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A Statistically Certified Test Approach for Self-Driving Cars

TOYOTA RESEARCH INSTITUTE

The Building Blocks of Autonomy

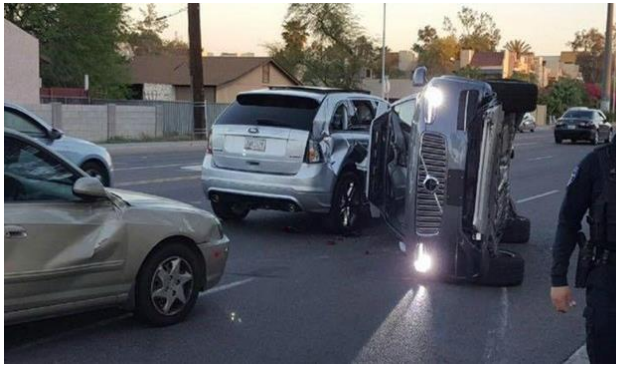
Prepared by VISION SYSTEMS INTELLIGENCE

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

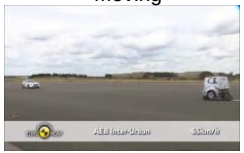
Pro: easy to execute, fast
Con: Pre-announced

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

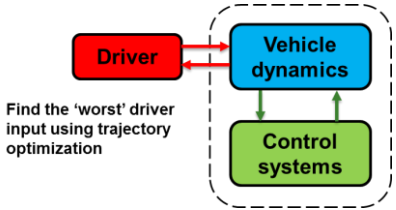
❖ 100 million mi / fatal crash (NHTSA 2013)

Monte Carlo Simulation

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



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

Evaluation/test of self-driving cars

Framework

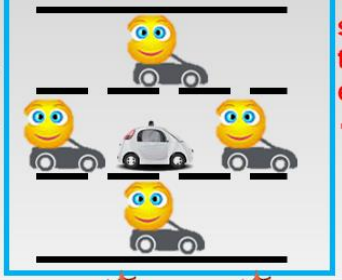
Recent/ongoing research

Statistically Equivalent

Real world data collection

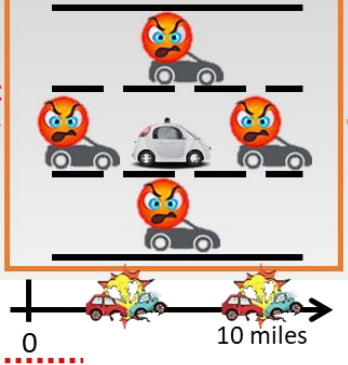
Build stochastic model

Naturalistic driving environment



"Skew" the statistics of the driving environment

Accelerated evaluation tests



Tests

Importance Sampling

"Skew back"

Performance metrics e.g. crash rate

Identify

Critical scenarios & probabilities

Driving Database

Time sequence data

Modeling Driving Environment

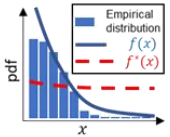
Bayesian Unsupervised Learning

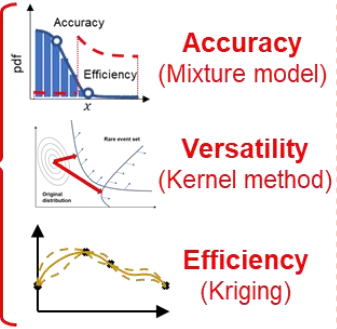
- Traffic primitive
- Variation
- Likelihood

Stochastic variation model

Evaluation Theories

Accelerated Evaluation





Accuracy (Mixture model)

Versatility (Kernel method)

Efficiency (Kriging)

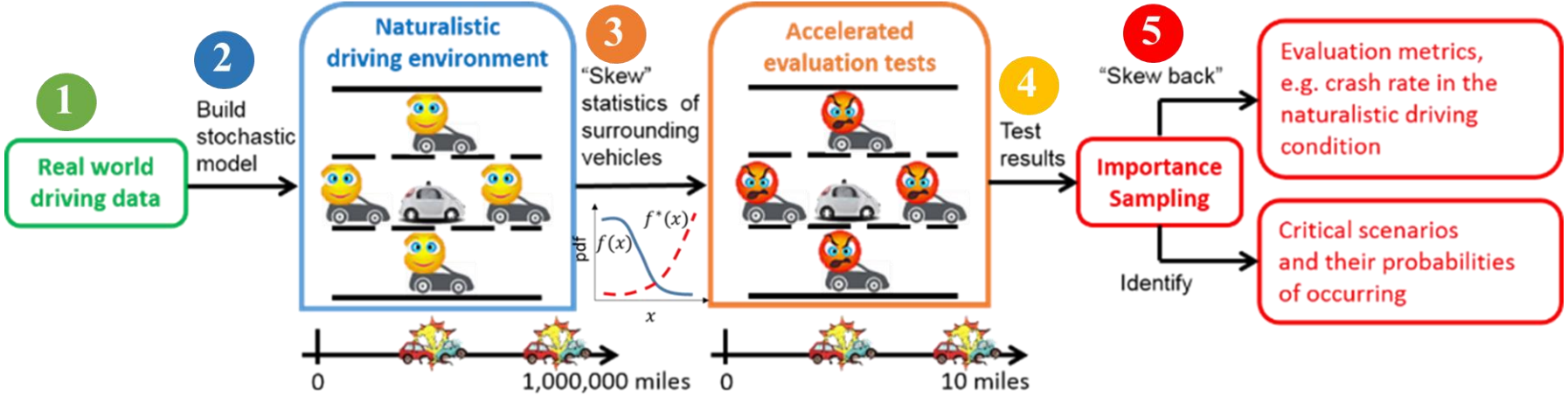
Testing Platforms

Virtual

Reality

Mixed Reality

Accelerated Evaluation



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

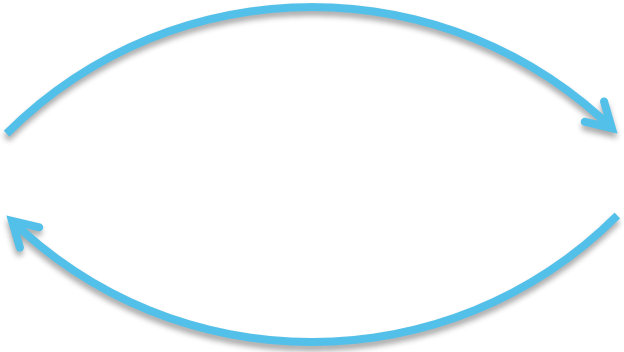
Five Steps of the Accelerated Evaluation

① Collect naturalistic driving data

② Model behaviors of “other vehicles” as disturbance

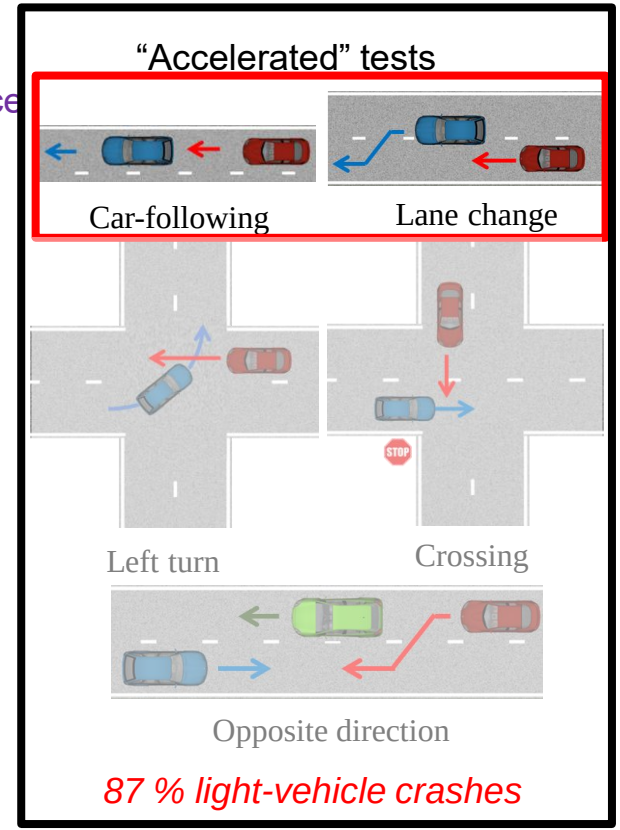
③ Skew the disturbance statistics to reduce the boring part of daily driving

Naturalistic driving

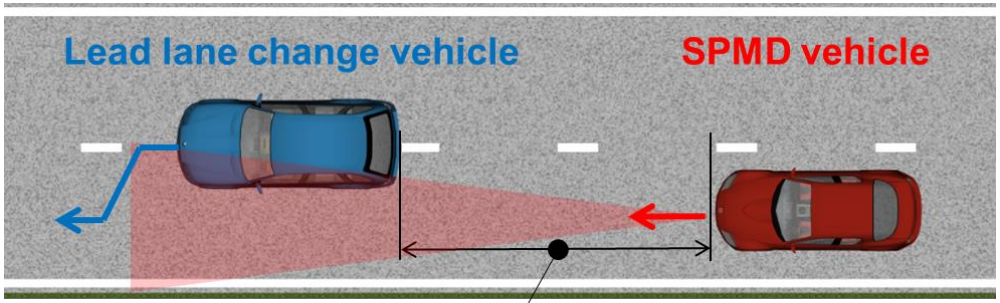


⑤ “Skew back” to understand real-world safety benefits

④ Simulate (at accelerated pace)



Case 1: Lane Change Scenarios



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

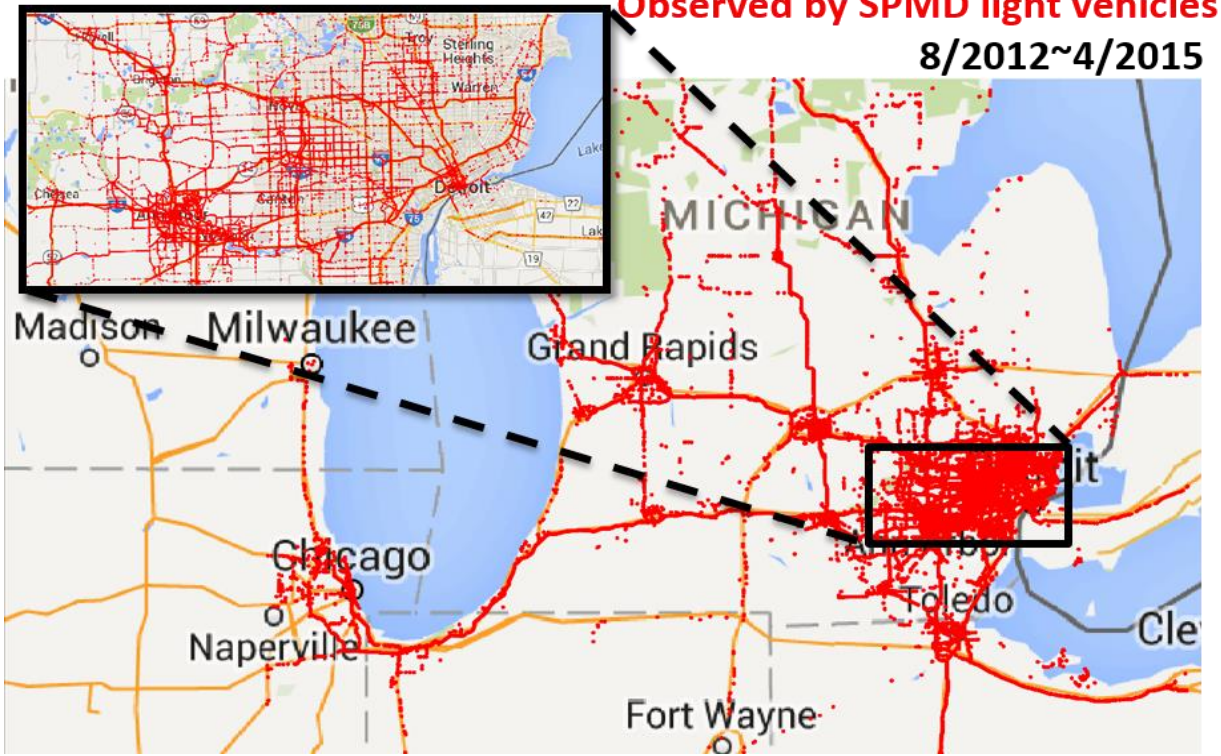
Range
$R_L(t) = \boldsymbol{D_L(t) - D(t)}$
Range rate
$\dot{\boldsymbol{R}}_{\boldsymbol{L}}(\boldsymbol{t}) = \frac{\boldsymbol{d}}{\boldsymbol{dt}}\boldsymbol{R_L(t)}$

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

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



Criteria:

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

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

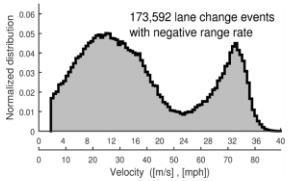
5 years
94 drivers
1.3 million miles
Out of 1200~2800 drivers

Importance Sampling Techniques

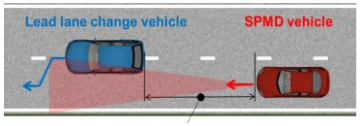
Motivation

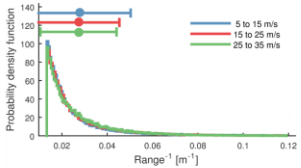
Gap acceptance → $[v_L, R_L, TTC_L]$

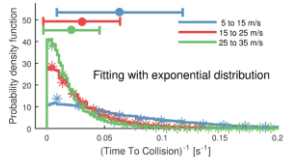
Execution



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







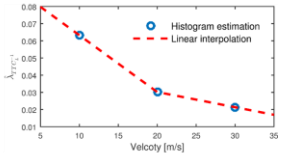
$f_{v_L} \rightarrow v_L \dashrightarrow f_{R_L^{-1}} \rightarrow R_L$

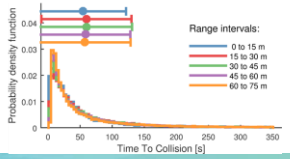
$f_{TTC_L^{-1}} \rightarrow TTC_L$

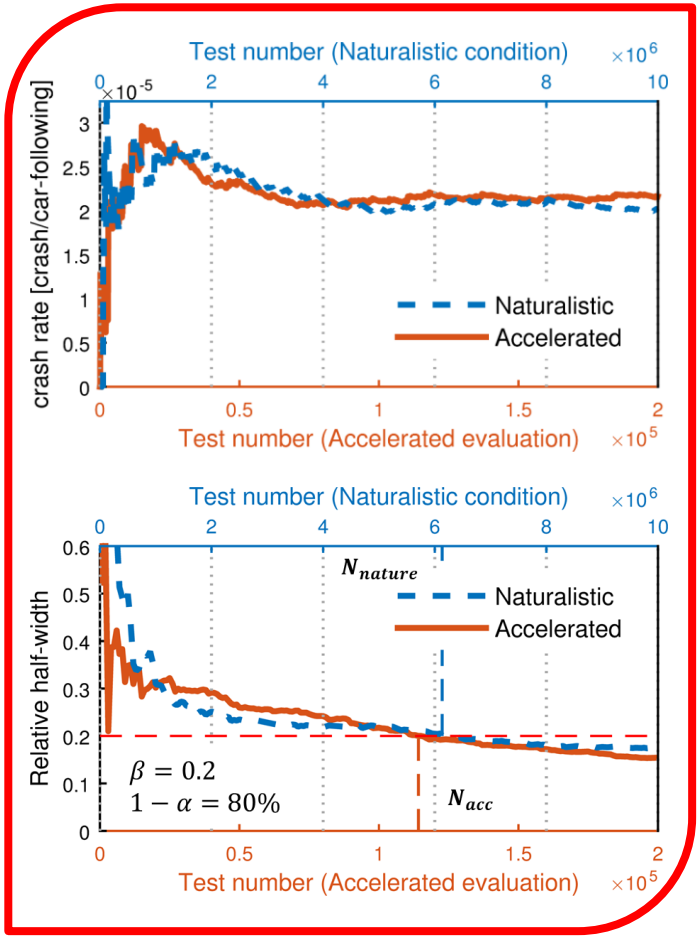
③ Skew the statistics

Importance Sampling

⑤ "Skew back"

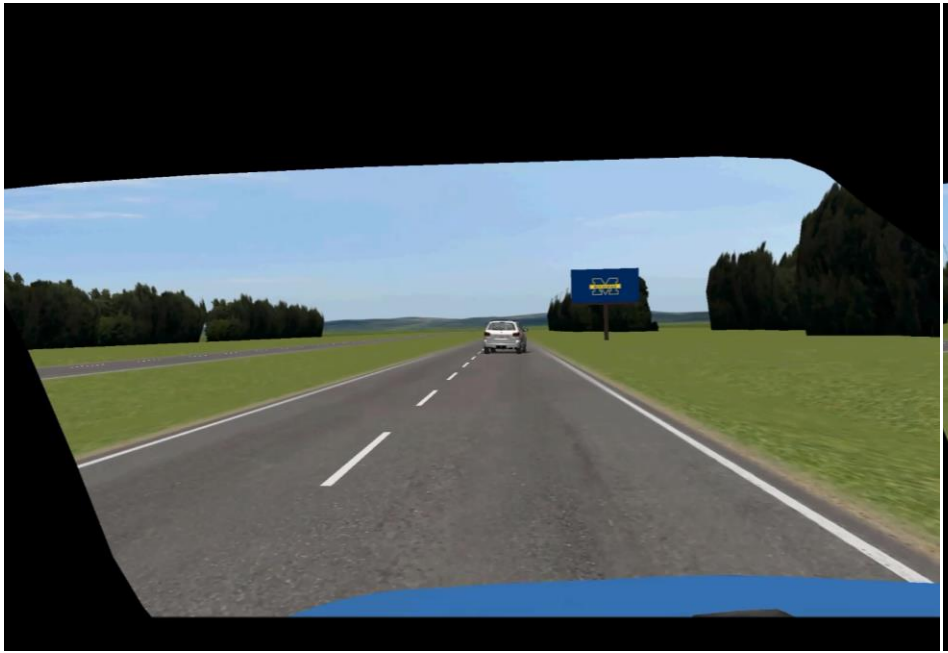






Naturalistic Driving vs Accelerated Tests

Naturalistic driving conditions



Accelerated tests

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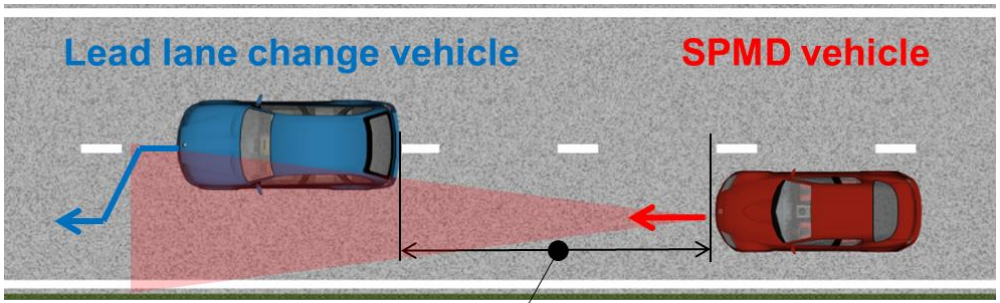

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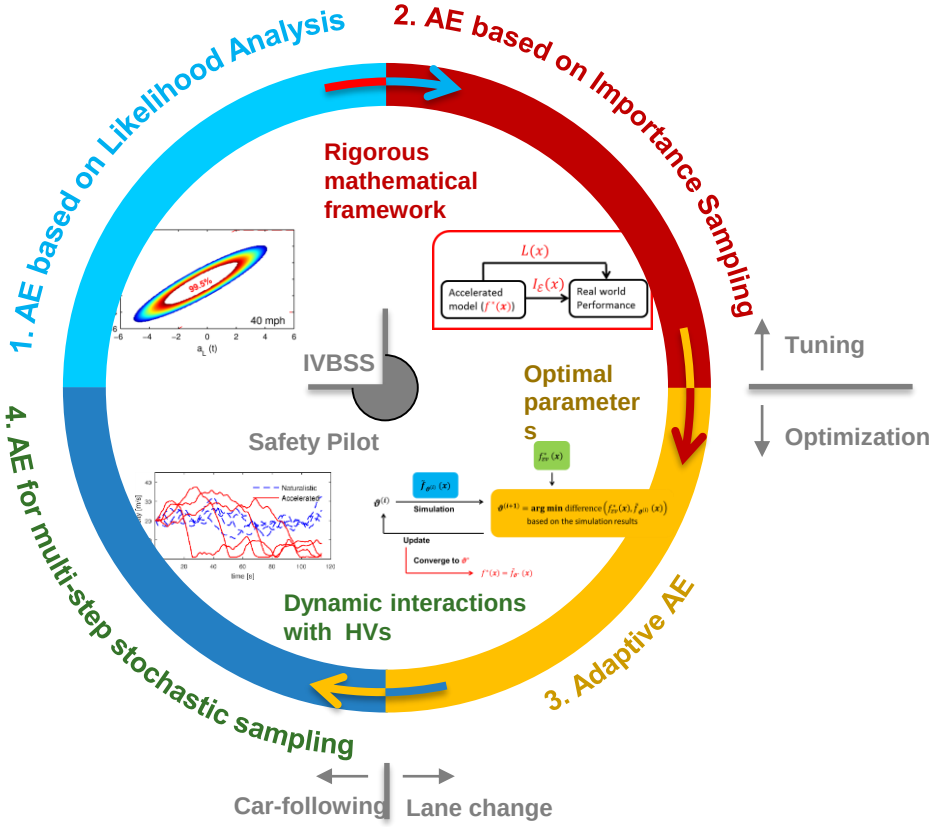
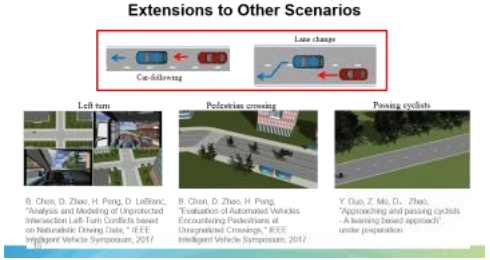
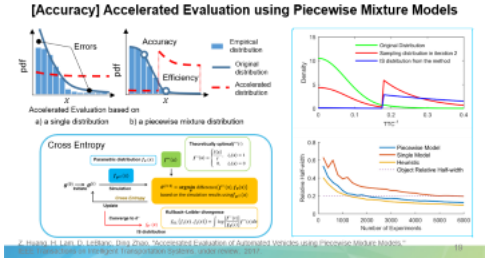
Extensions to the Accelerated Evaluation



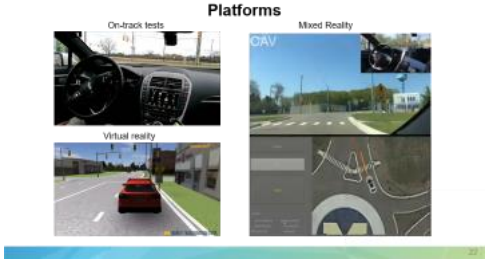
Variations



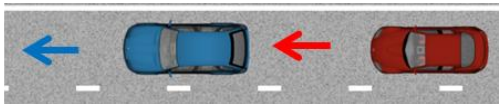
Theories



Platforms

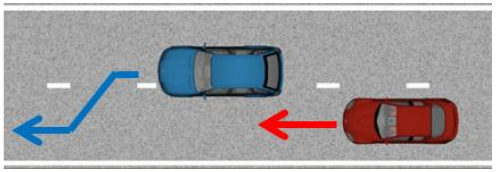


Extensions to Other Scenarios



Car-following

Lane change



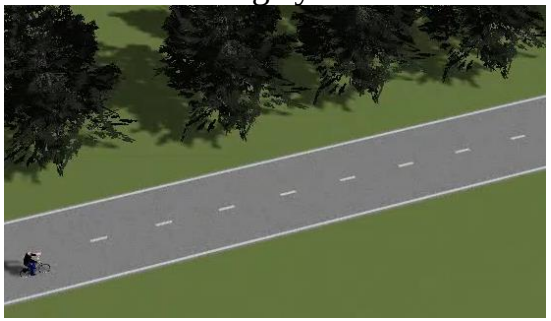
Left turn

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.

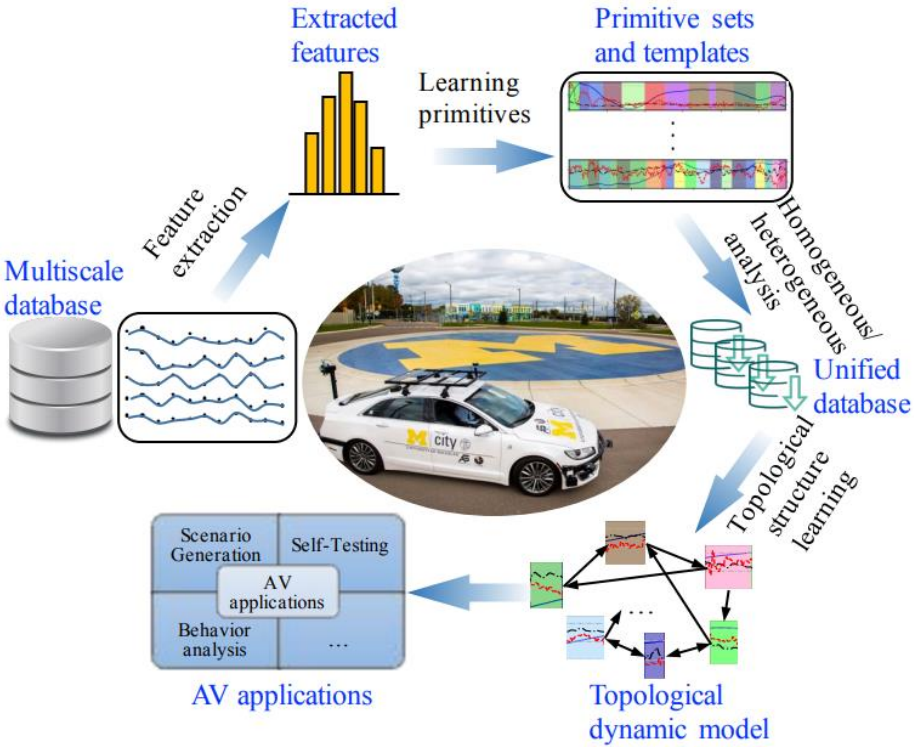
Extract Scenarios Automatically from Raw Data

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

- Subjectively-selected scenarios/variations

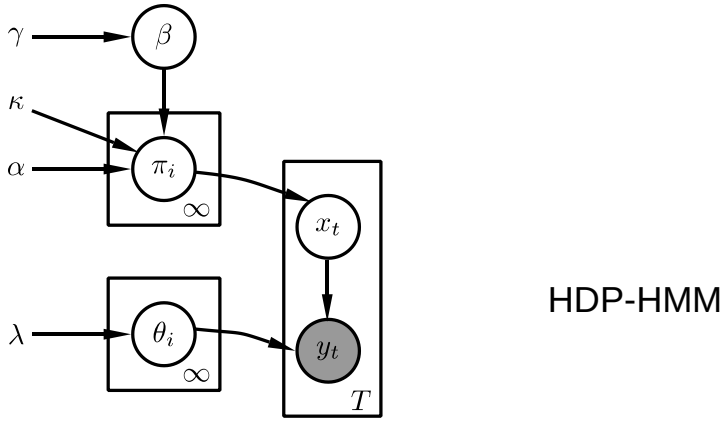
Traffic Primitive:
- Segment/cluster similar traffic scenes automatically using Bayesian nonparameter inference

- Objectively-selected scenarios/variations

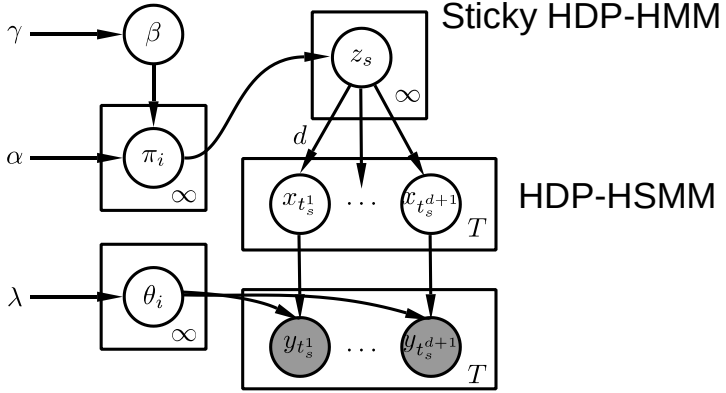


W. Wang, D. Zhao, "Extracting Traffic Primitives Directly from Naturalistically Logged Data for Self-Driving Applications *IEEE Robotics and Automation Letters (under review)*, arXiv 1709.03553, 2017.

Traffic Primitive: Extract Scenarios Automatically from Raw Data

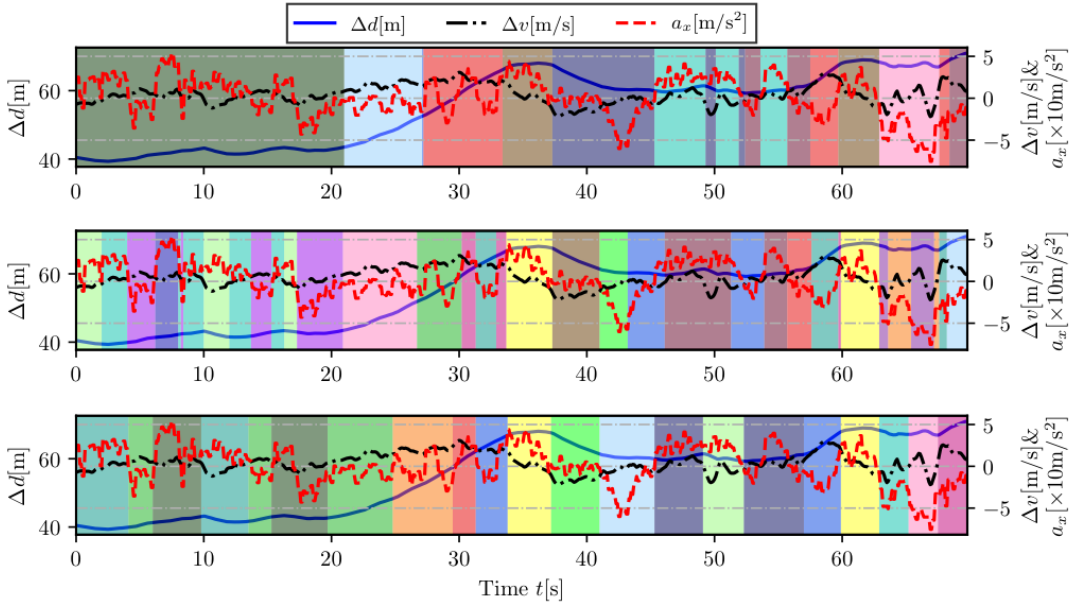


HDP-HMM



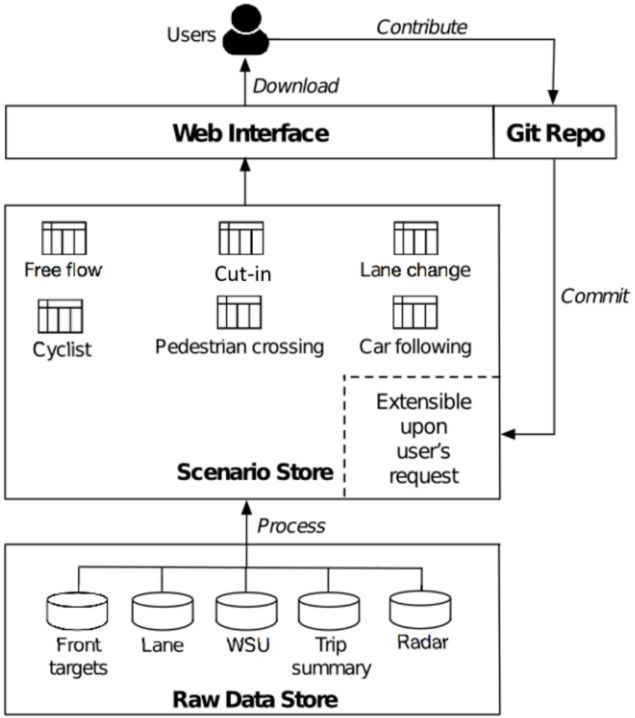
Sticky HDP-HMM

HDP-HSMM

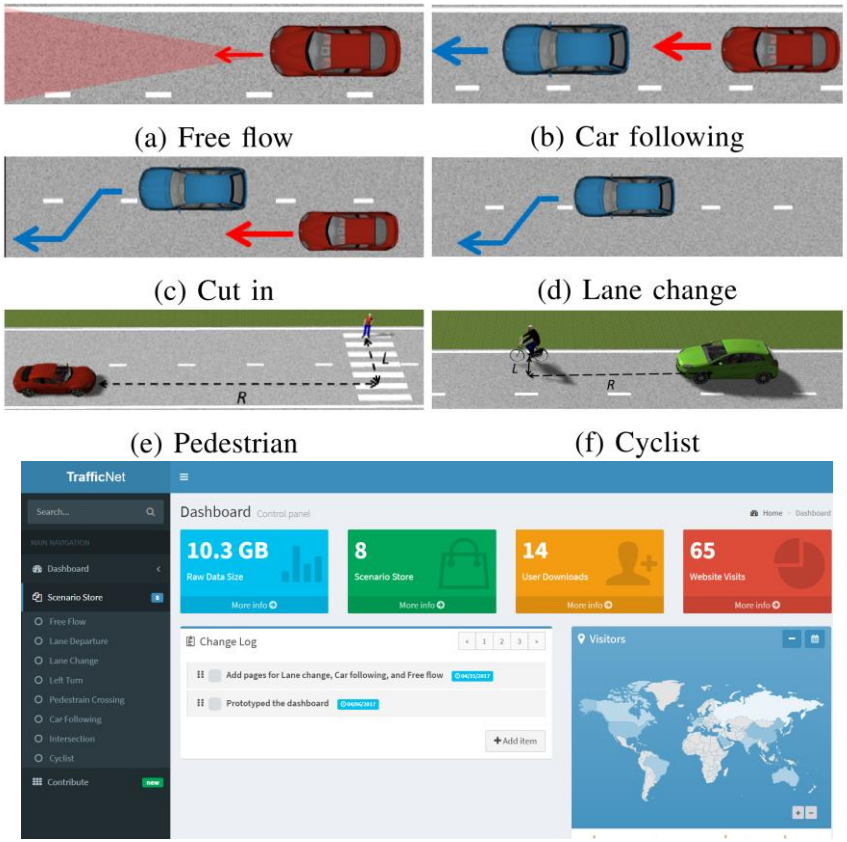


W. Wang, J. Xi, D. Zhao, " Driving Style Analysis Using Primitive Driving Patterns With Bayesian Nonparametric Approaches," under review.

TrafficNet: An Open Naturalistic Driving Scenario Library

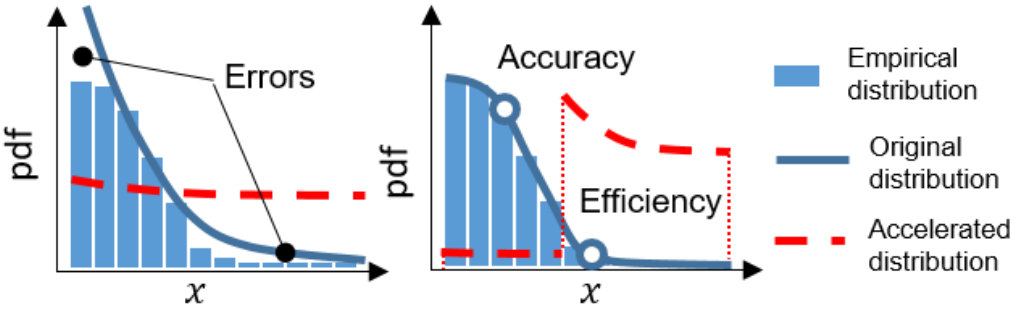


Framework of TrafficNet



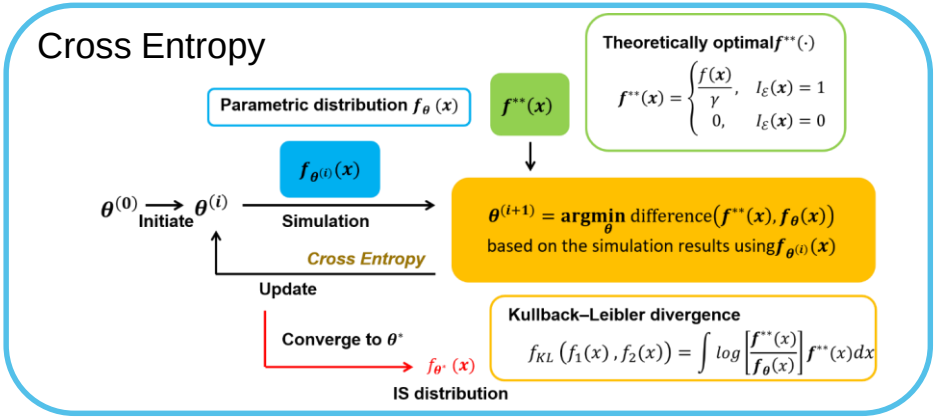
D. Zhao, Y. Guo, Y. J. Jia, "TrafficNet: An Open Naturalistic Driving Scenario Library," Proceedings of the IEEE 20th International Intelligent Transportation Systems Conference (ITSC), Yokohama, Japan, October 16-19, 2017.

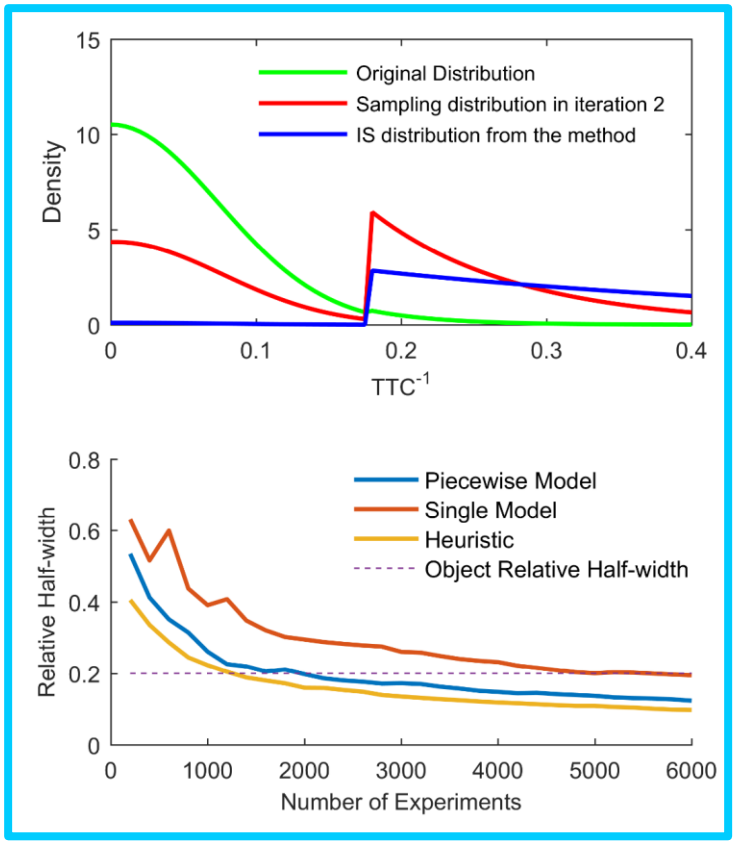
[Accuracy] Accelerated Evaluation using Piecewise Mixture Models



Accelerated Evaluation based on

a) a single distribution b) a piecewise mixture distribution

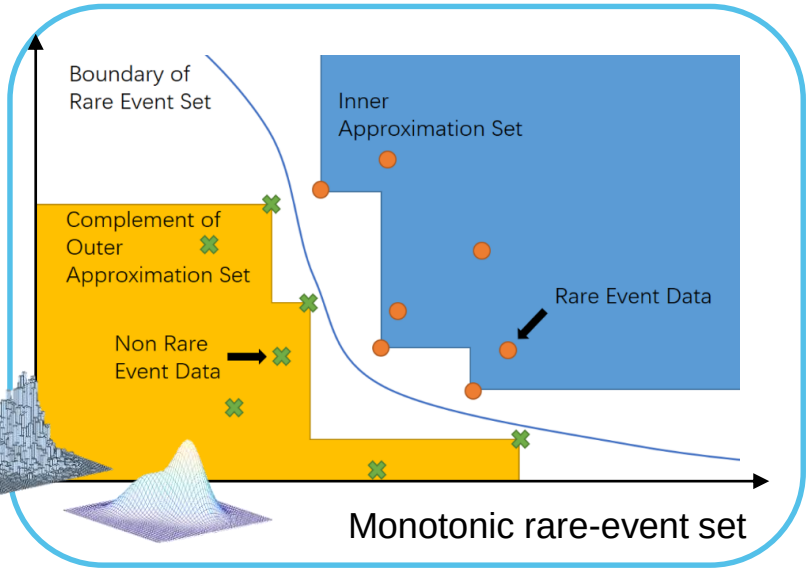


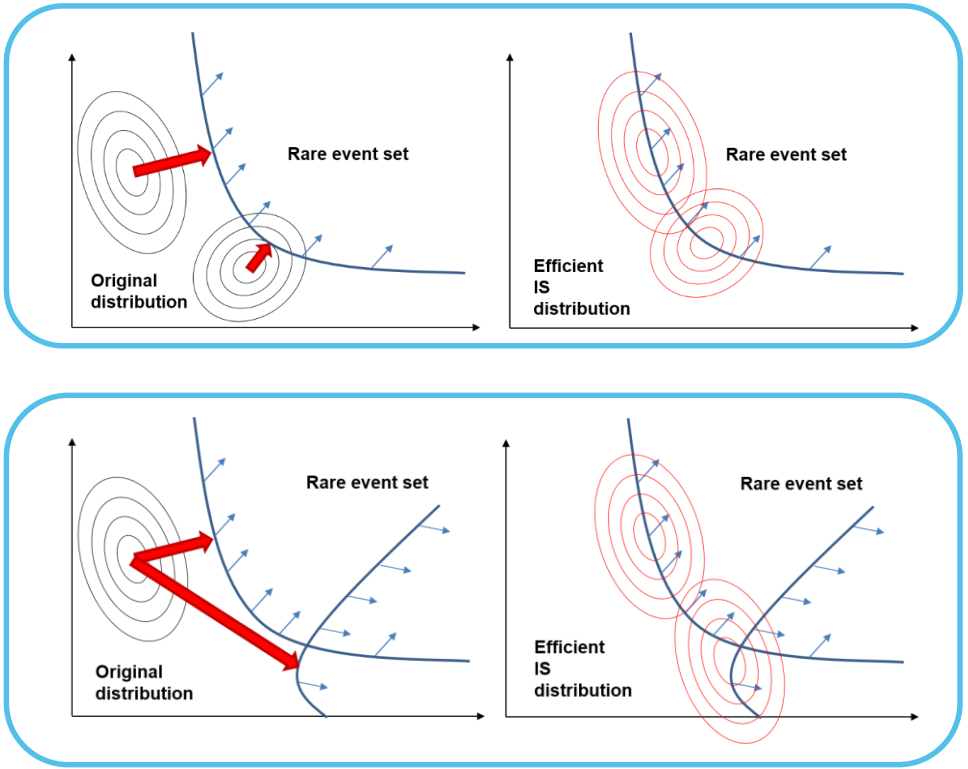


Z. Huang, H. Lam, D. LeBlanc, Ding Zhao, "Accelerated Evaluation of Automated Vehicles using Piecewise Mixture Models," IEEE Transactions on Intelligent Transportation Systems, under review, 2017.

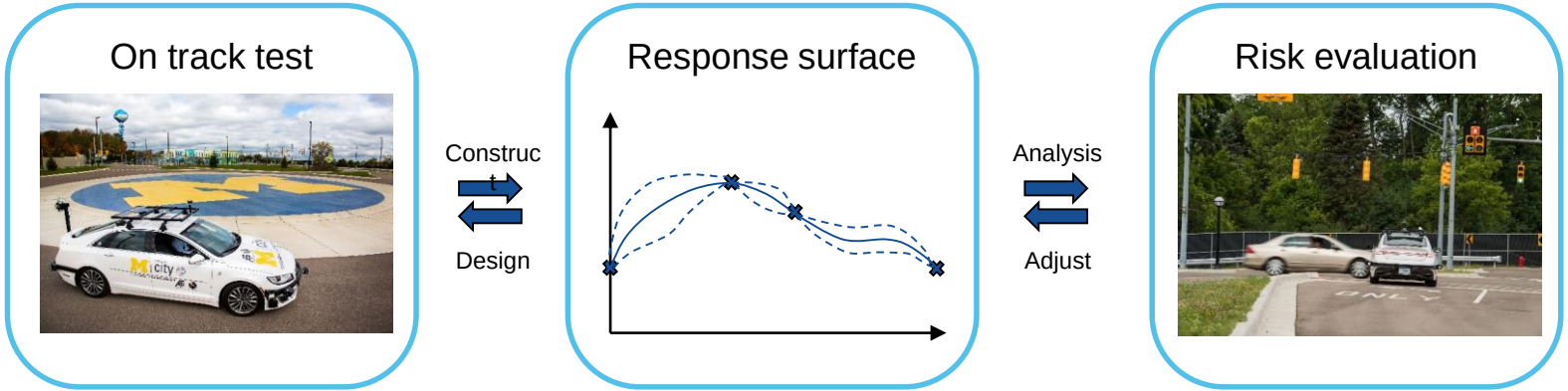
[Versatility] Accelerated Evaluation using Joint Distribution

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

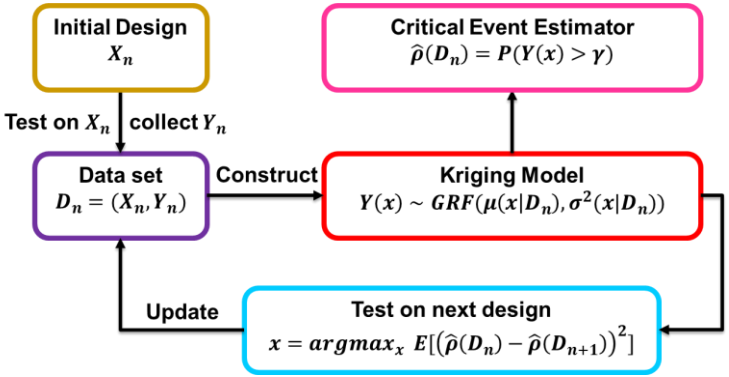




[Efficiency] Kriging-based Evaluation



- 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

Mixed Reality

Development of a "Primary Other Test Vehicle" for the Testing and Evaluation of High-Level Automated Vehicles

Ding Zhao, Huei Peng
Department of Mechanical Engineering
University of Michigan

Thanks for your attention

Papers / Contact