RecursiveMix: Mixed Learning with History

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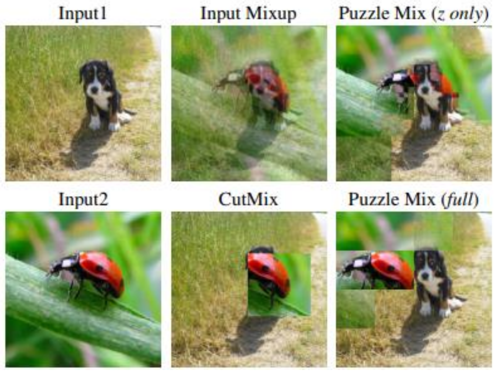
Background

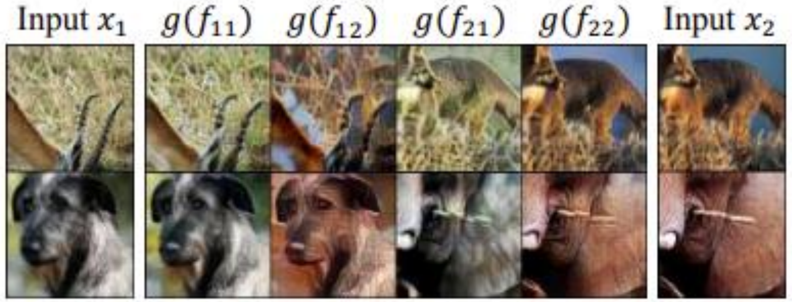
Mixup, ICLR 2018

CutMix, ICCV 2019

FMIX, Arxiv 2020



Puzzle Mix, ICML 2020



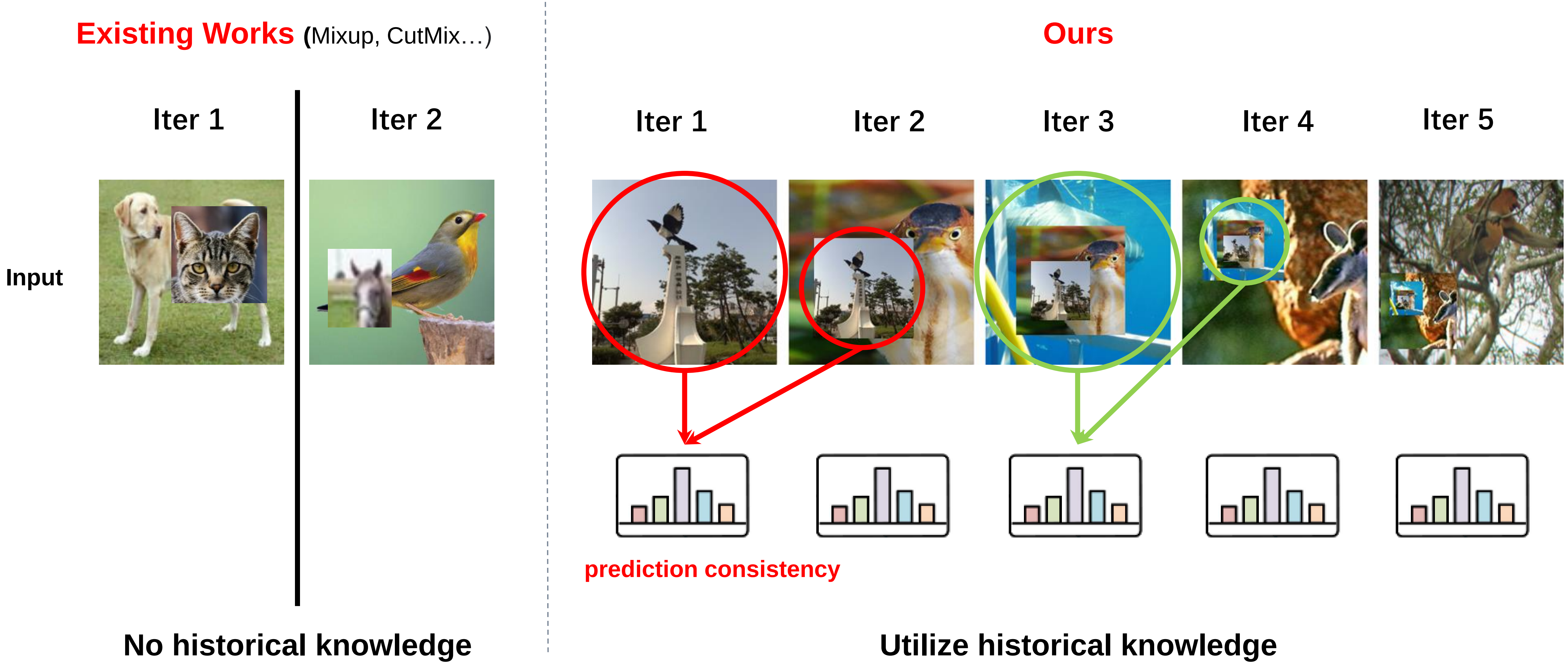
StyleMix, CVPR 2021

Mixed Sample Data Augmentation

$x_{mix}=mix_\lambda(x_1,x_2)$

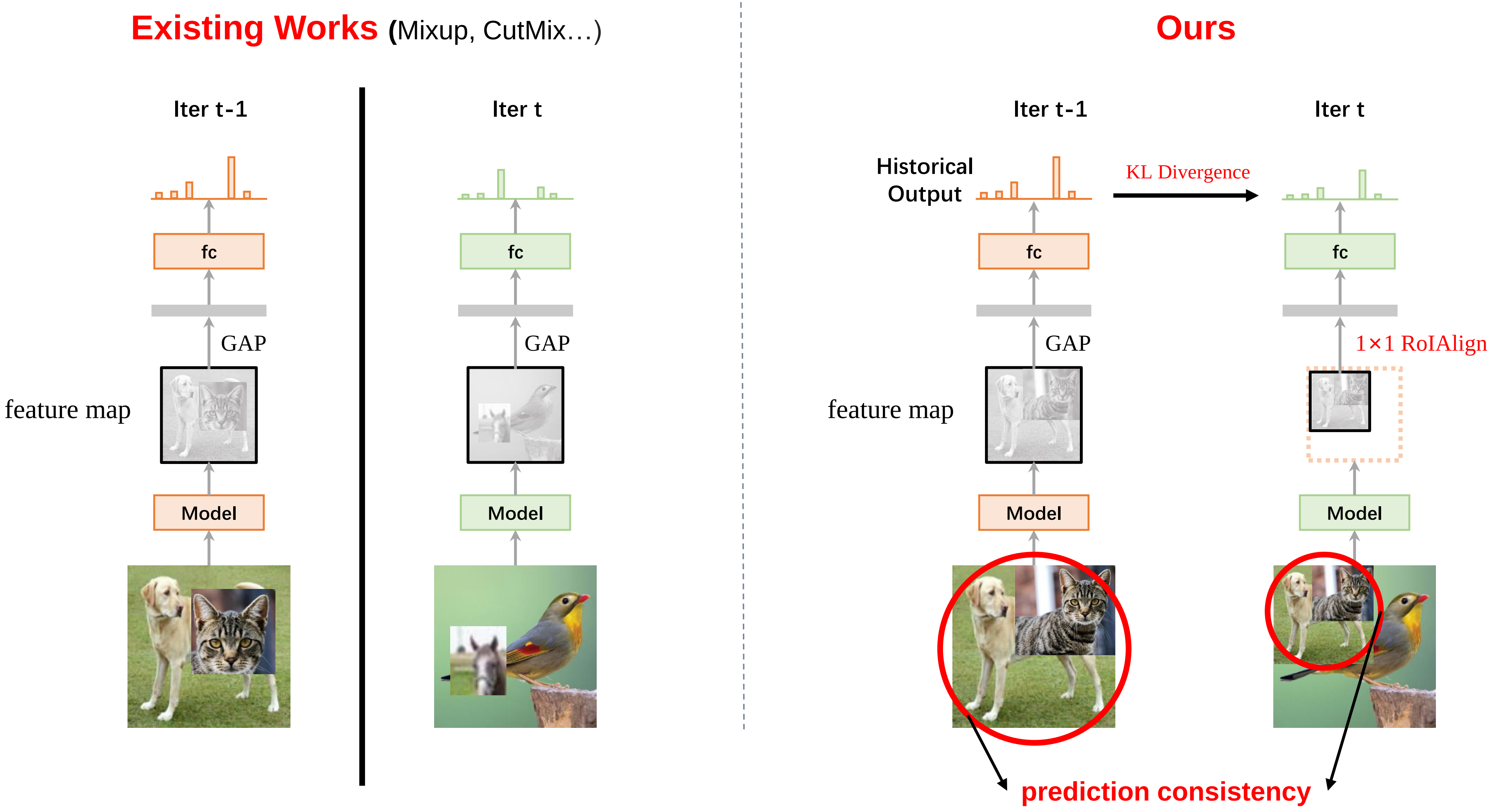
$y_{mix}=mix_\lambda(y_1,y_2)$

Background

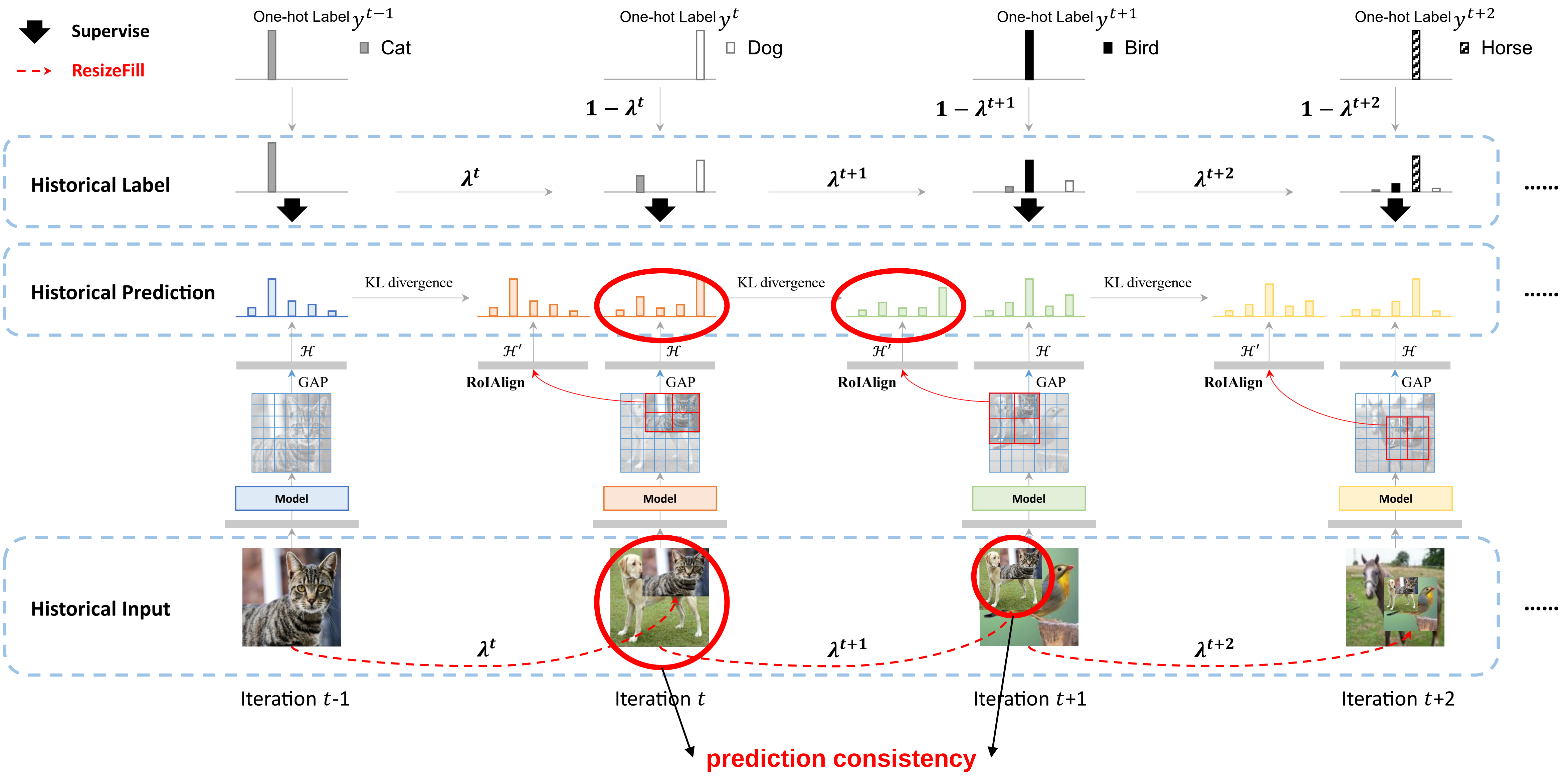


Existing Works (Mixup, CutMix…)
Ours
Iter 1
Iter 2
Input
Iter 1
Iter 2
Iter 3
Iter 4
Iter 5
prediction consistency
No historical knowledge
Utilize historical knowledge

Method


Existing Works (Mixup, CutMix…)
Iter t-1
Iter t
fc
GAP
feature map
Model
Ours
Iter t-1
Iter t
Historical Output
KL Divergence
fc
GAP
1×1 RoIAlign
feature map
Model
prediction consistency

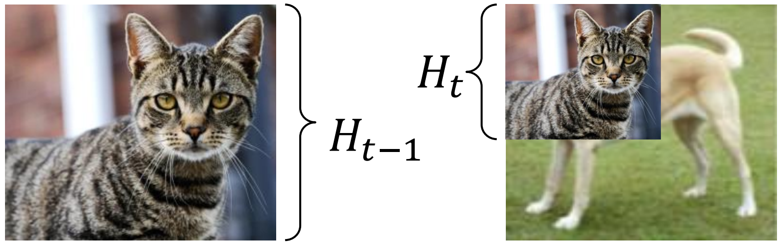
Method



Supervise
ResizeFill
One-hot Label y^{t-1}
Cat
One-hot Label y^{t}
Dog
One-hot Label y^{t+1}
Bird
One-hot Label y^{t+2}
Horse
$1-\lambda^t$
$1-\lambda^{t+1}$
$1-\lambda^{t+2}$
Historical Label
λ^t
λ^{t+1}
λ^{t+2}
......
Historical Prediction
KL divergence
KL divergence
KL divergence
......
$\mathcal{H}$
$\mathcal{H}'$
GAP
RoIAlign
Model
Historical Input
......
Iteration t-1
Iteration t
Iteration t+1
Iteration t+2
prediction consistency

Method

Resize and paste



$$\lambda = \text{Uniform}(0, \boldsymbol{\alpha})$$
$$H_t = \sqrt{\lambda} \cdot H_{t-1}$$

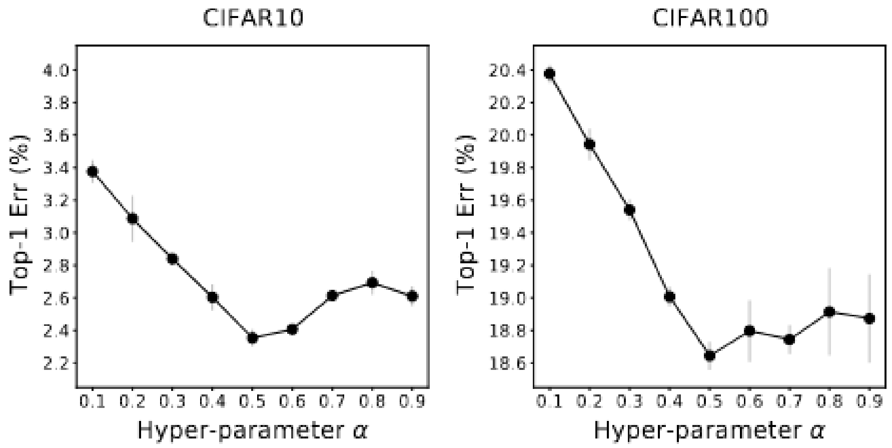


Figure: Ablation study on $\boldsymbol{\alpha}$.

Criterion

$$\mathcal{L} = \mathcal{L}_{CE}(\tilde{x}^t, \tilde{y}^t) + \boldsymbol{\omega} \lambda^t \mathcal{L}_{KL}(\tilde{p}^t_{roi}, p^h)$$

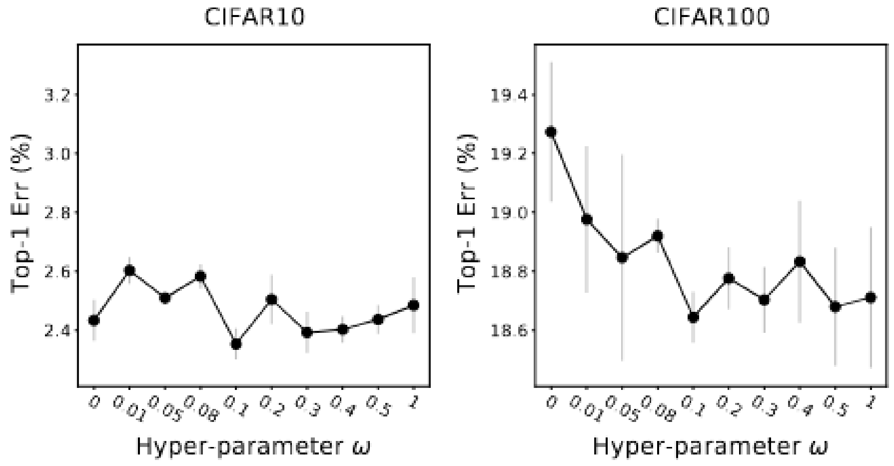


Figure: Ablation study on $\boldsymbol{\omega}$.

Analysis

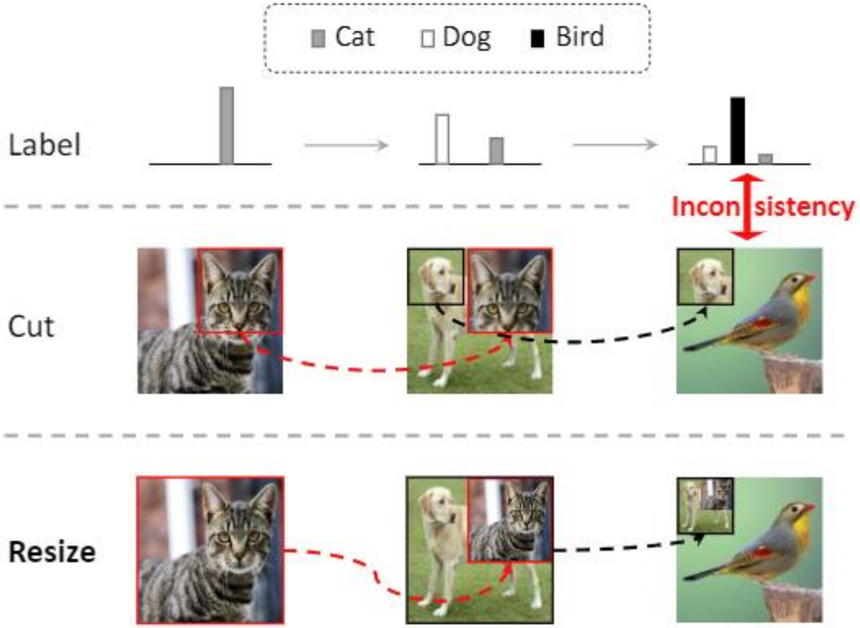


Figure: “Cut” may lead to inconsistency while
“Resize” concretely preserve the consistency.

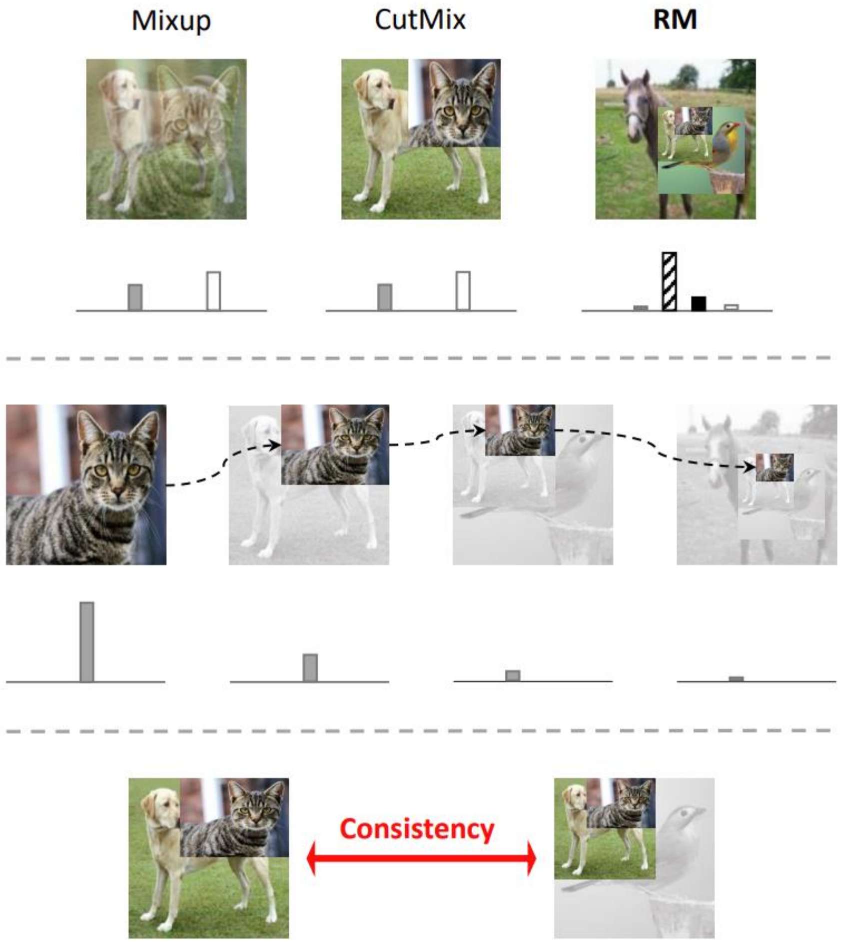
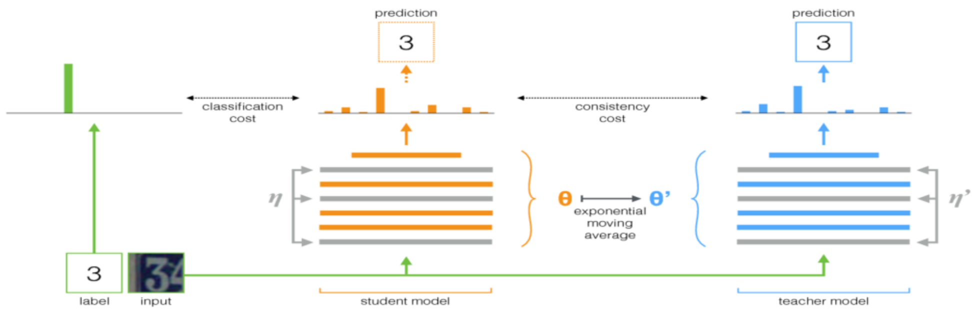


Figure: 1) Richer supervisions. 2) Multi-scale/-space views.
3) Explicit learning on the spatial semantic consistency.

Analysis

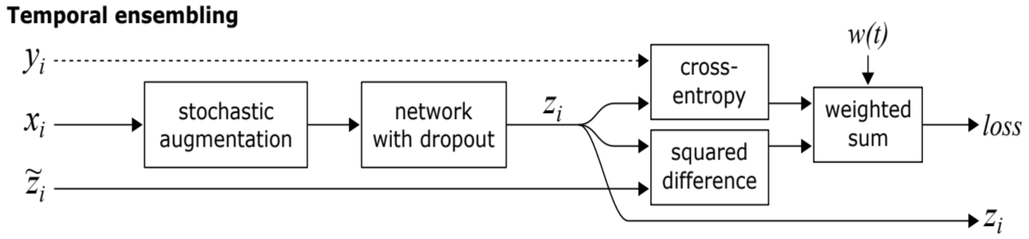
Existing Contrastive Learning Methods

Additional computation cost



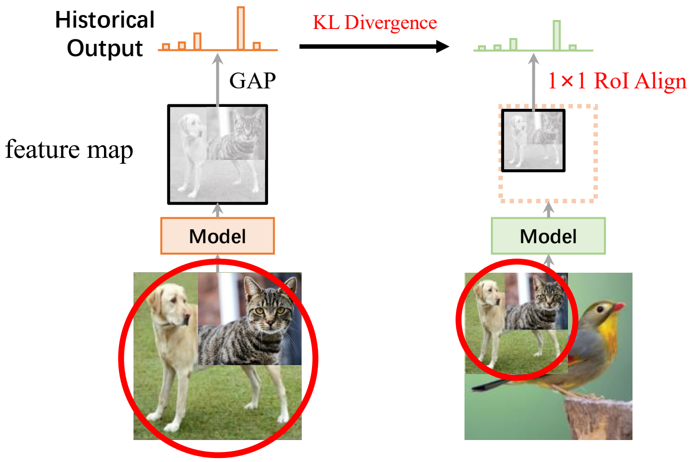
Mean teachers, NeurIPS 2017

Consume large memory



Temporal Ensemble , ICLR 2017

Ours



The additional computation/memory cost is negligible

ResNet-50 (300 epochs)	Memory	Flops	#P (deploy)	Top-1 Err (%)
Baseline	5.74 G	4.12 G	25.56 M	23.68
+ Mixup	5.74 G	4.12 G	25.56 M	22.58
+ CutMix	5.74 G	4.12 G	25.56 M	21.40
+ RM (ours)	5.74 G	4.12 G	25.56 M	**20.80**

Ablation Study

Classification

Model	RS	HS	CL	Top-1 Err (%)
PyramidNet	—	—	—	16.67
+CutMix [1]				15.59
+RM (ours)	√			15.36
	√	√		14.81
	√	√	√	**14.65**

Table: "RS": Resize strategy. "HS": Historical mix. "CL": Consistency loss.

Downstream

Detector	CL	AP	AP_{50}	AP_{75}
ATSS [2]		41.1	59.4	44.5
	√	**41.5**	**59.9**	**45.1**
GFL [3]		41.4	59.4	44.9
	√	**41.9**	**60.2**	**45.6**

Table: Object detection

Segmentor	CL	mIoU	mAcc	aAcc
PSPNet [4]		41.09	51.72	79.99
	√	**41.73**	**52.47**	**80.01**
UperNet [5]		41.88	**52.79**	79.94
	√	**42.30**	52.61	**80.14**

Table: Semantic segmentation

[1] Cutmix: Regularization strategy to train strong classifiers with localizable features. Yun S et al. ICCV 2019
[2] Bridging the gap between anchor-based and anchor-free detection via adaptive training sample selection, Zhang S et al. CVPR 2020
[3] Generalized focal loss: Learning qualified and distributed bounding boxes for dense object detection, Li X et al. NeurIPS 2020
[4] Pyramid scene parsing network, Zhao H et al. CVPR 2017
[5] Unified perceptual parsing for scene understanding, Xiao T et al. ECCV 2018.

Results

CIFAR10

PyramidNet-200 (300 epochs)	Top-1 Err (%)
Baseline	3.85
+ Label Smoothing	3.74
+ DropBlock	3.27
+ Stochastic Depth	3.11
+ Cutout	3.10
+ Mixup (α=1.0)	3.09
+ Manifold Mixup (α=1.0)	3.15
+ CutMix	2.88
+ MoEx	3.44
+ StyleCutMix (auto-γ)	2.55
+ RM (ours)	**2.35**

CIFAR100

Model (200 epochs)	Type	Top-1 Err (%)
ResNet-18	Baseline	21.70
	+ Mixup	20.99
	+ CutMix	19.61
	+ RM (ours)	**18.64**
ResNet-34	Baseline	20.62
	+ Mixup	19.19
	+ CutMix	17.89
	+ RM (ours)	**17.15**
DenseNet-121	Baseline	19.51
	+ Mixup	17.71
	+ CutMix	17.21
	+ RM (ours)	**16.22**
DenseNet-161	Baseline	18.78
	+ Mixup	16.84
	+ CutMix	16.64
	+ RM (ours)	**15.54**
PyramidNet-164	Baseline	16.67
	+ Mixup	16.02
	+ CutMix	15.59
	+ RM (ours)	**14.65**

ImageNet

ResNet-50 (300 epochs)	Top-1 Err (%)	Top-5 Err (%)
Baseline	23.68	7.05
+ Cutout	22.93	6.66
+ Stochastic Depth	22.46	6.27
+ Mixup	22.58	6.40
+ Manifold Mixup	22.50	6.21
+ DropBlock	21.87	5.98
+ Feature CutMix	21.80	6.06
+ CutMix	21.40	5.92
+ PuzzleMix	21.24	5.71
+ MoEx	21.90	6.10
+ CutMix + MoEx	20.90	5.70
+ RM (ours)	**20.80**	**5.42**

Results

Object detection

Detector	Pretrain Backbone	AP	AP_{50}	AP_{75}
ATSS	ResNet-50	39.4	57.6	42.8
	+ CutMix	40.1	58.4	43.4
	+ RM (ours)	**41.5**	**59.9**	**45.1**
	PVTv2-B1	39.3	57.2	42.5
	+ CutMix	41.8	60.3	45.5
	+ RM (ours)	**42.3**	**61.0**	**45.6**
GFL	ResNet-50	40.2	58.4	43.3
	+ CutMix	41.3	59.5	44.6
	+ RM (ours)	**41.9**	**60.2**	**45.6**
	PVTv2-B1	40.2	58.1	43.2
	+ CutMix	42.1	60.7	45.5
	+ RM (ours)	**43.0**	**61.6**	**46.5**

Semantic segmentation

Segmentor	Pretrain Backbone	mIoU	mAcc	aAcc
PSPNet	ResNet-50	40.90	51.11	79.52
	+ CutMix	40.96	51.16	79.93
	+ RM (ours)	**41.73**	**52.47**	**80.01**
	PVTv2-B1	36.48	46.26	76.79
	+ CutMix	37.99	48.70	77.50
	+ RM (ours)	**38.67**	**49.40**	**77.93**
UperNet	ResNet-50	40.40	51.00	79.54
	+ CutMix	41.24	51.79	79.69
	+ RM (ours)	**42.30**	**52.61**	**80.14**
	PVTv2-B1	39.94	50.75	79.02
	+ CutMix	41.73	52.99	80.02
	+ RM (ours)	**43.26**	**54.21**	**80.36**

Results

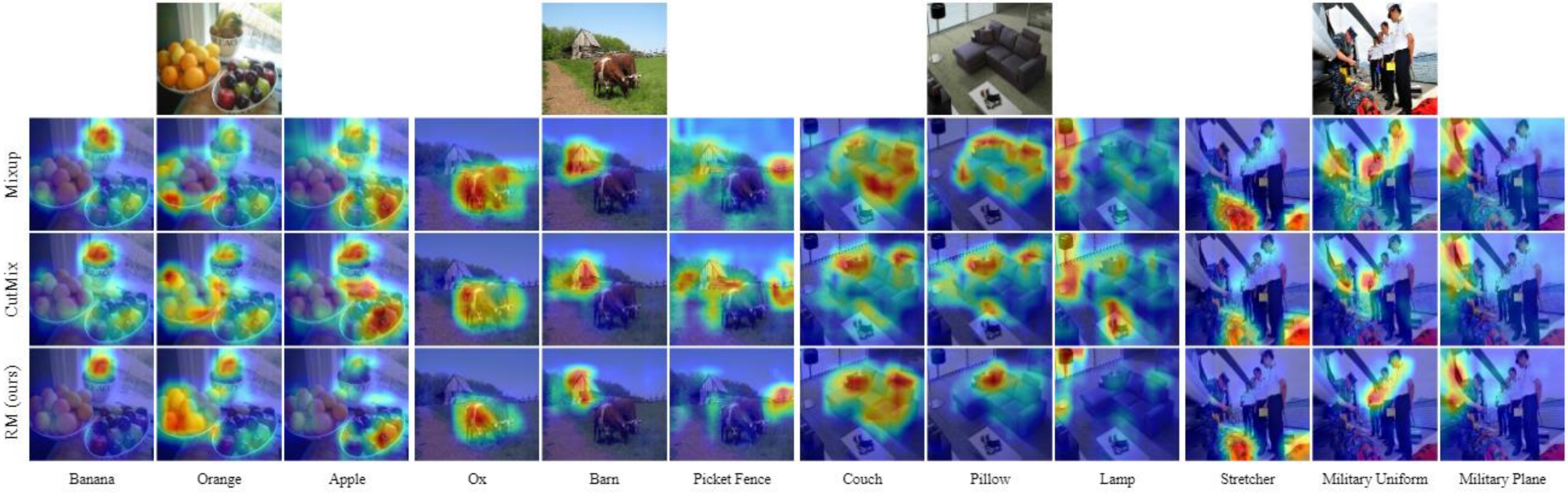


Figure: CAM visualization on natural samples with multiple labels.

- We propose recursive mix (RM) data augmentation, which constructs training pairs with identical inputs to learn spatial semantic consistency using historical prediction knowledge.
- RM shows better performance on image classification as well as various downstream tasks.

Thank you!

Codes and pretrained models are available at
https://github.com/implus/RecursiveMix