Mapping Cities into Mcity - Develop a Statistically Certified CAV Test Protocol, Leveraging on Traffic Primitives, Accelerated Evaluation, and Mixed Reality

城市折叠——基于统计正确性的智能网联汽车测试方法，集成交通基元、加速测试、和混合现实

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, CHANGAN, HONDA, GM, VOLVO, NISSAN, HYUNDAI, KIA MOTORS, Mercedes-Benz, BAIC, SAIC, GEELY, CHERY, Google, UBER, DELPHI, NVIDIA, Baidu 百度, BOSCH, Continental, VisLab.it Extend Your Vision, RENESAS, OTTO, navya, nuTonomy, ZMP Robot of Everything, drive.ai, ZOOX, Audi, BMW, PSA PEUGEOT CITROËN

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, HYUNDAI MOBIS, POINT GREY, Autoliv, TOSHIBA Leading Innovation, KOSTAL, DENSO, LG Innotek, Panasonic, MAGNA, HARMAN, FUJITSU TEN, Visteon, QUANERGY, Melexis Microelectronic Integrated Systems, Mando Corporation, FLIR SYSTEMS, OSRAM, applanix A TRIMBLE COMPANY, ON Semiconductor, LeddarTech, Neusoft, infineon, SONY, PEPPERL+FUCHS, TRILUMINA, ublox, Velodyne LiDAR, PHANTOM INTELLIGENCE

CONNECTIVITY

HITACHI, RENESAS, Peloton, Continental, NXP, BOSCH, DELPHI, intel, CohdaWireless 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

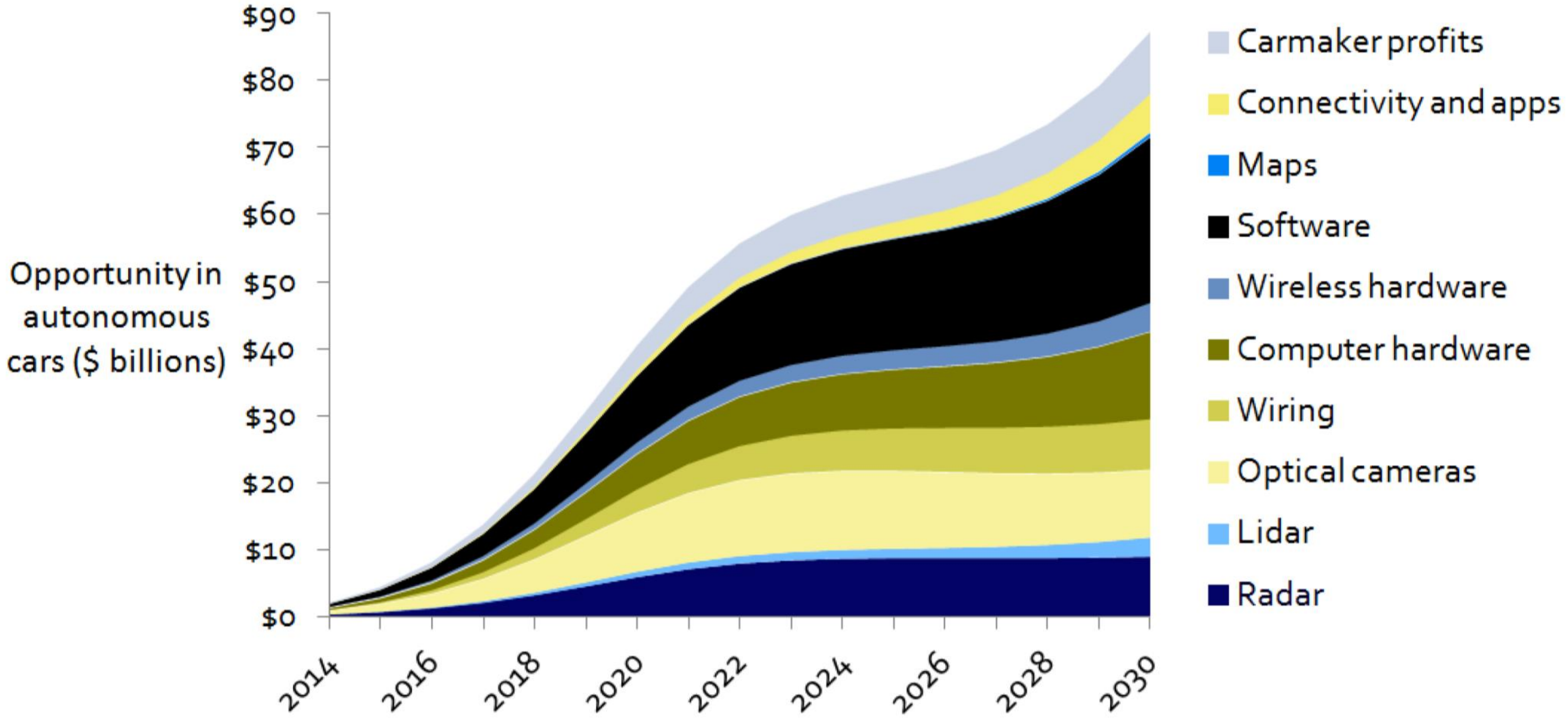
SECURITY/SAFETY

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

Estimated Market of AVs in 2030



2016: 680 million

OTTO UBER

2016: 1 billion

CRUISE GM

2017: 15 billion

MOBILEYE intel

LuxResearch, "Set Autopilot for Profits: Capitalizing on the $87 Billion Self-Driving Car Opportunity", 2014

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 …

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/s^2]	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

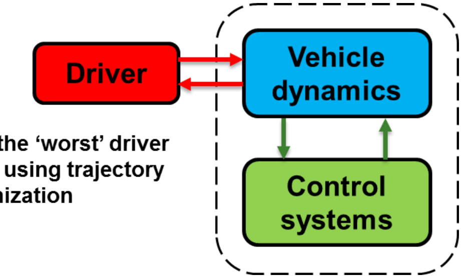
❖ 100 million mi / fatal crash (NHTSA 2013)

Monte Carlo Simulation

Distraction, time headway
H.-H. Yang and H. Peng, (2010)
Reaction time
J. Woodrooffe, et al , UMTRI-2011-36, (2014)

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

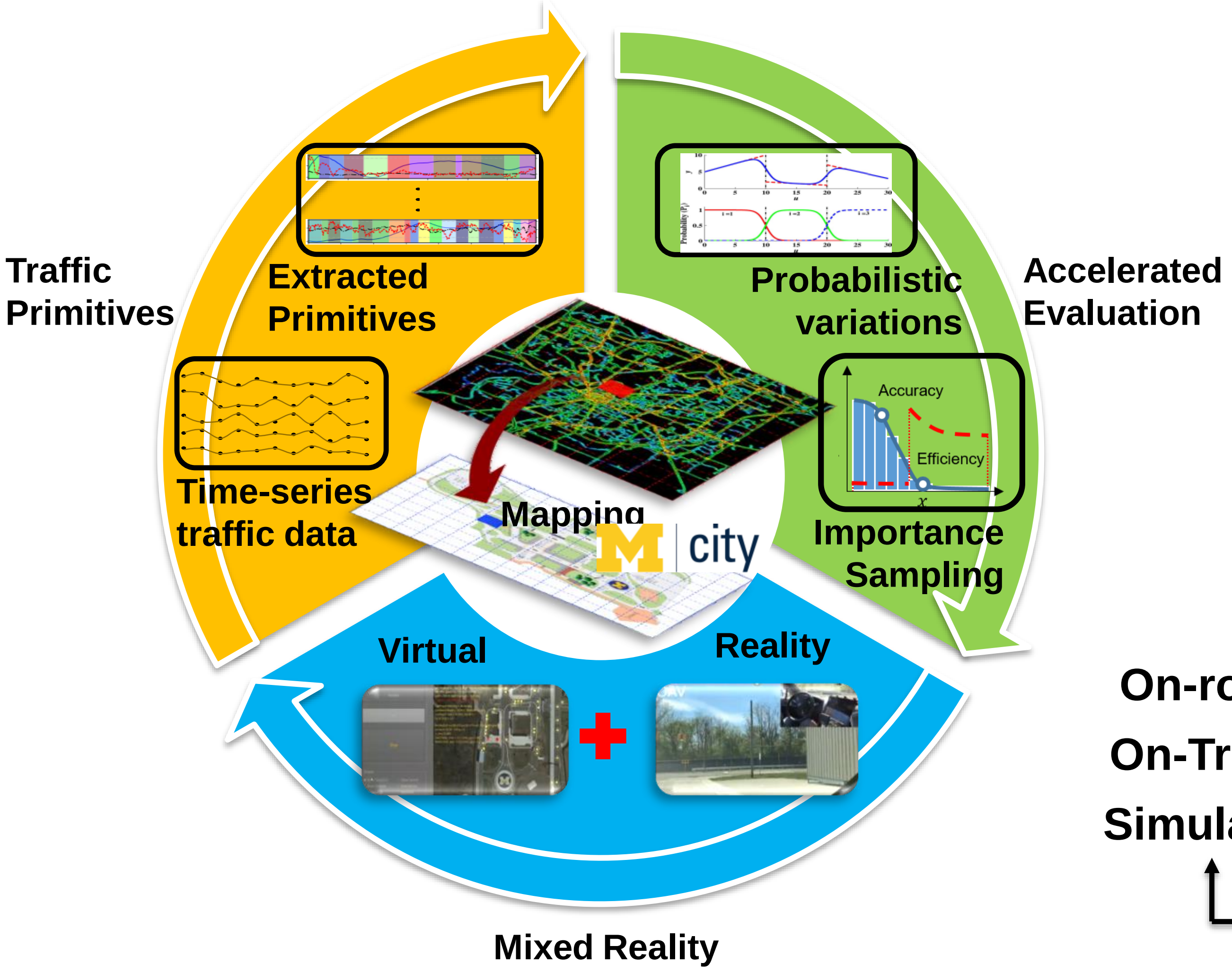
Ma and Peng (1999), Ungoren (2003), Kou, Peng, and Jung (2008)

Pro: Worst cases
Con: No probability information

NCAP: New Car Assessment Programme
AEB: Autonomous Emergency Braking

Earth from Sun: 93 million mi

A Statistically Certified CAV Testing Approach



Sequential Data

Traffic primitive (scenario,)

Frequency

Stochastic variation model

Accelerated Evaluation

On-road

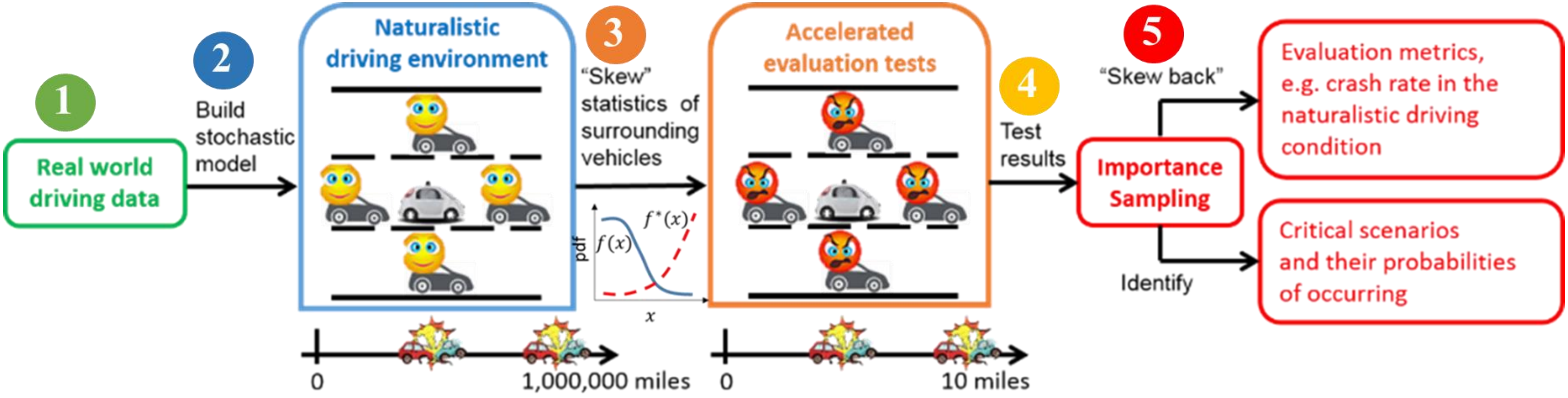
On-Track

Simulator

Driving database

Mixed reality

Accelerated Evaluation



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

Five Steps of the Accelerated Evaluation

④ Simulate (at accelerated pace)

① Collect naturalistic driving data

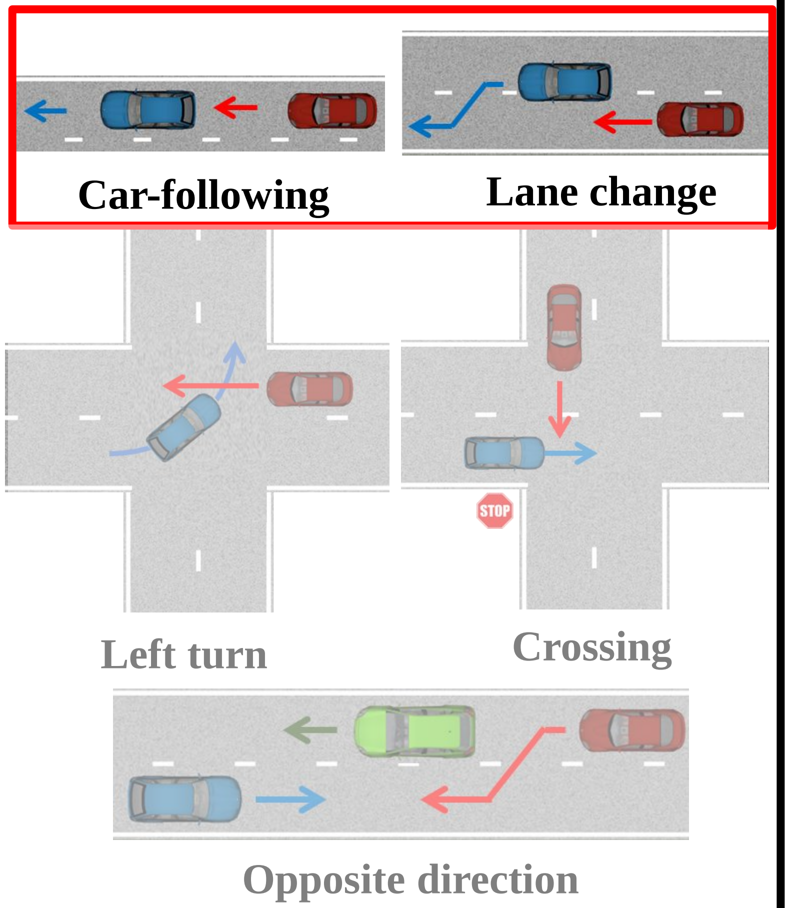
② Model behaviors of “other vehicles” as disturbance

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

Naturalistic driving

⑤ “Skew back” to understand real-world safety benefits

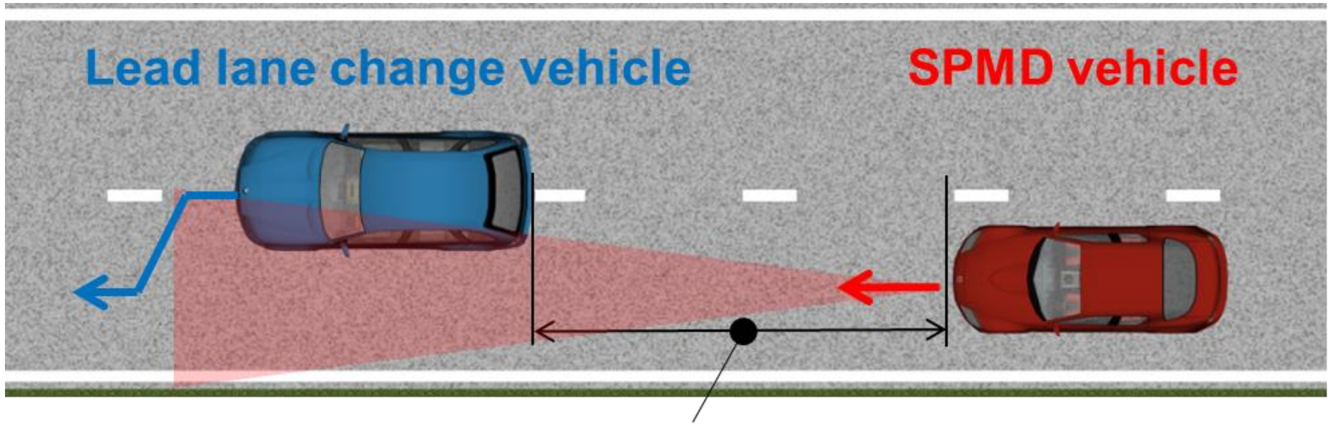
“Accelerated” tests



87 % light-vehicle crashes

W. G. Najm, et al, DOT HS 811 732, (2013)

Case 1: Lane Change 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
$$\dot{\boldsymbol{R}}_{\boldsymbol{L}}(\boldsymbol{t}) = \frac{\boldsymbol{d}}{\boldsymbol{dt}} \boldsymbol{R_L(t)}$$

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

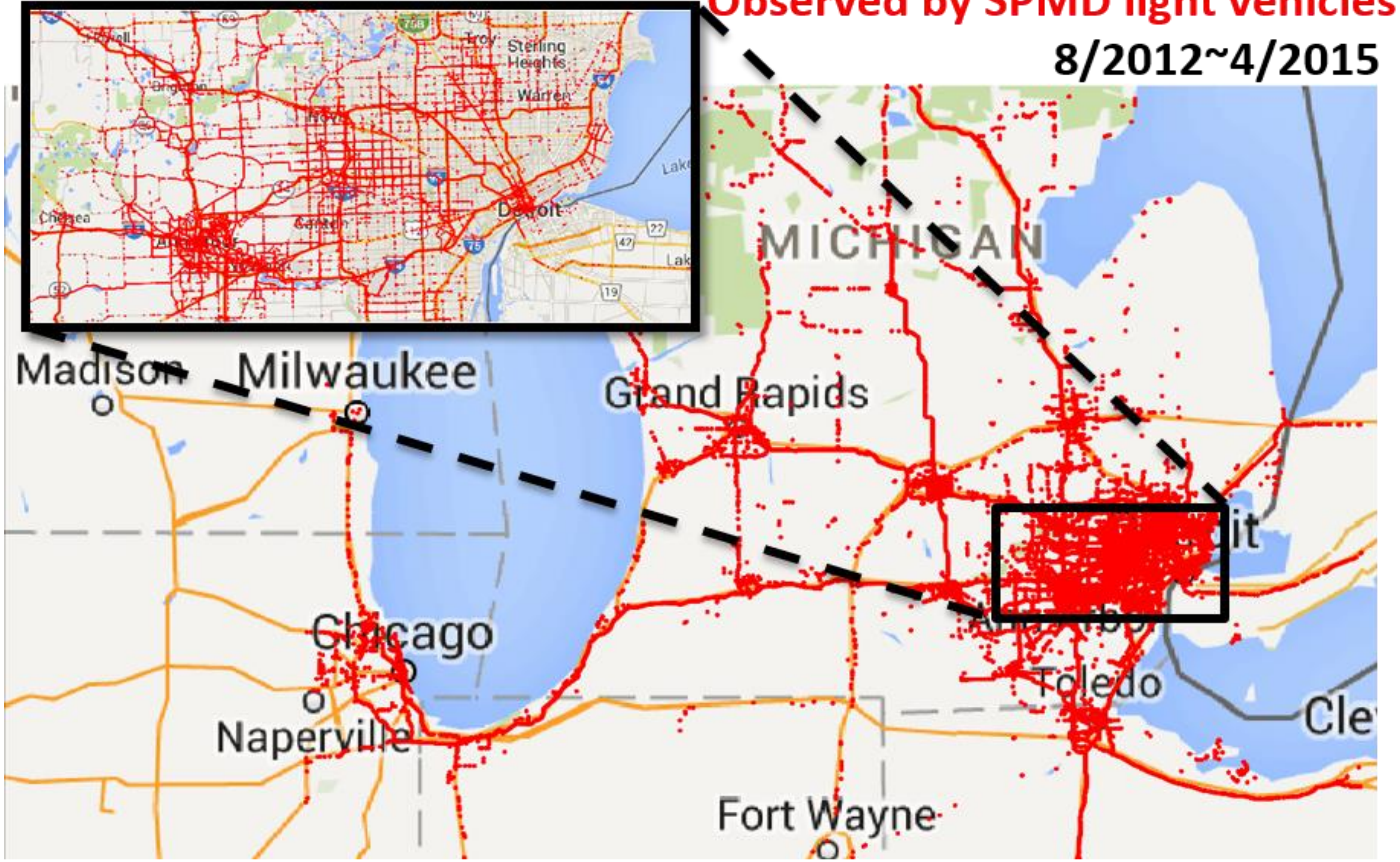
Criteria:

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

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



Importance Sampling Techniques

Motivation

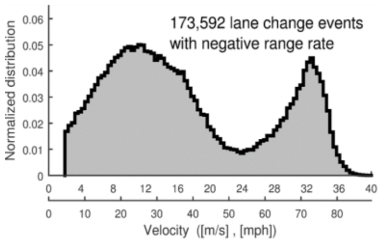
Gap acceptance → $[v_L, R_L, TTC_L]$

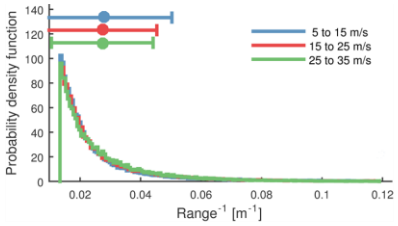
Execution

③ Skew the statistics

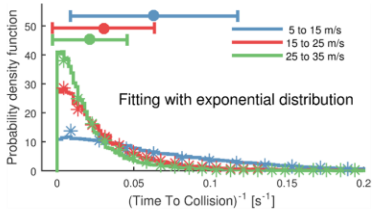
Importance Sampling

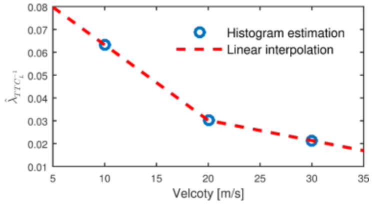
⑤ "Skew back"

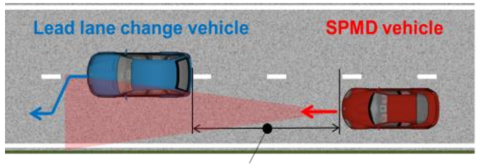




$f_{v_L} \longrightarrow v_L \dashrightarrow f_{R_L^{-1}} \longrightarrow R_L$

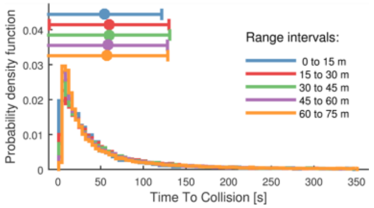


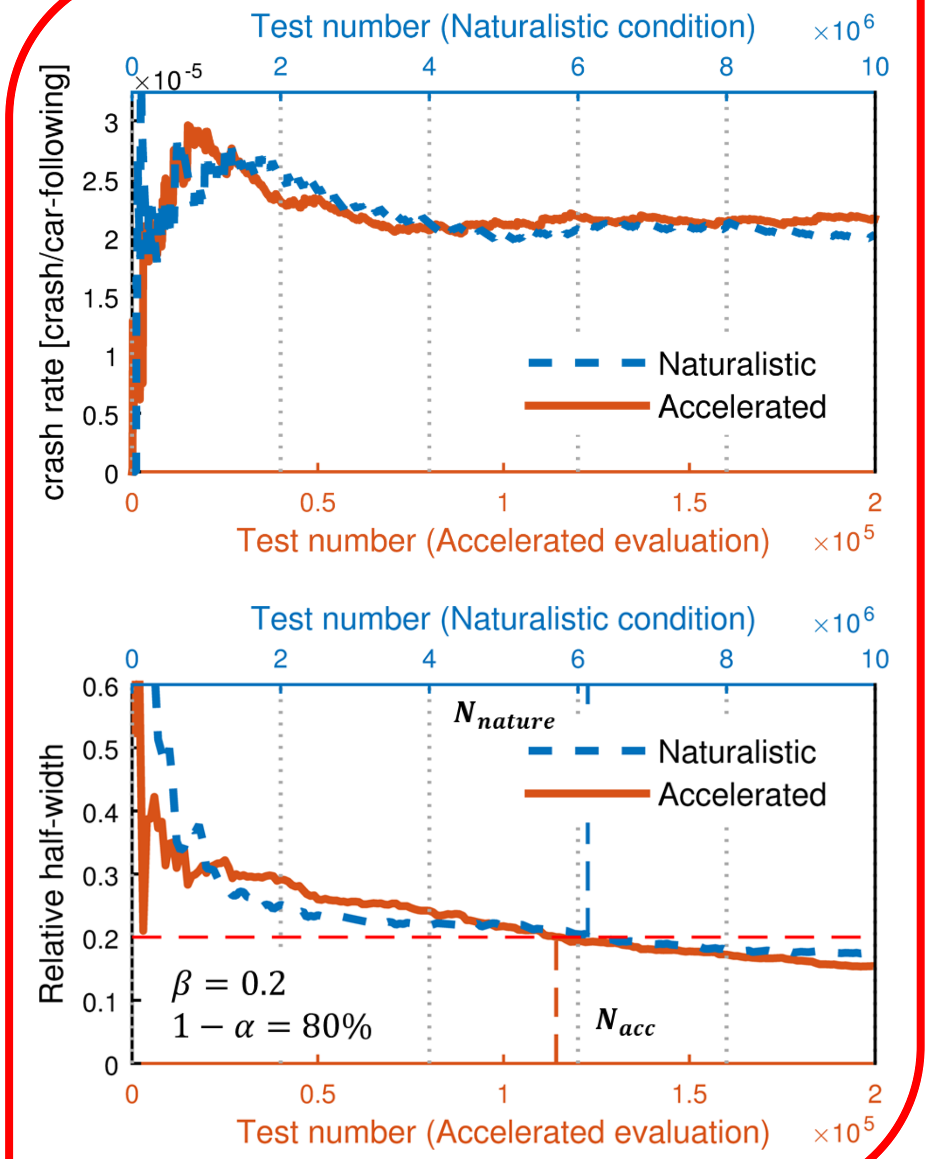




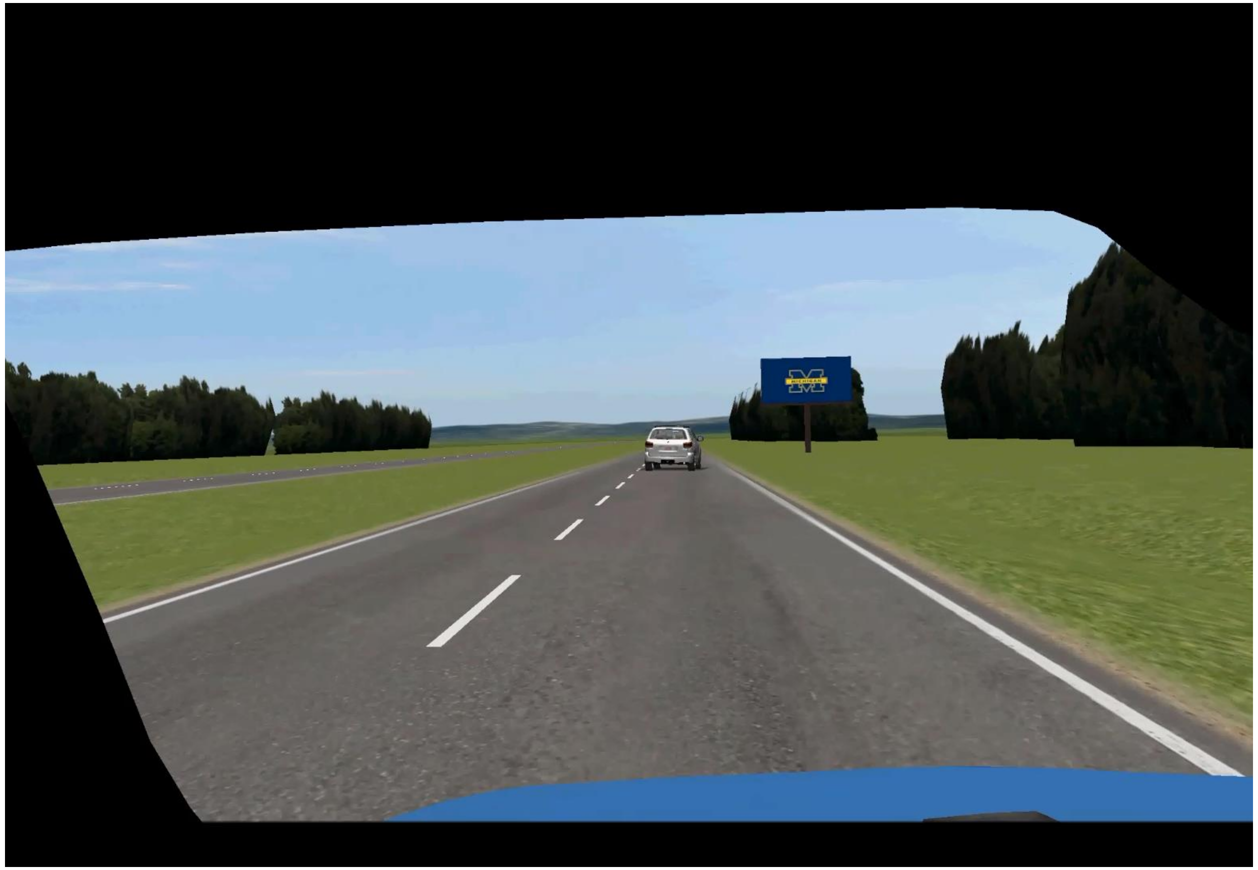
$f_{v_L} \longrightarrow v_L \dashrightarrow f_{R_L^{-1}} \longrightarrow R_L$

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





Naturalistic Driving vs Accelerated Tests

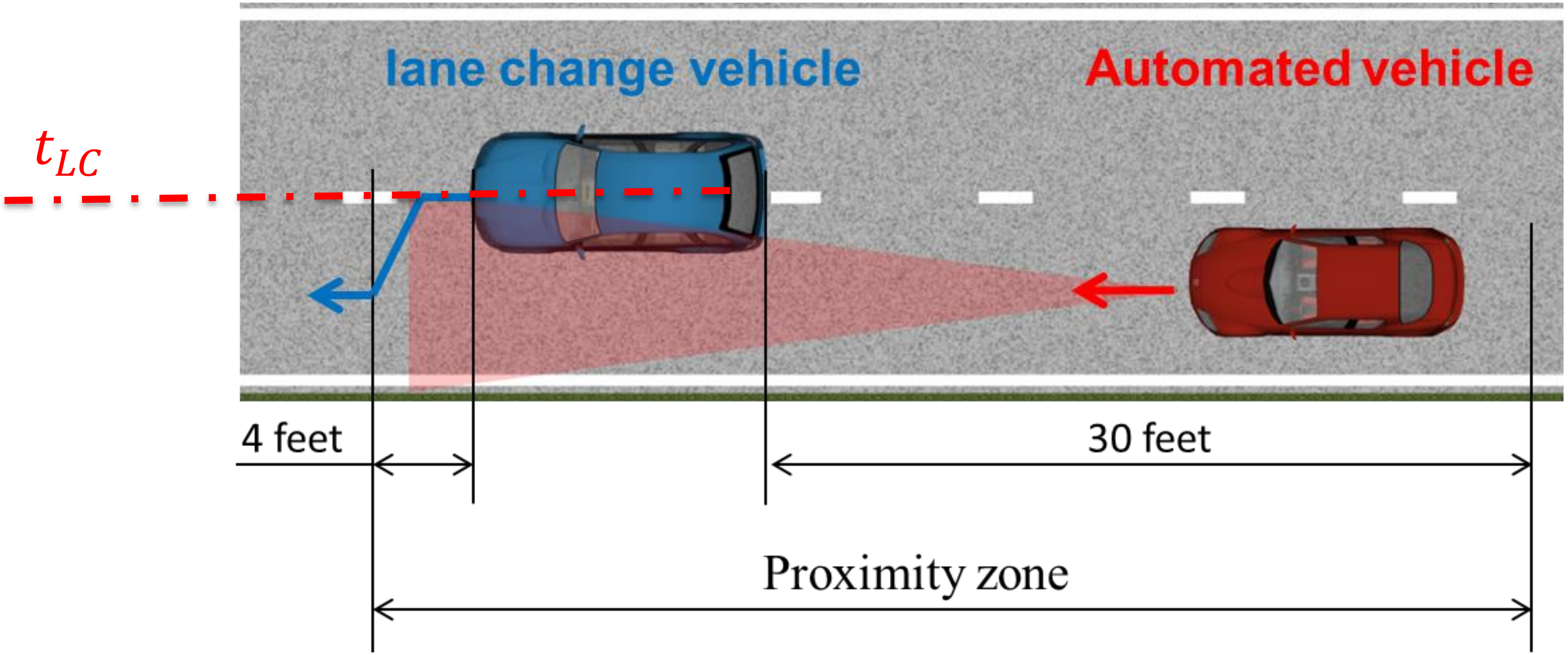
Naturalistic driving conditions	Accelerated tests
	

Accelerate Rate

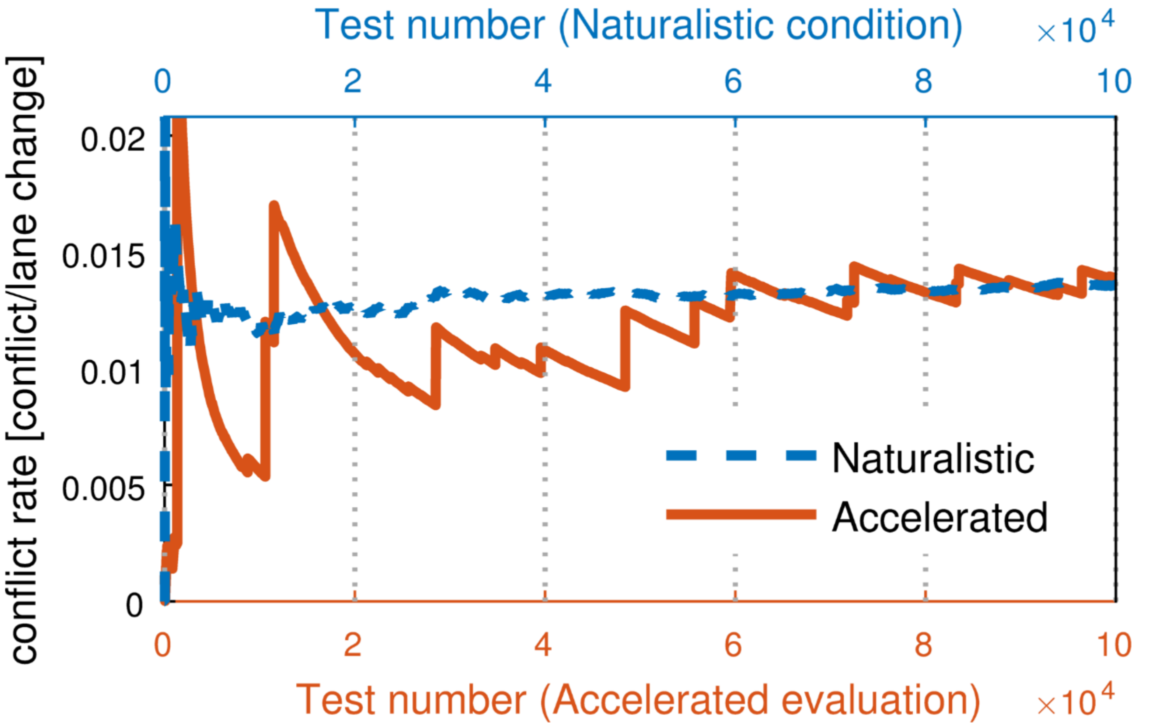
	D_{nature}	D_{acc}	r_{acc}
	mile	mile	-
Crash	4.71e7	7.48e3	6.30e3
Injury (belted)	4.70e7	4.85e3	9.70e3

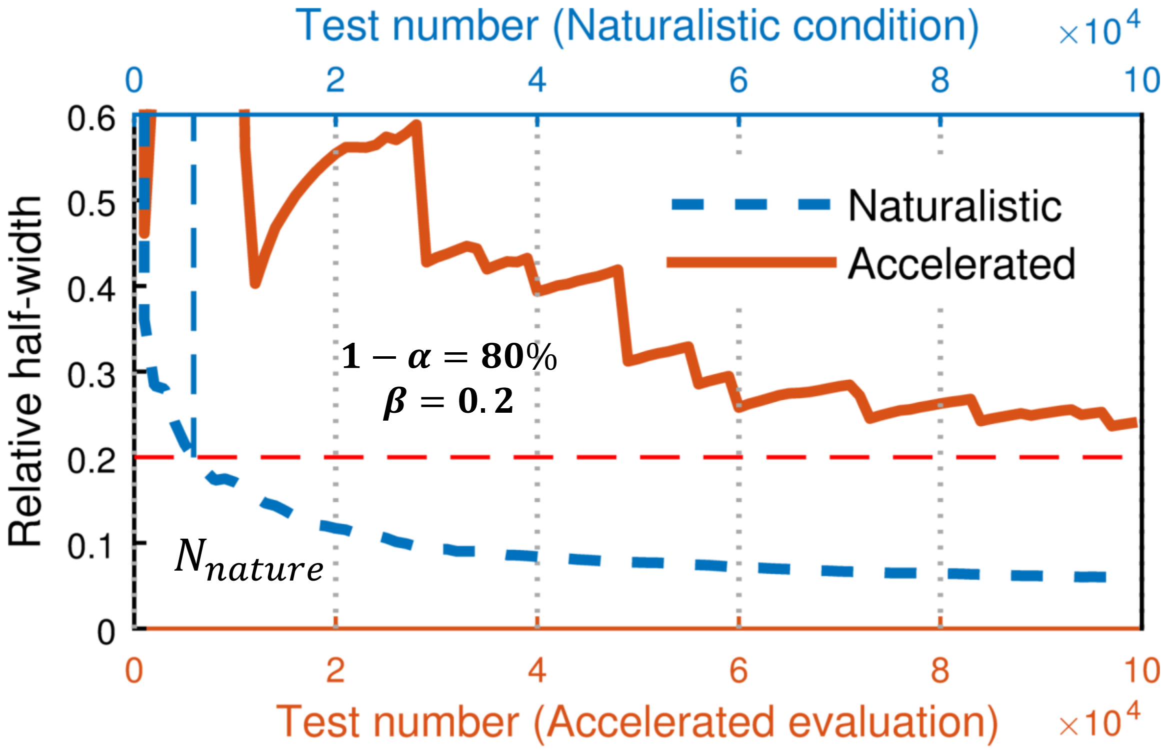
"Accelerated" Test with the Non-optimized AE Distribution

- Apply the previous AE distributions (f^*) on a new metric
  - Previous: crash, injury
  - New: conflict



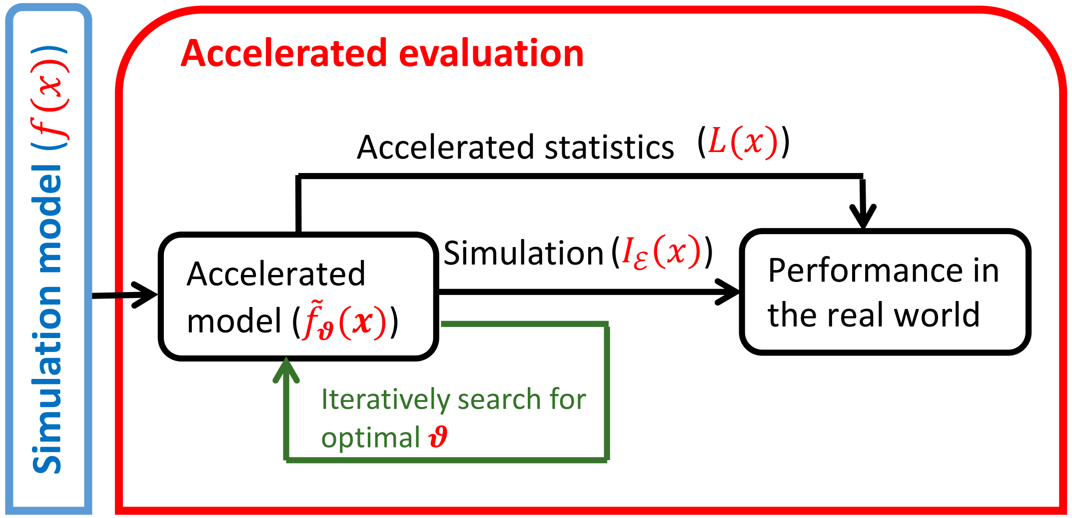
Simulation Results





Adaptive Accelerated Evaluation

- The core idea
  - Identify a family of distribution $\tilde{f}_{\vartheta}(x)$
  - Find a ϑ that can effectively accelerate the evaluation in a small amount of pre-test



Find Optimal $f^*(\cdot)$ Iternatively

Exponential twisting

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

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

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**

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

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

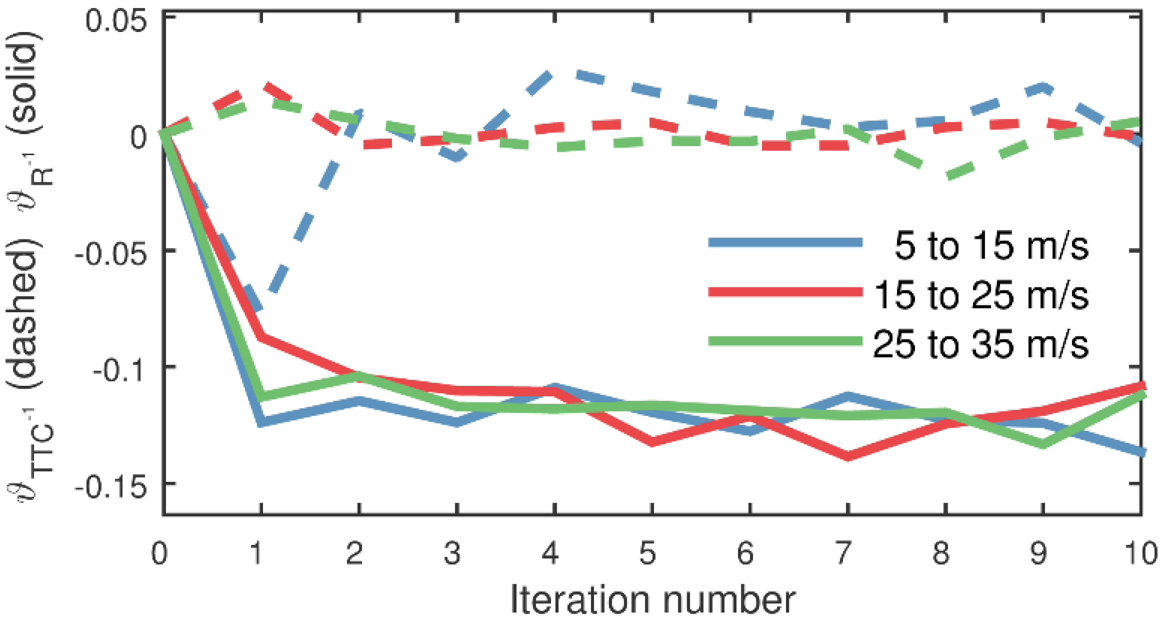
Cross Entropy

Update

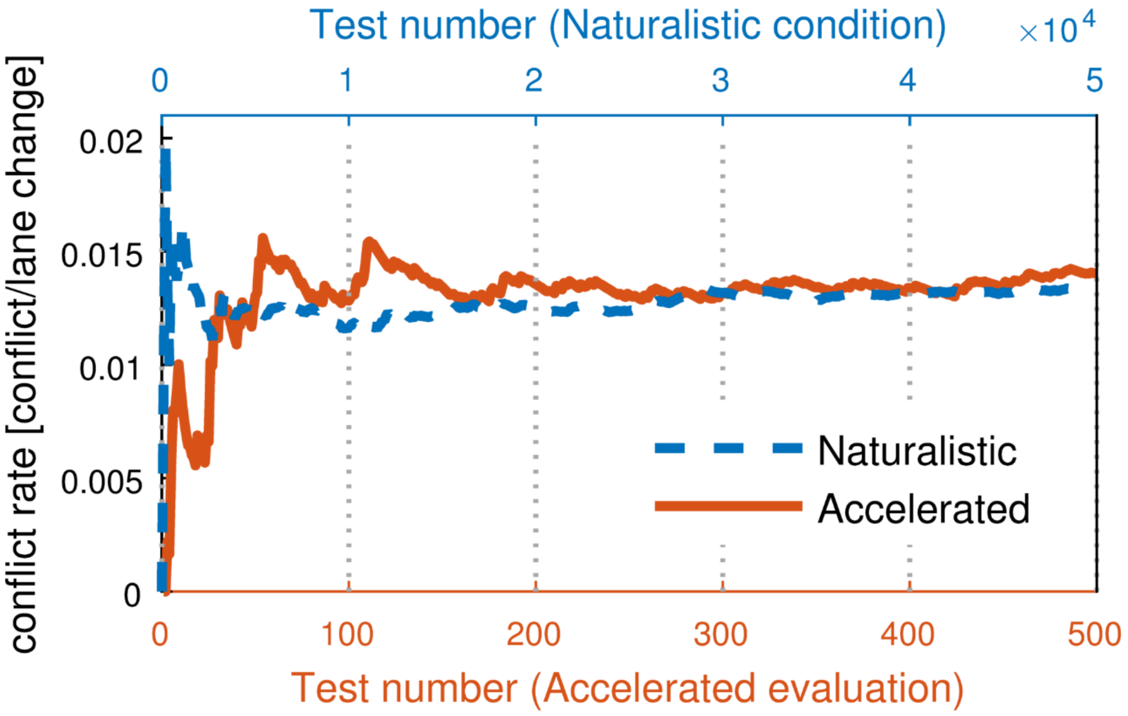
Kullback–Leibler divergence

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

Conflict Analysis



Find the optimal $f^*(\cdot)$ using the Cross Entropy method

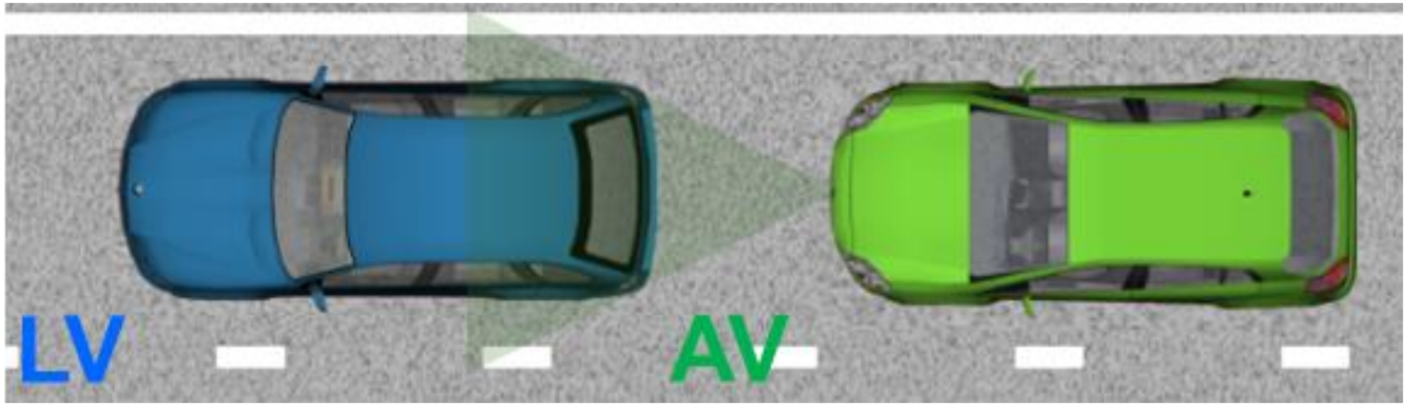


Estimate the probability of conflict

Summary

	D_{nature}	D_{acc}	r_{acc}	r_{acc} Non-optimal AE distribution
	mile	mile		
Conflict	4.53e4	16.4	2.77e3	<1
Crash	4.71e7	4.02e3	1.17e4	6.30e3
Injury	4.70e7	2.53e3	1.86e4	9.70e3

Case 2: Car-following Scenarios

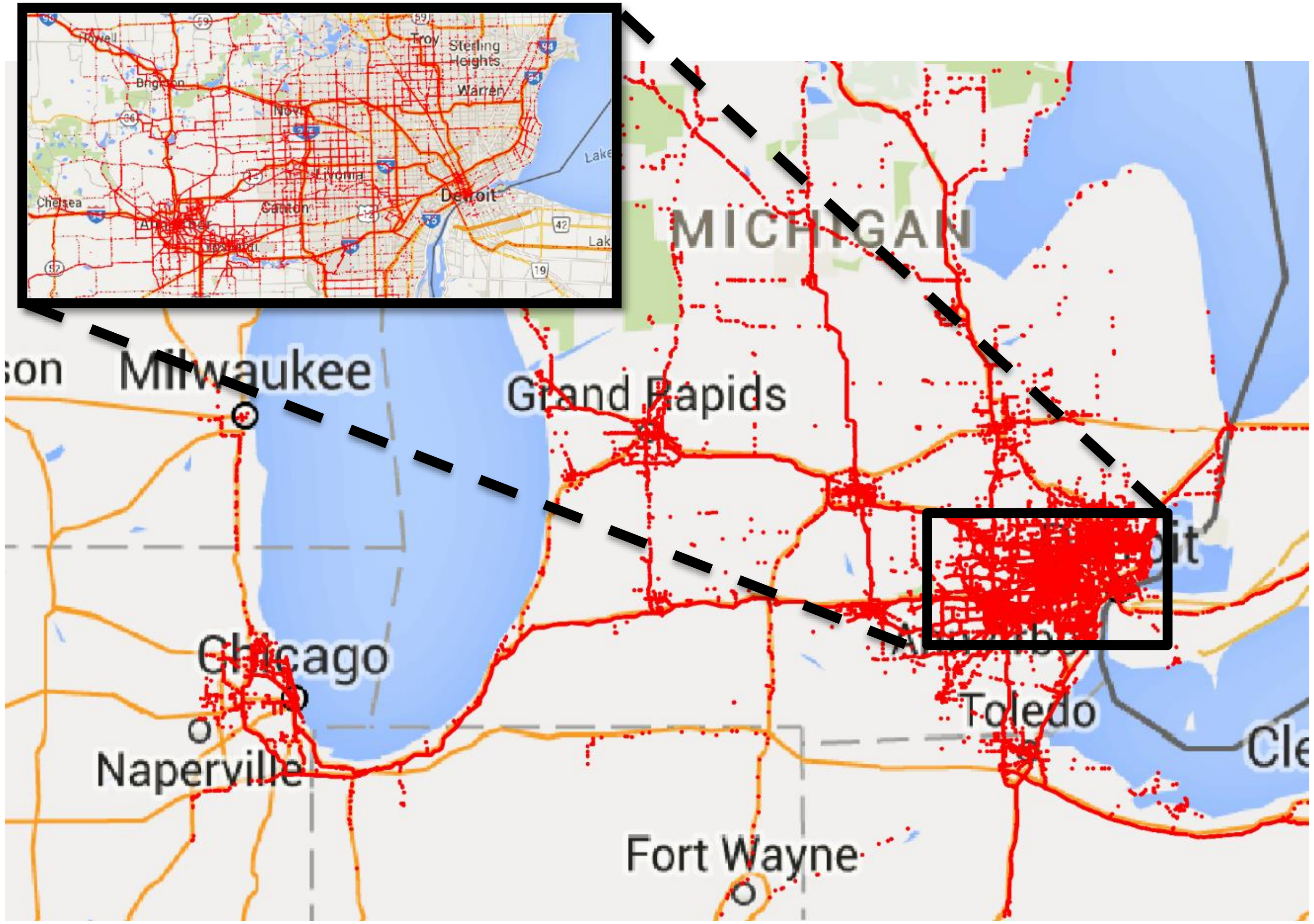


D. Zhao, X. Huang, H. Peng, H. Lam, D. LeBlanc, Accelerated Evaluation of Automated Vehicles in Car-Following Maneuvers. *IEEE Transactions on Intelligent Transportation Systems,* 2017
D. Zhao, H. Lam, H. Peng, S. Bao, D. LeBlanc, K. Nobukawa, C. Pan,"Accelerated Evaluation of Automated Vehicles using Extracted Naturalistic Driving Data," *Proceedings of the 24th Symposium of the International Association for Vehicle System Dynamics*, Graz, Austria, August 17-21, 2015.

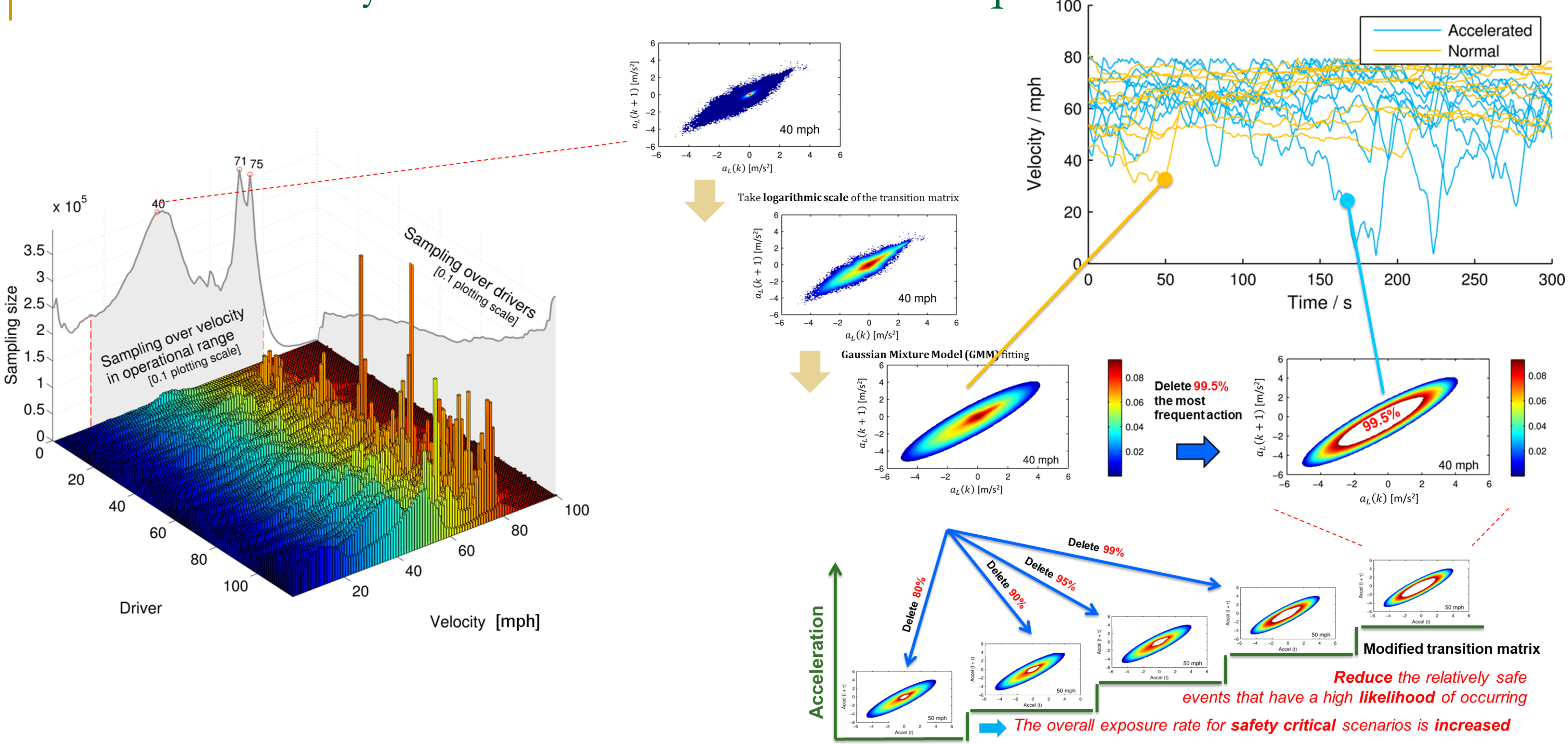
Query Car-following Events

163,332 car following events

- Criteria
  - $R_L(t) \in (0.1\ \text{m}, 90\ \text{m})$
  - Longitude $\in (-88.2°, -82.0°)$
  - Latitude $\in (41.0°, 44.5°)$
  - No cut-in vehicles between HV and SPMD vehicle
  - No lane changes of HV and SPMD vehicle
  - Duration of car-following> 50 s



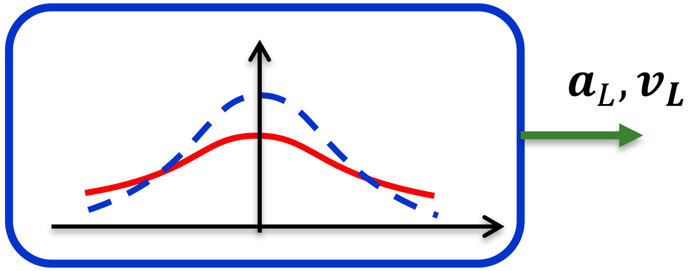
A "Naïve" Way to Accelerate: "Cut the Frequent Parts"



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.

Single-step Sampling vs Multi-step Sampling

Lane change
(single-step sampling)

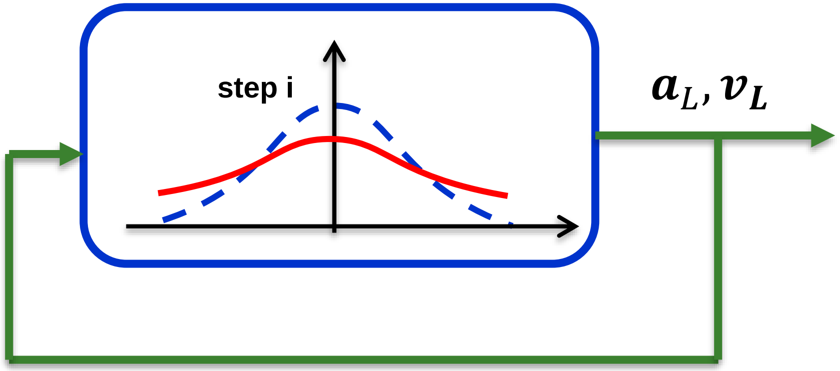


Lead vehicle

Naturalistic distribution

AE distribution

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



Lead vehicle

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

Accelerated Evaluation of the Dynamic Interaction

The optimal $\mathscr{b}(\mathrm{k})$ is calculated to achieve two goals

i) ***To make a crash happen at a specific time*** $k^*_{\mathcal{T}} = 1, \dots, K$

ii) ***To maximize the likelihood of the occurring of the events of interest***

Run the Accelerated Tests

$\mathscr{b}_{k^*_{\mathcal{T}}}(1:K)$

$a_L(1:k_{\mathcal{T}})$

$I_{\mathcal{E}}(n)$

Optimal change of HV statistics (off-line)

Likelihood ratio

$L(n)$

Crash, injury, conflict rates

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

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

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 of the Dynamic Interaction

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

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

Not converge

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

Run the Accelerated Tests

Importance sampling

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

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

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

$b_{k_{\mathcal{T}}^*}(1{:}K)$

$a_L(1{:}k_{\mathcal{T}})$

$I_{\varepsilon}(n)$

$L(n)$

Optimal change of HV statistics (off-line)

Likelihood ratio

Crash, injury, conflict rates

Converge

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

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

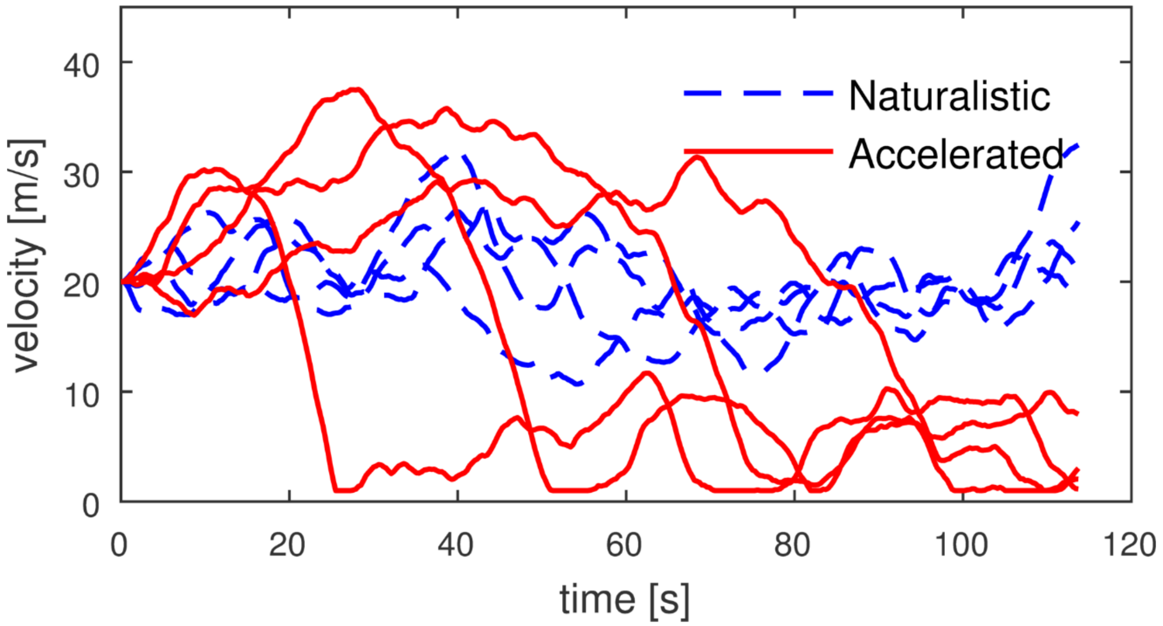
$$f^*(u(1{:}k_{\mathcal{T}} - 1)) = \sum_{k_{\mathcal{T}}^* = k_{\mathcal{T}min}^*}^{K} \tilde{f}(a_L(1{:}k_{\mathcal{T}} - 1) \mid k_{\mathcal{T}}^*) f_{k_{\mathcal{T}}^*}(k_{\mathcal{T}}^*)$$

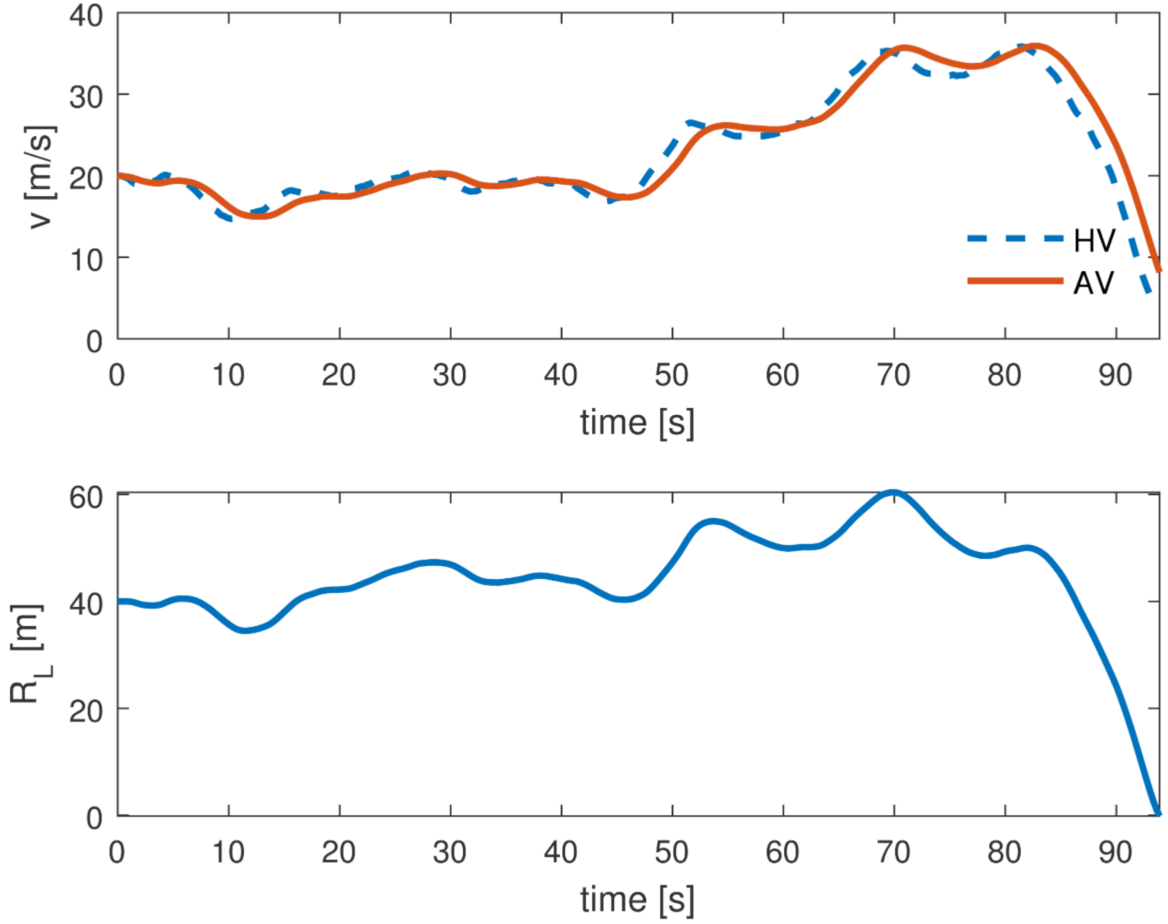
D. Zhao, X. Huang, H. Peng, H. Lam, D. LeBlanc, Accelerated Evaluation of Automated Vehicles in Car-Following Maneuvers. IEEE Transactions on Intelligent Transportation Systems, 2017

Examples of Accelerated Evaluation

An example of the crash event

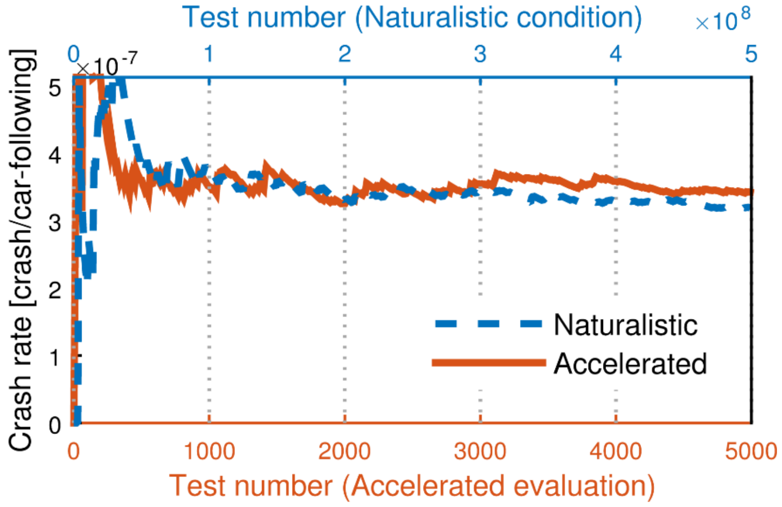
Examples of velocity profiles of the lead vehicle

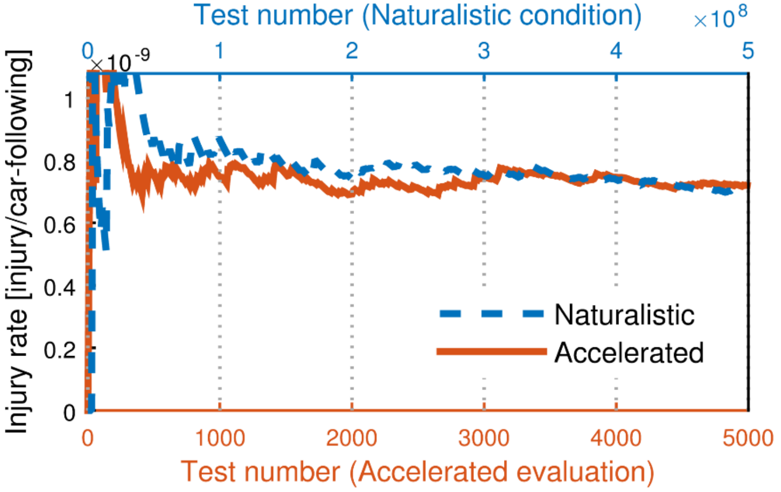


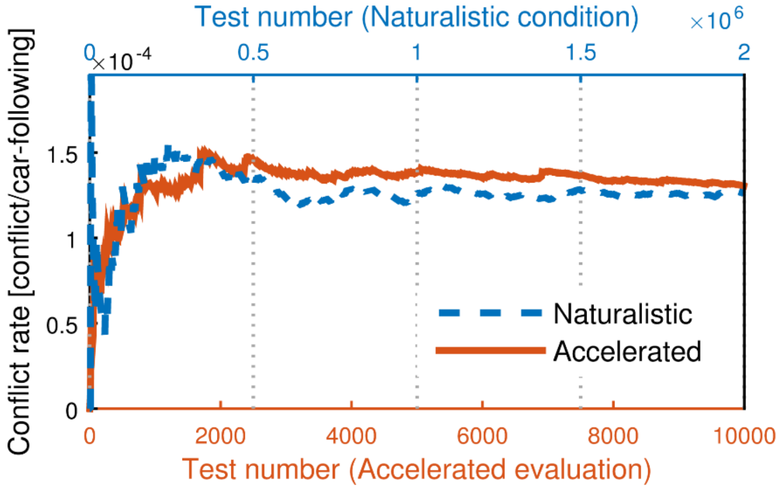


Estimation of Crash, Injury, and Conflict Rate

Estimation

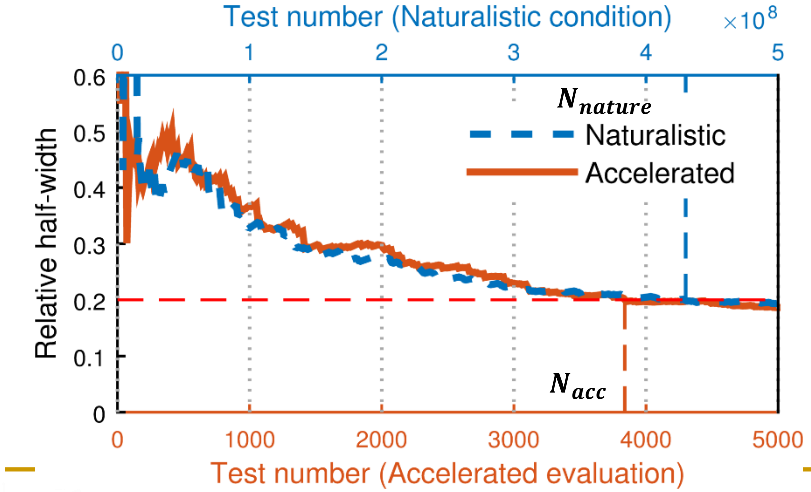


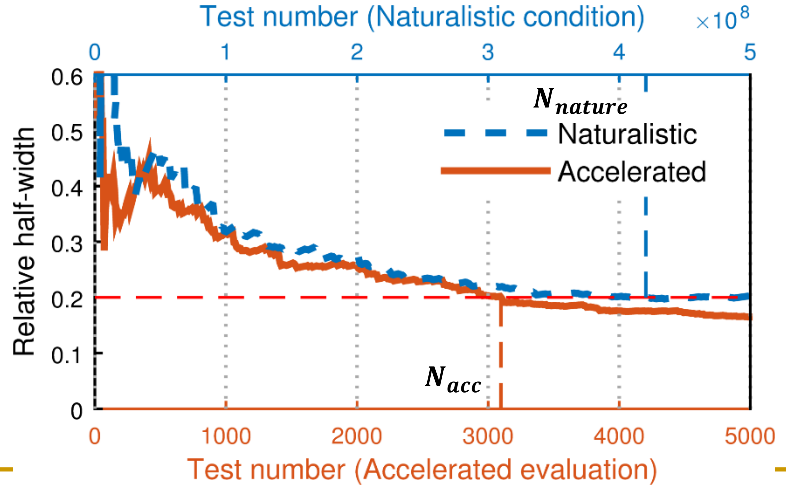


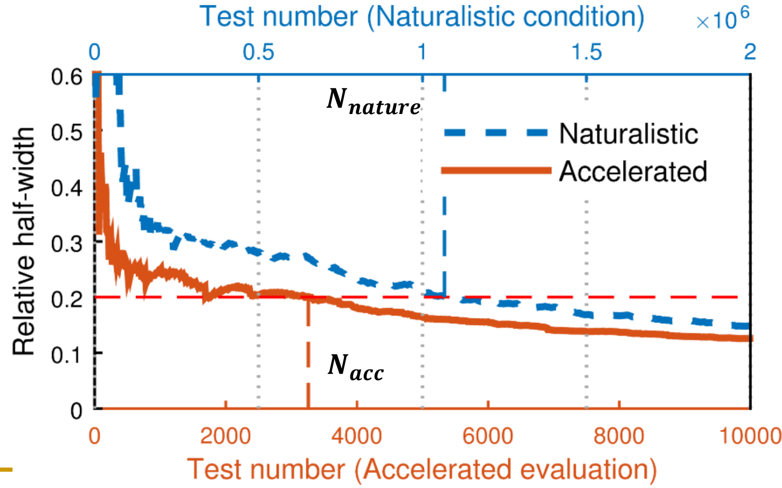


N_{nature}/N_{acc}: **Crash (1.12e5)** **Injury(1.35e5)** **Conflict (3.28e2)**

Convergence

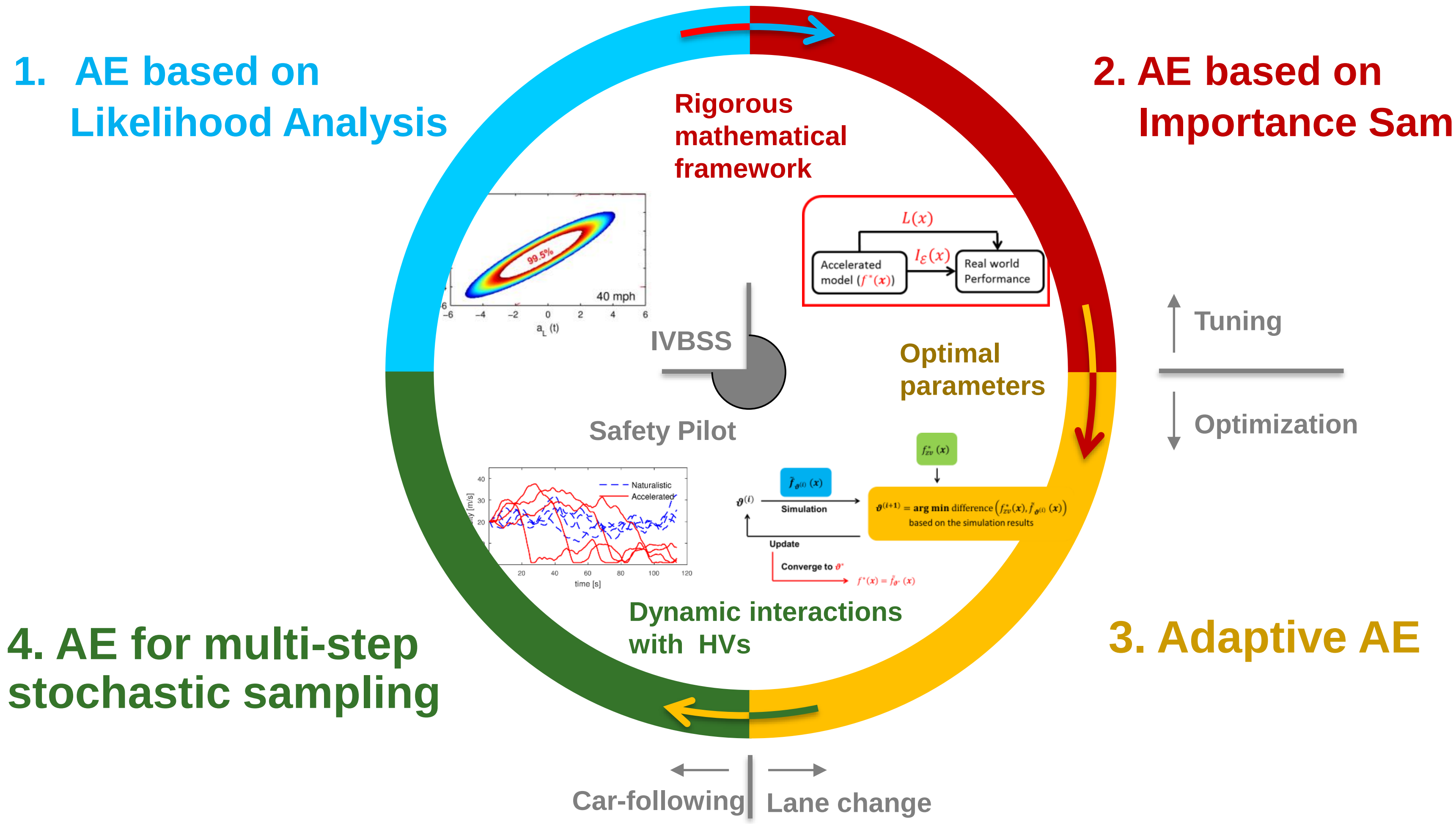




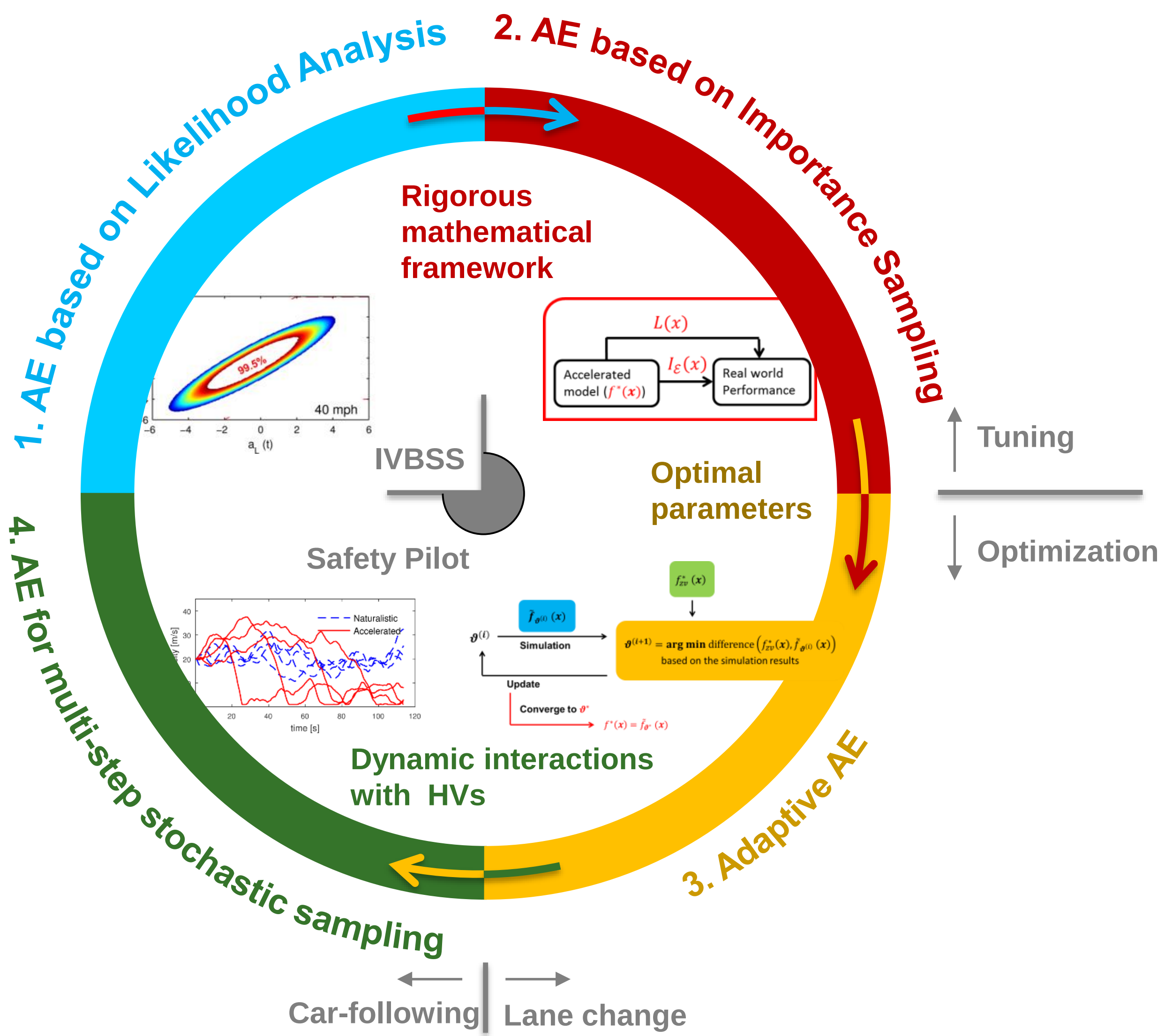


Summary: Four Methodologies of the Accelerated Evaluation (AE)

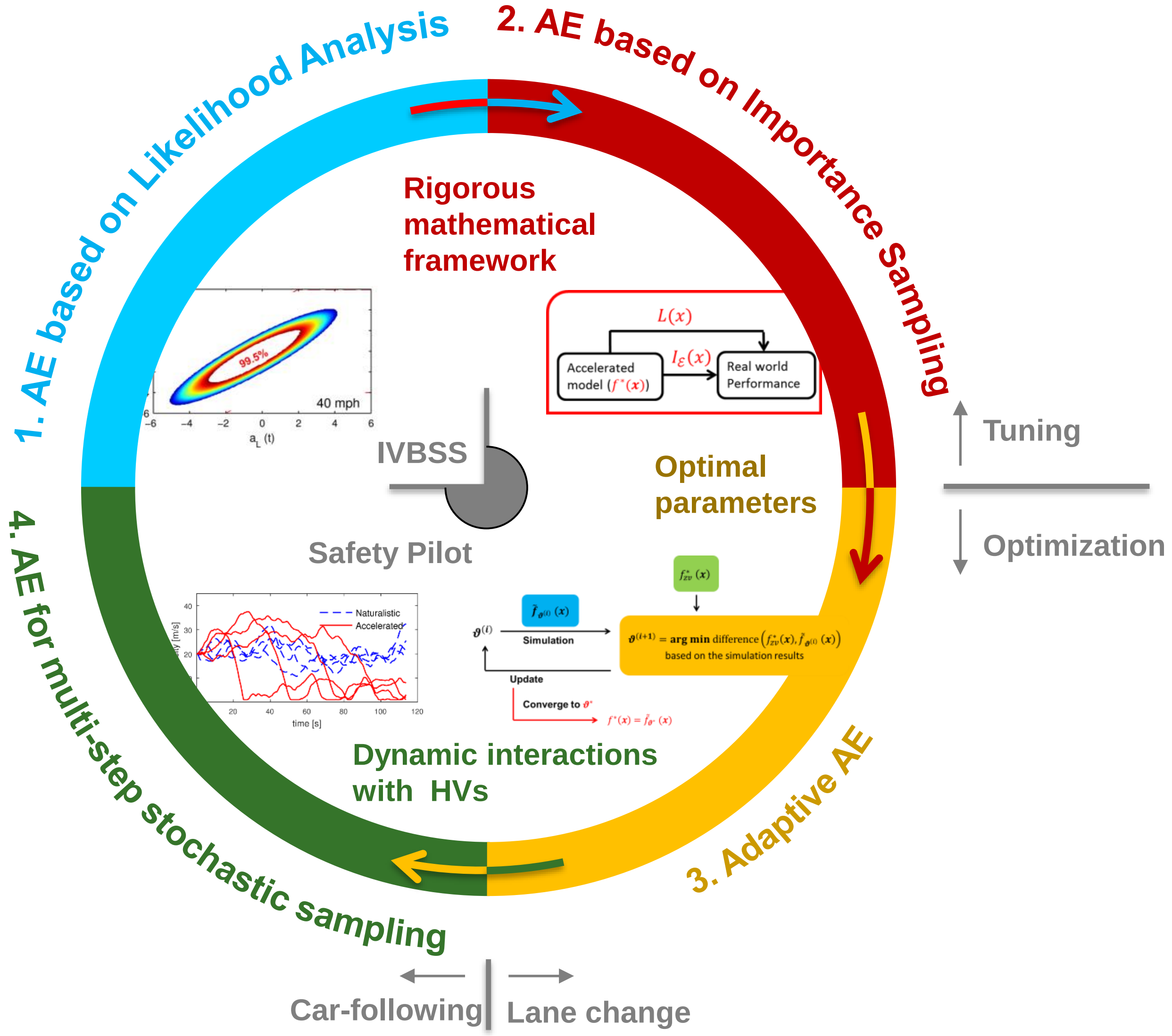
- The "Accelerated Evaluation" concept is new in the field of AV testing and evaluation.
- Four Accelerated Evaluation methods.



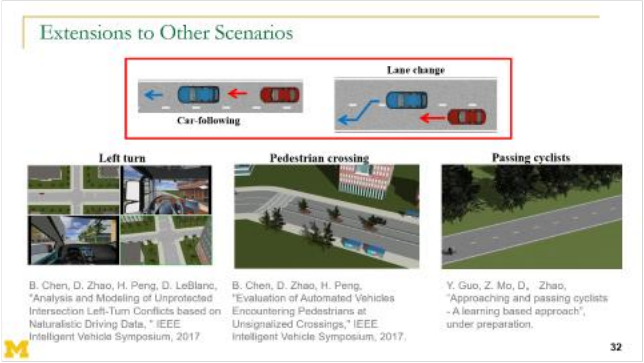
Extensions to the Accelerated Evaluation



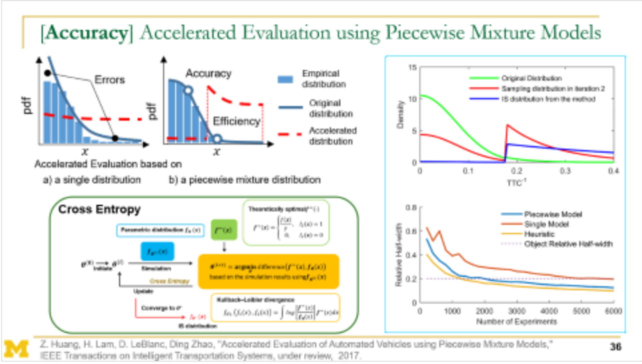
Extensions to the Accelerated Evaluation



Variations

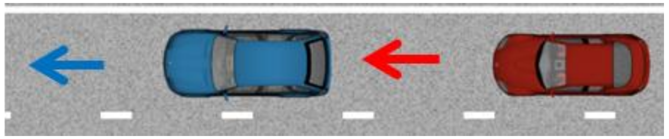


Theories



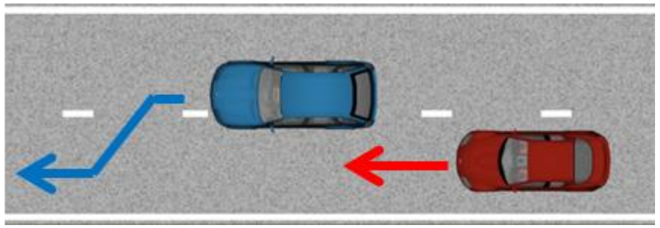
Platforms

Extensions to Other Scenarios



Car-following

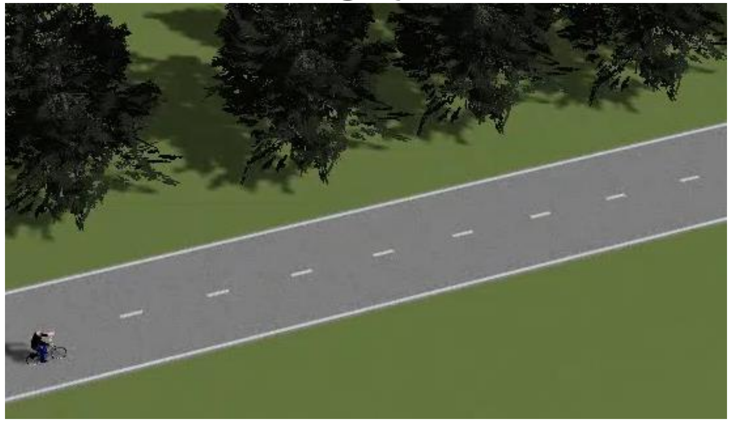
Lane change



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.

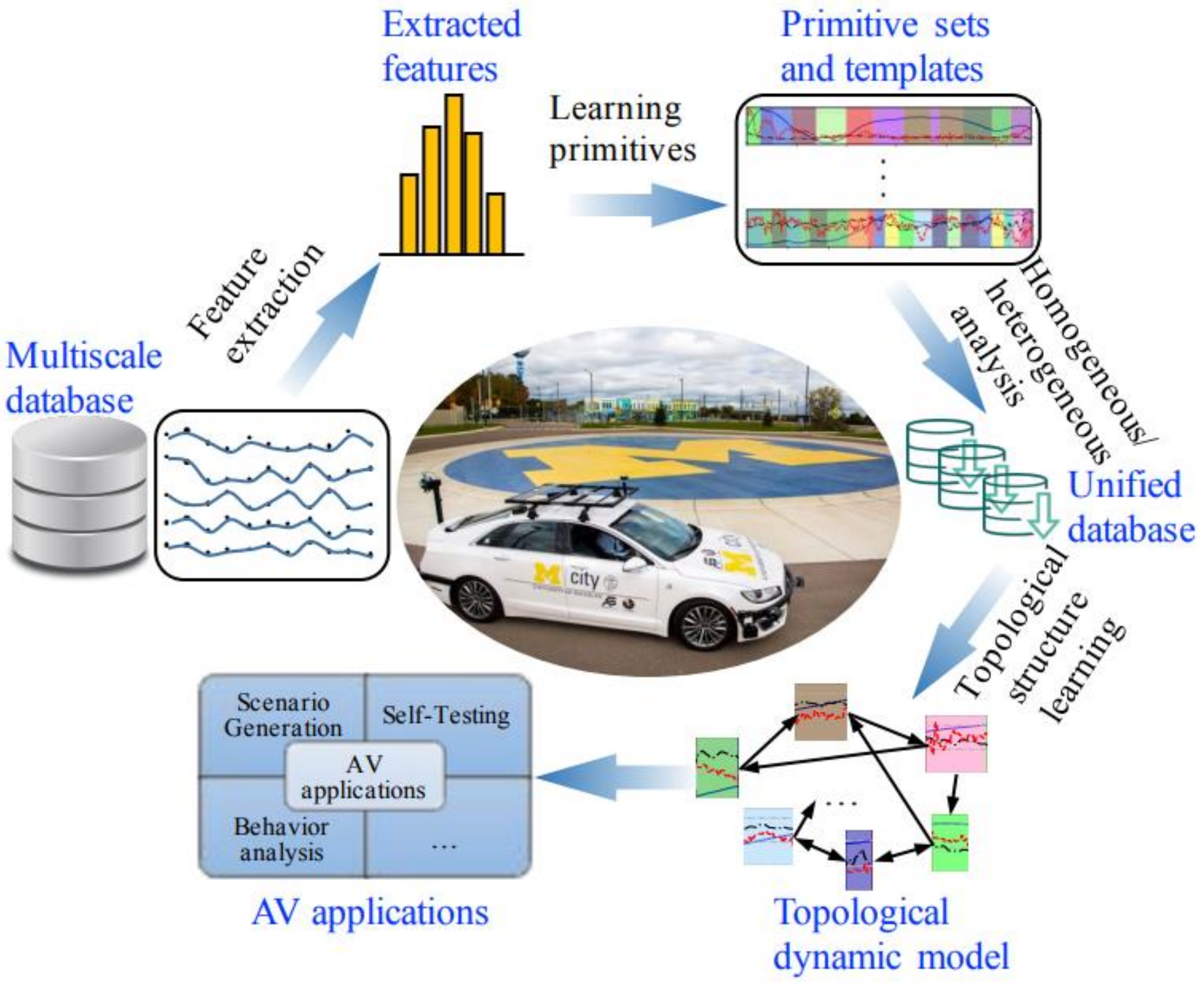
Recent Progress: Extract Scenarios Automatically from Raw Data

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

- Subjectively-selected scenarios/variations

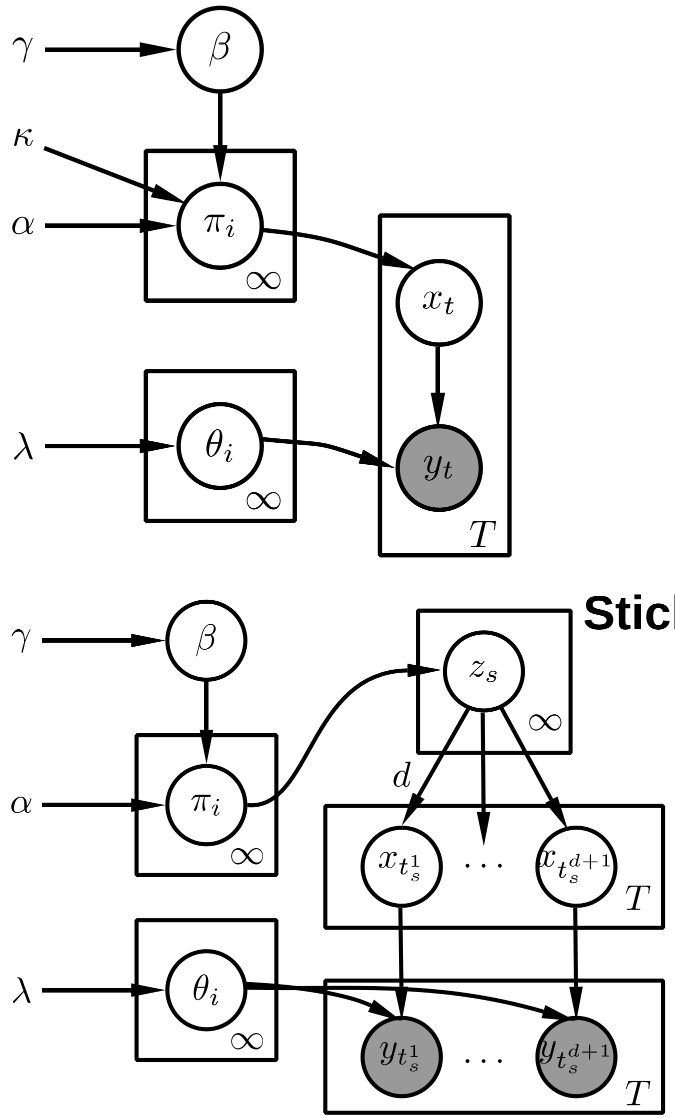
Traffic Primitive:
- Segment/cluster similar traffic scenes automatically using Bayesian nonparameter inference

- 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.

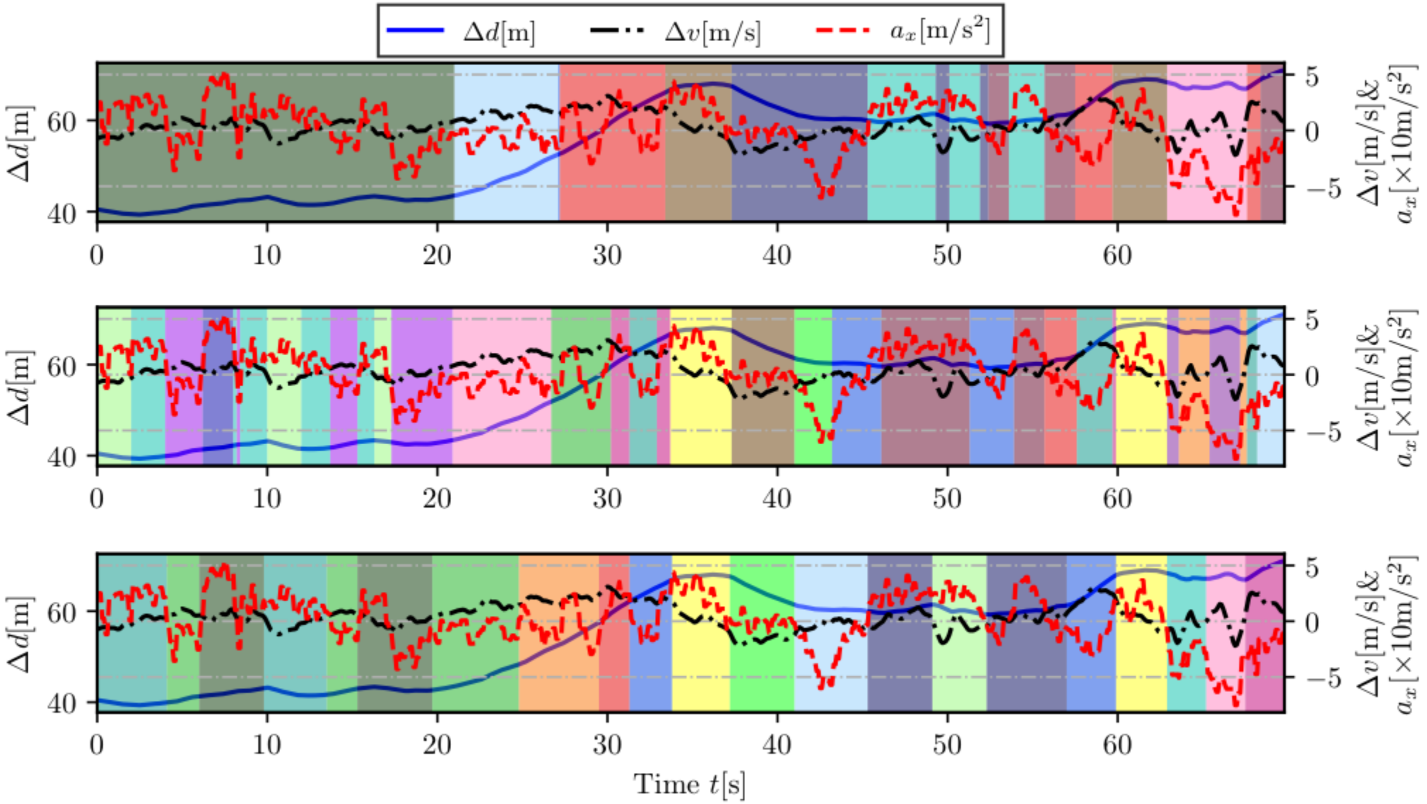
Traffic Primitive: Extract Scenarios Automatically from Raw Data



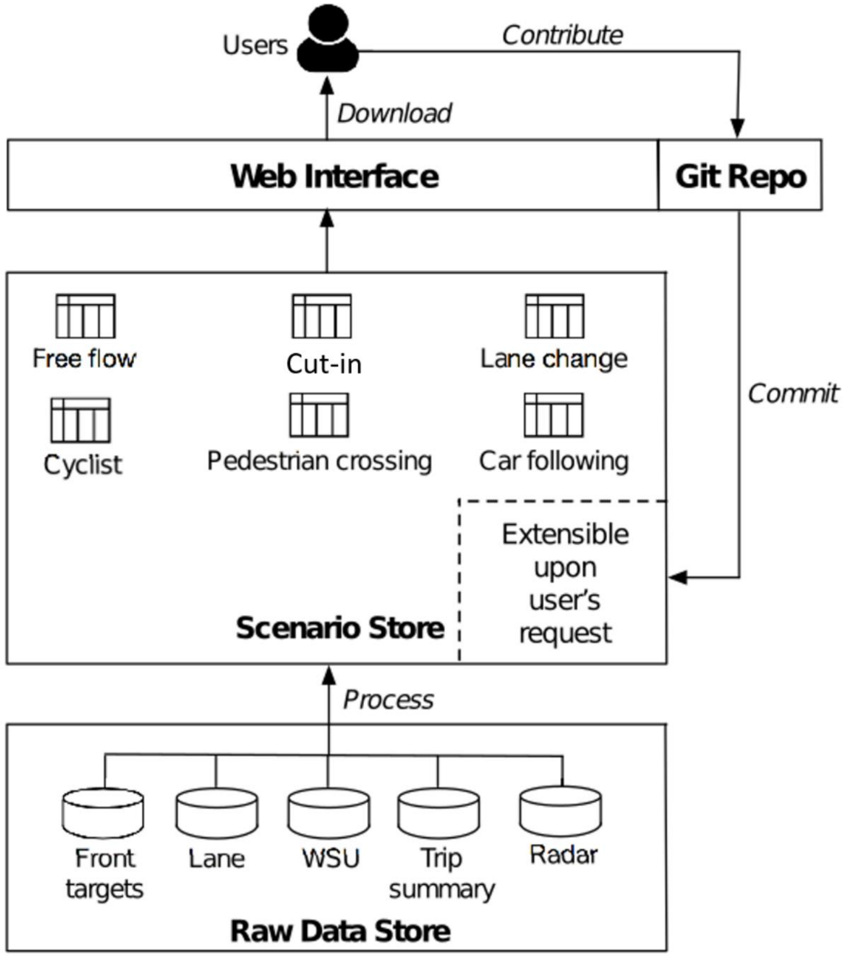
HDP-HMM

Sticky HDP-HMM

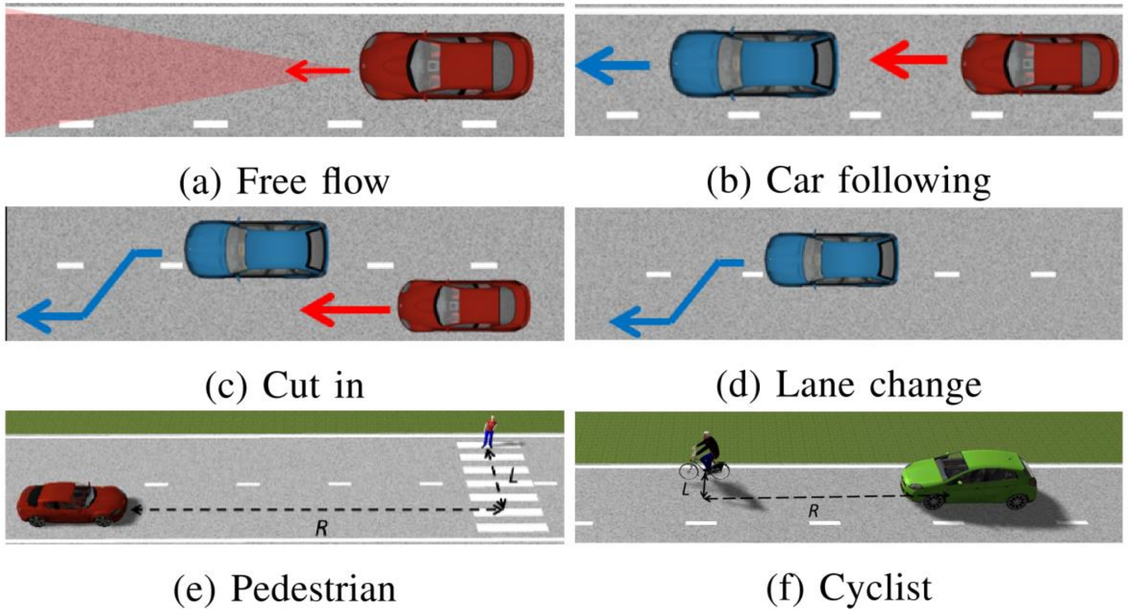
HDP-HSMM

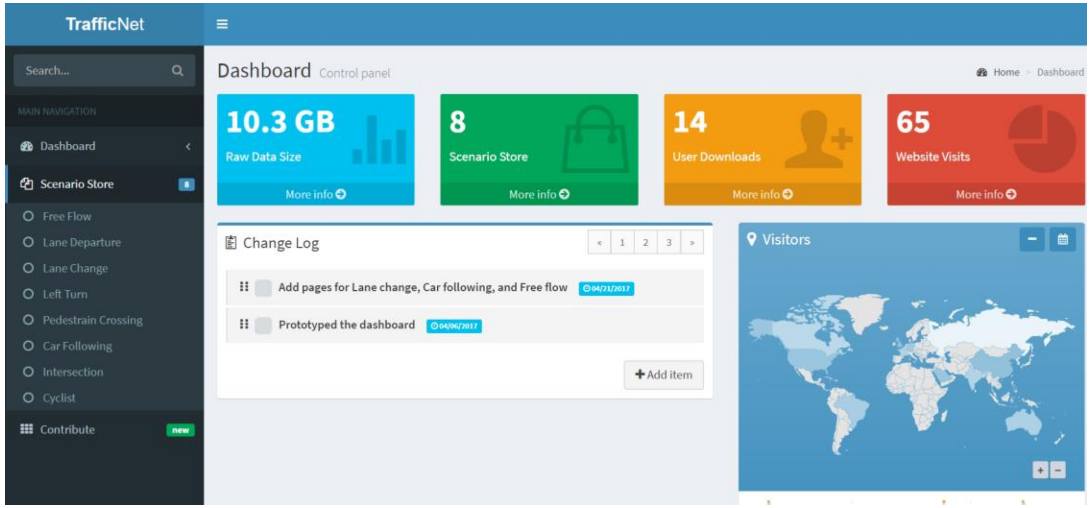


TrafficNet: An Open Naturalistic Driving Scenario Library

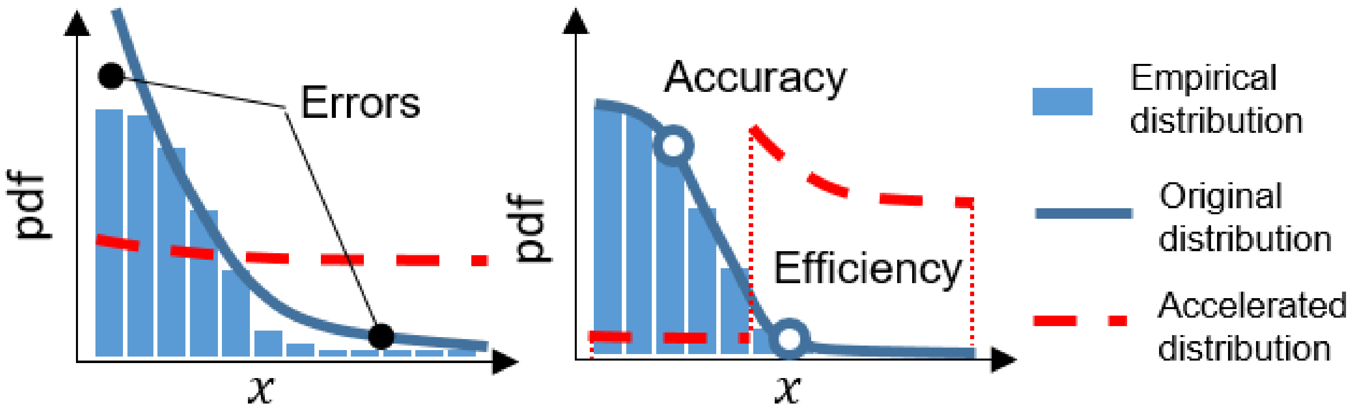


Framework of TrafficNet



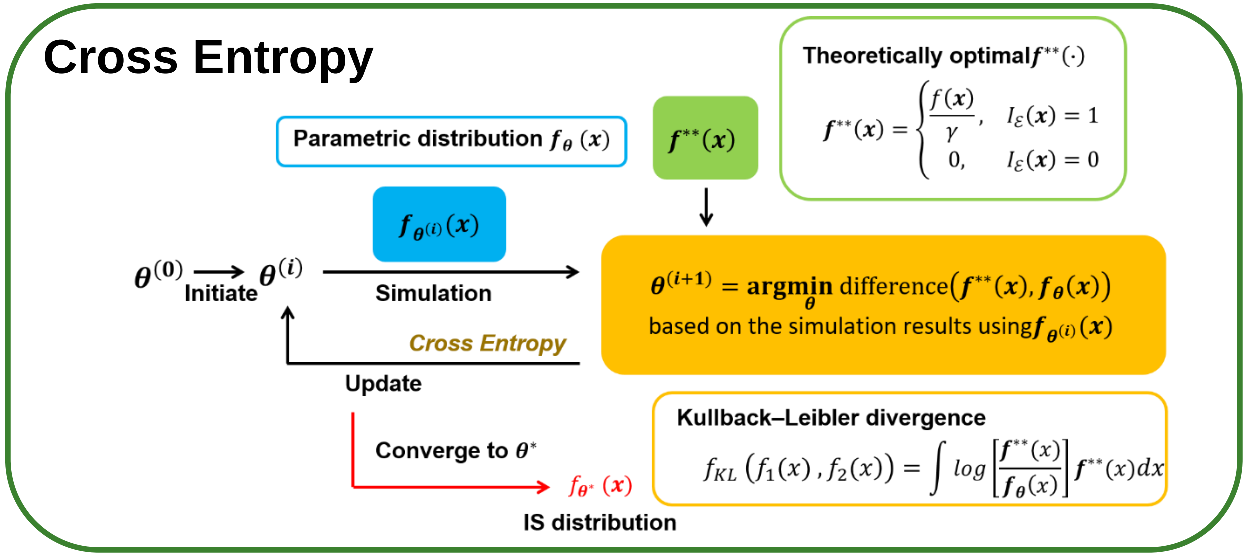


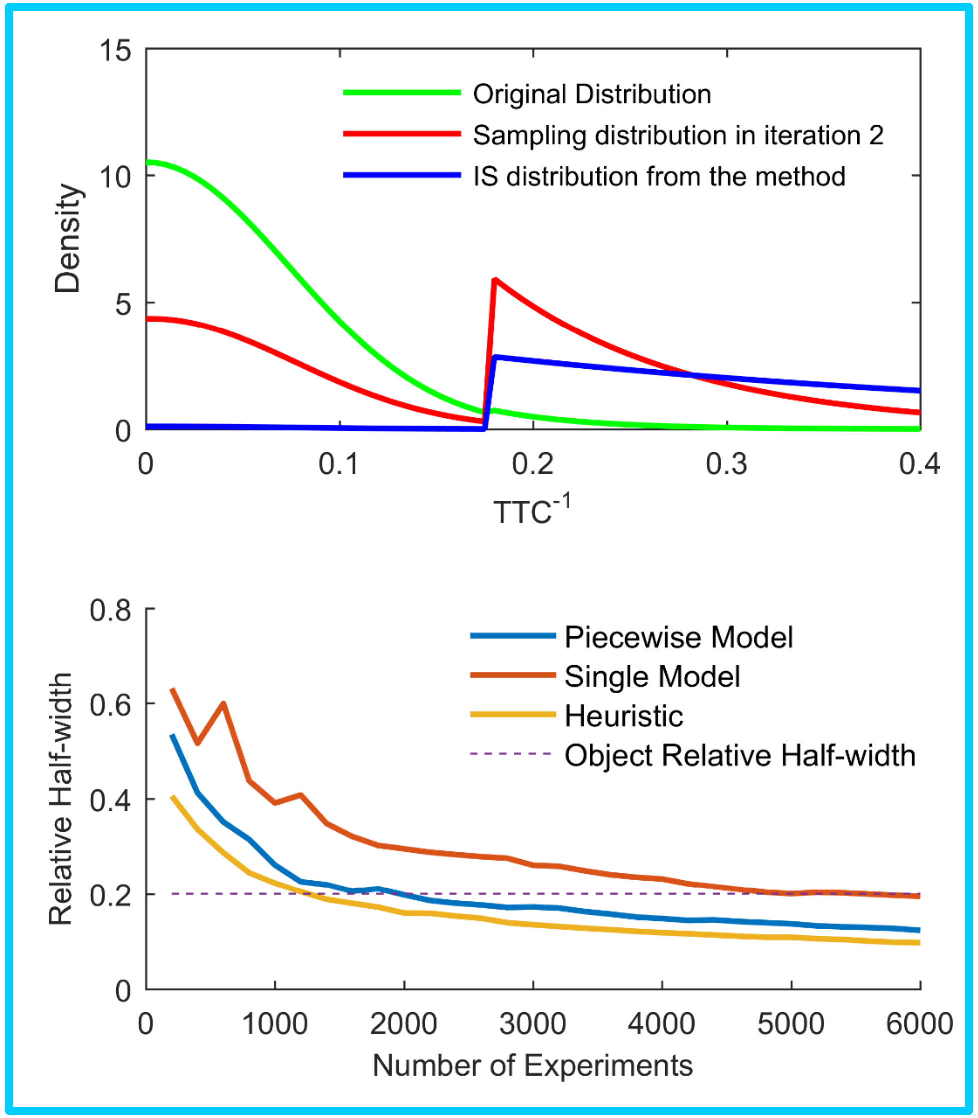
[**Accuracy**] Accelerated Evaluation using Piecewise Mixture Models



Accelerated Evaluation based on

a) a single distribution b) a piecewise mixture distribution

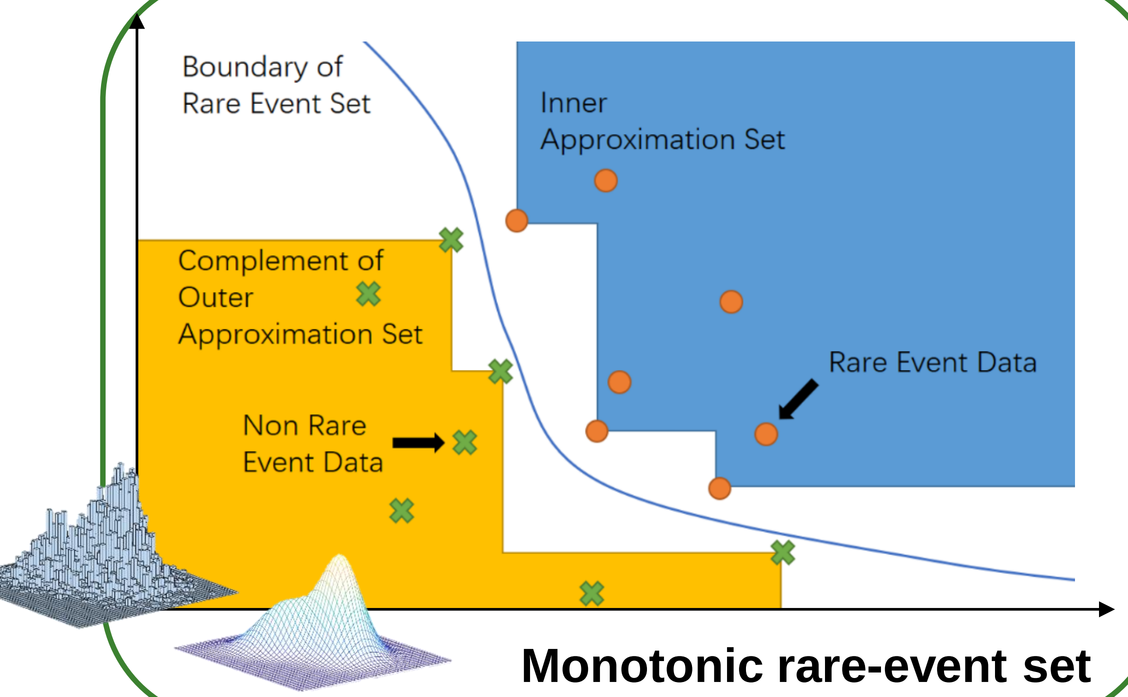




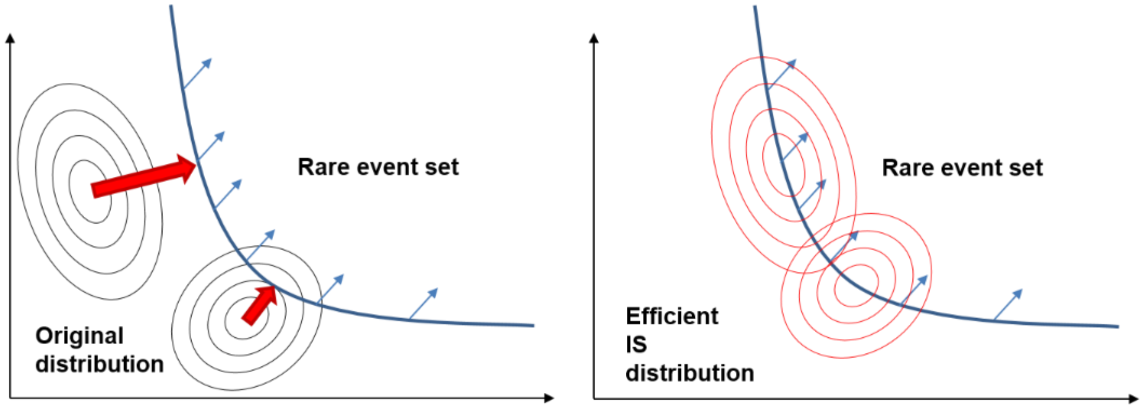
Z. Huang, H. Lam, D. LeBlanc, Ding Zhao, "Accelerated Evaluation of Automated Vehicles using Piecewise Mixture Models," IEEE Transactions on Intelligent Transportation Systems, under review, 2017.

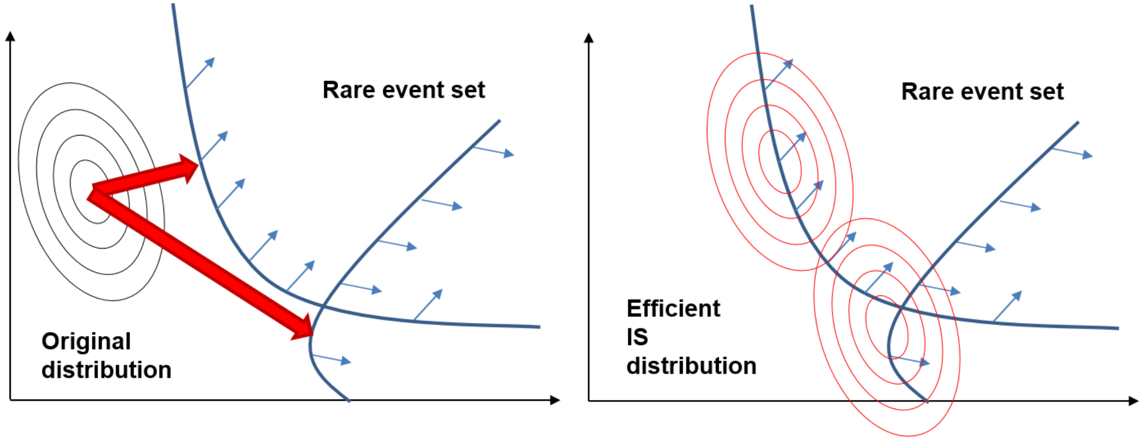
[Versatility] Accelerated Evaluation using Joint Distribution

- 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.

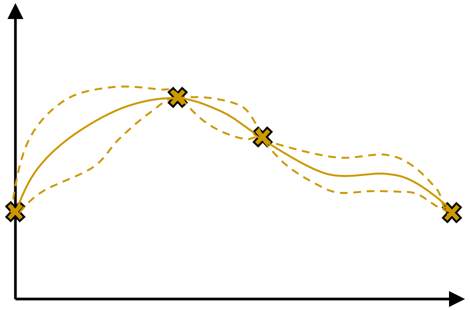
[Efficiency] Kriging-based Evaluation

On track test

Construct

Design

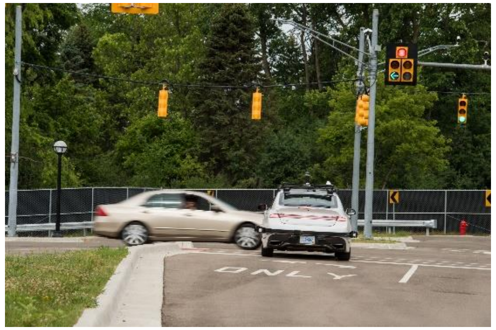
Response surface



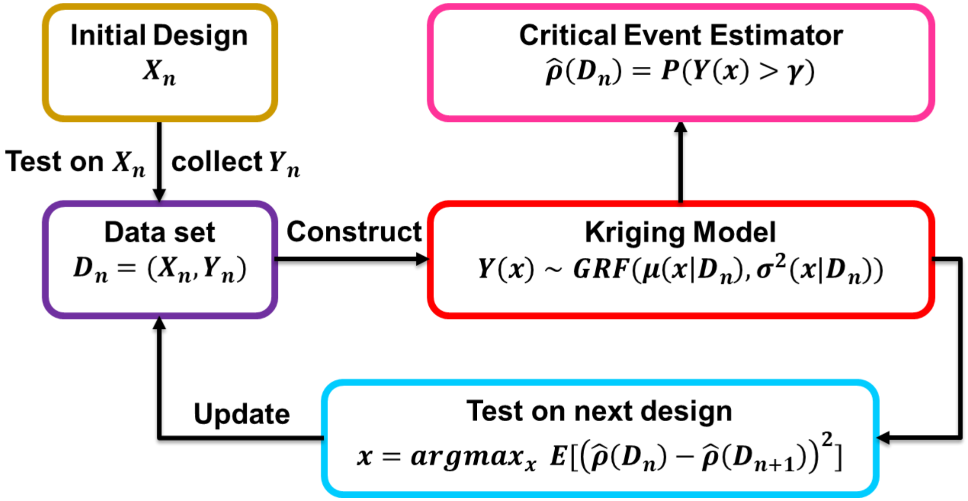
Analysis

Adjust

Risk 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

Thanks for your attention

Papers / Contact