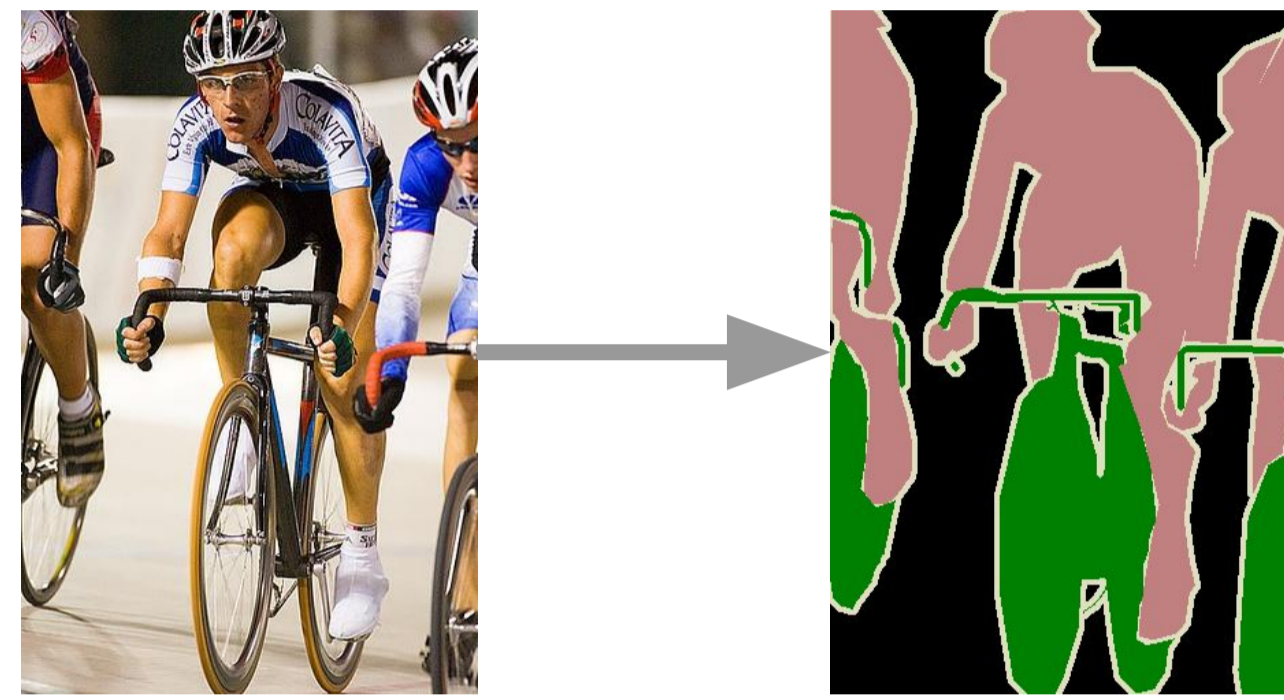


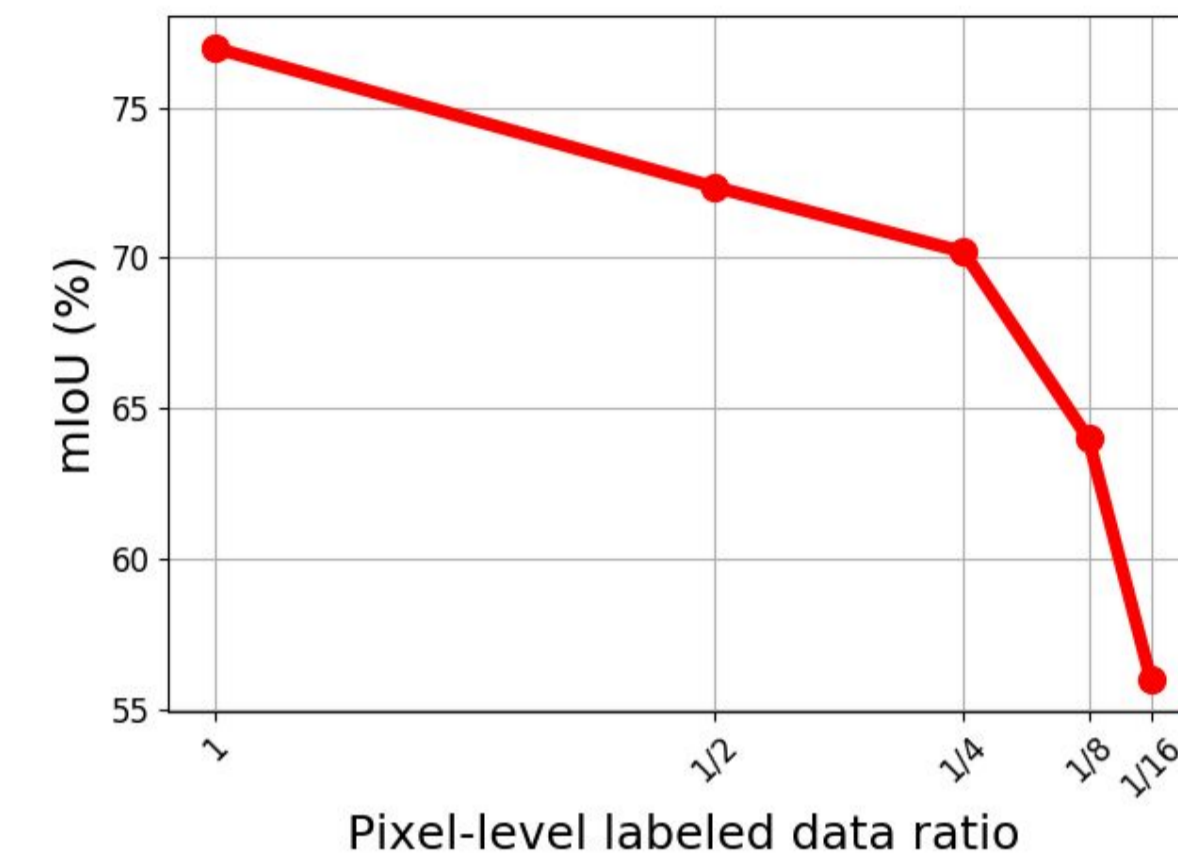


Motivation

Semantic Segmentation



Person
Bicycle



- Requiring a large amount of dense labels -> expensive
- Performance decreases quickly as we reduce the number of labels
- We want to improve the data efficiency of semantic segmentation

Unlabeled/Weakly-labeled Data to the Rescue



Fully-labeled data (limited)



Unlabeled data (a large amount)

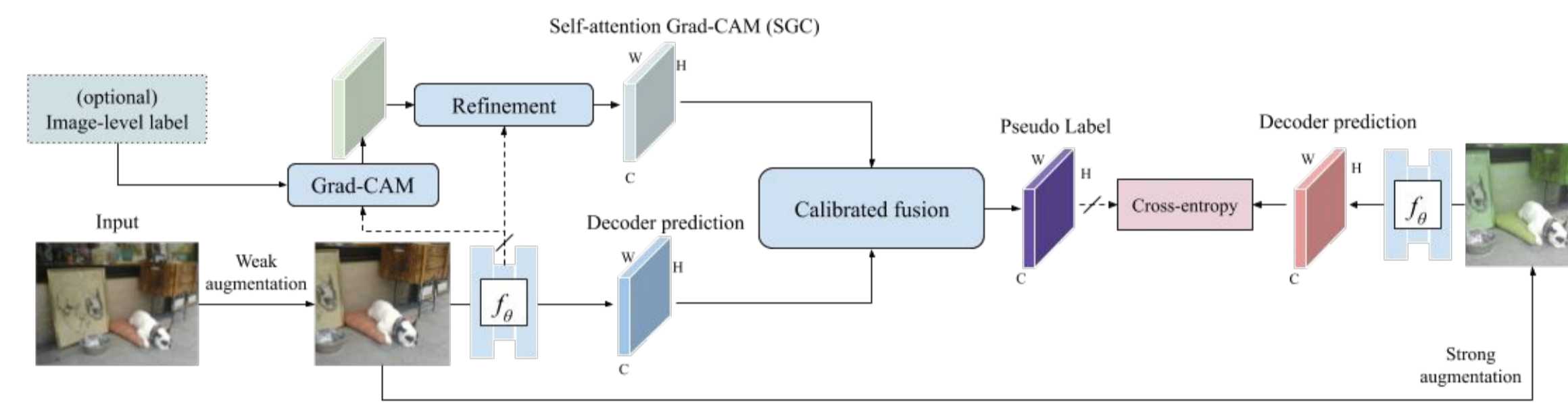


Weakly-labeled data (a lot)

Person
Horse

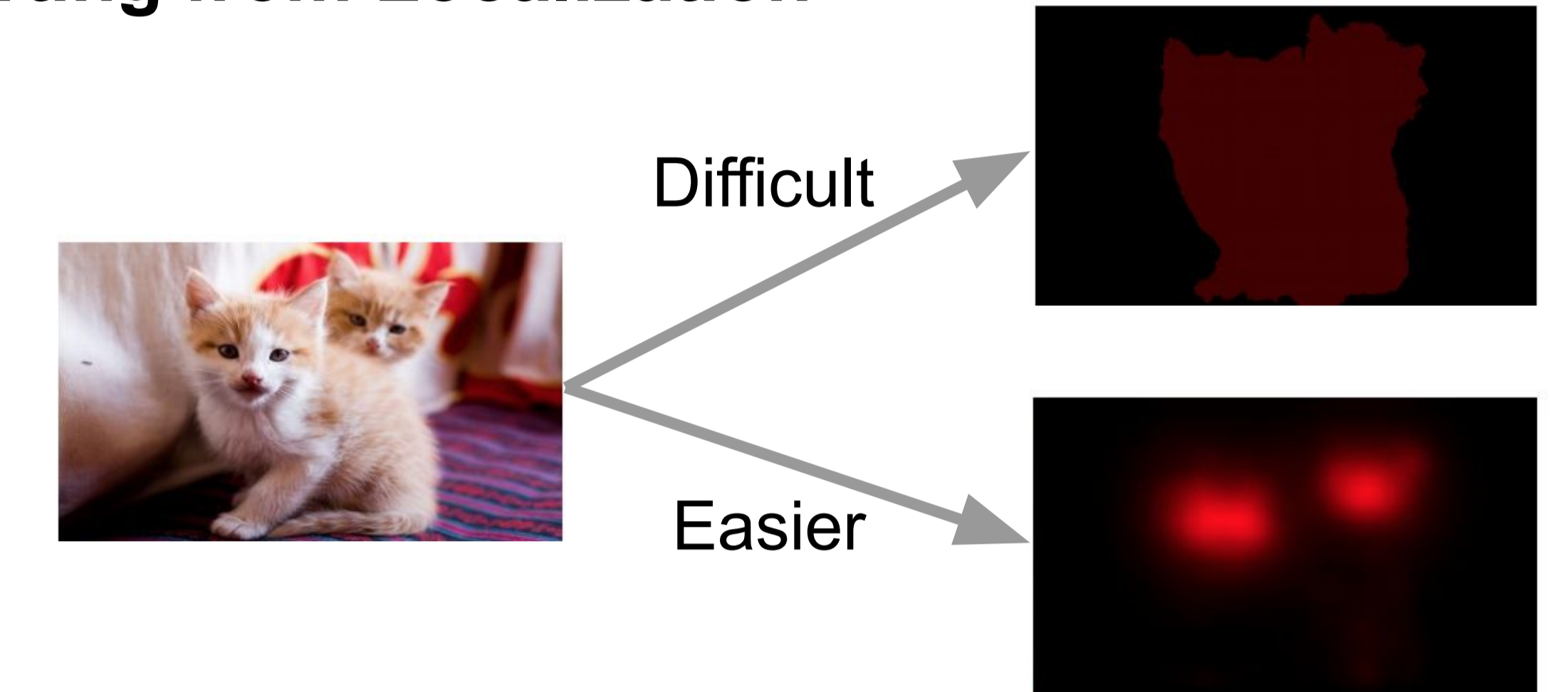
Designing Pseudo Labels for Semantic Segmentation

Overview



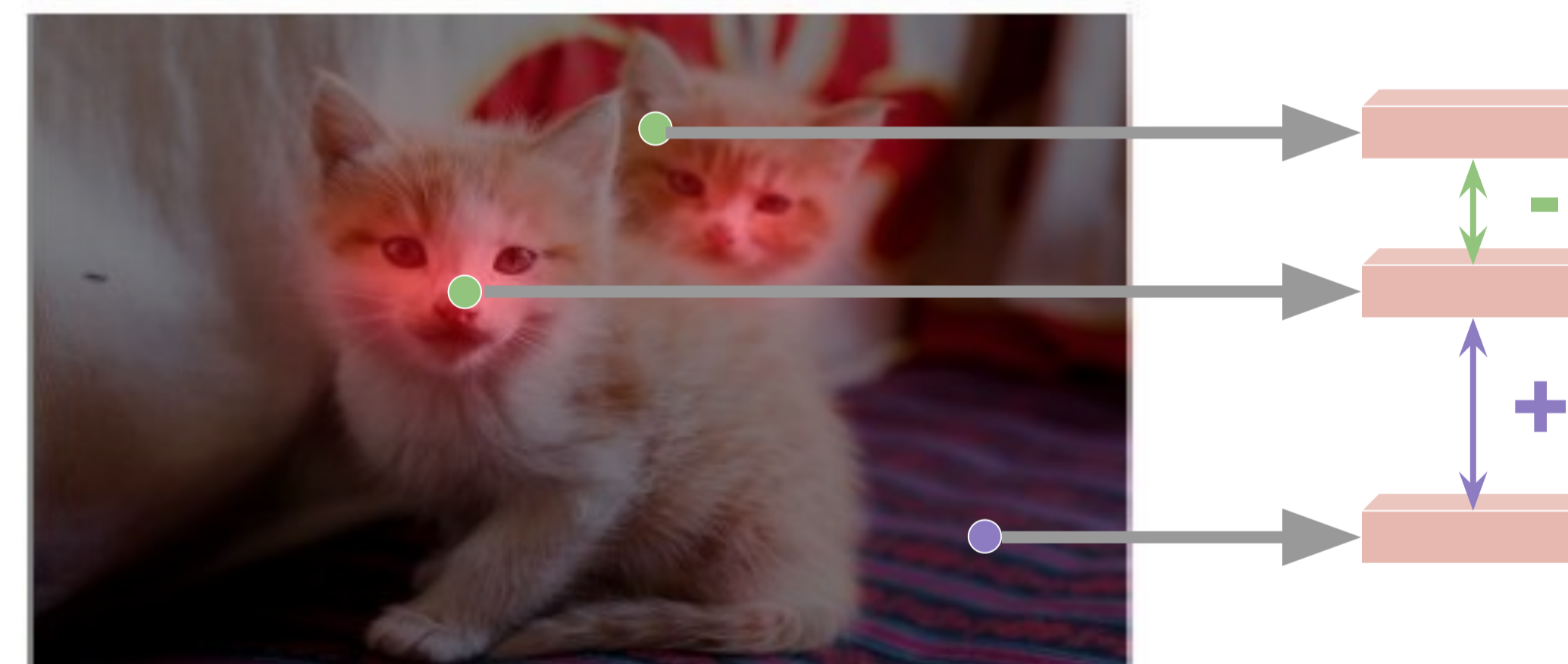
- Strong-weak dual branch consistency-based training
- Different decision mechanisms for distinct predictions
- Wisely fusing the predictions to construct well-calibrated pseudo labels

Starting from Localization



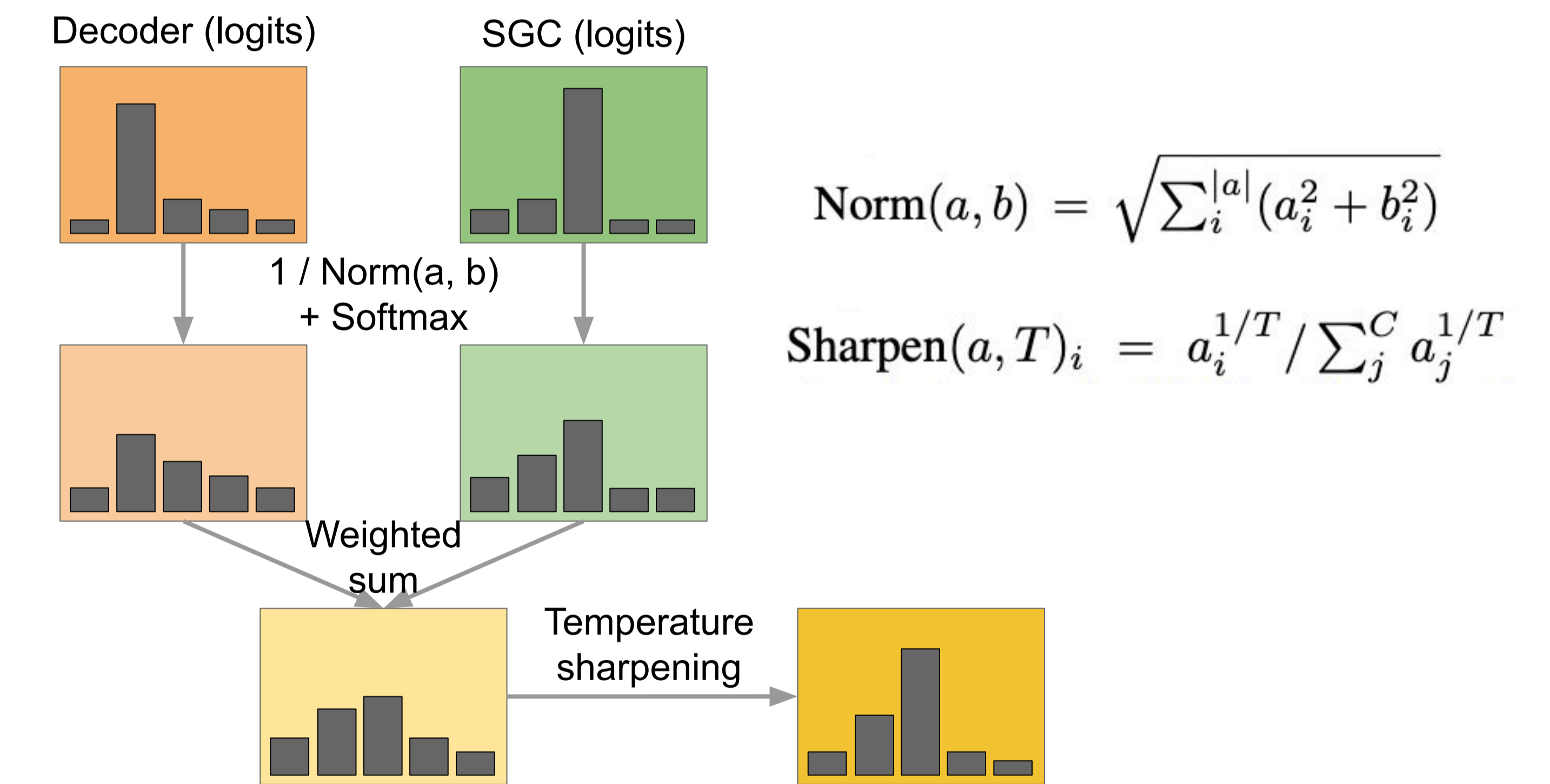
- Hard to get precise segmentation prediction in low-data regime
- Easier to get coarse localization of objects using Grad-CAM

From Localization to Segmentation



- Grad-CAM only localizes partial region of interest
- Propagating Grad-CAM scores with learned feature similarity
- Implemented with dot-product self-attention operation -> Self-attention Grad-CAM (SGC)

Calibrated Prediction Fusion

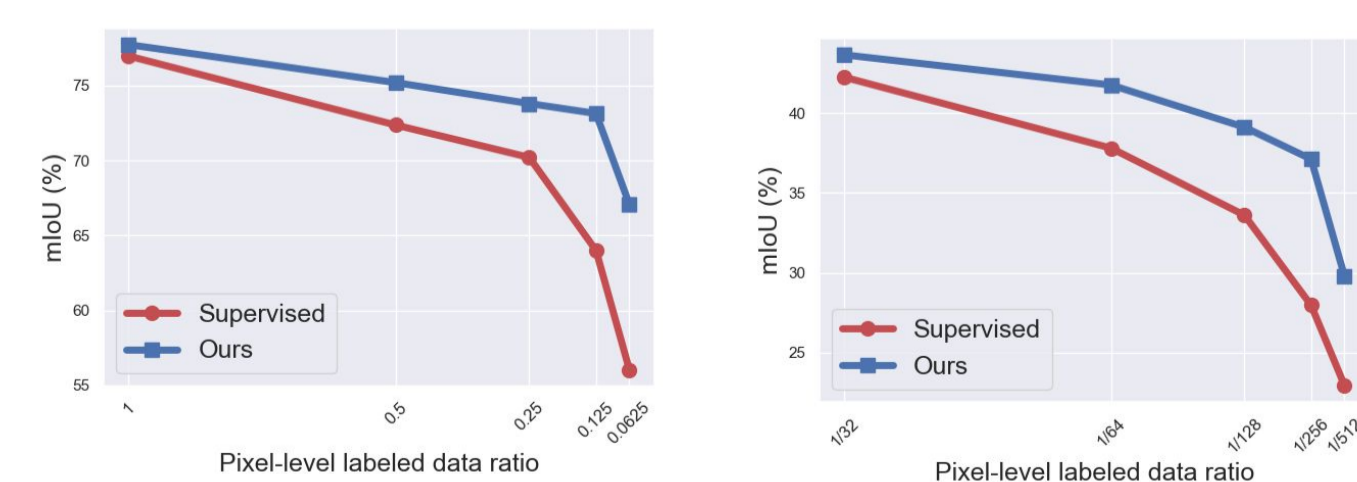


- Constructing well-calibrated pseudo labels from two predictions

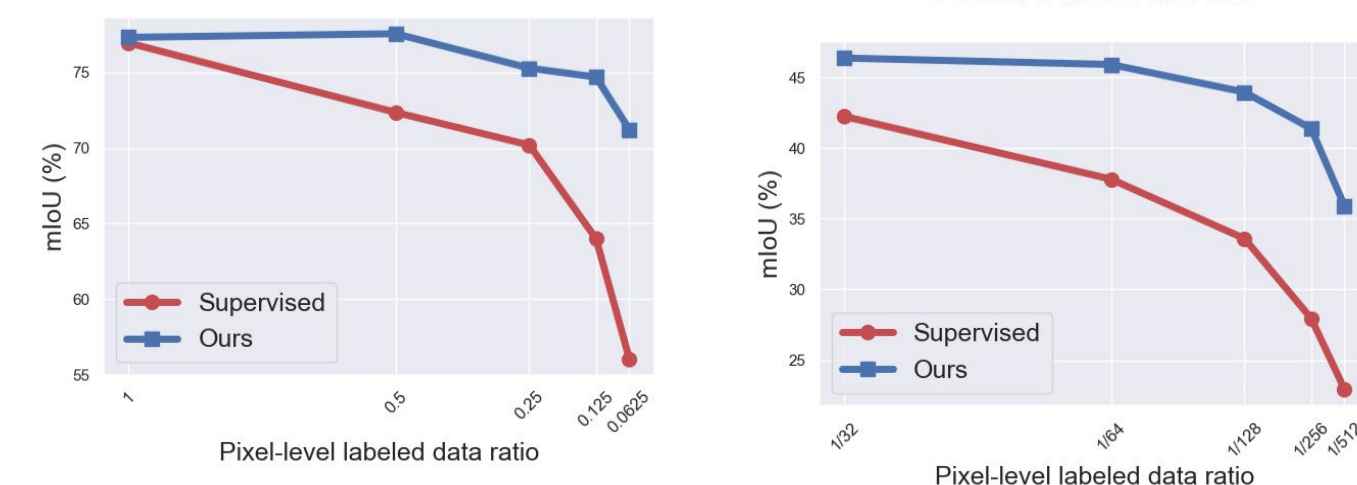
Experimental Results

Improvement over Supervised Baseline

Fully-labeled and unlabeled



Fully-labeled and weakly-labeled



VOC2012

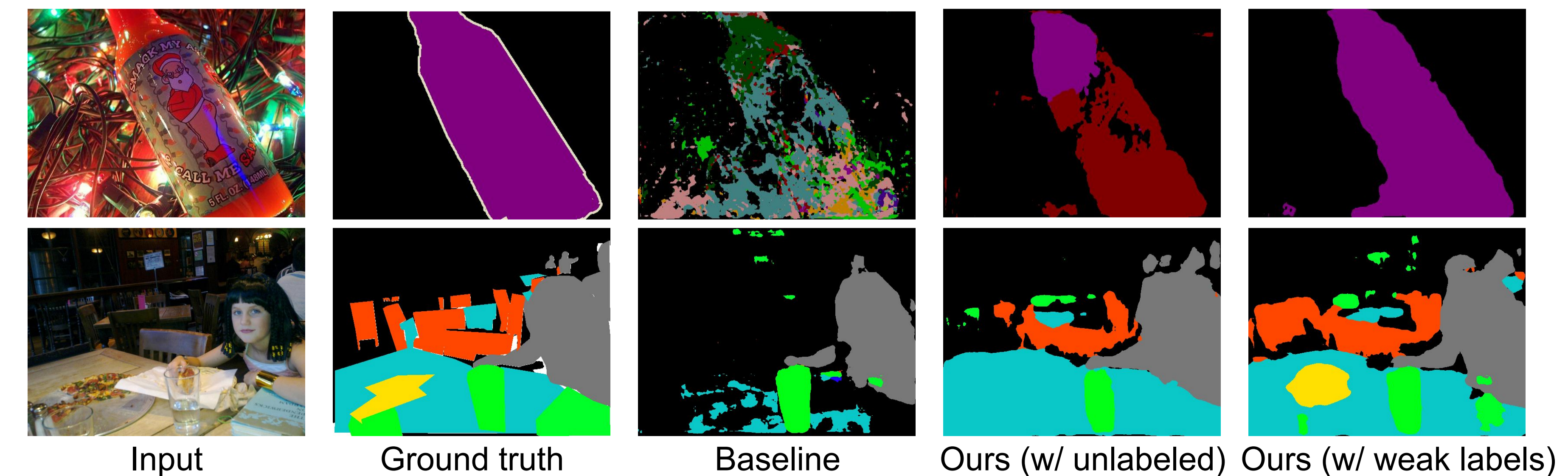
COCO

Improving Fully-Supervised Model with Extra Data

Method	Baseline	PseudoSeg (w/o image-level labels)		PseudoSeg (w/ image-level labels)	
Extra data	-	$C_{tr} + C_u$	$C_{tr} + C_u + V_{9k}$	C_{tr}	$C_{tr} + V_{9k}$
mIoU (%)	76.96	77.40 (+0.44)	78.20 (+1.24)	77.80 (+0.84)	79.28 (+2.32)

- Cross-dataset semi-supervised learning setting (VOC+COCO)
- Improving fully-supervised learning also in high-data regime

Qualitative Results



Input

Ground truth

Baseline

Ours (w/ unlabeled)

Ours (w/ weak labels)