Algorithmic Improvisation for Dependable and Secure Autonomy

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Joint work with:

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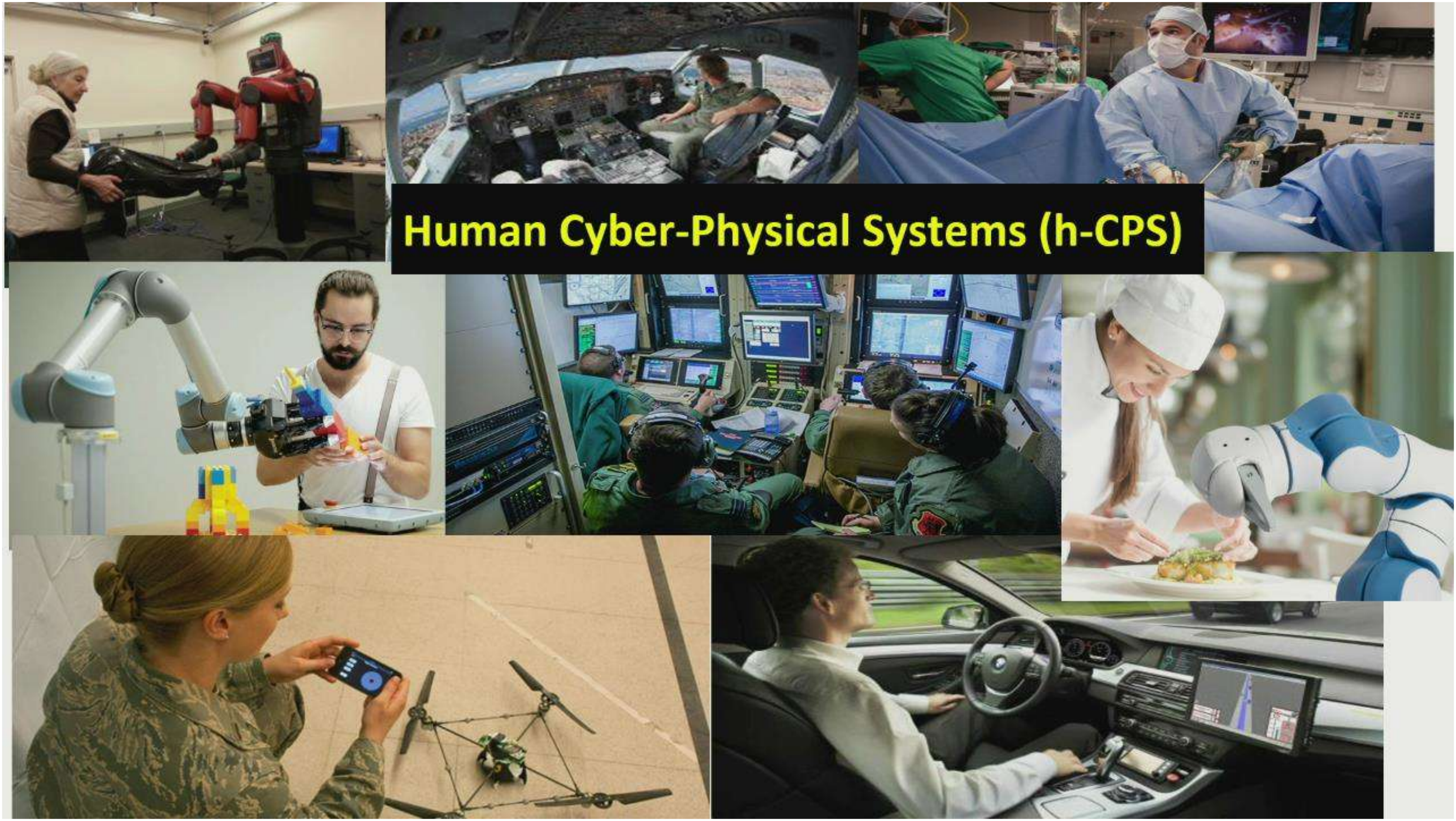
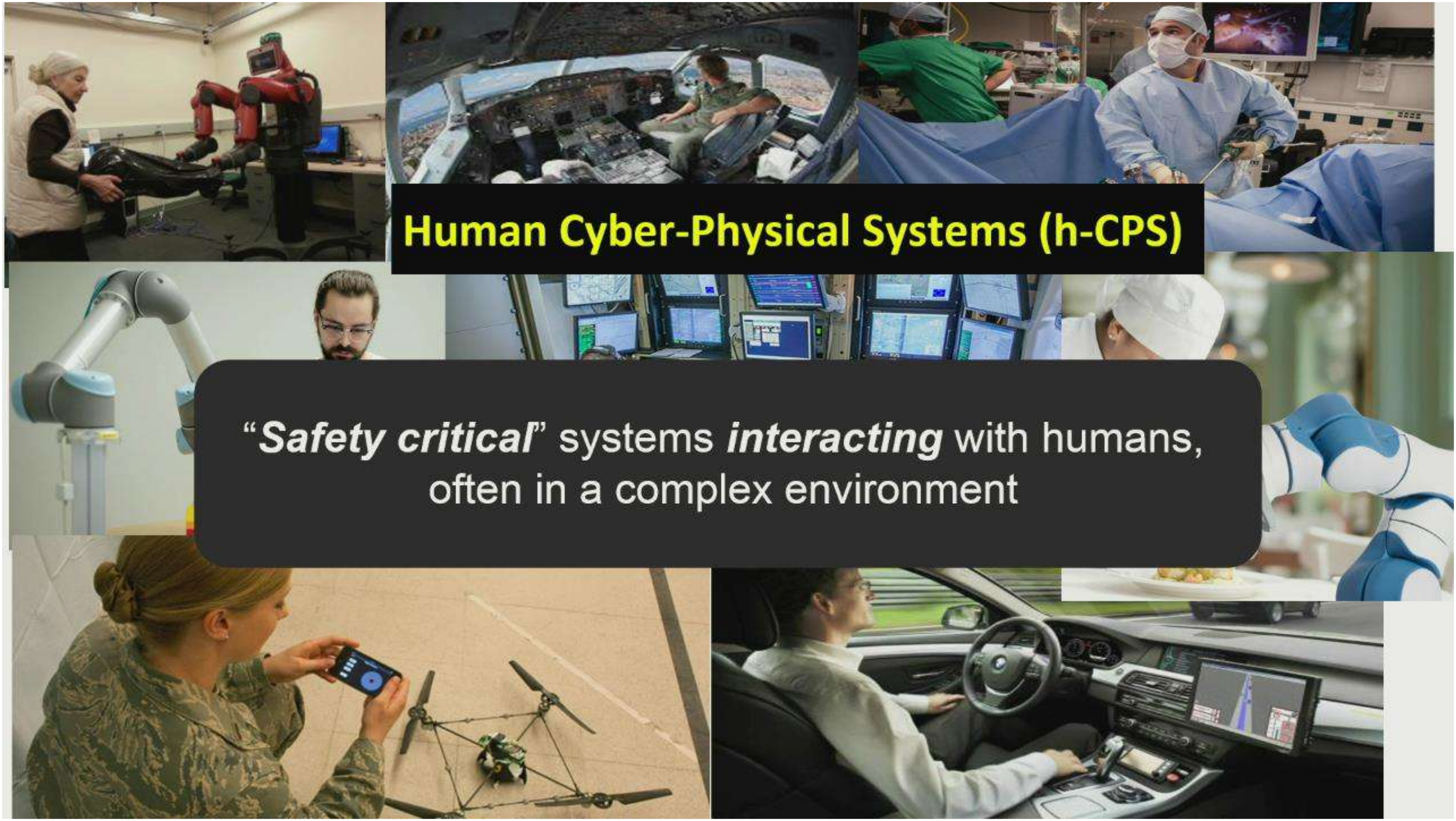
VeriCal

Microsoft Research India

August 1, 2019


Human Cyber-Physical Systems (h-CPS)



Human Cyber-Physical Systems (h-CPS)

"***Safety critical***" systems ***interacting*** with humans, often in a complex environment

[NTSB]

ars TECHNICA

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.

TIMOTHY B. LEE - 5/7/2018, 3:12 PM

[NTSB]

Investigators with the federal agency determined that the car's detection systems, including radar and laser instruments, observed a woman walking her bicycle across the road roughly six seconds before impact — likely enough time, in other words, for a vehicle driving 43 mph to brake and avoid fatally injuring the woman.

But it did not immediately identify the woman as a human pedestrian. Instead, the agency said, "as the vehicle and pedestrian paths converged, the self-driving system software classified the pedestrian as an unknown object, as a vehicle, and then as a bicycle with varying expectations of future travel path."

ars TECHNICA BIZ

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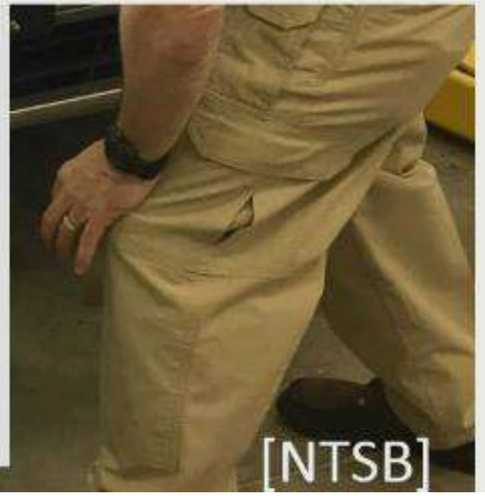

A Formal Methods Approach

Formal Methods: rigorous algorithmic techniques to model, design, and analyze systems based on formal mathematical reasoning.

"Towards Verified Artificial Intelligence", S. A. Seshia et al., 2016:
https://arxiv.org/abs/1606.08514

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A Formal Methods Approach

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Prove rigorous guarantees when possible;

do ***formally-guided, intelligent simulation/testing*** when not.

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Message of this Talk

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Randomness can play a crucial role in Formal Methods for Autonomy!

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- Modeling Autonomous Systems and Their Environments

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- Verification – Constrained-Random Simulation, Probabilistic Verification

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- Modeling Autonomous Systems and Their Environments
- Verification – Constrained-Random Simulation, Probabilistic Verification
- Synthesis: Randomized Planning/Control

Randomized Formal Methods for Safe Autonomy

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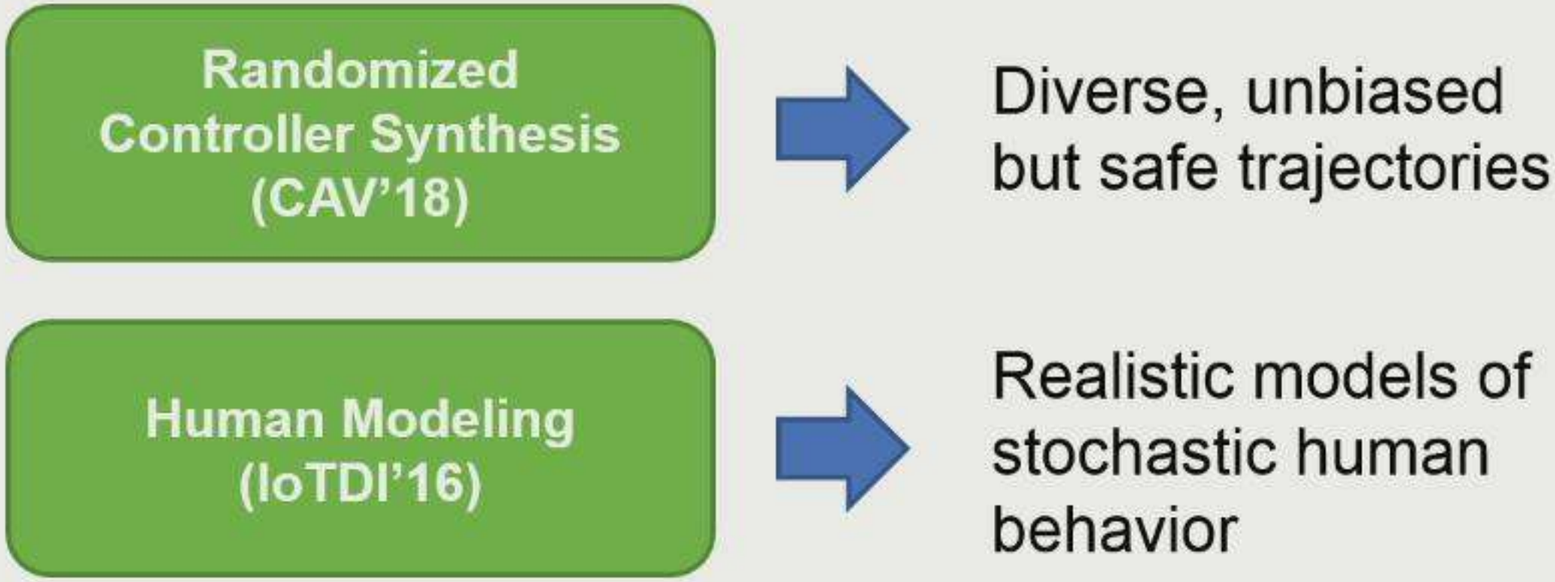
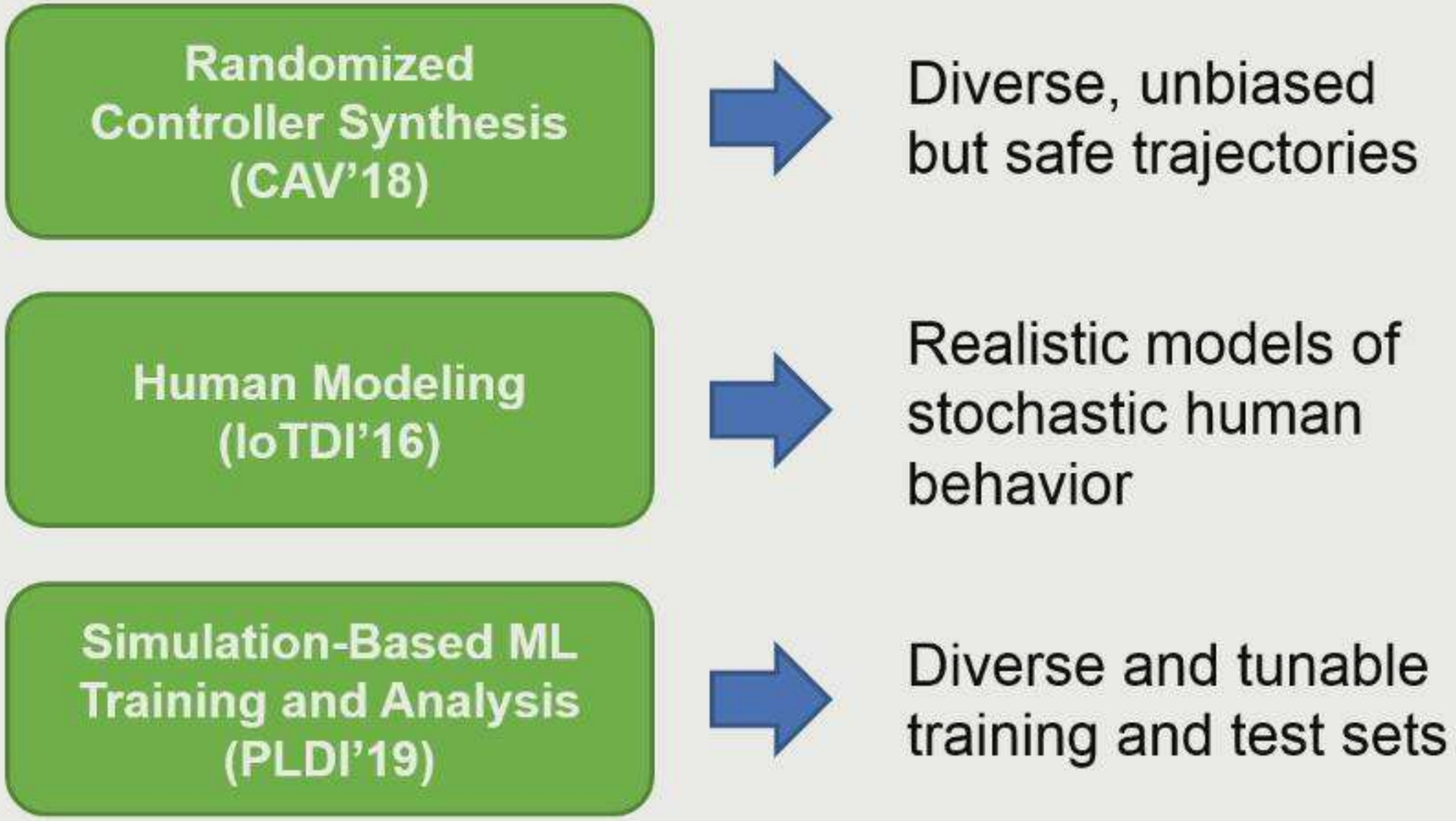
Randomized Controller Synthesis (CAV'18)

Diverse, unbiased but safe trajectories

Randomized Formal Methods for Safe Autonomy



Randomized Formal Methods for Safe Autonomy



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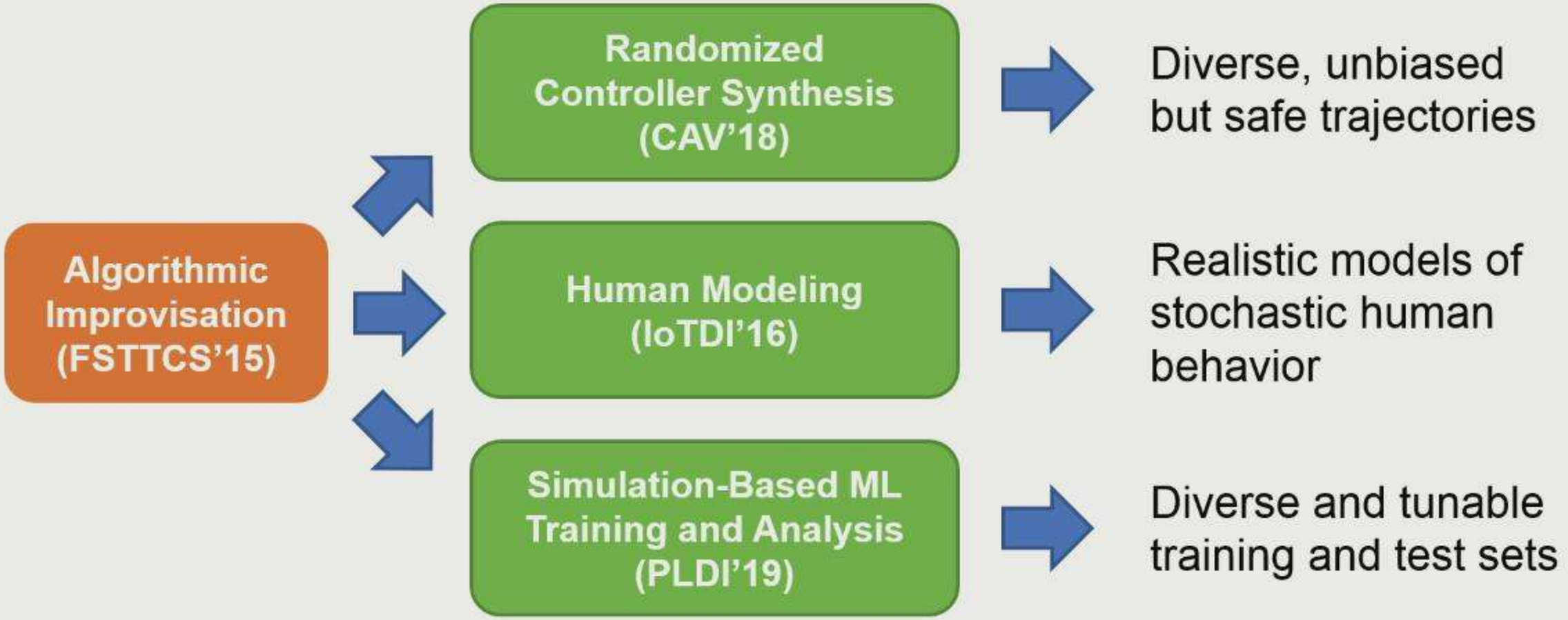


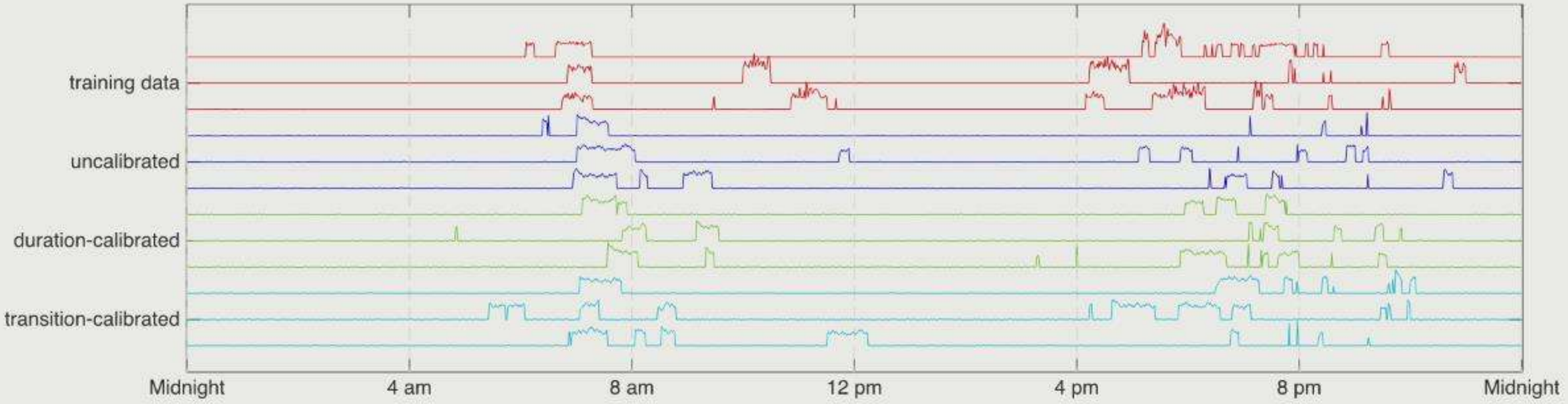
Why Randomness: Variety/Coverage

- Train/test set generator for an object-detecting neural network
  - "Generate images of bumper-to-bumper traffic"
  - Huge and diverse space of possibilities – randomness lets you cover it well

Fremont et al., *Scenic: A Language for Scenario Specification and Scene Generation*, PLDI 2019 (to appear).

Why Randomness: Realism

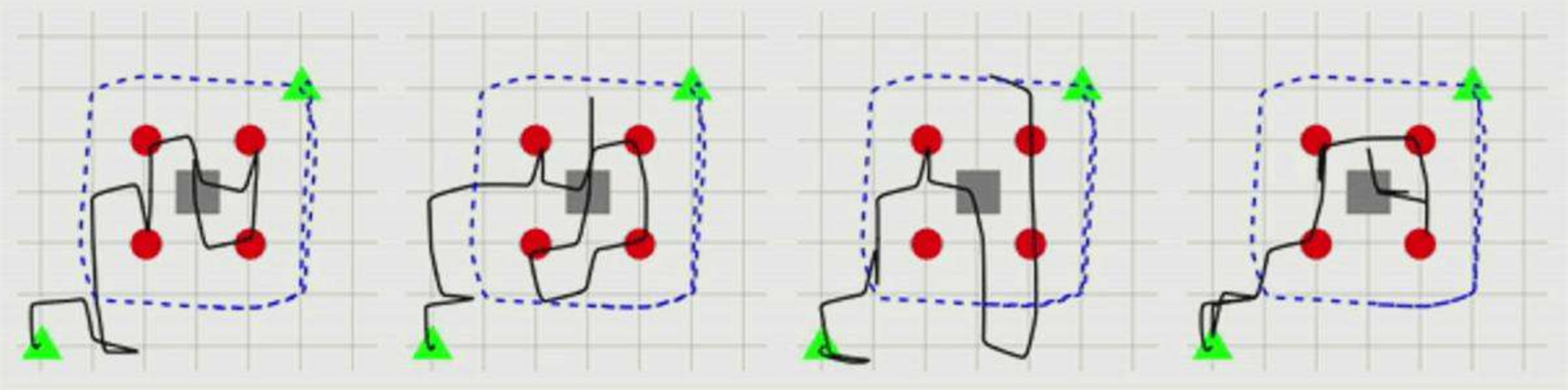
- Home automation lighting controller
  - "Mimic the user's typical behavior while they are away"
  - Deterministic models unrealistic – human behavior is random



Akkaya et al., *Control Improvisation with Probabilistic Temporal Specifications*, IoTDI 2016.

Why Randomness: Unpredictability

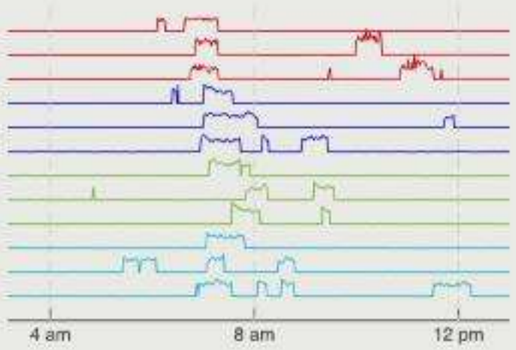
- Surveillance robot
  - “Patrol an area, visiting each important location sufficiently often”
  - Using a random route makes the robot’s future location harder to predict

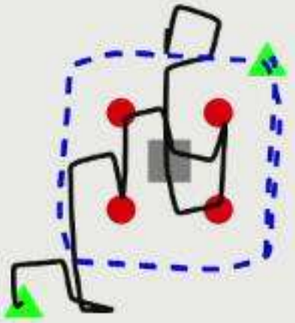


Fremont and Seshia, *Reactive Control Improvisation*, CAV 2018.

Randomness with Guarantees

- Randomness is essential for all these systems





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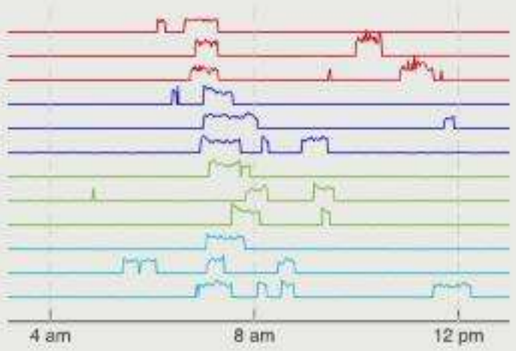

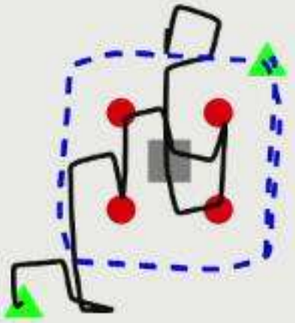

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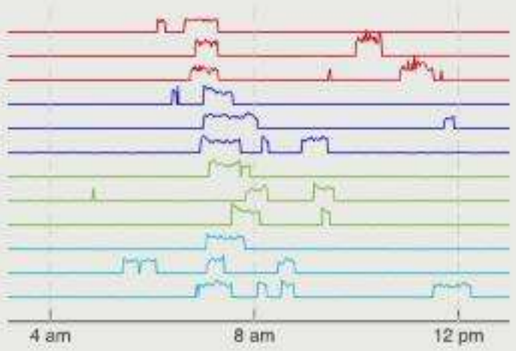

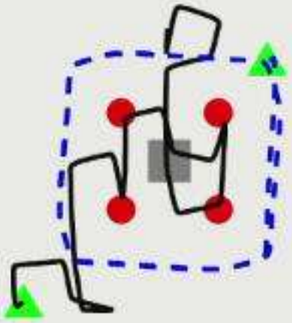

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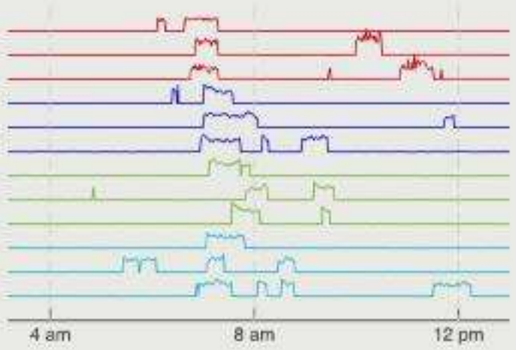

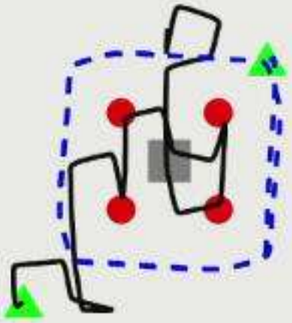

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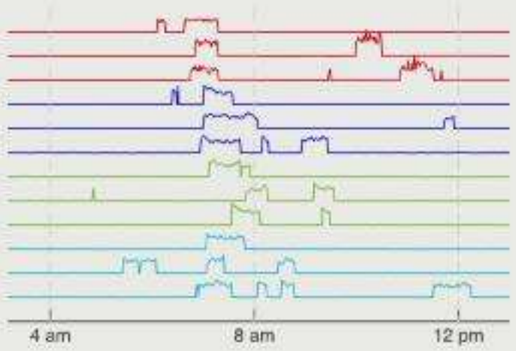

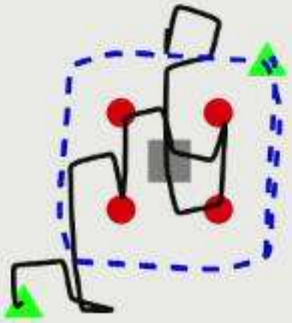

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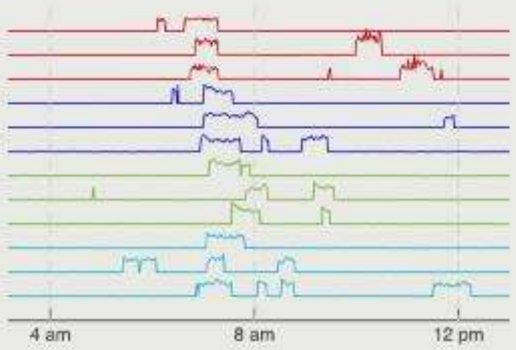

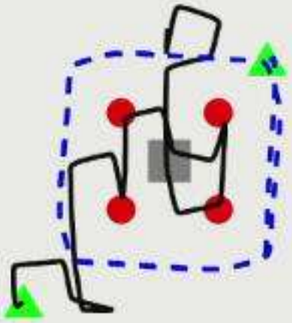

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- ***How to design a system with <u>random but controlled</u> behavior?***

Algorithmic Improvisation (Control Improvisation)

- A framework for automatically synthesizing (reactive) systems with random behavior but formal guarantees:

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- **Key novelty: Randomness is *part* of the specification!**

Outline

1. Control Improvisation
   - Definition and motivating applications

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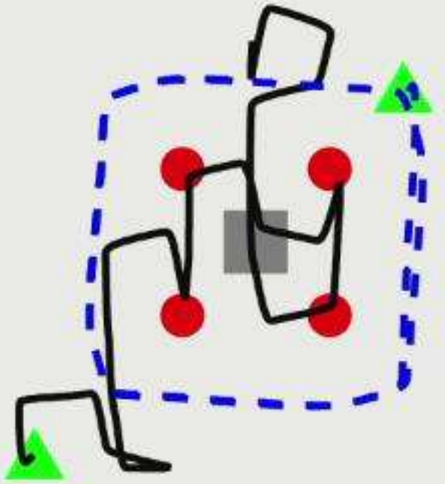
- **Robotic Surveillance**
  - “patrol an area in an unpredictable way”



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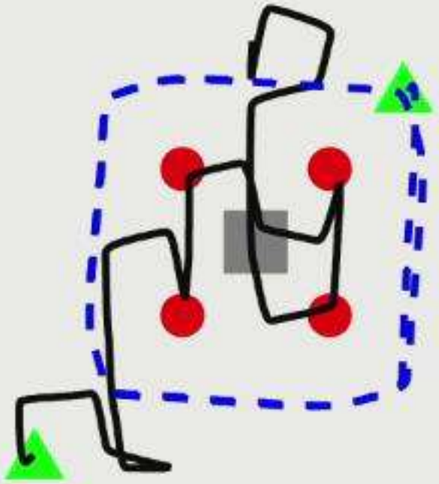

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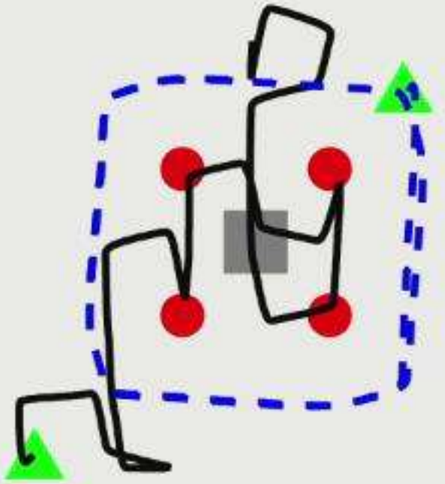

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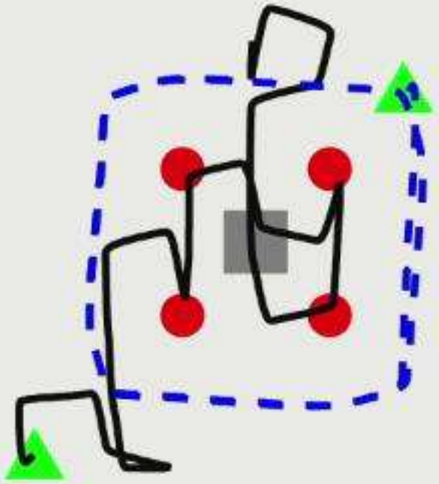

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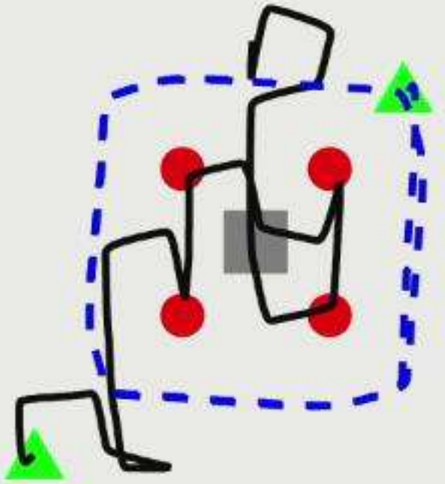

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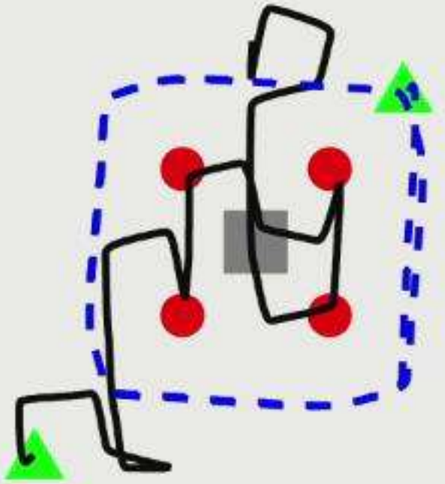

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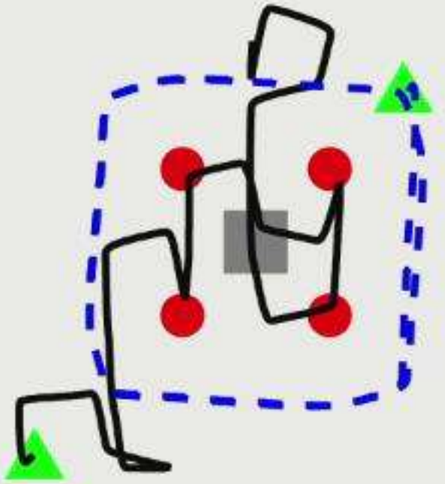

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Hard Constraint

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Soft Constraint

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Randomness Constraint

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Randomness Constraint

Commonalities

- These and other applications: music improvisation, fuzz testing…

Generate sequences subject to three kinds of constraints:

[D. Fremont et al., “Control Improvisation”, FSTTCS 2015. Extended version on arxiv, 2018.]

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Control Improvisation is a precisely-defined theoretical problem capturing these requirements

[D. Fremont et al., “Control Improvisation”, FSTTCS 2015. Extended version on arxiv, 2018.]

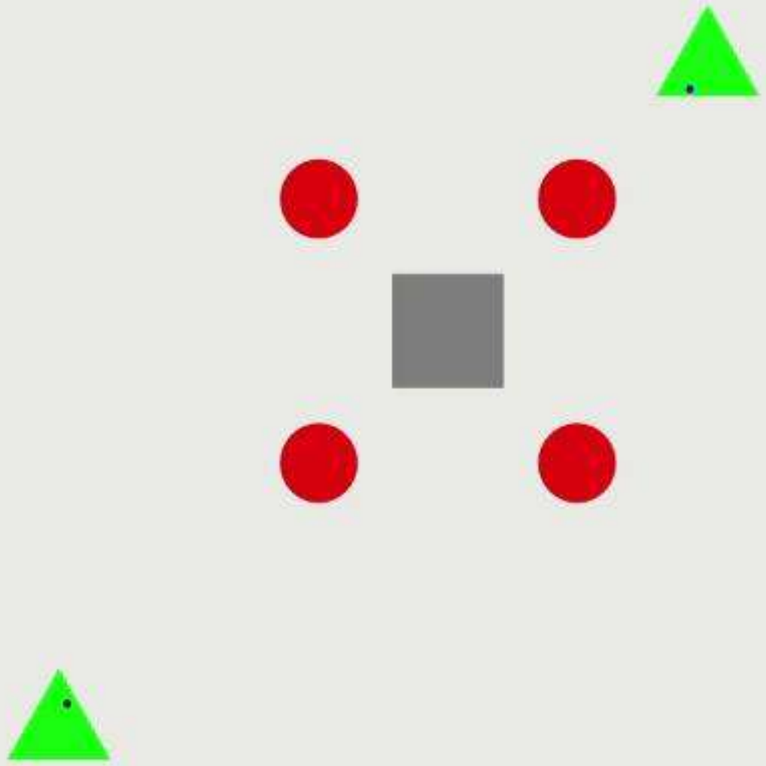
Related Work

- Control improvisation is a fundamentally new type of problem

	HARD	SOFT	RANDOM	REACTIVE
Factor Oracles [1]		■		
Mutational Fuzzers [2]		■		
Uniform Sampling [3]	■		■	
Generative Fuzzers [2,3]	■		■	
Reactive Synthesis [4]	■			■
Control Improvisation	■	■	■	■

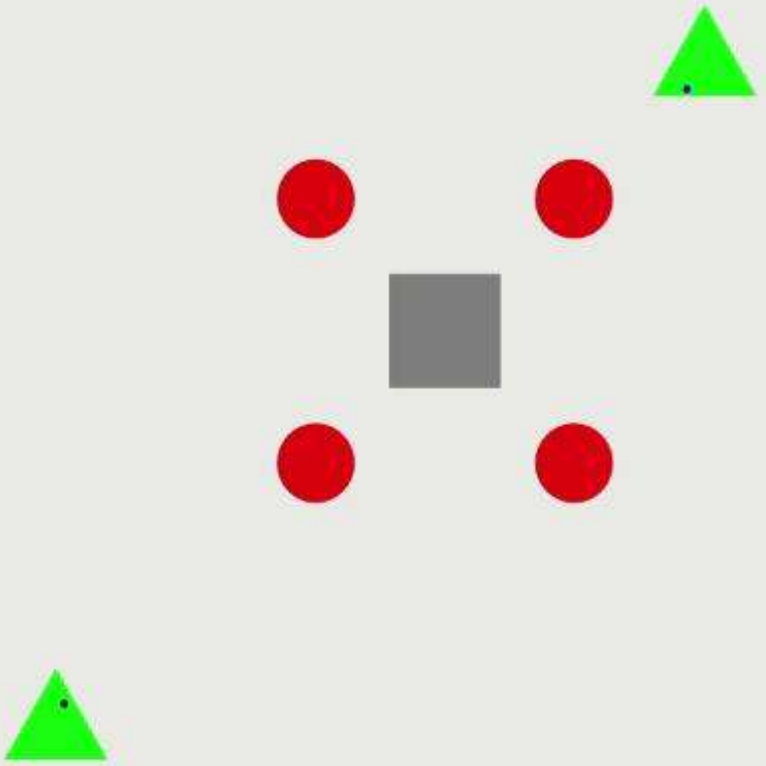
[1] Assayag & Dubnov, *Soft Computation*, 2004.
[2] see Sutton, Greene, & Amini, Addison-Wesley, 2007.
[3] e.g. Hickey & Cohen, *SIAM Journal on Computing*, 1983.
[4] e.g. Pnueli & Rosner, POPL 1989.

Components of the Definition



Components of the Definition

- Generate sequences of length *n* from a finite alphabet Σ
  - Σ = { N, S, E, W }, n = 30



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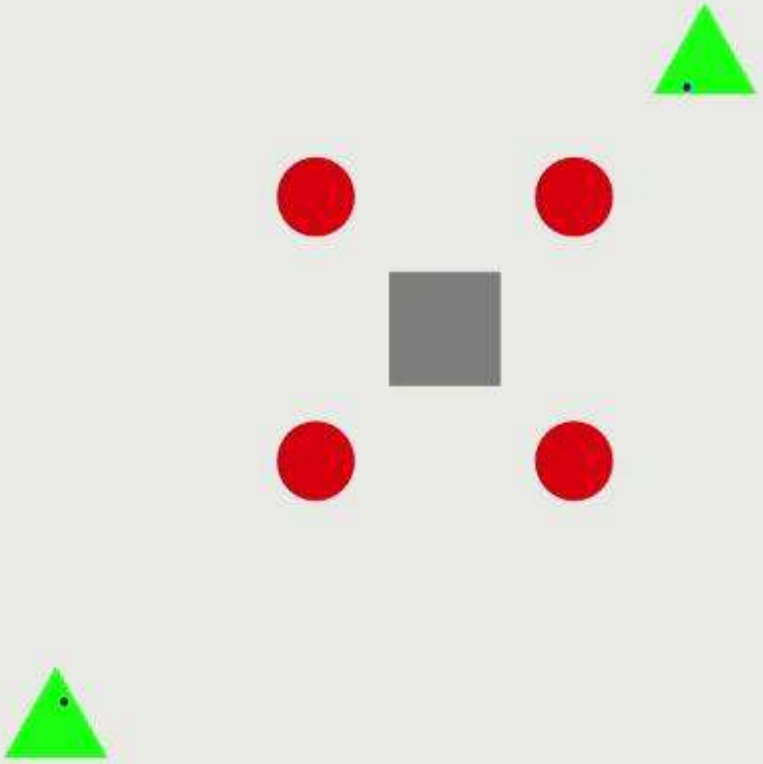

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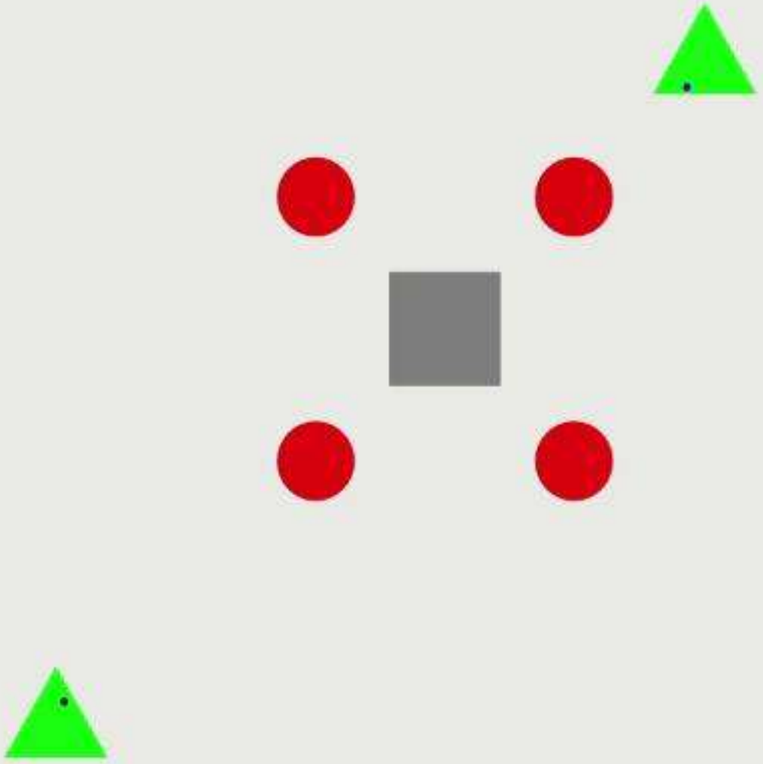

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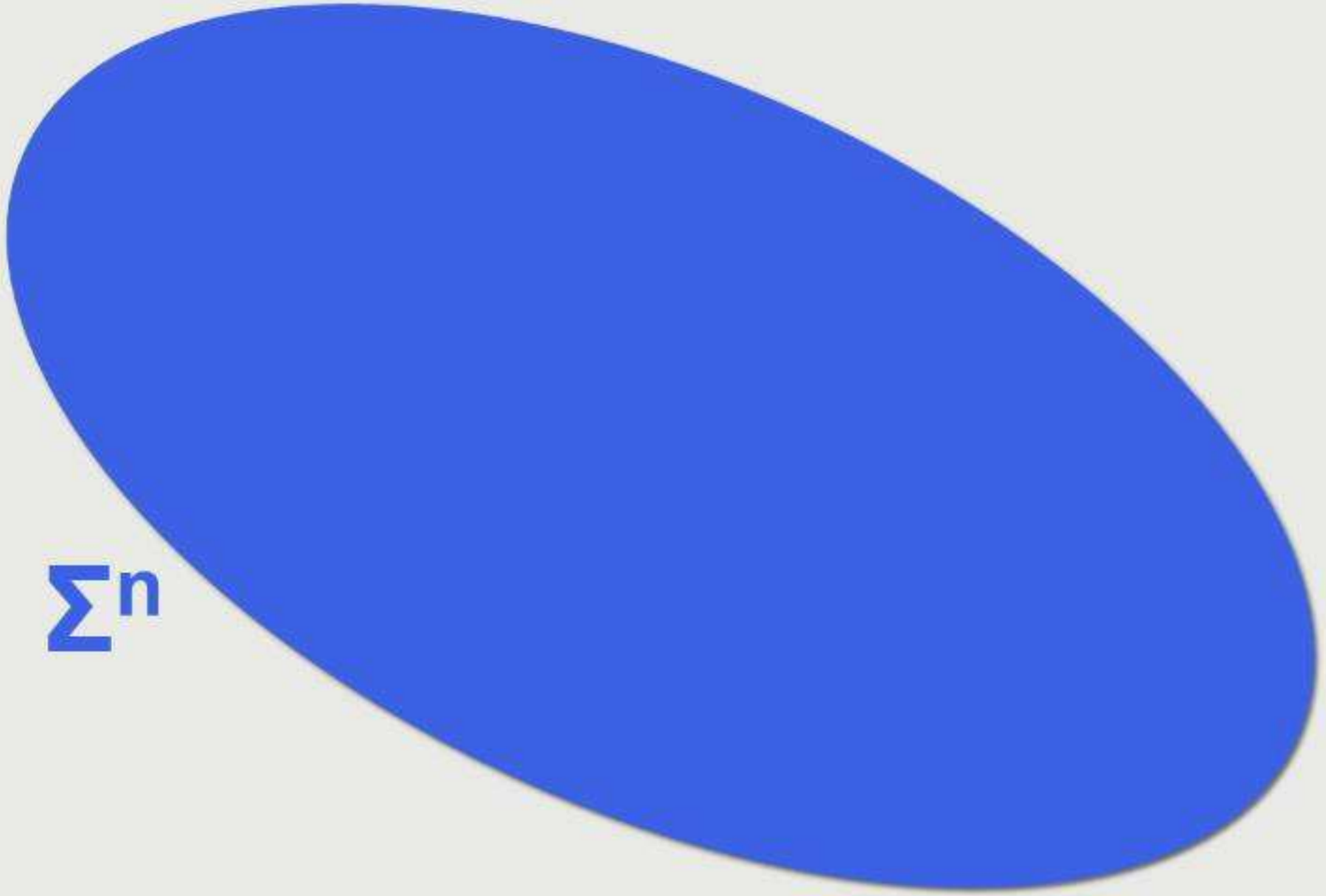

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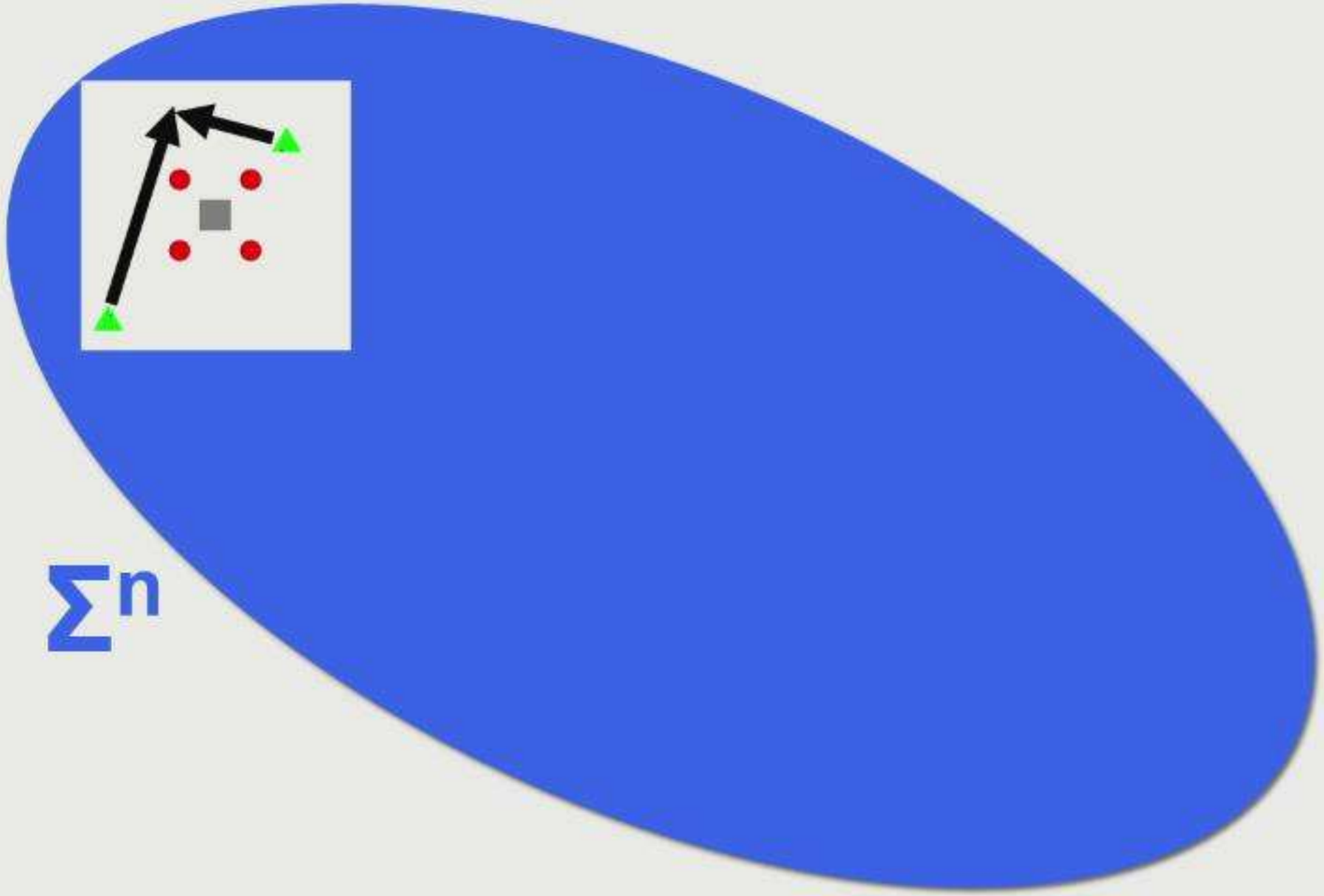

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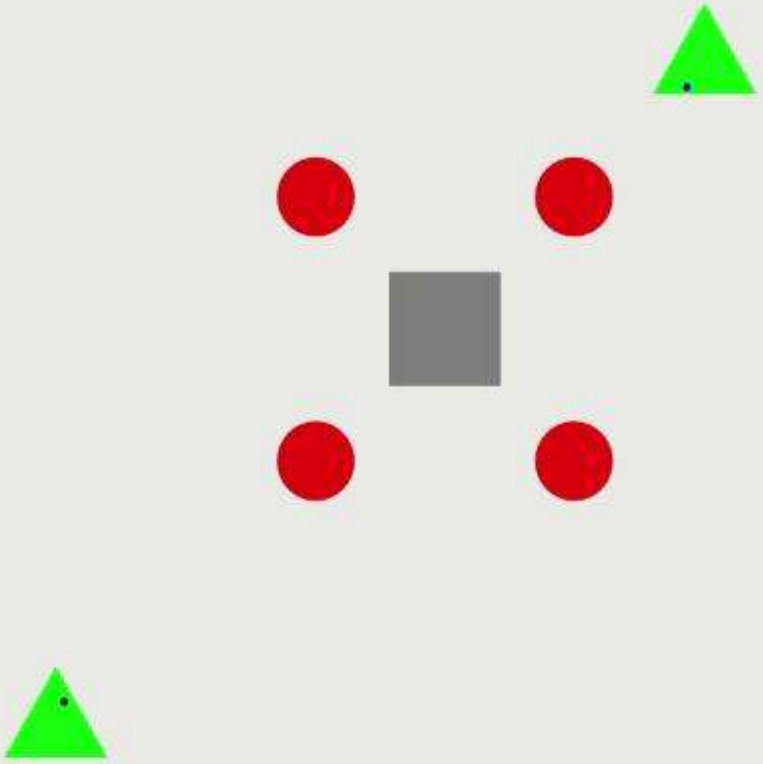

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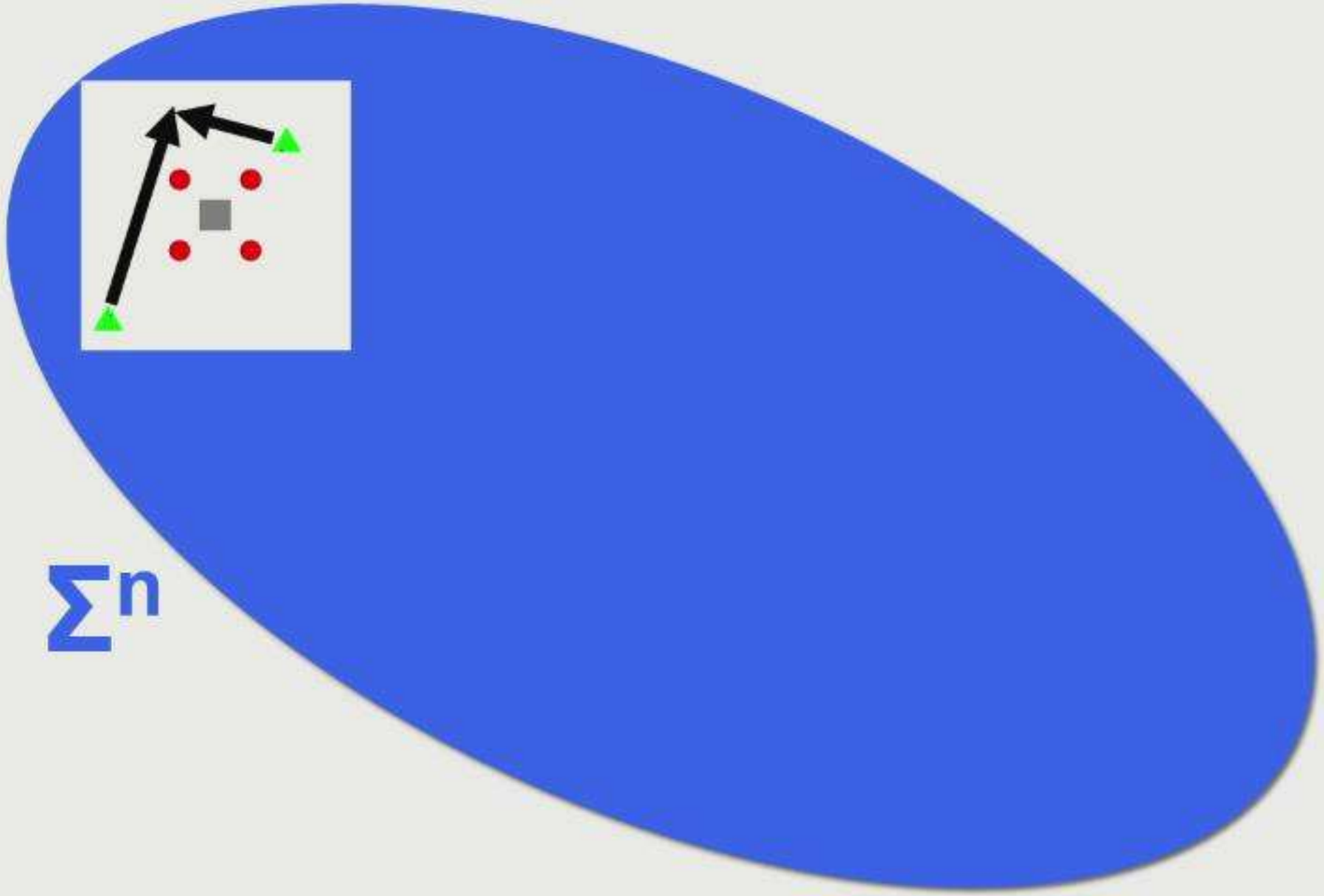

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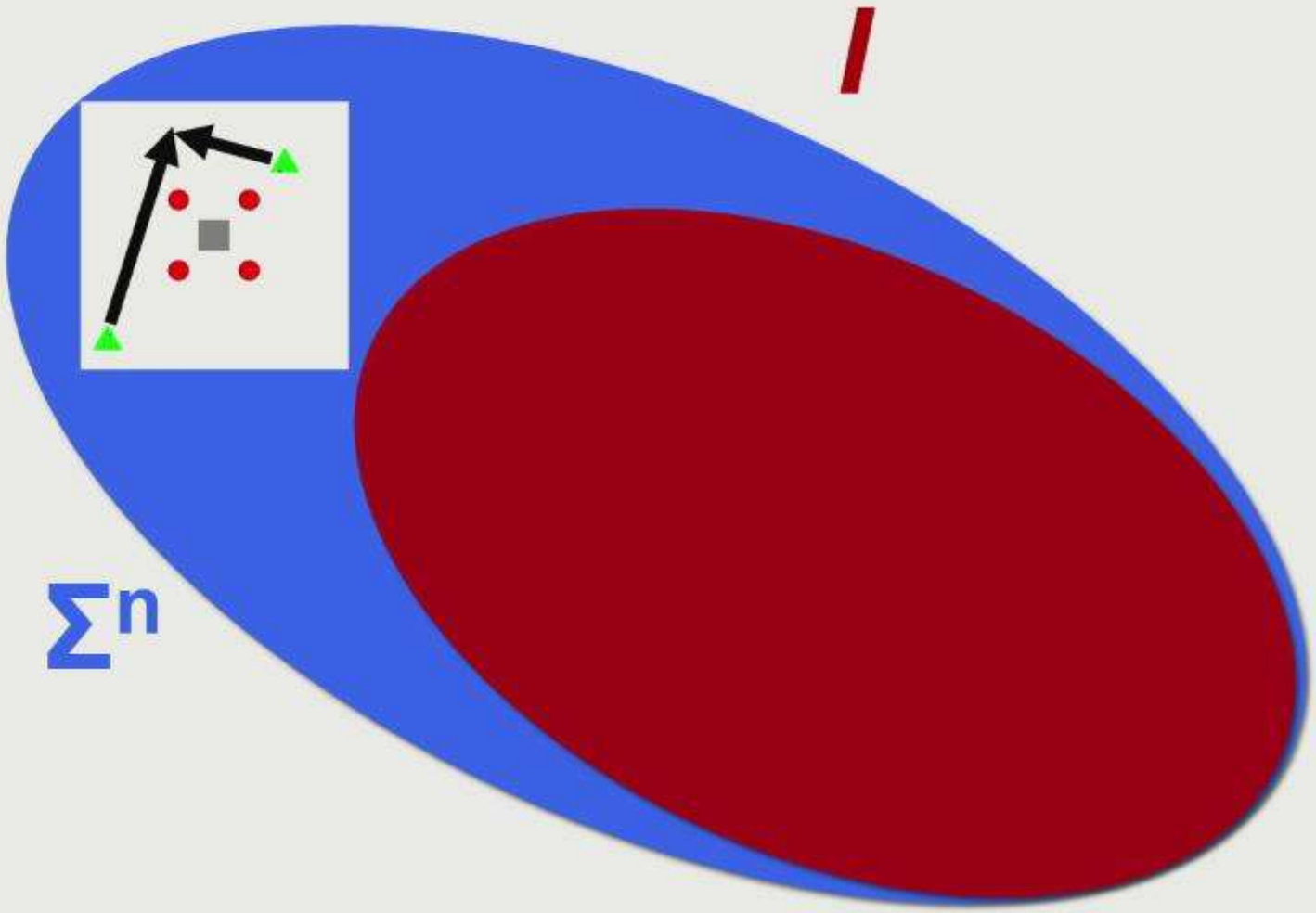

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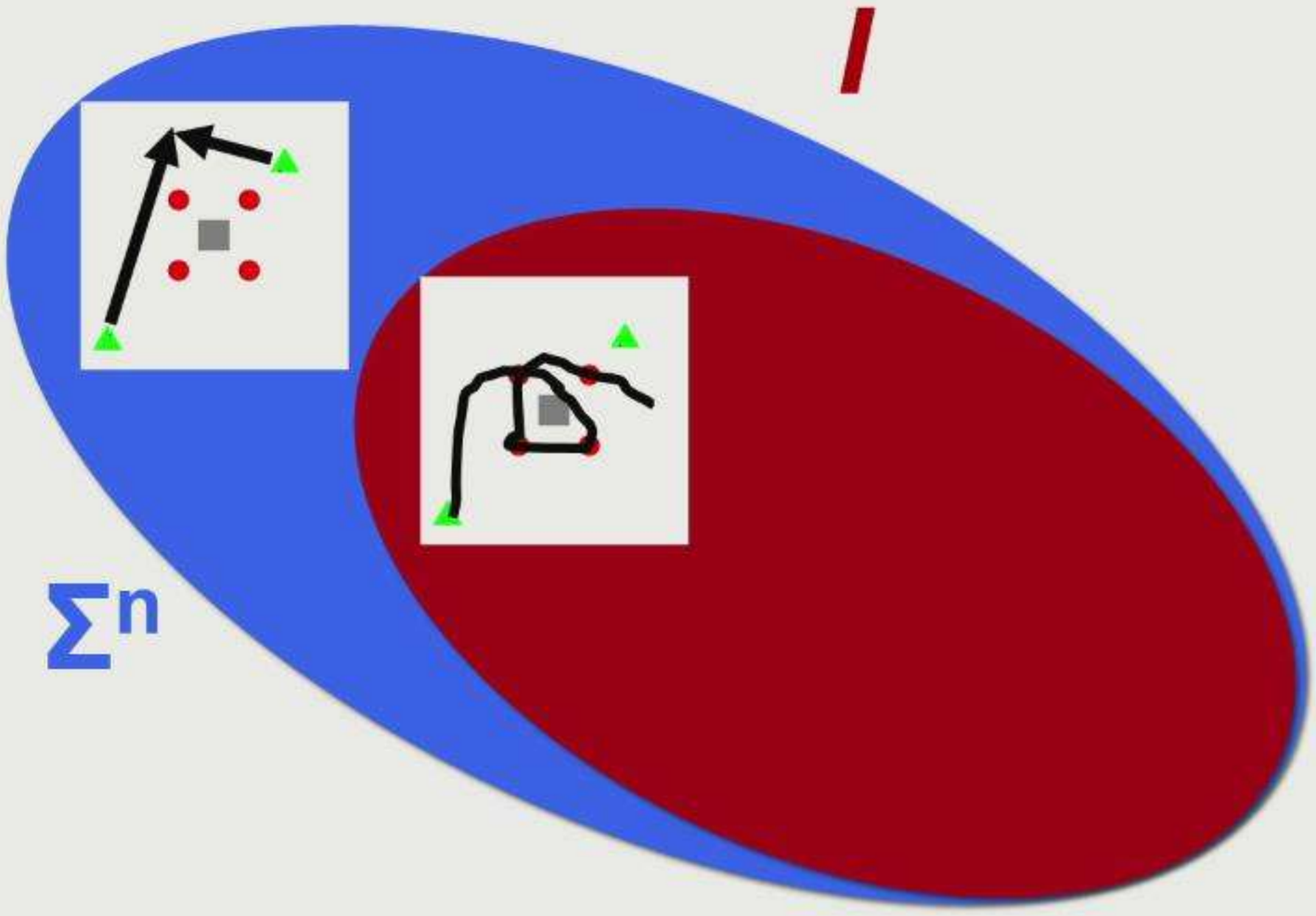

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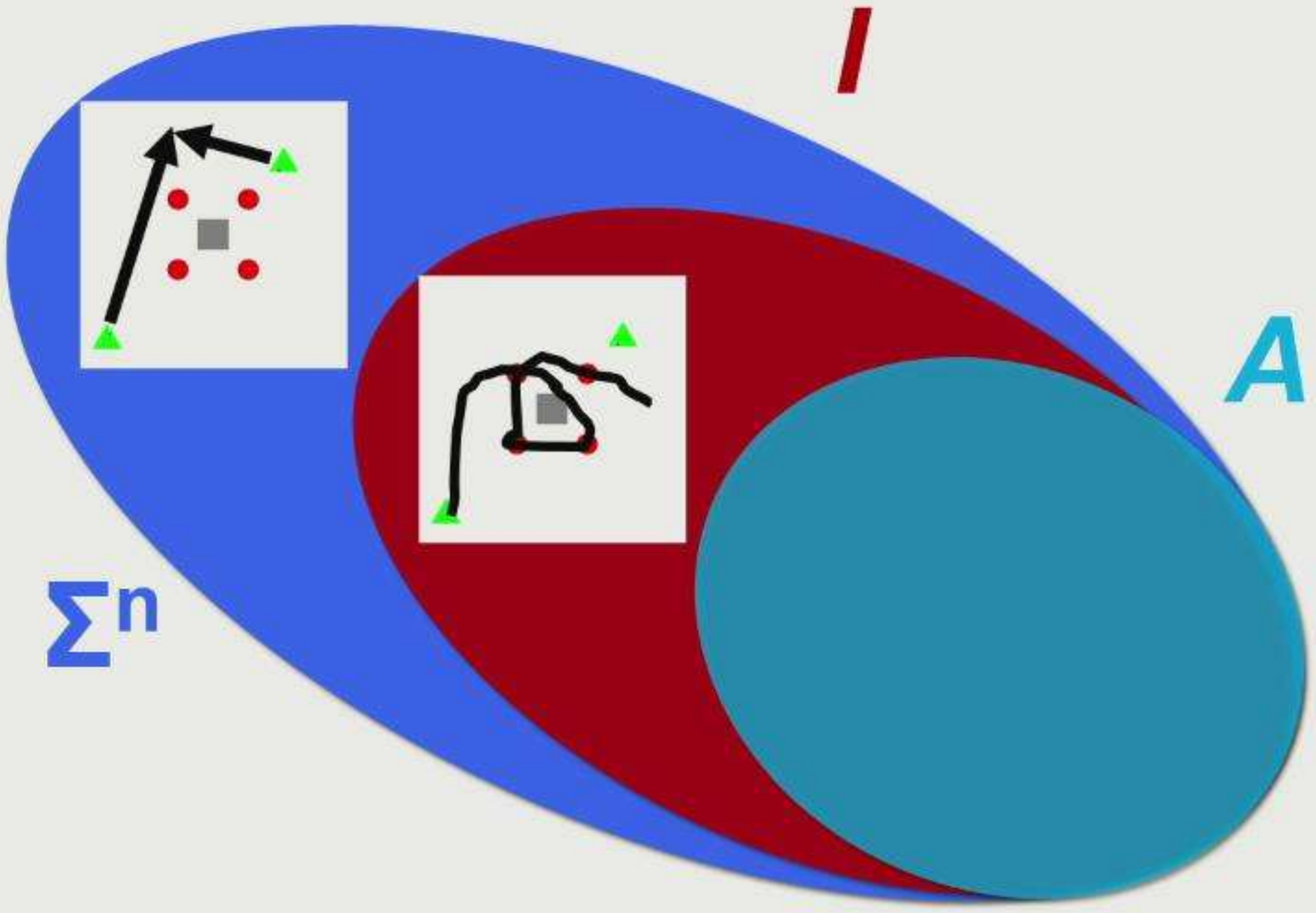

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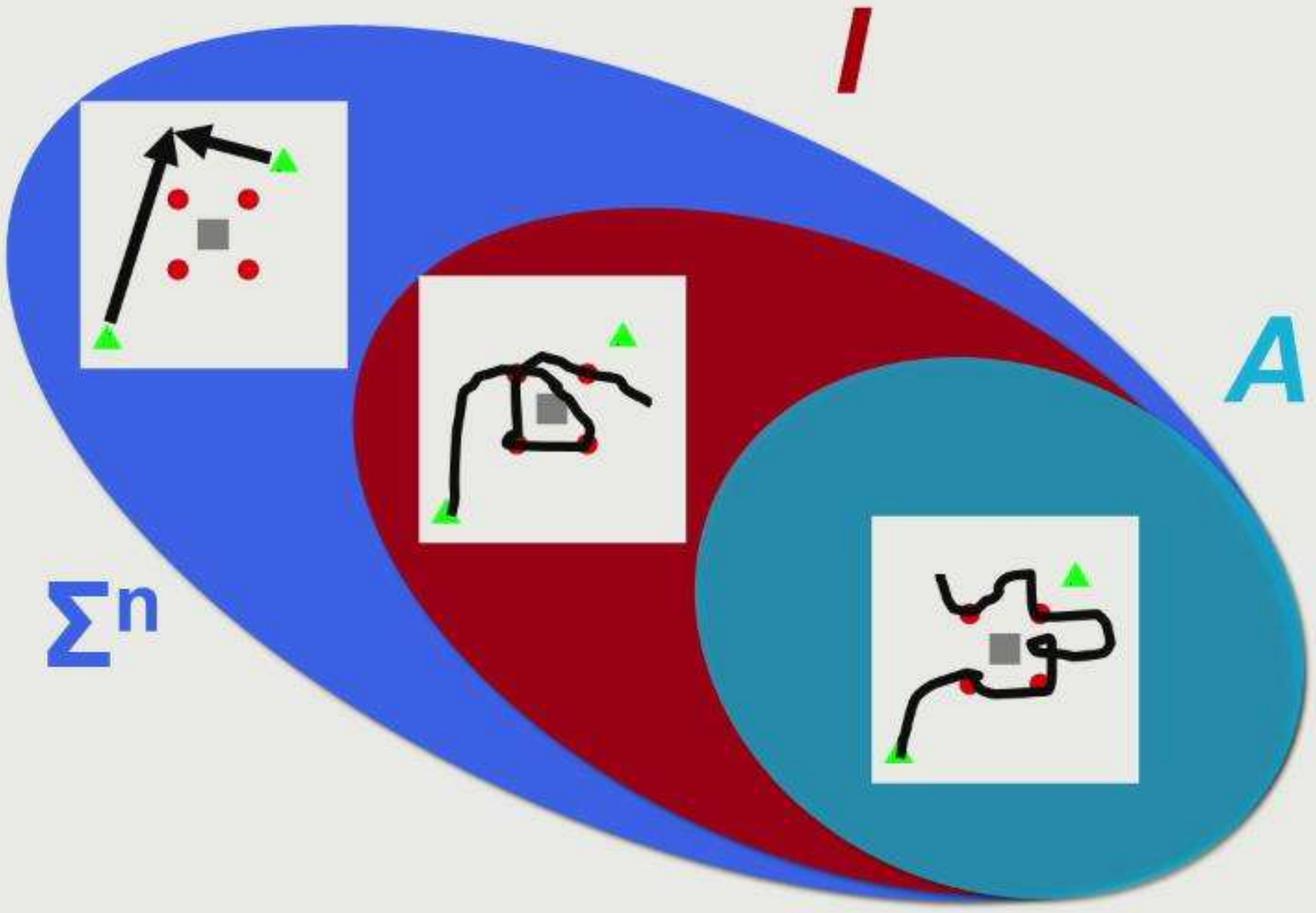

Definition of Control Improviser

Given H, S, n, an *error probability* $0 \leq \varepsilon \leq 1$, and bounds $0 < \lambda, \rho \leq 1$, a distribution $D : \Sigma^* \rightarrow [0,1]$ is an *improvising distribution* if:

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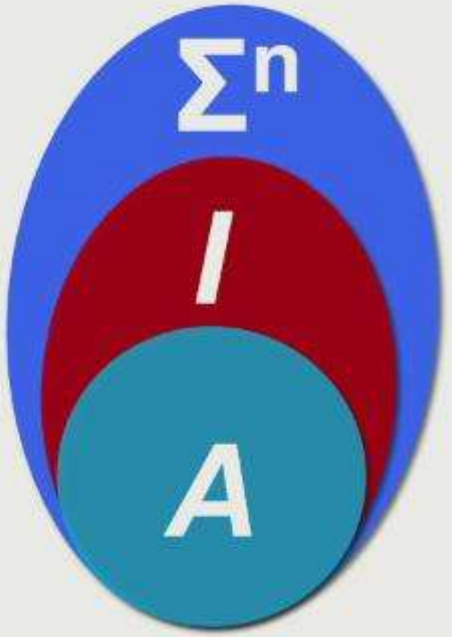

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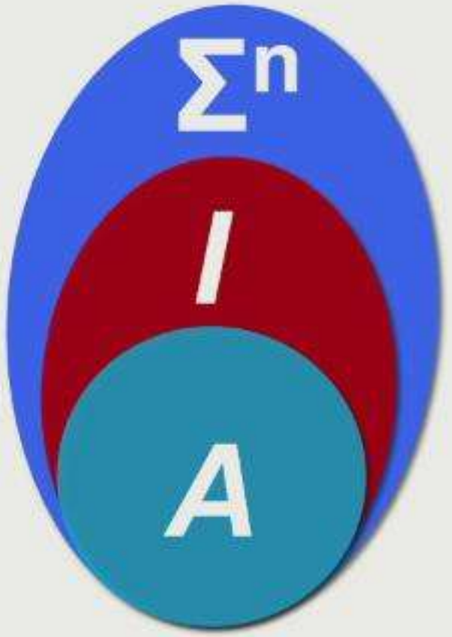

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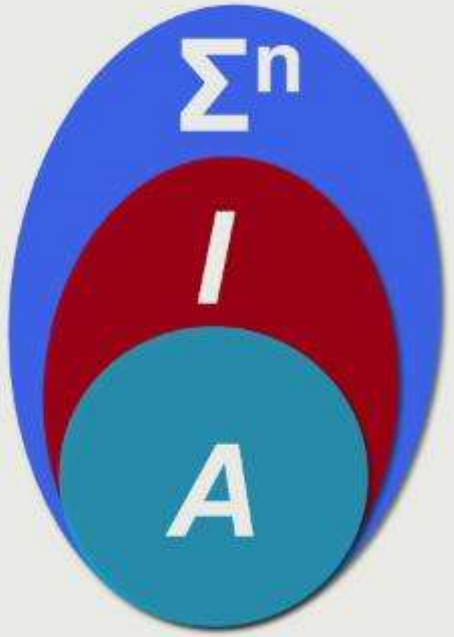

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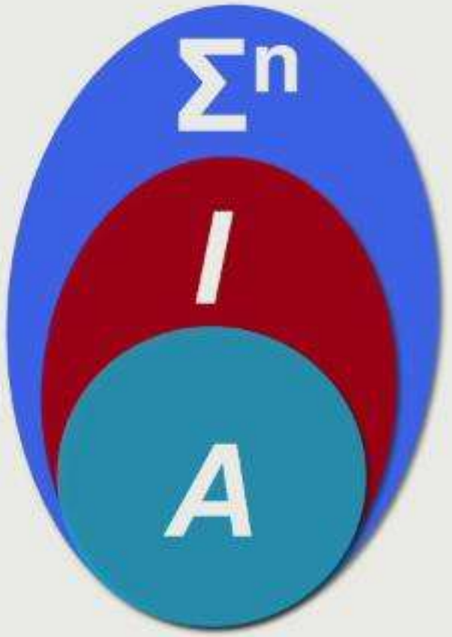

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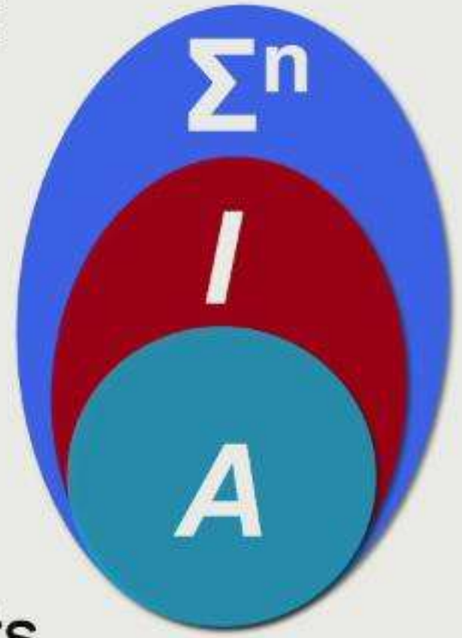

The CI instance $\mathcal{C} = (\mathcal{H}, \mathcal{S}, n, \epsilon, \lambda, \rho)$ is *feasible* if *D* exists.

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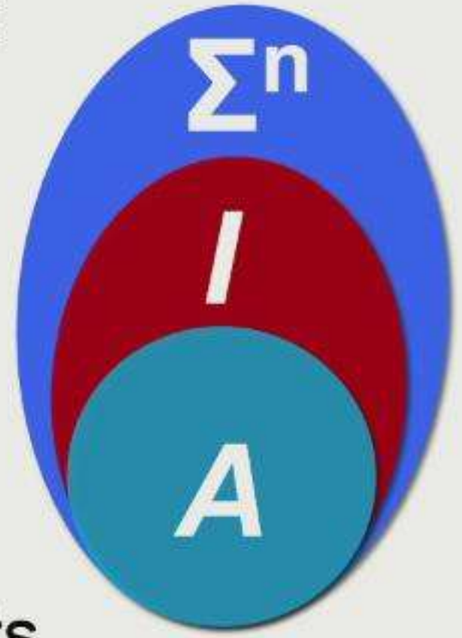

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An *improviser* is a probabilistic algorithm sampling from *D*.

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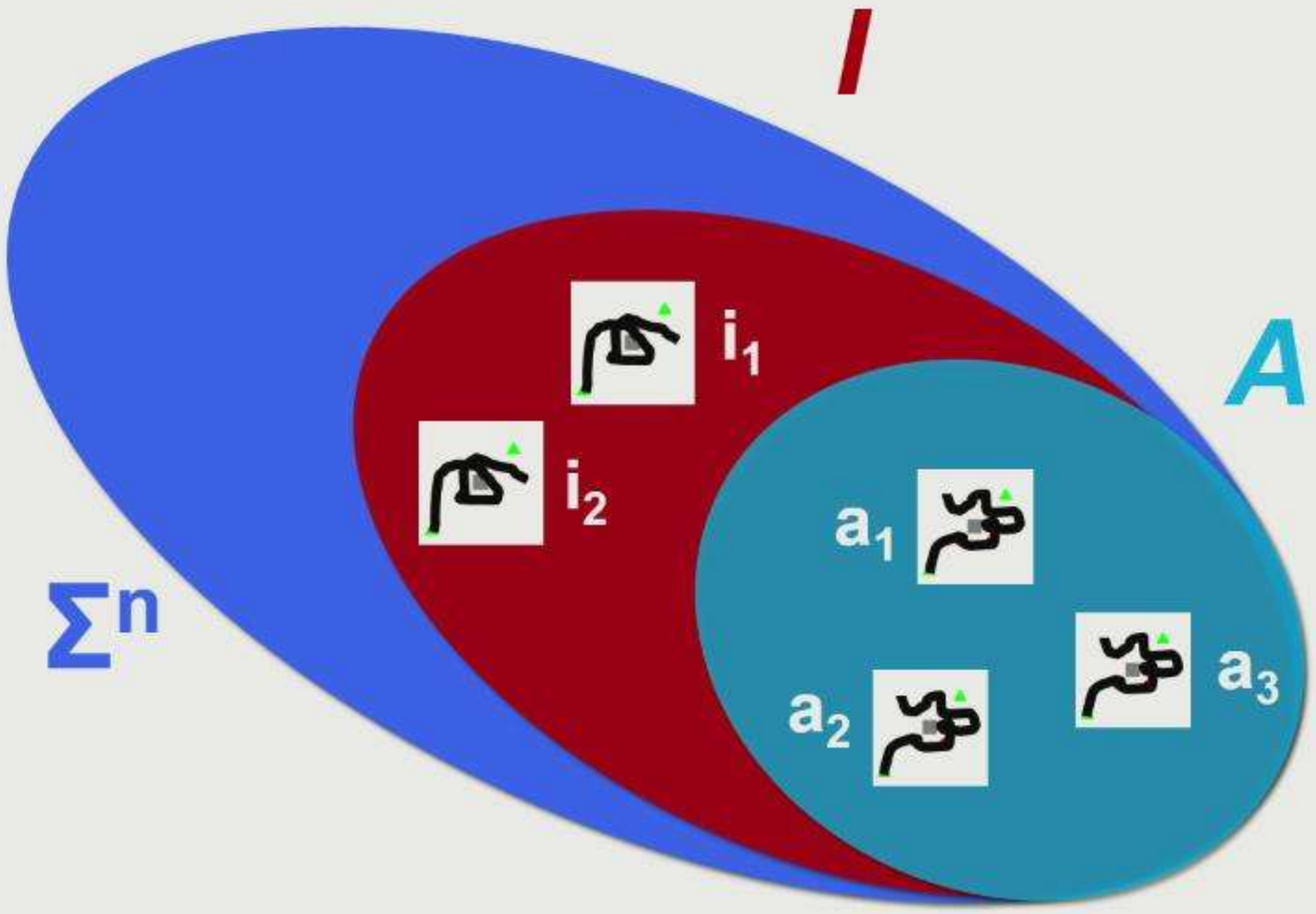
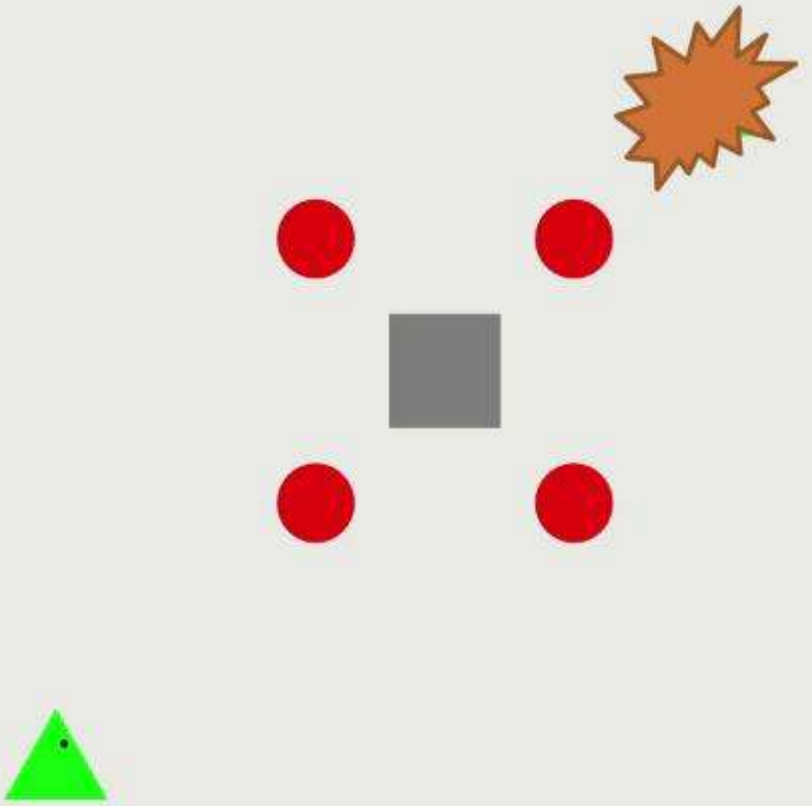
Example

- Suppose $A = \{\mathbf{a}_1, \mathbf{a}_2, \mathbf{a}_3\}$ and $I \setminus A = \{\mathbf{i}_1, \mathbf{i}_2\}$
- With $\varepsilon = \rho = 1/4$:
  - Return $\mathbf{a}_1$, $\mathbf{a}_2$, and $\mathbf{a}_3$ with probability ¼
  - Return $\mathbf{i}_1$ and $\mathbf{i}_2$ with probability ⅛



Reactive Control Improvisation



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Reactive Control Improvisation

- Changes to definition:
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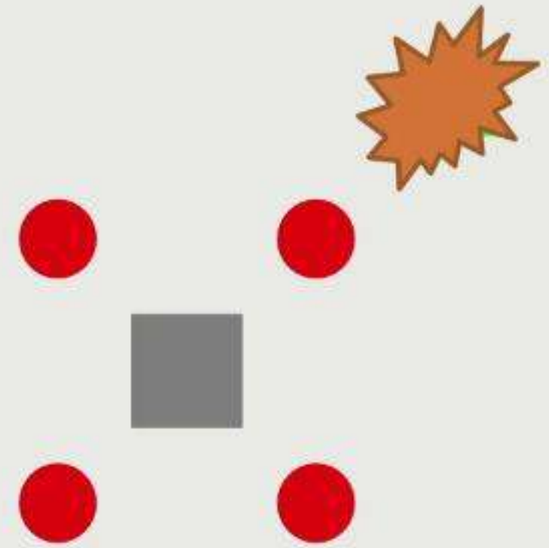

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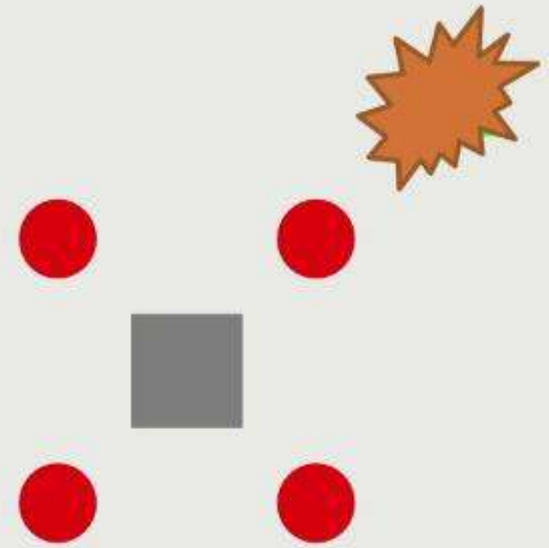

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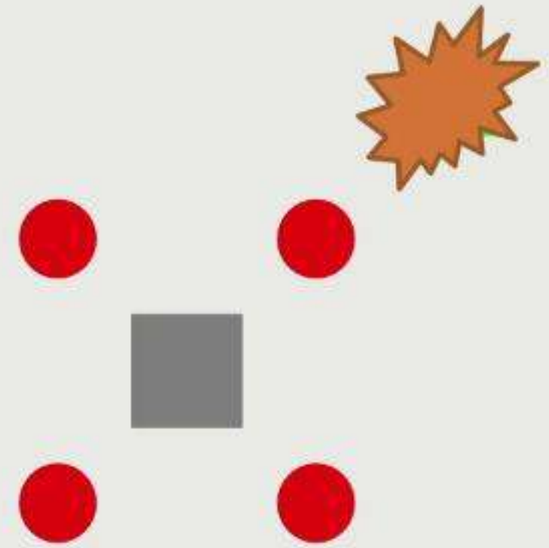

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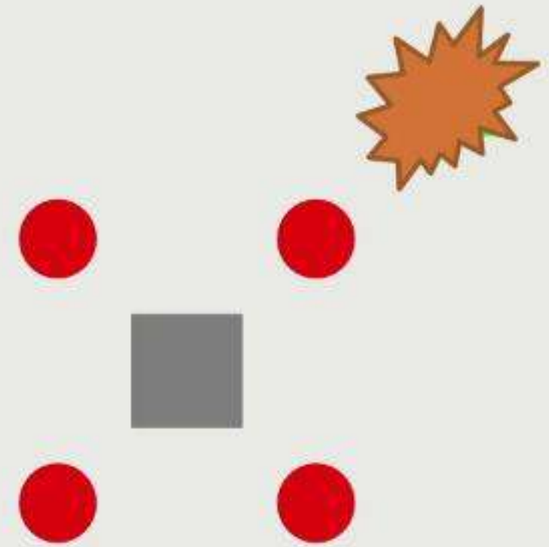
- This enables randomized reactive synthesis (for bounded time)



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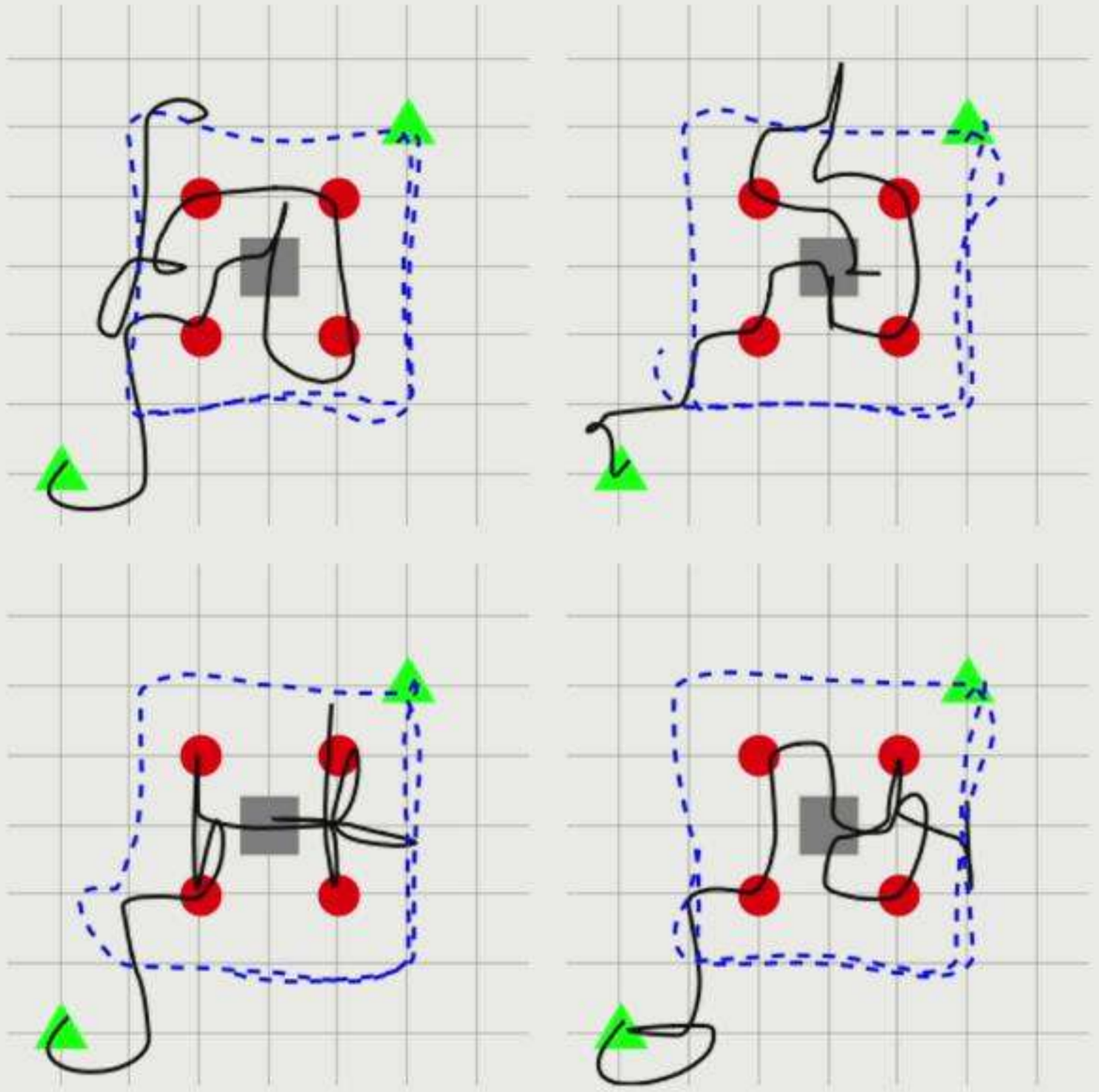
RCI Example

- Hard constraint:
  - Visit the 4 circles in 30 moves, avoiding the adversary
- Soft constraint:
  - 75% of the time, visit each circle exactly once
- Randomness requirement:
  - Use the smallest feasible ρ (about 10^{-12})



Outline

1. Control Improvisation
   - Definition and motivating applications
2. **Theory of CI**
   - Efficient algorithms and hardness results
3. Designing and Analyzing Perception Systems
4. Conclusion & Future Work

Existence of Improvisers

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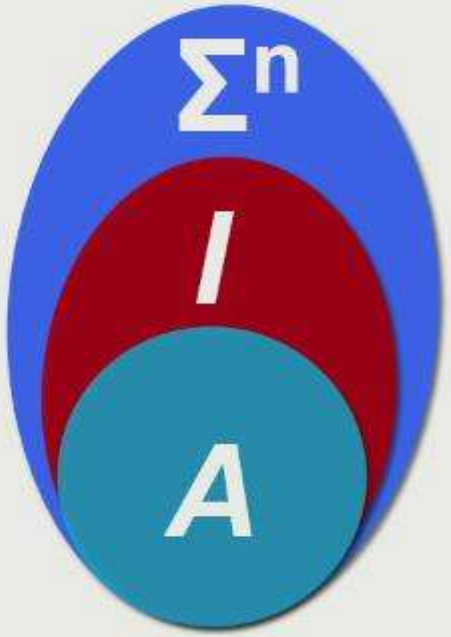

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Theorem. A CI instance $\mathcal{C} = (H, S, n, \epsilon, 0, \rho)$ is feasible if and only if:

- $|I| \geq 1/\rho$
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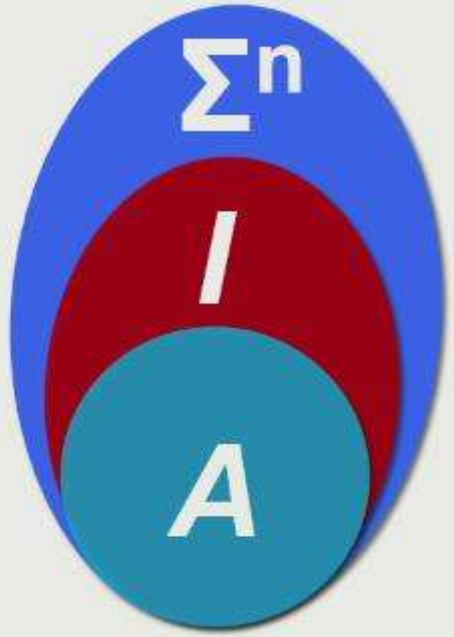

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Algorithms and Complexity

Fremont et al., *Control Improvisation*, arXiv:1704.06319, extending FSTTCS 2015.

Algorithms and Complexity

- Poly-time improvisation schemes for:
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			unamb.	amb.	
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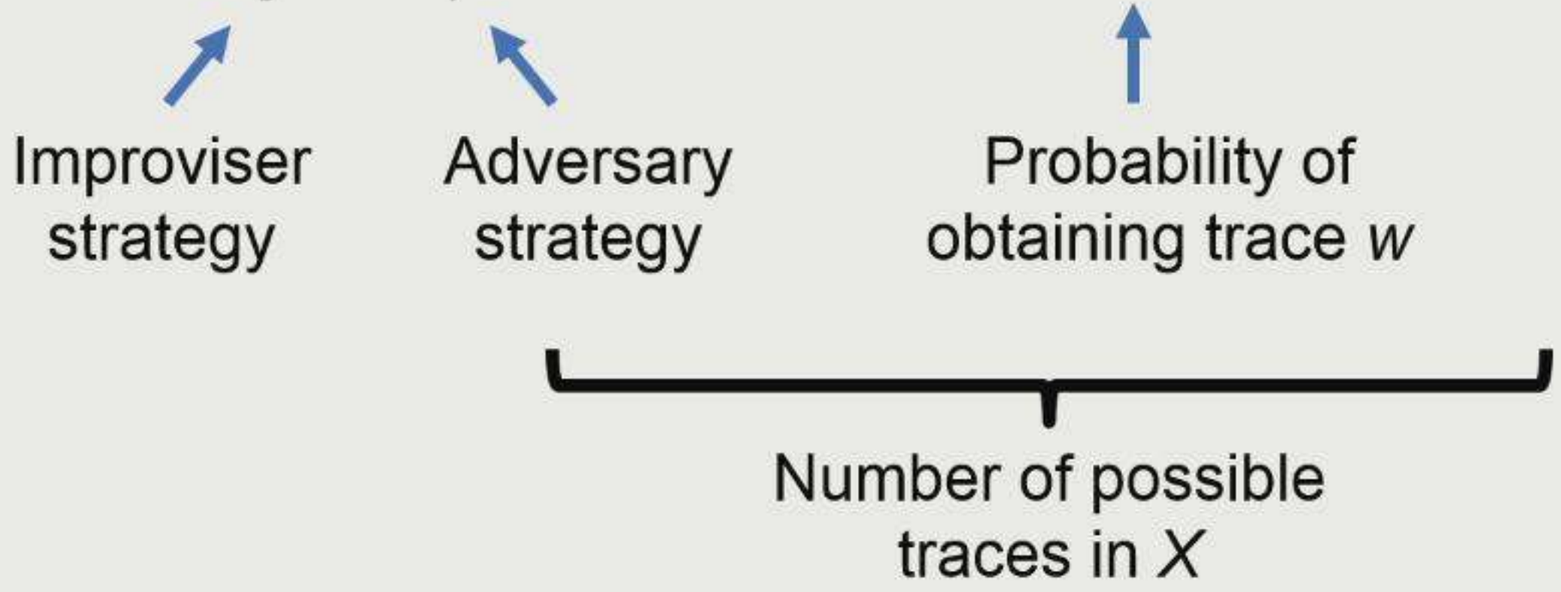

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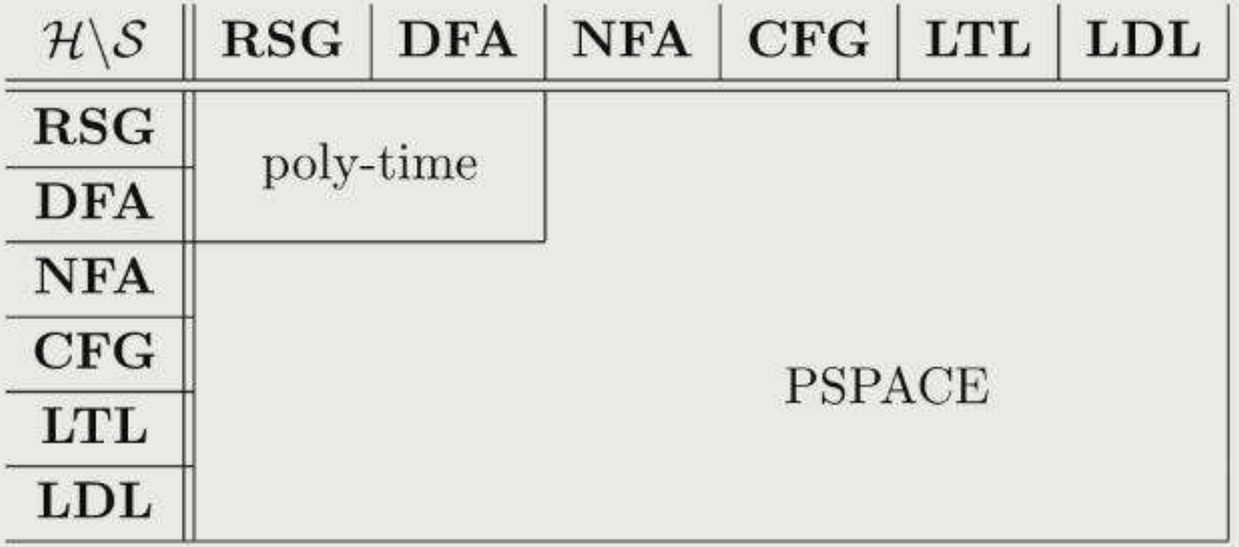

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Algorithms for RCI

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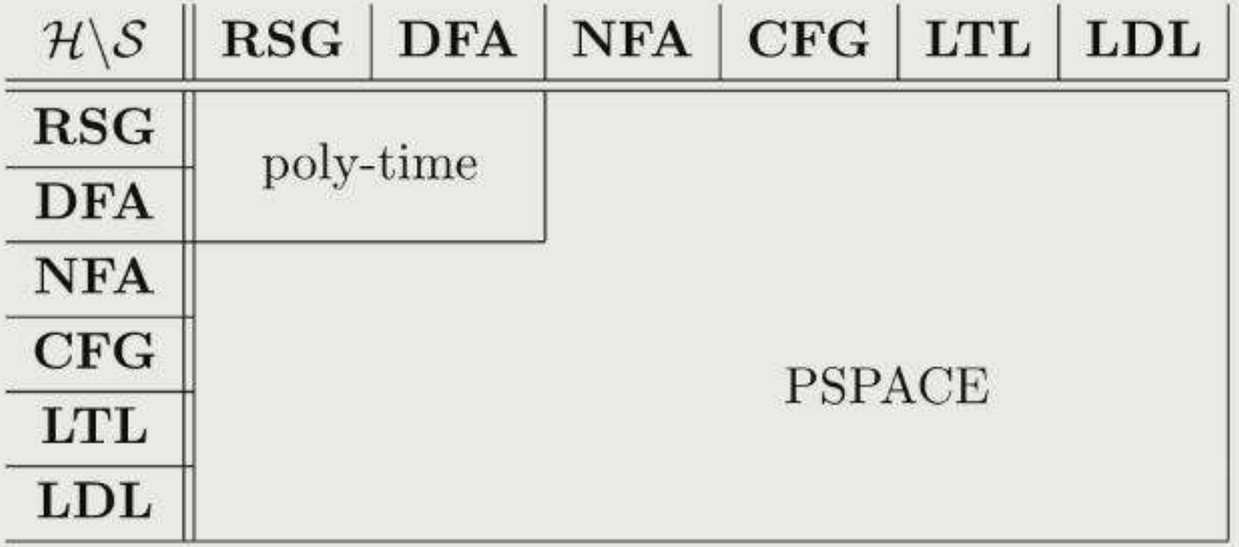
- PSPACE-equivalent for temporal logics



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- Collecting examples of real-world scenes is expensive
- We would like to generate realistic scenes automatically for training or testing

Generating Meaningful Scenes

- Scene space is large, high-dimensional


Car Model


Car Location


Car Orientation


Number of Cars


Reference


Scene Background


Car Color


Weather


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- We may be interested in particular types of scenes (e.g. highway traffic)
- Generating these is another instance of CI, but with what kind of specification?


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- How to encode these? A *probabilistic programming language*

SCENIC: a Scenario Description Language

- Defines a *distribution over scenes*

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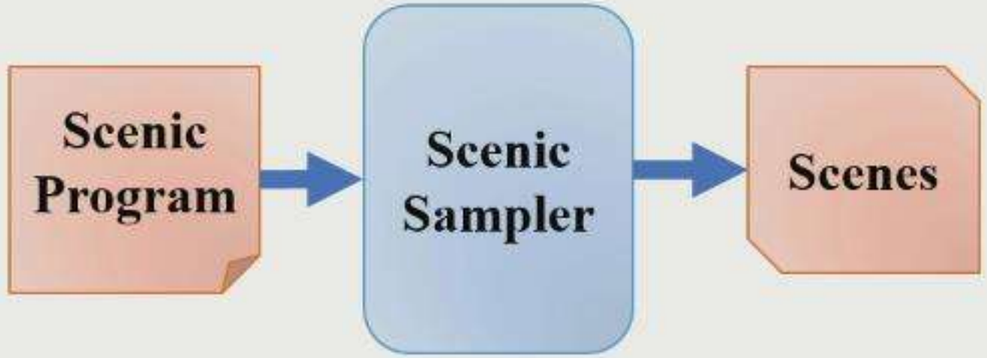
Designing and Analyzing Systems using a PPL

parkedCar.sc

```
ego = Car
Car offset by ...,
    facing ...
```

Designing and Analyzing Systems using a PPL



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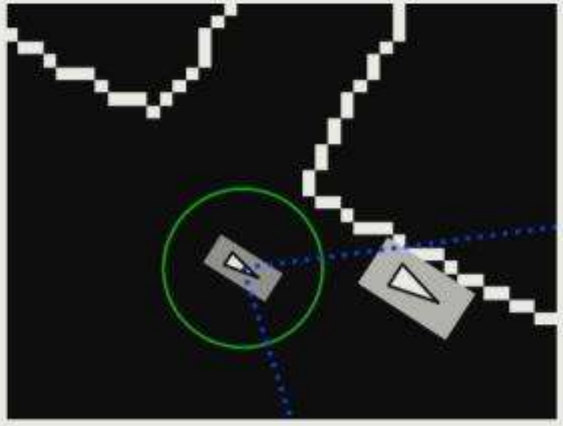

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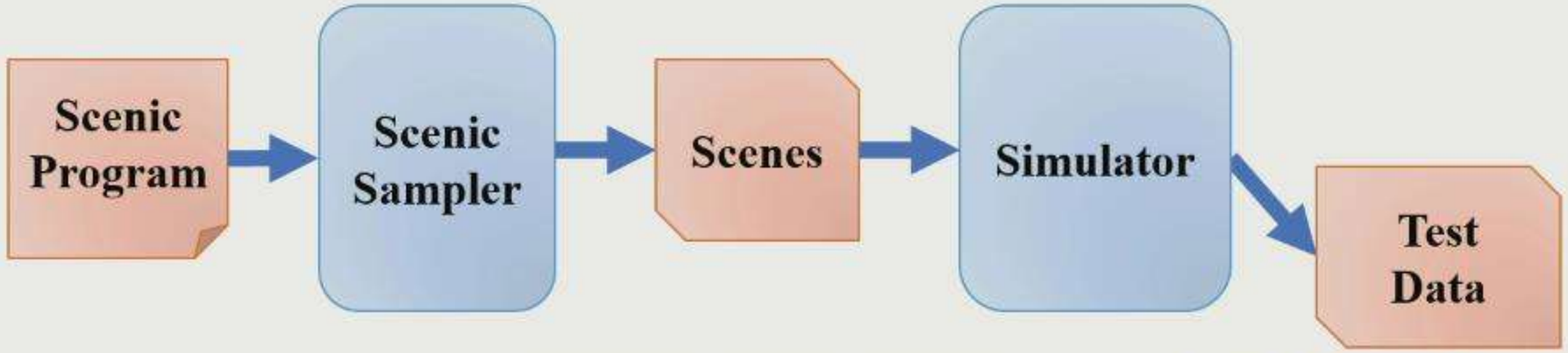

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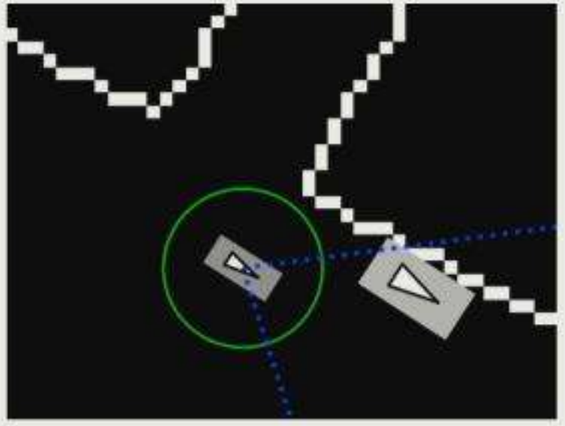

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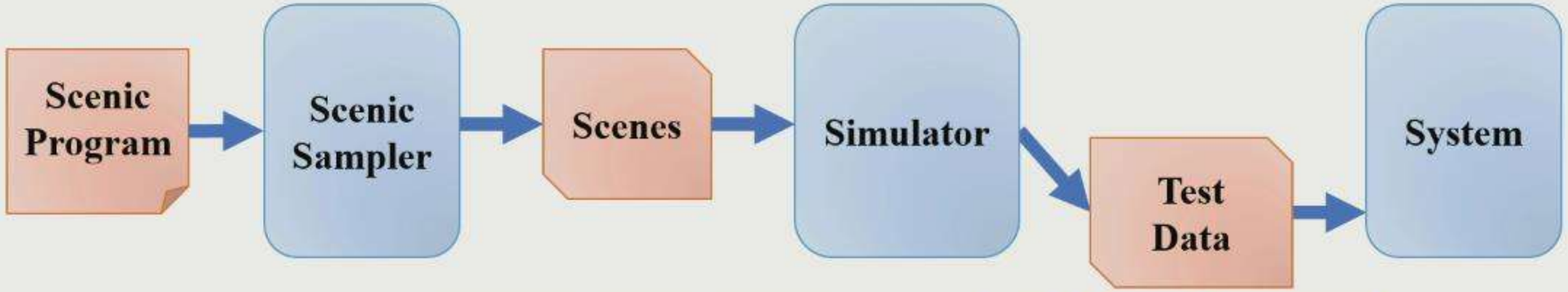

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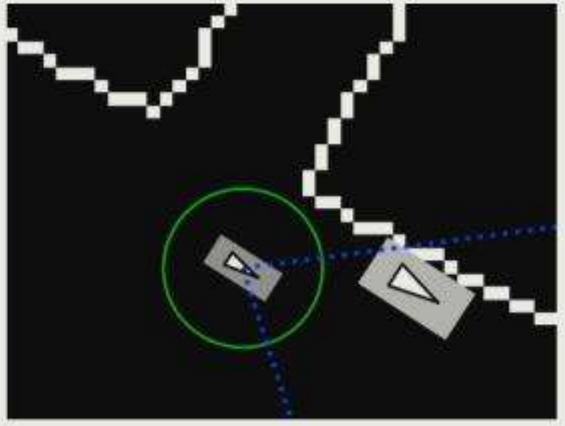

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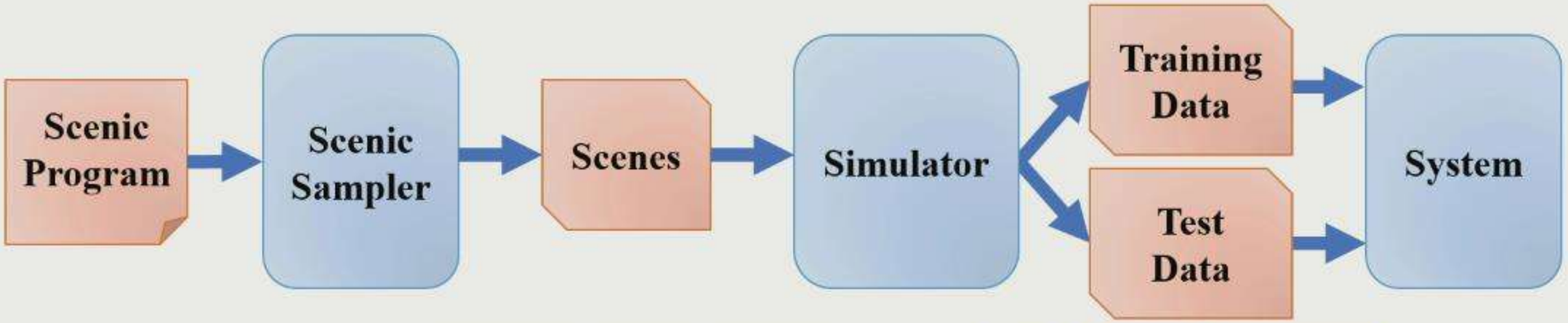

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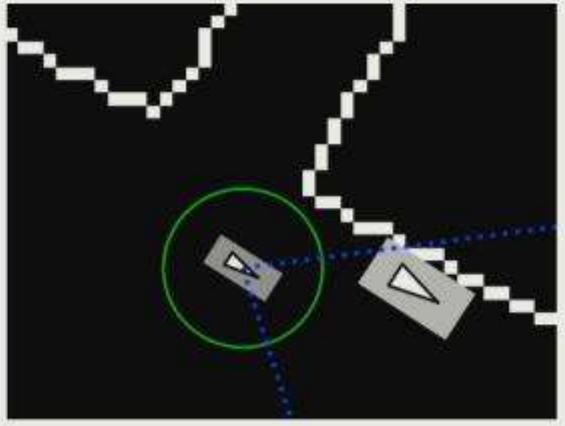

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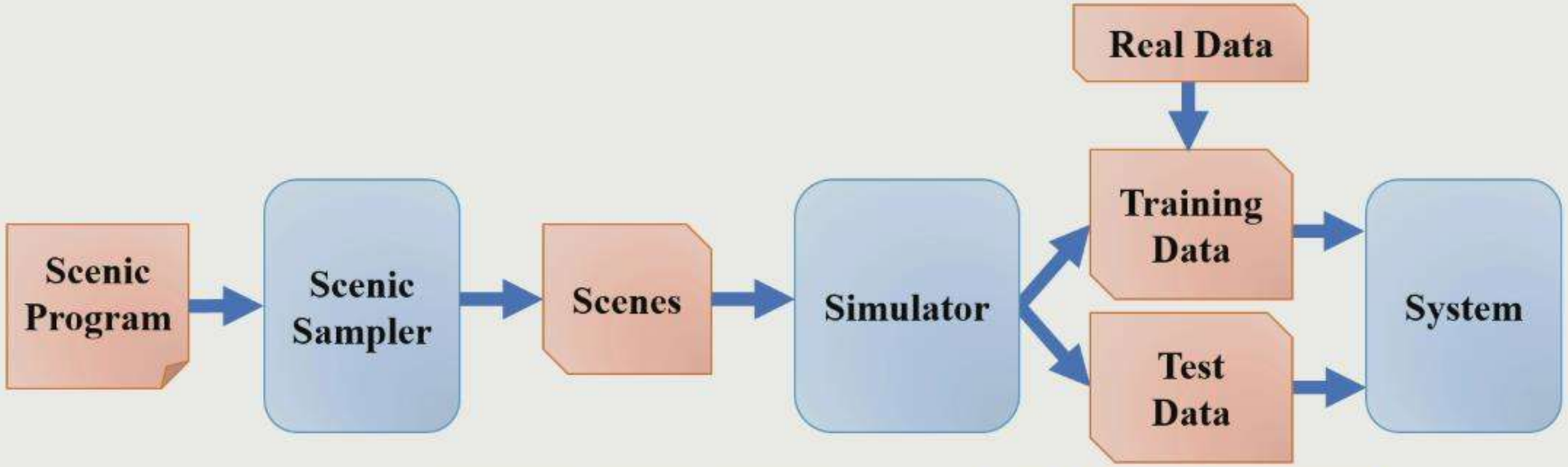

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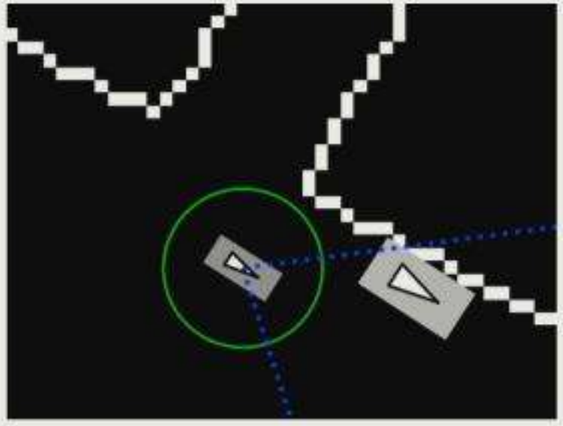

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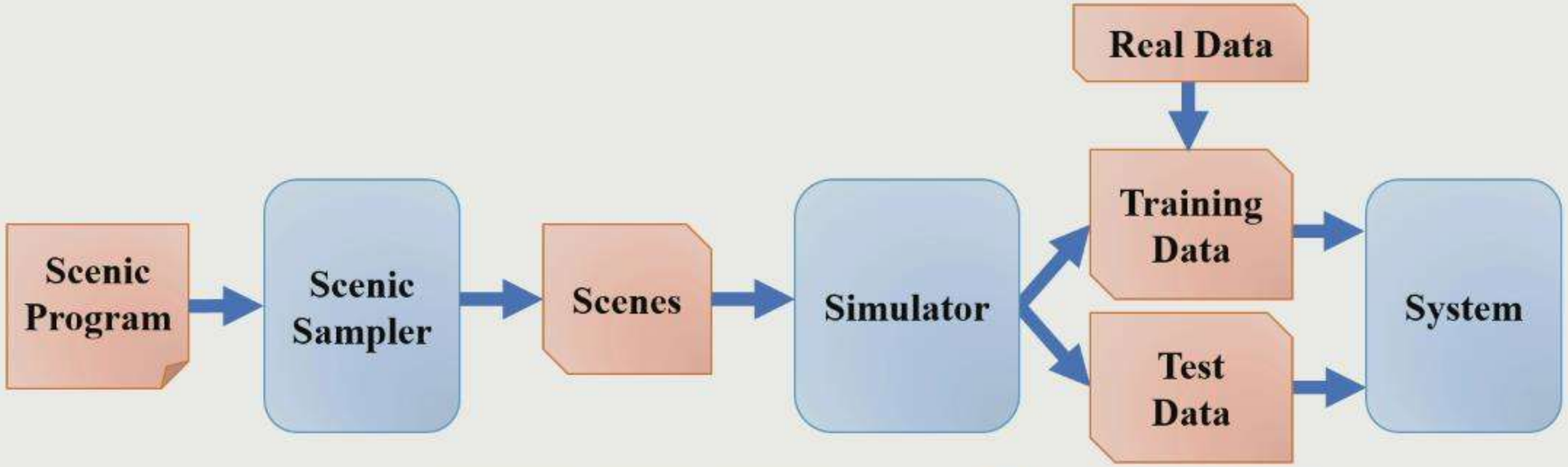

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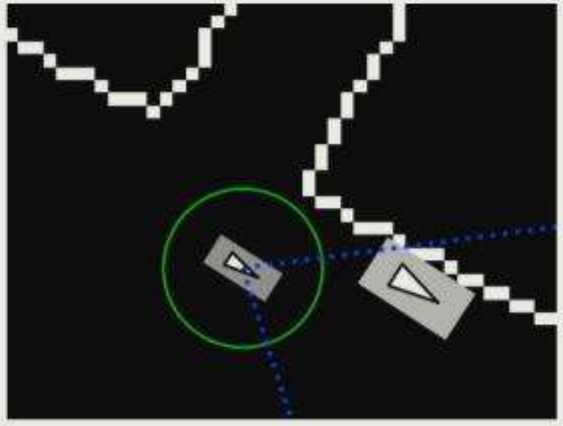

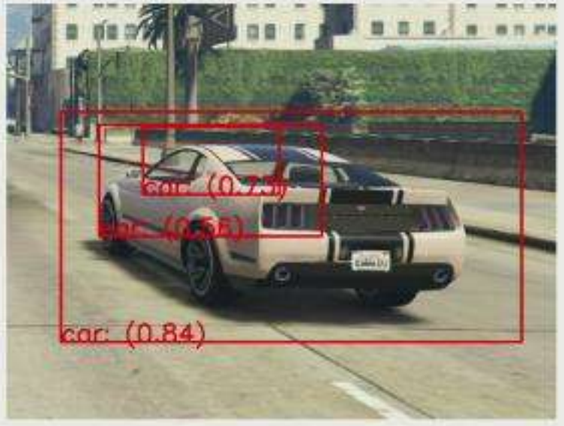

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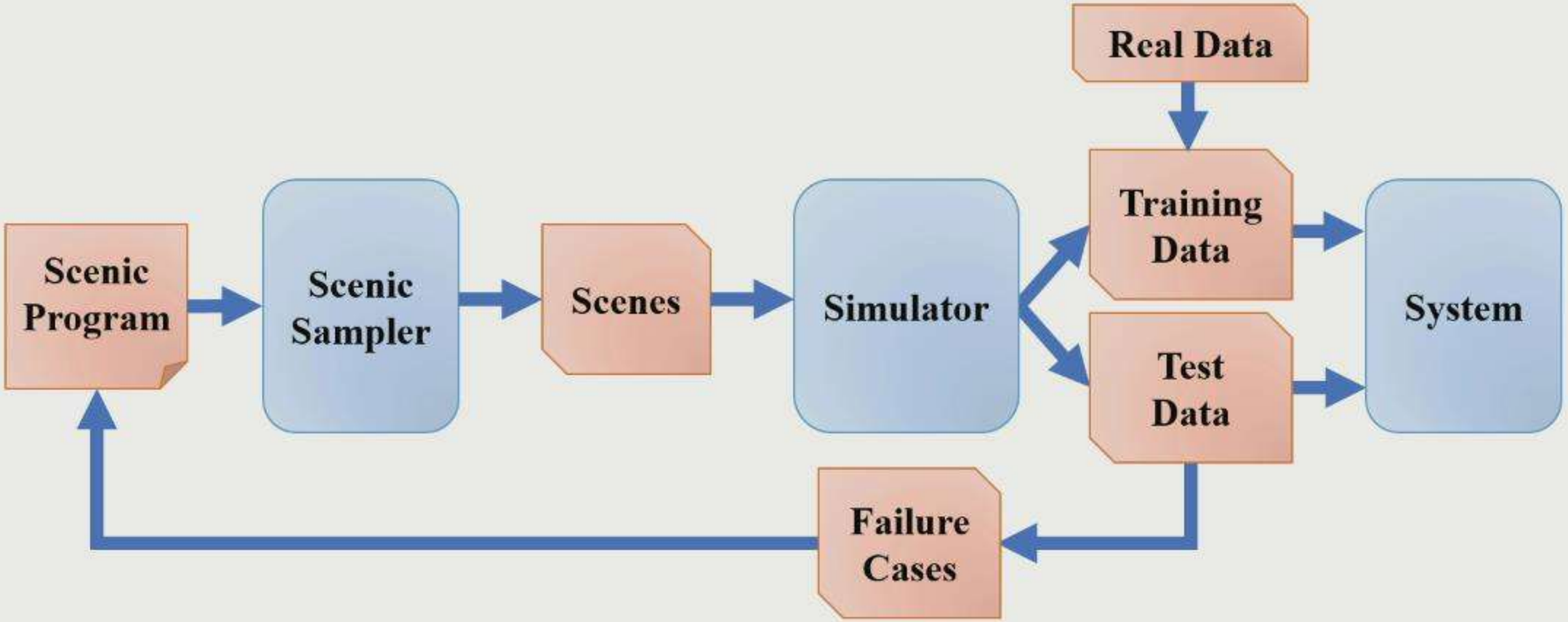

Related Work: PPLs

[1] Gordon et al., *FOSE 2014*.
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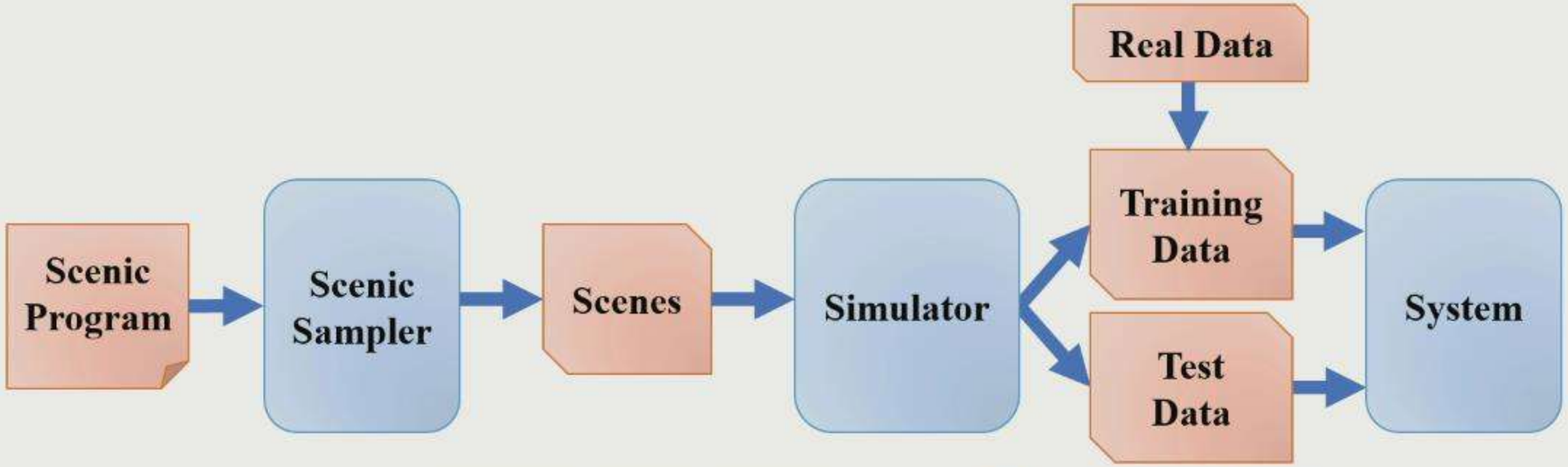

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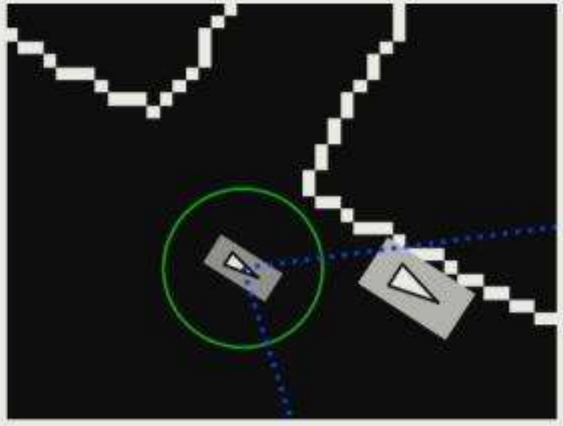

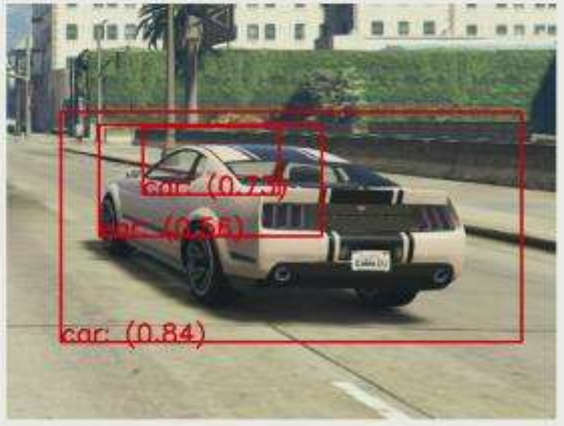

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- SCENIC's semantics is that of a standard imperative PPL (e.g. [1])
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- The main differences in SCENIC:
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  - domain-specificity

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Related Work: Graphics & ML

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- Scene synthesis from examples or grammars [4, 5]
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Related Work: Graphics & ML

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- Data augmentation/generation in ML [6, 7]
- The main differences in SCENIC:
  - more control
  - easy to use & interpret

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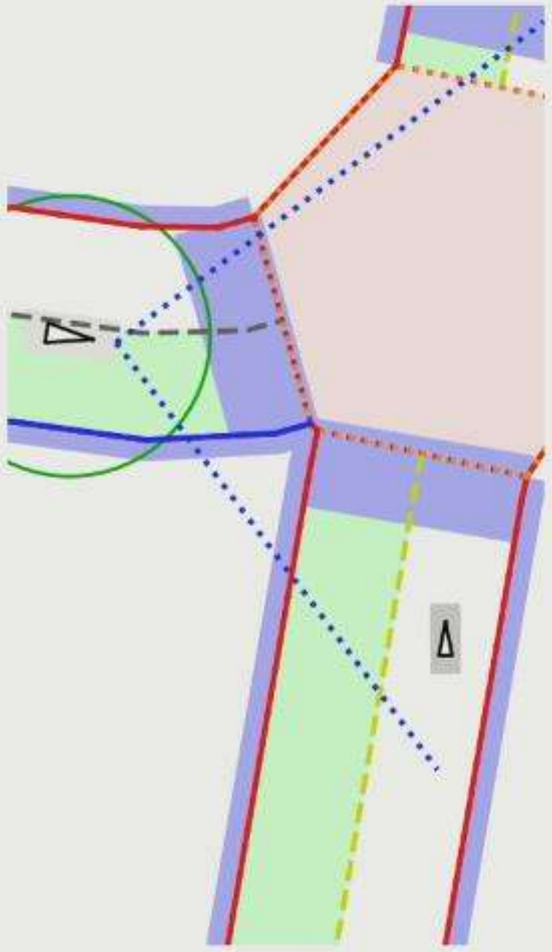

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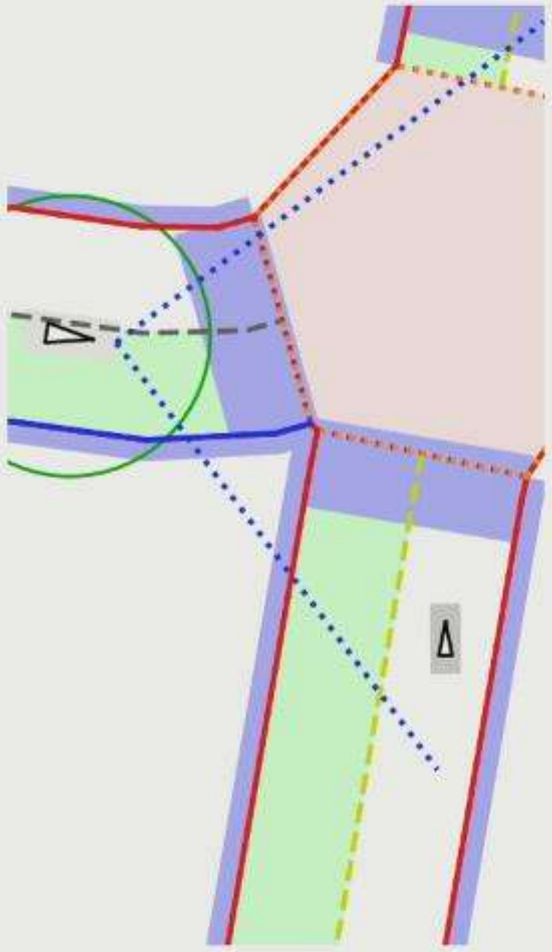

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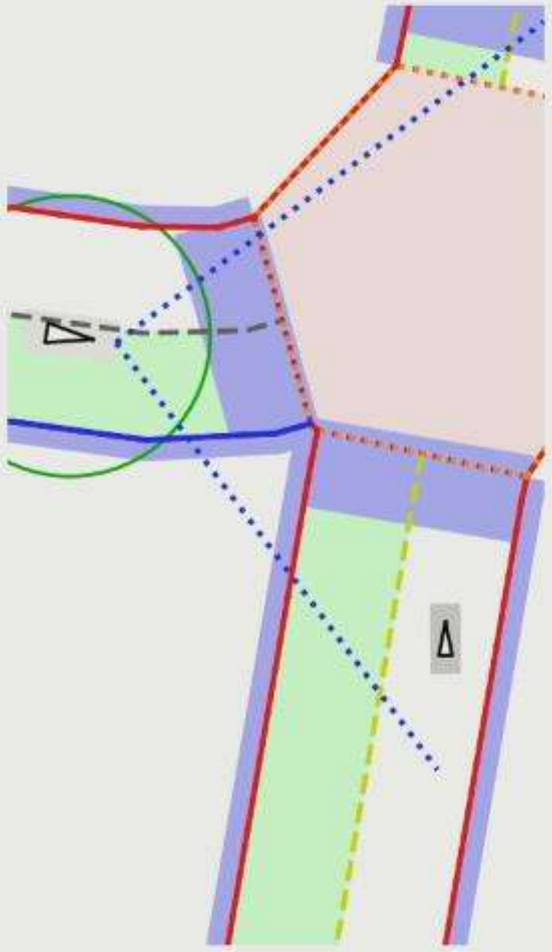

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Car left of (spot offset by -0.5 @ 0),
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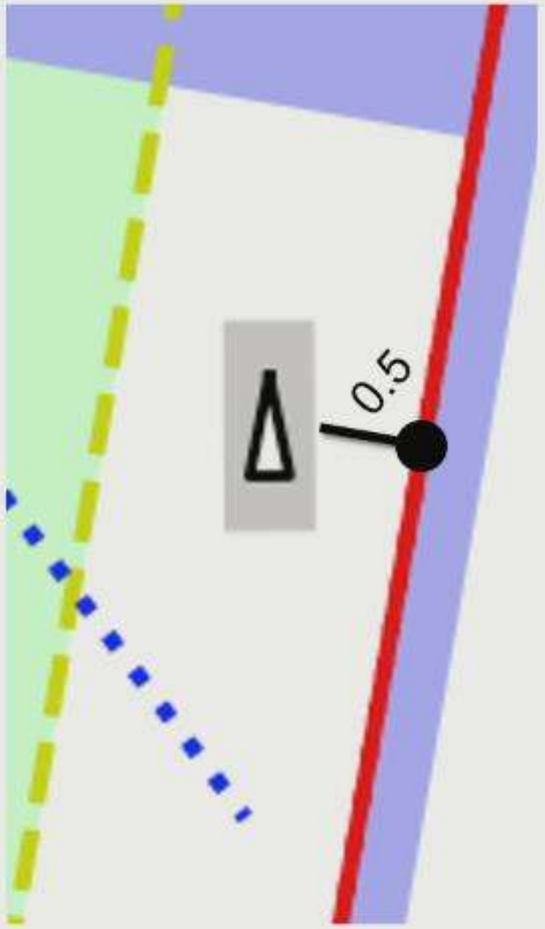


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ego = Car

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Car left of (spot offset by -0.5 @ 0),
    facing badAngle relative to roadDirection
```

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Specifiers

- Syntactic elements defining properties of an object
  - Can be combined in arbitrary ways to build up a complete definition

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Car at 120 @ 70, facing toward carWash
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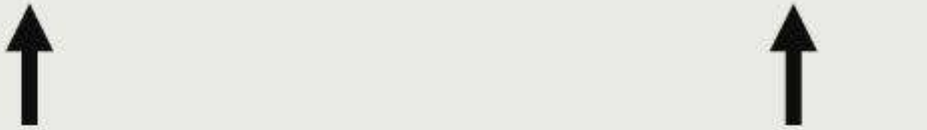

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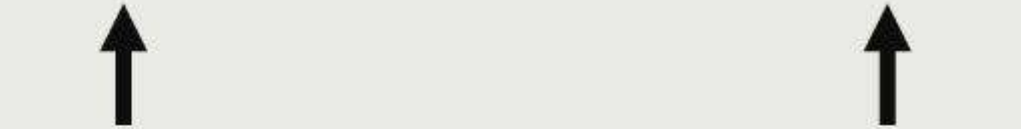

Specifies *position*

Specifies *heading*

- SCENIC has 9 completely different *position* specifiers
  - All mirroring ways we use natural language to talk about positions

Specifiers Capture Dependencies

- Can depend on other properties and other specifiers

```
Car left of taxi, facing 30 deg relative to roadDirection
```

Specifies *position*
given *width*

Specifiers Capture Dependencies

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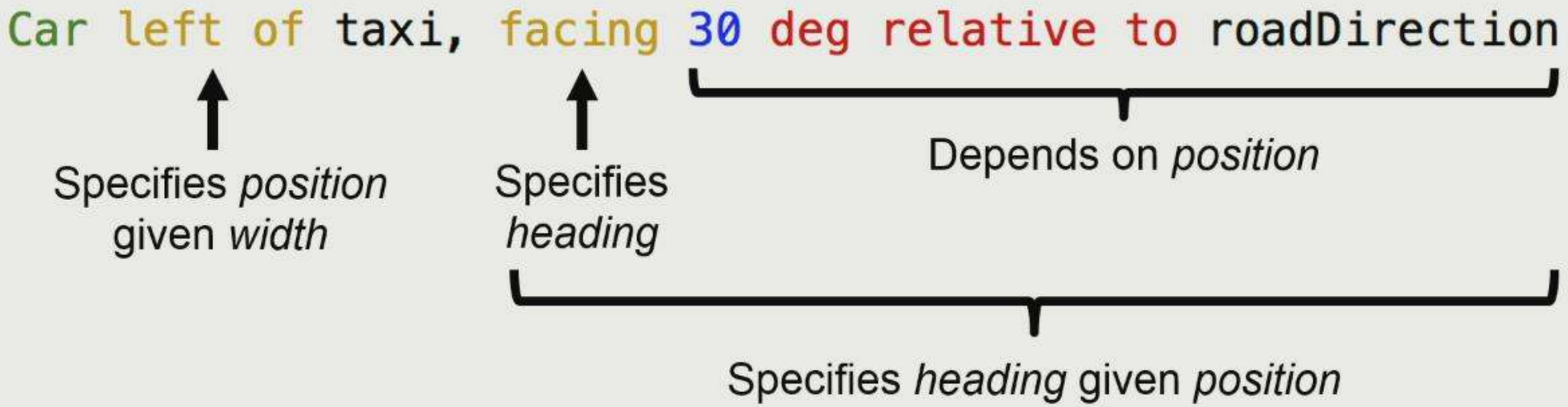

Domain-Specific Sampling Techniques

- Prune infeasible parts of the space by dilating polygons

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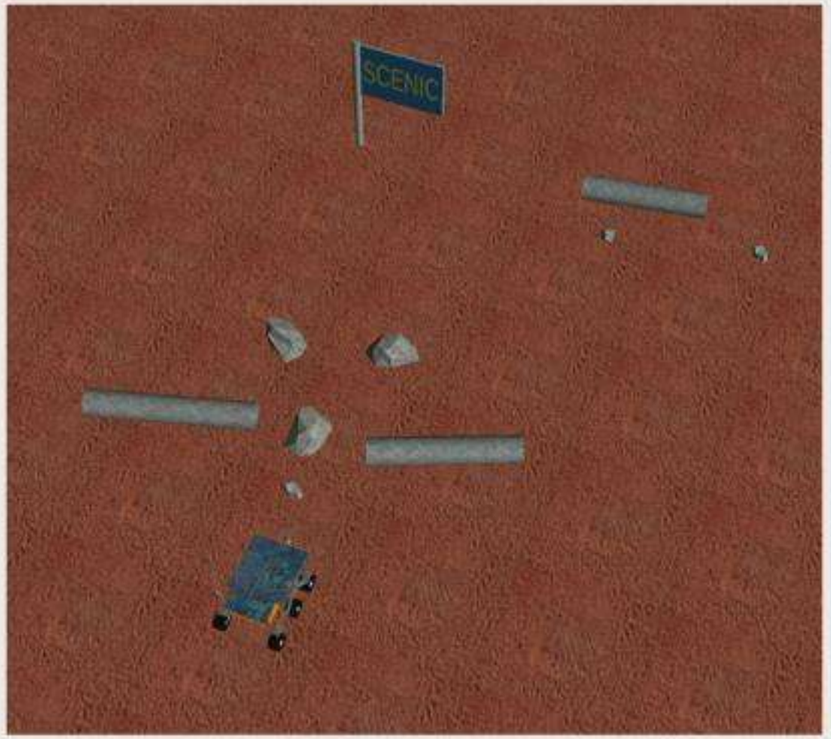
```
require distance to taxi <= 5
require 15 deg <= (relative
  heading of taxi) <= 45 deg
```

Applications of Scenic

- Exploring system performance
  - Generating specialized test sets



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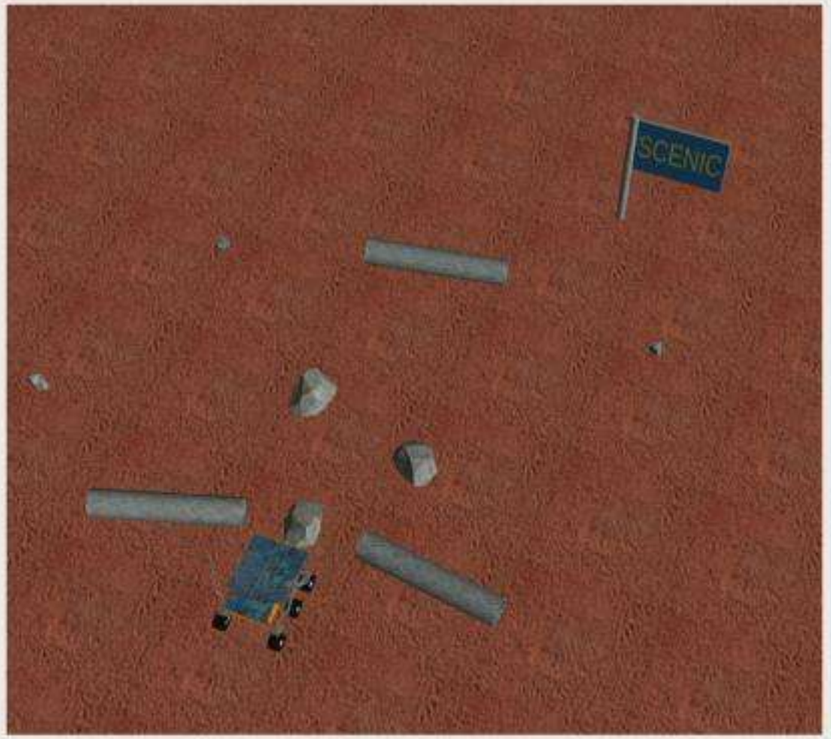

Applications of Scenic

- Exploring system performance
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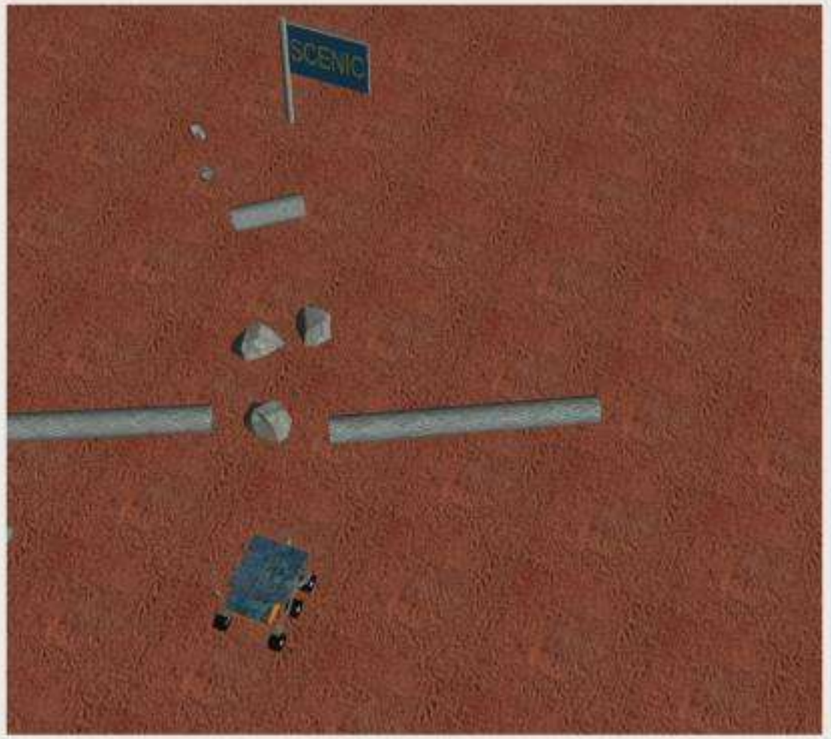
- Designing more effective training sets
  - Training on hard cases



Outline

1. Control Improvisation
   - Definition and motivating applications
2. Theory of CI
   - Efficient algorithms and hardness results
3. Designing and Analyzing Perception Systems
4. **Conclusion and Future Work**

Summary and Conclusions

- Algorithmic Improvisation: a framework for randomized synthesis
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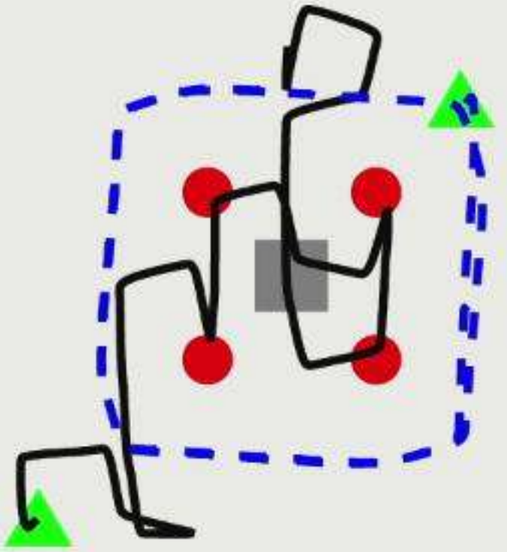

Summary and Conclusions

- Algorithmic Improvisation: a framework for randomized synthesis
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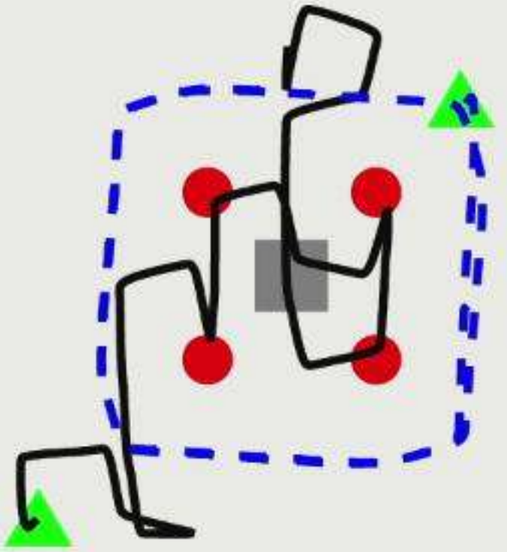
- Applications to safe autonomy
  - Controller synthesis, synthetic data generation
- Randomized formal methods can contribute in many ways to the design and verification of autonomous systems



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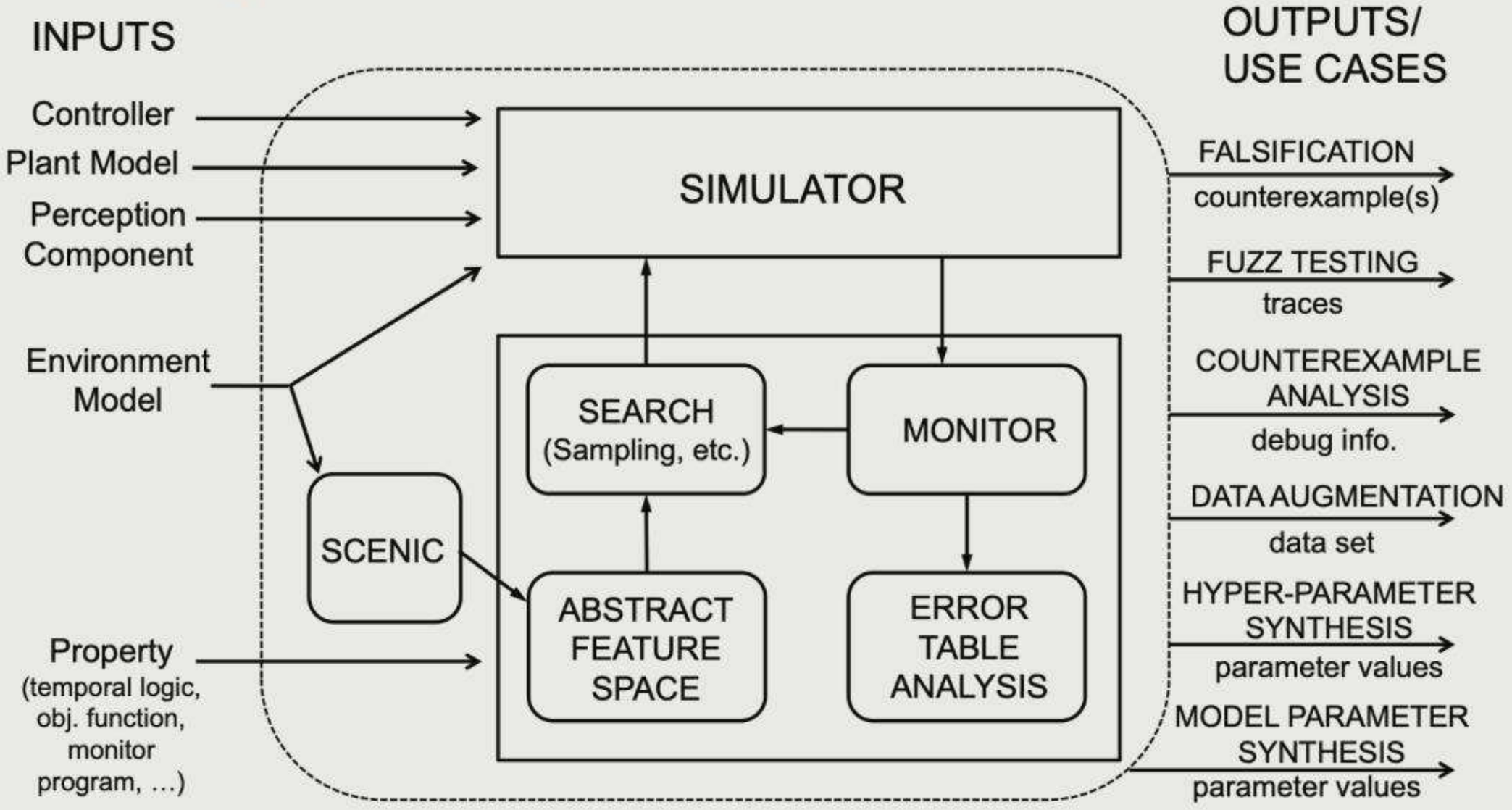
- Verifying ML/AI-based systems: the VerifAI toolkit [CAV 2019]

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

[CAV'19]

https://github.com/BerkeleyLearnVerify/VerifAI



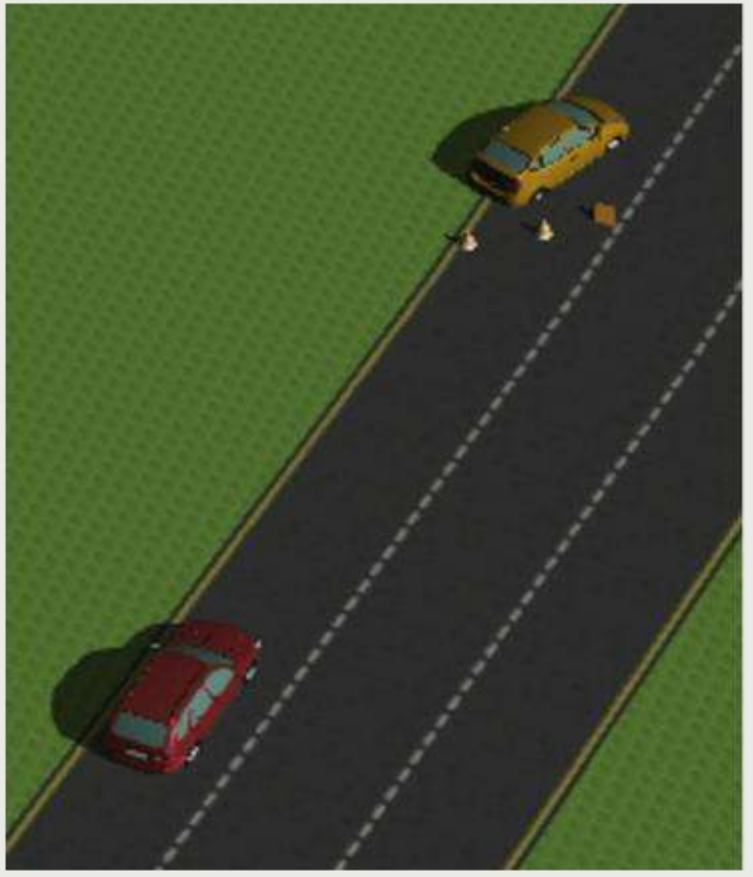
Modeling Case Study in the SCENIC Language

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

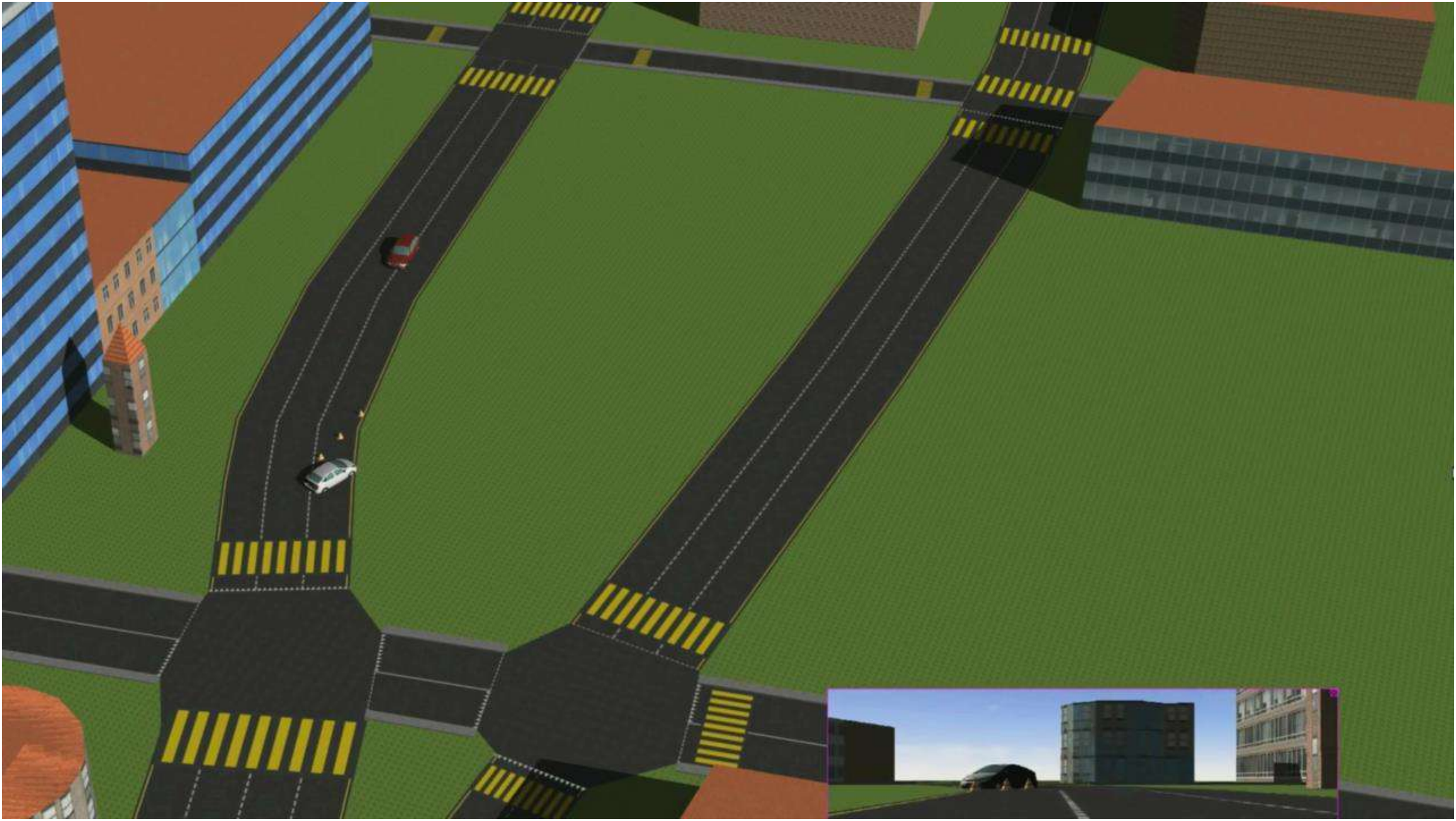
# Place traffic cones
spot1 = OrientedPoint left of blockageSite by (0.3, 1)
cone1 = TrafficCone at spot1,
                     facing (0, 360) deg

...

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



Fremont et al., *Scenic: A Language for Scenario Specification and Scene Generation*, PLDI 2019 (to appear).



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Thank you!