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Decoupling Learning and Remembering: a Bilevel Memory Framework with Knowledge Projection for Task-Incremental Learning

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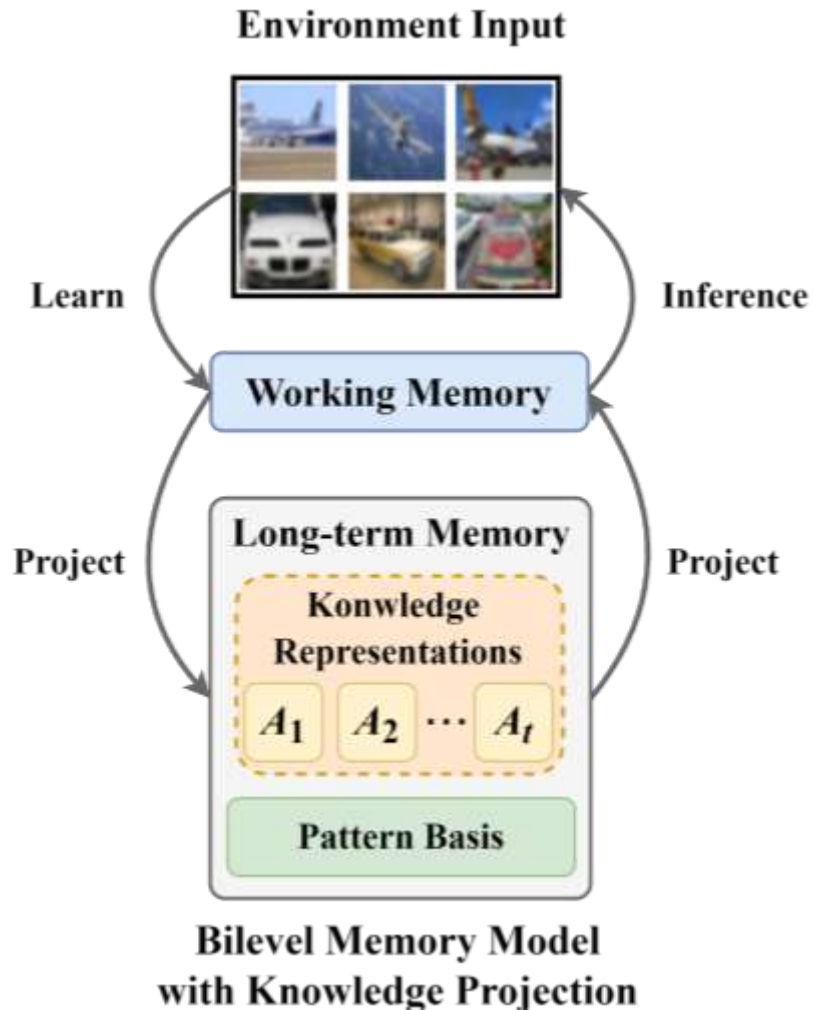
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Overview



Bilevel Memory model with Knowledge Projection (BMKP)

- **Working memory** responsible for new knowledge learning, to ensure **high plasticity**.
- **Long-term memory** in charge of storing learned knowledge, to guarantee **high stability**.
- **Knowledge projection**, project model knowledge of working memory into the compact representation, and then stored into long-term memory, to achieve **high memory efficiency**.

Introduction

- Incremental learning
- Conventional memory-based IL method vs. Multi-level human memory system

Method

- Bilevel memory framework
- Knowledge spaces
- Incremental learning process of BMKP

Experiment

Conclusion

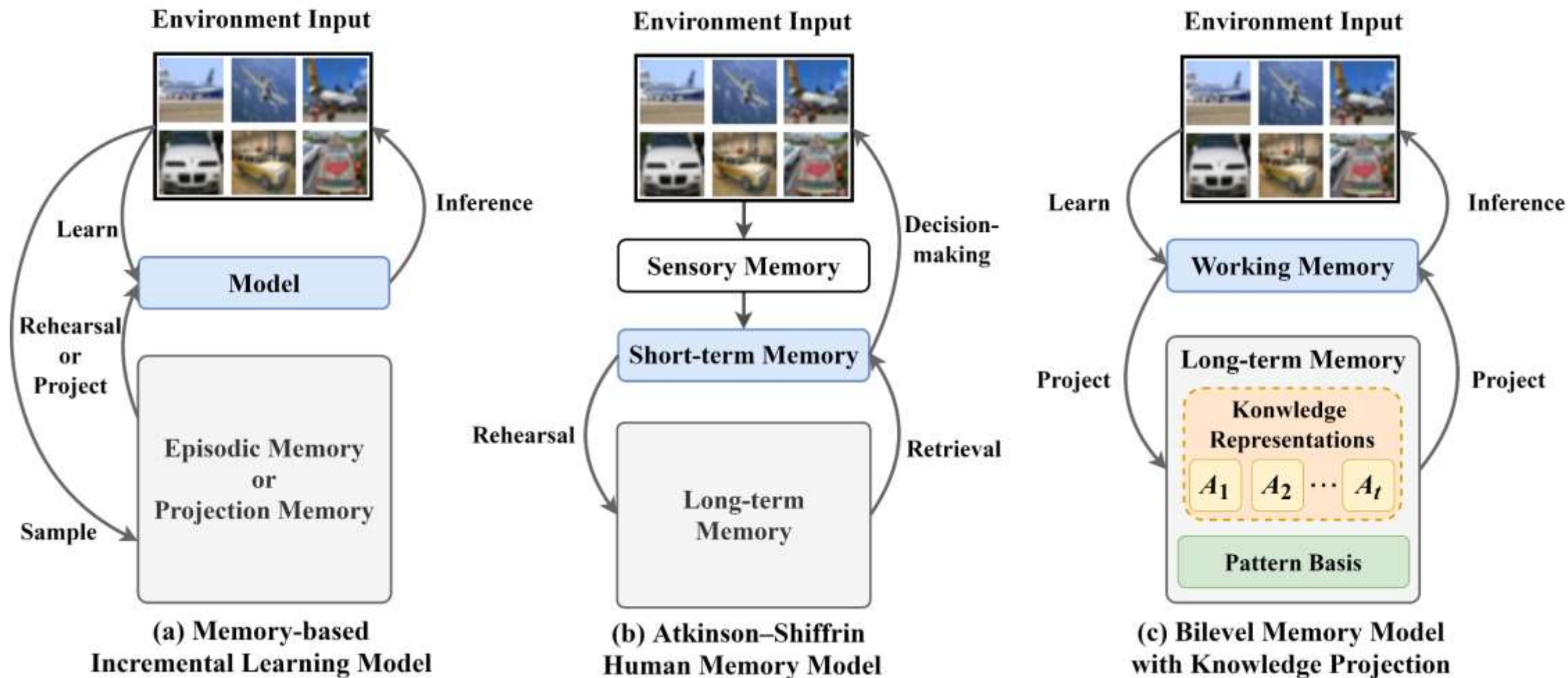
Incremental learning

- The ability to continuously learn new knowledge while keeping the memory of the old knowledge.



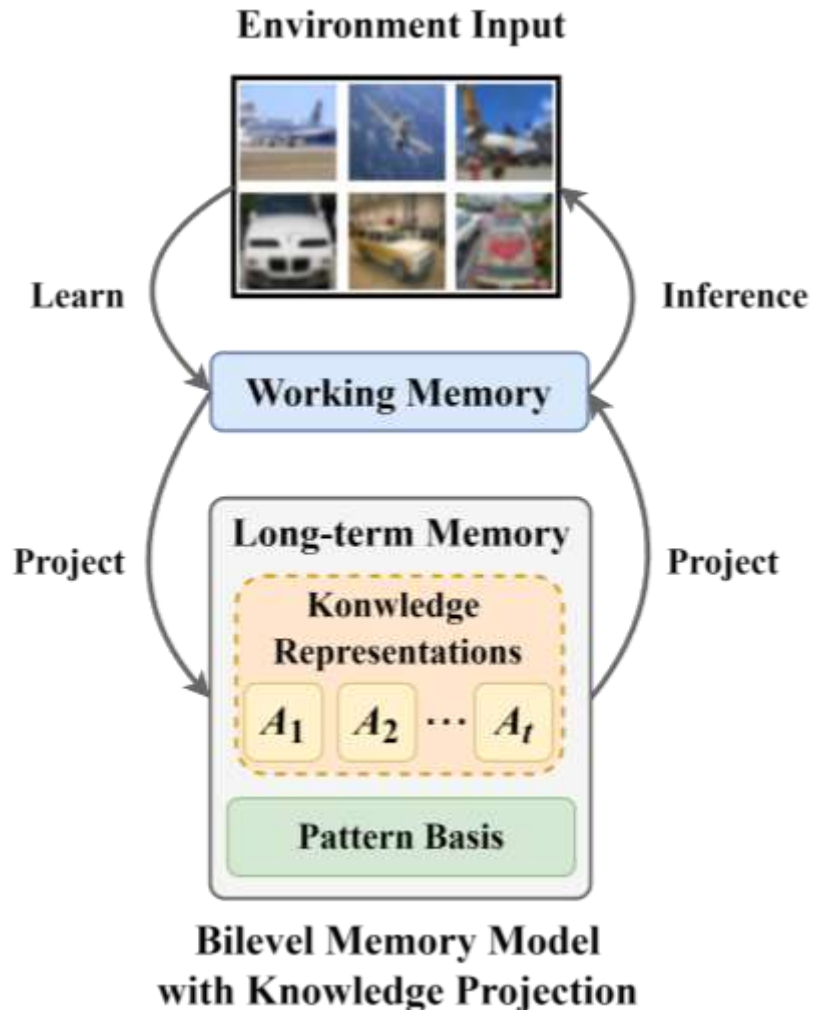


Introduction





Bilevel Memory Framework



Bilevel **M**emory model with **K**nowledge **P**rojection (BMKP)

- **Working memory** responsible for new knowledge learning, to ensure **high plasticity**.
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- **Knowledge projection**, project model knowledge of working memory into the compact representation, and then stored into long-term memory, to achieve **high memory efficiency**.

Knowledge Spaces

Knowledge: the ability to transfer a given input to the expected output.

Parameter Knowledge Space (PKS)

- The Space where the knowledge is represented as the trained parameters.

$$Z^l = W^l X^l$$

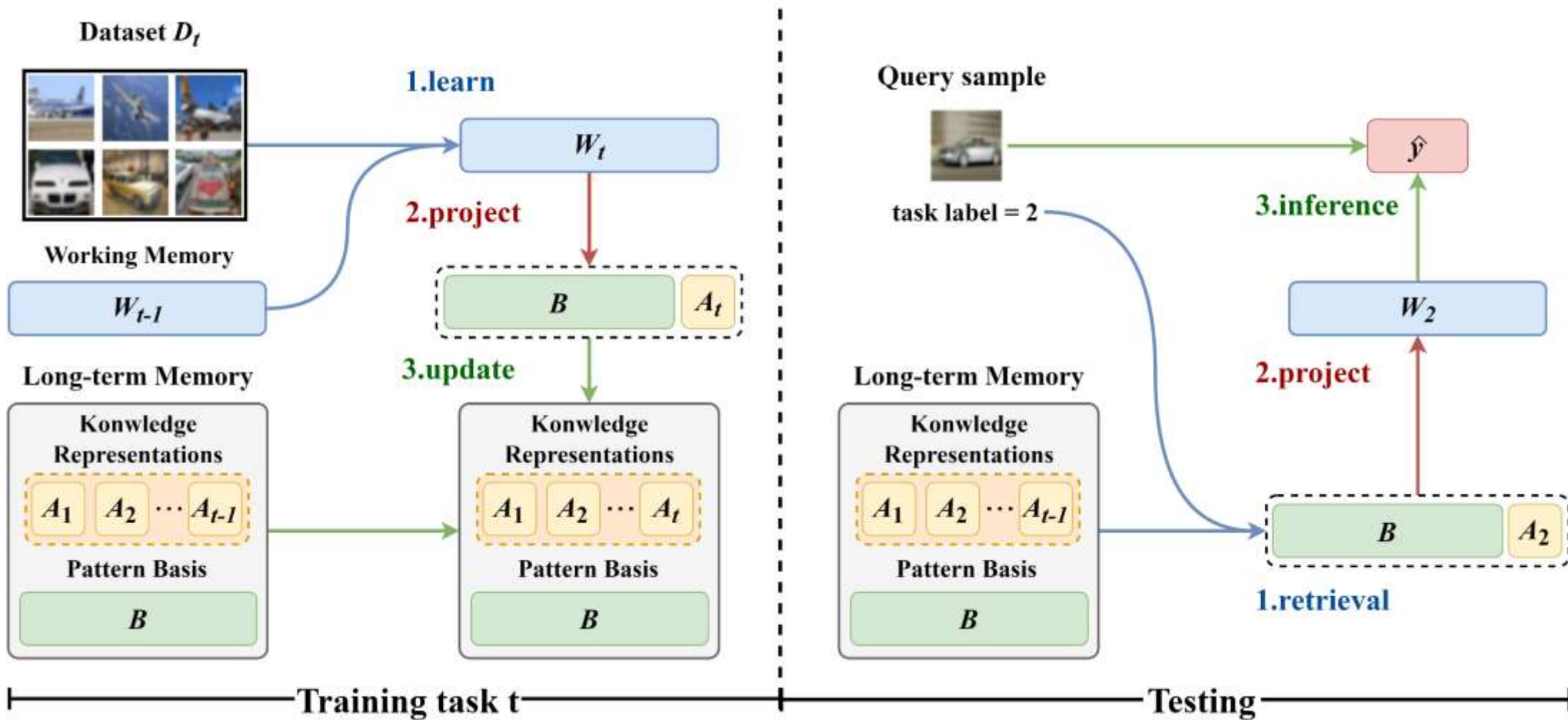
Core Knowledge Space (CKS)

- in which the knowledge can be organized in a quite compact form without loss of performance.

$$\begin{aligned} Z^l &= B^l B^{l\top} Z^l = B^l B^{l\top} W^l X^l \\ &= \hat{W}^l X^l \\ &= B^l A^l X^l, \end{aligned}$$



BMKP Training & Inference



Working Memory Learning

- Following the principle of minimum energy consumption, BMKP encourages the working memory to learn new knowledge with respect to the pattern basis B :

$$L_{reg}(W) = \sum_{l=1}^L \frac{\text{Trace} \left((W^l - \tilde{W}^l)^\top (W^l - \tilde{W}^l) \right)}{\left\| (W^l - \tilde{W}^l)^\top (W^l - \tilde{W}^l) \right\|_1}$$

Where $\tilde{W}^l = B^l B^{l\top} W^l$ denotes the orthogonal projection of W^l into CKS.

- The overall loss for task t learning is:

$$W_t \leftarrow \arg \min_W L_{task}(W, D_t) + \lambda L_{reg}(W)$$

Knowledge Projection

- We first extend CKS with new pattern basis:

$$U_t^l \Sigma_t^l V_t^{l\top} \leftarrow \text{SVD} \left(Z_t^l - B^l B^{l\top} Z_t^l \right)$$
$$B^l \leftarrow \begin{bmatrix} B^l & U_t^{l\top} \end{bmatrix}$$

- Then project knowledge into CKS:

$$A_t^l \leftarrow B^{l\top} W_t^l$$



Long-term Memory Updating

- The knowledge projection may not be perfect since some minor basis are dropped through threshold selection, We introduce a recall mechanism:

$$A_t \leftarrow \arg \min_{A_t} L_{task}(BA_t, D_t)$$



Experiment

Methods	Venue	CIFAR-10	CIFAR-100	Tiny-ImageNet	Average
Joint*	-	98.07	91.18	82.01	90.42
LwF [16]	TPAMI2017	91.91±0.7	63.78±4.3	58.61±1.8	71.43
SI [38]	ICML2017	76.15±2.6	62.21±2.6	60.91±1.3	66.42
DGR [29]	NIPS2017	91.06±7.4	44.53±2.5	-	-
GEM [17]	NIPS2017	85.14±2.1	62.80±2.7	44.66±1.7	64.20
oEWC [27]	ICML2018	64.17±4.8	38.40±1.9	31.91±0.9	44.83
LwM [9]	CVPR2019	78.01±0.8	68.88±0.9	45.57±0.2	64.15
DI [35]	CVPR2020	94.46±0.6	68.43±2.1	66.12±0.9	76.34
DER [3]	NIPS2020	93.13±0.3	73.26±1.3	51.22±1.5	72.54
DER++ [3]	NIPS2020	93.71±0.4	74.86±1.1	53.00±0.4	73.86
DER++ [†] [3]	NIPS2020	93.88±0.5	-	51.91±0.7	-
HAL [4]	AAAI2021	82.34±1.5	43.91±3.6	-	-
PASS [39]	CVPR2021	86.07±0.2	77.30±0.4	62.87±0.4	75.41
GPM [26]	ICLR2021	86.58±0.9	70.93±0.9	59.84±0.2	72.45
GPM [†] [26]	ICLR2021	-	72.48	-	-
Adam-NSCL [33]	CVPR2021	87.23±0.4	65.69±0.2	59.98±0.7	70.97
CLS-ER [2]	ICLR2022	93.53±0.3	72.11±0.5	57.36±0.7	74.33
WSN [12]	ICML2022	92.99±0.4	81.10±0.7	67.50±0.7	80.53
CF-IL [†] [23]	ICLR2022	93.12	-	67.42	-
FAS [22]	ICLR2022	90.89±1.3	70.89±0.6	60.10±0.2	73.96
BMKP (ours)	-	94.49±0.2	79.62±0.8	70.36±0.2	81.49

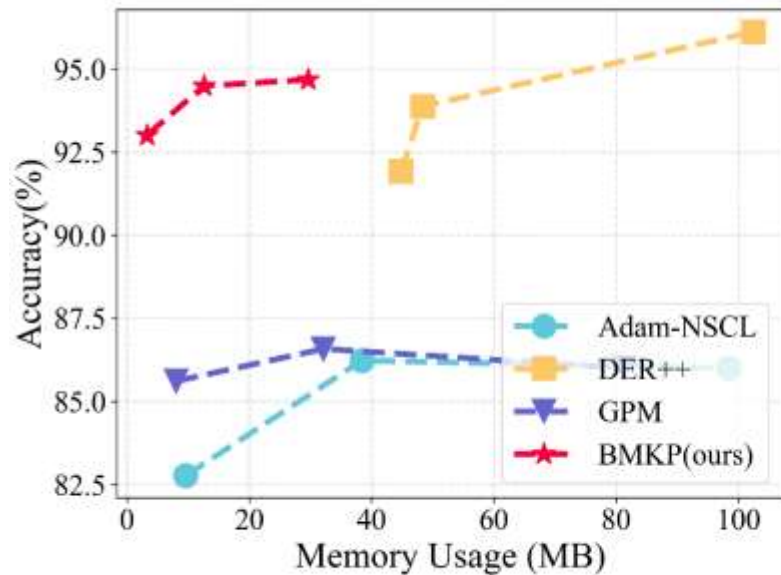


Ablation Study

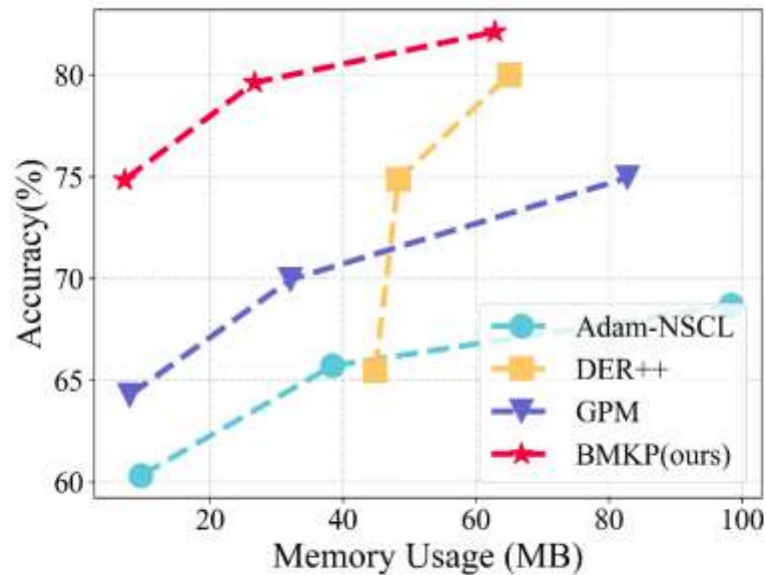
Methods	Split CIFAR-10	Split CIFAR-100	Split Tiny-ImageNet
BMKP w/o basis updating	79.44 ± 2.7	43.00 ± 1.9	28.27 ± 1.1
BMKP w/o retraining	94.07 ± 0.3	78.73 ± 0.6	68.12 ± 0.8
BMKP	94.49 ± 0.2	79.62 ± 0.8	70.36 ± 0.2



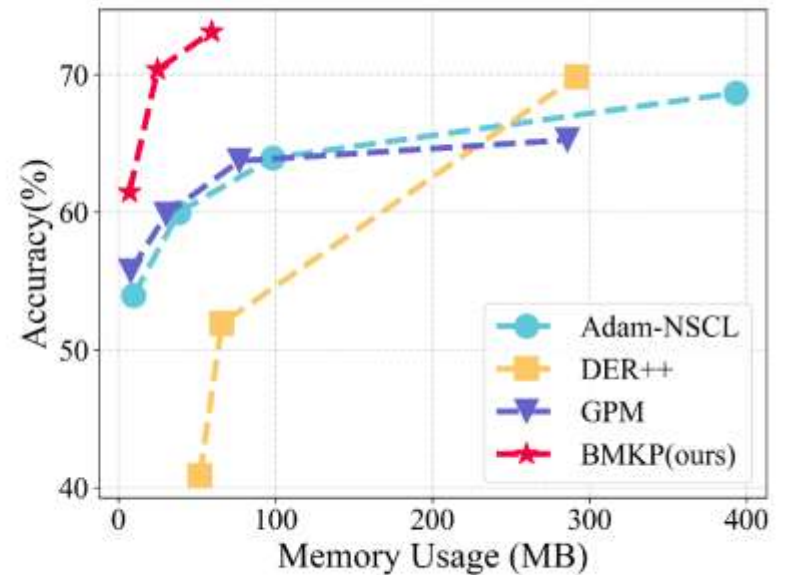
Memory Efficiency Analysis



CIFAR-10



CIFAR-100



Tiny-ImageNet



Conclusion

- 1. Inspired by the multi-level human memory system, we propose a bilevel-memory framework for incremental learning, which benefits from both high plasticity and stability.**
- 2. We propose a knowledge projection process to project knowledge from PKS into compact representation in CKS, which not only improves memory utilization efficiency but also enables forward knowledge transfer for incremental learning.**
- 3. We design a regularizer to encourage the working memory to reuse previously learned knowledge, which enhances both the memory efficiency and the performance of BMKP.**
- 4. The experimental results show that BMKP achieves state-of-the-art performance in most cases with lower memory usage.**

THANKS FOR WATCHING

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The code is available at

<https://github.com/SunWenJu123/BMKP>

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