Semi-Supervised Learning under Class Distribution Mismatch

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Research Purpose

Uncertainty-Aware Self-Distillation (UASD)

❖ Semi-Supervised Learning under Class Distribution Mismatch (AAAI, 2020)

- 영국 런던의 퀸 메리 대학에서 진행한 연구, 2022년 9월 23일 기준 58회 인용됨
- 현실과 유사한 class distribution mismatch 상황에서 안정된 Semi-supervised learning (SSL)을 진행하기 위해 Uncertainty-Aware Self-Distillation 방법론을 제안한 연구임

Semi-Supervised Learning under Class Distribution Mismatch

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Abstract

Semi-supervised learning (SSL) aims to avoid the need for collecting prohibitively expensive labelled training data. Whilst demonstrating impressive performance boost, existing SSL methods artificially assume that small labelled data and large unlabelled data are drawn from the *same* class distribution. In a more realistic scenario with class distribution mismatch between the two sets, they often suffer severe performance degradation due to error propagation introduced by irrelevant unlabelled samples. Our work addresses this under-studied and realistic SSL problem by a novel algorithm named *Uncertainty-Aware Self-Distillation* (UASD). Specifically, UASD produces soft targets that avoid catastrophic error propagation, and empower learning effectively from unconstrained unlabelled data with out-of-distribution (OOD) samples. This is based on joint *Self-Distillation* and *OOD filtering* in a unified formulation. Without bells and whistles, UASD significantly outperforms

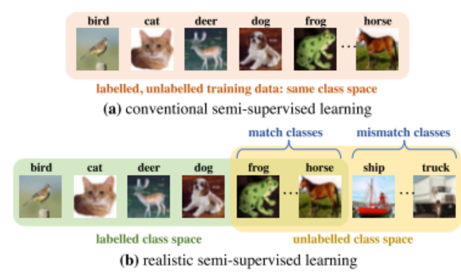


Figure 1: **(a)** In conventional semi-supervised learning, both labelled and unlabelled training data come from an identical class distribution. **(b)** In real-world scenario, however, class distribution mismatch often exits between the labelled and unlabelled data.

Reference: Chen, Yanbei, et al. "Semi-supervised learning under class distribution mismatch." Proceedings of the AAAI Conference on Artificial Intelligence. Vol. 34. No. 04. 2020.s

DMQA hcai

Proposed Method

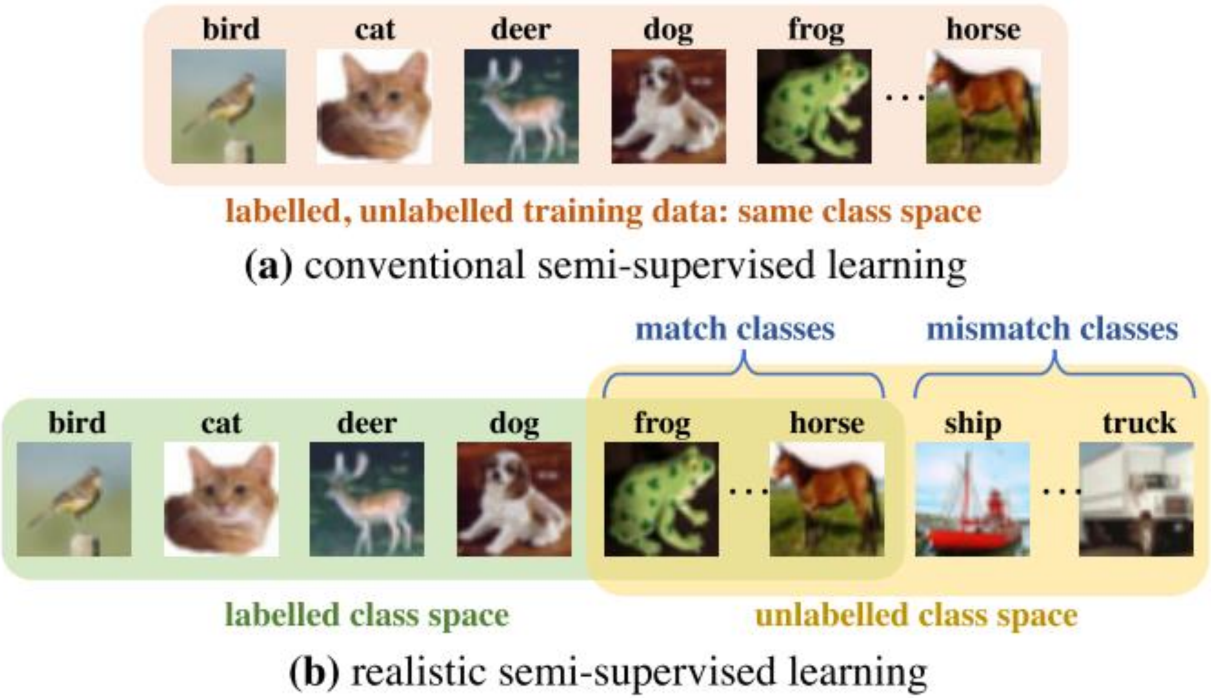
Realistic semi-supervised learning in mismatch

❖ 실제 현실 상황에서 발생하는 mismatch

a. 일반적인 semi-supervised learning 진행시 labelled, unlabelled data 모두 같은 class 공간에 존재

b. 실제 현실에서는 labelled data와 unlabelled data내에 다른 class가 존재하는 mismatch가 발생함

→ (b)와 같은 경우에서 semi-supervised learning을 안정적으로 진행할 수 있는 알고리즘 제안



Reference: Chen, Yanbei, et al. "Semi-supervised learning under class distribution mismatch." Proceedings of the AAAI Conference on Artificial Intelligence. Vol. 34. No. 04. 2020.s

Proposed Method

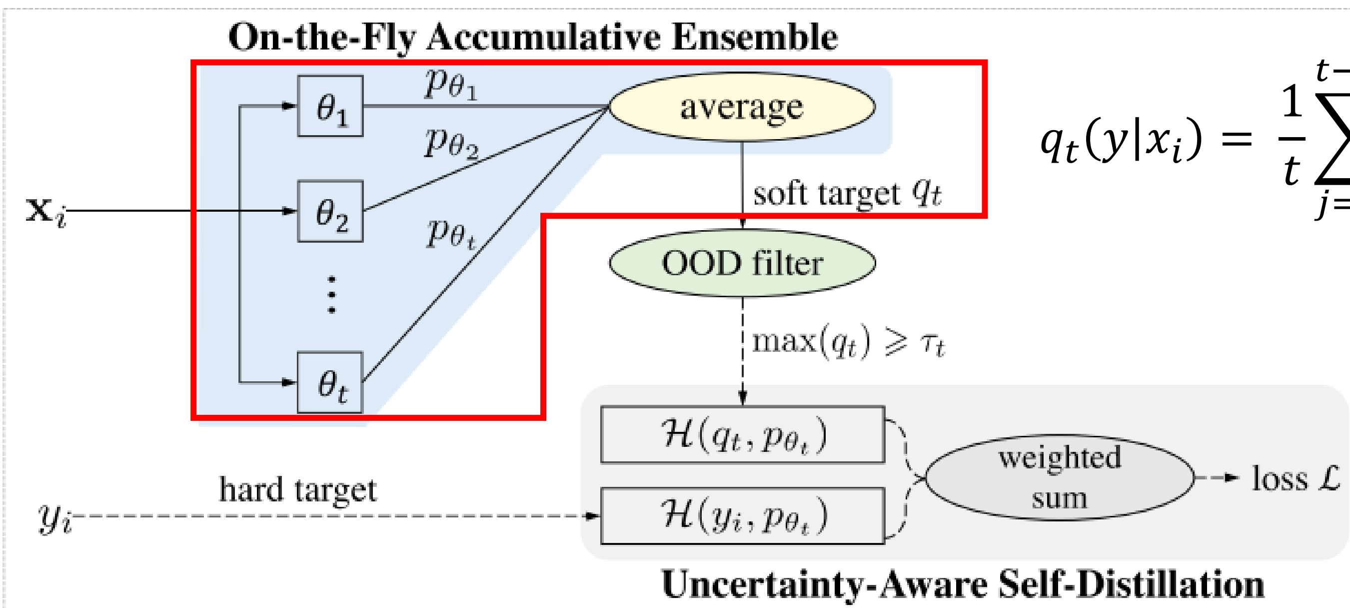
UASD Framework

❖ 전반적인 UASD Framework

① On-the-Fly Accumulative Ensemble

- 일반적인 DNN 모델은 입력 데이터에 대한 예측을 과신하는 overconfidence 문제가 발생함
- 모델 학습시 epoch별로 나온 결과에 대한 평균값을 class 예측 결과로 사용함

  → 여러 예측 결과를 종합해 불확실성까지 포함하여 overconfidence 문제를 완화할 수 있음



$$q_t(y|x_i) = \frac{1}{t}\sum_{j=0}^{t-1} p(y|x_i;\theta_j)$$

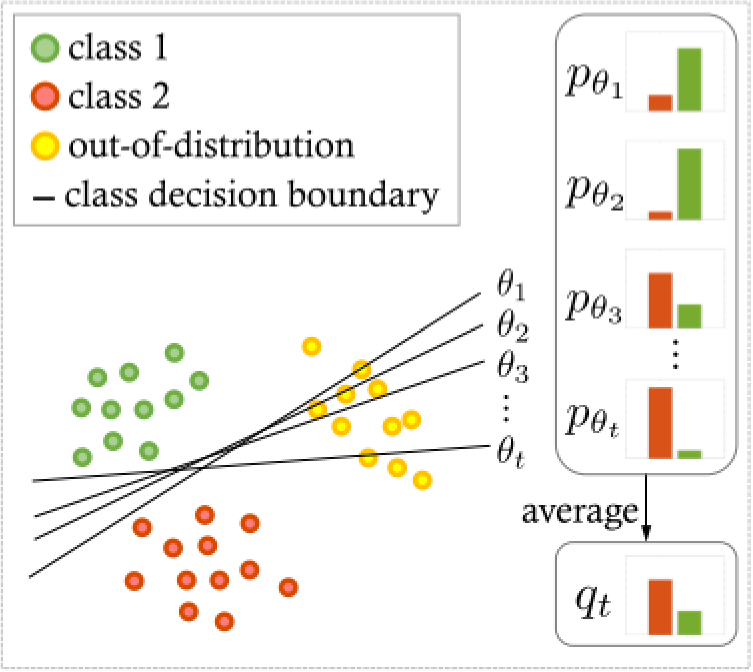
Reference: Chen, Yanbei, et al. "Semi-supervised learning under class distribution mismatch." Proceedings of the AAAI Conference on Artificial Intelligence. Vol. 34. No. 04. 2020.s

Proposed Method

On-the-Fly Accumulative Ensemble

❖ 앙상블을 적용했을 때 Feature space

- θ_i 가 모델이라고 할 때 $p\theta_i$는 입력 데이터에 대한 예측 확률이 도출 됨
- class 1과 class 2와 같이 학습에 사용한 class인 경우 $p\theta_i$ 값이 크게 변하지 않고 항상 잘 분류됨
- out-of-distribution 데이터는 $p\theta_i$ 값이 크게 바뀌며 모델마다 분류 결과가 달라질 수 있음



Reference: Chen, Yanbei, et al. "Semi-supervised learning under class distribution mismatch." Proceedings of the AAAI Conference on Artificial Intelligence. Vol. 34. No. 04. 2020.s

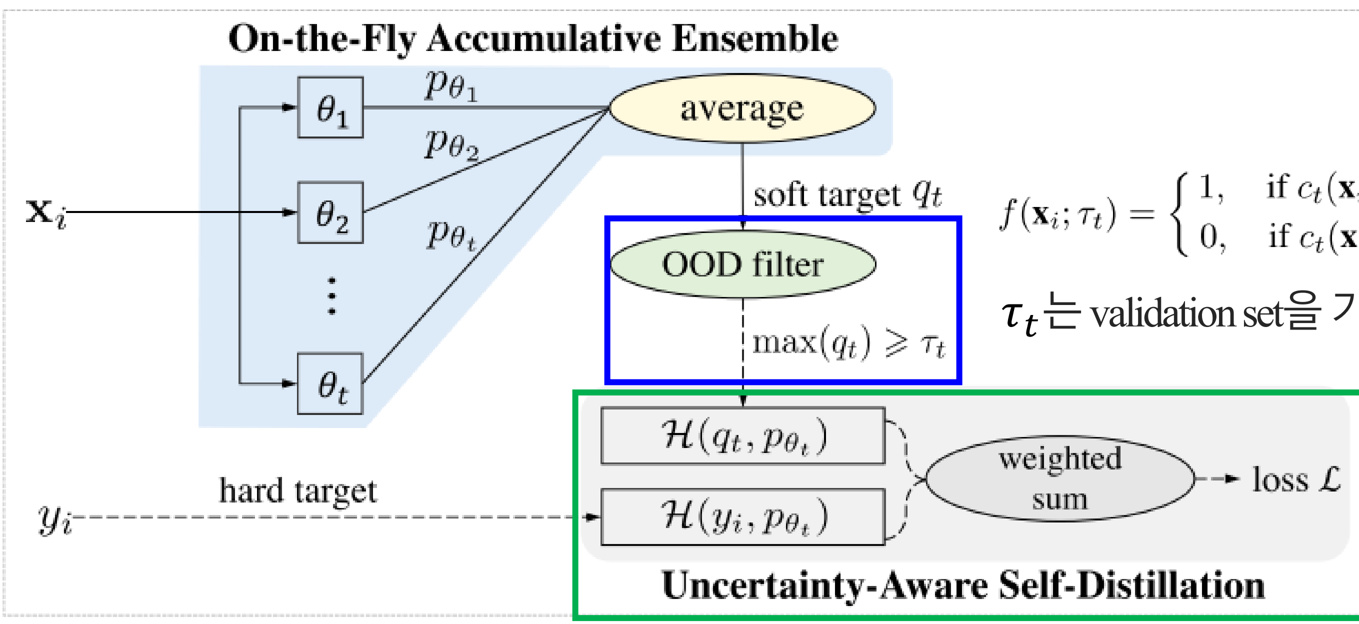
Proposed Method

UASD Framework

❖ 전반적인 UASD Framework

- ② **OOD Filter**: ①번에 산출된 결과 (q_t)를 기반으로 해당 데이터의 학습 사용 유무를 결정함
- ③ **Uncertainty-Aware Self-Distillation**: labelled data와 OOD Filter로 걸러지지 않고 사용된 unlabelled data의 loss를 결합해서 최종 loss를 산출하게 됨

** OOD = Out of distribution



$$f(\mathbf{x}_i; \tau_t) = \begin{cases} 1, & \text{if } c_t(\mathbf{x}_i) \geqslant \tau_t, \quad \text{selected} \\ 0, & \text{if } c_t(\mathbf{x}_i) < \tau_t, \quad \text{rejected} \end{cases}$$

τ_t는 validation set을 기준으로 산출함

Reference: Chen, Yanbei, et al. "Semi-supervised learning under class distribution mismatch." Proceedings of the AAAI Conference on Artificial Intelligence. Vol. 34. No. 04. 2020.s

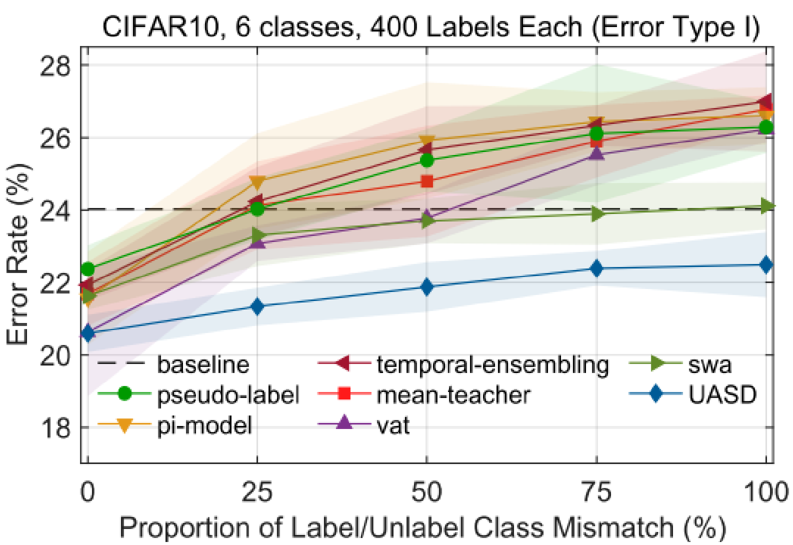
Experiment

Model performance

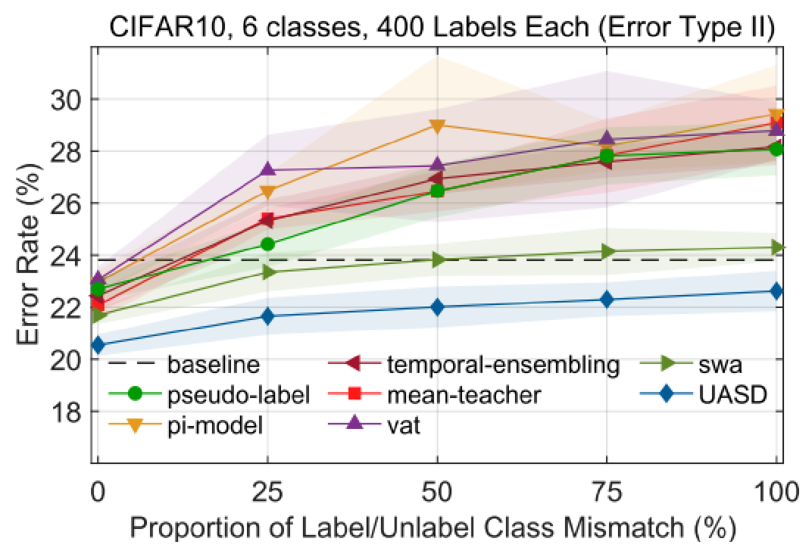
	CIFAR 10 class info		Mismatch ratio
	Labeled data (400)	Unlabeled data (4100)	
1.	Bird,cat,deer,dog,fog,horse	Deer, dog, fog, horse	0%
2.	Bird,cat,deer,dog,fog,horse	Airplane, dog, fog, horse	25%
3.	Bird,cat,deer,dog,fog,horse	Airplane, automobile, fog, horse	50%
4.	Bird,cat,deer,dog,fog,horse	Airplane, automobile, ship, horse	75%
5.	Bird,cat,deer,dog,fog,horse	Airplane, automobile, ship, truck	100%

- ❖ CIFAR 10 데이터셋을 기준으로 평가한 결과임
- ❖ 동물과 관련된 class 6개 (bird, cat, deer, dog, frog, horse)를 레이블링 된 데이터로 사용 후 평가
- ❖ 제안하는 UASD 알고리즘이 어떤 mismatch proportion에서도 가장 낮은 오류율을 보임

** 우측 상단: mismatch 비율에 따른 표



<Test error rates at the point of lowest validation error>



<The median test error rate in the last 20 epochs>

Reference: Chen, Yanbei, et al. "Semi-supervised learning under class distribution mismatch." Proceedings of the AAAI Conference on Artificial Intelligence. Vol. 34. No. 04. 2020.s
DMQA Open 세미나, 배진수, "Deep Semi-Supervised Learning with Out-of-distribution Unlabeled Data"

Experiment

Model performance

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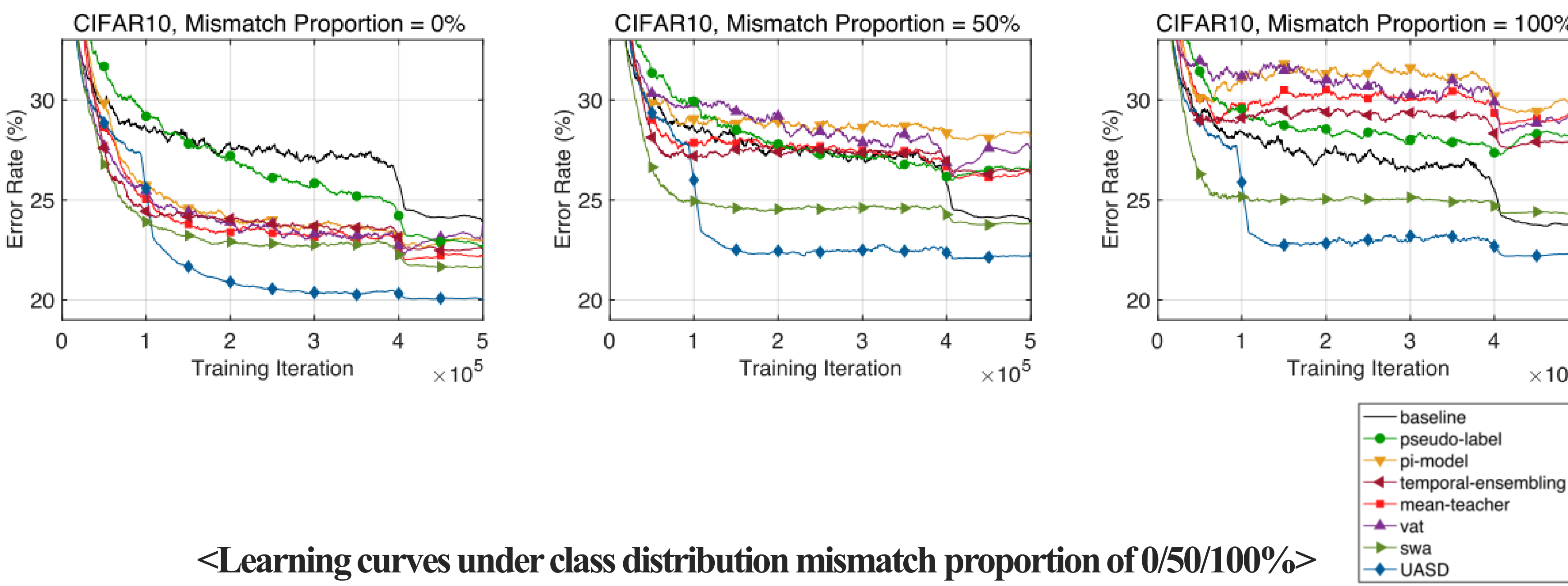
4.	Bird,cat,deer,dog,fog,horse	Airplane, automobile, ship, horse	75%
5.	Bird,cat,deer,dog,fog,horse	Airplane, automobile, ship, truck	100%

❖ Mismatch proportion이 0%, 50%, 100% 일 때 learning curve를 보여줌

❖ 다른 SSL 알고리즘 대비 더 빠르고 안정적으로 error rate가 떨어져 수렴하는 것을 확인

** 우측 상단: mismatch 비율에 따른 표



<Learning curves under class distribution mismatch proportion of 0/50/100%>

Reference: Chen, Yanbei, et al. "Semi-supervised learning under class distribution mismatch." Proceedings of the AAAI Conference on Artificial Intelligence. Vol. 34. No. 04. 2020.s
DMQA Open 세미나, 배진수, "Deep Semi-Supervised Learning with Out-of-distribution Unlabeled Data"

Experiment

Model performance with other datasets

- CIFAR10 외에 CIFAR100, TinyImageNet 데이터를 활용해서 모델의 성능을 검증함
- CIFAR100, TinyImageNet 데이터 에서도 제안하는 UASD 알고리즘의 성능이 가장 좋았음

Method	CIFAR100	TinyImageNet	CIFAR100 + TinyImageNet
baseline	39.79 ± 1.19	61.64 ± 0.59	48.31 ± 0.63
pseudo-label	43.30 ± 0.57	62.41 ± 0.57	53.3 ± 0.73
VAT	43.78 ± 1.15	63.75 ± 0.69	50.55 ± 0.55
Π-Model	42.96 ± 0.46	61.79 ± 0.67	53.05 ± 2.21
Temporal Ensembling	41.27 ± 0.76	60.69 ± 0.31	47.88 ± 0.64
Mean-Teacher	40.98 ± 0.98	$\mathbf{60.54 \pm 0.31}$	49.67 ± 1.95
SWA	$\mathbf{37.66 \pm 0.48}$	$\mathbf{57.97 \pm 0.42}$	$\mathbf{44.61 \pm 0.52}$
Ours	$\mathbf{35.93 \pm 0.60}$	$\mathbf{57.15 \pm 0.76}$	$\mathbf{42.83 \pm 0.25}$

<Results on CIFAR100 and TinyImageNet averaged over 5 runs>

Reference: Chen, Yanbei, et al. "Semi-supervised learning under class distribution mismatch." Proceedings of the AAAI Conference on Artificial Intelligence. Vol. 34. No. 04. 2020.s

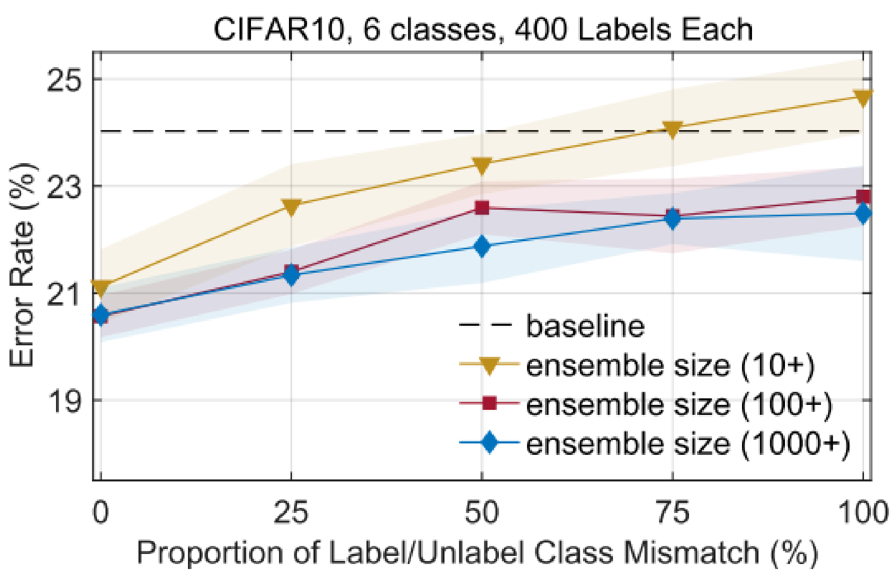
Experiment

Ablative evaluation

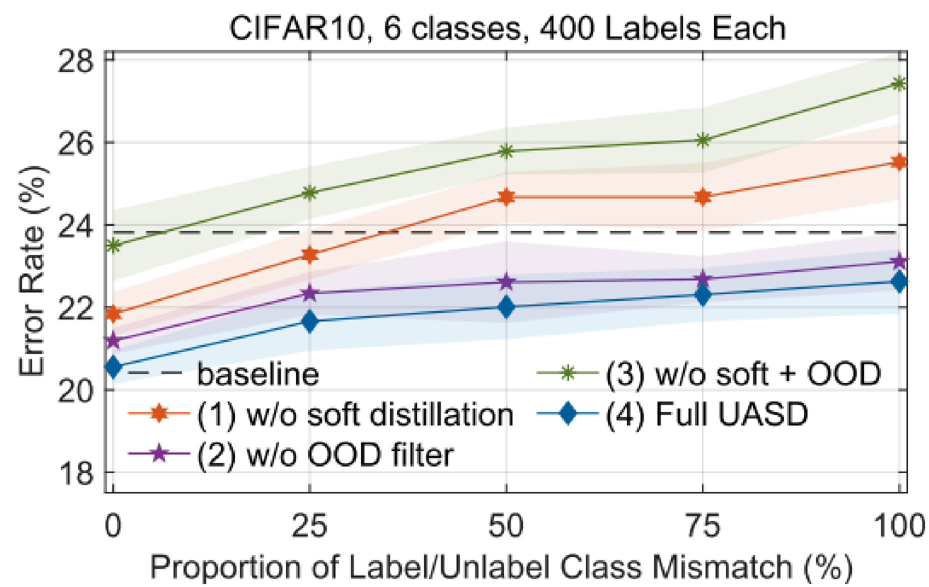
❖ (좌측) Ensemble size (=epoch size)에 따른 예측 결과를 보여줌

❖ (좌측) Ensemble size가 커질수록 예측 성능이 좋으나 100이 넘어가면 차이 별로 없음

❖ (우측) 제안하는 방법 중 soft target(①ensemble), ②OOD filte의 사용 유무에 따른 ablation study 결과를 보여줌. 결과적으로 제안한 모든 방법을 사용했을 때 성능이 가장 좋았음



<Test error rates on CIFAR10 with ensemble size>



<Ablation results>

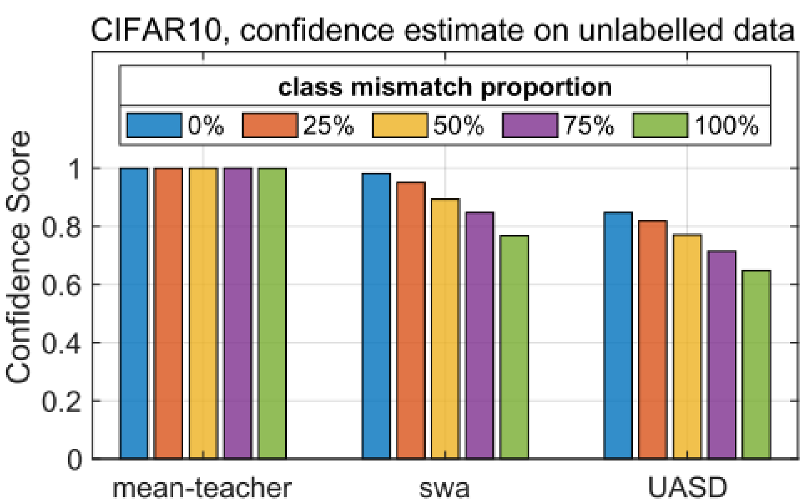
Reference: Chen, Yanbei, et al. "Semi-supervised learning under class distribution mismatch." Proceedings of the AAAI Conference on Artificial Intelligence. Vol. 34. No. 04. 2020.s

Experiment

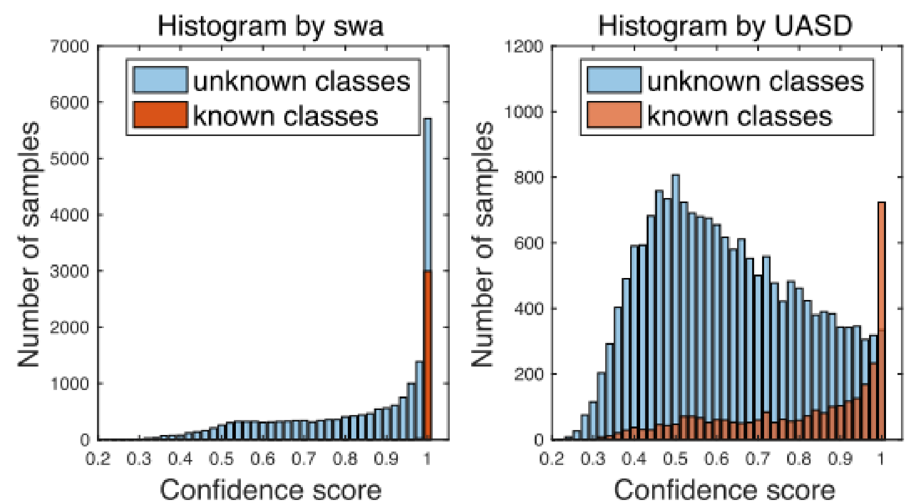
Confidence score

- ❖ (좌측) 기존의 SSL 방법론 대비 UASD가 unlabelled data에 대한 confidence score가 낮음
- ❖ (우측) Histogram으로 보았을 때도 UASD 알고리즘을 적용했을 때 unknown classes 데이터가 전반적으로 confidence score가 작음을 확인

→ UASD를 사용해 unlablled data에 대한 confidence score를 낮추도록 유도했음을 확인



<Average confidence score on unlabelled data>



<Histogram of confidence score>

Reference: Chen, Yanbei, et al. "Semi-supervised learning under class distribution mismatch." Proceedings of the AAAI Conference on Artificial Intelligence. Vol. 34. No. 04. 2020.s

Conclusion

❖ Conclusion

- 기존에는 mismatch(labelled data와 unlabelled data 간의 class가 다름) 상황에서 Semi-supervised learning(SSL) 성능이 하락하게 되는 문제가 발생하고 있음
- UASD는 현실과 유사한 mismatch 상황에서도 성능 하락 없이 SSL을 안정적으로 진행할 수 있게 해주는 알고리즘임
- UASD는 아래와 같은 총 3가지를 활용함
  ① On-the-Fly Accumulative Ensemble: 모델 학습시 epoch별로 나온 결과에 대한 평균값을 사용
  ② OOD Filter: ①번에서 산출된 결과 (q_t)를 기반으로 해당 데이터의 학습 사용 유무 결정
  ③ Uncertainty-Aware Self-Distillation: labelled data와 unlabelled data의 loss를 함께 활용해 학습 진행
- 본 방법론을 적용한다면 unlabelled data에 대한 confidence score를 낮춰 실제 모델 학습에 도움이 되는 sample만 추출해 안정적인 SSL 학습을 진행 할 수 있음

Thank You

Appendix

Appendix

Reference

❖ Chen, Yanbei, et al. "Semi-supervised learning under class distribution mismatch." Proceedings of the AAAI Conference on Artificial Intelligence. Vol. 34. No. 04. 2020.s