ICCV23
PARIS

The many faces of reliability of visual perception for autonomous driving

Performance monitoring

Andrei Bursuc

valeo.ai

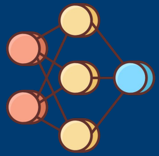
Learning to identify complex situations

Challenges of driving automation

Input data

unknown
scenario

Perception model



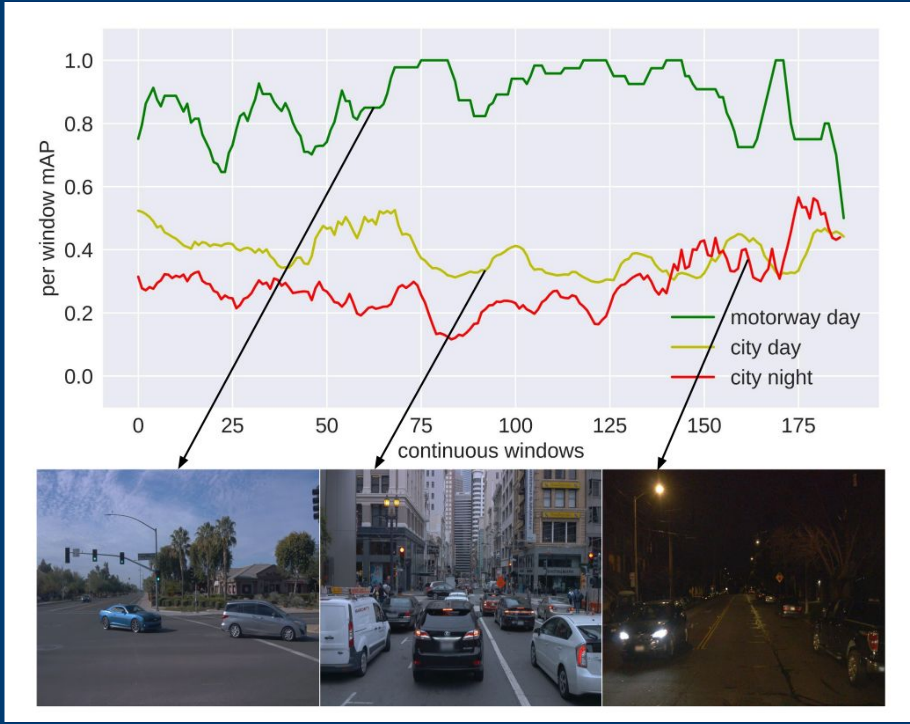
wrong prediction
(with confidence)

Driving stack

wrong behavior

How to identify/prevent incorrect predictions that can cause system failures?

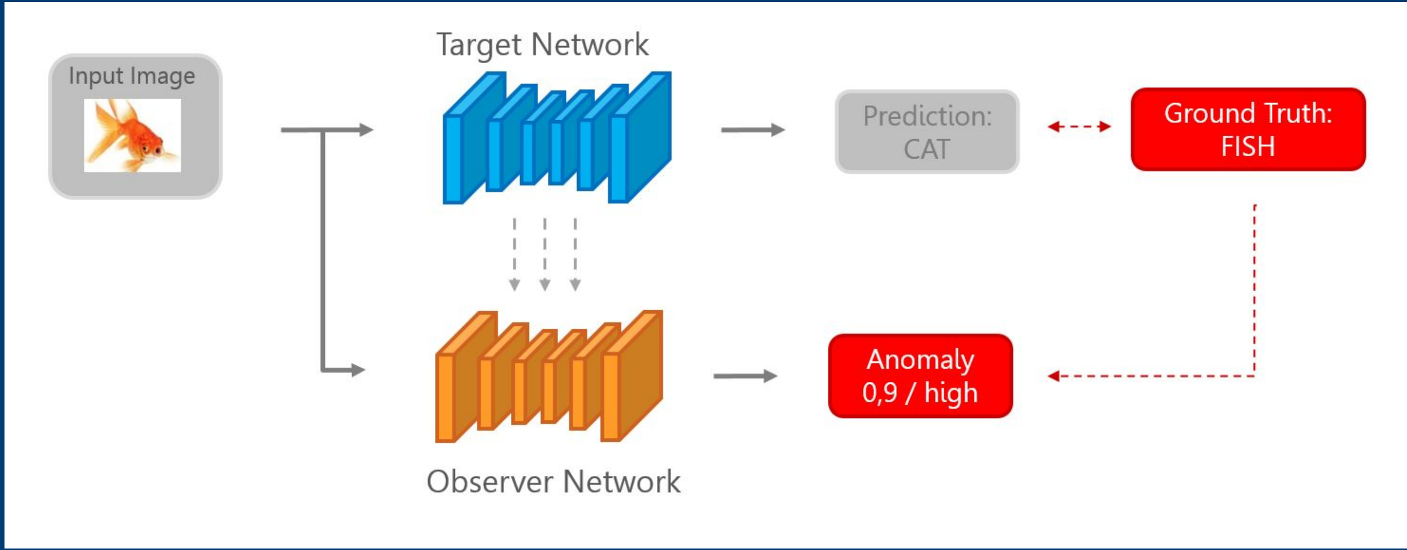
Challenges of driving automation



Performance can fluctuate depending on conditions and traditional engineered monitoring solutions cannot deal alone with the complexity of the world.

Q. M. Rahman et al., Online Monitoring of Object Detection Performance During Deployment, arXiv 2020

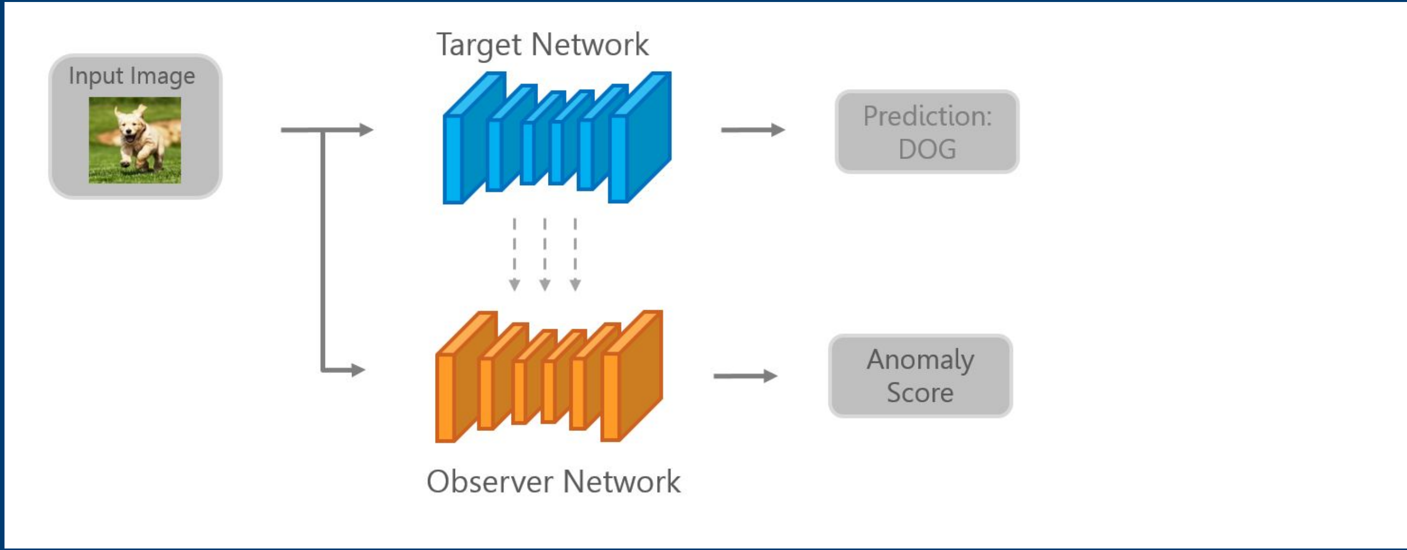
Observer Networks



- Target Network: (pre-trained) neural network for a task of interest
- Observer Network (ObsNet): auxiliary network connected to Target Network
    - Can have access to internal activations and predictions of Target
    - Trained to predict failures of Target Network
    - Produces confidence/failure/anomaly score

C. Corbieret al., Addressing Failure Prediction by Learning Model Confidence, NeurIPS 2019

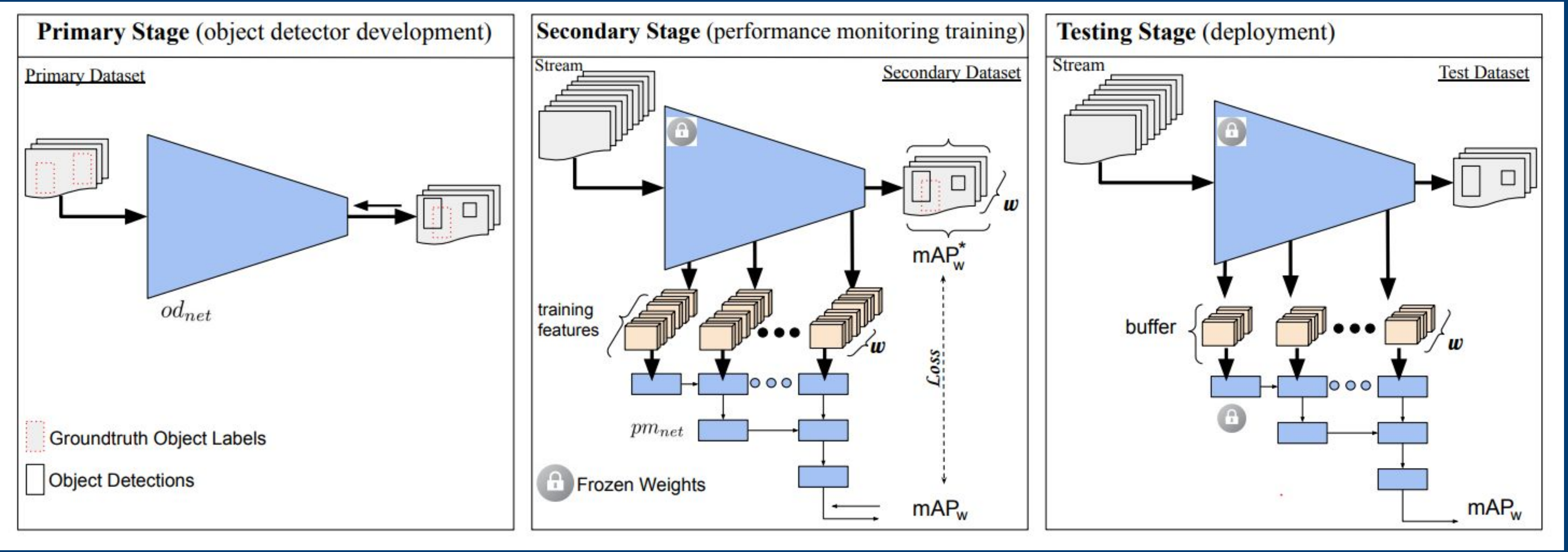
Observer Networks



- **Benefits:**
  - generic, fast, memory-efficient
- **Drawbacks:**
  - Needs a dedicated train set (Target Network makes few errors)
  - May not generalize to OOD data, not available at train time

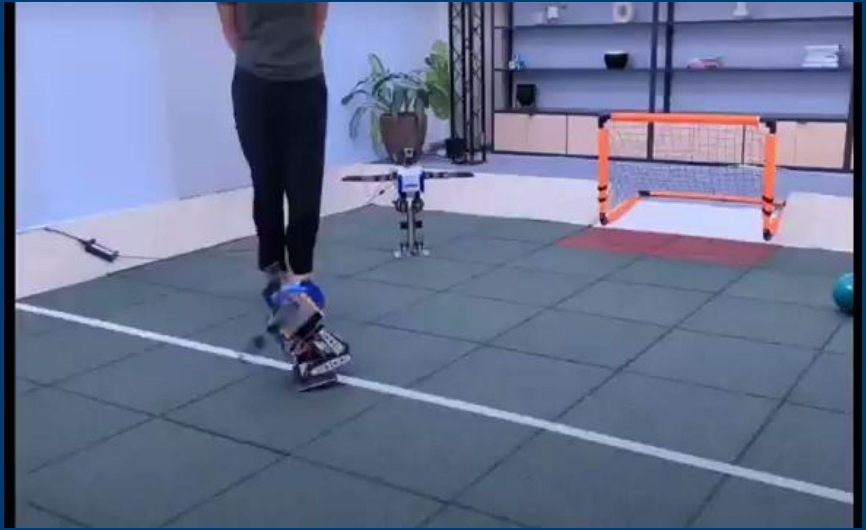
---
C. Corbieret al., Addressing Failure Prediction by Learning Model Confidence, NeurIPS 2019

Observer Networks



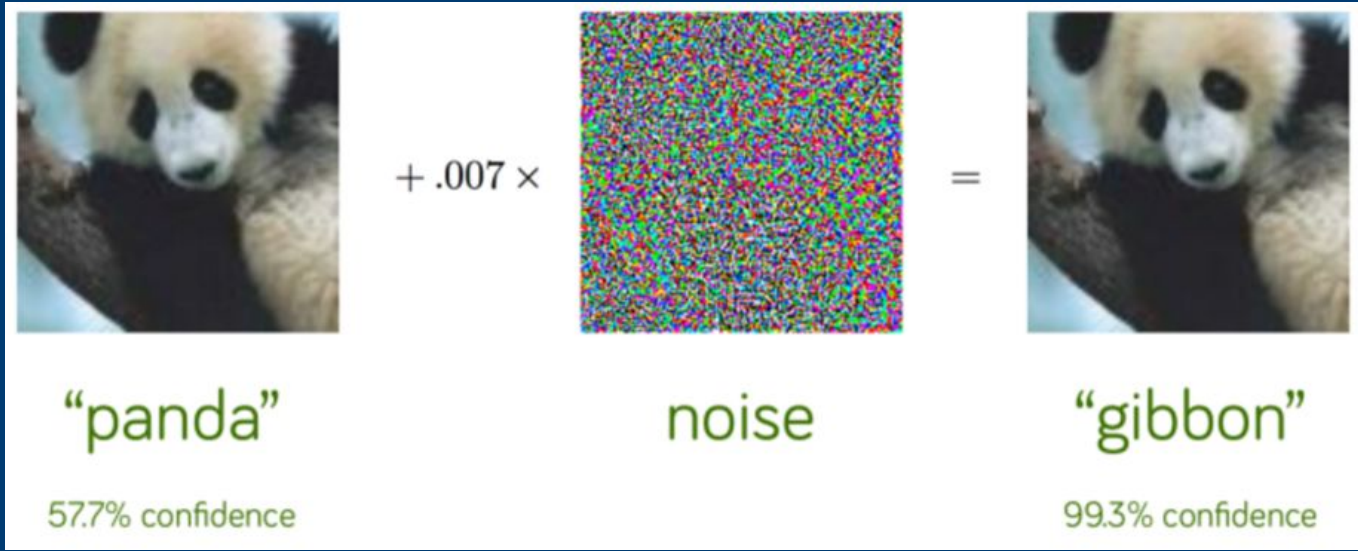
Earlier approaches leveraged temporal information to compile per sequence statistics and predict mAP

Q. M. Rahman et al., Online Monitoring of Object Detection Performance During Deployment, arXiv 2020



What if we make the Target fail and learn from that?

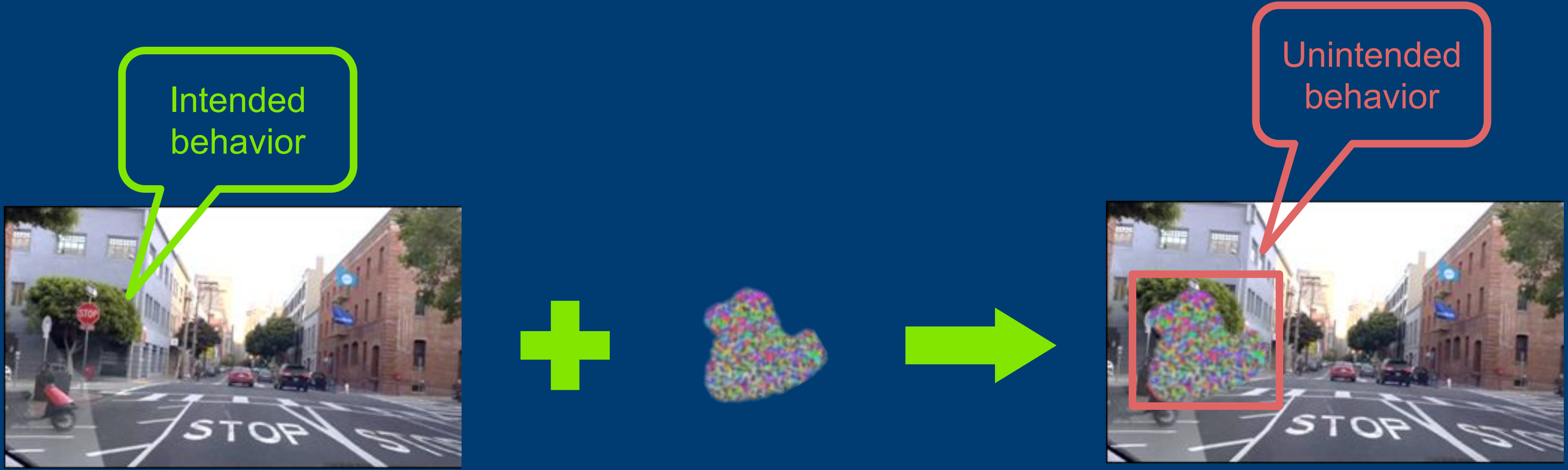
Adversarial Attacks



- Neural Networks can be fooled by perturbing the input image with constructed noise
- We use Adversarial Attacks in order to trigger failures of the target network

---
C. Szegedy al., Intriguing properties of neural networks, arXiv 2013

Local Adversarial Attacks



Training image

Local adversarial attack

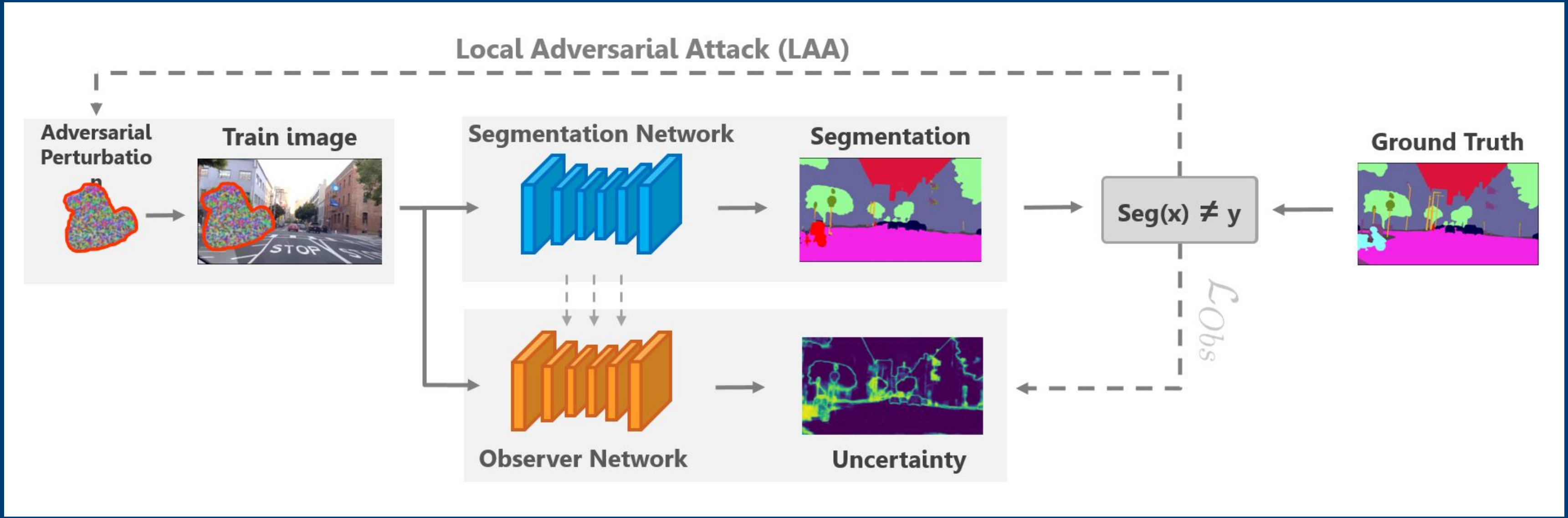
Augmented training image

- Use Local Adversarial Attacks (LAA) to “hallucinate” new class
- Edit a part of the image to decrease the target prediction in this location
- Encapsulate attack in random shape as proxy for unknown objects

---

V. Besnier al., Triggering Failures: Out-Of-Distribution detection by learning from local adversarial attacks in Semantic Segmentation, ICCV 2021

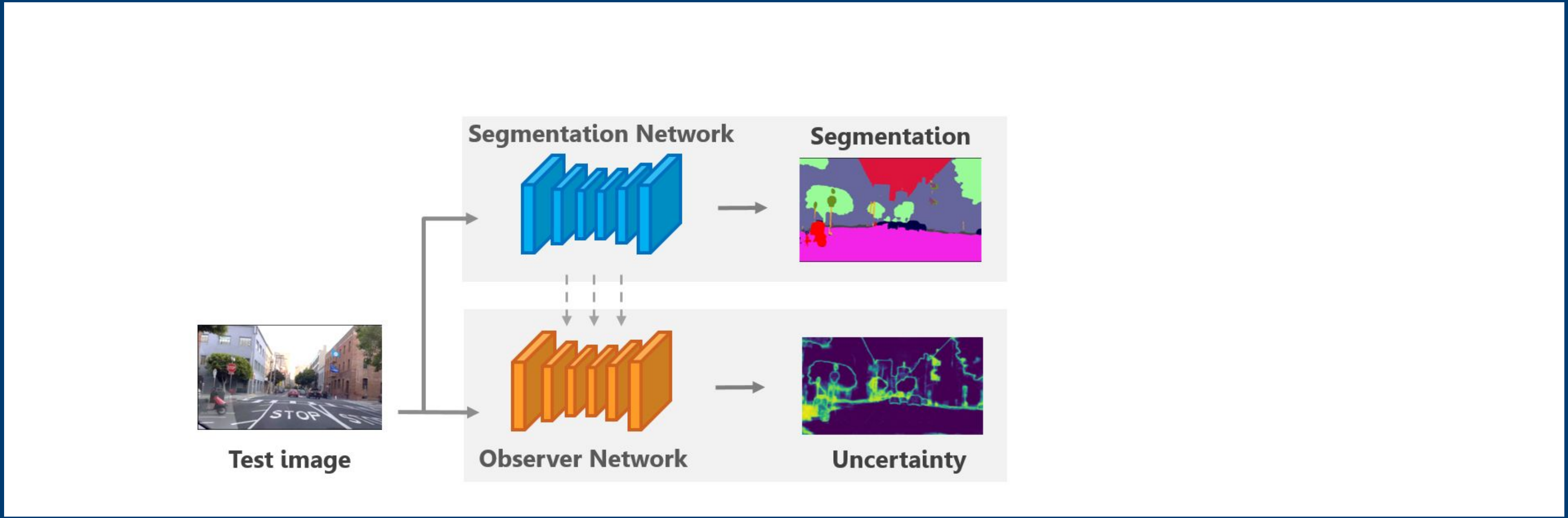
ObsNet - training setup



- The Observer learns failure behavior patterns of Target under attacks

---
V. Besnier al., Triggering Failures: Out-Of-Distribution detection by learning from local adversarial attacks in Semantic Segmentation, ICCV 2021

ObsNet - at runtime



- Generate classification predictions from Target and uncertainty from Observer

---
V. Besnier al., Triggering Failures: Out-Of-Distribution detection by learning from local adversarial attacks in Semantic Segmentation, ICCV 2021

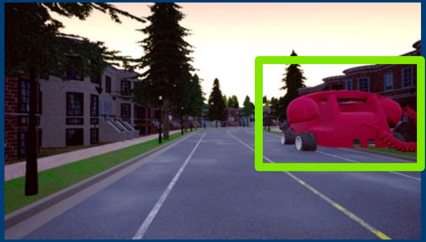
ObsNet Results

Method	Fpr95Tpr ↓	AuPR ↑	AuRoc ↑	ACE ↓
Softmax [HG17]	63.5	95.4	80.1	0.633
Void [BSN+19]	68.1	92.4	75.3	0.499
AE [HG17]	92.1	88.0	53.1	0.832
MCDA [AB18]	61.9	95.8	82.0	0.411
Temp. Scale [GPSW17]	61.8	95.8	81.9	**0.287**
ODIN [LSL18]	<u>60.6</u>	95.7	81.7	0.353
ConfidNet [CTBH+19]	61.6	95.9	81.9	0.367
Gauss P [MAG+20]	61.3	96.0	82.5	0.384
Deep Ensemble [LPB17]	**60.3**	<u>96.1</u>	82.3	0.375
MCDropout [GG16]	61.1	96.0	82.6	0.394
ObsNet + *LAA*	**60.3**	**96.2**	**82.8**	<u>0.345</u>

BDD Anomaly (OOD: train, motorcycle)

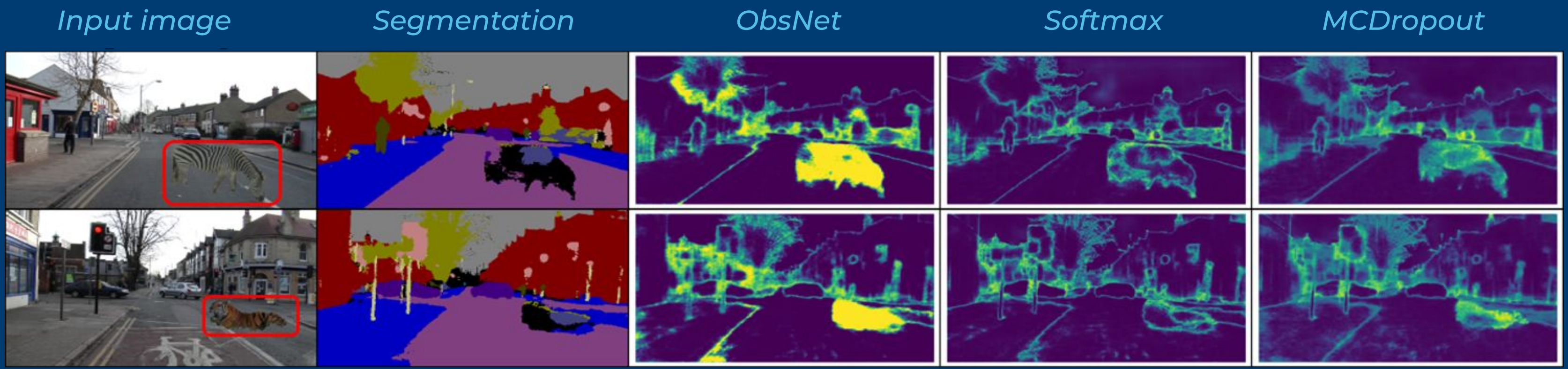
Method	Fpr95Tpr ↓	AuPR ↑	AuRoc ↑	ACE ↓
Softmax [HG17]	65.5	94.7	80.8	0.463
Void [BSN+19]	69.3	93.6	73.5	0.492
AE [HG17]	84.6	92.7	67.3	0.712
MCDA [AB18]	69.9	97.1	82.7	0.409
Temp. Scale [GPSW17]	65.3	94.9	81.6	**0.323**
ODIN [LSL18]	61.3	95.0	82.3	0.414
ConfidNet [CTBH+19]	60.1	98.1	90.3	0.399
Gauss P [MAG+20]	48.7	98.5	90.7	0.449
Deep Ensemble [LPB17]	51.7	98.3	88.9	0.437
MCDropout [GG16]	45.7	98.8	92.2	0.429
ObsNet + *LAA*	**44.7**	**98.9**	**92.7**	<u>0.383</u>

StreetHazards

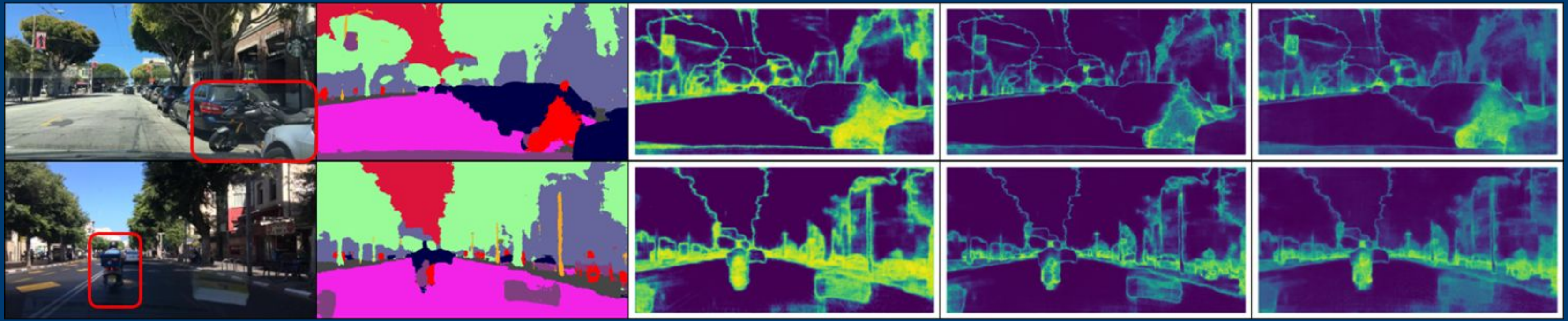


V. Besnier al., Triggering Failures: Out-Of-Distribution detection by learning from local adversarial attacks in Semantic Segmentation, ICCV 2021

ObsNet Quantitative Results



CamVid OOD



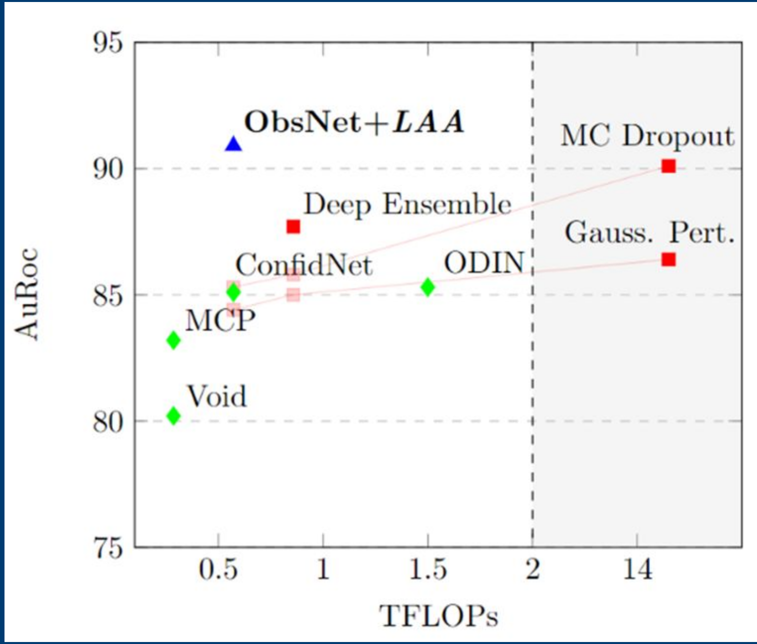
BDD Anomaly

V. Besnier al., Triggering Failures: Out-Of-Distribution detection by learning from local adversarial attacks in Semantic Segmentation, ICCV 2021

ObsNet

Takeaways

- Leverage adversarial attacks to find blind spots in the Target Network
- Focus on localized regions to mimic unknown objects
- Can generate infinite negative examples
- Cannot localize precisely the anomalous object
- The predicted error is generic, not easy to match a specific type of uncertainty



Precision vs test-time computational cost

V. Besnier al., Triggering Failures: Out-Of-Distribution detection by learning from local adversarial attacks in Semantic Segmentation, ICCV 2021

The end.