

# That Person Moves Like A Car: Misclassification Attack Detection for Autonomous Systems Using Spatiotemporal Consistency

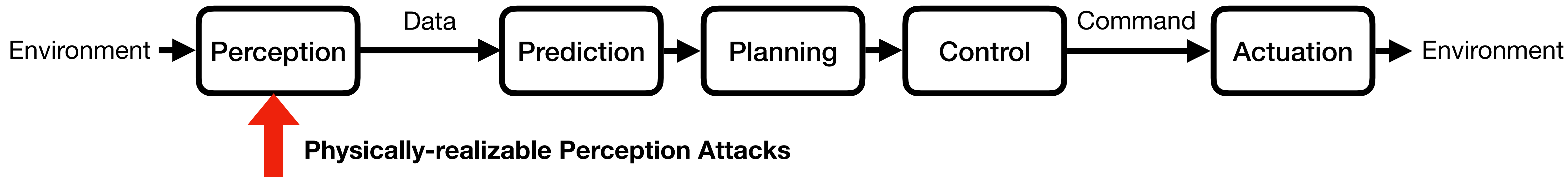
Yanmao Man<sup>#</sup>, Raymond Muller<sup>§</sup>, Ming Li<sup>#</sup>, Z. Berkey Celik<sup>§</sup>, Ryan Gerdes<sup>‡</sup>  
<sup>#</sup>University of Arizona   <sup>§</sup>Purdue University   <sup>‡</sup>Virginia Tech



# Autonomous Systems



# Perception Security



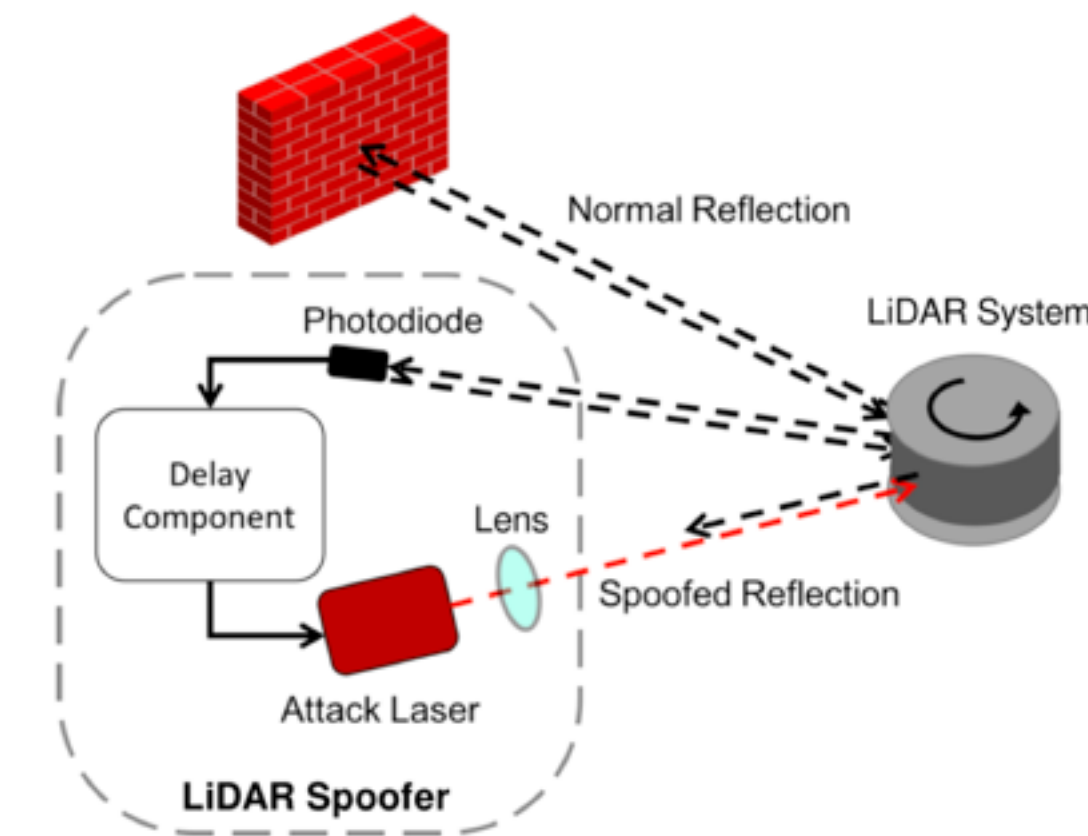
Stop Sign Sticker



Phantom Attack



GhostImage Camera Attack



LiDAR Spoofing

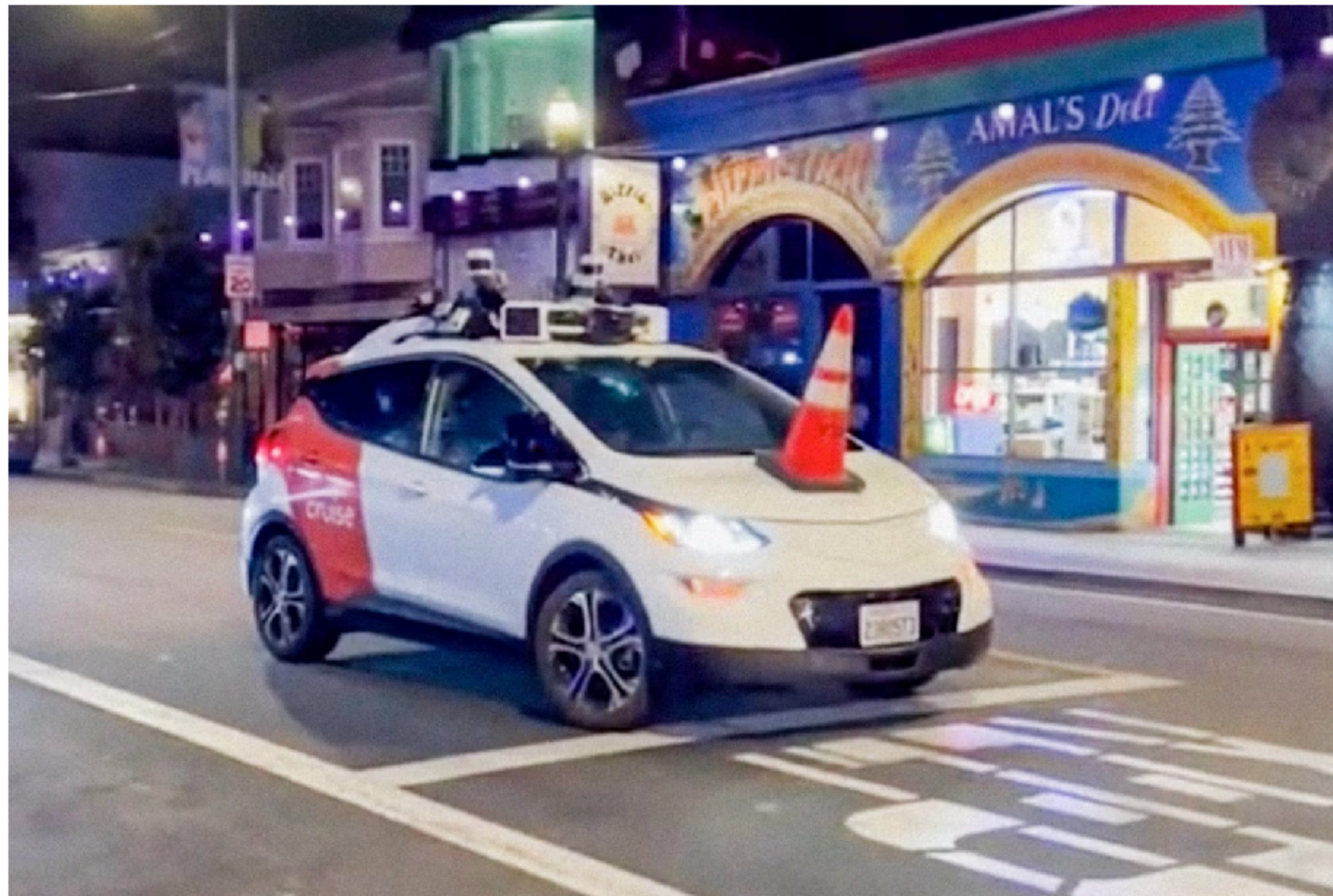
1. Eykholt, Kevin, et al. "Robust physical-world attacks on deep learning visual classification." *CVPR 2018*.
2. Nassi, Ben, et al. "Phantom of the adas: Securing advanced driver-assistance systems from split-second phantom attacks." *CCS 2020*
3. Man, Yanmao et al. "GhostImage: Remote perception attacks against camera-based image classification systems." *RAID 2020*
4. Cao, Yulong, et al. "Adversarial sensor attack on lidar-based perception in autonomous driving." *CCS 2019*.

# The Self-Driving Cars Wearing a Cone of Shame

There's a brilliant activist campaign to stop San Francisco's autonomous vehicles in their tracks.

BY ALISON GRISWOLD

JULY 11, 2023 • 10:45 AM

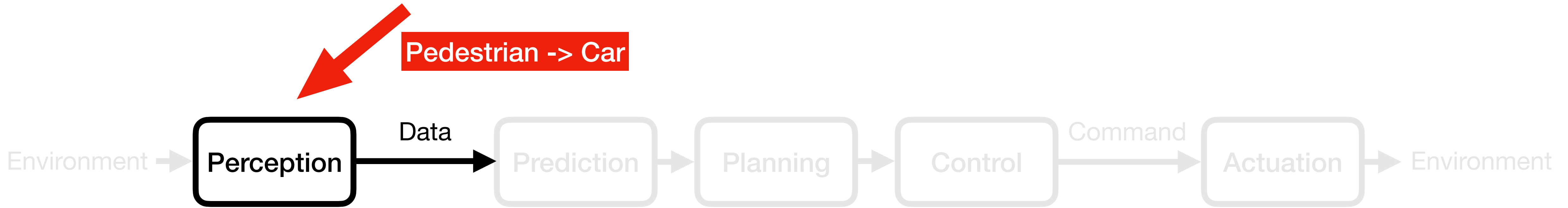


It looks like a sad unicorn (which, in a way, it is). Screenshot from TikTok/Safe Street Rebel

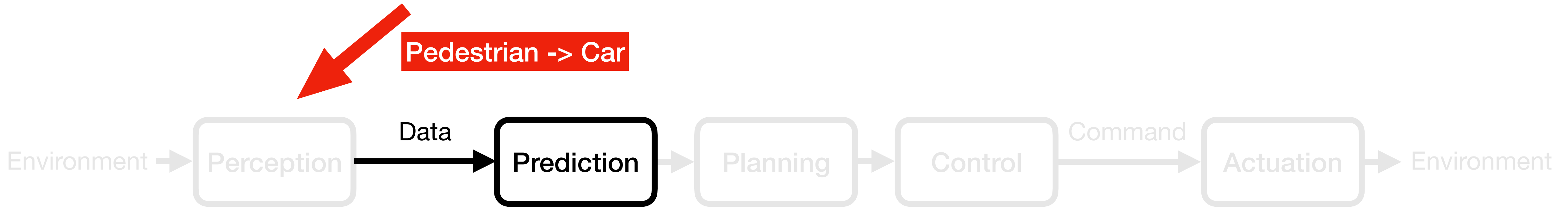
# Perception Security



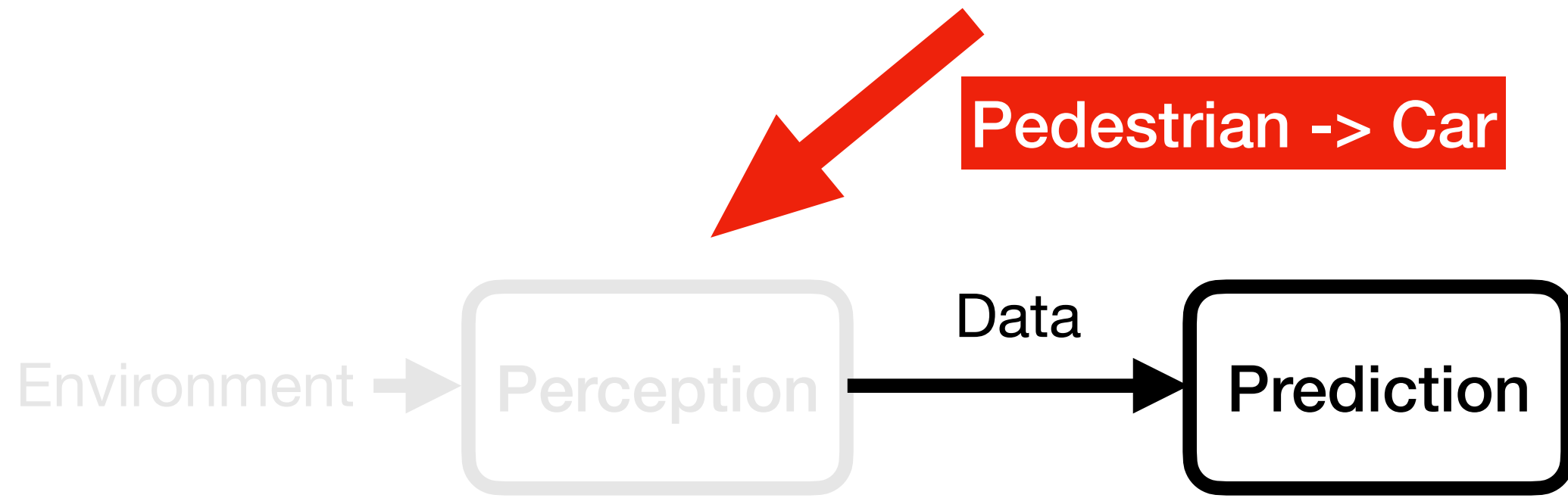
# Misclassification Attacks



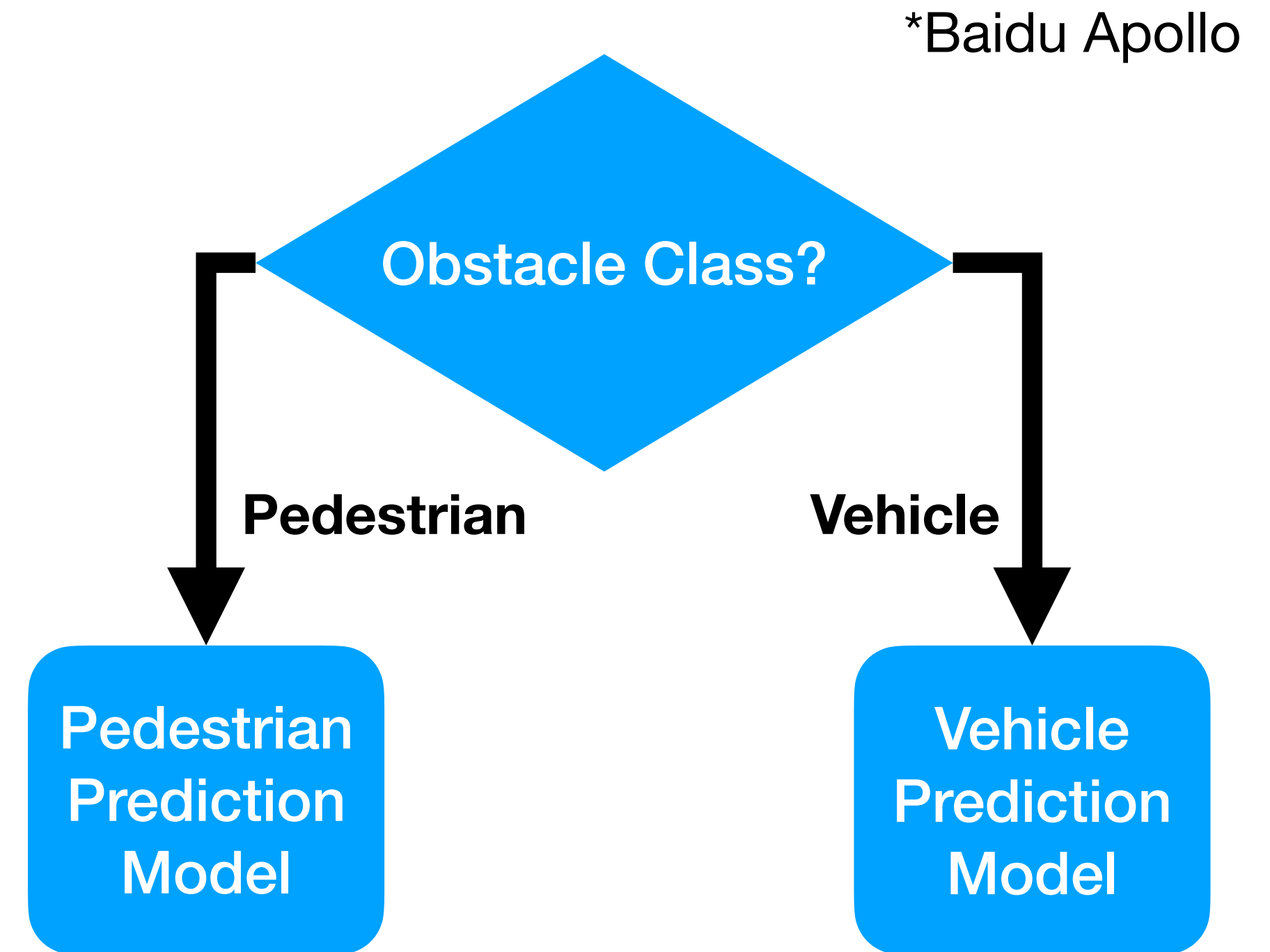
# Misclassification Attacks



# Misclassification Attacks

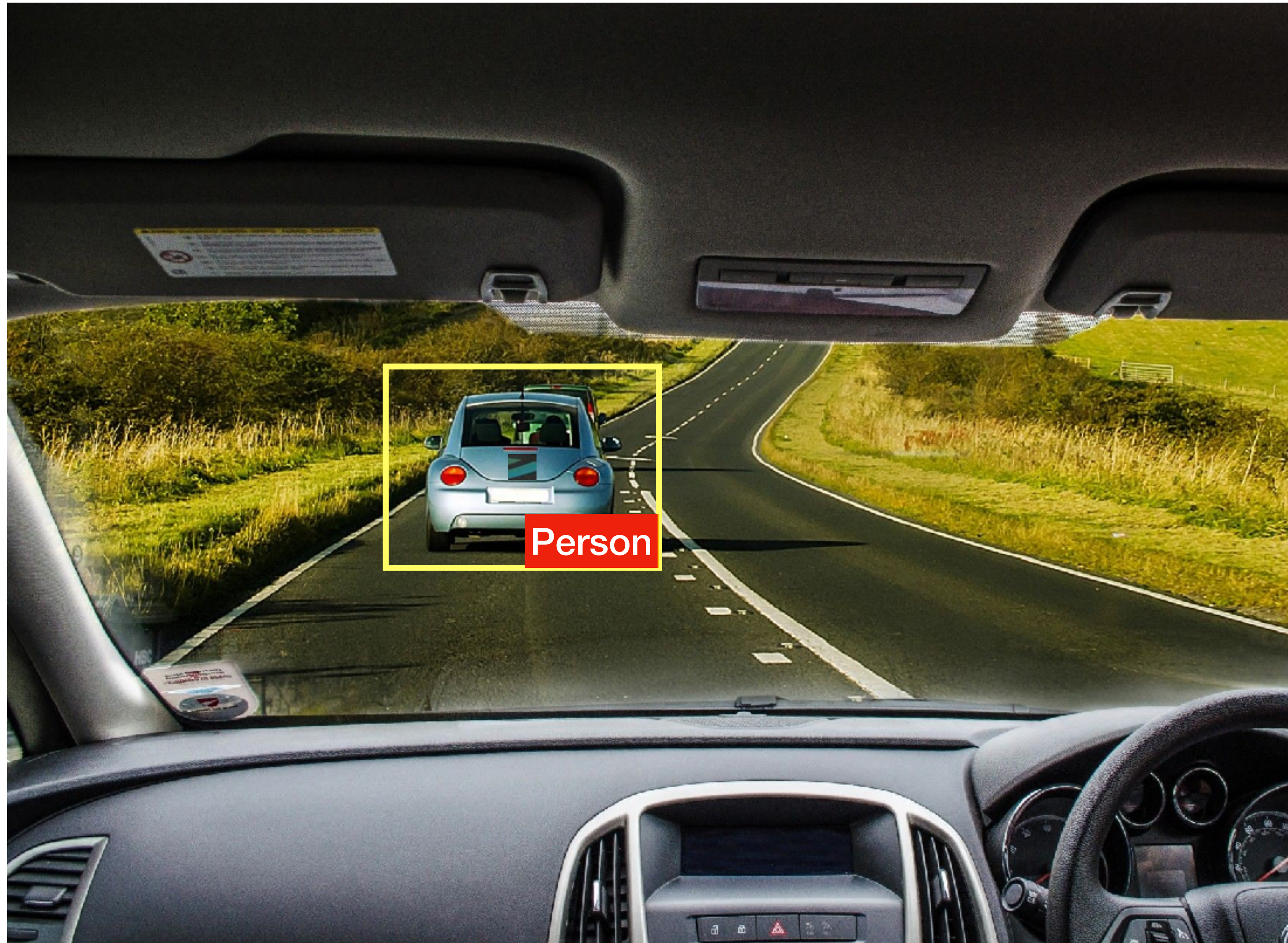


**Pedestrian -> Car**

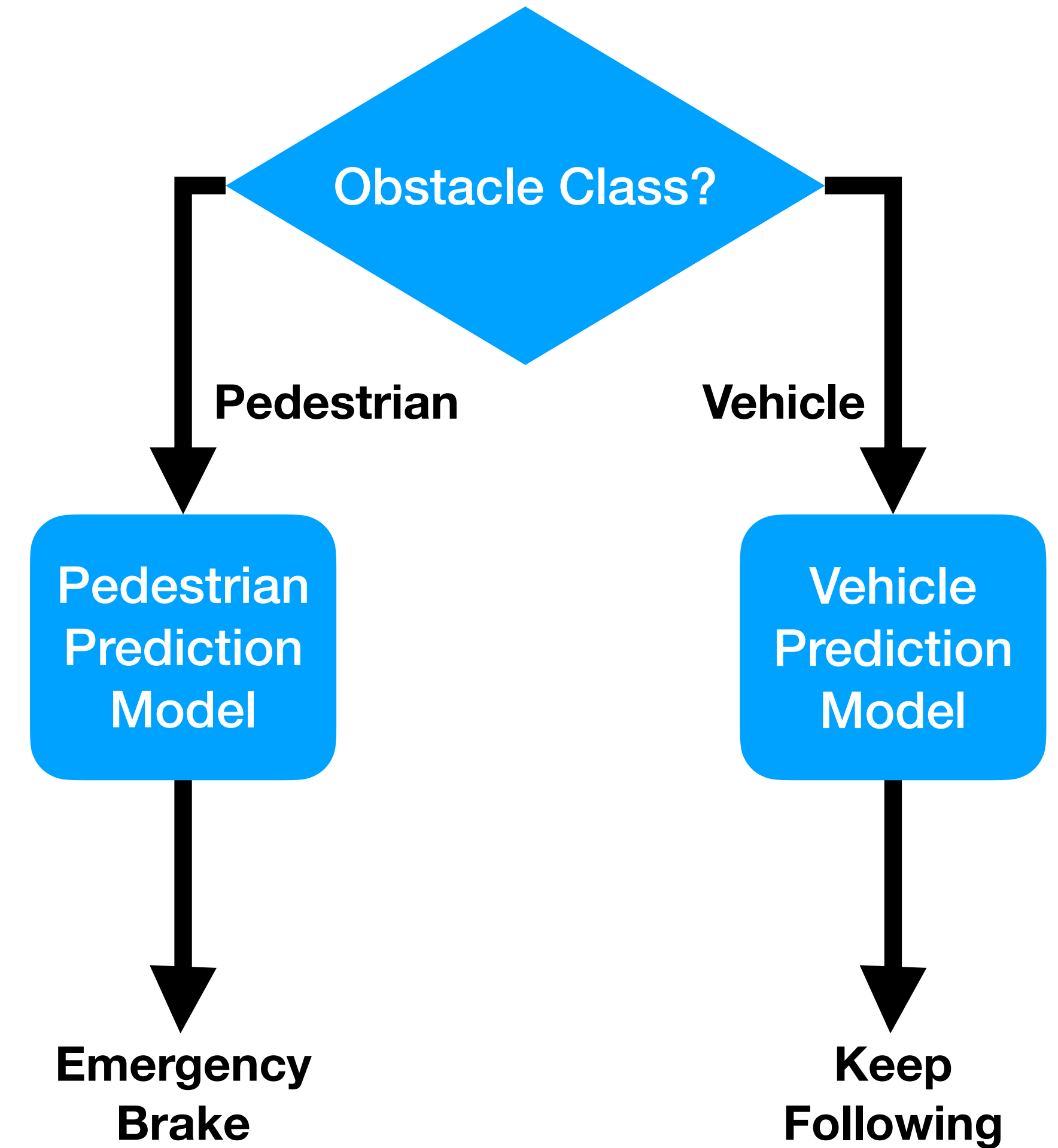




# Misclassification Attacks



<https://toocooltrafficschool.com/following-distance/>



[5] Man, Yanmao, et al. "Evaluating perception attacks on prediction and planning of autonomous vehicles." *USENIX Security Symposium Poster Session*. 2022.

# Misclassification Attacks

**Exorcising “Wraith”: Protecting LiDAR-based Object Detector in Automated Driving System from Appearing Attacks**

[USENIX Security 2023](#)

**Towards Robust LiDAR-based Perception in Autonomous Driving: General Black-box Adversarial Sensor Attack and Countermeasures**

[USENIX Security 2020](#)

**Drift with Devil: Security of Multi-Sensor Fusion based Localization in High-Level Autonomous Driving under GPS Spoofing**

[USENIX Security 2020](#)

**Anomaly Detection Against GPS Spoofing Attacks on Connected and Autonomous Vehicles Using Learning From Demonstration**

Chen  
ne  
ci.edu

[IEEE T-ITS 2023](#)

**SAVIOR: Securing Autonomous Vehicles with Robust Physical Invariants**

[USENIX Security 2020](#)

**ObjectSeeker: Certifiably Robust Object Detection against Patch Hiding Attacks via Patch-agnostic Masking**

[IEEE S&P 2023](#)

**AdvIT: Adversarial Frames Identifier Based on Temporal Consistency In Videos**

[IEEE ICCV 2019](#)

Chaowei Xiao<sup>1\*</sup> Ruizhi Deng<sup>2</sup> Bo Li<sup>3</sup> Taesung Lee<sup>4</sup>

Benjamin Edwards<sup>4</sup> Jinfeng Yi<sup>5</sup> Dawn Song<sup>6</sup> Mingyan Liu<sup>1</sup> Ian Molloy<sup>4</sup>

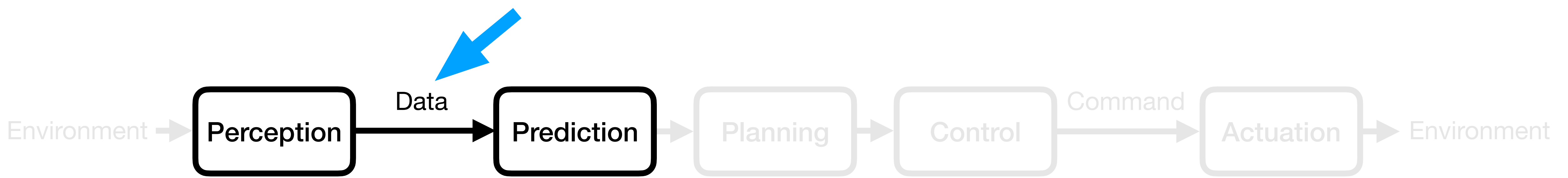
<sup>1</sup> University of Michigan, Ann Arbor <sup>2</sup> Simon Fraser University <sup>3</sup> UIUC

<sup>4</sup> IBM Research AI <sup>5</sup> JD.com <sup>6</sup> UC Berkeley

PercepGuard aims to detect misclassification attacks

Existing defenses against perception attacks are either

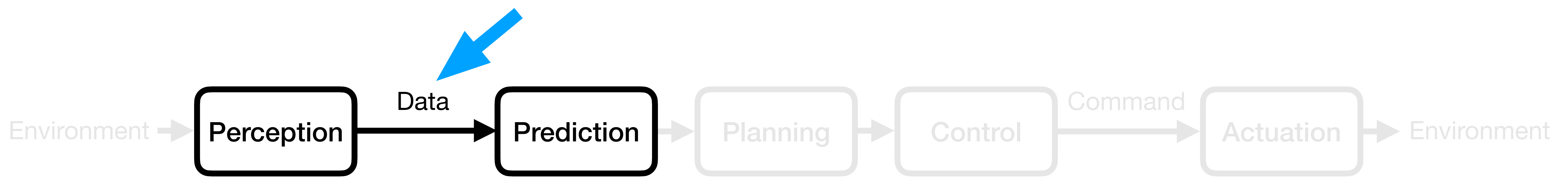
- Specific to some sensing modality
  - LiDARs
  - GPS
  - IMU
- Specific to some attack methodology
  - Adversarial Patch
  - Norm-bounded



Agnostic to

- Attack methodologies
- Object detection and tracking algorithms

PercepGuard aims to detect misclassification attacks



PercepGuard aims to detect misclassification attacks by verifying the spatiotemporal consistency of the perception result

# Spatio-temporal Consistency

t=1



# Spatio-temporal Consistency

t=2



# Spatio-temporal Consistency

t=3



# Spatio-temporal Consistency

t=3





# Spatio-temporal Consistency



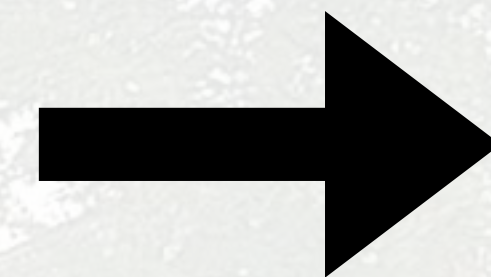
# Spatio-temporal Consistency

ODT  
⋮  
ODT

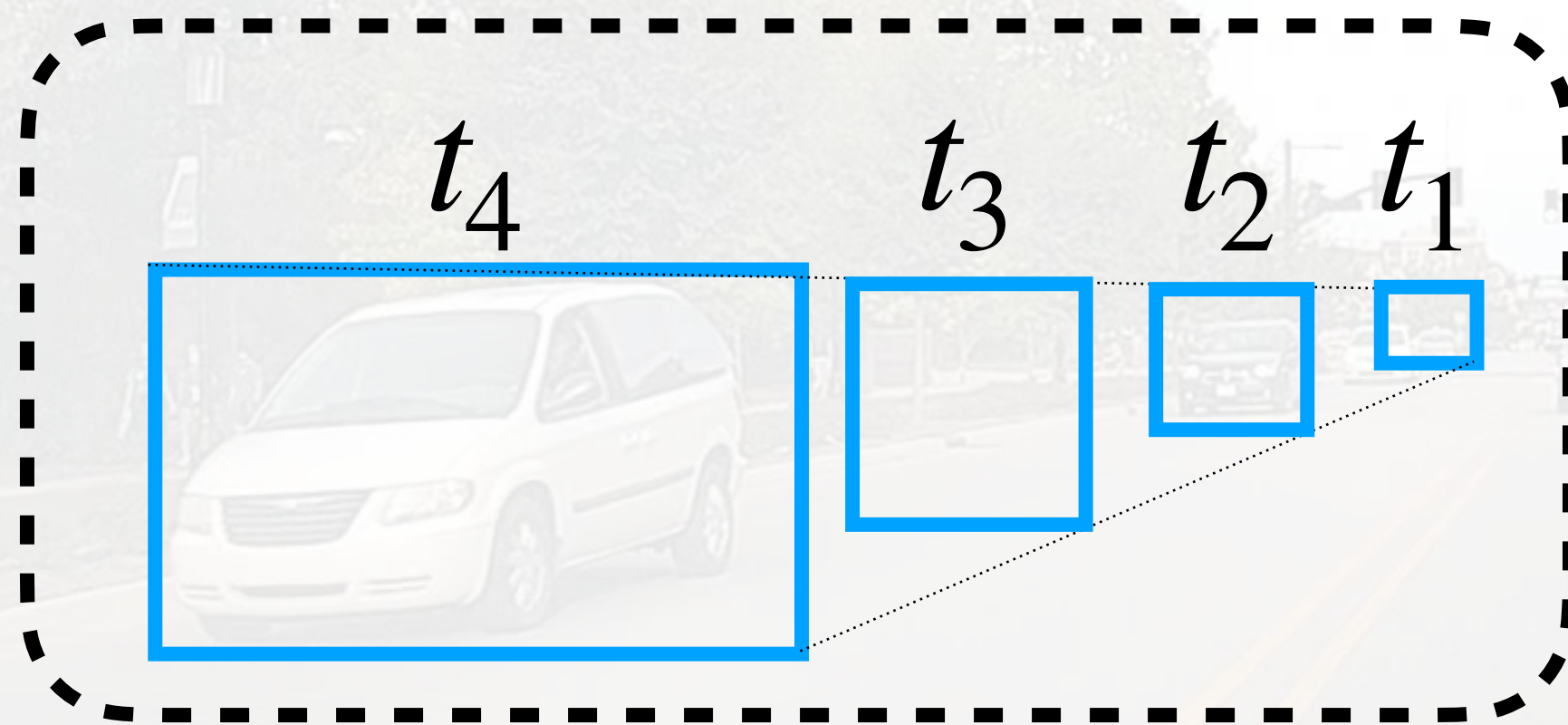
- Spatio-Temporal Features
- Object Class



**Our  
Defense**



Attacked?



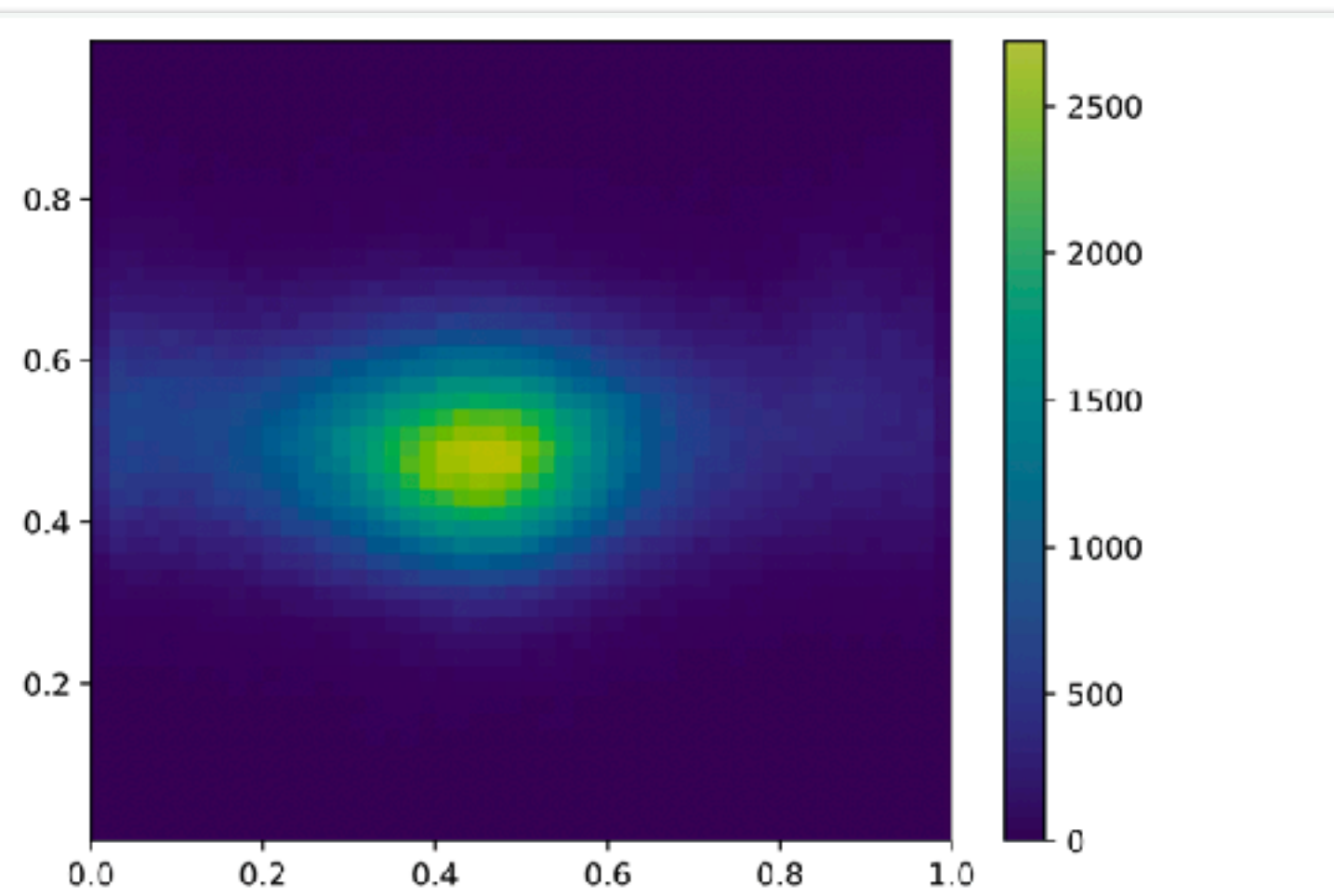
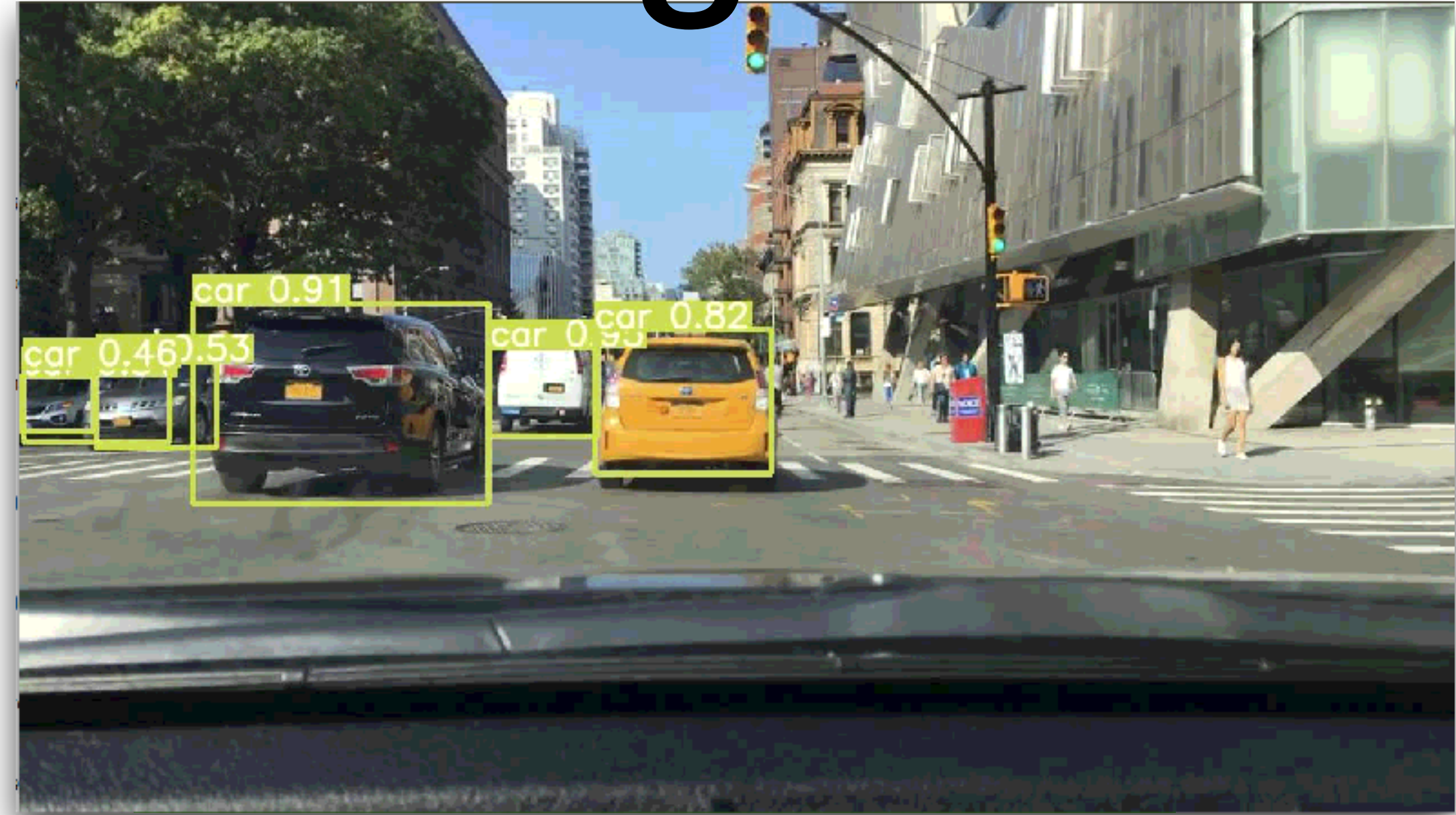
## **Research Questions:**

- Do bounding boxes provide statistically-sufficient information?
- Does the detection algorithm produce low false positive and negative rates?
- Is it robust against adaptive attackers?

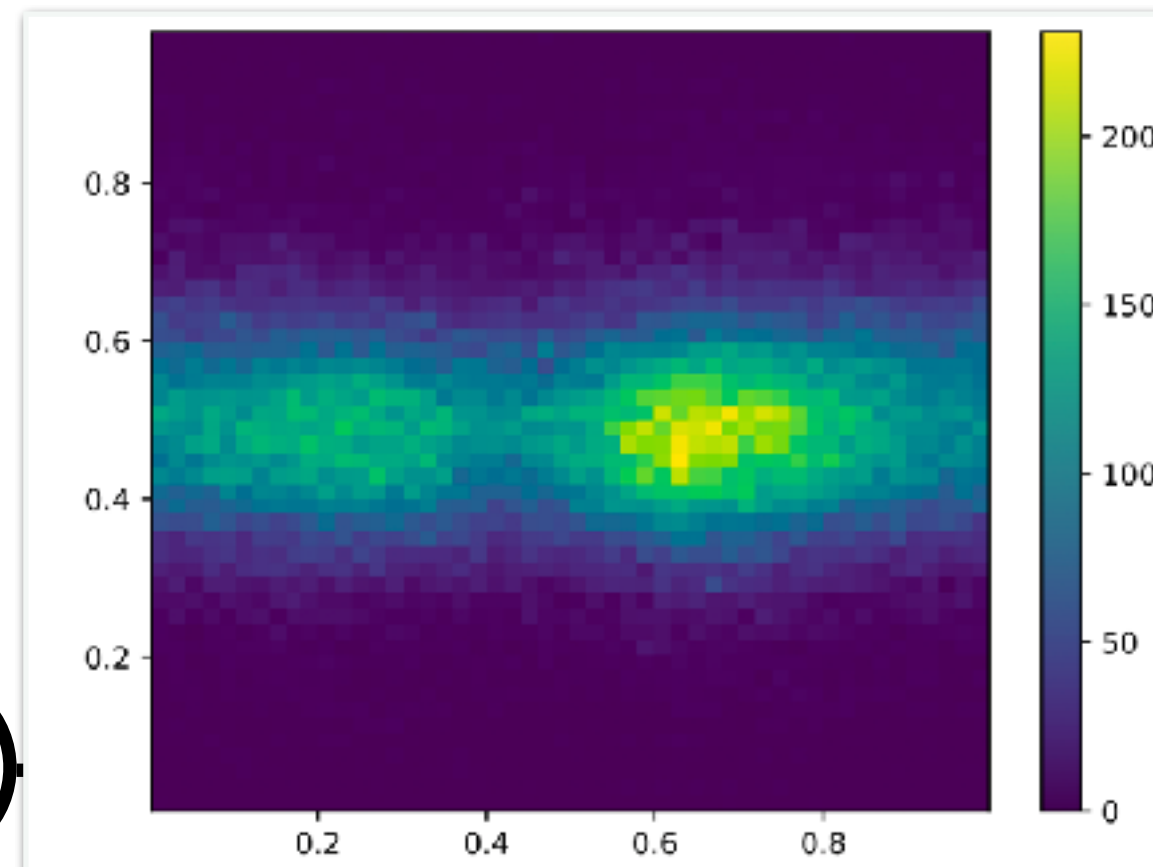
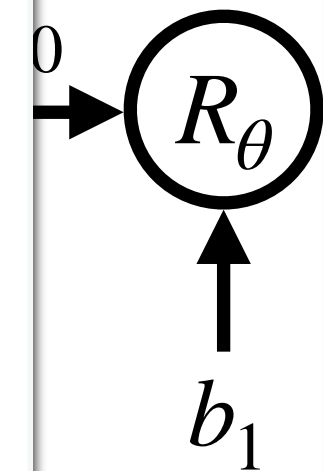
# PercepGuard Design

## Research Questions:

- Do bounding boxes provide statistically-sufficient information?

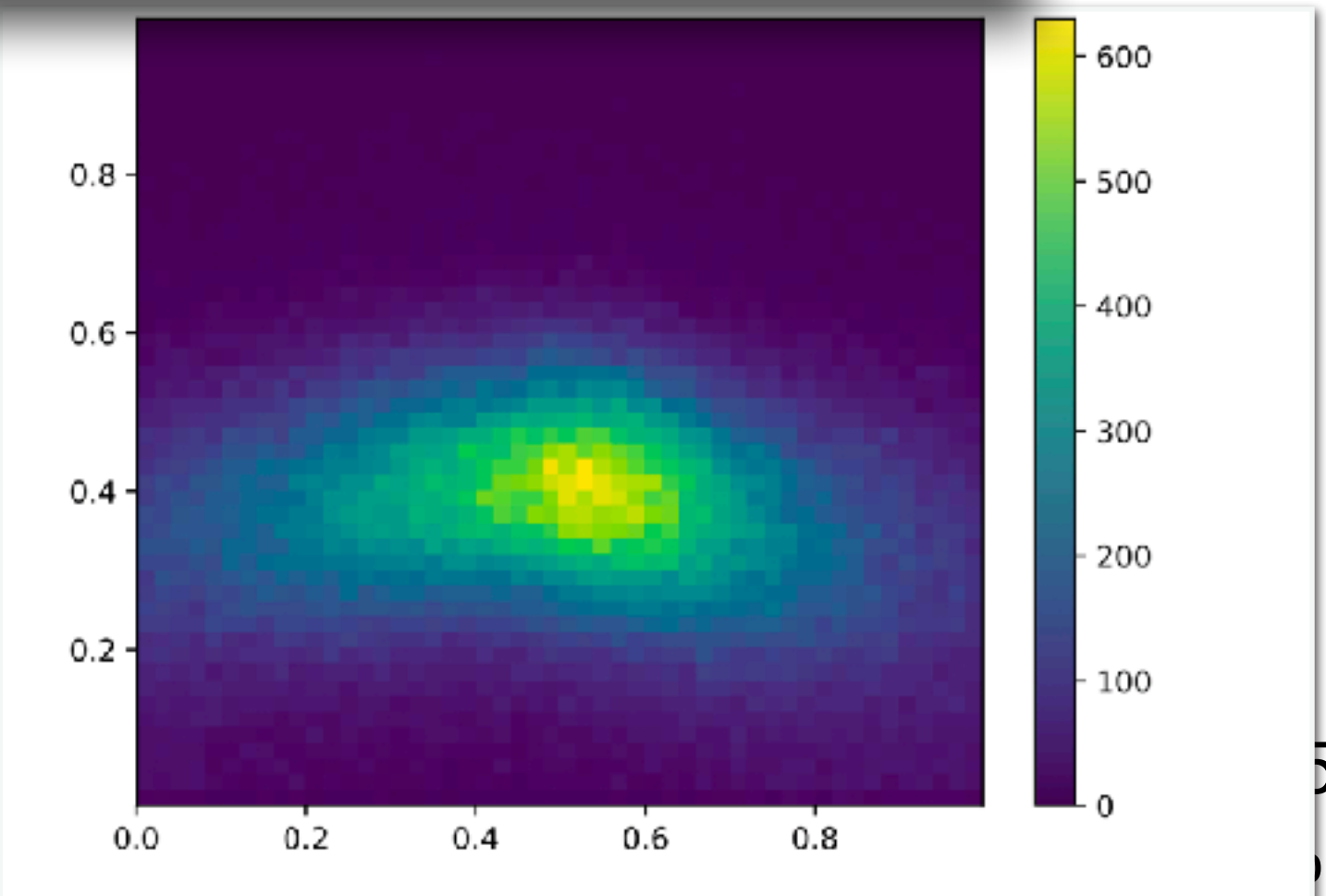
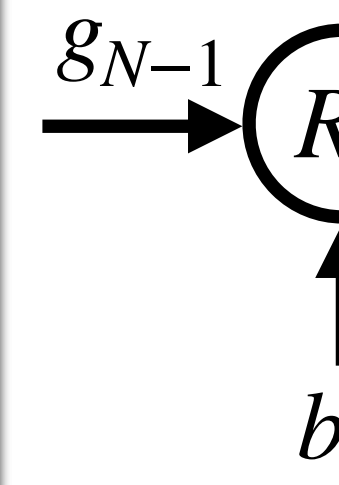


(a) Ground truth: Histogram of cars' locations.



(a) Ground truth: Histogram of locations.

Figure 2: Persons' locations. V



(a) Ground truth: Histogram of locations.

Figure 3: Traffic Signs' locations.

5%

## **Research Questions:**

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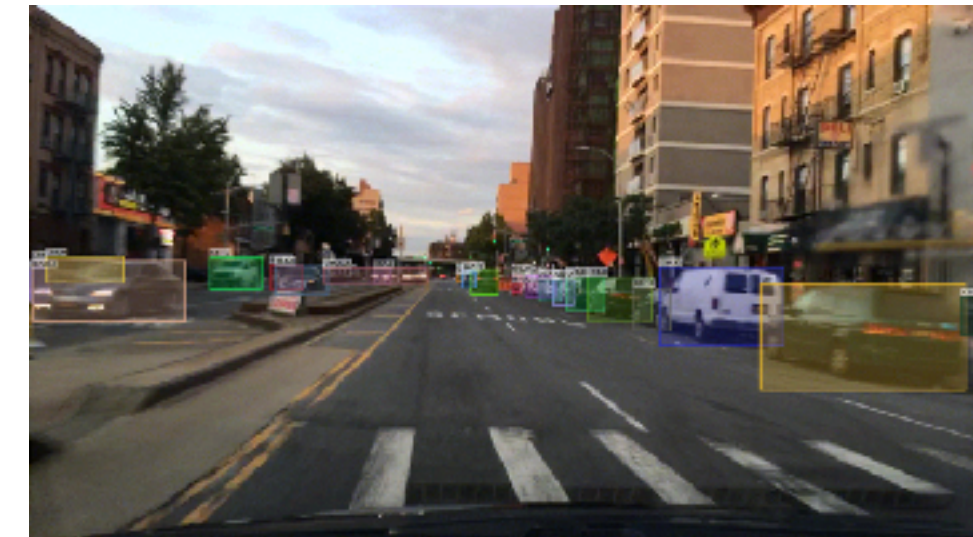
# Evaluation

## Research Questions:

- Do bounding boxes provide statistically-sufficient information?
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## Dataset:

- Berkeley Driving Dataset (BDD)
- Five object classes:
  - bike, bus, car, pedestrian, truck



Classification Accuracy: 95%  
False Negative Rate: 5%

# Evaluation

minimize  $\|\Delta\|$   
 $\Delta$

such that  $\bar{c} = c''$

"person"

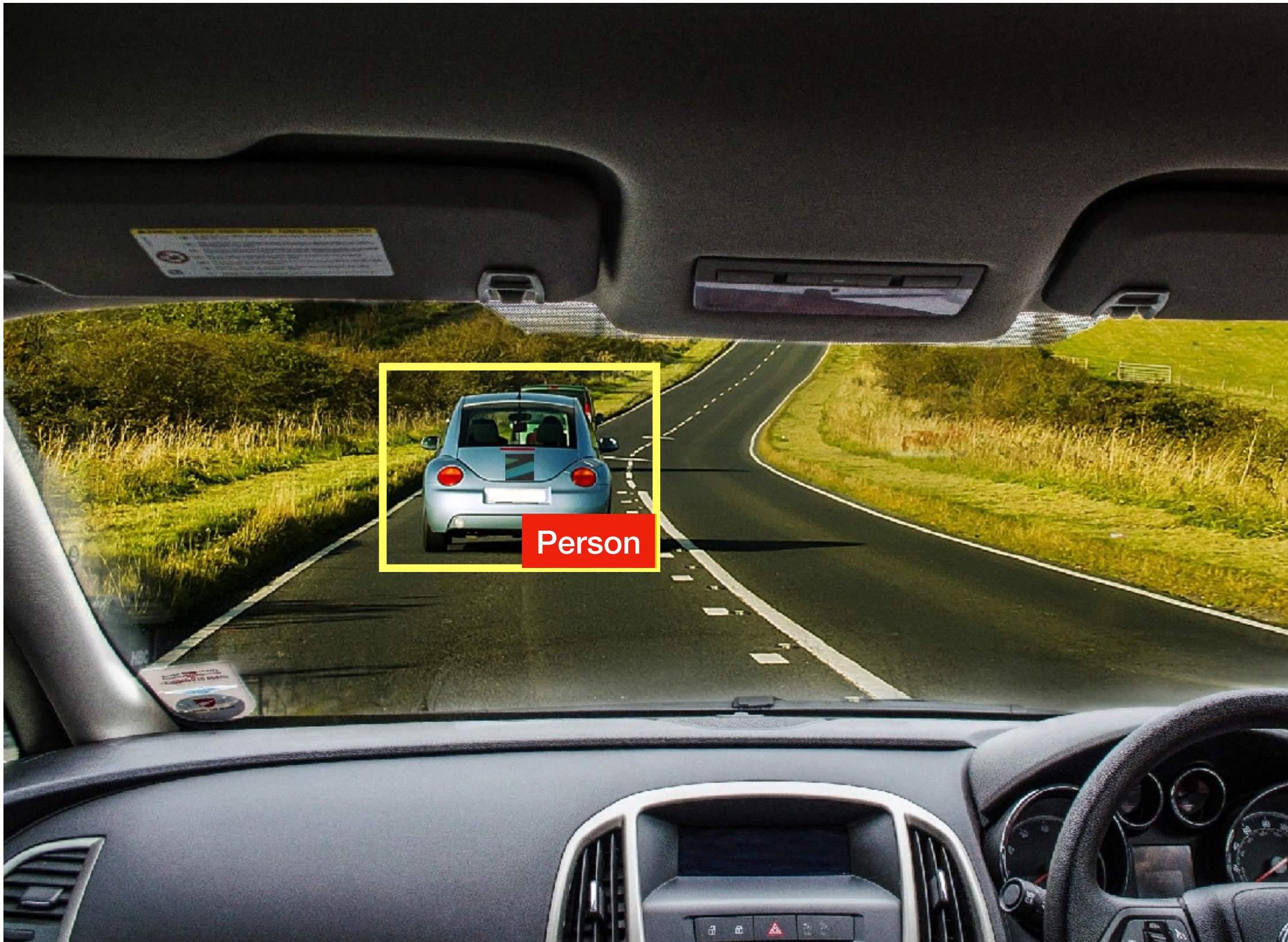
YOLO's  
classification  
result

## Attack Model:

- *Attack Goal:* Causing the rear car to recognize the front car as a person thus decides to stop (e.g., on a highway)
- *Attacker's Capability:* They utilize the adversarial machine learning to generate adversarial patches with white-box knowledge of the object detection algorithm (e.g., YOLO)

True Positive Rate: ??

False Negative Rate: 5%



# Evaluation

$$\underset{\Delta}{\text{minimize}} \|\Delta\| \quad \text{such that } \bar{c} = c''$$

"person"  $\rightarrow$   $\bar{c} = c'$   $\leftarrow$  Our classification result

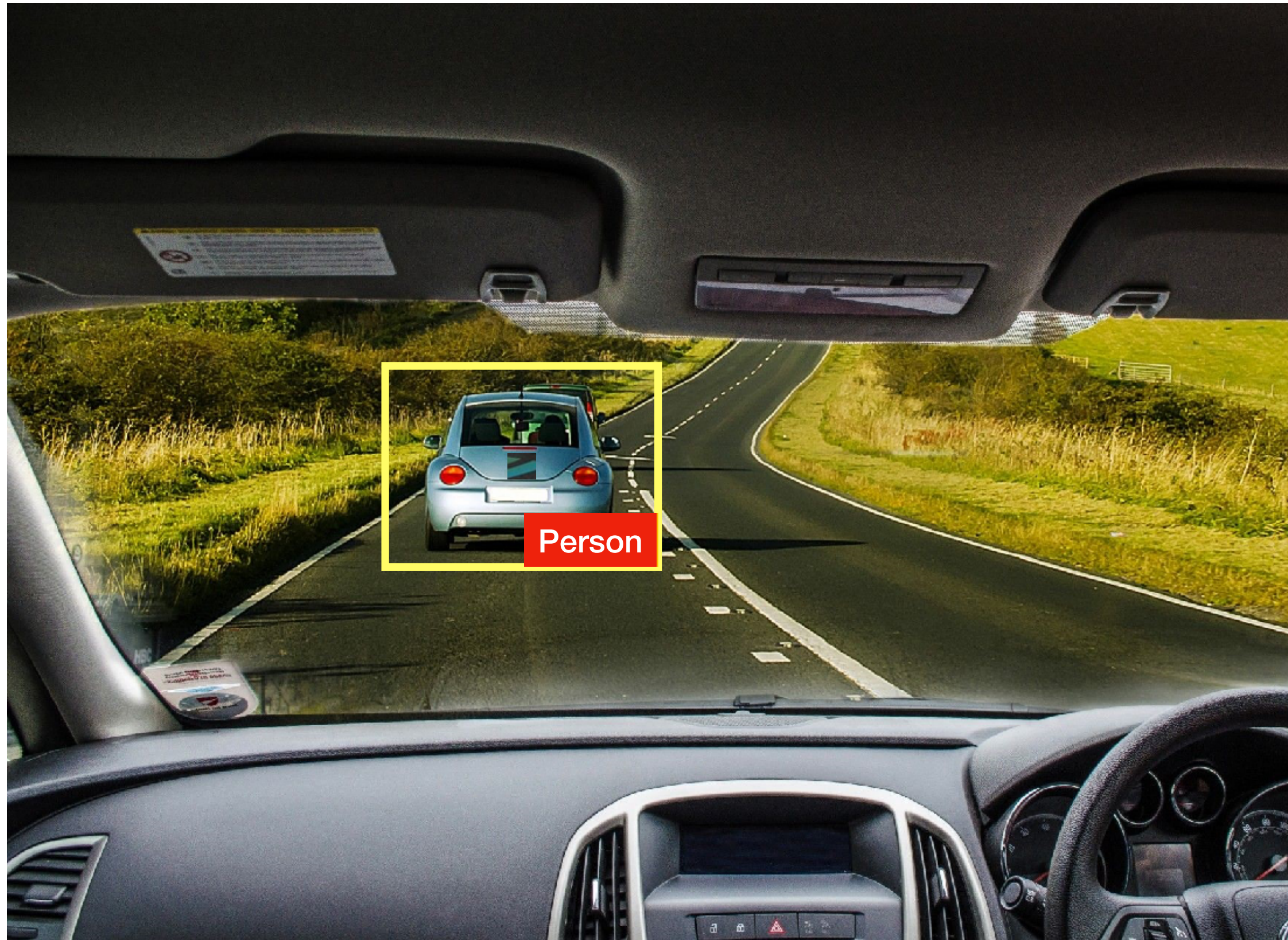


Table I: Adversarial patch attacks with BDD100K

Attack Type	Patch Size	A.M.R.	T.P.R.	A.S.R.
Defense-unaware	20 × 20	83.47%	99.63%	0.3%
	40 × 40	89.41%	100%	0%
	60 × 60	92.94%	100%	0%

But, what about adaptive attackers, who are aware of our defense and try to evade it?

True Positive Rate: Above 99%  
False Negative Rate: 5%



# Evaluation

$$\underset{\Delta}{\text{minimize}} \quad \|\Delta\| \quad \text{such that} \quad \begin{aligned} \bar{c} &= c'' \\ \bar{c} &= c' \end{aligned}$$

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Defense-aware	20 × 20	73.25%	98.74%	0.92%
	40 × 40	80.49%	90.33%	7.78%
	60 × 60	87.6%	85.67%	12.55%

True Positive Rate: Above 99%

False Negative Rate: 5%

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True Positive Rate: Above ~~99%~~ 85%  
False Negative Rate: 5%

# Evaluation

## Research Questions:

- Do bounding boxes provide statistically-sufficient information?
- Does the detection algorithm produce low false positive and negative rates?
- Is it robust against adaptive attackers?



## Contextual Information

- Ego-vehicle velocity
- Relative velocity to the object

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with contexts	60 × 60	88.76%	99.35%	0.6%

True Positive Rate: Above ~~99%~~ 85%  
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# Evaluation

## Research Questions:

- Do bounding boxes provide statistically-sufficient information?
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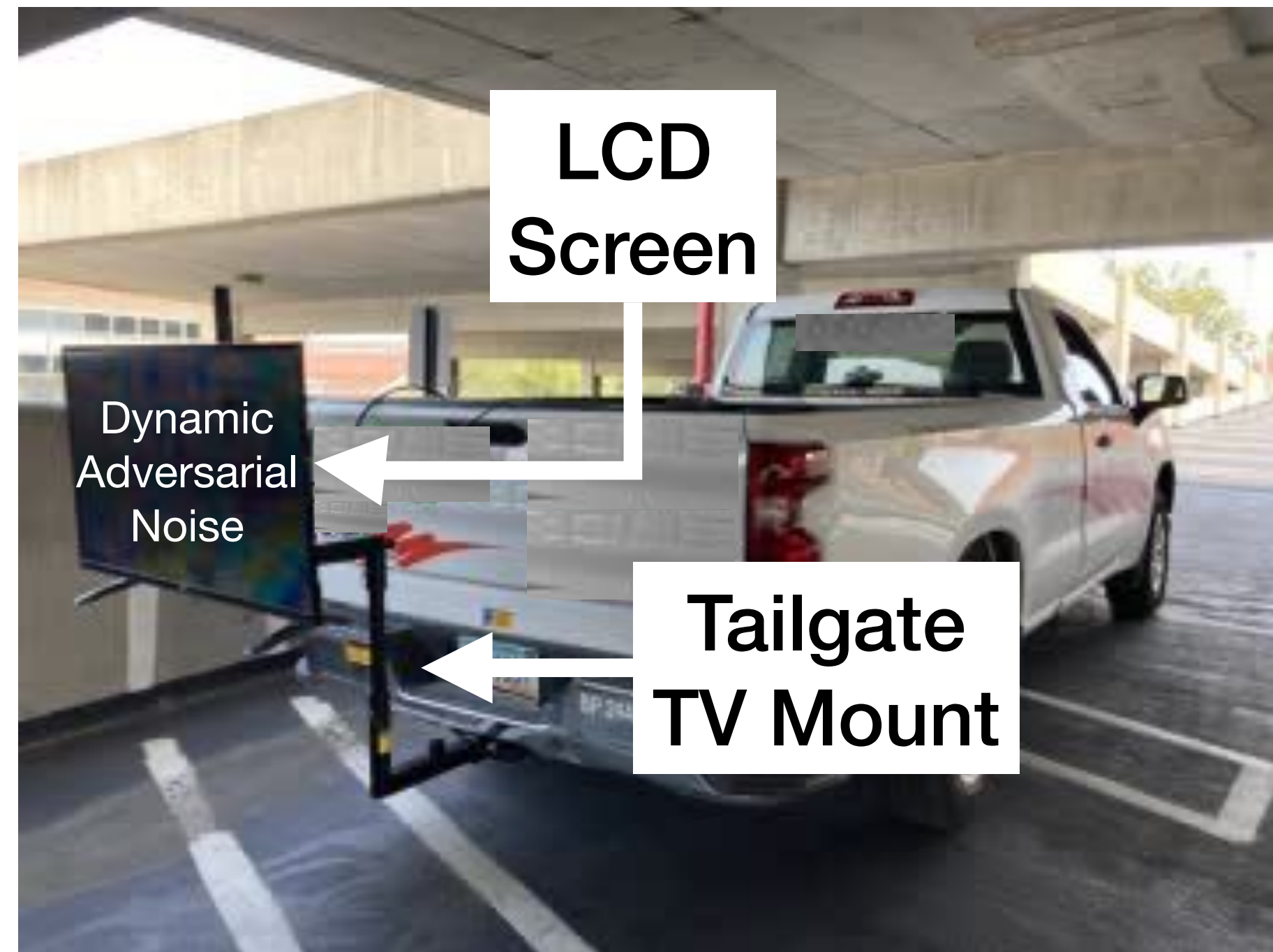
## Contextual Information

- Ego-vehicle velocity
- Relative velocity to the object

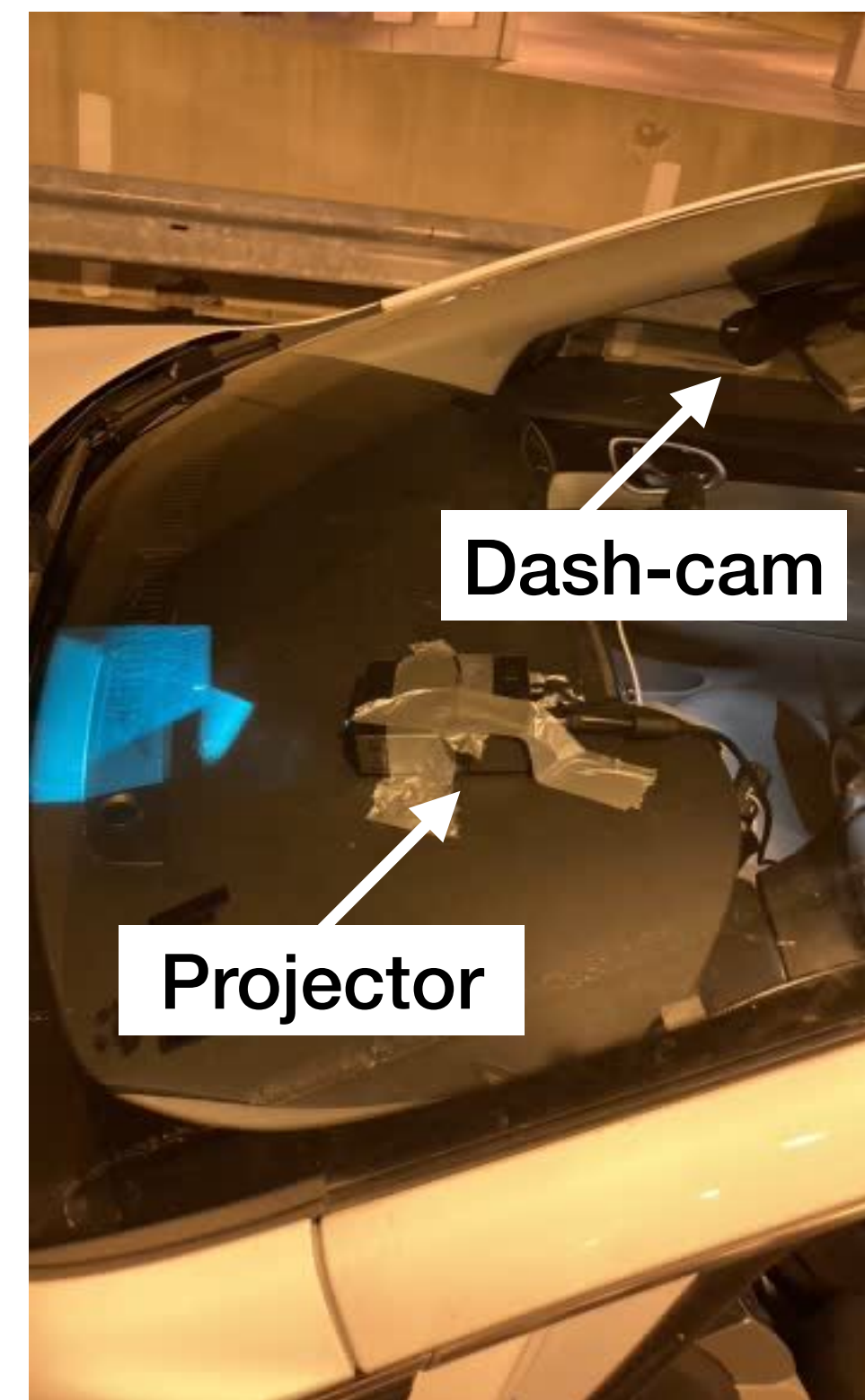
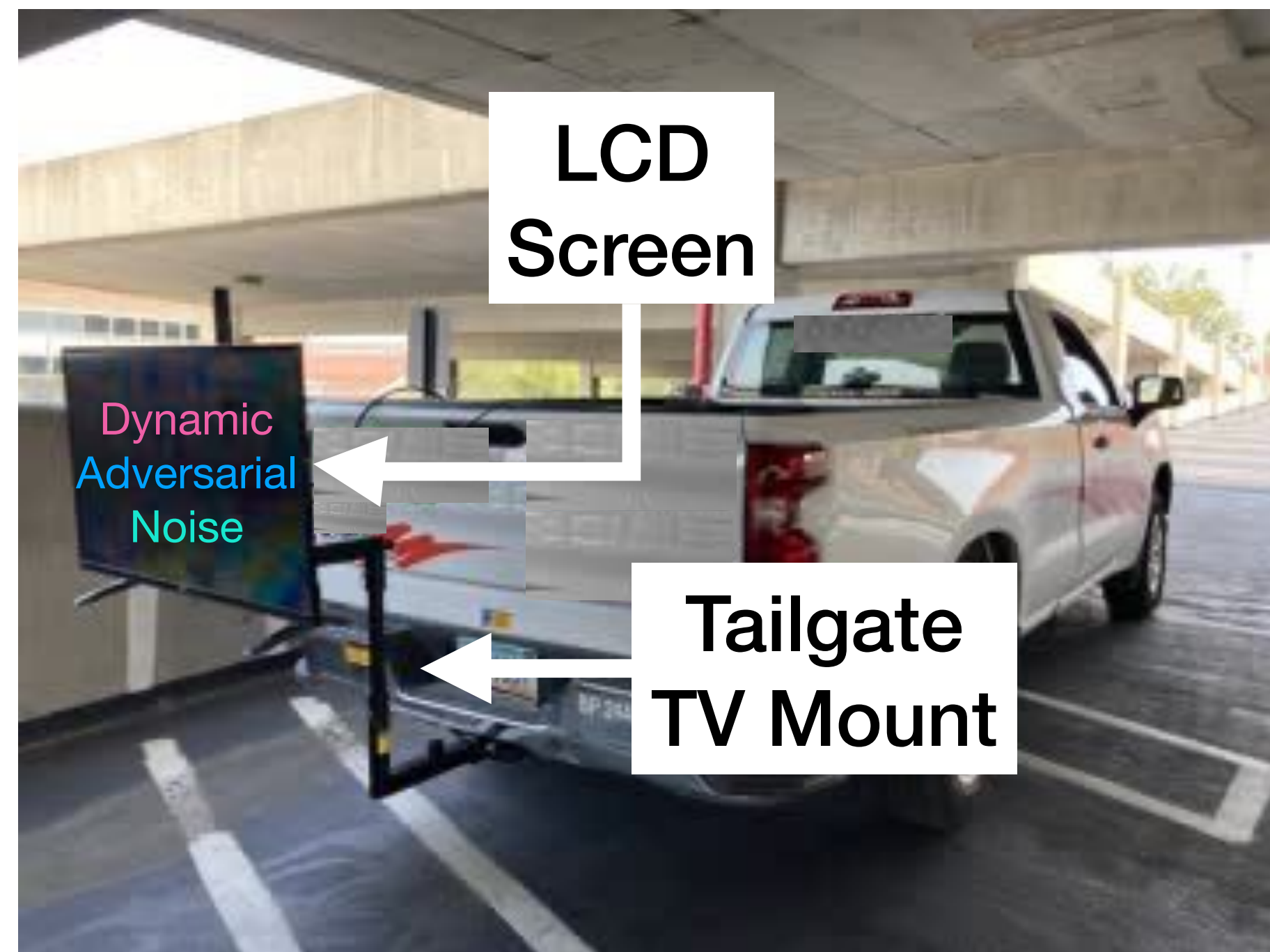
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True Positive Rate: Above ~~99%~~ 85%  
False Negative Rate: 5%      99%

# Real-world Experiments

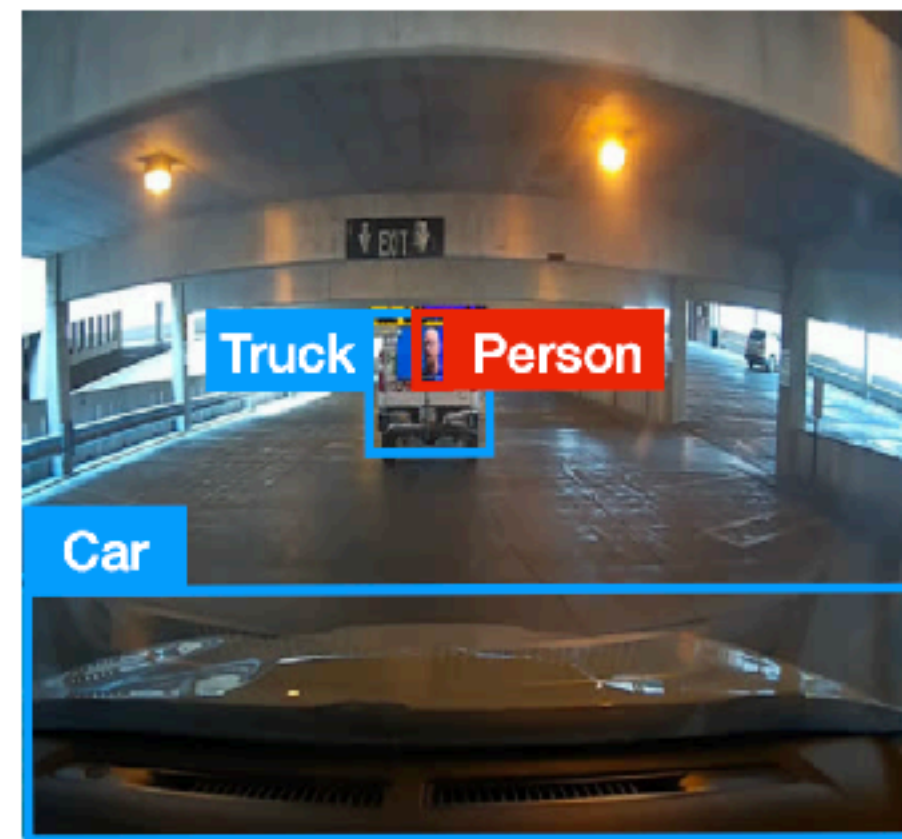


# Real-world Experiments





# Real-world Experiments



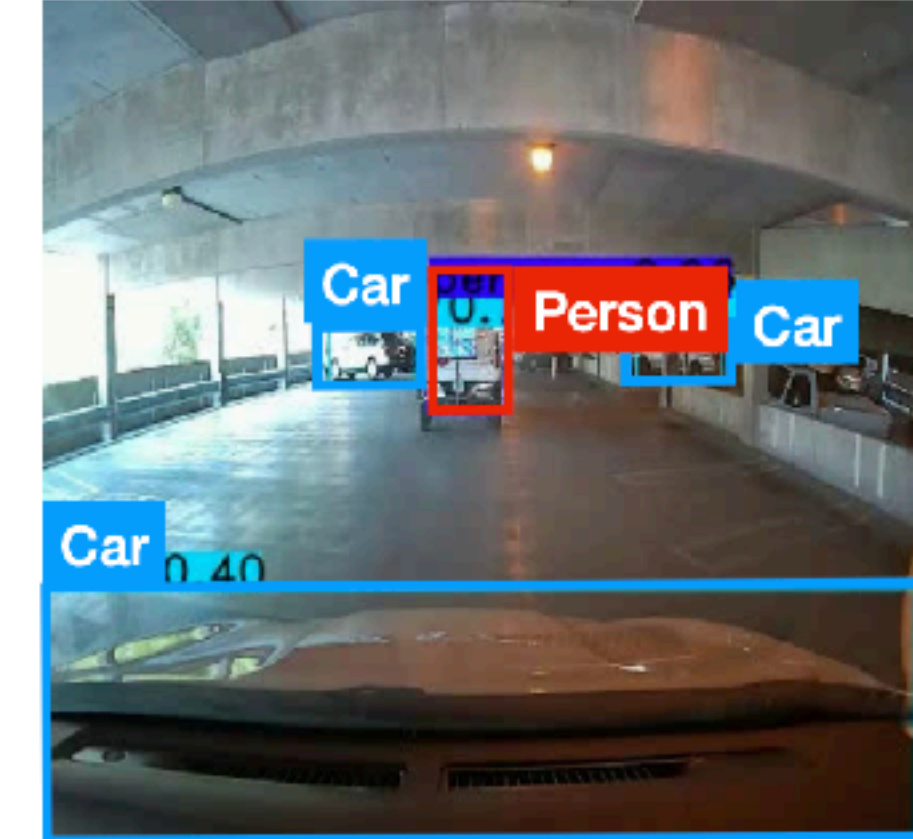
(a) Person



(b) Stop sign on monitor



(c) Projected stop sign



(d) Adversarial patch

Table 4: Real image attacks in the real-world

Real Images of	Device	ARR	TPR	ASR
People	Monitor	63.2%	83.3%	10.6%
	Projector	58.8%	100%	0%
Stop Signs	Monitor	40.0%	100%	0%
	Projector	20.0%	100%	0%

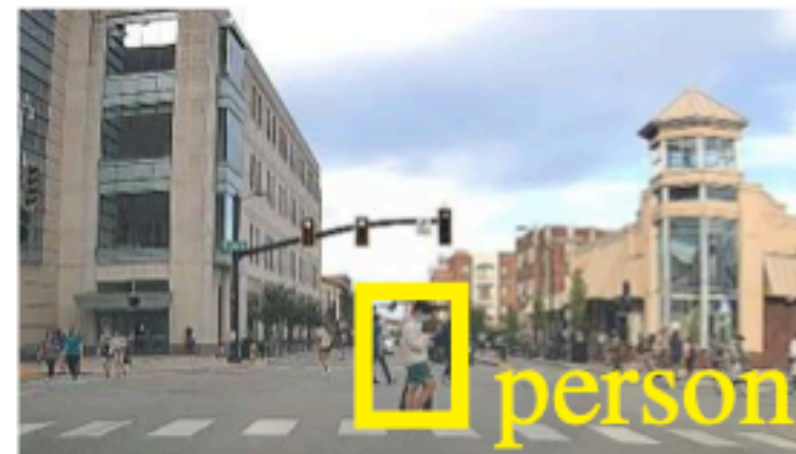
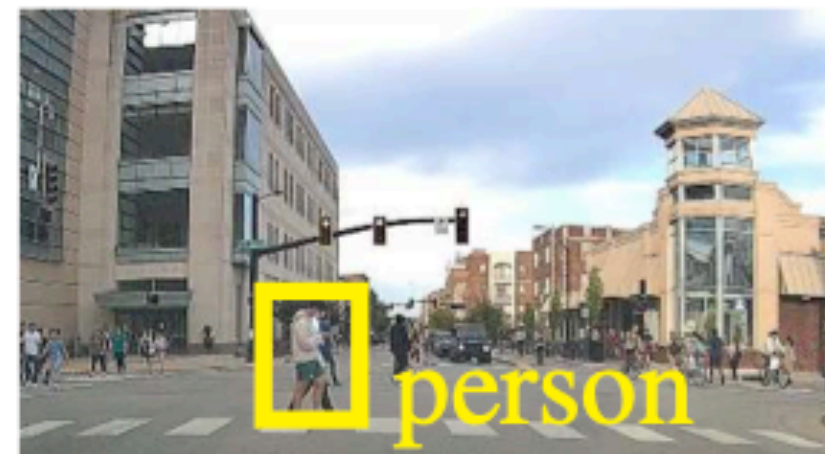
Table 5: Adversarial patch attacks in the real-world

Attack Type	Device	AMR	TPR	ASR
Defense-unaware	Monitor	52.2%	100%	0%
	Projector	27.3%	100%	0%
Defense-aware	Monitor	45.5%	100%	0%
	Projector	20.0%	100%	0%

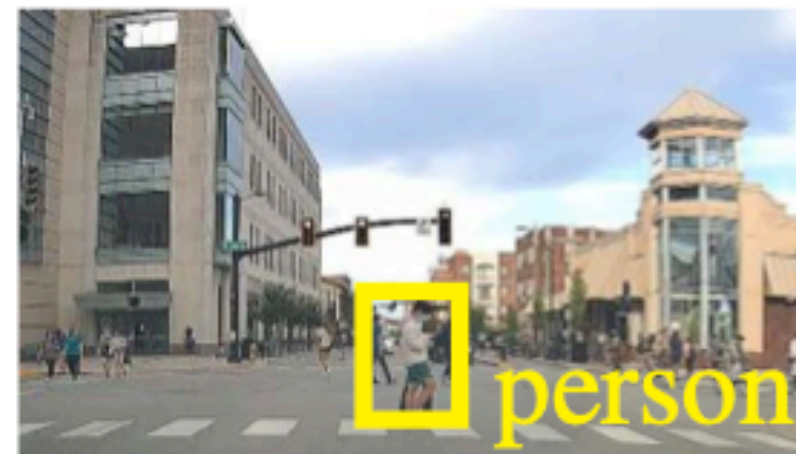
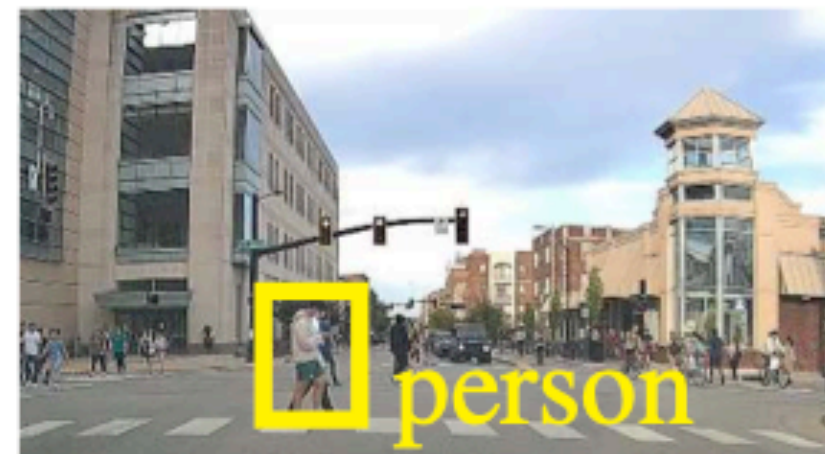
# More Evaluation

- Baseline comparison
- Sensitivity analysis
- Alternative operating points
- Additional features

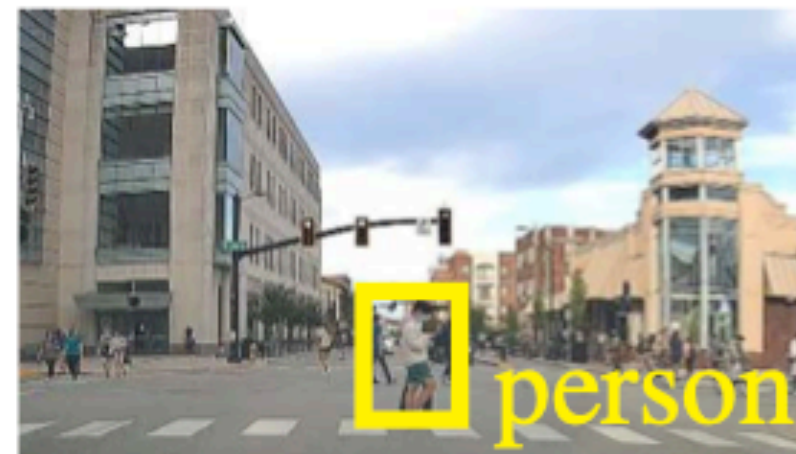
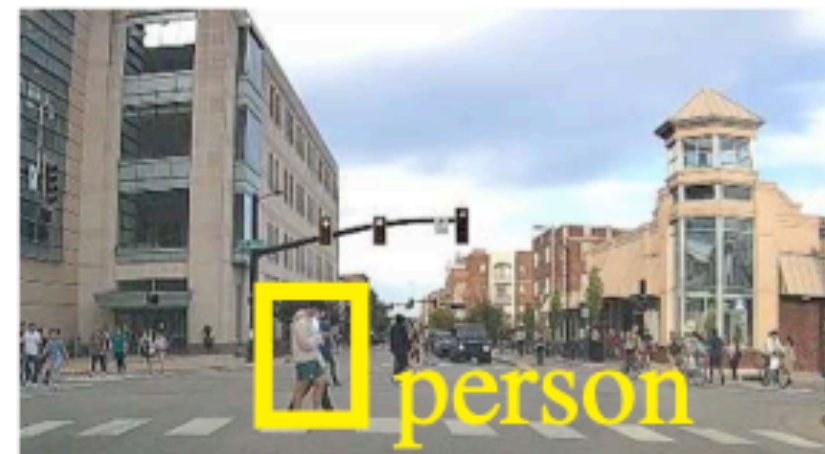
# That Person Moves Like A Car: Misclassification Attack Detection for Autonomous Systems Using Spatiotemporal Consistency



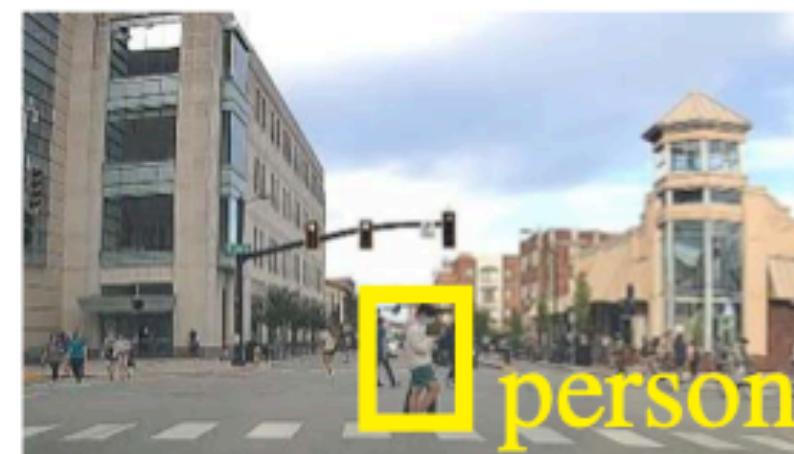
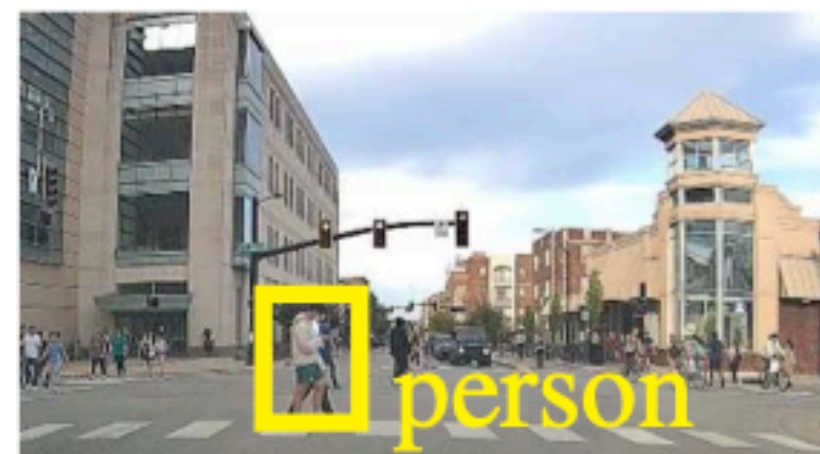
That Person Moves Like A Car:  
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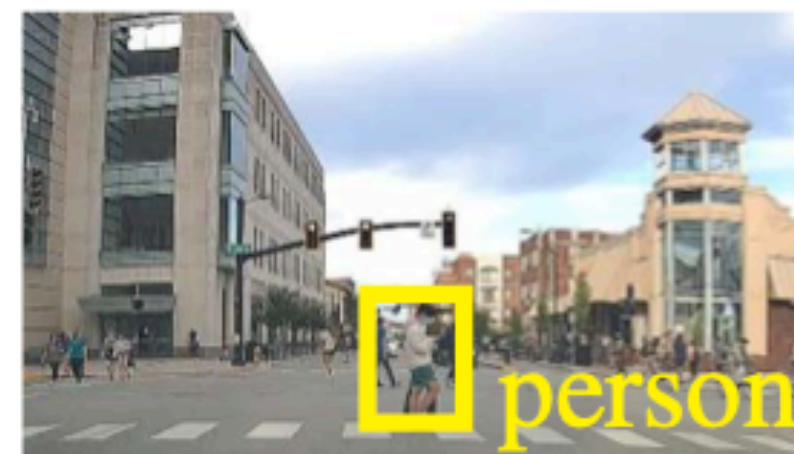
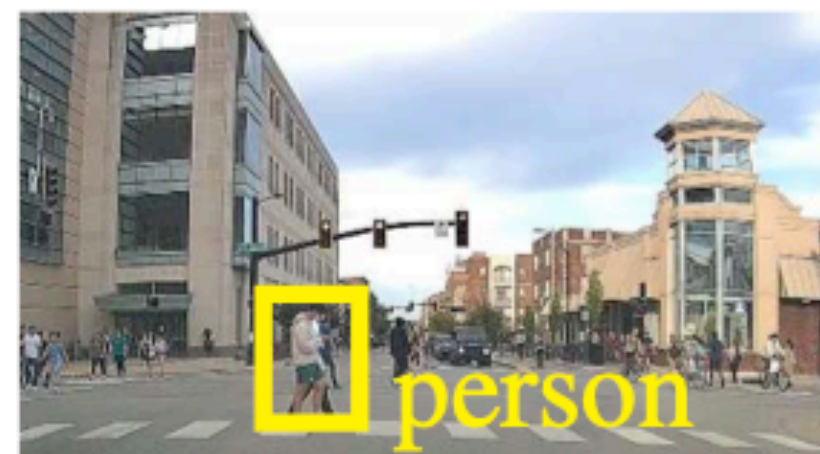


# That Person Moves Like A Car: Misclassification Attack Detection for Autonomous Systems Using **Spatiotemporal Consistency**



- Adaptive Attacks
- Contextual information
- True positive rate: above 99%
- False negative rate: 5%

# Future Work



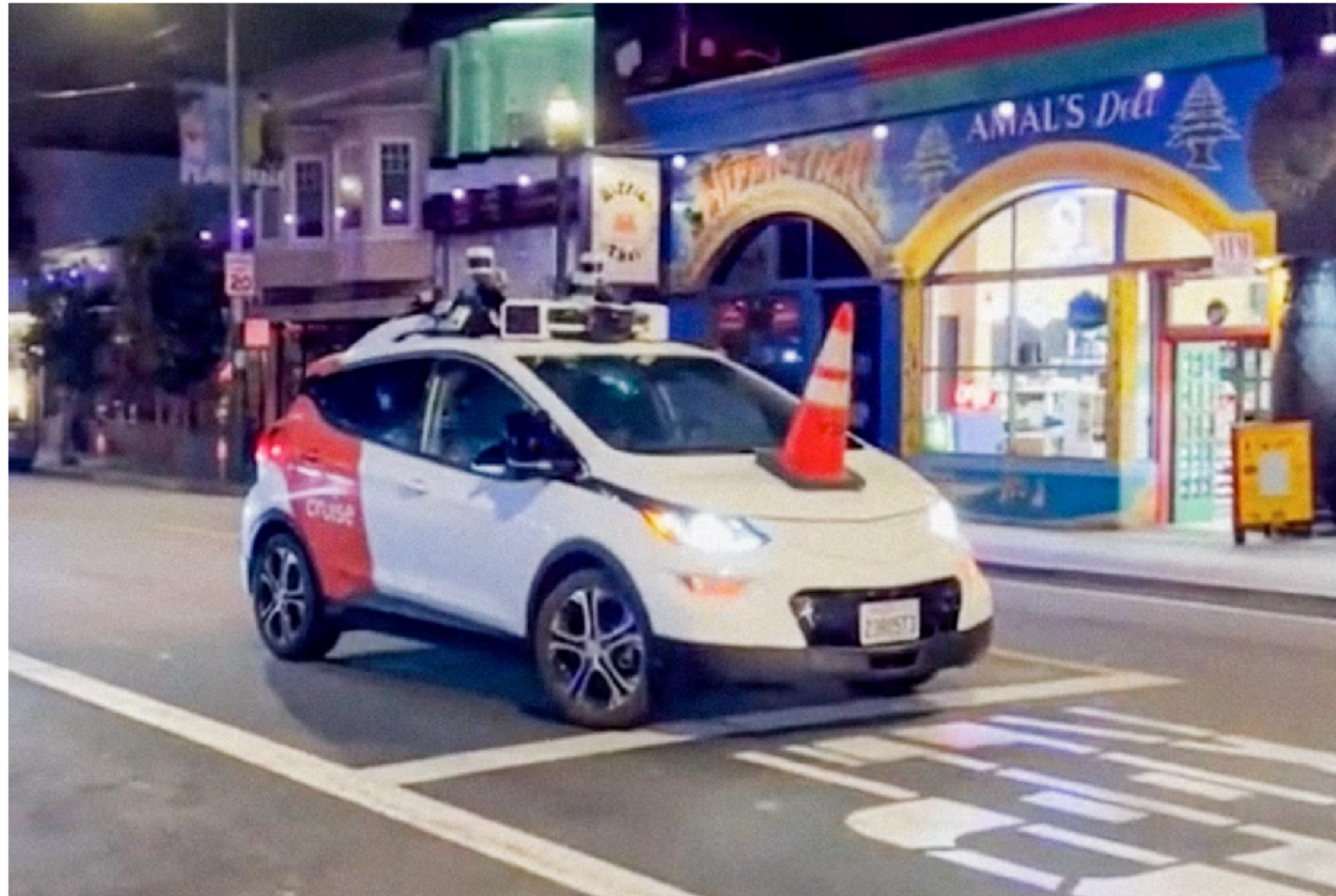
- More spatiotemporal features
  - Different Sensors
  - Semantic Segmentation
- Detecting object creation attacks
- Attention-based
- Sensor Configuration Randomization

# The Self-Driving Cars Wearing a Cone of Shame

There's a brilliant activist campaign to stop San Francisco's autonomous vehicles in their tracks.

BY ALISON GRISWOLD

JULY 11, 2023 • 10:45 AM



It looks like a sad unicorn (which, in a way, it is). Screenshot from TikTok/Safe Street Rebel



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