

Vehicle Computing: Vision and Challenges

Weisong Shi

University of Delaware

@TAMUIDS

<http://thecarlab.org>

Roadmap

👉 What is Vehicle Computing?

- Research activities @CAR Lab

The Era of CAVs

- **CV Market:**

- **\$65 billion** in 2021, **\$225 billion** by 2027 with a CAGR of **17%**
- **Every new** vehicle will be connected by 2025 (**400 million**)
- **50%** of national vehicles with connected features



Ford and Google to accelerate auto innovation and reinvent connected vehicle experience
March 31, 2021

Honda Partners with Google for In-Vehicle Services
September 28, 2021



Cruise and GM Team Up with Microsoft to Commercialize Self-Driving Vehicles

2021-01-19



Volkswagen Group teams up with Microsoft to accelerate the development of automated driving

Feb 11, 2021



Toyota and Amazon Web Services Collaborate on Toyota's Mobility Services Platform

August 17, 2020

Alibaba launches electric car in tie-up with SAIC
January 13, 2021



AWS and BMW Group Team Up to Accelerate Data-Driven Innovation

08.12.2020 PRESS RELEASE ARCHIVE

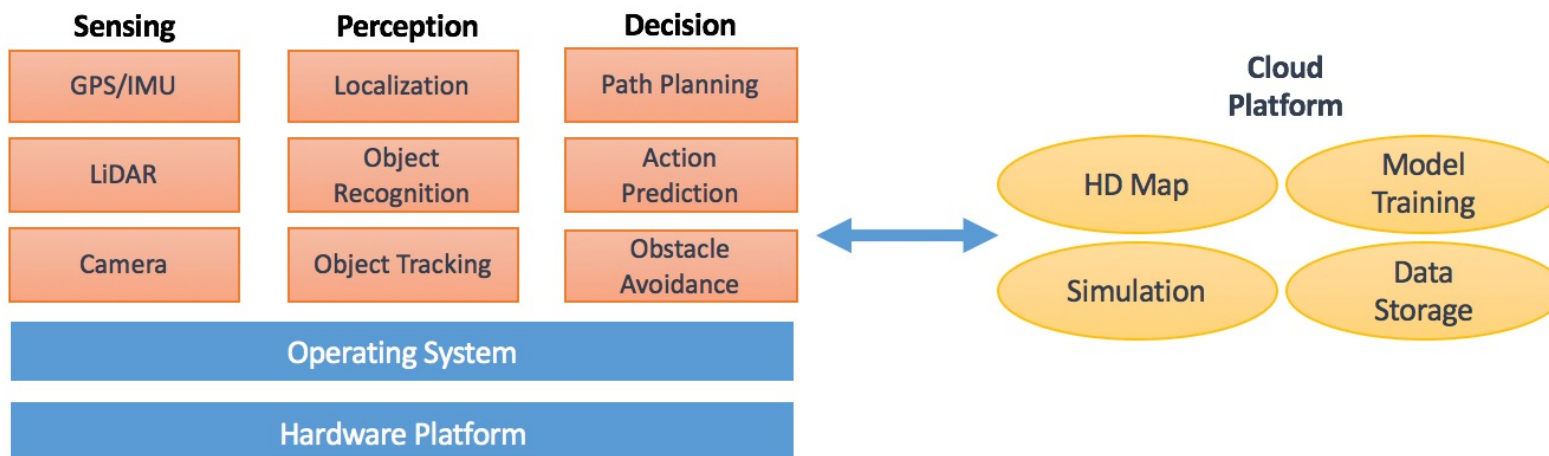


China's Baidu to create an intelligent EV company with automaker Geely

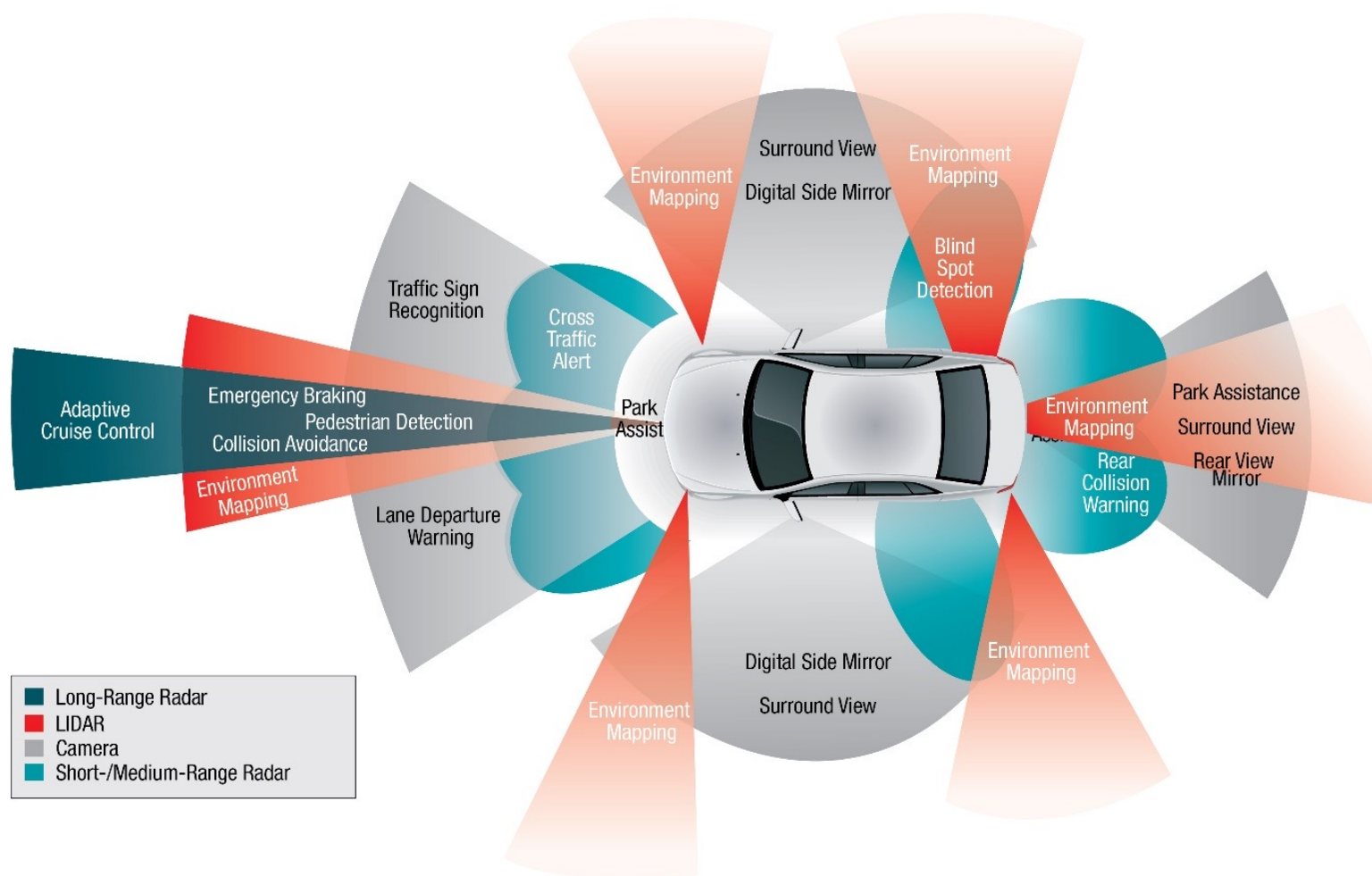
JANUARY 10, 2021



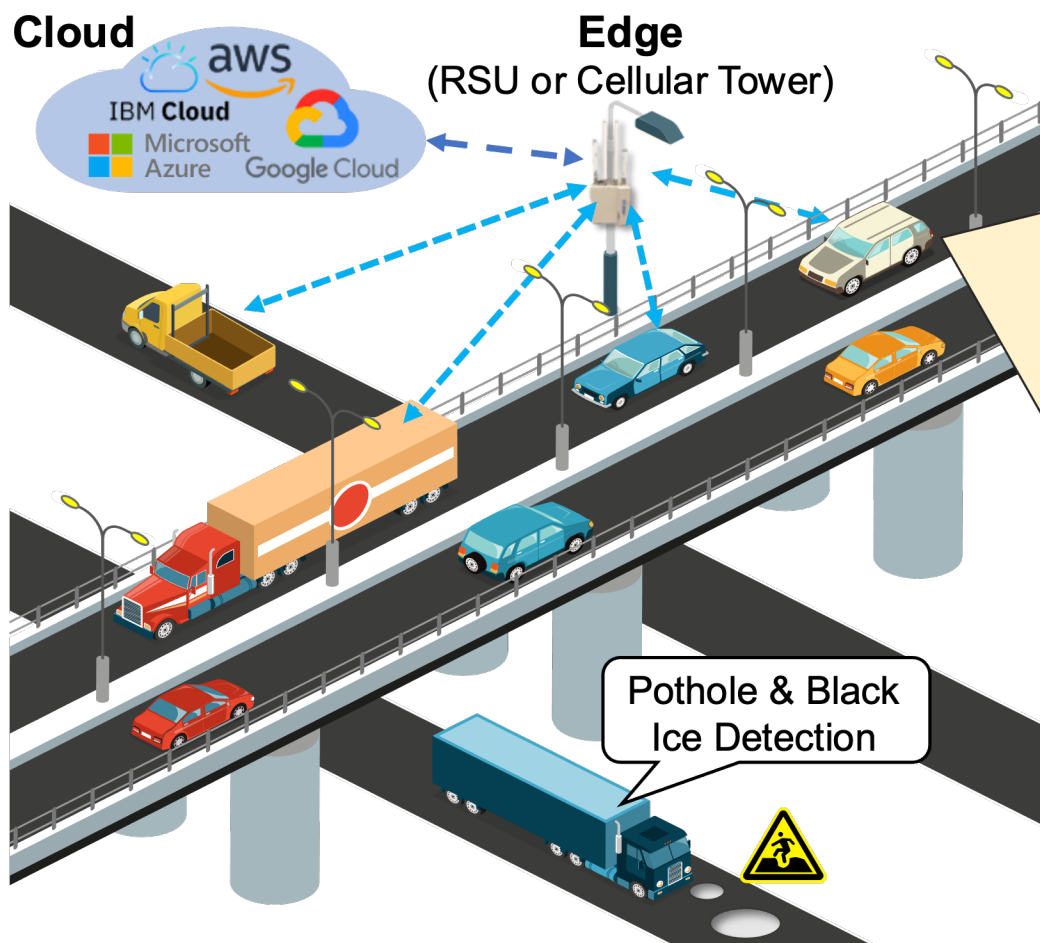
CAV: An Overview



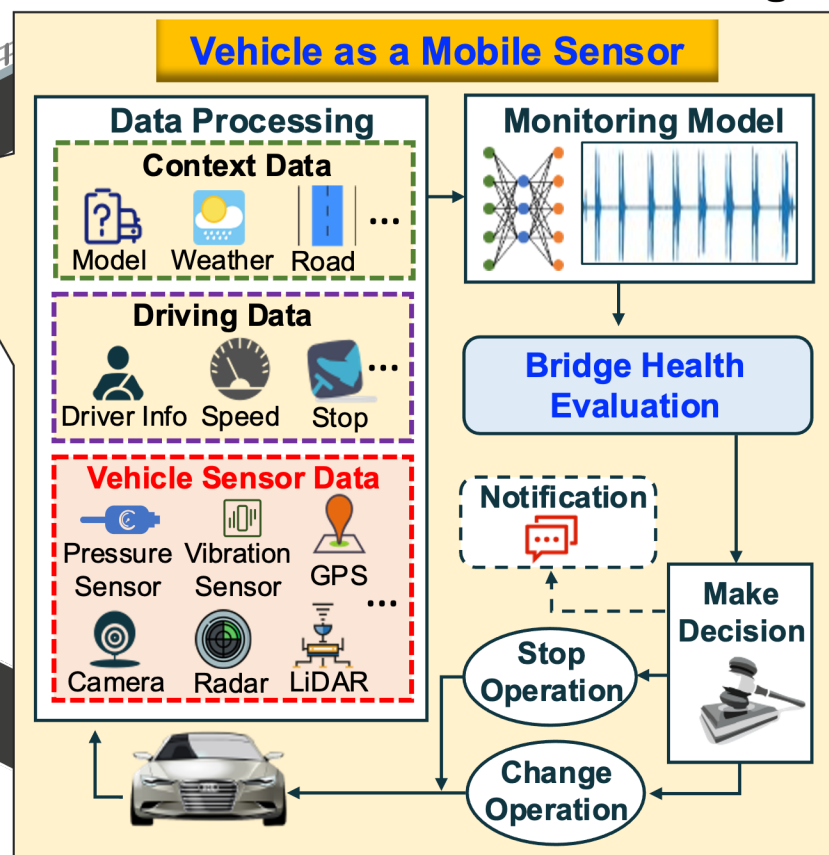
Perception Area of CAVs



Infrastructure Management



Infrastructure Health Monitoring



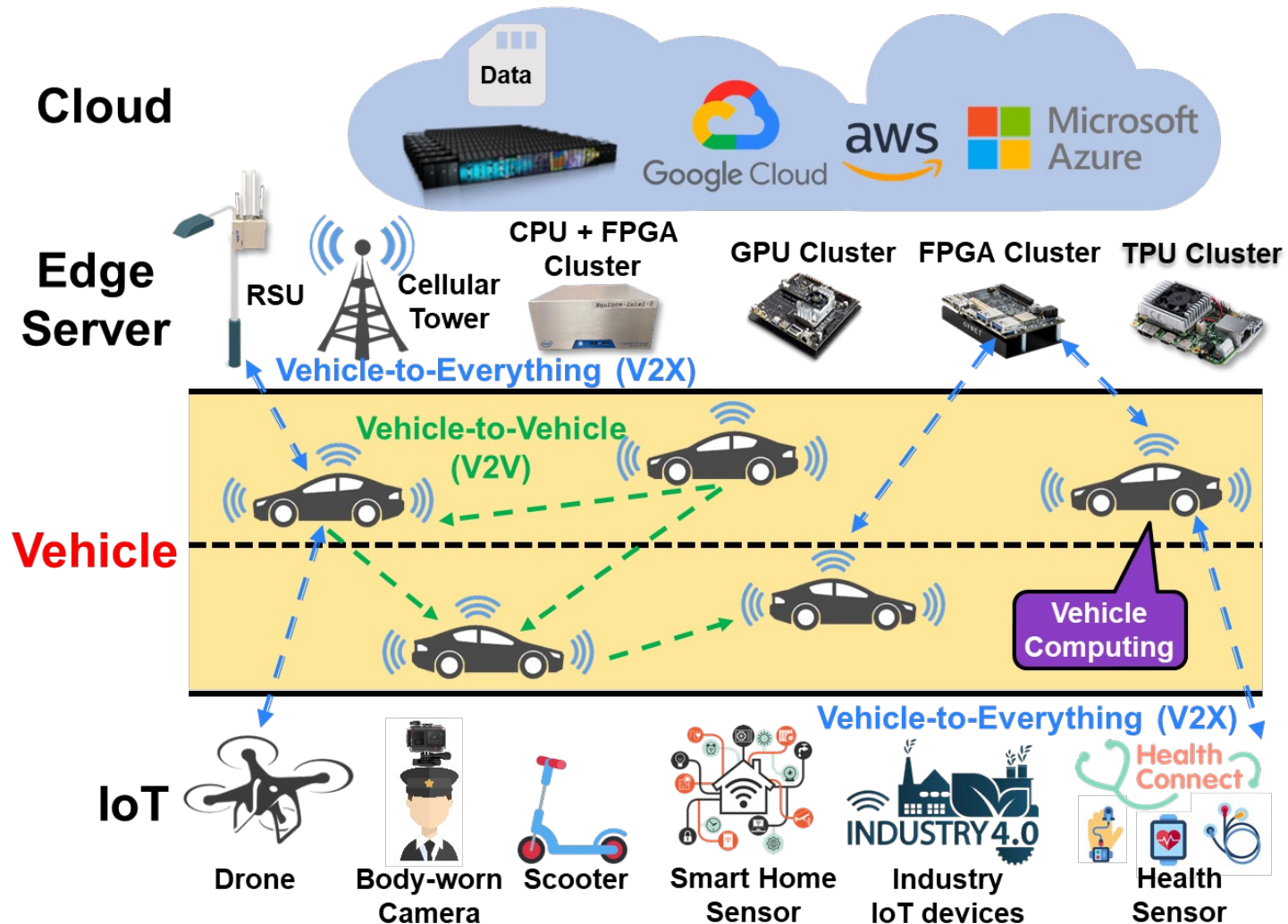
The Vehicle Computing Era



The 4-Tier Vehicle Computing Paradigm

Computing on
CVs based on
data from:

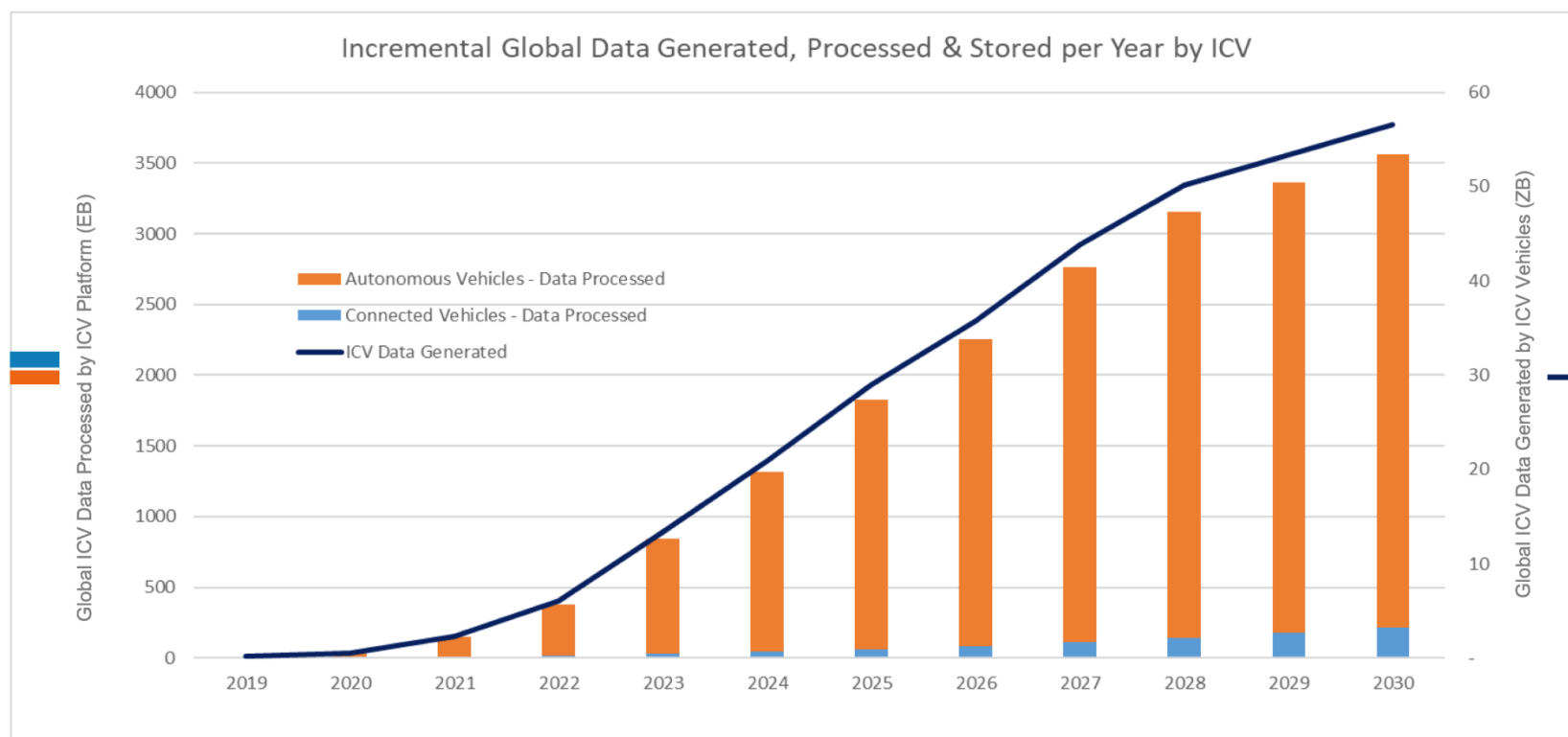
- In-vehicle sensors,
- Surrounding **connected devices**



Usage Revolutionary Change: 10% to 100%

Data Generated by CAVs

ICV Represents Over 17% of Global Data Generated by 2025



Autonomous Vehicles

THE COMING FLOOD OF DATA IN AUTONOMOUS VEHICLES

RADAR
~10-100 KB
PER SECOND

SONAR
~10-100 KB
PER SECOND

GPS
~50KB
PER SECOND

CAMERAS
~20-40 MB
PER SECOND

LIDAR
~10-70 MB
PER SECOND

AUTONOMOUS VEHICLES
4,000 GB
PER DAY... EACH DAY



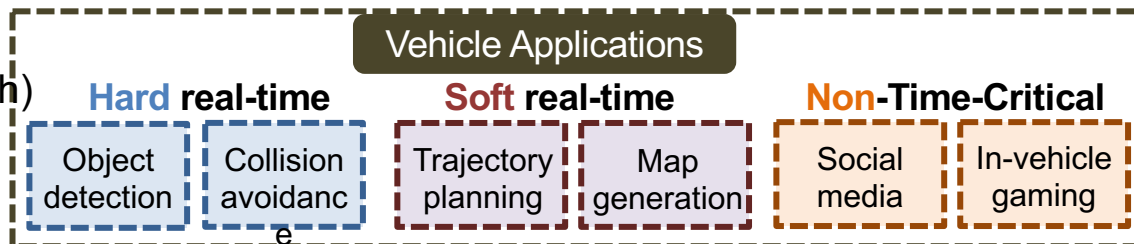
35TB, 1000W

Credit: Intel

Challenge #1: Computation Latency

- Time-sensitive services**

- Response Time **< 90 ms** (40 km/h)
- Computing Latency **< 164ms**
(avoid an obstacle at 5m away)

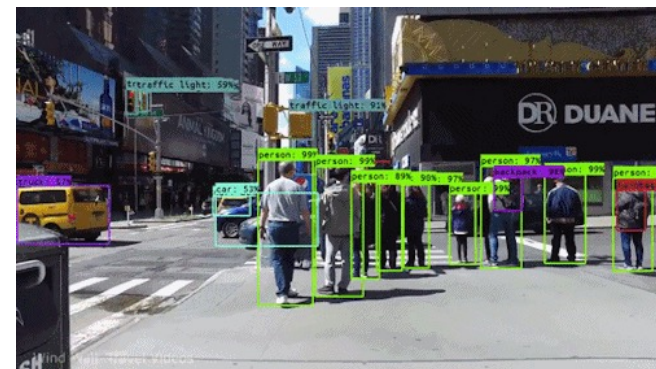


- Vehicle data & model size**

- Single CAV in **urban**: **40 TB** data / eight hours of driving
- CAV fleets on **highway**: **280 PB** data
- Increased model complexity

- Computation-constrained vehicles**

- Traditional non-luxury vehicle: **\$30K**
- CAV: **\$250K**
- Sensors and computing platform: **two-thirds** of the total price



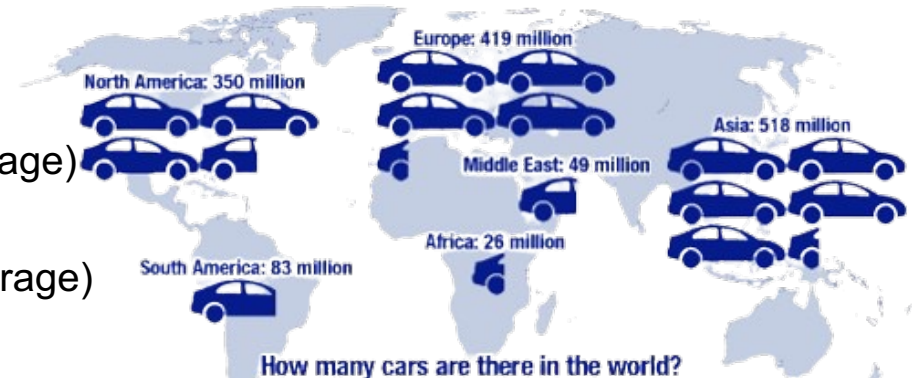
Reference: <https://towardsdatascience.com/how-do-self-driving-cars-see-13054aee2503>

Goal: **accelerate** the inference speed of time-sensitive vehicle applications

Challenge #2: Transmission Costs

- **Transmission**

- **Uplink:** **data**
 - 8GB data per vehicle, per day (on average)
- **Downlink:** **software/firmware update**
 - 500MB per vehicle, per update (on average)
 - Update frequency: once per quarter



1.4 billion vehicles globally in 2022
(21% vehicles are in U.S.)

- **Transmission costs**

- **Cost per usage:** 1 GB of mobile data worldwide: **\$8.53 (\$12.37 in U.S.)**
- **Unlimited prepaid data plan:** **\$20** per month (AT&T, Chevy)

The cost of data transmission for a **10-million vehicle** fleet can reach over **20 PB** of data and cost over **\$1 billion**, every year!

Enterprises can expect a **10 to 30% reduction** in costs from using **Edge Computing**.

Credit: <https://hedgescompany.com/blog/2021/06/how-many-cars-are-there-in-the-world/>

Challenge #3: Cyber-Physical Boundary

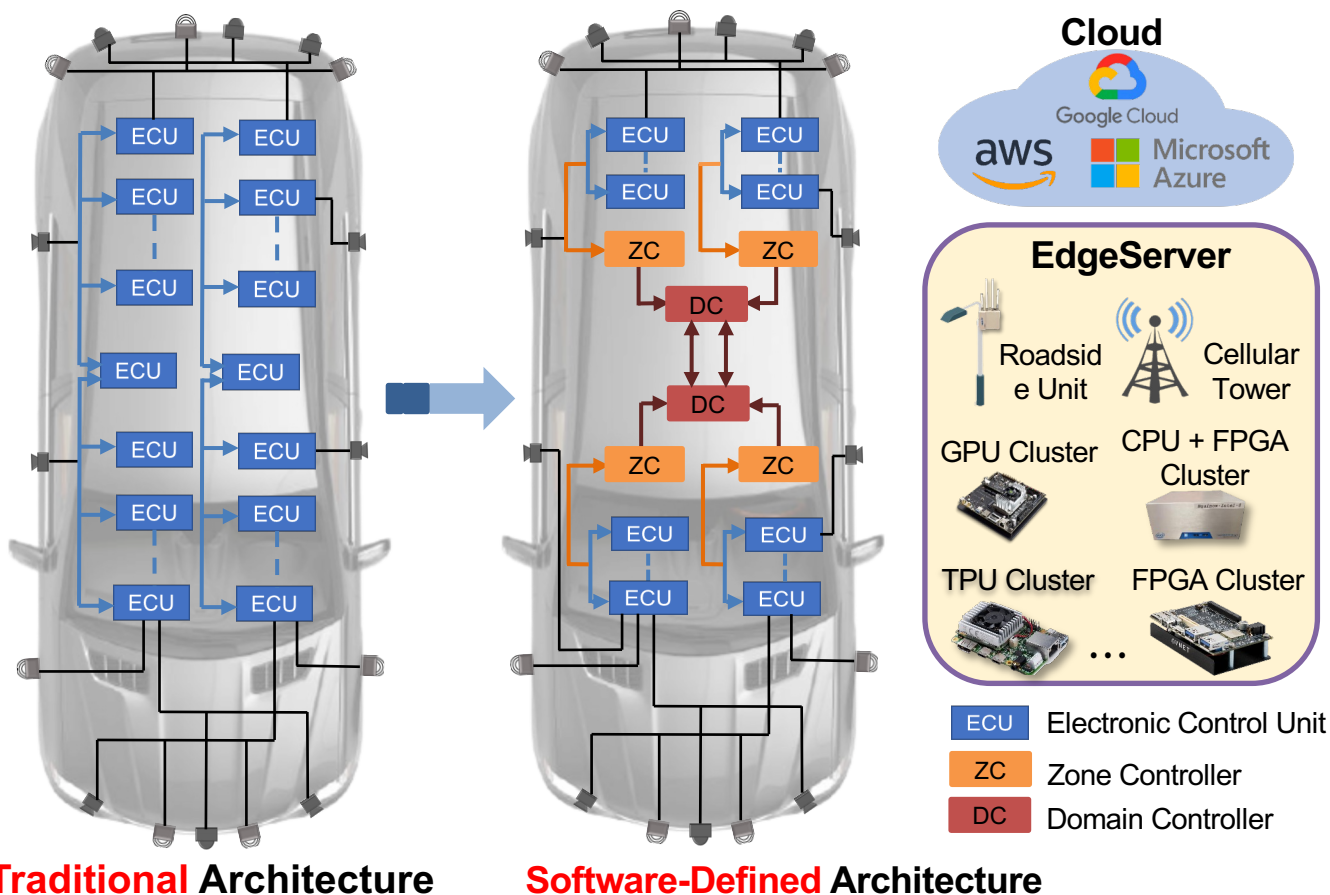
VEHICLE CONTROL DELAY FOR ACCELERATION, BRAKING, AND STEERING FOR SELECTED COMMERCIALIZED VEHICLES

Delay (ms)	Lincoln MKZ	Hongqi H7	Hongqi EV	NIO ES8	GAC Group Aion LX
<i>Acceleration</i>	280	200	484.2	120	236
<i>Braking</i>	230	362	191.7	120	266
<i>Steering</i>	136	128	124.8	108	120

Need predictability in the full stack on vehicles!

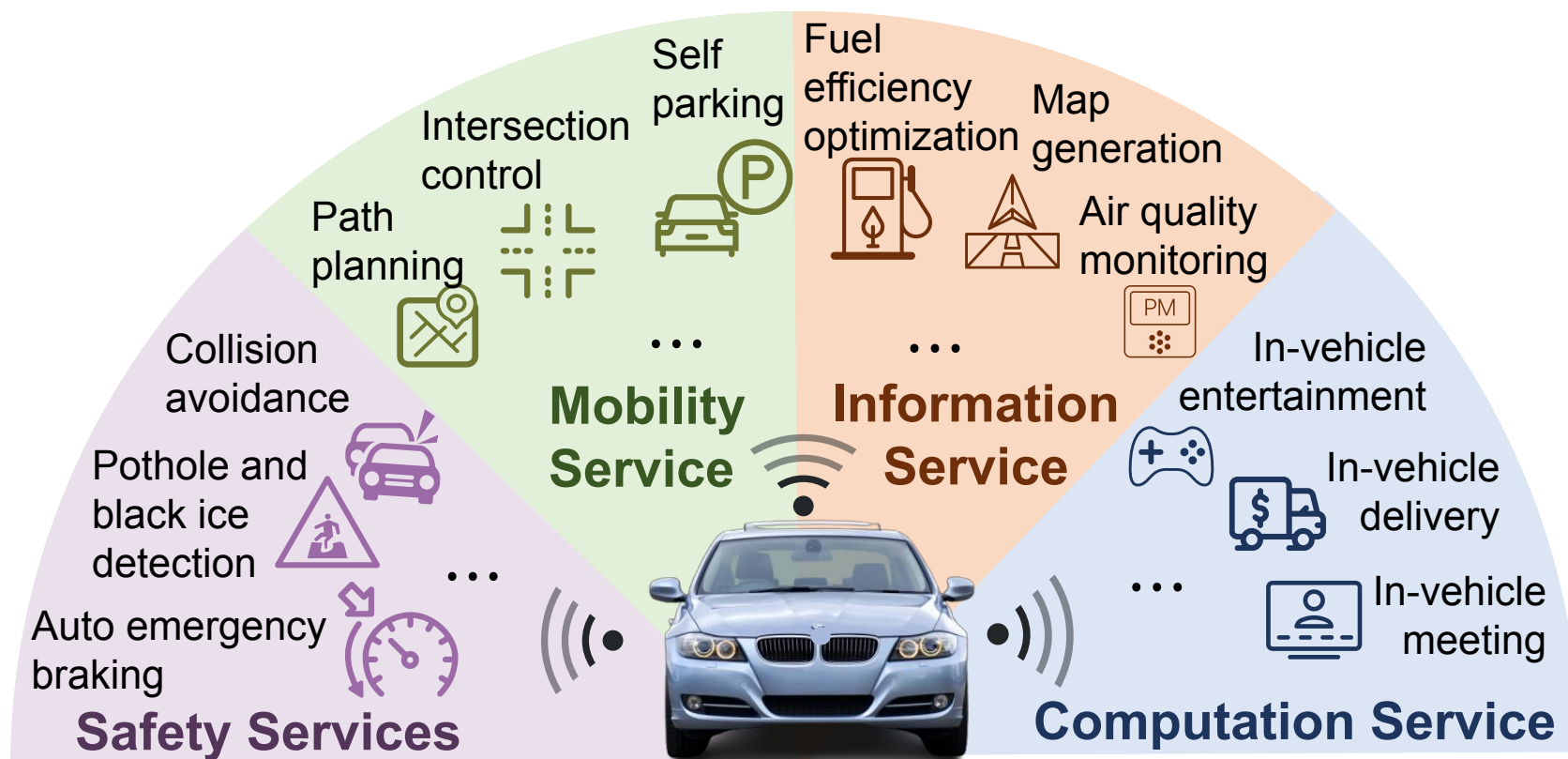
Liangkai Liu, Shaoshan Liu and Weisong Shi, [4C: A Computation, Communication, and Control Co-Design Framework for CAVs](#), IEEE Wireless Communication Magazine, Vol. 28, No. 4, pp. 42-48, August 2021.

The Evolution of Automotive Computing System



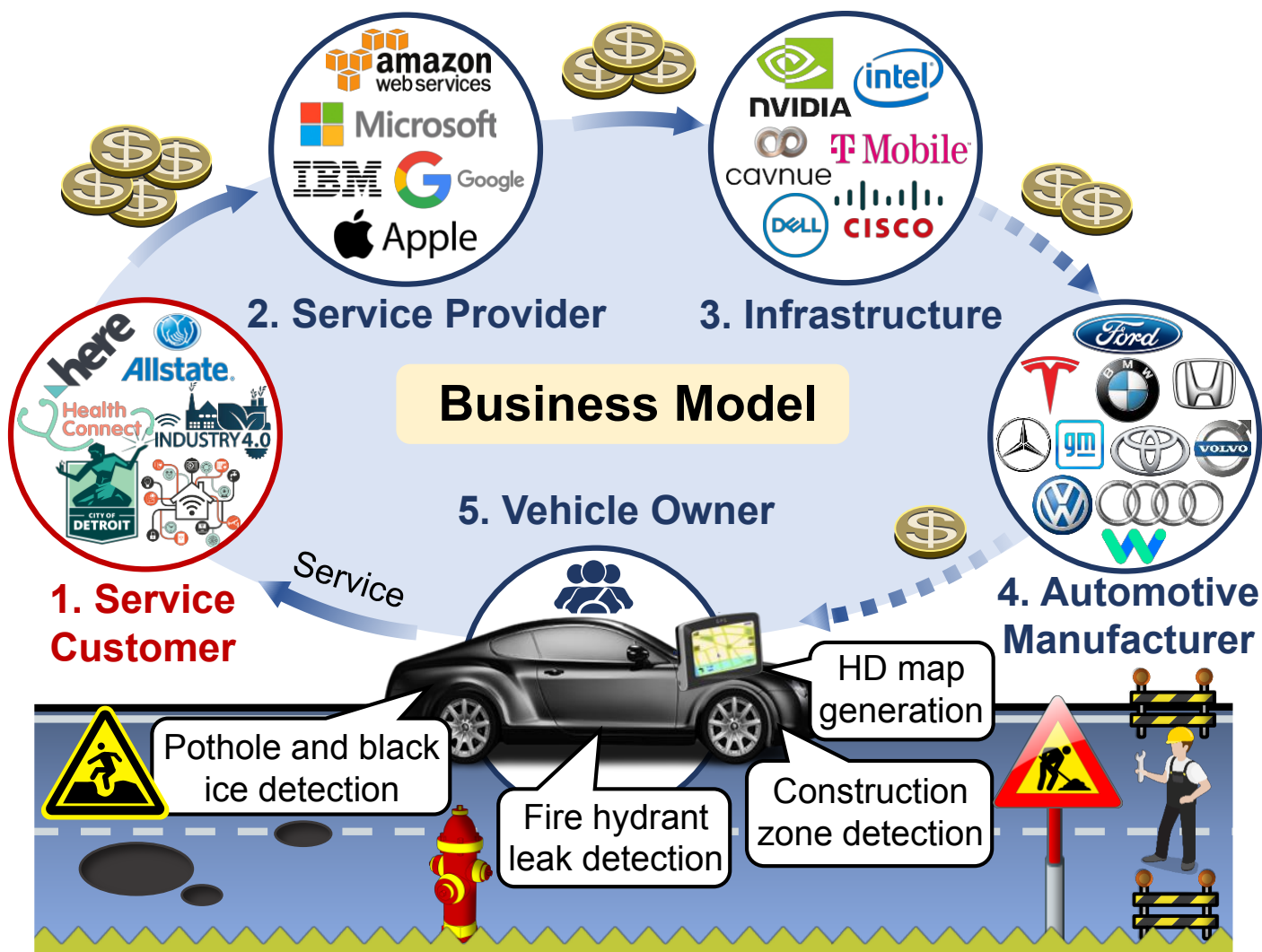
- **Shortcomings of traditional architecture:**
 - Difficult to deploy diverse **computation-intensive** applications.
- **Advantages of software-defined architecture:**
 - **Simplifies** vehicles' system interconnection
 - Makes the **deployment of software** to both ZCs and DCs possible

Software Defined Vehicles



Vehicles serve as both a sensor and a service producer and consumer.

CAV Key Players



Challenges in Vehicle Computing

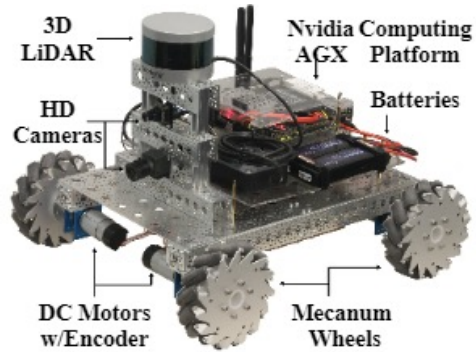
- Benchmarking and workload
- Distributed Real-time Operating Systems
 - E.g., V2X communication, C-V2X, 5G/6G, WIFI
- Programmability (decomposition)
 - E.g., Novel programming model
- Real-time Runtime support and scheduling
 - E.g., automatically partition and deployment
- Energy consumption
 - E.g., computing, communication, sensing
- Security and privacy
 - E.g., trusted edge servers, Privacy-preserving
- End-to-end optimization
 - E.g., Communication/Computation/Control/Cost
- Business model
 - Automotive/Physical Infrastructure/Telecom/Cloud?
 - Deployment/Incentives

Roadmap

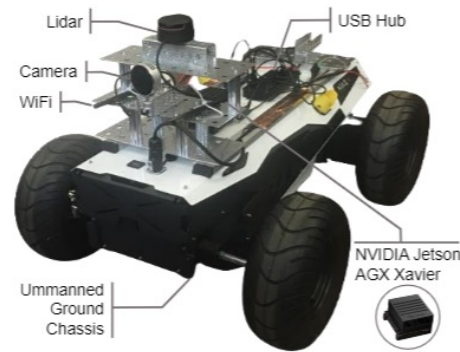
- What is Vehicle Computing?

👉 Research activities @CAR Lab

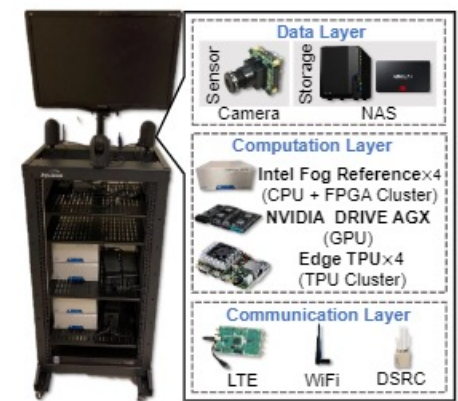
Research Platforms



HydraOne



Zebra



Equinox



ZebraT

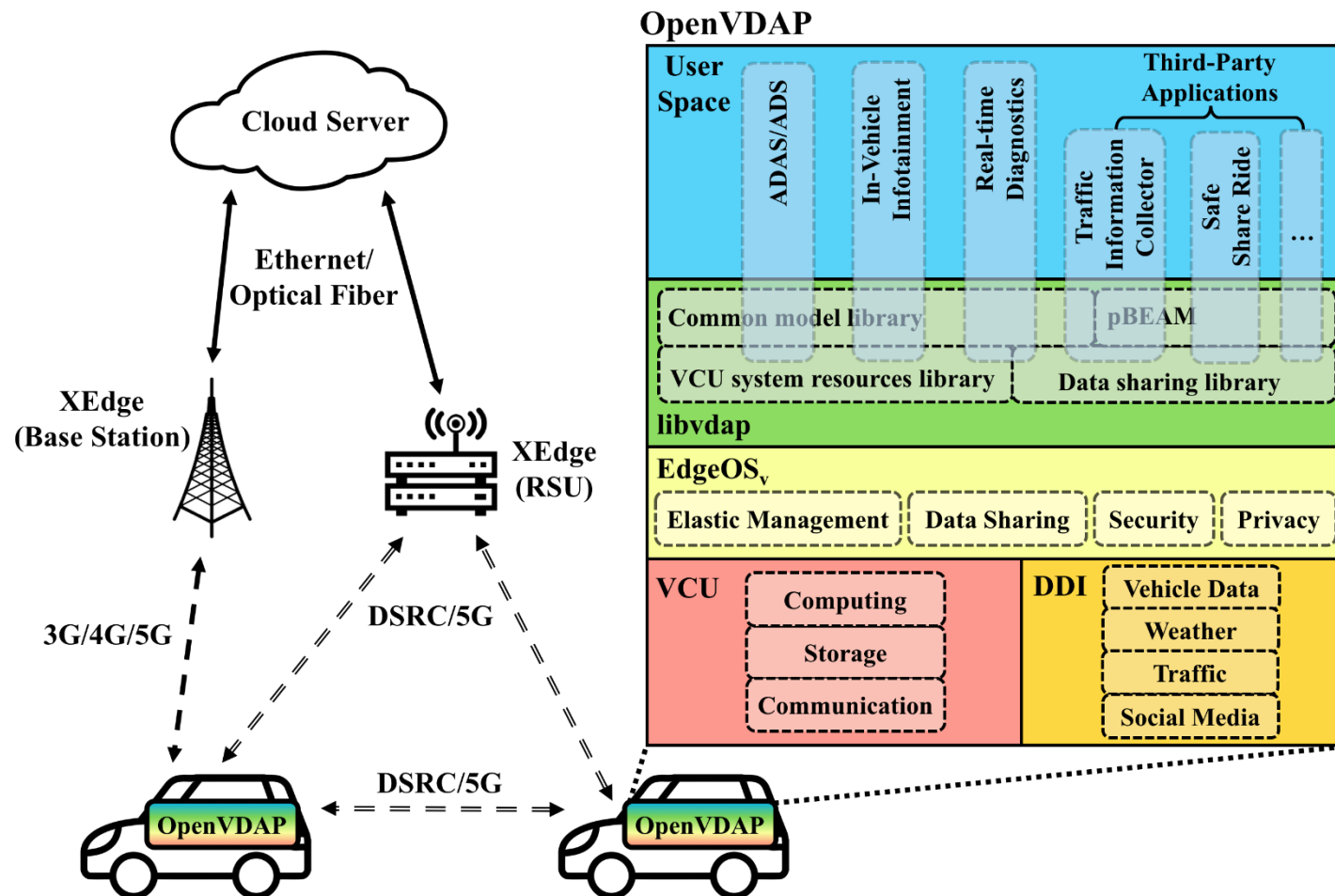


Hydra

OpenVDAP for SDV (ICDCS'18)

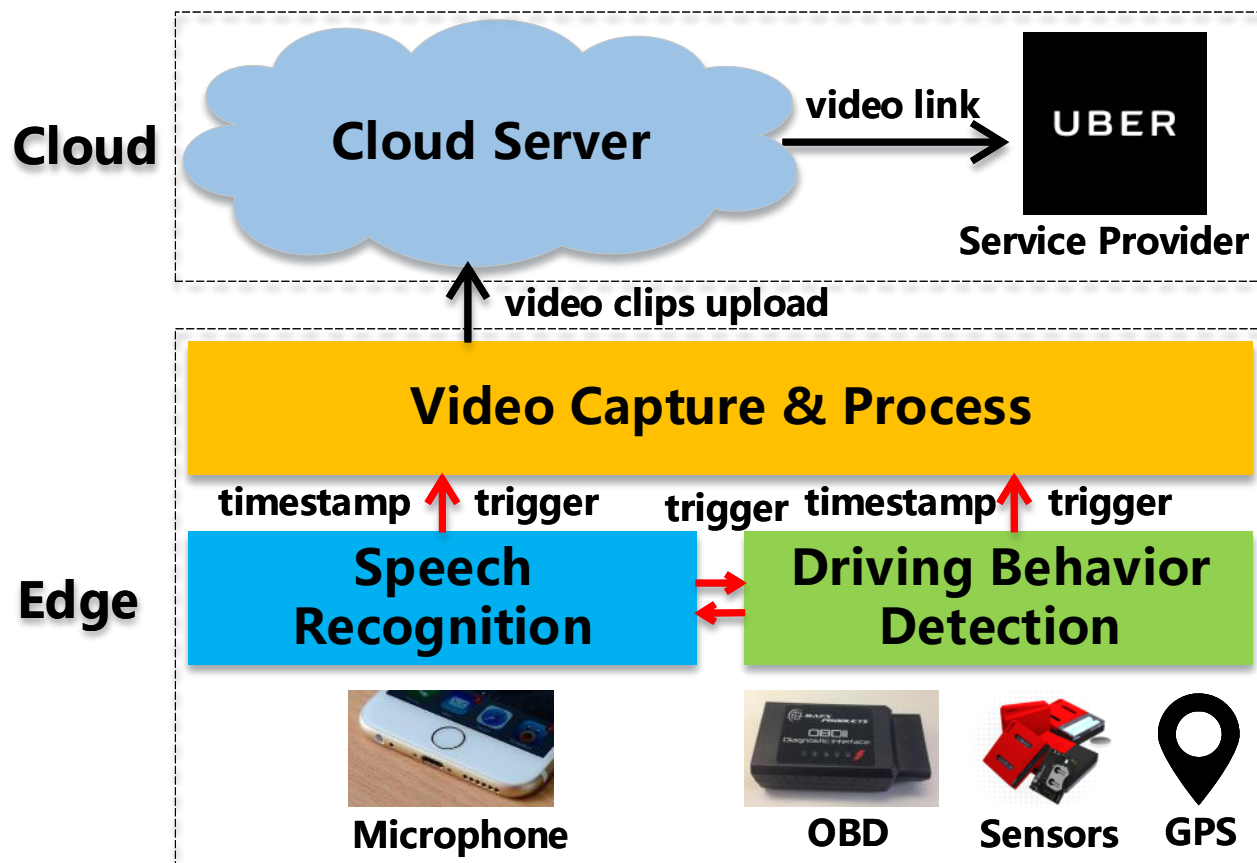


- **Open V**ehicular **D**ata **A**nalytics **P**latform



SafeShareRide (SEC'18)

- Voice + driving behavior + video



Bandwidth

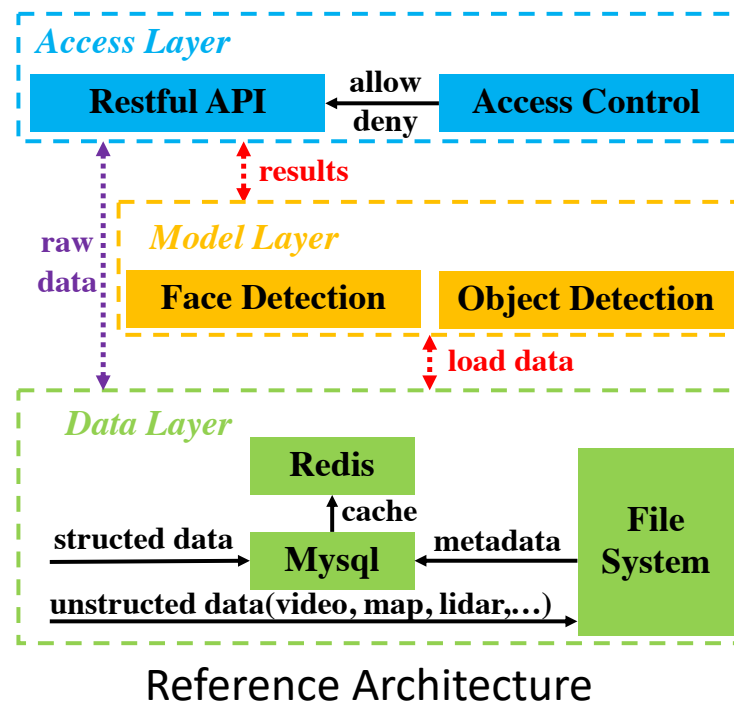
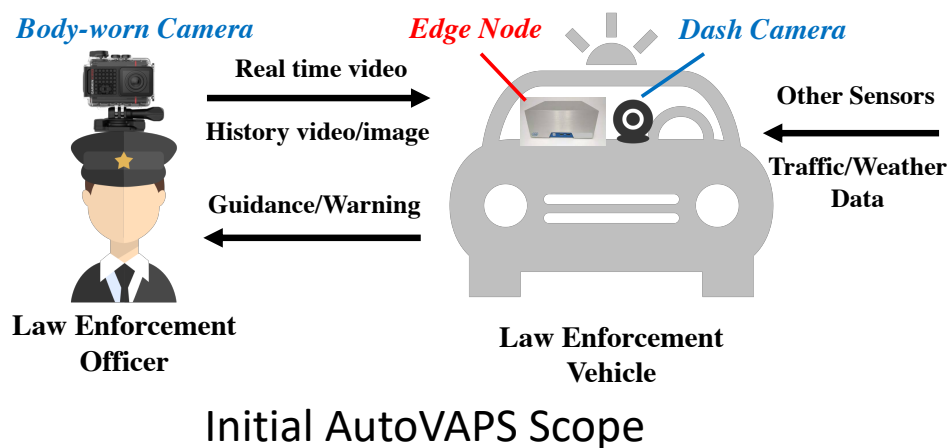
- Trigger mechanism
- Edge & Cloud Corporation

Latency

- Cache
- Multi-thread Scheduling
- Model Optimization

AutoVAPS (SCOPE'19)

- An IoT-Enabled Public Safety Service on Vehicles
 - Video Analytics for Public Safety(VAPS)
 - Lack of safety or mission critical requirements
 - Reference architecture for on vehicle VAPS is missing



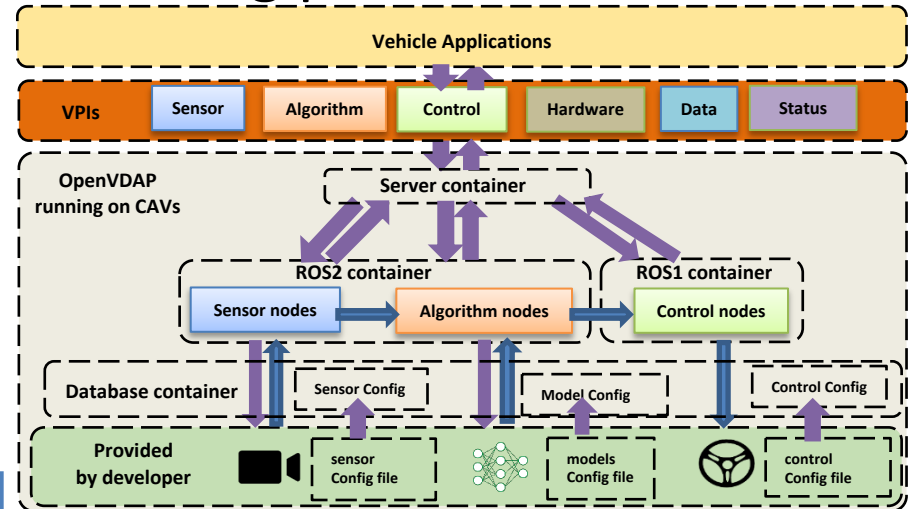
Vehicle Programming Interfaces



- Why VPIs?
 - No need the knowledge of vehicles, sensors, and communications
 - Only focus on application logic
 - Programming with less code
- Key VPIs design

VPI Types	VPI examples	Operations
Data	<code>vpi.data.getCameraData (front)</code>	get front camera data
	<code>vpi.data.getSpaTData()</code>	get SPaT data from infrastructure
Control	<code>vpi.control.setTwist(msg)</code>	Set Twist command to CANbus
	<code>vpi.control.setWiper(front, params)</code>	Set wiper with params
Algorithm	<code>vpi.algorithm(camera_front, e2e_lane_keeping_model)</code>	Run end-to-end lane keeping model using front camera data
	<code>vpi.algorithm([[camera_front_left, camera_front_right], lidar_top], [e2e_lane_keeping_model, collision_avoidance_model], test_case)</code>	Run multi algorithms on test case
...

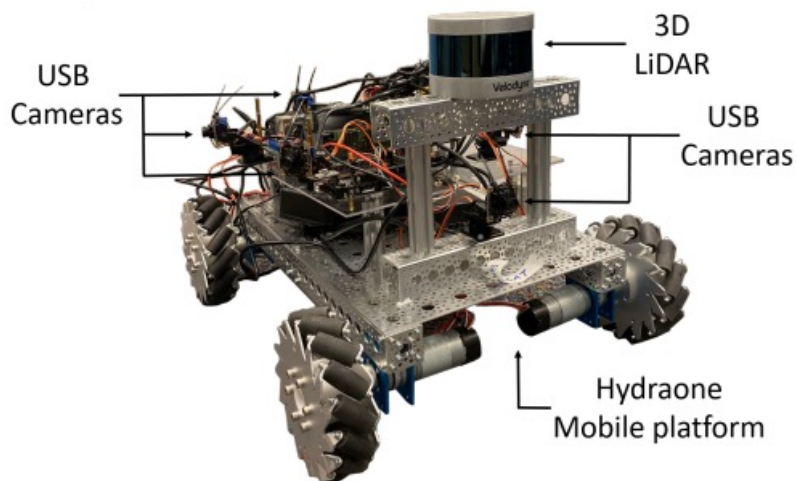
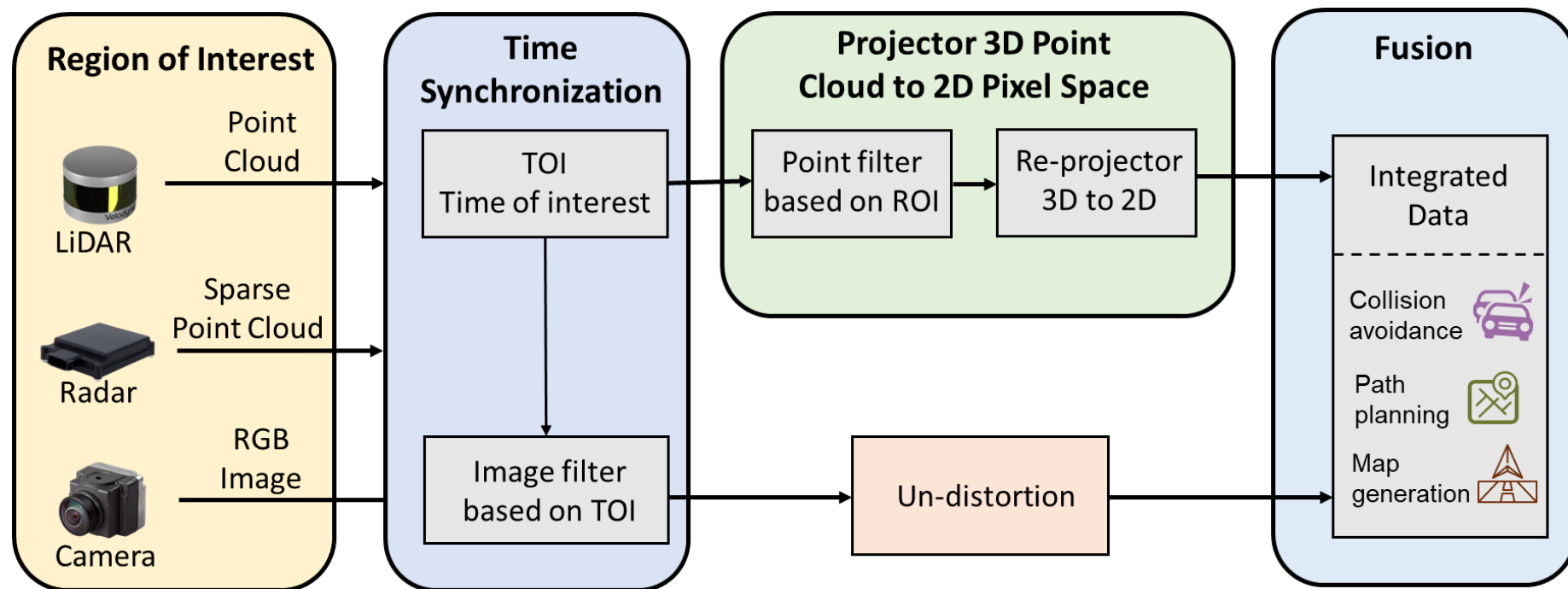
- The big picture



- An example
Lane keeping demo with 3 lines of code

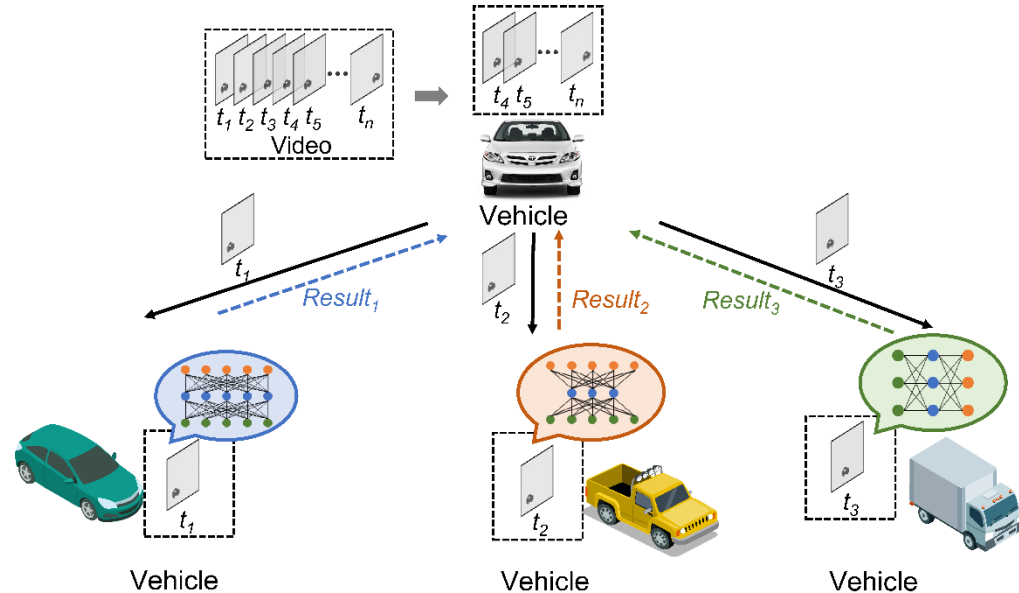
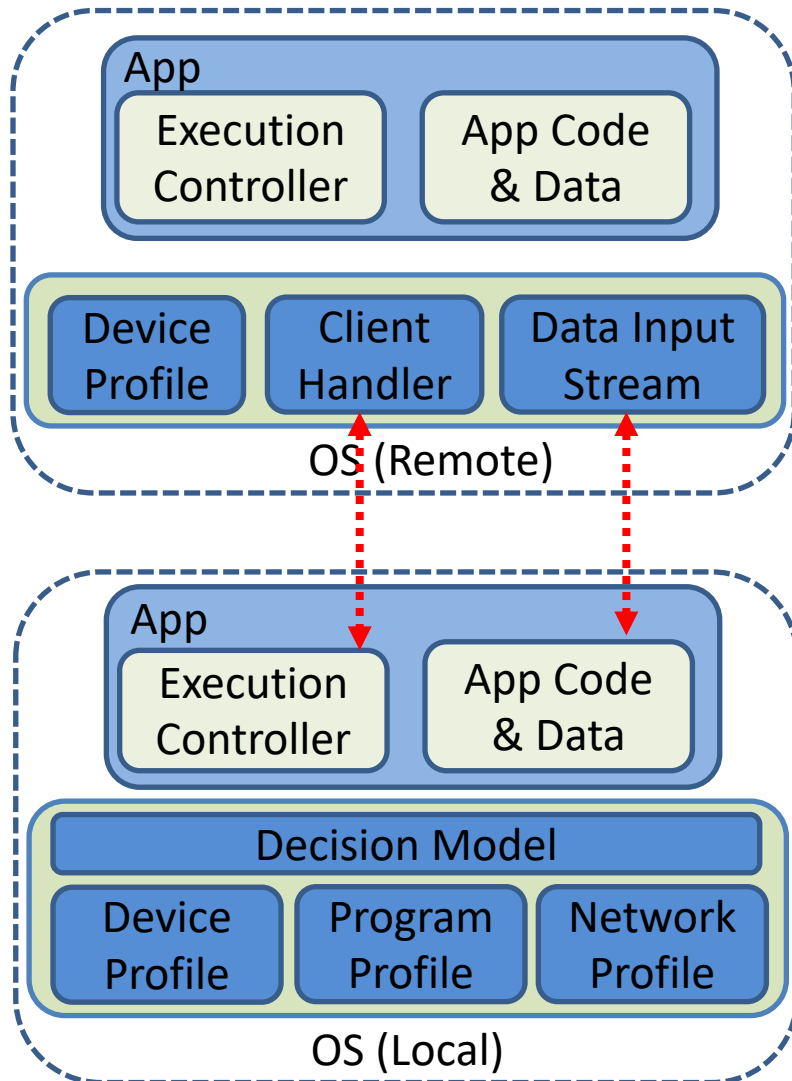
```
import vpi
control_msg = vpi.algorithm(camera_front, e2e_lane_keeping_model)
vpi.control.setTwist(control_msg)
```

360°-View Data Synchronization & Fusion



- **Time of Interest (TOI):** the period of time that represents the moment of scanning spatial area
- **Region of Interest (ROI):** relationship between spatial-point cloud data and the different views

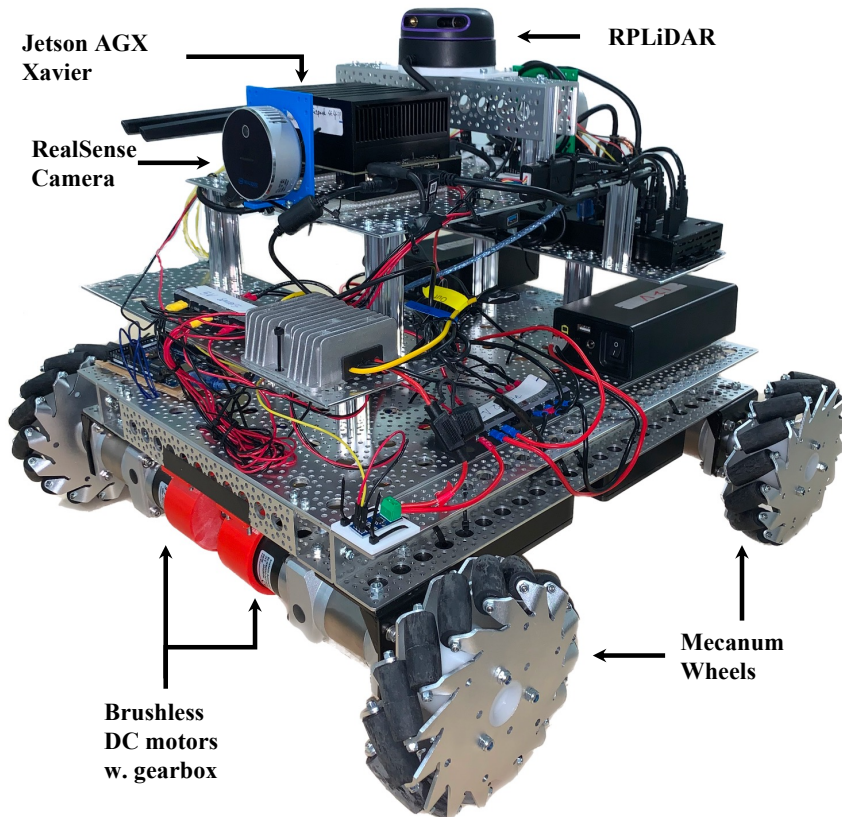
Distributed Computing for CVs (EdgeComm'22)



- Collaborative inference
 - **effectively utilize the heterogeneous resources** at each vehicle
 - improve user experience



Donkey Platform (ICRA'23)



Hardware:

- 4 BLDC motors w. gearbox
- 1 Jetson AGX Xavier
- 1 RPLiDAR
- 1 Intel RealSense L515 camera
- 1 24V Lithium ion battery with 42980mAh
- 1 12V Lithium ion battery with 38400mAh

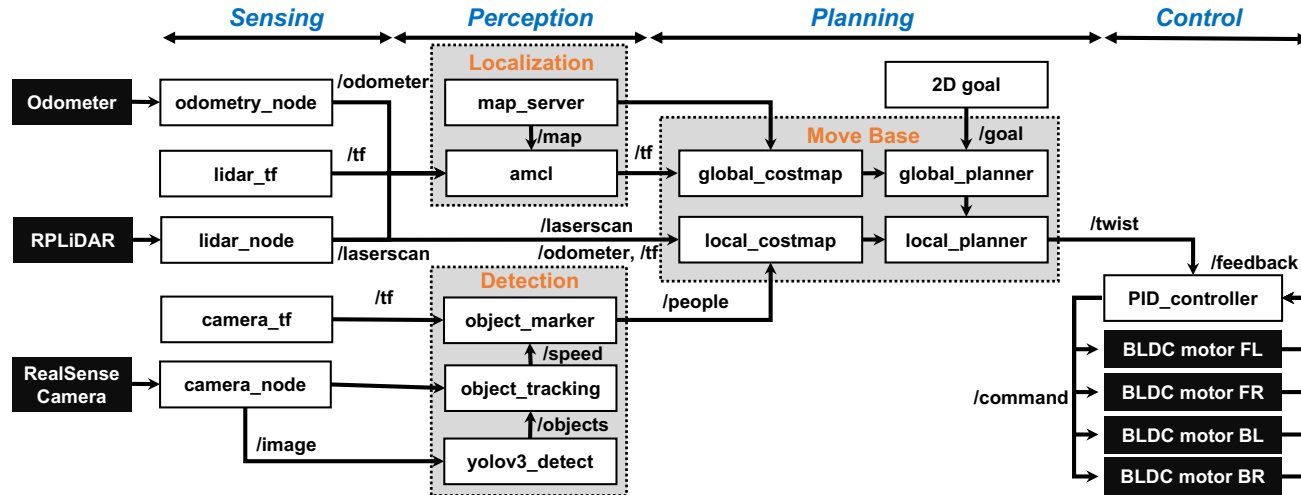
Software:

- TensorFlow 1.15
- PyTorch v1.5.0
- Torchvision v0.6.0
- CUDA 10.2
- cuDNN 8.0.0
- OpenCV 4.1
- ROS melodic

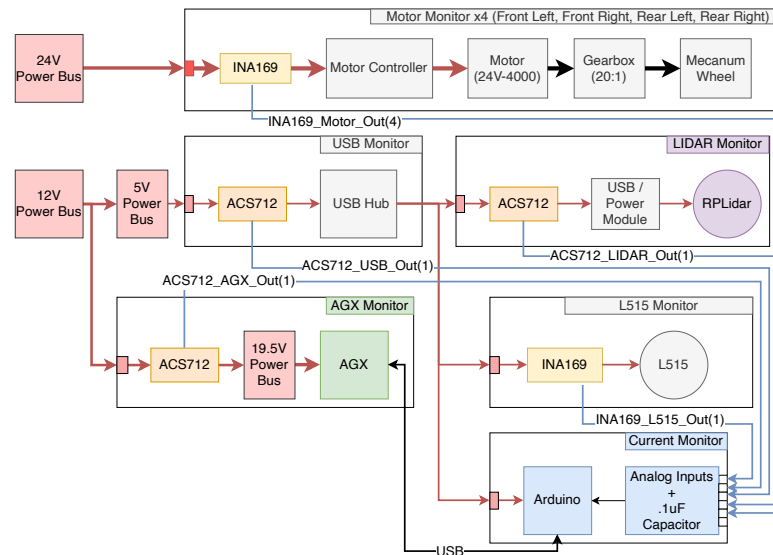
Donkey Software Stack



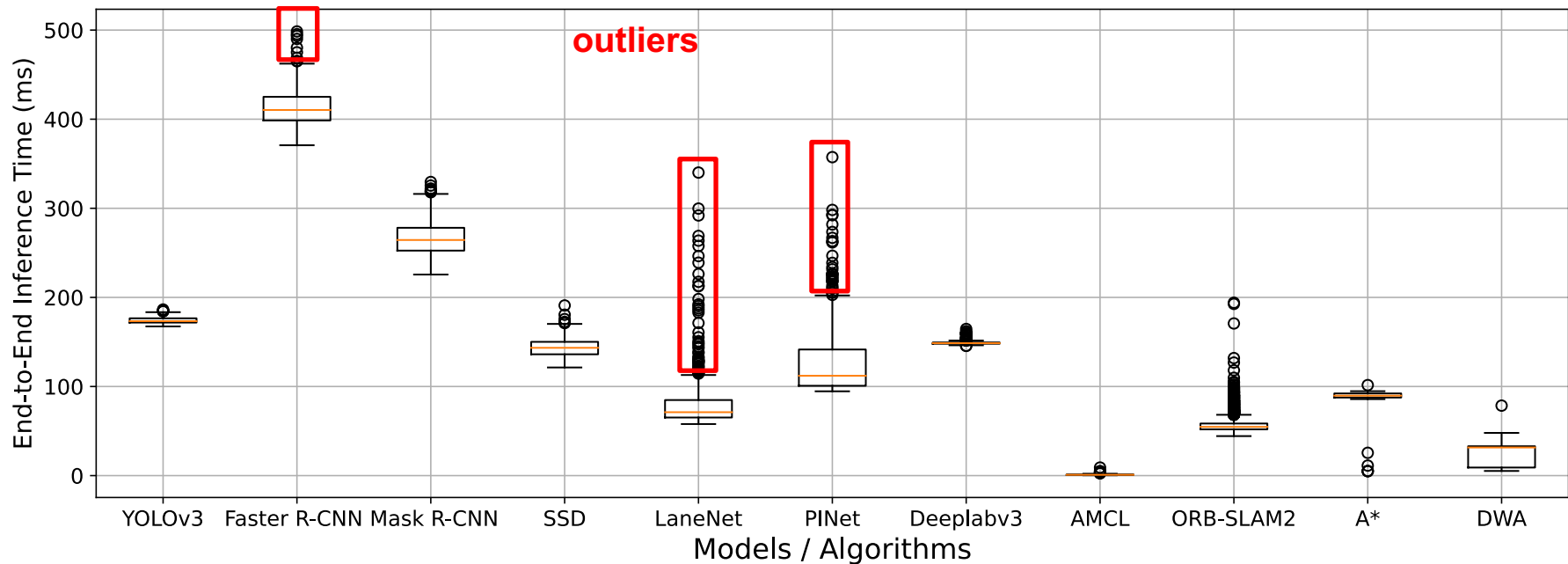
Software Pipeline:



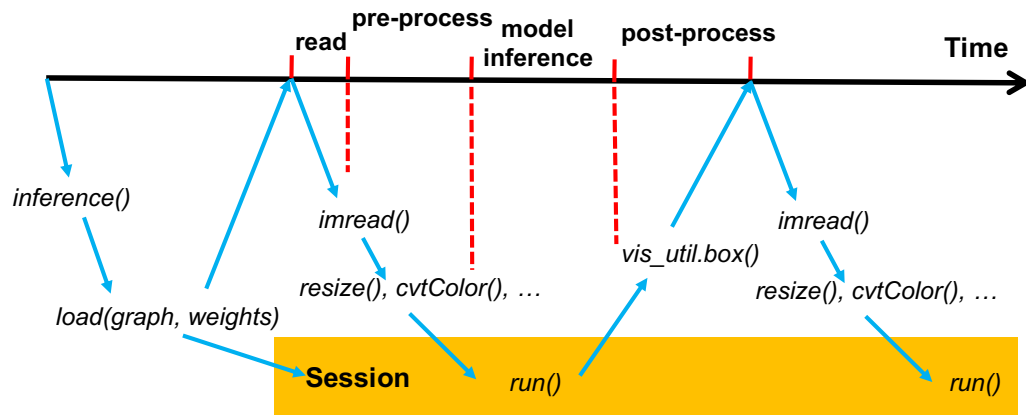
Power Distribution and Monitor System (PDMS):



DNN Inference Time Variations in AVs



Timeline Analysis:



Potential variabilities:

- **Read:** data, I/O methods
- **Pre-process:** data, hardware
- **Model inference:** model type, runtime, hardware
- **Post-process:** data, hardware

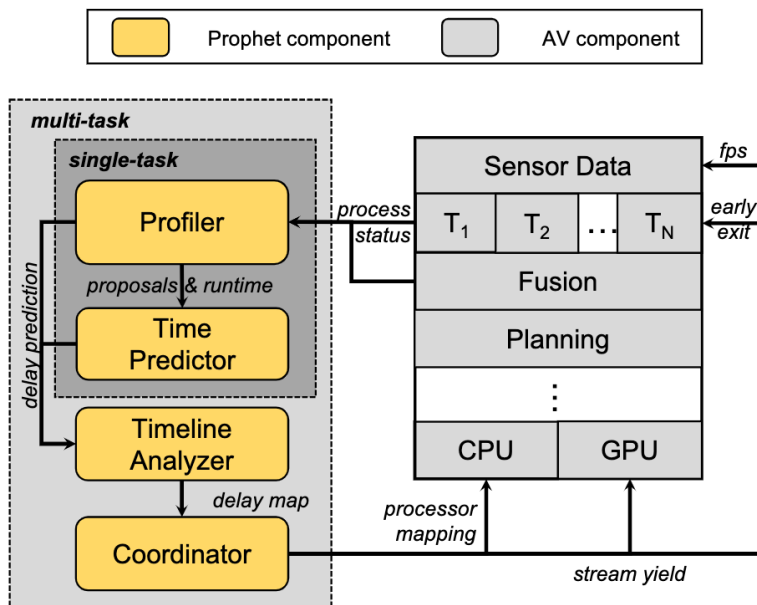
Six insights are derived in understanding the time variations for DNN inference.

Prophet: A Predictable Real-time Perception Pipeline for AVs (RTSS'22)



Two Insights from empirical study:

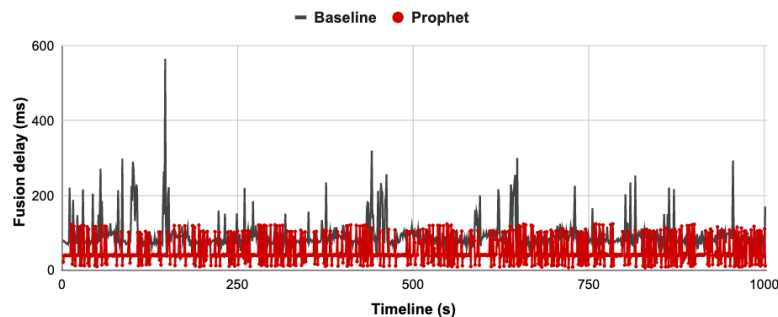
1. In silo mode, DNN's **structure** and the **runtime configurations** impacts the inference time variations.
2. In multi-tenant mode, proper **task coordination** is the key to addressing the time variations issue.



Inference time prediction:

Model	Real (ms)	Predicted (ms)	MAE (ms)	Accuracy (%)
<i>Faster R-CNN</i>	32.18	32.17	0.33	98.99
<i>LaneNet</i>	15.27	15.24	0.99	94.03
<i>PINet</i>	25.32	23.72	2.31	91.68

Perception system fusion delay:



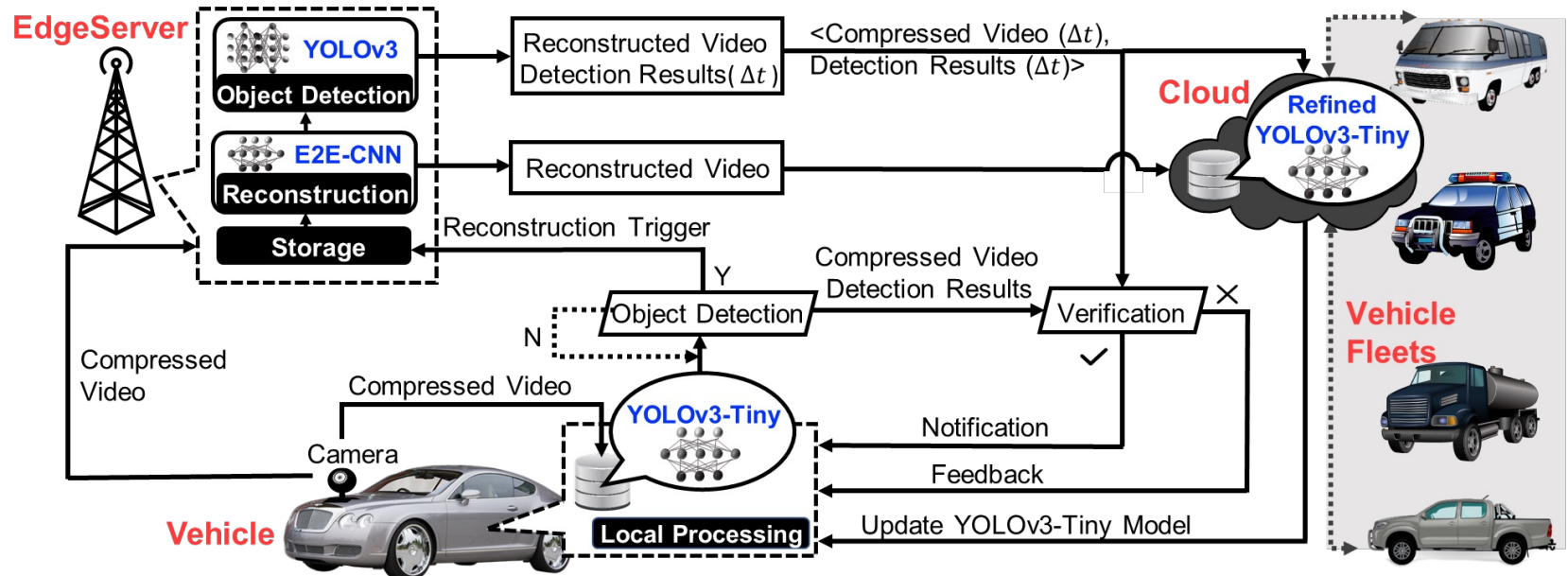
Key ideas:

- Predict inference time based on the **intermediate results** (proposals, raw points);
- **Early-exit** inference if the inference time is predicted to miss the deadline

Deadline miss rate:

5.4% (baseline) → **0.087% (Prophet)**

Vehicle-Edge-Cloud Framework (SEC'20)



1) Vehicle

- *Energy-efficient network*: make timely computation on compressed data

2) EdgeServer

- *Reconstruct* high-speed data with a triggered event
- *Verify* the detection results of the vehicle and send notifications

3) Cloud

- *Aggregates* all useful information
- *Big data analysis*: traffic control and path planning

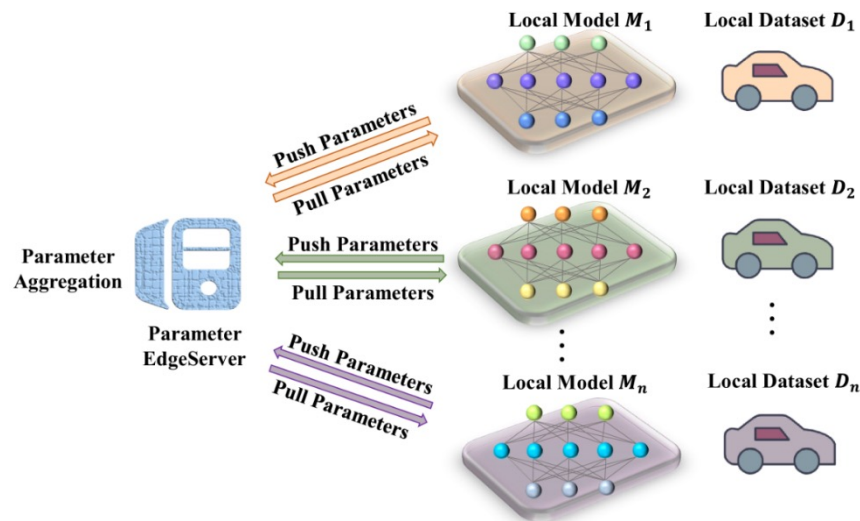
CLONE: Collaborative Learning on the Edges



➤ Why edges instead of datacenters or cloud?

Privacy issues, limited bandwidth.

➤ Framework of CLONE



- **Privacy Preserving**

-- raw data can always be kept in the device.

- **Latency / bandwidth Reduction**

-- upload parameters instead of the dataset.

- **Driver Personalization**

-- update local model by the private data.

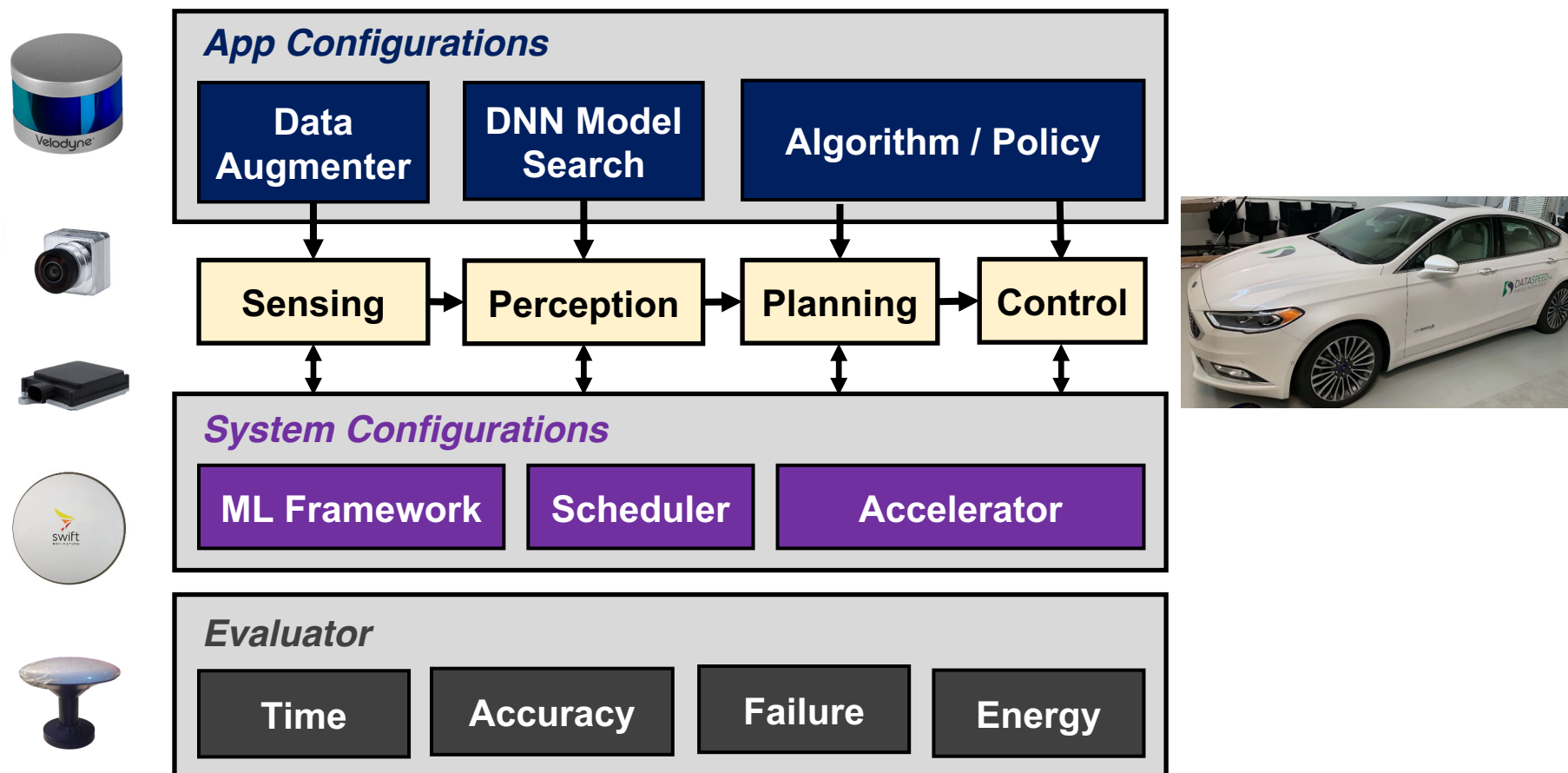
➤ Compared with Stand-alone learning

- Reduce model training time significantly,
- Achieve equal or even higher accuracy,
- Stable data throughput.



UD-AVSuite

Goal: An **End-to-End Configurable Benchmark Suite** for Autonomous Driving

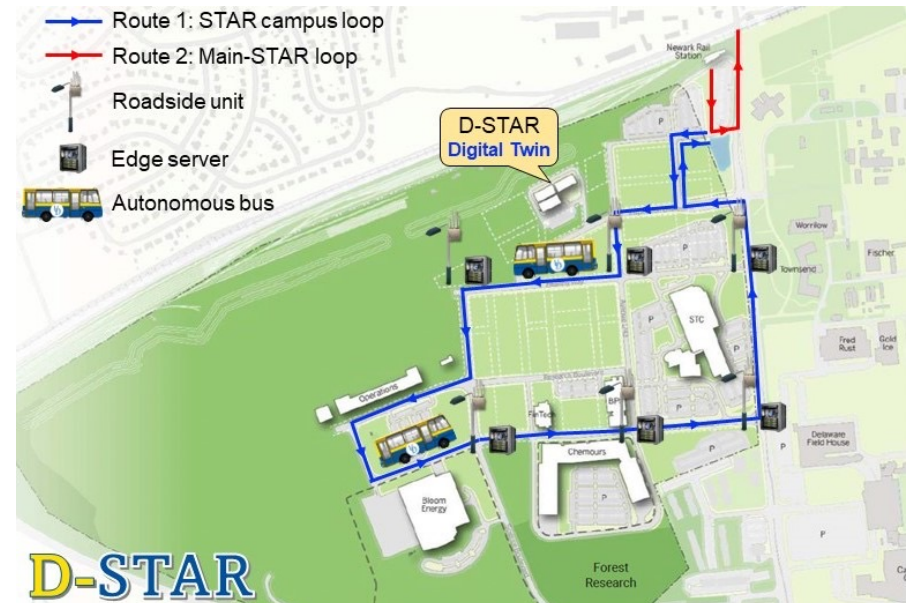


Liangkai Liu, Yanzhi Wang, and Weisong Shi, *CPT: A Configurable Predictability Testbed for DNN Inference in AVs*, under review.

Collaborators and Partners



robosense

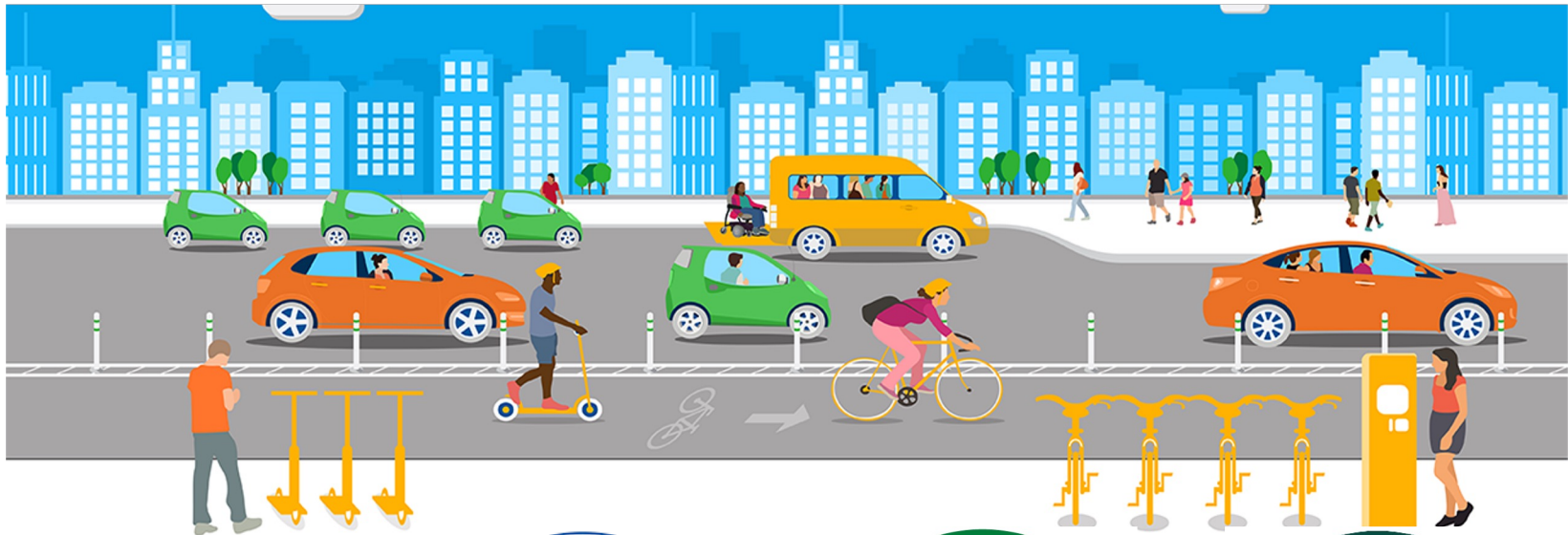




eCAT NSF IUCRC Center



Vision: To build a world-class industry-university research center for *sustainable mobility* technologies



Summary

- *Vehicle computing era is coming*
- A lot of opportunities
 - Applications
 - CAV applications
 - Architecture/storage
 - Machine learning
 - Security/privacy
 - Systems/networking/communication
 - Tools
 - 4C Optimization

Two Relevant Events

- ACM Journal of Autonomous Transportation Systems
 - Special Issue: Mobility
 - Deadline: **May 1, 2023**

- IEEE Conference on Mobility: Operations, Services, and Technologies (MOST'23)
 - <http://ieeemobility.org>
 - Dates: **May 17-19, 2023**

Additional Information

<http://thecarlab.org>

weisong@udel.edu

Liangkai Liu, Sidi Lu, Ren Zhong, Baofu Wu, Yongtao Yao, Qingyang Zhang, Weisong Shi, [*Computing Systems for Autonomous Driving: State-of-the-Art and Challenges*](#), **IEEE Internet of Things Journal**, Vol. 8, No. 8, April 2021.

Sidi Lu and Weisong Shi, [*Vehicle Computing: Vision and Challenges*](#), **Journal of Information and Intelligence**, Vol. 1, No. 1, January 2023.