

Unknown Sniffer for Object Detection: Don't Turn a Blind Eye to Unknown Objects

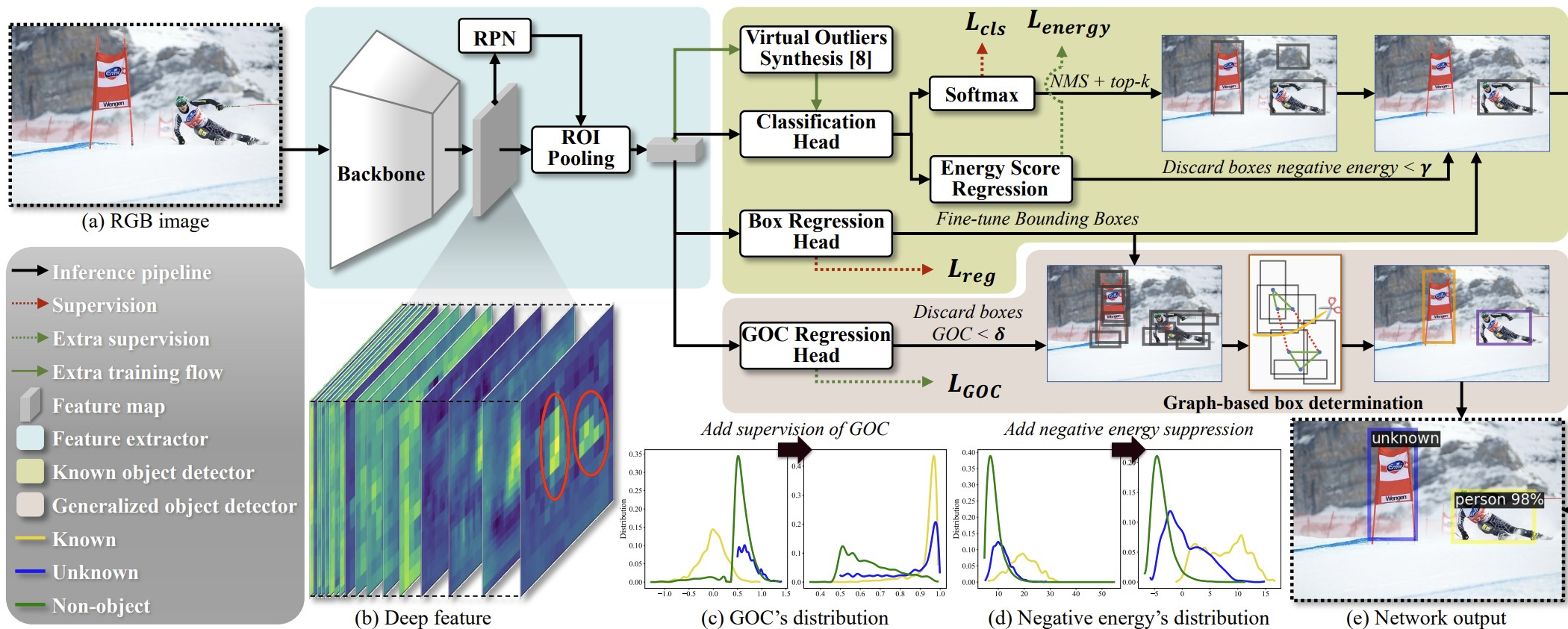
Wenteng Liang, Feng Xue, Yihao Liu, Guofeng Zhong, Anlong Ming*

Beijing University of Posts and Telecommunications

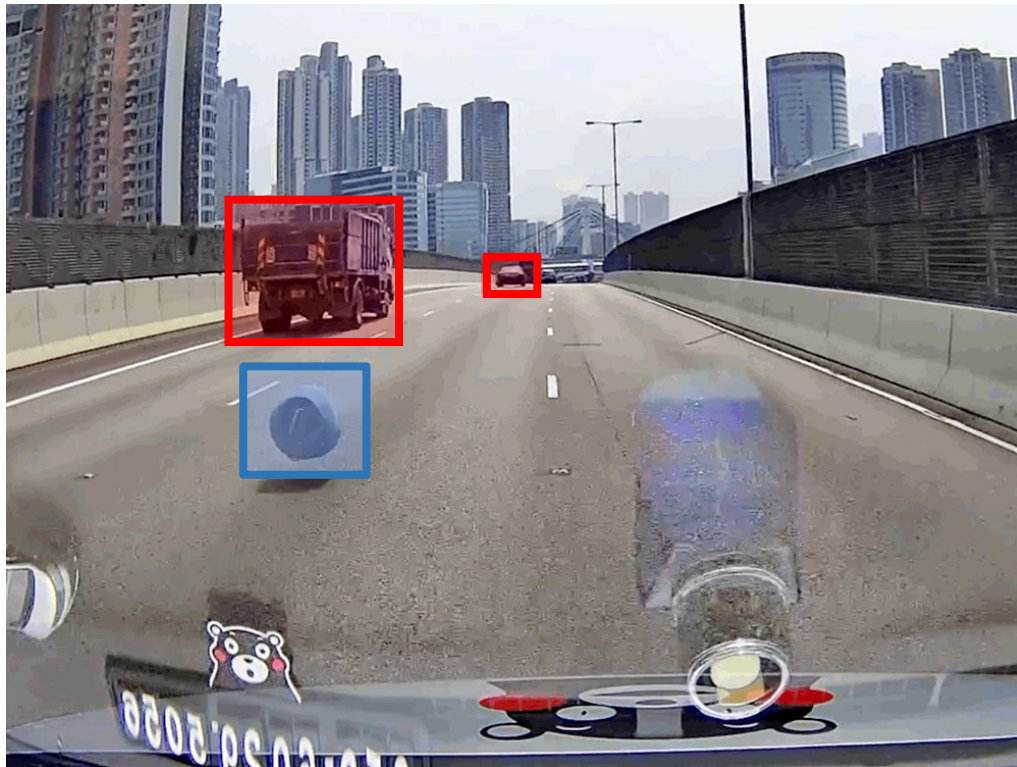
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Overview



Breaking through the closed-world setting



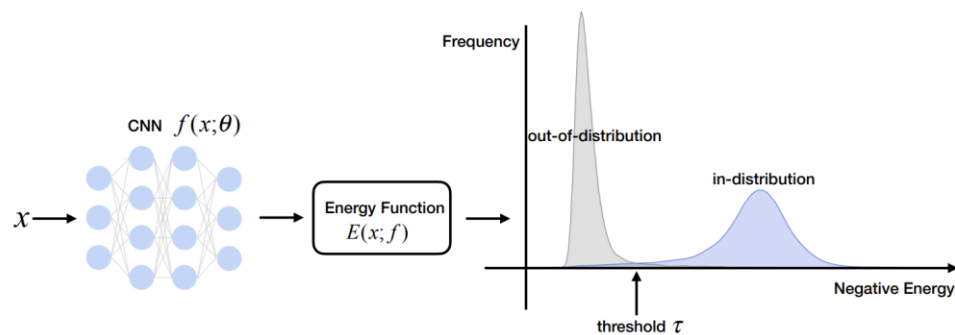
 Known object  Unknown object

- In a **closed-world** with a limited number of categories, deep learning has achieved great success in detection tasks.
- However, models based on the idealized assumption have been unable to meet **complex real-world** needs.

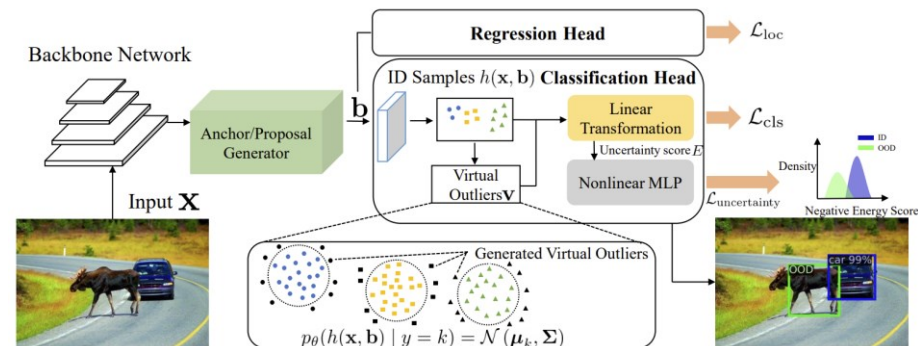


Previous Methods

■ Open-set classification & detection

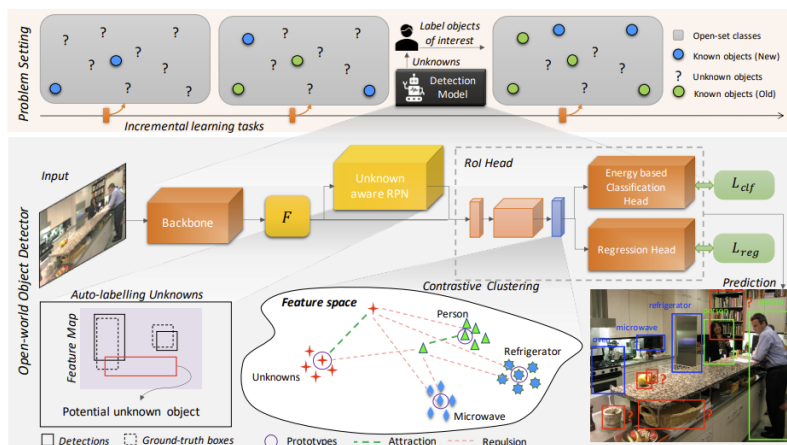


[Energy. NIPS 2020]

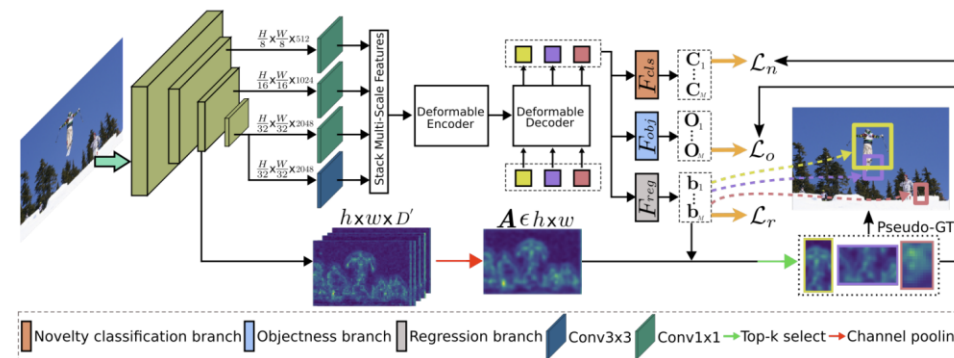


[VOS. ICLR 2022]

■ Open-world object detection



[ORE. CVPR 2021]



[OW-DETR. CVPR 2022]

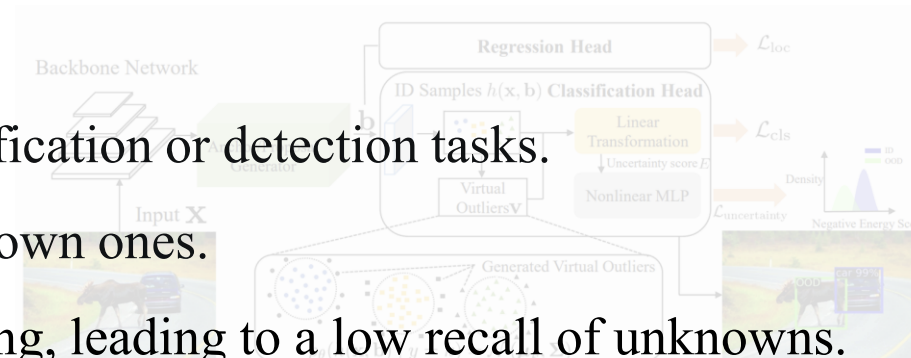


Previous Methods

■ Open-set classification & detection

- ☹️ Deal with unknown samples encountered in classification or detection tasks.
- ☹️ Focus on distinguishing unknown objects from known ones.
- ☹️ Suppress both unknowns and non-objects in training, leading to a low recall of unknowns.

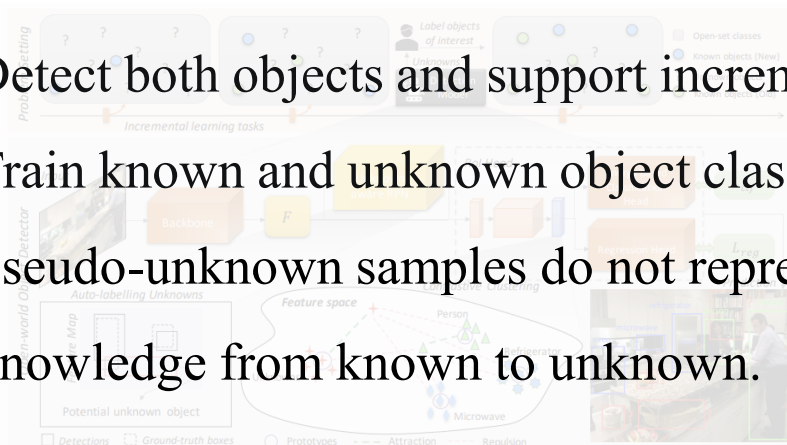
[Energy. NIPS 2020]



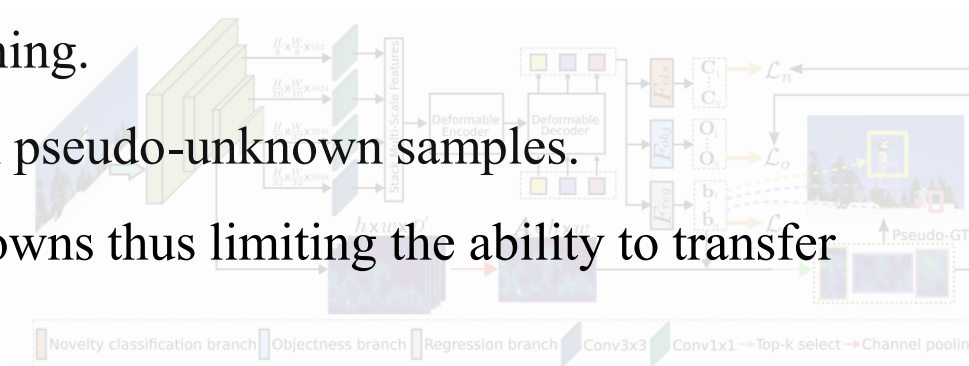
[VOS. ICLR 2022]

■ Open-world object detection

- ☹️ Detect both objects and support incremental learning.
- ☹️ Train known and unknown object classifiers with pseudo-unknown samples.
- ☹️ Pseudo-unknown samples do not represent unknowns thus limiting the ability to transfer knowledge from known to unknown.



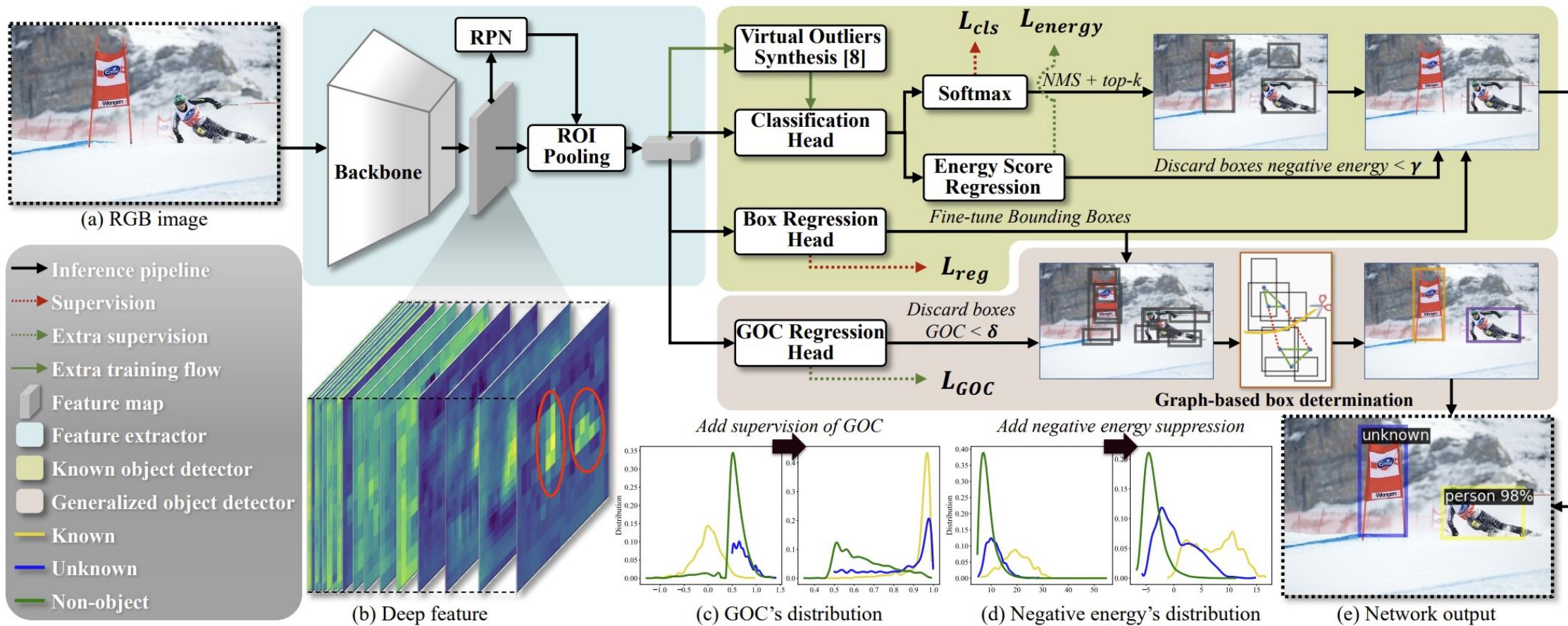
[ORE. CVPR 2021]



[OW-DETR. CVPR 2022]



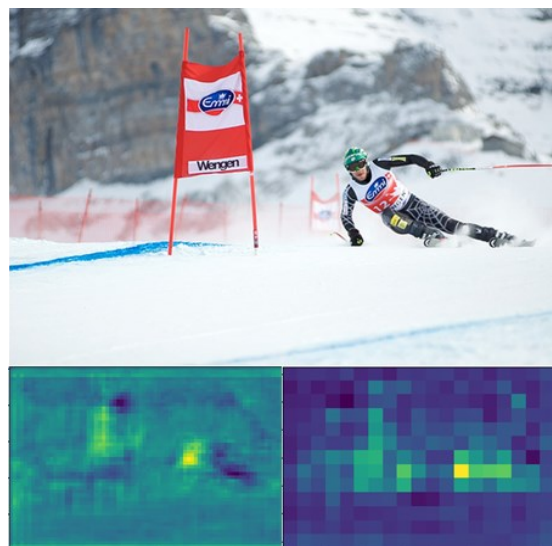
Overview



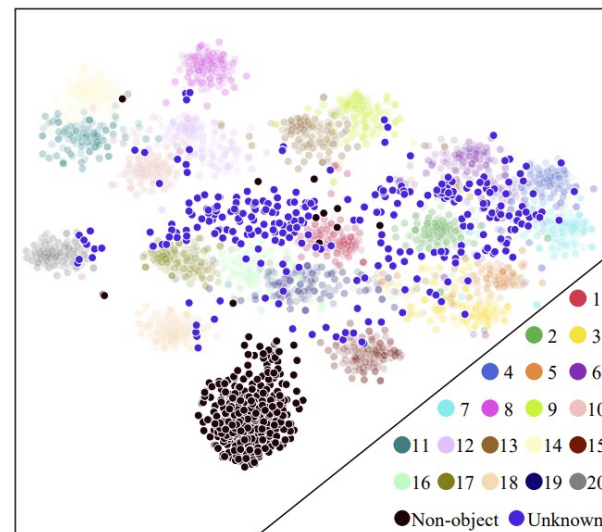
- Generalized Object Confidence (GOC)
- Negative Energy Suppression
- Graph-Based Box Determination



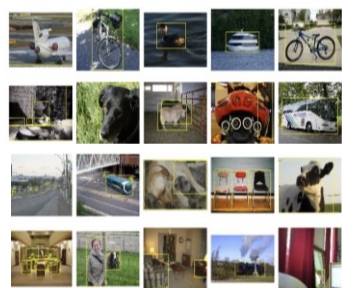
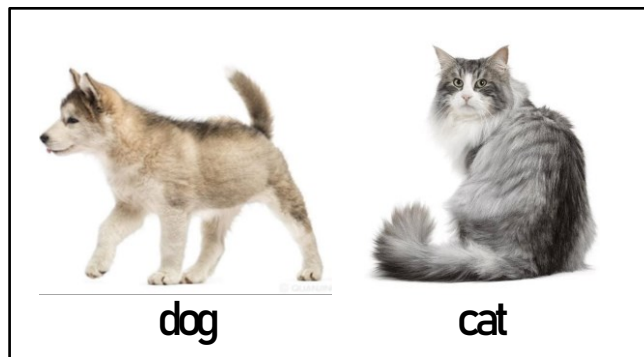
Generalized Object Confidence



Many unknowns are encoded by deep feature.

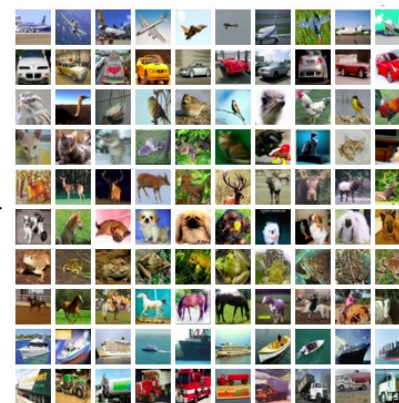


Similarity between “objects”

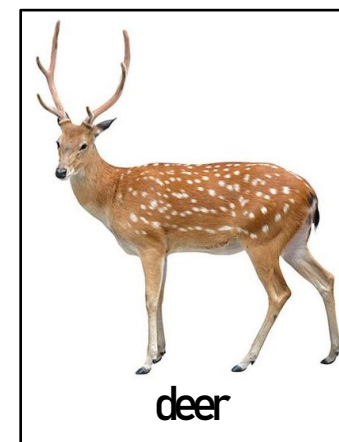


Known Objects

GOC
“Analogy”



Unknown Objects



Generalized Object Confidence

- Complete-object bounding boxes should have high GOC:

$$L_{pos} = \frac{1}{K} \sum_{k \in [1, K]} \frac{1}{|B_n^{k, c}|} \sum_{b_i \in B_n^{k, c}} (\Phi(f_i) - 1)^2$$

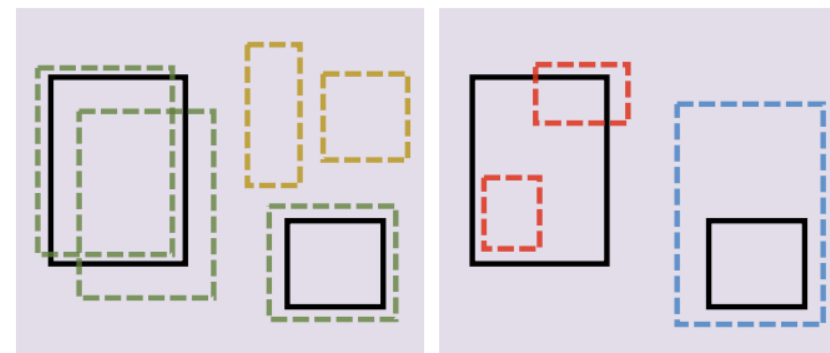
- More complete boxes have higher GOC:






$$L_{con} = \frac{1}{K} \sum_{k \in [1, K]} \left[\frac{2}{|B_n^{k, c}|} \right] \sum_{b_i, b_j \in B_n^{k, c}} \max\left(0, \frac{\Phi(f_i) - \Phi(f_j)}{\alpha} + \zeta\right)$$

- Partial-object or oversized boxes should have low GOC:

$$L_{neg} = \frac{1}{K} \sum_{k \in [1, K]} \frac{1}{|B_n^{k, po}|} \sum_{b_i \in B_n^{k, po}} \max(0, \Phi(f_i) - \delta)$$

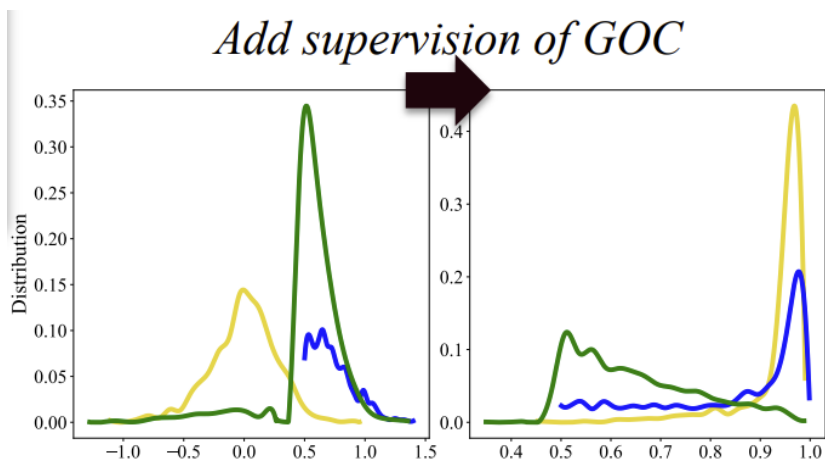
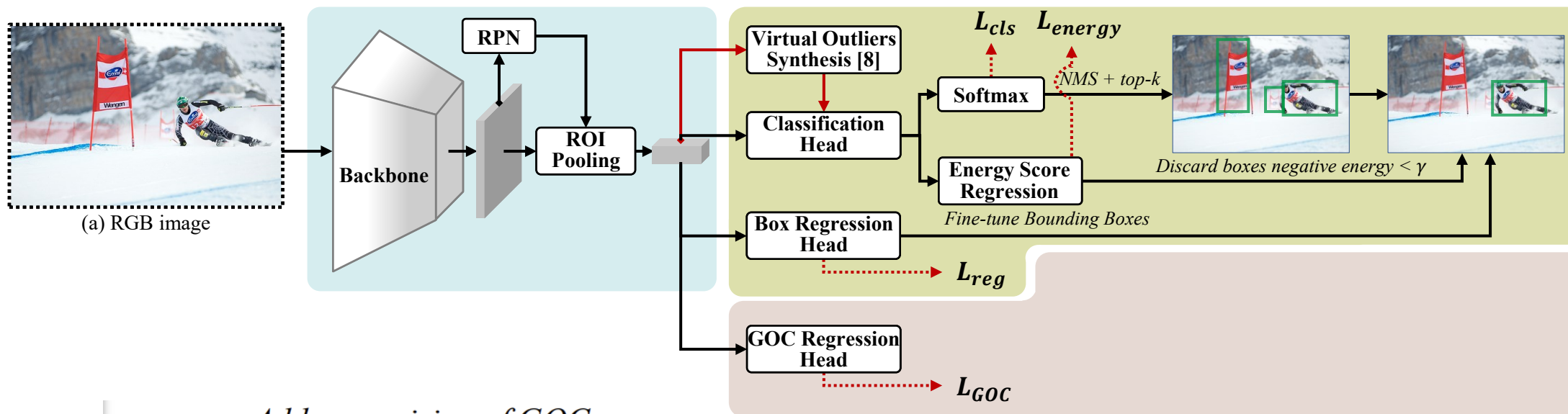
Total GOC loss $L_{GOC} = L_{neg} + L_{pos} + L_{con}$



-  *Ground-truth Boxes*
-  *Complete-object Boxes*
-  *Partial-object Boxes*
-  *Oversized Boxes*
-  *Non-object Boxes*
(Excluded for training)



Generalized Object Confidence



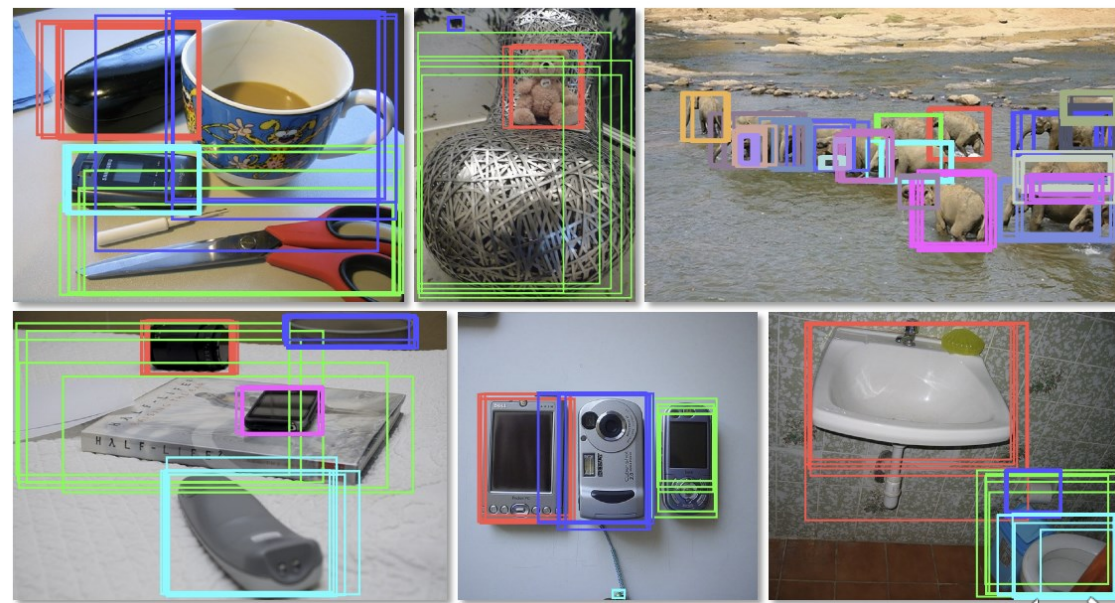
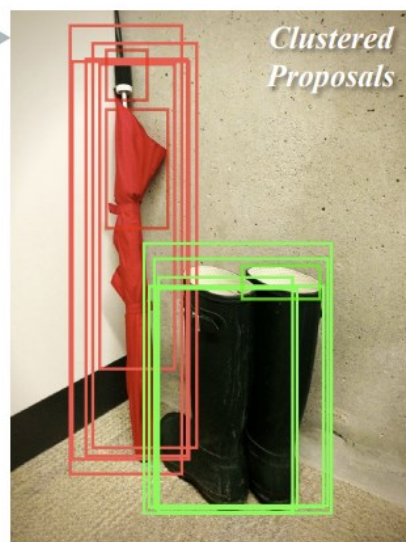
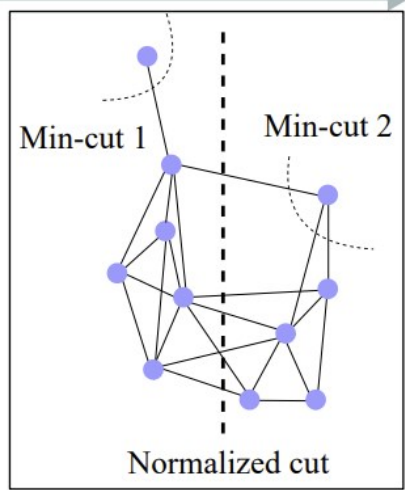
GOC's distribution

- Without L_{GOC} , unknown boxes have the same output as non-object.
- With L_{GOC} , unknown boxes have the same output as known objects.



Graph-based Top-scoring Box Determination

The top-scoring box determination \longrightarrow Graph partitioning $\left\{ \begin{array}{l} \text{Node represents a box} \\ \text{Edge represents the IoU} \end{array} \right.$

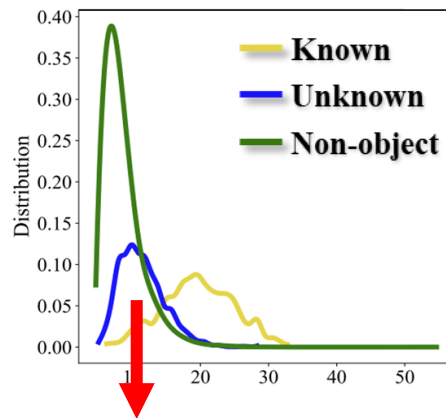


Negative Energy Suppression for Non-object

We follow the energy value of VOS to distinguish unknown objects from known ones :

$$E(b_i) = -\log \sum_{c \in [1, C]} \mathbf{w}_c \cdot \exp^{f_c}$$

Negative energy's distribution

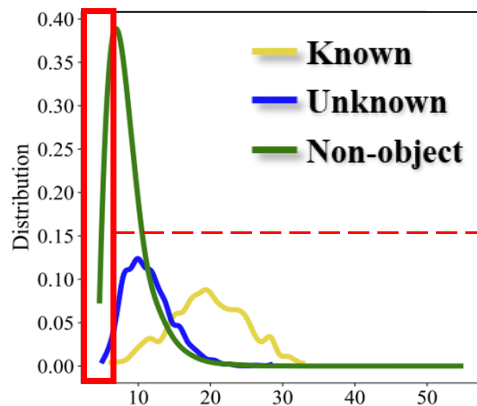


Indistinguishable

How to separate non-object from objects without the aid of non-object annotations ?



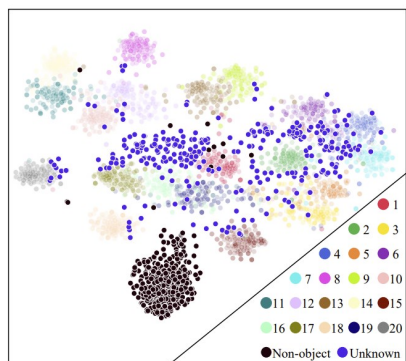
Negative Energy Suppression for Non-object



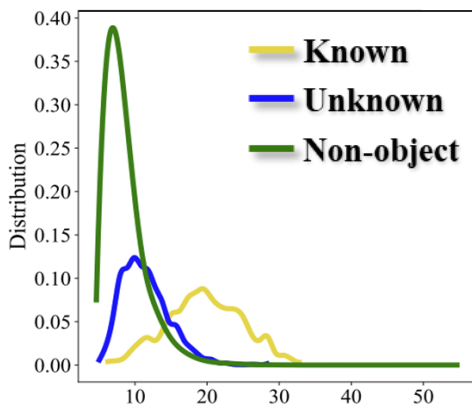
- Suppression loss is applied to the top-T proposals with the lowest negative energy scores.

$$L_{suppression} = \frac{1}{T} \sum_{i \in [1, T]} \max(0, -E(b_i))$$

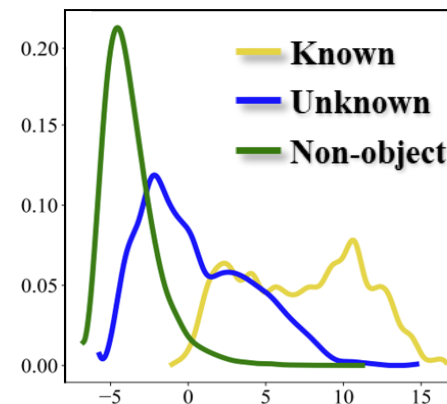
T-SNE



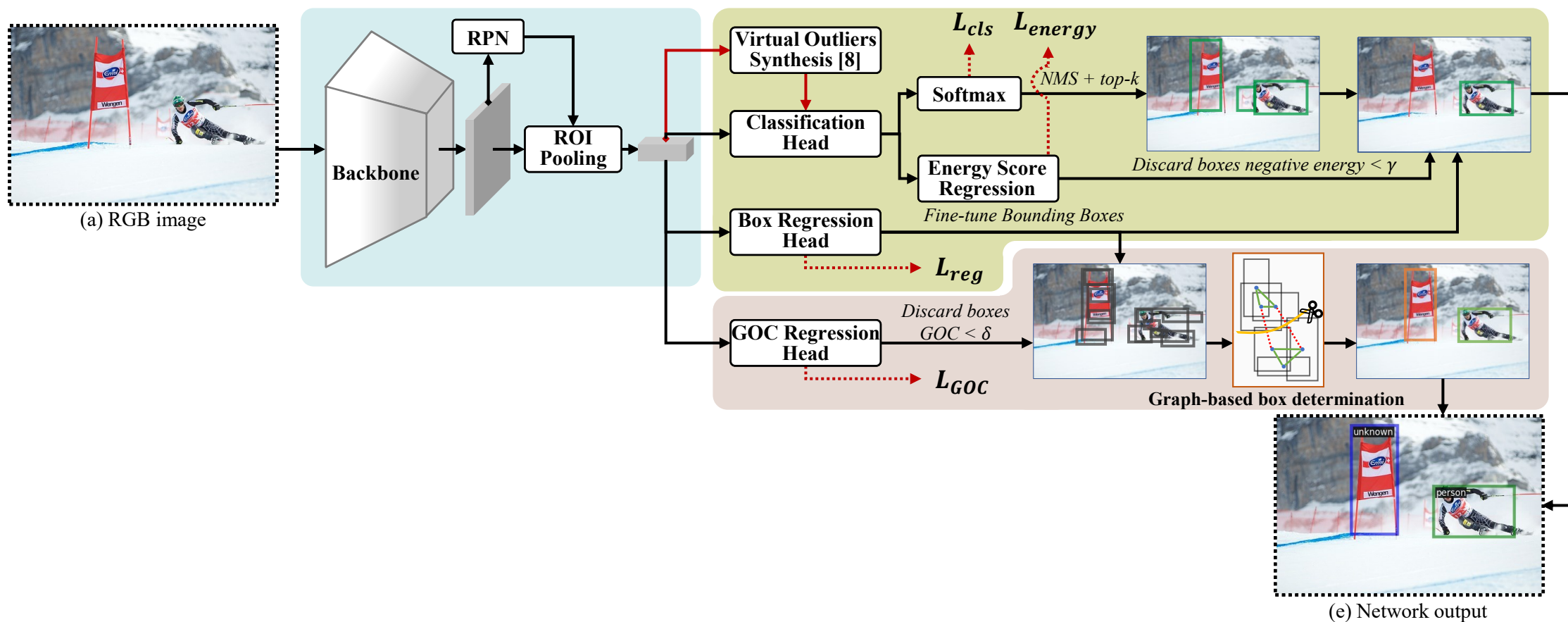
- Non-objects also have feature similarities, so **suppression will be transmitted**.



Indirectly widening the gap



Negative Energy Suppression for Non-object



The overall energy loss consists of our proposed $L_{suppression}$ and $L_{uncertainty}$ defined by VOS :

$$L_{energy} = L_{suppression} + L_{uncertainty}$$



Unknown Object Detection Benchmark

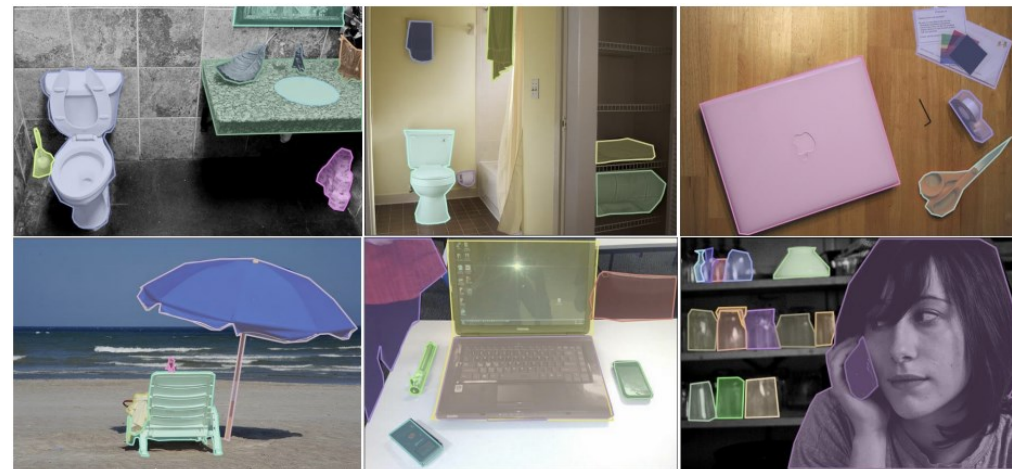
- **Training data:**

Pascal VOC dataset that contains 20 categories

- **Testing data:**

Datasets	Images	Known	Unknown
VOC-Pretest	200	5.09	0
VOC-Test	4952	3.02	0
COCO-OOD♣	504	0	3.28
COCO-Mixed♣	897	2.96	2.82

♣ denotes the augmented datasets



Annotated samples in COCO-OOD and COCO-Mix.



Unknown Object Detection Benchmark

Evaluation Metrics

For known objects:

- mAP

For unknown objects:

- Unknown Average Precision (U-AP)
- Unknown F1-Score(U-F1)
- Unknown Recall Rate (U-REC)
- Precision Rate of Unknown (U-PRE)

For mixed data:

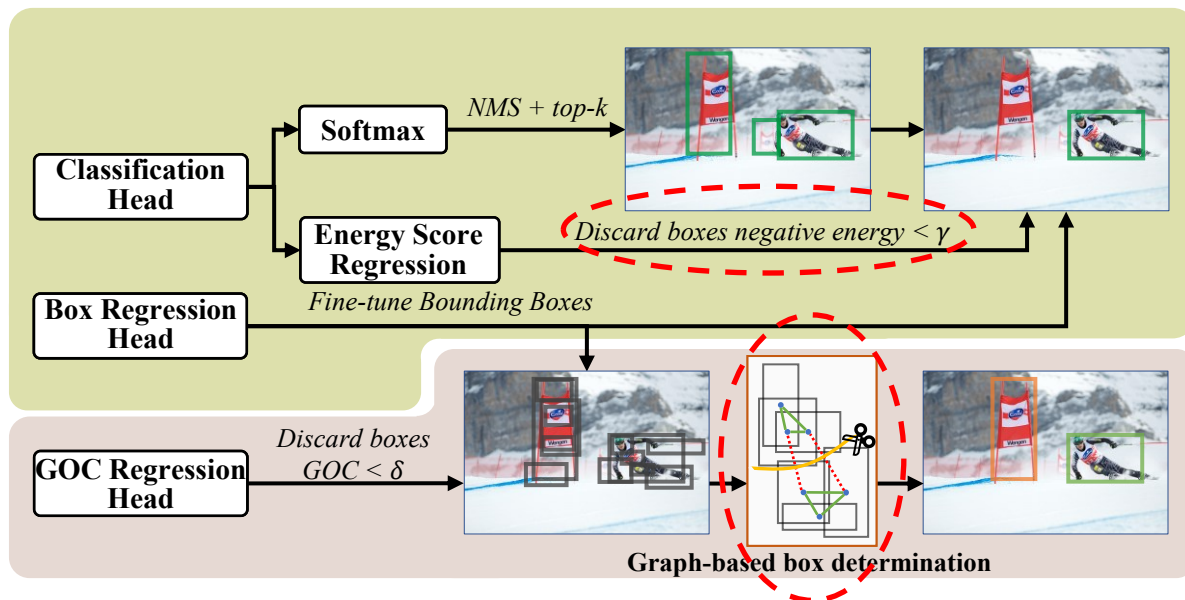
- Absolute Open-Set Error (A-OSE)



Pretest mode in the Benchmark

Datasets	Images	Known	Unknown
VOC-Pretest	200	5.09	0

- Select 200 images in the training set that do not contain any potential unknown objects.



1. The threshold γ is set by making 95% of predicted proposals have a negative energy score greater than it.
2. The threshold of NCut is determined when the AP of known objects is the largest.



Experiment

Groups	Methods	VOC-Test	COCO-OOD				COCO-Mix					
		mAP	U-AP	U-F1	U-PRE	U-REC	mAP	U-AP	U-F1	U-PRE	U-REC	AOSE
①	MSP [15]	0.470	0.213	0.314	0.279	0.359	0.364	0.055	0.169	0.190	0.153	588
	Mahalanobis [5]	0.447	0.129	0.271	0.309	0.241	0.351	0.051	0.149	0.207	0.116	604
	Energy score [23]	<u>0.474</u>	0.213	0.308	0.260	0.377	0.364	0.048	0.169	0.167	0.171	470
②	OW-DETR [11]	0.420	0.033	0.056	0.030	0.380	0.414	0.007	0.025	0.014	0.161	569
	ORE [17]	0.243	<u>0.214</u>	0.255	0.153	0.782	0.213	<u>0.140</u>	<u>0.175</u>	0.103	0.592	485
③	VOS ¹ [8]	0.485	0.135	0.196	<u>0.342</u>	0.137	<u>0.377</u>	0.040	0.101	0.262	0.062	640
	VOS ² [8]	0.469	0.205	<u>0.317</u>	0.291	0.348	0.364	0.051	0.172	0.184	0.163	<u>409</u>
④	Ours	0.464	0.454	0.479	0.433	<u>0.535</u>	0.359	0.150	0.287	<u>0.222</u>	<u>0.409</u>	398

Table 2. Comparisons with the detector using open-set classification ①, open-world object detection ②, and open-set detection ③ methods. VOS¹ denotes the model with the threshold given by the official repository¹, which is calculated on the BDD100K dataset [39]. And VOS² utilizes the threshold computed on the COCO-OOD dataset by using the official code². Best results are in bold, second best are underlined.



Experiment

Row	GOC	NES	GBD	U-AP	U-F1	U-PRE	U-REC
1	×	×	×	0.066	0.050	0.026	0.808
2	×	×	✓	0.250	0.434	0.395	0.481
3	×	✓	×	0.442	0.054	0.028	0.861
4	✓	×	×	0.479	0.323	0.215	0.646
5	×	✓	✓	0.409	<u>0.467</u>	0.437	0.502
6	✓	×	✓	0.455	0.454	0.399	<u>0.528</u>
7	✓	✓	✓	<u>0.454</u>	0.479	<u>0.433</u>	0.535

Table 3. **Ablation studies on COCO-OOD.** GOC, NES and GBD refer to ‘generalized object confidence’, ‘negative energy suppression’ and ‘graph-based box determination’, respectively. When ‘GBD’ is ×, we use NMS and top- k as post-processing with the same thresholds with the known detector for a fair comparison.

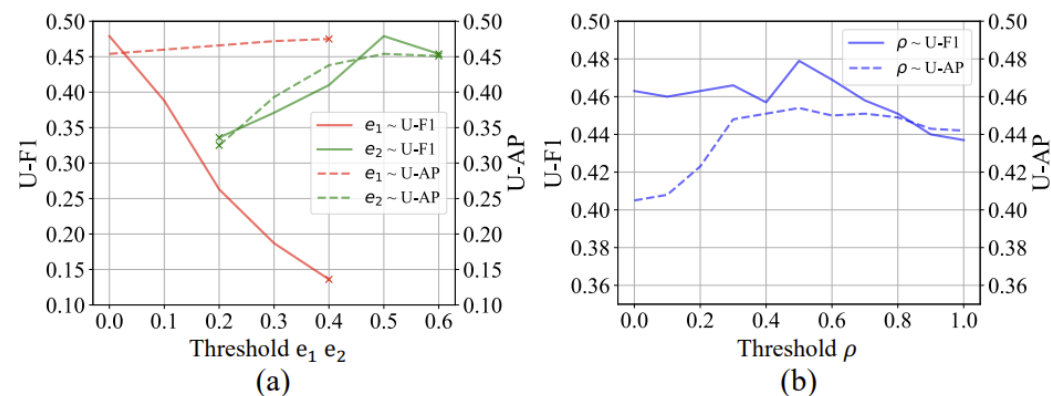


Figure 6. **Sensitivity analysis on (a) thresholds e_1, e_2 , and (b) threshold ρ .** × indicates the failed training outside this threshold.

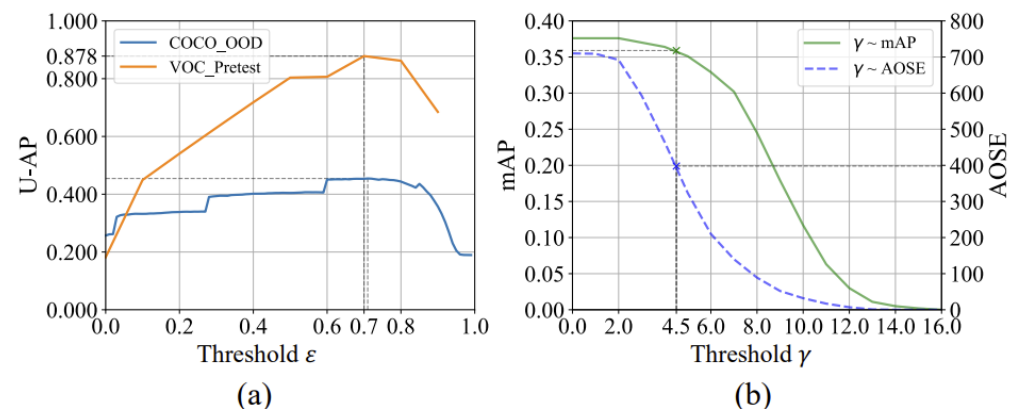
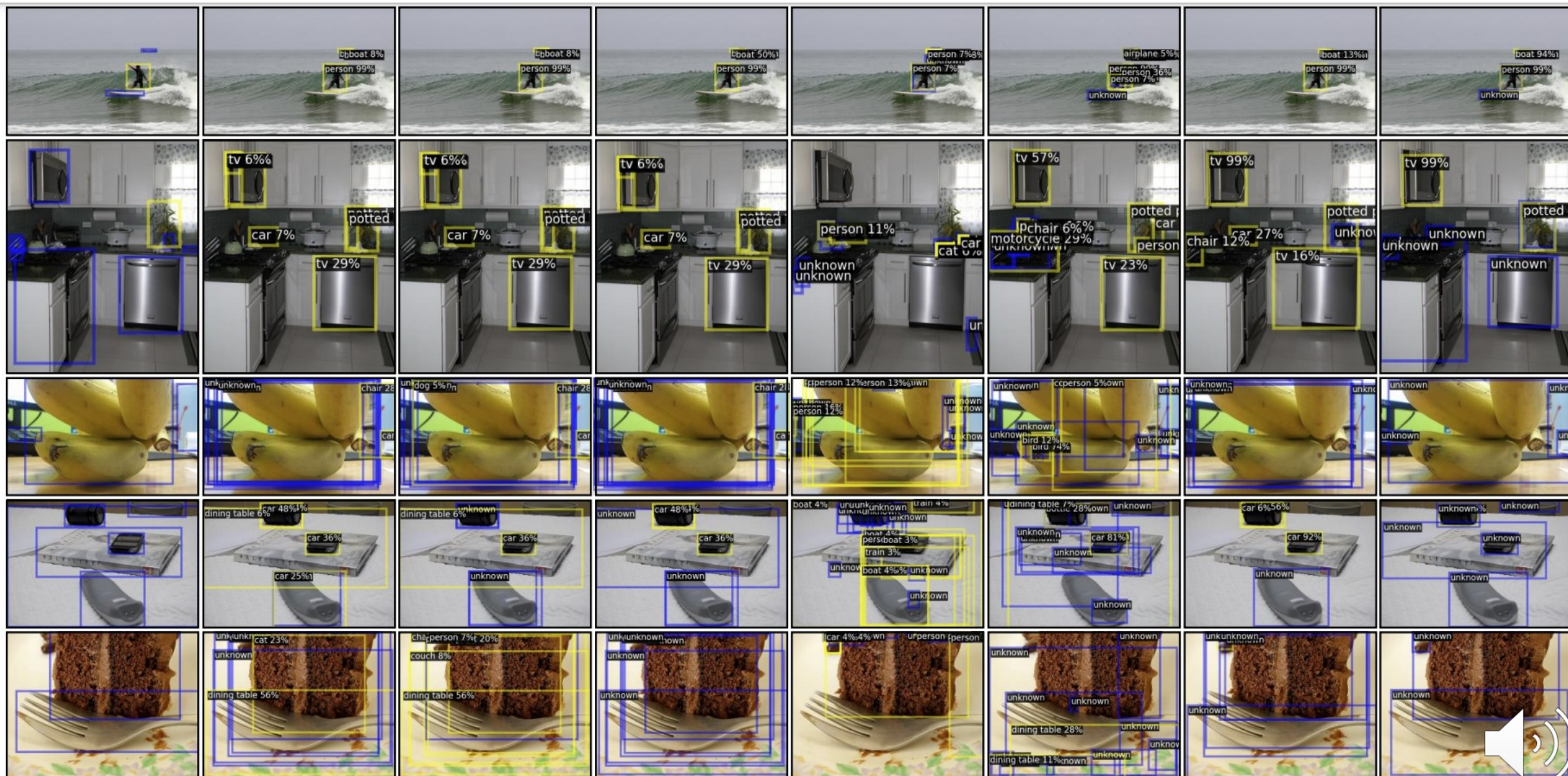


Figure 8. (a) Comparison between the thresholds ϵ determined in the pretest set and the COCO-OOD dataset. (b) Comparison of mAP and AOSE between the thresholds determined in the pretest (dot) and the COCO-Mix dataset (line).

Detection Results and Video Demos



Visualization



Ground Truth

MSP

Mahalanobis

Energy score

OW-DETR

ORE

VOS

Ours

Visualization



Ground Truth

MSP

Mahalanobis

Energy score

OW-DETR

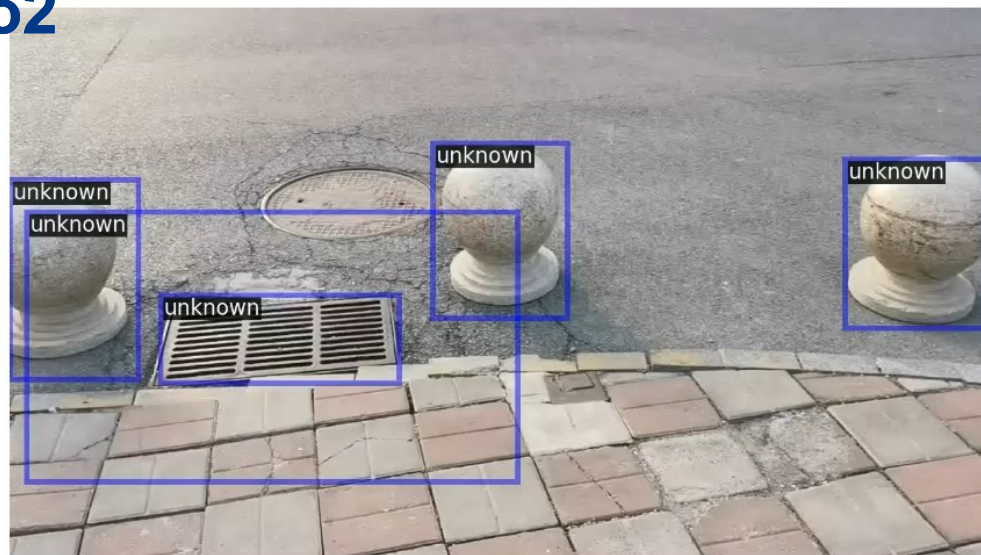
ORE

VOS

Ours



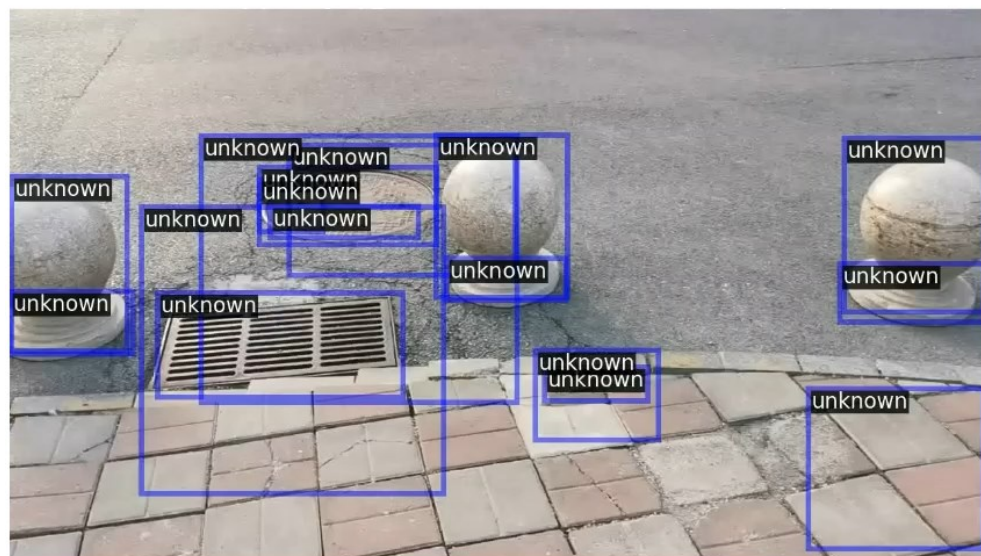
Video Demo2



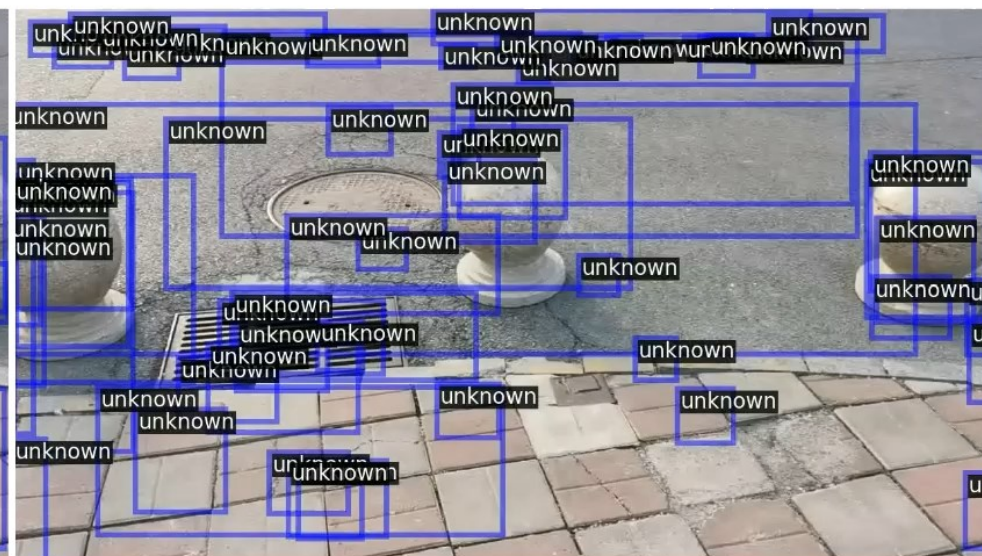
UnSniffer



VOS

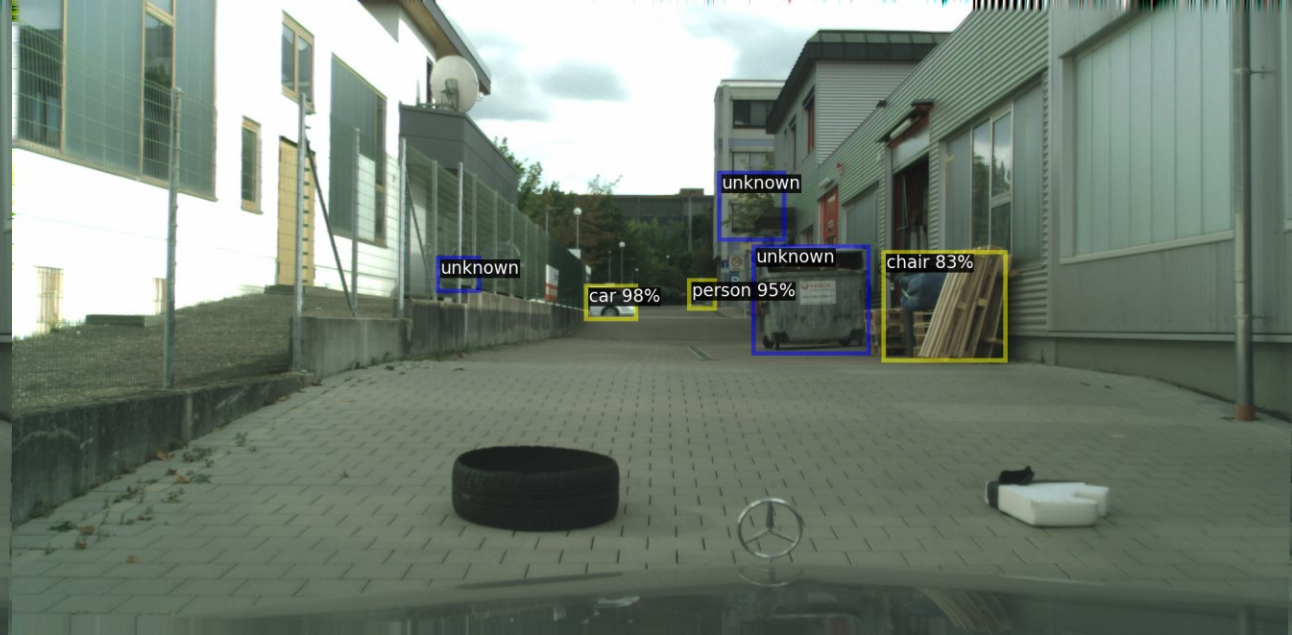
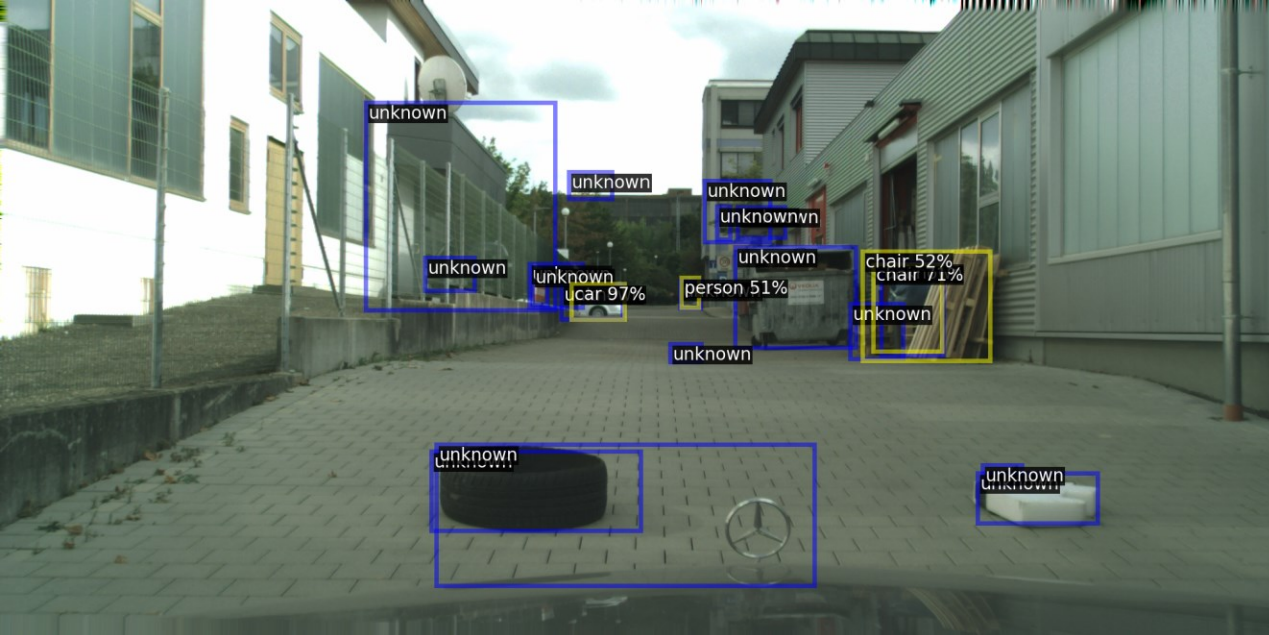


ORE



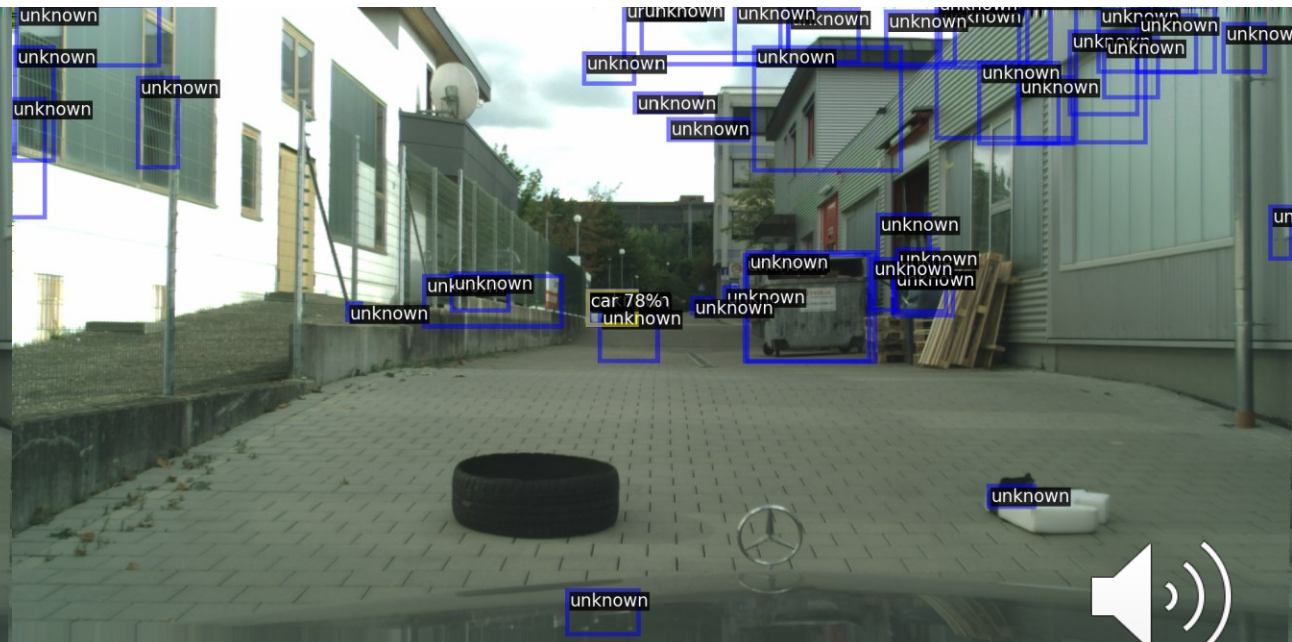
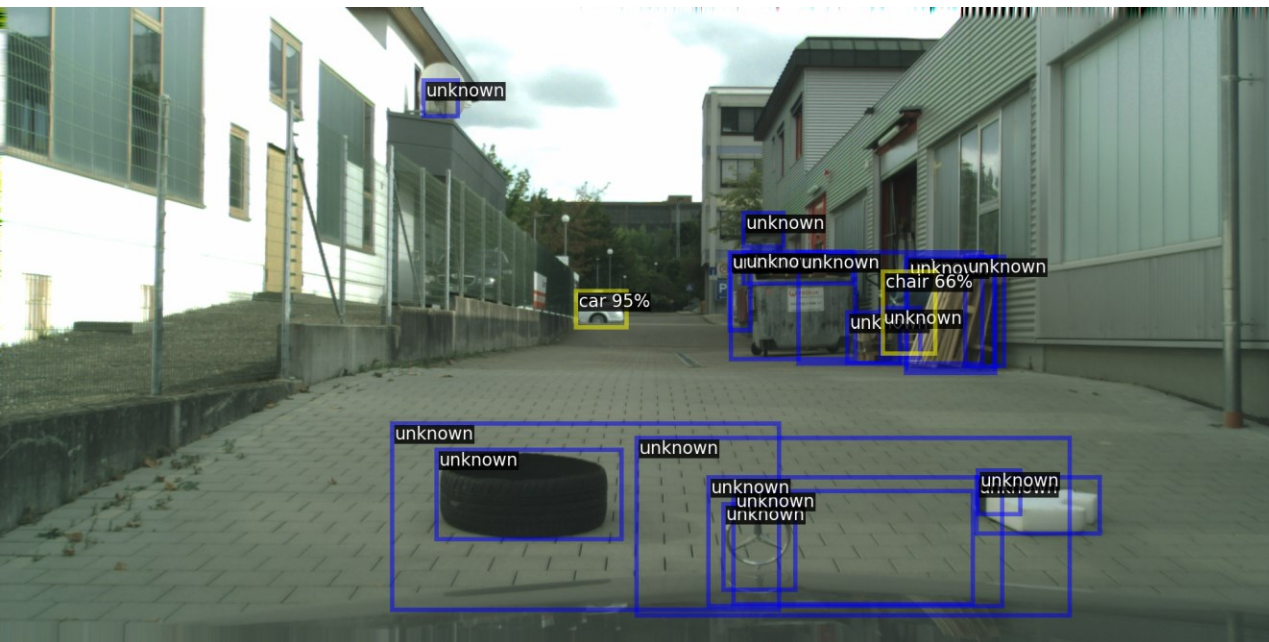
OW-DETR





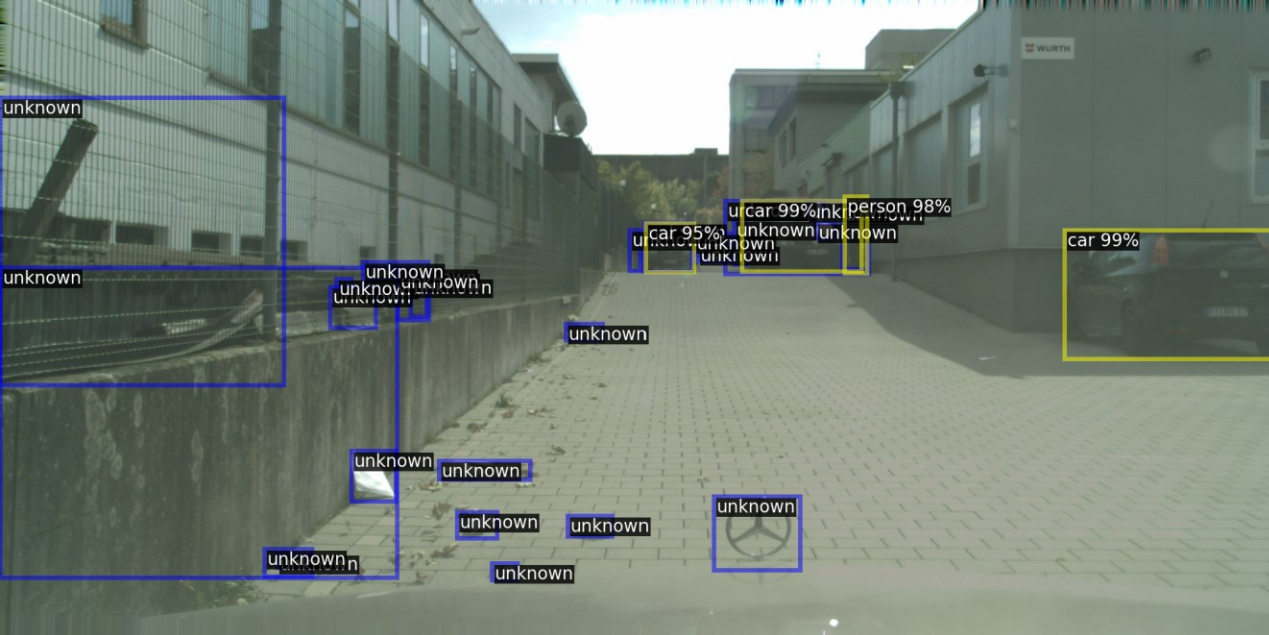
UnSniffer

VOS

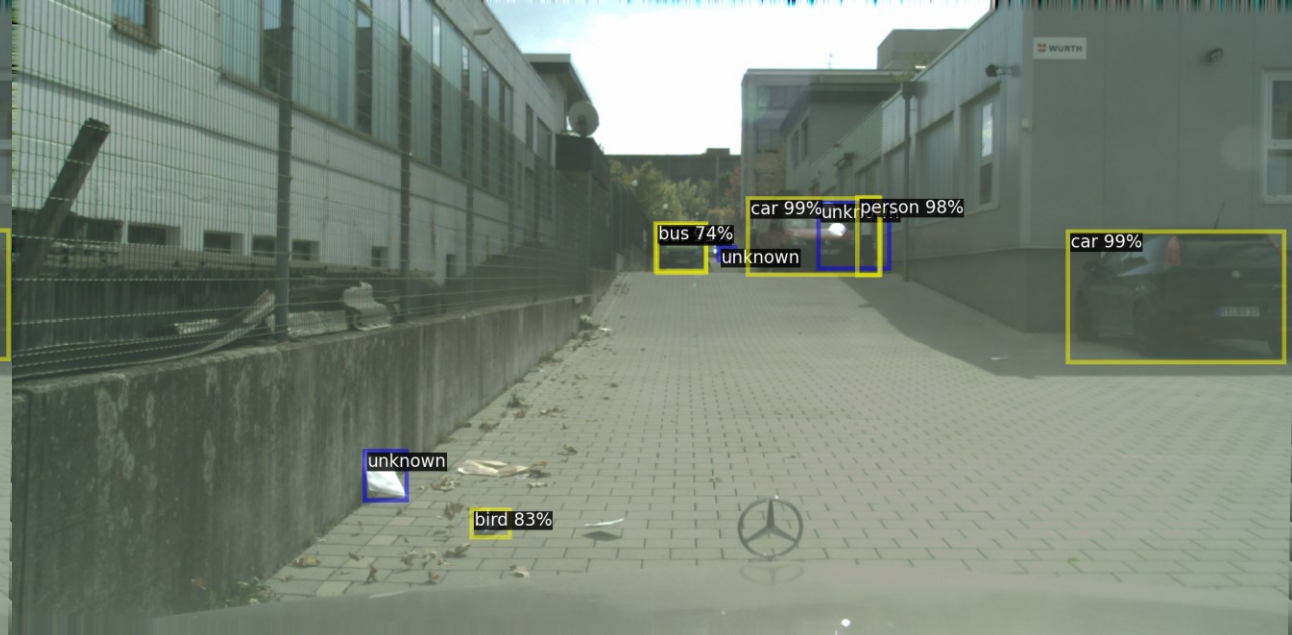


ORE

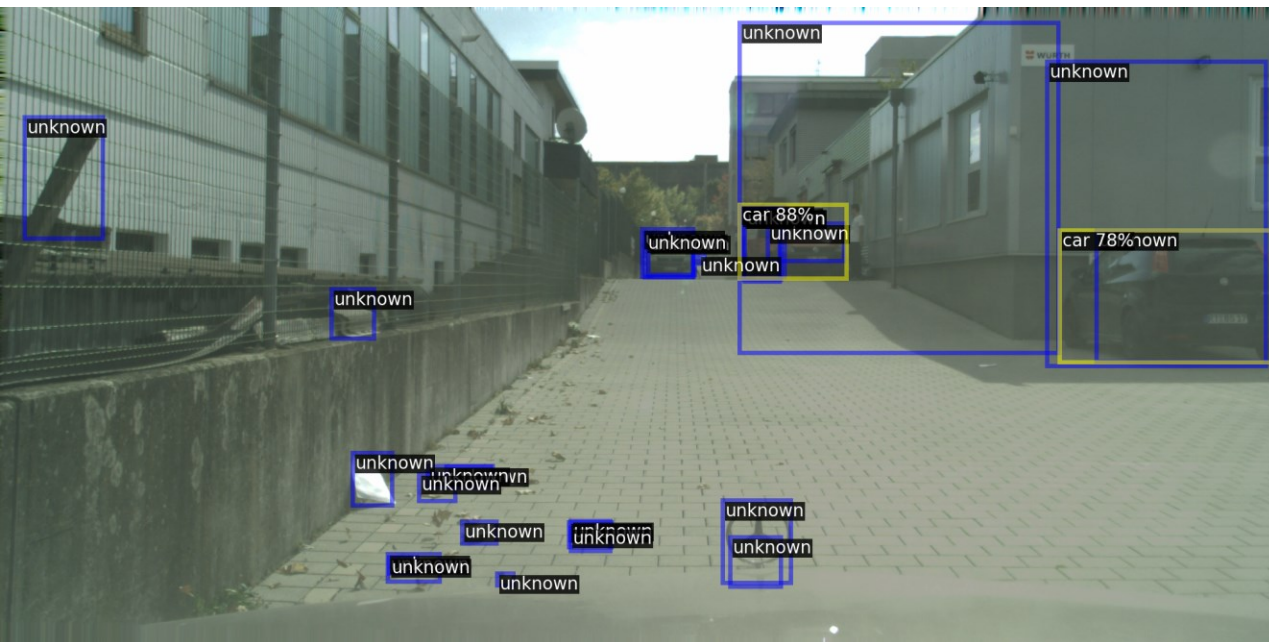
OW-DETR



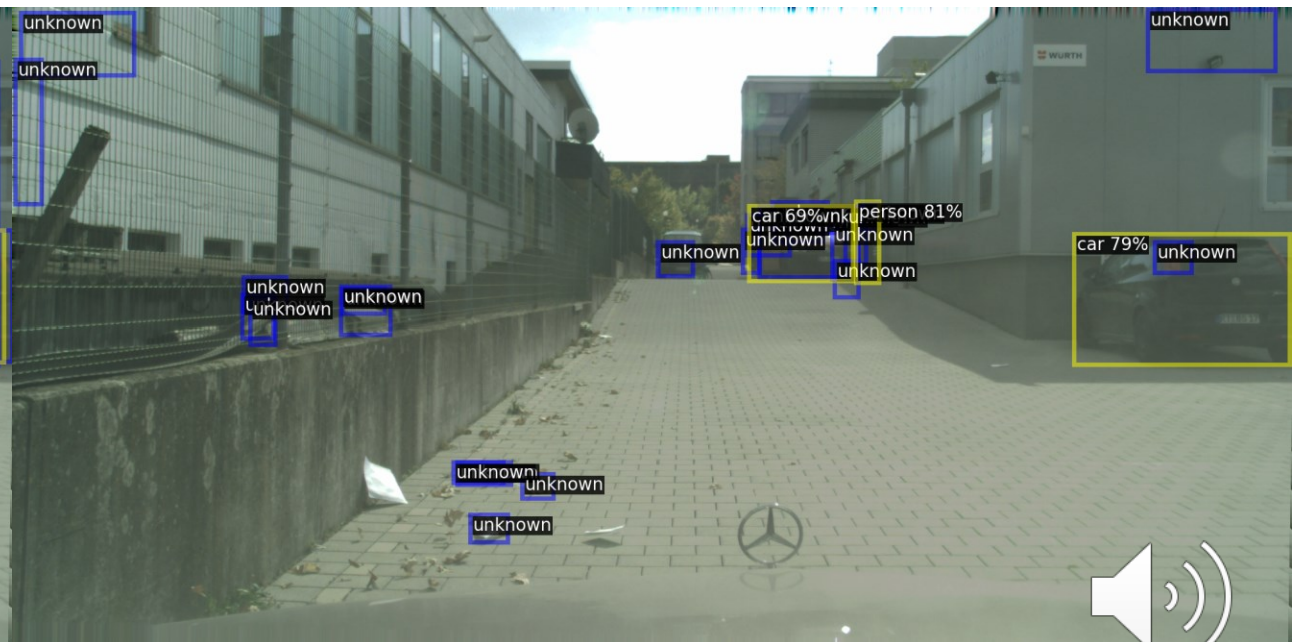
UnSniffer



VOS



ORE



OW-DETR

Thanks !!!

