

# Benchmarking Driving Efficiency using Data Science Techniques applied on Large-Scale Smartphone Data



## Dimitris Tselentis

Civil - Transportation Engineer  
Ph.D. Candidate – Researcher

[www.nrso.ntua.gr/dtsel/](http://www.nrso.ntua.gr/dtsel/)  
[dtsel@central.ntua.gr](mailto:dtsel@central.ntua.gr)

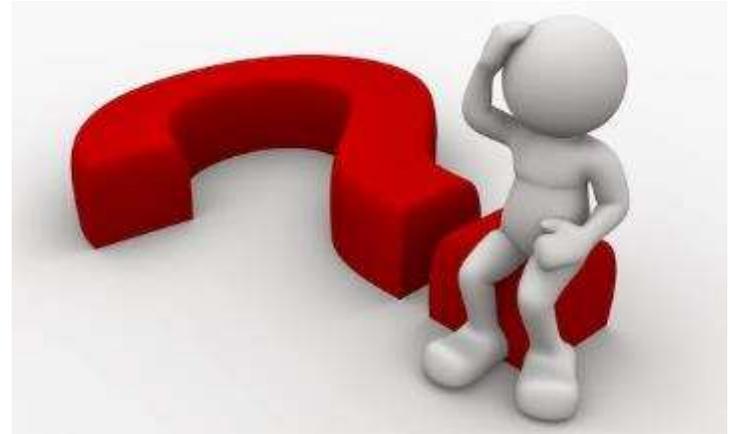
# Scope

- **Methodological approach** for driving safety efficiency benchmarking:
  - trip
  - driver
  - multi-criteria analysis
- **Safety efficiency index**
  - travel characteristics
  - driving behaviour metrics
  - smartphone devices
- **Smartphone** devices
  - large-scale data
  - naturalistic driving conditions



# Research questions

- How well can driving safety **efficiency** be **benchmarked**? Can data science techniques and large-scale data provide sufficient answers?
- What are the **temporal evolution** characteristics of driving efficiency? What do the drivers' groups formed represent?
- What is the required amount of **driving data** that should be collected for each driver?
- How can the **least efficient** trips of a database be identified?







# State-of-the-art (3/4)

## - **Driving data** collection

- Naturalistic driving experiments
- Driving simulator experiments
- In-depth accident investigation

## - Driving metrics - Adequate **amount**

- assessment of each driver
- deficient amount of data => uncertain or unreasonable results
- excessive amount of data => significantly increase required processing time



# State-of-the-art (4/4)

- **UBI** schemes
  - Pay-As-You-Drive (PAYD)
  - Pay-How-You-Drive (PHYD)
  - Pay-at-the-pump (PATP)
- **Travel** behaviour characteristics
  - Total distance
  - Road network type
  - Risky hours driving
  - Trip frequency
  - Vehicle type
  - Weather conditions
- **Driving** behaviour characteristics
  - Speeding
  - Harsh braking/ acceleration/ cornering
  - Seatbelt use
  - Mobile phone use



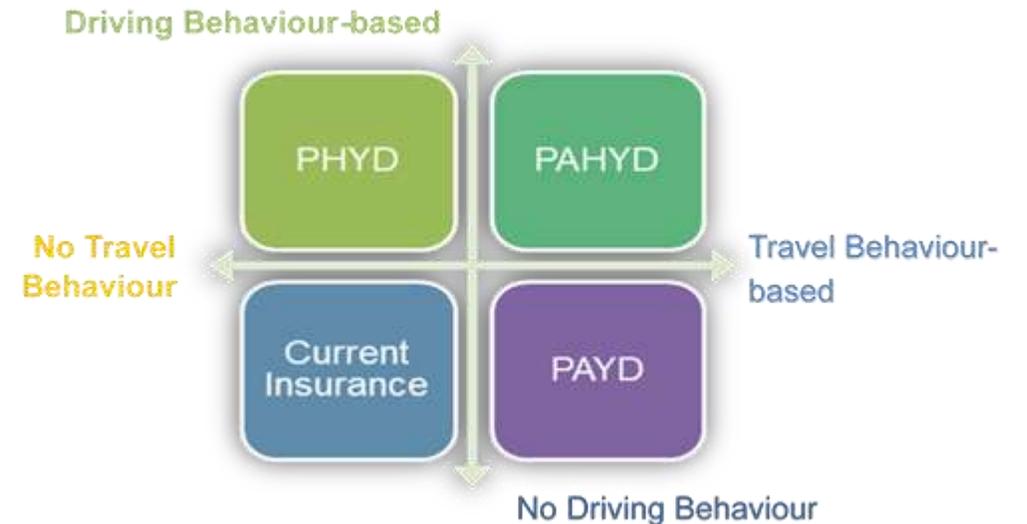
# Knowledge gap (1/2)

- **Benchmarking** driving safety efficiency
  - microscopic driving data
  - travel and driving behaviour
- **Large-scale** data from naturalistic driving experiments
- **Human factors** recorded from smartphone
  - Harsh acceleration/ braking events
  - Time of mobile usage
  - Time of driving over the speed limits



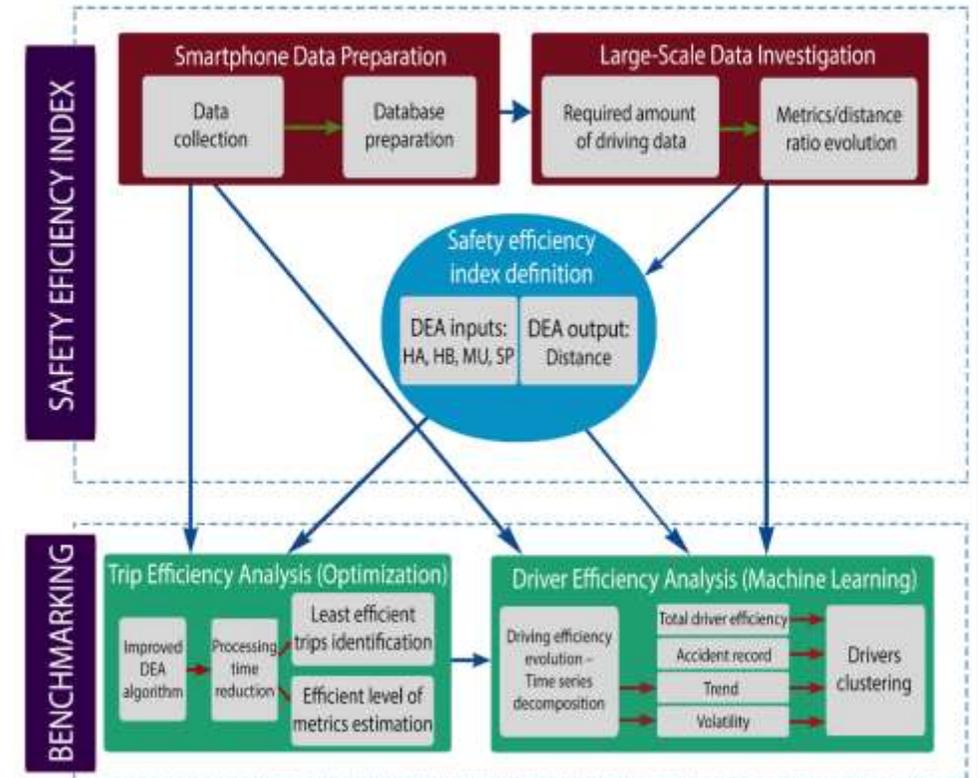
# Knowledge gap (2/2)

- Amount of **driving data** to be recorded
- **Usage-based** insurance (UBI) schemes
  - travel and driving behaviour
  - reduce annual mileage
  - improve their driving behaviour
- **Risk factor**
  - risk's increase rate
  - driving behaviour
  - mileage



# Methodological approach

- **Smartphone data** collection
  - data preparation
- Large-scale **data investigation**
  - investigation of metrics-distance ratio evolution
  - adequate driving data
- **Safety efficiency index** estimation
- **Trip efficiency** analysis
  - identification of the least efficient trips
  - estimation of the efficient level of metrics
- **Driver efficiency** analysis
  - time-series decomposition
  - drivers clustering



# Data envelopment analysis (1/2)

- **Optimization** technique
  - Performance measurement using **DEA**
    - Companies, banks, hospitals, staff etc.
- **Significant** computation cost
  - Exact solution
  - Reduced Basis Entry
  - Convex Hull
  - Reduce processing time
- **Decision-Making-Unit (DMU)**
  - Factory, company etc.
  - Trips, drivers
    - variables are continuous and quantitative
    - a driver should reduce the frequency of his driving characteristics for a given mileage



# Data envelopment analysis (2/2)

- **Efficiency index**  $Driving\_efficiency_B$
- **Input-oriented** DEA
  - minimize inputs (number of HA, HB events etc.) per driving distance
- **Constant-returns-to-scale** (CRS) problem
  - the sum of all inputs changes proportionally to the sum of driving output (distance)
- **Efficient level** of driving characteristics for a trip/ driver
  - inputs
  - outputs

$$\min(Driving\_Efficiency_B)$$

Subject to the following constraints:

$$Driving\_Efficiency_B * x_o - X * \lambda \geq 0$$

$$Y * \lambda \geq y_o$$

$$\lambda_i \geq 0 \forall \lambda_i \in \lambda$$

$$Metric_i = \sum_{j=1}^m \lambda_j * Metric_j$$

$$distance_{urban} = distance_i / Driving\_Efficiency_i$$

# Efficiency index parameters

## Risk exposure indicators:

- Total **distance** travelled

## Driving behaviour indicators:

### - **Harsh events**

- Number of harsh braking (longitudinal acceleration) (HA)
- Number of harsh acceleration (longitudinal acceleration) (HB)

### - **Speeding** (SP)

- seconds driving over the speed limit

### - **Mobile phone** use distraction (MU)

- seconds using the mobile phone

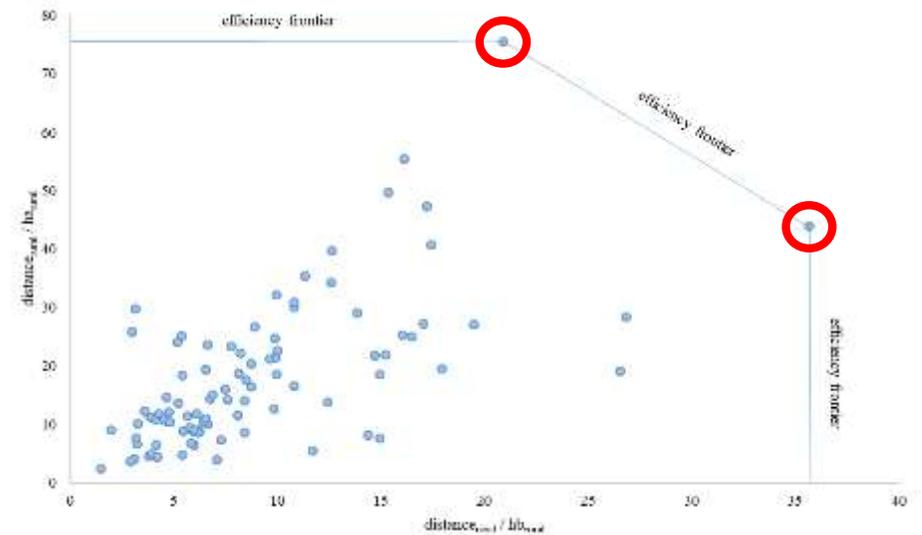
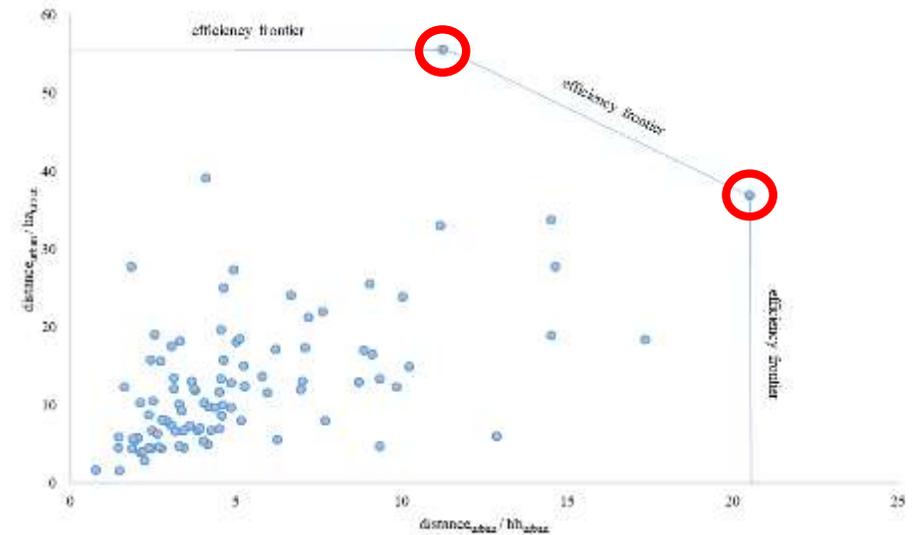
## Road types:

- Urban road network (signalized or not network, speed limit  $\leq 50$  km/h)
- Urban express road network (speed limit 50 – 90 km/h)
- Highways (speed limit  $\geq 90$  km/h)



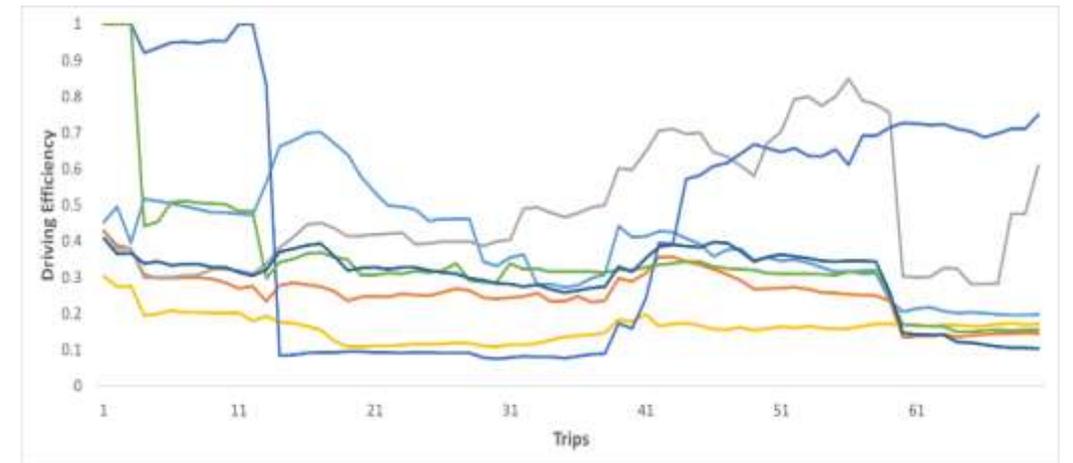
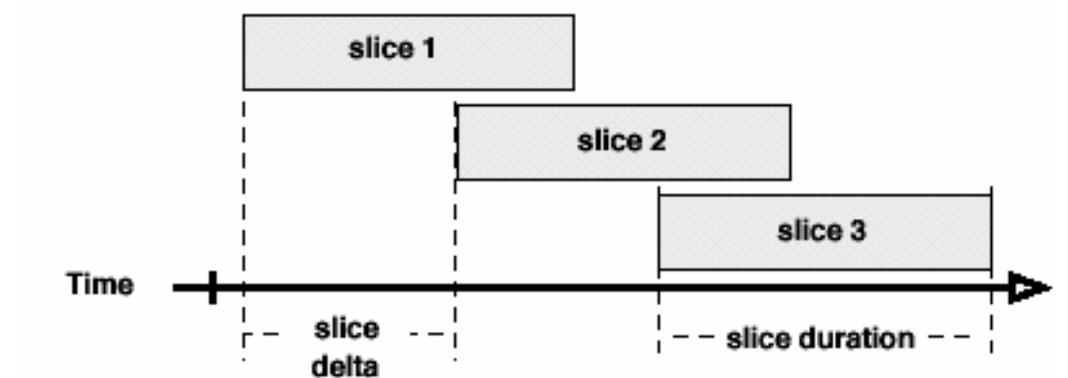
# Driving efficiency analysis using DEA

- DEA results **2-D illustration**
  - Urban
  - Rural
- DEA **inputs**
  - Number of harsh acceleration events
  - Number of harsh braking events
- DEA **outputs**
  - Trip distance



# Temporal evolution of efficiency

- **Aggregated** driving efficiency **benchmarking**
- Driving efficiency **benchmarking** in a **sliding window**
  - Driving behaviour changes
  - Time-series analysis
  - Time-series decomposition
    - Stationarity
    - Trend
    - Volatility
  - Road type



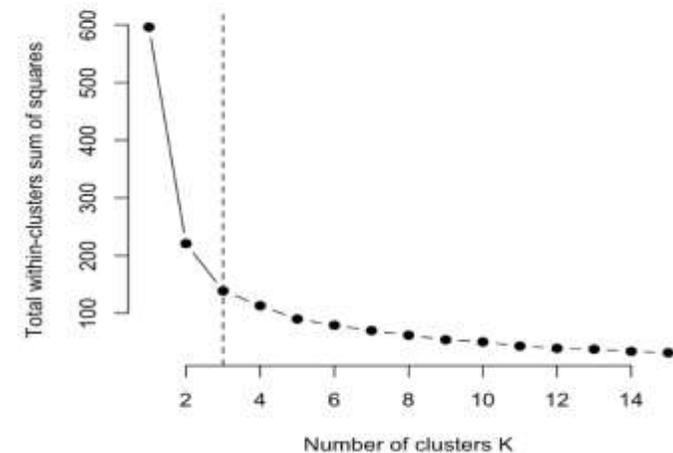
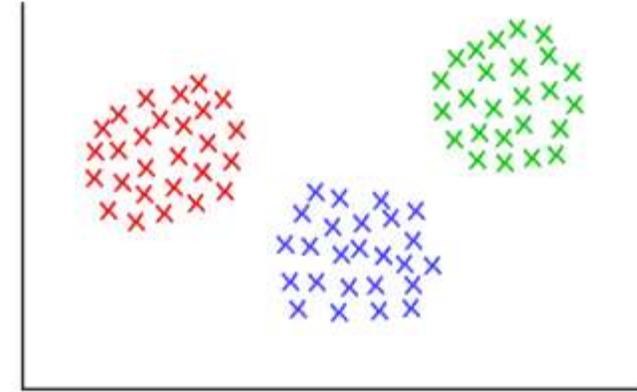
# Driver clustering

## - Clustering

- identify driving profile and their characteristics
- k-means algorithm
- elbow method

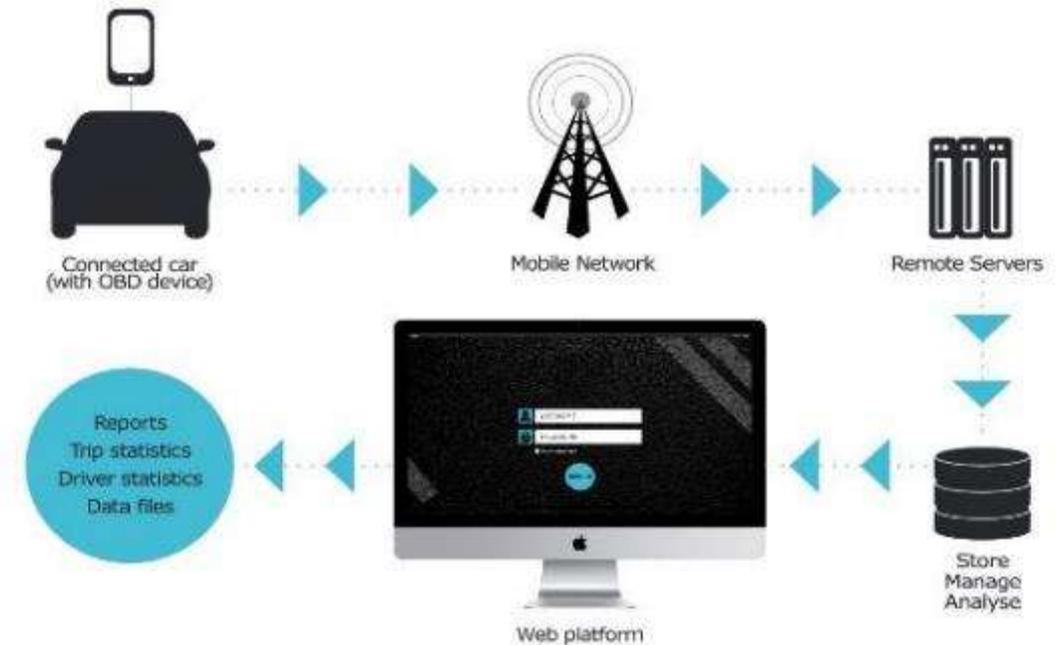
## - Clustering **attributes**

- total efficiency
- trend
- volatility
- with no accident history (data\_sample\_1)
- with accident history (data\_sample\_2)
- results comparison



# Smartphone data collection

- A mobile **application** to record user's driving behaviour (automatic start / stop)
- A variety of **APIs** is used to read mobile phone sensor data
- Data is **transmitted** from the mobile App to the central database
- Data are **stored** in a sophisticated database where they are managed and processed
- **Indicators** are designed using
  - machine learning algorithms
  - big data mining techniques



Source: OSeven Telematics

# Questionnaire data

- **Driving experience**
  - Years of driving experience
  - Mileage
- **Vehicle**
  - Age of the vehicle
  - Engine capacity
  - Ownership
  - Fuel consumption
- **Driving behaviour**
  - Accident history
  - Self-assessment
- **Demographics**
  - Age
  - Gender
  - Education



# Data preparation

- Data are **anonymized**
  - user-agnostic approach
  - identify driving behaviors and patterns
  - causality between behaviour and other factors
  - large-scale samples
  - no information on demographics or accident record
- **Python** programming language
  - filter aggregate data
  - retain only necessary information
  - aggregate data
  - data analysis



# Data sample

	Sampling time investigation	Trip efficiency analysis	Driver efficiency analysis			
			data_sample_1		data_sample_2	
			Urban	Rural	Urban	Rural
Number of drivers	171	88	100	100	43	39
Number of trips	49,722	10,088	23,000	15,000	9,890	5,850

# Data sample - Driver analysis

## - Criteria

- At least 50 more trips
  - than the minimum number required
  - to create the time series
- Positive mileage on both road types
- Positive sum of input attributes (HA, HB etc.)
- Maximum number of drivers

## - Urban

- 100 drivers & 23,000 trips – w/o questionnaire data
- 43 drivers & 9890 trips – w questionnaire data

## - Rural

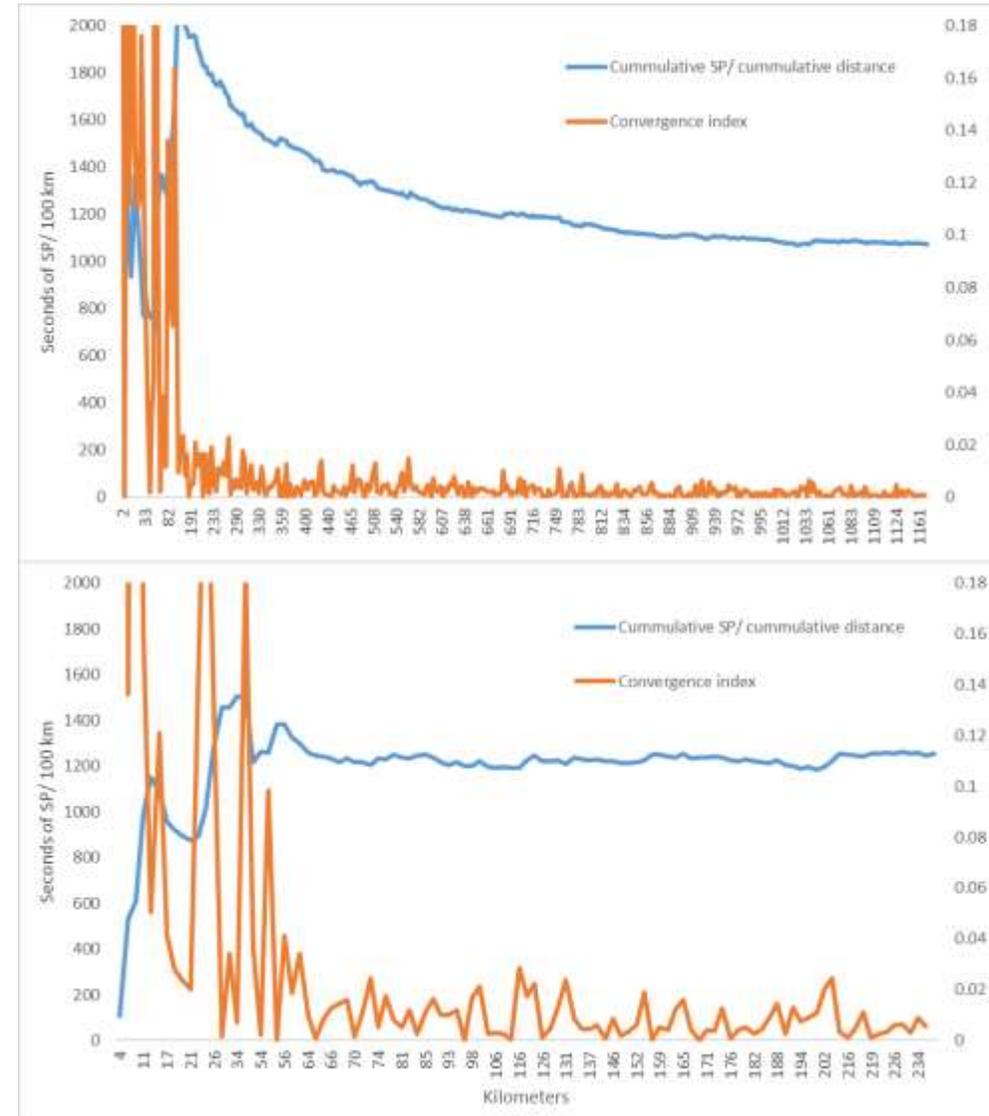
- 100 drivers & 15,000 trips – w/o questionnaire data
- 43 drivers & 5850 trips – w questionnaire data



# Data investigation (1/7)

## - Convergence index

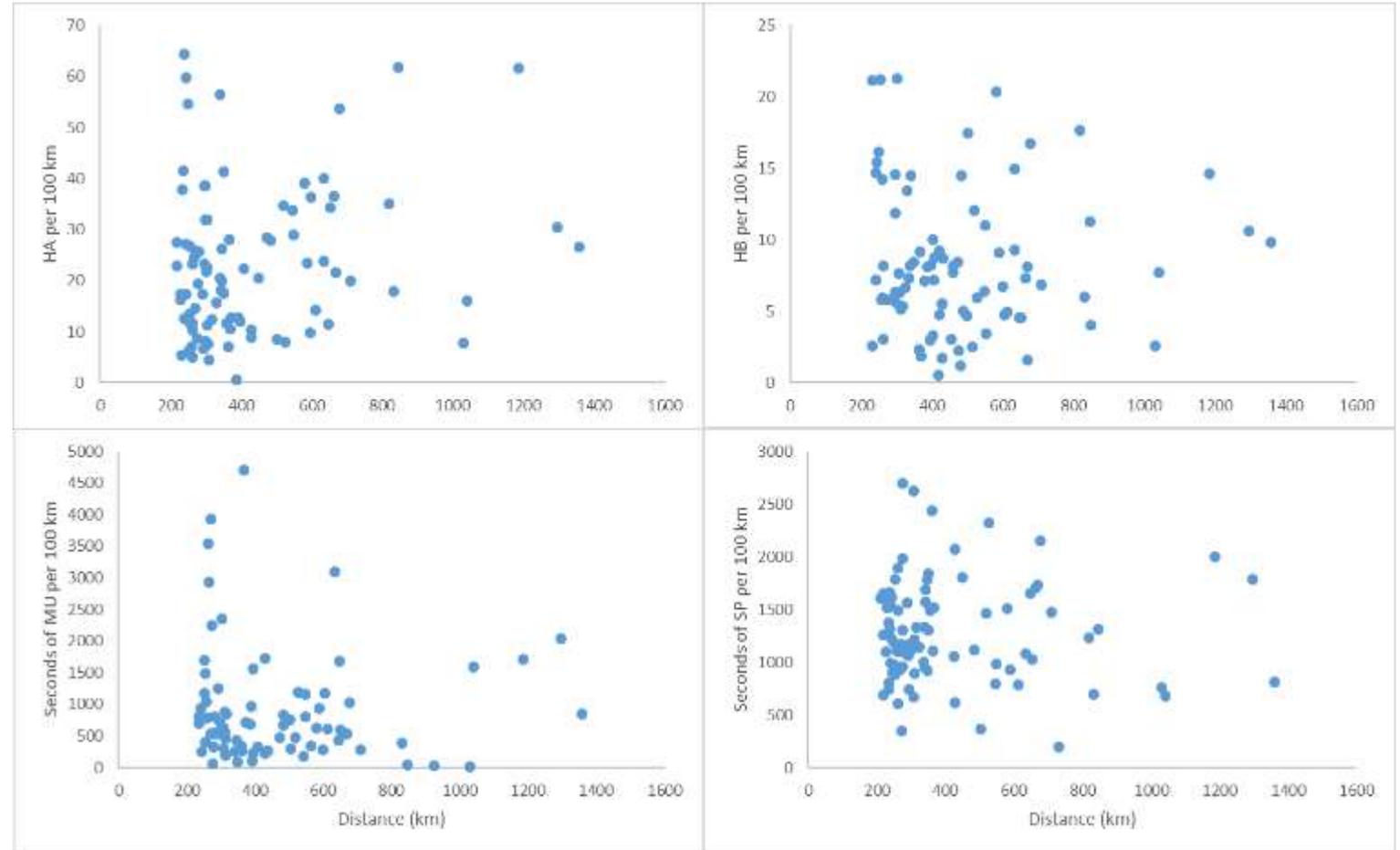
- Moving window of 40 trips
- at least 200 km
- $\leq 5\%$



# Data investigation (2/7)

## Urban RN

- Weak **positive correlation** between HA and required distance for convergence
- Required monitoring distance is **higher** for **more** aggressive drivers
- **No** apparent **trend** for the rest of the metrics



# Data investigation (3/7)

## Urban RN

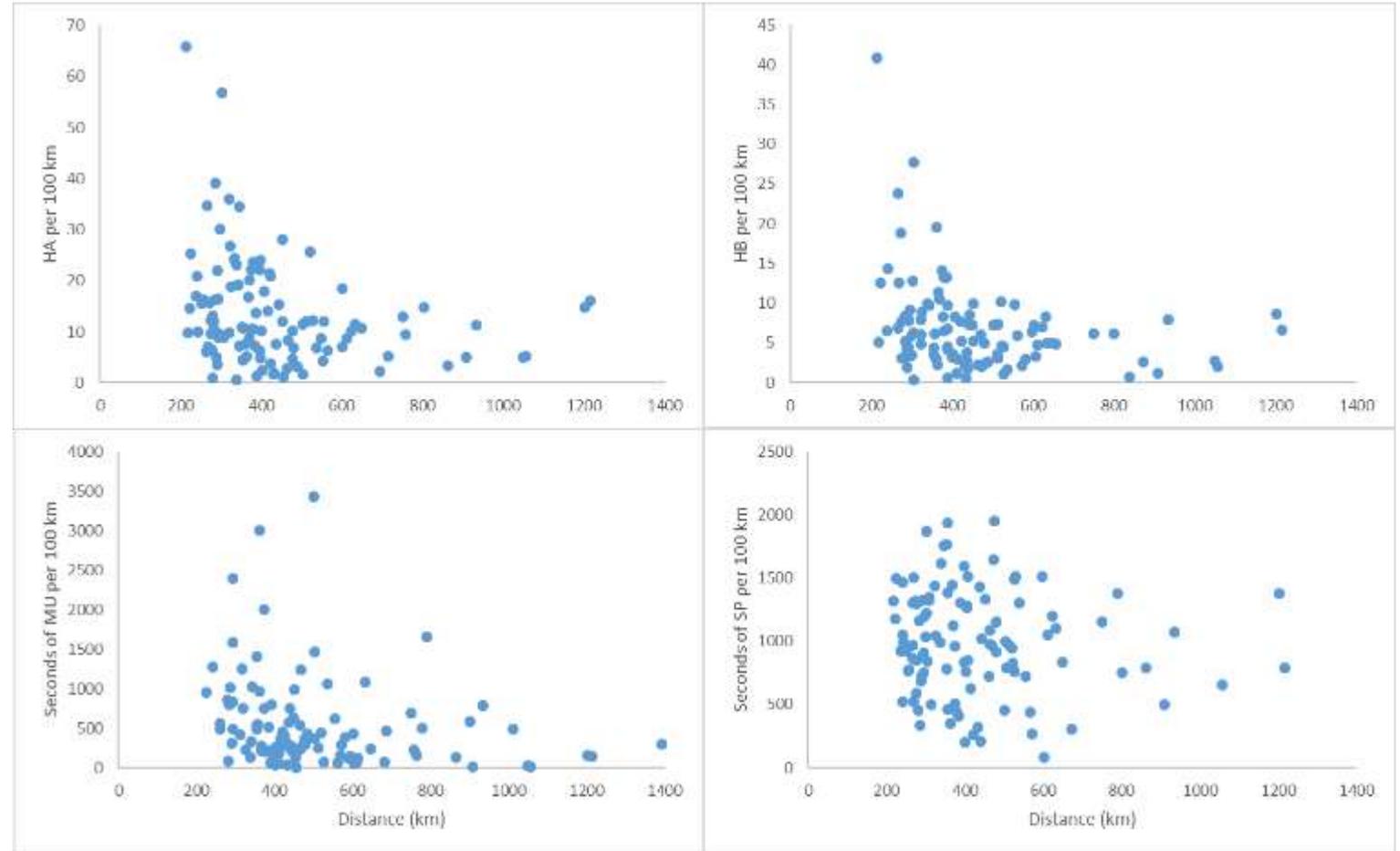
- **Same** sampling **periods** are required for drivers of different percentile value range
- **Maximum** median **distance** value
  - all metrics should have converged to their cumulative average
    - the driving sample acquired is adequate
    - the input/ output ratio is relatively constant to perform DEA analysis
- **519** km
  - 75 trips

Metric	Percentile range	Metric descriptive statistics				Distance to convergence		
		Average	St. Dev	Min	Max	Average	Median	St. Dev
HA	0% – 25%	8.18	2.61	-	11.61	389	309	177
	25% – 50%	15.92	2.8	11.61	20.54	399	336	208
	50% – 75%	25.01	2.48	20.54	30.14	415	322	246
	75% – 100%	43.23	10.92	30.14	-	526	519	293
HB	0% – 25%	3.05	1.26	-	4.95	515	478	179
	25% – 50%	6.17	0.69	4.95	7.32	408	335	155
	50% – 75%	8.6	0.83	7.32	10.61	558	431	300
	75% – 100%	15.65	3.12	10.61	-	469	341	248
MU	0% – 25%	204	101	-	332	559	407	395
	25% – 50%	495	78	332	606	440	347	174
	50% – 75%	799	111	606	1041	443	381	247
	75% – 100%	2063	994	1041	-	493	366	310
SP	0% – 25%	727	194	-	947	489	339	308
	25% – 50%	1081	67	947	1198	343	293	123
	50% – 75%	1402	119	1198	1594	378	312	188
	75% – 100%	1919	318	1594	-	455	348	287

# Data investigation (4/7)

## Urban express RN

- Weak **negative correlation** between HA, HB, mobile usage and the required distance for convergence
- Required monitoring distance is **higher** for **less** aggressive/ risky/ distracted drivers
- **No** apparent **trend** for speeding



# Data investigation (5/7)

## Urban express RN

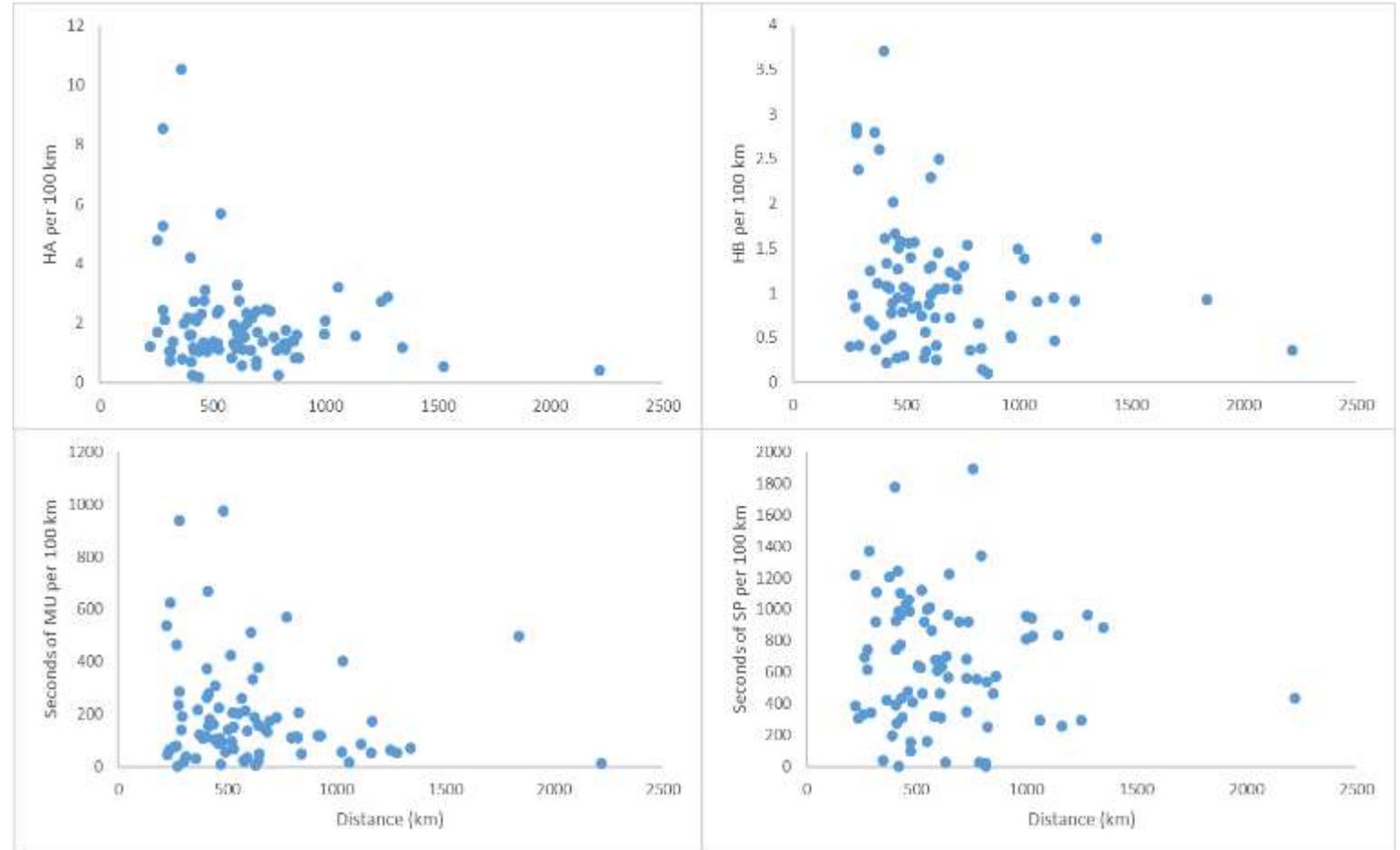
- **Different** sampling **periods** are required for drivers of different percentile value range
  - less volatile than in urban road
- **Maximum** median **distance** value
- **579** km
  - 81 trips

Metric	Percentile range	Metric descriptive statistics				Distance to convergence		
		Average	St. Dev	Min	Max	Average	Median	St. Dev
HA	0% – 25%	3.69	1.7	-	6.42	507	431	219
	25% – 50%	8.8	1.33	6.42	10.79	405	376	134
	50% – 75%	13.58	1.98	10.79	17.02	499	417	270
	75% – 100%	27.27	11.04	17.02	-	349	336	85
HB	0% – 25%	2.05	0.84	-	3.15	52	439	221
	25% – 50%	4.35	0.67	3.15	5.6	429	403	126
	50% – 75%	6.92	0.69	5.6	8.28	489	440	221
	75% – 100%	13.54	7.16	8.28	-	389	360	187
MU	0% – 25%	85	48	-	157	630	579	261
	25% – 50%	263	50	157	371	485	442	209
	50% – 75%	511	92	371	747	501	448	192
	75% – 100%	1334	684	747	-	411	362	166
SP	0% – 25%	454	170	-	745	448	399	189
	25% – 50%	851	74	745	970	444	397	221
	50% – 75%	1142	112	970	1315	419	388	172
	75% – 100%	1526	181	1315	-	425	356	195

# Data investigation (6/7)

## Highway

- Weak **negative correlation** between HA, HB, mobile usage and the required distance for convergence
- Required monitoring distance is **higher** for **less** aggressive/ risky/ distracted drivers
- **No** apparent **trend** for speeding



# Data investigation (7/7)

## Highway

- **Different** sampling **periods** are required for drivers of different percentile value range
- **Maximum** median **distance** value
- **611** km
  - is not investigated

Metric	Percentile range	Metric descriptive statistics				Distance to convergence		
		Average	St. Dev	Min	Max	Average	Median	St. Dev
HA	0% – 25%	0.74	0.29	-	1.1	678	585	440
	25% – 50%	1.26	0.12	1.1	1.54	639	605	234
	50% – 75%	1.87	0.24	1.54	2.3	607	611	242
	75% – 100%	3.77	2.12	2.3	-	593	529	289
HB	0% – 25%	0.36	0.12	-	0.56	705	592	413
	25% – 50%	0.83	0.1	0.56	0.97	700	562	376
	50% – 75%	1.15	0.13	0.97	1.38	572	606	174
	75% – 100%	2.05	0.64	1.38	-	542	472	251
MU	0% – 25%	35	20	-	66	722	592	468
	25% – 50%	101	18	66	135	623	498	285
	50% – 75%	174	26	135	223	564	540	196
	75% – 100%	455	206	223	-	533	445	349
SP	0% – 25%	193	124	-	346	610	550	285
	25% – 50%	505	91	346	641	649	592	392
	50% – 75%	807	100	641	950	666	601	295
	75% – 100%	1168	249	950	-	544	464	241

# Trip efficiency analysis (1/3)

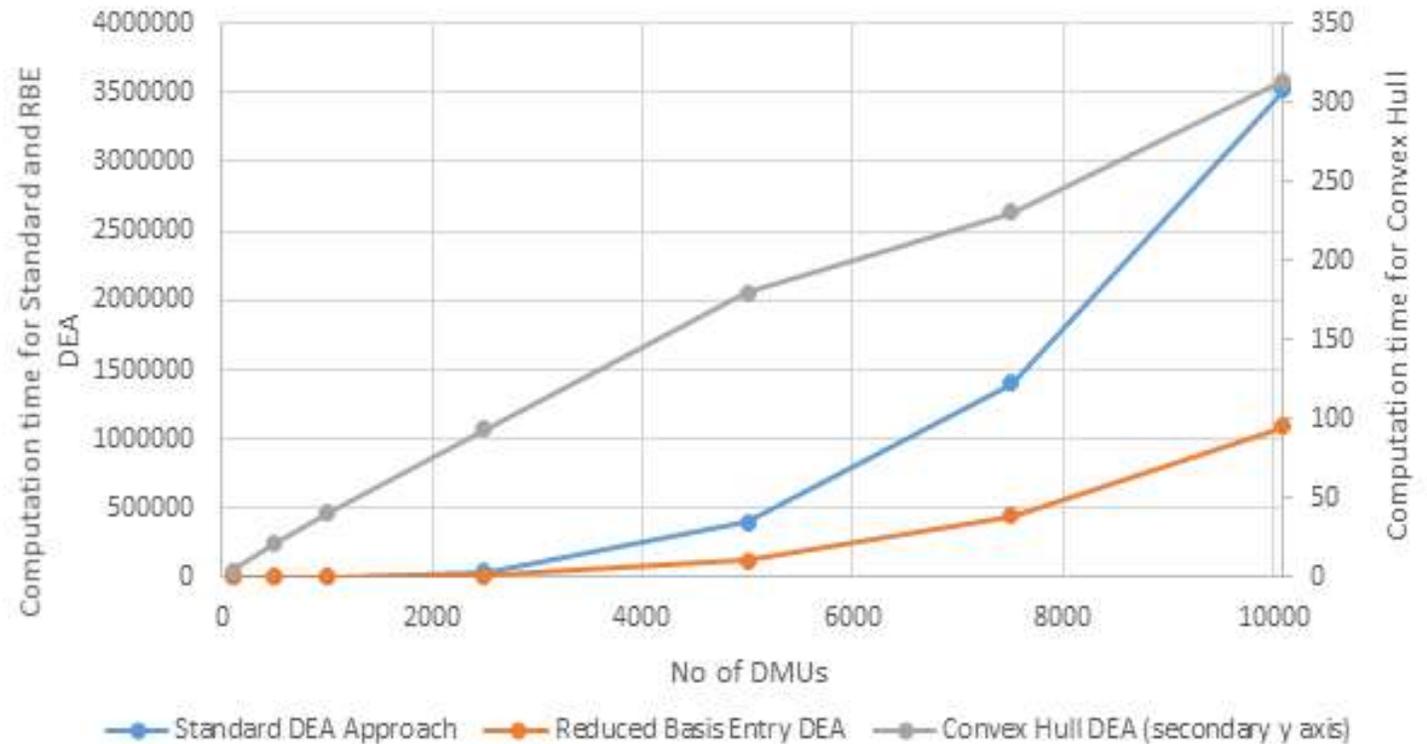
- **Convex Hull** technique outperforms
- Significant **time reduction**
  - As the database becomes larger
  - Convex Hull DEA – 5 minutes
  - RBE DEA – 12.6 days
  - Standard DEA – 40.7 days

No of DMUs	Computation time (sec)			CH DEA % computation time improvement over		RBE DEA % computation time improvement over Standard DEA
	Standard DEA Approach	RBE DEA	Convex Hull DEA	Standard DEA Approach	RBE DEA	
100	11	6	4	63.64%	33.33%	45.45%
500	477	169	21	95.60%	87.57%	64.57%
1000	3250	1121	41	98.74%	96.34%	65.51%
2500	44435	15570	94	99.79%	99.40%	64.96%
5000	398485	123986	180	99.95%	99.85%	68.89%
7500	1400909	444498	231	99.98%	99.95%	68.27%
10088	3519372	1089731	314	99.99%	99.97%	69.04%

\* Inputs = [ha<sub>urban</sub>, ha<sub>rural</sub>, ha<sub>highway</sub>], Outputs = [distance<sub>urban</sub>, distance<sub>rural</sub>, distance<sub>highway</sub>]

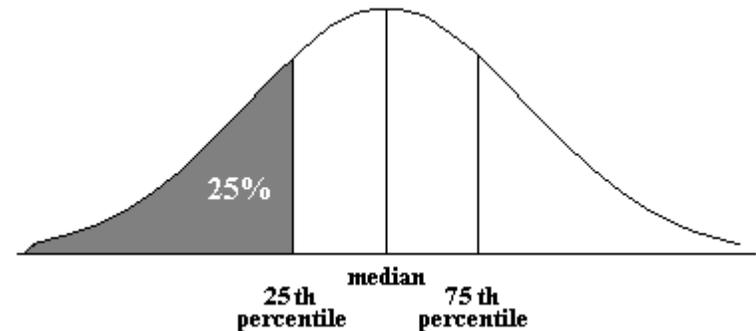
# Trip efficiency analysis (2/3)

- Convex Hull DEA
  - linearly increased
- Standard and RBE DEA
  - Exponentially increased



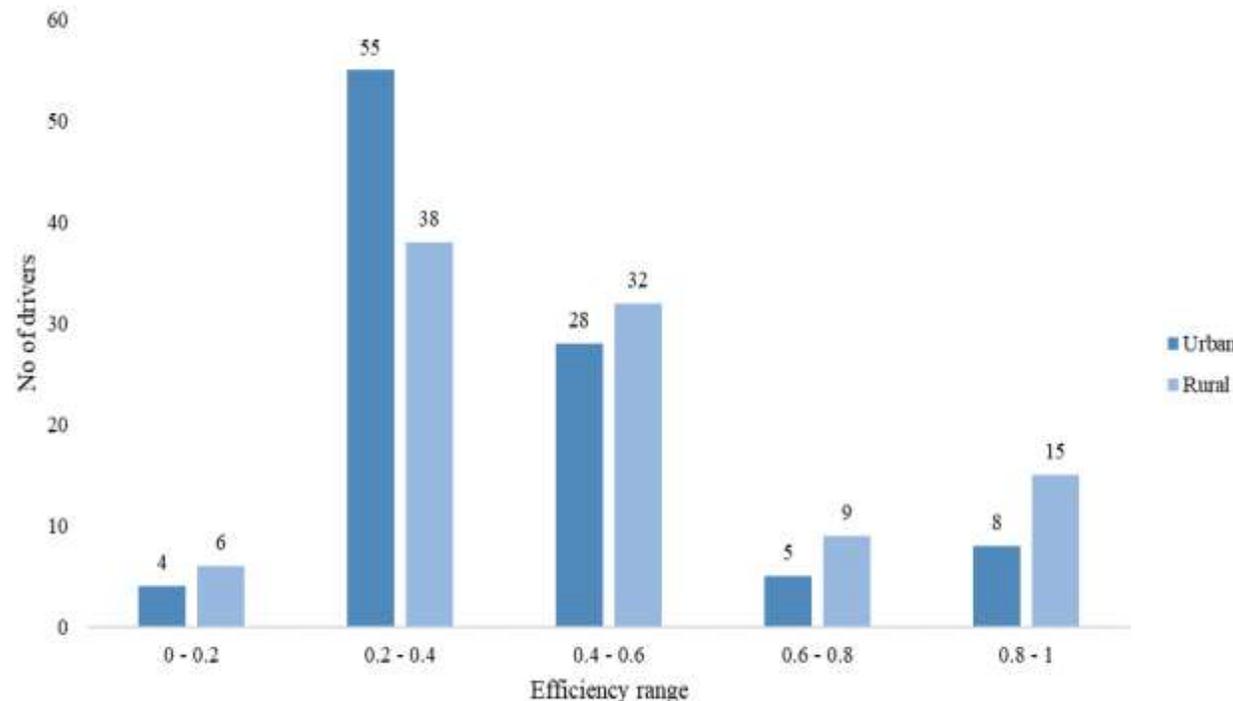
# Trip efficiency analysis (3/3)

- **Least efficient** trips
- **Efficiency** estimation
- **Sort**
  - larger to smaller
- **Percentile**
  - 5%, 10%, 25% etc.



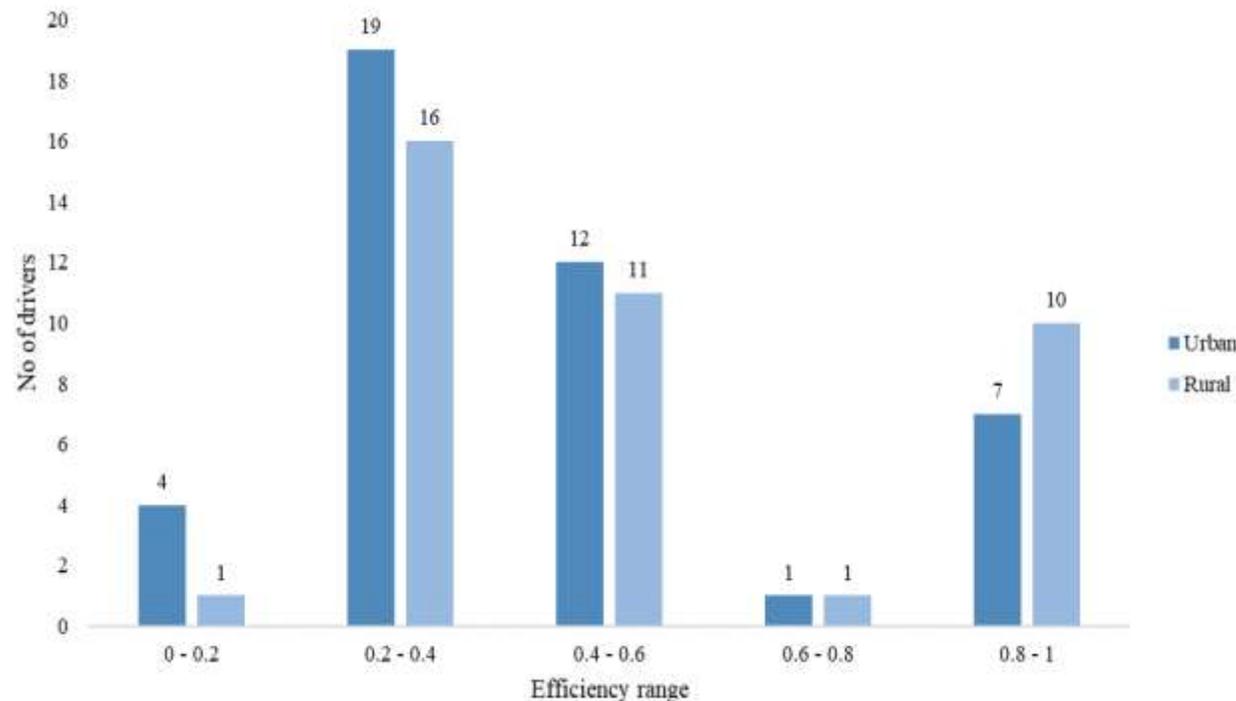
# Driver efficiency analysis - Aggregated efficiency (1/13)

- data\_sample\_1
- **Similar distribution** in both road types
- Drivers gathered in **low-medium** efficiency ranges
  - DEA provides a relative index



# Driver efficiency analysis - Aggregated efficiency (2/13)

- data\_sample\_2
- **Similar distribution** in both road types
- Drivers gathered in **low-medium** efficiency ranges
  - DEA provides a relative index



# Driver efficiency analysis - Aggregated efficiency (3/13)

- **Aggregated** driving behaviour
  - Percentiles of driving efficiency
  - Three efficiency classes
    - 1: Non-efficient drivers
    - 2: Weakly efficient drivers
    - 3: Efficient drivers
  - Median driving characteristics
- **Urban RN**
  - class 1 -> class 2
    - number of harsh acceleration/ braking events
  - class 2 -> class 3
    - time of speeding
- **Urban express RN**
  - class 1 -> class 2
    - time of speeding
  - class 2 -> class 3
    - number of harsh acceleration events
    - time of mobile usage

Sample type	Road type	No of drivers	Driving characteristics (/100km)	Efficiency classes		
				Class 1: 0 - 25 % percentile	Class 2: 25 - 75 % percentile	Class 3: 75 - 100 % percentile
data_sample_1	Urban	100	efficiency	0.22	0.36	0.61
			ha	21.49	11.82	8.82
			hb	9.64	5.31	3.68
			mu (sec)	316	205	141
	Rural	100	efficiency	0.24	0.42	0.90
			ha	34.11	24.06	11.30
			hb	14.92	9.16	5.42
			mu (sec)	529	419	165
data_sample_2	Urban	43	efficiency	0.21	0.38	1.00
			ha	39.26	21.71	9.98
			hb	16.38	8.07	4.19
			mu (sec)	751	553	100
	Rural	39	efficiency	0.28	0.44	1.00
			ha	23.04	11.86	7.49
			hb	9.28	5.21	3.16
			mu (sec)	316	305	160
			sp (sec)	1423	939	378

# Driver efficiency analysis - Aggregated efficiency (4/13)

## - Mobile usage

- Slight differences between classes 1 and 2
  - approximately the same usage for drivers of all classes
  - DEA sensitivity to outliers

- **Higher number** of harsh events in express Urban roads than in Urban roads

- Number of HA events = 2 \* Number of HB events

Sample type	Road type	No of drivers	Driving characteristics (/100km)	Efficiency classes		
				Class 1: 0 - 25 % percentile	Class 2: 25 - 75 % percentile	Class 3: 75 - 100 % percentile
data_sample_1	Urban	100	efficiency	0.22	0.36	0.61
			ha	21.49	11.82	8.82
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			mu (sec)	316	205	141
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data_sample_2	Urban	43	efficiency	0.21	0.38	1.00
			ha	39.26	21.71	9.98
			hb	16.38	8.07	4.19
			mu (sec)	751	553	100
	Rural	39	sp (sec)	1892	965	477
			efficiency	0.28	0.44	1.00
			ha	23.04	11.86	7.49
			hb	9.28	5.21	3.16
			mu (sec)	316	305	160
			sp (sec)	1423	939	378

# Driver efficiency analysis - Efficient level (5/13)

Driver No	Real level of metrics						Lamdass of peers: Driver No				Efficient level of metrics				
	distance <sub>urban</sub>	ha <sub>urban</sub>	hb <sub>urban</sub>	speeding <sub>urban</sub>	mobile <sub>urban</sub>	Theta	12	34	40	42	distance <sub>urban</sub>	ha <sub>urban</sub>	hb <sub>urban</sub>	speeding <sub>urban</sub>	mobile <sub>urban</sub>
1	1868	326	134	21712	9954	0.581	-	0.52	0.14	0.06	3214.3	159.8	77.9	12617.9	5784.7
2	2456	574	85	27049	13974	0.696	-	0.19	0.40	0.20	3526.5	154.8	59.2	18838.2	9732.1
3	1634	709	509	15888	42817	0.391	0.79	-	0.20	-	4182.6	277.0	78.1	6206.9	10434.2
4	2219	233	181	27052	12421	0.637	-	0.23	0.31	0.18	3481.0	148.5	59.1	17244.6	7917.9
5	4223	1088	309	37825	29581	0.613	0.30	1.16	0.47	-	6887.3	417.6	189.5	23192.7	18137.9
6	2773	652	251	25829	25887	0.529	0.60	0.51	0.30	-	5245.3	344.7	128.8	13654.8	13685.4
7	2086	265	149	20880	14036	0.619	-	0.52	0.28	0.04	3371.9	163.9	79.2	12917.2	8683.2
8	1789	460	323	17185	5960	0.656	-	0.75	-	0.01	2728.0	184.3	98.1	11269.8	3908.5
9	1630	184	82	30801	8955	0.528	-	-	0.21	0.22	3085.0	97.2	30.8	14784.6	4731.5
10	808	266	95	9985	6562	0.443	0.11	0.24	0.04	-	1824.6	97.2	42.1	4421.6	2905.8
11	3012	913	152	21604	43562	0.585	0.72	-	0.83	-	5149.6	308.3	88.9	12636.1	23107.5
12	1462	329	92	5074	7781	1.000	1.00	-	-	-	1462.0	329.0	92.0	5074.0	7781.0

\* Inputs = ['ha<sub>urban</sub>', 'hb<sub>urban</sub>', 'speeding<sub>urban</sub>', 'mobile<sub>urban</sub>'], Output = ['distance<sub>urban</sub>']

# Driver efficiency analysis - Temporal evolution (6/13)

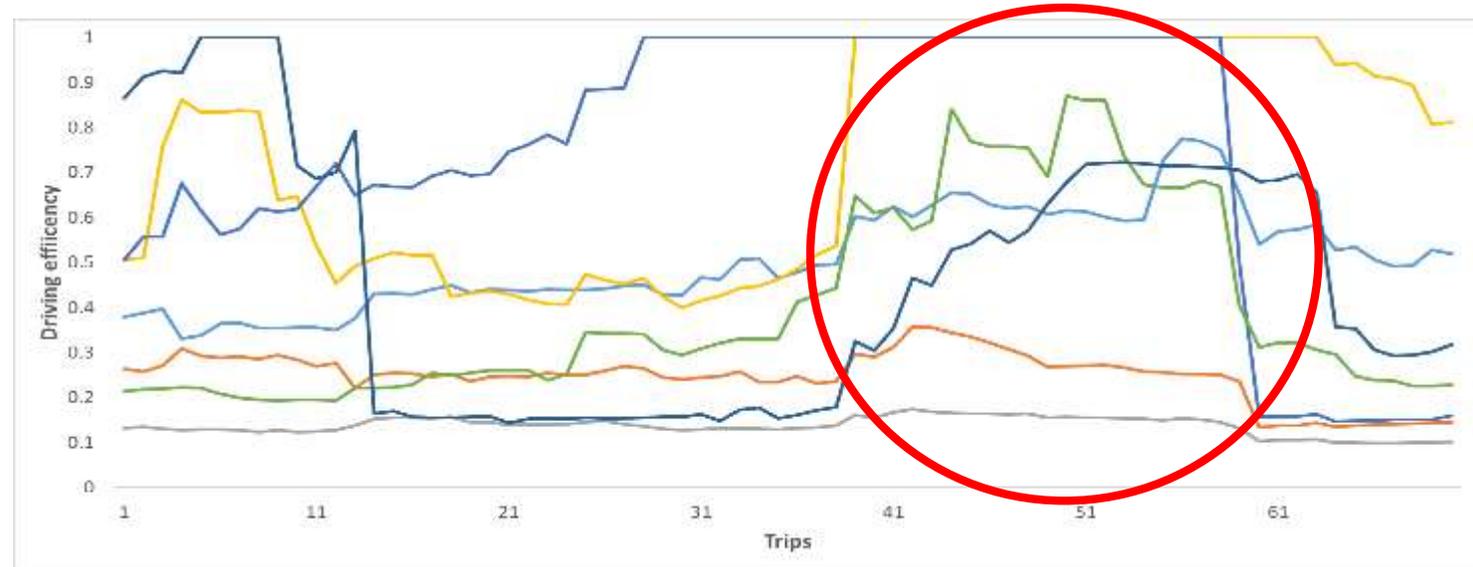
## - Temporal evolution

- time window
  - Urban: 75
  - Express Urban: 81

- **Less efficient** drivers are less volatile

- Common local **minimum** and **maximum** points

- outlier existence
- efficiency is benchmarked



# Driver efficiency analysis - Temporal evolution (7/13)

## - Time-series

## - Stationarity

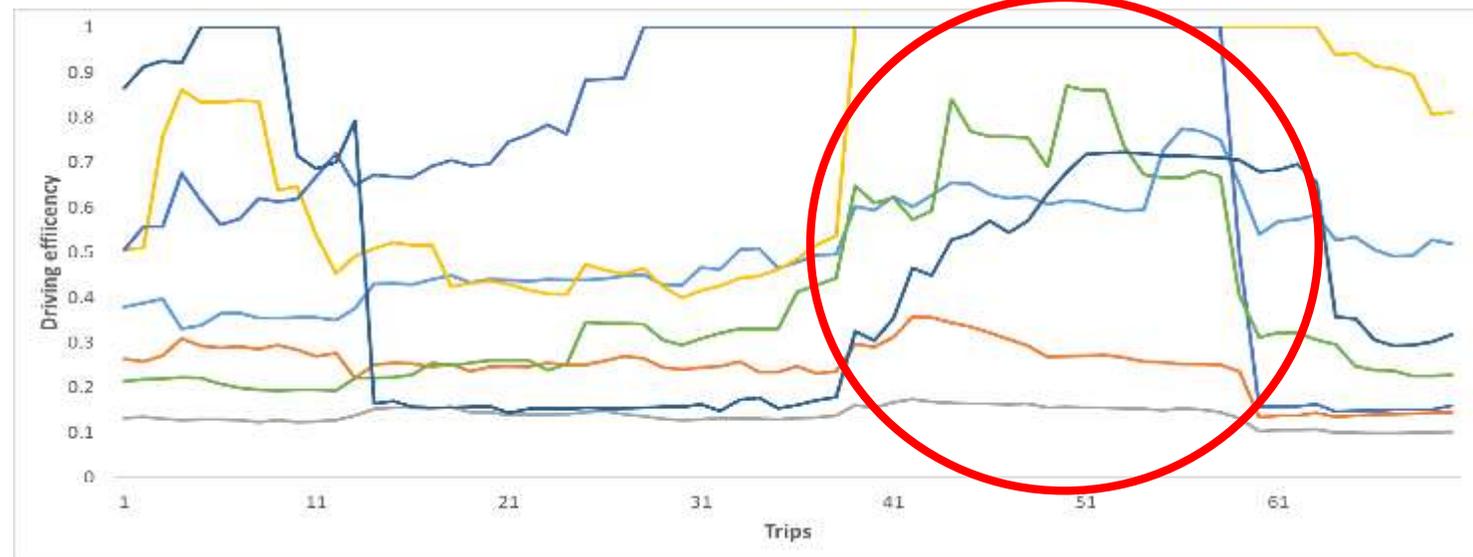
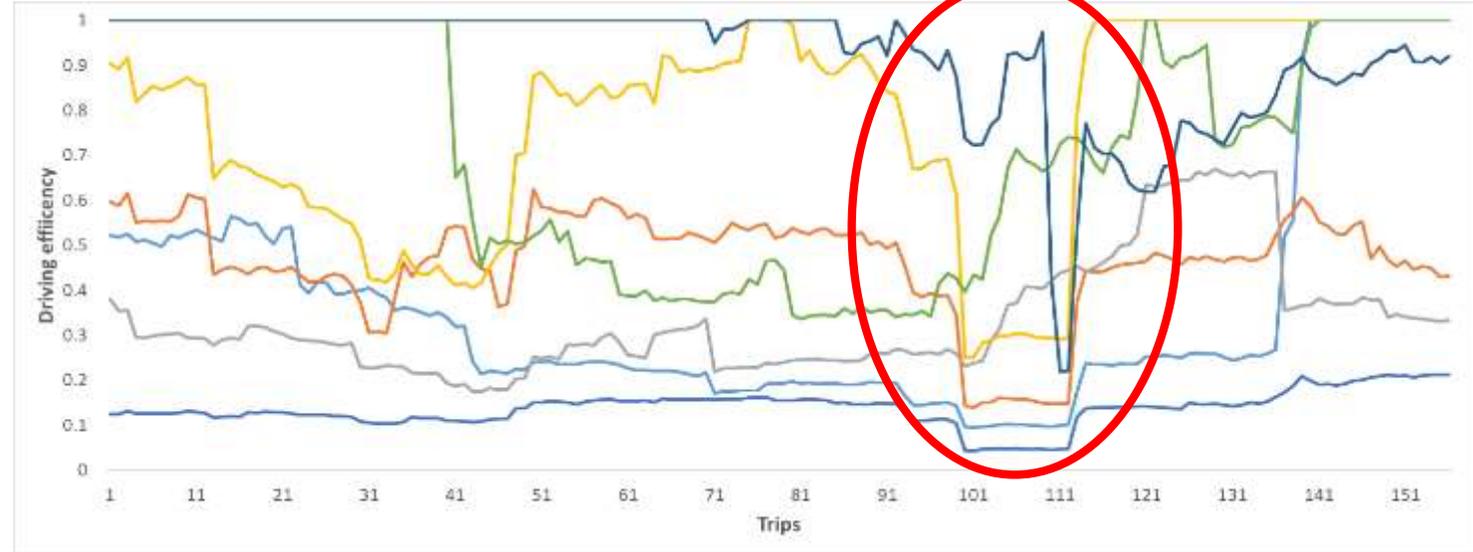
- no stationary urban road users
- insignificant number of rural road users

## - Trend

- average approximately the same in both road types
- higher range in rural road type

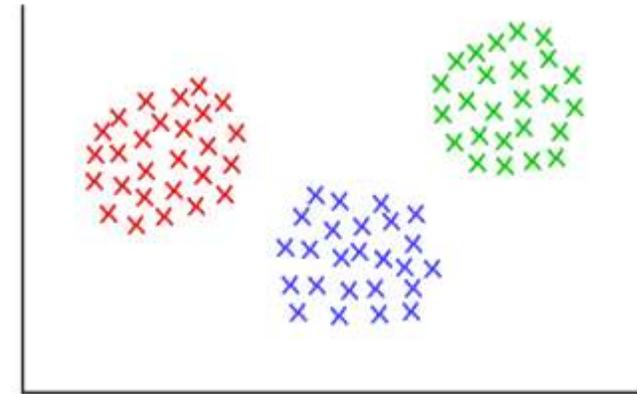
## - Volatility

- average approximately the same in both road types
- higher range in rural road type



# Driver efficiency analysis - Clustering (8/13)

- **Three clusters** for both samples
  - cluster 1: typical driver
  - cluster 2: unstable driver
  - cluster 3: cautious driver



# Driver efficiency analysis - Clustering (9/13)

## - **Typical** drivers:

- high number of drivers
- low total efficiency
- very low positive trend
- medium to high volatility
- low accident frequency

Sample type	Road type	Cluster	Trend (*10 <sup>-3</sup> )	Volatility	Efficiency	Accidents/ 10 years of driving experience
data_sample_1	Urban	1 (typical)	very low positive	medium - high	low	low - medium
		2 (unstable)	medium positive	medium - high	medium	low
		3 (cautious)	medium negative	low - medium	medium - high	low
	Rural	1 (typical)	low positive	medium	low	low - medium
		2 (unstable)	high negative	high	medium - high	medium - high
		3 (cautious)	high positive	medium - high	high	low
data_sample_2	Urban	1 (typical)	very low positive	medium	low	low
		2 (unstable)	low - medium positive	medium	low	high
		3 (cautious)	medium negative	low	high	low
	Rural	1 (typical)	barely no trend	medium - high	low	low
		2 (unstable)	low negative	medium	low	high
		3 (cautious)	high positive	medium - high	high	low

# Driver efficiency analysis - Clustering (10/13)

## - **Unstable** drivers:

### - efficiency

- medium to high total for data\_sample\_1
- low total for data\_sample\_2

### - trend

- medium positive for data\_sample\_1
- medium negative for data\_sample\_2

### - medium to high volatility

- high for data\_sample\_1
- medium for data\_sample\_2

### - medium to high accident frequency

Sample type	Road type	Cluster	Trend (*10 <sup>-3</sup> )	Volatility	Efficiency	Accidents/ 10 years of driving experience
data_sample_1	Urban	1 (typical)	very low positive	medium - high	low	low - medium
		2 (unstable)	medium positive	medium - high	medium	low
		3 (cautious)	medium negative	low - medium	medium - high	low
	Rural	1 (typical)	low positive	medium	low	low - medium
		2 (unstable)	high negative	high	medium - high	medium - high
		3 (cautious)	high positive	medium - high	high	low
data_sample_2	Urban	1 (typical)	very low positive	medium	low	low
		2 (unstable)	low - medium positive	medium	low	high
		3 (cautious)	medium negative	low	high	low
	Rural	1 (typical)	barely no trend	medium - high	low	low
		2 (unstable)	low negative	medium	low	high
		3 (cautious)	high positive	medium - high	high	low

# Driver efficiency analysis - Clustering (11/13)

## - **Cautious** drivers:

- high total efficiency
- trend
  - medium negative for urban road
  - high positive for express urban road
- medium volatility
  - low to medium for urban road
  - medium to high for express urban road
- low accident frequency

Sample type	Road type	Cluster	Trend (*10 <sup>-3</sup> )	Volatility	Efficiency	Accidents/ 10 years of driving experience
data_sample_1	Urban	1 (typical)	very low positive	medium - high	low	low - medium
		2 (unstable)	medium positive	medium - high	medium	low
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data_sample_2	Urban	1 (typical)	very low positive	medium	low	low
		2 (unstable)	low - medium positive	medium	low	high
		3 (cautious)	medium negative	low	high	low
	Rural	1 (typical)	barely no trend	medium - high	low	low
		2 (unstable)	low negative	medium	low	high
		3 (cautious)	high positive	medium - high	high	low

# Driver efficiency analysis - Clustering (12/13)

- Attributes' values are **reducing** while shifting to a class of **higher efficiency**
- **Typical** drivers
  - metrics' values in urban roads are twice as in express urban roads
- **Cautious** drivers
  - significantly lower level of driving characteristics for all metrics

Sample type	Road type	No of drivers	Driving characteristics	Cluster 1 (typical)	Cluster 2 (unstable)	Cluster 3 (cautious)
data_sample_1	Urban	100	efficiency	0.33	0.61	0.81
			ha	26.75	17.20	6.89
			hb	10.05	7.30	3.44
			mu	499	165	60
			sp	1095	619	1240
	Rural	100	efficiency	0.36	0.69	0.88
			ha	14.97	6.36	9.65
			hb	7.59	3.09	3.61
			mu	234	285	86
			sp	988	923	347
data_sample_2	Urban	43	efficiency	0.37	0.33	1.00
			ha	22.05	41.26	14.13
			hb	8.10	15.39	5.28
			mu	653	481	82
			sp	1349	1140	436
	Rural	39	efficiency	0.37	0.39	1.00
			ha	12.35	19.24	5.74
			hb	6.66	6.84	2.46
			mu	316	380	149
			sp	1125	1149	415

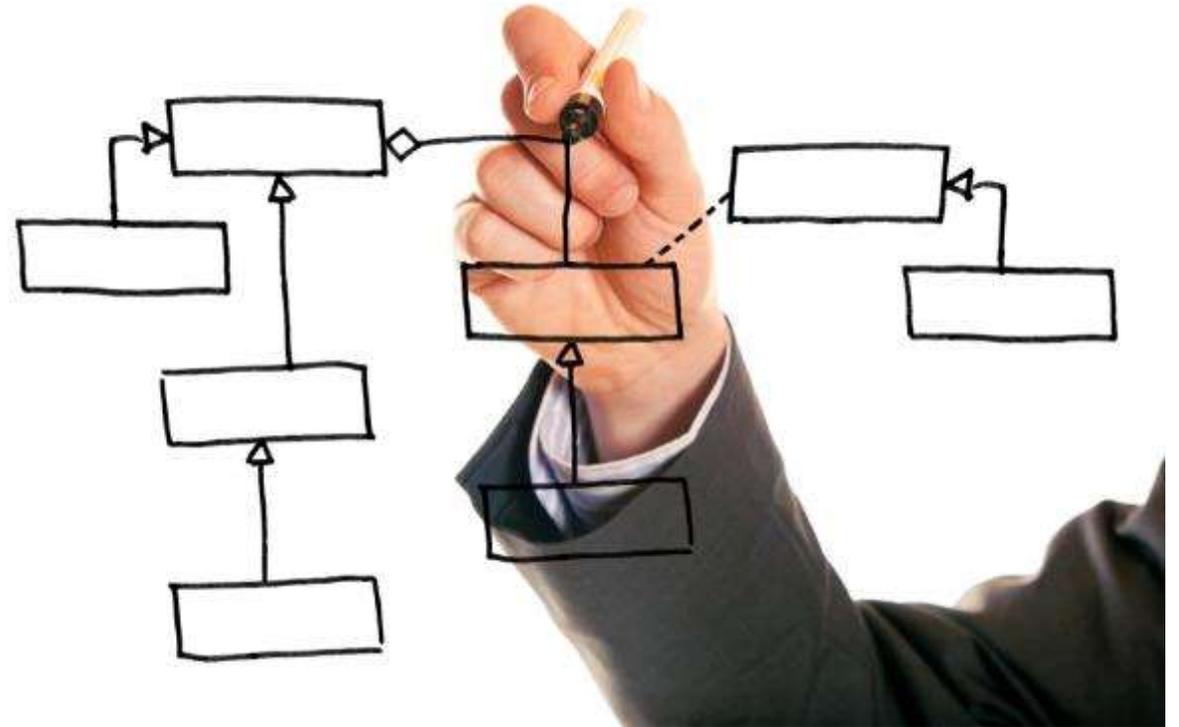
# Driver efficiency analysis - Clustering (13/13)

- **Unstable** drivers of data\_sample\_2
  - high number of accidents
  - low driving efficiency
  - highest number of harsh acceleration and braking events
  - highest mobile use and speeding in express urban road
- **Non-steady** drivers with **poor** driving behaviour => most **risky** drivers

Sample type	Road type	No of drivers	Driving characteristics	Cluster 1 (typical)	Cluster 2 (unstable)	Cluster 3 (cautious)
data_sample_1	Urban	100	efficiency	0.33	0.61	0.81
			ha	26.75	17.20	6.89
			hb	10.05	7.30	3.44
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			sp	1125	1149	415

# Conclusions (1/5)

- **Innovative methodological approach** for driving efficiency benchmarking as well as for estimating the efficient level of metrics of each driver.
- The **integration** of DEA with the **convex hull** algorithmic approach yielded significantly better results than the rest of the approaches tested



# Conclusions (2/5)

- The required **sampling** mileage is identified and is different for each:
  - road type
  - driving metric
  - driving aggressiveness/ risk/ distraction level
- **Not a single critical metric** to determine the required driving data amount
- **More** aggressive/ risky drivers need **less** monitoring in express urban road and highways



# Conclusions (3/5)

- **Insignificant difference** in mobile usage between drivers of medium and low efficiency classes
- The number of harsh **acceleration** events is **twice** as much as the number of harsh **braking** events
- The **shift** between efficiency classes is mainly affected by **different** driving **metrics** in urban and express urban road types



# Conclusions (4/5)

- Average **volatility** is approximately the **same** in both road types
- Average **trend** is approximately the **same** between the two road types
- **Stationarity** is similar for all drivers and road types



# Conclusions (5/5)

- There are **three** drivers' **clusters** the: a) typical, b) unstable and c) cautious drivers
- Drivers should be **continuously monitored** and re-evaluated to capture temporal shifts
- Prior **information** on driving **accident** data affects only the form of the most **unstable** drivers



# Contributions

- Develops a **methodological framework** for driving safety efficiency evaluation on trip and driver basis based on data science techniques
- **Quantifies** the **driving data** that should be collected when evaluating driving behaviour in terms of safety
- Provides insights on the main **driving** behaviour **profiles** that exist and their characteristics
- Makes use of an **innovative** smartphone **data collection** system



# Impact

- Personal and general **feedback** to drivers on
  - their overall driving efficiency and its evolution
  - an inefficient trip is performed
  - driving characteristics that should be improved
  - each road type
- **Reduce** individual driving **risk**
- Develop **insurance** pricing schemes
  - charge premiums based on driving efficiency



# Future challenges (1/2)

- Exploit a **larger** driving **sample**
  - highway road type investigation
  - safety efficiency estimation is more representative
  - DEA is less sensitive to outliers
  - metrics to distance ratio evolution
  - relationship between the aggressiveness of a driver and the necessary monitoring distance
  - known accident data record
  - investigate more on the computation time optimization
- Type of **approach**
  - macroscopic
    - shifts of drivers over long time periods
  - microscopic
    - study the spatiotemporal driving characteristics of each trip
  - combination
- **Prediction** of drivers' overall efficiency or cluster
  - provide recommendation on the level of metrics that should be reached



# Future challenges (2/2)

- **DEA limitations** – zero sum input attributes
- **Increase** the number of **attributes**
  - headways
  - lane changing
  - eye movement
  - drowsiness
- **Data recording** through
  - cameras
  - eye-tracking devices
  - radars
  - LiDARs
  - on-board-diagnostic devices (OBD)
- Study **dynamic evolution** of driving efficiency to quantify
  - how rapidly driving profiles change
  - how much driving profiles change



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*Thank  
you*



# Benchmarking Driving Efficiency using Data Science Techniques applied on Large-Scale Smartphone Data



## Dimitris Tselentis

Civil - Transportation Engineer  
Ph.D. Candidate – Researcher

[www.nrso.ntua.gr/dtsel/](http://www.nrso.ntua.gr/dtsel/)  
[dtsel@central.ntua.gr](mailto:dtsel@central.ntua.gr)