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模式分析与机器智能
工业和信息化部重点实验室
MIIT Key Laboratory of
Pattern Analysis & Machine Intelligence

Debiased Self-Training for Semi-Supervised Learning

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Introduction

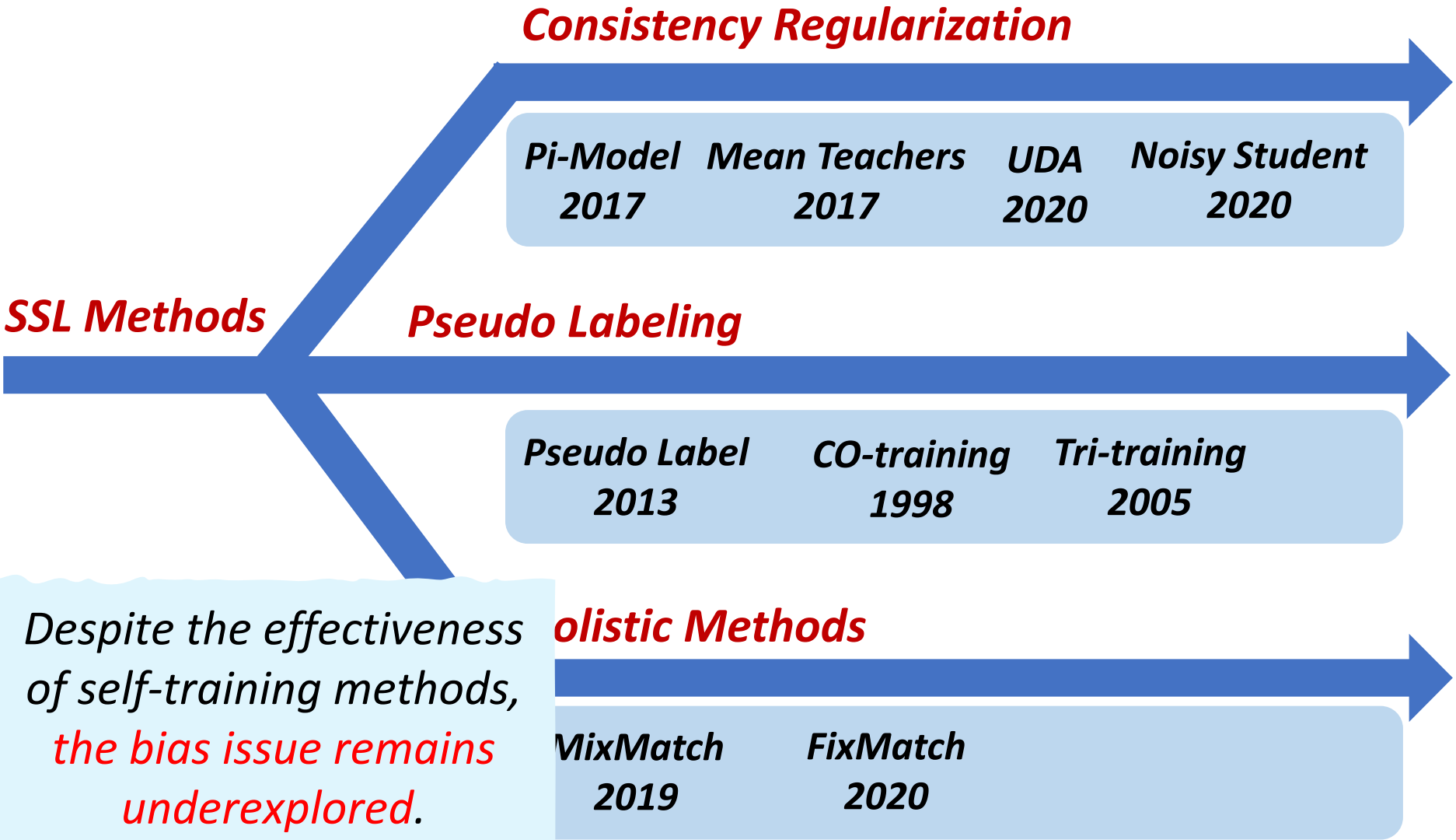
Semi-supervised Learning (SSL)

- *Aim to improve data efficiency of deep models*
- *Explore supervisson from unlabeled data*

Few Labeled Data $\mathcal{L}$

Numerous Unlabeled Data $\mathcal{U}$

Overview of SSL Methods

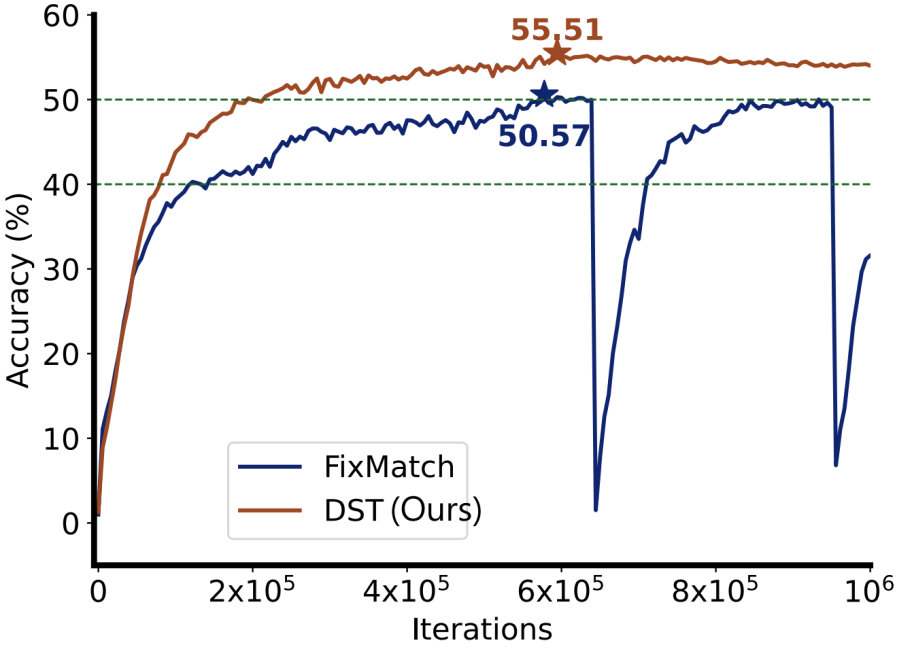


Despite the effectiveness of self-training methods, the bias issue remains underexplored.

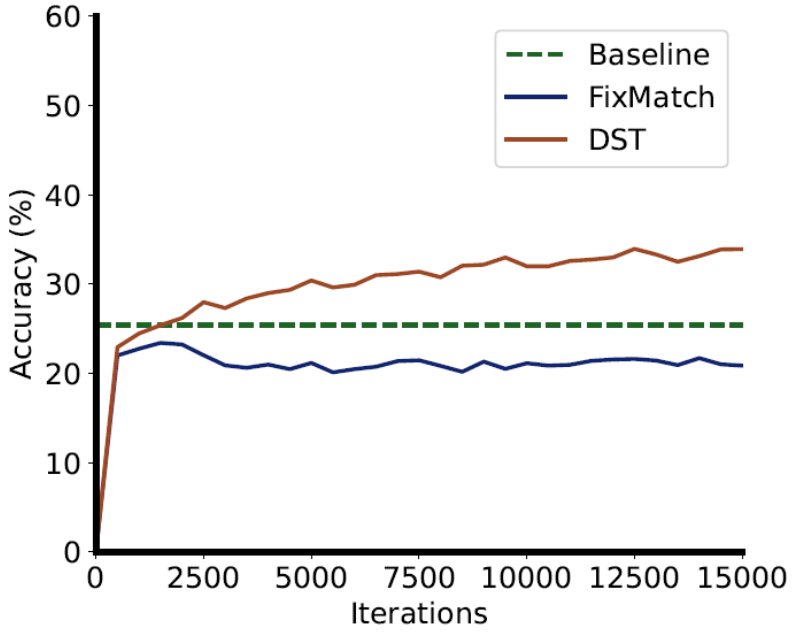
Bias Issue of Self-Training

Training Instability

- *Slow down convergence speed* ☹
- *Lead to catastrophic forgetting of pre-trained models* ☹



CIFAR-100 (trained from scratch)

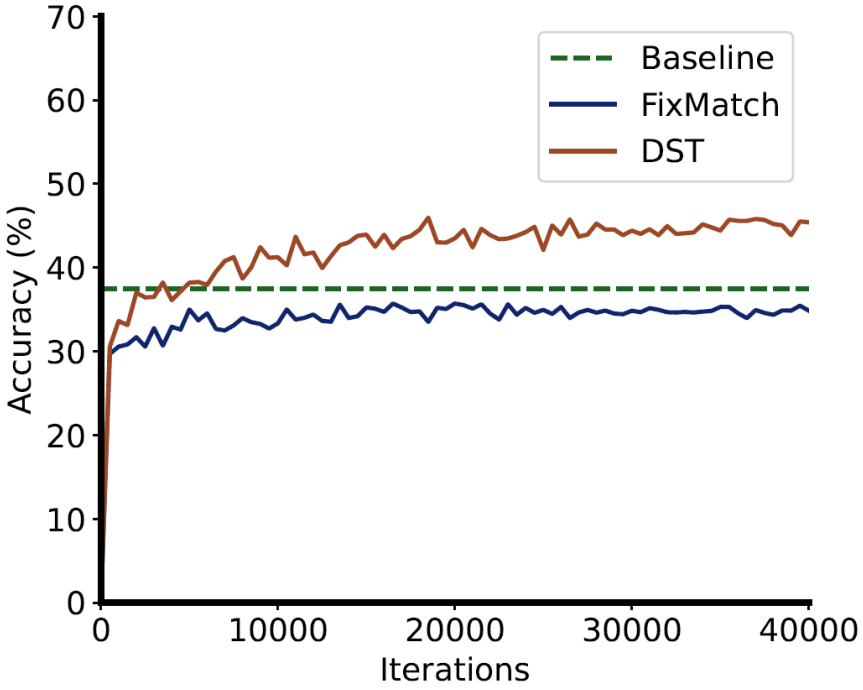


Aircraft (supervised pre-trained)

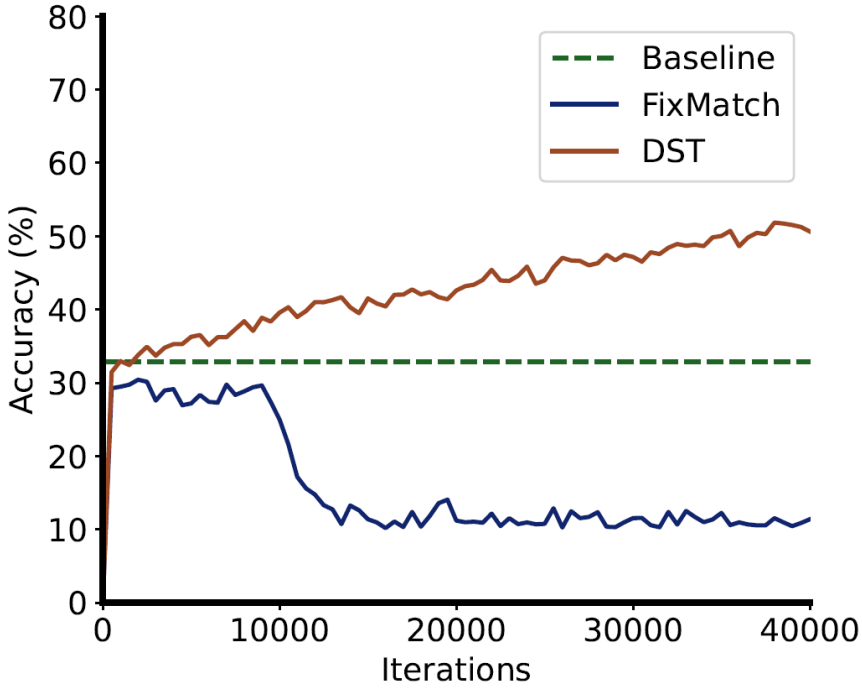
Bias Issue of Self-Training

Training Instability

- *Slow down convergence speed* ☹
- *Lead to catastrophic forgetting of pre-trained models* ☹



CUB (unsupervised pre-trained)



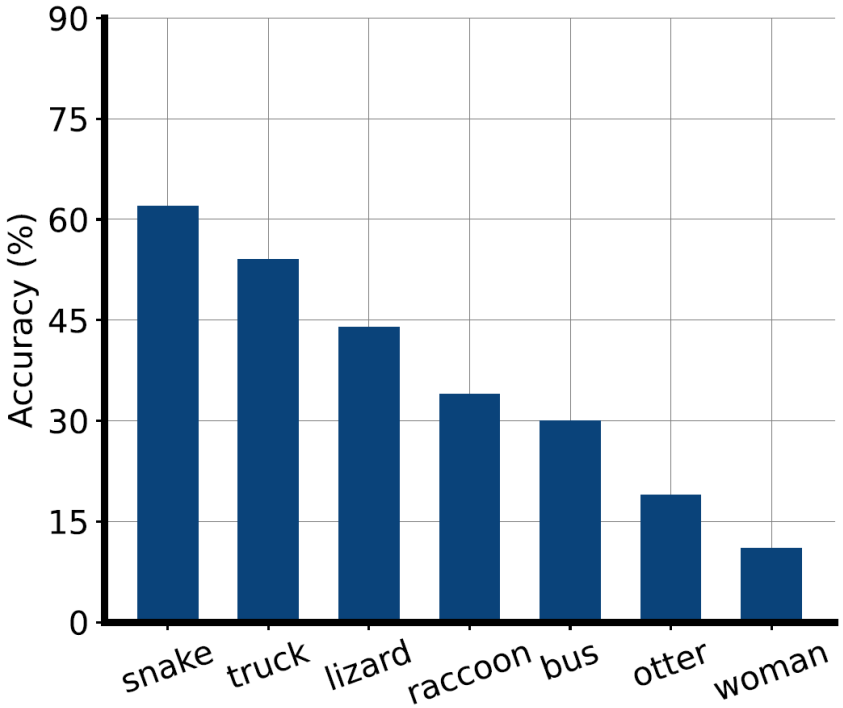
Food-101 (unsupervised pre-trained)

Bias Issue of Self-Training

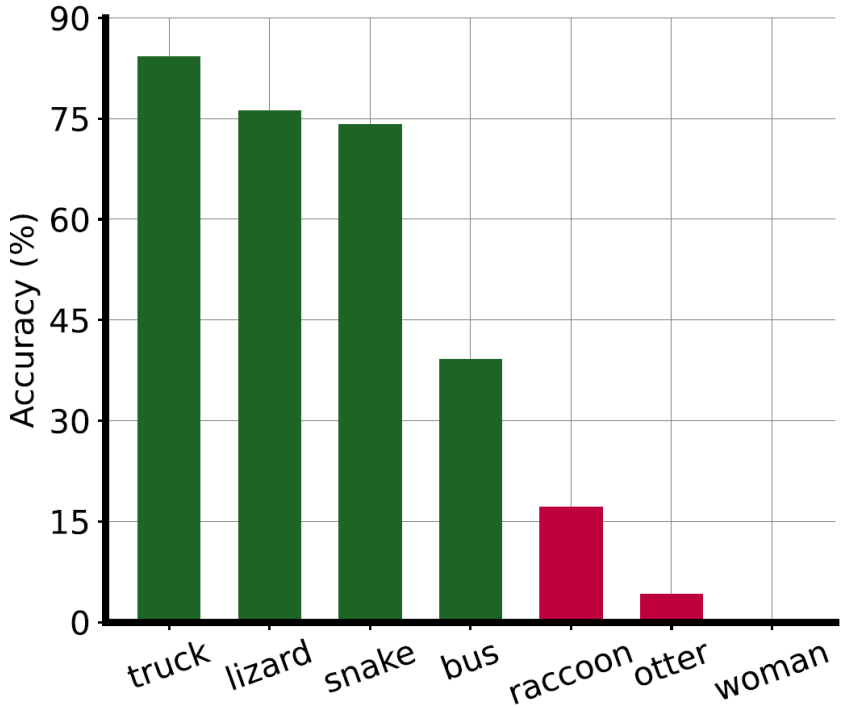
Matthew Effect

- *Enlarger performance imbalance across classes* ☹

Baseline



FixMatch



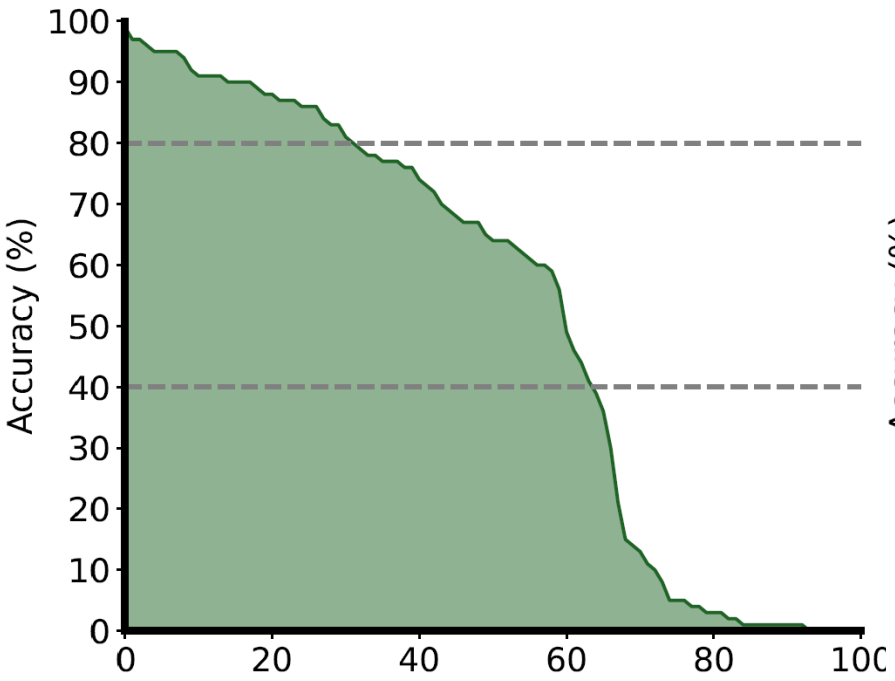
Top-1 Accuracy on 7 categories from CIFAR-100 (ResNet50, supervised pre-trained)

Bias Issue of Self-Training

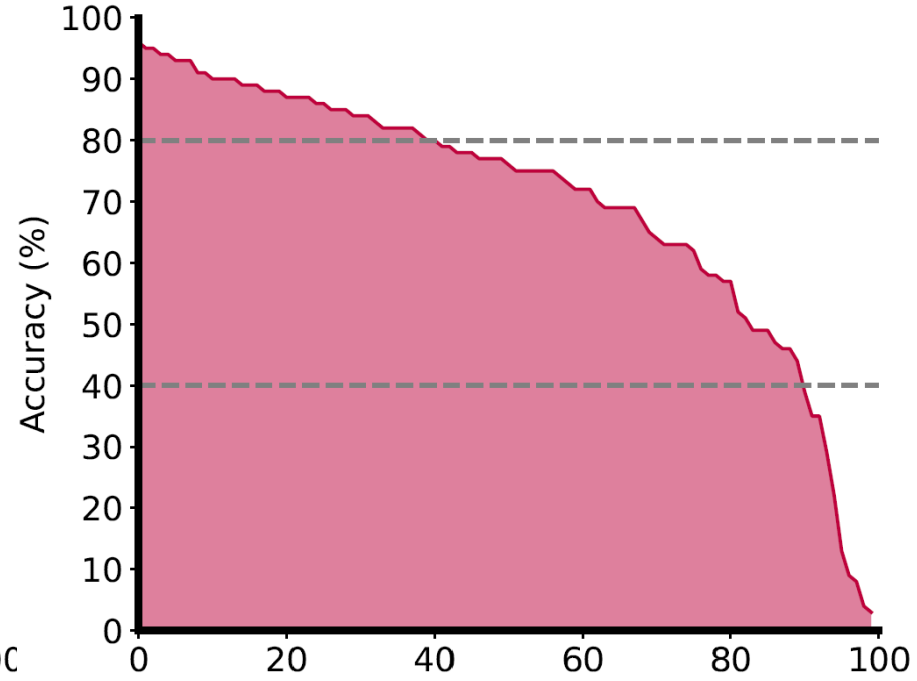
Matthew Effect

- *Enlarger performance imbalance across classes* ☹

FixMatch



DST



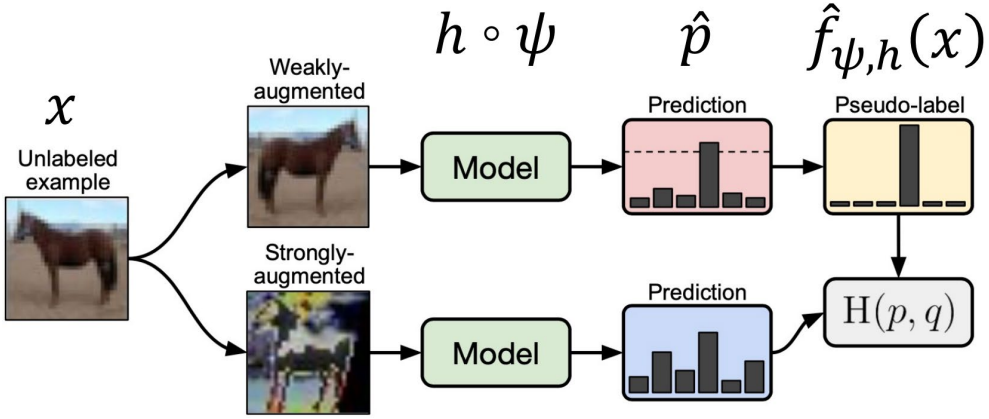
Top-1 Accuracy on all classes from CIFAR-100 (ResNet50, supervised pre-trained)

Previous Solutions of Self-Training Bias

Generate Higher Quality Pseudo Labels

- *Confidence thresholds (Static of Dynamic)*
- *Consistency regularization*

FixMatch, UDA, FlexMatch …



Data Flow of Fixmatch

$$\hat{f}_{\psi,h}(x) = \begin{cases} \operatorname{argmax} \hat{p}, & \max \hat{p} \geq \tau \\ -1, & \text{otherwise} \end{cases}$$

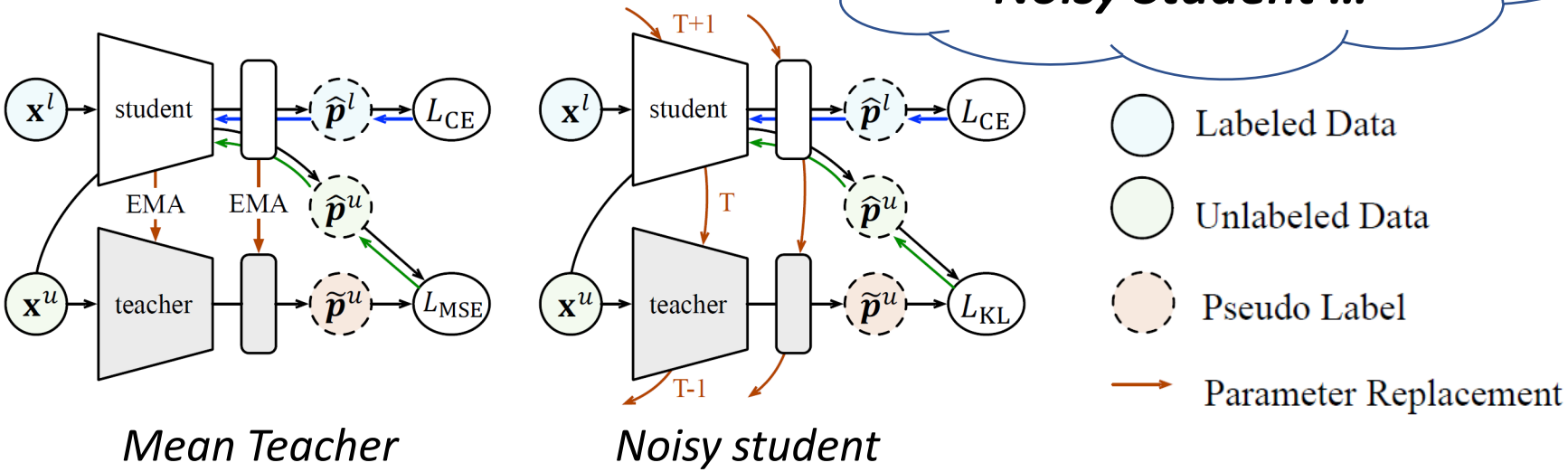
Relies on manual design of criteria to improve the quality of pseudo labels ☹

Previous Solutions of Self-Training Bias

Improve Tolerance to Inaccurate Pseudo Labels

- *Maintain discrepancy between generation and utilization of pseudo labels*

Mean Teacher, MMT, Noisy Student …



Mean Teacher *Noisy student*

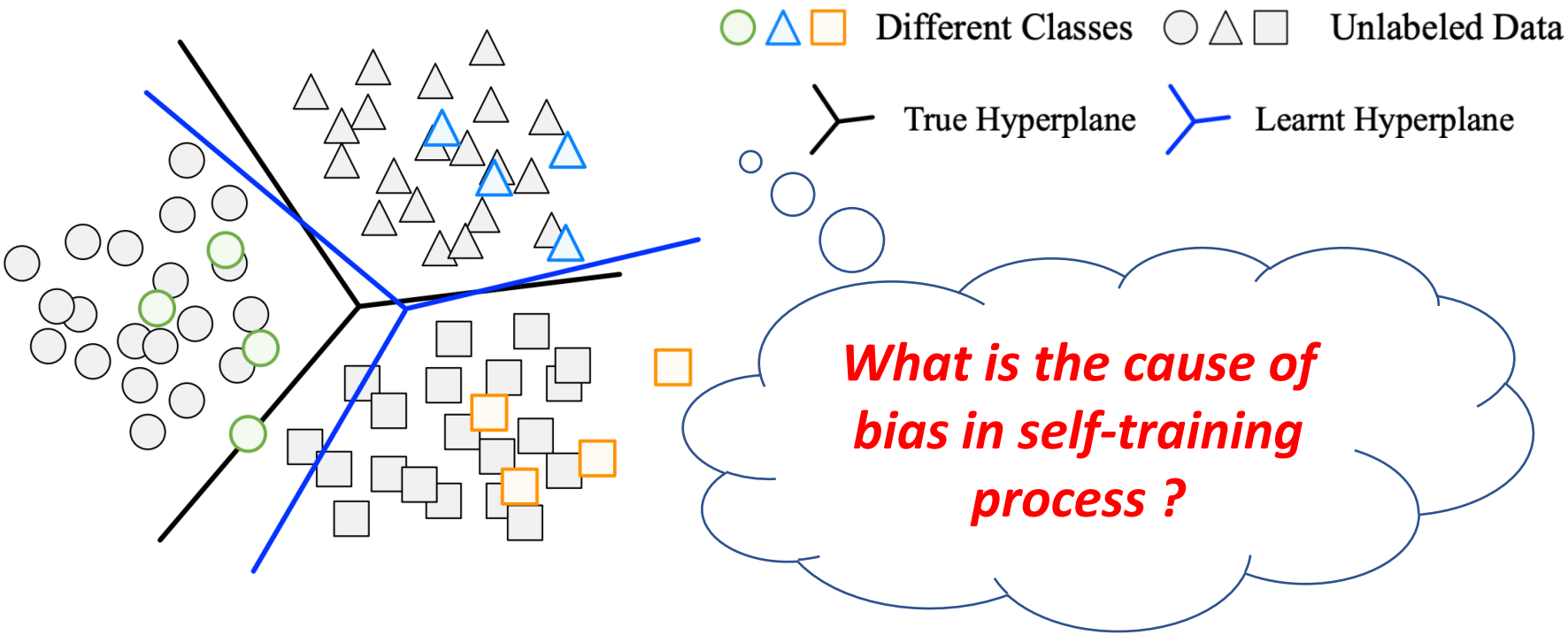
The decision boundary still has the potential to be damaged by incorrected pseudo labels ☹

Analysis

Analysis of Bias in Self-Training

Definition of Bias

- *The deviation between the learned decision hyperplanes and the true decision hyperplanes.*

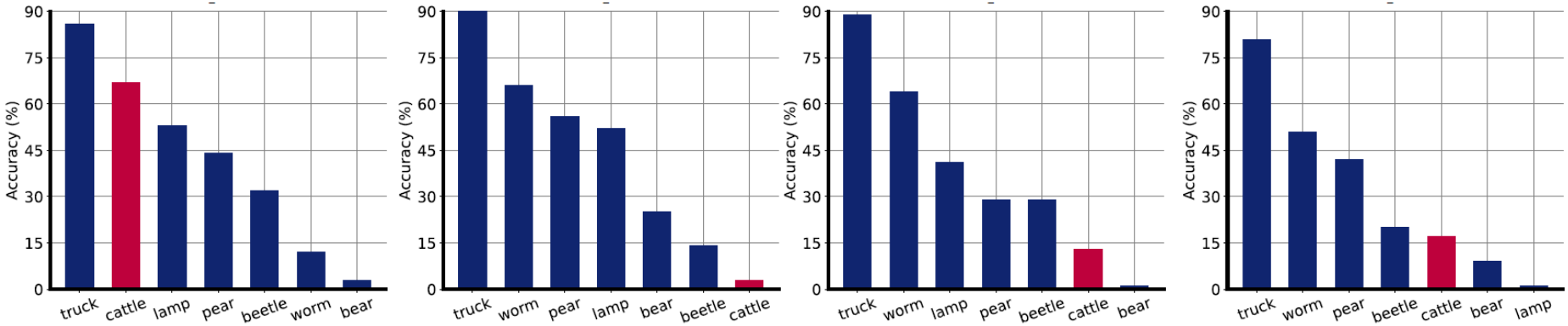


Analysis of Bias in Self-Training

Effect of Data Sampling

- *With fewer labeled data, the distances between supporting data of each categories and the true decision hyperplanes may vary.*

Sample 1 *Sample 2* *Sample 3* *Sample 4*



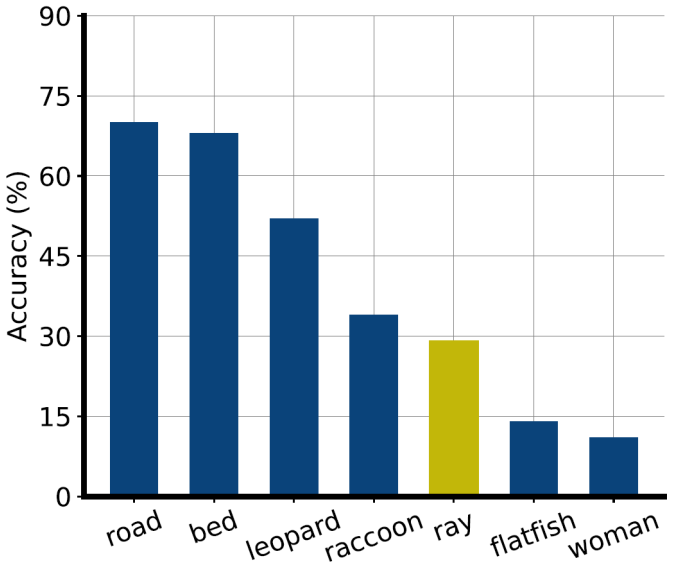
Top-1 Accuracy on 7 categories from CIFAR-100 with different labeled data sampling

Analysis of Bias in Self-Training

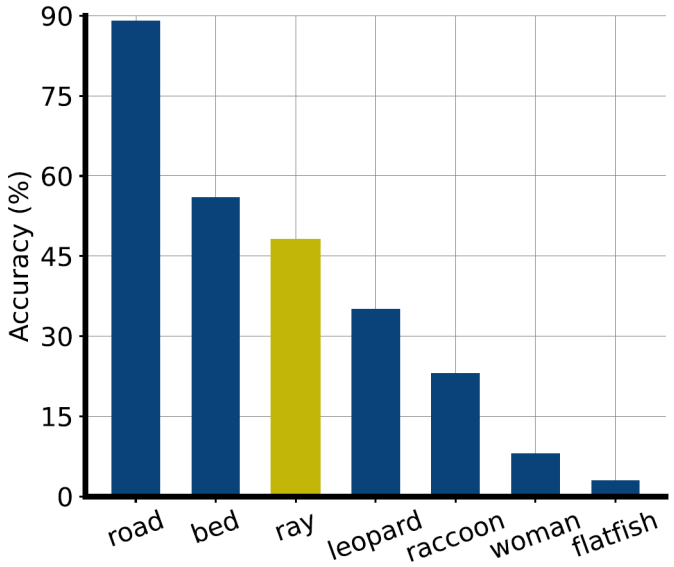
Effect of Pre-Trained Representations

- *The representations learned by different pre-trained models focus on different aspects of the data.*

Supervised Pre-Train



Unsupervised Pre-Train

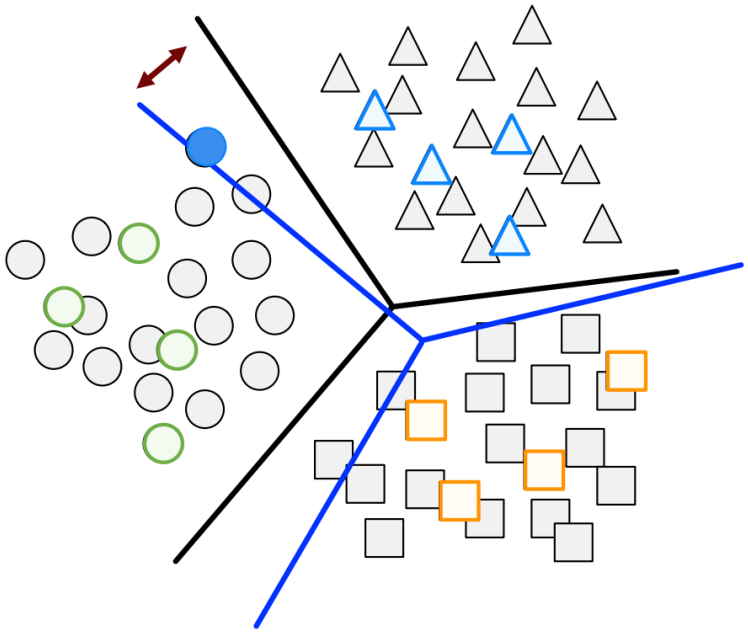


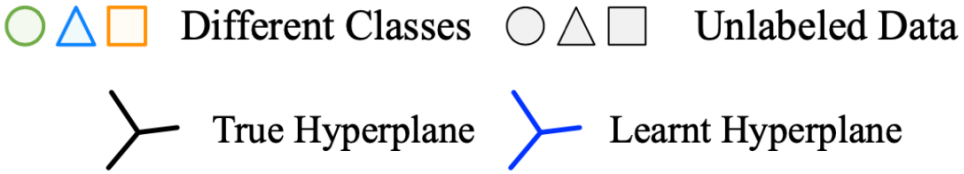
Top-1 Accuracy on 7 categories from CIFAR-100 with different pre-trained models

Analysis of Bias in Self-Training

Effect of Self-Training Algorithm

- *Training with pseudo labels aggressively in turn enlarges the self-training bias on some categories.*



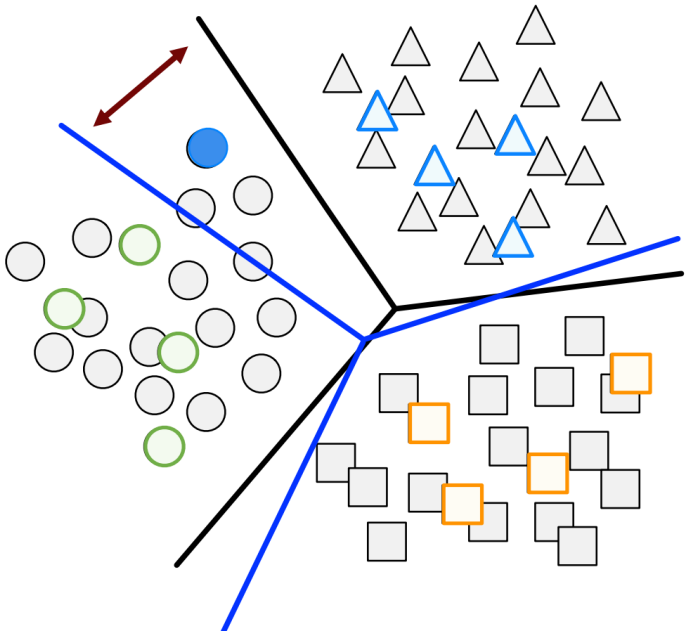


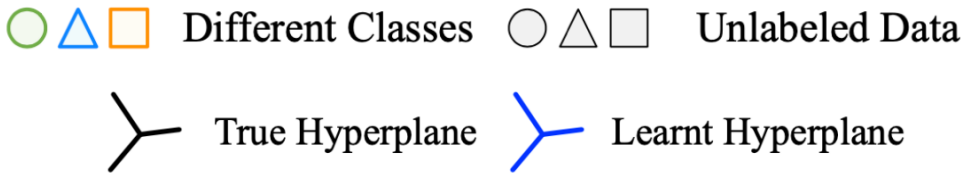
With biased learnt hyperplane, the model makes a mistake on data point

Analysis of Bias in Self-Training

Effect of Self-Training Algorithm

- *Training with pseudo labels aggressively in turn enlarges the self-training bias on some categories.*





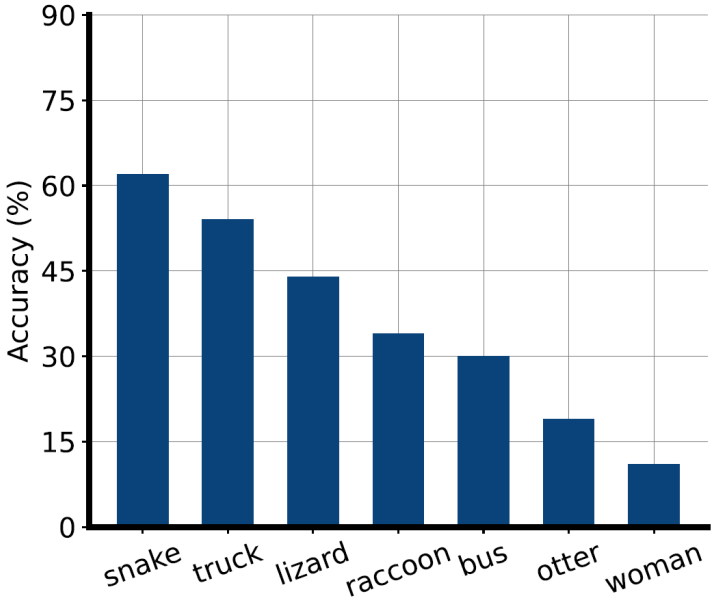
The misclassified data point further pushes the learnt hyperplane far away

Analysis of Bias in Self-Training

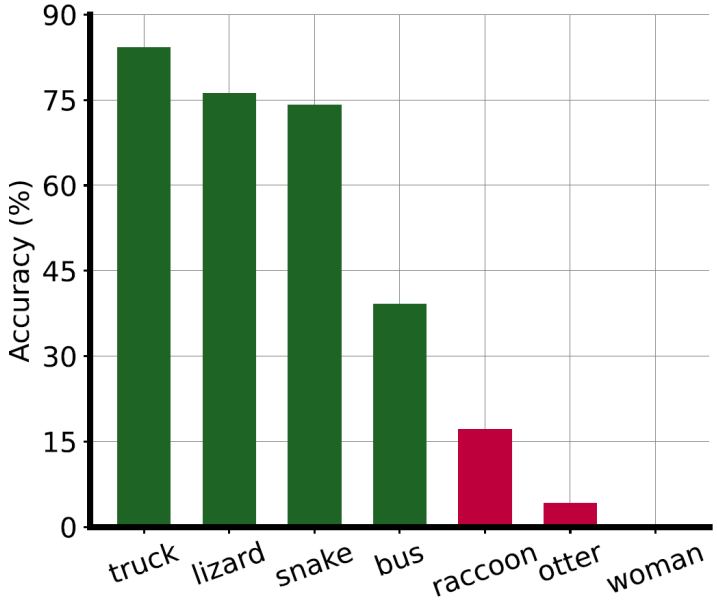
Effect of Self-Training Algorithm

- *Ultimately, the accuracy of some categories increases, while that of other categories decreases to nearly zero.*

Baseline



FixMatch



Top-1 Accuracy on 7 categories from CIFAR-100 with different training strategies

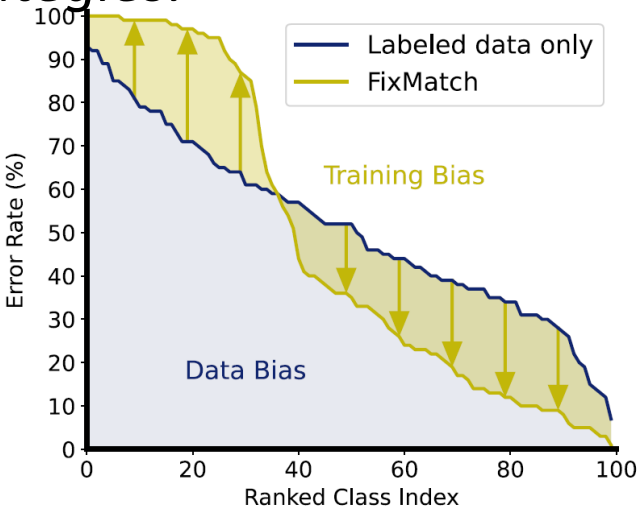
Decomposition of Bias in Self-Training

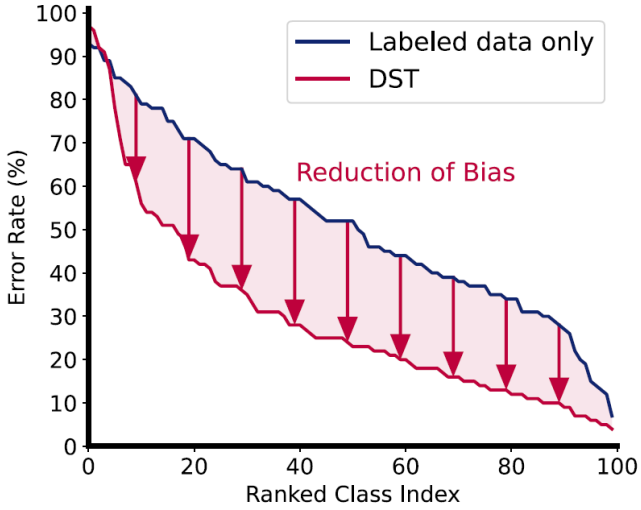
Data Bias

- *The bias inherent in semi-supervised learning tasks, such as the bias of sampling and pre-trained models.*

Training Bias

- *The bias increment brought by some unreasonable training strategies.*



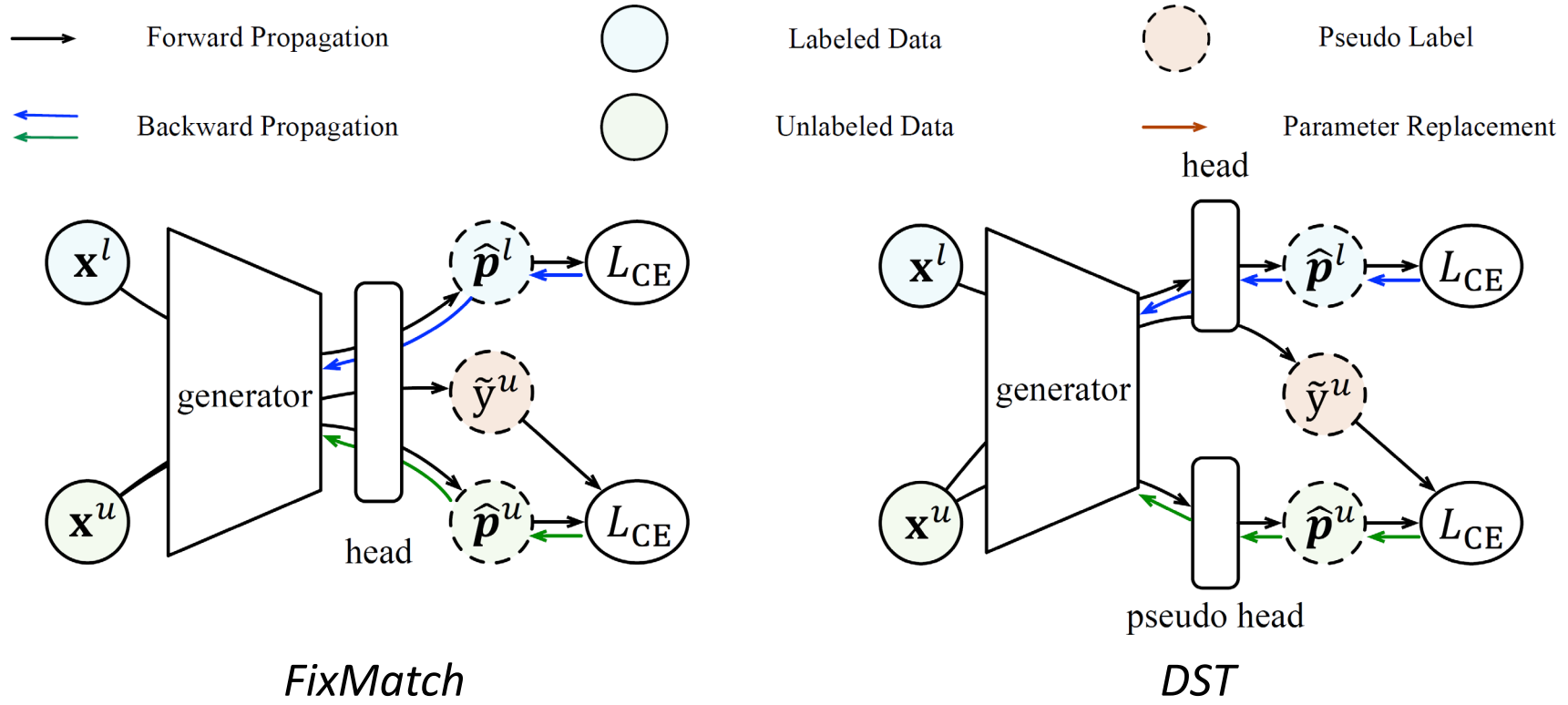


Approach

Debiased Self-Training

How to Decrease Training Bias ?

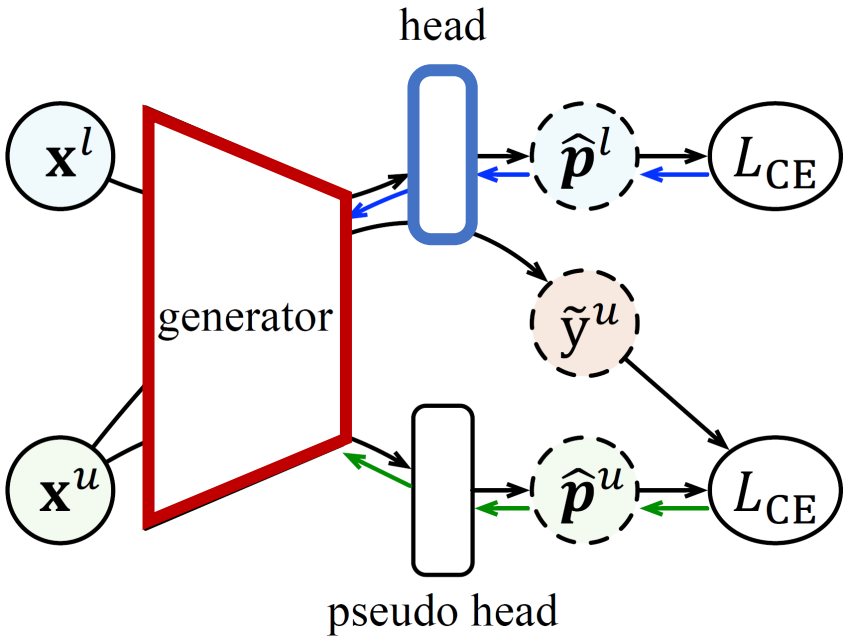
- *Decouple the generation and utilization of pseudo labels by introducing a completely parameter independent pseudo head.*



FixMatch *DST*

Debiased Self-Training

How to Decrease Training Bias ?



Classifier head:

- *More sensitive to noisy data*

Feature generator:

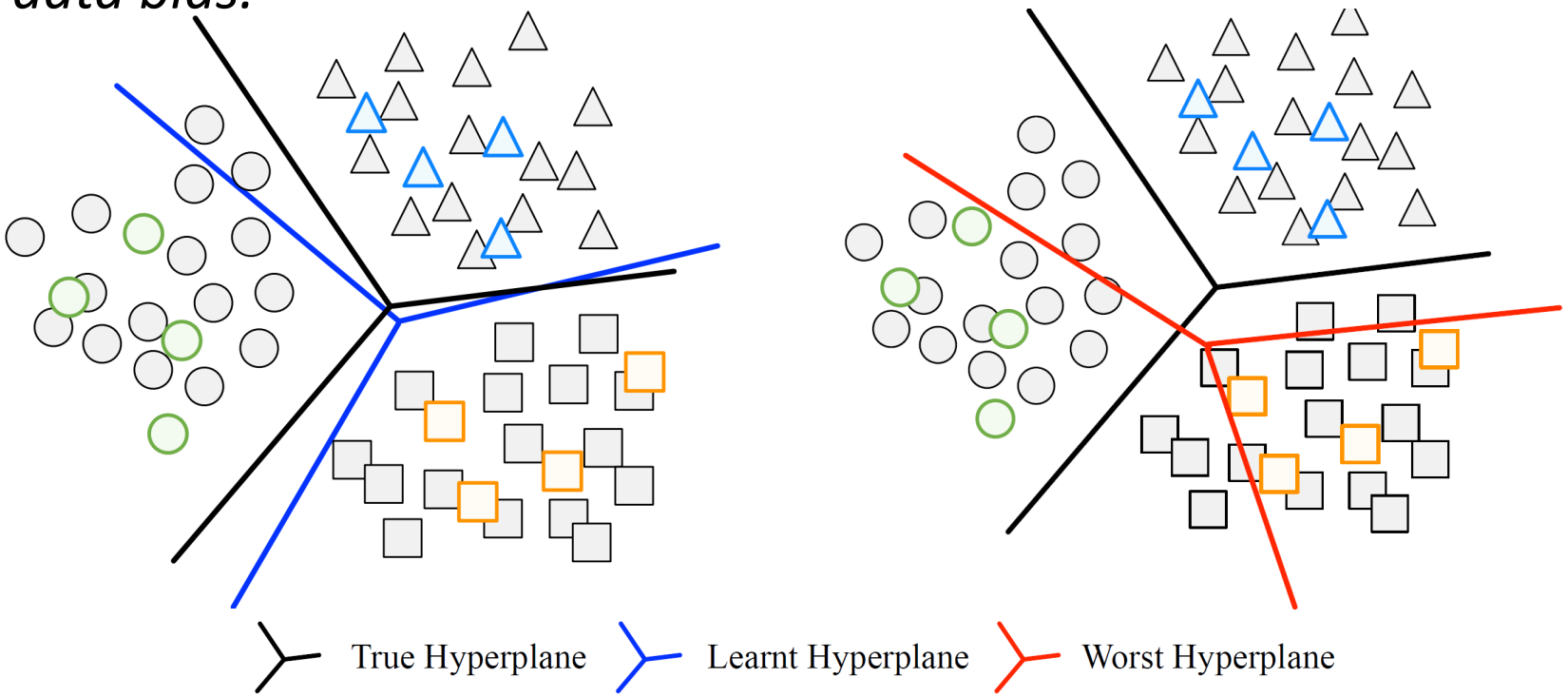
- *More parameters, data hungry*
- *Better tolerance to noisy data*

$$\min_{\psi,h,h_{\mathrm{pseudo}}} L_{\mathcal{L}}(\psi,h) + \lambda L_{\mathcal{U}}\left(\psi, h_{\mathrm{pseudo}}, \hat{f}_{\psi,h}\right)$$

Debiased Self-Training

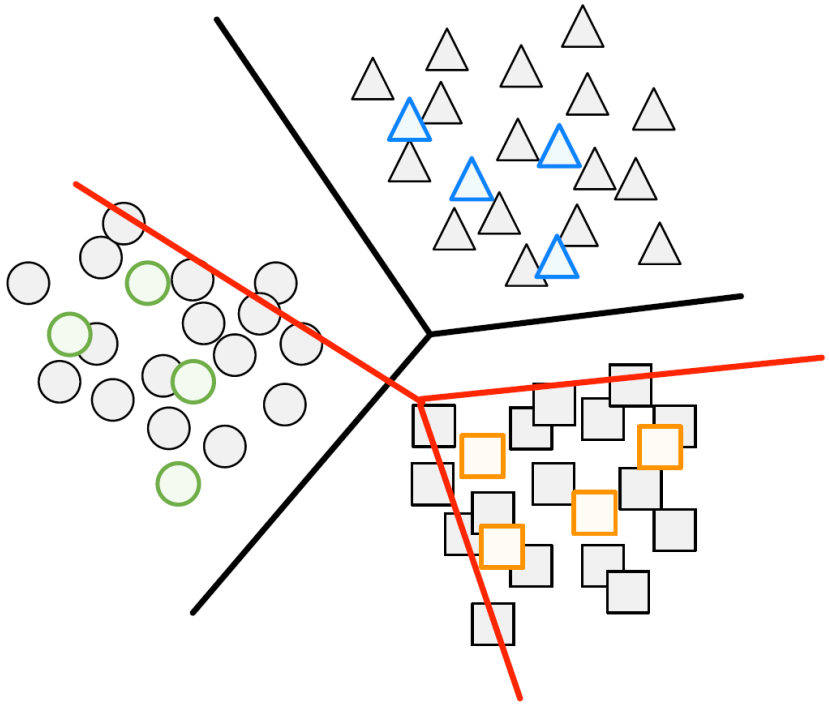
How to Decrease Data Bias ?

- *Training bias can be considered as the accumulation of data bias.*
- *The worst training bias that can be achieved is a good measure of data bias.*



Debiased Self-Training

How to Decrease Data Bias ?



True Hyperplane Learnt Hyperplane Worst Hyperplane

Estimate the worst training bias

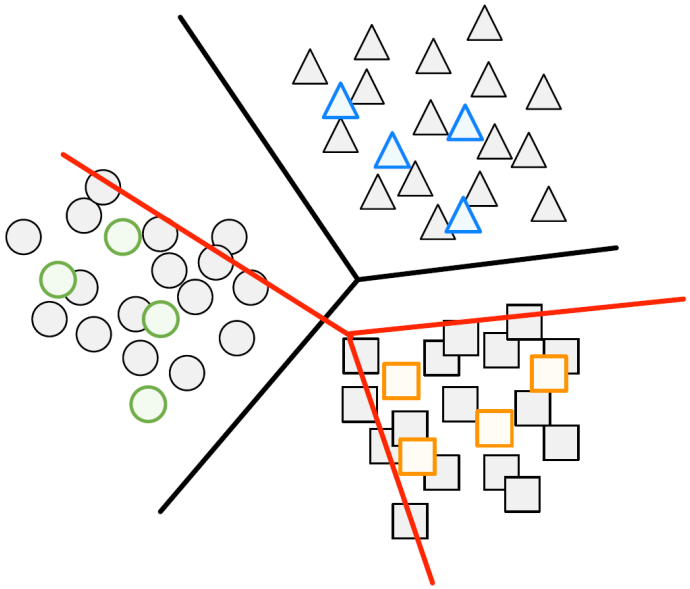
Introduce a worst case estimation head h',which:

- *Correctly classifies the labeled samples*
- *Deviates from the current hyperplanes as much as possible*

$$\max_{h'} L_{\mathcal{U}}\left(\psi, h', \hat{f}_{\psi,h}\right) - L_{\mathcal{L}}(\psi, h')$$

Debiased Self-Training

How to Decrease Data Bias ?



True Hyperplane Learnt Hyperplane Worst Hyperplane

Decrease the worst training bias

Encourage the features to be generated far away from the current hyperplanes

- *Optimize ψ and h' with stochastic gradient descent alternatively*
- *The optimization can be viewed as an alternative from of GAN*

$$\min_{\psi} \max_{h'} L_{\mathcal{U}}(\psi, h', \hat{f}_{\psi,h}) - L_{\mathcal{L}}(\psi, h')$$

Experiments

Standard SSL Benchmarks

Top-1 Accuracy on standard SSL benchmarks (train from scratch, 4 labels per class)

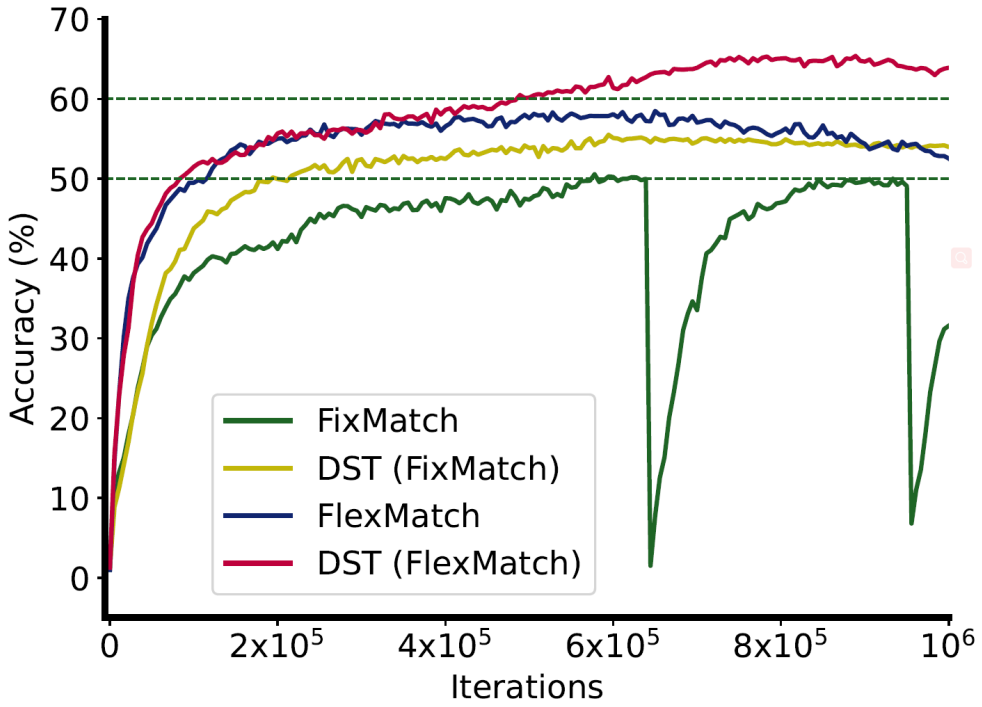
Method	CIFAR-10	CIFAR-100	SVHN	STL-10	Avg
Psuedo Label [30]	25.4	12.6	25.3	25.3	22.2
VAT [34]	25.3	15.1	26.1	25.5	23.0
ALI [15]	25.9	12.4	28.5	24.1	22.7
RAT [52]	33.2	20.5	52.6	30.7	34.2
MixMatch [4]	52.6	32.4	57.5	45.1	46.9
UDA [59]	71.0	40.7	47.4	62.6	55.4
ReMixMatch [3]	80.9	55.7	96.6	64.0	74.3
Dash [61]	86.8	55.2	**97.0**	64.5	75.9
FixMatch [49]	87.2	50.6	96.5	67.1	75.4
DST (FixMatch)	**89.3**	**56.1**	96.7	**71.0**	**78.3**
FlexMatch [64]	94.7	59.5	89.6	71.3	78.8
DST (FlexMatch)	**95.0**	**65.4**	**94.2**	**79.6**	**83.6**

DST yields consistent improvement on all tasks.

Especially on the challenging tasks CIFAR-100 and STL10

Standard SSL Benchmarks

DST increases the training stability



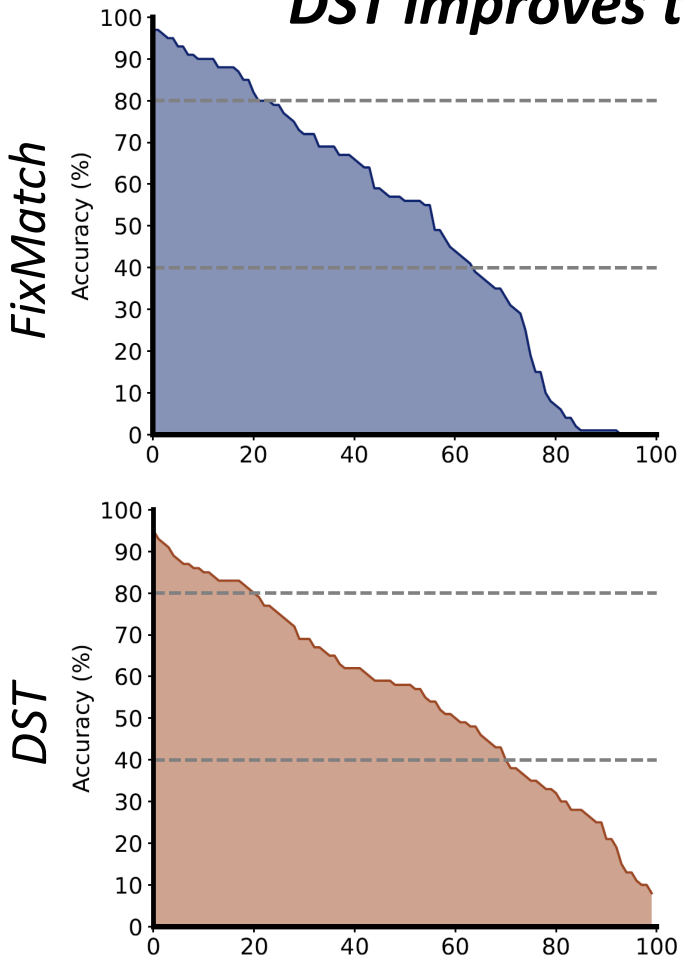
Top-1 Accuracy on CIFAR-100

(train from scratch, 4 labels per category)

Method	CIFAR-100
Psuedo Label [30]	12.6
VAT [34]	15.1
ALI [15]	12.4
RAT [52]	20.5
MixMatch [4]	32.4
UDA [59]	40.7
ReMixMatch [3]	55.7
Dash [61]	55.2
FixMatch [49]	50.6
DST (FixMatch)	**56.1**
FlexMatch [64]	59.5
DST (FlexMatch)	**65.4**

Standard SSL Benchmarks

DST improves the performance balance



Method	CIFAR-100
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Dash [61]	55.2
FixMatch [49]	50.6
DST (FixMatch)	**56.1**
FlexMatch [64]	59.5
DST (FlexMatch)	**65.4**

Top-1 Accuracy of each category on CIFAR-100

(train from scratch)

SSL with Supervised Pre-Trained Model

Top-1 Accuracy comparison results (supervised pre-trained, 4 labels per class)

	Caltech101	CIFAR-10	CIFAR-100	SUN397	DTD	Aircraft	CUB	Flowers	Pets	Cars	Food101	Average
Baseline	81.4	65.2	48.2	39.9	47.7	25.4	46.5	85.2	78.1	33.3	33.8	53.2
Pseudo Label [30]	86.3	83.3	54.7	41.0	50.2	27.2	54.3	92.3	87.8	41.4	38.0	59.7
Π-Model [29]	83.5	73.1	49.2	39.7↓	50.3	24.3↓	47.1	90.7	82.2	30.9↓	33.9	55.0
Mean Teacher [53]	83.7	82.1	56.0	37.9↓	51.6	30.7	49.6	91.0	82.8	39.1	40.3	58.6
VAT [34]	84.1	72.2	48.8	39.5↓	50.6	25.9	48.1	89.4	81.8	32.4↓	36.7	55.4
ALI [15]	82.2	69.5	46.3↓	36.4↓	50.5	21.3↓	42.5↓	82.9↓	77.4↓	29.8↓	31.7↓	51.9
RAT [52]	84.0	81.8	55.4	39.0↓	49.1	31.6	50.0	89.9	84.1	37.9	38.4	58.3
MixMatch [4]	85.4	82.8	53.5	41.8	50.1	24.7↓	51.7	91.5	83.3	42.5	38.2	58.7
UDA [59]	85.8	83.6	54.7	41.3	49.0	27.1	52.1	92.0	83.1	45.6	41.7	59.6
FixMatch [49]	86.3	84.6	53.1	41.3	48.6	25.2↓	52.3	93.2	83.7	46.4	37.1	59.3
Self-Tuning [55]	87.2	76.0	57.1	41.8	50.7	35.2	58.9	92.6	86.6	58.3	41.9	62.4
FlexMatch [64]	87.1	89.0	63.4	48.3	52.5	34.0	54.9	94.5	88.3	57.5	49.5	65.4
DebiasMatch [56]	88.6	91.0	65.7	46.6	52.4	37.5	58.6	95.6	86.4	60.5	53.5	66.9
DST (FixMatch)	89.6	94.9	70.4	48.1	53.5	43.2	68.7	94.8	89.8	71.0	**58.5**	71.1
DST (FlexMatch)	**90.6**	**95.9**	**71.2**	**49.8**	**56.2**	**44.5**	**70.5**	**95.8**	**90.4**	**72.7**	57.1	**72.2**

DST brings improvement on all the datasets

SSL with Supervised Pre-Trained Model

Top-1 Accuracy comparison results (unsupervised pre-trained, 4 labels per class)

	Caltech101	CIFAR-10	CIFAR-100	SUN397	DTD	Aircraft	CUB	Flowers	Pets	Cars	Food101	Average
Baseline	79.5	66.6	46.5	38.1	47.9	28.7	37.5	87.7	60.0	38.1	32.9	51.2
Pseudo Label [30]	86.2	70.8	49.8	38.6	50.0	26.6↓	41.8	93.0	68.4	37.3↓	32.8↓	54.1
Π-Model [29]	80.1	76.2	44.8↓	37.8↓	50.0	23.5↓	31.6↓	93.1	62.8	25.6↓	30.4↓	50.5
Mean Teacher [53]	80.4	80.8	51.3	34.2↓	48.8	33.8	41.6	92.9	67.0	50.5	39.1	56.4
VAT [34]	79.9	73.8	45.1↓	38.3	49.2	24.2↓	36.4↓	92.4	61.7	29.9↓	33.1	51.3
ALI [15]	76.4↓	69.2	44.4↓	34.9↓	50.1	22.2↓	33.8↓	84.9↓	59.6↓	33.1↓	31.0↓	49.1
RAT [52]	80.9	79.5	52.4	37.0↓	50.4	30.1	40.7	91.8	70.5	47.9	35.6	56.1
MixMatch [4]	84.1	81.5	51.7	38.4	47.0↓	31.7	39.8	93.5	66.4	47.1	34.6	56.0
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FixMatch [49]	83.1	82.2	51.4	39.2	43.9↓	30.1	36.8↓	94.3	65.7	48.6	36.8	55.6
Self-Tuning [55]	81.6	63.6↓	47.8	38.8	45.5↓	31.4	41.6	91.0	66.9	52.0	34.0	54.0
FlexMatch [64]	86.4	96.7	60.2	45.3	53.9	42.0	49.2	95.8	72.9	69.0	37.5	64.4
DebiasMatch [56]	86.4	96.3	66.3	44.5	53.9	44.8	51.2	95.4	70.9	72.5	53.6	66.9
DST (FixMatch)	90.1	95.0	68.2	46.8	54.2	**47.7**	53.6	95.6	**75.4**	72.0	**57.1**	68.7
DST (FlexMatch)	**90.4**	**96.9**	**68.9**	**48.8**	**55.9**	47.3	**55.2**	**96.4**	75.1	**74.6**	56.9	**69.7**

DST brings improvement on all the datasets

Ablation Study

Ablation study on CIFAR-100 with different pre-trained models

Method	Multiple Heads	Linear Pseudo Head	Nonlinear Pseudo Head	Worst Case Estimation	Supervised Pre-training	Unsupervised Pre-training
FixMatch					53.1	51.4
Mutual Learning	✓				53.4	52.5
DST w/o worst	✓	✓			58.2	59.0
DST w/o worst	✓		✓		60.6	60.9
DST	✓		✓	✓	**70.4**	**68.2**

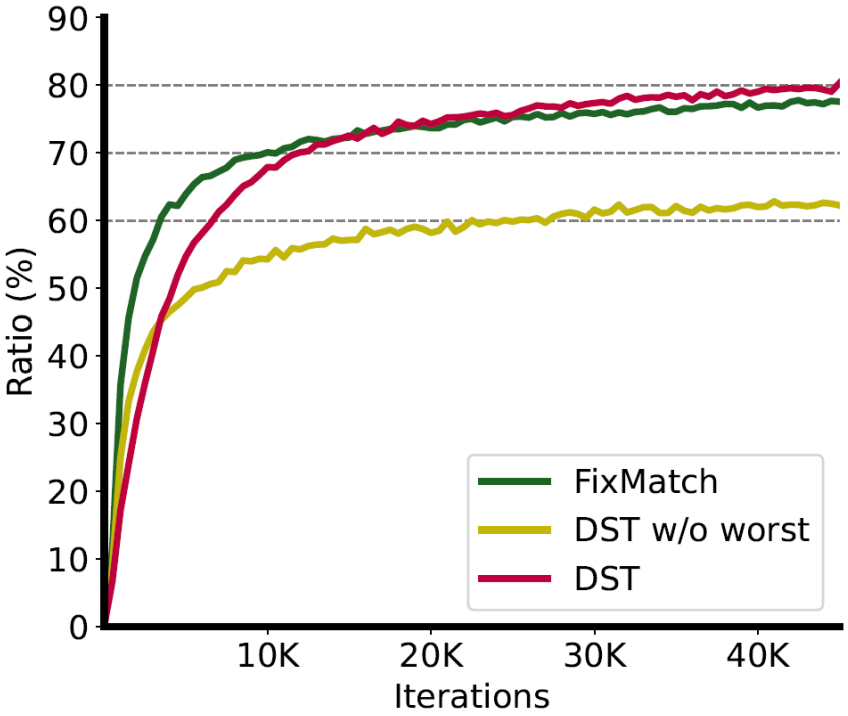
Compared with mutual learning, the decoupled pseudo labeling in DST can better reduce the training loss.

A nonlinear pseudo head is always better than a linear pseudo one. Possibly because it can reduce the degeneration of representation with biased pseudo labels.

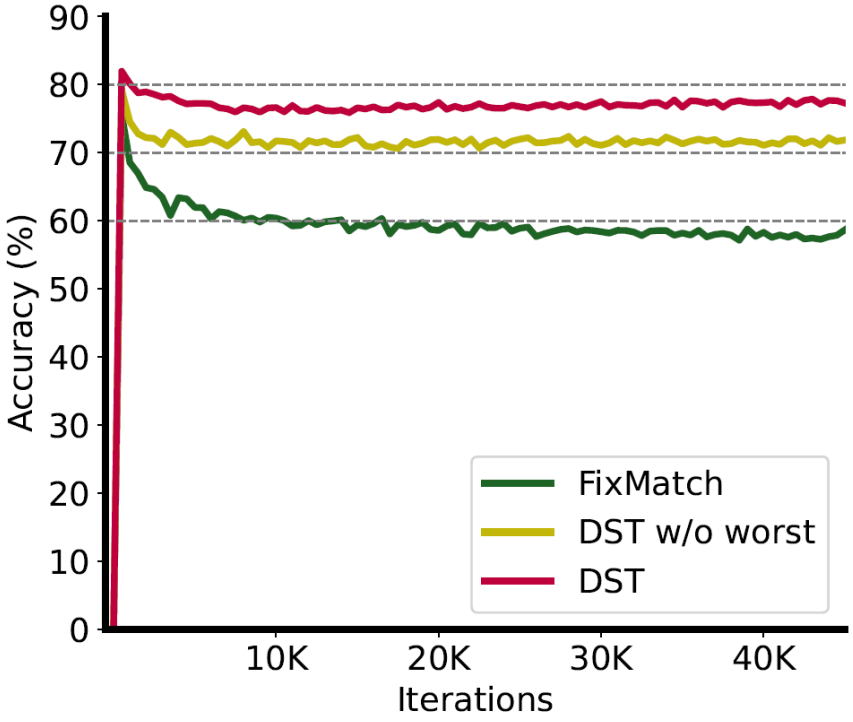
The worst-case estimation of pseudo labeling improves the performance by large margins.

Further Analysis

DST improves both the quantity and quality of pseudo labels



Quantity

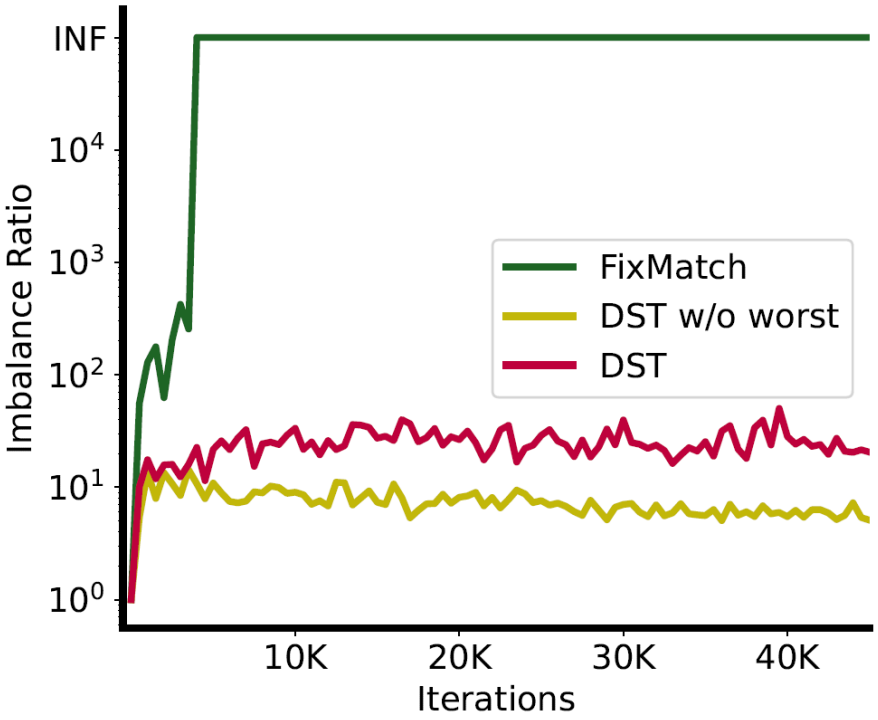


Quality

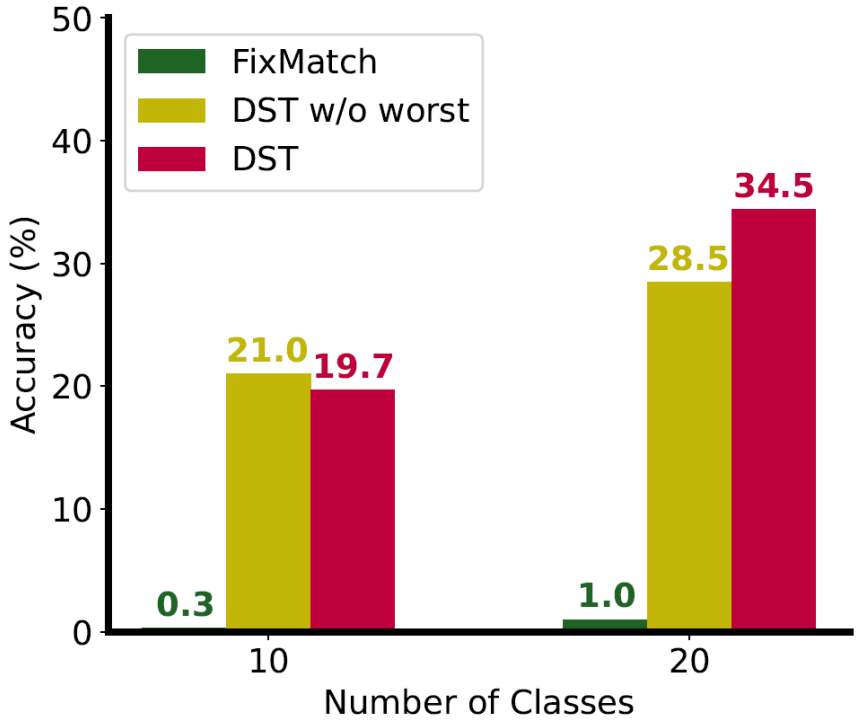
The quantity and quality of pseudo labels on CIFAR-100 (supervised pre-trained)

Further Analysis

DST generates better pseudo labels for poorly-behaved classes



Quantity of bad classes

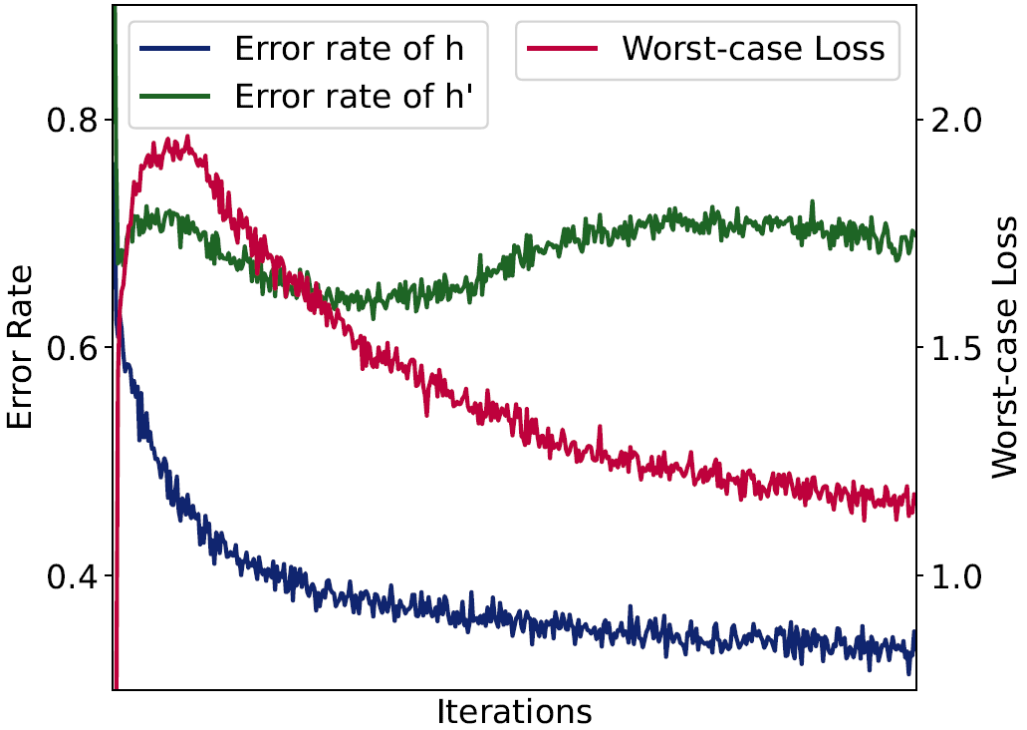


Quality of bad classes

The quantity and quality of pseudo labels on CIFAR-100 (supervised pre-trained)

Convergence and computation

DST introduces no additional computation cost during inference



Empirical error rate and loss on CIFAR-100

CIFAR-100 1000k iterations 4 x 2080 Ti GPUs	
FixMatch	***104 hours***
DST	***111 hours***

7% increase in training time

DST as a General Add-on

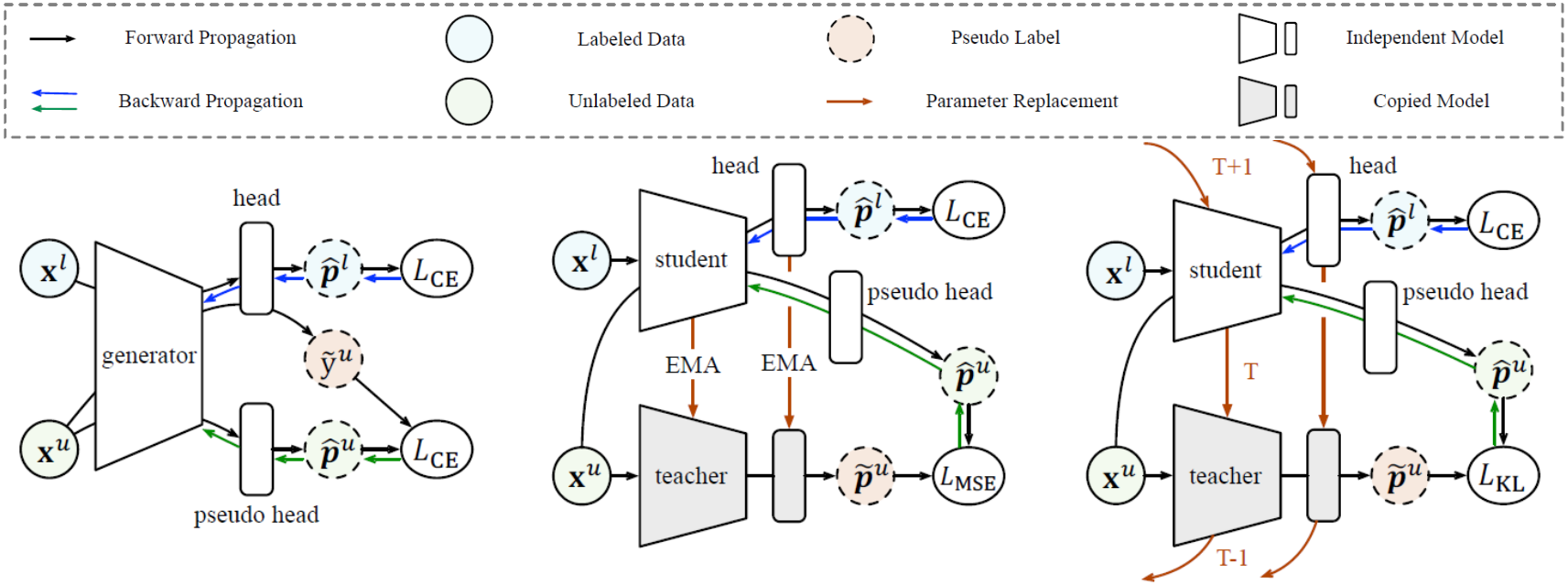
DST as a general add-on on CIFAR-100

Pre-training		Supervised		Unsupervised	
Label Amount		400	1000	400	1000
Mean Teacher	Base	56.0	67.0	51.3	63.5
	DST	**62.7**	**70.7**	**60.7**	**69.3**
Noisy Student	Base	52.8	64.3	55.6	65.8
	DST	**68.9**	**74.8**	**66.6**	**75.2**
DivideMix	Base	55.8	67.5	53.6	64.9
	DST	**69.1**	**75.1**	**65.0**	**74.2**
FixMatch	Base	53.1	67.8	51.4	64.2
	DST	**70.4**	**75.6**	**68.2**	**76.8**
FlexMatch	Base	63.4	71.2	60.2	71.1
	DST	**71.2**	**77.3**	**68.9**	**77.5**

DST yields larger improvement on all self-training methods

DST as a General Add-on

Illustrations on how different Debiased self-training methods generate and utilize pseudo labels.



Debiased FixMatch *Debiased Mean Teacher* *Debiased Noisy Student*

DST can be seamlessly incorporated into mainstream self-training methods to reduce bias and boost their performance


Thanks!