Persistence Homology Distillation for Semi-supervised Continual learning

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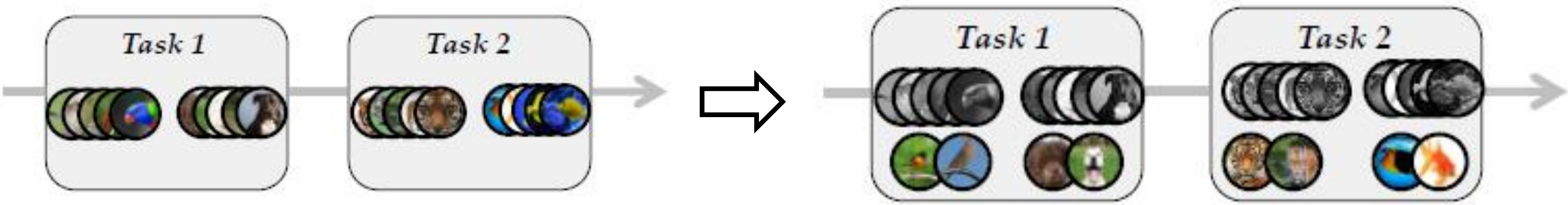
NEURAL INFORMATION PROCESSING SYSTEMS

Persistence Homology Distillation for Semi-supervised Continual learning

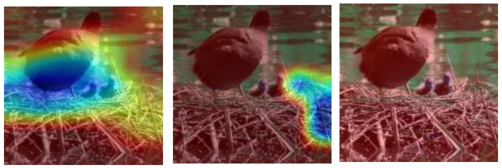
Background

Continual learning

Semi-supervised Continual Learning



Model Evolution



Attention Deficiency ☹

Model Evolution

Attention Bias ☹

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Enable stable model evolution by using knowledge of unlabeled data

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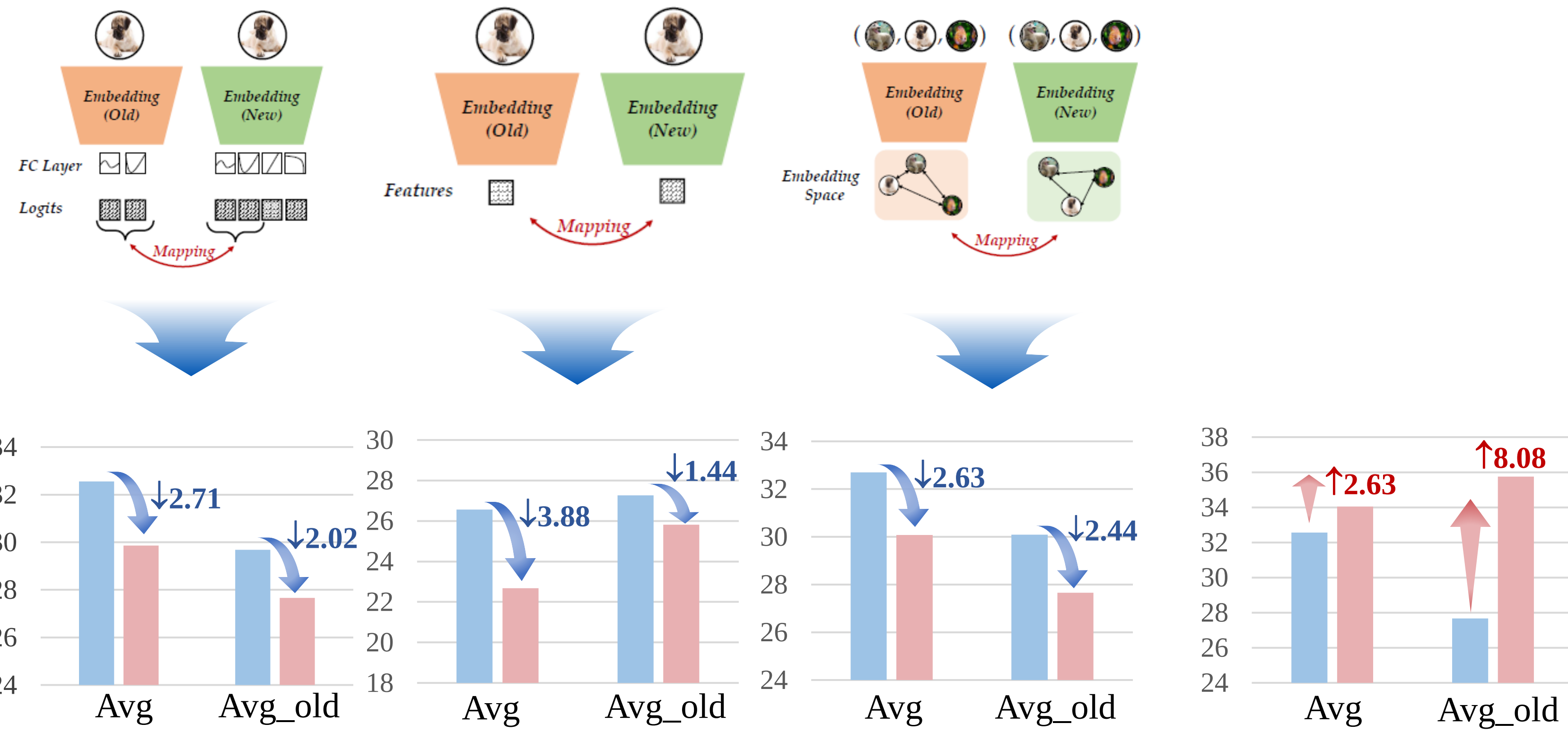
Knowledge Distillation



(a) Logits distillation (b) Feature distillation (b) Relation distillation (b) PH distillation (Ours)

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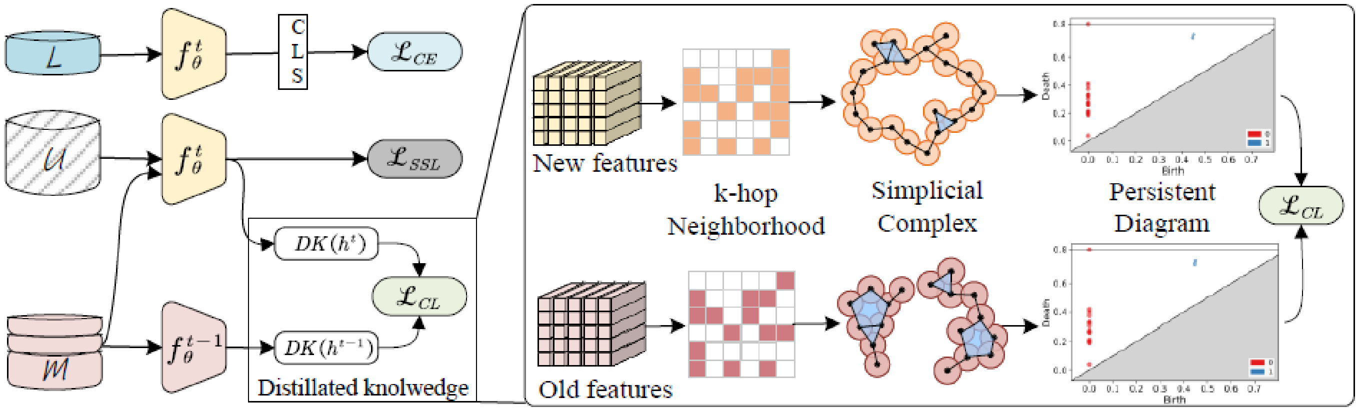
A more powerful noise insensitive distillation is needed for SSCL

Main contribution: persistence homology distillation



(a) (b)

- We utilize simplicial complexes to approximate vision data and explore stable topological feature representation of unlabeled data in semi-supervised continual learning.
- • We propose a novel persistence homology distillation strategy for SSCL that is insensitive to noise information interference, and devise an accelerating algorithm to reduce computation costs.
- • We demonstrate that our method outperforms existing methods on several benchmarks, and highlights the potential of utilizing unlabeled data to overcome catastrophic forgetting.

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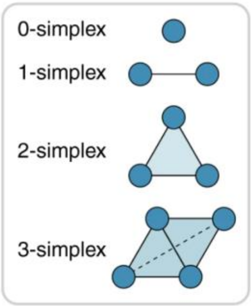
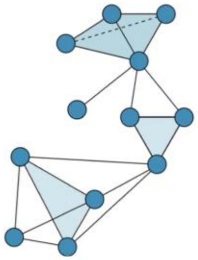
Persistence Homology Distillation for Semi-supervised Continual learning

Preliminary of Persistence Homology

- **Simplicial complex** : built from a set of simplices that satisfies Closure under Faces and Intersection Property.
  - **k-simplex**： k-dimensional polytope



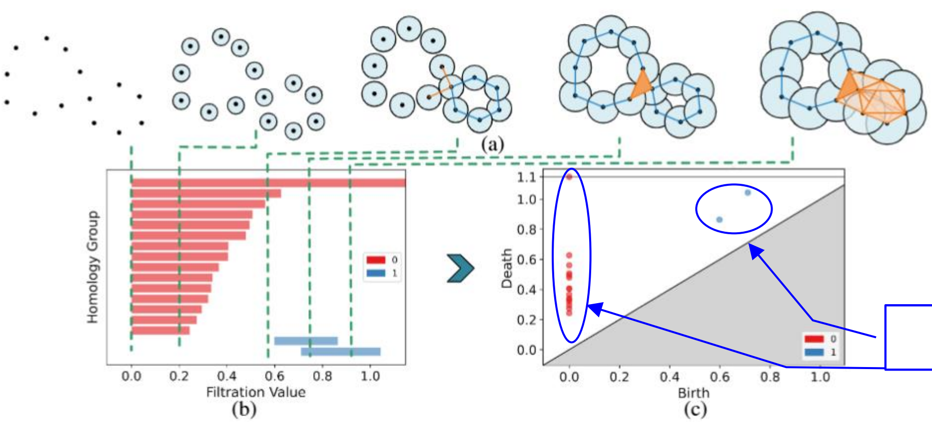


V-R simplicial complex

- **Persistence homology**： quantifying topological features over a range of length scales by defining a filtration on it.

Filtration: $K_r = \delta_X^{-1}((-\infty, r]) = \{y \in \mathbb{R}^d | \delta_X(y) \leq r\} = \cup_{x \in X} B(x, r)$

$$\emptyset = K_0 \subset K_1 \subset \cdots \subset K_m = K,$$



(x_σ, y_σ) : one simplex σ born in x_δ and dies in y_δ

$$Dgm = \{(x_\sigma, y_\sigma) \in \mathbb{R}^2 : x_\sigma < y_\sigma\} \cup \Delta$$

Value: Breaking the limitations of binary topological relationships

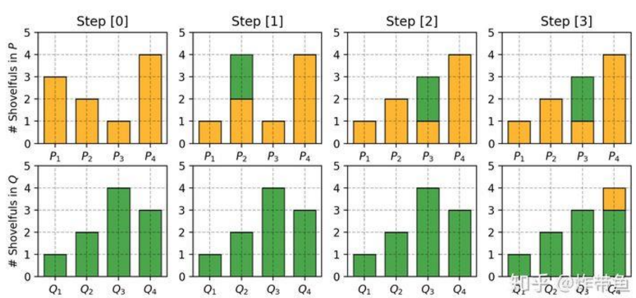
Persistence Homology Distillation

Topological representation：

- Adjcency Matrix： $G(V,E)$ $\quad W_{ij}=\begin{cases}1, if\ s_{ij}\geq\beta\\0, if\, s_{ij}<\beta\end{cases}$ $\quad s_{ij}=<h_i,h_j>=\frac{h_ih_j}{\|h_i\|\|h_j\|}$
- k-hop neighborhood： $\mathcal{N}(x_i,k)$ $x_j\in\mathcal{N}(x_i,k)$ if the shortest path between x_i and x_j is k.
- h-dim local persistence diagram： $Dgm_h(\mathcal{N}(x_i,k))$

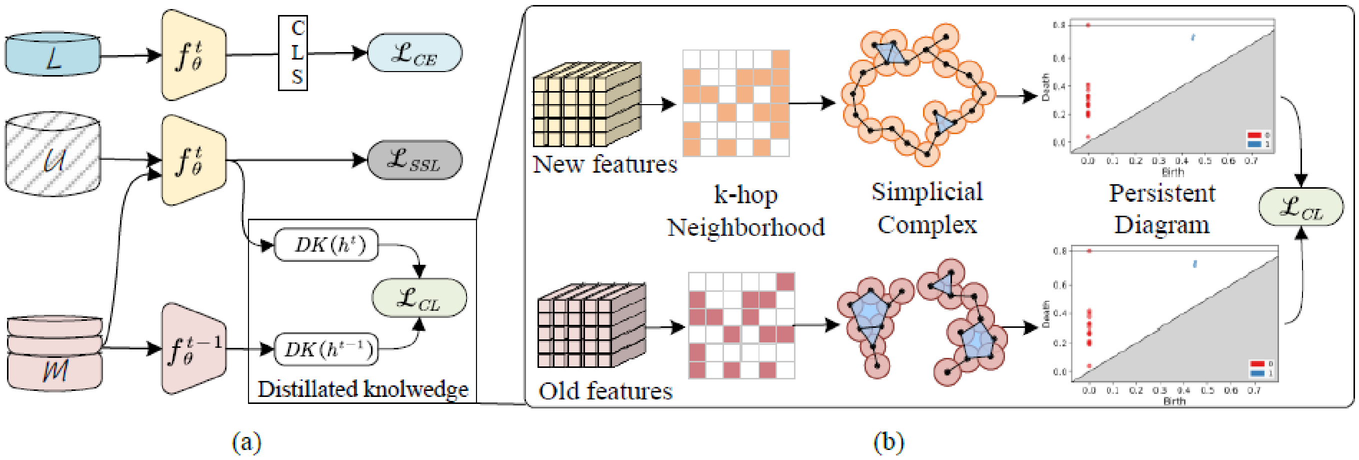
Topological distance : p-Wasserstein distance（Optimal transport distance)

$$d_{\mathcal{N}_x^k}(f_{old},f_{new})=inf_\gamma(\sum_{u\in Dgm_h(\mathcal{N}_x^k,f_{old})\cup\triangle}\|u-\gamma(u)\|^p)^{\frac{1}{p}}$$



Capture high-order relationships in vision data distribution

■ Persistence Homology Distillation



Overall Loss：

$$\mathcal{L}_{sscl} = \mathcal{L}_{CE} + \mathcal{L}_{SSL} + \lambda \mathcal{L}_{CL}$$

Persistence Homology Distillation loss：

$$\mathcal{L}_{hd} = \frac{1}{|S|} \sum_{x \in S} d_{\mathcal{N}_x^k}(f_{old}, f_{new})$$

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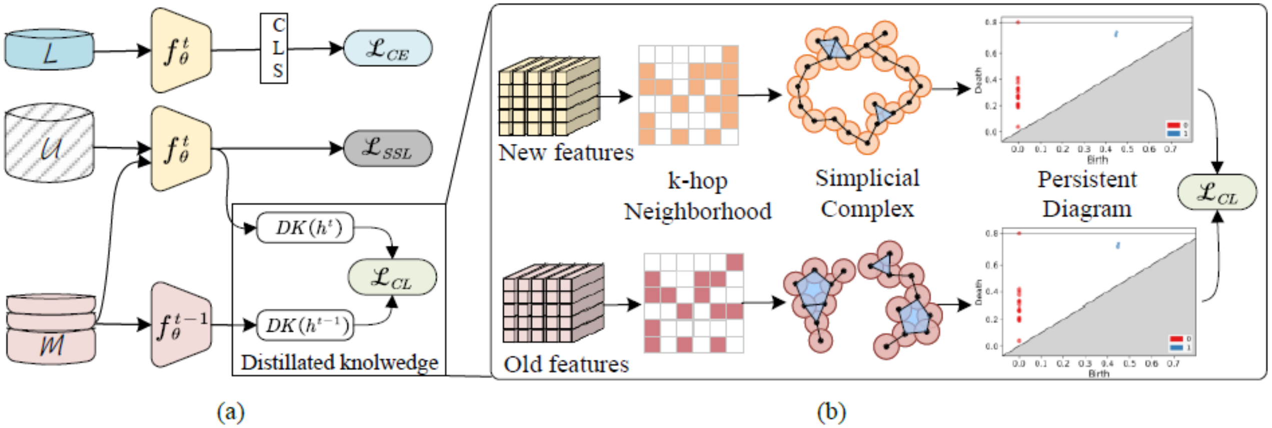
Preserce global knowledge through high-order homology features

Stability Analysis



Theorem 1. *Given the two feature space of point data as $\mathcal{P}_0$ and $\mathcal{P}_1$, for all $p \geq 1$ and $h \in \mathbb{Z}^+$, we have*

$$W_p(Dgm_h(\mathcal{R}(\mathcal{P}_0)), Dgm_h(\mathcal{R}(\mathcal{P}_1))) \leq \binom{M-1}{k}^{\frac{1}{p}} W_p^{pair}(\mathcal{P}_0, \mathcal{P}_1), \tag{7}$$

where $Dgm_h(\mathcal{R}(\mathcal{P}_0))$ and $Dgm_h(\mathcal{R}(\mathcal{P}_1))$ are the h-dimensional persistence diagram for the Vietoris-Rips filtration on the point set $\mathcal{P}_0$ and $\mathcal{P}_1$ respectively. W_p^{pair} represents the pair-wise distance between the point set $W_p^{pair}(\mathcal{P}_0, \mathcal{P}_1) = inf_\phi(\sum_{u,v\in\mathcal{P}_0} |\, \|v-u\| - \|\phi(v)-\phi(u)\|\, |^p)^{\frac{1}{p}})$, where ϕ is a bijection between the two set $\mathcal{P}_0$ and $\mathcal{P}_1$.

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Robustness to noise interference compared to similarity distillation

Experiment Results

- Better adaptable to unlabeled data compared to other knowledge distillation methods

Table 3: Comparison of different knowledge distillation methods applied on SSCL.

Method	Type	CIFAR10 5%	CIFAR10 25%	CIFAR100 5%	CIFAR100 25%
iCaRL[34]	logits	79.2	78.8	31.3	41.4
Foster[40]	logits	75.0	70.4	24.6	38.8
LUCIR[20]	feature	75.2	74.7	32.0	32.6
Podnet[12]	feature	57.9	69.0	21.4	21.1
R-DFIL[16]	relation	78.5	78.8	34.7	34.2
DSGD[14]	relation	79.1	79.0	35.9	43.1
TopKD[22]	topology	78.7	79.8	35.4	41.9
PsHD	topology	**81.5**	**81.4**	**38.8**	**43.2**

- Stability to noise interference

Table 4: Comparison of distillation methods with Gaussian noise interference. σ is the standard deviation.

σ	Podnet[12]		LUCIR[20]		R-DFCIL[16]		DSGD[14]		TopKD[22]		PsHD	
	BWT↓	ACC↑	BWT↓	ACC↑	BWT↓	ACC↑	BWT↓	ACC↑	BWT↓	ACC↑	BWT↓	ACC↑
0.2	31.8	55.6	21.8	71.5	19.2	77.5	18.1	76.7	19.7	76.5	**14.0**	**78.7**
1.0	44.4	27.9	34.3	57.3	28.2	62.1	27.1	64.2	23.0	67.2	**17.7**	**70.9**
1.2	49.8	34.6	36.4	56.4	26.4	61.8	23.7	64.1	22.8	65.8	**18.3**	**67.8**

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Robustness to noise interference compared to other distillation

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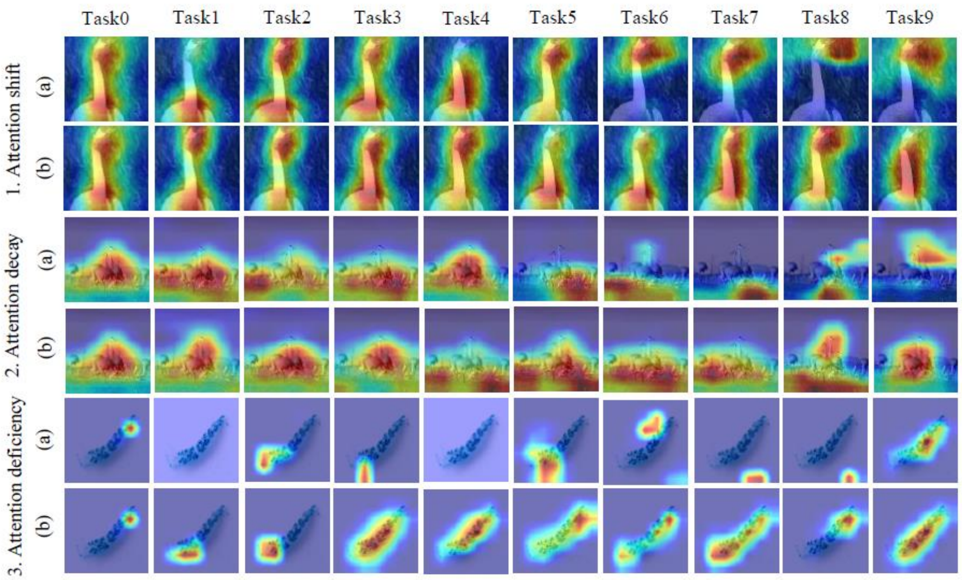
Experiment Results

Ablation Study

Table 5: Ablation study of proposed persistence homology distillation

Method	$\mathcal{L}_{SSL}$	$\mathcal{L}_{hd}$	CIFAR10_5%		CIFAR10_25%		CIFAR100_5%		CIFAR100_25%	
			avg	last	avg	last	avg	last	avg	last
iCaRL	√		83.7	79.2	82.9	78.8	54.2	36.1	58.4	41.1
	√	√	$85.3_{+1.5}$	$80.8_{+1.6}$	$85.4_{+2.6}$	$80.5_{+1.7}$	$56.4_{+2.2}$	$38.8_{+2.7}$	$59.2_{+0.8}$	$42.2_{+1.1}$
DER	√		86.1	81.2	84.9	81.4	57.8	46.3	68.1	57.2
	√	√	$86.2_{+0.1}$	$81.8_{+0.6}$	$87.9_{+3.0}$	$83.4_{+2.0}$	$58.2_{+0.4}$	$47.2_{+0.9}$	$68.3_{+0.2}$	$57.7_{+0.5}$



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Stable evolution under insufficient labeling is achieved

Thanks for your listening

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