

Scenic and VerifAI: Tools for Assured AI-Based Autonomy

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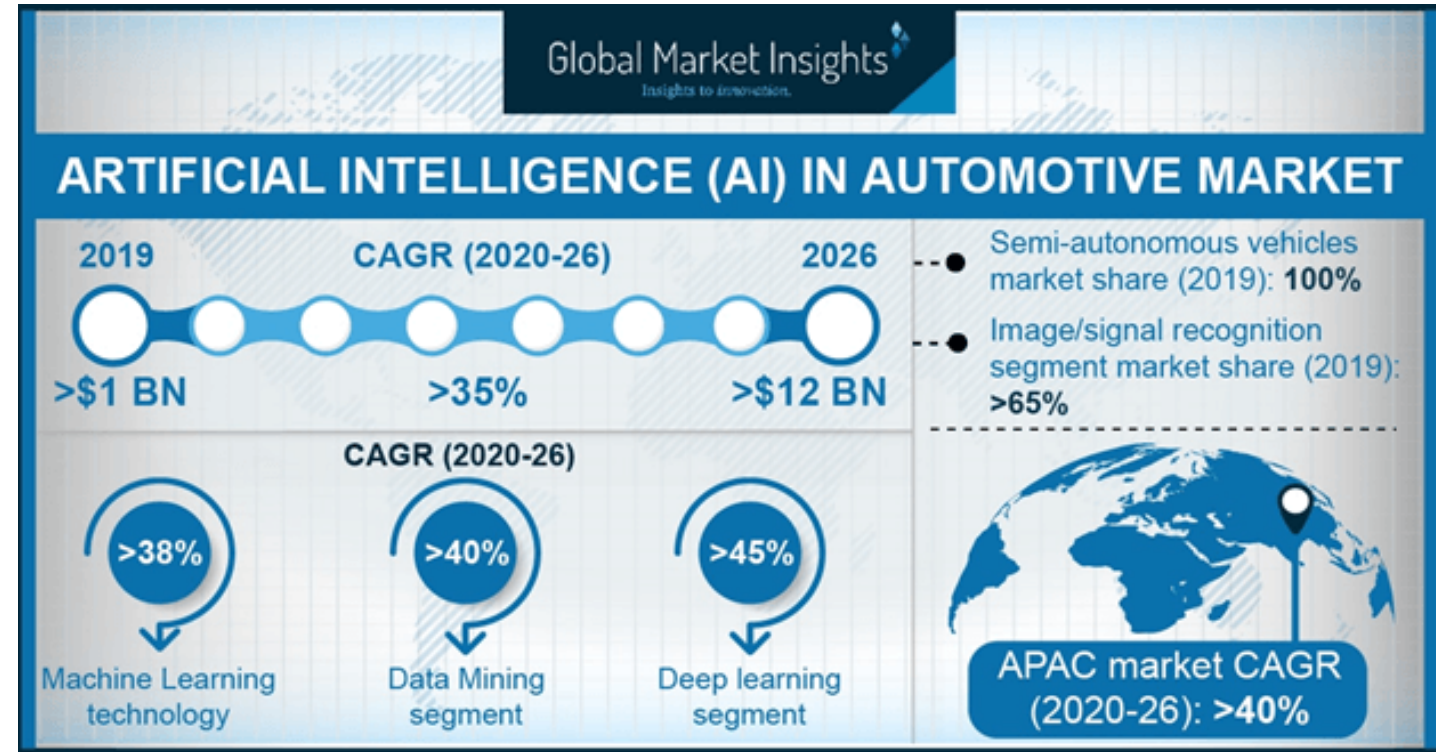
Webinar
August 20, 2020

Artificial Intelligence (AI) and Autonomy

Computational Systems that attempt to **mimic aspects of human intelligence**, including especially the ability to **learn from experience**.



Growing Use of Machine Learning/Artificial Intelligence in Safety-Critical Autonomous Systems



Source: gminsights.com

Growing Concerns about Safety:

- Numerous papers showing that *Deep Neural Networks can be easily fooled*
- *Accidents*, including some *fatal*, involving potential failure of AI/ML-based perception systems in self-driving cars

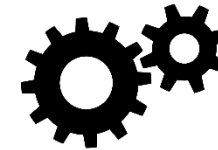
Can we address the Design & Verification Challenges of AI/ML-Based Autonomy with **Formal Methods**?

Precise, Programmatic **Environment/Scenario Modeling**



φ

Mathematical **Specification of Requirements and Metrics**



Scalable Algorithms for **Verification and Testing**



Methodologies for **Provably-Robust System Design**



Berkeley DeepDrive



Vertical
<http://vehical.org>

S. A. Seshia, D. Sadigh, S. S. Sastry.

Towards Verified Artificial Intelligence. July 2016. <https://arxiv.org/abs/1606.08514>.

Scenic

High-Level, Probabilistic Programming
Language for Modeling Environment Scenarios



Open-Source Tools

<https://github.com/BerkeleyLearnVerify/Scenic>
<https://github.com/BerkeleyLearnVerify/VerifAI>

for

Industry

Improve assurance
of the systems you
build

Share Scenarios and Metrics

Academia

Use these tools in
your research

Community

Government/ Regulators

Evaluate the safety
of AI-based
autonomous systems

Develop Corpus of Tools and Data

Outline for this Webinar

Part I: Overview

- Challenges for Assurance of Autonomous Driving Systems
- Overview of VerifAI and Scenic
- Case Study on Formal Scenario-Based Testing in Simulation and on the Road

Part II: Tutorial

- Spatial modeling, data generation, and debugging ML-based perception with Scenic
- Spatio-temporal scenario modeling, testing, falsification, debugging, retraining with Scenic and VerifAI

Conclusion & Outlook

Challenges for Assuring Safety of ADS

What We Mean By Safety in Autonomous Driving

Safety → “absence of unreasonable risk”

SAFETY



RISK



ISO 26262

Functional Safety (FuSa)

- *Hazards due to E/E system*



ISO/PAS 21448

(SOTIF) Safety of the Intended Functionality

- *Hazards due to nominal system operation*

Risk = f (Severity, Exposure, Controllability)

[ASIL, ISO 26262]

→ **Severity**

- types of injuries

→ **Exposure**

- frequency of hazards

→ **Controllability**

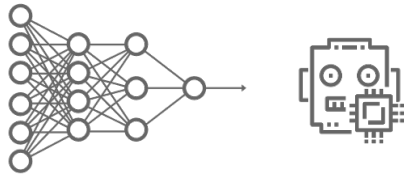
- how much driver can prevent injury

No system has absolutely zero risk

Improving Safety in Automated Driving Systems: Needs

Challenges for safety-critical systems

SENSE → PERCEIVE → PREDICT → PLAN → ACT



Handle **complex neural-network** based **perception** and **prediction** tasks, including planning and control



Toolchain that integrates **design** and **verification** with **data generation** and training/testing of ML components



Simulation is important for complex, **real-world scenarios** for which **real world data is difficult/dangerous**

Why Testing ADS is Complex

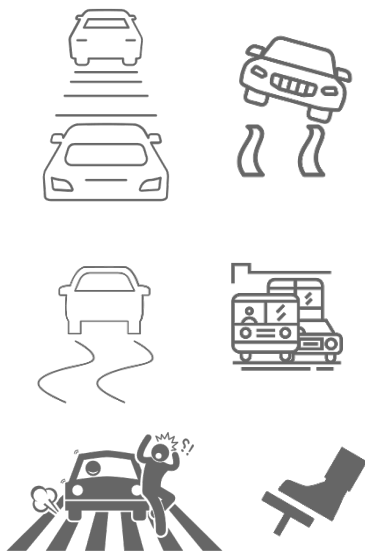


Verification & Validation: Assurance of “*positive risk balance*”
Scenario-based testing is one standard approach for V&V

Wide variety of functions and scenarios...

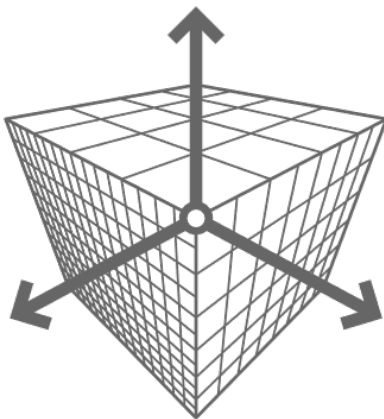
ADAS

- ACC
- FCW
- CAS
- AEB
- P-AEB
- LKA
- LDW
- BSM
- ISA
- ...



NHTSA, EuroNCAP, JNCAP

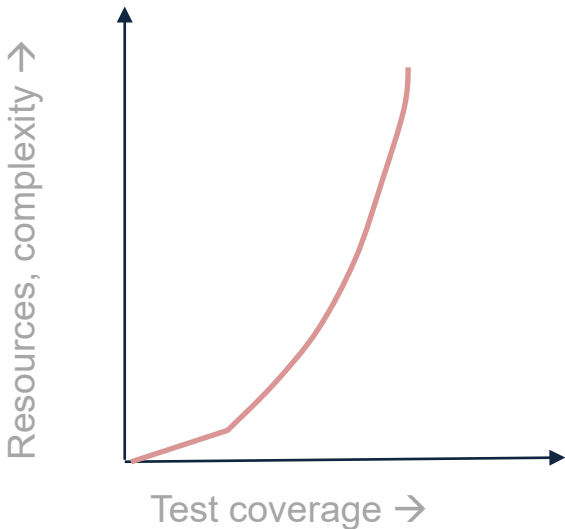
...lead to high-dimensionality of parameter search



f(speed, objects, agents, ...)

Test matrix

...resulting in high complexity



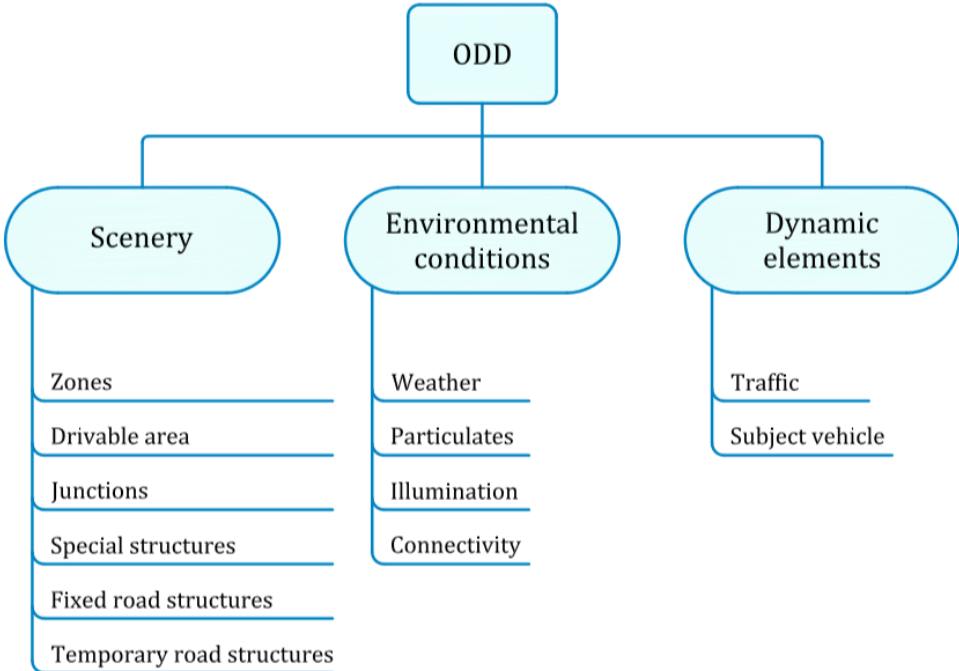
Operational Design Domain: What and Why

Operating environment within which an ADS can **safely** perform its dynamic driving task (**DDT**)

<u>Formulation</u>	<u>Requirements</u>	<u>Boundary conditions</u>
Category / sub-category / attributes Static and dynamic elements Additive / subtractive elements	Precisely definable Comprehensible (human / machine) Measurable Monitorable (by ADS / operator)	ODD detection / departure Min Risk Condition (MRC) Min Risk Maneuver (MRM) Fail Safe / Fail Operational

ODD Classification

Physical Infrastructure	Operational Constraints	Environmental Conditions	Zones	Objects	Connectivity
Roadway Types	Speed	Weather	Geo-fenced	Signage	Vehicles
Roadway Surfaces	Traffic Conditions	Weather induced Roadway conditions	Traffic management zones	Roadway Users	Remote / Teleops Mgmt
Roadway Geometry		Illumination	School / Construction zones	Non-roadway users / Obstacles	V2X Infra
Roadway Edges		Particulate Matter	Interference zones		
			Regions / States		



Source: NHTSA 13882 ADS Scenario Framework

Safety Metrics: How is Success / Failure Measured



System performance is context-dependent (mission/scenario/test-case/etc.)



“Disengagement” is not a safety metric



Standards /
Proposals...

ANSI / UL 4600 – “Safety Performance Indicators (SPIs)”

IEEE P2846 – “motion control based metrics”

Intel’s Responsibility-Sensitive Safety (**RSS**)

NVIDIA’s Safety Force-Field (**SFF**)

...Convergence

Vehicle Dynamics Based

- Min Safe Distance Violation
- Proper Response Action
- Min Safe Distance Factor
- Min Safe Distance Calc Error
- Collision Incident
- Rules-of-road violation
- ADS Active
- Human Traffic Control Detection Error Rate
- Time to Collision (TTC)
- Post-Encroachment Time
- Aggressive Driving
- Collision Avoidance Capability (CAC)

SPIs

- Incident rates
- Violation rates
 - By human exposure
 - By item exposure
- Hazard occurrence rates
- Unmitigated hazard rates
- Psychological comfort rates
- ODD departure rates
- ...
- Post-deployment defect rates
- Field failure rates
- Misclassification rates
- ...

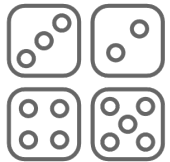
Sources:
1. “Driving Safety Performance Assessment Metrics for ADS-equipped Vehicles”, Wishart, et al (SAE WCX 2020)
2. “Collision Avoidance Capability Metric”, Silberling, et al (SAE WCX 2020)

Bridging Simulation and Real World

Testing on road/track is expensive but important, hence



- Need to carefully design road/track tests (e.g. NHTSA, NCAP, IIHS, ...)
- Customize test plans based on ODD, autonomy functions, infra, ...

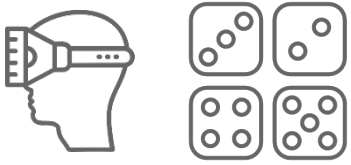


- Ensure that models in sim are fit for their test purpose
- Ensure match between simulation scenarios and road testing scenarios



- Need fallback options (e.g. MRC) in case safety cannot be assured
- Test boundary conditions very well

Simulation and Formal Methods can Make ADS Testing Efficient and Bridge the Gap with Road Testing



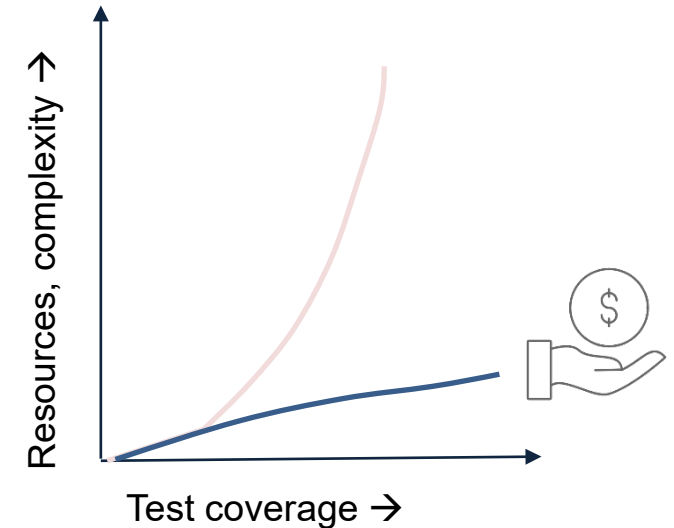
Simulation

- Efficiently search large space
- Create complex interactions safely



Formal methods

- Temporal logic
- Falsification
- Counterexample-guided retraining
- Parameter synthesis



“All models are wrong... but some are useful” – George P. Box

Overview of Scenic and VerifAI

SCENIC: Environment Modeling and Data Generation

- *Scenic* is a **probabilistic programming language** defining *distributions over scenes/scenarios*
- *Use cases*: data generation, test generation, verification, debugging, design exploration, etc.

```
model scenic.domains.driving.model

ego = Car

spot = OrientedPoint on visible curb
badAngle = Uniform(1.0, -1.0) * Range(10, 20) deg
parkedCar = Car left of spot by 0.5,
              facing badAngle relative to roadDirection
```

Example: Badly-parked car

Image
created
with
GTA-V



```
model scenic.domains.driving.model

behavior PullIntoRoad():
    while (distance from self to ego) > 15:
        wait
        FollowLaneBehavior(lane=ego.lane)

ego = Car with behavior DriveAvoidingCollisions

spot = OrientedPoint on visible curb
badAngle = Uniform(1.0, -1.0) * Range(10, 20) deg
parkedCar = Car left of spot by 0.5,
              facing badAngle relative to roadDirection,
              with behavior PullIntoRoad
```

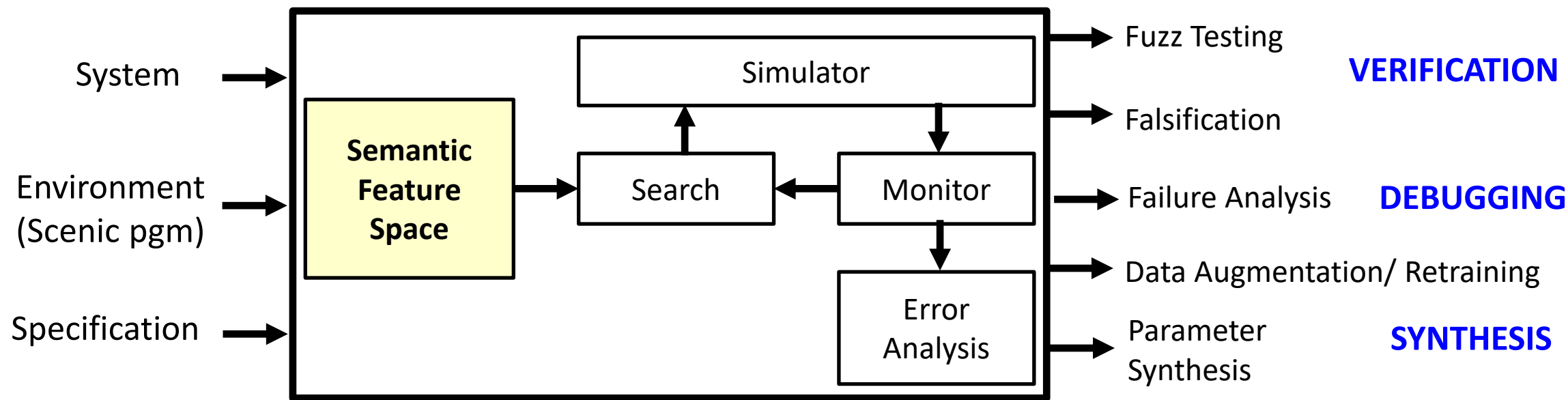


Video
created
with
CARLA

[D. Fremont et al., “Scenic: A Language for Scenario Specification and Scene Generation”, TR 2018, PLDI 2019.]

VERIFAI: A Toolkit for the Design and Analysis of AI-Based Systems

[Dreossi et al. CAV 2019, <https://github.com/BerkeleyLearnVerify/VerifAI>]



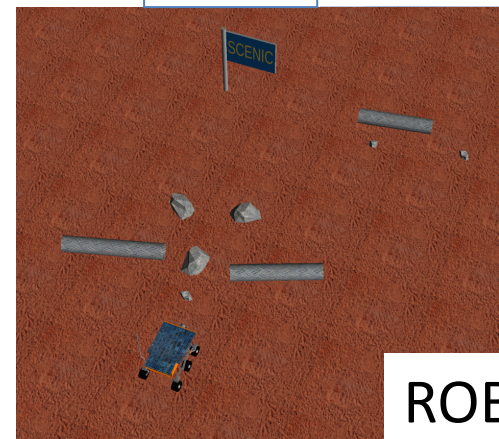
Webots

GTA-V

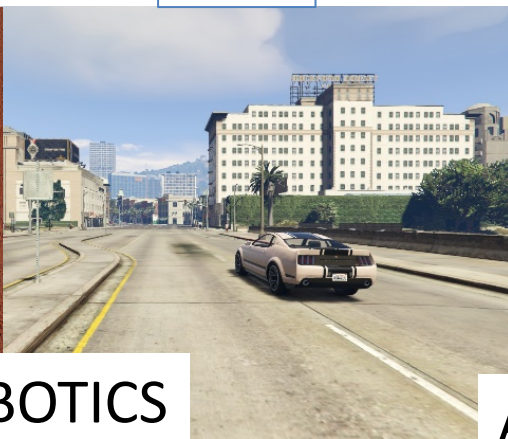
LGSVL

CARLA

X-Plane



ROBOTICS



AUTONOMOUS DRIVING



AIRCRAFT

Relevant Use Cases for Scenic and VerifAI

- Scenic Programs can specify ODDs and Test Scenarios
- Can specify Safety Properties/Metrics in VerifAI
- Scenic+VerifAI can
 - Automatically generate tests in simulation
 - Automatically find edge cases to safety
 - Generate data for training and testing ML models and perception
 - Automatically synthesize parameters for ML, planning, control
 - Debug and explain the behavior of perception, planning, control systems
 - Bridge the gap between simulation-based assessment and real-world/road testing
 - ...

Industrial Case Study:

**Formal Scenario-Based Testing
in Simulation and the Real World**

3-Way Project Collaboration



Northern California
Nevada & Utah



A. Acharya, P. Wells, X. Bruso

GoMentum Station proving ground
4Active pulley equipment,
pedestrian dummy, OxTS IMU,
dGPS, etc.



**S. A. Seshia, D. Fremont, E. Kim,
Y. V. Pant, H. Ravanbakhsh**

SCENIC scenario description
language,
VerifAI toolkit for design and
verification of AI based systems



LG Electronics R&D

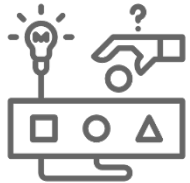
S. Lemke, Q. Lu, S. Mehta

LGSVL Simulator (open source)
LG's research AV with Baidu's
Apollo autonomy stack

Key Research Questions



#1 Safety violations in simulation: Do they transfer to the **real world**? How well?



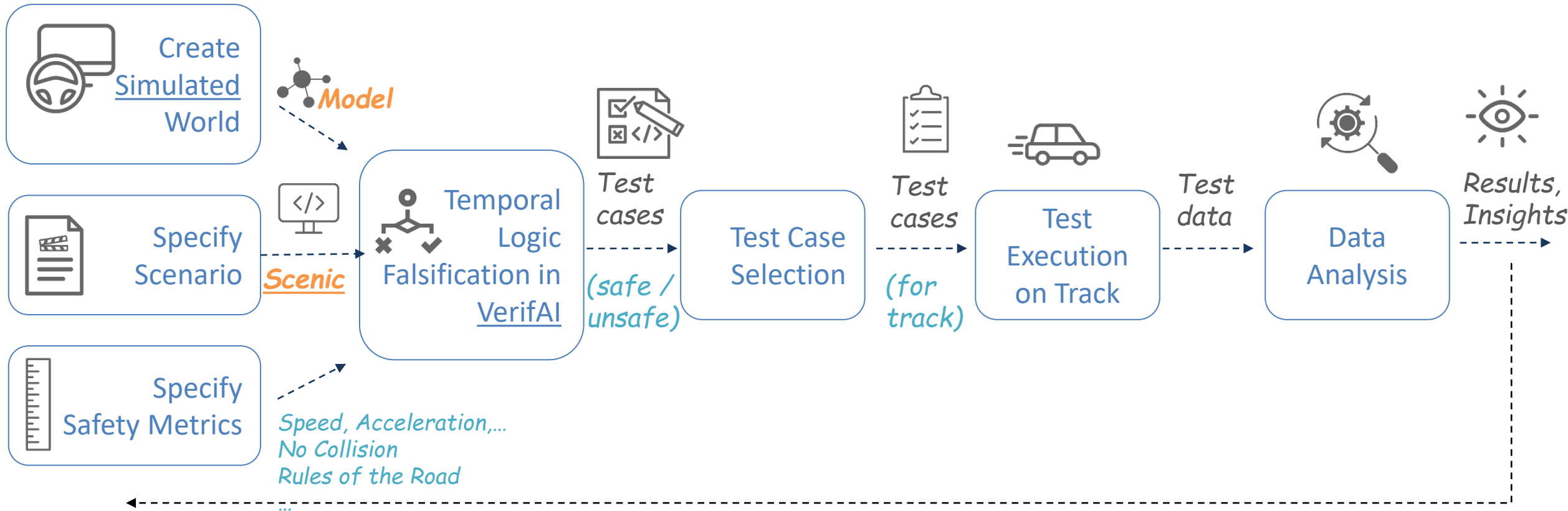
#2 Effective real-world testing: Can we use **formally guided simulation** to design effective **real-world tests**?

First use of formal methods for scenario-based testing of AI-based autonomy in both simulation and real world



Fremont, Kim, Pant, Seshia, Acharya, Bruso, Wells, Lemke, Lu, Mehta, ***“Formal Scenario-Based Testing of Autonomous Vehicles: From Simulation to the Real World”***, Arxiv e-prints, <https://arxiv.org/abs/2003.07739> [appearing **ITSC 2020**]

Formal Scenario-Based Testing (with Scenic and VerifAI)



Source: Fremont et al., "Formal Scenario-Based Testing of Autonomous Vehicles: From Simulation to the Real World", Intelligent Transportation Systems Conference (ITSC) 2020, to appear. <https://arxiv.org/abs/2003.07739>

Scenario Overview: Focus on Vulnerable Road Users (VRUs)

+53%



Pedestrian fatalities: 53% increase in the last decade (2009-2019)
2019: ~6500 (estimated)

17%



Of all traffic fatalities, 17% are **Pedestrians**

67%



Fatalities at **night** (low-light, limited vision environment)

Source:

GHSA: https://www.thecarconnection.com/news/1127308_pedestrian-deaths-reach-30-year-high-in-2019

IIHS: <https://www.iihs.org/topics/pedestrians-and-bicyclists>

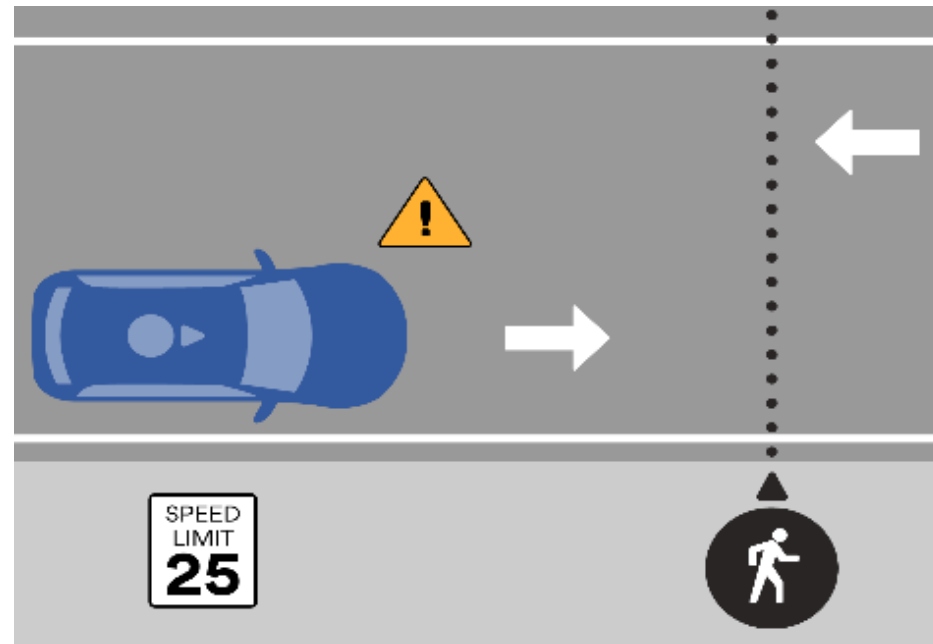
Test Equipment and Use at AAA GoMentum Testing Grounds

Robotic platform for Test Targets



Scenario Execution

[Shows EuroNCAP VRU AEB]



Scenario Evaluation

Object & Event Detection/Response: Metrics & Evaluation

- Object detection
- Time to collision
- Separation distance
- Deceleration profile
- Autonomy Disengagement

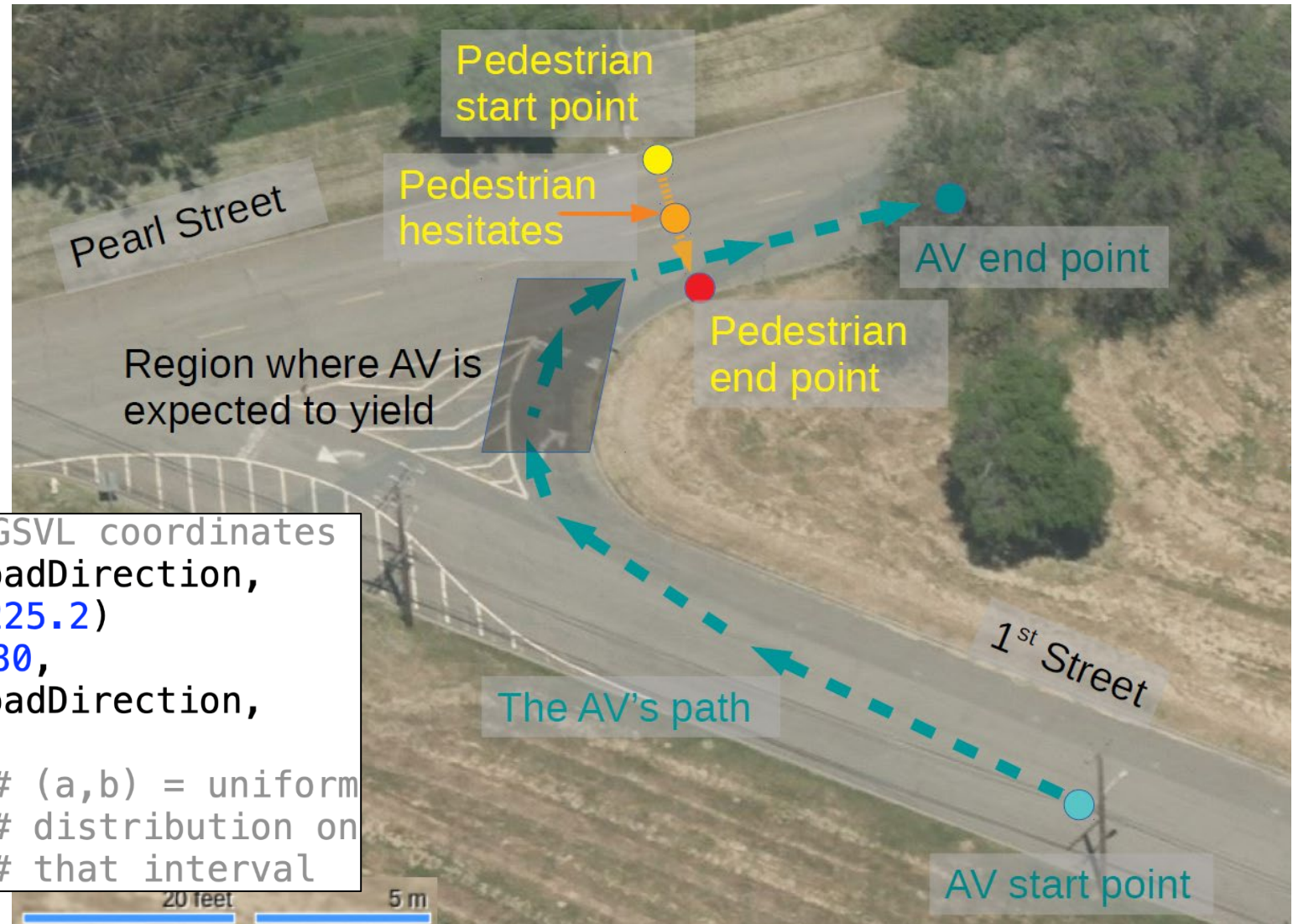
Example Scenario: AV making right turn, pedestrian crossing



Lincoln MKZ running Apollo 3.5

```
ego = EgoCar at 38.6 @ 183.9, # LGSVL coordinates  
    facing 10 deg relative to roadDirection,  
    with behavior DriveTo(40 @ 225.2)  
ped = Pedestrian at 19.782 @ 225.680,  
    facing 90 deg relative to roadDirection,  
    with behavior Hesitate,  
    with startDelay (7, 15), # (a,b) = uniform  
    with walkDistance (4, 7), # distribution on  
    with hesitateTime (1, 3) # that interval
```

Snippet of Scenic program



Results: Falsification and Test Selection

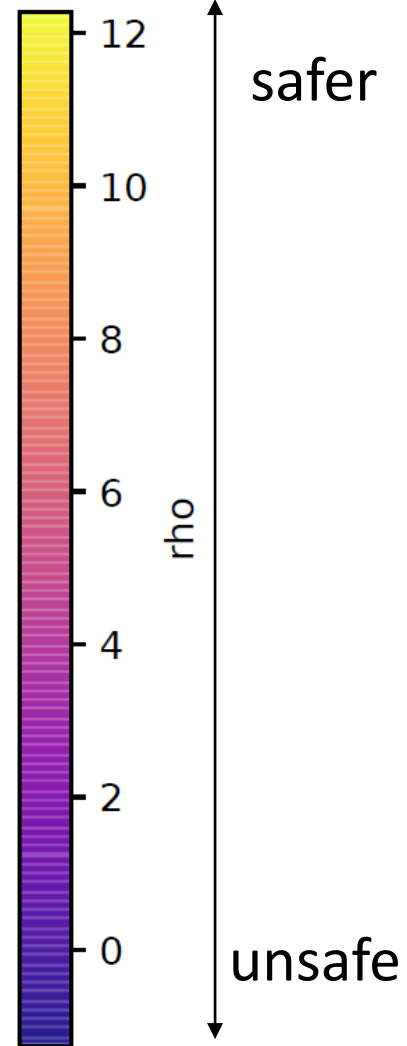
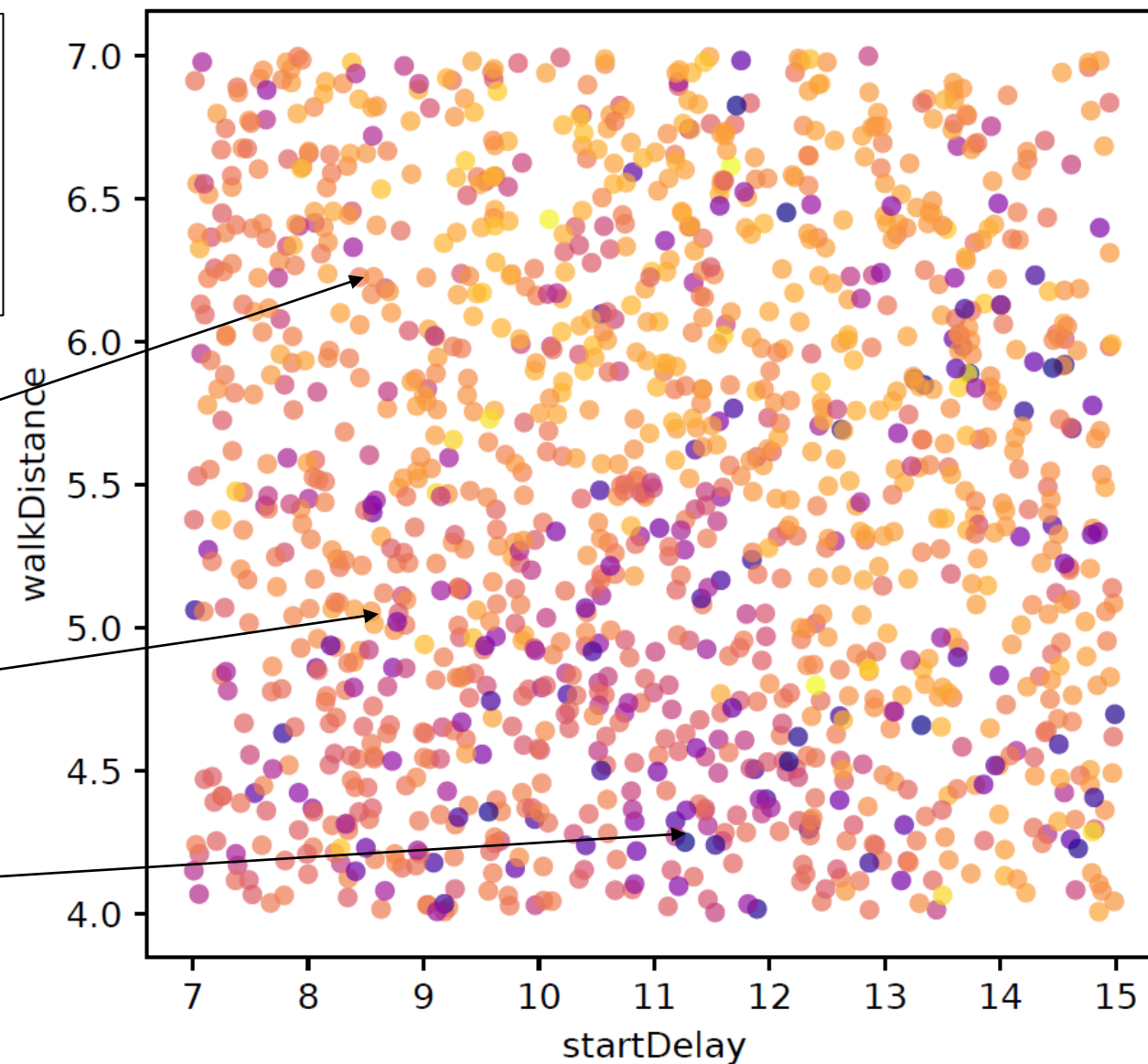
1294 simulations explored
2% violated safety property

Total 7 test cases selected

S2: robustly safe

M2: marginally safe

F2: collision



Results: Does Safety in Simulation → Safety on the Road?

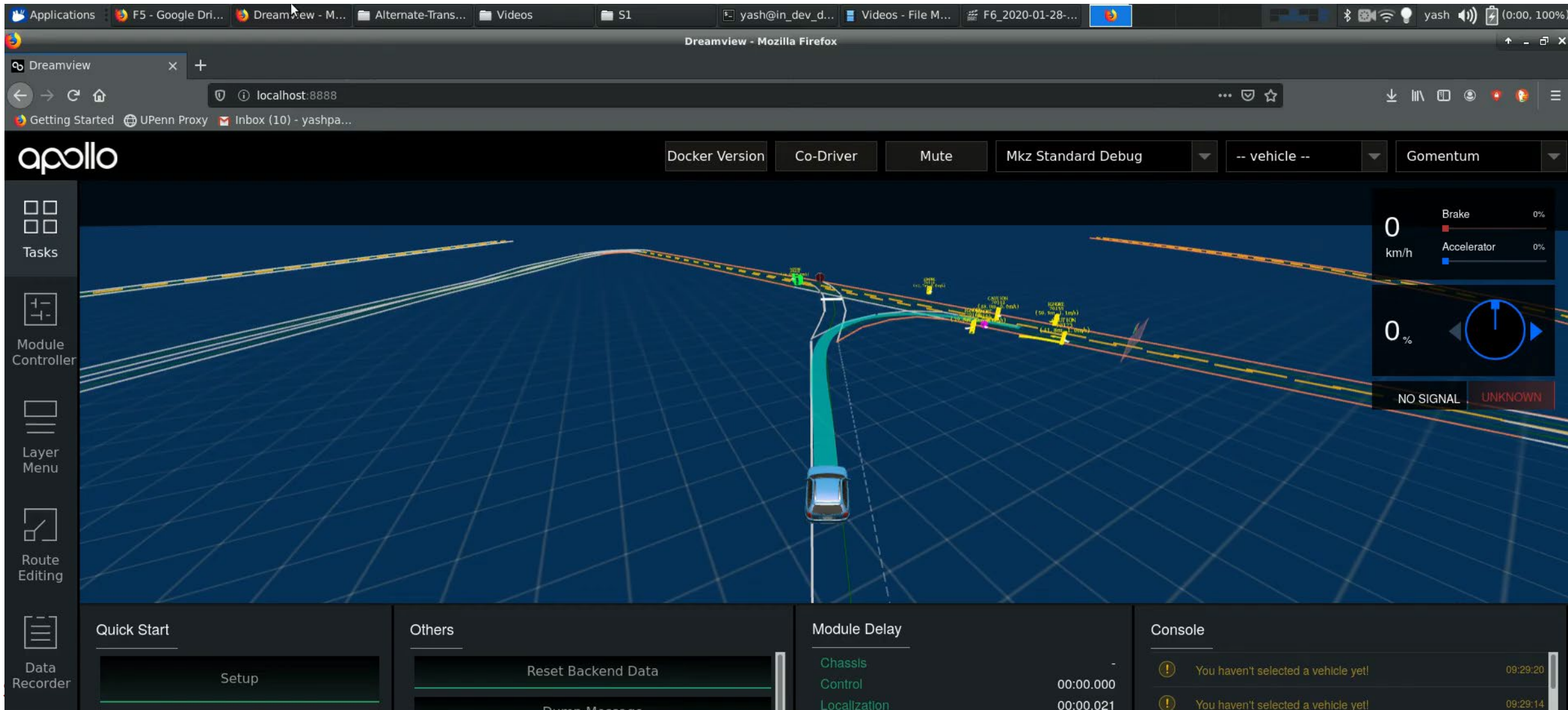
Unsafe in simulation → unsafe on the road: **62.5% (incl. collision)**

Safe in simulation → safe on the road: **93.5% (no collision)**



Results: Why did the AV Fail?

Perception Failure: Apollo 3.5 lost track of the pedestrian several times



Results: How well do the trajectories match?



S1 Run 2



F1 Run 1

Green – AV real
Blue – AV sim

Orange – Ped real
Yellow – Ped sim

Conclusion

- Scenic allows easy modeling of complex scenarios for AI-based autonomy + associated data generation
- VerifAI covers range of design, verification, and debugging tasks for AI-based autonomy
- ITSC 2020 Case Study: Scenic+VerifAI can be used to bridge the simulation-to-real world testing gap
 - Effectively evaluate safety via formally-guided simulation
 - Reduce expense of real-world testing by orders of magnitude
- Up next: 1 hour tutorial will give further details on Scenic and VerifAI and use cases for both tools

Ongoing Work and Directions

- Compiling a library of scenarios in Scenic
- Evaluation on more complex, higher-dimensional scenarios
- New algorithms for formal verification and synthesis
- Tools for automated analysis/triage of failure cases
- Improvements in track testing equipment and their connection to simulation

and more...

We welcome participation from the community!

<https://github.com/BerkeleyLearnVerify/VerifAI>

<https://github.com/BerkeleyLearnVerify/Scenic/>

Acknowledgments: Contributors, Co-authors, Collaborators

UC Berkeley

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Thank you!