

# Full or Weak annotations?

## An adaptive strategy for budget-constrained annotation campaigns

### Supplementary Material

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## 1. Implementation details

**Weakly-supervised segmentation model hyperparameters:** We used the U-Net segmentation model [5] for OCT, and the DeepLabV3 model [2] with a ResNet50 backbone on the SUIM, PASCAL, and Cityscapes datasets. For the U-Net, a classification head with max-avg pooling and one fully connected layer was appended at the end of the encoding module for the classification task. For the DeepLab-like models, we trained the entire ResNet-50 backbone on the classification task and then added the ASPP head for segmentation. In all cases, we used the cross-entropy loss for classification and the average of the Dice and cross-entropy losses for segmentation. Tab. 1 contains the details of batch sizes and optimizers.

Dataset	Model	Optimizer	Batch size
OCT	U-Net	Adam	8
VOC	DeepLabV3	SGD	16
SUIM	DeepLabV3	SGD	8
Cityscapes	DeepLabV3	SGD	16

Table 1. Hyperparameters and conditions for all experiments.

**Algorithm hyperparameters:** We measured the costs of annotations in terms of class-label equivalents setting  $\alpha_c = 1$  and leaving only  $\alpha_s$  as a hyperparameter of our method. We set to  $\alpha_s = 12$  for all datasets following previous studies on crowdsourced annotations [1]. We fixed the number of iterative steps to  $T = 8$  and the learning rate of the GP to 0.1. We set both the initial number of class annotations  $C_0$  and segmentation annotations  $S_0$  to 8% of the available labels for SUIM and Cityscapes. We reduced  $C_0$  in OCT and  $S_0$  in VOC to account for the higher number of labels available in those datasets, as detailed in Tab. 2.

Dataset	$C_0(\%)$	$S_0(\%)$	$B_0$
OCT	4	8	1'774
VOC	8	6	8'076
SUIM	8	8	1'586
Cityscapes	8	8	1'774

Table 2. Initial conditions for our method.  $B_0$  calculated with  $\alpha_s = 12$  and  $\alpha_c = 1$ .

## 2. Sensitivity to $\alpha_s$

Fig. 1 shows additional experiments on the sensitivity of our method to  $\alpha_s$  in the considered datasets.

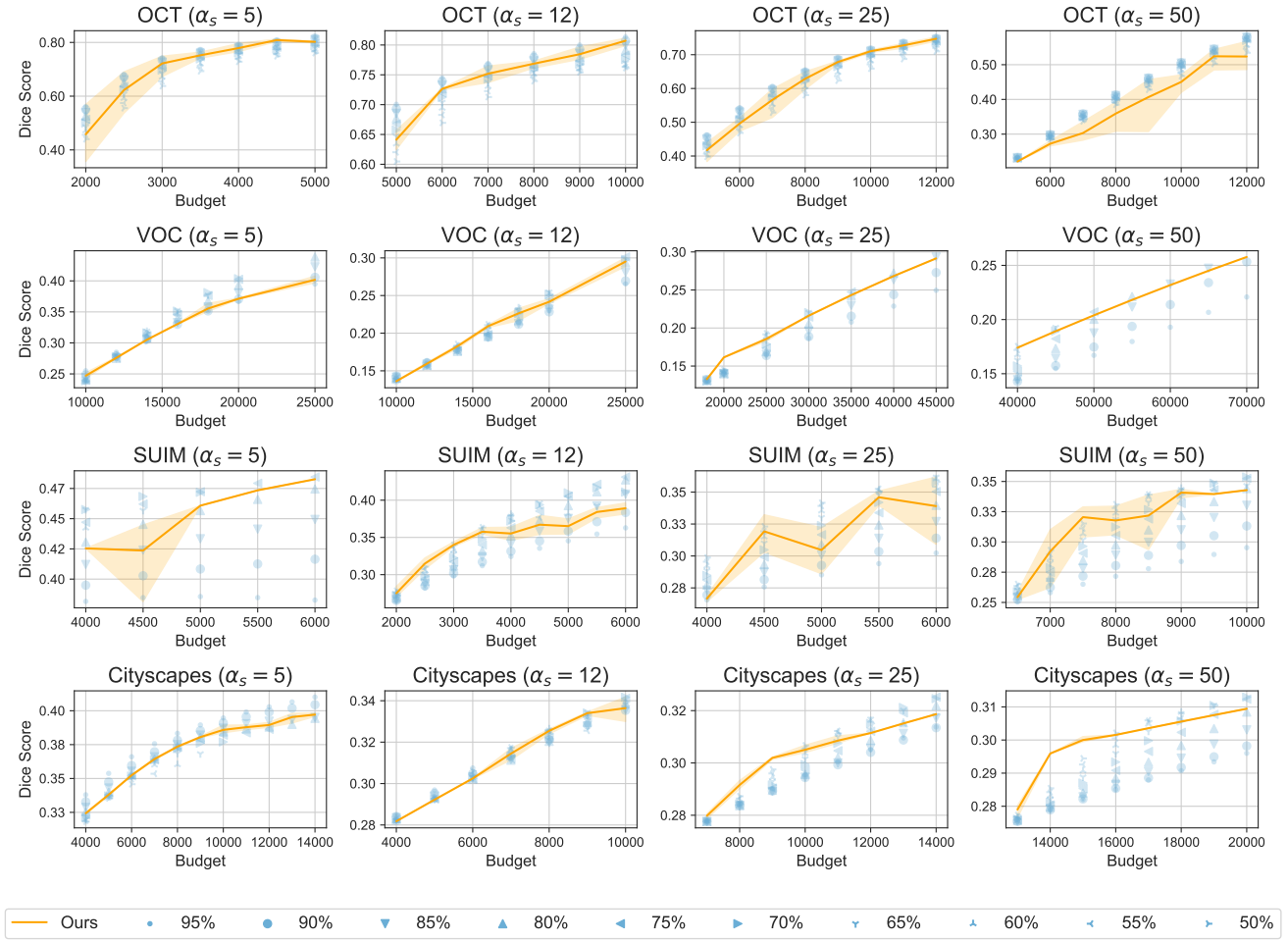


Figure 1. Performance our method with  $\alpha_s = \{5, 12, 25, 50\}$  on four datasets. One-sigma error bars were computed from three seeds. Blue marks show the performance of fixed strategies, with labels indicating the percentage of the budget allocated to segmentation annotations.

## 3. Average performance

We report in Table 3 the average relative performance for each dataset and segmentation split. Our method is best on average and for two datasets (SUIM and VOC), while it performs on par with the best baseline for Cityscapes and OCT.

Seg. Split	95	90	85	80	75	70	65	60	55	50	Ours
Cityscapes	<b>73.9</b>	73.2	73.0	73.1	73.3	73.5	73.5	72.5	72.3	71.4	73.4
OCT	<b>95.4</b>	94.6	93.8	93.0	92.1	91.3	90.5	89.7	88.8	87.7	92.6
SUIM	72.1	74.1	76.7	79.2	80.9	81.3	79.7	78.1	76.7	75.1	<b>81.9</b>
VOC	44.3	44.0	44.3	44.9	45.6	46.0	43.1	43.3	40.9	40.8	<b>46.0</b>
Average	71.4	71.5	71.9	72.5	73.0	73.0	71.7	70.9	69.7	68.8	<b>73.5</b>

Table 3. Relative performance (in %) against full supervision for each dataset and segmentation split.

## 4. Surfaces

To explain the drop in performance for SUIM after a budget of 3'500, we computed the true surfaces for all datasets (Fig. 2). We observed that segmentation performance grows logarithmically for OCT, VOC, and Cityscapes, but not for SUIM after a certain number of class annotations. Since our GP assumes a logarithmic relation between dataset size and performance, this observation is particularly relevant to explain the decline in performance for SUIM. Most notably, and confirming our hypothesis, this decline is not seen with other values of  $\alpha_s$  for this same dataset (Fig. 1). Due to the limited dataset size, larger values of  $\alpha_s$  constrain the area of the surface that can be reached in our experiments. In the case of SUIM,  $\alpha_s = 50$  translates to exploring zones where performance grows logarithmically with dataset size (low data regime).

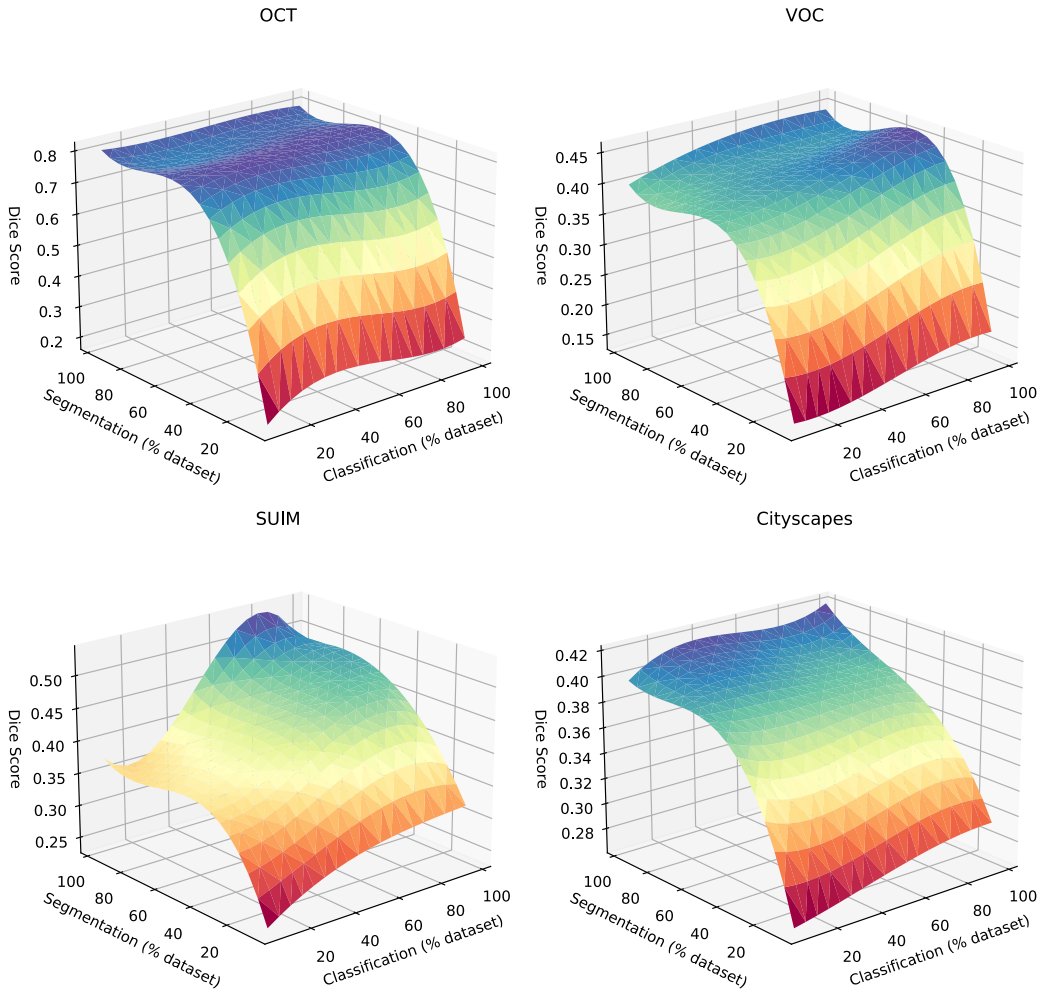


Figure 2. Segmentation performance grows logarithmically with training set size on Cityscapes, OCT, and VOC. This trend is not observed in the SUIM dataset.

## 5. Ground-truth approximation

To address the high computational demands of our experiments, we followed the procedure of [4] for ground-truth approximation. In particular, we built subsets of the training dataset by randomly sampling different proportions of the available annotated samples [3]. The proportions  $\rho_s$  and  $\rho_c$  for segmentation and classification samples, respectively, were chosen from the set  $\{2\%, 4\%, 6\%, 8\%, 10\%, 20\%, 30\%, 40\%, 60\%, 80\%, 100\%\}$ , for a total of  $11 \times 11 = 121$  possible training subsets. For each subset, we trained the weakly-supervised segmentation model and measured its Dice score on a fixed segmentation test set. We finally interpolated these scores with third-order supersplines to obtain a surface of ground-truth Dice scores. This

procedure allowed efficient estimations of the Dice Score values without retraining a new model for each strategy.

The proportions  $\rho_s$  and  $\rho_c$  are relative to the total amounts of available annotated samples in each dataset, which are shown in Tab. 4.

<b>Dataset</b>	<b>Segmentation</b>	<b>Classification</b>
<b>OCT</b>	902	22'723
<b>VOC</b>	10'582	5'717
<b>SUIM</b>	1'525	1'525
<b>Cityscapes</b>	2'975	2'975

Table 4. Number of training images for each dataset and modality.

## References

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- [3] Rafid Mahmood, James Lucas, David Acuna, Daiqing Li, Jonah Pillion, Jose M Alvarez, Zhiding Yu, Sanja Fidler, and Marc T Law. How much more data do i need? estimating requirements for downstream tasks. *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pages 275–284, 2022. [3](#)
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