Statistically Certified Test Approaches for Intelligent Physical System

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The Building Blocks of Autonomy

Prepared by VISION SYSTEMS INTELLIGENCE

Level of Integration

AUTONOMOUS SOLUTIONS

Toyota, Tesla, Ford, GM, Volvo, Hyundai, Kia Motors, Geely, Google, Uber, NVIDIA, Continental, nauya, ZMP Robot of Everything, Audi, BMW, Changan, Honda, Mercedes-Benz, Apple, Baidu 百度, VisLab.it Extend Your Vision, Otto, nuTonomy, PSA Peugeot Citroën, Nissan, BAIC, SAIC, Chery, Delphi, Bosch, Renesas, drive.ai, Zoox

PROCESSING

Renesas, NVIDIA, Mobileye, NXP, Toshiba Leading Innovation, CEVA, Cadence, Imagination, ARM, Analog Devices, Intel, Xilinx, videantis passion for video, Altera, Texas Instruments, Marvell, Qualcomm, Movidius, ST

SENSORS

Bosch, Delphi, Mitsubishi Electric, NXP, Continental, ibeo, Valeo, ZF, TRW, Hitachi, OmniVision, Pioneer, Autoliv, Toshiba Leading Innovation, Hyundai Mobis, Point Grey Innovation in Imaging, Kostal, Denso, LG Innotek, Panasonic, Magna, Harman, Fujitsu Ten, Visteon, Quanergy, Melexis Microelectronic Integrated Systems, Mando Corporation, applanix A Trimble Company, FLIR Systems, ON Semiconductor, Osram, LeddarTech, Neusoft, Infineon, Sony, Pepperl+Fuchs, TriLumina, u-blox, Velodyne LiDAR, Phantom Intelligence

CONNECTIVITY

Hitachi, Renesas, Peloton, Continental, NXP, Bosch, Delphi, Intel, Cohda Wireless Mobile Broadband, QNX, TTTech, Denso, Harman, Infineon, Mentor Graphics

MAPPING

TomTom, here, Google, NavInfo, mapscape, Harman, NVIDIA, GeoDigital, Increment P Feel the Space, Exonav Mapping Automation, Zenrin, applanix A Trimble Company, sanborn, Civil Maps, AND

ALGORITHMS

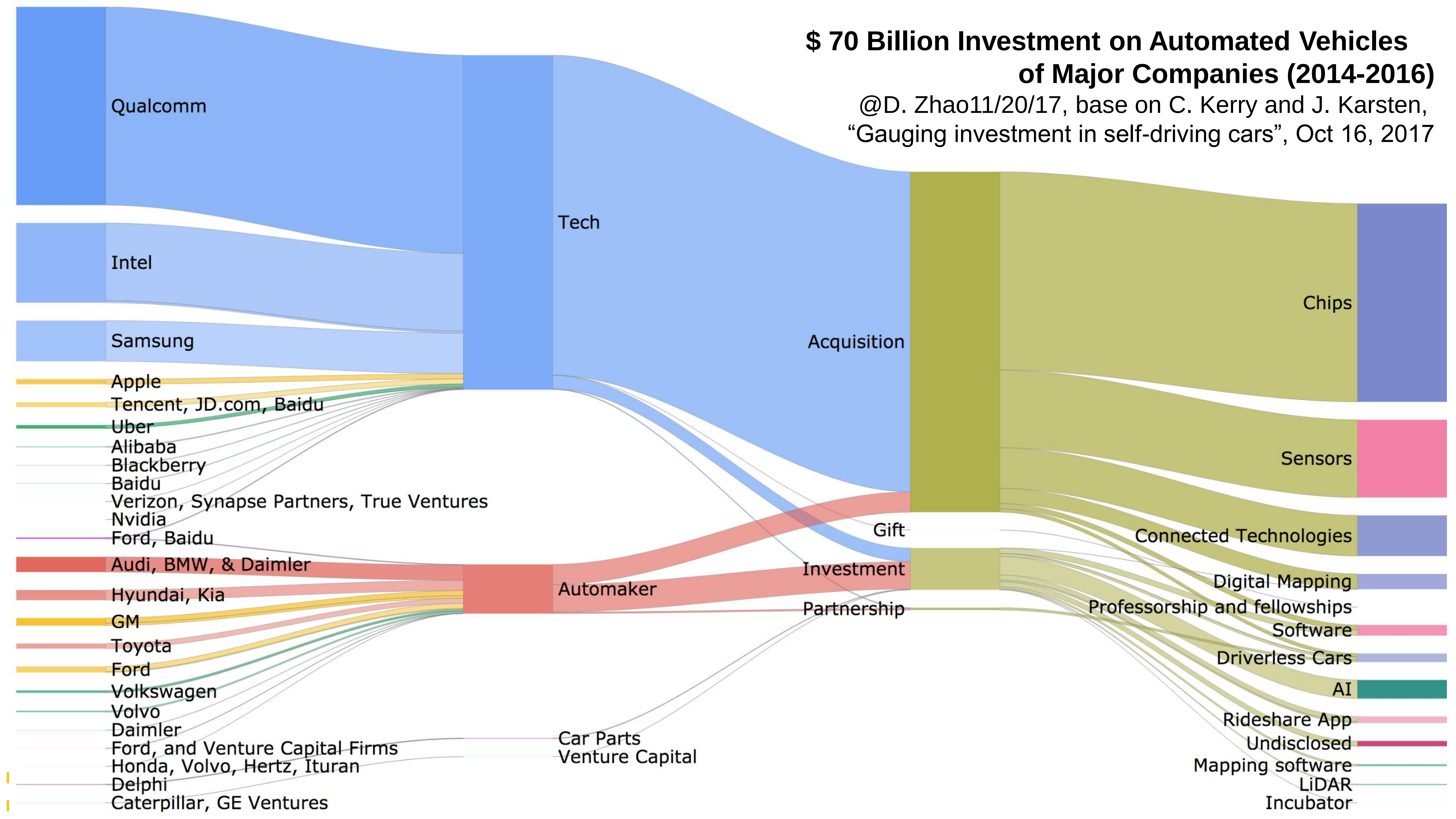
Mobileye, NVIDIA, Mitsubishi Electric, Elektrobit, dSPACE, AdasWorks, Neusoft, ETAS, Luxoft, KPIT, Vector

SECURITY/SAFETY

Hitachi, Renesas, Mentor Graphics, Bosch, Continental, Delphi, NXP, Wind, Argus Cyber Security, Elektrobit, Intel, QNX, Denso, ETAS, Green Hills Software, Harman, Infineon, KPIT, Vector

DEVELOPMENT TOOLS

Baselabs, IAR Systems, LDRA, MathWorks, Synopsys, Vector Software, automotive engineering IAV, Elektrobit, KPIT, Luxoft, Mentor Graphics, Harbrick, Kishonti Informatics, Intempora Multisensor Software Solutions, TASS International, TTTech, dSPACE, ETAS, Vector, QNX


$ 70 Billion Investment on Automated Vehicles
of Major Companies (2014-2016)
@D. Zhao11/20/17, base on C. Kerry and J. Karsten,
"Gauging investment in self-driving cars", Oct 16, 2017
Qualcomm
Intel
Samsung
Apple
Tencent, JD.com, Baidu
Uber
Alibaba
Blackberry
Baidu
Verizon, Synapse Partners, True Ventures
Nvidia
Ford, Baidu
Audi, BMW, & Daimler
Hyundai, Kia
GM
Toyota
Ford
Volkswagen
Volvo
Daimler
Ford, and Venture Capital Firms
Honda, Volvo, Hertz, Ituran
Delphi
Caterpillar, GE Ventures
Tech
Automaker
Car Parts
Venture Capital
Acquisition
Gift
Investment
Partnership
Chips
Sensors
Connected Technologies
Digital Mapping
Professorship and fellowships
Software
Driverless Cars
AI
Rideshare App
Undisclosed
Mapping software
LiDAR
Incubator

But Things Can Go Wrong … Even for the Leaders

Tesla Autopilot Fatal Crash, May, 2016

Google Car Accident, Sep, 2016

Uber Self-driving Rollover, March, 2017

How to prove the technology is safe

My Research are Trying to Answer

- Are CAVs safer?
  - Better than a human driver on average
- How safe?
  - Crash rate, injury rate, …
- Possible failure modes and their probabilities of occurring

and other companies …

How to Choose the Test Scenarios and Interpret the Test Results

Test matrix

Pro: easy to execute, fast
Con: Pre-announced

EURO NCAP AEB

Scenario	$v_L(t_0)$ [km/h]	a_L [m/s²]	R_L [m]	$v(t_0)$ [km/h]
1	0	0	100	30:5:80
2	20	0	100	30:5:70
3	50	-2 & -6	12 & 40	50

Static

Moving

Braking

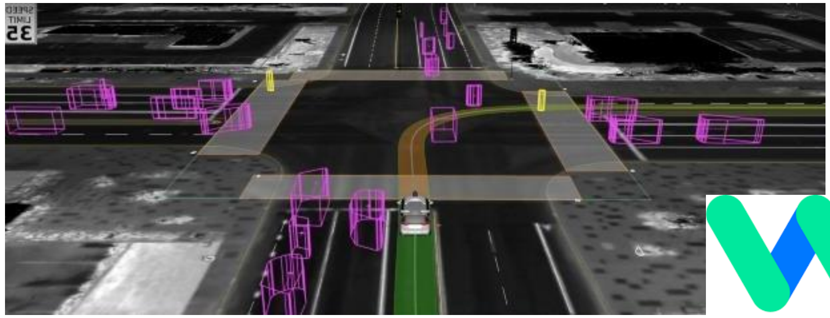
Naturalistic Field Operational Tests

Pro:
The real-world!

Con:
Slow, expensive
Low exposure to safety critical cases

❖ 100 million mi / fatal crash (NHTSA 2013)

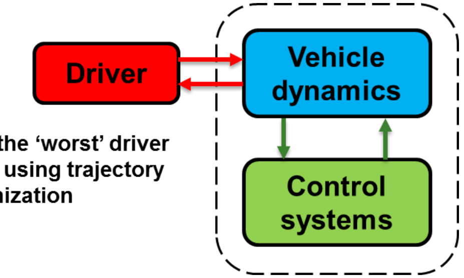
Monte Carlo Simulation



WAYMO

Pro: Stochastic
Con: Does not “accelerate” (cut the boring parts)

Worst-case Scenario Evaluation



Find the ‘worst’ driver input using trajectory optimization

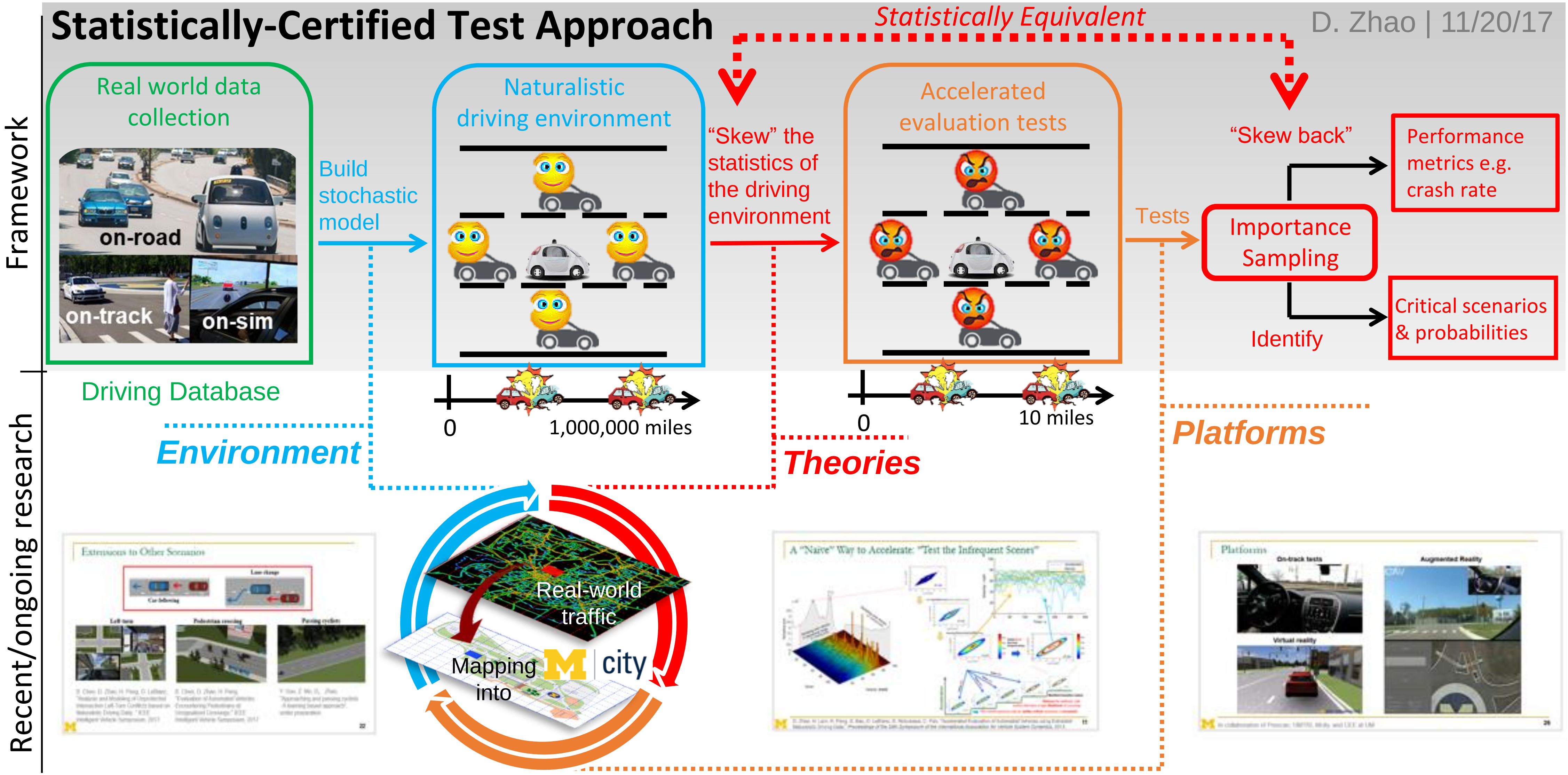
Roll-over analysis

Pro: Worst cases
Con: No probability information

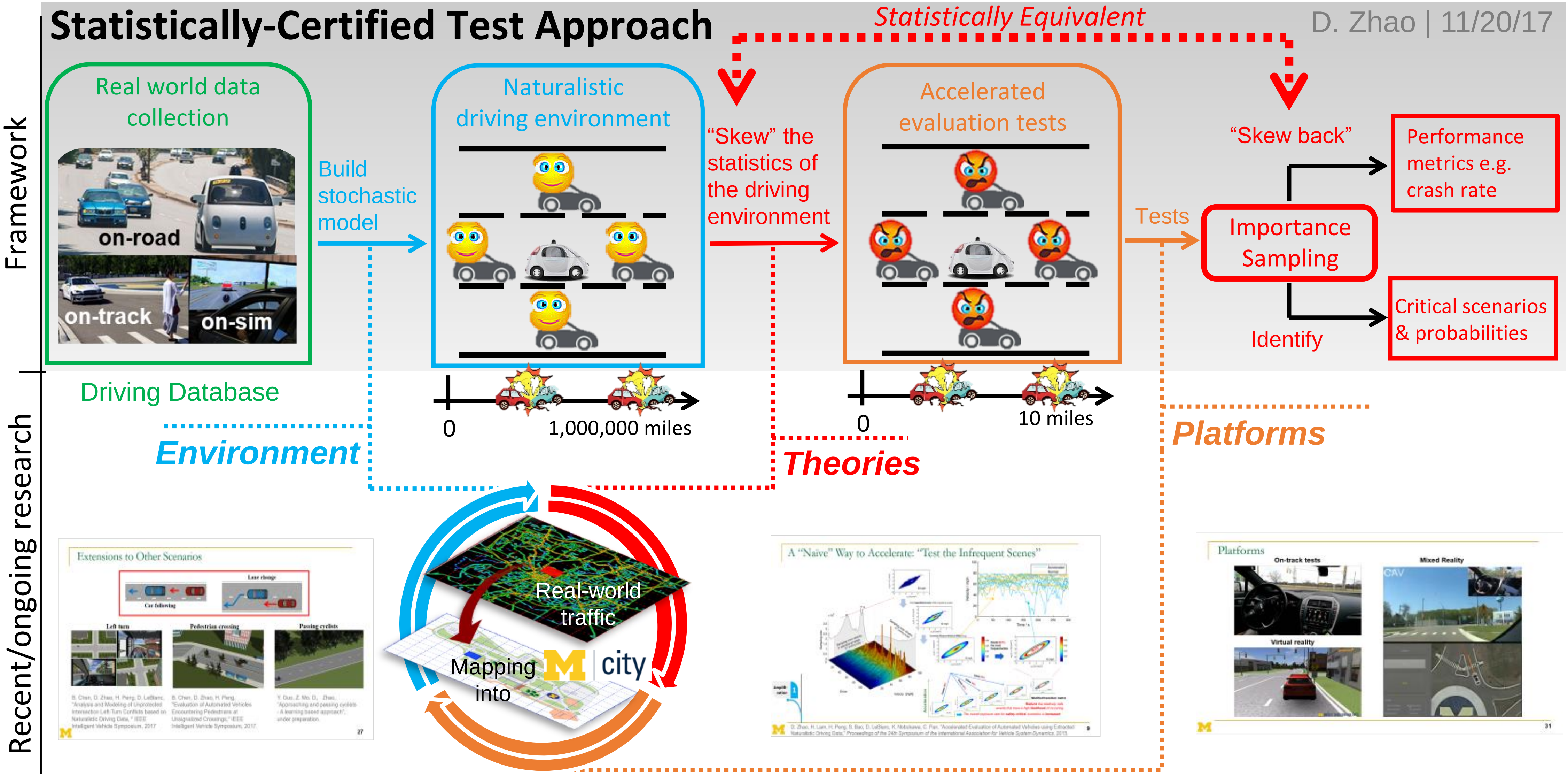
NCAP: New Car Assessment Programme
AEB: Autonomous Emergency Braking

Earth from Sun: 93 million mi

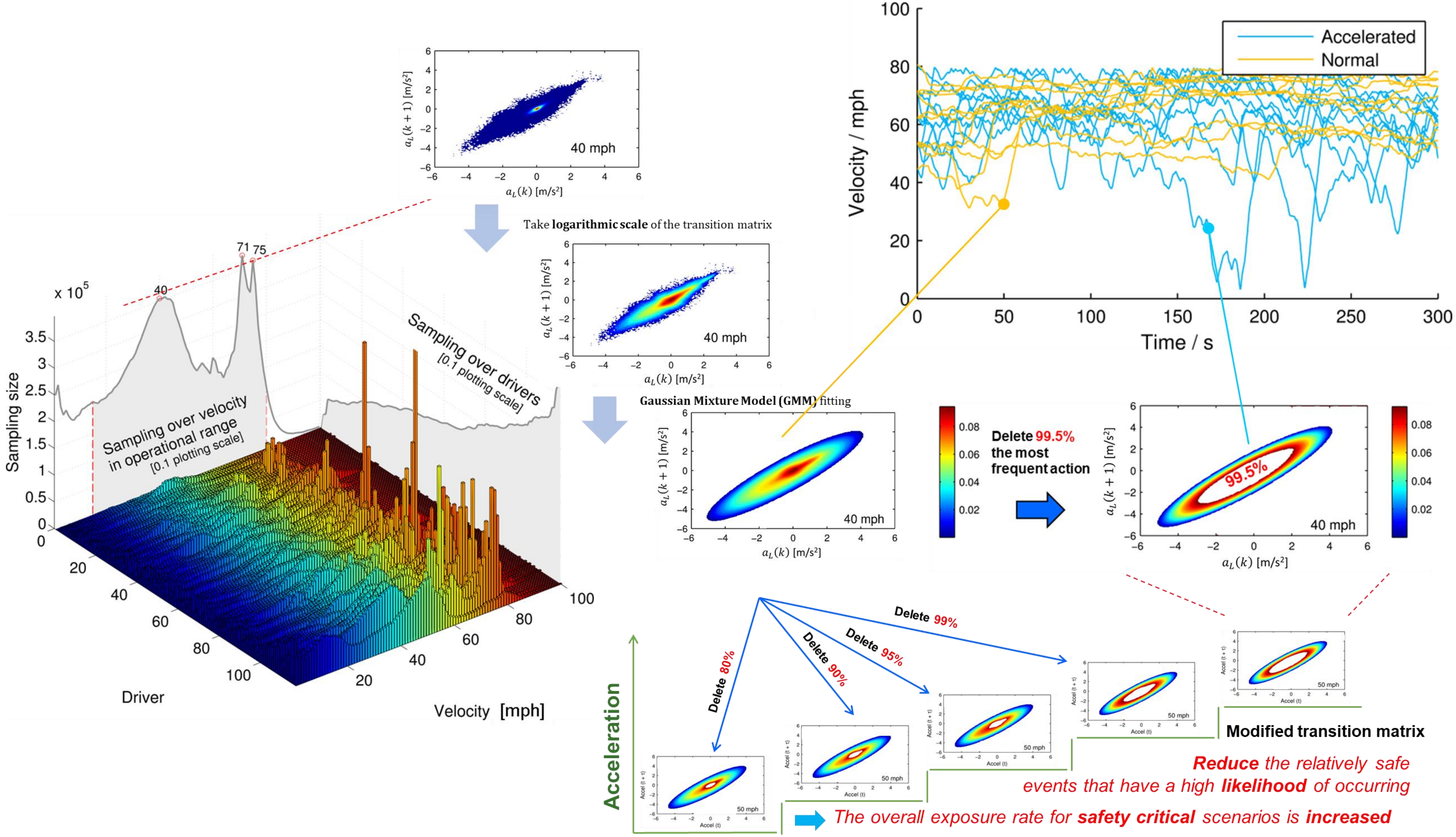
Statistically-Certified Automated Vehicles Evaluation Approach



Statistically-Certified Automated Vehicles Evaluation Approach



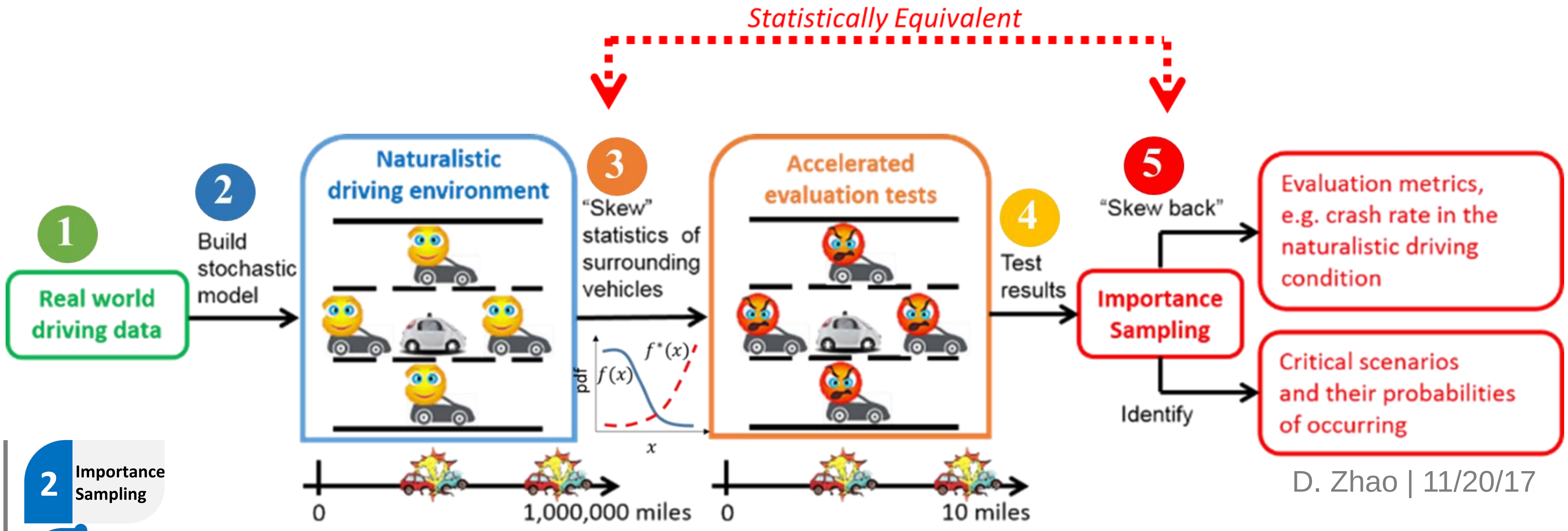
A "Naïve" Way to Accelerate: "Test the Infrequent Scenes"

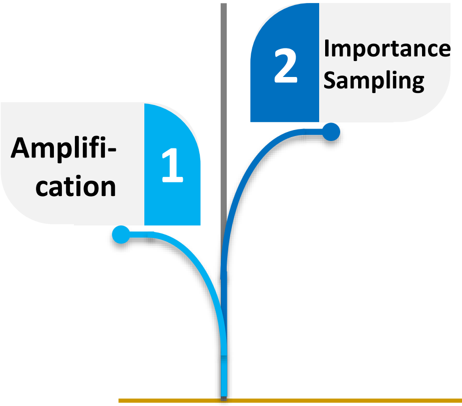


Amplifi-cation 1

D. Zhao, H. Lam, H. Peng, S. Bao, D. LeBlanc, K. Nobukawa, C. Pan, "Accelerated Evaluation of Automated Vehicles using Extracted Naturalistic Driving Data," *Proceedings of the 24th Symposium of the International Association for Vehicle System Dynamics*, 2015.

[**Rigor**] Accelerated Evaluation using Importance Sampling





D. Zhao, H. Lam, H. Peng, S. Bao, D. LeBlanc, K. Nobukawa, C. Pan, "Accelerated evaluation of automated vehicles in lane change scenarios, 2015," in Proceedings of the ASME 2015 Dynamic Systems and Control Conference (DSCC), Columbus, U.S.A., Oct 28-30, 2015.

Rare Event Simulation – Importance Sampling

- Suppose we are interested in the probability of rare event $\mathcal{E}$:

$$\boldsymbol{P}(x \in \mathcal{E}) = \int I_{\mathcal{E}}(x) f(x) dx = E[I_{\mathcal{E}}(x)]$$

- The importance sampling estimator is derived from:

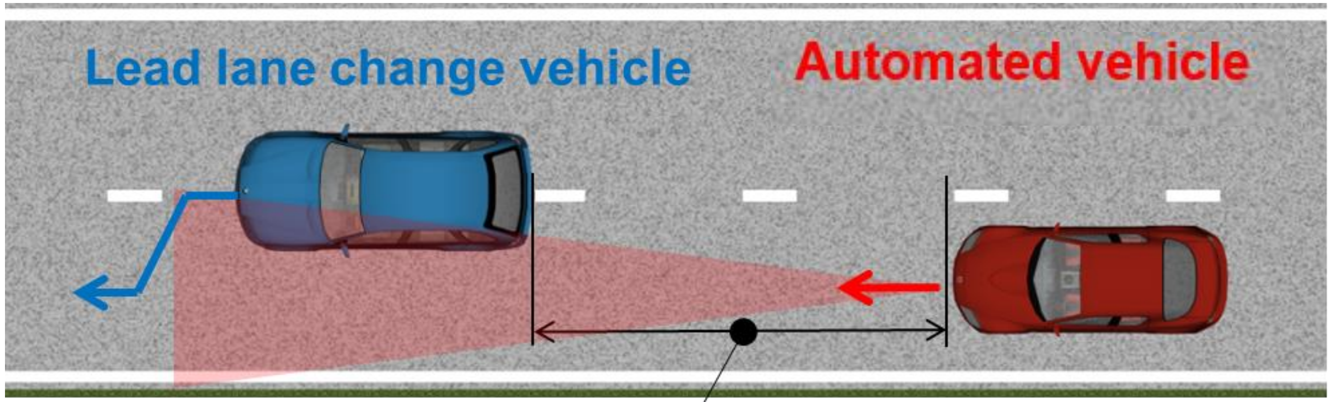
$$\boldsymbol{P}(x \in \mathcal{E}) = \int I_{\mathcal{E}}(x) f(x) dx = \int I_{\mathcal{E}}(x) \frac{f(x)}{\tilde{f}(x)} \tilde{f}(x) dx = \tilde{E}\left[I_{\mathcal{E}}(x) \frac{f(x)}{\tilde{f}(x)}\right] = \tilde{E}[I_{\mathcal{E}}(x) L(x)] \quad \boxed{L(x) = \frac{f(x)}{\tilde{f}(x)}}$$

- We generate $\boldsymbol{X}$ from $\tilde{f}$, then

$$\boxed{Z = I_{\mathcal{E}}(\boldsymbol{X}) L(x)} \longrightarrow \textbf{Unbiased Estimator}$$

- Powerful approach to reduce variance for estimation (Asmussen & Glynn 2007, Blanchet & Lam 2012, Juneja & Shahabuddin 2006, etc.).

Case 1: Cut-in Scenarios



Acceleration $\boldsymbol{a_L(t)}$
Velocity $\boldsymbol{v_L(t)}$
Position $\boldsymbol{D_L(t)}$

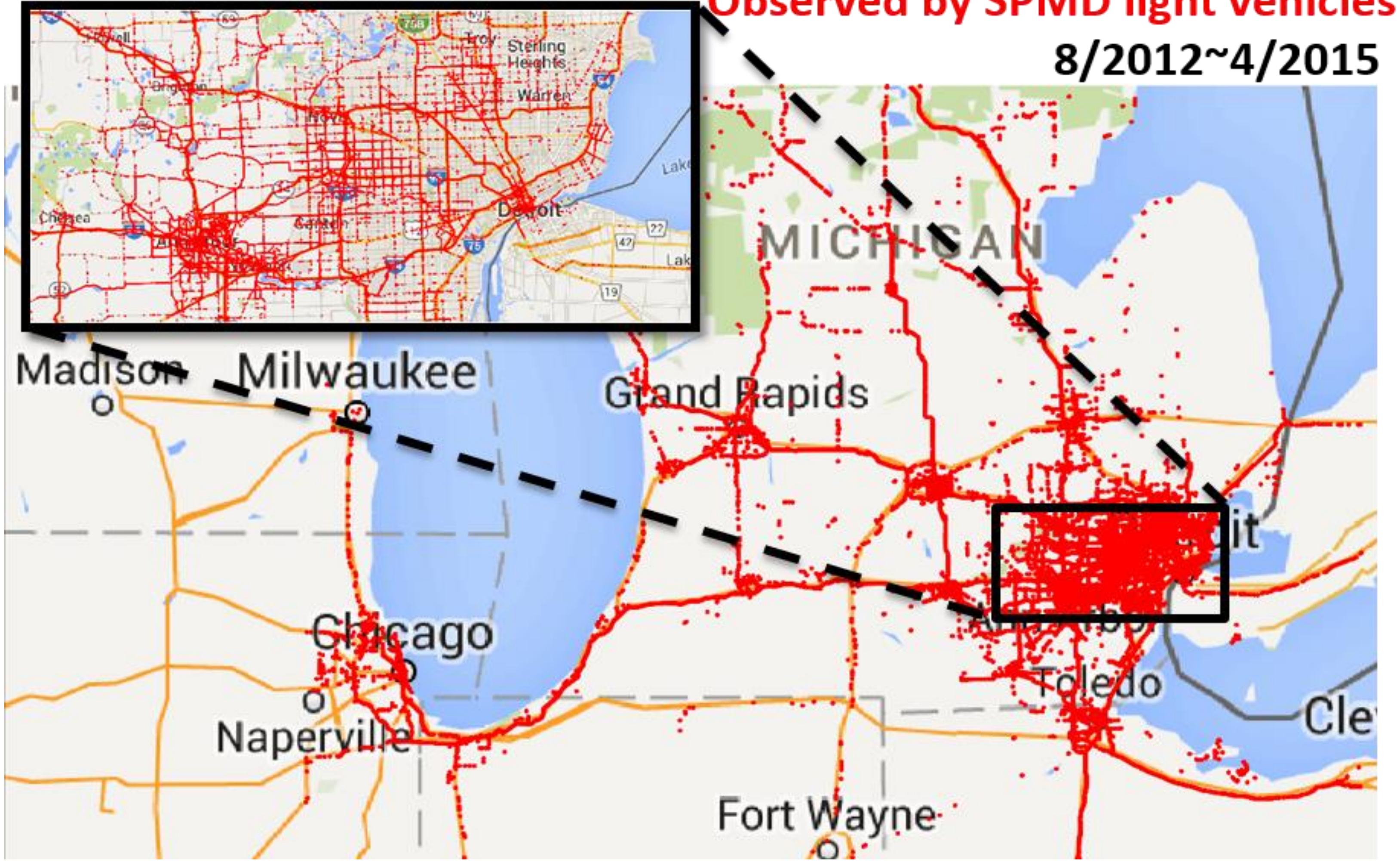
Range
$R_L(t) = \boldsymbol{D_L(t) - D(t)}$
Range rate
$$\dot{\boldsymbol{R}}_L(\boldsymbol{t}) = \frac{\boldsymbol{d}}{\boldsymbol{dt}} \boldsymbol{R_L(t)}$$

Acceleration $\boldsymbol{a(t)}$
Velocity $\boldsymbol{v(t)}$
Position $\boldsymbol{D(t)}$

D. Zhao, H. Lam, H. Peng, S. Bao, D. LeBlanc, K. Nobukawa, C. Pan, "Accelerated evaluation of automated vehicles safety in lane-change scenarios based on importance sampling techniques," *IEEE transactions on intelligent transportation systems*, *18*(3), 595-607, 2017

Lane Change Events in Safety Pilot Database

403,581 lane change events
Observed by SPMD light vehicles
8/2012~4/2015



Criteria:

Longitude $\in (-88.2°, -82.0°)$
Latitude $\in (41.0°, 44.5°)$

$v(t_{LC}) \in (2\text{ m/s}, 40\text{ m/s})$
$v_L(t_{LC}) \in (2\text{ m/s}, 40\text{ m/s})$
$R_L(t_{LC}) \in (0.1\text{ m}, 75\text{ m})$

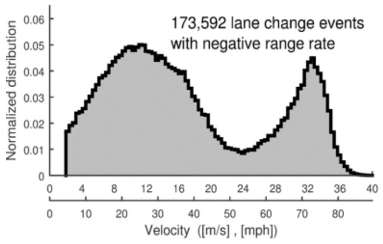
94 drivers
1.3 million miles

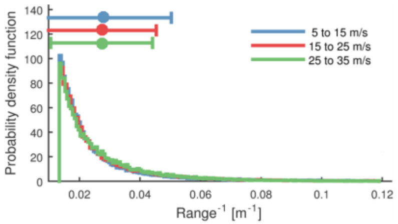
Importance Sampling Techniques

Motivation

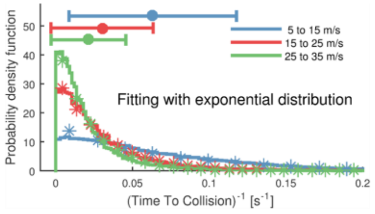
Gap acceptance → $[v_L, R_L, TTC_L]$

Execution





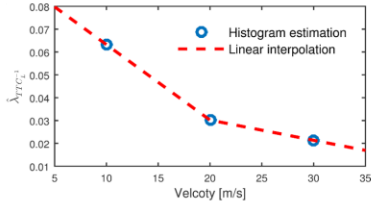
$f_{v_L} \rightarrow v_L \dashrightarrow f_{R_L^{-1}} \rightarrow R_L$

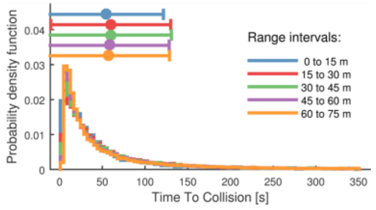


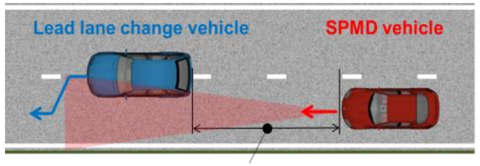
③ Skew the statistics

Importance Sampling

⑤ "Skew back"

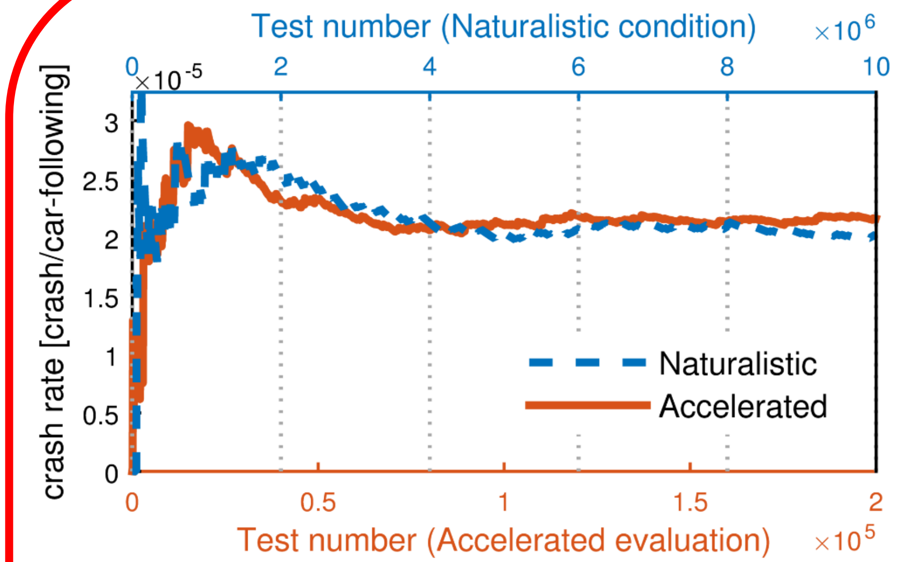


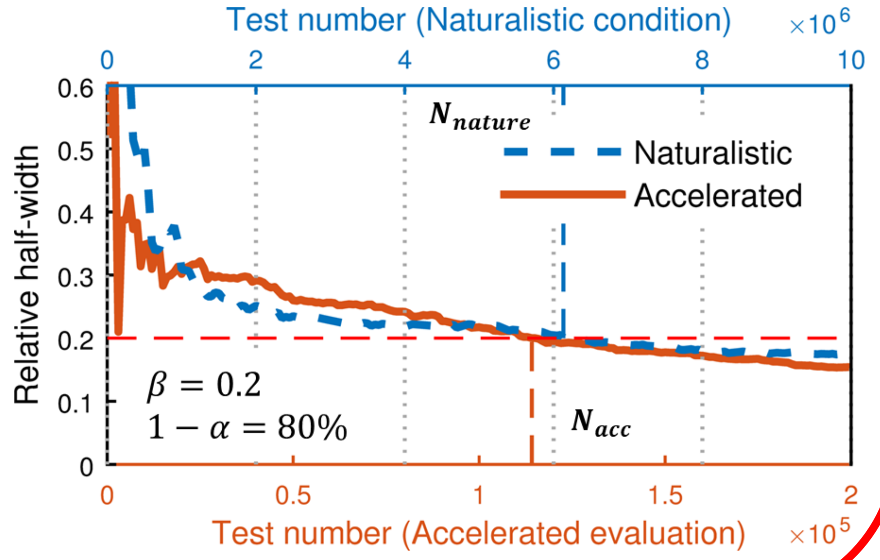




$f_{v_L} \rightarrow v_L \dashrightarrow f_{R_L^{-1}} \rightarrow R_L$

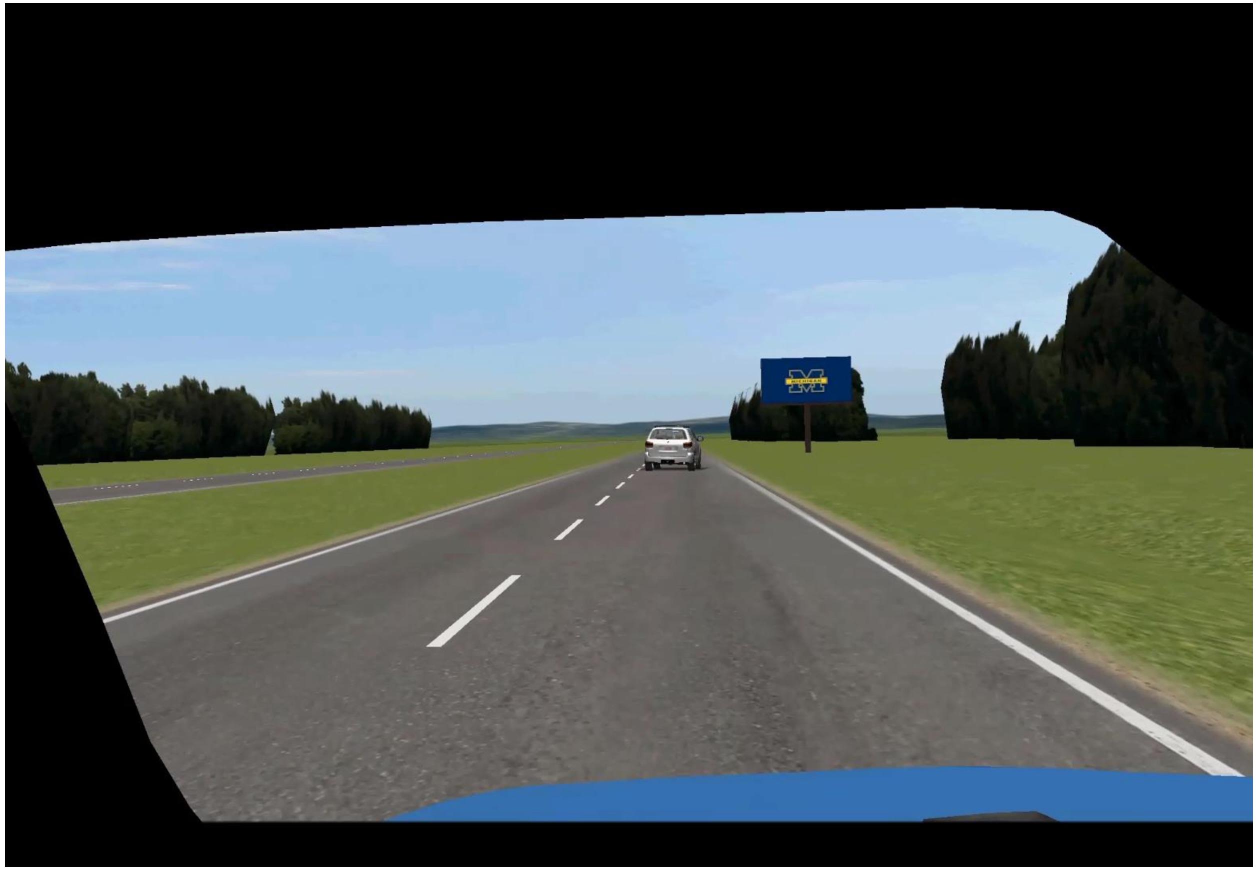
$f_{TTC_L^{-1}} \rightarrow TTC_L$





Naturalistic Driving vs Accelerated Tests

Naturalistic driving conditions



Accelerated tests

[**Adaptivity**] Adaptive Accelerated Evaluation using Cross Entropy

Exponential twisting

$$\tilde{f}_{\vartheta}(x) = exp\left(\vartheta x - \Psi(\vartheta)\right) f(x)$$

$$\Psi(\vartheta) = \log \mathrm{E}\left(\exp\left(\vartheta^{\mathrm{T}} x\right)\right)$$

Theoretically optimal $f^*(\cdot)$

$$f^*_{zv}(\boldsymbol{x}) = \begin{cases} \dfrac{f(\boldsymbol{x})}{\gamma}, & I_{\varepsilon}(\boldsymbol{x}) = 1 \\ 0, & I_{\varepsilon}(\boldsymbol{x}) = 0 \end{cases}$$

$f^*_{zv}(\boldsymbol{x})$

$\tilde{\boldsymbol{f}}_{\boldsymbol{\vartheta}^{(i)}}(\boldsymbol{x})$

$\boldsymbol{\vartheta}^{(i)}$ — **Simulation**

Cross Entropy

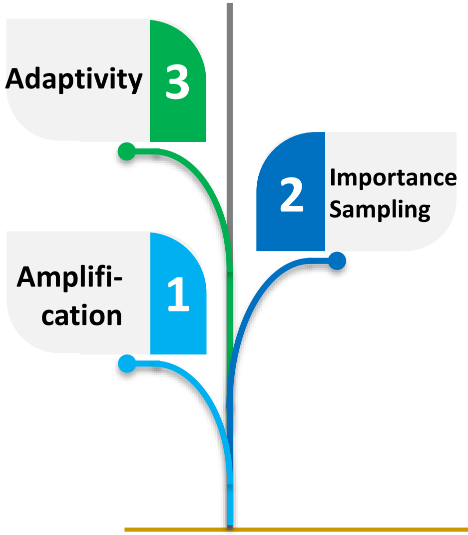
Update

$$\boldsymbol{\vartheta}^{(i+1)} = \underset{\boldsymbol{\vartheta}}{\mathbf{argmin}}\ \mathrm{difference}\left(f^*_{zv}(\boldsymbol{x}), \tilde{f}_{\boldsymbol{\vartheta}}(\boldsymbol{x})\right)$$

based on the simulation results using $\tilde{\boldsymbol{f}}_{\boldsymbol{\vartheta}^{(i)}}(\boldsymbol{x})$

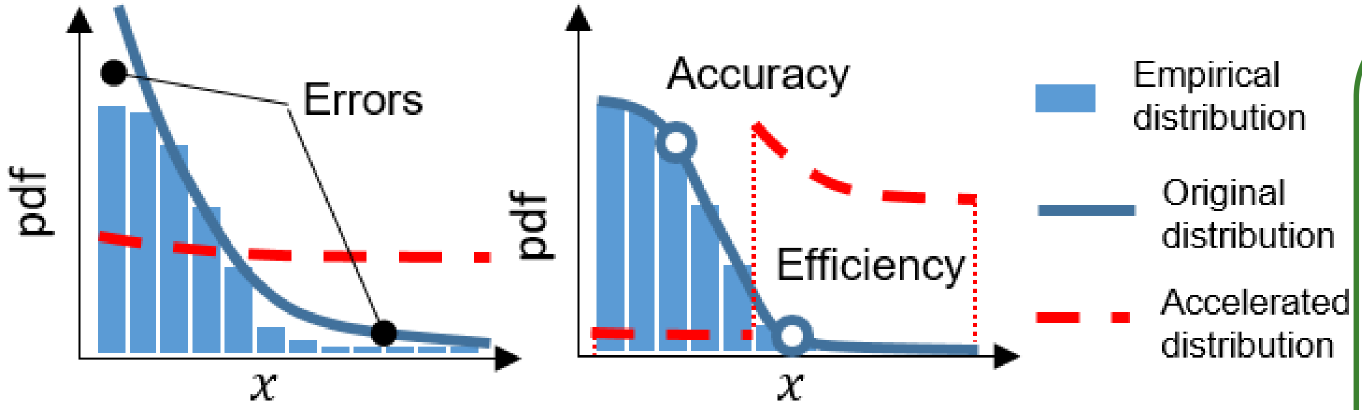
Kullback–Leibler divergence

$$f_{KL}\left(f_1(x), f_2(x)\right) = \int log\left[\frac{f^*_{zv}(x)}{\tilde{f}_{\vartheta}(x)}\right] f^*_{zv}(x)$$

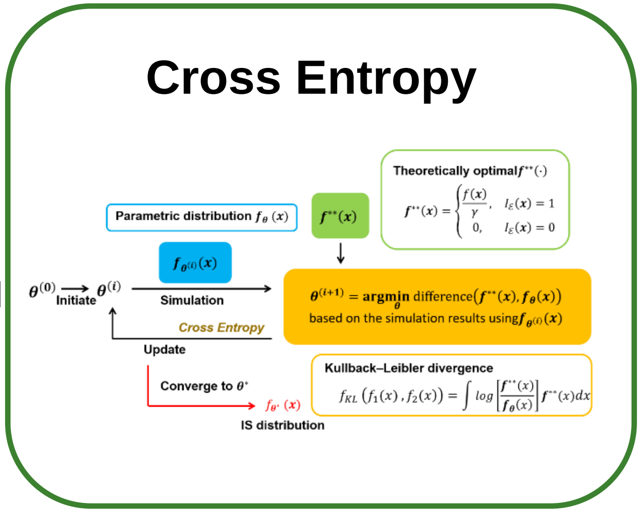


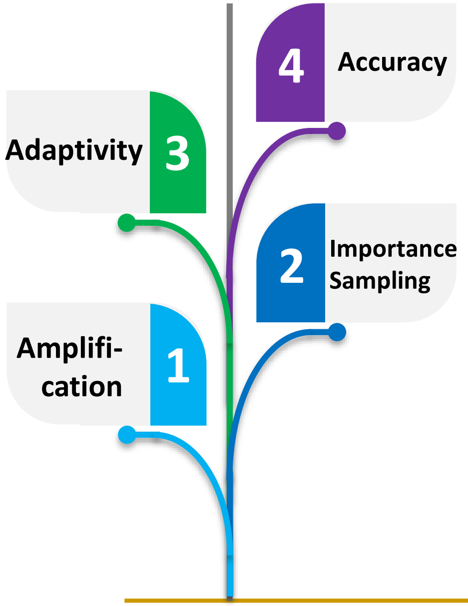
D. Zhao, H. Lam, H. Peng, S. Bao, D. LeBlanc, K. Nobukawa, C. Pan, "Accelerated evaluation of automated vehicles safety in lane-change scenarios based on importance sampling techniques," *IEEE transactions on intelligent transportation systems*, *18*(3), 595-607, 2017

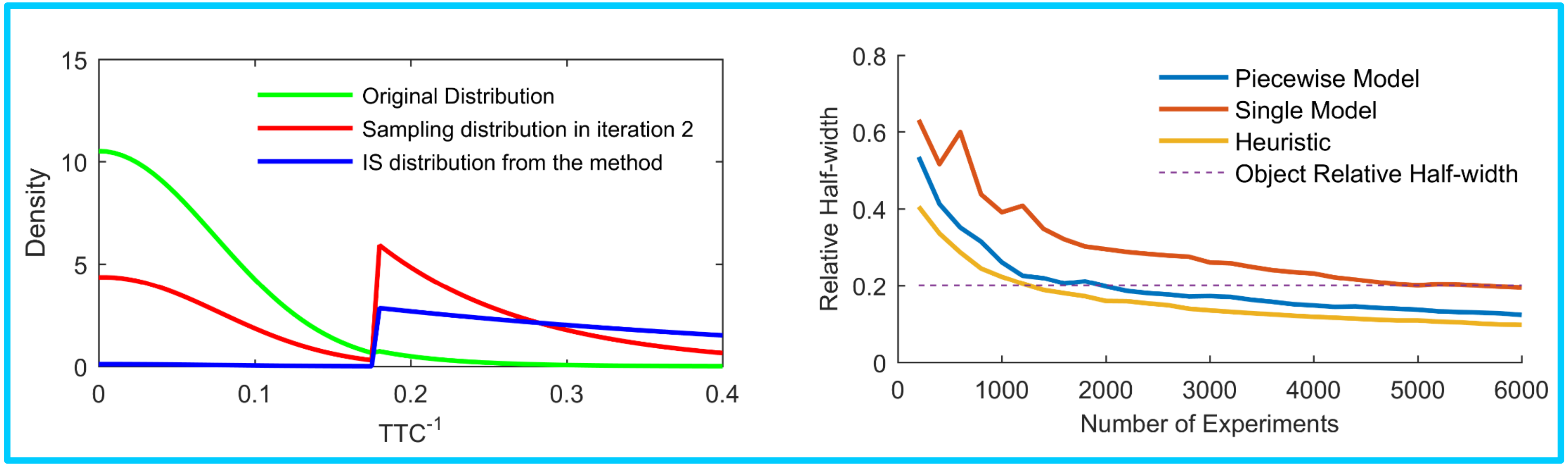
[**Accuracy**] Accelerated Evaluation using Piecewise Mixture Models



Accelerated Evaluation based on
a) a single distribution b) a piecewise mixture distribution

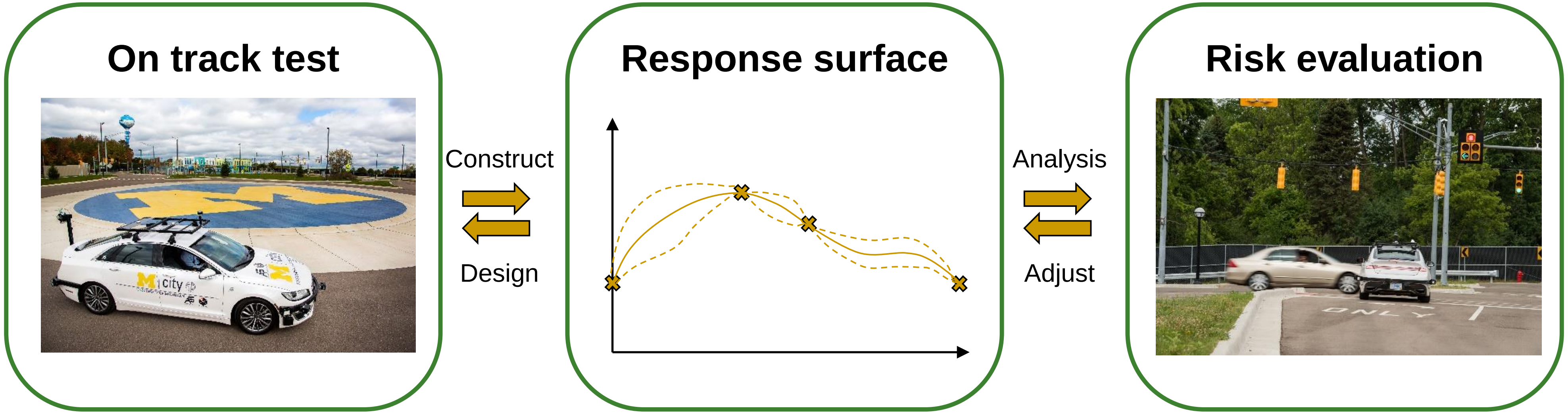


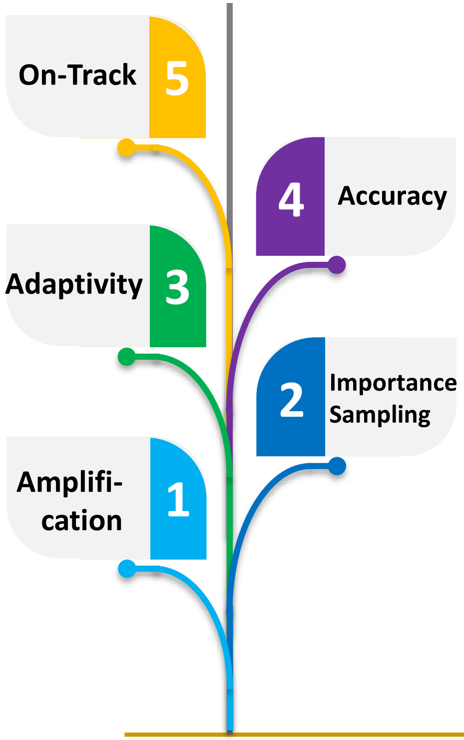




Z. Huang, H. Lam, D. LeBlanc, Ding Zhao, "Accelerated Evaluation of Automated Vehicles using Piecewise Mixture Models," IEEE Transactions on Intelligent Transportation Systems, under review, 2017.

[On-Track] Kriging-based Evaluation

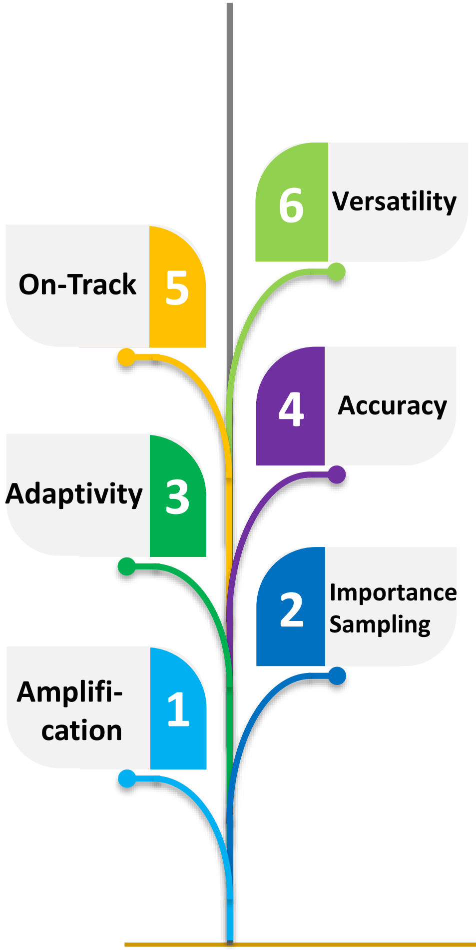




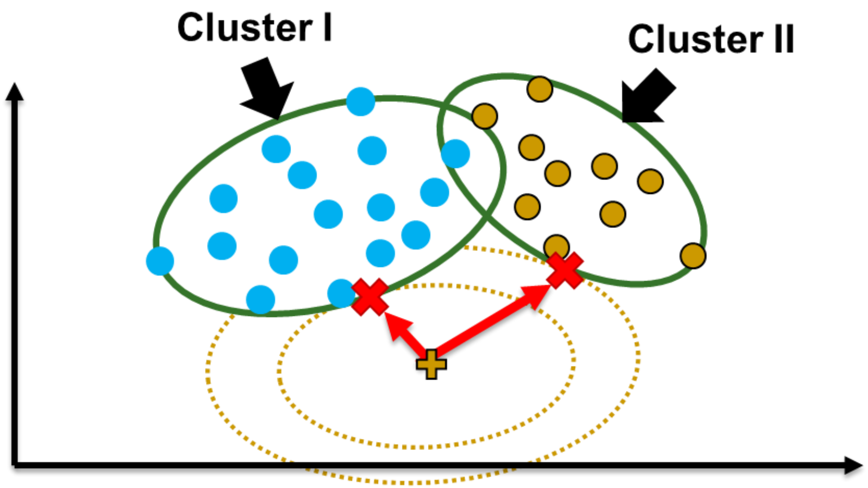
- On track tests are expensive and time-consuming
- Previous accelerated rate is high, but not enough
- **Objective**
  - **Introduce reasonable assumptions such that on-track test is affordable**

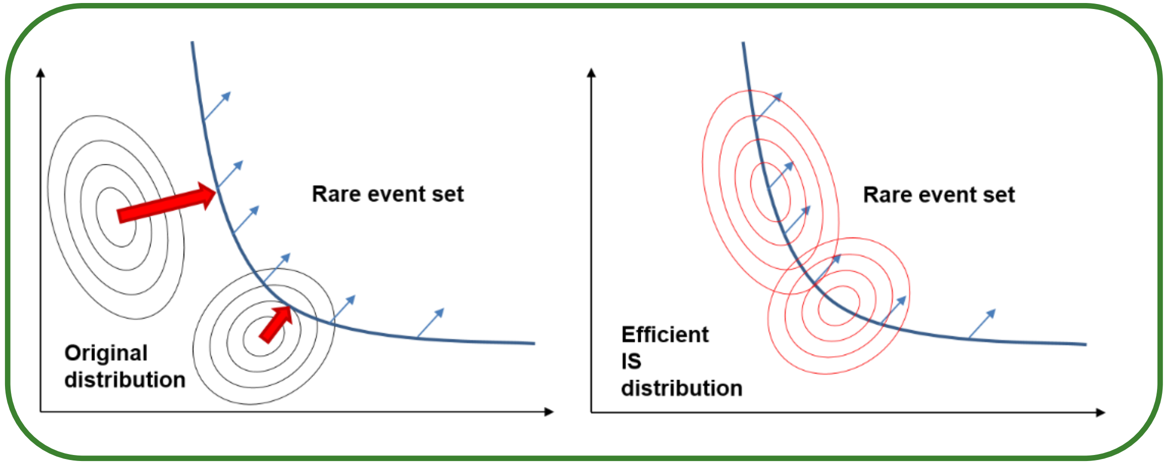
Z. Huang, H. Lam, Ding Zhao, "Towards Affordable On-track Testing for Autonomous Vehicle - A Kriging-based Statistical Approach," Proceedings of the IEEE 20th International Intelligent Transportation Systems Conference (ITSC), Yokohama, Japan, 2017.

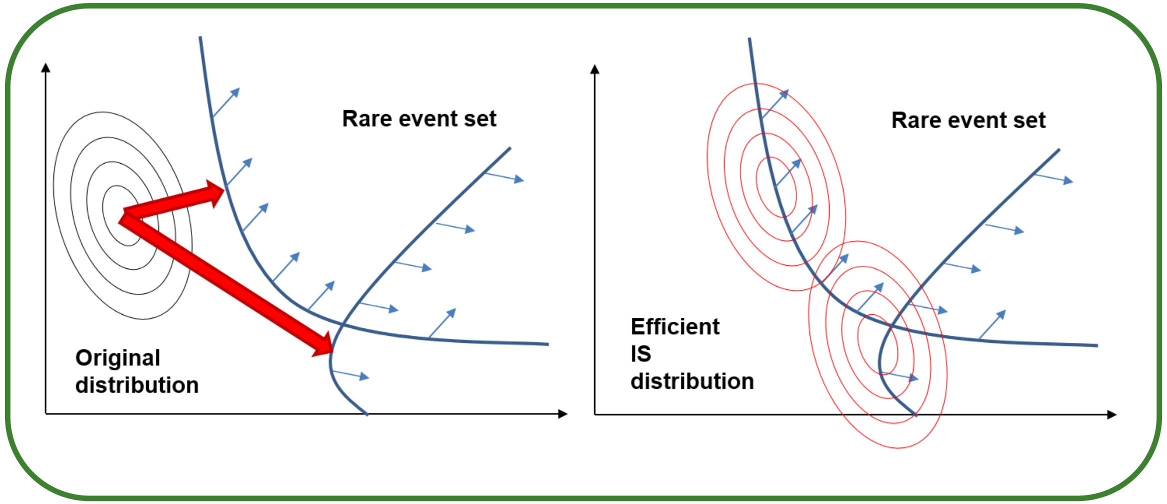
[Versatility] Accelerated Evaluation using Joint Distribution



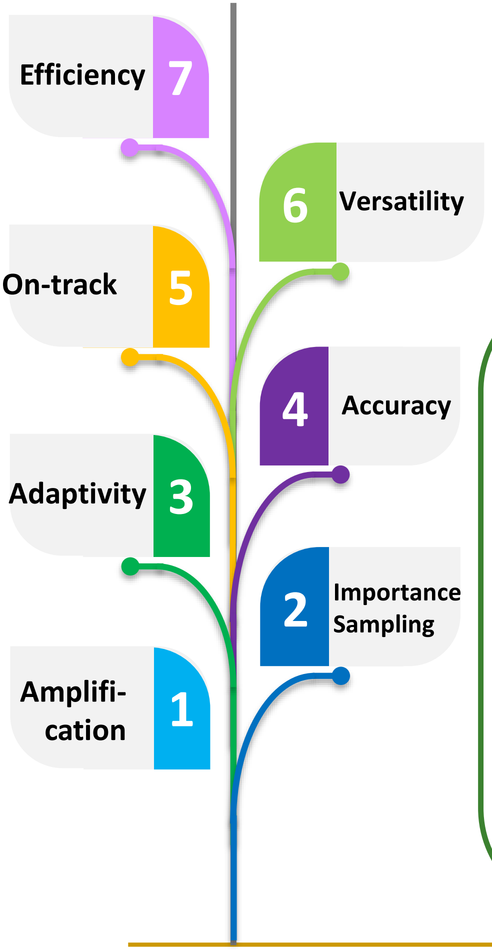
- Motivation
  - Capture the dependency between variables
  - A robust approach to all types of distribution
- **Challenges: Construct accelerated distribution**



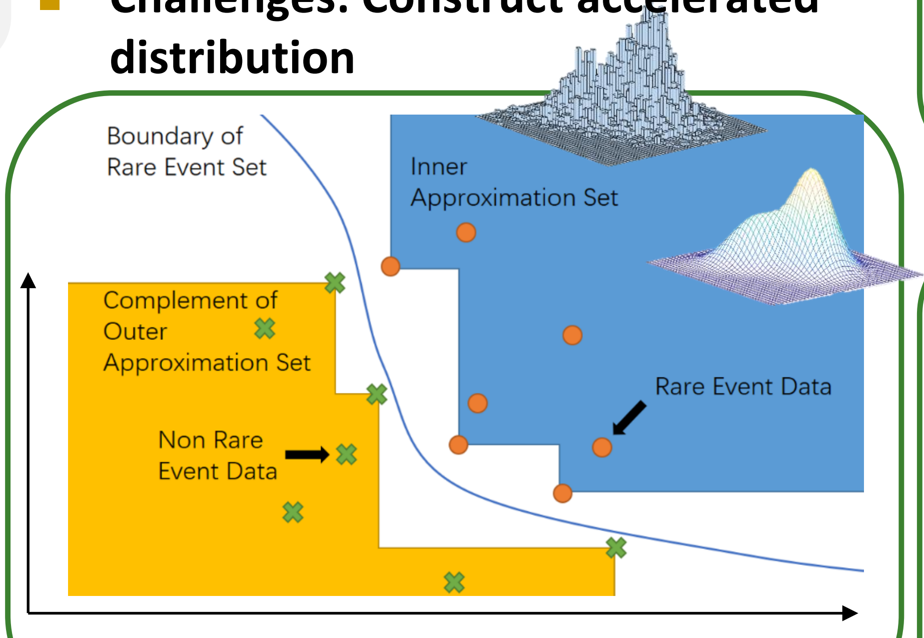




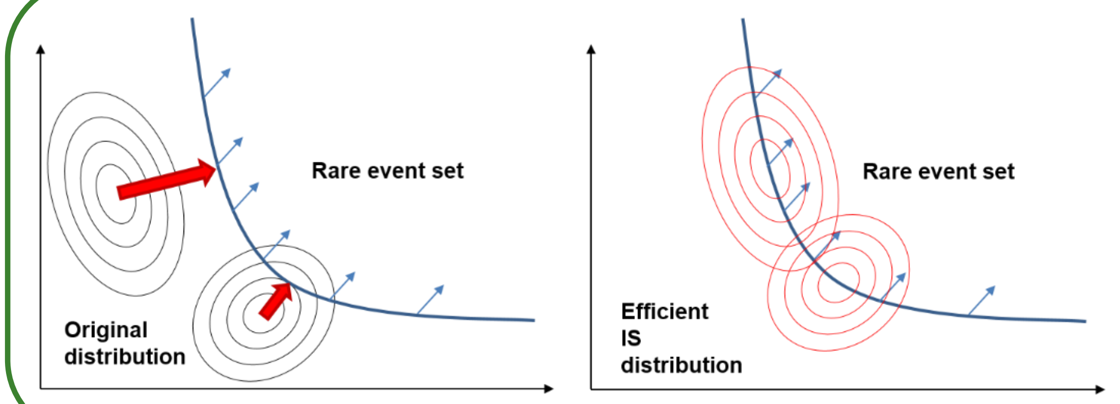
[Efficiency] Accelerated Evaluation using Joint Distribution

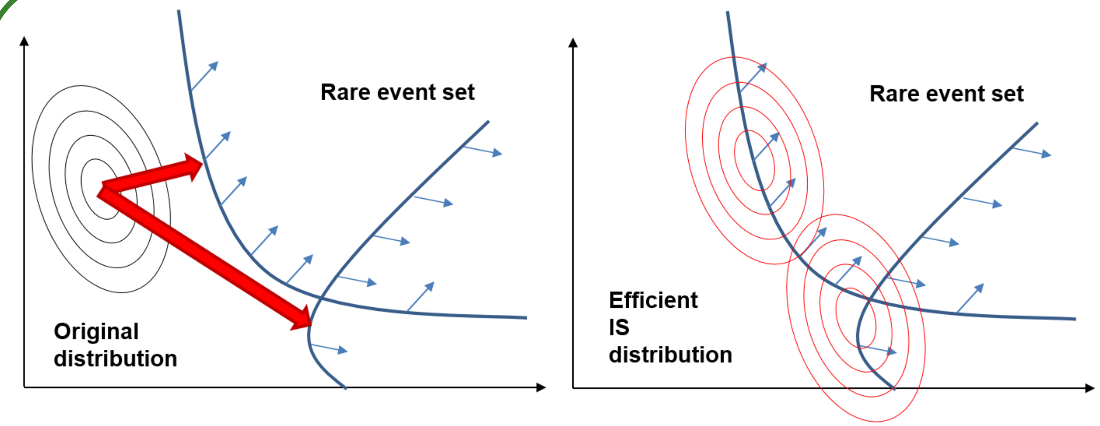


- Motivation
  - Capture the dependency between variables
  - A robust approach to all types of distribution
- **Challenges: Construct accelerated distribution**



Monotonic rare-event set

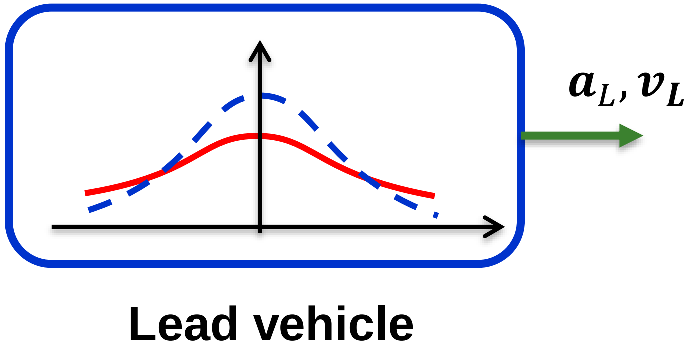




Z. Huang, H. Lam, Ding Zhao, "An Accelerated Testing Approach for Automated Vehicles with Background Traffic Described by Joint Distributions, " Proceedings of the IEEE 20th International Intelligent Transportation Systems Conference (ITSC), 2017.

[Dynamic] Accelerated Evaluation with Stochastic Optimization

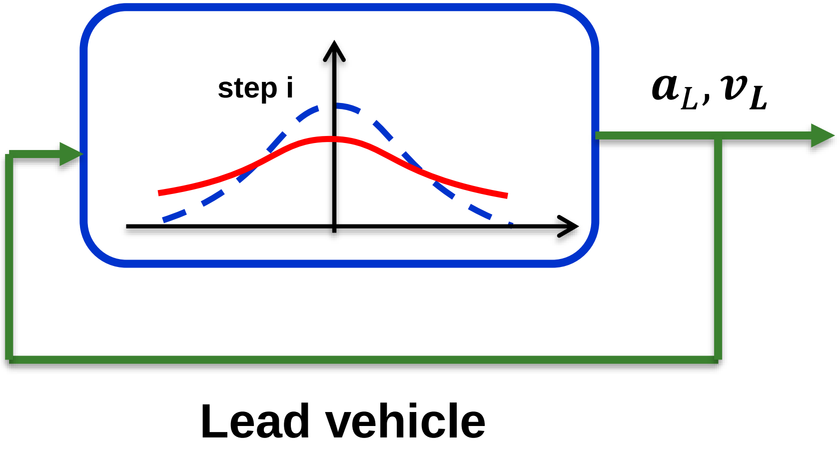
Lane change (single-step sampling)



Naturalistic distribution

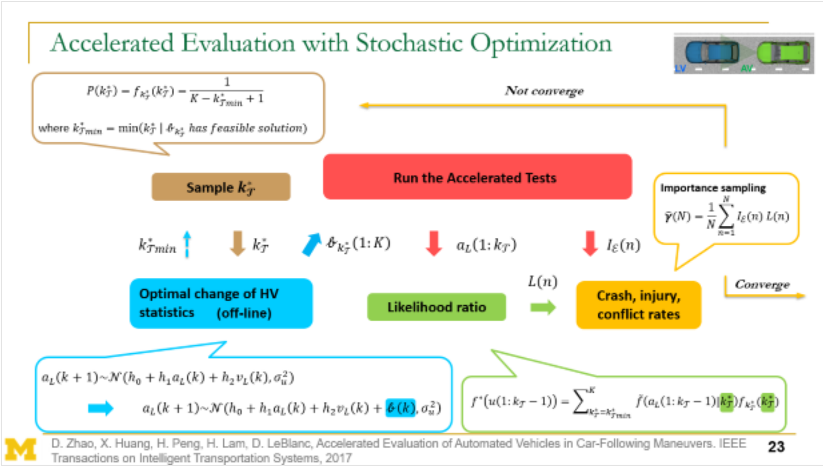
AE distribution

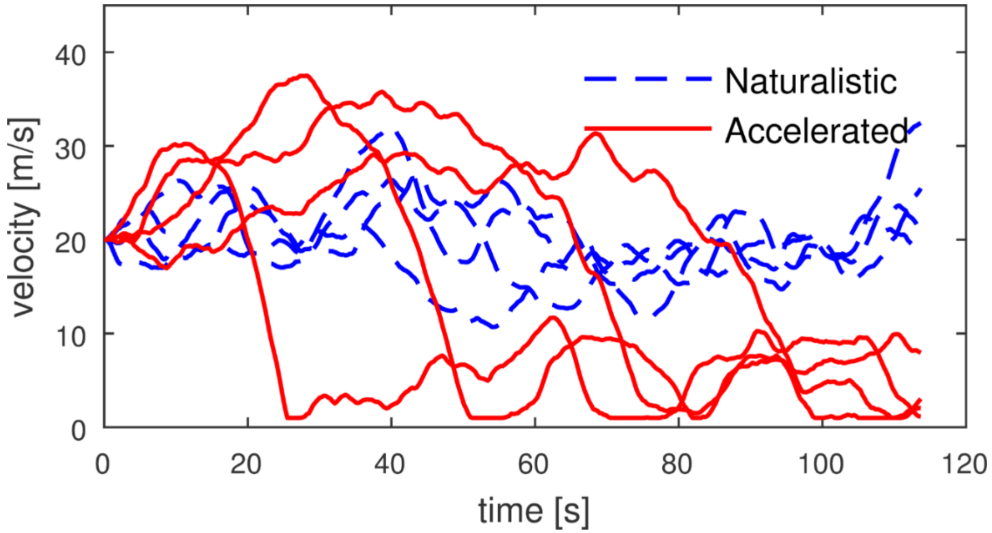
Car-following
Multi-step stochastic sampling
(Dynamic sampling)

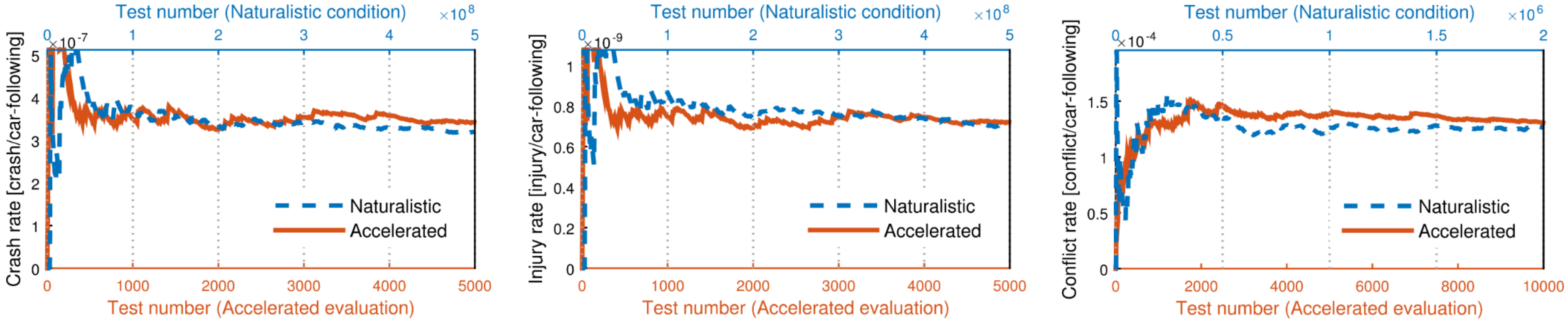


- Fold N-step dynamic sampling together to a N-dimensional distribution and solve the new problem with stochastic method.

[Dynamic] Accelerated Evaluation with Stochastic Optimization



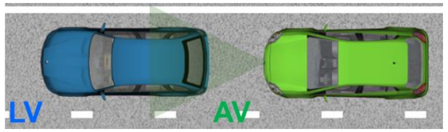




N_{nature}/N_{acc}: **Crash (1.12e5)** **Injury(1.35e5)** **Conflict (3.28e2)**

D. Zhao, X. Huang, H. Peng, H. Lam, D. LeBlanc, Accelerated Evaluation of Automated Vehicles in Car-Following Maneuvers. IEEE Transactions on Intelligent Transportation Systems, 2017

Accelerated Evaluation with Stochastic Optimization



$$P(k_{\mathcal{T}}^*) = f_{k_{\mathcal{T}}^*}(k_{\mathcal{T}}^*) = \frac{1}{K - k_{\mathcal{T}min}^* + 1}$$

where $k_{\mathcal{T}min}^* = \min(k_{\mathcal{T}}^* \mid \mathscr{b}_{k_{\mathcal{T}}^*}\ has\ feasible\ solution)$

Not converge

Sample $k_{\mathcal{T}}^*$

Run the Accelerated Tests

Importance sampling

$$\hat{\gamma}(N) = \frac{1}{N}\sum_{n=1}^{N} I_{\varepsilon}(n)\, L(n)$$

$k_{\mathcal{T}min}^*$ $\quad$ $k_{\mathcal{T}}^*$ $\quad$ $\mathscr{b}_{k_{\mathcal{T}}^*}(1{:}K)$ $\quad$ $a_L(1{:}k_{\mathcal{T}})$ $\quad$ $I_{\varepsilon}(n)$

$L(n)$

Converge

Optimal change of HV statistics (off-line)

Likelihood ratio

Crash, injury, conflict rates

$$a_L(k+1) \sim \mathcal{N}(h_0 + h_1 a_L(k) + h_2 v_L(k), \sigma_u^2)$$

$$\Rightarrow \quad a_L(k+1) \sim \mathcal{N}(h_0 + h_1 a_L(k) + h_2 v_L(k) + \mathscr{b}(k), \sigma_u^2)$$

$$f^*(u(1{:}k_{\mathcal{T}}-1)) = \sum_{k_{\mathcal{T}}^* = k_{\mathcal{T}min}^*}^{K} \tilde{f}(a_L(1{:}k_{\mathcal{T}}-1) \mid k_{\mathcal{T}}^*) f_{k_{\mathcal{T}}^*}(k_{\mathcal{T}}^*)$$

D. Zhao, X. Huang, H. Peng, H. Lam, D. LeBlanc, Accelerated Evaluation of Automated Vehicles in Car-Following Maneuvers. IEEE Transactions on Intelligent Transportation Systems, 2017

Summary of the Theories

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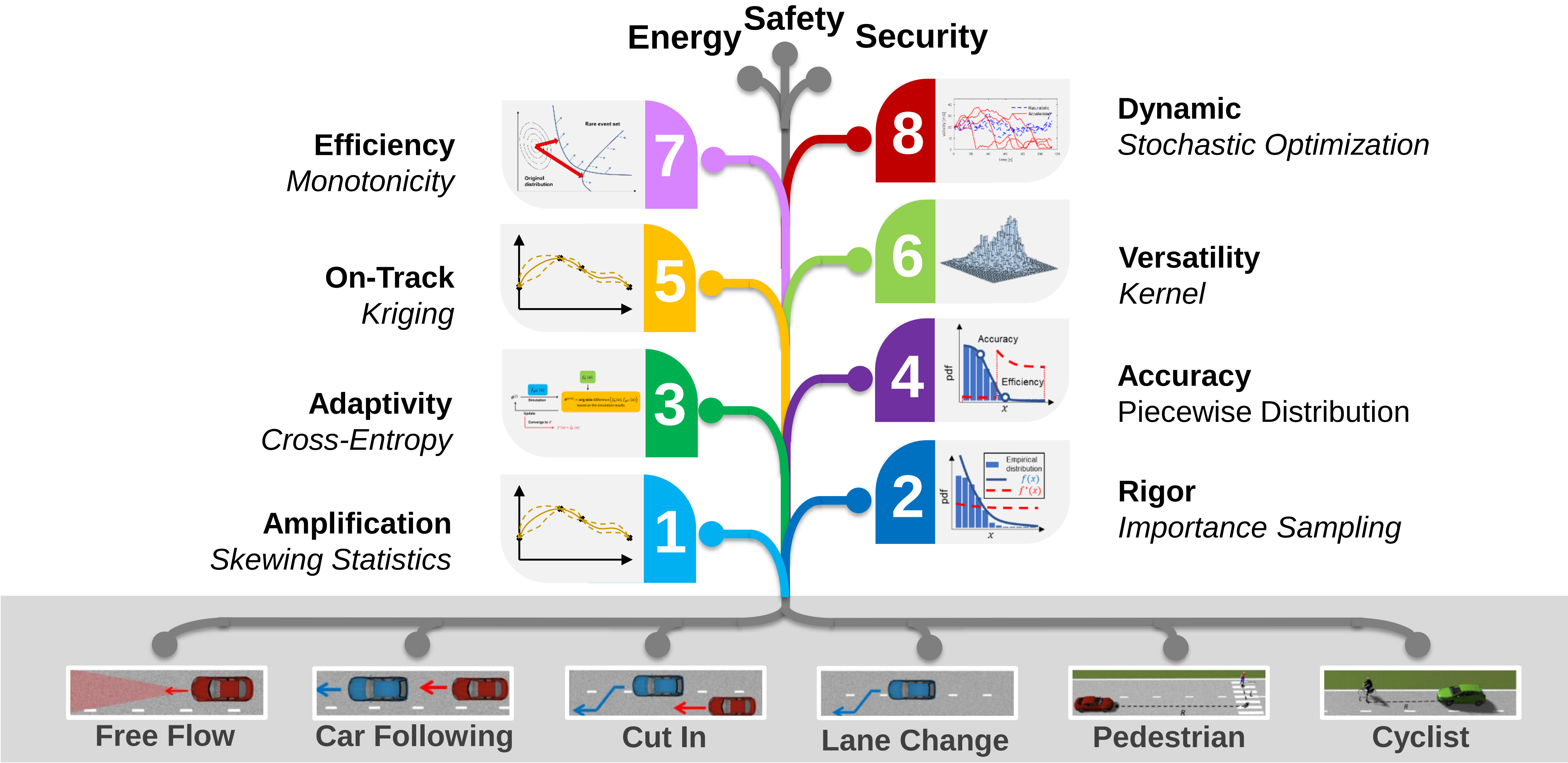
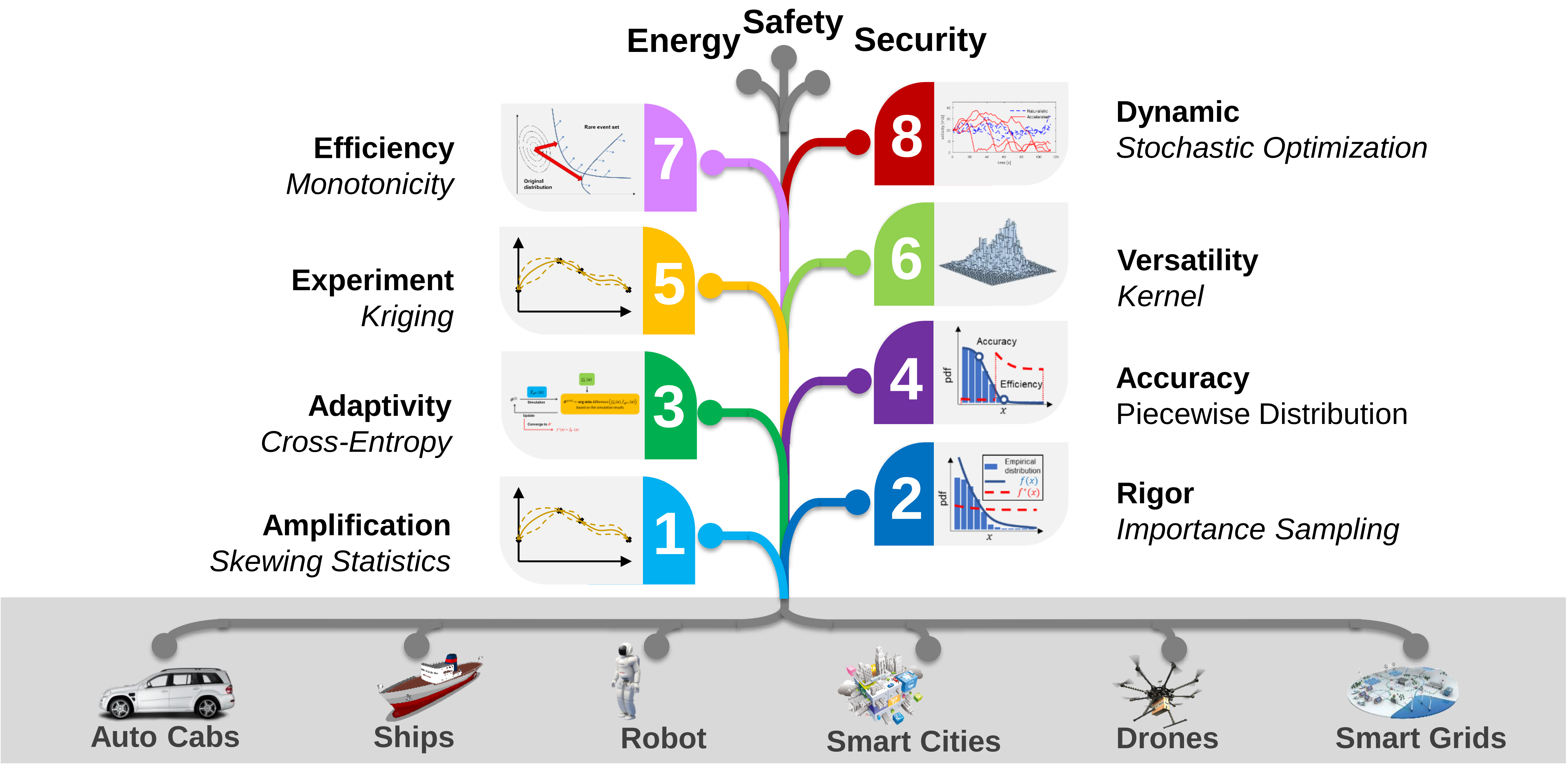
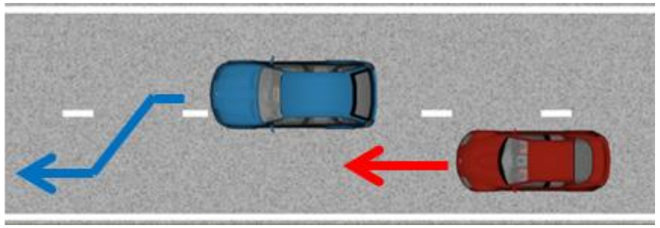


Summary of the Theories

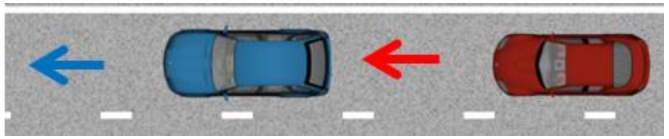


Extensions to Other Scenarios

Lane change



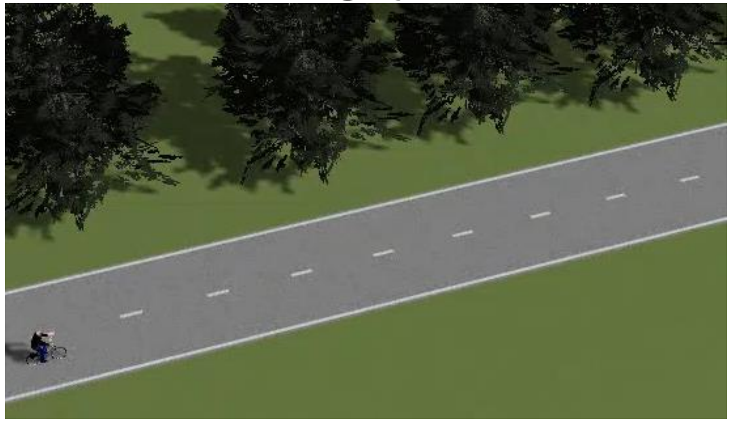
Car-following



Left turn

Pedestrian crossing

Passing cyclists



B. Chen, D. Zhao, H. Peng, D. LeBlanc, "Analysis and Modeling of Unprotected Intersection Left-Turn Conflicts based on Naturalistic Driving Data, " IEEE Intelligent Vehicle Symposium, 2017

B. Chen, D. Zhao, H. Peng, "Evaluation of Automated Vehicles Encountering Pedestrians at Unsignalized Crossings," IEEE Intelligent Vehicle Symposium, 2017.

Y. Guo, Z. Mo, D。 Zhao, “Approaching and passing cyclists - A learning based approach”, under preparation.

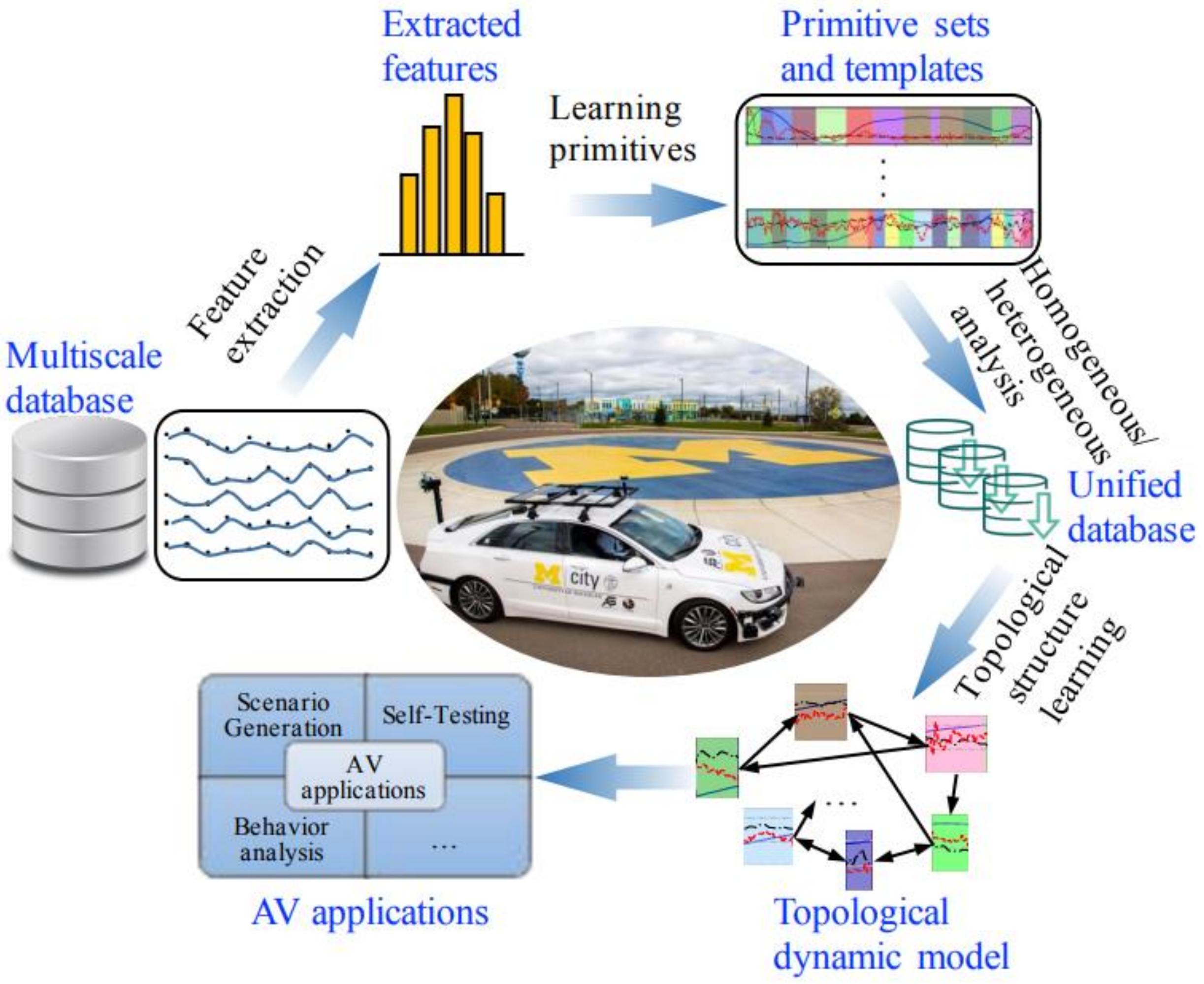
Recent Progress: Extract Scenarios Automatically from Raw Data

Previous method:
- Define scenario
- Create query condition manually
- Update query with trial and error

- Subjectively-selected scenarios/variations

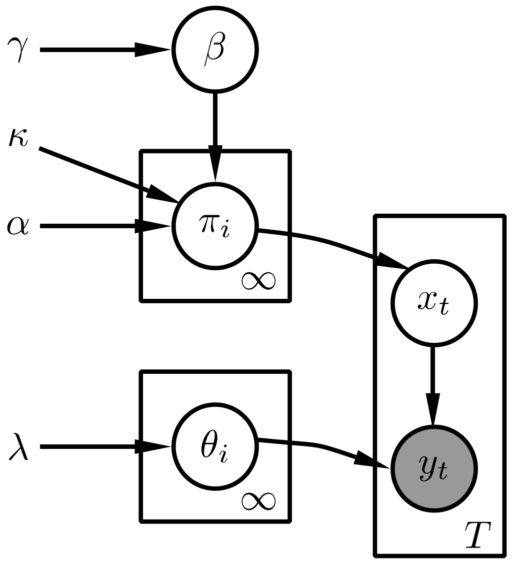
Traffic Primitive:
- Segment/cluster similar traffic scenes automatically using Bayesian nonparameter inference

- Objectively-selected scenarios/variations

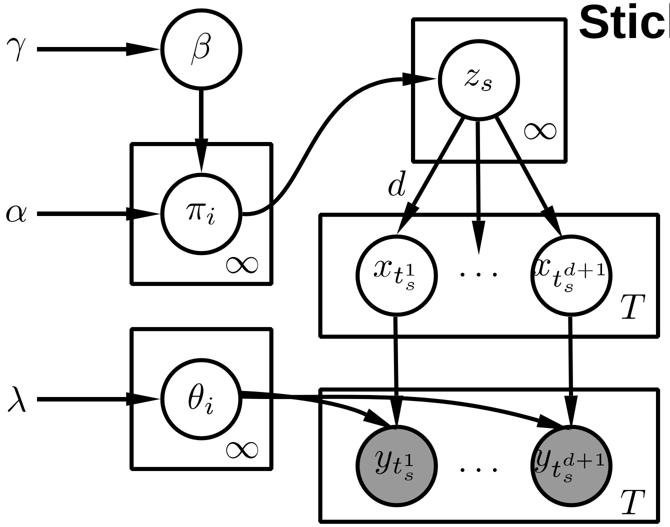


W. Wang, D. Zhao, "Extracting Traffic Primitives Directly from Naturalistically Logged Data for Self-Driving Applications IEEE Robotics and Automation Letters (under review), arXiv 1709.03553, 2017.

Traffic Primitive: Extract Scenarios Automatically from Raw Data

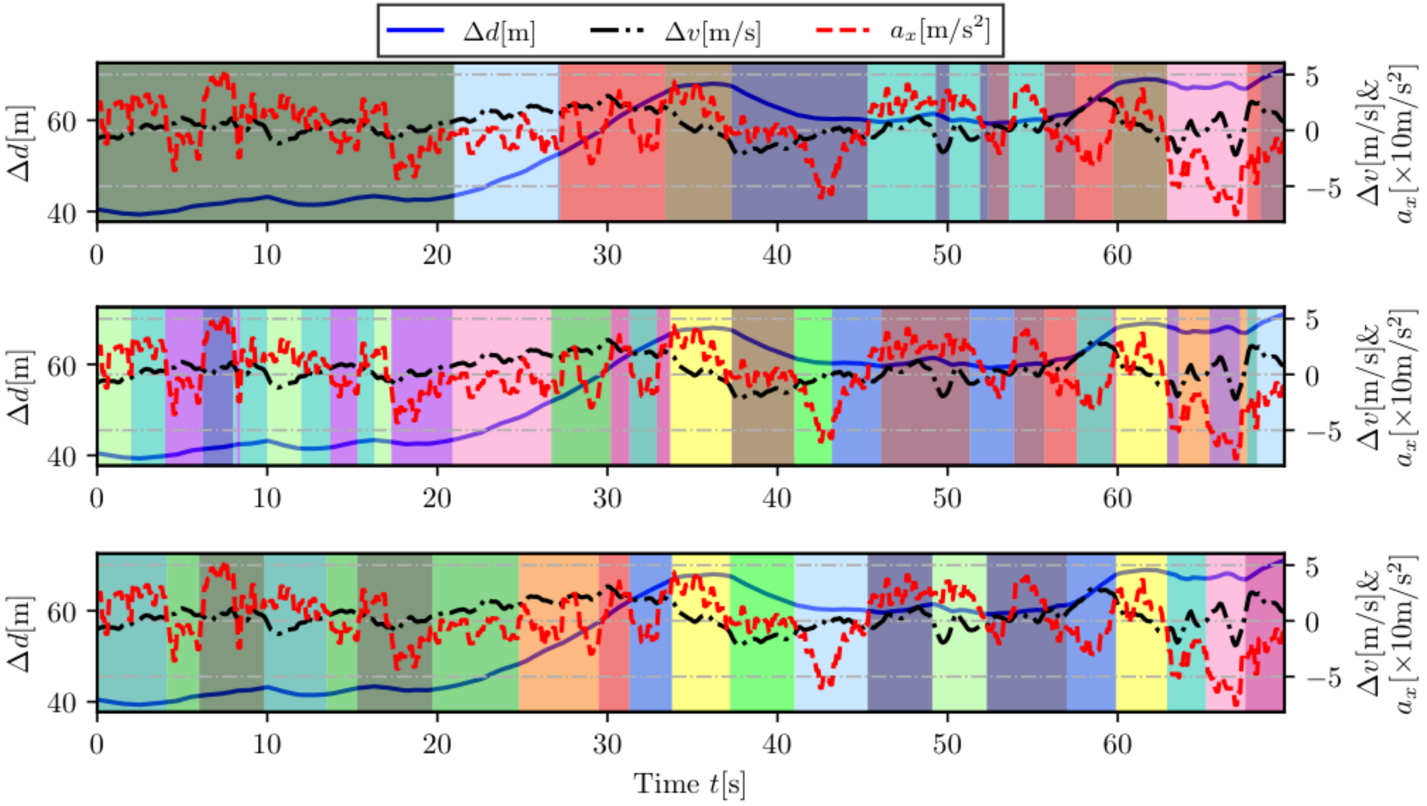


HDP-HMM



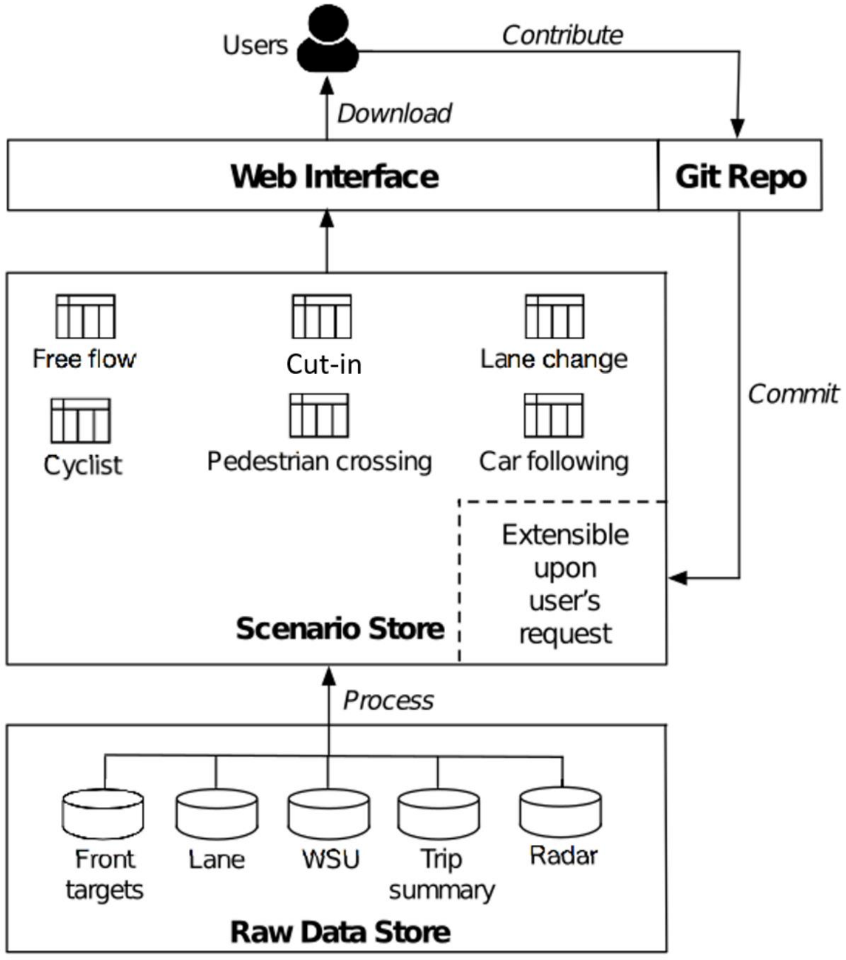
Sticky HDP-HMM

HDP-HSMM

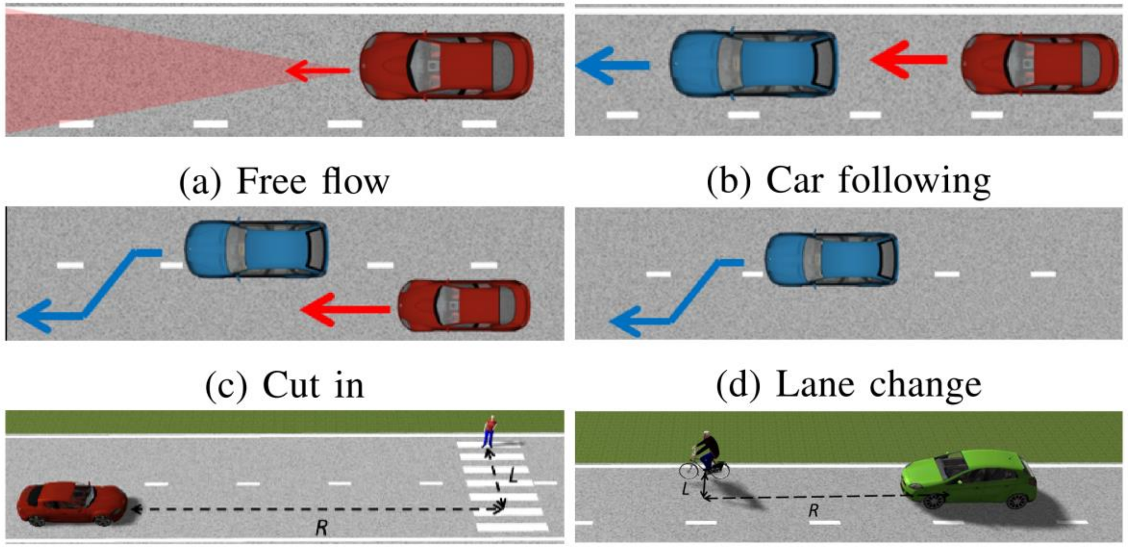


W. Wang, J. Xi, D. Zhao, " Driving Style Analysis Using Primitive Driving Patterns With Bayesian Nonparametric Approaches," under review.

TrafficNet: An Open Naturalistic Driving Scenario Library



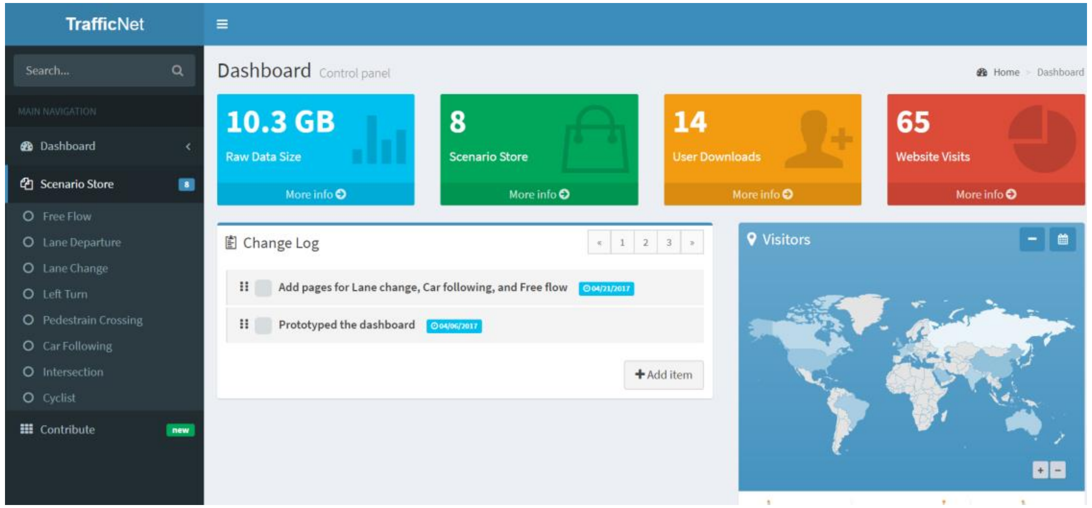
Framework of TrafficNet



(a) Free flow (b) Car following

(c) Cut in (d) Lane change

(e) Pedestrian (f) Cyclist



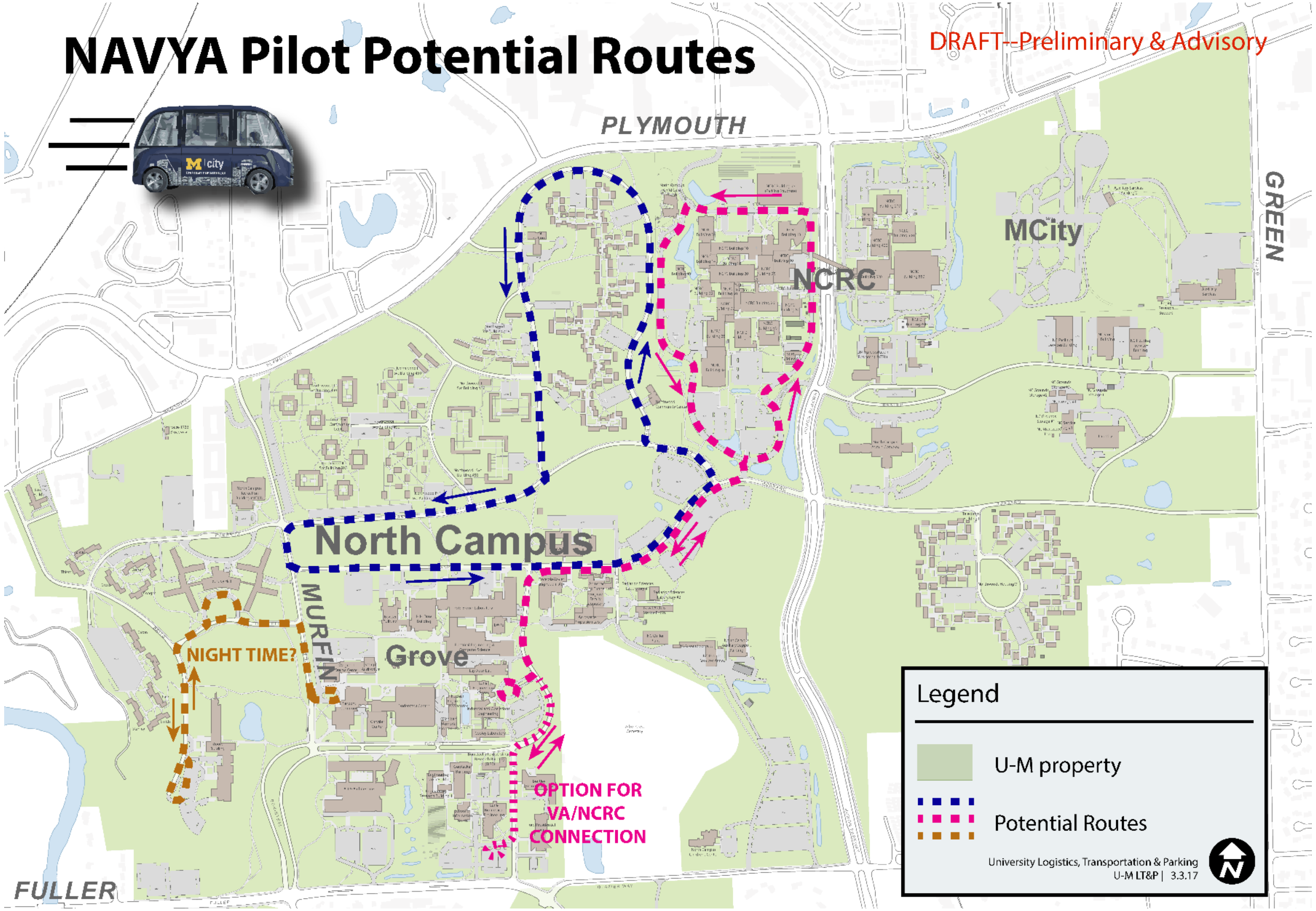
Platforms

On-track tests

Virtual reality

Mixed Reality

Deployment of Testing Vehicles



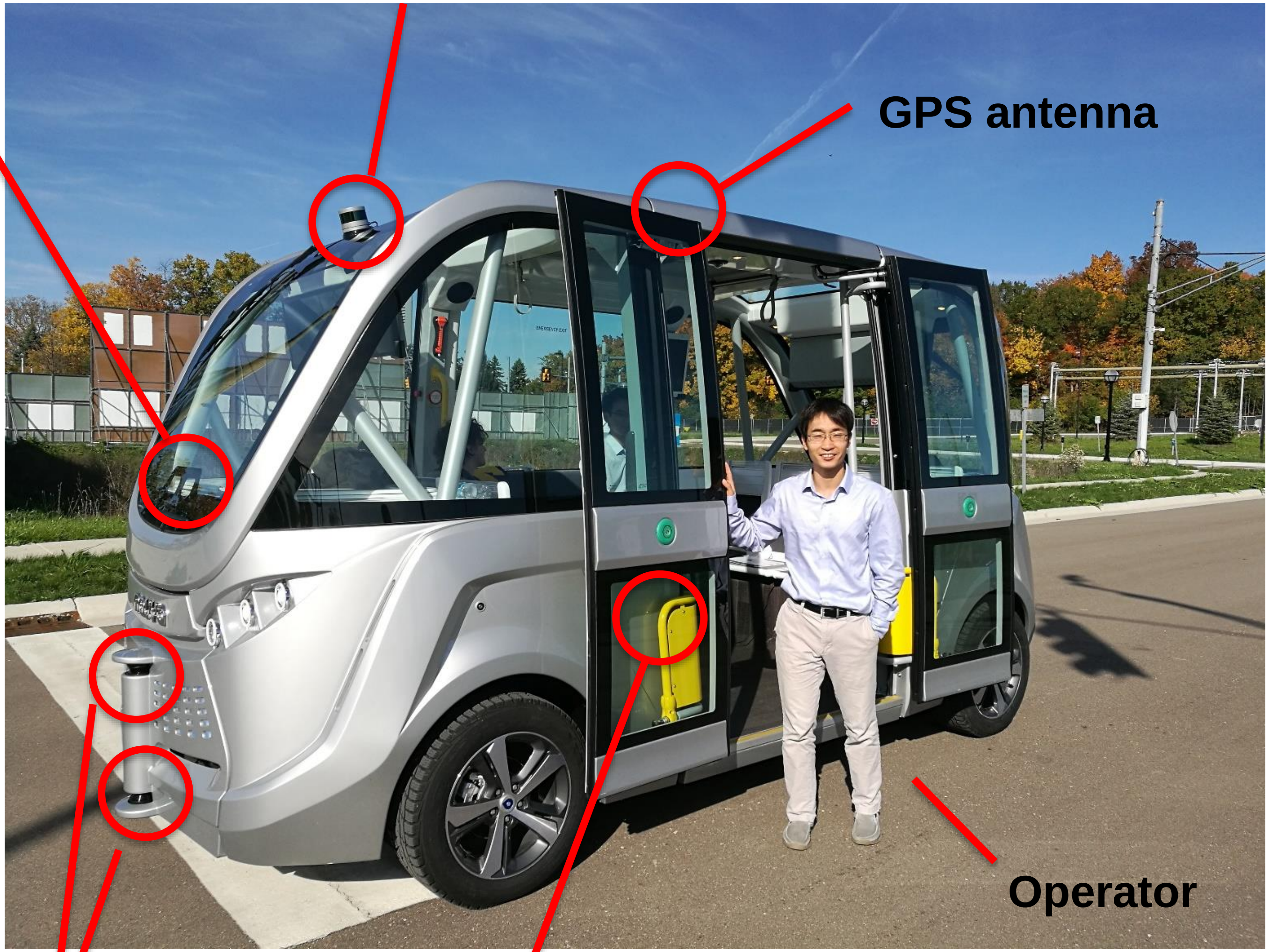
UNIVERSITY OF MICHIGAN

Recourses

- Hardware
  - NAVYA
- Software
  - Action, perception, decision
  - Built on windows, written in C++

Stereo camera

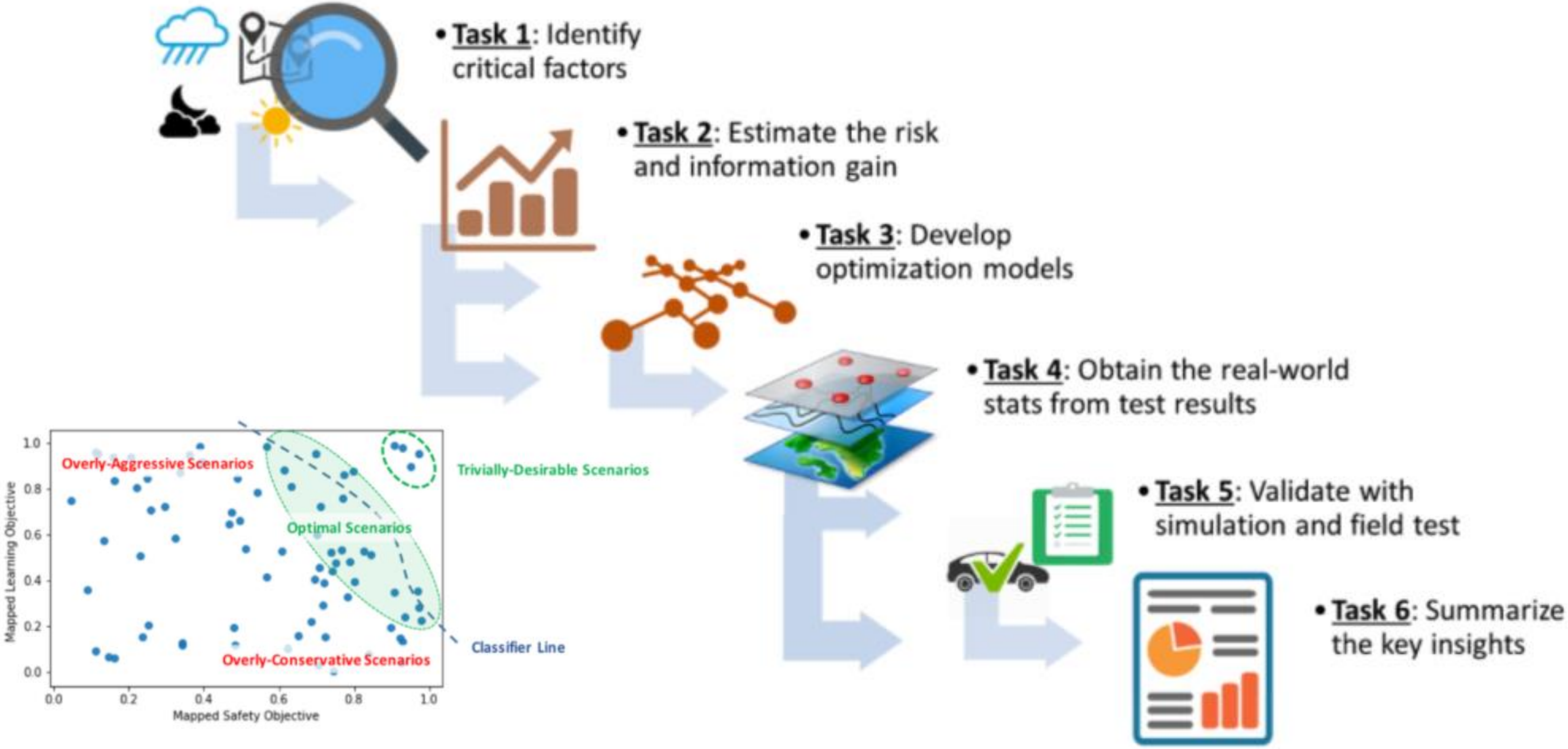
Velodyne 16 bin Lidar (front and rear)



Sick Lidar
(other 2 in the rear)

IBEO Lidar (one each side)

Design Deployment Policy



Dynamic Scenario Optimization

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city
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Ford

tass international

UMTRI

DENSO

SAIC
上汽集团
SAIC MOTOR

Autoliv

SOKON

Thanks for your attention

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PPT