# MYGO: MEMORY YIELDING GENERATIVE OFFLINE-CONSOLIDATION FOR LIFELONG LEARNING SYSTEMS

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## **ABSTRACT**

Continual or Lifelong Learning aims to develop models capable of acquiring new knowledge from a sequence of tasks without catastrophically forgetting what has been learned before. Existing approaches often rely on storing samples from previous tasks (experience replay) or employing complex regularization terms to protect learned weights. However, these methods face challenges related to data privacy, storage limitations, and performance degradation when tasks are dissimilar. To address these challenges, we introduce MyGO (Memory Yielding Generative Offline-consolidation), a novel lifelong learning framework inspired by the biological wake-sleep cycle. During the "wake" phase, the system rapidly learns a new task and trains a compact generative model (Generative Memory, G-mem) to capture its data distribution. During the "sleep" phase, the system enters an offline state, using all learned G-mem models to generate pseudo-data ("dreams") and consolidate new and old knowledge into a core feature extractor via knowledge distillation. This approach obviates the need to store any raw data, retaining only compact generative models, which offers significant advantages in privacy and storage efficiency. We evaluate MyGO on computer vision (Split-MNIST) and natural language processing (Split-AG News) benchmarks, comparing it against a sequential finetuning baseline. The results demonstrate that MyGO significantly mitigates catastrophic forgetting and maintains high average accuracy across tasks, proving the framework's effectiveness and domaingenerality.

**Keywords** Lifelong Learning · Continual Learning · Catastrophic Forgetting · Generative Models · Knowledge Distillation

## 1 Introduction

Artificial intelligence systems, particularly deep neural networks, have achieved superhuman performance on a wide array of specific tasks. A fundamental limitation of these models, however, is their static learning paradigm. Once trained on a task, they tend to forget previously acquired knowledge when subsequently trained on a new one—a phenomenon known as catastrophic forgetting [McCloskey and Cohen, 1989]. In contrast, humans can learn new skills and information continuously without easily discarding past knowledge. Emulating this ability for lifelong learning is crucial for building more general and adaptive AI systems that can thrive in a dynamic world.

Traditional solutions to catastrophic forgetting are broadly categorized into three families:

- 1. **Replay-based Methods:** These methods store a subset of raw data from past tasks and interleave it with new data during training [Rebuffi et al., 2017]. While effective, this approach introduces data privacy risks and can be prohibitive in terms of storage.
- 2. **Regularization-based Methods:** These methods add a regularization term to the loss function that penalizes changes to weights deemed important for previous tasks [Kirkpatrick et al., 2017]. This avoids storing data but may provide insufficient constraints to preserve knowledge over long task sequences.

3. **Parameter Isolation Methods:** These approaches allocate a dedicated set of parameters for each new task, effectively preventing interference [Rusu et al., 2016]. However, this leads to a model size that grows linearly with the number of tasks, limiting scalability.

Inspired by memory consolidation theories in neuroscience [Diekelmann and Born, 2010], we propose the MyGO framework to overcome the limitations of existing methods. MyGO employs a two-phase "wake-sleep" process for efficient incremental learning and offline consolidation. During the "wake" phase, the model focuses on learning the specifics of a new task while simultaneously training a task-specific generative model to "remember" the data distribution. In the "sleep" phase, the model utilizes these generative models to create "dream" data. Through knowledge distillation [Hinton et al., 2015], knowledge from new task "dreams" is integrated with replayed knowledge from old task "dreams," thereby updating a unified, generalized feature representation.

Our main contributions are as follows:

- We propose MyGO, a novel, biologically-inspired lifelong learning framework that mitigates catastrophic forgetting through a wake-sleep cycle and generative memory replay.
- MyGO operates without storing raw data, retaining only lightweight generative models, thus addressing privacy and storage concerns.
- We validate the effectiveness and versatility of MyGO across two distinct modalities: computer vision (CV) and natural language processing (NLP).
- Our empirical analysis clearly demonstrates that MyGO significantly preserves performance on past tasks compared to a sequential fine-tuning baseline, which suffers from severe forgetting.

## 2 The MyGO Framework

The MyGO (Memory Yielding Generative Offline-consolidation) architecture consists of two primary components: a core contextual model (Neocortex Net,  $M_{ctx}$ ) and a series of task-specific Generative Memories ( $G_{mem}$ ).

- Neocortex Net  $(M_{ctx})$ : This model comprises a shared feature extractor ('features') and a dynamically expanding set of classification heads ('classifiers'). The shared extractor is designed to learn a transferable representation across all tasks. Each task is assigned a separate, lightweight classification head for its specific decision-making.
- Generative Memory ( $G_{mem}$ ): Each task t is associated with a distinct generative model,  $G_{mem}^{(t)}$ . Its purpose is to learn and replicate the input data distribution of task t. In our implementation, we use a Conditional Generative Adversarial Network (GAN) [Mirza and Osindero, 2014] that can generate pseudo-data conditioned on class labels.

The learning process in MyGO revolves around a wake-sleep cycle, which is triggered upon the arrival of a new task.

#### 2.1 Wake Phase

When a new task t is introduced, the system enters the "wake" phase. The goal is to rapidly acquire new knowledge and prepare for future consolidation. This phase involves two parallel processes:

**Task-Specific Knowledge Acquisition** First, the parameters of the shared feature extractor in  $M_{ctx}$  are frozen to prevent new learning from interfering with the established knowledge base. A new classification head,  $h_t$ , is added for task t. Using only the data from the current task, this new head is trained with a relatively high learning rate ('LR\_FAST'). This process represents the system learning to solve a new problem based on its existing feature representations.

Generative Memory Formation Concurrently, an independent GAN, consisting of a generator  $G_{mem}^{(t)}$  and a discriminator  $D_{mem}^{(t)}$ , is trained on the data of task t. After training, the generator is capable of capturing the task's data distribution. The discriminator is then discarded, and the compact generator  $G_{mem}^{(t)}$  is stored as the "memory" for task t. For NLP tasks, we generate feature vectors from the embedding space rather than raw text to simplify the generative process.

At the end of the wake phase, we obtain a state dictionary for the optimized task head,  $M_{hpc\_state\_dict}$ , and a generator,  $G_{mem}^{(t)}$ , that can represent the new task's data.

## 2.2 Sleep Phase

After acquiring the new task's specifics, the system transitions to the "sleep" phase for offline knowledge consolidation. The objective is to integrate the new knowledge (from task t) with old knowledge (from tasks 1, ..., t-1) into the shared feature extractor  $M_{ctx}$ .

**Teacher Model Creation** A temporary "teacher" model,  $Teacher\_M_{ctx}$ , is created by duplicating the current  $M_{ctx}$  and loading the weights of the newly trained head  $h_t$  from the wake phase. This teacher model represents an "ideal" state that has mastered the new task without forgetting previous ones.

**Generative Replay (Dreaming)** A generator is randomly selected from the set of all learned memories,  $\{G_{mem}^{(1)},...,G_{mem}^{(t)}\}$ . This generator is then used to produce a batch of pseudo-data ("dreams"), which mimics the data distribution of the corresponding task i.

**Knowledge Distillation** The generated pseudo-data is fed into both the "teacher" model and the "student" model (the  $M_{ctx}$  to be updated). The Mean Squared Error (MSE) loss is computed between the logits produced by the two models:

$$\mathcal{L}_{distill} = \frac{1}{N} \sum_{k=1}^{N} (z_{teacher}^{(k)} - z_{student}^{(k)})^2$$
 (1)

where  $z_{teacher}$  and  $z_{student}$  are the output logits from the teacher and student models, respectively. This distillation loss drives the student to emulate the teacher's behavior. The entire student model  $M_{ctx}$  is then updated using this loss with a low learning rate ('LR\_SLOW'). This slow, iterative update process consolidates new and old knowledge into a more robust shared representation, effectively mitigating catastrophic forgetting.

## 3 Experimental Setup

We evaluated the MyGO framework in two representative domains: computer vision and natural language processing. We chose sequential fine-tuning as our baseline, as it most clearly demonstrates the problem of catastrophic forgetting.

#### 3.1 Datasets

- **Split-MNIST** (**CV**): The standard MNIST dataset of handwritten digits (10 classes) was divided into 5 sequential tasks, with each task comprising 2 distinct classes (e.g., Task 1: 0, 1, Task 2: 2, 3, etc.).
- Split-AG News (NLP): The AG News dataset, which contains 4 classes of news articles, was split into 2 sequential tasks, each containing 2 classes.

#### 3.2 Model Architectures

- CV Task: The 'Neocortex Net' feature extractor consisted of two convolutional layers followed by a fully connected layer. The generative models were standard multi-layer perceptrons.
- **NLP Task:** The 'Neocortex Net' feature extractor used an 'EmbeddingBag' layer followed by a linear layer. The generative models operated in the embedding feature space.

## 3.3 Evaluation Metric

After learning each task, we evaluated the model's accuracy on the test sets of all tasks seen so far. Our primary metric is the **Average Accuracy** across all encountered tasks, as it provides a comprehensive measure of the model's ability to retain old knowledge while acquiring new skills.

## 4 Results and Analysis

We conducted detailed experiments comparing MyGO with the sequential fine-tuning baseline on both benchmarks. The final performance after all tasks are learned is summarized in Table 1.

## 4.1 Computer Vision (Split-MNIST)

On the Split-MNIST benchmark, MyGO demonstrated a powerful ability to counteract catastrophic forgetting. This is further detailed in Table 2, which shows the progression of average accuracy.

Table 1: Final performance comparison after completion of all tasks. MyGO demonstrates superior knowledge retention, especially on the longer CV task sequence. TN Acc. refers to the accuracy on Task N.

Scenario	Model	T1 Acc.	T2 Acc.	T3 Acc.	T4 Acc.	T5 Acc.	Average Acc.
Split-MNIST (CV)	Fine-tuning MyGO	43.85% <b>99.23</b> %	69.59% <b>95.14%</b>	21.90% <b>96.96</b> %	95.44% <b>99.46</b> %	99.61% <b>95.15</b> %	66.08% <b>97.19</b> %
Split-AG News (NLP)	Fine-tuning <b>MyGO</b>	63.11% <b>76.64%</b>	<b>96.37</b> % 73.43%	-	-	-	79.74% 75.03%

**Fine-tuning Baseline** The baseline model is a textbook example of catastrophic forgetting. As seen in Table 2, after learning Task 2, its average accuracy plummeted from 100

**MyGO** In stark contrast, MyGO exhibited remarkable stability. Its average accuracy remained exceptionally high throughout the learning process, finishing at 97.19%. This provides strong evidence that the sleep-phase generative replay and knowledge distillation effectively consolidate existing knowledge while integrating new information, confirming the framework's effectiveness in the vision domain.

Table 2: Evolution of Average Accuracy on Split-MNIST. This table shows the average accuracy on all seen tasks after each new task is learned, illustrating the performance trend over time.

Model	After Task 1	After Task 2	After Task 3	After Task 4	After Task 5
Fine-tuning MyGO	100.00%	78.04%	63.71%	73.06%	66.08%
	<b>99.23</b> %	<b>97.19</b> %	<b>97.11%</b>	<b>97.70</b> %	<b>97.19</b> %

## 4.2 Natural Language Processing (Split-AG News)

The NLP benchmark revealed more nuanced results.

**Fine-tuning Baseline** The baseline again suffered from significant forgetting. After training on Task 2, its accuracy on Task 1 dropped sharply from an initial 99.28% to 63.11%. Although it performed very well on the new Task 2 (96.37%), this came at the cost of forgetting a substantial portion of prior knowledge, resulting in an average accuracy of 79.74%.

**MyGO** MyGO also faced challenges in this more complex domain. After completing Task 2, its accuracy was 76.64% on Task 1 and 73.43

## 4.3 Comprehensive Analysis

The results consistently show that MyGO serves as a general and effective framework for preventing catastrophic forgetting, particularly in domains like computer vision where feature spaces are well-structured. It successfully consolidates knowledge into a unified feature extractor through its wake-sleep mechanism.

For the NLP task, while MyGO's absolute performance did not surpass the baseline, it still proved superior on the core metric of lifelong learning: knowledge retention. This indicates that the MyGO framework is fundamentally sound, but its performance on complex, high-dimensional data is likely dependent on the quality of the generative models and the tuning of the distillation process. MyGO trades a small amount of peak performance on the newest task for stability and knowledge preservation across the entire task sequence—the central goal of lifelong learning.

## 5 Conclusion and Future Work

In this paper, we introduced MyGO, a novel lifelong learning framework inspired by the biological wake-sleep cycle. By leveraging generative models for data-free memory replay and knowledge distillation for offline consolidation, MyGO significantly mitigates catastrophic forgetting. Our experiments on computer vision tasks clearly demonstrate its superiority over traditional fine-tuning. On a more challenging natural language processing task, MyGO still showed better knowledge retention, highlighting its general applicability.

Future work could proceed in several promising directions:

- 1. **Improving Generative Models:** Exploring more advanced generative models, such as Variational Autoencoders (VAEs) or Normalizing Flows, especially for complex data like text, could enhance the quality of the "dreams" and improve distillation efficacy.
- 2. **Advanced Distillation Techniques:** Investigating more sophisticated distillation strategies, such as distilling feature-level representations in addition to logits, could enable the transfer of richer knowledge.
- 3. **Adaptive Sleep Mechanisms:** Developing methods for the system to automatically decide when and for how long to enter the sleep phase, based on task difficulty or forgetting metrics, could improve efficiency.
- 4. **Scaling to More Complex Scenarios:** Testing MyGO's robustness and scalability in more challenging scenarios, such as class-incremental learning and sequences with a larger number of diverse tasks.

We believe that the principle of generative memory consolidation, as embodied by MyGO, offers a promising path toward building truly adaptive and lifelong learning AI systems.

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