Appendix for SODA10M: A Large-Scale 2D Self/Semi-Supervised Object Detection Dataset for Autonomous Driving

A SODA10M dataset

We publish the SODA10M dataset, benchmark, data format and annotation instructions at our website https://soda-2d.github.io. It is our priority to protect the privacy of third parties. We bear all responsibility in case of violation of rights, etc., and confirmation of the data license.

License, Terms of use, Terms of privacy. The SODA10M dataset is published under CC BY-NC-SA 4.0 license, which means everyone can use this dataset for non-commercial research purpose. Find more details in Appendix F.

Participants' instructions: Full participants' instructions can be found in google drive: https://drive.google.com/file/d/1RVxXltsxkoo-XuzVvAplbZHQs5BGDpEp/view?usp=sharing.

Dataset documentation. https://soda-2d.github.io/documentation.html shows the dataset documentation and intended uses.

Data maintenance. https://soda-2d.github.io/download.html provides data download links for users (in Google Drive & Baidu YunPan). We will maintain the data for a long time and check the data accessibility regularly. We also plan to extend the scale of unlabeled data to a 100-million level to help develop robust models.

Benchmark and code. The codebases used in our benchmark are open-source. More details of the reproduction code and experiment settings are illustrated in Appendix B.

Data format & Evaluation metrics. Annotation files in SODA10M are stored in standard COCO format, which can be easily accessible to most object detection codebases. We follow the popular COCO API [14] to utilize the Average Precision metric for evaluating detection performance.

Limitations. The major limitation of SODA10M is that some domains exist in the unlabeled set but not in labeled sets, which raises the problem that we can not verify the domain adaptation abilities in these domains. To overcome the limitation, we plan to provide more labeled data in these domains in the future.

Discussion of round1: The main issues raised by round1 can be summarized and addressed as follows:

Q1: Need to show some interesting or distinct findings of self-supervised learning methods (refer to Sec. 4.3 and Sec. 4.5).

R1: Some interesting observations can be found under autonomous driving scope: Firstly, dense contrastive method (*i.e.*, DenseCL [19]) preforms better than Image-wise methods (*i.e.*, MoCo-v1 [10]) when pre-training on ImageNet (39.9% vs. 39.0%). However, Dense contrastive method preforms worse when pre-training on SODA10M (38.1% vs. 38.9%) due to the reason that pixel-wise contrastive loss may not suitable for complex driving scenario. Secondly, pre-training on ImageNet brings almost equal improvement in both day and night domain (+1.1% vs. +0.9%), and we assume that is because ImageNet [8] contains common images which achieve no special helps to the performance of night domain. On the other hand, pre-training on SDOA10M, which contains massive images collected at night, brings double improvement in night domain (+1.6%) compared to day domain (+0.7%). More observations can be found in Sec. 4.3 and Sec. 4.5.

Q2: Detailed comparison of current autonomous driving datasets (refer to Sec. 3.3).

R2: We compare the SODA10M with other large-scale autonomous driving datasets (including BDD100K [23], nuScenes [1] and Waymo [18]) in the field of scale, driving time, collecting cities, driving conditions and experiment results as upstream pre-training dataset.

Firstly, observed from Table 1 in Introduction, the number of images, driving time and collecting cities of SODA10M is 10M, 27833 hrs and 32 respectively, which is much larger than the current datasets BDD100K [23] (0.1M, 1111 hrs, 4 cities), nuScenes [1] (1.4M, 5.5 hrs, 2 cities) and Waymo [18] (1M, 6.4 hrs, 3 cities). Secondly, as shown the Table 1 in Appendix A, our SODA10M is more diverse in driving conditions compared with nuSceness [1] and Waymo [18], and achieves competitive results with BDD100K [23]. Finally, with above characteristics, SODA10M achieves better generalization

ability and best performance compared with the other three datasets in almost all (9/10) downstream detection and segmentation tasks when regarded as the upstream pre-training dataset.

B Implement Details

In order to make the experiment results reproducible, we further provide detailed experimental settings for each method in this paper. The primary differences compared with default setting is that the class number is set to 6, syncBN is on and multi-scale training (in supervised and semi-supervised methods) is utilized with scale 1920×(864, 907.2, 950.4, 993.6, 1036.8, 1080). Without specifying, all self-supervised and semi-supervised methods adopt ResNet50 [11] backbone. Our models are trained on servers with 8 Nvidia V100 GPU(32GB) cards with Intel Xeon Platinum 8168 CPU(2.70GHz).

B.1 Open-Source Codebase

Table 1: The codebases used in our benchmark.

Codebase	link
Detectron2 [20]	https://github.com/facebookresearch/detectron2
OpenSelfSup	https://github.com/open-mmlab/OpenSelfSup
VINCE [9]	https://github.com/danielgordon10/vince
STAC [17]	https://github.com/google-research/ssl_detection
Unbiased Teacher [15]	https://github.com/facebookresearch/unbiased-teacher

B.2 Supervised Methods

For the 1x schedule, the learning rate is set to 0.02, decreased by a factor of 10 at 8th, 11th epoch of total 12 epochs. Random crop is used as the only data augmentation method and SGD optimizer is adopted with momentum set as 0.9.

Table 2: Implement details for supervised learning benchmark on SODA10M with 8 Tesla V100.

Model	Train split	Default Setting	Difference	GPU hours
RetinaNet [13] 1x	train set	Detectron2	1. backbone no freeze. 2. turn on precise_bn.	0.78×8
Faster RCNN [16] 1x	train set	Detectron2	same as above	0.83×8
Cascaded RCNN [2] 1x	train set	Detectron2	same as above	0.92×8

B.3 Self-supervised Methods

We follow the default settings in OpenSelfSup[1] to train six state-of-the-art standard self-supervised learning methods, including MoCo-v1 [10], MoCo-v2 [5], SimCLR [4], SwAV [3], DetCo [21], DenseCL [19], and evaluate their performance by fine-tuning the pre-trained models on the SODA10M labeled data and other self-driving datasets like BDD100K [23] and Cityscapes [6] to verify the generalization ability. Due to the limit of hardware resources, we only use a 5-million unlabeled subset in each experiment by default, while we also make full use of the other 5-million subset in a sequential training manner (mentioned in †), following Hu et al. [12]. Specifically, the model pre-trained on the first subset will be used as initialization to continue pre-training on the second one. We follow the standard data augmentation pipeline adopted by MoCov2 [5], which consists of random resized crop, color jitter, gaussian blur and random horizontal flip, for all considered models except MoCov1 [10], which implements all augmentations except gaussian blur. Auto Augmentation [7] is further used in DetCo [21] following the original paper. Cosine learning rate decay is adopted for all models except MoCov1, which uses step-wise learning rate decay to decrease learning rate by 10x at 40 and 50 epochs. The base learning rates are 0.03, 0.03, 0.3, 4.8, 0.06, 0.03 sequentially for the models in Table 3. LARS optimizer [22] is used in SimCLR [4], while all other models implement SGD optimizer with momentum set as 0.9.

[1] https://github.com/open-mmlab/OpenSelfSup

For video-based self-supervised learning, MoCo-v1 [10], MoCo-v2 [5] and VINCE [9] are adopted. To ensure fairness, we apply the same data augmentation with VINCE to MoCo-v1 and MoCo-v2 to exploit temporal information and extra jigsaw augmentation to VINCE for better results.

We adopt 3700-epoch, 220-epoch, 325-epoch and 60-epoch pre-training on BDD100K [23], nuScenes [1] and Waymo [18] and SODA unlabeled set for image-based methods respectively, to maintain similar GPU hours with pre-training 200 epochs on ImageNet for fair comparison. Video-based approaches are trained for 800 epochs by considering time limit.

Table 3: Implement details for semi-supervised learning benchmark on SODA10M with 8 Tesla V100.

Model	Train split	Default Setting	Difference	GPU days
MoCov1 [10], MoCov2 [5], SimCLR [4], SwAV [3], DenseCL [19]	5-million unlabeled	OpenSelfSup	60 epochs	8.40×8
DetCo [21]	5-million unlabeled	OpenSelfSup	same as above	14.1×8
MoCov1 [10]†, MoCov2 [5]†, SimCLR [4]†	10-million unlabeled	OpenSelfSup	same as above	16.8×8
MoCov1 [10], MoCov2 [5], VINCE [9], VINCE+Jigsaw [9] on **VIDEO**	5-million unlabeled to 90k videos	VINCE	1. 800 epochs 2. VINCE augmentations	2.80×8

When finetuning on SODA10M labeled set and other datasets (Cityscape [6] & BDD100K [23]), the setting keeps consistent with the supervised methods and MoCo [10] respectively.

B.4 Semi-supervised Methods

For semi-supervised methods, considering the time limit, only 1-million unlabeled images (split 0) of SODA10M are used. Compared with self-supervised methods, semi-supervised methods are much more efficient. The learning rate of pseudo labeling, STAC [17] and unbiased teacher [15] is set to 0.02, 0.01 and 0.02 respectively. Color jitter, gaussian blur, affine transformation, cutout augmentation and random crop are adopted in STAC, while color jitter, gray scale, gaussian blur, random erasing and random crop are adopted in unbiased teacher. SGD optimizer is adopted in both methods with momentum set as 0.9.

Table 4: Implement details for semi-supervised learning benchmark on SODA10M with 8 Tesla V100.

Model	Train split	Default Setting	Difference	GPU days
Pseudo Labeling(50K)	50K unlabeled	Detectron2	1. backbone no freeze. 2. turn on precise_bn.	0.21×8
Pseudo Labeling(100K)	100K unlabeled	Detectron2	same as above	0.39×8
Pseudo Labeling(500K)	500K unlabeled	Detectron2	same as above	2.00×8
STAC [17]	1-million unlabeled	STAC	same as default	2.50×8
Unbiased Teacher [15]	1-million unlabeled	Unbiased Teacher	same as default	2.80×8

C More Experiments

To show that how the number of labeled images affects the final results in self/semi-supervised object detection task, we further conduct the experiments to show the self-supervised (with MoCov1 [10]) object detection performance under various downstream SODA10M dataset sizes (20%, 50%, 100%) and upstream pre-training datasets (Waymo [18], SODA10M). The results are shown in following:

Table 5: Self-supervised (with MoCov1 [10]) object detection performance mAP(%) under various downstream SODA10M dataset sizes (20%, 50%, 100%) and upstream pre-training datasets (Waymo [18], SODA10M). 20%, 50%, 100% denote for using 20%, 50%, 100% of SODA10M labeled set for downstrem fine-tuning.

	20%	50%	100%
pre-train on Waymo [18]	26.6	33.2	37.1
pre-train on SODA10M	$29.2^{+2.6}$	$35.3^{+2.1}$	$38.9^{+1.8}$

Observation can be made that more downstream labeled data bridge the gap between different self-supervised models. On the other hand, too few labeled images tend to have a large standard

deviation (SD) of the final performance, e.g, pre-training on SODA10M receives an 0.75 SD on 20% SODA10M labeled set, compared with the 0.11 SD on 100% SODA10M labeled set.

Table 6 shows the performance of existing self-supervised methods evaluated on SODA10M labeled set with a longer schedule and instance segmentation result on Cityscape [6] dataset. We observe that dense contrastive methods (Detco [21], DenseCL [19]) show excellent results when pre-trained on ImageNet [8], but relatively poor pre-trained on SODA10M unlabeled set. For semantic segmentation performance on Cityscapes with MoCo-v1 [10], the model pre-trained on SODA10M even surpasses the one pre-trained in ImageNet by 1.6%, further verifying the generalization ability of pre-training on SODA10M.

Table 6: Detection results(%) of self-supervised models evaluated on SODA10M labeled dataset (with object detection task) and Cityscapes (CS) dataset (with instance segmentation task).

		Faster-RCNN 2x (SODA)			RetinaNet 2x (SODA)			Mask-RCNN 1x	
Pre-train Dataset	Method	mAP	AP50	AP75	mAP	AP50	AP75	mAP (CS)	AP50 (CS)
	random init	29.6	49.8	31.2	20.9	35.4	21.4	25.4	51.1
	super. IN	38.7	61.0	41.5	35.0	57.0	36.0	32.9	59.6
ImageNet [8]	MoCo-v1 [10]	39.3	60.9	42.5	35.9	57.4	37.3	32.3	59.3
	MoCo-v2 [5]	40.4	62.7	43.6	37.4	59.1	39.3	33.9	60.8
	SimCLR [4]	37.9	61.0	40.4	32.7	53.3	33.8	32.8	59.4
	SwAV [3]	38.2	61.9	40.9	32.6	53.4	33.8	33.9	62.4
	DetCo [21]	39.8	62.1	43.3	35.8	57.5	37.5	34.7	63.2
	DenseCL [19]	40.6	62.9	43.8	37.5	59.4	39.2	34.3	62.5
SODA10M	MoCo-v1 [10]	38.7	60.9	41.1	33.4	56.2	34.3	33.9	60.6
	MoCo-v2 [5]	39.1	60.8	42.6	33.6	56.2	34.8	33.7	61.0
	SimCLR [4]	36.7	59.6	39.1	31.6	53.8	32.3	30.2	57.0
	SwAV [3]	36.0	59.8	37.9	29.7	50.0	30.4	29.4	57.7
	DetCo [21]	37.2	58.9	39.8	31.2	53.5	31.3	32.5	59.8
	DenseCL [19]	38.9	61.0	41.9	33.2	55.4	33.7	33.1	60.7

D Domain Illustration & Driving Conditions Comparison

The distribution of each fine-grained domain in the validation set, testing set, unlabeled set and labeled set is shown in the Table 7, Table 8, Table 9 and Fig. 1.

Table 7: The number of images in each domain in validation set.

	Daytime			Night		
	City street	Highway	Country road	City street	Highway	Country road
Clear	383	961	63	137	167	312
Overcast	597	517	240	288	627	59
Rainy	177	406	0	0	66	0

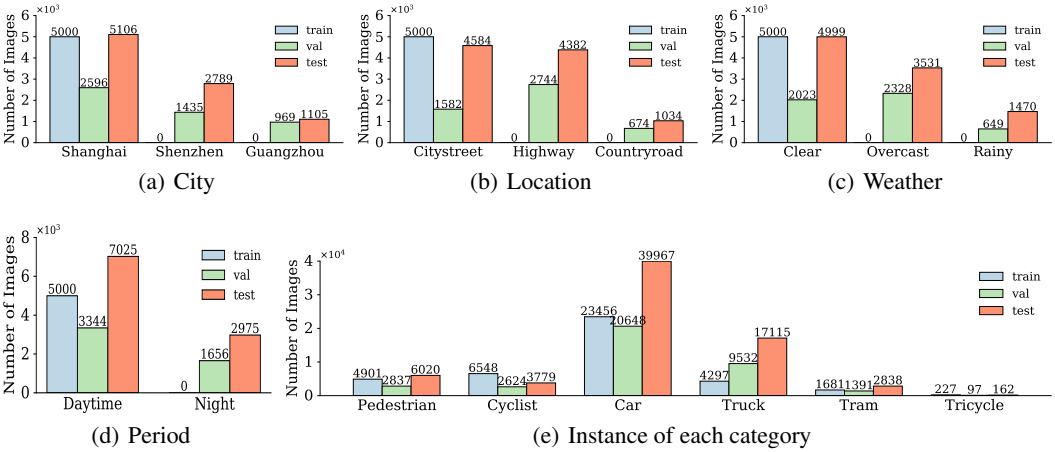
Table 8: The number of images in each domain in testing set.

	Daytime			Night		
	City street	Highway	Country road	City street	Highway	Country road
Clear	490	2024	250	1591	498	146
Overcast	1216	1103	481	361	237	133
Rainy	917	520	24	9	0	0

The driving conditions comparison is shown in Table 10.

Table 9: The number of images in each domain in unlabeled set.

	Daytime				Night				Dawn/Dusk			
	Clear	Overcast	Rainy	Snowy	Clear	Overcast	Rainy	Snowy	Clear	Overcast	Rainy	Snowy
City street	2247K	1483K	458K	140K	1274K	582K	157K	71K	325K	215K	62K	22K
Highway	506K	311K	114K	4K	186K	58K	24K	0.70K	37K	27K	9K	0.17K
Country road	499K	333K	69K	7K	170K	40K	12K	1K	38K	23K	5K	0.50K
Residential	146K	154K	29K	20K	61K	40K	7K	10K	9K	1K	2K	2K



(a) City (b) Location (c) Weather

(d) Period (e) Instance of each category

Figure 1: Statistics of the labeled set. (a) Number of images in each city. (b) Number of images in each location. (c) Number of images in each weather condition. (d) Number of images in each period. (e) Number of instances in each category.

Table 10: Driving conditions comparison between SODA10M and other autonomous driving datasets (i.e., nuScenes [1], Waymo [18] and BDD100K [23]), where '-' denotes for not having annotations in this field.

Dataset	Period	Weather	Location
nuScenes [1]	Day: 1045K(88.3%), Night: 138K(11.7%)	Sunny: 952K(80.4%), Rain: 231K(19.6%)	-
Waymo [18]	Day: 798K(80.7%), Night: 96K(9.8%), Dawn/Dusk: 93K(9.5%)	Sunny: 983K(99.4%), Rain: 5K(0.6%)	-
BDD100K [23]	Daytime: 41K(52.6%), Night: 31K(40.1%), Dawn/Dusk: 5K(7.3%)	Clear: 42K(60.6%), Overcast: 10K(14.2%), Rainy: 5K(8.1%), Snowy: 6K(8.9%), Partly cloudy: 5K(8.0%), Foggy: 143(0.2%)	City street: 49K(62.3%), Highway: 19K(25.1%), Residential: 9K(11.8%), Parking lot: 426(0.5%), Gas stations: 34(0.1%), Tunnel: 156(0.2%)
SODA10M	Daytime: 6536K(65.4%), Night: 2697K(26.9%), Dawn/Dusk: 786K(7.7%)	Clear: 5507K(55.7%), Overcast: 3283K(33.6%), Rainy: 949K(8.5%), Snowy: 278K(2.2%)	City street: 7045K(70.7%), Highway: 1283K(12.3%), Country road: 1199K(12.1%), Residential: 490K(4.9%)

More images in each domain are shown in Fig. 2.

E Acknowledgements

We thank our two data suppliers, named Testin[2] and Speechocean[3] (collected from King-IM-055), for helping us collect and annotate SODA10M dataset.

[2] http://www.testin.cn
[3] http://en.speechocean.com

Figure 2: More examples of challenging environments in our dataset.

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