Data driven Safety Assurance for Automated Driving

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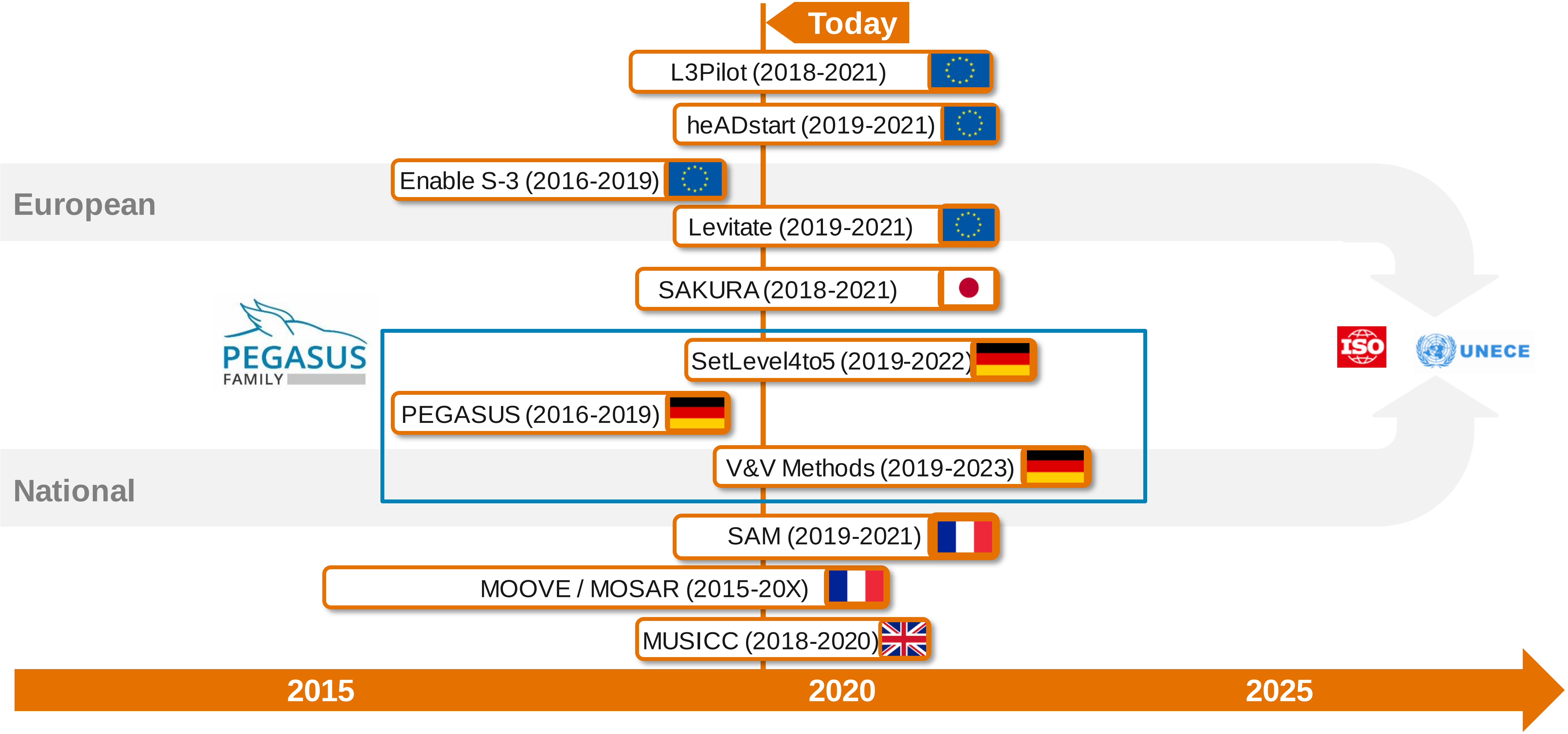
Motivation

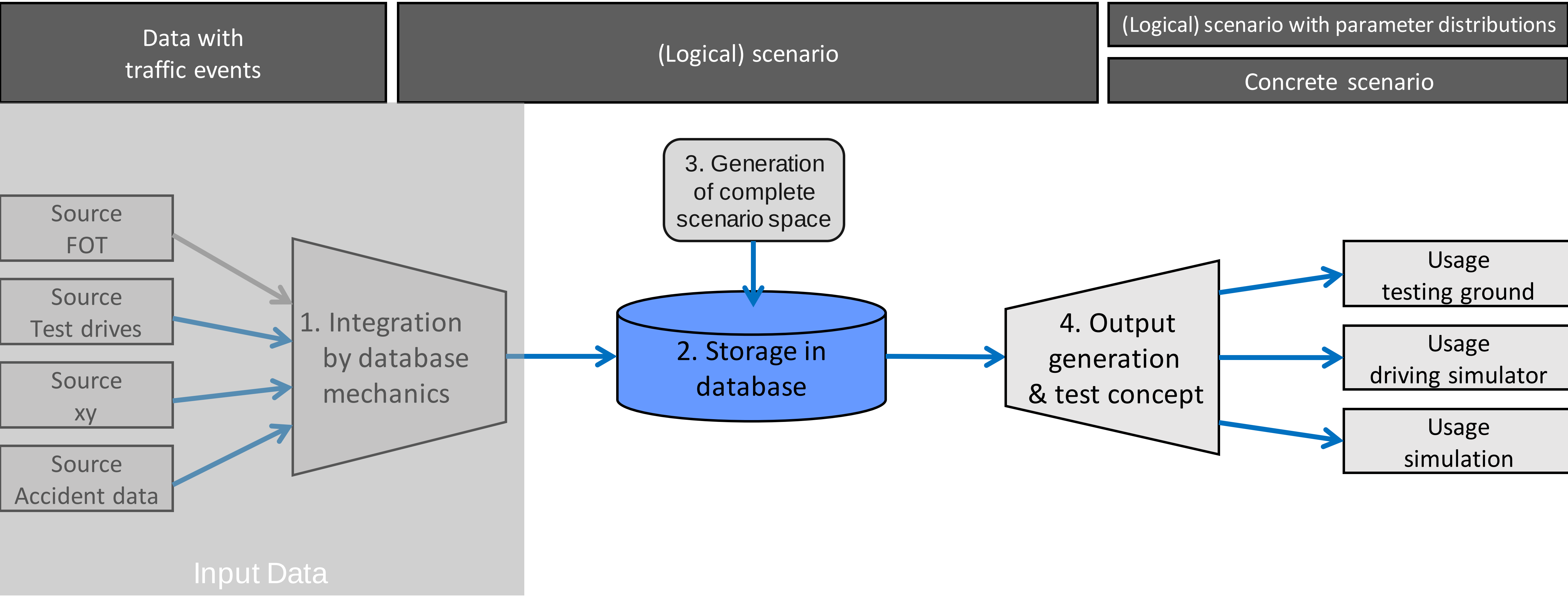
How to perform <u>safety assurance</u> of automated driving?

→ Safety Assurance Methodology currently in focus of research activities

Collaborative Research Projects on Safety Assurance



Data driven Methodology – fka‘s PEGASUS Database



Data Sources Possibilities for Senario Extraction

		Scenario Description	Scenario Relevance	Scenario Reference
How to measure?	**Real Traffic Data (uninfluenced driving)**	Is Scenario Description complete?	Frequency of scenarios for current traffic?	Human performance in scenario?
	FOT/Pilots with active AD function	Complete (depending on sensor setup)	Frequency of scenarios with HAD/ADAS-function	-
	NDS without AD function (Measurement vehicles)	Complete (depending on sensor setup)	Frequency of scenarios with human driver, but influenced driving	Good to identify human performance
	Proving ground (test track)	(forms the basis for the test)	-	Identification of human performance
	Simulation	Identification of physical boundaries of the scenarios	-	Theoretical performance
	Accident data	Limited, since ex post	Limited, only with statistical population	Examples for negative human performance
	Driving simulator	-	-	Identification of human performance

Comparison between different Data Collection Methods

Source: Tesla

Series-production vehicle

+ Flexibility
+ Efficient data collection

– **Insufficient environment perception**
– **Occlusion**
– **Naturalistic behaviour possible**

Comparison between different Data Collection Methods

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Source: UBER

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Measurement vehicle (L3+)

+ Environment perception
+ Flexibility

– **Very high effort and costs** for setting up the **vehicle**
– **Occlusion**
– The **traffic** and the **driver** are **influenced**

L3Pilot Driving Automation

Source: L3Pilot, VW

Uninfluenced Driving?


1,000
drivers
100
cars
10
countries
L3Pilot
Driving Automation
Field Data Collection

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Source: DLR

Infrastructure sensors

- \+ Efficient after installation
- \+ Accurate perception

- – Limited flexibility
- – **Occlusion**
- – **High effort and costs for installation**
- – Limited coverage area
- – **Traffic is influenced**

Source:harburg-aktuell.de

Source: welt.de

Uninfluenced naturalistic driving at sensor available?

Comparison between different Data Collection Methods

Source: Tesla

Source: UBER

Source: DLR

?

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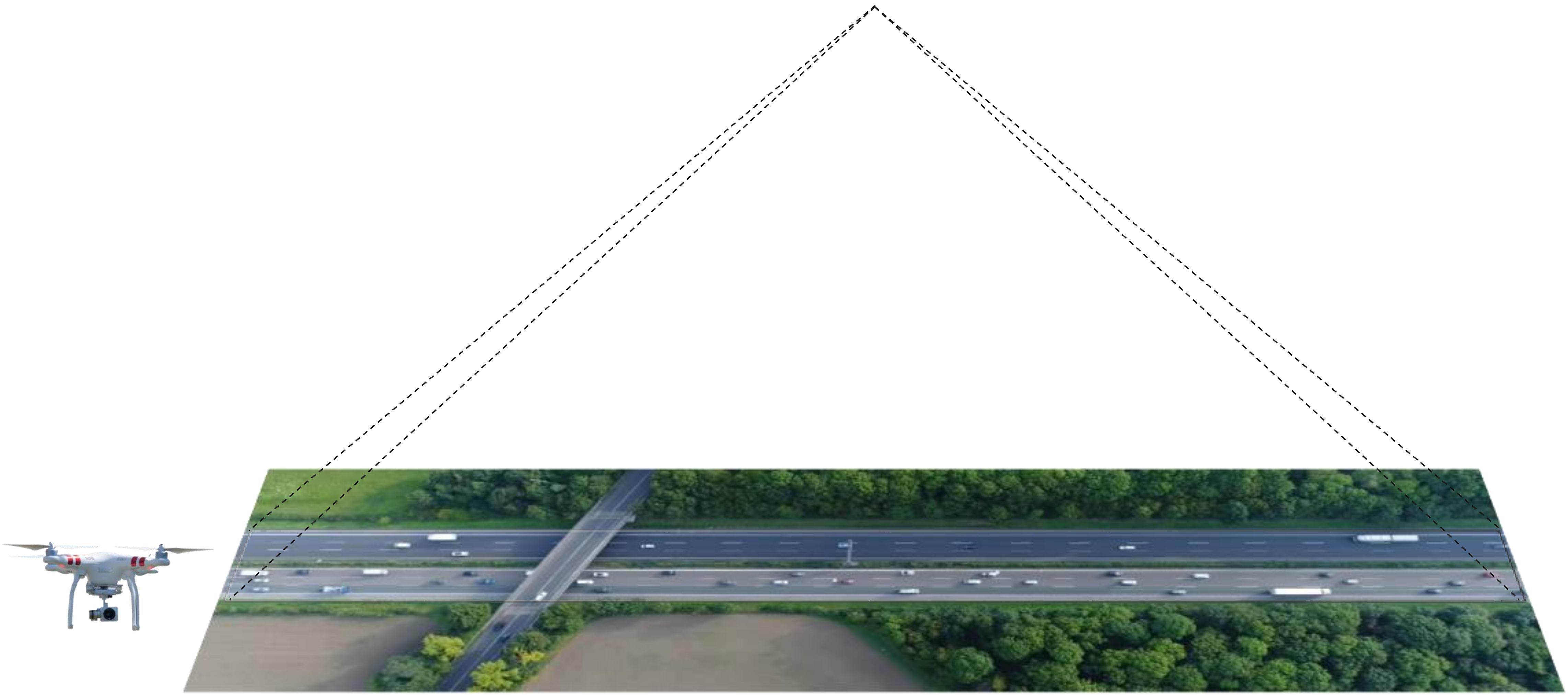
?

?

Uninfluenced Data Collection from an Aerial Perspective



HighD – The Highway Drone Dataset

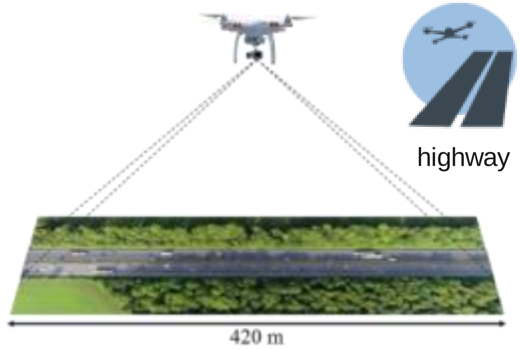
Method

Road user trajectories extracted from aerial videos captured by UAV using Deep Learning

Advantages:

- All road users are detected and tracked
- Completely naturalistic, uninfluenced driving behavior
- No or little occlusion due to “bird`s eye” perspective
- Very accurate with 4K camera and our algorithms
- High efficiency regarding cost and effort
- Recordings unbound to any location

→ Creation of a large-scale naturalistic trajectory dataset



highD

highway Drone Dataset

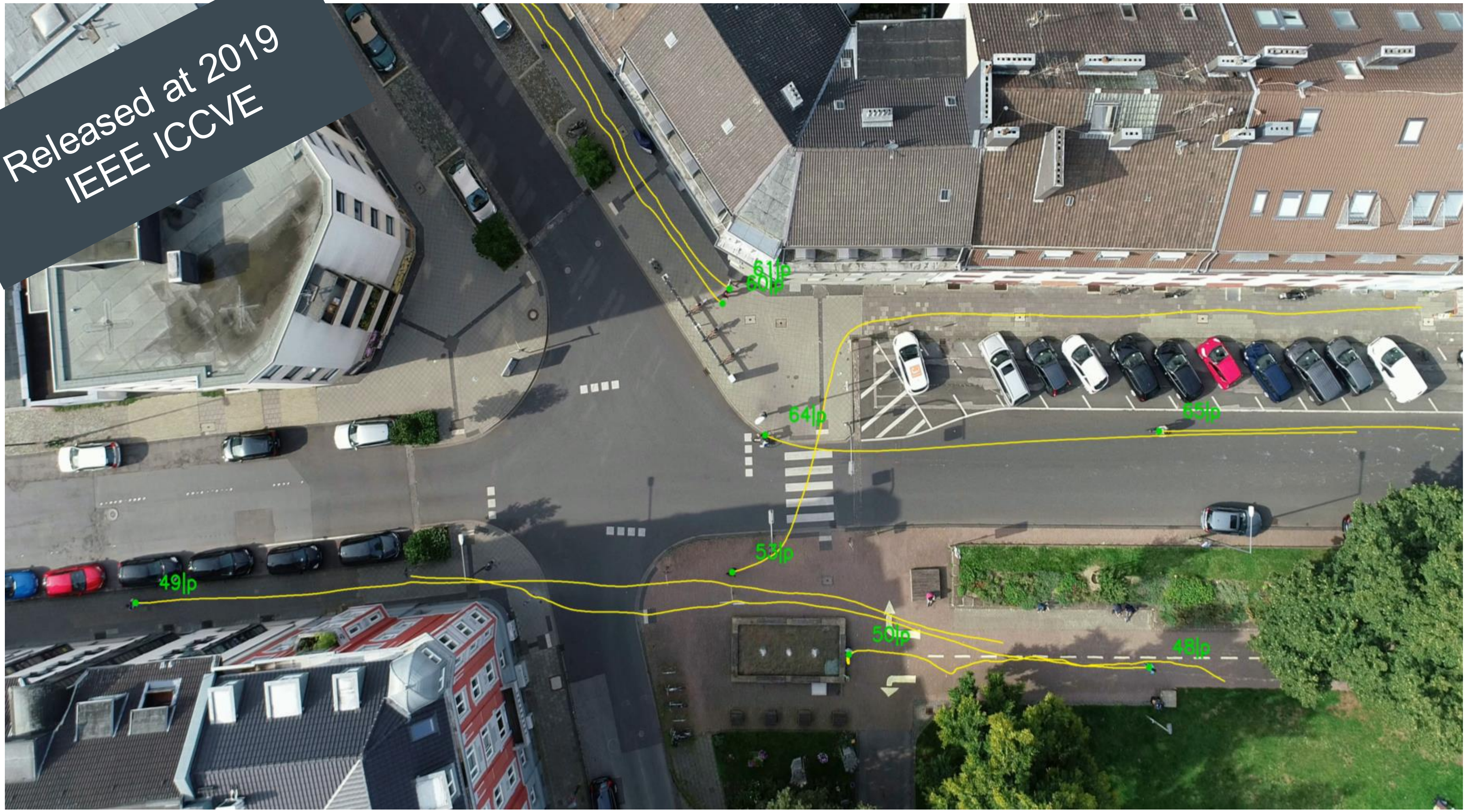
highD Dataset (free for non-commercial use) [1]

- 6 locations
- Number of vehicles: 110 000
- Driven distance: 45 000 km
- Pixel-level accuracy = 0.1-0.2 m

[1] Krajewski et al. 2018: The highD Dataset: A Drone Dataset of Naturalistic Vehicle Trajectories on German Highways for Validation of Highly Automated Driving Systems

inD - The intersection drone Dataset

Released at 2019
IEEE ICCVE



inD is a trajectory dataset,
not a computer vision dataset

Dataset at a Glance

- **Highly interactive intersections**
- **All road user types:** car, truck, bus, pedestrian, bicycle, motorcycle
- **4 measurement locations**
- **Pixel-level accuracy** (~0.1m)

levelXdata - International Datasets by fka GmbH

levelXdata.fka.de

Upload Process for Data into the Database

- Signals according to JSON definitions
- Minimum requirements on dataset
- Format: Mat or HDF5

Converting to JSON signal definition

Database Upload

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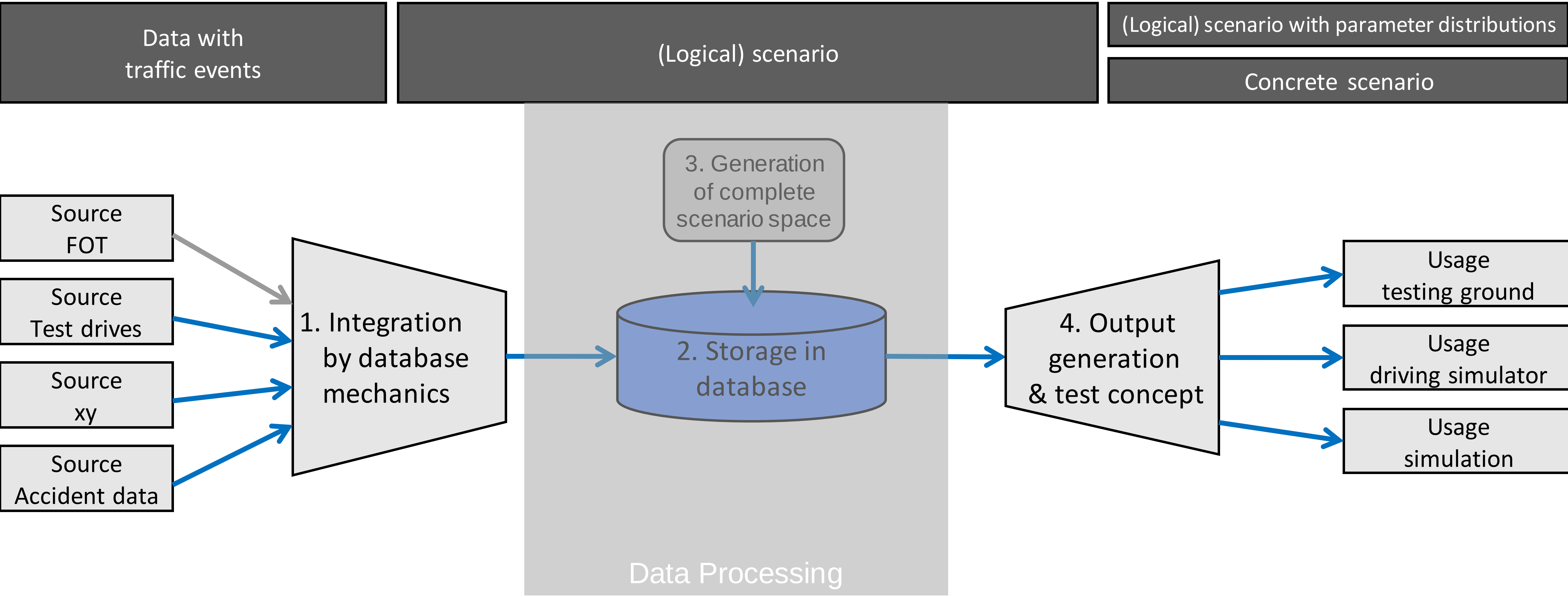
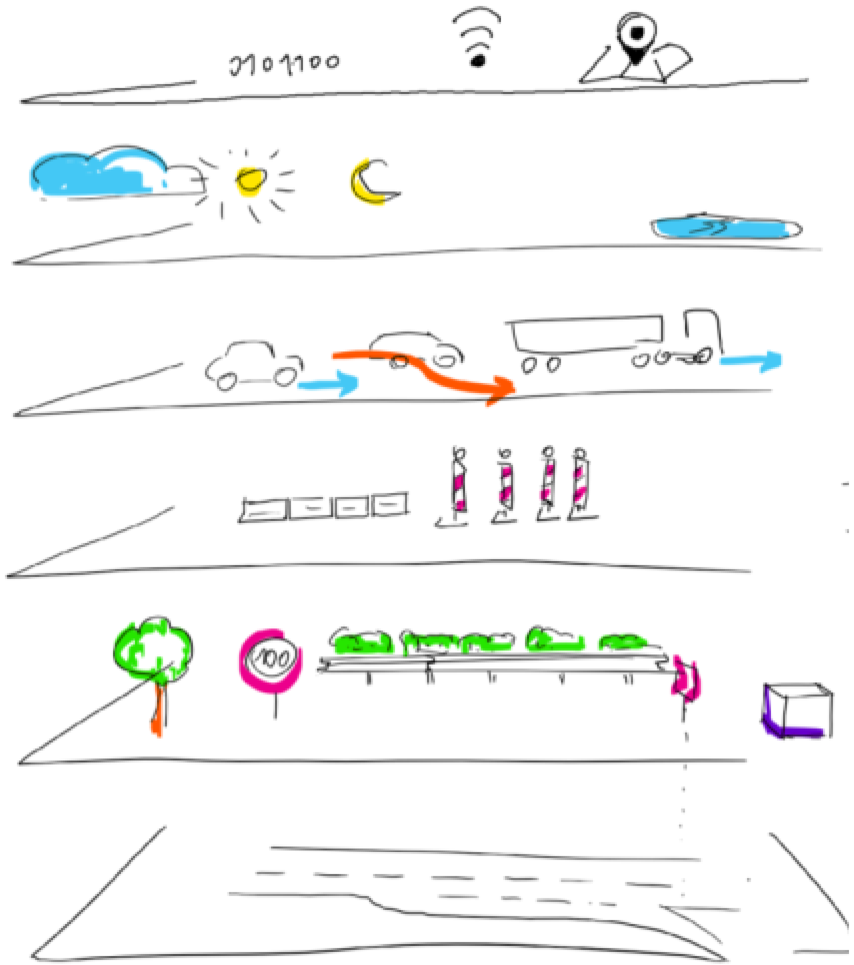


6 Layer Model for Database Scenario Description



Layer 6

Digital information:
e.g. V2X information on traffic signals, digital map data
=> *Availability and quality of information communicated to ownship*

Layer 5

Environmental conditions
Light situation, weather (rain, snow, fog…) temperature
=> *environmental influences on system performance*

Layer 4

Moving objects
Vehicles, pedestrians moving relatively to ownship
=> *relevant traffic participants and their motion incl. dependencies*

Layer 3

Temporal modifications and events
Road construction, lost cargo, fallen trees, dead animal
=> *temporary objects minimizing / influencing the driving space*

Layer 2

Road furniture and Rules
traffic signs, railguards, lane markings, bot dots, police instructions
=> *including rules, where to drive how*

Layer 1

Road layer
road geometry. Road uneveness (openCRG),
=> *physical description, no scenario logics*

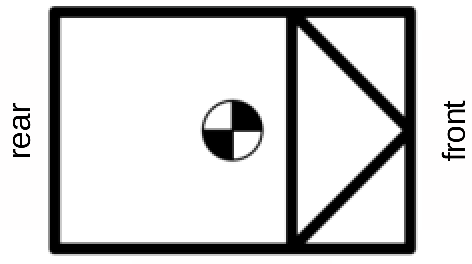
OPEN SCENARIO (Layers 4–5)

OPEN DRIVE (Layers 1–3)

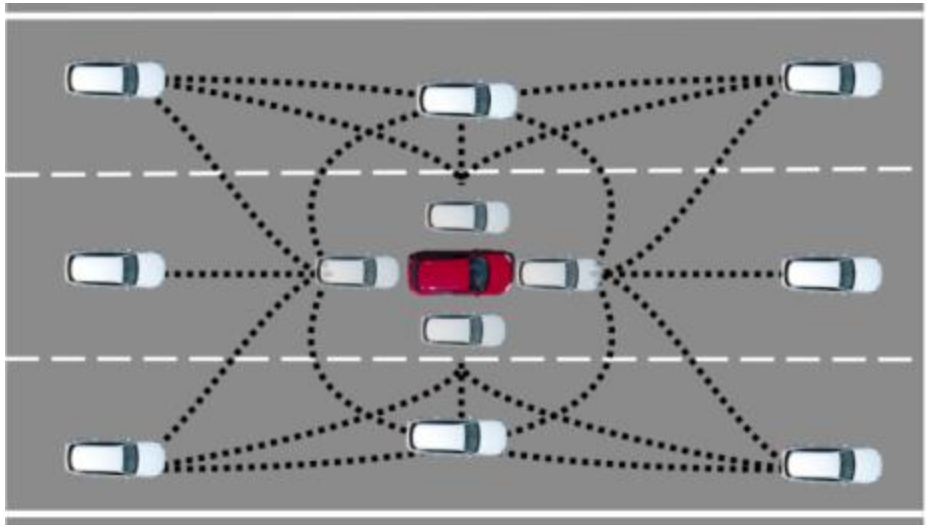
[1] Bock et al. 2018: Data Basis for Scenario-Based Validation of HAD on Highways
[2] Bagschik et al. 2018: Ontology based Scene Creation for the Development of Automated Vehicles

Challenger Scenario Concept for Layer 4

- **A challenging vehicle induces a reaction of the subject vehicle to prevent an accident [1]**
  - Description based on accident reconstruction
  - Relational description from the subject vehicle perspective with relative paths
  - Considering the potential impact location (front, side, rear) and the initial position of a challenger vehicle



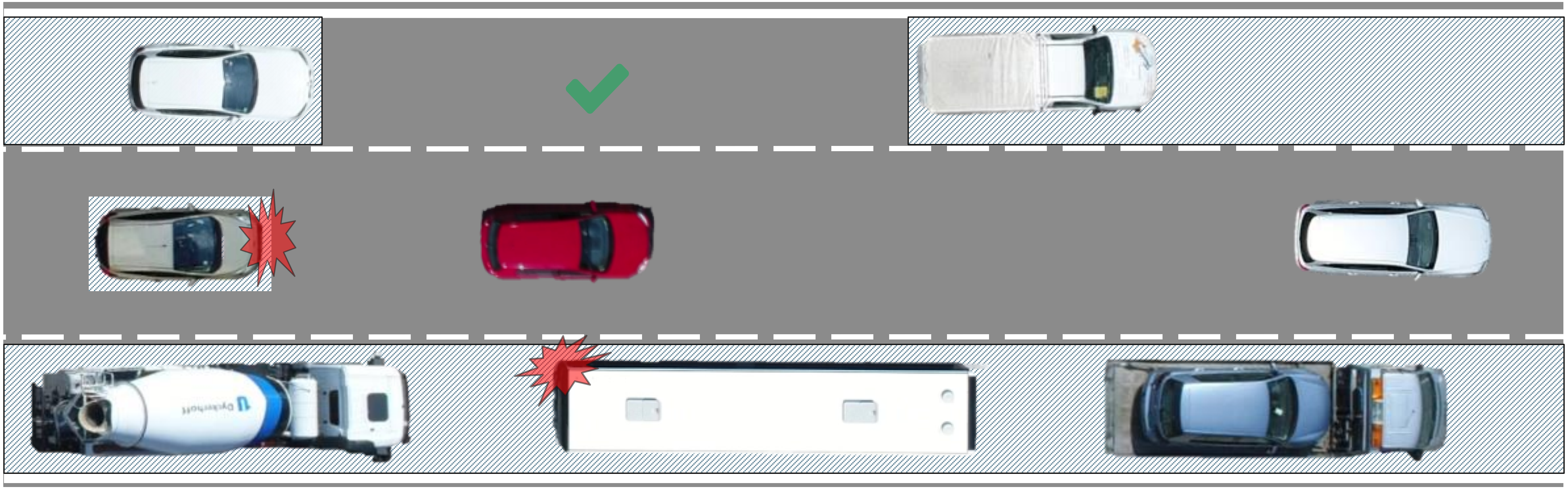
- **Challenger Vehicle**
  - 9 Scenario Types for influenced driving
  - 1 (non-) Scenario for uninfluenced driving
- **Further Vehicles:**
  - Occlude relevant information (“dynamic occlusion”)
  - Constrain possible actions of subject vehicle (“action constraints”)
  - Challenge the subject vehicle at the same time
  - Cause the challenger´s action (“challenger cause”)



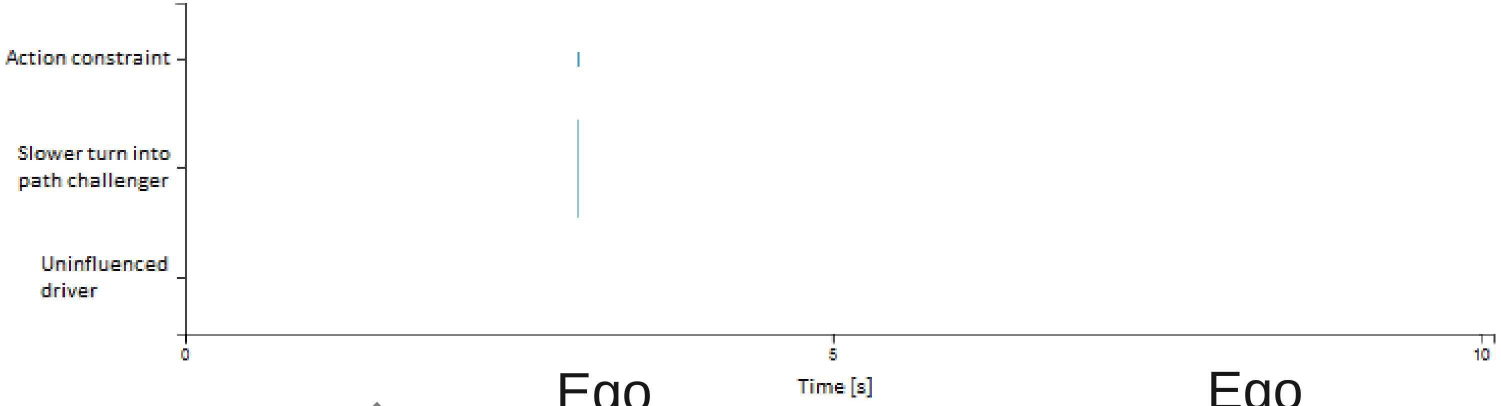
[1] Bock et al. 2018: Data Basis for Scenario-Based Validation of HAD on Highways
[2] Weber et al: A framework for definition of logical scenarios for safety assurance of automated driving

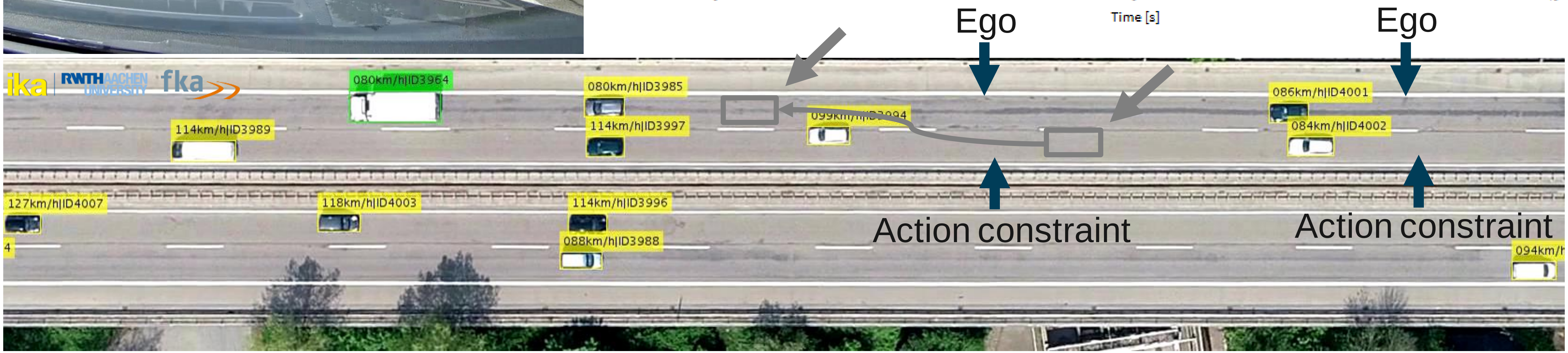
Challenger Concept - Example

- **Dynamic occlusions** restrict the subject vehicle´s perception
- Further surrounding vehicles **constraint the possibilities to react**
- Distinguish between **Object, Gap and Blockage** for each location around the vehicle (front/rear/left/right)



Database Mechanics - Determination of Scenario Affiliation





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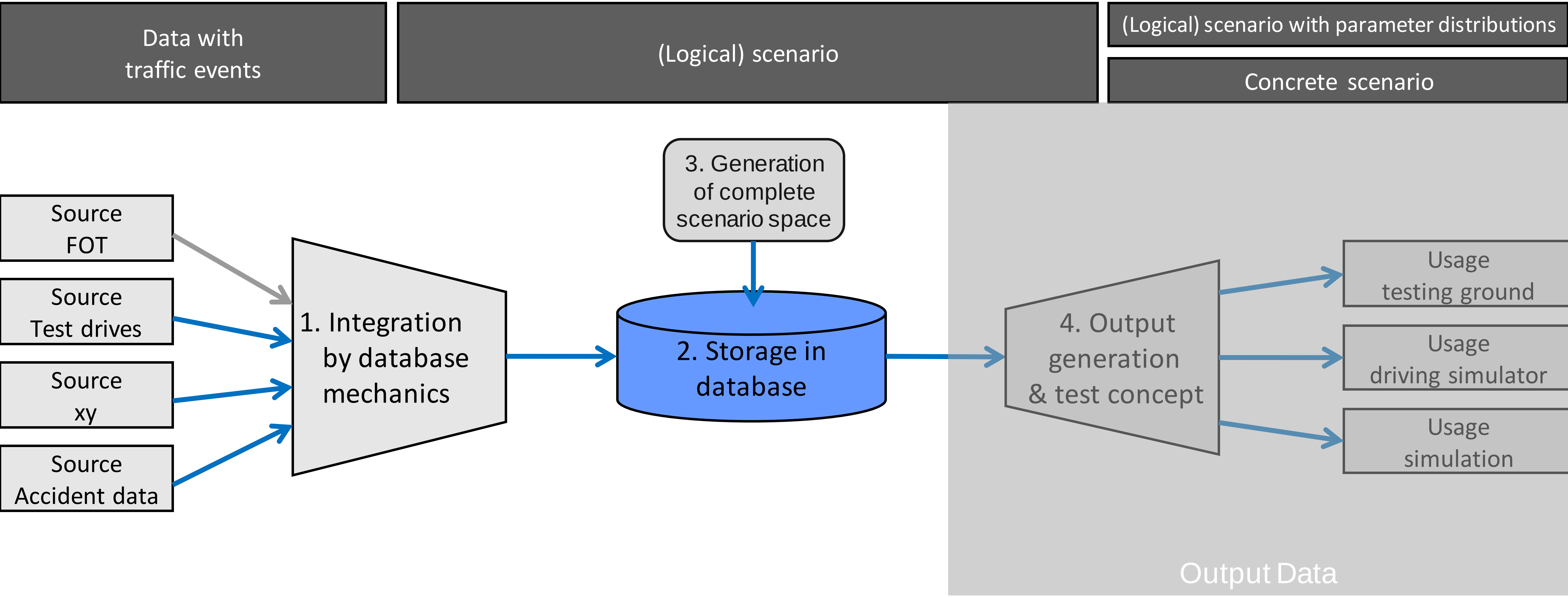


Testing of a Concrete Scenario in Simulation

- The selected concrete scenario can be reproduced in the simulation. A HAD-function integrated in the simulation can be tested.
- Here: “Slower turn into path challenger” (see screen 1)

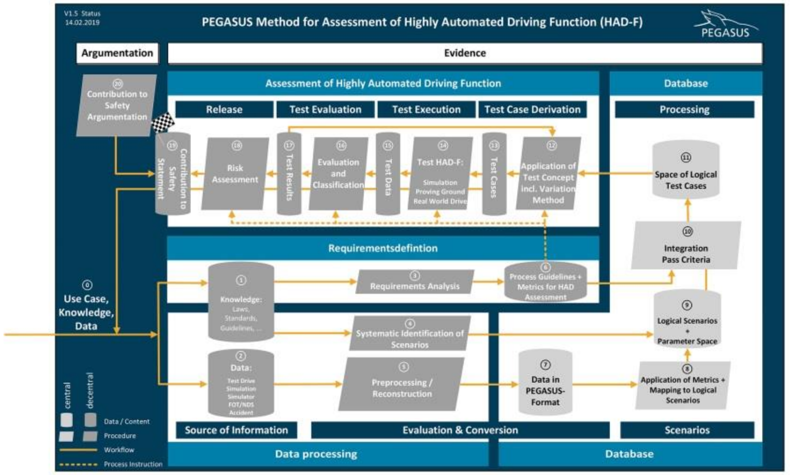
Testing of a Concrete Scenario on the Test Track

- The selected concrete scenario can be reproduced on the test track. A HAD-function integrated in VUT can be tested.
- Here: “Slower turn into path challenger” (see screen 1)

The Evolution of PEGASUS – The PEGASUS Project Family

PEGASUS

https://www.pegasusprojekt.de/en/home



Basic methodological framework

Focus: L3 on highways

SET Level 4to5
provides a simulation platform, toolchains and definitions for simulation-based testing of L4/5 automation in urban environments.

03/2019 – 08/2022, 20 partners, Vol. 30 Mio. €

VV Methods
develops methods, toolchains and specifications for technical assurance of L4/5 automation in urban environments.

07/2019 – 06/2023, 23 partners, Vol. 47 Mio. €

2015 | 2020 | 2025

Thank you for your attention!

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CREATING IDEAS &
DRIVING INNOVATIONS