Scenic and VerifAI: Tools for Assured AI-Based Autonomy

Part II: Tutorial

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Scenic

High-Level, Probabilistic Programming Language for Modeling Environment Scenarios

VerifAI


Open-Source Tools

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

Industry

Academia

Government/Regulators

Improve assurance of the systems you build

Use these tools in your research

Evaluate the safety of AI-based autonomous systems

Community

Share Scenarios and Metrics

Develop Corpus of Tools and Data

Evaluate the safety of AI-based autonomous systems
Basic Terminology

- **Scene**: A configuration of objects and agents in physical space, with associated attributes and behaviors
- **Concrete Spatial Scenario** = Scene
- **Concrete (Spatio-Temporal) Scenario**: A sequence of scenes over time
- **Abstract Scenario** = Set of Concrete Scenarios
- **Abstract Scenarios** can be **Probabilistic**, i.e., the set can have an associated distribution
**SCENIC: A Language for Scenario Specification and Data Generation**

- Scenic Program defines a **probabilistic abstract scenario** -- *distribution over scenes/concrete scenarios*

- First created in 2017-18

- Readable, concise syntax for common geometric and behavioral relationships

- Embedded DSL in Python

- Generative back-end implementing domain-specific sampling techniques

- Blends imperative and declarative programming

Scenic enables modeling Three Types of Constraints

- **Use Case: Synthetic Data Generation**
  - “create traffic images to train this neural network”
- **Use Case: Synthesizing Test Stimuli**
  - “generate edge cases in rush hour traffic scenario”

- **Objects should not intersect**  \(\text{Hard Constraint}\)
- **Usually, be similar to real-world traffic**  \(\text{Soft Constraint}\)
- **Generate a diverse image/test set from distribution**  \(\text{Randomness Constraint}\)
Scenic and VerifAI are Simulator-Agnostic
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
• Outlook
Tutorial on Static Environment Description
Overview of the Tutorial

- Modeling complex *spatial* relations among objects and agents
  - Starter Example: Badly Parked Car Scenario
  - Scaled Example: Bumper-to-Bumper Traffic Scenario
- Applications of Scenic
- Modelling *temporal* relations will be covered in the next part by Daniel Fremont
Example: a Badly-Parked Car Scenario
Example: a Badly-Parked Car

```python
from carla_models import Car, curb, roadDirection
```
Example: a Badly-Parked Car

```python
from carla_models import Car, curb, roadDirection

ego = Car
```
Definition of Car

class Car():

    position:  Point on road
    heading:  roadDirection at self.position
    model:  CarModel.defaultModel()
    color:  Color.defaultCarColor()
    width:  self.model.width
    height:  self.model.height
    viewAngle:  120 deg
    visibleDistance:  30 # meters
Example: a Badly-Parked Car

```python
from carla_models import Car, curb, roadDirection

go = Car
```
Example: a Badly-Parked Car

```python
from carla_models import Car, curb, roadDirection

go = Car

spot = OrientedPoint on visible curb
```

- **class**
- **specifier**
- **function**
Example: a Badly-Parked Car

```python
from carla_models import Car, curb, roadDirection

ego = Car

spot = OrientedPoint on visible curb
badAngle = Uniform(-1, 1) * Range(10, 20) deg
```

uniform distribution over these discrete choices
uniform distribution over this interval
Example: a Badly-Parked Car

```python
from carla_models import Car, curb, roadDirection

ego = Car

spot = OrientedPoint on visible curb
badAngle = Uniform(-1, 1) * Range(10, 20) deg
parkedCar = Car left of spot by 0.5
```
Example: a Badly-Parked Car

```
from carla_models import Car, curb, roadDirection

go = Car

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

Question: How can we generate the badly parked car closer to ego?
Enforcing explicit constraints

from carla_models import Car, curb, roadDirection

go = Car

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

require (distance to parkedCar) < 20
Example: a (closer) Badly-Parked Car
Scaling up with multiple agents in Scenic

Bumper-to-bumper Traffic Scenes (from Grand Theft Auto V)

Written with less than 20 lines of code!

Citation: Daniel Fremont, et al. “Scenic: A Language for Scenario Specification and Scene Generation,” PLDI 2019
Example: Bumper-to-bumper Traffic

```python
def createPlatoonAt(car, numCars, dist=Range(2, 8), shift=Range(-0.5, 0.5), wiggle=Range(-5, 5) deg):
    lastCar = car
    for i in range(numCars-1):
        center = follow roadDirection from (front of lastCar) for resample(dist)
        pos = OrientedPoint right of center by shift,
        facing resample(wiggle) relative to roadDirection
        lastCar = Car ahead of pos

ego = Car
c2 = Car
platoon = createPlatoonAt(c2, 5, dist=Range(2, 8))
```

```mermaid
graph TD
    c2 --> car
    car -->
    car -->
    car
```
Positioning Objects in Front

Car ahead of ego by 20

Car following roadDirection from ego by 20
Position Specifiers

Illustration of the `beyond`, `behind`, and `offset by` specifiers. Each `OrientedPoint` (e.g., `P`) is shown as a bold arrow.

Domain-Specific Sampling Techniques

- Prune infeasible parts of the space given require statements

require distance to taxi $\leq 5$

require $15 \, \text{deg} \leq \text{(relative heading of taxi)} \leq 45 \, \text{deg}$
Applications of Scenic

- Exploring system performance
  - Generating specialized test sets

- Debugging a known failure
  - Identify the root cause by exploring semantic space near the scene

- Designing more effective training sets
  - Training on hard cases
Application: Training on Hard Cases

- For car detection, a hard case is one car partially occluding another:
Application: Training on Hard Cases

- Train on untargeted GTA data ("matrix") [1], test on our overlapping cars scenario; then retrain on mixtures of the two [2]

<table>
<thead>
<tr>
<th></th>
<th>Precision on All Testset</th>
<th>Precision on Testset with Occlusion scenes</th>
</tr>
</thead>
<tbody>
<tr>
<td>Trainset (5k images)</td>
<td>72.9 %</td>
<td>62.8%</td>
</tr>
<tr>
<td>95% Trainset, 5% Occlusion</td>
<td>73.1 %</td>
<td>68.9%</td>
</tr>
</tbody>
</table>

- **Performance in the hard case improves, without hurting the typical case**

Application: Why did the neural network misdetect?

Citation: Edward Kim, et al. “A programmatic and semantic approach to explaining and debugging neural network-based object detectors,” CVPR 2020 [Oral Presentation]
Application: Why did the neural network misdetect?

User's Scenario

Misdetection: 34.7%

User's Scenario

Misdetection: 87.2%

Citation: Edward Kim, et al. “A programmatic and semantic approach to explaining and debugging neural network-based object detectors,” CVPR 2020 [Oral Presentation]
Q&A Session
Dynamic Scenarios in Scenic
Scenic can describe *dynamic scenarios* which evolve over time.

- Specifying initial conditions and parameters for simulations
  - Falsification of cyber-physical systems (collision-avoidance case study)
  - Analysis & retraining for ML-based systems (runway tracking case study)

- Specifying behaviors of *dynamic agents* which can react to their environment

- *Composing* scenarios in space and time
  - Falsification in dynamic environments (pedestrian scenario case study)
Outline

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Case Study: Falsifying a Collision-Avoidance System

Lane Keeping

Lane Change

Lane change complete

d < 15

d

Ego Car (AV)

Broken Car

Cones
Case Study: Falsifying a Collision-Avoidance System

• Question: does the system always avoid a collision?

• Falsification: automated search for inputs causing the system to violate its specification.
Using Scenic to Generate Initial Scenes

• A scene can be the initial condition for a simulation

```plaintext
# Pick location for blockage randomly along curb
blockageSite = OrientedPoint on curb

# Place traffic cones
spot1 = OrientedPoint left of blockageSite by (0.3, 1)
cone1 = TrafficCone at spot1,
    facing (0, 360) deg

... 

# Place disabled car ahead of cones
SmallCar ahead of spot2 by (-1, 0.5) @ (4, 10),
    facing (0, 360) deg
```

• Can also include parameters for controllers (e.g. reaction time, how quickly to swerve)
Using Scenic to Generate Initial Scenes
Using Scenic to Generate Initial Scenes
Using Scenic to Generate Initial Scenes
Setting up Falsification in VerifAI

```python
# Define semantic feature space
control_params = Struct(
    'x_init': Box([-0.05, 0.05]),
    'cruising_speed': Box([10.0, 20.0]),
    'reaction_time': Box([0.7, 1.0])
)
env_params = Struct(
    'broken_car_color': Box([0.5, 1.0], [0.25, 0.75], [0, 0.5]),
    'broken_car_rotation': Box([5.70, 6.28])
)
sample_space = {'control_params': control_params, 'env_params': env_params}

# Use sampler based on cross-entropy optimization
sampler_type = 'ce'

# System-level specification to falsify, as a Metric Temporal Logic formula
specification = '"G(collisioncone0 & collisioncone1 & collisioncone2)"

# Create and run falsifier
falsifier = mtl_falsifier(sample_space=sample_space, sampler_type=sampler_type,
                          specification=specification)
falsifier.run_falsifier()
```
Falsification
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A Full Design Iteration using Scenic & VerifAI

• In addition to discovering failures, VerifAI can help debug and fix them.

• Industrial case study on TaxiNet, a NN-based taxiing system [CAV 2020]
  – Modeling runway scenarios in SCENIC
  – Falsifying the system, finding scenarios when it violates its specification
  – Debugging to find distinct failures and their root causes
  – Retraining the system to eliminate failures and improve performance
Counterexample Analysis

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

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

- Use VERIFAI to generate a new training set (same size as original)
- Obtained much better performance
Retraining

- Eliminated dependence on time of day
- Used cross-entropy method to learn good training distributions
Outline

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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*

```plaintext
parkedCar = 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))
```
Behaviors and Actions

• Behaviors can call each other
  – Can define libraries of behaviors

• Scenic’s driving domain library
  – Classes for cars, pedestrians, etc.
  – Controllers for simple maneuvers
  – API for accessing road network geometry

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

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

Automatically rejects simulation if ego is not in a lane
A Simple Scenario: CARLA Challenge Scenario #2

- Based on NHTSA pre-crash typology scenario 25
  - Lead car decelerates because of obstacle; ego car must brake

```python
behavior LeadCarBehavior():
    brake = Range(0.9, 1)
    throttle = Range(0.5, 1)
    brakingDistance = Range(5, 10)
    while True:
        if (distance from self to trash) <= brakingDistance:
            take SetBrakeAction(brake), SetThrottleAction(0)
        else:
            take SetBrakeAction(0), SetThrottleAction(throttle)
```
A Simple Scenario: CARLA Challenge Scenario #2

- Based on NHTSA pre-crash typology scenario 25
  - Lead car decelerates because of obstacle; ego car must brake

```python
behavior LeadCarBehavior():
    brake = Range(0.9, 1)
    throttle = Range(0.5, 1)
    brakingDistance = Range(5, 10)
    while True:
        if (distance from self to trash) <= brakingDistance:
            take SetBrakeAction(brake), SetThrottleAction(0)
        else:
            take SetBrakeAction(0), SetThrottleAction(throttle)

lane = Uniform(*network.lanes)

trash = Trash on lane.centerline

leadCar = Car following roadDirection from trash for Range(-15, -30)

ego = Car following roadDirection from leadCar for Range(-10, -30)
```
A Simple Scenario: CARLA Challenge Scenario #2
More Advanced Temporal Constructs

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

```python
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

```plaintext
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

• Cross-platform scenario works in CARLA and LGSVL

```python
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) seconds
    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 = Car with behavior FollowLeadCar(safety_distance=10)
other = Car ahead of ego by 10,
    with behavior StopsAndStarts
require (Point ahead of ego by 100) in road
terminate when ego.lane is None
```
A Worked Example: CARLA
A Worked Example: LGSVL
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- *Composing scenarios in space and time*
  - Falsification in dynamic environments (pedestrian scenario case study)
Composing Scenarios

• Scenic allows scenarios to be defined modularly and combined into more complex scenarios

• Parallel, sequential, and more complex forms of composition

```java
import StopAndStart, BadlyParkedCar

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

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

scenario StartThenParkedCar():
    compose:
        try:
            do StopAndStart()
        override when ...
            do BadlyParkedCar()
```
Outline

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ITSC Case Study

- Pedestrian which crosses the road, hesitating for some amount of time

- Describe trajectory with 3 parameters:
  - Threshold distance
  - Time until hesitation
  - Length of hesitation

```python
behavior Hesitate():
    while ((distance from ego to self) > self.thresholdDistance):
        wait
        do WalkForward() for self.walkTime
        do Stop() for self.hesitateTime
        do WalkForward()

ped = Pedestrian at 14.9@208.2,
    facing 80 deg relative to ego,
    with behavior Hesitate,
    with thresholdDistance Range(10, 20),
    with walkTime Range(1.5, 3.5),
    with hesitateTime Range(1, 3)
```
**Scenic and VerifAI: Summary of Features and Use Cases**

- Classes, Objects, 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
- Scenario Composition

- Synthetic Data Generation
- Test Generation, Fuzz Testing
- Specifying (Safety) Requirements and Metrics
- Falsification (directed search for bugs, edge cases, etc.)
- Debugging and Error Explanation
- Data Augmentation
- Goal-Directed Parameter Synthesis
Documentation on Scenic and VerifAI – linked from GitHub

Welcome to Scenic's documentation!

Scenic is a domain-specific probabilistic programming language for modeling the environments of cyber-physical systems like robots and autonomous cars. A Scenic program defines a distribution over scenes, configurations of physical objects and agents; sampling from this distribution yields concrete scenes which can be simulated to produce training or testing data.

Scenic was designed and implemented by Daniel J. Fremont, Tommaso Dreoisi, Shromona Ghosh, Xiangyu Yue, Alberto L. Sangiovanni-Vincenelli, and Sanjit A. Seshia. For a description of the language and some of its applications, see our PLDI 2019 paper; a more in-depth discussion is in Chapters 5 and 8 of this thesis. Our publications page lists additional papers using Scenic.

Welcome to VerifAI's documentation!

VerifAI is a software toolkit for the formal design and analysis of systems that include artificial intelligence (AI) and machine learning (ML) components. VerifAI particularly seeks to address challenges with applying formal methods to perception and ML components, including those based on neural networks, and to model and analyze system behavior in the presence of environment uncertainty. The current version of the toolkit performs intelligent simulation guided by formal models and specifications, enabling a variety of use cases including temporal-logic falsification (bug-finding), model-based systematic fuzz testing, parameter synthesis, counterexample analysis.
Thank you!

• Scenic and VerifAI are available open source with documentation at:
  https://github.com/BerkeleyLearnVerify/Scenic
  https://github.com/BerkeleyLearnVerify/VerifAI

• Please complete our (short!) post-webinar survey at
  https://forms.gle/79sMYFH8NrTLB9V97
  You can also join our mailing list by completing this survey.

• Send us your feedback!

QUESTIONS?
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Thank you!