

Next-Generation Software Verification and Adaptation: An AI Perspective

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Software testing is about finding **failures**, assuming that failures are due to **faults** in the system under test (SUT)

What if **failures** happen but the **SUT is not faulty**?

A failure may indicate insufficiencies such as **performance limitations**, **physical constraints**, or **misuse by human operators**

This talk proposes to use **Interpretable Machine Learning** to learn insufficiencies caused by the SUT **environment**

The meaning of requirements (Michael Jackson)

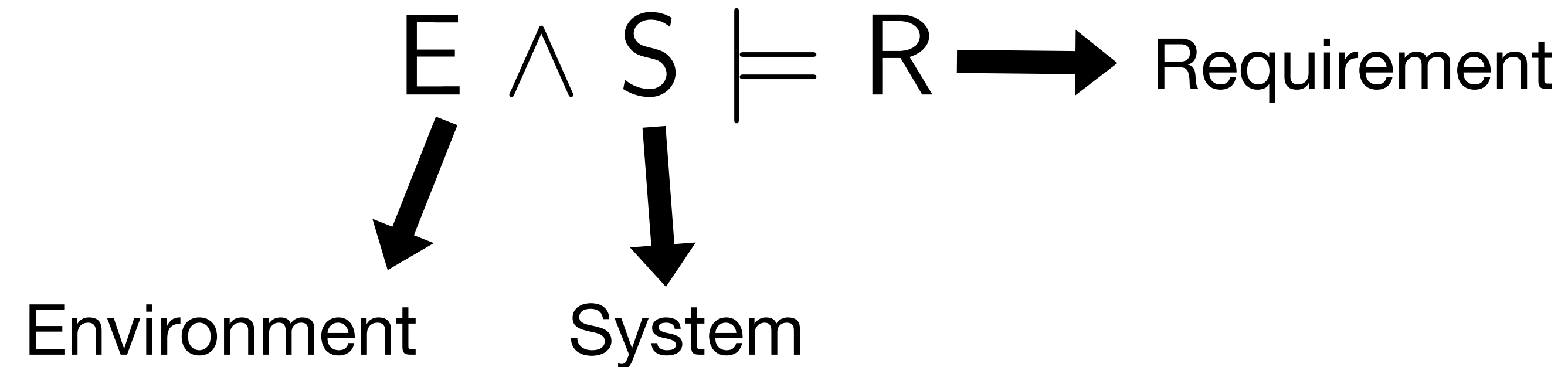
- Requirements are located in the *environment*, which is distinguished from the *machine* to be built. A requirement is a condition over *phenomena* of the environment. A *specification* is a restricted form of requirement, providing enough information for the implementer to build the machine (by programming it) without further environment knowledge.



Michael Jackson: *The Meaning of Requirements*. Annals of Software Engineering 3: 5-21 (1997)

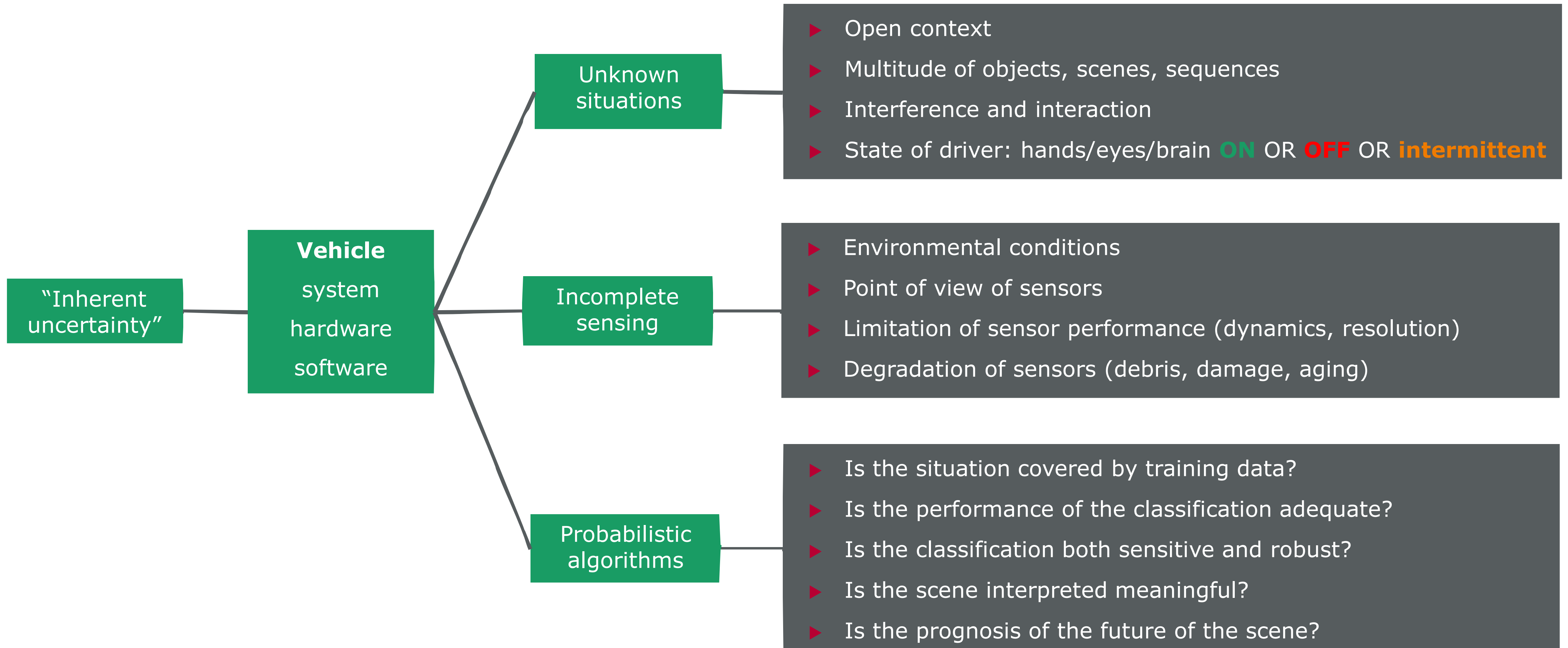
Verification

Demonstrating correctness of all system environments (usages):



Verification fails when there is a fault in **S**, or there is a mismatch between **S** and **E**

Environment and System Mismatches



Failure taxonomy for Safety of the Indented Functionality (SOTIF)
for self-driving systems

Testing

Checking the system for some normal and boundary usages (environments)

$$\exists E \cdot E \wedge S \wedge \neg R$$

Understanding the environment conditions leading to failures is becoming essential

- E.g., the chance of an accident is higher for an emergency breaking system when the car drives with a speed higher than 30km/h on a curved road ($> 60^\circ$)

Repair or Adaptation

- We observe a failure for some environment (\mathbf{E}^*)

$$E^* \wedge S \wedge \neg R$$

- We modify the system to resolve the failure

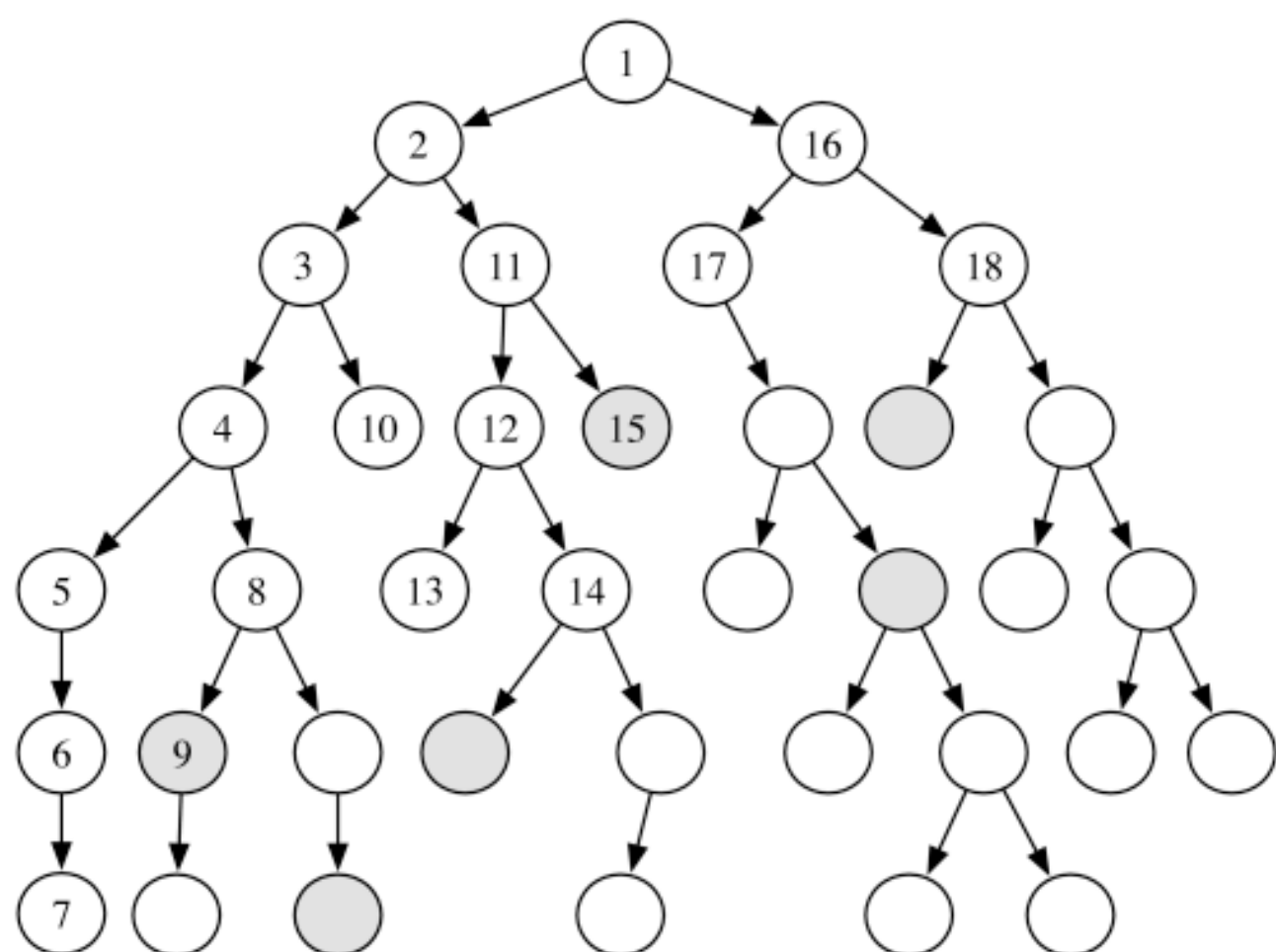
$$E^* \wedge S^* \rightarrow R$$

- But the focus of repair might be limited to a particular environment (\mathbf{E}^*)
 - Overfitting

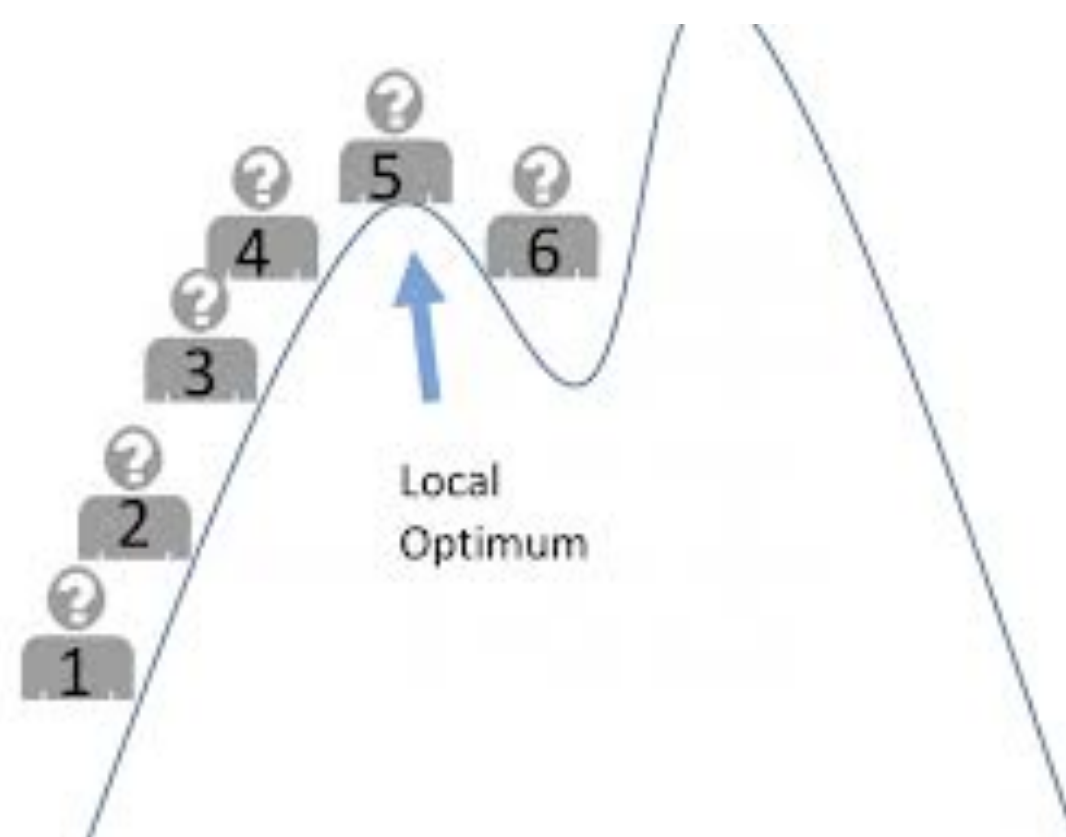
A Search Problem

- The core of formal verification, testing and adaptation is a **search problem**

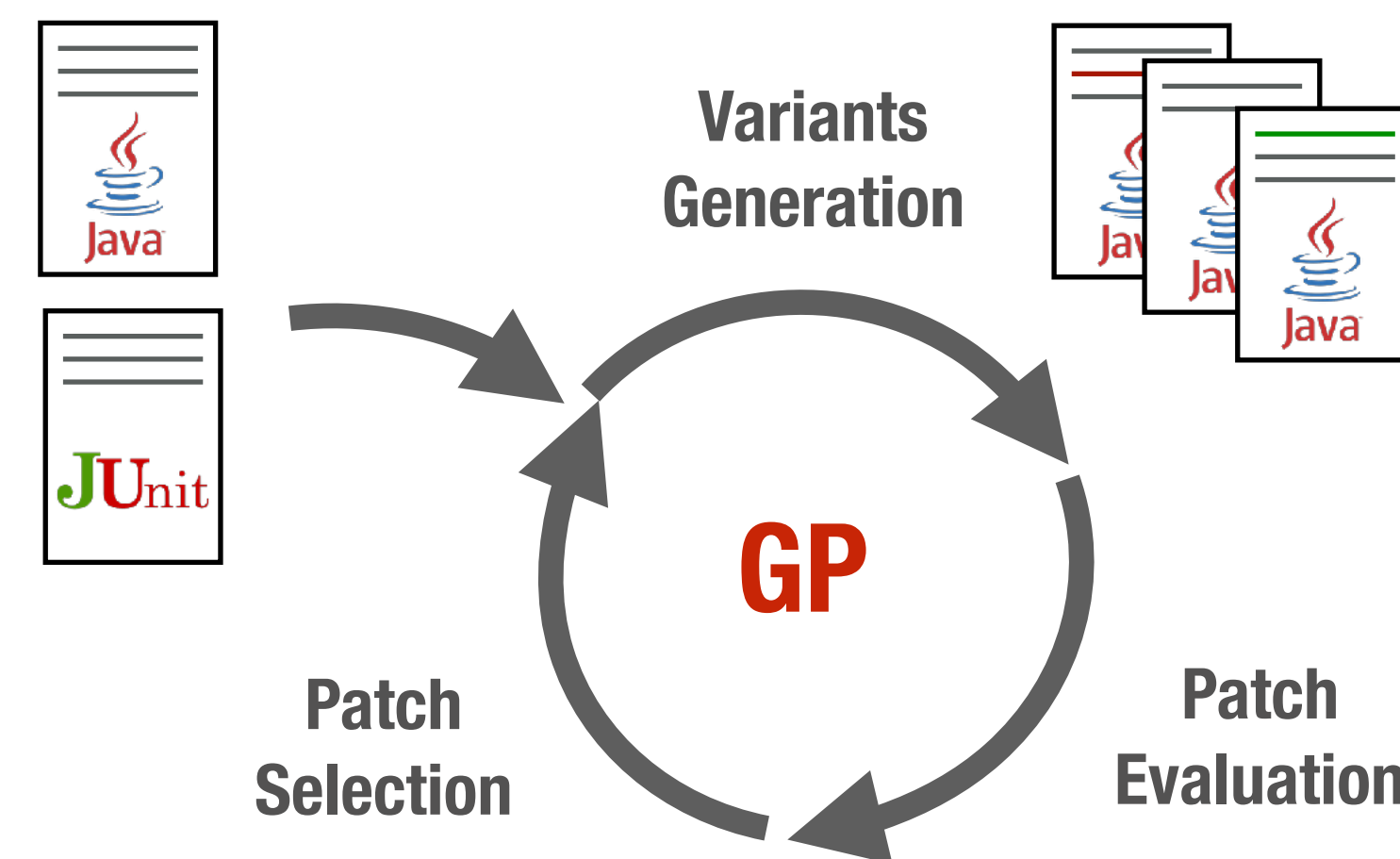
Verification
(Exhaustive Search)



Testing
(Heuristic Search)



Adaptation/Repair
(Heuristic Search)



Broadening the Search to Include Learning

- While we search, we should **learn**:
 - **environment** constraints that ensure satisfaction of requirements

$$\forall E \cdot E \wedge S \models R$$

- **environment** conditions explaining failures

$$\exists E \cdot E \wedge S \wedge \neg R$$

- repair/adaptation strategies valid for varying **environments**

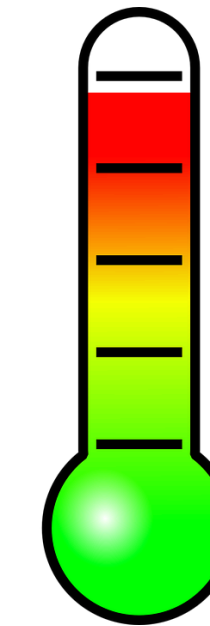
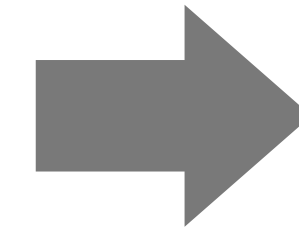
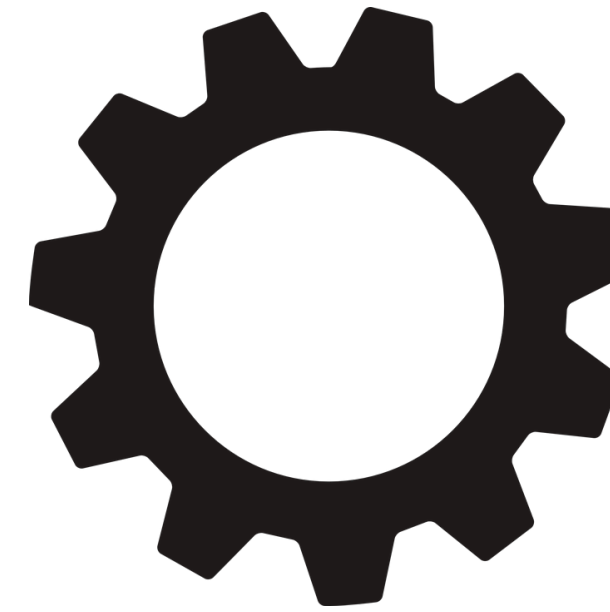
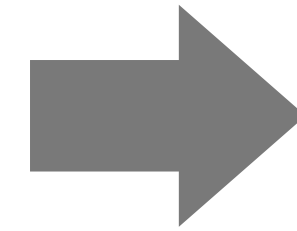
$$E^* \wedge S^* \rightarrow R$$

Broadening the focus of verification, testing and adaptation to learn about the SUT environment.

to learn about the SUT environment.

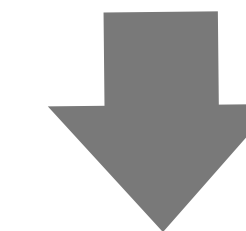
$$\forall E \cdot E \wedge S \models R$$

1	3	0.8	100
0	5	0.4	150



Satisfaction Measure, or

Test Oracle



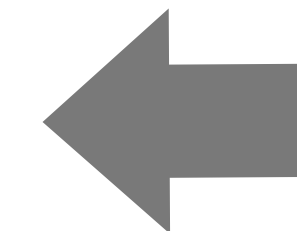
1	3	0.8	100	0.6
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0	5	0.4	150	-2.6
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or

0	5	0.4	150	F
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1	3	0.8	100	P
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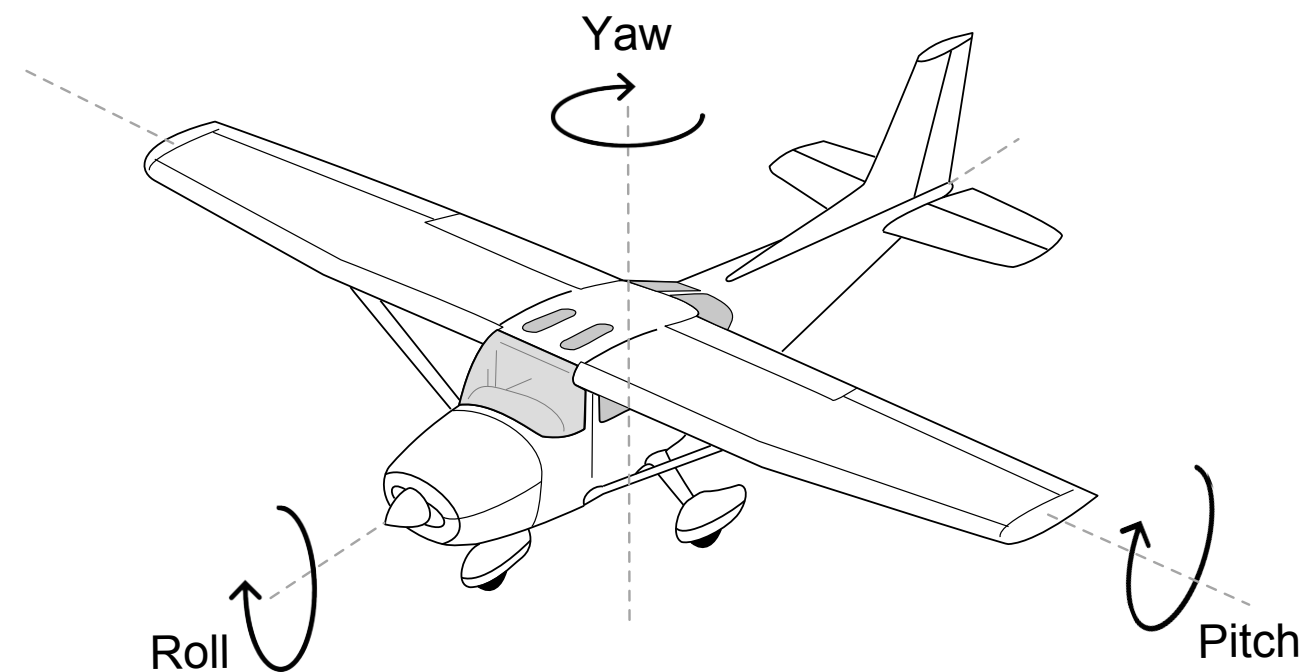


Executable System/Simulator

We use Interpretable ML to learn

- Constraints (assumptions) on environment to ensure satisfaction of some requirements
- Environment conditions leading to failures
- Fixes/adaptations that are valid for several environments

Mining Assumptions using Interpretable ML

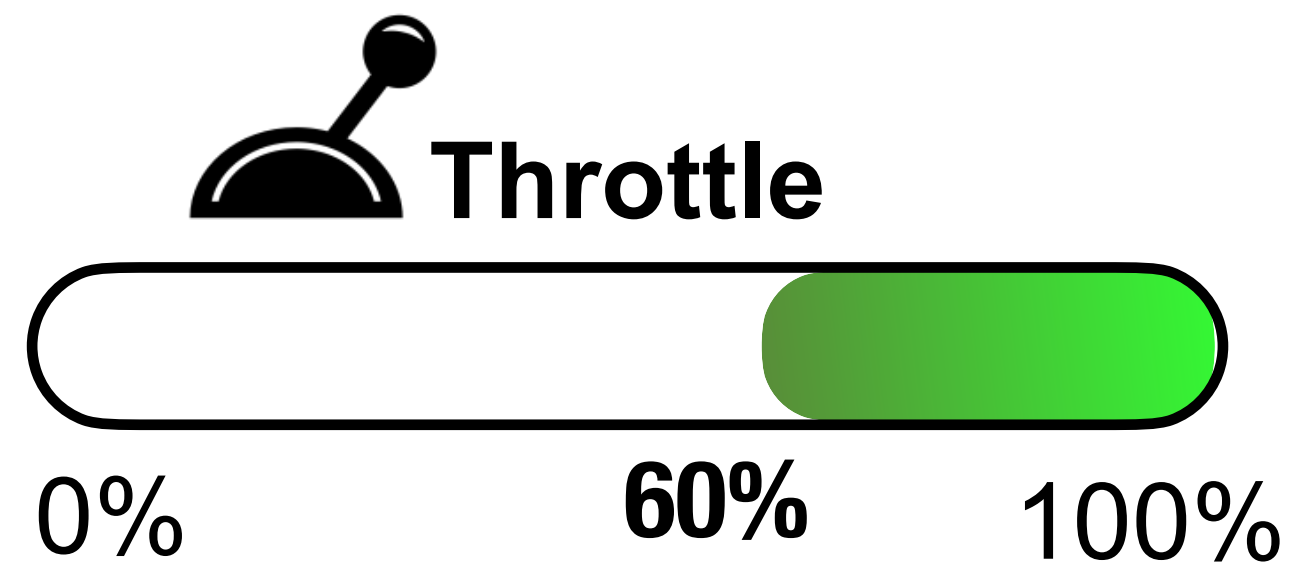
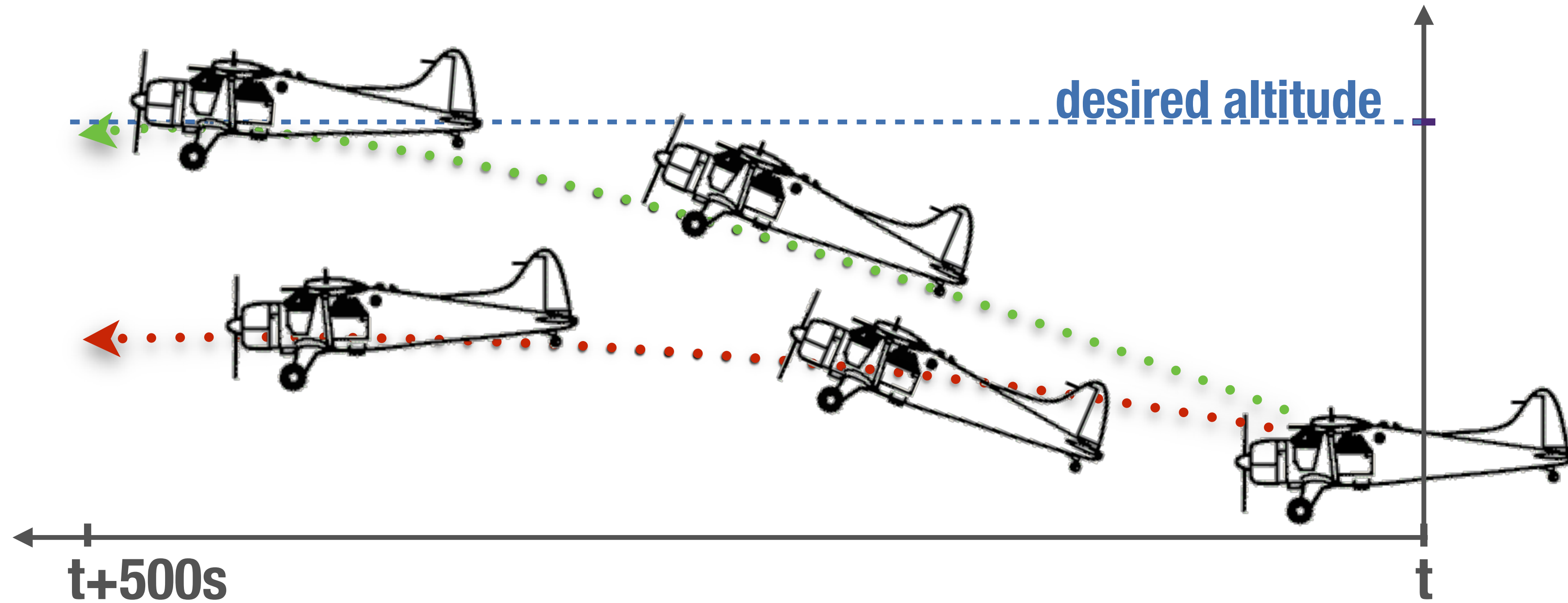


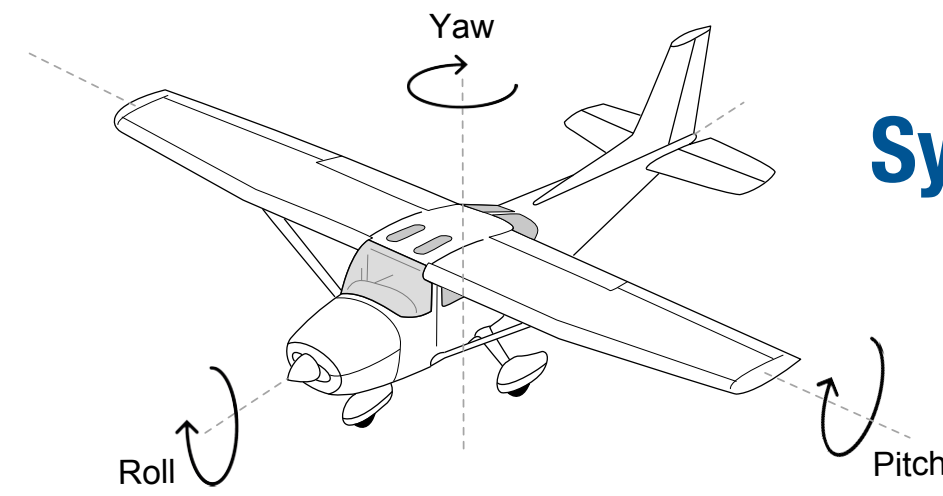
FAIL

Req: When the autopilot is enabled, the aircraft should reach the desired altitude within 500 seconds in calm air.

Missing assumption!

Autopilot Case Study





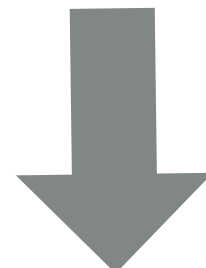
System + Requirement



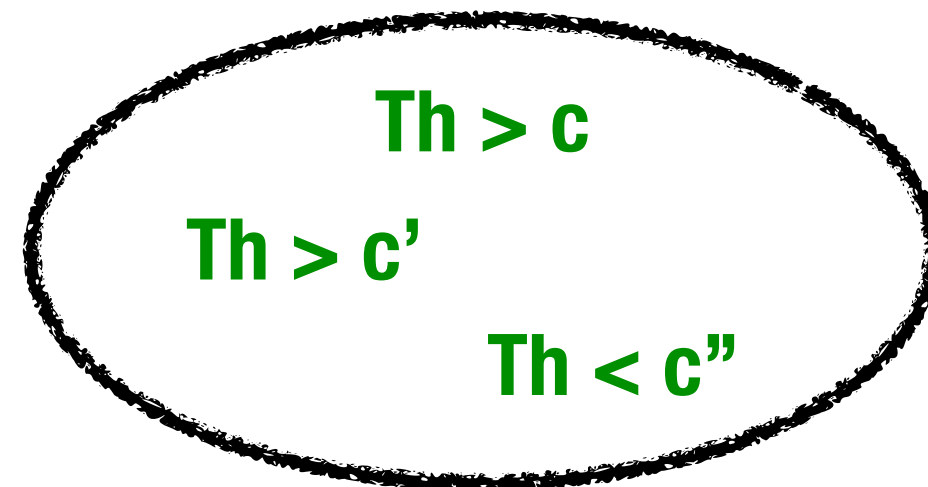
Test Generation

Test Inputs + pass/fail

Th = 20	P
Th = 0.4	F
Th = -3.6	F
Th = 100	P



Machine Learning



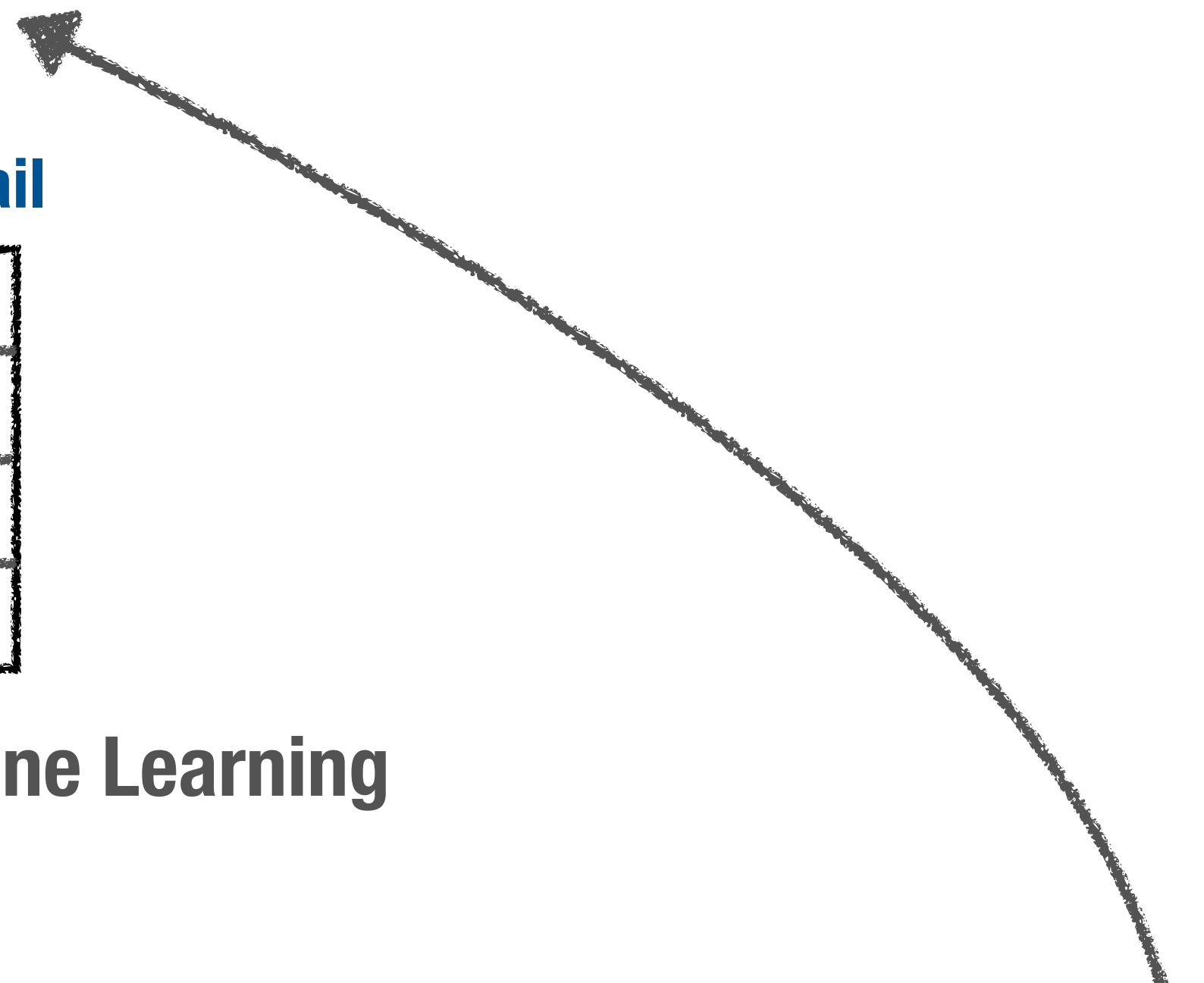
Candidate Environment Assumptions



Model Checking



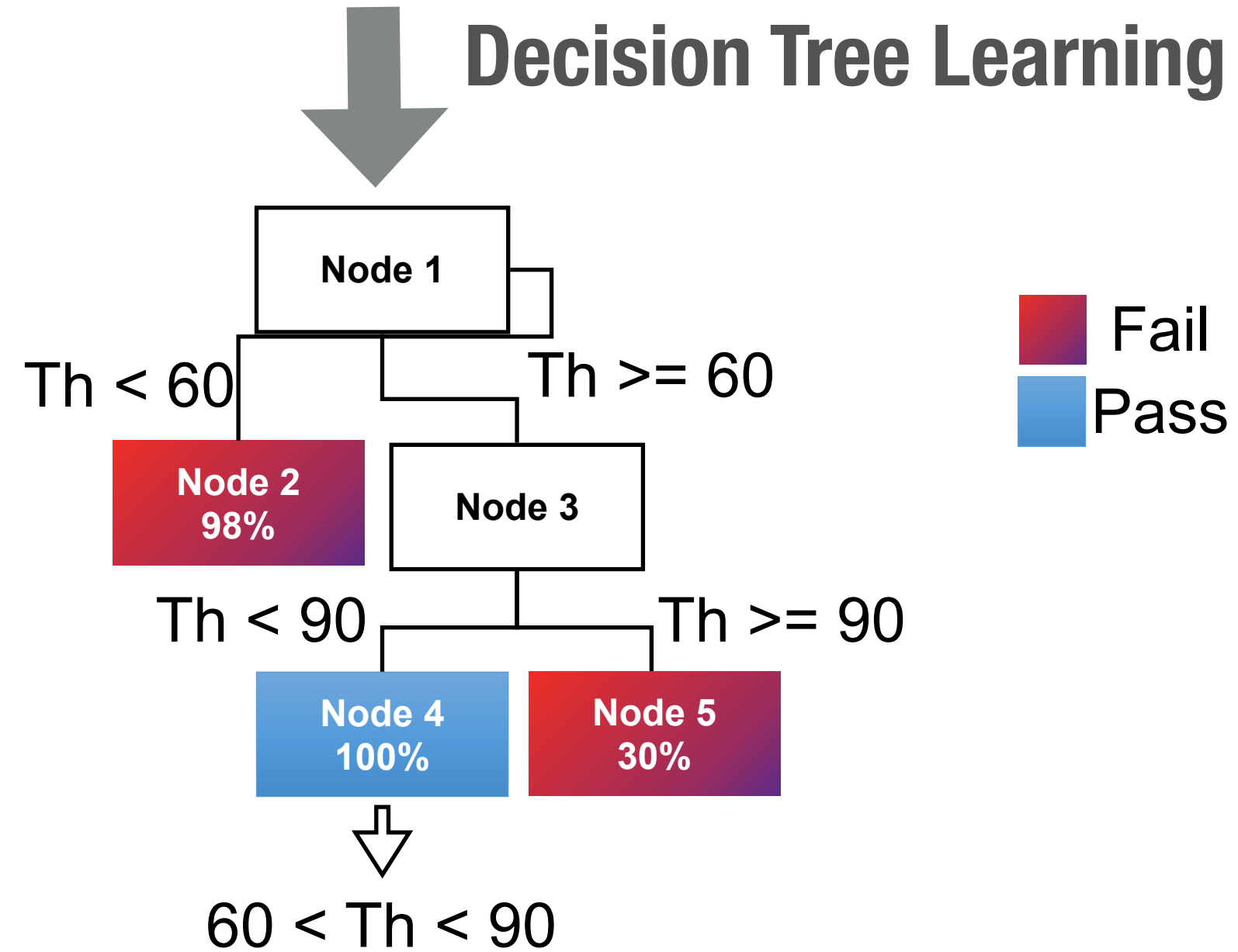
OR



Test Inputs + pass/fail

Th = 20	P
Th = 0.4	F
Th = -3.6	F
Th = 100	P

Decision Tree Learning



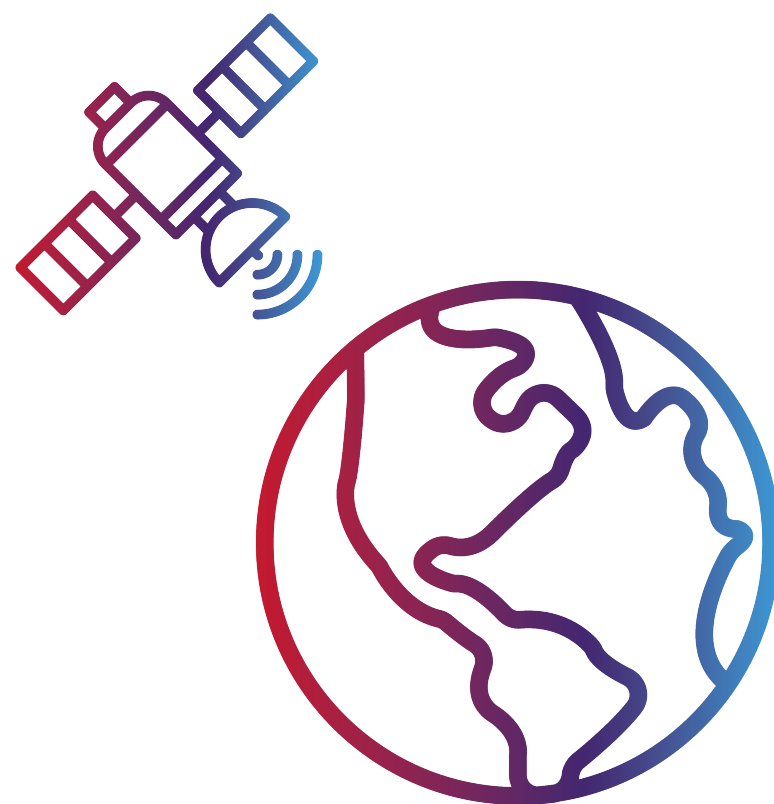
Assumptions learned by decision trees

- **Simple** conditions
- **Low** coverage

Khoulood Gaaloul, Claudio Menghi, Shiva Nejati, Lionel C. Briand, David Wolfe: *Mining assumptions for software components using machine learning*. ESEC/ SIGSOFT FSE 2020: 159-171

ESAIL Case Study - Attitude Control Component

“When the **norm** of the **attitude error quaternion** is lower than **0.001**, the **torque** commanded to the reaction wheel around the x-axis shall be within **[-0.001, 0.001]N.m**”



where:

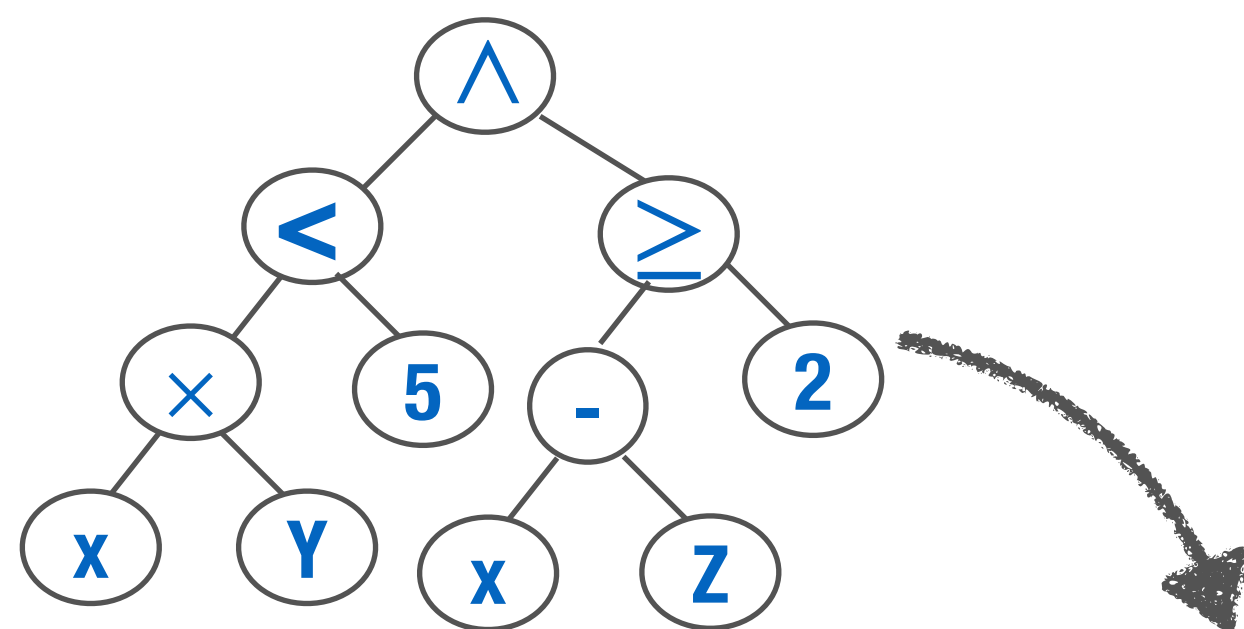
$$A_1 ::= \forall t \in [0, 1] : \left(\overbrace{\exp(t) + 1 \geq 0}^{P_1(t)} \wedge \overbrace{\exp(t) - 1 \leq 0}^{P_2(t)} \right)$$

$$\exp(t) = \underbrace{+783.3 \cdot \omega_{e-x}(t)}_{T1} \underbrace{-332.6 \cdot \omega_{e-y}(t)}_{T2} \underbrace{+3.5 \cdot \omega_{e-z}(t)}_{T3} \\ - 50.57 \cdot \omega_{e-x}(t) \cdot \omega_{e-y}(t) - 4751.8 \cdot \omega_{e-x}(t) \cdot \omega_{e-z}(t) \\ + 3588.7 \cdot \omega_{e-y}(t) \cdot \omega_{e-z}(t) \\ + 1000 \cdot \text{Rwh}_y(t) \cdot \omega_{e-z}(t) - 1000 \cdot \text{Rwh}_z(t) \cdot \omega_{e-y}(t) \\ \underbrace{-54.8 \cdot \omega_{e-y}(t)^2}_{T9} \underbrace{+54.8 \cdot \omega_{e-z}(t)^2}_{T10}$$

Test Inputs + pass/fail

x = 5.6	Y = 20	z = 120	P
x = 0.4	Y = -20	Z = 110	F
x = -3.6	Y = 0	Z = 111	F
x = 2.6	Y = 10	Z = 109	P

Genetic Programming



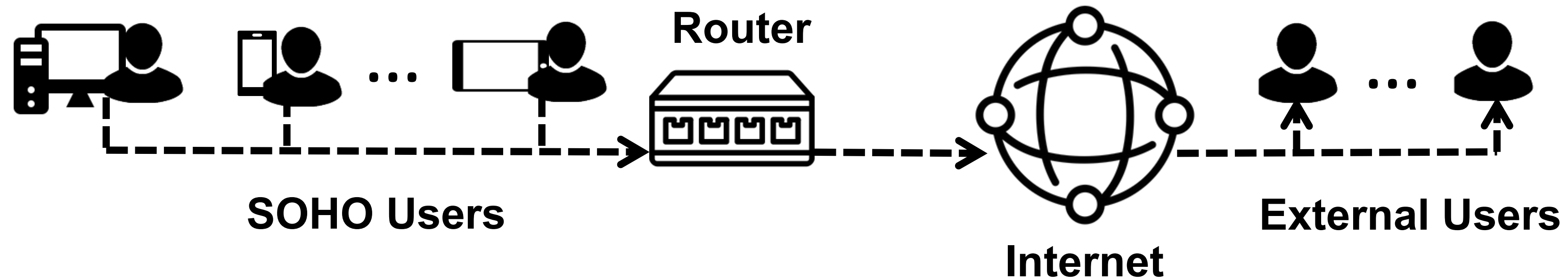
$$x \times y < 5 \wedge (x - z) \geq 2$$

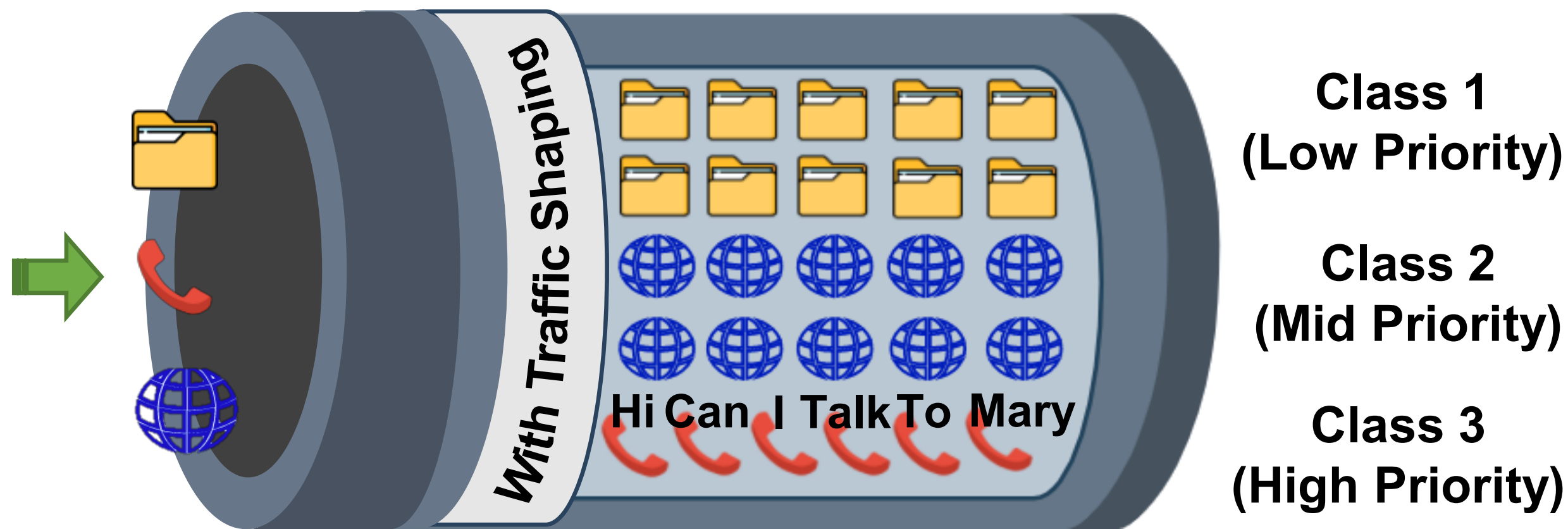
Complex linear and nonlinear formulas

Khouloud Gaaloul, Claudio Menghi, Shiva Nejati, Lionel C. Briand, Yago Isasi Parache: *Combining Genetic Programming and Model Checking to Generate Environment Assumptions*. IEEE TSE, 2022

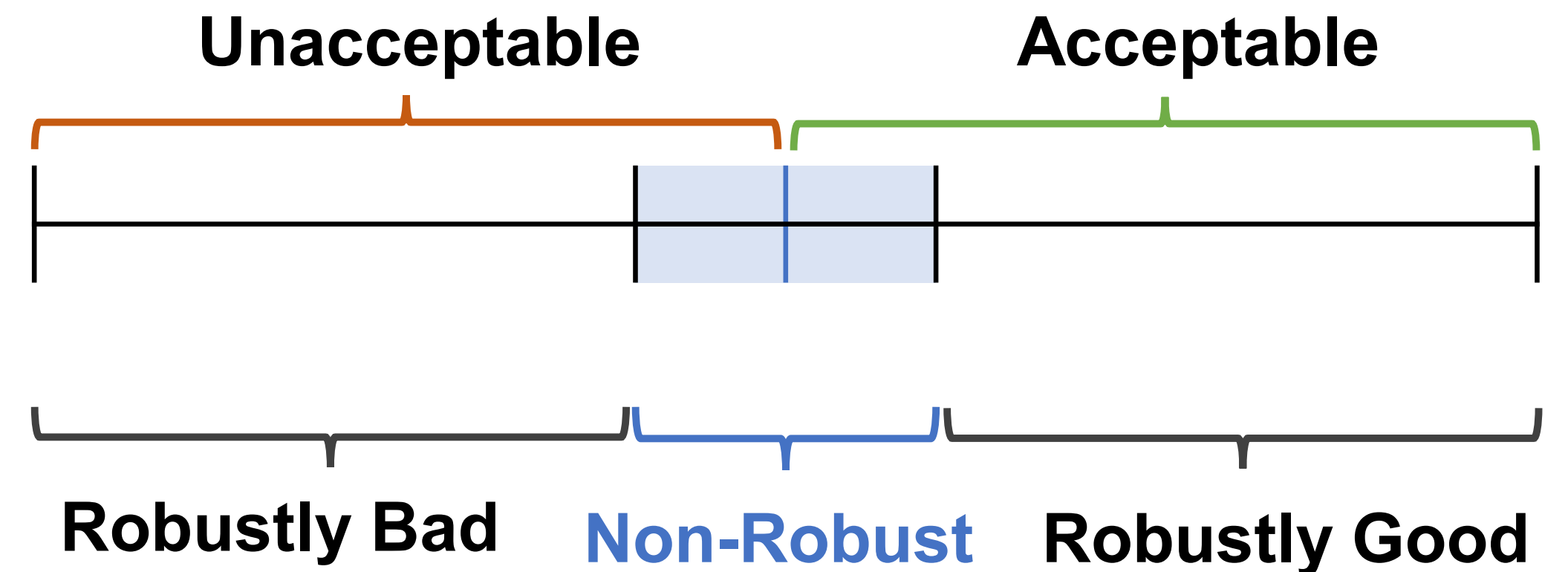
Learning Circumstances of Failures

A traffic management algorithm that provides Small Office/Home Office (SOHO) users with high quality connectivity for streaming applications (e.g., Zoom).





Measure of connection quality



Goal: Understanding conditions over the bandwidths of different priority classes leading to **non-robust** connectivity.

Test Generation and Learning

1. Build a **regression tree**
2. Find paths **that are closest to the boundary**
3. Identify **variables** on the paths and constraints for **the variable ranges**
4. Generate **more test cases** in the identified ranges, rebuild the tree, and go to step 2.

Input ranges leading to non-robustness:

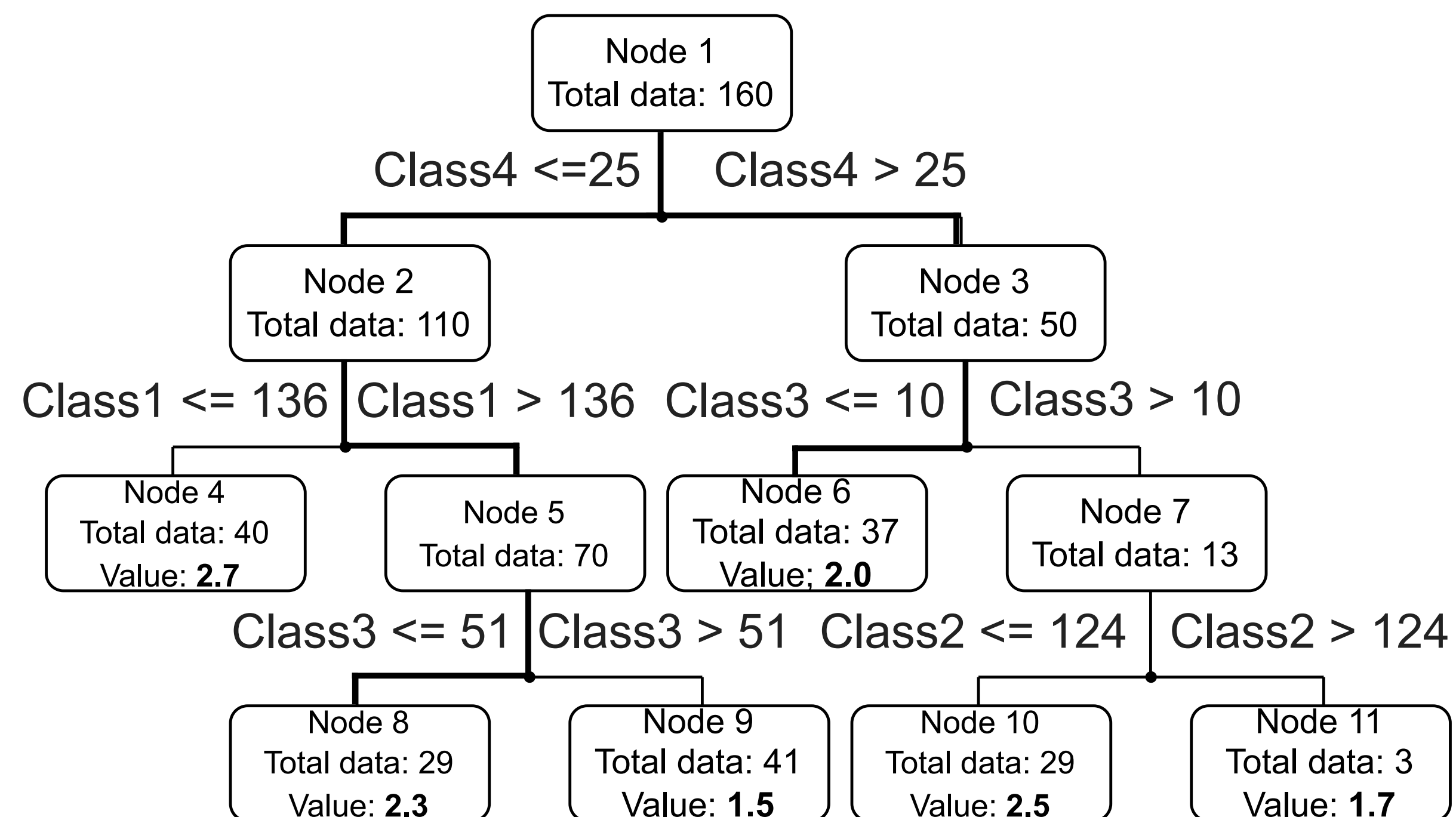
Class1: [18%TB , 28%TB]

Class2: [32%TB , 42%TB]

Class3: [6%TB , 16%TB]

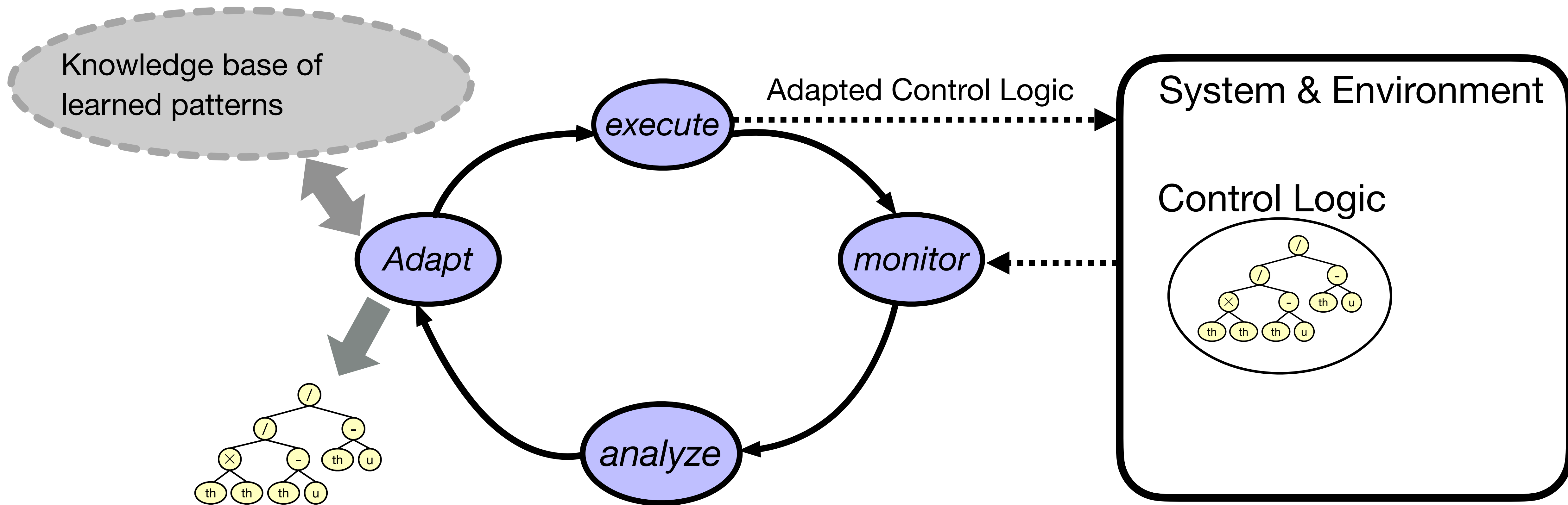
Class4: [0%TB , 7%TB]

**TB: Total Bandwidth



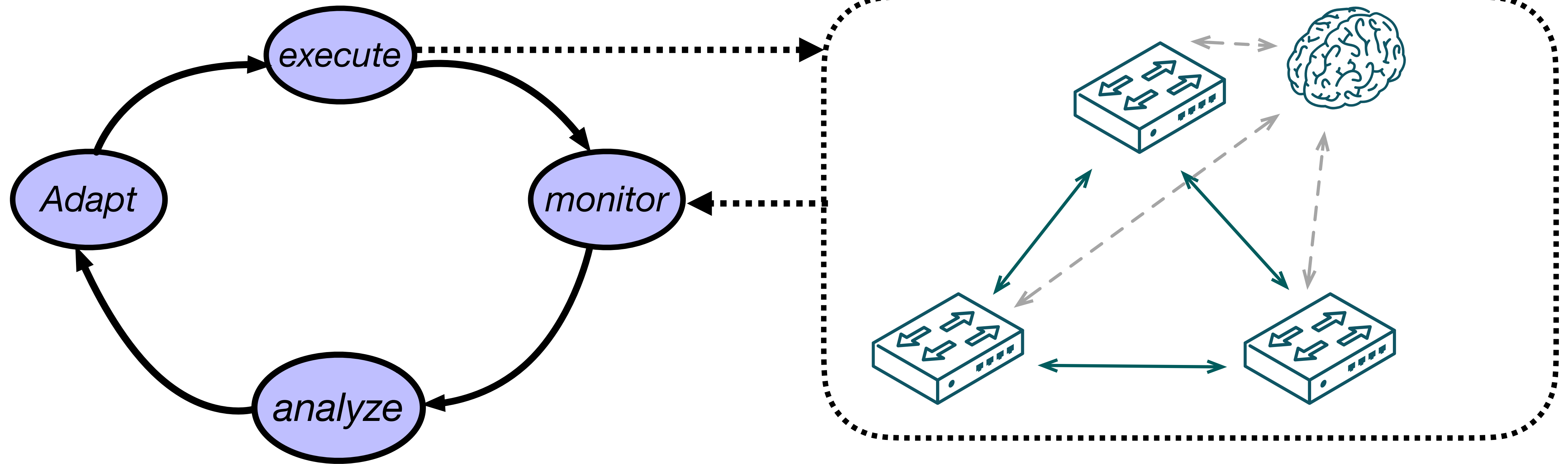
Baharin A. Jodat, Shiva Nejati, Mehrdad Sabetzadeh, Pat Saavedra, Learning Non-robustness using Simulation-based Testing: a Network Traffic-shaping Case Study. Under submission.

Self-Adaptation through Genetic Improvement of Software



Improve using Genetic Programming until the observed anomaly is resolved

Self-Adaption for Network Controllers



Jia Li, Shiva Nejati, Mehrdad Sabetzadeh: Learning Self-adaptations for IoT Networks: A Genetic Programming Approach. SEAMS 2022: 13-24

Conclusions

- For system-level testing, it is not difficult to find test scenarios leading to failures, and failures may not be due to a (traditional) fault in the SUT
- Understanding the environment conditions leading to failures is becoming essential
- We propose to shift the focus of verification and testing from the SUT to the SUT's environment
- As we perform search, we use interpretable ML to learn functional insufficiencies of the SUT