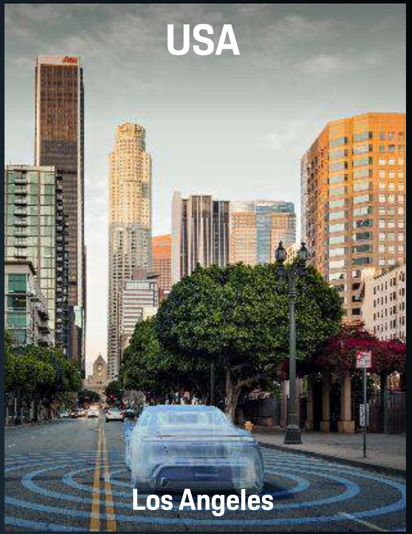
Customer-Centric Innovation in Automotive

Agenda

- Porsche Engineering Company Overview
- Engineering Ecosystem & Development Loop
- Use Cases
  - Signal Foundation Model
  - AI-Corrected Race GPS
  - Decoding the Fleet (Agentic Diagnosis)
- Summary

Porsche Engineering US is integrated into an international network of competence centers focusing on digital technologies.



- Market-specific vehicle functions
- Digital services
- Connectivity and infotainment

PEUS as Part of Porsche Engineering Group: Company Overview

HERITAGE

PORSCHE

100% subsidiary of
Dr. Ing. h.c. F. **Porsche AG**

Founded in **1931** by
Ferdinand Porsche in
Stuttgart

FOCUS

Technologies for the **intelligent** and **connected vehicles** of the **future**

Vehicle expertise

Digital technologies

LOCATIONS

13 Locations

in **Germany, Italy, Czech Republic, Romania, China** and **USA.**

EMPLOYEES

1.700 Employees

PEG Management

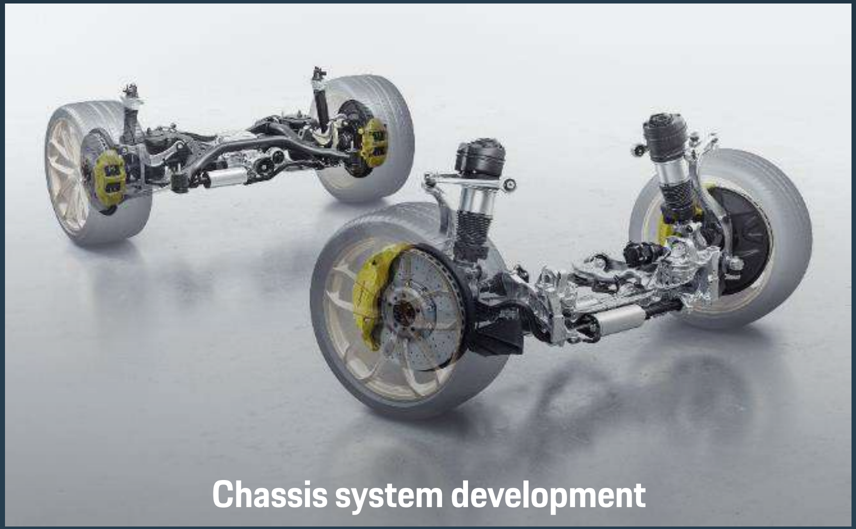
Markus-Christian Eberl
(CEO)

Dirk Lappe
(CTO)

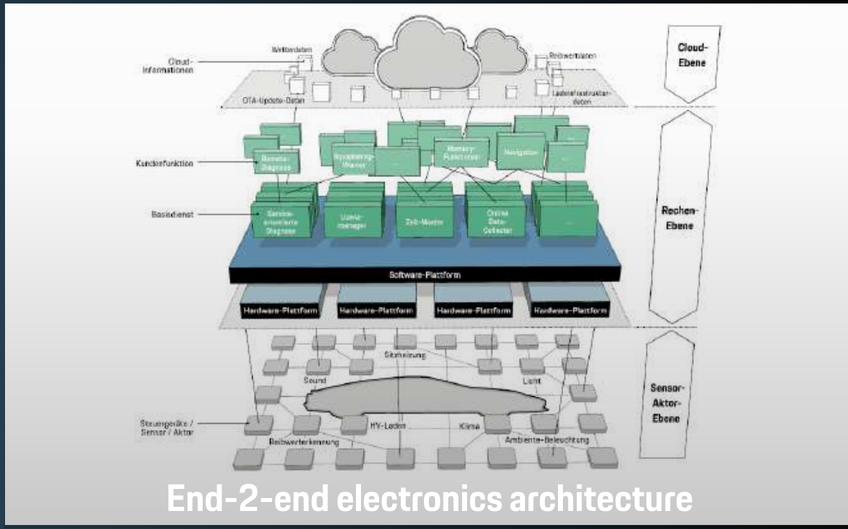
Dirk Philipp
(CFO/COO)

Our Experience in the Field of Vehicle and System Development Knows Many Examples.

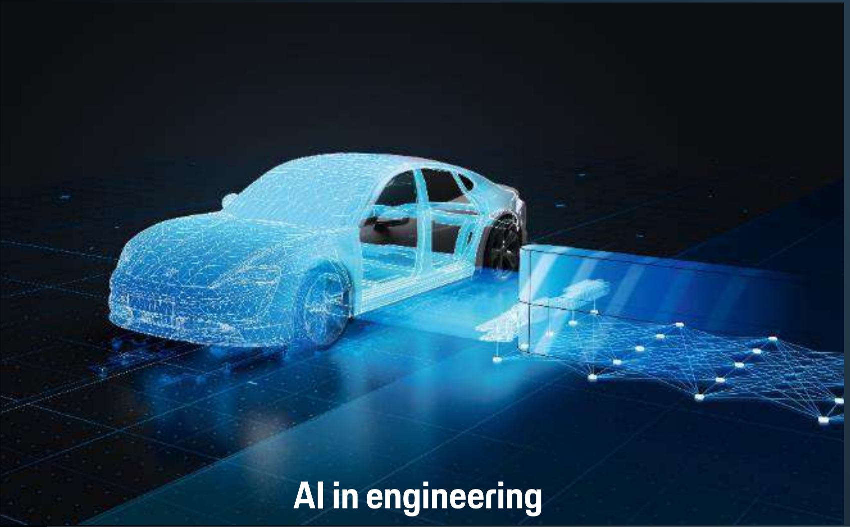
Complete vehicle development Cayenne Coupé



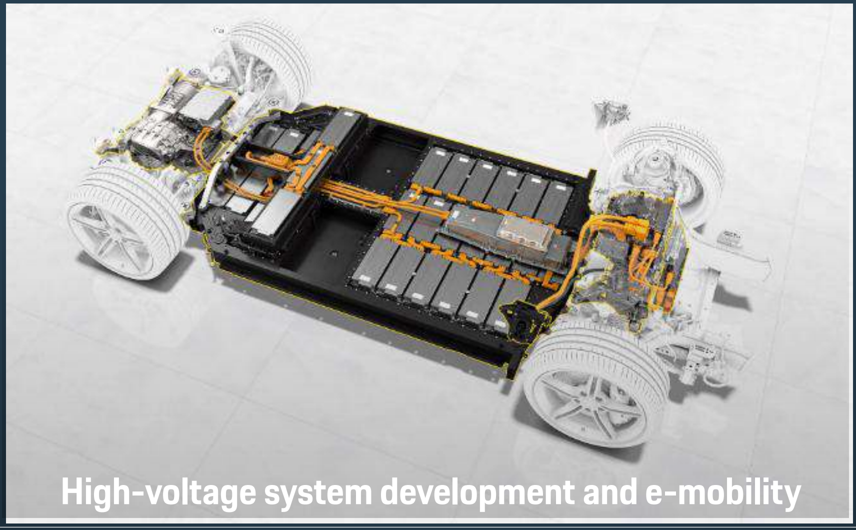
Chassis system development



End-2-end electronics architecture



AI in engineering



High-voltage system development and e-mobility

Function development and testing

Porsche Engineering Group (PEG) Projects

Commercial vehicle development

X-BOW with dual-clutch transmission

High-voltage system development 919 Hybrid

Chassis Demonstrator

Battery system development Seabob

Design and styling of Material Handling

Porsche Engineering x Sebastian Steudtner

No Matter What We Develop, We Always Keep an Eye on the Integration Throughout The Complete Vehicle. Quality Included.

We smartly use our ecosystem to reduce the 'Time To Car'

PROBLEM DESCRIPTION

Controller-centric workflows
→ Long iteration cycles

Offline recordings
→ Hand-operated data offload (USB/loggers)

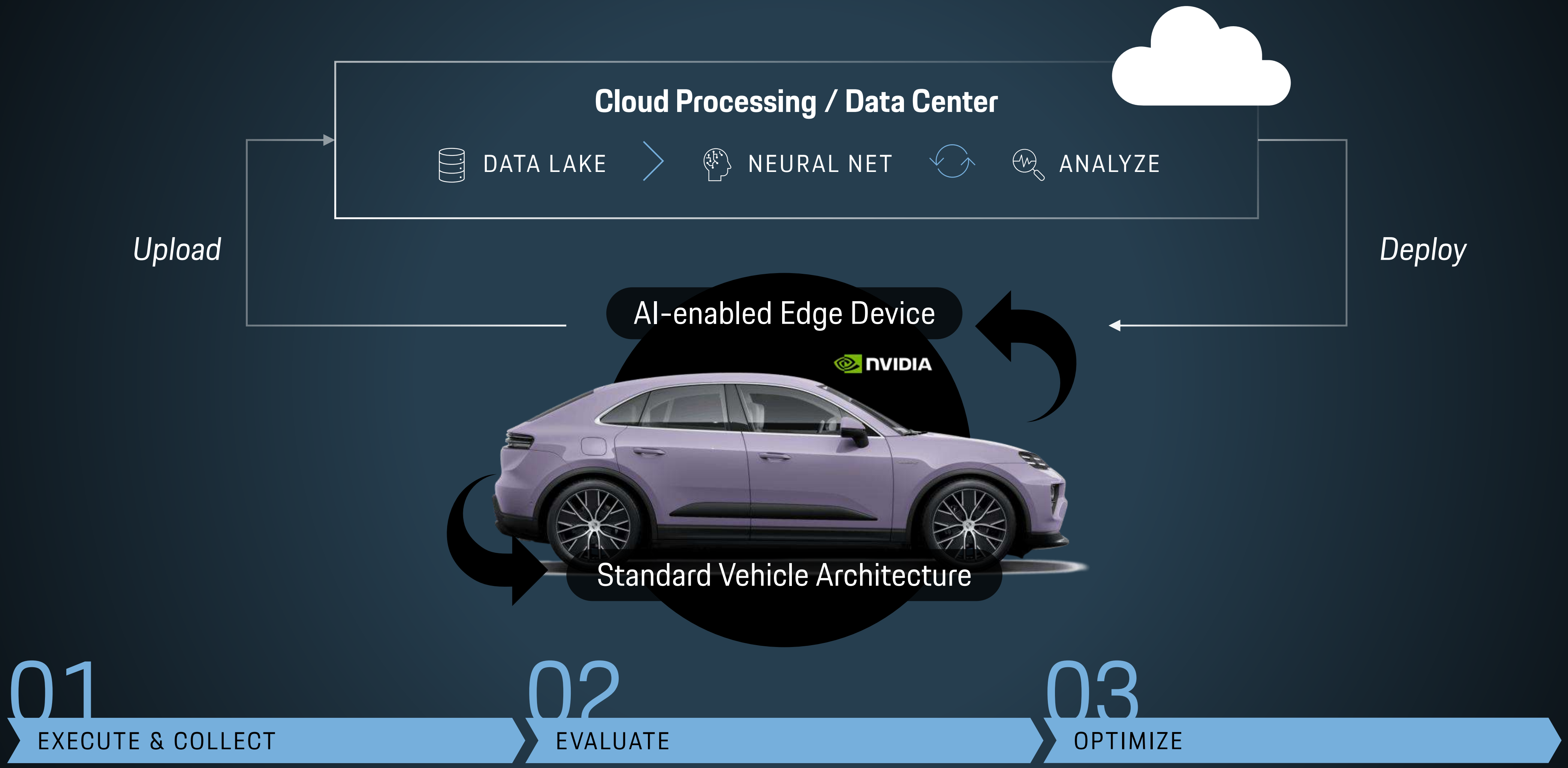
Manual measurement setup & configuration
→ High effort, low repeatability

Fleet testing at scale
→ Hard to manage, hard to compare results

Research ideas stayed long in lab environments
→ No final Confidence because of missing field tests

Transforming **from lab to real world evaluation** in the vehicle through our **Cloud Connected Realtime Ecosystem**

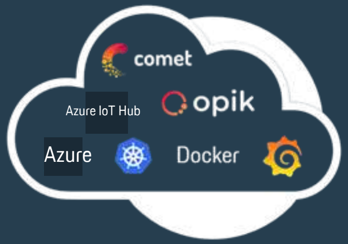
Overview of Our Development Loop



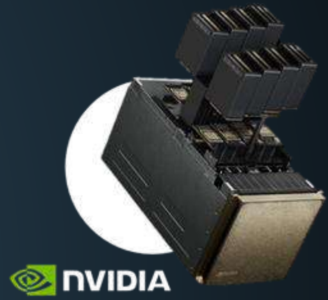
Technical Components in the Development Loop

TRAINED MODELS & DATA

Sensor Data & Model Results



MODELS



Edge Devices

Test Vehicle equipped with additional Edge Device Capabilities

Cloud-connected Vehicle Middleware

Cloud Resources

Centralized Data Lake

Experiment Tracking & Model Registry

Scalable Processing Platform

IoT Edge Platform with Fleet Monitoring

On-premise Resources

NVIDIA DGX Systems with Sharding Capabilities

Workload Management

Start at the Vehicle: the Edge Device as the Data Source

Edge

Devices

The CarDataBox Serves as Edge Device in Our AI Ecosystem.

Hardware

Software

Application Layer

Connected Vehicle Middleware

Custom Hardware Platform
powered by NVIDIA Jetson

NVIDIA

Technical Structure of the CarDataBox

Application Layer

Machine Learning Component
ROS interface

Real-Time Application
ROS interface

ROS
. . . . .

Azure Uploader Component
ROS interface

Docker **Connected Vehicle Middleware**

Core Software Layer

Core Runtime

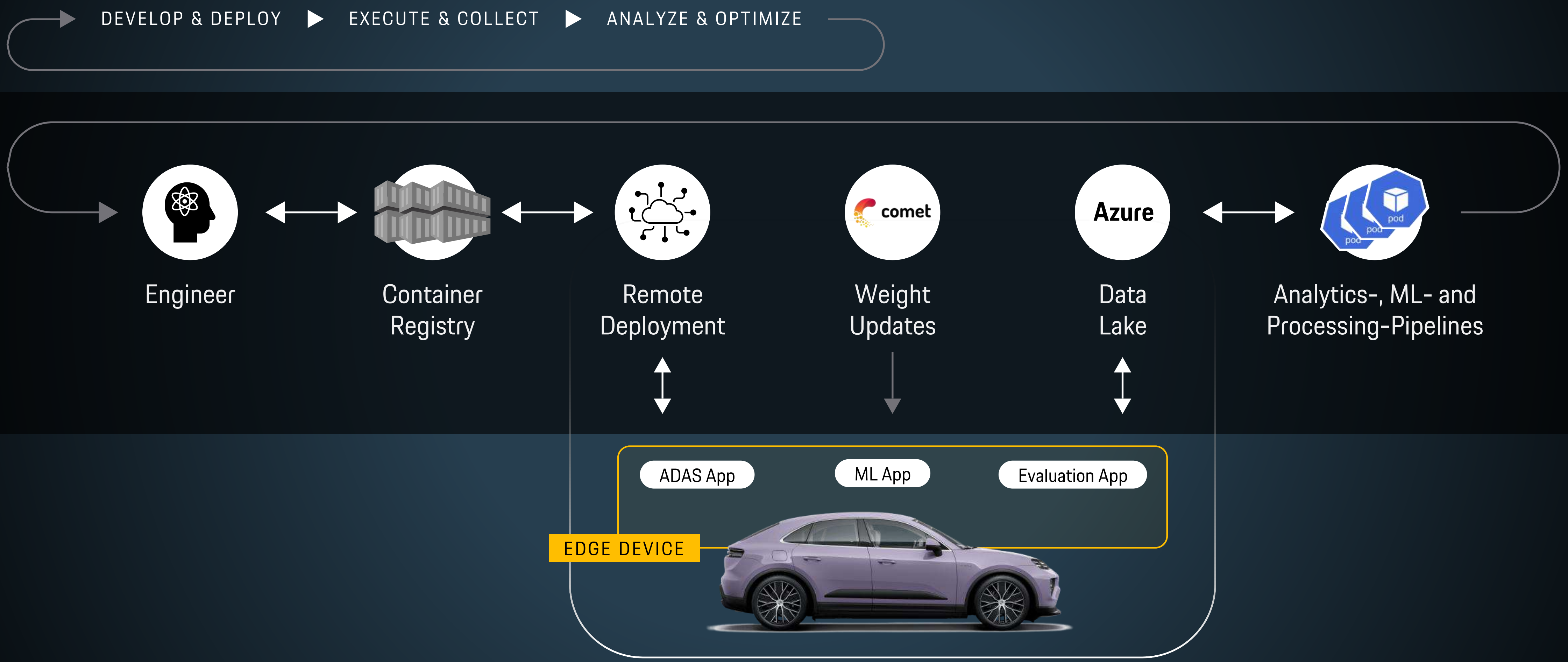
CAN Interpreter	FlexRay Interpreter	Automotive Ethernet
Camera Interpreter	Configuration Management	Application Manager

Core

Hardware Layer

NVIDIA **Custom Hardware Platform** (NVIDIA Jetson)

Remote Application Deployment on Edge Devices



Technical Components in the Development Loop

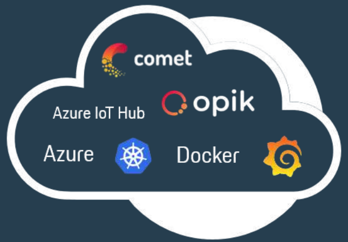
Edge Devices

Test Vehicle equipped with additional
Edge Device Capabilities

Cloud-connected Vehicle Middleware

TRAINED
MODELS
& DATA

*Sensor
Data &
Model
Results*



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Centralized Data Lake

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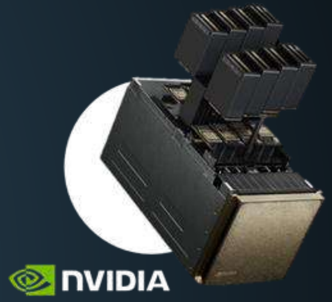
MODELS



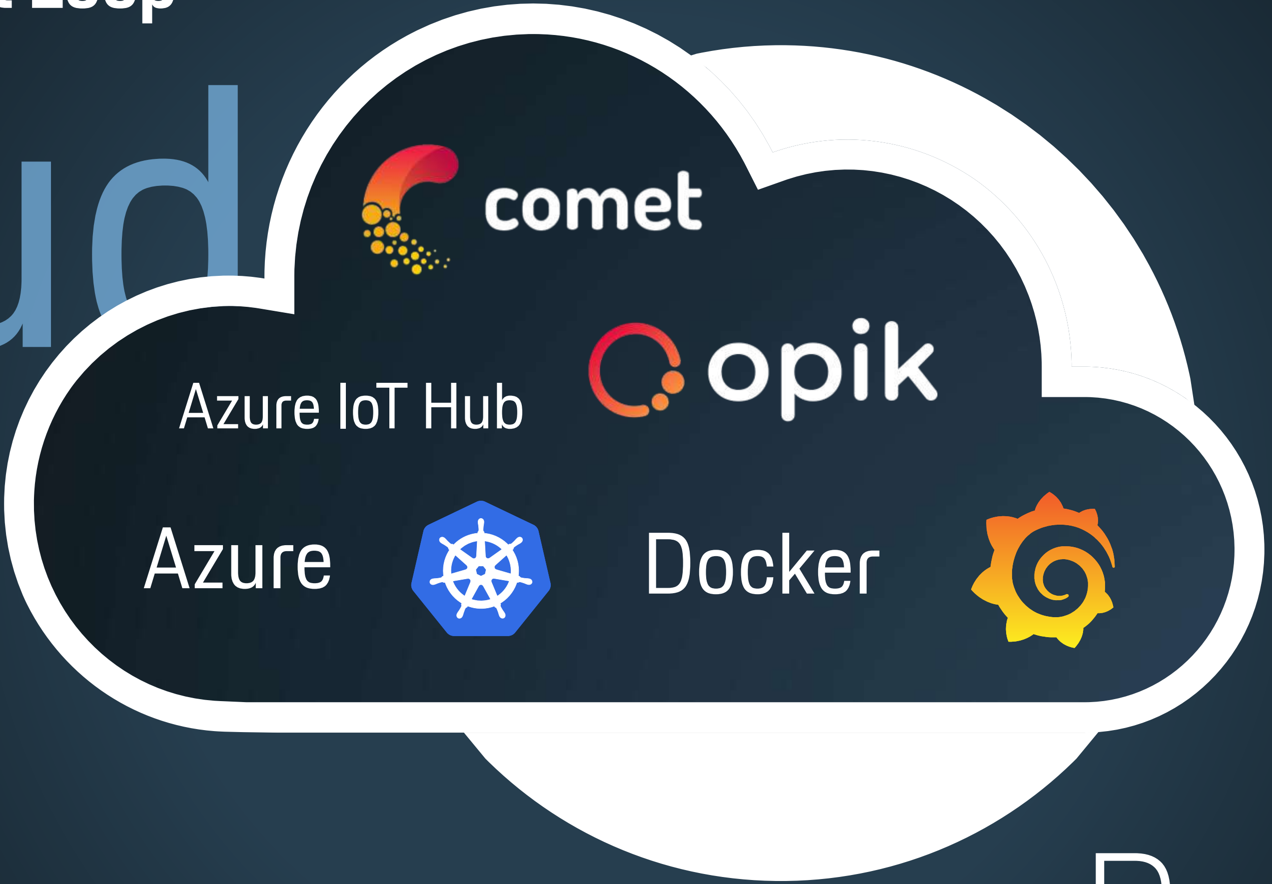
On-premise Resources

NVIDIA DGX Systems
with Sharding Capabilities

Workload Management

Technical Components in the Development Loop

Cloud



Resources

Processing the Collected Data in the Cloud

Azure IoT Hub

Azure

Data Lake

Indexed by

- Vehicle signals
- Vehicle derivate
- Locations
- Weather
- …

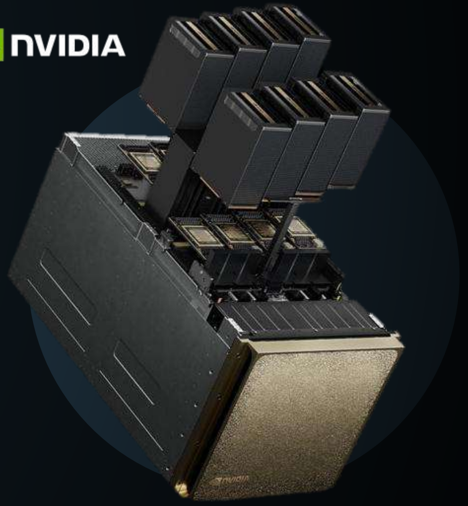
Kubernetes Spaces

Project space 1 → Fleet Analytics

Project space 2 → Small Model Training and Model Inference

Project space 3 → **Curated Datasets**

NVIDIA B200 on-premise

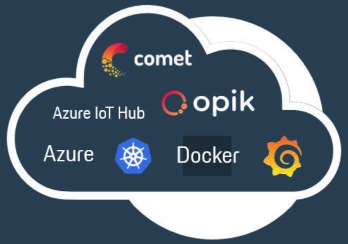


Large Model Training

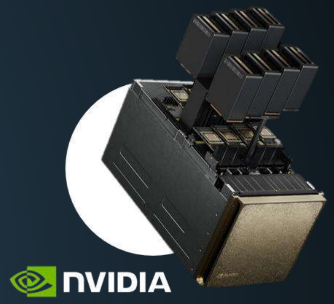
Technical Components in the Development Loop

TRAINED MODELS & DATA

Sensor Data & Model Results



MODELS



Edge Devices

Test Vehicle equipped with additional Edge Device Capabilities

Cloud-connected Vehicle Middleware

Cloud Resources

Centralized Data Lake

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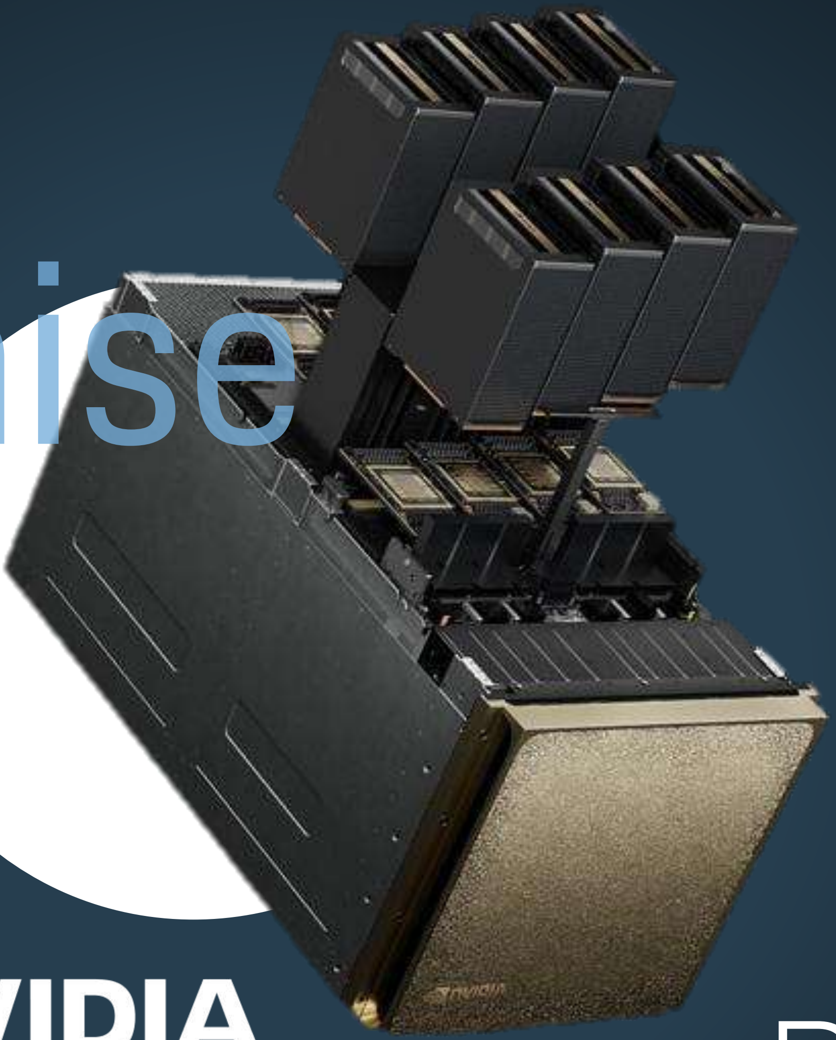
Workload Management

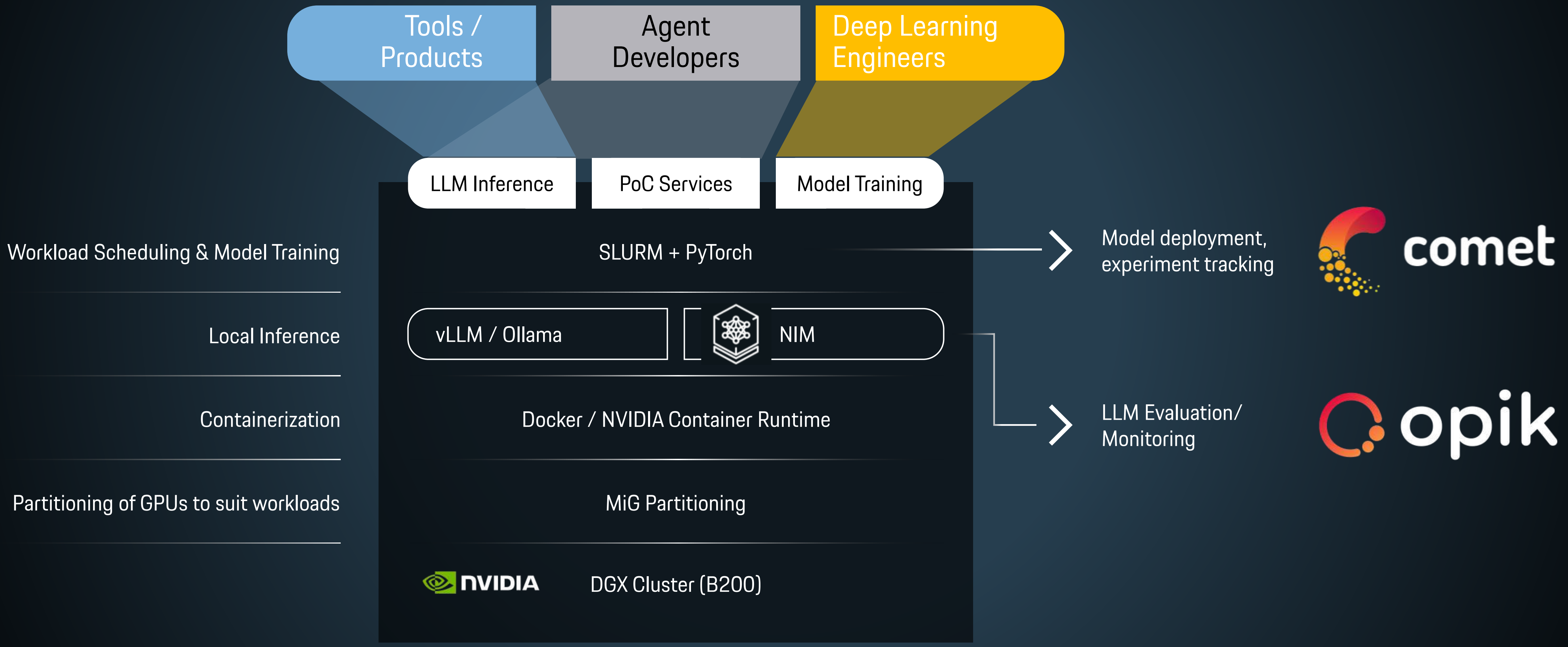
Technical components in the development loop

On-premise

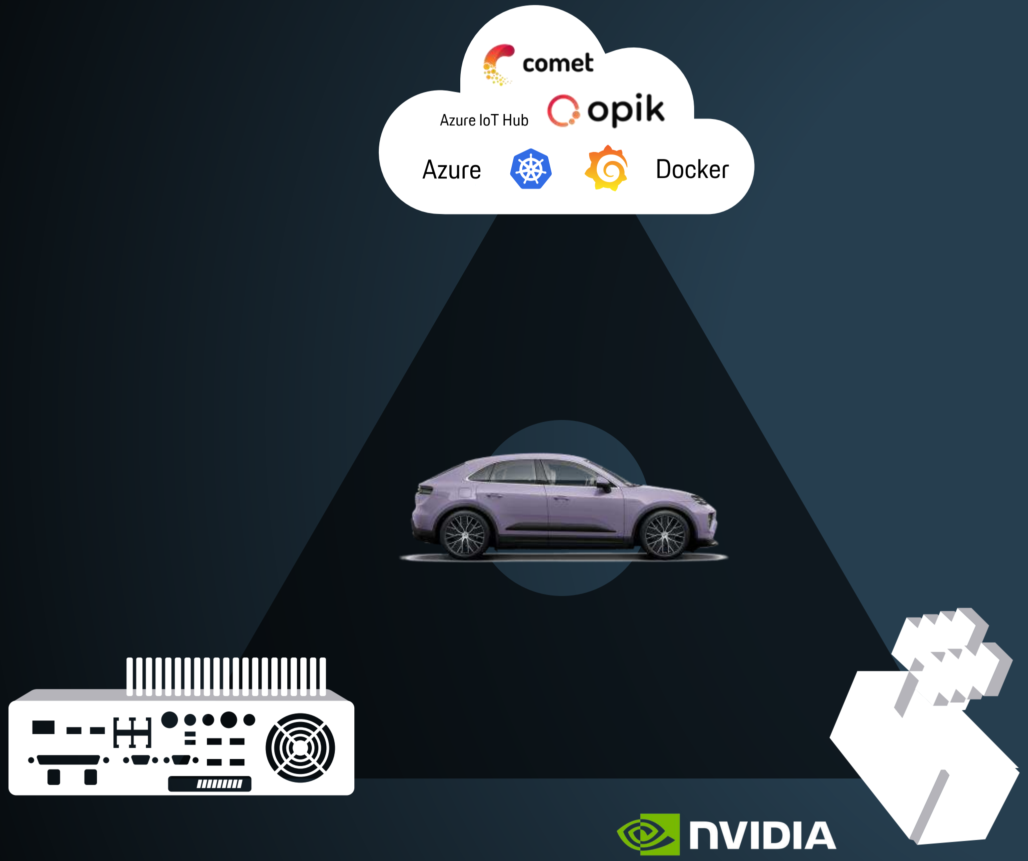


Resources

NVIDIA DGX Platform



Efficiency Gains From our Cloud & AI Ecosystem



- An end-to-end, consistent ecosystem spanning data collection, real-time validation, scalable training, and edge deployment
- Vehicle architecture-independent software development enabling flexible adaptation across platforms
- Fleet-scale operation, evaluation, and data collection
- Direct in-vehicle evaluation & Updated within minutes
- Unified global AI model lifecycle, experiment tracking, & governance

Applying our Ecosystem to Real-World Challenges

USE CASE **#1**

Signal Foundation Model

AI-based scenario, pattern and anomaly finder

USE CASE **#2**

Race GPS

Improving vehicle positioning accuracy during high dynamic driving

USE CASE **#3**

Vehicle Data Analysis

AI-Agent driven vehicle data analysis

USE CASE #1

Signal Foundation Model

AI-based scenario, pattern and anomaly finder

Signal Foundation Model
for ADAS Scenario Search, Clustering, and Description

CHALLENGE

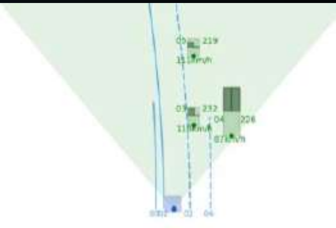
- Large amounts of unlabeled signal recordings
- Rare/safety-critical events are hard to find, compare, and quantify across fleets

APPROACH

Clustering existing database of signal recordings into searchable database of scenarios

INPUT

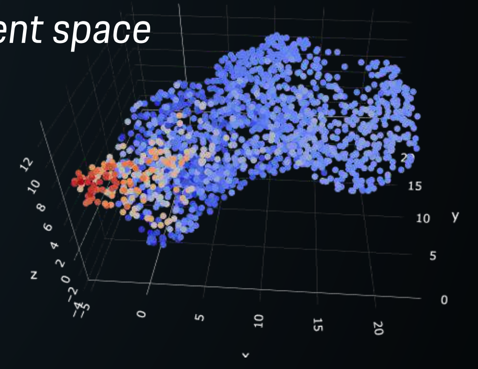
Driving scenarios as time series data



OUTPUT

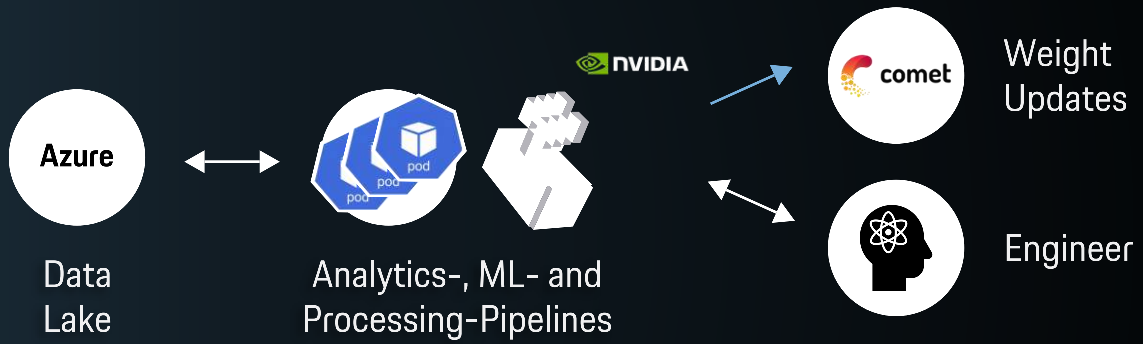
Searchable latent space

Latent space



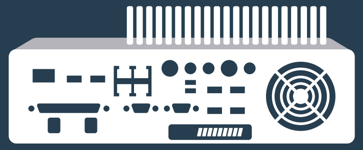
Applying Our Ecosystem

DEVELOP & DEPLOY ▶ EXECUTE & COLLECT ▶ ANALYZE & OPTIMIZE



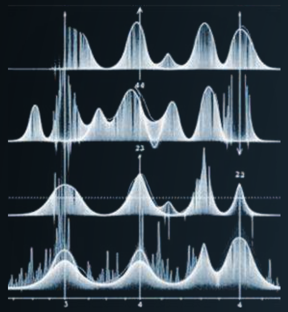
Signals Recorded

- Lane Detections
- Object Detection
- Acceleration/Speed
- ...



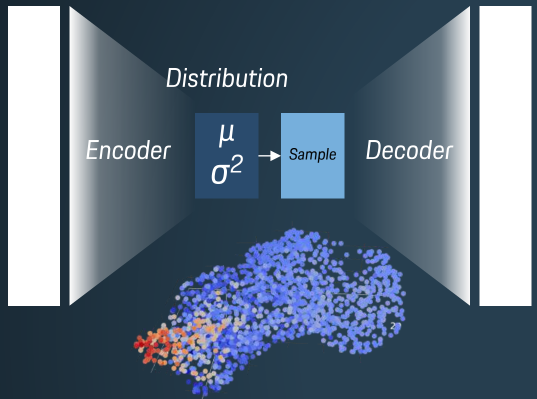
Signal Foundation Model

Time Series Data

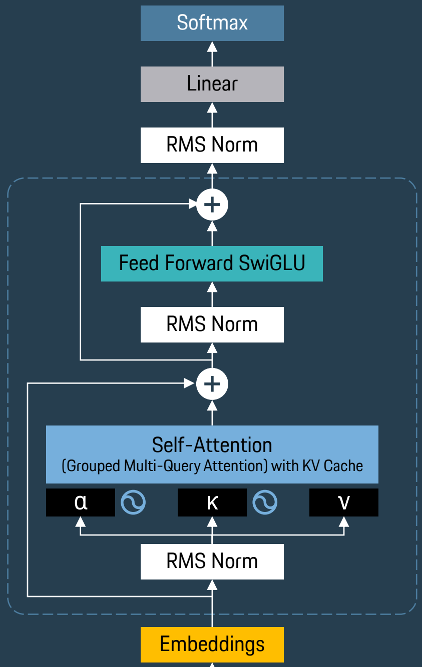


Domain
input signals

Time Series "Foundation Model"



Large Language Model



Embedding*

Description**

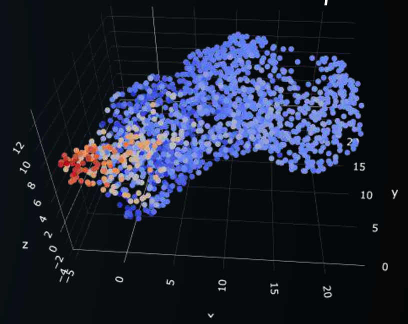
[label] A car at a medium distance in the middle lane ...

* Embedding – the coordinates of a single point in the latent space | ** Description – the label of the current scenario represented by the embedding

Description

- Extract the **important features** of the scenario
- Represent it by a **set of vectors called "embeddings"**
- Embedding is a collection of coordinates in a multidimensional space
- Similar **scenarios are residing in the same neighborhood** in this "Latent space"

Latent space

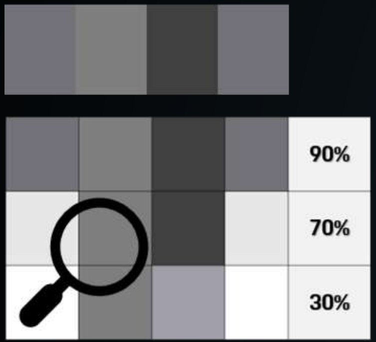


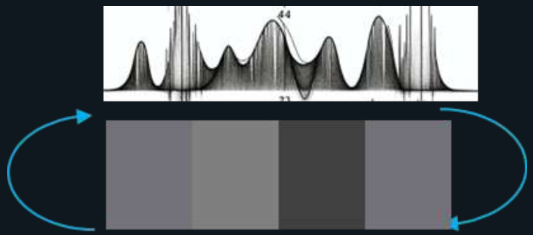
Use Cases

- Similarity searching using embeddings
- Generate similar scenarios using embeddings
- Similarity search using text
- Forecasting classification

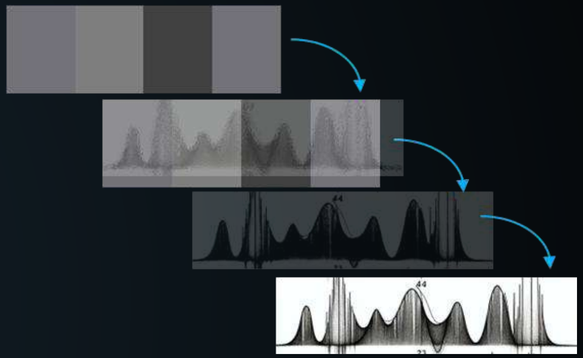
Signal Foundation Model

Initial application to ADAS





[label] A car at a
medium distance in the
middle lane...



Search Scenes

given a provided scene,
search for similar ones in a database

Describe Scene

given an encoded scenario,
describe in natural language

Generate Scenes

given an encoded scene,
generate signals for similar situations

Signal Foundation Model
Benefits

Turn raw recordings
into a **searchable scenario database**

Faster root-cause analysis
through similarity search

Generate scenario variants
to **expand test coverage**

Closed-loop improvement from
deployment to optimization

USE CASE #2

AI-Corrected Race GPS

for high-dynamic driving

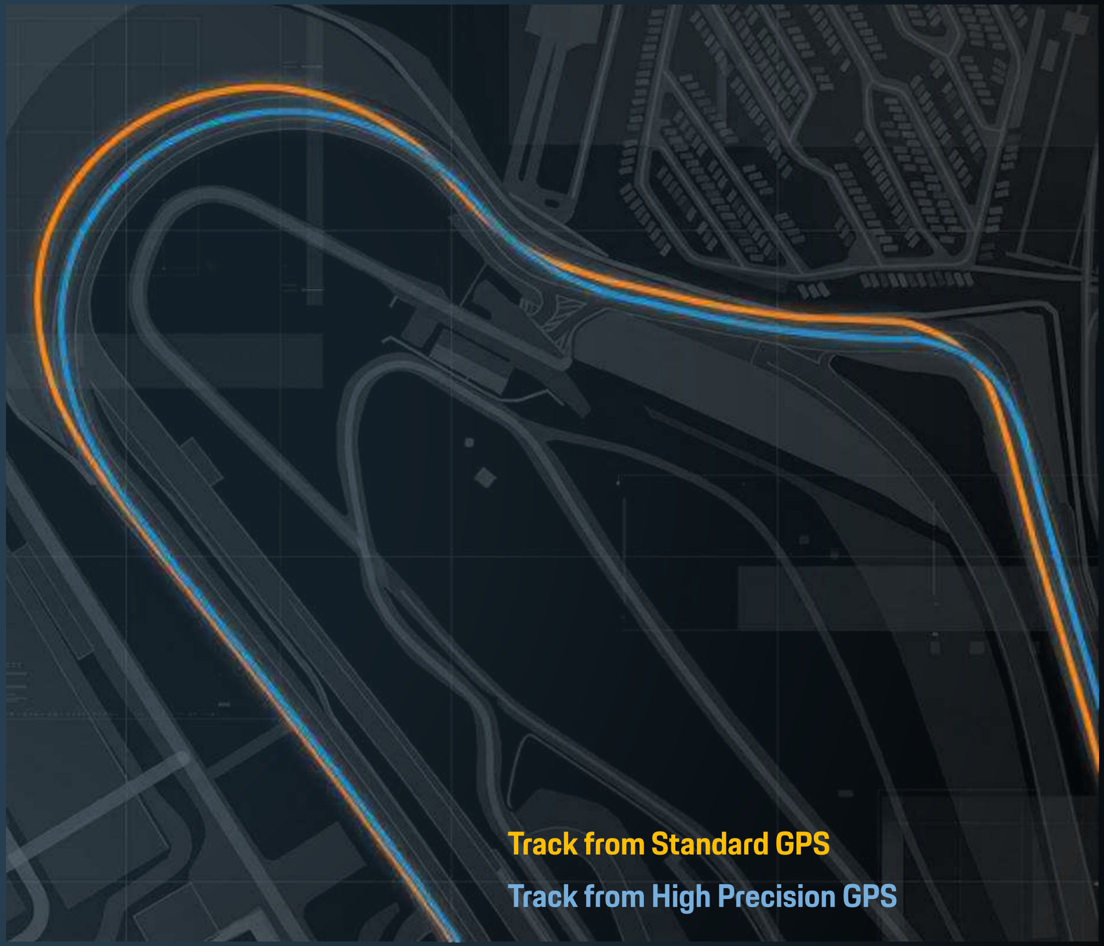
High Dynamic Driving Reduces GPS Accuracy

CHALLENGE

- Road car GPS noise: 5–10 m uncertainty
- Navigation systems leverage map matching & plausibility checks
- Classical GPS corrections fail in high dynamic driving situations

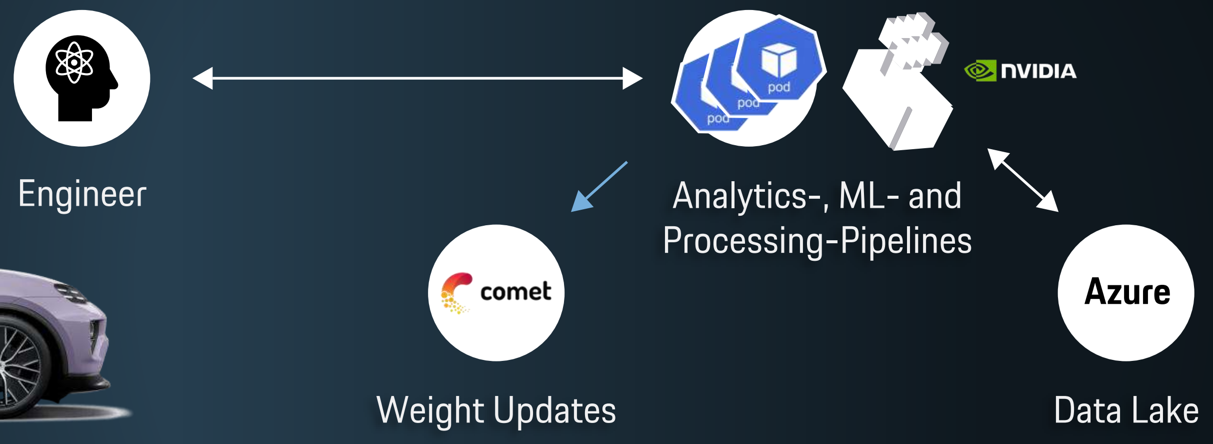
GOAL

- Predict and correct GPS position error directly from vehicle sensor data using machine learning
- Achieve accuracy close to high-precision DGPS



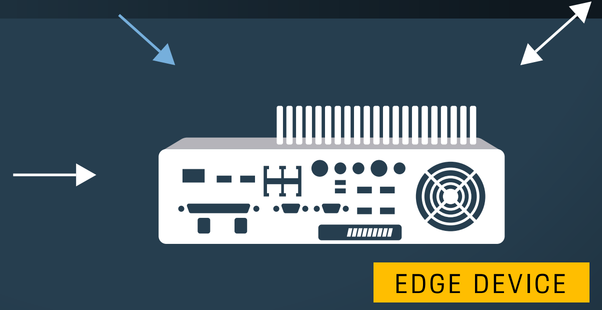
Solution
LSTM to increase GPS accuracy based on series signals

DEVELOP & DEPLOY ▶ EXECUTE & COLLECT ▶ ANALYZE & OPTIMIZE

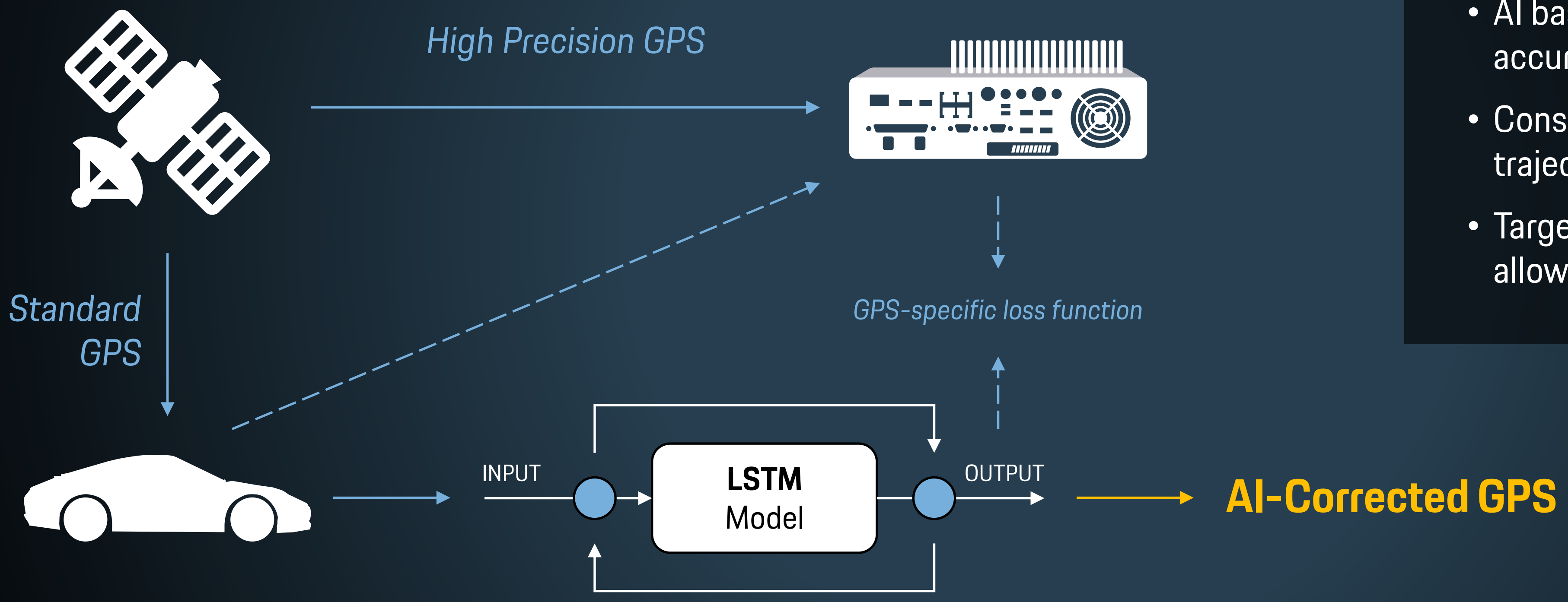


Series Signals Recorded

- High-precision GPS
- Steering / Yaw Angle
- Acceleration / Deceleration
- IMU (Inertial Measurement Unit)



GPS Accuracy Model



Description

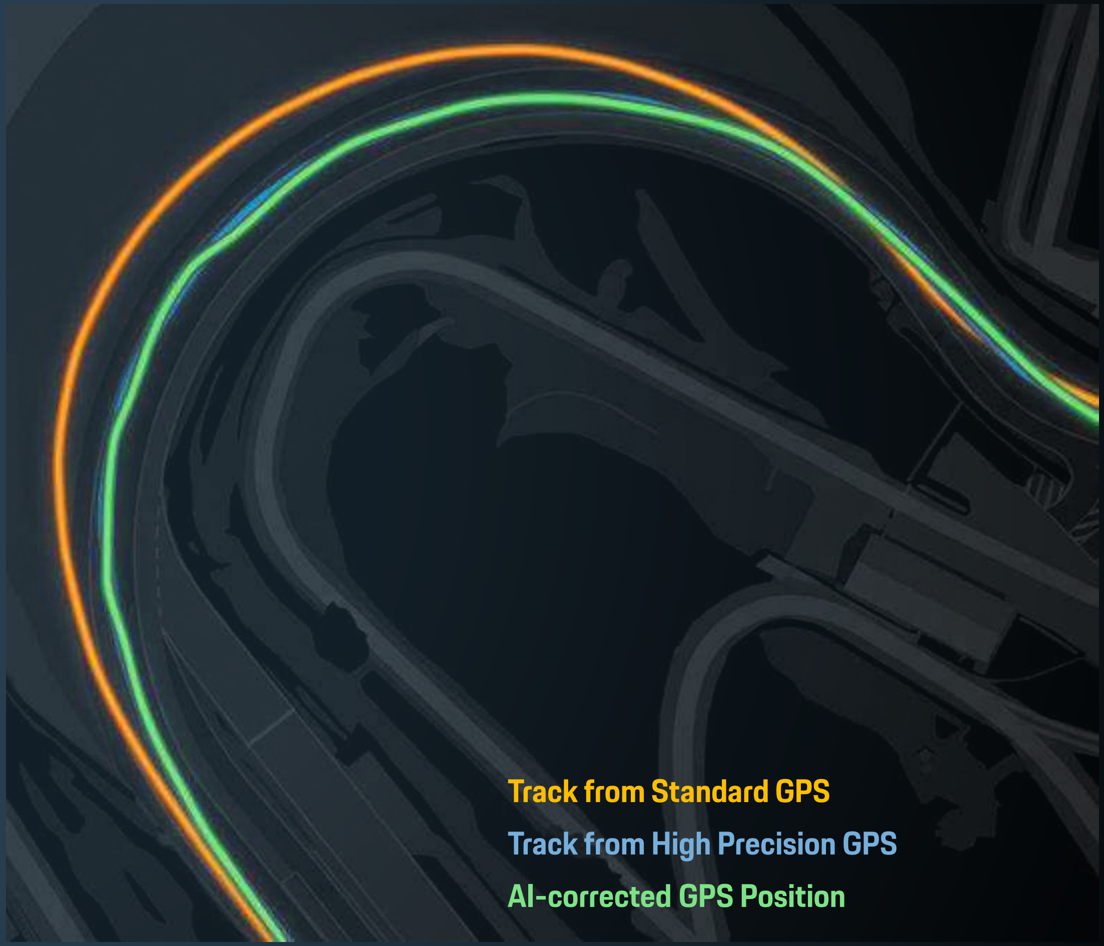
- AI based Sensor Fusion to improve accuracy based on dynamic features
- Considers time history of vehicle trajectory
- Targets low resource consumption to allow in vehicle processing

Benefits: Increased GPS Accuracy Through LSTM

Accuracy boost:
Achieves a ~95% error reduction
GPS 5–10 m → ~1–2 m (~1.4 m RMSE)

Real-world proof:
Validated on different cars (e.g., Porsche 911)
→ track-quality racing line & lap timing

Based on standard vehicle bus signals
high-precision GPS ground truth
(training on DGX, edge-ready)



USE CASE #3

Decoding the Fleet

AI Agent-Driven Vehicle Data Analysis

AI-driven Development Fleet Insights Reduce Time to Reaction

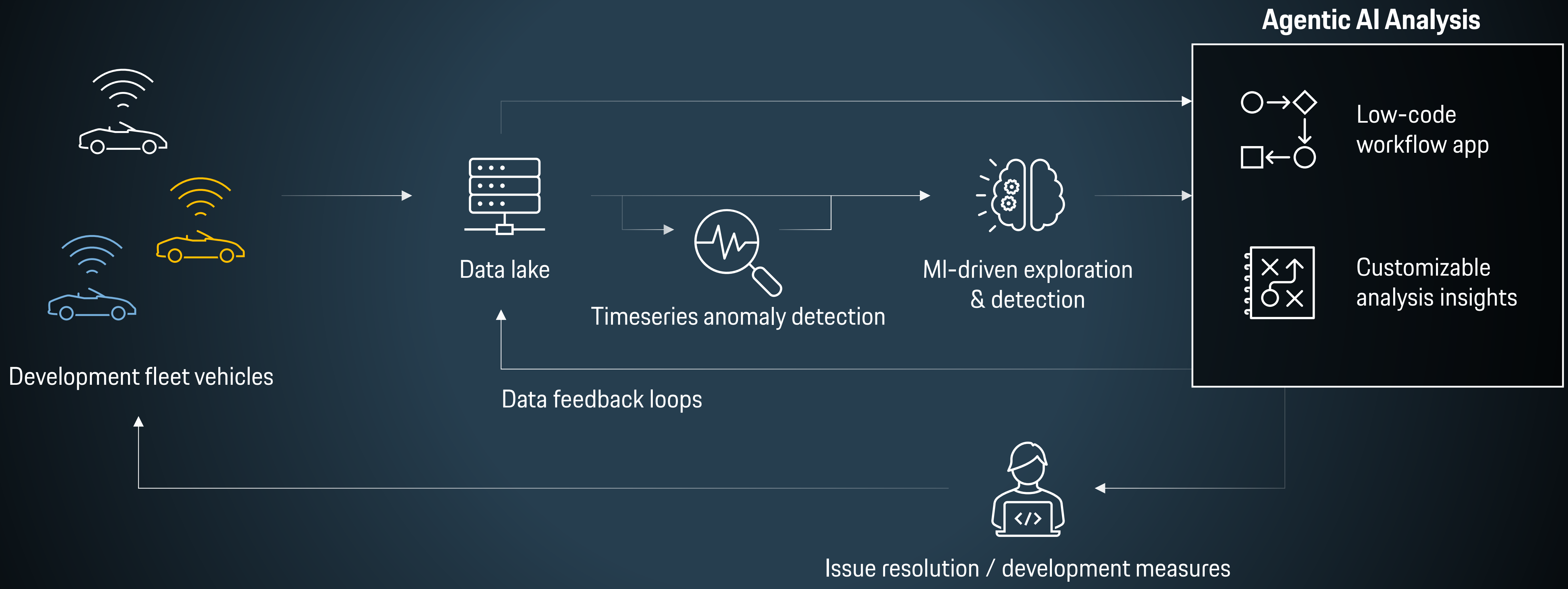
CHALLENGE

- Large amounts and many modalities of vehicle data
- Ambiguous relationships between diagnosis information
- High efforts around domain specific analyses

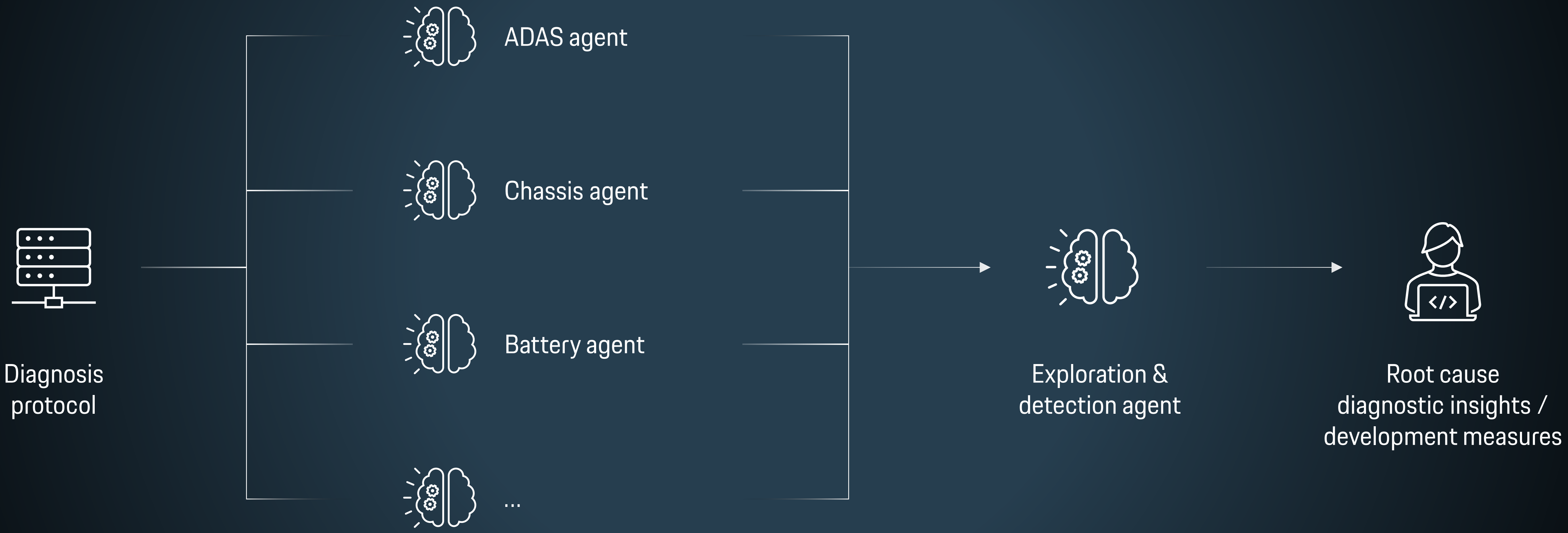
APPROACH

- Anomaly detection on a diagnosis protocol level
- Large Protocol Transformer–Decoder on development fleet protocols
- High level of automation with modular AI workflows

Our solutions integrate into the development data loop and enable early diagnosis.



Multi Agent Expert Process Provides Granular Diagnosis Insights



Benefits of the Agentic Diagnosis Insights

Managing complexity
Efficient handling of
large data volumes

Clarity
Information and causal relationships
at a glance

Enhance human expert knowledge
Multi-Agents provide insights where user
knowledge is limited

Time savings
Fast analysis of diagnosis information,
first hypotheses in **minutes vs hours**

Summary

Faster 'Time to Car' With a Cloud-Connected Real-Time AI Ecosystem

from lab workflows → in-vehicle evaluation at fleet scale

Why change

Controller-centric + offline workflows create **long iteration cycles** and high manual effort. Fleet testing is hard to manage and compare.

What we built

A repeatable loop connecting **vehicle edge → cloud data lake → on-prem training → deployment back to the vehicle**, including tracking/registry and workload management.

Why it matters

Signal foundation model

turns raw recordings into a searchable scenario database → faster root-cause analysis and scalable safety quantification.

Race GPS

improves positioning from 5–10m to ~1–2m (**~95% error reduction**).

Agentic diagnosis

First hypotheses in **minutes vs hours**, reducing dependency on scarce expert knowledge.

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