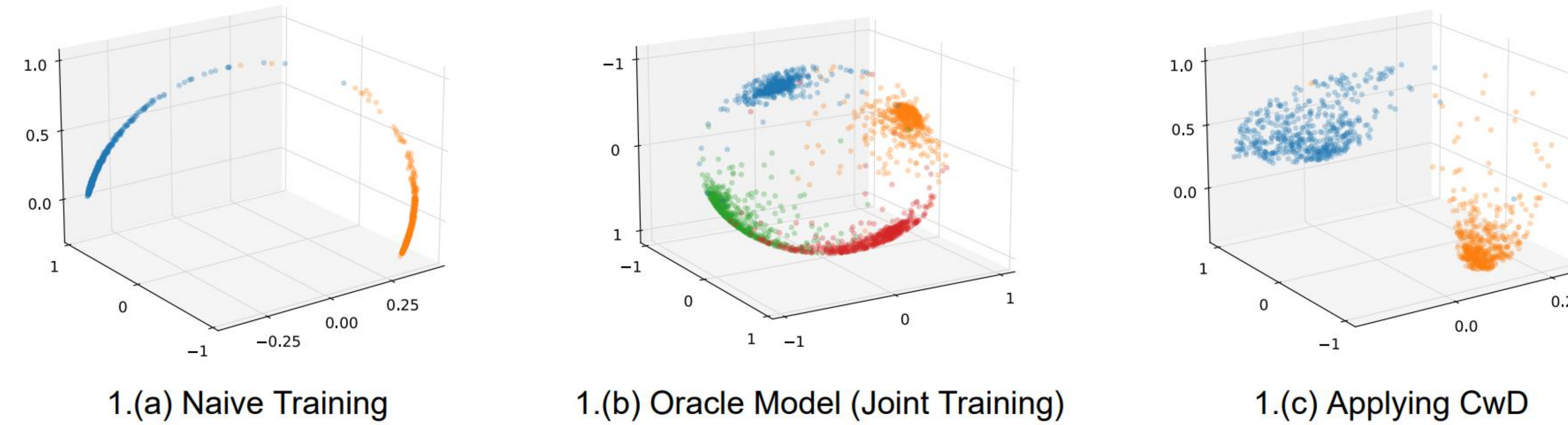


Mimicking the Oracle: An Initial Phase Decorrelation Approach for Class Incremental Learning

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Phase 0: ● class 1 ● class 2 Phase 1: ● class 3 ● class 4



3. An observation on representations

Next, we observe class-wise representations produced by an naively trained initial phase model and the oracle model. We find that representations output by the **naively trained model** reside in a **lower dimensional subspace** (see Fig. 1.(a)), while representations output by the **oracle model** can **better use the ambient space** (see Fig. 1.(b)).

4. Class-wise Decorrelation to mimic the oracle

Motivated by our observations, we propose a novel regularization objective at initial phase of CIL, termed **Class-wise Decorrelation (CwD)**:

$$L_{CwD} = \frac{1}{Cd^2} \sum_{c=1}^C \|K^{(c)}\|_F^2,$$

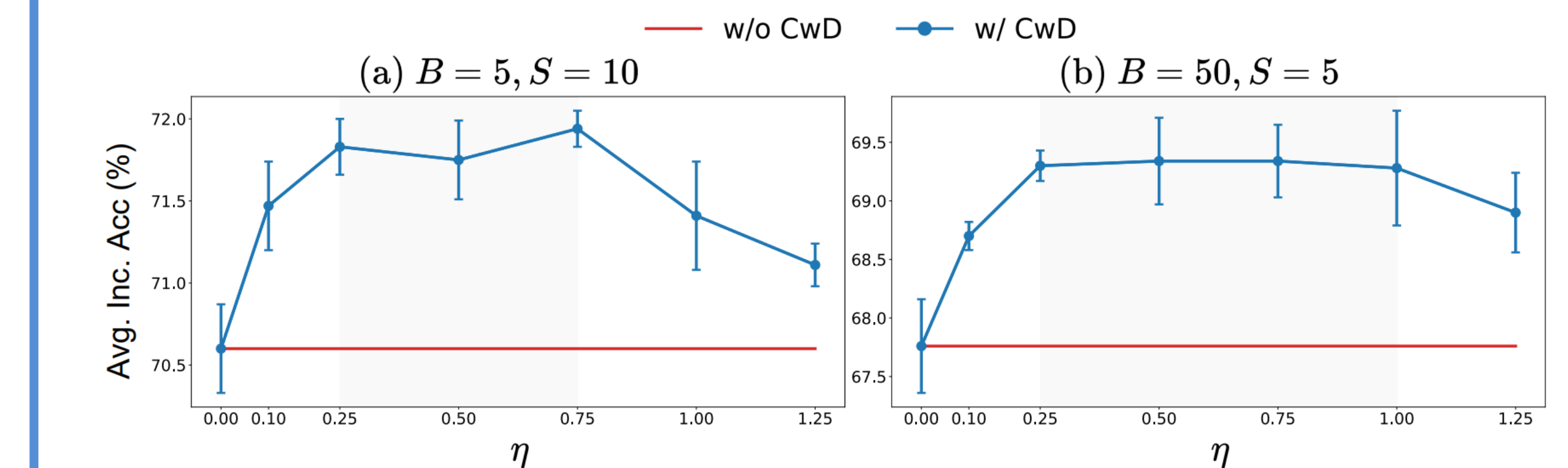
where $K^{(c)}$ is the correlation matrix of class c representations. With CwD, representations of each class can better use the ambient space instead of simply residing in a lower dimensional subspace (see Fig. 1.(c)).

5. Experiments

B : initial phase classes. S : classes per phase after the initial one. R : exemplars per class. η : coefficient of CwD objective. Results are averaged over 3 seeds. Without specific description, all results are with ImageNet100 and LUCIR.

Method	CIFAR100 ($B=50$)			ImageNet100 ($B=50$)			ImageNet ($B=100$)	
	$S=10$	5	2	10	5	2	100	50
LwF [18]	53.59±0.51	48.66±0.58	45.56±0.28	53.62 [†]	47.64 [†]	44.32 [†]	40.86±0.13	27.72±0.12
iCaRL [26]	60.82±0.03	53.74±0.25	47.86±0.41	65.44 [†]	59.88 [†]	52.97 [†]	49.56±0.09	42.61±0.15
BiC [33]	51.58±0.16	48.07±0.02	43.10±0.37	70.07 [†]	64.96 [†]	57.73 [†]	43.23±0.13	38.83±0.12
LUCIR [12]	66.27±0.28	60.80±0.29	52.96±0.25	70.60±0.43	67.76±0.40	62.76±0.22	56.40±0.10	52.75±0.18
+CwD (ours)	67.26±0.16	62.89±0.09	56.81±0.21	71.94±0.11	69.34±0.31	65.10±0.59	57.42±0.11	53.37±0.22
PODNet [8]	66.98±0.13	63.76±0.48	61.00±0.18	75.71±0.37	72.80±0.35	65.57±0.41	57.01±0.12	54.06±0.09
+CwD (ours)	67.44±0.35	64.64±0.38	62.24±0.32	76.91±0.10	74.34±0.02	67.42±0.07	58.18±0.20	56.01±0.14
AANet [19]	69.79±0.21	67.97±0.26	64.92±0.30	71.96±0.12	70.05±0.63	67.28±0.34	51.76*±0.14	46.86*±0.13
+CwD (ours)	70.30±0.37	68.62±0.17	66.17±0.13	72.92±0.29	71.10±0.16	68.18±0.27	52.30*±0.08	47.61*±0.20

S	B	LUCIR			↑	S	R	LUCIR			↑
		LUCIR	+CwD (ours)	↑				LUCIR	+CwD (ours)	↑	
10	10	57.01±0.14	57.90±0.07	+0.89	10	40	72.41±0.61	73.29±0.11	+0.88		
	20	61.21±0.35	62.49±0.36	+1.28		30	71.70±0.37	72.63±0.15	+0.93		
	30	64.82±0.38	66.54±0.35	+1.72		20	70.60±0.43	71.94±0.11	+1.34		
	40	67.68±0.37	69.70±0.10	+2.02		10	68.73±0.52	69.77±0.04	+1.04		
	50	70.60±0.43	71.94±0.11	+1.33		5	66.49±0.52	67.63±0.07	+1.14		
5	10	50.47±0.31	51.92±0.10	+1.45	5	40	70.74±0.49	72.06±0.11	+1.32		
	20	56.41±0.37	58.14±0.13	+1.73		30	68.56±0.42	70.04±0.12	+1.44		
	30	61.00±0.09	63.18±0.14	+2.18		20	67.76±0.40	69.34±0.31	+1.58		
	40	63.73±0.23	66.25±0.16	+2.52		10	64.07±0.38	66.07±0.46	+2.00		
	50	67.76±0.40	69.34±0.31	+1.58		5	60.41±0.77	62.58±0.53	+2.17		



1. Background & Introduction

Class Incremental learning (CIL) aims at learning a classifier in a phase-by-phase manner, where only data of a subset of classes are given at each phase. Previous works mainly focus on mitigating forgetting in phases after the initial one. However, **we find that improving CIL at its initial phase is also a promising direction.**

2. An Exploratory Experiment

Firstly, we show that **directly mimicking the oracle model** (i.e., a model jointly trained with all classes) **representations at initial phase** can improve CIL. We use the following objective at initial phase:

$$\min_{\theta} L_{ce}(x, y, \theta) + \beta \left(1 - \text{CosSim}(f_{\theta}(x), f_{\theta^*}(x)) \right),$$

where $f_{\theta}(x)$ and $f_{\theta^*}(x)$ denotes representations output by the initial phase model and the oracle model, respectively. Results are shown below.

