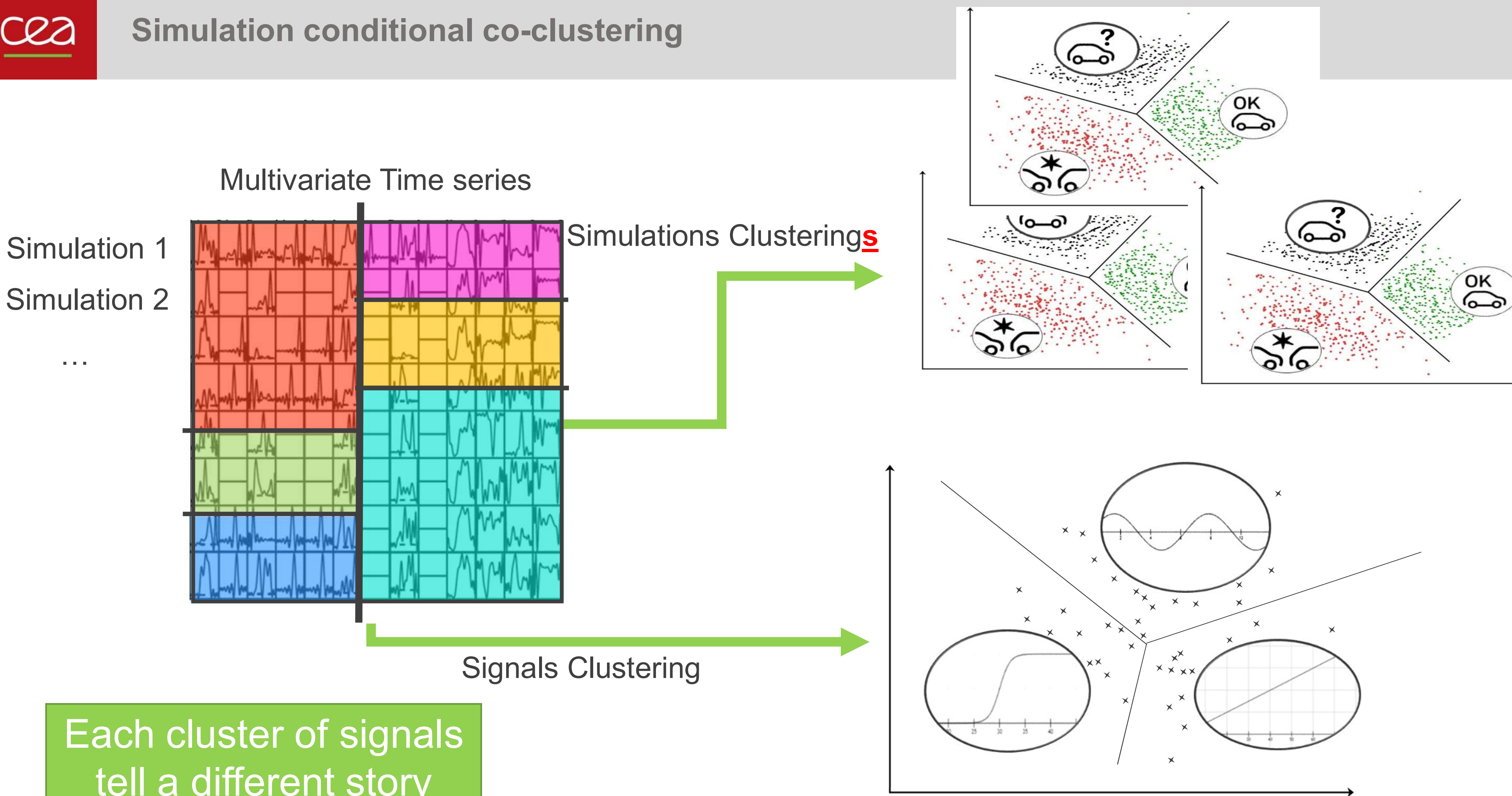
Simulations Clustering



Simulation co-clustering



Simulation conditional co-clustering



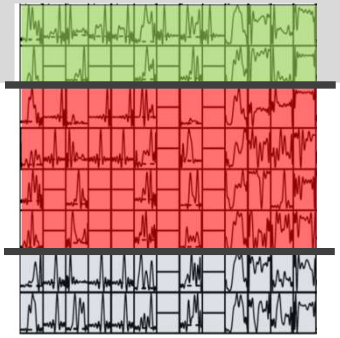
Each cluster of signals tell a different story

Model-based formulation

- **Notations:**
  - $(x_{ijs})_{ijs}$, dataset with $\boldsymbol{n}$ **observations** of $\boldsymbol{p}$ **features** in $\boldsymbol{d}$ **dimensions** (ie. After FFT + PCA + PCA)
  - Abuse of language and notations
    - the slice $(x_{\boldsymbol{i}js})_{js}$ is called a *"**row**"*
    - the slice $(x_{i\boldsymbol{j}s})_{is}$ is called a *"**column**"*
    - the index s will be omitted
  - $(z_{ik})_{ik}$ row cluster assignment variable
  - $(w_{jl})_{jl}$ column cluster assignment variable
  - θ hyperparameters

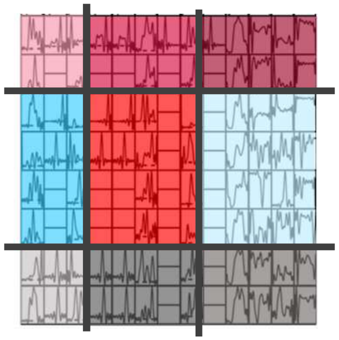
- **Model based methods for clustering**
  - Partitions will be represented with a mixture model
  - Cluster assignment uncertainty
  - Probabilistic outlier detection

Model based formulation



- Clustering with mixture models

$$p(x \mid \theta) = \sum_{z} p(x \mid z;\theta)p(z;\theta)$$

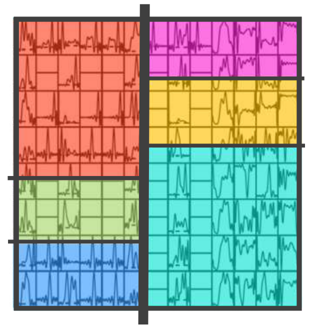


- Co-clustering with latent block models

$$p(x \mid \theta) = \sum_{z,w} p(x \mid z,w;\theta)p(z;\theta)p(w;\theta)$$

- Multi-clustering with latent block models

$$p(x \mid \theta) = \sum_{z,w} p(x \mid z,w;\theta)p(z \mid w;\theta)p(w;\theta)$$



- Gaussian assumption à la GMM

$$p\left(x_{ij} \mid z_i = k, w_j = l;\theta\right) \sim N(\mu_{kl}, \Sigma_{kl})$$

Inference process & model selection

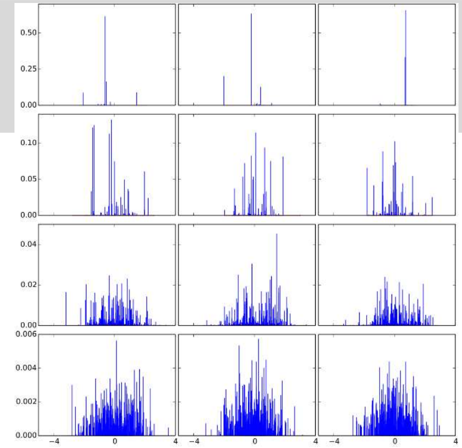
- **Inference process for latent block models: Stochastic Gibbs EM**
  - SE step: sample $p(z, w \mid x, \theta)$ with a Gibbs sampler
    - Sample $p(z \mid w, x, \theta)$
    - Sample $p(w \mid z, x, \theta)$
  - M step:
    - Update θ given (z, w)

- **Model selection (MS) using the integrated classification likelihood**

- **Issues**
  - Model selection is expensive
  - Without MS, the user must input additional parameters

- **Possible solution: introduce non-parametric Dirichlet Process**

Dirichlet process introduction



- **Intuitive formulation** of the Dirichlet process $DP(\alpha, G_0)$ (Chinese Restaurant Process)

$$p(Z_{n+1} \mid Z_n, \dots, Z_1) \propto \alpha\, G_0 + \sum_{k=1}^{K} n_k^* \delta_{Z_k^*}$$

Sampling from the distribution G_0

Sampling from the previous classes

- **Useful formulation** of the Dirichlet process $DP(\alpha, G_0)$ (Stick Breaking Process)

$$g_k \sim G_0, \qquad k = 1, \dots$$

$$\pi_k(r) = r_k \prod_{h=1}^{k-1} (1 - r_h), \qquad r_h \sim Beta(1, \alpha)$$

$$G = \sum_{k=1}^{\infty} \pi_k(r) \delta_{g_k} \sim DP(\alpha, G_0)$$

Symmetric Dirichlet process for co-clustering

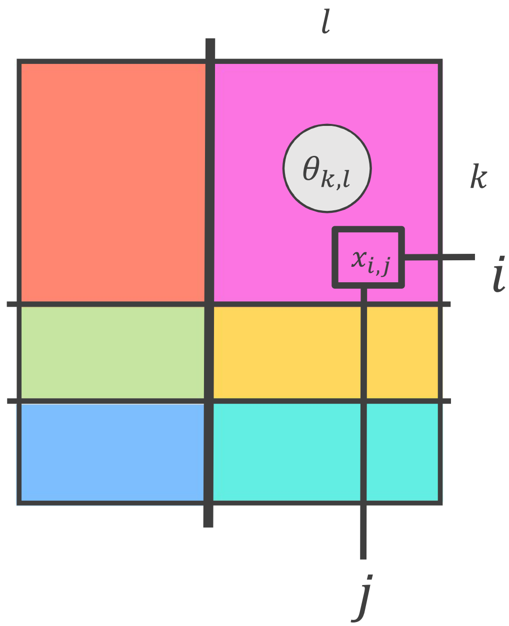
- **Model formulation**

$$x_{i,j} \mid \{z_i = k, w_j = l, \theta_{k,l}\} \sim F(\theta_{k,l}),\ \theta_{k,l} \sim G_0$$

$$\boldsymbol{z} \sim Mult(\boldsymbol{\pi}), \boldsymbol{w} \sim Mult(\boldsymbol{\rho})$$

$$\pi_k(\boldsymbol{r}) = r_k \prod_{h=1}^{k-1}(1 - r_h)\,, r_h \sim Beta(1, \alpha)$$

$$\rho_l(\boldsymbol{s}) = s_l \prod_{h=1}^{l-1}(1 - s_l)\,, s_l \sim Beta(1, \beta)$$



- **Bayesian Inference of $p(\boldsymbol{z}, \boldsymbol{w} \mid \boldsymbol{x}, \boldsymbol{\alpha}, \boldsymbol{\beta}, \boldsymbol{G_0})$ with a Gibbs sampler**
  - Sample row assignments $p(z \mid x, w, \alpha, \beta, G_0)$ row by row with the CRP
  - Sample column assignments $p(w \mid x, z, \alpha, \beta, G_0)$ column by column with the CRP

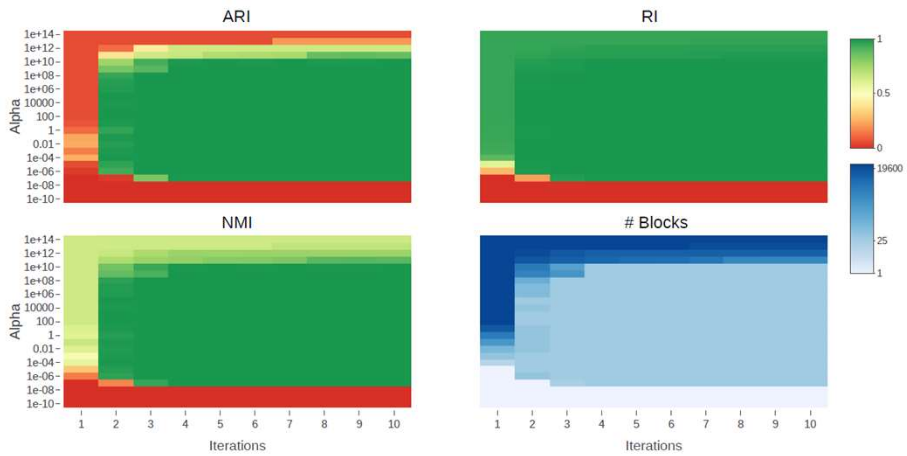
- **Complexity of the inference**

$$O(npd^2 + (n+p)\overline{K}\overline{L}d^3)$$

Benchmark on a synthetic dataset

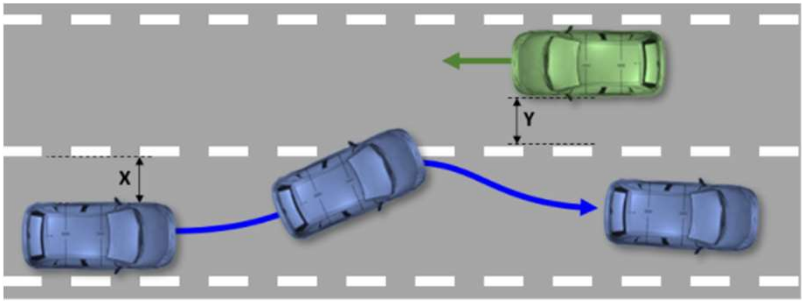
- **Synthetic dataset**
  - 5 row clusters with (20, 30, 40, 30, 20) observations
  - 5 column clusters with (40, 20, 30, 20, 30) observations
  - Each block has a Gaussian distribution
  - 19600 time series
- **Computer**
  - 12 processors Intel(R) Core(TM) i7-8850H CPU @ 2.60GHz
  - 32 Gb RAM

Method	ARI	RI	NMI	K	runtime (s)
$B\text{-}GMM$	0.825	0.982	0.946	25	18.6
$B\text{-}GMM_{MS}$	0.942	0.994	0.9803	30	85.9
$B\text{-}GMM_{14}$	0.979	0.997	0.994	25	89.3
LBM	0.823	0.913	0.887	25	17.5
LBM_{MS}	0.940	0.994	0.979	25	494.4
LBM_{49}	1	1	1	25	603.2
$B\text{-}DPMM$	0.670	0.958	0.906	16	25.3
$NPLBM$	**1**	**1**	**1**	25	**40**



Use case: ELK

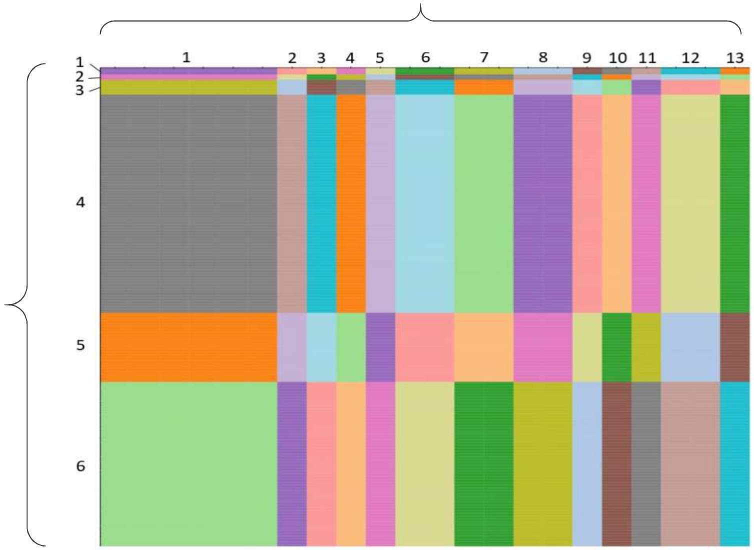
- **Emergency Lane Keeping (ELK)**
  - 400 simulations
  - 22 variables
  - Varying speeds
  - Varying decentering
  - Varying drifting angle
  - ...



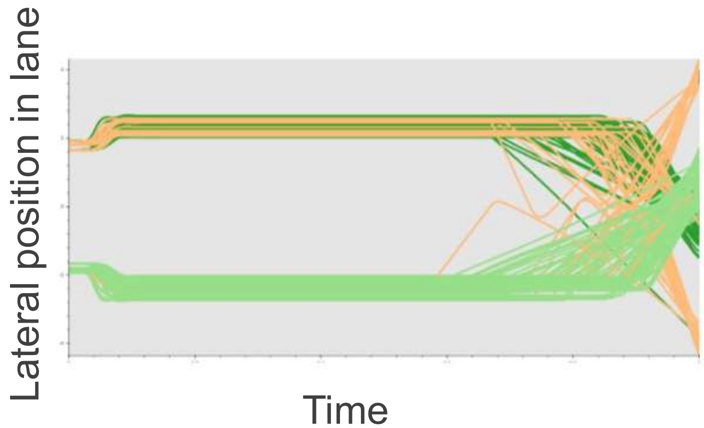
- **Result representation**

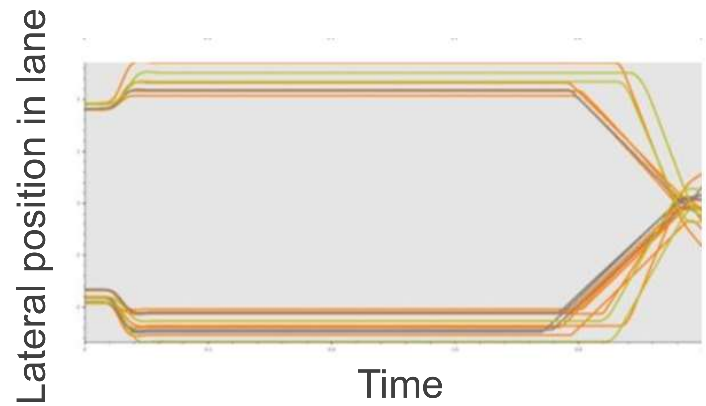
22 variables

400 simulations



Row clusters interpretations





Main row clusters:

- *Light Green:* drifting left and ELK fails
- *Dark Green:* drifting right and ELK fails
- *Orange:* ELK works

Other row clusters are outliers:

- ELK system activates too late

Conclusions & perspectives

- **Summary Part I**
  - Industrial simulation clustering workflow from large time series database
  - Main procedure in 4 steps
    - Vector representation of univariate time series
    - Dimension reduction of univariate vectors
    - Dimension reduction of multivariate components
    - Clustering in the reduced feature space
  - Classification based methodology in order to interpret clusters

- **Summary Part II**
  - Use pre-processing pipelines for co-clustering
  - Application of non-parametric co-clustering methodology for joined clustering of simulations and signals

- **Perspectives**
  - Better time series representation – replace FFT with wavelets, polynomials, ...
  - Scalability of the Dirichlet Process method
  - Multi-clustering visualization

- **For more details:**
  - E. Goffinet, M. Lebbah, H. Azzag, L. Giraldi and A. Coutant. A New Multivariate Time Series Co-clustering Non-Parametric Model Applied to Driving-Assistance Systems Validation, AALTD 2021
  - E. Goffinet, M. Lebbah, H. Azzag, L. Giraldi and A. Coutant. Multivariate Time Series Multi-Coclustering. Application to Advanced Driving Assistance System Validation. ESANN 2021

Merci de votre attention