A. Additional Implementation Details

In Tab. A.1, we list the DeepLab-related hyperparameters. They take either the recommended default values by [1] or the values from the public code of [8]. The learning rate is linearly annealed from 0.007 to 0 as training proceeds. The weight decay is 1e-4 for ResNets [5] and 4e-5 for Xception [2]. The input train crop size is set to 513 × 513 for all datasets. The eval crop size is set to 513 × 513 for VOC [4], 641 × 641 for COCO [6], and 1,025 × 2,049 for Cityscapes [3]. The DeepLab encoder output stride is chosen as 16. In the VOC experiments, the model is trained for 30,000 gradient steps that are distributed on 4 asynchronous replica workers. Each worker has 2 GPUs. The Cityscapes and COCO experiments require longer training duration, which takes a total of 130,000 and 200,000 steps, respectively, on 8 asynchronous workers of 2 GPUs. For both the labeled data and unlabeled data branches, the training batch size per GPU is 4, or equivalently 8 images per worker.

Tab. A.1: Summary of hyper-parameter settings. Hyperparameters take either the recommended default values by [1] or the values from the public code of [8].

| Hyper-parameter | VOC | Cityscapes | COCO |
|-----------------|-----|------------|------|
| Network         | ResNet50/101 | ResNet50/101 | Xception65 |
| Weight decay    | 1e-4 | 1e-4       | 4e-5 |
| Train crop size | 513 × 513 | 513 × 513 | 513 × 513 |
| Eval crop size  | 513 × 513 | 1,025 × 2,049 | 641 × 641 |
| Output stride   | 16   | 16         | 16   |
| Atrous rates    | [6, 12, 18] | [6, 12, 18] | [6, 12, 18] |
| Train steps     | 30,000 | 130,000   | 200,000 |
| Learning rate   | 0.07 → 0 | 0.07 → 0 | 0.07 → 0 |
| Dist. workers   | 4    | 8          | 8    |
| GPUs/worker     | 2 V100(16G) | 2 V100(16G) | 2 V100(16G) |
| Batch size/GPU  | 4    | 4          | 4    |

B. Additional Ablation Results

Dimension of Projection Layer. The impact of the dimension of the projection layer in our PC²Seg method is studied in Tab. B.1 under the VOC 1/8 ResNet-50 setting. For the results reported in the main paper, we chose the dimension as 128. We found that alternative values do not bring gains over the chosen value if other hyper-parameters are fixed. Alternative dimension values may require re-tuning some hyper-parameters to achieve better results.

Label Consistent Only. In Tab. B.2, we have compared PC²Seg
with its label-consistent-only version in the VOC 1/8 split setting. Here, we provide additional results with other data splits, which support the claim that the joint label-consistent and feature-contrastive regularization performs better than the label-consistent regularization alone. The label-consistent version essentially removes the pixel contrastive loss and keeps everything else unchanged. The VOC results are shown in Tab. B.2. We have a similar observation with the Cityscapes 1/8 split in Tab. B.3, where the label-consistent-only version achieves 71.79% validation mIoU in comparison to 72.11% mIoU of full PC²Seg with the joint contrastive-consistent regularization.

C. Training Time and Computational Cost

Since there is an additional unlabeled data branch in our semi-supervised method, the training inevitably takes longer time than the purely supervised baseline. As stated in the main paper, we measure the training time in the VOC ResNet-50 experiments. Our implementation of the supervised baseline took 38 minutes, while our PC²Seg with label consistency and feature contrastive learning took roughly 80 minutes, and the label-consistent-only version of PC²Seg took around 75 to 80 minutes. Such training time is comparable to existing approaches within the semi-supervised setting – e.g., state-of-the-art PseudoSeg [8] also took about 80 minutes.

We further show the cost reduced by our negative sampling strategy through a simple calculation. The feature tensor shape in practice is \([4, 33, 33, 128]\) for a batch of 4 images (512-by-512 pixels). If using all pixels as negatives, we need to compute a \([4 \cdot 33^2, 4 \cdot 33^2]\) inner-product matrix (19M elements) with \((4 \cdot 33^2)^2 \cdot 128 = 2, 428M\) MulAdd operations. But, if we only draw 200 negative pixels, it is reduced to computing a \([4 \cdot 33^2, 200]\) matrix (0.8M elements) with \(4 \cdot 33^2 \cdot 200 \cdot 128 = 111M\) operations. Considering the negative sampling itself requires \((4 \cdot 33^2)^2 \cdot 20 = 379M\) operations to compare the pseudo labels (20 is the number of VOC classes), the overall floating point operations are about 5 times fewer.

D. Visualization

To have a better understanding of PC²Seg, we use two complementary approaches to visualize the results: (1) the t-SNE plot [7] of the feature spaces in Fig. D.1, and (2) the predicted segmentation masks in Fig. D.2 and Fig. D.3.

From the t-SNE plot, we observe that both the label-consistent-only and the joint contrastive-consistent variants of our method generate feature spaces that are more separable than the supervised baseline. In the decoder feature space, joint contrastive-consistent variant seems to increase slightly the margins between a few categories, compared with the label-consistent-only variant. From the predicted masks, we can see some success and failure cases of PC²Seg. Please refer to the figure captions for detailed descriptions.

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Fig. D.2: VOC 2012 prediction results. Models are trained in the 1/8 split setting. Images are from the VAL set. The white pixels in the ground-truth masks indicate ignored regions. **Overall, both the label-consistent-only and the contrastive-consistent variants of our semi-supervised method produce significantly less noisy predictions than the supervised baseline.** The consistency regularization is able to suppress some background artifacts as in the 3rd row example. Some other success cases include the airplane in the 1st row and the train in the 2nd row, where our final method covers fuller extents of the objects. Some failure cases include the monitor in the 3rd to last row, where the model mistakenly classifies the (possibly co-occurring) machine into the monitor class, the mis-classification of the horse in the 2nd to last row, and the false positives in the last row.
Fig. D.3: Cityscapes prediction results. Models are trained in the 1/8 split setting. Images are from the VAL_FINE set. The dark areas in the ground-truth masks indicate ignored regions. We notice that there exist some \textit{substantially higher-quality} cases of our contrastive-consistent learning based semi-supervised method over others, such as the person’s bag in the 1st row, the sidewalk in the 2nd row, and the upper traffic sign in the 3rd row.