

What is Mixup?

Generate additional samples by interpolating samples:

$$\tilde{x} = \lambda x_a + (1-\lambda) x_b$$

Mixing of two images

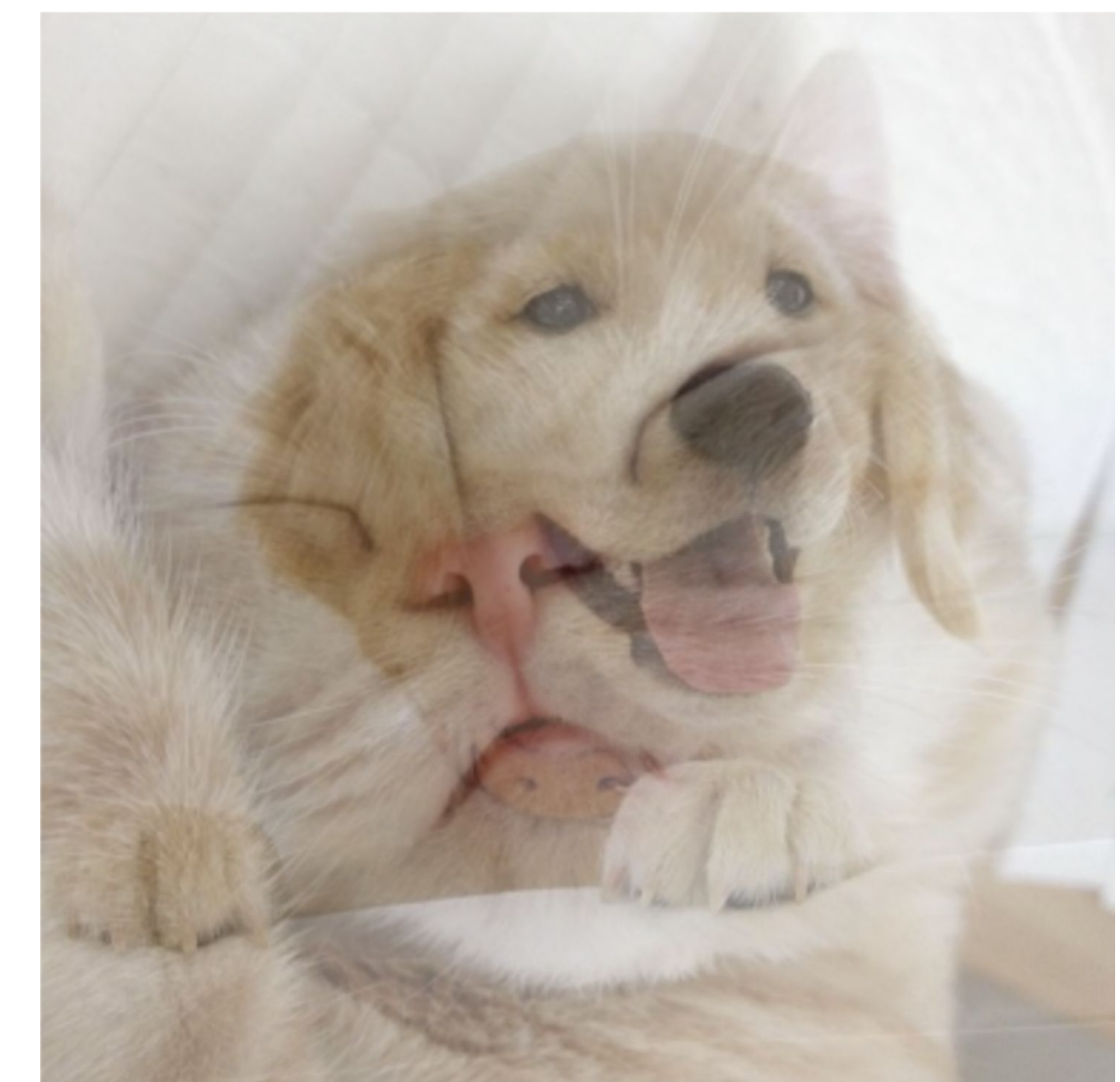
$$\tilde{y} = \lambda y_a + (1-\lambda) y_b$$

Mixing of one-hot labels

- 👍 Easy and effective way to enrich any training set
- 👍 Improves accuracy, calibration & out-of-distribution generalization
- 👎 Assumption: mixing should be done at output probability level
- 👎 Mixup wants linearity, but its not enforced in classifier space!

Motivation

Image: 40% dog and 60% cat



Mixup: Classify as 40% dog 60% cat.
Infinite Class Mixup: Classify this image 100% to the new class: 40% dog and 60% cat.

Mixup with Infinite Classes

Code available



Main idea: for each mixed sample, we construct a unique interpolated classifier:

$$w_{\tilde{c}} = \lambda w_a + (1-\lambda) w_b = W \tilde{y}$$

Optimize likelihood of interpolated classes:

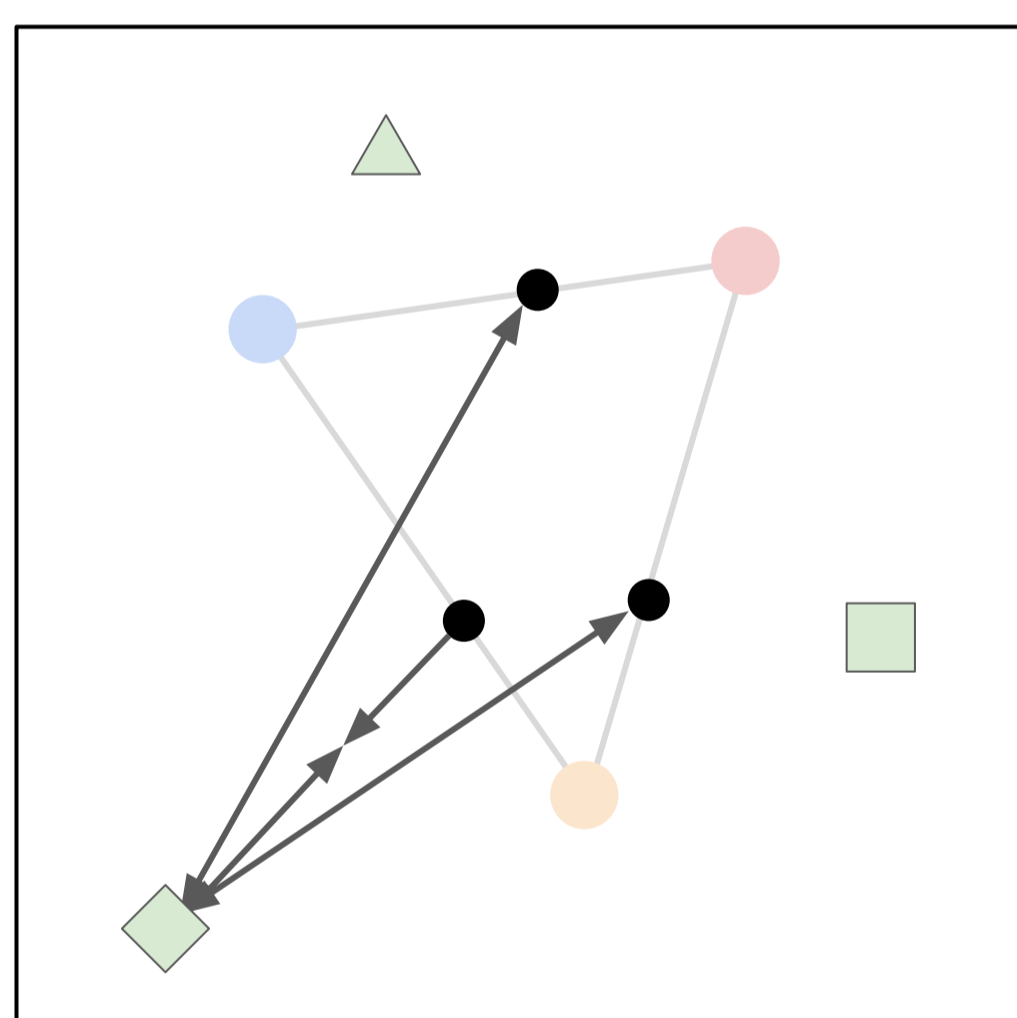
$$p(C_{\tilde{y}}|\tilde{x}) \propto \exp(f_{\theta}(\tilde{x})^T W \tilde{y})$$

via contrastive learning in two ways:

Class-axis

Contrast example against all interpolated classifiers in the batch.

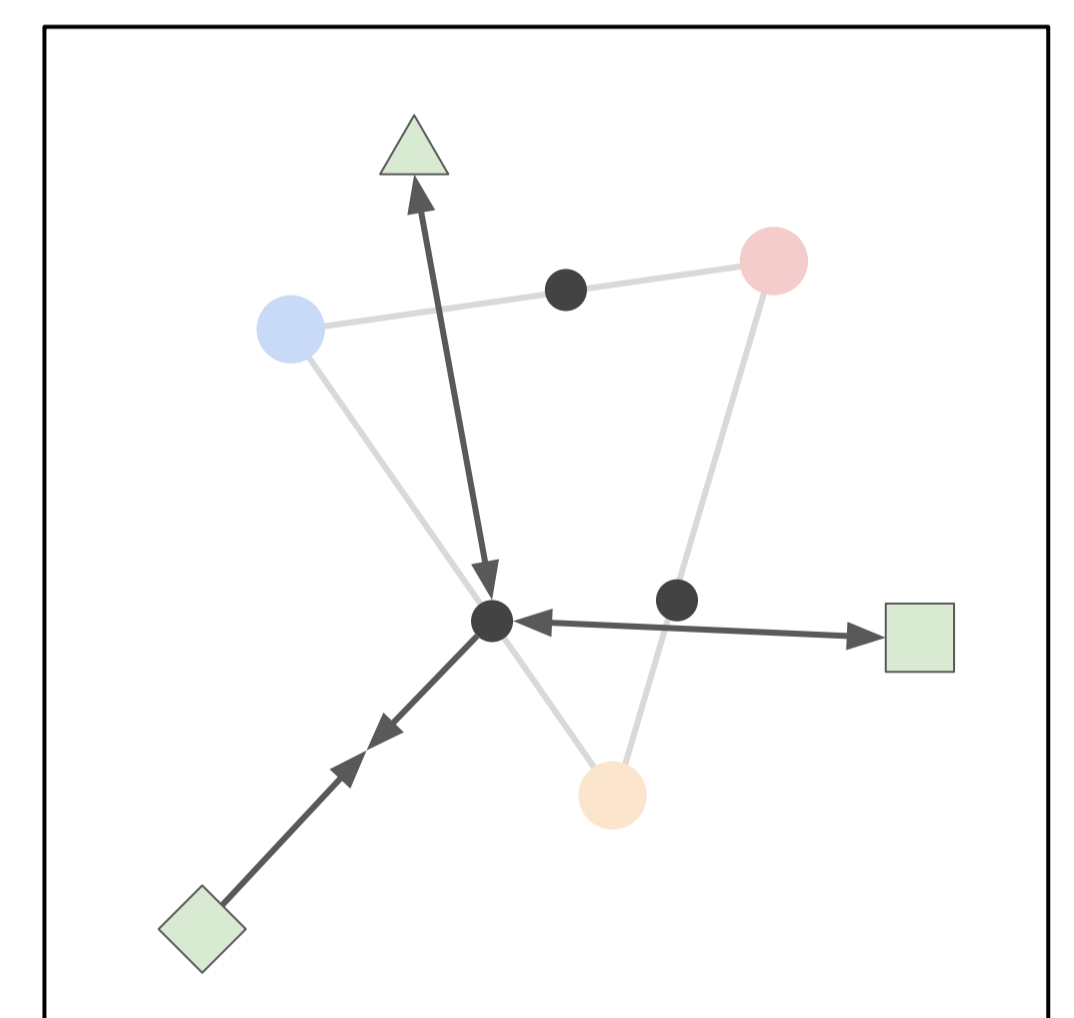
In the spirit of conventional contrastive learning.



Pair-axis

Contrast classifier against all interpolated samples in the batch.

Exists because of the unique construction of each classifier. Not (directly) applicable in Mixup.

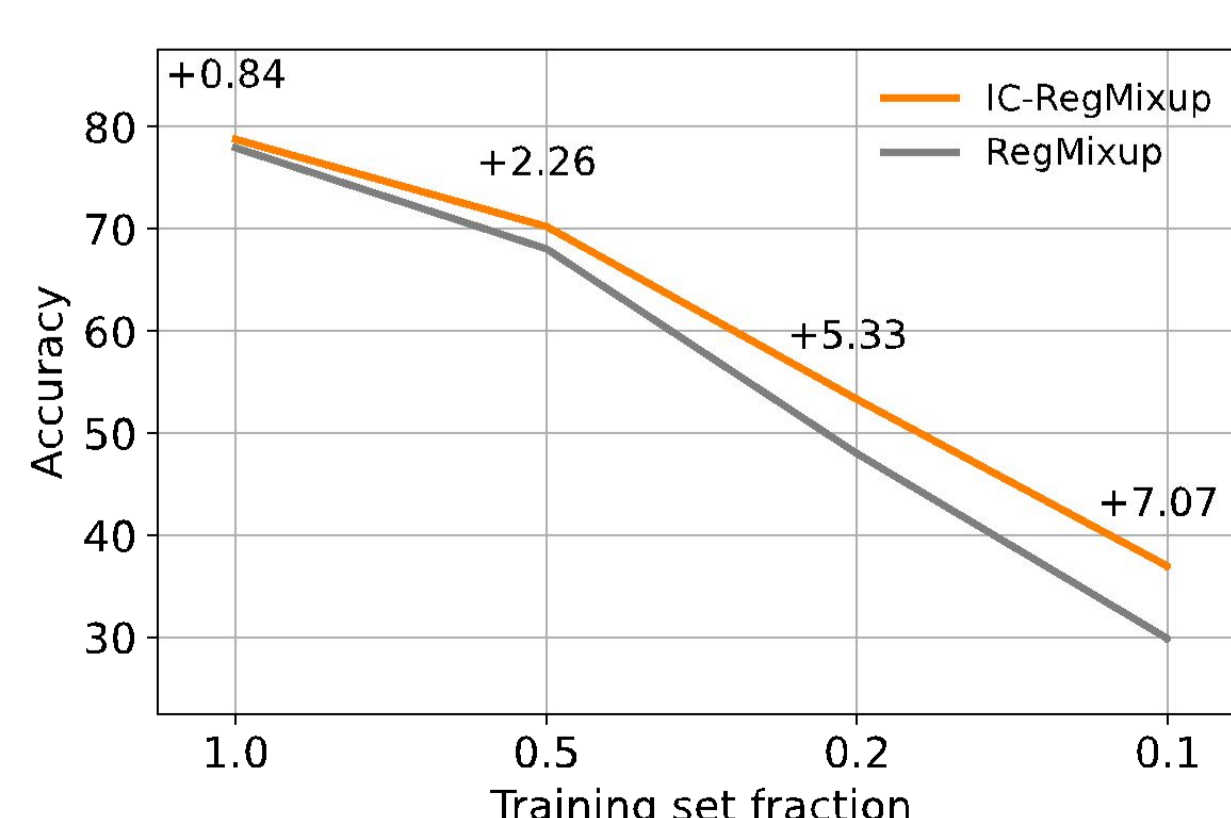


Optimization: $f_{\theta}(\tilde{x})^T W \tilde{y}$ is a B x B matrix for batch size B, we perform cross-entropy loss across both axes.

Experiments

contrastive axis		CIFAR-100 batch size		
class-axis	pair-axis	64	128	512
✓		74.90	76.75	76.17
	✓	75.38	77.62	76.09
✓	✓	76.20	77.90	77.08

The class- and pair-axes are complementary.



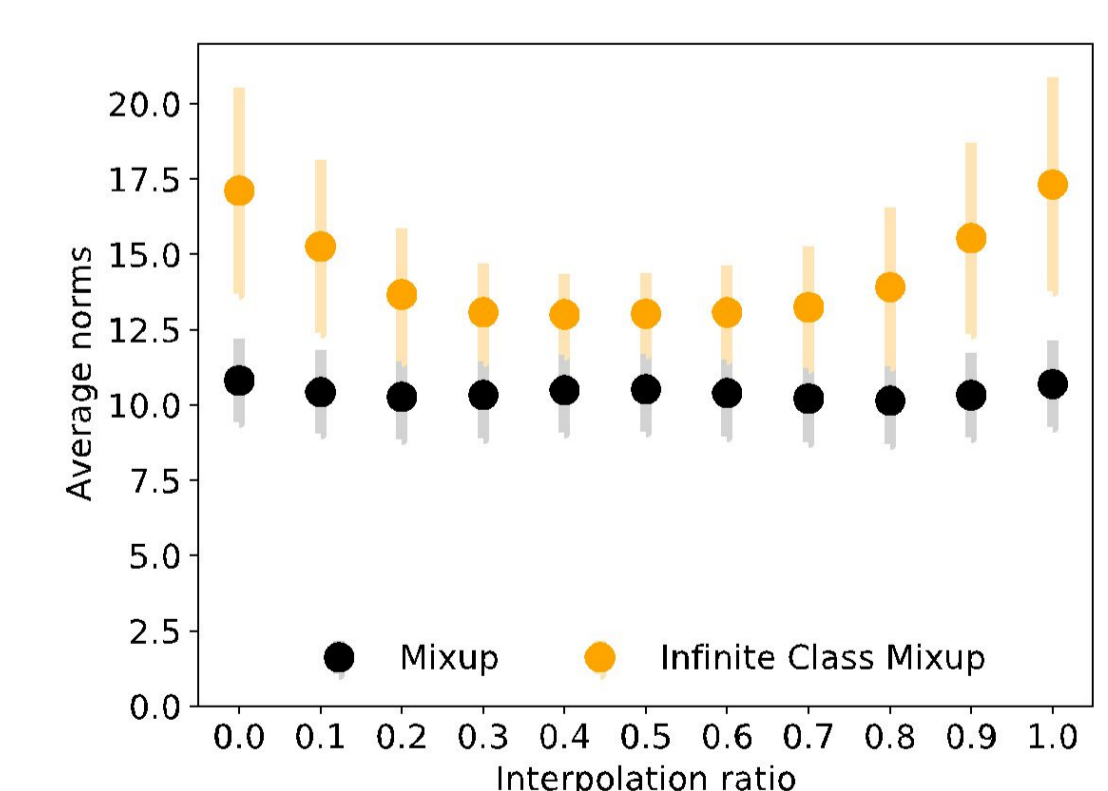
Enhances recent RegMixup (NeurIPS 2022).

	LT-CIFAR100		LT-CIFAR10	
	0.1	0.01	0.1	0.01
ERM	58.54	37.44	88.63	71.87
Mixup	62.68	39.21	89.63	72.82
IC-Mixup	64.30	43.31	89.89	76.81
	+1.62	+4.10	+0.26	+3.99
Remix	61.36	38.04	89.57	72.65
IC-Remix	64.56	46.01	90.26	79.28
	+3.20	+5.97	+0.67	+6.63

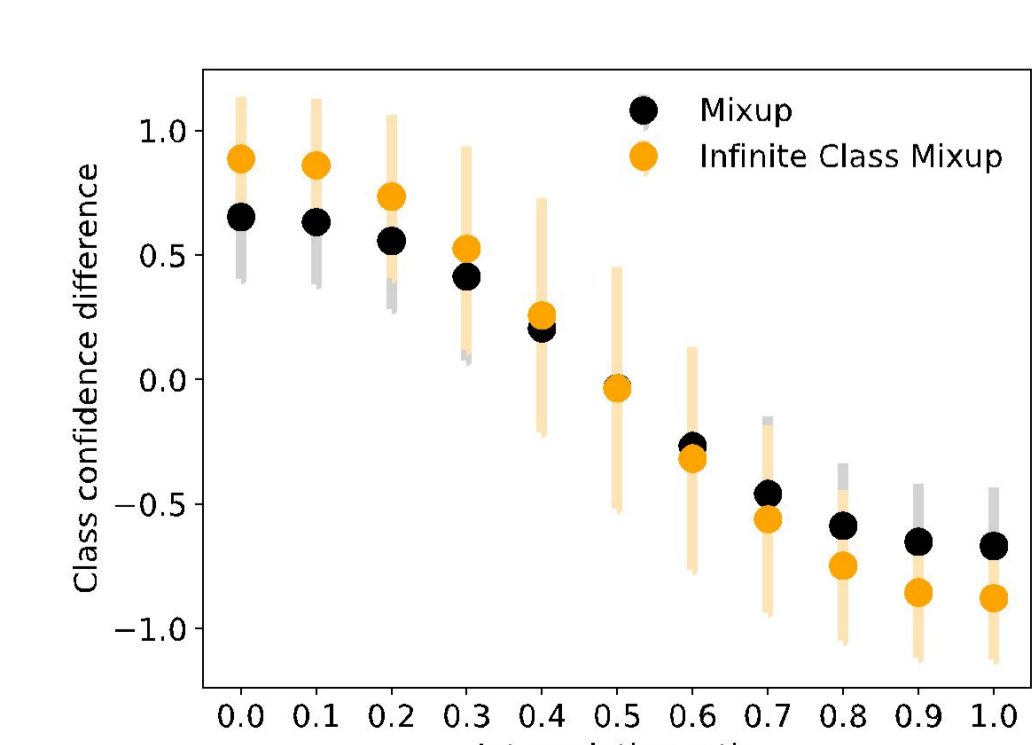
Improves long-tailed recognition.

	ciFAIR-10
Bietti et al. [4]	51.03
Oyallon et al. [40]	54.21
Kayhan and Gemert [22]	55.00
Ulicny et al. [49]	56.50
Kobayashi [27]	57.50
Brigato et al. [6]	58.22
+ IC-RegMixup	61.84

State-of-the-art in data-constrained learning.



Insight 1: Lower confidence for ambiguous samples.



Insight 2: Better differentiation between interpolations.