Autonomous Driving Towards Reducing Human Efforts in Visual Perception and Beyond

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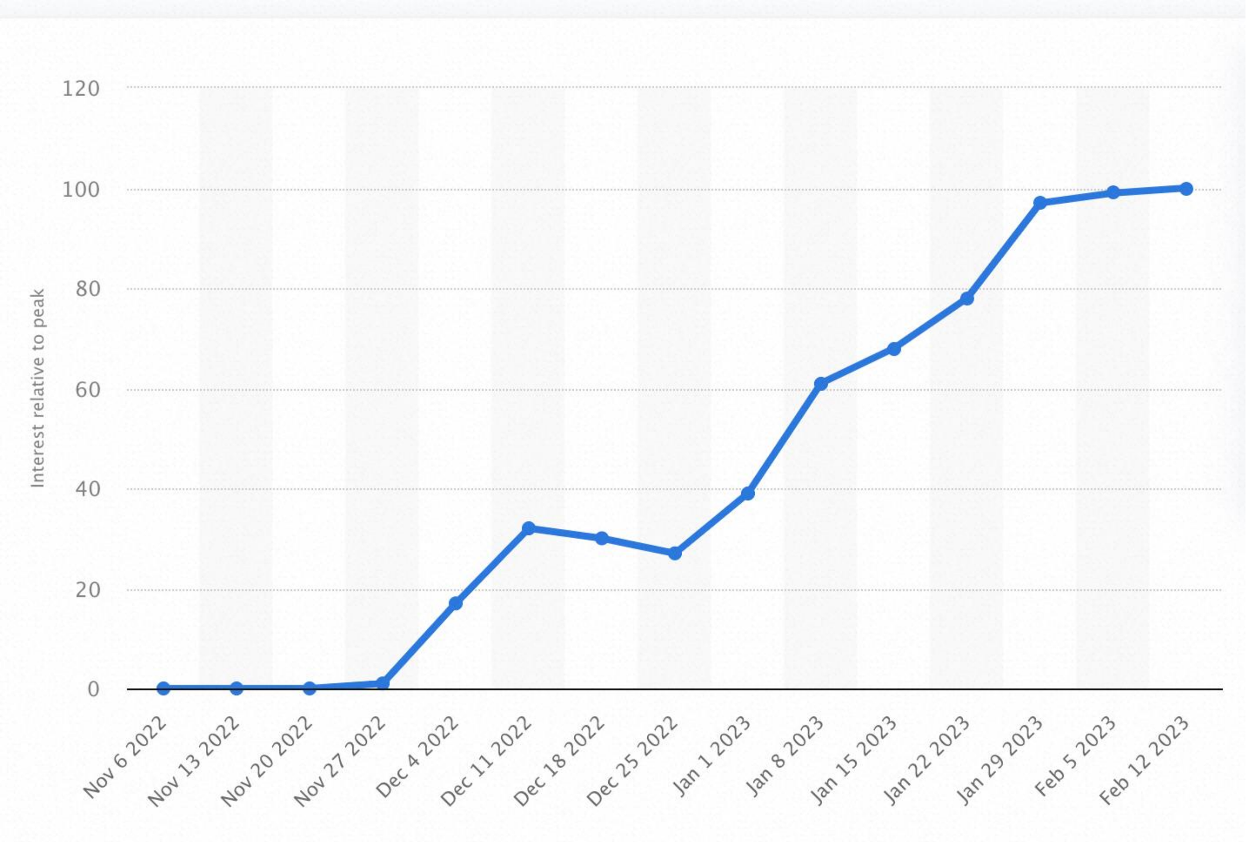
2025/05/22

Large AI Model Changes The World

ChatGPT is the **fastest app** reaches 1M Users
Only has **1** feature, Chat with GPT



Google Trends of ChatGPT

1. Statistica.com, https://www.statista.com/statistics/1366930/chatgpt-google-search-weekly-worldwide/, accessed on May 26th
2. Twitter Watcher.Guru, https://watcher.guru/news/how-long-did-it-take-chatgpt-to-reach-1-million-users, accessed on May 31th

Large AI Model Will Change The World Virtually

User

Computer (Desktop or Mobile)

Large AI Models

Closed Sourced

我是通义千问，
一个专门响应人类指令的
大模型。

Alibaba - Tongyi

文心一言

Baidu

ChatGPT + Bing

I'm Bard,

Google Bard

Claude

Open Sourced

Vicuna

LLaMA

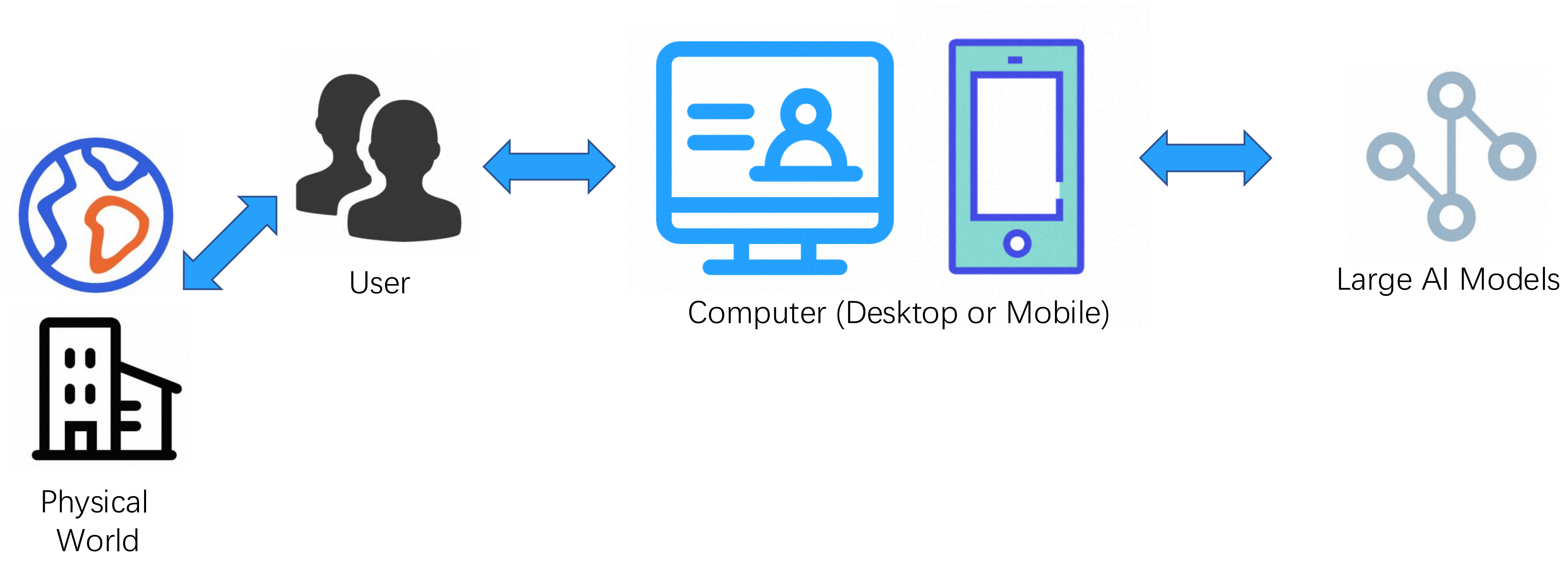
Stable Diffusion 2-1

Generative Agents

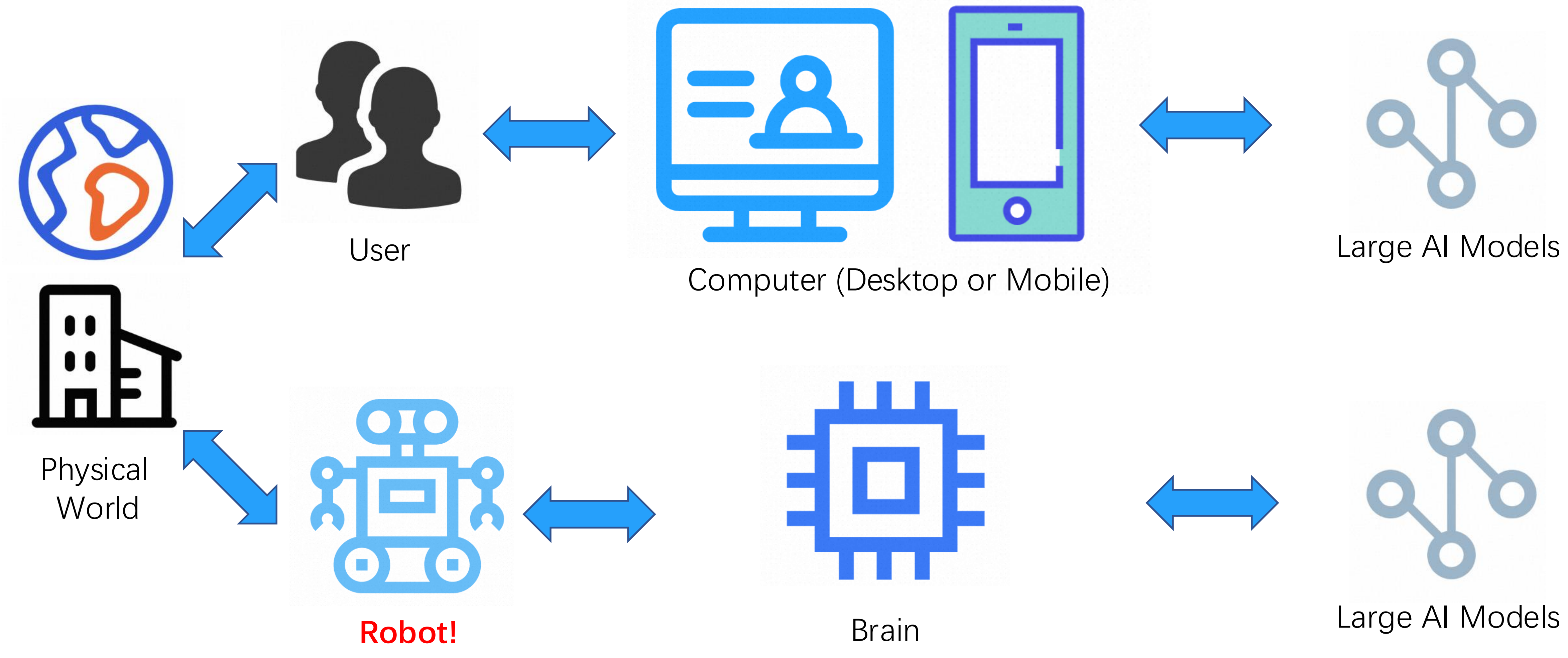
Auto gpt

AutoGPT

How does AI Model interact with physical world?



How does AI Model interact with physical world?



Autonomous Driving Vehicle Is Also A Robot

Autonomous Driving

Understand and Act in 3D World

Bus

Taxi

Heavy Truck

Carrier

Large-scale deployment of AV across China

Carrier
Largest Autonomous Driving in logistic

- **200+** Cities
- **800+** AutoVehicle
- **50M+** orders

Truck
Research -> Product

- **50+** routes across China
- **30+** test vehicles
- **100M+km** test milage

Heavy Truck
Preliminary Exploration

- Built 20+ Auto-Truck
- Cainiao, Shentong
- Release in 2027

PART I: General introduction of Autonomous Driving System (ADS)

Source: STDevCon19_7.5_Overview of ADAS-Active-Safety

Automotive ADAS Systems

Overall Automotive ADAS System

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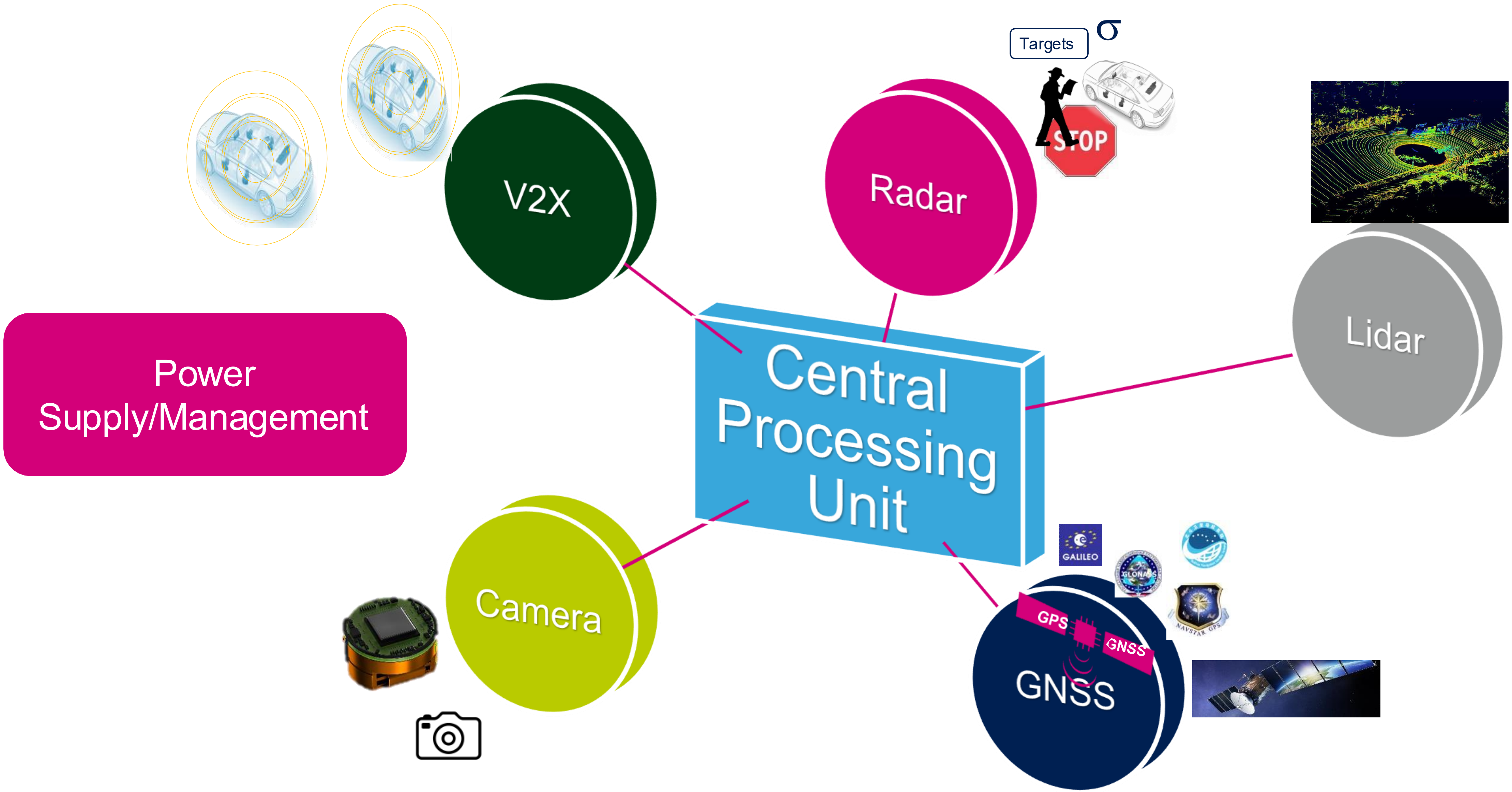
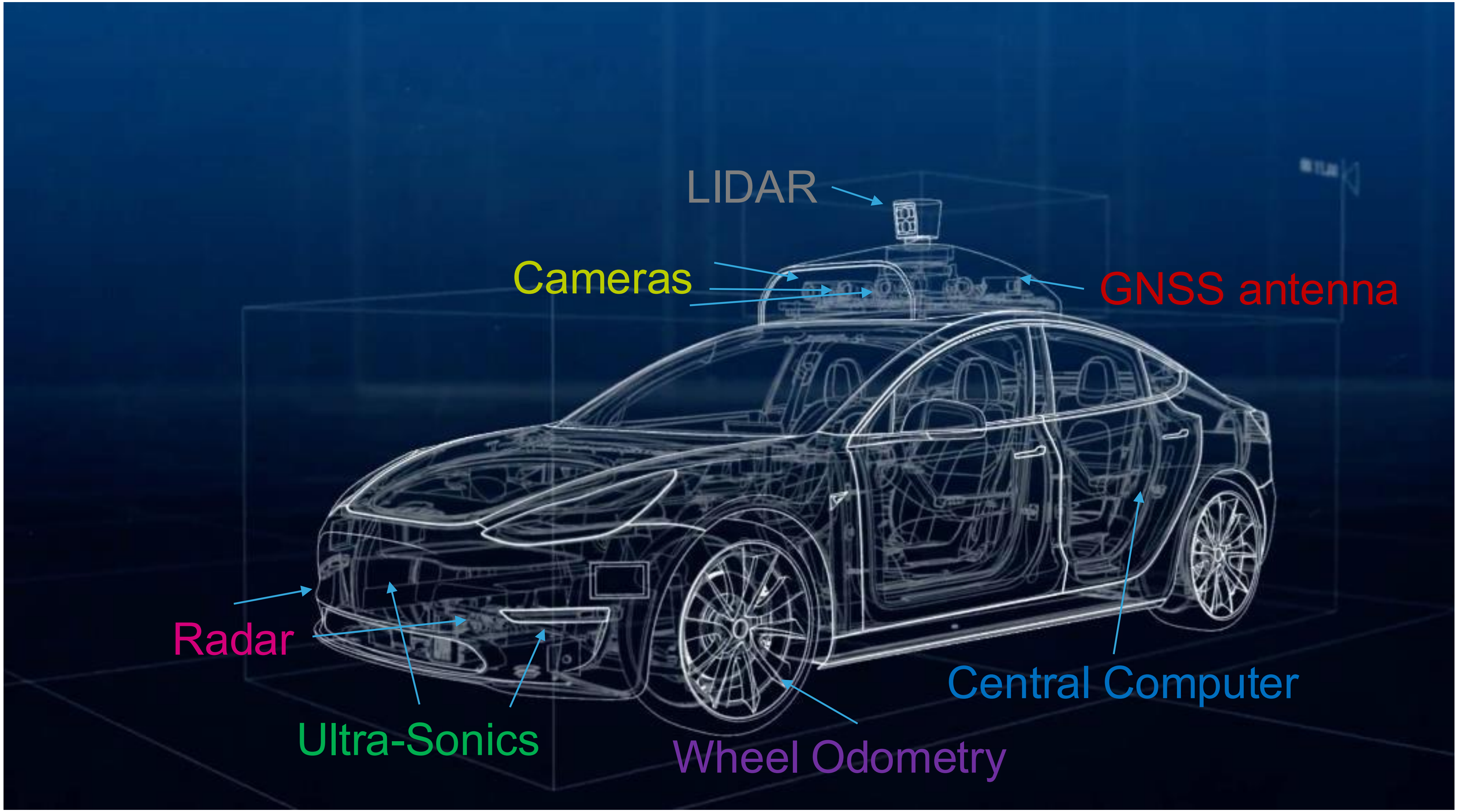
Automotive ADAS Systems

ADAS Overview

Overview of ADAS Technologies



ADAS Sensors - Needed for Perception



The 5 Levels of Vehicle Automation

Adding Senses

- Accelerometers and Gyro
- Steering Wheel Angle
- Ultrasonic sensors
- Front Radar Sensor
- Blind Spot sensor
- Rear View Cameras
- Front View Cameras
- Surround View Cameras

Learning to Drive

- Systems Networking
- Sensor Fusion
- Distance Measurement
- Traffic Sign Recognition
- Lane Reconstruction
- Free-path Definition
- Precise Positioning
- Real-time Mapping
- Driving Rules Implementation
- Critical Arbitration

0

No Automation (Level 0)

Driver in control

1

Driver Assistance (Level 1)

Driver in control

2

Partial Automation (Level 2)

Driver monitors system at all times

3

Conditional Automation (Level 3)

Driver needed to be able to resume control

4

High Automation (Level 4)

Driver is not required for specific use cases

5

Full Automation (Level 5)

No Driver Required

Source: SAE standard J3016

Levels 0-2 Human driver monitors the driving environment

Levels 3-5 Automated driving “system” monitors the driving environment

Sensor Fusion is Key to Autonomous

No sensor type works well for all tasks and in all conditions, so sensor fusion will be necessary to provide redundancy for autonomous functions

Most likely used fusion solution in future | Good | Fair | Poor

	Camera	Radar	LiDAR	Ultrasonic	LiDAR+Radar+ Camera
Object detection	Fair	Good	Good	Good	Good
Object classification	Good	Poor	Fair	Poor	Good
Distance estimation	Fair	Good	Good	Good	Good
Object edge precision	Good	Poor	Good	Good	Good
Lane tracking	Good	Poor	Poor	Poor	Good
Range of visibility	Fair	Good	Fair	Poor	Good
Functionality in bad weather	Poor	Good	Fair	Good	Good
Functionality in poor lighting	Fair	Good	Good	Good	Good

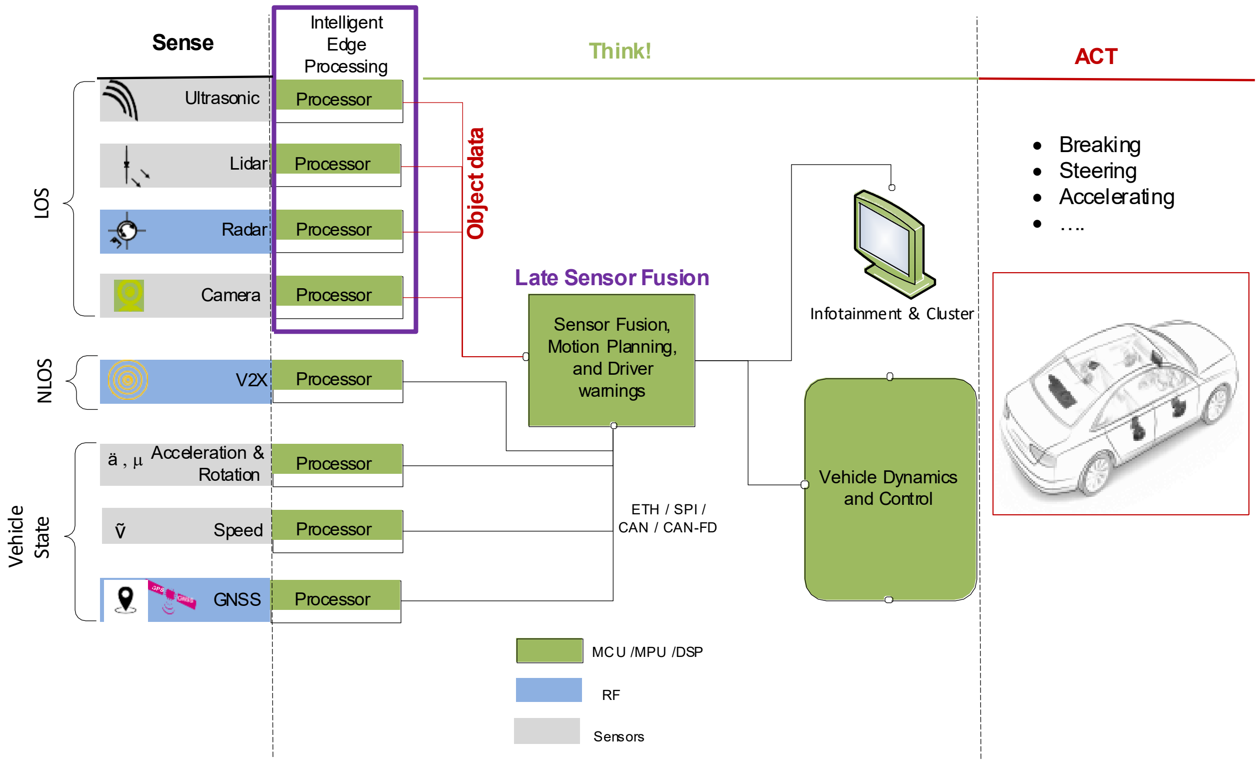
Source: Woodside Capital Partners (WCP), "Beyond the Headlights: ADAS and Autonomous Sensing", September 2016

Automotive ADAS Systems

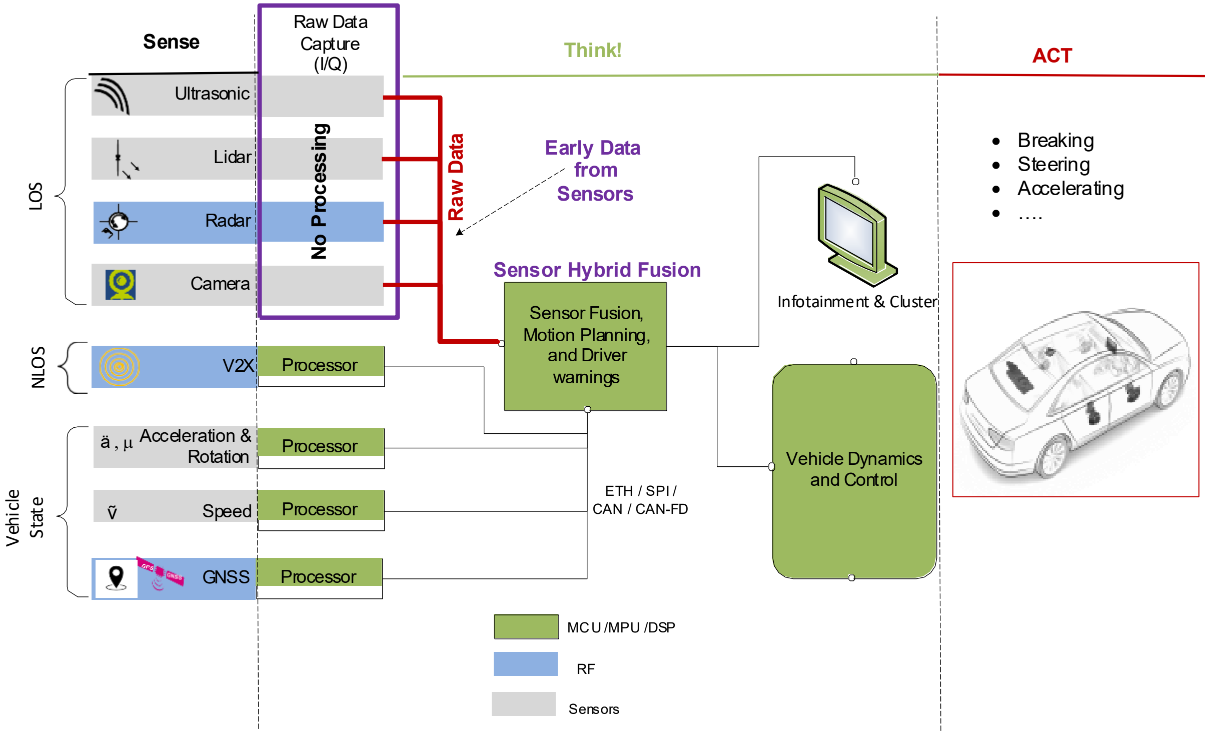
ADAS Vehicle Architectures

Distributed vs Centralized Processing

Distributed Processing with Object Level Fusion



Centralized Processing with Raw Data Fusion

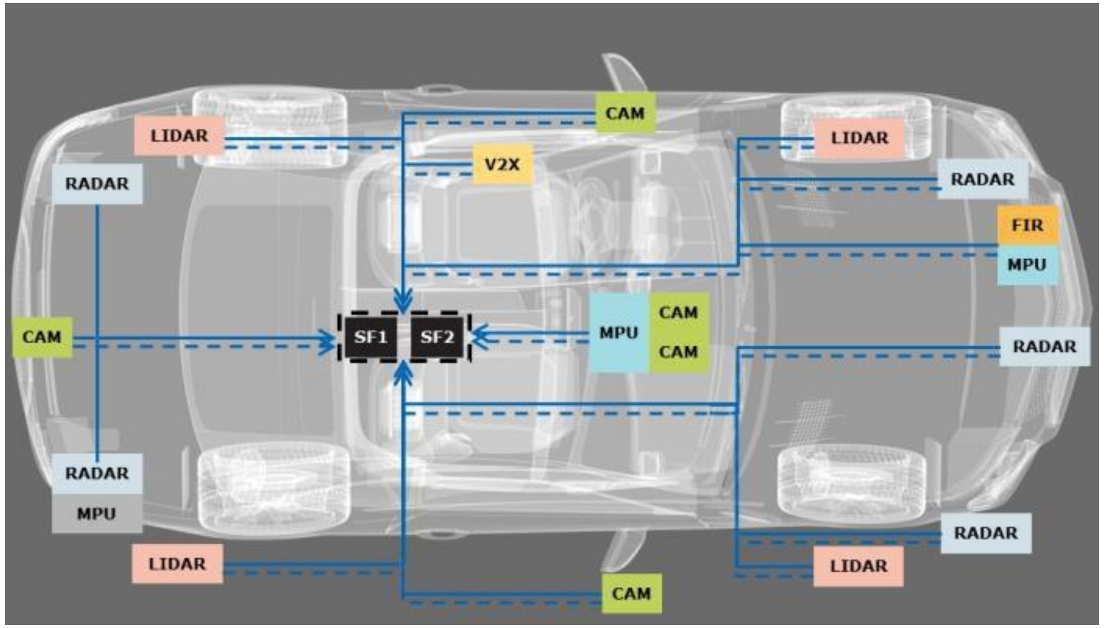


LOS: Line-of-Sight
NLOS: Non-Line-of-Sight

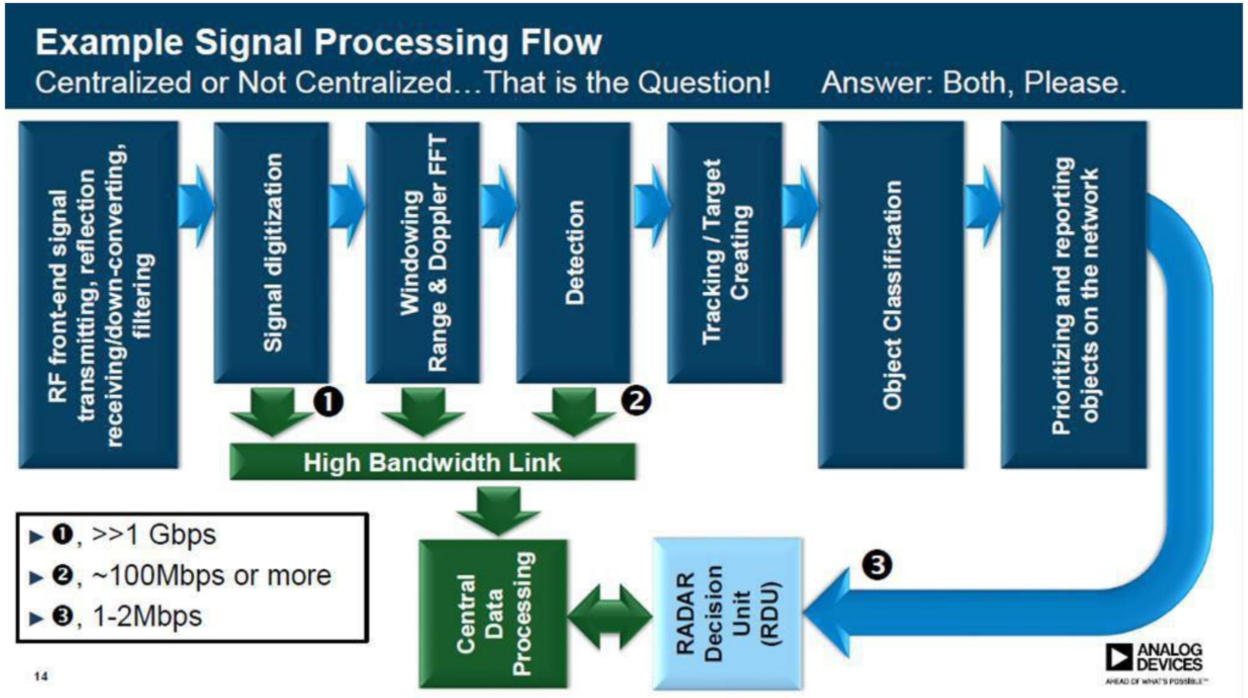
- Distributed Interfaces
  - ETH, SPI, I2C, CAN, CAN-FD
    - RADAR, Ultrasonic, V2X, IMU, Wheel Odomerty, GNSS
  - MIPI(CSI-2), GMSL(Maxim), FPD-Link(TI), PCIe, HDBaseT(Valens)
    - Video Cameras?
    - Lidar?

- Centralized Interfaces
  - ETH, SPI, I2C, CAN, CAN-FD
    - V2X, IMU, Wheel Odomerty, GNSS
  - MIPI(CSI-2), GMSL(Maxim), FPD-Link(TI), PCIe, HDBaseT(Valens)
    - Radar, Ultrasonic
    - Cameras
    - Lidar?

Distributed vs Centralized Processing



Source: 2018 IHS Markit – "Autonomous Driving-The Changes to come"



Source: ADI

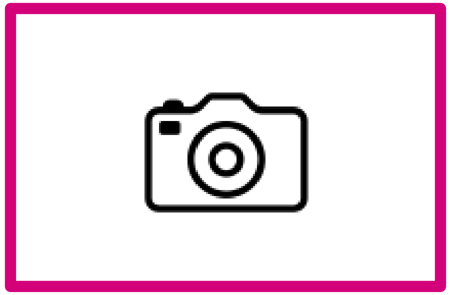
- What are the Data rates requirements for each sensor?
  - Centralized (i.e. SERDES?) vs Distributed (i.e. ETH?)
- Example: 4-5 Corner Radars are utilized in high end/premium vehicles.

Automotive ADAS Systems

Vision (Cameras) System

Camera

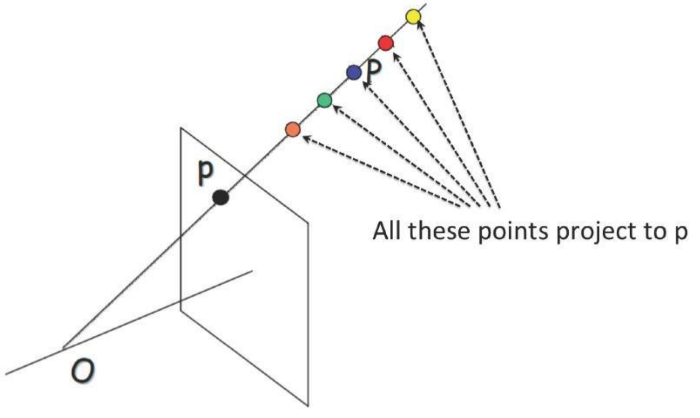
- Essential for correctly perceiving environment
- Richest source of raw data about the scene - only sensor that can reflect the true complexity of the scene.
- The lowest cost sensor as of today
- Comparison metrics:
  - Resolution
  - Field of view (FOV)
  - Dynamic range
- Trade-off between resolution and FOV?



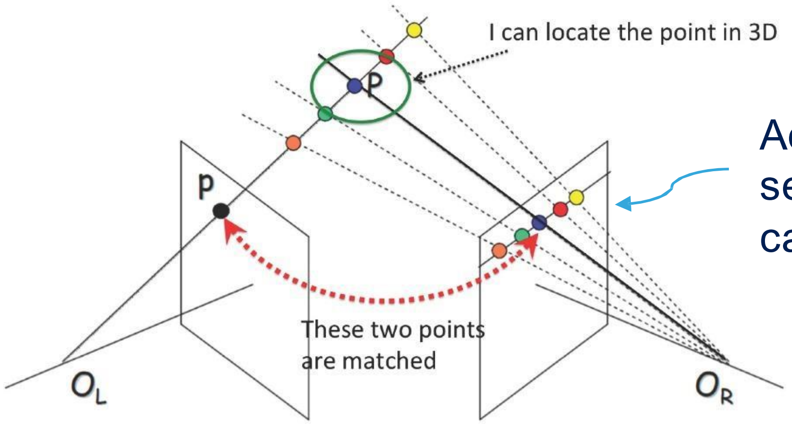
Camera-Stereo

- Enables depth estimation from image data

All points on projective line to P map to p

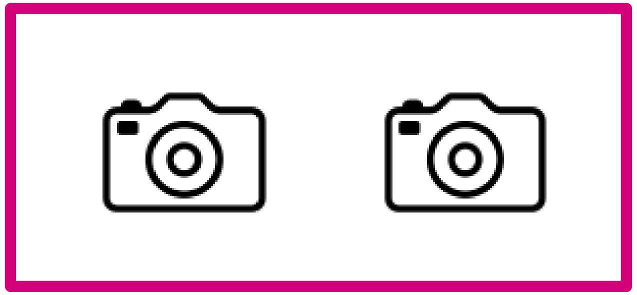


One camera



Add a second camera

Find a point in 3D by triangulation!

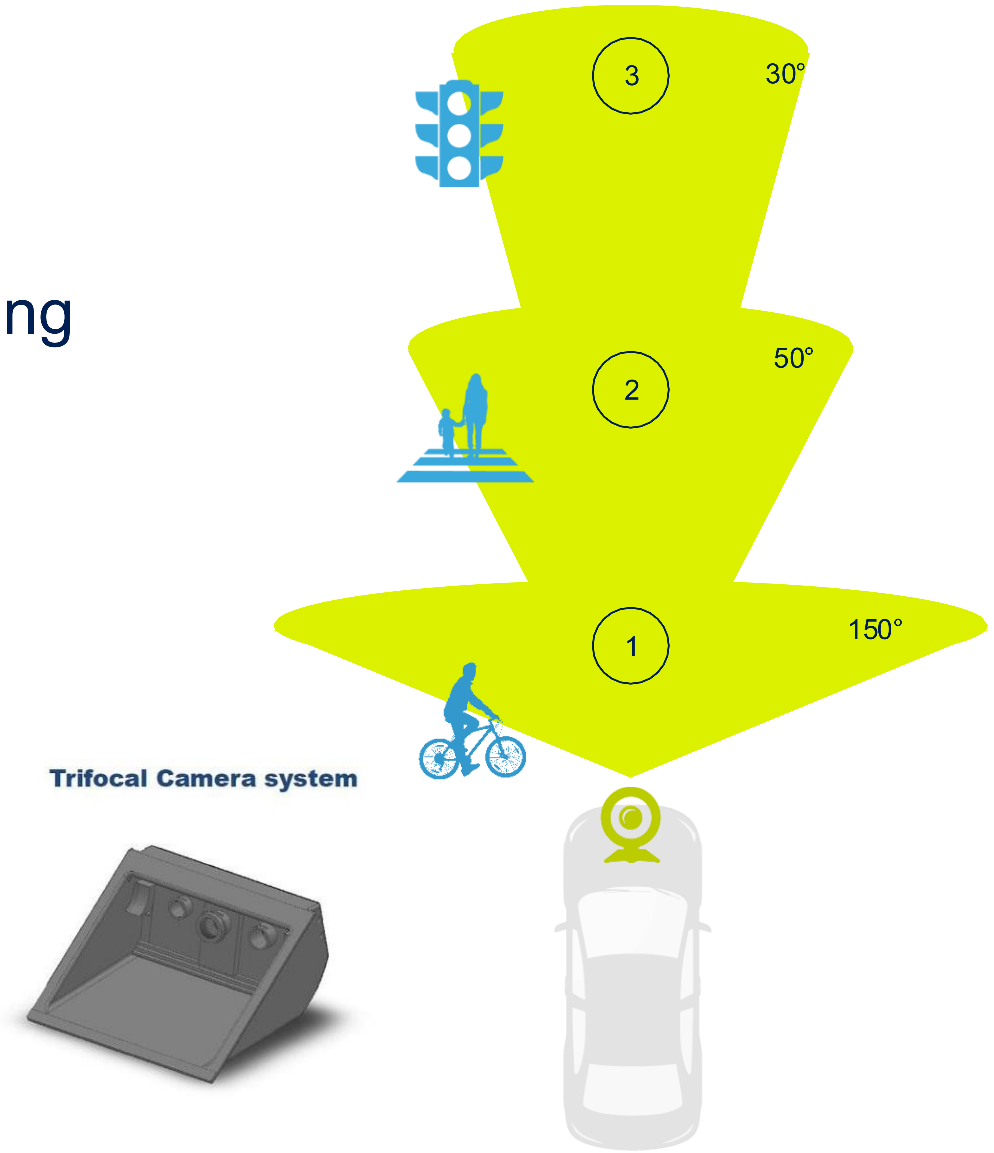


Left and right images

Source: Sanja Fidler, CSC420: Intro to Image Understanding

The Next Phase for Vision Technology

- From sensing to comprehensive perception
- Machine learning used already for object sensing
- Autonomous driving needs
  - Path planning based on holistic cues
  - Dynamic following of the drivable area
- Deep learning is now being applied



Machine Vision: ST & Mobileye

EyeQ3™ 3rd Generation vision processor

- Detection of driving lanes
- Recognition of traffic signs
- Detection of pedestrians and cyclists
- Seeing obstacles how the human eye sees them
- Adapting cruise speed
- Emergency braking when car ahead slows suddenly

MOBILEYE®

Partnership

EyeQ4™ 4th Generation enables

- Detection of more objects, more precisely
- More features required for automated driving Free-space Estimation, Road Profile Reconstruction
- Monitoring of environmental elements (fog, ice, rain) and their safety impact
- Detailed understanding of the road conditions allowing automatic suspension and steering adjustment
- Highly automated vehicles

EyeQ5™

EyeQ5™

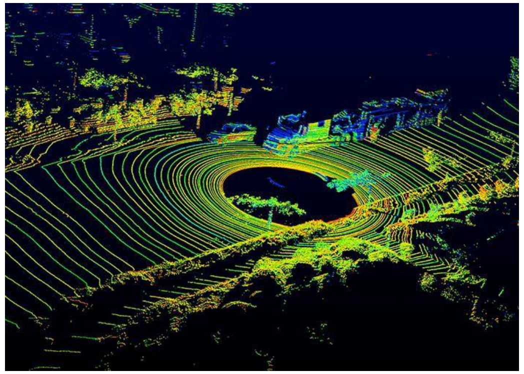
The Road to Full Autonomous Driving: Mobileye and ST to Develop EyeQ®5 SoC targeting Sensor Fusion Central Computer for Autonomous Vehicles

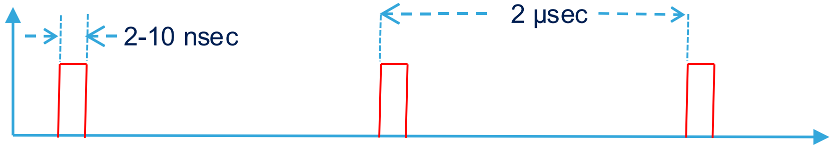
LiDAR Technology Overview

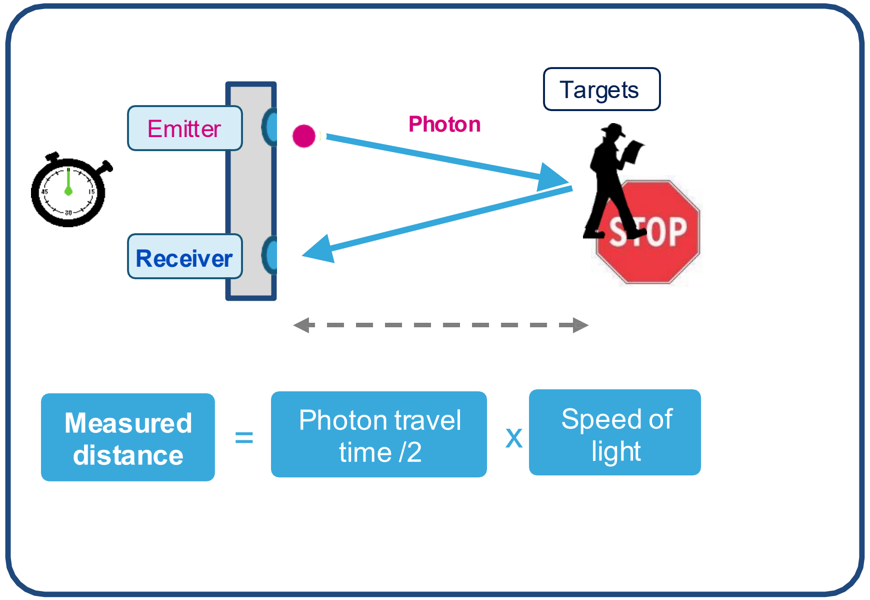
- LiDAR (light detecting and ranging, or “light radar”) sensors send one or more laser beams at a high frequency and use the Time-of-Flight principle to measure distances. LiDAR capture a high-resolution point cloud of the environment.

- Can be used for object detection, as well as mapping an environment
  - Detailed 3D scene geometry from LIDAR point cloud

- LiDAR uses the same principal as ToF sensor, but at much longer distances, minimum 75M for “near field” and 150-200M for “far field”.







Automotive ADAS Systems

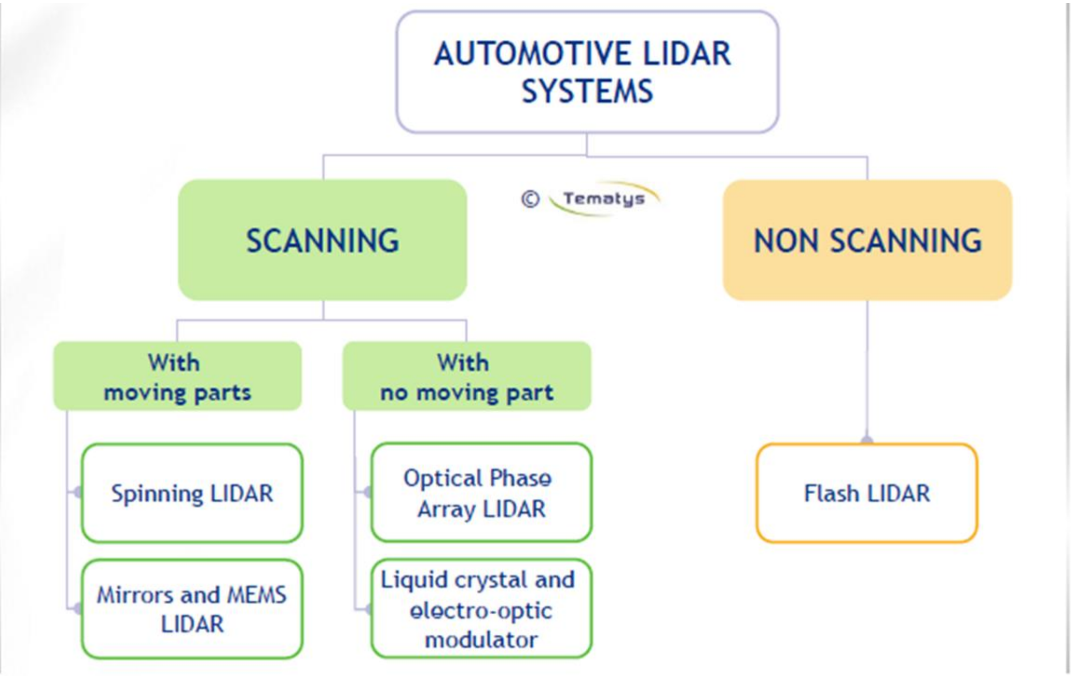
LiDAR System

LiDAR Techniques

- There are multiple techniques currently under evaluation for LiDAR including rotating assembly, rotating mirrors, Flash (single Tx source, array Rx), scanning MEMS micro-mirrors, optical phased array.

- From a transmitter/receiver (Tx/Rx) perspective the following technologies need to be developed or industrialized for automotive.
  - MEMS Scanning Micro-mirror technologies
  - SPAD (Single Photon Avalanche Detectors) - Rx
  - 3D SPAD - Rx
  - Smart GaN (Gallium nitride)

- Comparison metrics:
  - Number of beams: *8,16, 32, and 64 being common sizes*
  - Points per second: *The faster, the more detailed the 3D point cloud can be*
  - Rotation rate: *higher rate, the faster the 3D point clouds are updated*
  - Detection Range: *dictated by the power output of the light source*
  - Field of view: *angular extent visible to the LIDAR sensor*



Source: J. Cochard et.al., "LiDAR Technologies for the Automotive Industry", Tematsys, June 2018

Upcoming: Solid state LIDAR!

LiDAR Summary

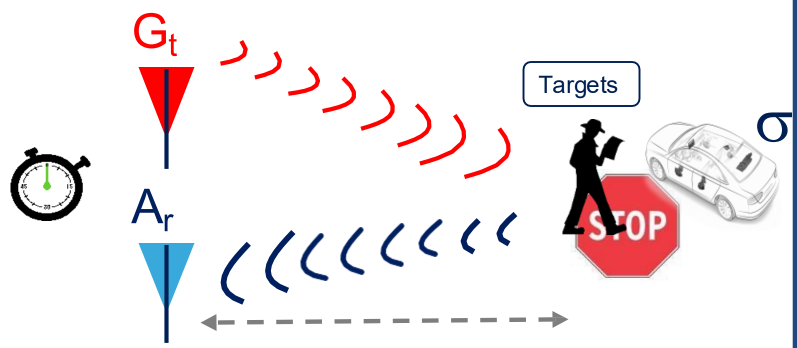
- Autonomous vehicles have been around for quite some time but only now the technologies are available for practical implementations
- No single sensor solution exists to cover all aspects – range, accuracy, environmental conditions, color discrimination, latency etc.
    - Multi-sensor fusion and integration will be a must
    - Each technology attempts to solve the overall problem while having multiple limitations
- Many LiDAR solutions (technologies) are available or being proposed with no clear winners
- Market is still in very early stage of development and experimentation
- When and which technology or system will be widely adopted and mass production starts is still unknown

Automotive ADAS Systems

Radar Systems

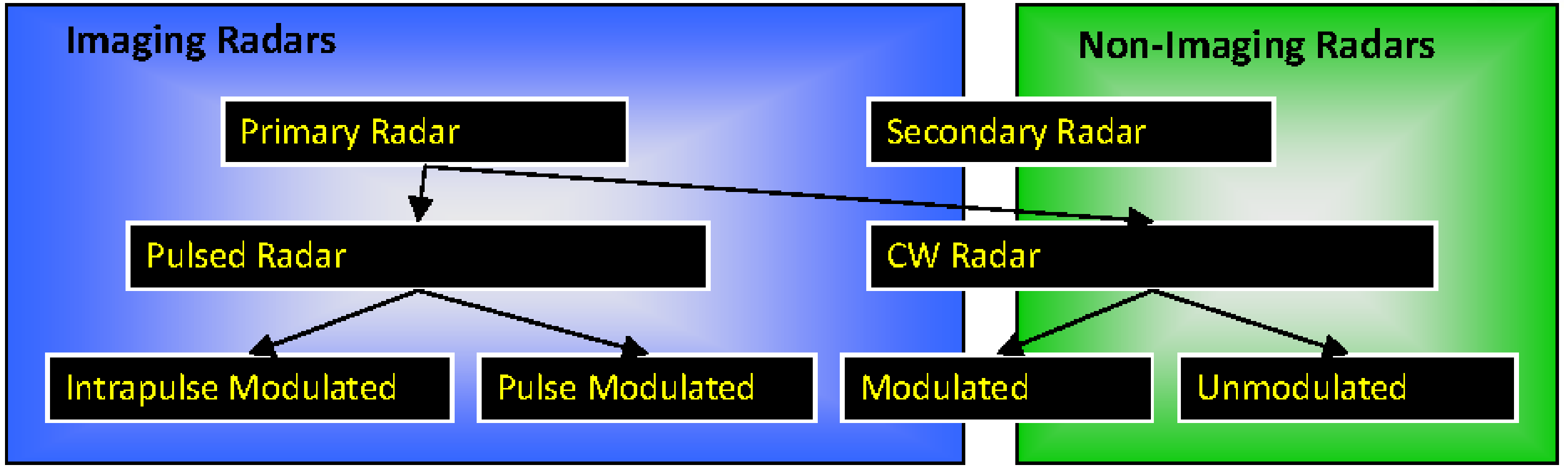
RADAR Technology Overview

- RADAR (**RA**dio **D**etection and **R**anging) is one necessary sensor for ADAS (Advanced Driver Assistance System) systems for the detection and location of objects in the presence of interference; i.e., noise, clutter, and jamming.
- Robust Object Detection and Relative Speed Estimation
- Transmit a radio signal toward a target, Receive the reflected signal energy from target
- The radio signal can the form of "Pulsed" or "Continuous Wave"
- Works in poor visibility like fog and precipitation!
- Automotive radars utilize Linear FM signal, Frequency Modulated Continuous Wave (FMCW)
  - FM results in a shift between the TX and RX signals that allows for the determination of time delay, Range and velocity.



Range (R) = Signal travel time /2 x Speed of propagation in medium (c in air)

RADAR Techniques



- Definitions:
  - **Imaging Radar:** Forms a picture of the object or area
  - **Non-Imaging Radar:** Measures scattering properties of the object or area
  - **Primary Radar:** Transmits signals that are reflected and received
  - **Secondary Radar:** Transponder that responds to interrogation with additional info
  - **Pulsed Radar:** High power signals are only present for a short duration and repeated at specific intervals
  - **CW Radar:** Signal is present continuously

2013 Defence & Security Forum, EuMW

- Comparison metrics:
  - Range
  - Field of view
  - Position and speed accuracy

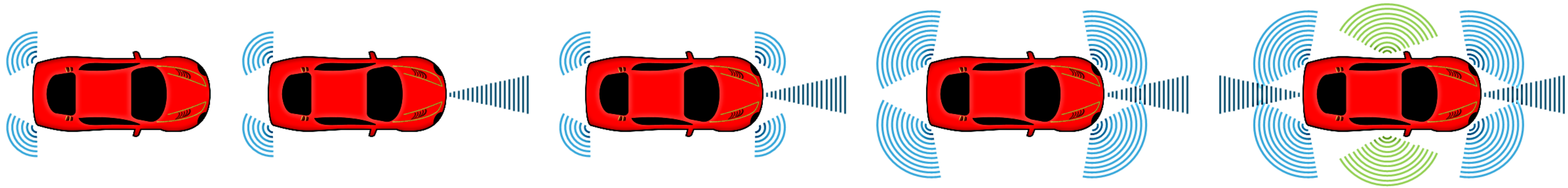
- Configurations:
  - Wide-FOV: Short Range
  - Narrow-FOV: Long Range

Source: Strategy Analytics Lunch & Learn the Market Session European Microwave Week 2013

Source: Rodhe & Schwarz - Automotive radar technology, market and test requirements, White paper – Oct 2018 (Salvo S. presentation)

Automotive Radar Vs. Automation Levels

< 2014 Level 1 Driver Assistance	2016 Level 2 Partial Automation	2018 Level 3 Conditional Automation	2019 / 2020 Level 4 High Automation	> 2028 Level 5 Full Automation



Object detection	**Object detection**	**High resolution target separation**	**3D detection**	**360° object recognition**
2x SRR	**2x SRR** **1x LRR**	**4x SRR** **1x LRR**	**4x SRR-MRR** **1x LRR**	**2x USRR** **4x SRR-MRR** **2x LRR**
Applications	**Applications**	**Applications**	**Applications**	**Applications**
BSD, LCA	**BSD, RCW, LCA** **ACC, AEB**	**BSD, RCW, LCA** **FCW, RCTA** **ACC, AEB**	**BSD, LCA, RCTA** **AEB pedestrian** **ACC, AEB**	**AVP, PA** **BSD, LCA, RCTA** **AEB pedestrian** **ACC, AEB**

USRR - Ultra Short Range Radar
SRR - Short Range Radar
MRR - Medium Range Radar
LRR - Long Range Radar

BSD - Blind Sport Detection
LCA - Lane Change Assist
RCW - Rear Collision Warning

ACC - Adaptive Cruise Control
AEB - Automatic Emergency Breaking
FCW - Forward Collision Warning

RCTA - Rear Cross Traffic Alert
AVP - Automated Valet Parking
PA - Parking Assist

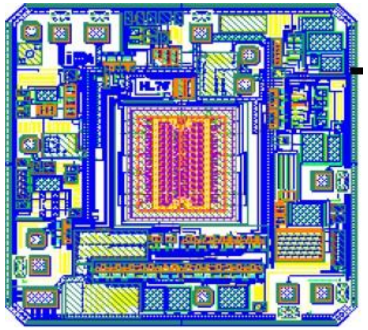
Automotive ADAS Systems

GNSS/IMU System

GNSS/IMU Positioning

- Global Navigation Satellite Systems and Inertial Measurement Units
- Direct measure of vehicle states
  - Positioning, velocity, and time (GNSS)
    - Varying accuracies: Real-time Kinematic (RTK-short base line), Precise Point Positioning (PPP), Differential Global Positioning System (DGPS), Satellite-based augmentation system (SBAS-Ionospheric delay correction)
  - Angular rotation rate (IMU)
  - Acceleration (IMU)
  - Heading (IMU, GPS)

GNSS/IMU



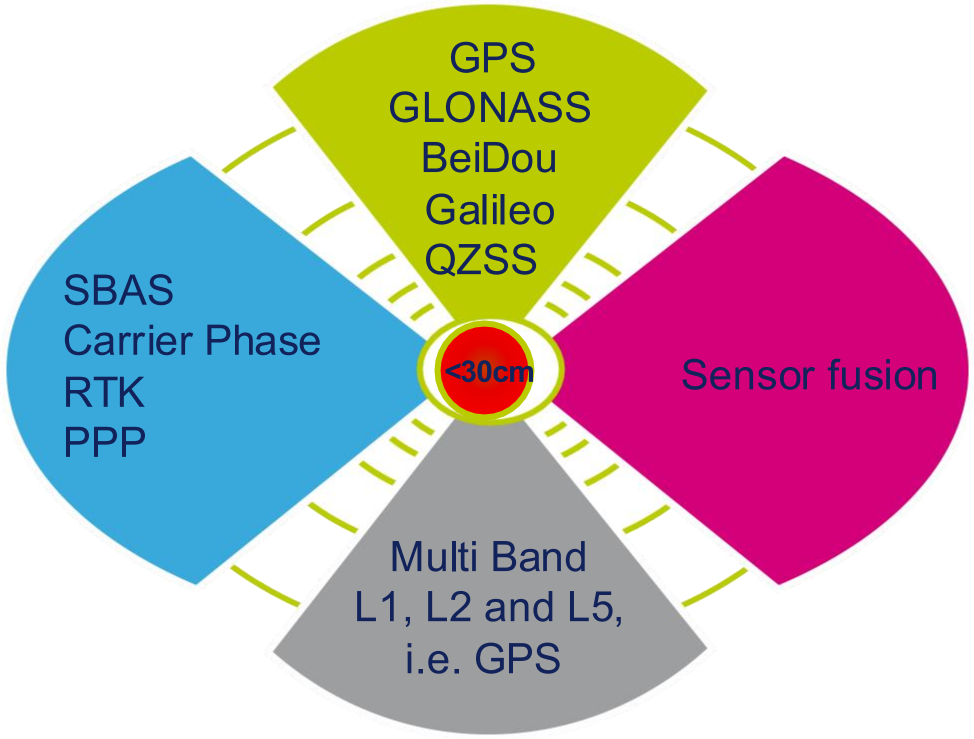
GNSS/IMU Positioning

More Precision Enables More Safety Features

Precise Positioning: Towards Autonomous Driving

Precise Positioning to enable < 30cm precision

- Lane detection
- Positioning data for V2X sharing
- Collision avoidance
- Autonomous parking
- Autonomous driving
- eCall accident location



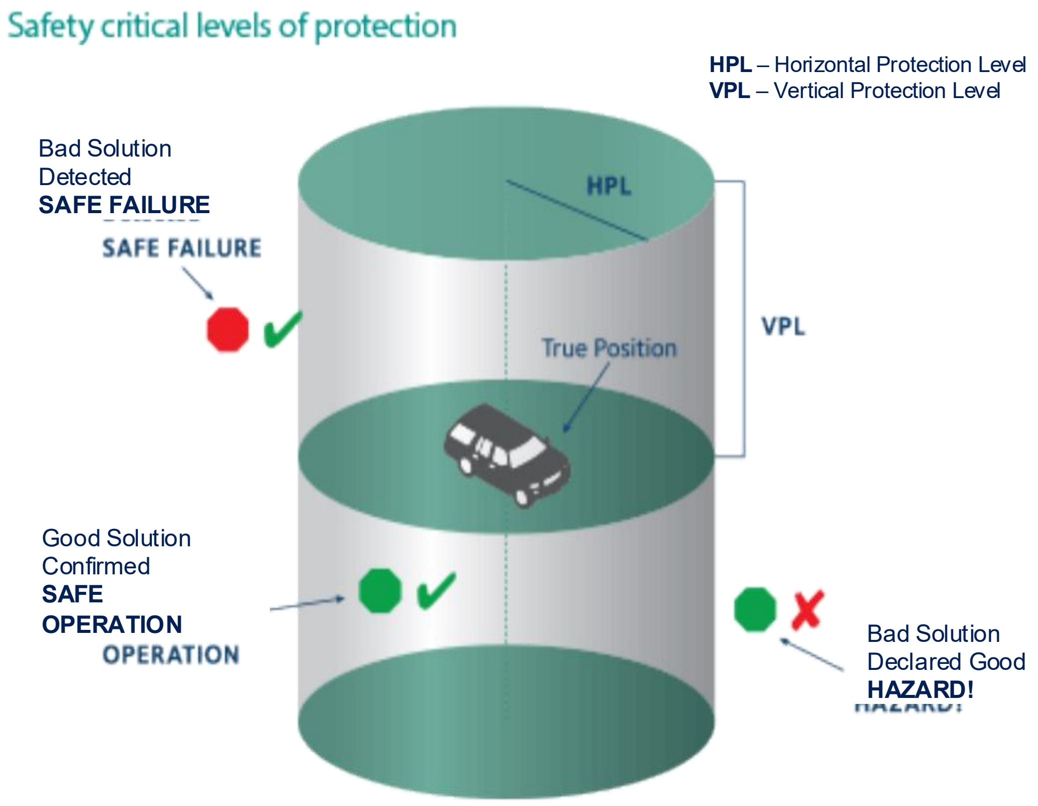
Precise GNSS is a Critical ADAS Sensor

Higher integrity requirements across safety-critical applications

- Semi- and Autonomous driving safety-related applications requirements **increase**
  - Higher safety levels
  - Added redundancy
  - More Robustness & integrity
  - Security

- **Teseo APP** (ASIL Precise Positioning) GNSS receiver, **new sensor** based on **ISO26262** concept with unique **Absolute and Safe** positioning information complementing **relative** positioning other sensor inputs(i.e. LIDAR, RADAR, etc.)

ST's GNSS Receiver Family for ADAS and AD



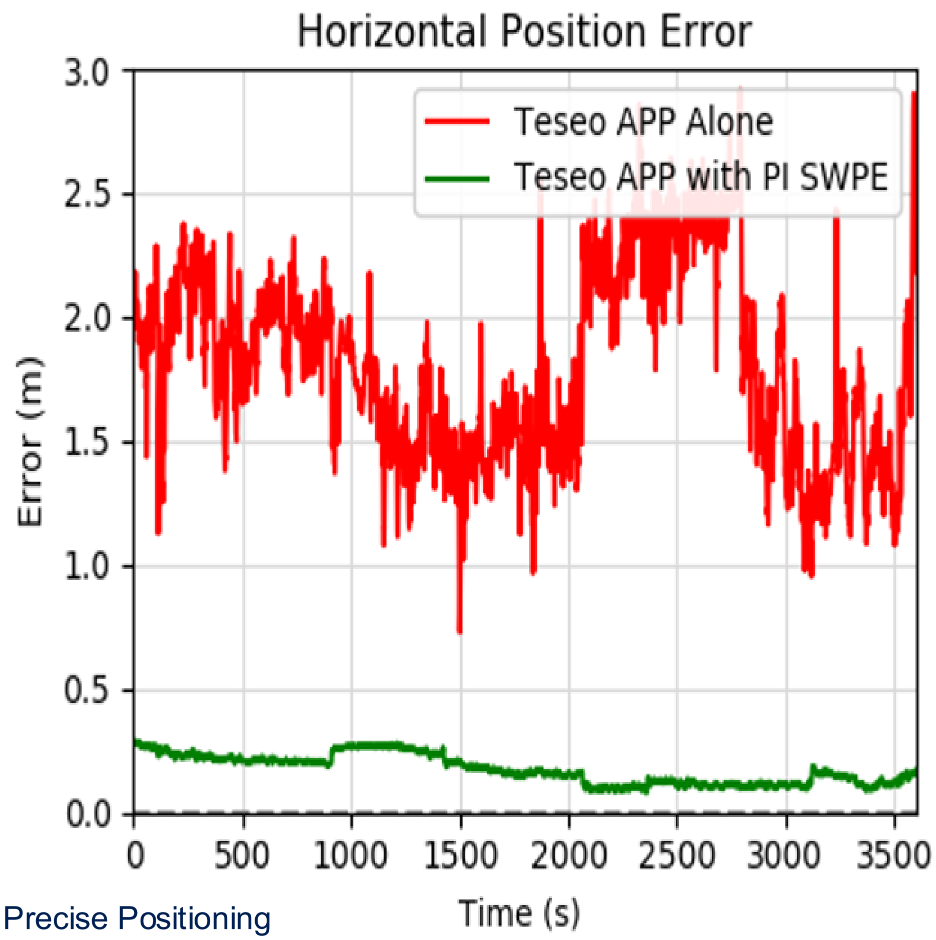
Courtesy of Hexagon PI

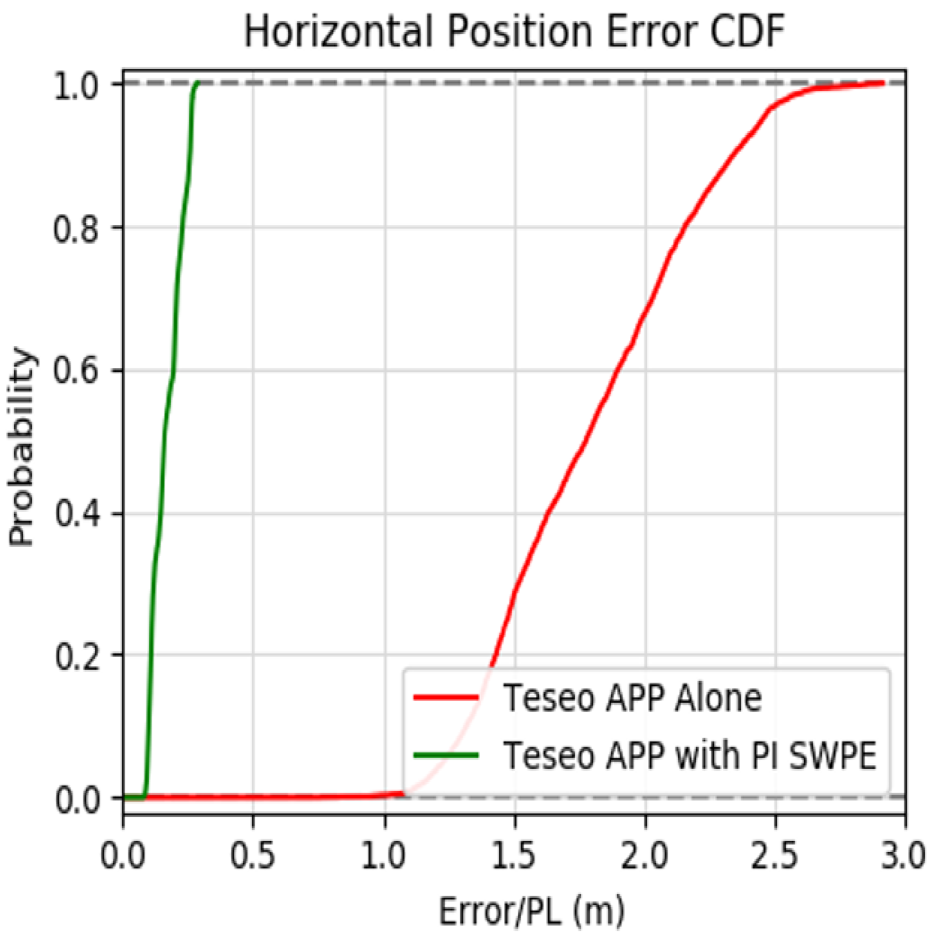
Precise GNSS is a Critical ADAS Sensor

GNSS Accuracy in Automotive Environment (using PPP – Precise Point Positioning)

Single Frequency (i.e. L1) multi-constellation/code-phase(1msec modulation signal)

Multi Frequency (i.e. L1, L2) multi-constellation/carrier-phase

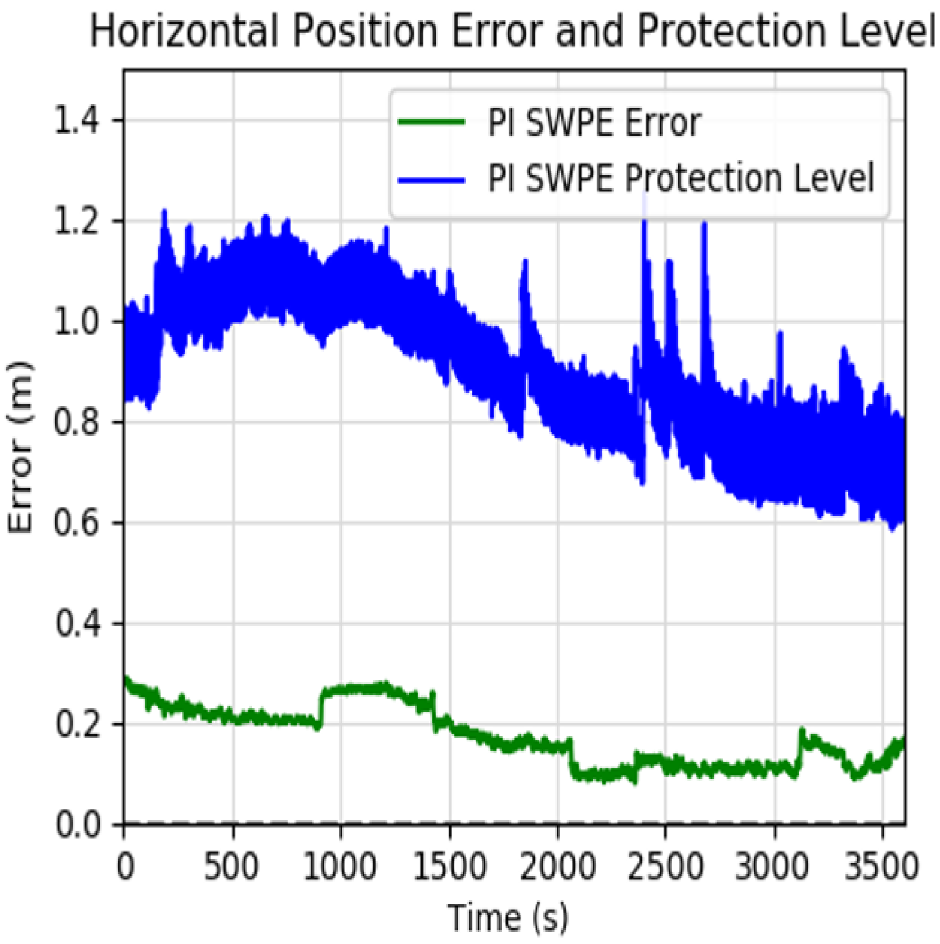


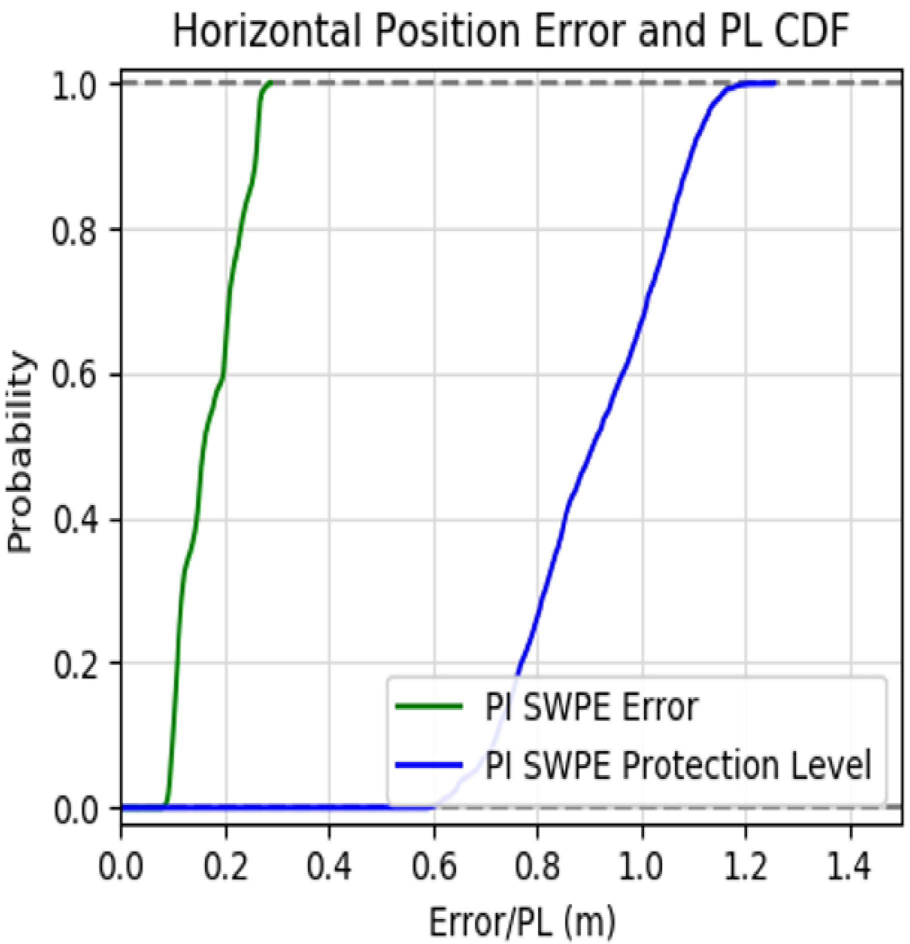


APP: ASIL Precise Positioning
SWPE: Software Positioning Engine

Precise GNSS is a Critical ADAS Sensor

GNSS Integrity – Protection Levels

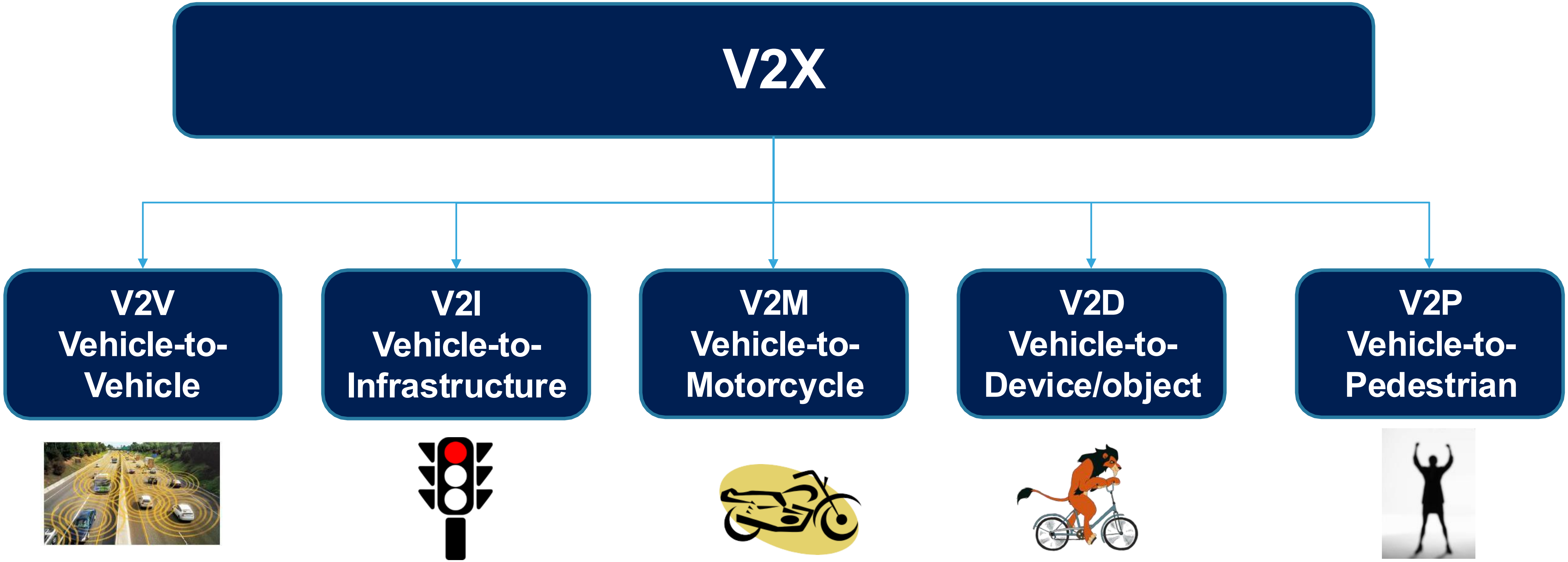




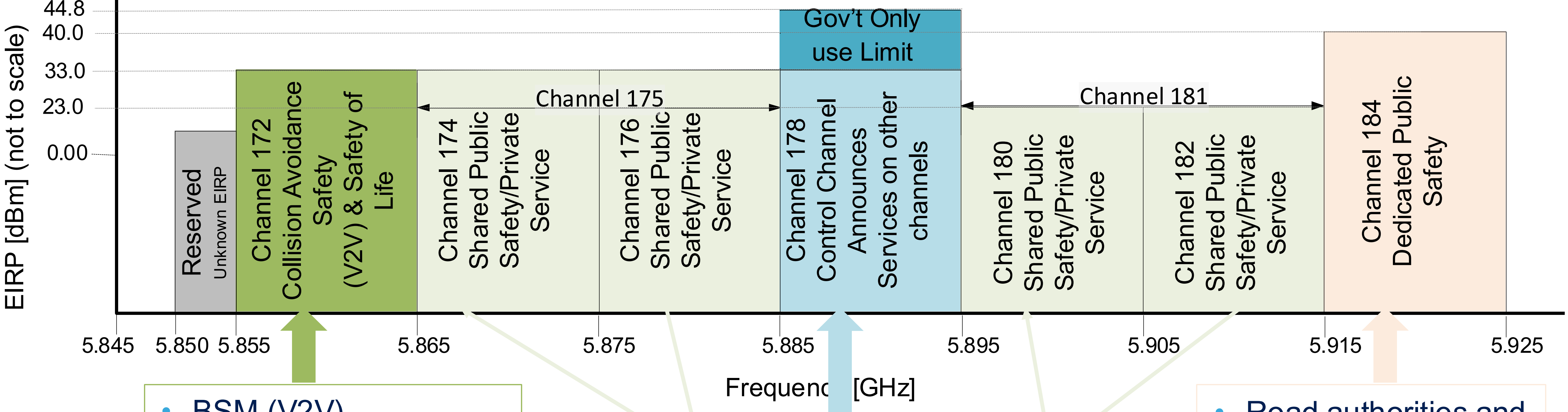
Automotive ADAS Systems

V2X System

Vehicle-to-Everything (V2X)



FCC Spectrum Allocation for DSRC of ITS



- BSM (V2V)
- MAP Message (V2I)
- SPAT (V2I)
- TX Power +20dBm

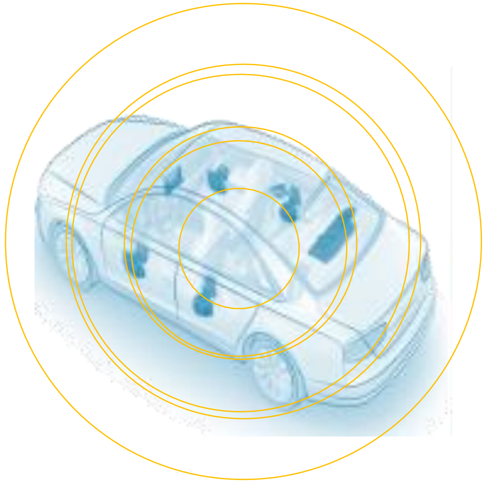
- Control Channel, Advertises and indicates how to access services on other "Service channels"

- Road authorities and public agencies primarily responsible for usage

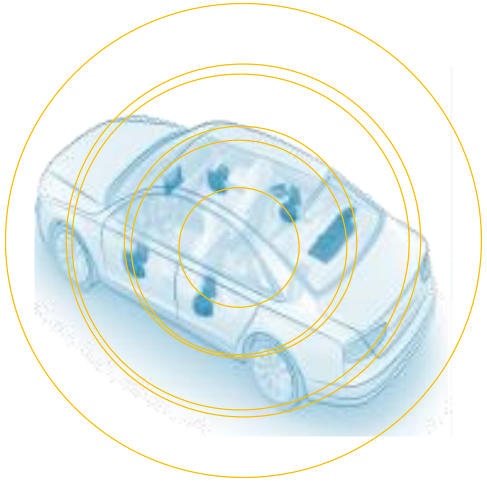
EIRP: Effective Isotropic Radiated Power
ITS: Intelligent Transportation Systems

Source: **Federal Communications Commission FCC 03-324**

DSRC

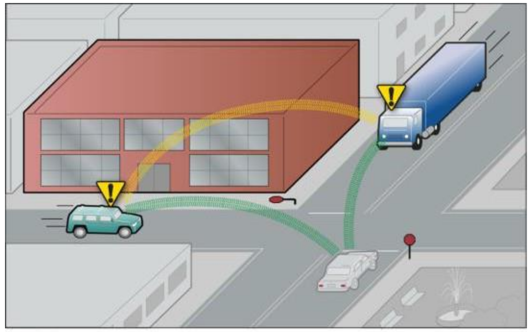


- Wireless Access in Vehicular Environments (WAVE)
  - Amendment to IEEE 802.11-2012 to support WAVE/DSRC
  - no authentication, no access point/no association
  - 5.8 – 5.9 GHz OFDM



- Fast Network Acquisition & low latency (<50msec)
- Priority for Safety Applications
- Interoperability
- Security and Privacy (ensured through a root certification system)

NLOS

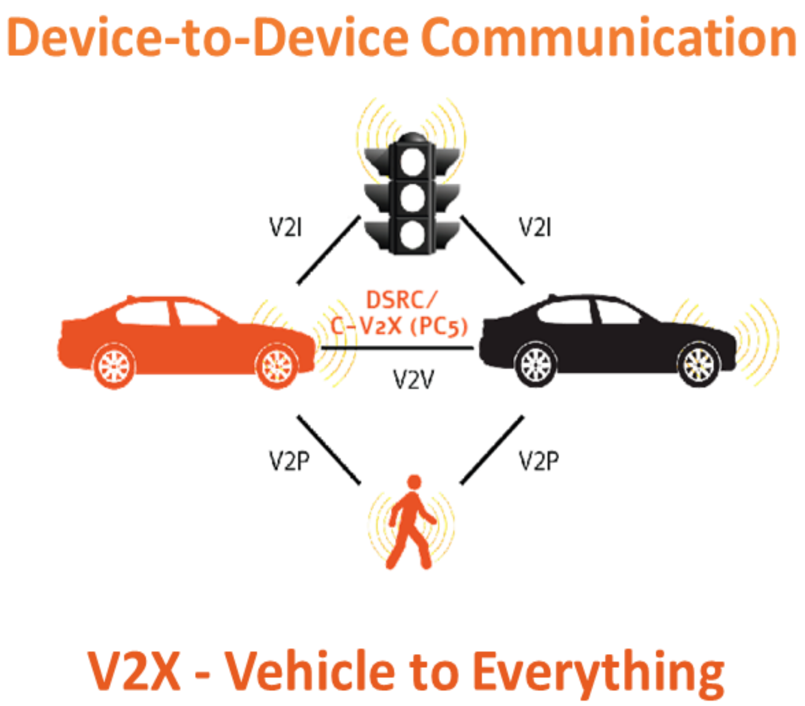


Source: GAO.

- Broadcasts BSMs 10 times per second
- Transmit power are about 100mW (20dBm @Antenna Port - Per IEEE802.11-D.2.2 Transmit power level) with a nominal range of 300m (360º coverage)
- DSRC units share the same channel

C-V2X Basics

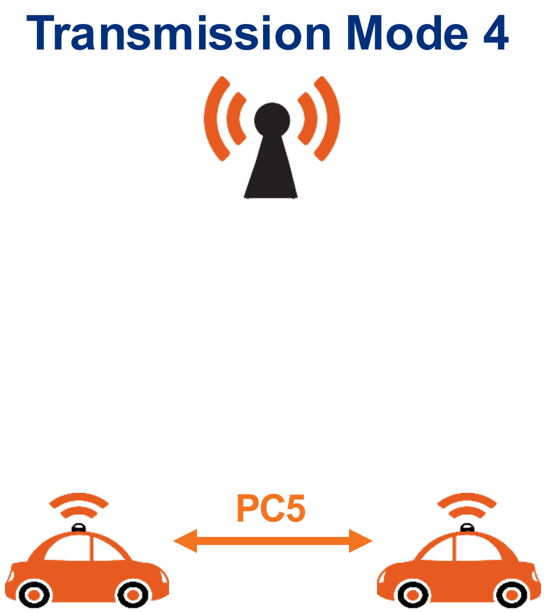
- C-V2X is a V2X radio layer:
  - C-V2X is Device-to-Device (D2D) communication service added to the LTE Public Safety ProSe (Proximity Services) Services
  - C-V2X makes use of the D2D interface – PC5 (aka Side Link) for direct Vehicle-to-Everything communication
  - C-V2X takes the place of DSRC radio layer in relevant regions
  - V2V, V2I and V2P



ITS Layers Remain Unchanged!

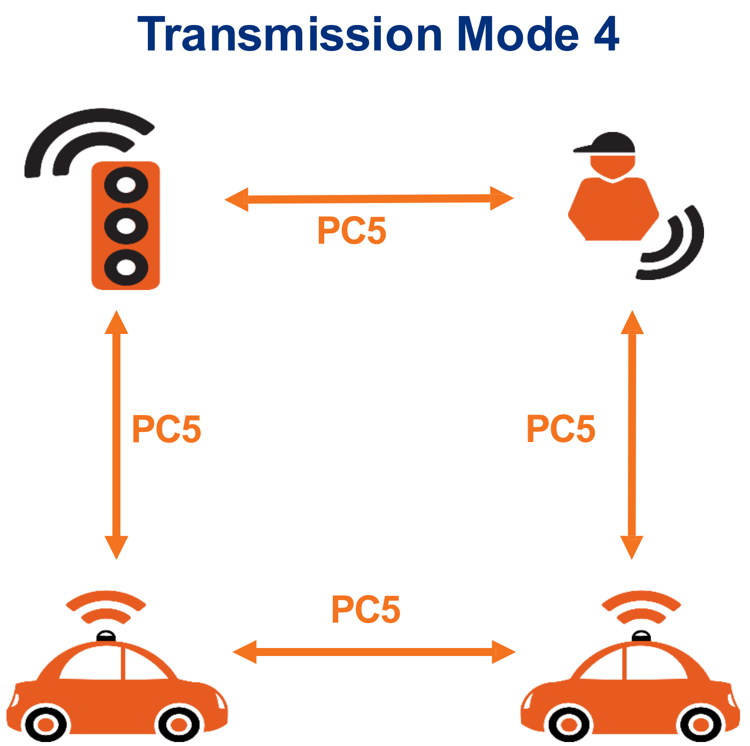
C-V2X Basics

- C-V2X Transmission Mode 4:
  - **Mode 4** – Stand alone, distributed
  - Uses GNSS for location and time for synchronization



C-V2X Basics

- Transmission Mode 4:
  - Out of Coverage operation: The transmitting vehicle is not connected to the network
  - No SIM card or inter-operator collaboration is required
  - Each vehicle performs its own scheduling and allocation
  - No dependency on inter-vehicle components (eNB, Allocation Server etc…)
  - Mandatory for SAE, ETSI



C-V2X Air Interface

- C-V2X is based on LTE (4G) uplink transmission - SC-FDMA (Single Carrier Frequency Division Multiple Access) signal:
  - A single carrier multiple access technique which has similar structure and performance to OFDMA
  - Utilizes single carrier modulation and orthogonal frequency multiplexing using DFT-spreading in the transmitter and frequency domain equalization in the receiver
  - A salient advantage of SC-FDMA over OFDM/OFDMA is low Peak-to- Average Power Ratio (PAPR). Enables efficient transmitter and improved link budget

In Summary

Both Technologies will do the JOB!

But:

- Industry is waiting for regulatory certainty, Government Mandate is preferred!
- C-V2X has to reach automotive production maturity
- Implementation and deployment will depend on OEM system architecture
- The market will demand standalone V2X module for OEMs and aftermarket because V2X is a safety critical sensor.

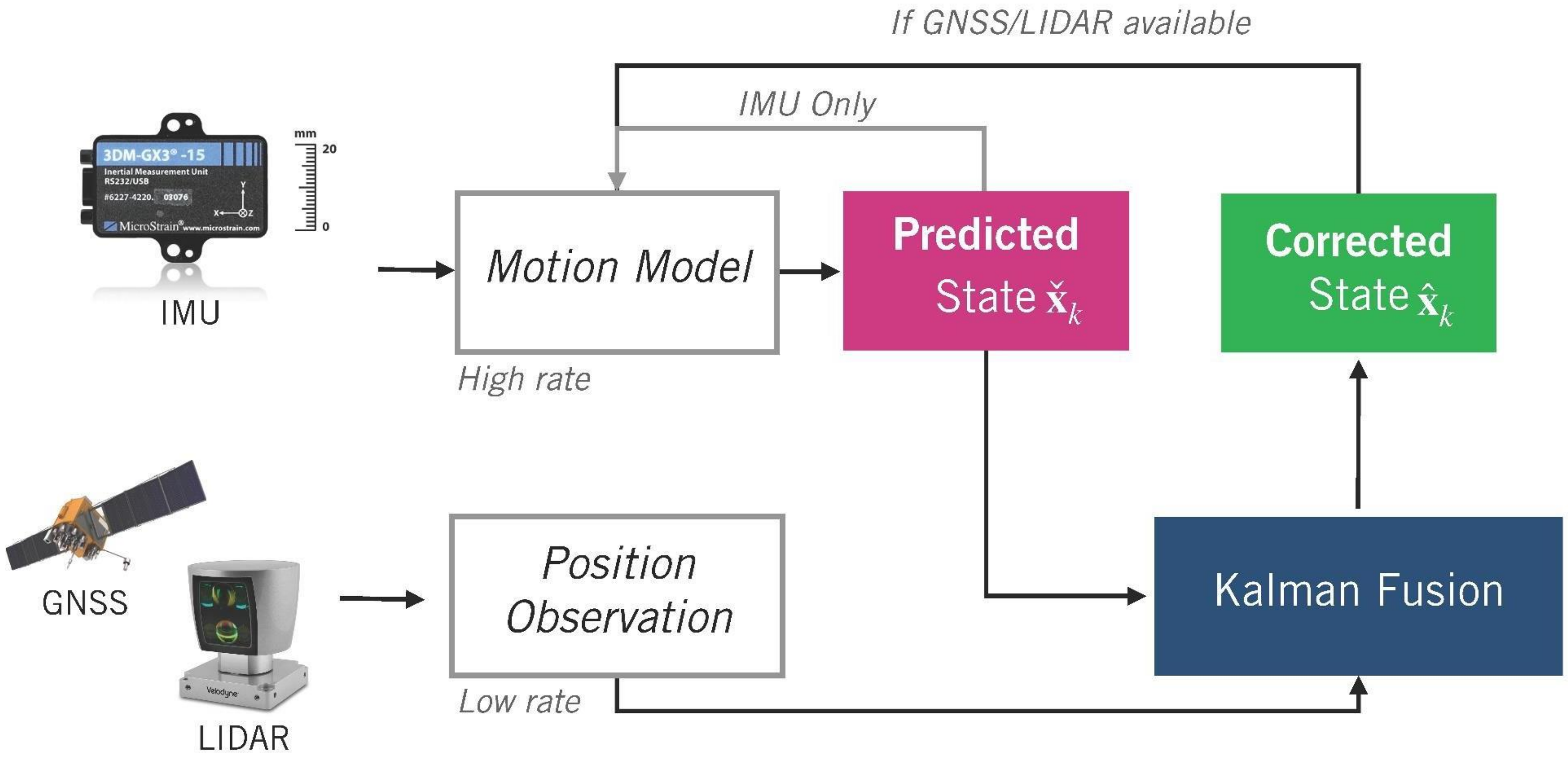
Automotive ADAS Systems

Sensor Fusion Example

Multi-sensor Fusion for State Estimation

Extended Kalman Filter | IMU + GNSS + LIDAR

This is a rule based fusion example, we will see another fusion later



Source: “State Estimation and Localization for Self-Driving Cars”, Coursera by University of Toronto

PART II: Reducing Human Efforts in Visual Perception

Autonomous Driving Lab, DAMO Academy

Carrier
Largest Autonomous Driving in logistic

200+ Cities

800+ AutoVehicle

50M+ orders

Truck
Research -> Product

50+ routes across China

30+ test vehicles

100M+km test milage

Heavy Truck
Preliminary Exploration

Built 20+ Auto-Truck

Cainiao, Shentong

Release in 2027

Autonomous Driving Vehicle Is Also A Robot

Autonomous Driving

Understand and Act in 3D World

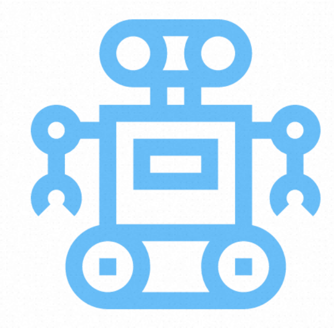
Bus

Taxi

Heavy Truck

Carrier

Common Framework of Robotic System



Robot!

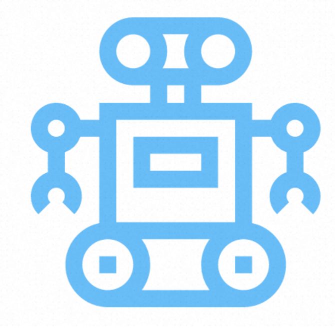
Understand the 3D world

Planning
Data creation

Decide what to do

Control in realistic space
Interact with the world

My Research Focus: Perception + Imagination



Robot

My Research Focus

Perception → Imagination → Decision → Control

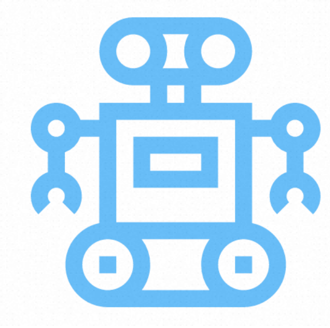
Perception: Understand the 3D world

Imagination: Planning; Data creation

Decision: Decide what to do

Control: Control in realistic space; Interact with the world

My Talk Focus: Perception



Robot

My Talk Focus

Perception → Imagination → Decision → Control

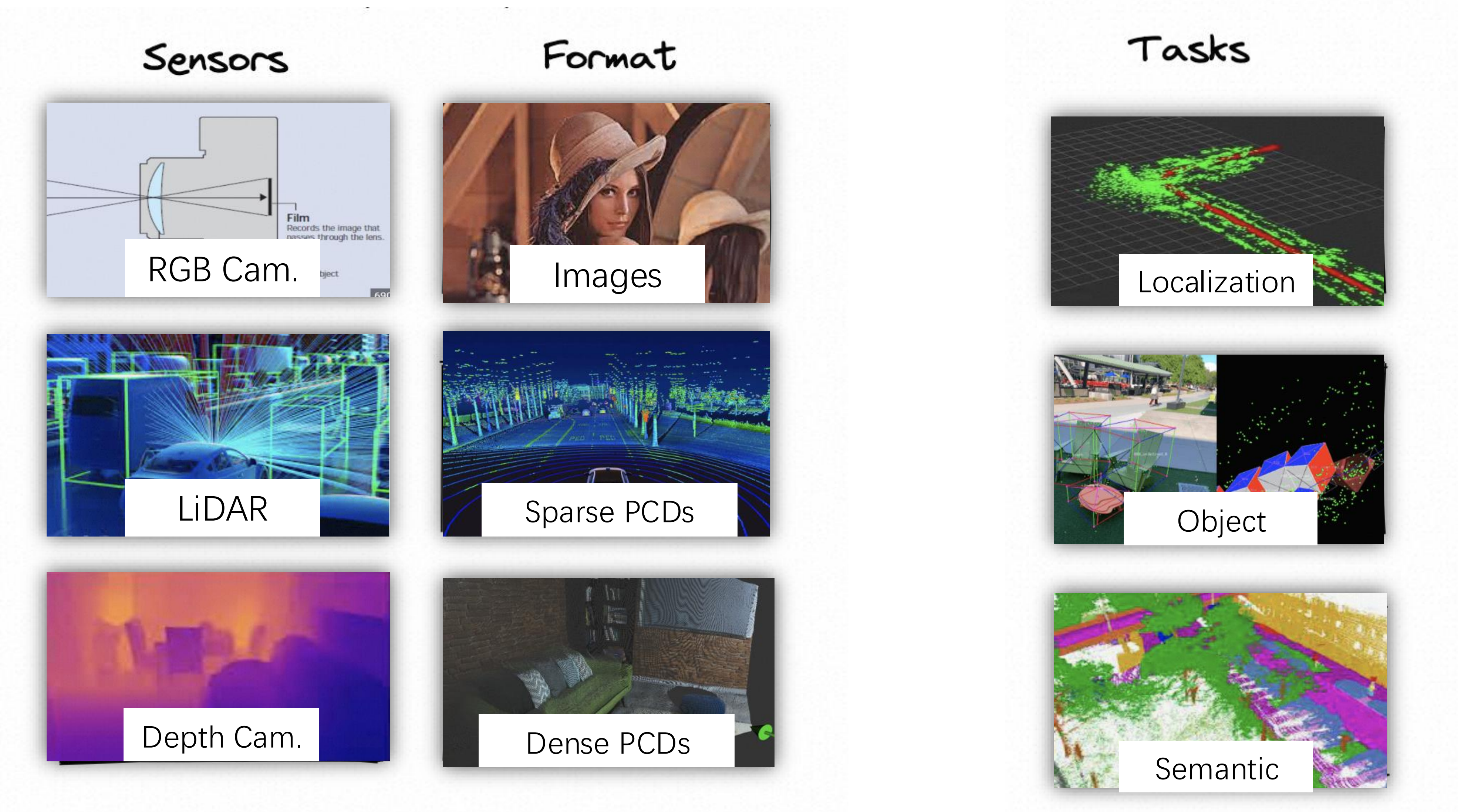
Perception
Understand the 3D world

Imagination
Planning
Data creation

Decision
Decide what to do

Control
Control in realistic space
Interact with the world

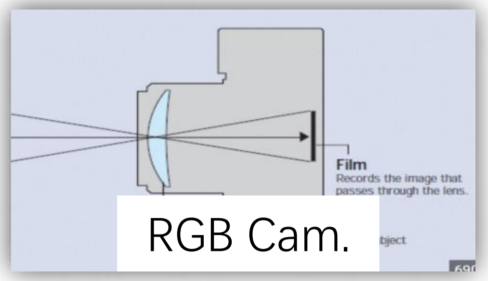
What is Visual Perception?

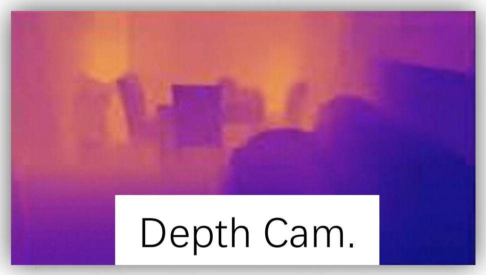


Visual Perception in 3D

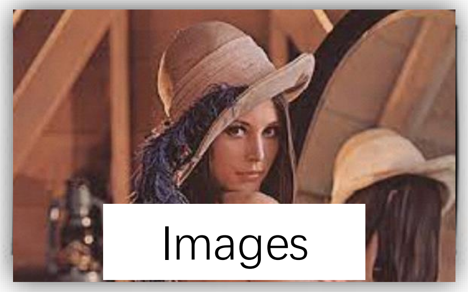
Perception → Imagination → Decision → Control

Sensors



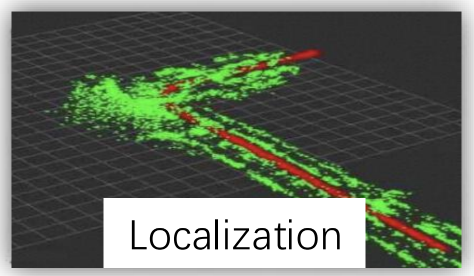


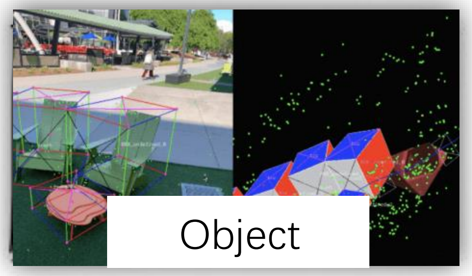
Format

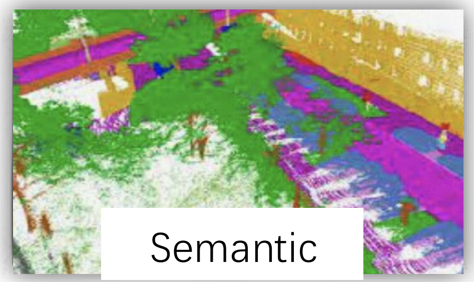


AI Models

Tasks

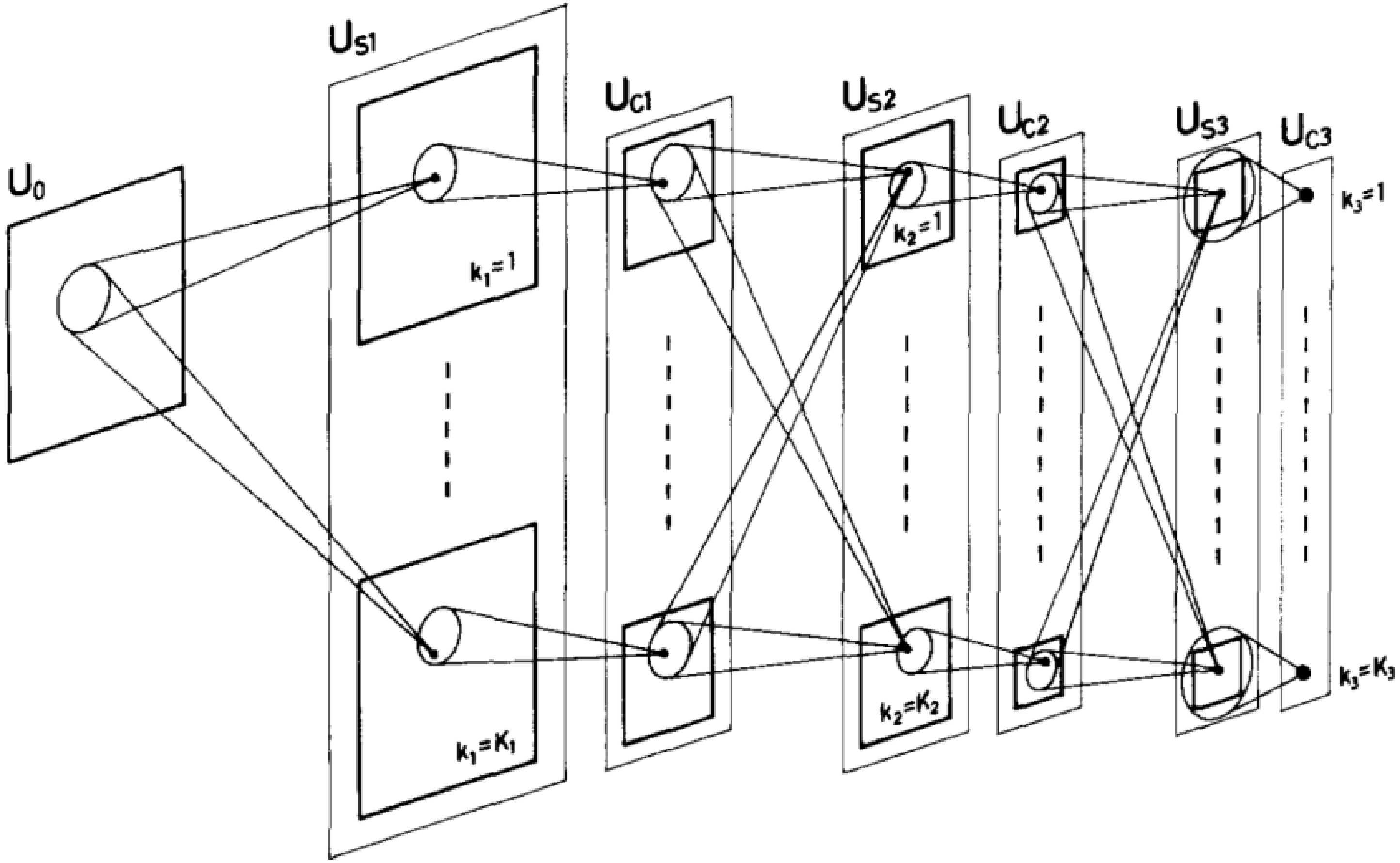






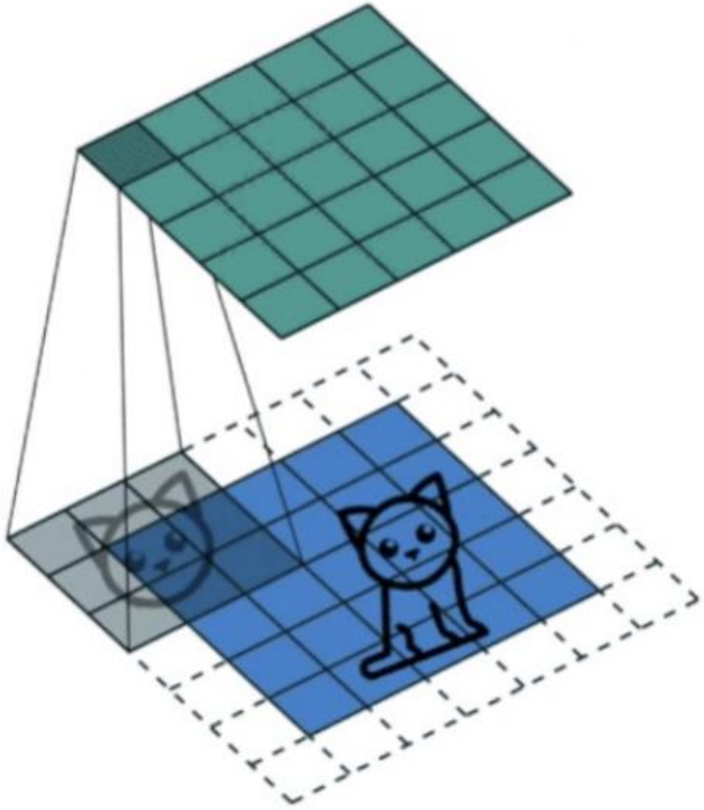
Convolutional neural network

Convolutional Neural Networks

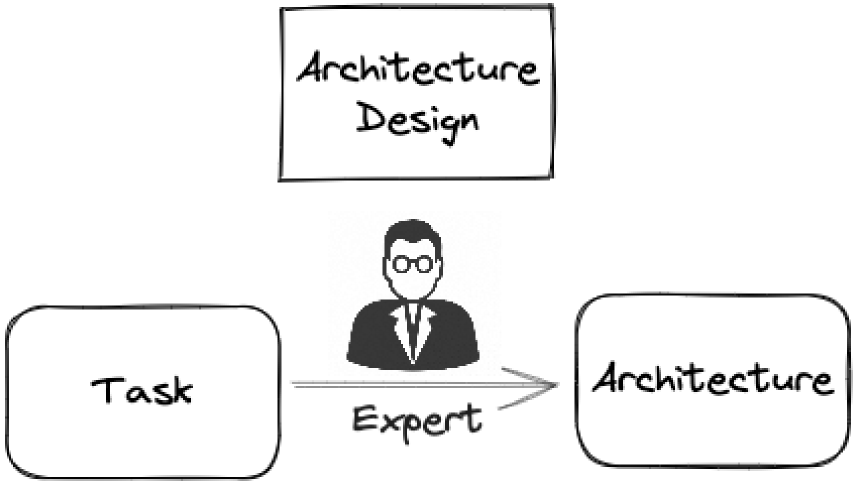


Convolution is template matching …

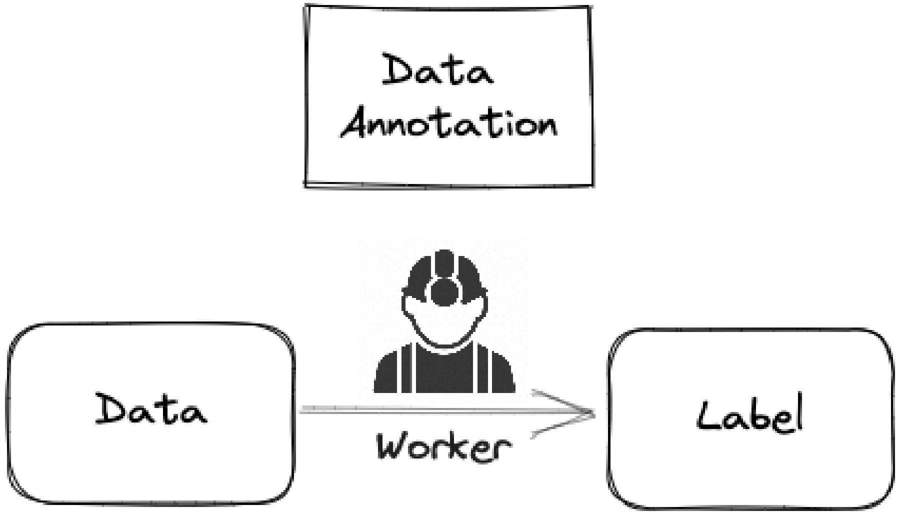
- with a sliding window
- abstract templates
- similarity measured by dot product
- stronger activation, better matching



Supervised Learning in Visual Perception



Manual Design Architectures



Large-scale Annotation

What are Key Challenges in Supervised Visual Perception?

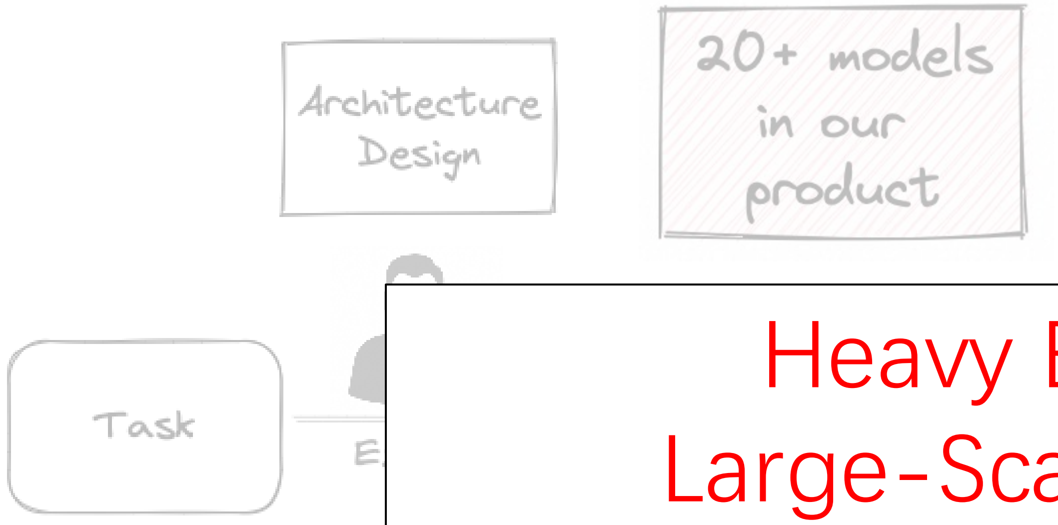
1. Large Efforts in Architecture Design

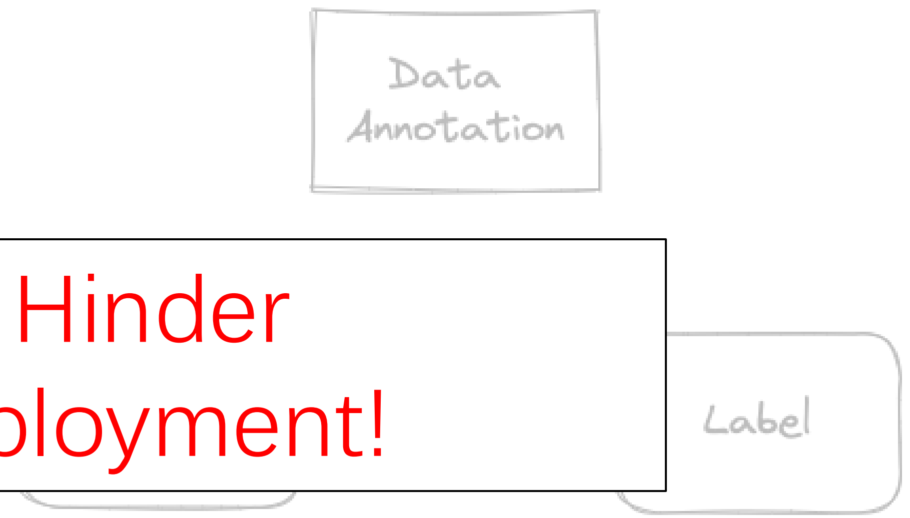
2. Large Efforts in Data Annotation

Heavy Human Efforts in Visual Perception

Key Challenge 1: Large Efforts in Architecture Design

Key Challenge 2: Large Efforts in Data Annotation





Heavy Efforts Hinder Large-Scale Deployment!

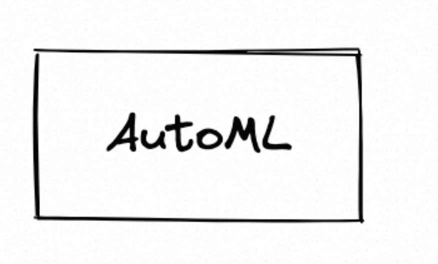
ML Expert
- designing network
- experiments
- maintaining system
- integration and etc.

Cost: 1 Million per person
Output: 1-2 Model per year

3D Data Annotation
- Low unit price
- Large-scale data
- > 10 Million annotation

Company Cost
> 40 Million per year

Reducing Human Efforts in Visual Perception



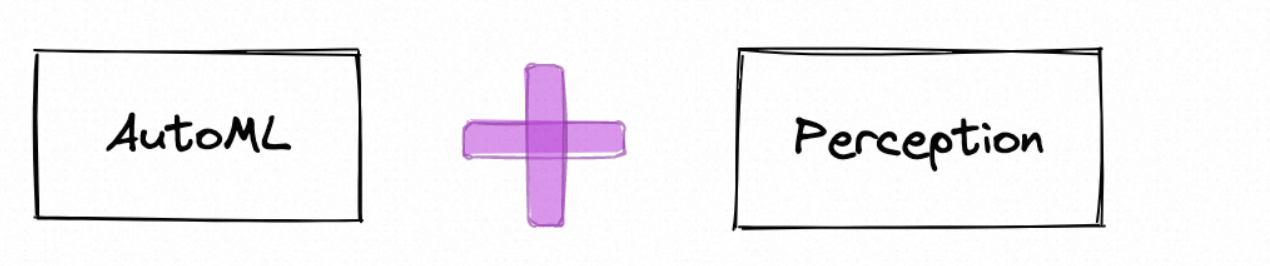
EvalNAS, ICLR 20
LR, CVPR 21
SuperNet, TPAMI 22
…

Address Challenge 1: Large Efforts in Architecture Design

- Identifying why NAS cannot surpass random search
- Our Landmark Regularization solution to address

We will not cover it in this lecture

Reducing Human Efforts in Visual Perception



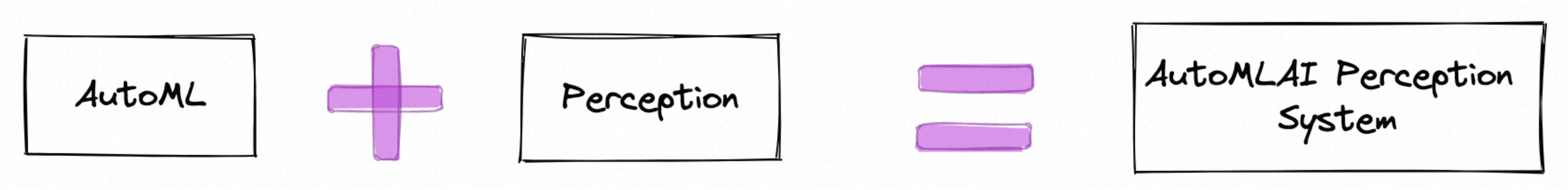
EvalNAS, ICLR 20
LR, CVPR 21
SuperNet, TPAMI 22
…

BEVFusion, NeurIPS 22
BEVHeight, CVPR 23
Rec.UNet, ICCV 19
SMSOP, ECCV 18
…

Address Key Challenge 2: Large Efforts in Data Annotation

- Auto-Labeling and pseudo labels to save human efforts
- High-performance and robust 3D perception framework

Reducing Human Efforts in Visual Perception

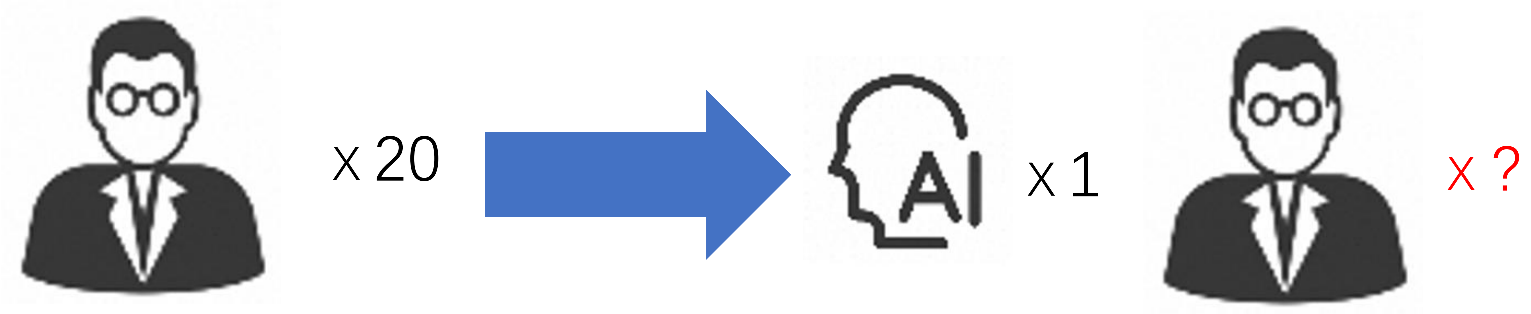


EvalNAS, ICLR 20
LR, CVPR 21
SuperNet, TPAMI 22
…

BEVFusion, NeurIPS 22
BEVHeight, CVPR 23
SMSOP, ECCV 18
…

AI System
- Role: Chief Architect
- Broader AutoML
- Deployed in Alibaba

Address Key Challenges 1 & 2:
- Address both challenges together
- A platform to integrate our latest research advances



Before

AutoML System V1

1 2 **3** 4 5

Key Challenge 1: Large Efforts in Architecture Design

Key Challenge 2: Large Efforts in Data Annotation

Perception in 3D World

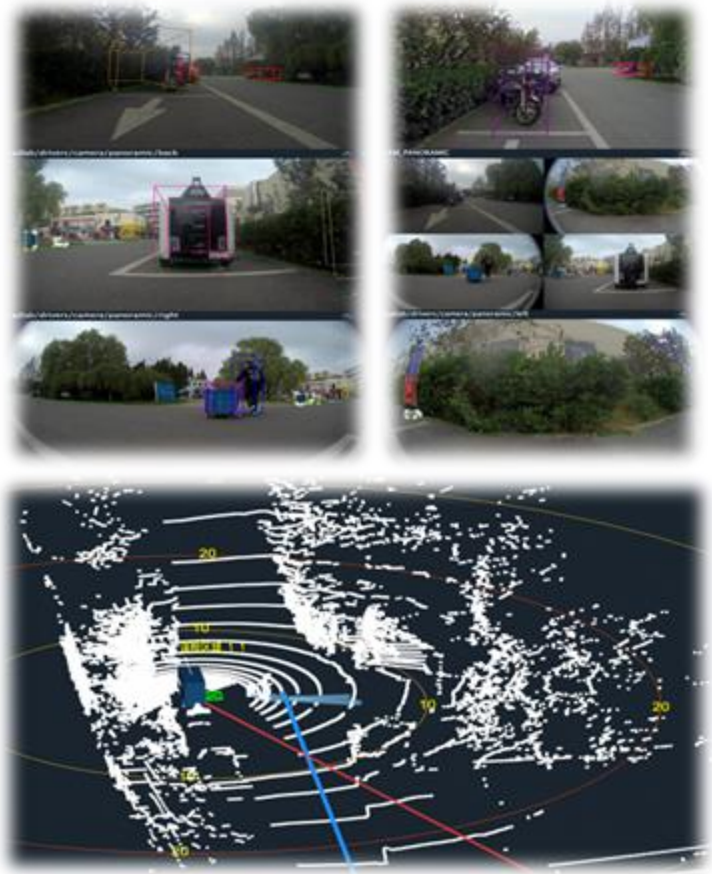
AutoML + Perception = AutoMLAI Perception System

Here

Perception in 3D Understanding

Sensor Data

Camera LiDAR Radar etc.



Perception

- Brain of robotics
  - Similar to human
- The only approach to understand the world!
  - Data centric
  - Deep Neural Networks

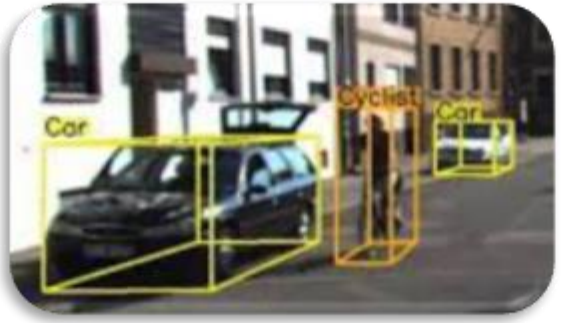
Vectorized space

3D digital world

3D Understanding Tasks

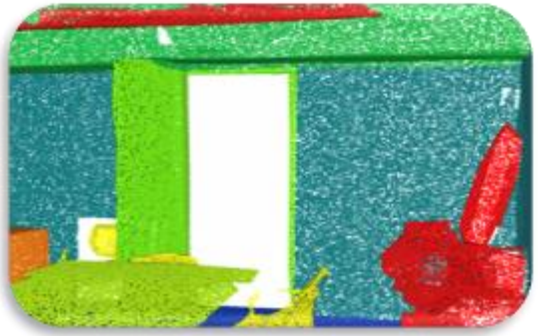
Perception

Multi-object Tracking



Object Detection

...



Point-cloud Segmentation

Depth Completion

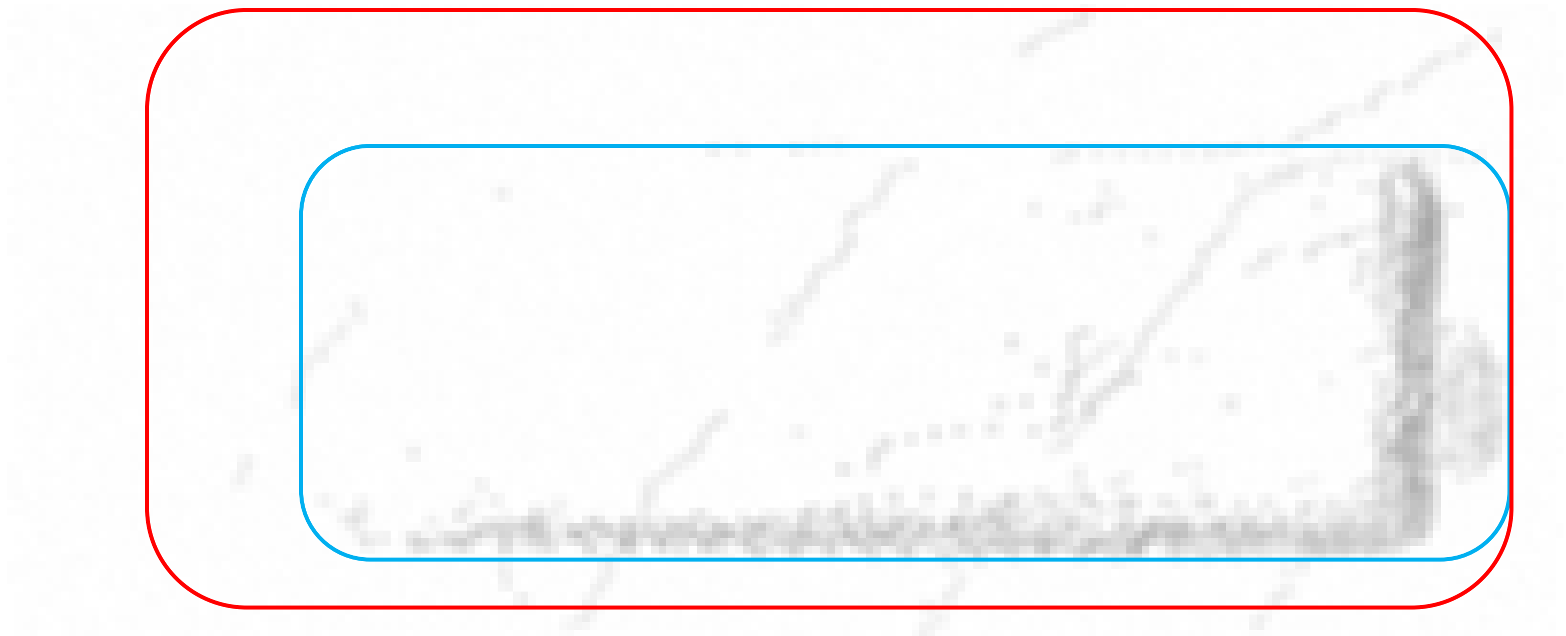
Why 3D Annotation with Multi-sensor Data Is Hard?

Red: GroundTruth

Example of 2D Object Box Annotation

Why 3D Annotation With Multi-sensor Data Is Hard?

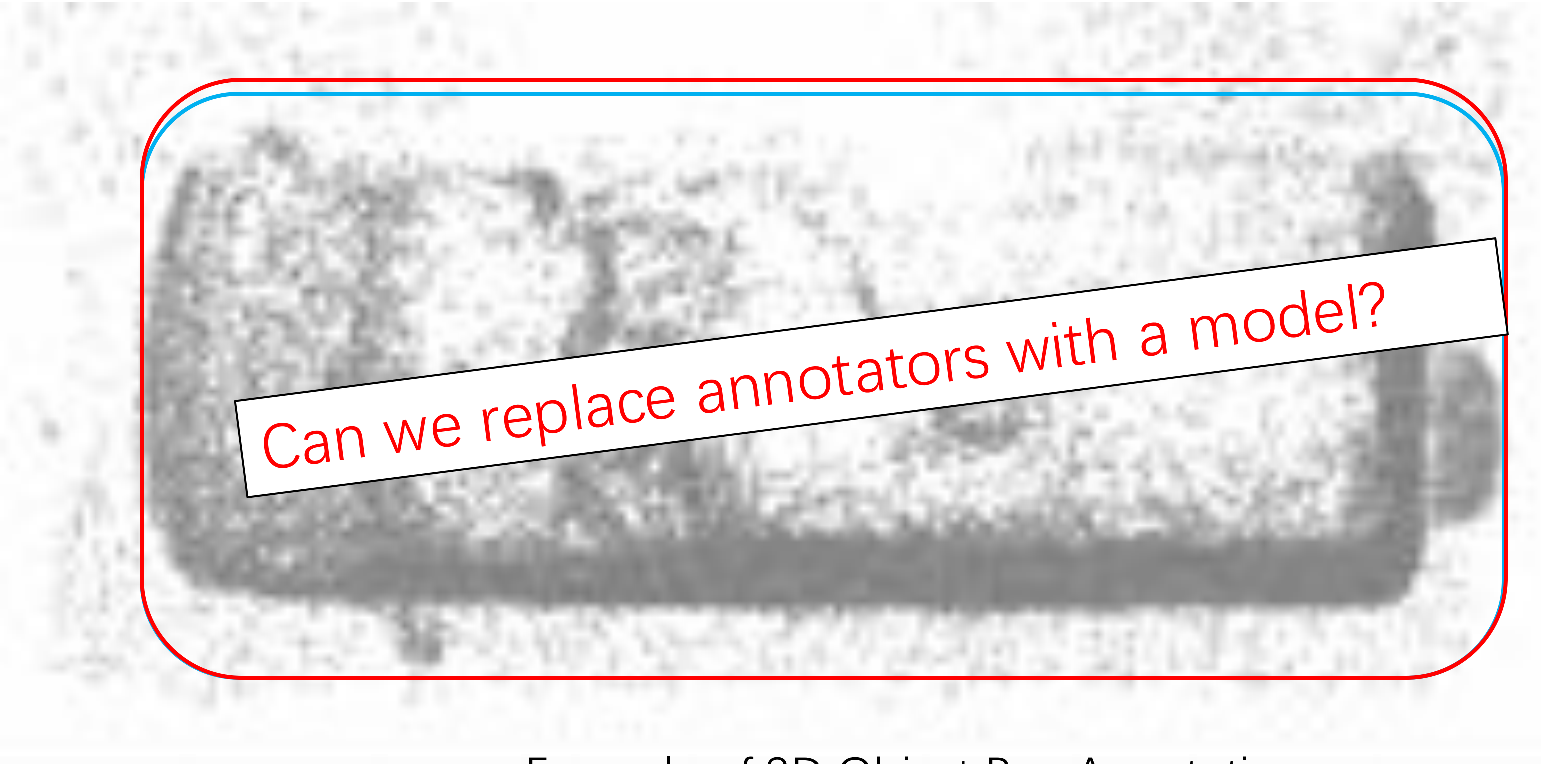
Red: GroundTruth
Blue: Common annotator



Example of 3D Object Box Annotation
(Bird eye view of 3D point clouds)

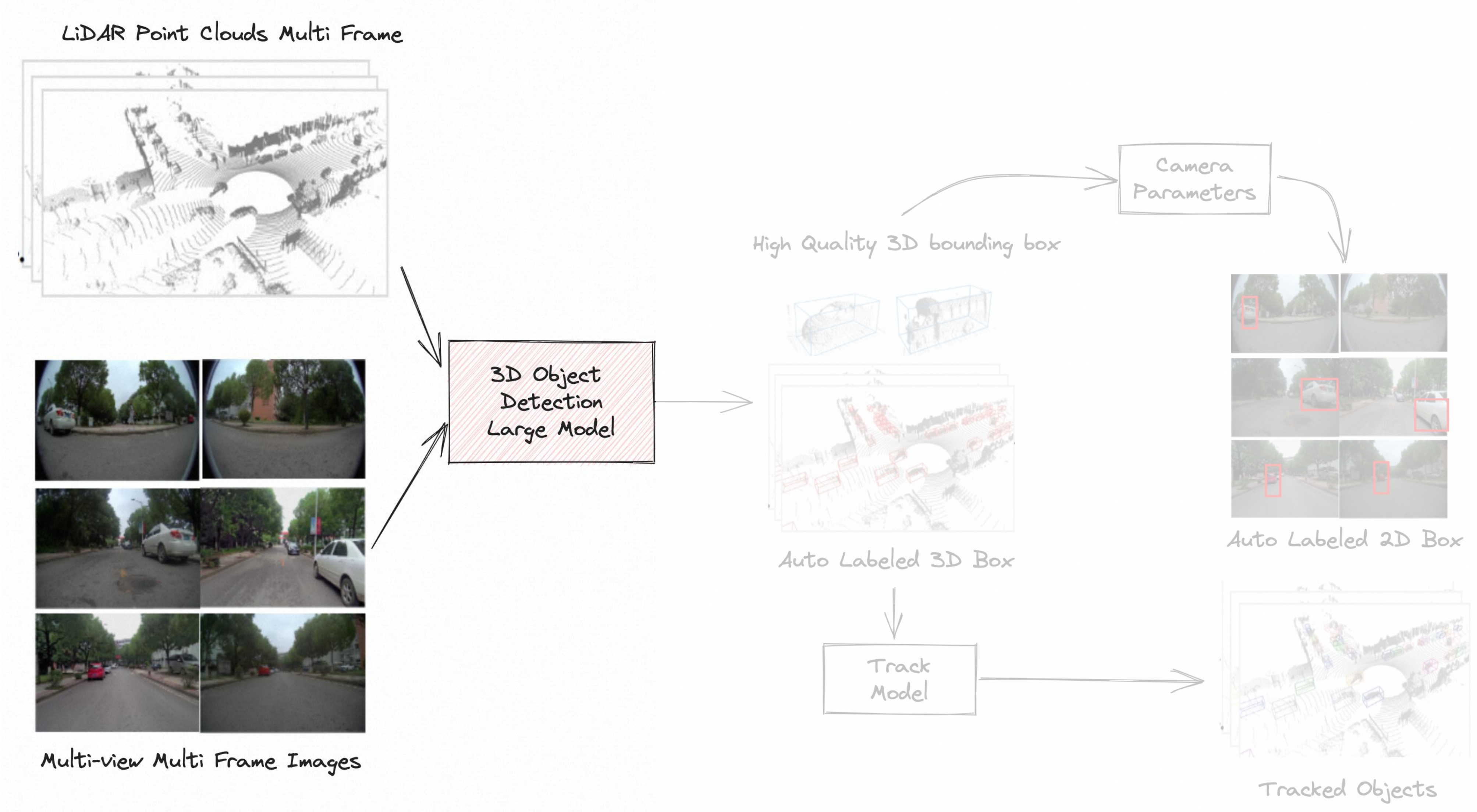
Why 3D Annotation With Multi-sensor Data Is Hard?

Red: GroundTruth
Blue: Common annotator

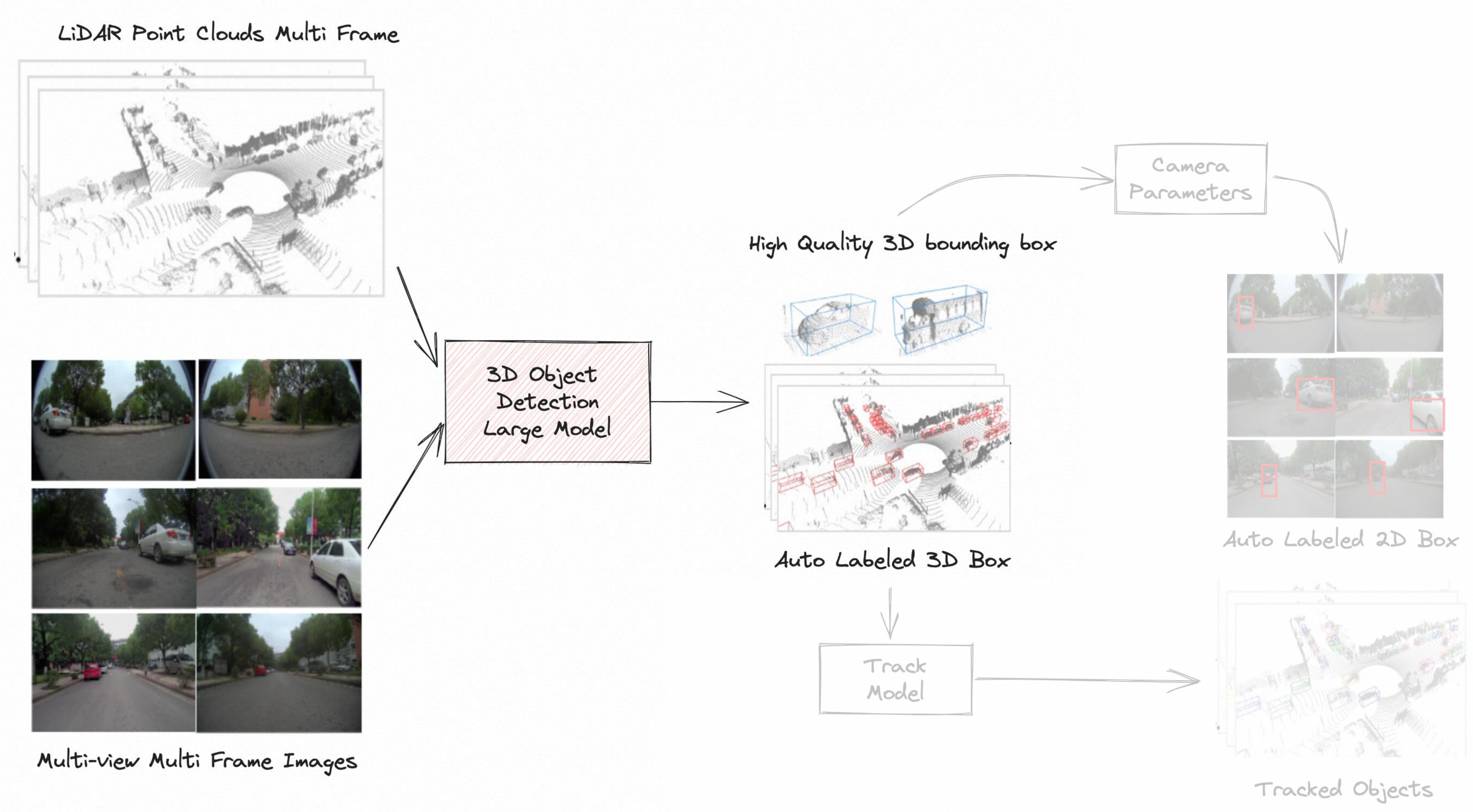


Example of 3D Object Box Annotation
(Bird eye view of 3D point clouds)
Aggregating 100+ frames!

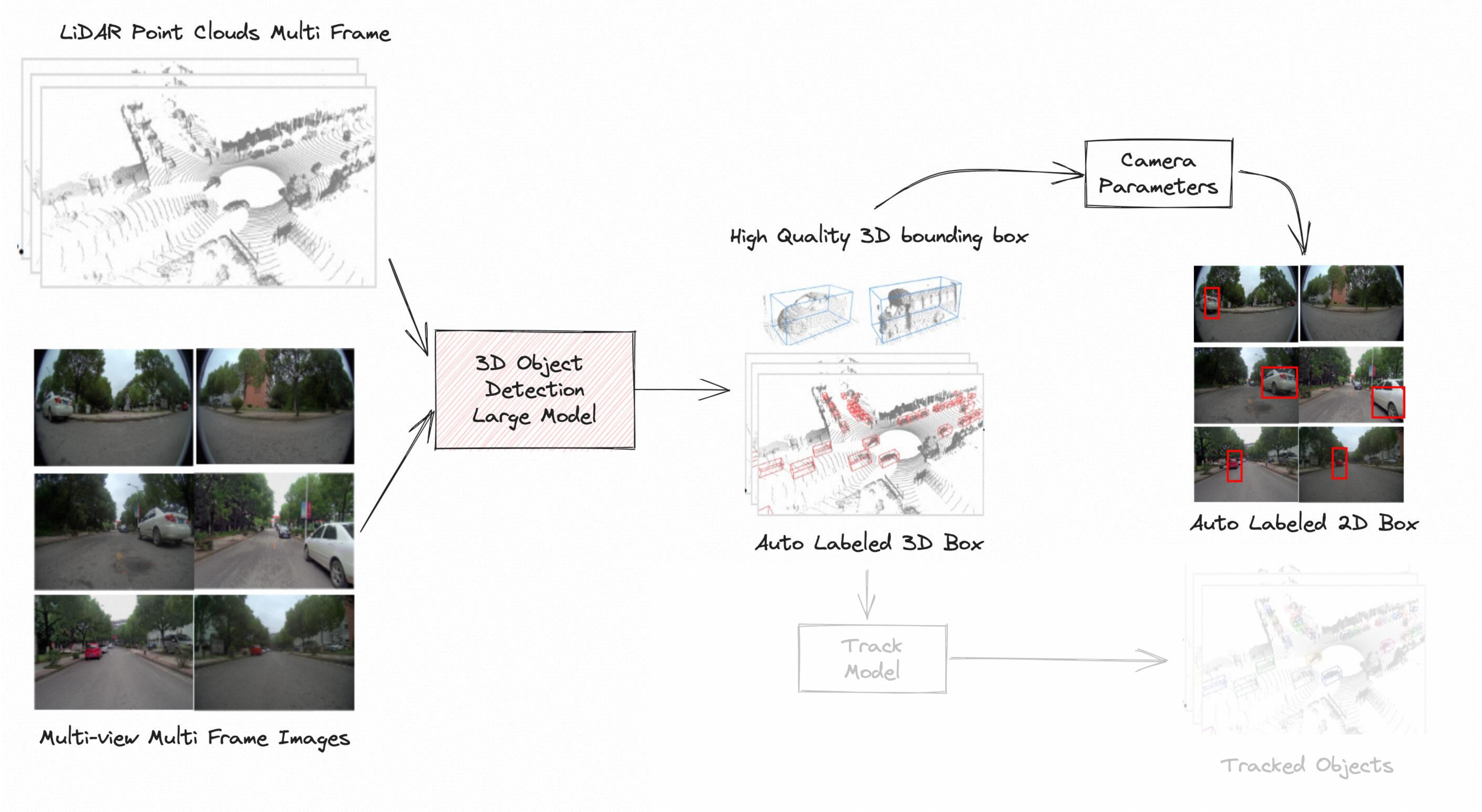
AutoLabel System: Large model as Pseudo Labeler



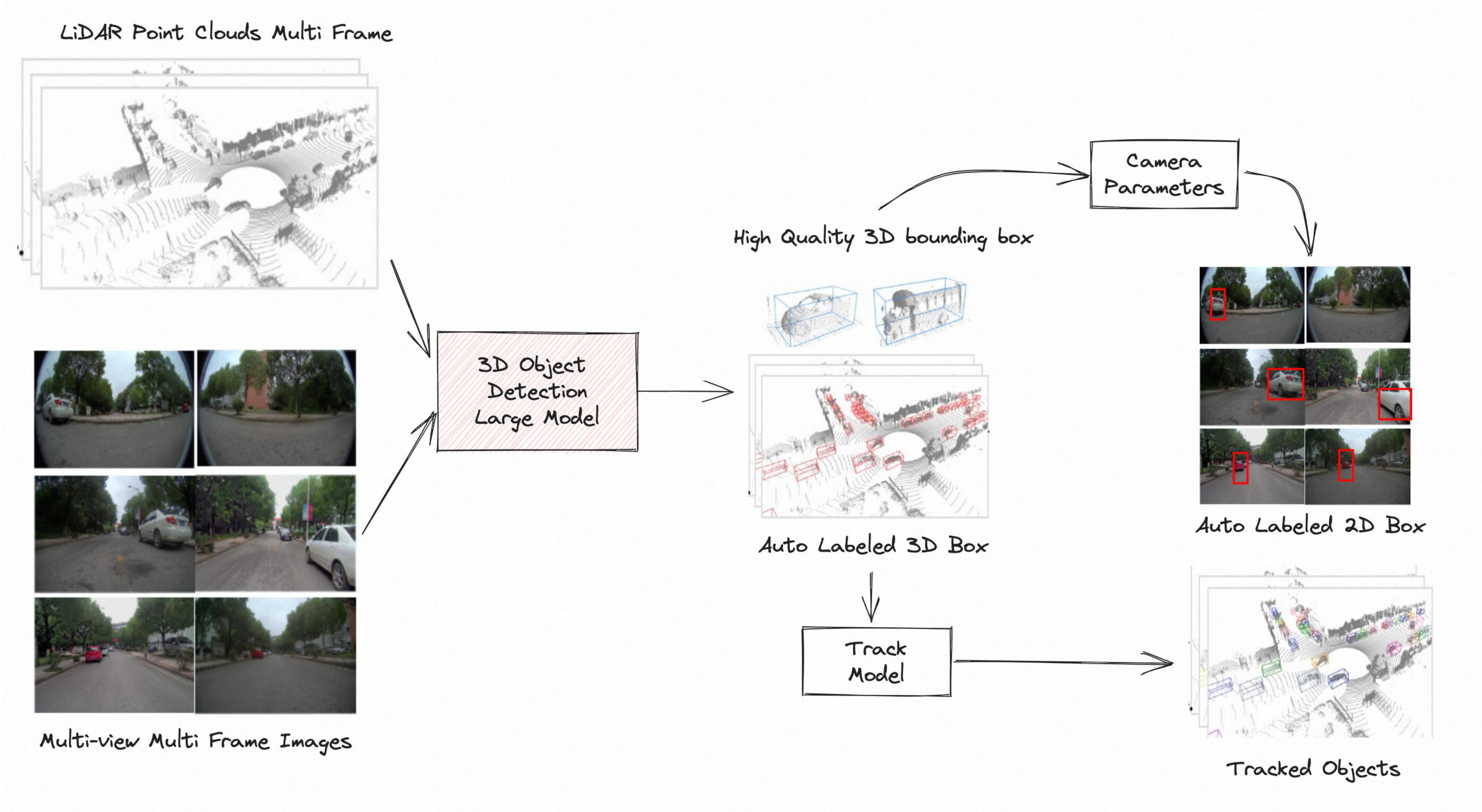
AutoLabel System: Large Model as Pseudo Labeler



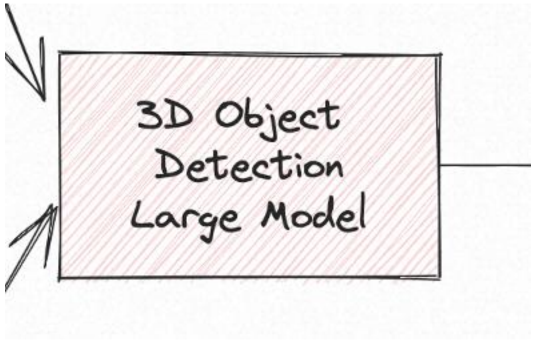
AutoLabel System: Large Model as Pseudo Labeler



AutoLabel System: Large Model as Pseudo Labeler

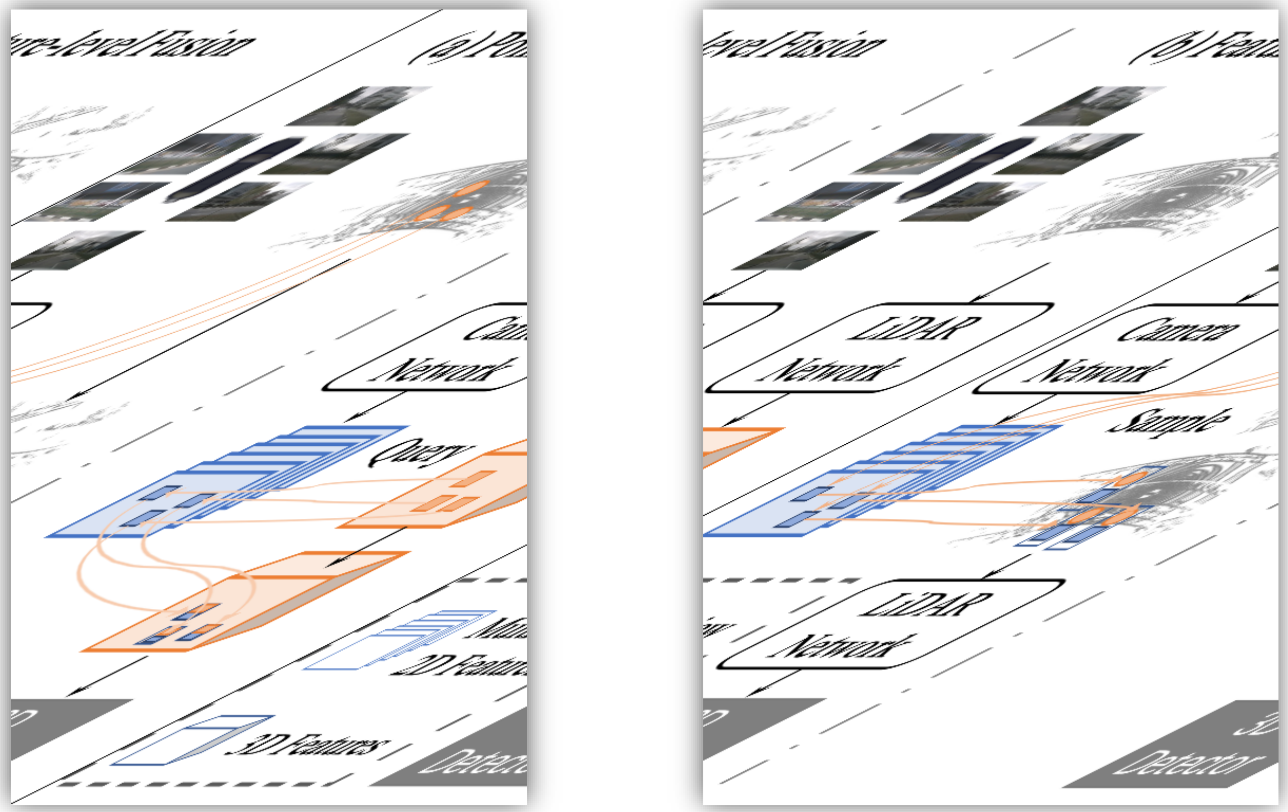


AutoLabel System: Large Model as Pseudo Labeler



Better Base Model	=	Reduce Human Efforts

State of The Art Multi-modality Base Model

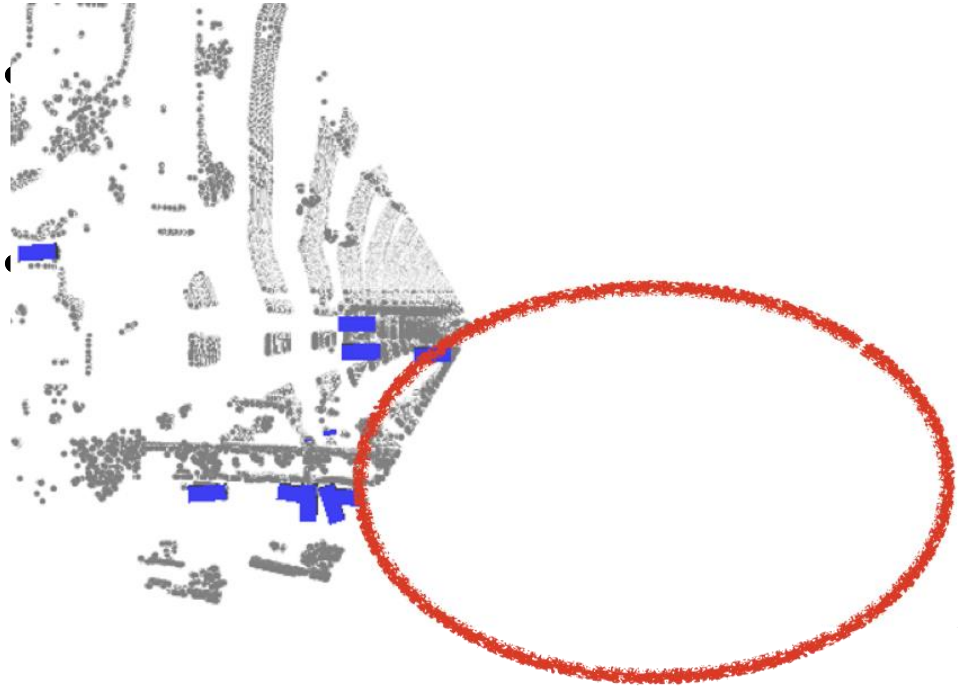


Existing Frameworks of camera-lidar fusion

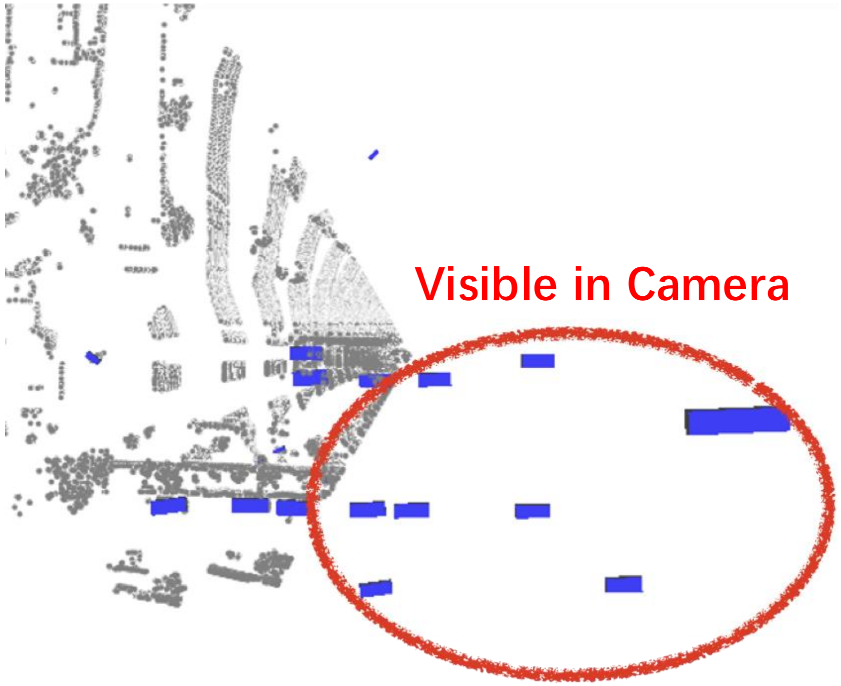
- Fusion starts from point clouds, what if LiDAR fails?

[1] Yu et al. Robustness benchmark of camera-lidar fusion in autonomous driving. CVPR'23 Dataset Paper

SoTA Base Model Fails w/o LiDAR Input



Predictions

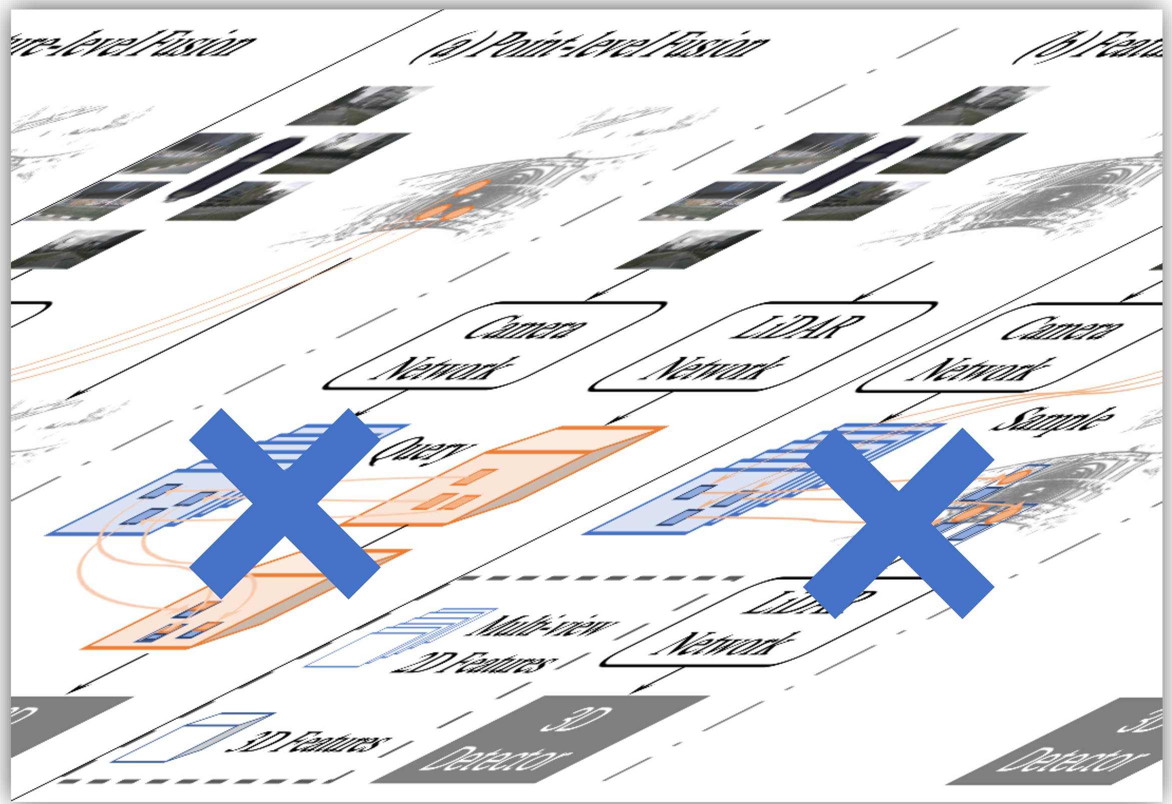


Ground-truth

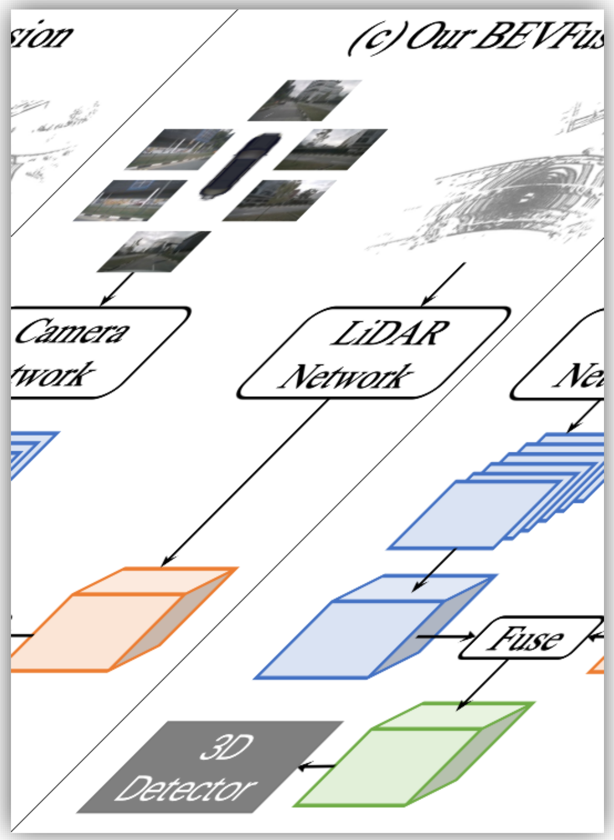
- Base model with 2 modalities **should not fail** when 1 missing

[1] Yu et al. Robustness benchmark of camera-lidar fusion in autonomous driving. CVPR'23 Dataset Paper

BEVFusion: A Simple yet Robust Base Model Framework

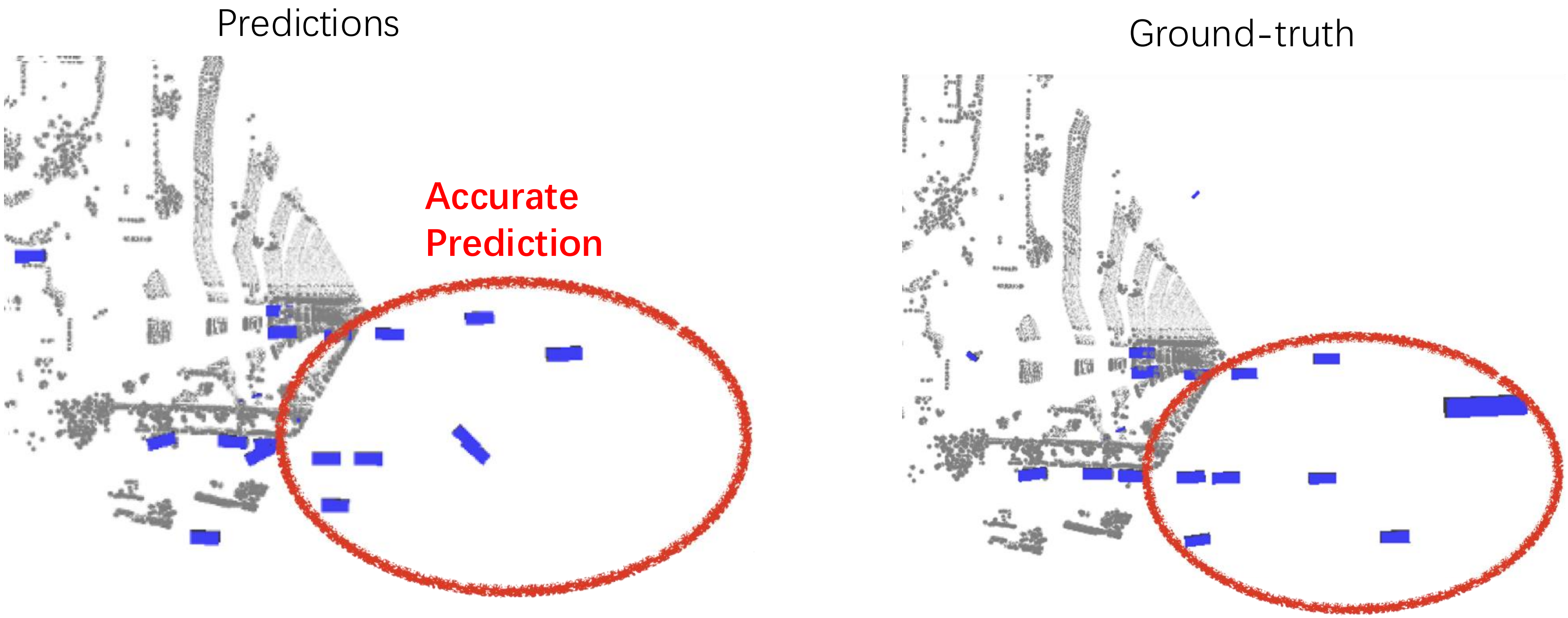


Existing Frameworks of camera-lidar fusion



[1] Liang et al. BEVFusion: A simple yet robust framework for camera-lidar fusion in 3D detection. NeurIPS'22, Spotlight, Supervised intern.

Our BEVFusion Framework is Robust to LiDAR Failure



- The first robust framework that is agnostic to LiDAR failure
- **+30 mAP** compared to baselines
- Become a de-facto standard
- Many follow ups (MetaBEV, BEVFusion 4D, etc.)

[1] Liang et al. BEVFusion: A simple yet robust framework for camera-lidar fusion in 3D detection. NeurIPS'22, Spotlight, Supervised intern.

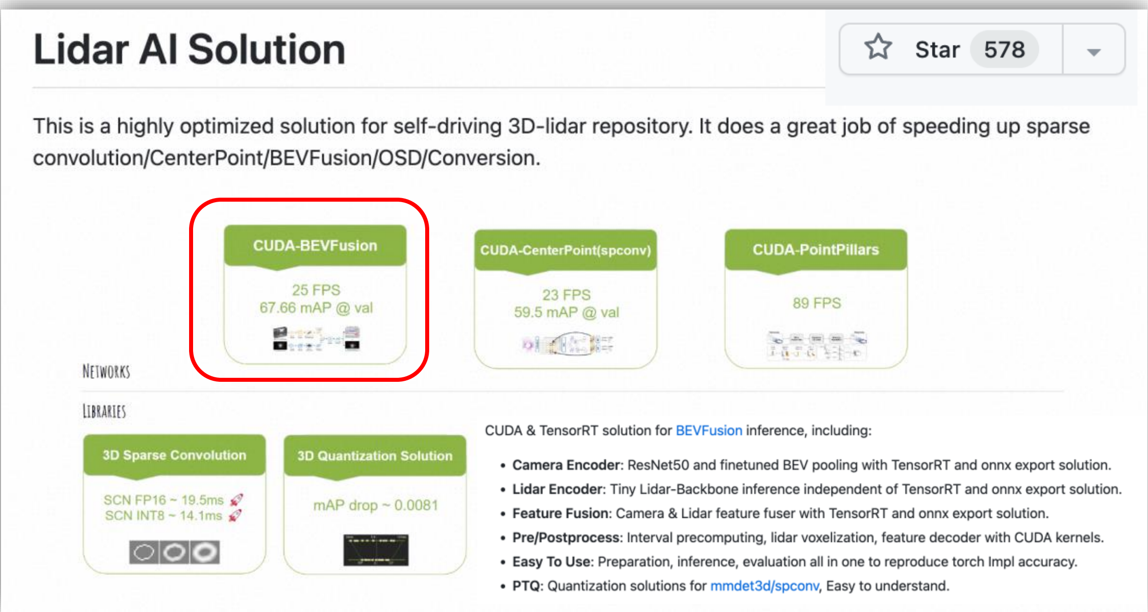
BEVFusion Deployed in Alibaba

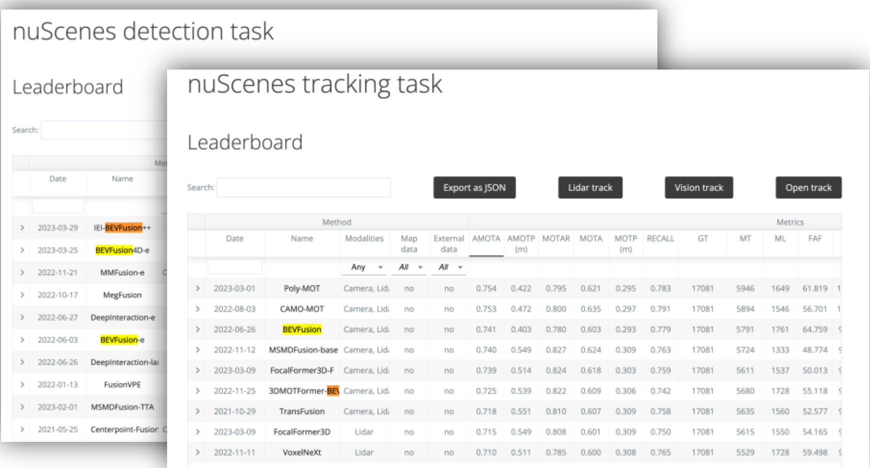
High-Quality Ground-truth	Labeler Army	v.s.	Auto Label	
Accuracy (mIoU)	83.12		91.35	(8.23+)
Time (per box)	25s		0.005s	(5000x faster)
Cost (per box)	1 RMB		0.0001 RMB	(10000x cheaper)

- BEVFusion + AutoLabel system surpasses human level annotation!
  - By a large margin

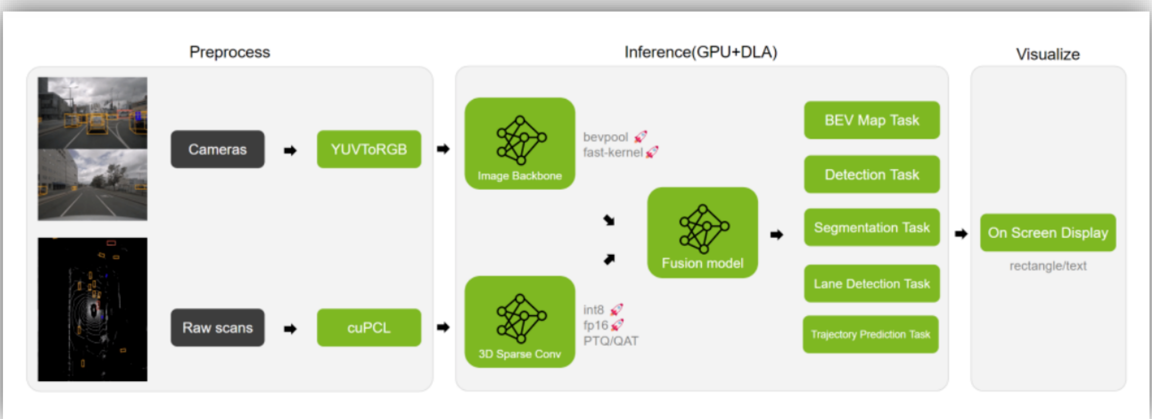
[1] Liang et al. BEVFusion: A simple yet robust framework for camera-lidar fusion in 3D detection. NeurIPS'22, Spotlight, Supervised intern.

BEVFusion Other Impact





Leading in various tracks of leaderboard

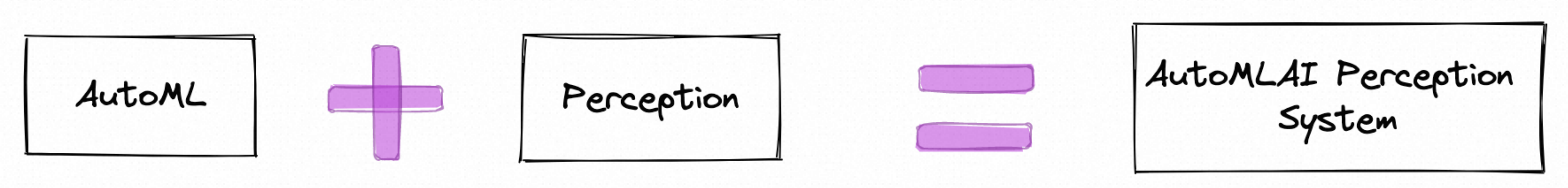


Nvidia Integration as a default AI solution

理想 NIO HAOMO.AI 達摩院 ALIBABA DAMO ACADEMY HUAWEI

Integration by various AV companies

AI System
ADLab AutoML System



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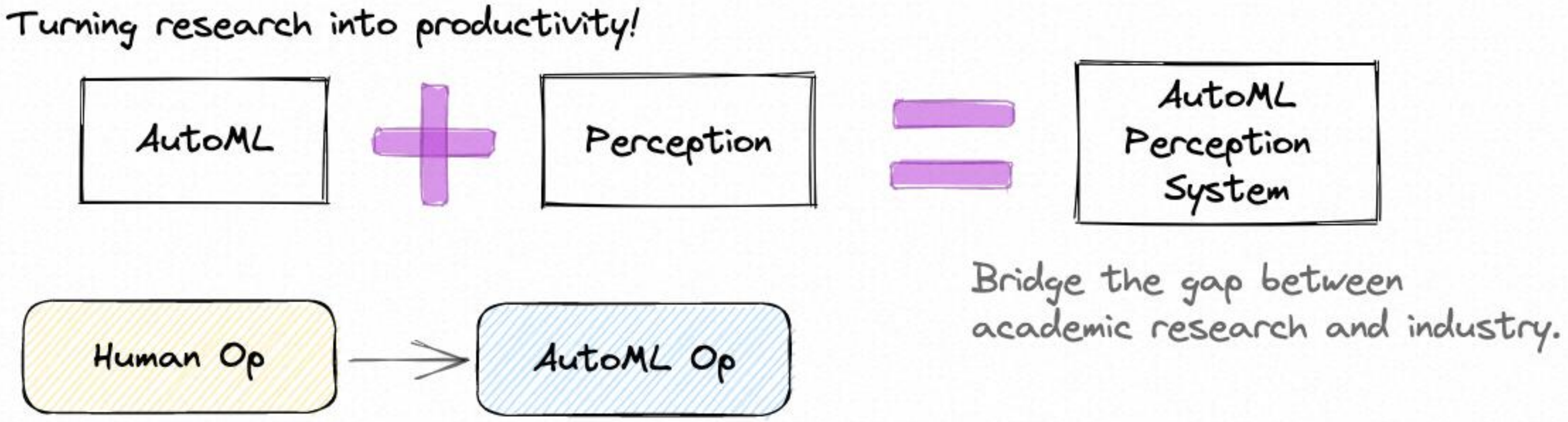
Key Challenge 1: Large Efforts in Architecture Design

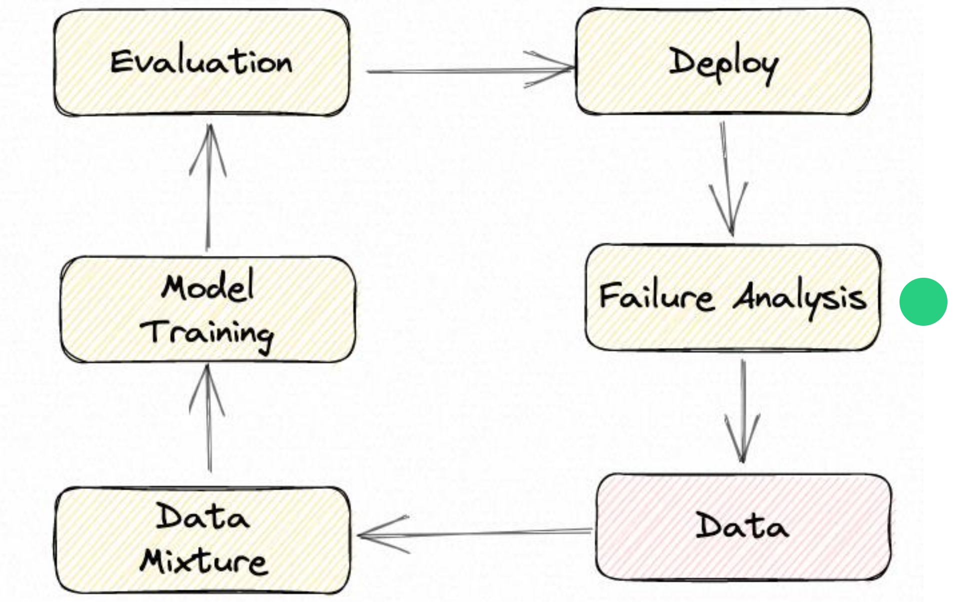
Key Challenge 2: Large Efforts in Data Annotation

Reducing human efforts by building an AI System

- Automatic machine learning as a system
- My Role: Chief architect

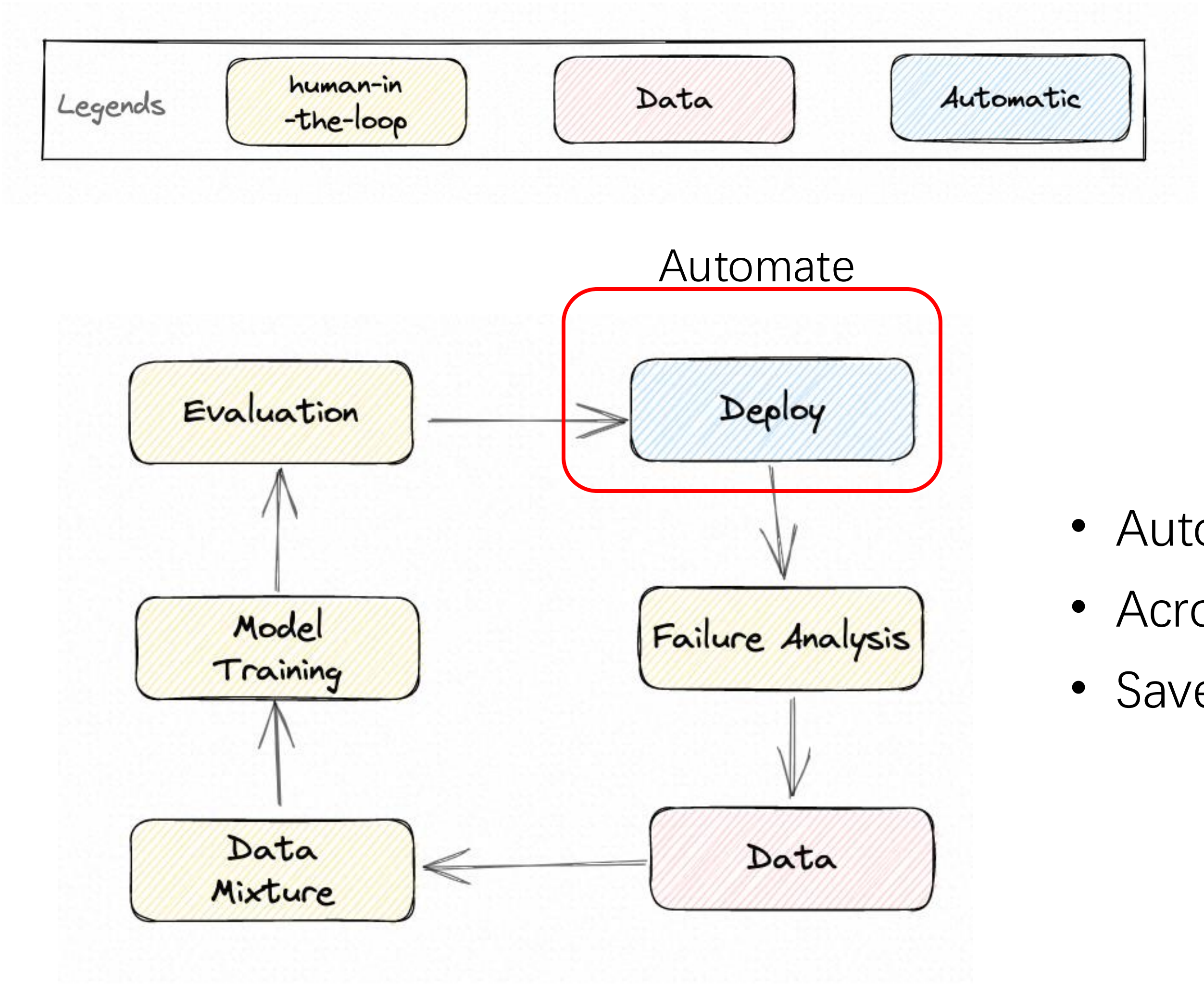


Manual update of an existing deep learning model



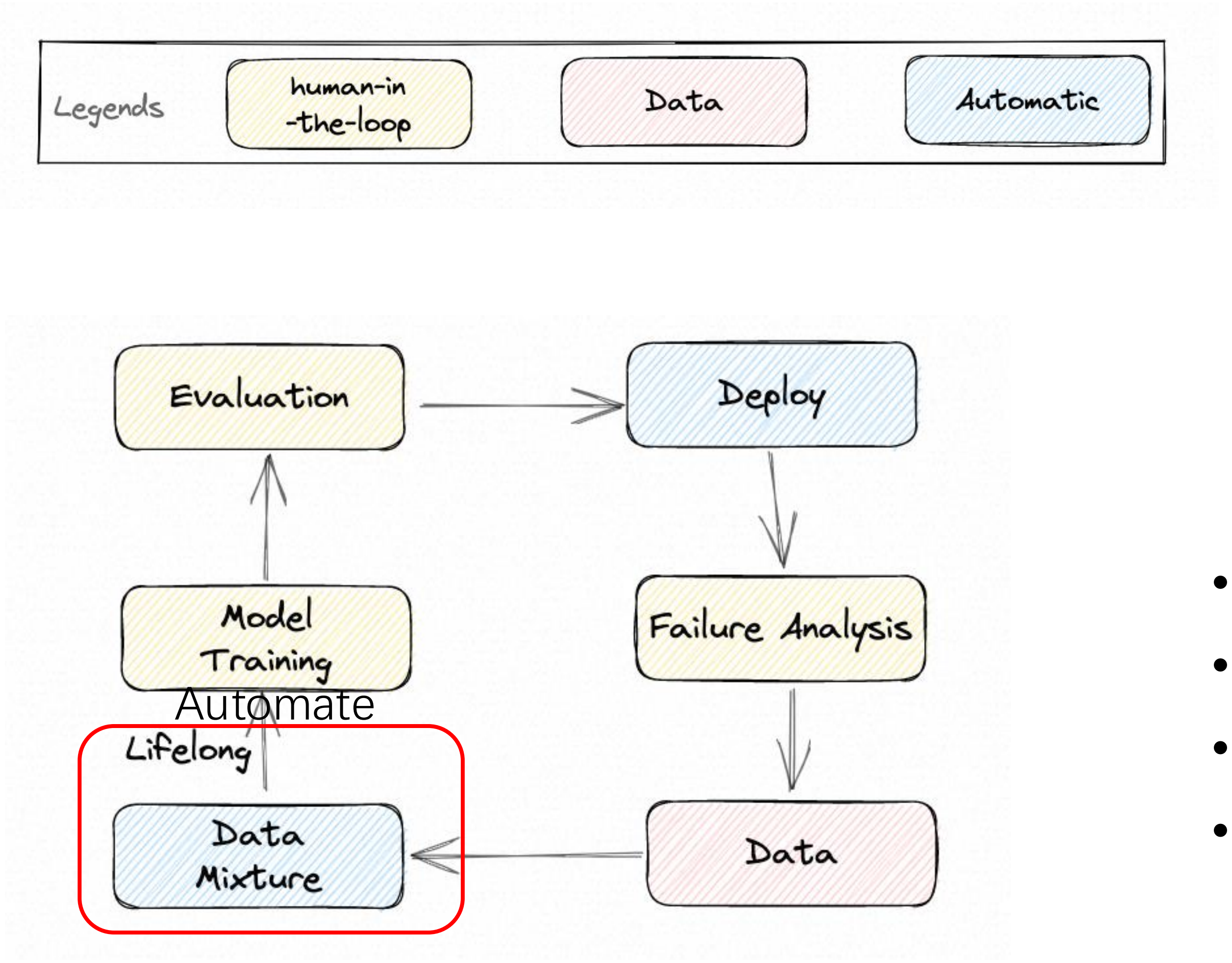
- All steps are manually done
- Cost 90 days for 1 model
  - Update an existing model
  - Does not include first design time

Step 1: Automatic deployment



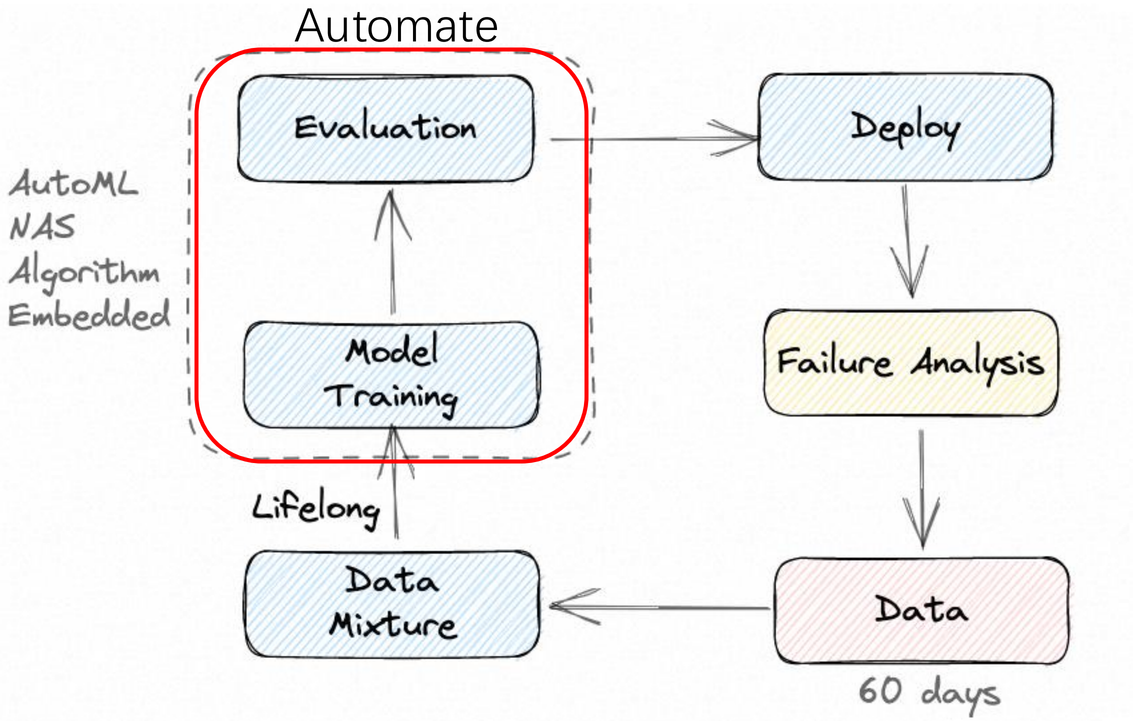
- Automation for API services
- Across 6 platforms from hard-ware deployed
- Save ~30 days

Step 2: Use active learning for data mixture process



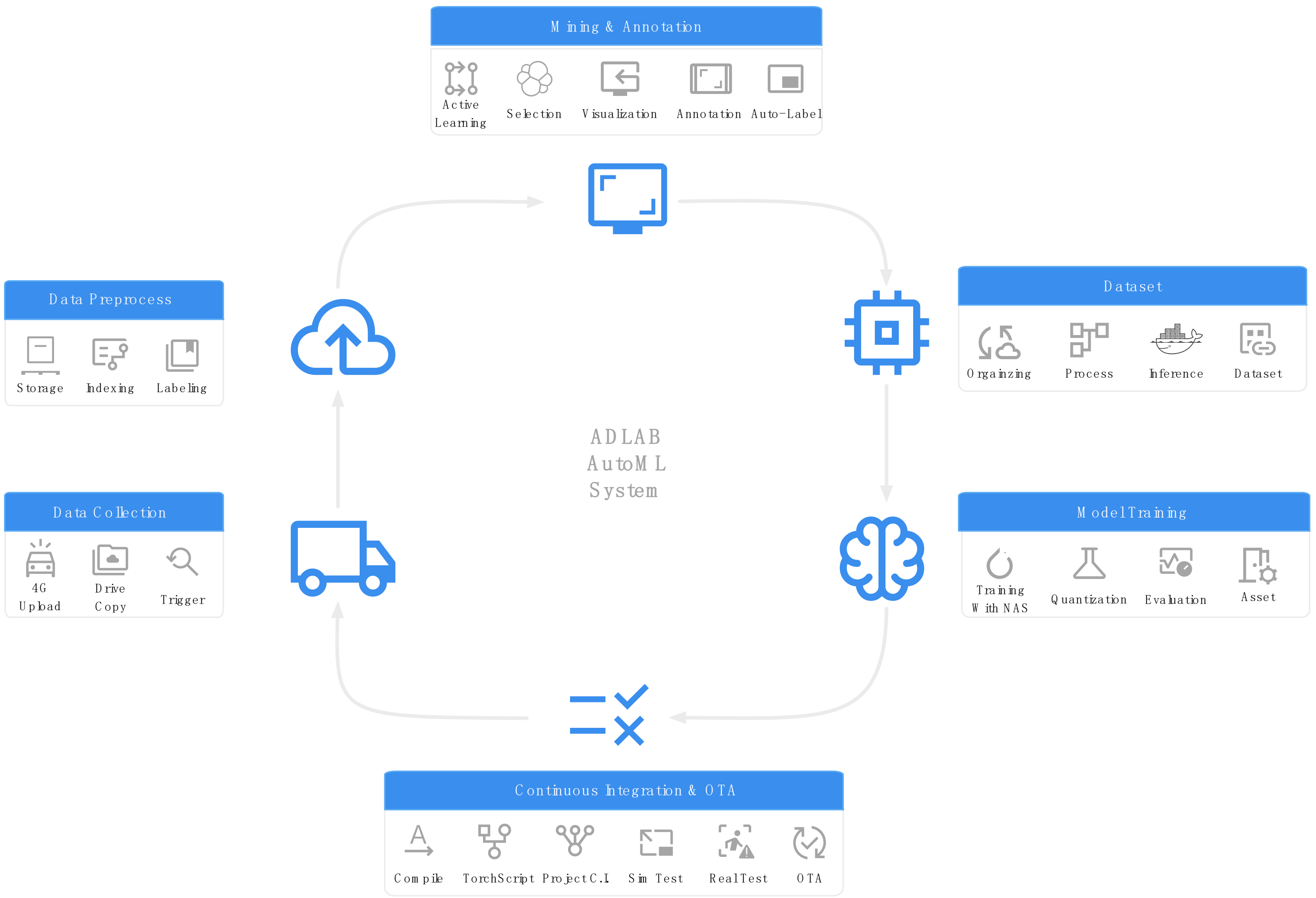
- Automatic data mixture
- Lifelong learning to train the network
- Save ~5 days
- Without performance drop

Step 3: Incorporate NAS into AutoML System



- Incorporate NAS in 3D backbone
- Support quantization
- Save ~20 days
- Performance Improves ~10%

Overview of the system



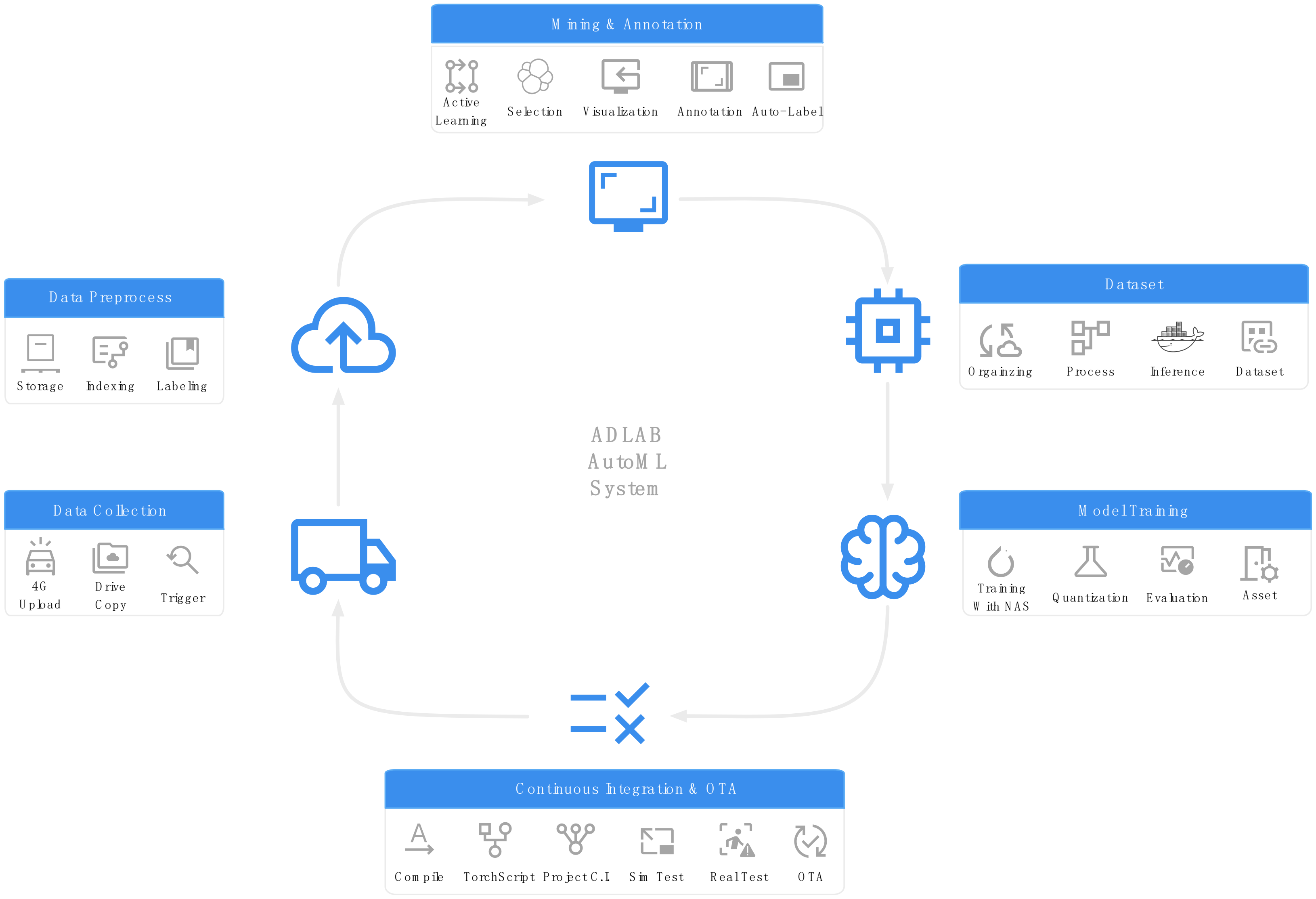
Overview of the system

Performance

- +10% mAP on object detection
- +5% mIoU on point-cloud segmentation
- Fix 150+ failures automatically

Efficiency

- Time spent: 90 → 35 (-60%)
- Manual steps: 192 → 7 (-97%)



Outcome: Deployment of AutoML System V1

Carrier

Largest Autonomous Driving in logistic

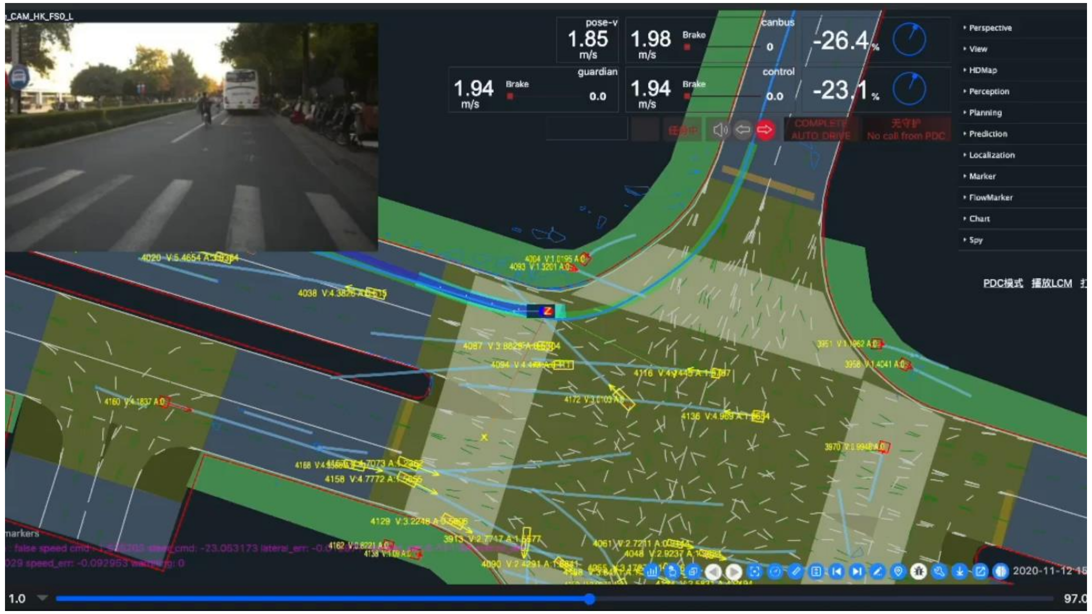
200+ Cities

800+ Vehicles

ders

x 20

Before



x 1

x 1!

AutoML System V1


取件就约
机器人！
浙

1 2 3 4 5

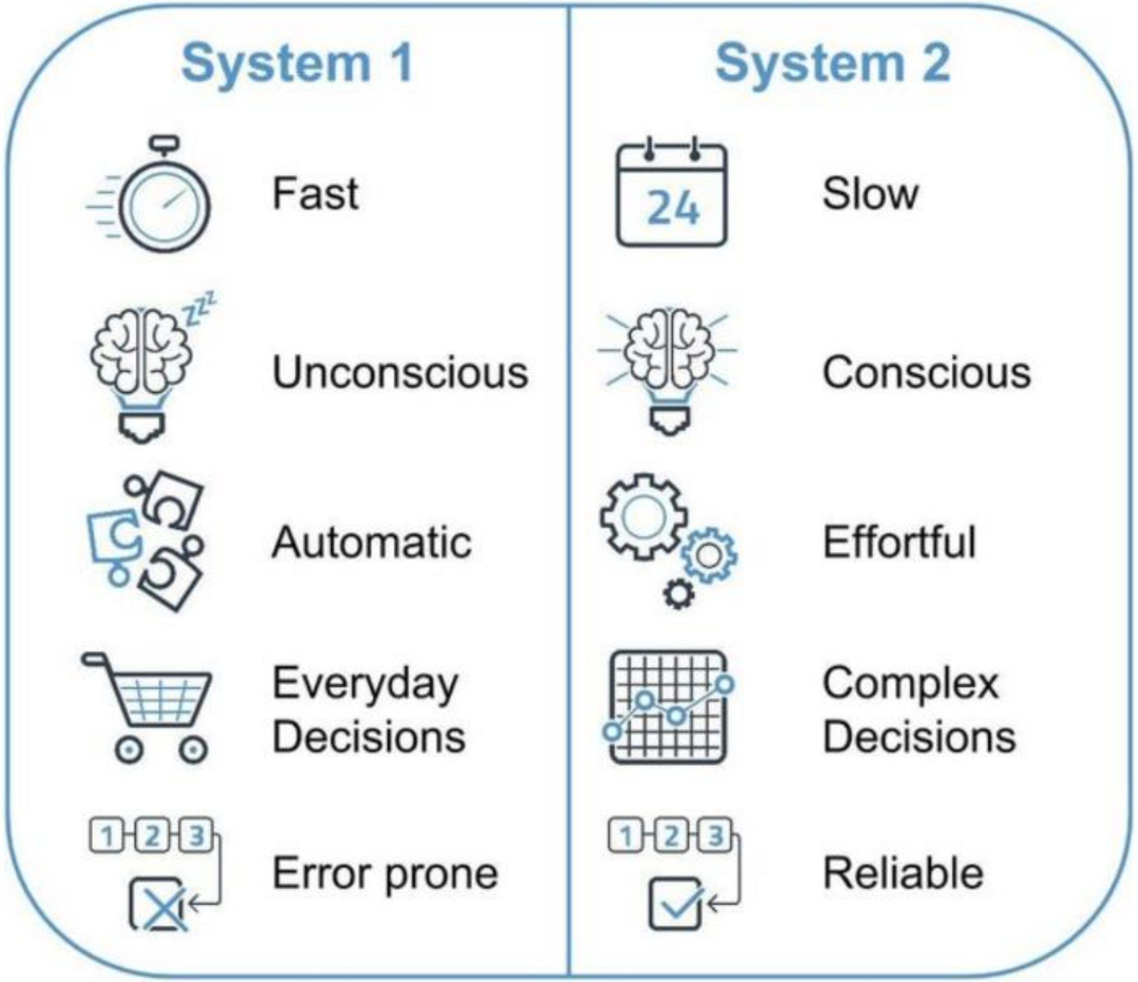
Conclusion
Future Work

从自动驾驶到自主智能
工程驱动的创新浅谈

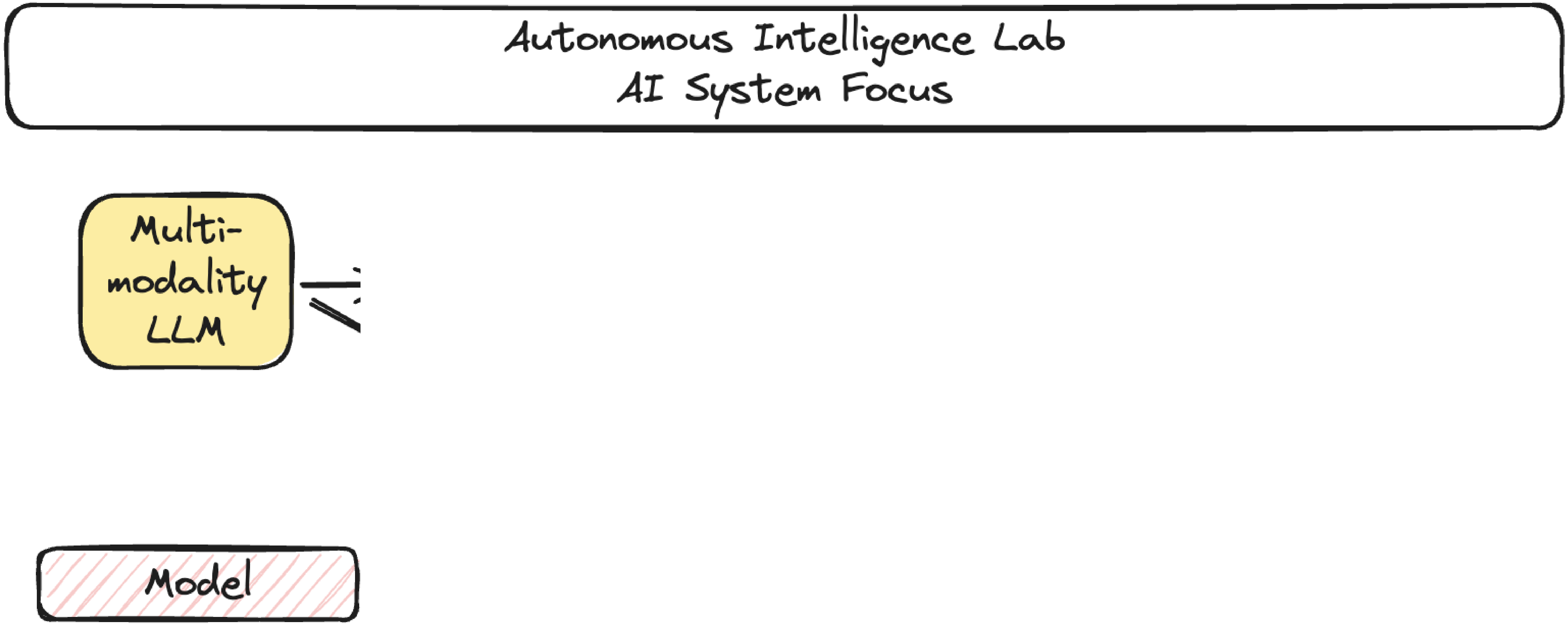
Kaicheng Yu
2025.5.16

Review of the Development of Multimodal Large Language Models

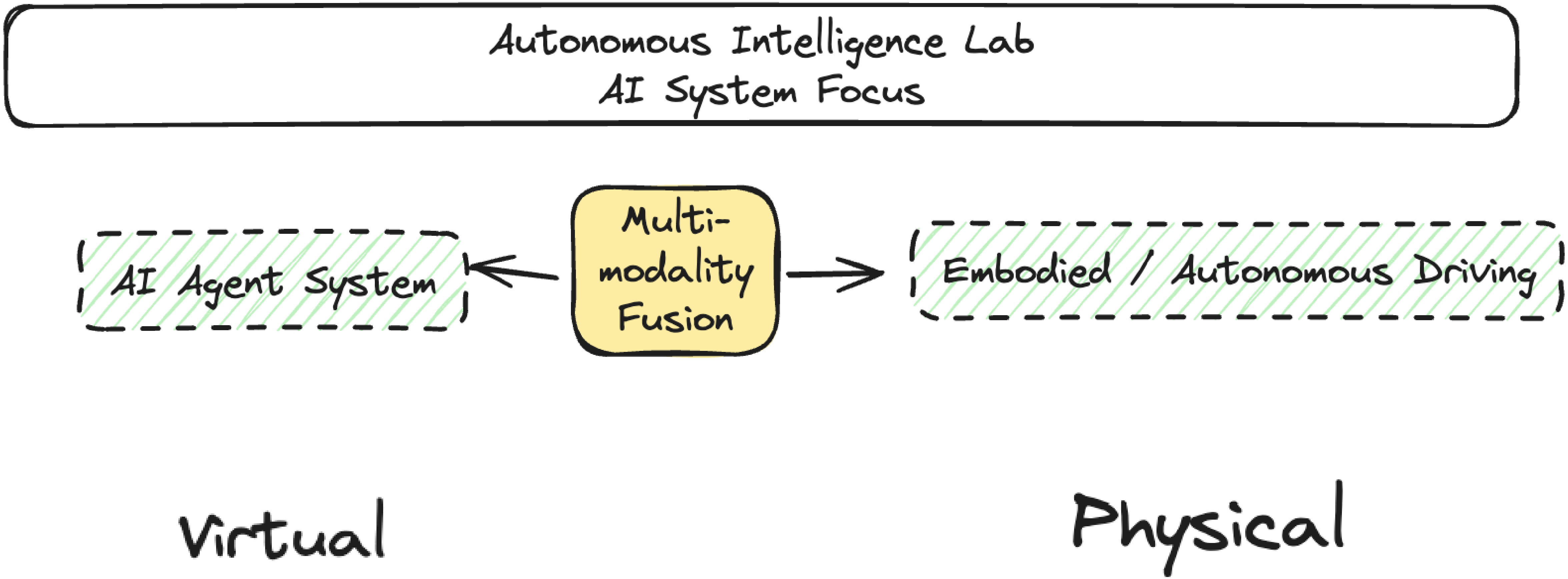
Large Model as System 1 v.s. Agent System as System 2?



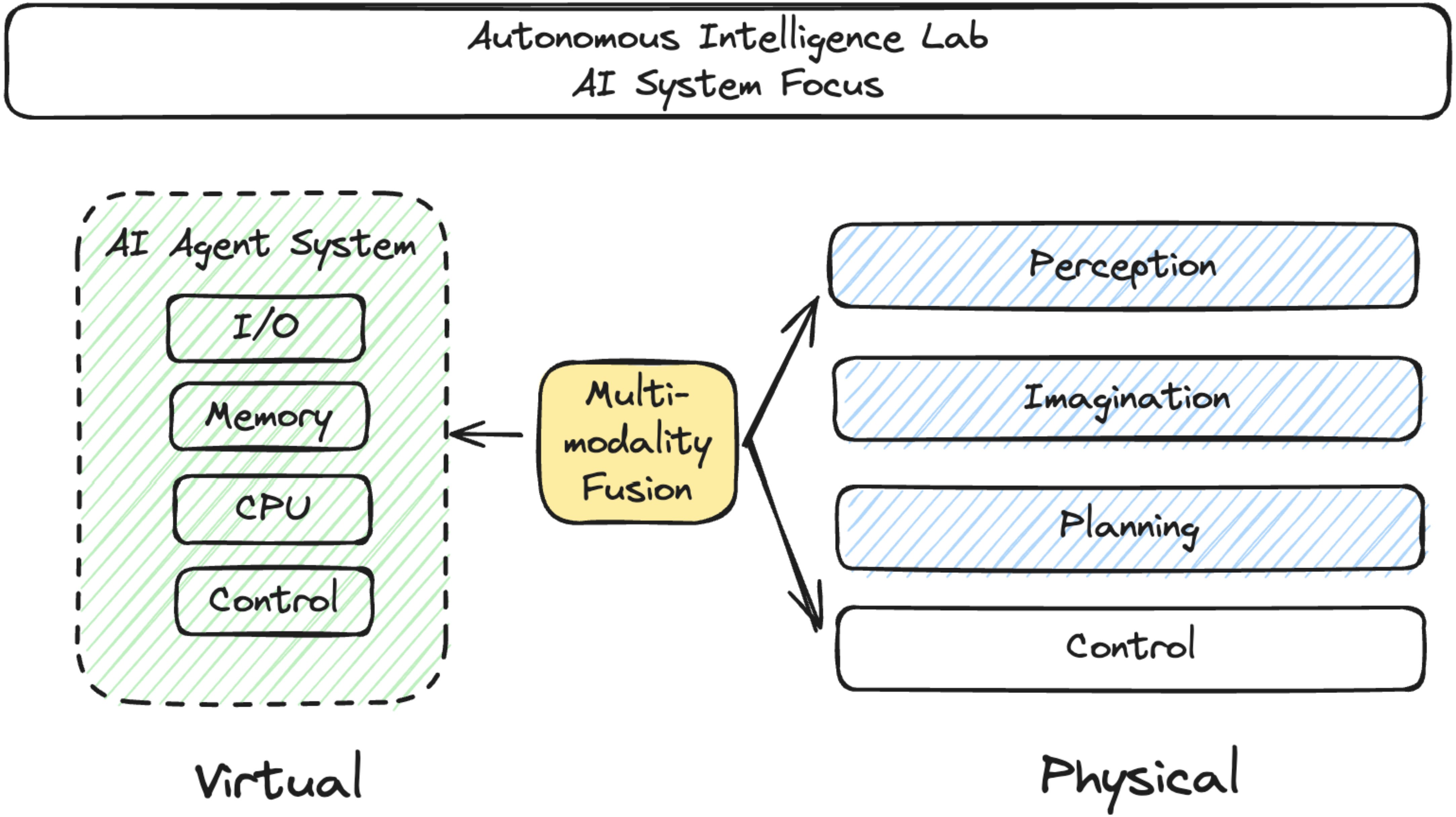
How MLLM interacts with the society: Our lab's approach



How MLLM interacts with the society: Our lab's approach

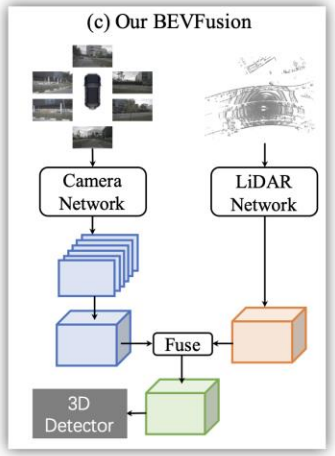


How MLLM interacts with the society: Our lab's approach

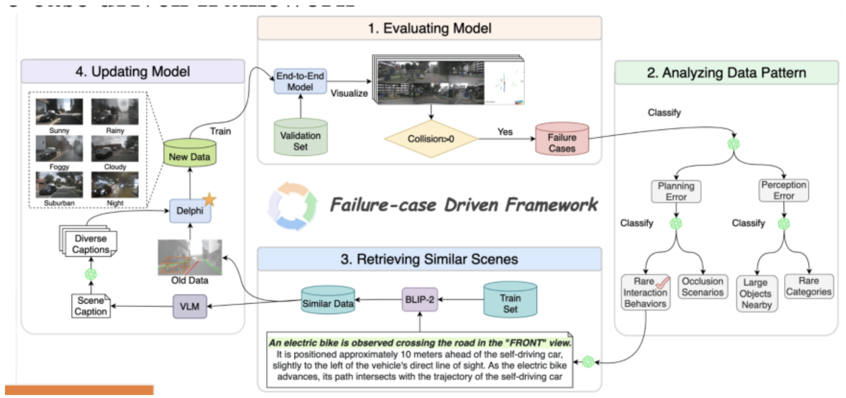


How MLLM interacts with the society: Our lab's approach

Autonomous Intelligence Lab
AI System Focus



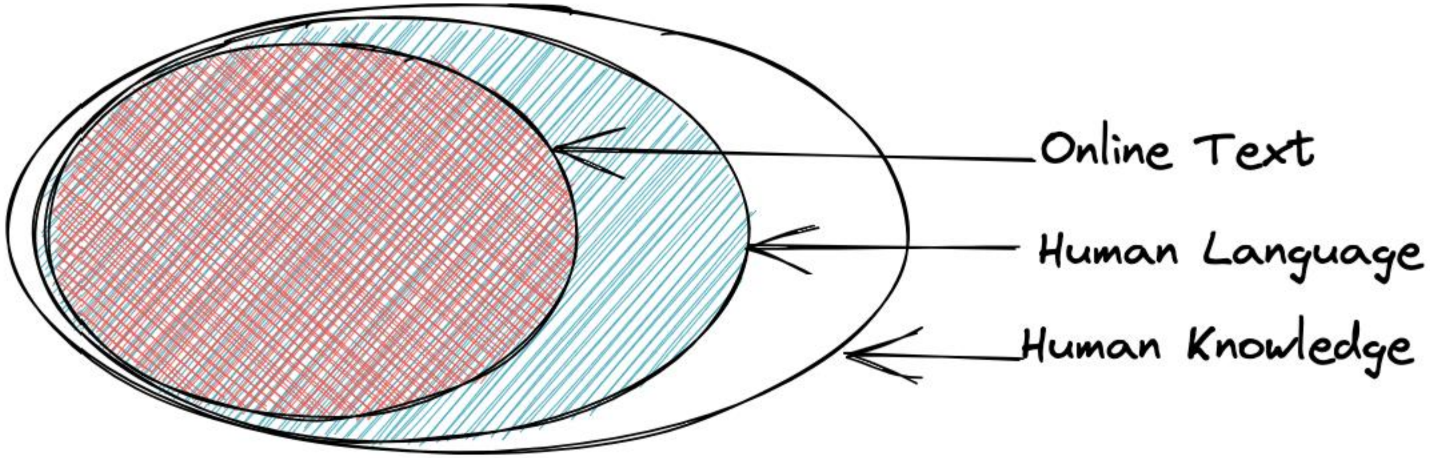
BEVFusion



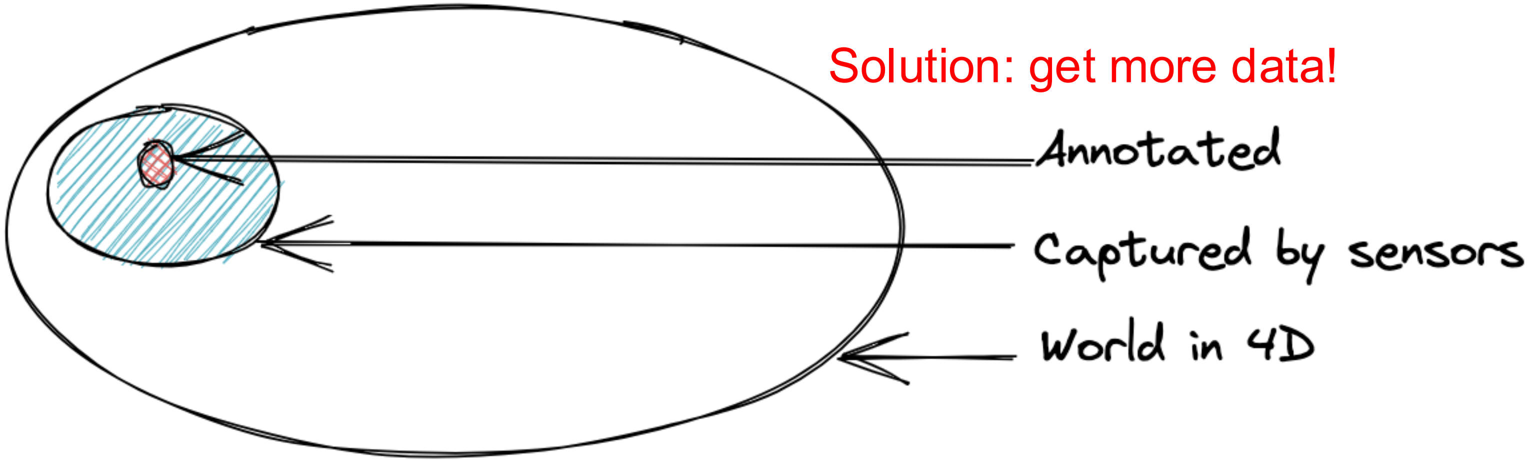
Closed-loop Data Engine to self-correct

Challenge: Lack of Sufficient 3D Data

NLP Knowledge

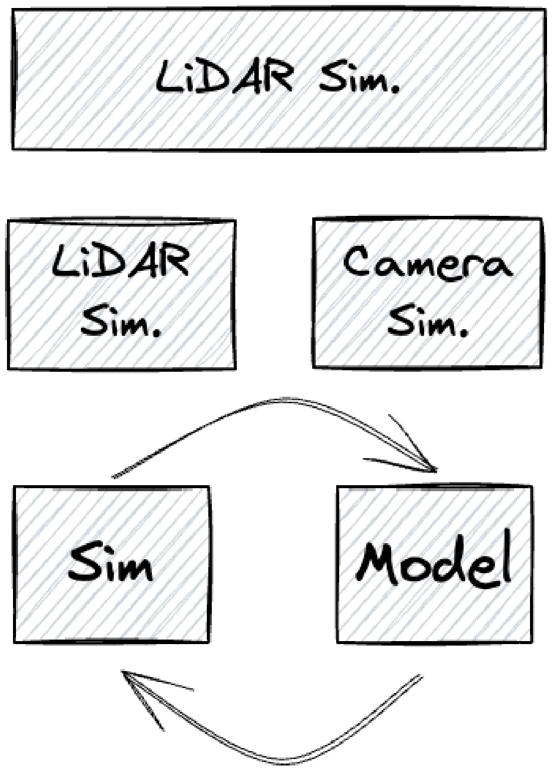


Visual Knowledge



Challenge: Perception Inevitably Fails when Lacking 3D Data

Work in Progress: Imagination via 3D Data Generation

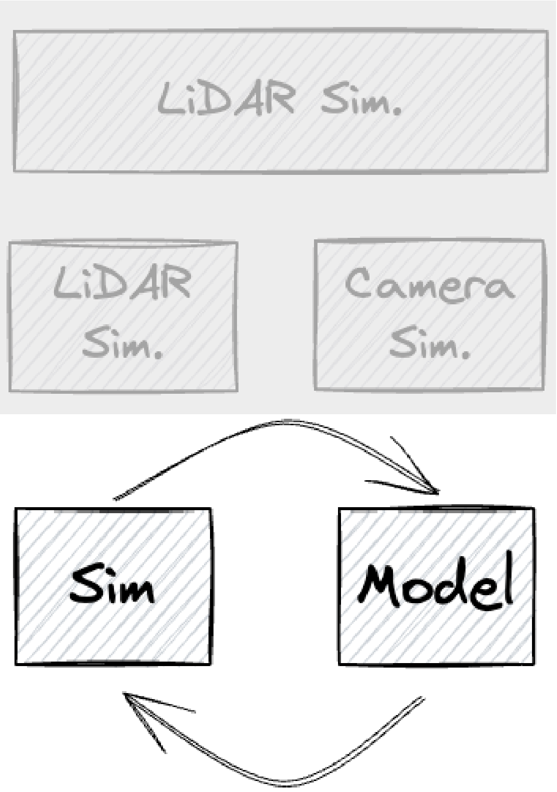


- LiDAR simulation via implicit rendering
- LiDAR + Camera in one NeRF
- Synt. Data -> Self-correct -> AD Perform.

Work in Progress: Imagination via 3D Data Generation

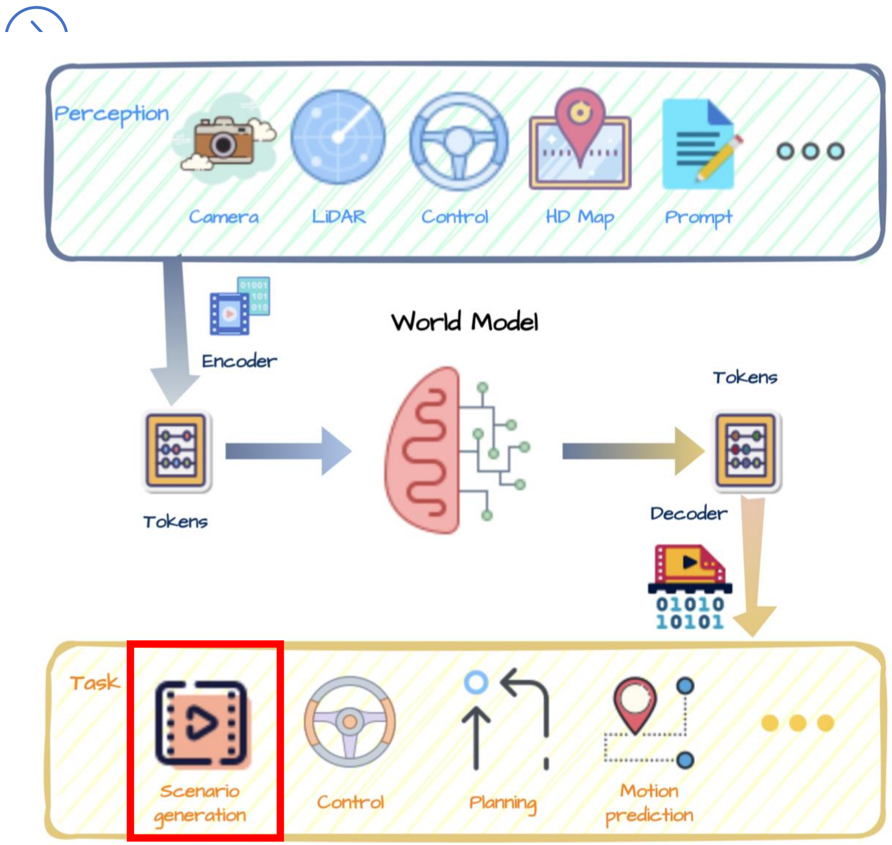
Imagination
Data synthesis

Long way to go

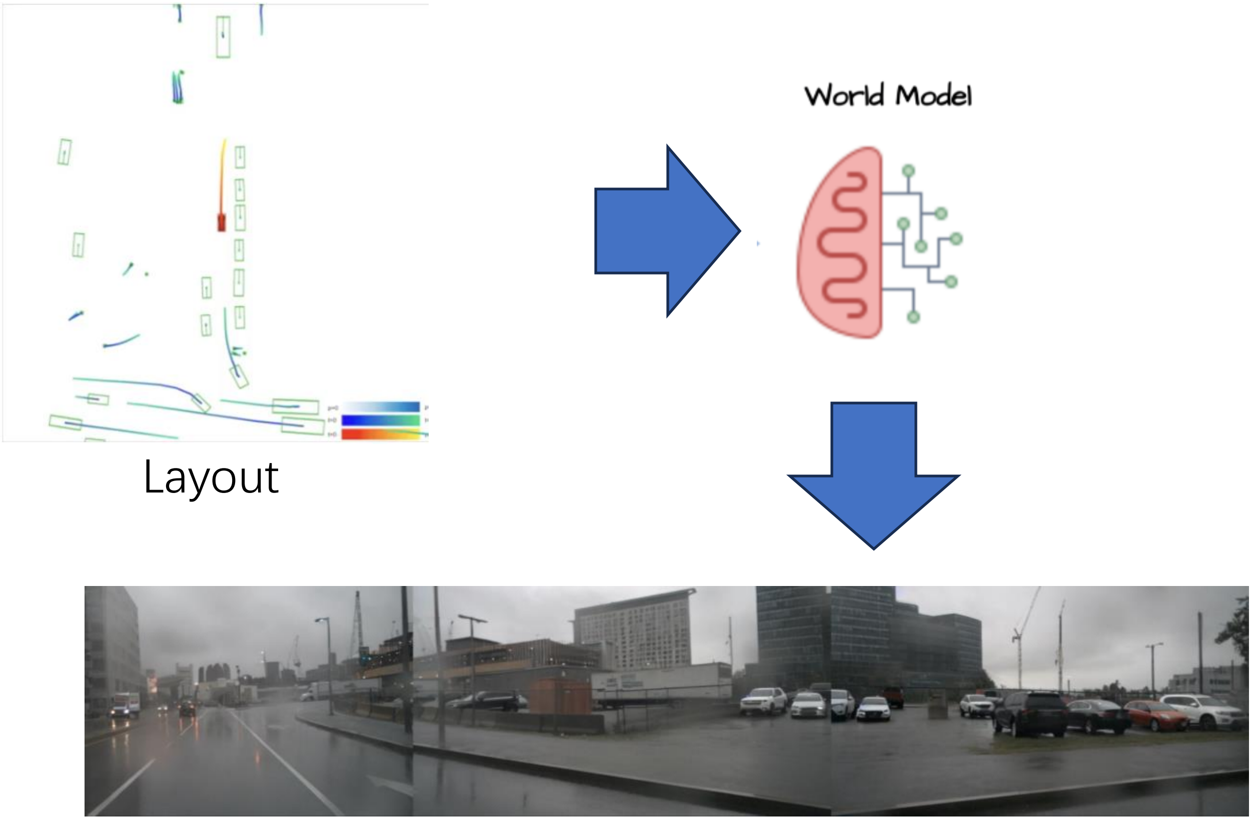


- LiDAR simulation via implicit rendering
- LiDAR + Camera in one NeRF
- Synt. Data -> Self-correct -> AD Perform.

MLLM in Real world: A World Model Approach

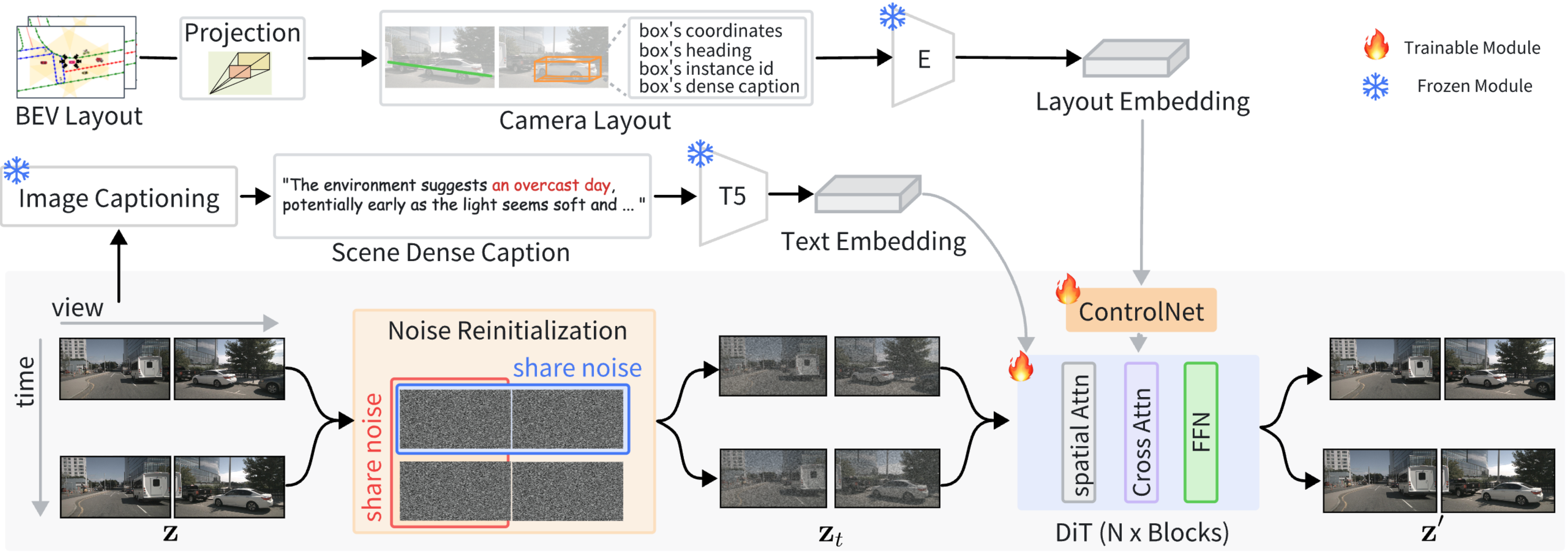


World Model in Autonomous Driving



Generated scene

Delphi: AD multi-view video generation model



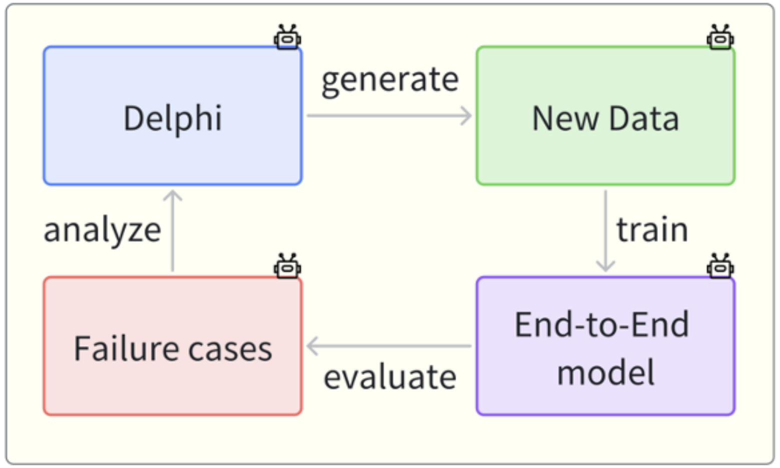
1 Rich multi-modal control information

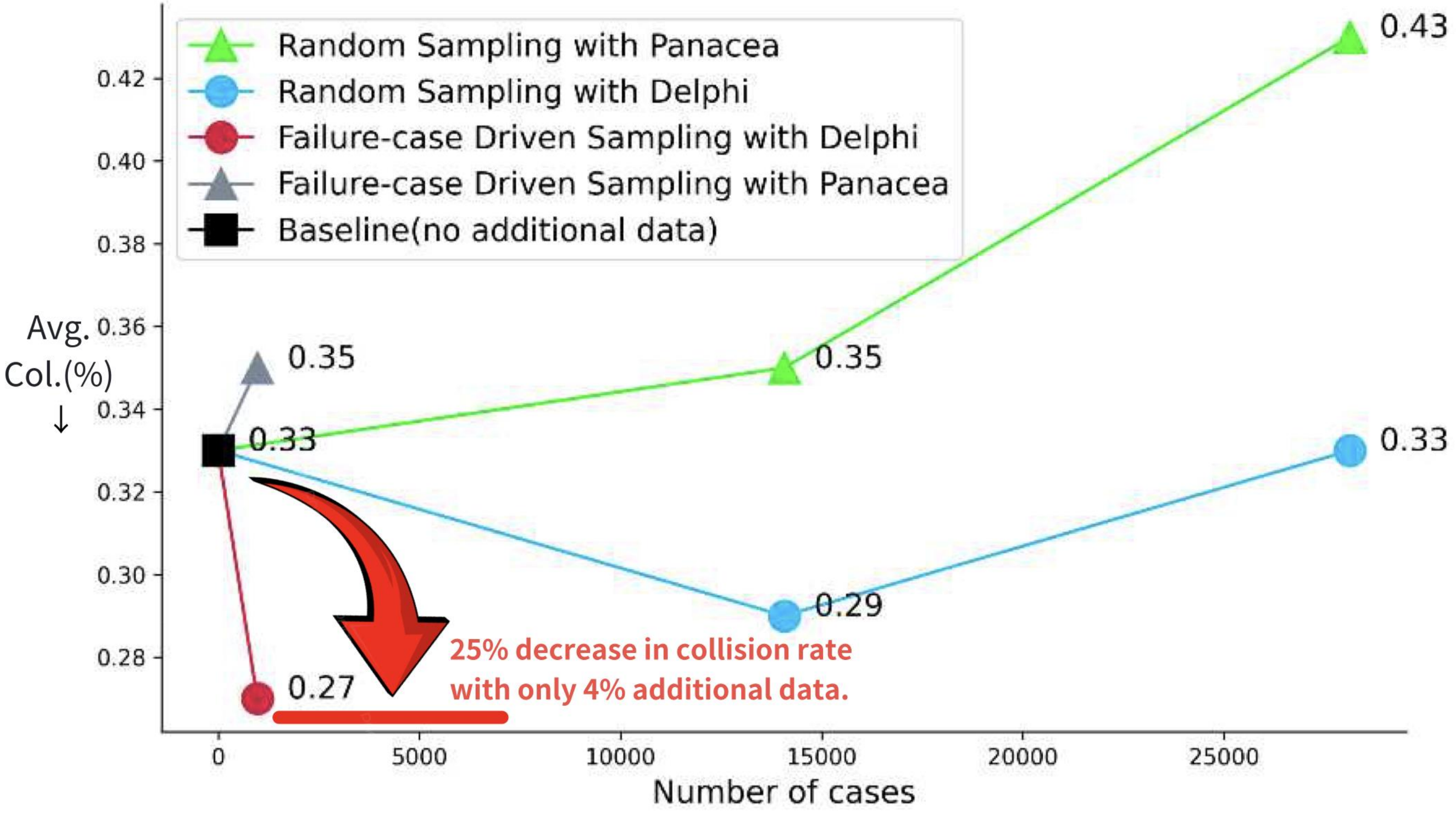
2 Noise Sharing modeling

3 Multi-view space-time interaction

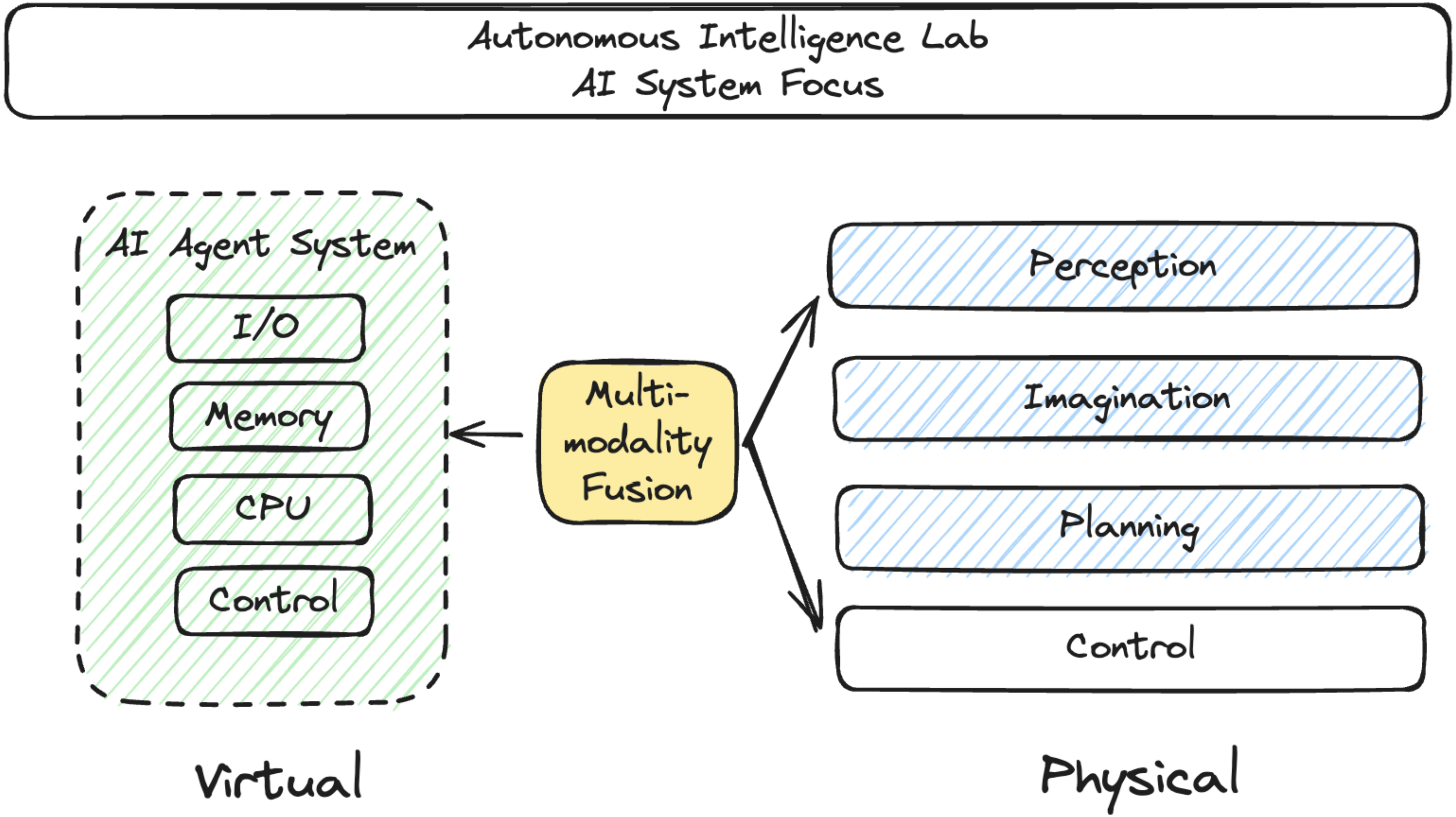
Long sequence generated results

A data engine to self-correct autonomous driving system



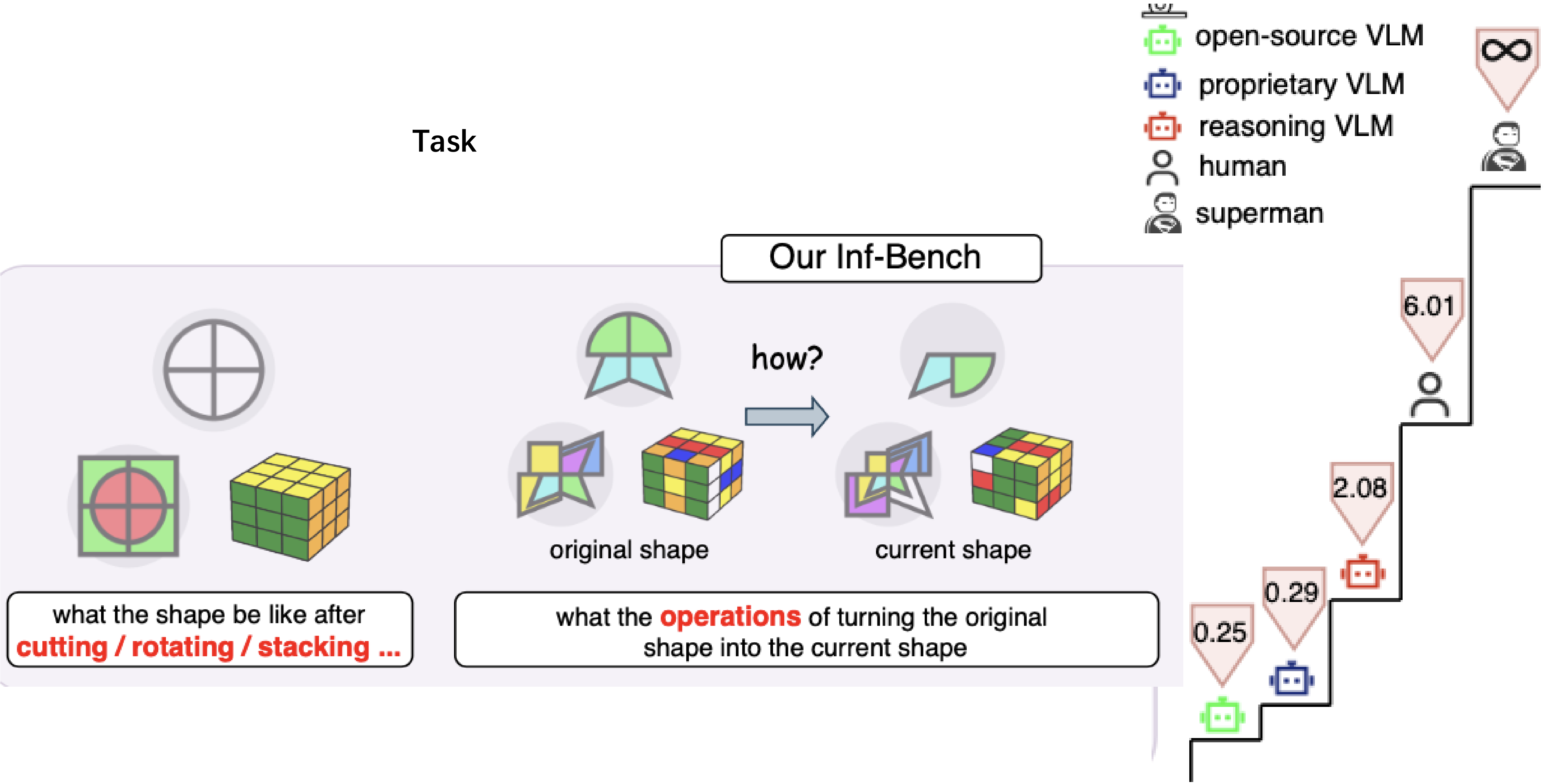


How MLLM interacts with the society: Our lab's approach

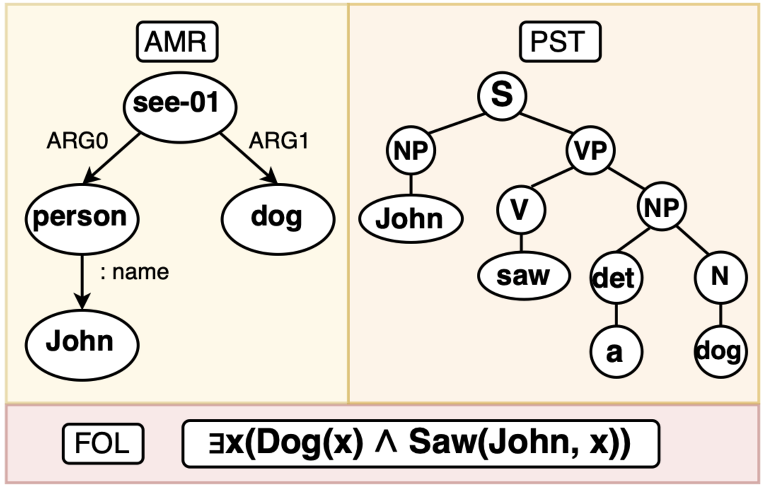


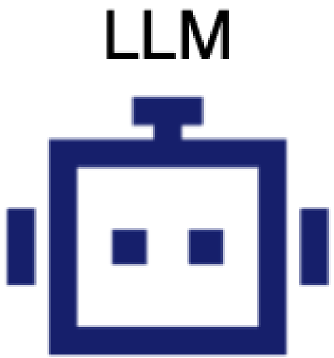
LLM: Fail to 'really' logical thinking in multi-modal

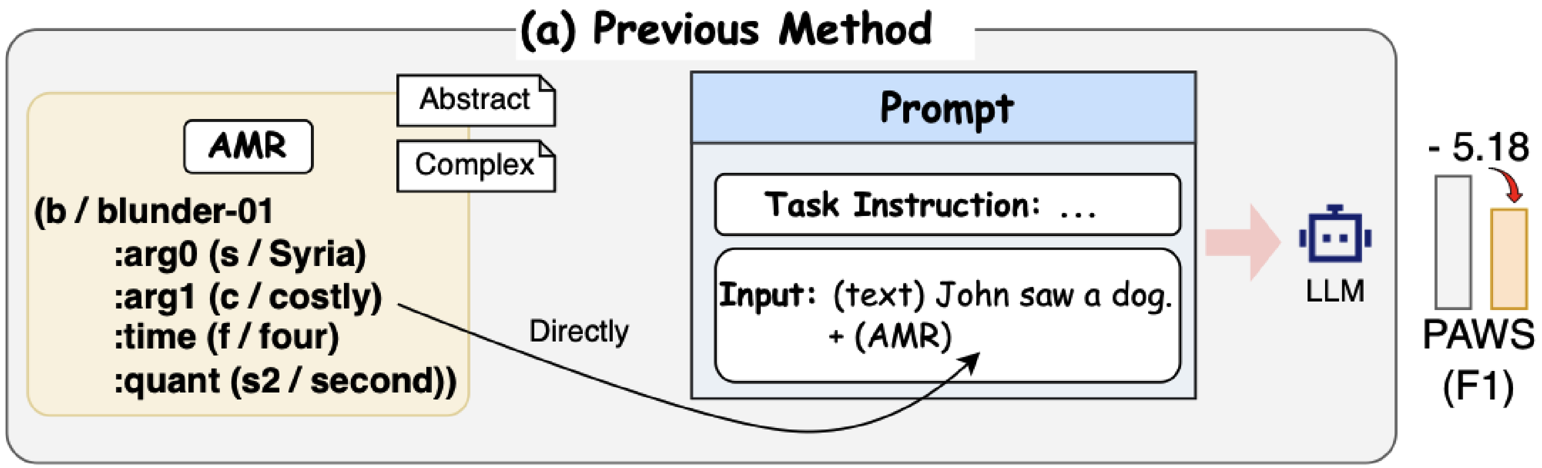
Task



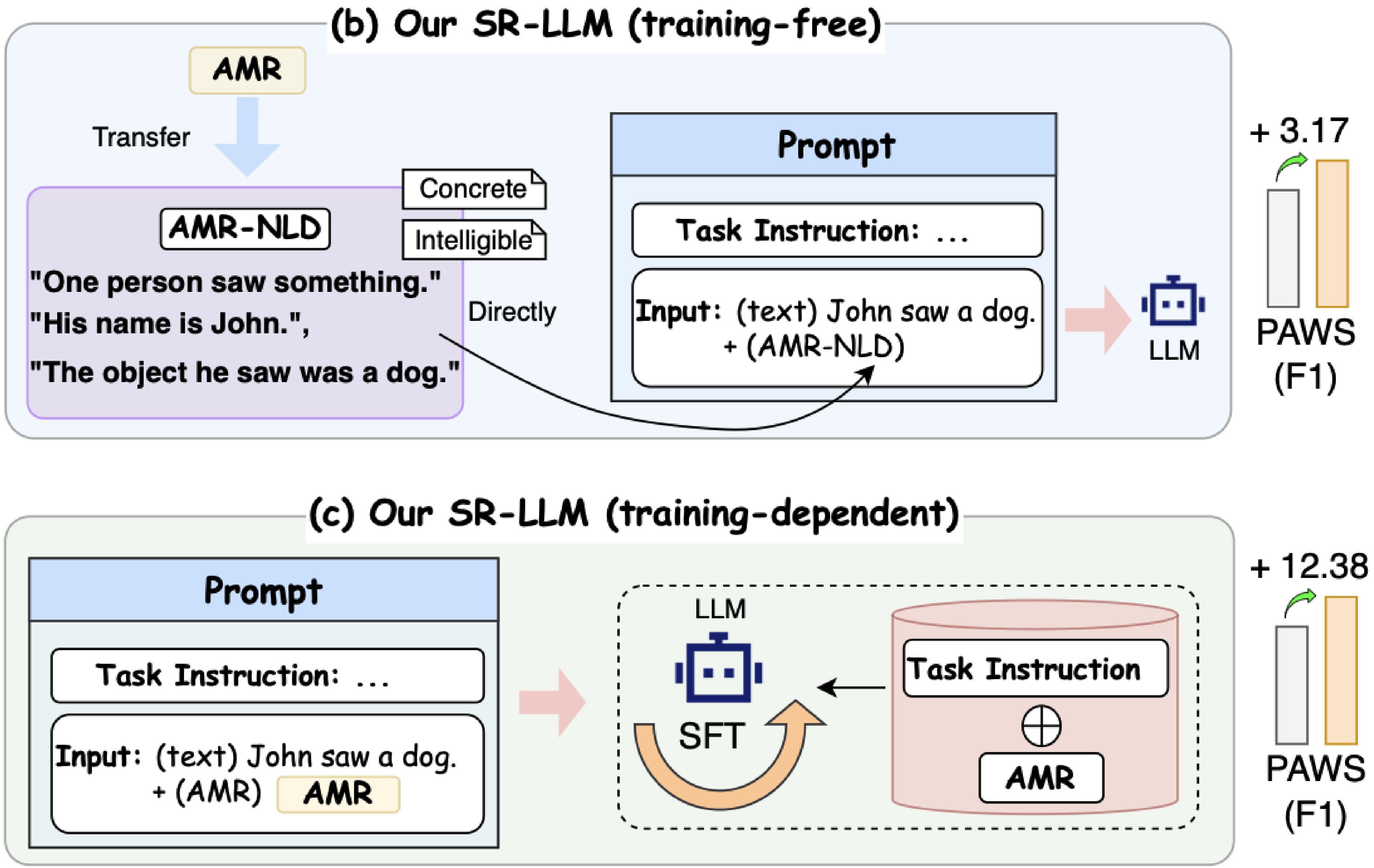
LLM + Structure Representation: A New Renaissance



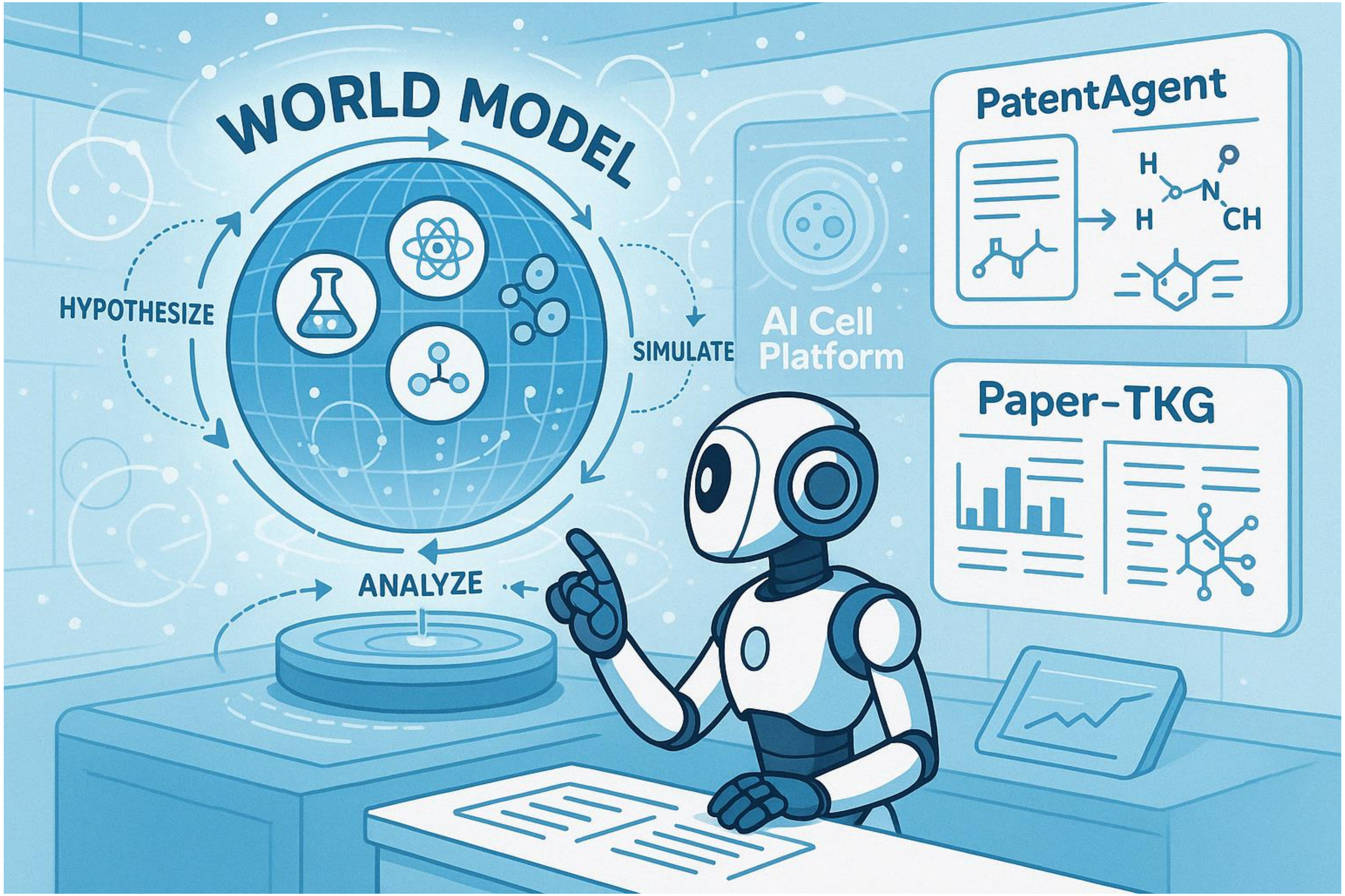




Structure Info Enhance the Reasoning



Future: Combine the knowledge for science discovery



Why Autonomous Intelligence?

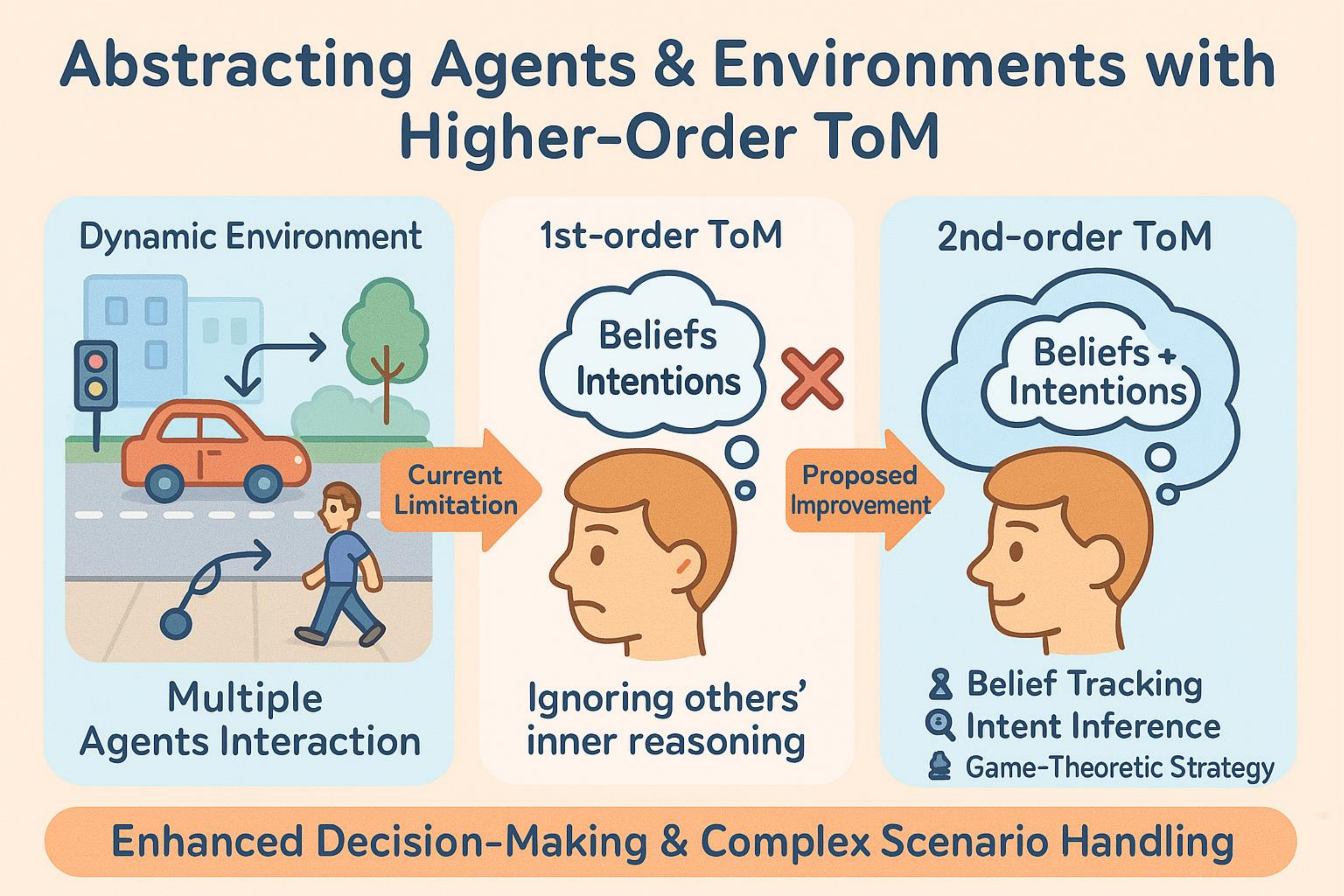
主流机器学习成就，依赖监督学习，在自动驾驶、具身智能数据是绝对瓶颈

机器目前来说，没有主动思考能力

对于人类20个小时的简单实操即可开车，但VLA算法几千小时的输入都不能泛化

我们期待：
结合认知心智理论、神经科学等科学研究，
实现规则驱动、增强机器学习系统的鲁棒和自主性

From Autonomous Driving to AI Agent



AutoLab:
We are hiring!

Position

- 博后 、 助理研究员
- PhD (26 Fall)
- 研究助理（全职）
- 访问学生

研究方向

- 认知驱动的AI 智能体行为研究
- 世界模型驱动的数据闭环联合优化
- 规则、知识驱动的大模型应用