Real data-based validation of highly automated driving functions using simulation methods

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Institut für Technik der Informationsverarbeitung (ITIV)

Agenda

- Motivation
- The real world random testing dilemma
- New concept: „Simulation-based validation using real data scenarios“
- Parts of the concept
- Evaluation using synthetic and real data sources
- Summary

Challenges for automated driving testing and validation

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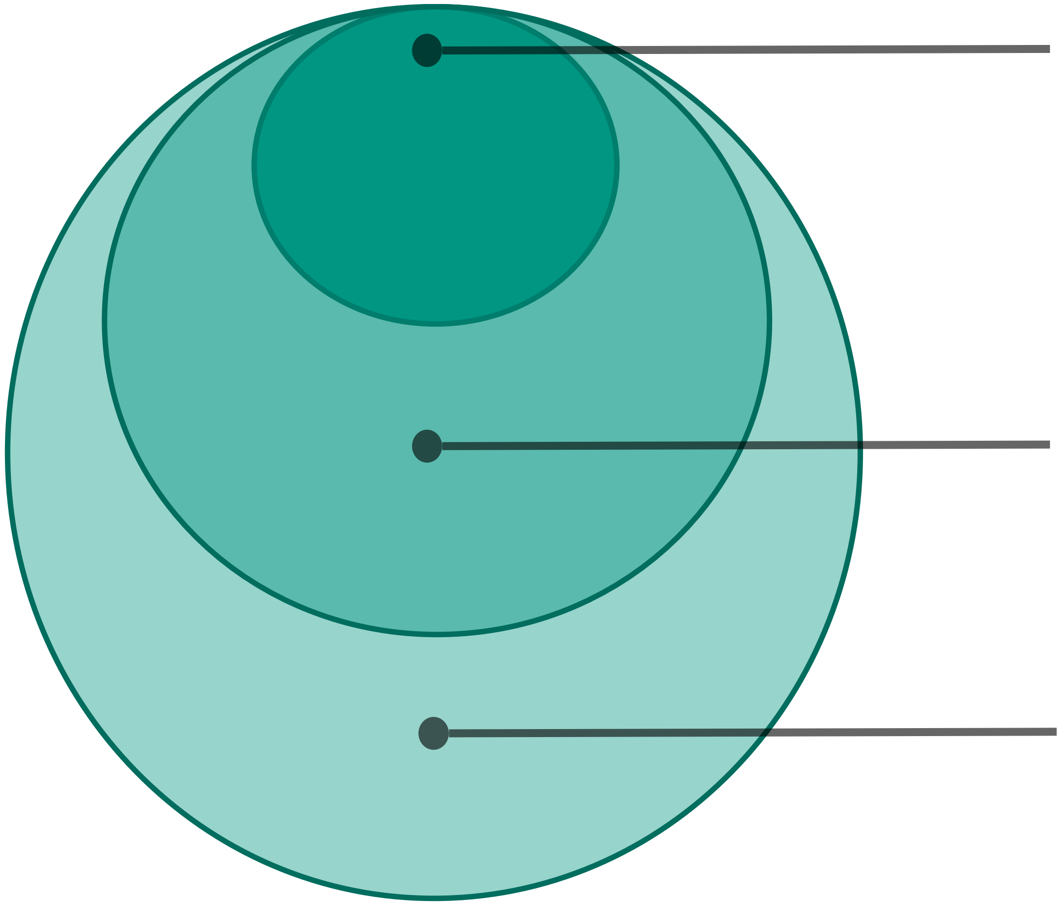

Known Knowns
- Requirements available
- Specifications available

→ Solutions for a defined space available
(Applies to all conventional ADAS: Human driver serves as a fallback)

Known Unknowns
- Requirements available
- Specifications partly available

→ Solutions possible

Unknown Unknowns
- Specific requirements not available
- Derivable specifications not available

→ Undefined solutions / Open world problem

For ADAS (up to level 2 according to SAE) this problem does not exist!

Motivation: Combinatorial test case explosion

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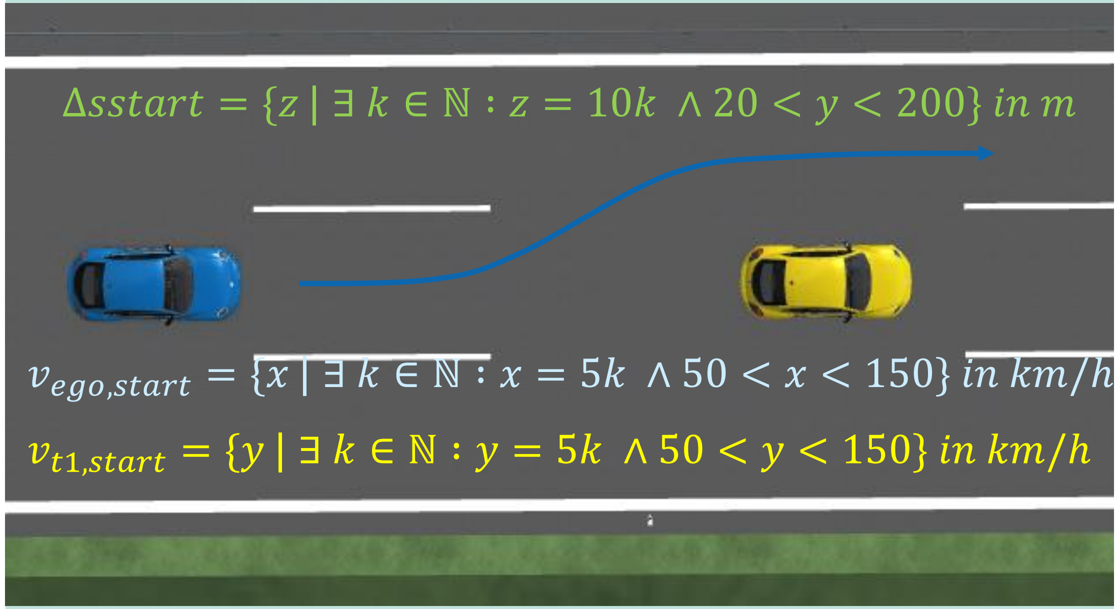
Function related variations:
Actuator and scenery conditions



$v_{ego,start} \times v_{t1,start} \times \Delta sstart$ = 21 x 21 x 19
= **7,600 variations**

Sensor related variations:
Weather and environmental conditions

Rain / Snow / Clear:	3 variations
Fog visibility:	3 variations
Day / Dawn / Night:	3 variations
Sonnenstand:	3 variations
Temperature:	3 variations
Air humidity:	3 variations
GPS reception:	3 variations
Road friction coefficient:	3 variations
…	???

3^8 = **6,561 variations**

In total: **49,863,600 variations** for a simple overtaking maneuver

The random testing dilemma (real world driving)

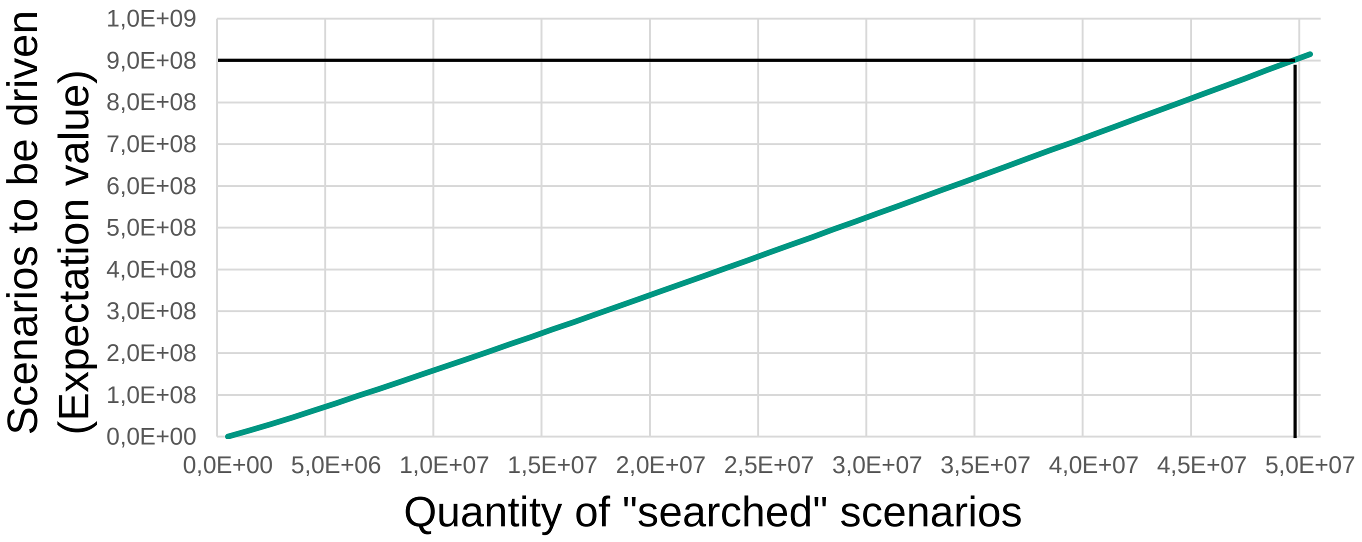
Assumption: 49.8 million scenarios represent the complete space for test coverage.

How many scenarios *N* would have to be driven to cover this test space in real world?

Standard Coupon Collectors Problem:

$$E(N) = N\left(\frac{1}{N} + \frac{1}{N-1} + \frac{1}{N-2} + \cdots + \frac{1}{1}\right) = NH_N$$

$$E(N) \approx N \cdot (\ln(N) + \gamma)$$



The random testing dilemma
(real world driving)

Assumption: 49.8 million scenarios represent the complete space for test coverage.

➡ **How many scenarios *N* would have to be driven to cover this test space in real world?**

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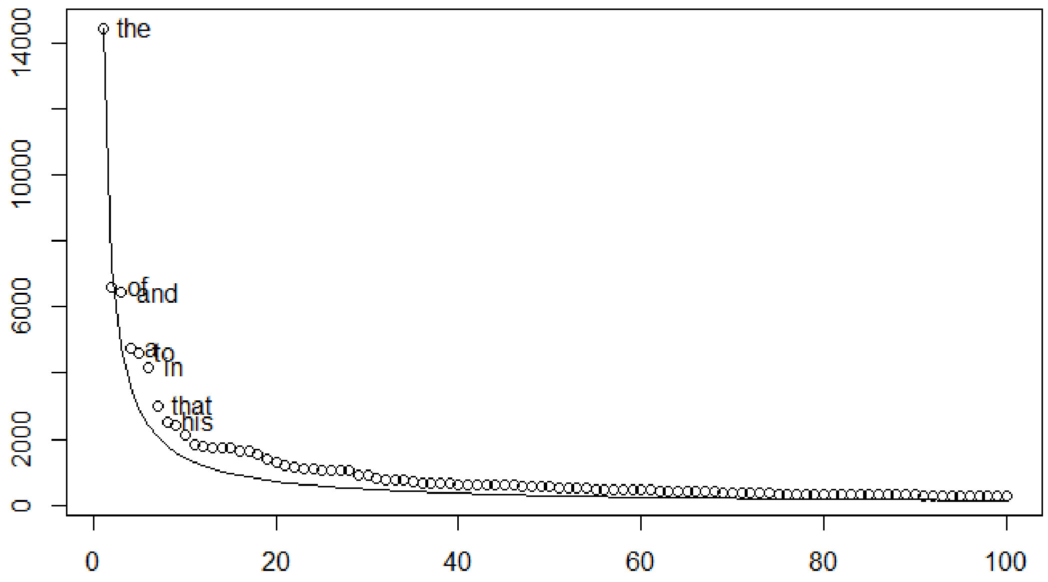
Standard Coupon Collectors Problem

Coupon Collectors Problem with Zipf:

⚠ Scenarios are not equally distributed

➡ Zipf distribution (natural processes)



The random testing dilemma (real world driving)

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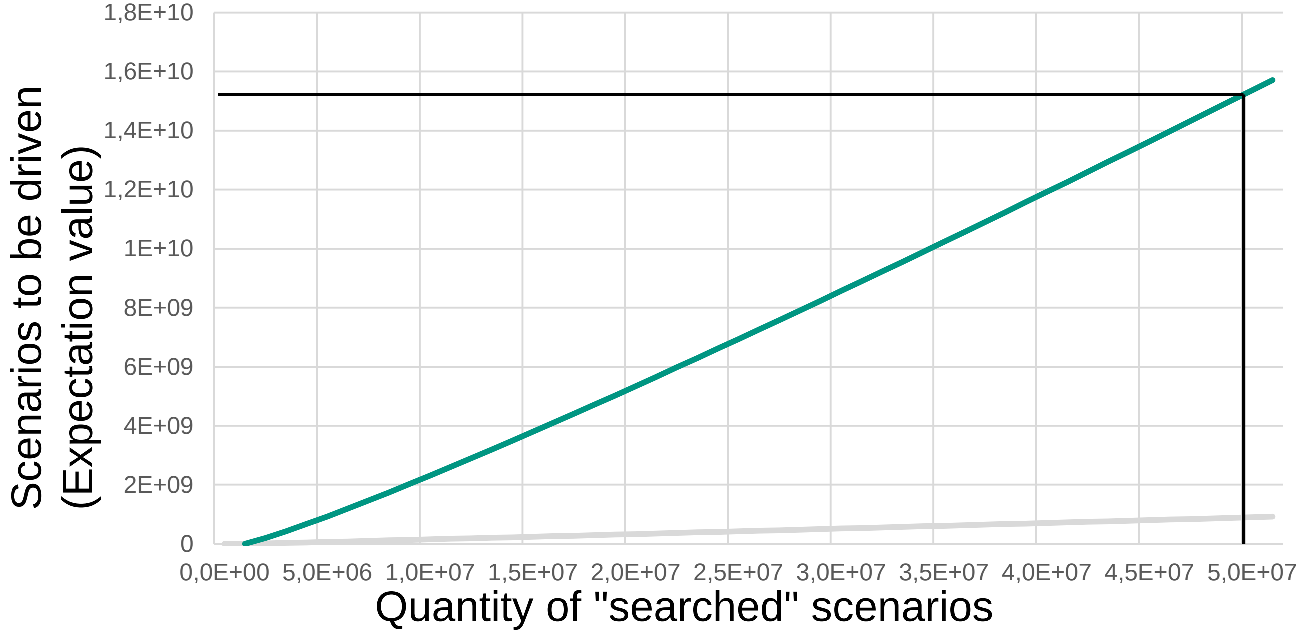
Standard Coupon Collectors Problem

Coupon Collectors Problem with Zipf:

Scenarios are not equally distributed

Zipf distribution (natural processes)

$E(N) \approx N \cdot (ln(N))^2$



The random testing dilemma (real world driving)

Assumption: 49.8 million scenarios represent the complete space for test coverage.

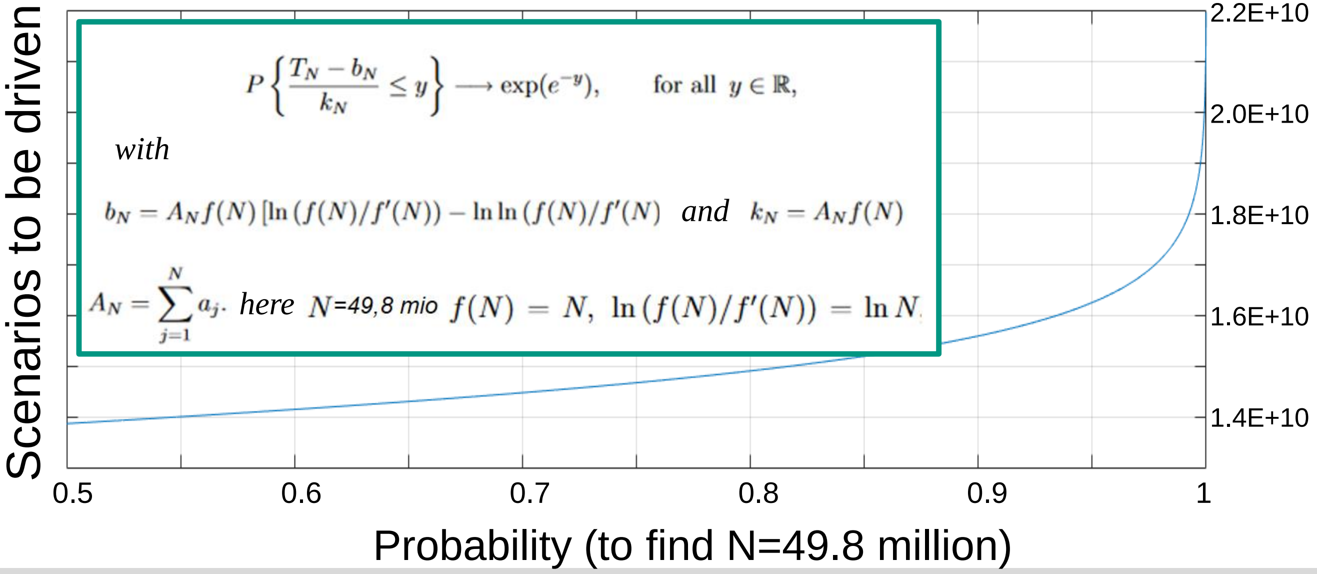
How many scenarios *N* would have to be driven to cover this test space in real world?

Expectation value not acceptable for validation

Distribution of probability

for *p=99,9%*: ~ 2 * 10^{10} scenarios

=> ~ 2 * 10^{9} km

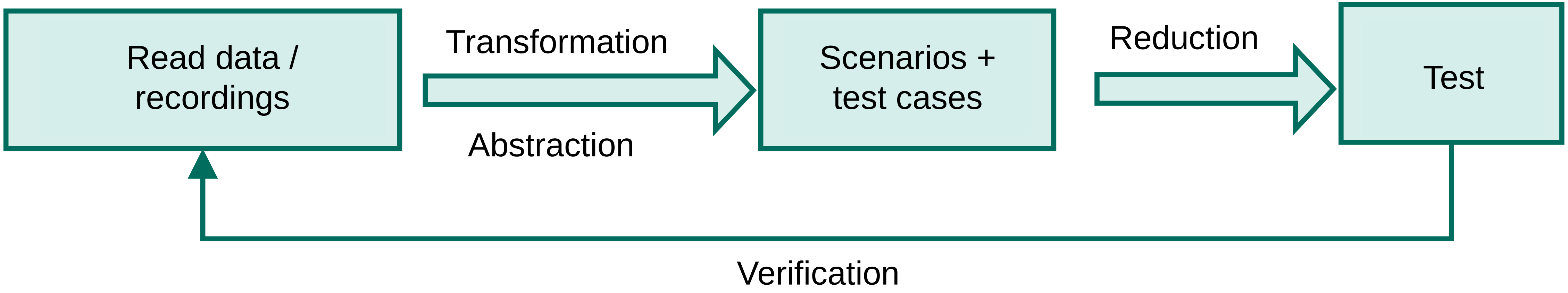


Concept idea

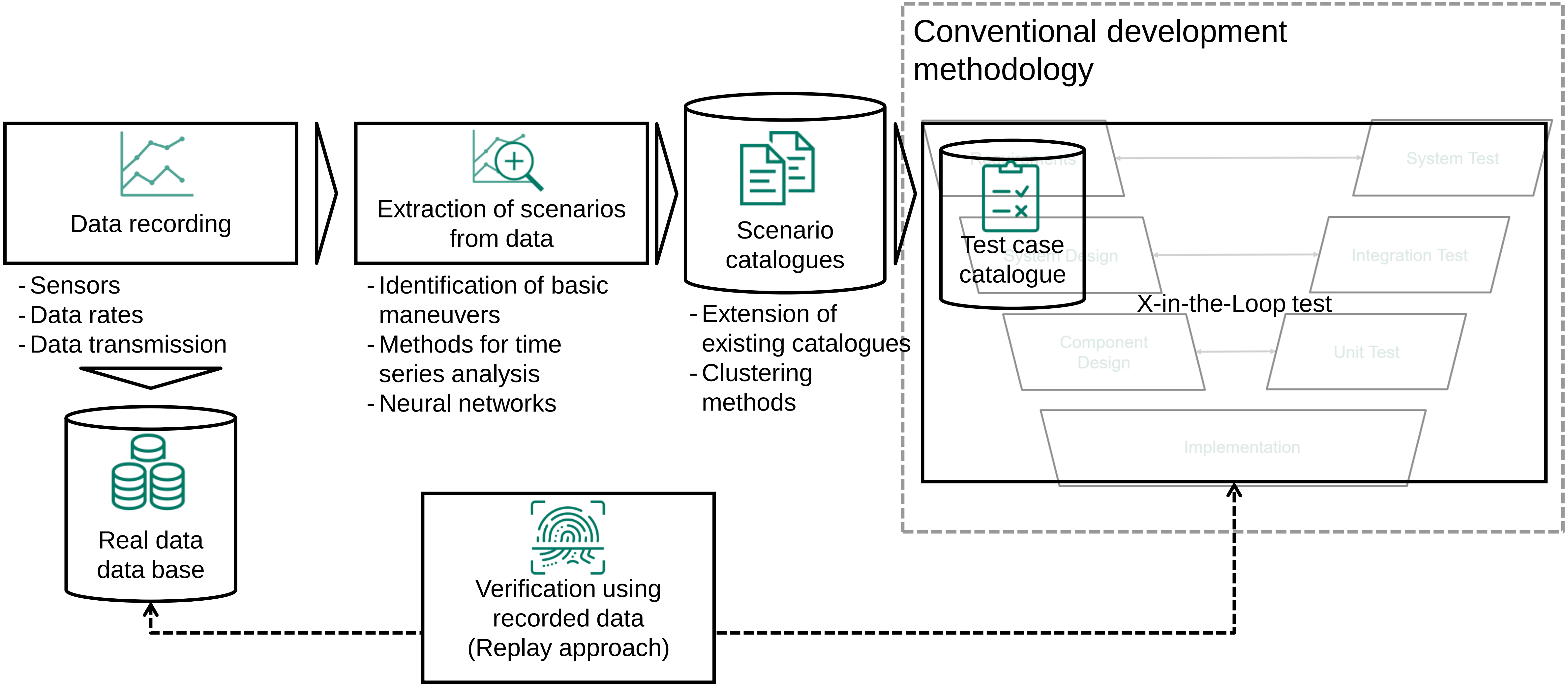
What is the difference between automated driving and conventional, solved V&V problems for systems in automotive development?

- Open World Problem
- The random testing dilemma exists
- Full test coverage using simulation only is not possible
- Human driver must be used as reference for the system for statistical validation

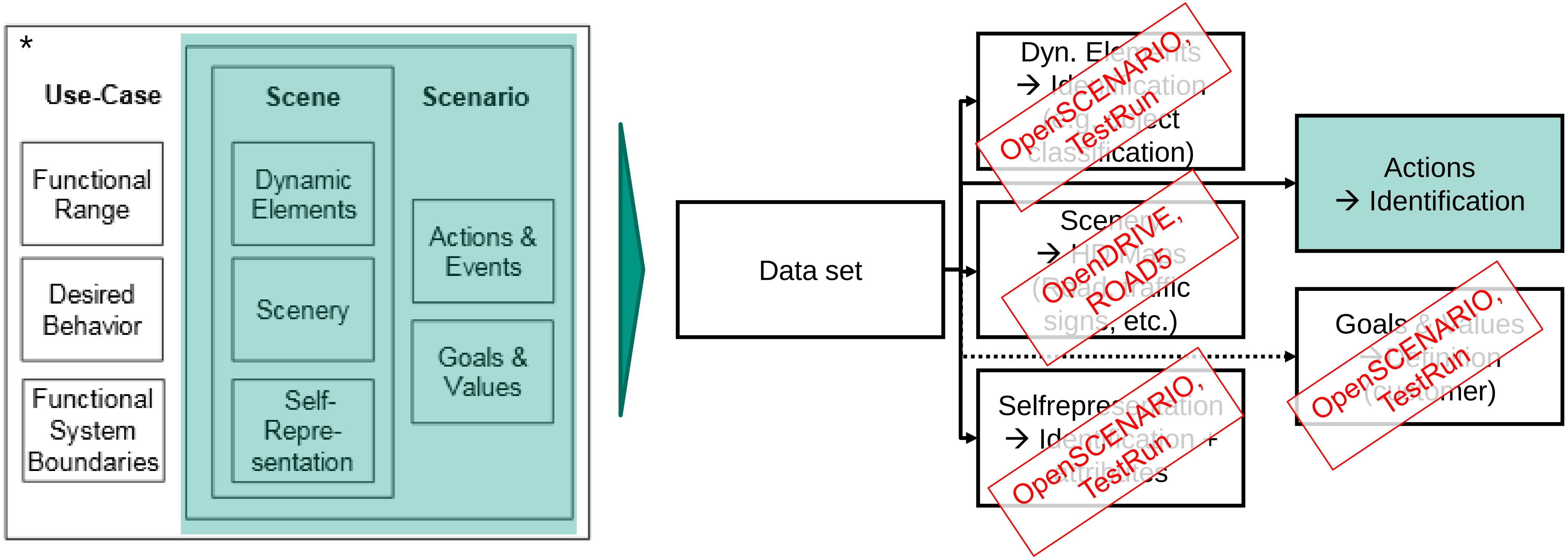
Key question: How can relevant test cases be derived by the reference system and be represented efficiently?



Concept: „Real data-based validation using simulation methods“



Elements of Scenario-Based-Testing



* Ulbrich et al (2015): Defining and Substantiating the Terms Scene, Situation, and Scenario for Automated Driving

Definitions of „Maneuver“ in Research/Literature

Fahrmanöver	Reichart [14]	Chaloupka [33]	Nagel [34]	Vollrath [35]	Verwey [36]	GDV [37]
Freie Fahrt	x	x	x	x		x
Reaktion auf Hindernis	x	x				x
Auffahren / Annähern			x	x		x
Folgen	x		x	x		x
Überholen	x	x	x	x		x
Abbiegen	x	x	x	x	x	x
Kreuzen	x	x	x	x	x	x
Spurwechsel	x	x	x	x		x
Wenden	x		x			x
Rückwärts fahren	x		x			x
Anhalten/Stand			x	x		x
Anfahren / Weiterfahren		x	x	x		x
Einparken			x	x		x
Ausparken			x	x		x
Kurvenfahrt		x			x	x

[14] Reichart, G.: Menschliche Zuverlässigkeit beim Führen von Kraftfahrzeugen. Nr. 7 der Reihe 22, Mensch-Maschine-Systeme, VDI Verlag, Düsseldorf, 2001.
[34] Nagel, H.-H.: A vision of 'vision and language' comprises action: an example from road traffic artificial intelligence. Review 8, S. 189-214, Springer Netherlands, Dortrecht, 1994.
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[36] Verwey, W.: Online driver workload estimation. Effects of road situation and age on secondary task measures. Ergonomics, Vol. 43, Nr. 2, S. 187 - 209, Taylor & Francis Online, Abingdon, 2000.
[37] Gesamtverband der Deutschen Versicherungswirtschaft e.V. (GDV), Institut für Straßenverkehr: Leitfaden zur Bestimmung des Unfalltyps. Köln, 1998.
[38] Bach, J.: Methoden und Ansätze für die Entwicklung und den Test prädiktiver Fahrzeugregelungsfunktionen, Dissertation, 2018

Extended Definition of „Maneuver“

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Fahrmanöver
Freie Fahrt
Reaktion auf Hindernis
Auffahren / Annähern
Folgen
Überholen
Abbiegen
Kreuzen
Spurwechsel
Wenden
Rückwärts fahren
Anhalten/Stand
Anfahren / Weiterfahren
Einparken
Ausparken
Kurvenfahrt

Reduction to an appropriate abstraction level for all dynamic objects

Scenario

+ Complete space of possible scenarios can be represented
+ (Metric) distance measures for scenarios can be defined
+ Requirement for classification / clustering

Extended Definition of „Maneuver“

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Abstraction level

low

High degree of accuracy that allows the description of as many phenomena as possible

Atomic Maneuvers

Basic actions of longitudinal and lateral control:

- Steering wheel angle input
- Gas pedal
- Brake pedal

medium

Reduction to a appropriate abstraction level for all dynamic objects

Basic Maneuvers H H

Basic units for an application environment:

- Keep lane
- lane change left/right
- Keep target speed
- Increase/reduce target speed

high

High level abstraction to describe relationships

Composite Maneuvers O H H

Can be combined out of basic maneuvers:

- e.g. following, overtaking

Scenario Meta Model (Actions and Events)

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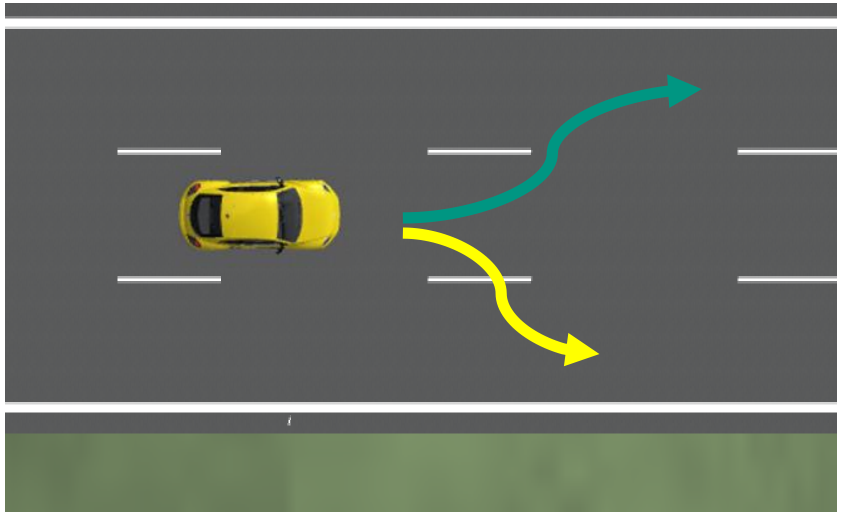
- Scenario: „Sequences of states and actions“
- **Action model (Basic Maneuvers):**

6 Basic Maneuvers (3 longitudinal, 3 lateral) for Ego-Vehicle and each Object *i*;

Modeling based on representative characteristics



$$\overrightarrow{M_{long}} = [t_{long}, v_s, v_e, \Delta t_{long}, \Delta x_{long}]$$

$$\overrightarrow{M_{lat}} = [t_{long}, y_s, y_e, \Delta t_{lat}]$$

Maneuver vector longitudinal:

t_{long}:	Time stamp at maneuver transition
v_s:	Start velocity of a maneuver
v_e:	End velocity of a maneuver
Δt_{long}:	Time length of a maneuver
Δx_{long}:	Driven distance during a maneuver

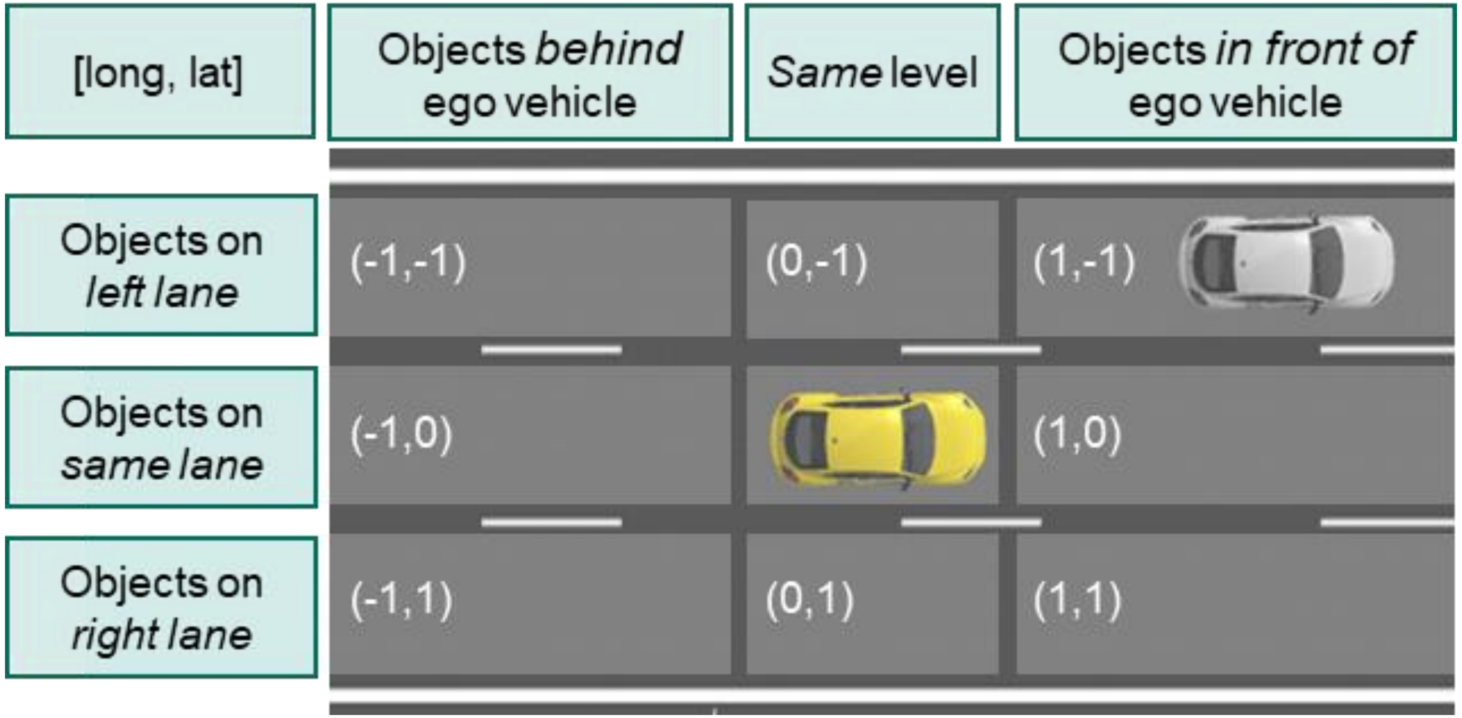
Maneuver vector lateral:

t_{long}:	Time stamp at maneuver transition
y_s:	Start position (laterally) of a maneuver
y_e:	End position (laterally) of a maneuver
Δt_{lat}:	Time length of a maneuver

Scenario Meta Model (States)

- Scenario: „ Sequences of states and actions“
- Action model (Basic Maneuvers)
- **State model (grid based):**

➡ Description of the state as an abstraction of the relationship between ego-vehicle and object *i* at a time *t* in a 2-tuple L_{st}:=[$L_{st,long}$, $L_{st,lat}$]



Realization Scenario Meta Model

- Scenario: „ Sequences of states and actions“
- Action model (Basic Maneuvers)
- State model (grid based)
- **Represented in a tensor model:**

➡ **Merging the models**

Description of a scenario between ego vehicle and object *i* in a time-based matrix:

$$
\left(\begin{array}{cccc}
t_{i,1} & t_{i,2} & \dots & t_{i,n} \\
v_{s,1} & v_{s,2} & \dots & v_{s,n} \\
v_{e,1} & v_{e,2} & \dots & v_{e,n} \\
\Delta t_1 & \Delta t_2 & \dots & \Delta t_n \\
\Delta x_1 & \Delta x_2 & \dots & \Delta x_n \\
y_{s,1} & y_{s,2} & \dots & y_{s,n} \\
y_{e,1} & y_{e,2} & \dots & y_{e,n} \\
ds_{x,1} & ds_{x,2} & \dots & ds_{x,n} \\
ds_{y,1} & ds_{y,2} & \dots & ds_{y,n} \\
L_{long,1} & L_{long,2} & \dots & L_{long,n} \\
L_{lat,1} & L_{lat,2} & \dots & L_{lat,n} \\
L_{st,long,1} & L_{st,long,2} & \dots & L_{st,long,n} \\
L_{st,lat,1} & L_{st,lat,2} & \dots & L_{st,lat,n}
\end{array}\right)
\begin{array}{l}
\leftarrow \text{time} \\
\left.\begin{array}{l} \\ \\ \\ \\ \end{array}\right\} \text{Maneuver longitudinal} \\
\left.\begin{array}{l} \\ \\ \\ \\ \end{array}\right\} \text{Maneuver lateral} \\
\left.\begin{array}{l} \\ \\ \\ \\ \end{array}\right\} \text{Maneuver label \& State Tupel}
\end{array}
$$

Realization Scenario Meta Model

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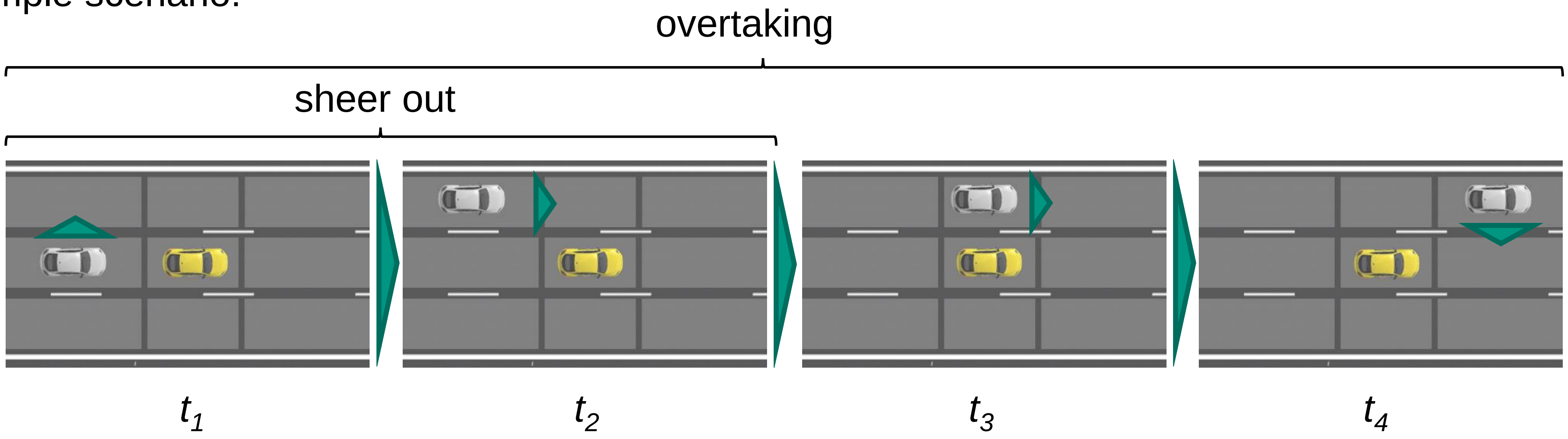
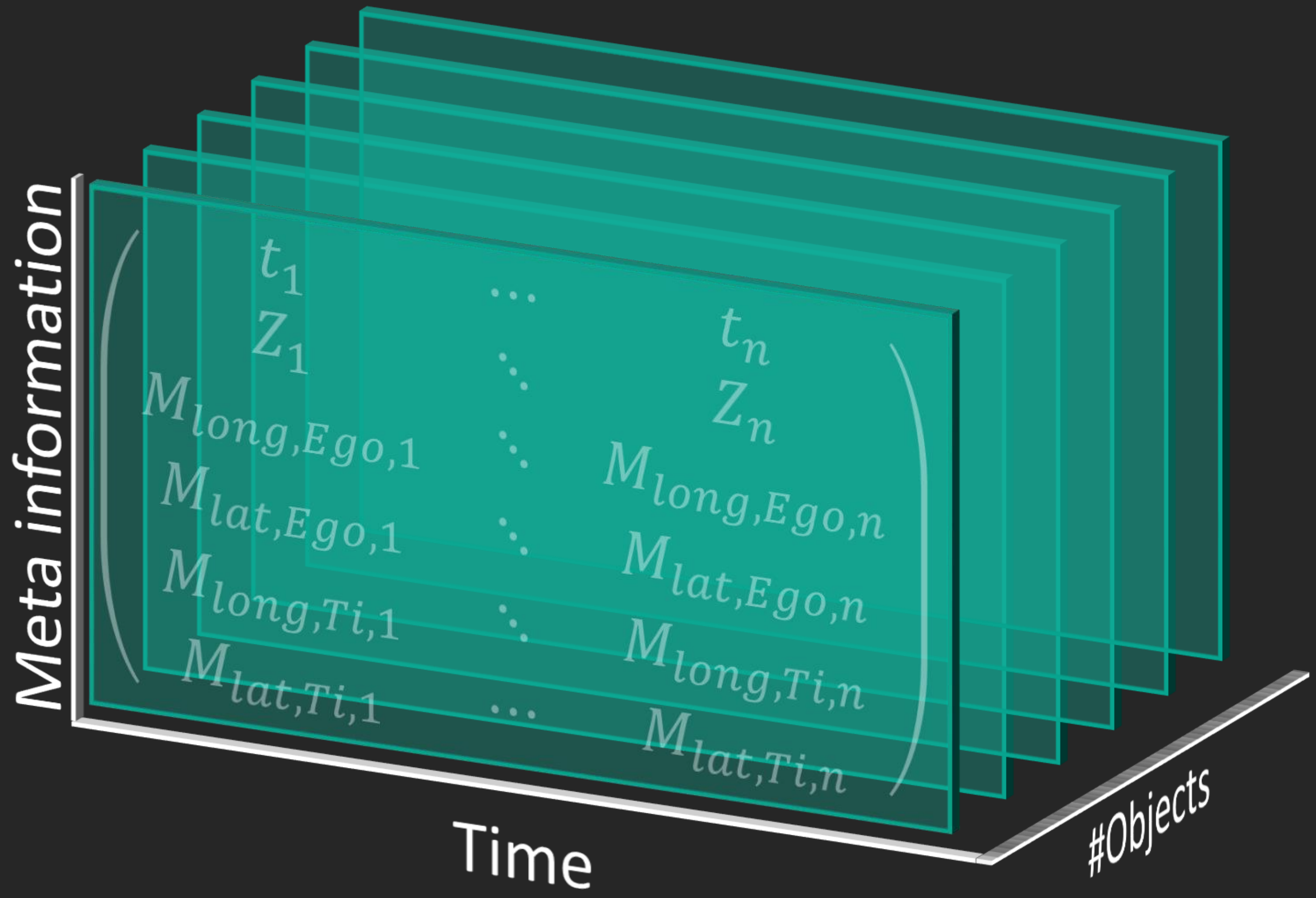
Example scenario:



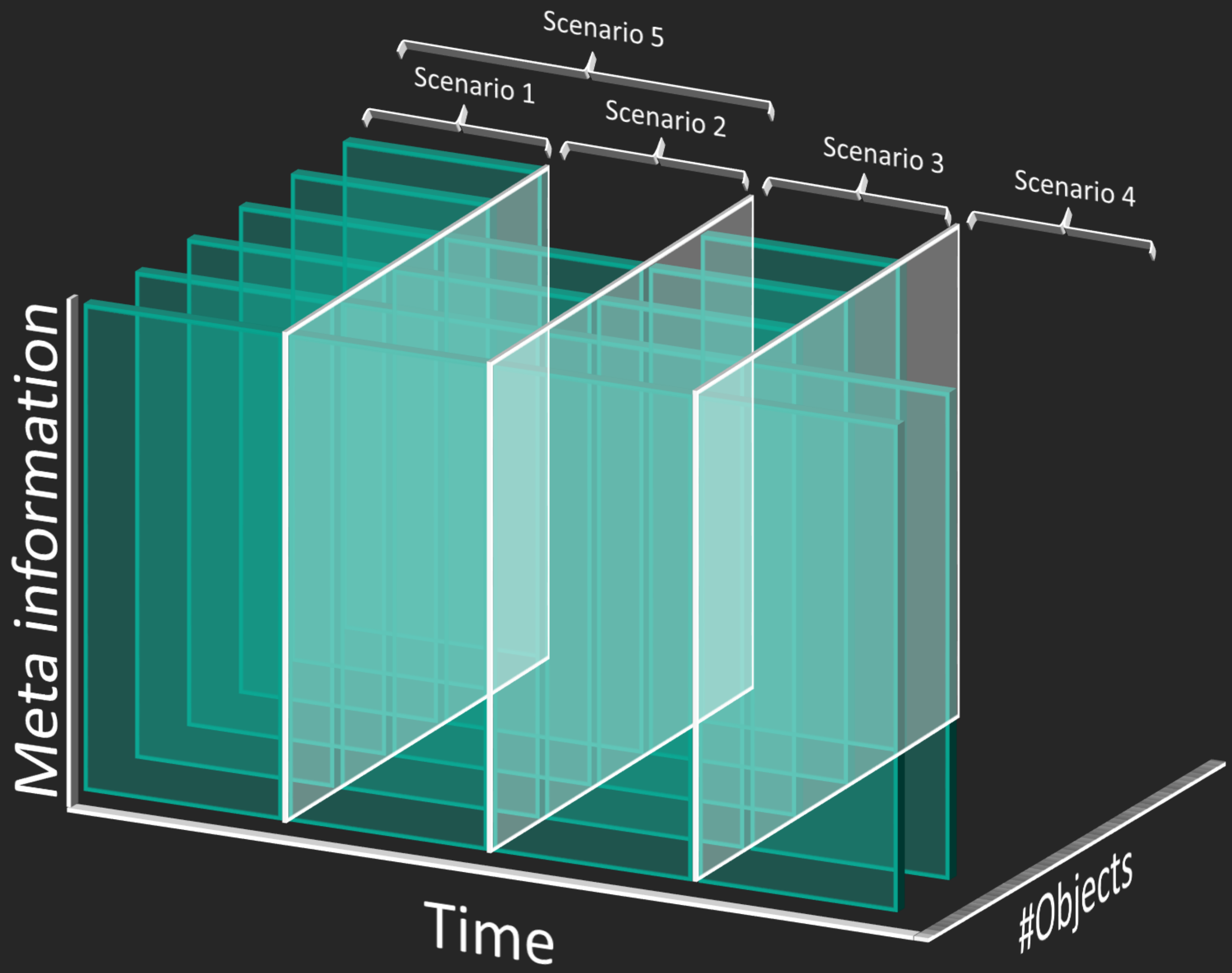
Results – Scenario Meta Model



Advantages:

- Can be extended with further (meta)information
- Thus also static information can be integrated
- Cutting along time dimension accesses included scenarios
- Depth adapts dynamically to the number of contained objects
- Representation suitable for filtering, clustering etc.
- Transferable to other scenario descriptions, e.g. OpenScenario, CarMaker TestRun
- Memory efficient format

Results – Scenario Meta Model



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Evaluation with Synthetic Data - Workflow

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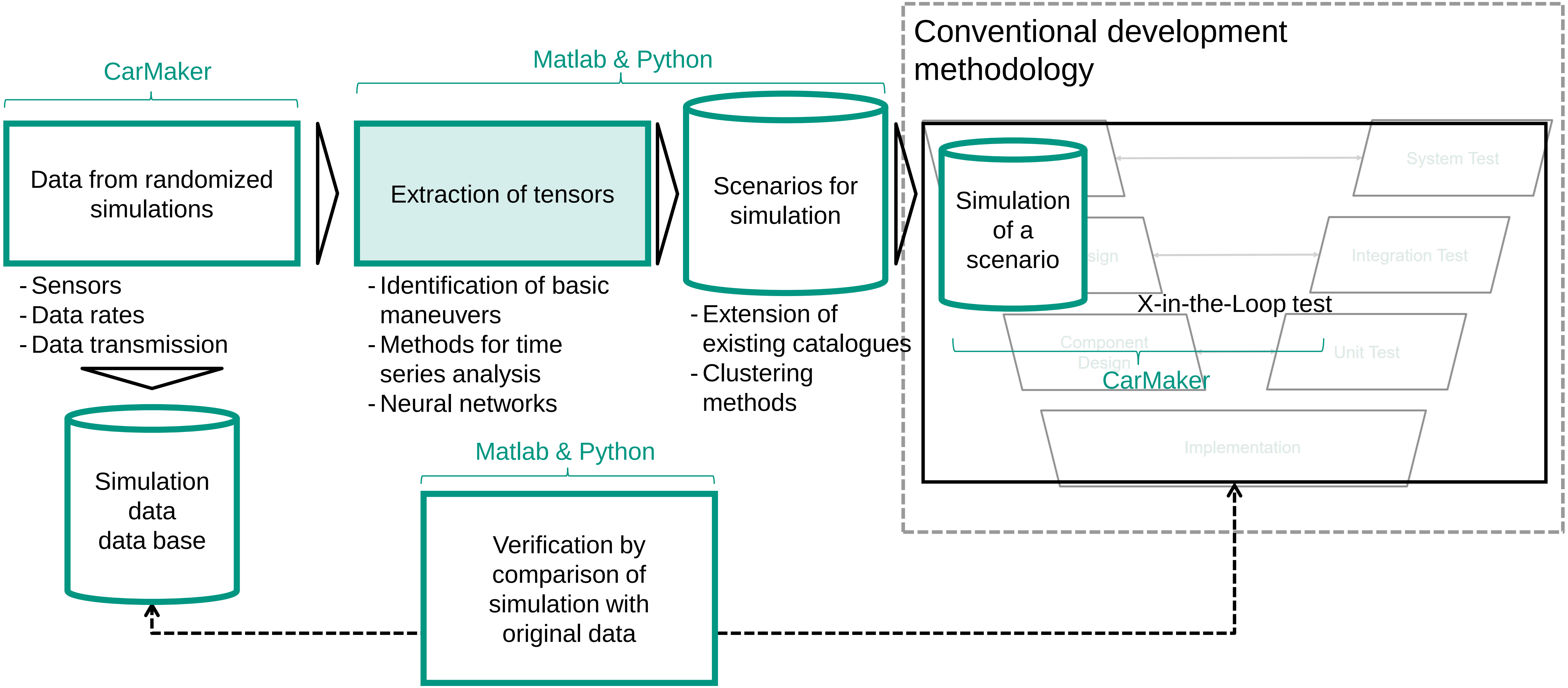
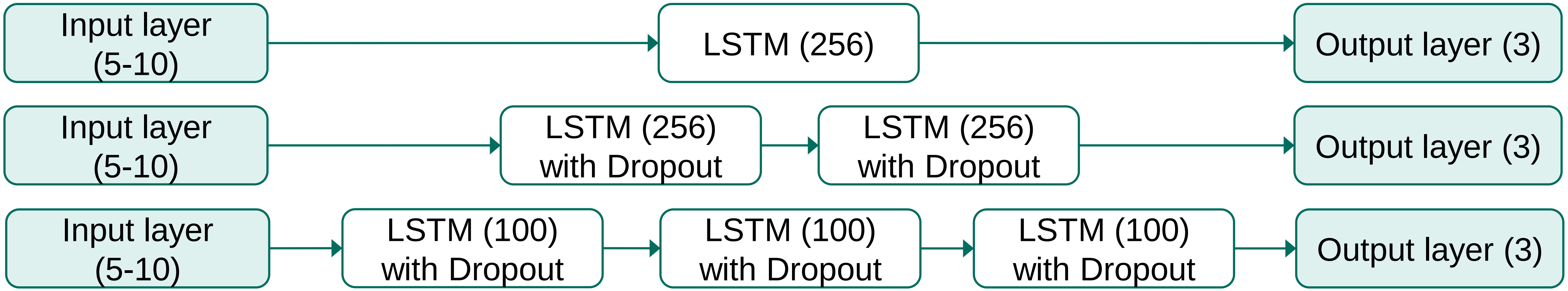
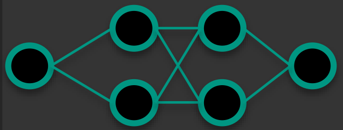
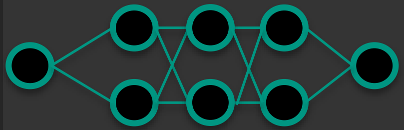


Scenario Extraction – using Neural Networks

- Architectures / Hyperparameters:
  - Input layer: depending on available signals (here: 5-10 signals)
  - Output layer: result of maneuver classification (3 units)
  - Hidden layer architecture: LSTMs in different combinations (e.g. number layer, number of neurons…)
  - …



Results – Scenario Extraction

Architecture	Number of input signals	Detection lane change right	Detection lane keeping	Detection lane change left	Overall Performance
 LSTM with 2 Hidden Layers	5	92,2 %	95,6 %	93,8 %	95,2 %
	9	95,2 %	96,0 %	97,3 %	
 LSTM with 3 Hidden Layers	5	93,7 %	95,3 %	95,1 %	95,1 %
	10	96,3 %	96,1 %	95,1 %	

Evaluation Methods – Synthetic Data

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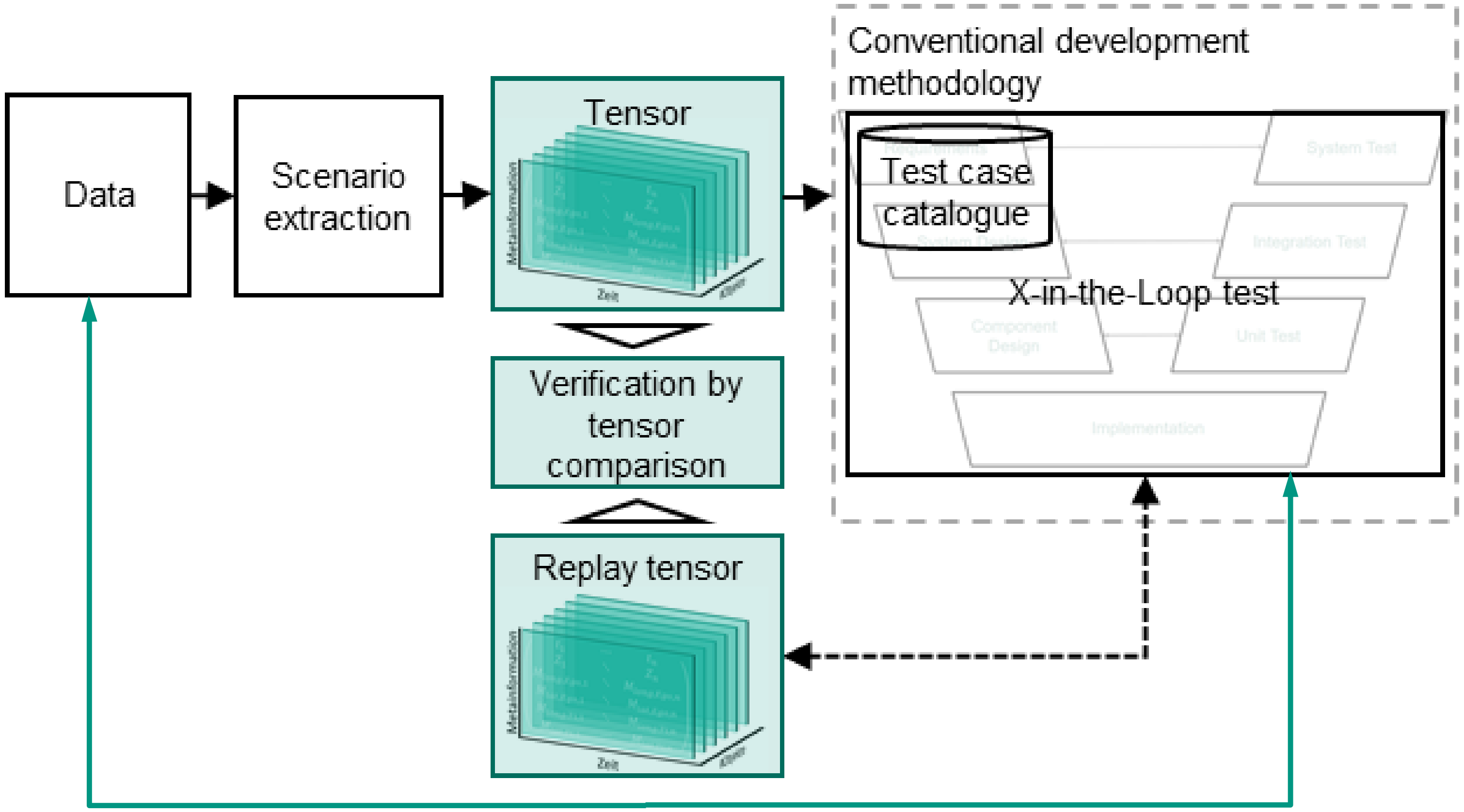
Evaluation workflow:



Three levels of verification

1. Internal verification
(Consistency check of tensor values)

2. Verification on abstraction level
(e.g. comparison of maneuver sequences)

3. Verification on data level (based on the concrete results/signals of the X-in-the-Loop test compared to the original data)

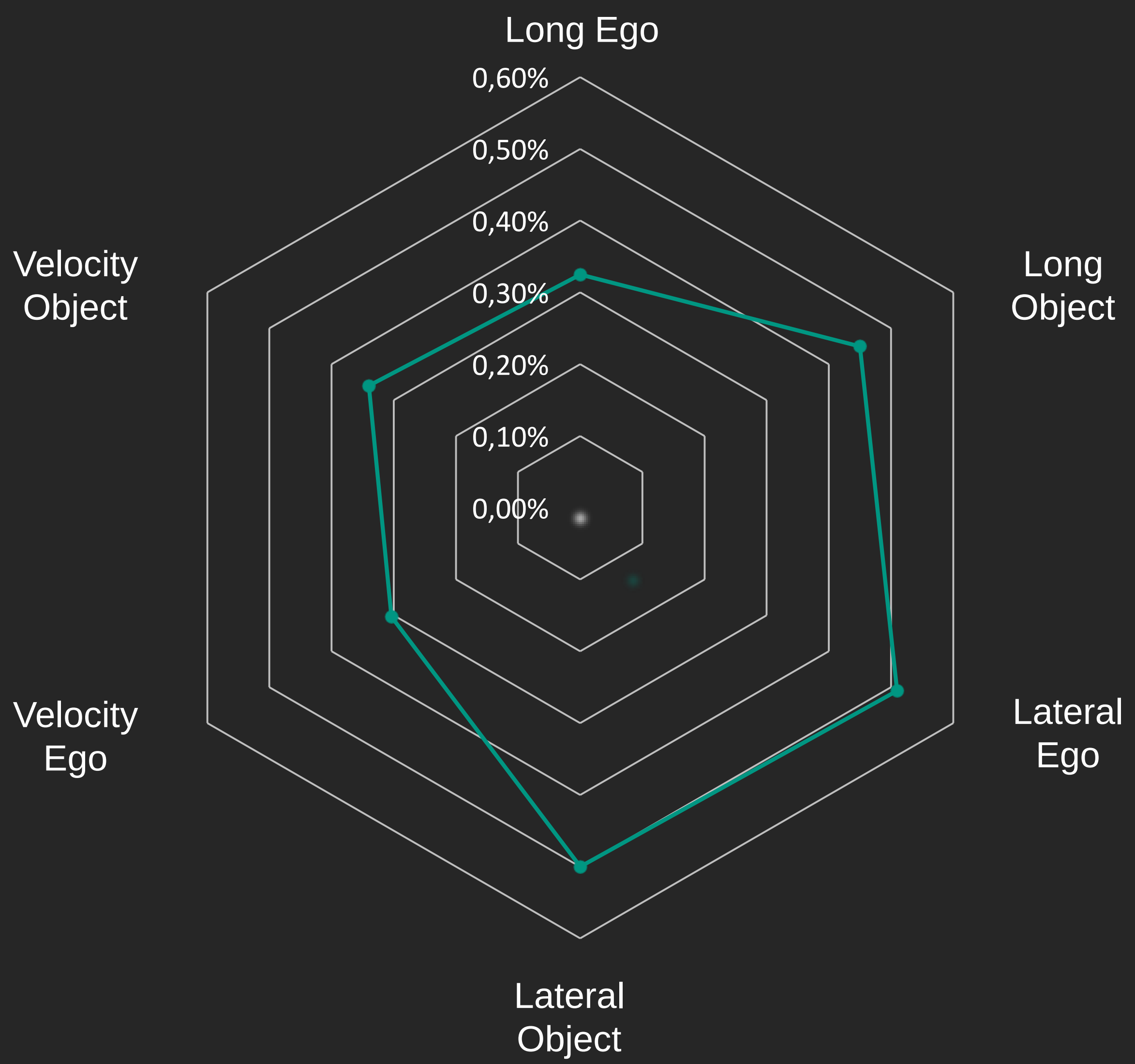
Evaluation Results – Synthetic Data

Mean absolute percentage error (*MAPE*) for:

Long Ego/Long Object:
Distance driven in longitudinal direction over time of ego-vehicle or dynamic objects

Lateral Ego/Lateral Object:
Lateral deviation to a reference line of the road over time of ego-vehicle or dyn. objects

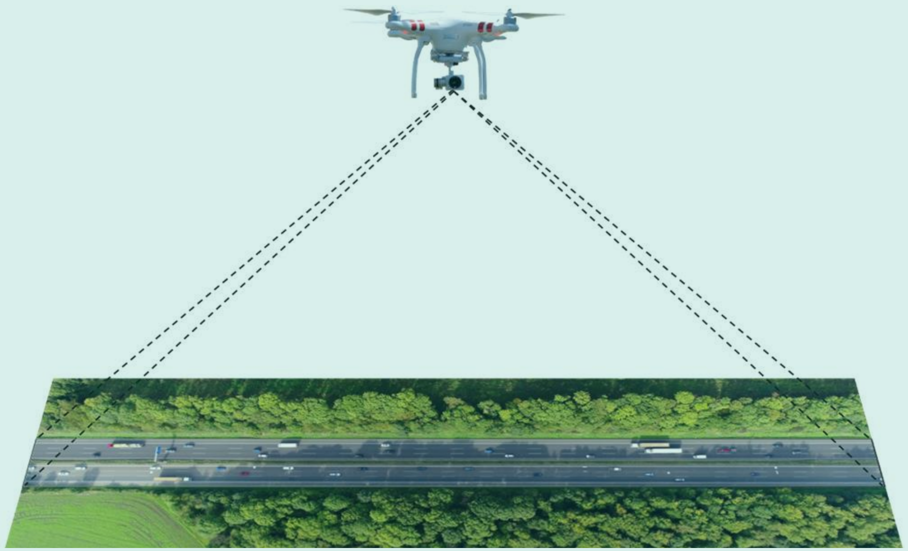
Velocity Ego/Velocity Object:
Velocity profile over time of ego-vehicle or dynamic objects



Evaluation – Real Data

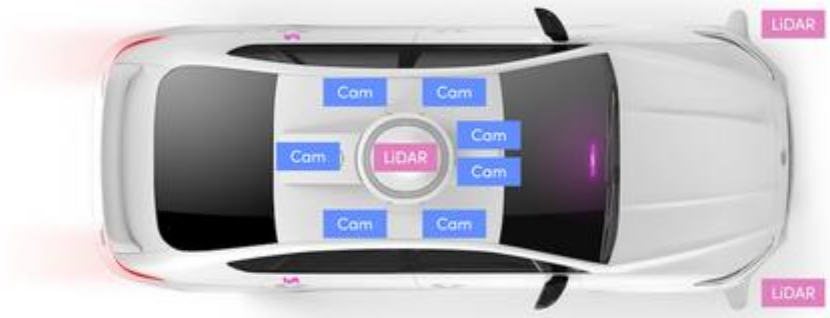
HighD data set

- 16.5h of recordings of drone data from German Highways
- Object information and trajectories available as .csv-data



Lyft data set

- 3x Lidar, 7x Camera, HD-map
- > 55.000 images in sequential order
- Ground truth annotations (3D bounding boxes)



Evaluation Results – Real Data

Visualization HighD data set

Transformation into Simulation (CarMaker)

Evaluation Results – Real Data

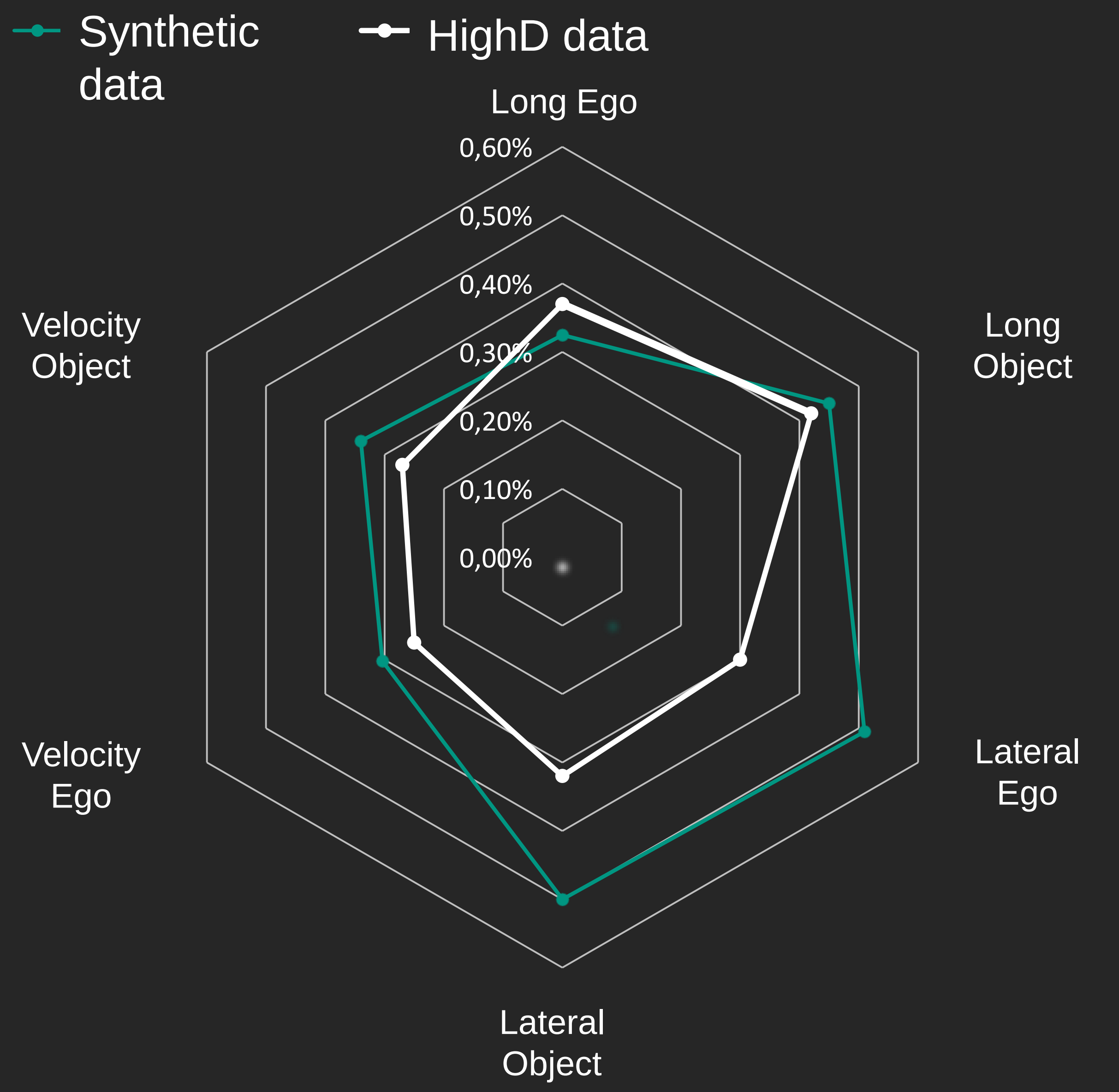
Data basis:

- 20,000 km generated total distance from an ego vehicle perspective in 100,000 sequences
- Duration per sequence: 2.5 s up to about 15 s
- 500 randomly selected sequences for analysis
- Determination of the quality of the closed-loop simulation

Evaluation Results – Real Data

Data basis:

- 20,000 km generated total distance from a first-person perspective in 100,000 sequences
- Duration per sequence: 2.5 s up to about 15 s
- 500 randomly selected sequences for analysis
- Determination of the quality of the closed-loop simulation



Summary

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- Test and validation for level 3+ functions require new methods
- Scenario-based test approach with derivation of scenarios from recorded data
- Based on: New scenario meta model
- High closed-loop re-simulation performance of recorded data using new scenario meta model