

2022 상반기 세미나

이제임스

Vision & Display Systems Lab.

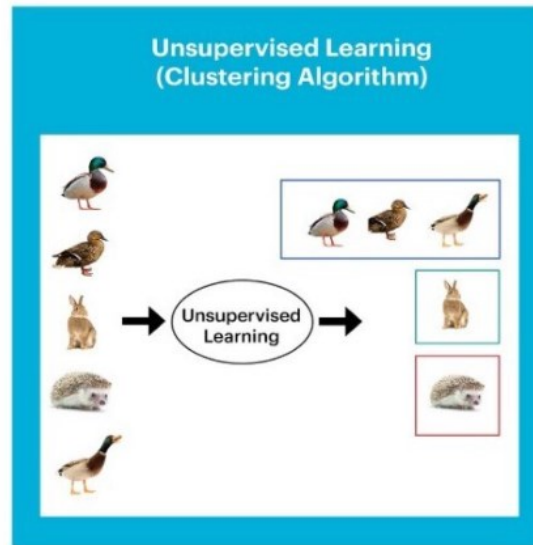
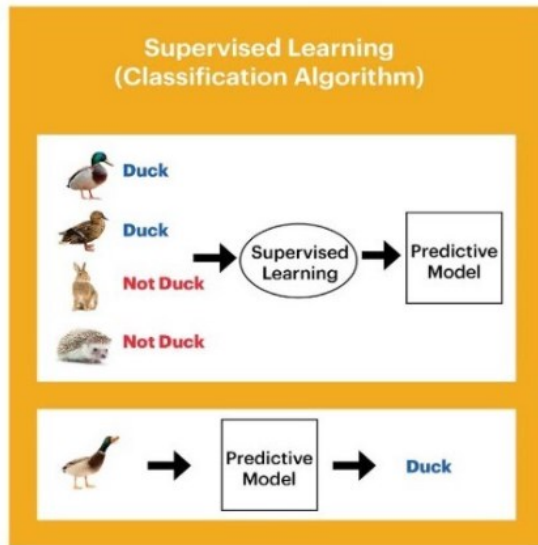
Dept. of Electronic Engineering, Sogang University

Outline

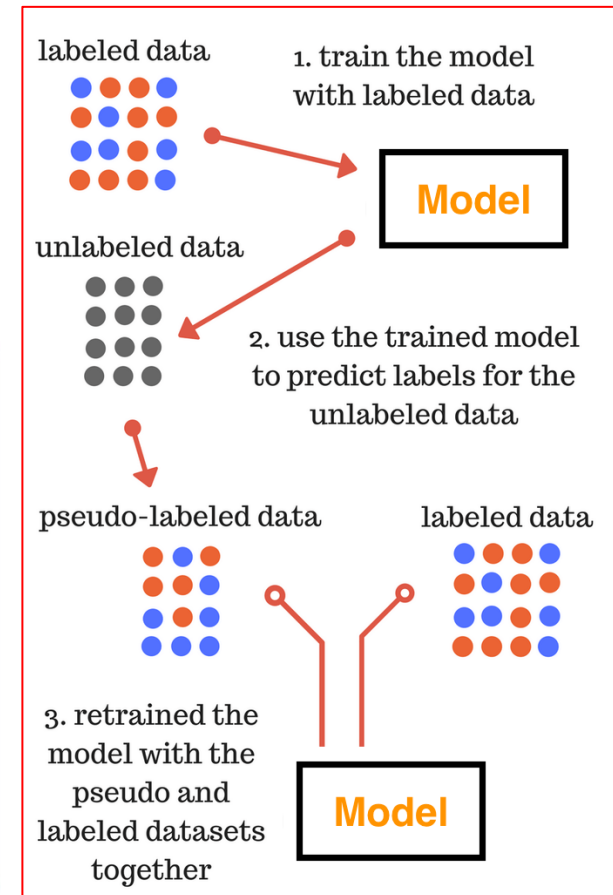
- Introduction
 - Supervised learning, unsupervised learning, semi-supervised learning
- Paper
 - Improving Unsupervised Image Clustering With Robust Learning (CVPR 2021)
- Application paper
 - Instance-Aware, Context-Focused, and Memory-Efficient Weakly Supervised Object Detection (CVPR 2020)
 - End-to-End Semi-Supervised Object Detection with Soft Teacher (ICCV 2021)

Introduction

- Machine learning
 - Supervised learning
 - Unsupervised learning
 - Semi-Supervised learning

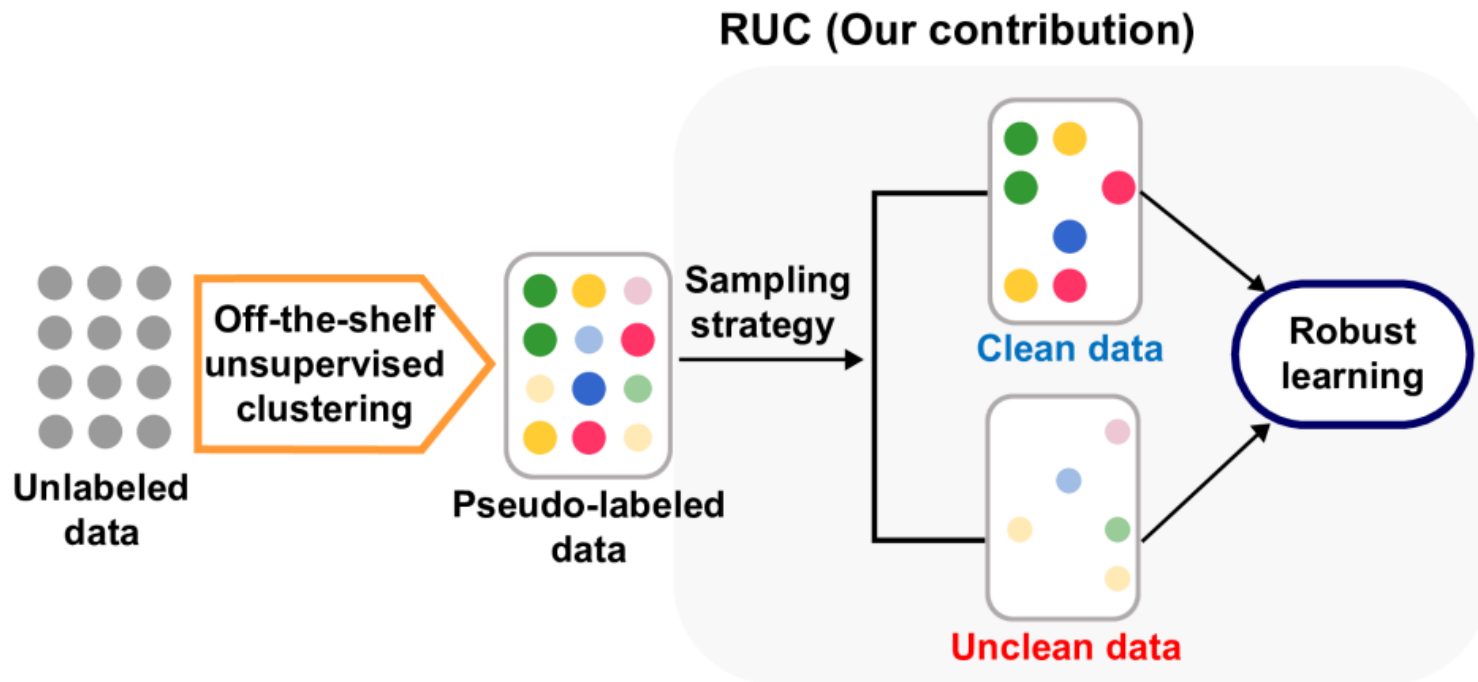


<Pseudo labeling>



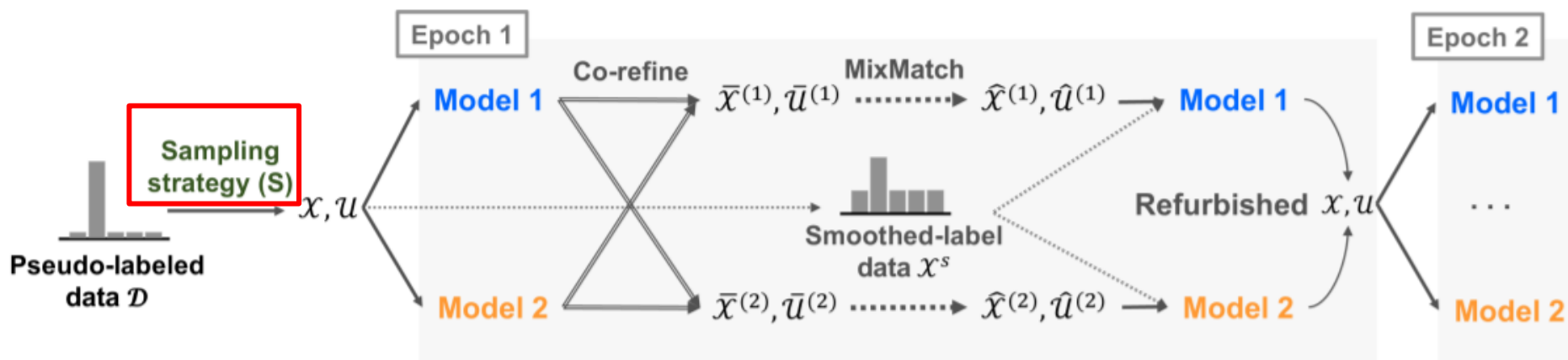
Paper

- Improving Unsupervised Image Clustering With Robust Learning (CVPR 2021)
 - Extracting Clean Samples
 - Retraining via Robust Learning



Method

- Extracting Clean Samples
 - Confidence-based strategy
 - Set a sufficiently high threshold for confidence score
 - Metric-based strategy
 - Leverages an additional embedding network learned in an unsupervised manner (SimCLR)
 - Non-parameteric classifier based on k-Nearest Neighbor
 - Hybrid strategy



Method

- Extracting Clean Samples
 - SCAN: Learning to Classify Images without Labels

- Unsupervised Image classification

☀ Pretext task

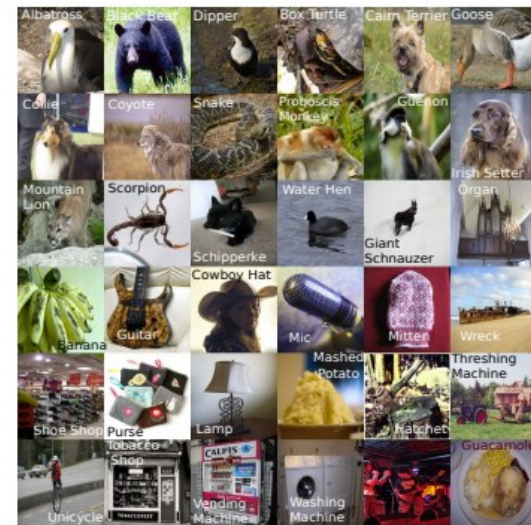
- ✓ Image representation learning without label (SimCLR)
- ✓ Learning semantic features that do not change according to image transformation

☀ Scan clustering

- ✓ Learn to predict the same cluster by maximizing the similarity of the closest neighbors by image

☀ Self-labeling

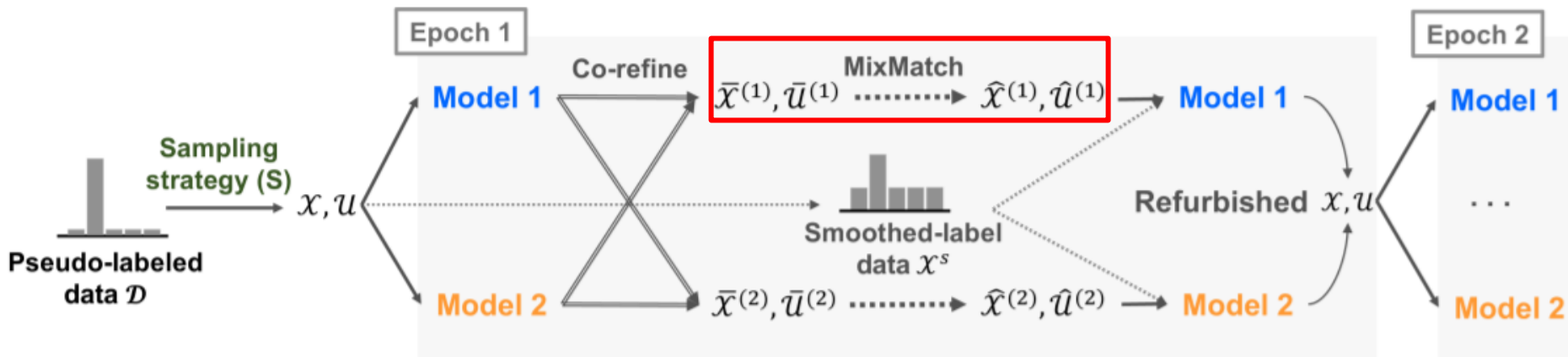
- ✓ Proceed with supervised learning based on the confidence of the well-clustered image



Method

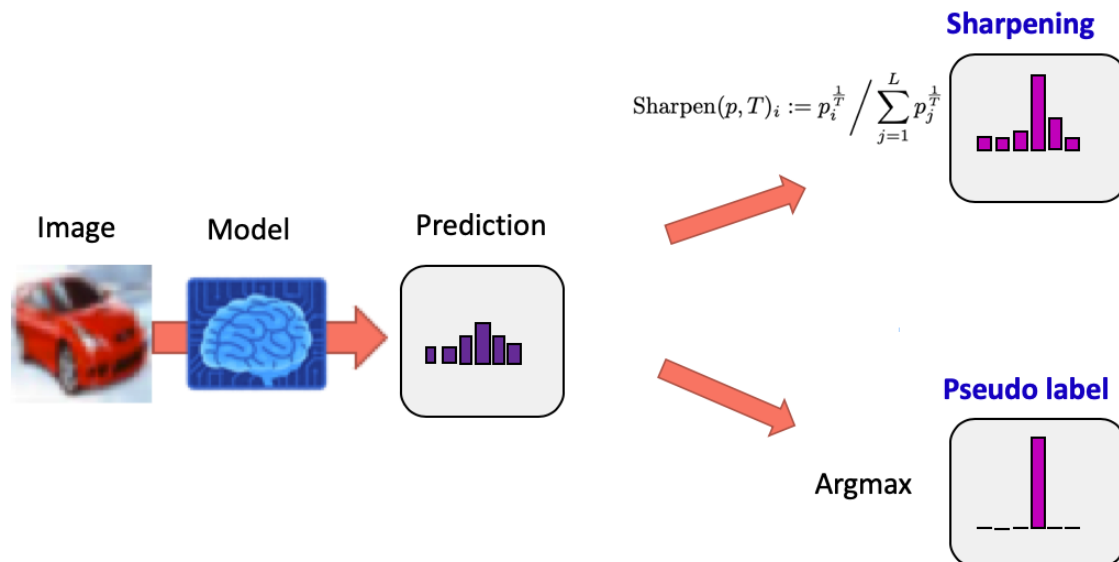
- Retraining via Robust Learning
 - Vanilla semi-supervised learning
 - MixMatch

- ✧ Estimates low-entropy mixed labels from unlabeled examples using MixUp augmentation
- ✧ Bring additional resistance against noisy labels
 - ✓ Consistency Regularization
 - ✓ Entropy Minimization
 - ✓ Mix up



Method

- Consistency Regularization
 - Data augmentation
 - Minimizing the pairwise difference of output
- Entropy Minimization
 - Distinguish the ambiguous ones near the decision boundary
 - MixMatch \rightarrow sharpening, FixMatch \rightarrow pseudo labeling

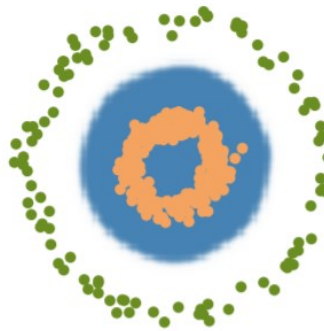


Method

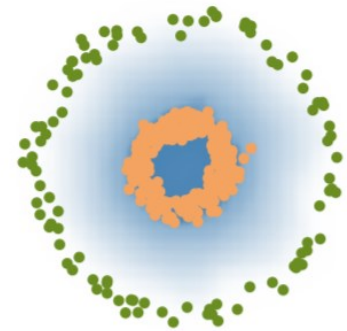
- Mixup
 - The solution for problem of overfitting training data
 - Use the distribution of training datasets in the vicinity → data augmentation
 - Labeled data
 - Augment one by data + label → convex combination → supervised loss
 - Unlabeled data
 - Augment K by data + guessed label → convex combination → consistency loss

$$\lambda \sim \text{Beta}(\alpha, \alpha)$$
$$x' = \lambda x_1 + (1 - \lambda)x_2$$
$$p' = \lambda p_1 + (1 - \lambda)p_2$$

ERM



mixup



Method

- Retraining via Robust Learning

- Label smoothing

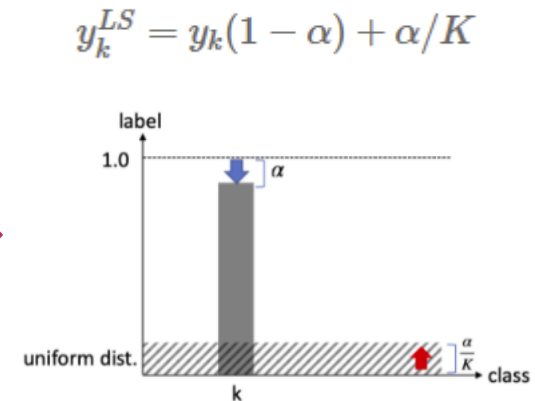
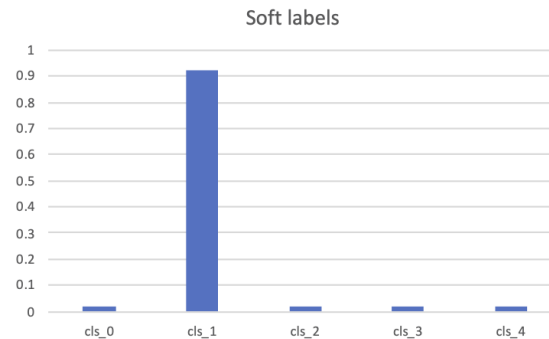
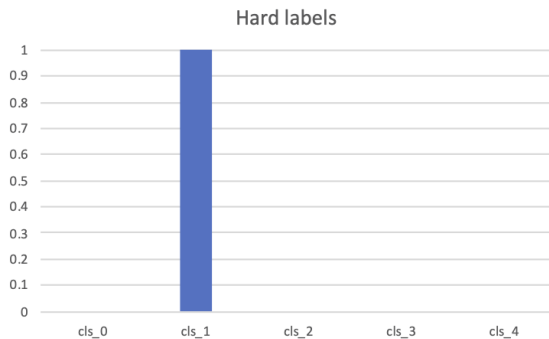
- Regularize the model from being overconfident to noisy predictions

- Hard label → soft label

- ⚡ Make a uniform distribution of classes except for the correct answer

- ✓ Inject uniform noise to all classes

- ⚡ Compute cross-entropy soft label and predicted label



Method

- Retraining via Robust Learning

- Co-training

- Single network → vulnerability of overfitting to incorrect pseudo-labels

- Two networks f_1, f_2 are trained in parallel and exchange their guesses

Labeled

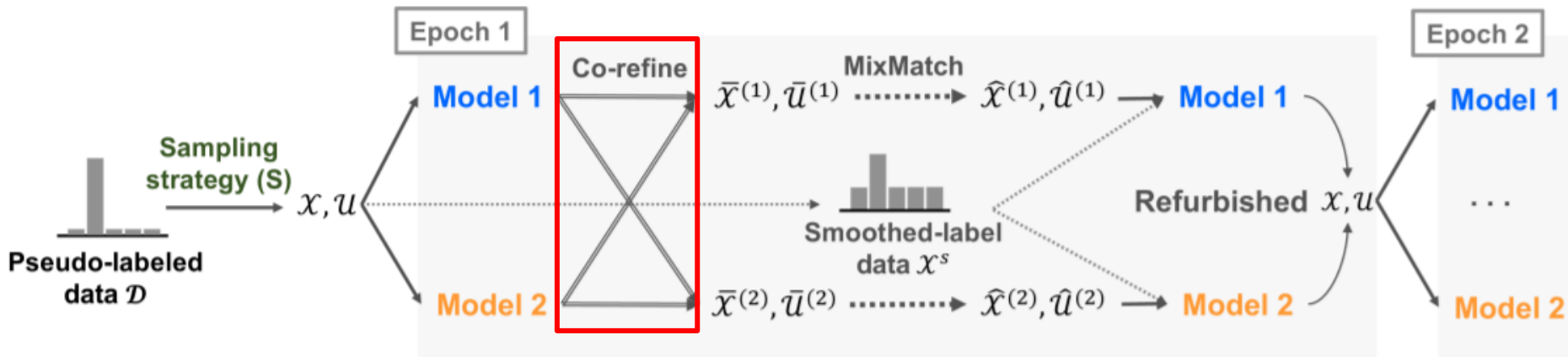
$$\bar{y} = (1 - w^{(2)}) \cdot y + w^{(2)} \cdot f_{\theta^{(2)}}(\mathbf{x})$$

$$\bar{y} = \text{Sharpen}(\bar{y}, T),$$

Unlabeled

$$\bar{q} = \frac{1}{2M} \sum_m (f_{\theta^{(1)}}(\mathbf{u}_m) + f_{\theta^{(2)}}(\mathbf{u}_m))$$

$$\bar{q} = \text{Sharpen}(\bar{q}, T),$$



Method

- Retraining via Robust Learning

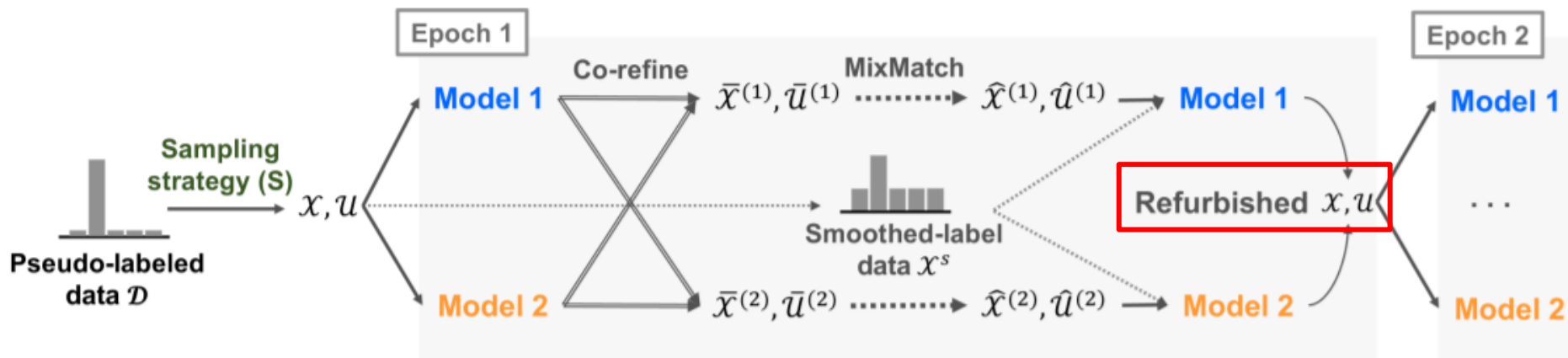
 - Co-refurbishing

 - Unclean data

 - ※ Refurbish the noise samples at the end of every epoch to deliver the extra clean samples

 - ※ The prediction probability of network exceeds the threshold value

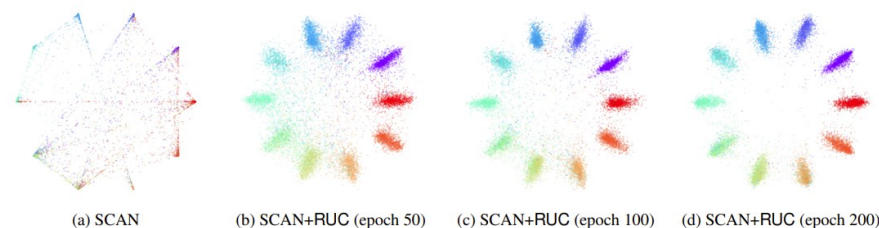
 - ✓ Add to the clean data and appended to the labeled set X



Experiments

- Unsupervised Image Clustering

Method	CIFAR-10	CIFAR-20	STL-10
<i>k</i> -means [45]	22.9	13.0	19.2
Spectral clustering [55]	24.7	13.6	15.9
Triplets [37]	20.5	9.9	24.4
Autoencoder (AE) [4]	31.4	16.5	30.3
Variational Bayes AE [24]	29.1	15.2	28.2
GAN [36]	31.5	15.1	29.8
JULE [52]	27.2	13.7	27.7
DEC [49]	30.1	18.5	35.9
DAC [8]	52.2	23.8	47.0
DeepCluster [6]	37.4	18.9	33.4
ADC [15]	32.5	16.0	53.0
IIC [22]	61.7	25.7	49.9
TSUC† [17]	80.2	35.5	62.0
SCAN† [42]	88.7	50.6	81.4
TSUC + RUC (Confidence)	81.8 / 82.5	39.6 / 40.6	65.1 / 65.5
TSUC + RUC (Metric)	82.5 / 82.9	39.5 / 40.4	66.3 / 66.6
TSUC + RUC (Hybrid)	82.1 / 82.8	39.5 / 40.6	66.0 / 66.8
SCAN + RUC (Confidence)	90.3 / 90.3	53.3 / 53.5	86.7 / 86.8
SCAN + RUC (Metric)	89.5 / 89.5	53.9 / 53.9	84.7 / 85.1
SCAN + RUC (Hybrid)	90.1 / 90.1	54.3 / 54.5	86.6 / 86.7

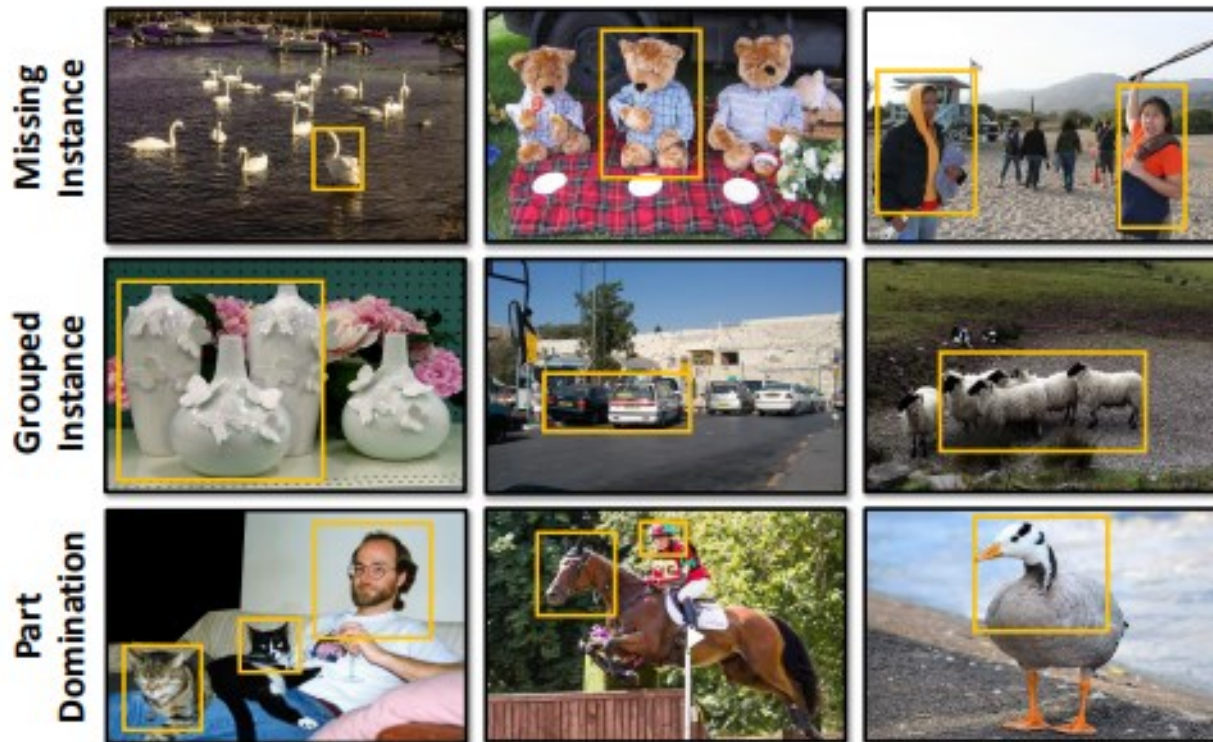


Method	SCAN (Best)	SCAN + RUC (Last / Best accuracy)
ImageNet-50	76.8	78.5 / 78.5

Setup	Last Acc	Best Acc
RUC with all components	86.7	86.8
without co-training	86.2	86.4
without label smoothing	85.5	85.8
with MixMatch only	85.2	85.4

Paper

- Instance-Aware, Context-Focused, and Memory-Efficient Weakly Supervised Object Detection (CVPR 2020)



Method

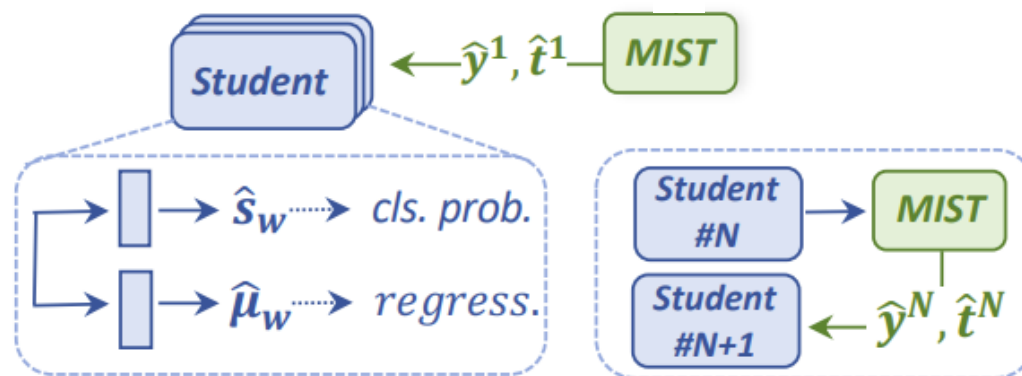
- Weakly Supervised Object Detection
 - Multiple instance learning (MIL)
 - Select major instances among them and accurately predict the label of the bundle
 - Training based on classification loss
 - To select the most confident positive proposals

Weakly Supervised Detection



Method

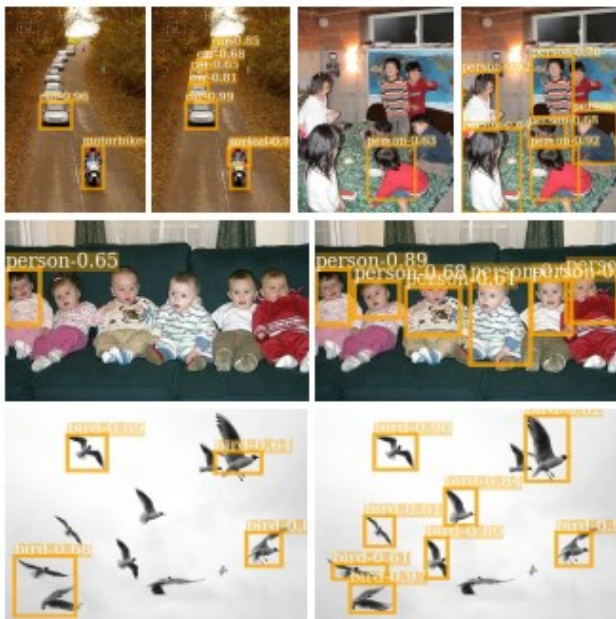
- Multiple instance self-training (MIST)
 - Input image \rightarrow Pretrained network \rightarrow proposal R (instance)
 - Sort the score of each class
 - High-scoring non-overlapping regions R' (pseudo label)
 - ⋈ Instance-level regression and classification label
 - ⋈ (Classification logits + detection) logits score
 - Teacher-student repetitive distilling process proceeds (self-training)



Experiments

- Comparison of the model to the baseline
 - Left: baseline, right: model results

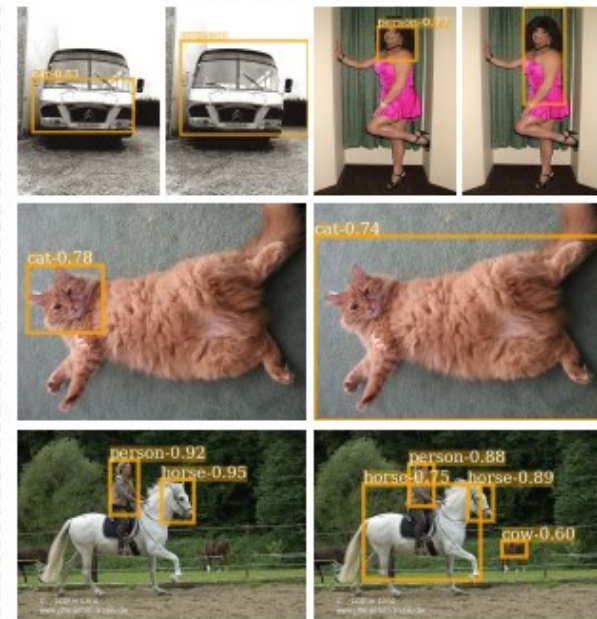
Missing Instance



Grouped Instance



Part Domination



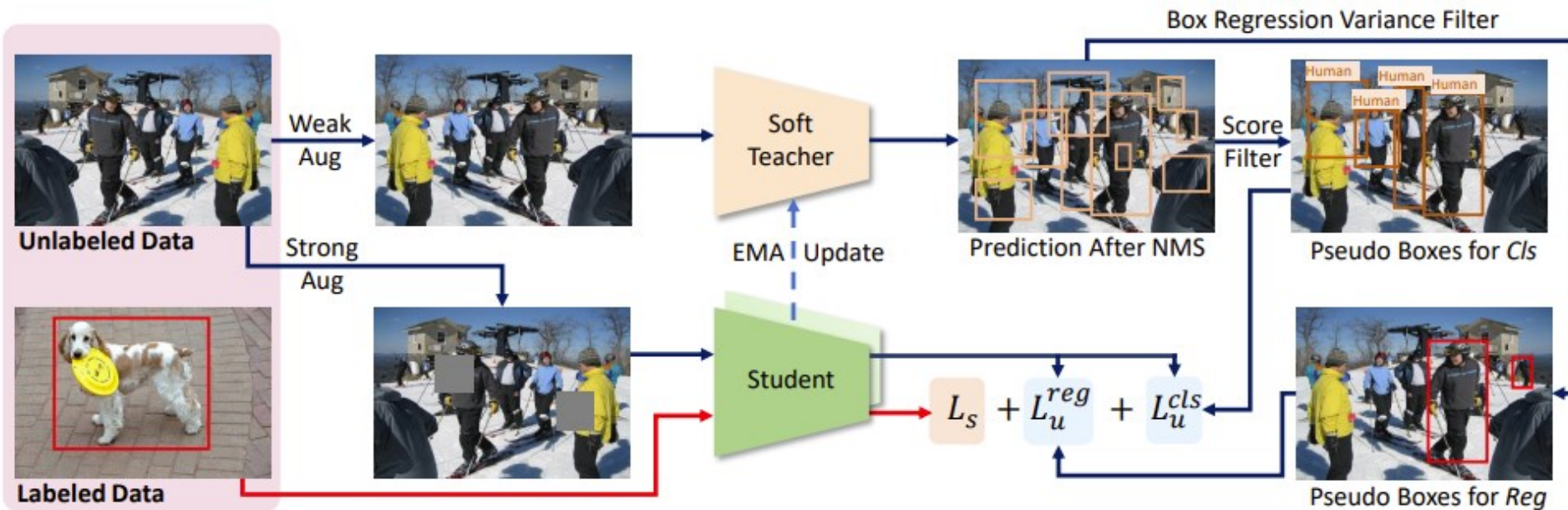
Paper

- End-to-End Semi-Supervised Object Detection with Soft Teacher (ICCV 2021)

- Method

- End-to-End Pseudo-Labeling Framework

- Soft Teacher



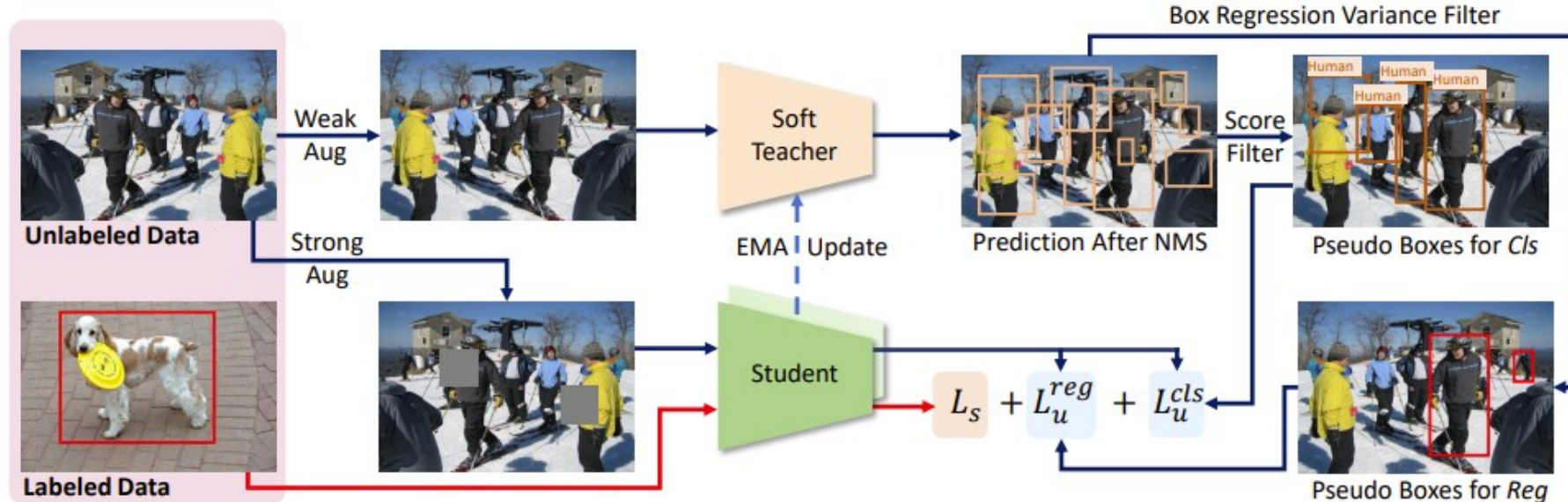
Method

- End-to-End Semi-Supervised Object Detection with Soft Teacher (ICCV 2021)

- Soft Teacher

- Teacher model

- ⊛ Weak augmentation (unlabeled data) → Soft Teacher → NMS → high-confidence score → Box regression variance filter
 - ⊛ EMA update (student → teacher)



Method

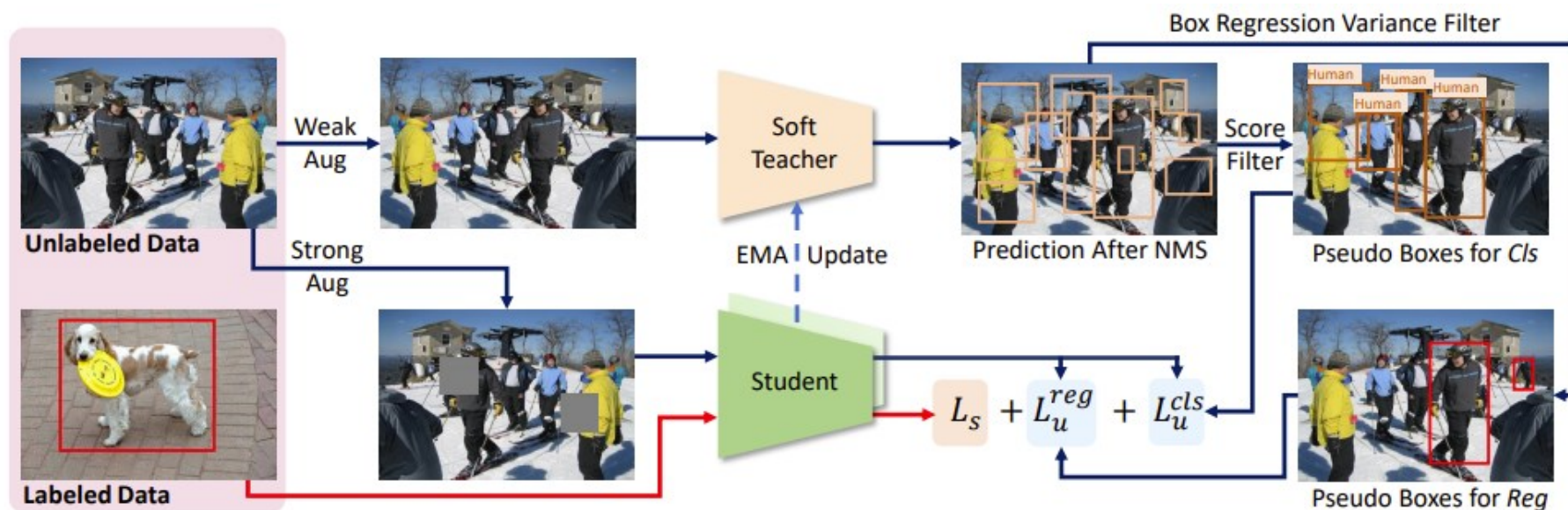
- End-to-End Semi-Supervised Object Detection with Soft Teacher (ICCV 2021)

- Soft Teacher

- Student model

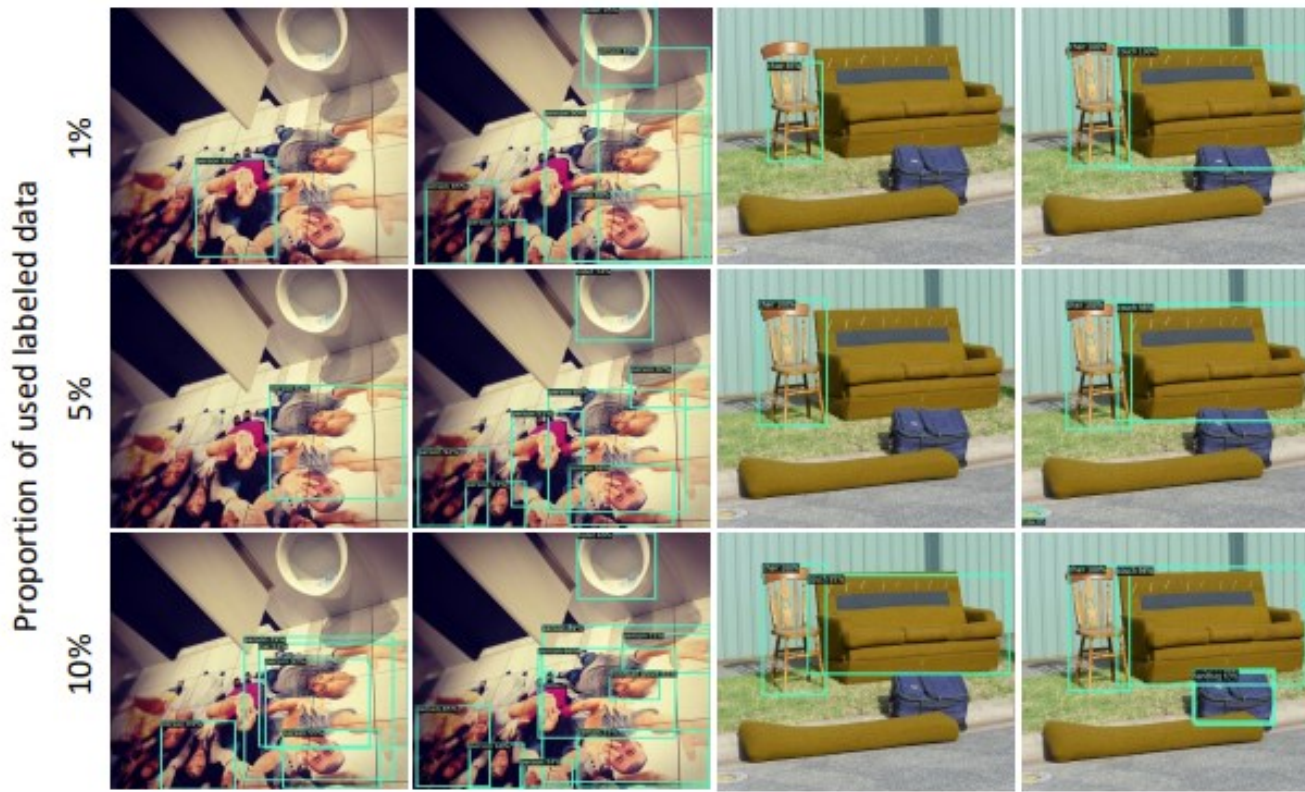
- ⊛ Labeled data + strong augmentation (unlabeled data) → prediction

- ⊛ Comparison prediction of student and pseudo labeled data produced by Soft teacher



Experiments

- Qualitative results
 - Left: baseline, right: model results



References

- Lee, Pilhyeon, Youngjung Uh, and Hyeran Byun. "Background suppression network for weakly-supervised temporal action localization." Proceedings of the AAAI conference on artificial intelligence. Vol. 34. No. 07. 2020.
- Zhao, Ting, and Xiangqian Wu. "Pyramid feature attention network for saliency detection." Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition. 2019.
- Zhang, Can, et al. "CoLA: Weakly-Supervised Temporal Action Localization with Snippet Contrastive Learning." Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition. 2021.

Thank you!