KI DELTA LEARNING
Scalable AI for Automated Driving

Severity of Catastrophic Forgetting in Object Detection for Autonomous Driving

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Training Strategies

Introduction

- Empirical study to investigate effects of catastrophic forgetting for Object Detection for Autonomous Driving
- Autonomous Systems are exposed to ever-changing data-distributions (Figure 1)
- Incremental training can lead to a degradation in performance, known as catastrophic forgetting
- Investigation of Domain-incremental Learning Class-incremental Learning (Figure 2) for BDD100K [1]

Metrics

Model is evaluated after each task (mAP) on all K tasks $P\in\mathbb{R}$^KxK

- Average mAP $$avg.\ mAP = \frac{1}{K}\sum_{i=1}^{K} P_{K,i}$$
- Backward Transfer [2] $$BWT = \frac{1}{K-1}\sum_{i=1}^{K-1} p_{K,i} - p_{i,i}$$
- Forward Transfer [2] $$FWT = \frac{1}{K-1}\sum_{i=2}^{K} p_{i-1,i} - \bar{b}_i$$

Results

The **order of tasks** and the **data distribution** of the input influences the severity of forgetting.

Order	avg. mAP	BWT(%)	FWT
Time of Day (Day, Night, Dawn/Dusk)			
Day → Dawn → Night	0.263	-10.5%	0.253
Day → Night → Dawn †	0.228	-15.0%	0.209
Dawn → Day → Night	0.241	-5.7%	0.21
Dawn → Night → Day ‡	0.264	**11.5%**	0.189
Night → Day → Dawn	0.263	-10.2%	**0.263**
Night → Dawn → Day	**0.268**	7.2%	0.223
Scene (Citystreet, Highway, Residential, ...)			
Descending by occurrences	0.244	-18.3%	**0.267**
Ascending by occurrences	**0.286**	**176%**	0.085

The **architecture** of the detector has an influence on the forgetting.

Architecture	avg. mAP	BWT(%)	FWT
Time of Day			
Faster-RCNN (ResNet)	0.263	-10.5%	0.253
Faster-RCNN (Swin)	0.270	-10.0%	0.261
FCOS (ResNet)	0.240	-12.6%	0.229
DDETR (ResNet)	**0.276**	**-8.1%**	**0.266**
Scene			
Faster-RCNN (ResNet)	0.244	-15.3%	0.267
Faster-RCNN (Swin)	**0.281**	**-7.4%**	**0.294**
FCOS (ResNet)	0.215	-20.2%	0.247
DDETR (ResNet)	0.219	-25.2%	0.291

Class-incremental learning leads to more severe forgetting compared to domain-incremental learning.

Inc.	AP Car	Truck	Bus	Mot.-cycle	Train	Rider	Bi-cycle	Tr. Sign	Tr. Light	Pedes-trian
5-5										
#1	**0.499**	**0.422**	**0.44**	**0.173**	0.00					
#2	0.00	0.00	0.00	0.00	0.00	**0.331**	**0.234**	**0.224**	**0.372**	**0.233**
9-1										
#1	**0.497**	**0.436**	**0.445**	**0.195**	0.00	**0.196**	**0.22**	**0.368**	**0.223**	
#2	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	**0.333**

Conclusion

- Continuous Learning highly depends on chosen scenario
- Unbalanced data distributions must be accounted for when training incrementally
- Task-agnostic RPN (Faster-RCNN) improves performance
- Future research should incorporate random orderings and more realistic scenarios

References

[1] Yu, F. et al. (2020), "Bdd100k: A diverse driving dataset for heterogeneous multitask learning." in CVPR (2020).
[2] Lopez-Paz, D. and Ranzato, M., "Gradient episodic memory for continual learning" in NeurIPS (2017).

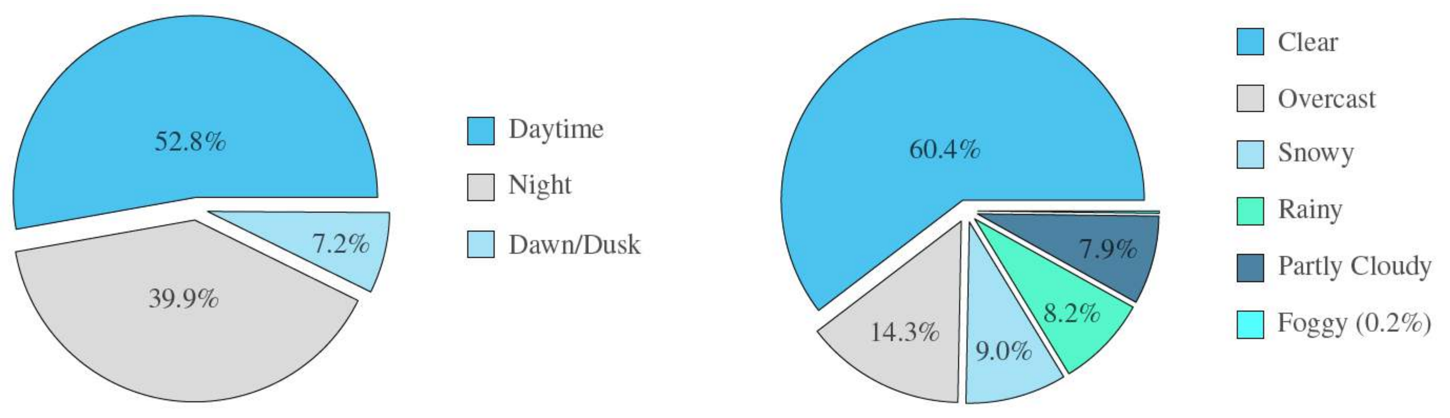
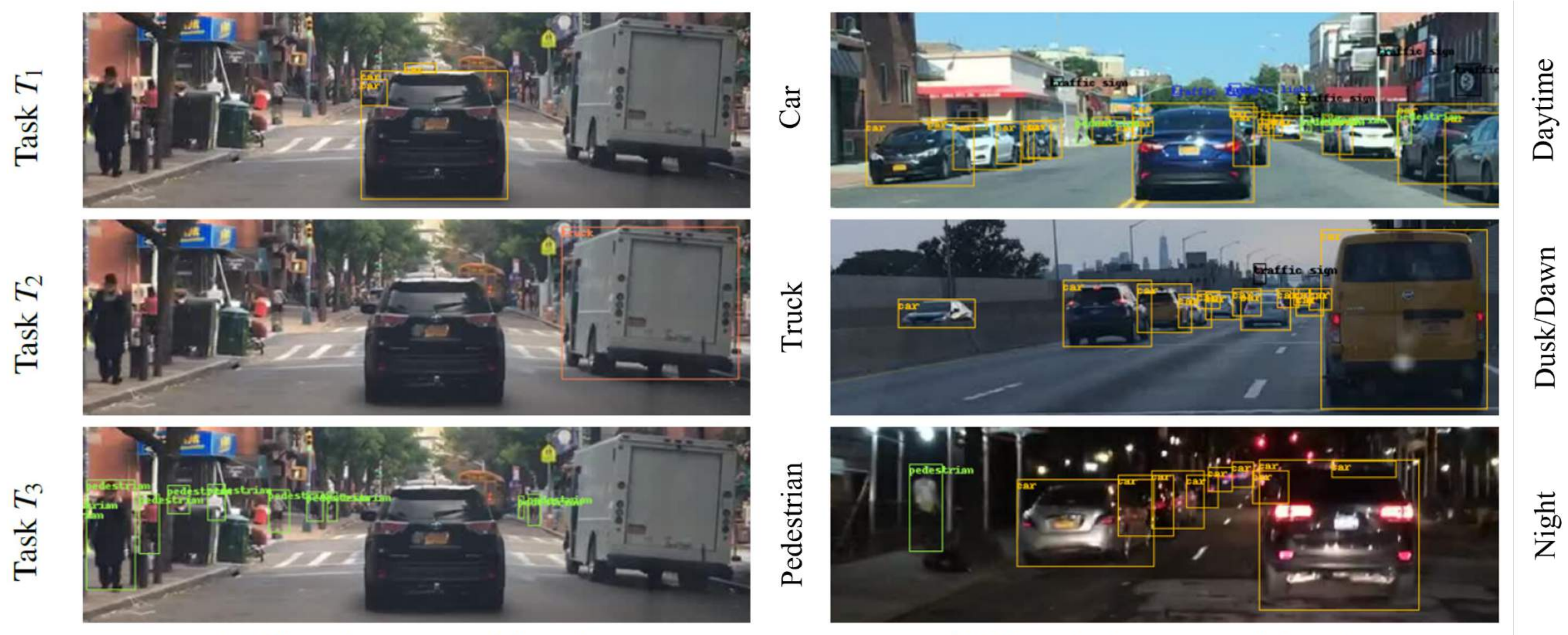


Figure 1: Distribution of Time of Day (left) and Weather (right). (©ZF Group)



(a) Class-incremental learning (b) Domain-incremental learning

Figure 2: a) Class-incremental and b) Domain-incremental Learning (©ZF Group)

Partners

External partners

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