Rehearsal-Free Modular and Compositional Continual Learning for Language Models

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Abstract

Continual learning aims at incrementally acquiring new knowledge while not forgetting existing knowledge. To overcome catastrophic forgetting, methods are either rehearsal-based, i.e., store data examples from previous tasks for data replay, or isolate parameters dedicated to each task. However, rehearsal-based methods raise privacy and memory issues, and parameter-isolation continual learning does not consider interaction between tasks, thus hindering knowledge transfer. In this work, we propose MoCL, a rehearsal-free **Mo**dular and **C**ompositional Continual **L**earning framework which continually adds new modules to language models and composes them with existing modules. Experiments on various benchmarks show that MoCL outperforms state of the art and effectively facilitates knowledge transfer.

1 Introduction

To effectively deploy machine learning (ML) models in real-world settings, they need to adopt *continual learning* (CL), i.e., incrementally acquire, update and accumulate knowledge to evolve continually and stay effective over time (Chen and Liu, 2018). However, CL often suffers from *catastrophic forgetting* (McCloskey and Cohen, 1989): The knowledge learned at early stages of training is overwritten by subsequent model updates.

A commonly used strategy to mitigate catastrophic forgetting is to store training samples from prior tasks along the continual learning process and train the model jointly with samples from prior and current tasks (*rehearsal*) (Rebuffi et al., 2017). However, training samples of prior tasks are not always available due to storage or privacy constraints (Wang et al., 2023a).

Another line of work allocates task-specific parameters to overcome catastrophic forgetting, often referred to as *parameter isolation-based* CL. Although inter-task interference leads to catastrophic forgetting (Wang et al., 2023a), knowledge transfer across tasks could be promising. However, those approaches do not enable effective knowledge transfer. Recent parameter isolation-based methods either separately train task-specific modules, completely excluding knowledge transfer (Wang et al., 2023d), or progressively concatenate all previous task-specific modules with the current task module (Razdaibiedina et al., 2022), without considering if the interaction between tasks is "positive" (knowledge transfer boosting performance) or "negative" (knowledge interference hurting performance).

To address these challenges, we introduce MoCL, a **Mo**dular and **C**ompositional Continual **L**earning framework for language models.[1] MoCL avoids catastrophic forgetting without storing additional data and facilitates effective knowledge transfer via module composition. Specifically, MoCL allocates task-specific parameters using prefix tuning (Li and Liang, 2021). During training, MoCL continually adds new task-specific modules to language models. To avoid catastrophic forgetting, the task-specific module is frozen once the training on the respective task is finished. Additionally, MoCL facilitates knowledge transfer across tasks by composing existing and new modules based on task matching weights while learning the new task.

In our evaluation on *near-domain* and *far-domain* continual learning benchmarks, MoCL outperforms state-of-the-art methods under the task-incremental learning setting where the task identities are available during testing. It further demonstrates strong abilities to transfer knowledge of previous tasks to the new tasks. Furthermore, the task matching strategy of MoCL enables task composition during testing. As a result, MoCL effectively addresses the continual learning problem in the challenging class-incremental setting where task identities are not provided during testing.

[1] We will release our code upon publication.

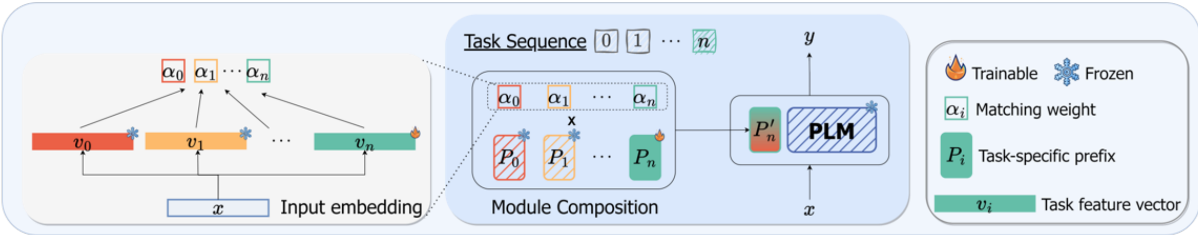

Figure 1: Overview of the MoCL framework for continual learning. MoCL continually adds new modules to language models and composes existing and new modules based on task matching weights for learning the new task.

2 Related Work

In line with previous work (De Lange et al., 2021; Ke and Liu, 2022; Wang et al., 2023a), we group CL strategies into three categories. (i) *Regularization*-based methods add explicit regularization terms to preserve the knowledge of previous tasks (Li and Hoiem, 2017; Kirkpatrick et al., 2017; Aljundi et al., 2018). As regularizing knowledge tends to have suboptimal performance, it is often used in combination with other methods. (ii) *Rehearsal*-based methods address catastrophic forgetting by saving old training samples in a memory buffer (Rebuffi et al., 2017; Rolnick et al., 2019; Zhang et al., 2022a), or training generative models to provide pseudo samples of previous tasks (Shin et al., 2017; Su et al., 2019) for future rehearsal. (iii) *Parameter isolation*-based methods assign isolated parameters dedicated to each task along the CL process to prevent interference between tasks (Madotto et al., 2020; Zhang et al., 2022b; Razdaibiedina et al., 2022; Wang et al., 2023d).

Since rehearsal-based methods raise memory and data privacy issues, we focus on rehearsal-free CL methods. MoCL falls into the category of parameter isolation-based continual learning, i.e., we allocate task-specific parameters to avoid knowledge interference. In contrast to related work, we additionally encourage knowledge transfer considering the relatedness across tasks.

3 Continual Learning Basics / Notation

In this work, we focus on continual learning (CL) on a sequence of text classification tasks. Specifically, we denote the sequence of tasks as $\{T_1, \ldots, T_N\}$. Each task T_n contains a set of input samples $\{(x_n^i, y_n^i)\}$, where x_n^i is the input text, y_n^i is the ground-truth label, and $n \in \{1, \ldots, N\}$ is the task identity. A CL model aims to solve the series of tasks which arrive sequentially. The overarching goal is to optimize the model's average performance across all tasks after learning them in the sequence. As we focus on rehearsal-free continual learning, data from earlier tasks is not available when training later tasks, i.e., our model does not suffer from the aforementioned shortcomings of rehearsal-based methods, such as memory issues.

While in many benchmark settings, the task identity n is provided, it is not a realistic assumption that task identities are available in real-world setups. Thus, we consider two setups: task-incremental learning (TIL) and class-incremental learning (CIL). In TIL, the task identities are available in both training and testing. In CIL, the task identities are only provided during training.[2]

4 Method

We propose MoCL, a novel CL approach for language models to tackle catastrophic forgetting and enhance knowledge transfer at the same time.

Avoiding Catastrophic Forgetting. We utilize prefix tuning (Li and Liang, 2021), a parameter-efficient fine-tuning (PEFT) approach, for allocating task-specific parameters to LMs, avoiding catastrophic forgetting without storing data samples.[3] In particular, prefix-tuning prepends a set of trainable parameters (*prefix*) to the frozen pretrained language model (PLM) for downstream task fine-tuning. Instead of updating the whole model, only a small number of prefix parameters is trained. As illustrated in Figure 1, MoCL uses trainable prefixes as the task-specific modules and keeps the PLM frozen. For each task $T_n \in \{T_1, \ldots, T_N\}$ in the sequence, we initialize a prefix P_n for fine-tuning. After the training on one task is finished, the corre-

[2] For better readability, we also refer to the domain-incremental learning (DIL), where tasks have the same label space but different input distributions, with and without test-time task identities as CIL and TIL, respectively; see Appendix A.2 for a more rigorous definition.

[3] Other PEFT modules such as Adapter (Houlsby et al., 2019) and LoRA (Hu et al., 2021) can also be combined with MoCL. We leave such exploration for future work.

sponding prefix parameters are frozen to preserve the task-specific knowledge in the following training process, thus avoiding catastrophic forgetting.

Enabling Knowledge Transfer. MoCL introduces task feature vectors for task matching and composes old and new modules for learning. This composition strategy facilitates effective knowledge transfer, which is often ignored by prior work.

In particular, while learning on T_n, the previously acquired knowledge, which is encoded in the respective prefixes $(P_1, \ldots, P_{n-1})$, is reused via a weighted summation, denoted as $P'_n = \sum_{k=1}^{n} \alpha_k P_k$. Here, P_k is the prefix specific to the k^{th} task and α_k is the weight determining the contribution of P_k for new task learning. We detail its computation below. Finally, the composed prefix P'_n is prepended to the PLM, consisting of all the prefix components up to the current task.

To calculate the prefix contribution weights α_k, we introduce trainable task feature vectors $V \in \mathbb{R}^{N \times D}$ to capture salient features of tasks in the CL sequence. Note that each task-specific vector $v \in \mathbb{R}^D$ has the same dimension as the input embeddings $x_n \in \mathbb{R}^D$ (i.e., the embeddings from the PLM encoder). Then, we calculate the cosine similarity between the input embeddings x_n and feature vectors up to the current n^{th} task $V[:n]$ as task matching scores $\alpha[:n] = \cos(x_n, V[:n])$.

Training and Inference. The training objective for the n^{th} task is to find the prefix P_n and the task feature vector v_n that minimize the cross-entropy loss of training examples, and, at the same time, maximize the cosine similarity between v_n and the corresponding task input embeddings x_n:

$$\min_{P_n, v_n} - \sum_{x_n, y_n} \log p(y_n | x_n, P'_n, \theta) - \sum_{x_n} \cos(x_n, v_n) \quad (1)$$

During inference, as the task identities are available in the TIL setting, we directly select the task-specific prefix for inference. In the CIL setting, we use the matching scores between input and task features vectors for prefix composition. The resulting prefix is prepended to the PLM for inference.

5 Experimental Setup

In this section, we describe our experimental setup.

5.1 Datasets

Following Wang et al. (2023d), we distinguish benchmarks according to the domain similarity of tasks. As *near-domain* benchmarks, we use the Web-of-Science document classification dataset (Kowsari et al., 2017) consisting of 7 tasks, and AfriSenti (Muhammad et al., 2023), a multilingual sentiment analysis dataset with 12 African languages. As *far-domain* benchmark, we use the widely adopted MTL5 dataset (de Masson D'Autume et al., 2019), including 5 text classification tasks. Following prior work, we apply different task orders for evaluation. Detailed task information are provided in Appendix A.1.

5.2 Training Details

We utilize three LMs for these datasets in line with previous work (Razdaibiedina et al., 2022; Wang et al., 2023d).[4] We use encoder-based models for WOS, AfriSenti and MTL5 datasets (BERT (Devlin et al., 2018), AfroXLMR (Alabi et al., 2022) and BERT, respectively), and the encoder-decoder T5 (Raffel et al., 2020) model for MTL5 under the few-shot setting. All reported results are averaged over 3 random seeds. The detailed experimental settings are provided in Appendix A.4.1.

5.3 Baselines

To compare different CL methods, we include the following baselines: **Sequential FT** continuously fine-tunes the language model (the prefix parameters in our case) on the task sequence; **Per-task FT** trains a separate prefix for each task; and the parameter isolation-based methods **ProgPrompt** (Razdaibiedina et al., 2022) and **EPI** (Wang et al., 2023d). A detailed description of these methods can be found in Appendix A.3.1.

Method	WOS	AfriSenti Orders			
		AVG	1	2	3
Sequential FT	53.86	6.17	5.62	6.52	6.30
Per-task FT	82.78	52.41	52.41	52.41	52.41
ProgPrompt	89.93	49.07	50.16	46.74	50.30
EPI	77.83	43.10	41.49	42.65	45.16
MoCL (Ours)	**90.59**	**56.77**	**57.05**	**56.52**	**56.74**

Table 1: TIL results on near-domain datasets.

6 Experimental Results

In this section, we discuss our experimental results.

6.1 MoCL for Task-Incremental Learning

Near-domain. As shown in Table 1, MoCL outperforms state-of-the-art methods on both benchmarks.

[4]In general, MoCL is compatible with any transformer-based model.

Method	MTL5 (BERT) Orders				
	AVG	1	2	3	4
Sequential FT	14.8	27.8	26.7	4.5	18.4
Per-task FT	79.0	79.0	79.0	79.0	79.0
ProgPrompt ◇	77.9	78.0	77.9	77.9	77.9
EPI †	77.3	77.4	77.3	77.2	77.4
MoCL (Ours)	**79.4**	**79.3**	**79.6**	**79.2**	**79.4**

Method	MTL5 (T5) Orders			
	AVG	1	2	3
Sequential FT	28.5	18.9	24.9	41.7
Per-task FT	75.1	75.1	75.1	75.1
ProgPrompt◇	75.1	75.0	75.0	75.1
EPI	56.4	49.7	54.1	65.3
MoCL (Ours)	**75.9**	**75.6**	**75.4**	**76.7**

Table 2: TIL results on far-domain MTL5 with BERT and T5 as the base model. ◇ and † indicate that results are taken from Razdaibiedina et al. (2022) and Wang et al. (2023d), respectively.

CIL	Datasets			
	WOS	AfriSenti	MTL5-BERT	MTL5-T5
EPI	77.83	43.10	**77.3**	56.4
Ours	**79.23**	**45.62**	74.1	**56.8**

Table 3: CIL results. We only compare MoCL and EPI as they are the only two rehearsal-free approaches that support this challenging task setting.

It is 7.81 and 4.36 points better than training each task with an individual model (per-task FT), indicating it realizes effective knowledge transfer.

Since EPI consists of task identification and per-task fine-tuning, its performance depends on the task identification accuracy. While it achieves comparable results with per-task fine-tuning on WOS, the performance degrades on AfriSenti, where different languages could be harder to differentiate.

While MoCL achieves comparable results to ProgPrompt on WOS (0.66 percentage points better), the performance gap on AfriSenti is considerably higher (7.7 points better). We assume this is due to the suboptimal knowledge transfer of ProgPrompt, which we will analyze in Section 6.3.

Far-domain. Table 2 provides the results on MTL5 using BERT (encoder model) and T5 (encoder-decoder model). MoCL again outperforms other CL methods in both cases across different task orders. Its advantage over per-task fine-tuning is less pronounced, which is due to the fact that far-domain tasks share weaker similarities.

FWT	Datasets			
	WOS	AfriSenti	MTL5-BERT	MTL5-T5
ProgPrompt	8.4	-3.5	-0.3	0
Ours	**8.9**	**4.8**	**0.3**	**0.3**

Table 4: Forward transfer (FWT) score comparison between ProgPrompt and MoCL across datasets.

6.2 MoCL for Class-Incremental Learning

Table 3 presents the class-incremental results. We compare MoCL only to EPI as they are the only two rehearsal-free CL methods applicable to this setting. Unlike EPI, our model has no explicit task identification component. Nevertheless, it still achieves better or competitive results.

6.3 Forward Transfer Analysis

We calculate the forward transfer scores (FWT) (Wang et al., 2023a) of MoCL and ProgPrompt in the TIL setting (see Table 4).[5]

The results show that ProgPrompt suffers from catastrophic forgetting on AfriSenti (FWT < 0) and explain the performance gap in Table 1. We assume the reason is negative interference between some of the languages, as observed in Wang et al. (2023c). ProgPrompt suffers from such interference as it concatenates all previous task-specific modules with the current task module, without considering task interaction. In contrast, MoCL composes task modules based on task matching, thus avoiding negative interference between tasks while exploiting similarities for knowledge transfer.

On the far-domain MTL5 dataset, MoCL still achieves higher scores than ProgPrompt. This suggests that our approach is better at transferring knowledge on various benchmarks, even with different levels of task similarities.

7 Conclusion

In this paper, we introduced MoCL, a modular and compositional continual learning framework for language models, effectively addressing the critical challenges of catastrophic forgetting and knowledge transfer in continual learning. Our broad evaluations across various benchmarks demonstrated MoCL's superior performance compared to existing state-of-the-art methods and showed its proficiency in knowledge transfer from previous tasks.

[5] As mentioned in 6.1, EPI consists of task identification and per-task FT. Thus, with given task IDs, EPI is identical to per-task FT, thus, includes no knowledge transfer (FWT $= 0$).

8 Limitation

One limitation of our work is the scope of evaluation. While MoCL is generally applicable to a wide range of tasks, we primarily focus on text classification tasks following prior work. Further experiments with other types of NLP tasks, especially generative tasks is left as a future work direction.

Besides, MoCL leverages prefix-tuning for parameter-efficient continual learning. It has not been evaluated with other prevalent parameter-efficient fine-tuning (PEFT) approaches such as Adapter (Houlsby et al., 2019) or LoRA (Hu et al., 2021). Future work could explore the synergy between our method and these alternative fine-tuning strategies.

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A Appendix

A.1 Dataset Information

Here we give detailed information of the datasets we use with in this work. For *near-domain* benchmarks, we use Web-of-Science (WOS) and AfriSenti. WOS is originally a hierarchical document classification datasets which collects published papers in 7 different domains, which are biochemistry, civil engineering, computer science, electrical engineering, medical science, mechanical engineering and psychology. These domains corresponds to 7 high-level classes for document classification, and there are several low-level subclasses under each high-level class. Following Wang et al. (2023d), we organize 7 continual learning tasks according to these high-level classes. AfriSenti is a multilingual sentiment analysis dataset which covers 12 low-resource African languages, including Amharic (am), Algerian Arabic (dz), Hausa (ha), Igbo (ig), Kinyarwanda(kr), Moroccan Arabic (ma), Nigerian Pidgin (pcm), Mozambican Portuguese (pt), Swahili (sw), Xitsonga (ts), Twi (twi) and Yoruba (yo).

For *far-domain* benchmarks, we adopt the commonly used MTL5 dataset, consisting of 5 text classification tasks. we summarize the details of MTL5 in Table 5. We experiment with BERT-base and T5-large models on this dataset in line with prior work (Razdaibiedina et al., 2022). For BERT-based experiments, we uses the same train and test sets follwoing prior work such as ProgPrompt (Razdaibiedina et al., 2022) and EPI (Wang et al., 2023d), consisting of 115,000 training and 7,600 text samples for each task. For T5-based experiments, 4 out of these 5 tasks (except Yelp) are used in line with Qin and Joty (2021) and Razdaibiedina et al. (2022), with 16 samples per task for training and the test sets are unchanged.

Following prior work, we report F1 score on the AfriSenti dataset (Muhammad et al., 2023; Wang et al., 2023b) and accuracy on WOS and MTL5 datasets (de Masson D'Autume et al., 2019; Razdaibiedina et al., 2022; Wang et al., 2023d). We use different task orders for each dataset to evaluate the robustness of continual learning methods against changing task orders. The task orders used are summarzied in Table 6.

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

Table 5: Details of the MTL5 dataset we use in the continual learning experiments.

A.2 Continual Learning Setting Details

Beyond the general formulation as introduced in Section 3, continual learning can be categorized into several detailed settings, [6] according to the distinction between incremental data batches and task identity availability. *Task-incremental learning* (TIL) refers to the scenario where the tasks have disjoint label space. Task identities are provided in both training and testing. This is the most studied continual learning scenario and also the easiest case of continual learning tasks.

Class-incremental learning (CIL) is a more challenging continual learning scenario where the task identities are not available during testing. The tasks still have disjoint label space and task identities are available during training.

Domain-incremental learning (DIL) assumes the class labels are the same across all tasks and the inputs are from different domains. Whether task identities are given during testing or not, it all belongs to this category. Strictly speaking, the AfriSenti benchmark used in this work belongs to the DIL category. In this multilingual sentiment analysis dataset, the data of different tasks (languages) is considered to have different input distributions, while the label space is shared across tasks (languages). In this work, we aim to evaluate MoCL in settings where the task identities are provided and are not provided during testing. We also consider the evaluation setting on AfriSenti as task-incremental learning and class-incremental learning, respectively. In our experiments, we assume tasks have disjoint label spaces, i.e., their classification heads are different. In this way, we use the AfriSenti benchmark for TIL and CIL evaluation as well.

A.3 Experimental Setup Details

In this section, we give more detailed information about the baseline methods we used in this work and the implementation details for experiments.

[6] We focus on some commonly studied continual learning settings here, for a more comprehensive categorization of continual learning settings please refer to (Wang et al., 2023a).

Dataset	Order	Model	Task Sequence
AfriSenti	1	AfroXLMR	am → dz → ha → ig → kr → ma → pcm → pt → sw → ts → twi → yo
	2	AfroXLMR	ma → pcm → kr → pt → ig → sw → ha → ts → dz → twi → am → yo
	3	AfroXLMR	am → dz → ha → ma → ig → kr → sw → ts → twi → yo → pcm → pt
WOS	1	BERT	1 → 2 → 3 → 4 → 5 → 6 → 7
MTL5	1	BERT	ag → yelp → amazon → yahoo → db
	2	BERT	yelp → yahoo → amazon → db → agnews
	3	BERT	db → yahoo → ag → amazon → yelp
	4	BERT	yelp → agnews → db → amazon → yahoo
MTL5	1	T5	db → amazon → yahoo → ag
	2	T5	db → amazon → ag → yahoo
	3	T5	yahoo → amazon → ag → db

Table 6: The different orders of task sequences used for continual learning experiments.

Method	RF	PE	CI	KT
EWC (Kirkpatrick et al., 2017)	✓			✓
MBPA++ (de Masson D'Autume et al., 2019)			✓	✓
IDBR (Huang et al., 2021)			✓	✓
LFPT5 (Qin and Joty, 2021)		✓		✓
ProgPrompt (Razdaibiedina et al., 2022)	✓	✓		✓
EPI (Wang et al., 2023d)	✓	✓	✓	
MoCL(Ours)	✓	✓	✓	✓

Table 7: Comparison between MoCL and existing CL approaches. RF: rehearsal-free; PE: parameter-efficient; CI: applicable to class-incremental learning, KT: enabled knowledge transfer.

A.3.1 Baseline Methods

In Section 6, we evaluate MoCL and prior continual learning methods on different benchmark datasets. Here we give a more detailed description of the baseline methods used in this work.

ProgPrompt (Razdaibiedina et al., 2022): a parameter isolation-based continual learning method which assigns task-specific parameters to avoid catastrophic forgetting. During continual learning, ProgPrompt progressively concatenates all task-specific modules to encourage forward transfer. Task identities are always required during training and testing.

EPI (Wang et al., 2023d): a parameter isolation-based method applicable to the class-incremental learning setting. EPI introduces a non-parametric task identification module that identifies tasks during testing. Given reliable task identification, the CIL performance could be comparable with TIL, where the ground truth task identities are given.

As discussed in the main paper, ProgPrompt and EPI are two closely related prior work to MoCL. ProgPrompt concatenates all previously learned parameters with the current learnable to encourage knowledge transfer while ignoring different levels of relatedness across tasks: There might be knowledge interference or transfer between different pairs of tasks. EPI focus on the class-incremental learning setting and the task-specific parameters are completely isolated, i.e., there is no knowledge transfer in their approach. In contrast, MoCL assigns different weights to previously learned task-specific modules based on the relatedness between tasks, therefore deftly balancing knowledge interference or transfer and leading to more effective knowledge transfer.

A.4 Experimental Results Details

In this section, we give detailed experimental results of MoCL, including the per-task results on the three datasets and the weight distribution on AfriSenti for prefix composition.

Per-task results From Table 8 to 11, we give the detailed per-task results on the aforementioned datasets under task-incremental learning and class-incremental learning settings.

WOS per-task results								
order 1	AVG	1	2	3	4	5	6	7
TIL	90.59	91.86	95.72	80.05	93.25	95.09	93.60	84.54
CIL	79.23	70.57	93.36	58.74	86.67	91.29	87.82	66.19

Table 8: Detailed per-task results on the WOS dataset under TIL and CIL settings.

Weight distribution In Figure 2, we visualize the weight distribution produced by MoCL on the AfriSenti dataset with the task order 2 (see Table 6) under the TIL setting. MoCL performs per-instance task matching and prefix composition, here we average the weight distributions across all examples

AfriSenti per-task results							
order1	**AVG**	**am**	**dz**	**ha**	**ig**	**kr**	**ma**
TIL	57.05	58.52	58.58	66.83	56.92	63.68	48.68
CIL	45.57	63.56	52.88	47.06	26.15	52.16	40.28
order1		**pcm**	**pt**	**sw**	**ts**	**twi**	**yo**
TIL		60.59	64.27	57.24	42.97	46.56	59.77
CIL		56.98	36.71	28.80	38.10	44.21	60.00
order2	**AVG**	**ma**	**pcm**	**kr**	**pt**	**ig**	**sw**
TIL	56.52	47.41	58.51	65.15	61.38	54.47	55.19
CIL	44.32	40.56	57.12	47.53	35.22	25.44	29.21
order2		**ha**	**ts**	**dz**	**twi**	**am**	**yo**
TIL		67.27	44.45	61.20	45.40	58.32	59.53
CIL		44.49	40.33	46.24	41.82	64.91	59.03
order3	**AVG**	**am**	**dz**	**ha**	**ma**	**ig**	**kr**
TIL	56.74	58.52	58.58	66.83	50.05	54.20	59.90
CIL	46.95	46.00	39.34	57.76	45.17	47.08	49.89
order3		**sw**	**ts**	**twi**	**yo**	**pcm**	**pt**
TIL		57.47	42.60	44.83	60.01	60.17	64.71
CIL		53.56	23.24	34.61	49.19	53.50	**CIL**

Table 9: Detailed per-task results on the AfriSenti dataset under TIL and CIL settings.

MTL5-BERT per-task results					
order1	**AVG**	**agnews**	**yelp**	**amazon**	**yahoo**	**db**
TIL	79.31	94.13	64.41	61.67	77.14	99.19
CIL	73.02	93.39	62.75	39.13	72.30	97.52
order2	**AVG**	**yelp**	**amazon**	**yahoo**	**db**	**agnews**
TIL	79.64	64.43	62.50	78.03	99.23	94.03
CIL	74.00	62.69	44.91	70.98	99.14	92.26
order3	**AVG**	**db**	**yahoo**	**agnews**	**amazon**	**yelp**
TIL	79.20	99.23	77.72	94.03	61.78	63.24
CIL	74.75	98.40	72.19	92.97	53.82	59.57
order4	**AVG**	**yelp**	**agnews**	**db**	**amazon**	**yahoo**
TIL	79.61	64.43	94.37	99.20	62.04	77.99
CIL	73.55	62.54	93.41	98.98	47.75	65.07

Table 10: Detailed per-task results on the MTL5 dataset using BERT as the base language model under TIL and CIL settings.

MTL5-T5 per-task results				
order1	**AVG**	**db**	**amazon**	**yahoo**	**agnews**
TIL	75.59	98.27	47.88	70.84	85.31
CIL	51.15	40.86	11.34	67.58	84.84
order2	**AVG**	**db**	**amazon**	**agnews**	**yahoo**
TIL	75.37	98.18	47.99	84.69	70.64
CIL	47.84	32.04	8.91	79.84	70.59
order3	**AVG**	**yahoo**	**amazon**	**agnews**	**db**
TIL	76.70	71.42	51.09	86.25	97.99
CIL	71.47	67.75	48.37	73.92	95.82

Table 11: Detailed per-task results on the MTL5 dataset using T5 as the base language model under TIL and CIL settings.

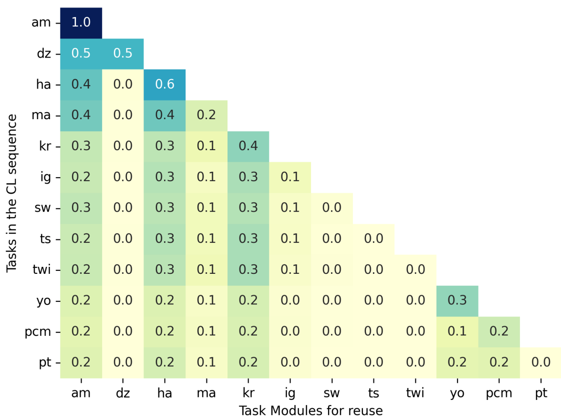

Figure 2: Average weight distribution on the AfriSenti dataset with the task order 2.

from a given task (i.e., language). As introduced in Section 4, while learning on the n^{th} task, we calculate the cosine similarity between the input embeddings and task feature vectors up to the current n^{th} task. Therefore, the heatmap of Figure 2 only has the lower left part. The heatmap entries quantify the extent of contribution from each task-specific module (denoted on the x-axis) to the subsequent tasks (represented on the y-axis).

Certain task-specific modules, such as am, ha, and kr, exhibit utility across a wide range of other tasks, while some, like dz, demonstrate exclusivity in utility to their respective tasks. Moreover, we observe that there is a pronounced sparsity in the learned weight distributions. Our task matching paradigm can be considered as a mixture-of-experts strategy where we use task-specific experts as the mixture components. Such a sparsity suggests that we can potentially reduce the number of experts, instead of using experts specific to each task in this work. This will be an interesting direction for future work.

A.4.1 Implementation Details

We use the AdamW optimizer (Loshchilov and Hutter, 2017) and the batch size of 8 for all experiments. We choose the same maximum sequence length and prefix length as prior work (Razdaibiedina et al., 2022; Wang et al., 2023d). Table 12 gives detailed hyperparameter choices of MoCL across different datasets. The training was performed on Nvidia A100 GPUs.[7]

[7] All experiments ran on a carbon-neutral GPU cluster.

Hyperparameters	
WOS-BERT	
Epochs	40
Early stop patience	5
Learning rate	3e-2
Max. sequence len.	256
Prefix len.	16
AfriSenti-AfroXLMR	
Epochs	40
Early stop patience	5
Learning rate	2e-4
Max. sequence len.	128
Prefix len.	8
MTL5-BERT	
Epochs	40
Early stop patience	5
Learning rate	8e-4 (db), 1e-3 (yahoo) 2e-3 (others)
Max. sequence len.	256
Prefix len.	20
MTL5-T5	
Epochs	40
Early stop patience	5
Learning rate	2e-2 (yahoo, db) 5e-2 (others)
Max. sequence len.	512
Prefix len.	50

Table 12: Hyperparameters used in this work across different CL experiments.