Beyond Prompt Degradation: Prototype-guided Dual-pool Prompting for Incremental Object Detection

Supplementary Material

8. Model Complexity Analysis

We provide a detailed comparison of model parameters and computational complexity with MD-DETR in Table 6. PDP introduces only a marginal increase in parameters (64.9M $\rightarrow$ 66.4M). During inference, the additional computational overhead is negligible (approximately 0.01 GFLOPs). Although a frozen teacher model is employed during training for distillation, it increases GPU memory usage by only approximately 1GB (from 12.3GB to 13.4GB), which does not impose significant practical burden. Importantly, the teacher network is discarded during inference and therefore does not affect deployment efficiency.

Table 6. Model parameters and FLOPs comparison.

Method	Params (M)	Training FLOPs (G)	Inference FLOPs (G)
MD-DETR	64.9	166.2 (12.3GB GPU)	166.17
PDP (Ours)	66.4	332.4 (13.4GB GPU)	166.18

9. Training Strategy in Incremental Stages

During each incremental stage (Task $i > 1$), distillation guided by PPG is applied to provide supervision for previously learned categories. In terms of parameter updates, all parameters in the shared prompt pool are updated throughout training. For the private prompt pool, only the prompts corresponding to the current categories are updated, while the private prompts associated with old and future categories remain frozen. This selective update strategy prevents catastrophic forgetting while maintaining adaptability to newly introduced classes.

10. Additional Results under the $40 + 20 \times 2$ Setting

To further validate the robustness and generality of PDP, we conduct experiments under the multi-step incremental setting of $40 + 20 \times 2$ on COCO. The results are presented in Table 7. Under the same Deformable DETR framework, PDP consistently outperforms prior methods, demonstrating strong adaptability in multi-step incremental scenarios.

11. Upper and Lower Bound Analysis under the $70 + 10$ Setting

We additionally report results under the $70+10$ incremental setting on COCO in Table 8. For completeness, we provide both a lower bound (direct fine-tuning) and an upper bound (joint training with full access to all data).Direct fine-tuning results in severe forgetting of old categories. In contrast, PDP achieves 43.8% AP on old categories and approaches the upper bound performance (47.4% AP). In terms of overall performance across all categories, PDP remains only 3.3% AP below the upper bound, demonstrating effective mitigation of catastrophic forgetting.

Table 7. Results under the $40 + 20 \times 2$ setting on COCO.

Method	Baseline	AP	AP_{50}
CL-DETR$_{\text{CVPR '23}}$	Deformable-DETR	35.3	–
SSDGR$_{\text{CVPR '24}}$	Deformable-DETR	41.1	59.5
DCA$_{\text{AAAI '25}}$	Deformable-DETR	40.3	54.1
PDP (Ours)	Deformable-DETR	**42.1**	**60.7**

Table 8. Performance under the $70 + 10$ setting on COCO.

Method	All Categories			Old Categories
	AP	AP_{50}	AP_{75}	AP
Fine-tune	4.2	–	–	0.7
Upper bound	46.2	65.2	50.0	47.4
PDP (Ours)	**42.9**	**61.1**	**47.1**	**43.8**