IPCL: ITERATIVE PSEUDO-SUPERVISED CONTRASTIVE LEARNING TO IMPROVE SELF-SUPERVISED FEATURE REPRESENTATION

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IEEE ICASSP 2024, Seoul, Korea

Outline

Background

Self-supervised Learning (SSL)

- **Unsupervised way of training** a deep learning model.
- **Generate supervisory single** from unlabeled image/video dataset [1].
- **Supervisory signal** is one of the **properties of the unlabeled dataset**.
- **The dark matter of intelligence** [2].

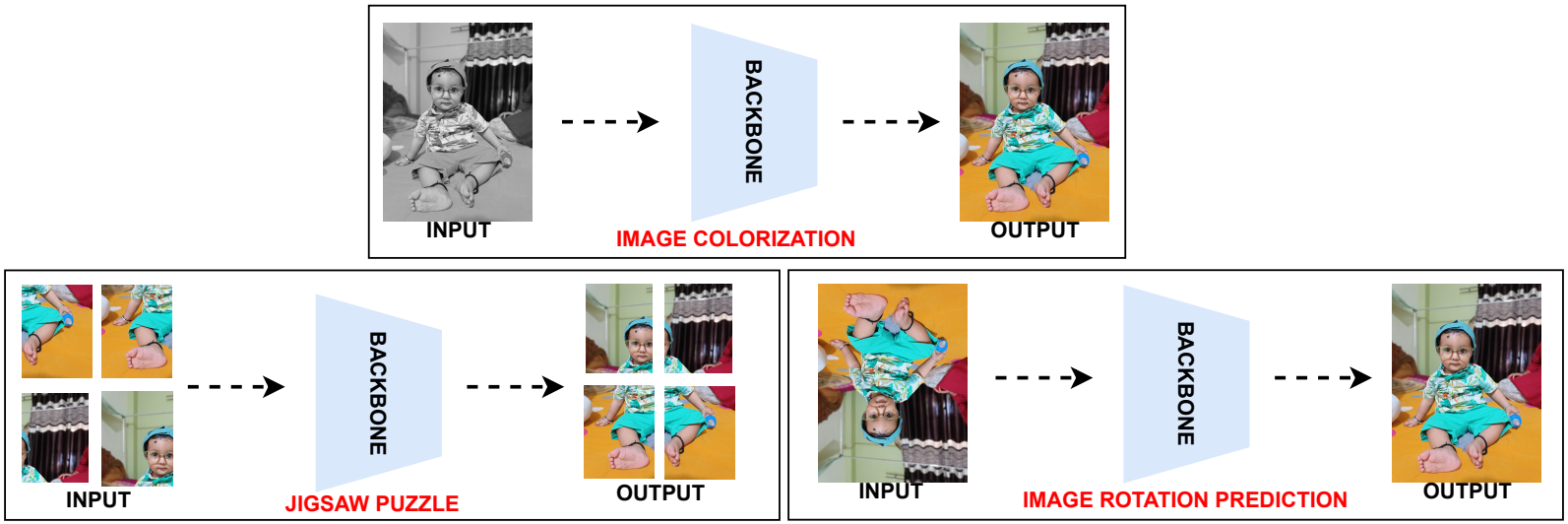


Figure 1: For **self-supervised training**, a series of **pretext tasks** are explored in the early stage.

SSL Framework

- Provides a strong baseline for various **downstream computer vision applications**.
- Performance of downstream tasks is **proportional** to the quality of the self-supervised feature representation [3].

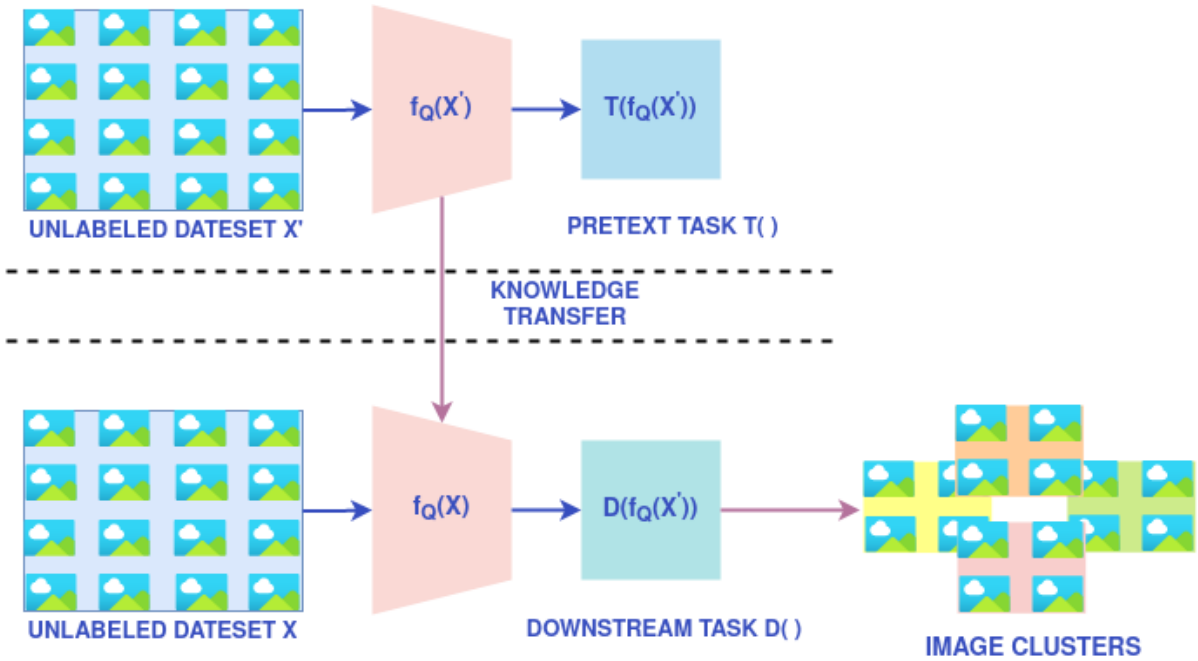


Figure 2: General Overview of SSL Framework.

Existing Works

- **Photometric and geometric prediction-based** pretext tasks **fail to learn** discriminative feature representations.
- Quality of feature representation is **further improved** by introducing a batch contrastive approach [4-6].

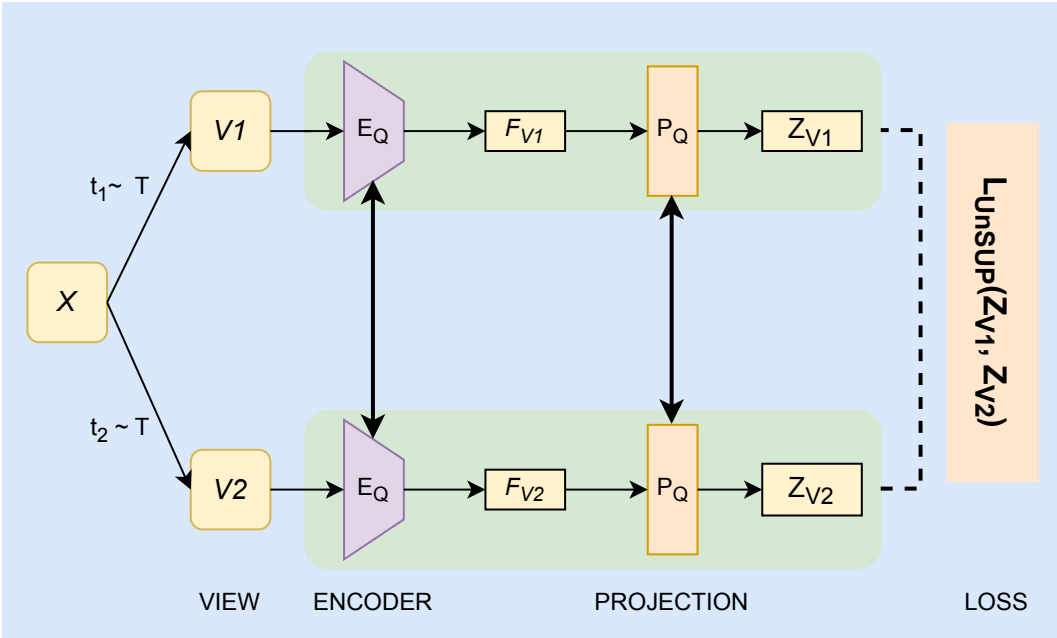


Figure 3: A General Batch Contrastive approach-based framework for Self-supervised Training (SimCLR).

Limitations

- Existing unsupervised contrastive batch approaches heavily depend on **data augmentation strategy**.

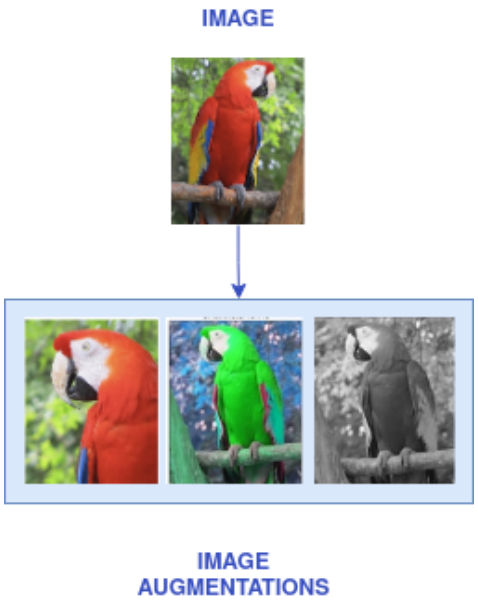


Figure 4: Generate **augmented versions** (positive pairs) of an image.

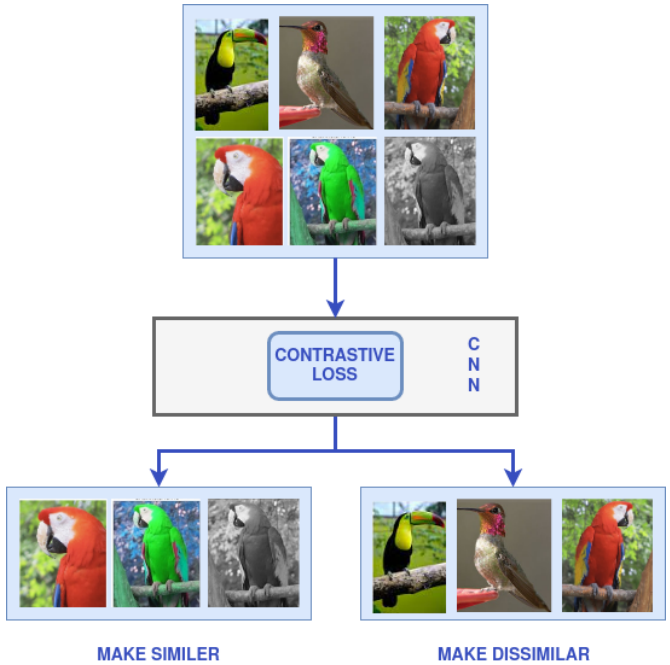
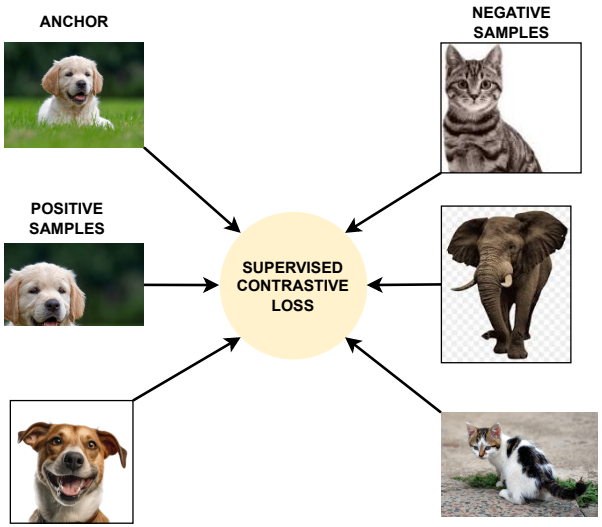


Figure 5: Attract positive pairs and repel negative pairs

Motivation

- Paper [7] study the **effect of replacing image augmentations** with **sample images from same class** in supervised setting.



- We argue that introducing intra-class variance in a batch contrastive approach can **further improve the quality** of self-supervised feature representation.
- Challenges in unsupervised setting:
  1. **Class-level information is not available.**
  2. **How to utilize the class-level information to converge the training?**

Proposed Architecture

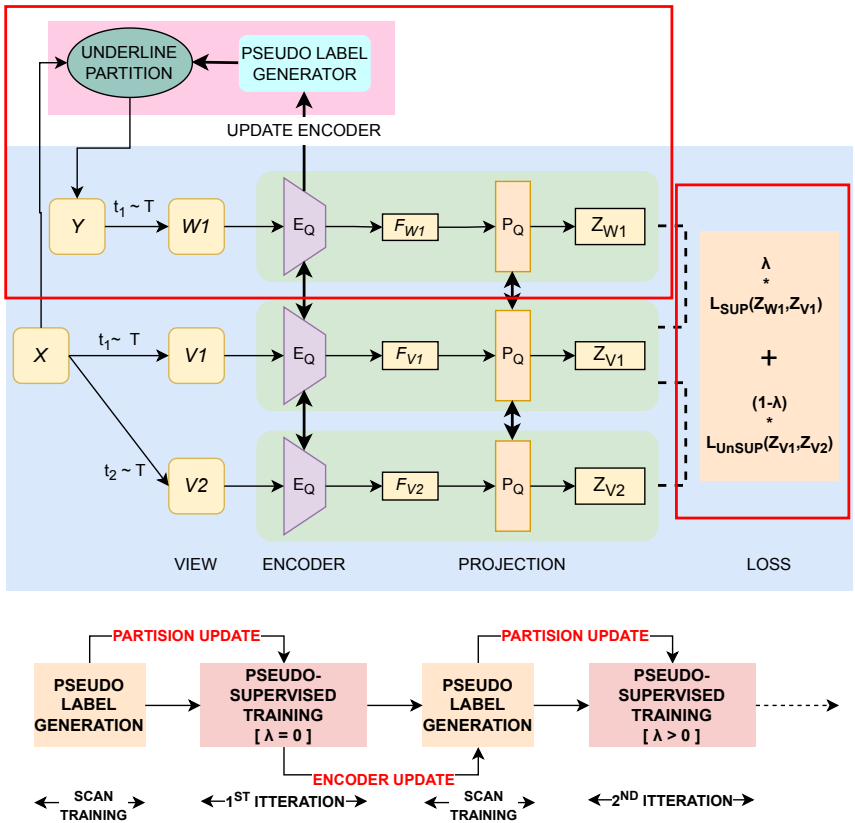


Figure 6: A high-level view of the proposed method, i.e., IPCL.

Major Contributions

- Pseudo-label Generator: Iteratively discovers the underlying partition of the unlabeled dataset in an unsupervised setting.
  - Utilizes **Semantic Clustering by Adopting Nearest Neighbors** (SCAN) [9] to generate pseudo labels.
  - Encoder's parameter of the SCAN framework is **updated with** the trained encoder from the previous training iteration.
- Pseudo-supervised Contrastive Loss ($\mathcal{L}_{\text{IPCL}}$): a convex combination of self-supervised and supervised contrastive loss to capture the benefits of both augmentations and pseudo-class information.

$$\mathcal{L}_{\text{IPCL}} = (1-\lambda)\mathcal{L}_{\text{UnSup}} + \lambda\mathcal{L}_{\text{Sup}} \tag{1}$$

  - λ is a weight factor determining the relative importance of the supervised and unsupervised losses

$\mathcal{L}_{\text{UnSup}}$ & $\mathcal{L}_{\text{Sup}}$

- **Self-supervised Contrastive Loss** ($\mathcal{L}_{\text{UnSup}}$) [4]: Utilizes the image augmentations to sample positive and negative pairs.

$$\mathcal{L}_{\text{UnSup}} = -\sum_{i=1}^{2N} \log \frac{\exp\left(\text{sim}(Z_i, Z_{i+N}) \,/\, \tau\right)}{\sum_{j=1, j\neq i}^{2N} \exp\left(\text{sim}(Z_i, Z_j) \,/\, \tau\right)} \tag{2}$$

  - Z_i and Z_{i+N} are feature representations of augmented views of an image, $2N$ is the multi-view batch size, τ is a temperature parameter, $\text{sim}(.,.)$ is a similarity function.

- **Supervised Contrastive Loss** ($\mathcal{L}_{\text{Sup}}$) [7]: Utilizes the pseudo-level information to sample positive and negative pairs.

$$\mathcal{L}_{\text{Sup}} = \sum_{i=1}^{2N} \frac{-1}{|A(i)|} \sum_{a\in A(i)} \log \frac{\exp\left(\text{sim}(Z_i, Z_a) \,/\, \tau\right)}{\sum_{b\in B(i)} \exp\left(\text{sim}(Z_i, Z_b) \,/\, \tau\right)} \tag{3}$$

  - A(i) and B(i) are the set of view indices from the same and different pseudo-class as i_{th} view in a multi-view batch of size 2N, respectively.

IPCL Algorithm.

Input D: dataset, E_Q: encoder, totalEpochs: total number of epochs, pretrainCount: number of epochs for pre-training, stepLength: number of epochs for an iteration, λ: weight factor, T: augmentation set
Initialize Encoder with random weights, nextIteration = pretrainCount
for $e = 0$ to totalEpochs **do**
    Sample mini-batch of size N from D
    Sample two transformations from T and obtain corresponding views of each image(2N total)
    if $e <$ *pretrainCount* **then**
        Train E_Q by setting $\lambda = 0$ in equation 1
    else
        if e == (nextIteration - 1) **then**
            Update encoder of pseudo-label generator
            Set nextIteration = nextIteration + stepLength
        end if
        Generate pseudo-labels for 2N.
        Train E_Q by setting λ to pre-defined non-zero value in equation 1
    end if
end for
Output Encoder

Experimental Settings

- Datasets:
  - **CIFAR-10** [9]: 50,000 training and 10,000 testing 32x32 color images, 10 classes, 6,000 images per category.
  - **STL-10** [10]: 100,000 training images and 8,000 test 96x96 color images, 10 classes.
- Architecture:
  - ResNet18 base encoder as a feature extractor.
  - A 2-layer MLP projection head Yield 128-dimensional feature vectors.
- Hyper-parameters:
  - Temperature coefficient of 0.1.
  - Stochastic gradient descent (SGD) optimizer (momentum $= 0.9$ and learning rate $= 0.4$) and a cosine learning rate scheduler.
  - Batch size of 512.

Metrics & Results

- Evaluate the effectiveness of the learned representations through:
  - K-nearest neighbors (KNN) assessment, and
  - Unsupervised classification (UnCls) [8] as a **downstream task**.

Table 1: Comparison of IPCL and SimCLR for Top-K NN precision over CIFAR-10 and STL-10 datasets

Dataset	Method	Top-1	Top-5	Top-20
CIFAR-10	SimCLR	83.33	79.98	75.23
	IPCL[100, 0.05]	**84.77**	**82.20**	**78.84**
STL-10	SimCLR	85.02	81.92	77.39
	IPCL[-, 0.025]	**85.55**	**82.62**	**78.73**

Here, IPCL[X, Y], with X representing the parameter *stepLength* and Y representing the parameter λ.

Downstream Results

- Compute the **cluster quality** using **Cluster Accuracy (Acc)**, **Normalized Random Index (NMI)**, and **Adjusted Random Index (ARI)** metrics.

Table 2: Results for downstream unsupervised classification(UnCls) task. Here, 'SL' denotes the method followed by the self-labeling (SL) step.

Dataset	Method	UnCls	Acc	NMI	ARI
CIFAR-10	SimCLR	k-means	65.9	59.8	50.9
	SimCLR	SCAN	81.86	72.64	66.66
	IPCL	SCAN	**84.44**	**74.24**	**69.78**
	SimCLR	SCAN+SL	87.96	79.11	76.44
	IPCL	SCAN+SL	**88.81**	**81.02**	**77.95**
STL-10	SimCLR	k-means	65.8	60.4	50.6
	SimCLR	SCAN	79.04	67.84	62.66
	IPCL	SCAN	**79.33**	**69.01**	**63.84**
	SimCLR	SCAN+SL	80.43	69.86	64.82
	IPCL	SCAN+SL	**80.91**	**70.97**	**66.12**

Ablation Study

Table 3: Ablation results with CIFER-10 dataset.

Method	Top-1	Top-5	Top-20
SimCLR	83.33	79.98	75.23
IPCL[-, 1.0]	72.74	72.69	72.53
IPCL[-, 0.1]	82.92	80.61	**77.73**
IPCL[-, 0.05]	**83.55**	**80.86**	77.56

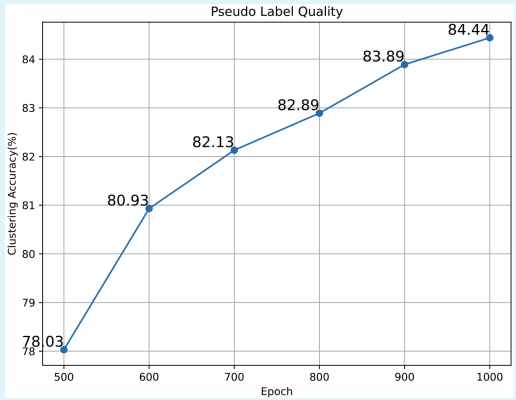
(a) **Effect of λ** on **Top-K NN precision**

Method	Top-1	Top-5	Top-20
SimCLR	83.33	79.98	75.23
IPCL[-, 0.1]	82.92	80.61	77.73
IPCL[250, 0.1]	83.76	81.42	78.32
IPCL[-, 0.05]	83.55	80.86	77.56
IPCL[100, 0.05]	**84.77**	**82.20**	**78.84**

(b) **Effect of stepLength** on **Top-K NN precision**

Method	Top-1	Top-5	Top-20
SimCLR	83.33	79.98	75.23
IPCL[-, 0.05](10 epochs)	**83.98**	80.84	77.27
IPCL[-, 0.05](50 epochs)	83.55	**80.86**	**77.56**

(c) **Effect of SCAN training time** on **Top-K NN precision**



(d) **Evolution of Clustering Accuracy (Acc.)** with the **number of epochs**.

Conclusion

- Proposes a novel self-supervised learning method, IPCL, to improve visual representation learning.
- Iteratively enhances the visual representation with a pseudo-level generator and novel pseudo-supervised contrastive loss function.
- Experiment on multiple datasets to show that the proposed method outperforms the baseline self-supervised method.
- Perform a detailed ablation study to understand the influence of parameters and sub-modules.

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Q&A

THANK YOU

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