

# Graceful Forgetting in Generative Language Models

Anonymous ACL submission

## Abstract

Recently, the pretrain-finetune paradigm has become a cornerstone in various deep learning areas. While in general the pre-trained model would promote both effectiveness and efficiency of downstream tasks fine-tuning, studies have shown that not all knowledge acquired during pre-training is beneficial. Some of the knowledge may actually bring detrimental effects to the fine-tuning tasks, which is also known as *negative transfer*. To address this problem, *graceful forgetting* has emerged as a promising approach. The core principle of graceful forgetting is to enhance the learning plasticity of the target task by selectively discarding irrelevant knowledge. However, this approach remains underexplored in the context of generative language models, and it is often challenging to migrate existing forgetting algorithms to these models due to architecture incompatibility. To bridge this gap, in this paper we propose a novel framework, Learning With Forgetting (LWF), to achieve graceful forgetting in generative language models. With Fisher Information Matrix weighting the intended parameter updates, LWF computes forgetting confidence to evaluate self-generated knowledge regarding the forgetting task, and consequently, knowledge with high confidence is periodically unlearned during fine-tuning. Our experiments demonstrate that, although thoroughly uncovering the mechanisms of knowledge interaction remains challenging in pre-trained language models, applying graceful forgetting can contribute to enhanced fine-tuning performance.

## 1 Introduction

In recent years, the *pretrain-finetune* paradigm has emerged as a dominant framework across natural language processing (NLP) tasks and various other domains (Zhou et al., 2023). This approach involves pre-training the model on large-scale corpora and subsequently fine-tuning it on smaller,

task-specific datasets to adapt to downstream applications. Its effectiveness has been evidenced by the success of prominent pre-trained models such as BERT (Devlin et al., 2019), GPT (Brown et al., 2020), and T5 (Raffel et al., 2020). And these models have become the backbone of many state-of-the-art AI applications (OpenAI, 2023; Rombach et al., 2022).

Despite offering compelling benefits such as data efficiency and reusability, this well-established paradigm continues to face a long-standing and prevalent issue, *negative transfer*, which surfaces in a new guise. While the typical interpretation of negative transfer in transfer learning refers to the performance degradation when learning conflicting tasks simultaneously or sequentially, its manifestation in the context of the pretrain-finetune paradigm takes on a different form, *the negative contribution of some pre-trained knowledge to the target fine-tuning task* (Zhang et al., 2023). This problem highlights a critical limitation of vanilla fine-tuning: treating all pre-trained knowledge indiscriminately is not always the optimal practice.

To address this issue, a promising approach is to suppress the influence of potentially harmful knowledge, a strategy known as *graceful forgetting* (or active forgetting). Originating in neuroscience, this concept describes a memory mechanism in biological intelligence where the ability to acquire new knowledge is enhanced by selective elimination of irrelevant or outdated information (Anderson and Hulbert, 2021). Recent advances have demonstrated the feasibility of emulating this mechanism in machine learning models (Zhou et al., 2022; D’Oro et al., 2023), leading to its adoption in various studies aimed at enhancing learning plasticity (Wang et al., 2021; Chen et al., 2023; Liang and Li, 2023; Shen et al., 2024).

However, most existing graceful forgetting methods are either tailored to vision tasks or designed for non-autoregressive models, making their ef-

forts incompatible or less effective when migrating to generative language models. This discrepancy primarily stems from the ambiguous knowledge boundaries inherent in language generation, which significantly complicate the identification of explicit and granular inter-task correlations (Pruksachatkun et al., 2020).

To address this gap, in this paper we investigate the graceful forgetting in generative language models. The central question guiding our study is: *can generative language models achieve more effective fine-tuning by gracefully forgetting unnecessary knowledge?* To answer this question, we propose a framework called Learning with Forgetting (LWF) to enable graceful forgetting in generative language models. Beginning from addressing the inaccessibility of pre-trained data, LWF leverages the inherent capabilities of generative models by expressing knowledge related to the forgetting task through self-generated texts. Furthermore, given the difficulty of identifying task-level correlations, LWF computes a data-wise *forgetting confidence* for each input by weighting the intended parameter updates with the Fisher Information Matrix. Based on this metric, LWF selects high-confidence data points and integrates machine unlearning techniques to periodically remove associated knowledge during the fine-tuning process.

To the best of our knowledge, LWF represents the first systematic exploration of graceful forgetting in generative language models. Through extensive experiments and analyses, we demonstrate the feasibility of improving fine-tuning performance through graceful forgetting. Hopefully, our empirical findings will contribute to a better understanding of this emerging topic and offer inspiration for future investigation and innovation.

## 2 Related Work

In this section, we provide an overview of how the critical concepts in our work are interpreted and applied across a broader research landscape, and analyze their commonalities and distinctions.

### 2.1 Negative Transfer

Negative transfer is a prevalent issue across multiple fields, with its interpretation and definition often varying depending on the context.

In Multi-Task Learning (MTL), negative transfer refers to the performance degradation caused by mutual interference among conflicting tasks (Go

et al., 2023). While the primary objective of MTL is to learn multiple tasks simultaneously, methods aimed at mitigating negative transfer typically focus on quantifying inter-task relationships using sophisticated metrics like gradient directions (Jiang et al., 2023; Riemer et al., 2019) or signal-to-noise ratio (Go et al., 2023). Based on these metrics, tasks can be clustered into separate groups (Ramesh and Chaudhari, 2022) to reduce learning conflicts. In the MTL context, strategies that involve sacrificing part of the model’s capacity, such as forgetting, are typically not regarded as appropriate solutions.

Another related domain is Continual Learning (CL), where different tasks are learned sequentially. In CL, negative transfer is bi-directional: it can refer to the interference of previously acquired knowledge with the learning of new tasks, or to the forgetting of past knowledge caused by learning new ones (Karakida and Akaho, 2022). While most CL methods focus on maintaining memory stability when learning new tasks (Kirkpatrick et al., 2017; Schwarz et al., 2018), recent studies have highlighted that this stability often comes at the cost of reduced learning plasticity. In response, these approaches actively weaken the preservation strength of past memory, seeking a balance between memory stability and learning plasticity (Liang and Li, 2023; Wang et al., 2021; Schwarz et al., 2018), which can be seen as an implicit form of forgetting.

In our context, the pretrain-finetune paradigm, negative transfer denotes the detrimental influence of certain pre-trained knowledge on the target fine-tuning task. A distinguishing characteristic of negative transfer in this paradigm is that the pre-training data is typically inaccessible during fine-tuning, which renders many countermeasures used in MTL and CL ineffective or inapplicable.

### 2.2 Graceful Forgetting

In many domains, forgetting is traditionally viewed as an undesirable phenomenon, reflecting a failure to retain previously acquired knowledge. This concern is particularly prominent in CL, where one of the primary objectives is to overcome catastrophic forgetting (Kirkpatrick et al., 2017).

However, recent studies have argued that striving for an omniscient model may be impractical due to limited model capacity and inevitable knowledge conflicts (Zhou et al., 2022; D’Oro et al., 2023). Drawing inspiration from neuroscience (Anderson and Hulbert, 2021), an increasing number of studies have explored the potential of improving

learning plasticity through actively forgetting irrelevant or outdated knowledge. In the context of CL, Wang et al. (2021) proposed a synaptic expansion-convergence mechanism to selectively forget preserved knowledge. Liang and Li (2023) realized controllable learning plasticity through gradient projection. In the context of fine-tuning, Chen et al. (2019) and Shen et al. (2024) incorporate model structural shrinkage regulation to enable implicit forgetting. While most of these methods were initially designed for image classification tasks, Chen et al. (2023) extended graceful forgetting to language models, improving multi-lingual learning during pre-training.

Despite these efforts, existing graceful forgetting approaches are either inapplicable or significantly less effective when adapted to the fine-tuning of generative language models.

### 2.3 Machine Unlearning

Machine unlearning is a vibrantly investigated topic studying removing specific data, patterns, or knowledge from trained models (Yao et al., 2023). In the context of generative language models, unlearning is usually applied to aligning language models with human values, such as protecting user privacy (Patil et al., 2024), removing harmful contents (Liu et al., 2024), and reducing hallucination (Yao et al., 2023). A variety of unlearning strategies have been proposed for generative language models, including gradient ascent (Jang et al., 2023), localization-informed unlearning (Jang et al., 2023), influence function-based methods (Jia et al., 2024), and so on. While current generative language model unlearning research primarily focuses on eradicating undesirable behaviors, our work repurposes unlearning as a mechanism to achieve graceful forgetting, thereby enhancing the plasticity of fine-tuning. In essence, we leverage unlearning for better learning.

## 3 Methodology

In this section, we detail the implementation of our framework for graceful forgetting in generative language models, Learning With Forgetting (LWF). It consists of three components: eliciting self-knowledge, evaluating forgetting confidence, and periodically unlearning. Fig 1 illustrates the overview. For the sake of convenience in exposition, we use  $\mathcal{D}_L$  to represent the learning task and  $\mathcal{D}_F$  to denote the forgetting task. It is important to

note, however, that the framework is task quantity-agnostic, which will be elaborated in Section 4.

### 3.1 Eliciting Self-Knowledge

The first step in forgetting specific knowledge is to acquire its representation. However, as discussed in Sec 2.1, the pre-training corpus is typically inaccessible in practice, making it uncertain whether  $\mathcal{D}_F$  can adequately represent the model’s knowledge. To address this issue, we exploit the inherent characteristics of generative language models as an alternative: leveraging self-generated data. Specifically, we input the prompts (e.g., questions or instructions) from  $\mathcal{D}_F$  into the base model  $\mathcal{M}_{base}$  and collect its responses to form the unlearning dataset, which we donate as  $\mathcal{D}_{self}$ . This approach also enables LWF to utilize unlabeled datasets.

### 3.2 Evaluating Forgetting Confidence

Not all kinds of knowledge forgetting contribute positively to model adaptation. To ensure that forgetting improves, rather than degrades, fine-tuning performance, we propose a confidence metric to evaluate the safety of unlearning specific knowledge. Considering the semantic richness of natural language, a task-level metric proves insufficiently nuanced (Pruksachatkun et al., 2020). Therefore, we define the *forgetting confidence* at the individual data point level, enabling fine-grained assessment of what should be forgotten.

For a generated text  $x$  in  $\mathcal{D}_{self}$ , the posterior  $P(\mathcal{D}_L|x)$  intuitively reflects to what extent  $\mathcal{D}_L$  and  $x$  are synergistic. The lower  $P(\mathcal{D}_L|x)$  is, the more likely  $x$  is conflicted with  $\mathcal{D}_{self}$ . Considering  $P(\mathcal{D}_L|x)$  is computationally intractable, we use  $P(\mathcal{D}_L|\theta^*(x))$  as a surrogate, where

$$\theta^*(x) = \arg \max_{\theta} P(\theta|x) \quad (1)$$

Since only the relative value is required, we can use  $P(\theta^*(x)|\mathcal{D}_L)$  to represent  $P(\mathcal{D}_L|\theta^*(x))$ , as the two are positively proportional according to the Bayes’ Theorem. Based on this, we define the forgetting confidence as:

$$FC(x) \propto -\log P(\theta^*(x)|\mathcal{D}_L) \quad (2)$$

Following prior works (Kirkpatrick et al., 2017; Wang et al., 2021), we assume  $P(\theta|\mathcal{D}_L)$  as a Gaussian distribution centered at  $\theta_L^* = \arg \max_{\theta} P(\theta|\mathcal{D}_L)$ , and this distribution can be approximated using a second-order Taylor expansion

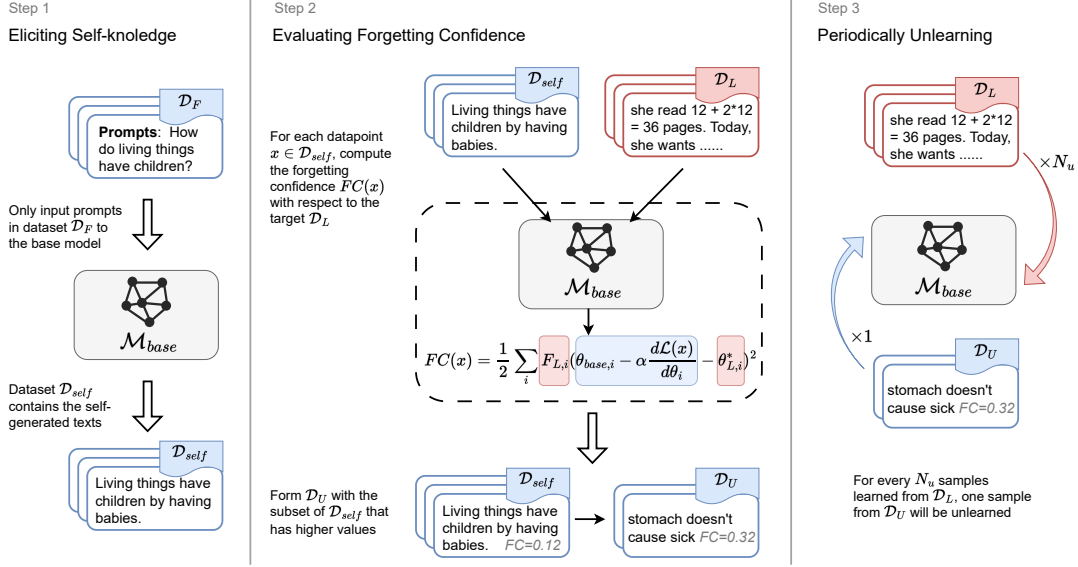


Figure 1: The overview of the LWF framework. Given the forgetting task  $\mathcal{D}_F$  and learning task  $\mathcal{D}_L$ , LWF first constructs  $\mathcal{D}_{self}$  through self-generated texts to represent the knowledge regarding the forgetting task. Then, with the Fisher Information Matrix  $F_L$  and the optimal parameters of the learning task approximated from  $\mathcal{D}_L$ , LWF calculates forgetting confidence for each data point in  $\mathcal{D}_{self}$ . Finally, data points with high forgetting confidence are selected for unlearning, represented by  $\mathcal{D}_U$ . The unlearning process is integrated into the fine-tuning process of  $\mathcal{D}_L$  and is executed periodically at intervals of  $N_u$ .

around  $\theta_L^*$ :

$$\log P(\theta|\mathcal{D}_L) \approx -\frac{1}{2}(\theta - \theta_L^*)^T \left( \frac{\partial^2 \log P(\theta|\mathcal{D}_L)}{\partial^2 \theta} \Big|_{\theta_L^*} \right) (\theta - \theta_L^*) \quad (3)$$

In practice, we integrate Equation 2 with Equation 3 and use a single-step update from the base model to represent  $\theta^*(x)$ , thereby reducing computational costs:

$$FC(x) = \frac{1}{2} \sum_i F_{L,i} (\theta_{base,i} - \alpha \frac{d\mathcal{L}(x)}{d\theta_i} - \theta_{L,i}^*)^2 \quad (4)$$

$F_L$  represents the Fisher Information Matrix (FIM), which is the negative expectation of the Hessian Matrix in Equation 3. The parameters of the base model are represented by  $\theta_{base}$ , while  $\mathcal{L}(x)$  refers to the cross-entropy loss of  $x$ .  $\alpha$  controls the length of the single-step update. The  $\theta_L^*$  is obtained by training the base model on  $\mathcal{D}_L$ .

Intuitively, Equation 4 measures the conflict between  $x$  and  $\mathcal{D}_L$  by evaluating the alignment between the intended parameter update induced by  $x$  and the target  $\theta_L^*$ . The FIM  $F_L$  serves as a weighting mechanism that captures the relative importance of each parameter.

### 3.3 Periodically Unlearning

With the forgetting confidence  $FC(x)$ , we select a subset  $\mathcal{D}_U$  from  $\mathcal{D}_{self}$  for unlearning, consisting of the top  $\frac{1}{N_u}$  fraction of samples with the highest confidence scores. However, due to the well-known instability of machine unlearning (Yao et al., 2023; Liu et al., 2024), simply unlearning  $\mathcal{D}_U$  may not yield consistent improvements. Particularly since the selected data are only potentially, rather than definitively, conflicting with the target task.

To mitigate the instability introduced by unlearning, we adopt a "periodically unlearning" strategy. Specifically, we perform learning on  $\mathcal{D}_L$  and unlearning on  $\mathcal{D}_U$  simultaneously, while maintaining a fixed interval  $N_u$  between consecutive unlearning sessions. For example, if the interval  $N_u = 7$ , then for every 7 data points learned from  $\mathcal{D}_L$ , one data point from  $\mathcal{D}_U$  will be unlearned.

We use *Gradient Ascent* as our unlearning algorithm, which merely involves negating the loss function. Specifically, for a periodic batch  $\mathcal{X} = \{x_1^l, \dots, x_{N_u}^l, x^u\}$  where  $\{x_1^l, \dots, x_{N_u}^l\} \subset \mathcal{D}_L$  and  $x^u \in \mathcal{D}_U$ , the loss can be written as:

$$\mathcal{L}_{pu}(\mathcal{X}) = \sum_{x \in \{x_1^l, \dots, x_{N_u}^l\}} \mathcal{L}(x) - \beta \mathcal{L}(x^u) \quad (5)$$

where  $\mathcal{L}$  is the *sft* loss and  $\beta$  is the unlearning rate.



## 4 Experiments

### 4.1 Setup

#### 4.1.1 Datasets

To evaluate the effectiveness of LWF, we apply our method to domain-specific question-answering tasks. This choice is motivated by the well-established evaluation metrics (i.e., accuracy) and the relatively clear delineation of knowledge boundaries across domains. We further discuss task generalizability in Appendix C.

We select five datasets spanning diverse domains: **gsm8k** (Cobbe et al., 2021) for mathematical reasoning; **qasc** (Khot et al., 2020) for elementary science; **sst5** (Socher et al., 2013) for sentiment classification; **dental**, a subset of MedMCQA (Pal et al., 2022) focusing on dental knowledge; and **psychol**, a subset of MMLU (Hendrycks et al., 2021) covering psychology.

#### 4.1.2 Implementation Details

We utilize Llama3.2-1B (Touvron et al., 2023) as the base model for all experiments. To elicit self-knowledge, we use a 3-shot prompt concatenated with the input question, employ a greedy decoding strategy, and constrain the maximum number of generated tokens to 256. When computing the forgetting confidence, we set the one step update coefficient  $\alpha$  to  $1e-2$  (as defined in Equation 4). To maintain the coherence of batch gradient descent during periodically unlearning, we combine  $\mathcal{D}_L$  and  $\mathcal{D}_U$  by incorporating one data point from  $\mathcal{D}_U$  for every  $N_u$  data points from  $\mathcal{D}_L$ . The training process uses a batch size of 4, a learning rate of  $1e-5$ , and spans in total one epoch.  $N_u$  is set to 7, and  $\beta$  (as defined in Equation 5) is either 0.1 or 0.05, depending on forgetting tasks. All training procedures are carried out on eight NVIDIA RTX 4090 GPUs with full parameter tuning. For more details please refer to Appendix A.

#### 4.2 Results on Question Answering

Table 1 shows the results on question-answering tasks. Each column corresponds to a distinct learning task, and each row represents a forgetting scenario. The first row, labeled *none*, indicates vanilla fine-tuning without forgetting, while the last row, labeled *mixed*, denotes a forgetting setting comprising all datasets except the learning one. As we note that previous forgetting methods for fine-tuning, such as BSS (Chen et al., 2019) and SRS (Shen et al., 2024), are significantly less effective when

	gsm8k	qasc	sst5	dental	psychol
none	19.71	42.98	49.55	36.87	46.42
gsm8k	-	+4.03%	+2.83%	+1.46%	+6.33%
qasc	+5.38%	-	+2.54%	-4.53%	+5.54%
sst5	+2.67%	+3.02%	-	+0.22%	+0.41%
dental	+10.40%	+5.28%	+2.10%	-	+1.59%
psychol	+1.17%	+2.00%	+1.27%	-4.10%	-
mixed	+6.95%	+5.54%	+2.10%	+1.46%	+7.93%

Table 1: Results on domain-specific question answering. Each column shares the same learning task and the rows represent different forgetting tasks. All percentages are calculated based on *none*.

	gsm8k	qasc	sst5	dental	psychol
none	56.56	68.36	55.52	49.39	80.00
gsm8k	-	+5.37%	+0.97%	+0.78%	+2.06%
qasc	+1.61%	-	+0.74%	-3.06%	+0.46%
sst5	+7.37%	+2.68%	-	+0.00%	+2.75%
dental	+1.20%	+1.26%	+1.30%	-	+0.91%
psychol	+1.47%	+4.42%	+0.24%	-0.14%	-
mixed	+4.56%	+7.90%	+1.06%	+0.78%	+1.60%

Table 2: Results on domain-specific question answering with a larger language model.

migrating to generative language models, we only include their performance in Appendix D.

As shown in the results, in most cases, LWF improves performance on the learning task compared to vanilla fine-tuning. Exceptions occur when learning dental while forgetting qasc or psychol, which we believe is attributed to the low forgetting confidence of self-generated samples. This is further evidenced by the results of the *mixed*, where consistent improvements across all learning tasks suggest that combining diverse forgetting datasets increases the pool of high-confidence candidates, thereby enhancing the likelihood of performance gains. *The mixed setting is also recommended in practice for stable effectiveness.*

We also examine the side effects of LWF, i.e., its impact on datasets that are neither part of the learning task nor the forgetting task. Details are discussed in Appendix B.

#### 4.3 Scalability Analysis

A natural question is that, would LWF be less effective in a larger generative language model since the increased model parameters are better capable of accommodating conflicting knowledge? In response, we apply LWF to a larger model, Llama3-8B. The results are shown in Table 2.

As we can see, LWF can still improve fine-tuning

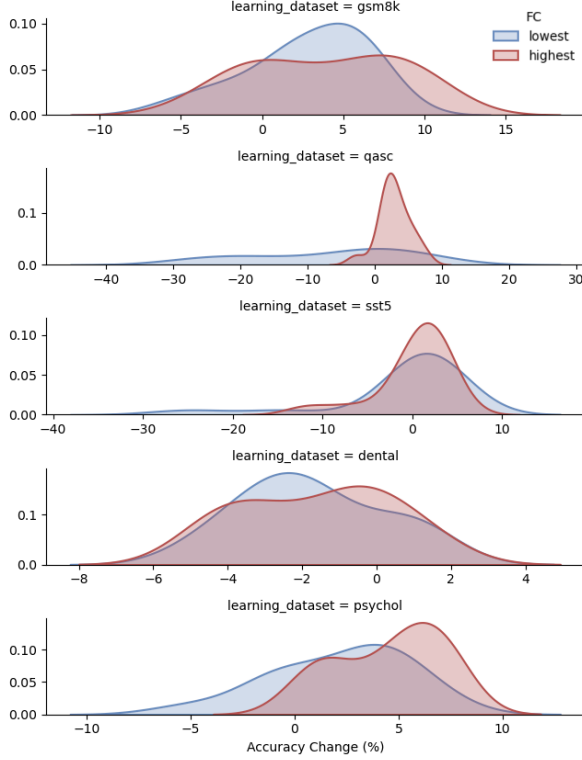


Figure 2: Distribution of accuracy changes between two filtering strategies. The y-axis represents distribution density. All percentages are calculated based on vanilla fine-tuning.

performance in most cases. While the magnitude of relative improvement has declined overall, this trend is partly due to the stronger baseline performance of the larger model. Notably, the insights about unlearning settings gained from the smaller model generalize well to the larger one: the *mixed* setting is still the best choice to achieve stable effectiveness.

#### 4.4 Analysis on Forgetting Confidence

A central component of LWF is the computation of forgetting confidence, which estimates the likelihood that forgetting a specific data point will benefit the learning task. While we propose a computable metric  $FC(x)$  (in Sec 3.2), it involves approximations and does not provide an exact mapping between gradient updates and performance outcomes. As a result,  $FC(x)$  should be viewed as a heuristic rather than an absolute measure. In practice, we also observe that unlearning data with relatively low  $FC$  does not necessarily lead to performance degradation.

To gain deeper statistical insight into the role of forgetting confidence, we design an ablation study using an inverse filtering strategy: selecting data

$\mathcal{D}_F$	gsm8k	qasc	sst5	dental	psychol
none	19.71	42.98	49.55	36.87	46.42
gsm8k	-	-65.6%	+0.5%	-0.8%	-9.9%
qasc	+5.0%	-	+0.4%	-7.4%	+3.6%
sst5	+4.3%	+7.8%	-	-3.5%	+9.1%
dental	-8.5%	-26.6%	+1.2%	-	+0.0%
psychol	-6.5%	-8.3%	-21.7%	-4.9%	-
mixed	-3.5%	-73.9%	+2.3%	+0.8%	-7.9%

Table 3: Results of *ahead unlearning*, ablation study for periodically unlearning, where unlearning is completed before fine-tuning.

$\mathcal{D}_F$	gsm8k	qasc	sst5	dental	psychol
none	19.71	42.98	49.55	36.87	46.42
gsm8k	-	-12.6%	-0.1%	-4.9%	+10.3%
qasc	-8.8%	-	+3.9%	-2.0%	+7.7%
sst5	-8.8%	-10.8%	-	-4.3%	+3.6%
dental	-6.5%	-6.9%	+1.8%	-	+7.5%
psychol	-5.0%	-13.1%	+2.1%	-2.7%	-
mixed	-6.5%	-10.1%	-0.5%	-4.9%	+9.5%

Table 4: Results of *randomly unlearning*, ablation study for periodically unlearning, where unlearning is randomly executed during fine-tuning.

with the lowest forgetting confidence. For each learning task, we compute the percentage change in accuracy relative to vanilla fine-tuning, across all forgetting tasks. To increase the sample size, we aggregate results over four unlearning rates:  $\beta \in \{0.05, 0.10, 0.20, 0.25\}$ .

Fig 2 shows the distribution of accuracy changes under the two filtering strategies. The *red* region corresponds to unlearning data with the *highest*  $FC$ , while the *blue* region represents unlearning data with the lowest. The x-axis indicates the percentage change in accuracy relative to vanilla fine-tuning. As shown, unlearning high- $FC$  data generally outperforms the alternative in two aspects: higher average performance gain and greater stability. Specifically, high- $FC$  unlearning yields smaller variance and narrower overall range, whereas unlearning low- $FC$  data leads to more volatile outcomes, including severe performance drops in extreme cases. In summary, prioritizing data with high forgetting confidence results in consistently better and more robust performance, making it a more reliable strategy in practice.

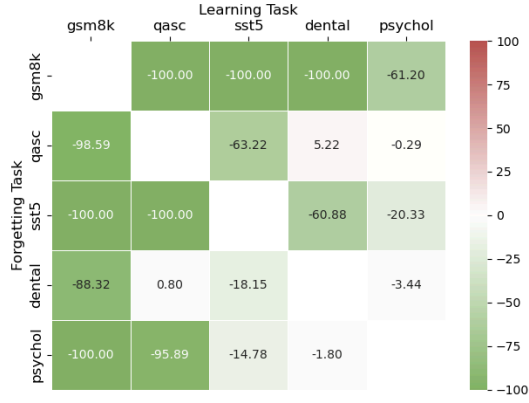


Figure 3: Accuracy change percentage of the forgetting task across different learning-forgetting combinations. Percentages are computed based on vanilla fine-tuning.

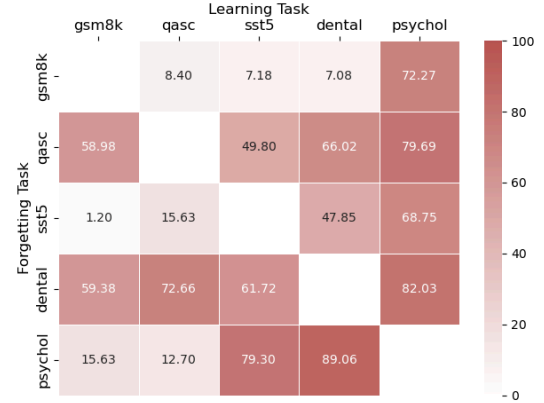


Figure 4: Cosine similarity between the outputs of forgetting tasks generated by the vanilla fine-tuned model and LWF resulting model. Values are multiplied by 100.

#### 4.5 Ablation on Periodically unlearning

To alleviate the vulnerability of machine unlearning, we propose the periodically unlearning strategy to stabilize the training process. In this section, we conduct an ablation study to demonstrate that periodically unlearning is the most effective strategy for integrating learning and unlearning.

We compare two alternative unlearning strategies. The first performs unlearning entirely before the learning process, which we refer to as *ahead unlearning*. The second interleaves unlearning steps randomly during training, termed *randomly unlearning*. For fairness, all three strategies, including *periodically unlearning*, maintain the same ratio of learning to unlearning samples.

Table 3 and Table 4 present the results of *ahead unlearning* and *randomly unlearning* respectively. As we can see, both strategies are generally much less effective than *periodically unlearning* (Table 1), with most learning-forgetting combinations resulting in performance degradation. Notably, *ahead unlearning* exhibits several extremely detrimental cases, primarily attributed to the unintended disruption to foundational pre-trained knowledge caused by premature unlearning steps. If such critical knowledge is compromised, the subsequent fine-tuning process may suffer severe performance loss. In conclusion, the interleaved learning and unlearning combination is better than conducting them separately, and switching them periodically is superior to randomly.

#### 4.6 Analysis on the Forgotten Task

In this section, we analyze the forgetting task to investigate how model performance on it evolves

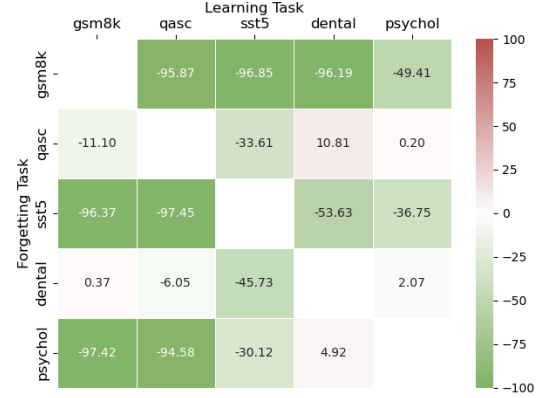


Figure 5: TTR change percentage of the forgetting task across different learning-forgetting combinations. Percentages are computed based on vanilla fine-tuning.

before and after the deployment of LWF. While it may seem intuitive that the model’s knowledge regarding the forgetting task would be largely erased, the empirical findings are more complicated. Fig 3 presents a heatmap showing the percentage change in accuracy on the forgetting tasks relative to vanilla fine-tuning. As shown, although there is a general decline in accuracy across most learning-forgetting combinations, the magnitude of degradation varies considerably. In approximately half of the cases, accuracy drops nearly 100%, while in others, the decrease is relatively minor, particularly when either the learning task or the forgetting task involves *dental* or *psychol*.

Additionally, we noticed that the accuracy alone merely reflects whether the final answer is correct, which is insufficient to fully capture the nuanced changes in the generated outputs of generative models. To gain deeper insights, we further analyze the

semantic shifts in the responses. Specifically, we use SimCSE model<sup>1</sup> (Gao et al., 2021) to obtain the sentence vectors of the responses generated by the vanilla fine-tuned model and LWF model when answering the same forgetting task questions. We then compute the cosine similarity between the resulting sentence embeddings to quantify the degree of semantic change. Results are presented in Fig 4.

Given that a cosine similarity score above 80% is typically required to confidently assert semantic similarity between two sentences, the results indicate that most learning-forgetting combinations exhibit substantial semantic changes. Notably, the cases where similarity approaches or exceeds this threshold largely coincide with those showing minimal accuracy drops, *i.e.*, combinations involving the *dental* or *psychol*. We believe this phenomenon may be attributed to that *dental* and *psychol* are inherently more complex than the other tasks. Acquiring or forgetting these domains likely requires engagement with richer, more structured knowledge, which in turn makes them more resistant to severe forgetting.

We also evaluate changes in lexical diversity, as shown in Fig 5, where Type Token Ratio (TTR) is the metric. Similar to the trends observed in accuracy changes, the TTR experiences a significant decline in most combinations, and the cases maintaining high accuracy and semantic similarity also largely preserve their lexical diversity.

#### 4.7 Multi-Task Learning

In this section, we examine the performance of LWF in multi-task learning scenarios. Specifically, we treat one of the five datasets as the forgetting task and use the remaining four as learning tasks. To mitigate catastrophic forgetting of earlier tasks, we train on a balanced mixture of all learning datasets. Fig 6 compares the overall multi-task accuracy between LWF and vanilla fine-tuning. As we can see, while not all individual learning task gets improved, LWF outperforms vanilla fine-tuning in general.

These results highlight the complexity of multi-task learning. Although LWF enables overall performance gains through controlled forgetting, the interactions among learning tasks are non-trivial. Improvements in some tasks may come at the expense of others.

<sup>1</sup><https://huggingface.co/princeton-nlp/unsup-simcse-bert-base-uncased>

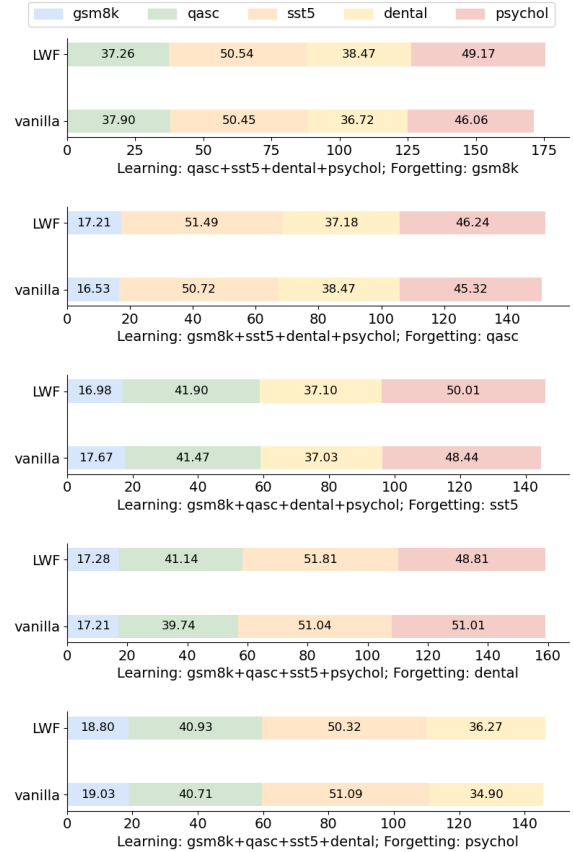


Figure 6: Accuracy results in the multi-task learning setting. Labeled below each subplot are the forgetting task and learning tasks.

## 5 Conclusion

In this paper, we propose a novel framework, Learning With Forgetting (LWF), to achieve graceful forgetting in generative language models. LWF addresses the inaccessibility of pre-trained data by leveraging self-generated knowledge, calculates forgetting confidence for each data point by weighting the intended parameter update with Fisher Information Matrix, and employs gradient ascent to periodically unlearn high-confidence data during fine-tuning. Empirical results on domain-specific question-answering tasks demonstrate the effectiveness of LWF. Furthermore, we conduct extensive experiments to analyze the contribution of each component of LWF, the effects of forgetting specific tasks, and the framework’s performance in learning or forgetting multiple tasks. While fully elucidating the mechanisms of inter-task interactions and achieving optimal graceful forgetting still need great effort, we hope our work provides valuable insights into this emerging area and inspires future research endeavors.



## Limitation

As the first framework for *graceful forgetting* in generative language models, LWF has several limitations that warrant further investigation. First, our proposed forgetting confidence relies on an analysis of intended parameter updates to select unlearning data. While empirical results demonstrate its statistical effectiveness, its performance may degrade when the pool of candidate forgetting data is limited. Given that quantifying interactions among training examples remains a long-standing challenge in knowledge transfer, we expect future research to yield more precise and robust metrics for measuring forgetting confidence.

Additionally, computing forgetting confidence introduces computational overhead, primarily due to gradient calculations required for each forgetting sample. As a result, the additional time cost is approximately equivalent to one full training epoch on  $\mathcal{D}_{self}$ . Considering our method is designed for task-specific fine-tuning, rather than large-scale pre-training, the additional overhead can be acceptable in most cases.

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## A More Implementation Details

Table 5, Table 6, Table 7, Table 8, and Table 9 present the few-shot CoT prompts designed for each dataset, which are utilized during both the self-knowledge elicitation and evaluation stages. As illustrated in the prompts, answers are formatted with the phrase ‘The answer is’ to facilitate the convenience of extracting answers. Any model output that deviates from this format is considered incorrect. In cases where multiple occurrences of ‘The answer is’ appear in the output, the first instance is treated as the definitive answer.

## B Side Effect

Although in Sec 4 we have verified that LWF can improve target fine-tuning task by sacrificing the unlearning task, it is unknown how this procedure will influence unintended tasks that are neither part of the learning task nor the forgetting task (for simplicity we denote them as side-tasks). In this section, we discuss the side effects of LWF.

Firstly, we notice a *superficial forgetting* problem, which happens between gsm8k and other four datasets. Specifically, while all five datasets used in our experiments are question-answering datasets, gsm8k is a free-form numerical QA dataset but the other four are multiple-choice QA datasets (see examples in Table 5 and Table 6). We observed that this format discrepancy can lead to significant performance degradation on side-tasks when gsm8k is the learning task and the other datasets are the forgetting tasks. By analyzing the model’s outputs, we identified that the model trained under this setting often fails to generate answers in the multiple-choice format. An illustration is provided in Table 10. As it shows, although the rationale portion of the output appears coherent, the resulting model fails to select a valid option at the end of its response.

This *superficial forgetting* suggests that, when applying LWF, the model tends to focus on the most superficial pattern differences to distinguish the learning task from the forgetting task. Therefore, to mitigate extreme side effects, it is better to ensure that there are no overly superficial format differences between the learning and forgetting tasks in practice.

Apart from the superficial forgetting issue introduced by gsm8k, we also compute the average accuracy of side-tasks on combinations of the other four datasets, and compare it to that of the vanilla fine-

tuned model. Table 11 shows the results, where each column represents the learning task and the row indicates the forgetting task. As observed, the side effects vary depending on the specific learning-forgetting combinations. In general, the impact is much milder when learning complex tasks like psychol and dental.

## C Task Generalizability

In Sec. 4, we evaluate the effectiveness of LWF on the domain-specific question-answering task. This is primarily motivated by its well-established evaluation metrics and delineated knowledge boundaries, which help isolate the impact of graceful forgetting by minimizing confounding variables. Additionally, to examine the task generalizability, we conducted experiments in two other settings, both related to the multi-lingual capability of generative language models.

First, we apply LWF to machine translation tasks. We selected four language datasets—German (DE), French (FR), Turkish (TR), and Chinese (ZH)—from the WMT (Kocmi et al., 2022) corpus to evaluate the model’s ability to translate from English into those languages. BLEU (Papineni et al., 2002) and BERTScore-F1 (Zhang et al., 2020) are used as evaluation metrics. As Table 12 shows, while LWF continues to yield performance gains in most cases, the extent of these improvements is considerably less pronounced compared to QA tasks. In addition, the results reflected by the two metrics are not entirely consistent, which is mainly due to the incompleteness of evaluation metrics in machine translation tasks.

The second experiment was conducted on the multi-lingual QA task. Specifically, we applied LWF to the gsm8k dataset across five different languages: English (EN), Italian (IT), Chinese (ZH), Spanish (ES), and Turkish (TR). From results presented in Table 13, we observed an interesting phenomenon: aside from the *mixed* approach, which consistently improves performance across all languages, the results are all positive when learning English with forgetting other languages, and vice versa. However, when the combination does not involve English, the outcomes are predominantly negative. We hypothesize that this phenomenon may stem from the disproportionate volume of English data used during the model’s pre-training, which help stabilize LWF’s performance when English is involved.

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**Question:** There are 15 trees in the grove. Grove workers will plant trees in the grove today. After they are done, there will be 21 trees. How many trees did the grove workers plant today? Let's think step by step.

**Answer:** We start with 15 trees. Later we have 21 trees. The difference must be the number of trees they planted. So, they must have planted  $21 - 15 = 6$  trees. The answer is 6.

**Question:** If there are 3 cars in the parking lot and 2 more cars arrive, how many cars are in the parking lot? Let's think step by step.

**Answer:** There are 3 cars in the parking lot already. 2 more arrive. Now there are  $3 + 2 = 5$  cars. The answer is 5.

**Question:** Leah had 32 chocolates and her sister had 42. If they ate 35, how many pieces do they have left in total? Let's think step by step.

**Answer:** Leah had 32 chocolates and Leah's sister had 42. That means there were originally  $32 + 42 = 74$  chocolates. 35 have been eaten. So in total they still have  $74 - 35 = 39$  chocolates. The answer is 39.

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Table 5: Few-shot prompts for gsm8k.

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**Question:** What type of water formation is formed by clouds? (A) pearls (B) streams (C) shells (D) diamonds (E) rain (F) beads (G) cooled (H) liquid Let's think step by step.

**Answer:** Beads of water are formed by water vapor condensing. Clouds are made of water vapor. Beads of water can be formed by clouds. The answer is (F).

**Question:** Removing what from food will preserve it? (A) flavor (B) body water (C) heat energy (D) color (E) Water (F) Bodily water (G) moisture (H) ingredients Let's think step by step.

**Answer:** Dehydrating food is used for preserving food. Dehydration preserves foods by removing moisture. Removing moisture from food preserves it. The answer is (G).

**Question:** Reproduction is the process by which living things what? (A) Most plants (B) allow growth (C) spread flower seeds (D) have wide set eyes (E) members of their own species (F) have birthing hips (G) have quiet laughter (H) give birth to babies Let's think step by step.

**Answer:** Reproduction is the process by which living things give rise to offspring. Whenever it starts to give birth, it gives birth up to two to four babies offspring. Reproduction is the process by which living things give birth to babies. The answer is (H).

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Table 6: Few-shot prompts for qasc.

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**Question:** What is the emotional attitude reflected in the sentence: "in his first stab at the form , jacquot takes a slightly anarchic approach that works only sporadically ."? (A) very negative (B) negative (C) neutral (D) positive (E) very positive Let's think step by step:

**Answer:** The phrase "first stab" suggests this is an initial attempt, which can imply inexperience but also experimentation. "Slightly anarchic approach" does have a mild negative connotation with "anarchic," but it's softened by "slightly." "Works only sporadically" indicates mixed results. It doesn't work consistently, but it does work sometimes, which isn't entirely negative. Given these considerations, while there are elements that lean towards a negative interpretation, the overall tone of the sentence is not strongly positive or negative. So the emotional attitude is neutral. The answer is (C)

**Question:** What is the emotional attitude reflected in the sentence: "one long string of cliches."? (A) very negative (B) negative (C) neutral (D) positive (E) very positive Let's think step by step:

**Answer:** The phrase "one long string" suggests an extended or continuous sequence, which in this context implies that there are many instances of something undesirable. The term "cliches" refers to expressions or elements that have been overused to the point of losing their original impact, freshness, or appeal. It generally carries a negative connotation because it indicates a lack of originality or creativity. Considering these points, the sentence does not contain any positive words or phrases and is clearly pointing out a flaw or criticism. Therefore, the emotional attitude reflected in the sentence is negative. Since it's a straightforward criticism without strong intensifiers (like "extremely" or "utterly"), we can conclude that the most fitting emotional attitude is negative. The answer is (B)

**Question:** What is the emotional attitude reflected in the sentence: "although laced with humor and a few fanciful touches, the film is a refreshingly serious look at young women."? (A) very negative (B) negative (C) neutral (D) positive (E) very positive Let's think step by step:

**Answer:** The word "although" introduces a concession, acknowledging that the film contains elements of humor and some imaginative aspects ("fanciful touches"). This part suggests that there are positive qualities present in the film. The main clause uses the term "refreshingly," which conveys a positive and invigorating experience. It indicates that the seriousness of the film's approach to its subject matter is not only appreciated but also seen as something new or different from what might be expected. The focus on "young women" being treated seriously adds depth to the evaluation. It implies that the film offers a thoughtful and mature perspective on its subject, which can be seen as commendable. Given these considerations, the overall tone of the sentence is appreciative and positive. The use of "refreshingly" especially signals a positive emotional response to the film's treatment of its subject. However, since the positivity is moderate and not overly enthusiastic or exuberant, the most fitting emotional attitude is positive. The answer is (D).

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Table 7: Few-shot prompts for sst5.



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**Question:** Resistance to lateral shifting or anteroposterior shifting is called as:? (A) Retention. (B) Stability. (C) Support. (D) None. Let's think step by step:

**Answer:** The question is asking about the term used to describe resistance to lateral (side-to-side) or anteroposterior (front-to-back) shifting. Retention generally refers to the ability to hold or keep something in place. In dentistry, for example, it refers to the resistance of a dental prosthesis to displacement in a vertical direction. Stability refers to the resistance to movement, particularly lateral or anteroposterior shifting. It is the ability of an object or structure to maintain its position when subjected to forces. Support refers to the ability to bear weight or hold something up, but it does not specifically refer to resistance to shifting. Based on the definitions, stability is the term that specifically refers to resistance to lateral or anteroposterior shifting. The answer is (B).

**Question:** Tannerella forsythia is a ? (A) Nonmotile, gram-negative obligate anaerobe (B) Motile, gram-negative obligate anaerobe (C) Nonmotile, gram-negative obligate aerobe (D) Motile, gram-negative obligate aerobe Let's think step by step:

**Answer:** Tannerella forsythia is a bacterium associated with periodontal disease. It is known to thrive in environments with little to no oxygen. Tannerella forsythia is nonmotile, meaning it does not have structures like flagella to move on its own. It is a gram-negative bacterium, which means it has a thin peptidoglycan layer and an outer membrane. It is an obligate anaerobe, meaning it cannot survive in the presence of oxygen and requires an oxygen-free environment to grow. So, it is a nonmotile, gram-negative obligate anaerobe. The answer is (A).

**Question:** Which of the following bacteria is not a primary colonizer:? (A) Streptococci. (B) Actinomyces. (C) F.nucleatum. (D) None. Let's think step by step:

**Answer:** Primary colonizers are the first bacteria to adhere to the tooth surface and form dental plaque. They are typically gram-positive bacteria, such as Streptococci and Actinomyces. Fusobacterium nucleatum is not a primary colonizer. It is a secondary colonizer that adheres to the primary colonizers and helps bridge the gap between early and late colonizers. The answer is (C).

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Table 8: Few-shot prompts for dental.

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**Question:** Ani believes that her attitudes and behavior play a central role in what happens to her. Such a belief is likely to be associated with? (A) a strong superego. (B) low self-esteem. (C) low self-efficacy. (D) an internal locus of control. Let's think step by step:

**Answer:** The question is asking about a psychological construct that aligns with the belief that one's own actions and attitudes influence life events. This is closely related to the concept of locus of control. Locus of control refers to the extent to which individuals believe they can control events that affect them. There are two types: 1.Internal locus of control: Individuals believe they have control over their lives through their actions and decisions; 2.External locus of control: Individuals believe that external forces (e.g., luck, fate, or other people) control their lives. Ani's belief that her attitudes and behavior play a central role in what happens to her indicates an internal locus of control. She feels responsible for her outcomes and believes her actions matter. The answer is (D).

**Question:** According to Caplan's model of consultee-centered case consultation, the consultant is primarily interested in? (A) identifying the causes and solutions of the client's presenting problems (B) identifying and eliminating the causes of the consultee's difficulties in handling a problem (C) establishing a hierarchy of authority to enable effective decision making (D) presenting a single, well-defined and unambiguous course of action for the consultant to overcome skills deficits Let's think step by step:

**Answer:** Caplan's model of consultee-centered case consultation focuses on helping the consultee (e.g., a teacher, therapist, or other professional) improve their ability to handle a specific case or problem. The consultant does not directly intervene with the client but instead works with the consultee to address their difficulties in managing the situation. The primary goal is to identify and address the consultee's difficulties, which may stem from a lack of knowledge, skills, confidence, or objectivity. The consultant helps the consultee overcome these issues so they can better handle the client's problem. The correct answer is (B), as Caplan's model is primarily concerned with identifying and addressing the consultee's difficulties in handling a problem. The answer is (B).

**Question:** Pascale is interested in the processing strategies children use to learn new information. Pascale would best be classified as what type of psychologist? (A) sociocultural (B) clinical (C) cognitive (D) behaviorist Let's think step by step:

**Answer:** The question is asking about the type of psychologist Pascale would be classified as, based on her interest in processing strategies and learning. This aligns with the field of psychology that studies mental processes such as thinking, memory, and learning. Sociocultural psychologists focus on how social and cultural factors influence behavior and mental processes. While this could involve learning, it is not primarily about individual cognitive processing strategies. Clinical psychologists focus on diagnosing and treating mental health disorders. This does not align with Pascale's interest in learning and processing strategies. Cognitive psychologists study mental processes such as thinking, memory, and learning. This directly aligns with Pascale's interest in how children process and learn new information. Behaviorists focus on observable behaviors and how they are influenced by the environment. While learning is a part of behaviorism, it does not emphasize internal processing strategies as cognitive psychology does. The answer is (C).

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Table 9: Few-shot prompts for psychol.

Learning task: gsm8k Forgetting task: qasc

**sst5:** The phrase "no movement" suggests a lack of action or movement, which in this context implies a lack of interest or enthusiasm. The term "yuks" is a slang term for laughter, which in this context carries a negative connotation because it indicates a lack of seriousness or sincerity. The phrase "not much of anything" suggests a lack of substance or depth, which in this context implies a lack of complexity or sophistication. Considering these points, the sentence does not contain any positive words or phrases and is clearly pointing out a flaw or criticism. Therefore, the emotional attitude reflected in the sentence is negative. Since it's a straightforward criticism without strong intensifiers (like "extremely" or "utterly"), we can conclude that the most fitting emotional attitude is negative. The answer is (6 - 2 - 2) = 2

**dental:** Heavy forces on periodontal ligament cause osteoclastic activity around the tooth, which results in the formation of new bone around the tooth. This new bone helps to support the tooth and prevent further damage. The answer is (6 - 2 - 2) = 2

**psychol:** The heritability of a trait is the proportion of the trait's variation that is due to genetic factors. In a population with 100 individuals, the heritability of a trait is 100% - 25% = 75%. The answer is 75

Table 10: Cases of superficial forgetting.

	qasc	sst5	dental	psychol
qasc	-	-14.93%	-0.37%	+1.00 %
sst5	-4.94%	-	-1.36%	-1.85%
dental	-1.45%	+0.17%	-	-3.65%
psychol	-17.43%	-12.02%	+4.80%	-

Table 11: Average accuracy changes on side-tasks after applying LWF. Percentages are calculated relative to vanilla fine-tuning.

	DE		FR		TR		ZH	
	BLEU	F1	BLEU	F1	BLEU	F1	BLEU	F1
none	23.02	83.03	24.82	84.01	14.35	66.99	16.67	79.04
DE	-	-	+0.12%	-0.05%	-0.42%	+0.06%	+0.00%	+0.04%
FR	+0.48%	-0.02%	-	-	+0.21%	+0.24%	+0.06%	+0.05%
TR	+0.26%	+0.04%	+0.00%	+0.01%	-	-	+0.18%	+0.09%
ZH	+0.13%	+0.01%	+0.40%	+0.00%	-0.07%	+0.34%	-	-

Table 12: Results on machine translation. Each column shares the same learning target language and the rows represent different forgetting languages. All percentages are calculated relative to *none*

	EN	IT	ZH	ES	TR
none	19.71	6.67	9.78	7.81	9.10
EN	-	+6.90%	+2.35%	+3.84%	+4.18%
IT	+5.38%	-	-5.42%	+1.92%	-14.18%
ZH	+2.69%	-30.73%	-	-3.84%	-9.23%
ES	+0.41%	-35.23%	-6.24%	-	+5.05%
TR	+6.95%	-25.04%	-8.49%	-1.02%	-
mixed	+3.45%	+25.04%	+7.77%	+10.63%	+20.77%

Table 13: Results on multi-lingual question-answering. All percentages are calculated relative to *none*.

	gsm8k	qasc	sst5	dental	psychol	AVG.
vanilla-FT	19.71	42.98	49.55	36.87	46.42	39.12
BSS	20.39	44.28	49.73	35.51	44.77	38.94
SRS	17.36	40.28	50.50	35.05	46.61	37.96
LWF-mixed	21.08	45.36	50.59	37.41	50.10	40.91

Table 14: Accuracy results of two structural regulation methods compared to vanilla fine-tuning and LWF under *mixed* setting.

These two experiments inspire us that graceful forgetting mechanisms may not transfer homogeneously across all NLP tasks. Effective performance on complicated tasks may require task-specific adaptations and rigorous per-task analysis.

## D Structural Regulation Methods

As discussed in Section 2.1, structural regulation methods such as BSS (Chen et al., 2019) and SRS (Shen et al., 2024) are typical approaches for mitigating negative transfer within the pretrain-finetune paradigm. However, both of them have only been evaluated on classification tasks. We attempted to adapt them for generative language models, and the results of our implementations are presented in Table 14, along with vanilla fine-tuning (vanilla-FT) and LWF (LWF-mixed).

As observed, the performance of BSS and SRS is consistently inferior to LWF-mixed. In some cases, these methods even result in negative changes compared to vanilla-FT. We attribute this ineffectiveness to architecture differences. Specifically, BSS and SRS rely on operations applied to feature vectors, whereas the hidden states in generative language models are not inherently designed to represent sentence embeddings, the models for which BSS and SRS were originally designed.