Confusion-Driven Self-Supervised Progressively Weighted Ensemble Learning for Non-Exemplar Class Incremental Learning

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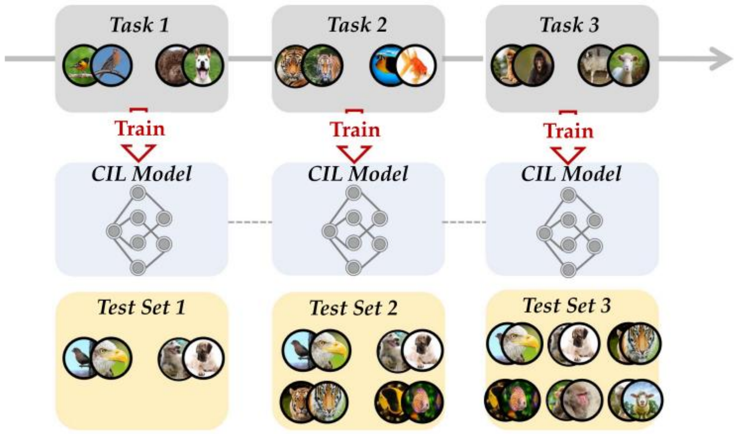
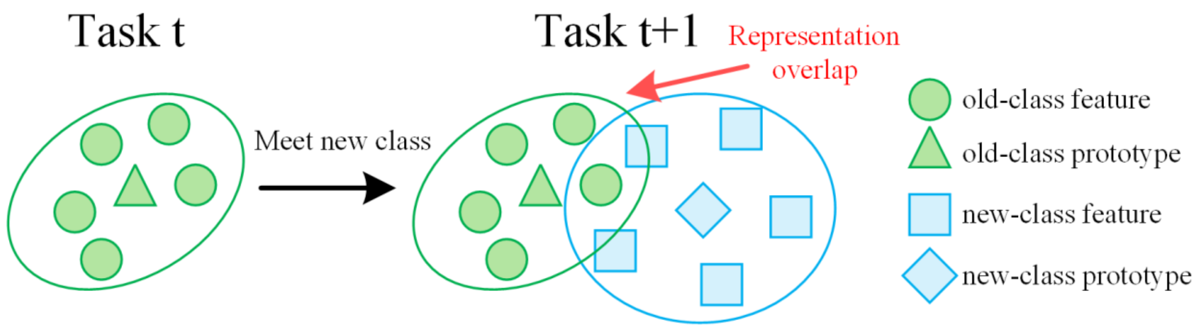
Contents

Background

- Non-exemplar class incremental learning aims to continuously adapt to newclasses while preventing forgetting previously learned ones without retaining earlier samples
- where, in existing frozen feature extractor-based methods, **the representations of new and old classes tend to exhibit substantial overlap within the feature space**. This overlap limits the model’ s ability to effectively distinguish between previously learned and newly introduced classes, ultimately leading to **catastrophic forgetting**



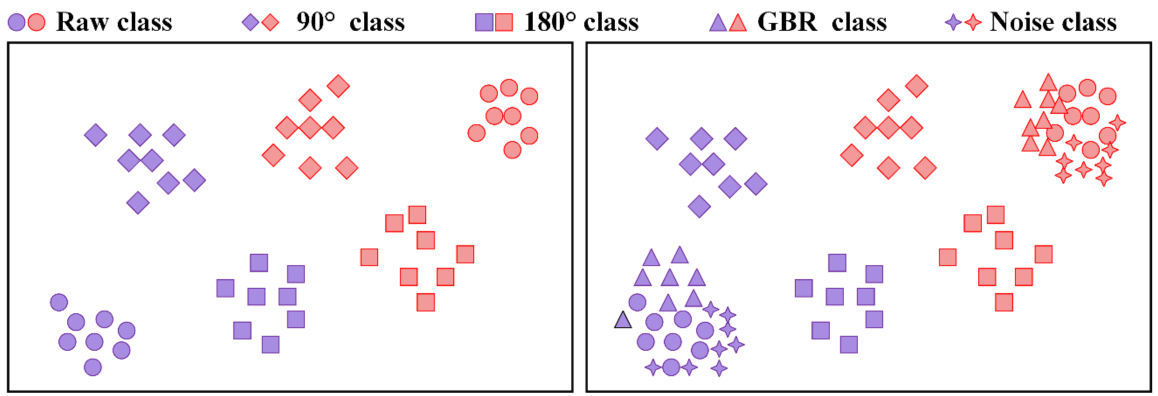
Non-Exemplar Class-Incremental Learning



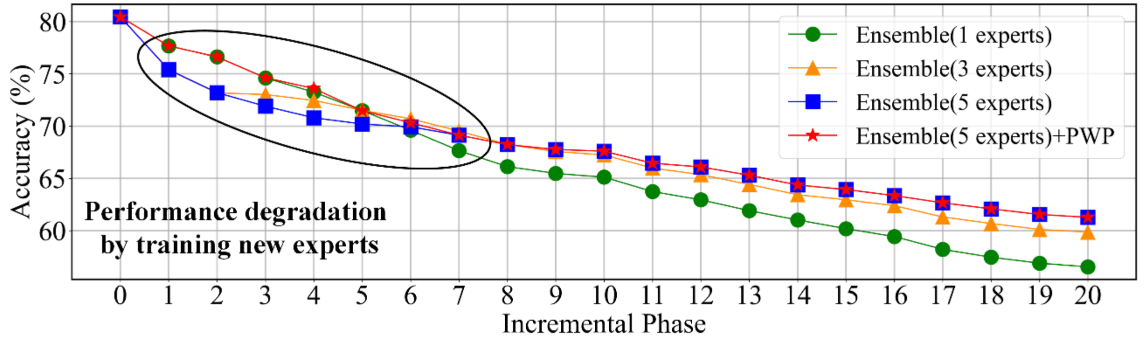
Overlapping Representations Between Old and New Classes

Motivation

- The overlap between new and old class representations arises from the **model's insufficient discriminative capability** between them
- Existing self-supervised learning methods **inadequately enhance representation discriminability**
- Existing ensemble learning methods suffer from **performance degradation** when new experts are introduced



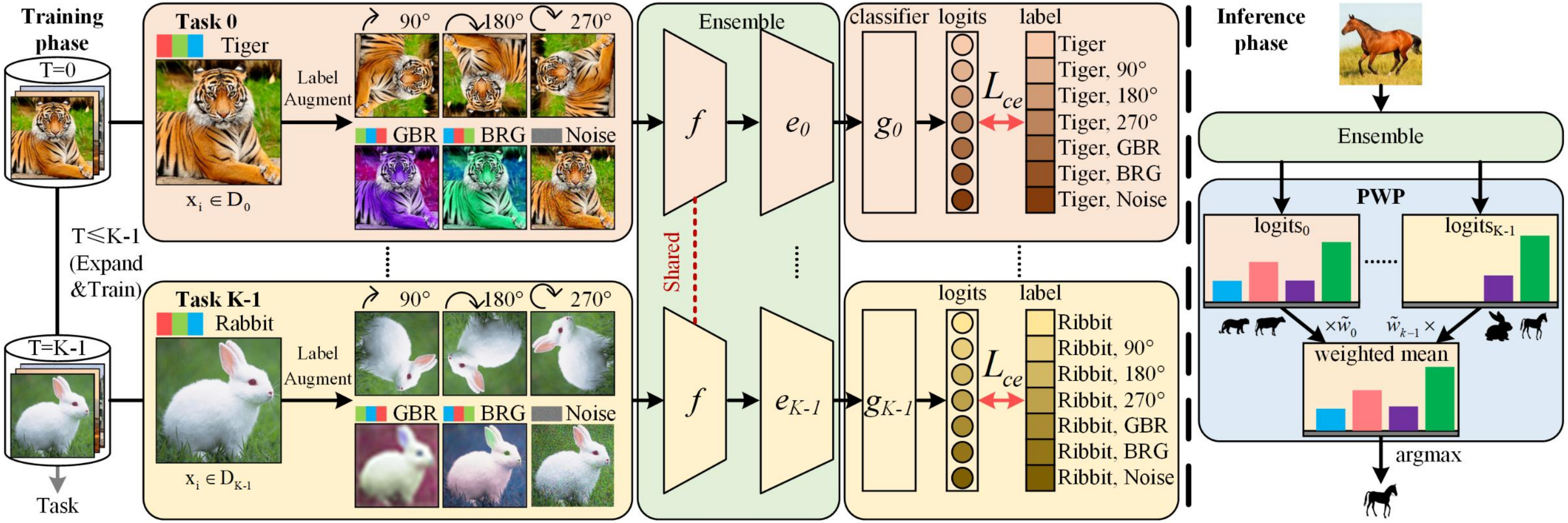
Distribution comparison of task-agnostic classes under SSL and CDSSL



Accuracy variation with different numbers of experts

Method : CLOVER

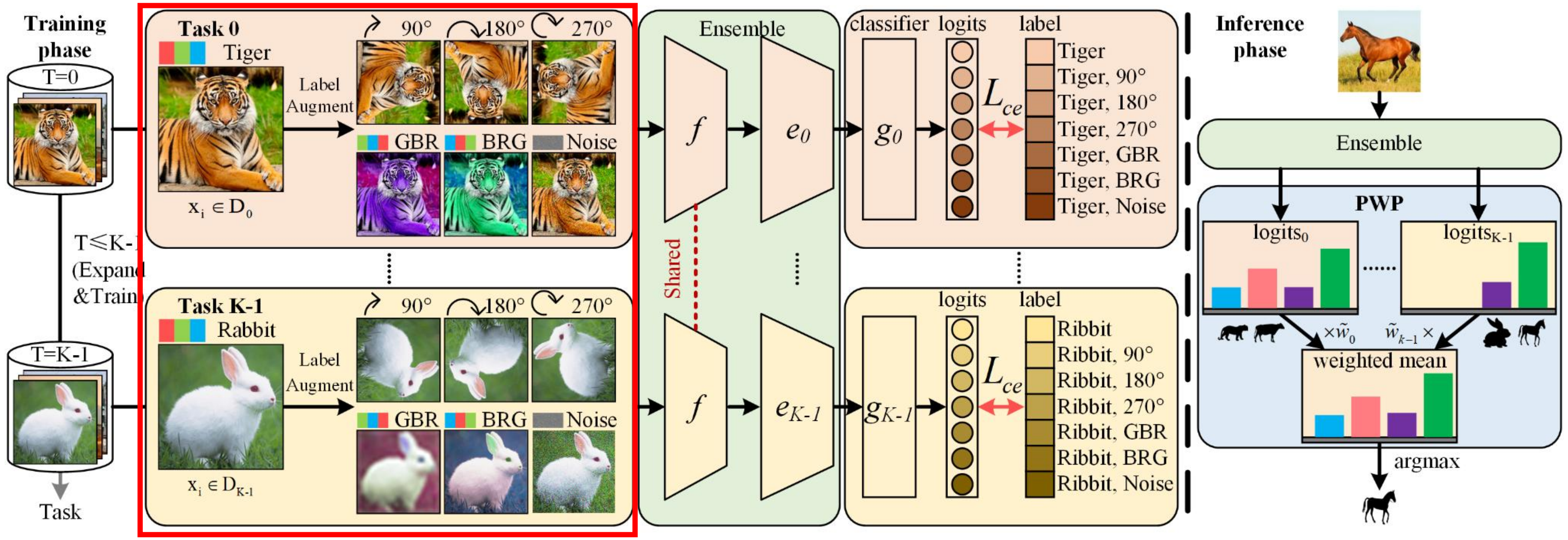
Confusion-driven seLf-supervised prOgressiVely weighted Ensemble leaRning(CLOVER) for Non-Exemplar Class Incremental Learning



The pipeline of the proposed CLOVER

Method : CLOVER

- **[contribution 1]: a Confusion-Driven Self-Supervised Learning method**



The pipeline of the proposed CLOVER

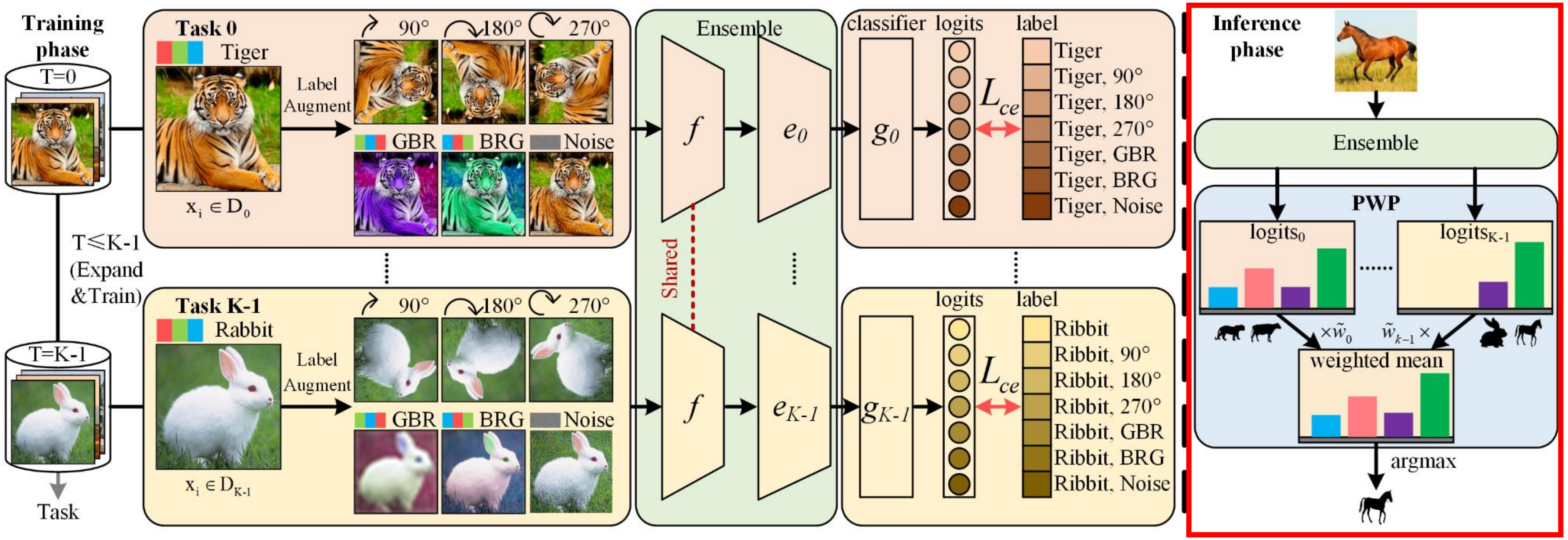
- ***Generate highly confusing classes***
- ***Enhances the capability for representation extraction***

$$\tilde{x}_{7i+j} = \begin{cases} x_i, & j=0 \\ ratate(x_i, j\times 90?), & j\le 3 \\ GBR(x_i), & j=4, \\ BRG(x_i), & j=5 \\ x_i + s\times noise(0,1), & j=6 \end{cases}$$

$$L = L_{CE}(g_i(e_i(f(\tilde{x}))), \tilde{y})$$

Method : CLOVER

- **[contribution 2]: a Progressively Weighted Prediction strategy**



The pipeline of the proposed CLOVER

- ***Mitigating the influence of unreliable experts***
- ***Mitigating overlapping representations***

$$w_i = \begin{cases} 1 - \sum_{j=1}^{K-1} w_j, & i = 0 \\ \min\{\alpha + \beta \times (t - i), \frac{1}{K}\}, & i > 0 \end{cases}$$

$$l_k^c(x) = -\frac{1}{2}[\ln(|\Sigma_k^c|) + S\ln(2\pi) + (r_k - \mu_k^c)^T (\Sigma_k^c)^{-1} (r_k - \mu_k^c)]$$

$$\bar{l}(x) = \left\{ \sum_{k=0}^{M_i - 1} \tilde{w}_k \times \overline{l_k^i} \right\}_{i=1}^{|C|} \qquad \tilde{w}_k = \frac{w_k}{\sum_{j=0}^{M_i - 1} w_j}$$

$$c = \arg\max(\bar{l}(x))$$

Experiments

● Quantitative evaluation

Method	CIFAR100						TinyImageNet						ImageNet-Subset					
	5 tasks		10 tasks		20 tasks		5 tasks		10 tasks		20 tasks		5 tasks		10 tasks		20 tasks	
	Avg	Last	Avg	Last	Avg	Last	Avg	Last	Avg	Last	Avg	Last	Avg	Last	Avg	Last	Avg	Last
LwF_MC [44]	45.9	36.1	27.4	17.0	20.1	15.9	29.1	17.1	23.1	12.3	17.4	8.8	34.9	24.1	31.2	20.0	27.5	17.4
PASS [9]	63.5	55.7	61.8	49.0	58.1	48.5	49.6	41.6	47.3	39.9	42.1	32.8	63.1	52.6	61.8	50.4	55.2	46.1
SSRE [10]	65.9	56.3	65.0	55.0	61.7	50.5	50.4	41.7	48.9	39.9	48.2	39.8	69.5	58.5	67.7	57.5	61.2	50.1
FeTrIL [15]	66.3	-	65.2	56.3	61.5	-	54.8	-	53.1	-	52.2	-	72.2	-	71.2	-	67.1	-
PRAKA [12]	70.0	61.6	68.9	60.4	65.9	56.2	53.3	46.4	52.6	45.2	49.8	40.6	-	-	69.0	61.3	-	-
POLO [26]	69.0	-	68.0	-	65.7	-	54.9	47.0	53.4	45.3	49.9	40.4	70.8	59.5	69.1	57.9	-	-
TASS [45]	68.8	59.3	67.4	57.9	62.8	53.8	55.1	44.1	54.2	43.9	52.8	43.6	74.3	63.1	72.6	57.9	68.8	57.6
FGKSR [41]	68.2	59.0	70.1	57.9	66.9	54.3	54.9	45.0	52.7	43.4	51.7	41.9	-	-	70.2	61.4	-	-
CEAT [40]	71.1	-	70.0	-	66.1	-	58.3	50.4	57.4	49.4	56.8	48.0	76.9	67.4	75.9	66.3	71.5	60.1
SEED* [39]	71.1	66.3	69.9	65.0	68.2	61.4	54.7	50.6	54.5	50.0	53.9	48.9	75.0	70.3	73.6	68.4	71.1	63.8
FeCAM [14]	70.9	62.1	70.8	62.1	69.4	58.5	59.6	52.8	59.4	52.8	**59.3**	**52.8**	**78.3**	70.9	**78.2**	70.9	**75.1**	66.3
CLOVER (Ours)	**72.7**	**68.0**	**72.3**	**67.5**	**71.0**	**64.9**	**60.2**	**56.0**	**59.9**	**54.1**	58.5	**52.8**	77.8	**73.2**	77.1	**71.5**	74.5	**67.5**

Comparisons of the average accuracy and last accuracy (%) at different settings on CIFAR100, TinyImageNet, and ImageNet-Subset.

Experiments

Quantitative evaluation

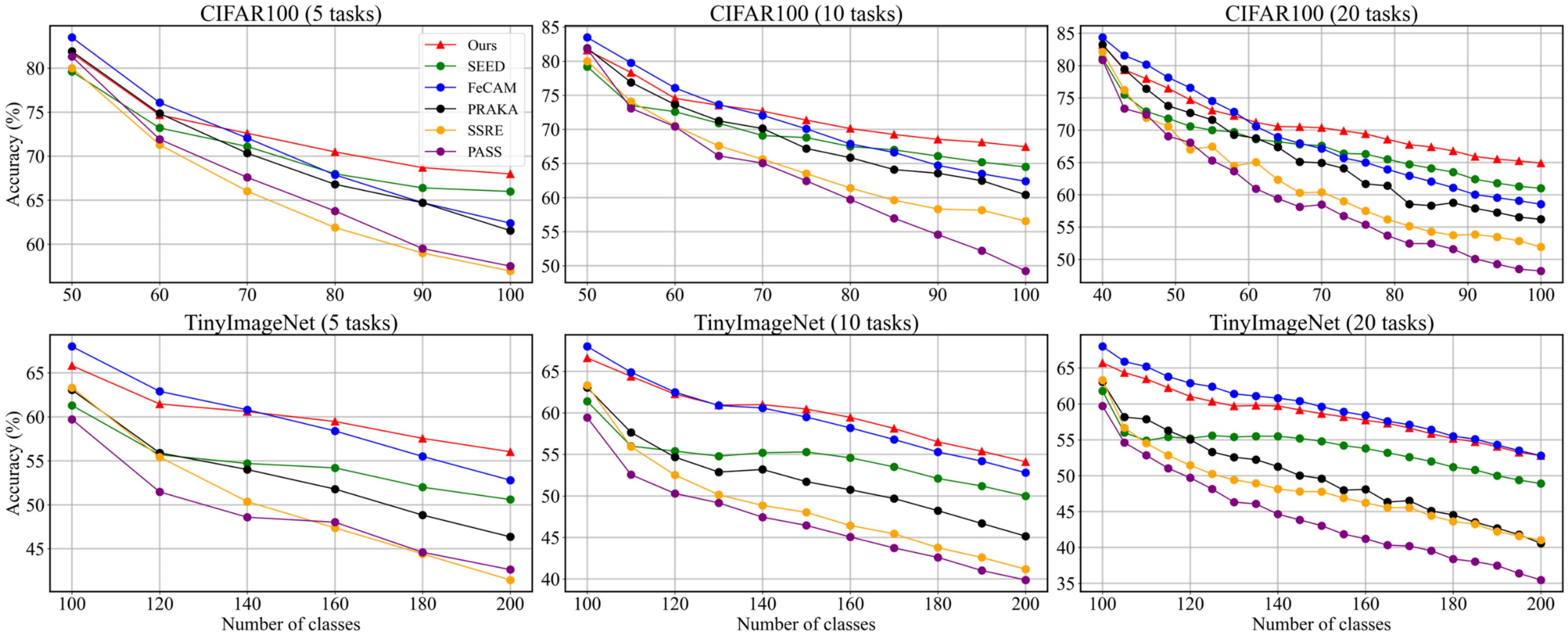
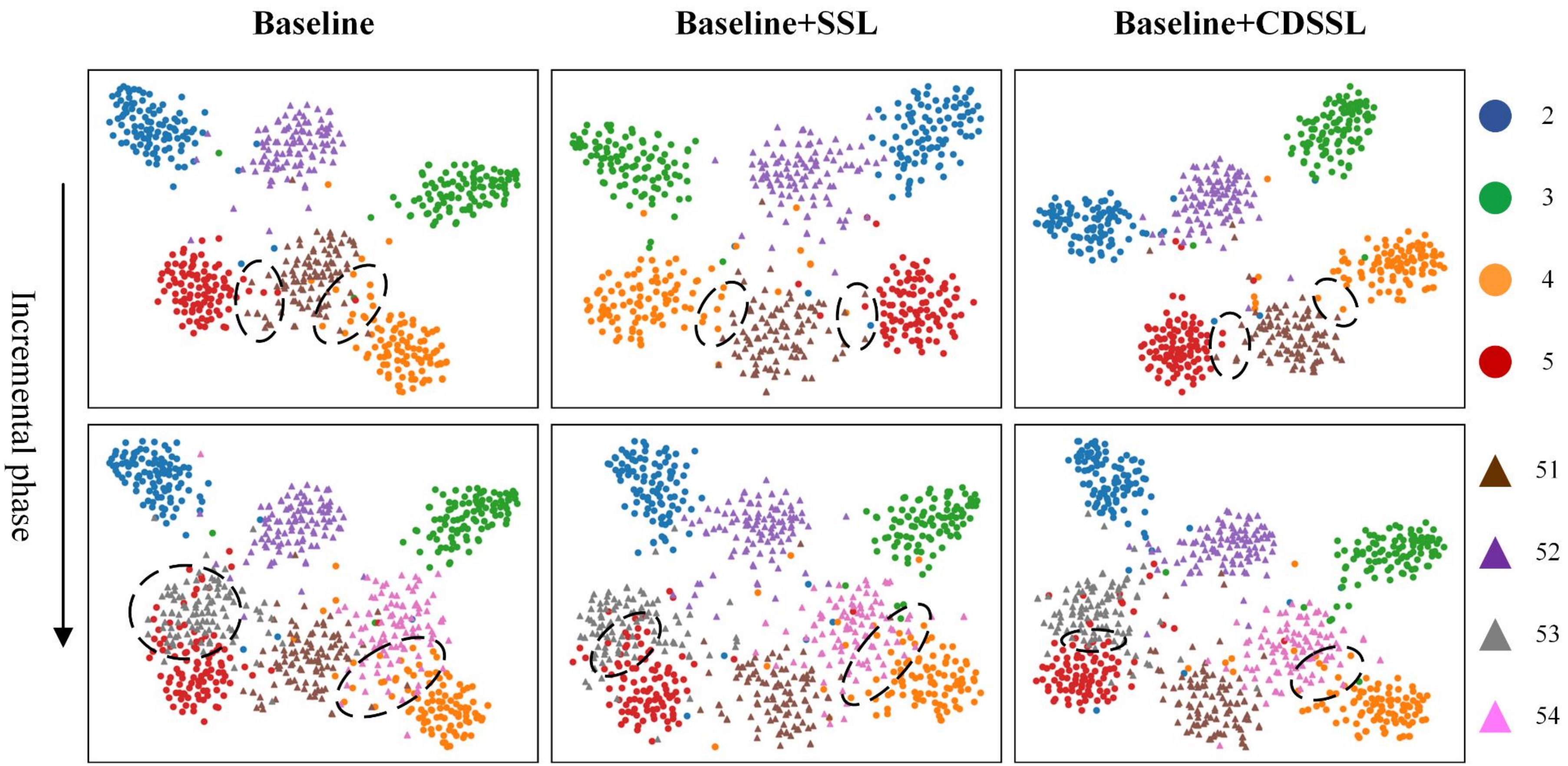


Illustration of the classification accuracy changes as tasks are being learned on CIFAR100 and TinyImageNet

Experiments

- **Qualitative evaluation**



The visualization illustrates the distribution of old and new class representations following the application of SSL and CDSSL, respectively

Experiments

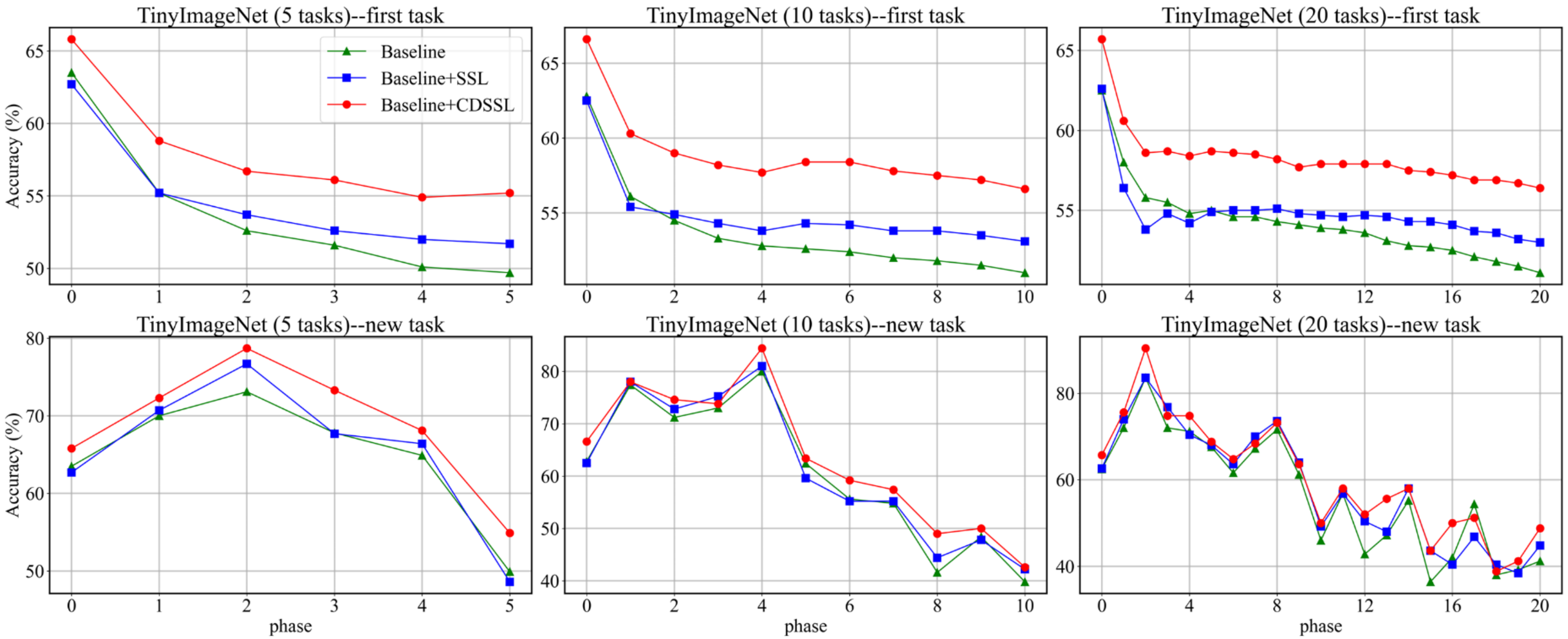
- **Ablation study**

Component			CIFAR100			TinyImageNet		
Baseline	*CDSSL*	*PWP*	5	10	20	5	10	20
✓			69.9	69.7	67.7	56.3	55.3	54.5
✓	✓		72.1	71.7	70.5	59.9	59.4	58.1
✓		✓	70.5	70.2	68.2	56.5	55.8	54.9
✓	✓	✓	**72.7**	**72.3**	**71.0**	**60.2**	**59.9**	**58.5**

Method				CIFAR100			TinyImageNet		
Baseline	Rot	Color	Noise	5	10	20	5	10	20
✓				69.9	69.7	67.7	56.3	55.3	54.5
✓	✓			70.7	70.8	69.2	57.2	55.9	54.9
✓		✓		70.5	70.0	68.3	56.4	55.3	54.6
✓			✓	70.3	69.9	68.1	56.4	55.4	54.6
✓	✓	✓		71.6	71.3	70.1	59.2	58.3	57.2
✓	✓		✓	71.8	71.3	70.1	59.3	58.0	57.0
✓		✓	✓	71.1	70.3	68.5	56.7	55.6	55.0
✓	✓	✓	✓	**72.1**	**71.7**	**70.5**	**59.9**	**59.4**	**58.1**

Experiments

- **Performance on old and new tasks**



- **Evolution of average Bhattacharyya distance during training**

Method			Task					
Baseline	SSL	*CDSSL*	0	1	2	3	4	5
✓			7.62	6.75	6.19	5.76	5.38	5.05
✓	✓		10.17	9.34	8.85	8.41	8.06	7.74
✓		✓	12.12	11.02	10.34	9.77	9.31	8.89

Thank you !