PRIVACY-AWARE LIFELONG LEARNING

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Paper under double-blind review

ABSTRACT

Lifelong learning algorithms enable models to incrementally acquire new knowledge without forgetting previously learned information. Contrarily, the field of machine unlearning focuses on explicitly forgetting certain previous knowledge from pretrained models when requested, in order to comply with data privacy regulations on the *right-to-be-forgotten*. Enabling efficient lifelong learning with the capability to selectively unlearn sensitive information from models presents a critical and largely unaddressed challenge with contradicting objectives. We address this problem from the perspective of simultaneously *preventing catastrophic forgetting* and *allowing forward knowledge transfer* during task-incremental learning, while *ensuring exact task unlearning* and *minimizing memory requirements*, based on a single neural network model to be adapted. Our proposed solution, privacy-aware lifelong learning (PALL), involves optimization of task-specific sparse subnetworks with parameter sharing within a single architecture. We additionally utilize an episodic memory rehearsal mechanism to facilitate exact unlearning without performance degradations. We empirically demonstrate the scalability of PALL across various architectures in image classification, and provide a state-of-the-art solution that uniquely integrates lifelong learning and privacy-aware unlearning mechanisms for responsible AI applications.

1 INTRODUCTION

Lifelong learning algorithms enhance the ability of machine learning models to incrementally acquire new skills or integrate new knowledge over time from sequentially observed data (van de Ven et al., 2022). This continual learning capability is essential for models to stay relevant in dynamic environments where the observed data distributions change. A widely studied challenge in this setting is to mitigate *catastrophic forgetting*, addressing the loss of prior knowledge as new tasks are learned. There has been various strategies proposed to prevent forgetting, while exploiting *forward knowledge transfer* to efficiently improve performance in new tasks. However, these lifelong learning approaches conventionally do not consider the factor of ensuring data privacy, whereas selectively forgetting (or *unlearning*) certain knowledge may be required to comply with the legal regulations on the *right-to-be-forgotten* (Mantelero, 2013) (e.g., deleting prior information from personalized recommendation systems). This introduces an additional dimension of complexity, which requires novel lifelong learning solutions that can ensure unlearning for privacy-awareness.

The field of machine unlearning focuses on explicitly removing the influence of specific data points from pretrained models (Cao & Yang, 2015). Ensuring *exact unlearning*, where the model is guaranteed to behave as if the unlearned data was never observed, presents a significant challenge that generally requires partial model retraining (Bourtoule et al., 2021). In particular, current unlearning solutions assume previous or all data to be available to facilitate exact unlearning, which does not apply to lifelong learning settings where the data is only sequentially observed. Accordingly, recent works have started to explore solutions at the intersection of task-incremental lifelong learning and machine unlearning (Shibata et al., 2021; Liu et al., 2022; Chatterjee et al., 2024), primarily via inexact unlearning methods which does not guarantee privacy for all previously learned tasks.

We consider a similar lifelong learning problem, where the learning sequence may include *exact* task unlearning requests for any of the previously learned tasks, with no access to prior data. A naive solution in this particular setting is to train independent models for each task, and discard the models corresponding to the tasks to be exactly unlearned upon request (Liu et al., 2022). However, this is inefficient since it does not enable knowledge transfer from prior tasks, and becomes memory demanding as the number of tasks increase. From a novel perspective, we present an efficient solution to this multidimensional problem by using a fixed-capacity neural network architecture.

We propose *privacy-aware lifelong learning (PALL)* as a novel framework that completely **alleviates catastrophic forgetting**, facilitates **selective knowledge transfer** from previously learned tasks, ensures **exact task unlearning guarantees** when requested, and provides a state-of-the-art solution to lifelong learning and unlearning with **minimal model memory requirements**. Our approach is based on jointly optimizing task-specific sparse subnetwork connectivity structures and their parameters within a single fixed-capacity model, and isolating this knowledge by freezing its parameters to prevent catastrophic forgetting. We facilitate learnable knowledge transfer through shared parameters by allowing this optimization process to also leverage connections with frozen weights from previous tasks, if preferred. We perform exact unlearning by resetting the subnetwork parameters that are optimized on the task to be unlearned, and use an episodic memory rehearsal mechanism to recover any performance degradation in the other tasks that may occur due to reinitialization of shared parameters which are unlearned. Our contributions are summarized as follows:

- We formulate a task-incremental learning and unlearning problem with strong privacy considerations, where exact unlearning is possible for all tasks during their lifetime.
- We present privacy-aware lifelong learning (PALL) as a memory-efficient algorithmic solution to this problem, which enables learning without catastrophic forgetting, allows learnable forward knowledge transfer, and ensures exact unlearning guarantees by design.
- We empirically demonstrate scalability of PALL on both convolutional benchmark architectures and attention-based vision transformers, yielding a stable performance in highly dynamic lifelong learning scenarios with randomly arriving unlearning requests.

2 RELATED WORK

2.1 LIFELONG LEARNING

Lifelong learning, or continual learning, explores the ability of machine learning models to adapt and learn continuously from a sequentially observed stream of data (De Lange et al., 2021; van de Ven et al., 2022; 2024). The central challenge is to address the problem of *catastrophic forgetting*, which is a widely studied phenomenon caused by traditional learning algorithms resulting in loss of previously acquired knowledge as new tasks are learned. Approaches to lifelong learning are also ideally expected to allow *forward knowledge transfer*, by using information from previous tasks to enhance performance on new ones. This is primarily a biologically inspired motivation towards designing models that mimic the brain's ability to continually and efficiently learn new skills by leveraging previous experiences (Kudithipudi et al., 2022; Wang et al., 2023a; 2024). Different lifelong learning scenarios are categorized as task-, class- or domain-incremental learning, which vary in terms of the target variable spaces. We focus on the task-incremental learning setting, which maintains separate label spaces for each task and assumes that the task is known by the agent. Existing approaches can be broadly divided into regularization-based, rehearsal-based, and architecture-based methods.

Regularization-based methods, such as elastic weight consolidation (EWC) (Kirkpatrick et al., 2017), learning without forgetting (LwF) (Li & Hoiem, 2017), synaptic intelligence (Zenke et al., 2017), and memory-aware synapses (Aljundi et al., 2018), aim to ensure that the network retains previously acquired knowledge while learning new ones by penalizing the updates to the parameters that are crucial for previously learned tasks in different ways.

Rehearsal-based methods, such as experience replay (Rolnick et al., 2019; Chaudhry et al., 2019) and generative modeling based rehearsal (Shin et al., 2017), store episodic training set exemplars in a buffer or use auxiliary generative models to synthesize and replay past data during training. These methods also extended to utilize gradient episodic memory (GEM) (Lopez-Paz & Ranzato, 2017), or combine replay with knowledge distillation to maintain balanced data representations (Rebuffi et al., 2017). Recently, dark experience replay (DER++) (Buzzega et al., 2020) proposed to regularize training with logit penalties to stabilize learning with respect to samples from the buffer. These methods were also lately used to improve lifelong learning with transformers (Wang et al., 2022).

Architecture-based methods exploit context-specific model components and reconfigure the neural network backbone structure. Progressive neural networks (Rusu et al., 2016) and dynamically expandable neural networks (Yoon et al., 2017) adjust the model by expanding the network layers to add new capacities for new tasks when needed. To completely eliminate forgetting, the *expert gate* method duplicates the model for each new task and uses an input gating mechanism to use the relevant expert at test-time (Aljundi et al., 2017). Considering limited model memory budget settings, another line of work proposes to use distinguished sets of parameters via task-specific subnetworks within a fixed model, which are kept frozen to alleviate forgetting. PackNet (Mallya & Lazebnik, 2018) and CLNP (Golkar et al., 2019) use magnitude-based pruning to obtain these sparse subnetworks, by reusing all weights from previous tasks for knowledge transfer. Recently, methods that partially reuse the weights from previous subnetworks were developed to allow selective knowledge transfer. Specifically, Dekhovich et al. (2023) used heuristic weight importance scores for pruning based on neuron activations, and winning subnetworks (WSN) (Kang et al., 2022) employ the idea of trainable importance scores to obtain task-specific subnetworks with selective weight sharing.

2.2 MACHINE UNLEARNING

Machine unlearning is the process of removing the influence of specific data points from a model (Cao & Yang, 2015; Ginart et al., 2019), in order to re-establish privacy following a user's request for certain data samples, e.g., her/his own, to be deleted from the training set of the model, to comply with legal regulations on the *right-to-be-forgotten* (Mantelero, 2013). Besides updating the training set, unlearning methods modify the pretrained model to remove any influence of these samples, such that complete retraining is not needed to prevent membership inference attacks (Shokri et al., 2017).

Exact unlearning methods aim to completely remove the influence of targeted data, ensuring the model behaves as if the data was never observed. Beyond certified data removal from smaller scale linear models (Guo et al., 2020), exact unlearning from neural networks generally requires compute-efficient model retraining methods. The state-of-the-art approach SISA (Bourtoule et al., 2021) partitions the training set into disjoint shards and trains separate models on each shard, such that unlearning only requires retraining on affected shards. This idea was later extended to exploit data dependency structures across shards for efficiency (Dukler et al., 2023). Other examples include leveraging ensemble learning of multiple one-class tasks to reduce retraining costs (Yan et al., 2022), or minimizing parameters of the architecture for faster retraining (Yu et al., 2022).

Approximate unlearning methods manipulate model parameters using gradient based information to perform more efficient (but inexact) unlearning with faster retraining (Wu et al., 2020; Golatkar et al., 2020; Sekhari et al., 2021; Graves et al., 2021; Neel et al., 2021). However, such inexact solutions have been shown to require rigorous evaluations due to potentially misleading interpretations (Goel et al., 2022; Hayes et al., 2024), and involve further privacy and fairness implications for the other samples in the datasets (Chen et al., 2021; Zhang et al., 2023). Notably, approximate unlearning methods also do not generalize in a setting with *adaptive requests* (Gupta et al., 2021), which refers to the scenario where unlearning requests arrive sequentially rather than all at once.

2.3 SELECTIVE FORGETTING IN LIFELONG LEARNING

Unlearning in lifelong learning settings has been recently explored in the context of *beneficial forgetting* (Wang et al., 2023b), as opposed to the problem of catastrophic forgetting that continual learning generally focuses on. One of the earliest methods, learning with selective forgetting (LSF) (Shibata et al., 2021), modifies models to make incorrect predictions on the unlearned data, by using auxiliary mnemonic codes to manipulate the input space. However, this only yields inexact unlearning, since poor model performance does not ensure privacy. Other works have similarly explored inexact unlearning methods, both for task-incremental learning using knowledge deposit modules (Ye et al., 2022) or student-teacher knowledge distillation mechanisms (Chatterjee et al., 2024), as well as class-incremental learning with data representation based approaches (Zuo et al., 2024).

Exact unlearning via dataset sharding and retraining (Bourtoule et al., 2021) is not applicable to lifelong learning, since there is no access to previous datasets. Recently, the continual learning and private unlearning (CLPU) framework (Liu et al., 2022) explored a related problem with another baseline approach. Specifically, CLPU defines task-incremental learning with instructions to *temporarily* or *permanently* learn the given tasks, and ensures exact unlearning on temporarily learned tasks by training independent models which are deleted upon request. In an open-world scenario with privacy guarantees on any continually learned task, this solution becomes memory inefficient.

3 PRIVACY-AWARE LIFELONG LEARNING (PALL)

3.1 PRELIMINARIES

Lifelong Learning: Consider a sequence of task IDs $t \in \Gamma$ where $\Gamma = \{1, \ldots, T\}$ in a supervised task-incremental learning scenario with training datasets $\mathcal{D}^t = \{(\boldsymbol{x}_1^t, y_1^t), \ldots, (\boldsymbol{x}_n^t, y_n^t)\}$, and test datasets $\mathcal{D}^t_{\text{test}} = \{(\boldsymbol{x}_1^{t,\text{test}}, y_1^{t,\text{test}}), \ldots, (\boldsymbol{x}_{n'}^{t,\text{test}}, y_{n'}^{t,\text{test}})\}$, where $\boldsymbol{x} \in \mathcal{X}$ and $y \in \mathcal{Y}^t$ denote the raw data and labels. The learner trains a neural network model $f_{\boldsymbol{\theta}}$ with parameters $\boldsymbol{\theta} \in \mathbb{R}^d$, by applying a learning algorithm $\mathcal{L}$ on $\mathcal{D}^t$ to sequentially optimize $\boldsymbol{\theta}^t \sim \mathcal{L}(\boldsymbol{\theta}^{t-1}, \mathcal{D}^t)$, often based on a cross-entropy loss $\ell_{\text{ce}}(\boldsymbol{x}, y; \boldsymbol{\theta})$, and estimates a probability distribution over $\mathcal{Y}^t$ via $\text{softmax}(f_{\boldsymbol{\theta}}(\boldsymbol{x}^t))$.

In lifelong learning, the learner loses access to $\mathcal{D}^{<t} = \{\mathcal{D}^1, \ldots, \mathcal{D}^{t-1}\}$ when learning task t. Moreover, for fixed model capacity, $\boldsymbol{\theta}^t$ depends on $\boldsymbol{\theta}^\tau$ for all $\tau < t$. This necessitates tailored learning algorithms to alleviate *catastrophic forgetting*, such that performance on $\mathcal{D}^{<t}_{\text{test}}$ can be maintained, while ideally achieving *forward knowledge transfer* by leveraging information from prior tasks.

Exact Task Unlearning: We consider a scenario where the learner is expected to *unlearn* part of the previously observed training datasets, i.e., a forget set, due to privacy related concerns. We define the forget set to be the whole training dataset $\mathcal{D}^\tau$ corresponding to a previously learned task τ.[1] For a learning algorithm $\mathcal{L}$ applied to $\mathcal{D}^{\leq t}$, and a previously observed task dataset $\mathcal{D}^\tau$ to be unlearned, an *exact task unlearning* mechanism $\mathcal{U}$ uses $\boldsymbol{\theta}^t$ as a reference and returns a model such that:

$$\mathcal{U}\left(\boldsymbol{\theta}^t \sim \mathcal{L}\left(\boldsymbol{\theta}^0, \mathcal{D}^{\leq t}\right), \tau\right) =_p \mathcal{L}\left(\boldsymbol{\theta}^0, \mathcal{D}^{\leq t} \setminus \mathcal{D}^\tau\right), \tag{1}$$

where $=_p$ indicates that the models share the same probability distribution. Specifically, if the unlearned model possesses no information about $\mathcal{D}^\tau$, an adversary cannot differentiate this model from a model trained on $\mathcal{D}^{\leq t} \setminus \mathcal{D}^\tau$ from scratch based on $\mathcal{L}$, thus $\mathcal{U}$ achieves exact unlearning. In lifelong learning, this constitutes a challenging problem since there is no access to previous datasets.

3.2 PROBLEM STATEMENT

We formulate a generalized lifelong learning problem with privacy considerations, by extending the traditional task-incremental learning setup to allow exact task unlearning instructions. We consider that the learner receives a sequence of r requests $\mathcal{R}_{1:r}$, consisting of T task learning and N_u task unlearning instructions which are provided in a logically consistent order (i.e., a task can only be unlearned after it has been learned). We assume that all tasks are to be learned once without repetition. The i-th request $\mathcal{R}_i$ in the sequence $\mathcal{R}_{1:r}$ is defined as follows:

$$\mathcal{R}_{1:r} = [\mathcal{R}_1, \mathcal{R}_2, \ldots, \mathcal{R}_r], \quad \text{such that} \quad \begin{cases} \mathcal{R}_i = (t, \mathcal{D}^t, \mathbf{L}) & \text{if task } \textit{learning}, \\ \mathcal{R}_i = (t, \mathbf{U}) & \text{if task } \textit{unlearning}, \end{cases} \tag{2}$$

where $\mathbf{L}$ and $\mathbf{U}$ are flag variables to indicate if the instruction corresponds to a learning or unlearning request. Furthermore, the learner keeps a dictionary Ω_i of the currently learned task IDs that were not unlearned: $\Omega_i \leftarrow \Omega_{i-1} \cup \{t\}$ if learning task t, and $\Omega_i \leftarrow \Omega_{i-1} \setminus \{t\}$ if unlearning task t.

The learner's goal is to solve this problem by defining a learning algorithm $\mathcal{L}$, and an unlearning algorithm $\mathcal{U}$, to be applied sequentially based on $\mathcal{R}_i$ to optimize the model parameters to achieve:

$$\boldsymbol{\theta}^i \sim \begin{cases} \mathcal{L}\left(\boldsymbol{\theta}^{i-1}, \mathcal{D}^t\right) \;\; \text{s.t.} \;\; \min\limits_{\boldsymbol{\theta}} \dfrac{1}{|\Omega_i|} \sum\limits_{t \in \Omega_i} \mathbb{E}_{(\boldsymbol{x},y)\sim\mathcal{D}^t_{\text{test}}}\left[\ell_{\text{ce}}(\boldsymbol{x}, y; \boldsymbol{\theta})\right] & \text{if } \mathcal{R}_i = (t, \mathcal{D}^t, \mathbf{L}), \\ \mathcal{U}\left(\boldsymbol{\theta}^{i-1}, t\right) \;\; \text{s.t.} \;\; \mathcal{U}\left(\boldsymbol{\theta}^{i-1}, t\right) =_p \mathcal{L}\left(\boldsymbol{\theta}^0, \mathcal{D}^{[\tau \in \Omega_i]}\right) & \text{if } \mathcal{R}_i = (t, \mathbf{U}). \end{cases} \tag{3}$$

A holistic solution to this problem would **mitigate catastrophic forgetting** as new tasks are learned, **allow forward knowledge transfer** for efficient learning, **ensure privacy-awareness** with exact unlearning guarantees, and **minimize memory requirements** of the algorithm. Our formulation differs from the CLPU (Liu et al., 2022) setting by generalizing the problem in terms of its privacy constraints such that *any* task can always be exactly unlearned (i.e., all tasks are temporarily learned).

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[1] Differently from traditional machine unlearning studies that generally define the forget set to be a subset of training samples or a certain class in the training dataset, we focus on whole task unlearning scenarios.

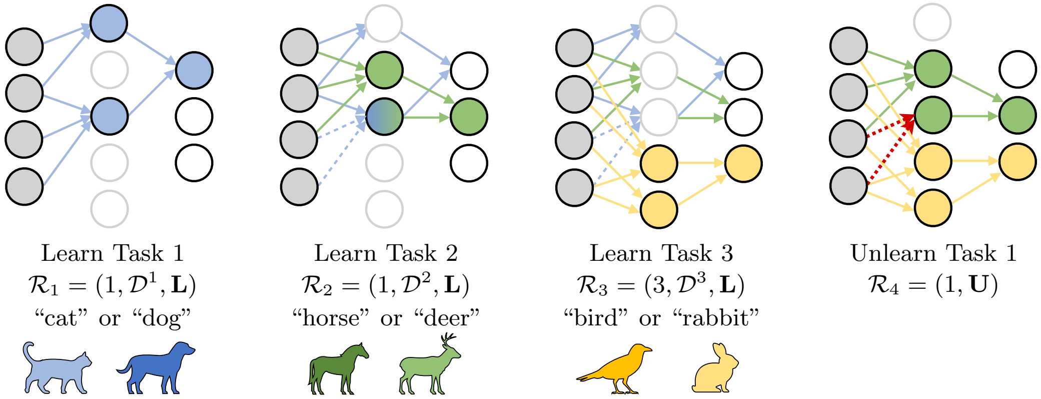
Learn Task 1
$\mathcal{R}_1 = (1, \mathcal{D}^1, \mathbf{L})$
"cat" or "dog"
Learn Task 2
$\mathcal{R}_2 = (1, \mathcal{D}^2, \mathbf{L})$
"horse" or "deer"
Learn Task 3
$\mathcal{R}_3 = (3, \mathcal{D}^3, \mathbf{L})$
"bird" or "rabbit"
Unlearn Task 1
$\mathcal{R}_4 = (1, \mathbf{U})$

Figure 1: Illustration of PALL. Task-specific subnetworks obtained after learning are indicated by color. The subnetwork mask $\mathbf{m}_2$ for Task 2 contains two shared, frozen parameters from Task 1 (dashed blue lines), as well as $\overline{\mathbf{m}}_2$ (green connections). Following the unlearning request for Task 1, we reset all parameters trained on $\mathcal{D}^1$ (blue connections), and retrain any of those parameters which were used for knowledge transfer in later tasks (shown by red connections) using experience replay.

3.3 EFFICIENT LIFELONG LEARNING WITH EXACT TASK UNLEARNING

Existing lifelong learning methods are not designed for exact task unlearning capabilities. Recent studies have only explored inexact unlearning methods in this context (Shibata et al., 2021; Chatterjee et al., 2024). A naive solution to satisfy Eq. (3) would be to train independent models for each task, where one can ensure exact unlearning by deleting the task-specific model upon request.[2] However, this approach becomes infeasible under limited memory as the number of tasks increases.

We propose **privacy-aware lifelong learning (PALL)** as a memory-efficient hybrid solution that utilizes an architecture-based lifelong learning approach, combined with an episodic memory rehearsal mechanism. We optimize task-specific subnetworks within a single architecture with *limited model memory*, where the associated parameters are kept frozen to *eliminate catastrophic forgetting*. During task-specific subnetwork optimization, we *allow learnable knowledge transfer* to future tasks by selectively reusing parameters from previous task subnetworks (Kang et al., 2022). We ensure *exact task unlearning* by resetting the associated task subnetwork upon request, and use experience replay to mitigate potential performance degradations in the other tasks that may occur due to the reinitialization of shared parameters. PALL is illustrated in Figure 1 and described in detail below.

Given a task learning request $\mathcal{R}_i = (t, \mathcal{D}^t, \mathbf{L})$, our goal is to optimize a sparse subset of the current parameters $\boldsymbol{\theta}^{i-1}$, and a binary subnetwork mask $\mathbf{m}_t \in \{0,1\}^d$, which will be used for inference on task t. We perform this by jointly optimizing the parameters that are *unused* in previous tasks, and task-specific importance scores $\mathbf{s}_t$, which quantifies the significance of each parameter:

$$\min_{\boldsymbol{\theta}, \mathbf{s}_t} \mathbb{E}_{(\boldsymbol{x}, y) \sim \mathcal{D}^t} \left[\ell_{\text{ce}} \left(\boldsymbol{x}, y; \boldsymbol{\theta} \odot \mathbf{m}_t(\mathbf{s}_t) \right) \right]. \tag{4}$$

We compute $\mathbf{m}_t$ at each iteration using the current largest $|\mathbf{s}_t|$ values on a per layer basis, based on a connectivity rate α (e.g., $\alpha = 0.1$ indicates 90% sparsity) (Ramanujan et al., 2020). Since we do not want to change the parameters trained on previous tasks, we perform masking of parameter updates:

$$\boldsymbol{\theta} \leftarrow \boldsymbol{\theta} - \eta \left(\frac{\partial \ell_{\text{ce}}}{\partial \boldsymbol{\theta}} \odot (1 - \mathbf{M}_{i-1}) \right), \qquad \mathbf{s}_t \leftarrow \mathbf{s}_t - \eta \left(\frac{\partial \ell_{\text{ce}}}{\partial \, \mathbf{s}_t} \right), \tag{5}$$

where $\mathbf{M}_{i-1} = \bigvee_{j \in \Omega_{i-1}} \mathbf{m}_j$ denotes the *cumulative binary mask* which identifies the combined set of used and frozen subnetwork parameters until the i-th request. The scores $\mathbf{s}_t$ are optimized via a straight-through estimator on the binarizing mask $\mathbf{m}_t(\mathbf{s}_t)$ during backpropagation.

This objective allows *learnable forward knowledge transfer* by optimizing $\mathbf{s}_t$ for all parameters of the model without masking, such that $\mathbf{m}_t$ for different tasks can be overlapping to share parame-

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[2] This is identical to the recently proposed CLPU solution (Liu et al., 2022) in our experimental setting that requires exact unlearning guarantees for any continually learned task.

ters. We indicate the parameter indices which are specifically trained using data from $\mathcal{D}^t$ with the submask $\overline{\mathbf{m}}_t$, and $\mathbf{m}_t - \overline{\mathbf{m}}_t$ correspond to the shared, frozen parameter indices from previous tasks. After task learning, we discard $\mathbf{s}_t$ and store the final $\mathbf{m}_t$ in a dictionary of binary subnetwork masks $\mathcal{M}_i = \{\mathbf{m}_j \,|\, j \in \Omega_i\}$. Due to the parameter masking strategy used during training, we can always use the corresponding $\mathbf{m}_t$ to make consistent predictions on $\mathcal{D}^t_{\text{test}}$ without catastrophic forgetting.

Importantly, we update $\mathbf{M}_i \leftarrow \mathbf{M}_{i-1} \vee \mathbf{m}_t$ and reset all unused parameters $\boldsymbol{\theta}^i \odot (1 - \mathbf{M}_i)$ by sampling from the weight initialization distribution $\phi(.)$ after training. This ensures that no information from $\mathcal{D}^t$ leaks into the remaining unused parameters outside the ones identified by $\mathbf{m}_t$, and helps to ensure future unlearning guarantees. Lastly, we store a set of randomly sampled exemplars and logits to an episodic memory buffer $\mathcal{B}^t = \{(\boldsymbol{x}_j, y_j, \boldsymbol{z}_j = f_{\boldsymbol{\theta}^i \odot \mathbf{m}_t}(\boldsymbol{x}_j)) \mid (\boldsymbol{x}_j, y_j) \sim \mathcal{D}^t\}_{1 \leq j \leq |\mathcal{B}^t|}$. We do not use this buffer for task learning, but will use these samples upon unlearning requests.

Given a task unlearning request $\mathcal{R}_i = (t, \mathbf{U})$, our goal is to update the model parameters $\boldsymbol{\theta}^{i-1}$, such that the new model does not possess any information about $\mathcal{D}^t$, i.e., none of its parameters have been optimized with the data observed from task t. We can facilitate this exactly by resetting the parameters $\boldsymbol{\theta}^{i-1} \odot \overline{\mathbf{m}}_t$, by sampling new values from the initialization distribution $\phi(.)$.

If the unlearning request $\mathcal{R}_i = (t, \mathbf{U})$ refers to the latest task that was learned in $\mathcal{R}_{i-1} = (t, \mathcal{D}^t, \mathbf{L})$, we can simply rewind this learning instruction by resetting $\boldsymbol{\theta}^{i-1} \odot \overline{\mathbf{m}}_t$. However, if the unlearning request refers to an earlier task t which was followed by other task learning requests $\tau > t$ and $\tau \in \Omega_i$, then purely resetting $\boldsymbol{\theta}^{i-1} \odot \overline{\mathbf{m}}_t$ will lead to a performance degradation for tasks τ, if $\mathbf{m}_\tau$ is overlapping with $\overline{\mathbf{m}}_t$ to share parameters from task t (red connections in Figure 1). To address this conflict between knowledge transfer and exact unlearning, we use memory buffer rehearsal and perform a short *retraining* step on such affected parameters following the objective:

$$\min_{\bar{\boldsymbol{\theta}}} \sum_{\substack{\tau > t \\ \tau \in \Omega_i}} \frac{1}{|\mathcal{B}^\tau|} \left[\sum_{(\boldsymbol{x}, y, \boldsymbol{z}) \sim \mathcal{B}^\tau} \ell_{\text{ce}}\left(\boldsymbol{x}, y; \boldsymbol{\theta} \odot \mathbf{m}_\tau\right) + \beta \cdot \sum_{(\boldsymbol{x}', y', \boldsymbol{z}') \sim \mathcal{B}^\tau} ||f_{\boldsymbol{\theta} \odot \mathbf{m}_\tau}(\boldsymbol{x}') - \boldsymbol{z}'||_2^2 \right], \qquad (6)$$

where $\bar{\boldsymbol{\theta}}$ denotes the affected subset of parameters within $\boldsymbol{\theta}$ that were reset, which are indicated by $\bigvee_{\tau > t, \tau \in \Omega_i} (\mathbf{m}_\tau \wedge \overline{\mathbf{m}}_t)$. Eq. (6) is a generalized formulation used in various rehearsal based lifelong learning methods, where $\beta = 0$ would yield vanilla experience replay (Chaudhry et al., 2019) and $\beta = 0.5$ yields DER++ (Buzzega et al., 2020). We perform N_f retraining iterations for Eq. (6). Finally, we delete $\mathcal{B}^t$ and $\mathbf{m}_t$, and re-compute $\mathbf{M}_i = \bigvee_{j \in \Omega_i} \mathbf{m}_j$. Our algorithm is in Appendix A.2.

4 EXPERIMENTAL SETUP

4.1 DATASETS AND MODELS

We performed experiments with sequential CIFAR10 (S-CIFAR10: 5 tasks × 2 classes), CIFAR100 (S-CIFAR100: 10 tasks × 10 classes) and TinyImageNet (S-TinyImageNet: 20 tasks × 10 classes, 40 tasks × 5 classes, or 100 tasks × 2 classes) datasets. We used ResNet-18 and ResNet-34 models in S-CIFAR10/100 experiments which are commonly used as benchmarks in lifelong learning, and attention-based ViT-T/8 architectures with S-TinyImageNet (see Appendix A.1 for details).

We designed lifelong learning scenarios with T task *learning* instructions, and N_u randomly chosen task *unlearning* instructions, which are arranged in a logically consistent manner, e.g., a user request sequence on S-CIFAR10 with $N_u = 3$ can be: $\mathcal{R}_{1:8} = [(1, \mathcal{D}^1, \mathbf{L}), (2, \mathcal{D}^2, \mathbf{L}), (3, \mathcal{D}^3, \mathbf{L}), (2, \mathbf{U}), (4, \mathcal{D}^4, \mathbf{L}), (3, \mathbf{U}), (5, \mathcal{D}^5, \mathbf{L}), (1, \mathbf{U})]$. Experiments are repeated using 20 random seeds (unless stated otherwise) for a given N_u, which results in randomly changing the allocation of the classes into different tasks, as well as the unlearning instructions and their order within $\mathcal{R}_{1:r}$.

4.2 MODEL TRAINING AND EVALUATIONS

Baseline Methods: We compare our results against state-of-the-art lifelong learning baselines: sequential learning by directly finetuning the model on each new task (Sequential), elastic weight consolidation (EWC) (Kirkpatrick et al., 2017), learning without forgetting (LwF) (Li & Hoiem, 2017), learning with selective forgetting (LSF) (Shibata et al., 2021), gradient episodic memory

(GEM) (Lopez-Paz & Ranzato, 2017), experience replay (ER) (Chaudhry et al., 2019), dark experience replay (DER++) (Buzzega et al., 2020), PackNet (Mallya & Lazebnik, 2018), winning subnetworks (WSN) (Kang et al., 2022), and task-specific independent model training (Independent) which is equivalent to the naive solution by CLPU (Liu et al., 2022) in our problem setting.

These baseline approaches, except for LSF (Shibata et al., 2021) and Independent (Liu et al., 2022), are not originally designed with task unlearning capabilities. Thus, we adapt these methods to the current problem. Particularly for GEM, ER and DER++, for task unlearning, we perform finetuning for N_f iterations on the remaining episodic memories and predict uniform distributions using the unlearned task's episodic memories to accelerate forgetting, prior to removing the corresponding episodic memory of the unlearned task. For Sequential, EWC, LwF, PackNet and WSN, we do not perform any changes to the model parameters for task unlearning. We only discard the algorithm-specific stored variables associated with the task to be unlearned, e.g., the subnetwork masks in PackNet and WSN (see "Unlearning Implementations" under Appendix A.2 for further details).

Training Configurations: We use a stochastic gradient descent (SGD) optimizer with momentum for 20 epochs per S-CIFAR10/100 task learning instruction, with a batch size of 32, learning rate of 0.01, and weight decay with parameter 0.0005. For S-TinyImageNet, we use an Adam optimizer for 100 epochs with a batch size of 256, and a cosine annealing learning rate scheduler with an initial value of 0.001. Here, we do not use weight decay but instead apply dropout to intermediate activations of ViT-T/8 with $p = 0.1$ (Steiner et al., 2022). All methods requiring a memory buffer had a total capacity of 500 and 1000 samples (evenly split across tasks) in S-CIFAR and S-TinyImageNet experiments, respectively. Unless otherwise specified, we use $N_f = 50$ and $\beta = 0.5$ for Eq. (6). Our implementations will be made publicly available. Further details are presented in Appendix A.2.

Evaluation Metrics: We evaluate average test set accuracies for the remaining learned tasks after processing $\mathcal{R}_{1:r}$, i.e., tasks in the set Ω_r, and the average test set accuracies for the unlearned tasks after processing $\mathcal{R}_{1:r}$, i.e., tasks in the set $\Gamma \setminus \Omega_r$, denoted as $\mathcal{A}_l$ and $\mathcal{A}_u$ as follows:

$$\mathcal{A}_l = \frac{1}{|\Omega_r|} \sum_{t \in \Omega_r} a_{r,t}, \qquad \mathcal{A}_u = \frac{1}{N_u} \sum_{t \in \Gamma \setminus \Omega_r} a_{r,t}, \tag{7}$$

where $a_{i,t}$ denotes the accuracy on $\mathcal{D}^t_{\text{test}}$ after request i was completed. We expect better privacy-aware lifelong learning methods to have higher $\mathcal{A}_l$, and chance-level $\mathcal{A}_u$ by performing random classification on unlearned tasks. However, it is important to note that a lower $\mathcal{A}_u$ does not necessarily correspond to an exact unlearning guarantee. We include $\mathcal{A}_u$ only to evaluate inexact unlearning baselines through a weak measure. We leave detailed investigation of inexact unlearning methods with better metrics, e.g., via empirical privacy auditing (Steinke et al., 2024), for future work.

We evaluate the forgetting impact of task learning and unlearning requests, similar to the notion of backward knowledge transfer in standard continual learning. Specifically, we define $\mathcal{F}_l$ and $\mathcal{F}_u$ by evaluating the average decrease in the test set performance for previously learned tasks, after processing a task learning or unlearning request, which are formally defined as:

$$\mathcal{F}_l = \frac{1}{T-1} \sum_{\substack{i \in \{2,\ldots,r\} \\ \mathcal{R}_i = (-,\mathbf{L})}} \sum_{t \in \Omega_{i-1}} \frac{(a_{i-1,t} - a_{i,t})}{|\Omega_{i-1}|}, \quad \mathcal{F}_u = \frac{1}{N_u} \sum_{\substack{i \in \{2,\ldots,r\} \\ \mathcal{R}_i = (-,\mathbf{U})}} \sum_{t \in \Omega_i} \frac{(a_{i-1,t} - a_{i,t})}{|\Omega_i|}. \tag{8}$$

We expect better privacy-aware lifelong learning methods to have lower $\mathcal{F}_l$ and $\mathcal{F}_u$ such that there is no degrading backward transfer impact of learning or unlearning requests.

5 EXPERIMENTAL RESULTS

5.1 COMPARISONS TO STATE-OF-THE-ART IN LIFELONG LEARNING

In Table 1 we evaluate our approach against state-of-the-art methods in lifelong learning, by extending various methods to the experimental setting of task incremental learning and unlearning. We consider independent model training for each task as an upper bound baseline with exact unlearning, which however requires a model size that linearly scales with the number of tasks for inference. Our method, PALL, provides a novel, state-of-the-art solution in a privacy-aware continual learning and unlearning setting, considering all four metrics together with model memory requirements.

Table 1: Evaluations across different datasets and models. In this experimental setting, using independent models (bottom row) is identical to CLPU (Liu et al., 2022). Methods with *exact* unlearning perform random classification on unlearned tasks ($\mathcal{A}_u$). Results are averaged over 20 random seeds, where the sequence of requests are randomly generated with $N_u = 3$ unlearning instructions (see Appendix A.3.5 for worst-case results across seeds). α: task-specific subnetwork connectivity rate.

	S-CIFAR10 ($T = 5$)				**S-CIFAR100** ($T = 10$)				**S-TinyImageNet** ($T = 20$)				Model Size (Inference)
	$\mathcal{A}_l \uparrow$	$\mathcal{A}_u \downarrow$	$\mathcal{F}_l \downarrow$	$\mathcal{F}_u \downarrow$	$\mathcal{A}_l \uparrow$	$\mathcal{A}_u \downarrow$	$\mathcal{F}_l \downarrow$	$\mathcal{F}_u \downarrow$	$\mathcal{A}_l \uparrow$	$\mathcal{A}_u \downarrow$	$\mathcal{F}_l \downarrow$	$\mathcal{F}_u \downarrow$	
Sequential	70.71	72.65	13.86	0.0	35.35	40.07	13.43	0.0	19.41	21.42	7.65	0.0	d
EWC	74.27	73.28	12.02	0.0	56.01	52.04	7.03	0.0	54.74	53.63	0.49	0.0	
LwF	91.65	86.99	1.54	0.0	58.83	63.94	4.41	0.0	43.88	49.53	2.10	0.0	
LSF	89.25	80.25	0.36	1.26	56.59	52.88	1.67	4.93	43.40	44.88	0.94	4.60	
GEM	87.70	54.14	4.10	1.28	57.44	42.80	6.50	3.76	42.62	29.32	4.32	1.11	
ER	87.88	58.48	3.45	1.61	57.63	42.69	4.67	7.91	42.30	28.02	4.44	0.64	
DER++	92.04	53.50	1.62	0.66	66.84	46.56	4.52	0.95	46.50	34.65	3.78	0.43	
PackNet	94.77	75.76	**0.0**	0.0	75.01	58.19	**0.0**	0.0	60.50	50.72	**0.0**	0.0	$d + \mathcal{M}_i$
WSN	94.15	74.76	**0.0**	0.0	73.64	51.52	**0.0**	0.0	63.67	15.16	**0.0**	0.0	
PALL ($\alpha = 0.05$)	94.01	***Exact***	**0.0**	0.30	70.60	***Exact***	**0.0**	0.51	62.14	***Exact***	**0.0**	0.64	
PALL ($\alpha = 0.1$)	94.50	***Exact***	**0.0**	0.24	72.35	***Exact***	**0.0**	0.40	61.36	***Exact***	**0.0**	0.72	
PALL ($\alpha = 0.2$)	94.34	***Exact***	**0.0**	0.60	72.50	***Exact***	**0.0**	1.10	61.11	***Exact***	**0.0**	0.91	
Independent	95.19	***Exact***	**0.0**	0.0	73.22	***Exact***	**0.0**	0.0	61.69	***Exact***	**0.0**	0.0	$d \times \lvert\Omega_i\rvert$

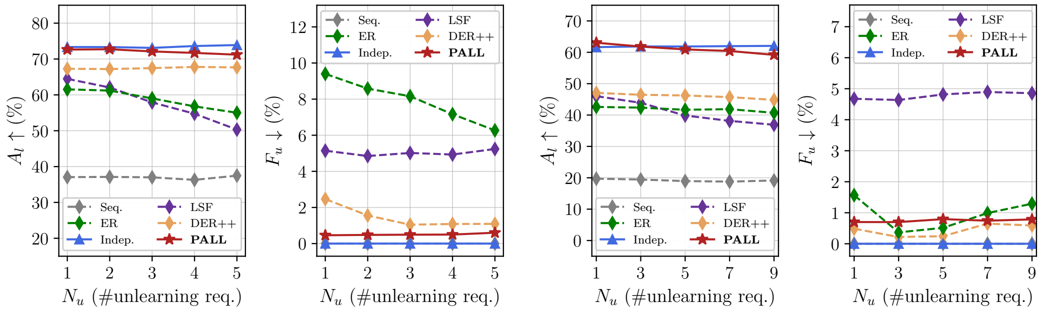
Regularization-based methods EWC and LwF, as well as sequential training, were indifferent to task unlearning instructions, since the original methods are not adapted to unlearning (i.e., $\mathcal{A}_u \approx \mathcal{A}_l$ and $\mathcal{F}_u = 0.0$). We observed LSF to strongly mitigate catastrophic forgetting (low $\mathcal{F}_l$), but its use of mnemonic codes (Shibata et al., 2021) for finetuning during unlearning was ineffective in our larger scale problems (i.e., above chance-level $\mathcal{A}_u$). Rehearsal based finetuning for unlearning with GEM, ER and DER++ resulted in better, lower $\mathcal{A}_u$ metrics closer to chance-levels. However, this is still an inexact unlearning approach, and all three methods still minimally suffer from catastrophic forgetting ($\mathcal{F}_l > 0$). Architecture-based methods PackNet and WSN mitigate catastrophic forgetting with frozen parameters ($\mathcal{F}_l = 0$), while only increasing the model size with $\mathcal{M}_i$, similar to PALL. PackNet and WSN also achieve $\mathcal{F}_u = 0$, since unlearning involves deletion of the corresponding mask without any change to the parameters. However, this makes unlearning inexact, since the parameters trained on the unlearned task remain. Generally, PackNet and WSN was found to perform well in task learning ($\mathcal{A}_l$), since they are not affected by parameter resetting in unlearning (e.g., PackNet: 75.01, WSN: 73.64, PALL ($\alpha = 0.2$): 72.50, Independent: 73.22 on S-CIFAR100).

Our method satisfies exact unlearning (i.e., random classification $\mathcal{A}_u$ on unlearned tasks), no catastrophic forgetting ($\mathcal{F}_l = 0$), and achieves $\mathcal{A}_l$ metrics very close to, or higher than training independent models with exact unlearning guarantees (e.g., Independent: 61.69, PALL ($\alpha = 0.05$): 62.14 on S-TinyImageNet). Moreover, rehearsal-based retraining of the reset parameters yields relatively low $\mathcal{F}_u$ ($\sim$below 1%), which shows the efficiency of the designed unlearning process.

Henceforth, we consider $\alpha = 1/T$ for PALL, which is determined by the experimental setting. If the number of tasks to be learned are not known a priori and $\alpha > 1/T$, PALL will still allow learning via knowledge transfer from frozen weights, until some tasks are unlearned to free trainable parameters.

Memory Requirements of PALL: Our method requires minimal memory overhead in the total model size for inference, by partitioning multiple tasks within a limited number of floating-point parameters. To achieve this, PALL stores an additional binary mask dictionary $\mathcal{M}_i$, which includes at most T masks to perform inference. This indicates d parameters (32-bits), and $\mathcal{M}_i = \{\mathbf{m}_j\}_{j \in \Omega_i}$ with d-dimensional boolean (1-bit) masks. Alternatively, training independent models for each task can reach to a maximum of $d \times T$ parameters (32-bits), in a scenario where all tasks are learned without unlearning. Therefore, between the two existing methods for lifelong learning with exact unlearning capabilities, PALL becomes the memory-efficient choice.

Specifically, our default ResNet-18 with $d = 11.2$M parameters on S-CIFAR10, ResNet-34 with $d = 21.3$M on S-CIFAR100, and ViT-T/8 models with $d = 5.4$M on S-TinyImageNet, represented in 32-bits had model sizes of 42.59 MB, 81.30 MB, and 20.63 MB, respectively. For PALL, as well as PackNet and WSN, the maximum model size that can be achieved where $|\Omega_r| = T$, yielded model sizes of 49.24 MB, 106.70 MB, and 34.41 MB, respectively, considering T additional binary masks for each layer. In the case of independent models, this scenario yields total model sizes of



(a) S-CIFAR100 ($T = 10$) (b) S-TinyImageNet ($T = 20$)

Figure 2: Evaluations with different number of unlearning requests N_u in $\mathcal{R}_{1:r}$ (averaged across 10 random seeds each), for the methods that perform retraining or finetuning after task unlearning. We excluded GEM since the performance was similar to ER. We use $\alpha = 1/T$ for PALL.

212.95 MB, 813.0 MB, and 412.6 MB, respectively, indicating that PALL provides approximately 4.3×, 7.6× and 12× more model size efficient solutions with exact unlearning.

Notably, to facilitate model updates, each method also involves additional storage requirements (e.g., previous model weights in EWC, mnemonic codes in LSF). Similarly, PALL additionally requires the memory buffers $\{\mathcal{B}^t\}_{t\in\Omega_i}$, which is also common in all rehearsal-based learning methods. We further compare training times of each algorithm in Table A8 of Appendix A.3.4.

5.2 EMPIRICAL ANALYSIS OF THE TASK UNLEARNING MECHANISM

In Figure 2 we demonstrate the impact of N_u, on the methods with retraining or finetuning instructions during task unlearning. We specifically aim to assess the performance of our algorithm in task-incremental lifelong learning scenarios with more frequent unlearning requests.

We observed that PALL yields a relatively stable performance close to the naive baseline of training independent models without memory-efficiency considerations (red vs. blue solid lines in Figure 2). Particularly for large N_u, PALL shows less performance degradation with a parameter reset and retraining mechanism, than alternative inexact unlearning methods with finetuning: $\mathcal{A}_l \uparrow / \mathcal{F}_u \downarrow$ on S-CIFAR100 at $N_u = 5$: LSF: 50.3/5.2, DER++: 67.7/1.1, PALL: 71.2/0.6, Indep.: 73.9/0.0, and on S-TinyImageNet at $N_u = 9$: LSF: 36.9/4.9, DER++: 44.8/0.6, PALL: 59.2/0.7, Indep.: 62.1/0.0. We present additional experiments on the scalability of PALL in longer lifelong learning scenarios with S-TinyImageNet ($T = 100$) and even larger N_u, in Table A6 of Appendix A.3.3.

Impact of Retraining After Unlearning: We investigate the impact of N_f during rehearsal-based retraining of the reset parameters in Appendix A.3.1. Mainly, our results show that simply resetting the affected parameters without retraining yields comparably worse performance (e.g., $\mathcal{A}_l$ for S-CIFAR100 with $N_f = 0$: 70.24 vs $N_f = 50$: 72.35), indicating the necessity of retraining the reset weights through a memory buffer. We were also able to achieve better performance recovery after unlearning by using longer retraining durations (e.g., $\mathcal{A}_l$ for S-CIFAR100 with $N_f = 100$: 72.46).

We also present results on the ratio of retrained parameters during unlearning, and obtained parameter values after retraining. We observed that only $1-4\%$ of the parameters needed to be retrained via Eq. (6), resulting in weights numerically different from those before unlearning.

Influence of Episodic Memory Rehearsal: We performed ablation experiments on our choices for the episodic memory rehearsal method in Appendix A.3.2. In brief, we observed that $\beta = 0.5$ is the preferable choice for retraining, as previously claimed by DER++ (Buzzega et al., 2020), and using a larger memory buffer size generally increases performance (e.g., S-CIFAR100, $\mathcal{A}_l \uparrow / \mathcal{F}_u \downarrow$ with buffer size 200: 71.90/0.72, buffer size 500: 72.35/0.40, buffer size 1000: 73.58/0.23).

We also investigate the influence of the random exemplar sampling method used to select the samples to be stored in the memory buffer in Appendix A.3.2. We observed that using prioritized sampling mechanisms (Rebuffi et al., 2017) that are different than random, did not improve performance.

5.3 COMPARISONS TO INDEPENDENT SUBNETWORKS WITHOUT KNOWLEDGE TRANSFER

We designed an ablation experiment where we evaluate independently trained smaller architectures with an equivalent total model size to PALL, i.e., using models with d/T parameters. Similar to our baseline *Independent*, this setting also ensures exact unlearning, no catastrophic forgetting ($\mathcal{F}_l = 0$), and no impact of unlearning ($\mathcal{F}_u = 0$). We consider two configurations: (1) *static sparsity*, where T *independent* sparse subnetworks with $1/T$ connectivity are randomly initialized within a model, (2) *dynamic sparsity*, where we also optimize the sparse connectivity structure of these T *independent* subnetworks via score optimization. The latter, i.e., independent models via dynamic sparsity, resembles to PALL with the only difference of not allowing knowledge transfer across subnetworks via weight sharing. This also eliminates the need for a memory buffer and parameter retraining for exact unlearning.

Table 2: Comparisons on S-TinyImageNet (40 tasks × 5 classes, and 100 tasks × 2 classes), with independent subnetworks at $1/T$ sparsity. Results are averaged over 10 random seeds with $N_u = 3$. PALL uses $N_f = 10$ retraining iterations.

	$T = 40$		$T = 100$		Model Size (Inference)
	$\mathcal{A}_l \uparrow$	$\mathcal{F}_u \downarrow$	$\mathcal{A}_l \uparrow$	$\mathcal{F}_u \downarrow$	
Static Sparse (Ind.)	70.30	0.0	80.70	0.0	$d + \mathcal{M}_i$
Dynamic Sparse (Ind.)	71.19	0.0	83.75	0.0	$d + \mathcal{M}_i$
PALL ($\alpha = 0.01$)	71.00	0.56	85.89	0.53	$d + \mathcal{M}_i$
PALL ($\alpha = 0.025$)	72.07	0.36	86.11	0.43	$d + \mathcal{M}_i$
PALL ($\alpha = 0.05$)	72.03	0.32	85.80	0.35	$d + \mathcal{M}_i$
Independent	71.76	0.0	86.80	0.0	$d \times \lvert\Omega_i\rvert$

In Table 2, we present our results on S-TinyImageNet with 40 or 100 tasks, where the architecture is divided into very small, task-specific subnetworks (e.g., 54K params at 99% sparsity), and learning without knowledge transfer becomes challenging. We observed that dynamic sparsity outperforms independent subnetworks with static sparsity, and PALL consistently outperforms all independent subnetworks with the use of knowledge transfer, e.g., for $T = 100$, PALL ($\alpha = 0.025$): 86.11, Dynamic: 83.75. This makes PALL favorable in longer lifelong learning scenarios, where the number of tasks can be very high or unknown.

6 DISCUSSION

Lifelong learning and machine unlearning explores two important, yet mostly independently studied aspects of truly adaptive, flexible, and responsible AI systems. We proposed PALL as an algorithmic solution combining these two challenging and contradicting aspects, by satisfying all key pillars in both domains (i.e., no catastrophic forgetting, forward knowledge transfer, exact unlearning guarantees, memory-efficiency), for the first time. Our empirical evaluations demonstrate the effectiveness and scalability of PALL in dynamic environments, where efficient task learning and exact unlearning capabilities are desired by state-of-the-art models. Notably, we have shown PALL to yield up to 12× more model size efficient solutions with better or comparable task learning performances, as opposed to the naive baseline of training independent models to satisfy exact unlearning.

Our method is partially based on architecture-based lifelong learning methods that allow selective knowledge transfer (Kang et al., 2022; Ramanujan et al., 2020), which we innovatively extended into a hybrid learning strategy that is also equipped with a rehearsal-based lifelong learning method (Buzzega et al., 2020). This enables our algorithm to handle exact task unlearning requests in the presence of knowledge transfer, which was not addressed to date. Additionally, we also performed critical modifications to the existing subnetwork optimization methods, such as reinitializing the scores and unused weights after each learning request. These were required to satisfy overall exact unlearning guarantees, and resulted in effective learning and unlearning abilities simultaneously.

In this work, we focus on task-incremental learning settings, where the task ID is available to the learner. Our approach is not yet readily applicable to a class- or domain-incremental scenario where all previously learned tasks' label spaces are unified, since PALL disentangles the choice of the task-specific subnetwork based on the task IDs to ensure exact unlearning. To be applicable in these settings, PALL can be extended with a privacy-aware auxiliary algorithm to first identify the task, and subsequently utilize task-specific subnetwork via gating (Aljundi et al., 2017; Von Oswald et al., 2019). Our work also does not yet consider selective data unlearning, but instead performs complete task unlearning. To achieve stricter privacy with deletion guarantees for each data sample, our approach can be combined with differentially private optimization methods (Lai et al., 2022), in future work. Finally, going beyond our scope on vision tasks, we believe that applying PALL to language processing tasks in future work would also be of broad interest for responsible AI systems.

Reproducibility Statement: We provide detailed descriptions of the training configurations and hyperparameters of the experiments reported in this paper, in Appendix A.1 and A.2. Our algorithm is also outlined in Appendix A.2, and our implementations will be made publicly available.

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