Cloud Object Detector Adaptation by Integrating Different Source Knowledge

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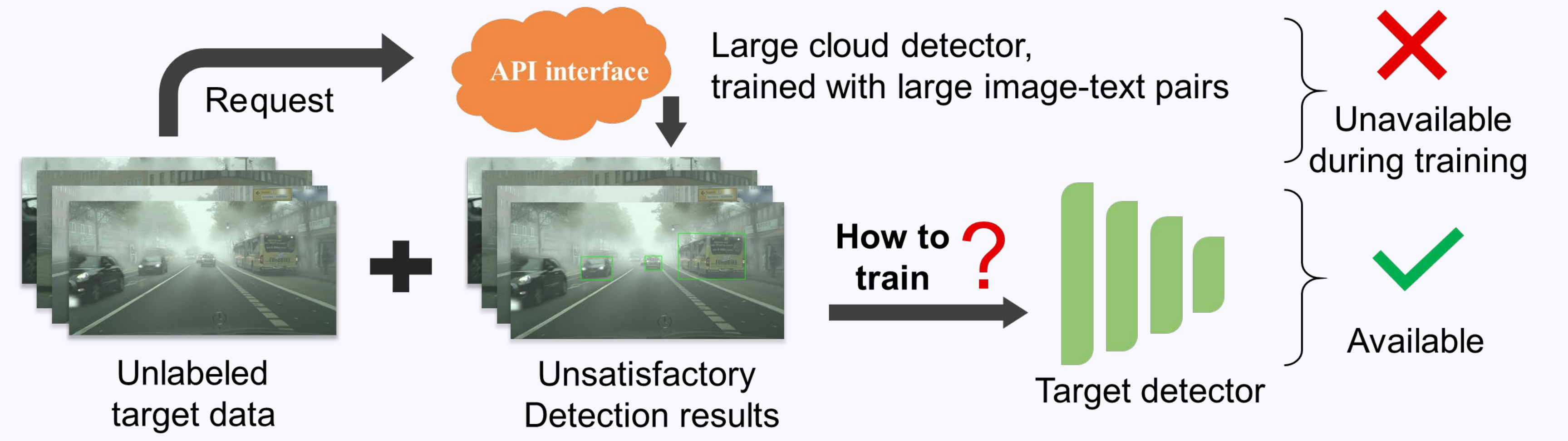
NEURAL INFORMATION PROCESSING SYSTEMS

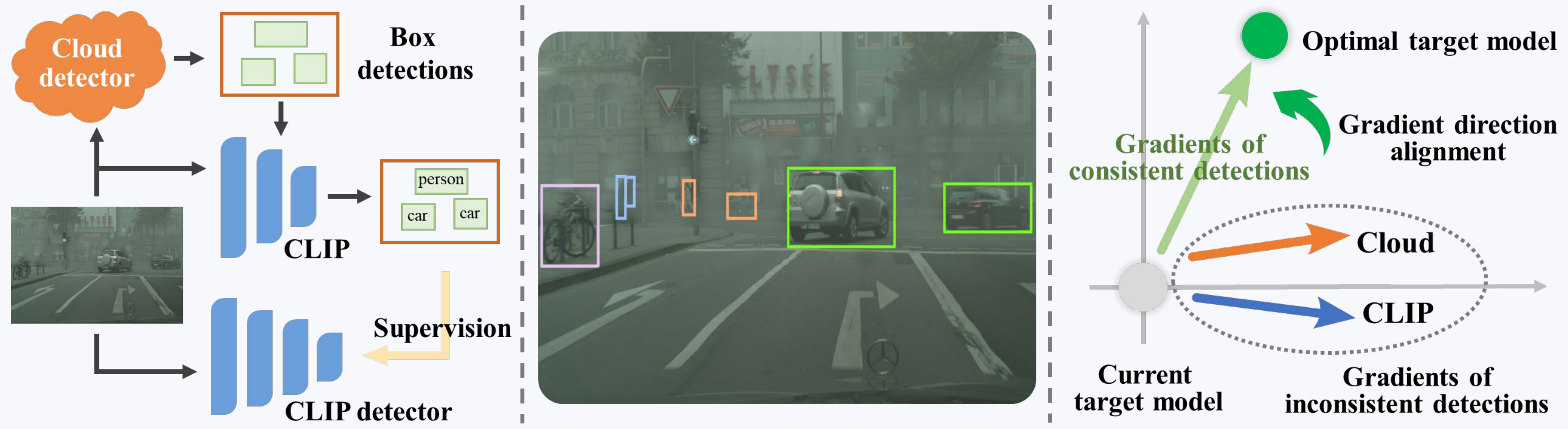
CODA: Cloud Object Detector Adaptation



CODA enables **open target scenarios** and **open object categories** adaptation due to large grounded pre-training of cloud detector.

Conditions	UDAOD	SFOD	Black-box DAOD	**CODA**
Source data access	✓	✗	✗	✗
Source model access	✓	✓	✗	✗
Cloud API access	✗	✗	✓	✓
High domain similarity	✓	✓	✓	✗
Ability				
Flexible architecture	✗	✗	✓	✓
Open categories	✗	✗	✗	✓
Open scenarios	✗	✗	✗	✓

Idea and Contributions



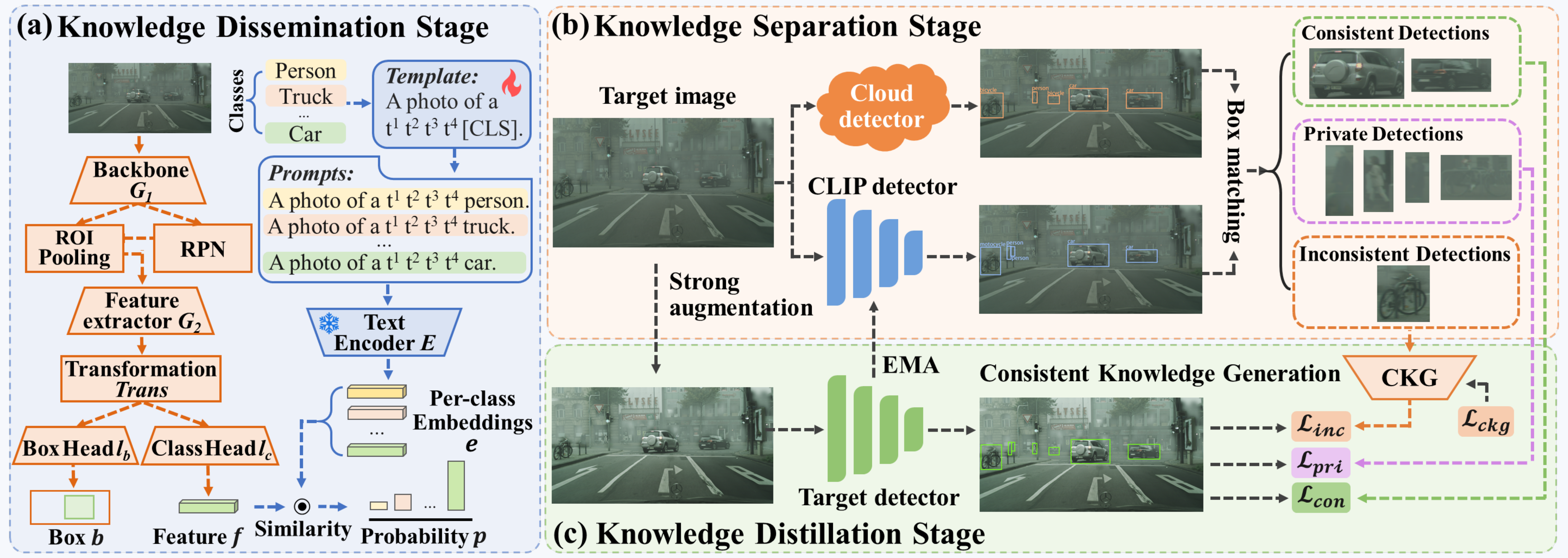
(a) Knowledge Dissemination (b) Knowledge Separation (c) Knowledge Distillation

1. ***Knowledge dissemination*** disseminates knowledge to a CLIP detector.
2. ***Knowledge separation*** separates detection results into three kinds.
3. ***Knowledge distillation*** fuses inconsistent detections by learning a CKG network using a self-promotion gradient direction alignment.

Contributions:

- Propose to explore a promising problem CODA.
- Propose a novel method COIN that acts in a divide-and-conquer manner.
- Propose a novel decision-level fusion strategy driven by gradient alignment.

Overall Pipeline of the Proposed COIN



- ***Knowledge dissemination pre-trains the CLIP detector with prompt learning:***

$$\min_{\theta_{clip}} \mathcal{L}_{RPN} + \mathcal{L}_{ROI} + \lambda \mathcal{L}^{1}_{align},$$

- ***Knowledge separation divides detections by box matching, resulting:***

$$\hat{\mathcal{P}} = \{(\boldsymbol{y}^{i}_{cld}, \boldsymbol{y}^{j}_{clip}) \,|\, \Gamma_{i,j} = 1, \boldsymbol{l}^{i}_{cld} = \boldsymbol{l}^{j}_{clip}\}, \tilde{\mathcal{P}} = \{(\boldsymbol{y}^{i}_{cld}, \boldsymbol{y}^{j}_{clip}) \,|\, \Gamma_{i,j} = 1, \boldsymbol{l}^{i}_{cld} \neq \boldsymbol{l}^{j}_{clip}\}$$

$$\mathcal{Q} = \{\boldsymbol{y}^{i}_{cld} \,|\, \Gamma_{i,*} = 0\} \cup \{\boldsymbol{y}^{j}_{clip} \,|\, \Gamma_{*,j} = 0\}$$

- ***Knowledge distillation distills detections to target detector, and fuses inconsistent detections with a CKG network, which is trained by a gradient direction alignment:***

$$\hat{g} = \nabla_{\theta_T} \|\hat{\boldsymbol{p}}_{stu} - \mathbb{I}(\hat{\boldsymbol{l}}_m)\|_2, \quad \tilde{g} = \nabla_{\theta_T} \|\tilde{\boldsymbol{p}}_{stu} - \tilde{\boldsymbol{p}}_{ckg}\|_2 \quad \min_{\theta_{ckg}} \mathcal{L}_{ckg} = (1 - sim(\hat{g}, \tilde{g})) + L_{kl}(\hat{\boldsymbol{p}}_{ckg}, \mathbb{I}(\hat{\boldsymbol{l}}_m))$$

Experiments on Benchmarks

Table 1: Results on **Foggy-Cityscapes** and **BDD100K** under GDINO. Object detection adaptation settings: U – Unsupervised, SF – Source-free, BB – Black-Box, C – Cloud. det: detector.

		Foggy-Cityscapes								
Methods	Type	Tuck	Car	Rder	Pson	Tain	Mcle	Bcle	Bus	mAP
MTOR [3]	U	21.9	44.0	41.4	30.6	**40.6**	28.3	35.6	38.6	35.1
ICR-CCR[59]	U	27.2	49.2	43.8	32.9	36.4	30.3	34.6	45.1	37.4
SED [35]	SF	25.5	44.5	40.7	33.2	22.2	28.4	34.1	39.0	33.5
LODS [33]	SF	27.3	48.8	45.7	34.0	19.6	33.2	37.8	39.7	35.8
A^{2}SFOD [10]	SF	28.1	44.6	44.1	32.3	29.0	31.8	38.9	34.3	35.4
IRG [53]	SF	24.4	51.9	45.2	37.4	25.2	31.5	41.6	39.6	37.1
LPU [9]	SF	24.0	55.4	**50.3**	39.0	21.2	30.3	**44.2**	46.0	38.8
BiMem [67]	BB	23.4	56.9	42.5	**42.2**	28.5	32.4	41.3	39.7	38.4
Cloud det [40]	C	**30.8**	47.5	18.6	34.3	21.0	**34.6**	41.1	**47.4**	34.4
CLIP [47]	C	9.7	28.6	11.5	19.5	1.1	12.8	17.9	21.9	15.4
CLIP det	C	8.2	46.9	27.5	34.1	16.5	24.9	31.5	36.2	28.2
COIN	C	27.4	**57.9**	42.3	41.6	25.9	32.7	41.2	43.1	**39.0**
Oracle	-	32.5	67.1	50.8	46.7	43.1	34.4	43.2	54.4	46.5

		BDD100K							
Methods	Type	Tuck	Car	Rder	Pson	Mcle	Bcle	Bus	mAP
SIGMA++ [34]	U	21.1	**65.6**	30.4	47.5	17.8	27.1	26.3	33.7
PT [7]	U	25.8	52.7	39.9	40.5	23.0	28.8	33.8	34.9
SED [35]	SF	20.6	50.4	32.6	32.4	18.9	25.0	23.4	29.0
PETS [39]	SF	19.3	62.4	34.5	42.6	17.0	26.3	16.9	31.3
A^{2}SFOD [10]	SF	33.2	36.3	**50.2**	26.6	28.2	24.4	22.5	31.6
BT [13]	SF	24.2	50.4	34.6	32.7	24.7	28.5	24.9	31.4
LPU [9]	SF	24.5	55.2	38.9	41.4	20.9	30.4	23.2	33.5
DRU [28]	SF	27.1	62.7	36.9	45.8	22.7	32.5	28.1	36.6
Cloud det [40]	C	38.7	46.0	11.4	**49.2**	**37.8**	**33.5**	**47.4**	37.7
CLIP [47]	C	23.6	31.1	4.4	6.7	18.0	11.4	27.7	17.5
CLIP det	C	34.3	53.4	14.1	31.7	28.7	24.6	36.7	31.9
COIN	C	**46.6**	56.8	23.5	45.5	32.0	33.0	40.6	**39.7**
Oracle	-	54.0	70.6	42.3	51.4	35.8	41.5	53.2	49.8

Experiments on Benchmarks

Table 3: Quantitative results on **KITTI** under GDINO. U – Unsupervised, C – Cloud. det: detector.

Type	Methods	AP of Car	Methods	AP of Car	Methods	AP of Car	Methods	AP of Car
U	DA-Faster [8]	64.1	MAF [23]	72.1	SCL [50]	72.7	ATF [24]	73.5
C	Cloud det [40]	45.2	CLIP [47]	62.1	CLIP det	79.9	**COIN**	**80.8**

Table 4: Quantitative results on **Cityscapes** and **Sim10K** under GDINO. C – Cloud. det: detector.

		Cityscapes									Sim10K
Methods	Type	Truck	Car	Rider	Person	Train	Mcycle	Bcycle	Bus	mAP	Car
Cloud det [40]	C	**37.5**	59.9	16.4	43.4	26.1	42.7	**48.4**	**62.6**	42.1	46.5
CLIP [47]	C	15.9	36.9	15.5	27.8	0.9	15.7	20.5	31.8	20.6	46.4
CLIP det	C	11.3	55.8	35.1	39.1	**33.8**	32.0	33.7	44.7	35.7	60.0
COIN	C	26.9	**64.3**	**47.5**	**47.0**	26.4	**44.4**	46.9	52.8	**44.5**	**62.4**
Oracle	-	34.7	70.4	56.4	50.5	43.0	38.7	46.9	58.9	49.9	79.2

Table 6: Ablation study for decision-level fusion of inconsistent detections on **Foggy-Cityscapes** under GDINO. Detections are filtered by $\pi = 0.7$ for fair comparison. det: detector. probs: probabilities. avg: average. s-avg: score-weighted average.

Methods	Truck	Car	Rider	Person	Train	Mcycle	Bcycle	Bus	mAP
COIN w/ cloud det probs	25.1	56.1	45.3	40.1	20.5	**33.7**	**41.3**	39.3	37.7
COIN w/ CLIP det probs	22.1	56.4	44.5	39.5	**26.8**	32.4	40.4	42.4	38.1
COIN w/ avg	24.8	55.8	44.1	39.9	21.7	32.8	40.9	**43.7**	38.0
COIN w/ s-avg	24.2	56.4	**45.9**	40.7	24.1	31.3	40.4	41.7	38.1
COIN w/ CKG	**27.4**	**57.9**	42.3	**41.6**	25.9	32.7	41.2	43.1	**39.0**

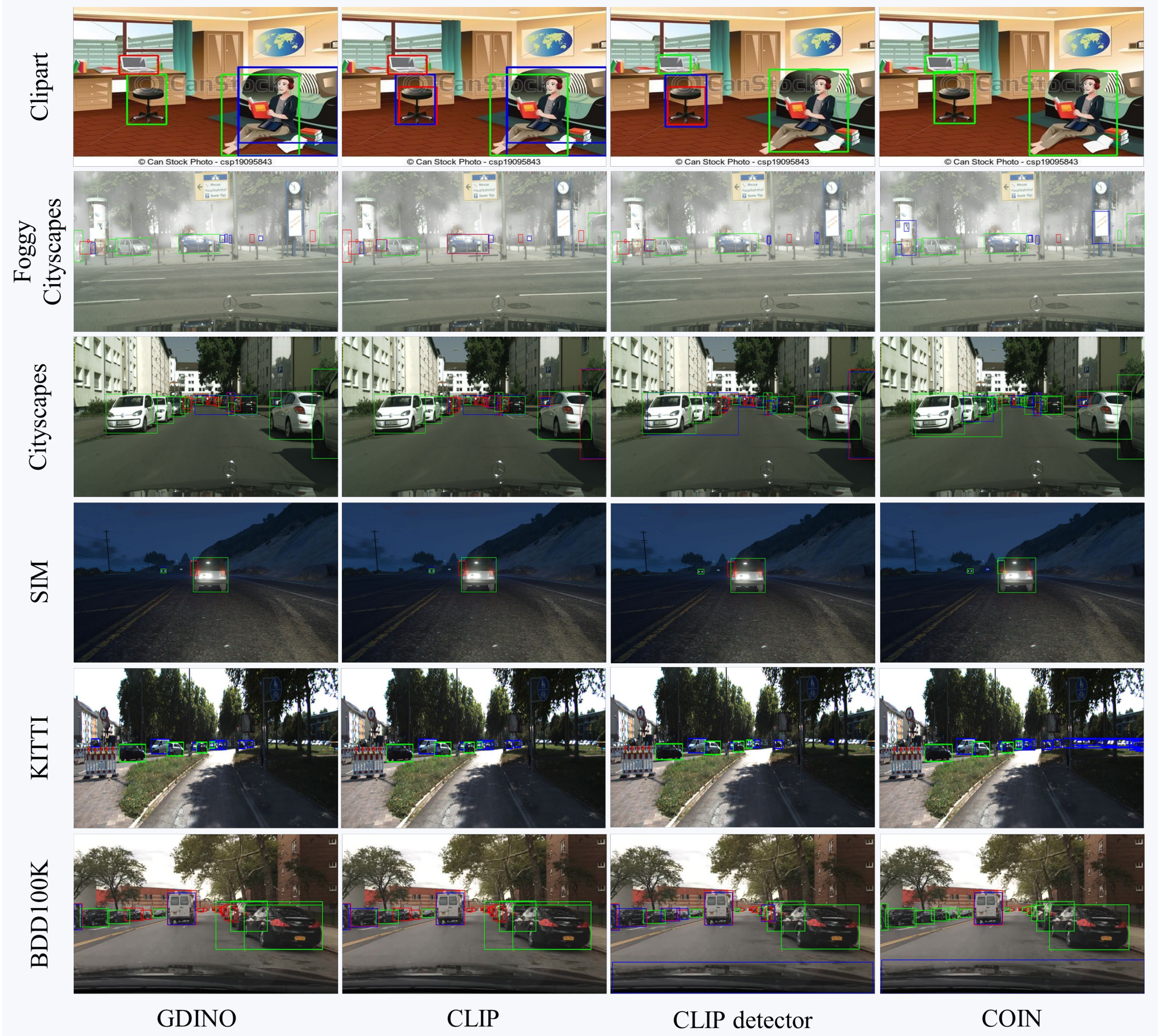


Figure 5: Qualitative results on Clipart, Foggy-Cityscapes, Cityscapes, SIM, KITTI and BDD100K. Green , red and blue boxes represent true positives (TP), false negatives (FN) and false positives (FP), respectively. *Zoom in for best view.*

Our COIN achieves the state-of-the-art performance on all datasets, and the proposed CKG works as above. For more information about this work, please refer to the full paper or slides with the following links.

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