CHALLENGES IN AUTONOMOUS VEHICLE TESTING AND VALIDATION

(CLIFF'S NOTES VERSION FOR IFIP)

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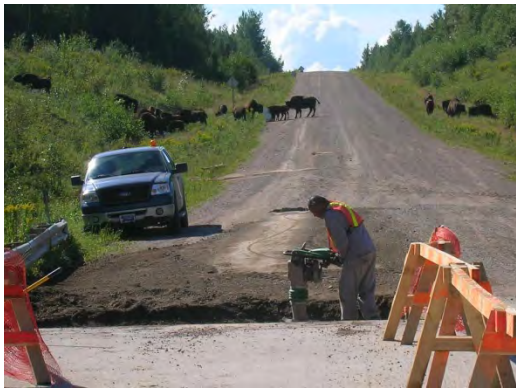
Getting Obvious Cases Covered Is Challenging

Extreme contrast

No lane infrastructure

Poor visibility

Unusual obstacles



Construction

Water (note that it appears flat!)

[Wagner 2014]

Validating High-ASIL Systems via Testing Is Challenging

Need to test for at least ~3x crash rate to validate safety

- Hypothetical fleet deployment: New York Medallion Taxi Fleet
  - 13,437 vehicles, average 70,000 miles/yr = 941M miles/year
    - 7 critical crashes in 2015

    [2014 NYC Taxi Fact Book]

    [Fatal and Critical Injury data / Local Law 31 of 2014]

    ➔ 134M miles/critical crash (death or serious injury)
- Assume testing representative; faults are random independent
  - $R(t) = e^{-lamba*t}$ is the probability of not seeing a crash during testing
- Illustrative: How much testing to ensure critical crash rate is at least as good as human drivers? ➔ (At least 3x crash rate)
  - These are optimistic test lengths…
    - Assumes random independent arrivals
    - Is simulated driving accurate enough?

Testing Miles	Confidence if NO critical crash seen
122.8M	60%
308.5M	90%
401.4M	**95%**
617.1M	99%

Using chi-square test from: http://reliabilityanalyticstoolkit.appspot.com/mtbf_test_calculator

But, Then There Is The Weird Stuff…
(Weirder than any one person can imagine)

http://piximus.net/fun/funny-and-odd-things-spotted-on-the-road
http://blogs.reuters.com/photographers-blog/2012/11/26/house-in-the-middle-of-the-road/
http://edtech2.boisestate.edu/robertsona/506/images/buffalo.jpg

Machine Learning Might Be Brittle & Inscrutable

Legibility: can humans understand how ML works?

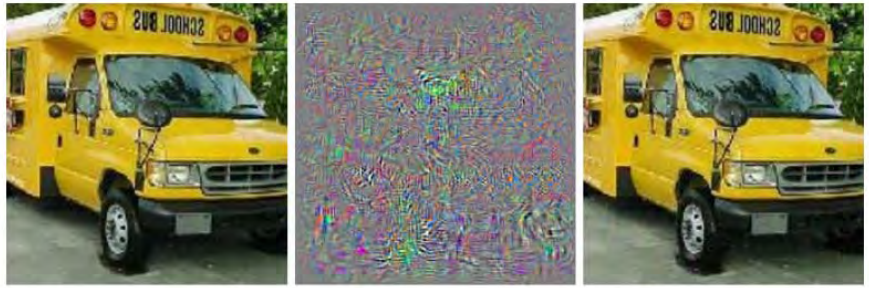
- Machine Learning “learns” from training data
  - Result is a weighted combination of “features”
- Commonly the weighting is inscrutable, or at least not intuitive
  - There is an unknown (significant?) chance results are brittle
    - E.g., accidental correlations in training data, sensitivity to noise

QuocNet:

Car | **Not a Car** | *Magnified Difference*

AlexNet:

Bus | *Magnified Difference* | **Not a Bus**

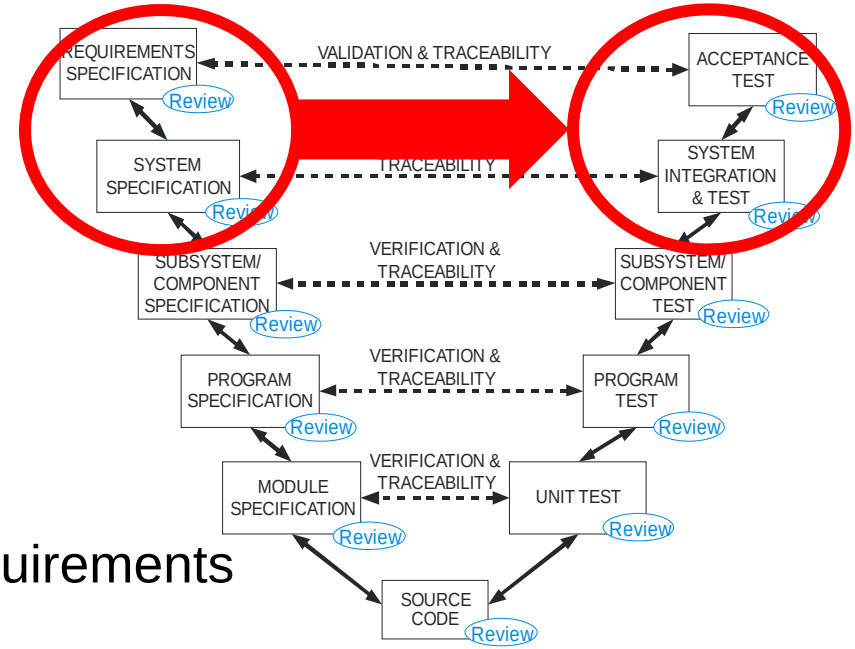


Szegedy, Christian, et al. "Intriguing properties of neural networks." *arXiv preprint arXiv:1312.6199* (2013).

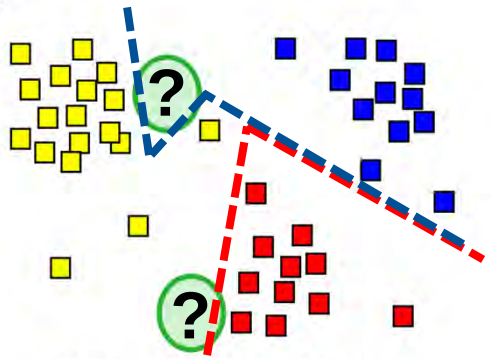
Where Are the Requirements for Machine Learning?

Machine Learning requirements are the training data

- V model traces reqts to V&V
- Where are the requirements in a machine learning based system?
  - ML system is just a framework
  - The **training data** forms de facto requirements



- How do you know the training data is "complete"?
  - Training data is safety critical
  - What if a moderately rare case isn't trained?
    - It might not behave as you expect
    - People's perception of "almost the same" does not necessarily predict ML responses!

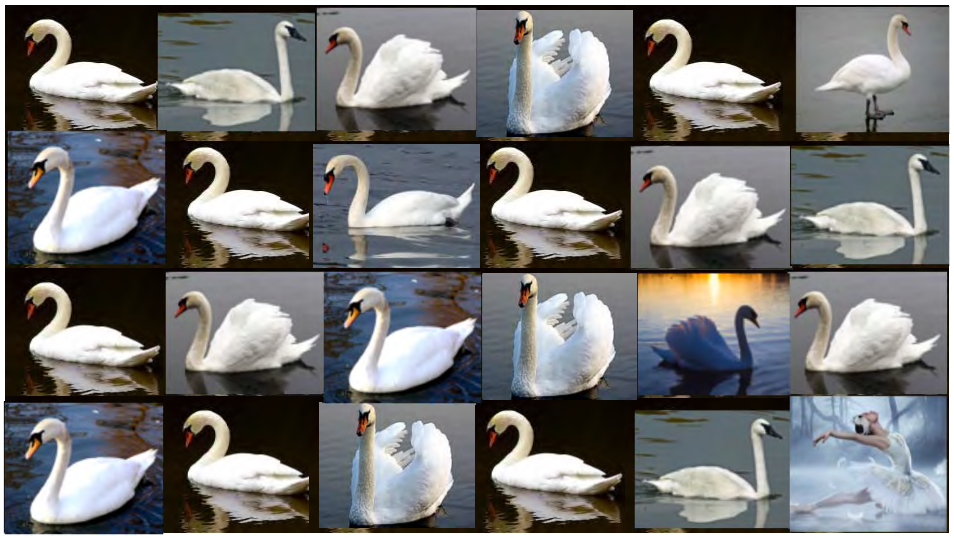


Cluster Analysis

The Black Swan Meets Autonomous Vehicles

Suggested Philosophy for Testing Autonomous Vehicles:

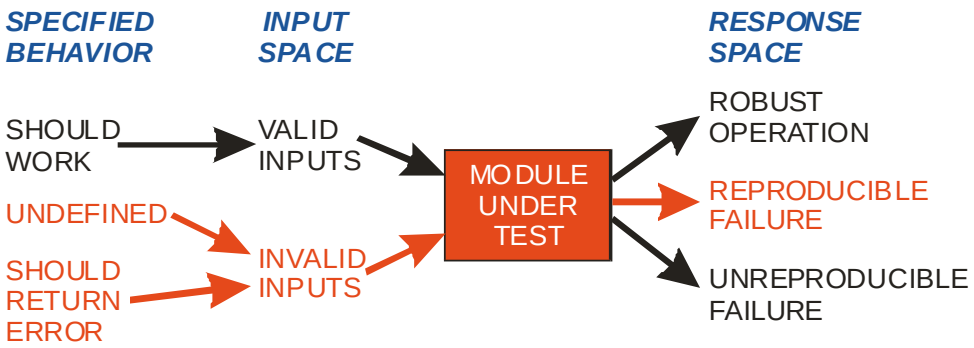
- Some testing should look for proper functionality
  - But, some testing should attempt to ***falsify a correctness hypothesis***
- Much of vehicle autonomy is based on Machine Learning
  - ML is inductive learning… which is vulnerable to "black swan" failures
  - We've found robustness testing to be useful in this role



Thousands of miles of "white swans"…

Make sure to fault inject some "black swans"

ASTAA:
Automated Stress Testing of Autonomy Systems



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Ballista Stress-Testing Tool

Robustness testing of defined interfaces

- Most test cases are exceptional
- Test cases based on best-practice software testing methodology
- Detects software hanging or crashing

Earlier work looked at stress-testing COTS operating systems

Uncovered system-killer crash vulnerabilities in top-of-the-line commercial operating systems

NREC Safety Monitor

Monitors safety invariants at run-time

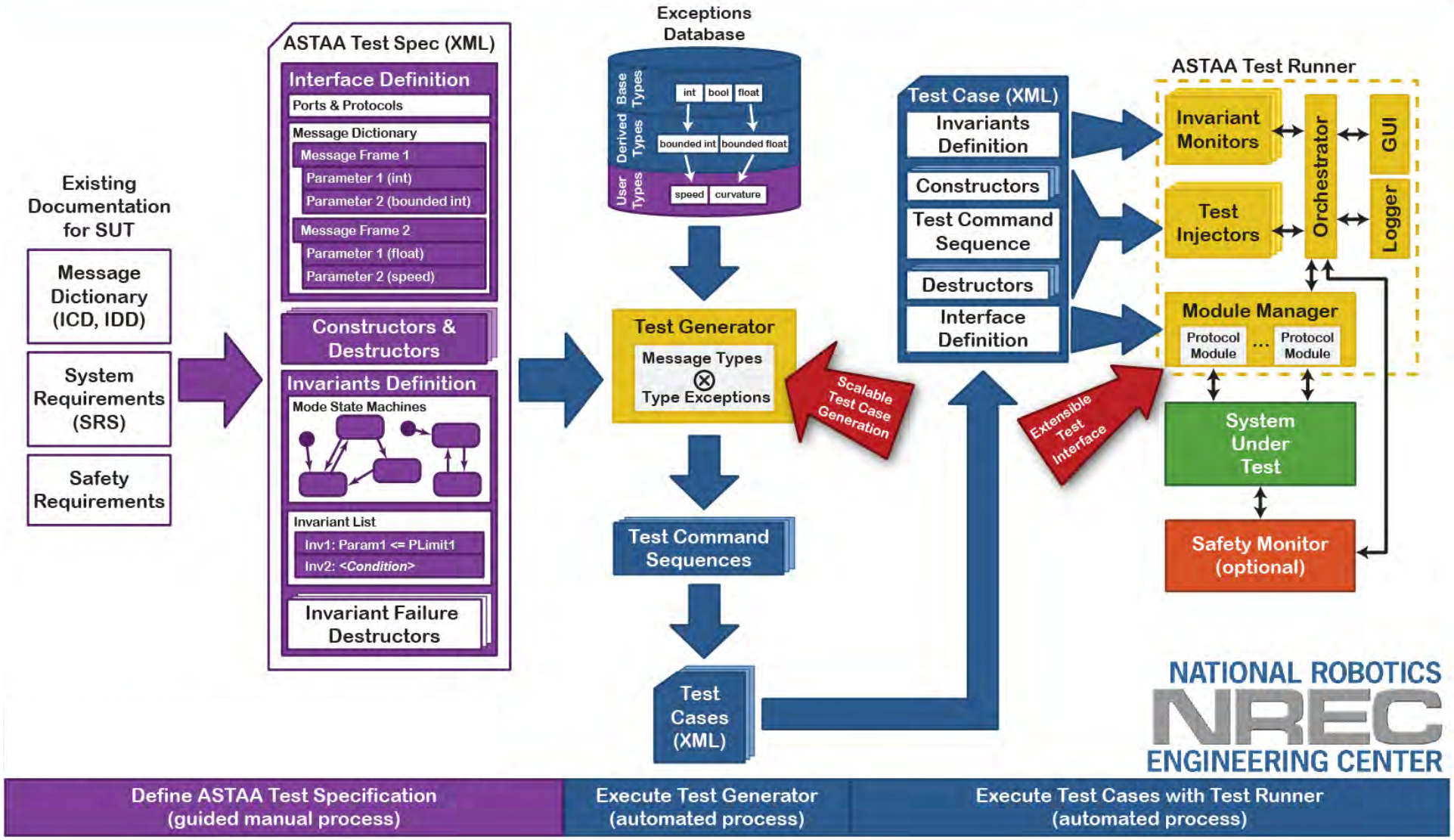
- Designed as run-time safety shutdown box for UAS applications

Independently senses system state to determine whether invariants are violated

Firewalls safety-criticality into a small, manageable subset of a complex UAS; prototype deployed on Autonomous Platform Demonstrator (APD), a 9-ton UGV capable of reaching 80 km/hr

Automated Stress-Testing for Autonomy Architectures

Test Specification and Execution Overview



Example Autonomous Vehicle Defects Found via Robustness Testing

ASTAA Project at NREC found system failures due to:

Improper handling of floating-point numbers:

- Inf, NaN, limited precision

Array indexing and allocation:

- Images, point clouds, etc…
- Segmentation faults due to arrays that are too small
- Many forms of buffer overflow, especially dealing with complex data types
- Large arrays and memory exhaustion

ROS

Time:

- Time flowing backwards, jumps
- Not rejecting stale data

Problems handling dynamic state:

- For example, lists of perceived objects or command trajectories
- Race conditions permit improper insertion or removal of items
- Vulnerabilities in garbage collection allow memory to be exhausted or execution to be slowed down