

DMQA Open Seminar

# Contrastive Semi-supervised Learning

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2023. 04. 14

고려대학교 산업경영공학과

Data Mining & Quality Analytics Lab.

임새린

# 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.ackr

# 목차

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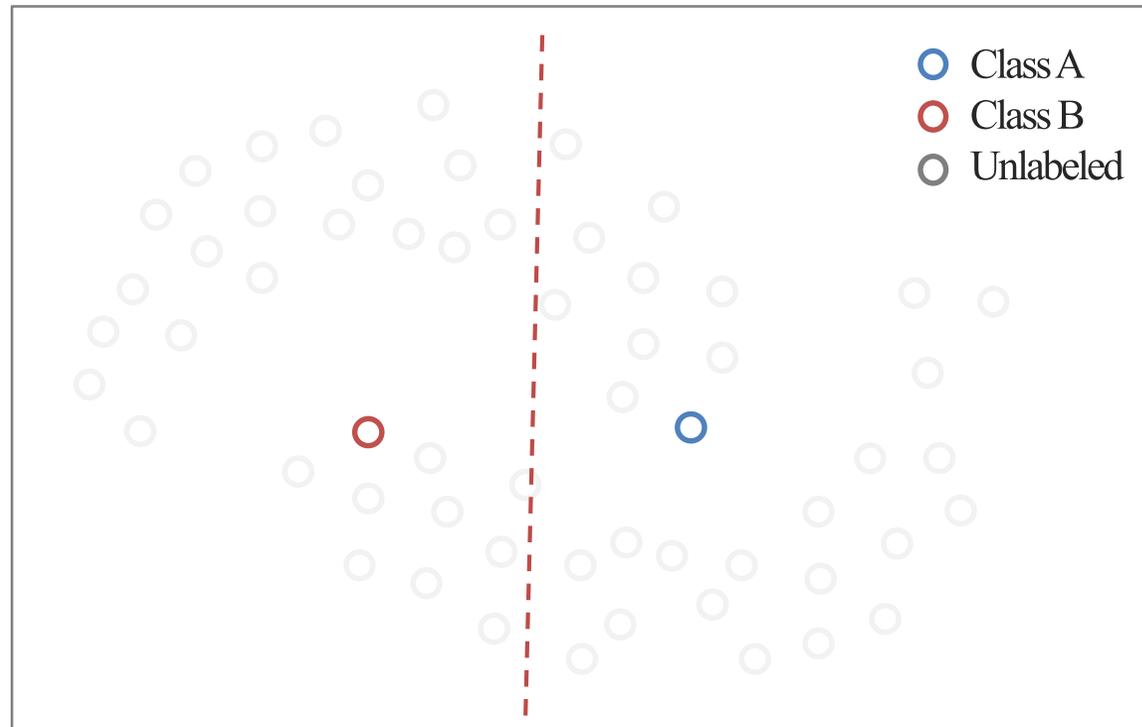
1. Background
2. Paper Reviews
3. Conclusions

# Background

## 준지도 학습

### ❖ Semi-Supervised Learning

- Unlabeled data를 활용해서 모델의 일반화 성능을 향상시키는 방법론

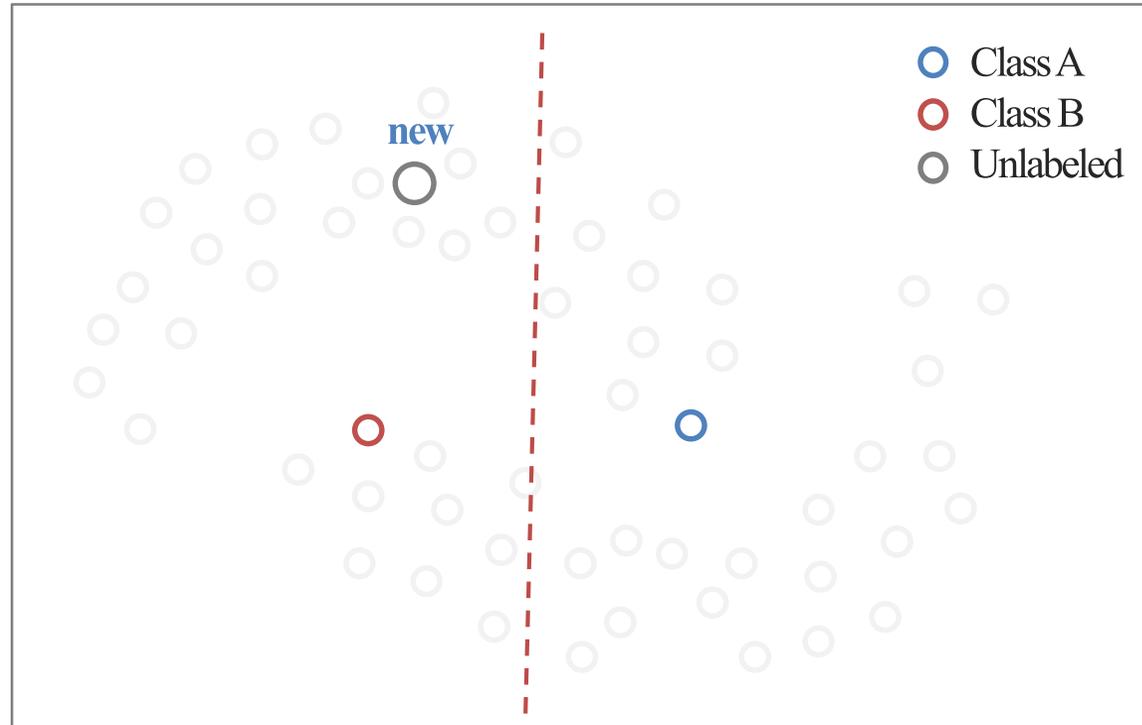


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## 준지도 학습

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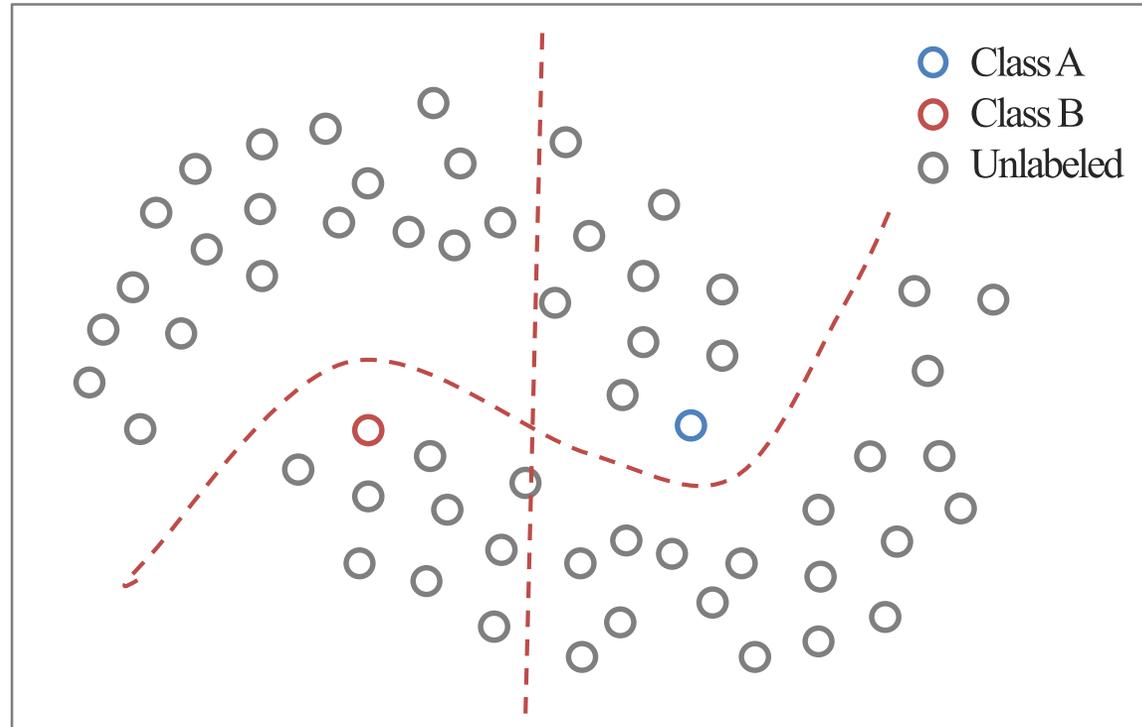


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## 준지도 학습

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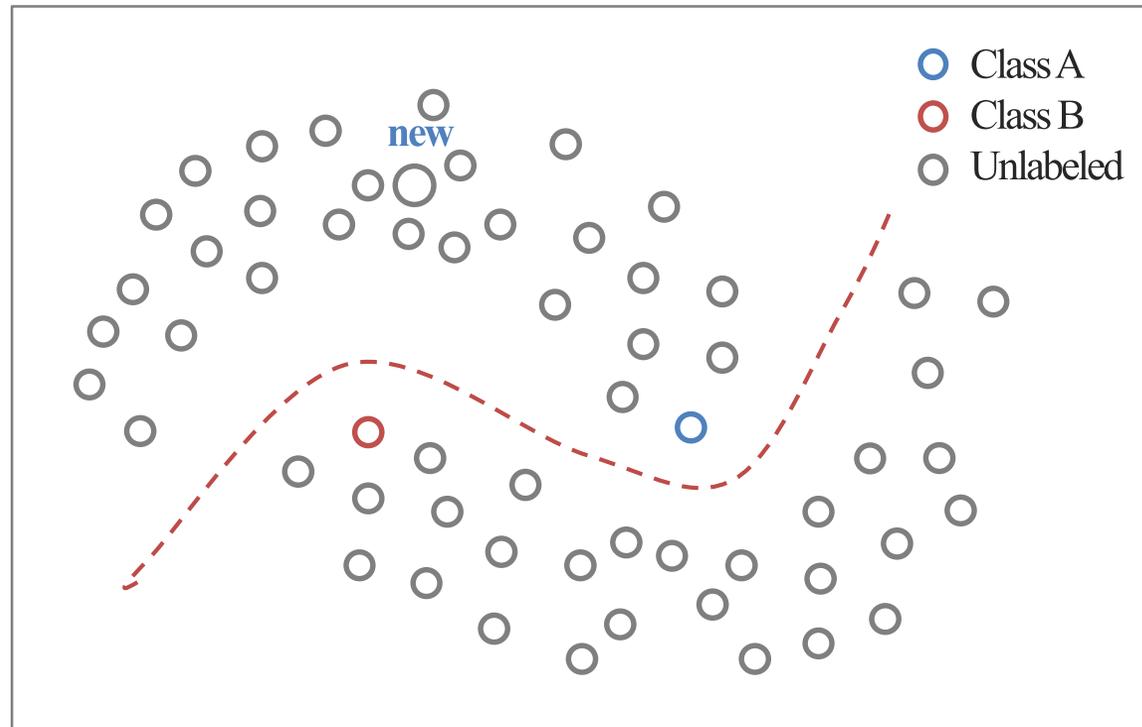


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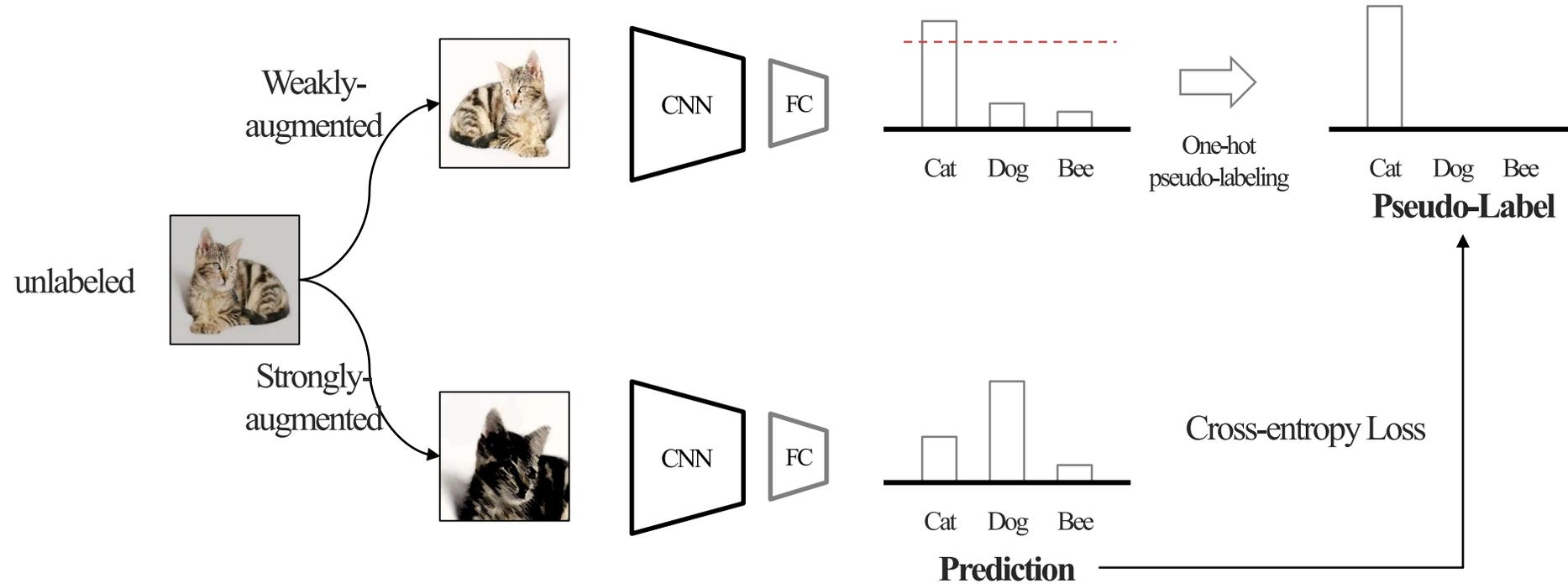


# Background

## 준지도 학습

### ❖ Fixmatch

- 여러 준지도 학습 방법론을 간단하게 통합하여 좋은 성능을 보인 방법론

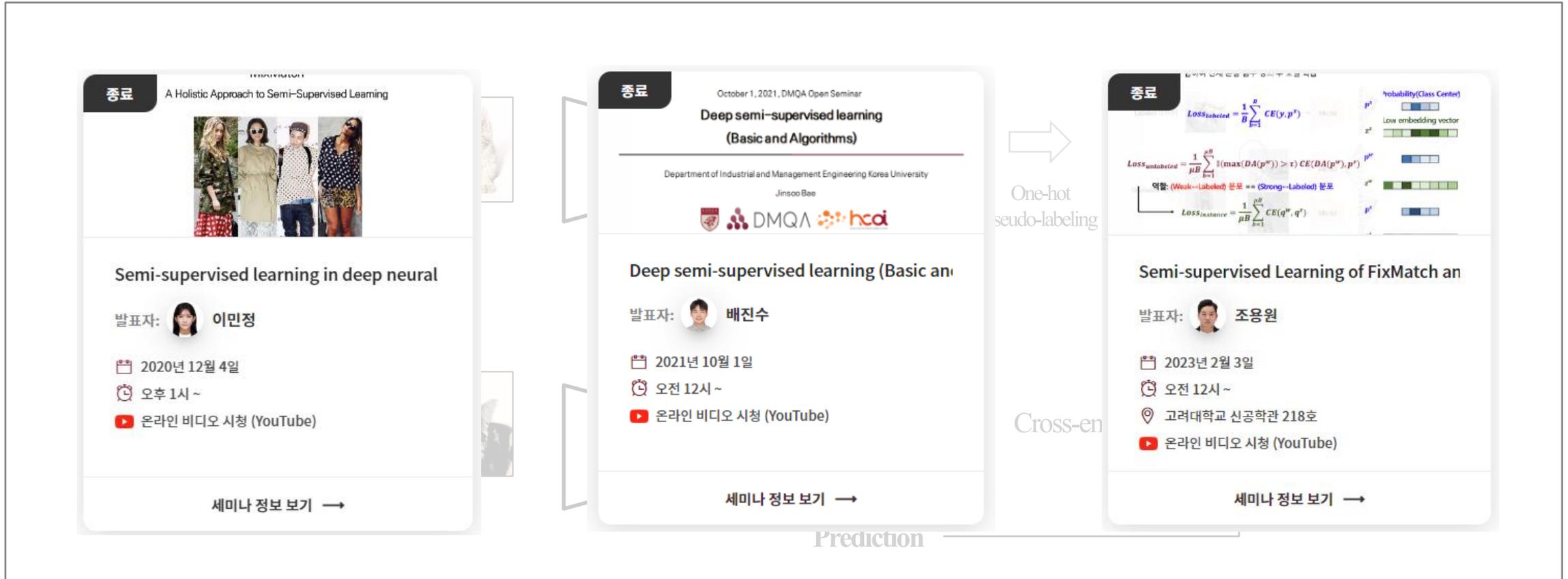


# Background

## 준지도 학습

### ❖ Fixmatch

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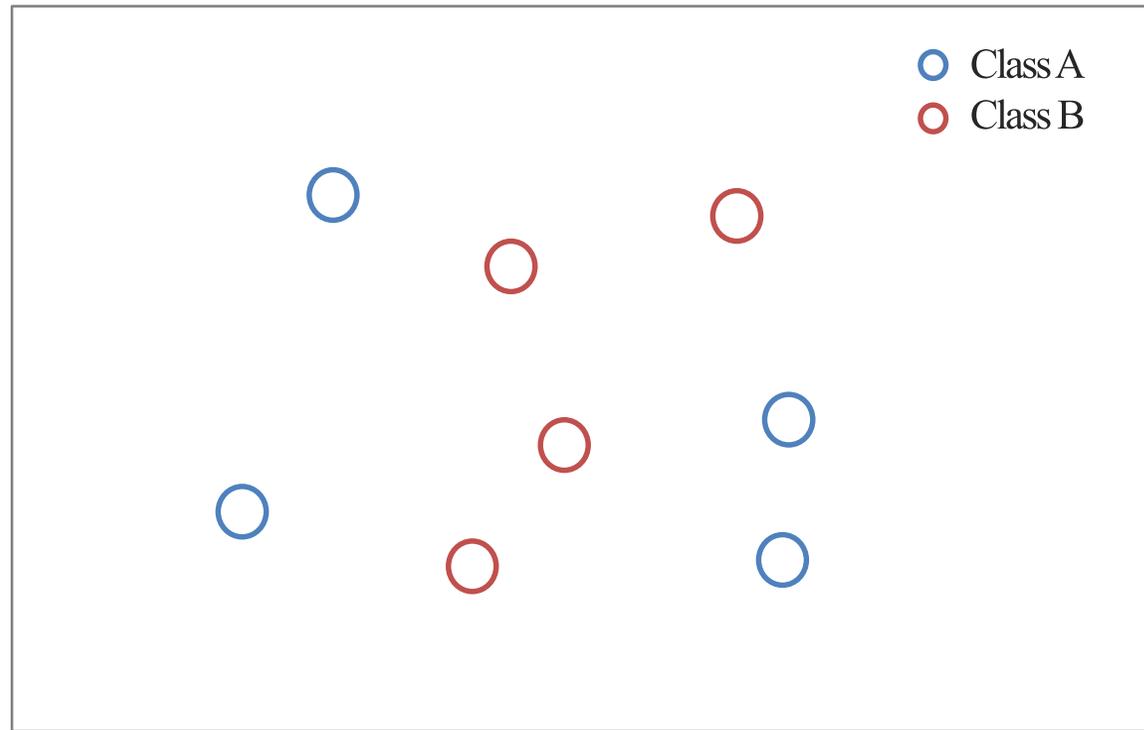


# Background

## 대조 학습

### ❖ Contrastive Learning

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



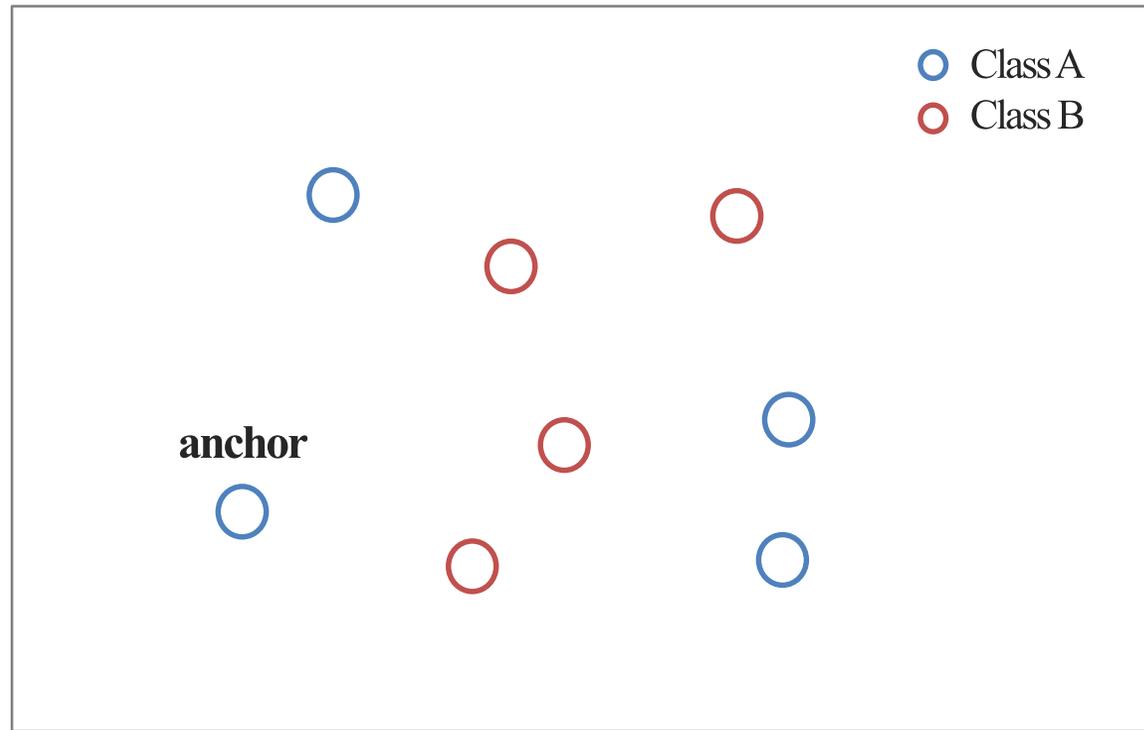
Original feature space

# Background

## 대조 학습

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- Metric Learning 방법론 중 하나로 데이터 간 유사도 정보를 통해서 데이터들을 구분하기 쉽게 해주는 거리 함수를 학습하는 것
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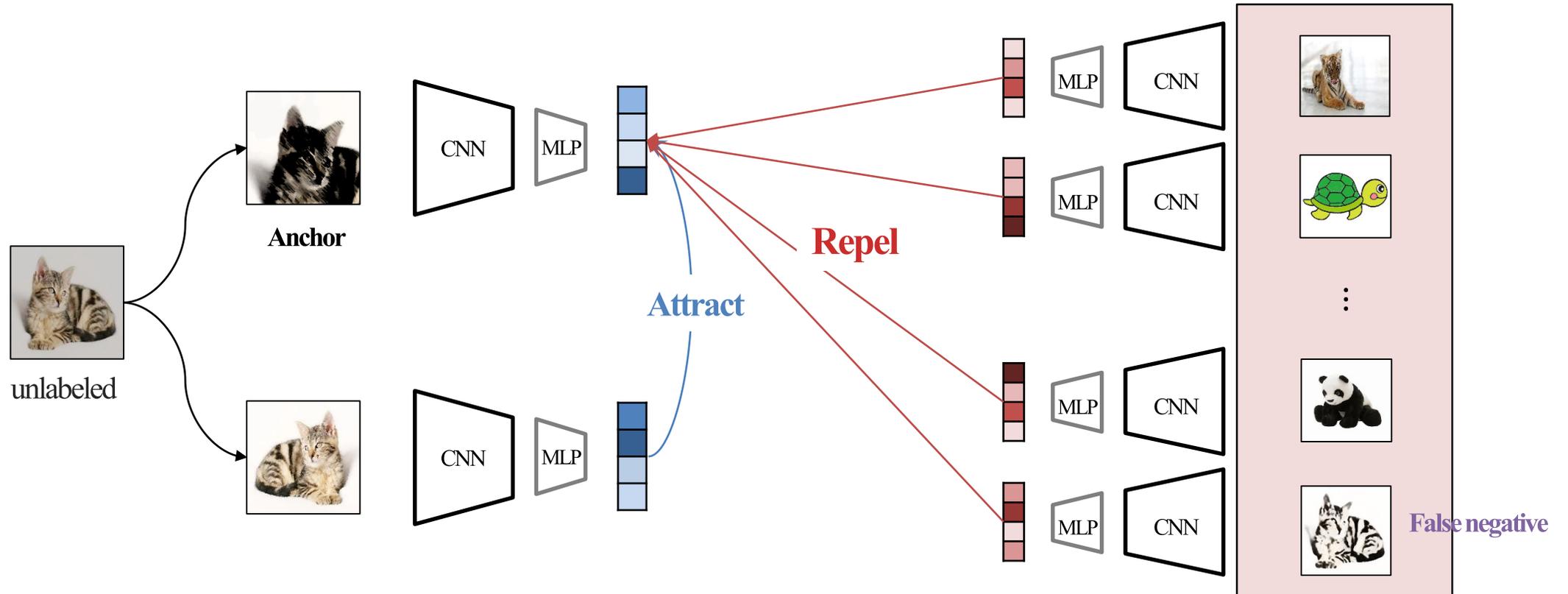
Embedding space

# 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

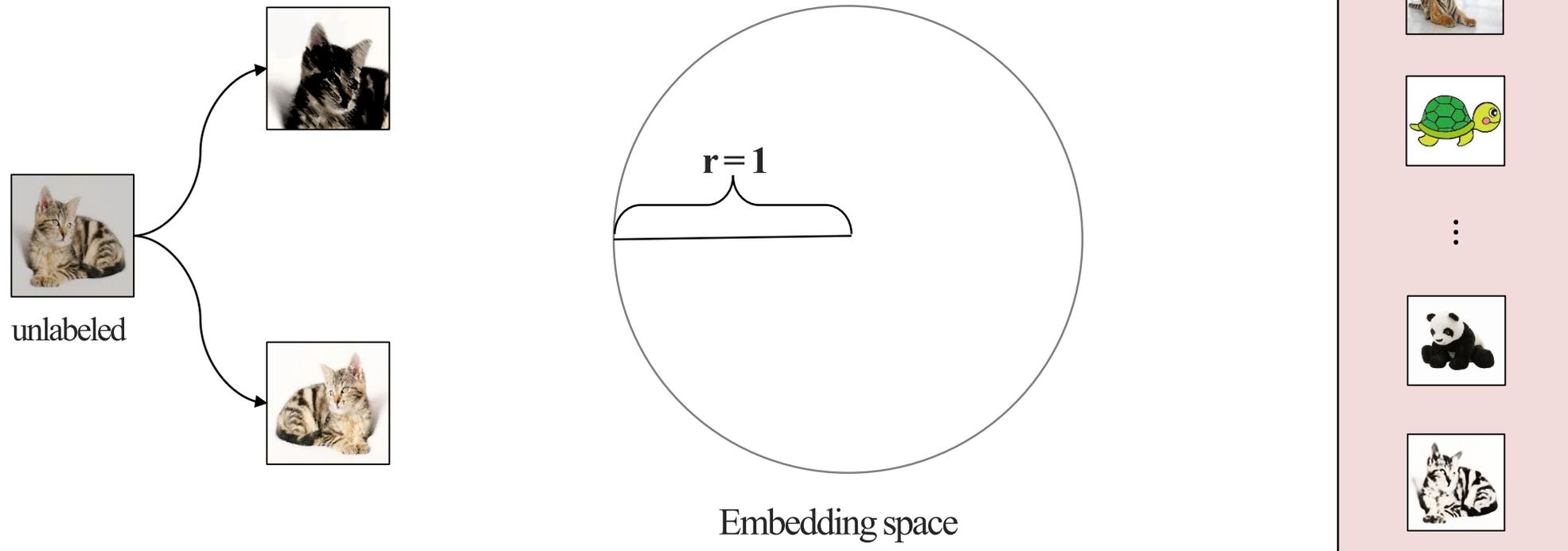


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## 대조 학습

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**종료** Understanding

**Towards Contrastive Learning**

발표자: **박민구**

📅 2021년 1월 29일  
🕒 오후 1시 ~  
▶ 온라인 비디오 시청 (YouTube)

세미나 정보 보기 →

= 1

**종료** Deal with Contrastive Learning

고은성

Korea University  
Data Mining & Quality Analytics Lab.

**Deal with Contrastive Learning**

발표자: **고은성**

📅 2021년 9월 10일  
🕒 오전 1시 ~  
▶ 온라인 비디오 시청 (YouTube)

세미나 정보 보기 →

### Other Images

Other Images

Embedding space

# Paper Reviews

논문 리뷰

## ❖ Paper List

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### CoMatch: Semi-supervised Learning with Contrastive Graph Regularization

Junnan Li, Cairning Xiang, Steven CH. Ho, Seidforde Research  
{junnan.li, cxiang, sho}@brainforce.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 contrastive 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 reduce the loss. The embeddings regularize the structure of the pseudo-labels, while the pseudo-labels regularize the structure of the embeddings through graph-based consistency learning. CoMatch achieves state-of-the-art performance on multiple datasets. It achieves substantial accuracy improvement on the label-free CIFAR-10 and STL-10. On ImageNet, CoMatch achieves a top-1 accuracy of 46.0%, outperforming FixMatch [12] by 12.6%. Furthermore, CoMatch achieves better representation learning performance on downstream tasks, improving both supervised learning and self-supervised learning. Code and pre-trained models are available at <https://github.com/stevencho/CoMatch>.

**1. Introduction**  
Semi-supervised learning (SSL) – learning from few labeled data and a large amount of unlabeled data – has been a long-standing problem in computer vision and machine learning. Recent state-of-the-art methods mostly fall into two trends: (1) using the model’s class prediction to produce a pseudo-label for each unlabeled sample so the label is used against [1], [2], [3]. (2) compromised or self-supervised pre-training, followed by supervised fine-tuning [4], [5], [6] and pseudo-labeling [7].

However, existing methods have several limitations. Pseudo-labeling (also called self-training) methods heavily rely on the quality of the model’s class prediction, thus suffering from confirmation bias when the prediction results would be consistent. Self-supervised training methods are task-specific, and the widely adopted contrastive learn-

ing [8], [9] may learn representations that are suboptimal for the specific classification task. Another branch of methods explore graph-based semi-supervised learning [10], [11], but have yet shown competitive performance especially on large datasets such as ImageNet [12].

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 input 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 reduce the loss in a shared framework. Specifically, the classification head is trained using memory-augmented pseudo-labels, where pseudo-labels are refined by aggregating information from nearby samples in the embedding space. The projection head is trained using consistency learning on a pseudo-label graph, where samples with similar pseudo-labels are trained to have similar embeddings. CoMatch unifies dominant ideas including consistency regularization, entropy maximization, contrastive learning and graph-based SSL.

We perform experiments on multiple datasets and compare with state-of-the-art self-supervised and self-supervised methods. CoMatch substantially outperforms all baselines across all benchmarks, especially in label-free scenarios. On CIFAR-10 with a labeled samples per class, CoMatch outperforms FixMatch [12] by 4.1% in accuracy. On STL-10, CoMatch outperforms FixMatch by 13.2%. On ImageNet with only 1% of labels, CoMatch achieves a top-1 accuracy of 46.0% (47.3% with self-supervised pre-training), which is the best baseline (CoMatch [1] trained by FixMatch [12]) by an accuracy of 59.9%. Furthermore, we demonstrate that CoMatch achieves better representation learning performance on downstream image classification and other domain tasks, outperforming both supervised learning and self-supervised learning.

**2. Background**  
To set the stage for CoMatch, we first introduce existing SSL methods, mainly focusing on current state-of-the-art methods that are relevant. More comprehensive reviews

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

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### Class-Aware Contrastive Semi-Supervised Learning

Fan Yang\*, Kai Wu\*, Sheng Zhang\*, Guanmin Jiang\*, Yong Liu\*, Feng Zheng\*, Wei Zhang\*, Chengjie Wang\*, Long Zeng\*, \*Tencent YouTu Lab, \*Southern University of Science and Technology, \*CATL

**Abstract**  
Pseudo-label based semi-supervised learning (SSL) has achieved great success on new 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 unclear 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 designed to improve the pseudo-label quality and enhance the model’s robustness to the real-world setting. Rather than treating real-world data as a noise set, our method separately handles reliable in-distribution data with class-wise clustering for identifying in-distribution nodes and noisy out-of-distribution data with image-wise consistency for better generalization. Furthermore, by applying target re-weighting, we successfully emphasize those labeled training and simultaneously reduce noisy label learning. Despite its simplicity, our proposed CCSSL has significant performance improvement over the state-of-the-art SSL methods on the standard datasets CIFAR100 [13] and STL10 [14]. On the real-world dataset Scene150 [2022], we improve FixMatch [12] by 3.6% on CIFAR-100 and CoMatch [5] by 1.8%. Code is available at <https://github.com/fanyang1995/class-aware-contrastive-ssl>.

**1. Introduction**  
Real data utilization is becoming a research focal point for its high accessibility and high flexibility. The definition of new data in the sense of in-distribution data (in-domain classes and balanced distribution) and out-of-distribution data [15] (unknown classes or unbalanced distribution, as shown in Fig. 1). For in-distribution datasets, semi-supervised learning (SSL) has achieved excellent performance with the help of pseudo-labeling [1, 2, 3, 16, 17]. The primary process for the pseudo-label based SSL is to create self-generated pseudo labels on new data, (2) training on pseudo labels, (3) repeating 1 and 2. The underlying assumption for training on pseudo labels is that the distribution of the labeled data is close to the unlabeled, and the unlabeled dataset does not contain any novel categories. This assumption often does not hold in the real-world applications with extensive out-of-distribution data, which contains unbalanced distribution or unknown classes. SSL’s training and labeling both rely on the real-world evidence of the in-domain new data introduced by pseudo-labeling on out-of-distribution data. The confirmation bias [18] (induced by noisy pseudo-labels) deteriorates SSL performance by a large margin [19].

SSL has used many techniques to alleviate the confirmation bias and achieved state-of-the-art results on standard in-

Figure 1: Illustration graph for class-aware contrastive semi-supervised learning. It represents real-world unlabeled data containing in-distribution and out-of-distribution data (unbalanced distribution or unknown classes). Unlike pseudo-label based semi-supervised learning in SSL, which merely chooses noisy out-of-distribution data (OoD) as a random noise by image-level consistency learning on out-of-distribution data while maintaining the class-wise learning ability for in-distribution data, our method: (1) creating self-generated pseudo labels on new data, (2) training on pseudo labels, (3) repeating 1 and 2. The underlying assumption for training on pseudo labels is that the distribution of the labeled data is close to the unlabeled, and the unlabeled dataset does not contain any novel categories. This assumption often does not hold in the real-world applications with extensive out-of-distribution data, which contains unbalanced distribution or unknown classes. SSL’s training and labeling both rely on the real-world evidence of the in-domain new data introduced by pseudo-labeling on out-of-distribution data. The confirmation bias [18] (induced by noisy pseudo-labels) deteriorates SSL performance by a large margin [19].

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

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### Contrastive Regularization for Semi-Supervised Learning

Duyun Lee, Sungsoo Kim, Ilhoon Kim, POSTECH, Kakao Brain, Kakao Brain, Kakao Enterprise, Youngjae Cho, Minso Cho, Woohyun Han\*, POSTECH, POSTECH, POSTECH, wcho@postech.ac.kr

**Abstract**  
Continuity regularization on label prediction has been a fundamental technique in semi-supervised learning, but it still requires a large number of training iterations for high performance. In this study, we analyze that the continuity regularization critic the propagation of labeling information due to the existence of samples with unconfident pseudo-labels in the model output. Thus, we propose continuity regularization to improve both efficiency and accuracy of the continuity regularization by well-filtered features of unlabeled data. In specific, after strongly augmented samples are assigned to clusters by their pseudo-labels, our continuity regularization reduces the model so that the features with confident pseudo-labels aggregate the features in the same cluster, while pushing away features in different clusters. As a result, the information of confident pseudo-labels can be effectively propagated via more unlabeled samples during training by the well-filtered features. On hundreds of semi-supervised learning tasks, our continuity regularization improves the previous continuity-based methods and achieves state-of-the-art results, especially with poor training iterations. Our method also shows robust performance on open-set semi-supervised learning where unlabeled data includes out-of-distribution samples.

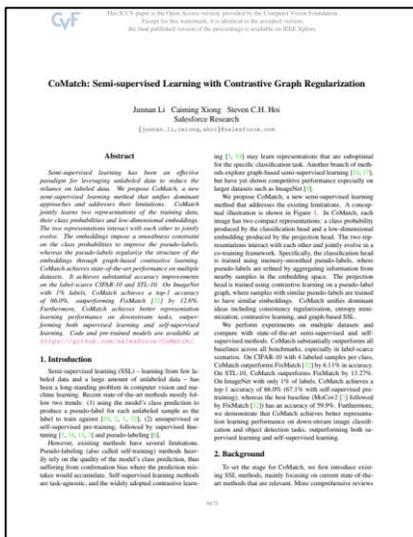
**1. Introduction**  
Recent semi-supervised learning (SSL) methods mostly make use of the consistency regularization to learn a specific task with sparse labels, showing competitive results in the fully supervised learning [1, 2, 3]. The consistency regularization enforces a model to produce consistent predictions on various augmented types of input with pseudo-labeling information.

Moreover, in order to avoid a confirmation bias [4] and increase the reliability of pseudo-labeling, a selection mask is typically used in the consistency regularization to exclude unconfident label predictions during SSL training. Consequently, the consistency regularization can propagate the labeling information into unlabeled samples among the augmented types of confident pseudo-labels [1].

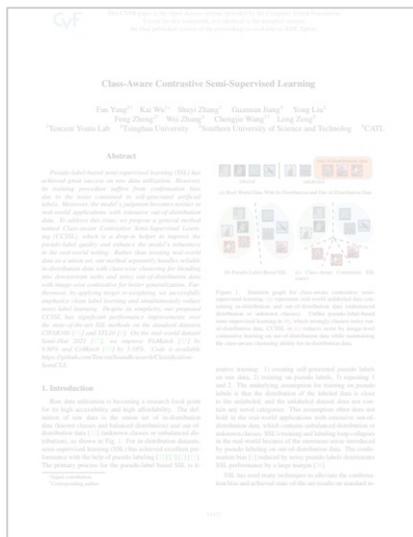
Despite its promising results, the existing consistency regularization requires an expensive training cost to achieve high performance. For example, although FixMatch [10] can achieve high SSL performance without pre-training on a large scale unlabeled data [1], it needs over 10,000 epochs to obtain the best performance even on small-scale datasets such as SVHN, CIFAR-10, or CIFAR-100. Thus, we first analyze the inefficiency of the consistency regularization in SSL, both theoretically and empirically, and then report (1) that the inefficiency is originated from the existence of the samples with unconfident pseudo-labels when applying a model. Namely, it restricts the active propagation of one-label labeling information into unlabeled samples, especially in the early stage of training.

Based on the above analysis, we propose continuity regularization to improve the performance of SSL-based consistency regularization. The main idea is described in Figure 1. The consistency regularization treats the features of strongly augmented samples having only confident pseudo-labels toward their corresponding class centers of the confident features by pseudo-labels. In contrast, the proposed continuity regularization filters class clusters based on both confident and unconfident pseudo-labels. Then, it moves the features having confident pseudo-labels toward the center positions of their clusters, while pushing the features of unconfident pseudo-labels in the same cluster and pushing the features in different clusters. Thus, a model can learn well-filtered features of unlabeled data, enabling the confident labeling

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



# 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



This ICCV paper is the Open Access version, provided by the Computer Vision Foundation.  
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the final published version of the proceedings is available on IEEE Xplore.

## 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,*

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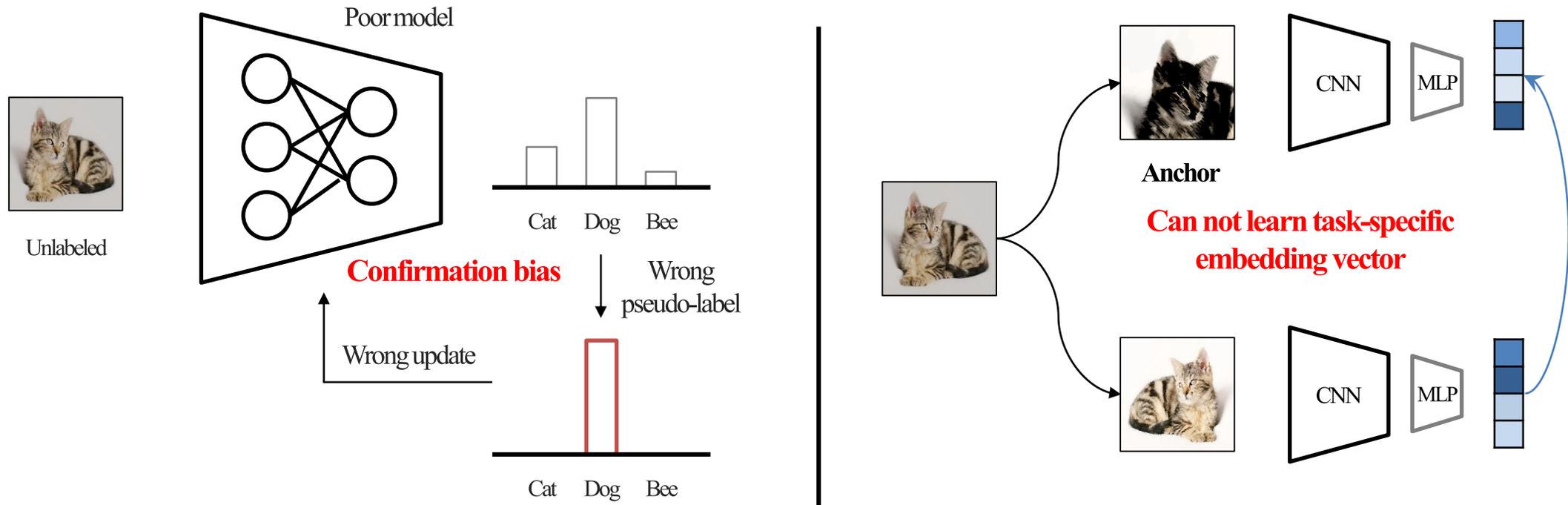
*We propose CoMatch, a new semi-supervised learning method that addresses the existing limitations. A conceptual illustration is shown in Figure 1. In CoMatch, each image has two compact representations: a class probability produced by the classification head and a low-dimensional embedding produced 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 맞는 embedding space를 학습하기 어려움

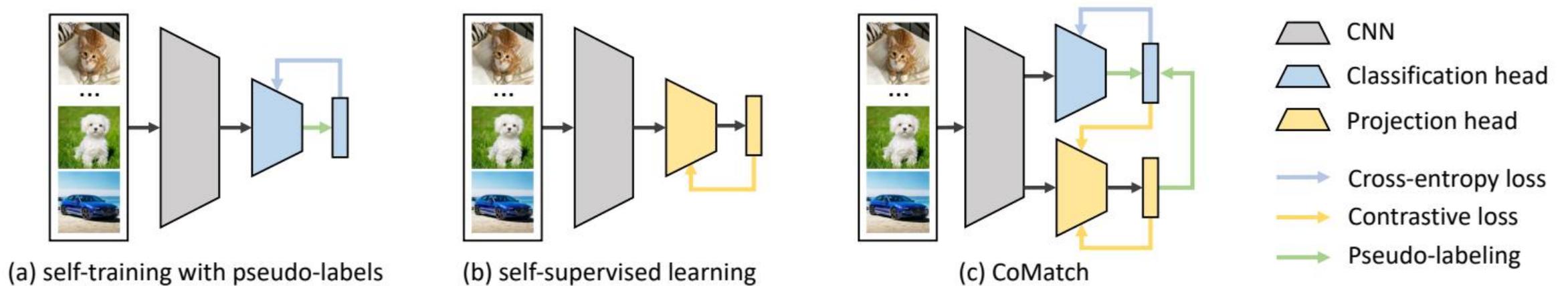


# Paper Reviews

## CoMatch: Semi-Supervised Learning with Contrastive Graph Regularization

### ❖ 연구 가설

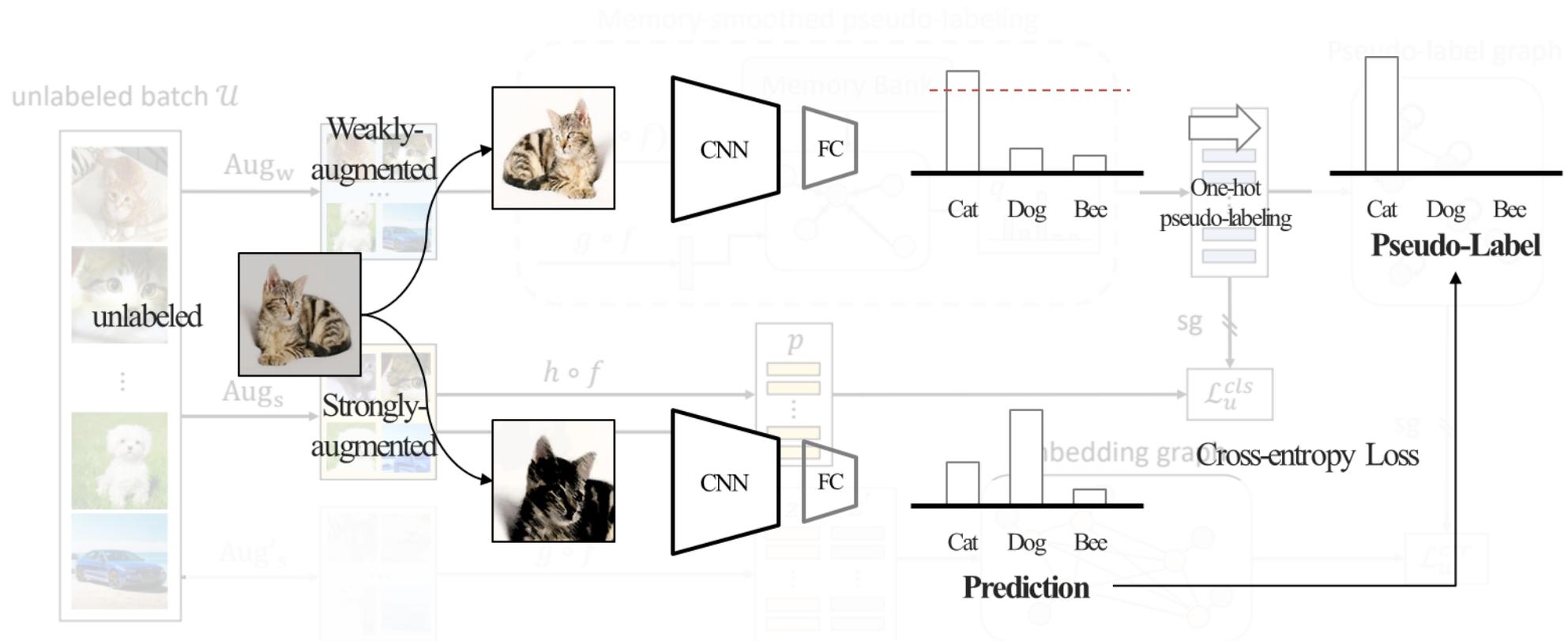
- Class probability와 low-dimensional embedding이 서로 도움을 주면서 동시에 학습하면 더 좋은 representation을 학습 할 수 있을 것



# Paper Reviews

## CoMatch: Semi-Supervised Learning with Contrastive Graph Regularization

### ❖ 제안 방법론



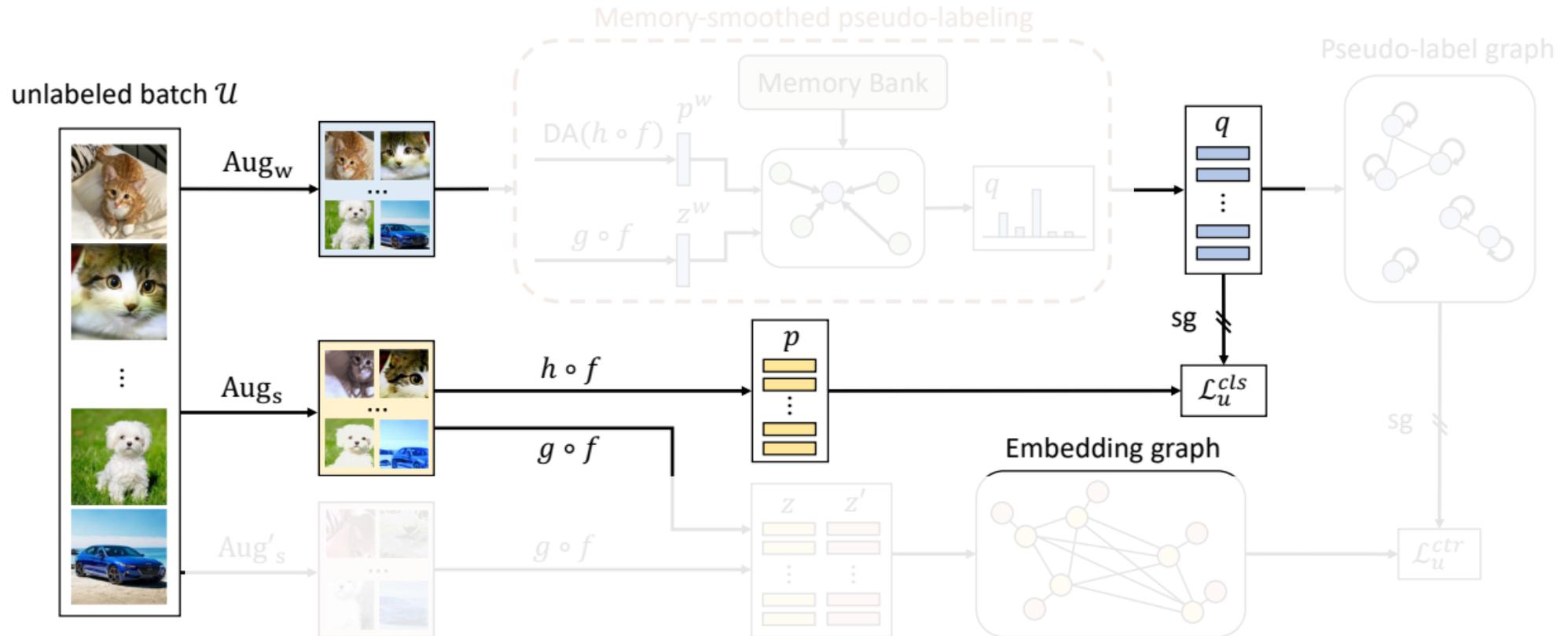
$$L_{comatch} = L_l^{cls} + L_u^{cls} + L_u^{ctr}$$

# Paper Reviews

## CoMatch: Semi-Supervised Learning with Contrastive Graph Regularization

### ❖ 제안 방법론

1. pseudo-label을 embedding vector를 통해 조정하는 모듈



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

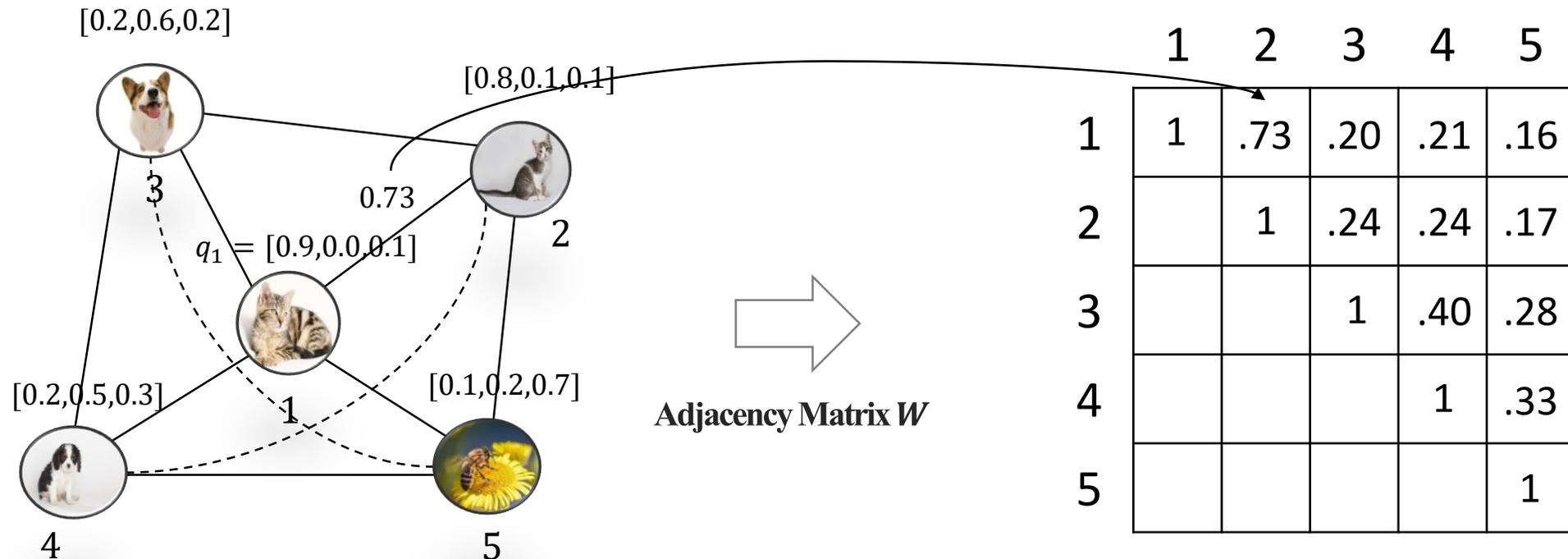
2. pseudo-label graph를 통해 embedding graph를 학습하는 모듈

# 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

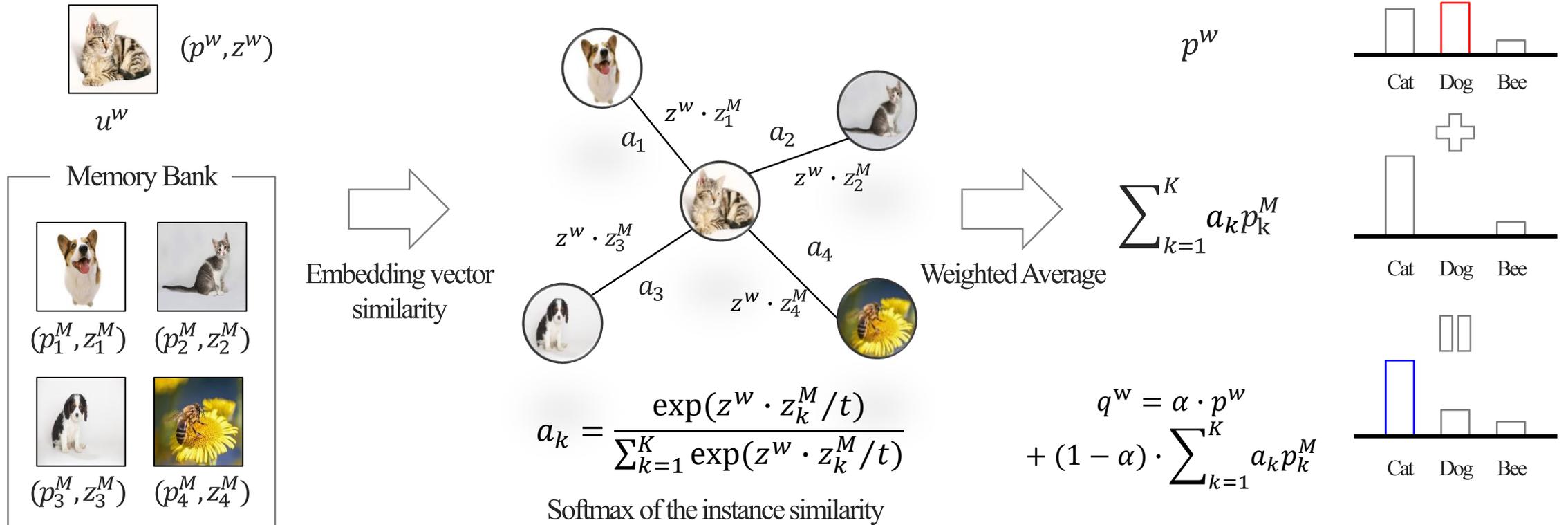


# Paper Reviews

## 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

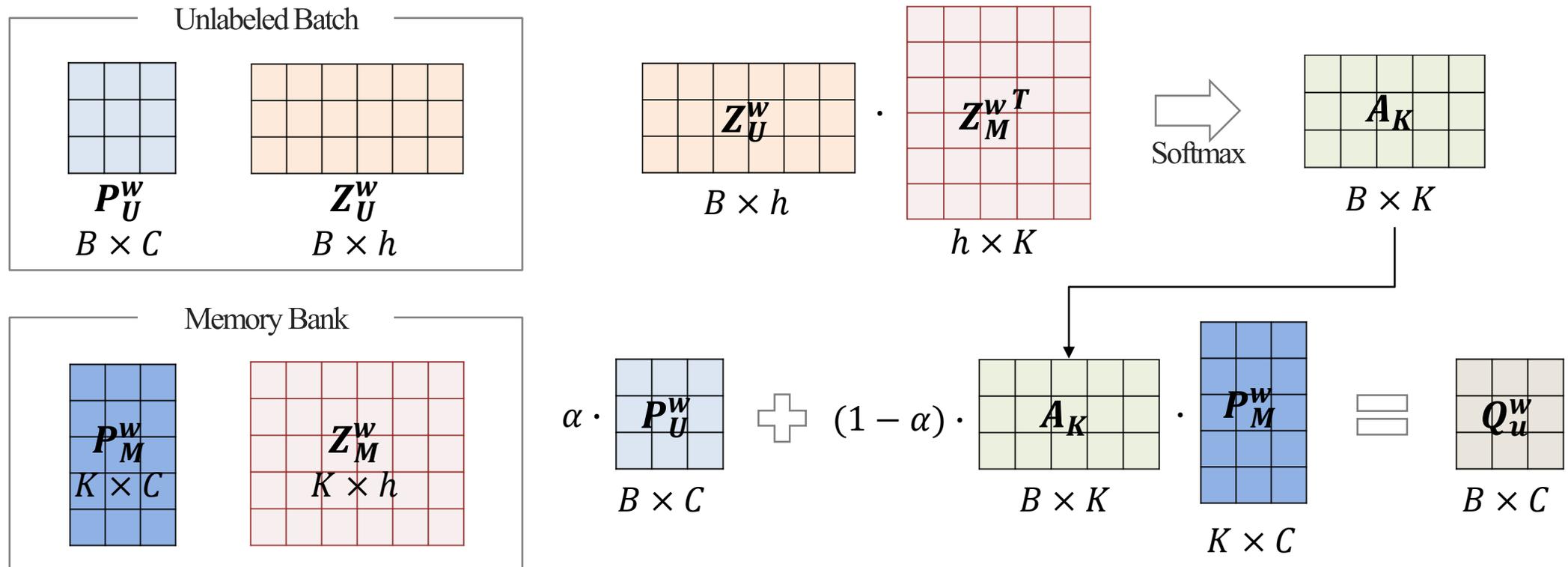


# Paper Reviews

## CoMatch: Semi-Supervised Learning with Contrastive Graph Regularization

### ❖ Memory-smoothed pseudo-labeling

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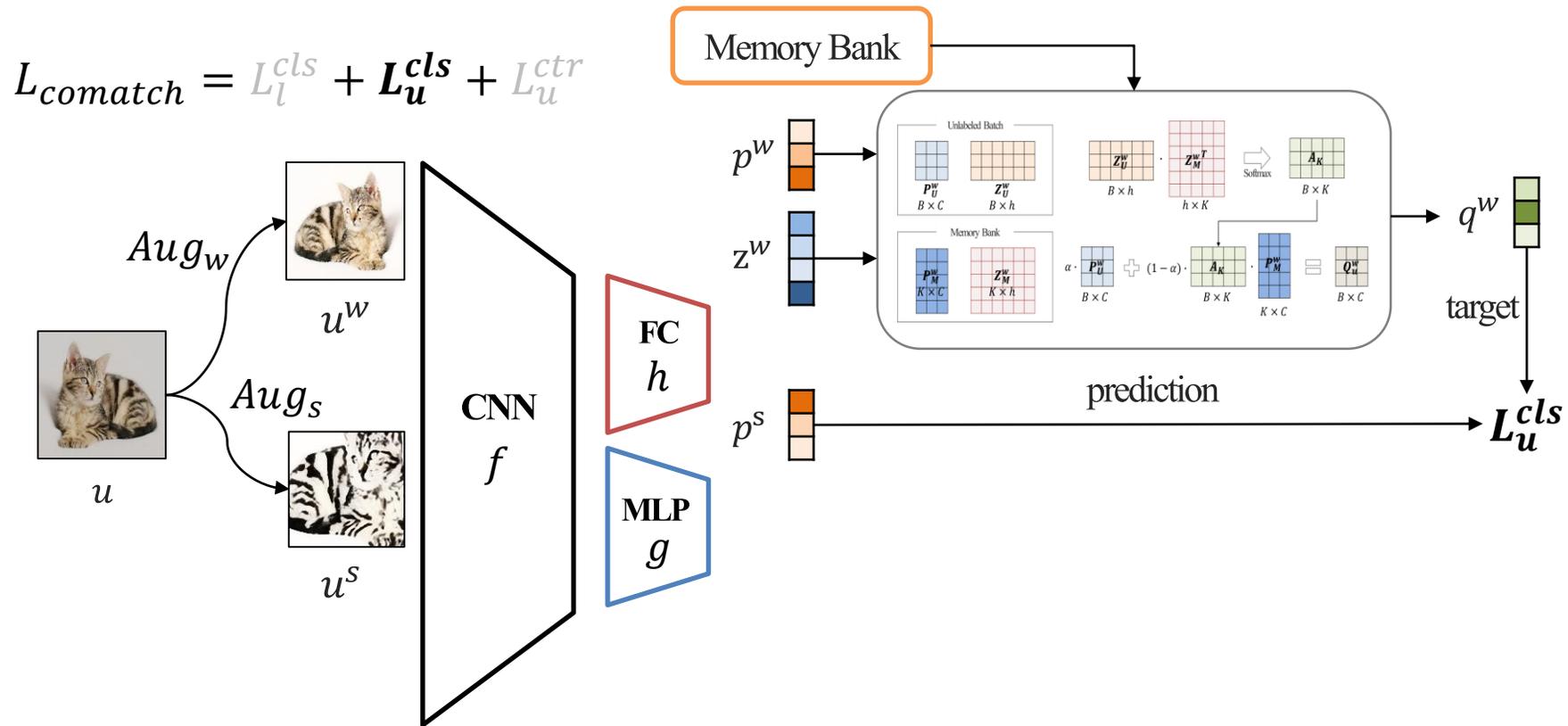


# Paper Reviews

## CoMatch: Semi-Supervised Learning with Contrastive Graph Regularization

### ❖ Fixmatch Loss with memory-smoothed pseudo-labeling

- $u^w$ 에 대한 Memory-smoothed pseudo-label  $q^w$ 와  $u^s$ 에 대한 class probability  $p^s$  사이의 cross-entropy를 통해  $L_u^{cls}$  정의

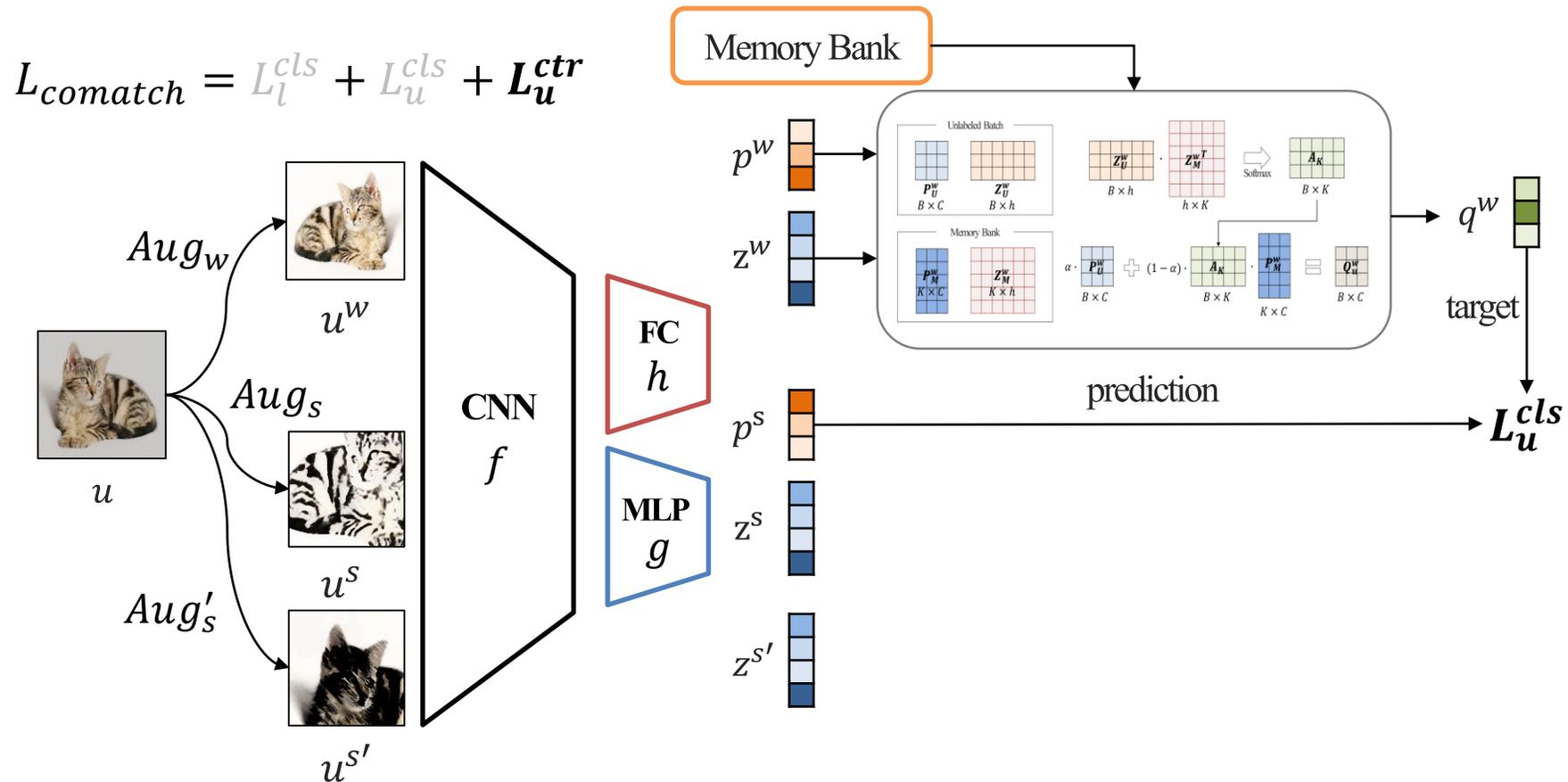


# Paper Reviews

## 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

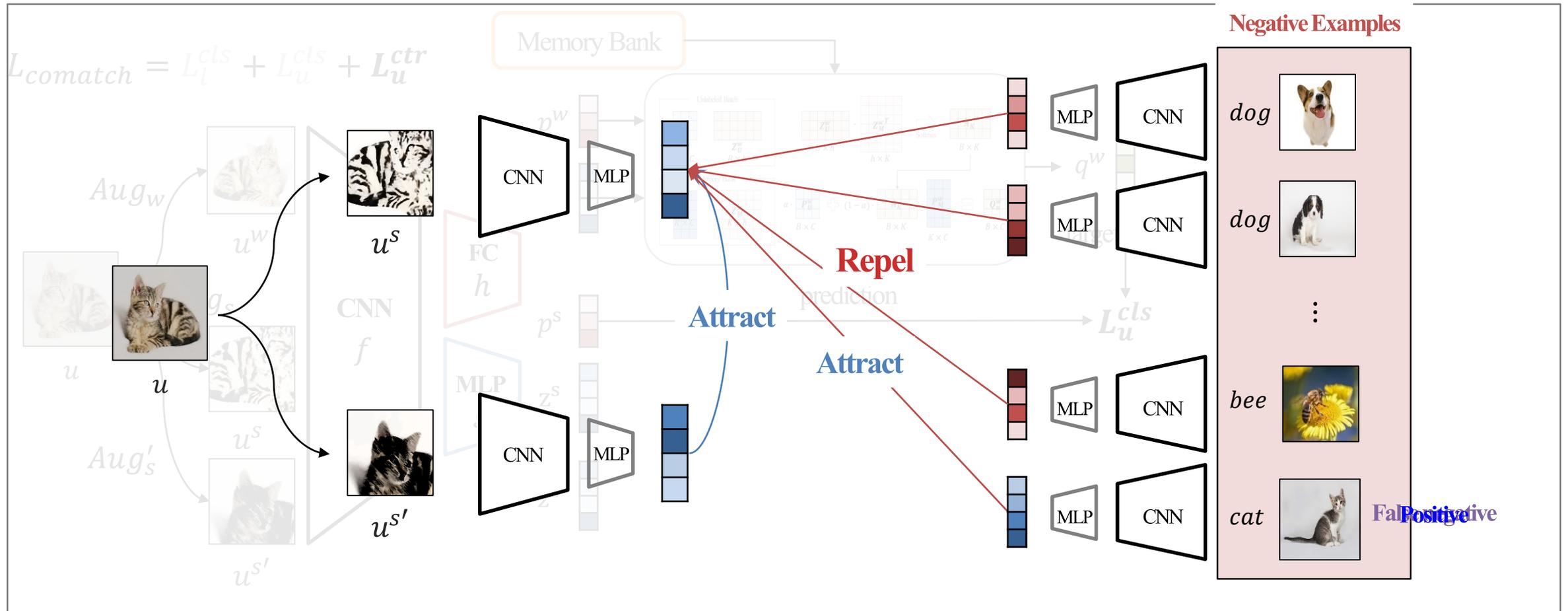


# Paper Reviews

## CoMatch: Semi-Supervised Learning with Contrastive Graph Regularization

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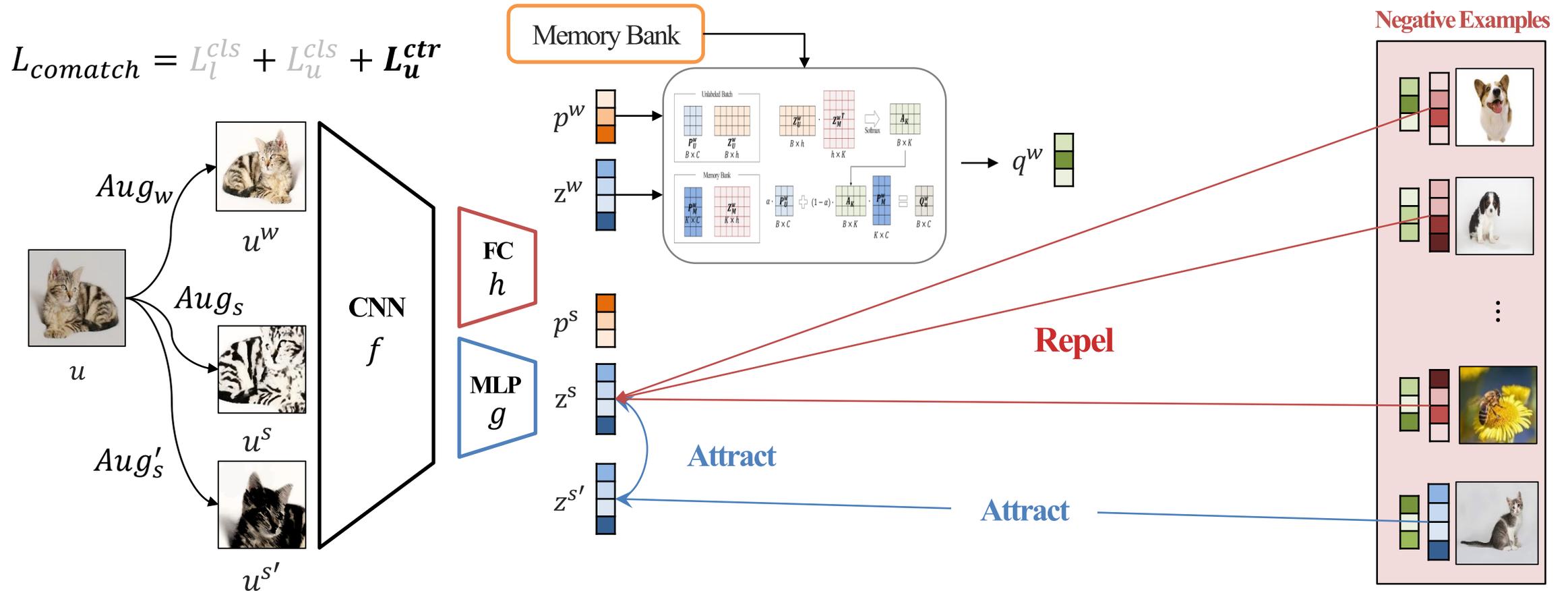


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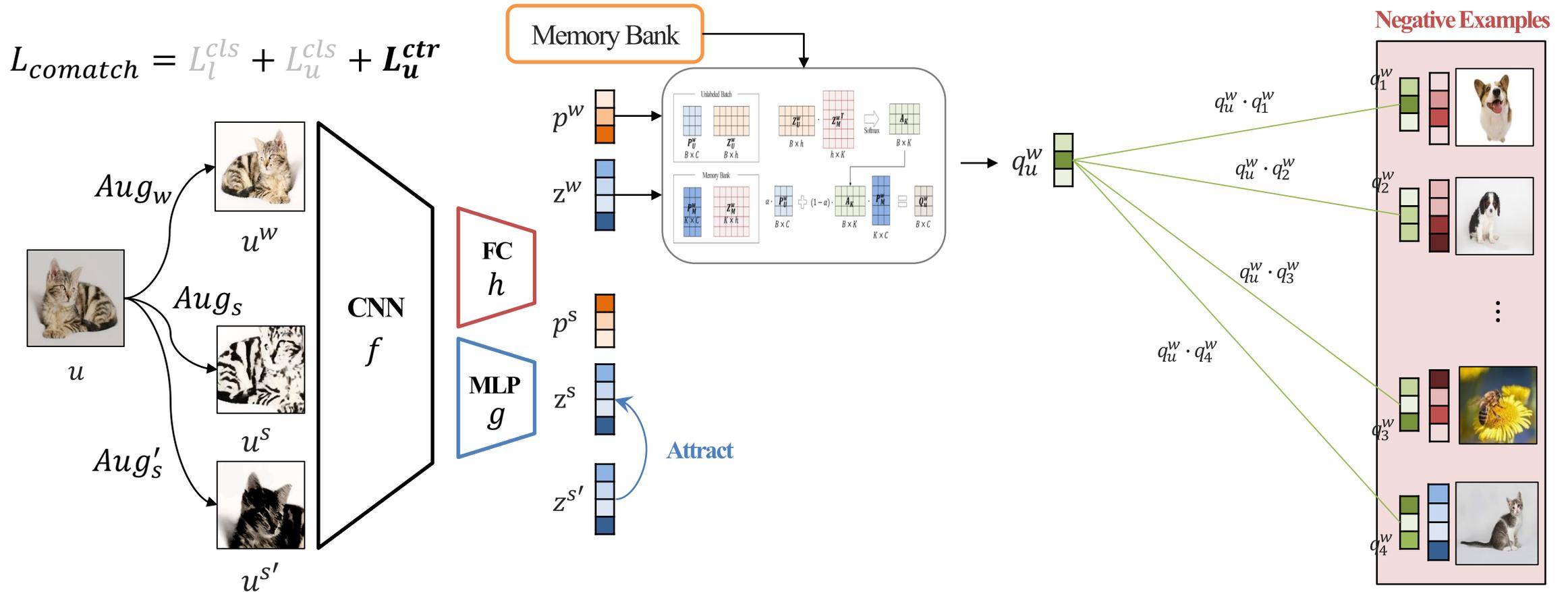


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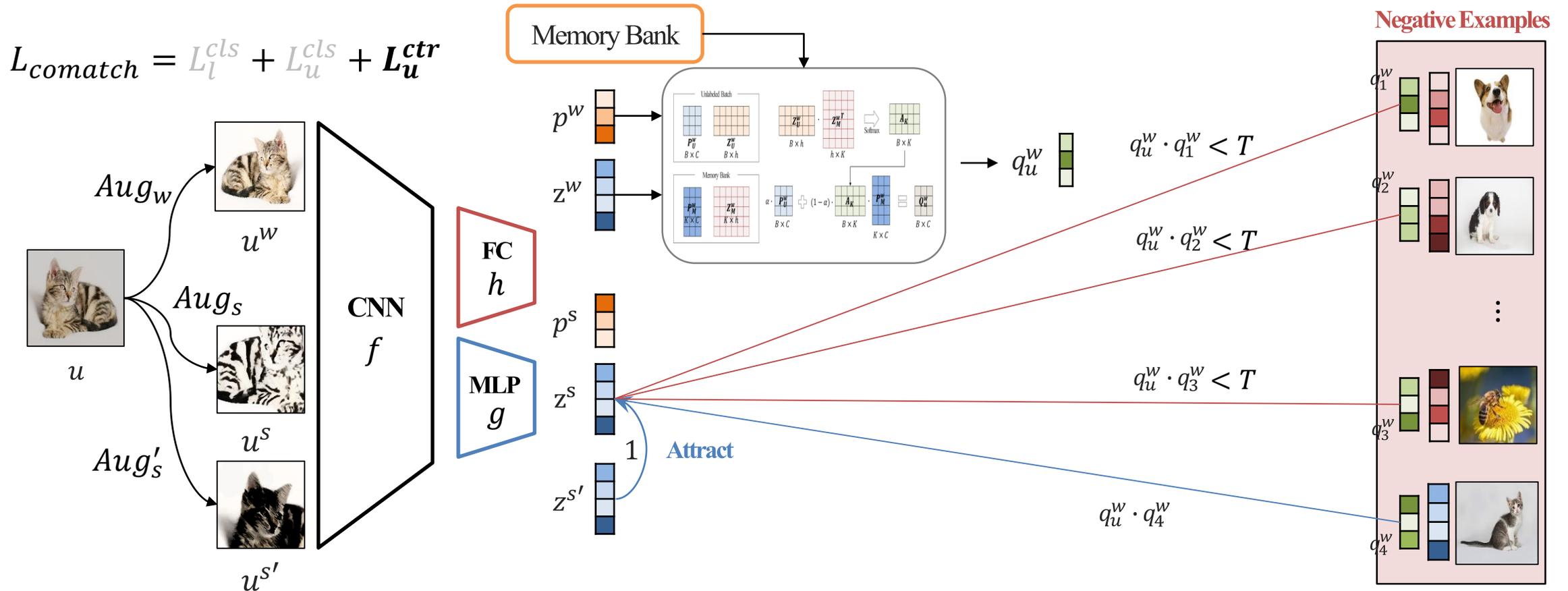


# Paper Reviews

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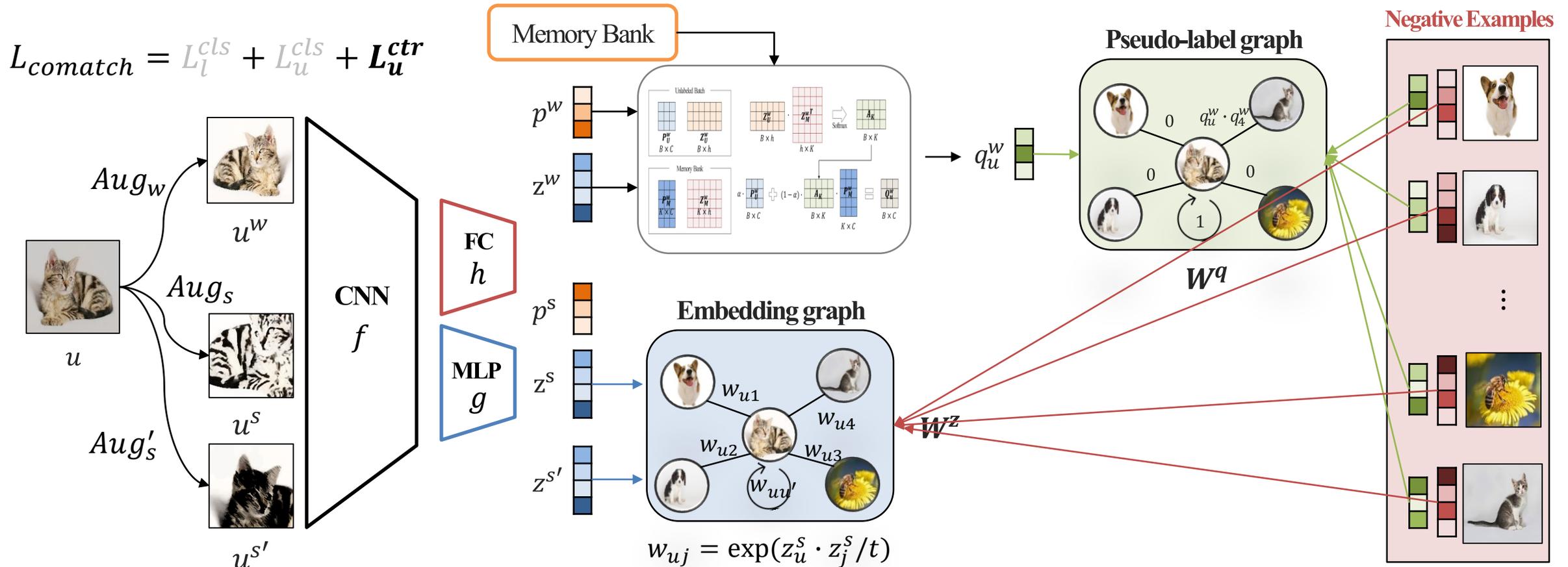


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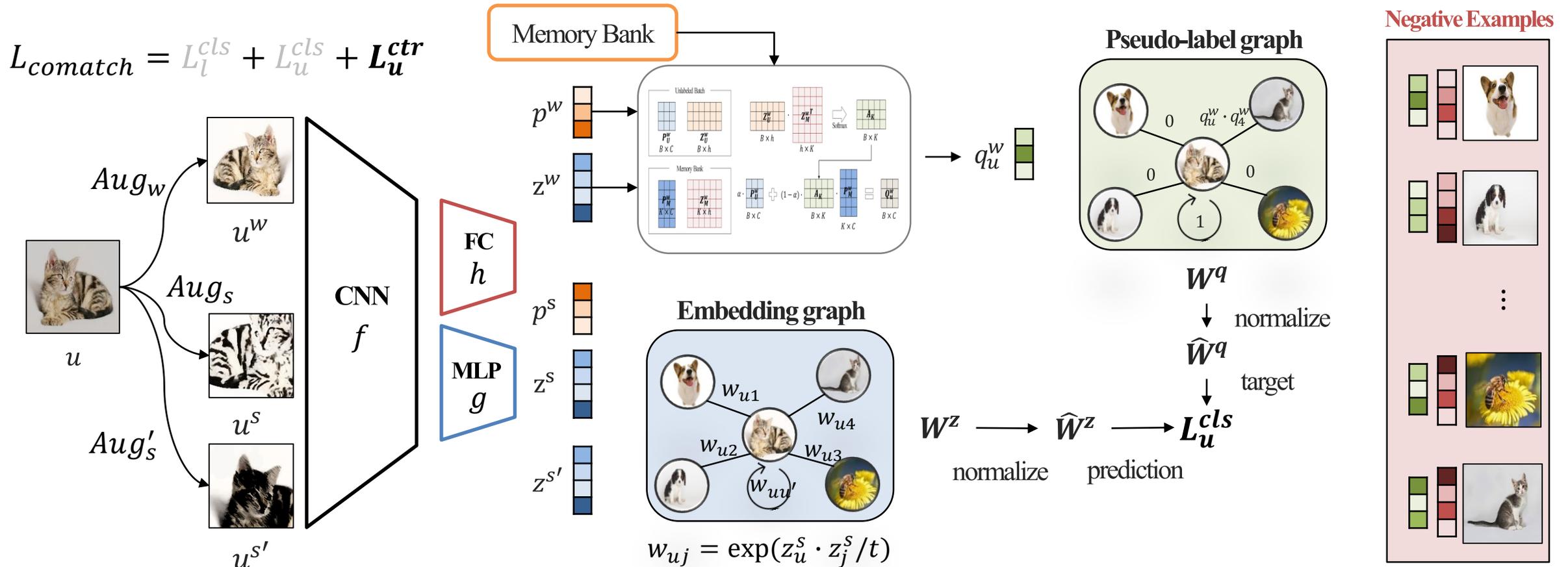


# Paper Reviews

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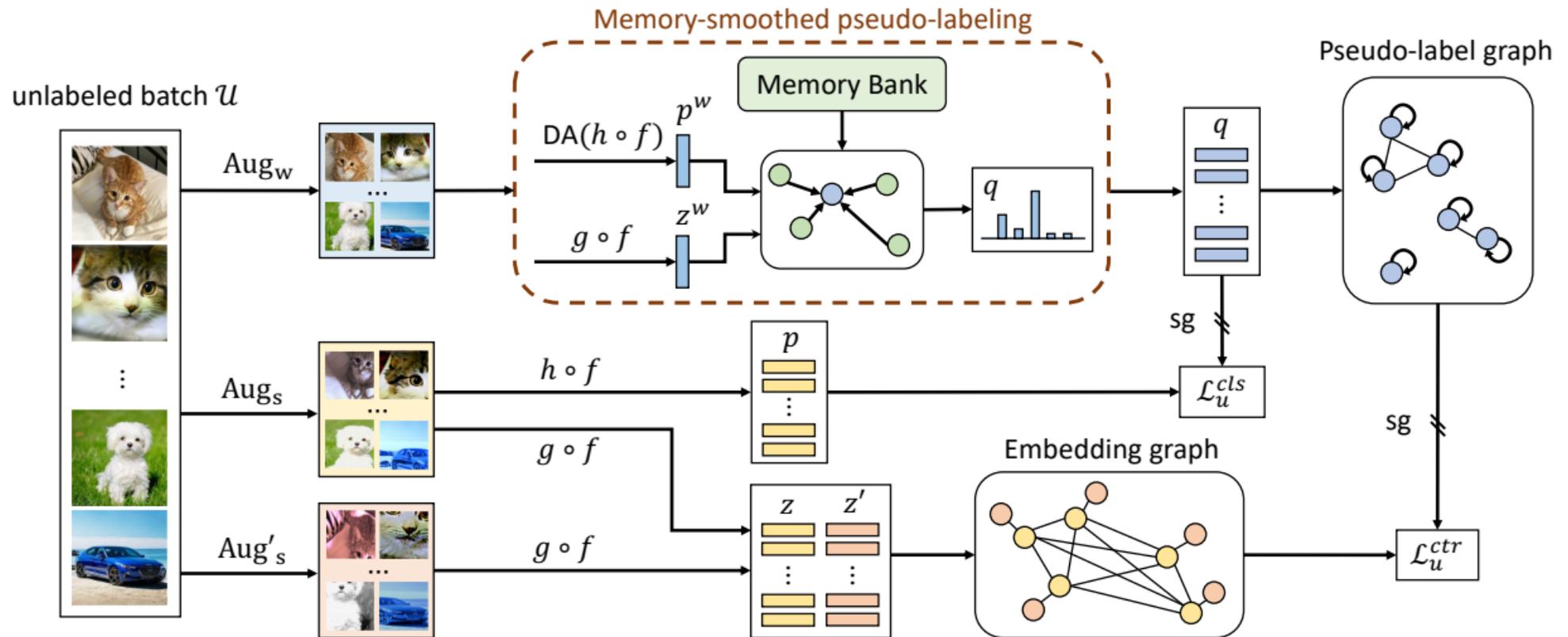


# Paper Reviews

## 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				STL-10
	20 labels	40 labels	80 labels	250 labels	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	<b>87.67±8.47</b>	<b>93.09±1.39</b>	<b>93.97±0.62</b>	<b>95.09±0.33</b>	<b>79.80±0.38</b>

Self-supervised Pre-training	Method	#Epochs	#Paramters (train/test)	Top-1 Label fraction		Top-5 Label fraction	
				1%	10%	1%	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	<b>66.0</b>	<b>73.6</b>	<b>86.4</b>	<b>91.6</b>
PIRL [25] PCL [21] SimCLR [5] BYOL [13] SwAV [3]	Fine-tune	~800	26.1M / 25.6M	30.7	60.4	57.2	83.8
		~200	25.8M / 25.6M	-	-	75.3	85.6
		~1000	30.0M / 25.6M	48.3	65.6	75.5	87.8
		~1000	37.1M / 25.6M	53.2	68.8	78.4	89.0
		~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
		~1200	30.0M / 25.6M	59.9	72.2	79.8	89.5
		~1200	30.0M / 25.6M	<b>67.1</b>	<b>73.7</b>	<b>87.1</b>	<b>91.4</b>
SimCLRv2* [6]	Fine-tune Teacher distillation	~800	34.2M / 29.8M	57.9	68.4	82.5	89.2
		~2400	829.2M / 29.8M	73.9	77.5	91.5	93.4

ImageNet

# Paper Reviews

## CoMatch: Semi-Supervised Learning with Contrastive Graph Regularization

### ❖ 실험 결과

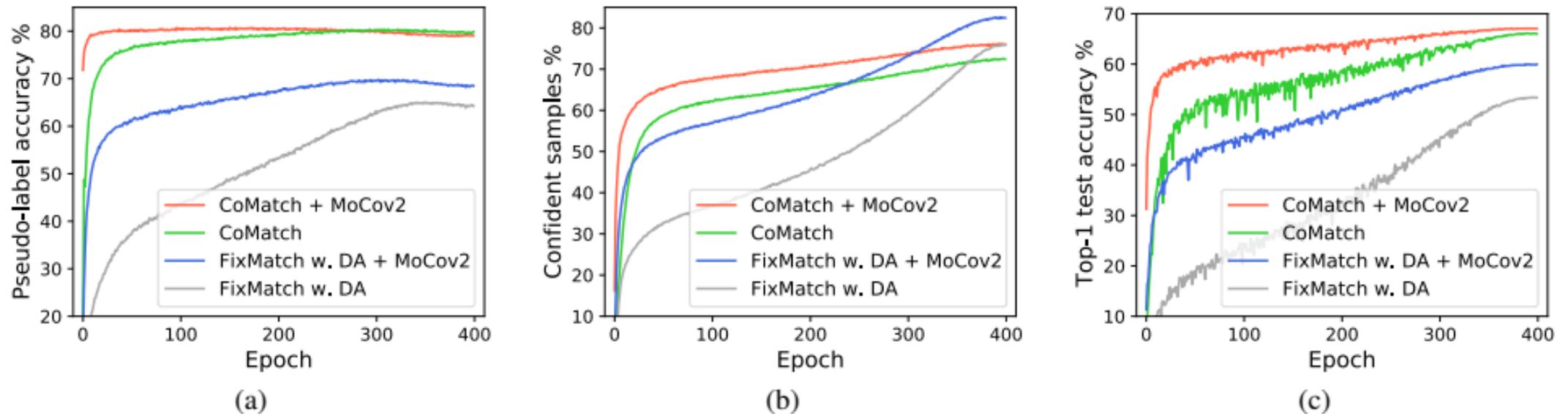


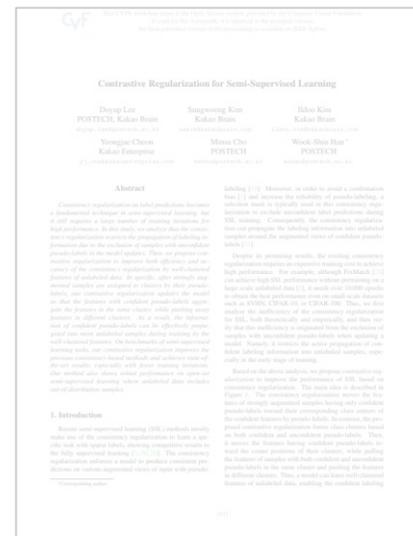
Figure 3: Plots of different methods as training progresses on ImageNet with 1% labels. (a) Accuracy of the confident pseudo-labels *w.r.t* to the ground-truth labels of the unlabeled samples. (b) Ratio of the unlabeled samples with confident pseudo-labels that are included in the unsupervised classification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

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the final published version of the proceedings is available on IEEE Xplore.

### Class-Aware Contrastive Semi-Supervised Learning

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

(a) Real-World Data With In-Distribution and Out-of-Distribution Data

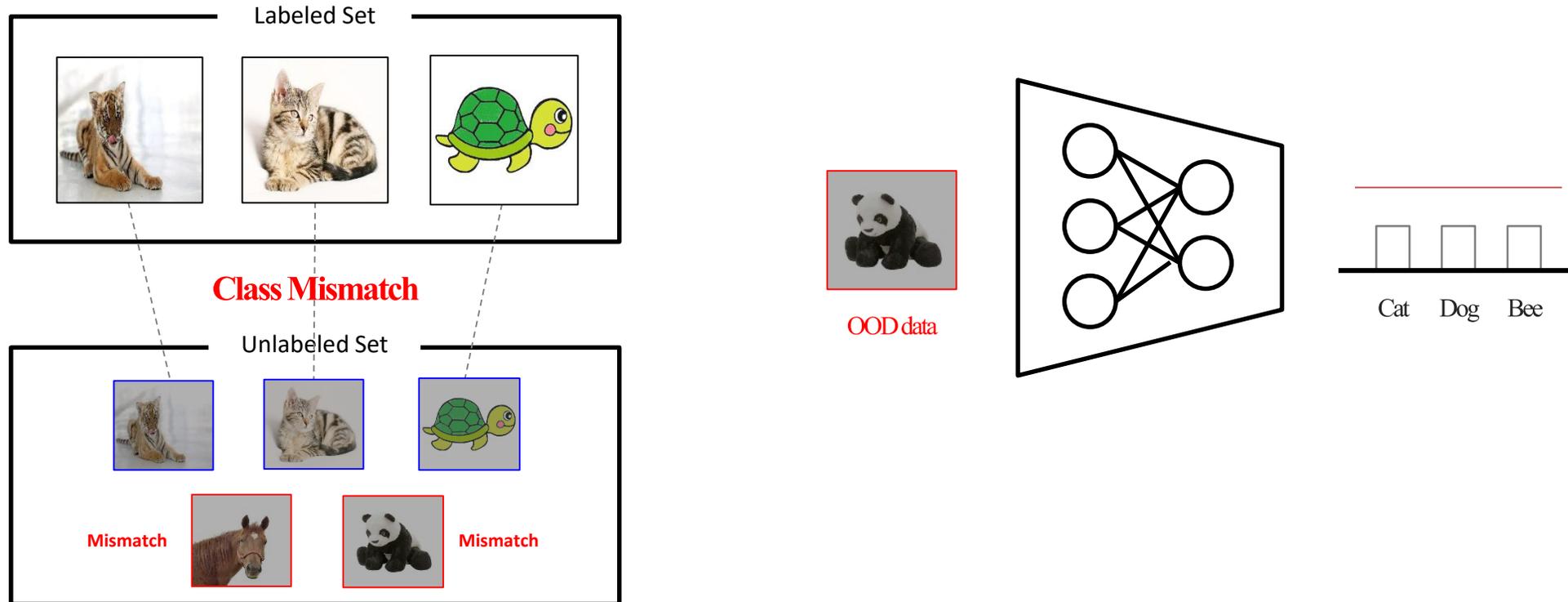
(b) Pseudo-Label-Based SSL (c) Class-Aware Contrastive SSL (ours)

# Paper Reviews

## Class-aware Contrastive Semi-Supervised Learning

### ❖ 연구 배경

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

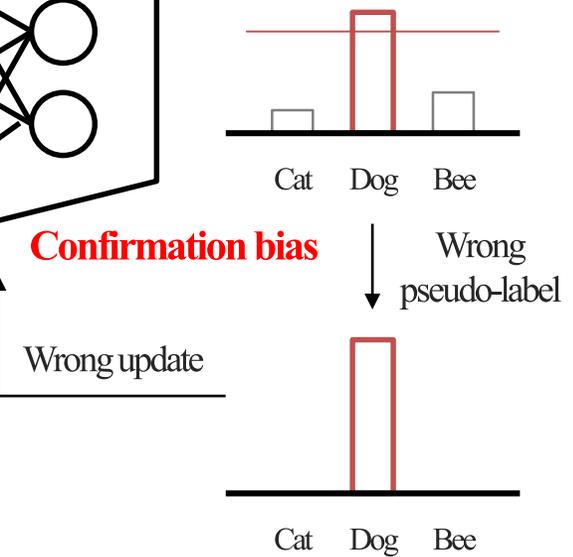
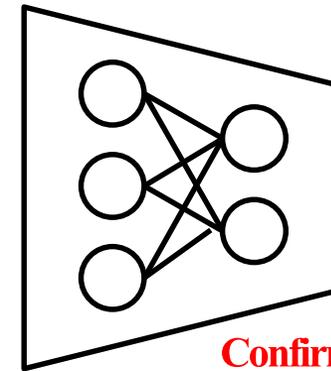
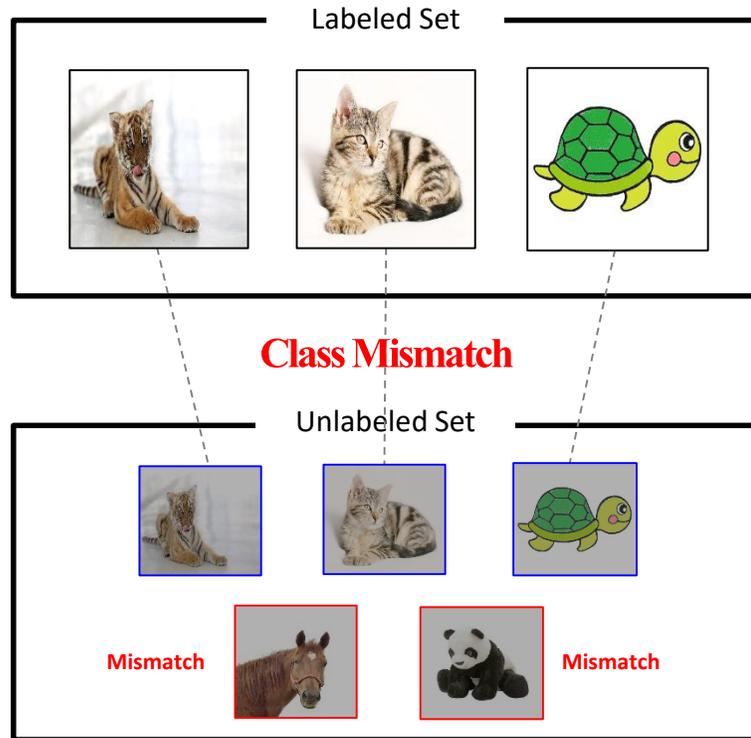


# Paper Reviews

## Class-aware Contrastive Semi-Supervised Learning

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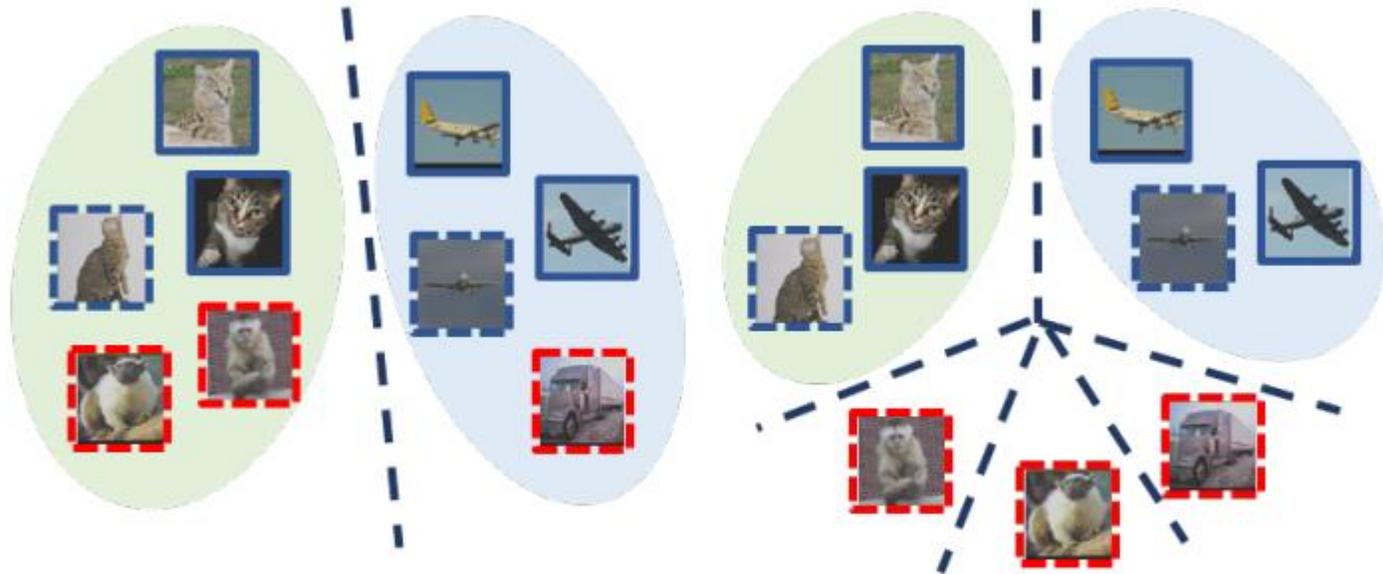


# Paper Reviews

## Class-aware Contrastive Semi-Supervised Learning

### ❖ 연구 가설

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



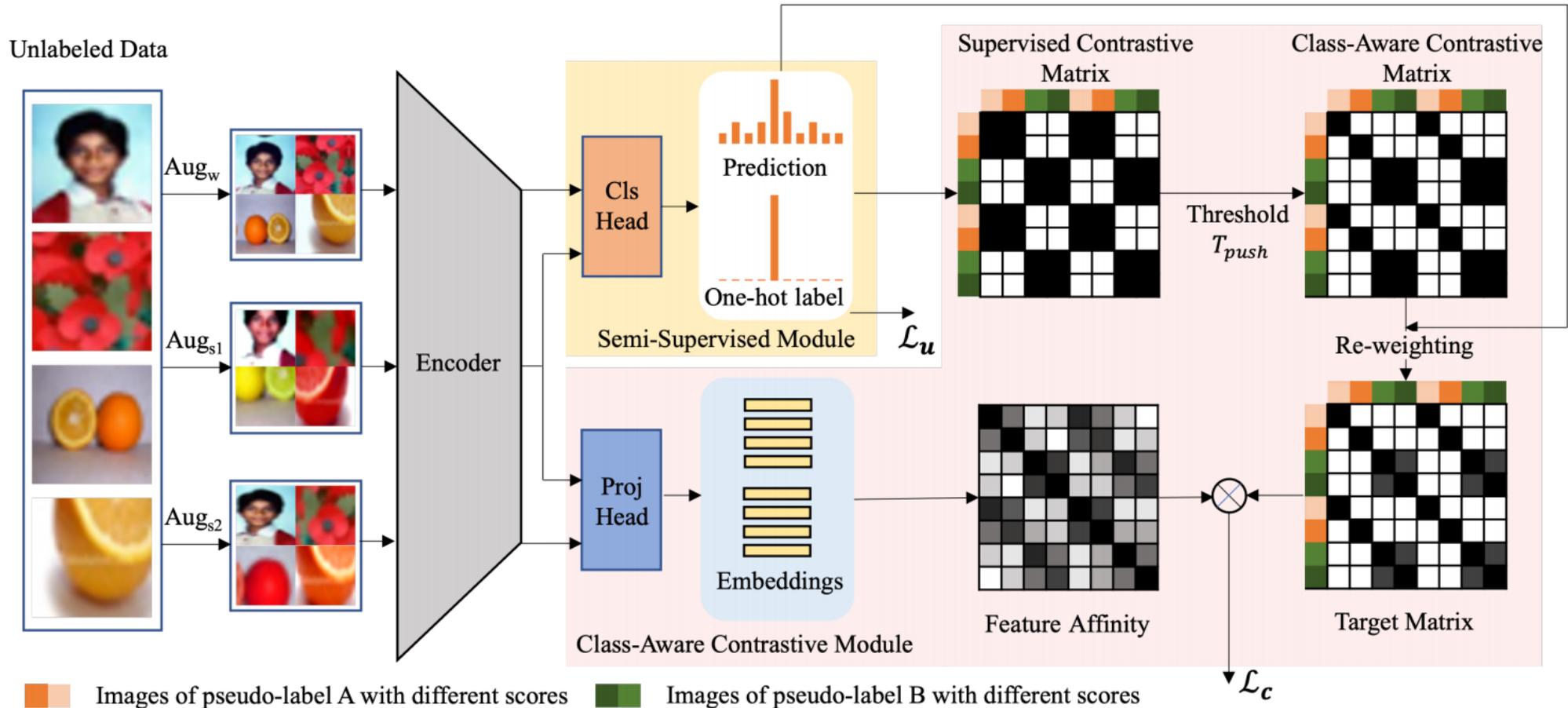
(b) Pseudo-Label-Based SSL

(c) Class-Aware Contrastive SSL  
(ours)

# Paper Reviews

## Class-aware Contrastive Semi-Supervised Learning

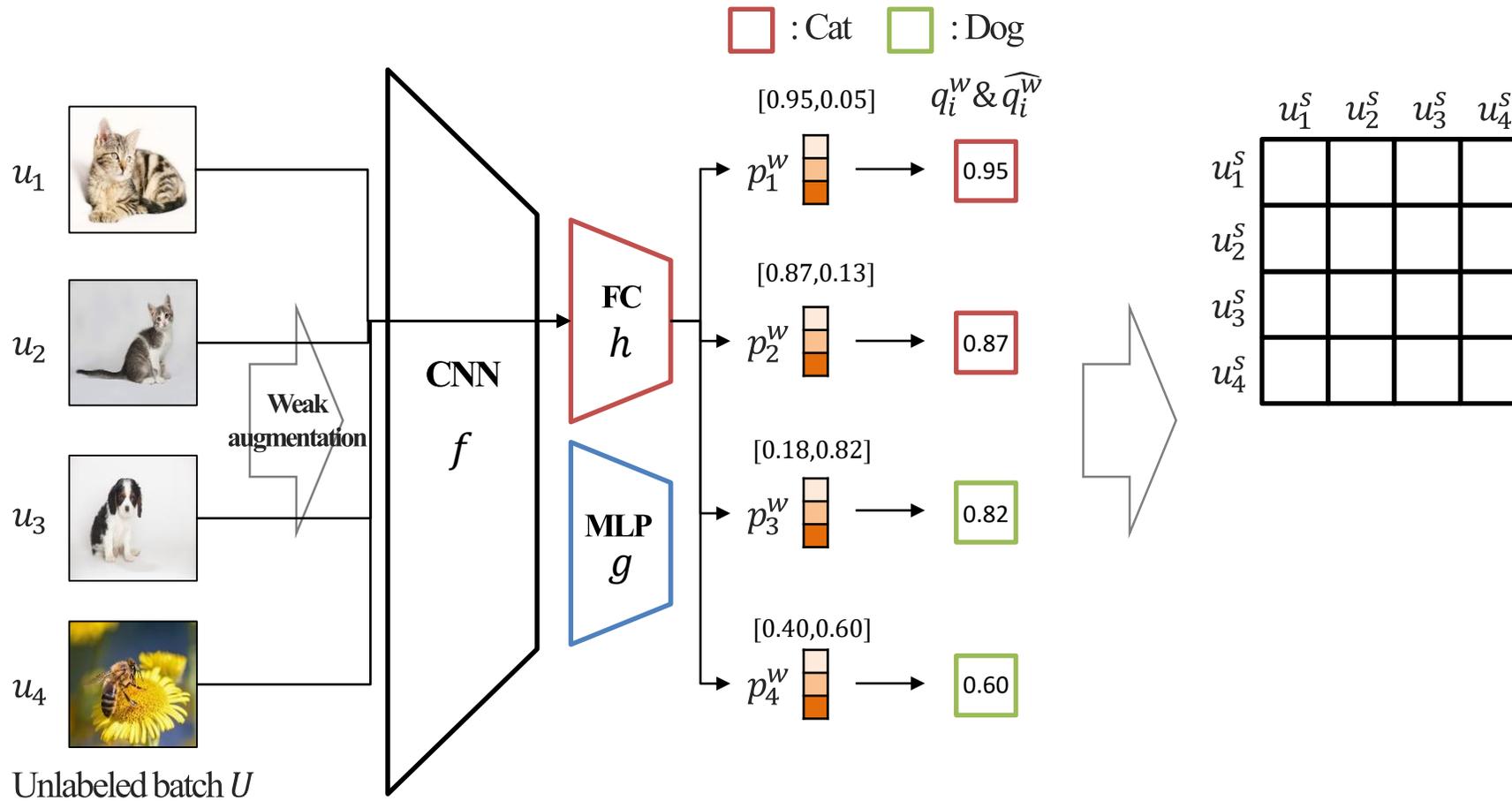
### ❖ 제안 방법론



# Paper Reviews

## Class-aware Contrastive Semi-Supervised Learning

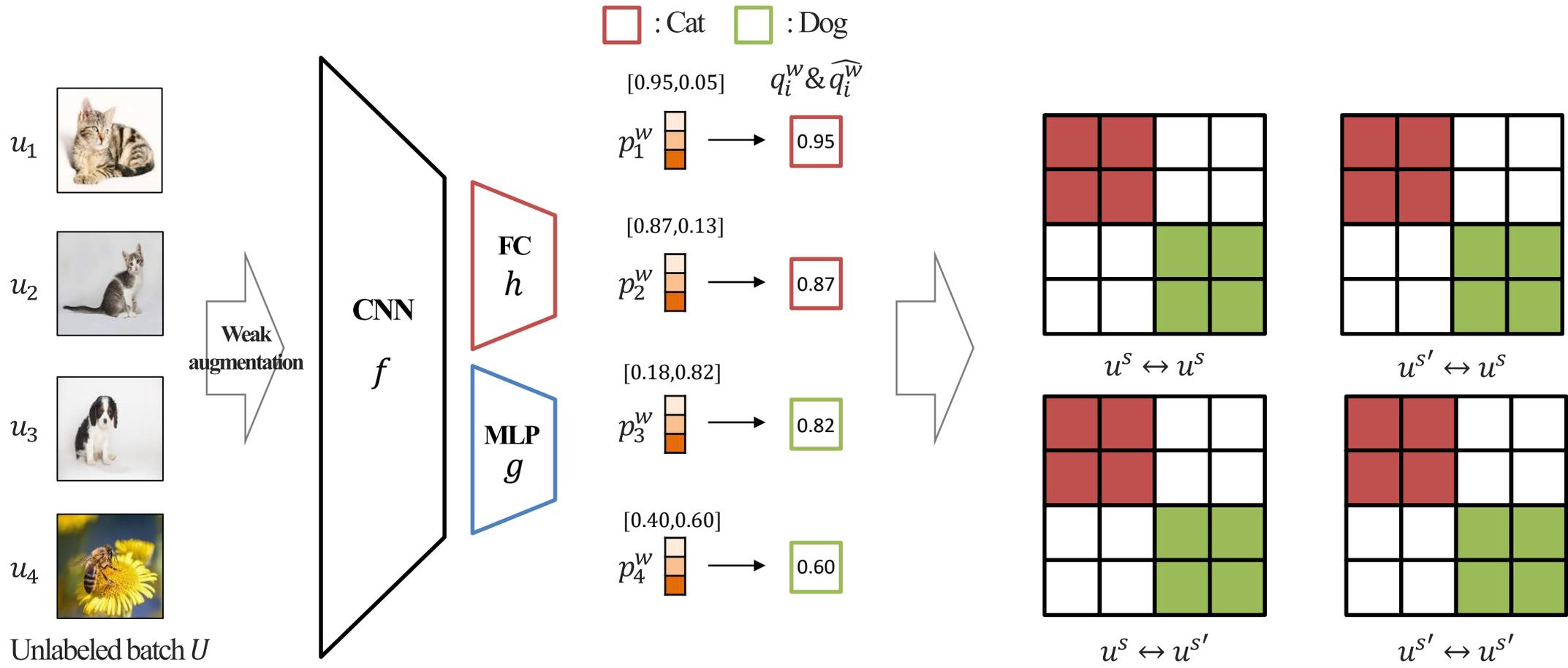
### ❖ Class-aware Contrastive Module



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## Class-aware Contrastive Semi-Supervised Learning

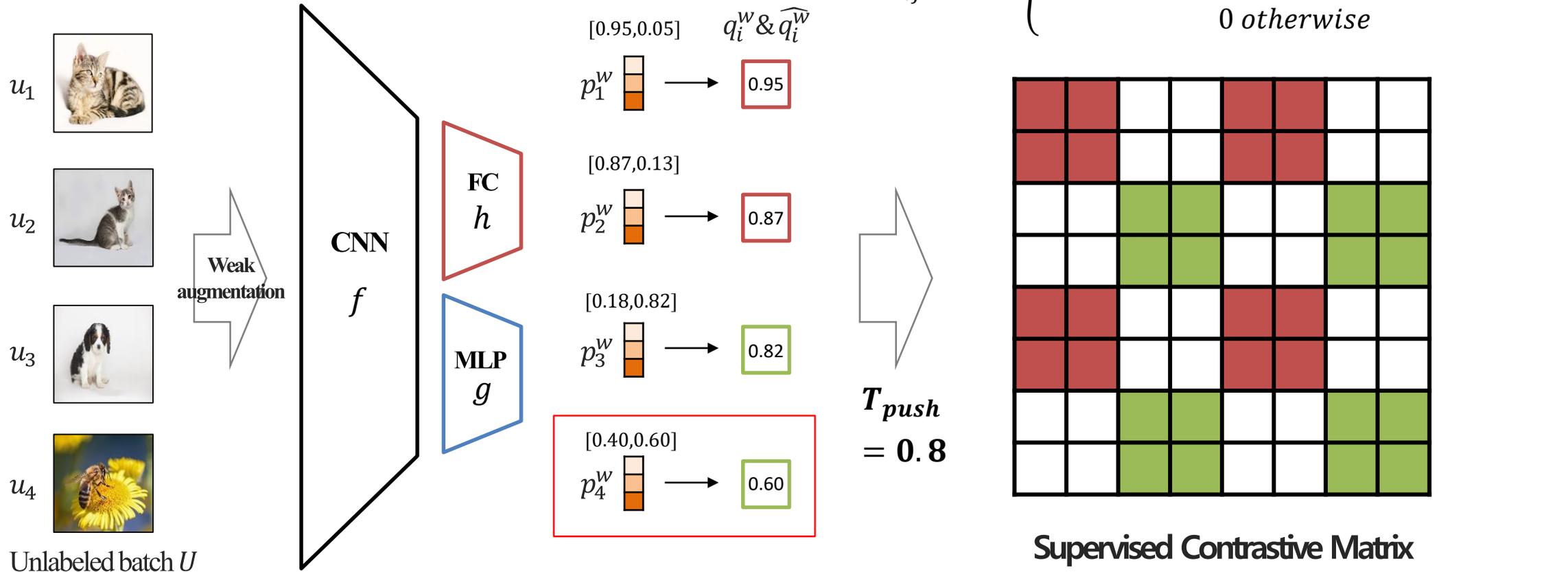
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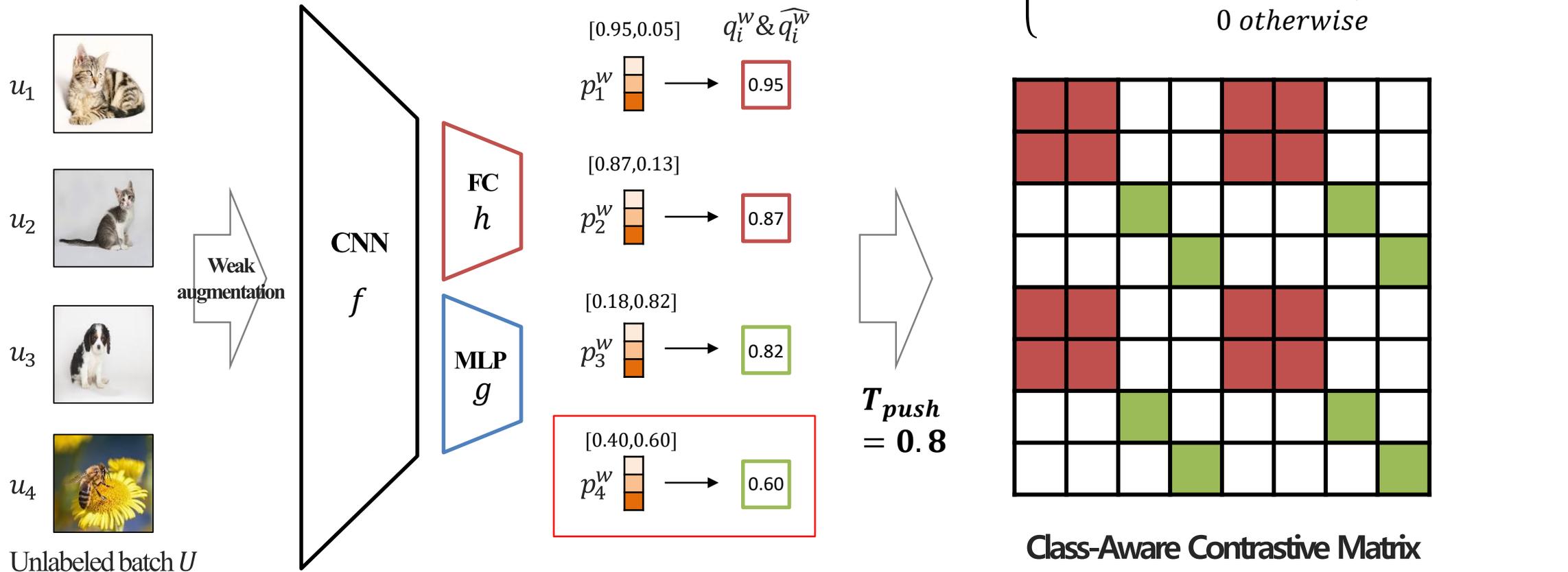
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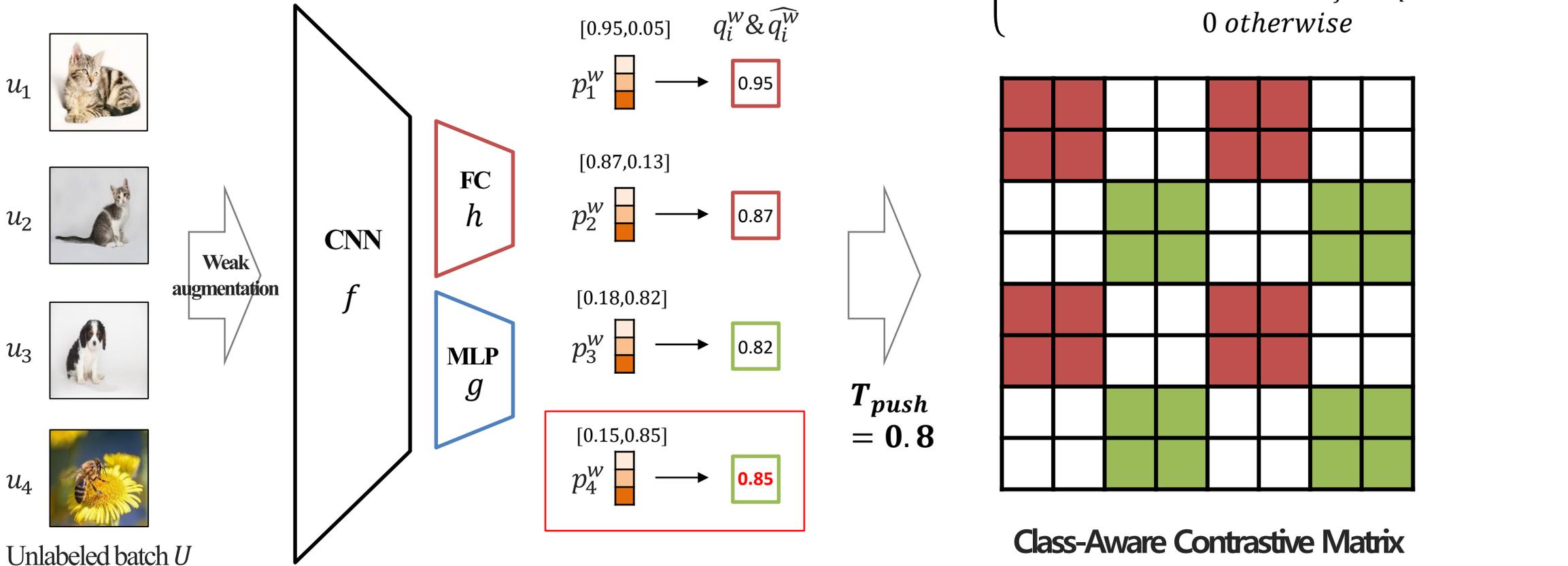
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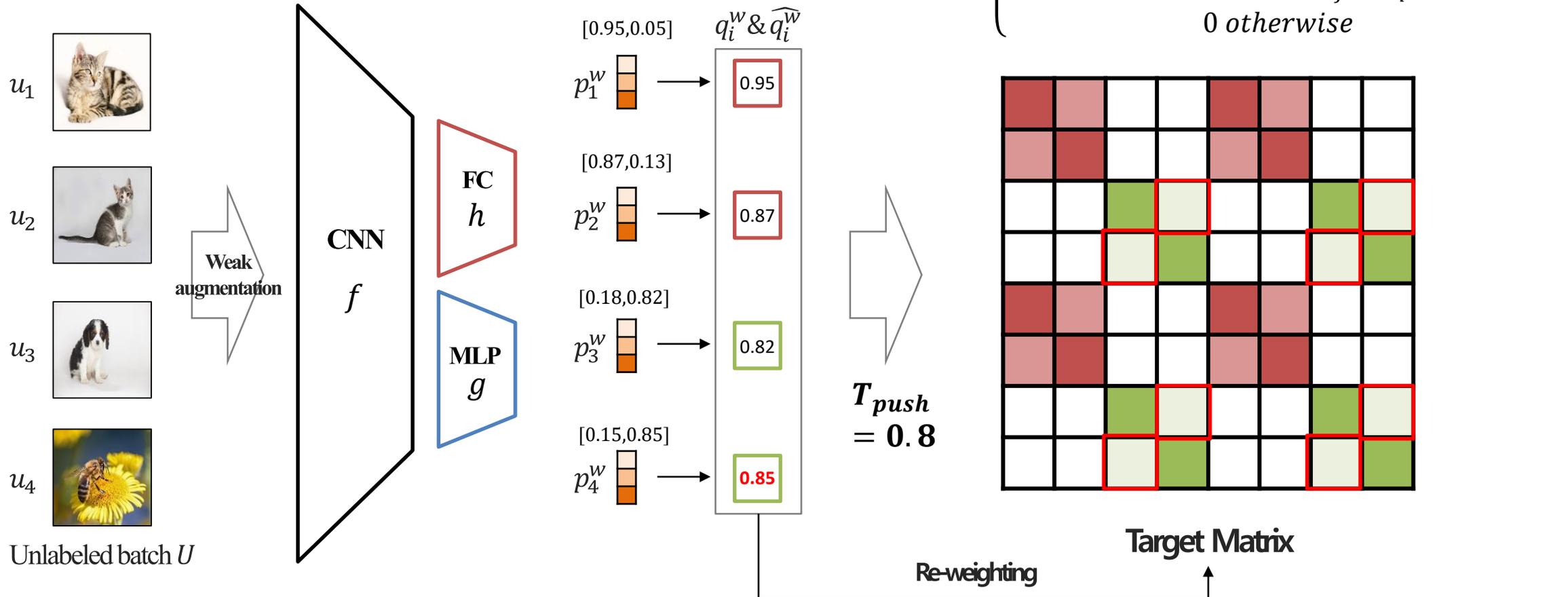
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# Paper Reviews

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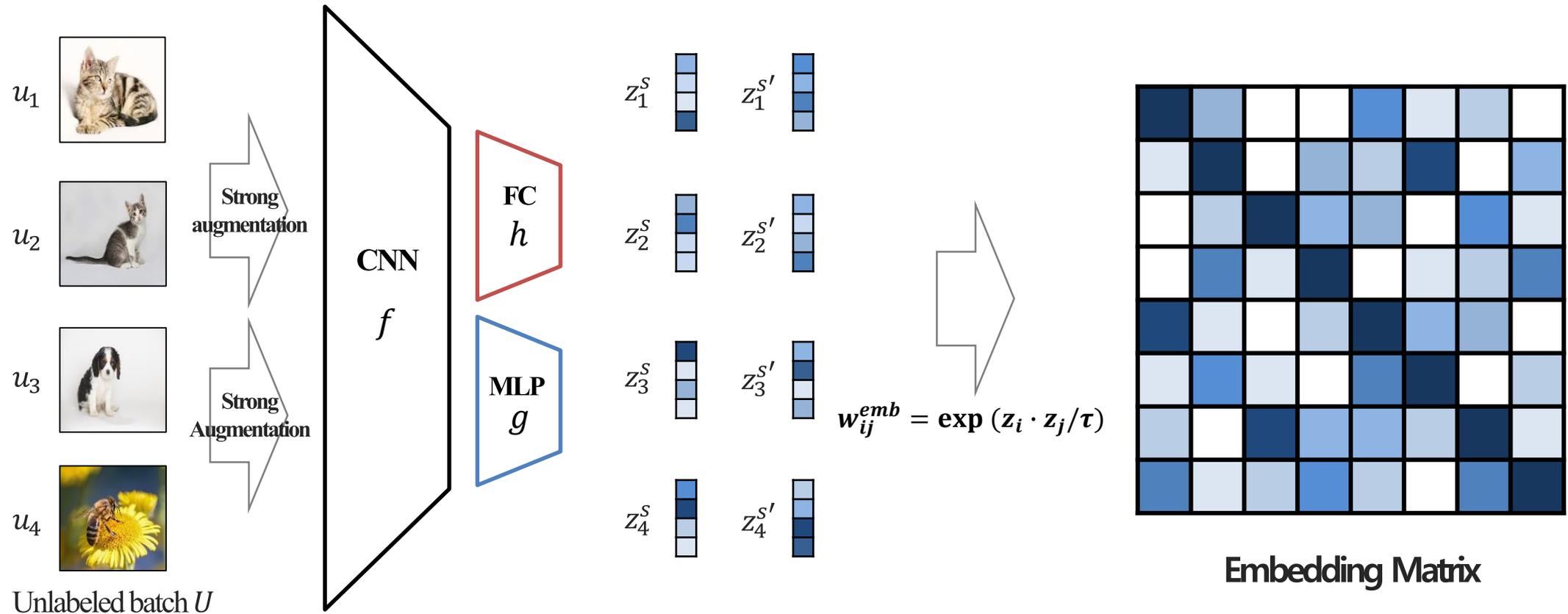
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# Paper Reviews

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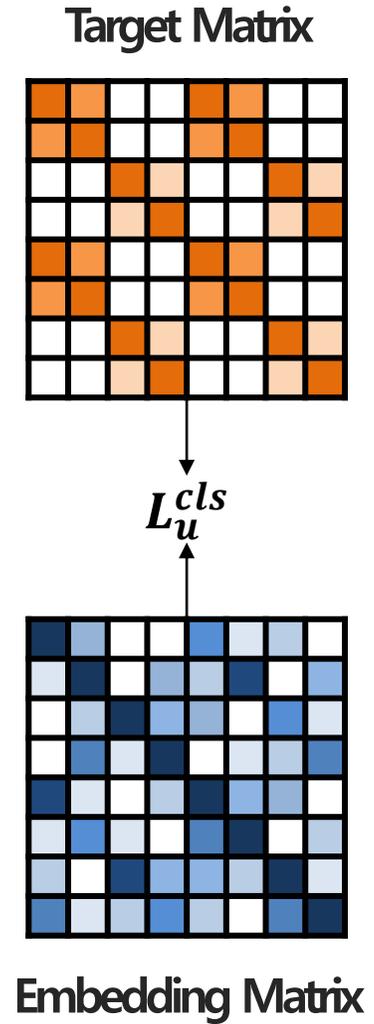
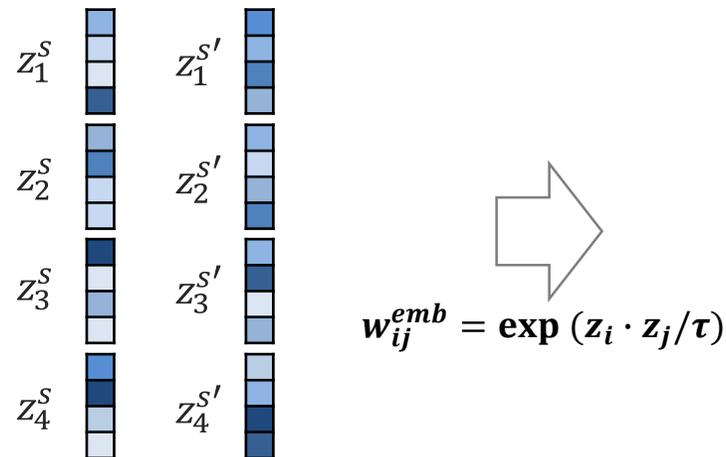
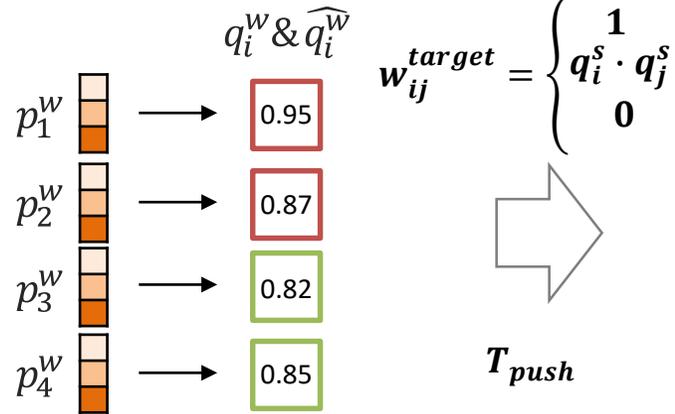
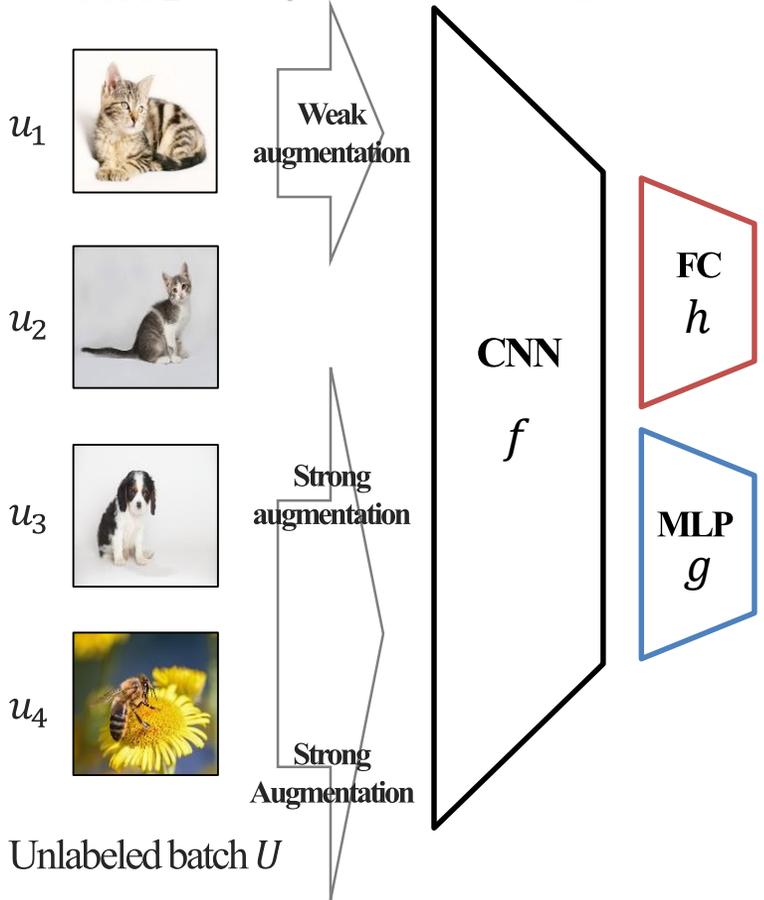


# Paper Reviews

## Class-aware Contrastive Semi-Supervised Learning

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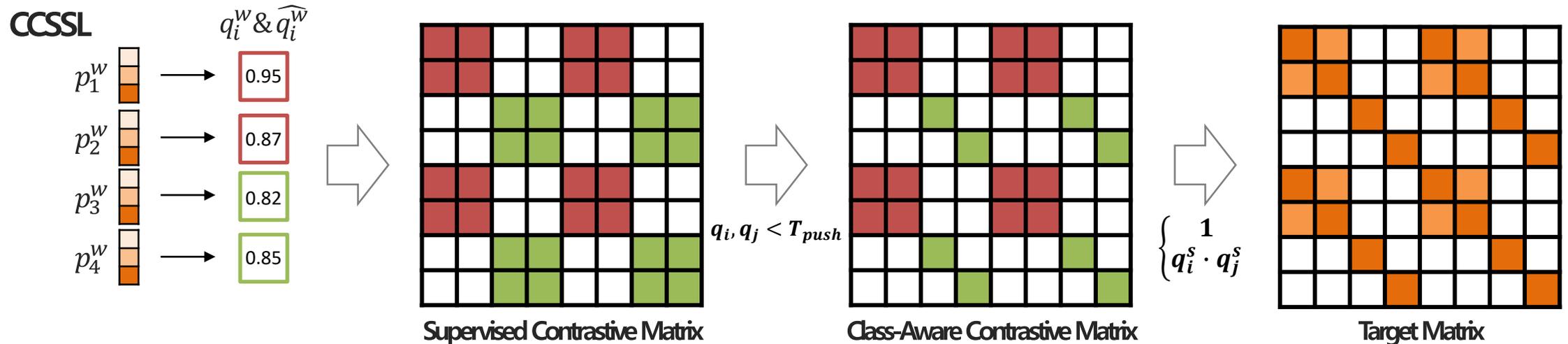
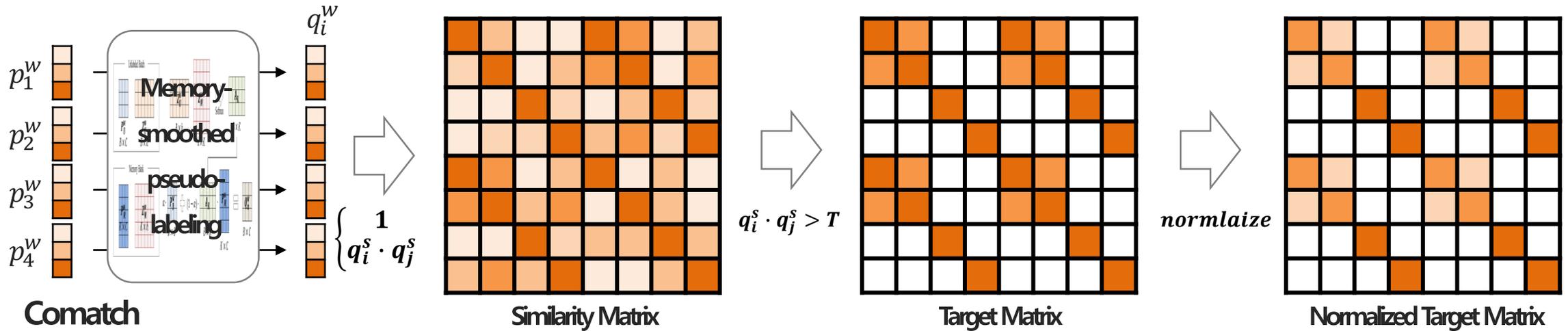
$$L_{CCSSL} = L_l^{cls} + L_u^{cls} + L_u^{ctr}$$



# Paper Reviews

## Class-aware Contrastive Semi-Supervised Learning

### ❖ Comatch & CCSL



# Paper Reviews

## Class-aware Contrastive Semi-Supervised Learning

### ❖ 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	<b>93.09±1.39</b>	<b>95.09±0.33</b>	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	<b>95.74±0.05</b>	65.38±0.42
<b>CCSSL(FixMatch)</b>	<b>61.19±1.65</b>	<b>75.7±0.63</b>	<b>80.68±0.16</b>	90.83±2.78	94.86±0.55	95.54±0.20	<b>80.01±1.39</b>

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.

# Paper Reviews

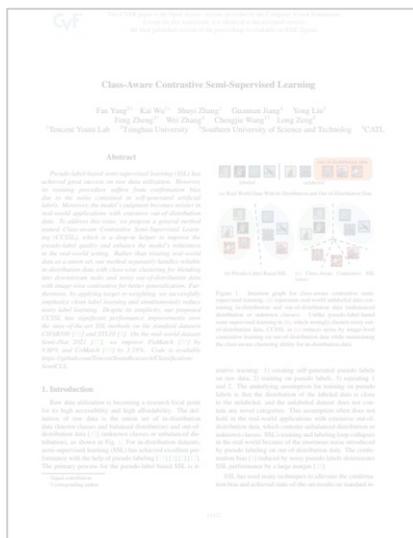
## Class-aware Contrastive Semi-Supervised Learning

### ❖ 실험 결과

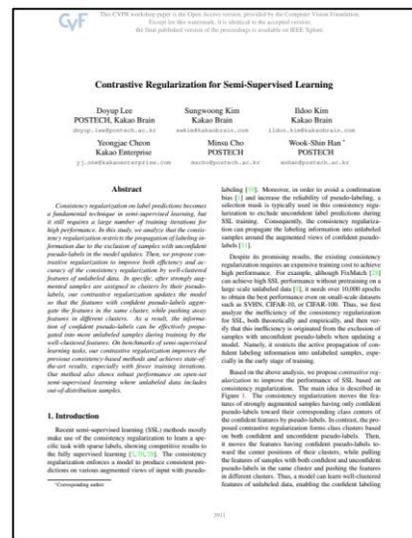
Method	Semi-iNat 2021			
	From Scratch		From MoCo Pretrain	
	Top1	Top5	Top1	Top5
Supervised	19.09	35.85	34.96	57.11
MixMatch [3]	16.89	30.83	-	-
<b>+CCSSL</b>	<b>19.65</b>	<b>35.09</b>	-	-
FixMatch [25]	21.41	37.65	40.3	60.05
<b>+CCSSL</b>	<b>31.21</b>	<b>52.25</b>	<b>41.28</b>	<b>64.3</b>
CoMatch [19]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



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



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## 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@kakaenterprise.com

Minsu Cho  
POSTECH  
mscho@postech.ac.kr

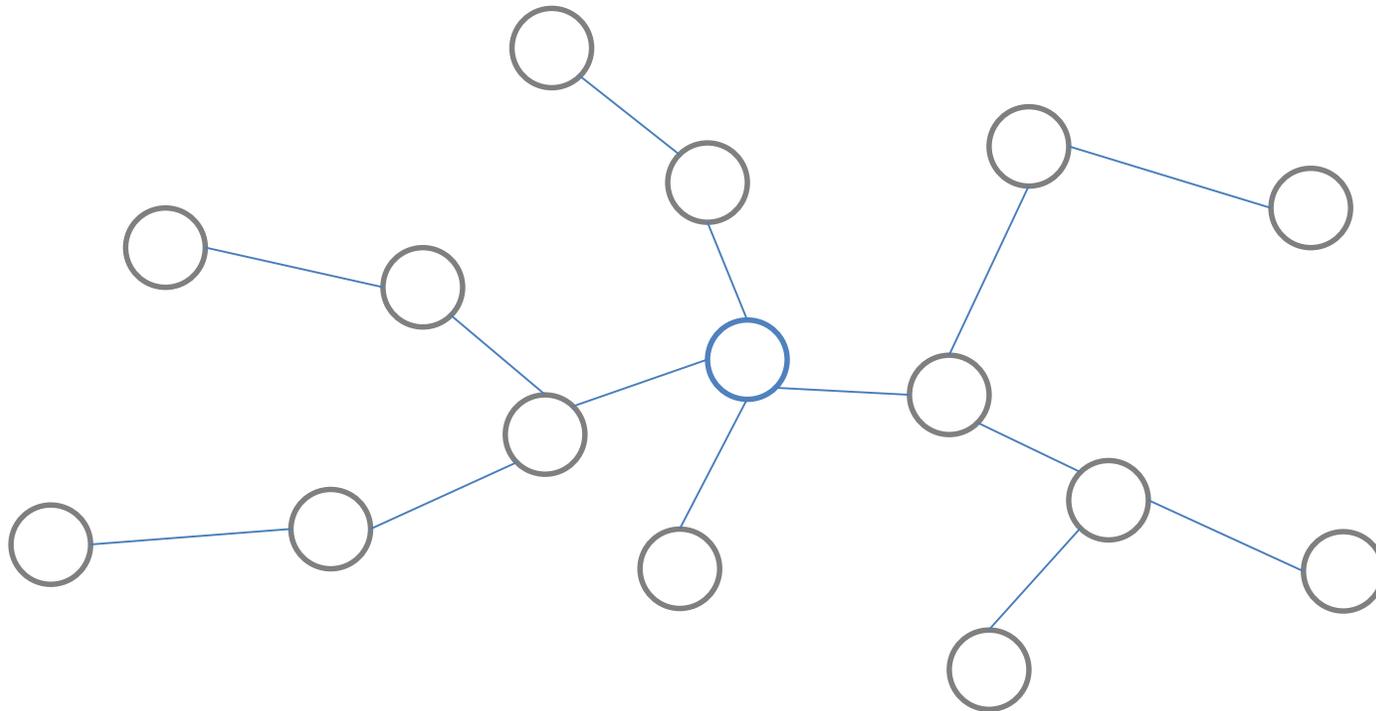
Wook-Shin Han \*  
POSTECH  
wshan@postech.ac.kr

# 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 =  $2^{20} \approx 1M$ )

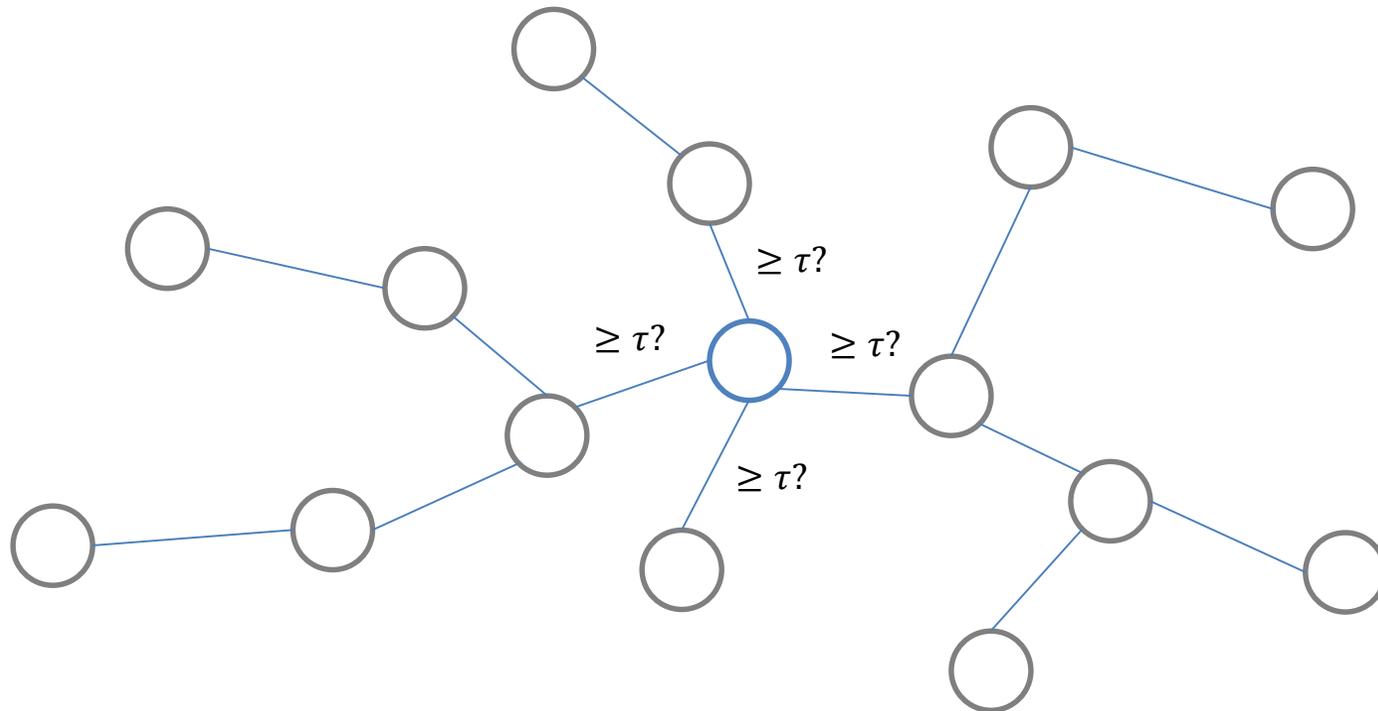


# Paper Reviews

## Contrastive Regularization for Semi-Supervised Learning

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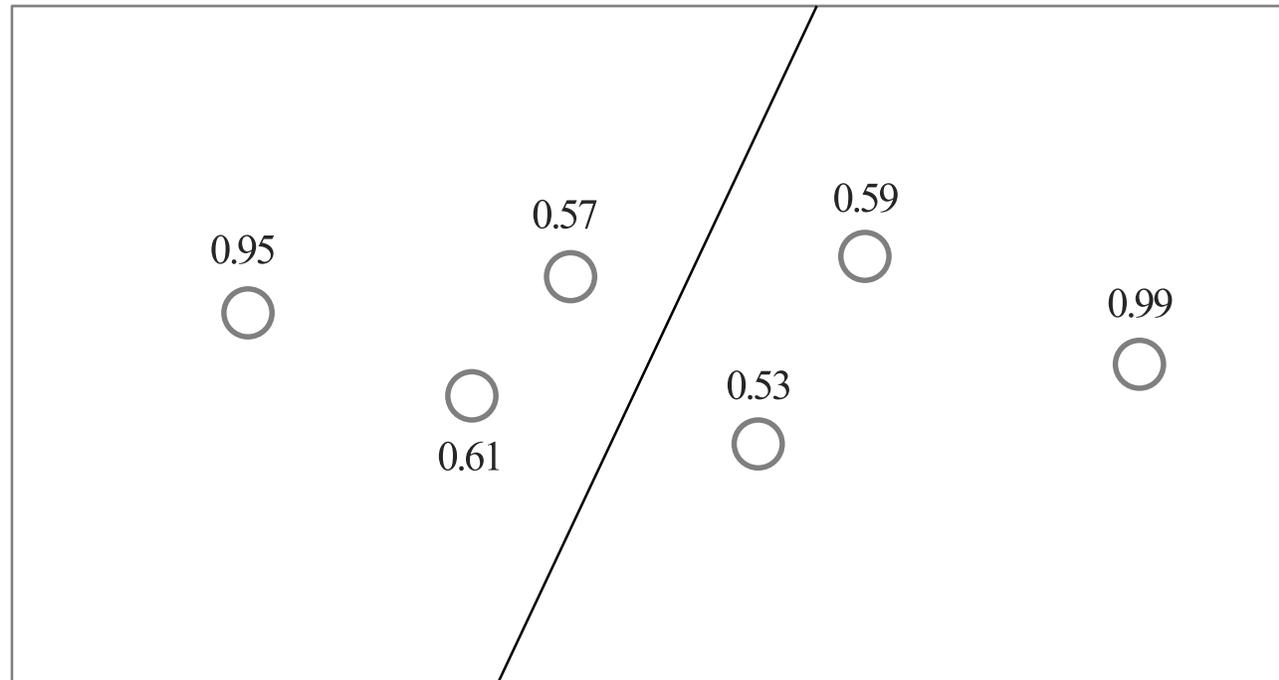


# Paper Reviews

## 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

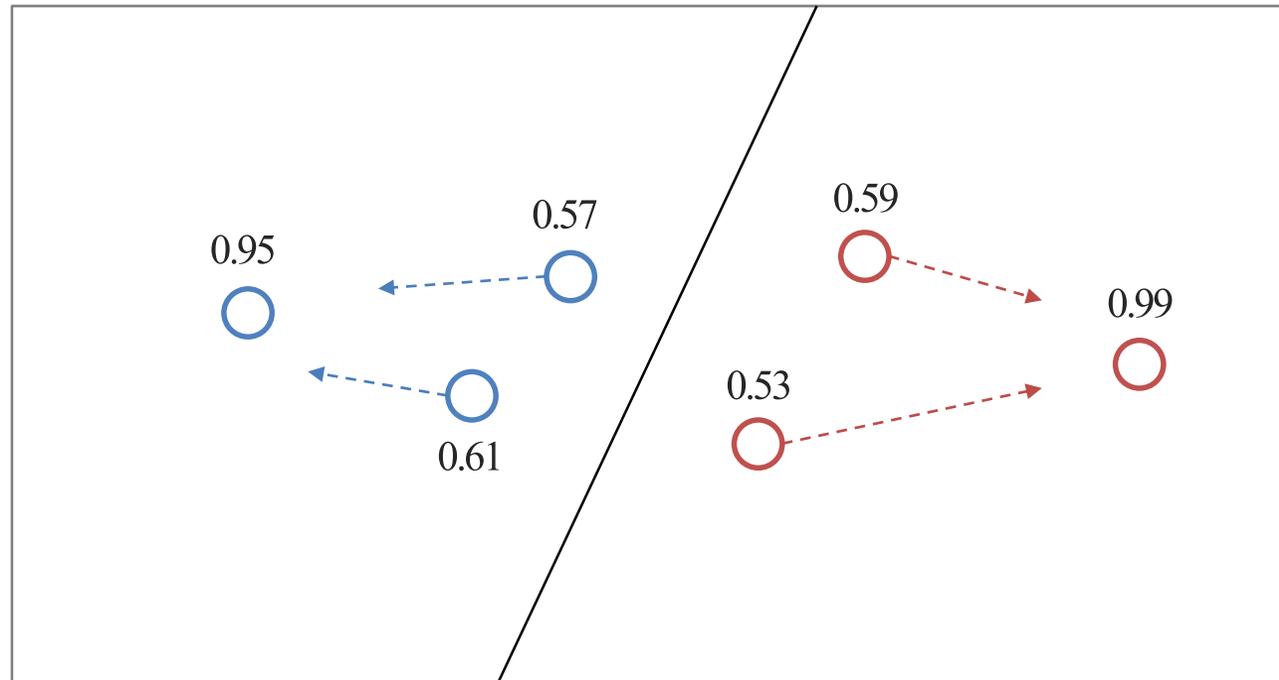


# Paper Reviews

## Contrastive Regularization for Semi-Supervised Learning

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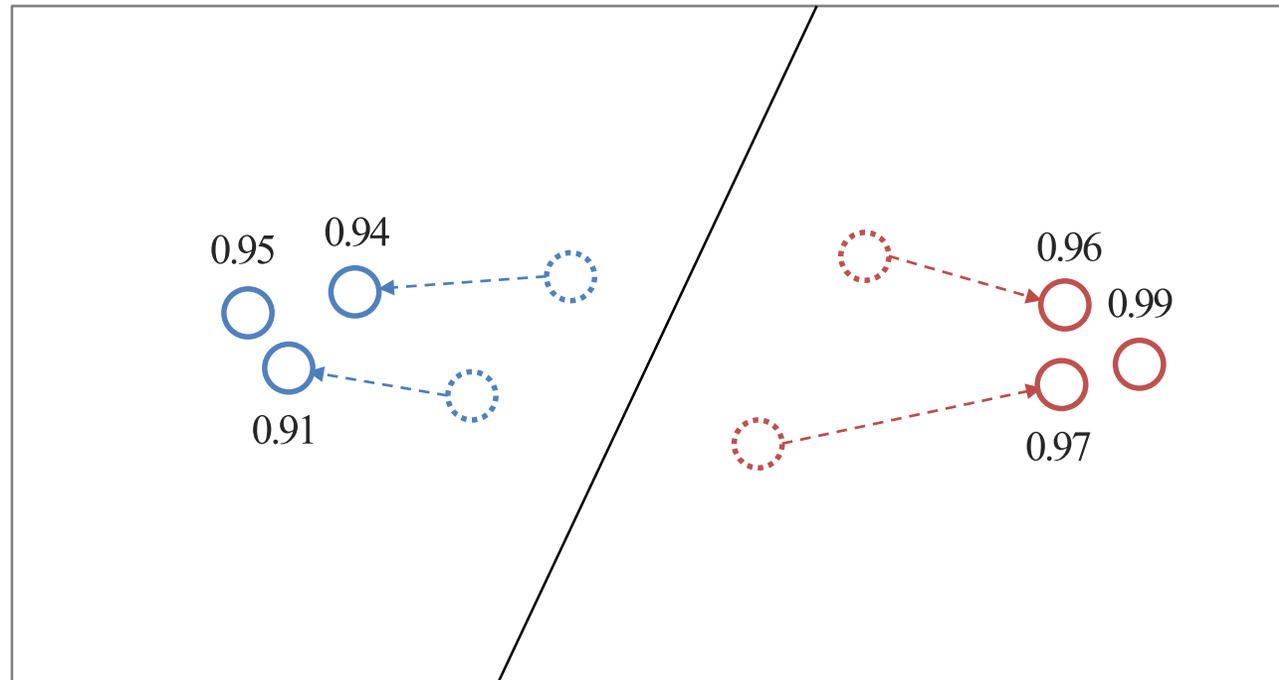


# Paper Reviews

## Contrastive Regularization for Semi-Supervised Learning

### ❖ 연구 가설

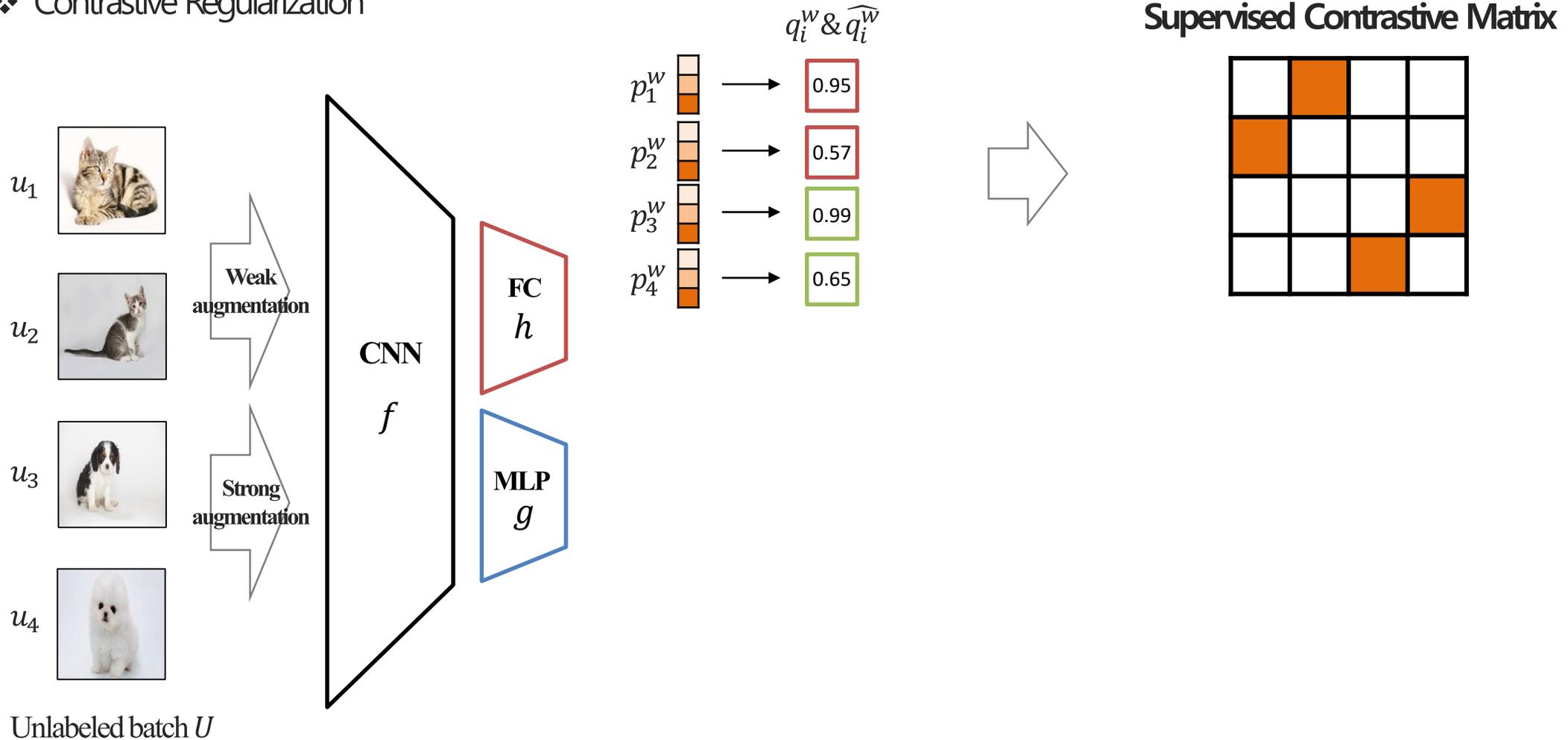
- 결정 경계 근처의 Confidence level이 낮은 데이터를 confidence level이 높은 데이터 쪽으로 당겨주면 빠른 label propagation이 가능할 것



# Paper Reviews

## Contrastive Regularization for Semi-Supervised Learning

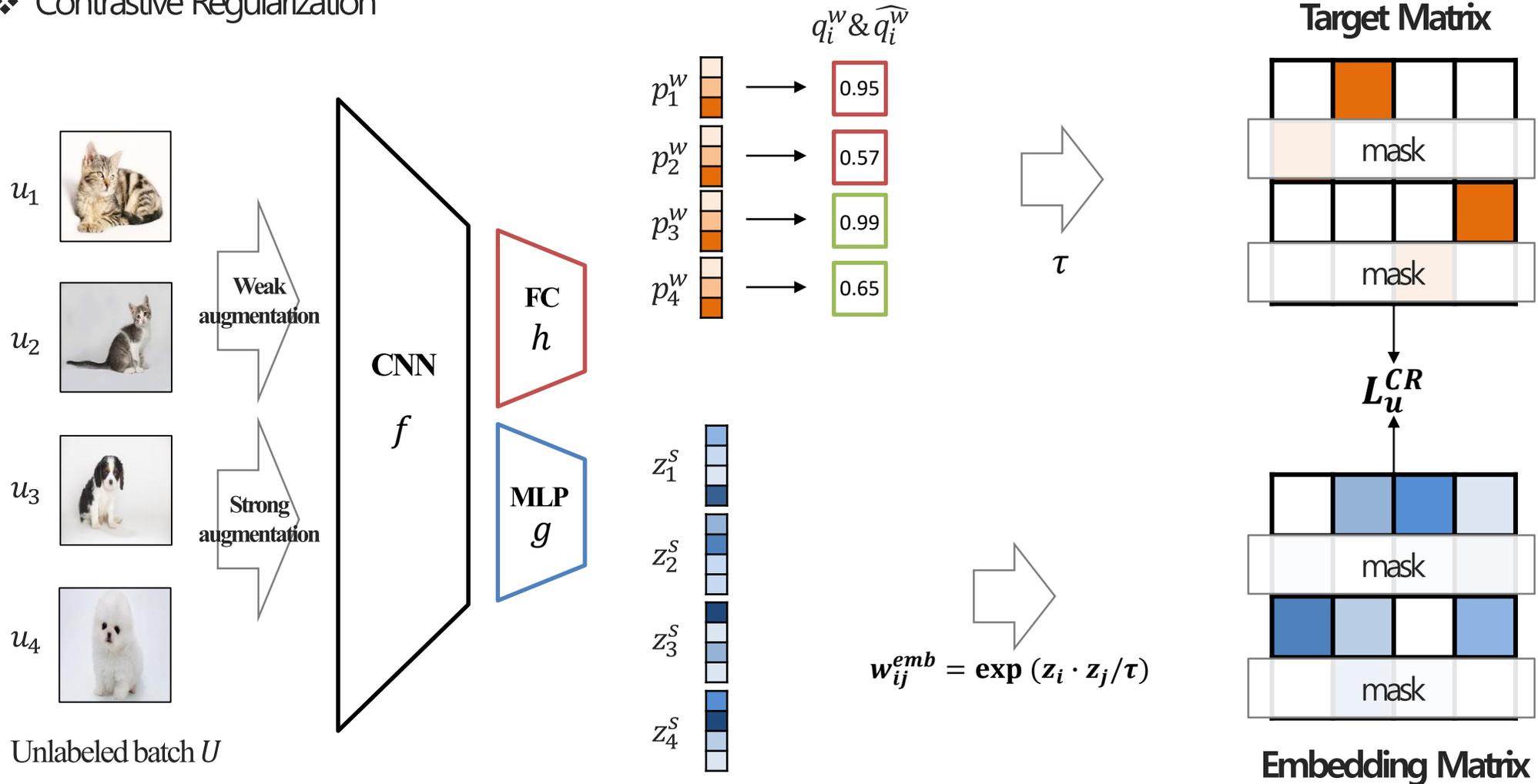
### ❖ Contrastive Regularization



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### ❖ 실험 결과

Method	SVHN				CIFAR-10			
	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*	-	<b>96.66±0.20</b>	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	<b>94.96±4.77</b>	96.33±1.84	<b>97.55±0.08</b>	<b>97.61±0.06</b>	<b>88.26±1.38</b>	<b>94.31±0.90</b>	<b>94.96±0.30</b>	<b>95.84±0.13</b>
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++	<b>96.88±0.60</b>	<b>97.05±0.28</b>	<b>97.95±0.09</b>	<b>98.11±0.05</b>	<b>94.24±3.48</b>	<b>95.26±0.70</b>	<b>96.00±0.31</b>	<b>96.68±0.18</b>

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

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

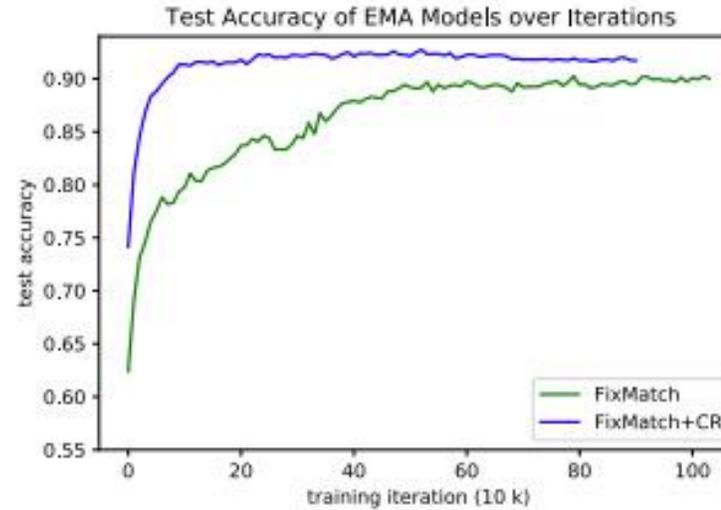
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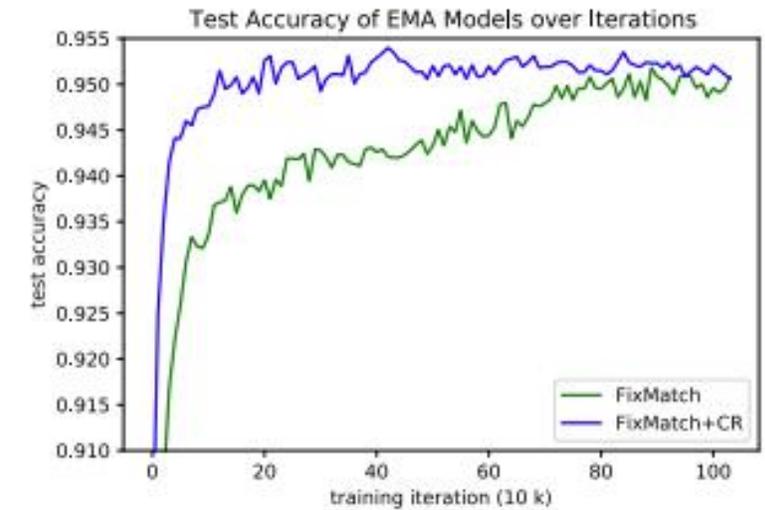
### ❖ 실험 결과



CIFAR-100, 10000 labels



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

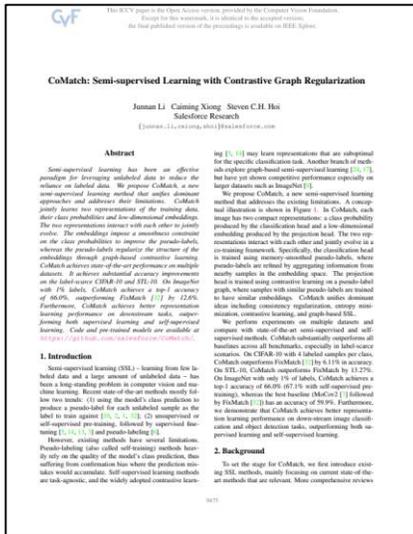


(b) Test Accuracy of the EMA Model (STL-10, 5000 labels)

# Conclusions

## 결론

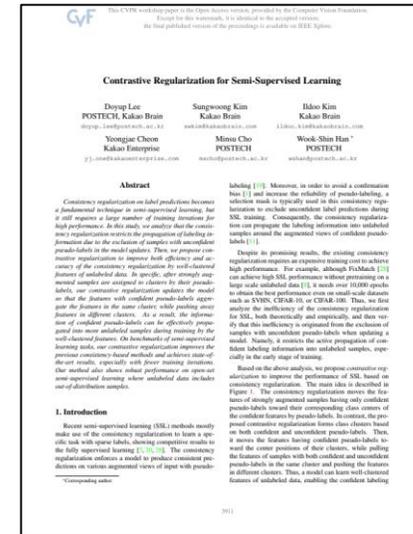
### ❖ Paper List



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