PLOP: Learning without Forgetting for Continual Semantic Segmentation

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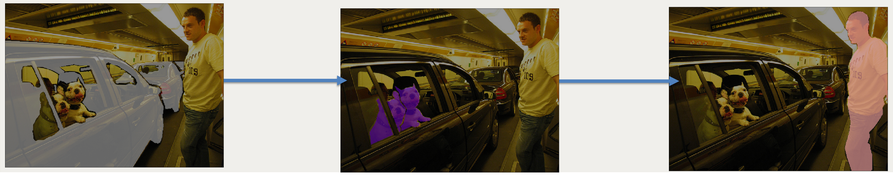
1. Challenges in Continual Semantic Segmentation

- **#1 Catastrophic Forgetting** when learning incrementally classes

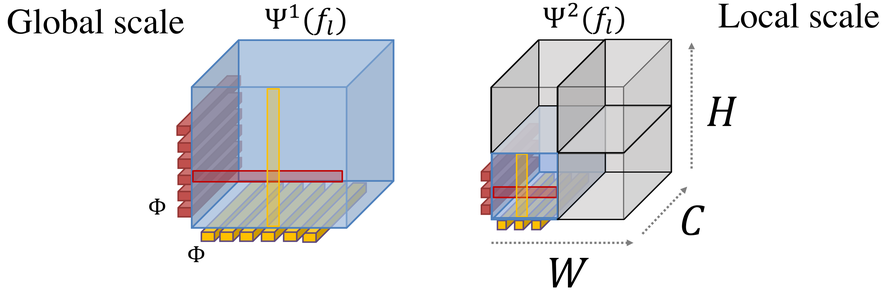
car → dog → person

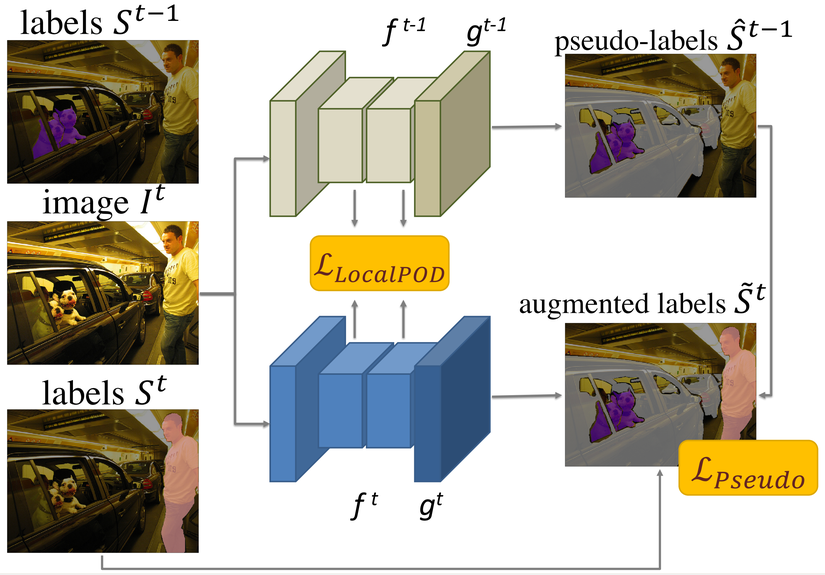
- **#2 Background shift** with partially labeled images



2. Local POD against catastrophic forgetting

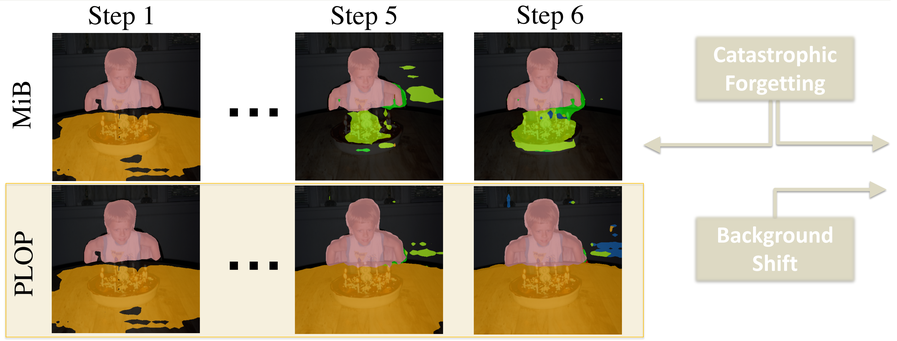
- **Long-range dependencies** across horizontal and vertical axis
  - $\Phi(\boldsymbol{x}) = \left[\frac{1}{W}\sum_{w=1}^{W} \boldsymbol{x}[:,w,:] \,\|\, \frac{1}{H}\sum_{h=1}^{H} \boldsymbol{x}[:h:,:]\right] \in \mathbb{R}^{(H+W)\times C}$
- **Short-range dependencies** with a multi-scale approach
  - Emphasis on POD embeddings for local patches
  - $\Psi^s(\boldsymbol{x}) = \left[\Phi(\boldsymbol{x}^s_{0,0}) \,\|\, \dots \,\|\, \Phi(\boldsymbol{x}^s_{s-1,s-1})\right] \in \mathbb{R}^{S\times(H+W)\times C}$
- $\mathcal{L}_{LocalPOD} = \frac{1}{L}\sum_{l=1}^{L} \left\| \Psi^s\left(f_l^t(I)\right) - \Psi^s\left(f_l^{t-1}(I)\right) \right\|^2$





3. Pseudo-labeling alleviating background shift

- Pseudo-labelize old classes using model from previous task
- Entropy-based threshold + adaptive per-image importance weight
- $\mathcal{L}_{pseudo}(\Theta^t) = -\frac{\nu}{W'H'} \Sigma_{w,h}^{W,H} \Sigma_{c\in C^t} \tilde{S}(w,h,c) \log \hat{S}^t(w,h,c)$



4. Results

- X-Y : Learning X classes in one step then Y classes per step
- Reporting mean IoU %
- **Pascal-VOC 2012**, with 20 classes in total:

	15-1 (6 tasks)				10-1 (11 tasks)			
	0-15	16-20	*all*	*avg*	0-10	11-20	*all*	*avg*
ILT	8.75	7.99	8.56	40.16	7.15	3.67	5.50	25.71
MiB	34.22	13.50	29.29	54.19	12.25	13.09	12.65	42.67
PLOP	**65.12**	**21.11**	**54.64**	**67.21**	**44.03**	**15.51**	**30.45**	**52.32**

- **ADE20k**, with 150 classes in total:

	100-10 (6 tasks)				150-5 (11 tasks)			
	0-15	16-20	*all*	*avg*	0-10	11-20	*all*	*avg*
ILT	0.11	3.06	1.09	12.56	0.08	1.31	0.49	7.83
MiB	38.21	11.12	29.24	35.12	36.01	5.66	25.96	32.69
PLOP	**40.48**	**13.61**	**31.59**	**36.64**	**39.11**	**7.81**	**28.75**	**35.25**