Random Replaying Consolidated Knowledge in the Continual Learning Model

Guanglu Wang, Xinyue Liu*, Wenxin Liang, Linlin Zong, Xianchao Zhang
Dalian University of Technology, Dalian, China
wgl.dut@hotmail.com, {xyliu, wxliang, llzong, xczhang}@dlut.edu.cn

Abstract

A continual learning (CL) model is designed to solve the catastrophic forgetting problem, which damages the performance of neural networks by overwriting previous knowledge with new knowledge. The fundamental cause of this problem is that previous data is not available when training new data in the CL setting. The memory-based CL methods leverage a memory buffer to address this problem by storing a limited subset of previous data for replay, and most methods of this type adopt random storage and replay strategies. In the human brain, the hippocampus replays consolidated knowledge from the neocortex in a random manner, e.g., random dreaming. Inspired by this memory mechanism, we propose a memory-based method, which replays more consolidated memory data while maintaining the randomness. Our work highlights that random replaying is important for the CL model, which confirms the effectiveness of random dreaming in the human brain.
Keywords: consolidated knowledge; memory-based methods; continual learning; catastrophic forgetting; random replaying

Introduction

Human beings have the ability to continuously learn new knowledge without forgetting old knowledge, which benefits from the complex memory system in the brain and the replay mechanism of experienced knowledge. Neural networks are expected to have the same ability as human beings nevertheless suffer from the notorious catastrophic forgetting problem (Mccloskey & Cohen, 1989; McClelland, McNaughton, & O'Reilly, 1995). The main reason for this problem is that the neural networks train new samples without the participation of the old samples, which leads to the neural networks being more biased towards the new samples and the performance of the old samples becoming worse. Continual learning (CL) is designed to solve this problem in neural networks. In the CL setting, previous data is not available when training new data, which simulates the human learning process.

Various types of CL methods have been proposed to overcome the catastrophic forgetting problem in neural networks (Parisi, Kemker, Part, Kanan, & Wermter, 2019; Mai et al., 2021; Wang, Zhang, Su, & Zhu, 2023). Among these methods, the memory-based CL methods have gained more attention and obtained superior performance compared to other methods (Aljundi, Caccia, et al., 2019; Lin, Zhang, Feng, Li, & Ye, 2023). Inspired by the memory system in the brain, the memory-based CL methods establish an extra memory mechanism to simulate the learning process of the human brain. In the brain, there is a complementary learning system (CLS) theory between the hippocampus and the neocortex, and the CLS highlights that catastrophic forgetting arises when learning takes place too quickly in overlapping representations (McClelland et al., 1995; O'Reilly, Bhattacharyya, Howard, & Ketz, 2014; Russin, Zolfaghar, Park, Boorman, & O'Reilly, 2022). To overcome catastrophic forgetting, the hippocampus exhibits short-term adaptation and allows for the rapid learning of novel knowledge which will be transmitted to the neocortex for its long-term retention (Lange et al., 2019). Dreaming is the result of memory replay when the new learning memory is transferred from the temporary memory to the long-term memory (Zhang, 2005), which can enhance memory consolidation (Wamsley & Stickgold, 2019). Furthermore, the activation-synthesis theory considers that dreams arise from random signals in the brain (A. Hobson, 1992; J. A. Hobson & McCarley, 1977).

Similar to the memory process in the brain, the memory-based CL methods establish a memory buffer to store a limited subset of previous data for replay, which is like the process of dreaming (Chaudhry et al., 2019; Aljundi, Lin, Goujaud, & Bengio, 2019; Aljundi, Caccia, et al., 2019; Caccia et al., 2022). Most methods adopt a random sampling strategy to replay previous data from the memory buffer (Chaudhry et al., 2019; Caccia et al., 2022; Lin et al., 2023), which is consistent with the randomness of dreaming. However, these methods leverage a random strategy to store samples in the memory buffer, which will cause the neural network to miss some important data for consolidating the memory.

Inspired by the memory mechanism in the human brain, we propose a memory-based CL method, which stores consolidated data in the memory buffer and employs a random replay strategy. To this end, we design an indicator to measure the sample consolidation degree by the gap between the maximum prediction probability and the second-largest prediction probability. We conduct extensive experiments to show that the combination of storing consolidated data with the random replay strategy can aid the CL model in inhibiting forgetting, which fits with replaying consolidated knowledge from the neocortex. Furthermore, we try to replay the consolidated memory data directly nevertheless the catastrophic forgetting issue becomes more serious, which shows the necessity of the random sampling strategy in the CL process and verifies the effectiveness of random dreaming in the human brain (A. Hobson, 1992; J. A. Hobson & McCarley, 1977).

*Corresponding author.

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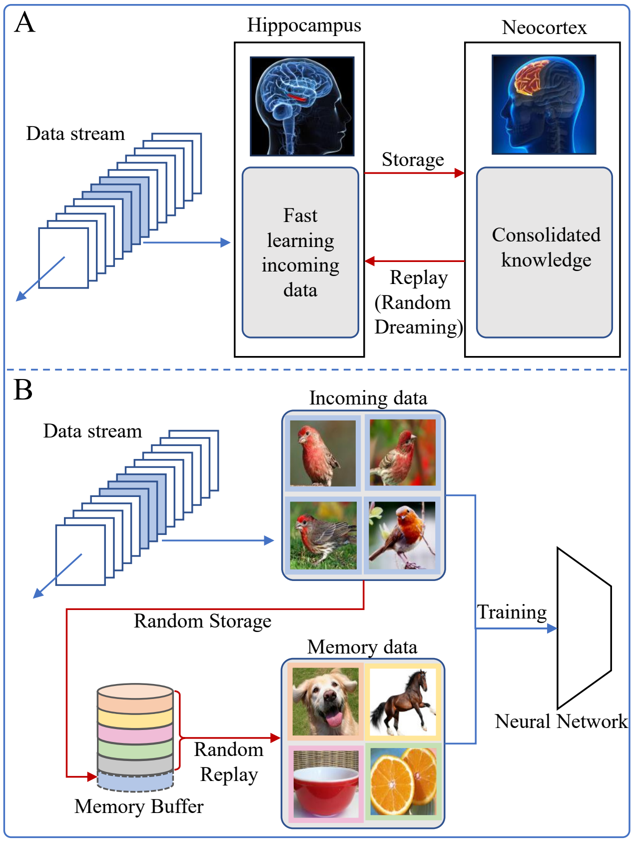

Figure 1: The learning processes of the human brain and the CL model. (A) The human brain learns novel data quickly through the hippocampus and forms consolidated knowledge stored in the neocortex. Meanwhile, the neocortex will replay the stored knowledge by random dreaming to aid the hippocampus learning. (B) The CL model simulates the process of the human brain learning new knowledge. There are two procedures in the buffer, which is the same as the brain memory system between the hippocampus and the neocortex.

We train the neural network model in the online continual learning setting where the model trains each novel data for one epoch. Following the way that the brain learns, the new incoming data will be first learned by the hippocampus to acquire new knowledge, as shown in Figure 1(A). Then the new knowledge will be integrated into consolidated knowledge and stored in the neocortex. In turn, the neocortex replays the consolidated knowledge to help the hippocampus quickly learn new knowledge by the replay manner like random dreaming. In this way, the brain preserves both the plasticity and the stability during learning (i.e., the stability-plasticity dilemma (Zenke, Gerstner, & Ganguli, 2017; Power & Schlaggar, 2017; Lewkowicz, 2014)). The key to solving the stability-plasticity dilemma is the degree to which new knowledge is integrated and adapted and how this adaptation process stabilizes neural activity to prevent the occurrence of catastrophic forgetting (Ditzler, Roveri, Alippi, & Polikar, 2015; Mermillod, Bugaiska, & BONIN, 2013).

To mimic the brain learning style introduced above, the CL model is set to face a never-ending data stream, as shown in Figure 1(B). In particular, the memory-based CL model adds an extra memory buffer to store data observed in the past for replay, like the neocortex. To comply with the principle of limited resources, the memory buffer is restricted to a fixed size, which means that there will be a memory update process (removing some samples from the buffer to absorb new coming samples) when the buffer is full (Rebuffi, Kolesnikov, Sperl, & Lampert, 2017; Zhao, Xiao, Gan, Zhang, & Xia, 2020). During the training phase, the CL model will encounter the incoming data from the data stream and the memory data from the memory buffer. Existing methods propose to employ random strategies in the memory update process and the memory replay process (Chaudhry et al., 2019; Caccia et al., 2022), nevertheless, the random strategies cannot guarantee the replayed samples with consolidated knowledge. Therefore, we investigate the potential for random replaying consolidated samples to alleviate catastrophic forgetting as the coordination between the neocortex and the hippocampus (O'Reilly & Norman, 2002; Kitamura et al., 2017).

Methodology

In the human brain, the neocortex plays an important role in the memory system due to the formation and use of consolidated knowledge (Brodt & Gais, 2020; Moscovitch & Gilboa, 2022). In the CL setting, we argue that the memory buffer should play the same role in helping neural networks overcome catastrophic forgetting. To this end, we propose to design an indicator to score the degree of sample consolidation and explore the role of the consolidated samples in the memory update process and the memory replay process.

Preliminary

This work considers the standard online continual learning setting to solve the classification tasks. In this setting, the data stream is split into multiple tasks, and each task contains novel and unique classes. Concretely, these classes $\{c_1, c_2, \cdots, c_t, \cdots\}$ are arranged in a chronological order, and the memory buffer $\mathcal{M}$ can contain up to M samples. These samples are presented as $\{\mathcal{M}_{\mathbf{x}_1}, \mathcal{M}_{\mathbf{x}_2}, \cdots, \mathcal{M}_{\mathbf{x}_M}\}$, and $\{\mathcal{M}_{\mathbf{y}_1}, \mathcal{M}_{\mathbf{y}_2}, \cdots, \mathcal{M}_{\mathbf{y}_M}\}$ are the corresponding labels, respectively. When training, the data stream provides new streaming data to the agent for learning novel class information. Meanwhile, the memory buffer replays one-batch buffered data to the agent to alleviate catastrophic forgetting.

When the buffer is full, it is necessary to remove some buffered samples to make room for new ones because the buffer is limited and needs to absorb new class data to prevent forgetting in future training. Most memory-based CL methods will select some of these samples by the traditional reservoir sampling method (Vitter, 1985) which can ensure the random sampling operation with the uniform distribution. Here, we advocate retaining the consolidated samples for replay. Furthermore, we adopt the same supervised loss function as the method of ER-ACE (Caccia et al., 2022).

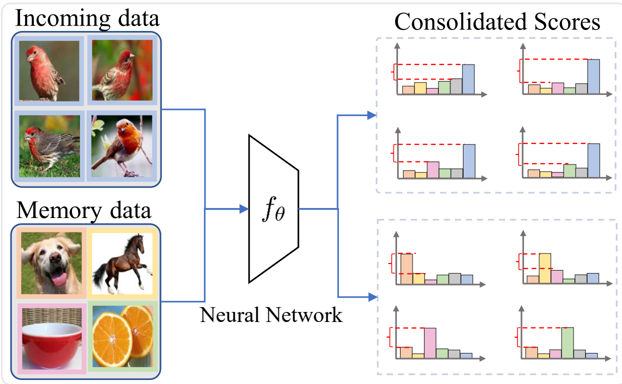

Figure 2: The presentation of consolidated scores. We use the length of the red bracket to represent the degree of the sample consolidation, which measures the gap between the largest prediction probability and the second-largest prediction probability.

Sample Consolidation Degree Measurement

It is a challenge to measure the degree of consolidation for a sample. In a neural network, viewing that the prediction vector of probabilities can reflect the prediction confidence for each possible class, we attempt to excavate the information contained in the prediction vector. The class corresponding to the maximum prediction probability in the vector is regarded as the predicted class, and the second-largest prediction probability is the greatest threat to the maximum one. To this end, we leverage the gap between the maximum prediction probability and the second-largest prediction probability to express the value of consolidation for this sample, as shown in Figure 2. A large gap will prevent the sample from being affected by other class samples, thus protecting the decision boundary of the sample class and alleviating catastrophic forgetting. Thus, we get the consolidated scores of a sample $\mathbf{x}$ as follows:

$$\mathbf{Score}(\mathbf{x}) = f_\theta(\mathbf{x})[0] - f_\theta(\mathbf{x})[1], \tag{1}$$

where f is the prediction model parameterized by θ, $f(\cdot)[0]$ represents the maximum number and $f(\cdot)[1]$ is the second-largest number in the prediction vector $f(\cdot)$.

Memory Update Process

The operation of memory update occurs when the memory buffer is full. Most memory-based methods apply reservoir sampling (Vitter, 1985) directly to update the memory buffer. Reservoir sampling is a classical random sampling algorithm for drawing a fixed-size subset from streaming data in a single pass, which applies to the setting of online continual learning. Concretely, we receive a stream of data S with N samples being observed, and the data volume is still increasing. There is a reservoir that can contain up to M samples. Reservoir sampling aims to select a subset from S in a single pass with $\mathrm{M} \ll \mathrm{N}$, and it has been proven that each streaming sample has the same probability of being stored in the reservoir. Due to the sampling randomness in the streaming data, most memory-based methods utilize this sampling method to update the memory buffer, nevertheless, these methods have not noticed that such uniform sampling will mistakenly miss valuable samples which are beneficial for overcoming catastrophic forgetting such as consolidated samples.

Reservoir sampling can keep the randomness during the whole memory update process. How to combine this sampling theory with the consolidated samples becomes a challenge. We propose a sampling strategy to select the consolidated samples based on reservoir sampling. First, reservoir sampling randomly selects new coming data $\mathbf{x}_t$, $\mathbf{y}_t$ and determines to replace the buffered sample $\mathcal{M}_{\mathbf{x}_j}$, $\mathcal{M}_{\mathbf{y}_j}$. Unlike a direct random replacement by reservoir sampling, we aim to select the low-value consolidated sample for the replacement. Second, we sample a candidate subset $X_{c_{\mathbf{x}_j}}$ from the buffer where the candidates have the same label as $\mathcal{M}_{\mathbf{y}_j}$. Then, we calculate the consolidated scores for the candidates as per Eq.(1) and select the sample with the least value to be replaced as follows:

$$\mathcal{M}_{\mathbf{x}_{replace}} = \underset{\mathcal{M}_{\mathbf{x}_k} \in X_{c_{\mathbf{x}_j}}}{\operatorname{argmin}} \mathbf{Score}(\mathcal{M}_{\mathbf{x}_k}). \tag{2}$$

Thus, we replace buffered data $\mathcal{M}_{\mathbf{x}_{replay}}$, $\mathcal{M}_{\mathbf{y}_{replay}}$ ($\mathcal{M}_{\mathbf{y}_{replay}} = \mathcal{M}_{\mathbf{y}_j}$) with $\mathbf{x}_t$, $\mathbf{y}_t$. The above operations can ensure the randomness of the memory update process and the retention of consolidated samples.

Memory Replay Process

When the CL model encounters the incoming data, the memory buffer provides the historical data to the model with the incoming data together, which is the main strategy to mitigate catastrophic forgetting. Most memory-based methods use a random strategy to replay data from the memory buffer, like the manner of random dreaming. Each sample has the same probability of being selected to participate in the replay process as follows,

$$\mathcal{M}_{\mathbf{x}_{replay}} \overset{\frac{1}{\mathrm{M}}}{\sim} \{\mathcal{M}_{\mathbf{x}_1}, \mathcal{M}_{\mathbf{x}_2}, \cdots, \mathcal{M}_{\mathbf{x}_\mathrm{M}}\}. \tag{3}$$

where $\frac{1}{\mathrm{M}}$ is the probability of the uniform sampling from the memory buffer and $\mathcal{M}_{\mathbf{x}_{replay}}$ represents the sample to be replayed. In the experiments, we test the effectiveness of replaying the consolidated samples and the maximally interfered samples (MIR) (Aljundi, Caccia, et al., 2019).

Implementation Details

To validate the performance of retaining the consolidated samples and random replay, we evaluate the proposed method on various data streams with three metrics, Average Accuracy (Acc), Average Anytime Accuracy (AAA) (Caccia et al., 2022) and training time, compared to several excellent memory-based CL baselines. In Acc, $a_{T,t}$ is the accuracy evaluated on the held-out test set of task t after training the network from task 1 to T.

$$\mathrm{Acc} = \frac{1}{T}\sum_{t=1}^{T} a_{T,t}. \tag{4}$$

Table 1: Acc and AAA across baselines under various memory sizes on **Split Cifar10**, and each number is the mean of 15 experiments. The best results are marked in bold.

Methods	M=20			M=50			M=200		
	Acc	AAA	Time	Acc	AAA	Time	Acc	AAA	Time
ER	19.3±0.9	41.0±1.7	67	20.3±1.5	42.8±1.8	68	28.1±2.2	51.3±2.5	69
MIR	19.7±0.9	41.4±1.3	123	21.5±1.6	44.1±1.4	124	30.7±2.5	53.2±2.1	125
GSS	18.4±0.5	39.7±1.0	231	18.7±0.6	39.9±0.9	322	25.2±1.8	44.7±1.3	517
ASER	19.5±0.6	41.7±1.1	102	19.3±1.1	40.6±1.2	115	26.0±2.7	43.7±1.8	149
DER	19.8±1.2	39.6±1.7	84	22.4±1.7	42.2±2.2	85	30.6±3.1	48.1±1.4	85
AML	23.9±2.7	46.0±2.4	97	30.4±1.8	51.5±1.7	98	41.7±1.6	58.4±1.7	99
ACE	25.2±3.6	49.0±2.2	66	33.2±2.2	53.4±1.7	67	41.7±2.8	59.1±1.6	67
Ours	**27.2±3.5**	**50.3±2.0**	67	**34.4±3.1**	**54.6±1.7**	68	**43.0±1.6**	**59.7±1.7**	71

Table 2: Acc and AAA on **Split Cifar100**.

Methods	M=500		M=2000	
	Acc	AAA	Acc	AAA
ER	9.3±0.7	17.3±0.9	14.5±1.0	22.0±0.9
MIR	9.1±0.8	17.7±0.8	14.7±1.2	22.4±0.7
GSS	8.8±0.8	17.4±0.7	13.1±0.9	20.6±0.5
ASER	11.2±0.8	19.2±0.7	16.4±1.4	23.6±0.6
DER	5.8±0.3	12.3±0.6	13.7±0.8	20.8±0.9
AML	12.8±0.7	20.6±0.8	17.2±1.0	23.6±0.8
ACE	14.6±0.8	22.9±0.8	19.2±0.8	26.3±0.8
Ours	**16.0±0.8**	**23.7±0.9**	**20.5±0.8**	**27.0±0.7**

Table 3: Acc and AAA on **Split Mini-ImageNet**.

Methods	M=500		M=2000	
	Acc	AAA	Acc	AAA
ER	7.8±0.6	16.3±0.7	13.4±1.6	20.4±0.8
MIR	8.0±0.5	16.7±0.6	13.8±2.3	20.8±0.9
GSS	7.3±0.9	16.4±0.8	13.8±1.3	20.4±1.0
ASER	8.6±0.8	16.4±0.5	12.3±1.0	19.6±0.9
DER	4.3 ±0.5	10.9 ±0.4	13.1±0.7	19.5 ±1.0
AML	9.6±1.0	18.6±0.8	14.4±2.0	22.5±0.9
ACE	12.8±1.0	21.9±1.1	18.8±1.6	25.9±0.7
Ours	**14.0±0.8**	**22.4±1.0**	**19.7±1.3**	**26.0±1.0**

In our work, we report the AAA (Caccia et al., 2022), which can measure how well the model performed over the learning experience. We define the Anytime Accuracy AA_k at time k as the average accuracy on the test sets of all distributions seen up to time k. When the learning experience lasts T steps, then AA_T is equivalent to the final accuracy. The formulation of AAA is as follows:

$$\mathrm{AAA} = \frac{1}{T}\sum_{t=1}^{T}\mathrm{AA}_t. \tag{5}$$

The dataset settings are split into balanced data streams and imbalanced data streams. The balanced data streams are as follows: **Split Cifar10** splits the Cifar10 dataset (Krizhevsky, 2009) into 5 different tasks with two non-overlapping classes. **Split Cifar100** and **Split Mini-ImageNet** divide the Cifar100 dataset (Krizhevsky, 2009) and the Mini-ImageNet dataset (Vinyals, Blundell, Lillicrap, Kavukcuoglu, & Wierstra, 2016) into 10 disjoint tasks with 10 different classes per task. The imbalanced data streams are as follows: **Blurry Cifar10** consists of 5 tasks, and each task keeps 90% of the data for each task and introduces 10% of data from the other tasks following the works in (Aljundi, Lin, et al., 2019; Caccia et al., 2022). Furthermore, we introduce **Imbalanced Cifar100** with the same setting as (Lange & Tuytelaars, 2021), where the data stream S comprises significantly more data in task T_i, denoted by $S(T_i)$. **Imbalanced Cifar100** uses a 20-task sequence and allocates 2500 samples for T_i and 1000 samples for other tasks ($i \in \{1,5,10,15,20\}$).

We focus our evaluation on the memory-based CL methods, due to their outstanding performance than other approaches in the online continual learning setting. We consider the following baselines: ER (Chaudhry et al., 2019), GSS (Aljundi, Lin, et al., 2019), MIR (Aljundi, Caccia, et al., 2019), ASER (Shim et al., 2020), ER-AML (AML for short) (Caccia et al., 2022), ER-ACE (ACE for short) (Caccia et al., 2022) and DER (Buzzega, Boschini, Porrello, Abati, & Calderara, 2020). All of these methods train the model with a single pass through the data stream. Similar to (Chaudhry et al., 2019; Shim et al., 2020; Lopez-Paz & Ranzato, 2017), we employ the neural networks of reduced ResNet18 and ResNet34 to validate these baselines. All methods use the SGD optimizer to update the parameters with a learning rate of 0.1 following (Shim et al., 2020; Caccia et al., 2022). The sizes of the incoming batch and the memory batch are set to 10, and all results are the average values of 15 runs.

Results

We conduct extensive experiments on balanced data streams, imbalanced data streams, the longer task and the deeper neural network. We also explore various combination methods in the memory update process and the memory replay process.

Results on Balanced Data Streams

Split Cifar10. To evaluate the performance of our proposed methods on Split Cifar10, we measure Acc and AAA in our experiments. We set the memory size as 20, 50 and 200, and each class can averagely store 2, 5 and 20 samples. Table 1 shows the results of these three metrics, and we find that our proposed method outperforms the state-of-the-art (SOTA) baselines in the Acc and AAA metrics with various memory

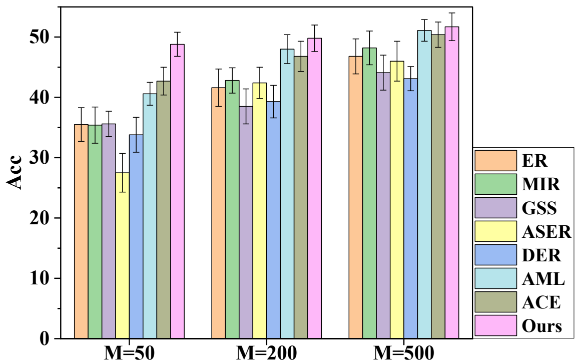

Figure 3: Acc of **Blurry Cifar10**.

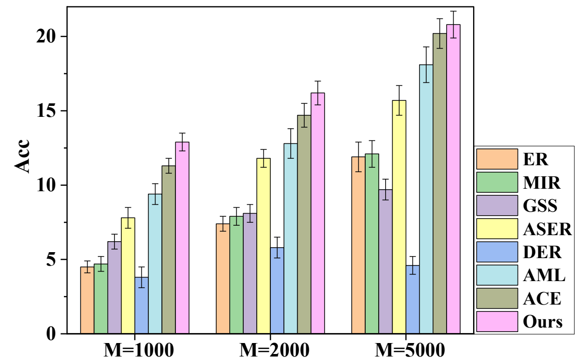

Figure 5: Acc of 50 tasks on **Split Cifar100**.

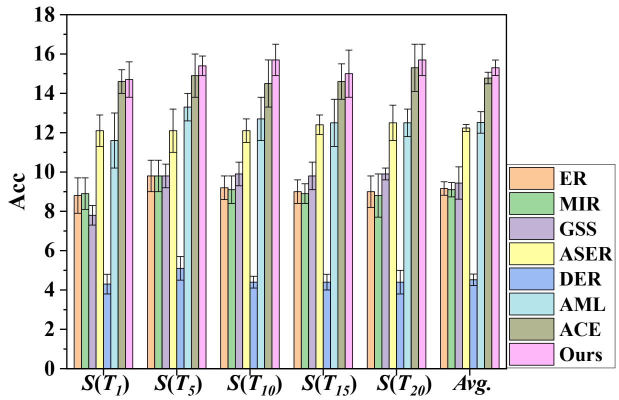

Figure 4: Acc of **Imbalanced Cifar100**.

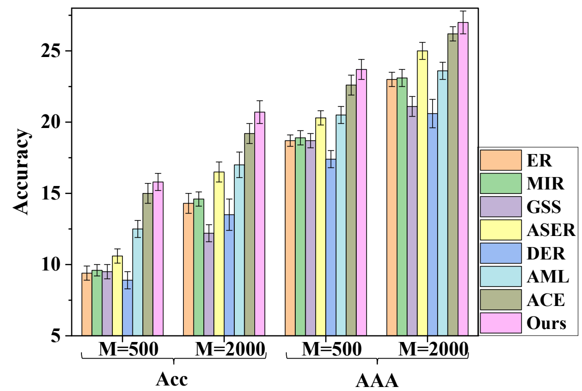

Figure 6: Acc and AAA on ResNet34 with **Split Cifar100**.

sizes, which demonstrates the effectiveness of our proposed method. Furthermore, ER, ACE and our proposed method consume less training time than other baselines, which proves that our proposed method is efficient.

Split Cifar100. To validate the performance on the dataset with more classes, we show the results on Split Cifar100, as shown in Table 2. The memory sizes are set as 500 and 2000 respectively. Our method achieves the SOTA performance on the metrics of Acc and AAA.

Split Mini-ImageNet. We present the results on Split Mini-ImageNet in Table 3. With the same memory sizes as Split Cifar100, our method outperforms the SOTA performance.

Results on Imbalanced Data Streams

Blurry Cifar10. Similar to the settings in (Aljundi, Lin, et al., 2019; Caccia et al., 2022), we explore the scenario where there are no clear task boundaries in the data stream, which is a more practical setting. As introduced earlier, we keep the majority of the examples for one task while we randomly swap a small percentage of the examples with other tasks. Note that the data distribution in one task is non-i.i.d. due to the imbalanced amount of classes. As shown in Figure 3, our method outperforms other methods by large margins with various memory sizes, which illustrates that our method is more applicable to this realistic scenario.

Imbalanced Cifar100. In the imbalanced data streams, the agent faces lopsided amounts of samples in different tasks. Figure 4 shows the results containing 5 variations with various online continual learning approaches, and our method outperforms other baselines in most variations and achieves the best results on different data streams.

Results on the Longer Task

The dataset in the CL setting is usually divided into 5 tasks or 10 tasks. To test the performance of our method on more tasks, we set a longer sequence of tasks. As shown in Figure 5, we show 50-task sequence training modes on Split Cifar100, where there are 100 classes, and each task has two classes. From the results, we can conclude that our method outperforms the baselines under various memory sizes.

Results on the Deeper Neural Network

To verify the performance of these methods on the other model, we conduct experiments on the model of ResNet34. As shown in Figure 6, we conduct experiments on Split Cifar100. The memory sizes are set as 500, 2000 for this dataset. From the results in the table, we can observe that our method achieves the SOTA performance on the metrics of Acc and AAA with different memory sizes.

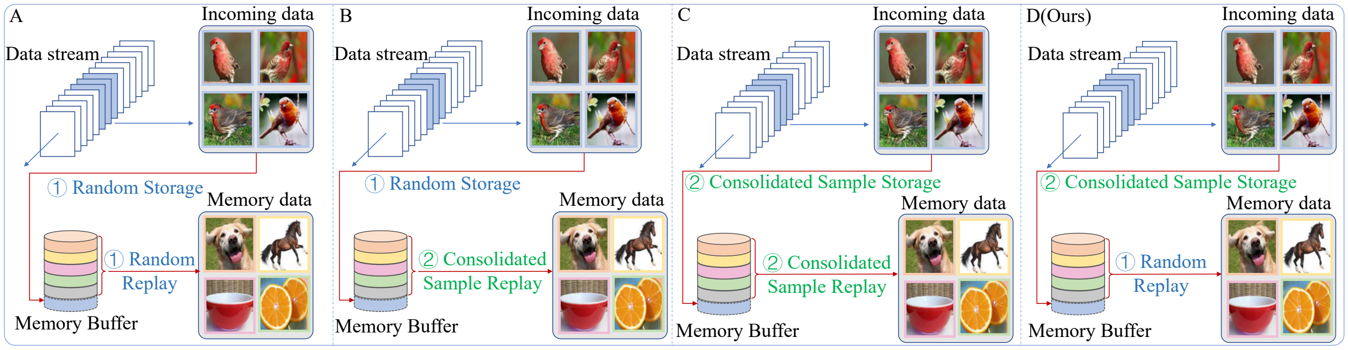

Figure 7: Four combination methods about ①random operations (random storage and random replay) and ②consolidated sample operations (consolidated sample storage and consolidated sample replay).

Table 4: Acc and AAA on **Split Cifar10**.

Methods	M=50		M=200	
	Acc	AAA	Acc	AAA
A	33.2±2.2	53.4±1.7	41.7±2.8	59.1±1.6
B	25.3±3.0	48.6±2.3	30.7±3.2	52.3±2.0
C	25.5±3.1	49.0±2.7	31.2±2.2	51.7±2.3
D(Ours)	**34.4±3.1**	**54.6±1.7**	**43.0±1.6**	**59.7±1.7**

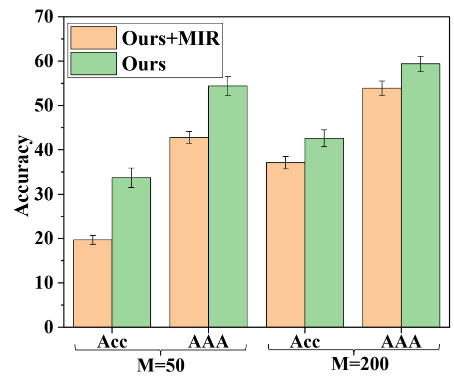

Figure 8: Acc and AAA on **Split Cifar10**.

Discussion

The memory-based CL model overcomes catastrophic forgetting by employing the memory buffer to replay previous data. There are two strategies for the memory buffer, memory update and memory replay, just like the brain's memory formation between the hippocampus and the neocortex (Winocur, Moscovitch, & Bontempi, 2010; Brodt et al., 2016). The neocortex stores consolidated knowledge and replays the knowledge to help the hippocampus learn new knowledge quickly. Random dreaming is an important replay manner that can consolidate knowledge when human beings are sleeping (Hudachek & Wamsley, 2023; Ataei et al., 2023). We can conclude that random dreaming and consolidated knowledge are two key factors for the brain to alleviate forgetting. Therefore, we simulate these two factors on the memory buffer and combine them in four ways to explore the effectiveness of overcoming catastrophic forgetting in the CL model, as shown in Figure 7. "A" employs random storage and random replay strategies and shows the random operations. "B" leverages the random storage strategy and the consolidated sample replay strategy which selects the most consolidated samples from the memory buffer for replay. "C" uses the consolidated sample storage strategy and the consolidated sample replay strategy. "D" is our proposed method which utilizes the consolidated sample storage and random replay strategy like the neocortex memory mechanism.

We conduct experiments on Split Cifar10 to validate the performance on the above four combinations in Table 4. Overall, the performance of "A" and "D" is better than "B" and "C", indicating that the random replay operation is more effective than the consolidated sample replay operation and further verifying the importance of random dreaming in overcoming forgetting. By comparing the results between "A" and "B", we can see that the consolidated sample replay operation is the main reason for the performance degradation, which demonstrates that the consolidation sample selection is not suitable for the memory replay process. We can also obtain a similar conclusion that using random replay is better than consolidated sample replay by comparing the results of "C" and "D". Besides, based on the performance of "A" and "D", we find that the consolidated sample strategy contributes to improving the CL model. "D" is our proposed method and achieves the best performance, which demonstrates the superiority of the combination of the consolidated sample storage and the random replay, and also confirms the effectiveness of the neocortex preservation of consolidated samples and random dreaming in the human brain.

Furthermore, to evaluate the performance of our proposed method with the other replay strategy (e.g., MIR (Aljundi, Caccia, et al., 2019)), we demonstrate the results on Split Cifar10 in Figure 8. We find that the performance decreases on both metrics after the combination. This phenomenon shows that the combination of the consolidated sample storage and the MIR replay strategy has no effect. Instead, the MIR replay strategy is inhibiting the performance of our method, which highlights the importance of random replay in our method.

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