

# **Robustness Evaluation of Visual Perception Systems**

Huang Yihao

1, Sep, 2023

# Background

- Self-driving faces serious security problem

**Slight Street Sign Modifications Can Completely Fool Machine Learning Algorithms** › Minor changes to street sign graphics can fool machine learning algorithms into thinking the signs say something completely different

BY EVAN ACKERMAN | 04 AUG 2017 | 5 MIN READ |



BBC Sign in Home News Sport Reel Worklife

## NEWS

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Tech

### Uber's self-driving operator charged over fatal crash

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TESLA SET TO FACE TWO CASES INVOLVING AUTOPILOT FATALITY



Elon Musk's FSD v12 demo includes a near miss at a red light and doxxing Mark Zuckerberg



The 45-minute video was meant to demonstrate v12 of Tesla's Full Self-Driving but ended up being a list of things not to do while using FSD.

By Andrew J. Hawkins, transportation editor with 10+ years of experience who covers EVs, public transportation, and aviation. His work has appeared in The New York Daily News and City & State.

Aug 29, 2022, 2:04 AM GMT+8 | 210 Comments / 210 New



# Background

- **Visual perception systems**



# Segmentation



# Recognition



# Detection

- **Security problem**

## Adversarial attack



*x*  
“panda”  
57.7% confidence

+ .007 >



sign( $\nabla_{\boldsymbol{x}} J(\boldsymbol{\theta}, \boldsymbol{x}, y)$ )  
“nematode”  
8.2% confidence

2



$\epsilon$ sign( $\nabla_x J(\theta, x, y)$ )  
“gibbon”  
99.3 % confidence

# Corruption

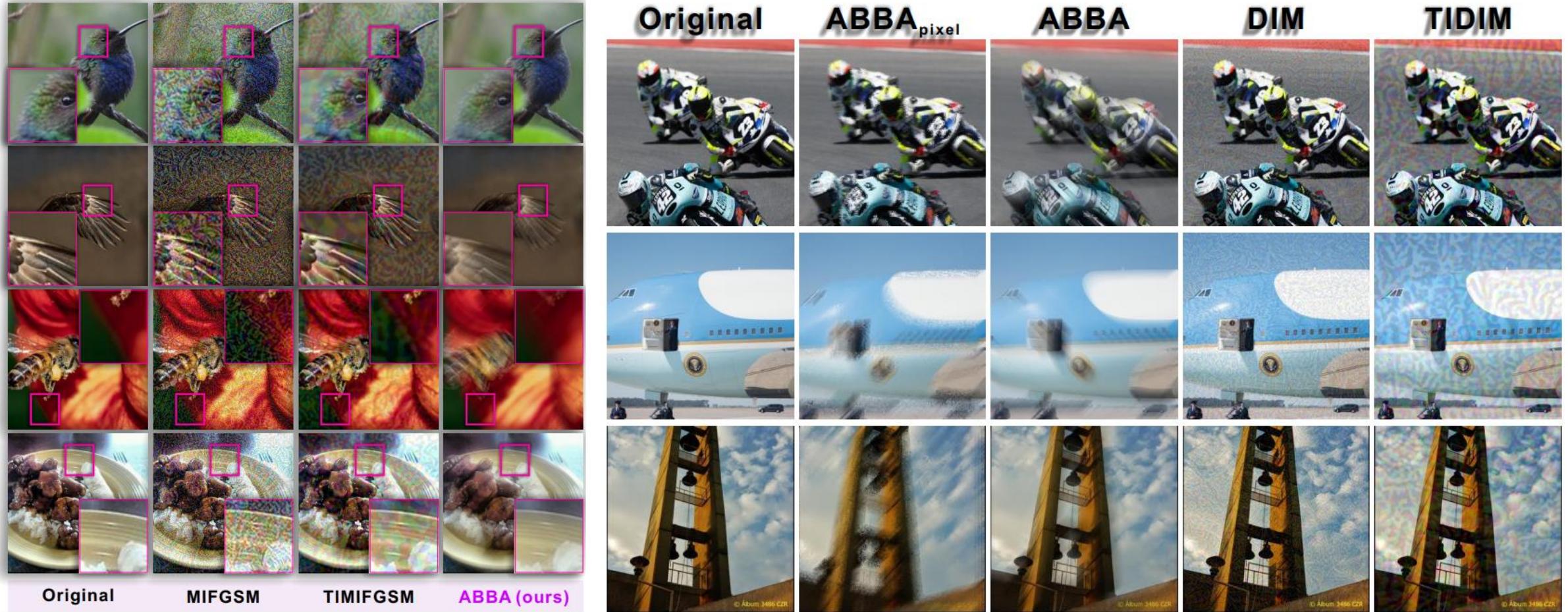


# Snow



## Rain

# Attack



# Attack

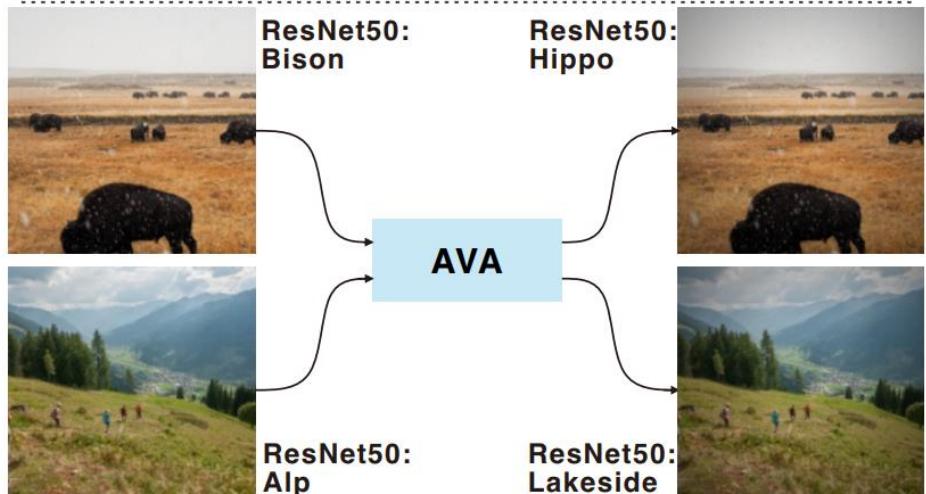


**Figure II:** Comparison between adversarial-blurred images and blurred images for training deblurring models.

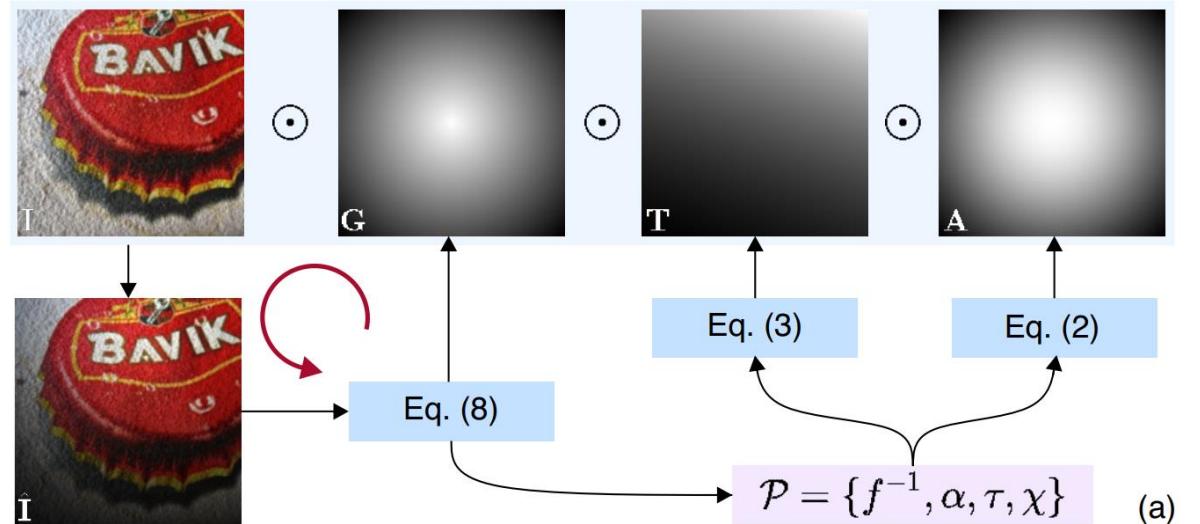


**Figure VII:** Comparing the visualization examples of ABBA<sub>physical</sub> with those of ABBA.

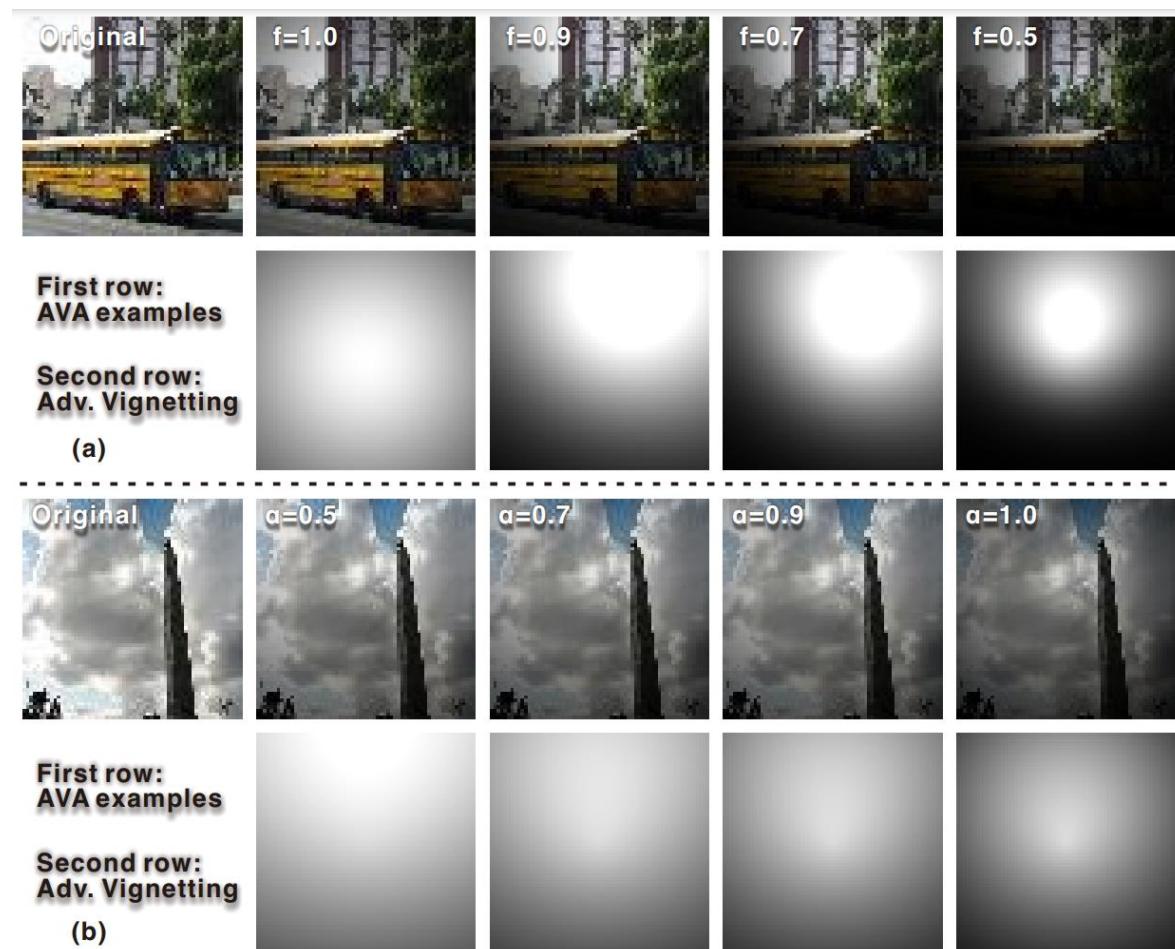
# Attack



(b) Adversarial Vignetting Examples

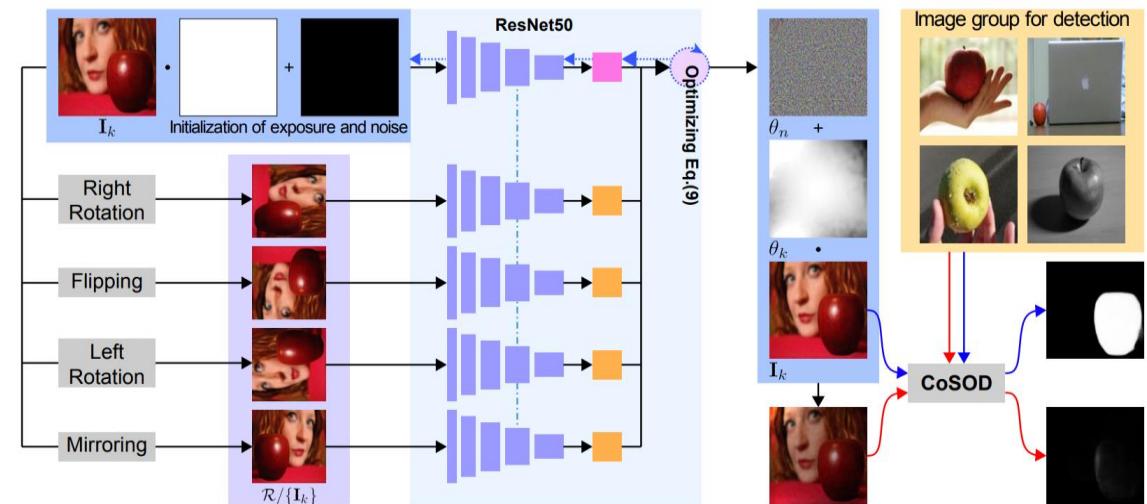
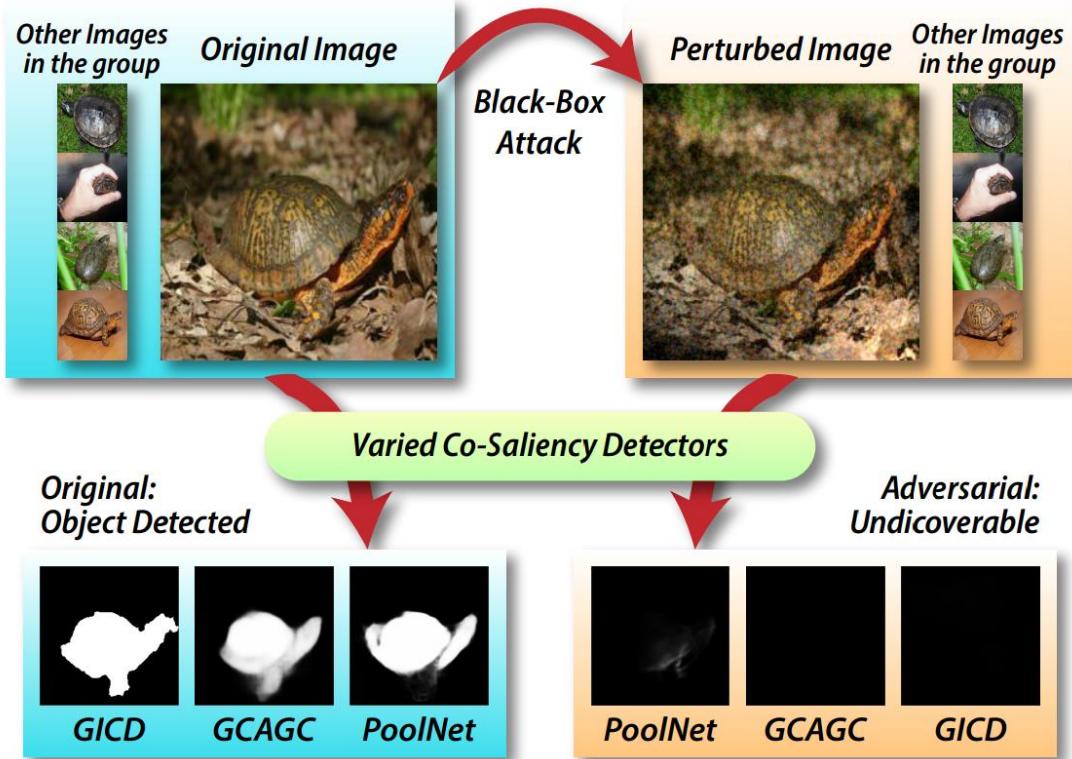


# Attack



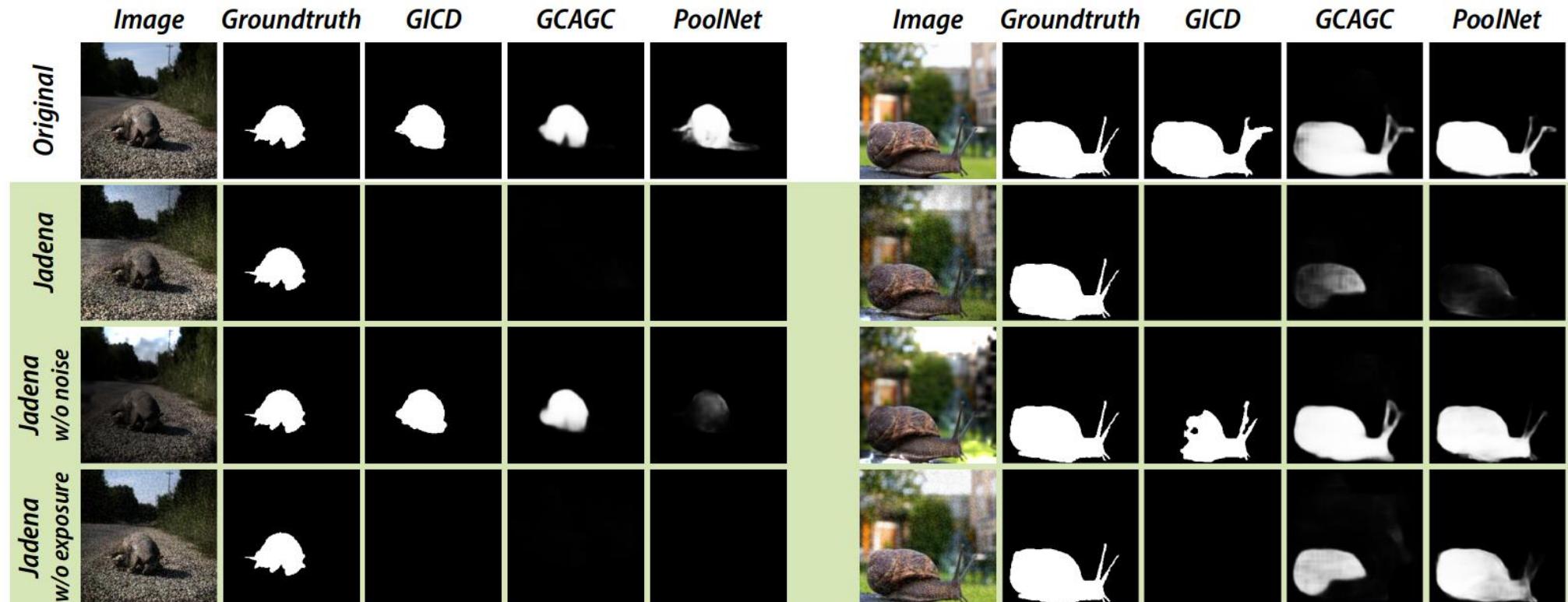
**Figure 4:** Visualization results of different ball bound for  $f$  and  $\alpha$ .

# Attack



**Figure 2.** Pipeline of the *joint adversarial exposure and noise attack*. The clean image is augmented to generate references and the gradient back-propagates along the blue dashed lines.

# Attack



# Attack

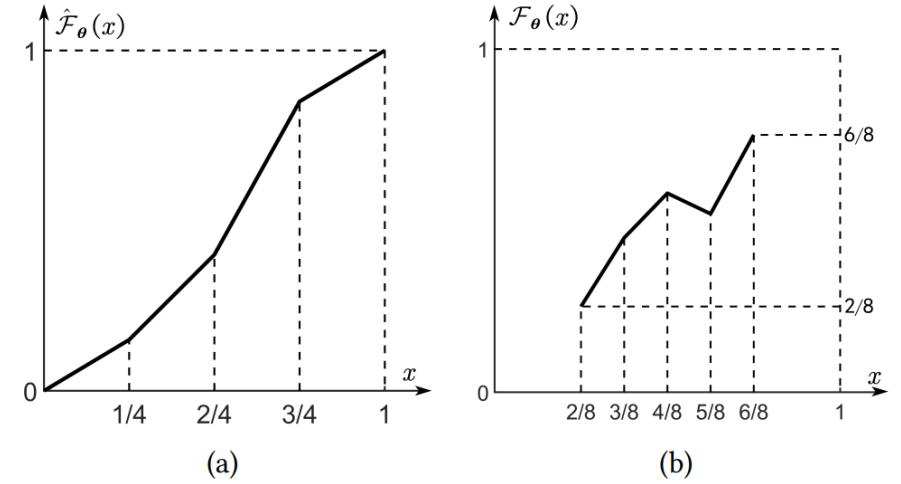
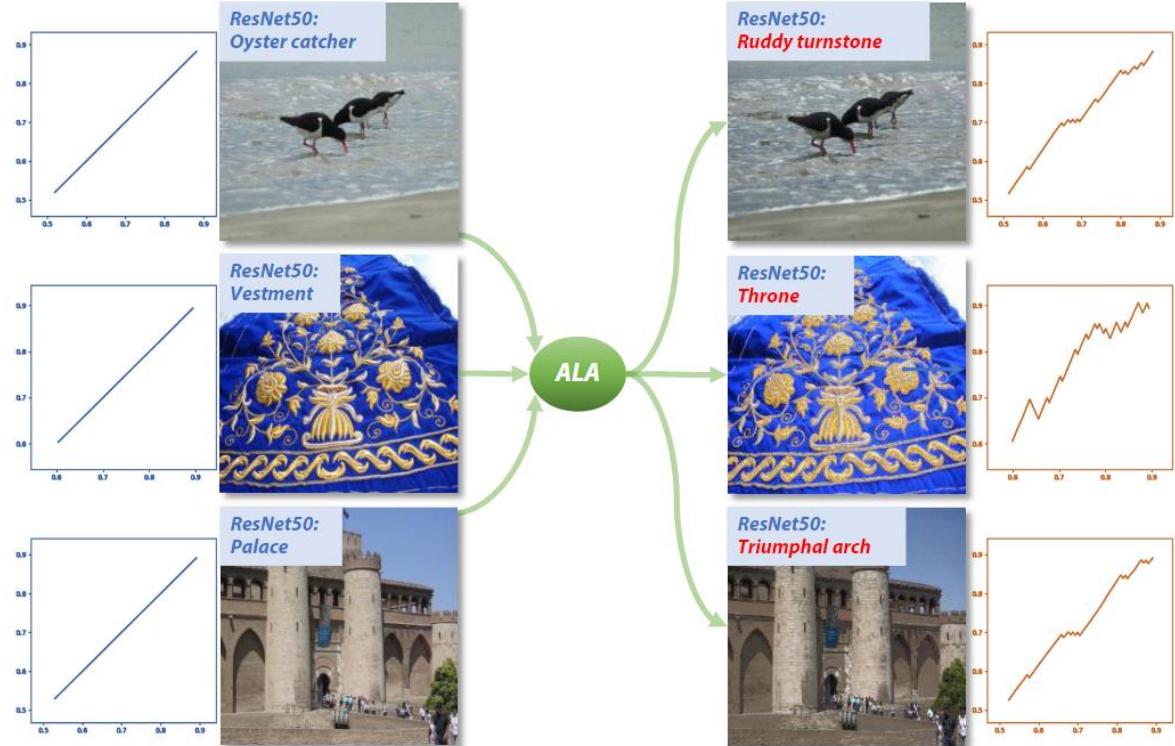
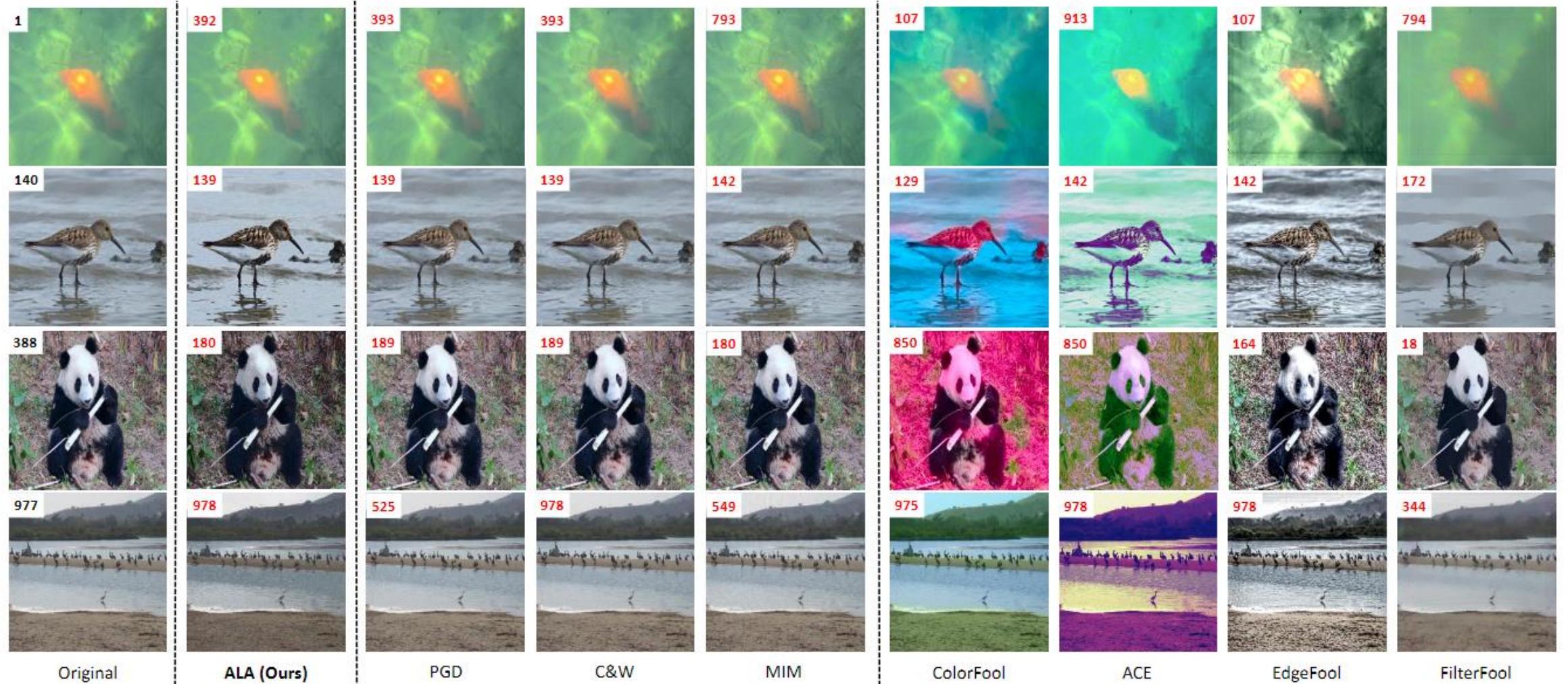


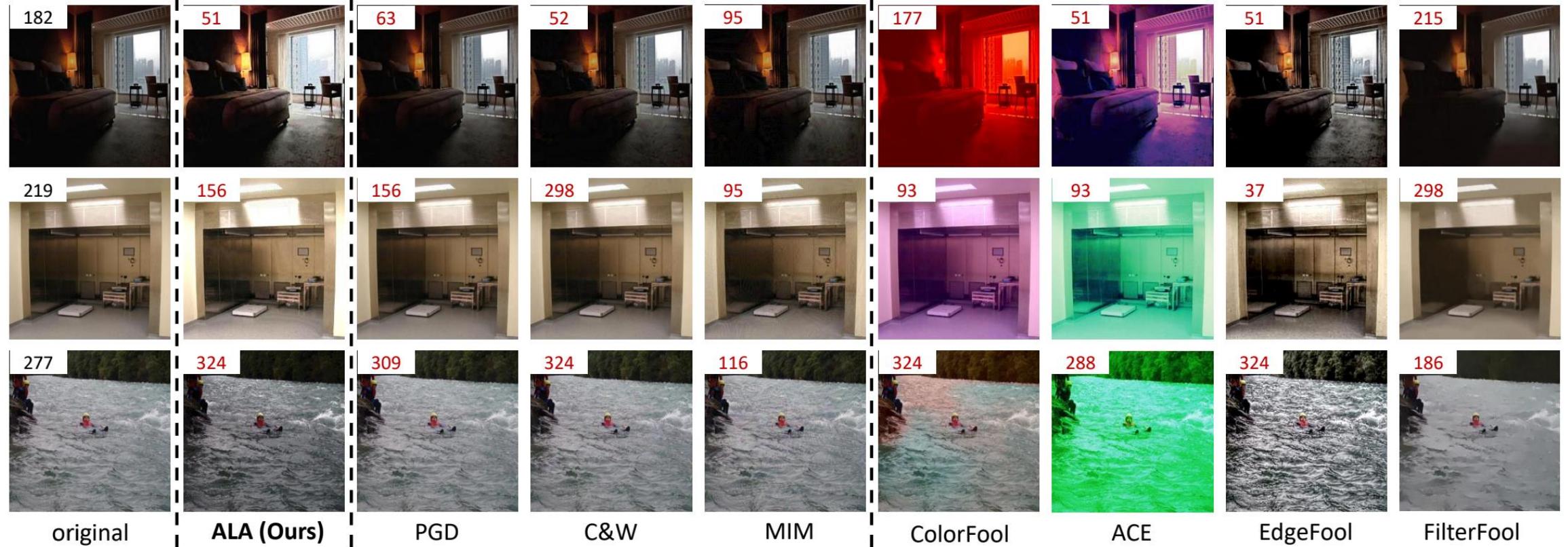
Figure 2: (a) monotonic filter  $\hat{\mathcal{F}}_\theta$ . (b) scene-adaptive filter  $\mathcal{F}_\theta$  with the valid range from  $2/8$  to  $6/8$ . Both filters are segmented into 4 pieces, i.e.,  $T = 4$  in Eq. (1).

# Attack



Huang Y, Sun L, et al. ALA: Adversarial lightness attack via naturalness-aware regularizations[C]. ACM MM, 2023.

# Attack



# Large Model

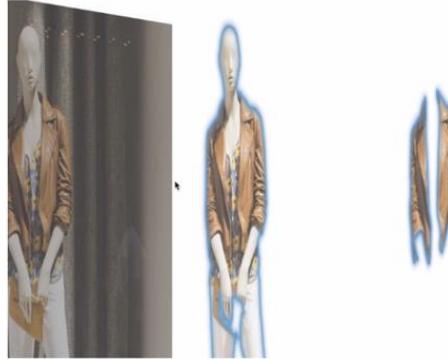
- **Segment anything model (SAM)**
  - universality of perception system



Prompt it with interactive points and boxes.



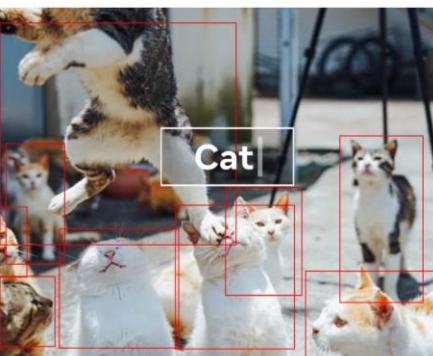
Automatically segment everything in an image.



Generate multiple valid masks for ambiguous prompts.



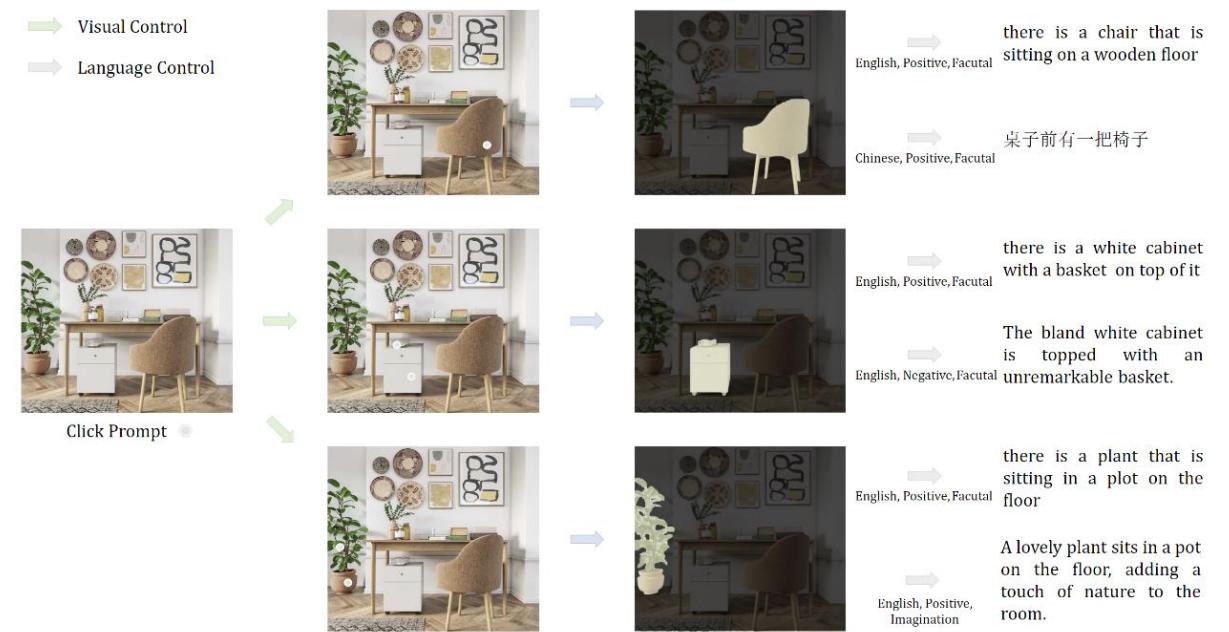
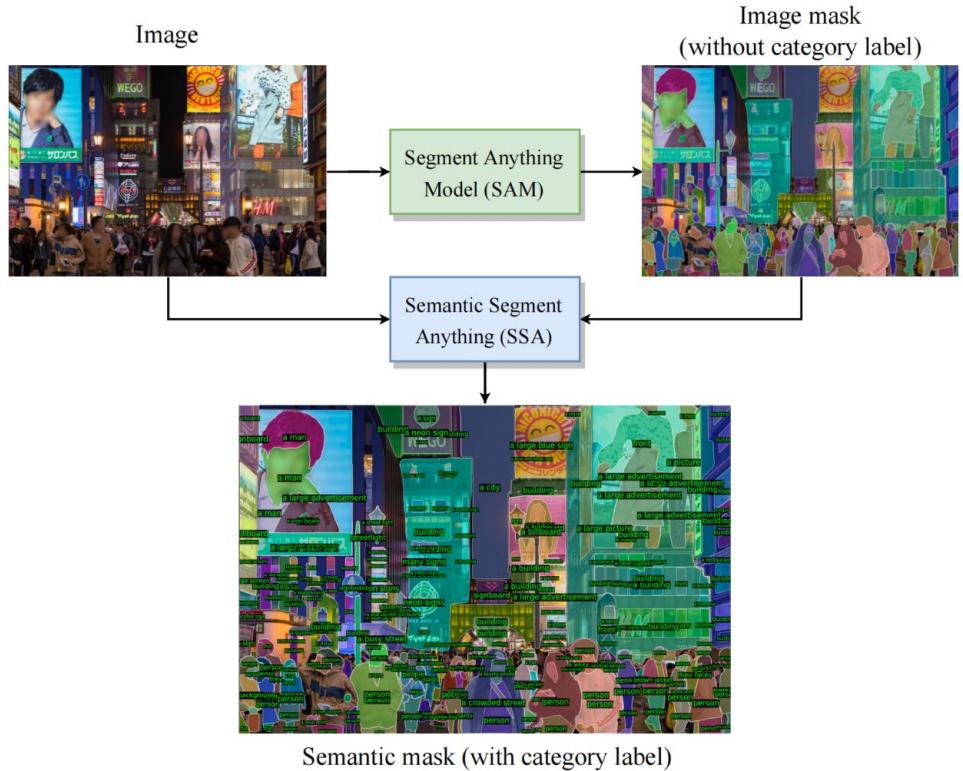
SAM can take input prompts from other systems, such as in the future taking a user's gaze from an AR/VR headset to select an object. This footage uses our [open sourced Aria pilot dataset](#).



Bounding box prompts from an object detector can enable text-to-object segmentation.

# Large Model

- **SAM-related system**

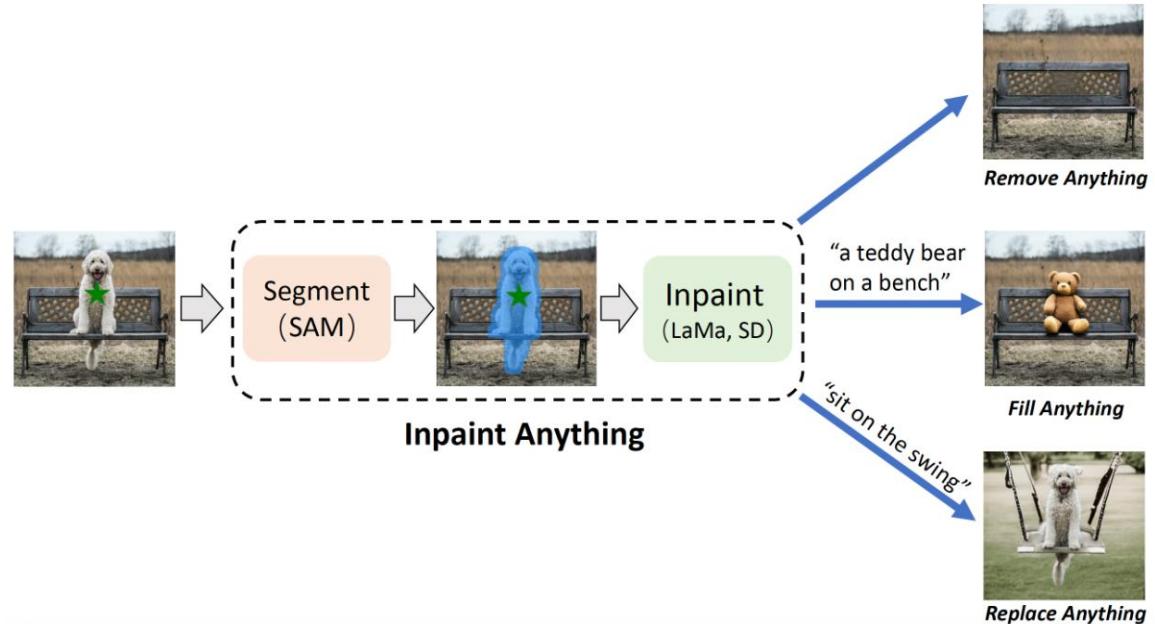


<https://github.com/fudan-zvg/Semantic-Segment-Anything>

<https://github.com/ttengwang/Caption-Anything>

# Large Model

- **SAM-related system**



## Anything-NeRF

In this section, we showcase the integration of [Segment Anything](#) with [NeRF](#) to generate new perspectives of objects set against intricate backgrounds. When an object is positioned in front of a plain, perspective-less background, NeRF typically struggles to reconstruct the scene. However, by eliminating the background, we can enhance NeRF's performance and facilitate more accurate reconstructions of scenes with objects presented in novel views.

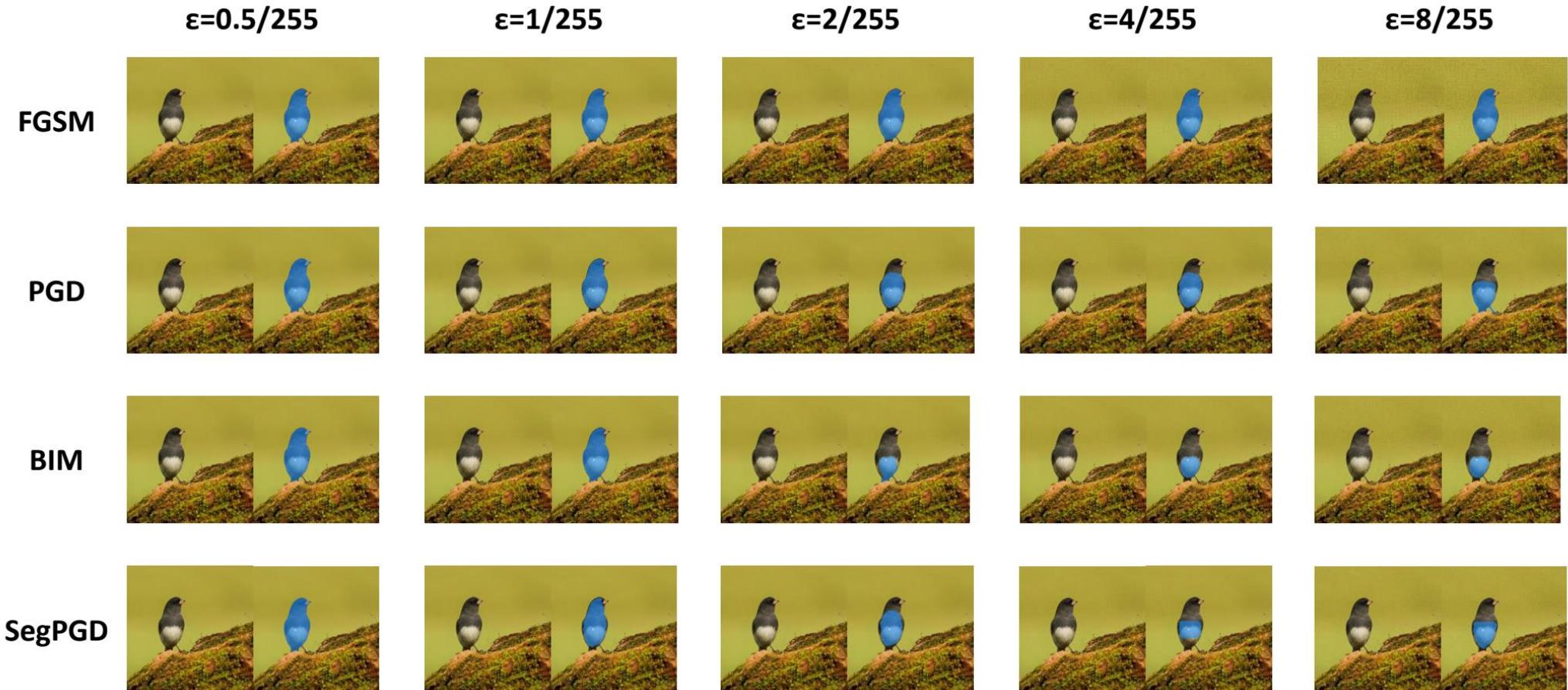
Segmentation-1	Segmentation-2	Result

<https://github.com/geekyutao/Inpaint-Anything>

<https://github.com/Anything-of-anything/Anything-3D>

# Evaluation

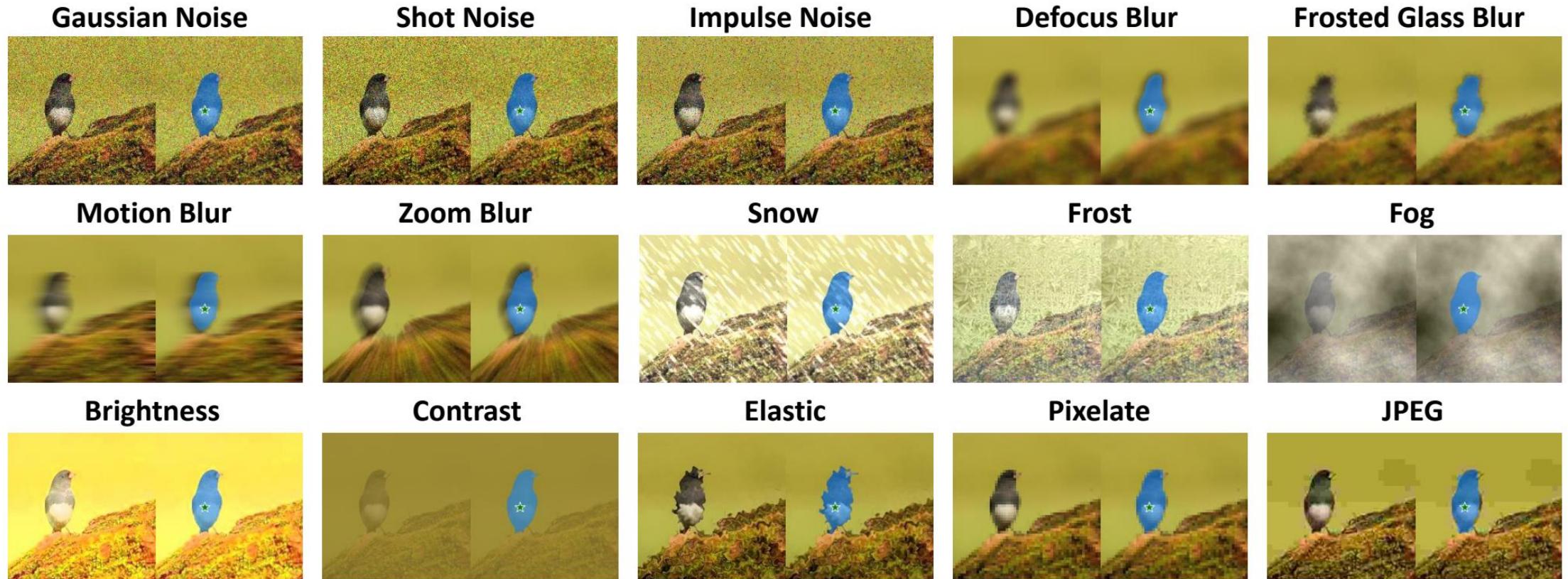
- **Adversarial attack**



**Fig. 1:** Adversarial attacks examples under 4 kinds of attacks with 5 different severities and corresponding masks predicted by SAM.

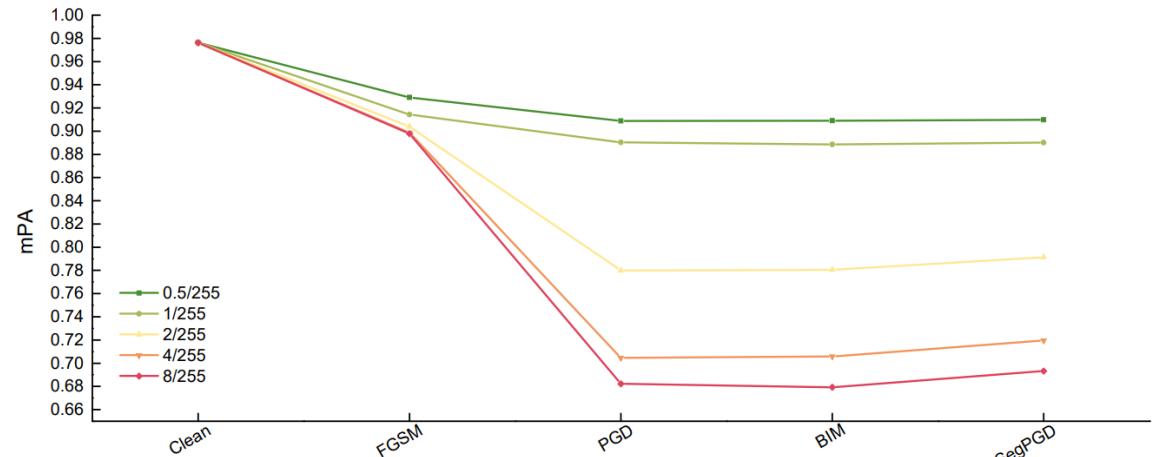
# Evaluation

- **Corruptions**

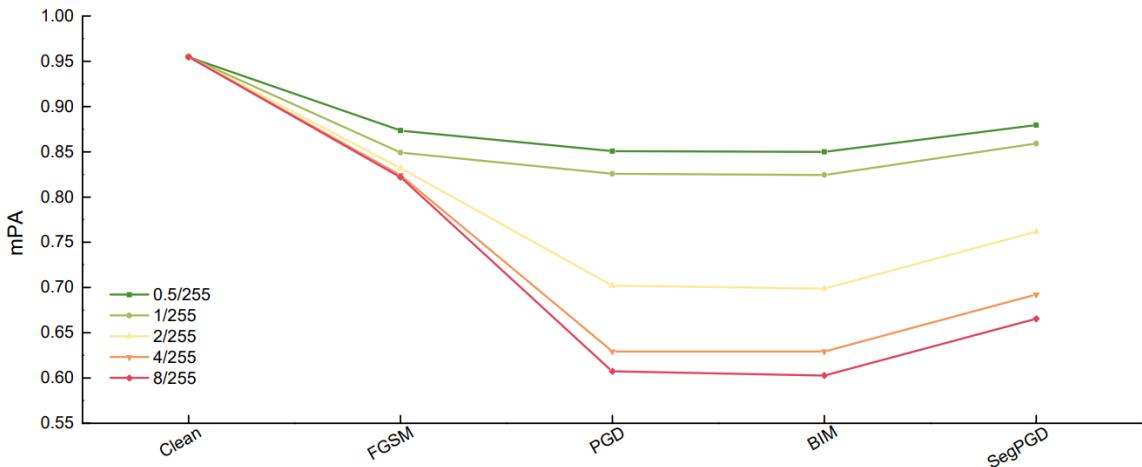


**Fig. 2:** Corruption examples of 15 diverse types and corresponding masks predicted by SAM.

# Evaluation

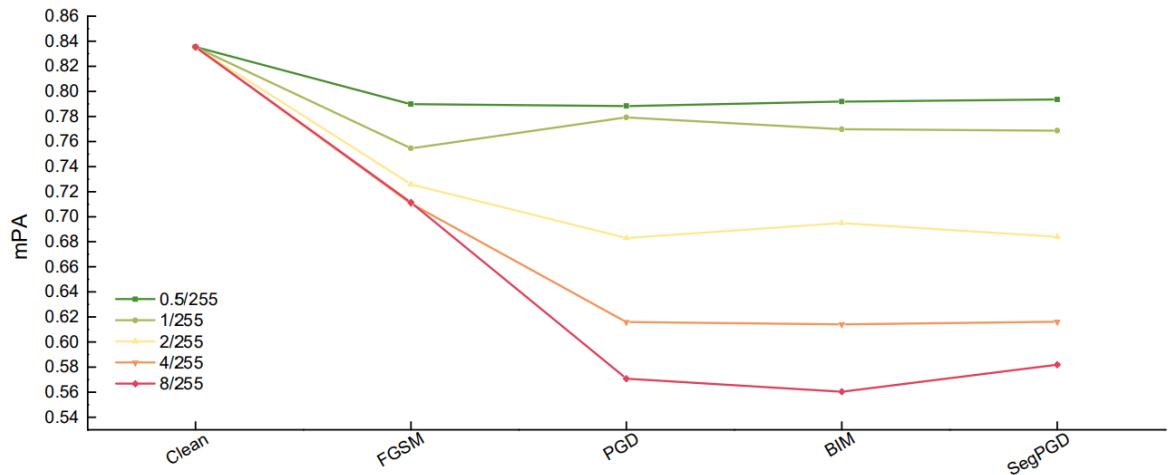


**Fig. 3:** The mPA values of SAM on SA-1B under 4 adversarial attacks and 5 severities.

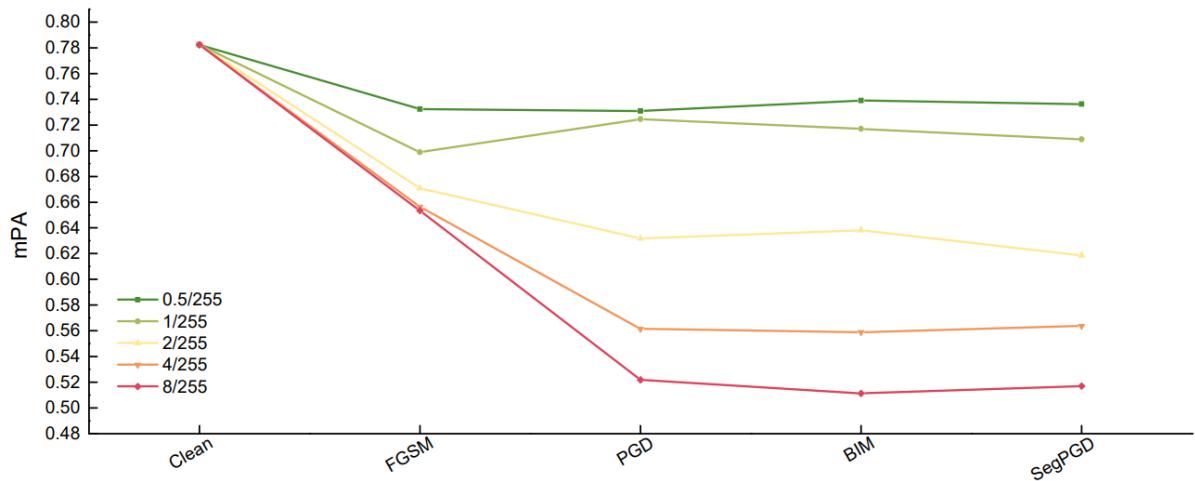


**Fig. 4:** The mIoU values of SAM on SA-1B under 4 adversarial attacks and 5 severities.

# Evaluation

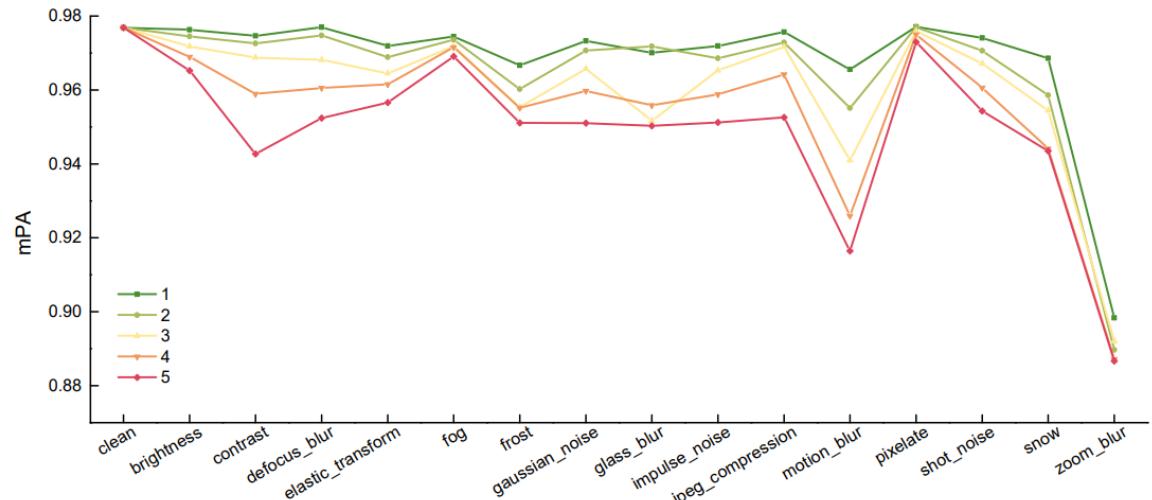


**Fig. 11:** The mPA values of SAM on KITTI under 4 adversarial attacks and 5 severities using MSE loss.

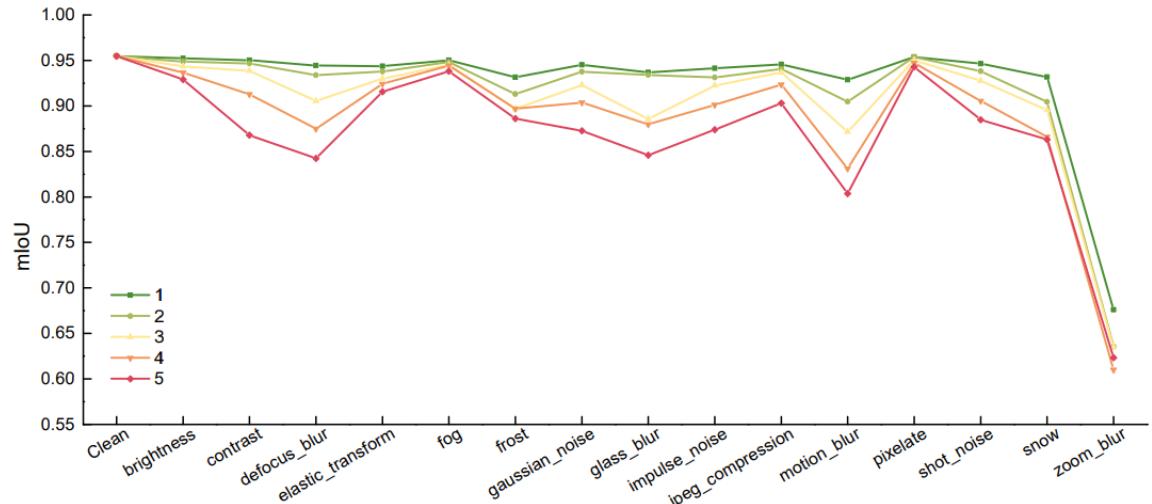


**Fig. 12:** The mIoU values of SAM on KITTI under 4 adversarial attacks and 5 severities using MSE loss.

# Evaluation

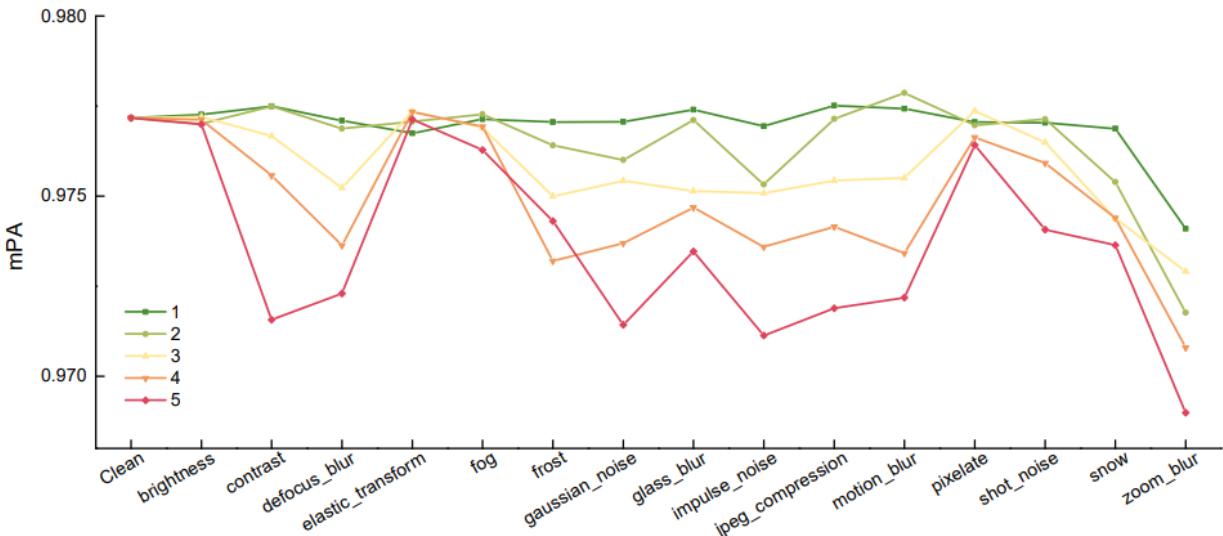


**Fig. 17:** The mPA values of SAM on SA-1B under 15 corruptions and 5 severities.

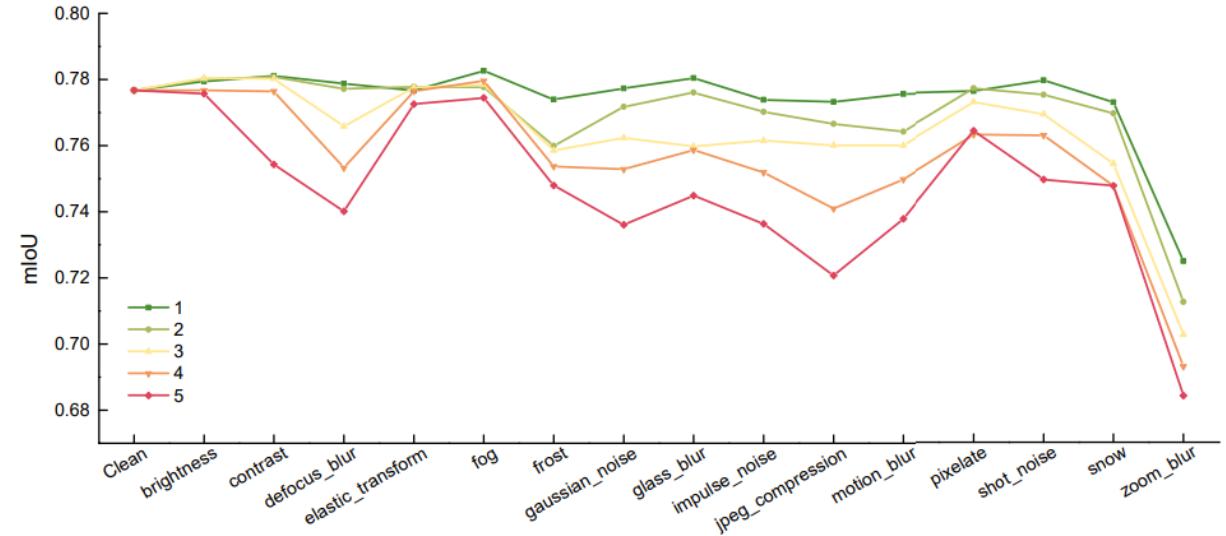


**Fig. 18:** The mIoU values of SAM on SA-1B under 15 corruptions and 5 severities.

# Evaluation



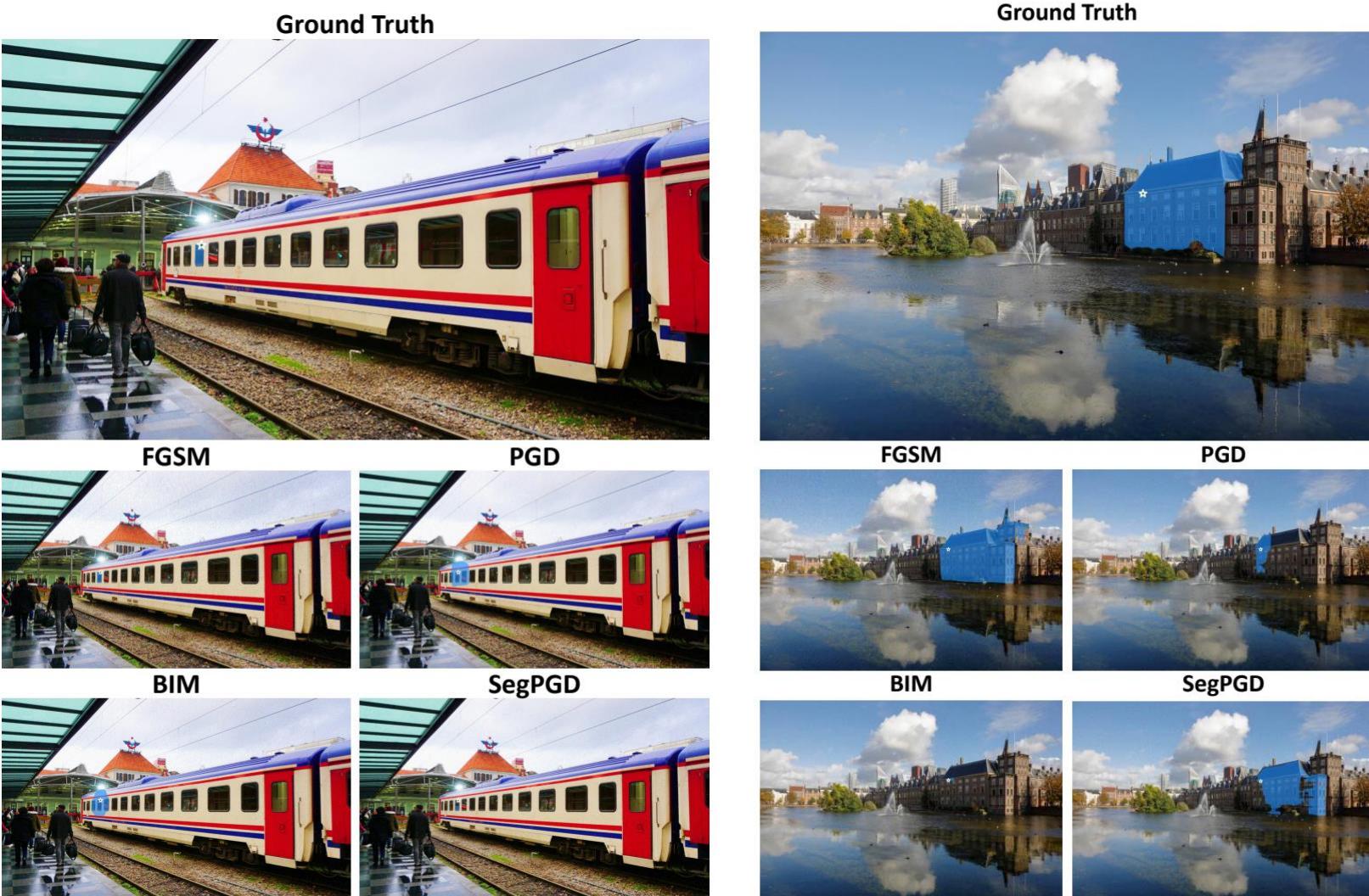
**Fig. 19:** The mPA values of SAM on KITTI under 15 corruptions and 5 severities.



**Fig. 22:** The mIoU values of SAM on big objects of KITTI under 15 corruptions and 5 severities.

# Evaluation

- SA-1B



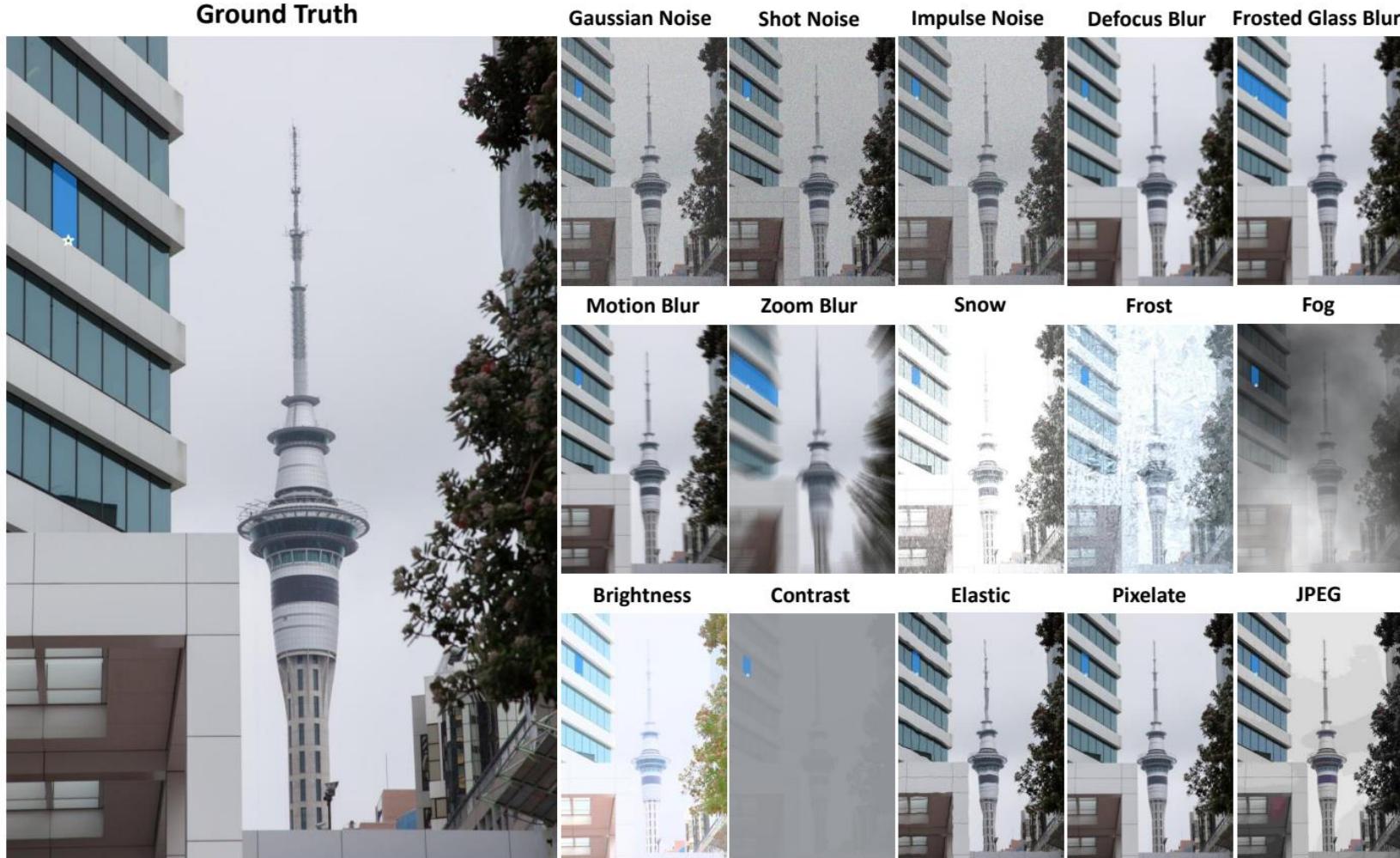
# Evaluation

- **KITTI**



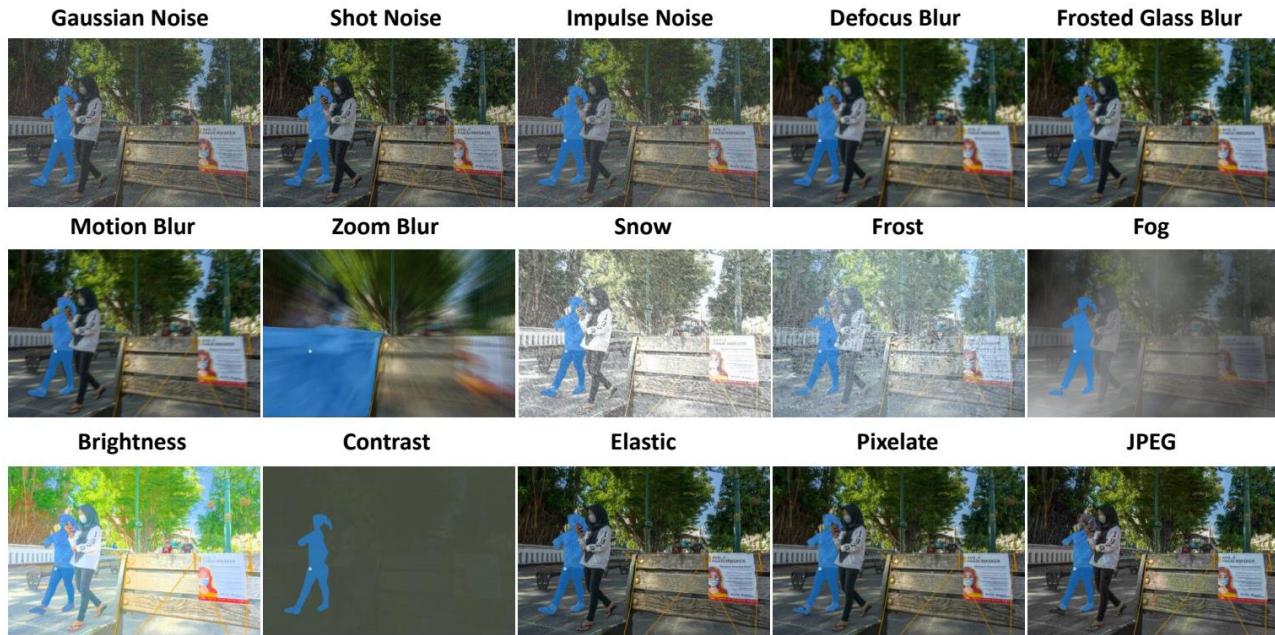
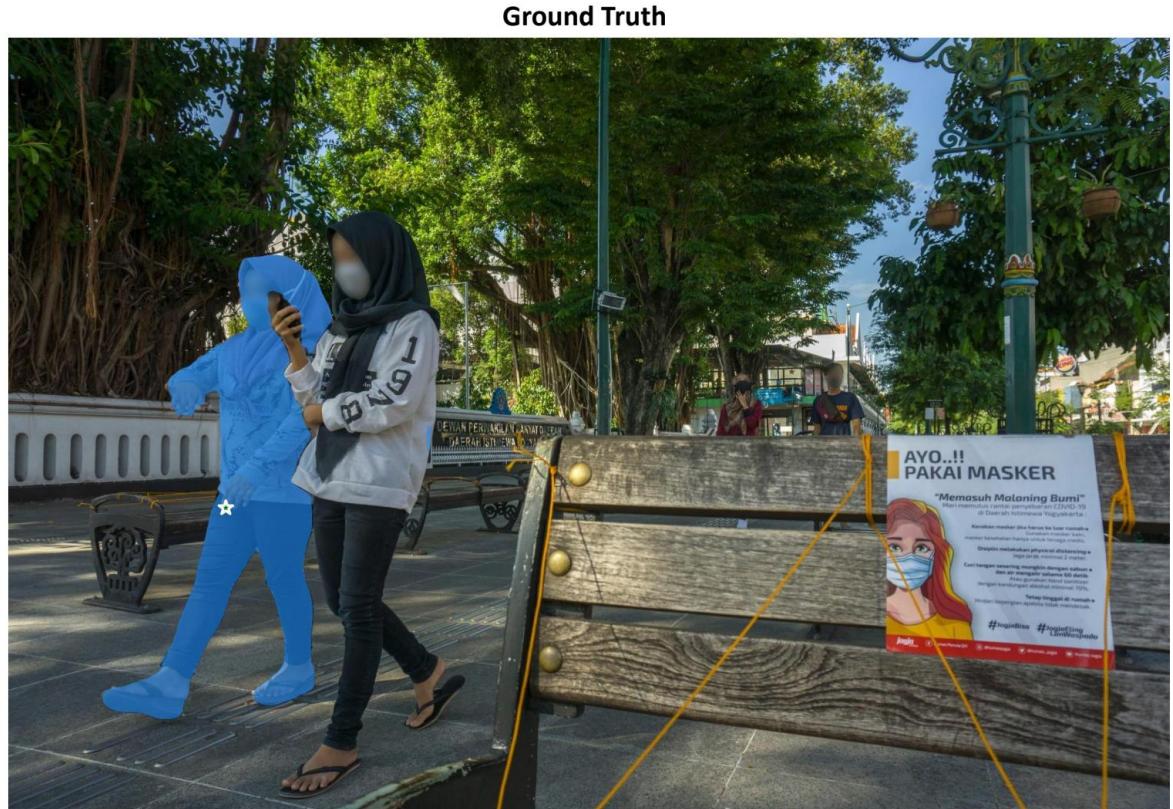
# Evaluation

- **SA-1B**



# Evaluation

- SA-1B



# Evaluation

- **KITTI**

**Ground Truth**



Gaussian Noise



Shot Noise



Impulse Noise



Defocus Blur



Frosted Glass Blur



Motion Blur



Zoom Blur



Snow



Frost



Fog



Brightness



Contrast



Elastic



Pixelate

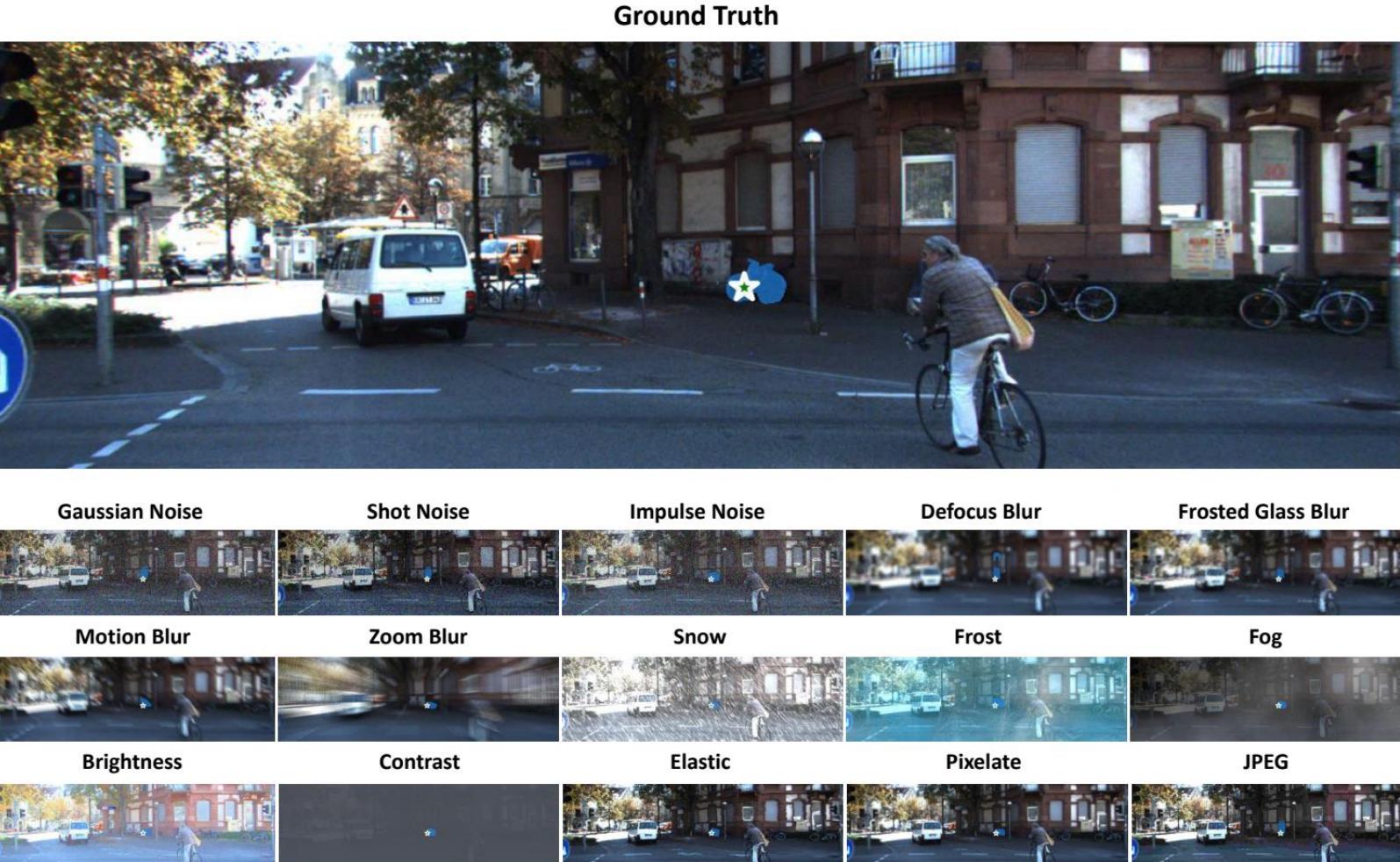


JPEG



# Evaluation

- **KITTI**





**Thanks for listening!**