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- Problem / objective
 - Label ambiguity issue in Partial-Label Learning
- Contribution / Key idea
 - Propose novel partial-label learning method called CroSel

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Partial Label 이란?

- Candidate label set
- 각 이미지마다 candidate label set 할당
- Candidate label set 의 구성 : 하나의 true label + 여러 negative labels
- 주의 : Candidate label set 에는 true label 이 반드시 포함되어 있다는 전제.

Partial Label Learning 이란?

- Task : Multi-class classification
- 학습 목표 : 각 이미지마다 주어진 candidate label set 에서 true label 찾아내는 능력을 학습

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Ours 등장 배경

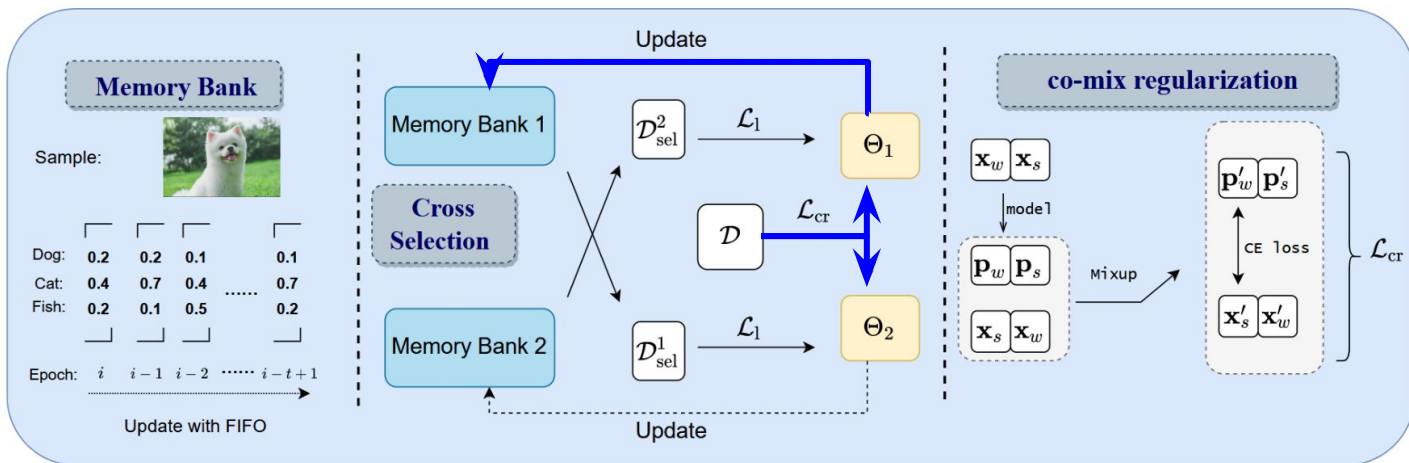
Partial Label Learning 의 한계 : Negative labels 들이 multi-class classifier 의 학습을 방해

Ours :

- Candidate label set 에서 true label 찾아내서, 모델 학습 중에 다른 negative labels 의 방해를 최소화시키겠다.
- 선택한 true labels 들을 사용하여 supervised learning 을 하겠다.

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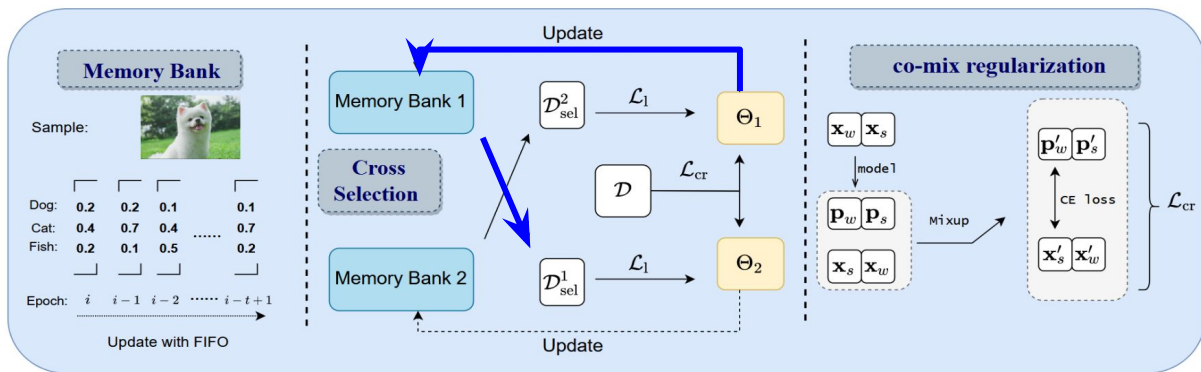
Warm up



- 두 모델에 대하여, 10 에포크만큼 학습 및 메모리뱅크 업데이트
- 학습 목표 : 이미지의 true label 은 candidate label set 안에 반드시 존재한다.

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High-confident data selection



$$\beta_1 = \mathbb{I}(\text{argmax}(\mathbf{q}^i) \in S), \quad (1)$$

$$\beta_2 = \mathbb{I}(\text{argmax}(\mathbf{q}^i) = \text{argmax}(\mathbf{q}^{i+1})), \quad (2)$$

$$\beta_3 = \mathbb{I}(\frac{1}{t} \sum_{i=1}^t \max(\mathbf{q}^i) > \gamma), \quad (3)$$

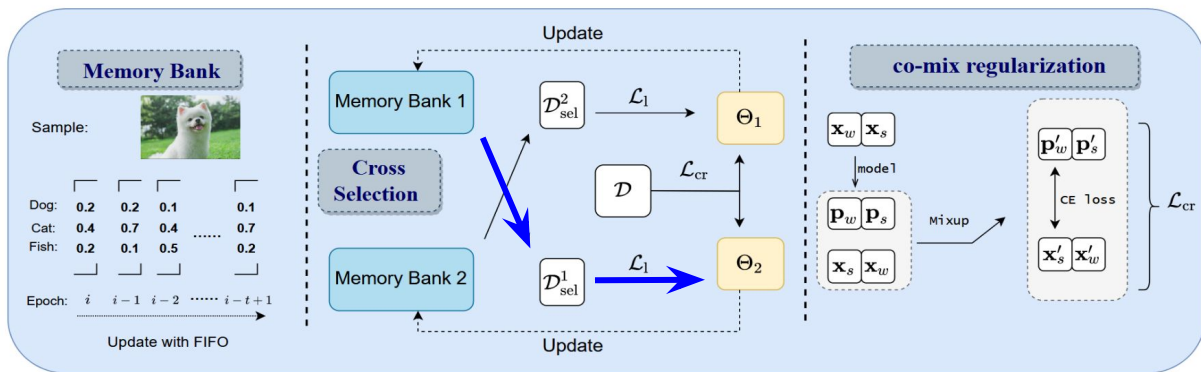
High-confident pseudo label 선택 기준 3가지

$$\mathcal{D}_{\text{sel}} = ((\mathbf{x}_i, \text{argmax}(\mathbf{q}_i^t)) | (\beta_1^i \wedge \beta_2^i \wedge \beta_3^i) = 1, \mathbf{x}_i \in \mathcal{D}), \quad : \text{위 3가지 기준 모두 만족해야 선택.}$$

(4) 즉, 위 3가지 기준 모두 만족하면 **clean label** 로 간주. 전유진

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Cross-supervised training



1. Cross selection : 모델 1 이 선택한 데이터로 모델 2 학습. 마찬가지로, 모델 2 가 선택한 데이터로 모델 1 학습.

- Cross selection 이유 : 두 모델이 서로 다른 decision boundary 를 만들어서, 앞서 선택했던 confident pseudo labels 에서 noisy label 이 있다면 이를 바로 잡아주기 위함.

2. Selected label loss

$$\mathcal{L}_1 = \frac{1}{|\mathcal{D}_{sel}|} \sum_{\mathbf{x} \in \mathcal{D}_{sel}} \mathcal{L}_{CE}(f(\mathbf{x}_w), \hat{y}), \quad (5)$$

$\hat{y} = \operatorname{argmax}(\mathbf{q}^t)$: selected pseudo-label

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Co-mix Consistency Regulation

1. pseudo-label 생성

$$p_i = \begin{cases} \frac{\exp(f_i(\mathbf{x})^{\frac{1}{T}})}{\sum_{i \in S} \exp(f_i(\mathbf{x})^{\frac{1}{T}})}, & i \in S, \\ 0, & i \notin S, \end{cases} \quad (7)$$

2. MixUp

$$\lambda \sim \text{Beta}(\alpha, \alpha), \quad (8)$$

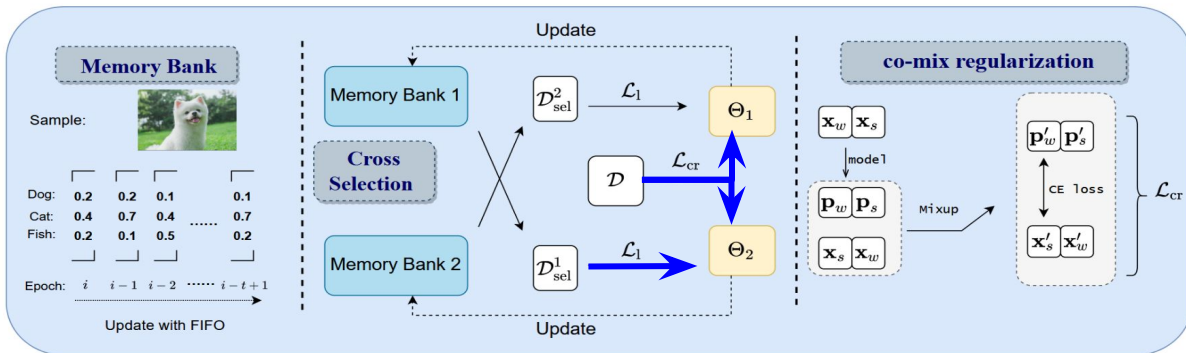
$$\lambda' = \max(\lambda, 1 - \lambda), \quad (9)$$

$$\mathbf{x}' = \lambda' \mathbf{x}_1 + (1 - \lambda') \mathbf{x}_2, \quad (10)$$

$$\mathbf{p}' = \lambda' \mathbf{p}_1 + (1 - \lambda') \mathbf{p}_2, \quad (11)$$

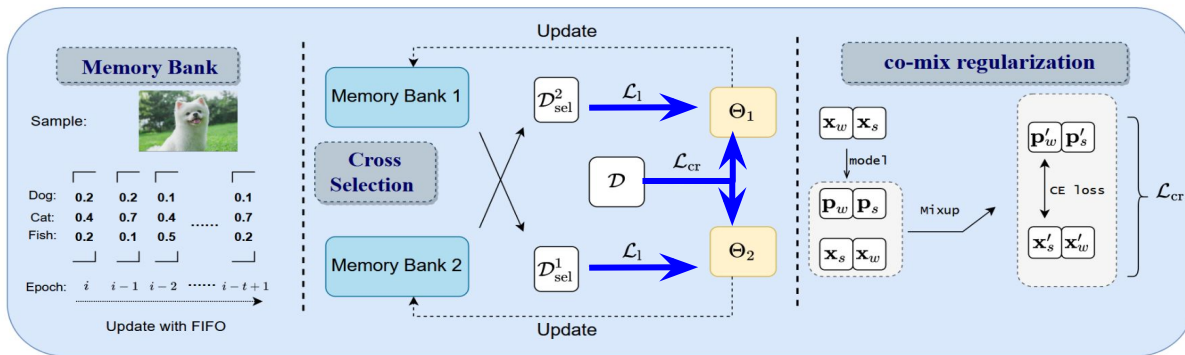
3. Consistency regulation loss

$$\mathcal{L}_{\text{cr}} = \frac{1}{2n} \sum_{i=1}^{2n} \mathcal{L}_{\text{CE}}(f(\mathbf{x}'_i), \mathbf{p}'_i), \quad (12)$$



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Overall loss



$$\mathcal{L}_{all} = \mathcal{L}_1 + \lambda_d * \mathcal{L}_{cr}, \quad (13)$$

$$\lambda_d = (1 - r_s) * \lambda_{cr}, \quad (14)$$

$$\mathcal{L}_1 = \frac{1}{|\mathcal{D}_{sel}|} \sum_{\mathbf{x} \in \mathcal{D}_{sel}} \mathcal{L}_{CE}(f(\mathbf{x}_w), \hat{y}), \quad (5)$$

$$\mathcal{L}_{cr} = \frac{1}{2n} \sum_{i=1}^{2n} \mathcal{L}_{CE}(f(\mathbf{x}'_i), \mathbf{p}'_i), \quad (12)$$

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Experiments

Table 1. Accuracy (mean \pm std) comparisons on benchmark datasets.

Dataset	q	Ours	PoP	CRDPLL	PiCO	PRODEN	LWS	CC
CIFAR-10	0.1	97.31 \pm .04%	97.17 \pm .01%	97.41\pm.06%	96.10 \pm .06%	95.66 \pm .08%	91.20 \pm .07%	90.73 \pm .10%
	0.3	97.50\pm.05%	97.08 \pm .01%	97.38 \pm .04%	95.74 \pm .10%	95.21 \pm .07%	89.20 \pm .09%	88.04 \pm .06%
	0.5	97.34\pm.05%	96.66 \pm .03%	96.76 \pm .05%	95.32 \pm .12%	94.55 \pm .13%	80.23 \pm .21%	81.01 \pm .38%
SVHN	0.1	97.71\pm.05%	97.55 \pm .06%	97.63 \pm .06%	96.58 \pm .04%	96.20 \pm .07%	96.42 \pm .09%	96.99 \pm .17%
	0.3	97.96\pm.05%	97.50 \pm .03%	97.65 \pm .07%	96.32 \pm .09%	96.11 \pm .05%	96.15 \pm .08%	96.67 \pm .20%
	0.5	97.86\pm.06%	97.31 \pm .01%	97.70 \pm .05%	95.78 \pm .05%	95.97 \pm .03%	95.79 \pm .05%	95.83 \pm .23%
CIFAR-100	0.01	84.24\pm.09%	83.03 \pm .04%	82.95 \pm .10%	74.89 \pm .11%	72.24 \pm .12%	62.03 \pm .21%	66.91 \pm .24%
	0.05	83.92\pm.24%	82.79 \pm .02%	82.38 \pm .09%	73.26 \pm .09%	70.03 \pm .18%	57.10 \pm .17%	64.51 \pm .37%
	0.10	84.07\pm.16%	82.39 \pm .04%	82.15 \pm .20%	70.03 \pm .10%	69.82 \pm .11%	52.60 \pm .54%	61.50 \pm .36%

$q = P(\bar{y} \in S | \bar{y} \neq y)$: candidate label set 구성 기준. 결국, noise magnitude

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Table 2. Selection ratio and selection accuracy (mean \pm std) on benchmark datasets. S-ratio represents the selection ratio and S-acc represents selection accuracy in \mathcal{D}_{sel} .

Experiments

Datasets	Setting	Index	Performance
CIFAR-10	$q = 0.1$	S-ratio	99.09 \pm .07%
		S-acc	99.79 \pm .05%
	$q = 0.3$	S-ratio	98.10 \pm .10%
		S-acc	99.55 \pm .03%
	$q = 0.5$	S-ratio	96.25 \pm .12%
		S-acc	99.44 \pm .06%
SVHN	$q = 0.1$	S-ratio	97.25 \pm .14%
		S-acc	99.84 \pm .06%
	$q = 0.3$	S-ratio	76.42 \pm .21%
		S-acc	99.77 \pm .06%
	$q = 0.5$	S-ratio	73.21 \pm .15%
		S-acc	99.34 \pm .02%
CIFAR-100	$q = 0.01$	S-ratio	96.58 \pm .13%
		S-acc	99.71 \pm .06%
	$q = 0.05$	S-ratio	95.45 \pm .21%
		S-acc	98.29 \pm .15%
	$q = 0.10$	S-ratio	93.61 \pm .12%
		S-acc	97.93 \pm .11%

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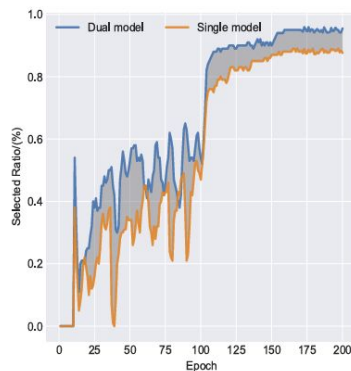
Experiments

Table 3. Results on CIFAR-100 in fine-grained settings.

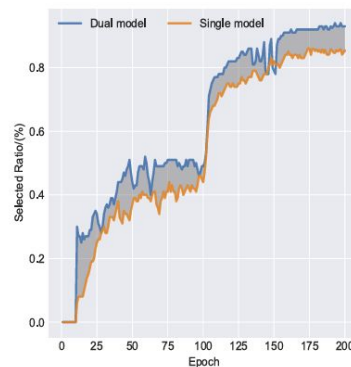
Method	Accuracy	Method	Accuracy
PoP	82.04%	CRDPLL	81.53%
PiCO	73.38%	PRODEN	71.16%
LWS	54.08%	CC	64.91%
CroSel (ours)		83.34%	

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Experiments



(a) CIFAR-10 comparison.



(b) CIFAR-100 comparison.

Figure 3. Selection ratio comparison between dual model and single model on CIAFR-10 and CIAFR-100.