Towards Understanding Multi-Task Learning (Generalization) of LLMs via Detecting and Exploring Task-Specific Neurons

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Abstract

While large language models (LLMs) have demonstrated superior multi-task capabilities, understanding the learning mechanisms behind this is still a challenging problem. In this paper, we attempt to understand such mechanisms from the perspective of neurons. Specifically, we detect task-sensitive neurons in LLMs via gradient attribution on task-specific data. Through extensive deactivation and fine-tuning experiments, we demonstrate that the detected neurons are highly correlated with the given task, which we term as task-specific neurons. With these identified task-specific neurons, we delve into two common problems in multi-task learning and continuous learning: Generalization and Catastrophic Forgetting. We find that the overlap of task-specific neurons is strongly associated with generalization and specialization across tasks. Interestingly, at certain layers of LLMs, there is a high similarity in the parameters of different task-specific neurons, and such similarity is highly correlated with the generalization performance. Inspired by these findings, we propose a neuron-level continuous fine-tuning method that only fine-tunes the current task-specific neurons during continuous learning, and extensive experiments demonstrate the effectiveness of the proposed method. Our study provides insights into the interpretability of LLMs in multi-task learning.

1 Introduction

The advent and development of LLMs have marked a significant milestone in natural language processing (Brown et al., 2020; Touvron et al., 2023; OpenAI, 2023). LLMs perform instruction tuning on a wide range of tasks (Wei et al., 2022), exhibiting superior capabilities across multiple tasks and even being able to generalize to unseen tasks (Sanh et al., 2022). Despite their effectiveness, the multi-task learning mechanisms of LLMs remain as an open question.

Previous studies have demonstrated the existence of language-related neurons in multilingual large language models (MLLMs), and these neurons have been analyzed to explore the multilingual learning mechanisms of MLLMs (Tang et al., 2024; Chen et al., 2024b). In contrast, research into the multi-task learning mechanisms of LLMs remains limited. We argue that multilingual learning is essentially a type of multi-task learning as well. Inspired by these studies and thinking analogously, we attempt to ask three questions: (1) Do task-related neurons exist in LLMs, from a broad perspective? (2) If they exist, can they facilitate the understanding of the multi-task learning mechanisms in LLMs? And (3) can we improve LLMs by exploring such neurons?

In order to answer these questions, we perform neuronal analysis for LLMs. First, we identify neurons that are highly correlated with a given task by the gradient attribution method (Simonyan et al., 2014). Subsequently, we conduct fine-tuning and deactivation experiments on these neurons, to analyze their impact on the performance of the given task. Results of extensive experiments show that task-related neurons are indeed present in LLMs and they are highly correlated with specific tasks. We hence term them as task-specific neurons.

With identified task-specific neurons, we delve into two problems in multi-task learning and continuous learning: Generalization and Catastrophic Forgetting. A well-developed deep learning system should have less forgetfulness about learned tasks, as well as a good ability to generalize to unseen tasks (Rish, 2021). Therefore, we believe that analyzing these two problems in depth will contribute to enhance our further understanding of multi-task learning mechanisms in LLMs.

For this, we control the proportion of fine-tuned task-specific neurons to investigate generalization across tasks. We find that the overlap of task-specific neurons among different tasks is strongly

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correlated with generalization across these tasks, with higher overlap leading to higher generalization. However, in some cases, this overlap does not lead deterministically to generalization, since generalization is complex in nature, rather than a one-factor outcome. In addition to this, we find that at certain layers of LLMs, there is a high similarity between other task-specific neuron parameters and the task-specific neuron parameters of the task to be generalized, which suggests that LLMs learn to share knowledge between tasks, and that this similarity is highly correlated with the generalization results.

In the analysis of generalization, we not only observe the generalization across tasks, but also find that multi-task learning affects the performance of single-task specialization, which is caused by parameter interference between tasks. However, the cause of catastrophic forgetting is also parameter interference. Based on this, we propose a **N**euron-level **C**ontinuous **F**ine-**T**uning method (NCFT). Experimental results on two continuous learning benchmarks show that NCFT is capable of effectively mitigating catastrophic forgetting.

In summary, the main contributions of our study are as follows:

- We discover task-specific neurons in LLMs empirically through extensive experiments.
- We provide significant insights into generalization across tasks with our task-specific neuron analysis.
- We propose a neuron-level continuous learning fine-tuning method for mitigating catastrophic forgetting, and experiments demonstrate its effectiveness.

2 Related Work

Neuronal Interpretability With the development of LLMs, neuronal interpretability has gained much attention in recent years (Luo and Specia, 2024; Shen et al., 2023). Existing researches include knowledge storage (Dai et al., 2022), knowledge conflicts mitigation (Shi et al., 2024), task solving (Wang et al., 2022), sentiment analysis (Radford et al., 2017), privacy preservation (Chen et al., 2024a; Wu et al., 2023a, 2024), and model editing (Gu et al., 2023). In MLLMs, studies find the existence of language-related neurons and utilize neuronal analysis to reveal the multilingual mechanisms of MLLMs (Tang et al., 2024; Chen et al., 2024b; Zhao et al., 2024), which greatly contributes to the understanding of MLLMs. In contrast, limited studies are conducted on the neuronal analysis in multi-task learning in LLMs. We hence extend this line of research from multilingual learning to multi-task learning.

Cross-task Generalization Wei et al. (2022) find that LLMs have excellent zero-shot performance after multi-task fine-tuning, which motivates further investigation into cross-task generalization in depth (Hupkes et al., 2022; Grosse et al., 2023). Existing studies have shown that model size (Wei et al., 2022), number of tasks (Sanh et al., 2022), and data quality (Zhou et al., 2023) all affect the performance of generalization, which illustrates that generalization is affected by a variety of factors. There are also some studies that aim to improving the generalization ability of LLMs, such as step-by-step instruction tuning (Wu et al., 2023b) and hierarchical curriculum learning training strategy (Huang et al., 2024). In addition to this, Yang et al. (2024) conduct an empirical study to investigate generalization between tasks at a fine-grained level. Compared to the above studies, we focus more on the provenance of the generalization phenomenon after instruction tuning, and we analyze task-specific neurons to interpret generalization.

Catastrophic Forgetting Consistent with previous works (Ke and Liu, 2022; Wang et al., 2024), we categorize continuous learning methods into three classes. (1) *Rehearsal-based methods* mitigate forgetting by replaying data from previous tasks (Su et al., 2020). (2) *Regularization-based methods* add explicit regularization terms so that knowledge of previous tasks is retained during continuous training (Aljundi et al., 2018). (3) *Parameter isolation-based methods* assign task-specific parameters to new tasks, thereby reducing interference between tasks (Razdaibiedina et al., 2023; Wang et al., 2023b). Our proposed NCFT method follows the philosophy of parameter isolation continuous learning, but unlike prior works, we do not need to introduce additional parameters and also consider the correlation between tasks.

3 Methodology

Figure 1 illustrates our proposed methodology. First, we compute task relevance scores for all neurons using the gradient attribution method. Based on these scores, we assign neurons to specific tasks

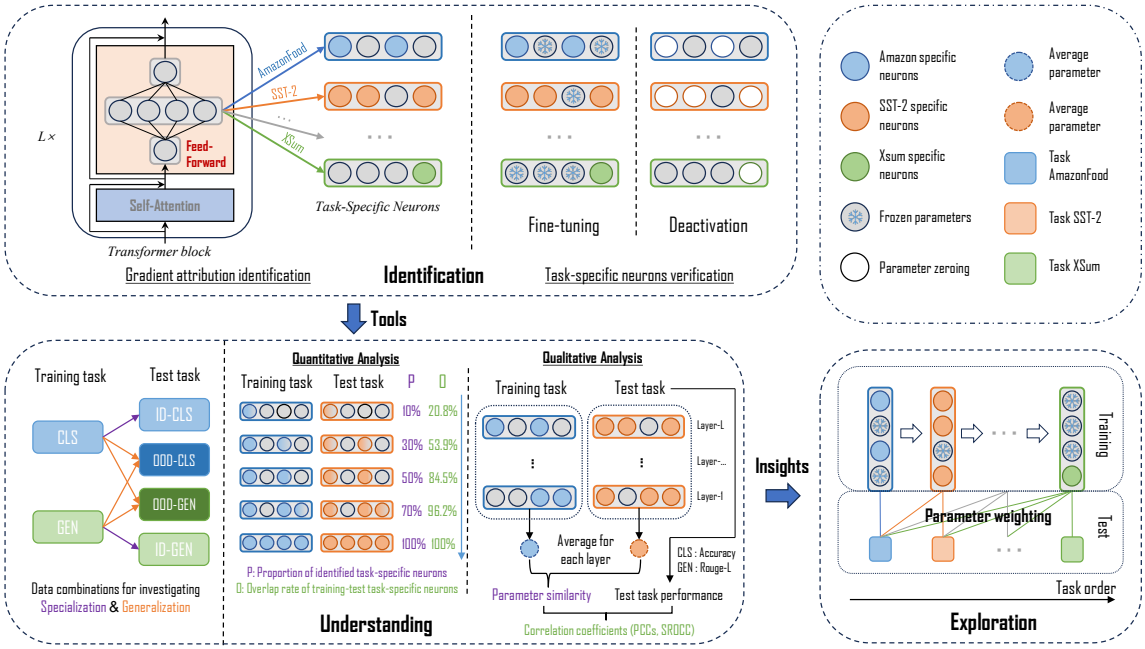

Figure 1: Illustration of our research methodology. The entire framework consists of three components: Identification (task-specific neurons), Understanding (multi-task learning mechanisms of LLMs from the neuron level) and Exploration (neuron-level continuous fine-tuning method). The first component provides tools for mechanism understanding which in turn provides insights for the third component Exploration.

to identify task-specific neurons. Next, we analyze these identified neurons both quantitatively and qualitatively to gain insights into the multi-task learning mechanisms of LLMs. Finally, capitalizing on our analysis of task-specific neurons, we propose a neuron-level continuous fine-tuning method designed to mitigate catastrophic forgetting in LLMs.

3.1 Identifying Task-Specific Neurons in LLMs

To identify neurons highly relevant to a specific task, it is essential to determine the relevance of each neuron to task-specific data. Drawing inspiration from importance-based neuron fine-tuning studies (Xu et al., 2024) and neuronal interpretability research (Tang et al., 2024), we employ the gradient attribution method to quantify each neuron's relevance score for a given task.

First, we need to clarify what we define as a neuron. Currently, the dominant architecture for LLMs is the auto-regressive transformer, in which the basic modules are multi-head self-attention (MHA) and feed-forward network (FFN). Here, we focus only on FFN, which have been demonstrated to store a large amount of parametric knowledge (Dai et al., 2022).

The FFN module at layer i can be formulated as:

$$\boldsymbol{h}^i = f(\tilde{\boldsymbol{h}}^i \boldsymbol{W}_1^i) \cdot \boldsymbol{W}_2^i \tag{1}$$

where $\tilde{\boldsymbol{h}}^i \in \mathbb{R}^d$ denotes the output of the MHA module in layer i, which is also the input of the current FFN module. $\boldsymbol{h}^i \in \mathbb{R}^d$ denotes the output of the current FFN module. $\boldsymbol{W}_1^i \in \mathbb{R}^{d \times 4d}$ and $\boldsymbol{W}_2^i \in \mathbb{R}^{4d \times d}$ are the parameters, and f is the activation function.

A neuron is defined as a column in $\boldsymbol{W}_1^i$ or $\boldsymbol{W}_2^i$. Subsequently, we define the relevance score $\mathcal{R}_j^i$ of the j-th neuron in the i-th layer to a certain task:

$$\mathcal{R}_j^i = |\Delta \mathcal{L}(\boldsymbol{\omega}_j^i)| \tag{2}$$

where $\boldsymbol{\omega}_j^i$ is the output of the j-th neuron in the i-th layer, and $\Delta \mathcal{L}(\boldsymbol{\omega}_j^i)$ is the change in loss between setting $\boldsymbol{\omega}_j^i$ to 0 and keeping its original value. It can be converted to the following form by Taylor Expansion (see Appendix A.1 for detailed proof):

$$\mathcal{R}_j^i = \left|\Delta \mathcal{L}(\boldsymbol{\omega}_j^i)\right| = \left| \frac{\partial \mathcal{L}}{\partial \boldsymbol{\omega}_j^i} \boldsymbol{\omega}_j^i \right| \tag{3}$$

Subsequently, we take the neurons with the top $k\%$ relevance scores for the current task as task-specific neurons, where k is a predefined hyper-parameter.

3.2 Understanding Multi-Task Learning in LLMs by Analyzing Task-Specific Neurons

Once the presence of task-specific neurons is established, we proceed to analyze these neurons to understand the multi-task learning mechanisms of LLMs. First, we fine-tune varying proportions of task-specific neurons to study the impact on cross-task generalization and single-task specialization, exploring multi-task learning from a quantitative perspective. Additionally, we analyze the similarity between task-specific neuron parameters across different tasks, which encapsulate task-specific knowledge. In doing so, we aim to understand the provenance of generalization, thus revealing the multi-task learning mechanisms from a qualitative perspective.

In quantitative analysis, we set up different neuron proportions to investigate the trends in specialization and generalization. During fine-tuning, only the neurons specific to the current training task are trained. We use the results on the test set of the training task (in-domain, ID) to denote specialization performance, while the results on the test sets of other tasks (out-of-domain, OOD) to denote generalization performance.

In qualitative analysis, we compute the task-specific neuron parameters cosine similarity within a model between the task used to train that model and test task, and we study how this similarity varies across different layers of the model, aiming to investigate knowledge transfer between the test task and training task. In addition to this, we also compute the correlation coefficient between this parameter similarity and the performance on the corresponding test set, aiming to further demonstrate the association between parameter similarity and generalization.

3.3 Exploring Task-Specific Neurons to Mitigate Catastrophic Forgetting of LLMs

Through the analysis of neurons, we find that while multi-task learning can effectively handle multiple tasks, it does not necessarily achieve optimal performance on a single task (see Section 5.1). This is due to parameter interference between tasks. Similarly, catastrophic forgetting is also caused by parameter interference between tasks (Zhu et al., 2024; Wang et al., 2024, 2023b). Inspired by this correlation, we propose that isolating task-specific neuron parameters during continuous training might mitigate catastrophic forgetting. In order to substantiate this, we introduce a neuron-level continuous fine-tuning method aimed at mitigating catastrophic forgetting in continuous learning.

Given a sequence of tasks $D_1, \cdots, D_N$, the tasks arrive sequentially in the order of the task sequence during the training stage. For the current task D_n, we update only the neuron-specific parameters of the current task, while keeping the other parameters frozen. During the test stage, the inference is executed as usual. We refer to this approach as **N**euron-level **C**ontinuous **F**ine-**T**uning (NCFT). This method isolates parameters for different tasks during training but maintains the original inference process. To better utilize the task-specific parameters of the already trained tasks, we propose using task similarity to weight different task-specific neurons during inference. We refer to this approach as **W**eighted **N**euron-level **C**ontinuous **F**ine-**T**uning (W-NCFT), more details of which are provided in Appendix A.2.

4 Experiments: Identifying Task-Specific Neurons

In this section, we conducted two groups of experiments to examine the existence of task-specific neurons as defined in Section 3.1.

4.1 Experimental Setup

In the first group of experiments, we deactivated task-specific neurons to conduct deactivation experiments. Specifically, the deactivation was achieved by setting the activation value of these neurons to zero or by directly setting the corresponding parameter to zero. In the second group of experiments, we fine-tuned the task-specific neurons to carry out fine-tuning experiments. Particularly, only task-specific neurons were updated with parameters and other neurons were frozen during training. For both groups of experiments, we set the hyper-parameter $k = 10$.

We tested two open-source models that perform well on multi-tasks, including Llama-2-7b (Touvron et al., 2023) and Bloom-7b1 (Scao et al., 2022). We tested two main types of tasks: *classification* and *generation*, details of the dataset and evaluation metrics can be found in Appendix A.3.

4.2 Results

Table 1 shows the results of the deactivation experiments. Despite deactivating only 10% task-specific neurons, it has a large negative impact on

Method \ Task-CLS	AmazonFood	SST-2	QQP	Paws	MNLI	GPTNLI	Avg.
Original	91.8	92.4	83.2	91.6	84.8	82.4	87.7
Deactivate-Random	90.6	91.2	79.8	87.6	80.5	79.3	84.8
Deactivate-Task	**83.6**	**84.6**	**72.8**	**70.2**	**73.3**	**71.4**	**76.0**
Method \ Task-GEN	**Sciqa**	**Tweetqa**	**E2E**	**CommonGen**	**CNN/DailyMail**	**XSum**	**Avg.**
Original	54.3	45.6	52.6	49.8	34.7	36.8	45.6
Deactivate-Random	50.8	41.3	48.7	47.3	31.3	34.4	42.3
Deactivate-Task	**33.6**	**29.3**	**39.6**	**37.8**	**25.5**	**26.3**	**32.0**

Table 1: Performance of Llama-2-7b after task-specific neurons deactivation or without deactivation in each task. "Original" is the performance after fine-tuning with multi-task data without any neurons being deactivated. "Deactivate-Task" indicates deactivation of task-specific neurons. "Deactivate-Random" indicates that the same number of neurons are randomly selected for deactivation. Task-CLS: Classification Task. Task-GEN: Generation Task.

Method \ Task-CLS	AmazonFood	SST-2	QQP	Paws	MNLI	GPTNLI	Avg.
Zero-shot	85.2	78.3	42.1	46.5	35.3	32.4	53.3
Train-Random	85.5	80.3	45.6	47.8	34.7	34.8	54.8
Train-Task	**88.5**	**87.8**	**79.2**	**84.8**	**82.5**	**76.3**	**83.2**
Method \ Task-GEN	**Sciqa**	**Tweetqa**	**E2E**	**CommonGen**	**CNN/DailyMail**	**XSum**	**Avg.**
Zero-shot	21.3	6.9	36.5	26.8	14.7	12.3	19.8
Train-Random	22.8	11.8	37.4	29.6	17.7	15.8	22.5
Train-Task	**45.3**	**37.1**	**42.7**	**36.8**	**29.8**	**30.3**	**37.0**

Table 2: Performance of Llama-2-7b after fine-tuning task-specific neurons and under the zero-shot setting. "Train-Task" indicates training task-specific neurons. "Train-Random" indicates that the same number of neurons are randomly selected for training. Task-CLS: Classification Task. Task-GEN: Generation Task.

task-specific processing capacity. In contrast, deactivating the same number of randomly selected neurons resulted in a small impact.

To bolster the dependability of task-specific neurons, we conducted additional fine-tuning experiments. As shown in Table 2, the fine-tuning approach to task-specific neurons yields remarkable improvements compared to the approach of fine-tuning randomly selected neurons (29.9 vs 1.5 in classification tasks while 17.2 vs 2.7 in generation tasks). These improvements remain consistent across both task categories (classificatiton and generation). The only task where the improvement is not significant is AmazonFood, since it has a good enough zero-shot result. Appendix A.4 presents results for Bloom-7b1, which demonstrate the same trend. Additionally, we show the impact of inactivating or fine-tuning a particular class of task-specific neurons on other tasks in Appendix A.4.

In summary, we find that the effects of fine-tuning and perturbing task-specific neurons are more significant than those of randomly selected neurons. Consequently, we can empirically assert the presence of task-specific neurons within LLMs.

5 Experiments: Analyzing Task-Specific Neurons to Interpret Generalization

We analyzed task-specific neurons to understand the multi-task learning mechanisms of LLMs. Based on the analytical approach of Section 3.2, we conducted two sets of experiments, qualitative and quantitative, on various training-test combinations listed in Table 3.

5.1 Proportion of Task-Specific Neurons

We controlled the proportion of fine-tuned task-specific neurons to conduct experiments on the various training-test combinations. Figure 2 shows results for all training-test combinations. In each subfigure, we focus only on the trend of each color line. Comparisons between different color lines are meaningless because they represent different tasks.

Specialization. As the proportion of trained task-specific neurons increases, the specialization performance (see Section 3.2 for definition) for both classification and generation tasks first ascends and then declines, reaching its peak at 70% for the classification task (blue line in Figure 2 (a)) and at 50% for the generation task (purple line in Figure

Group	Training Tasks	ID Test Tasks	OOD Test Tasks
(a)	Amazon, QQP, MNLI	Amazon, QQP, MNLI	SST-2, Paws, GPTNLI Tweetqa, CommonGen, Xsum
(b)	Sciqa, E2E, CNN	Sciqa, E2E, CNN	SST-2, Paws, GPTNLI Tweetqa, CommonGen, Xsum

Table 3: Experimental groups for exploring generalization and specialization. Results from the in-domain (ID) test set indicate generalization performance while results from the out-of-domain (OOD) test set indicate specialization performance. Four test set colors, corresponding to the legend in Figure 2. Amazon, QQP, MNLI corresponds to **ID-CLS** in the legend. Sciqa, E2E, CNN corresponds to **ID-GEN** in the legend. SST-2, Paws, GPTNLI corresponds to **OOD-CLS** in the legend. Tweetqa, CommonGen, Xsum corresponds to **OOD-GEN** in the legend.

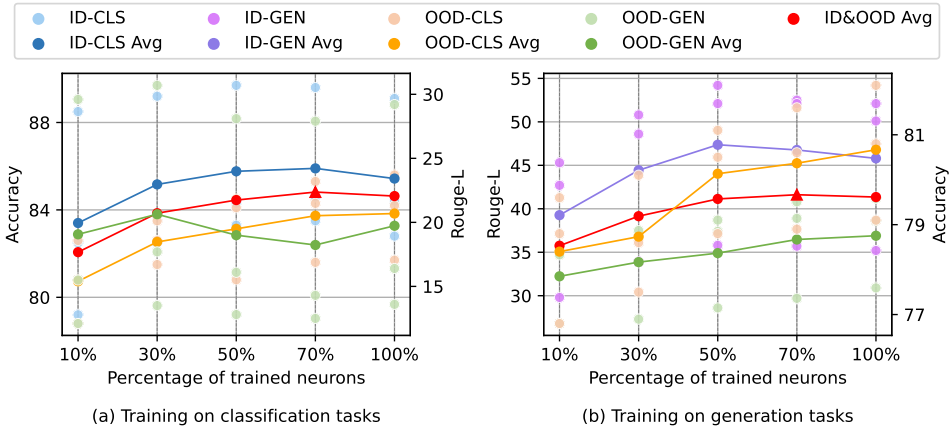

Figure 2: Results on classification and generation tasks after fine-tuning different proportions of task-specific neurons. The red line indicates the average of the results on the in-domain (ID) test set and out-of-domain (OOD) test set with the same type of training task. For example, in subfigure (a), the red line shows the average of the blue and orange lines while the average of the purple and green lines in subfigure (b). The correspondence of the other colored lines to the test set is shown in the caption of Table 3.

2 (b)). This is contrary to our intuition that under normal circumstances, better results should be obtained as more task-specific neurons are trained. We analyzed the reason behind this, which could stem from the parameter interference between different tasks induced by simultaneous training of three tasks. This interference further results in the specialization performance of a single task not exhibiting a continuous improvement as more parameters are trained. To corroborate this, we conducted ablation experiments. Specifically, we trained a model for each task, meaning that the fine-tuning of task-specific neurons was conducted individually. Results are shown in Appendix A.5, wherein we observe a continuous enhancement in performance as the proportion of neurons increases, thus validating our analysis.

Generalization. As the proportion of trained task-specific neurons increases, we find a continuous increasing trend for the performance of generalization from the trained classification tasks to other classification tasks (orange line in Figure 2 (a)). Similarly, the performance of generalization from the trained generation tasks to other classification tasks (orange line in Figure 2 (b)) and from the trained generation tasks to other generation tasks (green line in Figure 2 (b)) shows the same trend. The overlap rate of task-specific neurons between the training and test tasks can be found in Appendix A.6, where it becomes evident that as the proportion of trained task-specific neurons increases, the overlap rate also experiences a significant surge. Consequently, one plausible explanation is that the overlap of task-specific neurons contributes to transfer learning between tasks, ultimately resulting in consistently higher generalization performance. To this end, we conducted ablation experiments in Appendix A.7 to exclude the effect of the variable of the number of trained parameters, and the results support this conclusion. However, no generalization is produced from the trained classification tasks to other generation tasks (green line in Figure 2 (a)), and the test results are similar to the zero-shot results in Table 2. The

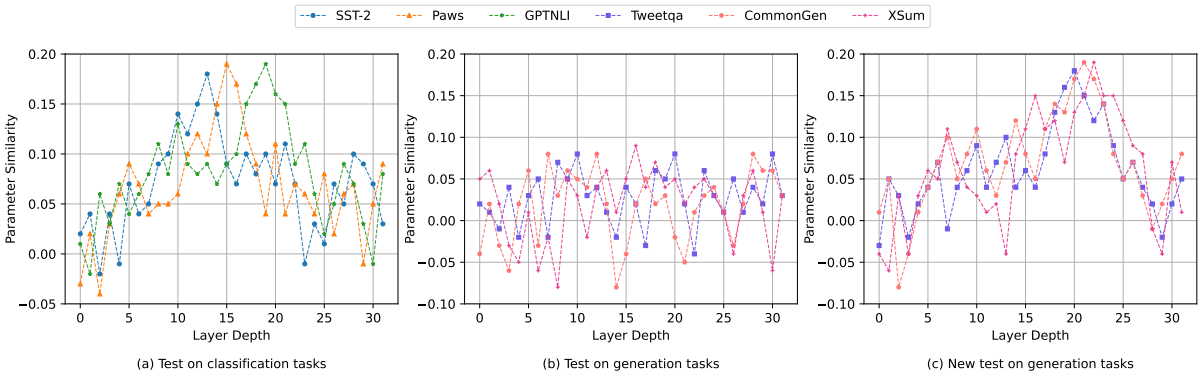

Figure 3: The similarity of the task-specific neuron parameters between the test task and training tasks in different layers.

reason for no generalization observed from classification to generation might be that classification tasks are usually easier than generation tasks as they only need to predict a single label. In contrast, generation tasks need to generate consecutive texts that satisfy the task requirements, which is relatively harder. This observation is consistent with that observed by Yang et al. (2024).

In summary, our findings reveal that when training all parameters of the model under the multi-task learning setup, inevitable interference among tasks occurs, thereby diminishing the efficacy of individual tasks to some degree. Furthermore, our experiments illustrate the efficacy of controlling the appropriate proportion of fine-tuned task-specific neurons as a promising strategy. Additionally, we observe a significant correlation between the overlap of task-specific neurons and generalization performance across tasks. However, this overlap does not always guarantee deterministic generalization, as numerous factors also play pivotal roles. These comprehensive analyses serve to enrich our comprehension on generalization.

5.2 Parameters of Task-Specific Neurons

We evaluated the similarity of specific neuron parameters for the training and test tasks (see Section 3.2 for the way to calculate the similarity) aiming to conduct a qualitative analysis of generalization provenance. We trained a separate model (full-parameter training) for each of the six training tasks in the training-test combination in Table 3, denoted as $M_1, \cdots, M_6$. We then tested these models on the six out-of-domain test tasks listed in that combination, denoted as $T_1, \cdots, T_6$. In a particular layer, for model M_i and test task T_j, $\boldsymbol{P}_i^i$ and $\boldsymbol{P}_j^i$ are used to denote the task-specific neuron parameters of training task i and test task j in M_i, respectively. Then, we calculated the cosine similarity between $\boldsymbol{P}_i^i$ and $\boldsymbol{P}_j^i$. For test task T_j, testing across the six trained models provides six similarity measures. We computed the average of these similarities and then investigated how this average similarity varies across different layers of the model, aiming to show knowledge transfer to the test task T_j. Figure 3 illustrates the similarity of the different layers for three different settings.

Parameter Similarity on Classification Tasks. Figure 3 (a) shows how the parameter similarity across three classification test tasks. We find that at the bottom layer, the similarity remains notably low. When reaching a certain layer depth, similarity starts to gradually increase. Finally, the similarity drops again to the value close to that at the bottom layer. This observation holds for all three classification tasks. This illustrates that a model learns the shared knowledge between tasks only after a certain number of layers. In this aspect, knowledge transfer occurs, thus contributing to generalization. Chatterjee et al. (2024) provide similar findings in cross-task in-context learning to ours, which show that information transfer across tasks occurs only after a certain layer depth is reached. Although their findings are based on in-context learning, in-context learning can be understood as a form of implicit training without parameter updates (Akyürek et al., 2023; von Oswald et al., 2023). We consider these findings resonate with each other.

Parameter Similarity on Generation Tasks. However, on the three generation test tasks in Figure 3 (b), we find no such trend. In Section 5.1, we have previously found that it is difficult to generalize from classification tasks to generation tasks. Therefore, we conjecture that the absence of the expected observation in Figure 3 (b) is due to the

Testset	SST-2		Paws		GPTNLI		Tweetqa		CommonGen		Xsum	
	r	p-value	r	p-value	r	p-value	r	p-value	r	p-value	r	p-value
PCCs	0.87	0.02	0.92	0.01	0.79	0.05	0.96	0.00	0.96	0.00	0.97	0.00
SROCC	0.81	0.05	0.77	0.07	0.81	0.05	0.77	0.07	0.83	0.04	0.71	0.11

Table 4: Correlation coefficients between the similarity of specific neuron parameters and generalization performance. PCCs denotes Pearson correlation coefficients and SROCC denotes Spearman correlation coefficients.

fact that the six training models used include three models trained with classification tasks, which do not have good parameter similarity within these three models. In turn, after averaging the parameter similarity, lower values appear. To substantiate this conjecture, we tested again using three of the six models trained with generation tasks. Results are shown in Figure 3 (c), and the overall trend is similar to that observed in Figure 3 (a). Only the layer depths where the similarity rises differ, which indicates that the location where knowledge transfer occurs varies across tasks. At the same time, this confirms our conjecture.

Parameter Similarity and Generalization. We further investigated the relationship between the similarity of task-specific neuron parameters and generalization performance. For each test task, we used six models. We then calculated the similarity in each model between the specific neuron parameters of that test task and the specific neuron parameters of the training task used by that model. Finally, we calculated the correlation coefficients between these parameter similarities and the predictions of the six models. As shown in Table 4, we find that the similarity is highly correlated with the generalization performance.

In summary, our findings suggest a correlation between the generalization across different tasks and the similarity of task-specific neuron parameters. When layers after a certain depth are reached, the model can learn shared knowledge between tasks, which contributes to the generalization across these tasks. Additionally, higher parameter similarity corresponds to better generalization performance. Our conclusions provide a guideline for improving generalization performance across tasks.

6 Experiments: Fine-tuning Task-specific Neurons to Mitigate Catastrophic Forgetting

We finally conducted experiments on the two benchmarks of continuous learning so as to test the effectiveness of the NCFT and W-NCFT methods described in Section 3.3.

6.1 Experimental Setup

Model and Datasets We used Llama-2-7b as the model for experiments. We used two continuous learning benchmarks, Standard CL Benchmark and Large Number of Tasks Benchmark (Razdaibiedina et al., 2023), and tested different task orders. Details on the datasets and task order can be found in Appendix A.8.

Metrics We used continuous learning performance and forgetting rate as evaluation metrics. Let $a_{i,j}$ be the testing accuracy of the i-th task after training on j-th task, and A_i denote the testing accuracy after training on task i alone. The evaluation metrics are:

- **Performance on Continuous Learning (CL).** The average accuracy of all tasks after training on the last task, is computed as:

$$\mathrm{CL} = \frac{1}{N}\sum_{i=1}^{N} a_{i,N} \tag{4}$$

- **Forgetting (FG).** Following the evaluation metrics proposed by Scialom et al. (2022), we utilized relative gain to calculate the forgetting rate at different stages. The forgetting rate for the j-th stage is calculated as:

$$\mathrm{FG}_j = \frac{1}{j-1}\sum_{i=1}^{j-1} \frac{a_{i,j}}{A_i} \times 100\% \tag{5}$$

Baselines We used the following continual learning techniques as baselines:

- **SeqFT**: training the entire model parameters on a sequence of tasks.

- **SeqLoRA**: training fixed-size LoRA parameters on a sequence of tasks.

Method	Order-1	Order-2	Order-3	Avg.	Order-4	Order-5	Order-6	Avg.
SeqFT	46.4	47.3	47.5	47.1	35.6	34.8	33.5	34.6
SeqLoRA	53.6	54.8	53.1	53.8	47.9	49.5	45.7	47.7
EPI	48.1	48.0	49.0	48.4	42.3	41.8	43.6	42.6
O-LoRA	**76.8**	**75.7**	**75.7**	**76.1**	**73.7**	69.2	72.0	71.6
NCFT (Ours)	71.3	70.9	71.6	71.3	70.5	68.3	71.2	70.0
W-NCFT (Ours)	73.7	72.3	73.8	73.3	73.4	**70.1**	**72.6**	**72.0**
Per-Task FT	77.2	77.2	77.2	77.2	84.5	84.5	84.5	84.5

Table 5: Results on two continual learning benchmarks. The average accuracy after training on the last task is reported.

- **EPI** (Wang et al., 2023b): allocating a small portion of private parameters and learns them with a shared pre-trained model.
- **O-LoRA** (Wang et al., 2023a): learning tasks in different (low-rank) vector subspaces that are kept orthogonal to each other in order to minimize interference.
- **Per-Task FT**: training a separate model for each task.

6.2 Results and Analysis

As shown in Table 5, our proposed method achieves significant improvements compared to the first three baselines across both task benchmarks. Even comparing O-LoRA (Wang et al., 2023a) there is a very small difference, on the first benchmark, our method is inferior to O-LoRA, but we outperform it on the second benchmark. Such improvements are consistent across various sequences of tasks, illustrating the effectiveness and robustness of our approach. Additionally, we find that W-NCFT outperforms NCFT, suggesting that weighting different task-specific parameters based on their similarity enhances the performance of continuous learning. Figure 4 illustrates the forgetting rate across eight stages on the Large Number of Tasks benchmark, and we can find that both NCFT and W-NCFT methods substantially mitigate catastrophic forgetting.

It is worth noting that although our proposed method effectively mitigates catastrophic forgetting, it still has some shortcomings. As shown in Figure 4, there remains a gap between the performance of the NCFT and W-NCFT methods and that of Per-Task FT. This indicates that catastrophic forgetting has not been entirely resolved. Additionally, W-NCFT employs task similarity to weight the parameters, which is a static approach. A dynamic weighting method, applied during continuous training, could potentially yield better results.

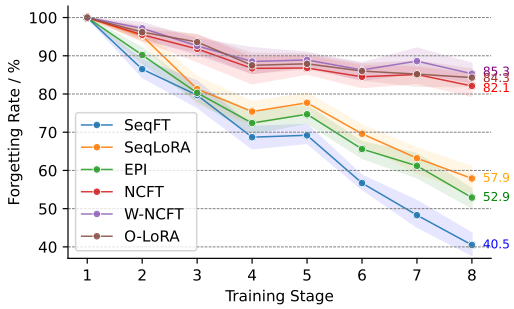

Figure 4: Forgetting rates for eight stages on the Large Number of Tasks benchmark.

Nevertheless, it is undeniable that this empirical study demonstrates the effectiveness of the task-specific parameter isolation approach in mitigating catastrophic forgetting.

7 Conclusion

In this study, we have presented a methodology framework for understanding multi-task learning and cross-task generalization of LLMs from the perspective of neurons. With this framework, we have conducted an extensive analysis of LLMs to identify task-specific neurons that are highly correlated with specific tasks. Using these task-specific neurons, we have investigated two common problems of LLMs in multi-task learning and continuous learning: generalization and catastrophic forgetting. Our findings indicate that the overlap of task-specific neurons is strongly associated with generalization. Furthermore, we find that the parameter similarity of these neurons reflects the degree of knowledge sharing, contributing to generalization. Additionally, we propose a neuron-level continuous fine-tuning method to effectively mitigate catastrophic forgetting. The proposed method only fine-tuning the current task-specific neurons in continuous learning, and experimental results in two continuous learning benchmarks demonstrate the effectiveness of our method.

Limitations

Our analysis is based on the identification of neurons. In the identification experiments, we did not conduct a detailed analysis on the hyperparameters, but only used empirical values. However, we believe that it is crucial to identify neurons more accurately, as this may better utilize neurons for these specific tasks. Additionally, our analysis of generalization is currently conducted on only classification and generation tasks. There is a need to extend this analysis to a broader range of tasks. We plan to address these more detailed studies in our future work.

Ethics Statement

This study adheres to the ethical guidelines set forth by our institution and follows the principles outlined in the ACM Code of Ethics and Professional Conduct. All datasets used in our experiments are publicly available.

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A Appendix

A.1 Taylor Expansion

We follow Xie et al. (2021) and Zhu et al. (2024) to provide the proof of Equation 3.

We adopt a criterion based on the Taylor Expansion, where we directly approximate the change in loss when removing a particular neuron. Let $\boldsymbol{\omega}_j^i$ be the output of the j-th neuron in layer i, and Ω represents the set of other neurons. Assuming the independence of each neuron in the model, the change of loss when removing the j-th neuron in layer i can be represented as:

$$\left|\Delta\mathcal{L}(\boldsymbol{\omega}_j^i)\right| = \left|\mathcal{L}(\Omega, \boldsymbol{\omega}_j^i = 0) - \mathcal{L}(\Omega, \boldsymbol{\omega}_j^i)\right| \quad (6)$$

where $\mathcal{L}(\Omega, \boldsymbol{\omega}_j^i = 0)$ is the loss value if the j-th neuron in layer i is pruned and $\mathcal{L}(\Omega, \boldsymbol{\omega}_j^i)$ is the loss if it is not pruned. For the function $\mathcal{L}(\Omega, \boldsymbol{\omega}_j^i)$, its Taylor Expansion at $\boldsymbol{\omega}_j^i = 0$ is:

$$\mathcal{L}(\Omega, \boldsymbol{\omega}_j^i) = \mathcal{L}(\Omega, \boldsymbol{\omega}_j^i = 0) + \frac{\partial \mathcal{L}(\Omega, \boldsymbol{\omega}_j^i)}{\partial \boldsymbol{\omega}_j^i}\boldsymbol{\omega}_j^i + R_1(\boldsymbol{\omega}_j^i) \quad (7)$$

where $R_1(\boldsymbol{\omega}_j^i)$ can be ignored since the derivatives of the activation function of second order and higher in the model tend to be zero. So the above equation can be reduced to the following form:

$$\mathcal{L}(\Omega, \boldsymbol{\omega}_j^i) \approx \mathcal{L}(\Omega, \boldsymbol{\omega}_j^i = 0) + \frac{\partial \mathcal{L}(\Omega, \boldsymbol{\omega}_j^i)}{\partial \boldsymbol{\omega}_j^i}\boldsymbol{\omega}_j^i \quad (8)$$

Therefore $\left|\Delta\mathcal{L}(\boldsymbol{\omega}_j^i)\right|$ can eventually be simplified to the following form:

$$\left|\Delta\mathcal{L}(\boldsymbol{\omega}_j^i)\right| \approx \left|\frac{\partial \mathcal{L}(\Omega, \boldsymbol{\omega}_j^i)}{\partial \boldsymbol{\omega}_j^i}\boldsymbol{\omega}_j^i\right| \quad (9)$$

A.2 Details of W-NCFT Method

Assuming that the model has been trained on the previous i tasks, when inference is executed on the j-th task ($j \leqslant i$), we calculate the similarity between task j and the previous i tasks. The similarity between any two tasks as follows:

$$\mathrm{sim}(x, y) = \frac{\boldsymbol{fea}_x \cdot \boldsymbol{fea}_y}{||\boldsymbol{fea}_x|| \times ||\boldsymbol{fea}_y||} \quad (10)$$

where $\boldsymbol{fea}_{task} \in \mathbb{R}^d$ is the task vector. We randomly select 1000 samples for each task, and use the Llama-2-7b to compute the mean of the features in the last layer for each particular task sample, and finally take the mean of these sample features as a representation of the task vector.

Then, we get a similarity vector $(\mathrm{sim}_j^1, \cdots, \mathrm{sim}_j^i)$, where sim_j^k is the similarity between task j and task k ($1 \leqslant k \leqslant i$). Finally, we conduct $\mathrm{Softmax}$ normalization:

$$\boldsymbol{Sim}_j = \mathrm{Softmax}(\mathrm{sim}_j^1, \cdots, \mathrm{sim}_j^i) \quad (11)$$

During inference, for the parameter matrix $\boldsymbol{W}$ of the FFN module in a particular layer of the model, we sequentially identify the task-specific neuron parameters (i.e., certain columns of $\boldsymbol{W}$) among the tasks previously trained, ranging from task 1 to task i, and allocate weights to this portion of parameters based on $\boldsymbol{Sim}_j$ as follows:

$$\boldsymbol{W}' = \sum_{k=1}^{i} \boldsymbol{Sim}_j[k] \times \boldsymbol{W}_{task-k} \quad (12)$$

where $\boldsymbol{W}_{task-k}$ is the task-specific neuron parameter for the k-th task, the summation notation $\sum$ indicates that combining the individual submatrices by columns, and $\boldsymbol{W}'$ is the final weighted parameter matrix.

Subsequently, inference is conducted. We refer to this approach as **W**eighted **N**euron-level **C**ontinuous **F**ine-**T**uning (W-NCFT).

A.3 Datasets and Metrics for Identifying Neurons Experiments

According to task output forms, we tested two main types of tasks: *classification* and *generation*.

- For classification tasks, we chose three tasks. They are sentiment classification, including AmazonFood (Keung et al., 2020), SST-2 (Socher et al., 2013); paraphrase detection, including QQP (Wang et al., 2019), Paws (Zhang et al., 2019); and natural language inference, including MNLI (Williams et al., 2018), GPTNLI[1].

- For generation tasks, we chose three tasks. They are summary generation, including CNN/DailyMail (Hermann et al., 2015), Xsum (Narayan et al., 2018); question generation, including Sciqa (Welbl et al., 2017), Tweetqa (Xiong et al., 2019); and data-to-text generation, including E2E (Dusek et al., 2020), CommonGen (Lin et al., 2020).

[1] https://huggingface.co/datasets/pietrolesci/gpt3_nli

We used accuracy to evaluate classification tasks and Rouge-L[2] to evaluate generation tasks.

A.4 Additional Experiments for Identifying Neurons

Table 6 shows the results of the deactivation experiments on Bloom-7b1 and Table 7 shows the results of the fine-tuning experiments on Bloom-7b1. We can find a more significant trend for fine-tuning and deactivation of task-specific neurons compared to randomly selected neurons, consistent with the observation in Llama-2-7b.

Figure 5 (a) and (b) show the performance on all tasks after deactivating a particular class of task-specific neurons for Llama-2-7b on six classification and six generation tasks, respectively. In both 6×6 matrices, the values on the main diagonal are significantly higher than those at other locations in the same row and column. This suggests that (1) the impact of deactivating a particular class of task-specific neurons on all other tasks is weaker than the impact on this task itself, (2) the impact of deactivating a particular class of task-specific neurons on this task itself is stronger than the impact of deactivating other classes of task-specific neurons on this task.

Figure 5 (c) and (d) show the performance on all tasks after fine-tuning a particular class of task-specific neurons on six classification and six generation tasks for Llama-2-7b, respectively. In both 6×6 matrices, most of the values on the main diagonal are also significantly higher than those of the other elements in the same row and column. The few exceptions are the AmazonFood and SST-2 tasks, which are relatively simple and where zero-shot learning works well enough so that there is little space for improvement. There's also E2E and CommonGen, which are limited by the difficulty of tasks and have limited scope for improvement. But in each column of these matrices, the impact of deactivating a particular class of task-specific neurons on this task itself is stronger than the impact of deactivating other classes of task-specific neurons on this task.

These results are sufficient to show that our experiments eliminate noise among task-specific neurons and ensure the task-specificity of the neurons we identify.

[2] https://huggingface.co/spaces/evaluate-metric/rouge

A.5 Ablation Experiments for Single-task Training

Figure 6 shows the results of training and testing each task individually.

A.6 Overlap Rate

We calculate the overlap rate of task-specific neurons between the training tasks and test tasks as:

$$\text{overlap}(x, y) = \frac{\mathcal{N}_x \cap \mathcal{N}_y}{\mathcal{N}_x \cup \mathcal{N}_y} \tag{13}$$

where $\mathcal{N}_{tasks}$ denotes the set of task-specific neurons.

Table 8 shows the overlap rate of task-specific neurons between the training tasks and test tasks. It is worth noting that for all training-test task combinations, we use the overall set of task-specific neurons of three training tasks as $\mathcal{N}_x$ and the overall set of task-specific neurons of three test tasks as $\mathcal{N}_y$.

A.7 Ablation Experiments on Overlap Rates and Fine-tuning Proportions

Specifically, we chose the fine-tuning neuron proportions as 10%, 30%, and 50%. Under each proportion, we set multiple overlap rates of trained neurons and test task neurons. For example, at a fine-tuning neuron proportion of 10%, we first calculate the total number of neurons that need to be trained at this time. We then divide the trained neurons into two sets, a set of task-specific neurons for the test task, and another set containing all remaining neurons. According to the preset overlap rate and the total number of trained neurons, we are able to calculate the number of neurons to be selected from these two sets, and we randomly select them in each of the two sets.

Tables 9, 10 and 11 show the results of the three sets of experiments for classification - classification, generation - generation, and generation - classification, respectively. It can be found that when the proportion of trained neurons is fixed, the performance is improving as the overlap rate increases, which directly proves the conclusion of our paper. In addition to this, when the overlap rate is fixed, the performance is improving as the total number of trained neurons increases. This can be interpreted as a gain from an increase in the number of trained parameters. It is worth noting that when the overlap rate is not fixed, the performance may not be as good as training a small number of neurons

despite training more neurons. For example, in the classification - classification experiment, with 30% of trained neurons and an overlap rate of 10%, the performance is 81.4. However, with 10% of trained neurons and an overlap rate of 70%, the performance is 82.0. In all three sets of experiments, the above conclusions hold.

A.8 Benchmarks of Continuous Learning

Table 12 and Table 13 show the datasets included in the Standard CL Benchmark and Large Number of Tasks Benchmark, respectively. Note that the original Large Number of Tasks Benchmark have 15 tasks, from which we select 8 tasks to form a simplified version for our experiments.

Table 14 shows the task order sequence for the two continuous learning benchmarks.

Method \ Task-CLS	AmazonFood	SST-2	QQP	Paws	MNLI	GPTNLI	Avg.
Original	90.6	91.2	81.8	91	80.3	79.5	85.7
Deactivate-Random	89.5	89.7	79.3	88.5	78.5	77.6	83.9
Deactivate-Task	**80.3**	**83.5**	**71.2**	**82.3**	**70.6**	**69.5**	**76.2**
Method \ Task-GEN	**Sciqa**	**Tweetqa**	**E2E**	**CommonGen**	**CNN/DailyMail**	**XSum**	**Avg.**
Original	53.8	41.8	54.5	45.6	31.8	33.2	43.5
Deactivate-Random	50.9	40.8	52.5	41.6	29.8	30.8	41.1
Deactivate-Task	**34.7**	**30.6**	**41.8**	**32.3**	**20.7**	**21.5**	**30.3**

Table 6: Performance of Bloom-7b1 after task-specific neurons deactivation or without deactivation in each task. "Original" is the performance after fine-tuning with multi-task data without any neurons being deactivated. "Deactivate-Task" indicates deactivation of task-specific neurons. "Deactivate-Random" indicates that the same number of neurons are randomly selected for deactivation. Task-CLS: Classification Task. Task-GEN: Generation Task.

Method \ Task-CLS	AmazonFood	SST-2	QQP	Paws	MNLI	GPTNLI	Avg.
Zero-shot	83.7	79.1	46.5	44.3	33.6	34.2	53.6
Train-Random	84.1	80.5	48.0	46.1	35.2	36.1	55.0
Train-Task	**87.6**	**88.3**	**77.6**	**82.3**	**79.4**	**72.0**	**81.2**
Method \ Task-GEN	**Sciqa**	**Tweetqa**	**E2E**	**CommonGen**	**CNN/DailyMail**	**XSum**	**Avg.**
Zero-shot	23.1	10.3	33.2	23.6	12.5	13.4	19.4
Train-Random	23.8	12.7	34.8	25.2	14.2	15.5	21.0
Train-Task	**42.0**	**34.3**	**40.4**	**33.0**	**27.1**	**28.6**	**34.2**

Table 7: Performance of Bloom-7b1 after fine-tuning task-specific neurons and under the zero-shot setting. "Train-Task" indicates training task-specific neurons. "Train-Random" indicates that the same number of neurons are randomly selected for training. Task-CLS: Classification Task. Task-GEN: Generation Task.

Group	10%	30%	50%	70%	100%
CLS-CLS	20.8	53.9	84.5	96.2	100
CLS-GEN	12.9	41.6	71.5	83.5	100
GEN-CLS	11.8	40.2	69.3	81.8	100
GEN-GEN	21.6	52.5	82.0	94.3	100

Table 8: The overlap rate of task-specific neurons between training tasks and test tasks when controlling the proportion of task-specific neurons.

Overlap rate \ Percentage of trained neurons	10%	30%	50%
10%	80.2	81.4	81.8
20.8%	*80.7*	-	-
30%	81.1	82.0	82.3
50%	81.5	82.3	82.8
53.9%	-	*82.5*	-
70%	82.0	82.7	83.0
84.5%	-	-	*83.1*
100%	82.2	83.1	83.6

Table 9: Results at different fine-tuned neuron proportions (10%, 30%, 50%) controlling the overlap rate under the classification - classification combination. Italics indicate the original experimental results and overlap rates.

Overlap rate \ Percentage of trained neurons	10%	30%	50%
10%	31.6	32.1	32.3
21.6%	*32.2*	-	-
30%	32.5	32.9	33.5
50%	32.7	33.4	33.8
52.5%	-	*33.8*	-
70%	32.9	34.0	34.1
82.0%	-	-	*34.9*
100%	33.1	34.4	35.1

Table 10: Results at different fine-tuned neuron proportions (10%, 30%, 50%) controlling the overlap rate under the generation - generation combination. Italics indicate the original experimental results and overlap rates.

Overlap rate \ Percentage of trained neurons	10%	30%	50%
10%	78.2	78.5	78.6
11.8%	*78.4*	-	-
30%	78.8	78.7	79.3
40.2%	-	*78.7*	-
50%	79.0	79.4	79.7
69.3%	-	-	*80.1*
70%	79.3	79.6	80.3
100%	79.5	79.9	80.8

Table 11: Results at different fine-tuned neuron proportions (10%, 30%, 50%) controlling the overlap rate under the generation - classification combination. Italics indicate the original experimental results and overlap rates.

Dataset	Class	Task Type	Domain
AGNews	4	Topic classification	News
Amazon	5	Sentiment anlysis	Amazon reviews
DBPedia	14	Topic classification	Wikipedia
Yahoo	10	Q&A	Yahoo Q&A

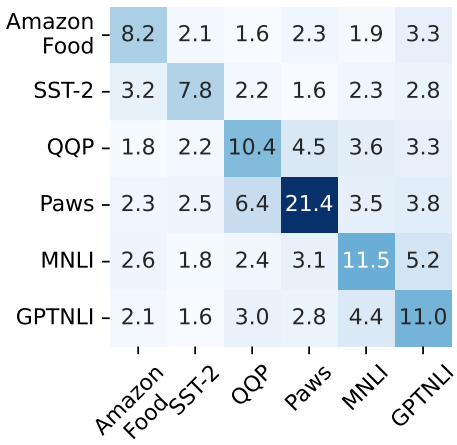
Table 12: Details of the Standard CL Benchmark.

Dataset	Class	Task Type	Domain
Amazon	5	Sentiment anlysis	Amazon reviews
DBPedia	14	Topic classification	Wikipedia
Yahoo	10	Q&A	Yahoo Q&A
AGNews	4	Topic classification	News
MNLI	3	NLI	various
QQP	2	Paragraph detection	Quora
RTE	2	NLI	news, Wikipedia
SST-2	2	Sentiment analysis	movie reviews

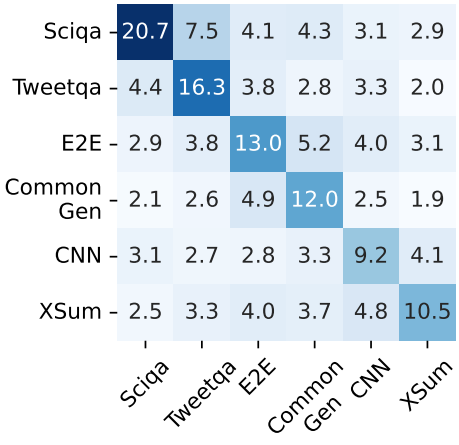
Table 13: Details of the simplified version Large Number of Tasks Benchmark.

Order	Task Sequence
1	DBPedia → Amazon → Yahoo → AGNews
2	DBPedia → Amazon → AGNews → Yahoo
3	Yahoo → Amazon → AGNews → DBPedia
4	MNLI → QQP → RTE → Amazon → SST-2 → DBPedia → AGNews → Yahoo
5	Amazon → AGNews → Yahoo → QQP → RTE → MNLI → DBPedia → SST-2
6	AGNews → Yahoo → SST-2 → RTE → QQP → MNLI → DBPedia → Amazon

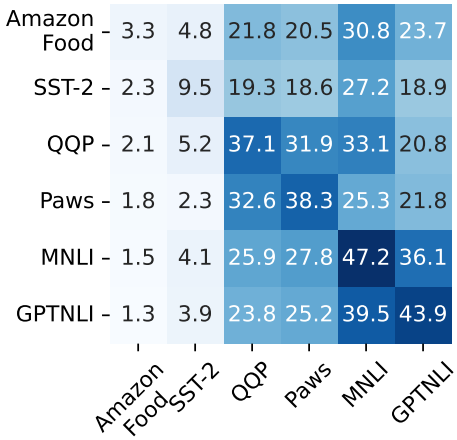
Table 14: Task order sequence for two continuous learning benchmarks.



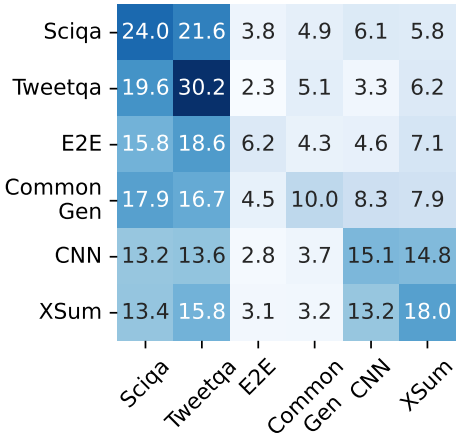
(a) Deactivation on classification tasks



(b) Deactivation on generation tasks

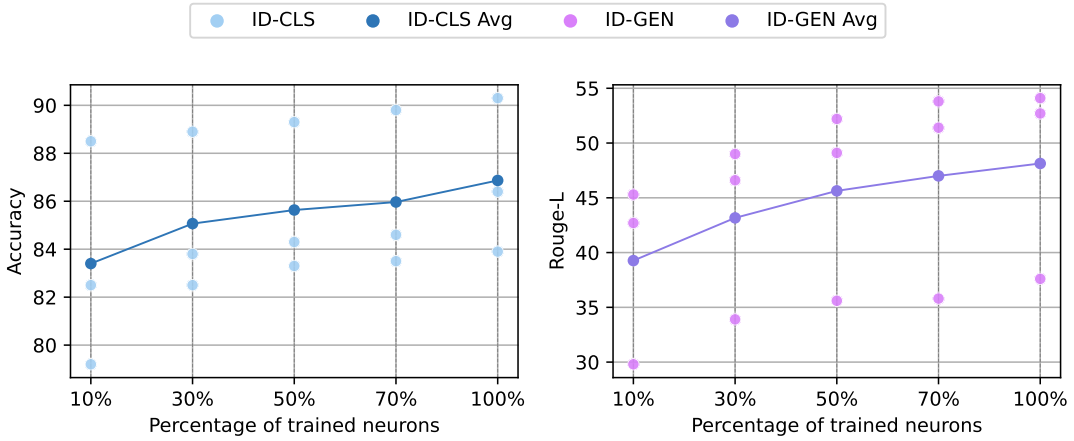


(c) Fine-tuning on classification tasks



(d) Fine-tuning on generation tasks

Figure 5: Performance of Llama-2-7b on all tasks after deactivation or fine-tuning a particular class task-specific neurons. The element in the i-th row and j-th column is the performance change for task j due to deactivation or fine-tuning of the task i specific neurons.



(a) Training on classification tasks

(b) Training on generation tasks

Figure 6: Results of training and testing each task individually for observing specialization.