Machine Learning & Active Safety Using Autonomous Driving and NVIDIA DRIVE PX

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Agenda

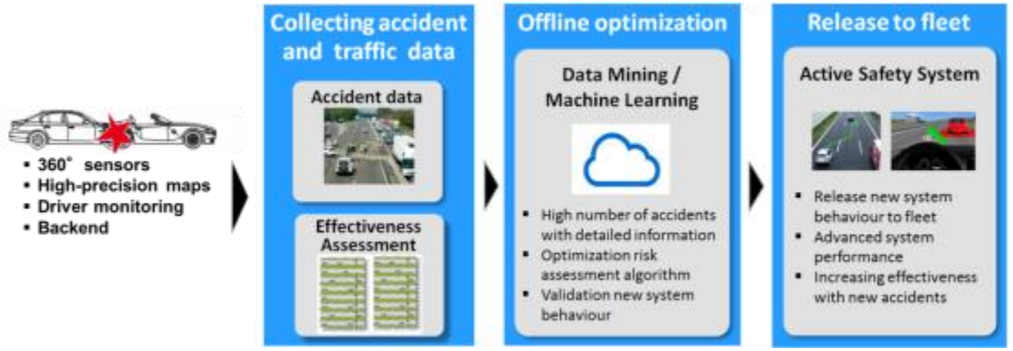
1	Open vehicle research platform

3	Austrian Test & Validation Region

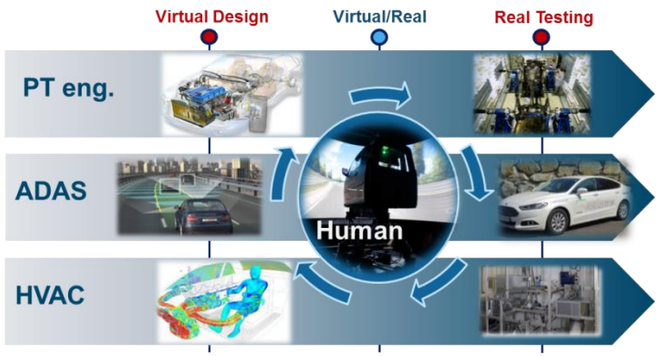
ALP.Lab

Austrian Light Vehicle Proving Region for Automated Driving

2	Machine Learning & Active Safety



4	Fully digital tool chain



Open vehicle platform

Automated Driving Demonstrator

Open vehicle platform: Roadmap

NVIDIA DRIVE PX 2

HW-Platform
Nvidia, Infineon Aurix, dSPACE, Data logging & measurement equipment, self-diagnostics

Deep learning
Scene interpretation, Advanced HMI augmented reality, …

Electrified vehicle with internal access; steer, brake, drive by wire, dual energy storage
Demonstrator Vehicle

in ½ year

in ½- ¾ year

in ¾ -1 year

in 1 year

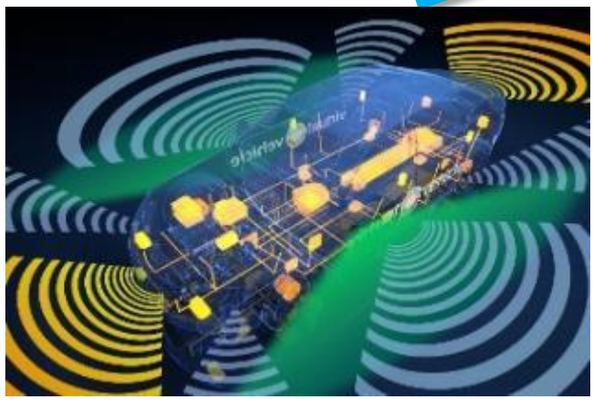
in 1,5 years

~1,5 years+

ADAS Sensor Integration
Radar, Camera, GPS, IMU, Ultrasonic, Lidar, Interior-Camera, C2X, Battery-monitoring
Sensor-Fusion

ADAS Functions Implementation
Advanced control (LKA, ACC, LCA, Motorway Assistant, EBA), Online Driver Monitoring, Collision detection, Traffic-Light-Assistant, Infrastructure interaction, sensor self-diagnostics …

Optimization and Validation
HW-SW co-simulation, Distributed vehicle-Testing, Testdrives, Function optimization
Vehicle in the loop tests



Open vehicle platform: Components

4 x Sekonix SF3323 Automotive Camera
(100° aperture angle for 360° surround vision)

2 x Sekonix SF3322 Automotive Camera
(60° aperture angle for long range vision)

1 x Mobileye 630
(Full Extended Log Data)

1 x Infineon ToF Camera prototype*
(evaluation for park assistance)

2 x ScaLa LIDAR sensor*

2 x Continental Long Range Radar ARS 408

4 x Continental Short Range Radar SRR208

*planned in Future

Open vehicle platform: Data Rate

SONAR
~10-100 KB
PER SECOND

RADAR
~10-100 KB
PER SECOND

GPRS
~50 KB
PER SECOND

AUTONOMOUS VEHICLES
4.000 GB
PER DAY

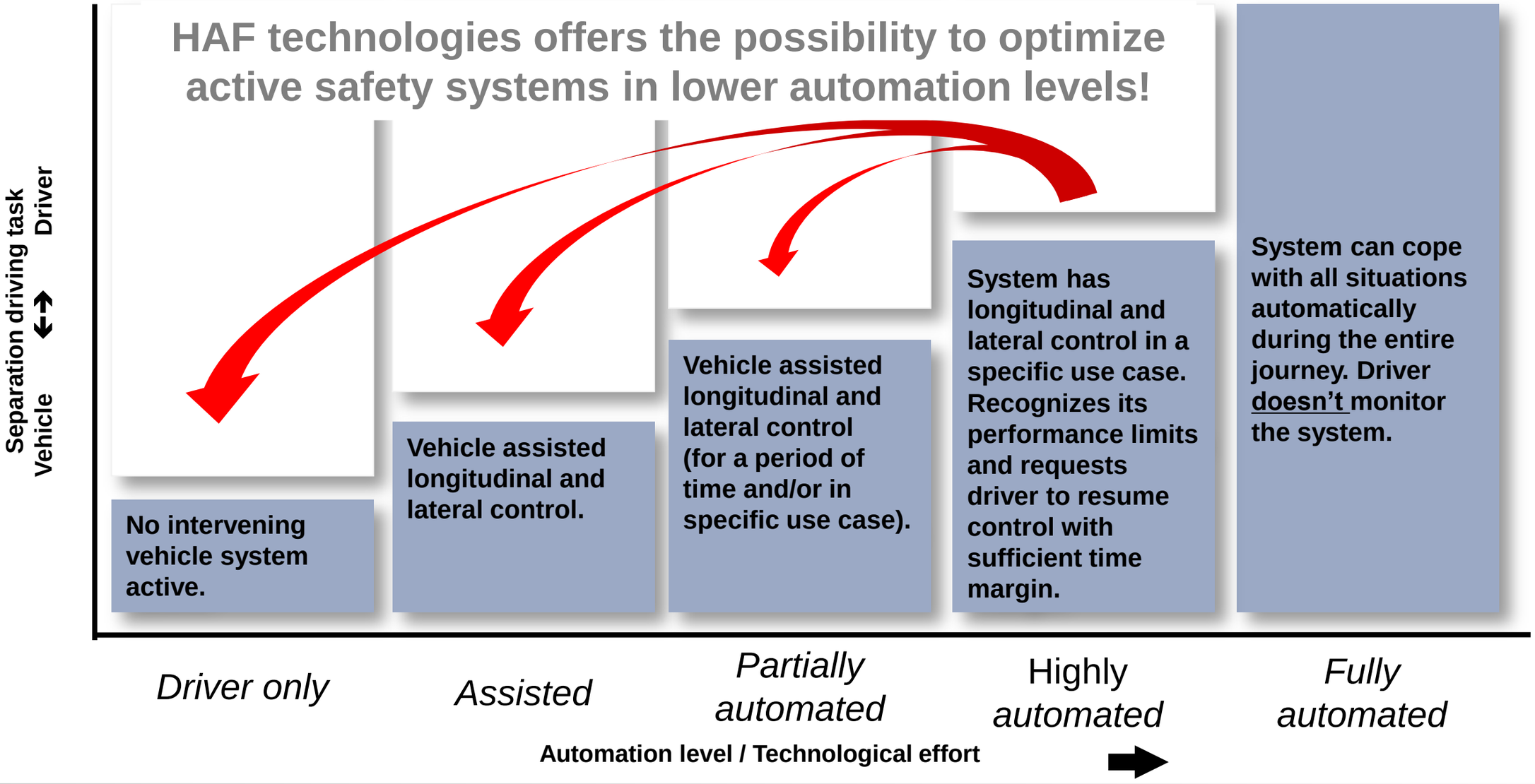
CAMERAS
~20-40 MB
PER SECOND

LIDAR
~10-70 MB
PER SECOND

Source: Intel

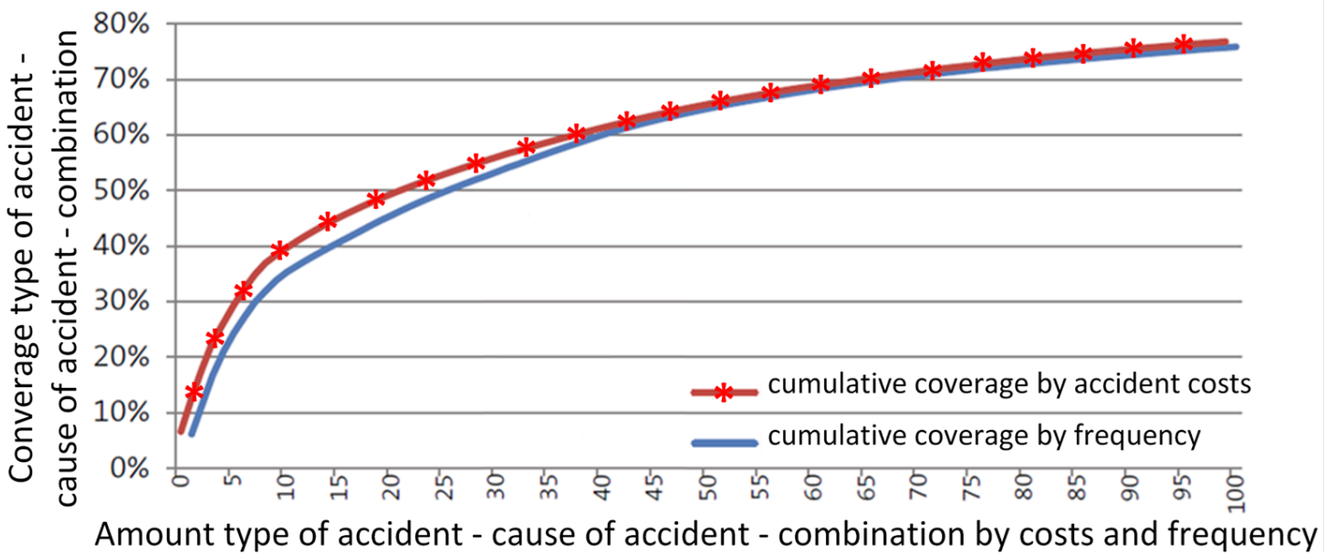
Machine Learning & Active Safety

Motivation.
Active Safety vs. Automated Driving



Problem: Complexity and high variation of accidents

- Thinking of safety functions for every combination of accident **type** and **cause**



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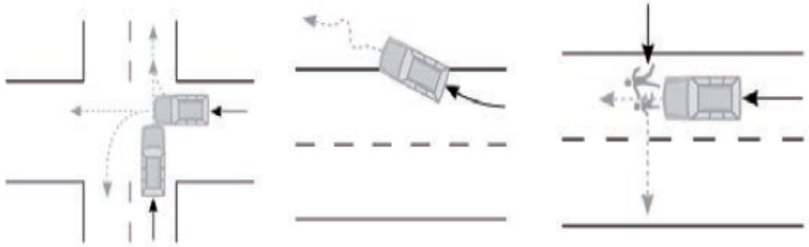


Cause: speeding, slippery road, etc

First 50%: 26 types and causes of accidents

Last 50%: 5287 types and causes of accidents

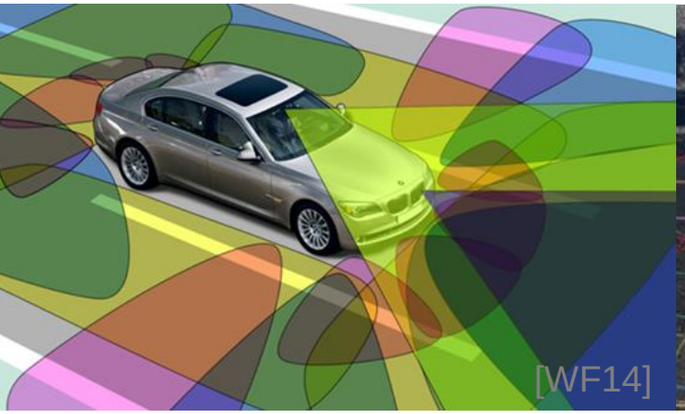
- Function design based an **quantitative** (e.g. DESTATIS) and **qualitative** accident databases (e.g. GIDAS Pre-Crash-Matrix)

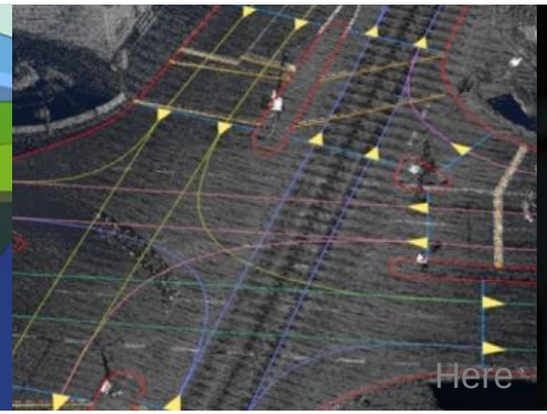
Exponentially growing effort → tiny increase in accident coverage
How to cover wide range of variations?

Required Technologies for Highly Automated Driving:

- Redundant 360°environment recognition
- High-precision digital maps incl. localization
- Driver monitoring
- Automated driving until the high dynamic limits
- Backend communication

Backend As A Sensor





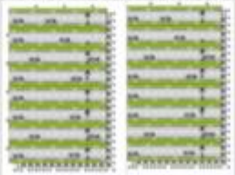
Vision. Optimization based on real world traffic data.

- 360° sensors
- High-precision maps
- Driver monitoring
- Backend

Collecting accident and traffic data

Accident data

Effectiveness Assessment



Offline optimization

Data Mining / Machine Learning

- High number of accidents with detailed information
- Optimization risk assessment algorithm
- Validation new system behaviour

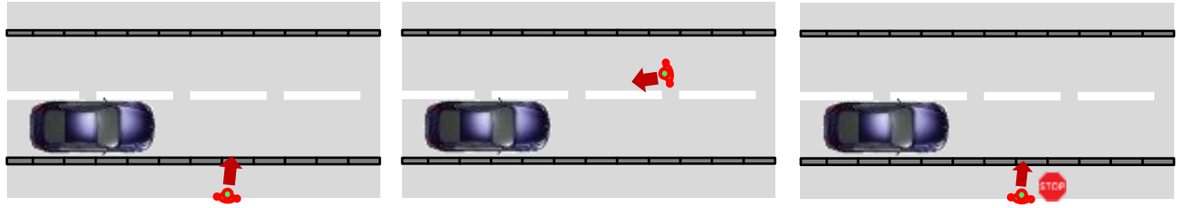
Release to fleet

Active Safety System

- Release new system behaviour to fleet
- Advanced system performance
- Increasing effectiveness with new accidents

Our use case: Crossing pedestrian (75% of all pedestrian accidents)

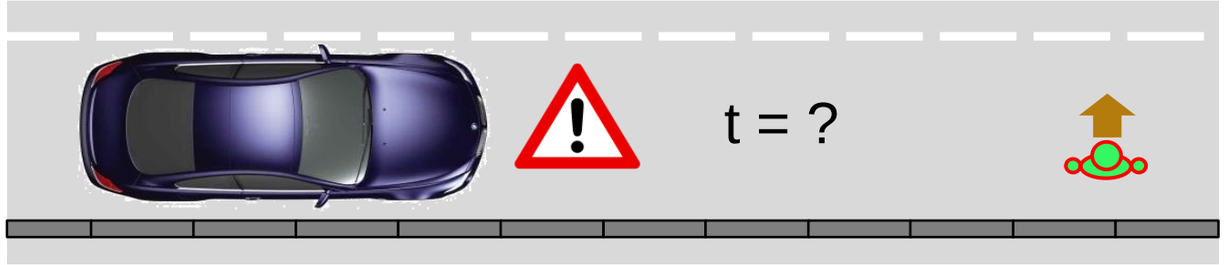
- Generated pedestrian scenarios from the Effectiveness analysis



Crossing scenarios	Total scenarios	Accidents
Training data	1840	242
Test data	1829	243

Machine Learning.
What are we going to learn?

Point of No Return – Learning of the brake time based on the accident data, when the emergency brake assistance needs to brake. The **brake time** is a result of the **system limitations** of the Active Safety System. The **uncertainties** of the pedestrian and the driver behavior will be considered by the variation of the accident data.



FEATURES

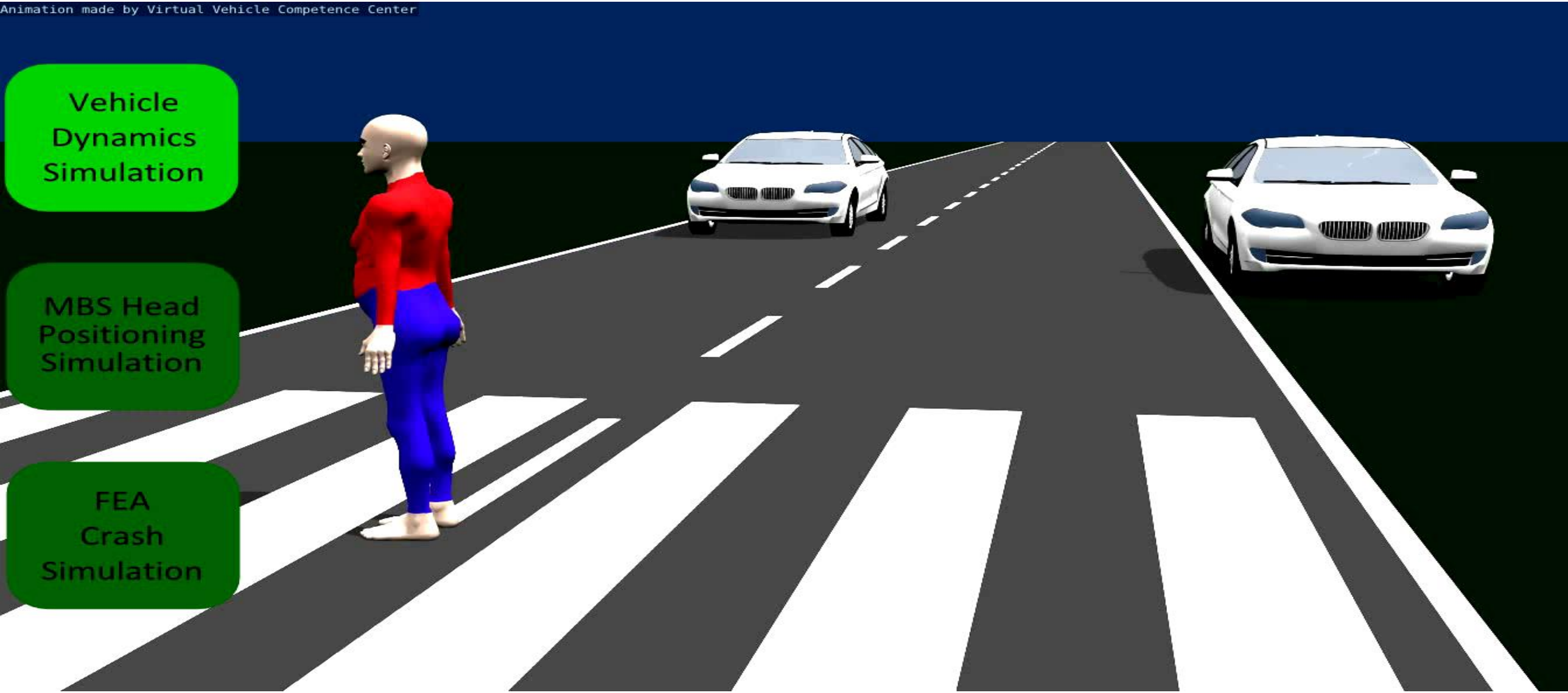
1. Velocity Vehicle*
2. Acceleration Vehicle*
3. x/y-position Pedestrian*
4. Rel. velocity x/y-direction Pedestrian*
5. Brake pedal position
6. Angle Vehicle – Pedestrian*
7. Distance Vehicle – Pedestrian*
8. Velocity Pedestrian*
9. Orientation Pedestrian*
10. **Time-To-Collision***
11. **Predicted pedestrian position at TTC=0***

Simplified labeling datasets:

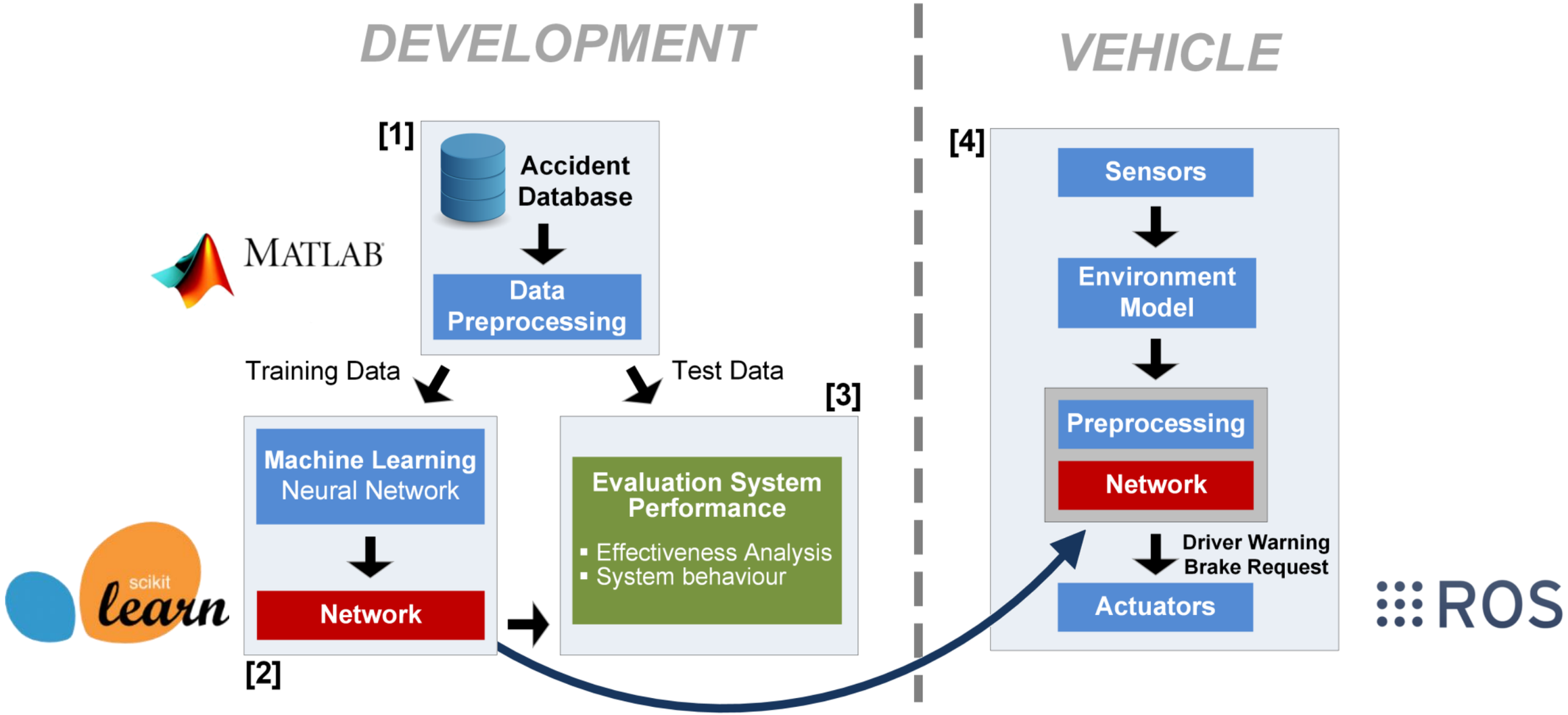
```
a = 10;            % Acceleration vehicle [m/s²]
td = 0.2;          % Delay brake        [s]
ts = 0.2;          % Delay max. brake pressure [s]
SAFETY_GAP_SIDE = 0.7;                  [m]
```

```
ttb = (ego.v - a/2*ts)/a + ts + td;
if ( ttb > ttc) && abs(object.y_pred) < ego.width/2 )
    avoidable_aeb = 0;
else
    avoidable_aeb = 1;
```

Example – VRU Safety



Concept.
Function Development Active Safety System.

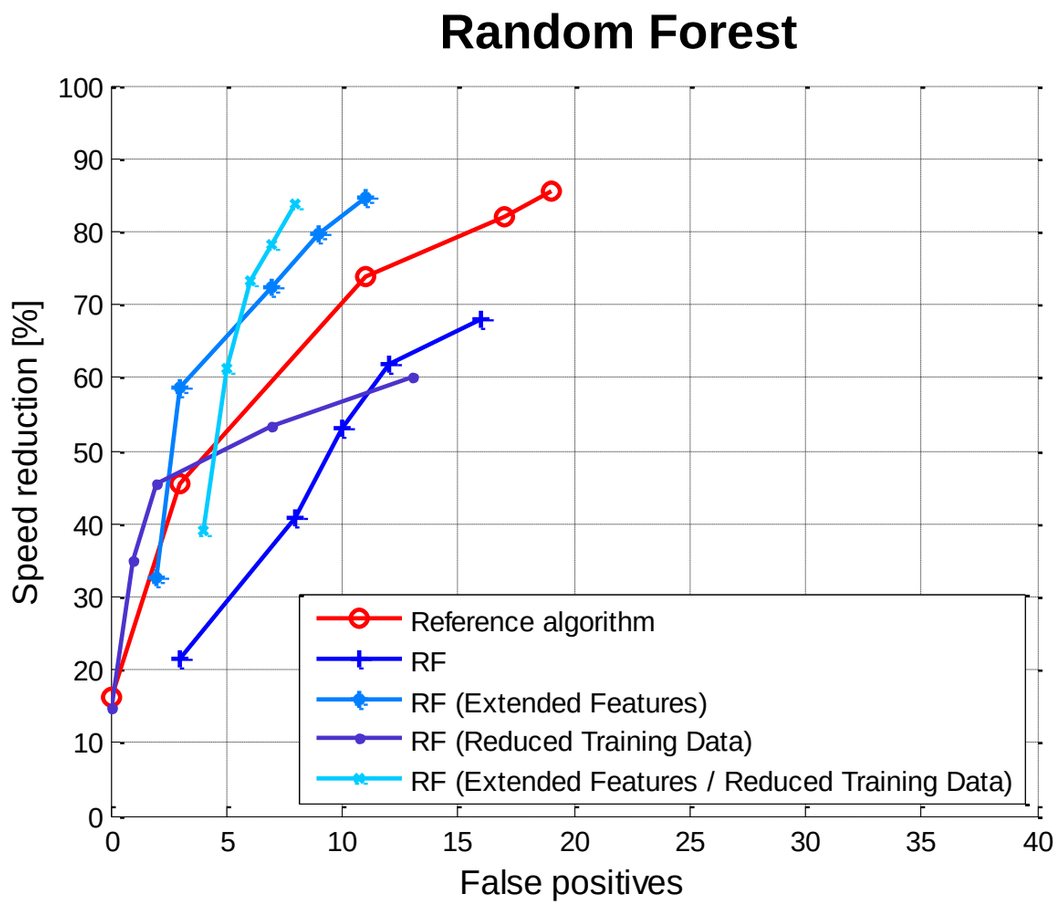


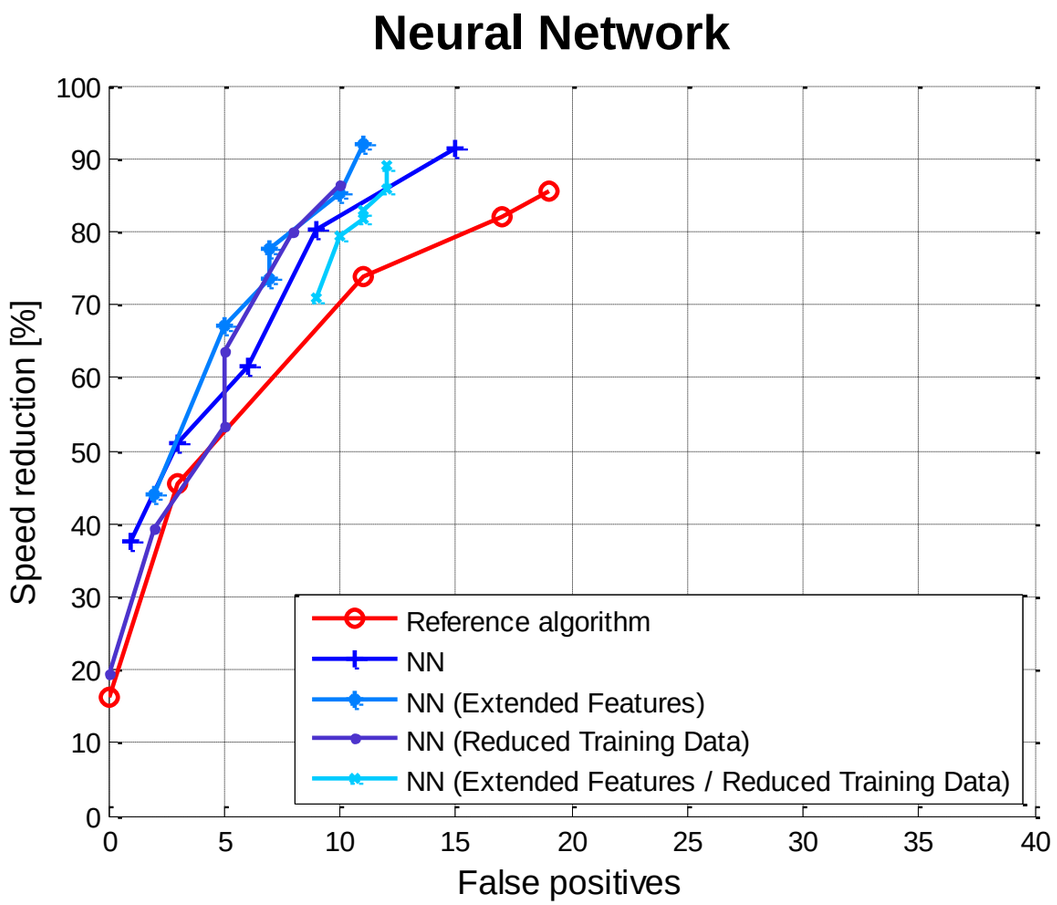
Simulation Results. False positives vs. speed reduction

Variation by the algorithm evaluation:

1) Feature set (feature variation)

2) Training data (reduced speed range pedestrian)

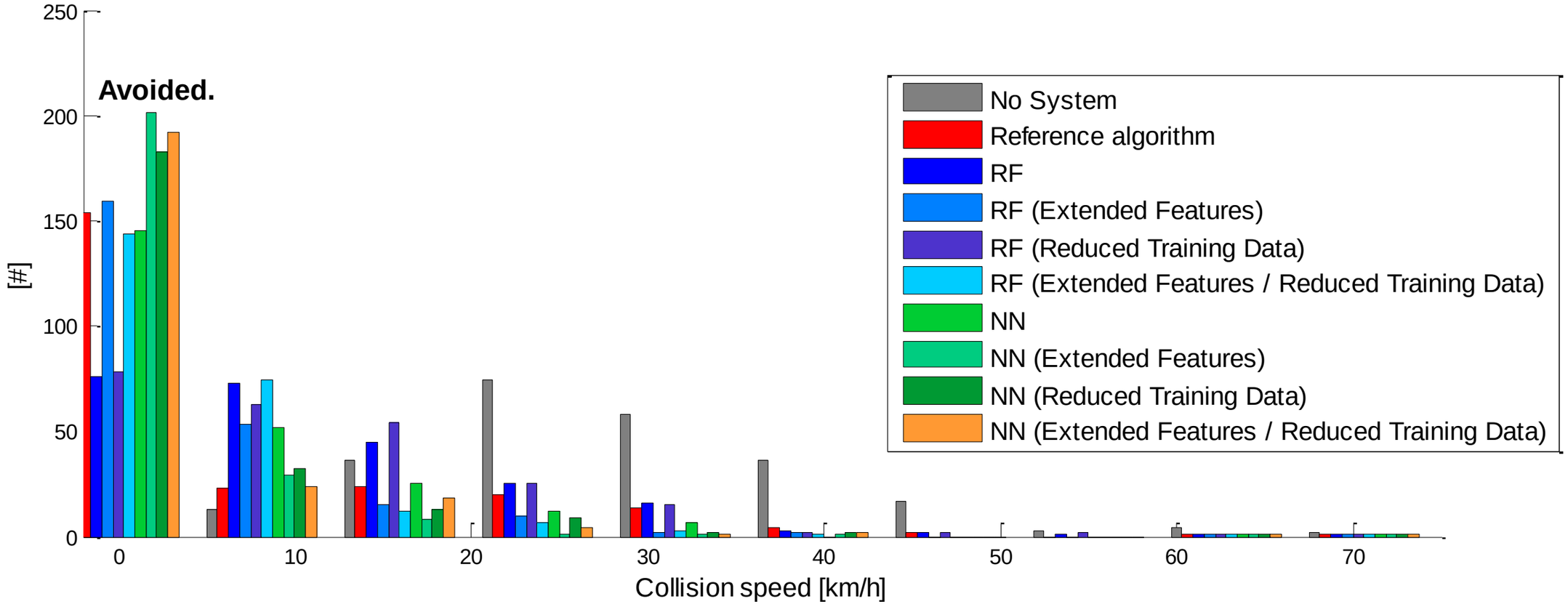




Simulation Results. Distribution speed reduction

	Speed reduction
Reference Implementation	73.7%
Random Forest	83.4%
Neural Network	92.0%

Operating point algorithms: *equal amount of false positives (10)*



Summary. Active Safety uses Machine Learning

Limitations in our consideration:

- Theoretical analysis of the method, without the consideration of legal aspects. Proof-of-concept.
- **Series application only based on real world data.**

Results:

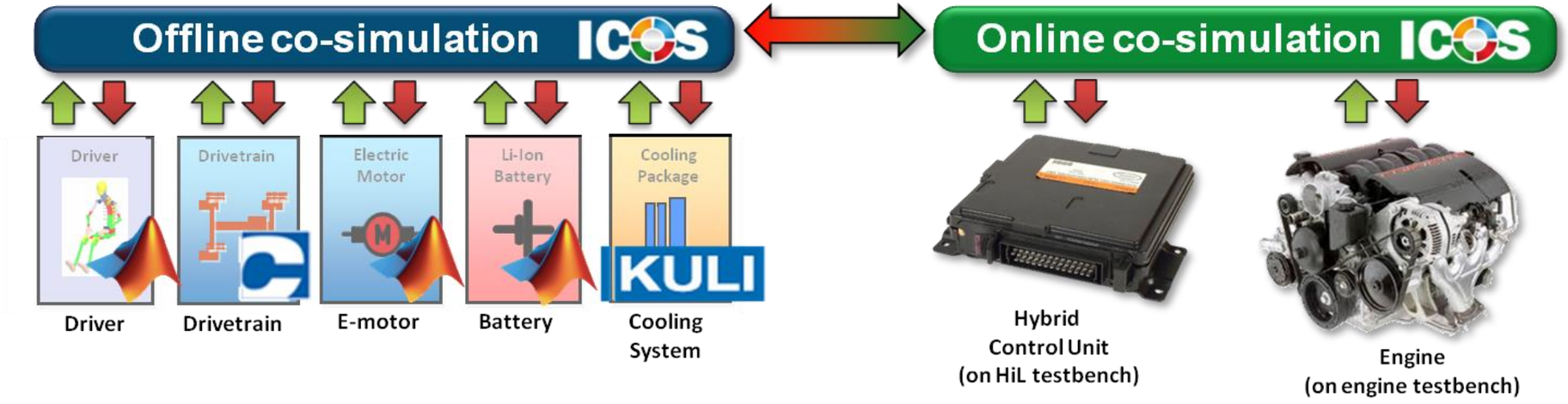
- Machine Learning offers the potential to improve Active Safety Systems. **But** the verification of the system raises new challenges.
- Required system behavior is reachable, technical design for defined effectiveness or FP/FN is possible.
- Neural Networks handle the missing excluded speed range of the pedestrian and a standard feature set without a performance drop compared to the Random Forest.

Challenges:

- Required real world data: amount, quality and more complex scenarios.
- Verification of the system behavior

Fully digital tool chain
Initiative: Open Connected Testbed

Real-Time Co-Simulation



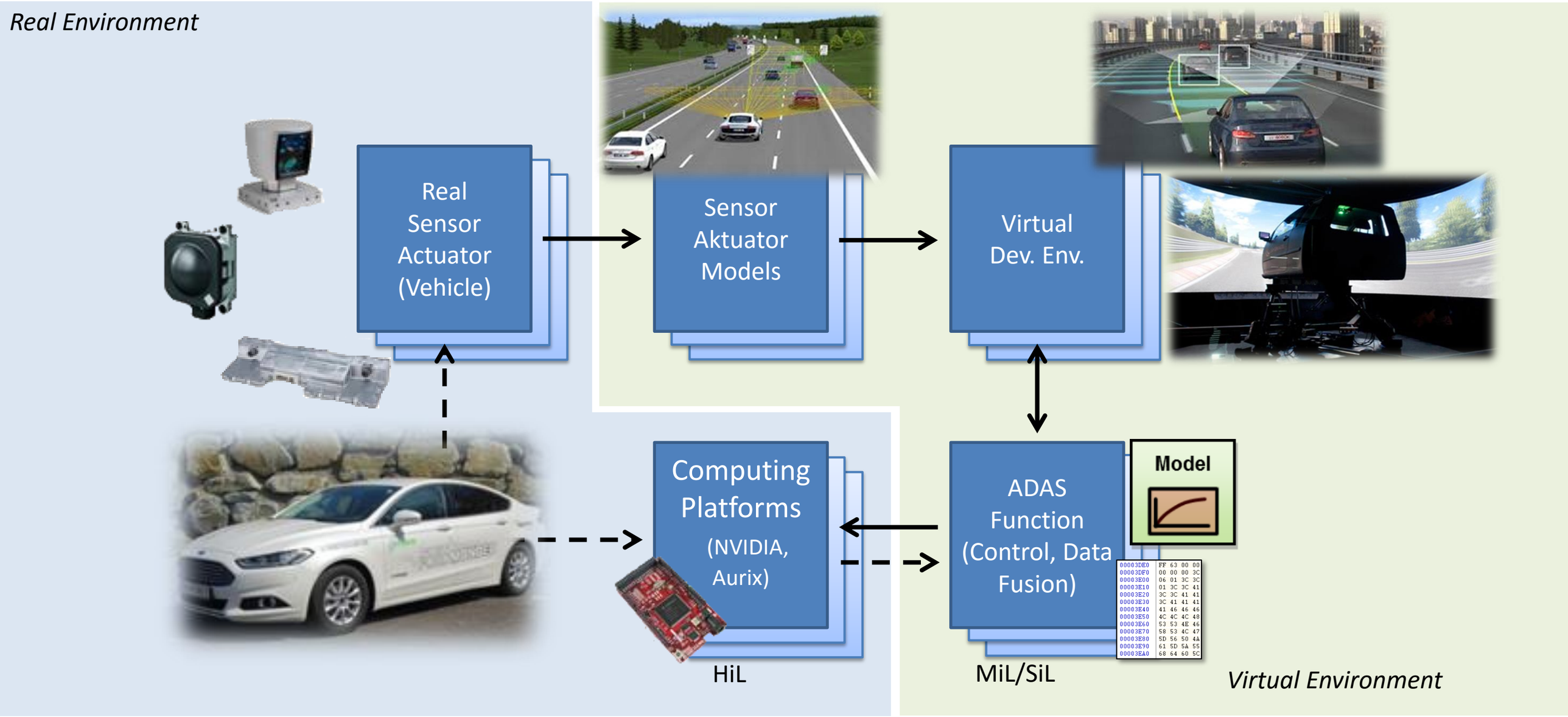
System Simulation / RT capability

- Combine simulation models from very different tools

- Seamlessly from MiL from SiL to HiL

Key technology
Energy preserving algorithms for stability (patented)

VIR-REAL Environment



Agenda

ALP.Lab

Austrian Light Vehicle Proving Region for Automated Driving

ALP.Lab: testing possibilities

Private

in preparation

Magna & AVL proving grounds,
Graz/ Styria

planned

Research@ZaB,
Eisenerz/ Styria
(tunnel)

planned

Lungau proving grounds,
Salzburg
(tunnel, toll station, snow)

planned

The Red Bull Ring, Formula 1
Spielberg/ Styria

Public

in preparation

Motorway A2,
Graz-Ost – Laßnitzhöhe
Mooskirchen – Graz-Ost (planned)

planned

Motorway A9, A2
St. Michael – Graz-Ost
(tunnel, toll station)

planned

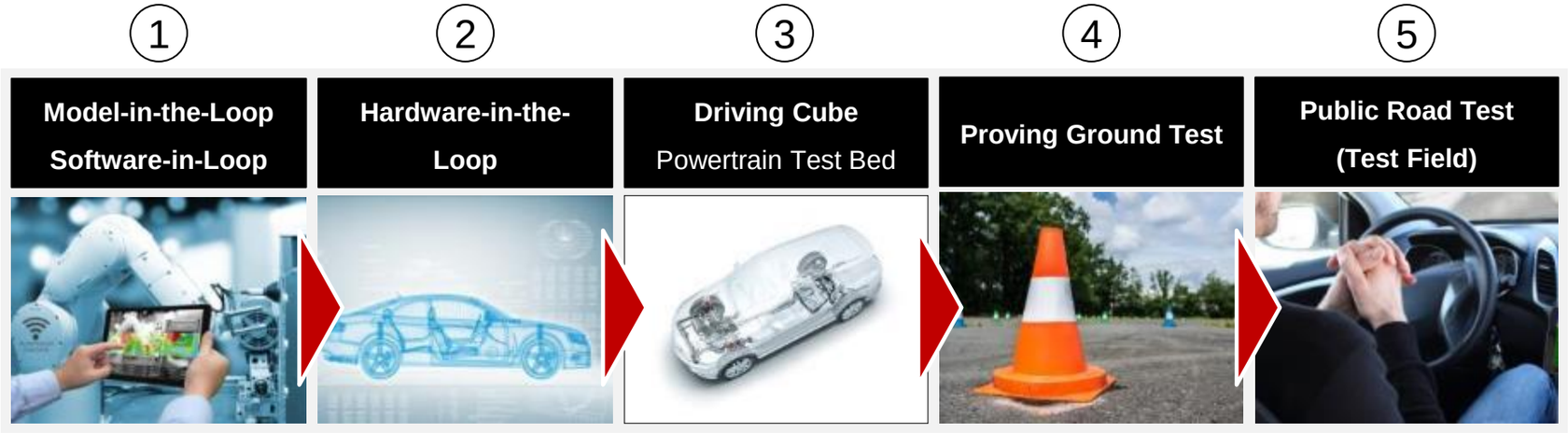
Motorway S6, S36, A9
Leoben – SLO
(border crossing)

planned

City of Graz public roads,
Graz/ Styria

…with more testing grounds that will follow

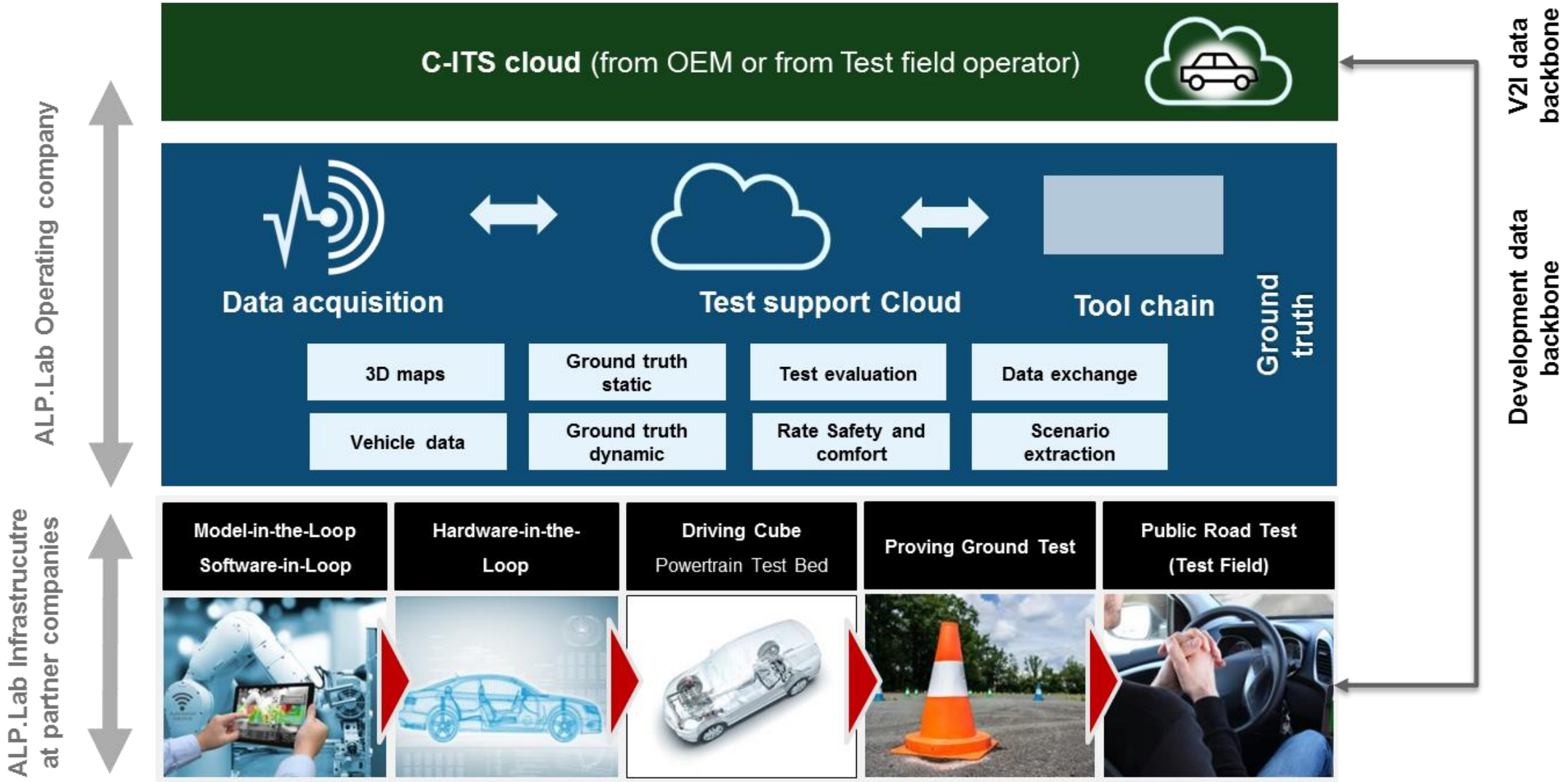
Full digitally integrated test chain



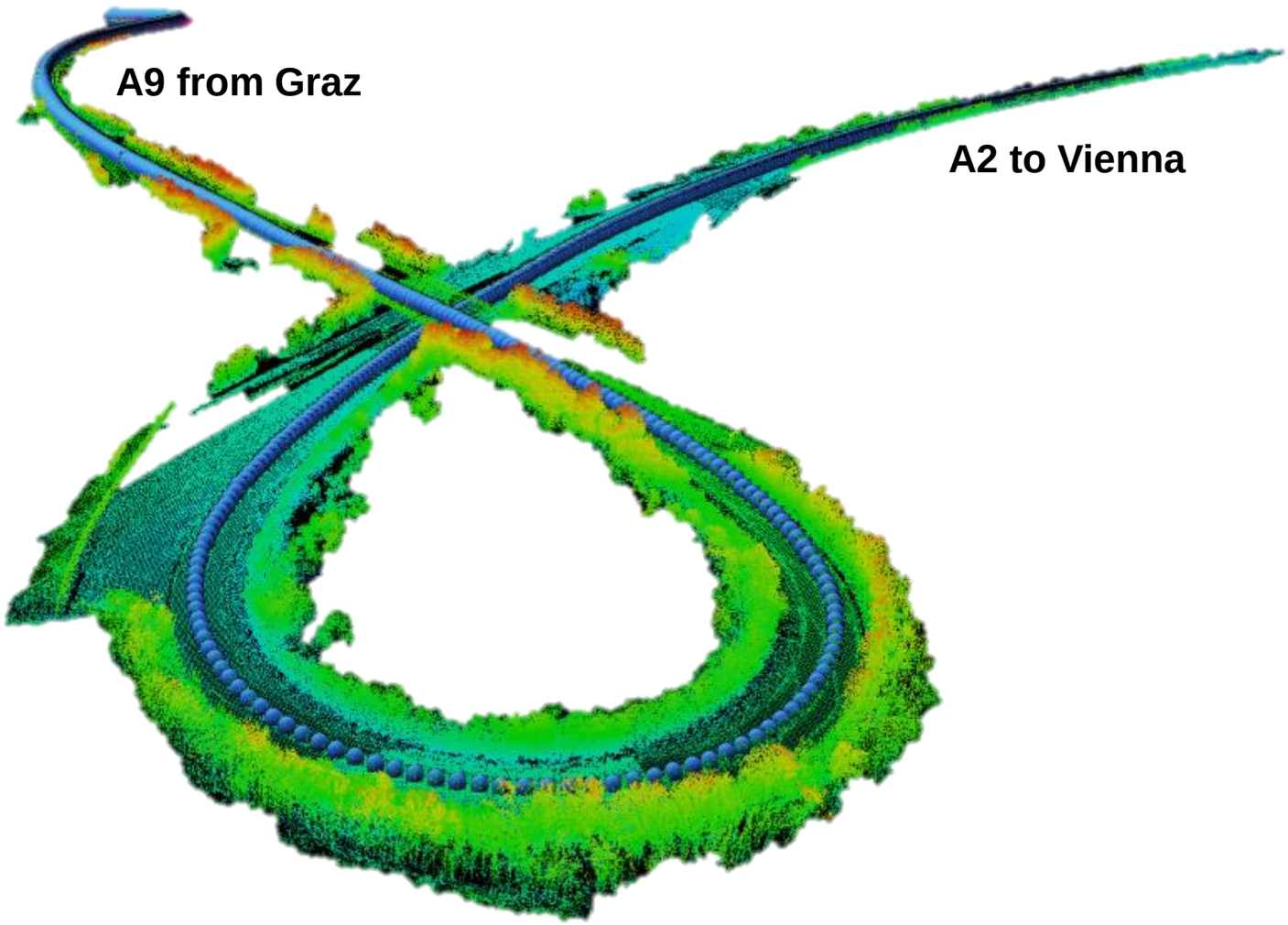
1	**MiL / SiL (Simulation):**	Testing of ADAS/ADV software functions
2	**HiL:**	Driving simulator (test of human interactions) Sensor validation and qualification
3	**ViL (Driving Cube):**	ADAS/ADV vehicle qualification prior road test
4	**Proving Ground:**	Reproducible test of dangerous scenarios
5	**Public Road Testing:**	Test in regional-specific real-world scenarios

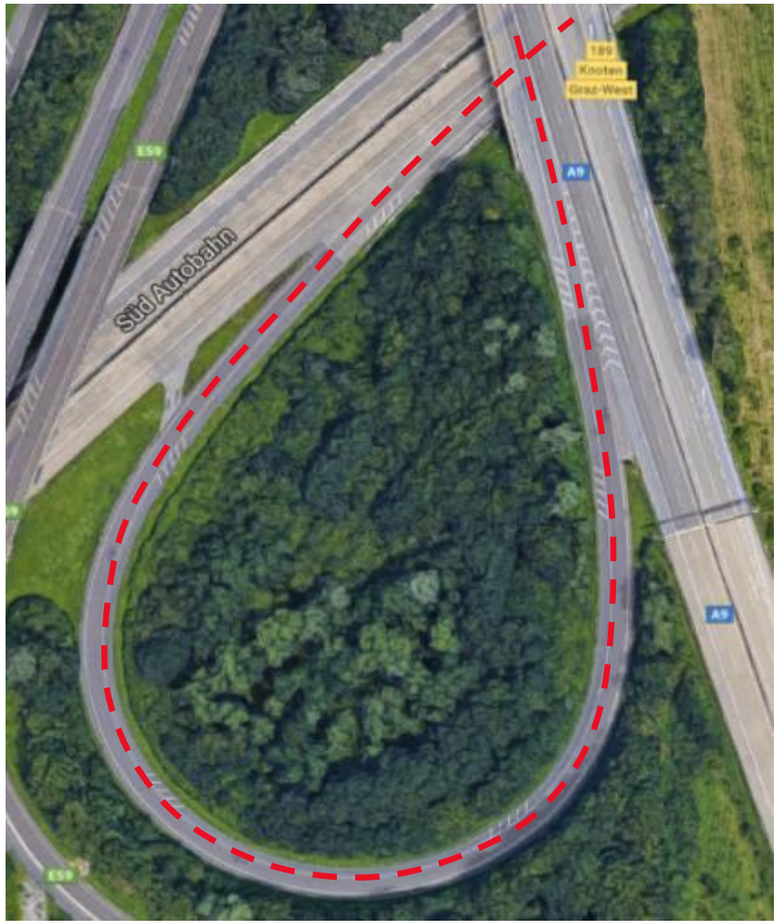
The 5 testing stages are embedded in a **system of comprehensive tools and models, for data management, processing and reporting**

ALP.Lab at a glance



ALP.Lab – Examples of point cloud and image data



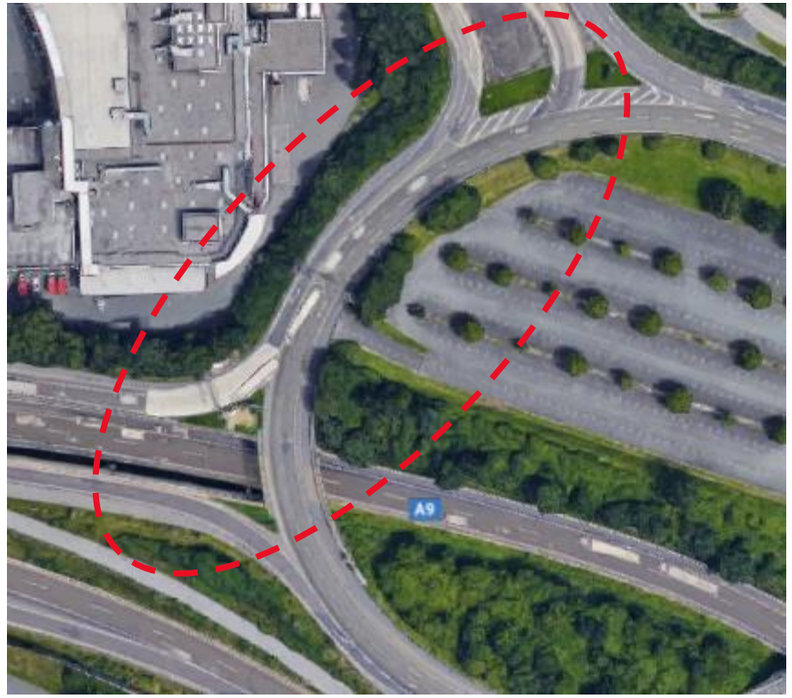


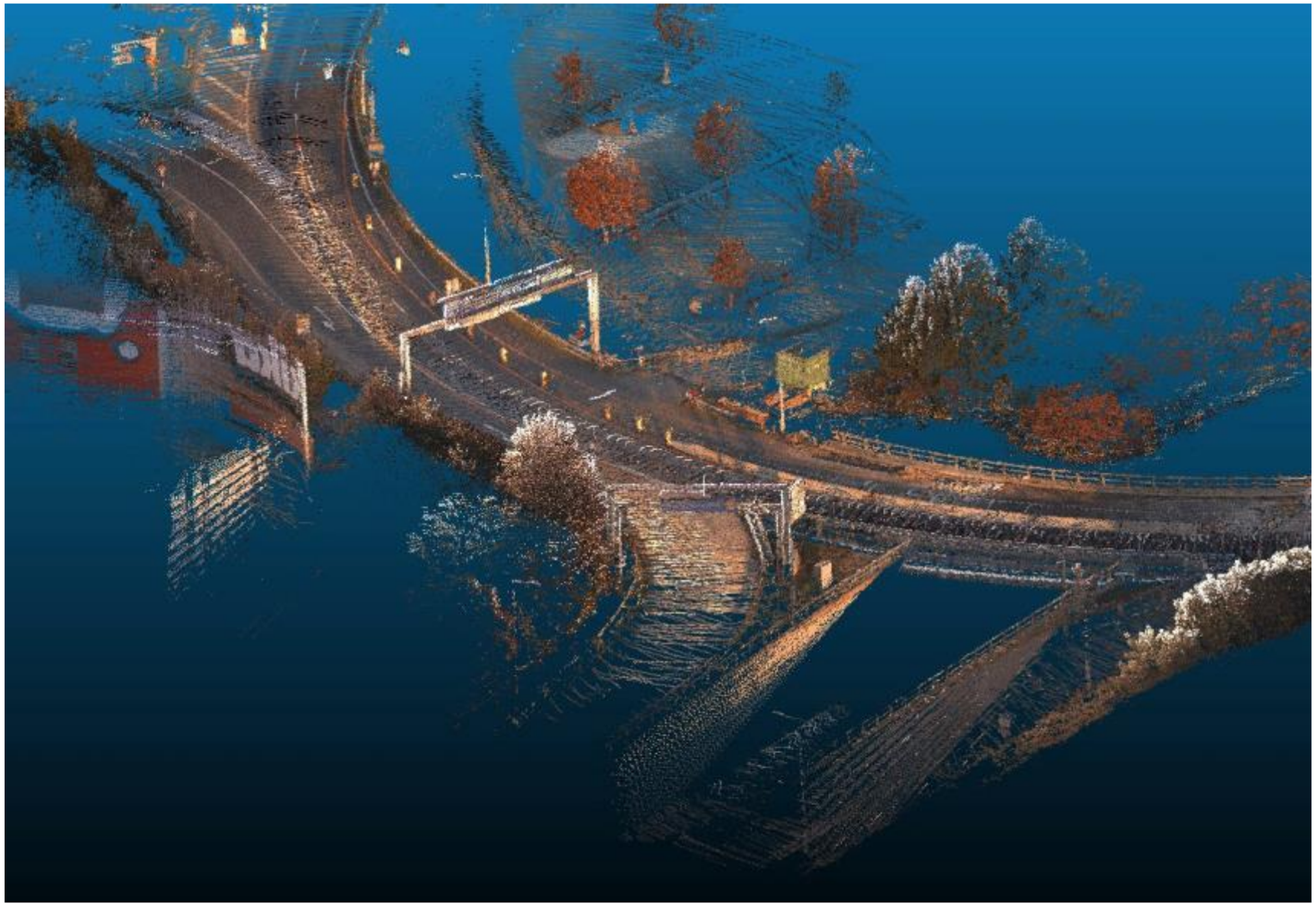
Graz West A9/ A2

Dense 3D LiDAR point cloud

Color represent Elevation

ALP.Lab – Examples of point cloud and image data



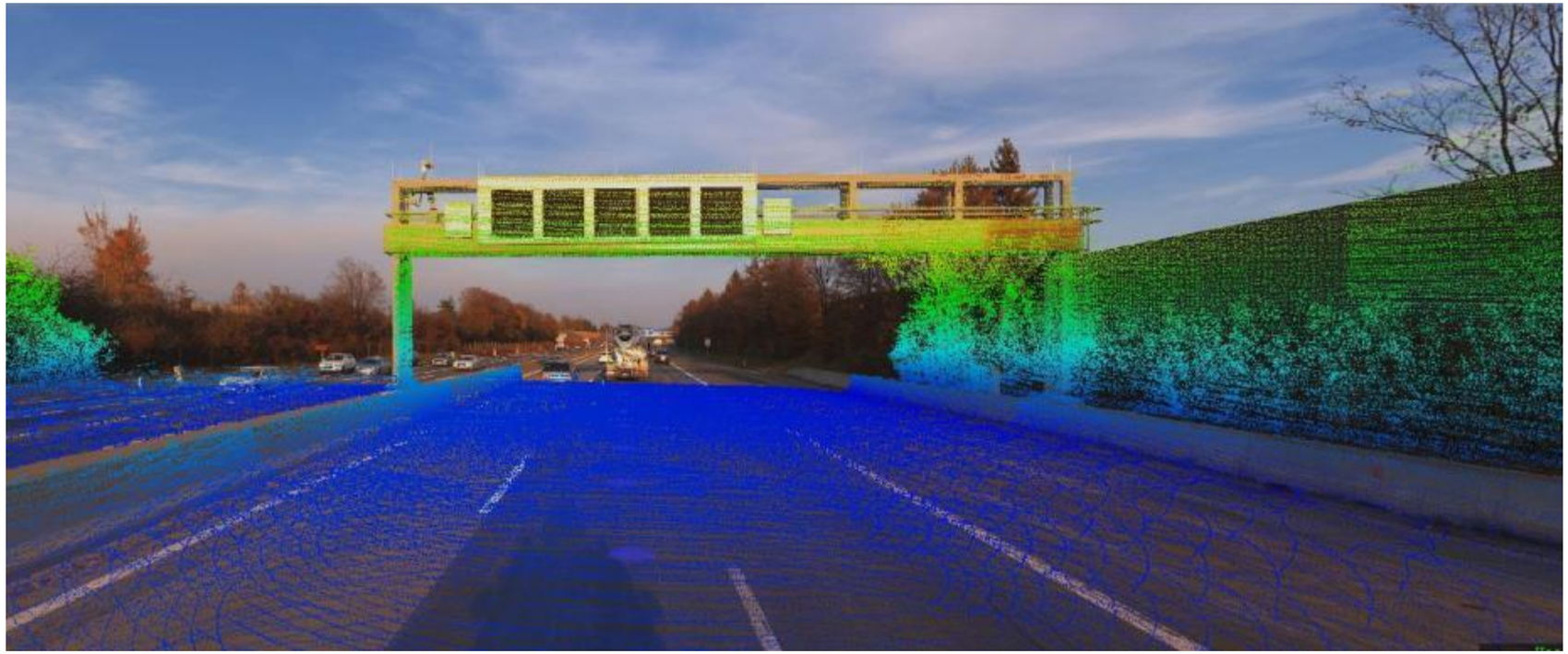


Graz Webling

Dense 3D LiDAR point cloud

Color from UltraCam Panoramic Image Data

ALP.Lab – Examples of point cloud and image data



A2 between Graz West and Graz Airport

Dense LiDAR Point Cloud and Image Data

Color Code of the Point Cloud: Elevation

SUMMARY

Proof of Concept: Machine Learning can improve active saftey systems

Flexible Research Platform for Autonomous Driving is available

Austrian Test & Proving Ground including a full digitally integrated test chain is build starting in June 2017

Combined virtual & real simulation environment prepares future virtual homologation of complex systems.

Thank you

Dr. Jost Bernasch

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Graz, Austria