



# Novel Scenes & Classes: Towards Adaptive Open-set Object Detection

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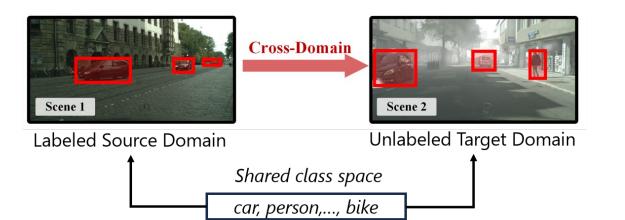
**PARIS** 

### Background

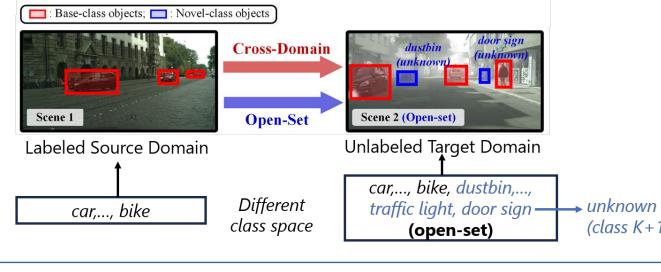
#### Adaptive Open-set Object Detection (AOOD)

AOOD aims transfer an object detector from a labeled source domain to an unlabeled target domain with open-set classes, different from existing DAOD with shared class definition.

#### Domain Adaptive Object Detection (DAOD)

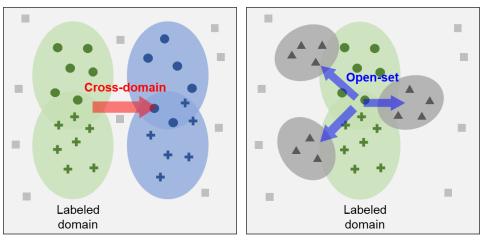


### **Adaptive Open-set Object Detection (AOOD)**



#### Motivation

#### Problem Analysis



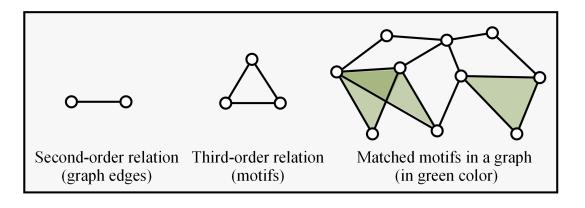
■: Background • : Class-1 objects

+ : Class-2 objects • : Novel-class objects

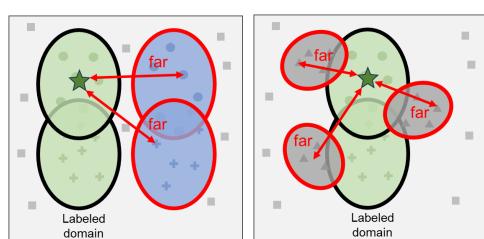
#### **AOOD** needs to address

- cross-domain challenge
- open-set challenge

#### Preliminaries



#### Challenges



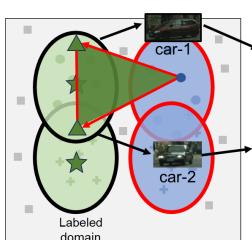
★: Class centers ▲: Class extremes

#### What limits AOOD?

 Cross-domain/open-set objects are both out of labeled distribution, leading to the failure of existing low-order solutions, e.g., selecting objects with low confidence.

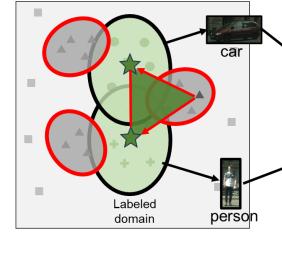
**Motif** is a statistically significant subgraph with high-order pattern.

### ■ The Proposed High-order Solutions



### **Cross-domain Solution**

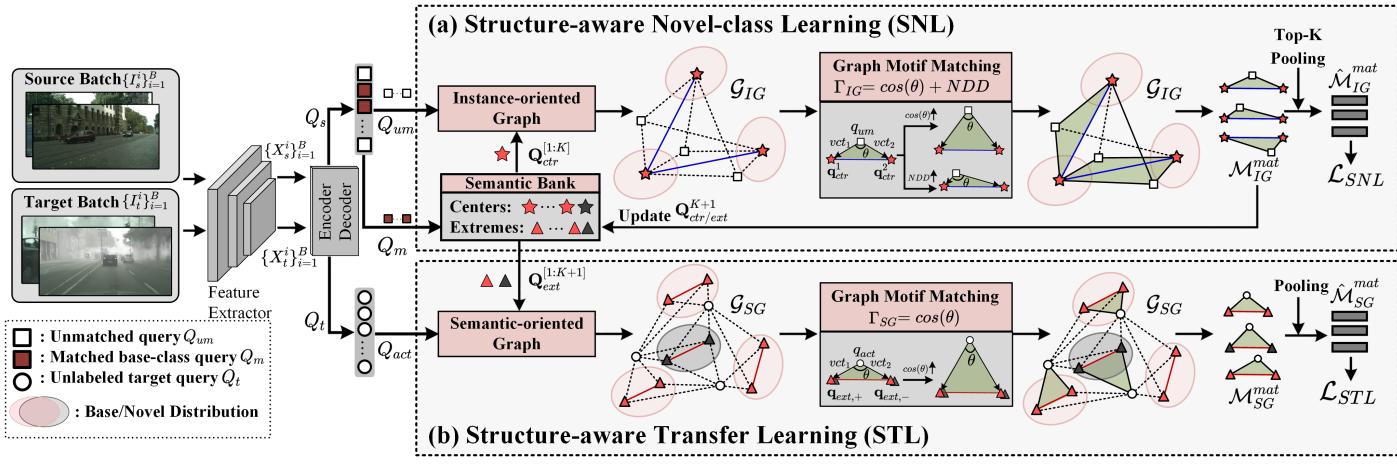
 Exploring withinclass diversity for each class



### **Open-set Solution**

 Exploring object-level property shared among different classes

## Methodology



### Structure-aware Novel-class Learning (SNL)

Establish a semantic bank saving class centers and extremes

$$\mathbf{Q}_{ctr}^{k} \leftarrow \alpha f_{\text{mean}}(Q_{m}^{k}) + (1 - \alpha)\mathbf{Q}_{ctr}^{k}$$
$$\mathbf{Q}_{std}^{k} \leftarrow \alpha f_{\text{std}}(Q_{m}^{k}) + (1 - \alpha)\mathbf{Q}_{std}^{k}$$

Build up the instance-oriented graph

Link class centers with the farthest counterpart Link unmatched object queries with class centers

Select motifs via a high-order metric

$$M_{IG}^{mat} = \operatorname{argmin}_{\Gamma_{IG}} \mathcal{M}_{IG}$$
 where  $cos(\theta) := \frac{vct_1 \cdot vct_2}{||vct_1||_2 \cdot ||vct_2||_2}$   $NDD := |\frac{||vct_1||_2 \cdot ||vct_2||_2}{||\mathbf{q}_{otr}^1 - \mathbf{q}_{otr}^2||_2}$ 

Optimize with selected motifs

$$\mathcal{L}_{SNL} = -\frac{1}{K} \sum_{i=1}^{K} log(p(f_{cls}(\hat{M}_{IG,i}^{mat}) = K + 1 | \hat{M}_{IG,i}^{mat}))$$
Unknown posterior

### Structure-aware Transfer Learning (STL)

Build up the semantic-oriented graph

Link class extreme pairs in the same class
Link activated object queries with class extremes

Select motifs via a high-order metric

$$M_{SG}^{mat} = \operatorname{argmin}_{\Gamma_{SG}} \mathcal{M}_{SG}$$
 where  $cos(\theta) := \frac{vct_1 \cdot vct_2}{||vct_1||_2 \cdot ||vct_2||_2}$ 

$$\Gamma_{SG} := cos(\theta)$$

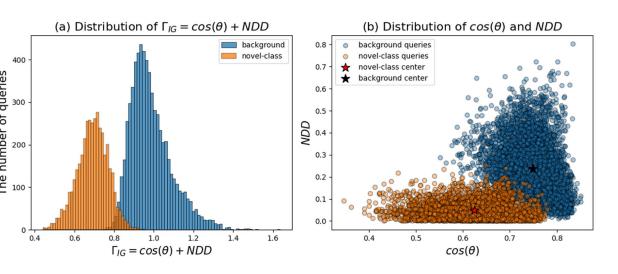
Optimize with selected motifs

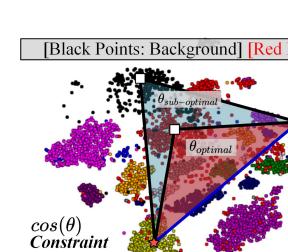
$$\mathcal{L}_{STL} = -\frac{1}{|\mathcal{M}_{SG}^{mat}|} \sum_{i=1}^{|\mathcal{M}_{SG}^{mat}|} \tilde{y} log(p(f_{cls}(\hat{M}_{SG,i}^{mat})|\hat{M}_{SG,i}^{mat}))$$
Pseudo labels

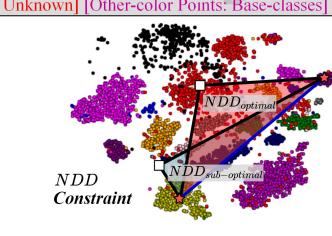
### Experiments

Method	Set	num. novel-class: 3			num. novel-class: 4				num. novel-class: 5				
		$mAP_b\uparrow$	$AR_n\uparrow$	WI↓	AOSE↓	$mAP_b\uparrow$	$AR_n\uparrow$	WI↓	AOSE↓	$mAP_b\uparrow$	$AR_n\uparrow$	WI↓	AOSE↓
DDETR [60] <sub>ICLR'21</sub>	het-sem	47.52	0.00	0.341	459	45.24	0.00	0.506	1028	42.38	0.00	0.659	1968
PROSER [59] <sub>CV PR</sub> /21		46.92	1.80	0.271	218	44.19	2.02	0.415	531	41.99	2.00	0.584	1127
OpenDet $[19]_{CVPR/22}$		47.04	1.92	0.269	221	45.71	1.89	0.499	511	42.09	1.70	0.579	922
OW-DETR $[18]_{CVPR'22}$		43.31	1.84	0.432	192	42.52	2.10	0.619	451	39.92	1.98	0.684	814
SOMA (ours)		50.87	3.78	0.268	139	48.06	4.41	0.412	340	45.55	4.08	0.526	649
DDETR [60] <sub>ICLR'21</sub>	nom-sem	44.62	0.00	1.860	2937	43.55	0.00	2.000	3565	40.18	0.00	2.462	6770
PROSER $[59]_{CVPR/21}$		43.15	4.59	1.842	2146	43.31	4.99	2.018	2641	39.99	5.99	2.563	4963
OpenDet $[19]_{CVPR/22}$		45.51	5.28	1.336	1458	44.02	5.67	1.653	1798	40.87	6.58	2.303	3416
OW-DETR $[18]_{CVPR'22}$		43.22	3.15	1.355	1076	42.83	3.46	1.593	1320	39.45	4.38	2.384	3399
SOMA (ours)	_	48.67	6.96	1.257	915	47.02	7.42	1.527	1232	43.37	8.42	2.281	2886
DDETR [60] <sub>ICLR'21</sub>	freq-dec	56.99	0.00	0.579	1240	55.02	0.00	0.835	2136	53.89	0.00	0.93	2625
PROSER [59] <sub>CVPR</sub> /21		55.70	6.68	0.589	536	54.51	7.88	0.780	952	53.43	8.22	0.943	1072
OpenDet $[19]_{CVDR/22}$		57.28	9.35	0.519	720	54.89	10.59	0.781	1251	53.51	10.37	0.839	1470
OW-DETR [18] <sub>CVPR'22</sub>		56.63	6.61	0.585	698	55.45	7.90	0.745	930	53.60	7.90	0.807	1105
SOMA (ours)		59.18	11.41	0.507	669	56.85	12.47	0.723	1140	55.63	12.36	0.759	1315
DDETR [60] <sub>ICLR'21</sub>	freq-inc	44.72	0.00	2.862	2859	43.91	0.00	3.270	4907	41.12	0.00	3.609	8291
PROSER [59] <sub>CV PR/91</sub>		44.23	2.94	2.881	1090	42.47	2.98	2.745	1866	39.11	3.01	3.119	3242
OpenDet $[19]_{CVDR/22}$		44.85	3.23	2.579	1700	42.92	3.30	2.741	2835	40.34	3.44	2.970	4965
OW-DETR $[18]_{CVPR'22}$		43.92	3.85	2.032	1377	43.01	3.99	2.219	1891	40.21	2.98	2.184	2293
SOMA (ours)		46.62	8.32	1.452	733	47.30	8.43	1.566	1166	44.45	7.95	1.792	1974









#### Conclusion

- A more practical problem definition, Adaptive Open-set Object Detection (AOOD) by considering both novel classes and novel scenes.
- Exploring the low-order limitation in the AOOD scenario.
- Solving AOOD with a unified motif-based framework with high-order evidence, including the structure-aware novel-class learning and transfer learning.