
Statistically Certified Test Approaches for Intelligent Physical System

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The Building Blocks of Autonomy

Prepared by  VISION SYSTEMS INTELLIGENCE

AUTONOMOUS SOLUTIONS



Level of Integration ↑

PROCESSING



SENSORS



CONNECTIVITY



MAPPING



ALGORITHMS



SECURITY/SAFETY

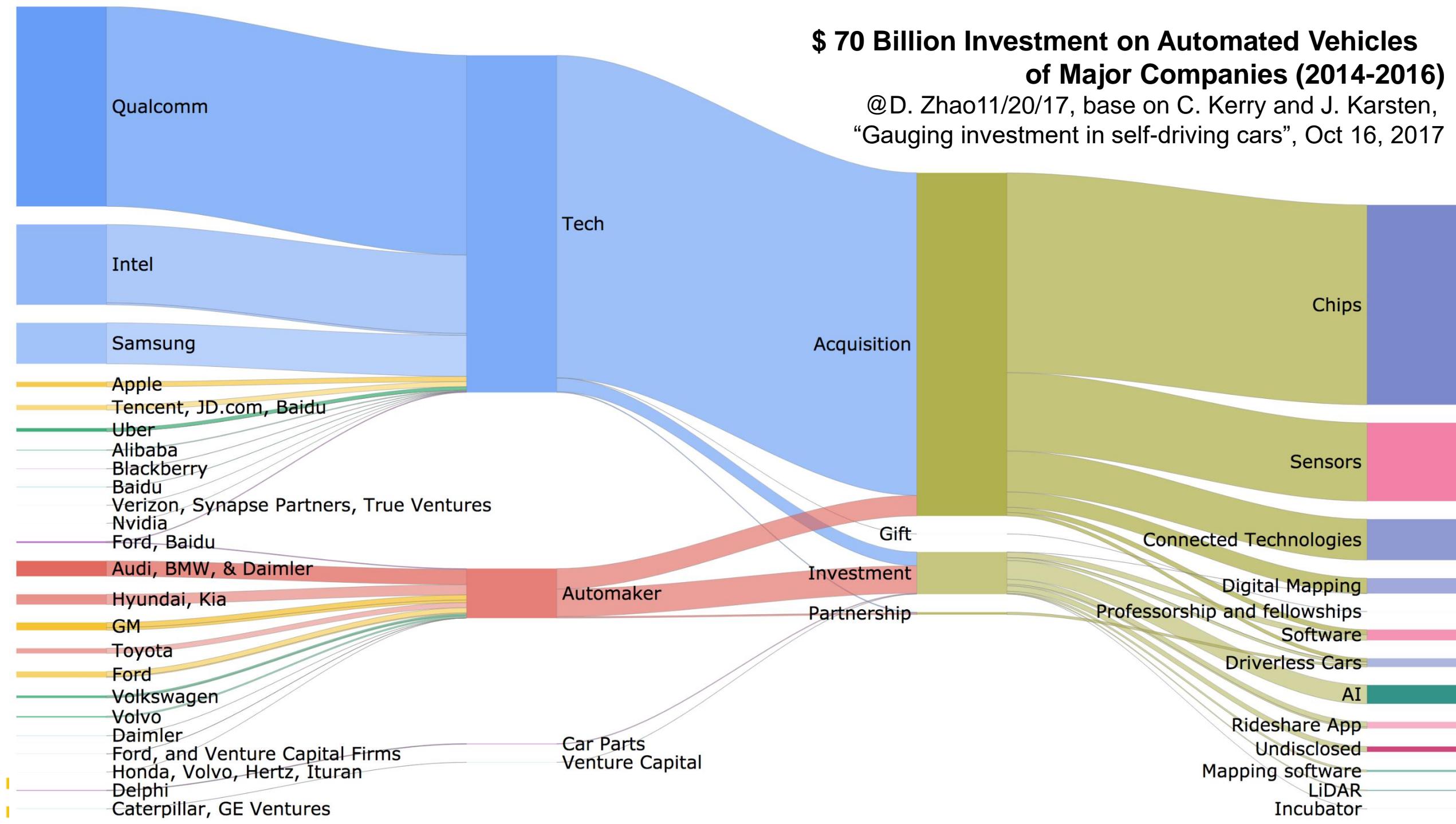


DEVELOPMENT TOOLS



\$ 70 Billion Investment on Automated Vehicles of Major Companies (2014-2016)

@D. Zhao 11/20/17, base on C. Kerry and J. Karsten,
“Gauging investment in self-driving cars”, Oct 16, 2017



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

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

Static



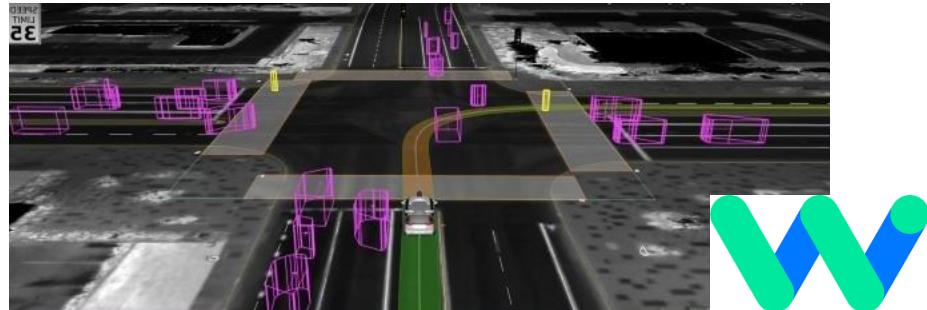
Moving



Braking



Monte Carlo Simulation



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

Naturalistic Field Operational Tests

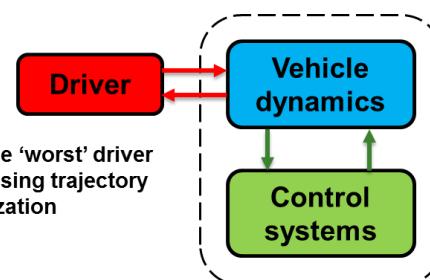


Pro:
The real-world!

Con:
Slow, expensive
Low exposure to safety critical cases

❖ 100 million mi / fatal crash (NHTSA 2013)

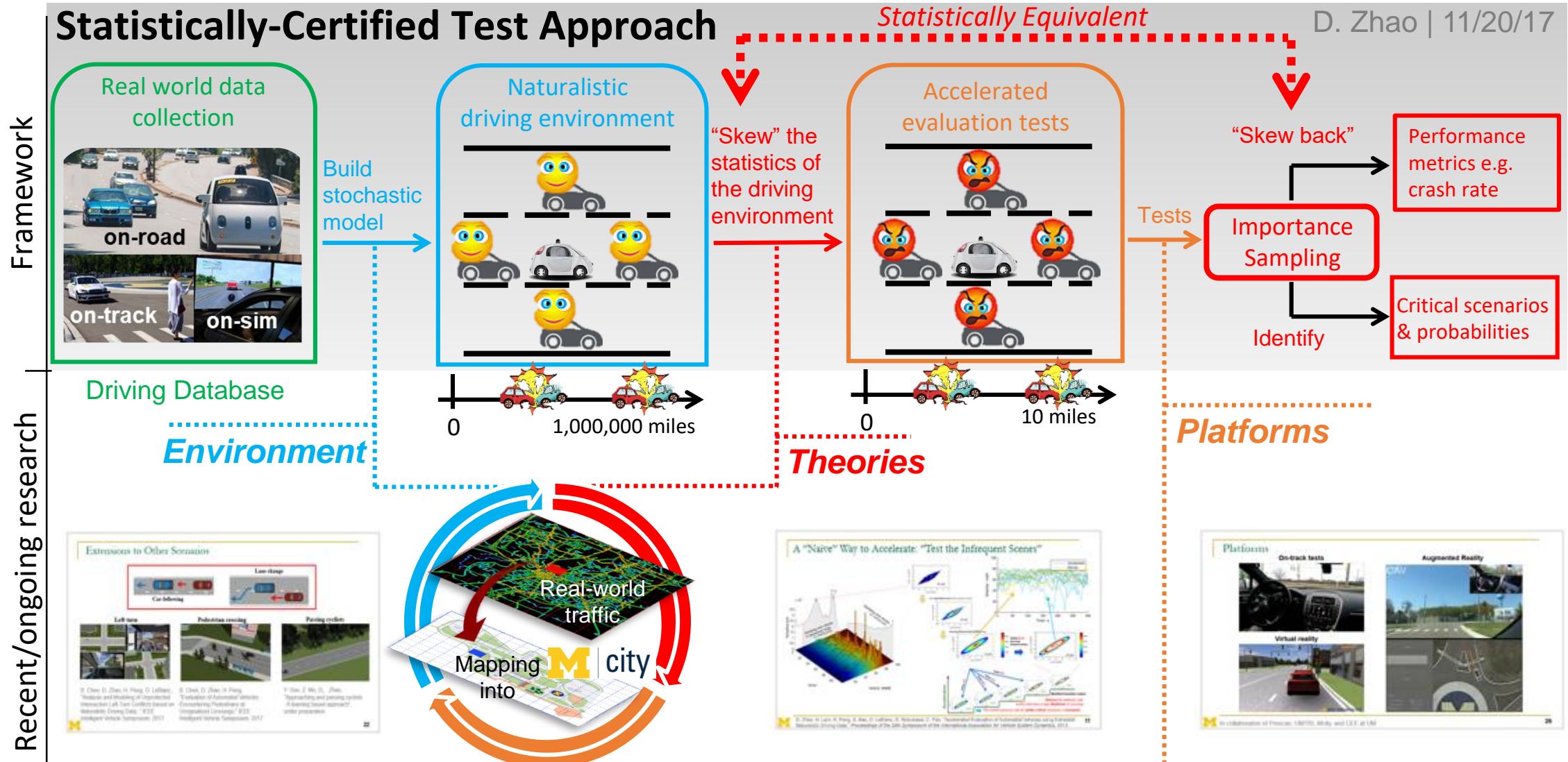
Worst-case Scenario Evaluation



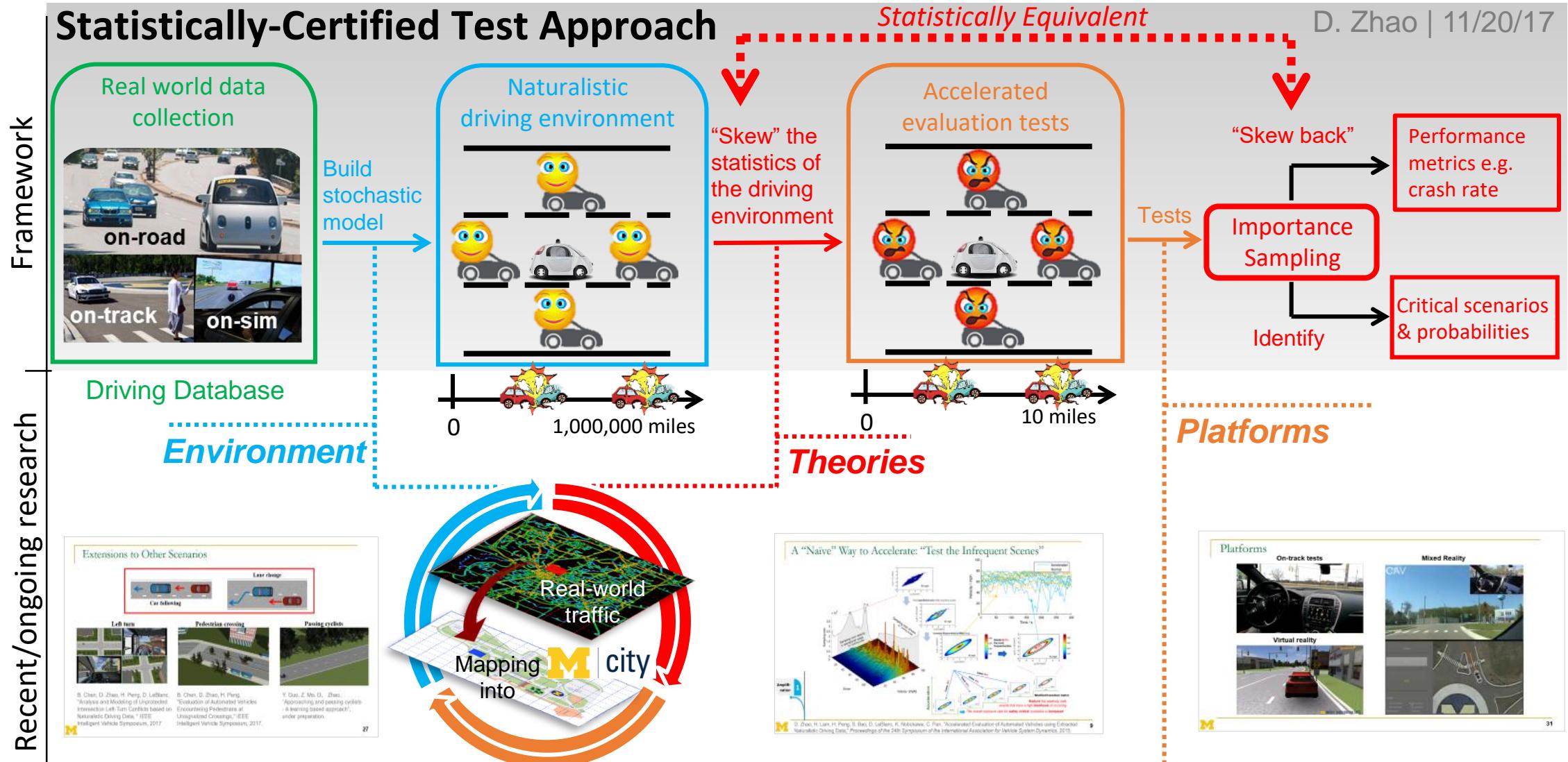
Roll-over analysis

Pro: Worst cases
Con: No probability information

Statistically-Certified Automated Vehicles Evaluation Approach

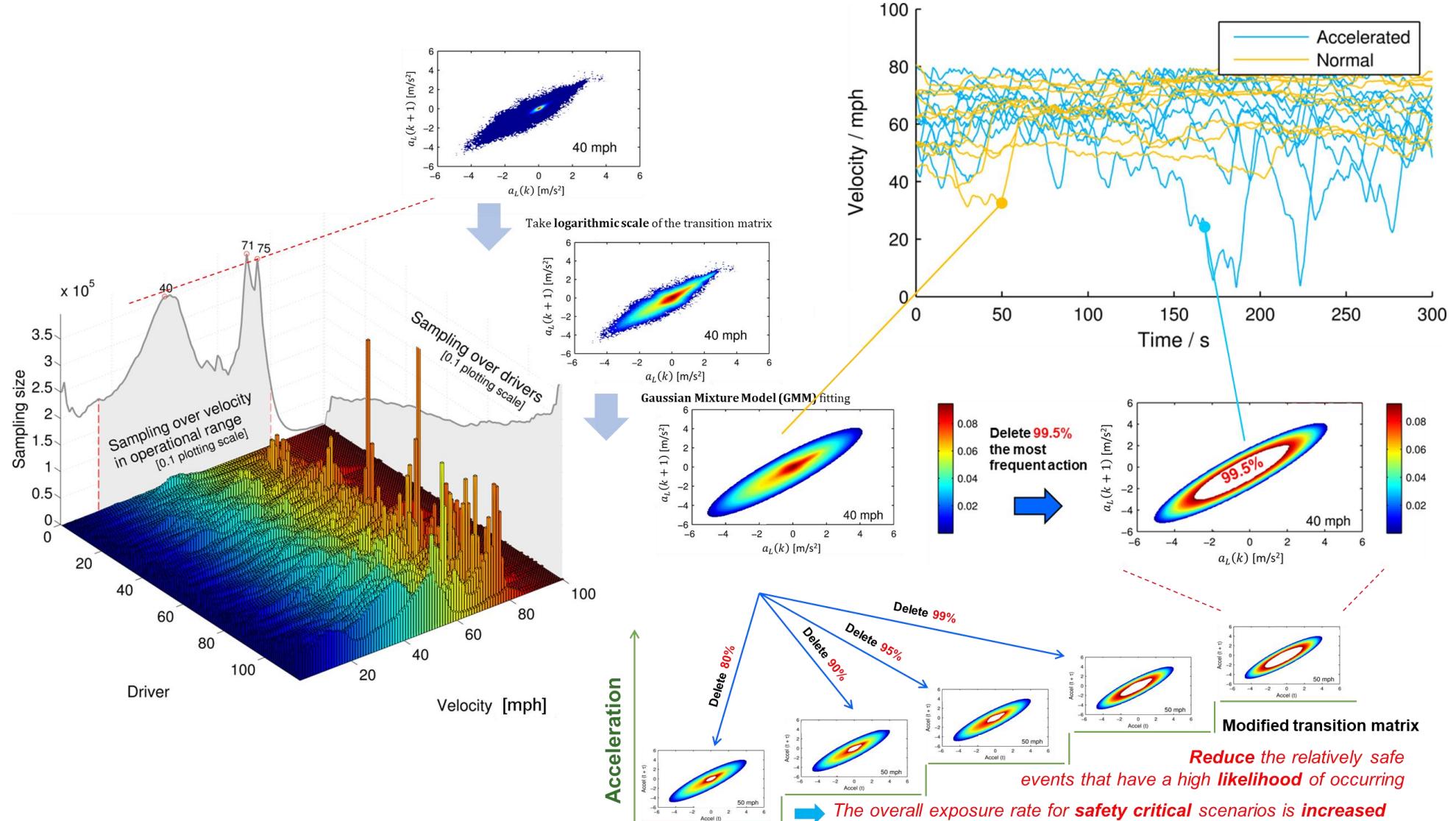


Statistically-Certified Automated Vehicles Evaluation Approach

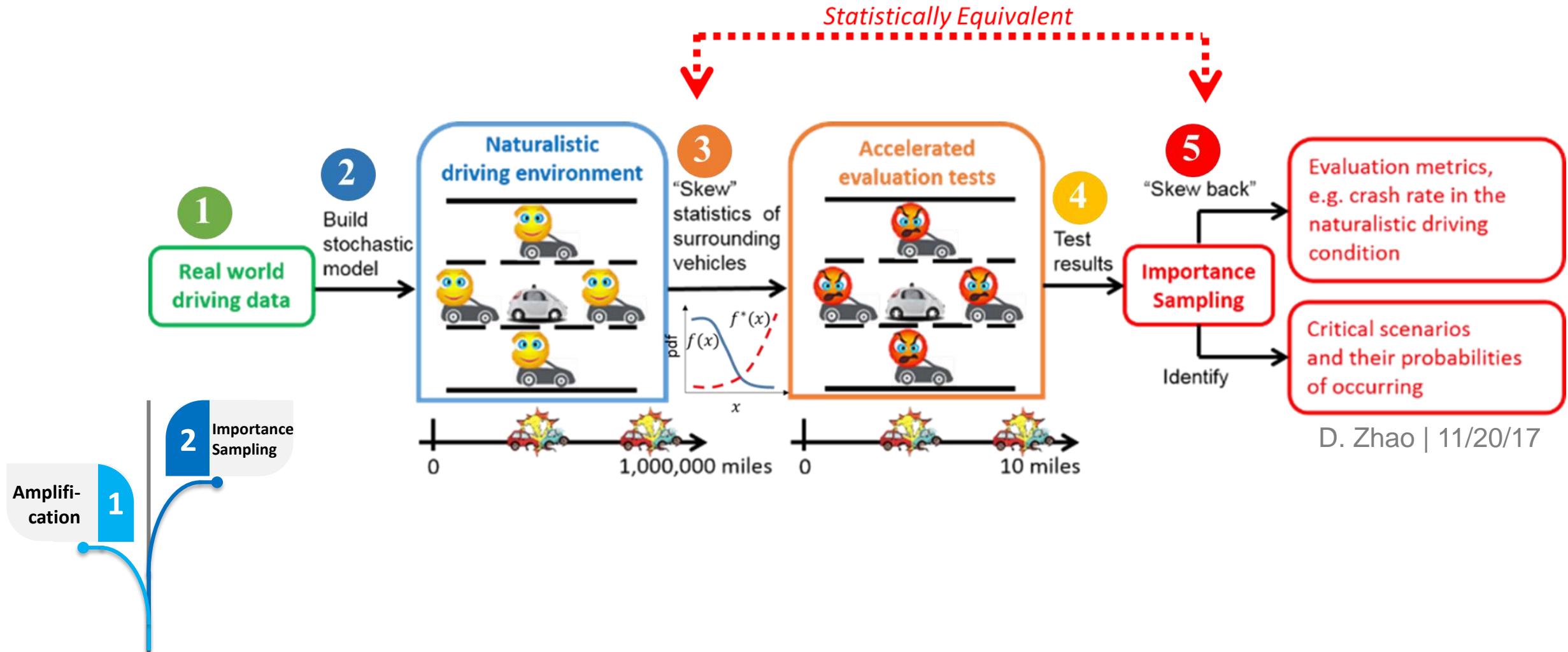


A “Naïve” Way to Accelerate: “Test the Infrequent Scenes”

Amplification
1



[Rigor] Accelerated Evaluation using Importance Sampling



Rare Event Simulation – Importance Sampling

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

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

- The importance sampling estimator is derived from:

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

$L(x) = \frac{f(x)}{\tilde{f}(x)}$

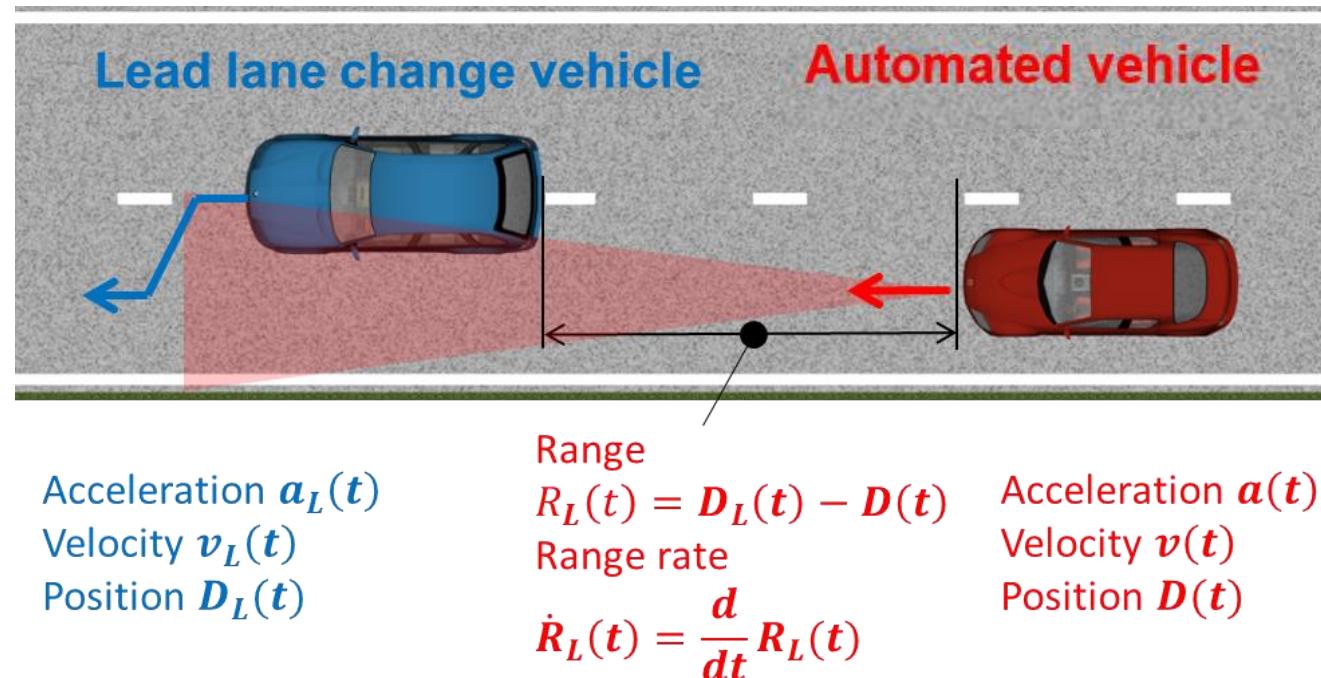
- We generate X from \tilde{f} , then

$$Z = I_{\mathcal{E}}(X)L(x)$$

→ **Unbiased Estimator**

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

Case 1: Cut-in 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

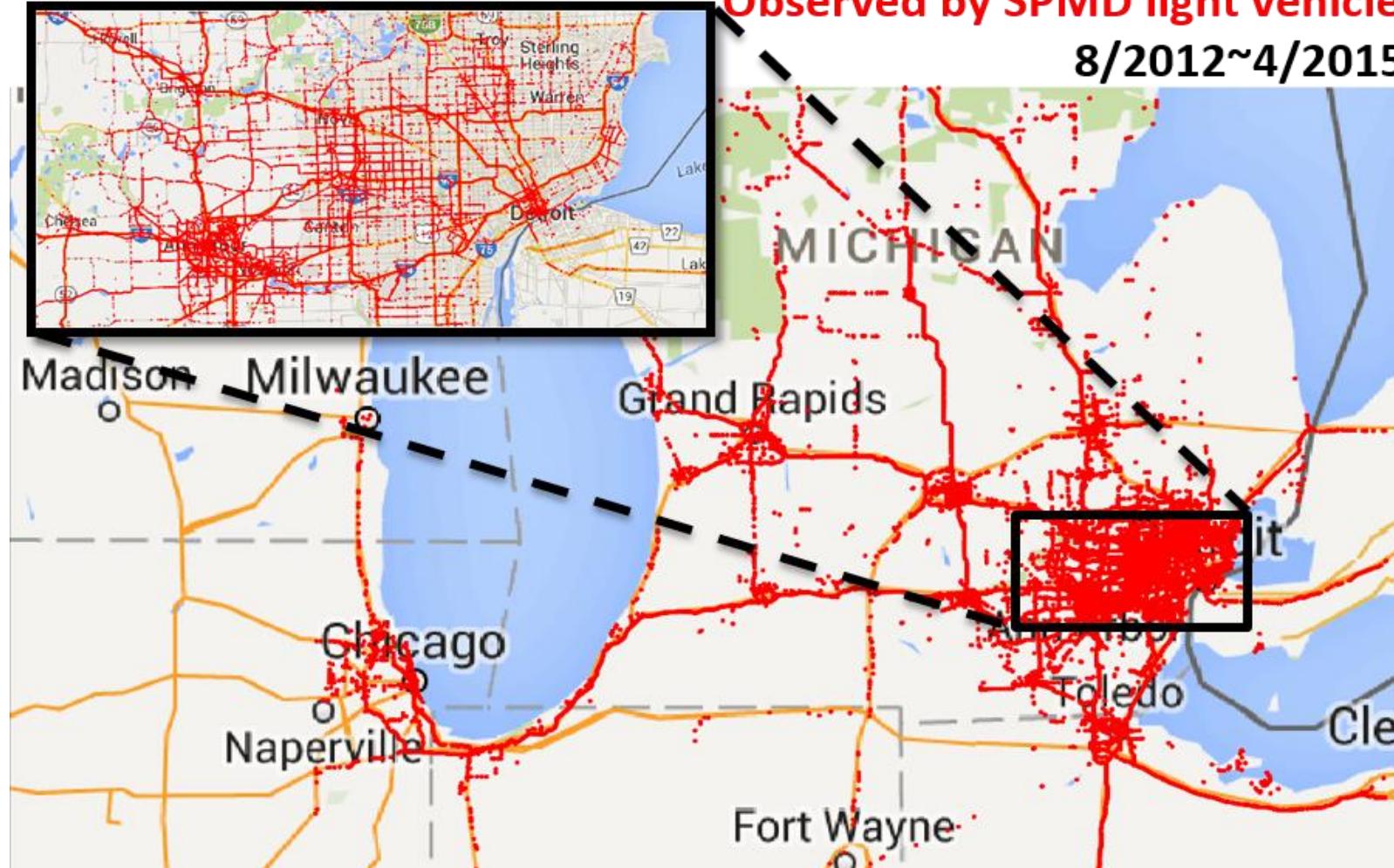
Criteria:

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

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

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

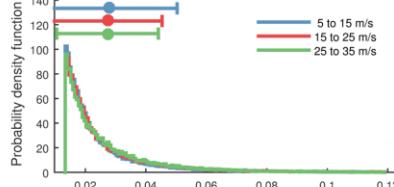
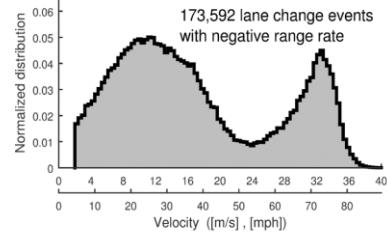
$[v_L, R_L, TTC_L]$

Execution

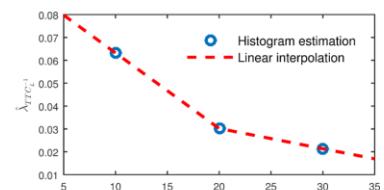
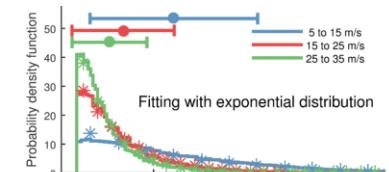
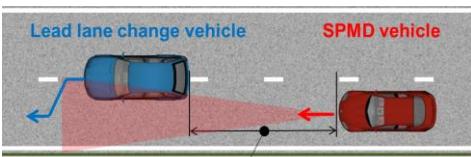
③ Skew the statistics

Importance Sampling

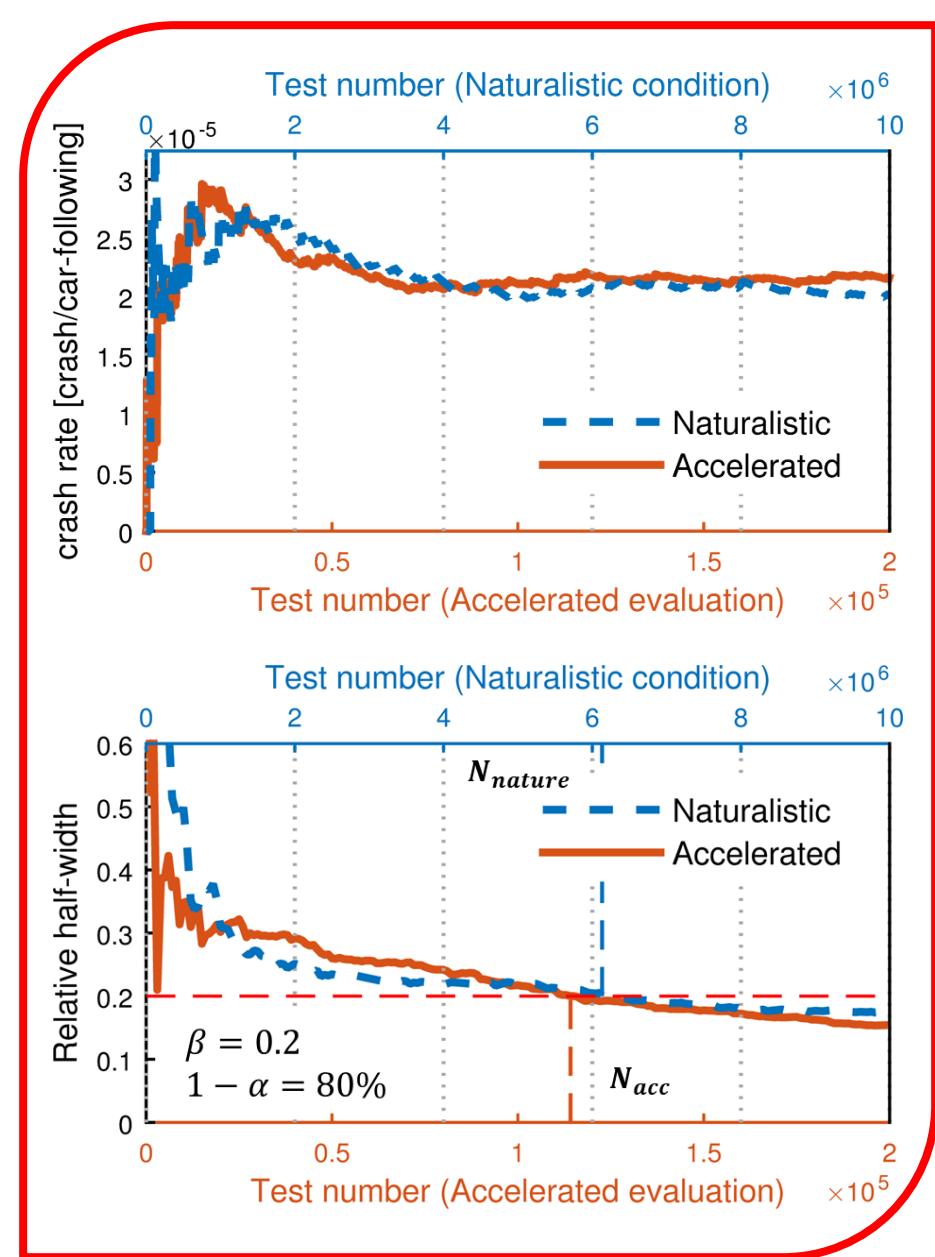
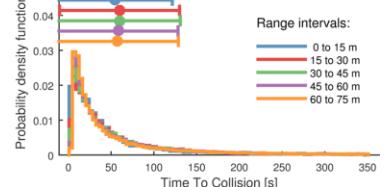
⑤ "Skew back"



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

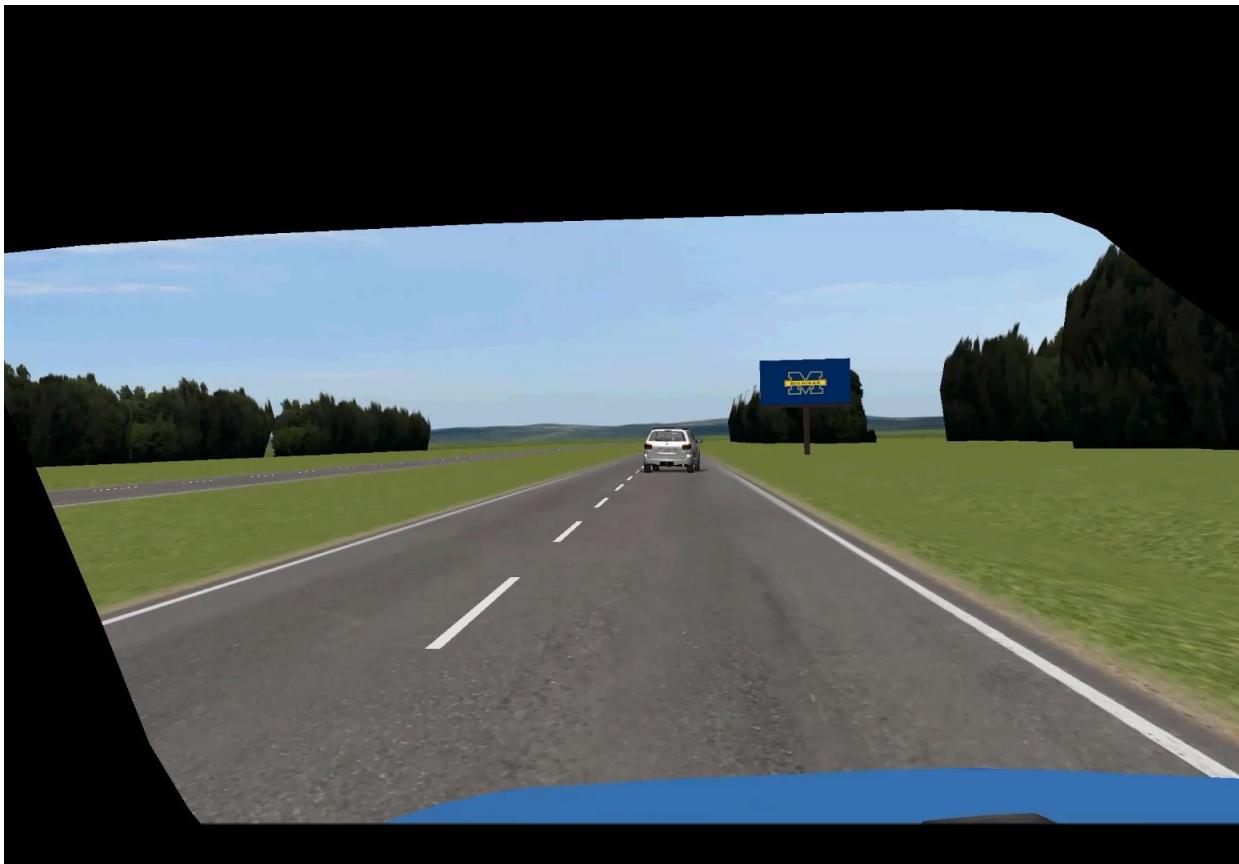


$$f_{v_L} \rightarrow v_L \rightarrow f_{R_L^{-1}} \rightarrow R_L \rightarrow f_{TTC_L^{-1}} \rightarrow TTC_L$$



Naturalistic Driving vs Accelerated Tests

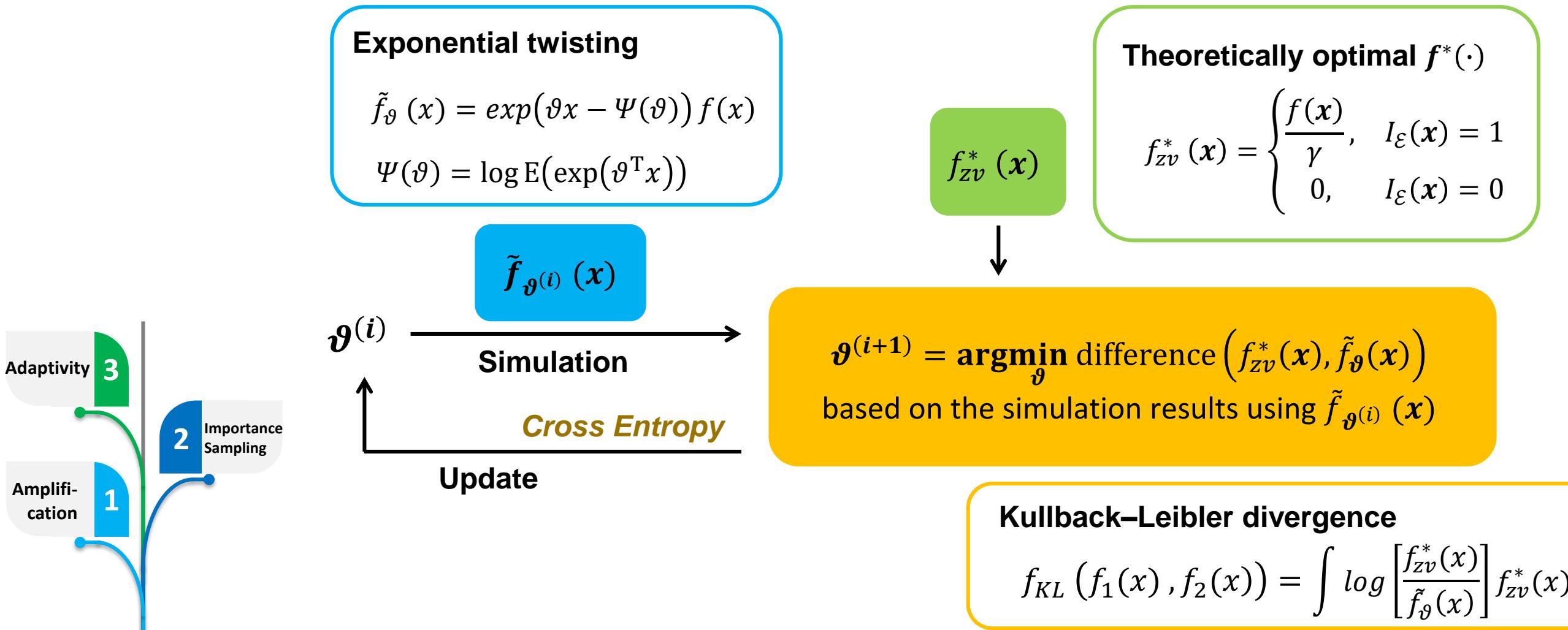
Naturalistic driving conditions



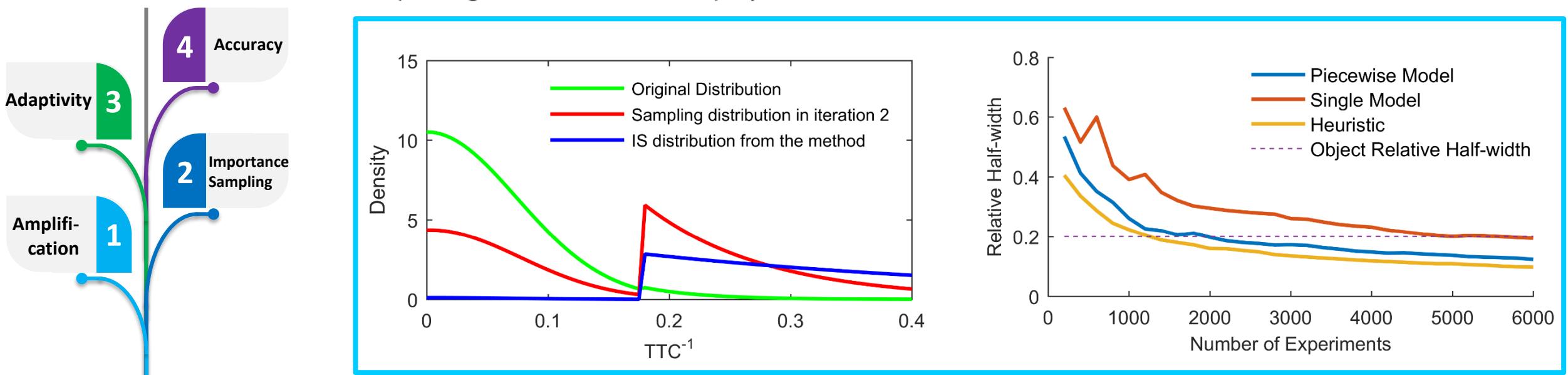
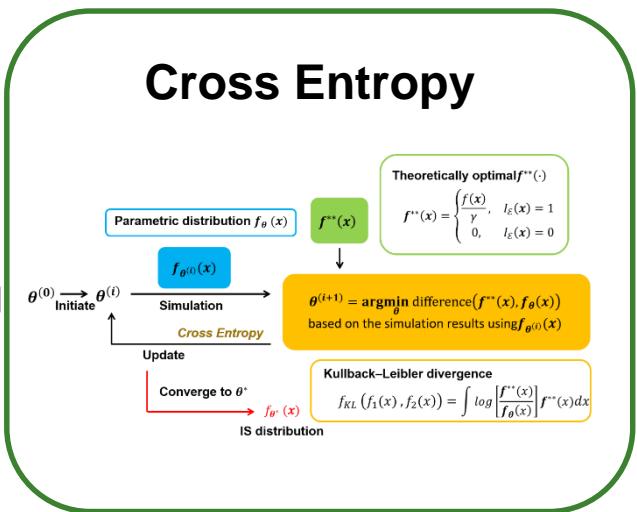
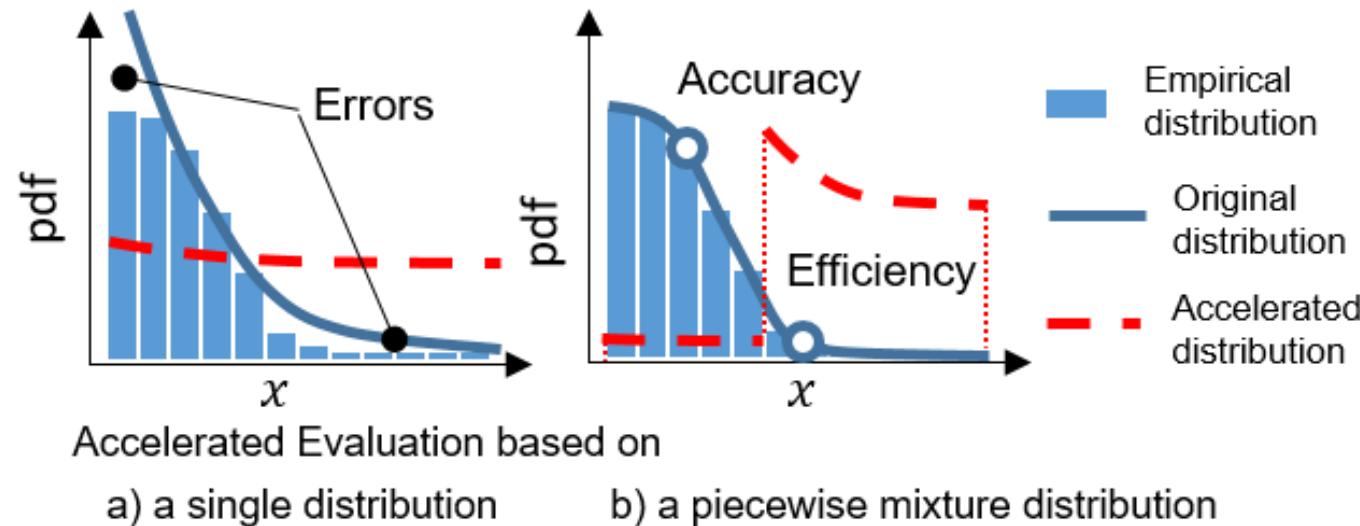
Accelerated tests



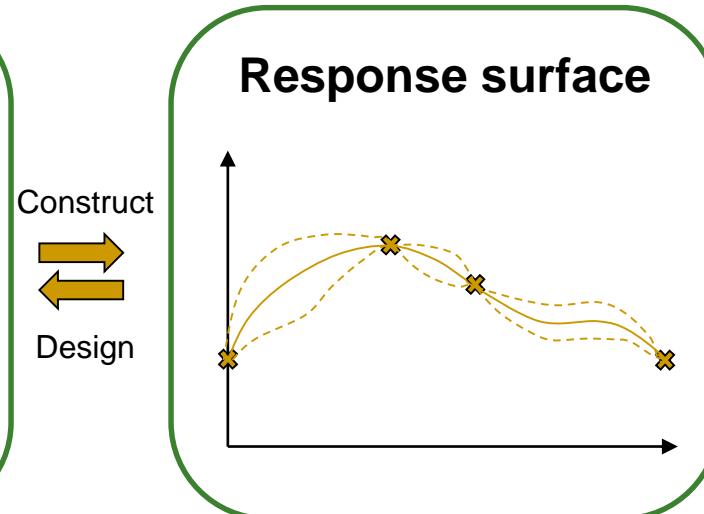
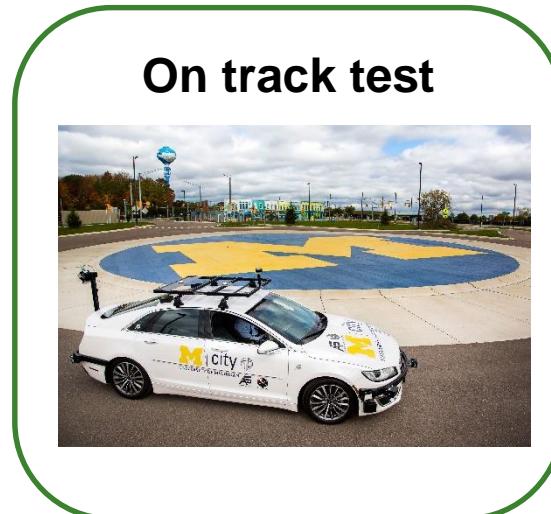
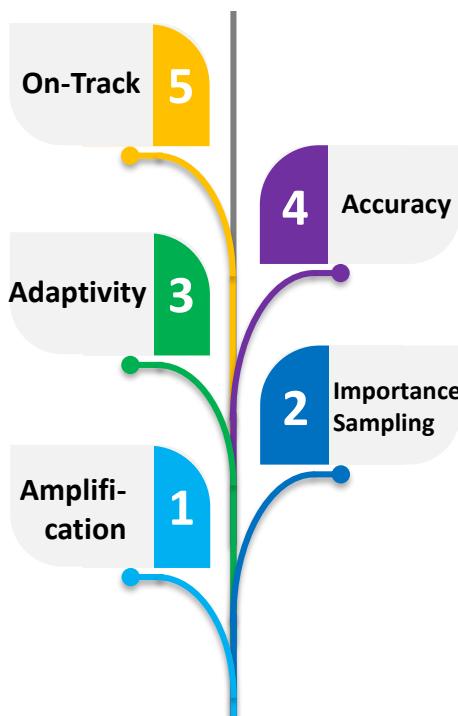
[Adaptivity] Adaptive Accelerated Evaluation using Cross Entropy



[Accuracy] Accelerated Evaluation using Piecewise Mixture Models

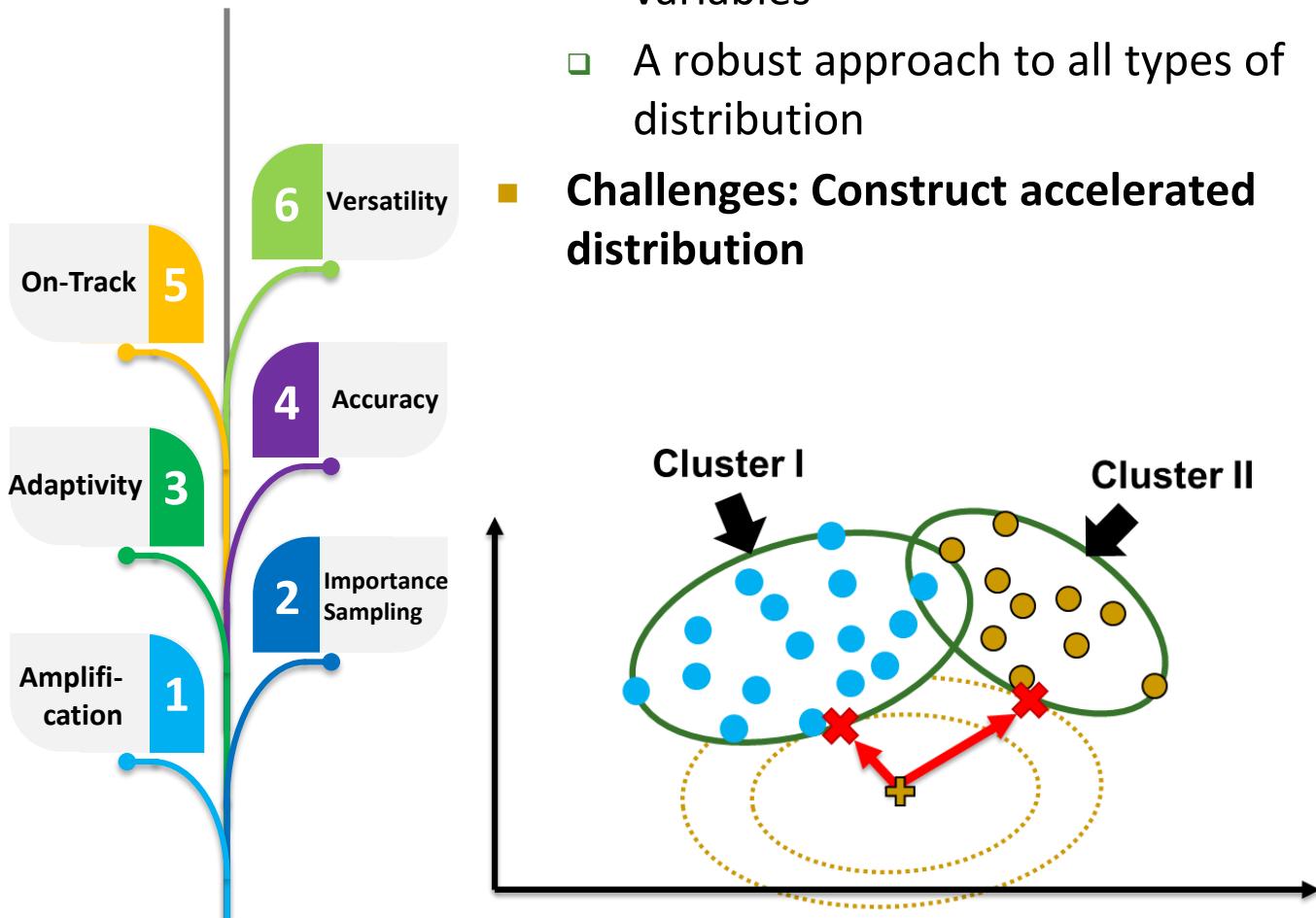


[On-Track] Kriging-based Evaluation

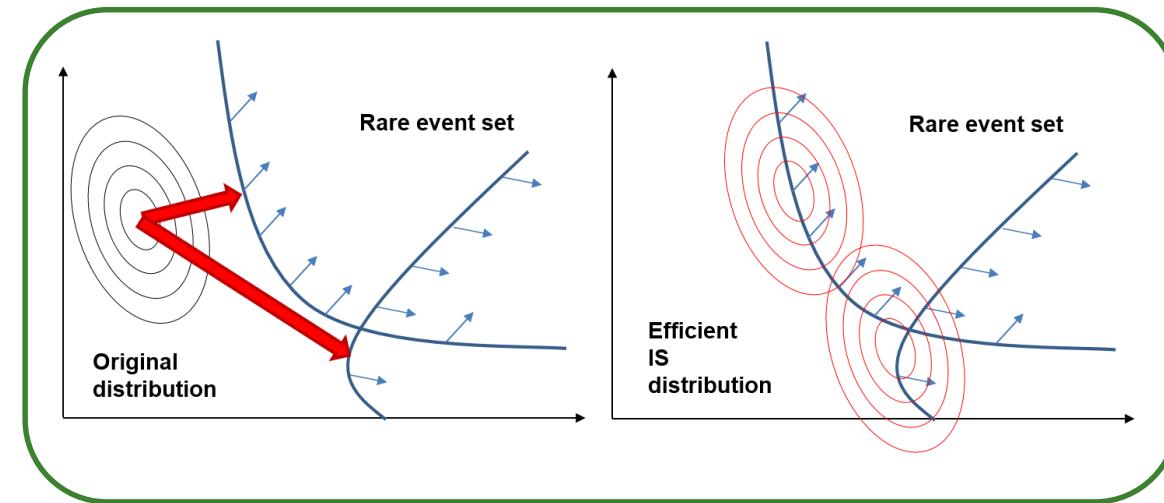
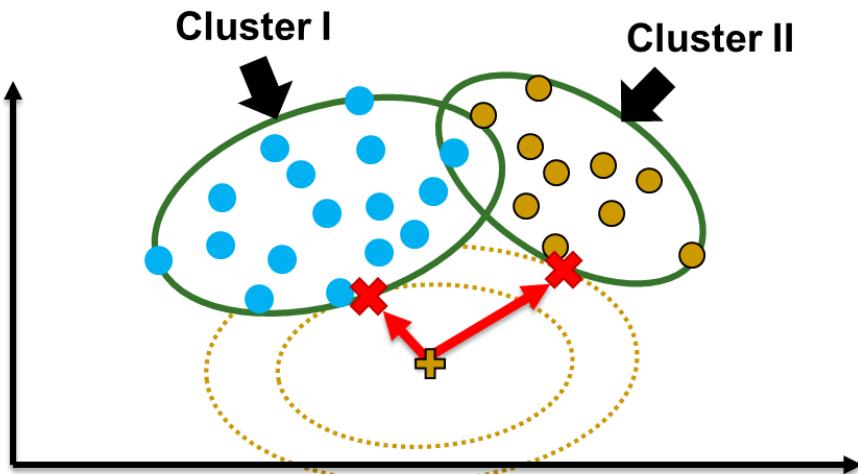
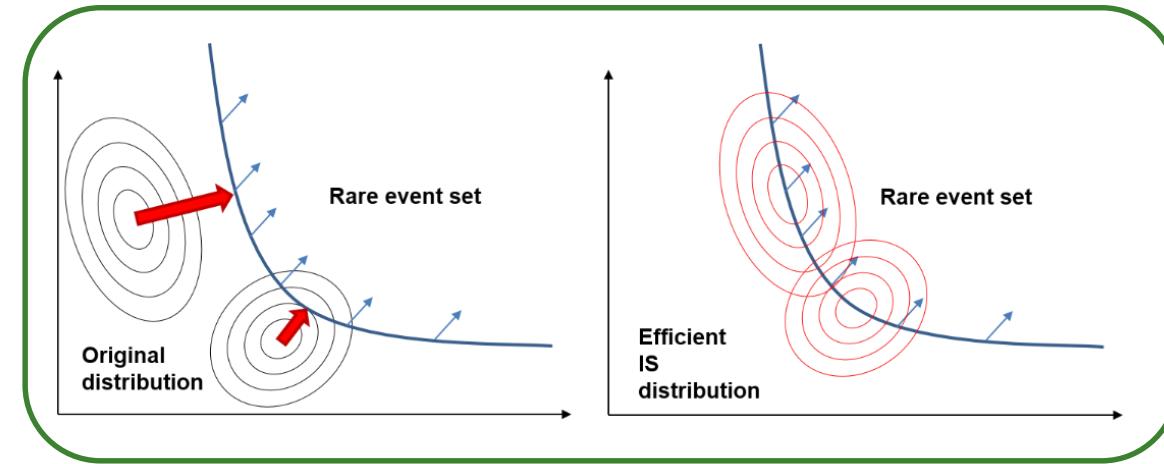


- On track tests are expensive and time-consuming
- Previous accelerated rate is high, but not enough
- **Objective**
 - Introduce reasonable assumptions such that on-track test is affordable

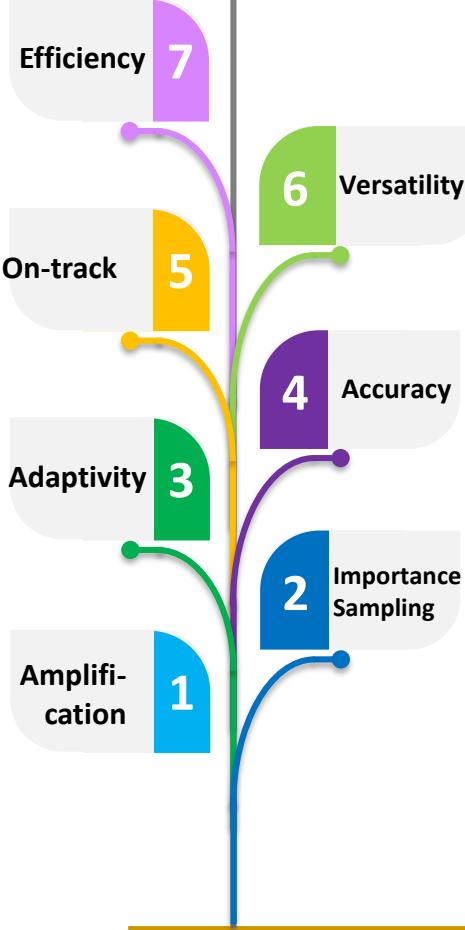
[Versatility] Accelerated Evaluation using Joint Distribution



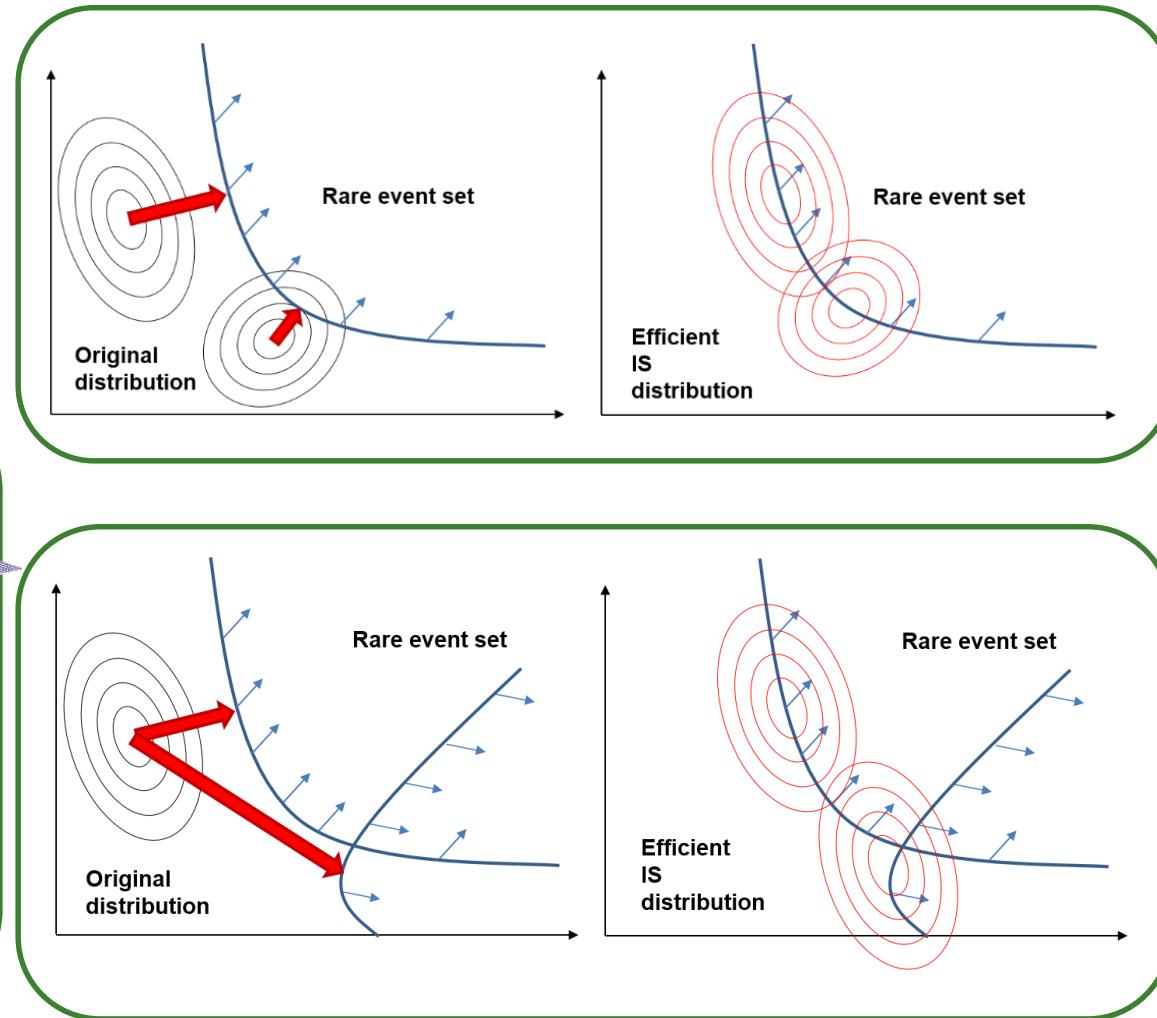
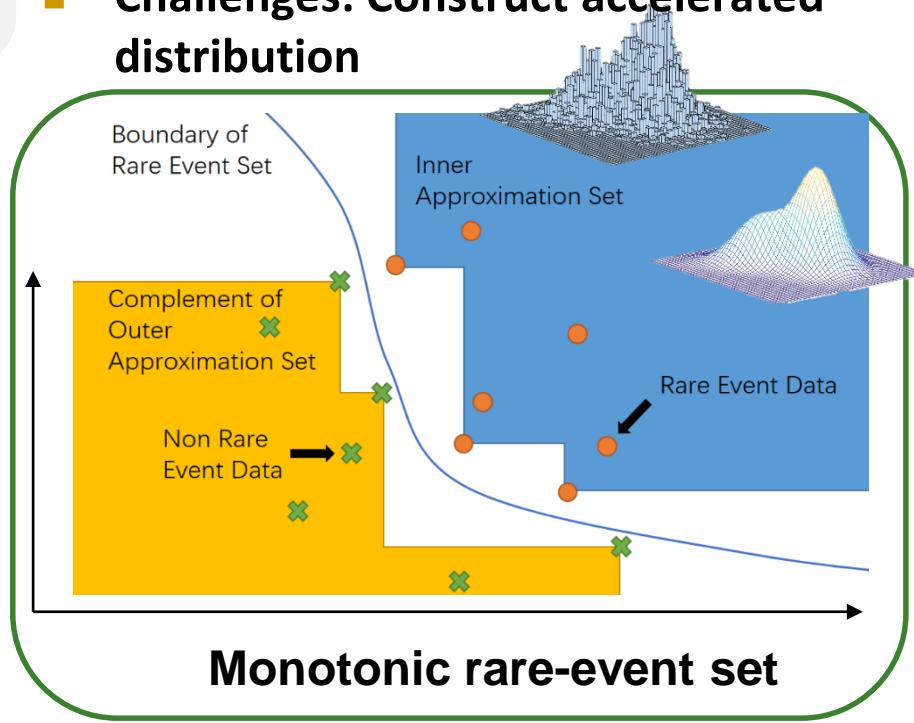
- Motivation
 - Capture the dependency between variables
 - A robust approach to all types of distribution
- Challenges: Construct accelerated distribution



[Efficiency] Accelerated Evaluation using Joint Distribution



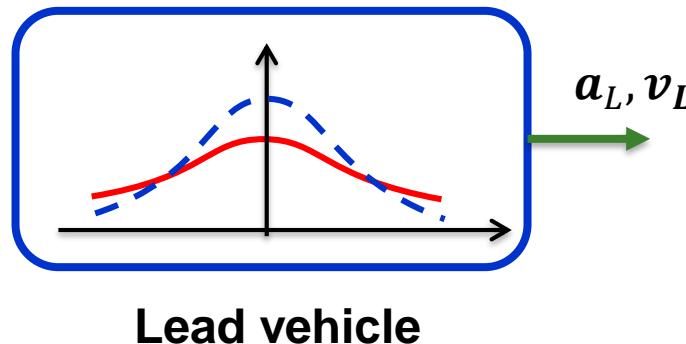
- Motivation
 - Capture the dependency between variables
 - A robust approach to all types of distribution
- Challenges: Construct accelerated distribution**



[Dynamic] Accelerated Evaluation with Stochastic Optimization

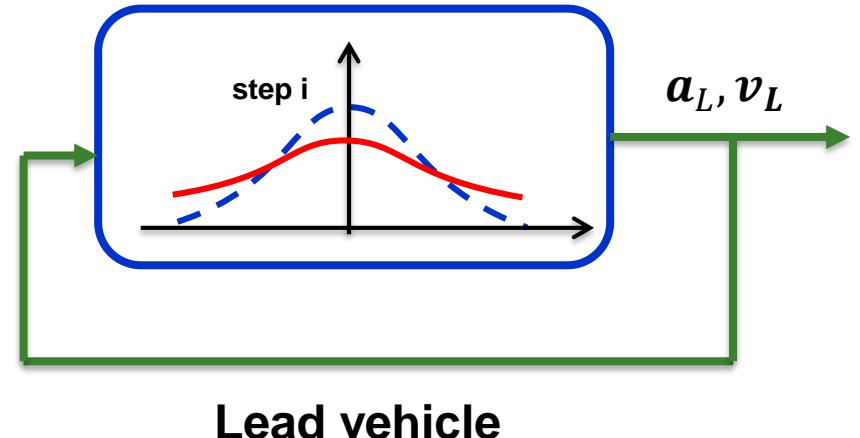


Lane change (single-step sampling)



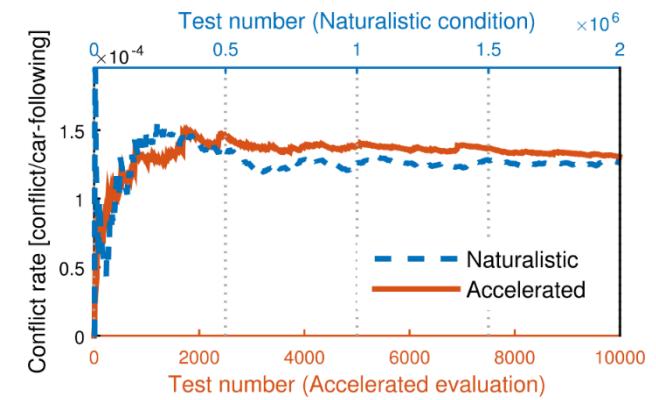
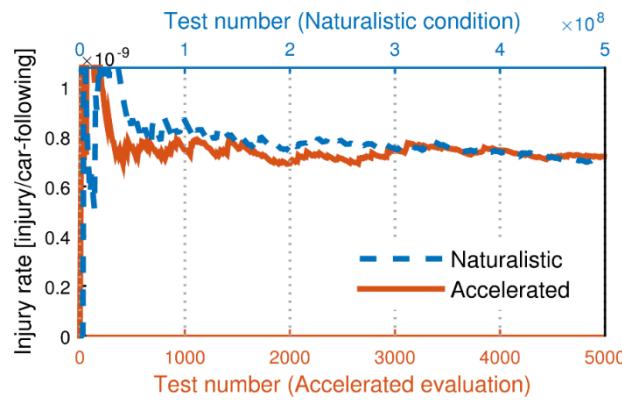
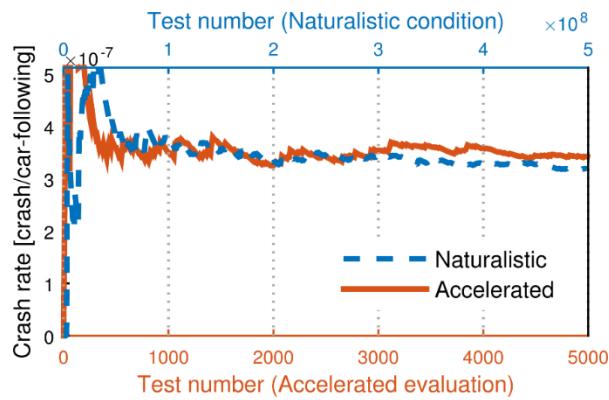
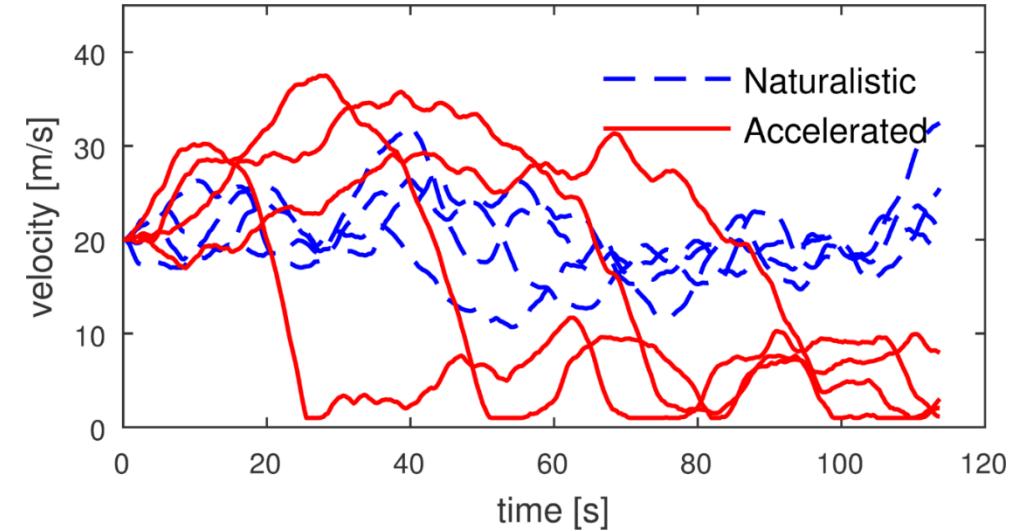
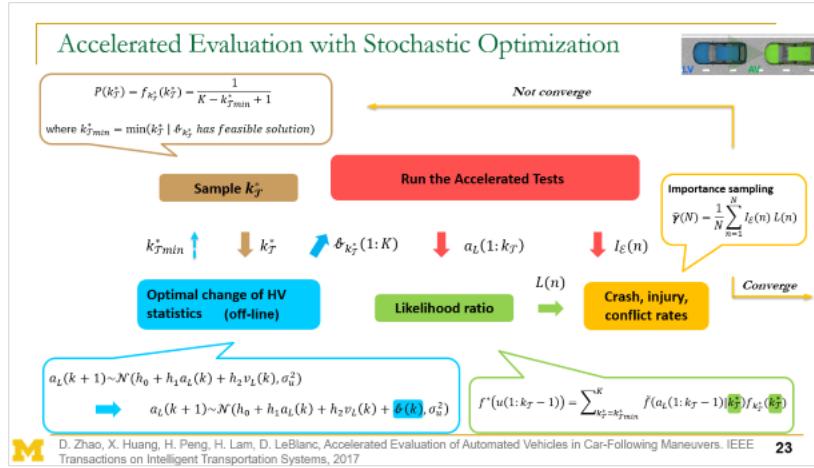
Naturalistic distribution
AE distribution

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

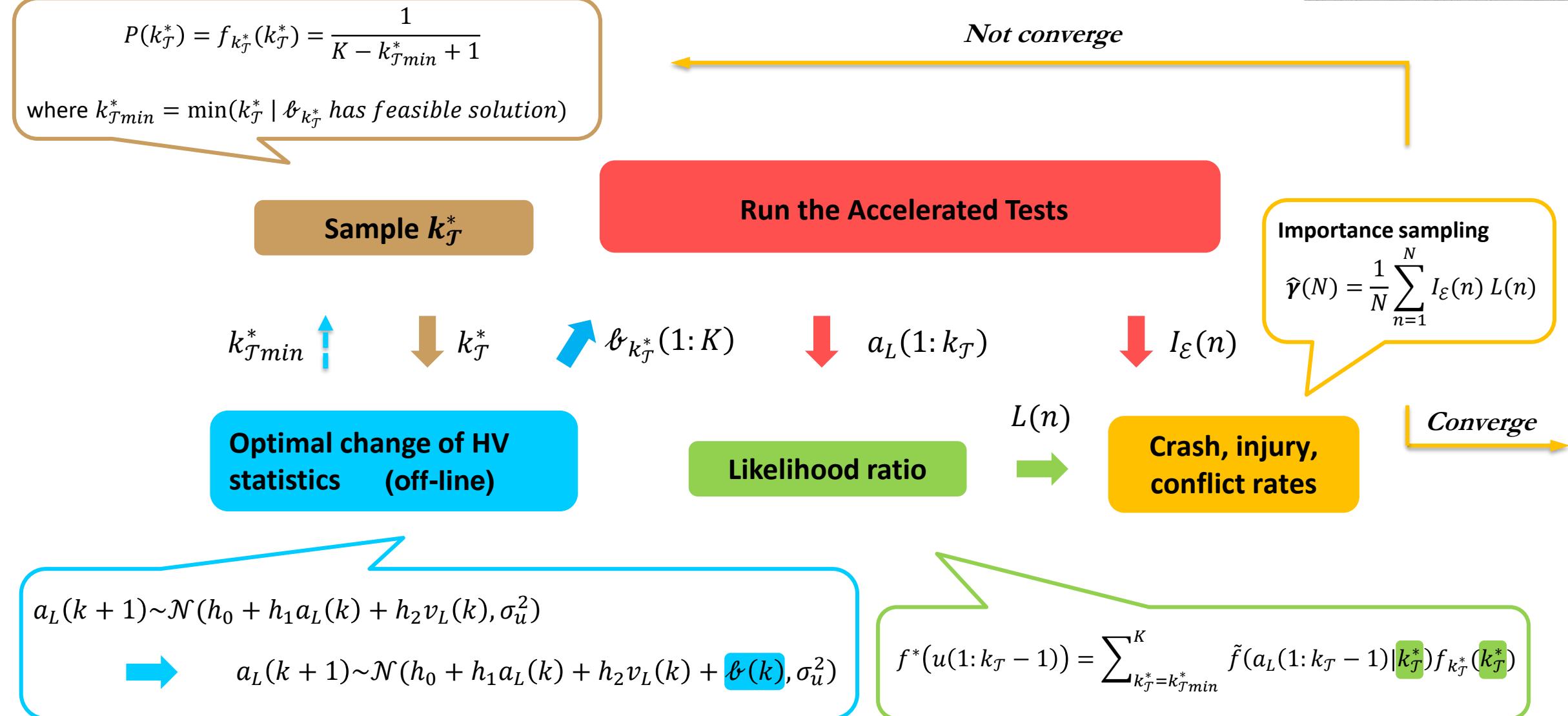
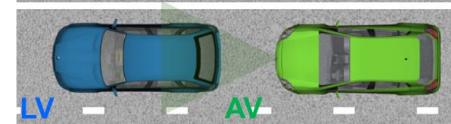


N_{nature}/N_{acc} : Crash (1.12e5)

Injury(1.35e5)

Conflict (3.28e2)

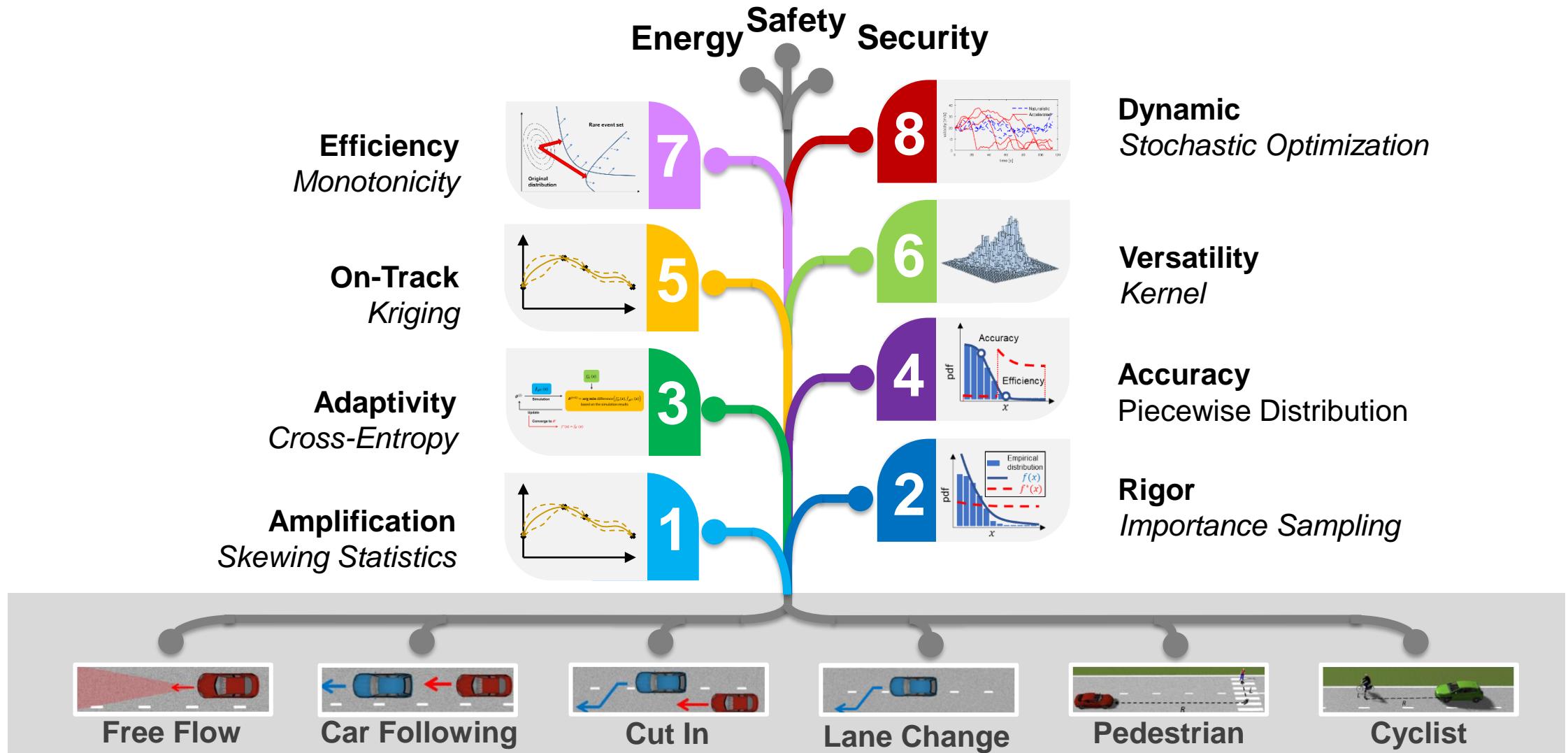
Accelerated Evaluation with Stochastic Optimization



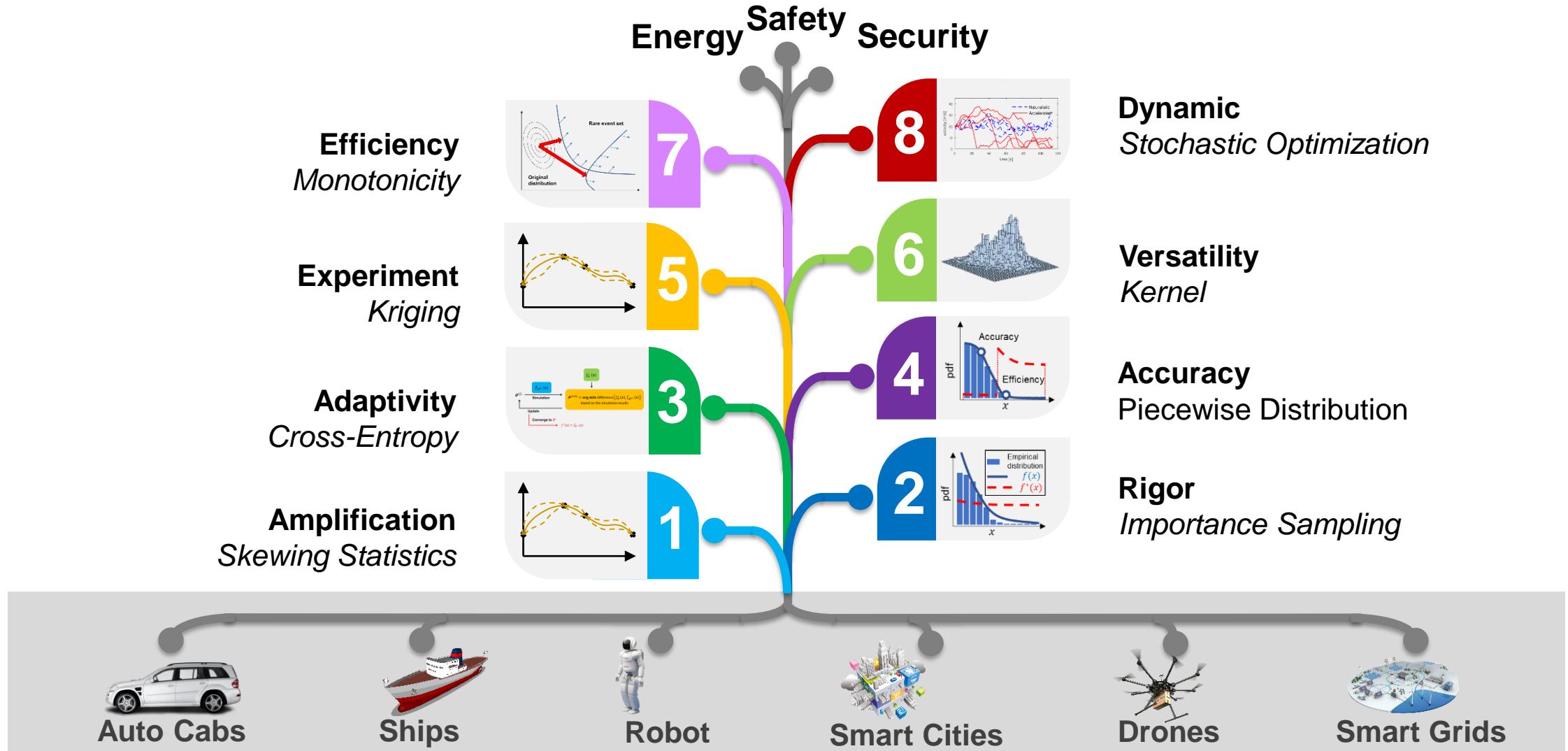
Summary of the Theories



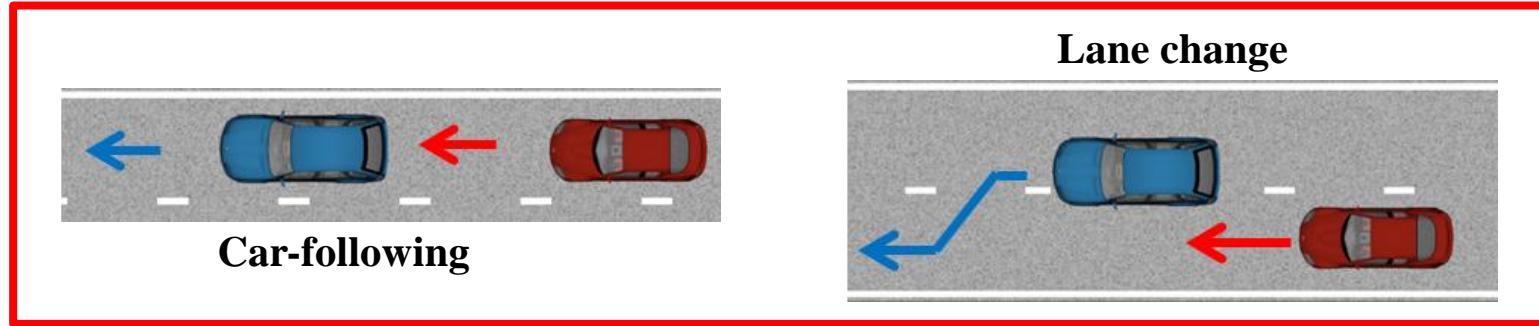
Summary of the Theories



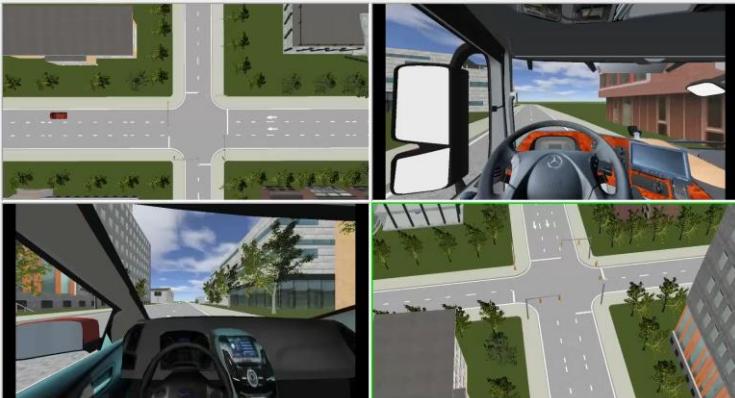
Summary of the Theories



Extensions to Other Scenarios



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:

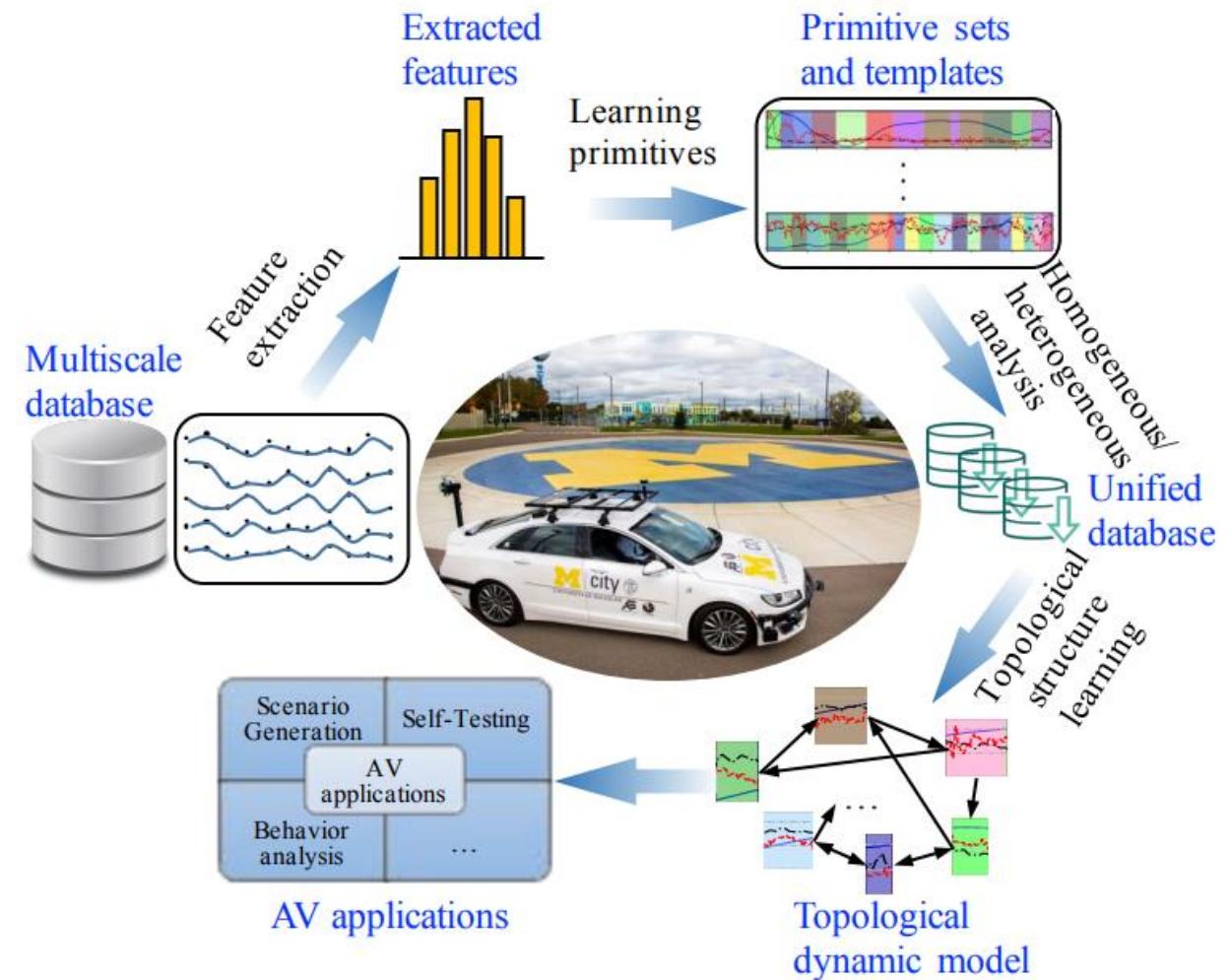
- Define scenario
- Create query condition manually
- Update query with trial and error

- Subjectively-selected scenarios/variations

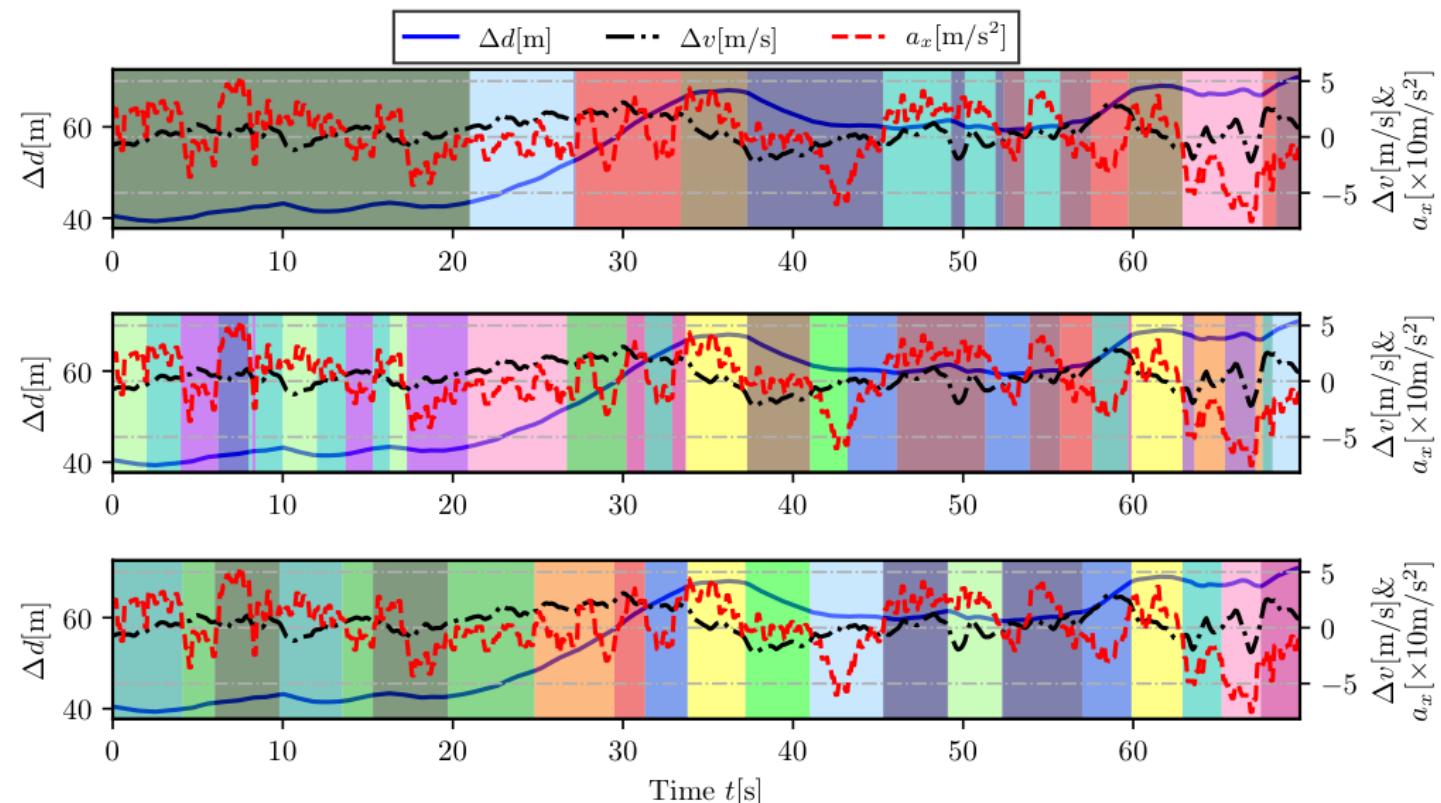
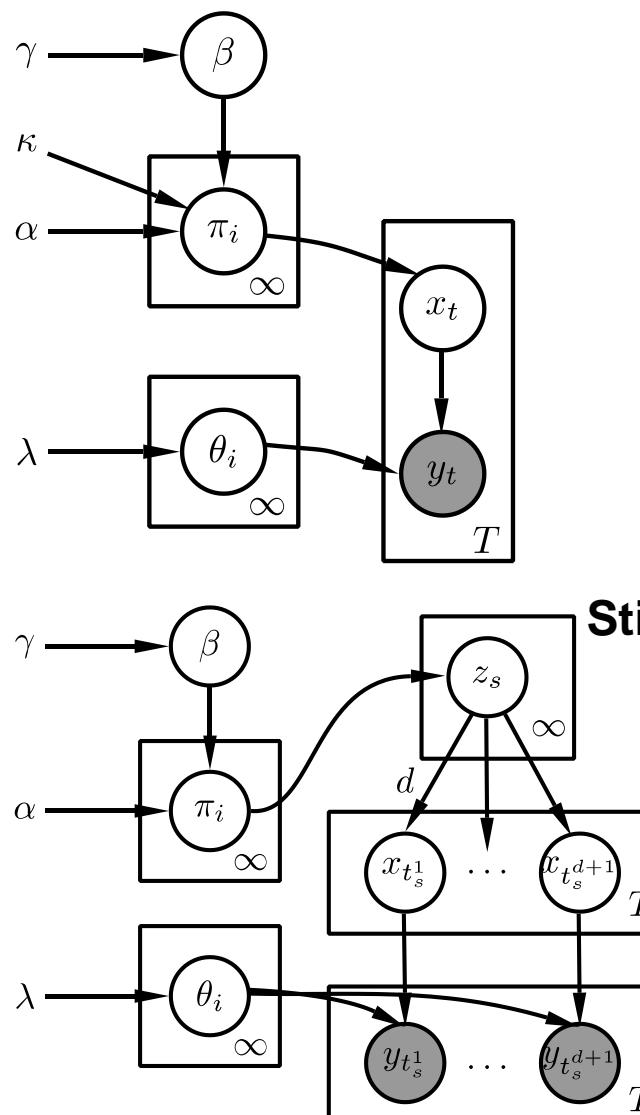
Traffic Primitive:

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

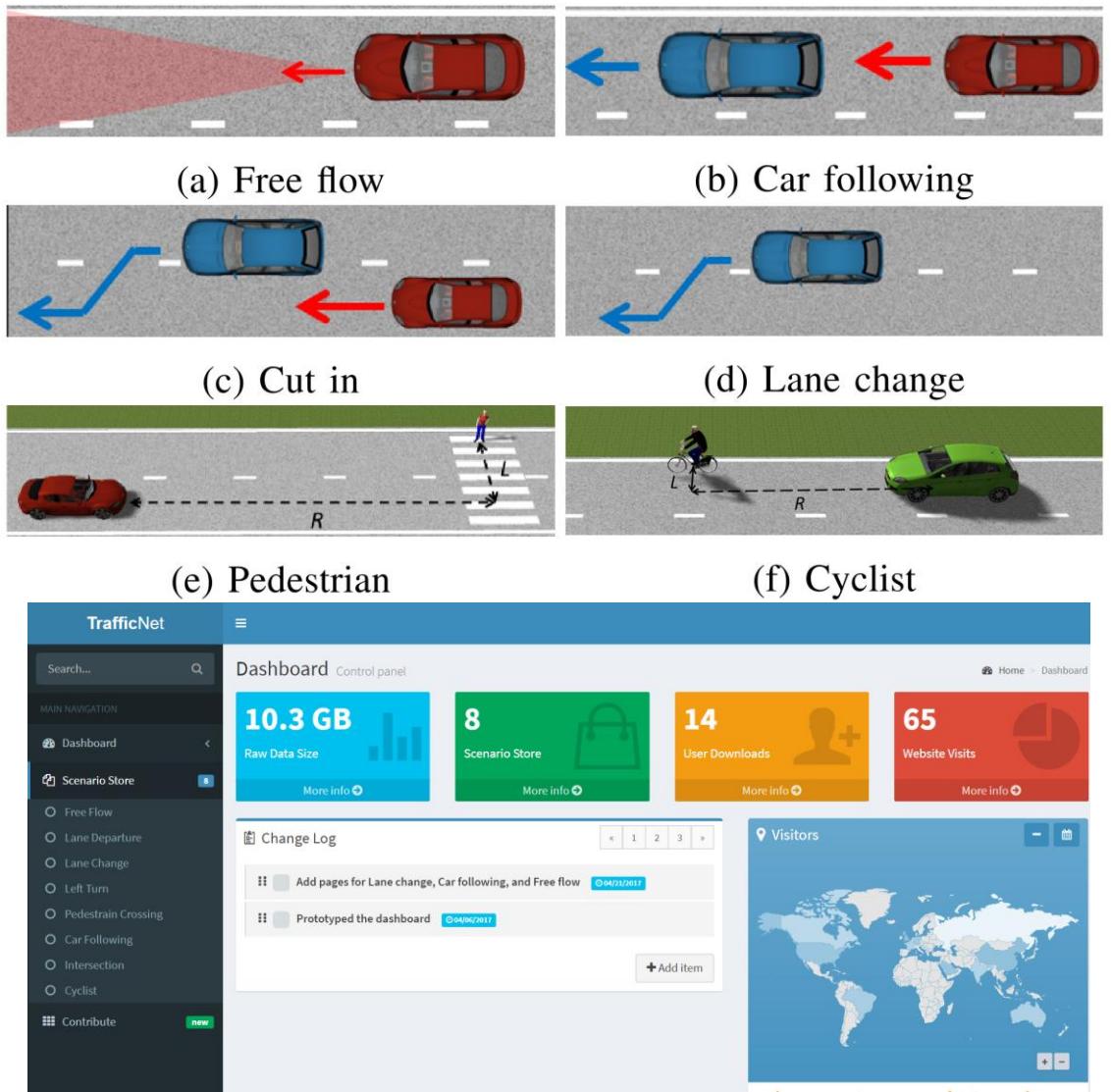
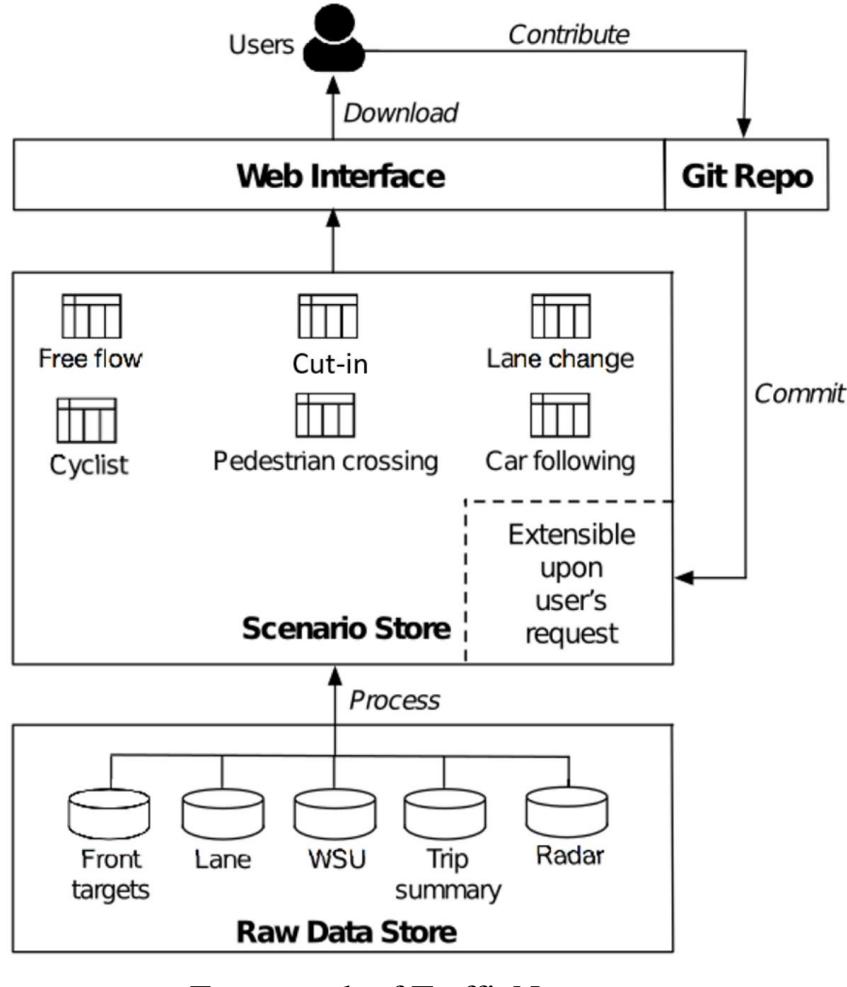
- Objectively-selected scenarios/variations



Traffic Primitive: Extract Scenarios Automatically from Raw Data



TrafficNet: An Open Naturalistic Driving Scenario Library



Platforms

On-track tests

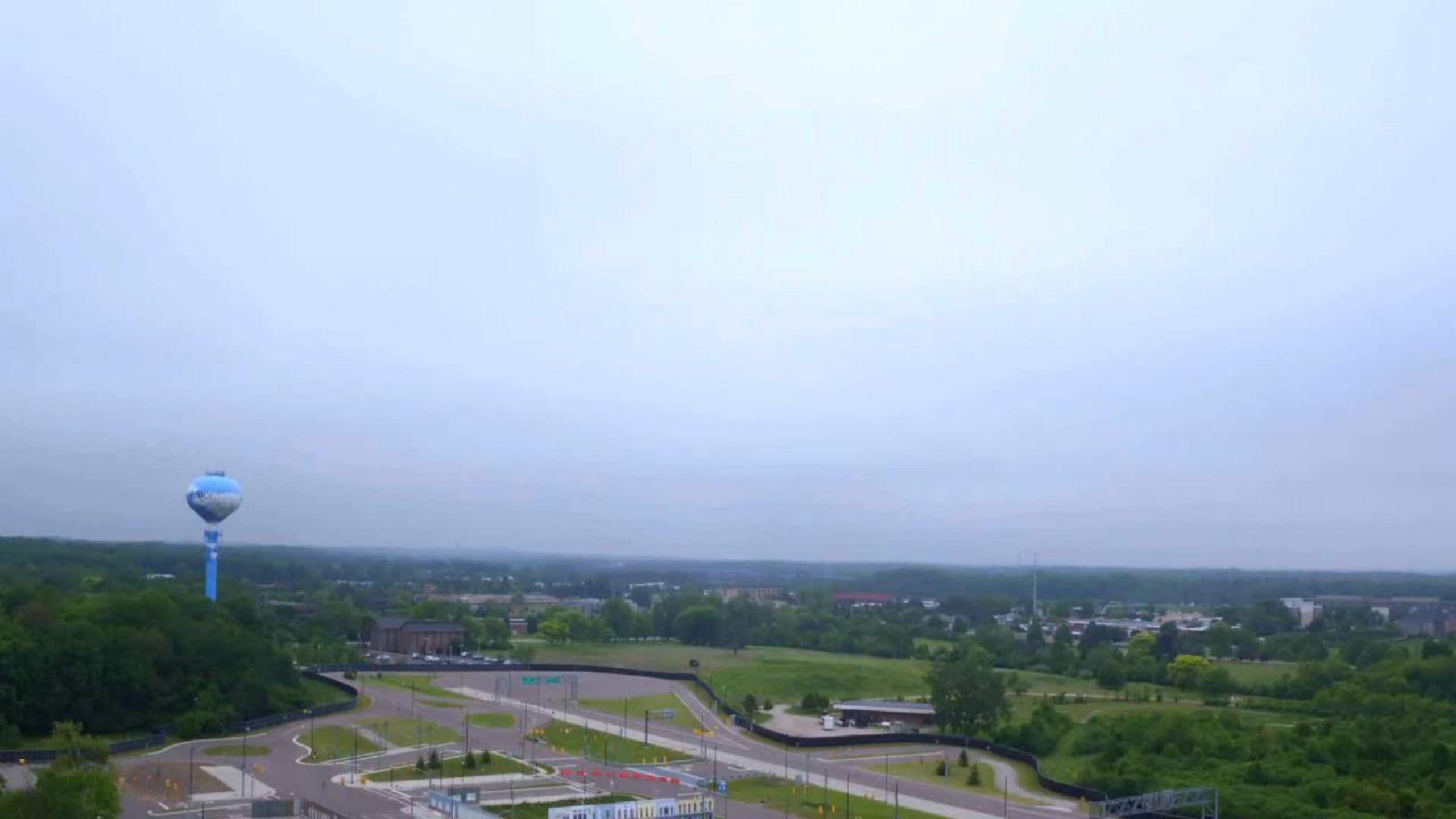


Virtual reality

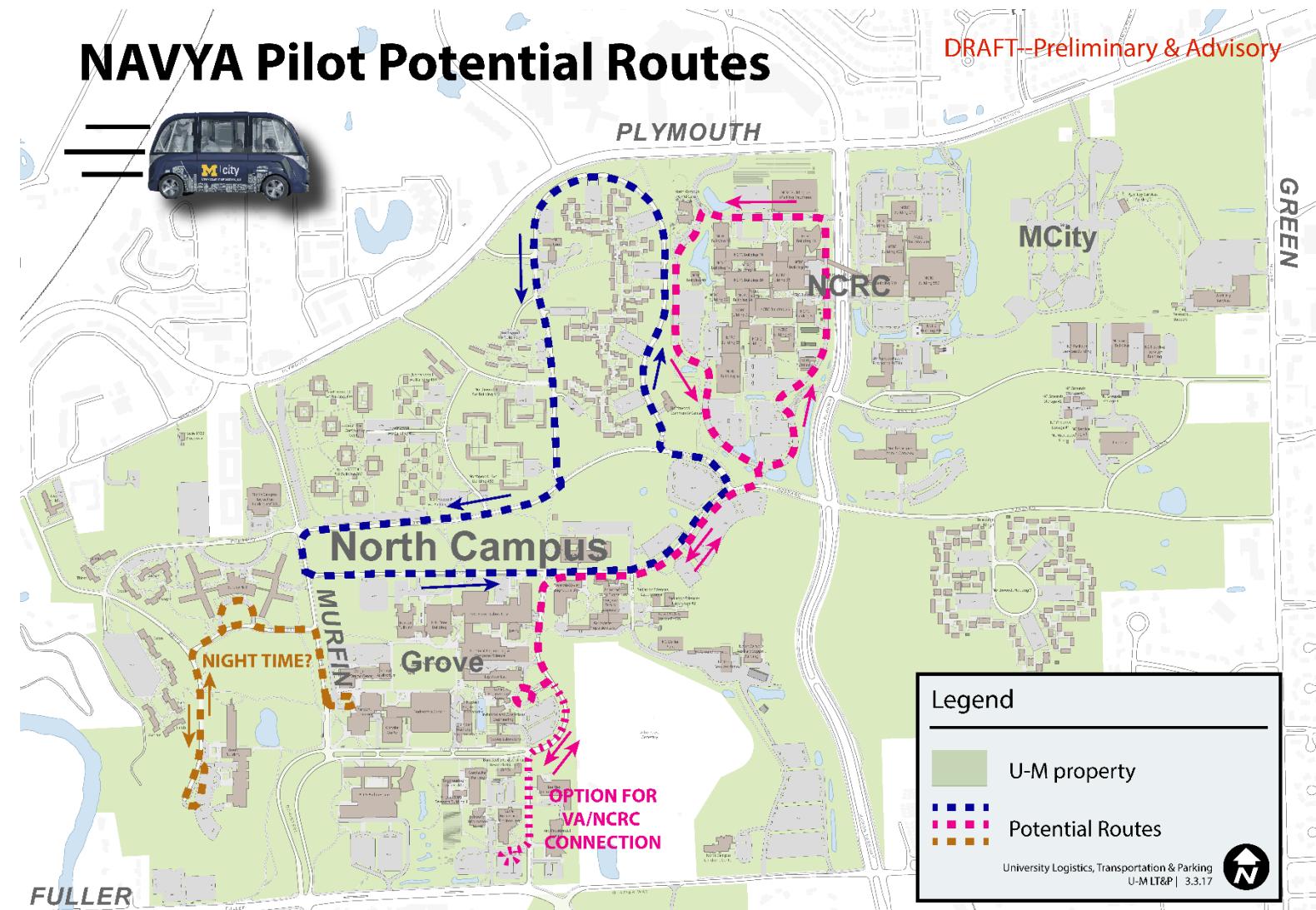


Mixed Reality





Deployment of Testing Vehicles

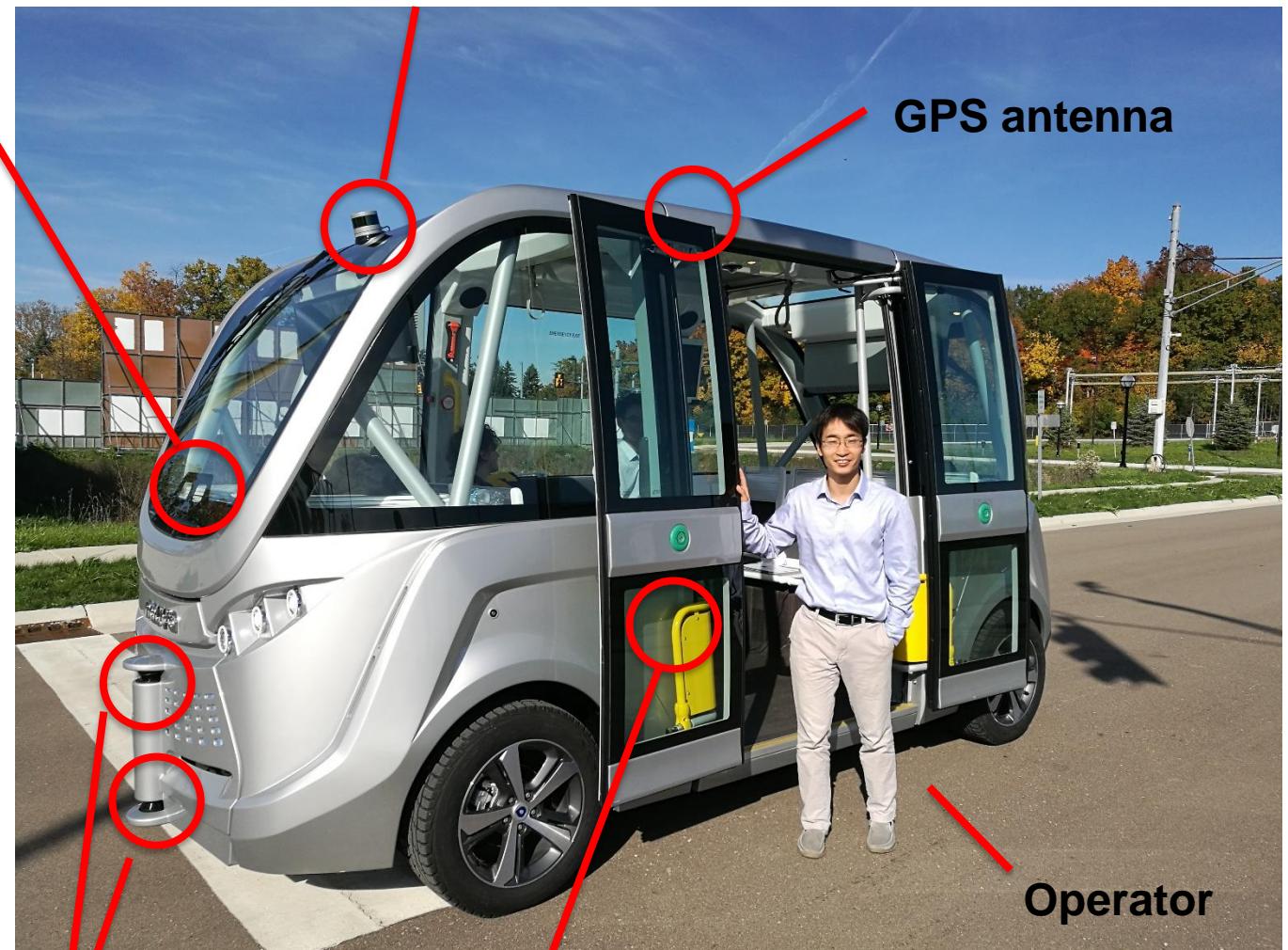


Recourses

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

Stereo camera

Velodyne 16 bin Lidar (front and rear)

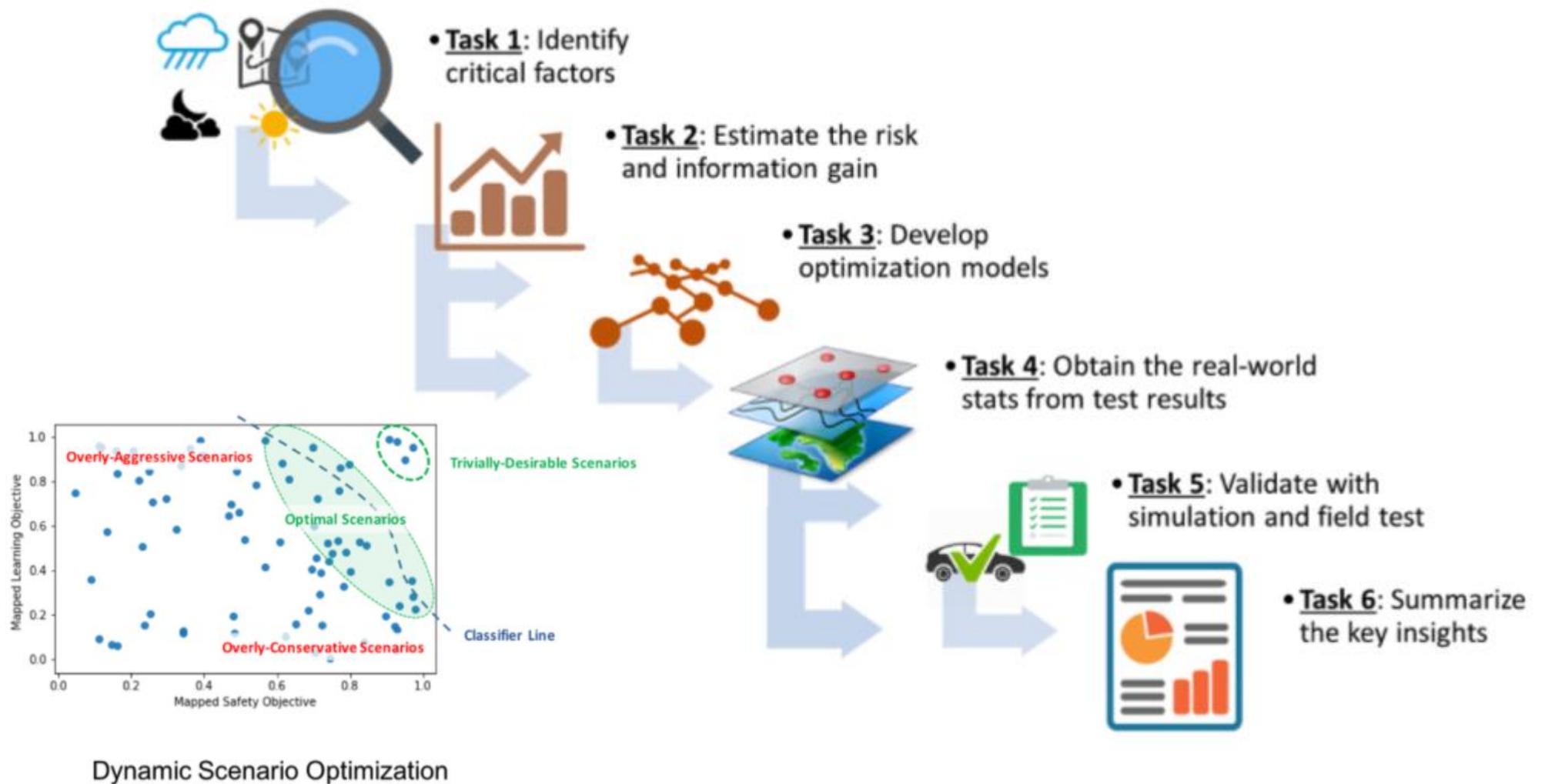


Stereo camera
Velodyne 16 bin Lidar (front and rear)
GPS antenna
IBEO Lidar (one each side)
Operator

Sick Lidar
(other 2 in the rear)

D. Zhao | 10/25/16

Design Deployment Policy



Acknowledgement



TOYOTA



DENSO



上汽集团
SAIC MOTOR



Autoliv SOKON

Thanks for your attention

Papers / Contact



PPT

