

# On the Semantic AI Security in CPS: *The Case of Autonomous Driving*

Qi Alfred Chen

*Assistant Professor, UC Irvine*



UCIRVINE

***AS<sup>2</sup>Guard***  
Autonomous & Smart Systems  
Guard Research Group

# A bit about myself & my group

- Assistant Professor of Computer Science, UC Irvine (2018 - )
  - Ph.D., University of Michigan
- Group: **AS<sup>2</sup>Guard** (Autonomous & Smart Systems Guard)
- Expertise: **AI/Systems/Network Security**, mainly in **mobile/CPS/IoT**

**AS<sup>2</sup>Guard**  
Autonomous & Smart Systems  
Guard Research Group



# Impact: Demo & vulnerability report



NDSS'16  
Euro S&P'17



IEEE S&P'16



Usenix  
Sec'14

Apple

comcast.



apollo



DAIMLER



NDSS'18



CCS'15

CCS'17

Usenix Sec'20

# My research so far in mobile/CPS/IoT security

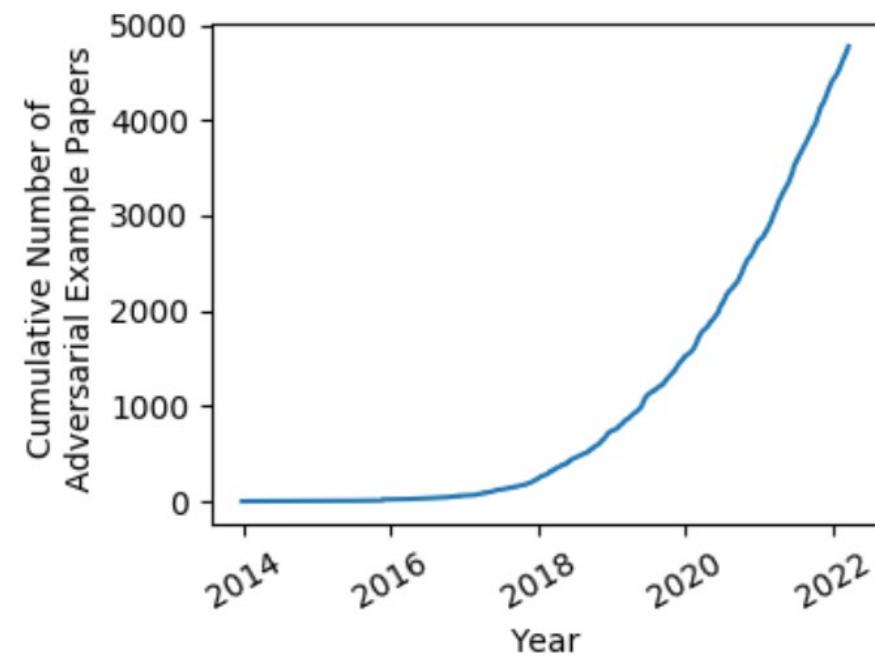
- **CPS AI Security**
  - Autonomous Driving (AD) [ACM CCS'19, Usenix Security'20 (a), '20 (b), '21, IEEE S&P'21, NDSS'22, CVPR'22, ICLR'20]
  - Intelligent transportation [NDSS'18, TRB'18,'19,'20, ITS'21]
- **Network Security**
  - Connected Vehicle (CV) [Usenix Security'21]
  - Automotive IoT [Usenix Security'20, NDSS'20]
  - Network protocol [ACM CCS'15,'18, IEEE S&P'16]
- **UI (User Interface) Security**
  - Smartphone [Usenix Security'14, MobiSys'19]
- **Access Control / Policy Enforcement**
  - Smartphone [NDSS'16]
  - Smart home [NDSS'17]
- **Side Channel**
  - Smartphone [Usenix Security'14]
  - Network [ACM CCS'15]

# Most recent focus (2018+): CPS AI security

- **CPS AI Security**

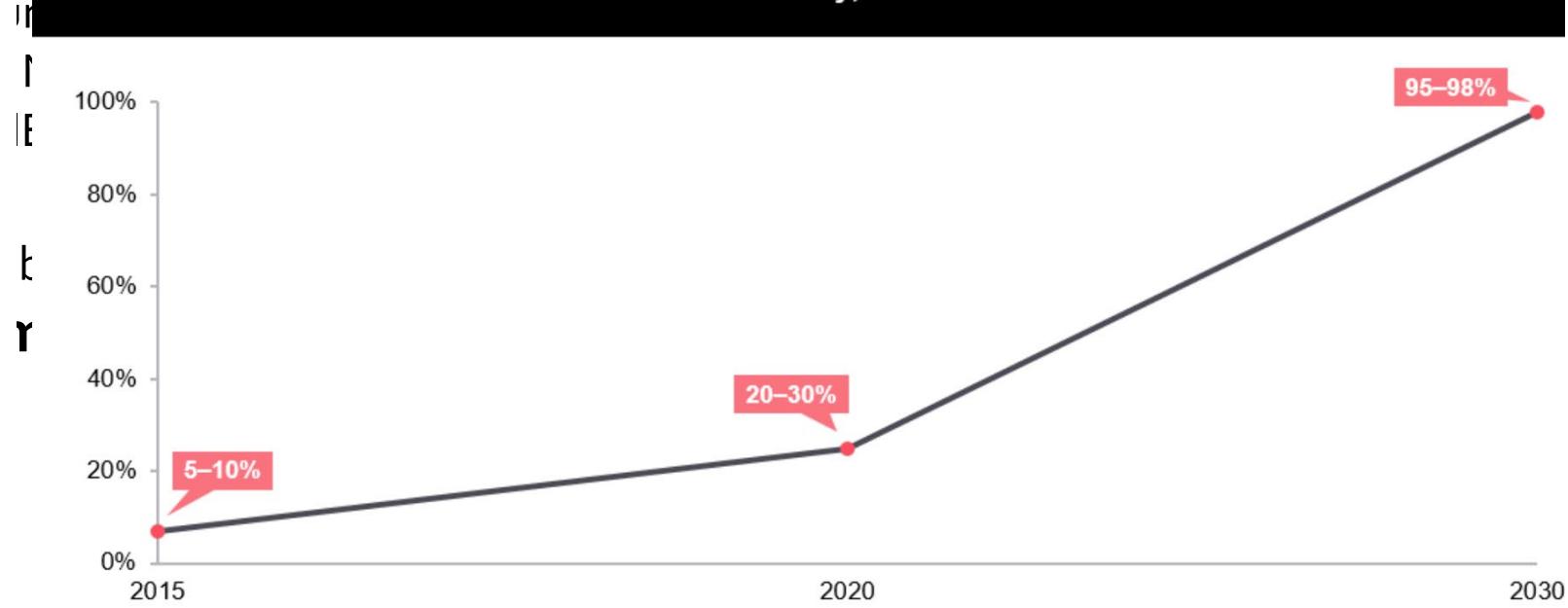
- **Autonomous Driving (AD)** [ACM CCS'19, Usenix Security'20 (a), '20 (b), '21, IEEE S&P'21, NDSS'22, CVPR'22, ICLR'20]
- **Intelligent transportation** [NDSS'18, TRB'18, '19, '20, ITS'21]

- Relatively new area:
  - AI security: Since 2013 [Szegedy et al., “Intriguing properties of neural networks”]
  - AI penetration in real-world CPS (e.g., since ~2015 in automotive industry)



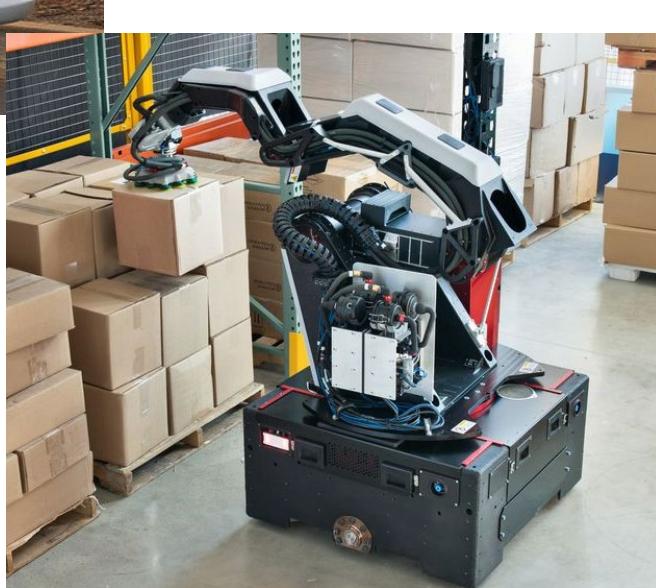
(\*Image credit: Nicholas Carlini)

EXHIBIT 7: Penetration of AI in the Automotive Industry, 2019–2030



Source: FutureBridge Analysis and Insights

# More recently, various kinds of AI-enabled autonomous systems coming into real life



# Highly desired to study their security



- In charge of highly safety-critical decision-making in the physical world  
→ Security problems can have ***unprecedentedly high impacts on public safety & society*** (e.g., fatal crashes)



An Uber self-driving car hit & killed a woman crossing street in Arizona since it cannot classify her as a pedestrian. [1] [2]



Fatal crash of a Tesla model X w/ Autopilot on in 2018 at California [3]. From the 2016 crash that killed a Florida driver, >20 Autopilot-related crashes have occurred [4].

[1] <https://www.nbcnews.com/tech/tech-news/self-driving-uber-car-hit-killed-woman-did-not-recognize-n1079281>

[2] <https://www.theverge.com/2019/11/6/20951385/uber-self-driving-crash-death-reason-ntsb-documents>

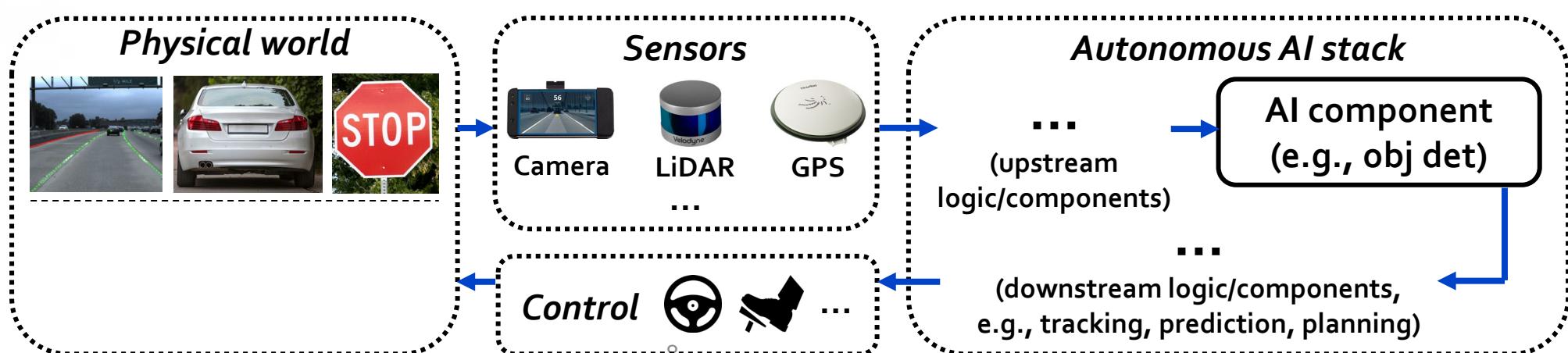
[3] <https://www.bbc.com/news/world-us-canada-43604440>

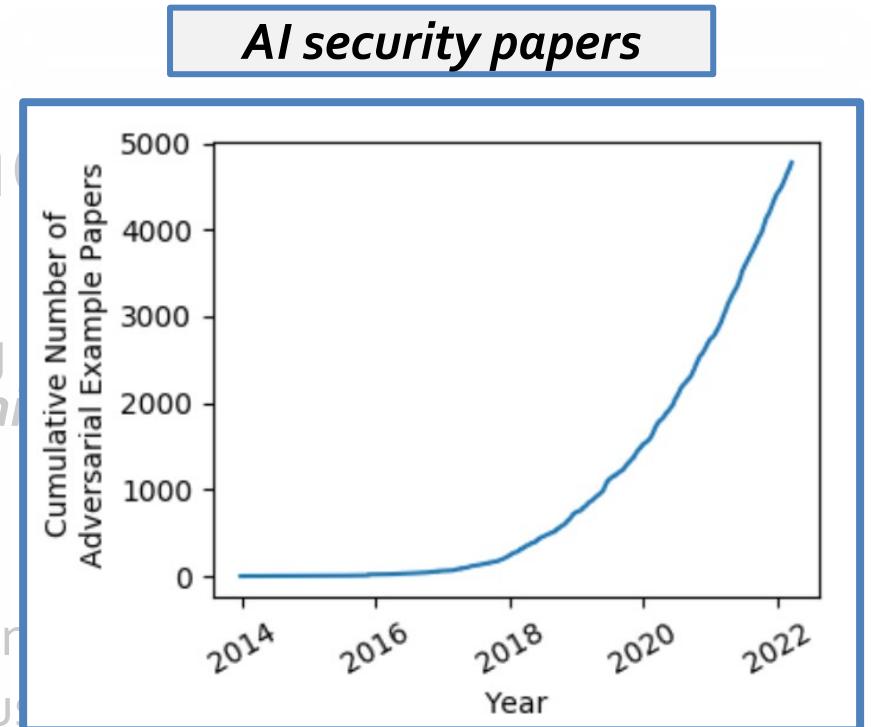
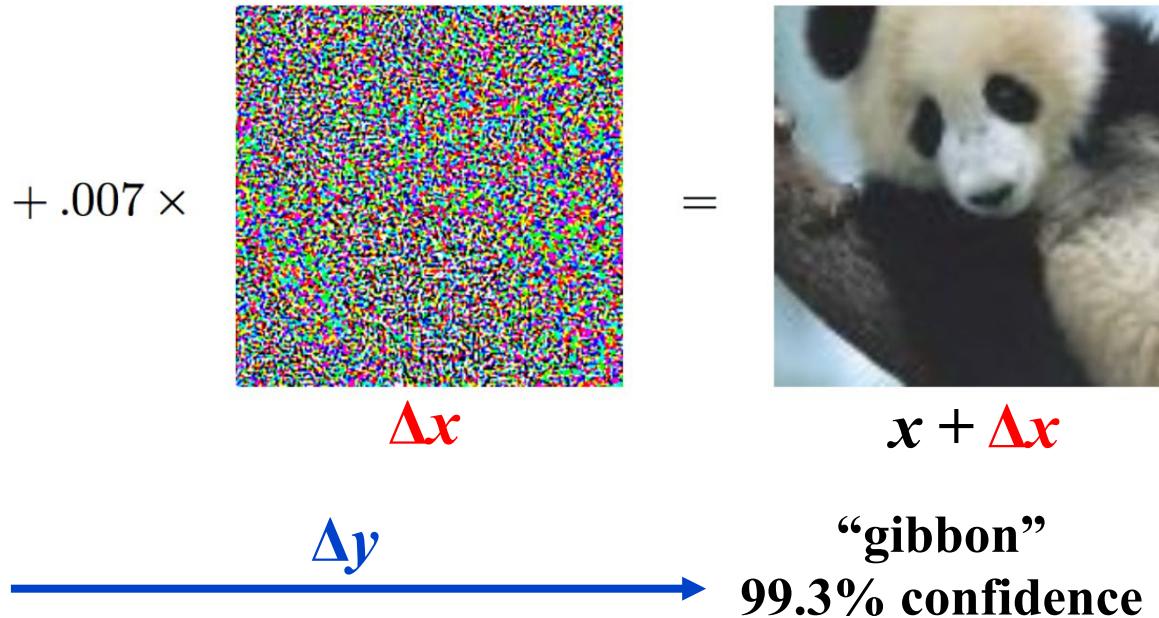
[4] <https://www.nytimes.com/2021/03/23/business/teslas-autopilot-safety-investigations.html>

# Highly desired to study their security



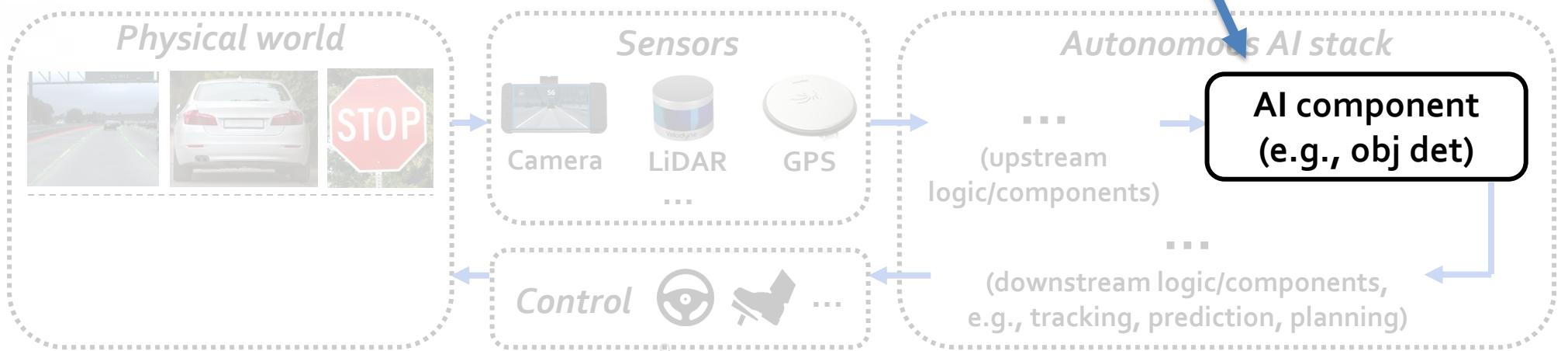
- In charge of highly safety-critical decision-making in the physical world  
→ Security problems can have ***unprecedentedly high impacts on public safety & society*** (e.g., fatal crashes)
- Domain-specific system components that may come with **new security properties**
- To meaningfully affect the AI-enabled autonomous decision-making (e.g., driving), face new research challenges **as a “semantic AI security” problem**
  - Proposed by us recently<sup>1</sup>, generalized from “semantic adv deep learning” by Seshia et al. in 2018<sup>2</sup>





face new research challenges as a “semantic AI security” problem

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# Highly desired to study their security



- In charge of highly safety-critical decision-making in the physical world  
→ Security problems can have ***unprecedentedly high impacts on public safety & society*** (e.g., fatal crashes)

System-level attack input spaces (e.g., add stickers, laser shooting)  
→ those at AI component level (e.g., image pixel changes)

- *Fundamentally challenging due to inverse feature-mapping problem<sup>3</sup>*



face new research

- Proposed by us recently
- Need to further address

*Physical world*



that may come with ***new security properties***  
in autonomous decision-making (e.g., driving),

as a “*semantic AI security*” problem

alized from the “*semantic AI security*” problem

From AI component-level attack effects (e.g., misdetected objects)  
→ those at CPS system level (e.g., vehicle collisions)

- *Challenging due to the high end-to-end system-level complexity in CPS & dynamics from closed-loop control<sup>2,4,5</sup>*

*System-to-AI semantic gap*

Camera LIDAR GPS ...

(upstream logic/components)

Control

*AI-to-system semantic gap*

e.g., tracking, prediction, planning

# My recent focus (2018-): Automotive & transportation domain

## Autonomous Driving (AD)



## V2X-based Intelligent Transp.



ZOOX



Qualcomm



11

# My recent focus (2018-): Automotive & transportation domain

## Autonomous Driving (AD)



- **Fastest growing AI-enabled autonomous system in industry today**
- **Highly safety-critical**
  - *Heavy, fast-moving, & operate in public spaces*
- **Highly complex (to get right)**
  - Need to handle broad range of *weather, lighting, road & traffic conditions*, while being *safe* & complying to *traffic rule*



WAYMO



ZOOX



TOYOTA

Qualcomm



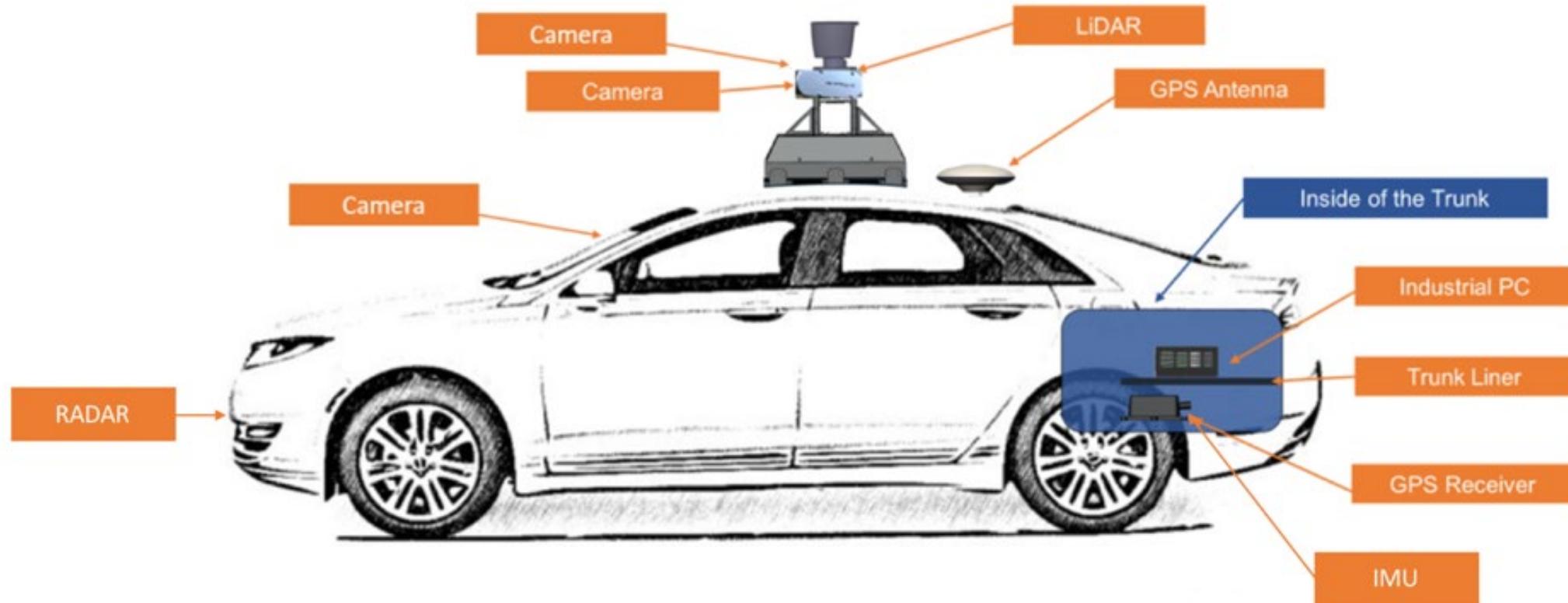
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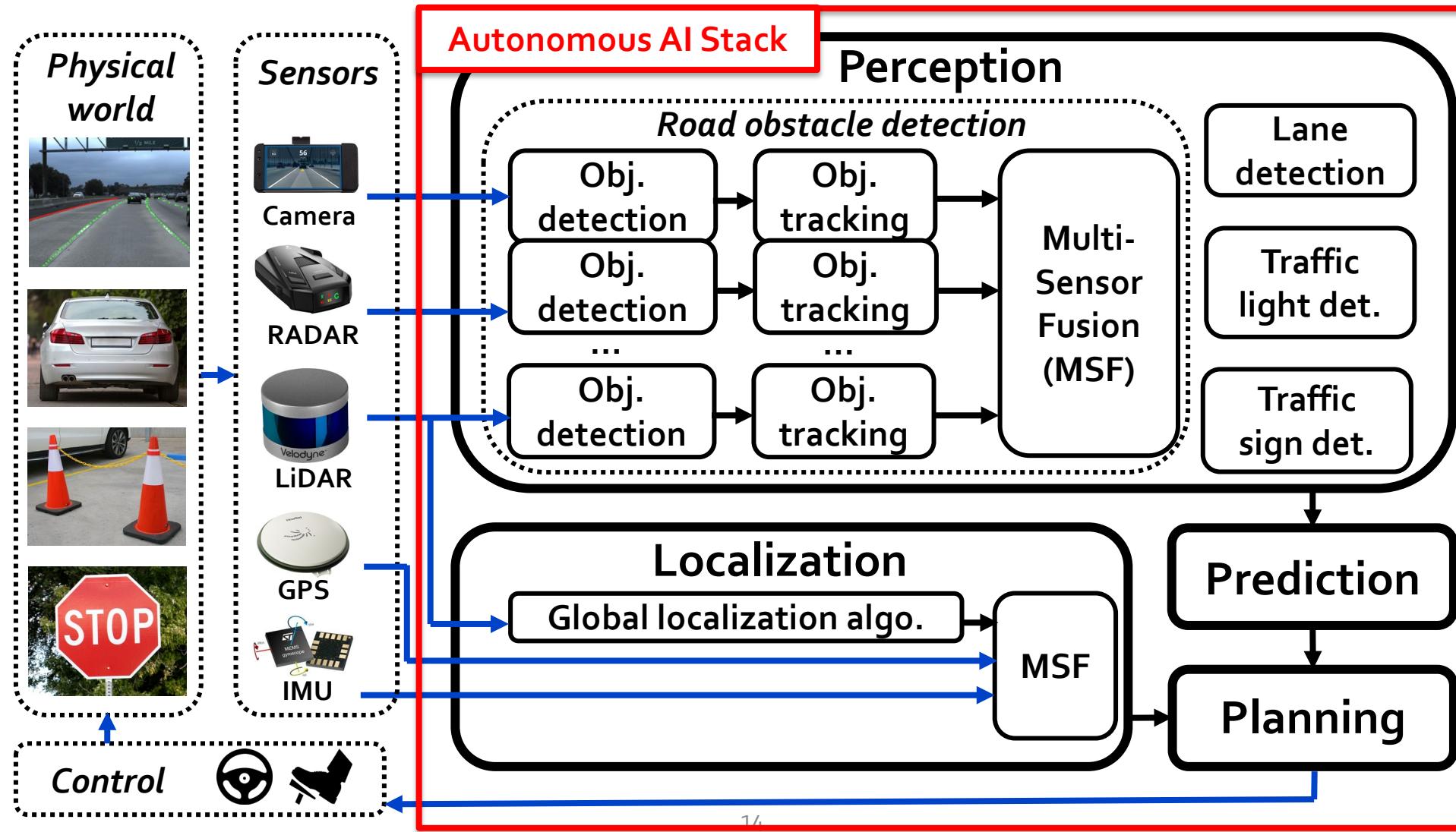
U.S. Department  
of Transportation

# Background: Autonomous Driving (AD) technology

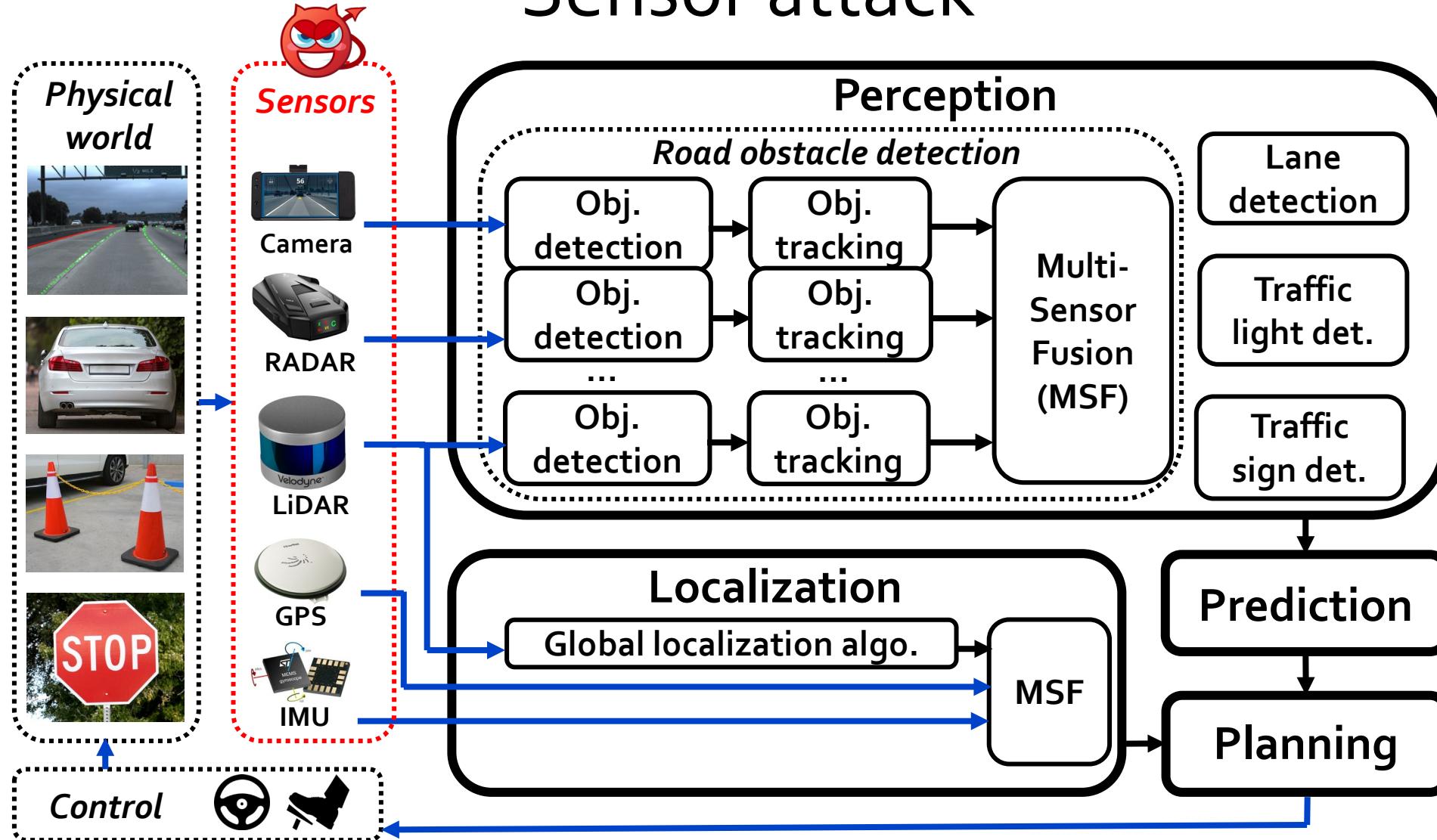
- Equip vehicles with various types of sensors to enable self driving



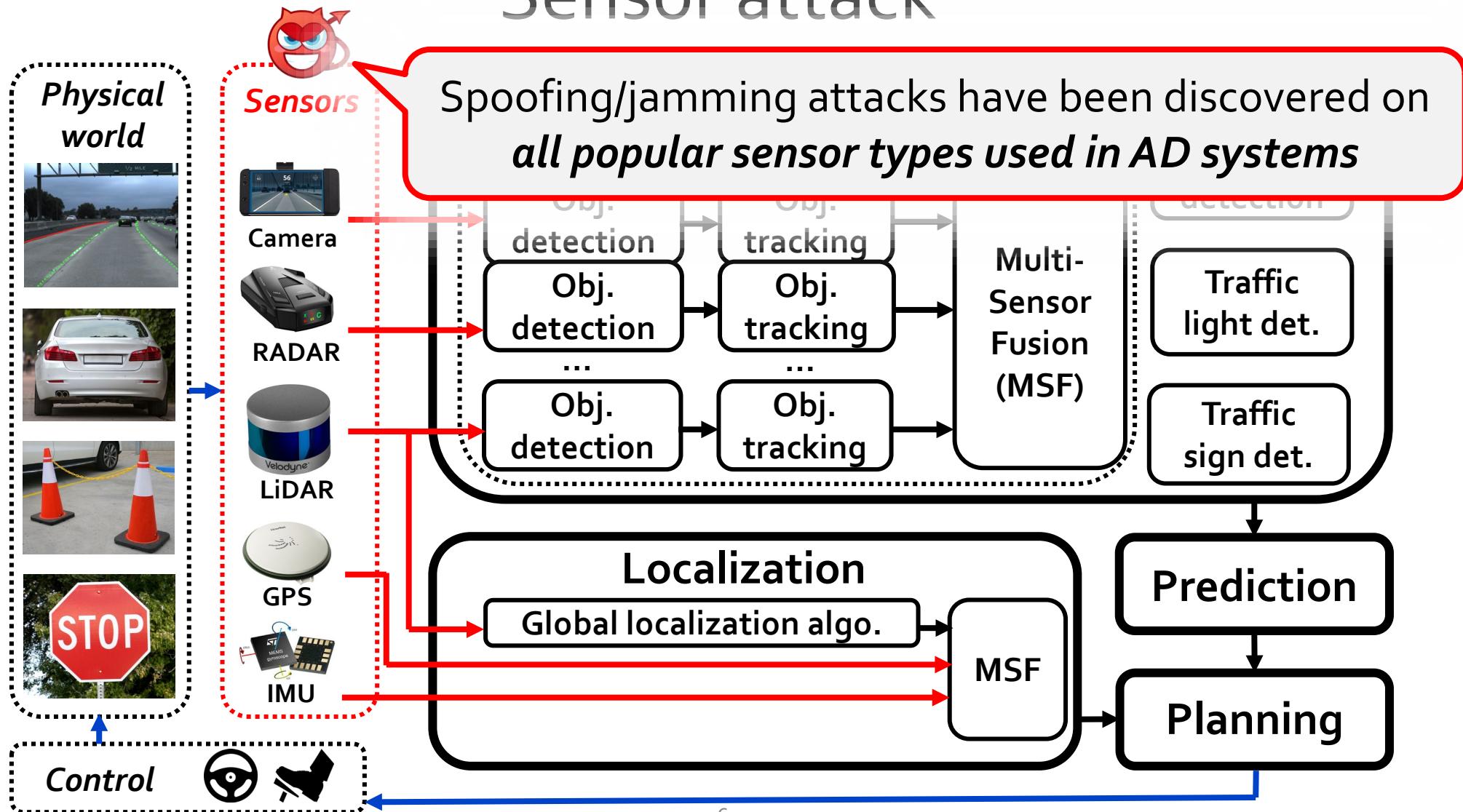
# Background: System architecture of industry-grade AD



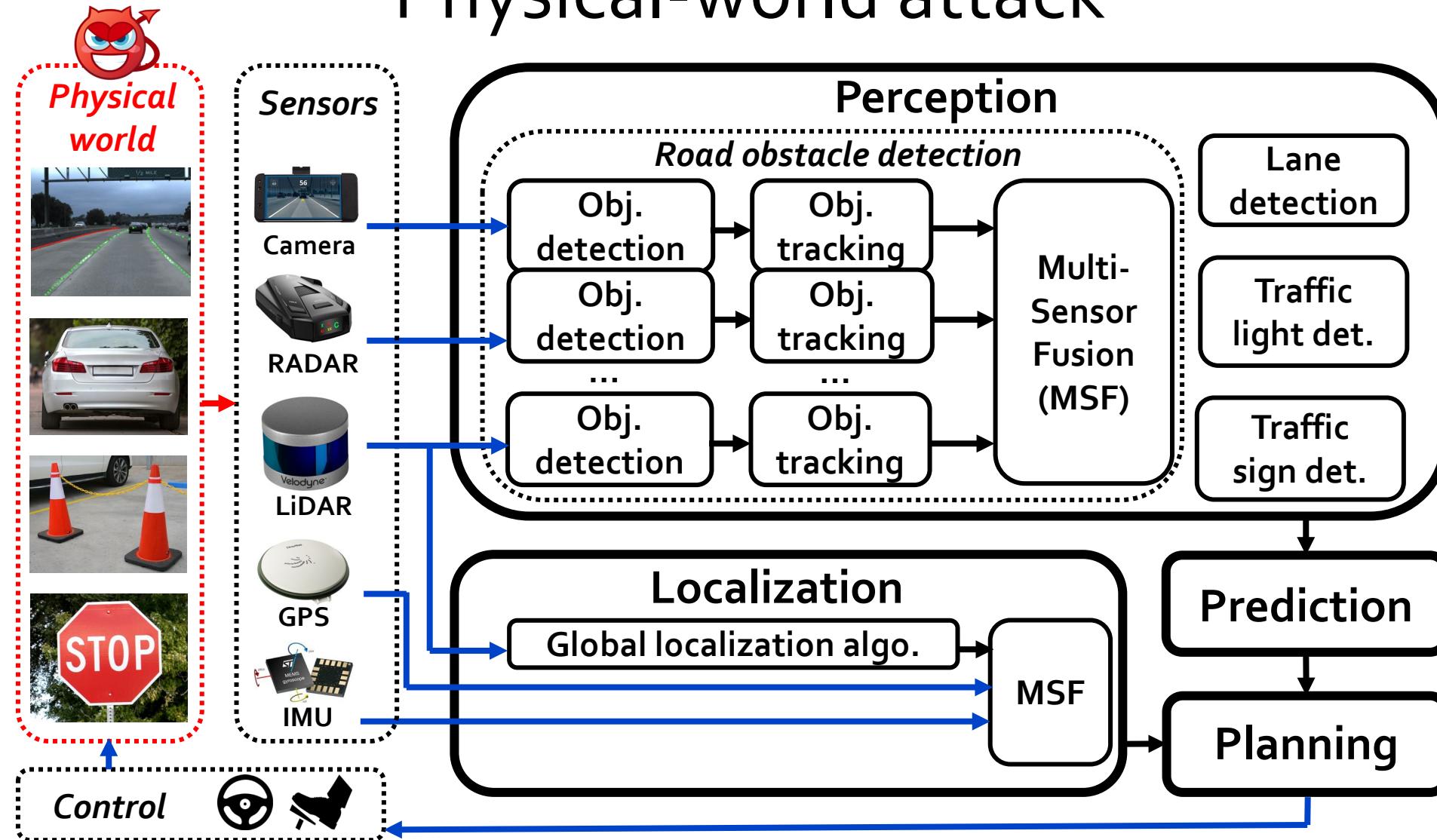
# General & fundamental attack surface #1: Sensor attack



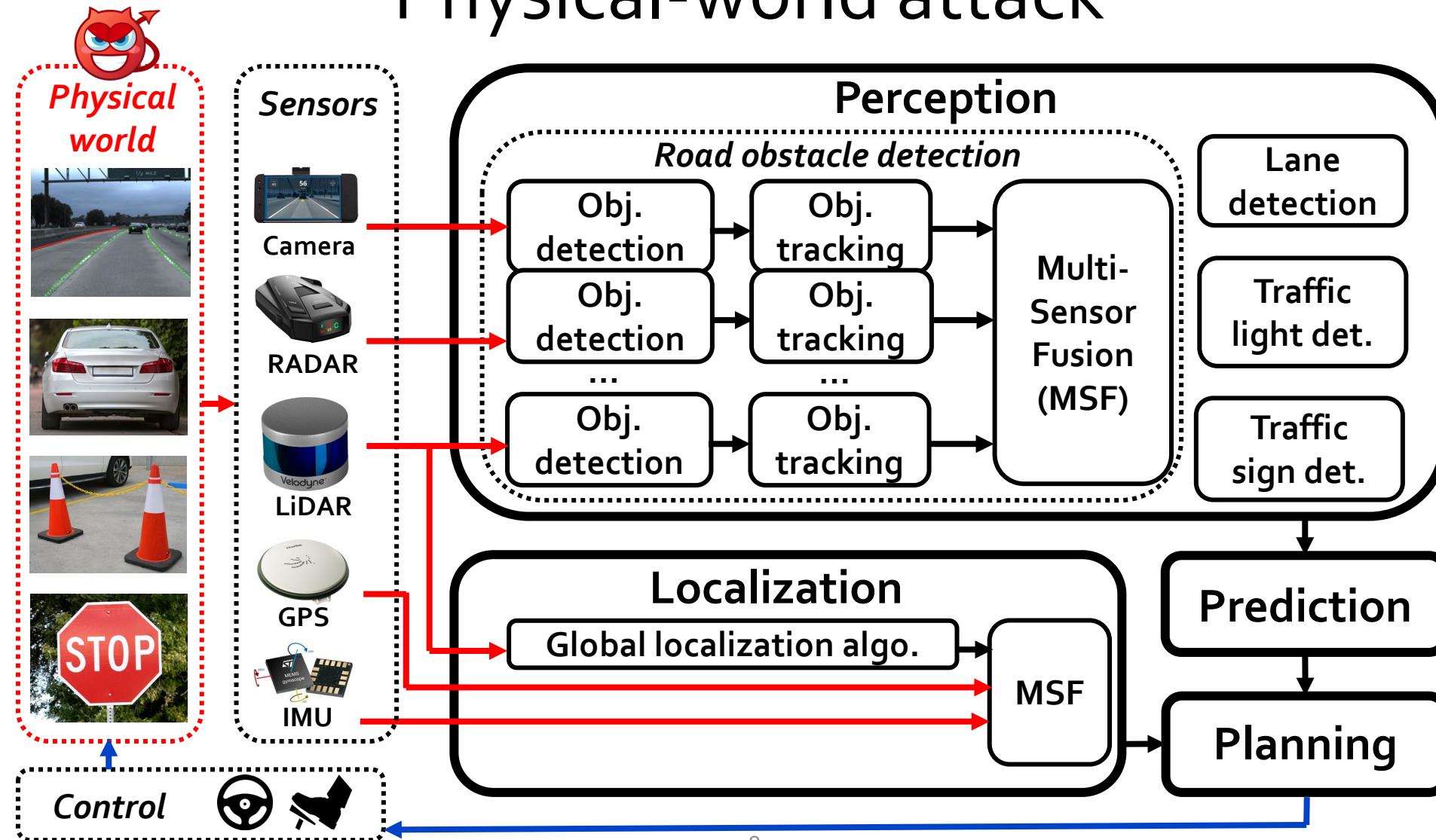
# General & fundamental attack surface #1: Sensor attack



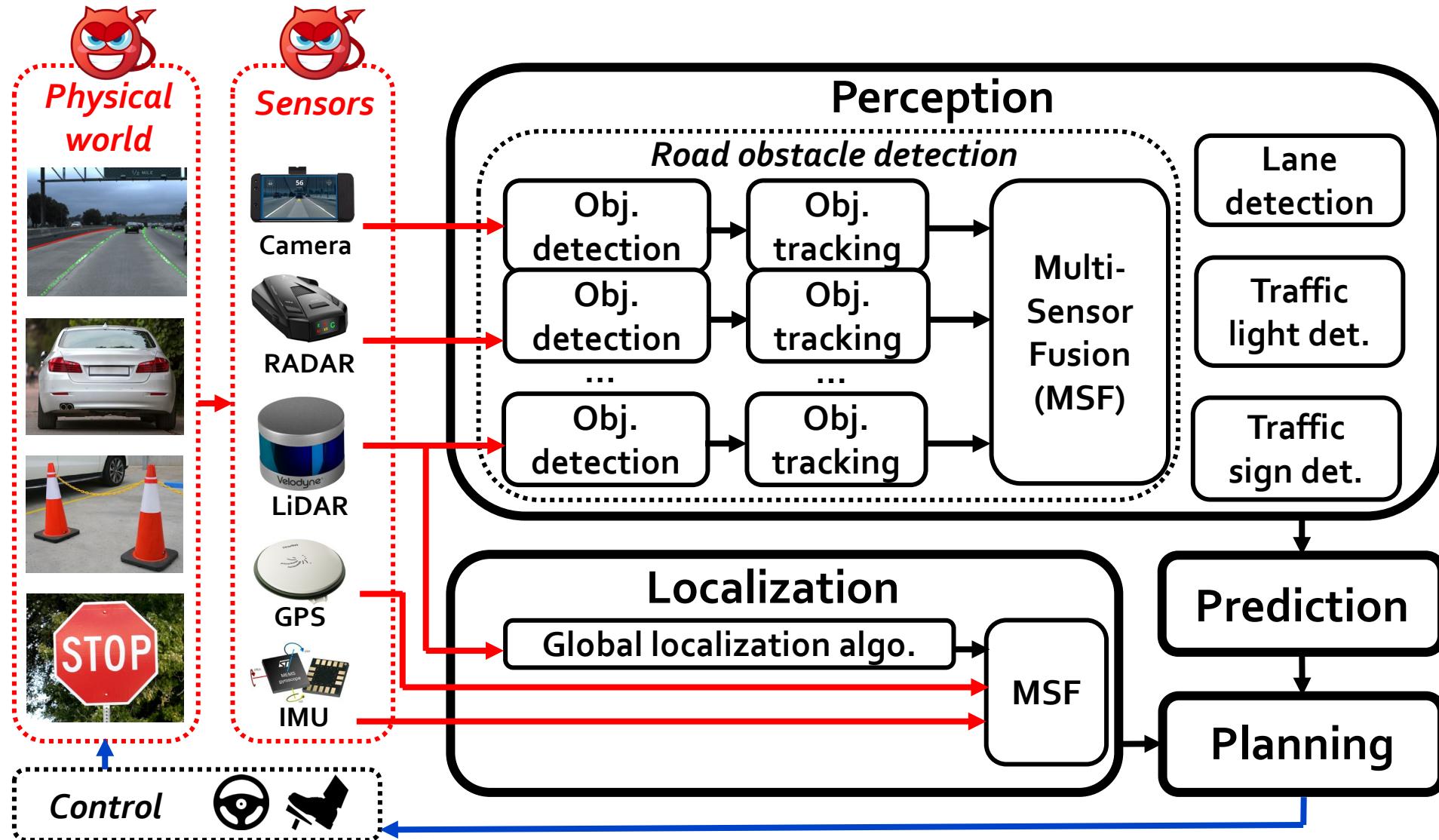
# General & fundamental attack surface #2: Physical-world attack



# General & fundamental attack surface #2: Physical-world attack

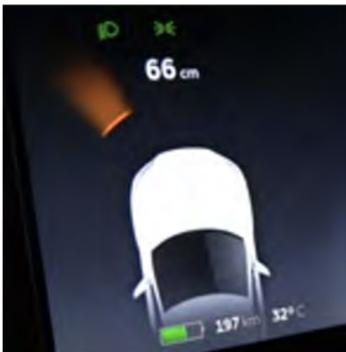
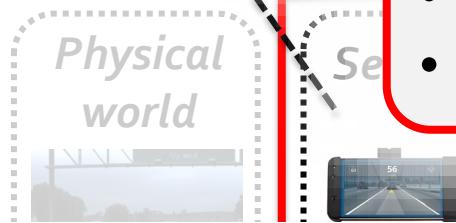


# Both are considered in my research

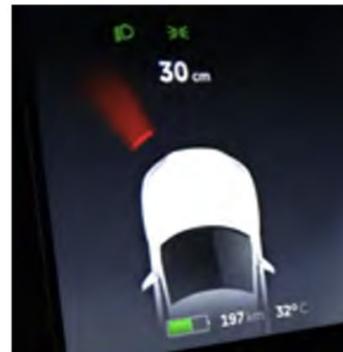


*Black Hat'15,  
DEF CON'16*

- Target: Sensors in production AD systems (e.g., Tesla)
- Attack vector: Sensor spoofing/jamming
- Impact: Make road obstacle disappear, or spoof fake ones



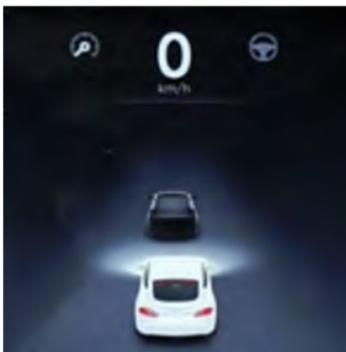
(a) Normal.



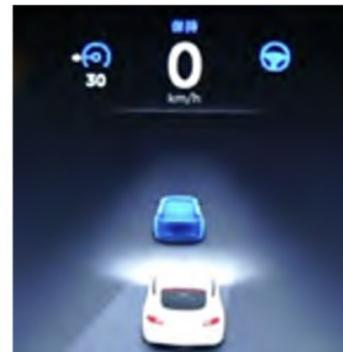
(b) Spoofed.



(c) Jammed.



(a) Drive gear.

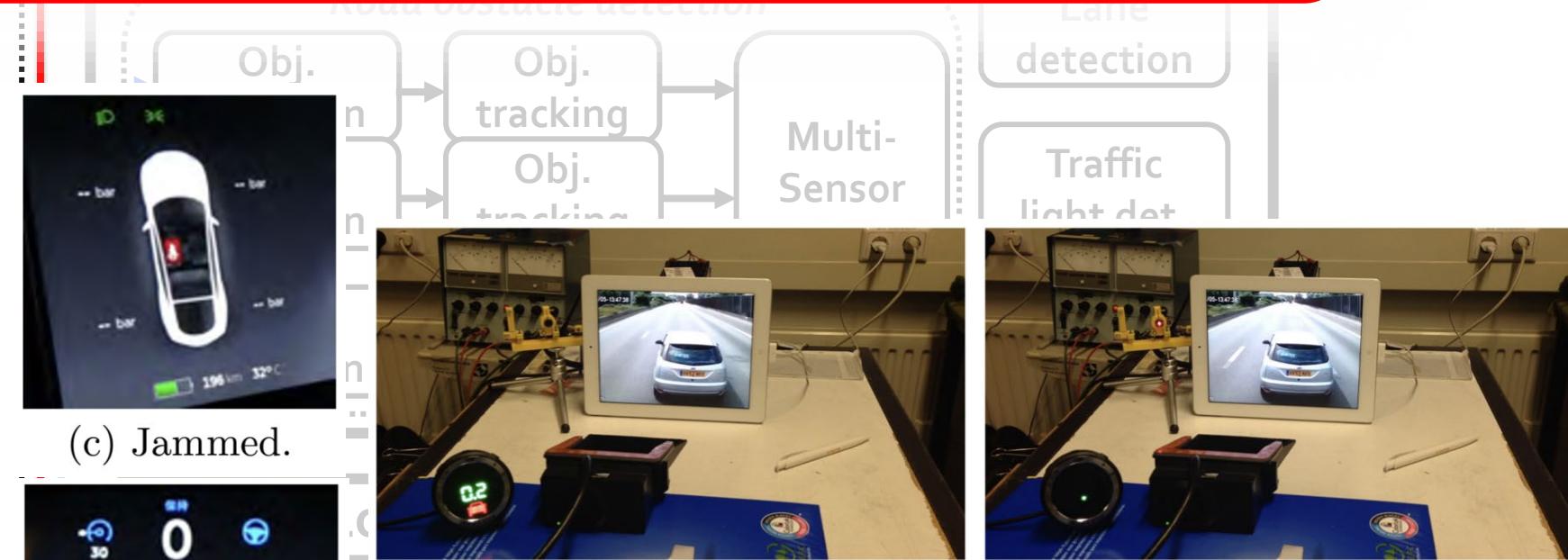


(b) Autopilot.



(c) Jammed.

[Yan et al. @ DEF CON 2016]



- (a) Laser off, normal behavior of MobilEye C2-270
- (b) Laser on, MobilEye C2-270 does not detect vehicle ahead

[Petit et al. @ Black Hat 2015]



*Physical world*



*Control*

*Sensors*

Camera

RADAR

LiDAR  
Velodyne®

GPS

IMU

**Perception**

*Road obstacle detection*

Obj.  
detection

Obj.  
detection

Obj.  
detection

Obj.  
tracking

Obj.  
tracking

Obj.  
tracking

Multi-  
Sensor  
Fusion  
(MSF)

Lane  
detection

Traffic  
light det.

Traffic  
sign det.

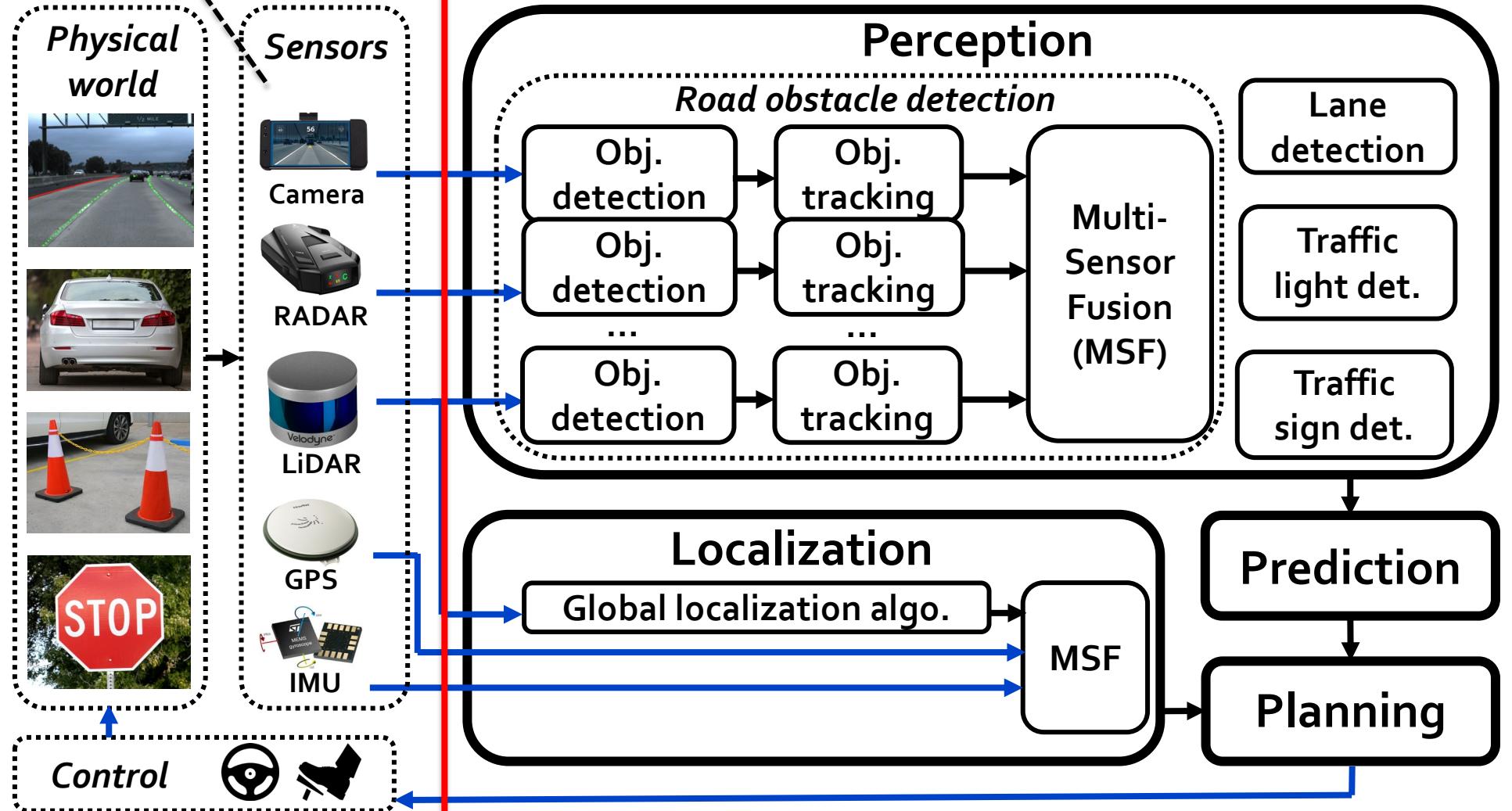
**Localization**

Global localization algo.

MSF

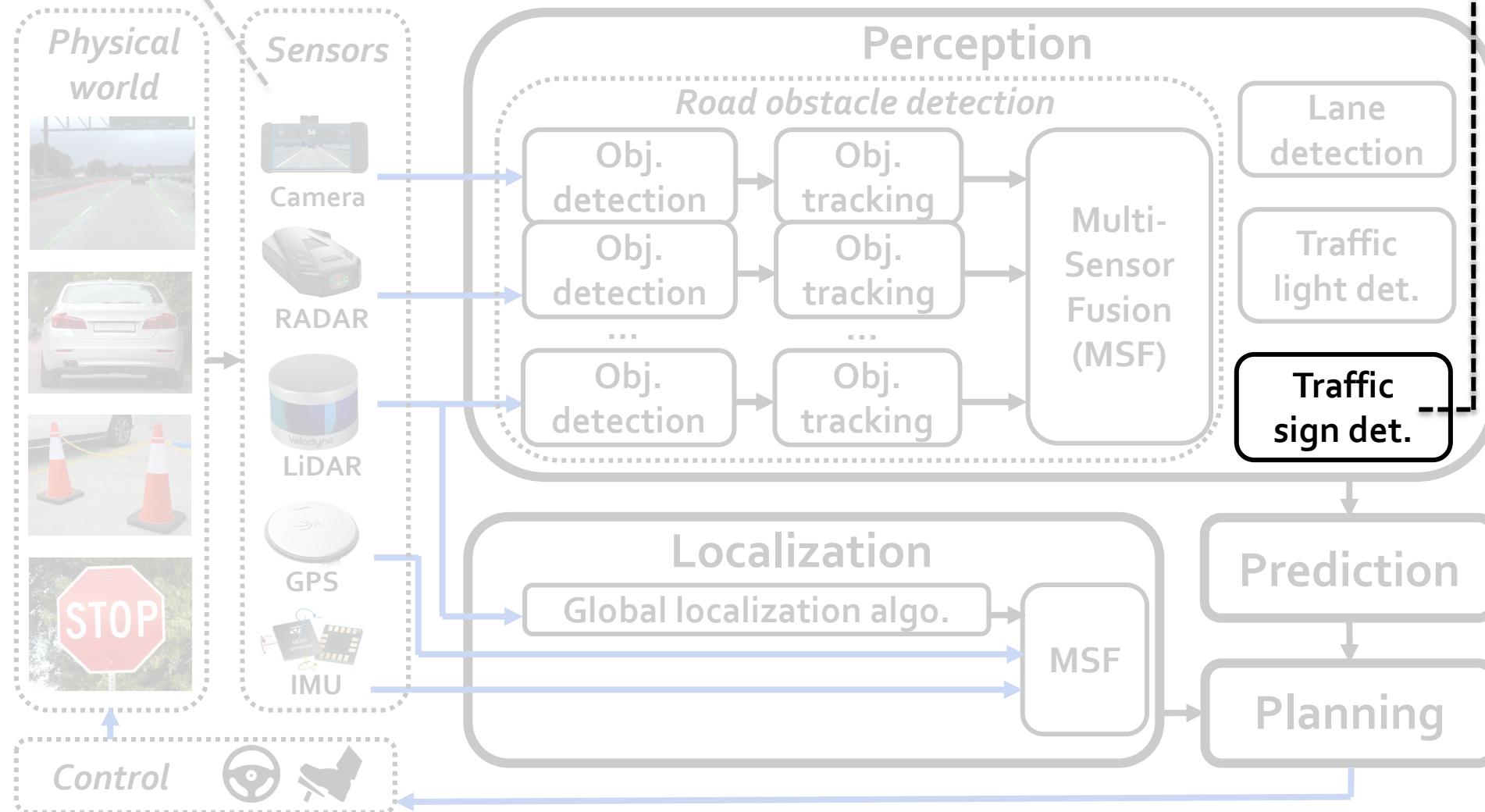
**Prediction**

**Planning**



*Black Hat'15,  
DEFCON'16*

*CVPR'18,  
WOOT'18,  
..., CCS'19*

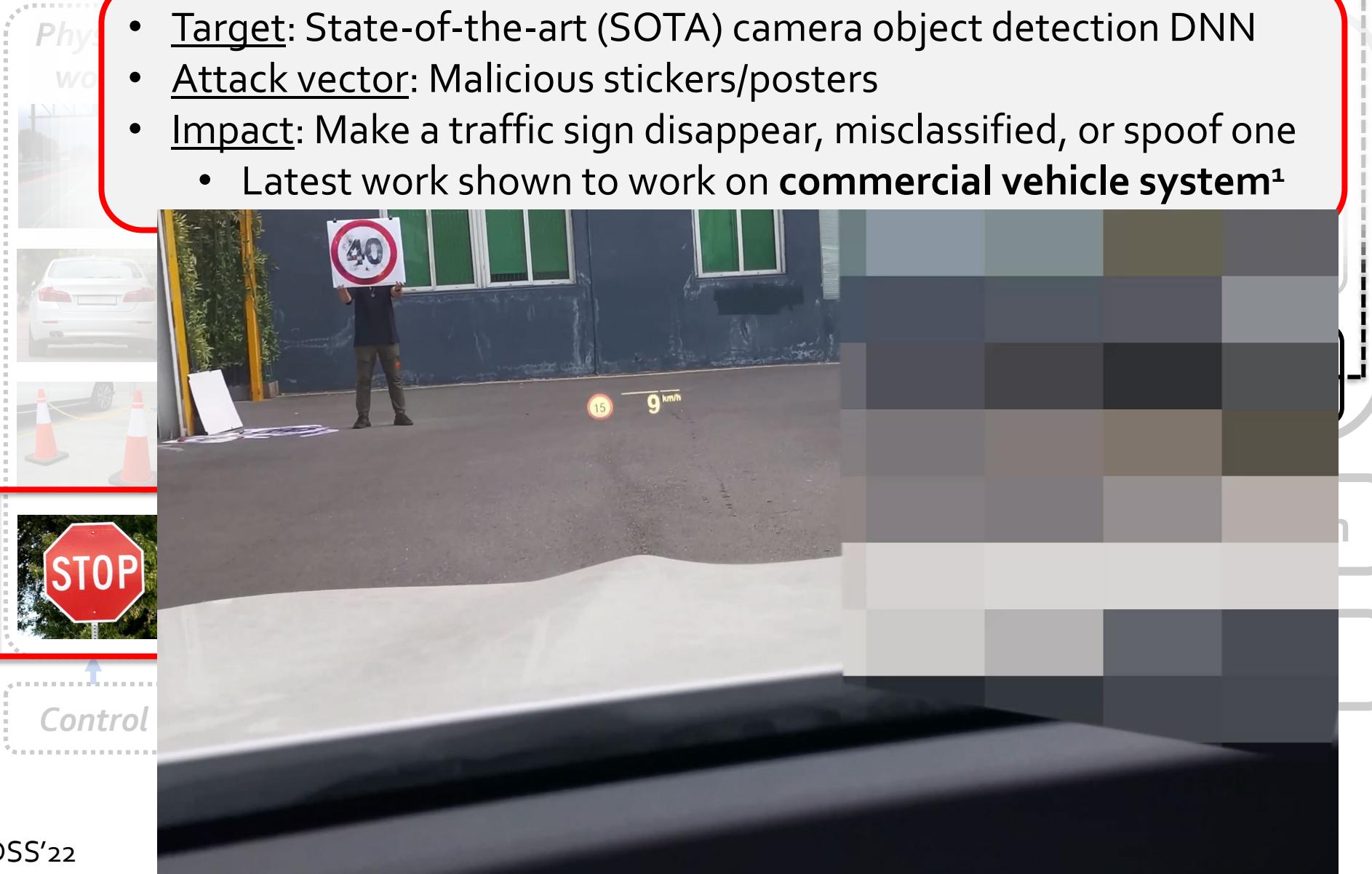


- Target: State-of-the-art (SOTA) camera object detection DNN
- Attack vector: Malicious stickers/posters
- Impact: Make a traffic sign disappear, misclassified, or spoof one



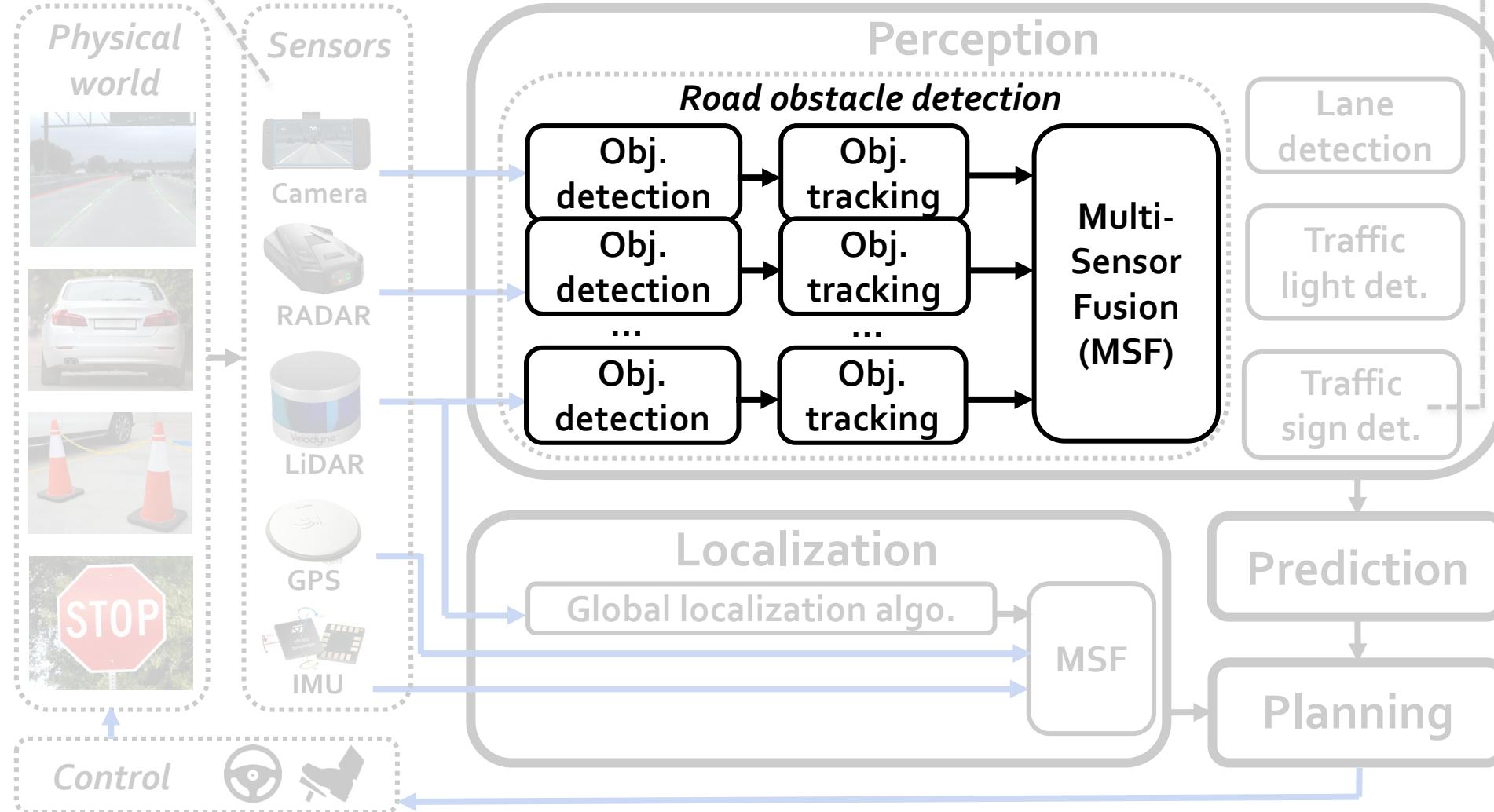
[Zhao et al. @ CCS'19]

- Target: State-of-the-art (SOTA) camera object detection DNN
- Attack vector: Malicious stickers/posters
- Impact: Make a traffic sign disappear, misclassified, or spoof one
  - Latest work shown to work on **commercial vehicle system<sup>1</sup>**



*Black Hat'15,  
DEFCON'16*

*CVPR'18,  
WOOT'18,  
..., CCS'19*

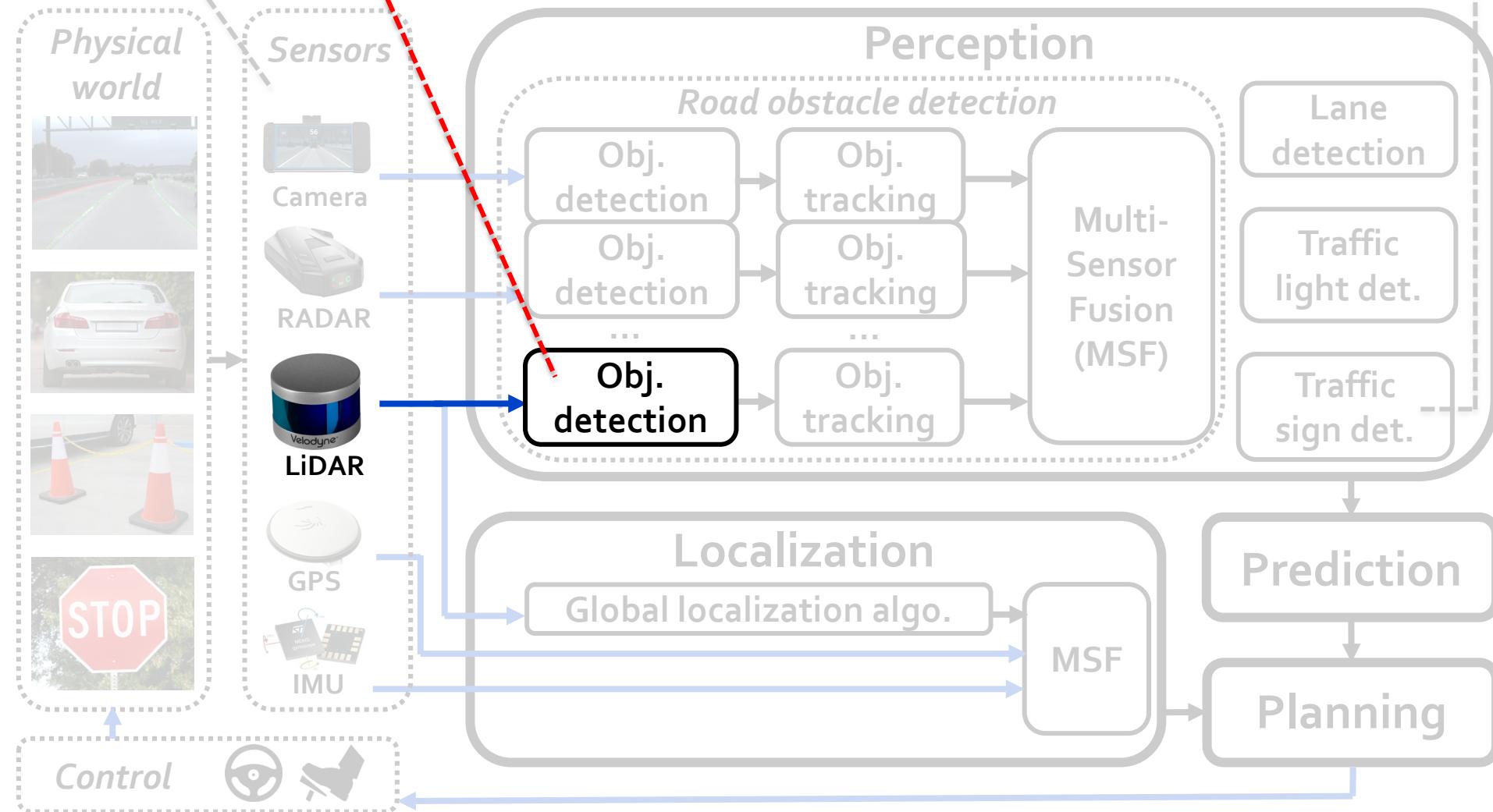


*Black Hat'15,  
DEFCON'16*

**CCS'19 (attack),  
Usenix Security'20  
(defense)**

*CVPR'18,  
WOOT'18,  
..., CCS'19*

 My group's  
paper



*Black Hat'15,  
DEFCON'16*

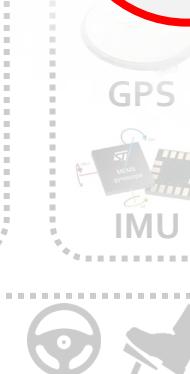
*CCS'19 (attack),  
Usenix Security'20  
(defense)*

*CVPR'18,  
WOOT'18,  
..., CCS'19*

*Physical  
world*



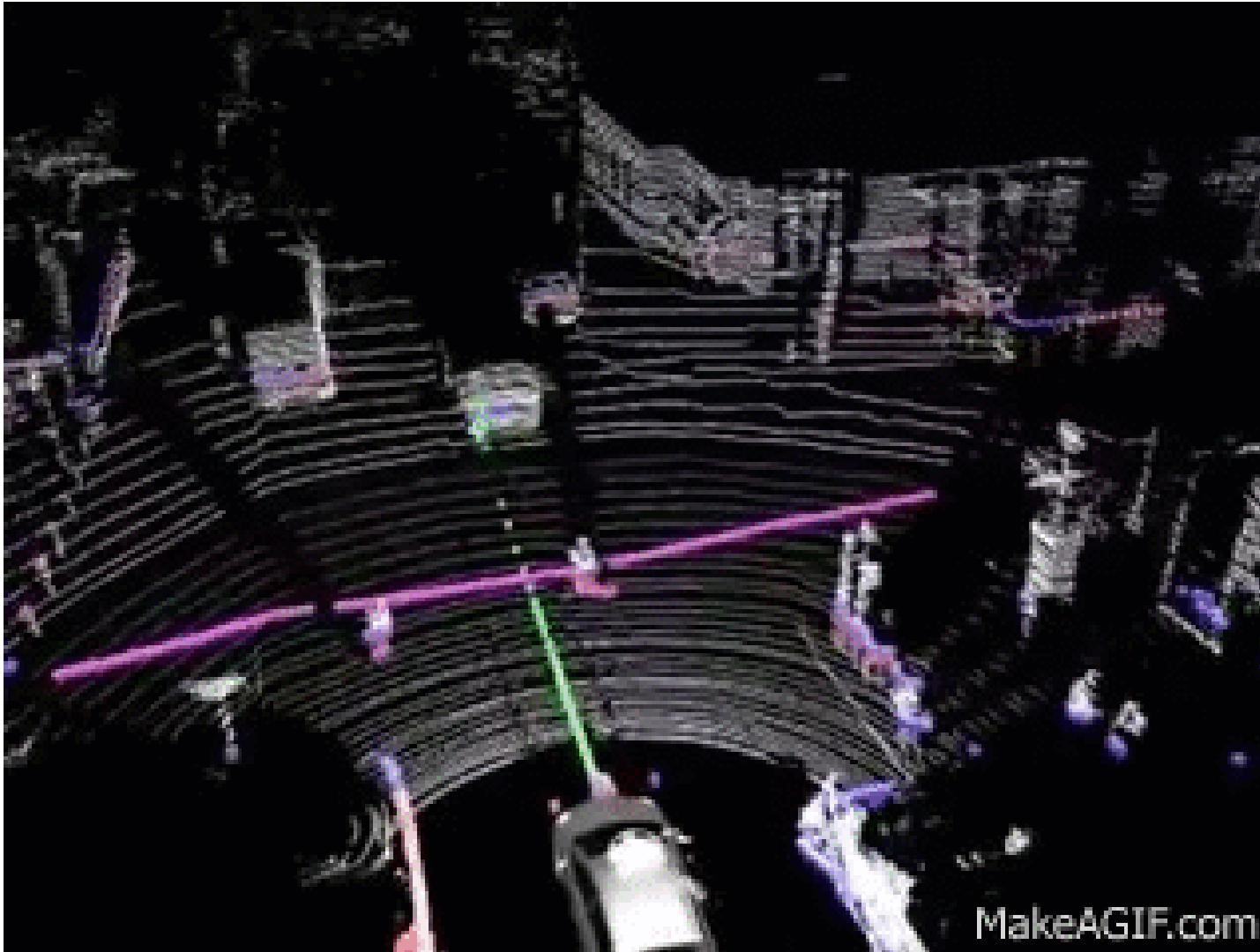
*Control*



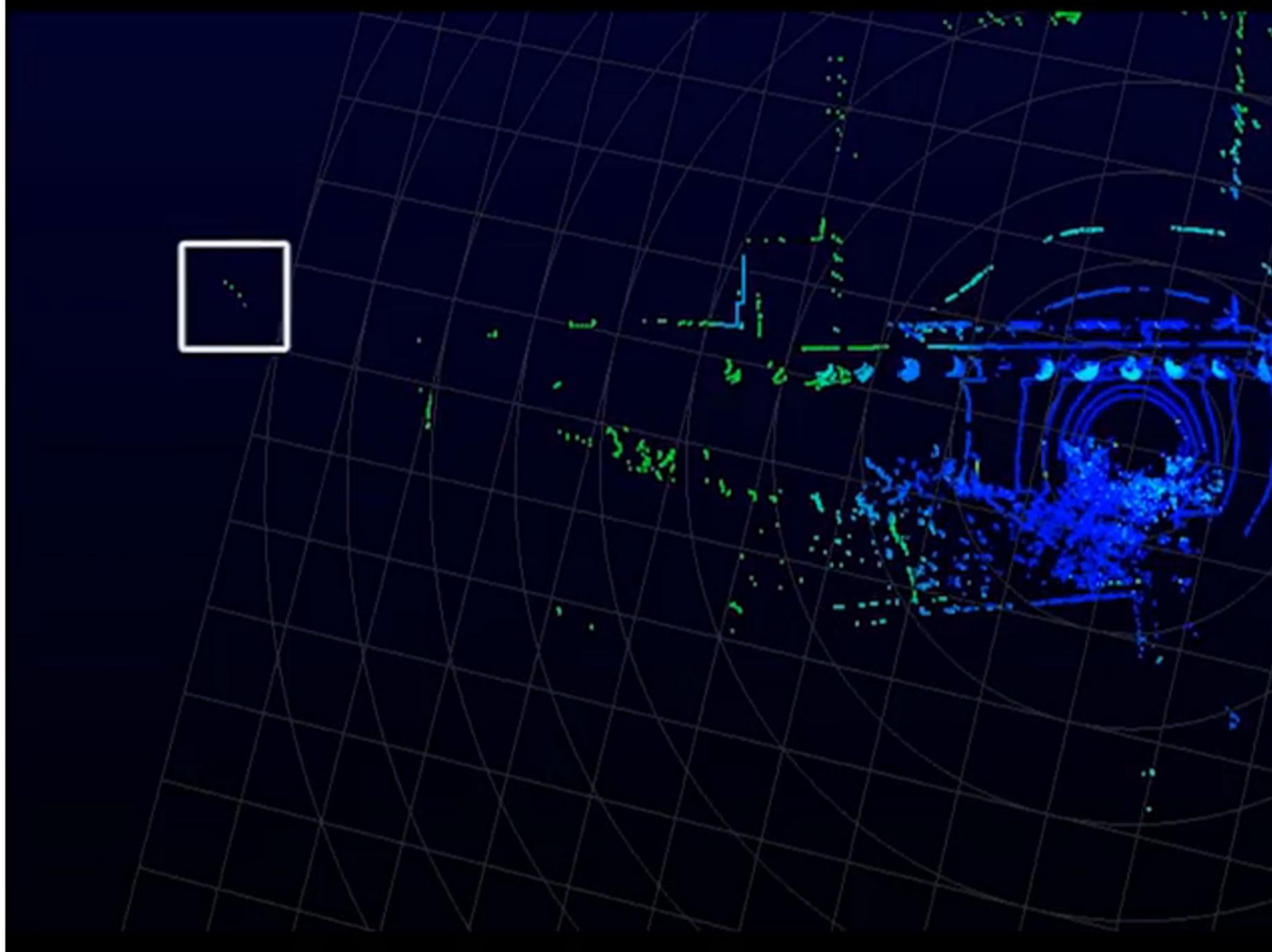
- ***First*** security analysis for **3D object detection**
- Attack vector: LiDAR spoofing

*My group's  
paper*

# Background: LiDAR basics

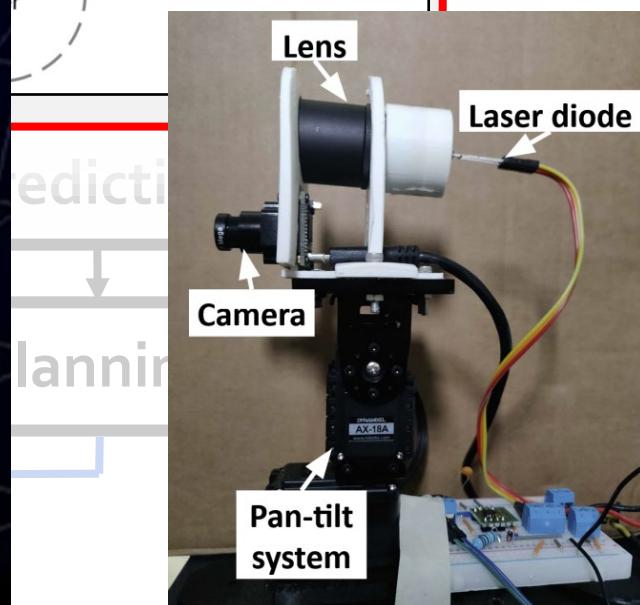
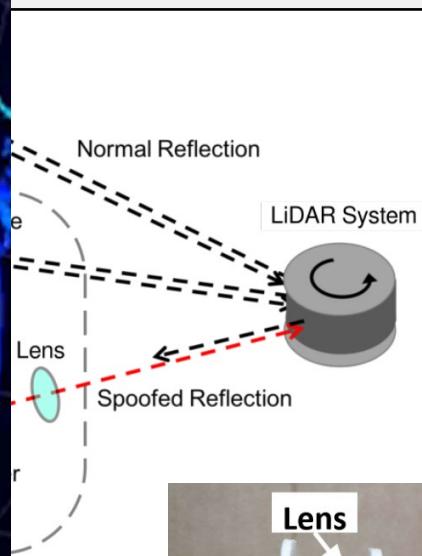


MakeAGIF.com



CVPR'18,  
WOOT'18,  
..., CCS'19

My group's  
paper



[Cao et al. @ AutoSec'21]

Black Hat'15,  
DEFCON'16

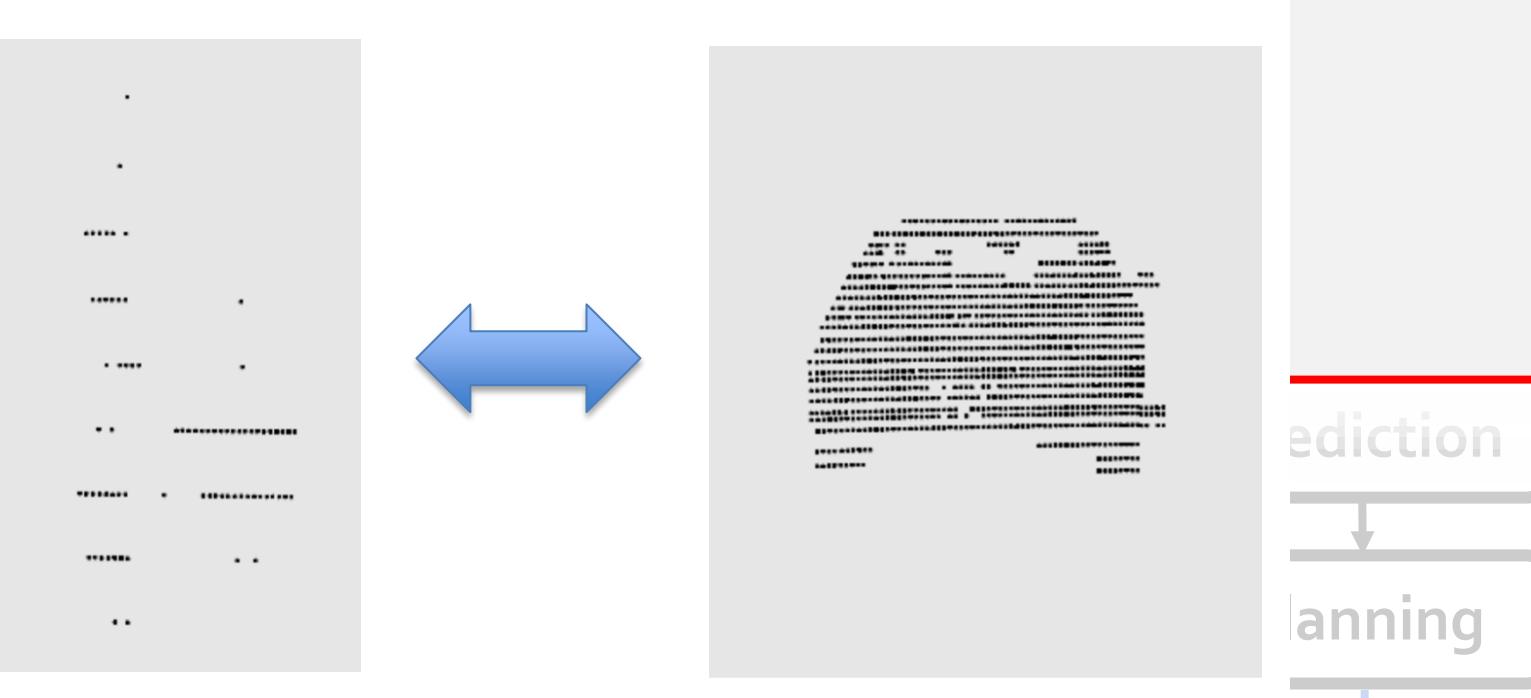
CCS'19 (attack),  
Usenix Security'20  
(defense)

CVPR'18,  
WOOT'18,  
..., CCS'19



- **First** security analysis for 3D object detection
- Attack vector: LiDAR spoofing

My group's paper



Blind spoofing is not enough: Tried various different angles & shapes, cannot spoof fake obstacles at SOTA LiDAR detection model output at all

Black Hat'15,  
DEFCON'16

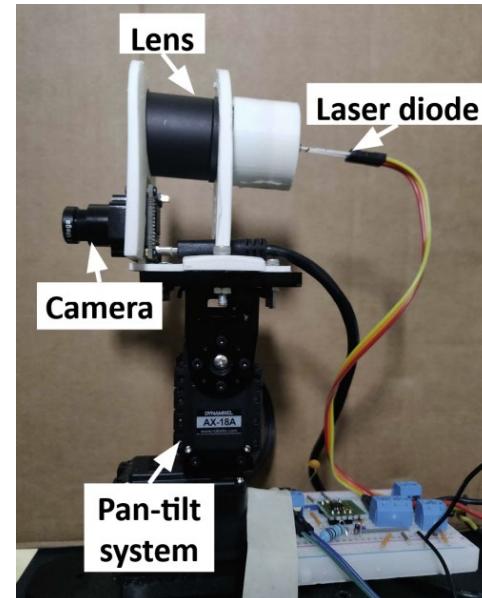
CCS'19 (attack),  
Usenix Security'20  
(defense)

CVPR'18,  
WOOT'18,  
..., CCS'19

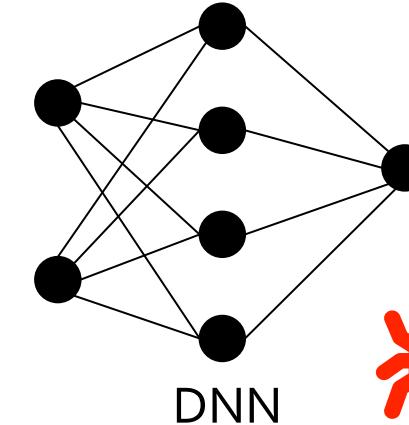
Physical world



Control



### LiDAR object detection



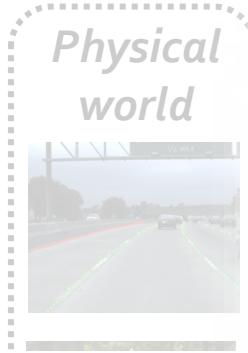
**First sensor-AI co-designed attack**

- Call it “adversarial sensor attack”

My group's paper

Black Hat'15,  
DEFCON'16

CCS'19 (atta  
Userix Securi  
(defense)

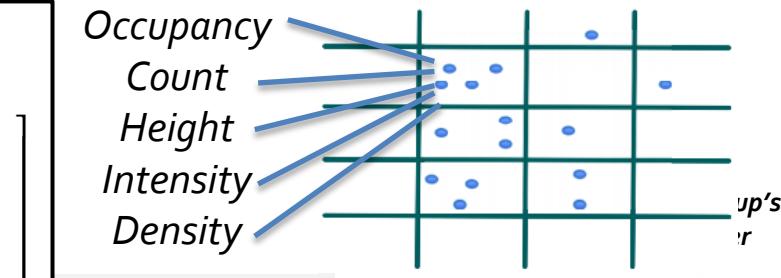


- First
- Attack
- Solu

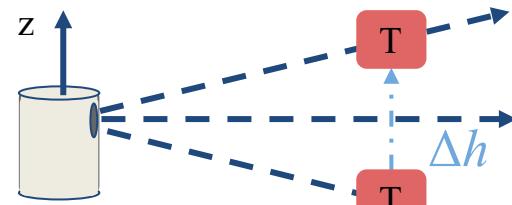
Differentiable

$$x' = x \oplus t'$$

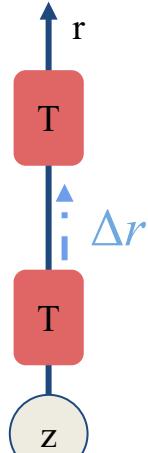
$$= \begin{bmatrix} (I_{avg\_h}^x \cdot I_{cnt}^x + I_{avg\_h}^{t'} \cdot I_{cnt}^{t'}) / (I_{cnt}^x + I_{cnt}^{t'}) \\ \max(I_{max\_h}^x, I_{max\_h}^{t'}) \\ (I_{avg\_int}^x \cdot I_{cnt}^x + I_{avg\_int}^{t'} \cdot I_{cnt}^{t'}) / (I_{cnt}^x + I_{cnt}^{t'}) \\ \sum I_{max\_int}^x \cdot 1\{I_{max\_h}^x = \max\{I_{max\_h}^x, I_{max\_h}^{t'}\}\} \end{bmatrix}$$



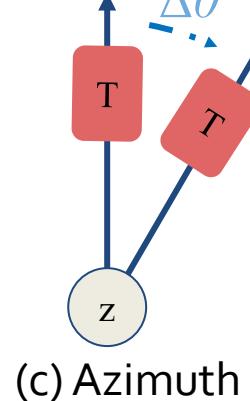
Optimize w/ **differentiable spoofing capability modelling** & **spatial transformation** of attack trace



(b) Altitude



(a) Distance



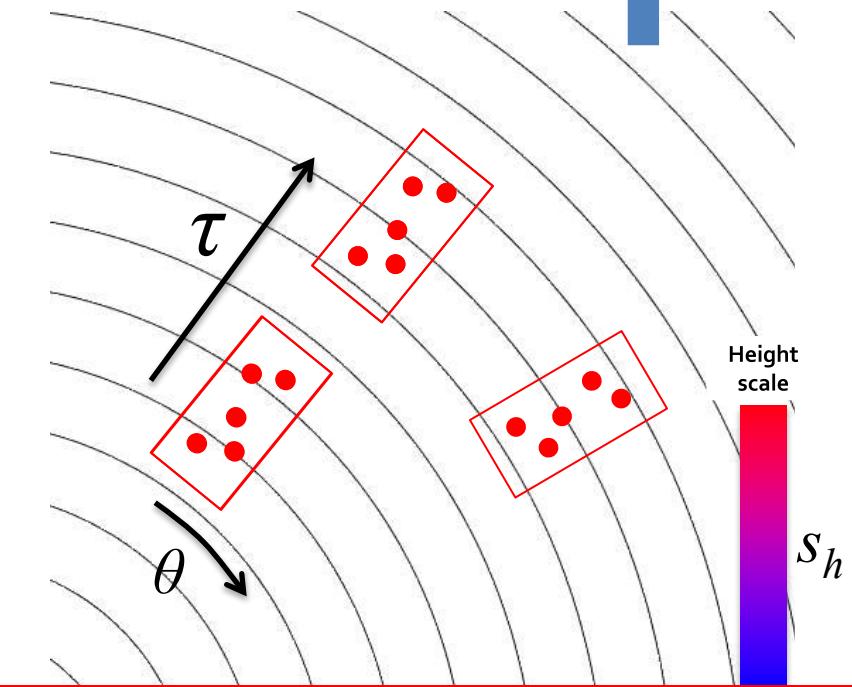
(c) Azimuth

Differentiable

$$\begin{bmatrix} T'_{w_x} \\ T'_{w_y} \\ T'_{w_z} \\ 1 \end{bmatrix} = \begin{bmatrix} \cos \theta & -\sin \theta & 0 & \tau_x \\ \sin \theta & \cos \theta & 0 & 0 \\ 0 & 0 & s_h & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \cdot \begin{bmatrix} T_{w_x} \\ T_{w_y} \\ T_{w_z} \\ 1 \end{bmatrix}$$

### Spatial Transformation

$$G_t(\theta, \tau_x, s_h; t)$$



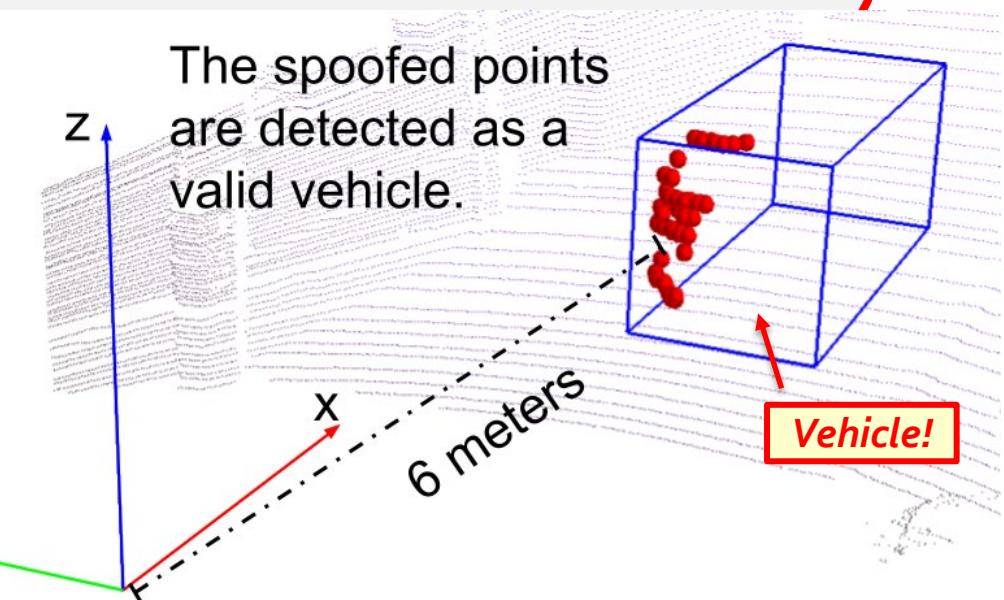
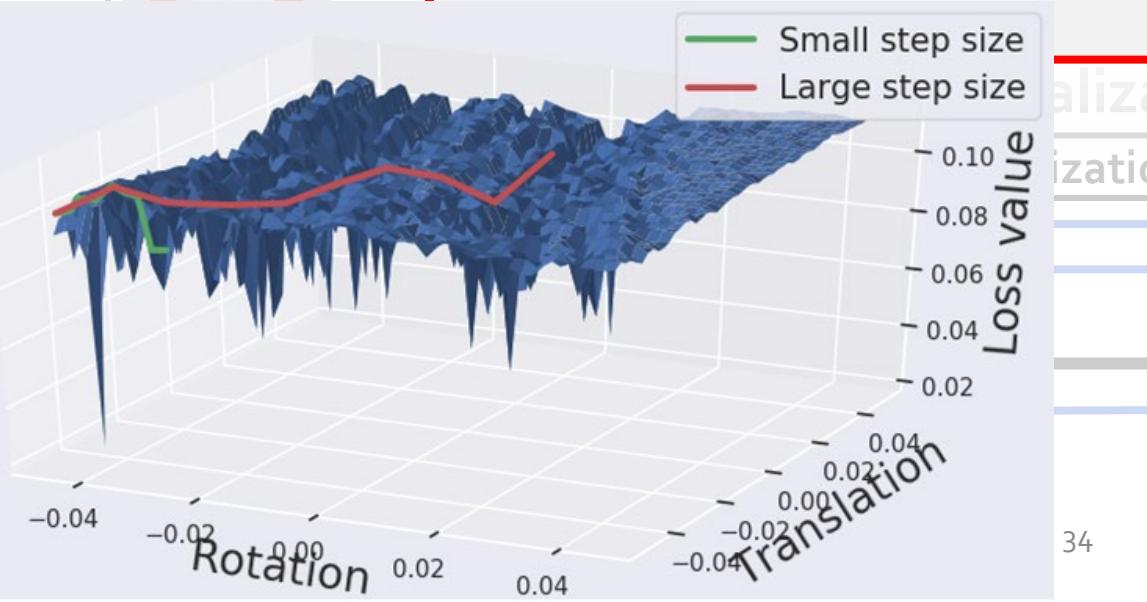
Addressing System-to-AI semantic gap: from attack perturbation capability at CPS system input space (i.e., LiDAR spoofing capability) to that at AI component input space (i.e., DNN model input)

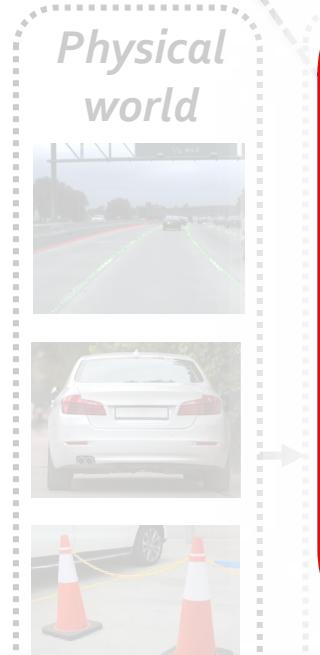
Physical world



- **First** security analysis for **3D object detection**
- Attack vector: LiDAR spoofing
- Solution: Combine sensor spoofing with adversarial AI attack!
  - Optimize w/ **differentiable spoofing capability modelling & spatial transformation** of attack trace
  - **Global sampling** to avoid trapping at local minima due to hard perturbation constraints imposed by spoofing capability
  - **0% → 75% success rate** in spoofing a near-front vehicle!

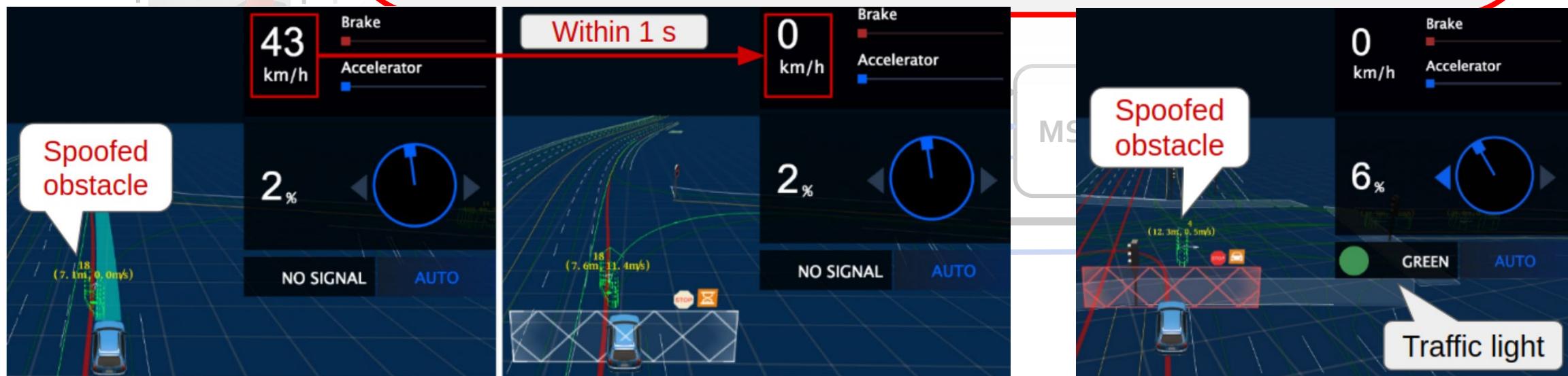
My group's paper





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  - **0% → 75% success rate** in spoofing a near-front vehicle!
- Impact: Causing emergency brake or permanent stop

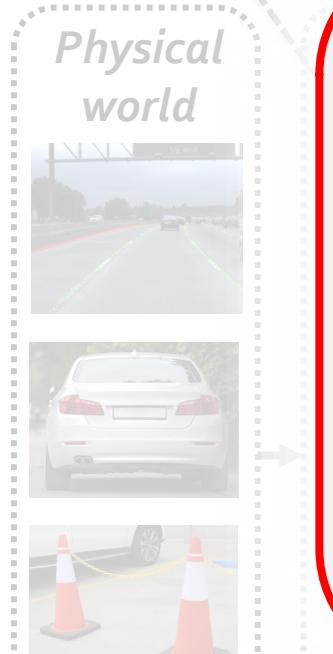
My group's paper



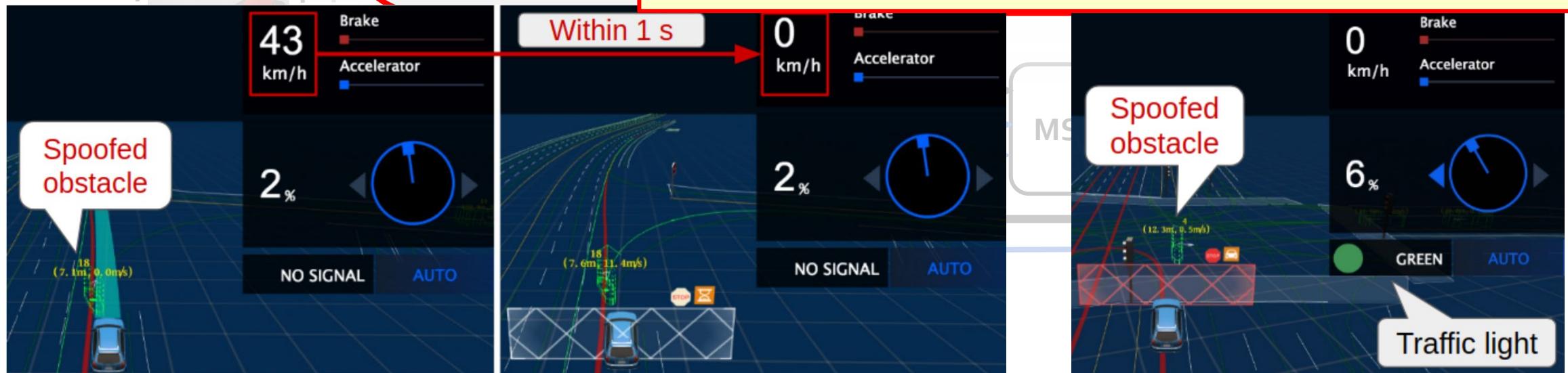
Black Hat'15,  
DEFCON'16

CCS'19 (attack),  
Usenix Security'20  
(defense)

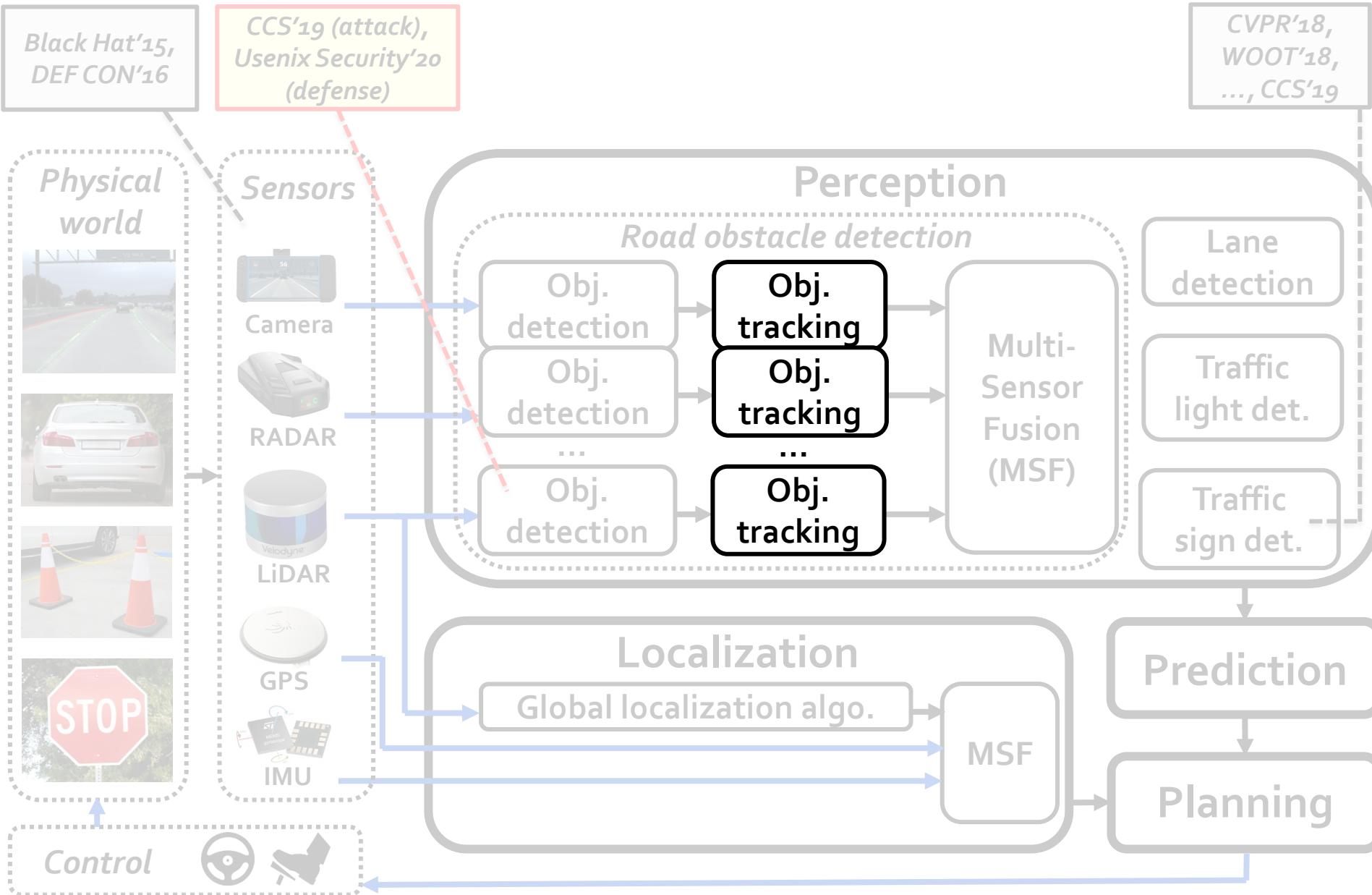
CVPR'18,  
WOOT'18,  
..., CCS'19



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  - **0% → 75% success rate** in spoofing a near-front vehicle!
- Impact: Causi... Addressing AI-to-System semantic gap: from AI component-level errors (i.e., DNN output misdetection) to CPS system-level attack effect (i.e., emergency brake)



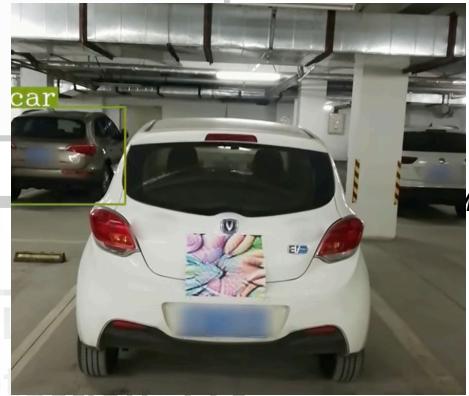
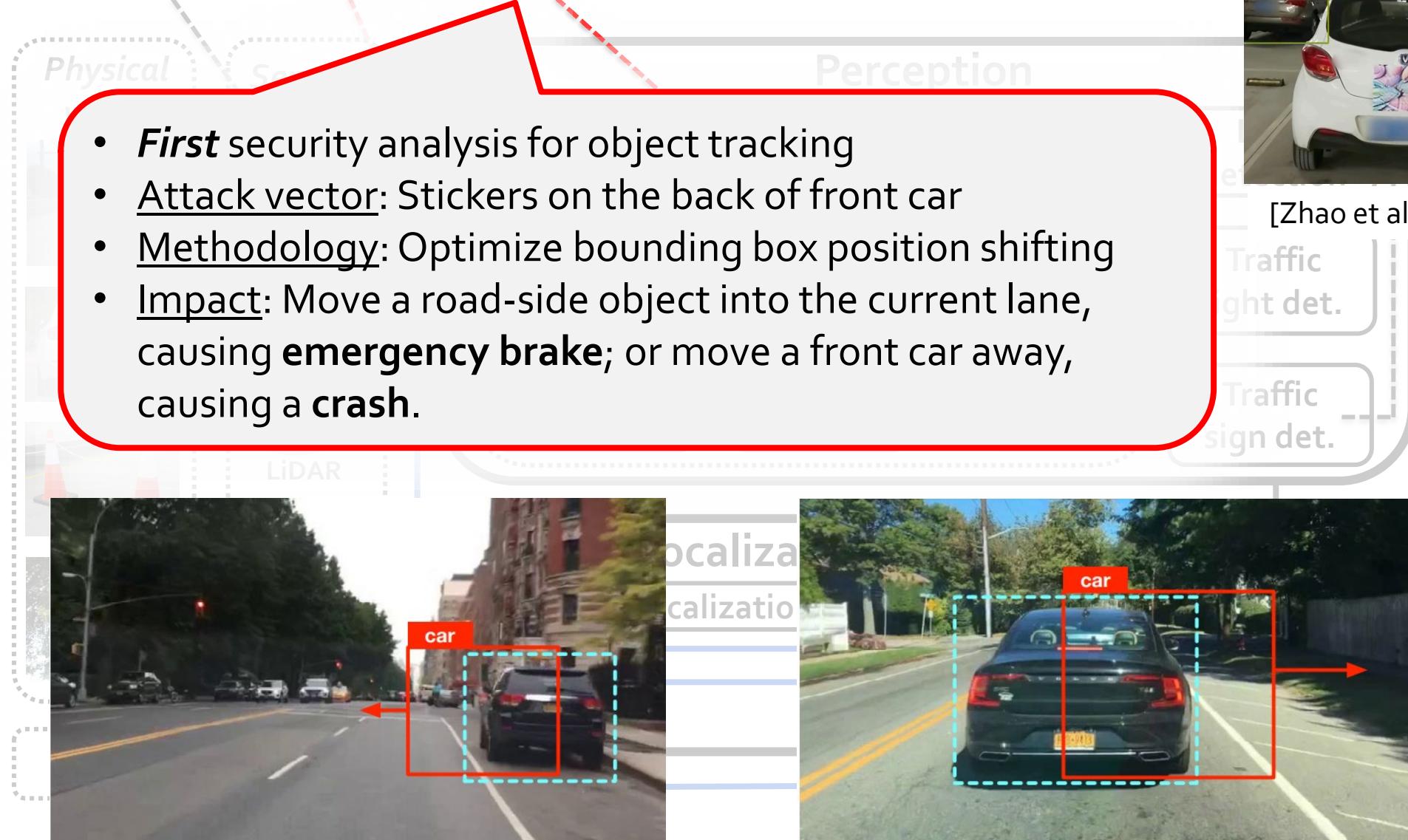
My group's paper



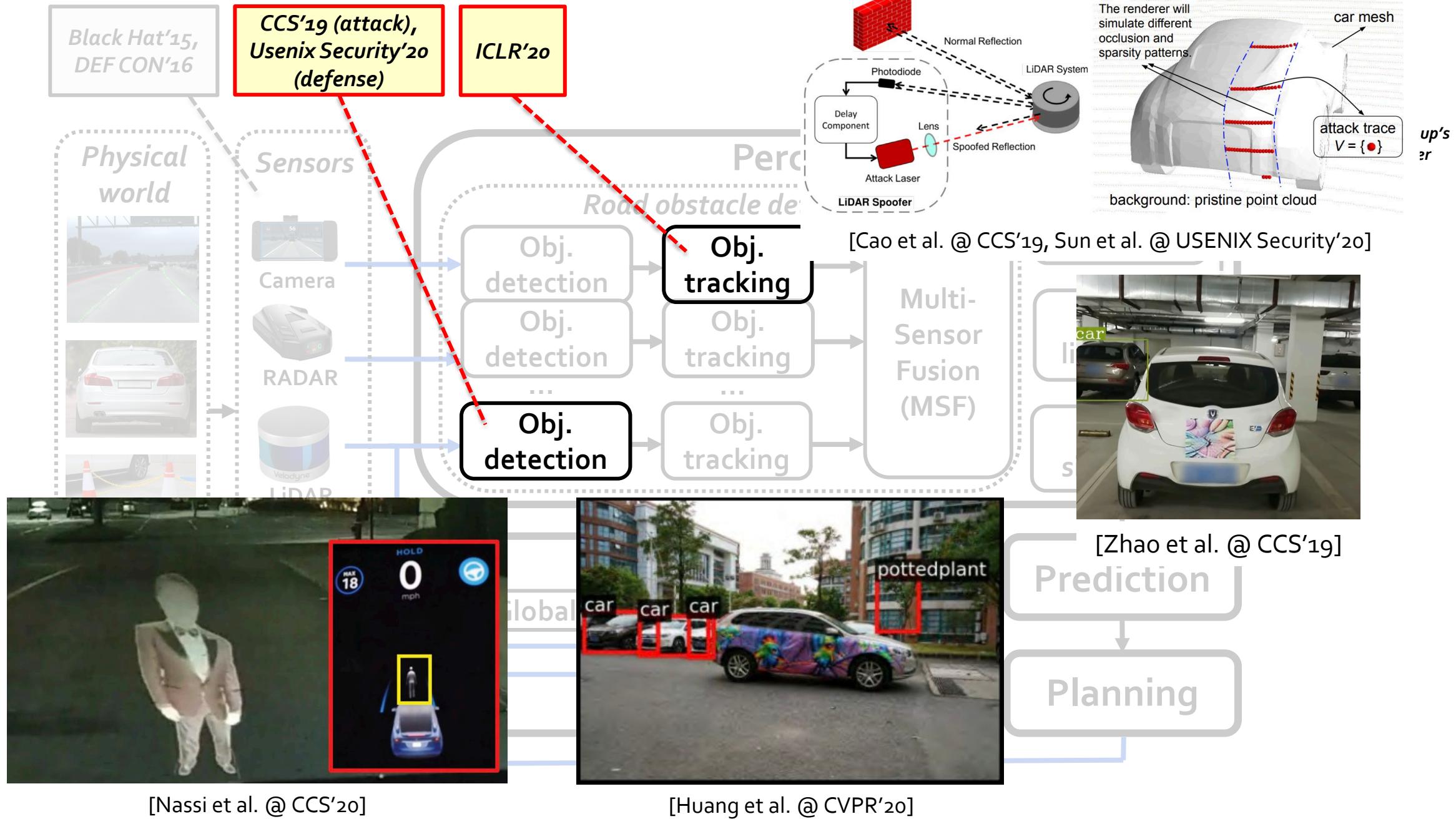
Black Hat'15,  
DEFCON'16

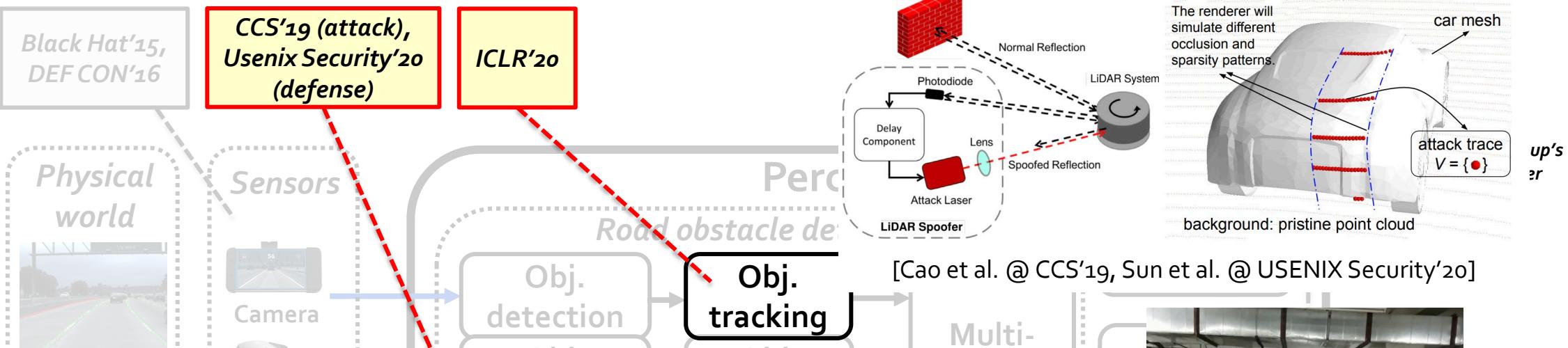
CCS'19 (attack),  
Usenix Security'20  
(defense)

ICLR'20



[Zhao et al. @ CCS'19]





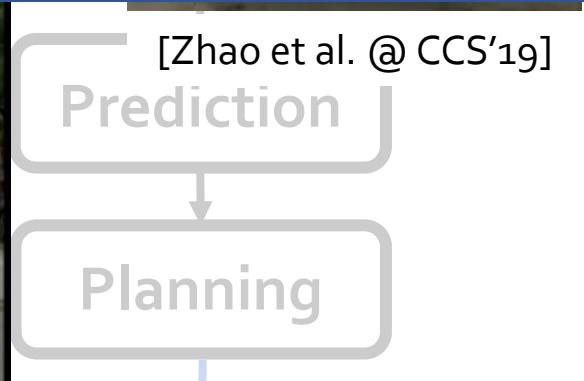
*All limited to attacks on a single source of AD perception,  
e.g., camera- or LiDAR-based AD perception alone!*



[Nassi et al. @ CCS'20]

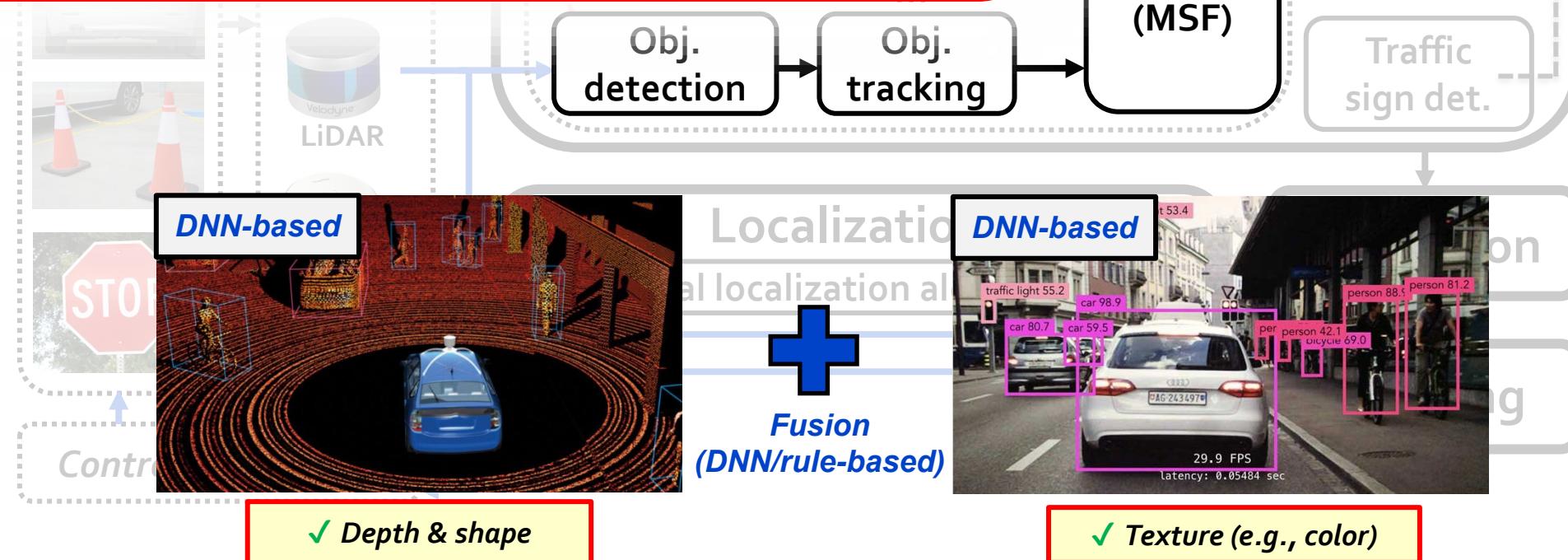


[Huang et al. @ CVPR'20]



- Generally adopted by production AD to achieve overall high robustness & accuracy in practical settings
  - Typically *camera + LiDAR*, based on *DNN*
- Assuming not all perception sources are (or can be) attacked simultaneously, should generally be able to *at least detect single-source attacks*

Basic security design assumption:  
**Believed to hold in general**



# MSF: Widely recognized as a general defense strategy against existing attacks on AD perception

10.3.2 *Sensor-Level Defenses.* Several defenses could be adopted against spoofing attacks on LiDAR sensors:

**Detection techniques.** Sensor fusion, which intelligently combines data from several sensors to detect anomalies and improve performance, could be adopted against LiDAR spoofing attacks. Systems are often equipped with sensors beyond LiDAR. Cameras, radars, and ultrasonic sensors provide additional information redundancy to detect and handle an attack on LiDAR.

[Cao et al. @ CCS'19]

As the system's autonomy increases, so does the concern about its security. In modern vehicles, a malicious attacker may deceive the controller into performing a dangerous action by altering the measurements of some sensors [1], [2]. Depending on the attacker's goal and capabilities, the consequences range from minor disturbances in performance to catastrophic loss of human lives. Consequently, performing attack sensor fusion is essential for the safety of such systems.

[Ivanov et al. @ DATE'14]

## 5.2 Potential Countermeasures

**Redundancy and Fusion:** If a vehicle is equipped with multiple lidars having an overlapping field of view, the effect of saturating and spoofing can be mitigated to a certain extent. However, this directly increases the cost, and is not a definitive solution because attackers can spoof one lidar while the others are unaffected. Besides, it is also not easy to detect specific spoofing in non-overlapped zones. Likewise, the fusion of data from multiple sensors [44] has been revealed to be vulnerable to spoofing.

[Shin et al. @ CHES'17]

In this work, we do not assume any particular sensing or actuation workflow to be trusted. However, we do assume that not all sensor readings can be corrupted simultaneously.

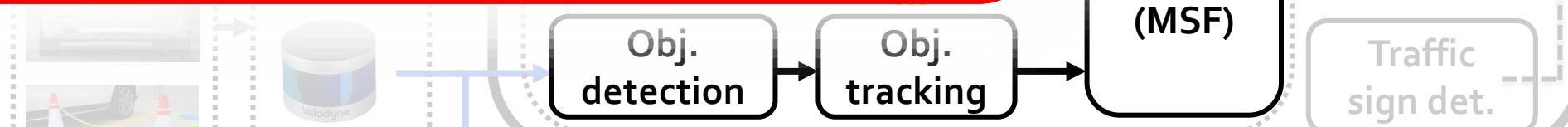
Under the design where workflows run with isolation (see Section II-A), attacks or failures in a workflow can be constrained within. Admittedly, such cases could be possible in carefully crafted attacks. However, it is difficult for attackers. Firstly, for heterogeneous sensors, holding a vulnerability and a corresponding exploit which targets one sensing workflow is already costly [6], [9], not to mention corrupting all. Secondly, even if an attacker is capable of corrupting all sensors, the attacker must launch the attacks simultaneously to avoid being detected at challenge to launch such coordinated attacks on target sensing workflows [9].

[Guo et al. @ DSN'18]

## 2.1 System Model and Current Approach

We consider a system with  $n$  sensors measuring the same physical variable. As mentioned above, we assume abstract sensors; therefore, each sensor provides the controller with an interval of all possible values. We assume the system queries all the sensors periodically such that a centralized estimator receives measurements from all sensors, and then performs attack detection/identification and sensor fusion (SF). We now explain the current approach to attack detection, referred to herein as a SF-based detector, before providing the improved version addressed in this paper.

- **Generally adopted by production AD to achieve overall high robustness & accuracy in practical settings**
  - Typically *camera + LiDAR*, based on *DNN*
- Assuming not all perception sources are (or can be) attacked simultaneously, should generally be able to ***at least detect single-source attacks***



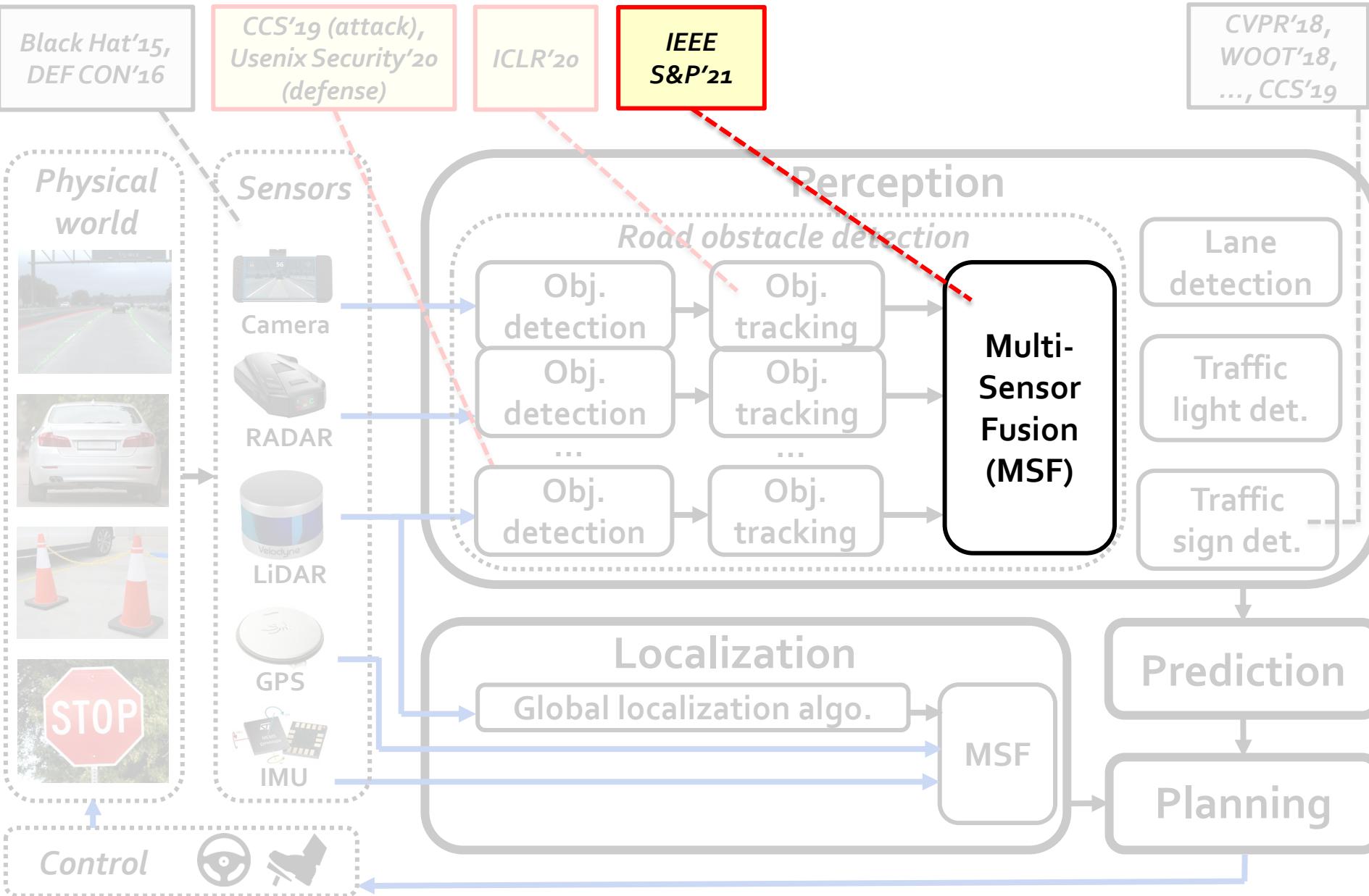
Basic security design assumption:  
***Believed to hold in general***

## Research Question:

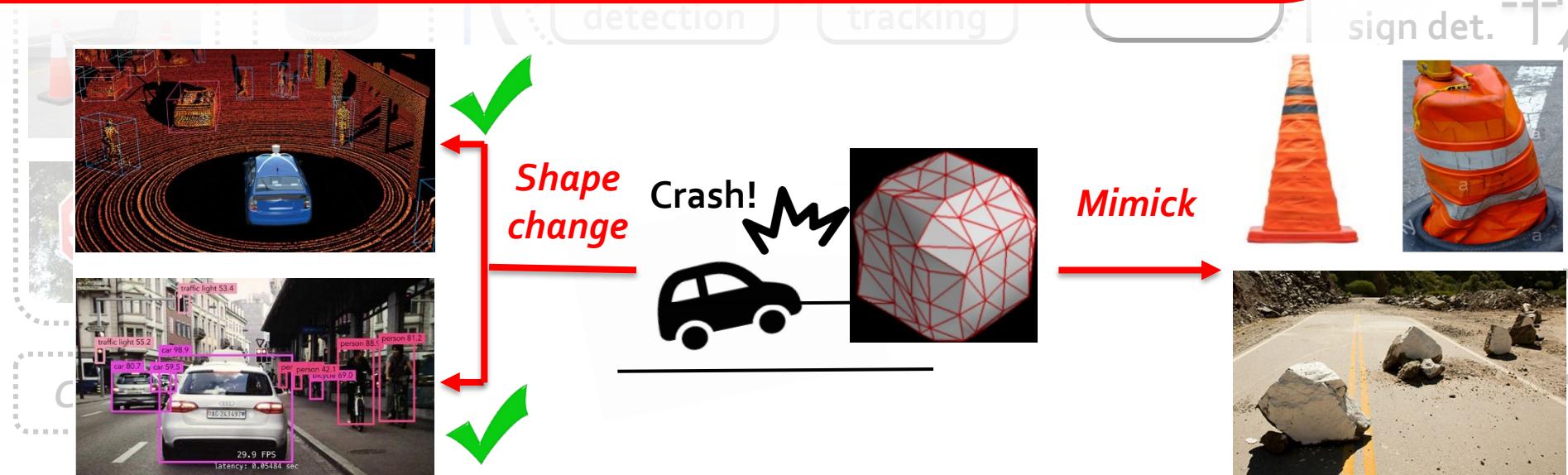
Can such basic security design assumption actually be broken, especially in practical AD settings?

✓ Depth & shape

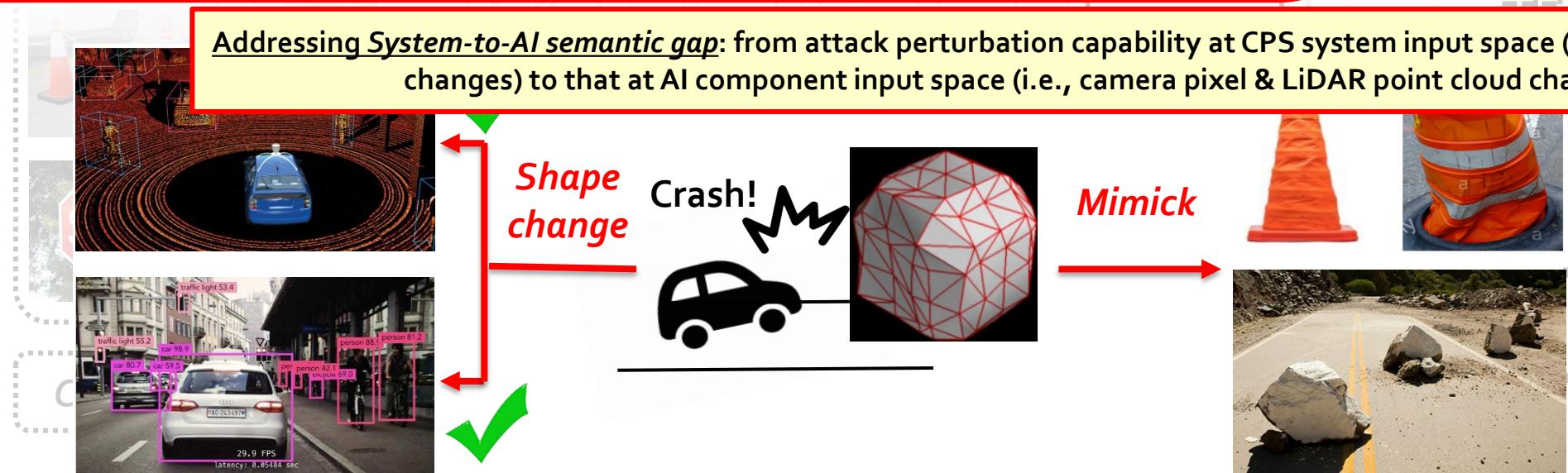
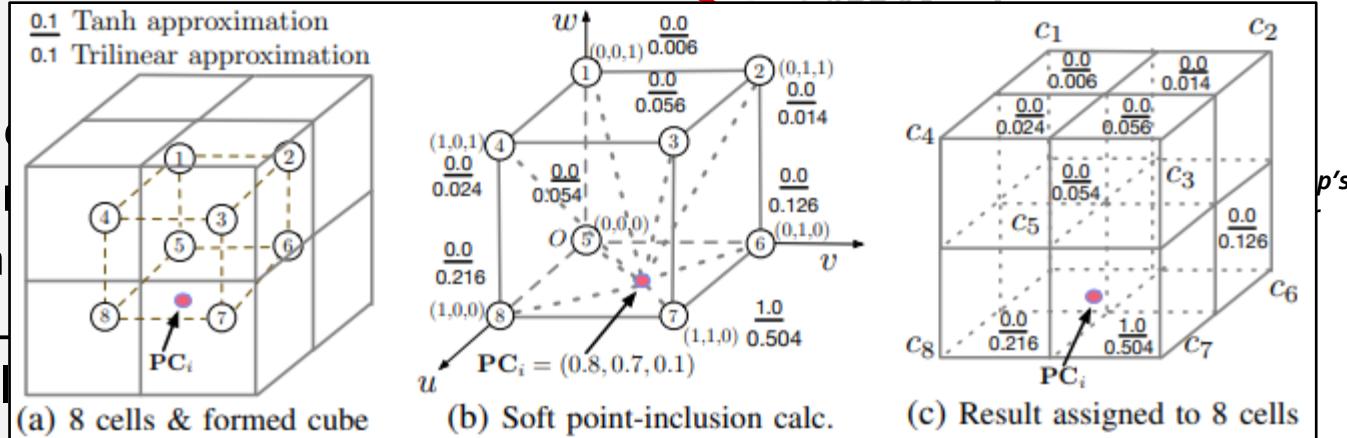
✓ Texture (e.g., color)



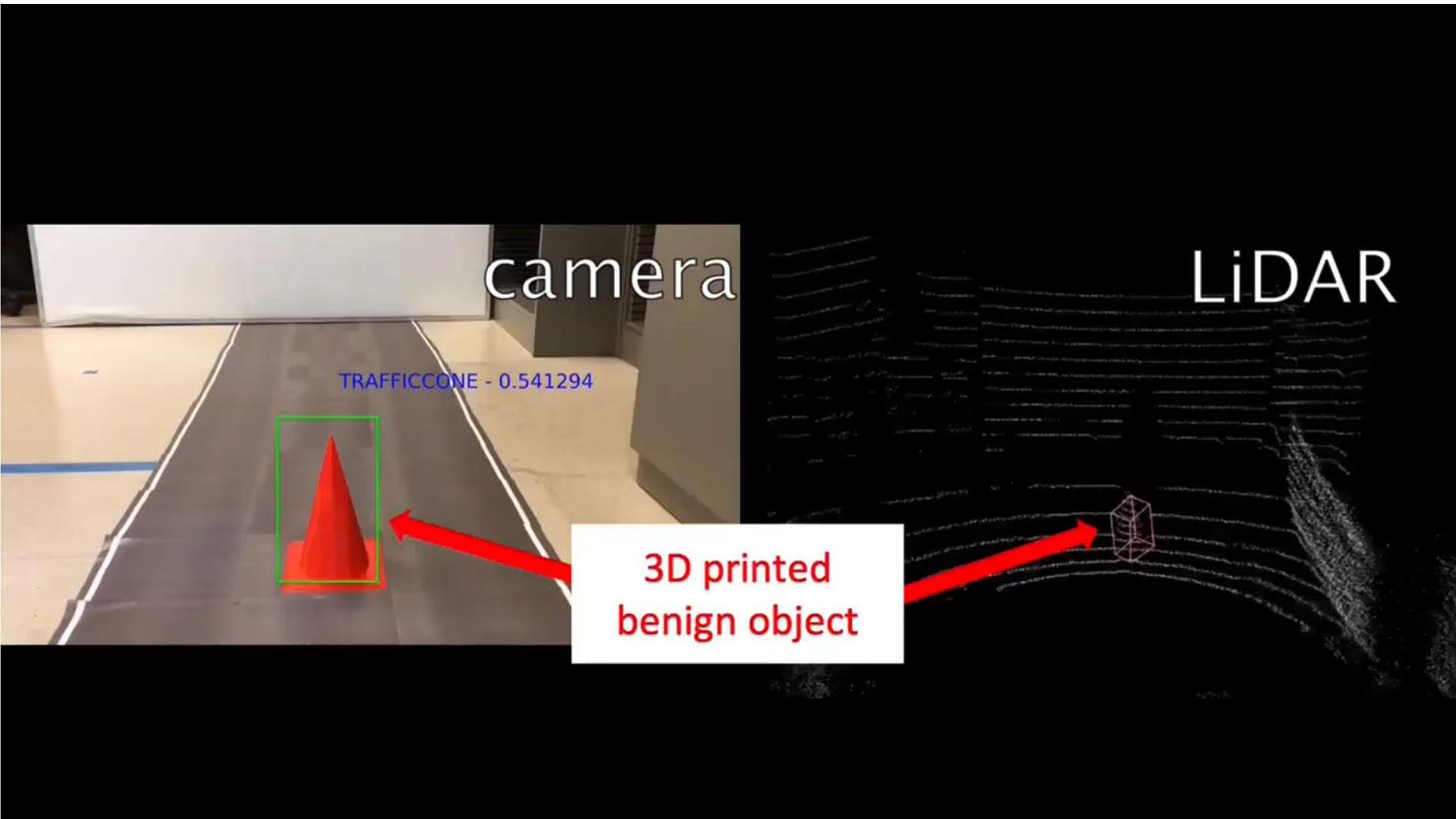
- **First** study on security of MSF perception
- Directly challenge security design assumption: explore possibility of **effectively** & **simultaneously** attacking **all** perception sources
- New attack vector: Maliciously-shaped adversarial 3D object (e.g., traffic cone or rock) → can influence both camera pixels & LiDAR point cloud
  - Fool victim to fail in detecting front obstacle, thus **crash into it**
  - **Physically-realizable** (via 3D printing) & **stealthy** (by mimicking)



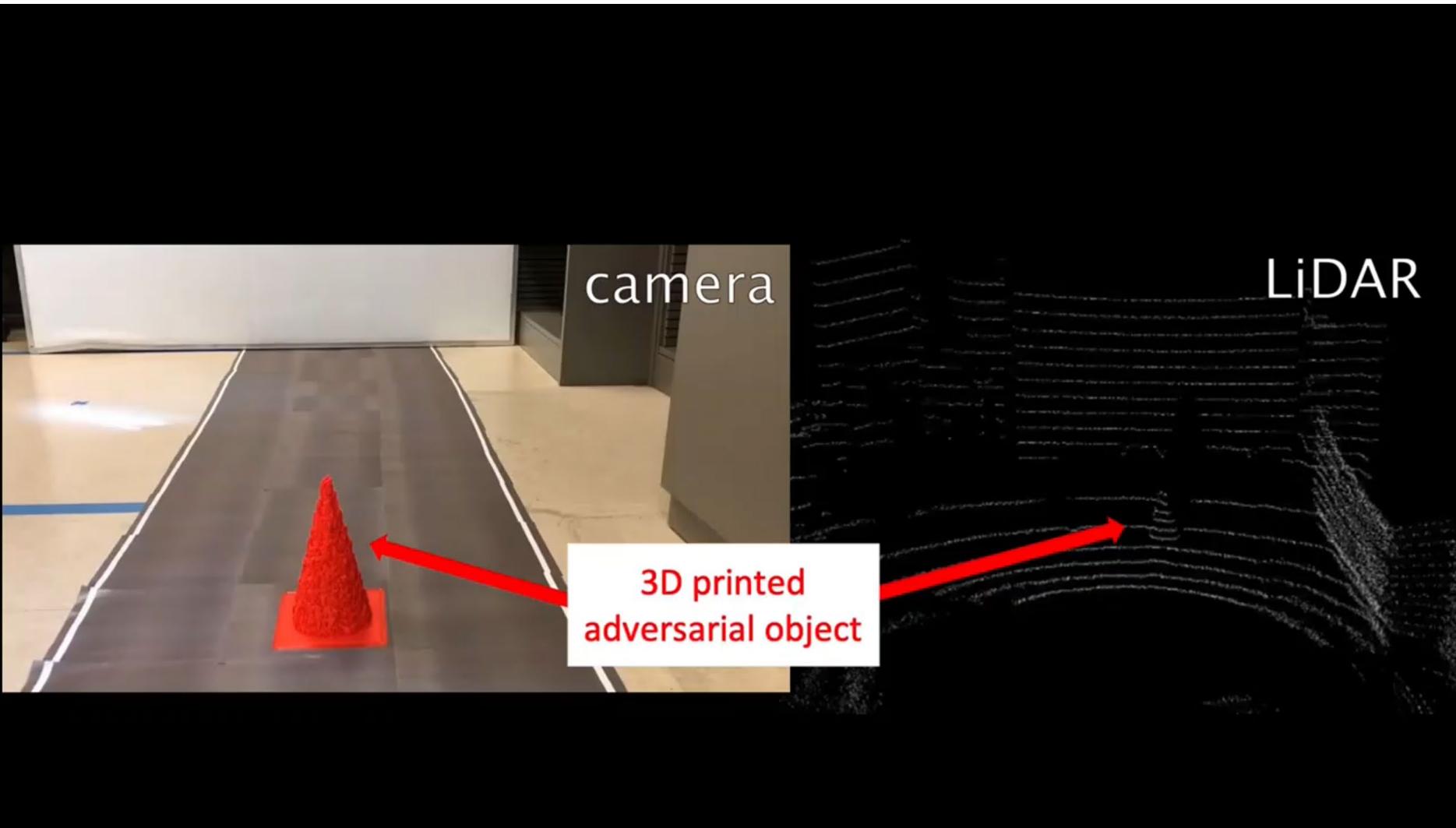
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  - Fool victim to fail in detecting front obstacle
  - **Physically-realizable** (via 3D printing) & **stealthy** (by mimicking)
- New methodology: Customized differentiable rendering & new differentiable approx func designs for pre-processing (esp. cell-level aggregated feature calc)
  - <10% → 100% in attack success rate



# Attack demos: Benign case



# Attack demos: Adversarial case



# Attack demos



Demo website: <https://sites.google.com/view/cav-sec/msf-adv>

*Black Hat'15,  
DEF CON'16*

*CCS'19 (attack),  
Usenix Security'20  
(defense)*

*ICLR'20*

*IEEE  
S&P'21*

*NDSS'20 Best  
Poster, Usenix  
Security'21*

*CVPR'18,  
WOOT'18,  
..., CCS'19*

*My group's  
paper*

- **One of the first** to study production lane detection DNN
- Attack vector: Malicious dirty road patterns



Traffic  
light det.

Lane  
detection

Object  
recognition

Segmentation

Black Hat'15,  
DEFCON'16

CCS'19 (attack),  
Usenix Security'20  
(defense)

ICLR'20

IEEE  
S&P'21

NDSS'20 Best  
Poster, Usenix  
Security'21

CVPR'18,  
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..., CCS'19

My group's  
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- One of the first to study production lane detection DNN
- Attack vector: Malicious dirty road patterns
- Method: Optimization-based method



Real-World  
Road Patch



Dirty Patterns



Lane  
detection

Traffic  
light det.

Traffic

ion

ng

Black Hat'15,  
DEFCON'16

CCS'19 (attack),  
Usenix Security'20  
(defense)

ICLR'20

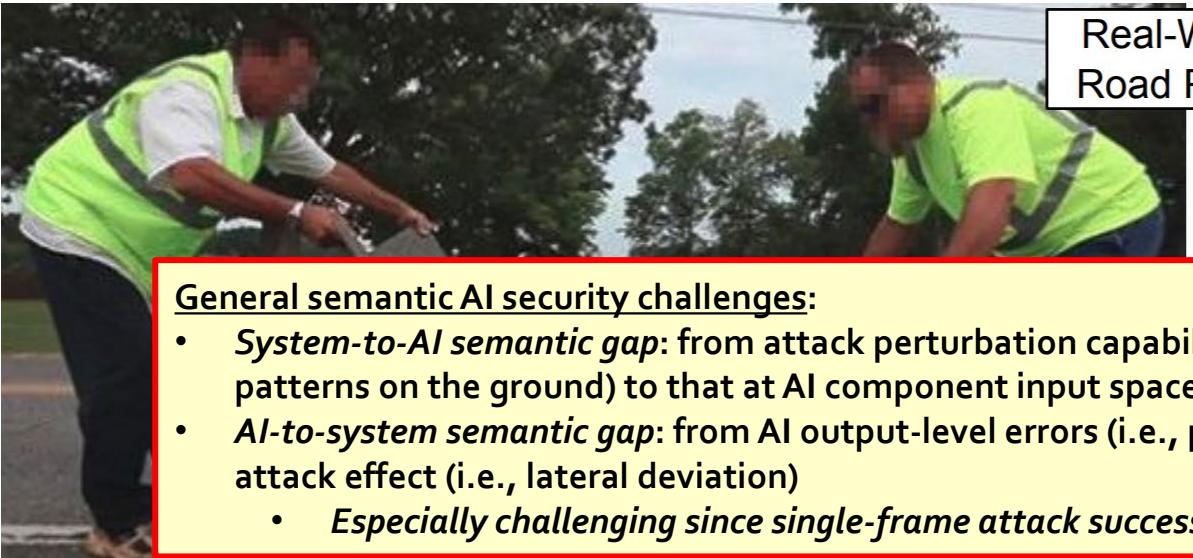
IEEE  
S&P'21

NDSS'20 Best  
Poster, Usenix  
Security'21

CVPR'18,  
WOOT'18,  
..., CCS'19

My group's  
paper

- One of the first to study production lane detection DNN
- Attack vector: Malicious dirty road patterns
- Method: Optimization-based method
- Impact: Cause a victim to ***drive out of the current lane boundaries within 1 sec***
  - Far below normal driver reaction time (~2.5 sec)



#### General semantic AI security challenges:

- System-to-AI semantic gap: from attack perturbation capability at CPS system input space (i.e., malicious dirty patterns on the ground) to that at AI component input space (i.e., camera pixel changes)
- AI-to-system semantic gap: from AI output-level errors (i.e., per-frame lane bending/shifting) to CPS system-level attack effect (i.e., lateral deviation)
  - Especially challenging since single-frame attack success can only lead to <= 0.3 mm lateral dev. at 45 mph

Attacker can pretend to be road workers to  
deploy the attack using adhesive road patch [51].

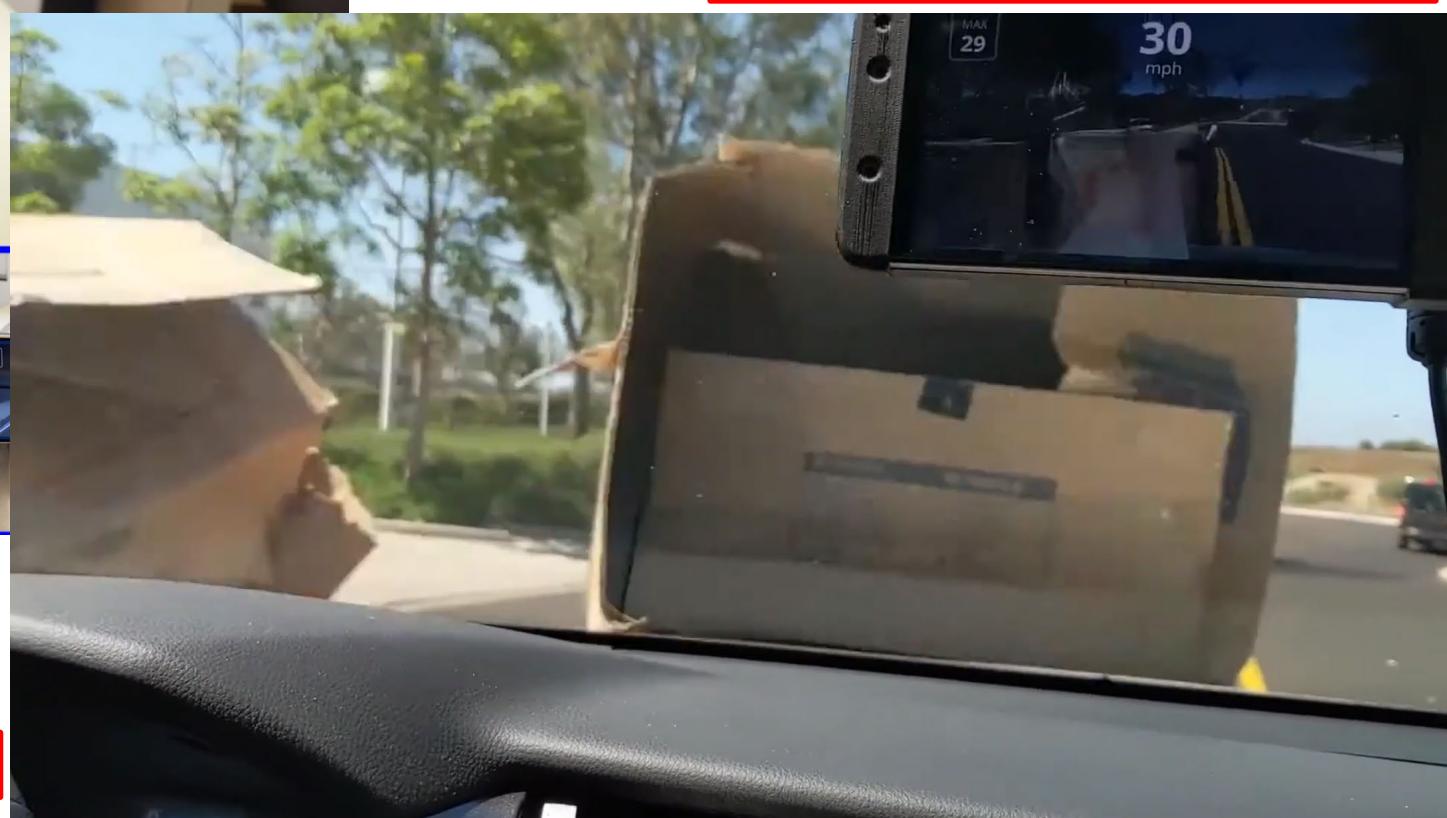


# Demo: Dirty road patch attack on lane detection

Attack



**100% (10/10) crash rate for  
real vehicle w/ AEB**



Demo website: <https://sites.google.com/view/cav-sec/drp-attack/>

Black Hat'15,  
DEFCON'16

CCS'19 (attack),  
Usenix Security'20  
(defense)

ICLR'20

IEEE  
S&P'21

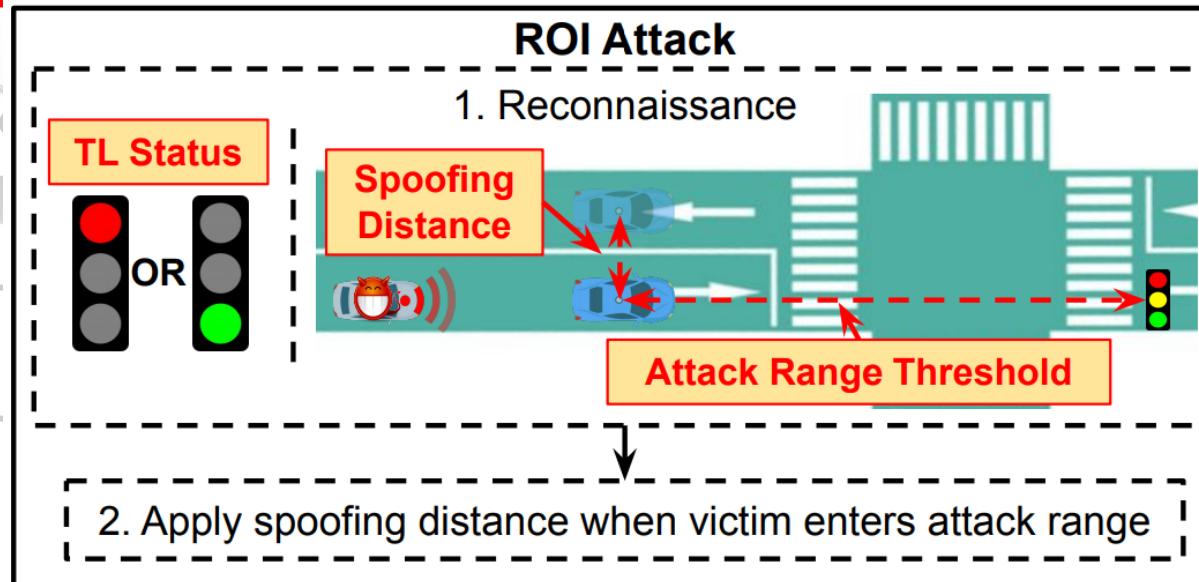
AutoSec  
2021

NDSS'20 Best  
Poster, Usenix  
Security'21

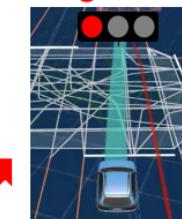
CVPR'18,  
WOOT'18,  
..., CCS'19

My group's  
paper

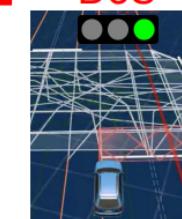
- First security analysis of traffic light detection
- Target: Industry-grade AD traffic light detection pipeline
  - Specifically, the use of **ROI (Region-of-Interest)** to narrow down detection scope in raw camera input
- Attack vector: GPS spoofing
- Impact: Move right traffic light out of ROI, causing **DoS**; or move wrong traffic light into ROI, causing **red light running**
- Demo website: <https://sites.google.com/view/roiattack>

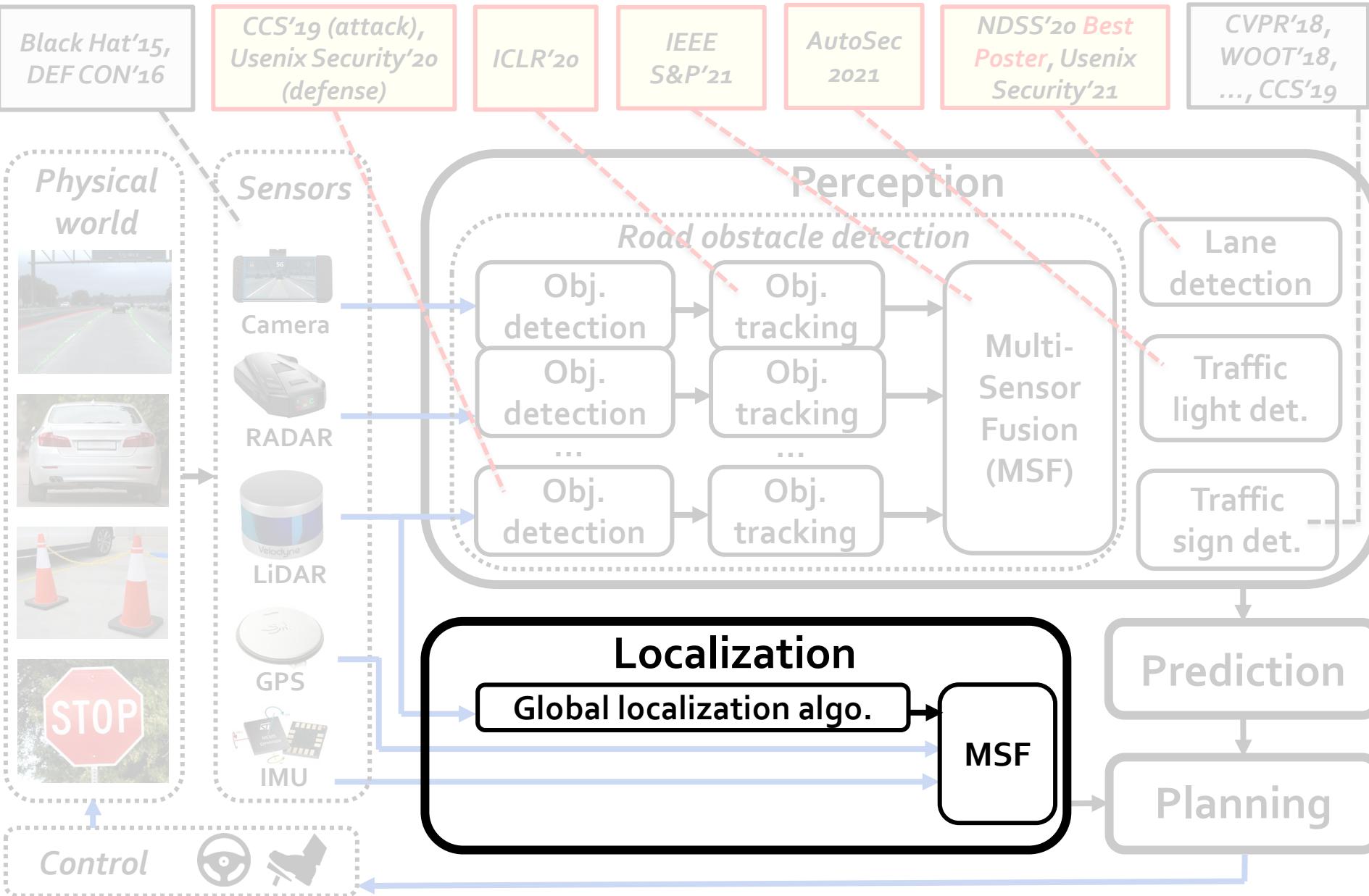


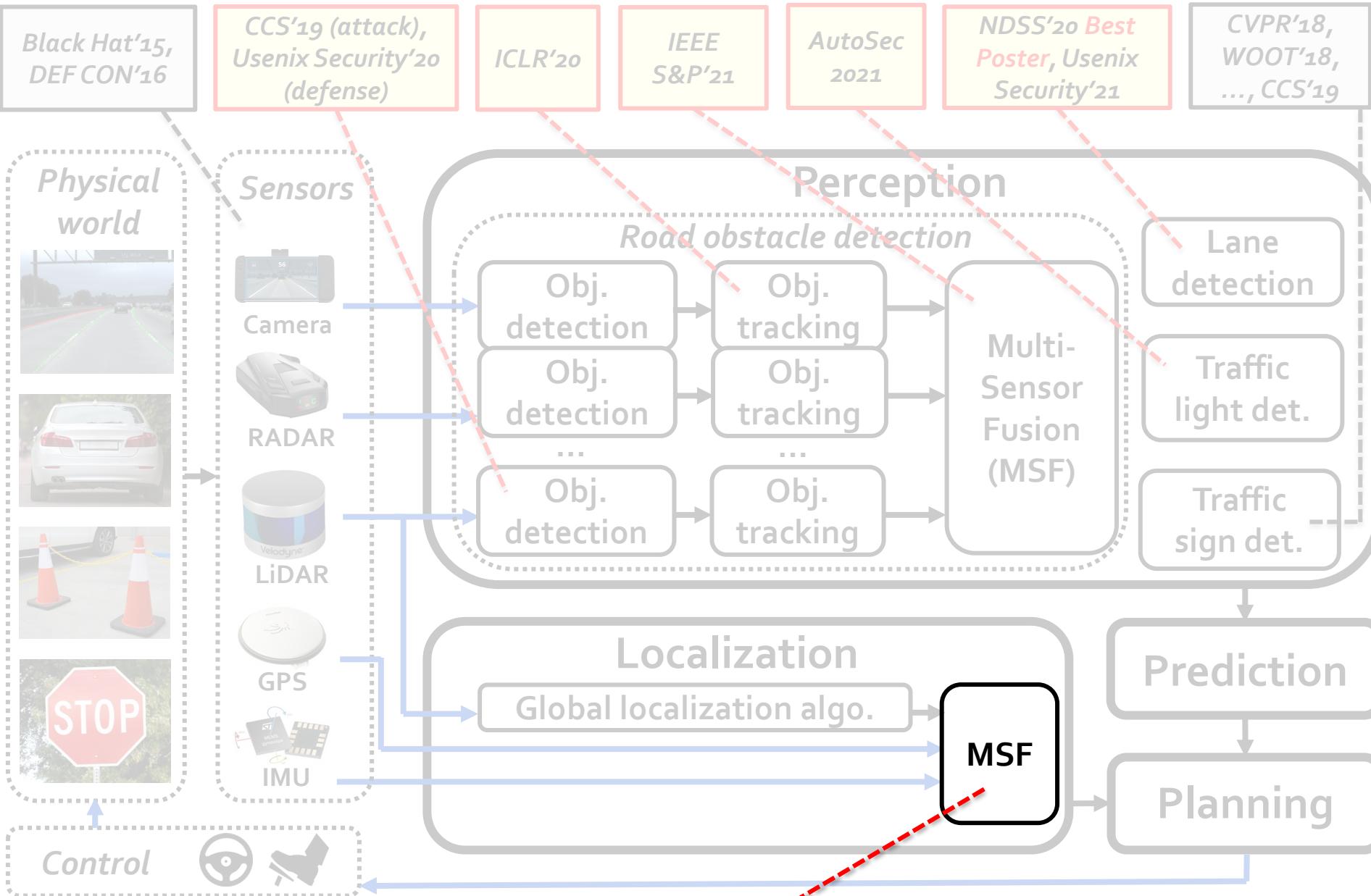
Red light runner



DoS







*Black Hat'15,  
DEFCON'16*

*CCS'19 (attack),  
Usenix Security'20  
(defense)*

*ICLR'20*

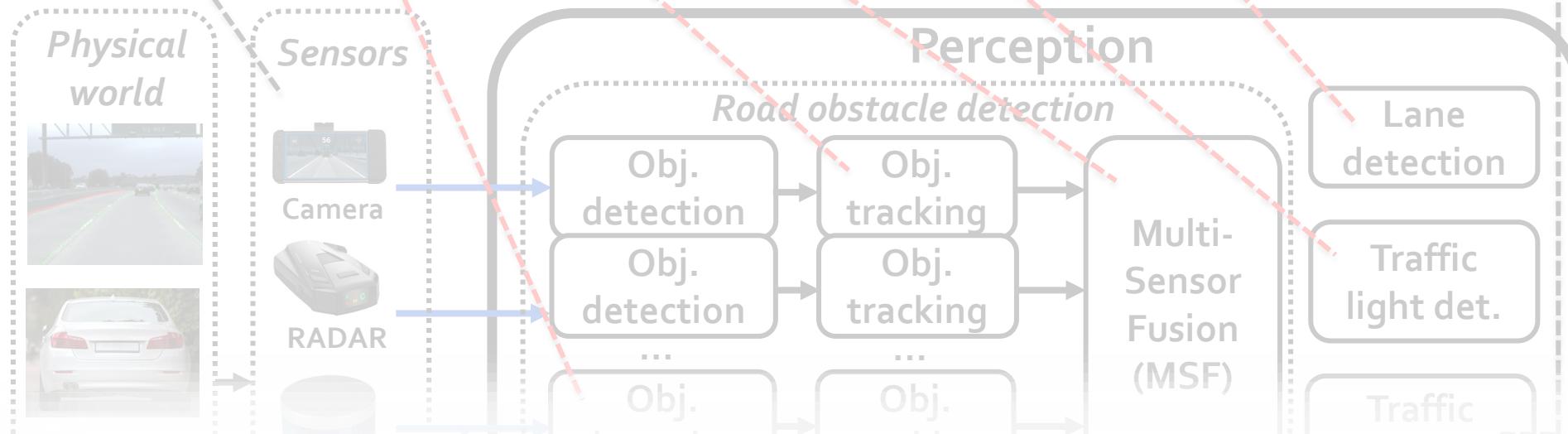
*IEEE  
S&P'21*

*AutoSec  
2021*

*NDSS'20 Best  
Poster, Usenix  
Security'21*

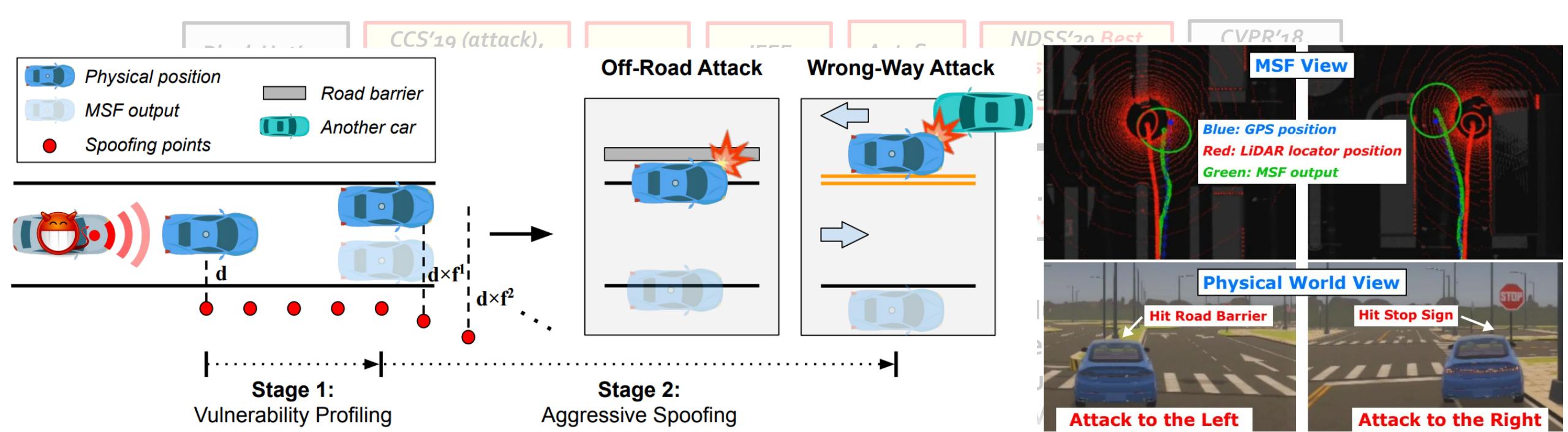
*CVPR'18,  
WOOT'18,  
..., CCS'19*

 My group's  
paper



***First*** security analysis of SOTA MSF-based AD localization (Kalman Filter based)  
• Attack vector: GPS spoofing

*NDSS'19 Best Poster,  
Usenix Security'20*

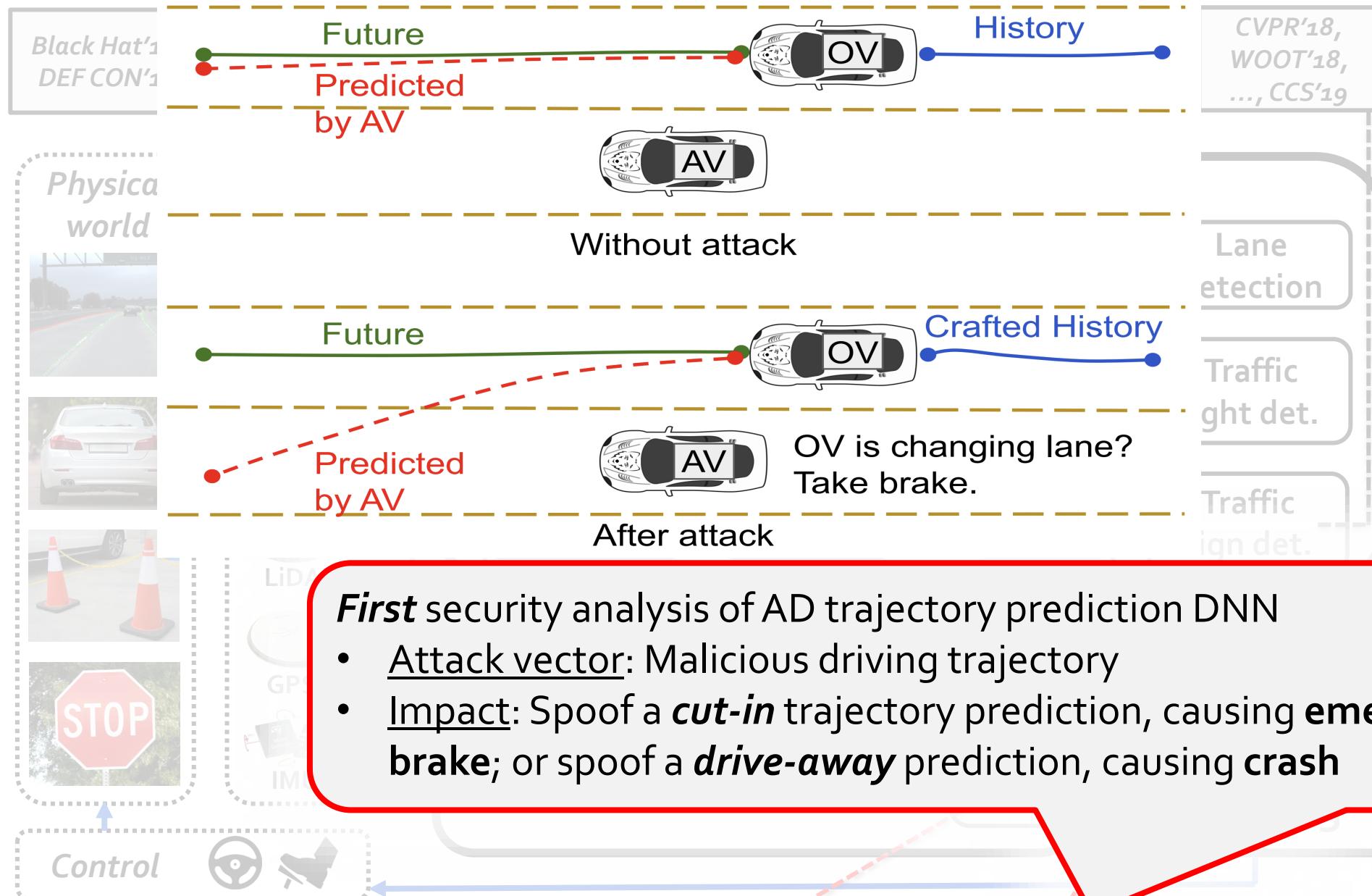


**First** security analysis of SOTA MSF-based AD localization (Kalman Filter based)

- Attack vector: GPS spoofing
- Impact: If tailgate for **2 min**, **almost always (97% chance)** can find an opportunity to break sensor fusion, and cause a victim to **drive off road or to the wrong way**
- Demo website: <https://sites.google.com/view/cav-sec/fusionripper>



NDSS'19 Best Poster,  
Usenix Security'20

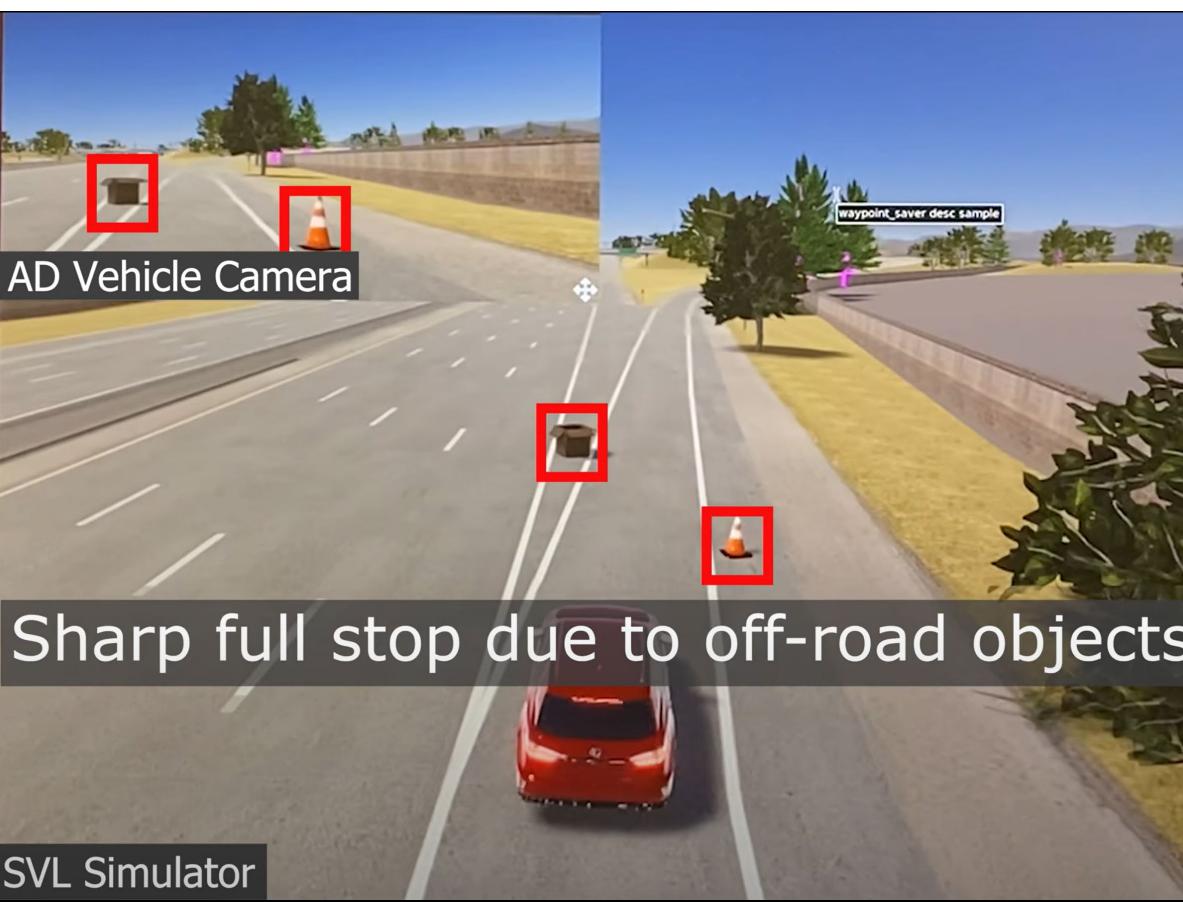


***First*** security analysis of AD trajectory prediction DNN

- Attack vector: Malicious driving trajectory
- Impact: Spoof a *cut-in* trajectory prediction, causing **emergency brake**; or spoof a *drive-away* prediction, causing **crash**

*NDSS'19 Best Poster,  
Usenix Security'20*

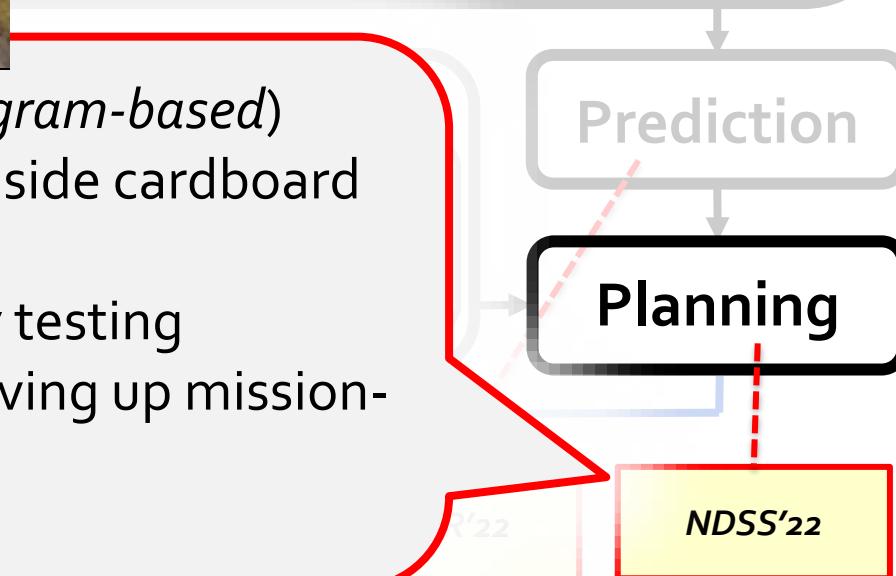
*CVPR'22*

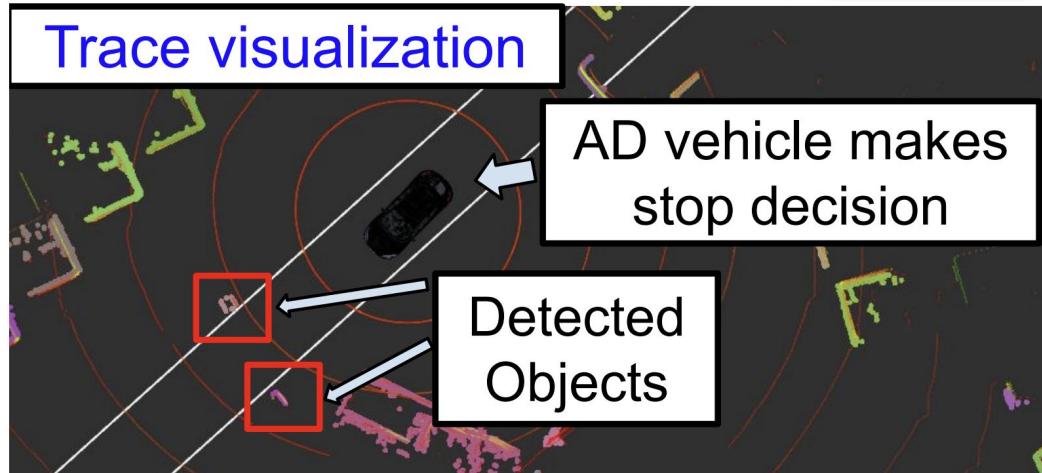
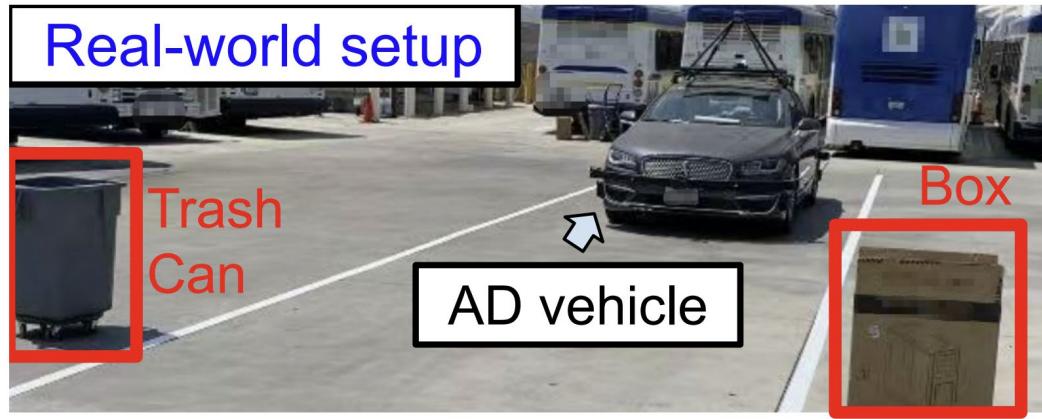
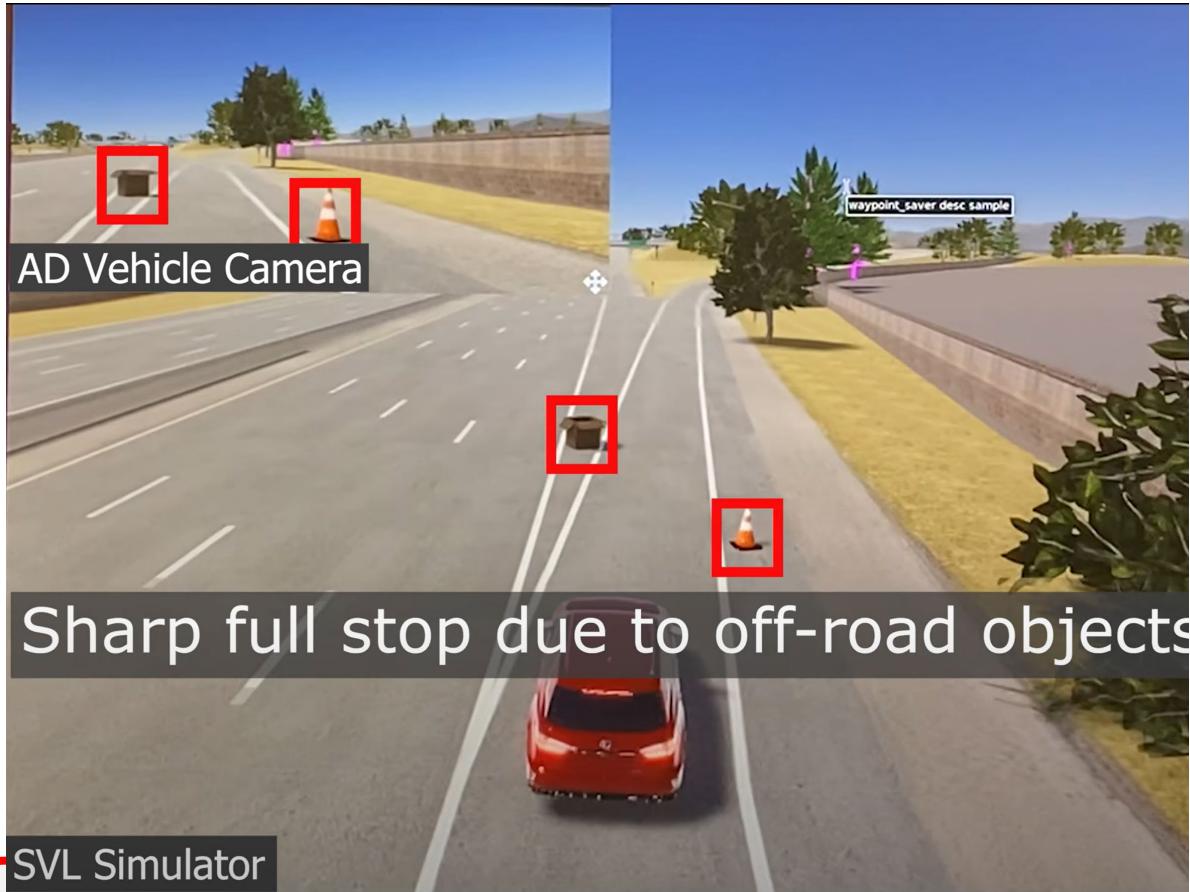


SVL Simulator

**First** security analysis of AD behavior planning (*program-based*)

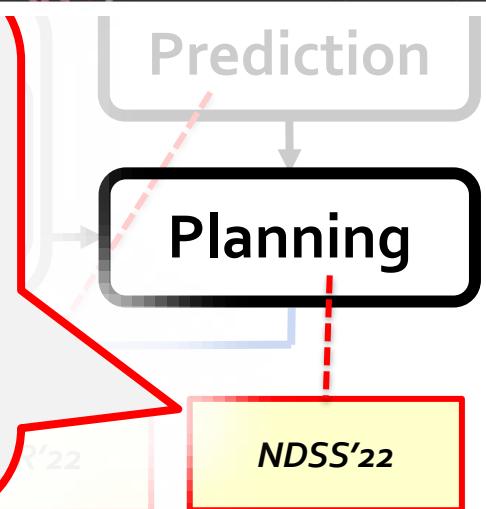
- Attack vector: Common road objects (e.g., road-side cardboard boxes, parked bikes, etc.)
- Methodology: Domain-customized evolutionary testing
- Impact: Unnecessary sharp braking, stopping, giving up mission-critical driving decisions, etc.

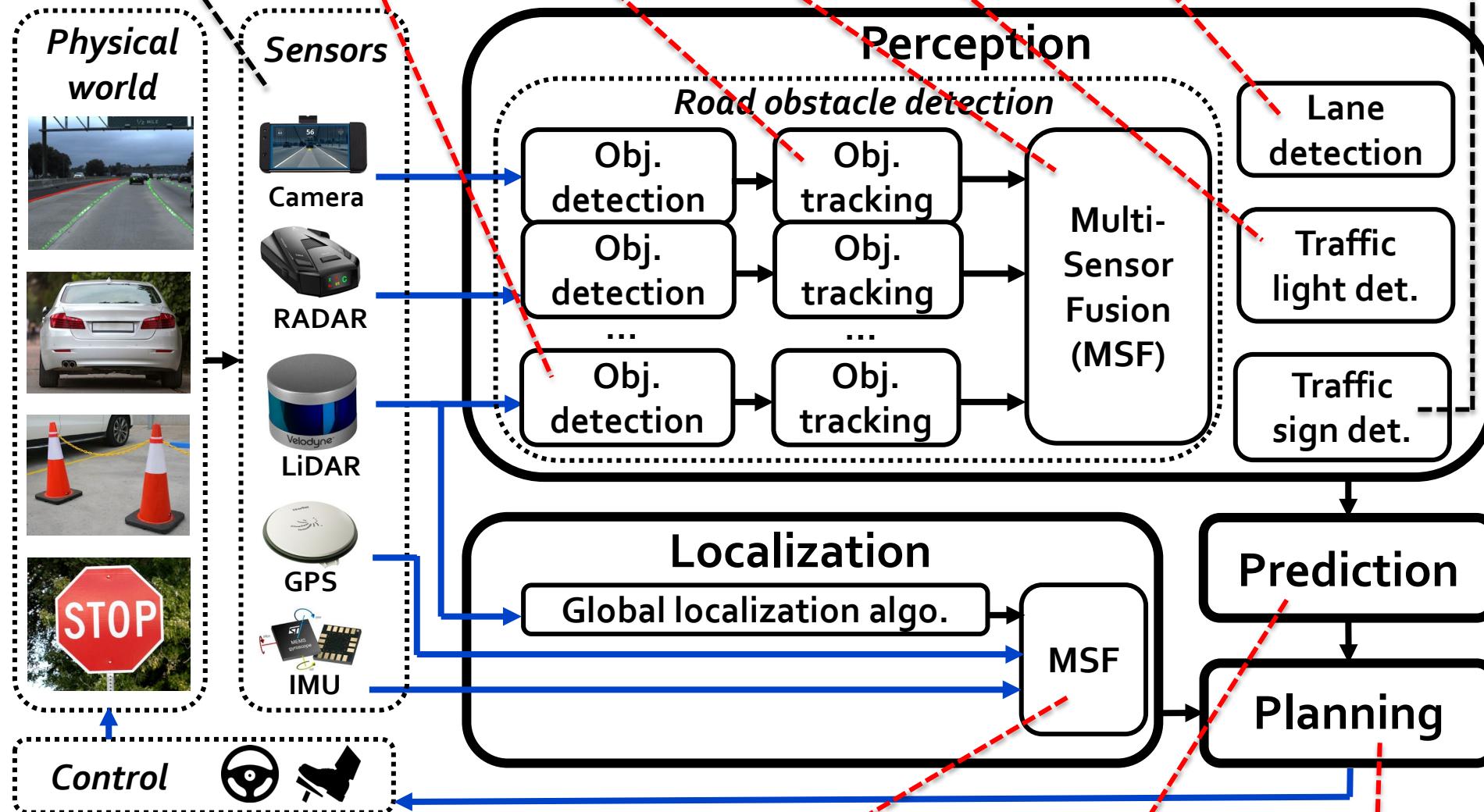
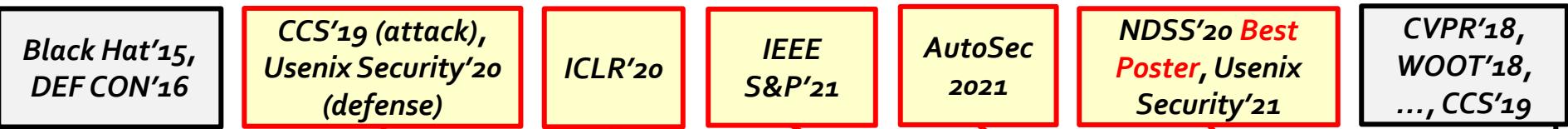




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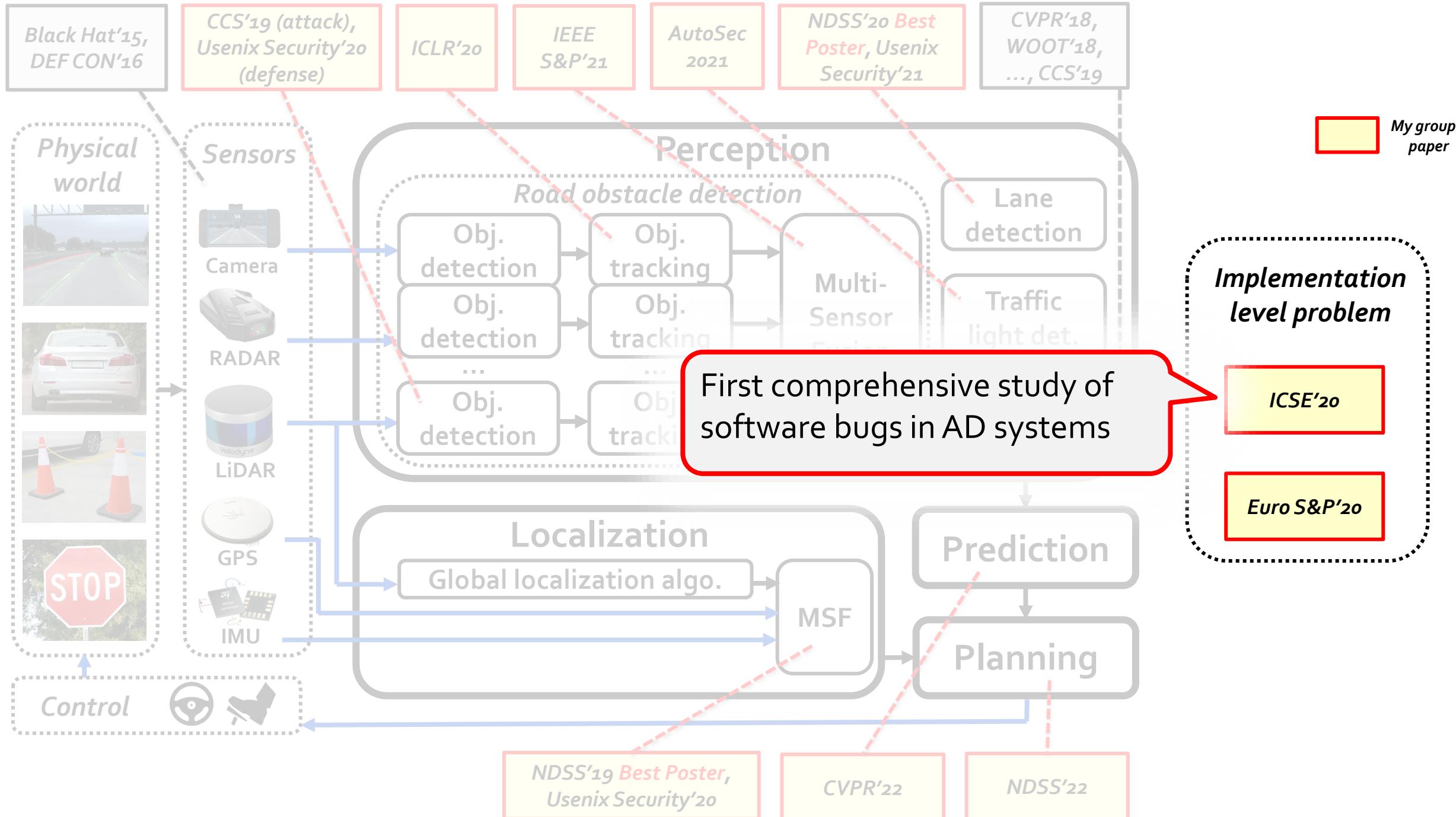




NDSS'19 Best Poster,  
Usenix Security'20

CVPR'22

NDSS'22

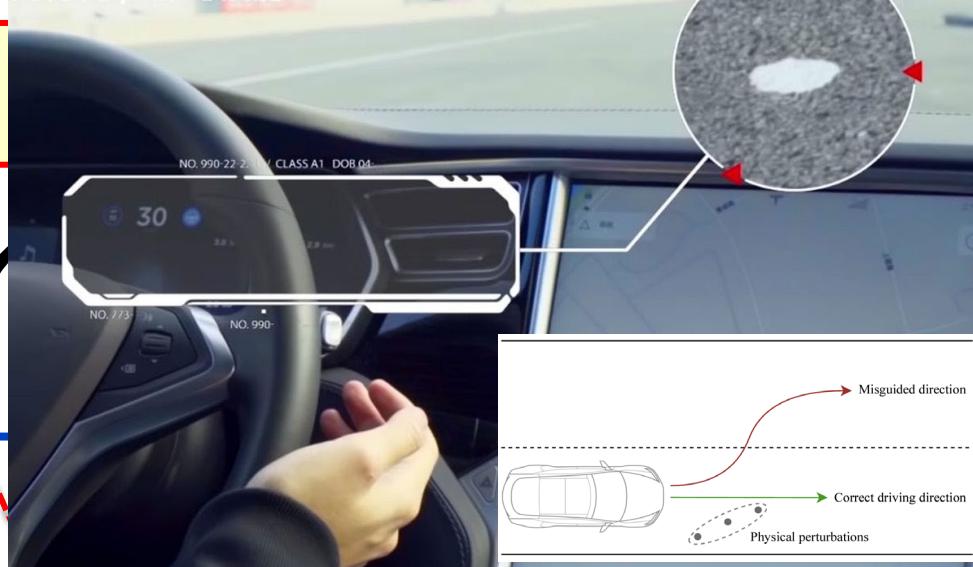
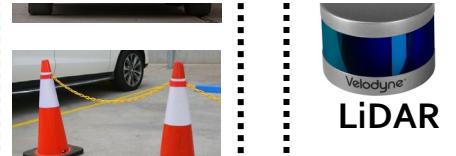


*Black Hat'15,  
CCS'15*

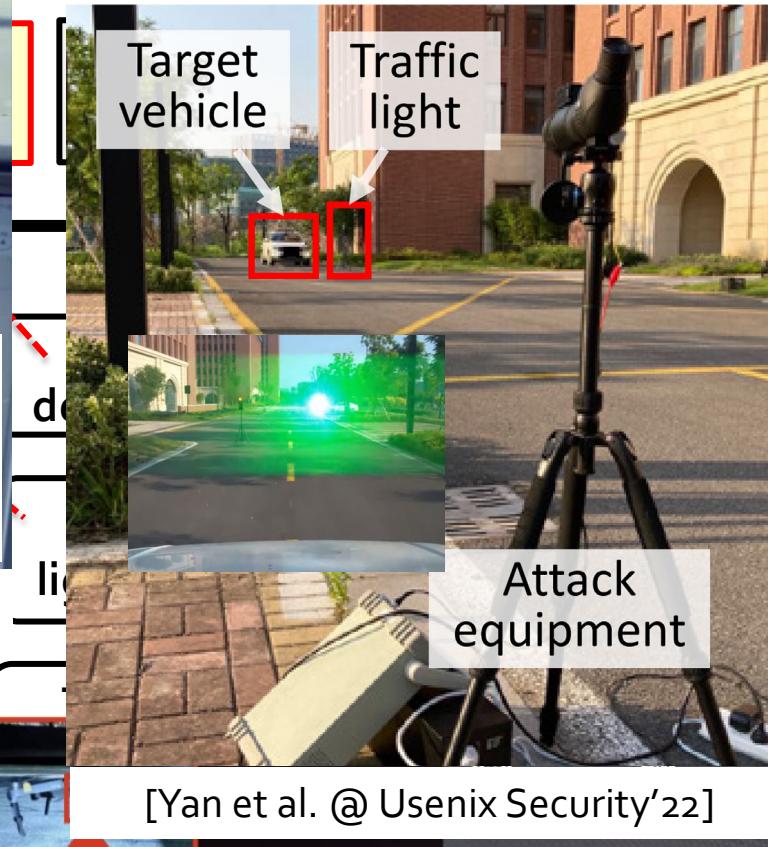
*CCS'19 (attack),  
Usenix Security'20*



[Zhao et al. @ CCS'19]



[Jing et al. @ Usenix Security'21]



Target  
vehicle  
Traffic  
light

Attack  
equipment

[Yan et al. @ Usenix Security'22]

Infrared Light LEDs

DJI Robot Master



[Nassi et al. @ CCS'20]

[Huang et al. @ CVPR'20]  
*NDSS'19 Best Poster,  
Usenix Security'20*

CVPR'22

[Wang et al. @ CCS'21]

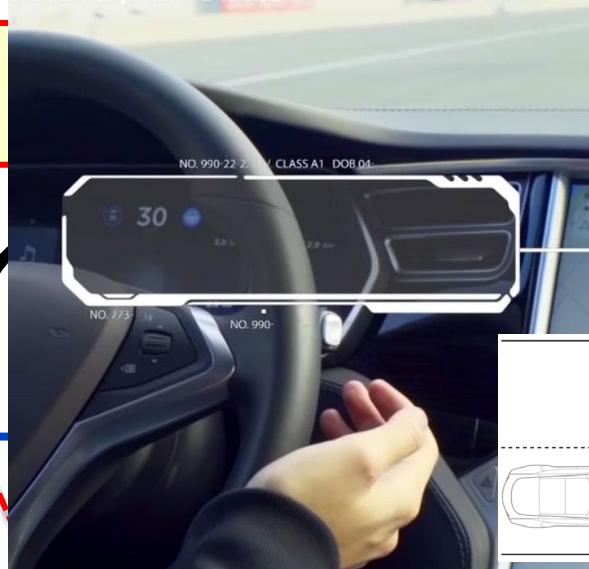
group's  
paper

Black Hat'15,  
CCS'15

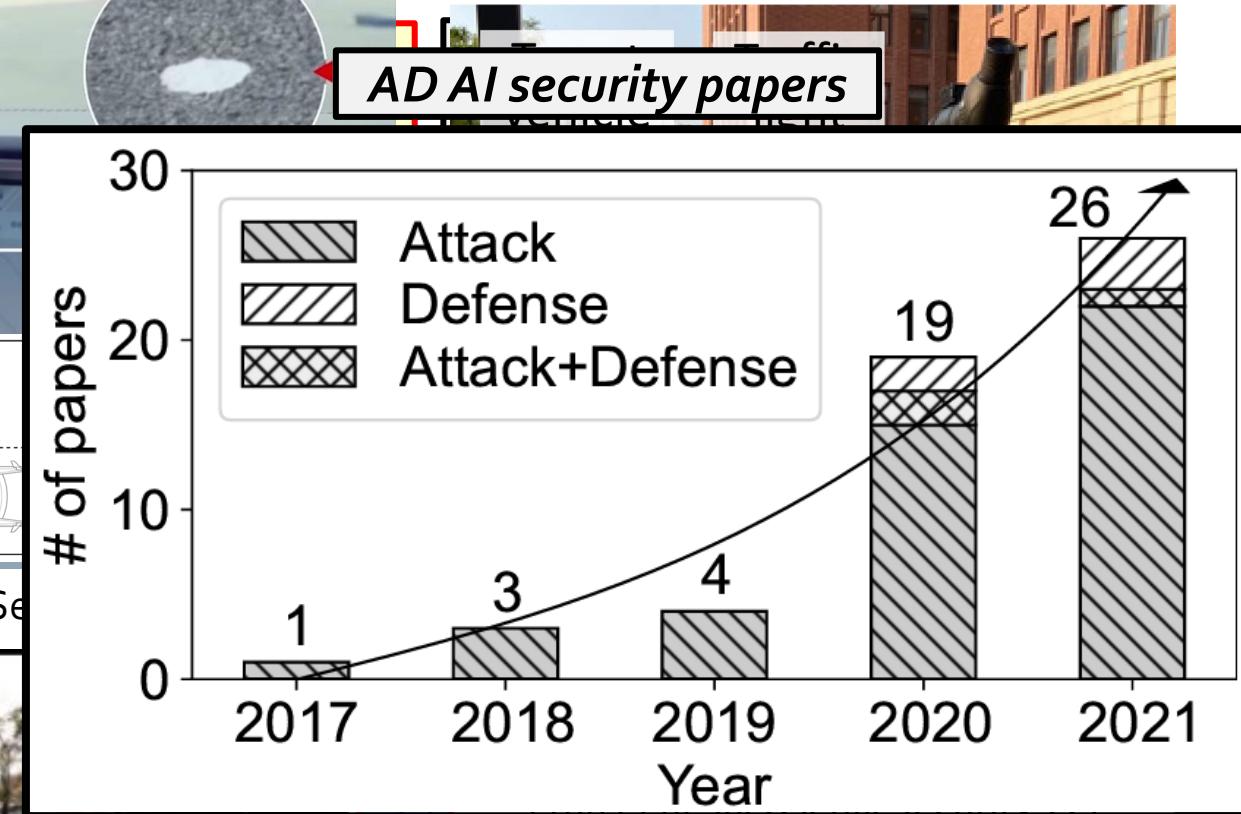
CCS'19 (attack),  
Usenix Security'20



[Zhao et al. @ CCS'19]



[Jing et al. @ Usenix Se



(\*Systematization of Knowledge (SoK) effort from my group)



[Nassi et al. @ CCS'20]

[Huang et al. @ CVPR'20]  
NDSS'19 Best Poster,  
Usenix Security'20

CVPR'22

Infrared Light LEDs

DJI Robot Master



[Wang et al. @ CCS'21]

# Automotive and Autonomous Vehicle Security (AutoSec) Workshop 2022

Note: All times are in PDT (UTC-7) and all sessions

**Best Demo Award Voting (end at 4:40pm):** <https://www.surveymonkey.com/r/9Q7JJMH>

**Future of AutoSec Voting (always open for your input):**

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AutoSec2022@NDSS  
@autosec\_conf

First-ever AutoSec PC meeting just occurred!! >18 PCs attended & lots of paper debating and even new ideas on how to run the workshop in the future --- what a healthy community 😊 ! Paper decisions will come out tomorrow. Stay tuned! #autosec22  
@NDSSSymposium

Proceedings Frontmatter

Sunday April 24

9:00 am - 9:10 am Welcome to AutoSec 2022 and

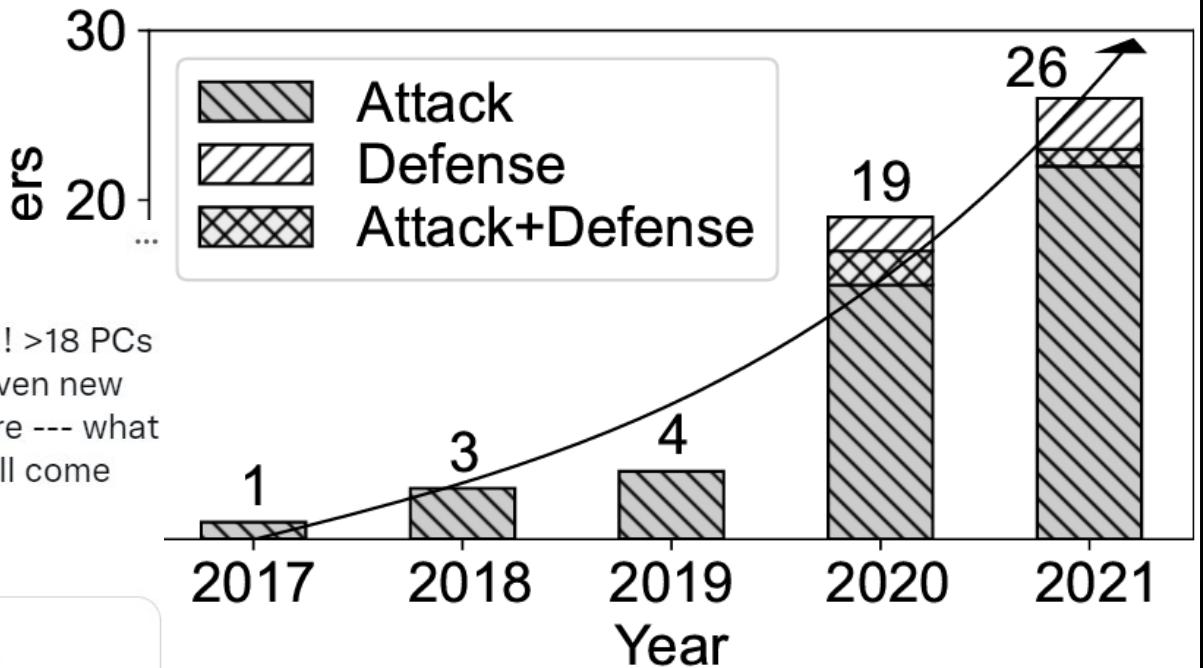
9:10 am - 10:10 am Keynote #1: Prof. Dongyan Xu  
Conte Professor of Computer Science  
Purdue University)

Keynote #1

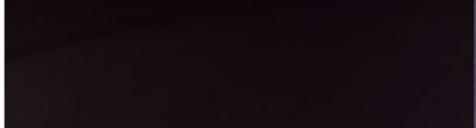
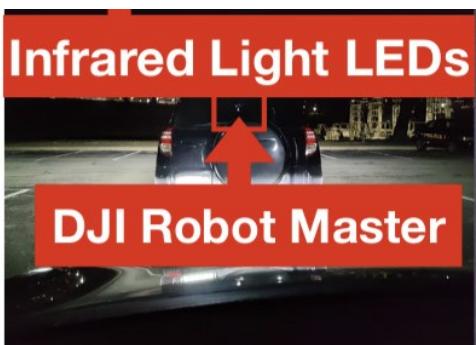


[Nassi et al. @ CCS'21]

AD AI security papers



(\*Systematization of Knowledge (SoK) effort from my group)



[Wang et al. @ CCS'21]

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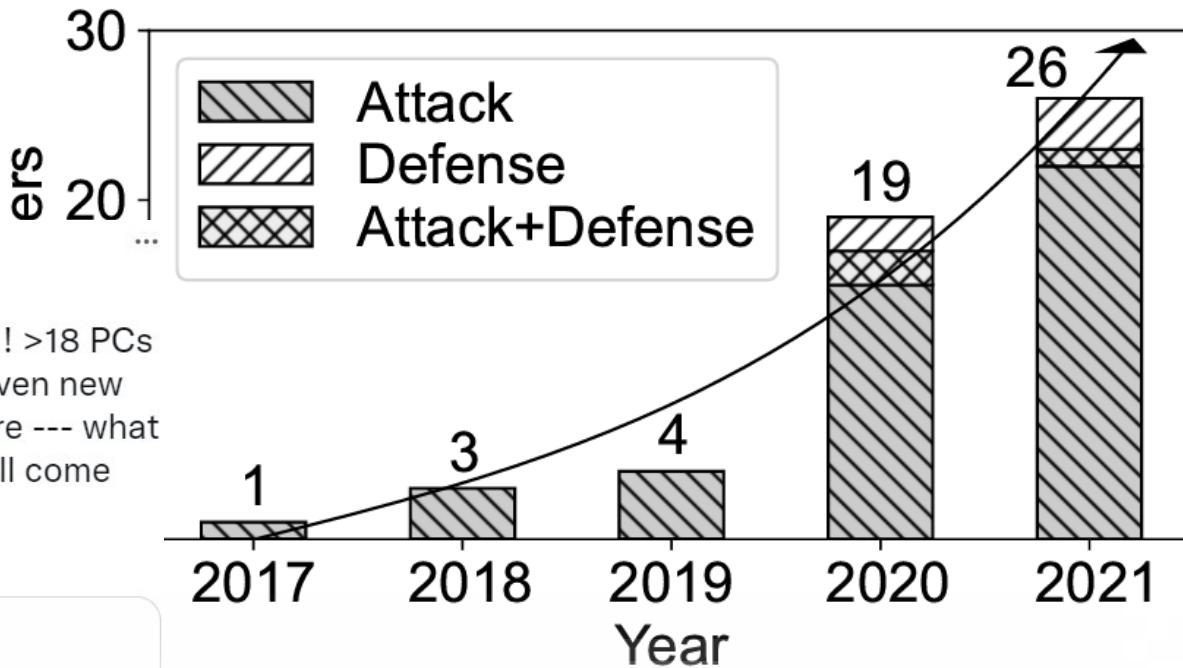
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Keynote #1



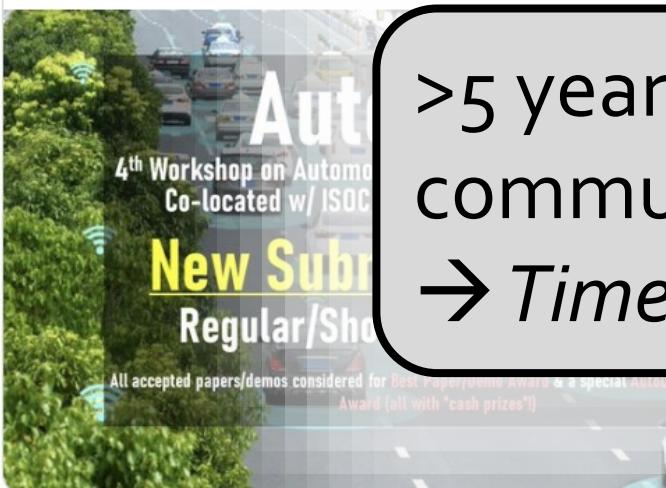
[Nassi et al. @ CCS'

AD AI security papers



(\*Systematization of Knowledge (SoK) effort from my group)

Infrared Light LEDs



>5 years of growth in research space & community now!  
→ Time for some reflection?

VPR'22

[Wang et al. @ CCS'21]

# A reflection of the 5+ years of AD AI security research

- Conduct the first **Systemization of Knowledge (SoK)** effort on **semantic AI security** research in AD
  - Collect & analyze *53 papers in past 5 years*, mainly from *top-tier venues in security, CV (Computer Vision), ML (Machine Learning), AI, and robotics*

## SoK: On the Semantic AI Security in Autonomous Driving

Junjie Shen, Ningfei Wang, Ziwen Wan, Yunpeng Luo, Takami Sato, Zhisheng Hu<sup>†</sup>, Xinyang Zhang<sup>†</sup>,  
Shengjian Guo<sup>†</sup>, Zhenyu Zhong<sup>†</sup>, Kang Li<sup>†</sup>, Ziming Zhao<sup>‡</sup>, Chunming Qiao<sup>‡</sup>, Qi Alfred Chen

{junjies1, ningfei.wang, ziwenw8, yunpel3, takamis, alfchen}@uci.edu,  
<sup>†</sup>{zhishenghu, xinyangzhang, sjguo, edwardzhong, kangli01}@baidu.com, <sup>‡</sup>{zimingzh, qiao}@buffalo.edu  
UC Irvine, <sup>†</sup>Baidu Security, <sup>‡</sup>University at Buffalo

Link: <https://arxiv.org/abs/2203.05314>

# Our SoK effort

- **Taxonomization, status & trend analysis,**  
based on critical research aspects for security
  - E.g., attack/defense goal, attack vector, defense deployability, evaluation methodologies, etc.

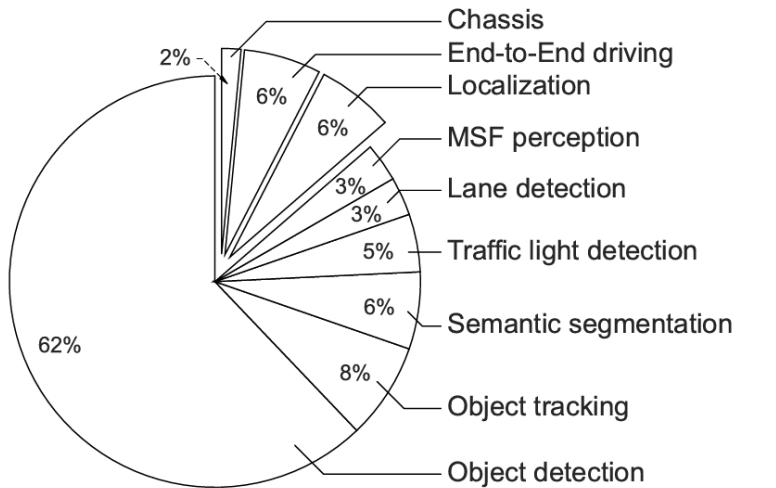


Figure 6: Distribution of (attack/defense) targeted AI components in semantic AD AI security papers.

Targeted AI component	Paper	Year	Field	Integrity	Confidentiality	Availability	Attack vector		Attack goal	Eval. level
							Physical-layer			
							Phys. world	Sensor attack	ML backdoor	Malware & s/w compromise
Camera perception	Lu et al. [54]	'17	V	✓			✓			Component-level
	Eykholz et al. [18]	'18	S	✓			✓			System-level
	Chen et al. [37]	'18	M	✓			✓			Open source
	Zhao et al. [26]	'19	S	✓			✓			
	Xiao et al. [55]	'19	V	✓			✓			
	Zhang et al. [56]	'19	M	✓			✓			
	Nassi et al. [57]	'20	S	✓			✓			
	Man et al. [58]	'20	S	✓			✓			
	Hong et al. [59]	'20	S	✓			✓			
	Huang et al. [60]	'20	V	✓			✓			
LiDAR perception	Wu et al. [61]	'20	V	✓			✓			
	Xu et al. [62]	'20	V	✓			✓			
	Hu et al. [63]	'20	V	✓			✓			
	Hamdi et al. [64]	'20	M	✓			✓			
	Ji et al. [65]	'21	S	✓			✓			
	Lovisotto et al. [66]	'21	S	✓			✓			
	Wang et al. [67]	'21	S	✓			✓			
	Kohler et al. [68]	'21	S	✓			✓			
	Wang et al. [69]	'21	S	✓			✓			
	Zolfi et al. [70]	'21	V	✓			✓			
RADAR perception	Wang et al. [71]	'21	V	✓			✓			
	Zhu et al. [72]	'21	M	✓			✓			
	Nakka et al. [73]	'20	V	✓			✓			
	Nesti et al. [74]	'22	V	✓			✓			
	Jha et al. [75]	'20	S	✓			✓			
	Jia et al. [76]	'20	M	✓			✓			
	Ding et al. [76]	'21	M	✓			✓			
	Chen et al. [77]	'21	M	✓			✓			
	Sato et al. [78]	'21	S	✓			✓			
	Jing et al. [79]	'21	S	✓			✓			
Chassis	Wang et al. [67]	'21	S	✓			✓			
	Tang et al. [80]	'21	S	✓			✓			
	Cao et al. [19]	'19	S	✓			✓			
	Sun et al. [81]	'20	S	✓			✓			
	Hong et al. [59]	'20	S	✓			✓			
	Tu et al. [82]	'20	V	✓			✓			
	Zhu et al. [83]	'21	S	✓			✓			
	Yang et al. [84]	'21	S	✓			✓			
	Hau et al. [85]	'21	S	✓			✓			
	Li et al. [86]	'21	V	✓			✓			
End-to-end driving	Zhu et al. [87]	'21	O	✓			✓			
	Tsai et al. [88]	'20	M	✓			✓			
	Zhu et al. [87]	'21	O	✓			✓			
	Sun et al. [89]	'21	S	✓			✓			
	Cao et al. [38]	'21	S	✓			✓			
	Tu et al. [90]	'21	O	✓			✓			
	Luo et al. [91]	'20	S	✓			✓			
	Shen et al. [92]	'20	S	✓			✓			
	Wang et al. [67]	'21	S	✓			✓			
	Hong et al. [59]	'20	S	✓			✓			
Other	Liu et al. [93]	'18	S	✓			✓			
	Kong et al. [94]	'20	V	✓			✓			
	Hamdi et al. [64]	'20	M	✓			✓			
	Boloor et al. [95]	'20	O	✓			✓			

Field: S = Security, V = Computer Vision, M = ML/AI, O = Others, e.g., Robotics, arXiv;  
Attacker's knowledge: ○ = white-box, ● = gray-box, ■ = black-box

Table I. Overview of existing semantic AD AI attacks in our SoK scope (§II-C). (s/w = software)

# Our SoK effort: Scientific gaps identification

- Most importantly, identify **6 most substantial scientific gaps**
  - Observed based on quantitative comparisons both ***vertically*** among existing AD AI security works and ***horizontally*** with security works from closely-related domains
  - **Scientific Gap 1: Evaluation**: General lack of system-level evaluation
    - Only 25.4% of existing works perform system-level evaluation
  - **Scientific Gap 2: Research goal**: General lack of defense solutions
    - Only 14.3% propose defenses
    - In comparison, much more balanced in drone security area (49% on defense)
  - **Scientific Gap 3: Attack vector**: Cyber-layer attack vectors under-explored
    - Only 11.1% assume cyber-layer attack vectors, e.g., malware, ML backdoors
  - **Scientific Gap 4: Attack target**: Downstream AI components under-explored
    - Limited study on prediction & planning
  - **Scientific Gap 5: Attack goal**: Attack goals other than “integrity” under-explored
    - Limited study on confidentiality & availability
  - **Scientific Gap 6: Community**: Substantial Lack of Open Sourcing
    - <20.6% (7/34) papers from security conferences release source code



***Our SoK effort***

(<https://arxiv.org/abs/2203.05314>)

# Most critical gap: General lack of system-level evaluation

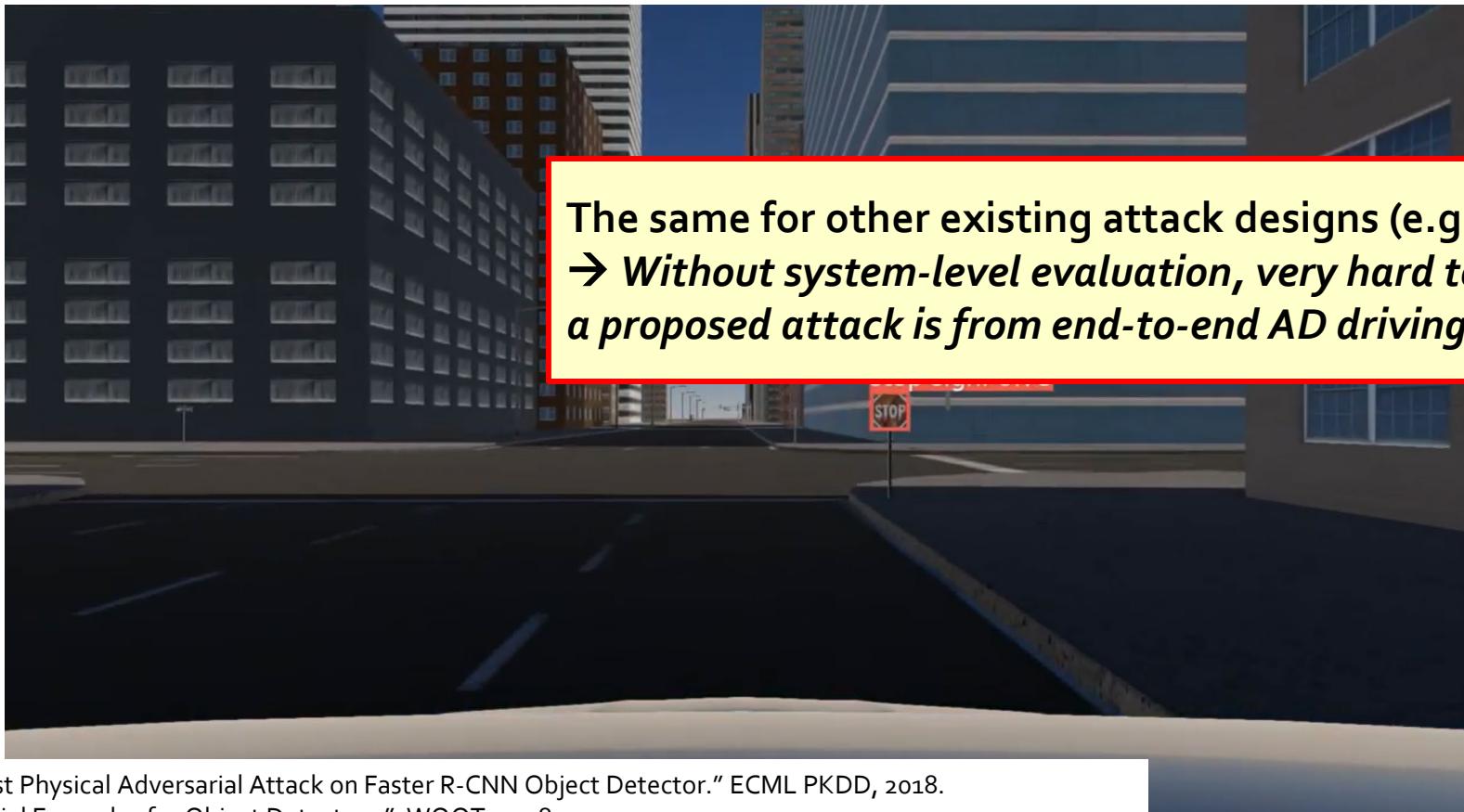
- Most importantly, identify **6 most substantial scientific gaps**
  - Observed based on quantitative comparisons both *vertically* among existing AD AI security works and *horizontally* with security works from closely-related domains
  - Scientific Gap 1: Evaluation: General lack of system-level evaluation
    - Only 25.4% of existing works perform system-level evaluation
  - Scientific Gap 2: Research goal: General lack of defense solutions
    - Only 20.6% of existing works release source code
- Widely recognized that in autonomous system, AI component-level errors (e.g., obj det errors) **do not necessarily lead to system-level effect (e.g., collisions)**
  - Essentially the AI-to-system semantic gap mentioned earlier
- However, today **vast majority (74.6%)** of existing works **did not perform any form of system-level evaluation**
  - I.e., eval w/ full-stack AD system & closed-loop control via simulation/real-vehicle setups
- Without it, may lead to **meaningless** attack/defense progress at the system level



<20.6% (754) papers from security conferences release source code

# Demo: Necessity of system-level evaluation

- Setup: Existing STOP sign disappearance attack [1]
  - Effective at component level: > 70% *frame-level success rate* to make STOP sign disappear (consistent success pattern w/ [1])
  - However, failed at system level: 0% *stop sign violation rate* due to object tracking



The same for other existing attack designs (e.g., [2] [3])  
→ *Without system-level evaluation, very hard to know how meaningful a proposed attack is from end-to-end AD driving perspective!*

[1] Chen et al., "ShapeShifter: Robust Physical Adversarial Attack on Faster R-CNN Object Detector." ECML PKDD, 2018.

[2] Eykholt et al., "Physical Adversarial Examples for Object Detectors," WOOT, 2018

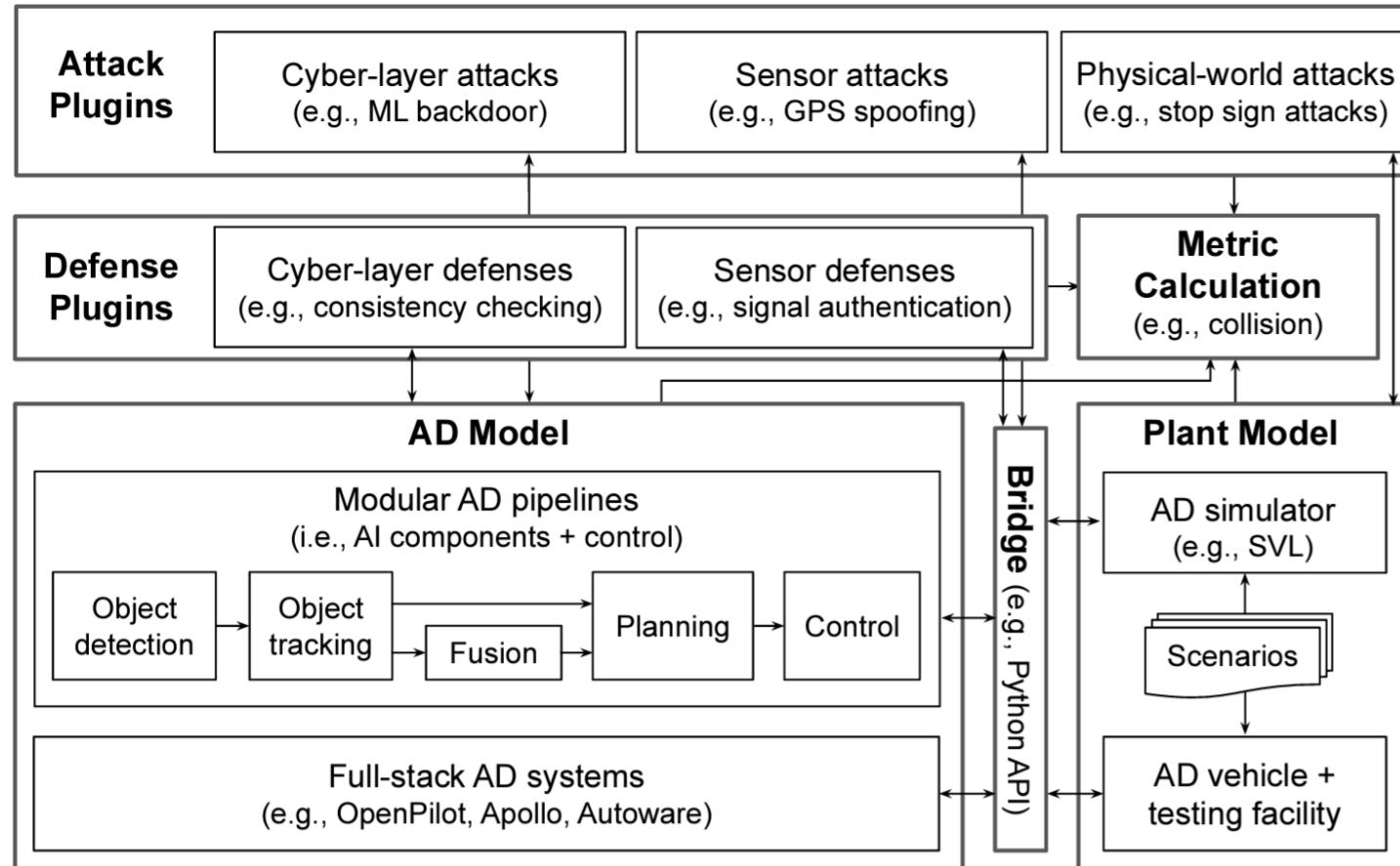
[3] Zhao et al., "Seeing isn't Believing: Towards More Robust Adversarial Attack Against Real World Object Detectors," ACM CCS, 2019

# How to systematically address this?

- **Various challenges** to effectively fill this gap **at the *research community* level**
  - Real AD vehicle testing: Low affordability/accessibility, safety, flexibility, & reproducibility
  - Simulation-based testing: Still non-trivial engineering efforts to instrument simulation environment & engine for security testing
- A **community-level effort** can greatly help!
  - Collectively build a ***common system-level evaluation infrastructure***
  - Benefits:
    - (1) Avoid repeated engineering efforts in instrumenting the simulator/vehicle
    - (2) Improve result comparability due to the more unified evaluation setup, benefitting scientific advances

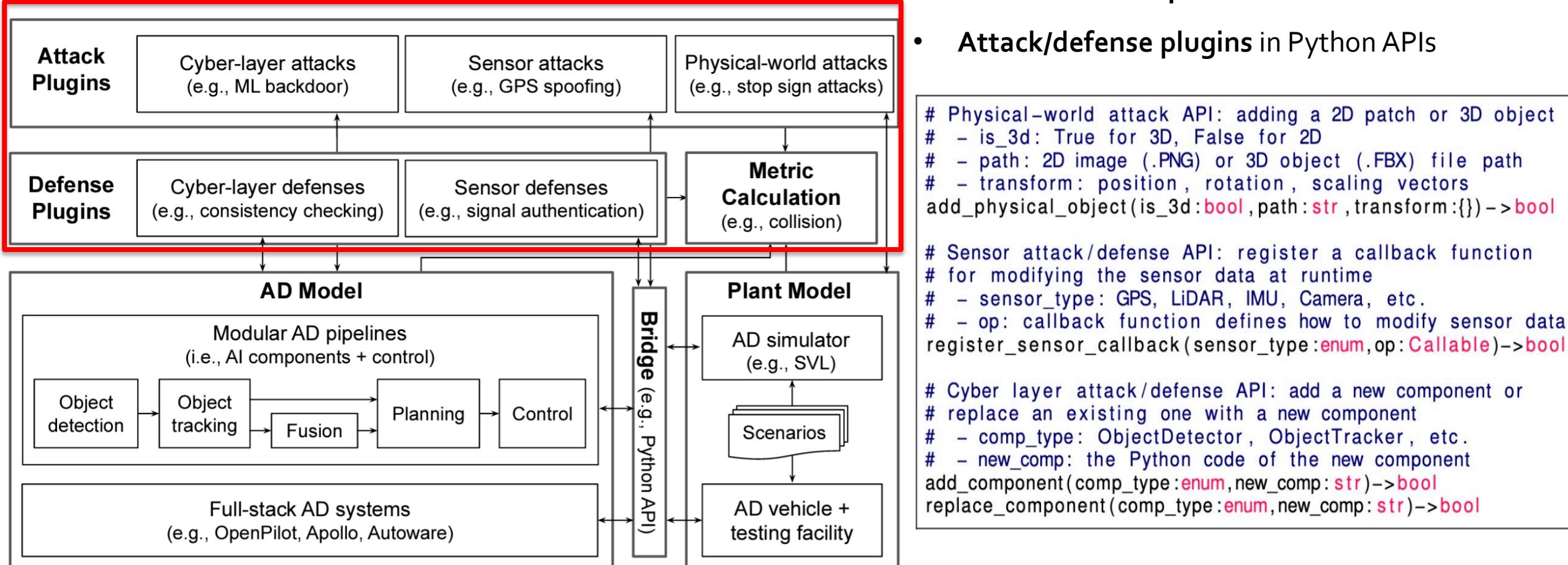
# Our proposal: PASS (Platform for Autonomous driving Security and Safety)

- *Open, uniform & extensible* system-driven evaluation platform



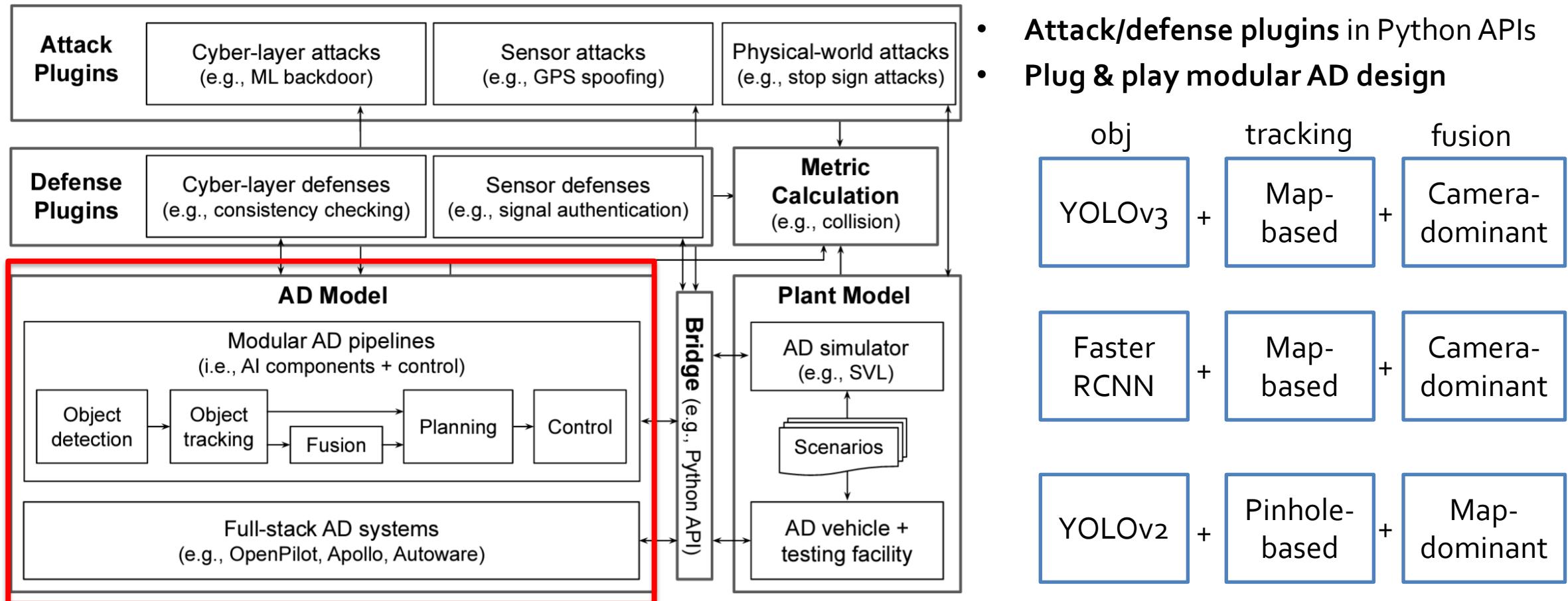
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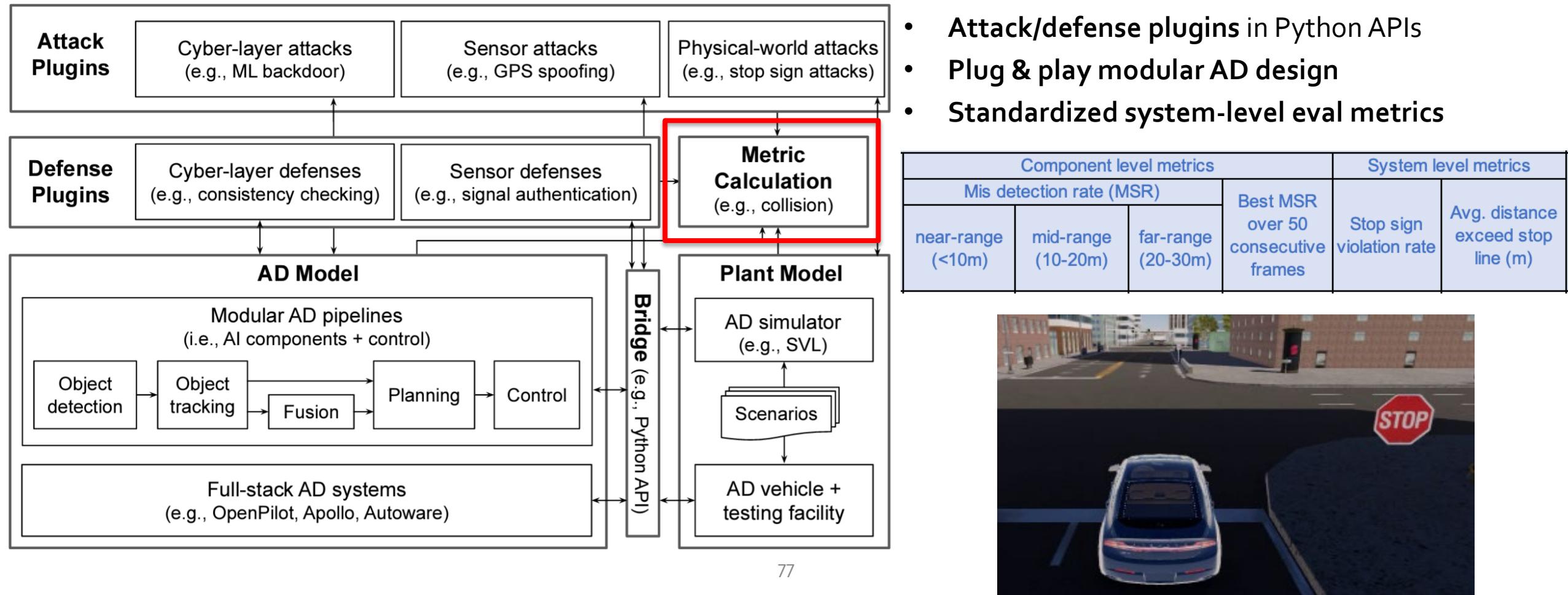
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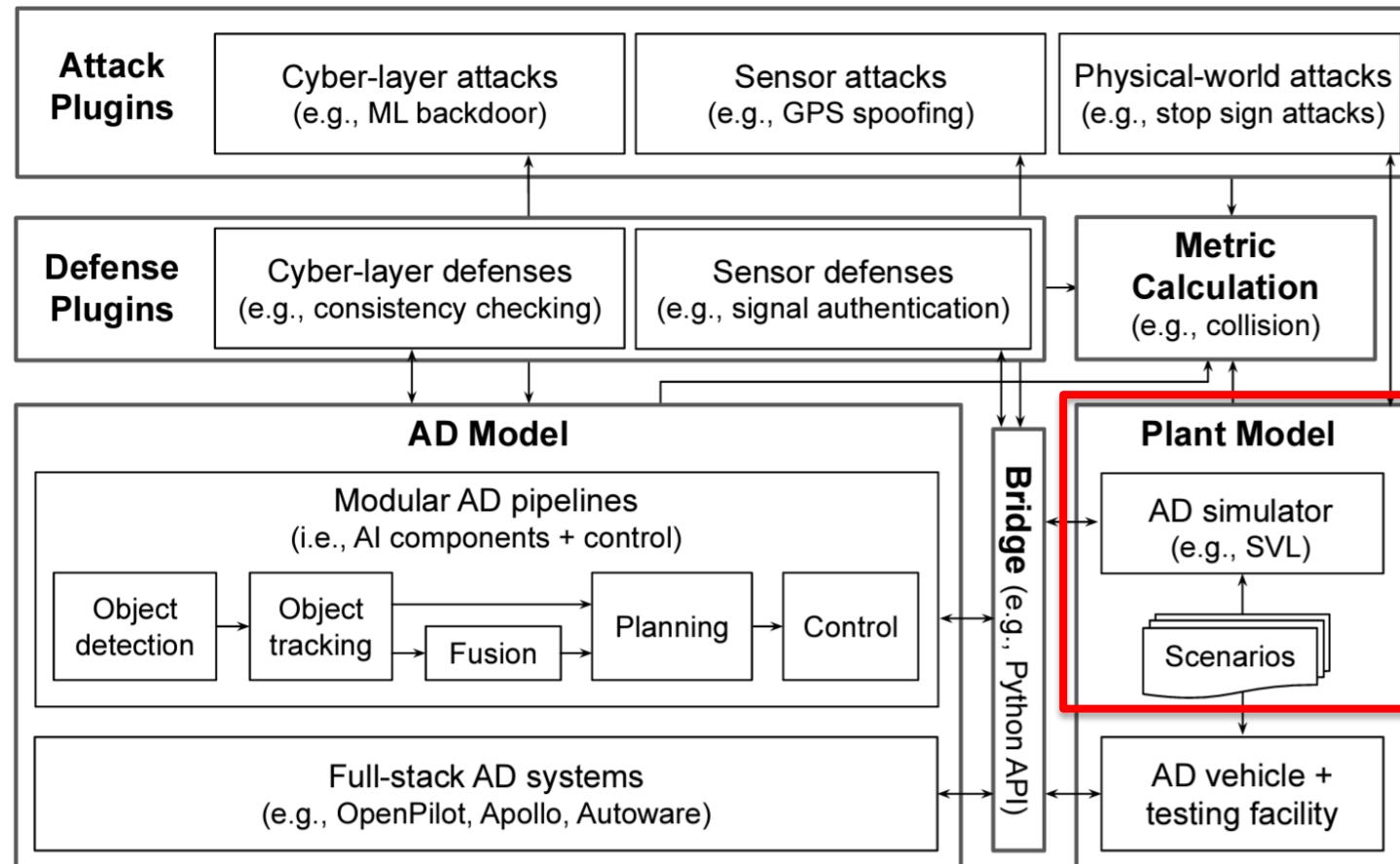
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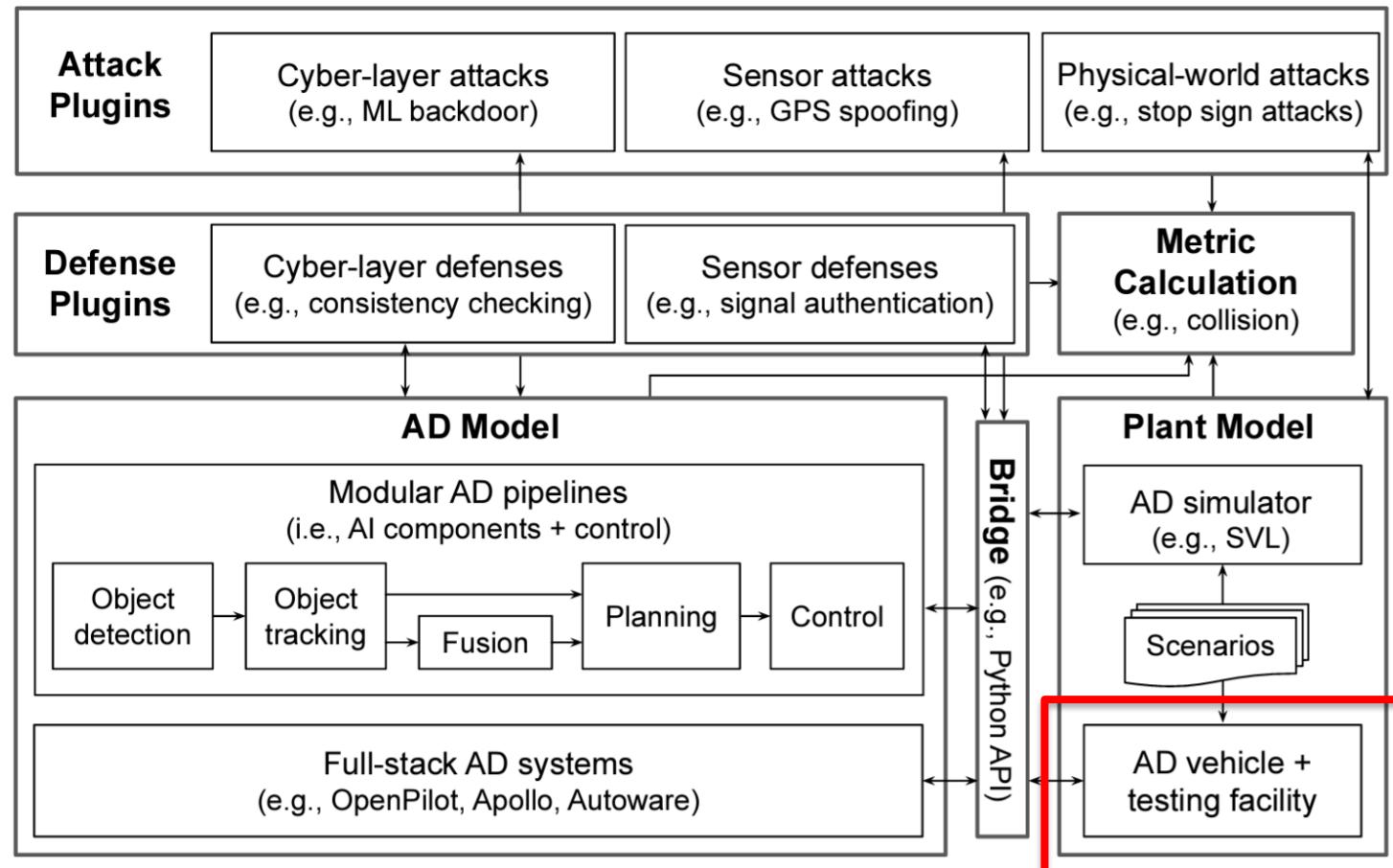


- Attack/defense plugins in Python APIs
- Plug & play modular AD design
- Standardized system-level eval metrics
- Simulation-centric design for affordability, accessibility, safety, flexibility & reproducibility



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- Attack/defense plugins in Python APIs
- Plug & play modular AD design
- Standardized system-level eval metrics
- Simulation-centric design for affordability, accessibility, safety, flexibility & reproducibility
- Test AD vehicles for fidelity improvement



# In the process of soliciting community feedback!

- Do you think such a platform can be **useful/beneficial** to you (e.g., in *research, education, training, and/or outreaching*)?
- Any **features** you wish to *add/improve*?
- Any **concerns** you have regarding our current *design/vision*?
- Feel free to let us know your feedback anytime via ***the survey below*** or ***directly email me!***
  - Such info can also be found at the PASS website: <https://sites.google.com/view/cav-sec/pass>



*Platform feedback Survey*

(<https://docs.google.com/forms/u/1/d/e/1FAIpQLSfq4hAZMKCdWL5uROGnFrml7XUakxYNkSA9JZydPZUM4l5fg/viewform>)



*Our SoK effort*

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# Conclusion

- My group: *Actively developing* research space on **autonomous system AI security**, currently most in AD & intelligent transportation
  - Collection of our efforts: <https://sites.google.com/view/cav-sec>
- *Only the beginning* of this research problem space
  - Now mostly on attack side, need more on *defense & research infra.* sides
  - To facilitate community building & broader impacts:
    - Co-founded **ACM/ISOC AutoSec (Automotive & Autonomous Vehicle Security) Workshop (2019 - )**, co-located w/ **NDSS'21 & '22**
    - Co-created **DEF CON's first AutoDriving-themed hacking competition** in 2021 (one of world's most famous hacker convention)
    - Served on **NIST focused group & panel on AD AI test standards & metrics**

Sponsors:



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    - Served on **NIST focused group & panel on AD AI test standards & metrics**
  - Happy to chat more & form collaborations!

Sponsors:



Qualcomm

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