DMQA Open Seminar

Contrastive Semi-supervised Learning

2023. 04. 14

고려대학교 산업경영공학과

Data Mining & Quality Analytics Lab.

임 새 린

발표자 소개

❖ **임새린 (Saerin Lim)**

- 고려대학교 산업경영공학과 Data Mining & Quality Analytics Lab.
- Ph.D. Student (2021.03 ~ Present)
- 지도 교수 : 김성범 교수님

❖ **Research Interest**

- Multivariate time-series data analysis
- Self-supervised learning & Semi-supervised learning

❖ **Contact**

- E-mail : momo_om@korea.ac.kr

목차

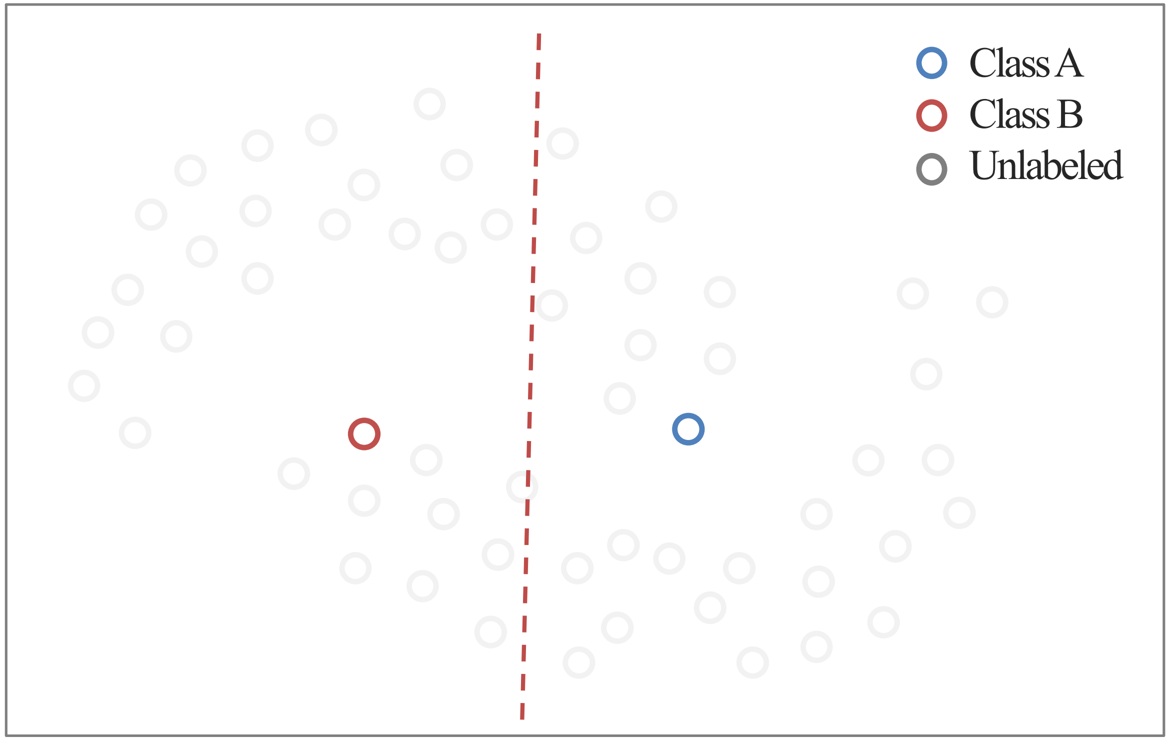
Contents

Background

준지도 학습

❖ Semi-Supervised Learning

- Unlabeled data를 활용해서 모델의 일반화 성능을 향상시키는 방법론

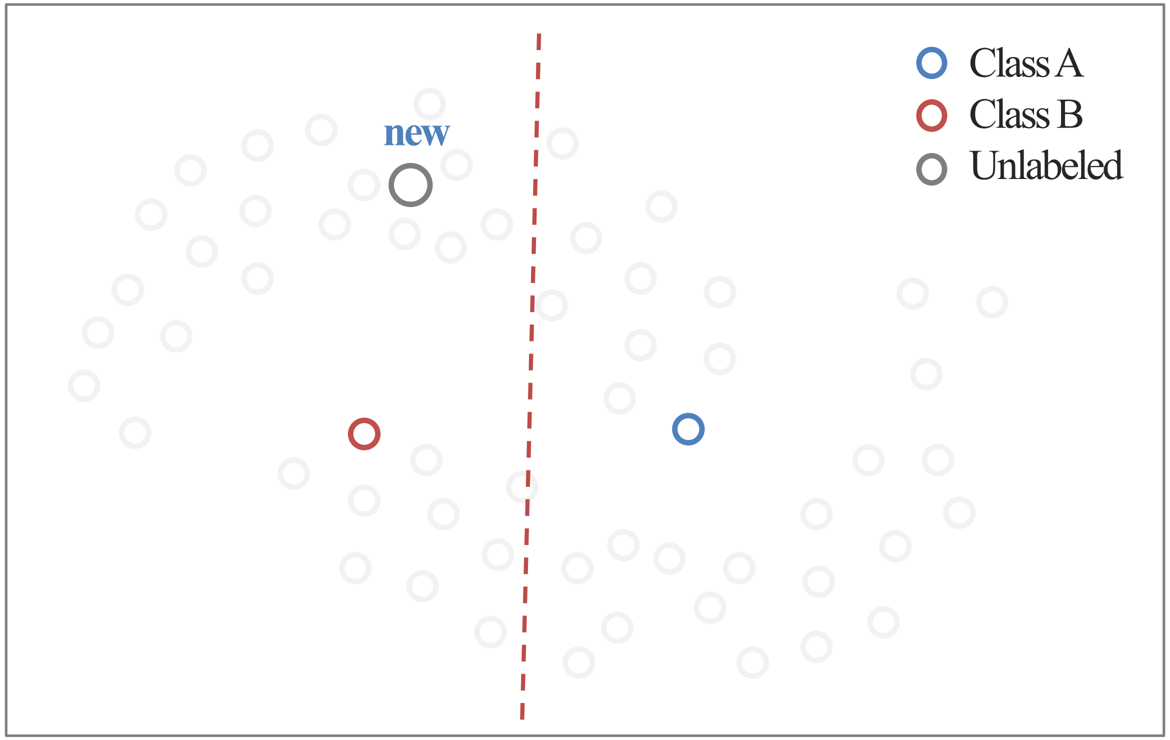


Background

준지도 학습

❖ Semi-Supervised Learning

- Unlabeled data를 활용해서 모델의 일반화 성능을 향상시키는 방법론

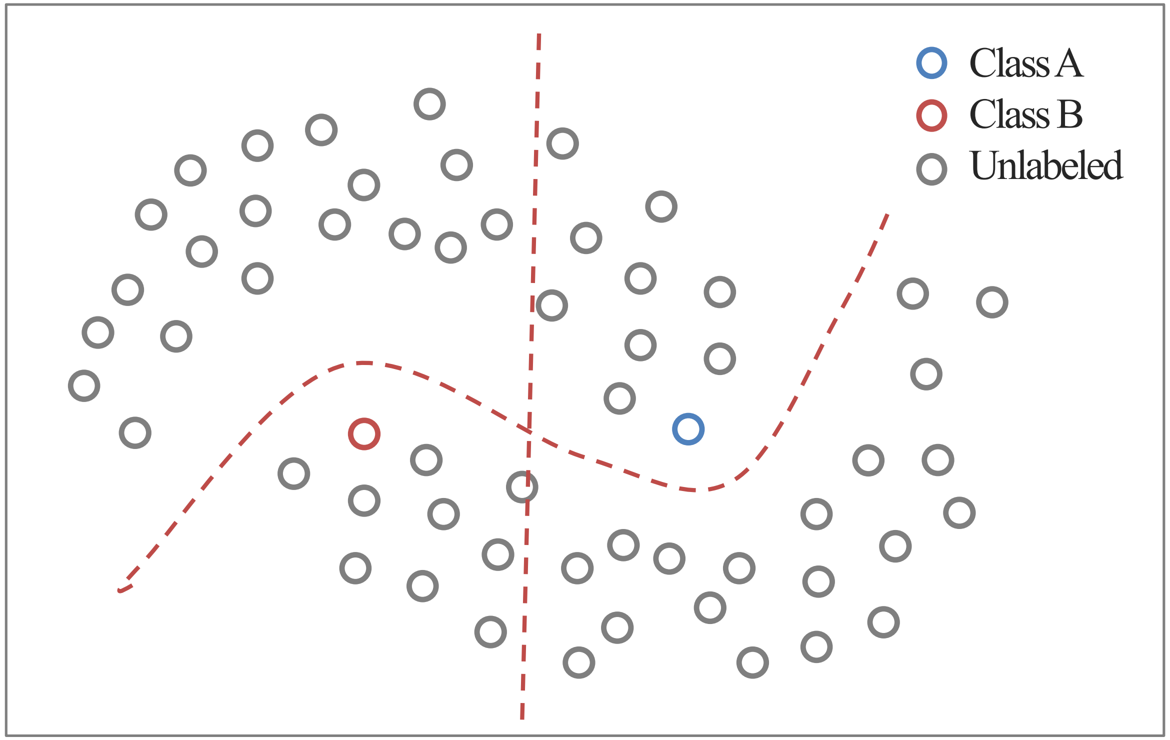


Background

준지도 학습

❖ Semi-Supervised Learning

- Unlabeled data를 활용해서 모델의 일반화 성능을 향상시키는 방법론

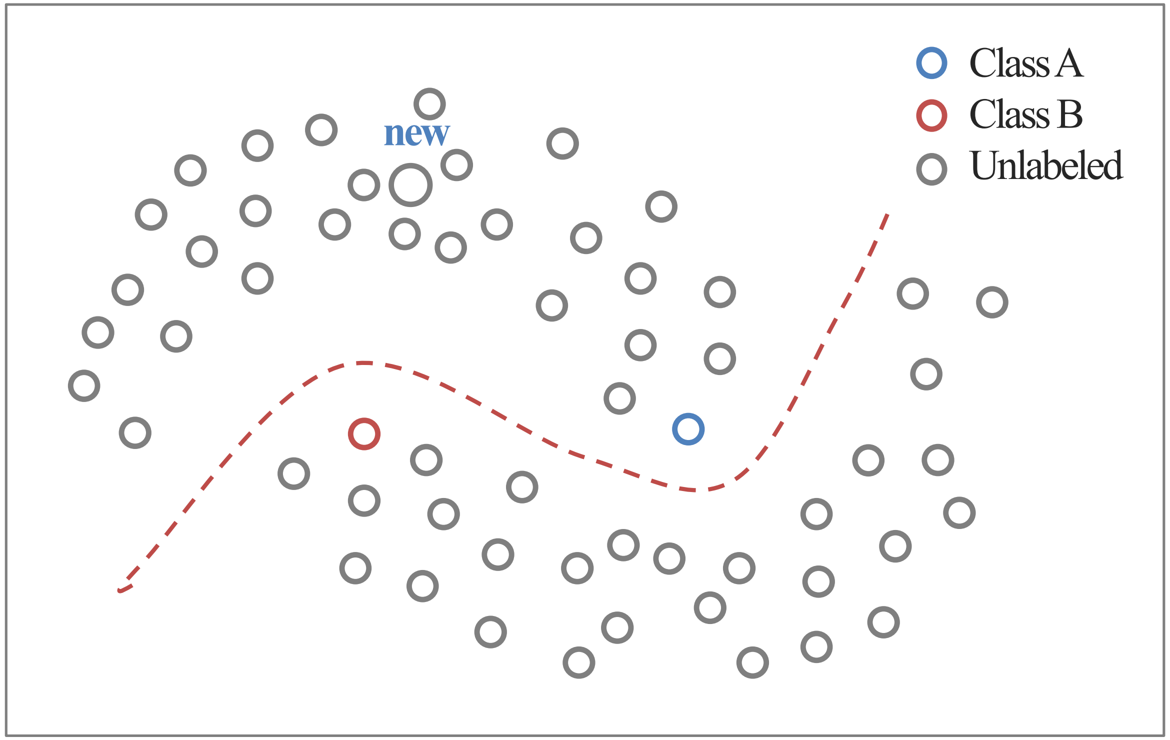


Background

준지도 학습

❖ Semi-Supervised Learning

- Unlabeled data를 활용해서 모델의 일반화 성능을 향상시키는 방법론

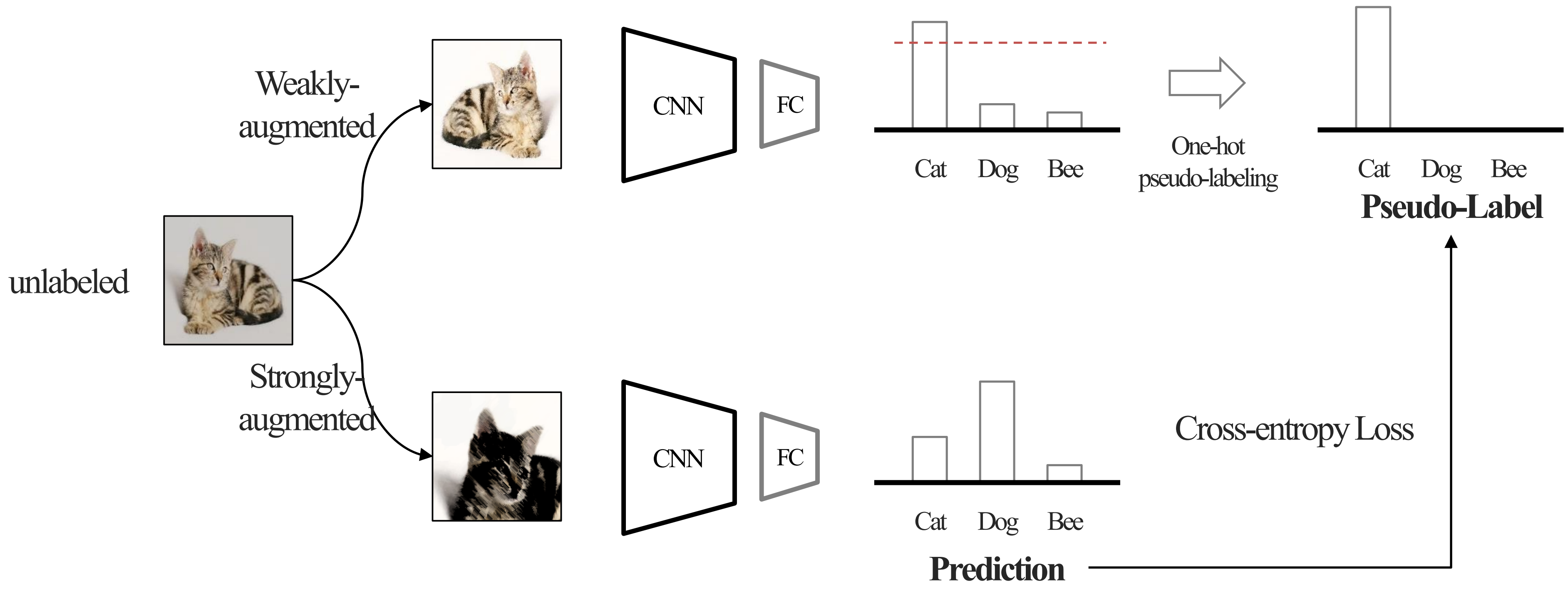


Background

준지도 학습

❖ Fixmatch

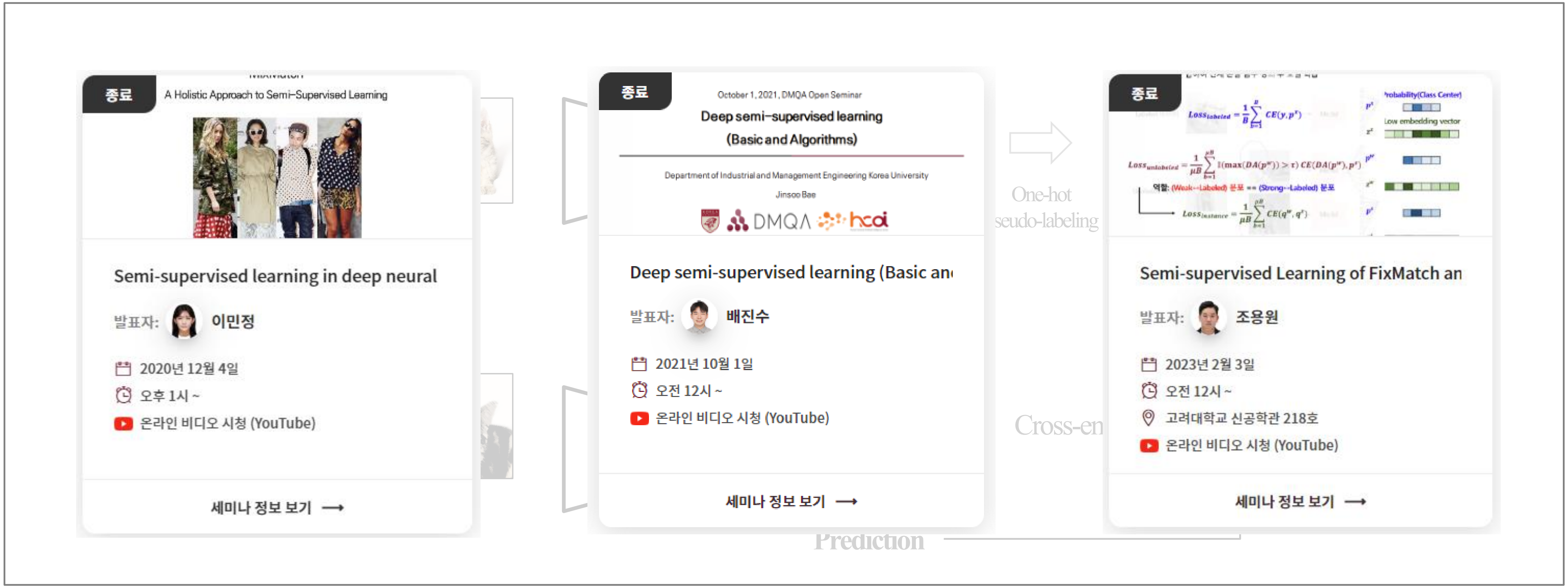
- 여러 준지도 학습 방법론을 간단하게 통합하여 좋은 성능을 보인 방법론



Background
준지도 학습

❖ Fixmatch

• 여러 준지도 학습 방법론을 간단하게 통합하여 좋은 성능을 보인 방법론

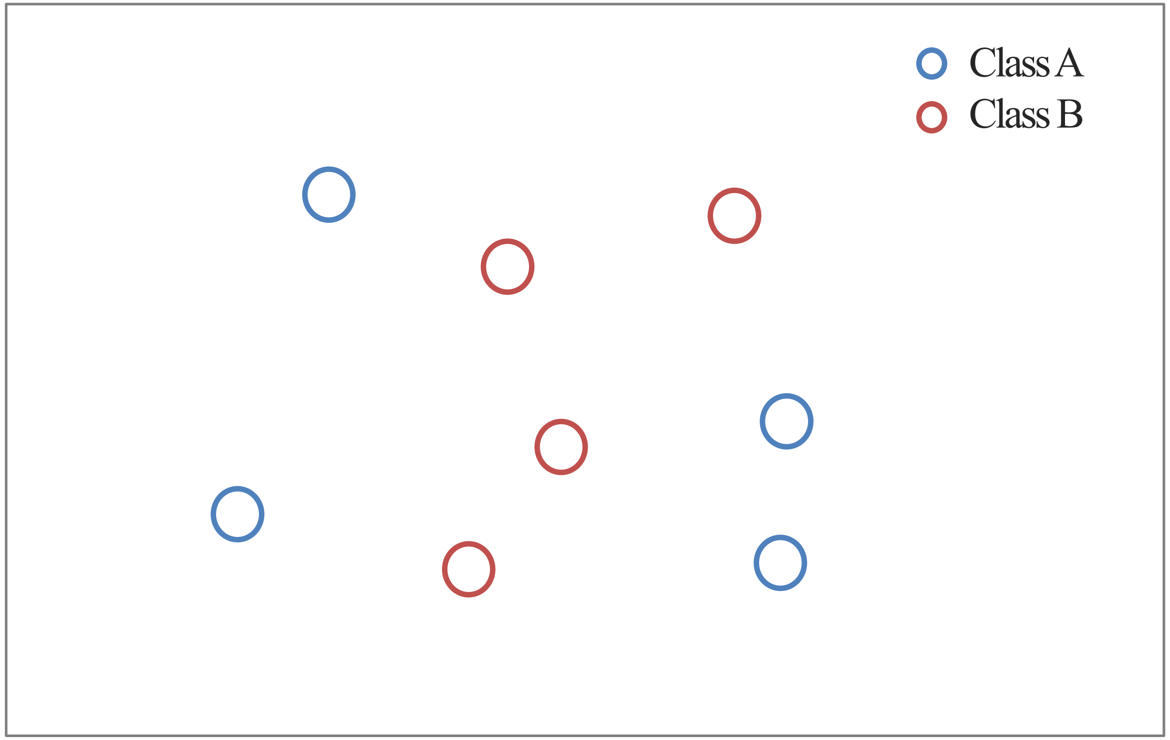


Background

대조 학습

❖ Contrastive Learning

- Metric Learning 방법론 중 하나로 데이터 간 유사도 정보를 통해서 데이터들을 구분하기 쉽게 해주는 거리 함수를 학습하는 것
- **Anchor**를 기준으로 **Positive samples**는 가깝도록, **Negative samples**는 멀도록 학습



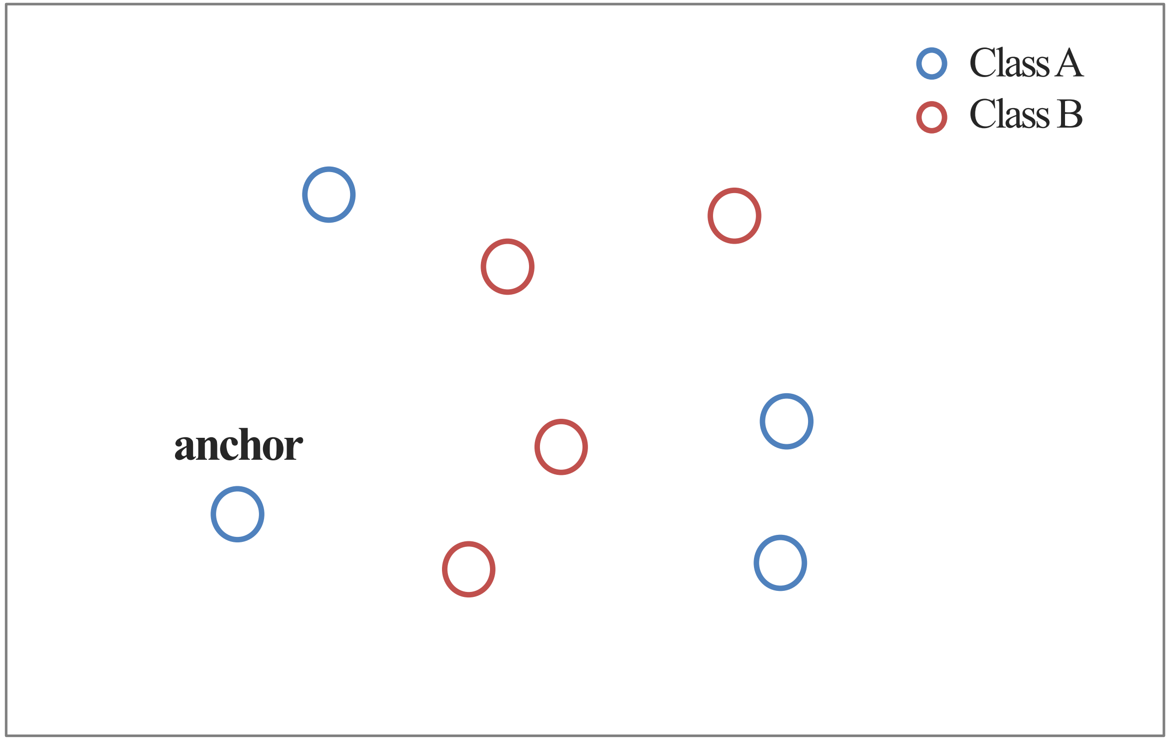
Original feature space

Background

대조 학습

❖ Contrastive Learning

- Metric Learning 방법론 중 하나로 데이터 간 유사도 정보를 통해서 데이터들을 구분하기 쉽게 해주는 거리 함수를 학습하는 것
- **Anchor**를 기준으로 **Positive samples**는 가깝도록, **Negative samples**는 멀도록 학습



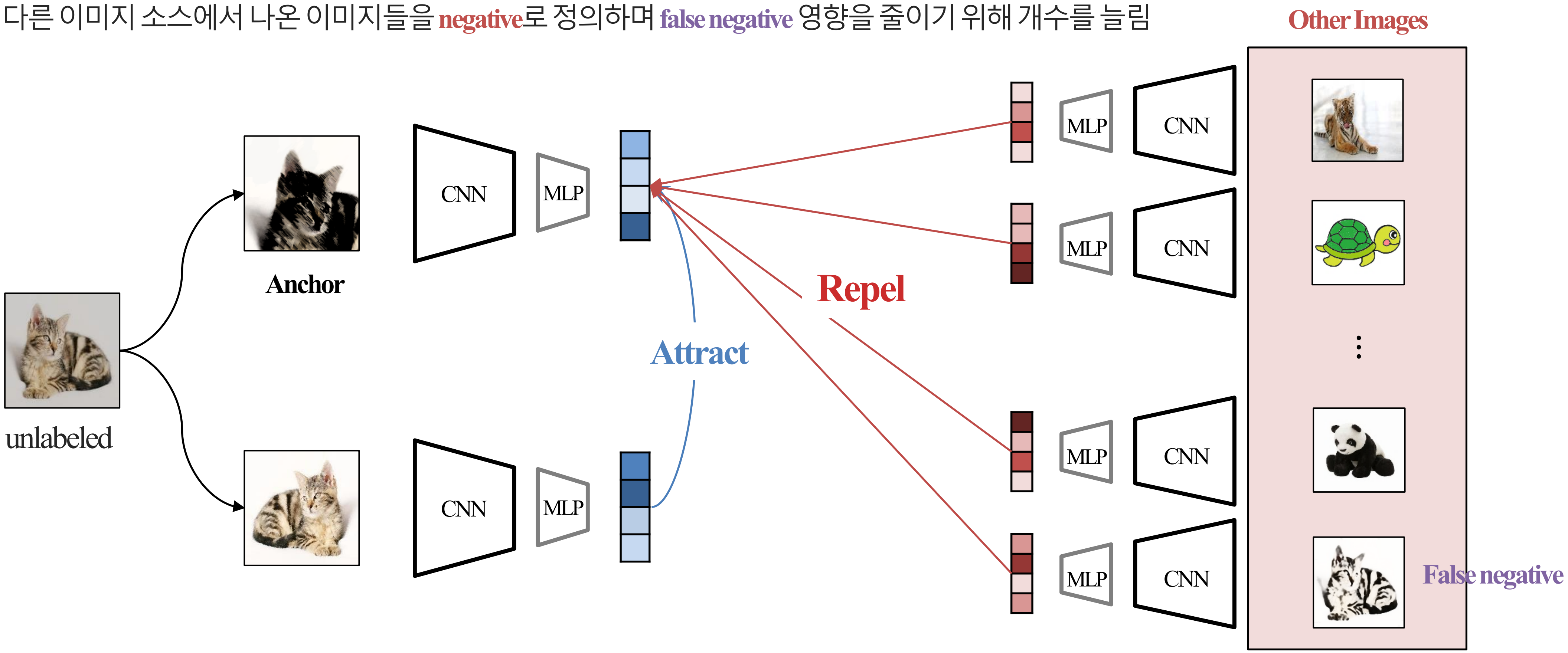
Embedding space

Background

대조 학습

❖ Self-supervised Contrastive Learning

- 이미지 증강 기법을 통해서 같은 소스에서 나온 이미지들을 **positive**로 정의
- 다른 이미지 소스에서 나온 이미지들을 **negative**로 정의하며 **false negative** 영향을 줄이기 위해 개수를 늘림

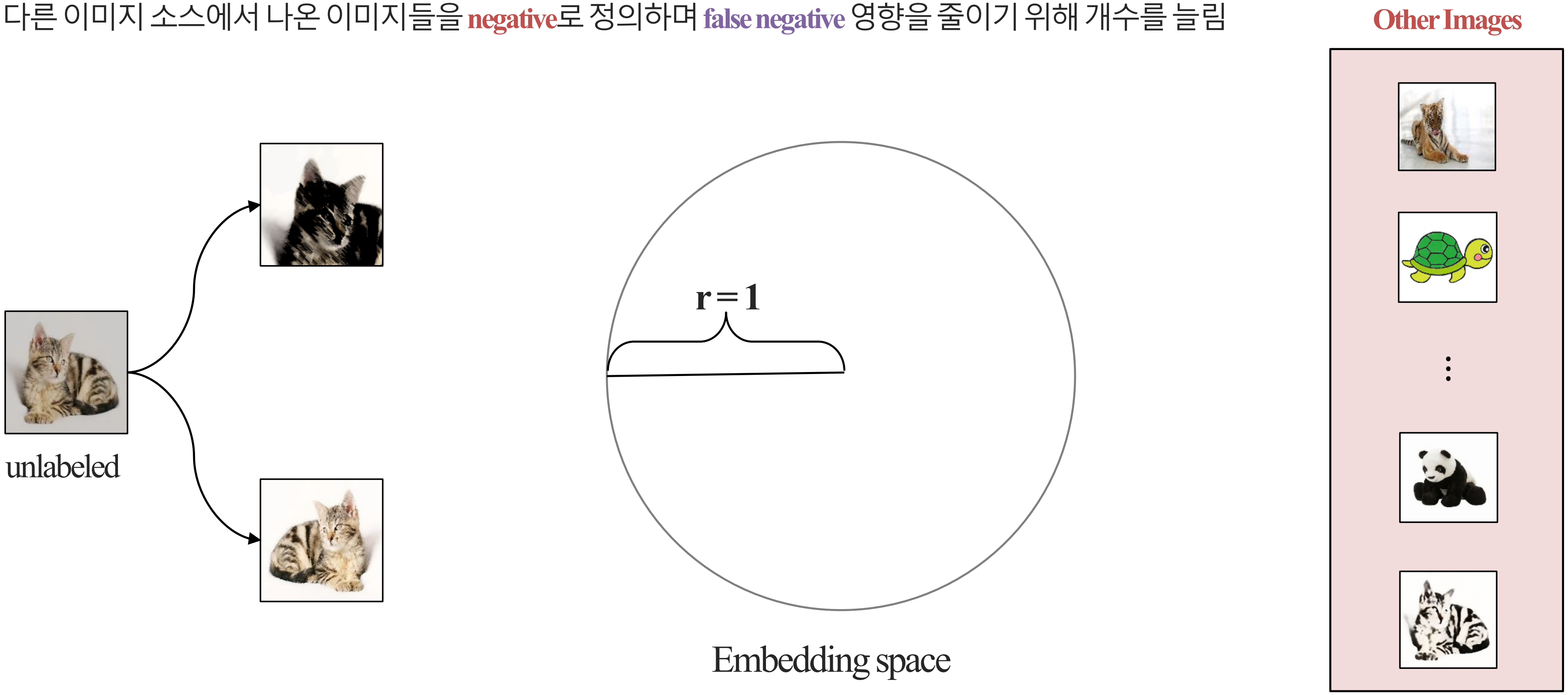


Background

대조 학습

❖ Self-supervised Contrastive Learning

- 이미지 증강 기법을 통해서 같은 소스에서 나온 이미지들을 **positive**로 정의
- 다른 이미지 소스에서 나온 이미지들을 **negative**로 정의하며 **false negative** 영향을 줄이기 위해 개수를 늘림

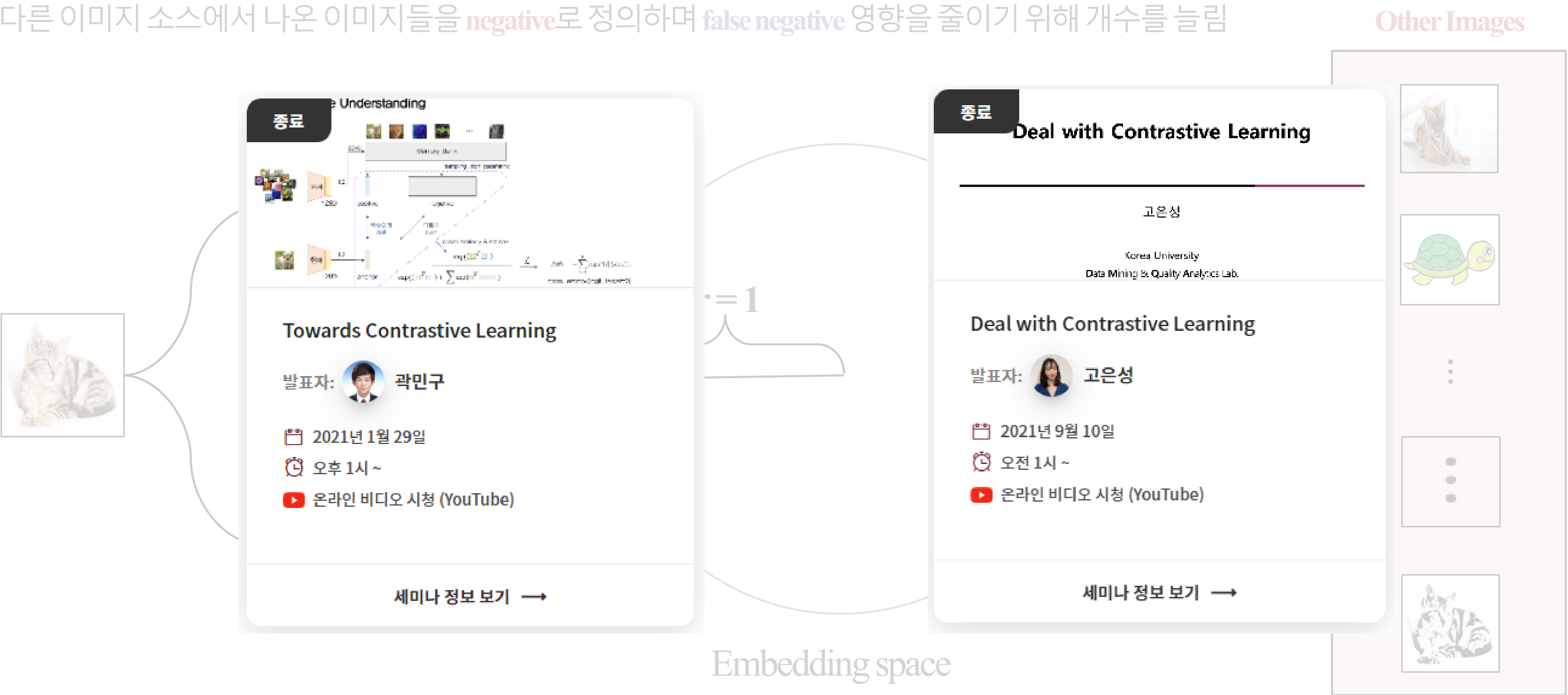


Background

대조 학습

❖ Self-supervised Contrastive Learning

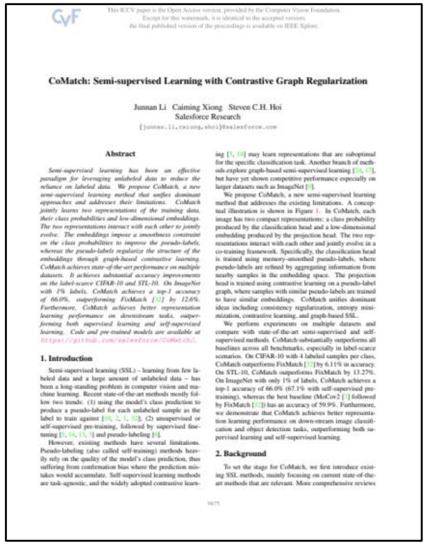
- 이미지 증강 기법을 통해서 같은 소스에서 나온 이미지들을 positive로 정의
- 다른 이미지 소스에서 나온 이미지들을 negative로 정의하며 false negative 영향을 줄이기 위해 개수를 늘림



Paper Reviews

논문 리뷰

❖ Paper List



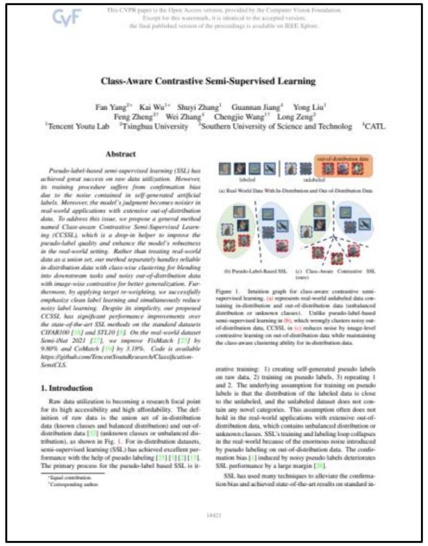
CoMatch: Semi-supervised Learning with Contrastive Graph Regularization

Junnan Li Caiming Xiong Steven C.H. Hoi
Salesforce Research

CoMatch: Semi-Supervised Learning

With Contrastive Graph Regularization

(2021, ICCV)

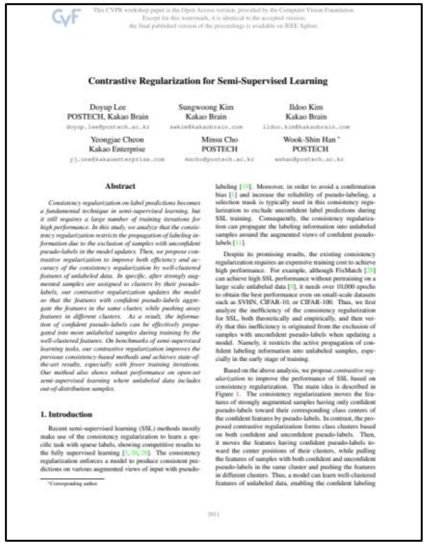


Class-Aware Contrastive Semi-Supervised Learning

Class-Aware Contrastive

Semi-Supervised Learning

(2022, CVPR)

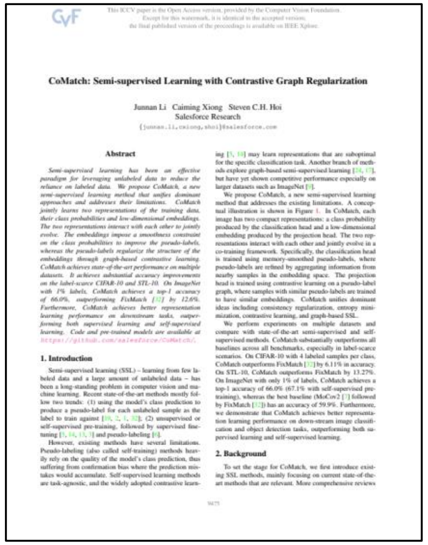


Contrastive Regularization for Semi-Supervised Learning

Contrastive Regularization

for Semi-Supervised Learning

(2022, CVPR)


CoMatch: Semi-supervised Learning with Contrastive Graph Regularization

Junnan Li Caiming Xiong Steven C.H. Hoi
Salesforce Research

CoMatch: Semi-Supervised Learning With Contrastive Graph Regularization (2021, ICCV)

Class-Aware Contrastive Semi-Supervised Learning (2022, CVPR)

Contrastive Regularization for Semi-Supervised Learning (2022, CVPR)

Paper Reviews

논문 리뷰

❖ CoMatch : Semi-Supervised Learning with Contrastive Graph Regularization

- 2021년 ICCV에서 발표된 논문으로 발표 당시 SOTA 성능 달성
- 최초로 FixMatch에 Contrastive learning을 결합한 방법론

CoMatch: Semi-supervised Learning with Contrastive Graph Regularization

Junnan Li   Caiming Xiong   Steven C.H. Hoi
Salesforce Research
{junnan.li,cxiong,shoi}@salesforce.com

Abstract

Semi-supervised learning has been an effective paradigm for leveraging unlabeled data to reduce the reliance on labeled data. We propose CoMatch, a new semi-supervised learning method that unifies dominant approaches and addresses their limitations. CoMatch jointly learns two representations of the training data, their class probabilities and low-dimensional embeddings. The two representations interact with each other to jointly evolve. The embeddings impose a smoothness constraint on the class probabilities to improve the pseudo-labels,

ing [5, 14] may learn representations that are suboptimal for the specific classification task. Another branch of methods explore graph-based semi-supervised learning [24, 17], but have yet shown competitive performance especially on larger datasets such as ImageNet [9].

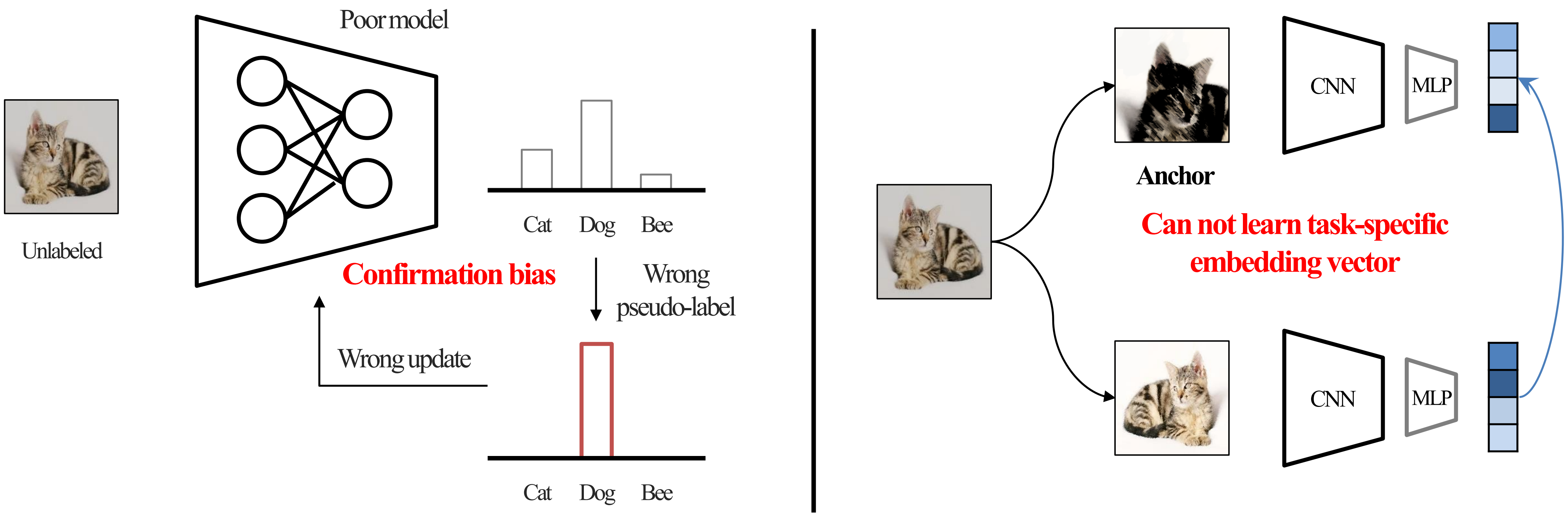
We propose CoMatch, a new semi-supervised learning method that addresses the existing limitations. A conceptual illustration is shown in Figure 1. In CoMatch, each image has two compact representations: a class probability produced by the classification head and a low-dimensional embedding produced by the projection head. The two representations interact with each other and jointly evolve in a

Paper Reviews

CoMatch: Semi-Supervised Learning with Contrastive Graph Regularization

❖ 연구 배경

- 대부분의 준지도 학습 방법론에서 사용하는 pseudo-label은 모델 예측 결과 퀄리티에 크게 의존적이며 confirmation bias가 존재
- 자가지도 학습 방법론은 task-agnostic한 방법론이기 때문에 실제 task에 정확히 맞는embedding space를 학습하기 어려움

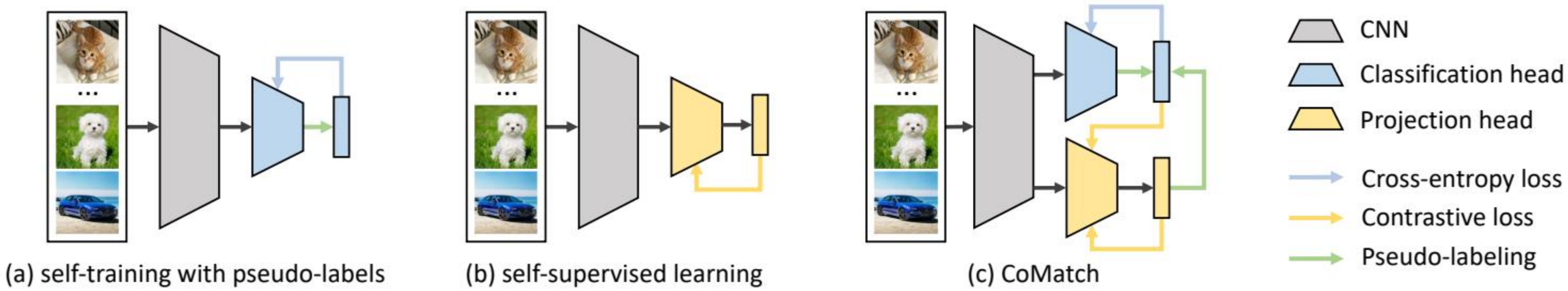


Paper Reviews

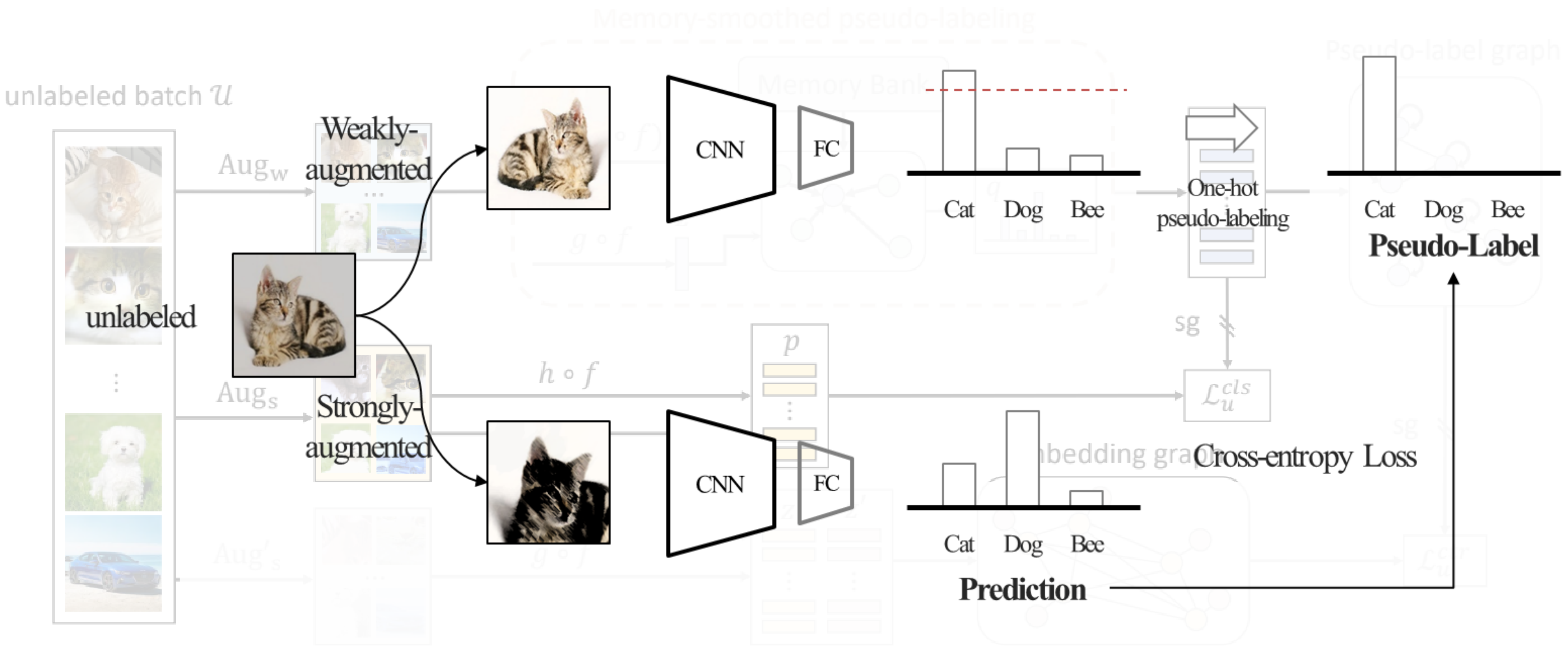
CoMatch: Semi-Supervised Learning with Contrastive Graph Regularization

❖ 연구 가설

- Class probability와 low-dimensional embedding이 서로 도움을 주면서 동시에 학습하면 더 좋은 representation을 학습 할 수 있을 것



❖ 제안 방법론



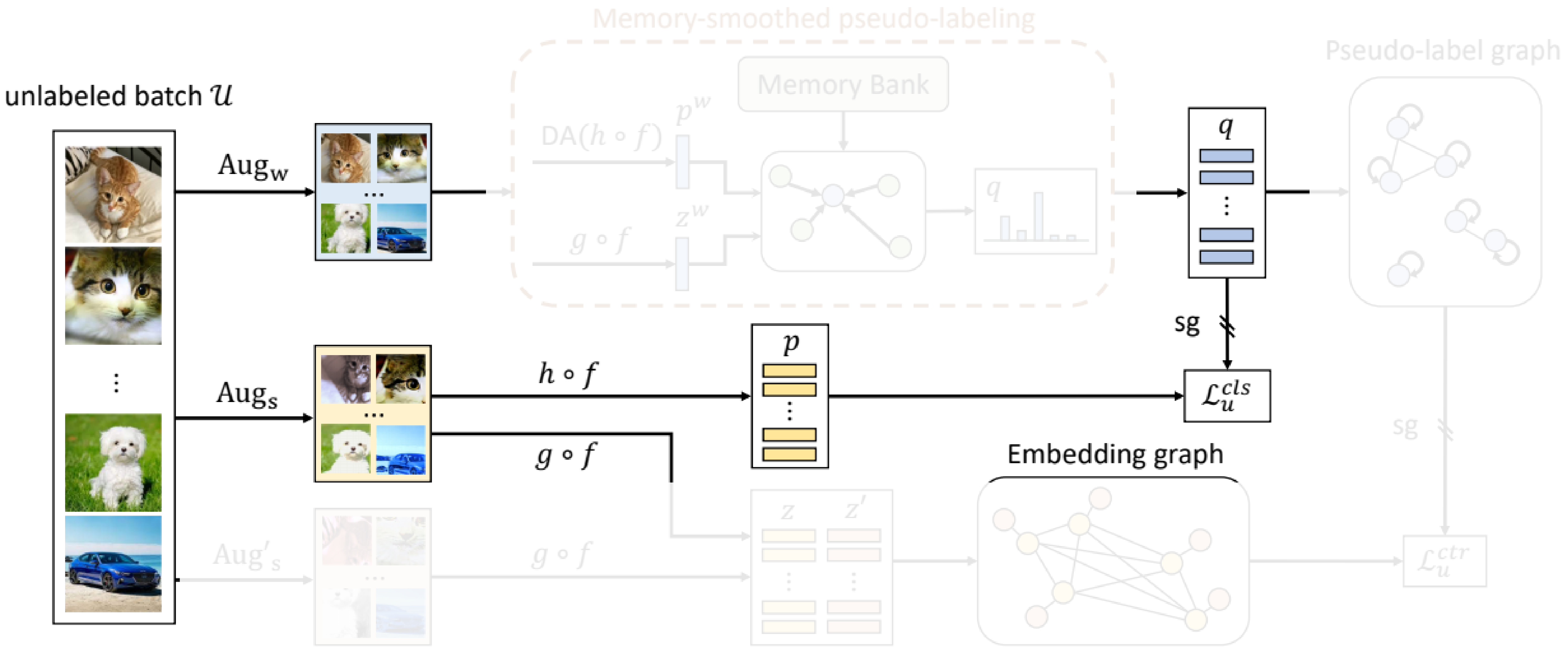
$$L_{comatch} = L_l^{cls} + L_u^{cls} + L_u^{ctr}$$

Paper Reviews

CoMatch: Semi-Supervised Learning with Contrastive Graph Regularization

❖ 제안 방법론

1. pseudo-label을 embedding vector를 통해 조정하는 모듈



$$L_{comatch} = L_l^{cls} + L_u^{cls} + L_u^{ctr}$$

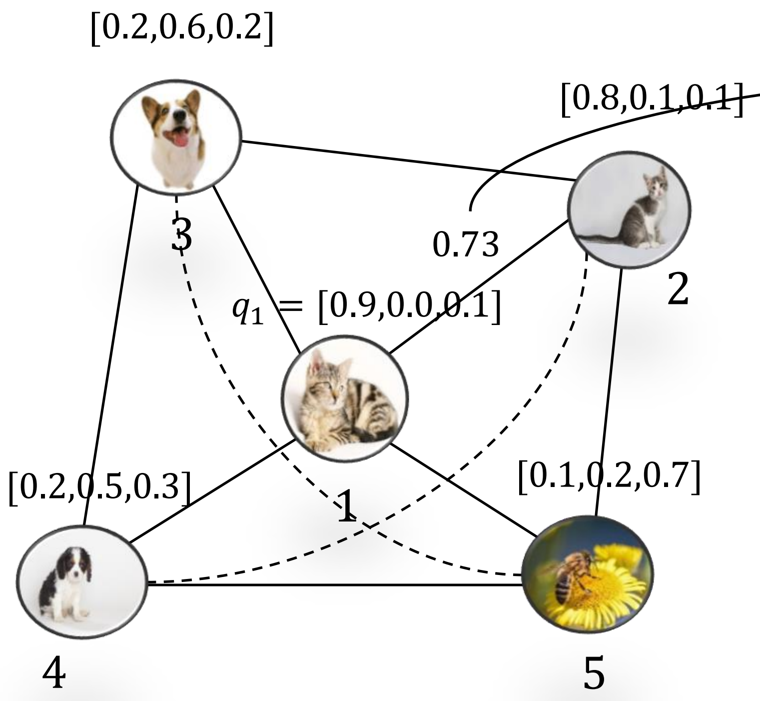
2. pseudo-label graph를 통해 embedding graph를 학습하는 모듈

Paper Reviews

CoMatch: Semi-Supervised Learning with Contrastive Graph Regularization

❖ Graph Representation of Data

- 이미지(데이터 포인트)를 노드로 이미지 간의 유사도를 엣지로 정의하여 그래프 구성



Adjacency Matrix W

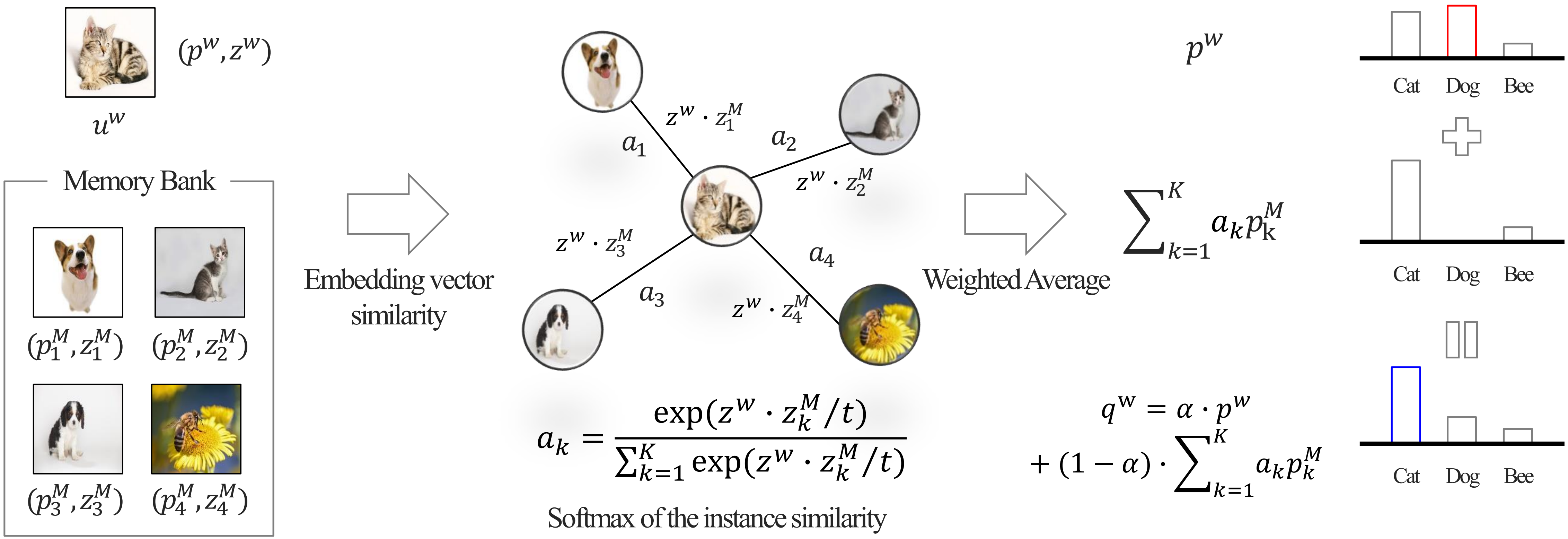
	1	2	3	4	5
1	1	.73	.20	.21	.16
2		1	.24	.24	.17
3			1	.40	.28
4				1	.33
5					1

Paper Reviews

CoMatch: Semi-Supervised Learning with Contrastive Graph Regularization

❖ Memory-smoothed pseudo-labeling

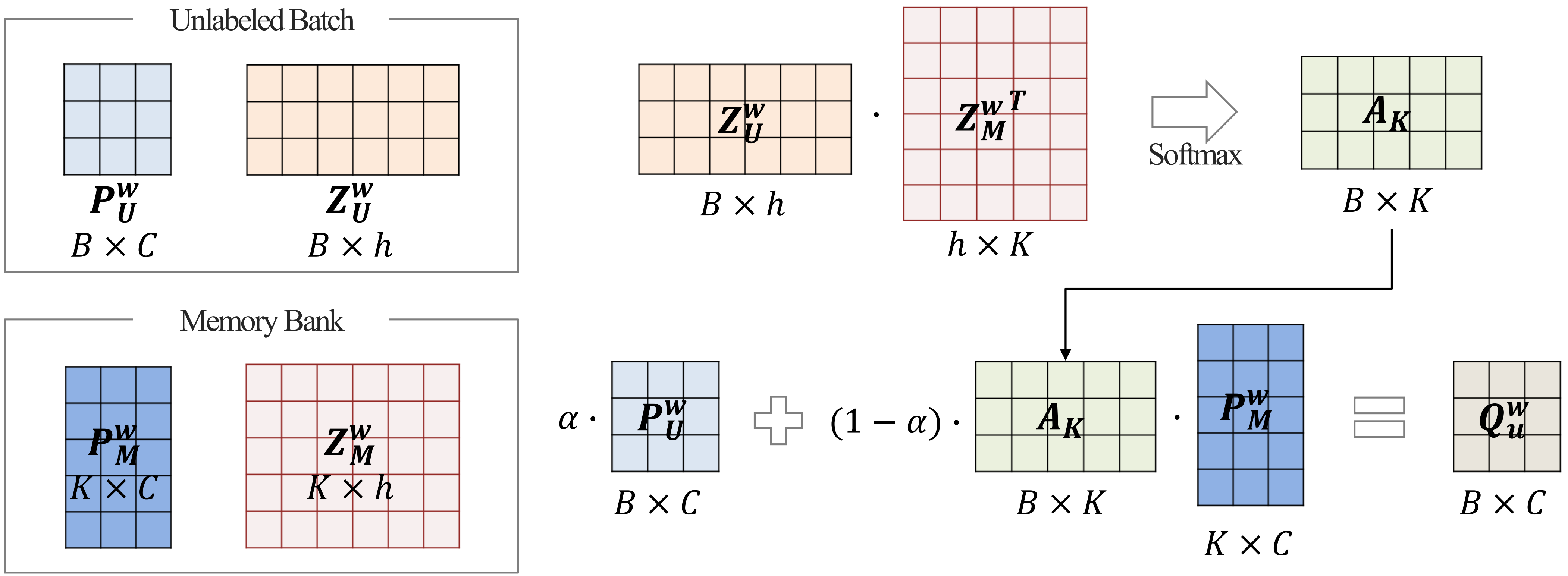
- Weakly-augmented image에 대한 pseudo-label의 확증 편향을 완화하기 위해 embedding vector 유사도를 반영
- Memory Bank에 과거 K개의 weakly-augmented image의 pseudo-label과 embedding vector를 저장하여 사용



CoMatch: Semi-Supervised Learning with Contrastive Graph Regularization

❖ Memory-smoothed pseudo-labeling

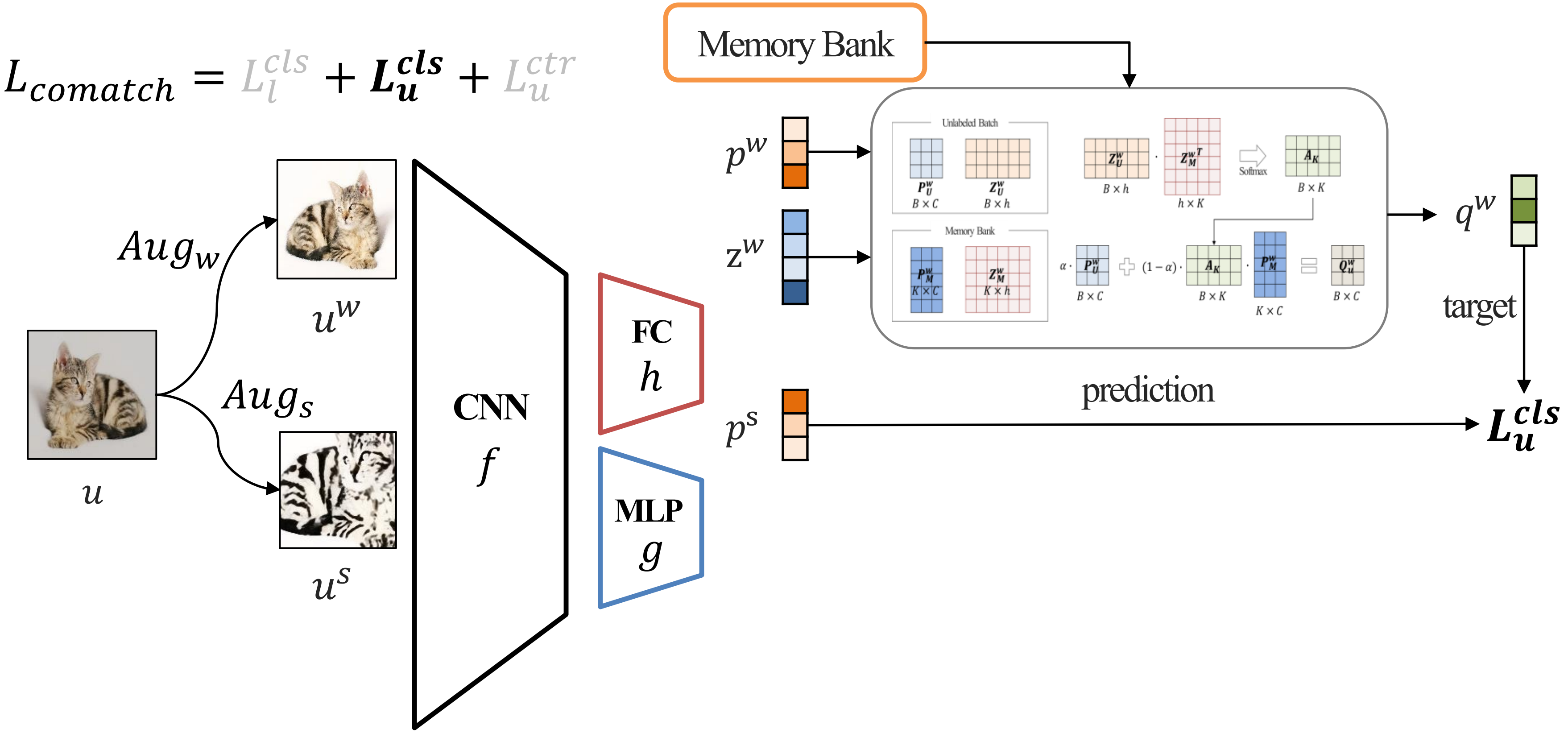
- Weakly-augmented image에 대한 pseudo-label의 확증 편향을 완화하기 위해 embedding vector 유사도를 반영
- Memory Bank에 과거 K개의 weakly-augmented image의 pseudo-label과 embedding vector를 저장하여 사용



❖ Fixmatch Loss with memory-smoothed pseudo-labeling

- u^w에 대한 Memory-smoothed pseudo-label q^w와 u^s에 대한 class probability p^s 사이의 cross-entropy를 통해 L_u^{cls} 정의

$$L_{comatch} = L_l^{cls} + \boldsymbol{L_u^{cls}} + L_u^{ctr}$$



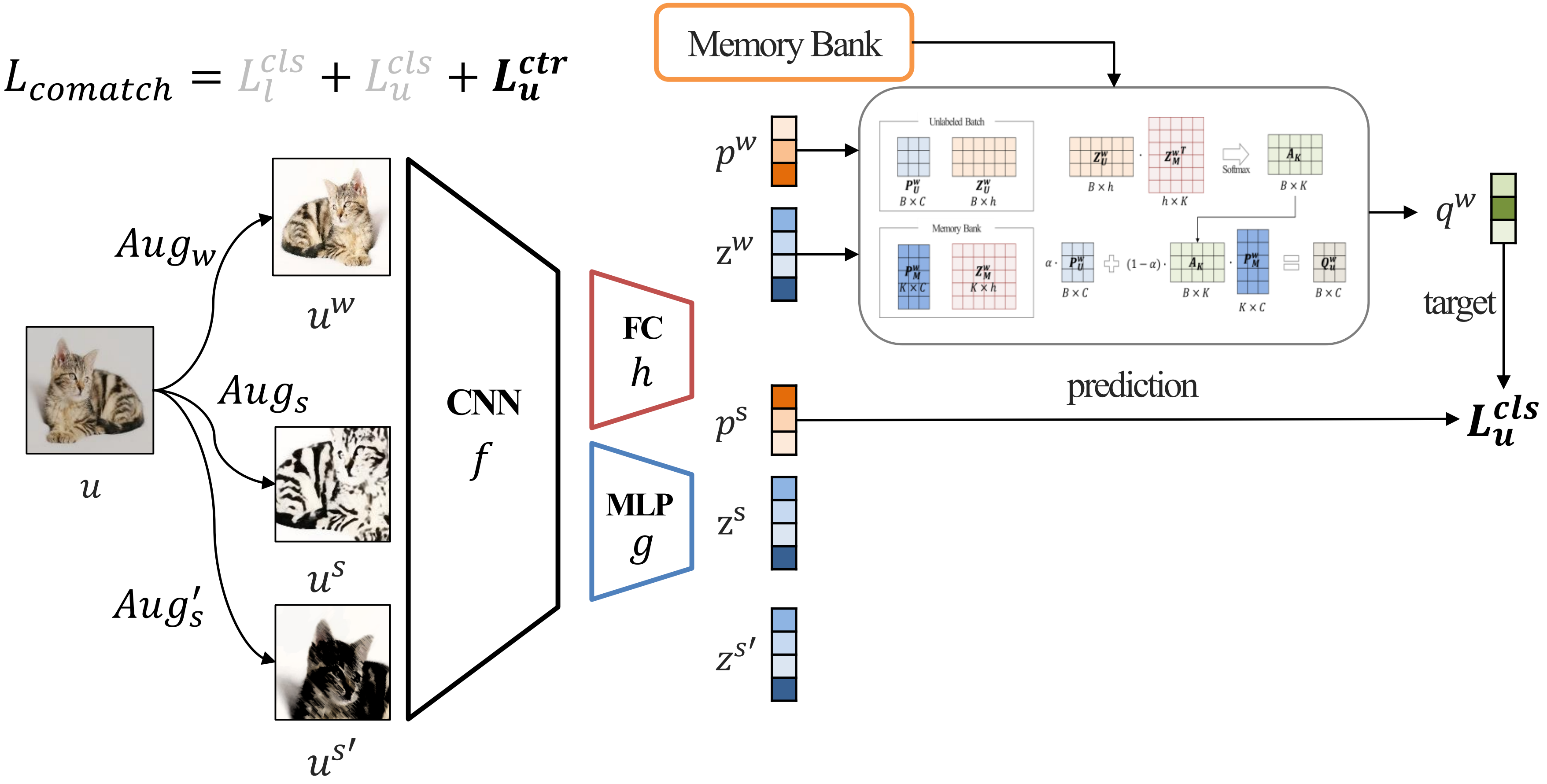
Paper Reviews

CoMatch: Semi-Supervised Learning with Contrastive Graph Regularization

❖ Graph-based Contrastive Learning

- Class끼리 군집을 이룰 수 있도록 pseudo-label의 유사도를 통해 같은 class를 가질 것 같은 이미지를 positive sample로 정의

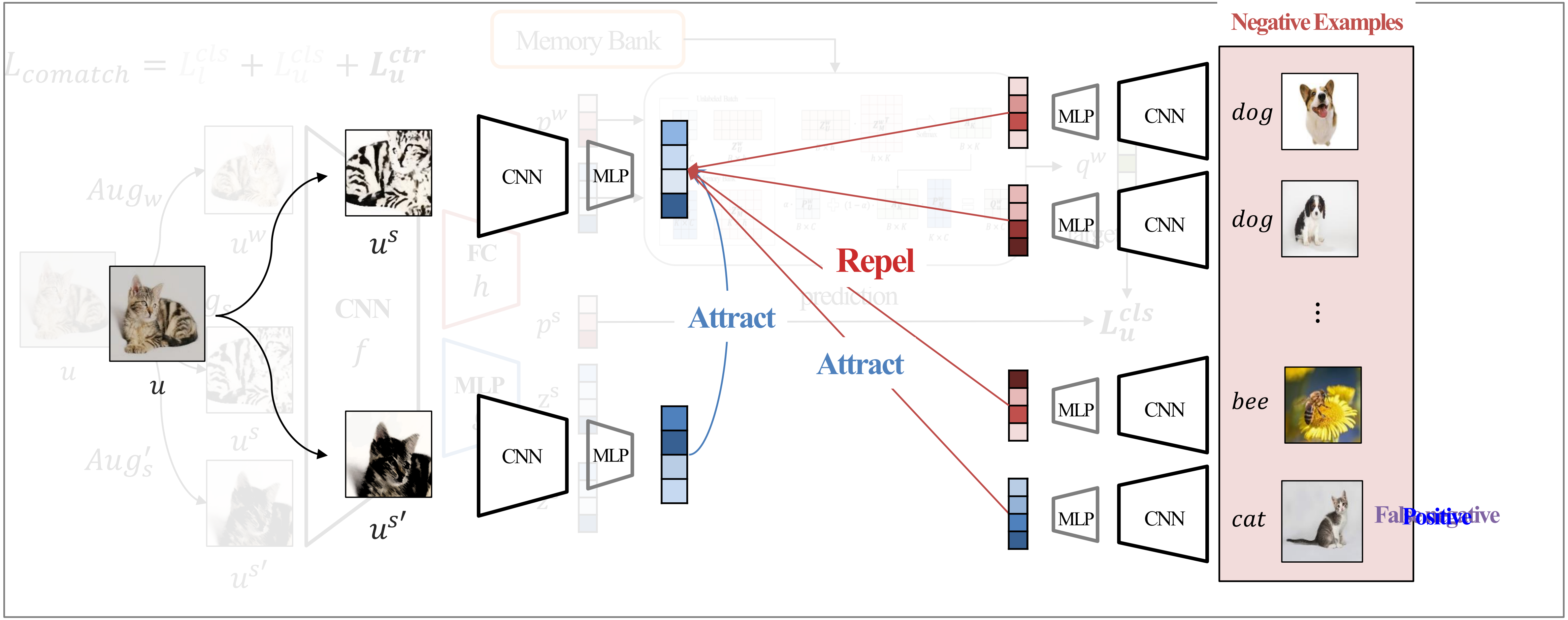
$$L_{comatch} = L_l^{cls} + L_u^{cls} + \boldsymbol{L_u^{ctr}}$$



CoMatch: Semi-Supervised Learning with Contrastive Graph Regularization

❖ Graph-based Contrastive Learning

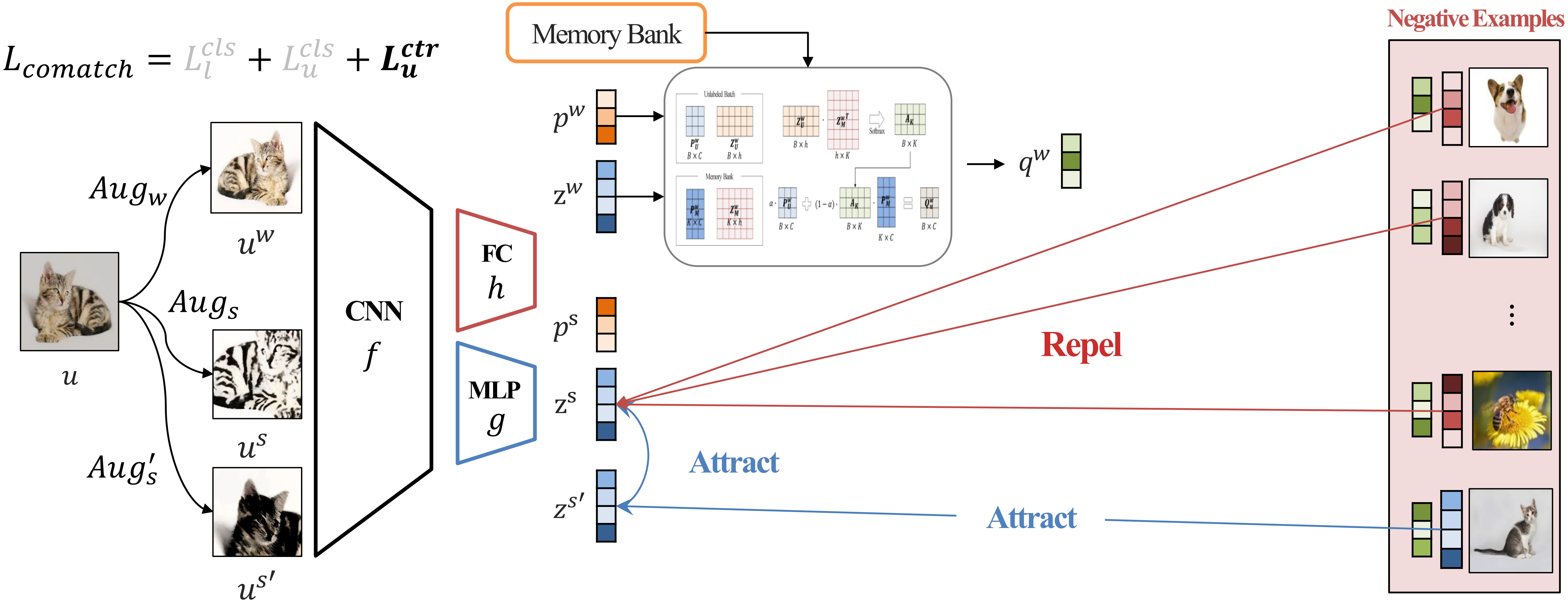
- Class끼리 군집을 이룰 수 있도록 pseudo-label의 유사도를 통해 같은 class를 가질 것 같은 이미지를 positive sample로 정의



❖ Graph-based Contrastive Learning

- Class끼리 군집을 이룰 수 있도록 pseudo-label의 유사도를 통해 같은 class를 가질 것 같은 이미지를 positive sample로 정의

$$L_{comatch} = L_l^{cls} + L_u^{cls} + \boldsymbol{L_u^{ctr}}$$



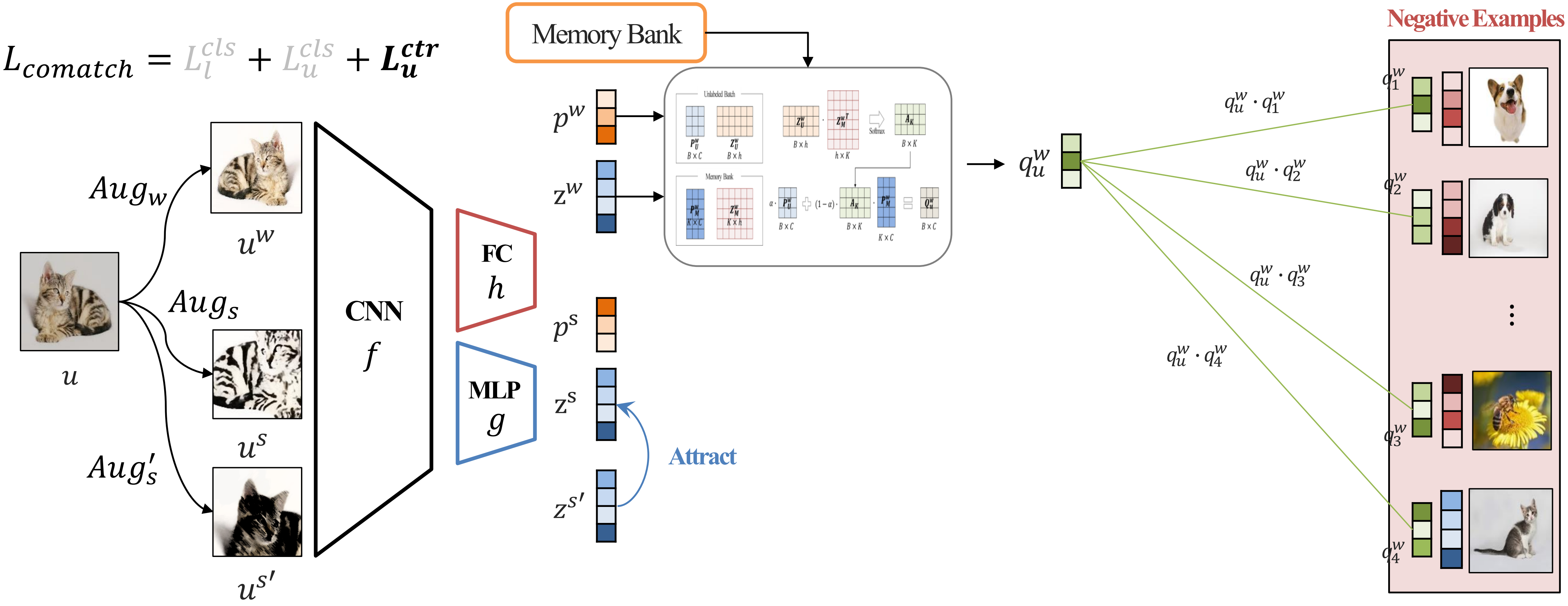
Paper Reviews

CoMatch: Semi-Supervised Learning with Contrastive Graph Regularization

❖ Graph-based Contrastive Learning

- Class끼리 군집을 이룰 수 있도록 pseudo-label의 유사도를 통해 같은 class를 가질 것 같은 이미지를 positive sample로 정의

$$L_{comatch} = L_l^{cls} + L_u^{cls} + \boldsymbol{L_u^{ctr}}$$



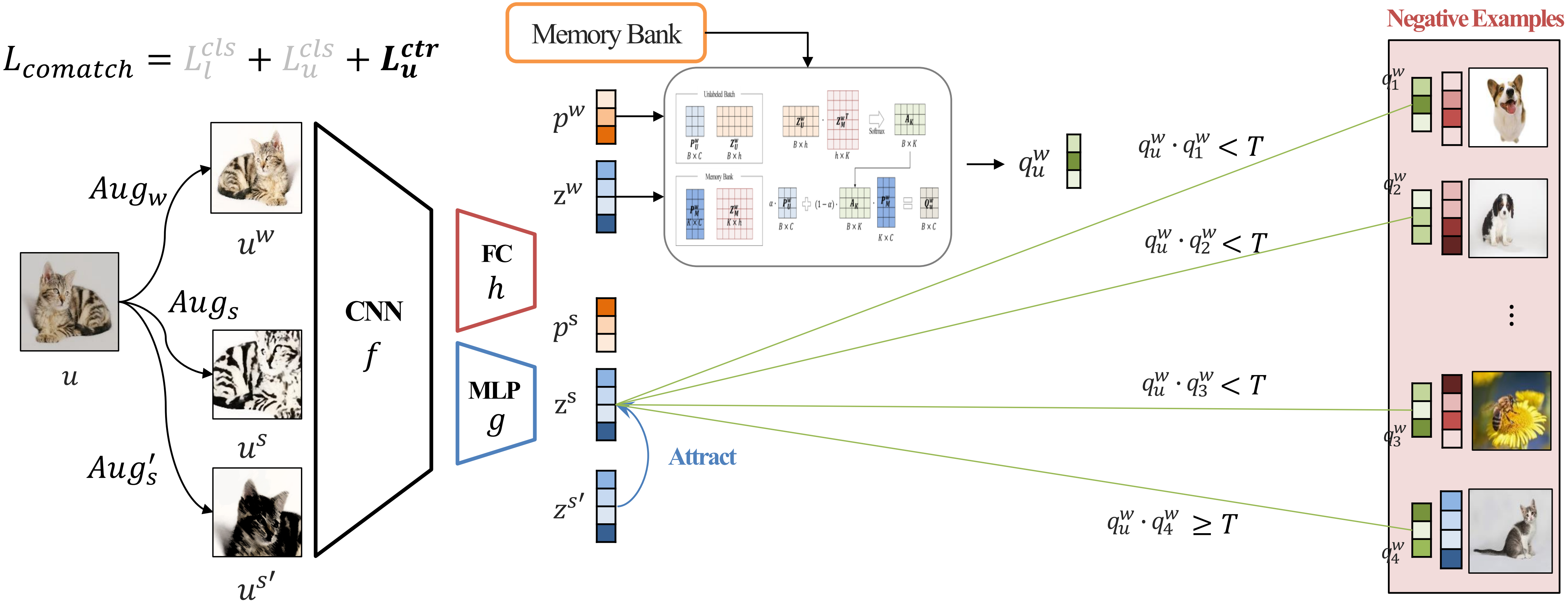
Paper Reviews

CoMatch: Semi-Supervised Learning with Contrastive Graph Regularization

❖ Graph-based Contrastive Learning

- Class끼리 군집을 이룰 수 있도록 pseudo-label의 유사도를 통해 같은 class를 가질 것 같은 이미지를 positive sample로 정의

$$L_{comatch} = L_l^{cls} + L_u^{cls} + \boldsymbol{L_u^{ctr}}$$



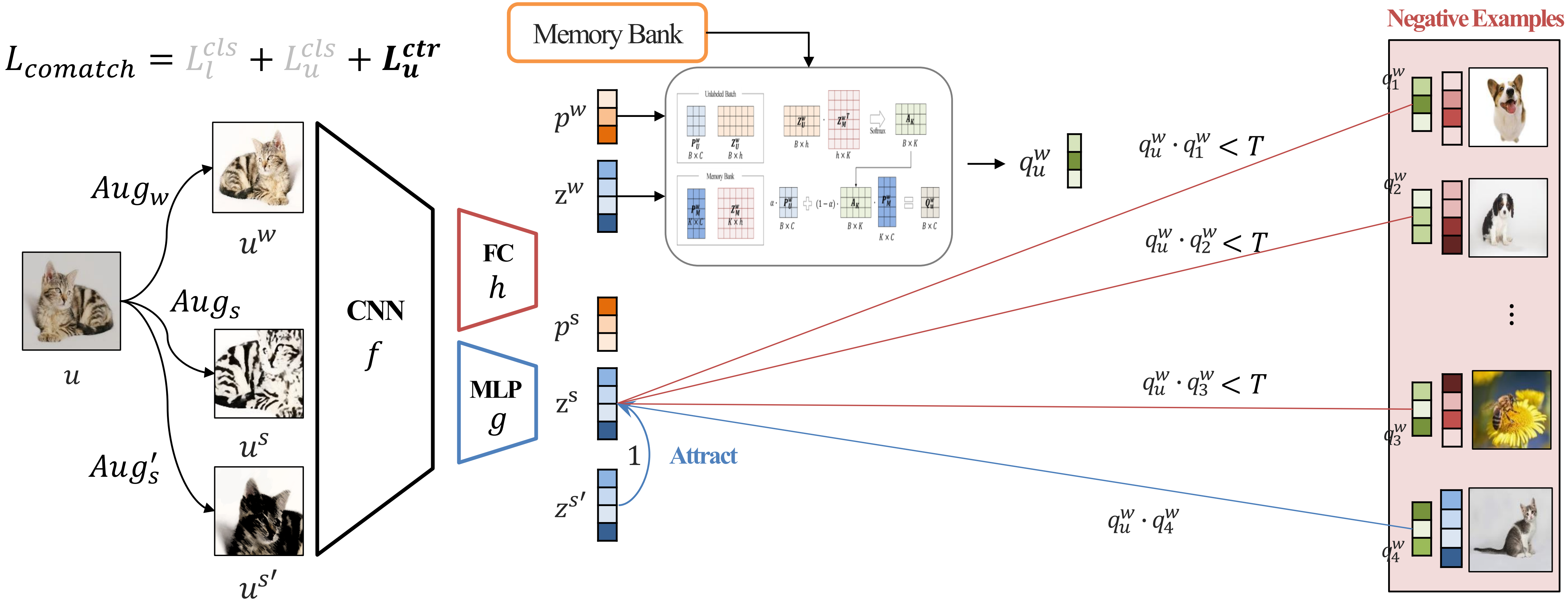
Paper Reviews

CoMatch: Semi-Supervised Learning with Contrastive Graph Regularization

❖ Graph-based Contrastive Learning

- Class끼리 군집을 이룰 수 있도록 pseudo-label의 유사도를 통해 같은 class를 가질 것 같은 이미지를 positive sample로 정의

$$L_{comatch} = L_l^{cls} + L_u^{cls} + \boldsymbol{L_u^{ctr}}$$

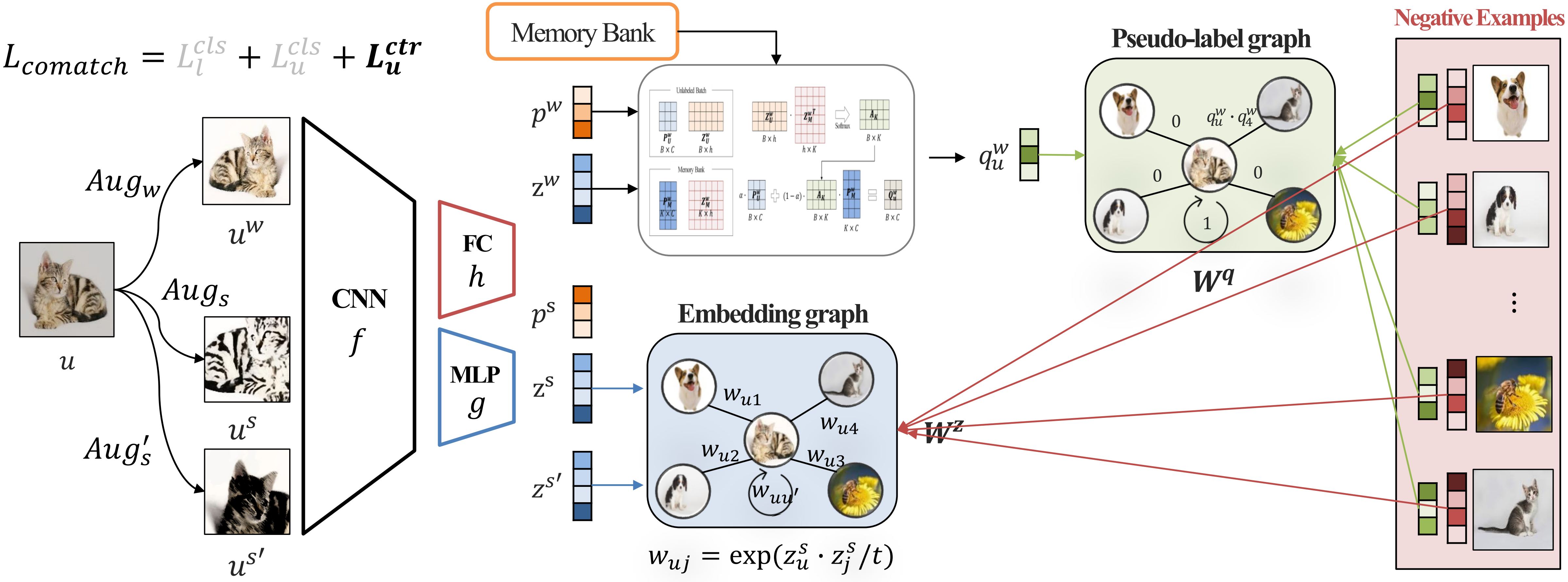


CoMatch: Semi-Supervised Learning with Contrastive Graph Regularization

❖ Graph-based Contrastive Learning

- Class끼리 군집을 이룰 수 있도록 pseudo-label의 유사도를 통해 같은 class를 가질 것 같은 이미지를 positive sample로 정의

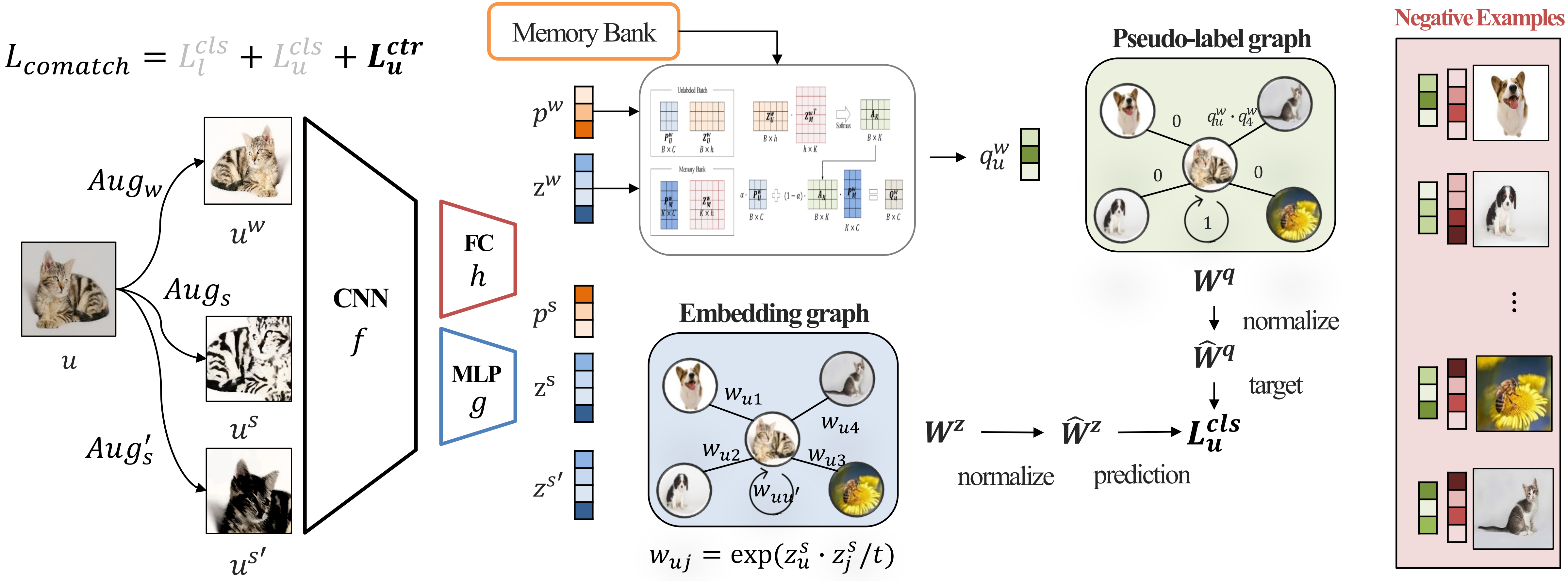
$$L_{comatch} = L_l^{cls} + L_u^{cls} + \boldsymbol{L_u^{ctr}}$$



❖ Graph-based Contrastive Learning

- Class끼리 군집을 이룰 수 있도록 pseudo-label의 유사도를 통해 같은 class를 가질 것 같은 이미지를 positive sample로 정의

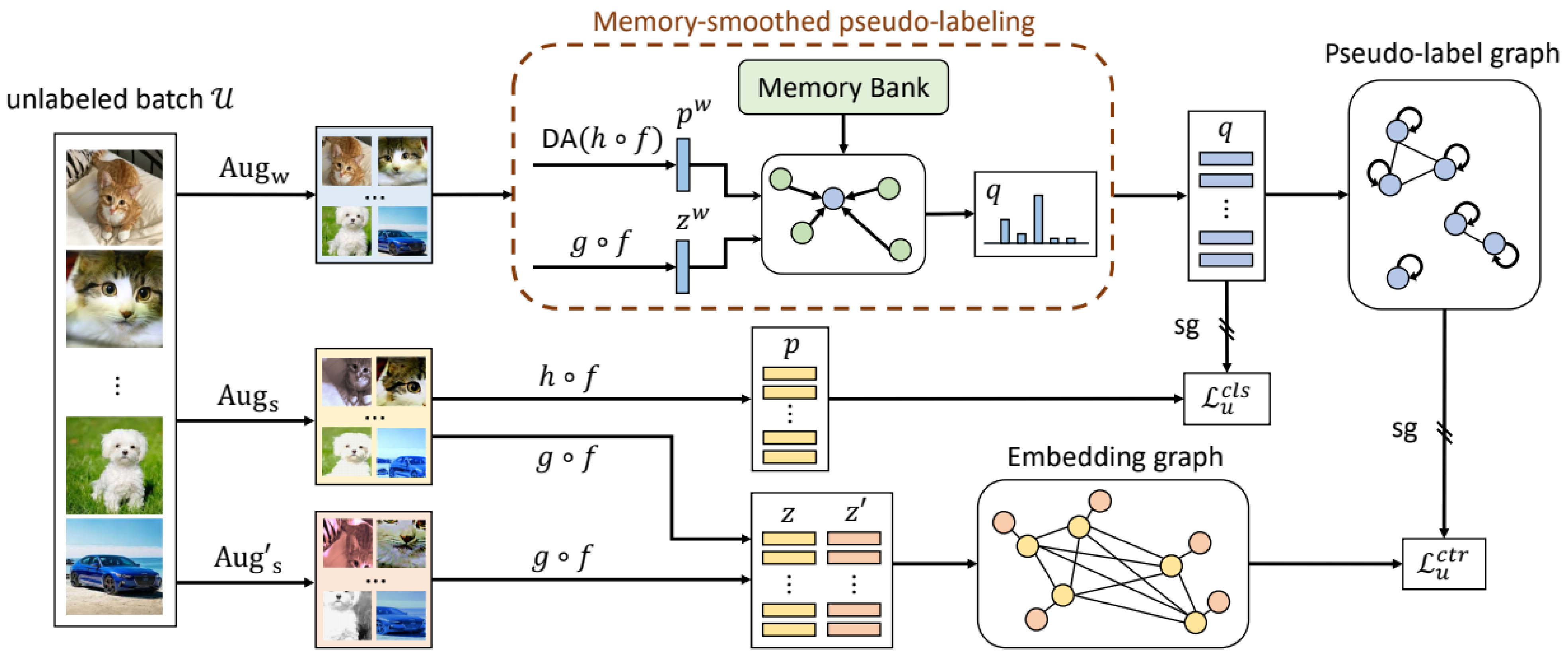
$$L_{comatch} = L_l^{cls} + L_u^{cls} + \boldsymbol{L_u^{ctr}}$$



CoMatch: Semi-Supervised Learning with Contrastive Graph Regularization

❖ Comatch 정리

- Class probability와 embedding vector를 co-training함으로써 확증 편향 문제를 해결하고 task-specific한 embedding space를 구축



Paper Reviews

CoMatch: Semi-Supervised Learning with Contrastive Graph Regularization

❖ 실험 결과

Method	CIFAR-10 20 labels	CIFAR-10 40 labels	CIFAR-10 80 labels	CIFAR-10 250 labels	STL-10 1000 labels
MixMatch [2]	27.84±10.63	51.90±11.76	80.79±1.28	88.97±0.85	38.02±8.29
FixMatch [32]	82.32±9.77	86.12±3.53	92.06±0.88	94.90±0.67	65.38±0.42
FixMatch [32] w. DA [1]	83.81±9.35	86.98±3.40	92.29±0.86	94.95±0.66	66.53±0.39
CoMatch	**87.67**±8.47	**93.09**±1.39	**93.97**±0.62	**95.09**±0.33	**79.80**±0.38

ImageNet

Self-supervised Pre-training	Method	#Epochs	#Paramters (train/test)	Top-1 Label fraction 1%	Top-1 Label fraction 10%	Top-5 Label fraction 1%	Top-5 Label fraction 10%
None	Supervised baseline [38]	~20	25.6M / 25.6M	25.4	56.4	48.4	80.4
	Pseudo-label [19, 38]	~100	25.6M / 25.6M	-	-	51.6	82.4
	VAT+EntMin. [26, 12, 38]	-	25.6M / 25.6M	-	68.8	-	88.5
	S4L-Rotation [38]	~200	25.6M / 25.6M	-	53.4	-	83.8
	UDA (RandAug) [36]	-	25.6M / 25.6M	-	68.8	-	88.5
	FixMatch (RandAug) [32]	~300	25.6M / 25.6M	-	71.5	-	89.1
	FixMatch w. DA	~400	25.6M / 25.6M	53.4	70.8	74.4	89.0
	CoMatch	~400	30.0M / 25.6M	**66.0**	**73.6**	**86.4**	**91.6**
PIRL [25]	Fine-tune	~800	26.1M / 25.6M	30.7	60.4	57.2	83.8
PCL [21]		~200	25.8M / 25.6M	-	-	75.3	85.6
SimCLR [5]		~1000	30.0M / 25.6M	48.3	65.6	75.5	87.8
BYOL [13]		~1000	37.1M / 25.6M	53.2	68.8	78.4	89.0
SwAV [3]		~800	30.4M / 25.6M	53.9	70.2	78.5	89.9
MoCov2 [7]	Fine-tune	~800	30.0M / 25.6M	49.8	66.1	77.2	87.9
	FixMatch w. DA	~1200	30.0M / 25.6M	59.9	72.2	79.8	89.5
	CoMatch	~1200	30.0M / 25.6M	**67.1**	**73.7**	**87.1**	**91.4**
SimCLRv2* [6]	Fine-tune	~800	34.2M / 29.8M	57.9	68.4	82.5	89.2
	Teacher distillation	~2400	829.2M / 29.8M	73.9	77.5	91.5	93.4

Paper Reviews

CoMatch: Semi-Supervised Learning with Contrastive Graph Regularization

❖ 실험 결과

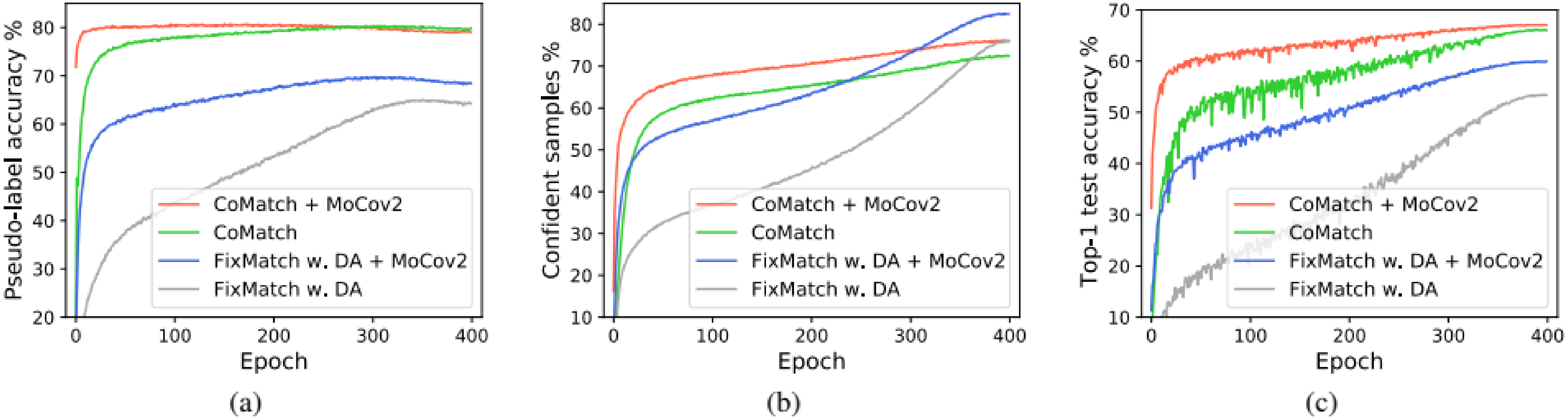
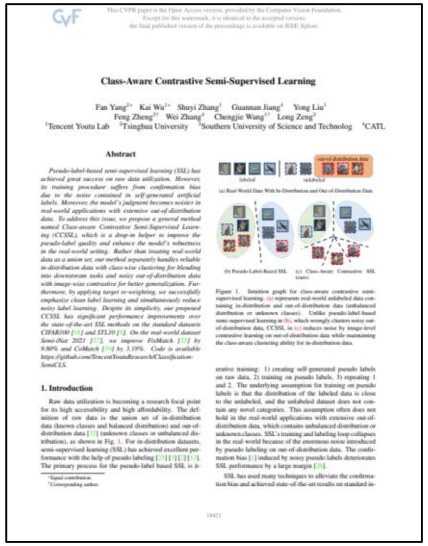


Figure 3: Plots of different methods as training progresses on ImageNet with 1% labels. (a) Accuracy of the confident pseudo-labels *w.r.t* to the ground-truth labels of the unlabeled samples. (b) Ratio of the unlabeled samples with confident pseudo-labels that are included in the unsupervised classification loss. (3) Top-1 accuracy on the test data.

CoMatch: Semi-Supervised Learning With Contrastive Graph Regularization (2021, ICCV)



Class-Aware Contrastive Semi-Supervised Learning

Class-Aware Contrastive Semi-Supervised Learning (2022, CVPR)

Contrastive Regularization for Semi-Supervised Learning (2022, CVPR)

Paper Reviews

논문 리뷰

❖ Class-aware Contrastive Semi-Supervised Learning(CCSSL)

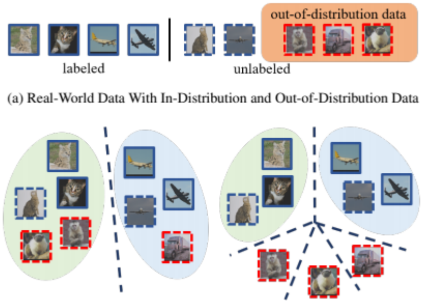
- 2022년 CVPR에서 발표된 논문으로 Comatch와 마찬가지로 contrastive learning을 결합해 확증 편향 문제를 해결하고자 함

Class-Aware Contrastive Semi-Supervised Learning

Fan Yang[2*] Kai Wu[1*] Shuyi Zhang[1] Guannan Jiang[4] Yong Liu[1]
Feng Zheng[3†] Wei Zhang[4] Chengjie Wang[1†] Long Zeng[2]
[1]Tencent Youtu Lab [2]Tsinghua University [3]Southern University of Science and Technolog [4]CATL

Abstract

Pseudo-label-based semi-supervised learning (SSL) has achieved great success on raw data utilization. However, its training procedure suffers from confirmation bias due to the noise contained in self-generated artificial labels. Moreover, the model's judgment becomes noisier in real-world applications with extensive out-of-distribution data. To address this issue, we propose a general method named Class-aware Contrastive Semi-Supervised Learning (CCSSL), which is a drop-in helper to improve the pseudo-label quality and enhance the model's robustness in the real-world setting. Rather than treating real-world data as a union set, our method separately handles reliable in-distribution data with class-wise clustering for blending into downstream tasks and noisy out-of-distribution data



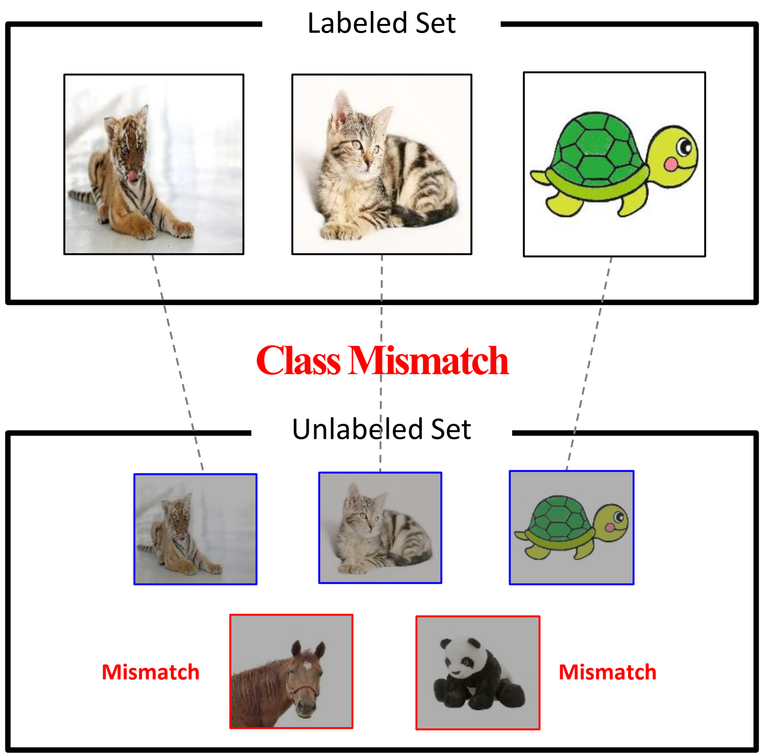
(b) Pseudo-Label-Based SSL (c) Class-Aware Contrastive SSL (ours)

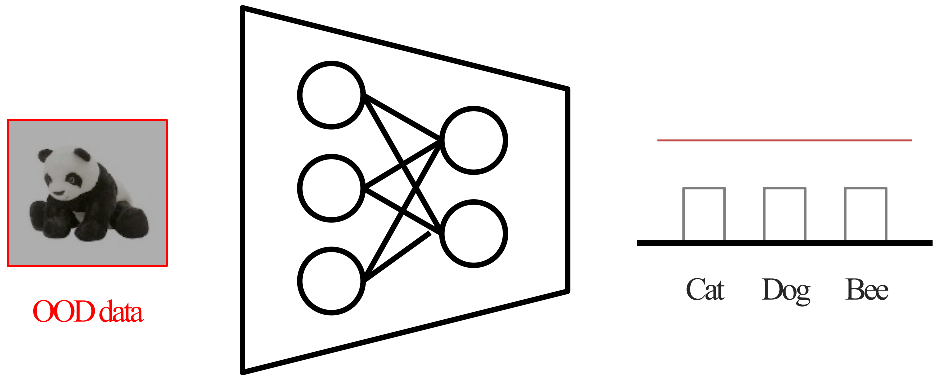
Paper Reviews

Class-aware Contrastive Semi-Supervised Learning

❖ 연구 배경

- Unlabeled data에 OOD data가 존재하는 mismatch 상황에서 확증 편향은 성능 하락을 유발



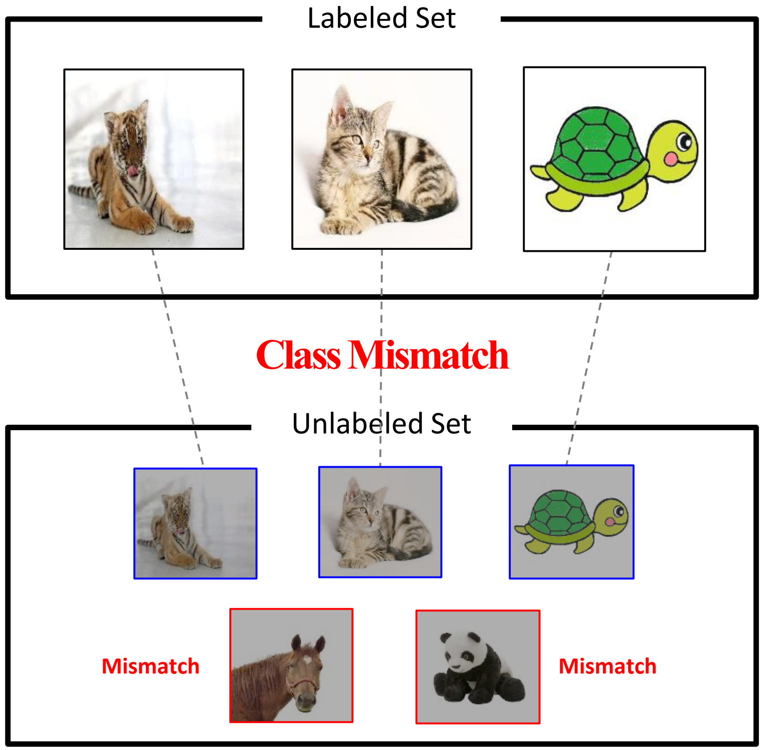


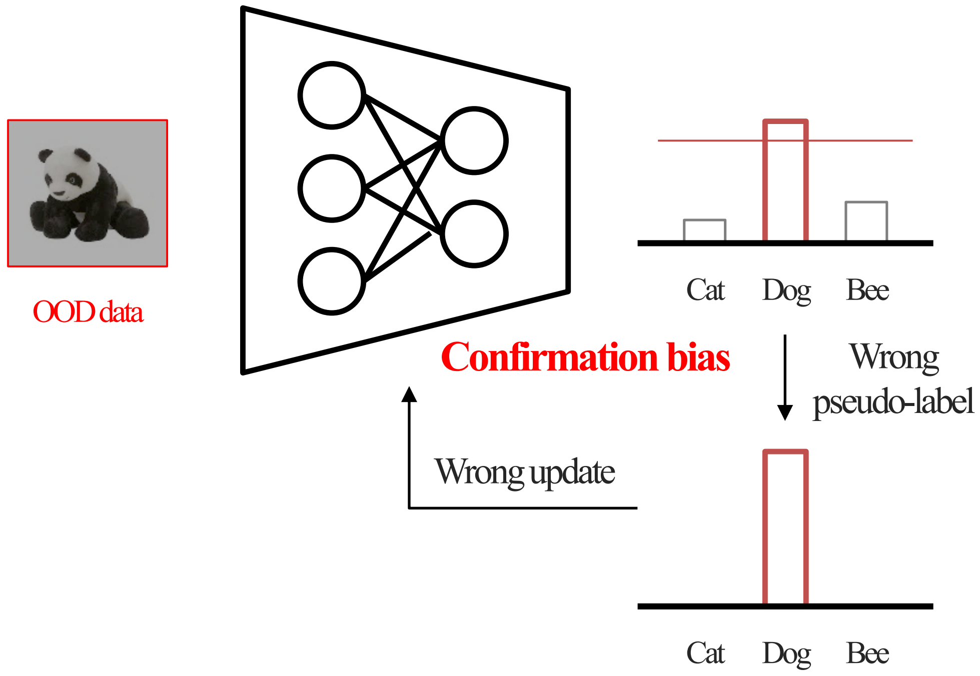
Paper Reviews

Class-aware Contrastive Semi-Supervised Learning

❖ 연구 배경

- Unlabeled data에 OOD data가 존재하는 mismatch 상황에서 확증 편향은 성능 하락을 유발



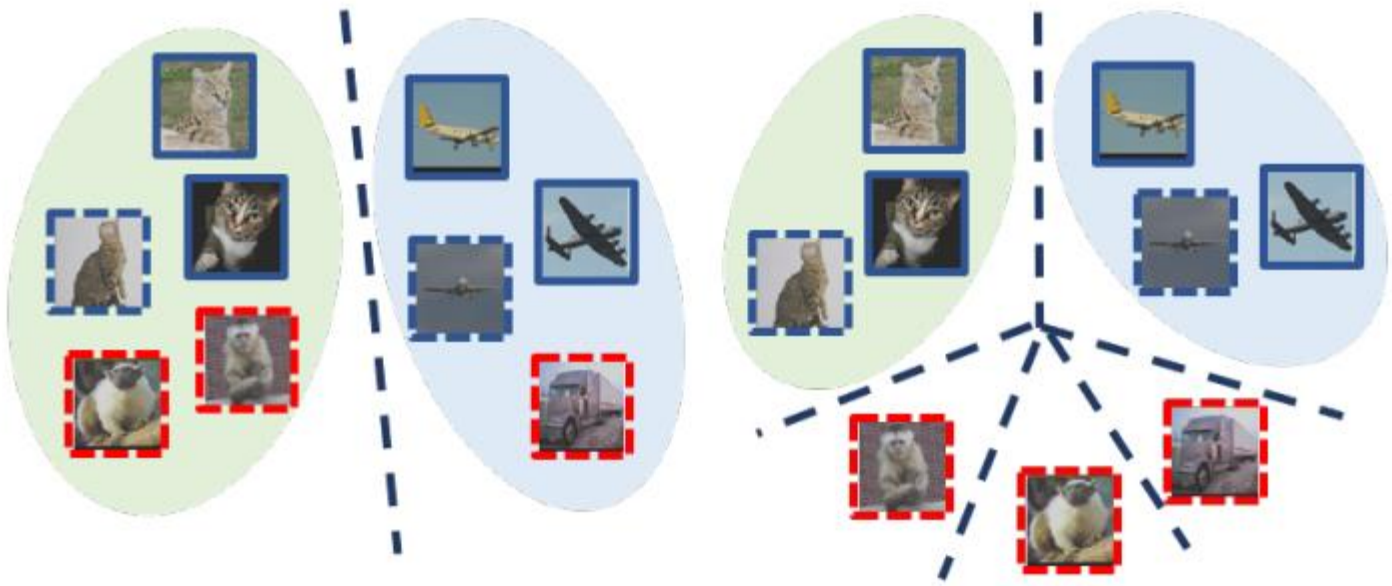


Paper Reviews

Class-aware Contrastive Semi-Supervised Learning

❖ 연구 가설

- Embedding space에서 ID data와 OOD data를 잘 구분할 수 있다면 OOD data로 인한 확증 편향 문제를 완화 할 수 있을 것

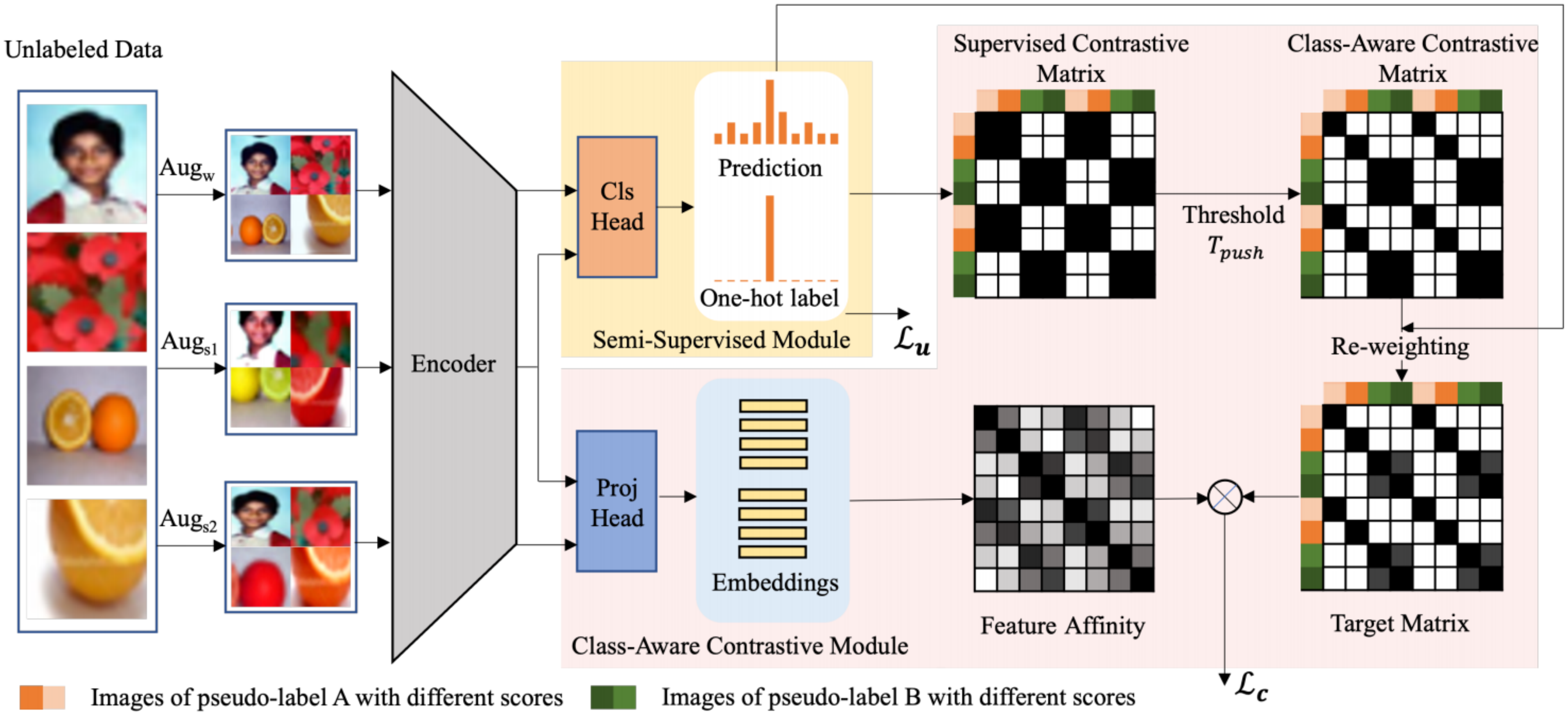


(b) Pseudo-Label-Based SSL (c) Class-Aware Contrastive SSL (ours)

Paper Reviews

Class-aware Contrastive Semi-Supervised Learning

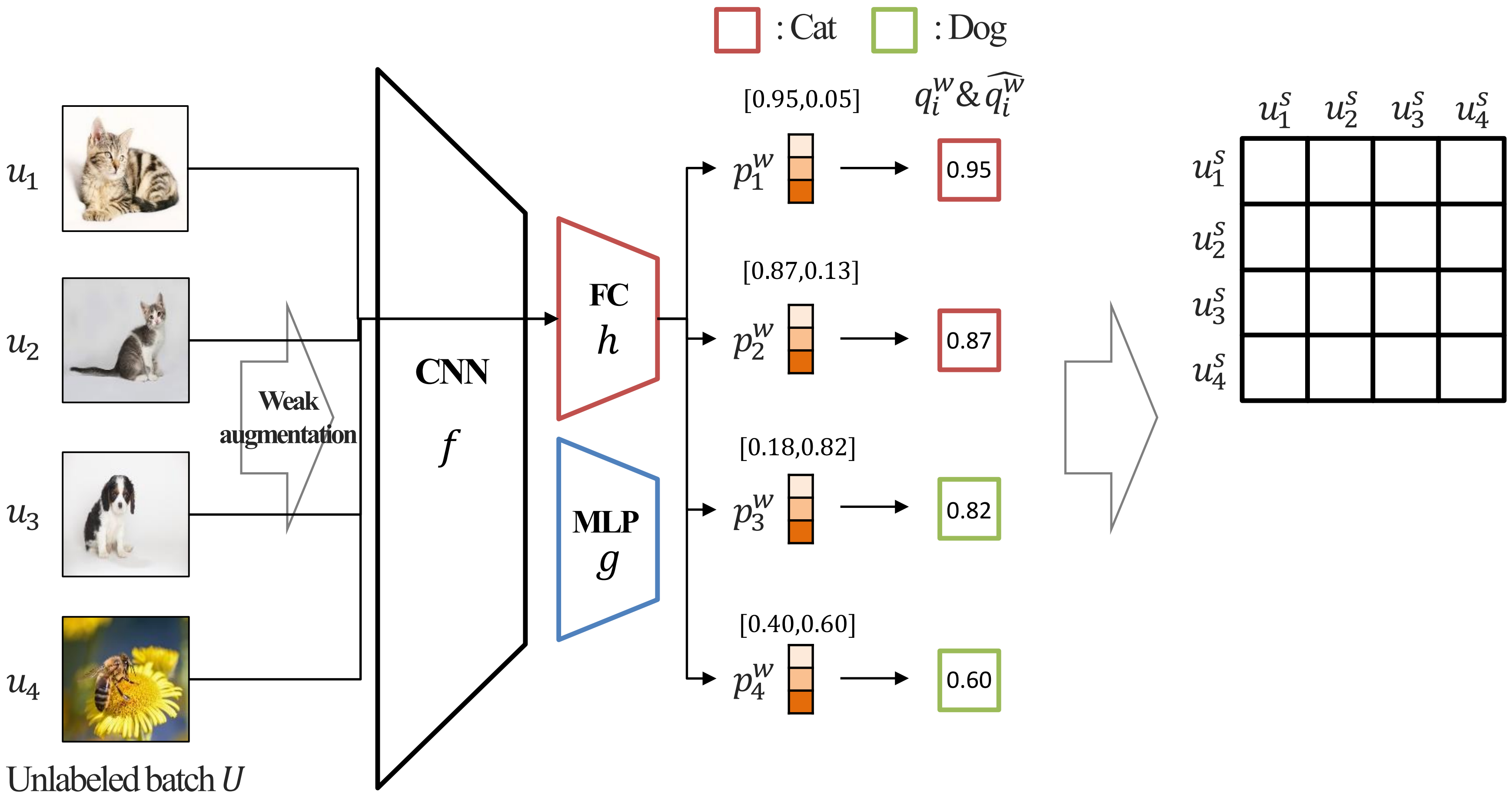
❖ 제안 방법론



Paper Reviews

Class-aware Contrastive Semi-Supervised Learning

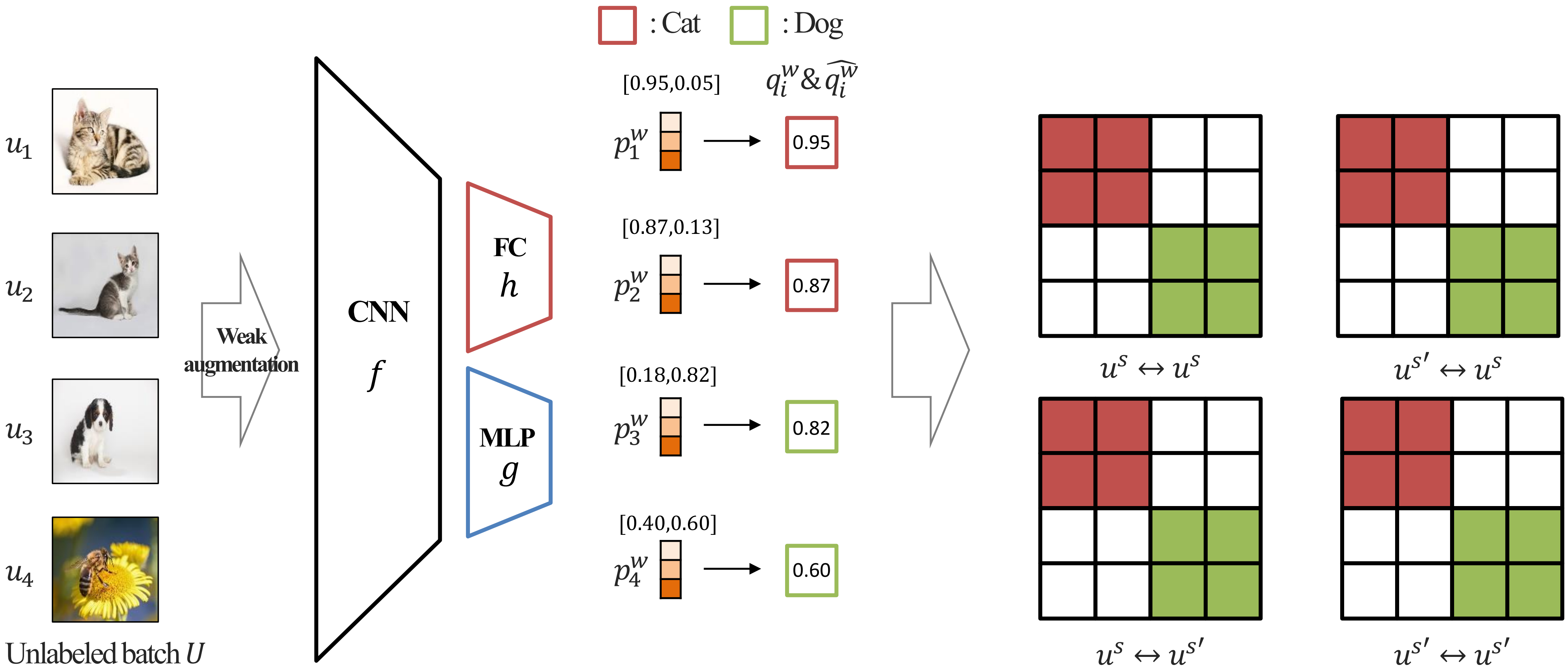
❖ Class-aware Contrastive Module



Paper Reviews

Class-aware Contrastive Semi-Supervised Learning

❖ Class-aware Contrastive Module

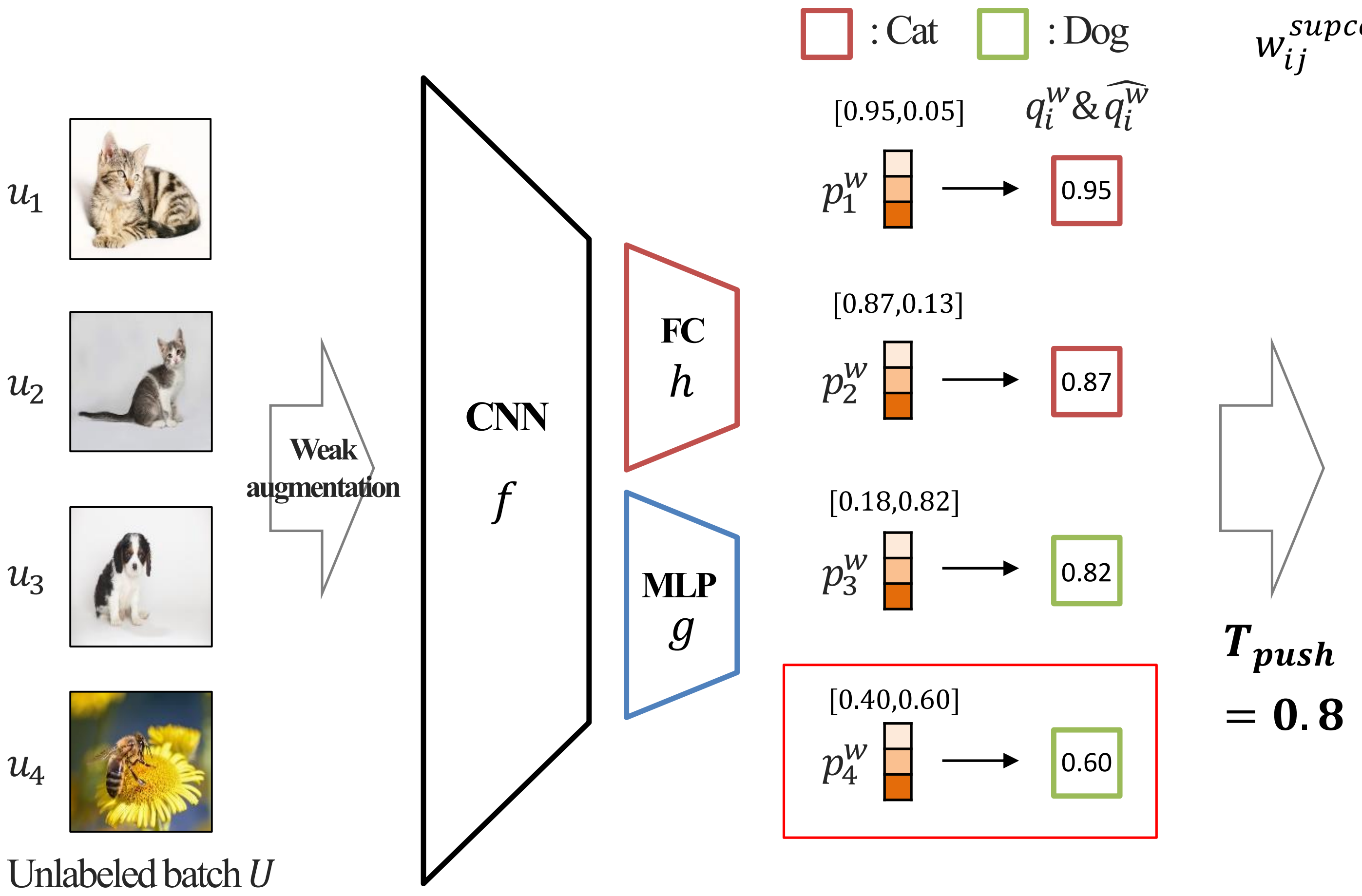


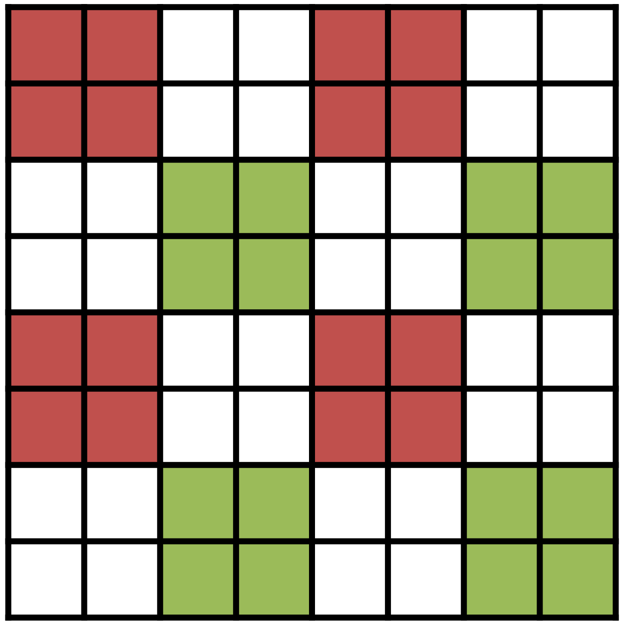
Paper Reviews

Class-aware Contrastive Semi-Supervised Learning

❖ Class-aware Contrastive Module

$$w_{ij}^{supcon} = \begin{cases} 1 \ \ if \ i = j \ or \ i \ and \ j \ have \ a \ same \ source \\ 1 \ if \ i \ and \ j \ have \ a \ same \ pseudo \ label \\ 0 \ otherwise \end{cases}$$





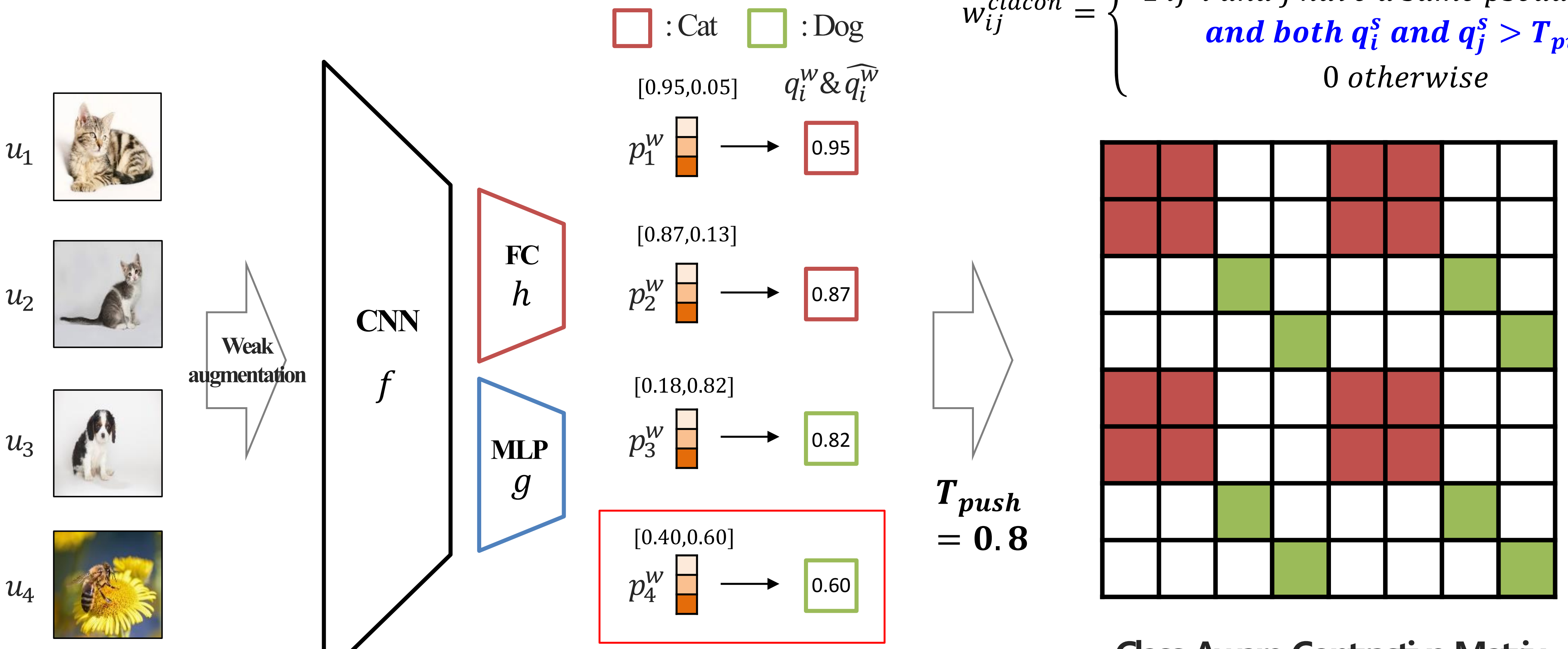
Supervised Contrastive Matrix

Paper Reviews

Class-aware Contrastive Semi-Supervised Learning

❖ Class-aware Contrastive Module

$$w_{ij}^{clacon} = \begin{cases} 1 \ \ if\ i = j\ or\ i\ and\ j\ have\ a\ same\ source \\ 1\ if\ i\ and\ j\ have\ a\ same\ pseudo\ label, \\ \boldsymbol{and\ both\ q_i^s\ and\ q_j^s > T_{push}} \\ 0\ otherwise \end{cases}$$



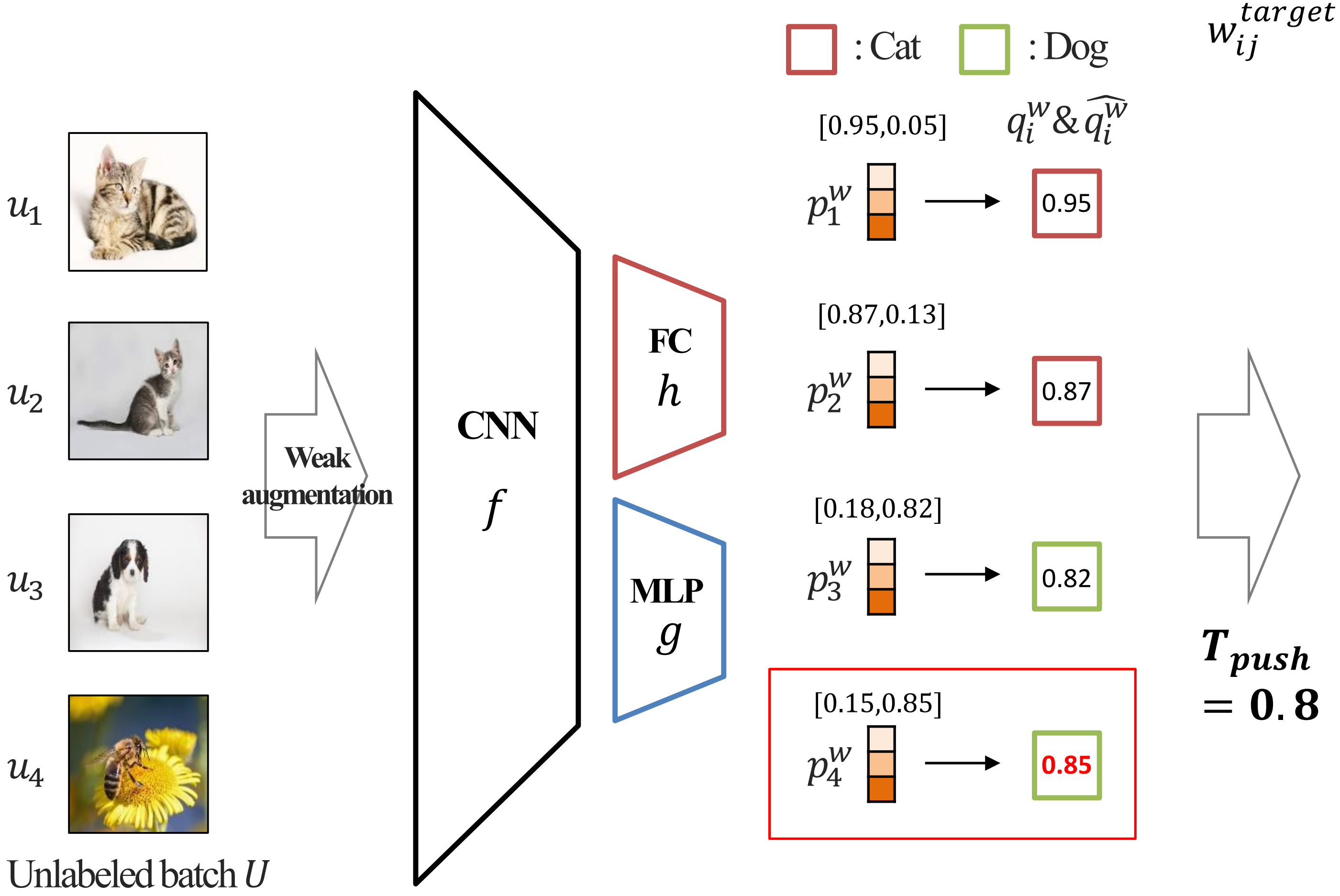
Class-Aware Contrastive Matrix

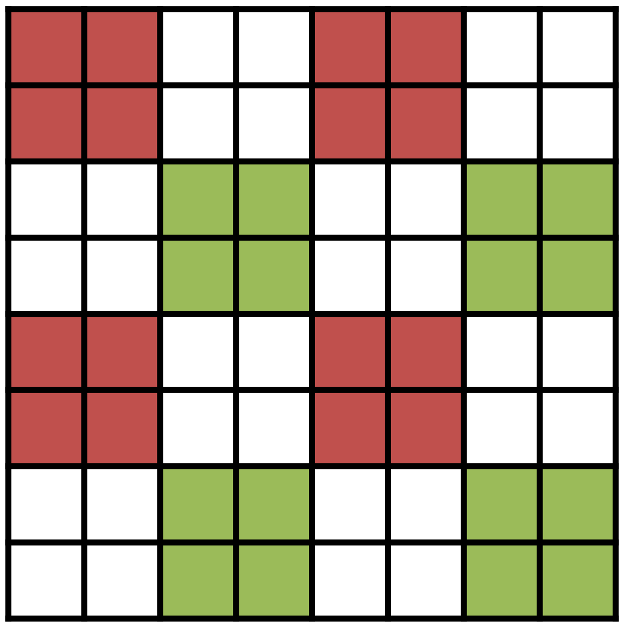
Paper Reviews

Class-aware Contrastive Semi-Supervised Learning

❖ Class-aware Contrastive Module

$$w_{ij}^{target} = \begin{cases} 1 \ \ if\ i = j\ or\ i\ and\ j\ have\ a\ same\ source \\ \boldsymbol{q_i^s \cdot q_j^s}\ if\ i\ and\ j\ have\ a\ same\ pseudo\ label, \\ \quad and\ both\ q_i^s\ and\ q_j^s > T_{push} \\ 0\ otherwise \end{cases}$$





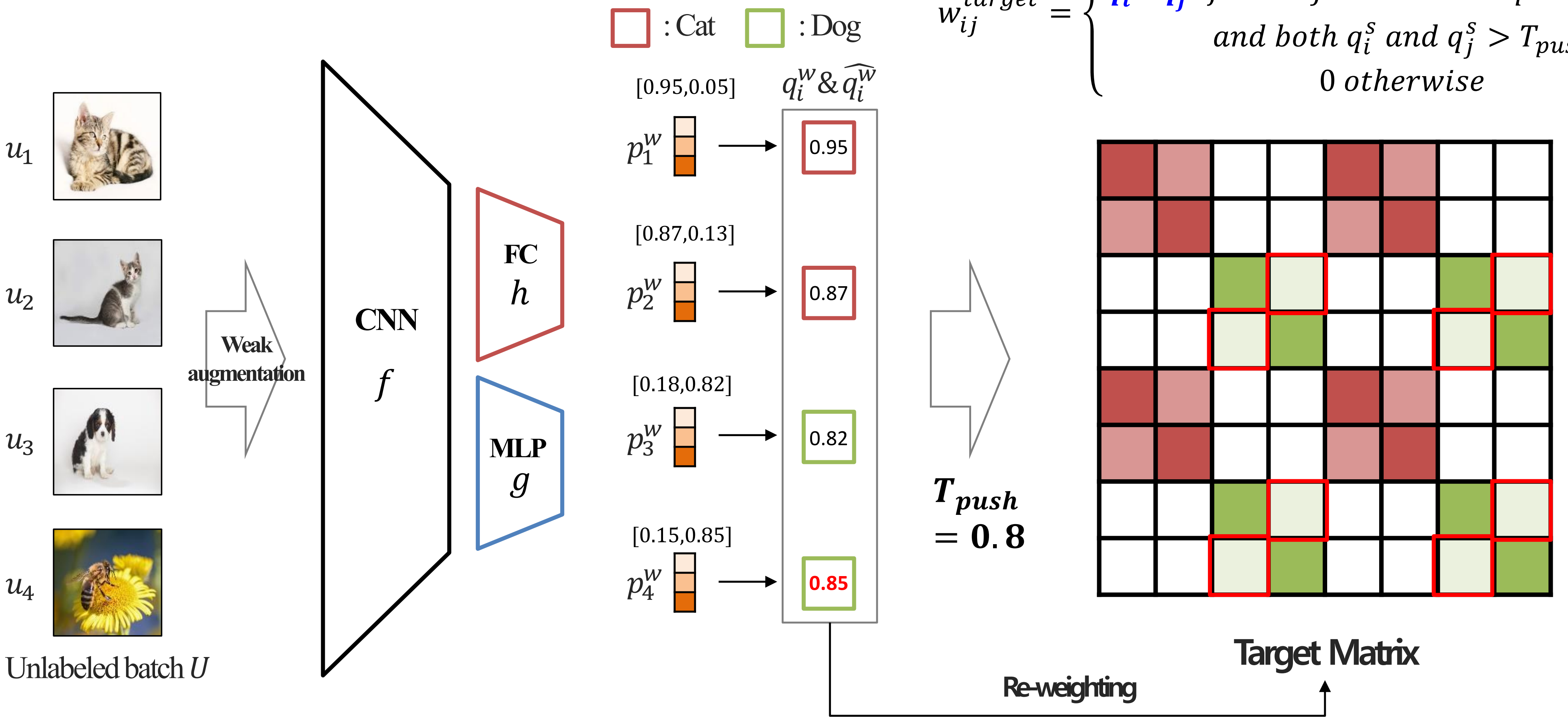
Class-Aware Contrastive Matrix

Paper Reviews

Class-aware Contrastive Semi-Supervised Learning

❖ Class-aware Contrastive Module

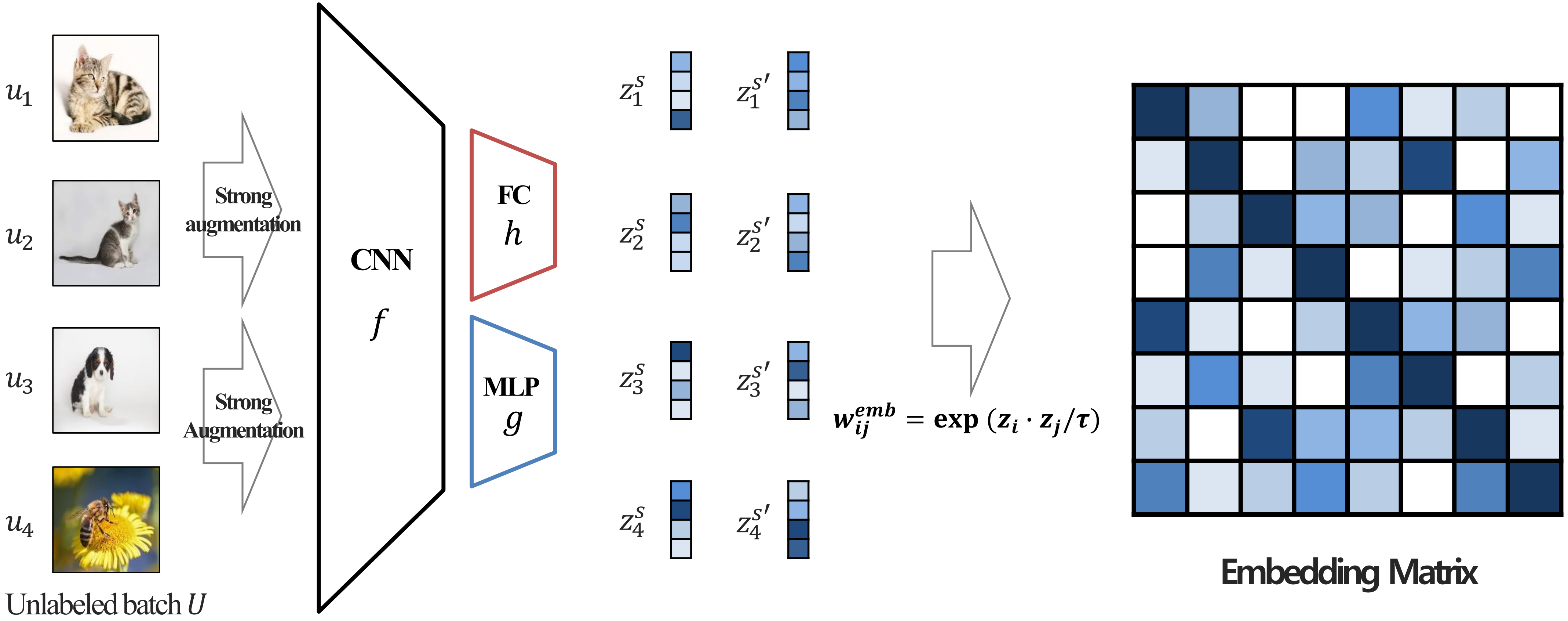
$$w_{ij}^{target} = \begin{cases} 1 \ \ if\ i = j\ or\ i\ and\ j\ have\ a\ same\ source \\ \boldsymbol{q_i^s \cdot q_j^s}\ if\ i\ and\ j\ have\ a\ same\ pseudo\ label, \\ \quad and\ both\ q_i^s\ and\ q_j^s > T_{push} \\ 0\ otherwise \end{cases}$$



Paper Reviews

Class-aware Contrastive Semi-Supervised Learning

❖ Class-aware Contrastive Module

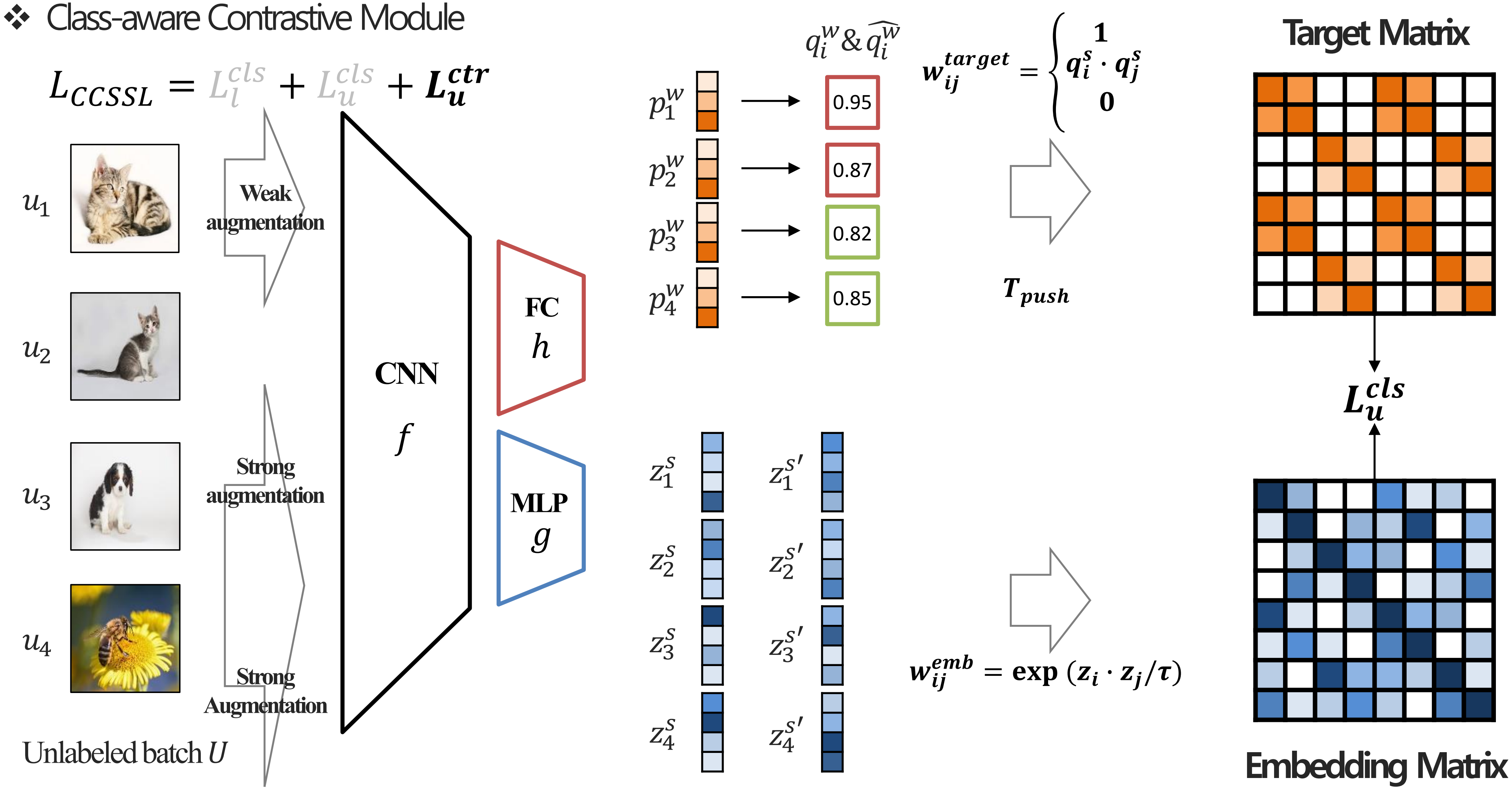


Paper Reviews

Class-aware Contrastive Semi-Supervised Learning

❖ Class-aware Contrastive Module

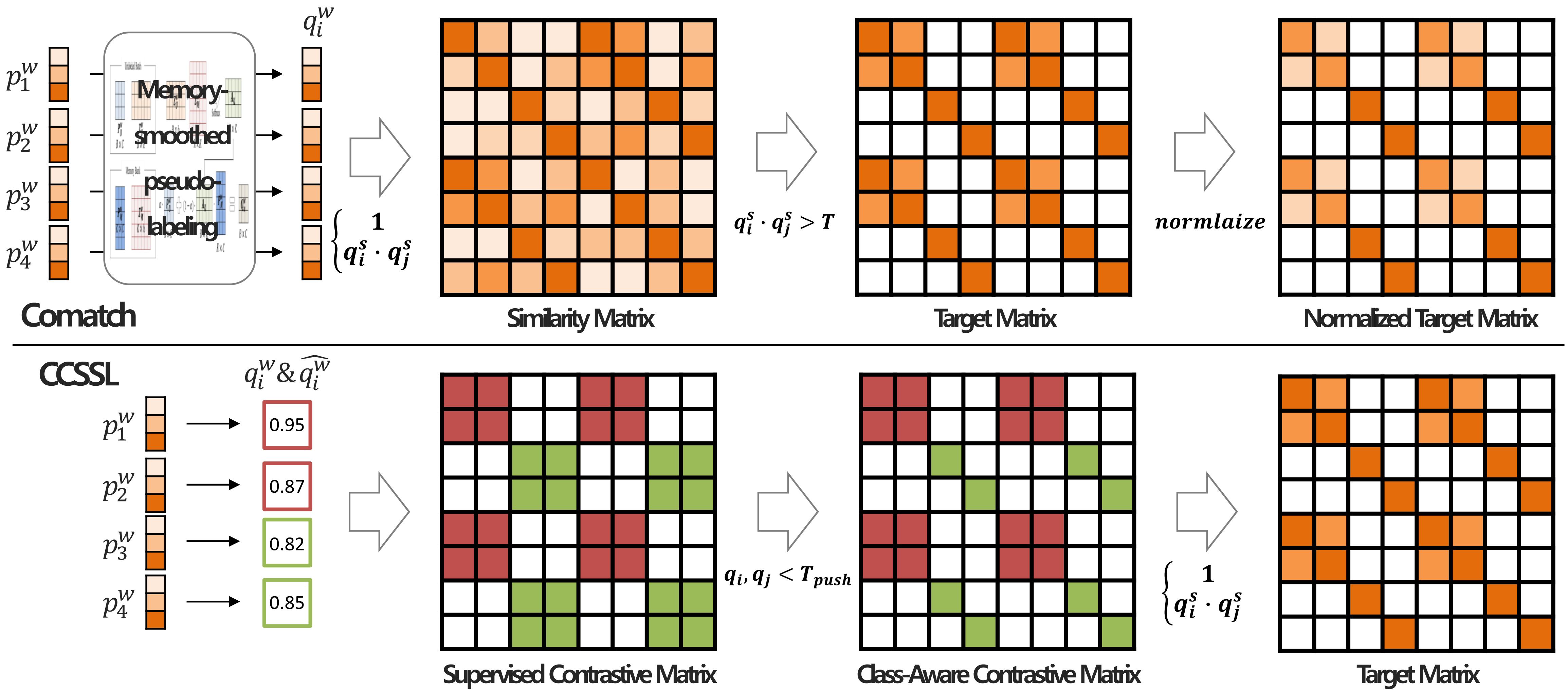
$$L_{CCSSL} = L_l^{cls} + L_u^{cls} + \boldsymbol{L_u^{ctr}}$$



Paper Reviews

Class-aware Contrastive Semi-Supervised Learning

❖ Comatch & CCSSL



❖ 실험 결과

Method	CIFAR100			CIFAR10			STL10
	400	2500	10000	40	250	4000	
Mixmatch [3]	32.39±1.32	60.06±0.37	71.69±0.33	52.46±11.5	88.95±0.86	93.58±0.10	38.02±8.29
ReMixMatch [2]	55.72±2.06	72.57±0.31	76.97±0.56	80.90±9.64	94.56±0.05	95.28±0.13	-
SSWPL [28]	-	73.48±0.45	79.12±0.85	-	-	-	-
LaplaceNet [23]	-	68.36±0.02	73.40±0.23	-	-	95.35±0.07	-
CoMatch [19]	58.11±2.34	71.63±0.35	79.14±0.36	**93.09±1.39**	**95.09±0.33**	95.44±0.20	79.80±0.38
FixMatch [19]	51.15±1.75	71.71±0.11	77.40±0.12	86.19±3.37	94.93±0.65	**95.74±0.05**	65.38±0.42
CCSSL(FixMatch)	**61.19±1.65**	**75.7±0.63**	**80.68±0.16**	90.83±2.78	94.86±0.55	95.54±0.20	**80.01±1.39**

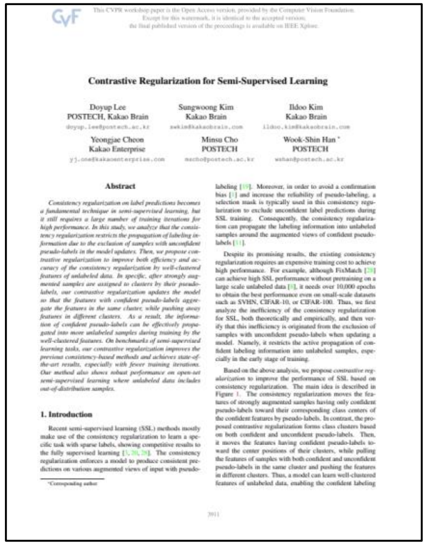
Table 1. Top-1 Accuracy for in-distribution datasets including CIFAR100, CIFAR10, and STL10. On high noise-level datasets CIFAR100 and STL10, we achieve the best performance by simply adding CCSSL to Fixmatch. On the easier dataset CIFAR10 with less noise, CCSSL only provides marginal performance gain. '-' means not self-implemented.

❖ 실험 결과

Method	Semi-iNat 2021			
	From Scratch		From MoCo Pretrain	
	Top1	Top5	Top1	Top5
Supervised	19.09	35.85	34.96	57.11
MixMatch [3]	16.89	30.83	-	-
+CCSSL	**19.65**	**35.09**	-	-
FixMatch [25]	21.41	37.65	40.3	60.05
+CCSSL	**31.21**	**52.25**	**41.28**	**64.3**
CoMatch [19]	20.94	38.96	38.94	61.85
+CCSSL	**24.12**	**43.23**	**39.85**	**63.68**

CoMatch: Semi-supervised Learning with Contrastive Graph Regularization

Class-Aware Contrastive Semi-Supervised Learning


This CVPR workshop paper is the Open Access version, provided by the Computer Vision Foundation.
Except for this watermark, it is identical to the accepted version;
the final published version of the proceedings is available on IEEE Xplore.

Contrastive Regularization for Semi-Supervised Learning

Doyup Lee, POSTECH, Kakao Brain, doyup.lee@postech.ac.kr
Sungwoong Kim, Kakao Brain, swkim@kakaobrain.com
Ildoo Kim, Kakao Brain, ildoo.kim@kakaobrain.com
Yeongjae Cheon, Kakao Enterprise, yj.one@kakaoenterprise.com
Minsu Cho, POSTECH, mscho@postech.ac.kr
Wook-Shin Han *, POSTECH, wshan@postech.ac.kr

CoMatch: Semi-Supervised Learning
With Contrastive Graph Regularization
(2021, ICCV)

Class-Aware Contrastive
Semi-Supervised Learning
(2022, CVPR)

Contrastive Regularization
for Semi-Supervised Learning
(2022, CVPR)

Paper Reviews

논문 리뷰

❖ Contrastive Regularization for Semi-Supervised Learning(CR)

- 2022년 CVPR에서 발표된 논문으로 contrastive learning을 활용해 label propagation 속도를 높여 학습 효율을 향상시킴

Contrastive Regularization for Semi-Supervised Learning

Doyup Lee
POSTECH, Kakao Brain
doyup.lee@postech.ac.kr

Sungwoong Kim
Kakao Brain
swkim@kakaobrain.com

Ildoo Kim
Kakao Brain
ildoo.kim@kakaobrain.com

Yeongjae Cheon
Kakao Enterprise
yj.one@kakaoenterprise.com

Minsu Cho
POSTECH
mscho@postech.ac.kr

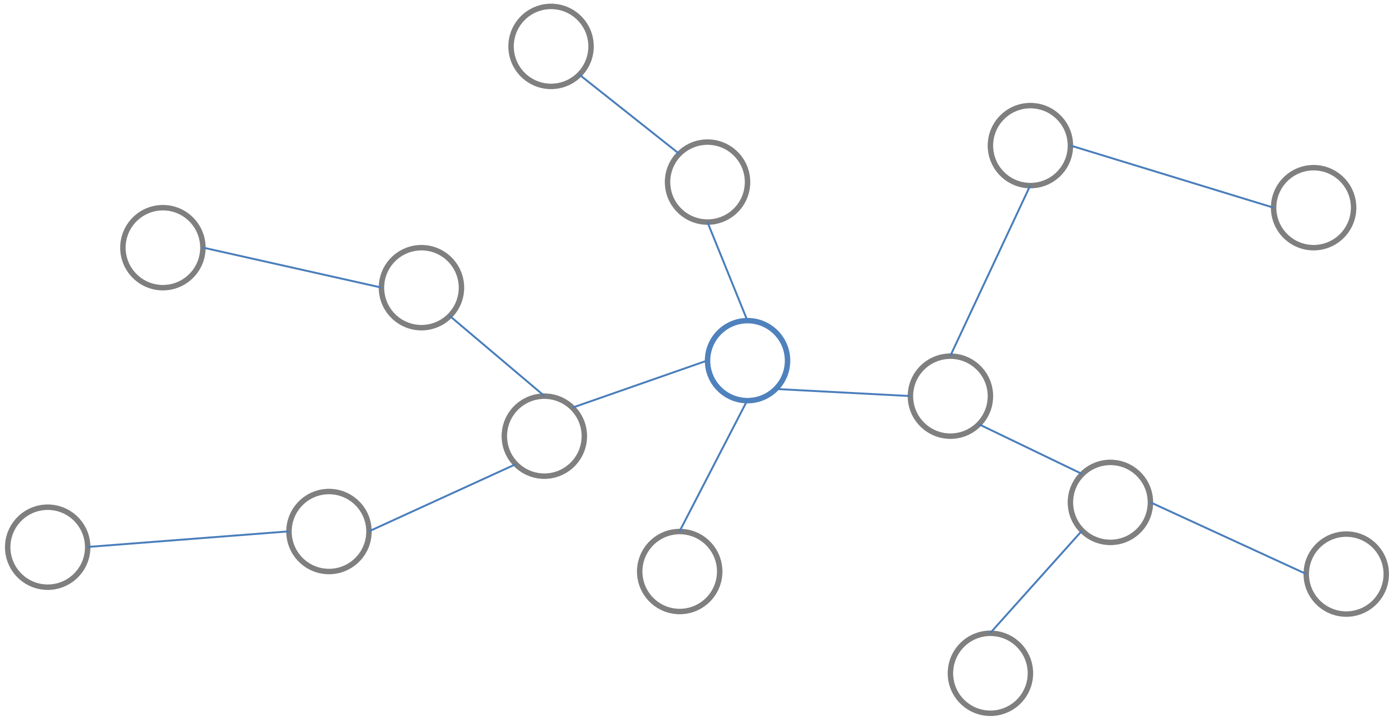
Wook-Shin Han *
POSTECH
wshan@postech.ac.kr

Paper Reviews

Contrastive Regularization for Semi-Supervised Learning

❖ 연구 배경

- Fixmatch와 같이 수도 레이블을 기반으로 한 방법론들은 신뢰도를 위해 높은 threshold를 활용
- 때문에 label propagation이 느려지게 되고 학습 속도 역시 느려지게 됨(Fixmatch training iterations for CIFAR10 = $2^{20} \approx$ 1M)

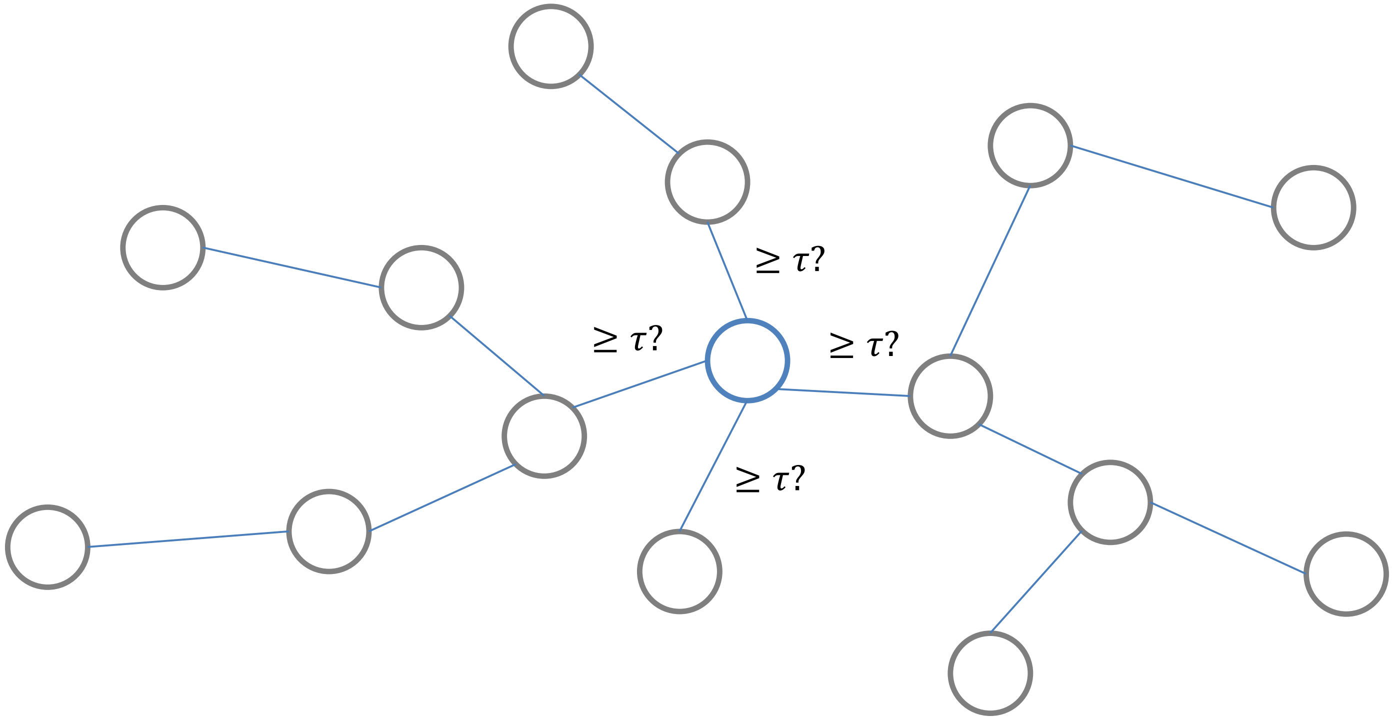


Paper Reviews

Contrastive Regularization for Semi-Supervised Learning

❖ 연구 배경

- Fixmatch와 같이 수도 레이블을 기반으로 한 방법론들은 신뢰도를 위해 높은 threshold를 활용
- 때문에 label propagation이 느려지게 되고 학습 속도 역시 느려지게 됨(Fixmatch training iterations for CIFAR10 = $2^{20} \approx 1M$)

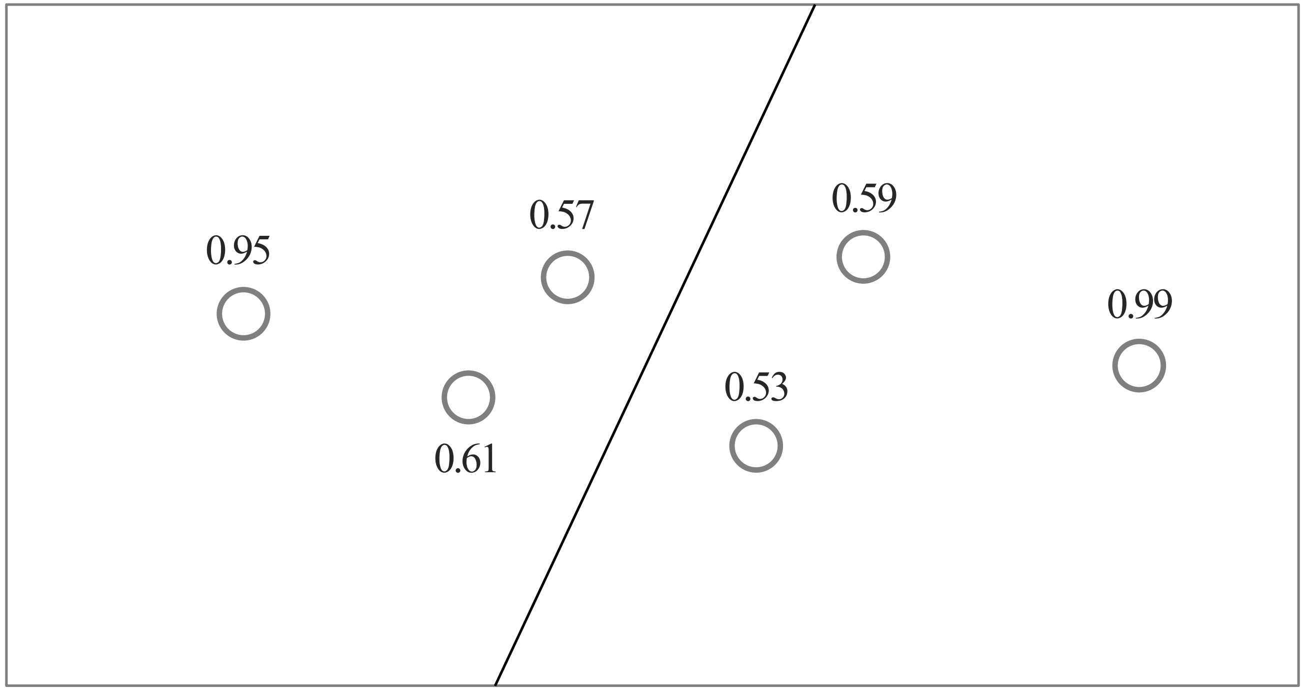


Paper Reviews

Contrastive Regularization for Semi-Supervised Learning

❖ 연구 가설

- 결정 경계 근처의 Confidence level이 낮은 데이터를 confidence level이 높은 데이터 쪽으로 당겨주면 빠른 label propagation이 가능할 것

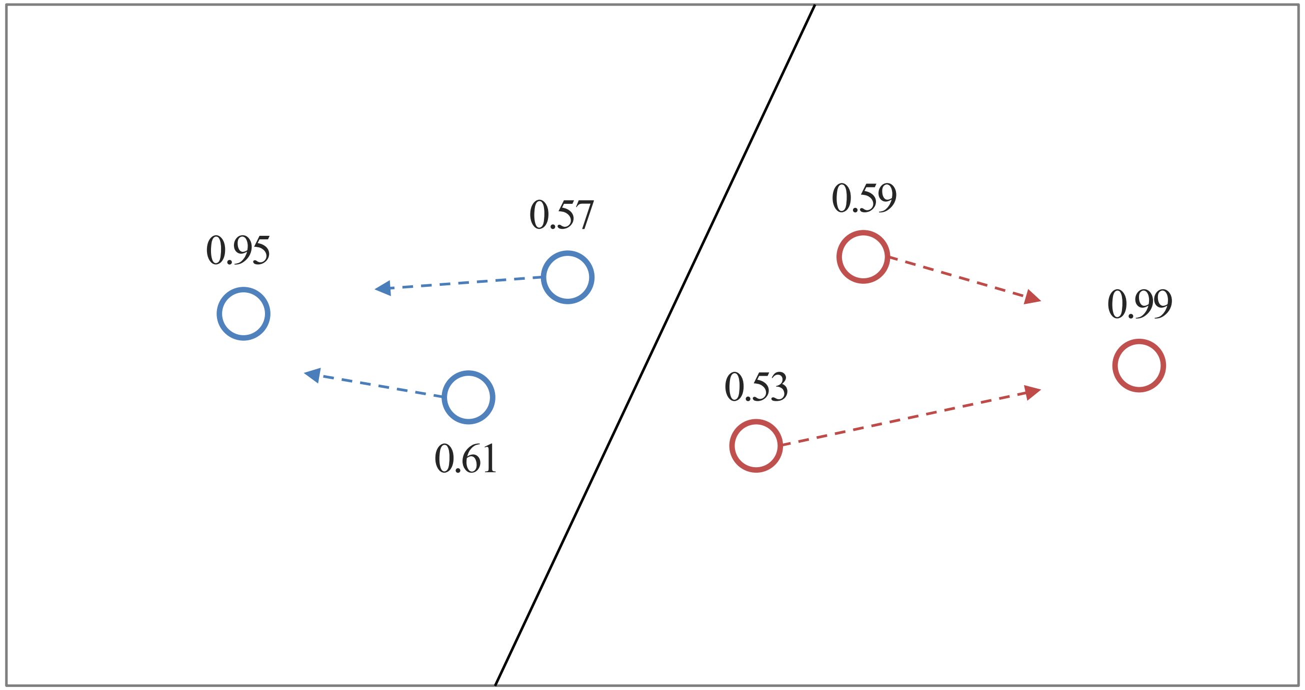


Paper Reviews

Contrastive Regularization for Semi-Supervised Learning

❖ 연구 가설

- 결정 경계 근처의 Confidence level이 낮은 데이터를 confidence level이 높은 데이터 쪽으로 당겨주면 빠른 label propagation이 가능할 것

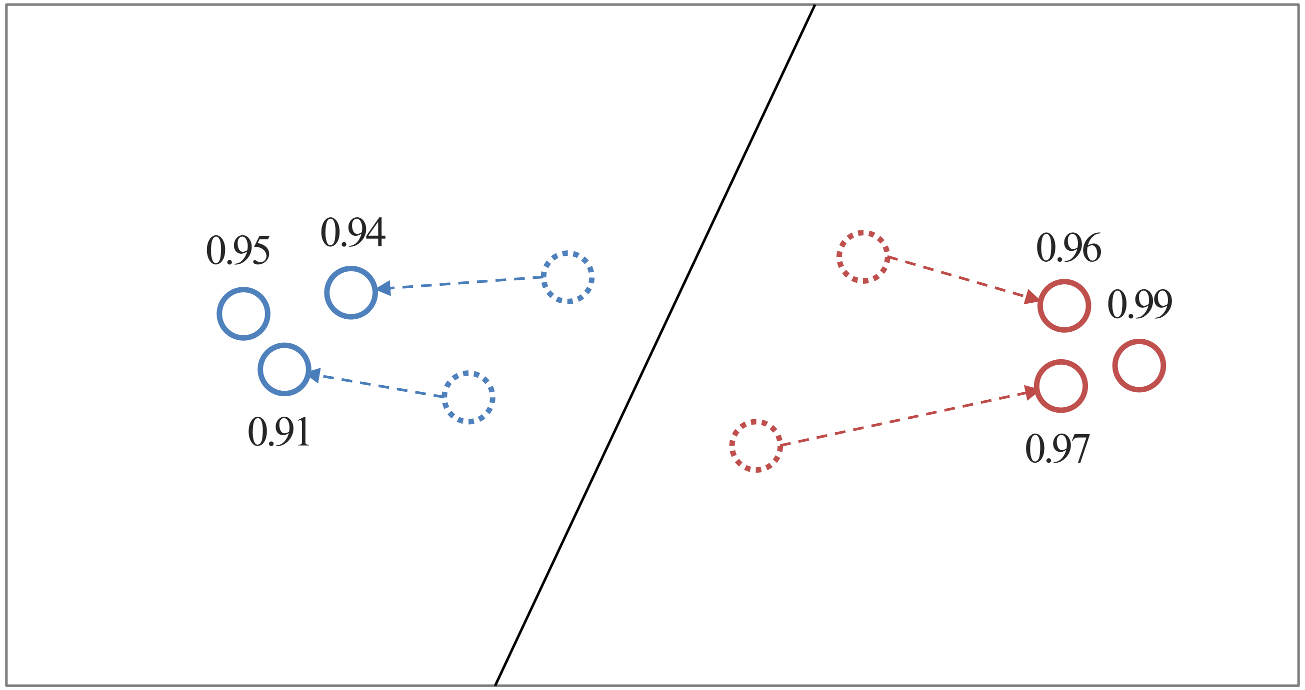


Paper Reviews

Contrastive Regularization for Semi-Supervised Learning

❖ 연구 가설

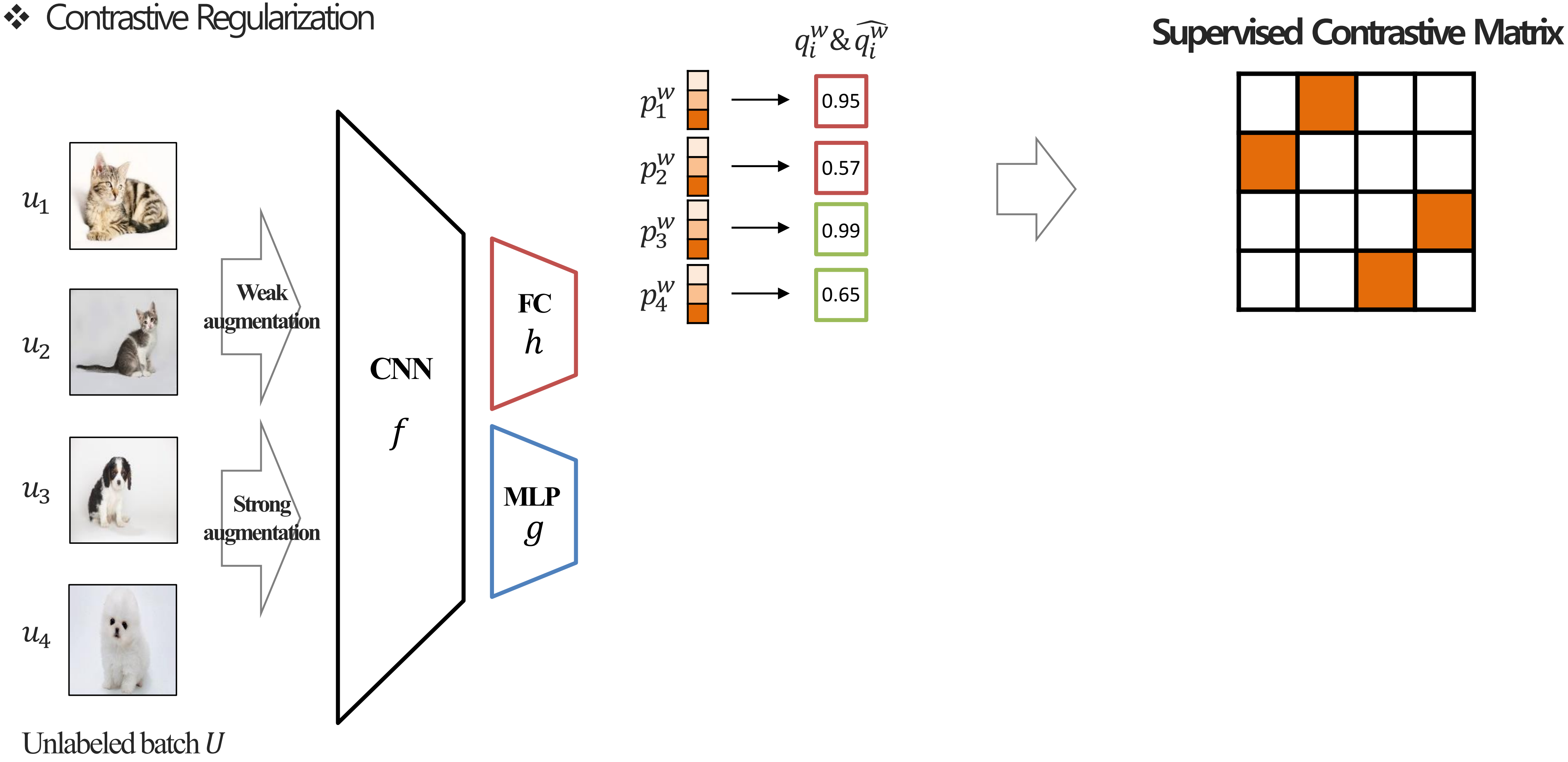
- 결정 경계 근처의 Confidence level이 낮은 데이터를 confidence level이 높은 데이터 쪽으로 당겨주면 빠른 label propagation이 가능할 것



Paper Reviews

Contrastive Regularization for Semi-Supervised Learning

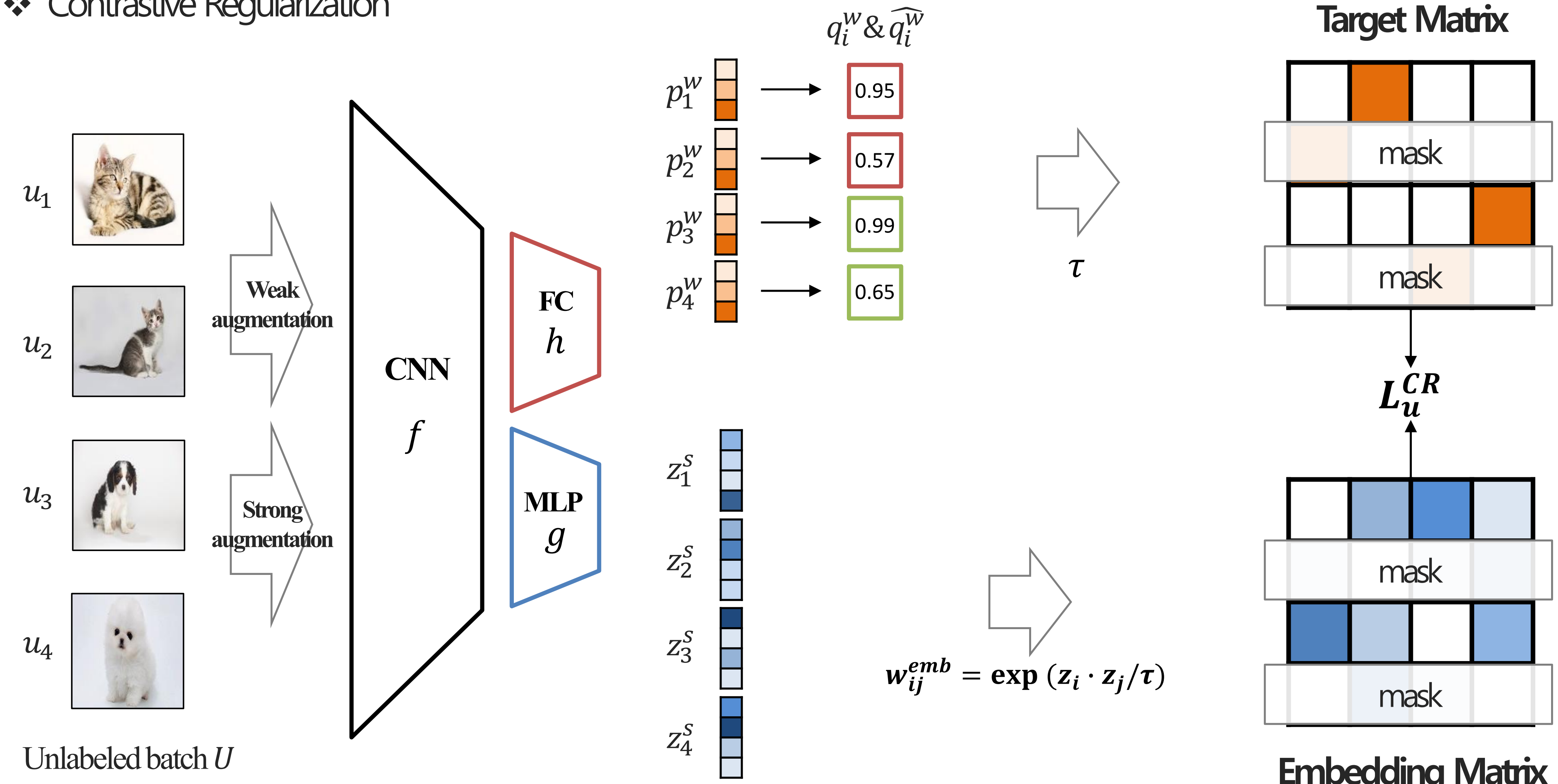
❖ Contrastive Regularization



Paper Reviews

Contrastive Regularization for Semi-Supervised Learning

❖ Contrastive Regularization



Paper Reviews

Contrastive Regularization for Semi-Supervised Learning

❖ 실험 결과

	SVHN				CIFAR-10			
Method	20 labels	40 labels	250 labels	1000 labels	20 labels	40 labels	250 labels	4000 labels
MixMatch*	-	57.45±14.53	96.02±0.23	96.50±0.28	-	52.46±11.50	88.95±0.86	93.58±0.10
UDA*	-	43.75±20.51	94.31±2.76	97.54±0.24	-	70.95±5.93	91.18±1.08	95.12±0.18
ReMixMatch*	-	**96.66±0.20**	97.08±0.48	97.35±0.08	-	81.90±9.64	94.46±0.05	95.28±0.13
CoMatch*	-	-	-	-	81.85±5.56	91.51±2.15	-	-
FixMatch	90.05±8.01	94.83±2.24	97.28±0.66	97.46±0.09	74.98±11.38	91.24±3.72	94.67±0.28	95.57±0.05
FixMatch+CR	**94.96±4.77**	96.33±1.84	**97.55±0.08**	**97.61**±0.06	**88.26**±1.38	**94.31**±0.90	**94.96**±0.30	**95.84**±0.13
SelfMatch*	-	96.58±1.02	97.37±0.43	97.49±0.07	-	93.19±1.08	95.13±0.26	95.94±0.08
FixMatch+CR++	**96.88**±0.60	**97.05**±0.28	**97.95**±0.09	**98.11**±0.05	**94.24**±3.48	**95.26**±0.70	**96.00**±0.31	**96.68**±0.18

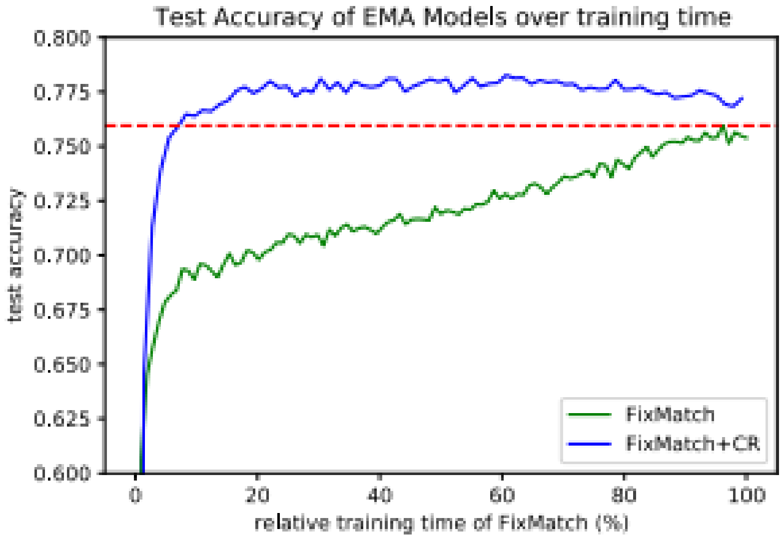
	CIFAR-100		
Medthod	400 labels	2500 labels	10000 labels
UDA	48.02±2.66	70.50±0.53	77.07±0.33
UDA+CR	**49.91**±0.79	**72.12**±0.28	**78.58**±0.11
FixMatch	48.48±0.55	71.53±0.29	78.03±0.26
FixMatch+CR	**50.77**±0.79	**72.42**±0.37	**78.97**±0.23

	STL-10	ImageNet	
Method	1,000 labels	1% labels	10% labels
FixMatch	89.34±1.79	51.29 (72.48)	72.18 (89.98)
FixMatch+CR	**93.04**±0.42	**57.77 (78.12)**	**72.77 (90.15)**

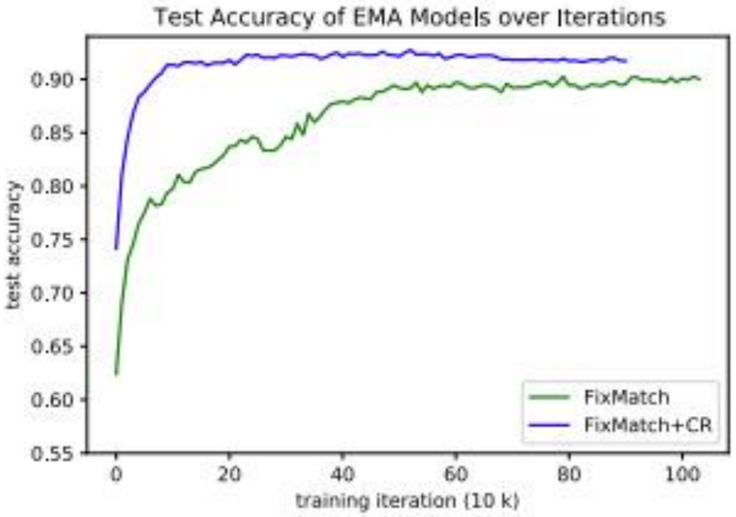
Paper Reviews

Contrastive Regularization for Semi-Supervised Learning

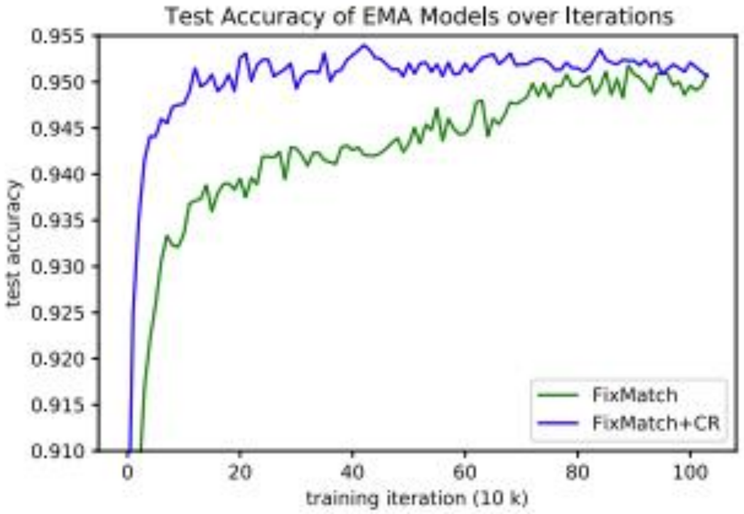
❖ 실험 결과



CIFAR-100, 10000 labels



(a) Test Accuracy of the EMA Model (STL-10, 1000 labels)



(b) Test Accuracy of the EMA Model (STL-10, 5000 labels)

Conclusions

결론

❖ Paper List

CoMatch: Semi-Supervised Learning With Contrastive Graph Regularization (2021, ICCV)

Class-Aware Contrastive Semi-Supervised Learning (2022, CVPR)

Contrastive Regularization for Semi-Supervised Learning (2022, CVPR)

Reference

reference

1. Li, Junnan, Caiming Xiong, and Steven CH Hoi. "Comatch: Semi-supervised learning with contrastive graph regularization." Proceedings of the IEEE/CVF international conference on computer vision. 2021.
2. Yang, Fan, et al. "Class-aware contrastive semi-supervised learning." Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition. 2022.
3. Lee, Doyup, et al. "Contrastive regularization for semi-supervised learning." *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*. 2022.

감사합니다