RBC: Rectifying the Biased Context in Continual Semantic Segmentation -Supplemental Material-

Overview. In this supplemental material, we provide more experimental results on the CSS benchmarks in the main manuscript. More visualization results of PLOP and our method under the *Overlapped* setting of VOC-15-1 are presented in Section A. In Section B, we provide the the class-based evaluation with the backward and forward transfer (BWT, FWT) metric on the VOC-15-1. The learning curves of our method and PLOP on VOC-*overlapped*-15-5 are provided in Section C. In Section D, we compare our method with PLOP by the per-class results on VOC-*overlapped*-15-1

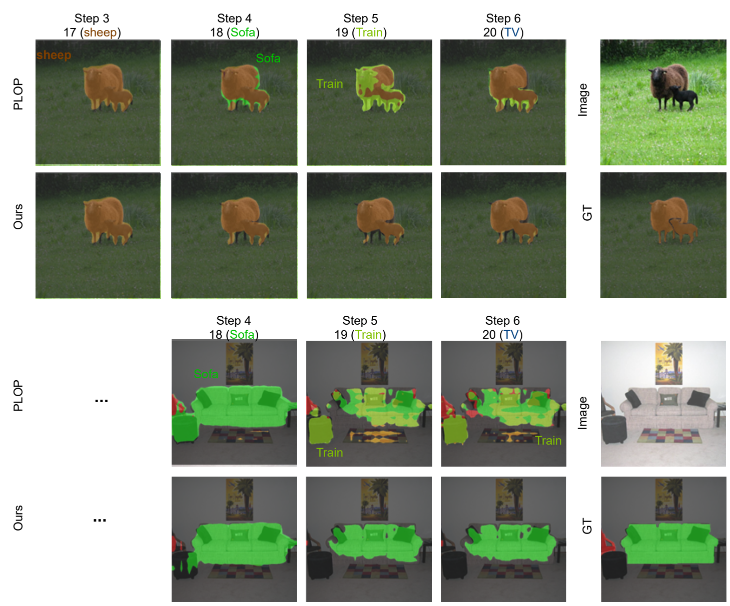

Fig. A. Visualization results of PLOP and our method at different steps under the *Overlapped* setting of VOC-15-1.

A Visualization

In this section, we provide more visualization results for both PLOP (Baseline) and our method at different steps under the *Overlapped* setting of VOC-15-1.

As shown in Figure A, we have taken two images as the examples. As for the first sample mainly consisting the sheep-class pixels, the sheep-class is learned at step 3 firstly and PLOP has more serious old-class forgetting than ours (e.g. mis-classify the sheep-class pixels as train-class at step 5 and step 6). As for the second sample mainly consisting of sofa-class pixels, the sofa-class is added at the step 4 and the new-class overfitting problem of PLOP is also more serious than ours (e.g. mis-classify the background-class pixels as train-class at step 5). All of these results demonstrate that the biased context leads to the aggravation of old-class forgetting and new-class overfitting and our method can effectively rectified the biased effect in CSS.

B Evaluation via Backward and Forward Transfer

We have conducted the class-based evaluation with the backward and forward transfer (BWT, FWT) metric on the VOC-15-1. The BWT results are shown in Table A. VOC-15-1 consists of six tasks and the first task contains 15 semantic classes and 1 background class. We can observe that our method achieves more positive BWT than PLOP. Besides, the FWT to future classes are near zero for all the Continual Semantic Segmentation methods since the pixels of unseen future semantic classes are learned as the background class in CSS problem.

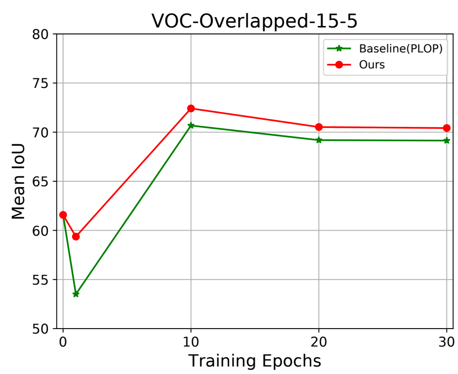

Fig. B. mIoU learning curve.

C Evaluation via Learning Curve

In this section, we have evaluated our method with the learning curves on VOC-*overlapped*-15-5. As shown in Figure B, the mean IoU of our method consistently outperforms that of PLOP at different epochs of the training process.

Table A. Backward transfer results on VOC-*overlapped*-15-1.

Method	Task 1															
	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
PLOP	-7.80	-14.32	-6.74	-13.49	-10.30	-12.76	-5.45	-3.32	-7.28	**-5.31**	-9.48	4.08	-5.74	-5.11	-6.82	-8.17
Ours	**-2.93**	**-3.31**	**-1.31**	**-8.16**	**-3.82**	**-7.58**	**-2.67**	**-0.47**	**-2.91**	-15.27	**-3.63**	**-1.82**	**-4.79**	**-2.61**	**-2.32**	**-7.29**

Table B. Per-class IoU on VOC-*overlapped*-15-1.

Method	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
PLOP	81.75	73.25	30.54	64.56	55.59	63.47	79.23	80.91	78.05	**30.92**	58.14	**54.77**	76.49	74.26	72.61	70.66	**13.82**	45.15	8.74	6.51	2.76
Ours	**89.95**	**84.72**	**38.84**	**79.43**	**60.98**	**68.92**	**87.33**	**88.51**	**87.92**	12.59	**63.35**	43.38	**78.88**	**79.93**	**78.86**	**73.11**	3.88	**56.94**	**26.19**	**28.83**	**23.47**

D Evaluation via Per-Class Results

In this section, we have provided the per-class IoU of our method and PLOP on VOC-*overlapped*-15-1. As shown in Table B, we can observe that our method achieves higher IoU than PLOP on most of classes.