TUE-PM-333

JUNE 18-22, 2023 CVPR VANCOUVER, CANADA

On the Pitfall of Mixup for Uncertainty Calibration

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Southeast University, Tencent, CUHK

Outline

- Background
- Mixup for Calibration: Does It Really Work?
- How to Fix Mixup's Issue?
- Experiments

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- ☐ Background Uncertainty Calibration
- ☐ Mixup for Calibration: Does It Really Work? ✗
- ☐ How to Fix Mixup's Issue? The MIT Approach
- ☐ Experiments

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Background

Real-world Applications of Calibration

Autonomous driving

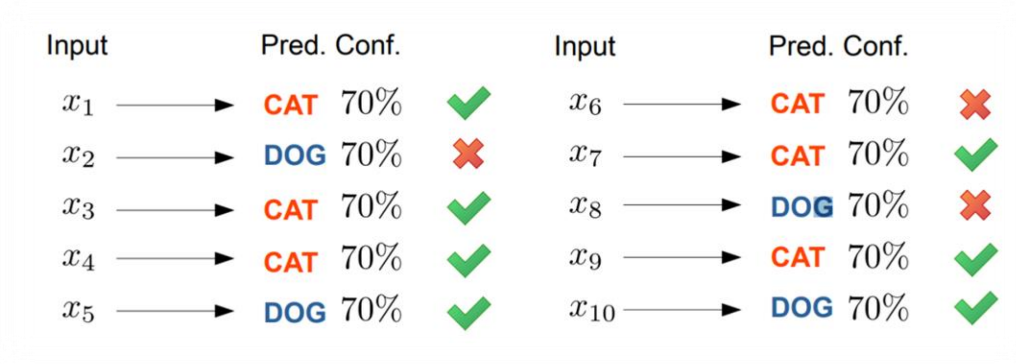
Smart healthcare

Uncertainty Calibration is important for Safety-aware Scenarios

Background

Intuitive explanation:

The average confidence reflects models's accuracy



Formally:

A perfect classifier satisfies: $\mathbb{P}(\hat{y} = y | \hat{p} = p) = p$

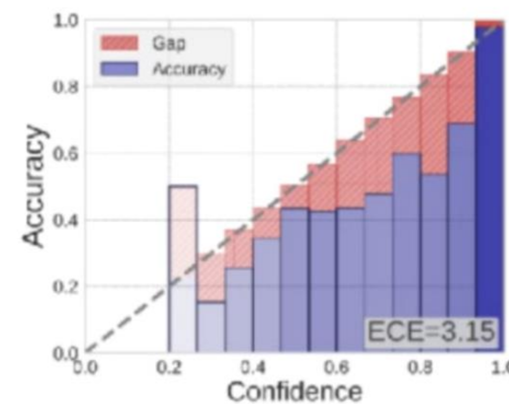
Background

Intuitive explanation:

The *average confidence* *reflects models's* *accuracy*

Input	Pred.	Conf.		Input	Pred.	Conf.	
x_1 →	CAT	70%	✓	x_6 →	CAT	70%	✗
x_2 →	DOG	70%	✗	x_7 →	CAT	70%	✓
x_3 →	CAT	70%	✓	x_8 →	DOG	70%	✗
x_4 →	CAT	70%	✓	x_9 →	CAT	70%	✓
x_5 →	DOG	70%	✓	x_{10} →	DOG	70%	✓

In a real case



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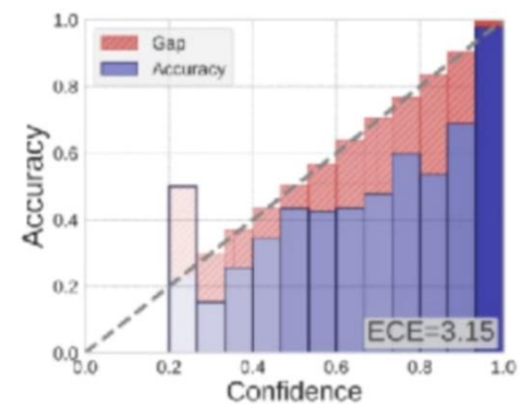
x_4	$\longrightarrow$	CAT	70%	✓	x_9	$\longrightarrow$	CAT	70%	✓
x_5	$\longrightarrow$	DOG	70%	✓	x_{10}	$\longrightarrow$	DOG	70%	✓

In a real case



Formally:

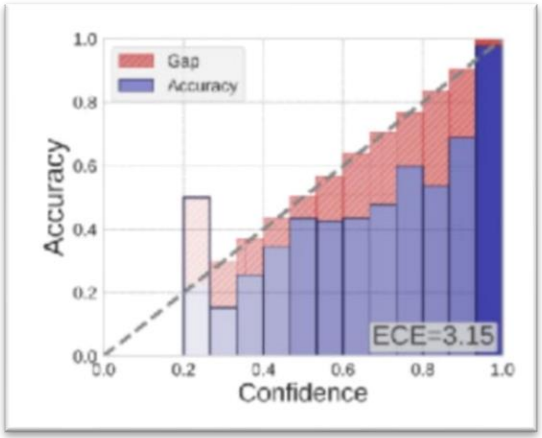
A perfect classifier satisfys: $\mathbb{P}(\hat{y} = y | \hat{p} = p) = p$

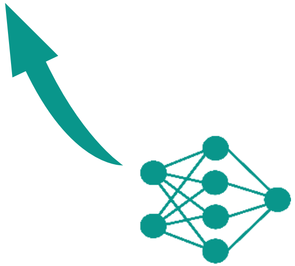
Evaluation Metric: $ECE = \sum_{m=1}^{M} \frac{|B_m|}{n} |acc(B_m) - conf(B_m)|$

Background

Solve the calibration issue: Post-hoc Calibration

raw outputs





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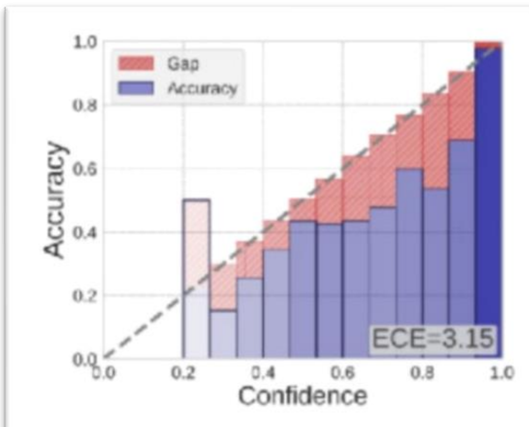

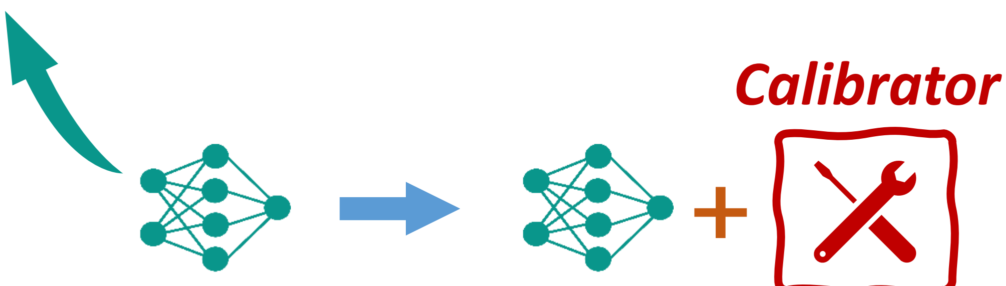

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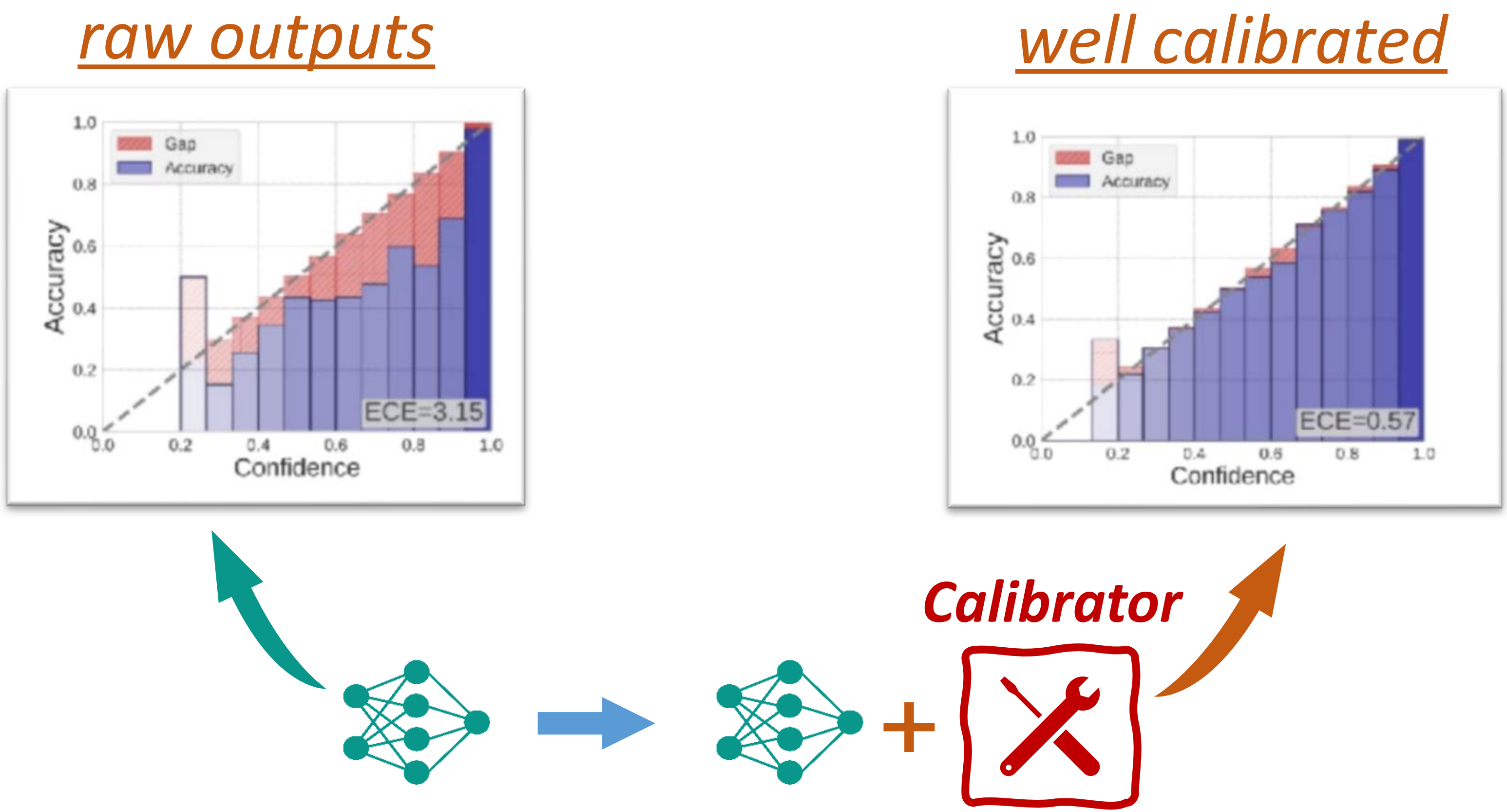
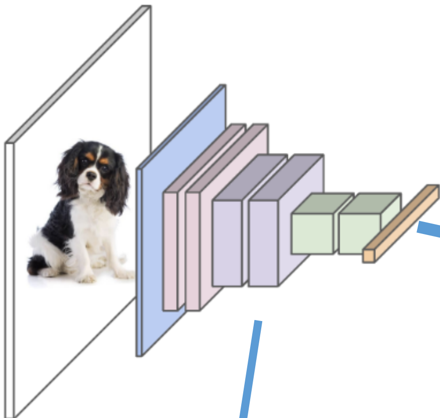


Background

Temperature Scaling



$$P_i = \frac{e^{\boxed{\frac{y_i}{T}}}}{\sum_{k=1}^{n} e^{\boxed{\frac{y_k}{T}}}}$$

Model trained on training set

Find the best T in validation set

Temperature Scaling (*TS*) achieves surprising performance

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- ◻ **Mixup for Calibration: Does It Really Work?**
- ◻ How to Fix Mixup's Issue?
- ◻ Experiments

Mixup for Calibration: Does It Really Work?

[1] On Mixup Training: Improved Calibration and Predictive Uncertainty for Deep Neural Networks, *NeurIPS 2020*

They empirically find that DNNs trained with mixup are significantly better calibrated.

[2] When and How Mixup Improves Calibration, *ICML 2022*

They theoretically prove that Mixup improves calibration in high-dimensional settings.

[3] Combining Ensembles and Data Augmentation Can Harm Your Calibration, *ICLR 2021*

Mixup may hurt calibration in some cases!

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[4] Pitfalls of in-domain uncertainty estimation and ensembling in deep learning, *ICLR 2019*

Comparison without post-hoc calibration might be not fair.

 +  **Does mixup really improve Calibration?**

Mixup for Calibration: Does It Really Work?

$$P_i = \frac{e^{\boxed{\frac{y_i}{T}}}}{\sum_{k=1}^{n} e^{\boxed{\frac{y_k}{T}}}}$$

Temperature Scaling (TS)

Datasets	Metrics	ERM				mixup ($\alpha=0.1$)				mixup ($\alpha=0.5$)				mixup ($\alpha=1.0$)			
SVHN	ECE	2.15	2.67	2.43	2.56	3.96	1.89▲	2.46	1.38▲	11.2	9.48	8.04	9.37	14.8	13.7	13.8	12.9
	Calibrated ECE	0.50	0.87	0.75	0.90	0.99▼	1.03▼	1.08▼	1.05▼	1.23▼	1.21▼	1.28▼	1.21▼	1.12▼	1.18▼	1.14▼	1.04▼
	Optimal ECE	0.24	0.56	0.45	0.58	0.75▼	0.74▼	0.85▼	0.68▼	1.12▼	0.95▼	0.95▼	0.88▼	1.04▼	0.98▼	0.88▼	0.78▼
CIFAR-10	ECE	3.33	3.99	3.78	3.47	2.57▲	2.22▲	2.55▲	2.53▲	6.87	6.25	6.55	6.20	12.1	11.5	10.5	11.2
	Calibrated ECE	0.65	0.79	0.83	0.65	1.04▼	1.07▼	1.08▼	1.12▼	1.15▼	1.15▼	0.95▼	1.05▼	0.94▼	0.91▼	0.83	0.76▼
	Optimal ECE	0.59	0.63	0.61	0.52	0.97▼	0.98▼	1.01▼	1.01▼	0.97▼	1.03▼	0.88▼	0.88▼	0.85▼	0.80▼	0.71▼	0.65▼
CIFAR-100	ECE	10.9	12.5	11.9	11.7	2.43▲	6.63▲	5.95▲	5.59▲	10.8▲	3.89▲	3.91▲	3.85▲	13.0	7.44▲	7.50▲	7.55▲
	Calibrated ECE	2.56	2.41	2.64	2.42	1.76	1.87	1.37	1.67	1.22	2.63▼	3.21▼	2.57▼	1.25	2.66▼	3.02▼	3.52▼
	Optimal ECE	2.45	2.29	2.44	2.31	1.60	1.59	1.23	1.45	0.98	2.46▼	3.04▼	2.39▼	1.09	2.54▼	2.85▼	3.38▼
Tiny-ImageNet	ECE	23.2	20.5	20.7	21.6	8.57▲	7.51▲	9.76▲	10.4▲	3.98▲	3.92▲	2.16▲	3.29▲	6.85▲	7.44▲	4.98▲	5.93▲
	Calibrated ECE	1.33	1.23	1.36	1.33	1.32	1.28▼	1.55▼	2.08▼	1.33	1.46▼	1.52▼	1.82▼	1.49▼	1.65▼	2.26▼	2.00▼
	Optimal ECE	1.14	1.00	1.16	1.16	1.02	1.05▼	1.40▼	1.93▼	1.08	1.21▼	1.23▼	1.60▼	1.20▼	1.30▼	1.91▼	1.69▼

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Without TS

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$$\begin{aligned} \widetilde{x}_i &= \bar{x} + \bar{\lambda}(x_i - \bar{x}) + (\lambda - \bar{\lambda})x_i + (1-\lambda)x_j - (1-\bar{\lambda})\bar{x}, \\ \widetilde{y}_i &= \underbrace{\bar{y} + \bar{\lambda}(y_i - \bar{y})}_{\text{Data Transformation } x'_i, y'_i} + \underbrace{(\lambda - \bar{\lambda})y_i + (1-\lambda)y_j - (1-\bar{\lambda})\bar{y}}_{\text{Random Perturbation } \epsilon_i^x, \epsilon_i^y}, \end{aligned} \quad (2)$$

where $\bar{x}, \bar{y}$ *are the mean of inputs and labels of all training samples, and the perturbation terms satisfy* $\mathbb{E}_{\lambda,j}\epsilon_i^x = \mathbb{E}_{\lambda,j}\epsilon_i^y = 0$.

Mixup

↓

Data Augmentation

+

Label Smoothing

Label smoothing hurts post-hoc calibration! ***[4]***

[3] On mixup regularization, JMLR 2022

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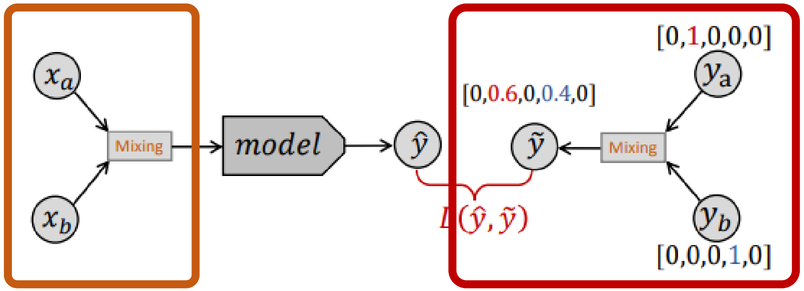
How to Fix Mixup's Issue?

Avoiding label smoothing, but remaining data augmentation



Data augmentation

(a) Mixup

Label smoothing

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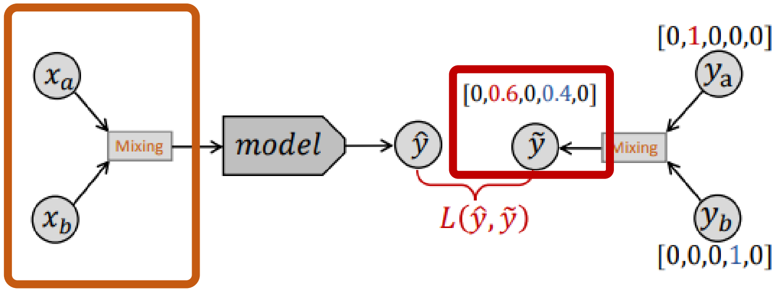

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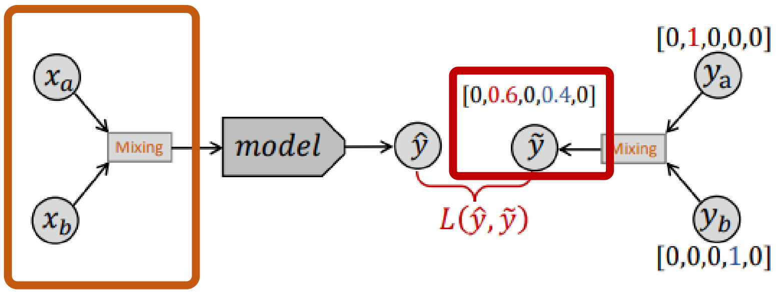

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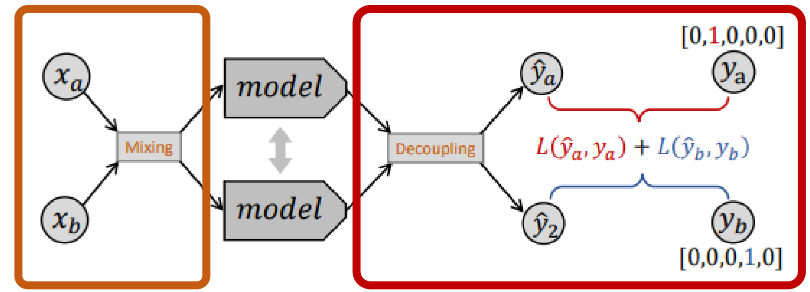


(b) MIT-L

~~Label smoothing~~

Decoupling

How to Fix Mixup's Issue?

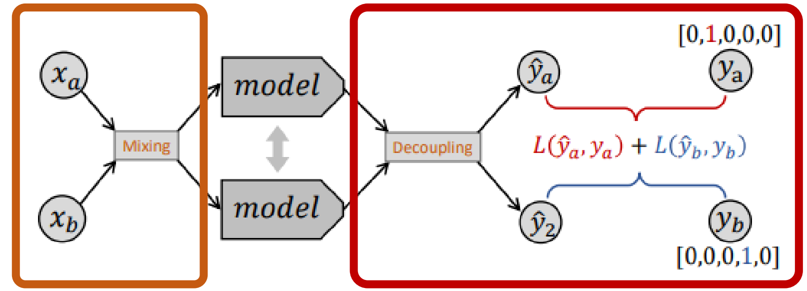
Avoiding label smoothing, but remaining data augmentation

Remark 2. *Recall the basic idea of mixup: linear interpolations of feature vectors should lead to linear interpolations of the output space. Based on this assumption, by mixing two samples twice with $\lambda_1 \neq \lambda_2 \in (0,1)$, as is*

$$\begin{aligned} \widetilde{x}_1 &= \lambda_1 x_a + (1-\lambda_1) x_b, \\ \widetilde{x}_2 &= \lambda_2 x_a + (1-\lambda_2) x_b, \end{aligned} \tag{3}$$

we can decouple these two samples in outputs space:

$$\begin{aligned} \widehat{y}_a &= \frac{f(\widetilde{x}_1) - f(\widetilde{x}_2)(1-\lambda_1)/(1-\lambda_2)}{\lambda_1 - \lambda_2(1-\lambda_1)/(1-\lambda_2)}, \\ \widehat{y}_b &= \frac{f(\widetilde{x}_1) - f(\widetilde{x}_2)\lambda_2/\lambda_1}{1-\lambda_2-(1-\lambda_1)\lambda_2/\lambda_1}. \end{aligned} \tag{4}$$



(b) MIT-L

~~Label smoothing~~

Decoupling

Outline

- Background
- Mixup for Calibration: Does It Really Work?
- How to Fix Mixup's Issue?
- **Experiments**

Experiments

ECE ↓

	Backbones	ERM	Mixup (0.1)	Mixup (0.5)	Mixup (1.0)	Mixup (DT)	Mixup (TO)	Mixup (SC)	Mixup (IO)	**MIT-A**	**MIT-L** ($\Delta\lambda > \frac{1}{2}$)	**MIT-A** ($\Delta\lambda > \frac{1}{2}$)
SVHN	ResNet18	0.50 (2)	0.99 (7)	1.23 (11)	1.12 (10)	1.01 (8)	1.05 (9)	0.50 (3)	0.61 (5)	**0.47 (1)**	0.65 (6)	0.53 (4)
	ResNet50	0.87 (6)	1.03 (7)	1.21 (9)	1.18 (8)	1.55 (11)	1.39 (10)	0.59 (4)	0.50 (2)	**0.49 (1)**	0.52 (3)	0.66 (5)
	ResNet110	0.75 (6)	1.08 (7)	1.28 (9)	1.14 (8)	1.39 (10)	1.43 (11)	0.50 (2)	0.60 (4)	**0.48 (1)**	0.53 (3)	0.70 (5)
	ResNet152	0.90 (6)	1.05 (8)	1.21 (9)	1.04 (7)	1.28 (10)	1.37 (11)	0.57 (2)	0.65 (4)	0.61 (3)	**0.53 (1)**	0.67 (5)
	Avg. gain	—	+ 0.28	+ 0.47	+ 0.36	+ 0.55	+ 0.55	– 0.21	– 0.16	– 0.24	– 0.19	– 0.11
CIFAR-10	ResNet18	0.65 (6)	1.04 (8)	1.15 (9)	0.94 (7)	1.70 (11)	1.45 (10)	0.62 (4)	0.61 (3)	**0.56 (1)**	0.59 (2)	0.62 (5)
	ResNet50	0.79 (6)	1.07 (8)	1.15 (9)	0.91 (7)	1.81 (11)	1.64 (10)	0.65 (4)	**0.46 (1)**	0.63 (3)	0.59 (2)	0.68 (5)
	ResNet110	0.83 (7)	1.08 (9)	0.95 (8)	0.83 (6)	1.52 (10)	1.56 (11)	0.54 (3)	**0.50 (1)**	0.52 (2)	0.54 (4)	0.78 (5)
	ResNet152	0.65 (4)	1.12 (9)	1.05 (8)	0.76 (7)	1.55 (11)	1.42 (10)	0.67 (5)	**0.48 (1)**	0.57 (3)	0.50 (2)	0.67 (6)
	Avg. gain	—	+ 0.34	+ 0.34	+ 0.13	+ 0.91	+ 0.78	– 0.11	– 0.21	– 0.15	– 0.17	– 0.04
CIFAR-100	ResNet18	2.56 (9)	1.76 (5)	**1.22 (1)**	1.25 (2)	5.24 (11)	3.33 (10)	2.00 (7)	1.87 (6)	1.44 (3)	2.18 (8)	1.75 (4)
	ResNet50	2.41 (7)	1.87 (2)	2.63 (8)	2.66 (9)	4.86 (11)	4.55 (10)	**1.82 (1)**	2.10 (5)	1.90 (3)	2.15 (6)	1.97 (4)
	ResNet110	2.64 (7)	**1.37 (1)**	3.21 (9)	3.02 (8)	4.70 (11)	4.45 (10)	1.76 (2)	1.93 (3)	1.98 (4)	2.25 (6)	2.00 (5)
	ResNet152	2.42 (6)	1.67 (2)	2.57 (8)	3.52 (9)	4.19 (11)	3.97 (10)	**1.65 (1)**	1.98 (4)	1.71 (3)	2.47 (7)	2.17 (5)
	Avg. gain	—	– 0.84	– 0.10	+ 0.10	+ 2.24	+ 1.56	– 0.69	– 0.53	– 0.74	– 0.24	– 0.53
Tiny-ImageNet	ResNet18	1.33 (4)	1.32 (2)	1.33 (3)	1.49 (8)	2.22 (11)	1.55 (10)	1.38 (5)	**1.30 (1)**	1.47 (7)	1.54 (9)	1.41 (6)
	ResNet50	1.23 (3)	1.28 (4)	1.46 (6)	1.65 (9)	2.08 (11)	1.83 (10)	1.59 (8)	1.58 (7)	**1.18 (1)**	1.23 (2)	1.36 (5)
	ResNet110	1.36 (4)	1.55 (8)	1.52 (7)	2.26 (11)	2.14 (10)	**1.28 (1)**	1.92 (9)	1.49 (6)	1.35 (3)	1.29 (2)	1.39 (5)
	ResNet152	1.33 (3)	2.08 (10)	1.82 (7)	2.00 (8)	1.81 (6)	2.06 (9)	1.46 (5)	2.19 (11)	1.43 (4)	**1.17 (1)**	1.30 (2)
	ResNet18†	1.12 (2)	1.43 (5)	1.22 (3)	1.31 (4)	2.83 (11)	1.90 (10)	1.58 (7)	1.72 (8)	1.56 (6)	1.79 (9)	**1.11 (1)**
	ResNet152†	1.96 (6)	1.57 (4)	2.75 (9)	2.74 (8)	4.83 (10)	6.60 (11)	**1.19 (1)**	1.68 (5)	1.37 (3)	2.58 (7)	1.26 (2)
	Avg. gain	—	+ 0.14	+ 0.29	+ 0.51	+ 1.26	+ 1.14	+ 0.13	+ 0.27	0.00	+ 0.21	– 0.08

Experiments

ECE ↓

	Backbones	ERM	Mixup (0.1)	Mixup (0.5)	Mixup (1.0)	Mixup (DT)	Mixup (TO)	Mixup (SC)	Mixup (IO)	**MIT-A**	**MIT-L** ($\Delta\lambda > \frac{1}{2}$)	**MIT-A** ($\Delta\lambda > \frac{1}{2}$)
SVHN	ResNet18	0.50 (2)	0.99 (7)	1.23 (11)	1.12 (10)	1.01 (8)	1.05 (9)	0.50 (3)	0.61 (5)	**0.47 (1)**	0.65 (6)	0.53 (4)
	ResNet50	0.87 (6)	1.03 (7)	1.21 (9)	1.18 (8)	1.55 (11)	1.39 (10)	0.59 (4)	0.50 (2)	**0.49 (1)**	0.52 (3)	0.66 (5)
	ResNet110	0.75 (6)	1.08 (7)	1.28 (9)	1.14 (8)	1.39 (10)	1.43 (11)	0.50 (2)	0.60 (4)	**0.48 (1)**	0.53 (3)	0.70 (5)
	ResNet152	0.90 (6)	1.05 (8)	1.21 (9)	1.04 (7)	1.28 (10)	1.37 (11)	0.57 (2)	0.65 (4)	0.61 (3)	**0.53 (1)**	0.67 (5)
	Avg. gain	—	+ 0.28	+ 0.47	+ 0.36	+ 0.55	+ 0.55	– 0.21	– 0.16	– 0.24	– 0.19	– 0.11
CIFAR-10	ResNet18	0.65 (6)	1.04 (8)	1.15 (9)	0.94 (7)	1.70 (11)	1.45 (10)	0.62 (4)	0.61 (3)	**0.56 (1)**	0.59 (2)	0.62 (5)
	ResNet50	0.79 (6)	1.07 (8)	1.15 (9)	0.91 (7)	1.81 (11)	1.64 (10)	0.65 (4)	**0.46 (1)**	0.63 (3)	0.59 (2)	0.68 (5)
	ResNet110	0.83 (7)	1.08 (9)	0.95 (8)	0.83 (6)	1.52 (10)	1.56 (11)	0.54 (3)	**0.50 (1)**	0.52 (2)	0.54 (4)	0.78 (5)
	ResNet152	0.65 (4)	1.12 (9)	1.05 (8)	0.76 (7)	1.55 (11)	1.42 (10)	0.67 (5)	**0.48 (1)**	0.57 (3)	0.50 (2)	0.67 (6)
	Avg. gain	—	+ 0.34	+ 0.34	+ 0.13	+ 0.91	+ 0.78	– 0.11	– 0.21	– 0.15	– 0.17	– 0.04
CIFAR-100	ResNet18	2.56 (9)	1.76 (5)	**1.22 (1)**	1.25 (2)	5.24 (11)	3.33 (10)	2.00 (7)	1.87 (6)	1.44 (3)	2.18 (8)	1.75 (4)
	ResNet50	2.41 (7)	1.87 (2)	2.63 (8)	2.66 (9)	4.86 (11)	4.55 (10)	**1.82 (1)**	2.10 (5)	1.90 (3)	2.15 (6)	1.97 (4)
	ResNet110	2.64 (7)	**1.37 (1)**	3.21 (9)	3.02 (8)	4.70 (11)	4.45 (10)	1.76 (2)	1.93 (3)	1.98 (4)	2.25 (6)	2.00 (5)
	ResNet152	2.42 (6)	1.67 (2)	2.57 (8)	3.52 (9)	4.19 (11)	3.97 (10)	**1.65 (1)**	1.98 (4)	1.71 (3)	2.47 (7)	2.17 (5)
	Avg. gain	—	– 0.84	– 0.10	+ 0.10	+ 2.24	+ 1.56	– 0.69	– 0.53	– 0.74	– 0.24	– 0.53
Tiny-ImageNet	ResNet18	1.33 (4)	1.32 (2)	1.33 (3)	1.49 (8)	2.22 (11)	1.55 (10)	1.38 (5)	**1.30 (1)**	1.47 (7)	1.54 (9)	1.41 (6)
	ResNet50	1.23 (3)	1.28 (4)	1.46 (6)	1.65 (9)	2.08 (11)	1.83 (10)	1.59 (8)	1.58 (7)	**1.18 (1)**	1.23 (2)	1.36 (5)
	ResNet110	1.36 (4)	1.55 (8)	1.52 (7)	2.26 (11)	2.14 (10)	**1.28 (1)**	1.92 (9)	1.49 (6)	1.35 (3)	1.29 (2)	1.39 (5)
	ResNet152	1.33 (3)	2.08 (10)	1.82 (7)	2.00 (8)	1.81 (6)	2.06 (9)	1.46 (5)	2.19 (11)	1.43 (4)	**1.17 (1)**	1.30 (2)
	ResNet18†	1.12 (2)	1.43 (5)	1.22 (3)	1.31 (4)	2.83 (11)	1.90 (10)	1.58 (7)	1.72 (8)	1.56 (6)	1.79 (9)	**1.11 (1)**
	ResNet152†	1.96 (6)	1.57 (4)	2.75 (9)	2.74 (8)	4.83 (10)	6.60 (11)	**1.19 (1)**	1.68 (5)	1.37 (3)	2.58 (7)	1.26 (2)
	Avg. gain	—	+ 0.14	+ 0.29	+ 0.51	+ 1.26	+ 1.14	+ 0.13	+ 0.27	0.00	+ 0.21	– 0.08

Experiments

ECE ↓

						With LS		Without LS				
	Backbones	ERM	Mixup (0.1)	Mixup (0.5)	Mixup (1.0)	Mixup (DT)	Mixup (TO)	Mixup (SC)	Mixup (IO)	**MIT-A**	**MIT-L ($\Delta\lambda>\frac{1}{2}$)**	**MIT-A ($\Delta\lambda>\frac{1}{2}$)**
SVHN	ResNet18	0.50 (2)	0.99 (7)	1.23 (11)	1.12 (10)	1.01 (8)	1.05 (9)	0.50 (3)	0.61 (5)	**0.47 (1)**	0.65 (6)	0.53 (4)
	ResNet50	0.87 (6)	1.03 (7)	1.21 (9)	1.18 (8)	1.55 (11)	1.39 (10)	0.59 (4)	0.50 (2)	**0.49 (1)**	0.52 (3)	0.66 (5)
	ResNet110	0.75 (6)	1.08 (7)	1.28 (9)	1.14 (8)	1.39 (10)	1.43 (11)	0.50 (2)	0.60 (4)	**0.48 (1)**	0.53 (3)	0.70 (5)
	ResNet152	0.90 (6)	1.05 (8)	1.21 (9)	1.04 (7)	1.28 (10)	1.37 (11)	0.57 (2)	0.65 (4)	0.61 (3)	**0.53 (1)**	0.67 (5)
	Avg. gain	—	+ 0.28	+ 0.47	+ 0.36	+ 0.55	+ 0.55	– 0.21	– 0.16	– 0.24	– 0.19	– 0.11
CIFAR-10	ResNet18	0.65 (6)	1.04 (8)	1.15 (9)	0.94 (7)	1.70 (11)	1.45 (10)	0.62 (4)	0.61 (3)	**0.56 (1)**	0.59 (2)	0.62 (5)
	ResNet50	0.79 (6)	1.07 (8)	1.15 (9)	0.91 (7)	1.81 (11)	1.64 (10)	0.65 (4)	**0.46 (1)**	0.63 (3)	0.59 (2)	0.68 (5)
	ResNet110	0.83 (7)	1.08 (9)	0.95 (8)	0.83 (6)	1.52 (10)	1.56 (11)	0.54 (3)	**0.50 (1)**	0.52 (2)	0.54 (4)	0.78 (5)
	ResNet152	0.65 (4)	1.12 (9)	1.05 (8)	0.76 (7)	1.55 (11)	1.42 (10)	0.67 (5)	**0.48 (1)**	0.57 (3)	0.50 (2)	0.67 (6)
	Avg. gain	—	+ 0.34	+ 0.34	+ 0.13	+ 0.91	+ 0.78	– 0.11	– 0.21	– 0.15	– 0.17	– 0.04
CIFAR-100	ResNet18	2.56 (9)	1.76 (5)	**1.22 (1)**	1.25 (2)	5.24 (11)	3.33 (10)	2.00 (7)	1.87 (6)	1.44 (3)	2.18 (8)	1.75 (4)
	ResNet50	2.41 (7)	1.87 (2)	2.63 (8)	2.66 (9)	4.86 (11)	4.55 (10)	**1.82 (1)**	2.10 (5)	1.90 (3)	2.15 (6)	1.97 (4)
	ResNet110	2.64 (7)	**1.37 (1)**	3.21 (9)	3.02 (8)	4.70 (11)	4.45 (10)	1.76 (2)	1.93 (3)	1.98 (4)	2.25 (6)	2.00 (5)
	ResNet152	2.42 (6)	1.67 (2)	2.57 (8)	3.52 (9)	4.19 (11)	3.97 (10)	**1.65 (1)**	1.98 (4)	1.71 (3)	2.47 (7)	2.17 (5)
	Avg. gain	—	– 0.84	– 0.10	+ 0.10	+ 2.24	+ 1.56	– 0.69	– 0.53	– 0.74	– 0.24	– 0.53
Tiny-ImageNet	ResNet18	1.33 (4)	1.32 (2)	1.33 (3)	1.49 (8)	2.22 (11)	1.55 (10)	1.38 (5)	**1.30 (1)**	1.47 (7)	1.54 (9)	1.41 (6)
	ResNet50	1.23 (3)	1.28 (4)	1.46 (6)	1.65 (9)	2.08 (11)	1.83 (10)	1.59 (8)	1.58 (7)	**1.18 (1)**	1.23 (2)	1.36 (5)
	ResNet110	1.36 (4)	1.55 (8)	1.52 (7)	2.26 (11)	2.14 (10)	**1.28 (1)**	1.92 (9)	1.49 (6)	1.35 (3)	1.29 (2)	1.39 (5)
	ResNet152	1.33 (3)	2.08 (10)	1.82 (7)	2.00 (8)	1.81 (6)	2.06 (9)	1.46 (5)	2.19 (11)	1.43 (4)	**1.17 (1)**	1.30 (2)
	ResNet18†	1.12 (2)	1.43 (5)	1.22 (3)	1.31 (4)	2.83 (11)	1.90 (10)	1.58 (7)	1.72 (8)	1.56 (6)	1.79 (9)	**1.11 (1)**
	ResNet152†	1.96 (6)	1.57 (4)	2.75 (9)	2.74 (8)	4.83 (10)	6.60 (11)	**1.19 (1)**	1.68 (5)	1.37 (3)	2.58 (7)	1.26 (2)
	Avg. gain	—	+ 0.14	+ 0.29	+ 0.51	+ 1.26	+ 1.14	+ 0.13	+ 0.27	0.00	+ 0.21	– 0.08

Experiments

ECE ↓

	Backbones	ERM	Mixup (0.1)	Mixup (0.5)	Mixup (1.0)	Mixup (DT)	Mixup (TO)	Mixup (SC)	Mixup (IO)	MIT-A	MIT-L ($\Delta\lambda>\frac{1}{2}$)	MIT-A ($\Delta\lambda>\frac{1}{2}$)
SVHN	ResNet18	0.50 (2)	0.99 (7)	1.23 (11)	1.12 (10)	1.01 (8)	1.05 (9)	0.50 (3)	0.61 (5)	**0.47 (1)**	0.65 (6)	0.53 (4)
	ResNet50	0.87 (6)	1.03 (7)	1.21 (9)	1.18 (8)	1.55 (11)	1.39 (10)	0.59 (4)	0.50 (2)	**0.49 (1)**	0.52 (3)	0.66 (5)
	ResNet110	0.75 (6)	1.08 (7)	1.28 (9)	1.14 (8)	1.39 (10)	1.43 (11)	0.50 (2)	0.60 (4)	**0.48 (1)**	0.53 (3)	0.70 (5)
	ResNet152	0.90 (6)	1.05 (8)	1.21 (9)	1.04 (7)	1.28 (10)	1.37 (11)	0.57 (2)	0.65 (4)	0.61 (3)	**0.53 (1)**	0.67 (5)
	Avg. gain	—	+ 0.28	+ 0.47	+ 0.36	+ 0.55	+ 0.55	– 0.21	– 0.16	– 0.24	– 0.19	– 0.11
CIFAR-10	ResNet18	0.65 (6)	1.04 (8)	1.15 (9)	0.94 (7)	1.70 (11)	1.45 (10)	0.62 (4)	0.61 (3)	**0.56 (1)**	0.59 (2)	0.62 (5)
	ResNet50	0.79 (6)	1.07 (8)	1.15 (9)	0.91 (7)	1.81 (11)	1.64 (10)	0.65 (4)	**0.46 (1)**	0.63 (3)	0.59 (2)	0.68 (5)
	ResNet110	0.83 (7)	1.08 (9)	0.95 (8)	0.83 (6)	1.52 (10)	1.56 (11)	0.54 (3)	**0.50 (1)**	0.52 (2)	0.54 (4)	0.78 (5)
	ResNet152	0.65 (4)	1.12 (9)	1.05 (8)	0.76 (7)	1.55 (11)	1.42 (10)	0.67 (5)	**0.48 (1)**	0.57 (3)	0.50 (2)	0.67 (6)
	Avg. gain	—	+ 0.34	+ 0.34	+ 0.13	+ 0.91	+ 0.78	– 0.11	– 0.21	– 0.15	– 0.17	– 0.04
CIFAR-100	ResNet18	2.56 (9)	1.76 (5)	**1.22 (1)**	1.25 (2)	5.24 (11)	3.33 (10)	2.00 (7)	1.87 (6)	1.44 (3)	2.18 (8)	1.75 (4)
	ResNet50	2.41 (7)	1.87 (2)	2.63 (8)	2.66 (9)	4.86 (11)	4.55 (10)	**1.82 (1)**	2.10 (5)	1.90 (3)	2.15 (6)	1.97 (4)
	ResNet110	2.64 (7)	**1.37 (1)**	3.21 (9)	3.02 (8)	4.70 (11)	4.45 (10)	1.76 (2)	1.93 (3)	1.98 (4)	2.25 (6)	2.00 (5)
	ResNet152	2.42 (6)	1.67 (2)	2.57 (8)	3.52 (9)	4.19 (11)	3.97 (10)	**1.65 (1)**	1.98 (4)	1.71 (3)	2.47 (7)	2.17 (5)
	Avg. gain	—	– 0.84	– 0.10	+ 0.10	+ 2.24	+ 1.56	– 0.69	– 0.53	– 0.74	– 0.24	– 0.53
Tiny-ImageNet	ResNet18	1.33 (4)	1.32 (2)	1.33 (3)	1.49 (8)	2.22 (11)	1.55 (10)	1.38 (5)	**1.30 (1)**	1.47 (7)	1.54 (9)	1.41 (6)
	ResNet50	1.23 (3)	1.28 (4)	1.46 (6)	1.65 (9)	2.08 (11)	1.83 (10)	1.59 (8)	1.58 (7)	**1.18 (1)**	1.23 (2)	1.36 (5)
	ResNet110	1.36 (4)	1.55 (8)	1.52 (7)	2.26 (11)	2.14 (10)	**1.28 (1)**	1.92 (9)	1.49 (6)	1.35 (3)	1.29 (2)	1.39 (5)
	ResNet152	1.33 (3)	2.08 (10)	1.82 (7)	2.00 (8)	1.81 (6)	2.06 (9)	1.46 (5)	2.19 (11)	1.43 (4)	**1.17 (1)**	1.30 (2)
	ResNet18†	1.12 (2)	1.43 (5)	1.22 (3)	1.31 (4)	2.83 (11)	1.90 (10)	1.58 (7)	1.72 (8)	1.56 (6)	1.79 (9)	**1.11 (1)**
	ResNet152†	1.96 (6)	1.57 (4)	2.75 (9)	2.74 (8)	4.83 (10)	6.60 (11)	**1.19 (1)**	1.68 (5)	1.37 (3)	2.58 (7)	1.26 (2)
	Avg. gain	—	+ 0.14	+ 0.29	+ 0.51	+ 1.26	+ 1.14	+ 0.13	+ 0.27	0.00	+ 0.21	– 0.08

Experiments

Without LS

Accuracy ↑

	Backbones	ERM	Mixup (0.1)	Mixup (0.5)	Mixup (1.0)	Mixup (DT)	Mixup (TO)	Mixup (SC)	Mixup (IO)	**MIT-A**	**MIT-L** ($\Delta\lambda>\frac{1}{2}$)	**MIT-A** ($\Delta\lambda>\frac{1}{2}$)
SVHN	ResNet18	95.4 (5)	95.5 (4)	94.8 (7)	94.5 (8)	95.6 (3)	**96.0 (1)**	94.3 (9)	93.5 (10	95.0 (6)	93.2 (11)	95.7 (2)
	ResNet50	96.0 (4)	96.0 (3)	95.8 (5)	95.5 (8)	95.5 (7)	95.7 (6)	95.3 (9)	94.9 (10	96.2 (2)	94.3 (11)	**96.2 (1)**
	ResNet110	96.0 (5)	96.1 (4)	96.3 (3)	95.8 (7)	95.6 (8)	95.9 (6)	95.4 (9)	95.3 (10	96.5 (2)	95.0 (11)	**96.7 (1)**
	ResNet152	96.2 (5)	96.6 (2)	96.4 (4)	96.2 (6)	95.6 (8)	95.9 (7)	95.5 (9)	95.5 (10	96.5 (3)	94.9 (11)	**96.7 (1)**
	Avg. gain	—	+ 0.11	− 0.10	− 0.40	− 0.32	− 0.06	− 0.78	− 1.12	+ 0.14	− 1.55	+ 0.41
CIFAR-10	ResNet18	94.5 (9)	95.1 (6)	95.7 (3)	95.8 (2)	93.9 (11)	94.5 (8)	94.4 (10)	94.7 (7)	95.5 (4)	95.2 (5)	**95.9 (1)**
	ResNet50	94.4 (9)	95.3 (7)	95.8 (3)	**96.0 (1)**	93.1 (11)	94.2 (10)	94.5 (8)	95.3 (6)	95.8 (4)	95.7 (5)	96.0 (2)
	ResNet110	94.7 (9)	95.7 (6)	**96.3 (1)**	96.2 (2)	93.7 (11)	94.3 (10)	95.1 (8)	95.4 (7)	96.1 (4)	96.0 (5)	96.1 (3)
	ResNet152	95.1 (8)	95.8 (7)	96.4 (2)	**96.7 (1)**	93.9 (11)	94.8 (10)	95.0 (9)	95.8 (6)	96.3 (4)	96.2 (5)	96.4 (3)
	Avg. gain	—	+ 0.78	+ 1.36	+ 1.53	− 1.01	− 0.21	+ 0.08	+ 0.64	+ 1.27	+ 1.12	+ 1.41
CIFAR-100	ResNet18	74.4 (8)	75.3 (7)	76.8 (2)	**77.2 (1)**	72.4 (11)	76.4 (4)	72.6 (9)	72.5 (10	76.2 (5)	75.9 (6)	76.6 (3)
	ResNet50	73.9 (9)	76.4 (6)	78.3 (2)	77.8 (3)	68.2 (11)	75.1 (7)	72.9 (10)	74.5 (8)	**78.3 (1)**	76.6 (5)	77.7 (4)
	ResNet110	76.1 (9)	77.9 (6)	**80.1 (1)**	79.3 (2)	70.9 (11)	77.3 (7)	74.6 (10)	76.7 (8)	78.7 (4)	77.9 (5)	79.1 (3)
	ResNet152	75.3 (9)	78.2 (6)	79.7 (2)	79.6 (3)	72.5 (11)	76.9 (7)	75.1 (10)	76.7 (8)	79.1 (4)	78.2 (5)	**79.8 (1)**
	Avg. gain	—	+ 2.01	+ 3.79	+ 3.55	− 3.92	+ 1.50	− 1.12	+ 0.18	+ 3.14	+ 2.24	+ 3.38
Tiny-ImageNet	ResNet18	46.1 (9)	46.6 (7)	47.4 (5)	47.8 (4)	36.5 (11)	47.1 (6)	43.0 (10)	46.6 (8)	**49.5 (1)**	48.5 (3)	49.3 (2)
	ResNet50	49.3 (7)	49.5 (6)	50.0 (5)	50.4 (4)	37.5 (11)	49.0 (8)	46.4 (10)	48.8 (9)	51.4 (2)	51.0 (3)	**51.8 (1)**
	ResNet110	48.5 (3)	43.6 (7)	42.7 (9)	42.6 (10)	35.6 (11)	44.6 (4)	43.9 (6)	43.5 (8)	48.6 (2)	44.4 (5)	**50.8 (1)**
	ResNet152	47.3 (2)	44.7 (5)	42.3 (9)	44.6 (6)	34.5 (11)	45.5 (4)	43.0 (8)	39.7 (10	46.1 (3)	43.8 (7)	**50.0 (1)**
	ResNet18†	53.6 (6)	53.5 (8)	54.0 (5)	53.5 (7)	44.1 (11)	**54.7 (1)**	49.7 (10)	50.5 (9)	54.5 (3)	54.4 (4)	54.7 (2)
	ResNet152†	62.4 (6)	63.2 (2)	**63.7 (1)**	63.0 (3)	49.6 (11)	62.6 (4)	58.8 (10)	59.9 (9)	61.9 (7)	62.5 (5)	61.6 (8)
	Avg. gain	—	− 1.01	− 1.18	− 0.87	− 11.5	− 0.60	− 3.70	− 3.04	+ 0.81	− 0.41	+ 1.83

Experiments

Accuracy ↑

	Backbones	ERM	Mixup (0.1)	Mixup (0.5)	Mixup (1.0)	Mixup (DT)	Mixup (TO)	Mixup (SC)	Mixup (IO)	MIT-A	MIT-L ($\Delta\lambda > \frac{1}{2}$)	MIT-A ($\Delta\lambda > \frac{1}{2}$)
SVHN	ResNet18	95.4 (5)	95.5 (4)	94.8 (7)	94.5 (8)	95.6 (3)	**96.0 (1)**	94.3 (9)	93.5 (10	95.0 (6)	93.2 (11)	95.7 (2)
	ResNet50	96.0 (4)	96.0 (3)	95.8 (5)	95.5 (8)	95.5 (7)	95.7 (6)	95.3 (9)	94.9 (10	96.2 (2)	94.3 (11)	**96.2 (1)**
	ResNet110	96.0 (5)	96.1 (4)	96.3 (3)	95.8 (7)	95.6 (8)	95.9 (6)	95.4 (9)	95.3 (10	96.5 (2)	95.0 (11)	**96.7 (1)**
	ResNet152	96.2 (5)	96.6 (2)	96.4 (4)	96.2 (6)	95.6 (8)	95.9 (7)	95.5 (9)	95.5 (10	96.5 (3)	94.9 (11)	**96.7 (1)**
	Avg. gain	—	+ 0.11	− 0.10	− 0.40	− 0.32	− 0.06	− 0.78	− 1.12	+ 0.14	− 1.55	+ 0.41
CIFAR-10	ResNet18	94.5 (9)	95.1 (6)	95.7 (3)	95.8 (2)	93.9 (11)	94.5 (8)	94.4 (10)	94.7 (7)	95.5 (4)	95.2 (5)	**95.9 (1)**
	ResNet50	94.4 (9)	95.3 (7)	95.8 (3)	**96.0 (1)**	93.1 (11)	94.2 (10)	94.5 (8)	95.3 (6)	95.8 (4)	95.7 (5)	96.0 (2)
	ResNet110	94.7 (9)	95.7 (6)	**96.3 (1)**	96.2 (2)	93.7 (11)	94.3 (10)	95.1 (8)	95.4 (7)	96.1 (4)	96.0 (5)	96.1 (3)
	ResNet152	95.1 (8)	95.8 (7)	96.4 (2)	**96.7 (1)**	93.9 (11)	94.8 (10)	95.0 (9)	95.8 (6)	96.3 (4)	96.2 (5)	96.4 (3)
	Avg. gain	—	+ 0.78	+ 1.36	+ 1.53	− 1.01	− 0.21	+ 0.08	+ 0.64	+ 1.27	+ 1.12	+ 1.41
CIFAR-100	ResNet18	74.4 (8)	75.3 (7)	76.8 (2)	**77.2 (1)**	72.4 (11)	76.4 (4)	72.6 (9)	72.5 (10	76.2 (5)	75.9 (6)	76.6 (3)
	ResNet50	73.9 (9)	76.4 (6)	78.3 (2)	77.8 (3)	68.2 (11)	75.1 (7)	72.9 (10)	74.5 (8)	**78.3 (1)**	76.6 (5)	77.7 (4)
	ResNet110	76.1 (9)	77.9 (6)	**80.1 (1)**	79.3 (2)	70.9 (11)	77.3 (7)	74.6 (10)	76.7 (8)	78.7 (4)	77.9 (5)	79.1 (3)
	ResNet152	75.3 (9)	78.2 (6)	79.7 (2)	79.6 (3)	72.5 (11)	76.9 (7)	75.1 (10)	76.7 (8)	79.1 (4)	78.2 (5)	**79.8 (1)**
	Avg. gain	—	+ 2.01	+ 3.79	+ 3.55	− 3.92	+ 1.50	− 1.12	+ 0.18	+ 3.14	+ 2.24	+ 3.38
Tiny-ImageNet	ResNet18	46.1 (9)	46.6 (7)	47.4 (5)	47.8 (4)	36.5 (11)	47.1 (6)	43.0 (10)	46.6 (8)	**49.5 (1)**	48.5 (3)	49.3 (2)
	ResNet50	49.3 (7)	49.5 (6)	50.0 (5)	50.4 (4)	37.5 (11)	49.0 (8)	46.4 (10)	48.8 (9)	51.4 (2)	51.0 (3)	**51.8 (1)**
	ResNet110	48.5 (3)	43.6 (7)	42.7 (9)	42.6 (10)	35.6 (11)	44.6 (4)	43.9 (6)	43.5 (8)	48.6 (2)	44.4 (5)	**50.8 (1)**
	ResNet152	47.3 (2)	44.7 (5)	42.3 (9)	44.6 (6)	34.5 (11)	45.5 (4)	43.0 (8)	39.7 (10	46.1 (3)	43.8 (7)	**50.0 (1)**
	ResNet18†	53.6 (6)	53.5 (8)	54.0 (5)	53.5 (7)	44.1 (11)	**54.7 (1)**	49.7 (10)	50.5 (9)	54.5 (3)	54.4 (4)	54.7 (2)
	ResNet152†	62.4 (6)	63.2 (2)	**63.7 (1)**	63.0 (3)	49.6 (11)	62.6 (4)	58.8 (10)	59.9 (9)	61.9 (7)	62.5 (5)	61.6 (8)
	Avg. gain	—	− 1.01	− 1.18	− 0.87	− 11.5	− 0.60	− 3.70	− 3.04	+ 0.81	− 0.41	+ 1.83

Thanks!

See details in our paper~ ☺

Deng-Bao Wang