

A Differential Testing Framework to Identify Critical AV Failures Leveraging Arbitrary Inputs

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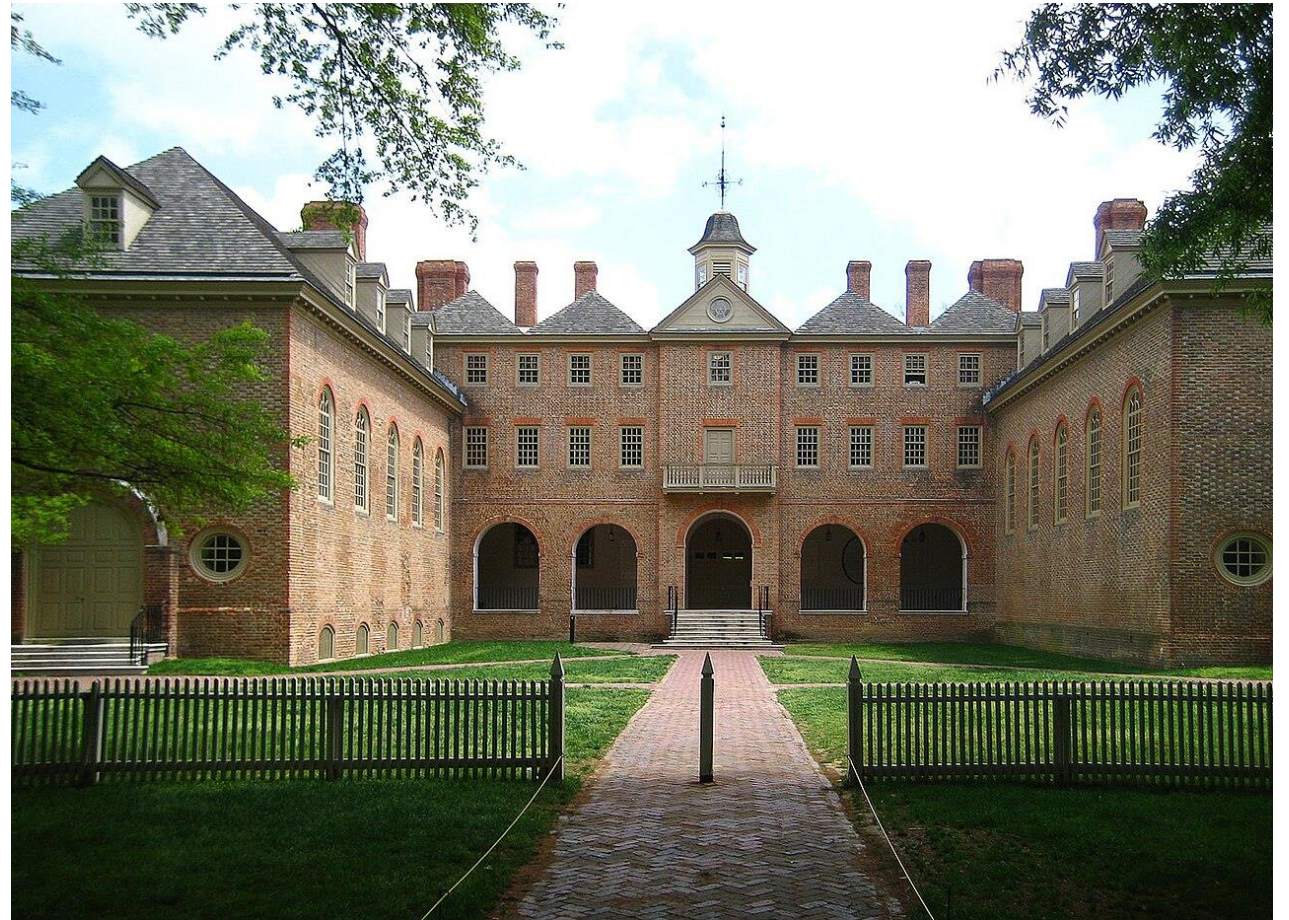
University of Virginia

Trey Woodlief



WILLIAM
& MARY

CHARTERED 1693



I am joining William & Mary
Fall'25 as Assistant Prof

AV Failures

The New York Times

MOTORTREND

News

Reviews

Buyer's Guide

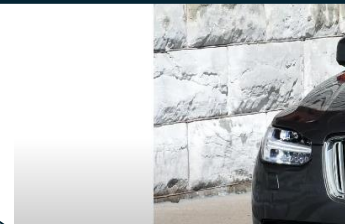
Magazines

The Future

Videos

Free TV

How can we improve AV safety?



This article is more than 3 years old.

Video from Taiwan reveals a disturbing Tesla [TSLA -0.2%](#) crash, where the vehicle plows directly into the top of a large truck lying on its side, straddling two lanes of a freeway. The driver states the vehicle was in Autopilot mode. The driver did not hit the brakes himself until far too late, indicating he was probably not paying attention. The road has light traffic and visibility is very good. Nobody was injured.



How do AVs work?



Input



AV



Output

Goal: produce safe outputs for every input

How do AVs work?



Input



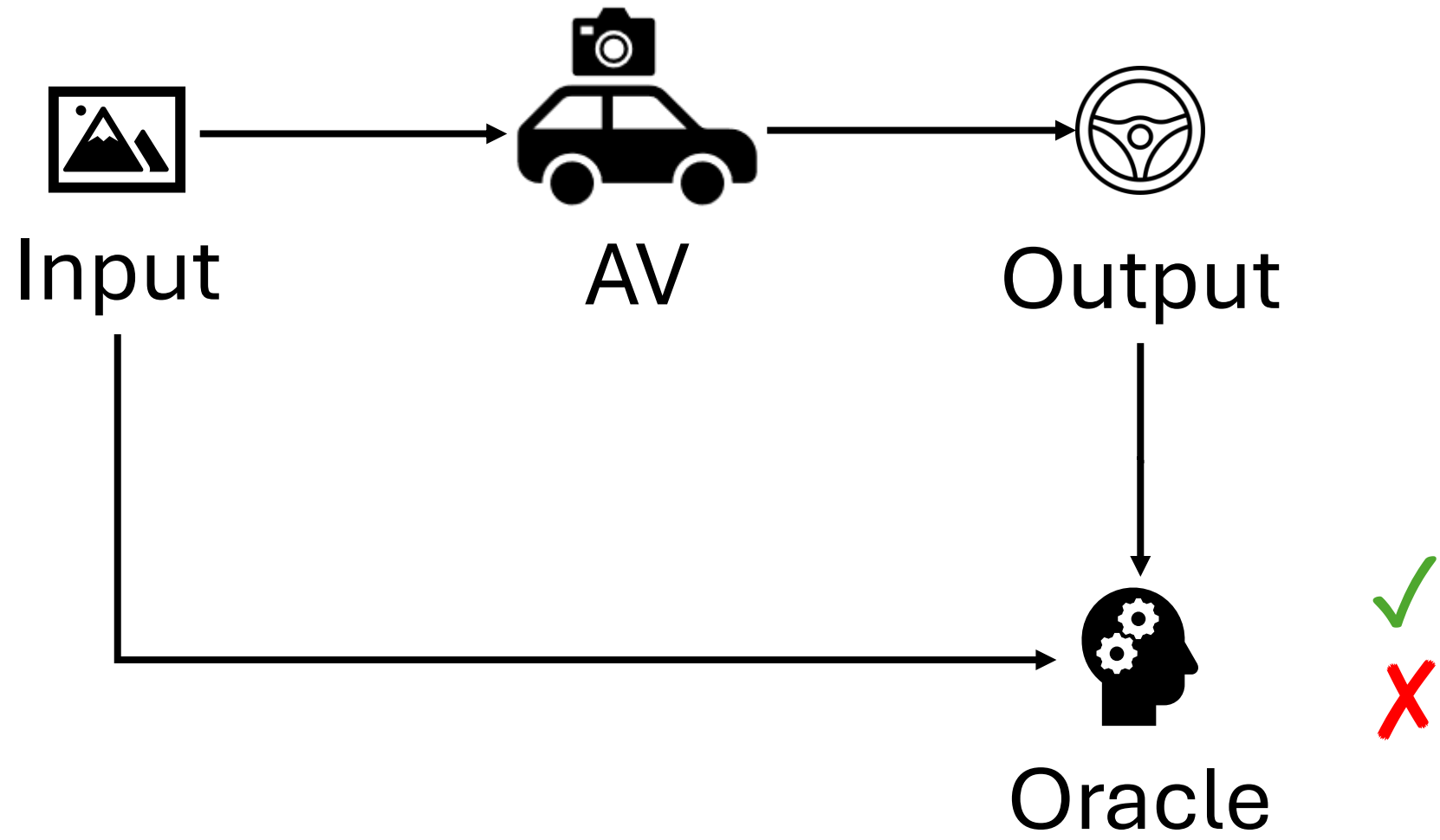
AV



Output

Validate: produce safe outputs for every input

Validation



Test Inputs

In 2015, Tesla obtained
sensor data from
1 million miles every 10 hours

IEEE Spectrum

Tesla's Autopilot Depends on a Deluge of Data

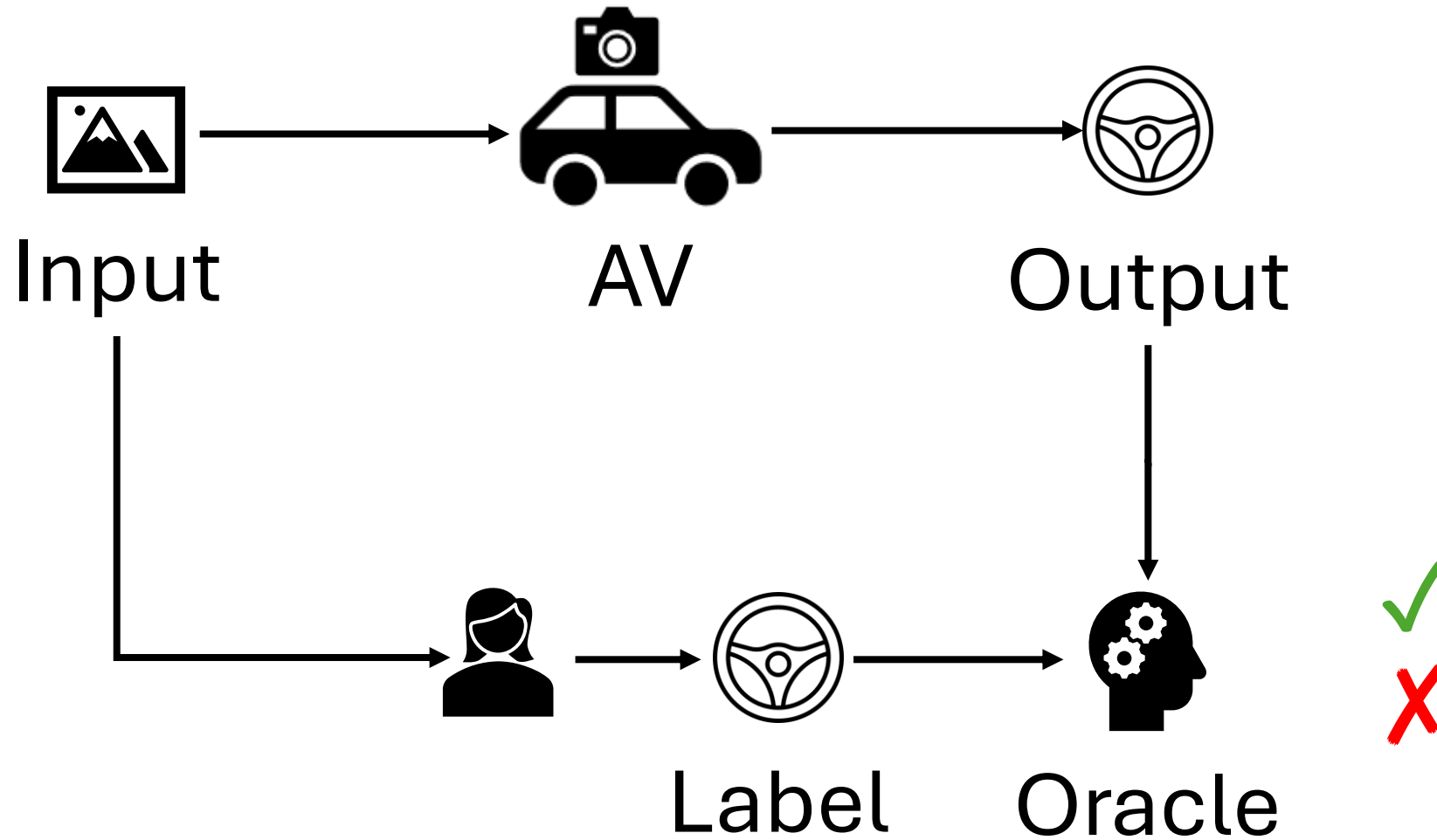
Q Type to search



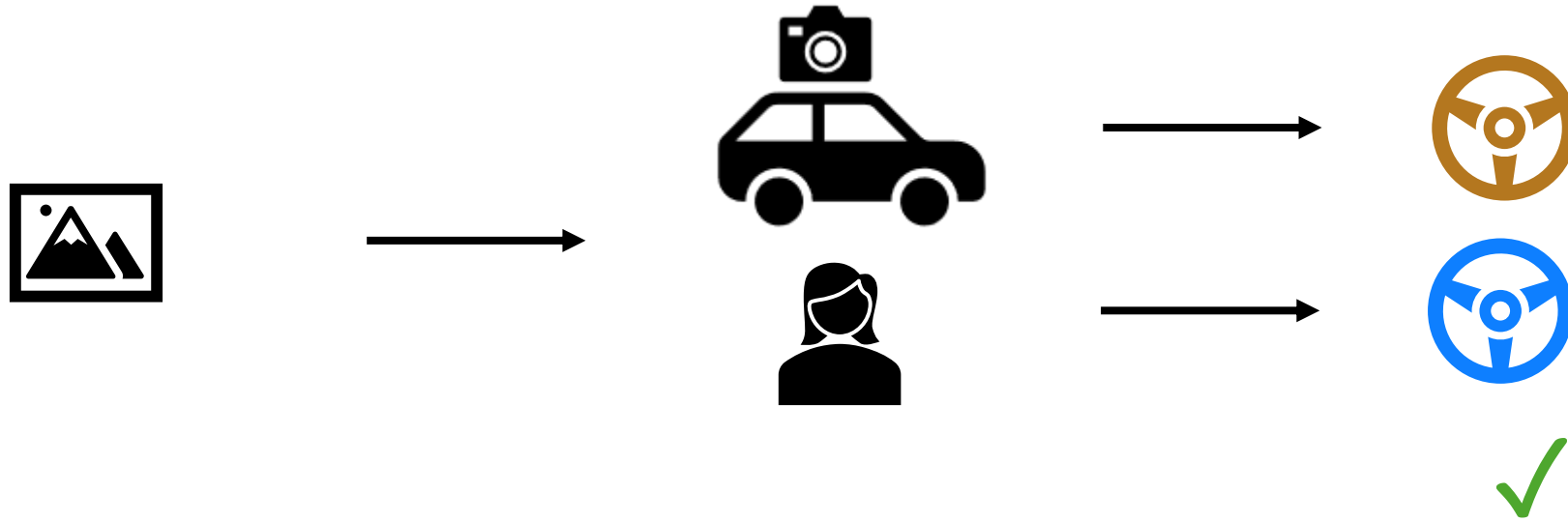
PHILIPP HANDLER/UNSPLASH

In Shadow Mode, operating on Tesla vehicles since 2016, if the car's Autopilot computer is not controlling the car, it is simulating the driving process in parallel with the human driver. When its own predictions do not match the driver's behavior, this might trigger the recording of a short "snapshot" of the car's cameras, speed, acceleration, and other parameters for later uploading to Tesla. Snapshots are also triggered when a Tesla crashes.

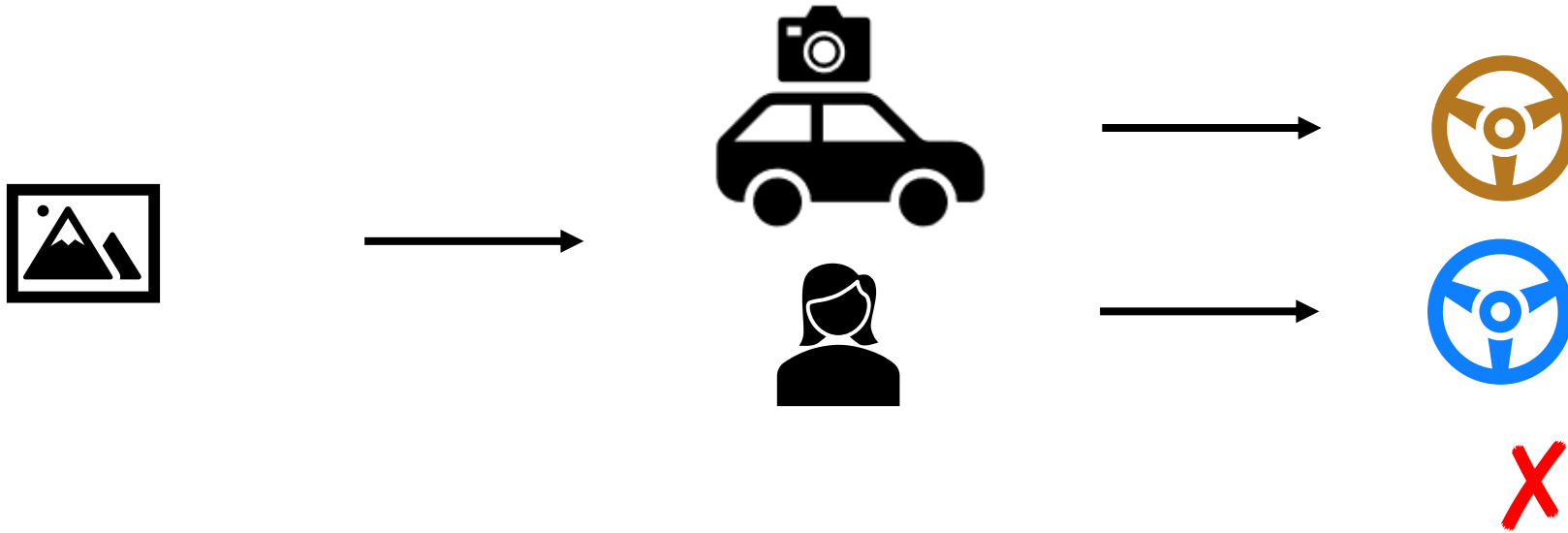
Test Oracles



Existing Test Suites



Existing Test Suites



Existing Test Suites

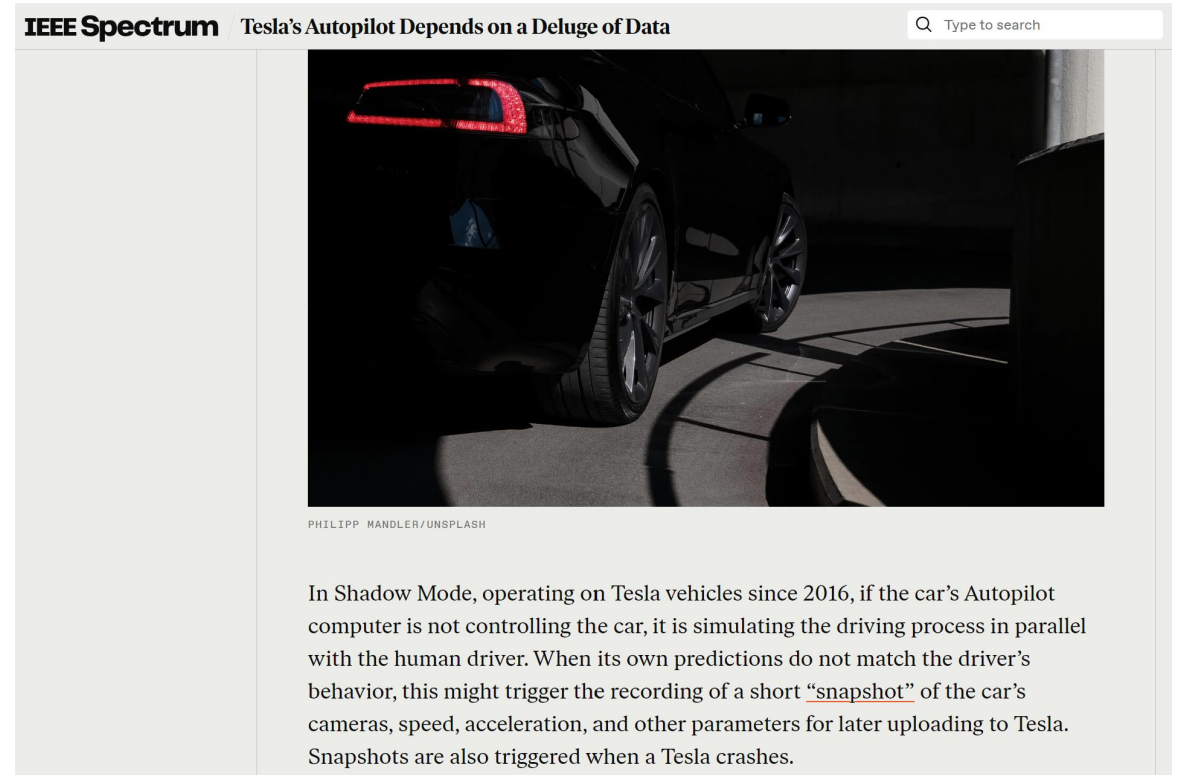


How do we get enough labeled data?
What if the original label is wrong?

Cautious Aggressive Drunk Distracted

Differential Testing

- Use **unlabeled** data
- **Leverage multiple systems** to find the correct answer



WAYMO

Differential Testing



Cautious



Aggressive



Drunk



Distracted

Differential Testing



AV1



AV2



AV3



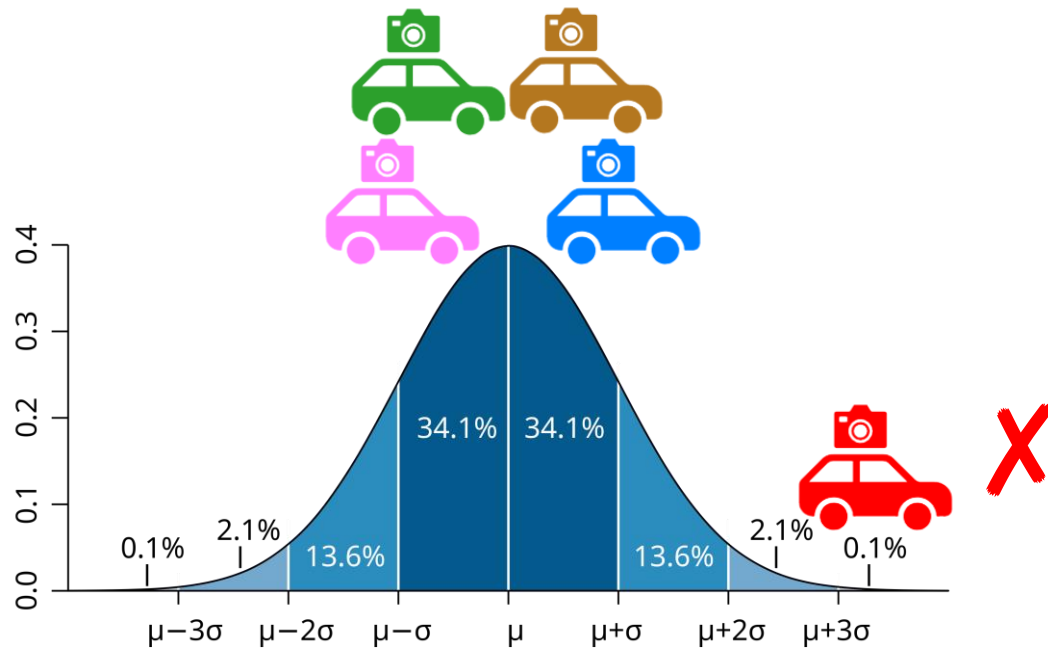
AV4

Differential Testing

- Use **unlabeled** data
- **Leverage multiple systems** to find the correct answer



Statistical Outlier Detection



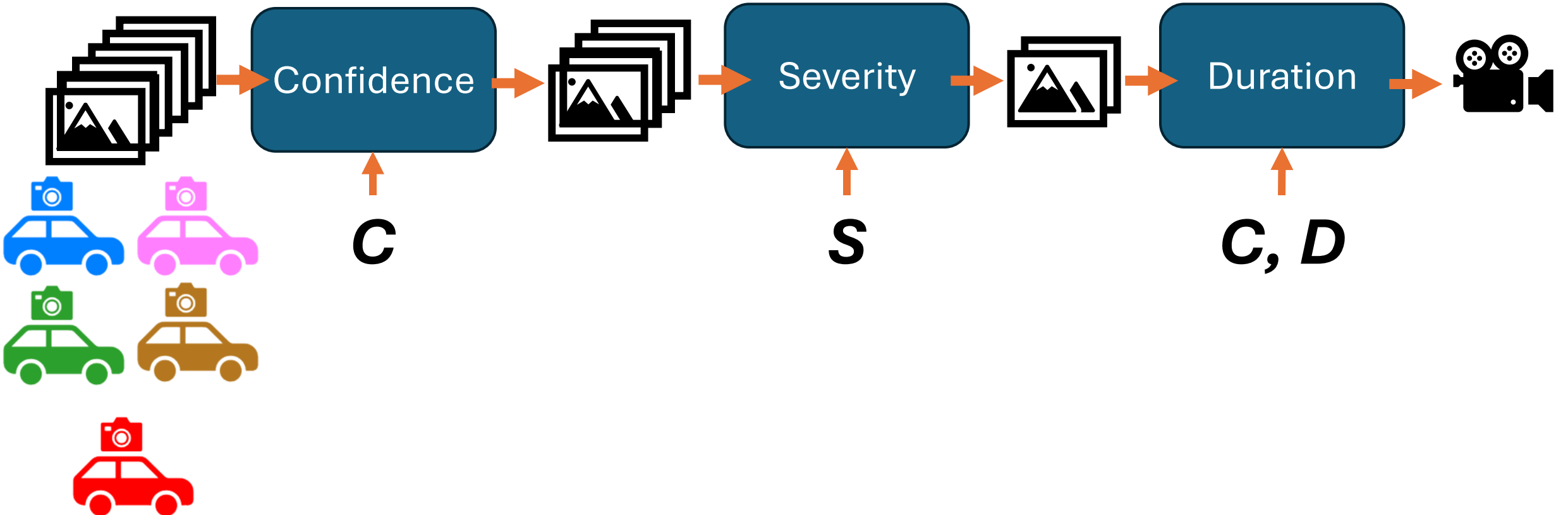
This requires knowing the distribution!

Building an Oracle

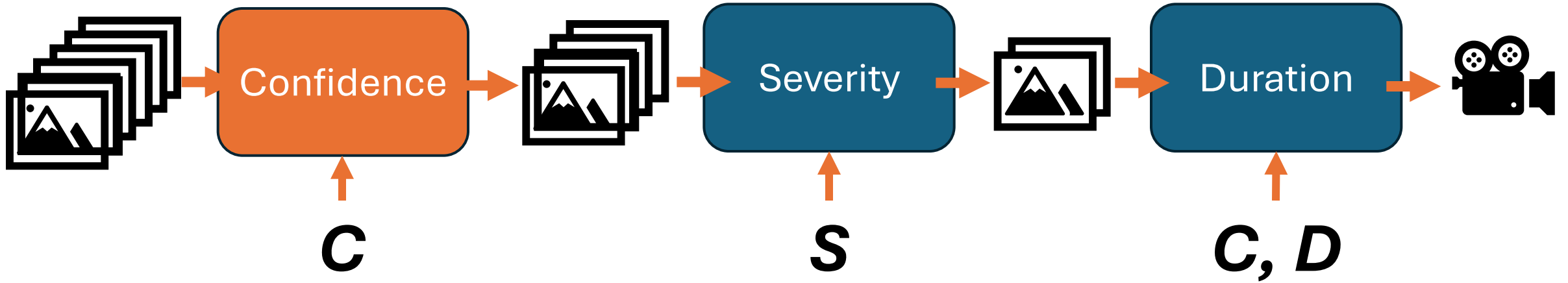
- Confidence
- Severity
- Duration



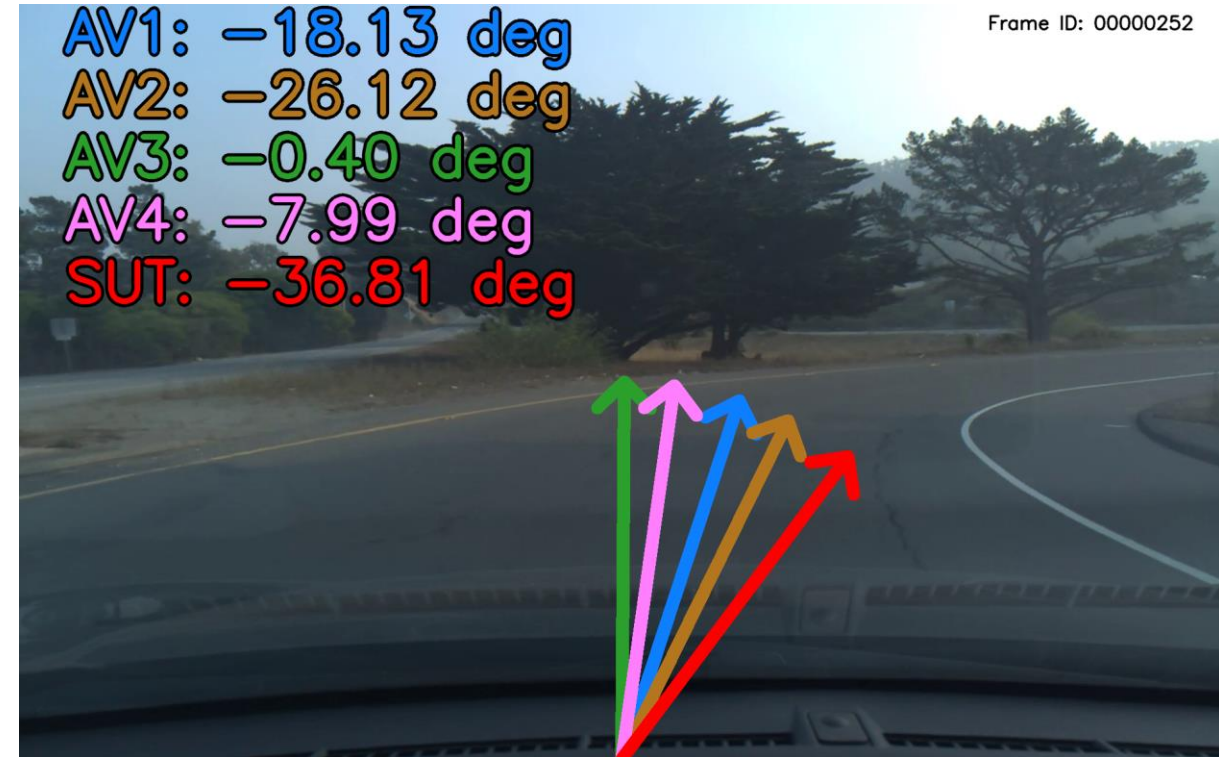
DiffTest4AV Approach



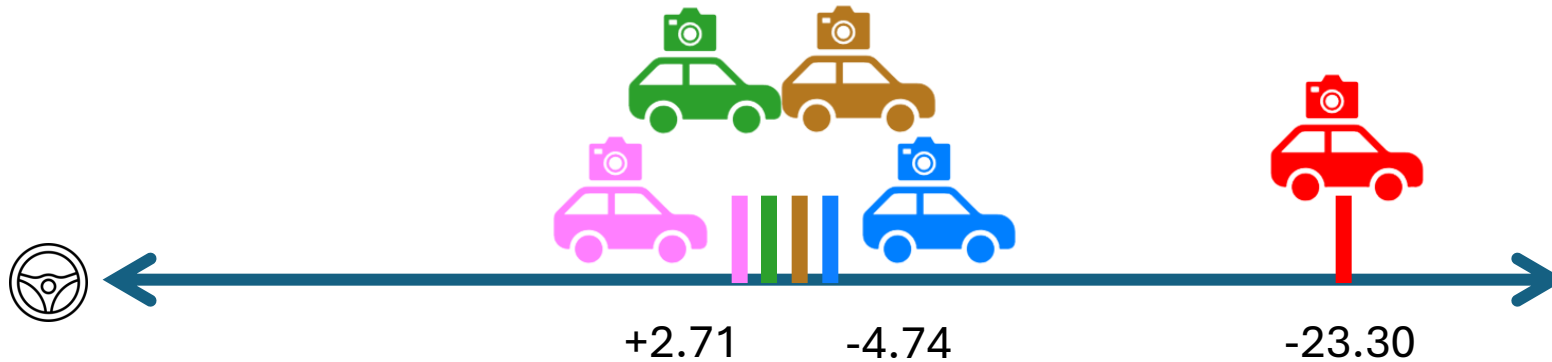
DiffTest4AV Approach



Why do we need confidence?



Confidence Through Outliers



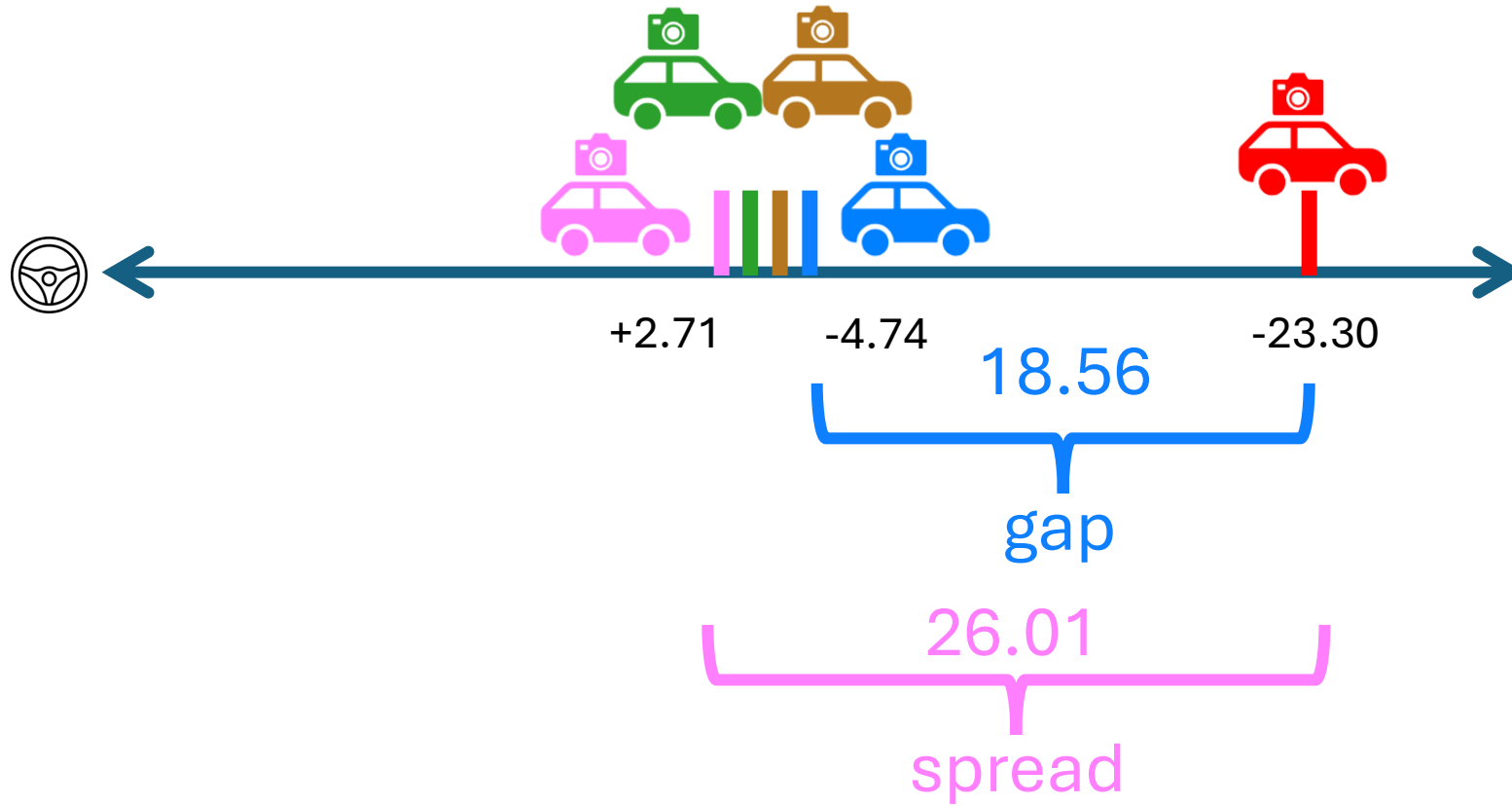
$$Q = \frac{\max_i |Y_i - \bar{Y}|}{Y_{max} - Y_{min}}$$

SAMPLE CRITERIA FOR TESTING OUTLYING OBSERVATIONS

by
Frank E. Grubbs

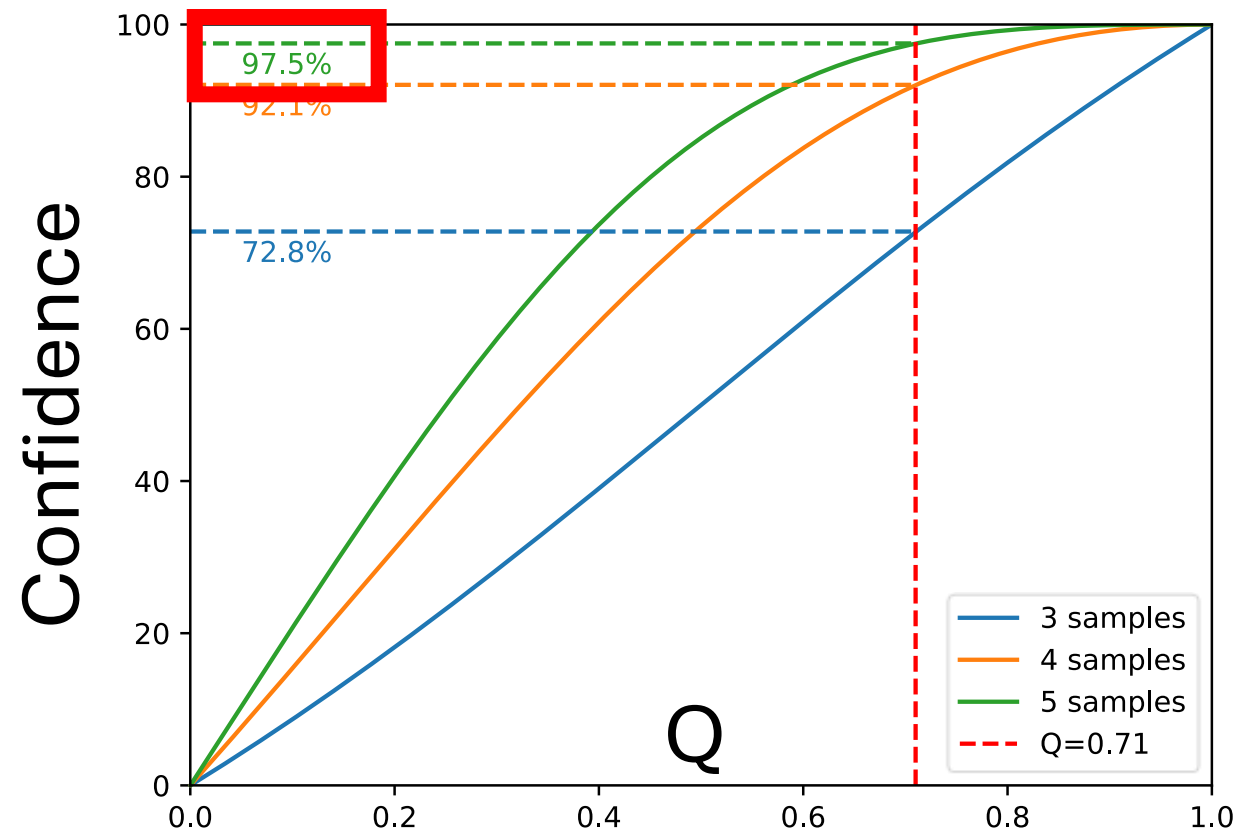
A Dissertation Submitted in Partial Fulfillment of the
Requirements for the Degree of Doctor of Philosophy in
the University of Michigan.

Confidence: Grubbs's Q Test

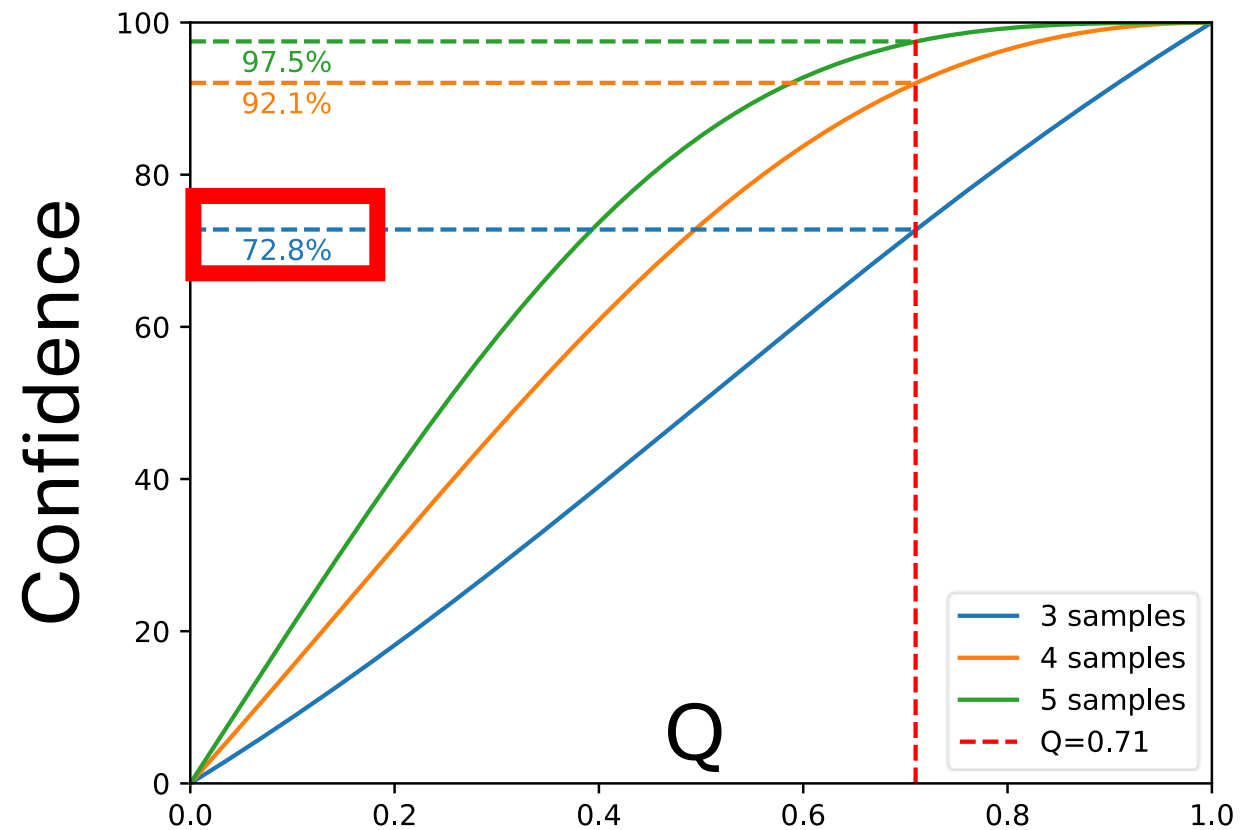
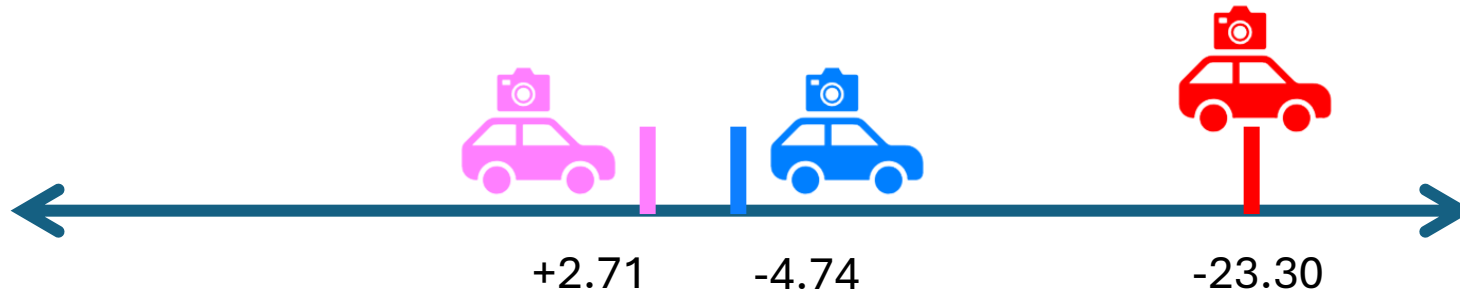


$$Q = \frac{\text{gap}}{\text{spread}} = \frac{18.56}{26.01} = .71$$

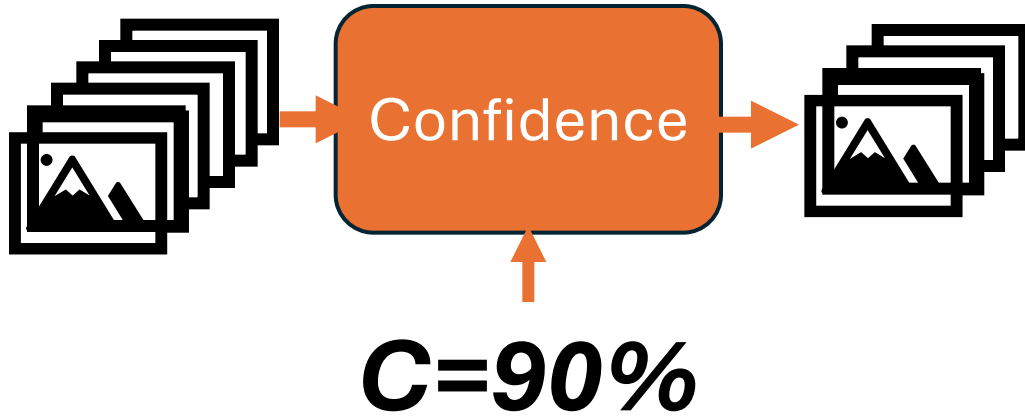
Confidence: Grubbs's Q Test



Confidence: Grubbs's Q Test



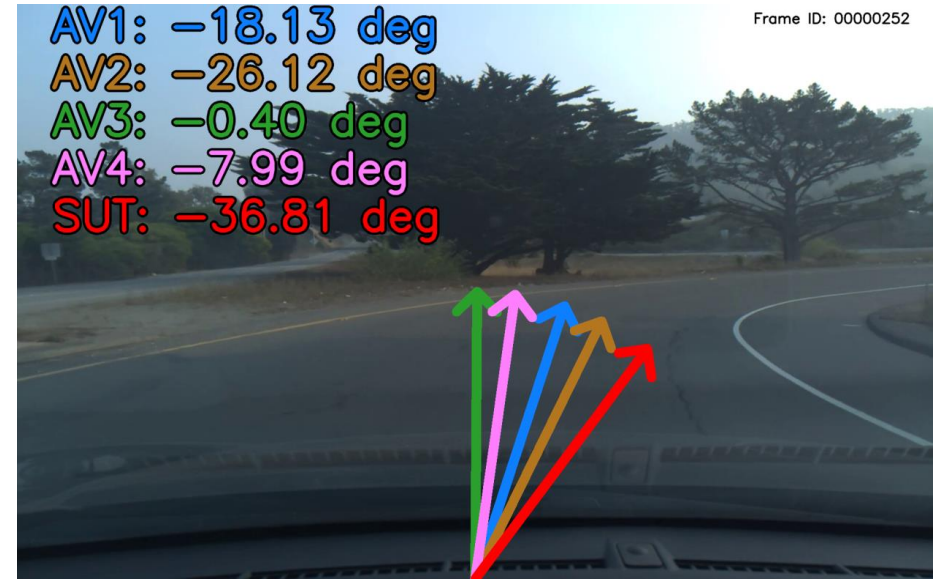
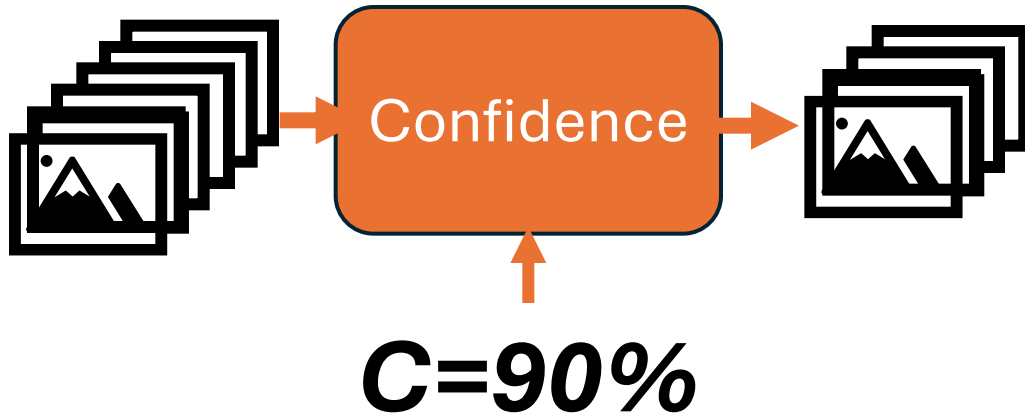
Threshold by Confidence



Confidence: 97.3%



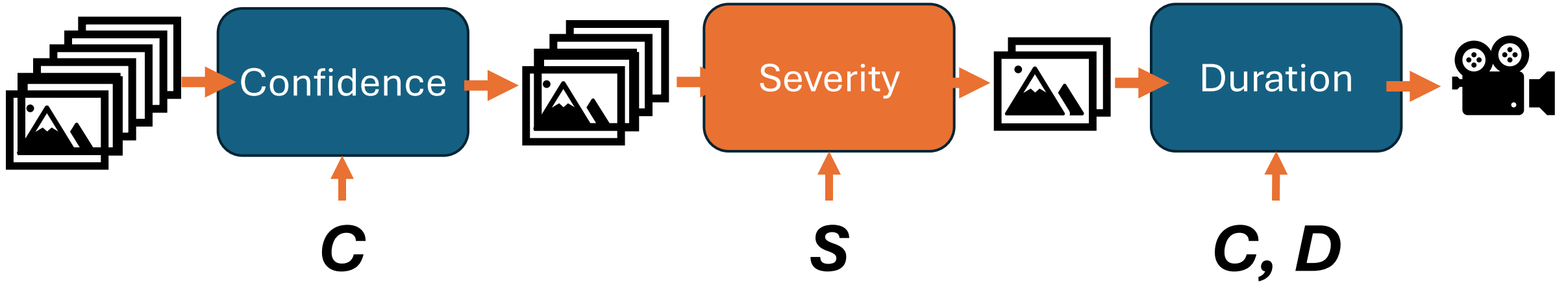
The Need for Confidence



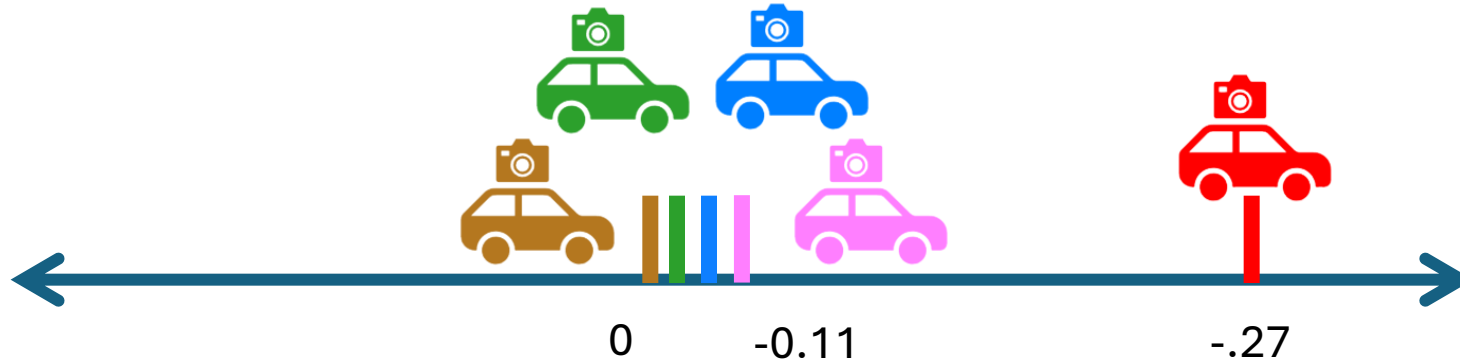
$$Q = \frac{\text{gap}}{\text{spread}} = \frac{10.7}{36.4} = .26$$

Confidence: 57.6% **X**

DiffTest4AV Approach



The Need for Severity

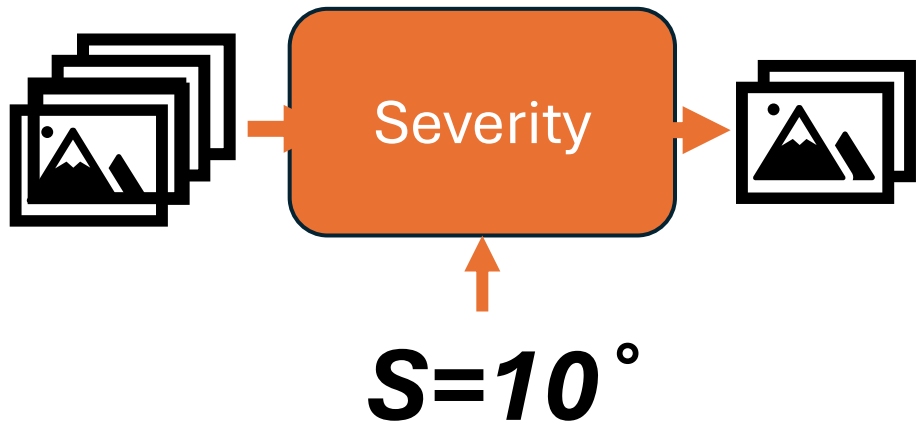


$$Q = \frac{\text{gap}}{\text{spread}} = \frac{0.16}{0.27} = .59$$

confidence = 92.3%



Finding High Impact Failures

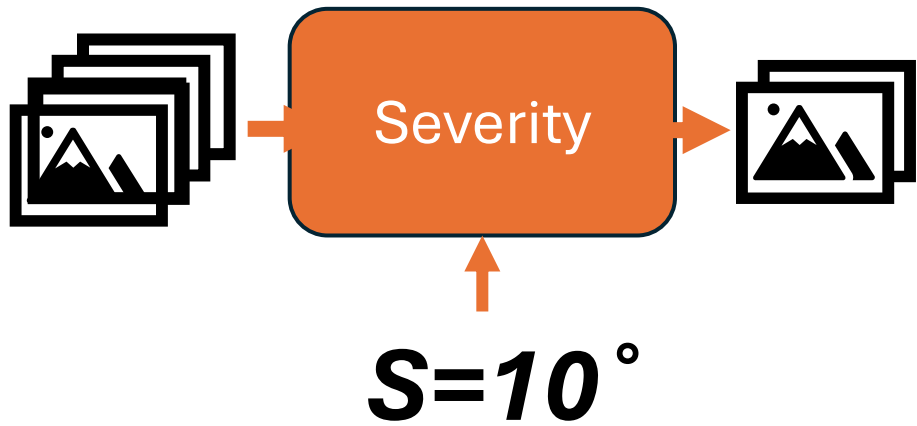


Confidence: 92.3%

Severity: 0.16°

X

Finding High Impact Failures

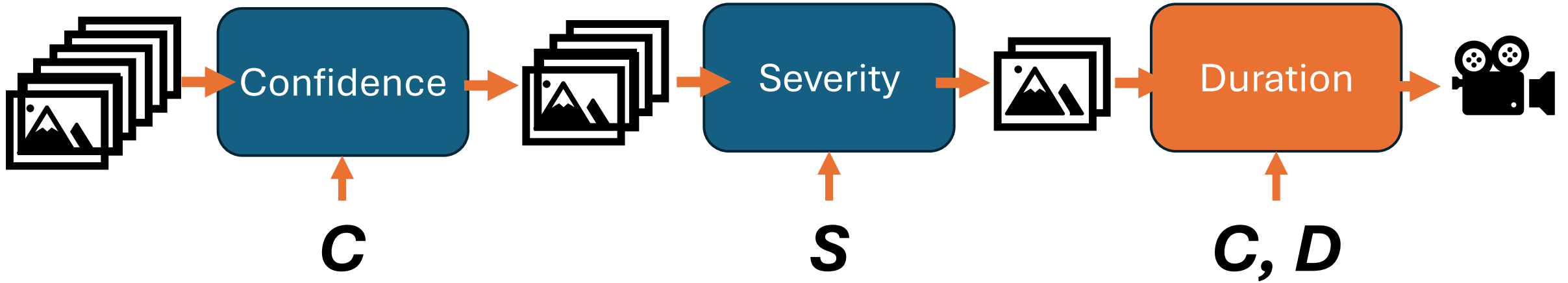


Confidence: 97.3%

Severity: 18.56°

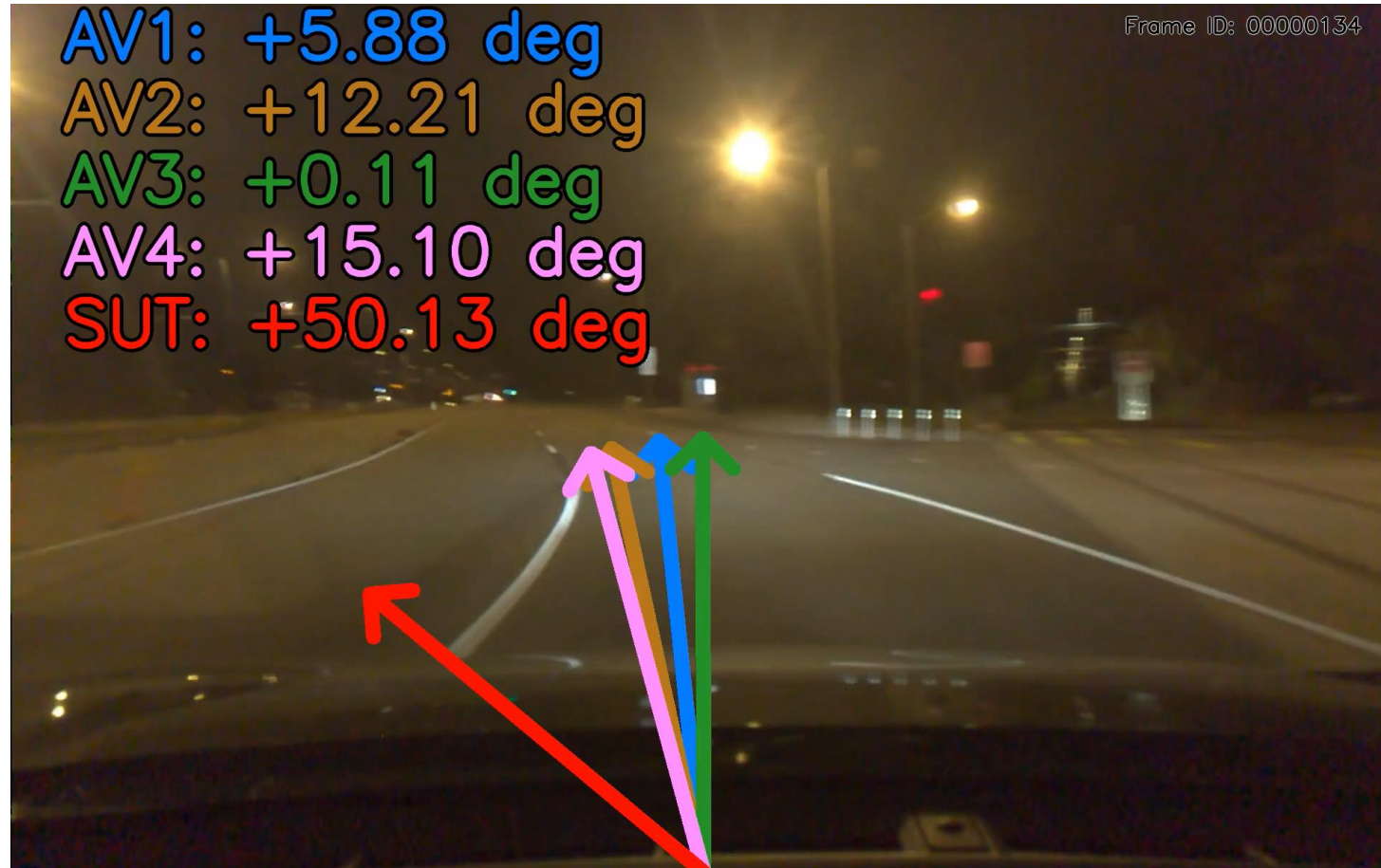


DiffTest4AV Approach



Duration

- Continuous failures escalate to system failures



Duration

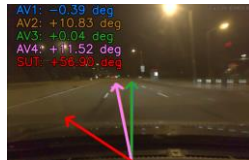
- Continuous failures escalate to system failures



Frame	142	143	144	145	146	147	148	149	150	151	152
Conf: (%)	98.78	98.93	98.65	99.16	99.48	99.51	99.51	99.7	99.7	99.88	99.87

Duration

- Continuous failures escalate to system failures



Frame	142	143	144	145	146	147	148	149	150	151	152
Conf: (%)	98.78	98.93	98.65	99.16	99.48	99.51	99.51	99.7	99.7	99.88	99.87

Option 1: Filter by minimum confidence

98.65%

Duration

- Continuous failures escalate to system failures



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Conf: (%)	98.78	98.93	98.65	99.16	99.48	99.51	99.51	99.7	99.7	99.88	99.87

Option 1: Filter by minimum confidence

98.65%

Option 2: Cumulative Confidence

93.37%

$$\prod_{i=j}^{j+m} confidence(t_i)$$

Duration

- Continuous failures escalate to system failures



$$\prod_{i=j}^{j+m} confidence(t_i)$$



Frame	142	143	144	145	146	147	148	149	150	151	152
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Option 1: Filter by minimum confidence

98.65%



$D=10$

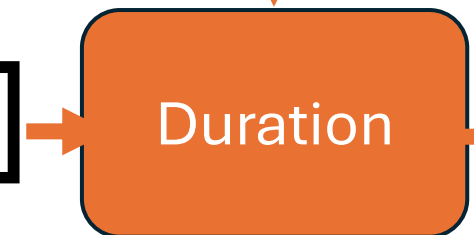
Option 2: Cumulative Confidence

93.37%



$C=95\%$

$$\prod_{i=j}^{j+m} confidence(t_i)$$



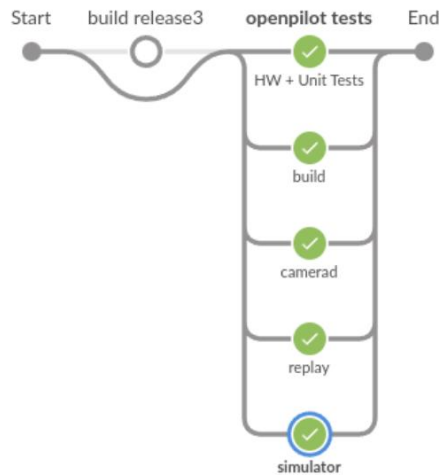
Study

- RQ1: High-confidence failures
- RQ2: High-confidence & High-severity failures
- RQ3: High-impact & long-running failures

Experiment Setup: AV

- comma.ai OpenPilot

Continuous integration testing



CI tests that run on every openpilot commit on comma 3 hardware





Experiment Setup: AV

- comma.ai OpenPilot
 - Apr 2022 (AV1)
 - Jul 2022 (AV2)
 - Nov 2022 (AV3)
 - Mar 2023 (AV4)
 - Jun 2023 (SUT)

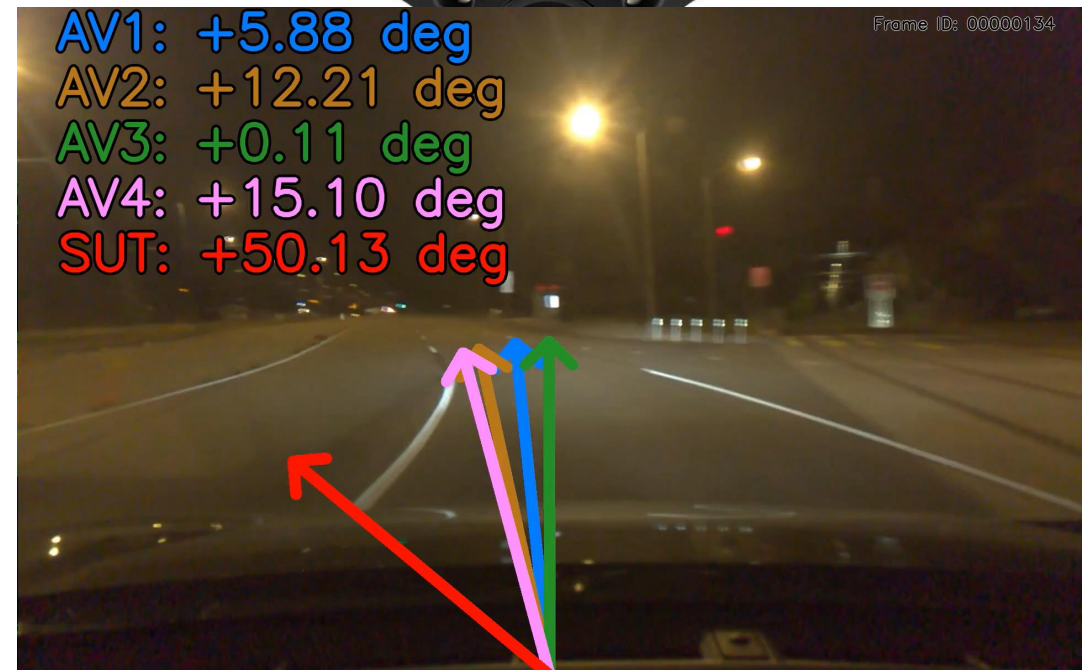


Experiment Setup: Data

- comma.ai 2016 
 - 11 videos; 391,843 images
- comma.ai 2k19 
 - 2035 videos; 1,825,111 images
- External JUtah
 - 50 videos; 2,362,708 images

Some Interesting Data

- At 90% Confidence:
 - External JUtah has the most failures, but $\sim 2\% > 10^\circ$
 - Comma.ai 2k19 has all the $> 50^\circ$ failures and the longest failure



Takeaways

From 4,579,662 inputs
identify 81 (0.002%)
high-impact failures at
90% confidence and 50° severity
Including failures up to 72 frames (4.8s)

Takeaways

In 2015, Tesla obtained
1 million miles every 10 hours

Even if Tesla failed 1 million
times less often, DiffTest4AV
would find 31 failures per year!

IEEE Spectrum

Tesla's Autopilot Depends on a Deluge of Data

Q Type to search



PHILIPP HANDLER/UNSPLASH

In Shadow Mode, operating on Tesla vehicles since 2016, if the car's Autopilot computer is not controlling the car, it is simulating the driving process in parallel with the human driver. When its own predictions do not match the driver's behavior, this might trigger the recording of a short “snapshot” of the car's cameras, speed, acceleration, and other parameters for later uploading to Tesla. Snapshots are also triggered when a Tesla crashes.

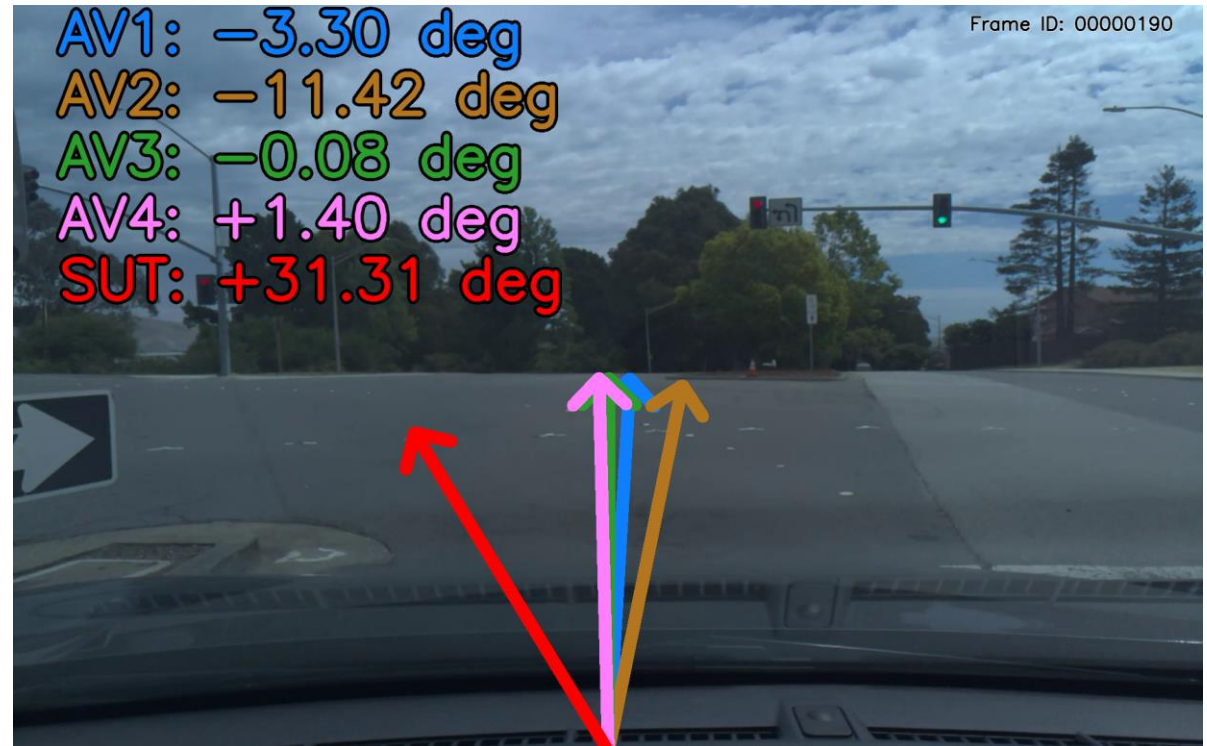
Future Work

- Removing False Positives:

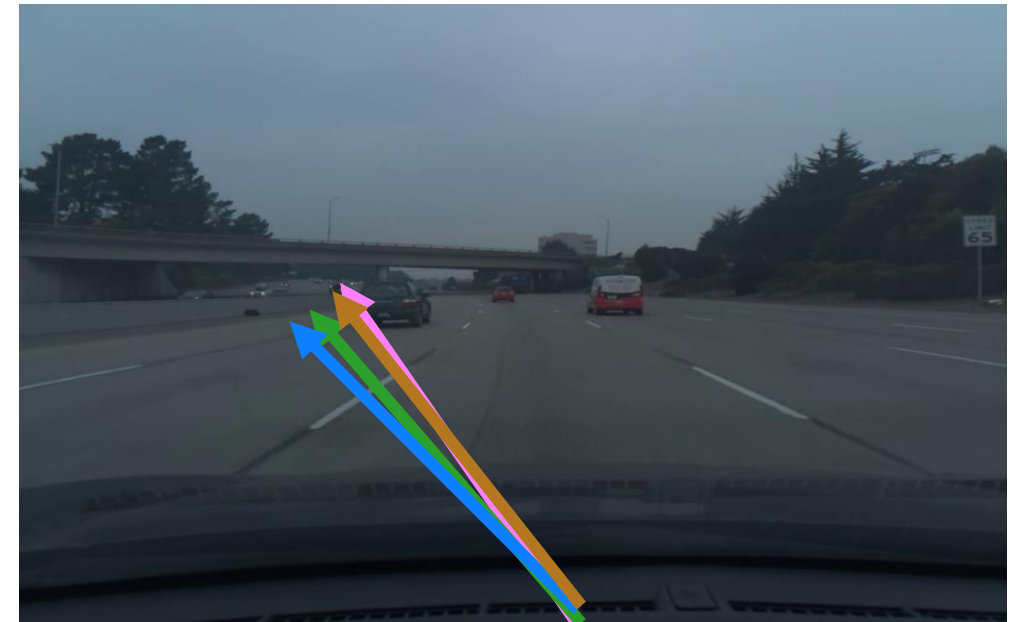
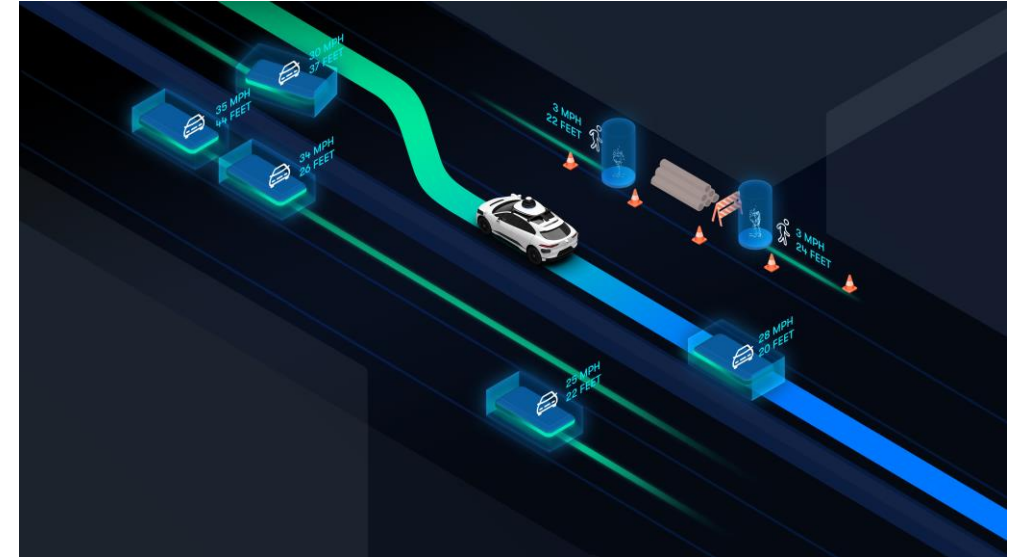
Check Requirement Preconditions: ODD

Limitations of openpilot ALC and LDW

- When in sharp curves, like on-off ramps, intersections etc.; openpilot is designed to be limited in the amount of steering torque it can produce.



- Multidimensional Behavior
- Statistical Assumptions & Oracle Strength



Questions?



<https://github.com/less-lab-uva/DiffTest4AV>

A Differential Testing Framework to Identify Critical AV Failures Leveraging Arbitrary Inputs

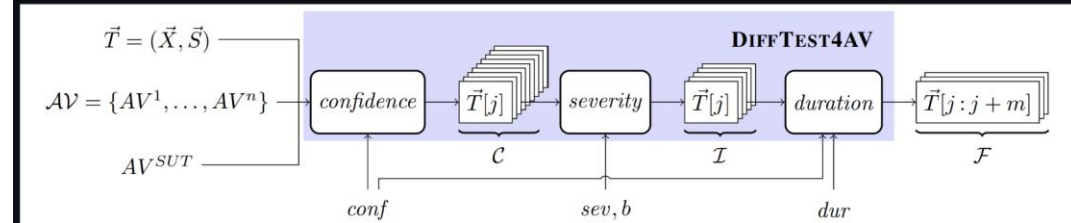
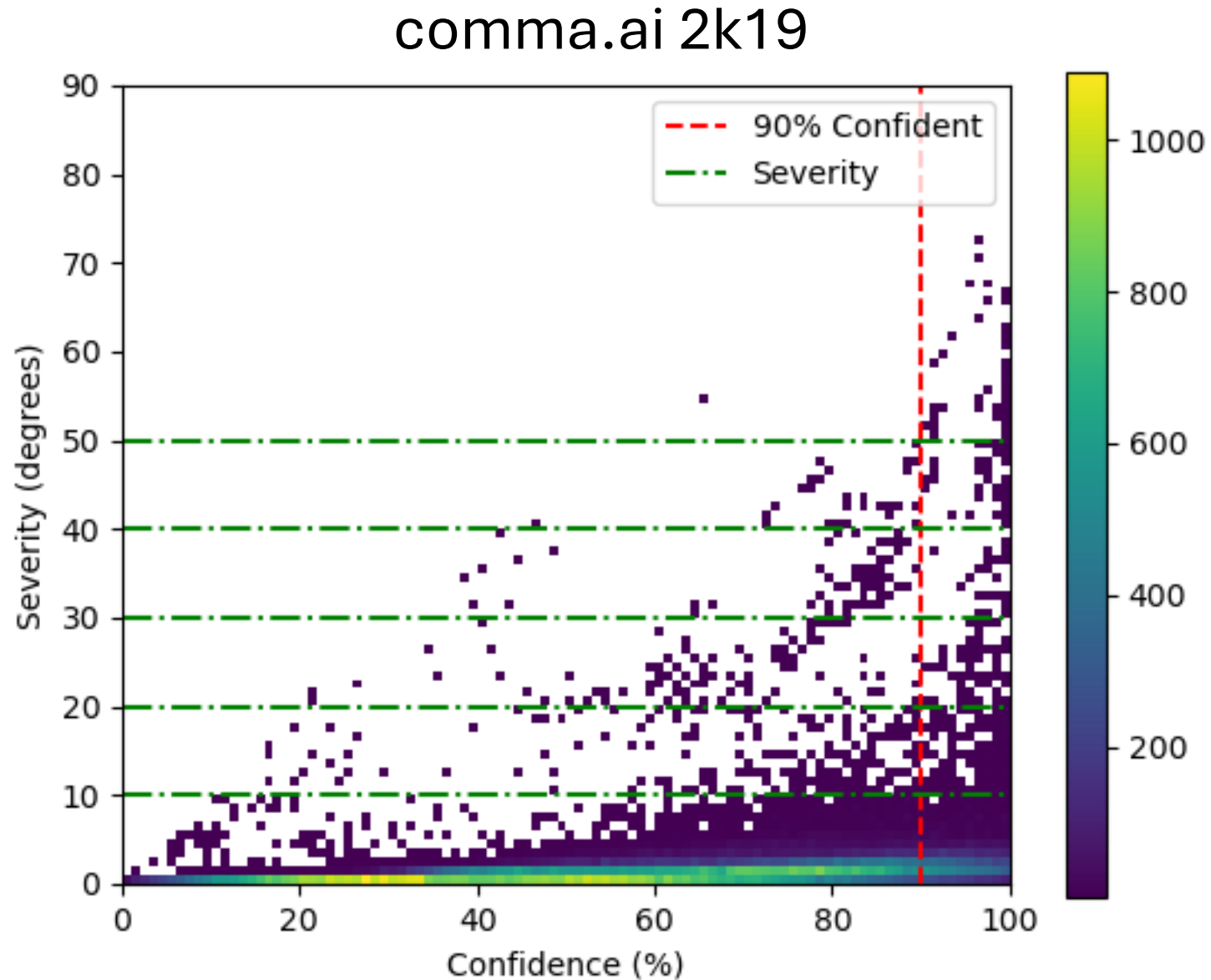


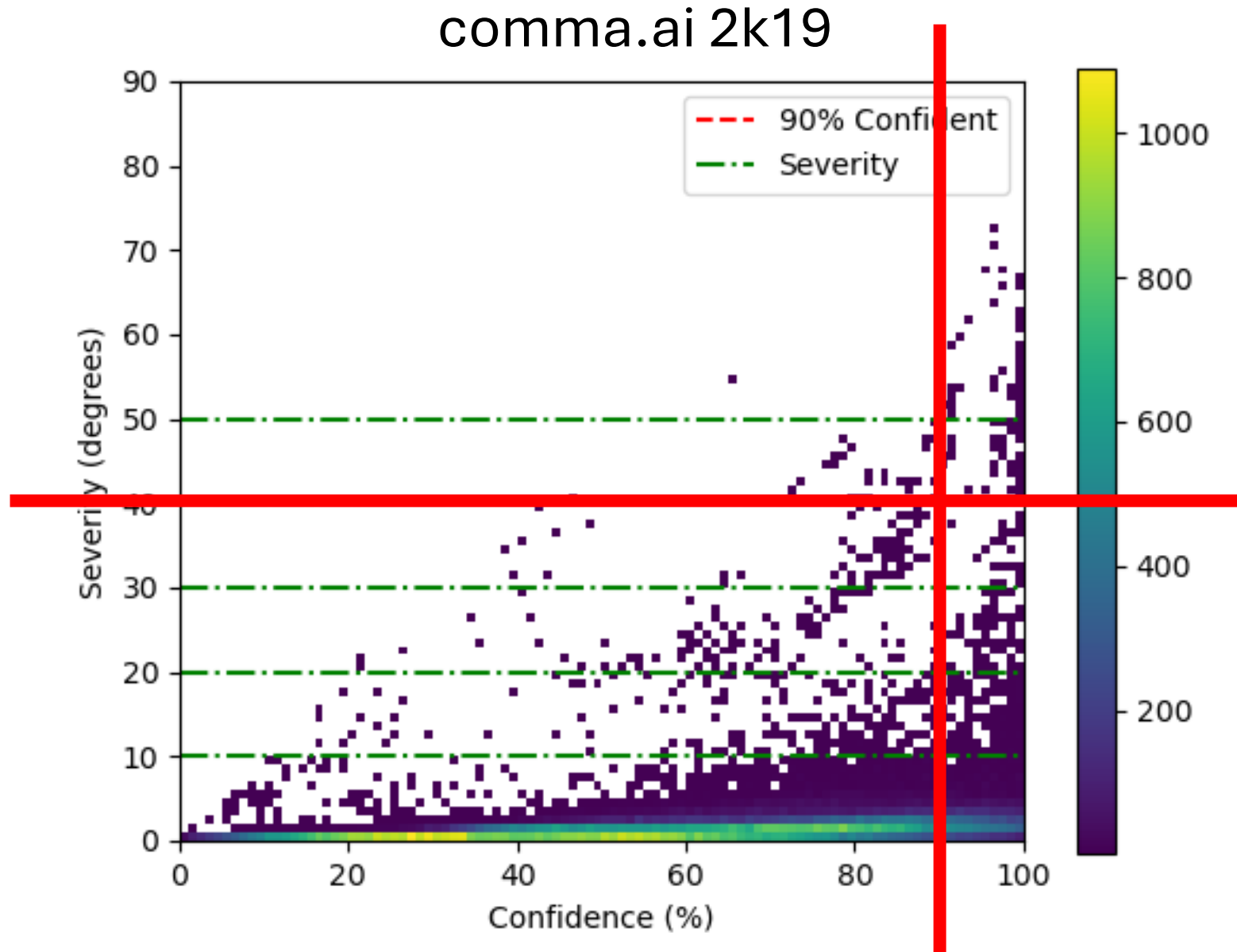
Fig. 2: DIFFTEST4AV pipeline for a single test case \vec{T} .



Experimental Results: Confidence vs Severity

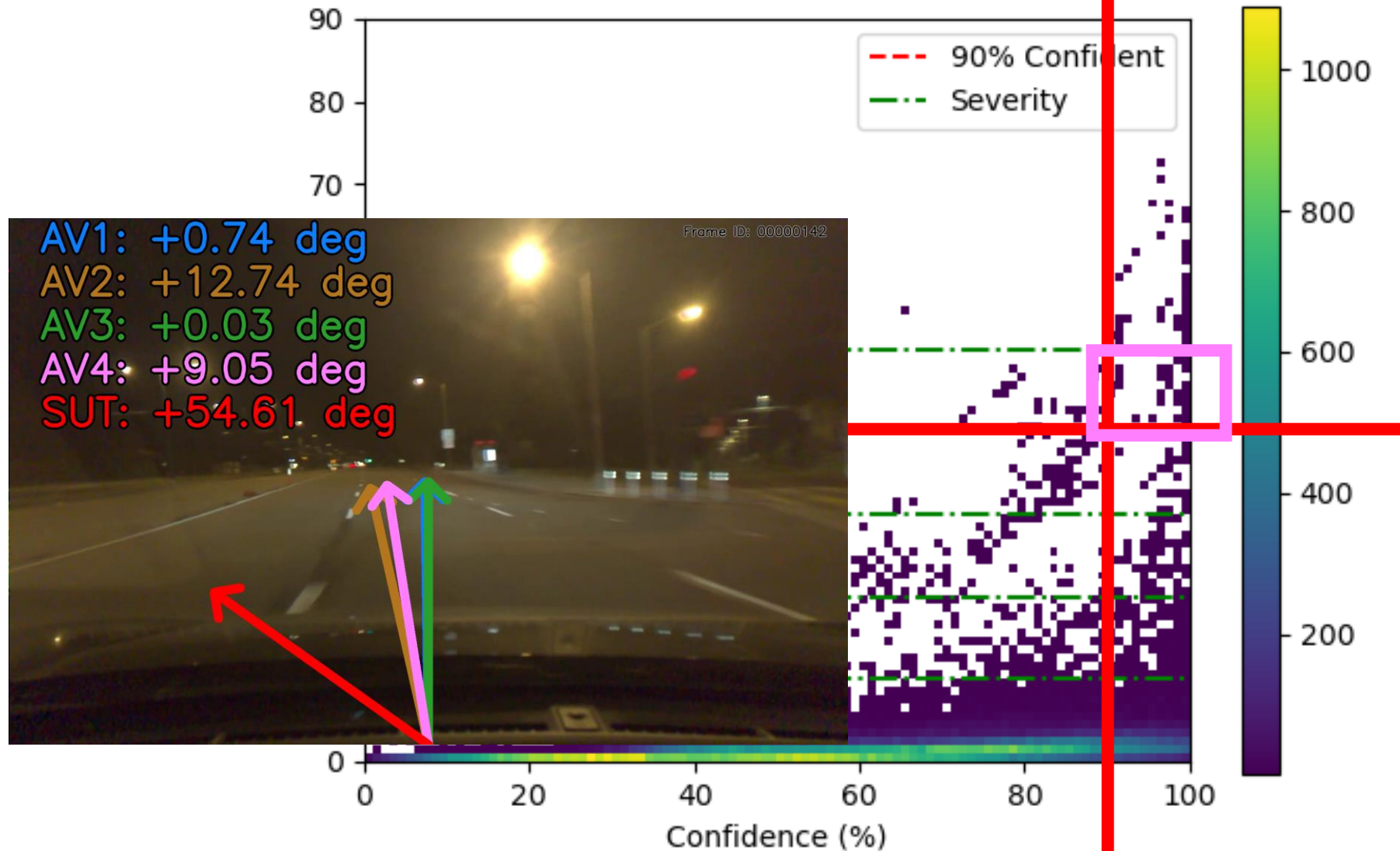


Experimental Results: Confidence vs Severity



Experimental Results: Confidence vs Severity

comma.ai 2k19



Study

- RQ1: High-confidence failures
- RQ2: High-confidence & High-severity failures
- RQ3: High-impact & long-running failures

Experimental Results: Duration

Frames

	50%	75%	90%	95%	99%
10 °	72	58	34	22	14
20 °	64	56	34	22	14
30 °	52	48	34	20	14
40 °	42	42	27	19	11
50 °	33	33	27	19	5

