Validating Machine Learning-Based Systems

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Why Not Use a Traditional Driver Test?

Written test

- Does ADS know traffic laws?
- Does ADS know behavioral expectations?

Road test

- Can ADS execute traffic laws?
- Can ADS negotiate effectively with human drivers?
- Does ADS exhibit good driver hygiene?
- Can ADS resolve potentially ambiguous driving situations?
- Being a 16 year old human
 - How do we measure ADS judgment maturity?
 - Does the ADS know when it doesn't know what to do? © 2021 Philip Koopman 11



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Machine Learning Challenges



Inductive learning

- Collect lots of training data
- Adjust learned model; iterate
- Declare success when tests pass
- Fundamental challenges:
 - Assurance on novel inputs
 - What if it over-fitted to data?
 - Gaps in training data
 - Did it learn what you hoped?
 - Prone to "gaming" the learning
 - What was actually learned?



Traditional Validation Vs. Machine Learning

Use traditional software safety where you can

..BUT..

- Machine Learning (inductive training)
 - No requirements



- Training data is difficult to validate
- No design insight

- Generally inscrutable; prone to gaming and brittleness

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Early Testing: Public Road Testing

Good for identifying "easy" cases

Expensive and potentially <u>dangerous for closed loop testing</u>



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Validation Via Brute Force Road Testing?

If 200M miles/critical mishap...

- Test 3x-10x longer than mishap rate
 - → Need 2 Billion miles of testing

That's ~50 round trips on every road in the world

With fewer than 10 critical mishaps

And what if the answer is: "not safe enough; try again?"

WolframAlpha^{*} computational knowledge engine miles of roads

(1994 to 2008)

(based on 225 values; 24 unavailable)



Summary

median

highest

lowest

20.46 million mi

4.97 mi (Tuvalu)

4.03 million mi (United States)

11630 mi



Closed Course Testing

Safer, but expensive

- Not scalable
- Only tests things you have thought of!





Volvo / Motor Trend

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Simulation



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Highly scalable; fidelity vs. cost tradeoff

- Need to build highly detailed models
- Challenge of matching real world data into simulation models
- Only tests things you have thought of!



Scenario-Based Simulation



Scenarios must cover Operational Design Domain (ODD)

THE PEGASUS METHOD

https://www.pegasusprojekt.de/en/pegasus-method



NHTSA-inspired pre-crash scenarios

We have selected 10 traffic scenarios from the NHTSA pre-crash typology to inject challenging driving situations into traffic patterns encountered by autonomous driving agents during the challenge.



Traffic Scenario 01: Control loss without previous action

Definition: Ego-vehicle loses control due to bad conditions on the road and it
 must recover, coming back to its original lane.

Traffic Scenario 02: Longitudinal control after leading vehicle's brake

 Definition: Leading vehicle decelerates suddenly due to an obstacle and egovehicle must react, performing an emergency brake or an avoidance maneuver.

Traffic Scenario 03: Obstacle avoidance without prior action

 Definition: The ego-vehicle encounters an obstacle / unexpected entity on the road and must perform an emergency brake or an avoidance maneuver.

Traffic Scenario 04: Obstacle avoidance with prior action

 Definition: While performing a maneuver, the ego-vehicle finds an obstacle / unexpected entity on the road and must perform an emergency brake or an avoidance maneuver.

https://carlachallenge.org/challenge/nhtsa/

Simulation Components



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Simulation Validity

Fidelity & qualification

- Environment; road users
- Perception as well as vehicle motion
- Appropriate safety metrics
- Tool & model qualification

Experimental design



CARLA https://youtu.be/2c-KIQ8SFcc

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- Coverage of ODD & high-risk edge cases
- Matching simulated scenario to real-world scenario
- Experimental design for validation of simulation itself

"All models are wrong, but some are useful." - George Box

What Does It Mean for a Test To Pass?

- Traditional test paradigm:
 - You think design is right
 - Test validates engineering done properly
 - Test traces to requirements/design

Inductive training test paradigm:

- You think system was trained properly
- Test determines whether training worked
 - Weak traceability to test set, if any
 - Hope to detect training data gaps, overfitting
- BUT: nondeterministic, opaque "design"
 - Robust test plan is essential









Changing Validation Approaches

Machine Learning (ML) breaks the "V"
Simulation validity (including models & test plan)
Are you simulating perception (the hardest part)?

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