

# *Scenic:* An Open-Source Probabilistic Programming System for Data Generation and Safety in AI-Based Autonomy

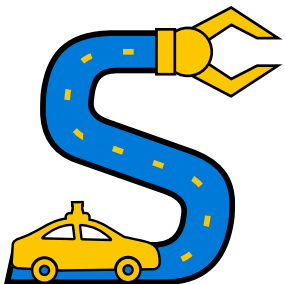
**Daniel J. Fremont**

**Edward Kim**

**Sanjit A. Seshia**

UC Santa Cruz

UC Berkeley



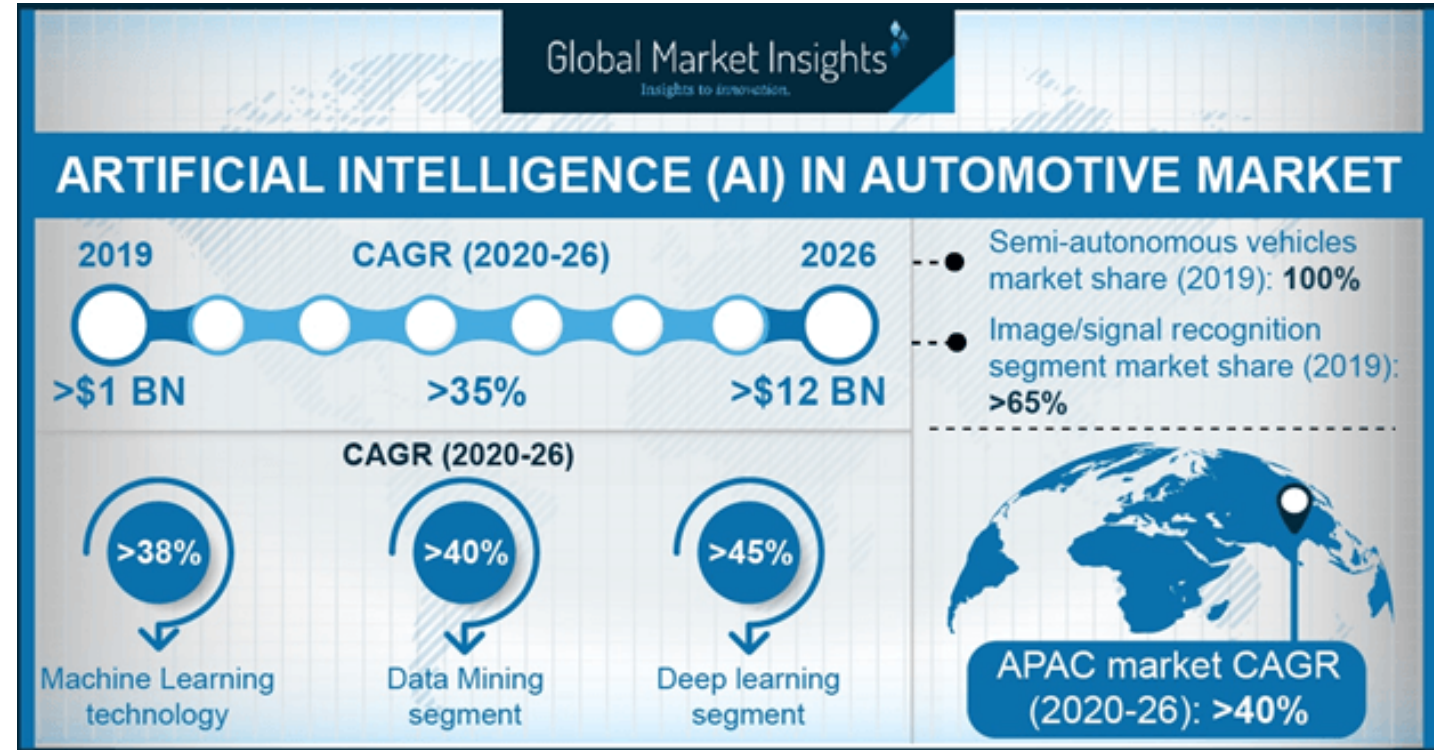
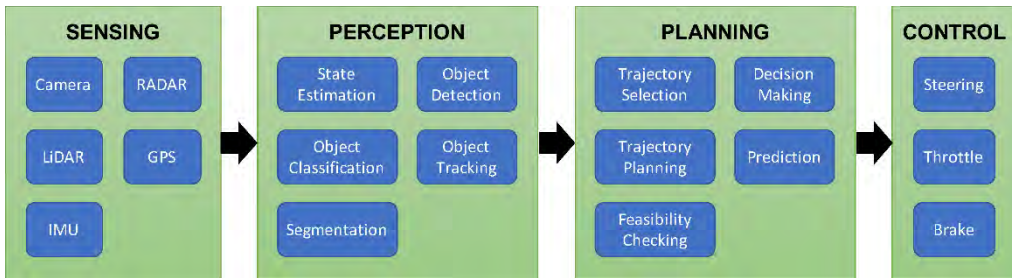
Thanks to our many Scenic Team Members and Contributors  
<https://docs.scenic-lang.org/en/latest/credits.html>

<https://scenic-lang.org>

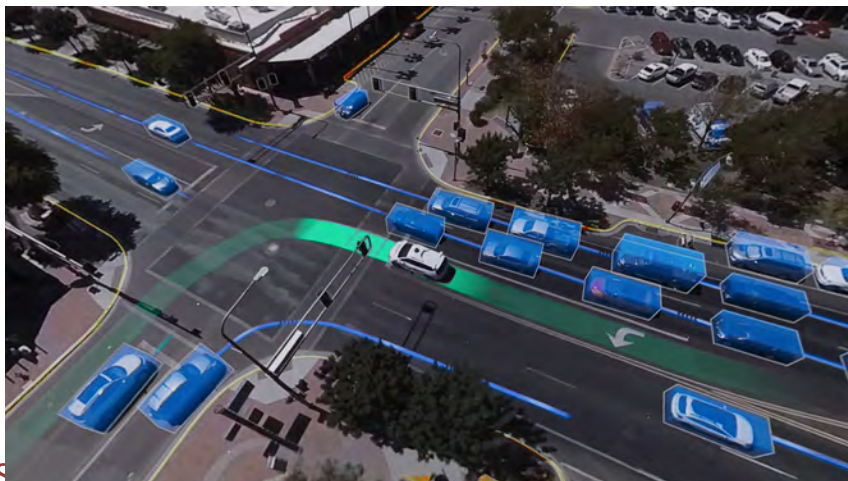
CVPR Tutorial  
June 17, 2024

<https://scenic-lang.org/cvpr24/>

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



Source: gminsights.com



Source: Waymo



# Lack of Safety, Dependability, Robustness a Major Obstacle



2015

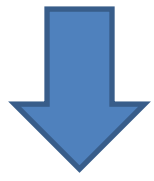
## Self-driving cars: from 2020 you will become a permanent backseat driver

Driverless cars will revolutionise motoring, claim the manufacturers. But is the greatest danger that they will be too safe?

**Tim Adams**

@TimAdamsWrites

Sun 13 Sep 2015 05.05 EDT



2021

## Self-Driving Cars Could Be Decades Away, No Matter What Elon Musk Said

Experts aren't sure when, if ever, we'll have truly autonomous vehicles that can drive anywhere without help. First, AI will need to get a lot smarter.

By *Christopher Mims*

Follow

Jun. 5, 2021 12:00 am ET

## Cruise's Driverless Taxi Service in San Francisco Is Suspended

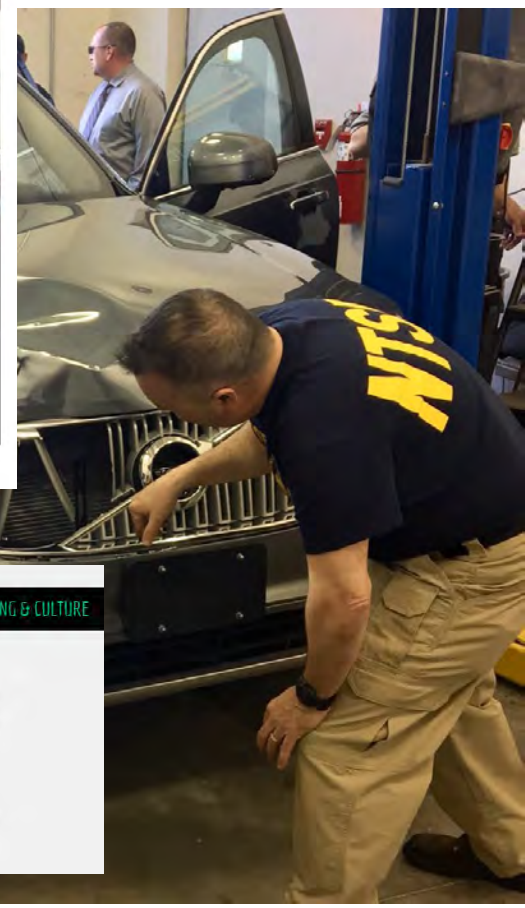
Oct. 24, 2023



## Tesla driver dies in first fatal autonomous car crash in US



Hands-off driving faces tough questions  
Beck Diefenbach/Reuters



BIZ & IT TECH SCIENCE POLICY CARS GAMING & CULTURE

### DRIVERLESS CAR SAFETY —

## Report: Software bug led to death in Uber's self-driving crash

Sensors detected Elaine Herzberg, but software reportedly decided to ignore her.

# The *Verified AI* Research Agenda

**Create a *Design Flow* for AI-based Autonomy supported by Theory, Techniques, and Tools ensuring Safety, Dependability, and Robustness**

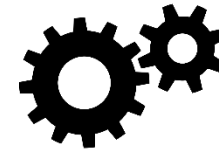
S. A. Seshia, D. Sadigh, S. S. Sastry. *Towards Verified Artificial Intelligence*.  
July 2016. <https://arxiv.org/abs/1606.08514>. Revision in Communications of the ACM, July 2022.

# Formal Methods: A Key Enabler for Design of Safe AI

Precise, Programmatic **Environment/System Modeling**




  $\varphi$  Mathematical **Specification of Requirements and Metrics**



Scalable Algorithms for **Verification, Synthesis, Testing, Debugging**



 Methodologies for **Provably-Robust System Design**



# Scenic

High-Level, Probabilistic Programming  
Language for World/Environment Modeling

# VerifAI

Requirements Specification + Algorithms  
for Design, Verification, Testing, Debugging



**Open-Source Tools**

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

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

for

## Industry

Improve assurance of industrial AI systems

## Academia

Leverage tools in research & education

## Government/ Regulators

Evaluate the safety of AI-based autonomy

Share Scenarios and Metrics

**Community**

Develop Corpus of Tools and Data

# Tutorial Outline

- Overview of Scenic and Its Applications
    - Scenic, VerifAI, and Two Industrial Case Studies
  - Introduction to the Scenic 3.0 Language
    - Major Language Features with Examples and Hands-On Coding
- Coffee Break*
- Applications of Scenic
    - Systematically test and debug perception, behavior prediction, and planning components or the full autopilot stack in simulation
    - Generate sensor data (e.g. RGB, LiDAR) and labels (e.g. segmentation, 3D bounding boxes) using Scenic, and perform sim-to-real validation
  - Ongoing and Future Directions
    - Extended Reality, Large Language Models, and more...



# 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 = new Car

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

## Example: Badly-parked car



Image  
created  
with  
GTA-V

```
model scenic.simulators.carla.model

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

ego = new Car with behavior EgoBehavior()

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



Video  
created  
with  
CARLA

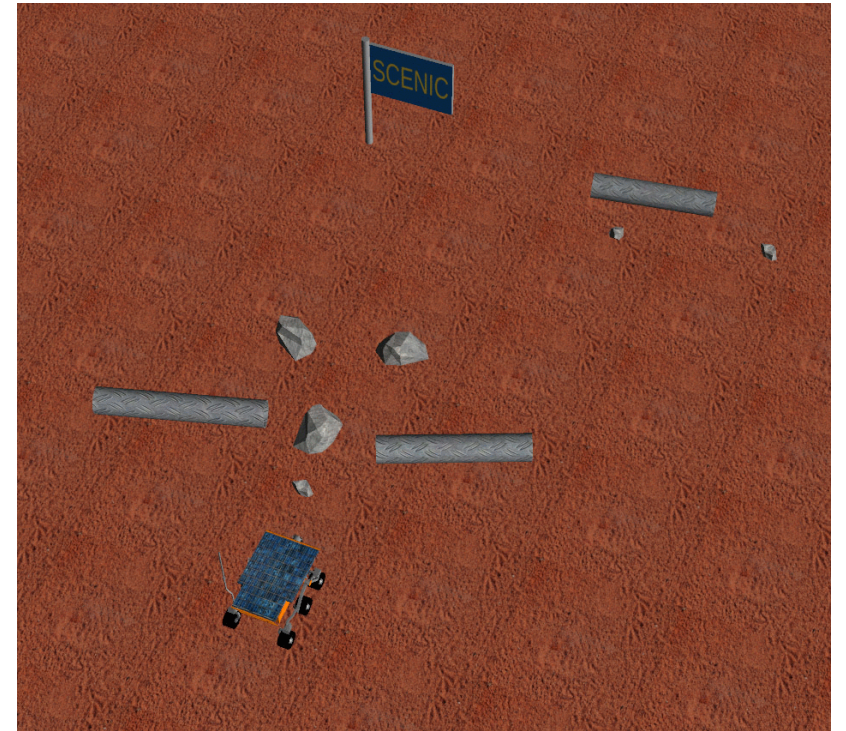
[D. Fremont et al., "Scenic: A Language for Scenario Specification and Scene Generation", TR 2018, PLDI 2019,



# Some Applications of Scenic

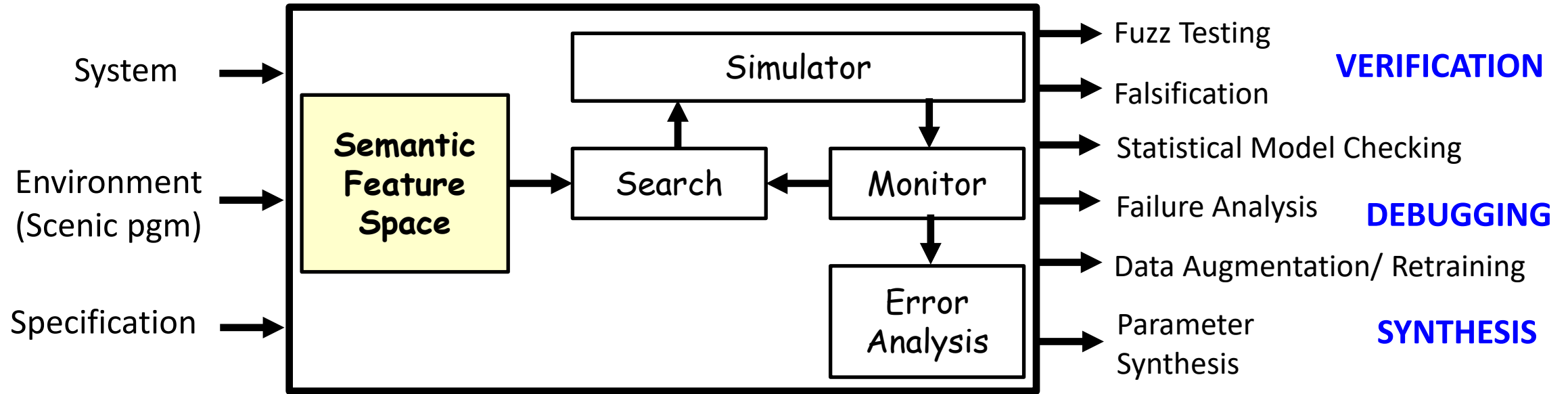
[see PLDI'19, MLJ'22 papers]

- Modeling, testing, verification
  - Generating specialized test sets
- Debugging a known failure
  - Generalizing in different directions
- Designing more effective training sets
  - Training on hard cases
- Design space exploration



# VERIFAI: A Toolkit for the Design and Analysis of AI-CPS

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



Webots

GTA-V

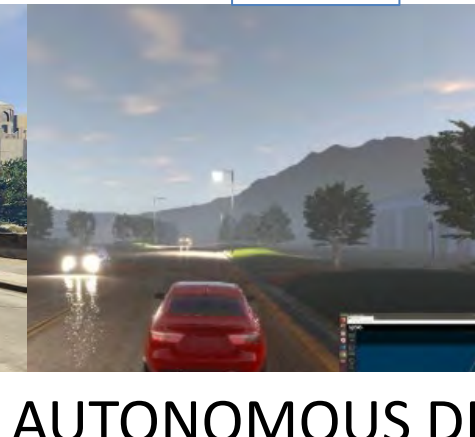
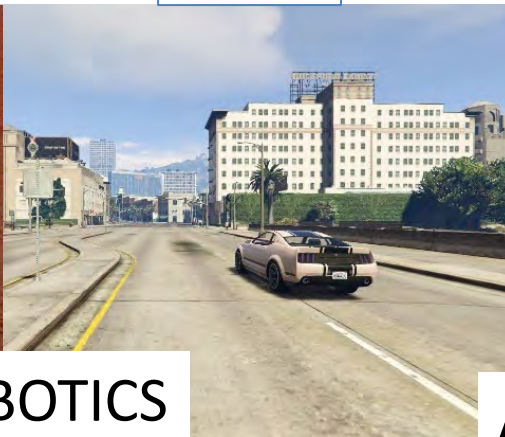
LGSVL

CARLA

X-Plane



ROBOTICS



AUTONOMOUS DRIVING



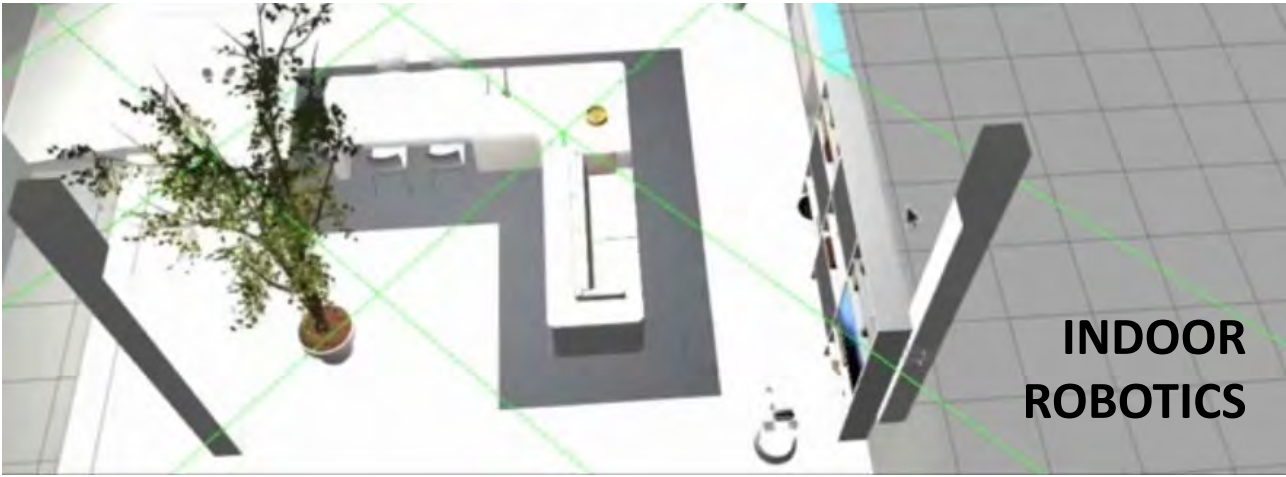
AIRCRAFT



# Many Application Domains



**AUTONOMOUS VEHICLES**



**INDOOR ROBOTICS**



**MULTI-AGENT LEARNING SYSTEMS**



**AEROSPACE SYSTEMS**



**AUGMENTED REALITY**



# A Full Design Iteration: Autonomous Airplane Taxiing

Modeling → Verification → Synthesis/Training  
→ Run-Time Assurance



Assured Autonomy

Collaboration with:

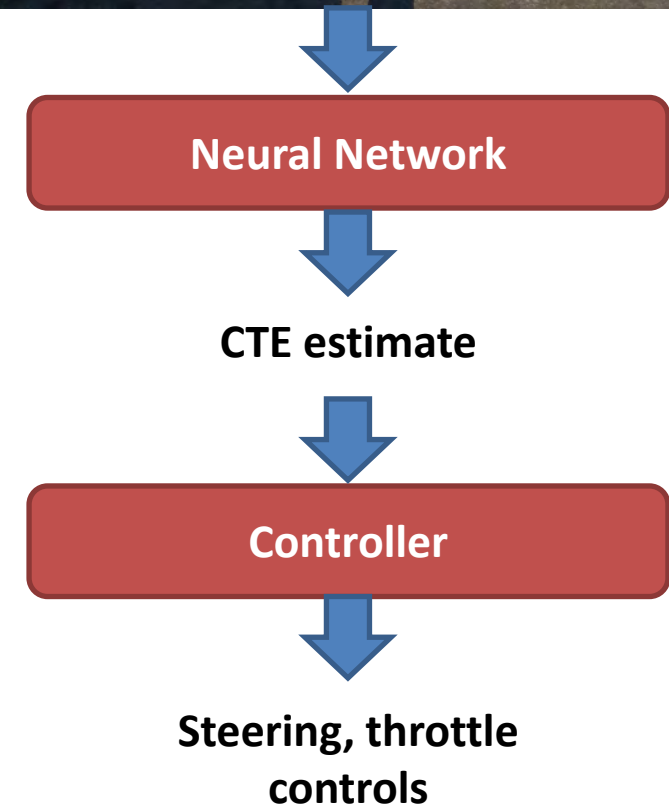
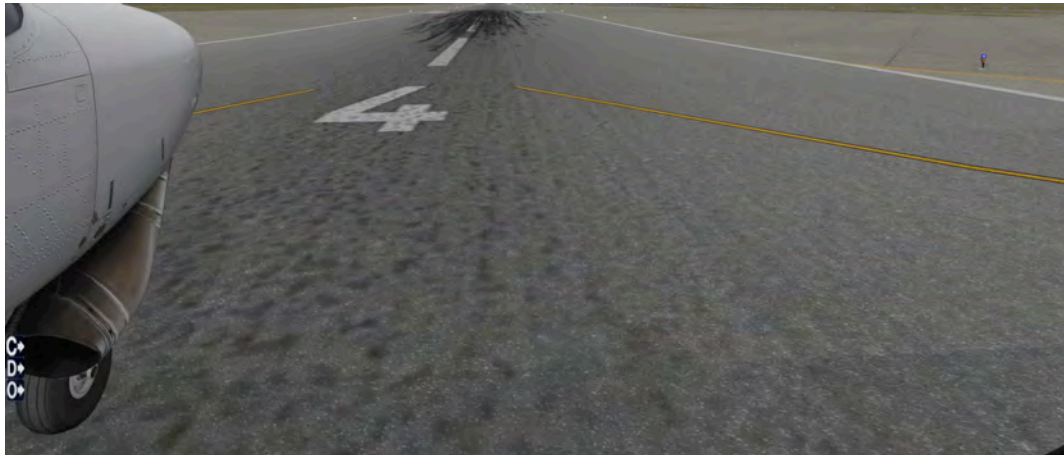


D. Fremont et al. *Formal Analysis and Redesign of a Neural Network-Based Aircraft Taxiing System with VerifAI*. In 32nd International Conference on Computer Aided Verification (CAV), July 2020.

H. Torfah et al. *Learning Monitorable Operational Design Domains for Assured Autonomy*. In Proceedings of the International Symposium on Automated Technology for Verification and Analysis (ATVA), October 2022.

# TaxiNet: Deep Learning for Autonomous Taxiing

- Experimental autonomous aircraft taxiing system developed by Boeing
- Neural network uses camera image to estimate the *cross-track error*
  - CTE = distance from centerline
- Specification: plane must track centerline to within 1.5 meters



# A Full Design Iteration using Scenic & VerifAI

- **Modeling** runway scenarios in SCENIC
- **Specifying** the safety requirement
- **Falsifying** the system, finding scenarios when it violates its safety specification
- **Debugging** to find distinct failures and their root causes
- **Retraining** the neural network to eliminate failures and improve performance
- **Runtime assurance** to predict and handle unsafe situations at run time





# Modeling with the Scenic Language

```
model scenic.simulators.xplane.model

# Time of day: from 6am to 6pm. (+8 to get GMT, as used by X-Plane)
param zulu_time = (Range(6, 18) + 8) * 3600 # in seconds

# Rain: 1/3 of the time.
# Clouds: rain requires types 3-5; otherwise, 0-5.
clouds_and_rain = Options({
    tuple([Uniform(0, 1, 2, 3, 4, 5), 0]): 2,
    tuple([Uniform(3, 4, 5), (0.25, 1)]): 1
})

param cloud_type    = clouds_and_rain[0]
param rain_percent  = clouds_and_rain[1]

# Plane: up to 8m left/right, 2000 m down the runway, 30 deg left/right
ego = new Plane at Range(-8, 8) @ Range(0, 2000),
    facing Range(-30, 30) deg
```

**Semantic features:**  
time, clouds, rain,  
position/  
orientation of plane  
on the runway

# Falsification: Algorithmic Search for Unsafe Behaviors

1. Specify safety condition as temporal logic assertion

$$\varphi_{\text{eventually}} = \diamond_{[0,10]} \square (\text{CTE} \leq 1.5)$$

2. Transform assertion into cost function

$$\rho_{\text{eventually}} = \sup_{t \in [0,10]} \inf_{[t,\infty]} (1.5 - \text{CTE}(t))$$

3. Find safety violation by minimizing cost function

- Cost function  $< 0 \rightarrow$  Safety violation

- Falsification: out of  $\sim 4,000$  auto-generated simulations

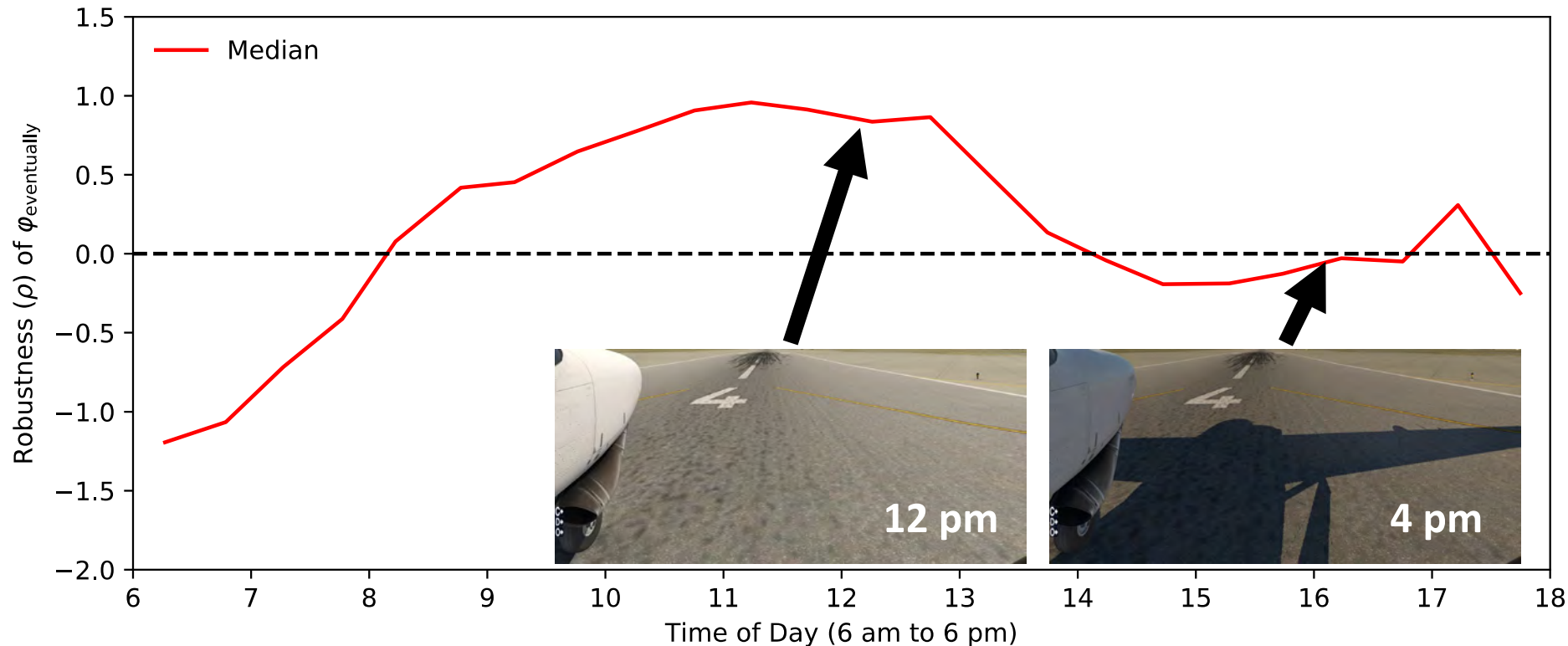
- **45% violated**  $\varphi_{\text{eventually}}$

- **9% left runway entirely**



# What Went Wrong? → Debugging & Root Causing

- Falsification found several types of failures, e.g. sensitivity to time

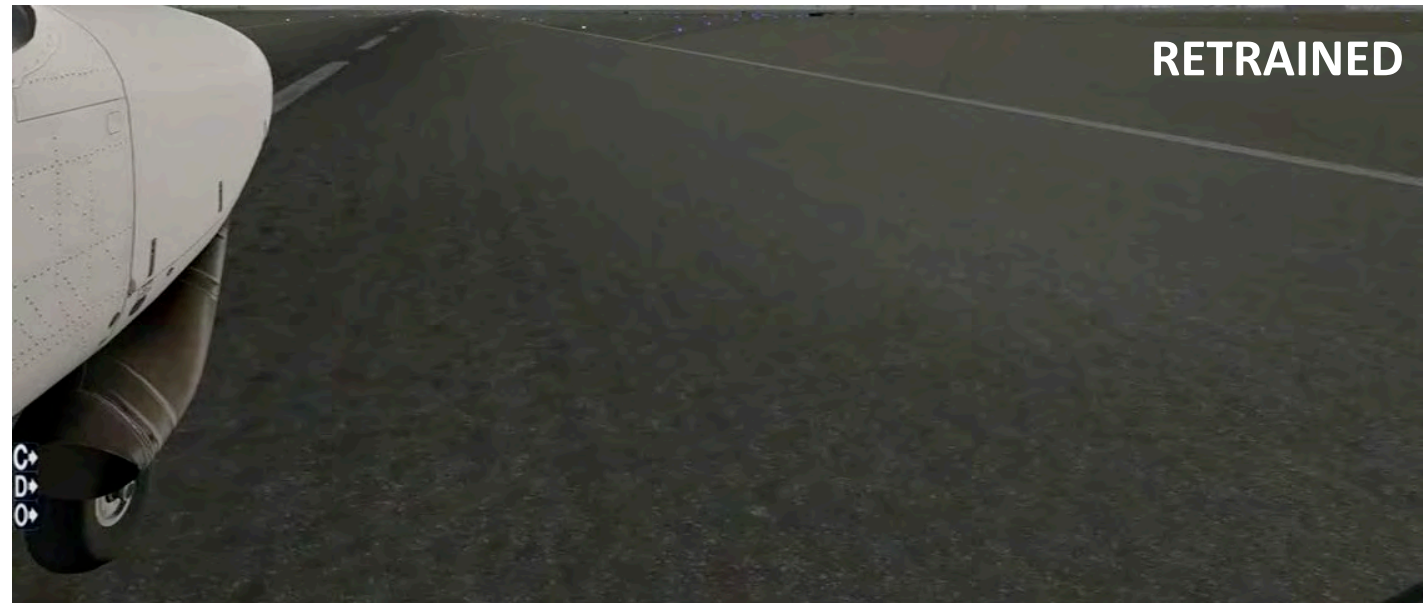


- Follow-up experiments confirmed root cause is the plane's shadow



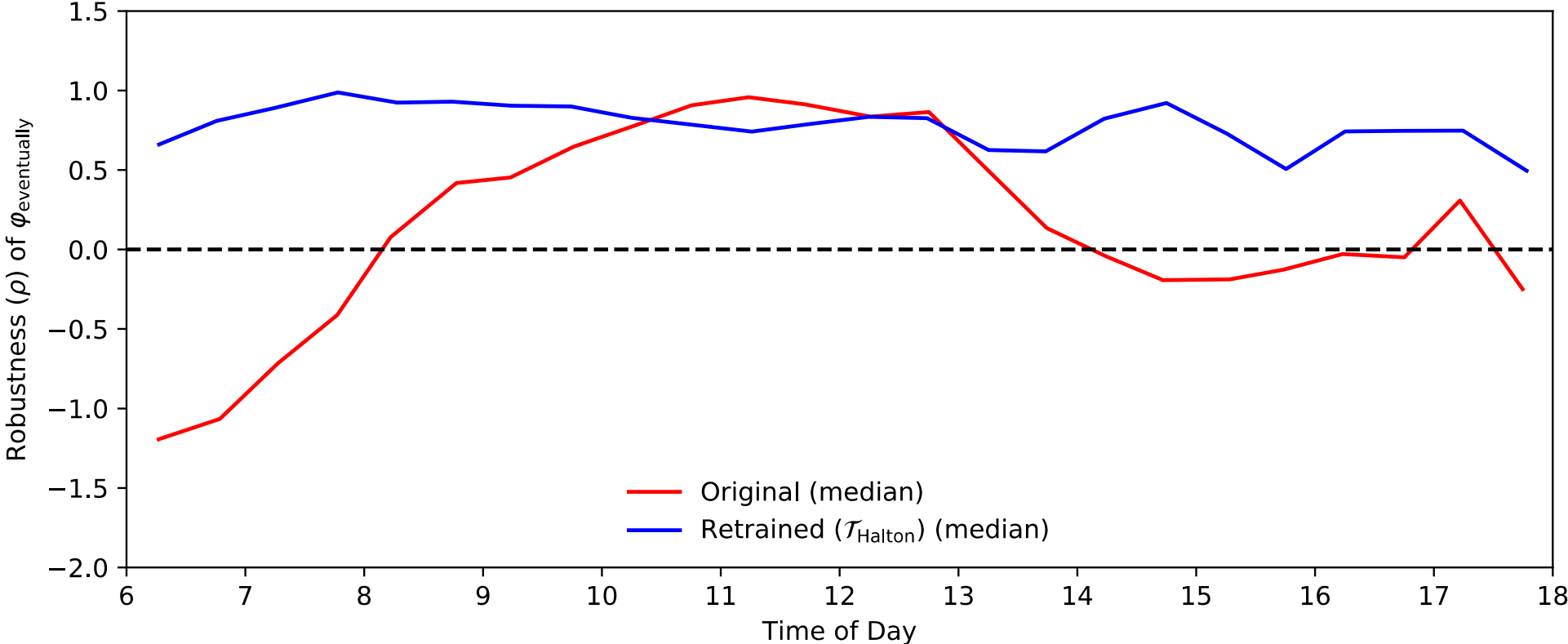
# Scenic-Guided Retraining

- Use VERIFAI to generate a new training set (same size as original)
- Obtained much better performance
  - **17%** violated  $\varphi_{\text{eventually}}$  (vs. 45%)
  - **0.6%** left runway entirely (vs. 9%)



# Retraining

- Eliminated dependence on time of day



# Robust Operation: Runtime Monitoring and Failure Mitigation

- Automatically **extract environment assumptions** from Scenic model
- Use the **Simplex fault-tolerant architecture** with detection of potentially unsafe scenarios





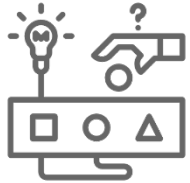
# From Simulation to Real-World Testing

D. Fremont et al. *Formal Scenario-Based Testing of Autonomous Vehicles: From Simulation to the Real World*. In 23rd IEEE International Conference on Intelligent Transportation Systems (ITSC), September 2020.

# From Simulation to Real-World Testing: Key Questions



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



**#2 Scenario testability:** Can we use formally guided simulation to effectively design 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, Brusio, 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> [ITSC 2020]

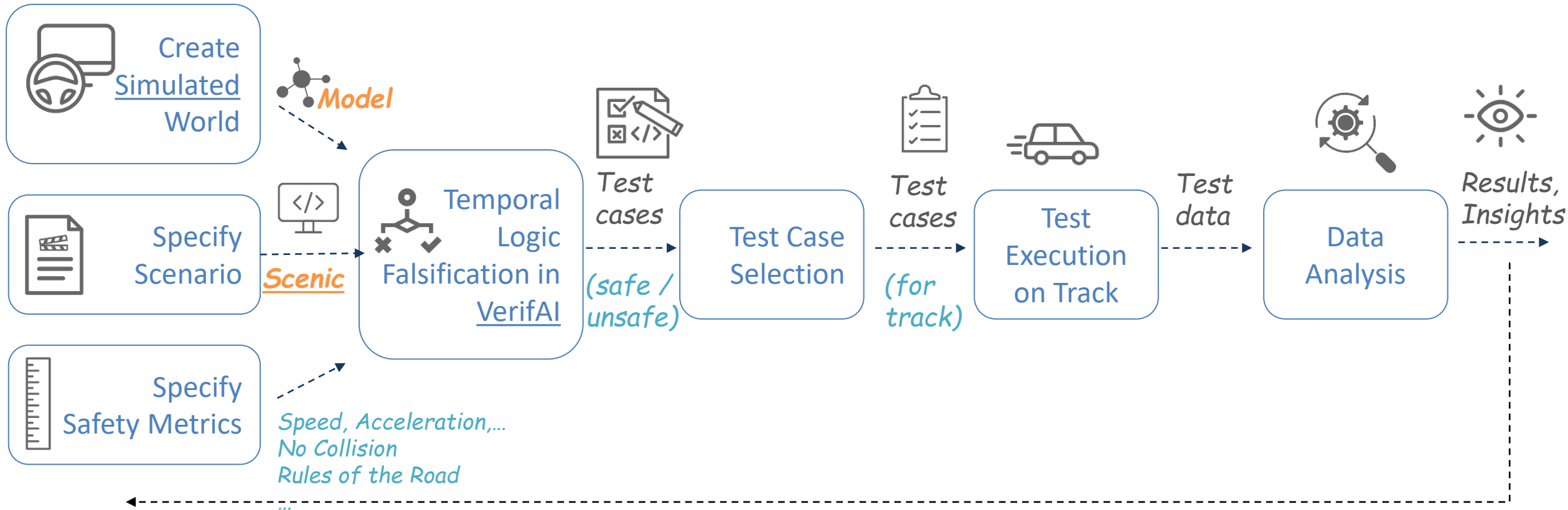


Owned and Operated by AAA NCNU



Simulation software to accelerate safe autonomous vehicle development

# 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), September 2020. <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](https://www.thecarconnection.com/news/1127308_pedestrian-deaths-reach-30-year-high-in-2019)

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

# Example Scenario: AV making right turn, pedestrian crossing

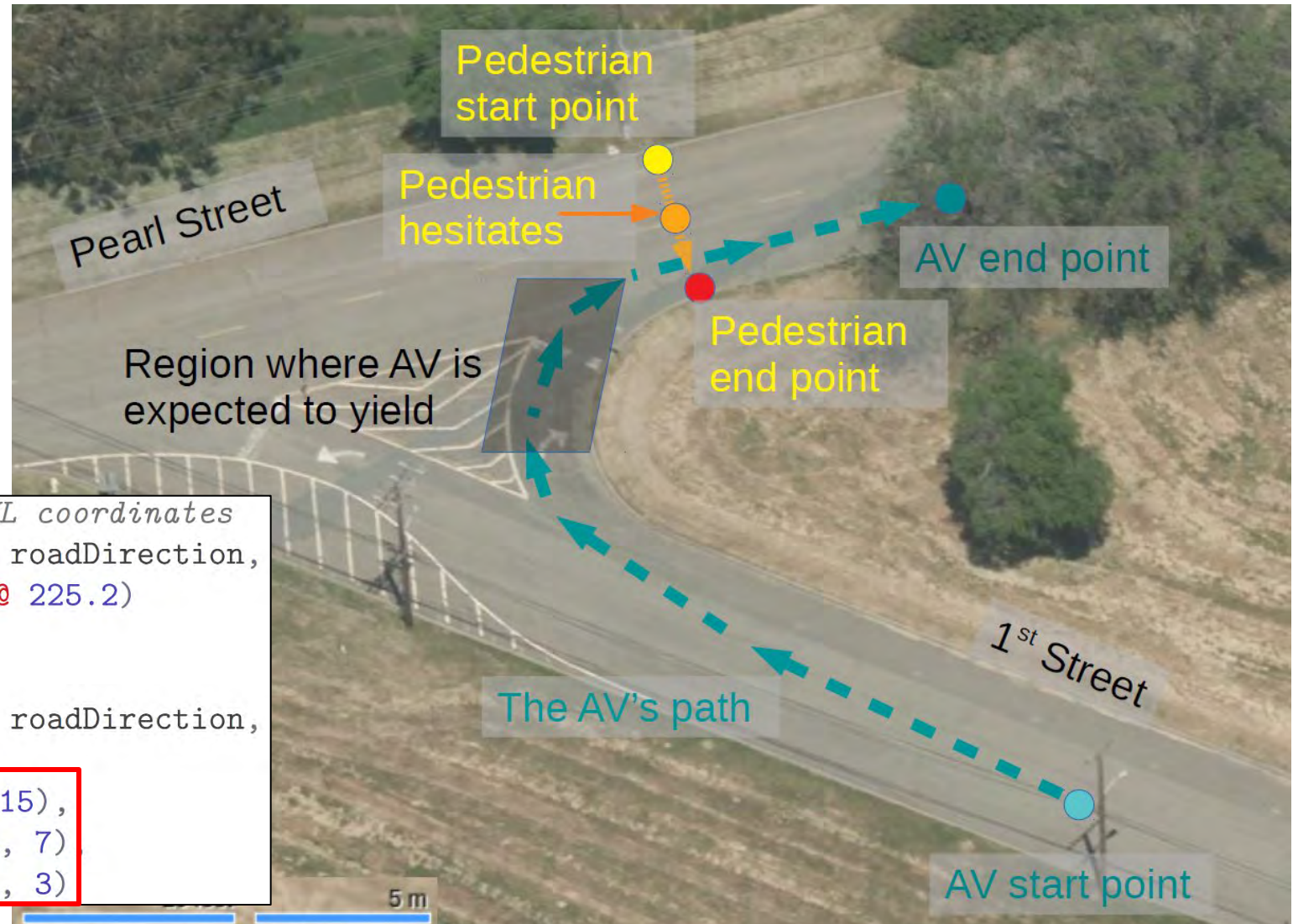


Lincoln MKZ running Apollo 3.5

```
ego = new Autopilot at 38.6 @ 183.9, # SVL coordinates
    facing 10 deg relative to roadDirection,
    with behavior DriveTo(40 @ 225.2)

ped = new Pedestrian at 19.78 @ 225.68,
    facing 90 deg relative to roadDirection,
    with behavior Hesitate()
    with startDelay Range(7, 15),
    with walkDistance Range(4, 7)
    with hesitateTime Range(1, 3)
```

Snippet of Scenic program





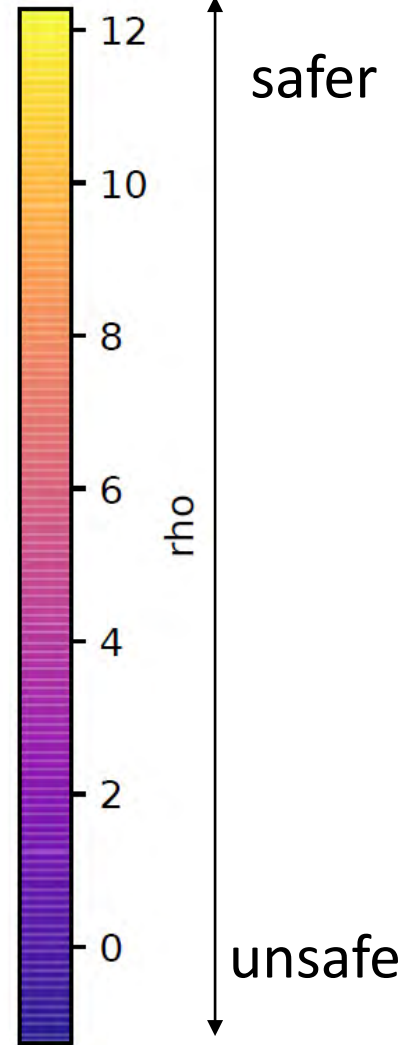
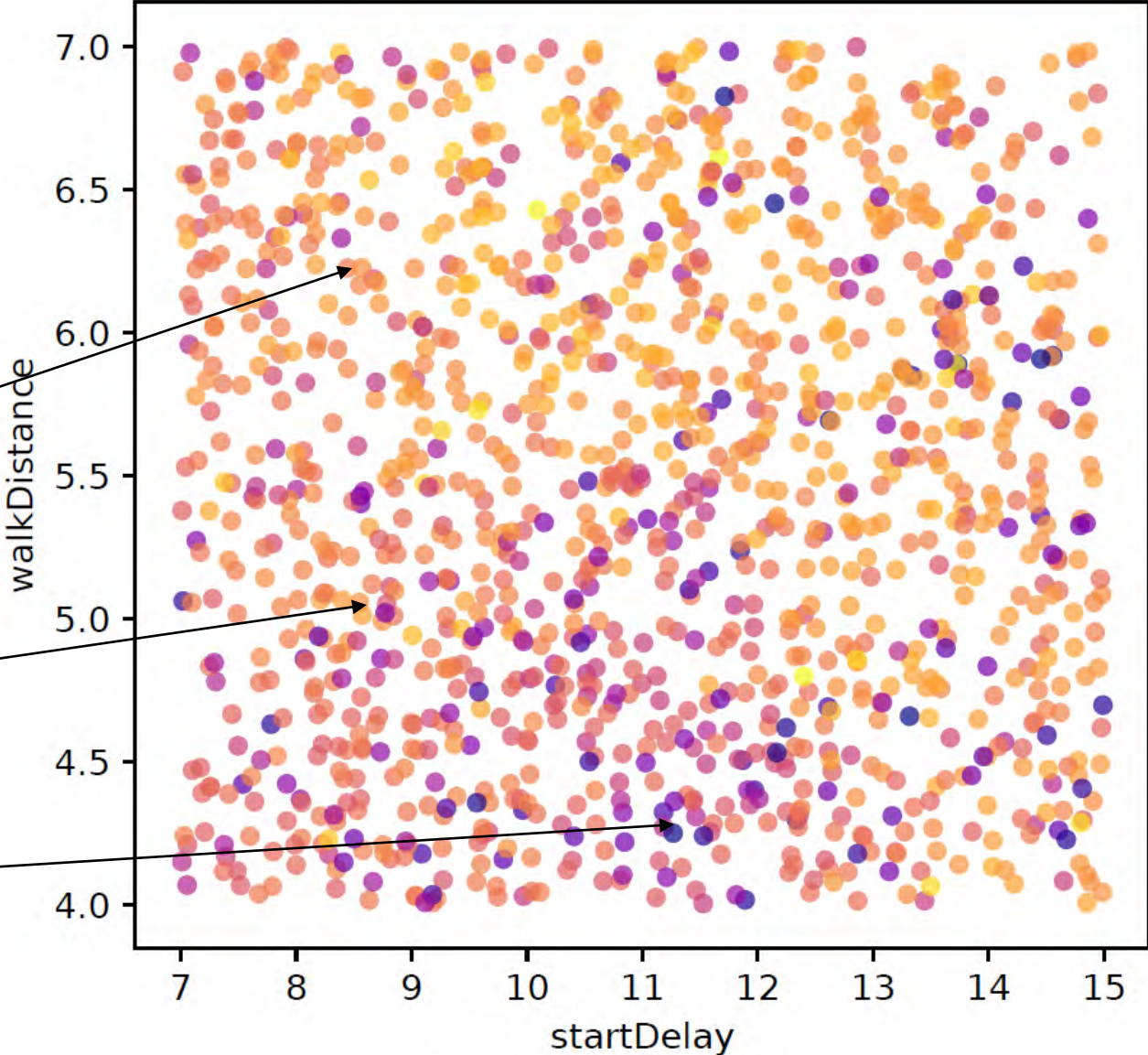
# Results: Falsification and Test Selection

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

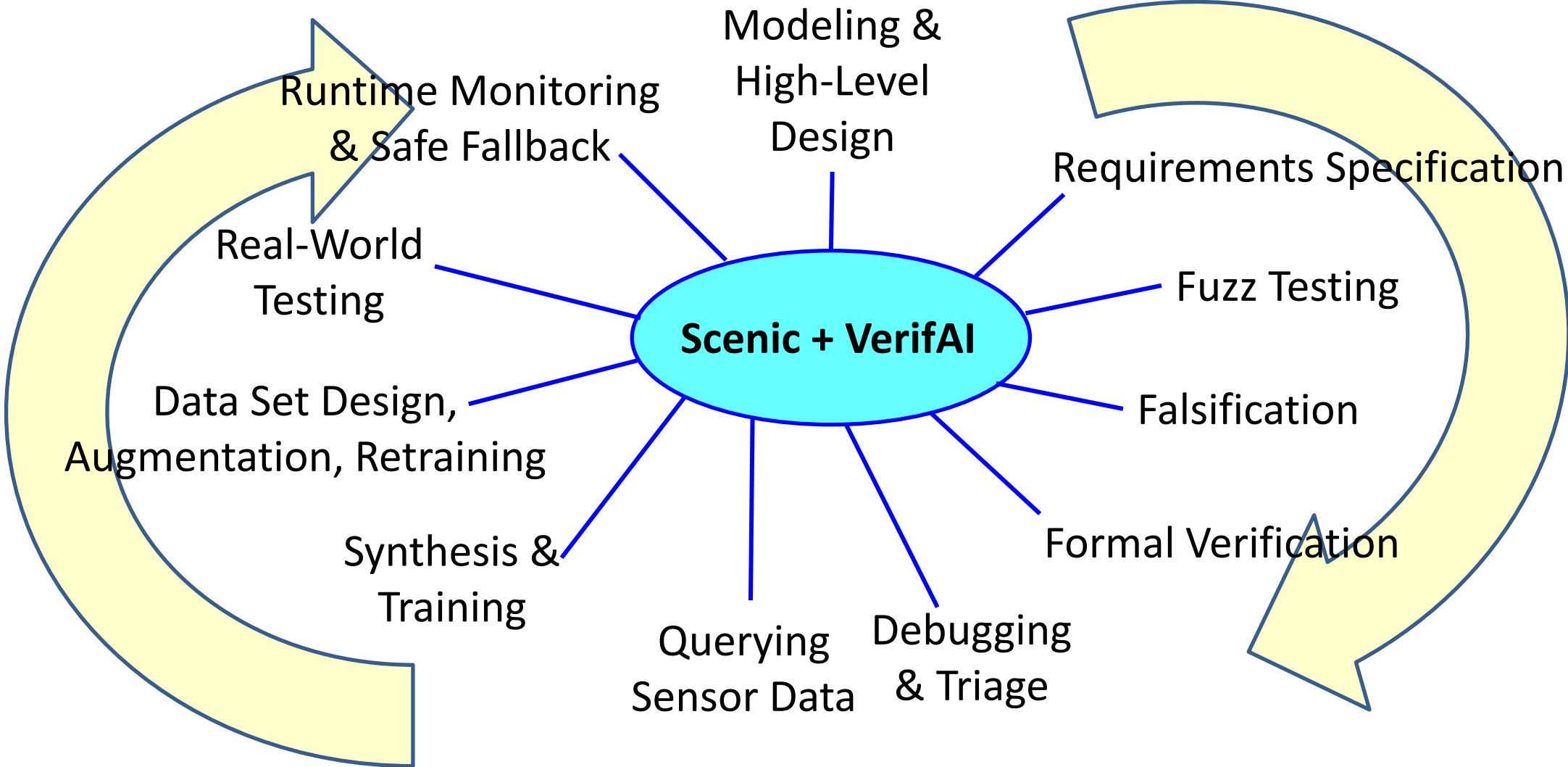
The screenshot shows the Apollo 3.5 simulation interface running in a Mozilla Firefox browser window. The browser's address bar shows 'localhost:8888'. The interface includes a top navigation bar with the 'apollo' logo and several control buttons: 'Docked Version', 'Co-Driver', 'Mute', 'Mkz Standard Debug', '-- vehicle --', and 'Gomentum'. On the left side, there is a vertical toolbar with icons for 'Tasks', 'Module Controller', 'Layer Menu', 'Route Editing', and 'Data Recorder'. The main area is a 3D simulation of a road with a blue car in the center. The road is marked with yellow dashed lines, and there are various colored markers and labels on the road, including 'CAUTION' and 'STOP'. On the right side, there is a control panel with 'Brake' and 'Accelerator' sliders, both set to 0%. Below the sliders is a circular gauge and a status indicator showing 'NO SIGNAL' and 'UNKNOWN'. At the bottom of the interface, there are several panels: 'Quick Start' with a 'Setup' button, 'Others' with a 'Reset Backend Data' button, 'Module Delay' with a table of delays, and 'Console' with a log of messages.

Module	Delay
Chassis	00:00.000
Control	00:00.000
Localization	00:00.021

Console Log:

- You haven't selected a vehicle yet! 09:29:20
- You haven't selected a vehicle yet! 09:29:14

# Ecosystem of Design Tools for AI-based Autonomy

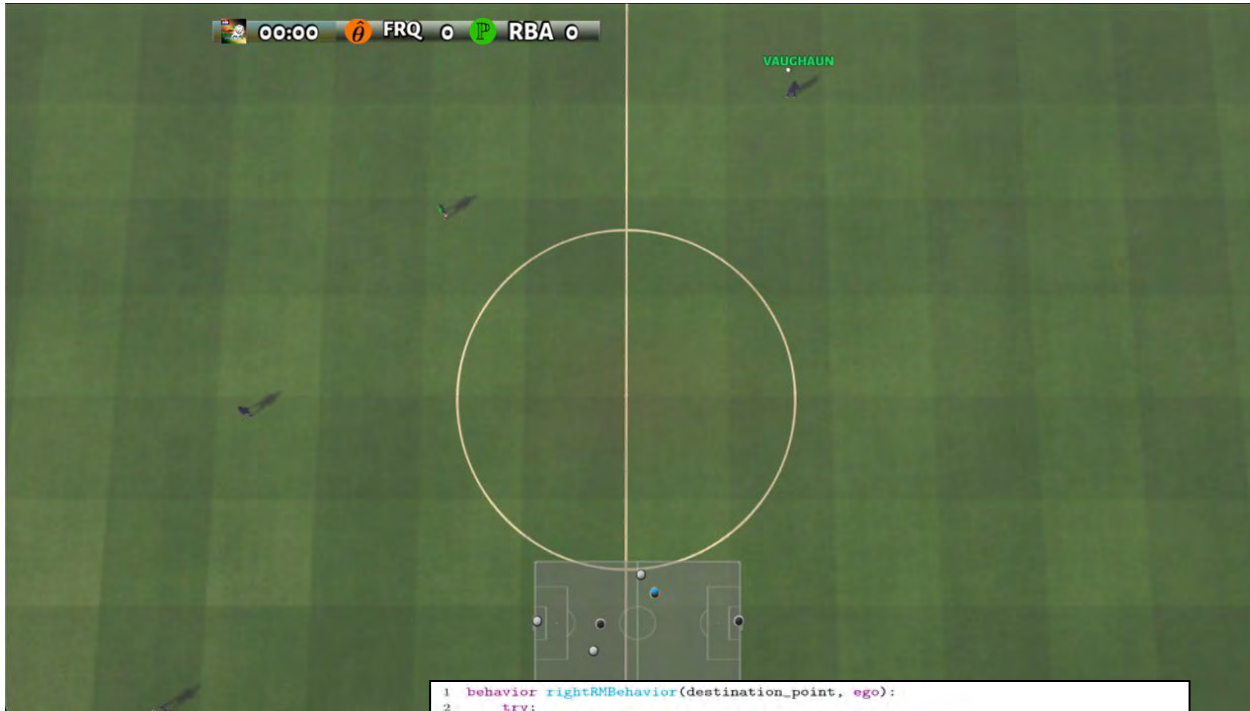


**Supporting the Full Design Cycle**



# Scenic for Multi-Agent Strategy Games and Extended Reality

## Programmatic Training of Reinforcement Learning Agents

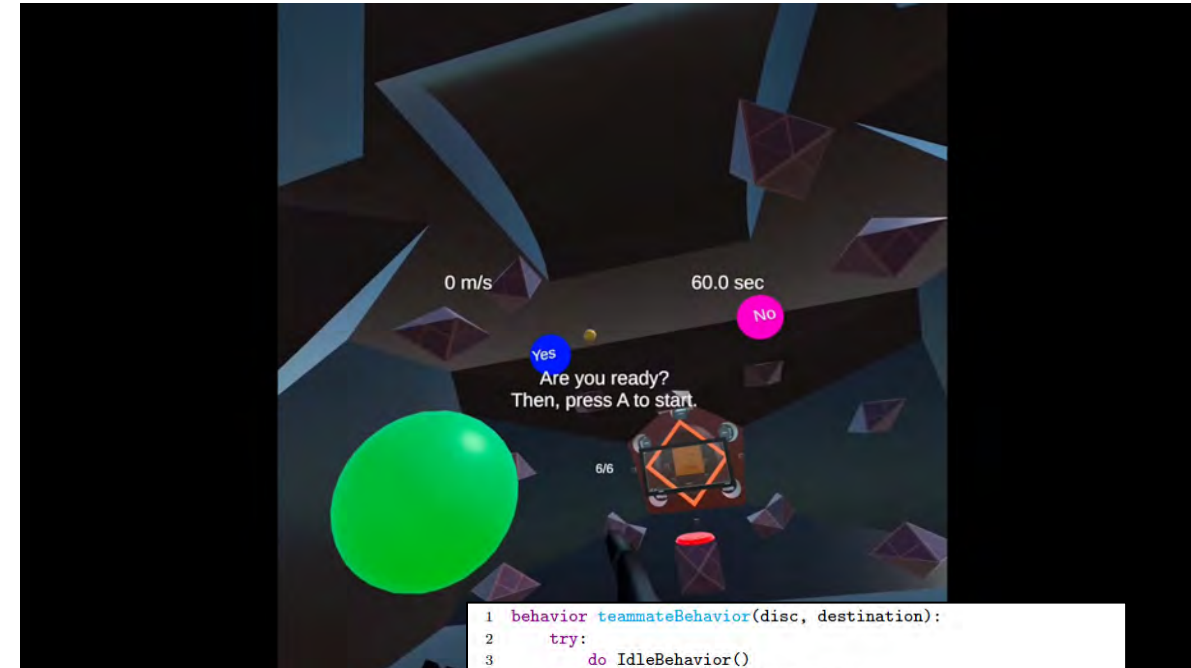


Google Research Football (soccer) simulator

```
1 behavior rightRMBehavior(destination_point, ego):
2   try:
3     do Uniform(HighPassTo(ego), LowPassTo(ego))
4     do MoveToPosition(destination_point, sprint=True)
5     new_dest_point = Point on rightRMAttackRegion
6     do egoBehavior(new_dest_point)
7     interrupt when opponentTeamHasBallPossession(self):
8       do FollowObject(ball, sprint=True)
9
10  LeftGK
11  LeftRB
12  LeftLM on LeftMidRegion
13
14  RightGK
15  ego_destinationPoint = Point on egoAttackRegion
16  rightRM_destinationPoint = Point on rightRMAttackRegion
17
18  ego = RightAM on egoInitialRegion, with behavior egoBehavior(ego_destinationPoint)
19  rightRM = RightRM with behavior rightRMBehavior(rightRM_destinationPoint, ego)
20  ball = Ball ahead of rightRM by Range(2,3)
```

A. Azad, E. Kim, et al. "Programmatic Modeling and Generation of Real-time Strategic Soccer Environments for Reinforcement Learning," AAI 2022.

## Training Human eSports Players in Virtual Reality (VR)



```
1 behavior teammateBehavior(disc, destination):
2   try:
3     do IdleBehavior()
4     interrupt when disc.heldByHuman:
5       take MoveToAction(destination)
6     interrupt when (distance from self to disc) < 0.5:
7       take GrabDiscAction(True)
8
9  behavior disableThrustBrake():
10   take disableThrustAction(), disableBrakeAction()
11
12  ego = HumanPlayer at (0, 0, 0), facing toward goal,
13   with behavior disableThrustBrake()
14
15  GreenSphere ahead of ego
16
17  disc = Disc offset by (Range(-2, 2), Range(-2, 2), Range(-2, 2))
18
19  tm = BluePlayer behind ego by Range(3, 5),
20   with behavior teammateBehavior(disc, goal)
```

Modeled on Meta/Oculus EchoArena Virtual Reality Game

**... on to Part 2!**

**A Hands-On Introduction to the Scenic 3.0 Language**

# INTRODUCTION TO WRITING SCENIC SCENARIOS

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Daniel J. Fremont

University of California, Santa Cruz

# The plan

- 9:30: defining static scenarios in Scenic
- 9:40: hands-on time with Colab notebook 1
  
- 10:05: defining dynamic scenarios in Scenic
- 10:15: hands-on time with Colab notebook 2
  
- 10:40: more Scenic features
- 10:45: coffee break



# The history of Scenic

- We'll be working with Scenic 3.0, the latest version. A bit of history:
- Scenic 1.0 (tech. report 2018; PLDI 2019)
  - Static 2D scenarios; interfaces to GTA V and Webots
- Scenic 2.0 (*Machine Learning Journal* 2022)
  - Dynamic 2D scenarios
  - Library for driving scenarios; interfaces to CARLA and LGSVL
- Scenic 3.0 (CAV 2023)
  - 3D scenarios; precise modeling of shapes & occlusion
  - Temporal logic requirements

# WRITING STATIC SCENARIOS

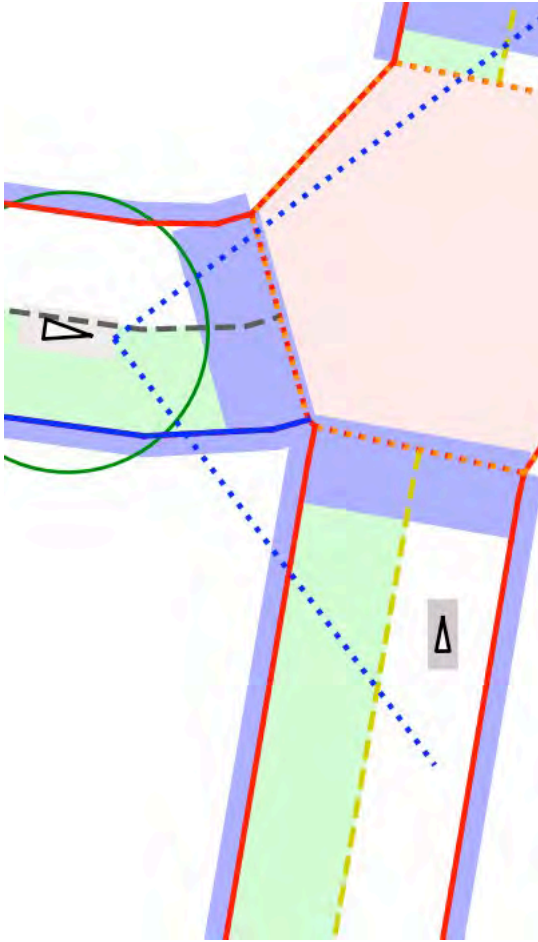
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# Example: a Badly-Parked Car



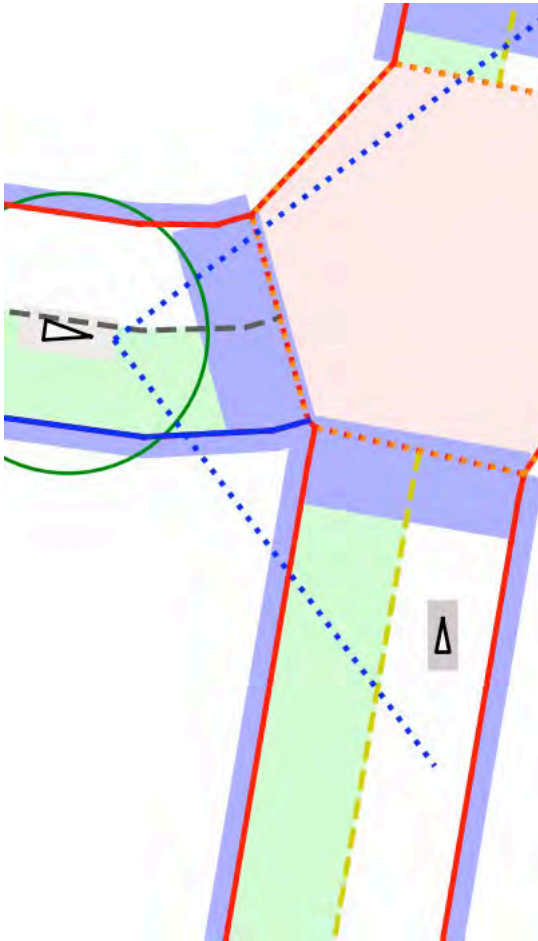


# Example: a Badly-Parked Car



```
model scenic.domains.driving.model # defines Car, etc.
```

# Example: a Badly-Parked Car



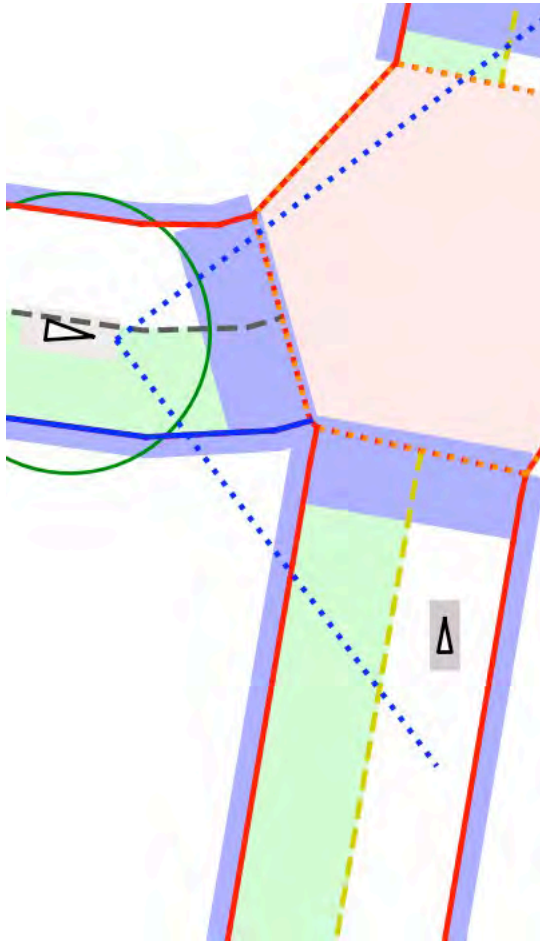
```
model scenic.domains.driving.model # defines Car, etc.
```

```
ego = new Car
```



use default values for **position**,  
**orientation**, and other properties

# Example: a Badly-Parked Car



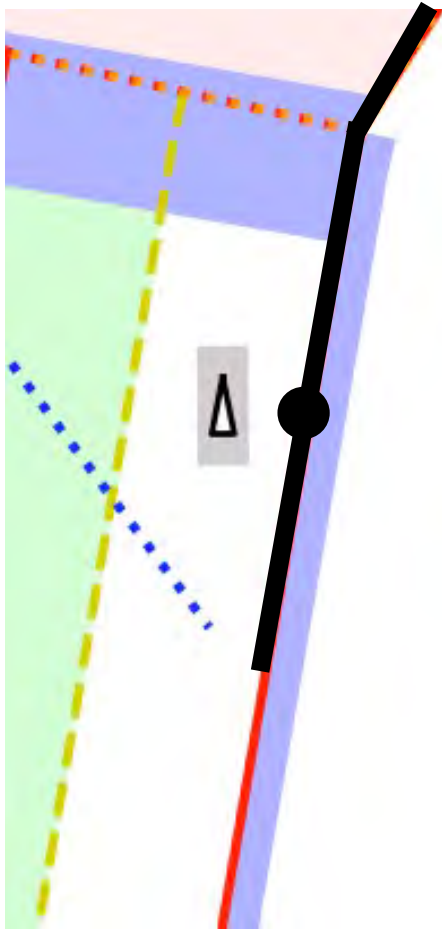
```
model scenic.domains.driving.model # defines Car, etc.
```

```
ego = new Car
```

```
spot = new OrientedPoint on visible curb
```



# Example: a Badly-Parked Car



```
model scenic.domains.driving.model # defines Car, etc.
```

```
ego = new Car
```

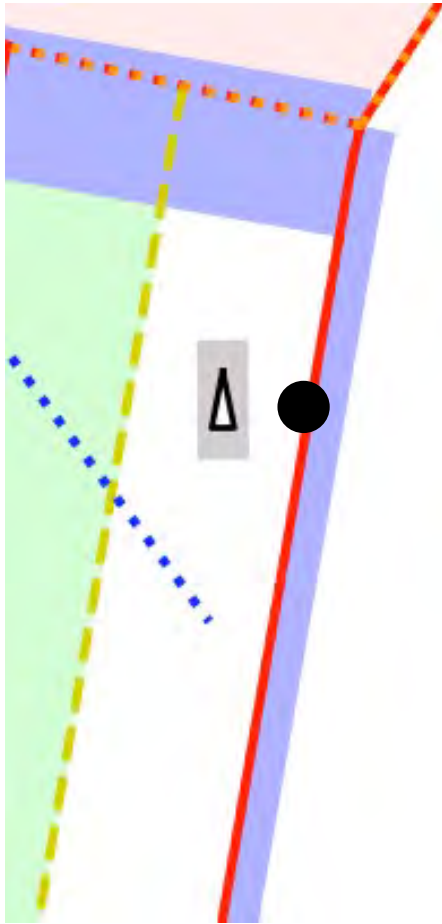
```
spot = new OrientedPoint on visible curb ← region
```

↑  
class

↑  
specifier

↙  
function

# Example: a Badly-Parked Car



```
model scenic.domains.driving.model # defines Car, etc.
```

```
ego = new Car
```

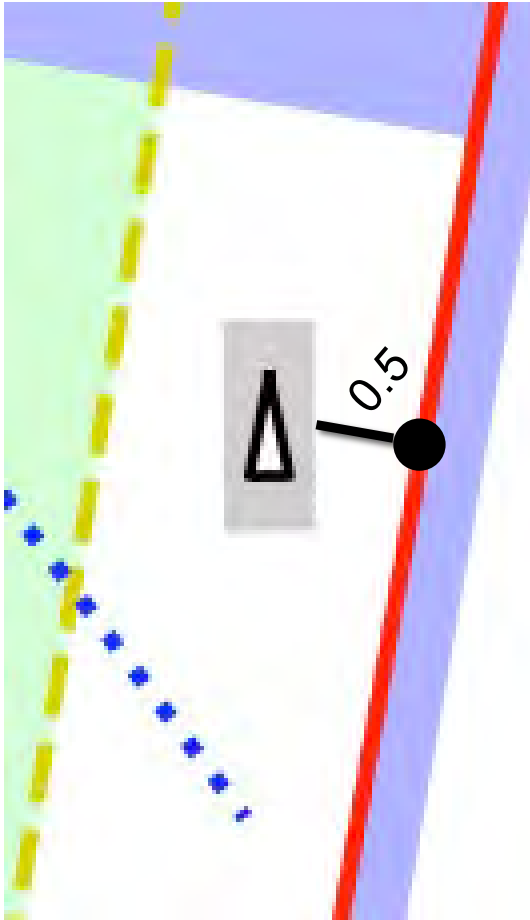
```
spot = new OrientedPoint on visible curb
```

```
badAngle = Uniform(1, -1) * Range(10, 20) deg
```

↑  
uniform choice of  
one of these values

↑  
uniform distribution  
over this interval

# Example: a Badly-Parked Car



```
model scenic.domains.driving.model # defines Car, etc.
```

```
ego = new Car
```

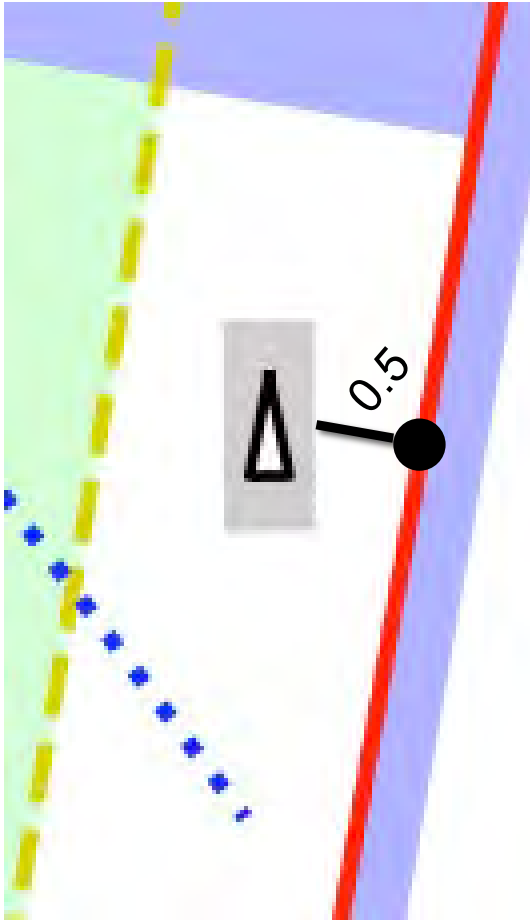
```
spot = new OrientedPoint on visible curb  
badAngle = Uniform(1, -1) * Range(10, 20) deg  
new Car left of spot by 0.5,
```



specifier depending  
on car's width



# Example: a Badly-Parked Car



```
model scenic.domains.driving.model # defines Car, etc.
```

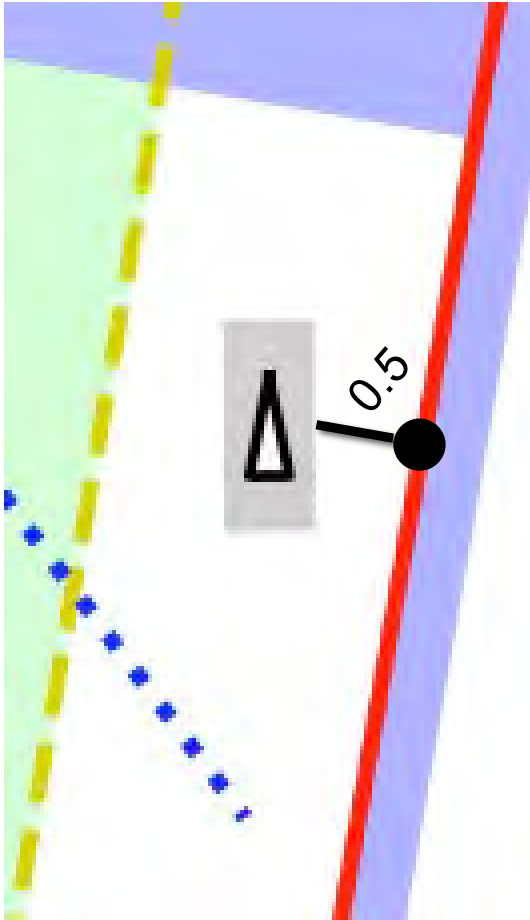
```
ego = new Car
```

```
spot = new OrientedPoint on visible curb  
badAngle = Uniform(1, -1) * Range(10, 20) deg  
new Car left of spot by 0.5,  
facing badAngle relative to roadDirection
```

↑  
operator depending  
on car's **position**

↑  
vector field

# Example: a Badly-Parked Car



```
model scenic.domains.driving.model # defines Car, etc.
```

```
ego = new Car
```

```
spot = new OrientedPoint on visible curb  
badAngle = Uniform(1, -1) * Range(10, 20) deg  
new Car left of spot by 0.5,  
        facing badAngle relative to roadDirection
```

Implicit hard constraints: objects don't overlap, cars are contained in the road, ego can see the other car.

# Example: a Badly-Parked Car





# Hands-on Scenic: Static Scenarios

- Work through some examples in our Colab notebook
- Feel free to try anything out; we're here to help!



# Static Scenic Cheat Sheet

```
# Built-in classes with their main properties
new Point # position, visibleDistance
new OrientedPoint # adds orientation, viewAngles
new Object # adds shape, width, length, height, etc.

# Defining an object with specifiers
new MyObjClass with prop value, # set any property
  at (x, y, z),
  above positionOrObject by distance,
  left of ... by ...,
  offset by vector, # position relative to ego
  in region, # place center randomly in region
  contained in region, # whole object fits in region
  on surface,
  following vectorField from start for distance,
  visible, # likewise "not visible"
  visible from obj,
  facing (yaw, pitch, roll),
  facing toward position, # likewise "away from"
  facing directly toward position
```

```
# Probability distributions
Range(low, high) # uniform on interval
Uniform(option1, option2, option3)
Uniform(*listOfOptions)
Discrete{opt1: wt1, opt2: wt2}
Normal(mean, stdDev)

# Requirements
require condition
require[probability] condition

# Operators
angle deg # write an angle in degrees
distance from X to Y
obj can see positionOrObject
positionOrObject in region
visible region # likewise "not visible"

# Class definitions
class MyClass: # superclass is Object
  prop: defaultValue # can be random
```

# WRITING DYNAMIC SCENARIOS

---



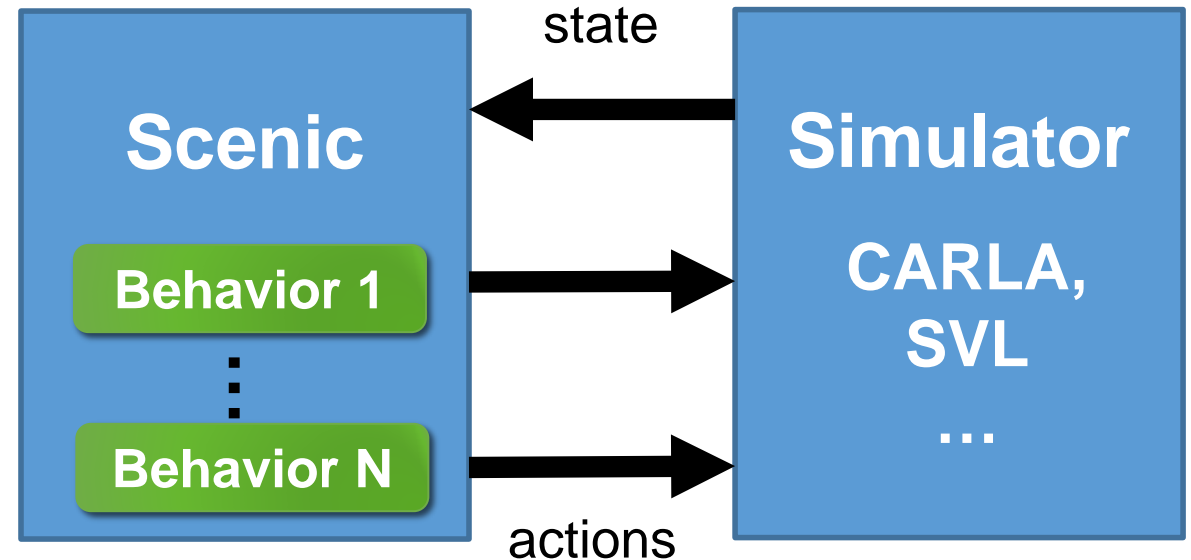
# Going Beyond Initial Conditions

- Scenic can also describe *dynamic agents* which take actions over time, reacting to a changing environment
- Example: "a badly-parked car, which suddenly pulls into the road as the ego car approaches"
- The dynamic actions of the car are specified by giving it a *behavior*

```
parkedCar = new Car left of spot by 0.5,  
            facing badAngle relative to roadDirection,  
            with behavior PullIntoRoad
```

# Behaviors and Actions

- Behaviors are functions running in parallel with the simulation, issuing *actions* at each time step
  - e.g. for AVs: set throttle, set steering angle, turn on turn signal
  - Provided by a Scenic library for the driving domain
  - Abstract away details of simulator interface
- Behaviors can access the state of the simulation and make choices accordingly



```
behavior FollowLaneBehavior(lane):  
    while True:  
        throttle, steering = ...  
        take (SetThrottleAction(throttle),  
             SetSteerAction(steering))
```

# More Advanced Temporal Constructs

- *Interrupts* allow adding special cases to behaviors without modifying their code

```
behavior FollowLeadCar(safety_distance=10):  
    try:  
        do FollowLaneBehavior(target_speed=25)  
    interrupt when distance to other < safety_distance:  
        do CollisionAvoidance()
```

- *Temporal requirements and monitors* allow enforcing constraints during simulation

```
require always taxi in lane  
require eventually ego can see pedestrian
```

# A Worked Example

- OAS Voyage Scenario  
2-2-XX-CF-STR-CAR:02
- Lead car periodically stops and starts; ego car must brake to avoid collision

```
behavior FollowLeadCar(safety_distance=10):  
  try:  
    do FollowLaneBehavior(target_speed=25)  
  interrupt when distance to other < safety_distance:  
    do CollisionAvoidance()
```

```
behavior StopsAndStarts():  
  stop_delay = Range(3, 6)  
  last_stop = 0  
  try:  
    do FollowLaneBehavior(target_speed=25)  
  interrupt when simulation().currentTime - last_stop > stop_delay:  
    do FullBraking() for 5 seconds  
    last_stop = simulation().currentTime
```

```
ego = new Car with behavior FollowLeadCar(safety_distance=10)  
other = new Car ahead of ego by 10,  
        with behavior StopsAndStarts
```

```
require (new Point ahead of ego by 100) in road
```

```
terminate when ego._lane is None
```



# A Worked Example: CARLA



# Hands-on Scenic: Dynamic Scenarios

- We'll use Scenic's built-in simple Newtonian physics simulator
- As before, feel free to improvise!
- We can run some of your scenarios in CARLA at the end



# Dynamic Scenic Cheat Sheet

```
new Object with behavior MyBehavior(args)
```

```
behavior MyBehavior(arg=defaultValue):
```

```
  take Action1(), Action2() # take actions this step  
  wait
```

```
  do OtherBehavior() # run another behavior
```

```
  do Other() for 5 seconds
```

```
  do Other() until condition
```

```
  try:
```

```
    do A() # do this...
```

```
  interrupt when condition: # until this happens
```

```
    do B() # then run this and resume A
```

```
  if condition: # as in Python; random conditions OK
```

```
    ...
```

```
  while condition:
```

```
    ...
```

```
  require condition # at start  
  require always condition  
  require eventually condition
```

```
  terminate after 15 seconds  
  terminate when condition
```

# MORE SCENIC FEATURES

---



# Composing Scenarios

- Scenic allows scenarios to be defined modularly and combined into more complex scenarios
- Parallel, sequential, and more complex forms of composition

```
import StopAndStart, BadlyParkedCar

scenario StopStartWithParkedCar():
  compose:
    do StopAndStart(), BadlyParkedCar()

scenario StopStartThenParkedCar():
  compose:
    do StopAndStart()
    do BadlyParkedCar()

scenario StopStartThenParkedCar():
  compose:
    try:
      do StopAndStart()
    interrupt when ...:
      do BadlyParkedCar()
```

# Orchestrating Simulations

- Recording data from simulations

```
record ego can see pedestrian as "ped_visible"  
record final distance to goal as "end_dist"
```

- Saving and replaying scenes and simulations

```
scenario = scenic.scenarioFromFile('examples/gta/parkedCar.scenic', mode2D=True)  
scene, _ = scenario.generate()  
data = scenario.sceneToBytes(scene)
```

- Integration with *VerifAI* for falsification, optimization, etc.

# Resources for Learning More

- Documentation: [docs.scenic-lang.org](https://docs.scenic-lang.org)
  - Installation instructions for all major platforms
  - Full versions of today's tutorials, plus others
  - Syntax Guide and detailed Language Reference
  - Python API
  - How to interface Scenic to a new simulator
- Community forum: [forum.scenic-lang.org](https://forum.scenic-lang.org)

Main website:  
[scenic-lang.org](https://scenic-lang.org)

# Applications of Scenic (Part I)

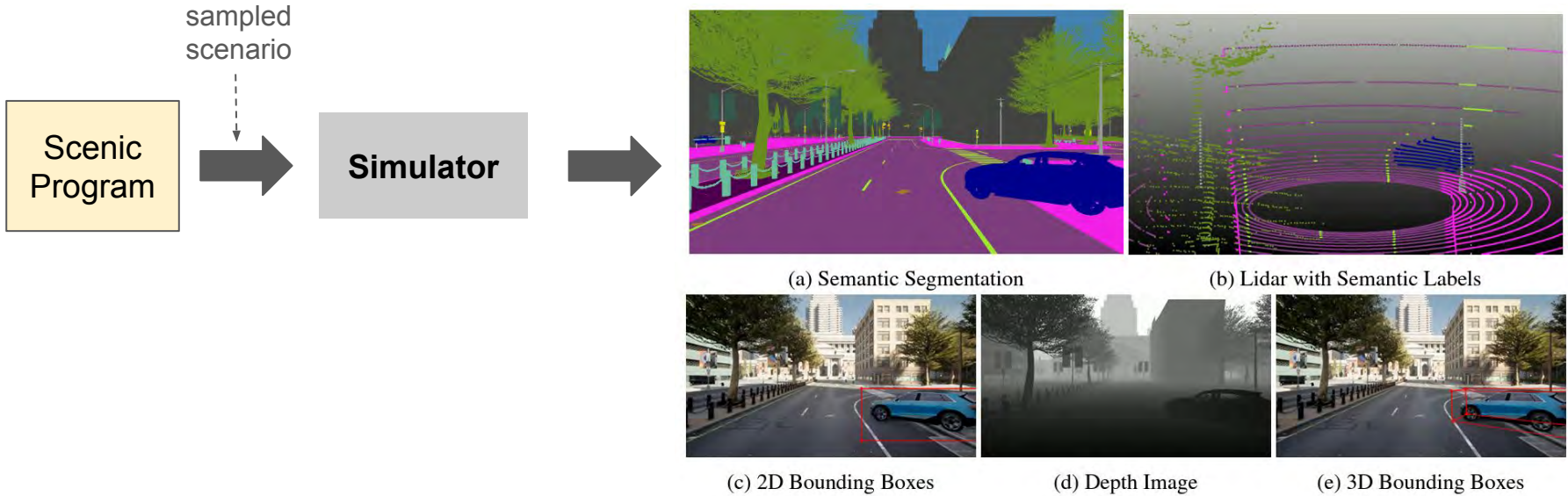
Edward Kim  
EECS, UC Berkeley



# Outline

1. Sensor Data Collection
2. Testing Perception, Behavior Prediction, and Planners with VerifAI
3. Interfacing Scenic to Your Simulator of Choice

# Sensor Data Collection



# Sensor Data Generation

```
model scenic.simulators.carla.model
```

```
# Sample a lane at random
```

```
lane = Uniform(*network.lanes)
```

```
spot = new OrientedPoint on lane.centerline
```

```
car_model = "vehicle.tesla.model3"
```

```
# Spawn car on that spot with logging autopilot behavior and
```

```
# - SSSensor : a semantic segmentation sensor
```

```
# - RGBSensor: an RGB Camera
```

```
ego = new Car at spot,
```

```
  with blueprint car_model,
```

```
  with behavior AutopilotBehavior(),
```

```
  with sensors {"front_rgb": RGBSensor(offset=(1.6, 0, 1.7),
```

```
              "front_ss": SSSensor(offset=(1.6, 0, 1.7))}]
```

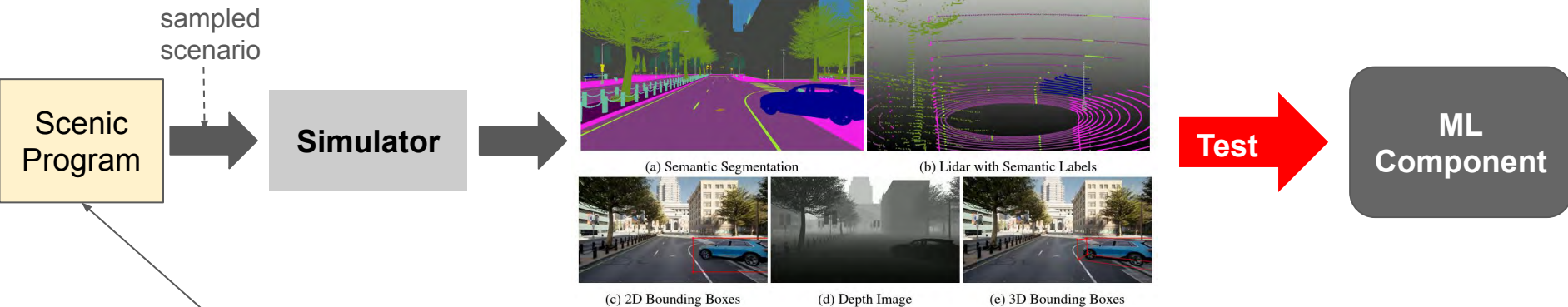
```
other = new Car offset by 0 @ Range(10, 30),
```

```
  with behavior AutopilotBehavior()
```

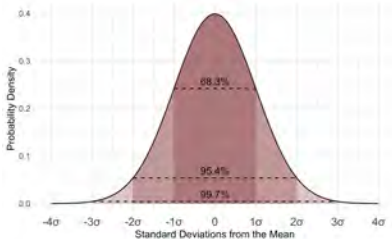
```
record ego.observations["front_rgb"] as "front_rgb" every 0.1 sec
```

```
record ego.observations["front_ss"] as "front_ss" every 0.1 sec
```

# Testing Perception, Behavior Prediction, and Planners



Defines a Distribution of Scenarios



How to Search/Sample Scenarios from the Distribution?

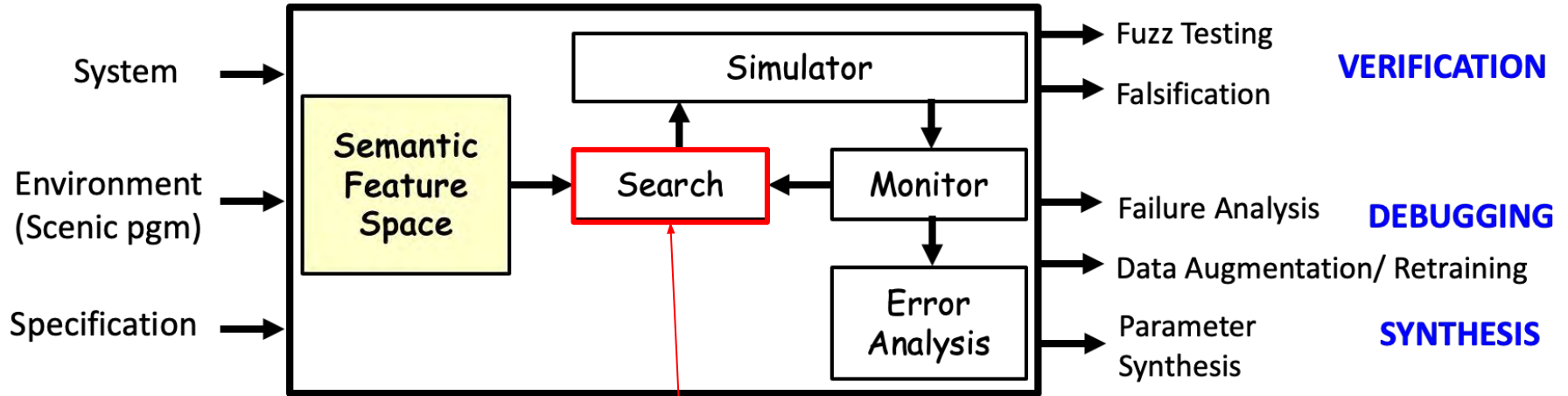
Exploration

Exploitation

Challenge:



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



Supports **Different Search Strategies**: [You Can Add Your Own Samplers Too]  
Bayesian Optimization, Multi-Arm Bandit, Cross Entropy, Simulated Annealing, Halton, Random

# Testing with Scenic & VerifAI

```
model scenic.simulators.carla.model
import pytorch

# import the machine learning model
ML_model = pytorch.load(...)

# Sample a lane at random
lane = Uniform(*network.lanes)

spot = new OrientedPoint on lane.centerline

car_model = "vehicle.tesla.model3"

# Spawn car on that spot with logging autopilot behavior and
# - SSSensor : a semantic segmentation sensor
# - RGBSensor: an RGB Camera
ego = new Car at spot,
  with blueprint car_model,
  with behavior AutopilotBehavior(),
  with sensors {"front_rgb": RGBSensor(offset=(1.6, 0, 1.7),
    "front_ss": SSSensor(offset=(1.6, 0, 1.7))}]

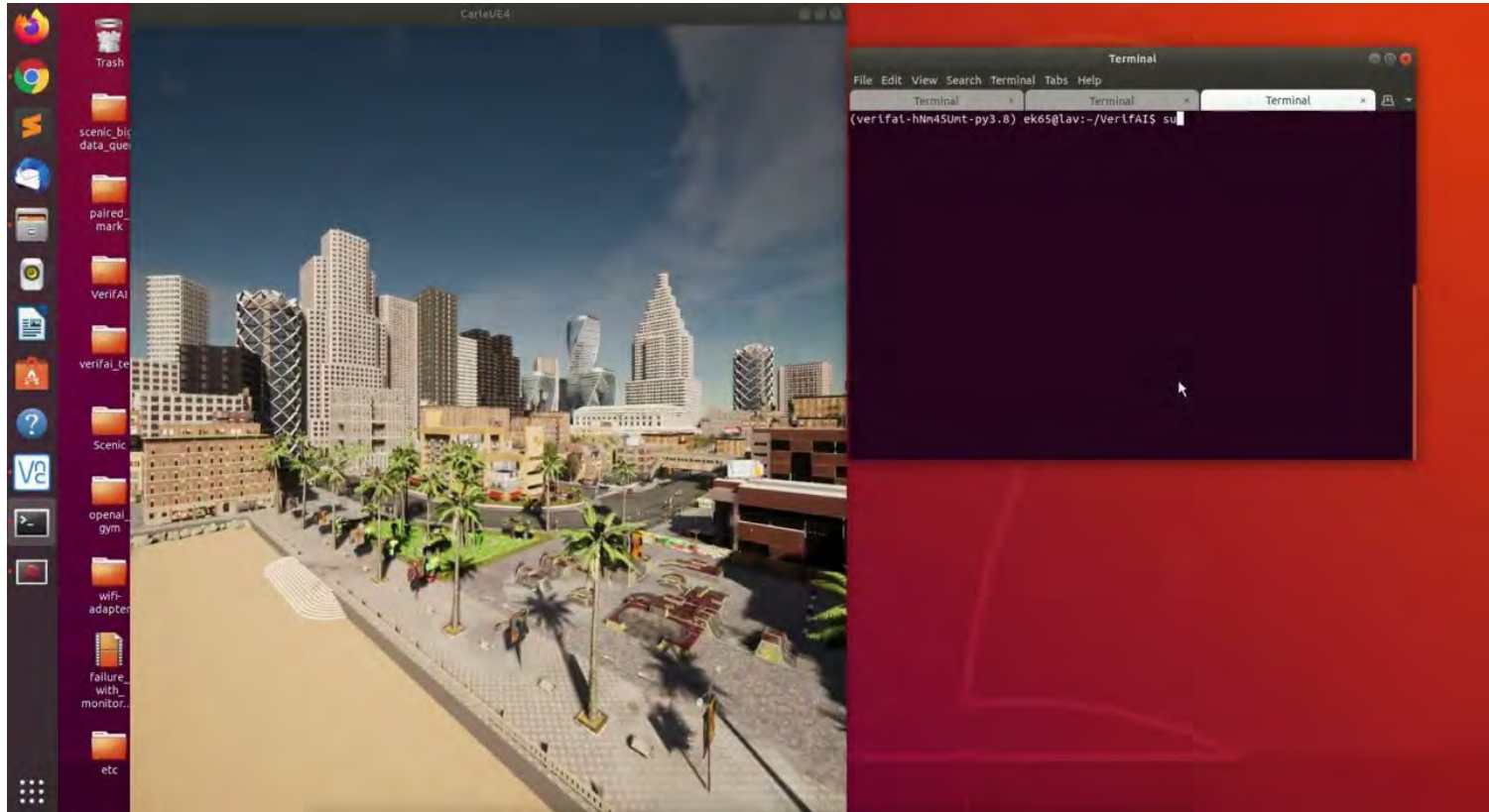
other = new Car offset by 0 @ Range(10, 30),
  with behavior AutopilotBehavior()

record ego.observations["front_rgb"] as "front_rgb" every 0.1 sec
record ego.observations["front_ss"] as "front_ss" every 0.1 sec
record ML_model(ego.observations["front_rgb"],
  ego.observations["front_ss"]) as "ml_performance" every 0.1 sec
```

# Testing with Scenic & VerifAI

```
1 from verifai.monitor import specification_monitor
2 # The specification must assume specification_monitor class
3 class evaluation_metric(specification_monitor):
4     def __init__(self):
5         def specification(simulation_results):
6             time_series_I0U = simulation_results['ml_performance']
7             mean_I0U = compute_Mean_I0U(time_series_I0U)
8             return mean_I0U
9         super().__init__(specification)
10
11
12 from dotmap import DotMap
13 falsifier_params = DotMap(
14     n_iters=1000, # Number of simulations to run (or None for no limit)
15     max_time=20, # Time limit in seconds, if any
16     fal_thres=0.5, # Monitor return value below which a sample is considered a violation
17     save_error_table=True, # Record samples that violated the monitor/specification
18     save_safe_table=False, # Don't record samples that satisfied the monitor/specification
19     sampler_params=None # optional DotMap of sampler-specific parameters
20 )
```

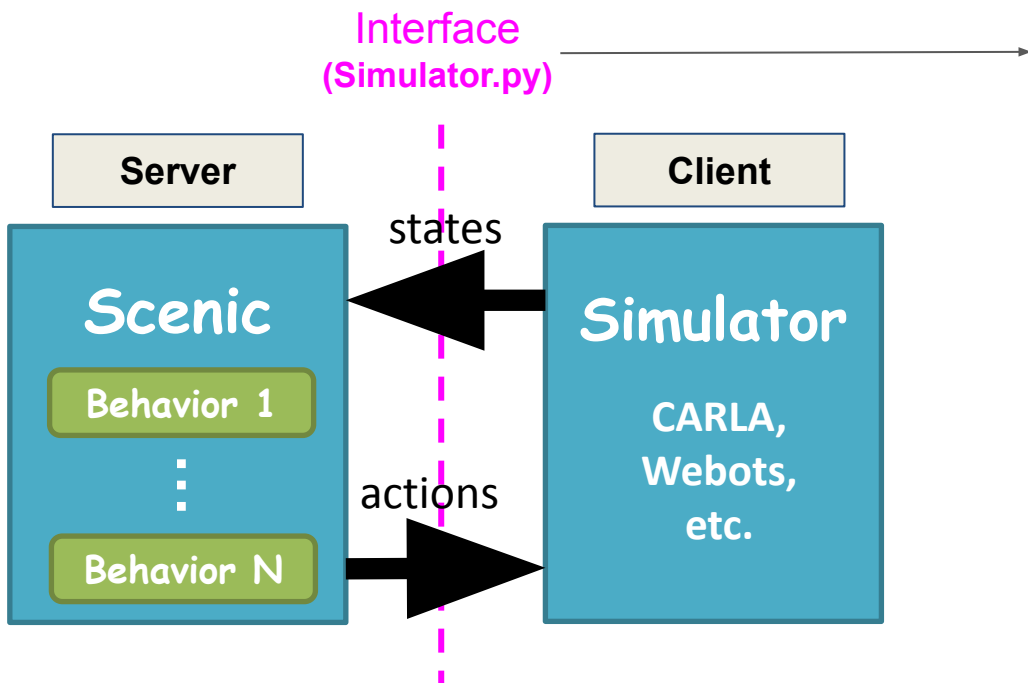
# Demo





Q & A

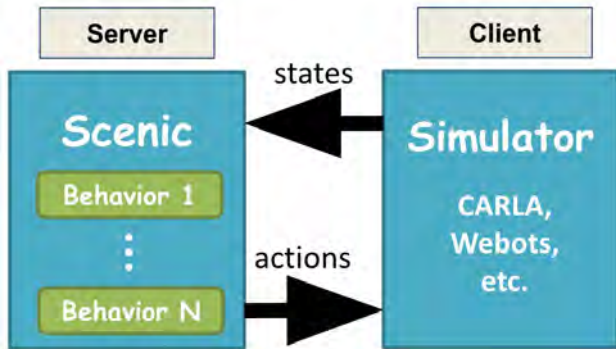
# Interfacing Scenic to Your Simulator of Choice



## Roles of the Interface

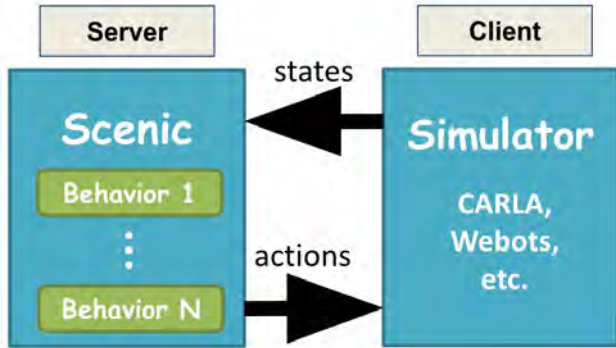
- Initiate Client/Server Communication
- Instantiate the Map, Agents / Objects
- Control the actions of each agent
- Simulate the actions for 1 timestep
- Update the world state at each timestep

# Interfacing Scenic to Your Simulator of Choice



```
class TemplateSimulator(Simulator):  
    """  
    Implementation of `Simulator` in scenic.core.simulator.  
    At each simulation, Simulator creates a Simulation class  
    The Simulation class then runs the actual simulation.  
    """  
  
    def __init__(self):  
        """  
        Initialize server <> client relation between Scenic and the simulator  
        """  
  
        super().__init__()
```

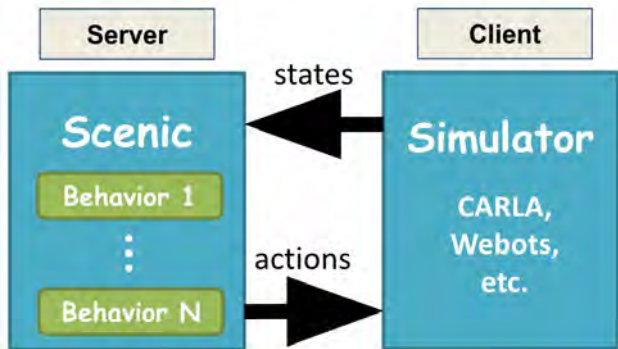
# Interfacing Scenic to Your Simulator of Choice



```
def createObjectInSimulator(self, obj):  
    """  
    Arg  
    Object obj: a Scenic obj/agent  
  
    Spawns a single object/agent in the simulator  
    with the desired parameters (position, orientation, color, etc.)  
    """
```



# Interfacing Scenic to Your Simulator of Choice

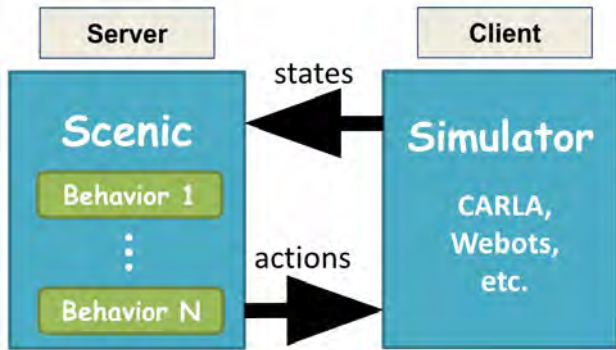


```
def step(self):  
    """
```

```
This function unfreezes the simulation world and  
advances the physics by 1 timestep.
```

```
When this function is called, all the Scenic Actions will be executed and  
rendered in simulation.
```

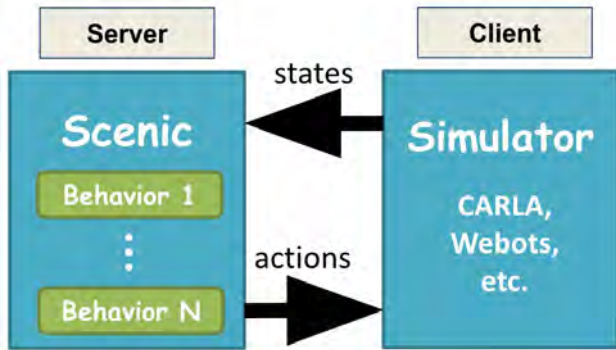
# Interfacing Scenic to Your Simulator of Choice



```
def getProperties(self, obj, properties):
    """
    Args:
        obj (Object): Scenic object in question.
        properties (set): Set of names of properties to read from the simulator.
        It is safe to destructively iterate through the set if you want.

    Returns:
        values (dict): A dictionary that with the property names as keys
        that returns the current value of the property
```

# Interfacing Scenic to Your Simulator of Choice



```
def executeActions(self, allActions):
    """
    Args:
    allActions: a :obj:`~collections.defaultdict` mapping each agent to a tuple
                of actions, with the default value being an empty tuple. The order of
                agents in the dict should be respected in case the order of actions matters.

    Iterates through all the Scenic Actions to be carried out for all the agents.
    For each Scenic Action, this function calls the applyTo() method of the Action's class
    as defined in actions.py.
```

# Interfacing Scenic to Your Simulator of Choice



The screenshot shows the Scenic documentation website. The top navigation bar is blue with the Scenic logo and 'latest' version indicator. A search bar is present. The left sidebar is dark grey with a menu of links. The main content area is white and displays the article 'Interfacing to New Simulators'.

Scenic  
latest

Search docs

INTRODUCTION

- Getting Started with Scenic
- Notes on Installing Scenic
- What's New in Scenic

TUTORIALS

- Scenic Fundamentals
- Dynamic Scenarios
- Composing Scenarios

LANGUAGE AND TOOL REFERENCE

- Syntax Guide

Home / Interfacing to New Simulators [Edit on GitHub](#)

## Interfacing to New Simulators

To interface Scenic to a new simulator, there are two steps: using the Scenic API to compile scenarios, generate scenes, and orchestrate dynamic simulations, and writing a Scenic library defining the virtual world provided by the simulator.

### Using the Scenic API

Scenic's Python API is covered in more detail in our [Using Scenic Programmatically](#) page; we summarize the main steps here.

Compiling a Scenic scenario is easy: just call the `scenic.scenarioFromFile` function with the path to a Scenic file (there's also a variant `scenic.scenarioFromString` which works on strings). This returns a `Scenario` object

[https://scenic-lang.readthedocs.io/en/latest/new\\_simulator.html](https://scenic-lang.readthedocs.io/en/latest/new_simulator.html)

# Summary

1. Flexible Sensor Data Generation using Scenic
2. Testing Perception, Behavior Prediction, and Planners with Scenic & VerifAI
3. Scenic is Simulator-Agnostic & Can be Interfaced to a Simulator of Choice



# Applications of Scenic (Part II)

Edward Kim  
EECS, UC Berkeley

# Outline

1. Debugging ML Models
2. Sim-to-Real Validation
3. Sensor Data Exploration
4. Extended Reality

# Debugging ML Models

## Test Image Generation



## User's Scenario

```
param time = {t+40, t+60}
ego = Car at -209.091 0 -484.232
spot = OrientedPoint on visible curb
heading = {+90, 90} deg
otherCar = Car at spot,
        facing heading relative to ego.heading
        with model CarFromTemplate

require otherCar in ego.visibleRegion
require (angle to otherCar) - ego.heading) < 0
require (distance from ego.position to otherCar) >= 5
require (distance from ego.position to otherCar) <= 20
```

## Failure Inducing Rule Extraction

**x\_coordinate <= -200.76  
distance <= 8.84  
car model = PRANGER**

## Failure Scenario

```
param time = {t+40, t+60}
ego = Car at -209.091 0 -484.232
spot = OrientedPoint on visible curb
heading = {-90, 90} deg
modelName = {PRANGER}
models = {}
for name in modelNames:
    model = CarFromTemplate(modelName)
otherCar = Car at spot,
        facing heading relative to ego.heading,
        with model CarFromTemplate

require otherCar in ego.visibleRegion
require (angle to otherCar) - ego.heading) < 0
require (distance from ego.position to otherCar) >= 5
require (distance from ego.position to otherCar) <= 8.84
require (otherCar.position.x < -200.76)
```

## Failure Image Generation



## Success Inducing Rule Extraction

**x\_coordinate >= -198.1**

## Success Scenario

```
param time = {t+40, t+60}
ego = Car at -209.091 0 -484.232
spot = OrientedPoint on visible curb
heading = {+90, 90} deg
otherCar = Car at spot,
        facing heading relative to ego.heading

require otherCar in ego.visibleRegion
require (angle to otherCar) - ego.heading) < 0
require (distance from ego.position to otherCar) >= 5
require (distance from ego.position to otherCar) <= 20
require (otherCar.position.x >= -198.1)
```

## Success Image Generation



— Prediction Bounding Box

— Ground Truth Bounding Box

# Data Generation Pipeline

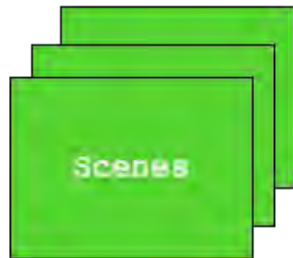
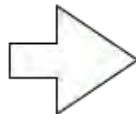
## Scenic Program

```
param time = (1*60, 10*60);
ego = Car at -178.5181 8 -42.7771;
agent0 = Car offset by -3.8 8 4.3,
        facing (90, 50) deg relative to roadDirection;

distance_perturbation1 = (1.2, 1.5)
movevel1 = follow roadDirection from (front of agent0) for
resample(distance_perturbation1)
agent1 = Car ahead of center1,
        facing (80, 80) deg relative to roadDirection;

distance_perturbation2 = (1.2, 1.5)
center2 = follow roadDirection from (front of agent1) for
resample(distance_perturbation2)
agent2 = Car ahead of center2,
        facing (-10, 30) deg relative to roadDirection;

require agent0 in ego.visibleRegion
require agent1 in ego.visibleRegion
require agent2 in ego.visibleRegion
```



Simulator



## Images



Neural Network



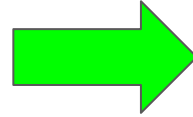
Correct Detection



Incorrect Detection

# Data Collection

Scenes	Labels
<e1_1, e1_2, ..., e1_n>	→ correct
<e2_1, e2_2, ..., e2_n>	→ correct
<e3_1, e3_2, ..., e3_n>	→ incorrect
<e4_1, e4_2, ..., e4_n>	→ correct
.	.
.	.
.	.
.	.
.	.
<em_1, em_2, ..., em_n>	→ correct



**Classification Problem**

e.g. <weather='snowy,' car\_model='cybertruck,' .... >

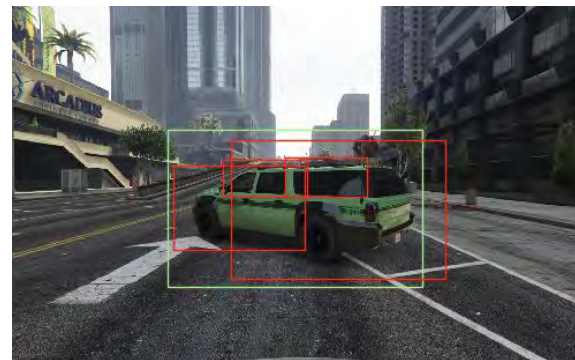
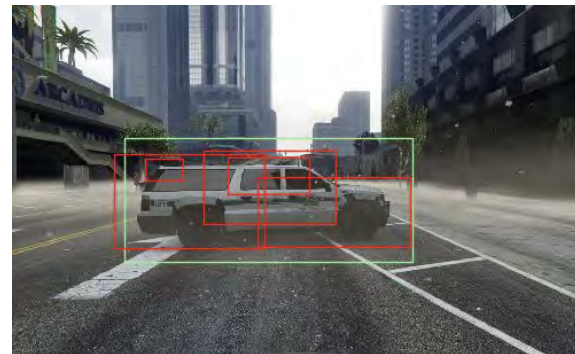


# Summary on Worst Failure Inducing Rules

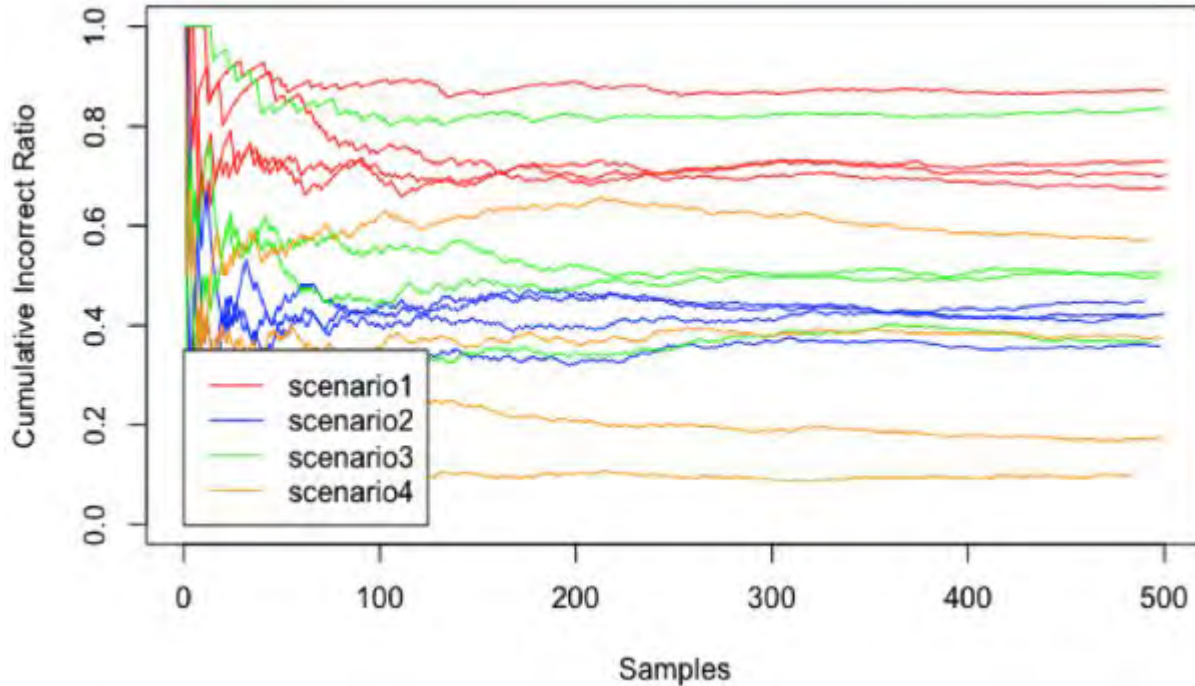
Scenario # (Baseline→Rule Precision)	Rules
Scenario 1 (34.7% → 87.2%)	$x \text{ coordinate} \leq -200.76 \wedge$ $\text{distance} \leq 8.84 \wedge$ $\text{car model} = \text{PRANGER}$
Scenario 2 (27.7% → 44.9%)	$\text{hour} \geq 7.5 \wedge$ $\text{weather} = \text{all except Neutral} \wedge$ $\text{car0 distance from ego} < 11.3$
Scenario 3 (38.3% → 83.4%)	$\text{weather} = \text{neutral} \wedge$ $\text{agent0 heading} = \leq 218.08 \text{ deg} \wedge$ $\text{hour} \leq 8.00 \wedge$ $\text{car2 red color} \leq 95.00$
Scenario 4 (10.4% → 57.3%)	$\text{car0 model} = \text{PATRIOT} \wedge$ $\text{car1 model} = \text{NINEF} \wedge$ $\text{car2 model} = \text{BALLER} \wedge$ $92.25 < \text{car0 green color} \leq 158 \wedge$ $\text{car0 blue color} \leq 84.25 \wedge$ $178.00 < \text{car2 red color} \leq 224$



From Failure Scenic Program



# Based on Debugging, Generate Failure Inducing Data



# Outline

1. Debugging ML Models
2. Sim-to-Real Validation
3. Sensor Data Exploration
4. Extended Reality

# Sim-to-Real Validation

Do system / component failures identified in simulation actually occur in reality?



## Potential Causes of Discrepancy

1. Sensor Data
2. Dynamics Models
3. Agent Behaviors



# Sim-to-Real Validation



Daniel J Fremont, Edward Kim, Yash Vardhan Pant, Sanjit A Seshia, Atul Acharya, Xantha Brusco, Paul Wells, Steve Lemke, Qiang Lu, Shalin Mehta, "Formal scenario-based testing of autonomous vehicles: From simulation to the real world," International Conference on Intelligent Transportation Systems (ITSC), 2020



# Experiment Results

Collision

Near-Collision

Unsafe with Larger Margin

## Effectiveness of the Methodology to Design Test Cases:

Unsafe Tests in Simulation → unsafe in real-world: 62.5%

Marginally safe in simulation → safe in real world: 90%

Robustly safe in simulation → safe in real world: 100 %

Test Run	Minimum TTC	Minimum Distance	$\rho$
F1 Simulation	–	2.23	-0.27
F1 Run1	2.10	2.06	-0.44
F1 Run2	1.27	2.24	-0.26
F1 Run3	2.97	4.02	1.52
F1 Run4	5.05	6.19	3.69
F2 Simulation	–	1.91	-0.59
F2 Run1	0.94	2.44	-0.06
F2 Run2	2.70	3.24	0.74
F2 Run3	1.20	1.58	-0.92
F2 Run4	1.05	2.24	-0.26
M1 Simulation	–	4.05	1.55
M1 Run1	6.07	7.20	4.70
M1 Run2	7.16	7.89	5.39
M2 Simulation	–	4.78	2.28
M2 Run1	3.24	3.40	0.90
M2 Run2	6.16	8.01	5.51
M2 Run3	9.10	14.38	11.88
M2 Run4	6.80	8.05	5.55
M2 Run5	7.69	8.48	5.98
M3 Simulation	–	5.85	3.35
M3 Run1	0.75	1.94	-0.56
M3 Run2	6.00	6.36	3.86
M3 Run3	4.27	5.73	3.23
S1 Simulation	–	5.45	2.95
S1 Run1	1.32	2.79	0.29
S1 Run2	9.72	8.50	6.00
S1 Run3	9.35	7.85	5.35
S2 Simulation	–	5.95	3.45
S2 Run1	3.13	6.36	3.86
S2 Run2	8.66	9.00	6.50

# Outline

1. Debugging ML Models
2. Sim-to-Real Validation
3. Sensor Data Exploration
4. Extended Reality

In this era of AI, terabytes of sensor data are being collected and labelled.



The **size** of data matters, but also **contents** matters

e.g. what if a self-driving car's training dataset does not contain any unprotected left turn scenario?



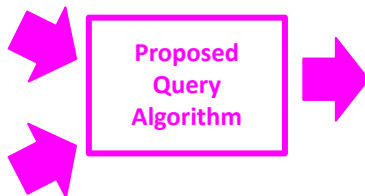
How can we algorithmically explore and understand the dataset?

# Part 3: Sensor Data Retrieval

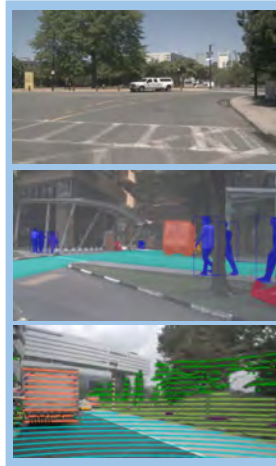
## Encode Failures as a Scenario Program

```
1 param time = (6*60, 18*60)
2 ego = Car at -209.021 # -586.231
3
4 spot = OrientedPoint on visible curb
5 badAngle = (-90, 90) deg
6
7 otherCar = Car at spot,
8   facing badAngle relative to ego.heading
9
10 require otherCar in ego.visibleRegion
11 require ((angle to otherCar) - ego.heading) < 0
12 require (distance from ego.position to otherCar) >= 5
13 require (distance from ego.position to otherCar) <= 20
```

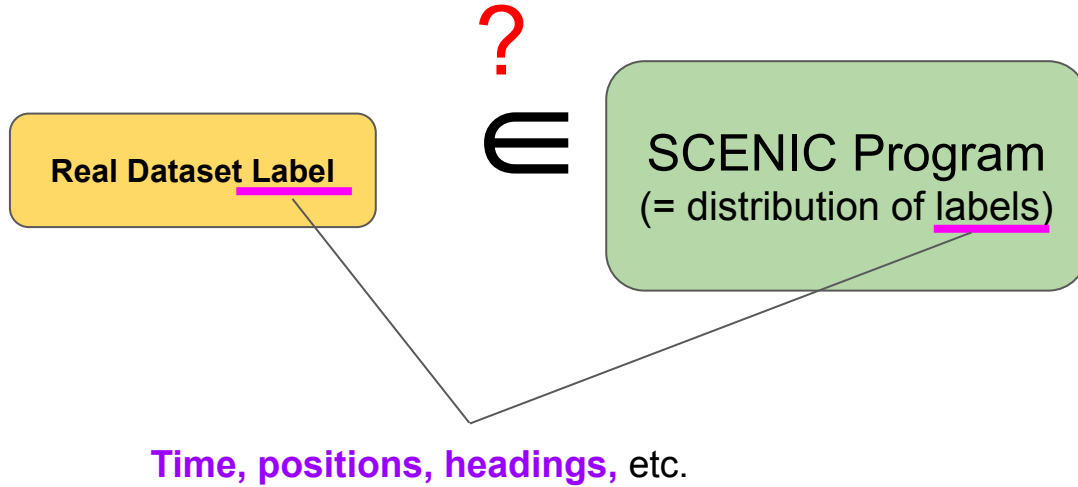
A Given Labelled  
Real World Dataset



## Matching Subset of Real World Sensor Data to the Scenario Description

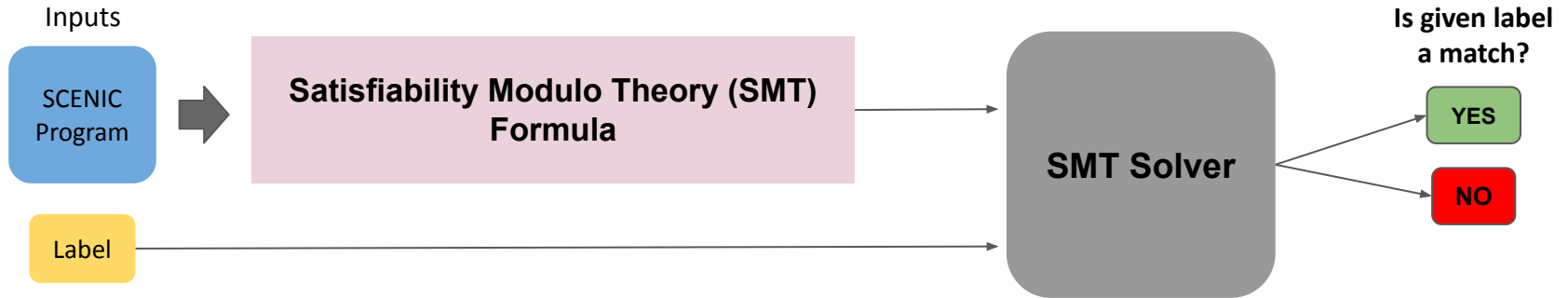


# Query Problem



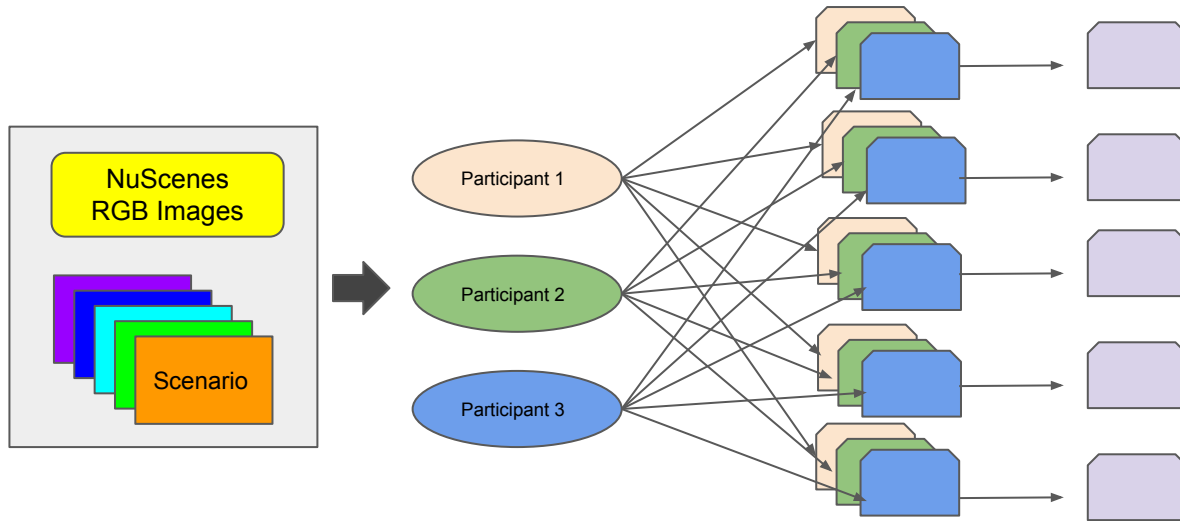


# Methodology



# Experiment

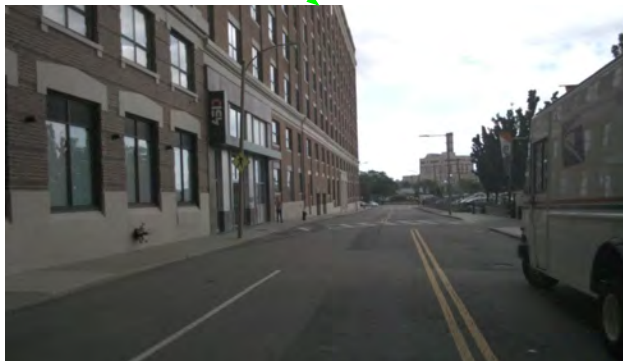
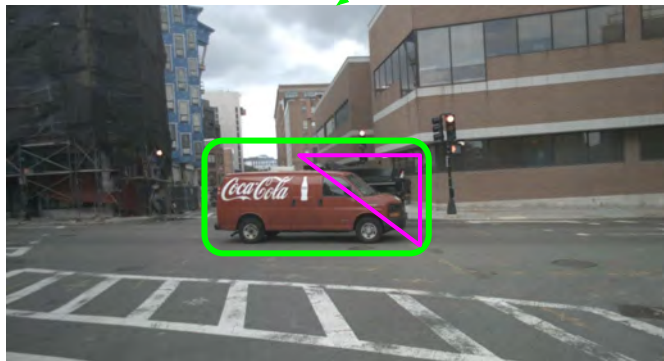
- 1) Can we query for interesting and realistic scenarios?
- 2) Do the outputs of the algorithm correspond to the intuitive notion of scenario matching?



# Experiment

Scenario #	1	2	3	4	5
Matching images (humans)	42	5	0	2	0
Matching images (our algorithm)	58	7	2	2	0

Table 1: For several scenarios, the number of images identified by 3 human subjects (unanimously) and our algorithm.



# Experiment 1 Results

Scenario #	1	2	3	4	5
Matching images (humans)	42	5	0	2	0
Matching images (our algorithm)	58	7	2	2	0

Table 1: For several scenarios, the number of images identified by 3 human subjects (unanimously) and our algorithm.

**Error in the label**



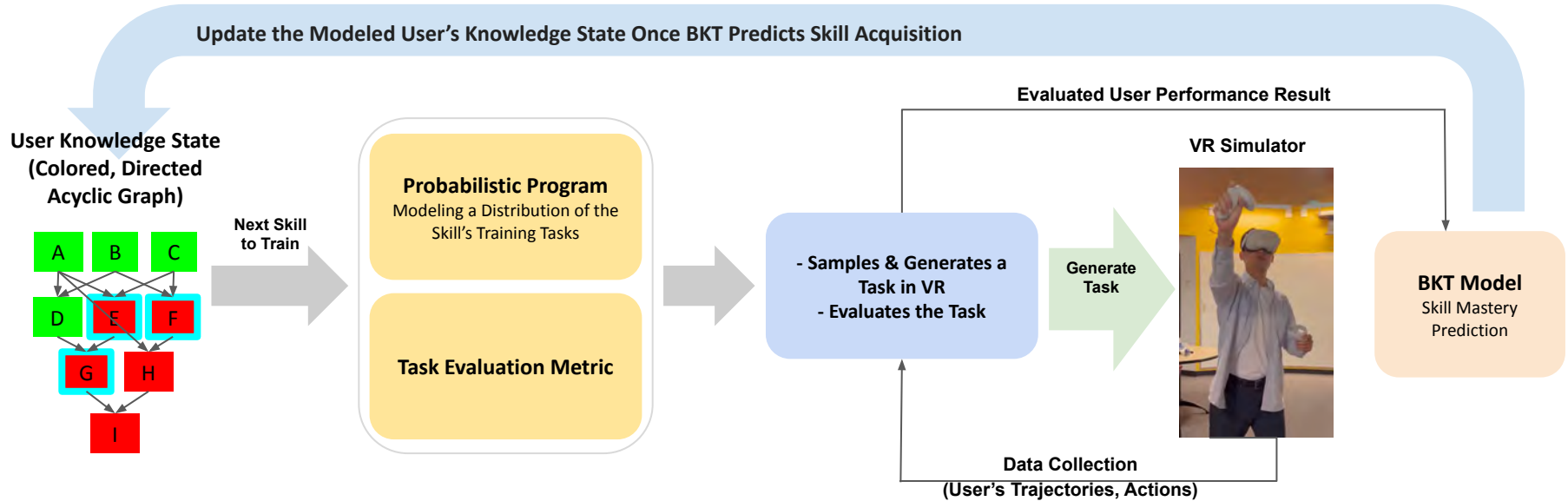
Limitation: the query accuracy hinges on the labels' accuracy

# Outline

1. Debugging ML Models
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3. Sensor Data Exploration
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# Training Motor Skills for Humans in XR

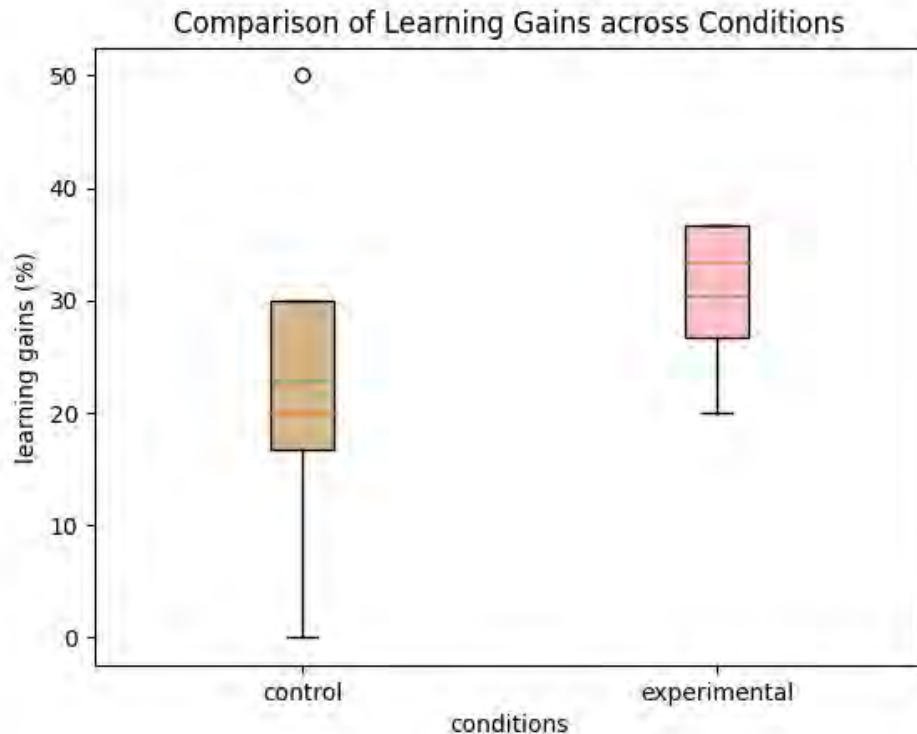


Edward Kim, Zachary Pardos, Bjoern Hartmann, Sanjit Seshia, "A Principled Intelligent Occupational Training of Psychomotor Skills in Virtual Reality," UC Berkeley EECS Technical Report No. UCB/EECS-2023-17

# Example: Passing to a Dynamic Player



# Experiment Result



Edward Kim, Zachary Pardos, Bjoern Hartmann, Sanjit Seshia, "A Principled Intelligent Occupational Training of Psychomotor Skills in Virtual Reality," UC Berkeley EECS Technical Report No. UCB/EECS-2023-17

# Summary

We covered different applications of Scenic

1. Testing & Debugging ML Models
2. Test Case Generation for Track Testing for Sim-to-Real Validation
3. Sensor Data Exploration using Scenic as a Query Language
4. Training Humans for Motor Skills in Extended Reality

# Summary of Tutorial Topics

- Introduction to Scenic and VerifAI
  - Two Industrial Case Studies
- Hands-On Introduction to the Scenic 3.0 Language
- Applications of Scenic
  - Synthetic Data Generation
  - Testing and Falsification
  - Interfacing to Simulators
  - Debugging ML Models
  - Sim-to-Real Validation
  - Querying Data with Scenic
  - Training in Extended Reality



# Scenic and VerifAI: Summary of Features and Use Cases



- Classes, Objects, 3D Geometry, and Distributions
- Local Coordinate Systems
- Readable, Flexible Specifiers
- Declarative Hard & Soft Constraints
- Externally-Controllable Parameters
- Agent Actions and Behaviors, Interrupts, Termination
- Monitors, Temporal Constraints
- Logging Simulation Data
- Scenario Composition

...

- Synthetic Data Generation
- Test Generation, Fuzz Testing
- *Requirements Specification*
- Falsification, *Statistical Model Checking*
- Debugging and Triage
- Data Augmentation
- *Goal-Directed Parameter Synthesis*
- *Run-Time Monitor Generation*
- Sim-to-Real Validation
- *Training Reinforcement Learning Agents*
- Training People in Extended Reality

...<your use case here!>

# New: Generating Scenic Programs from Natural Language

*We generate Scenic programs from natural language descriptions of Autonomous Vehicle crash reports*

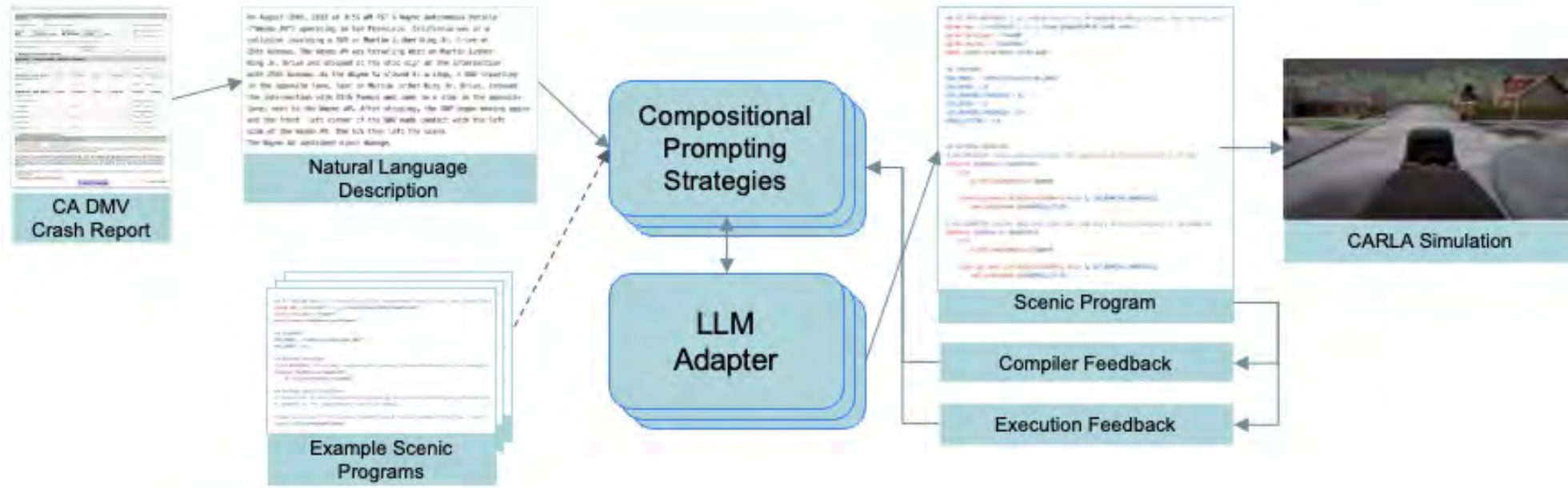
## ScenicNL: Compound AI System

Input:

Over 500 California DMV Crash Reports of Autonomous Vehicles for the last 5 years

Output:

A dataset of classified scenarios and corresponding Scenic programs for a subset of those scenarios



K. Elmaaroufi, D. Shankar, A. Cismaru, A. Sangiovanni-Vincentelli, M. Zaharia, and S. A. Seshia, "Generating Probabilistic Scenario Programs from Natural Language," April 2024.

# Generating Scenic Programs from Natural Language

# SCENARIO DESCRIPTION

# A Cruise autonomous vehicle ("Cruise AV"), operating in autonomous mode, was traveling eastbound on Clay Street at the intersection with Kearny Street when the Cruise AV slowed down. The driver of the Cruise AV disengaged from autonomous mode and, shortly thereafter, a bicyclist proceeding straight on northbound Kearny Street made contact with the right rear fender of the Cruise AV, damaging its fender. The bicyclist left the scene without exchanging information. There were no injuries and police were not called.

```
param map = localPath('.././../assets/maps/CARLA/Town01.xodr')
param carla_map = 'Town01'
model scenic.simulators.carla.model
EGO_MODEL = "vehicle.lincoln.mkz_2017"
EGO_SPEED = 1
EGO_BRAKING_THRESHOLD = .1
BICYCLE_SPEED = 10
BRAKE_ACTION = 1.0
behavior EgoBehavior(speed=10):
  try:
    do FollowLaneBehavior(speed)
  interrupt when withinDistanceToAnyObjs(self, EGO_BRAKING_THRESHOLD):
    #take SetBrakeAction(BRAKE_ACTION)
    do AutopilotBehavior()
behavior BicycleBehavior(speed=5):
  do FollowLaneBehavior(speed)
intersection = Uniform(*network.intersections)
egoLane = Uniform(*intersection.incomingLanes)
bicycleLane = egoLane # Uniform(*intersection.incomingLanes)
egoSpawn = new OrientedPoint on egoLane.centerline
ego = new Car at egoSpawn,
  with blueprint EGO_MODEL,
  with behavior EgoBehavior(EGO_SPEED)
bicycleSpawn = new OrientedPoint on bicycleLane.centerline
bicycle = new Bicycle at bicycleSpawn,
  with behavior BicycleBehavior(BICYCLE_SPEED)
```

# All Scenic code and CARLA renderings generated by scenicNL system



# Join the Scenic Open-Source Project!



- This Tutorial: <https://scenic-lang.org/cvpr24/>
- Detailed Documentation: <https://docs.scenic-lang.org>
- Community Forum: <https://forum.scenic-lang.org>
- GitHub: <https://github.com/BerkeleyLearnVerify/Scenic/>
- August 26-28: Scenic Workshop & “Bootcamp” at UC Santa Cruz

***Thank you!***

<https://scenic-lang.org>

Thanks to our many Scenic Team Members and Contributors  
<https://docs.scenic-lang.org/en/latest/credits.html>

S. A. Seshia, D. Sadigh, S. S. Sastry. *Towards Verified Artificial Intelligence*.  
Communications of the ACM, July 2022.