Evaluation and Testing of Automated Vehicles

Ding Zhao (赵鼎)

Assistant Research Scientist

Department of Mechanical Engineering

Robotics Institute

Michigan Institute for Data Science

University of Michigan, Ann Arbor

The Building Blocks of Autonomy

Prepared by VISION SYSTEMS INTELLIGENCE

Level of Integration

AUTONOMOUS SOLUTIONS

TOYOTA, TESLA, Ford, GM, HYUNDAI, KIA MOTORS, VOLVO, GEELY, Google, UBER, NVIDIA, Continental, nauyo, ZMP, CHANGAN, HONDA, Mercedes-Benz, Baidu 百度, VISLAB, OTTO, nuTonomy, Audi, BMW, 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, ALTERA, TEXAS INSTRUMENTS, MARVELL, QUALCOMM, Movidius, ST

SENSORS

BOSCH, DELPHI, MITSUBISHI ELECTRIC, NXP, Continental, ibeo, Valeo, ZF, TRW, HITACHI, OmniVision, Pioneer, HYUNDAI MOBIS, POINT GREY, Autoliv, TOSHIBA Leading Innovation, KOSTAL, DENSO, LG Innotek, Panasonic, MAGNA, HARMAN, FUJITSU TEN, Visteon, QUANERGY, Melexis, Mando Corporation, FLIR SYSTEMS, OSRAM, applanix, ON Semiconductor, LeddarTech, Neusoft, Infineon, SONY, PEPPERL+FUCHS, TRILUMINA, ublox, Velodyne LiDAR, PHANTOM INTELLIGENCE

CONNECTIVITY

HITACHI, RENESAS, Peloton, Continental, NXP, BOSCH, DELPHI, intel, CohdaWireless, QNX, TTTech, DENSO, HARMAN, Infineon, Mentor Graphics

MAPPING

TOMTOM, here, NAVINFO, mapscape, HARMAN, NVIDIA, GeoDigital, Increment P, EXONAV, ZENRIN, applanix, 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, ETAS, DENSO, HARMAN, Green Hills SOFTWARE, 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

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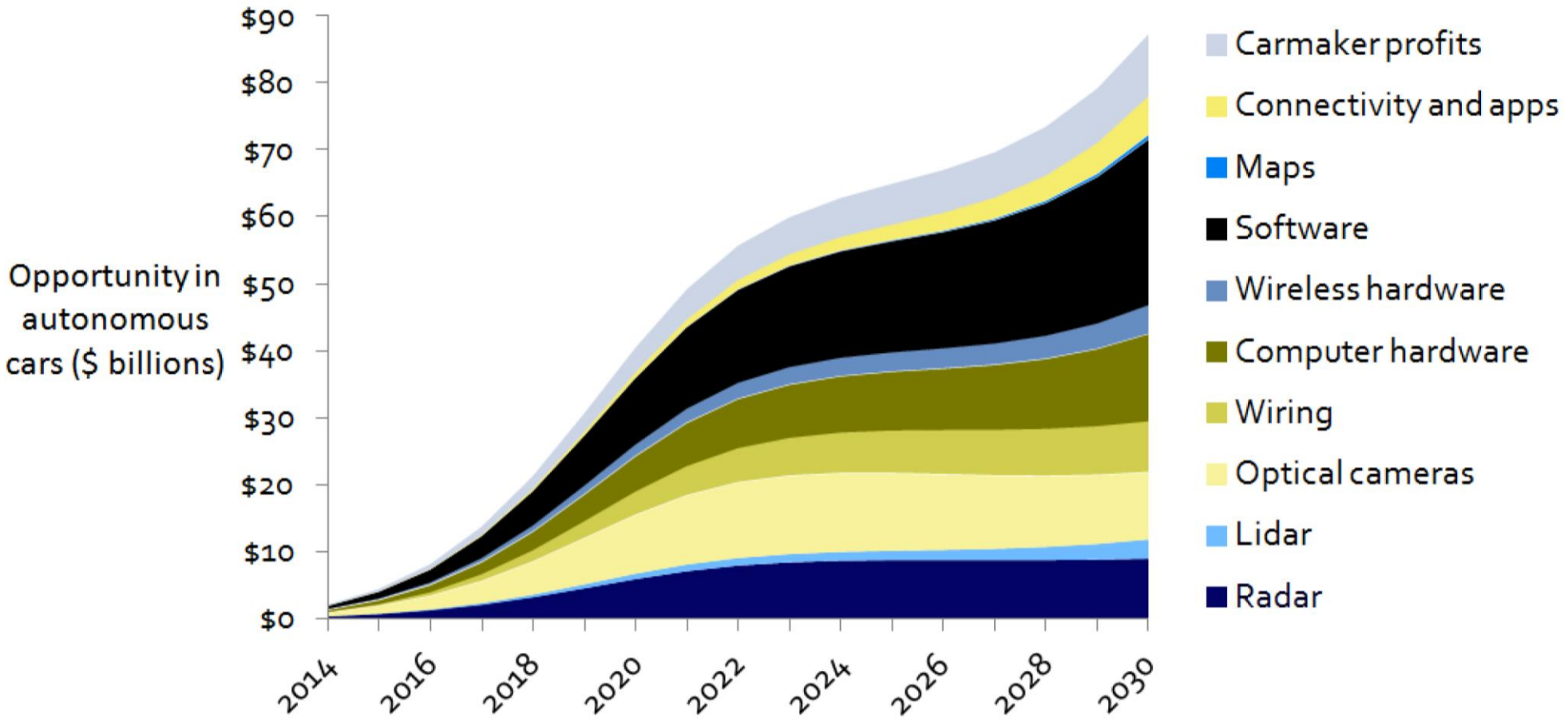
Estimated Market of AVs in 2030



2016: 680 million

OTTO

UBER

2016: 1 billion

CRUISE

GM

2017: 15 billion

MOBILEYE®

intel

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 …

S. Shead, Business insider, 2016

Existing AV Evaluation Methods

Test matrix

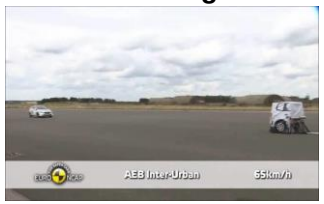
Pro: easy to execute, fast
Con: Pre-announced

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

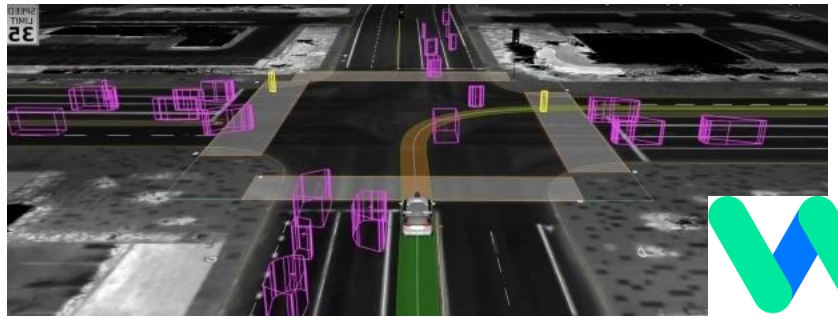
Naturalistic Field Operational Tests

Pro:
The real-world!

Con:
Slow, expensive
Low exposure to safety critical cases

❖ 100 million mi / fatal crash (NHTSA 2013)

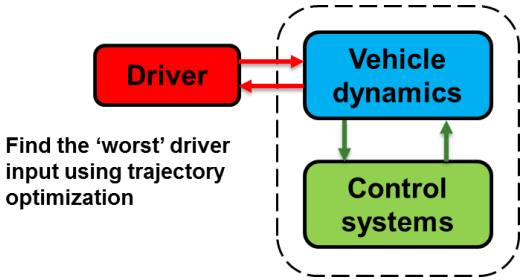
Monte Carlo Simulation



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

Evaluation/test of self-driving cars

Framework

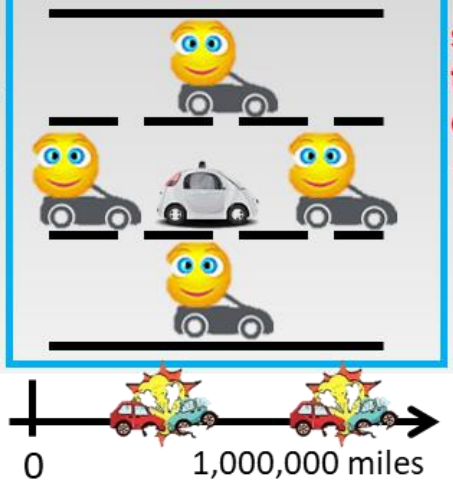
Recent/ongoing research

Statistically Equivalent

Real world data collection

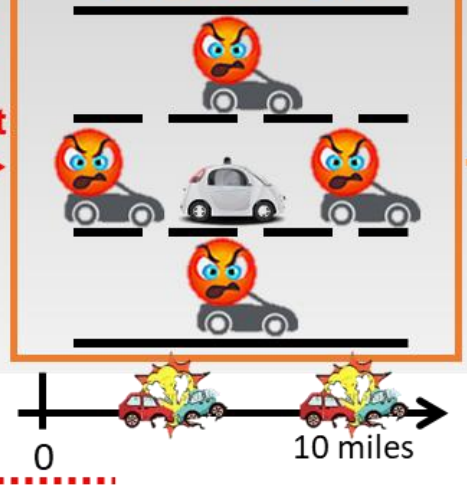
Build stochastic model

Naturalistic driving environment



"Skew" the statistics of the driving environment

Accelerated evaluation tests



Tests

"Skew back"

Importance Sampling

Performance metrics e.g. crash rate

Critical scenarios & probabilities

Identify

Driving Database

Time sequence data

Modeling Driving Environment

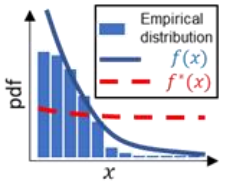
Bayesian Unsupervised Learning

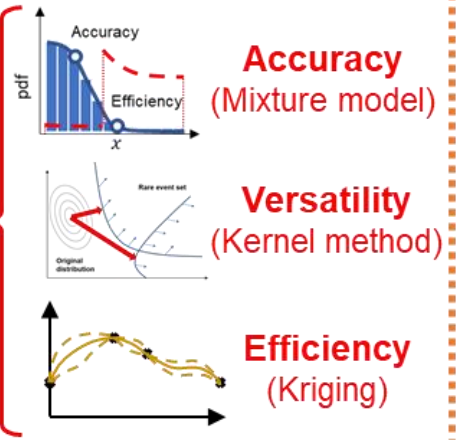
- Traffic primitive
- Variation
- Likelihood

Stochastic variation model

Evaluation Theories

Accelerated Evaluation





Accuracy (Mixture model)

Versatility (Kernel method)

Efficiency (Kriging)

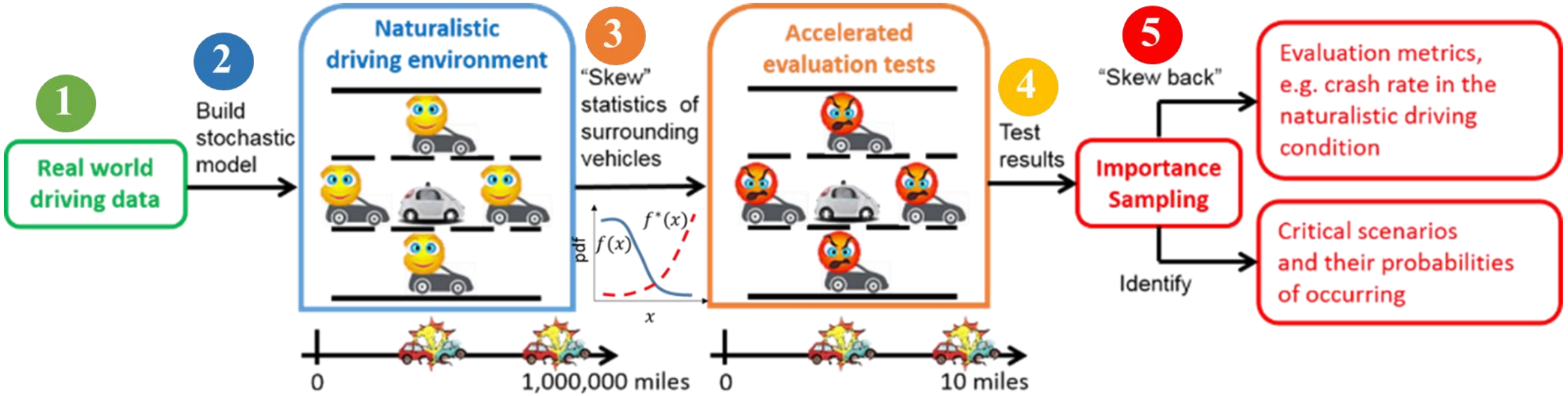
Testing Platforms

Virtual

Reality

Mixed Reality

Accelerated Evaluation



Zhao, Ding. "Accelerated Evaluation of Automated Vehicles." *PhD dissertation, The University of Michigan*, 2016.

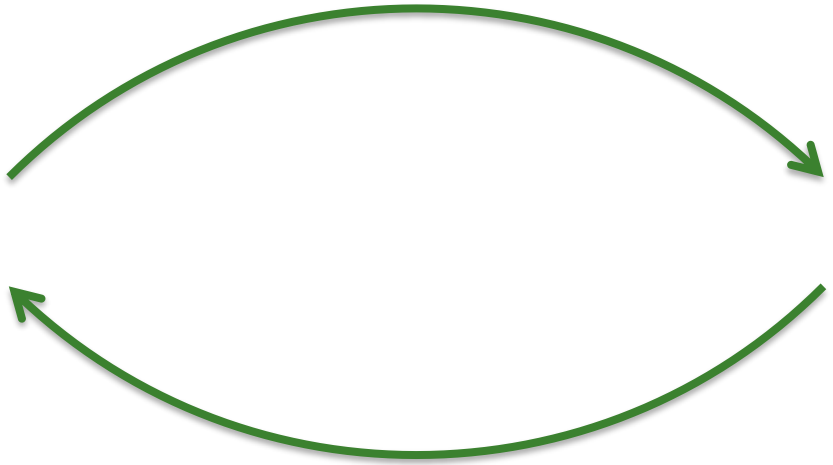
Five Steps of the Accelerated Evaluation

① Collect naturalistic driving data

② Model behaviors of "other vehicles" as disturbance

③ Skew the disturbance statistics to reduce the boring part of daily driving

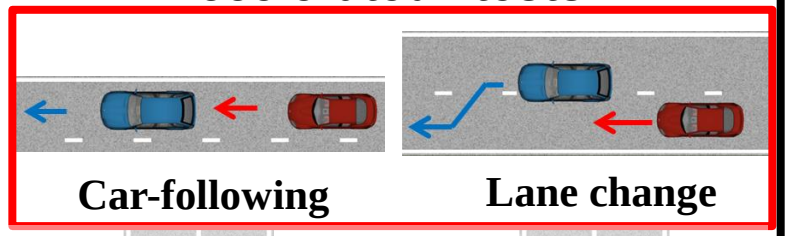
Naturalistic driving

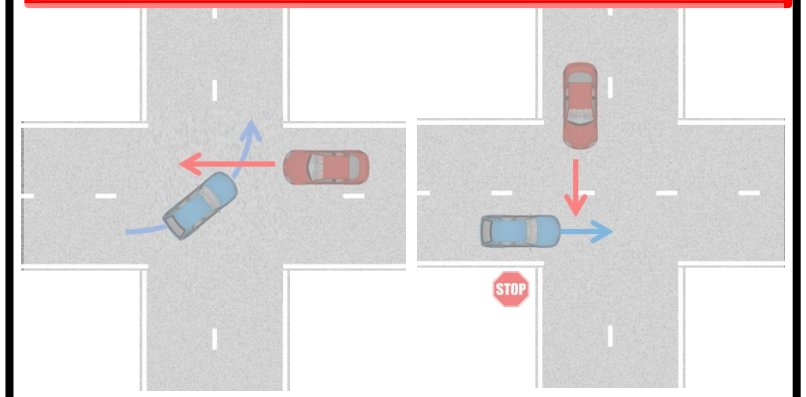


⑤ "Skew back" to understand real-world safety benefits

④ Simulate (at accelerated pace)

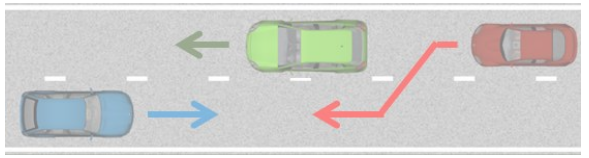
"Accelerated" tests





Left turn

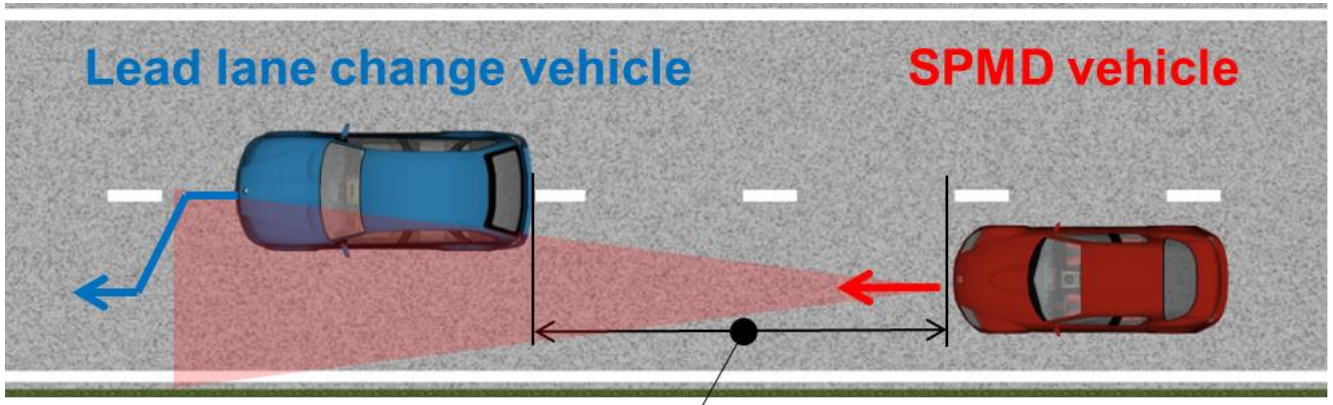
Crossing



Opposite direction

87 % light-vehicle crashes

Case 1: Lane Change Scenarios



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

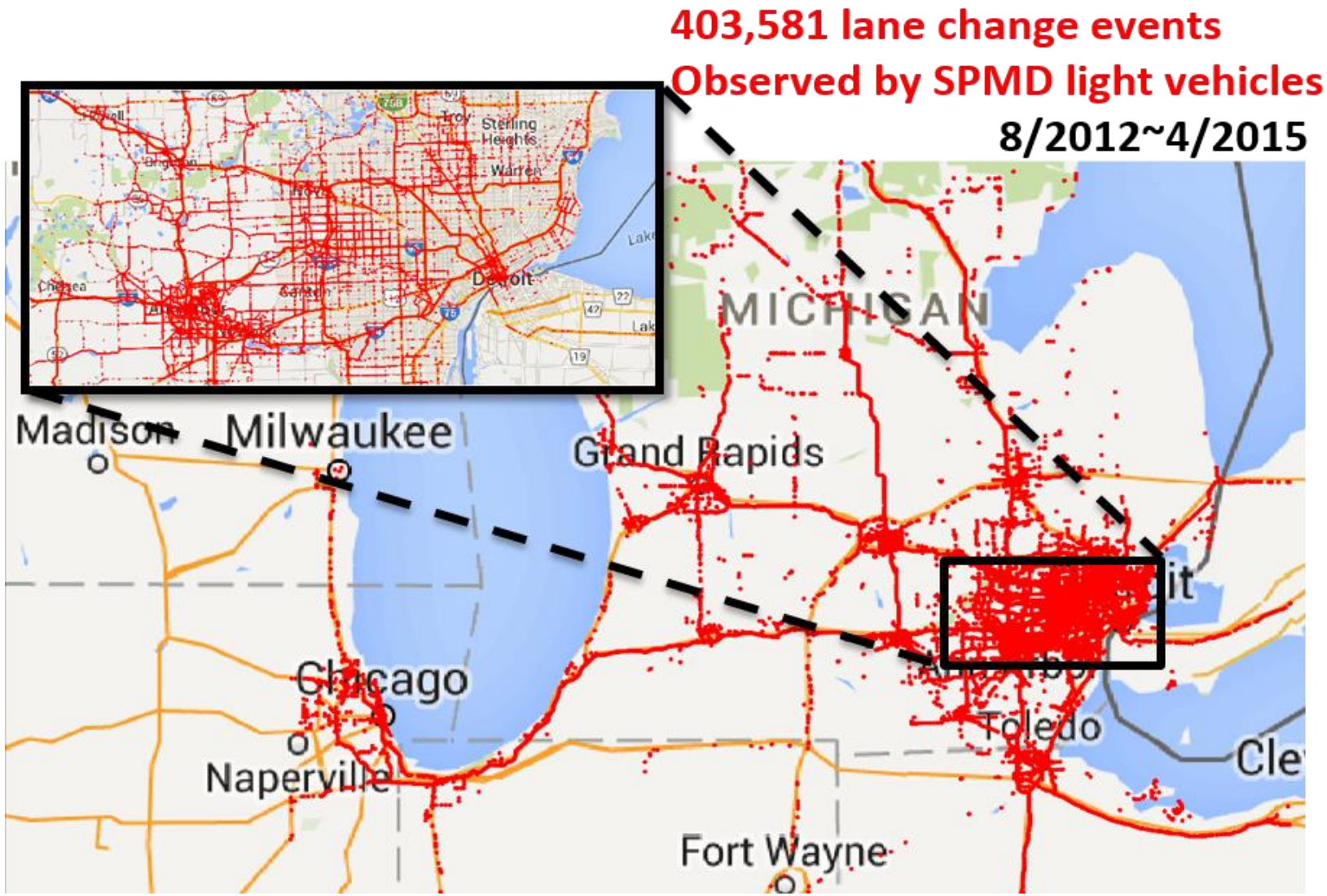
Lane Change Events in Safety Pilot Database

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

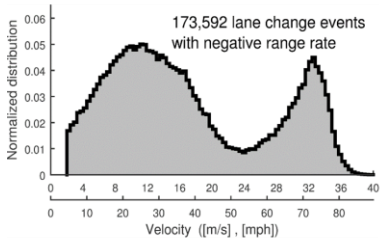


Importance Sampling Techniques

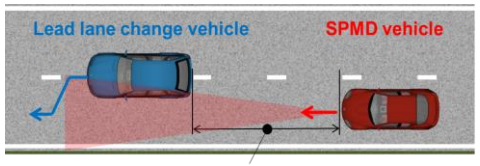
Motivation

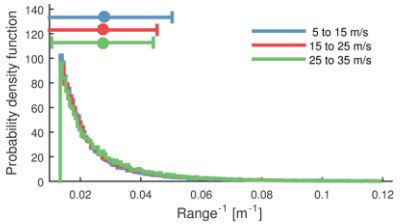
Gap acceptance → $[v_L, R_L, TTC_L]$

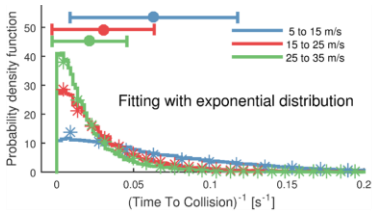
Execution



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







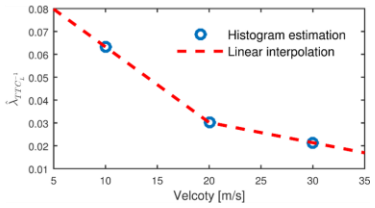
$f_{v_L} \rightarrow v_L \dashrightarrow f_{R_L^{-1}} \rightarrow R_L$

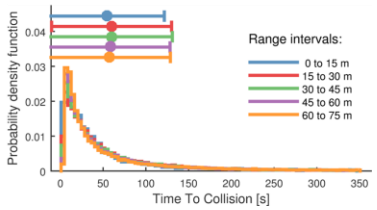
$f_{TTC_L^{-1}} \rightarrow TTC_L$

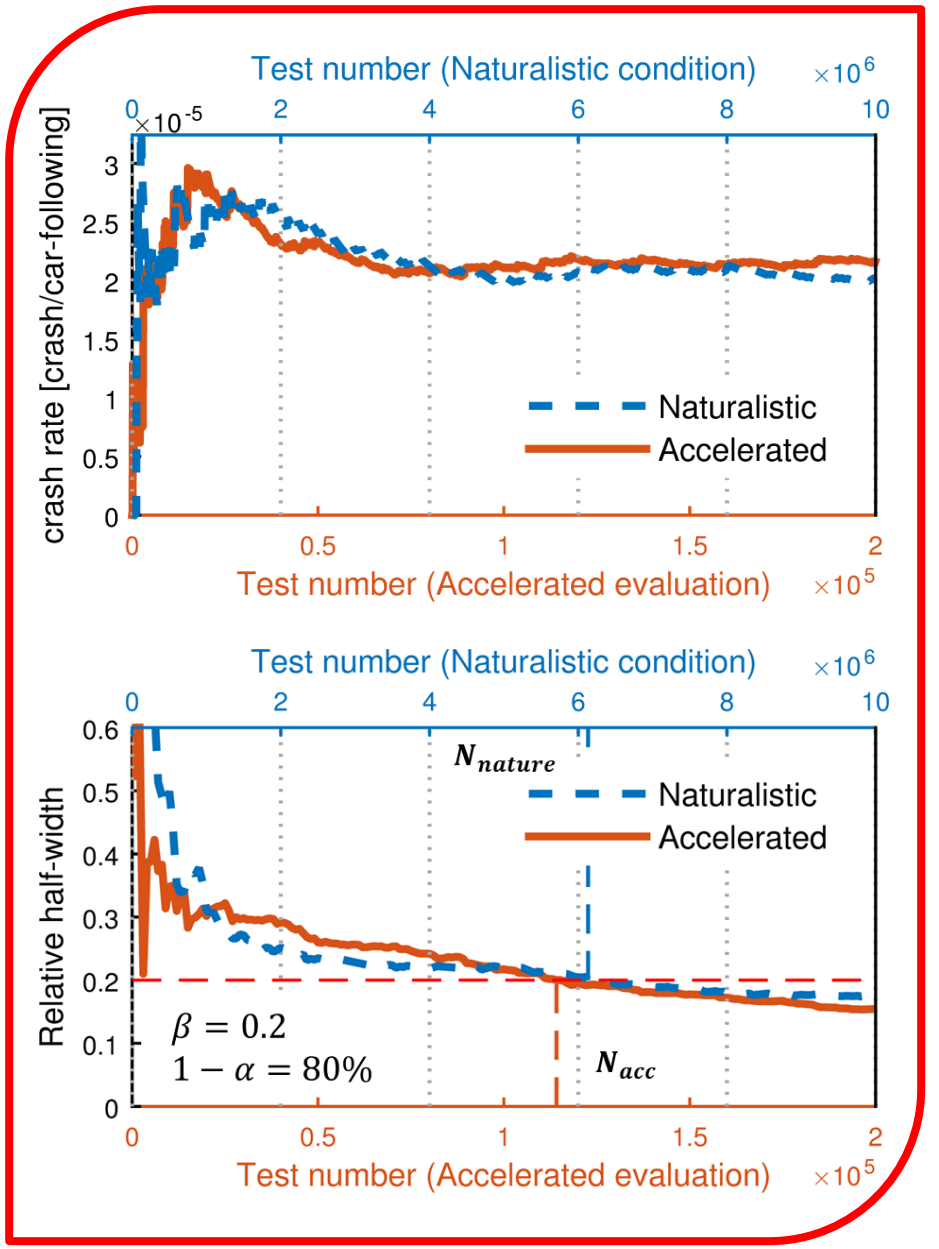
③ Skew the statistics

Importance Sampling

⑤ "Skew back"

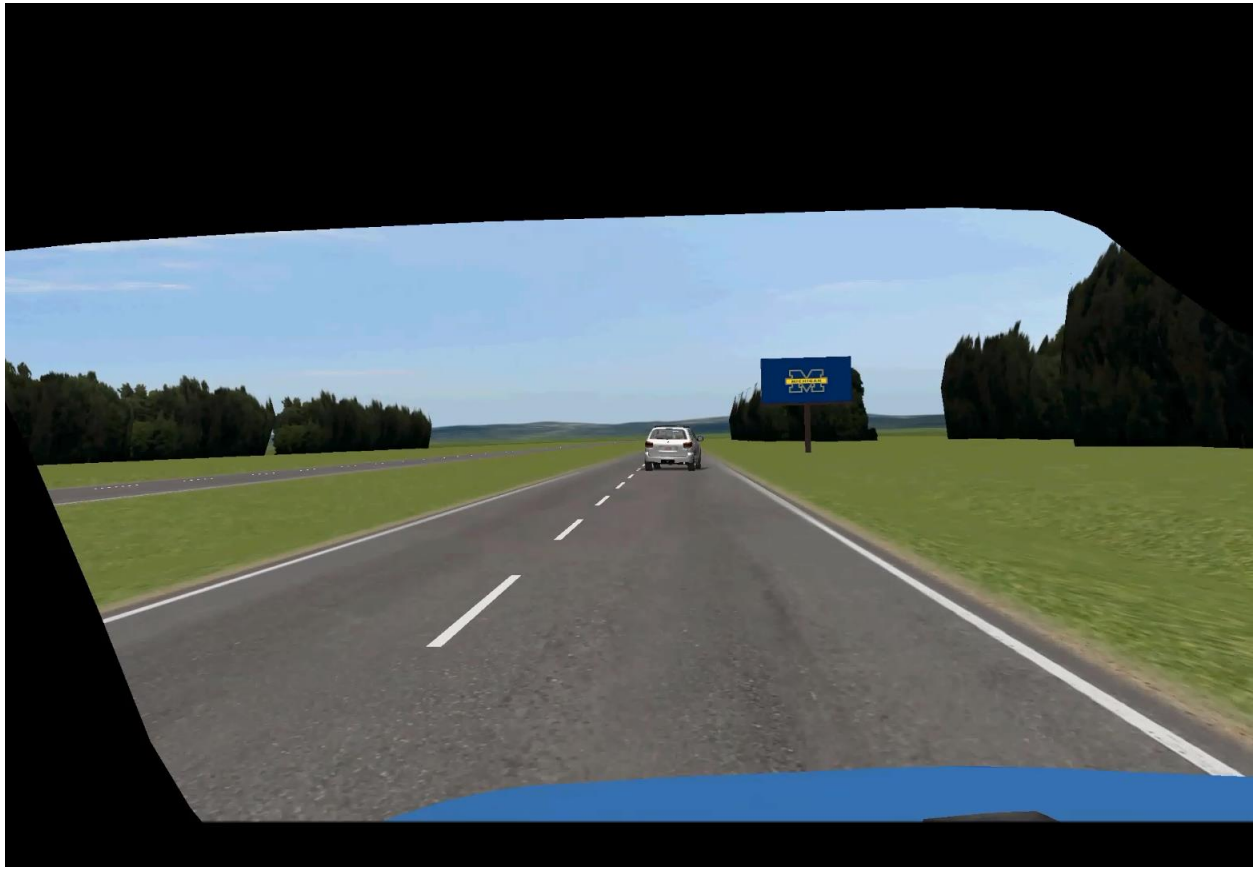






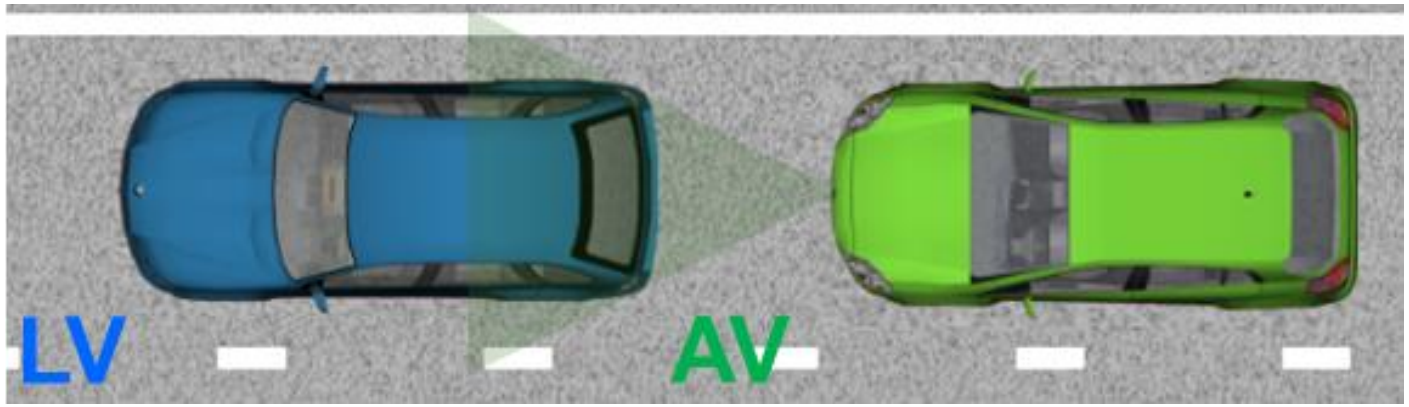
Naturalistic Driving vs Accelerated Tests

Naturalistic driving conditions



Accelerated tests

Case 2: Car-following Scenarios



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

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*, Graz, Austria, August 17-21, 2015.

Accelerated Evaluation of the Dynamic Interaction

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

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

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

$k_{\mathcal{T}min}^*$ ↑ ↓ $k_{\mathcal{T}}^*$ ↗ $\mathscr{b}_{k_{\mathcal{T}}^*}(1:K)$ ↓ $a_L(1:k_{\mathcal{T}})$ ↓ $I_{\mathcal{E}}(n)$

Optimal change of HV statistics (off-line)

Likelihood ratio $L(n)$ →

Crash, injury, conflict rates

Converge

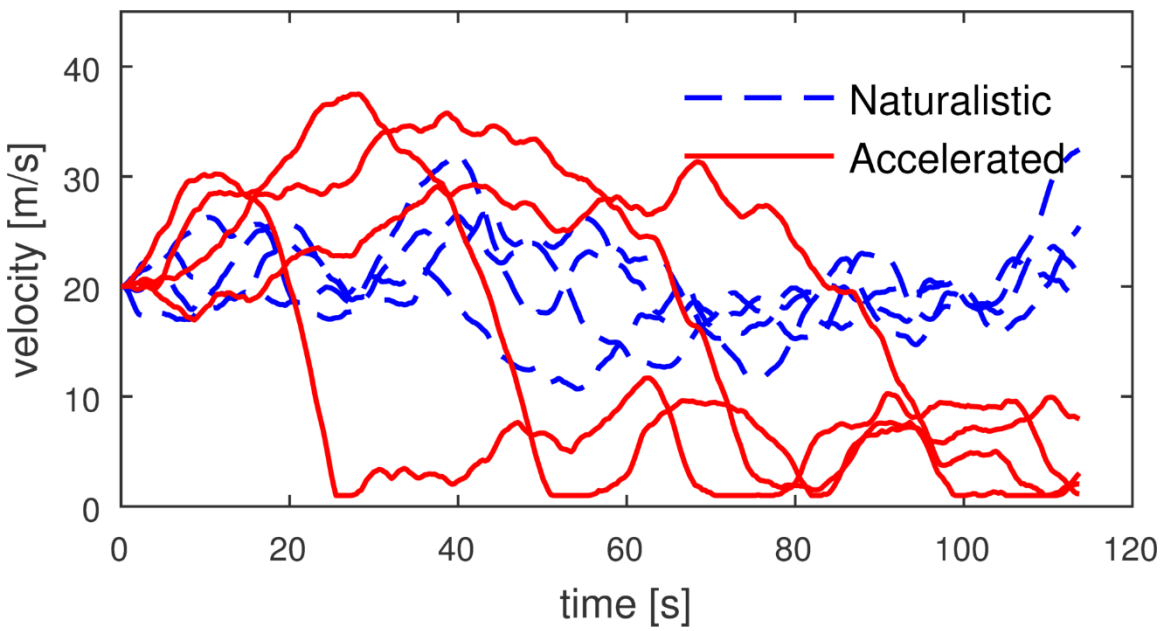
$$a_L(k+1) \sim \mathcal{N}(h_0 + h_1 a_L(k) + h_2 v_L(k), \sigma_u^2)$$

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

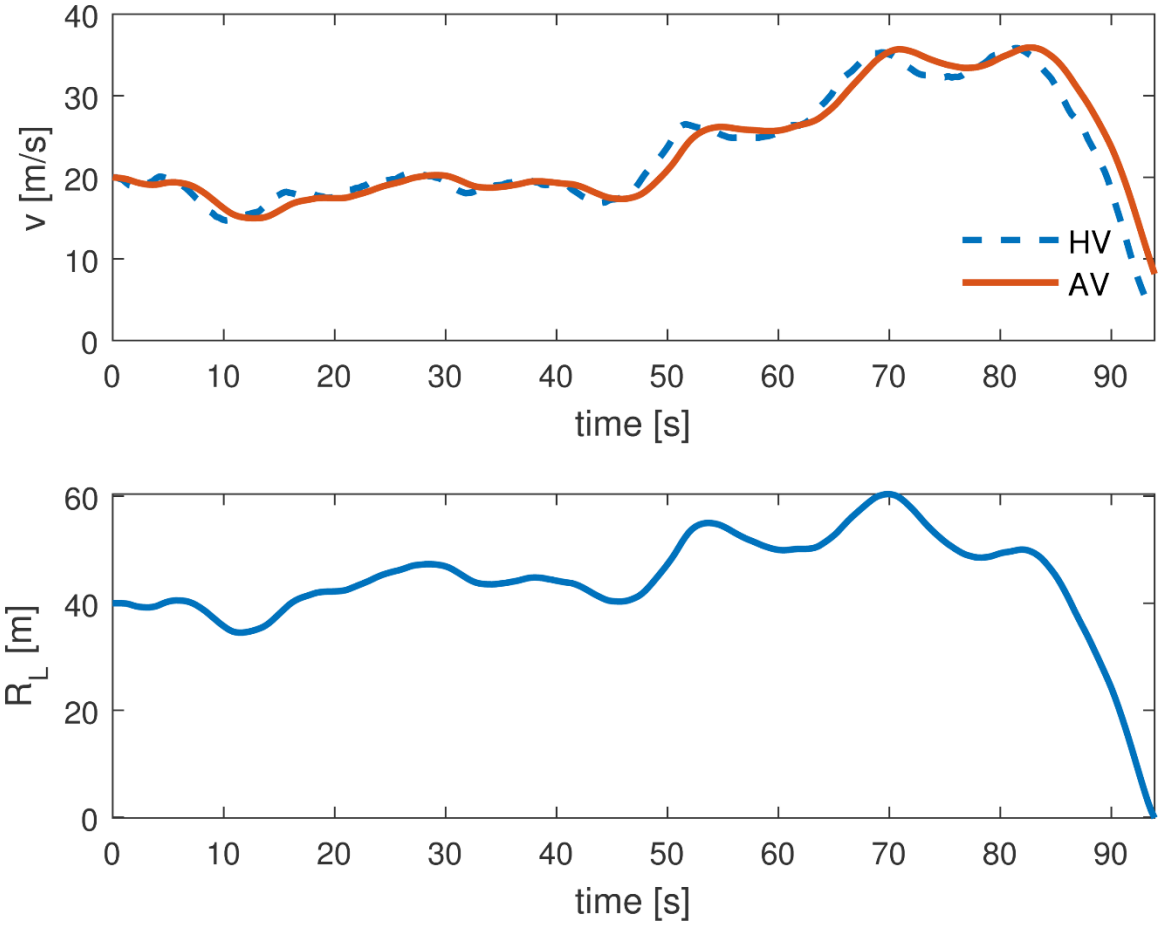
$$f^*(u(1:k_{\mathcal{T}}-1)) = \sum_{k_{\mathcal{T}}^* = k_{\mathcal{T}min}^*}^{K} \tilde{f}(a_L(1:k_{\mathcal{T}}-1) \mid k_{\mathcal{T}}^*) f_{k_{\mathcal{T}}^*}(k_{\mathcal{T}}^*)$$

Examples of Accelerated Evaluation

Examples of velocity profiles of the lead vehicle

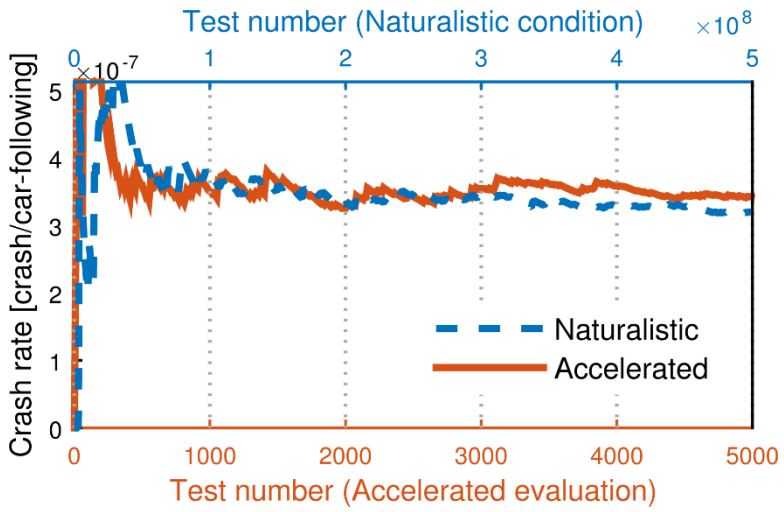


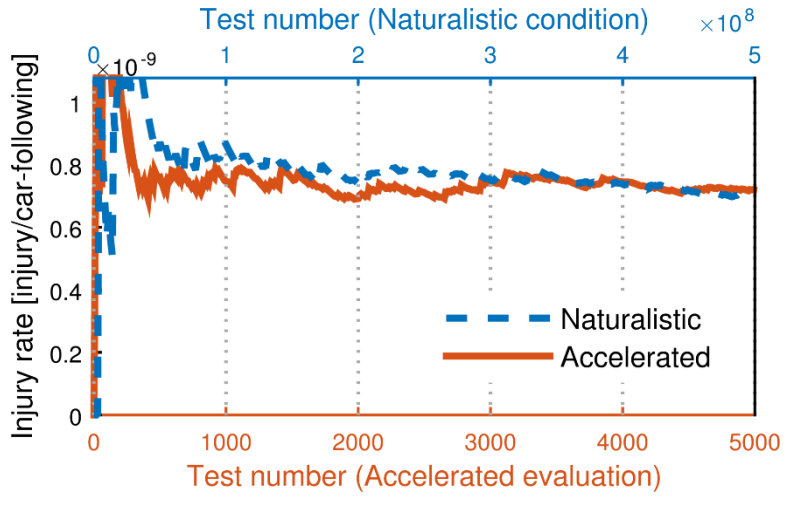
An example of the crash event

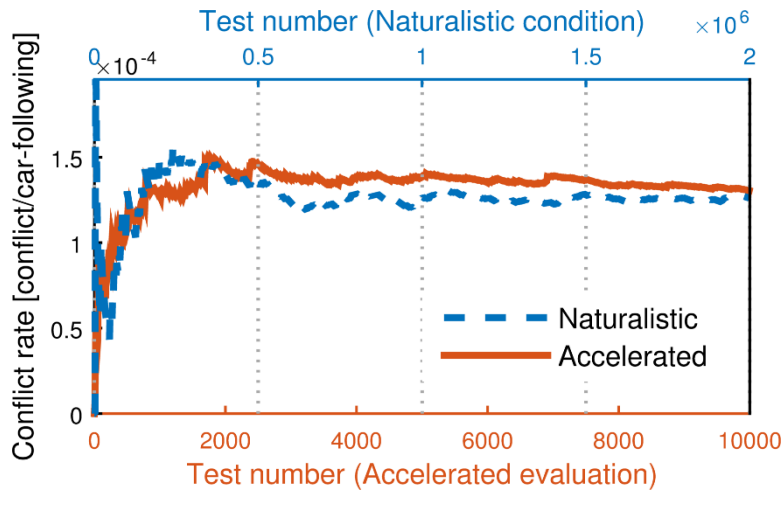


Estimation of Crash, Injury, and Conflict Rate

Estimation

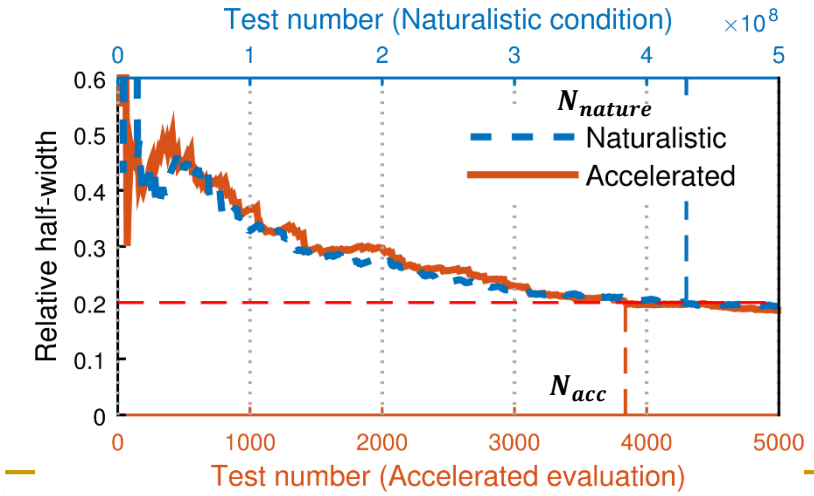


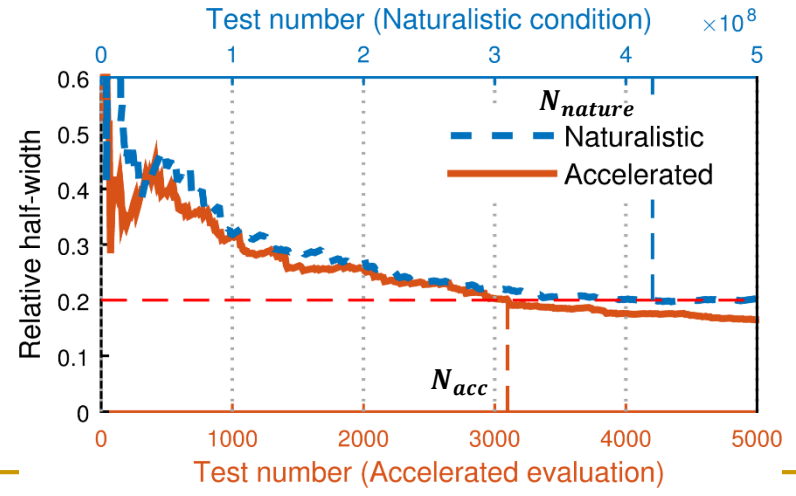


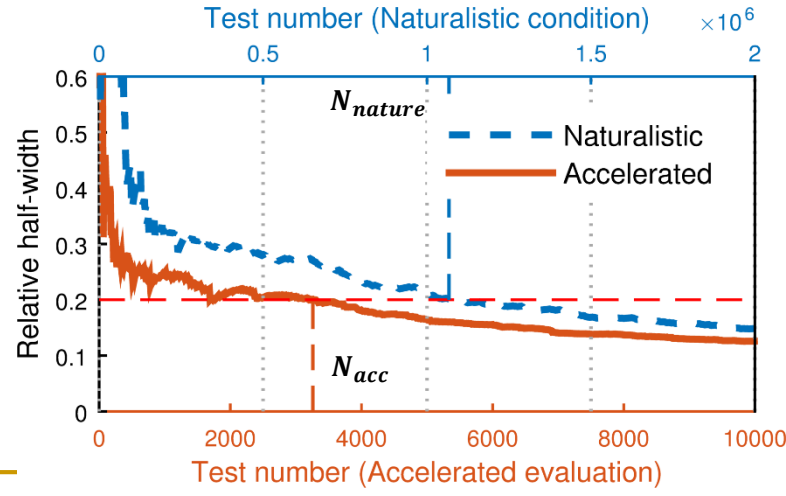


N_{nature}/N_{acc}: **Crash (1.12e5)** **Injury(1.35e5)** **Conflict (3.28e2)**

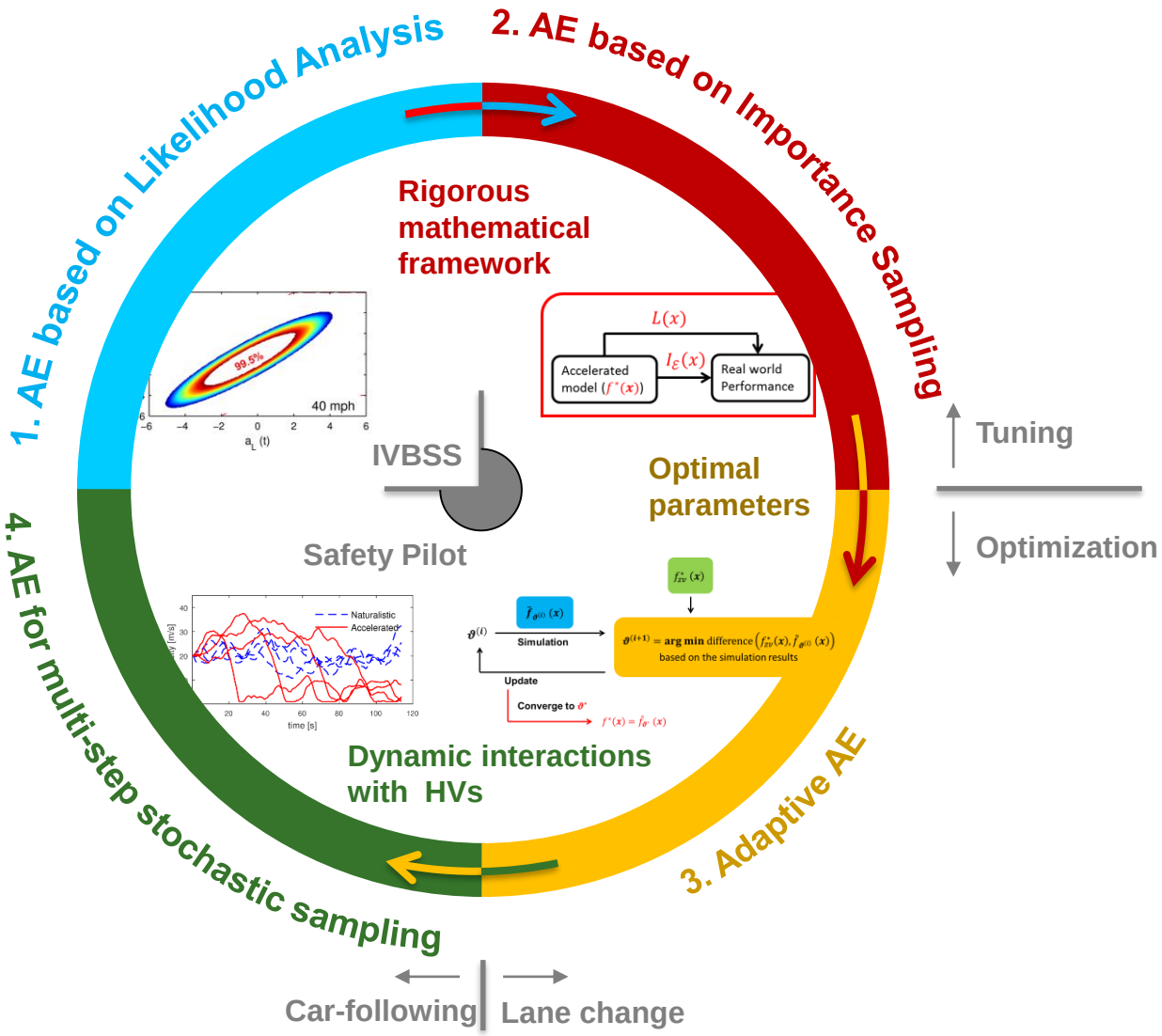
Convergence



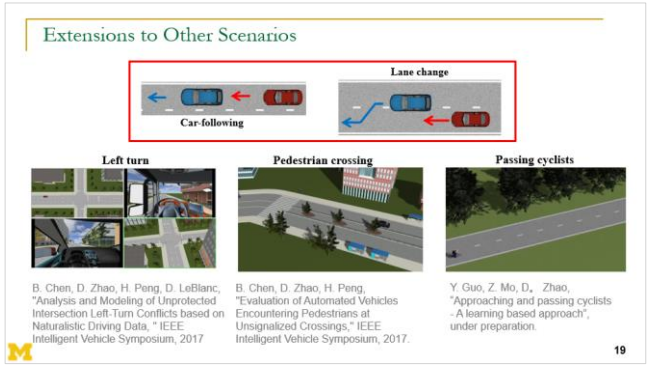




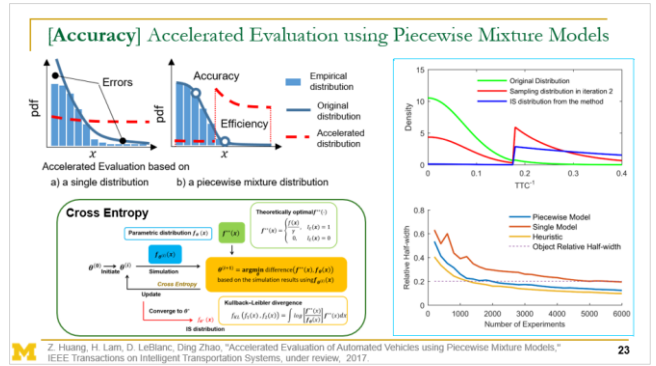
Extensions to the Accelerated Evaluation



Variations

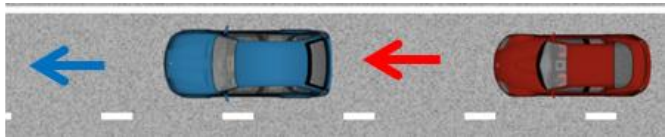


Theories



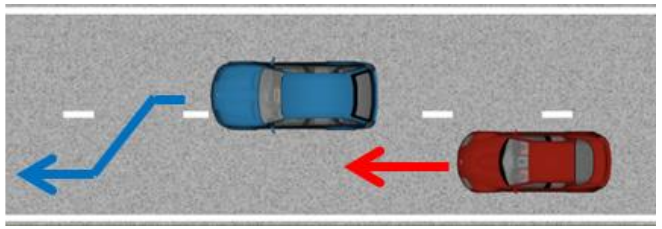
Platforms

Extensions to Other Scenarios



Car-following

Lane change



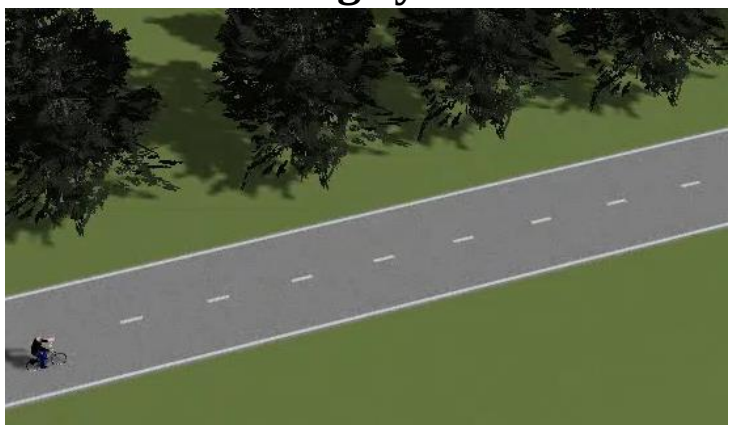
Left turn

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

Pedestrian crossing

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

Passing cyclists



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:

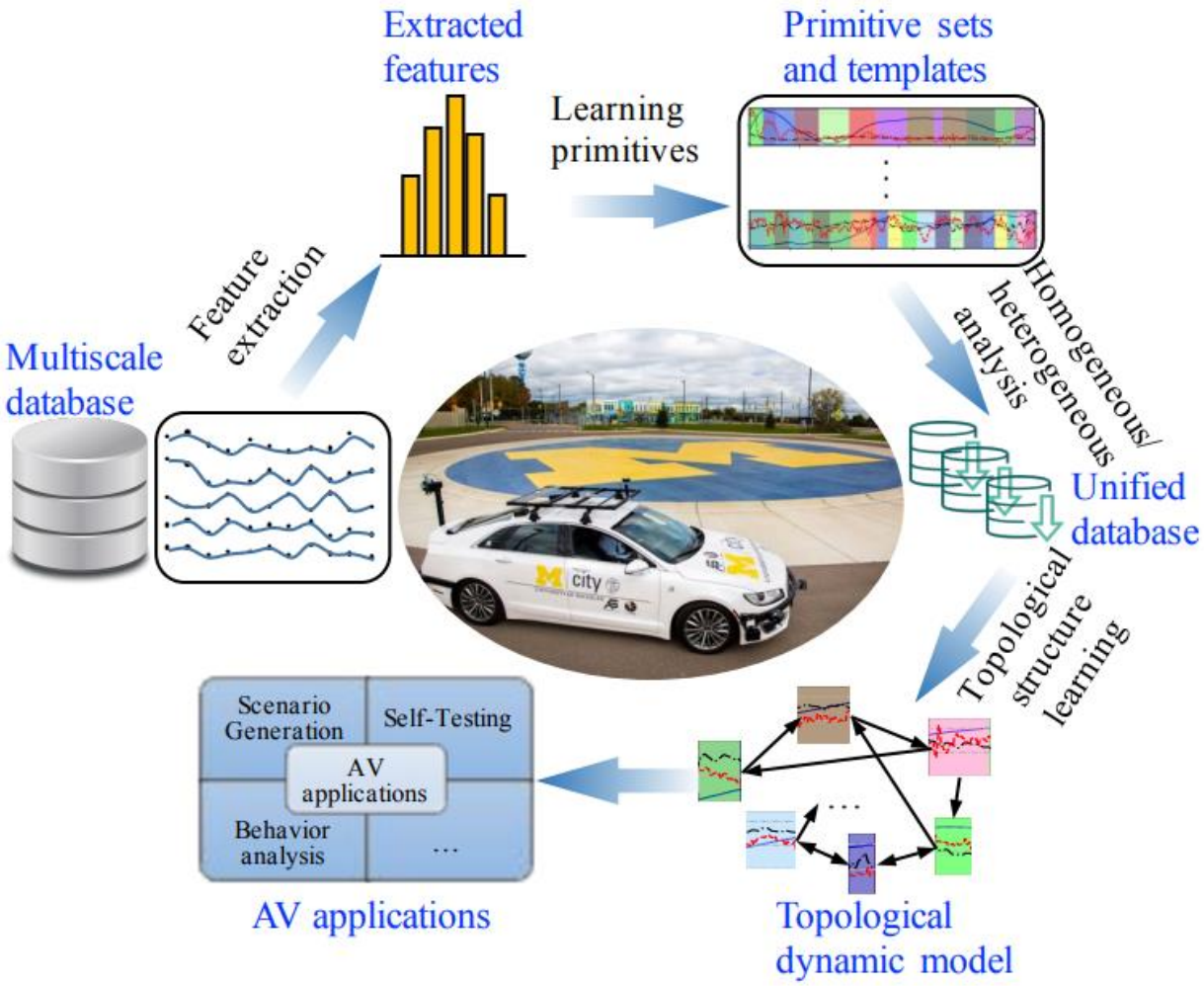
- Define scenario
- Create query condition manually
- Update query with trial and error

- Subjectively-selected scenarios/variations

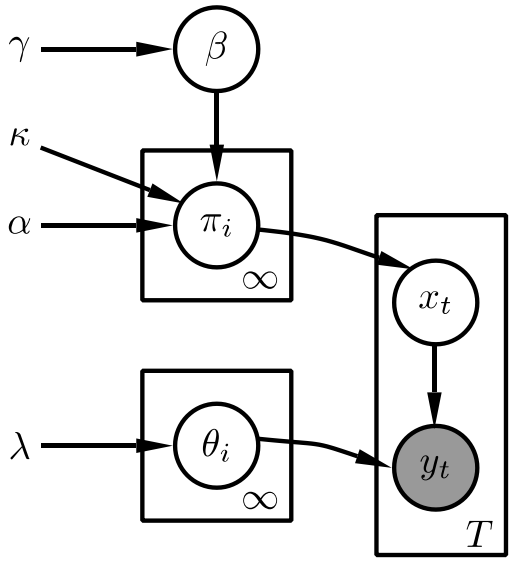
Traffic Primitive:

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

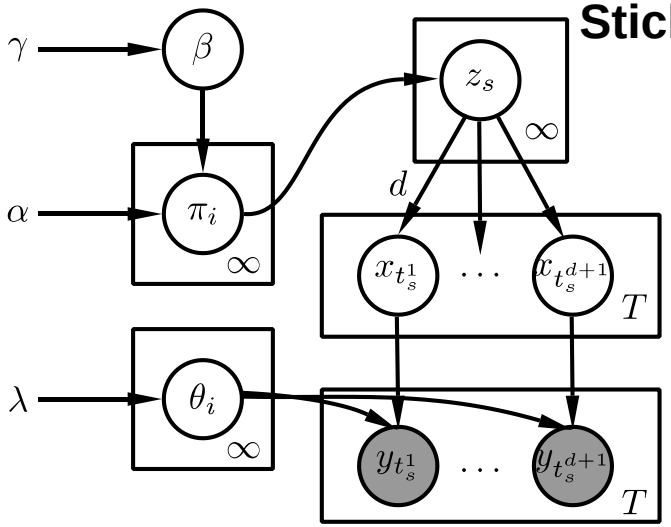
- Objectively-selected scenarios/variations



Traffic Primitive: Extract Scenarios Automatically from Raw Data

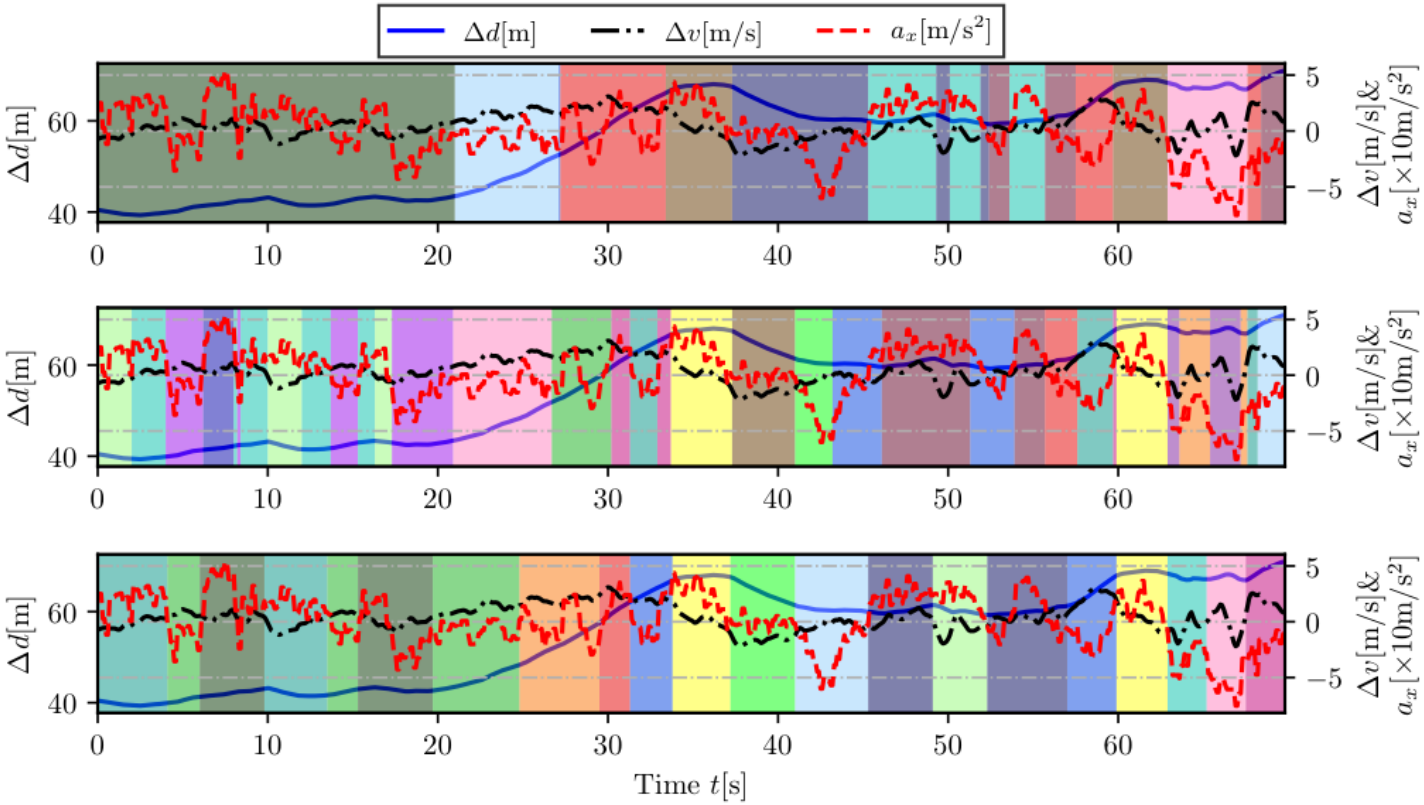


HDP-HMM

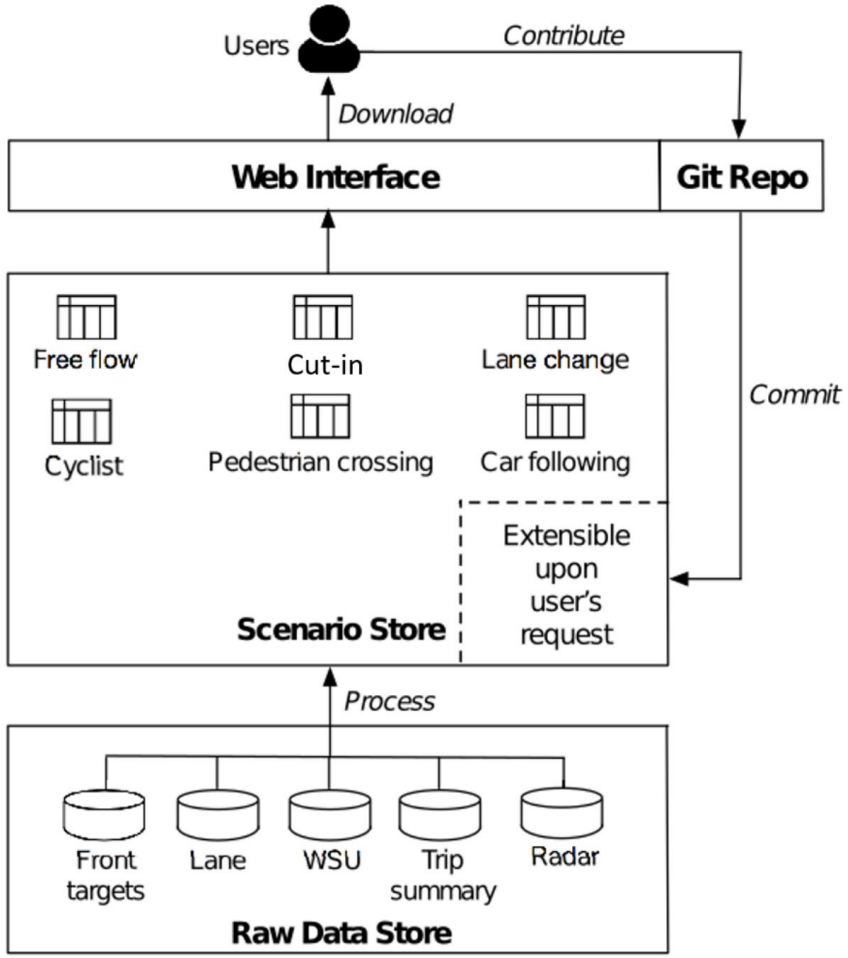


Sticky HDP-HMM

HDP-HSMM

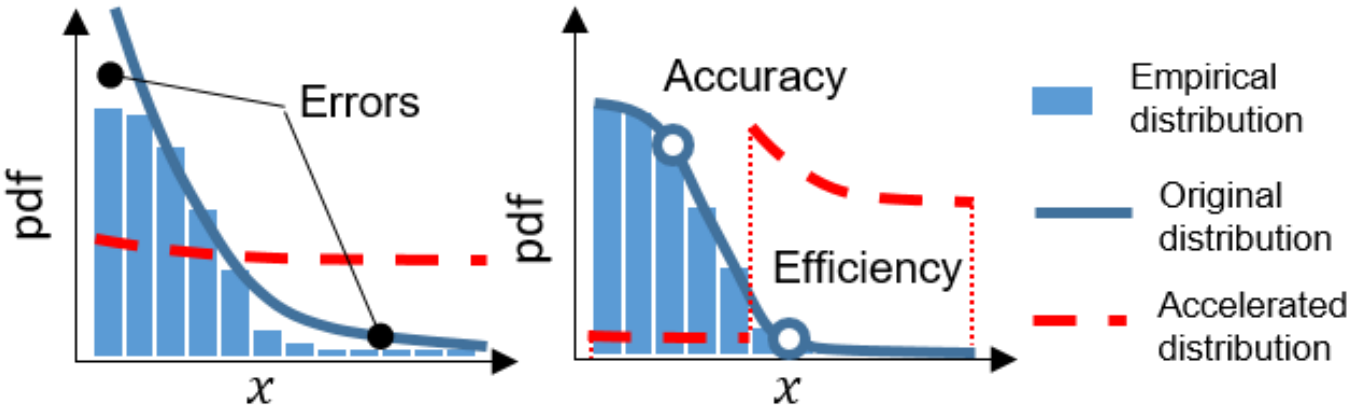


TrafficNet: An Open Naturalistic Driving Scenario Library



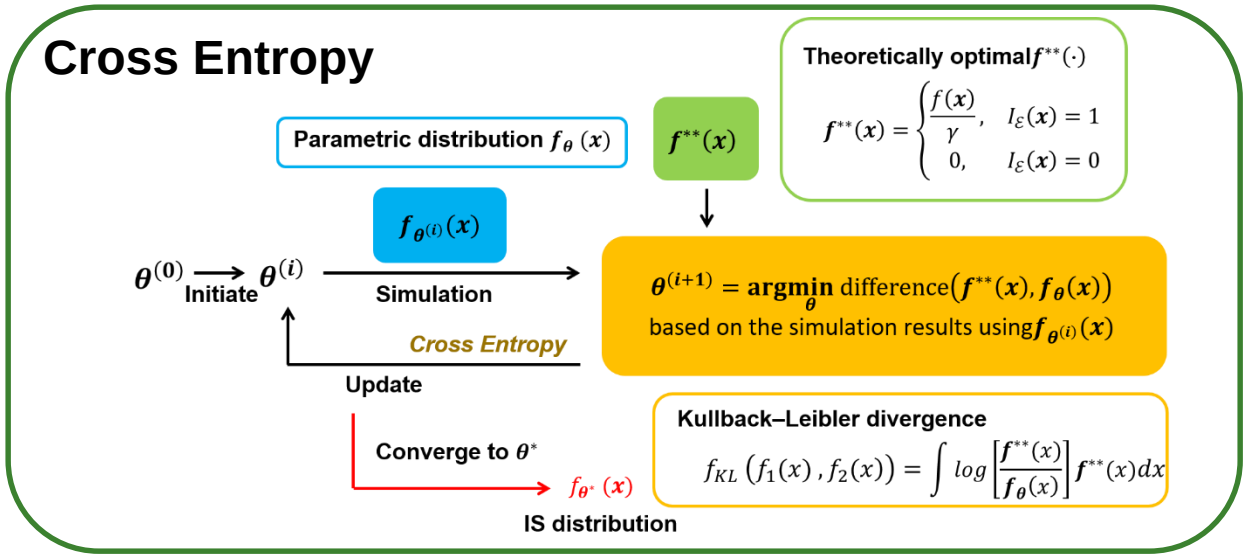
Framework of TrafficNet

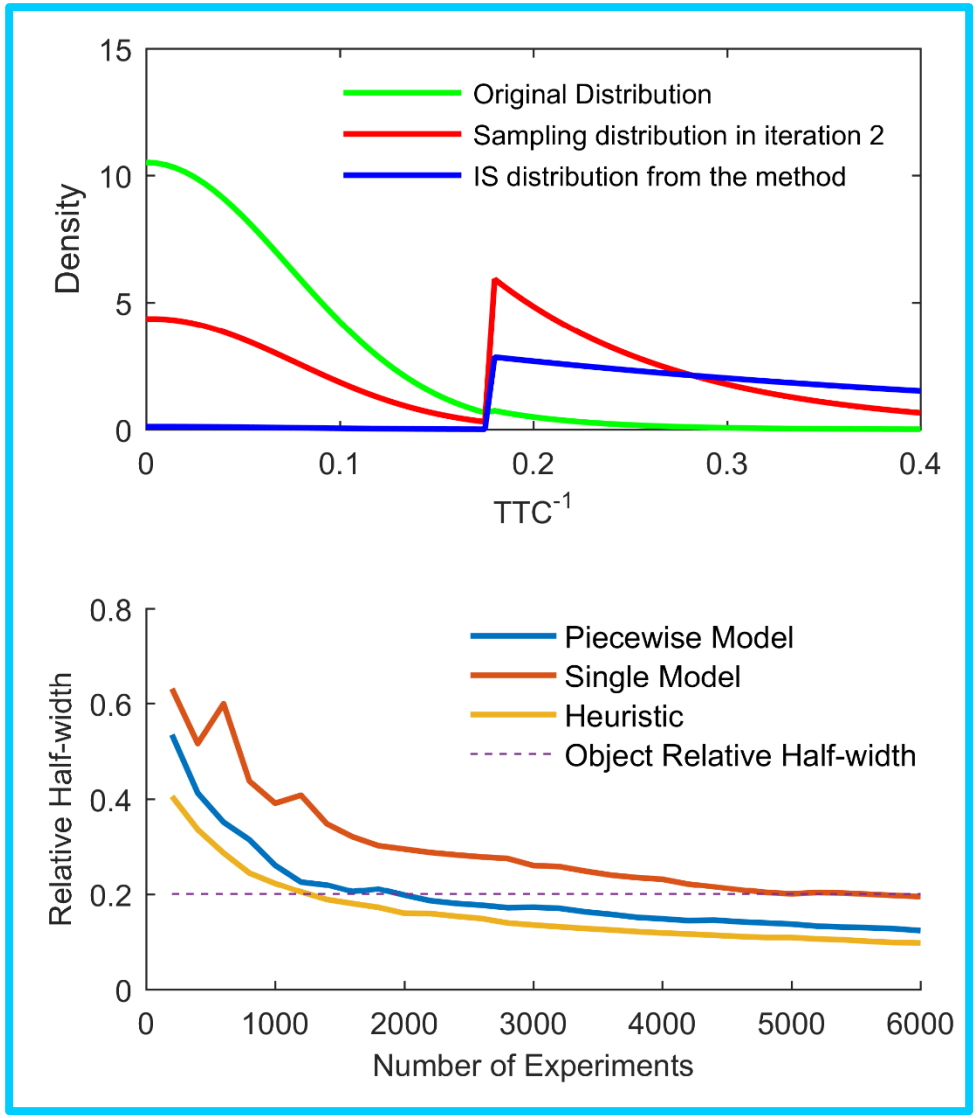
[**Accuracy**] Accelerated Evaluation using Piecewise Mixture Models



Accelerated Evaluation based on

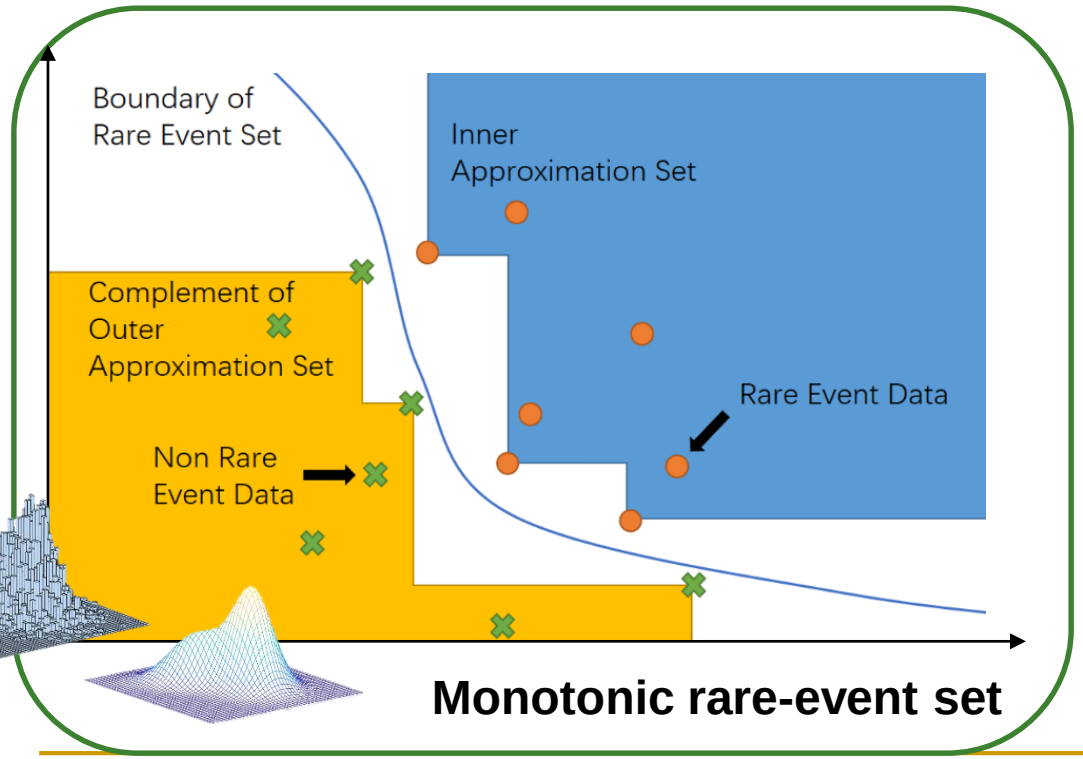
a) a single distribution b) a piecewise mixture distribution



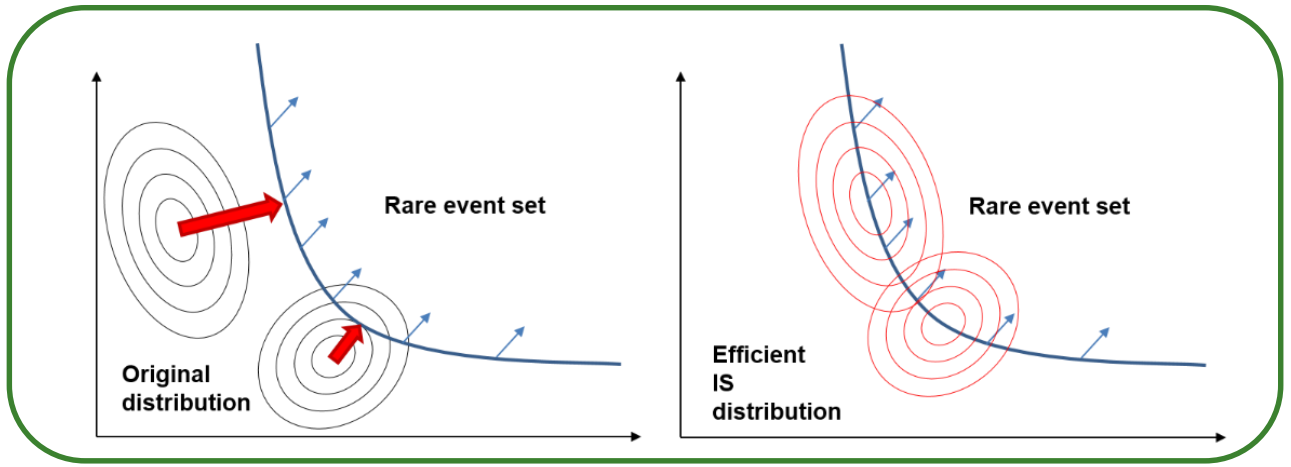


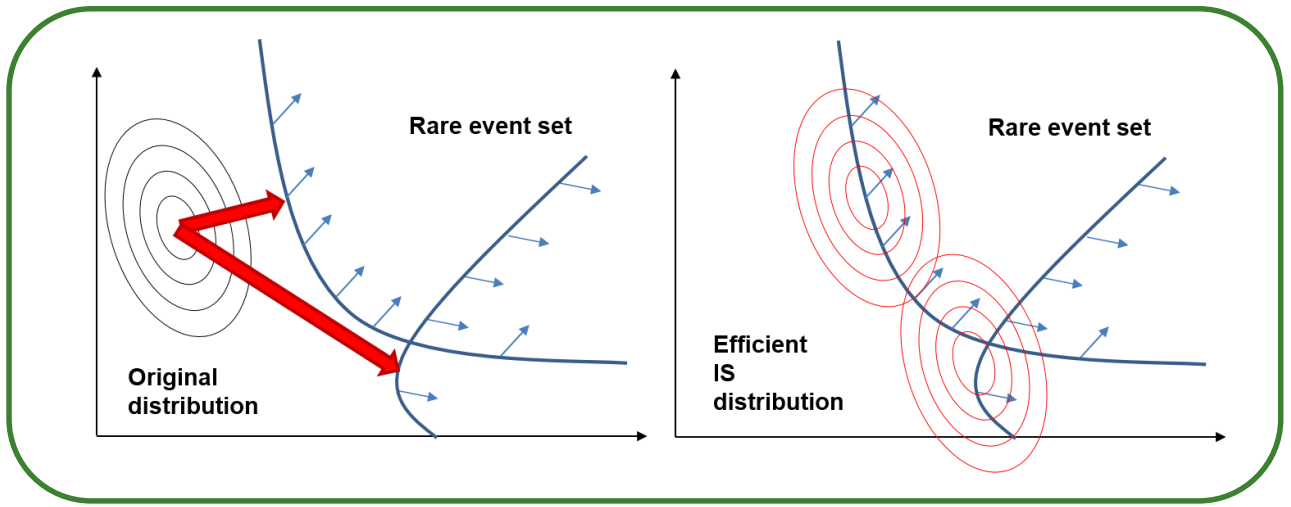
[**Versatility**] Accelerated Evaluation using Joint Distribution

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



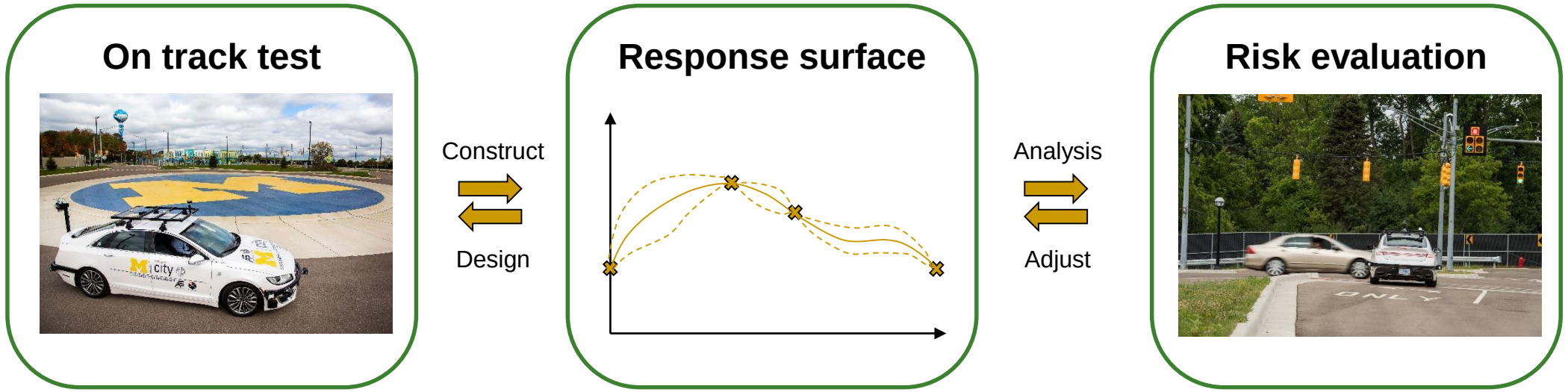
Monotonic rare-event set



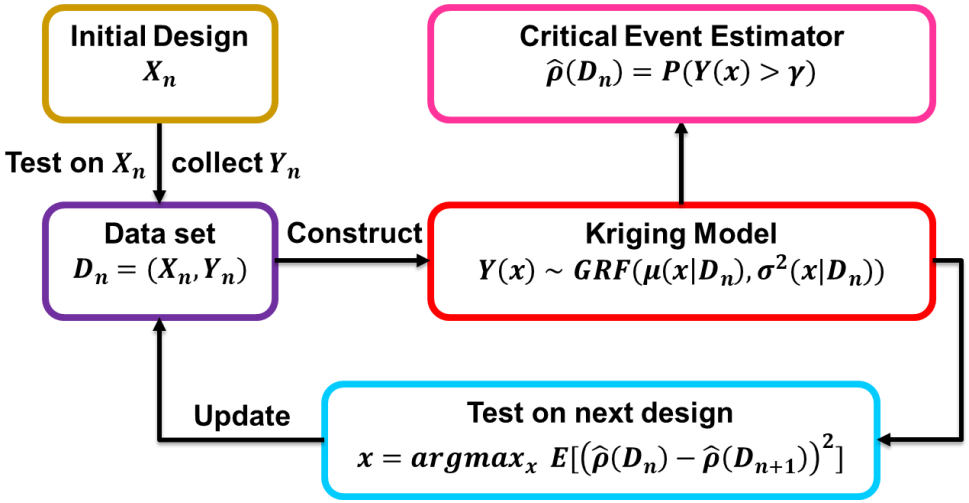


Z. Huang, H. Lam, Ding Zhao, "An Accelerated Testing Approach for Automated Vehicles with Background Traffic Described by Joint Distributions, " Proceedings of the IEEE 20th International Intelligent Transportation Systems Conference (ITSC), 2017.

[Efficiency] Kriging-based Evaluation



- On track tests are expensive and time-consuming
- Previous accelerated rate is high, but not enough
- **Objective**
  - **Introduce reasonable assumptions s.t. 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.

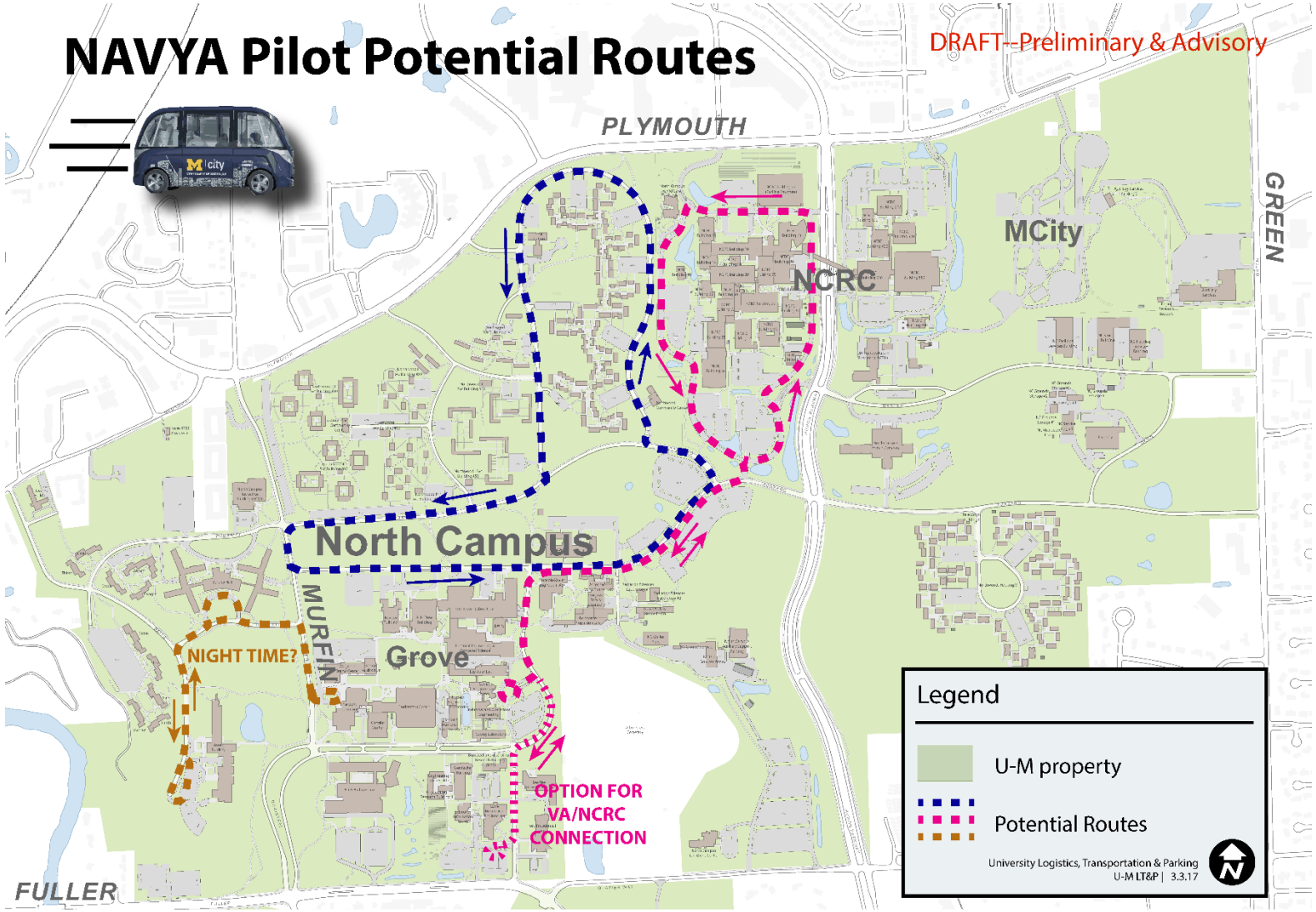
Platforms

On-track tests

Virtual reality

Augmented Reality

Deployment of Testing Vehicles



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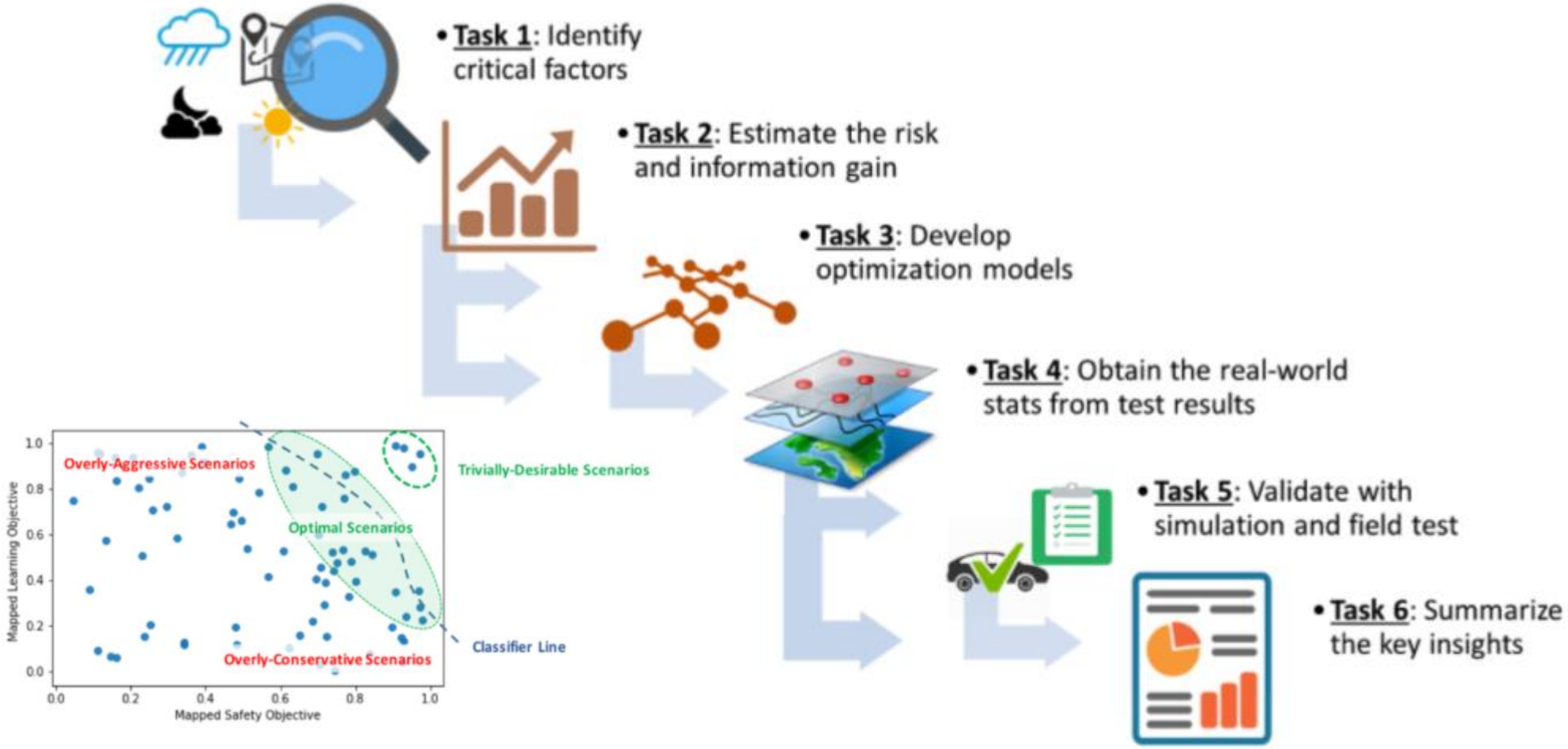
Design Deployment Policy



Dynamic Scenario Optimization

Acknowledgement

Thanks for your attention

Papers / Contact

PPT