

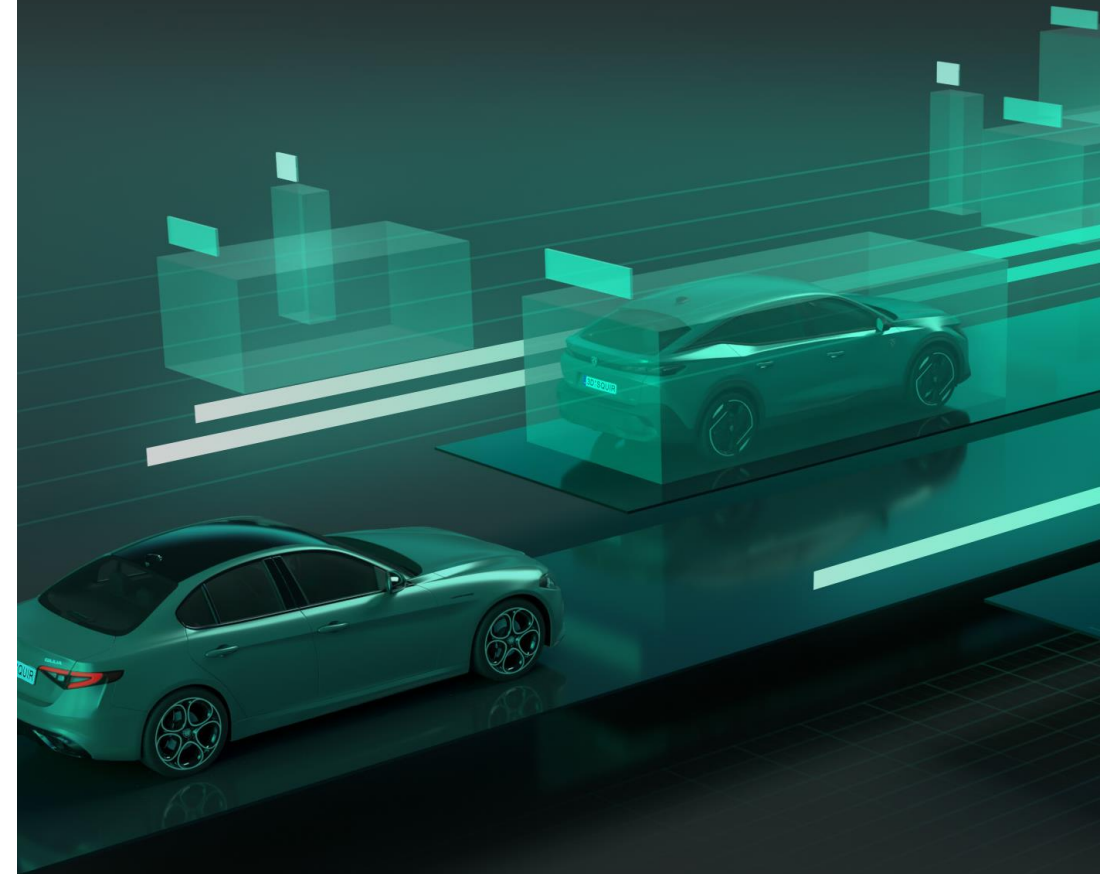
# How 3D data processing enables automated driving development

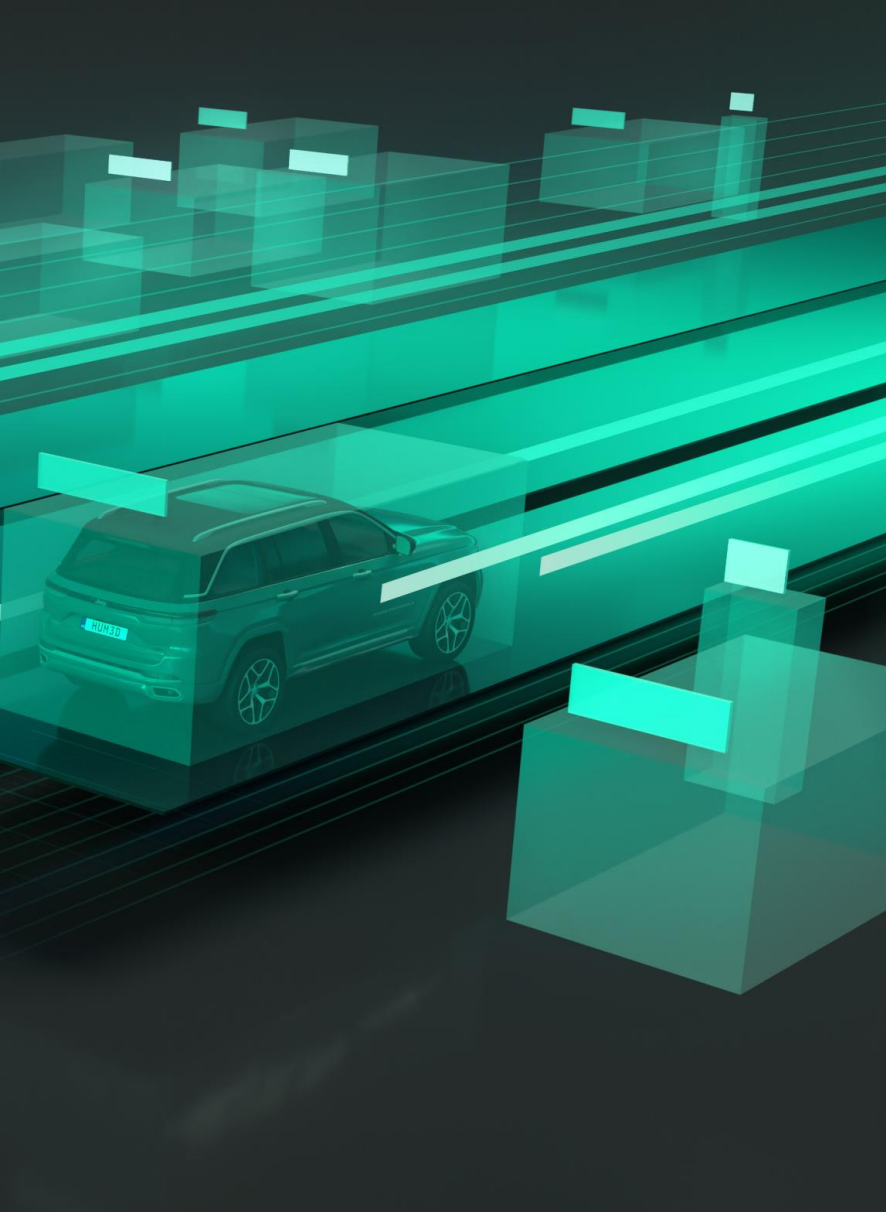
**PÉTER T. KOVÁCS**  
Senior VP / aiData / aiMotive



# 3D data is all around us

- **Automated driving is inherently a robotic challenge in which vehicles operate in a 3D world**
- **Vehicles sense the world with multiple sensors**
  - Some of which have depth sensing capabilities, while others don't
  - Multiple sensors have to be calibrated to produce a consistent representation of the 3D world
- **Real-time operation**
  - Real-time processing of sensor data to reconstruct a 3D world model (why 3D? think overpasses)
  - Neural networks for easier generalization and less manual tuning
  - Requires GPUs or neural network inference accelerators
  - Multiple compute units to enable redundant operation





## 3D data is all around us

- **Neural network training**
  - Produces a model that generates the 3D world model from the sensor data
  - Required large quantity of balanced reference data for training (expected input-output pairs)
  - Requires synchronized, calibrated multisensor data
  - Requires GPUs and multiple compute units to enable parallel training
- **3D data generation**
  - Manual, automatic or assisted
  - Automatic methods rely on a combination of neural nets (non-realtime) and classic methods
  - Automatic and assisted methods require GPUs to enable fast neural network inference
  - Real-time operation is not a requirement, but rapid data processing still requires a lot of optimization

# aiMotive at a glance

## Company

- Founded in 2015 by CEO Laszlo Kishonti
- Incorporated in Germany, headquartered in Budapest

## Global footprint

- Offices in Silicon Valley, Yokohama, Munich
- Testing locations: Hungary, USA, Germany, Japan

## Team & Expertise

- Largest independent team of 230+ highly qualified colleagues
- In-house developed AI algorithms, hardware IP and validation toolchain

## Strong traction

- Validated by top OEMs globally
- Revenue from day one

## Now part of Stellantis

- Stellantis acquired aiMotive at the end of 2022
- aiDrive is now exclusive to Stellantis, to develop AutoDrive 2.0



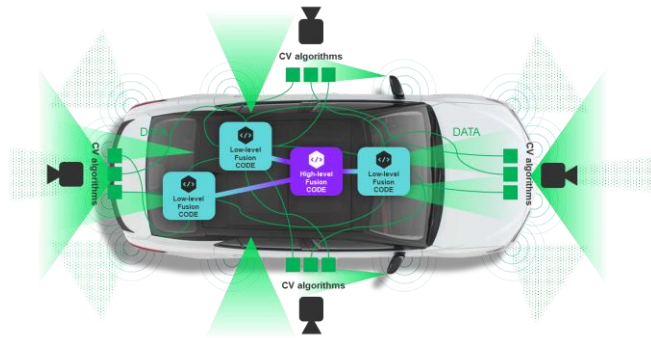
## REFERENCE CUSTOMERS & PARTNERS








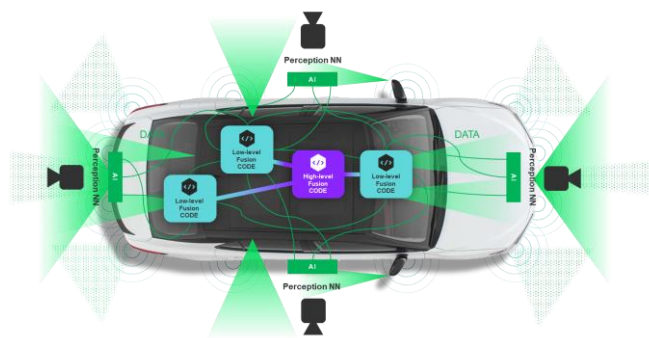
# History of perception pipelines





## 1<sup>ST</sup> GENERATION



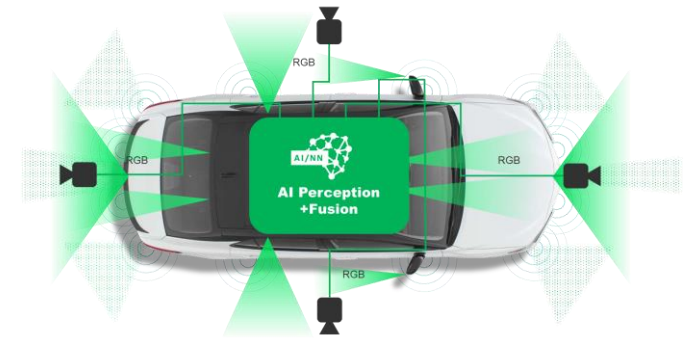
-  Single task
-  Single camera
-  Hand-crafted algorithms both for perception and fusion




## 2<sup>ND</sup> GENERATION



-  Multi-task
-  Single camera
-  Data-driven perception
-  Hand-crafted fusion

## 3<sup>RD</sup> GENERATION

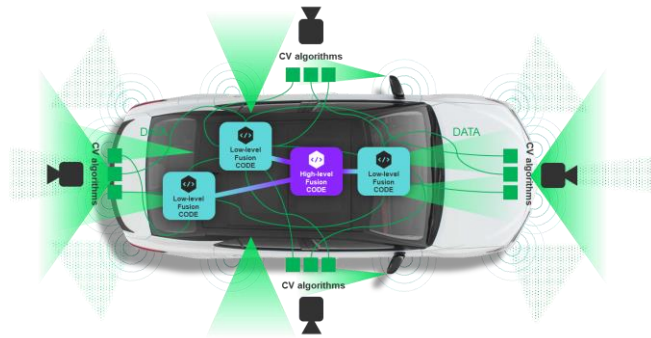





-  Multi-task
-  Multi-sensor (multi-camera & radar)
-  Data-driven perception and fusion

Third generation pipelines enable data-driven evolution of multi-sensor full environmental modeling

# History of perception pipelines

## 1<sup>ST</sup> GENERATION



-  Single task
-  Single camera
-  Hand-crafted algorithms both for perception and fusion

- Classic CV (eg. hand-crafted lane detectors) or generic 2D NNs (semantic segmentation, instance segmentation, 2D bounding boxing and classification)
- Reuse what was available in the literature at the time
- Generic metrics to evaluate quality of results
- Estimate position of the vehicle by projecting 2D detections back to 3D
- Fuse independent world models and resolve differences between sensor-specific world models “manually”
- Estimate velocity based on change of position

 Data-driven perception

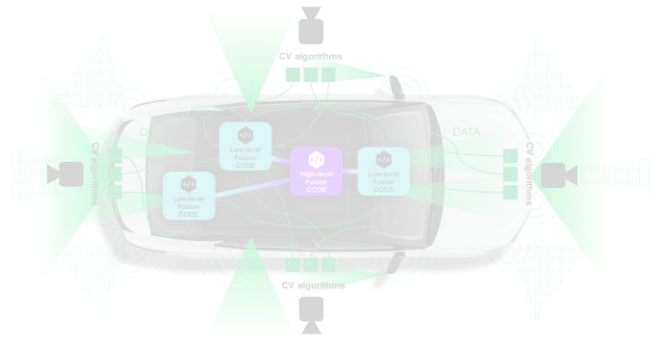
 Hand-crafted fusion




 Data-driven perception and fusion

Third generation pipelines enable data-driven evolution of multi-sensor full environmental modeling

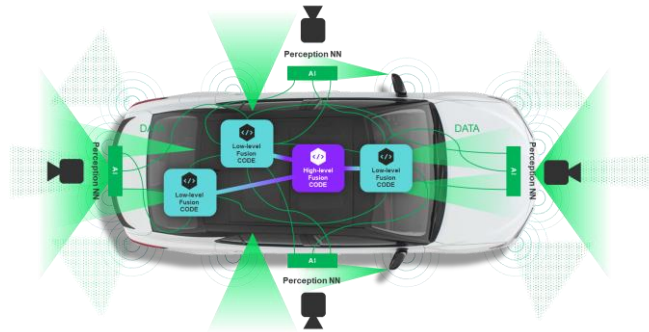
# History of perception pipelines





## 1<sup>ST</sup> GENERATION



-  Single task
-  Single camera
-  Hand-crafted algorithms both for perception and fusion

## 2<sup>ND</sup> GENERATION



-  Multi-task
-  Single camera
-  Data-driven perception
-  Hand-crafted fusion

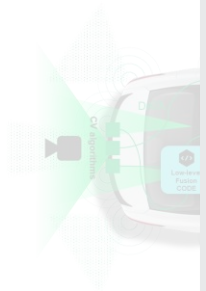
- Combine multiple tasks performed on the same image to one NN (e.g. semantic segmentation, 2D bounding boxing and lane detection)
- Mainly driven by runtime performance reasons on embedded platforms

-  Multi-sensor (multi-camera & radar)
-  Data-driven perception and fusion

Third generation pipelines enable data-driven evolution of multi-sensor full environmental modeling

# History of perception pipelines

## 1<sup>ST</sup> GENERATION



- Everything is handled in one shot: sensor data in – 3D world model out
- Object velocities are estimated by the NN over multiple frames, as opposed to estimating them from the derivative of object position
- No explicit sensor fusion module needed
- Requires training data with the same structure

 Single task

 Single camera

 Hand-crafted algorithms both for perception and fusion

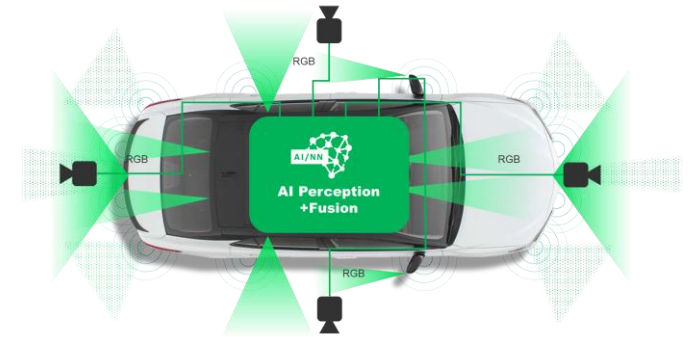
 Multi-task

 Single camera

 Data-driven perception

 Hand-crafted fusion

## 3<sup>RD</sup> GENERATION



 Multi-task

 Multi-sensor (multi-camera & radar)

 Data-driven perception and fusion

**Third generation pipelines enable data-driven evolution of multi-sensor full environmental modeling**



# Lessons learned

- **Most Neural Network-related literature was quite generic (in 2015)**
  - Generic object detection
  - Generic object classification
- **KPIs were also quite generic**
  - Not necessarily representative for the use case at hand
  - See examples on the next slides



# Mis-classification example

Confusion matrix shows that bus and truck classes are often mixed up, also bikes and motorbikes

		Real object class						
		Pedestrian	Car	Bus	Truck	Motorbike	Bicycle	Road surface
Predicted object class	Pedestrian	859	3	1	0	12	18	1
	Car	5	4882	56	98	4	4	2
	Bus	2	13	654	140	0	0	0
	Truck	0	2	258	498	0	2	0
	Motorbike	4	1	0	0	169	58	0
	Bicycle	23	2	1	0	296	893	2
	Road surface	2	3	0	0	0	1	6828

# Mis-classification example

Does this problem have the same weight as classifying a pedestrian or a bike as road surface?

		Real object class						
		Pedestrian	Car	Bus	Truck	Motorbike	Bicycle	Road surface
Predicted object class	Pedestrian	859	3	1	0	12	18	1
	Car	5	4882	56	98	4	4	2
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# Mis-classification example

Does this problem have the same weight as classifying road surface as object?

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	Motorbike	4	1	0	0	169	58	0
	Bicycle	23	2	1	0	296	893	2
	Road surface	2	3	0	0	0	1	6828

## Mis-classification example 2

Confusion matrix shows that the yellow light is sometimes mis-classified as red light

		Real traffic light color		
		Red	Yellow	Green
Predicted traffic light color	Red	397	19	5
	Yellow	31	128	3
	Green	2	0	735



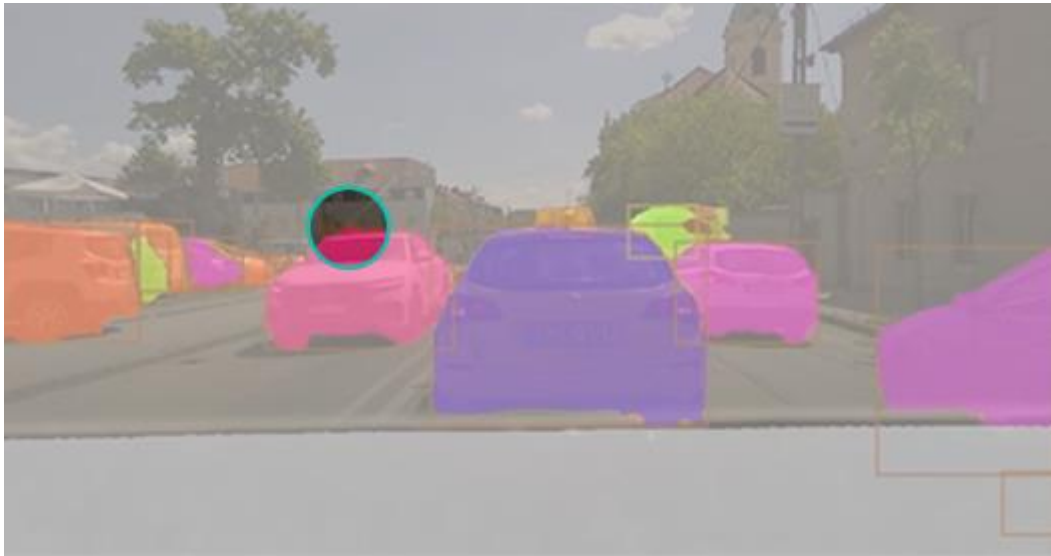
## Mis-classification example 2

Does this problem have the same weight as classifying a red light as green light?

		Real traffic light color		
		Red	Yellow	Green
Predicted traffic light color	Red	397	19	5
	Yellow	31	128	3
	Green	2	0	735

# Segmentation error

- When segmentation is measured with Intersection over Union, all pixels have the same weight
- Does the top part of the object matter as much as the bottom part?
- Projected in the 3D world
  - One would result in a distance error (which then propagates to diffspeed error)
  - While the other will err on the height of the object
- Which one would you worry about more?



# Lessons learned: specific use cases need specific solutions and KPIs

- **Ask the NN for what you want to know for the use case**
  - (Not what you think it can or cannot do)
  - Example: As opposed to asking for classifying pixels in an image, much better results can be obtained by asking for distance directly – see 3rd generation perception pipeline
  - Example: As opposed to asking for positions and deriving those, much better results can be obtained by training and inferring diffspeed directly (think ACC)
- **What about end-to-end learning then?**  
(e.g. Bojarski et al, 2016)
  - Network architectures are much more elaborate today
  - Networks are constructed piece by piece, with visibility into what each block can do, pre-trained separately
  - Networks are also much deeper and much bigger today



# Spinoffs from aiDrive



## Automated driving software platform

Modular software suite for  
Level 2 to Level 4 automated driving



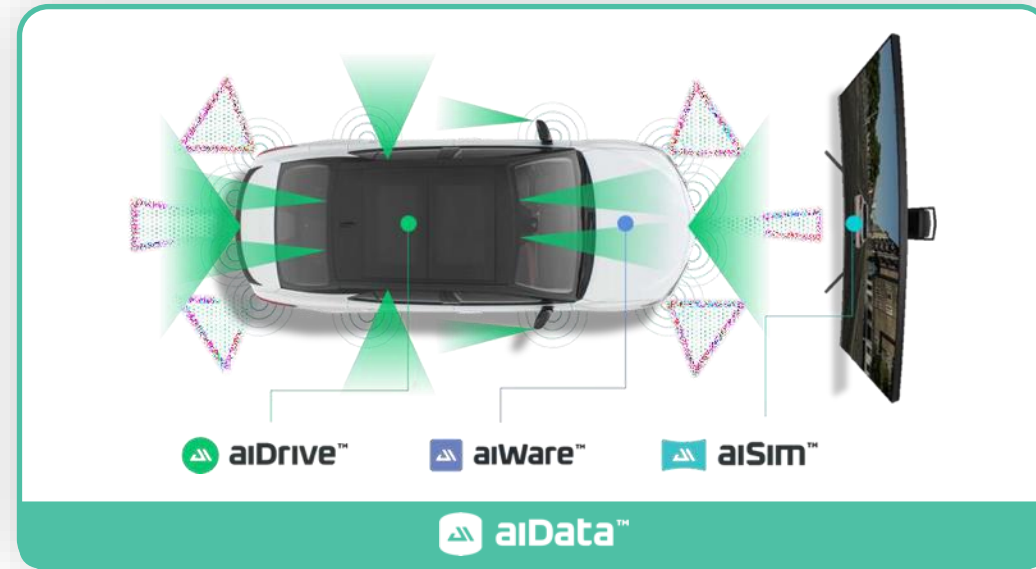
## Virtual simulation environment

Realistic virtual environment for verification  
and validation of AD systems



## Industry-leading hardware IP

NN accelerator IP for automotive-grade, low-  
power, high-performance embedded computing



## aiRec

Automated data collection  
focusing on gaps and edge cases

## aiNotate

Automated annotation

## aiFab

Synthetic training data generation

## aiMetrics

Integrated metrics evaluation

**Integrated product portfolio amplified by proprietary data tools,  
enabling customers to efficiently roll out automated driving features**

# Spinoffs from aiDrive

## aiDrive™

Automated driving software platform

Modular software suite for  
Level 2 to Level 4 automated driving

## aiSim™

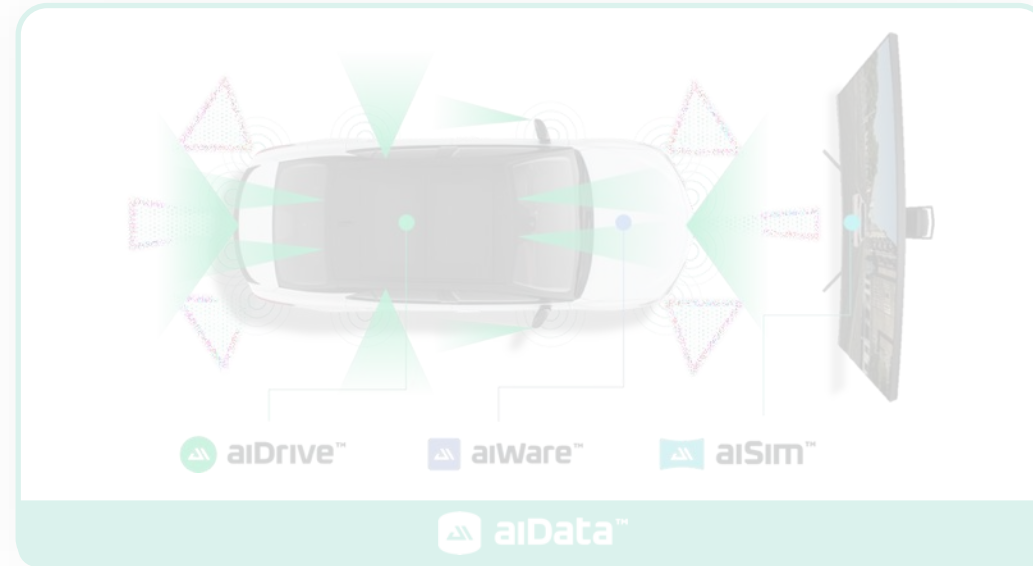
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## aiWare™

Industry-leading hardware IP

NN accelerator IP for automotive-grade, low-  
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## aiData™

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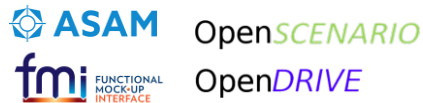
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# aiSim virtual validation suite from concept to production



## OPEN STANDARD SUPPORT:



## SELECTED PARTNERS AND CUSTOMERS:



## aiSIM™ FEATURES:

### Single tool from R&D to production

- World's first ISO 26262 certified tool up to ASIL-D
- Wide range of ODDs from L2 to L4 including Highway, Parking and Urban scenarios
- Supports real-time operation in strict Hardware-in-the-Loop environment

### Continuous integration & delivery

- Massively parallel running
- Existing database of 1,000s of different scenarios
- Scenario-based verification and validation of Euro NCAP, ALKS, ACC and further AD standards

### Purpose-built rendering engine

- Ensures deterministic operation
- 20+ available physics-based sensor models, including camera, lidar, radar
- API for 3rd party sensors

**aiSim™ already supports multiple use cases of our global automotive partners and is ramping up for large-scale deployment projects**

# Spinoffs from aiDrive



## Automated driving software platform

Modular software suite for  
Level 2 to Level 4 automated driving



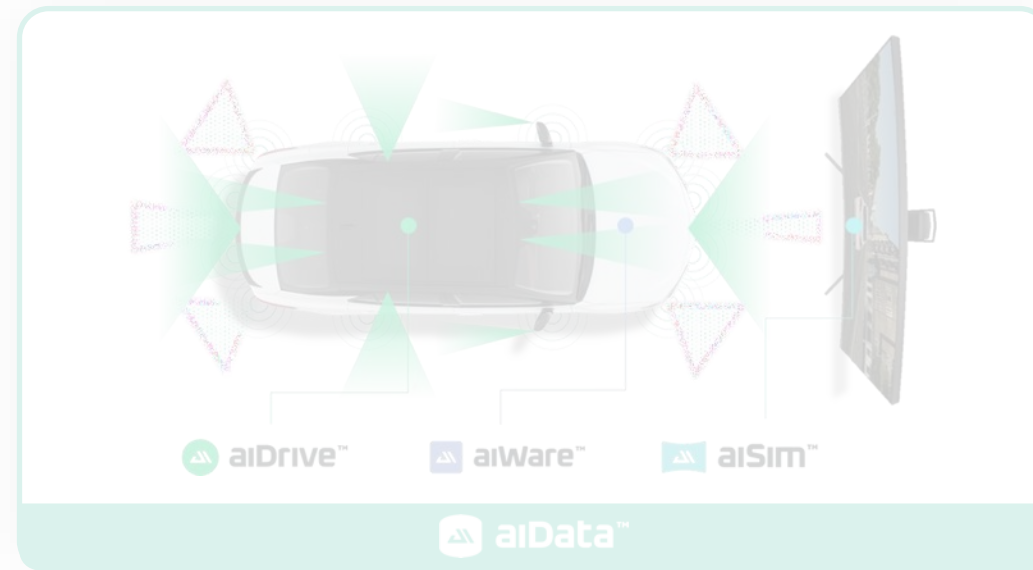
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**Integrated product portfolio amplified by proprietary data tools,  
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# Data collection & processing challenges



## Data collection

- Ensure technical prerequisites (calibration, synchronization, etc.)
- **>95% of the collected data** would be unwanted surplus w/o additional quality improvement



## Data labeling

- Manual annotation is incredibly expensive
- Complex, AI-based higher-level AD features need a vast amount of training data under various ODDs

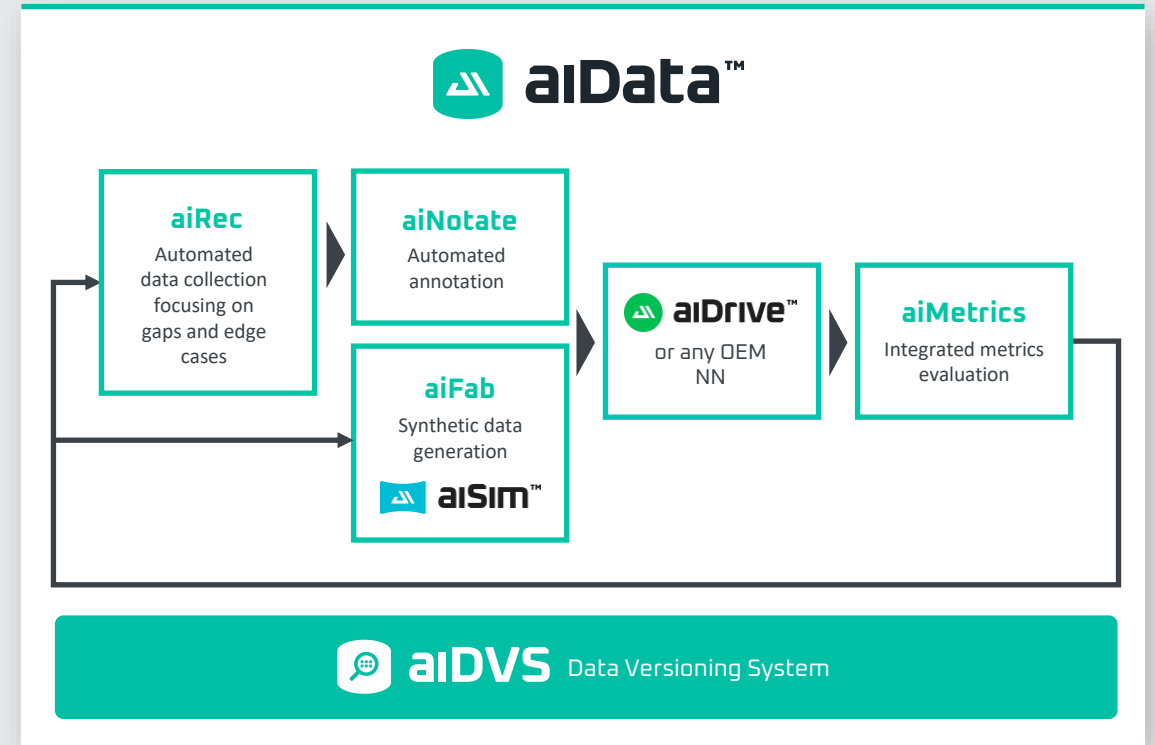


## Data management

- Efficiently storing, managing, using and harvesting data becomes key
- Traceability is fundamental to safe SW development and maintenance

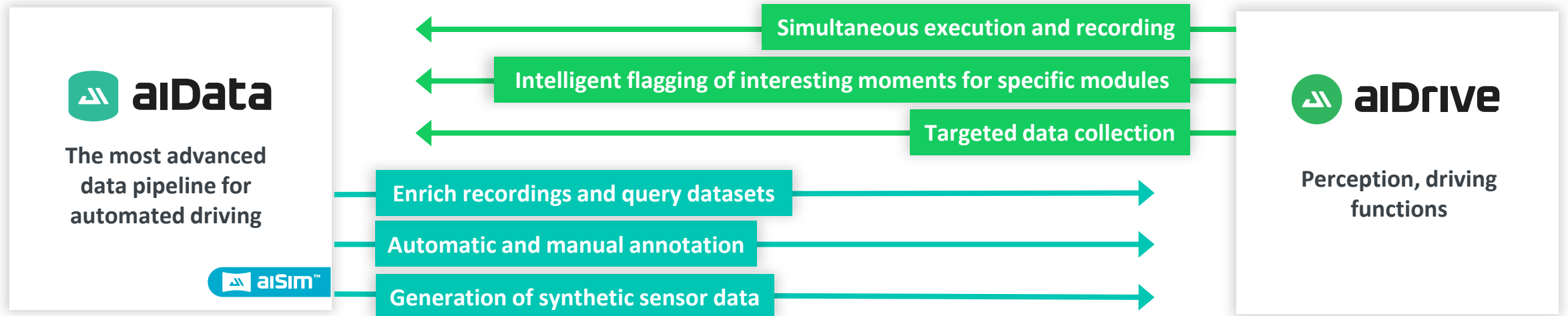
# The data factory behind aiDrive

Integrated, cost-efficient, data-driven pipeline for automated driving

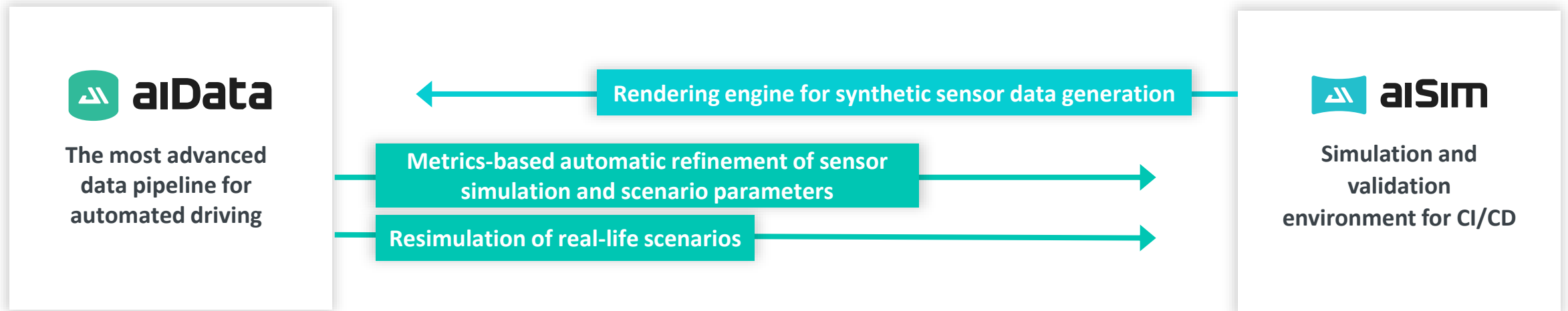


Efficient collection, processing and query of multisensor data is a must for developing NN-based products

# aiData and aiDrive cooperate to support each other



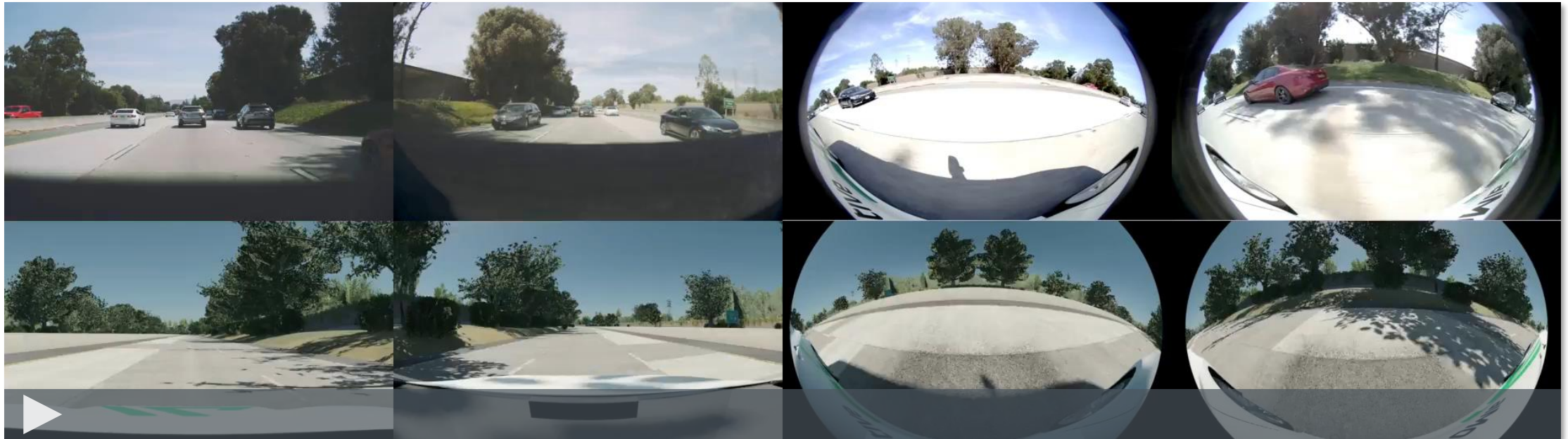
# aiData and aiSim cooperate to support each other





# Resimulation

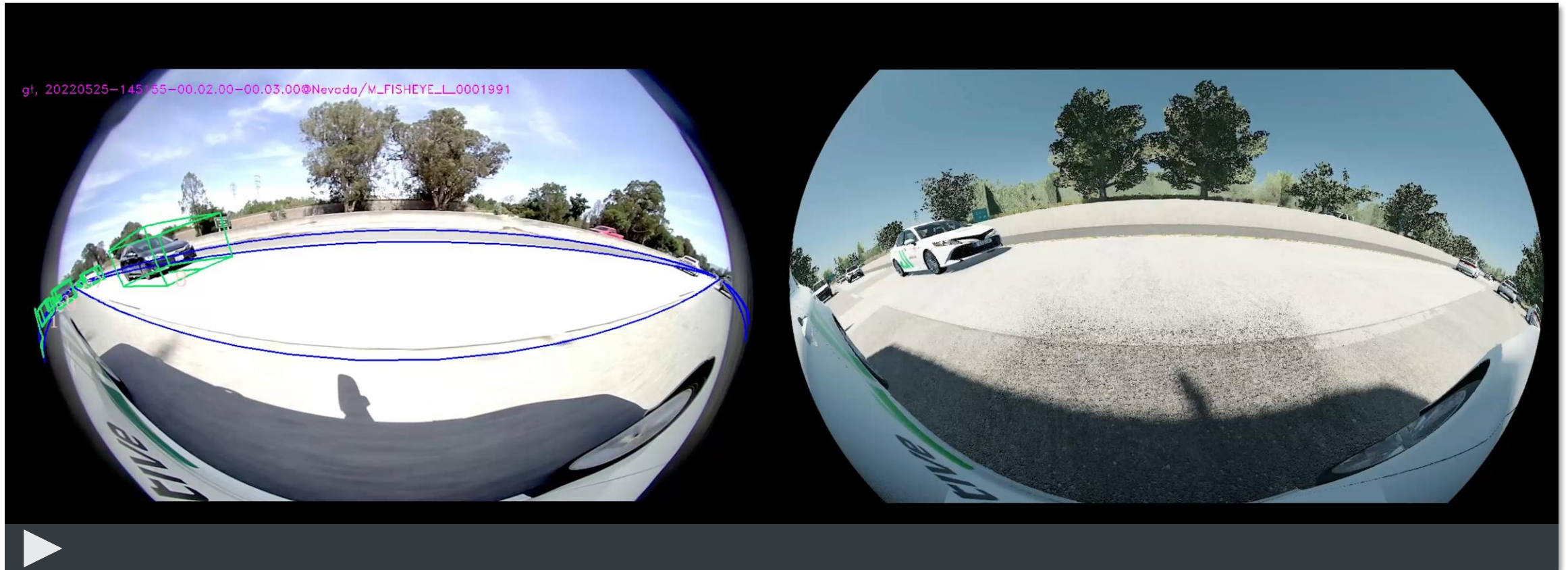
- aiNotate automatically annotates elements of the scene
- aiSim generates worlds from HD maps
- For every vehicle detection a car will be spawn in aiSim
- Scene is placed to the same location in aiSim, based on GPS coordinates
- Once scenario is created, **closed-loop simulation can be run**, while also allowing for changing parameters



# Recording vs Automatic annotation



# Automatic annotation vs Resimulation





# aiMotive inside Stellantis



Link to video: <https://aimotive.com/w/stellantis-ceo-on-aidrive-the-embedded-software-stack-for-automated-driving>

# aiMotive inside Stellantis

- **aiMotive is a fully owned, but independent subsidiary of Stellantis**
- **Intention is to keep its independence from Stellantis, and keep the startup way of working**
- **While aiDrive is exclusive to Stellantis, aiData, aiSim and aiWare are still available for all**
- **These products are strengthened by the feedbacks and requirements from other companies**
  - Chinese Wall has been set up between departments to avoid information leak from other clients to Stellantis
- **aiSim and aiData tools are already used by multiple Stellantis teams**
  - Simulated testing
  - Auto-annotation of data from vehicle fleets
  - Query and retrieval of annotated data
- **aiData and aiDrive profits from the scale of Stellantis**
  - Connected vehicle fleet
  - Compute infrastructure
  - Experience of multiple brands
  - Experience of a multi-continent team





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