Can AI technology mitigate the risk of AI?

2023.07.06

Kazuya TAKEDA, Nagoya University/TierIV

Overview

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- Data-centric approach to the driving behavior modeling
- AI Risk Management for L4 mobility services
- Opensource community and collaborative research

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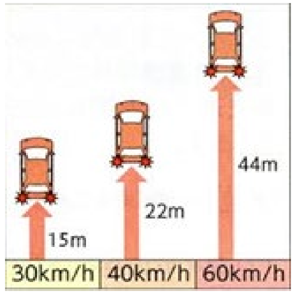
Signal processing and machine learning

Behavior Science and Digital Signal Processing

BF Skinner

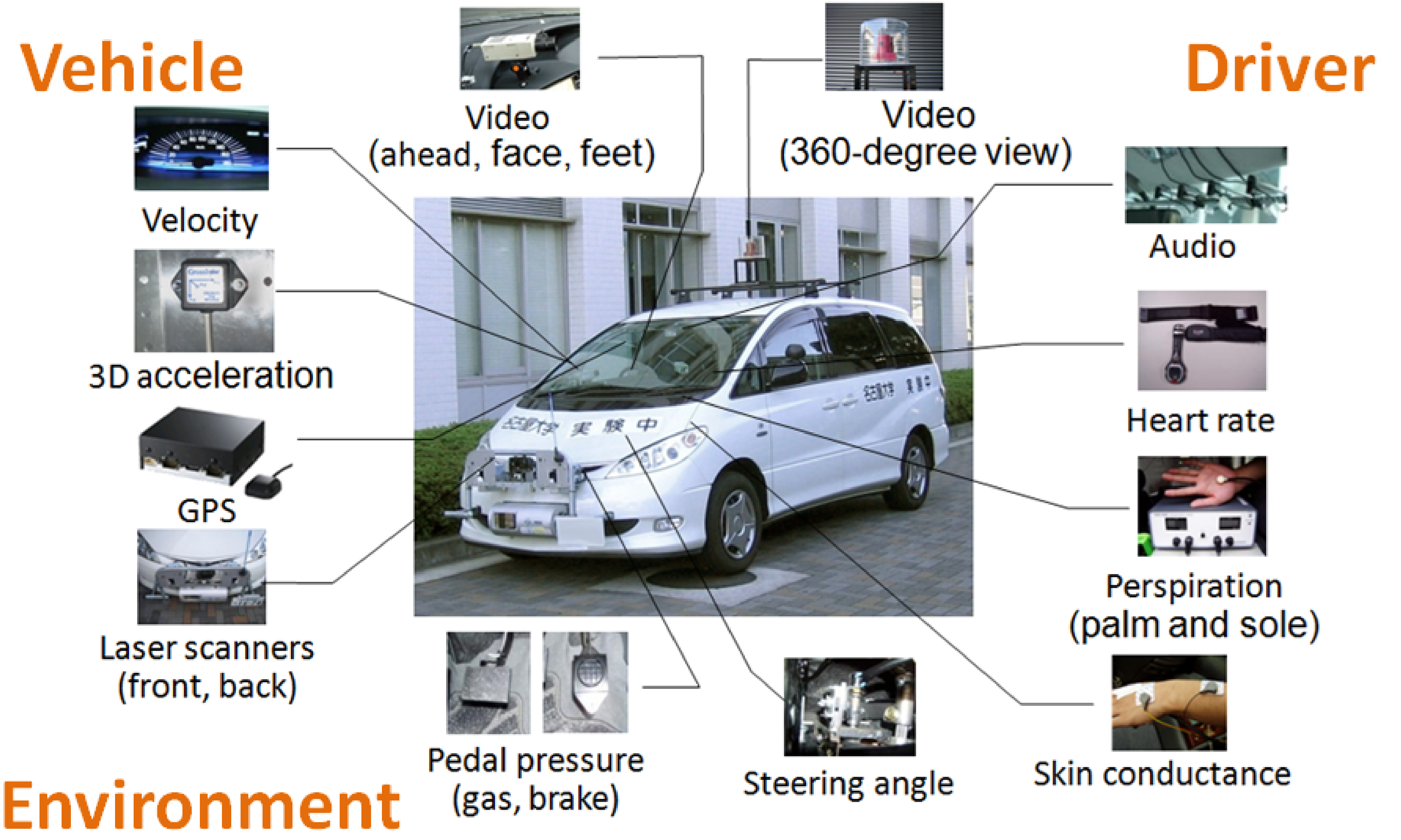
Environmental context → human → behavior

Three types of driving knowledge

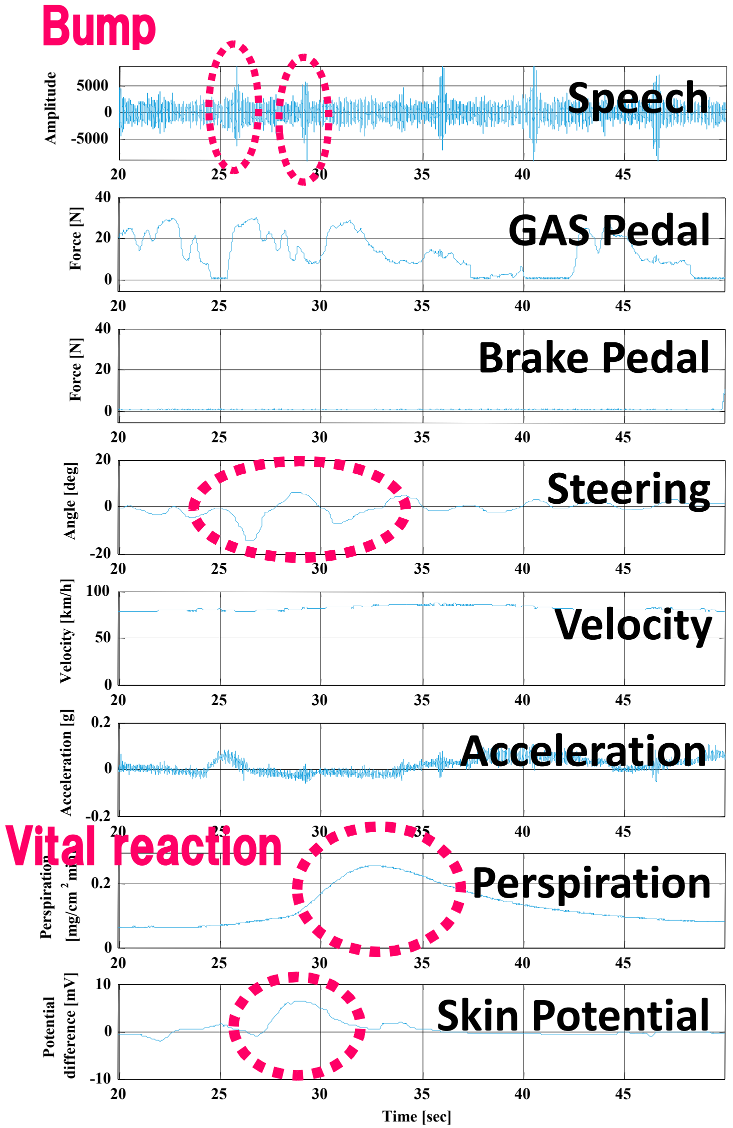


	Physical	Legal, Cultural (Societal)	Empirical (Personal)
Example variables	Location, Distances Velocity	Speed limit Priority lane	Subjective feelling Driver behavior
Form	Mathematical Forms ‘if-then’ rules	Text Data Distribution	Learning capability

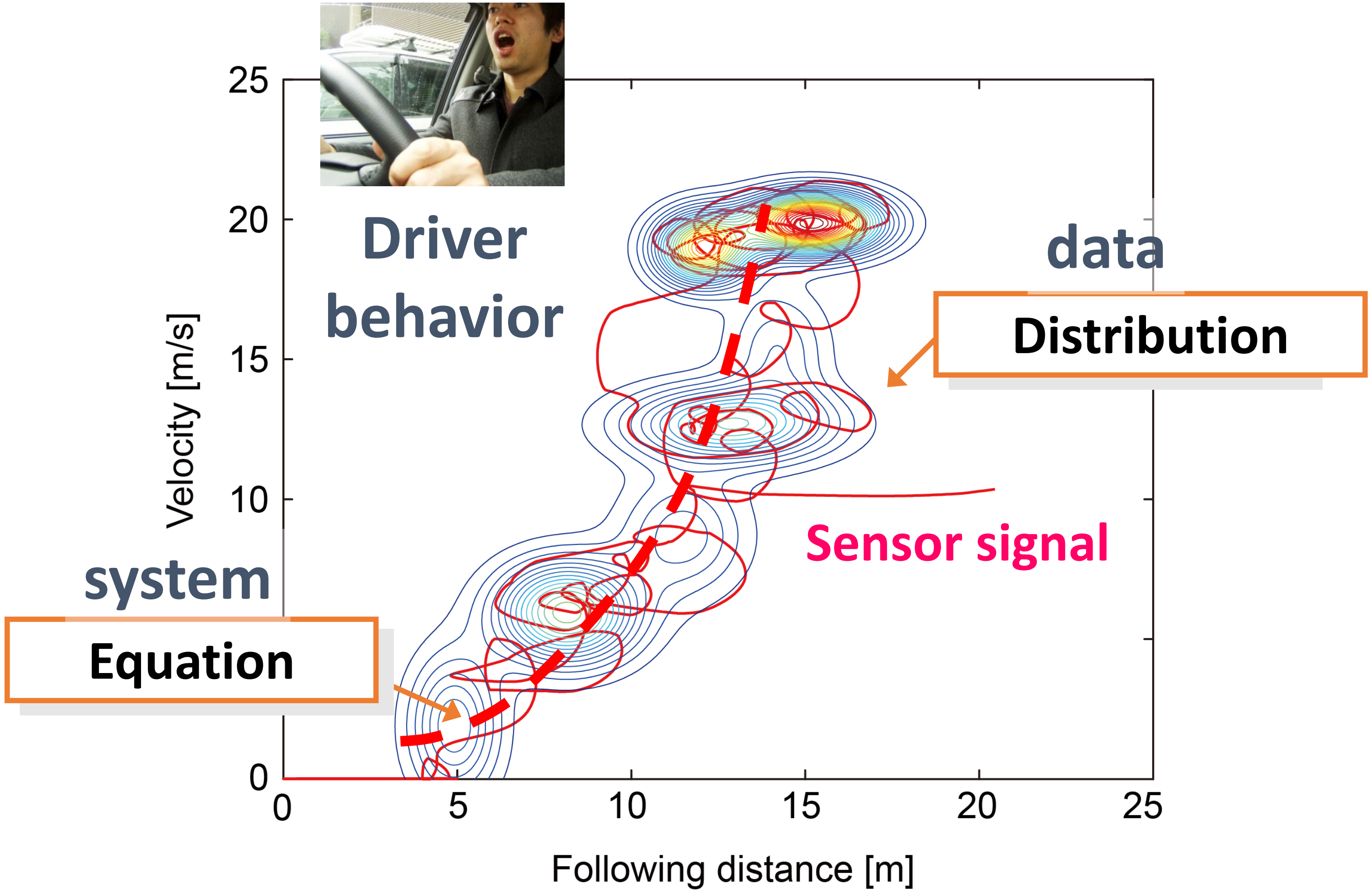
Data collection (1999-)



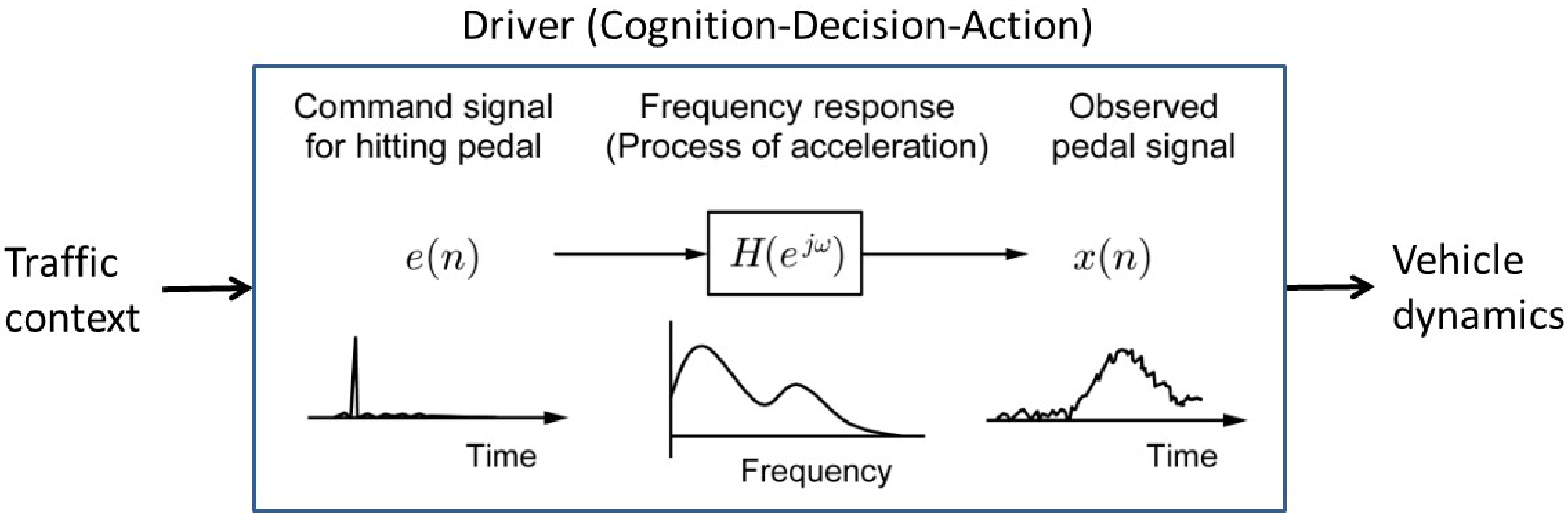
Signal Information of Driving



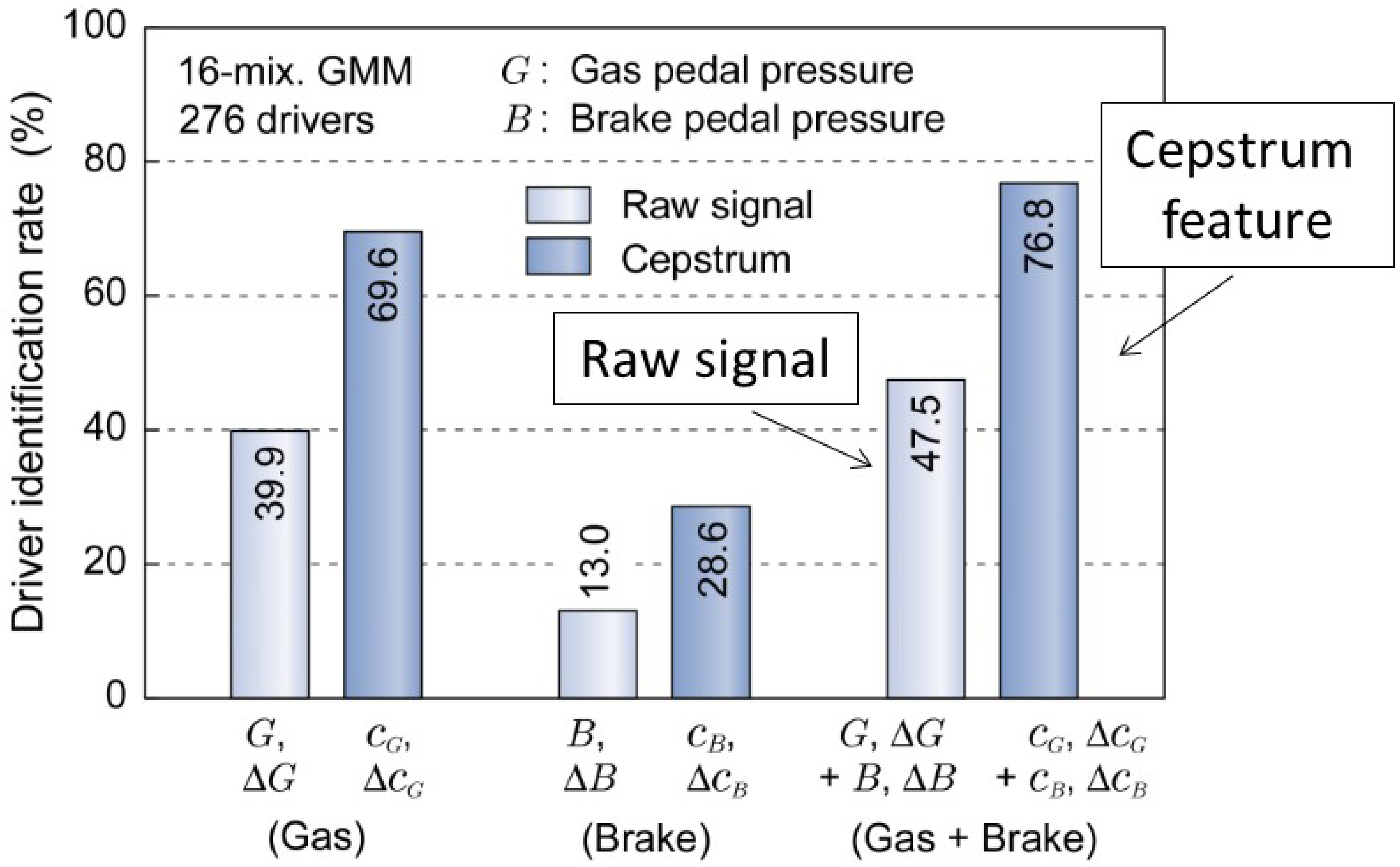
Data centric approach for driving behavior



Driver Identification through driving behavior



Driver identification results (2007, Miyajima)



Miyajima, Chiyomi; Nishiwaki, Yoshihiro; Ozawa, Koji; Wakita, Toshihiro; Itou, Katsunobu; Takeda, Kazuya; Itakura, Fumitada; ,Proceedings of the IEEE, vol.95,2,427-437,2007

Projects on driver behavior research

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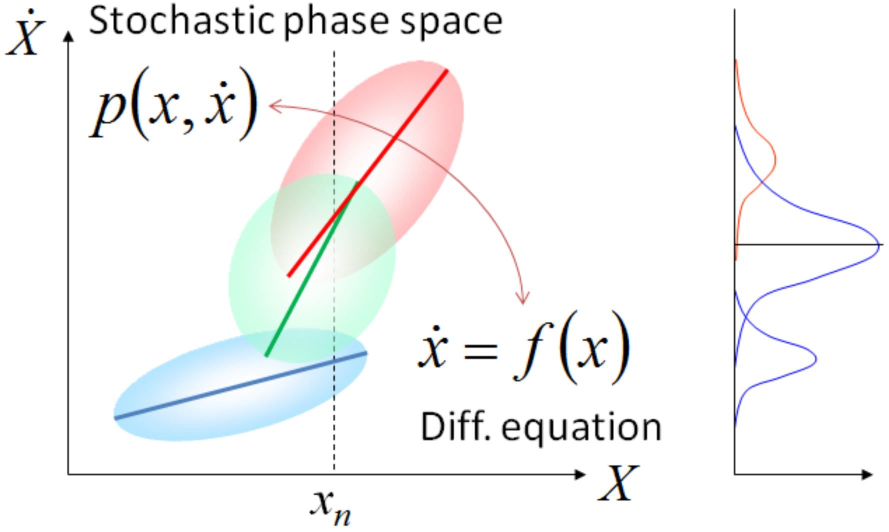
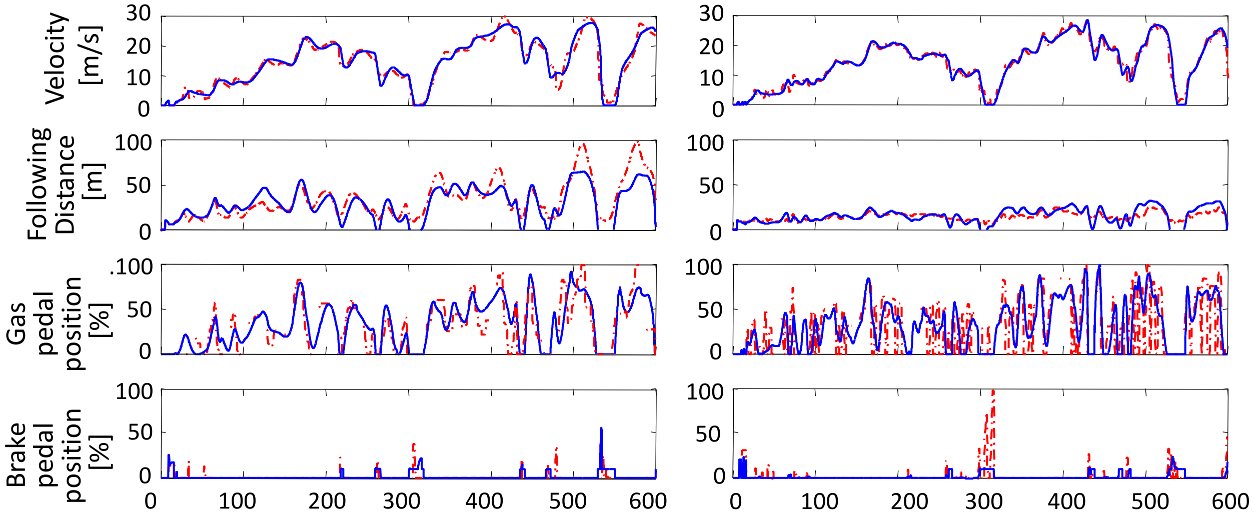
- Driver identification (GMM)
- Modeling car following behavior (GMM)
- Modeling lane-change trajectories (HMM+GMM)
- Detection of driver irritation (Bayesian network)
- Hazardous point detection from driving behavior
- Driver risk evaluation using event recorders
- Driving diagnosis and feedback system
- Driving data retrieval system
- Modeling driver gaze and vehicle operation (HMM)
- Tracking roadside signage observed by drivers
- Analysis of driver gaze behavior while automated driving
- Passenger anxiety detection using eye-blinking (Point process)
- Automated driving using deep leaning (CNN, RNN, AE, GAN, Transformer….)

Maximum likelihood prediction of driving behavior





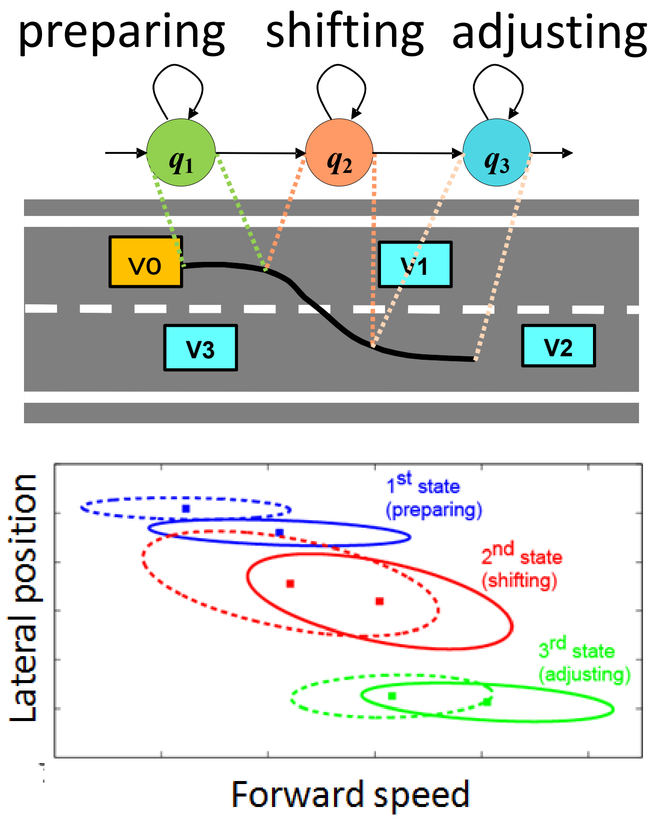
Driver A
(conservative driver)

Driver B
(tailgater)

$$\hat{x}_n = \underset{x_n}{\operatorname{argmax}} P(x_n | x_{n-1}) = \underset{x_n}{\operatorname{argmax}} P(x_{n-1}, \underbrace{x_n - x_{n-1}}_{\approx \dot{x}})$$

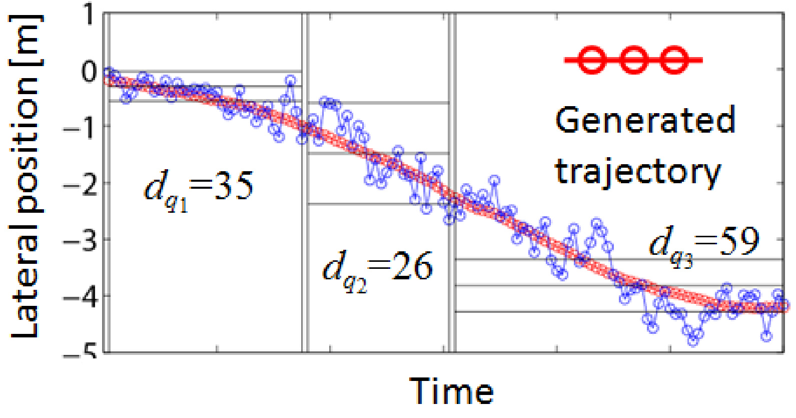
Nishiwaki, Yoshihiro; Miyajima, Chiyomi; Kitaoka, Norihide; Itou, Katsunobu; Takeda, Kazuya; ,2007 IEEE Intelligent Vehicles Symposium, vol.,,823-827,2007

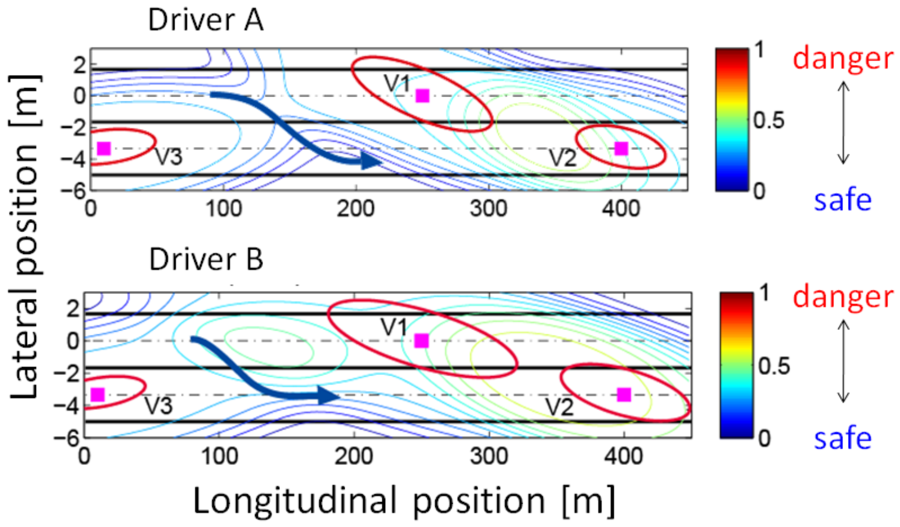
Extending to lane change behavior



Trajectory model (HMM)

Sampling

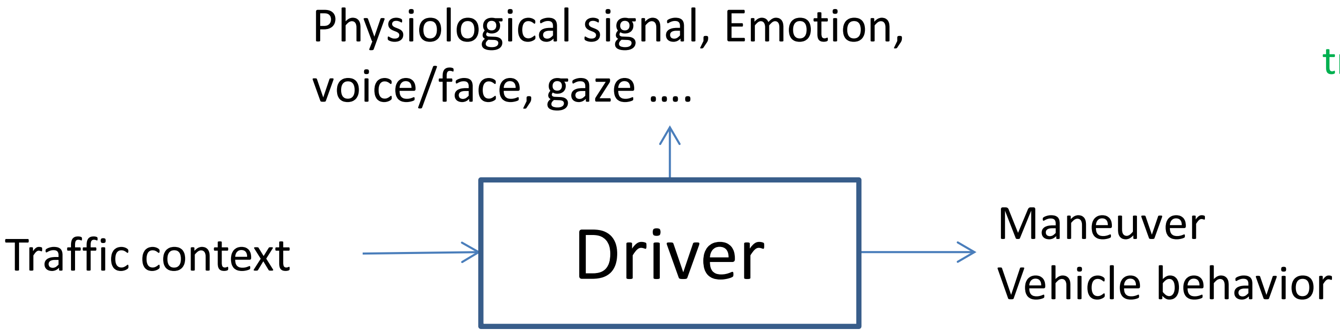


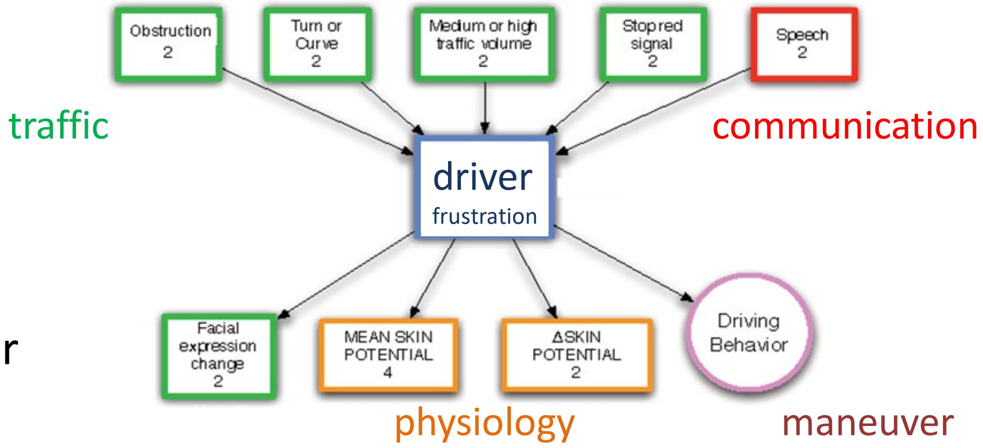


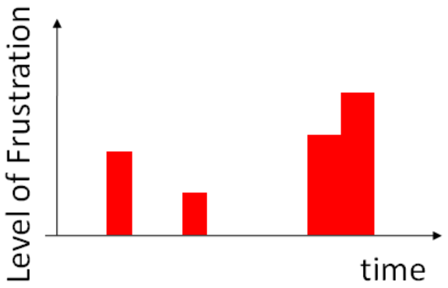
Personalized safe map

Nishiwaki, Yoshihiro; Miyajima, Chiyomi; Kitaoka, Hidenori; Takeda, Kazuya; ,2009 IEEE international conference on Acoustics, Speech and Signal Processing, vol.,,1377-1380,2009

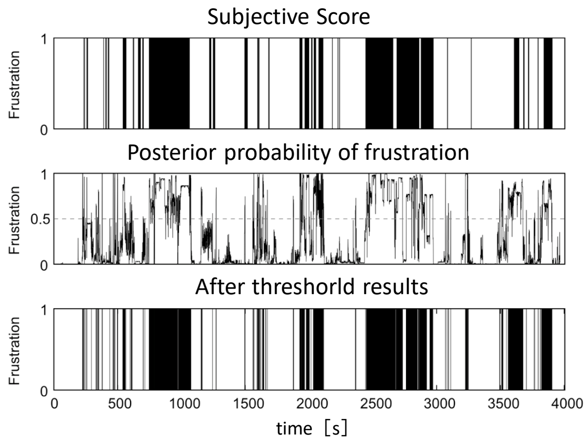
Estimating driver's mental status

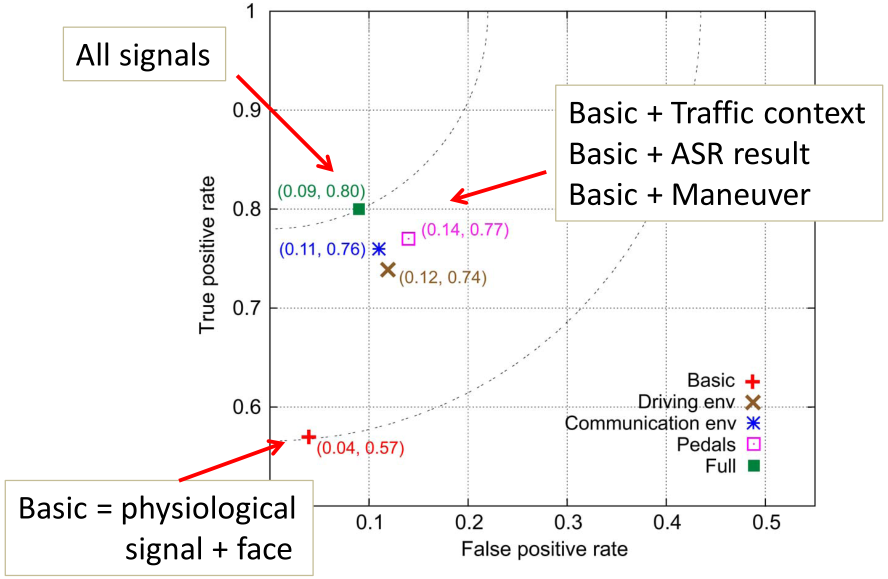






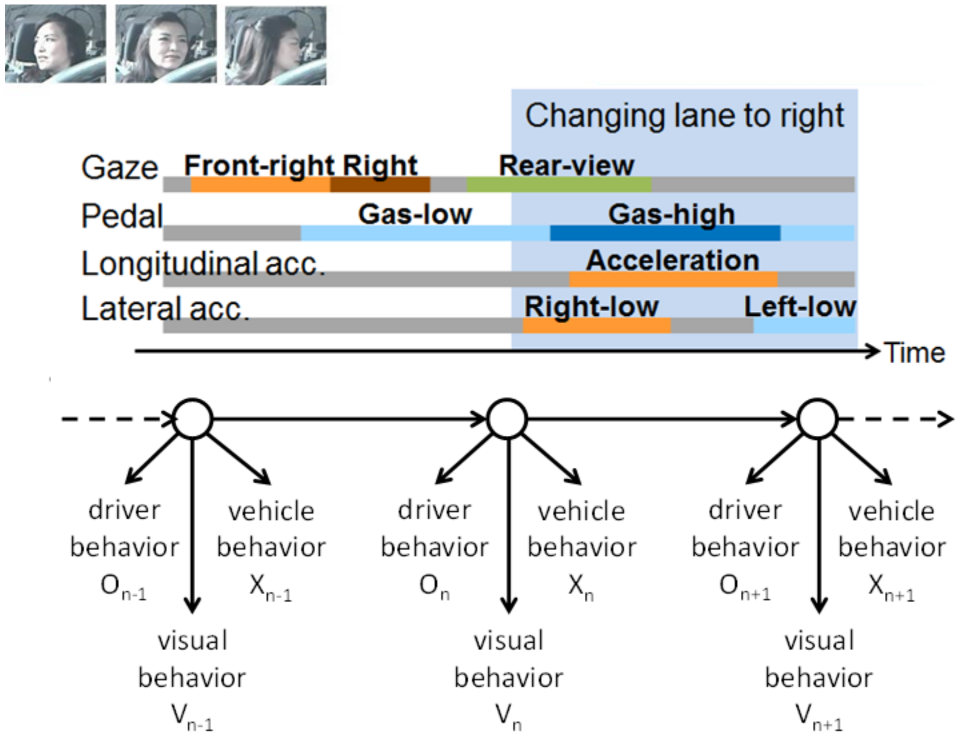
80% accuracy（with 9% false alarm）

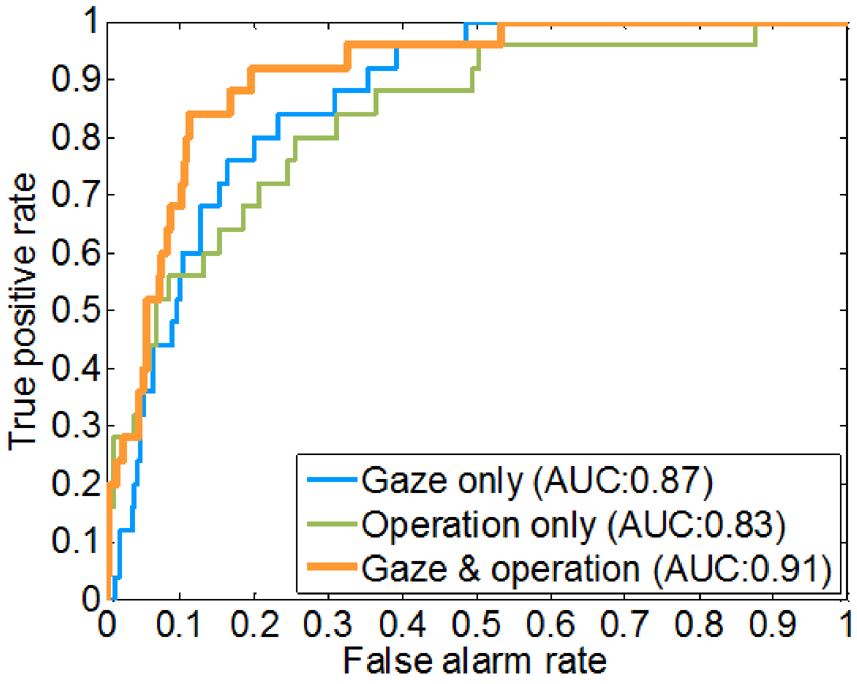




Malta, Lucas; Miyajima, Chiyomi; Takeda, Kazuya; ,IEEE Transactions on Intelligent Transportation Systems, vol.10,2,201-210,2009

Visual behavior as a key of inattentive driving

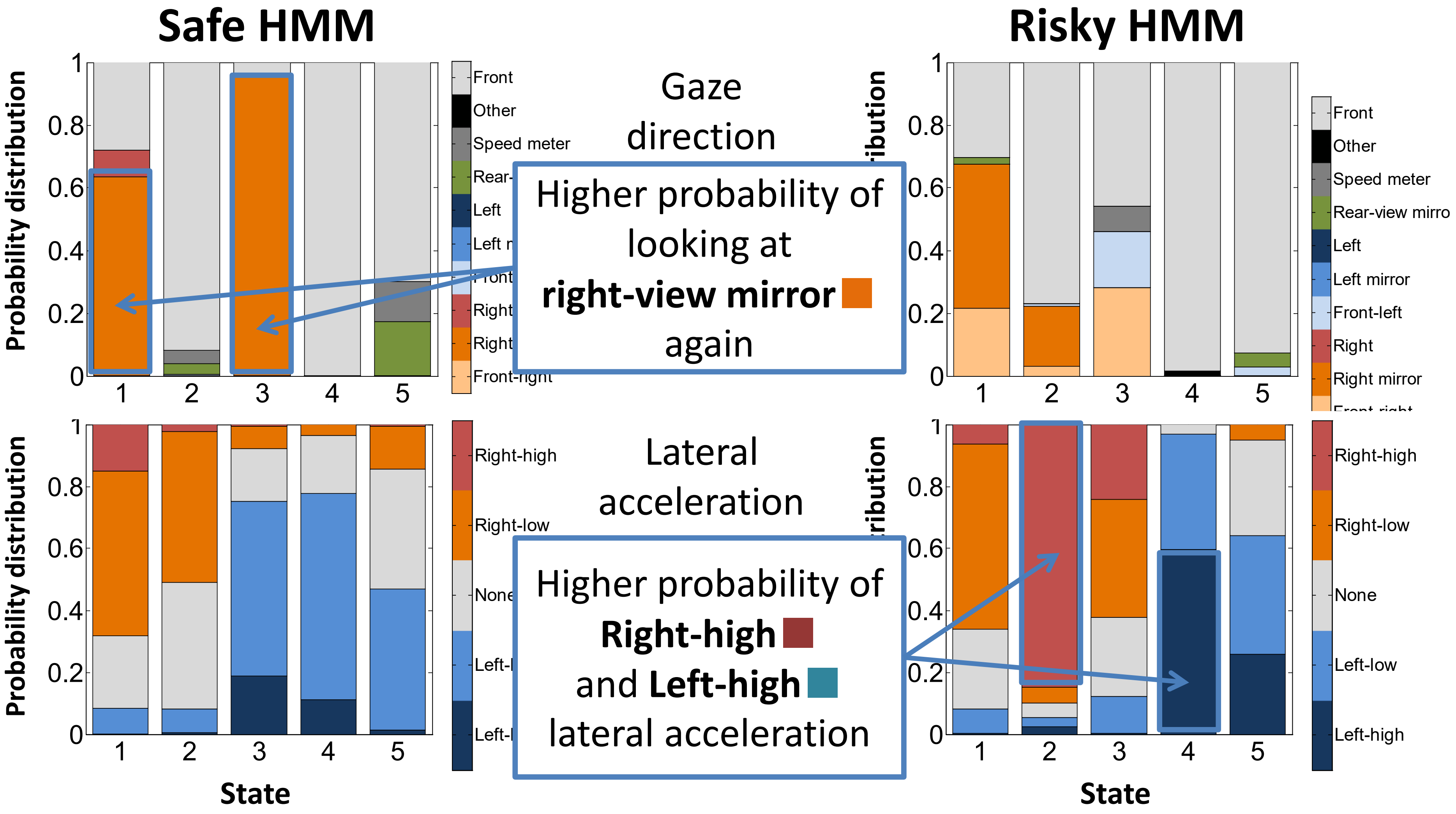




Accuracy of Detecting 5% Risky Lane Change

Mori, Masataka; Miyajima, Chiyomi; Hirayama, Takatsugu; Kitaoka, Norihide; Takeda, Kazuya; ,Intelligent Transportation Systems-(ITSC), 2013 16th International IEEE Conference on, vol.,,2020-2025,2013

Visual behavior of Risky/Safe lane change

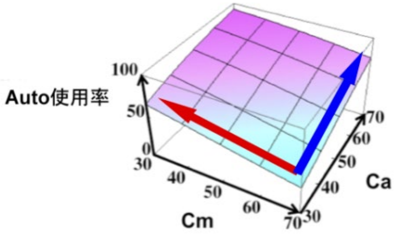


Excessive trust of the auto-driving

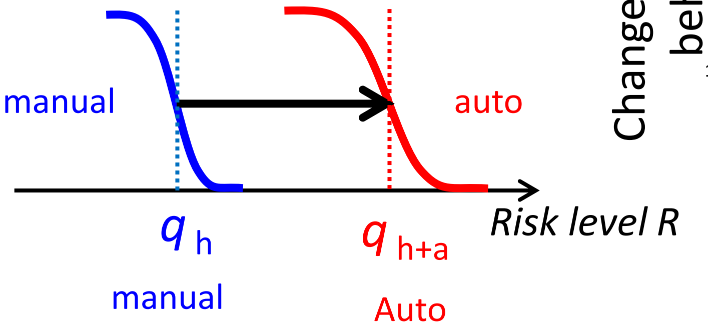
Excessive trust

Preference of AD

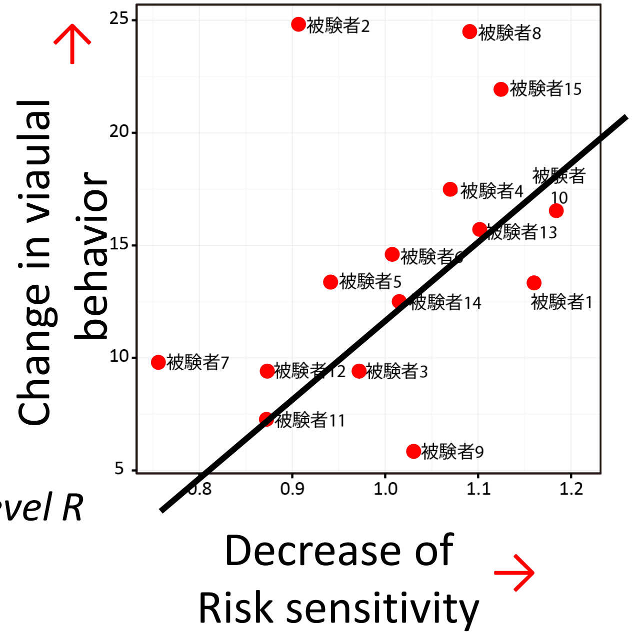
Degree of misuse



Exp. psychology model

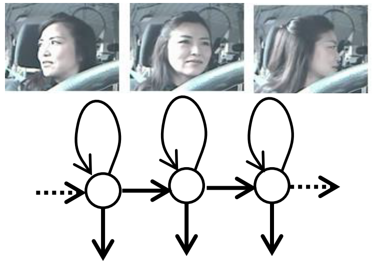


less sensitivity

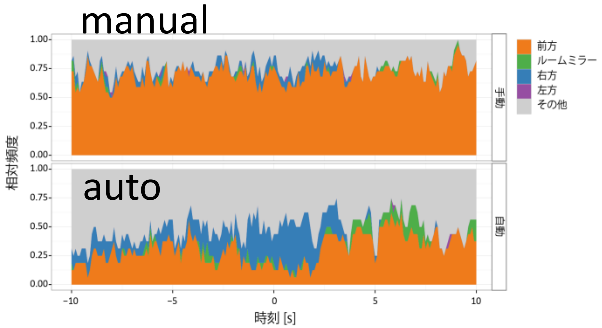


Gaze behavior

likelihood

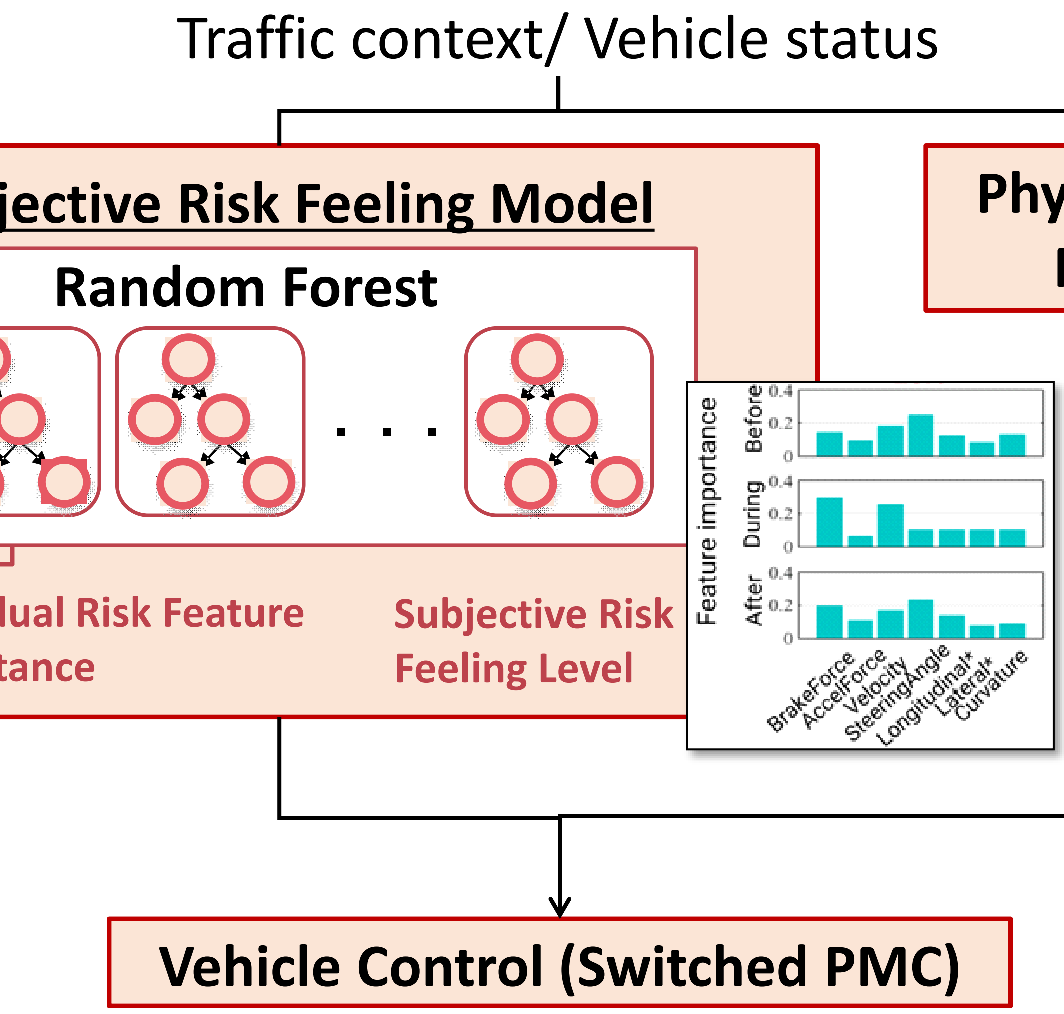


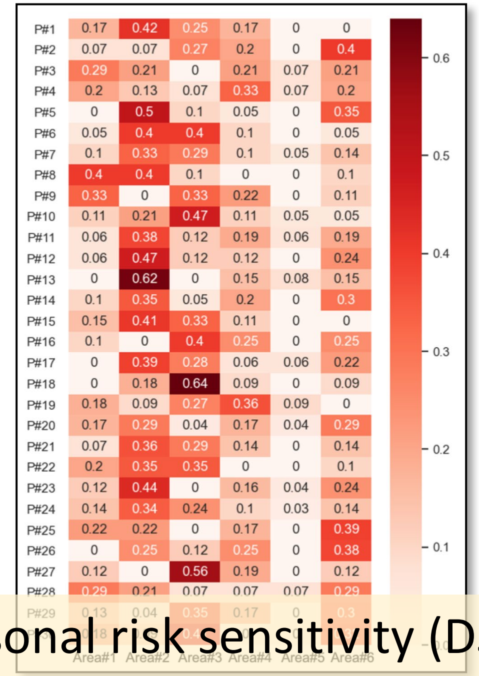
Behavior signal model



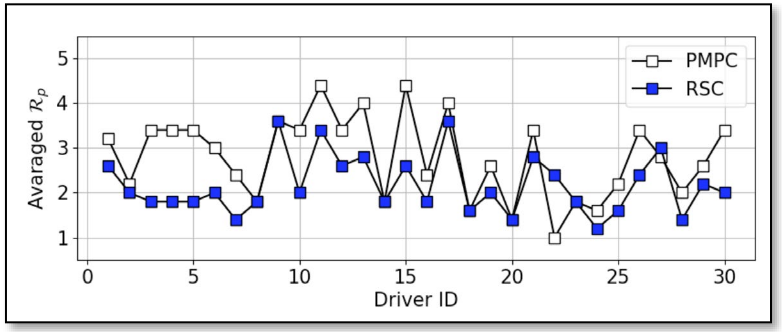
Discrepancy from manual

Personalized Safety-focused Control of AD





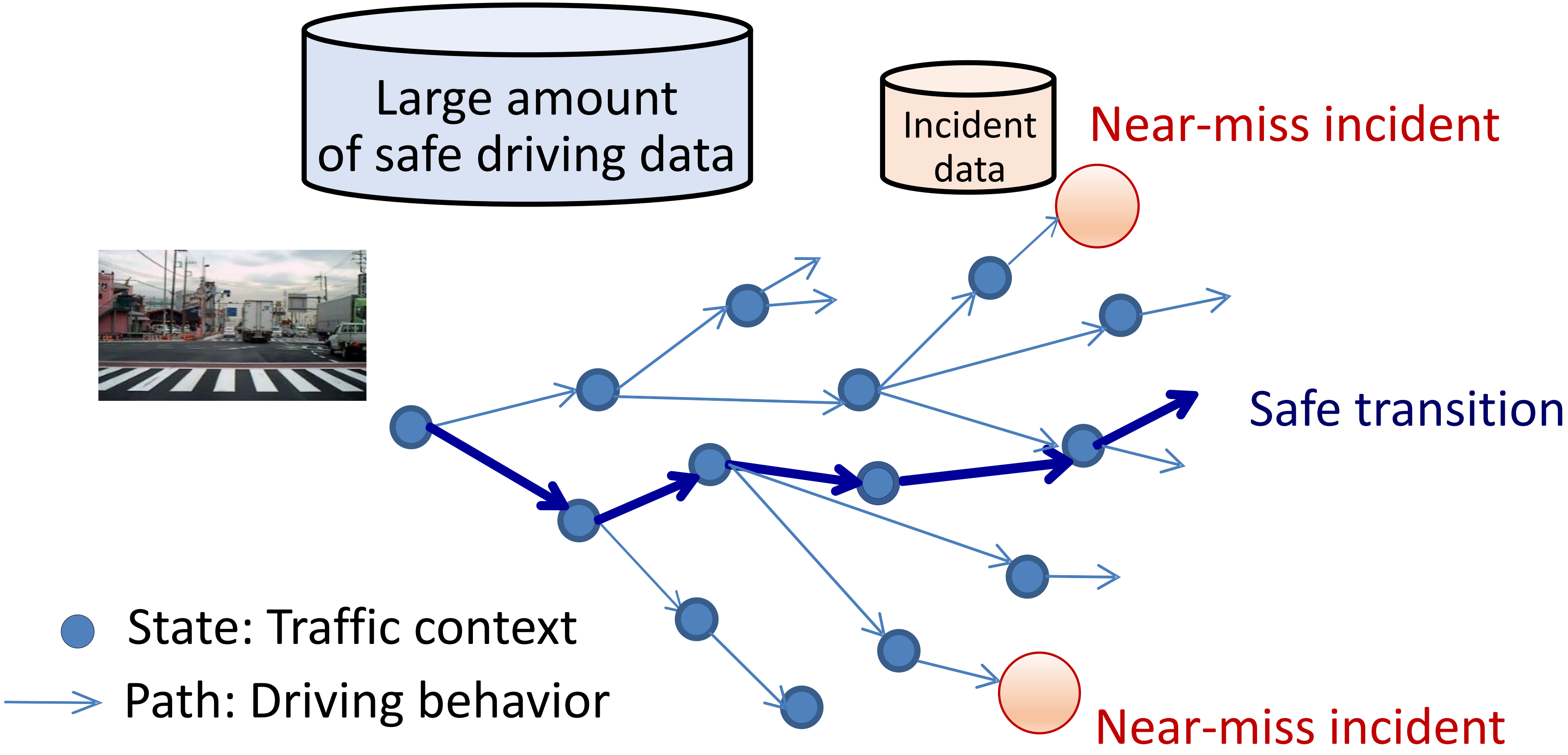
Personal risk sensitivity (DS study)



Reduction of perceived risk

Bao, Naren; Yang, Dongfang; Carballo, Alexander; Özgüner, Ümit; Takeda, Kazuya; ,2019 IEEE Intelligent Transportation Systems Conference (ITSC), vol.,,3853-3858,2019

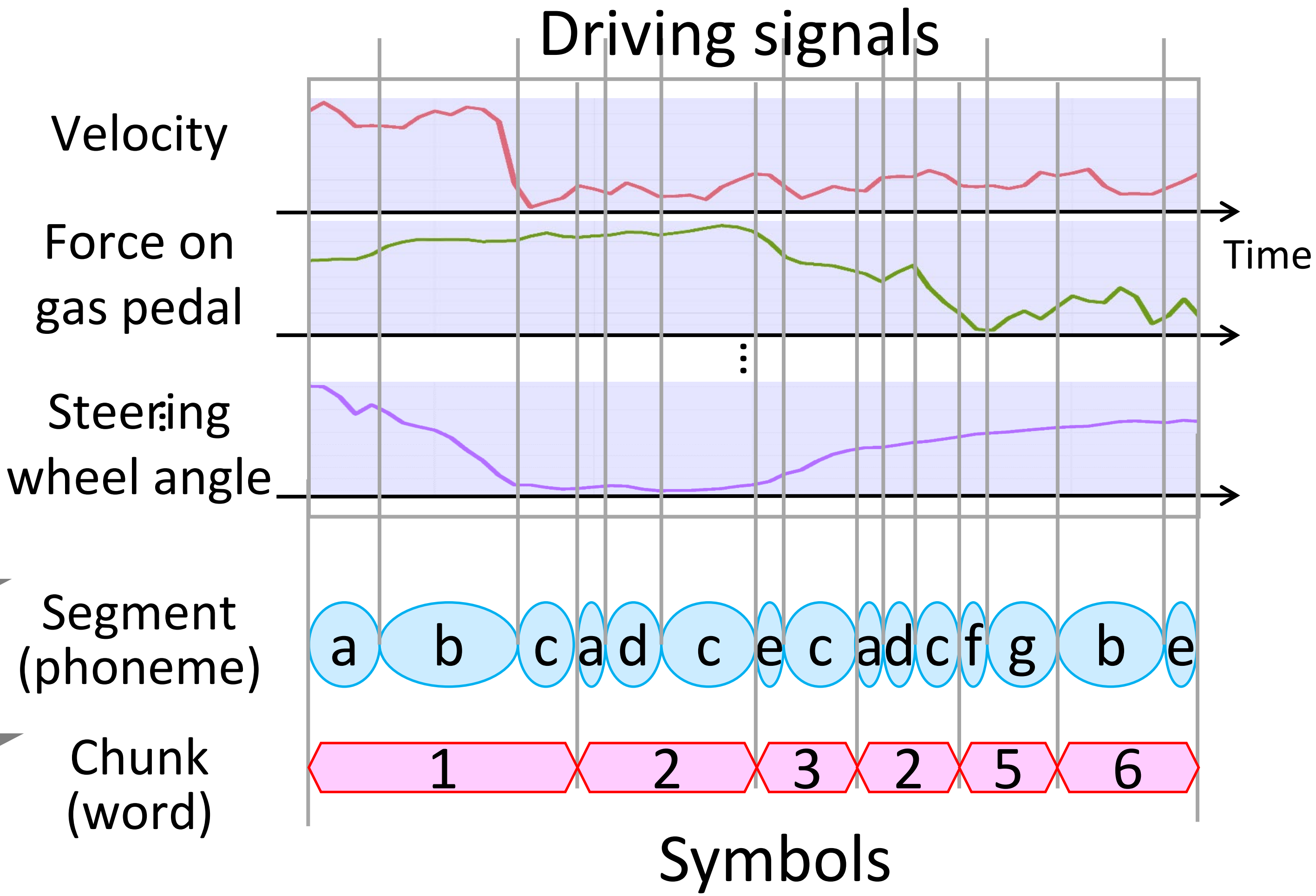
Does machine learning work for general traffic?



- Defining the set of states for general traffic is the central issue.

Takeda, "Data to Value through Real World Data Circulation," In the 2015 ITS World Congress, Context Network

Signal Symbolization



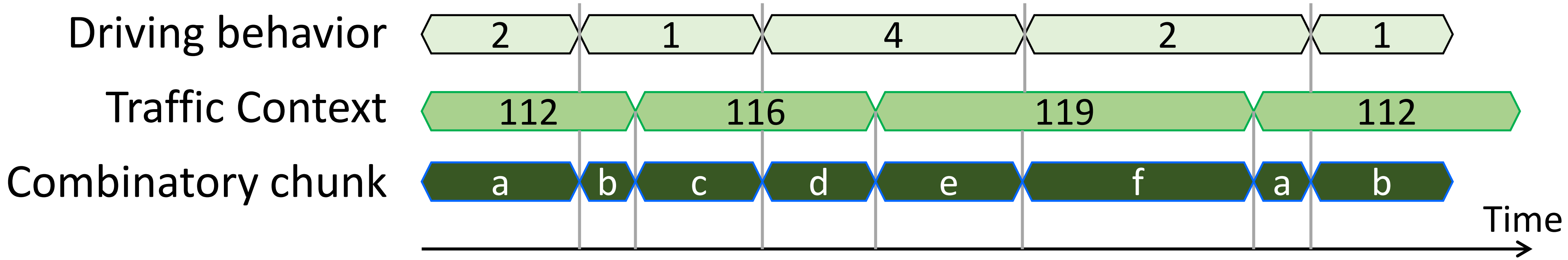
HDP (hierarchical Dirichlet process) HMM

NPY (Nested Pitman-Yor) LM

- Bottom-up approach for defining the discrete state set from large data.

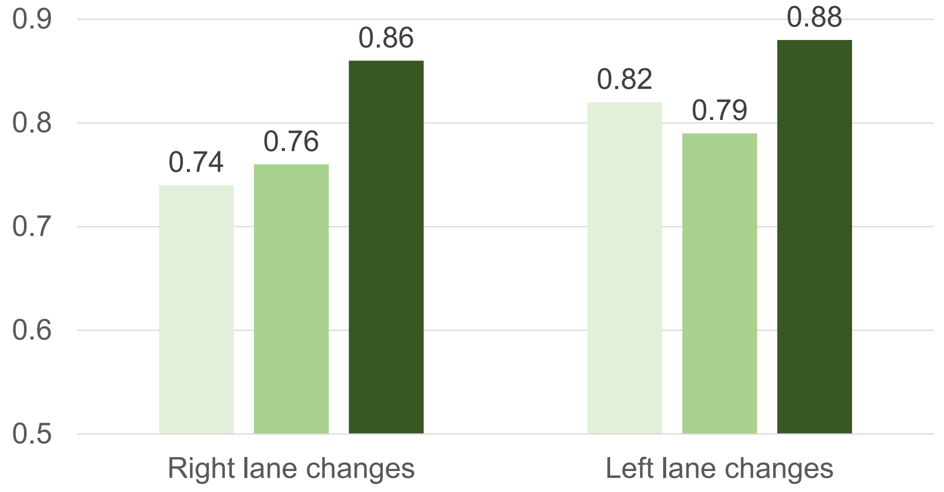
[1] T. Taniguchi et al., Proc. IEEE-IV '12, pp. 849 – 853, 2012.

Discrete representation of latent space



Encoding 9hrs. driving signals

	Driving	Traffic	Comb.
Total # of chunks	10,122	1,601	11,615
# of types	512	1,453	9,833
Average length	3.22 sec	20.37 sec	2.81 sec
Maximum length	143.6 sec	128.7 sec	112.3 sec



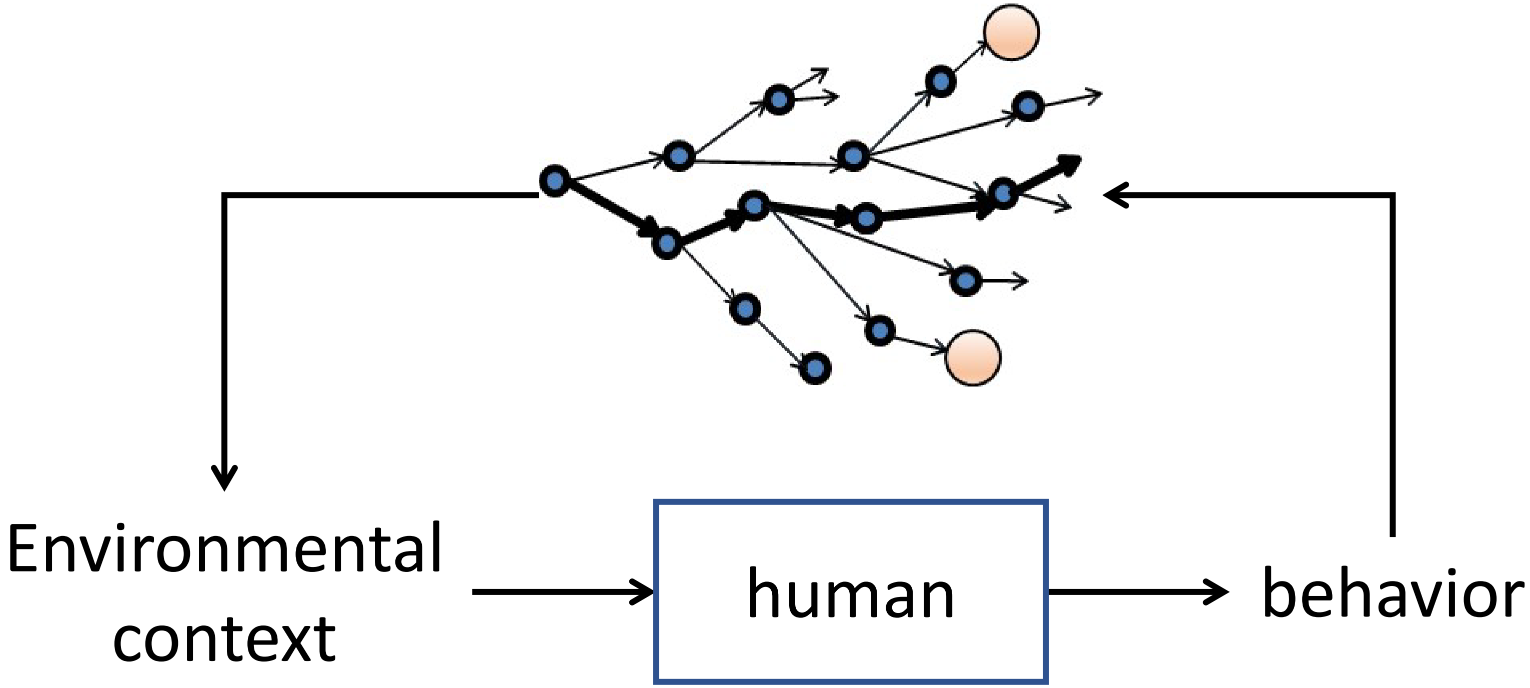
Detection acc. (AUC) of risky lane changes

- 10K states is not easy to handle.

Mori, Takenaka, Bando et al., Prof. of 2015 IEEE Intelligent Vehicles Symposium (IV) June 28 - July 1, 2015. COEX, Seoul,

Behavior Science and Digital Signal Processing

- 10K discrete states or latent space?



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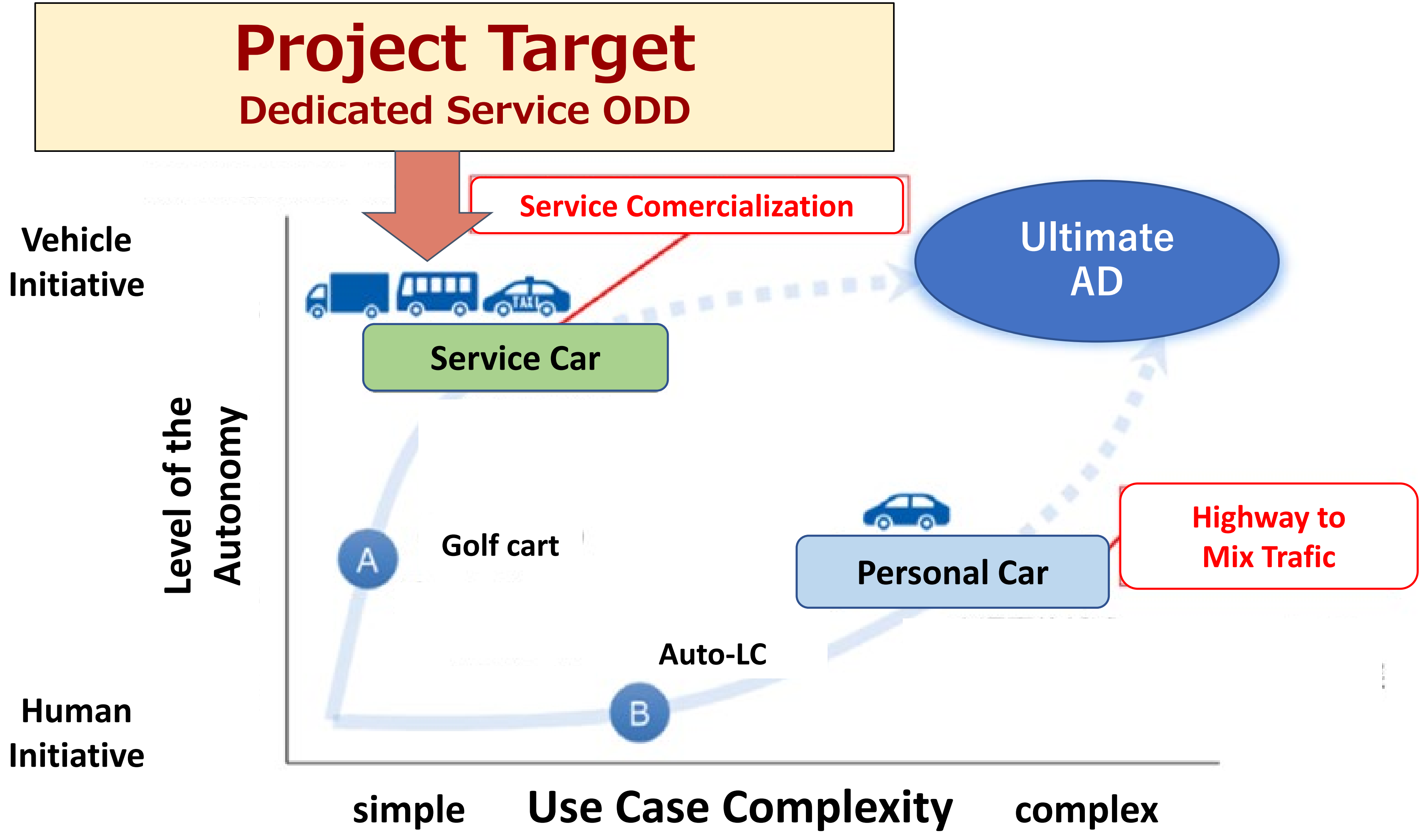
Scene description for AD risk assessment

NEDO/XAI project
Scene captioning for AD risk assessment

Social Deployment of AD Tech.



Japan’s National Project: RoAD to the L4

- Penetration of Remote Level 4 Service
  - Deployment of driverless mobility technology for commercial uses 50 services in 50 areas in 2025
  - Incorporation with IoT/AI tech. for the new MaaS applications:
  - Human resource development
  - Building social acceptance: Solving liability issues, Social acceptance and behavior change through experience opportunity.

Project on **R**esearch, Development, Demonstration and Deployment (RDD&D) **o**f **A**utonomous **D**riving **to**ward **the L**evel **4**and its Enhanced Mobility Services

Rural Area

Closed area (Factory)

Closed area (Campus)

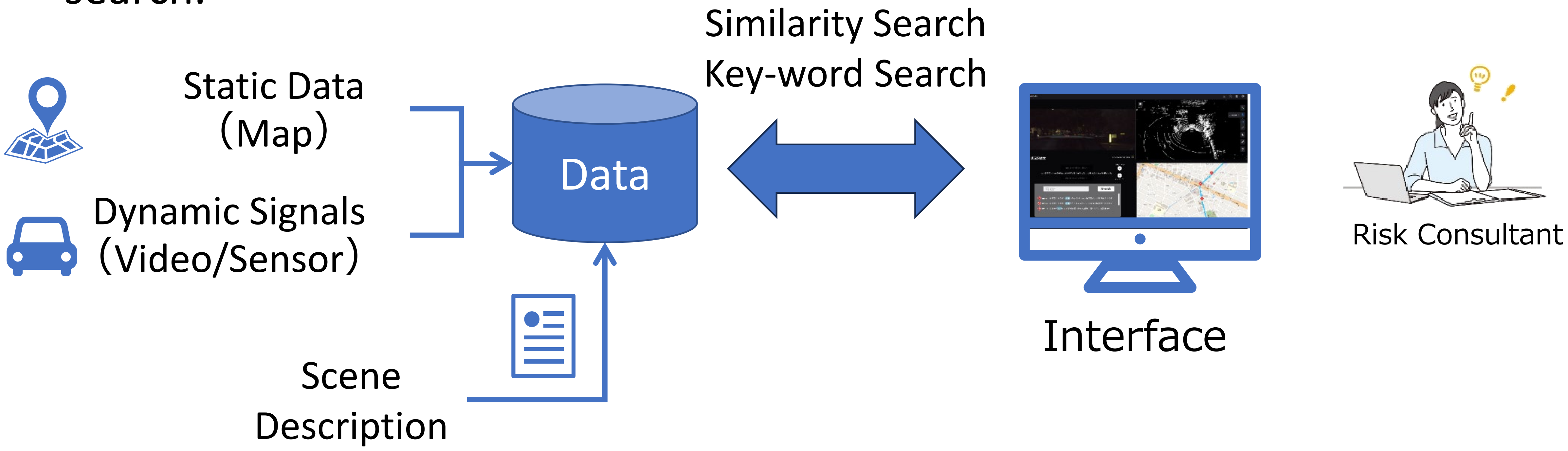
Managing Risk is the key to Innovations

Technology	Regulation	Economy
Imperfect performance	Social tolerance	Loss recovery

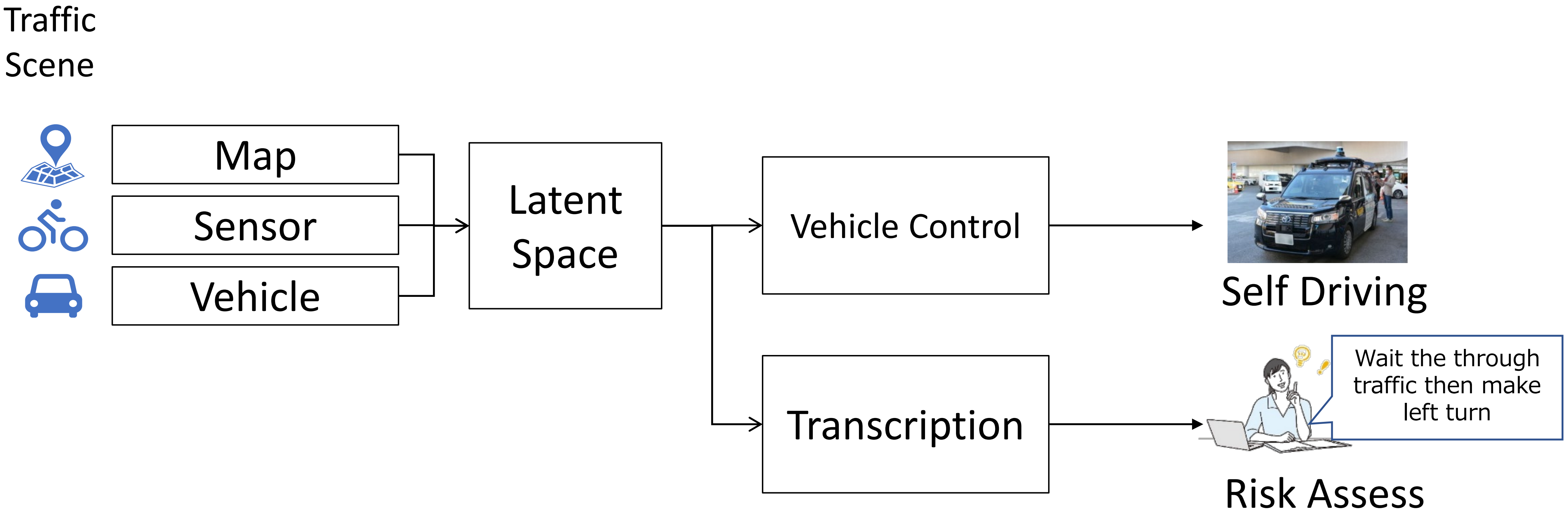
- To ensure reliability, final risk assessments are conducted by a human expert, drawing upon their professional experience and available evidence."
- While real traffic scenes can be compiled into a vast signal database, the lack of transcriptions renders it unsearchable.
- We need an AI that aids human experts by transcribing traffic scenes into readable text. This enables experts to assess risk based on relevant facts.
- The AI responsible for transcribing should have a shared understanding of the traffic scene with the autonomous driving (AD) system.

The goal of the project: D-Risk Assess System

- Using tags and texts generated for the traffic scene, it becomes possible to identify when, where, what type of risky events happened through risk mining technology combining the similarity search and the key-word search.



Unified structure of driving intelligence



NEDO/XAI project (2018-2022, 4.2M USD)

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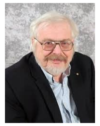
NEDO

Principle Investigator
□Kazuya Takeda


NAGOYA UNIVERSITY

Nagoya University
- ■ Vehicle DSP
  Prof. Kazuya Takeda
- ■ NLP
  Prof. Koichi Takeda

Ohio State U
- ■ vehicle dynamics
  Prof. Umit Ozguner



THE OHIO STATE UNIVERSITY

University Texas at Dallas
- ■ Sequential data analytics
  Prof. John Hansen

Johns Hopkins, Carnegie Melon
- ■ end-to-end DNN modeling
  Prof. Shinji Watanabe
  Dr. Kevin Duh, Senior Research Scientist


JOHNS HOPKINS UNIVERSITY


Tier IV (AD open source)
University Startup
- ■ **POC, Consulting**

Tier IV

Aisan Technology
- ■ POC

AISAN TECHNOLOGY CO.,LTD.


Human Dataware Lab.)
- ■ Signal and Data analytics

HDL Human Dataware Lab.

SOMPO Japan
- ■ Digital Risk Management

SOMPO

Meitetsu (regional railway)c

MEITETSU

Hitachi Butsuryu（Logistics）

日立物流

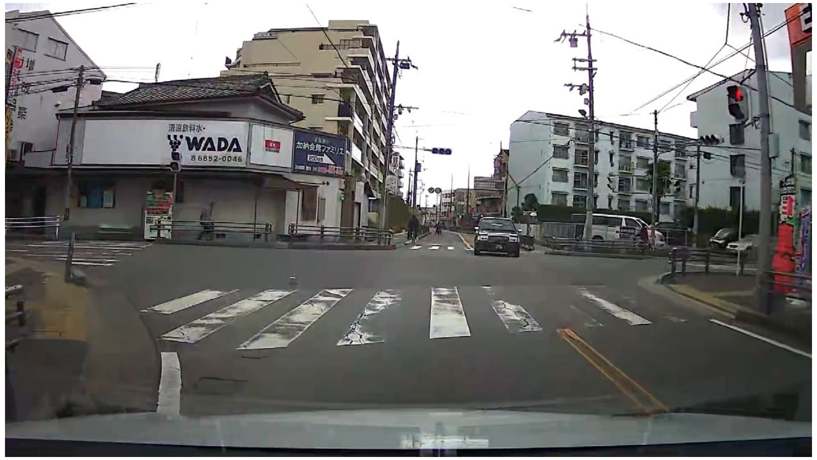
Minami holdings (driving school) Outsource (Data)

Minami

Group of US-Jpn Universities, Start ups, Insurance company

Transcription examples

Pedestrians and a bicyclist while turning left



Subjective Risk Level: 3

Situation Description: The car turned left at the intersection. Afterward, **a bicycle crossed the crosswalk**.

A near miss

Subjective Risk Level:

Situation Description: While proceeding along a street **without a crosswalk**, the car stopped to **avoid a bicyclist** riding from the front.

Data resources

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Highway Lane Change Dataset (LC)

- Scenes of lane changing on Japanese highways
- **988 scenes** labeled with risk level, situation, etc.


Urban Travel Dataset (UT)

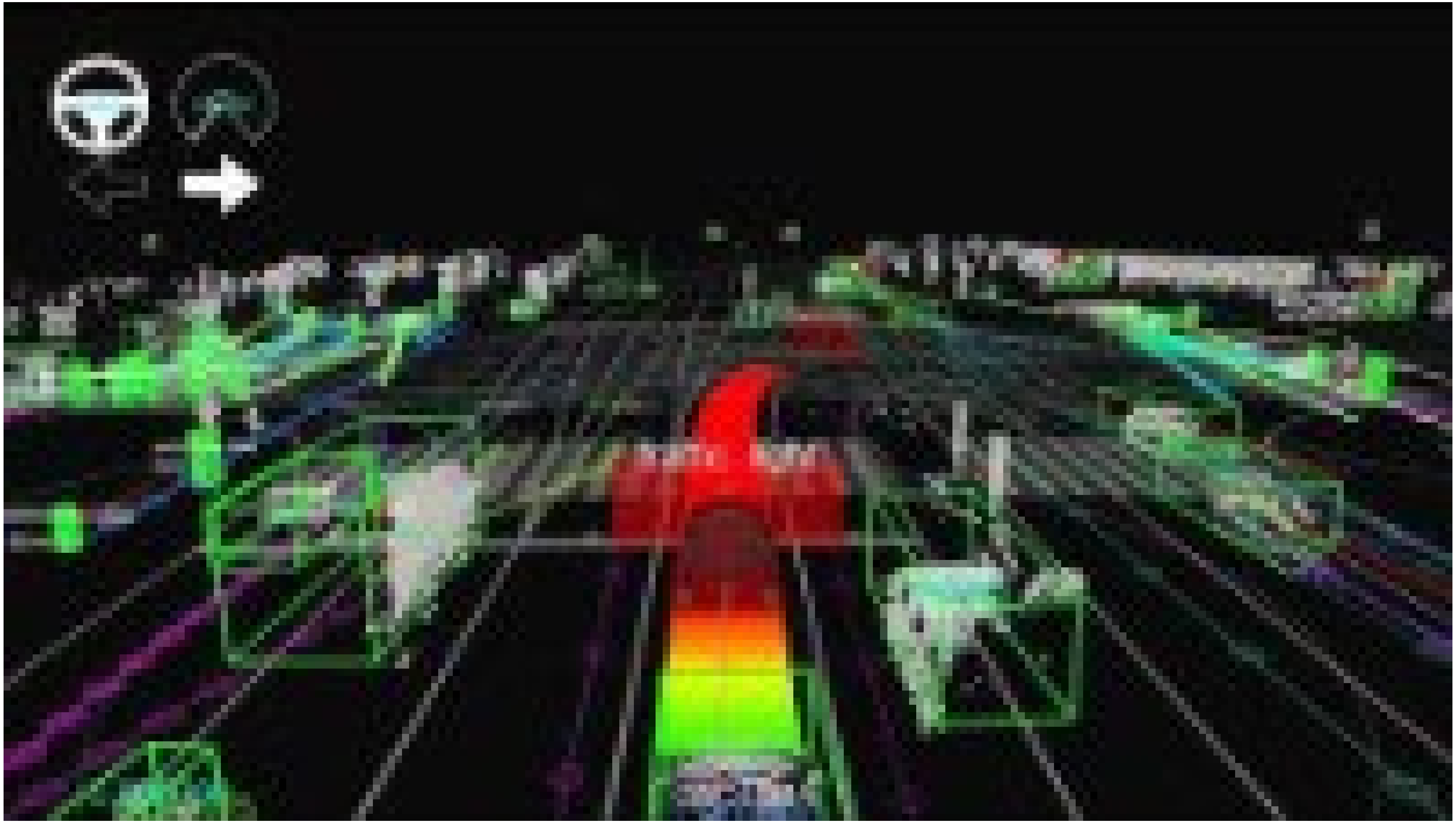
- Scenes of urban travel throughout Japan
- **2687 scenes** with annotations


West-Shinjuku Dataset (WS)

- Self-driving proof-of-concept data, Nishi-Shinjuku
- **478 scenes** with annotations


West Shinjuku data collection

West Shinjuku Data collection



Lexical simplification

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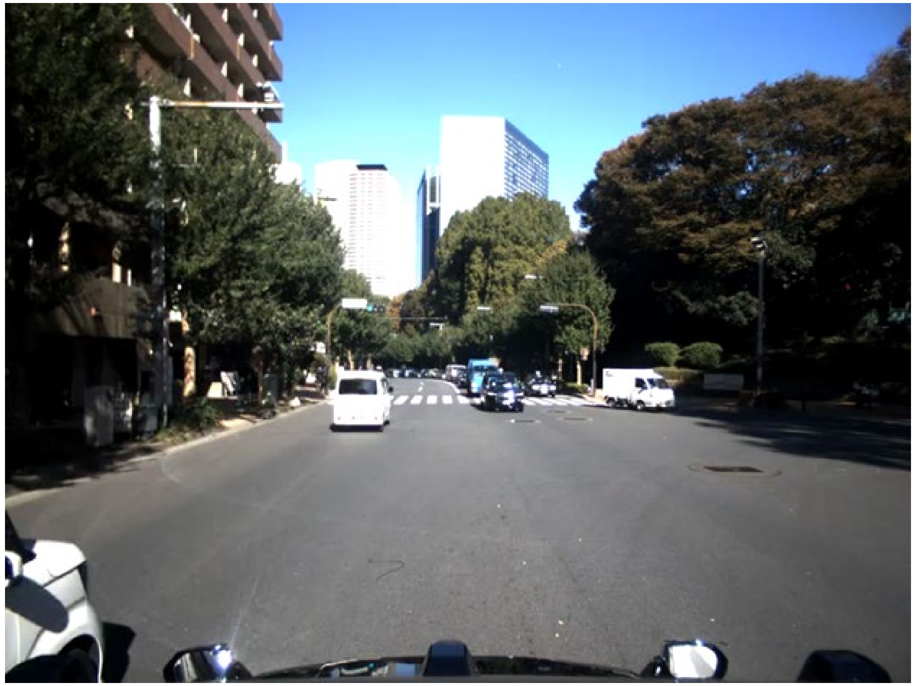


In response to feedback from risk assessors, vocabulary related to on-street parking and buses was also examined and incorporated

Example (Partial Excerpt):

<u>Multiple cars</u> and buses proceeded straight through an intersection.

<u>Multiple oncoming vehicles</u> proceeded straight through an intersection.

<u>Multiple vehicles</u> in the oncoming lane proceeded straight through the intersection.

↓

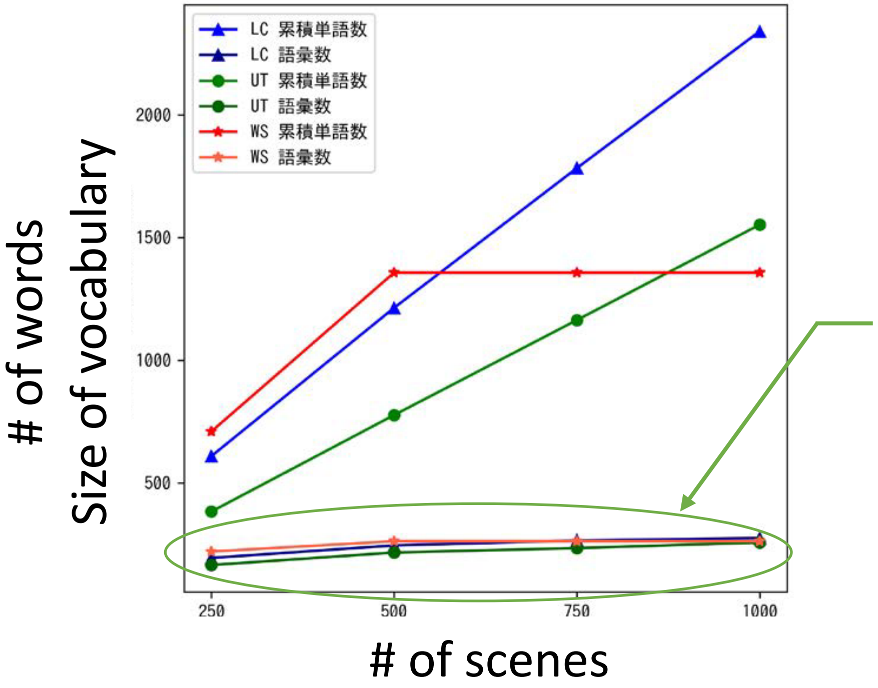
<u>Multiple vehicles</u> and buses proceeded straight through the intersection.

<u>Multiple vehicles</u> proceeded straight through the intersection.

<u>Multiple vehicles</u> in the oncoming lane proceeded straight through the intersection.

Regularizing the vocabulary

# of scenes	LC W. count	LC Voc. size	UT W. count	UT Voc. size	WS W.count	WS Voc. size
250	60,878	194	38,295	165	70,937	220
500	121,349	245	77,632	216	135,701	262
750	178,255	265	116,350	234	NA	NA
1000	233,988	275	155,174	257	NA	NA



LC: Highway Lane Change Database (988 Scenes)
UT: Urban Travel Database (2687 Scenes)
WS: Nishi-Shinjuku Proof-of-Concept Database (478 Scenes)

The speed of vocabulary growth is about 5%, 5 new words for every 100 sentences, after the regularization.

- Transfer learning is feasible
- Risk mining is consistent

Technology benchmarking (in-domain, UT/UT)

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(1) Effectiveness of using multi-modal signals

Signals used	BLEU-4	ROUGE-L	CIDEr
Video + Image + Driving	**0.868**	**0.881**	**2.330**
Video	0.839	0.862	2.087
Video + Driving	0.858	0.874	2.270

(2) Effectiveness of using visual language model (vs. LSTM)

Models used	BLEU-4	ROUGE-L	CIDEr
Transformer visual language model	**0.868**	**0.881**	**2.330**
Recurrent Neural Network model	0.843	0.864	2.242

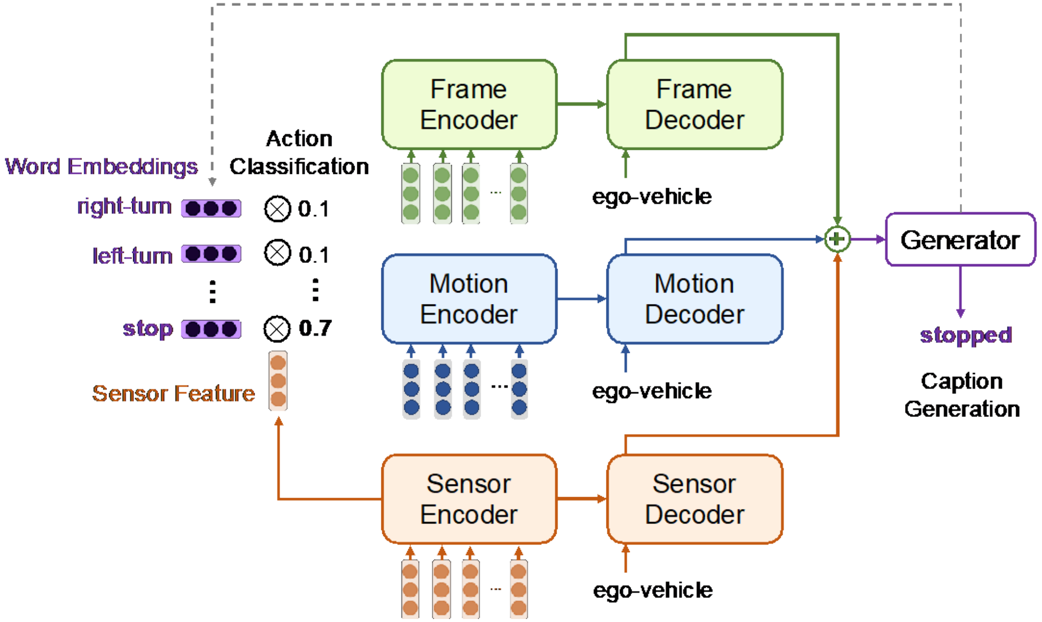
(3) Effectiveness of multi-label training with scene/behavior classes

Tasks trained for	Precision	Recall	F-value
For captioning and scene/behavior class	**92.6**	**34.0**	**49.8**
Only for captioning	91.5	32.8	48.3

Performance under the new domain

- Urban Traffic data set (UT)
  - 2687 traffic scenes including (at least) 100 risky scenes selected out from 30K scenes of human urban driving signals.

- West Shinjuku AD POC (WS)
  - 478 traffic scenes collected through AD POC at West Shinjuku Area.



Signals are chunked into fix-length (6 sec.) segments, i.e., a scene. Class labels as well as the transcriptions for the are given to 478 scenes.

Domain adaptation

- Transfer learning from general traffic model (train by UT: 2687 scenes) to the Nishi-Shinjuku service ODD (WS: 478) using 80% (360 scenes) of the dataset for training and 20% (90 scenes) for testing.
  - The length of the sentence is added to the Loss function.
  - The scene classification tag is also added for training (multi-task training).

	BLEU-4	ROUGE-L	CIDEr	Average S. length
Matched (Train UT / Test UT)	0.868	0.881	2.330	14.1
Unmatched (Train UT / Test WS)	0.176	0.433	0.062	11.9

Domain adaptation

- Transfer learning from general traffic model (train by UT: 2687 scenes) to the Nishi-Shinjuku service ODD (WS: 478) using 80% (360 scenes) of the dataset for training and 20% (90 scenes) for testing.
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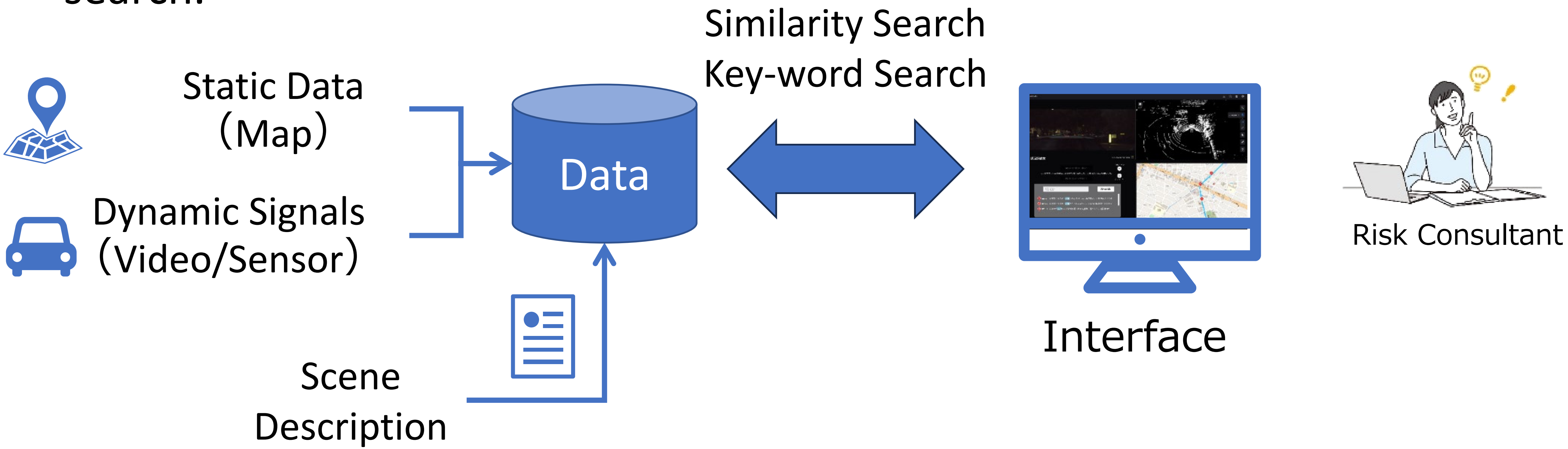
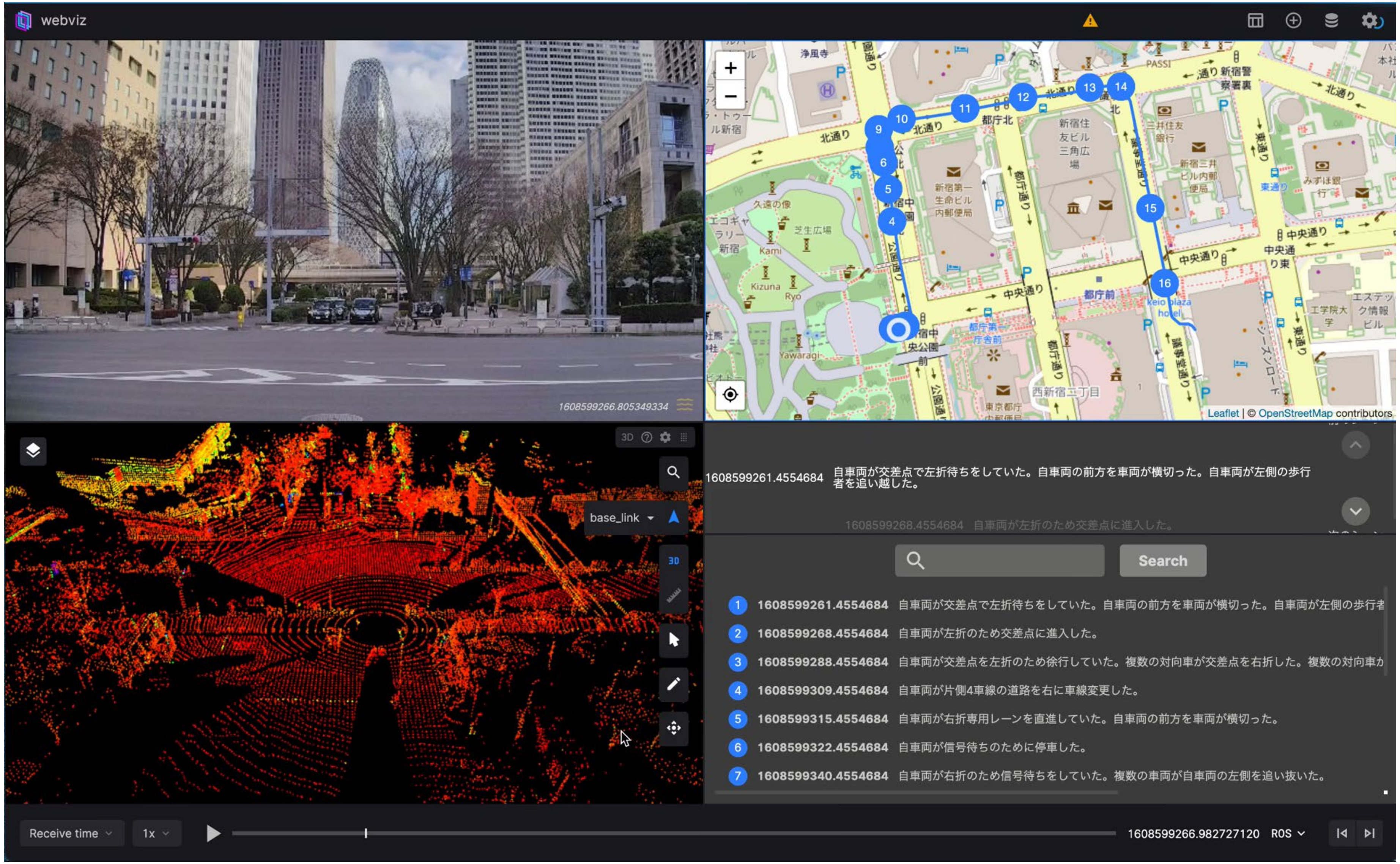
	BLEU-4	ROUGE-L	CIDEr	Average S. length
Matched (Train UT / Test UT)	0.868	0.881	2.330	14.1
Unmatched (Train UT / Test WS)	0.176	0.433	0.062	11.9
Transfer (Train UT & WS / Test WS)	**0.680**	**0.683**	**0.883**	28.8

The goal of the project: D-Risk Assess System

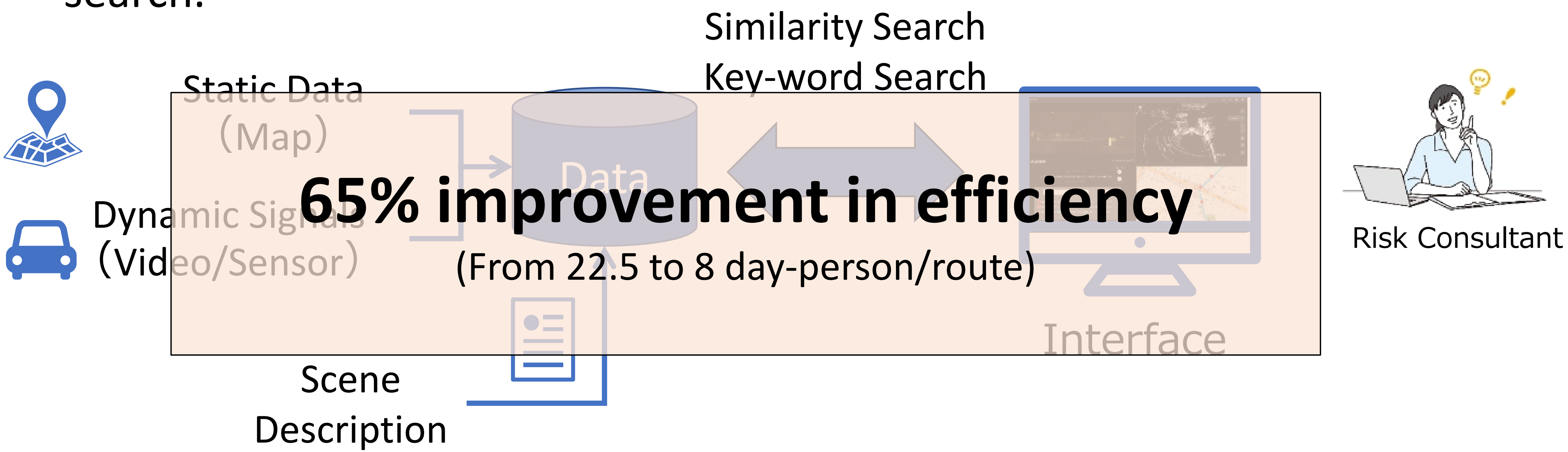
- Using tags and texts generated for the traffic scene, it becomes possible to identify when, where, what type of risky events happened through risk mining technology combining the similarity search and the key-word search.




webviz
1608599266.805349334
1608599261.4554684 自車両が交差点で左折待ちをしていた。自車両の前方を車両が横切った。自車両が左側の歩行者を追い越した。
1608599268.4554684 自車両が左折のため交差点に進入した。
Search
1 1608599261.4554684 自車両が交差点で左折待ちをしていた。自車両の前方を車両が横切った。自車両が左側の歩行者
2 1608599268.4554684 自車両が左折のため交差点に進入した。
3 1608599288.4554684 自車両が交差点を左折のため徐行していた。複数の対向車が交差点を右折した。複数の対向車が
4 1608599309.4554684 自車両が片側4車線の道路を右に車線変更した。
5 1608599315.4554684 自車両が右折専用レーンを直進していた。自車両の前方を車両が横切った。
6 1608599322.4554684 自車両が信号待ちのために停車した。
7 1608599340.4554684 自車両が右折のため信号待ちをしていた。複数の車両が自車両の左側を追い抜いた。
base_link
Receive time
1x
1608599266.982727120
ROS
Leaflet | © OpenStreetMap contributors

The goal of the project: D-Risk Assess System

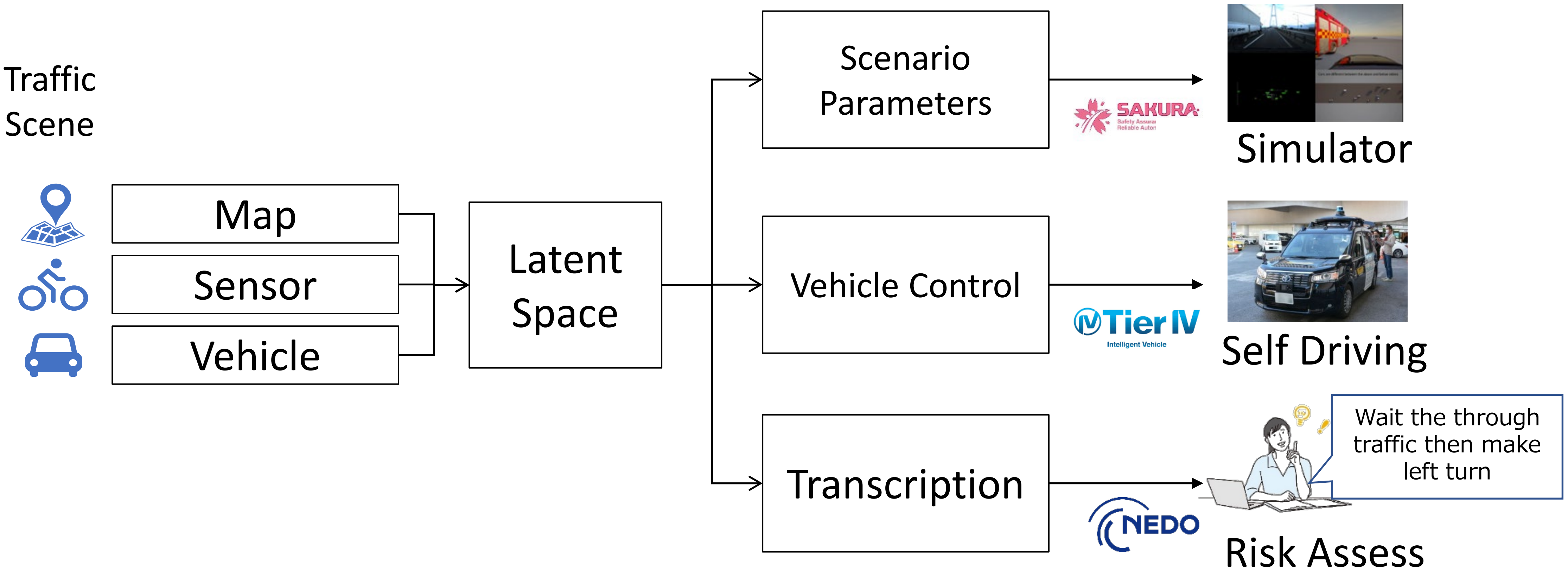
- Using tags and texts generated for the traffic scene, it becomes possible to identify when, where, what type of risky events happened through risk mining technology combining the similarity search and the key-word search.



65% improvement in efficiency

(From 22.5 to 8 day-person/route)

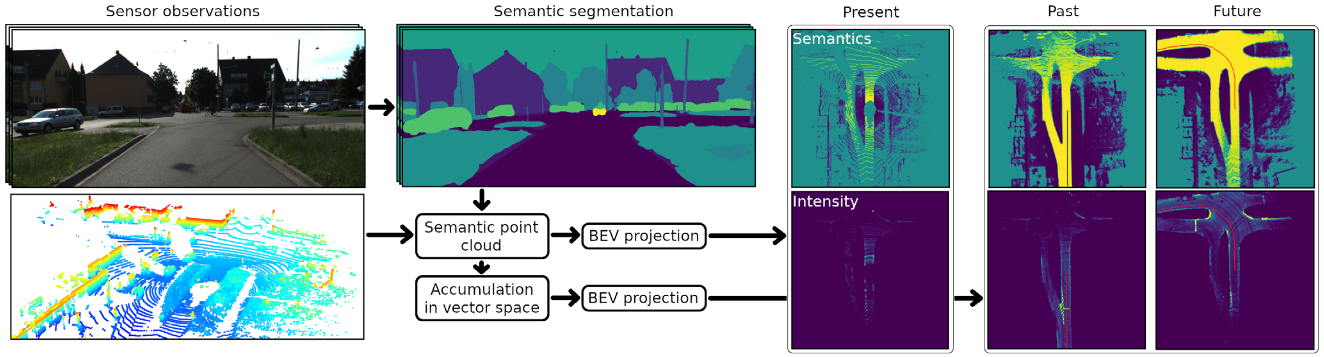
Unified structure of driving intelligence



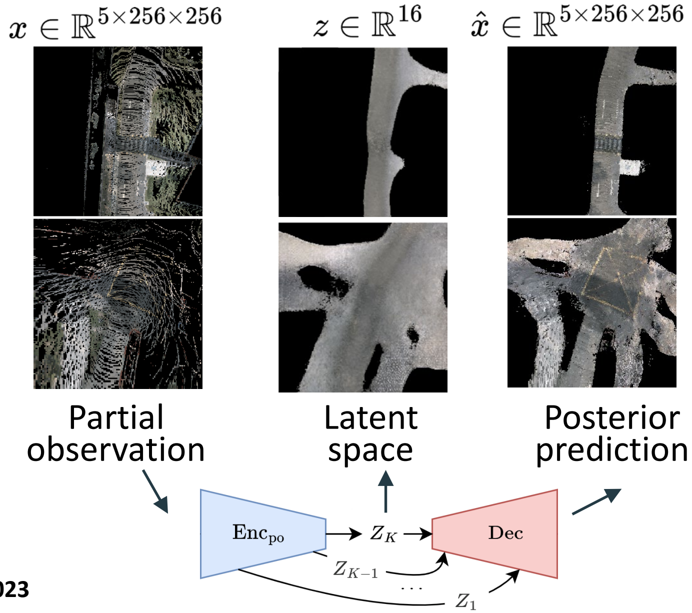
Latent space as a predictive world model

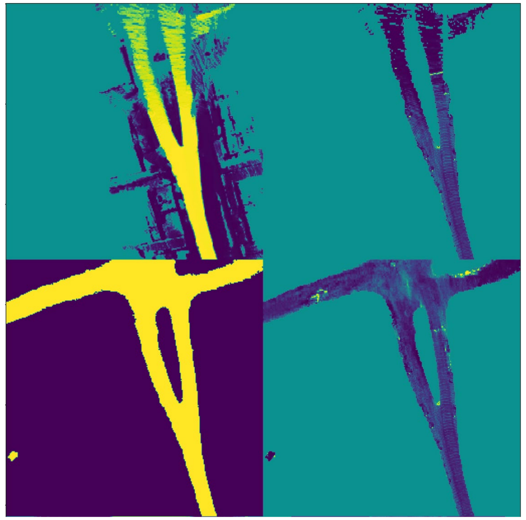
- Learning rich predictive world model from partial observations only.
- Extended to path generation

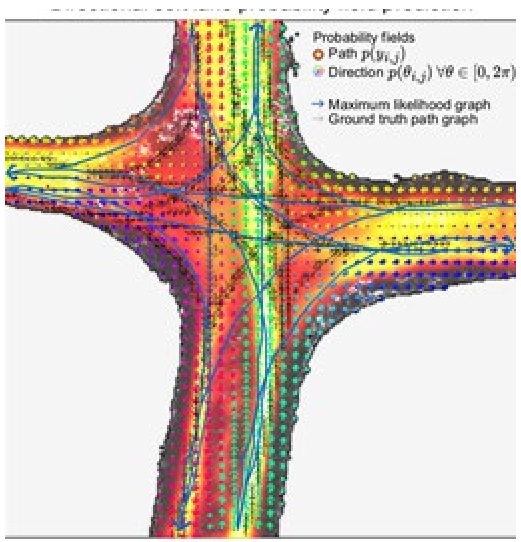
BEV of accumulated semantically labeled point clouds



Latent distribution of plausible road geometries



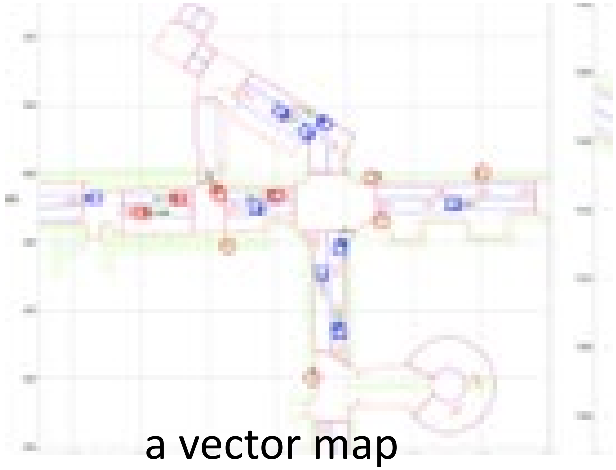




[1] R. Karlsson, et al., "Predictive World Models from Real-World Partial Observations" (IEEE MOST) 2023
[2] R. Karlsson, et al., "Learning to Predict Navigational Patterns from Partial Observations", arXiv preprint, 2023

Graph representation of the semantics

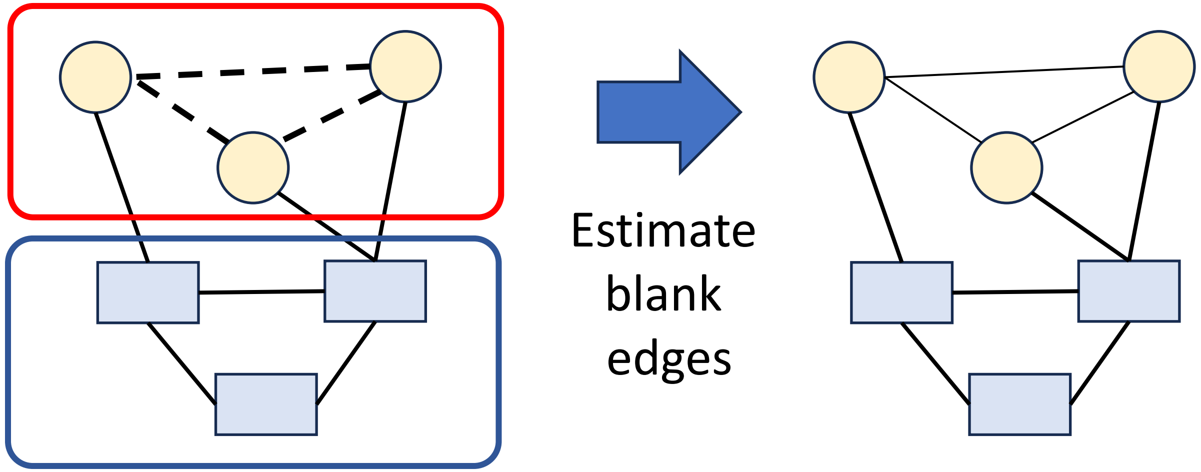
- **Road Scene Graph:** Estimating pair-wise relationships among traffic objects and map components, arrange them as a topological graph.
- **Real-to-Synthetic:** Generate near-realistic traffic scenes from RSG.
- **RSG-Search:** Querying the traffic scene dataset with RSG as a key.



a vector map
with actor information

Traffic observation

Actor interaction sub-graph
(incomplete)



Road connection sub-graph

Vanila graph

Structural semantics

Y Tian, A Carballo, R Li, K Takeda, 2021 IEEE Intelligent Vehicles Symposium (IV), 546-552, 2021

MAKE NEW STANDARDS.
東海国立大学機構
名古屋大学

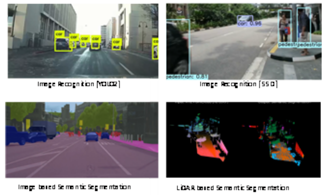
Opensource community and collaborative research

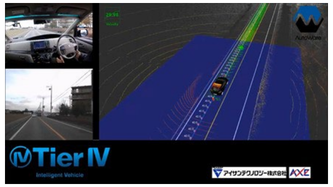
Opensource community and collaborative research

Autoware and Autoware Foundation

Building blocks of mobility services

Services





Autonomous functions

Vehicle platforms

Building blocks of mobility services

Services

Autoware

OSS ADkit

Vehicle platforms

What is Autoware and the Autoware Foundation (AWF)?

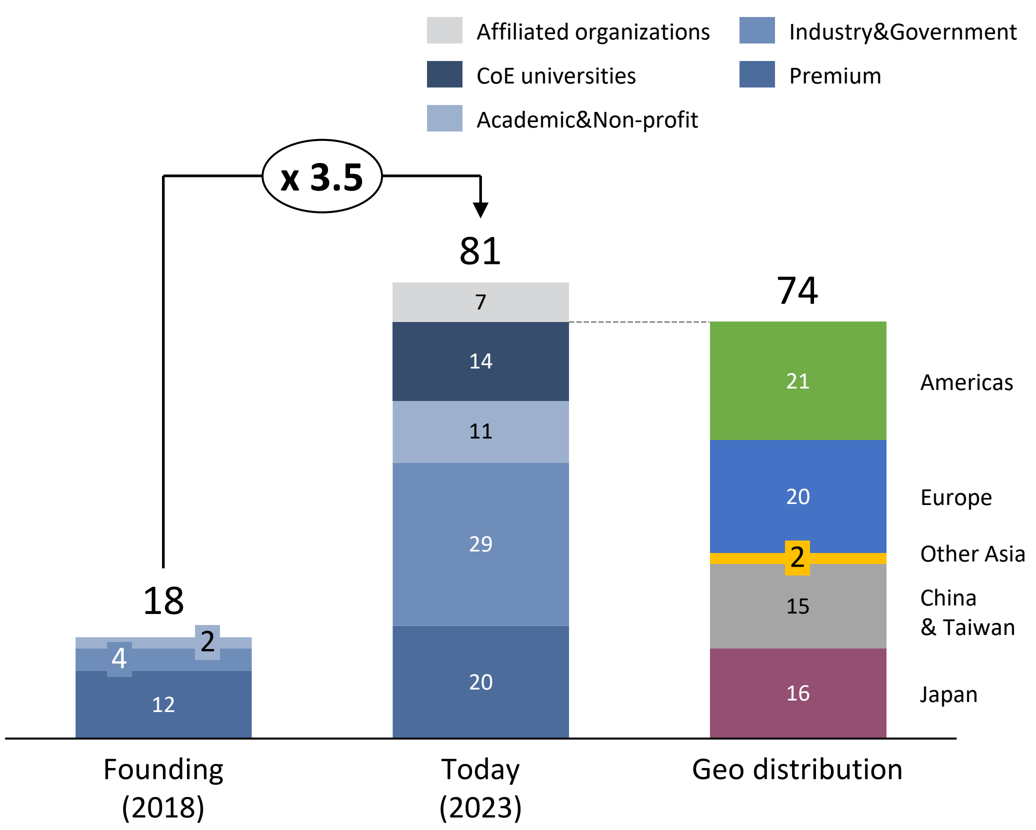
Autoware®

- **The first all-in-one open source software for autonomous driving** (AD). Apache License 2.0.
- Built on Robot Operating System (ROS) and enables commercial deployment of AD in a broad range of vehicles and applications.

The Autoware Foundation (AWF)

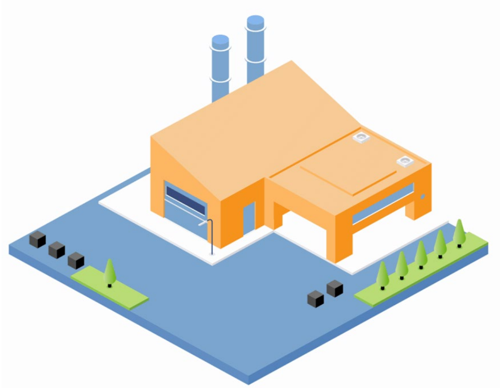
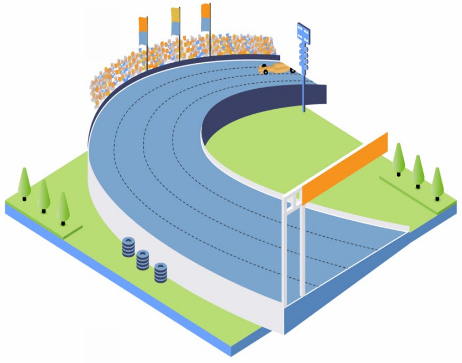
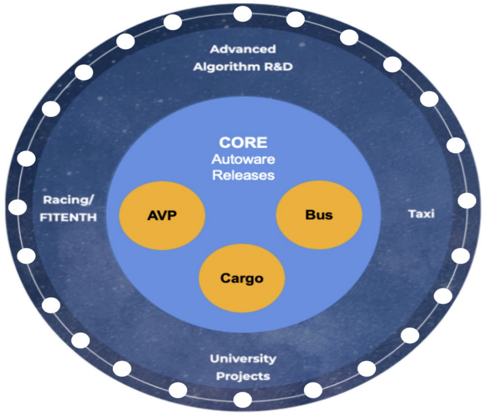
- **A not-for-profit organization** based in Japan, aiming at promoting **the industry penetration and R&D of Autoware®**
- Established in 2018; **80+ companies, government organizations and universities world-wide** joining the AWF on top of **1000+ individual active engineering contributors**.
- **Showed up many academic/industry events annually** e.g.. IEEE IV, ICRA and Automotive Expos**.**
- Held **meetups/gatherings globally** to promote collaborations and business development.

Growth of the Autoware Foundation



- The AWF made a steady growth worldwide.
- The membership portfolio is well balanced in terms of industry and geography.

Autoware ODD Roadmap (not exhaustive)

2020	2021	2022	2023~
Autonomous Valet Parking (AVP) support in Autoware.Auto v1 	**Cargo Delivery** support in Autoware.Auto v2  **Autonomous Racing** Autoware base package for IAC 	**Bus** on predefined route support developed in Autoware.Universe  **Autonomous Racing** Autoware running on F1TENTH 	**AVP, Cargo and Bus** support in Autoware.Core  **Taxi** use case development in Autoware.Universe ● Improved Object Detection ● High speed highway driving ● Dense urban driving scenarios ● Autoware usability enhancements ● Open AD Kit 3.0

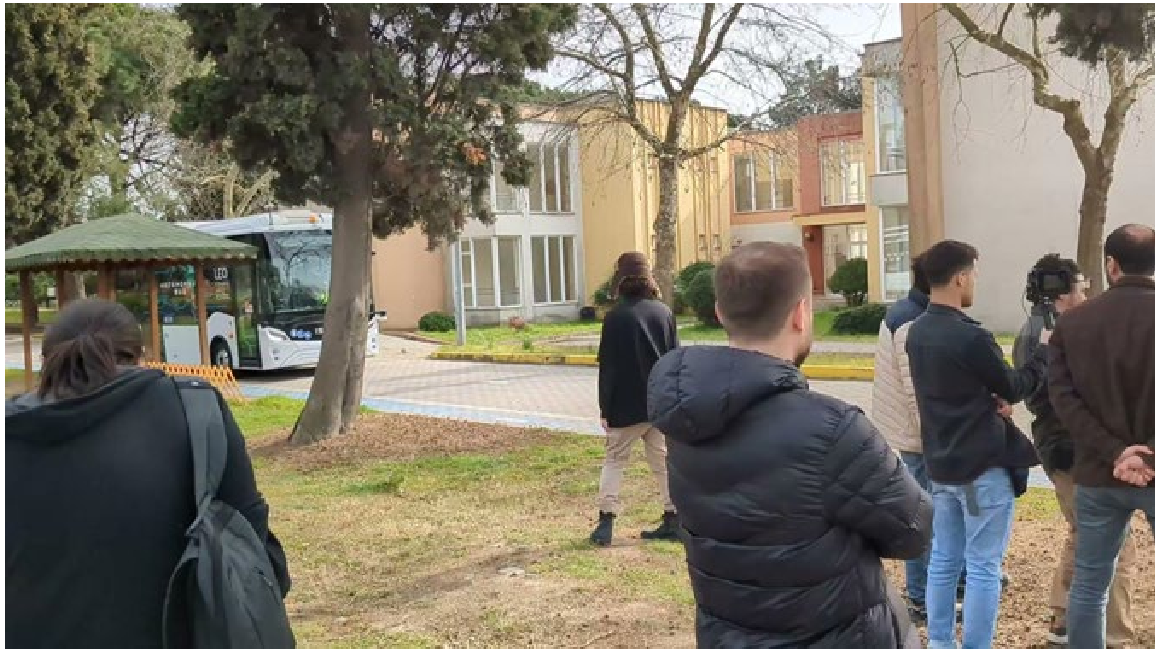
Example of technical output (1/4) – Autonomy Software WG

ITRI (Taiwan) and LeoDrive (Turkey) leading tests with real vehicle

- Video shooting done with LeoDrive in February
- Almost ready to be released in public
- Another demo planned with ITRI bus in August

Next Step

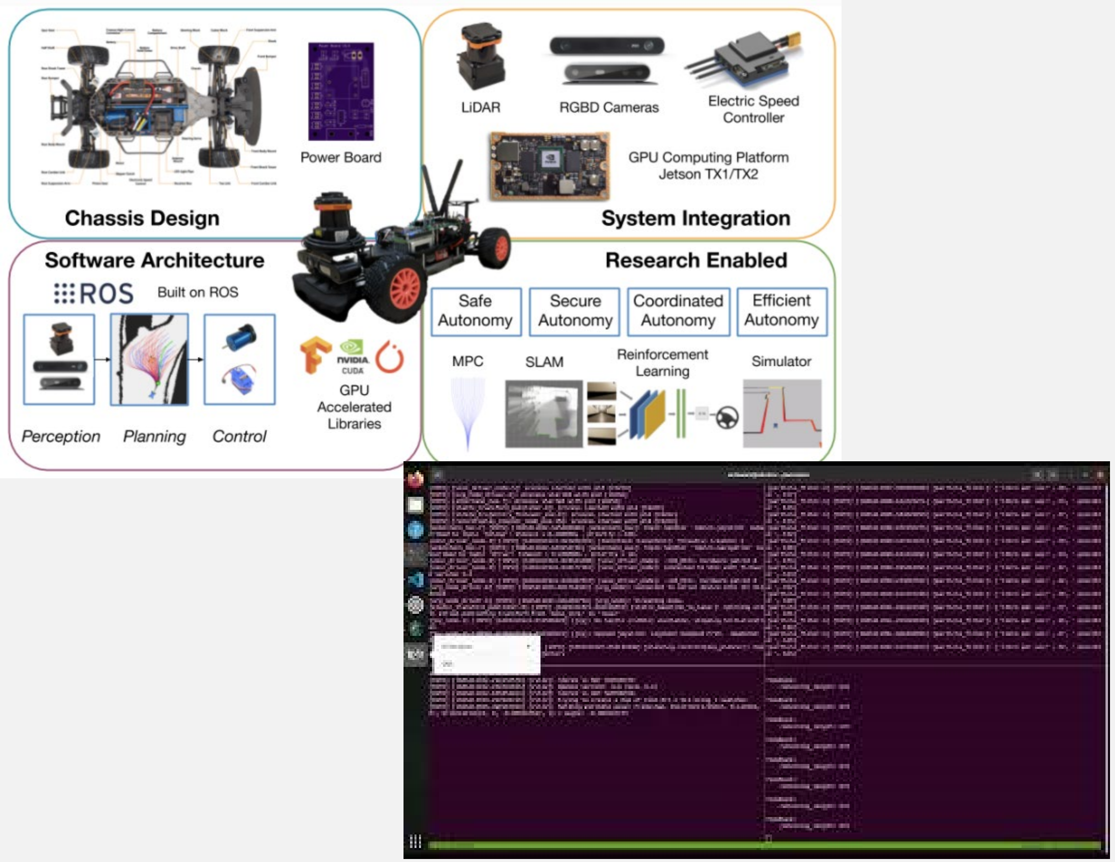
- Clean up the code in Universe repository
- Start working on Autoware Core implementation



Example of technical output (2/4) – Racing WG

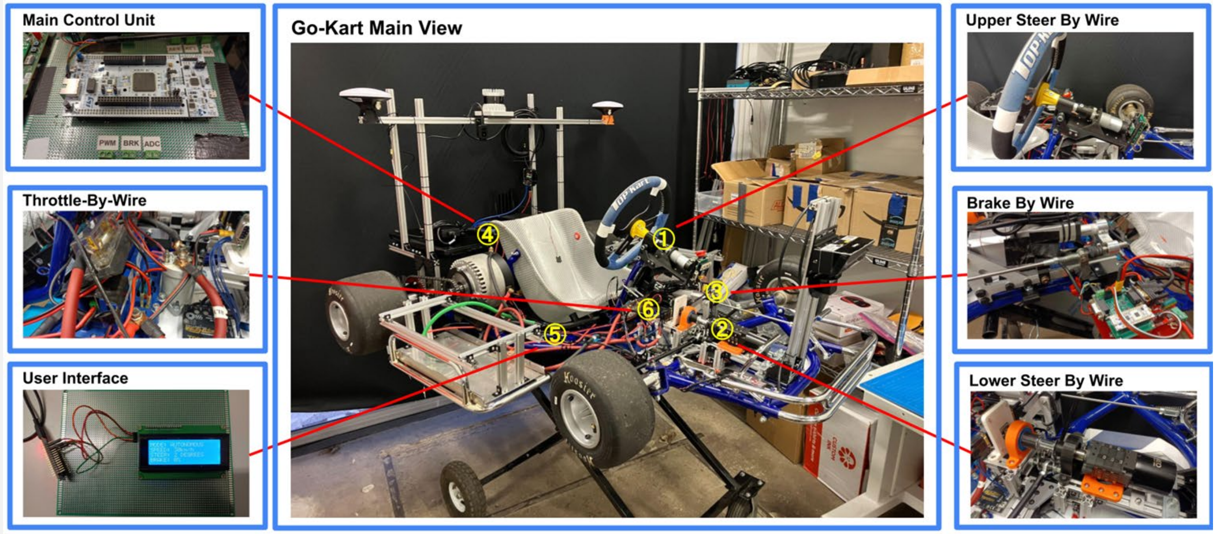
F1Tenth

- Integrating F1Tenth to Autoware Core/Universe.
- Create training course using F1Tenth
- Holding a tutorial session in IV2023



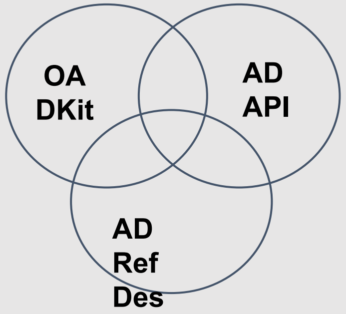
EV GoKart

- EV Grand Prix Competition took place in May : [video link]
- Planning to set this as a reference design platform for Center of Excellence



Example of technical output (3/4) – Reference Design WG

Objective	**Focus on defining reference design for hardware and OS/Middleware Layer (e.g., E/E architecture)**



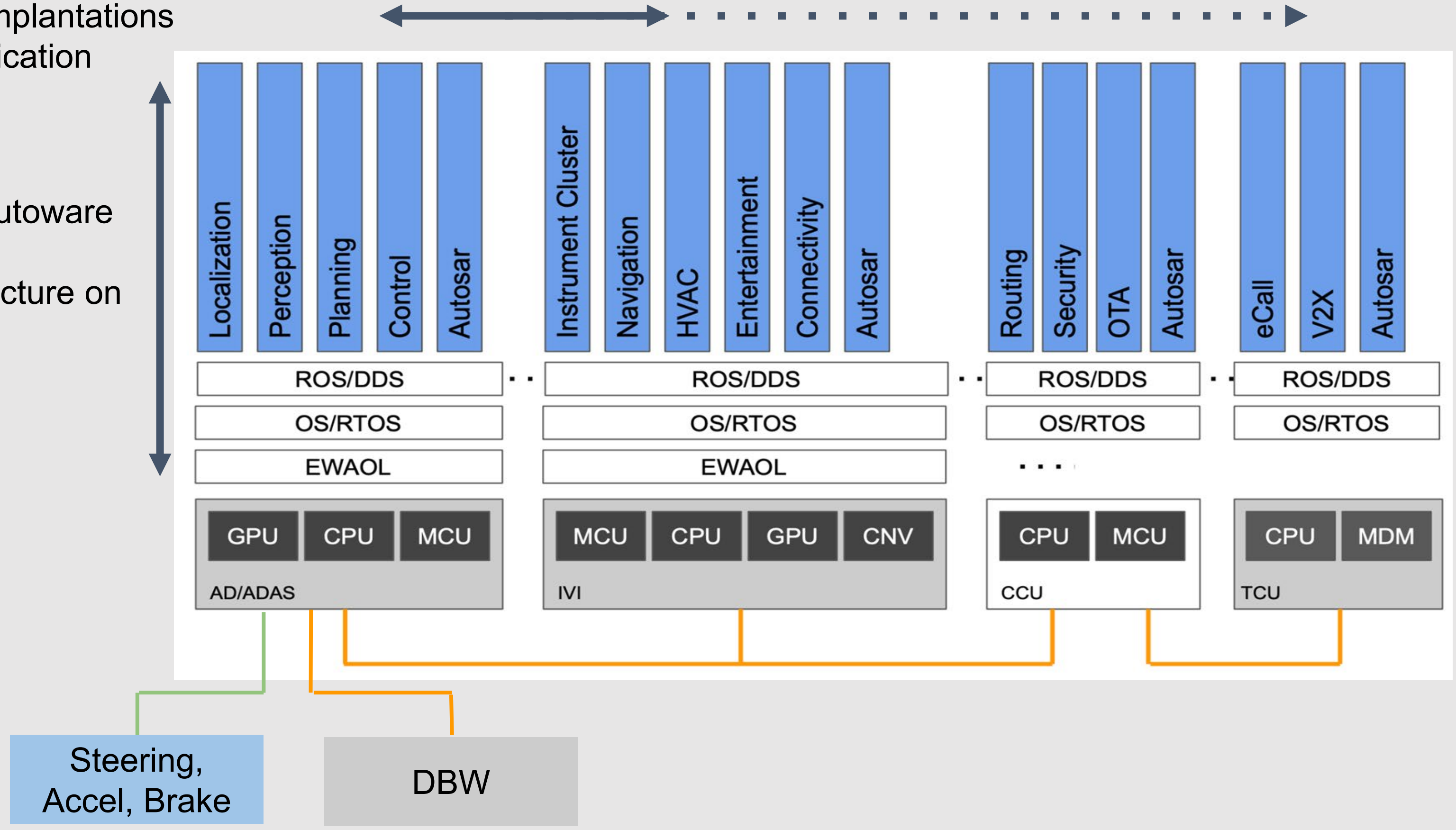
WGs to align areas of collaboration

- Reference Implantations
- Safety/Certification
- etc.

AD API WG: APIs to other Applications (e.g. IVI, V2X)

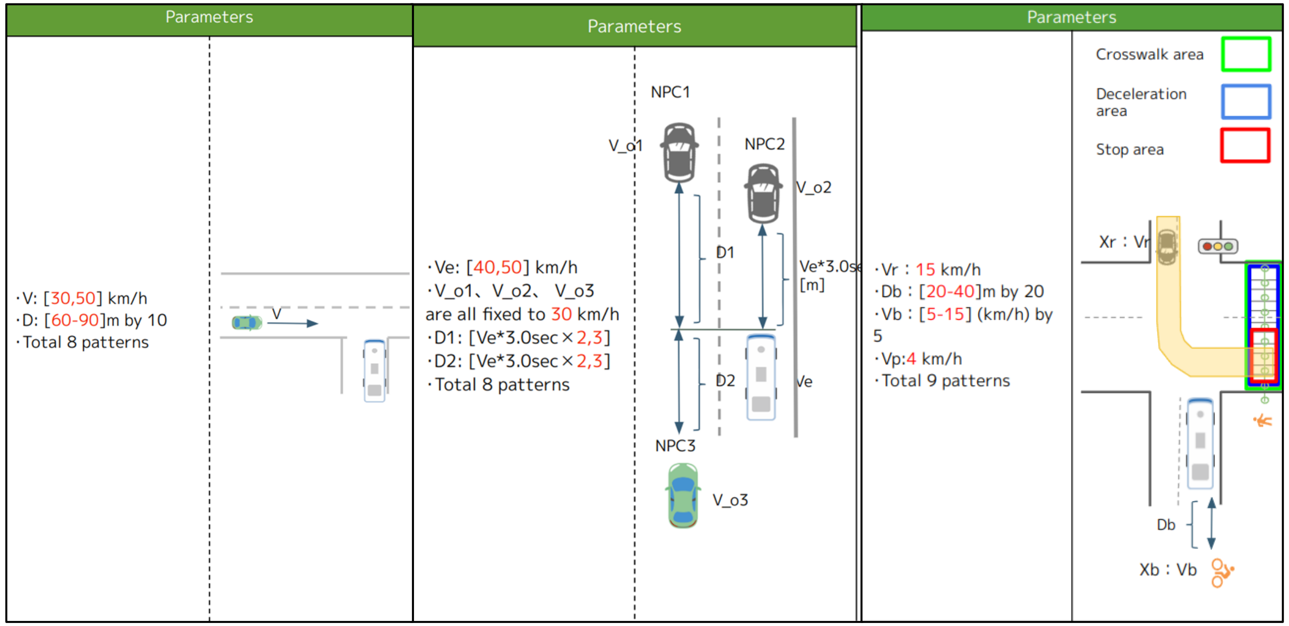
Open AD Kit WG: Autoware implemented in a microservices architecture on SOAFEE (EWAOL)

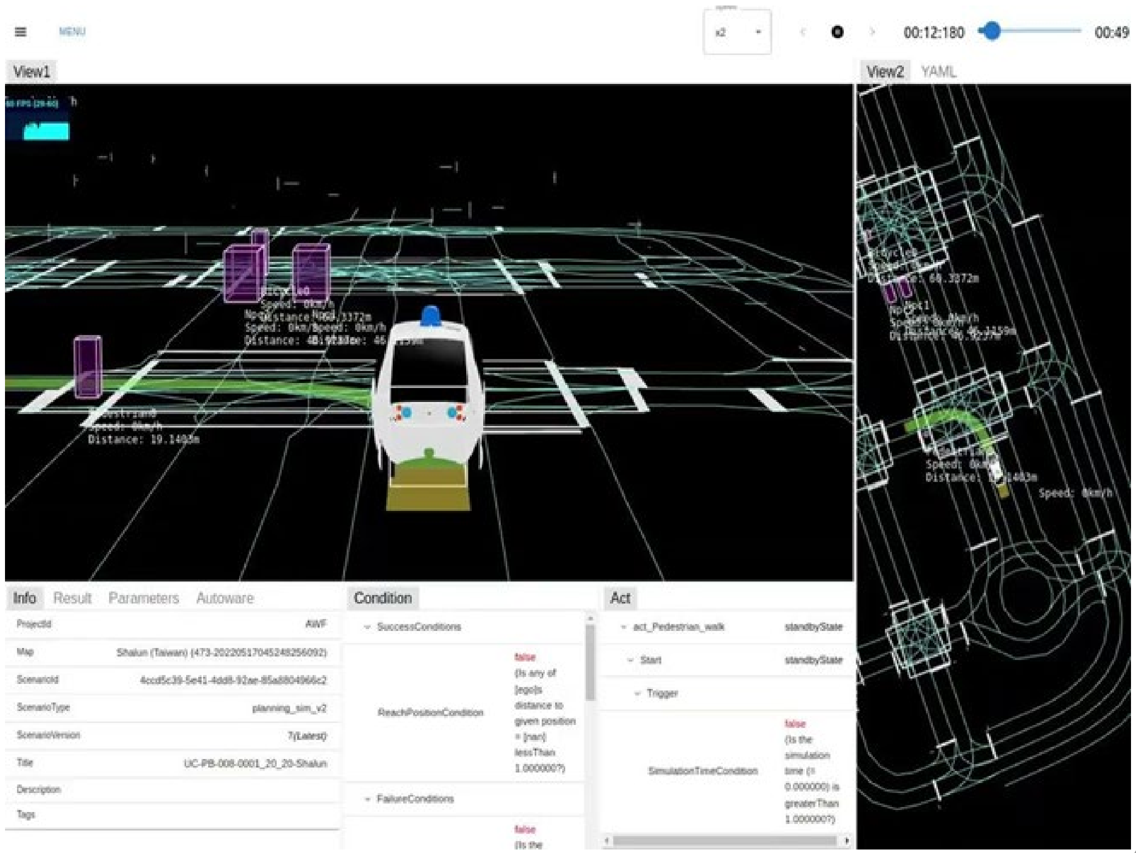
Ref Des WG: HW Architecture, OS/RTOS, and Middleware to address requirements for Auto and Safety



Example of technical output (4/4) – ODD WG

Achievements	Define ODD parameters for Bus Service Create test scenarios from use cases for Bus service scene CI runs tests against 138 scenarios every week to check regression
On-going Tasks	Started to define new scenarios for robo-taxi areas





Example of strategic planning output (1/2)

Vision

The AWF SPC helps to coordinate Industry and Academic alliances and creates business opportunities for member organizations to engage and promote their solutions.

Many opportunities to engage with and promote solutions thru the Autoware Foundation driven initiatives:

- AWF Alliances: Collaborative engagements to commercialize Autoware based AD solutions
- Autoware Open AD Kit: Platform and ecosystem to enable SDV development of Autoware based AD solutions
- Autoware Center of Excellence: Engagement with academic community to advance Autoware development
- Autoware I/O: Promote solutions on AWF website and thru Autoware based Reference Designs

THE AUTOWARE FOUNDATION

+

AVC CONSORTIUM

eSync ALLIANCE

F1 TENTH

SOAFEE

MIH

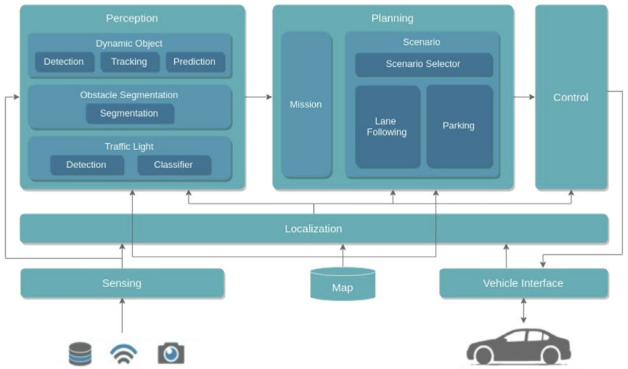
seL4 FOUNDATION

⋮

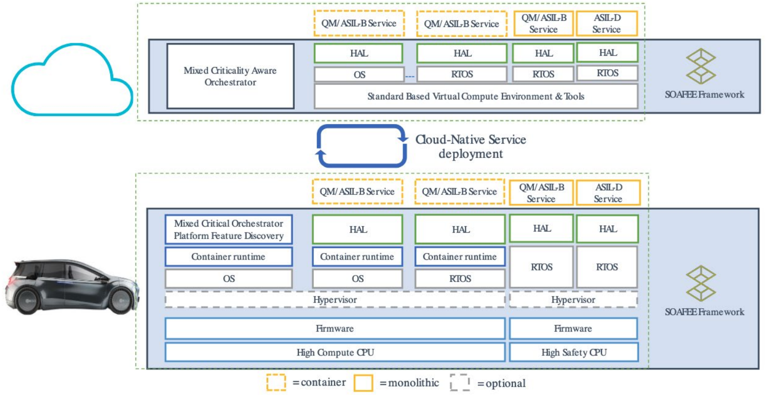
Example of strategic planning output (2/2)

Vision

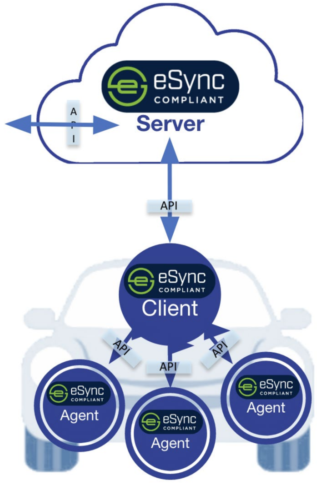
The AWF SPC helps to coordinate across Alliance partners in executing initiatives such as the Autoware Open AD Kit.



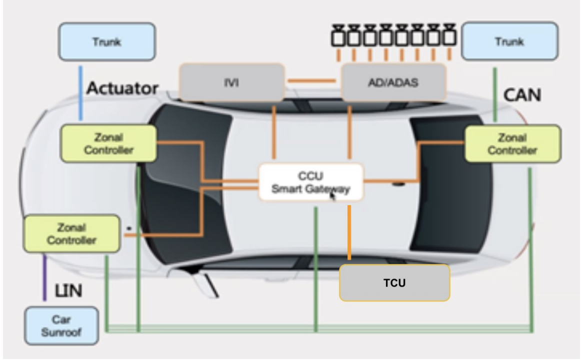
Full OSS stack for Autonomous Driving



SDV architecture with cloud/edge parity of containerized Automotive Applications



Specifications for OTA updates in Automotive



Open specifications for integration and verification of Automotive Functions

Autoware Open AD Kit brings multiple ecosystems together to advance AD solutions for SDVs

Autoware CoE Network

Goal is to expand the ecosystem of developers actively contributing/advancing Autoware

North America

THE AUTOWARE FOUNDATION
Center of Excellence

Penn
UNIVERSITY of PENNSYLVANIA

WAYNE STATE UNIVERSITY

Racing '22

Cargo '23

Open EV '24

Autoware + V2X

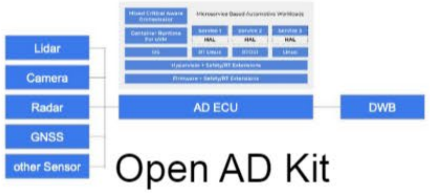
Europe

POLITECHNIKA POZNAŃSKA
Poznan University of Technology

TUM

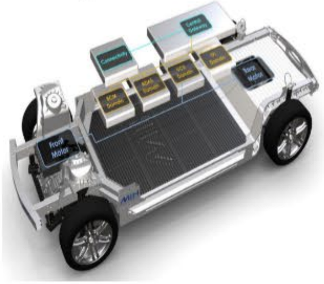
Weis'n Shuttle '24

National Taiwan University



Open AD Kit

MIH Open EV



Asia

東京大学
THE UNIVERSITY OF TOKYO

NAGOYA UNIVERSITY

JSAE Auto AI Challenge

Penn 1st Place

and more universities interested in joining…

- Data-centric approach to the driving behavior modeling
- AI Risk Management for L4 mobility services
- Open-source community and collaborative research

Thank you for your attention.

kazuya.takeda@nagoya-u.jp