Perception Challenge: Autonomous Vehicles

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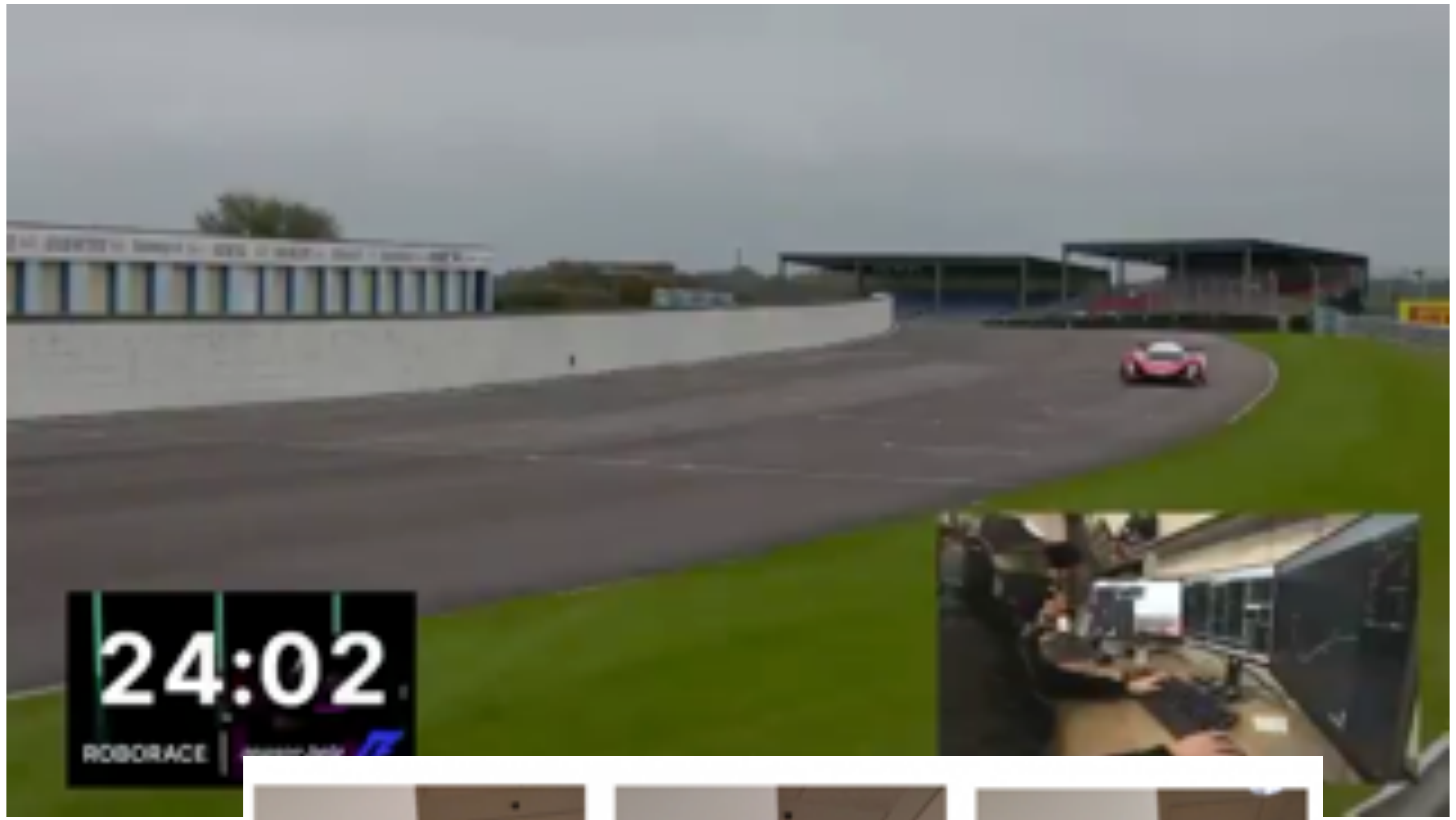
with Adam Amos-Binks and Dustin Dannenhauer

Autonomous Vehicles are Prone to Failure

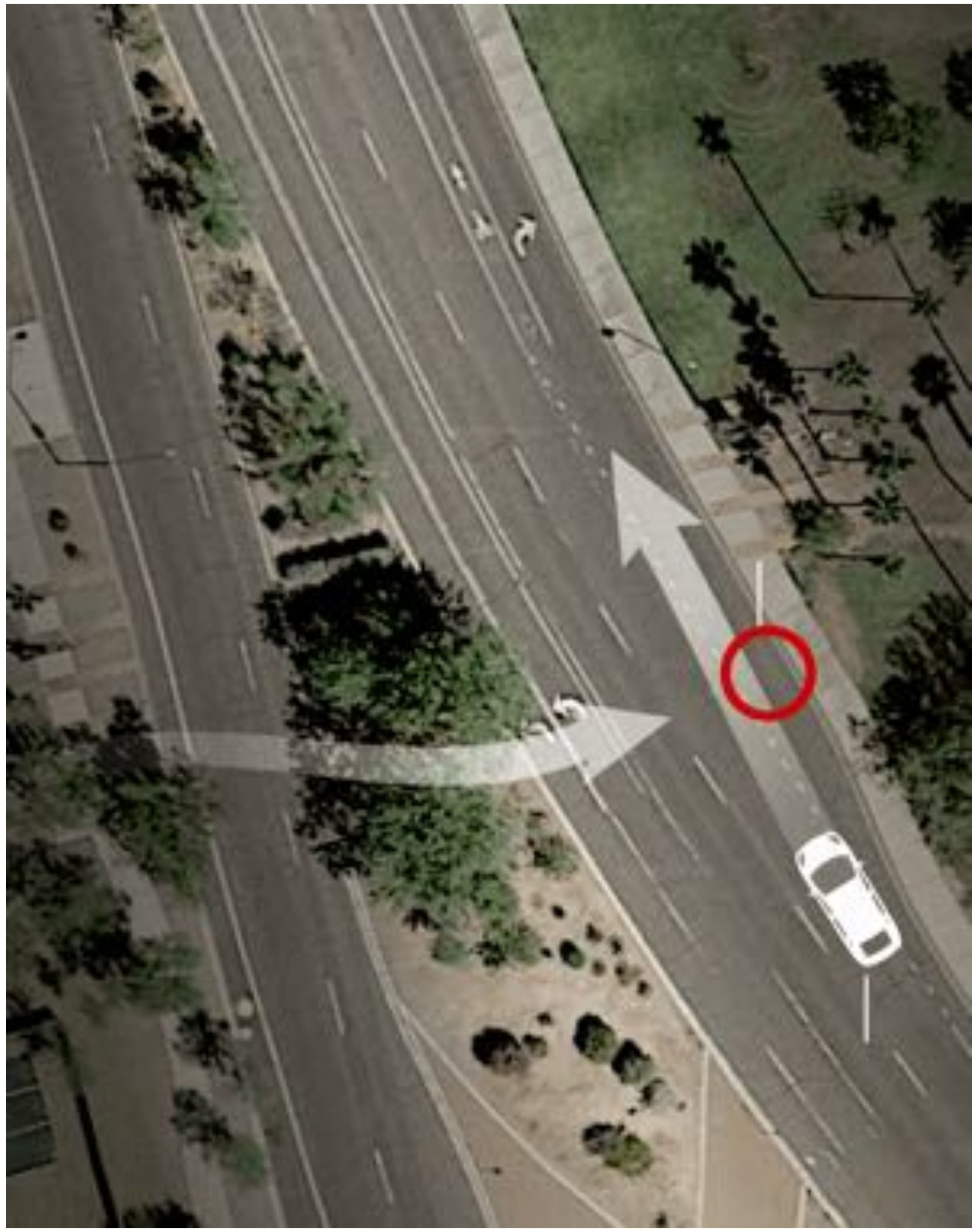


K. Eykholt et al. “Robust Physical-World Attacks on Deep Learning Visual Classification.”

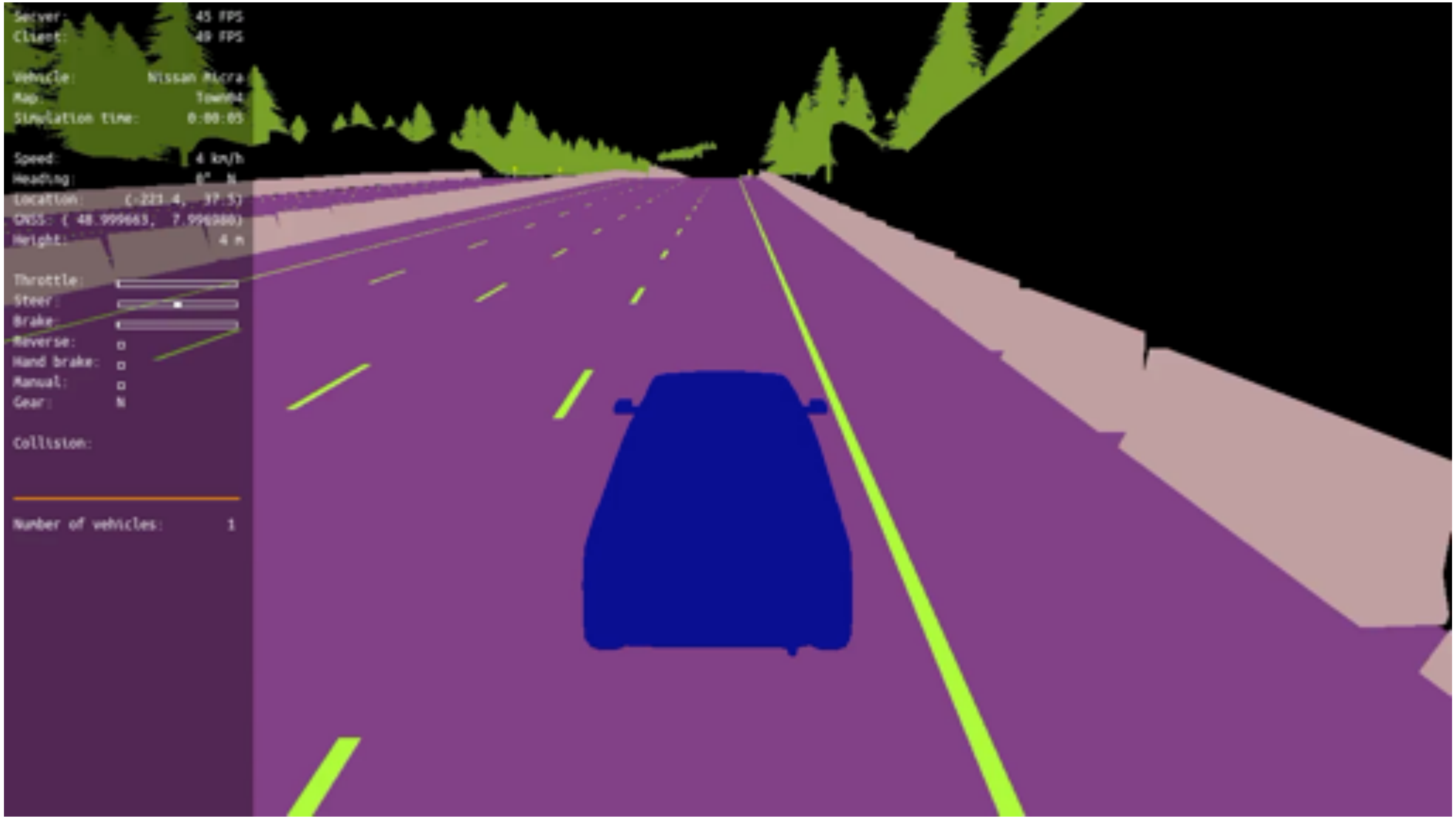
Predictive Inequity in Object Detection

Benjamin Wilson [1] Judy Hoffman [1] Jamie Morgenstern [1]

Uber Example in my PhD Work



Uber Example in my PhD Work



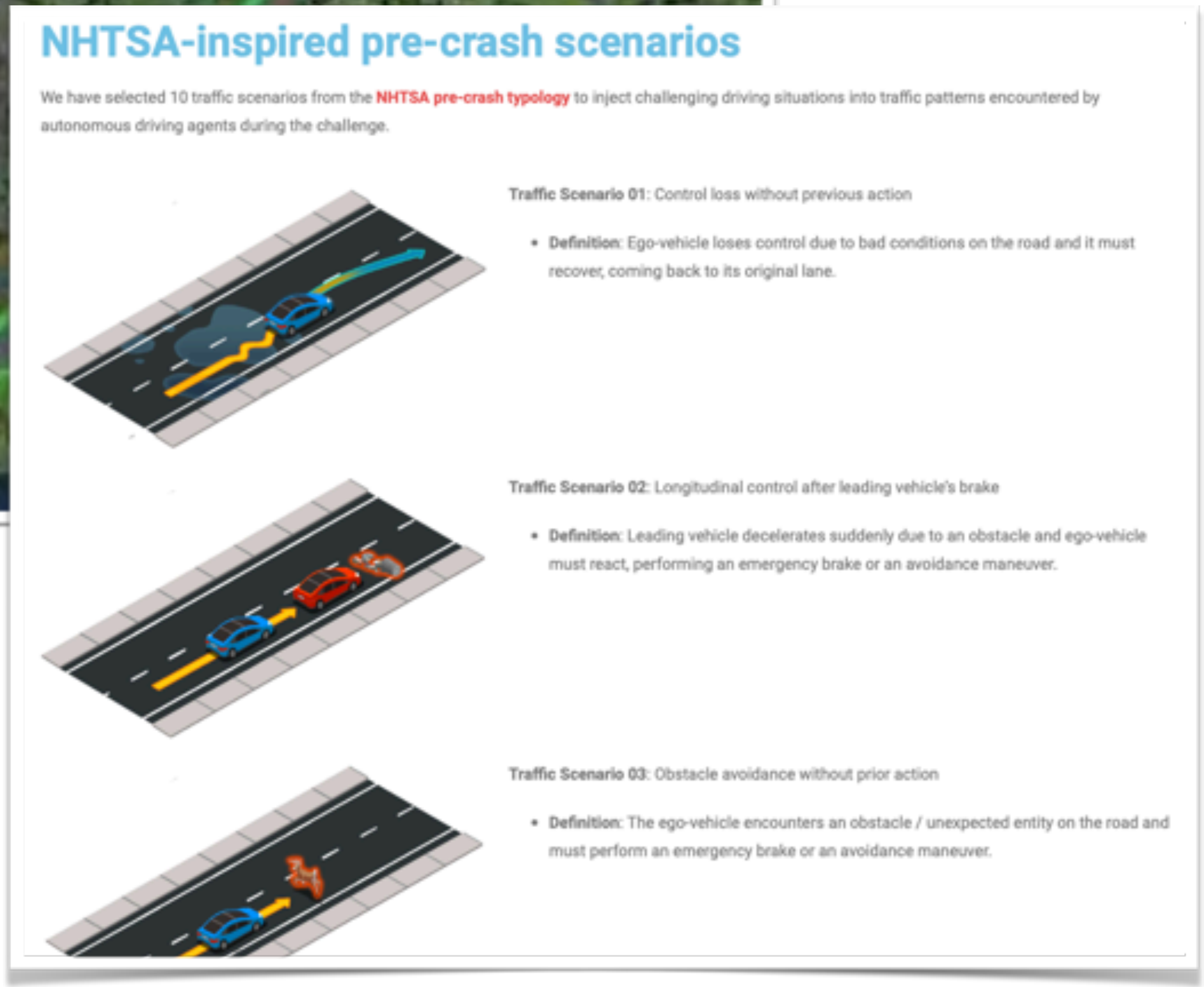
L. H. Gilpin, V. Penubarthi and L. Kagal, "Explaining Multimodal Errors in Autonomous Vehicles," *2021 IEEE 8th International Conference on Data Science and Advanced Analytics (DSAA)*, 2021, pp. 1-10, doi: 10.1109/DSAA53316.2021.9564178.

Lack of Data and Challenges for AVs

- Existing Challenges
    - Targeted as optimizing a mission or trajectory and not safety.
    - Data is hand-curated
- Failure data is not available
    - Unethical to get it (cannot just drive into bad situations).
    - Want the data to be realistic (usually difficult in simulation).
- Develop a set of challenges and stress tests that **generate** new errors.

Existing Challenges and Benchmarks

Not Focused on Out of Domain Errors



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

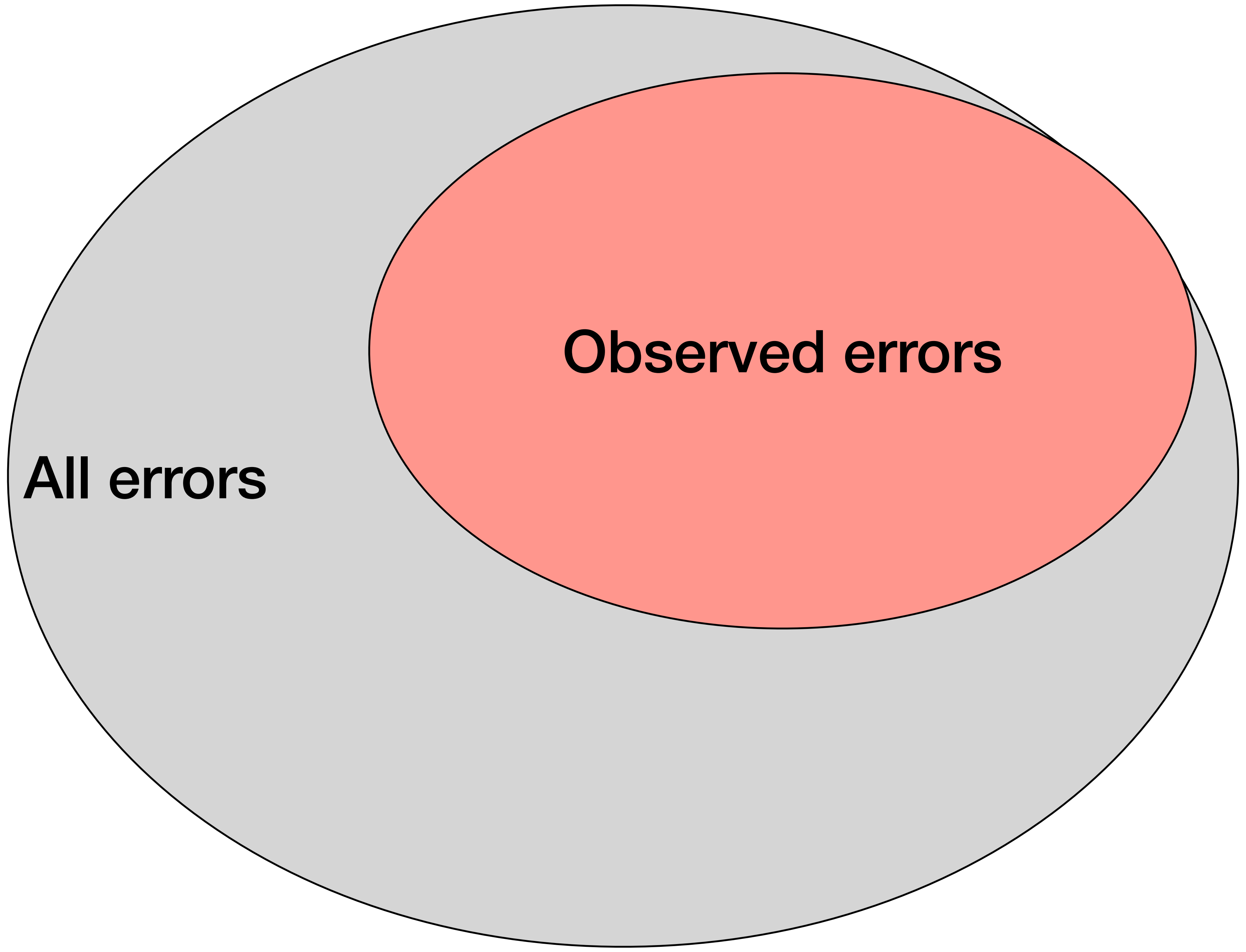
- **Definition**: Ego-vehicle loses control due to bad conditions on the road and it must recover, coming back to its original lane.

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

- **Definition**: Leading vehicle decelerates suddenly due to an obstacle and ego-vehicle 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.

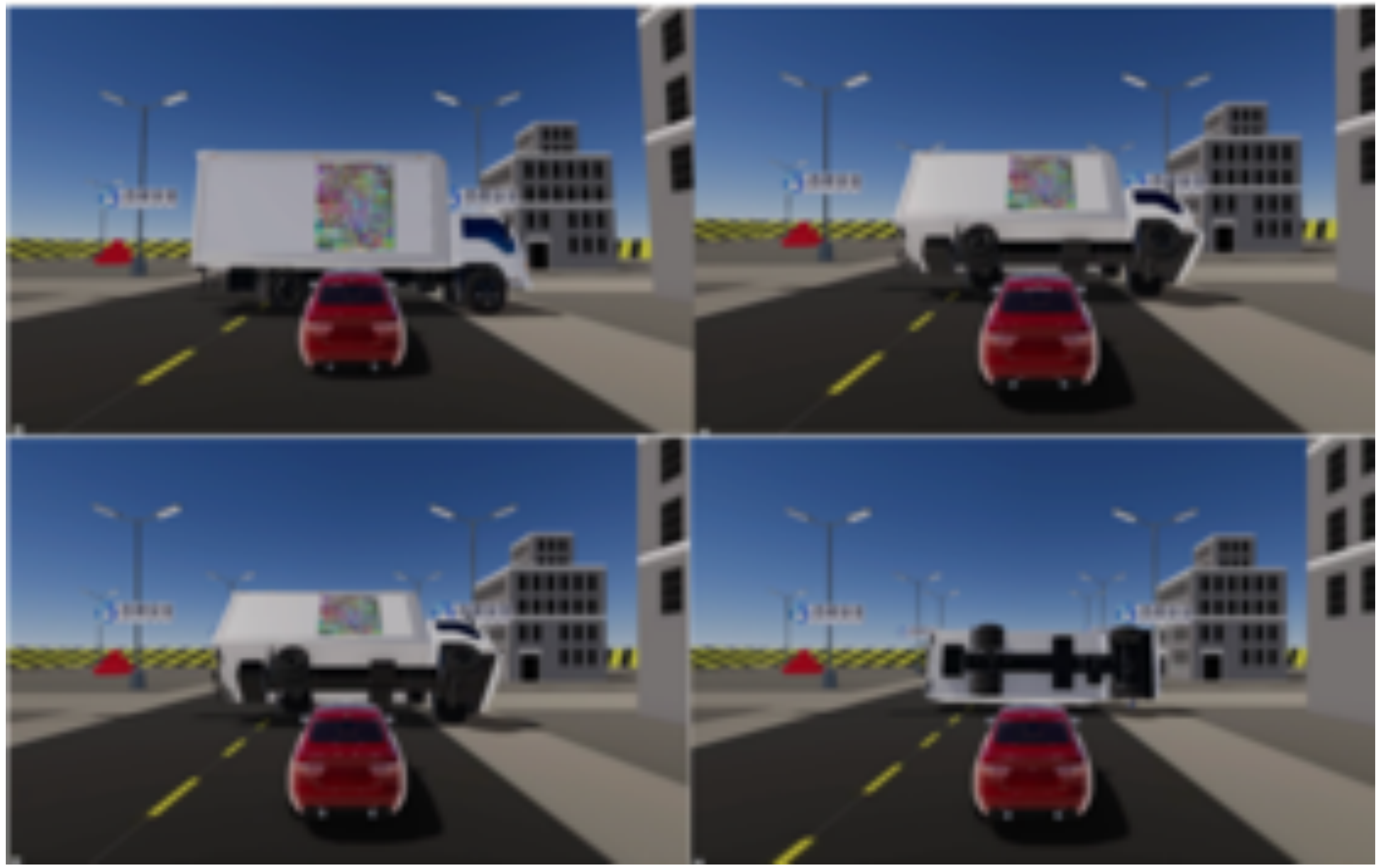


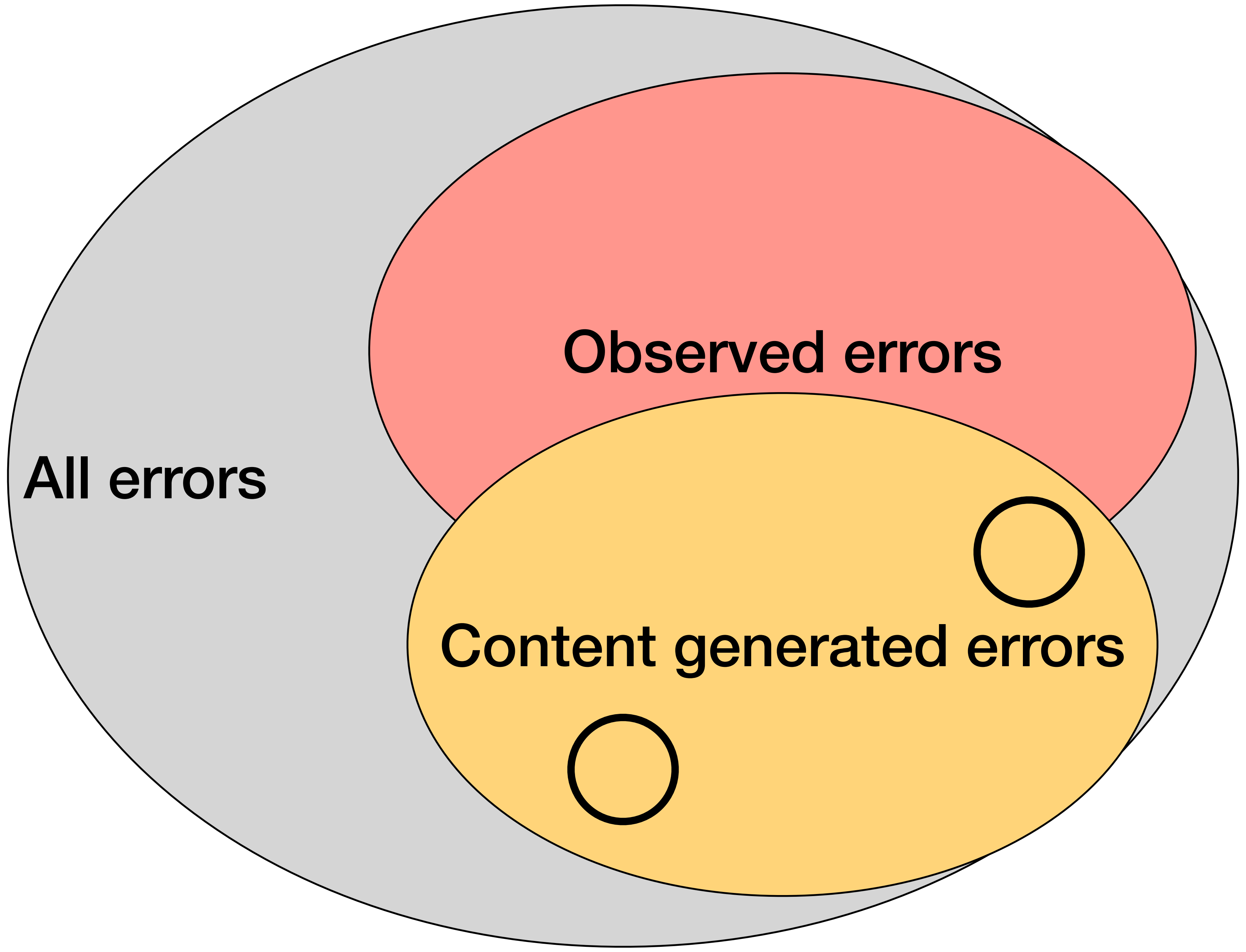
Other Challenges Not Anticipatory

Not Focused on Error Detection

AutoDriving CTF

WELCOME TO AUTONOMOUS DRIVING CTF CONTEST





Autonomous Vehicle Limitations

- Complexity
  - Complex system build out of sensors, opaque software, and machinery.
  - It’s difficult to trace back what happened.
- Opaqueness
  - Proprietary mechanisms
  - Computer vision systems that are too opaque and dense to understand.

Current Approaches for Robust AVs

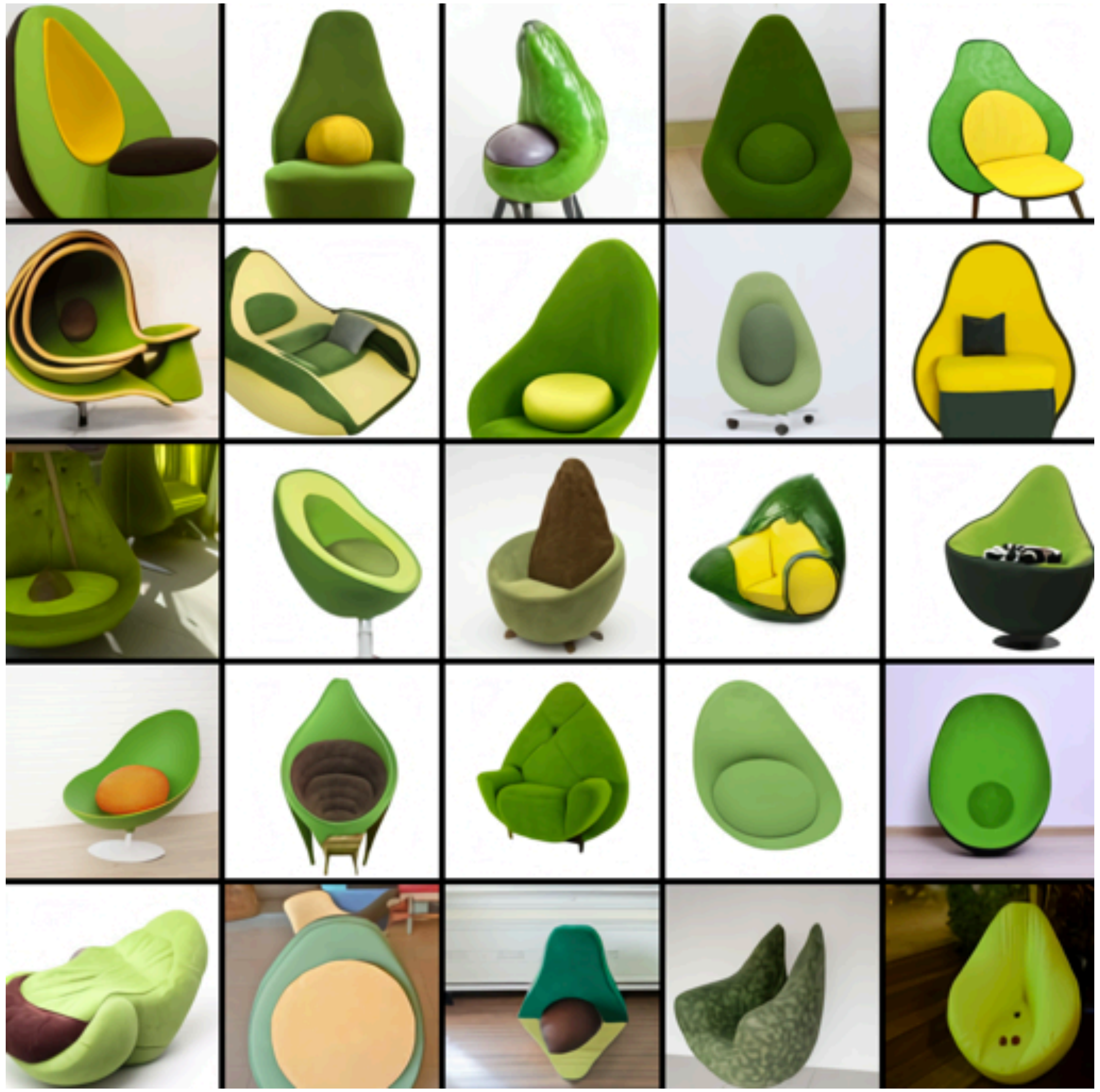
1. Error and failure analysis is **post mortem and reactive** instead of anticipatory

2. Explanations are a **post mortem** tool.

3. **Lack of Redundancy**: Unlike aircrafts (that purposely has components that are repeated), autonomous vehicles that rely entirely on a single system for perception (e.g., Tesla camera system) and it is prone to failure and error.

Approach: Content Generation

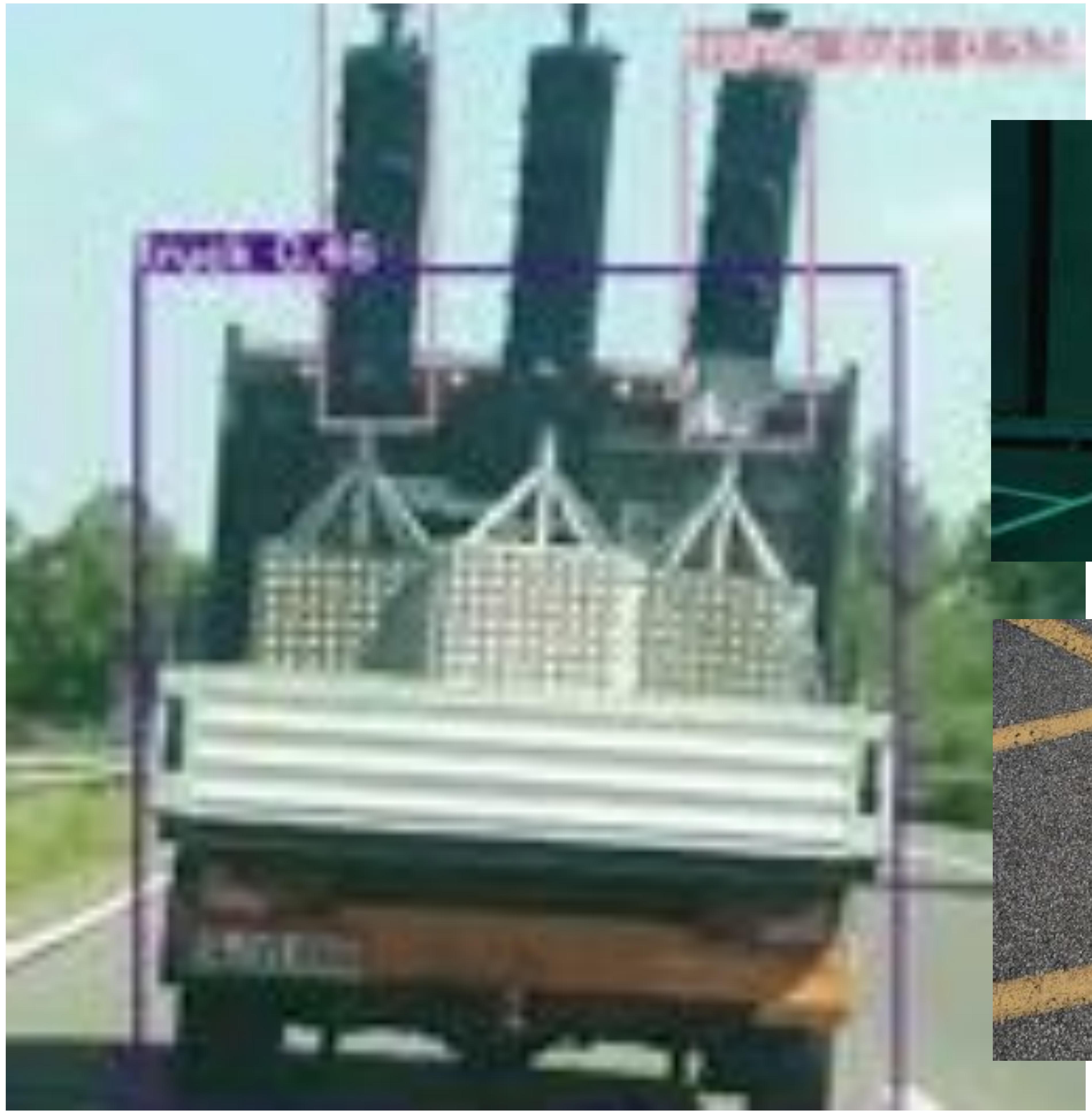
Anticipatory Thinking Layer for Error Detection



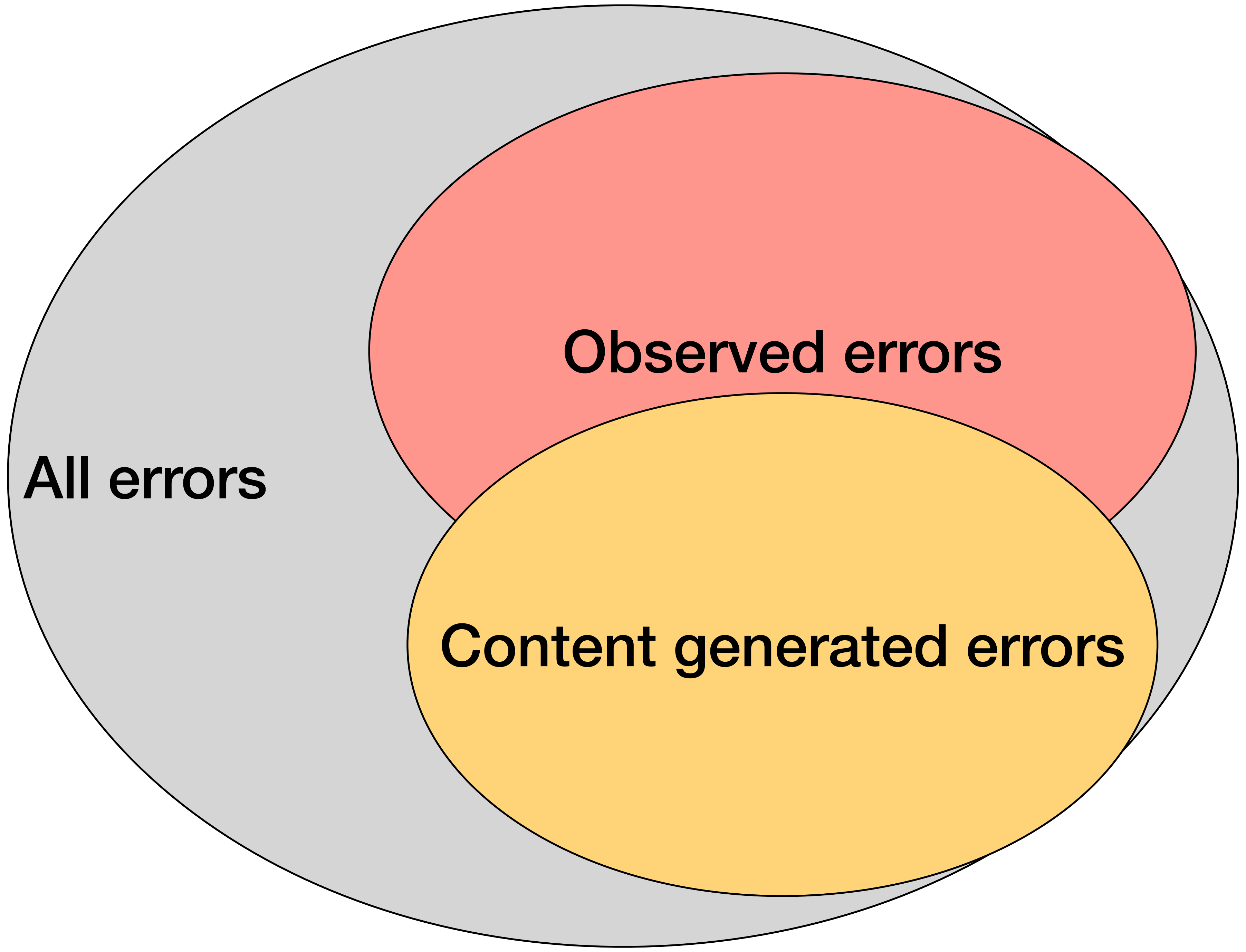
DALL-E Generates “A chair in the shape of an avocado”

Synthetic images produced by StyleGAN, a GAN created by Nvidia researchers.

Need for Context



“Realistic” Adversarial examples

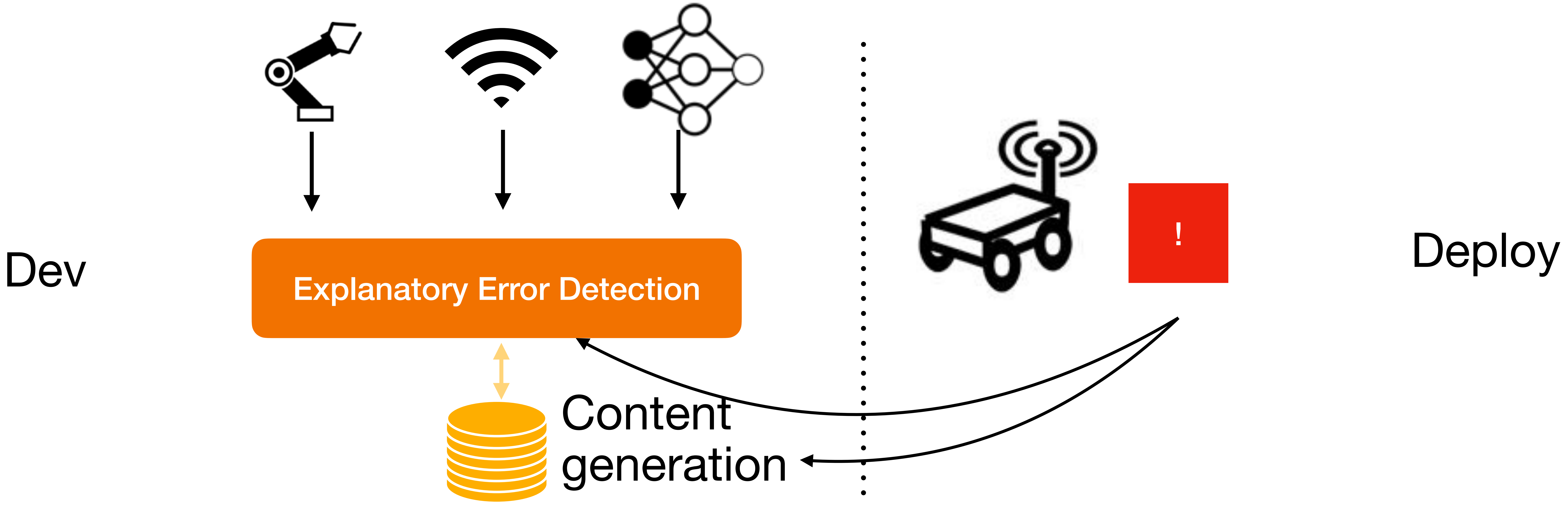


Approach: How it Works

Use Adversarial Images in Dev Testing

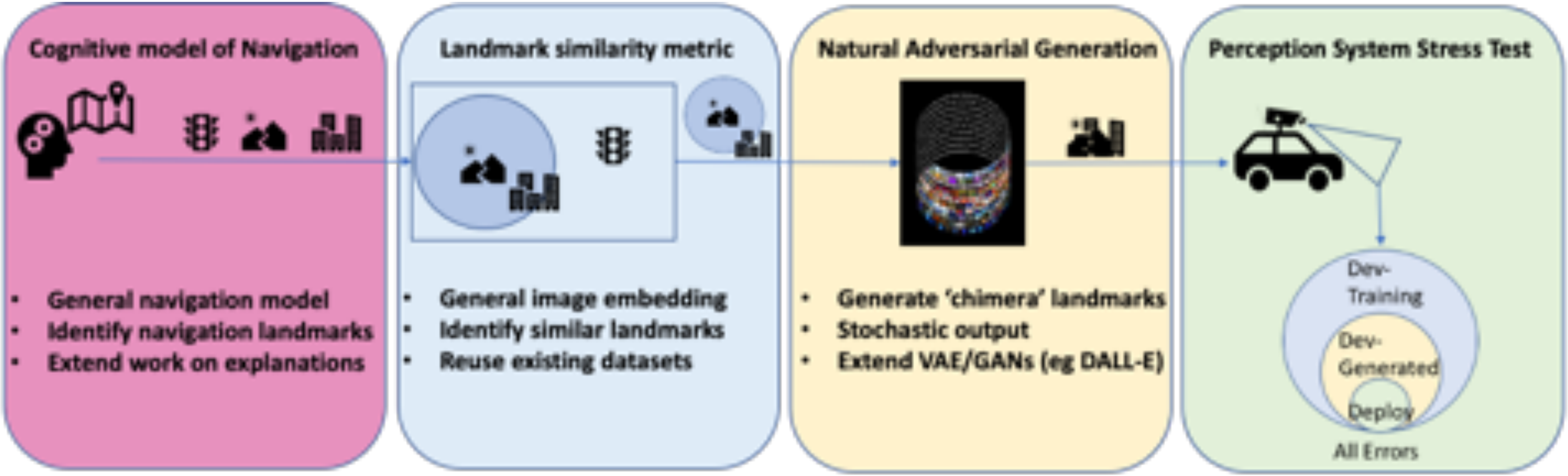
- Solution: Use a cognitive architecture that helps to anticipate and understand these failure cases.

- Assess autonomous vehicles for their risk management capabilities **before** being deployed and provide incident level risk management explanations in human readable form.



Dev
Deploy
Isolated error detection
Error detection
Error detection
Error detection
!
All errors
Observed errors
Integrated error detection
Explanatory Error Detection
Content generation
!
All errors
Observed errors
Content generated errors

Larger Approach



Impact

Anticipatory Thinking Layer for Error Detection

- Goal - Develop methods that a priori can explain an autonomous vehicle's ability to manage the risks stemming from errors in perceiving their environment.

- One possible solution is to explain why the autonomous behavior is safe (or risky, trustworthy, etc.) or not.

- Impact - Consumer confidence and safety features, appropriate legal and regulatory oversight.