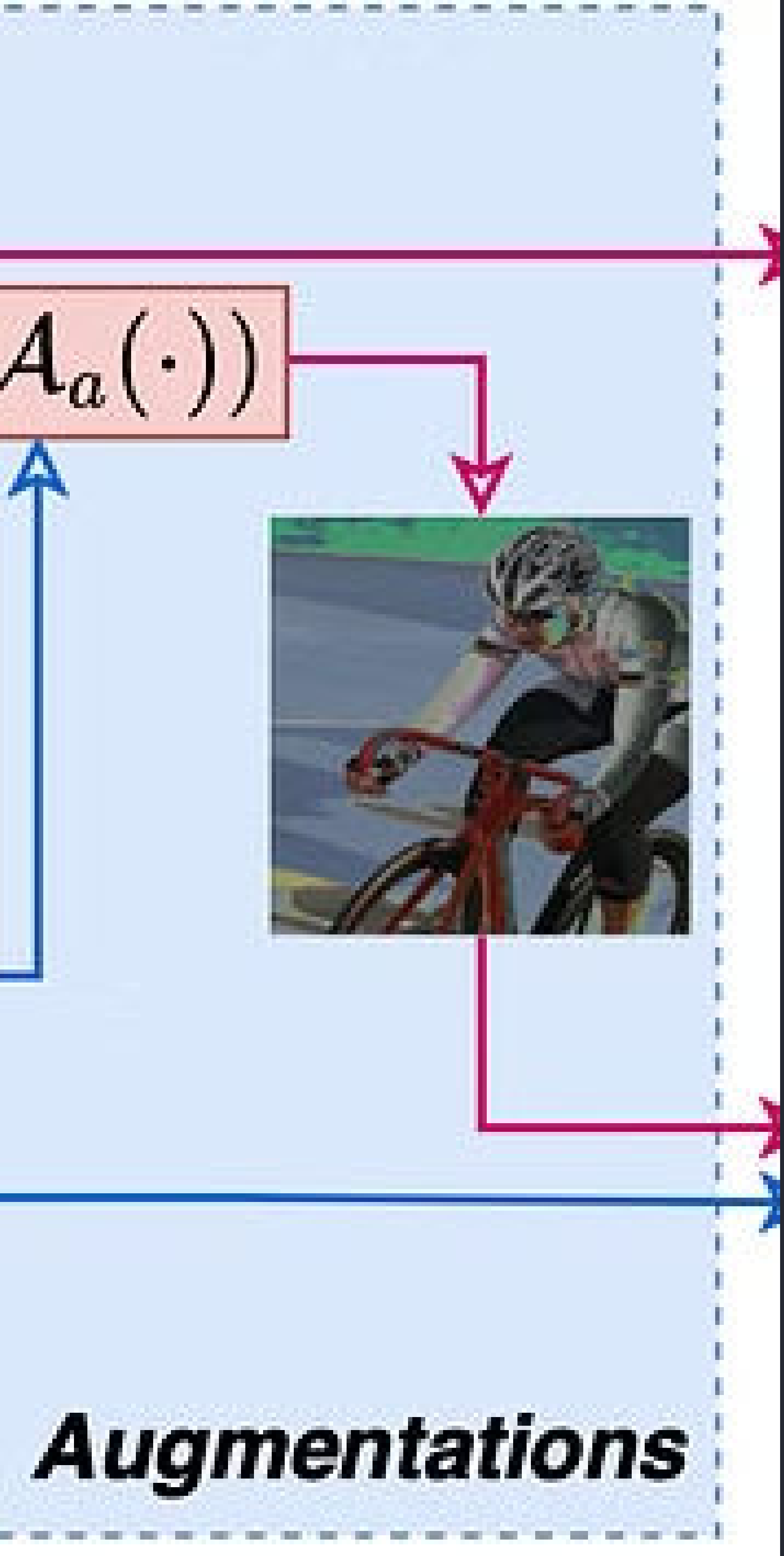

Augmentation Matters: A Simple-yet-Effective Approach to Semi-supervised Semantic Segmentation

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Methodology

Augmentation

Utilizes a blend of augmentation techniques to boost model performance.

Weak Geometrical Augmentation

Applies standard resizing, cropping, and flipping to labeled images for robust feature learning.

Random Intensity Based Augmentation

Introduces random intensity-based augmentations to perturb unlabeled data without over-distortion.

Adaptive Label Aided Augmentation

Strategically uses labeled data to assist in training on less confident unlabeled instances.

Teacher-Student Model

Employs a teacher-student model learning in tandem, with the teacher model evolving through exponential moving averaging of the student's weights.

Loss and Perturbation

Adopts pixel-wise cross-entropy loss for supervised training and leverages data perturbation to create prediction disagreements for unsupervised learning.

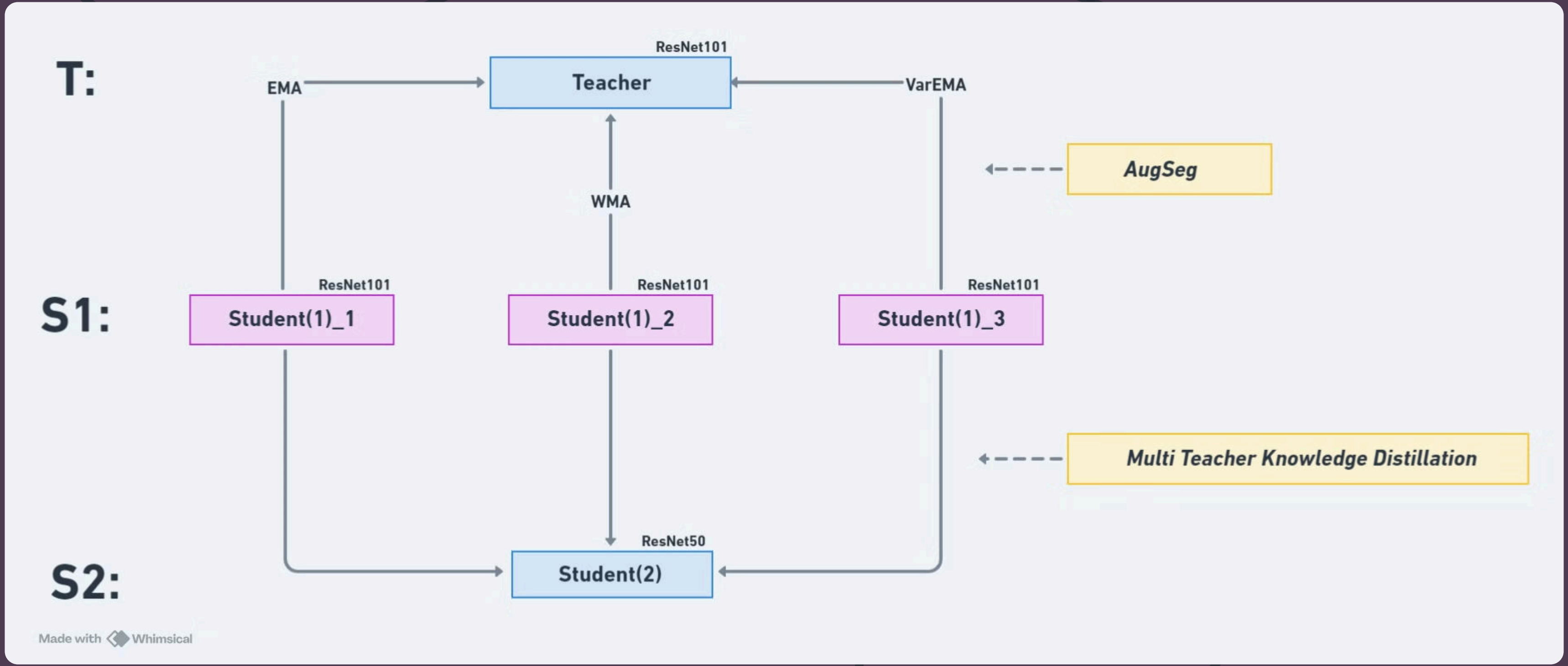
Contributions

1 Different means to update teacher's weights

- Exponential Moving Average (EMA).
- Weighted Moving Average (WMA).
- Exponential Moving Average with variable decay rate

2 Multi Teacher Knowledge Distillation

Employs a hierarchical student-teacher architecture, where multiple larger models refine their learning strategies to distill knowledge into a compact model, enhancing overall performance.


T:
S1:
S2:
EMA
ResNet101
Teacher
VarEMA
WMA
AugSeg
ResNet101
Student(1)_1
ResNet101
Student(1)_2
ResNet101
Student(1)_3
Multi Teacher Knowledge Distillation
ResNet50
Student(2)
Made with Whimsical

Datasets

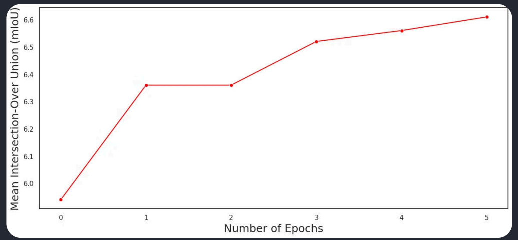
Cityscapes

The Cityscapes dataset, essential for urban scene analysis, enables AugSeg to demonstrate its robust semi-supervised segmentation capabilities using a mixture of labeled and unlabeled data, with performance evaluated by mean intersection-over-union (mIoU).

Pascal VOC

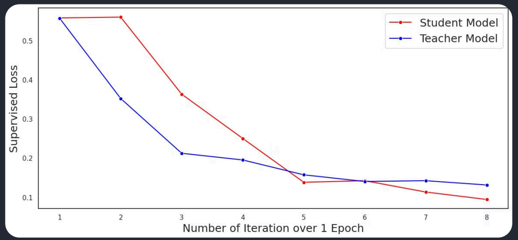
The Pascal VOC 2012 dataset, combined with SBD for a total of 10,582 images, showcases AugSeg's advanced performance in semi-supervised semantic segmentation, effectively utilizing both densely and sparsely labeled data, measured by mIoU.

Training Plots



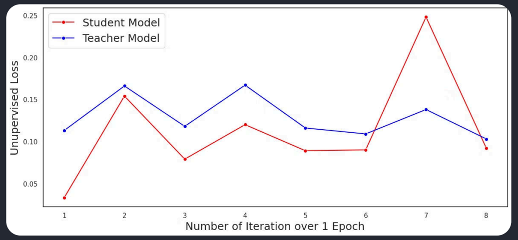
mIoU vs No. of Epochs

The graph illustrates a consistent improvement in model accuracy, as shown by the increasing mean intersection-over-union (mIoU) values, over the course of five training epochs.



Supervised Loss vs No. of Epochs

The plot reveals a decreasing trend in supervised loss for both student and teacher models, with the student model starting at a higher loss but converging towards the teacher's performance over iterative training within a single epoch.



Unsupervised Loss vs No. of Epochs

The chart shows fluctuations in unsupervised loss for both models across iterations, with the student model generally experiencing greater variance and a notable peak at the final iteration compared to the teacher model.

Evaluation Metrics and Comparison

Metric	Paper Implementation (5 Epoch)	From Paper
Mean IoU (Pascal VOC)	6.61	75.45

AugSeg's effectiveness in semi-supervised semantic segmentation is evaluated using mIoU, offers a comprehensive assessment of its segmentation precision.

Conclusion

- Leverages data augmentation and adaptive label-aided techniques.
- Reduces reliance on extensive annotated datasets.
- Demonstrates state-of-the-art performance on Cityscapes and Pascal VOC 2012.
- Shows robustness with both densely and sparsely labeled data.
- Prioritizes model simplicity and efficient training.
- Future work includes exploring additional augmentations and data leveraging strategies.