Multitask Multilingual Model Adaptation with Featurized Low-Rank Mixtures

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Abstract

Adapting pretrained large language models (LLM) to various downstream tasks in tens or hundreds of human languages is computationally expensive. Parameter-efficient fine-tuning (PEFT) significantly reduces the adaptation cost, by tuning only a small amount of parameters. However, directly applying PEFT methods such as LoRA (Hu et al., 2022) on diverse dataset mixtures could lead to suboptimal performance due to limited parameter capacity and negative interference among different datasets. In this work, we propose Featurized Low-rank Mixtures (FLix), a novel PEFT method designed for effective multitask multilingual tuning. FLix associates each unique dataset feature, such as the dataset's language or task, with its own low-rank weight update parameters. By composing feature-specific parameters for each dataset, FLix can accommodate diverse dataset mixtures and generalize better to unseen datasets. Our experiments show that FLix lead to significant improvements over a variety of tasks for both supervised learning and zero-shot settings using different training data mixtures.

1 Introduction

Large language models (LLMs) have shown impressive performance on various real world applications in many different human languages Brown et al. (2020); Soltan et al. (2022); Google et al. (2023). To adapt to different languages and data distributions, it is often necessary to further fine-tune an LLM. But full fine-tuning can be computationally and financially prohibitive. Parameter-efficient fine-tuning methods (PEFT) such as LoRA (Hu et al., 2022) and prompt tuning (Lester et al., 2021) reduce the computational costs of adapting LLMs to a downstream task. They parametrize LLM fine-tuning with a small set of trainable parameters, keeping the majority of LLM parameters frozen. In particular, LoRA does not augment the LLM with additional layers: it achieves parameter efficiency under the assumption that fine-tuning an LLM on the training dataset only results in a low-rank adaptation ΔW of pretrained LLM weights W_0 .

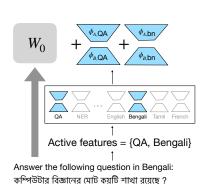
For multitask and multilingual adaptation, one might consider adapt a single PEFT model to a mixture of datasets from different tasks or languages. However, while PEFT has been shown to be effective in single-dataset adaptations, it is still unclear how we can best apply PEFT for dataset mixtures that consist of diverse languages and tasks. There would be significant engineering overhead and computational cost if one were to model each dataset in the mixture separately using PEFT. Moreover it is still unclear whether they can generalize to unseen task-language combinations. (Vu et al., 2022) proposed adding a multilingual pretraining stage to prompt tuning using multilingual unlabeled data mixture to improve zero-shot summarization. (Wang et al., 2023b) proposed a multitask prompt tuning method that learns a single soft prompt which could be used to be adapt to other target tasks. Yet these methods focused only on either multilingual or multitask learning, so it is not clear how they could be used for data mixtures in many different languages and tasks. They also require multiple tuning stages, which limits applicability in practice.

In this paper, we propose Featurized Low-rank Mixtures (FLix), an extension of LoRA for modeling diverse dataset mixtures. Compared to LoRA which applies the same low-rank adaptation for all inputs,

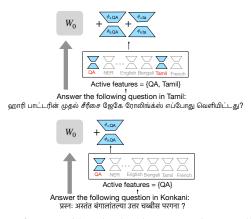
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(a) Training FLix on diverse data mixtures.



(b) Inference with trained FLix. *Top*: FLix naturally supports new test data with feature combinations unseen at training time; *Bottom*: FLix also supports new test data with partially unseen features. Since the Konkani language was not in the training mixture, FLix only uses the available parameters corresponding to the QA feature.

Figure 1: Training and inference with FLix.

FLix parametrizes such updates to *decompose* linearly as a sum of feature-specific low-rank adaptations, each associated with an active dataset feature, such as language or task ID. Under FLix, different adaptations can be learned for different features. The compositional nature of FLix also provides an inductive bias for learning generalizable adaptations. Moreover, FLix is generally computationally efficient: it only needs to activate a tiny fraction of trainable parameters for each input, making both tuning and deployment efficient. FLix is related to prior works on sub-network composition (Lin et al., 2021; Ilharco et al., 2022), which show that models fine-tuned on different tasks could be composed together as a single model.

The rest of this paper is structured as follows: in §2 we first formulate the multitask multilingual learning setting, and discuss the challenges associated with the current PEFT methods. In §3, we describe the design of FLix, and how FLix adapts to zero-shot scenarios. We also propose to train FLix with feature dropout, which encourages positive transfer and generalization. We evaluate FLix on multitask or multilingual learning setting (§5.1), and later on joint multilingual multitask tuning and zero-shot generalization (§5.2). The experiment results and ablations show that FLix brings significant improvements over standard PEFT methods for all settings, and it is especially effective when used with very diverse training mixture and at zero-shot generalizations (§5, §6).

2 Multitask multilingual learning

We consider a multitask learning Caruana (1997) setting where datasets are indexed using task-language tuples. We assume that there are N tasks $\{w_1 \dots w_N\}$ and M languages $\{\ell_1 \dots \ell_M\}$. And our goal is to serve fine-tuned LLMs for each of these $N \cdot M$ task-language combinations. It is worth noting that two special cases of this setup are multilingual modeling (N = 1) and multitask modeling (M = 1).

Parameter-efficient tuning (PEFT) is a popular method to adapt a pretrained LLM to downstream tasks without incurring large computational cost. In this work, we want to use PEFT to support $O(M \cdot N)$ languages and tasks.

2.1 Low-rank Adaptation

We focus on Low-rank Adaptation (LoRA) (Hu et al., 2022), an effective PEFT method that incurs minimal additional inference cost. Let $W_0 \in \mathbb{R}^{d \times k}$ be the pretrained weight matrix, LoRA keeps the much larger weight matrix W_0 unchanged, and instead only optimizes low-rank factorized weight

adaptation matrix $\Delta W = \phi^A \phi^B$. The final weight matrix is

$$W = W_0 + \Delta W = W_0 + \phi^A \phi^B, \tag{1}$$

where $\phi^A \in \mathbb{R}^{d \times r}$, $\phi^B \in \mathbb{R}^{r \times k}$. Empirically LoRA often compares competitively with full fine-tuning, even when $r \ll \min(d, k)$. LoRA can thus significantly reduce the size of trainable parameters.

2.2 Challenges

PEFT methods such as LoRA have been shown to be very effective for tuning LLMs, achieving comparable results to full fine-tuning while incurring only a fraction of the computational cost. However, there are several challenges with the multitask multilingual learning problem that the current PEFT methods might not be able to address.

Interference among different datasets Multitask multilingual training with PEFT requires one to fine-tune an LLM on a diverse data mixture, from up to $N \cdot M$ different datasets spanning N tasks and M languages. This approach has significantly lower overhead than modeling each dataset individually, and allows positive transfer. However, training a single set of PEFT parameters over all datasets could also lead to negative interference among tasks and languages that are dissimilar.

Generalizing to unseen task and language Publicly available wide-coverage multitask and multilingual datasets are often incomplete. For example, many task-language combinations are missing in XTREME-UP. Moreover, some underrepresented languages may still be missing from such datasets. Standard PEFT methods could have difficulty generalizing to unseen task-language combinations and unseen languages: they simply optimize a single set of parameters on all tasks without explicit modeling assumptions that capture the relationships and similarities between different datasets. And it is not clear how to transform such PEFT parameters to a new task or language at inference time.

3 Featurized Low-Rank Mixtures

We propose Featurized Low-Rank Mixtures (FLix), an effective multitask PEFT method that supports diverse training data mixture, and excels at zero-shot generalization to new task-language combinations. Under FLix, NLP tasks and languages are featurized as discrete features. And each feature is associated with a low-rank weight update matrix. Figure 1 shows the training and inference processes of FLix.

3.1 Model Architecture

Given a diverse data mixture from N tasks where each tasks are in M languages, first we define a set of D = N + M features where each feature could represent either a task, a language, or any other data attribute. We assign a low-rank factorized weight matrix $\phi_i^A \phi_i^B$ for each feature $i \in [1, D]$.

Let **x** be an input to the model, let $f(\mathbf{x})$ represent the features of **x**, where $f_i(\mathbf{x}) = 1$ indicates that **x** has feature i, and $f_i(\mathbf{x}) = 0$ otherwise.

$$W(\mathbf{x}) = W_0 + \sum_{i=1}^{D} f_i(\mathbf{x}) \phi_i^A \phi_i^B, \tag{2}$$

where $\phi_i^A \in \mathbb{R}^{d \times r_i}$, $\phi_i^B \in \mathbb{R}^{r_i \times k}$, and r_i is the maximum rank of the i-th feature's adaptation matrix. Note that compared to LoRA in equation (1) that applies the same ΔW (and therefore same W) for all inputs, FLix uses different adaptation matrices based on the features of the input data $f(\mathbf{x})$.

Feature Dropout One potential problem of training FLix is that the model might become overly reliant on the feature annotation of the training dataset, limiting positive transfer and making the model brittle to inputs different from training distribution. We randomly turn off a subset of active features at training time with a predetermined feature dropout probability. Experiments in §6 show that feature dropout brings consistent gains to FLix.

Exploiting feature sparsity for low training and serving costs. While the number of trainable parameters under FLix grows linearly with the number of features D, in practice we only need to load the parameters of the features associated with each input data; and this is a relatively small value in our multitask multilingual learning settings. Therefore, the compute costs of FLix could still remain constant when scaling to increasingly more tasks and languages.

3.2 Zero-shot Composition

We find FLix to be particularly effective at zero-shot generalization, likely because of the explicit feature composition assumption. While previous work proposed using language-specific modules at *pretraining* time to enhance crosslingual transfer (Vu et al., 2022; Pfeiffer et al., 2023), our work shows that sparse modularized PEFT architecture is also effective for directly adapting *dense* pretrained models to unseen datasets.

In this paper, we consider how FLix adapts to unseen datasets in two different zero-shot scenarios:

Unseen combinations. We want to do inference for a dataset that has a combination of active features that did not appear in the training mixture. For example, say the training data mixture contains QA data in French and semantic parsing data in Bengali; and we want to test the model on QA in Bengali. FLix naturally supports such features; and no change is required while applying equation (2).

Unseen languages. The test data could have a subset of features that are not covered by any of the dataset in the training mixture. Specifically, we focus on the setting where the test data is from a new language unseen during training. In this case, we only use the task feature of the data to calculate the model weights in equation (2).

In §5, we show that FLix significantly outperforms the baselines for both types of zero-shot settings.

4 Experiments

For all experiments, we use instruction fine-tuned PaLM-2 small Google et al. (2023) as the base model. We use a subset of the FLAN dataset Chung et al. (2022) as the instruction tuning dataset.

Datasets. We train and evaluate on various languages and tasks from the XTREME-UP dataset Ruder et al. (2023). We prepend templated prompts that encode task and language information to each input, to allow both FLix and vanilla LoRA models perform multitask and multilingual learning (Wang et al., 2023a). For different experiments, we use different language and task subsets from XTREME-UP. Dataset details are described in §5.²

Metrics. We report F1 scores for both in- and cross-lingual QA tasks, and NER tasks. For semantic parsing, we report exact-match accuracy. All numbers are normalized between [0, 100]. We report average normalized metric scores for (monolingual) multitask experiments.

Hyperparameters. We use a batch size of 512 during training for all experiments. For FLix, we also set the feature dropout probability to be 0.7.

Ranks. Compute-matched LoRA baselines have rank-6 adaptation matrices³ in all experiments. In this paper, every dataset has both task and language features; and we allocate feature-specific parameter counts such that the trainable parameters of active features under FLix always match compute-matched baselines. More specifically, we let task and language features have either rank-2 or rank-4 adaptation matrices. We allocate smaller matrices (rank-2) for task features in multitask experiments (§5.1), and larger matrices in both multilingual (§5.1) and joint multitask-multilingual (§5.2) experiments. We adjust the ranks of language features' adaptation matrices accordingly, to ensure that every dataset's adaptation matrices have a total rank = 6.

¹In preliminary experiments we found the presence of such prompts significantly improves multitask learning performance for vanilla LoRA models.

²A list of all experiments' training and evaluation tasks can also be found in Appendix B.

³Strictly speaking their ranks \leq 6; we slightly abused the terminology to reduce clutter.

Method	Multilingual Learning				Multitask Learning		Avg.
	QA CrossLang	QA InLang	Semantic Parsing	NER	Swahili	Bengali	8-
Compute-matched	77.3	88.5	40.5	81.3	66.0	63.8	69.6
Param-matched	76.2	89.0	47.2	83.2	66.8	65.8	71.3
FLix	77.6	89.4	45.0	84.3	70.2	69.0	72.6

Table 1: Results of either multitask learning or multilingual learning (complete tables are in Appendix C). While there is not a single baseline that is consistently better than others, FLix leads to consistent improvement over the LoRA baseline with similar computational cost.

Method	QA CrossLang	QA InLang	Semantic Parsing	NER			Zero-shot Unseen Lang	Avg.
Compute-matched	83.1	86.6	35.4	76.3	82.1	17.7	74.6	65.1
Param-matched	83.2	87.3	47.1	81.6	80.0	28.4	74.7	68.9
FLix	85.2	89.4	45.6	84.0	82.8	42.6	77.2	72.4

Table 2: Comparison of our method and baseline PEFT methods on multilingual multitask tuning (complete tables are in Appendix D). Note that **QA CrossLang** results in this table are evaluated only on XOR-TyDiQA languages, and are *not* directly comparable against those from Table 1. FLix achieves significant improvements over the compute-matched LoRA and it out-performs param-matched LoRA on three out of the four tasks. FLix also achieves much better performance on zero-shot generalization in cross-lingual QA.

Model selection. We evaluate on validation splits every 200 iterations, and train for a maximum of 2000 steps. For every multilingual and multitask task, we choose the checkpoint that has the best averaged metric numbers across languages or tasks, and subsequently evaluate on the test splits.

Baselines. We compare to the vanilla LoRA method under several different settings to ensure the fairness of comparison:

- **Compute-matched** sets the rank *r* of the vanilla LoRA model to be equivalent to the maximum sum of the rank of feature-specific adaptations under FLix. This ensures LoRA and FLix uses comparable computation during training and inference.
- **Param-matched** sets the rank *r* of the vanilla LoRA model such that the total number of trainable parameters is the same as its FLix counterpart.⁴

5 Results

5.1 Study A: Multitask or multilingual learning

First, we examine the performance of our method and the baselines on data mixtures with a single type of feature. That is, we train and evaluate on datasets of a single task from several different languages (multilingual learning), or datasets of a single language with different tasks (multitask learning). We also add additional baselines for this setting where we train a separate LoRA model for each individual dataset (denoted as Single-Lang and Single-Task in Table 1). This approach alleviates the capacity constraint of vanilla LoRA on diverse datasets, but adds more engineering overhead (as we briefly noted in §1) and cannot leverage positive transfer between datasets.

Specifically, we use subsets of the XTREME-UP dataset to construct these datasets:

• Multilingual learning. We experiment on four tasks: semantic parsing, NER, in-language QA, and cross-lingual QA. For each task, we train and evaluate on all languages that is available from the XTREME-UP dataset.

⁴The number of trainable parameters in FLix grows linearly with the number of features in a dataset. Therefore the param-matched counterpart's rank can be a relatively large number from around 20 to 90, depending on the task.

• Multitask learning. We evaluate on two under-represented languages: Swahili and Bengali. We use the subset of tasks available for each language in XTREME-UP. For Swahili, we use semantic parsing, QA (in-language), and NER. For Bengali we use semantic parsing and QA (both in-language and cross-lingual).⁵

No baseline method consistently out-performs other baselines. We report the performance of our method and the baselines in Table 1. For each experiment, we list the average result over all languages or tasks in the datasets. First, we find that among the different baseline methods, there is no method that consistently out-performs others. Specifically, param-matched LoRA tends to have advantage for multitask learning and tasks that are very different from pretraining (semantic parsing and NER), while compute-matched LoRA appears to be superior on multilingual QA tasks. We suspect that this is because param-matched LoRA benefits from its higher capacity for the model to learn to generate into targets that are very different from the pretraining data, and it is also helpful for supporting generation into diverse target tasks. However, param-matched LoRA has significantly higher numbers of trainable parameters. This could lead to much higher computational overhead compared to compute-matched LoRA. Moreover, we observe that compute-matched LoRA is actually more competitive on tasks such as crosslingual QA, likely because it reduces over-fitting by tuning a much smaller number of parameters.

FLix achieves much better performance than vanilla LoRA with the same computation budgets. FLix consistently outperforms compute-matched LoRA baseline on all settings, achieving significant gains without adding additional serving cost. Furthermore, our proposed method also outperforms param-matched LoRA on five out of the six data mixtures we evaluated.

We hypothesize that param-matched LoRA is better than FLix at semantic parsing but worse at other tasks because semantic parsing requires the LLM to generate into structured data that are very different from the pretraining data distribution, which might require particularly large model capacity to learn. In fact, Table 1 shows that param-matched LoRA with a higher rank is much better than compute-matched LoRA for semantic parsing, while being worse or comparable on question answering tasks. While param-matched LoRA could be particularly helpful for the semantic parsing task, it requires more computational resources to scale to large number of datasets. These results indicate that our method is an effective and computationally-efficient strategy for tuning LLMs on diverse data mixtures.

5.2 Study B: Joint Multitask Multilingual Learning

In §5.1 we have shown that FLix is very effective under multilingual and multitask learning settings, where only datasets in the training mixture vary by exactly one feature. In this section, we evaluate the performance of FLix and baselines on a more diverse data mixture, where datasets have different language and task features.

5.2.1 Multitask multilingual tuning

We conduct multitask multilingual tuning on both vanilla LoRA and our proposed FLix model. Again, we evaluate on four tasks from XTREME-UP covering a wide variety of use cases and languages: crosslingual QA, in-language QA, semantic parsing, NER. In addition, we also add training data from machine translation to the data mixture since it has the best language coverage which allows cross-lingual transfer. We use all languages in in-language QA, semantic parsing, NER, and a subset of languages in cross-lingual QA as training data.⁶ In addition, we also include the corresponding machine translation datasets of languages from these 4 datasets.

FLix significantly outperforms baselines under multitask multilingual tuning. The overall results are listed in Table 2. We can see that FLix out-performs the the best LoRA baseline for all tasks other than semantic parsing. While it loses to param-matched LoRA on semantic parsing, FLix has

⁵The mismatch between task choices between these two languages is due to the sparsity of available datasets in XTREME-UP.

⁶ We only use the languages included in the original XOR-TyDi QA (Asai et al., 2021): Arabic, Bengali, Japanese, Finish, Korean, Russian, Telugu. The rest of the cross-lingual QA languages — all Indic languages — are evaluated for zero-shot generalization in §5.2.2.

significantly less computational cost in comparison and it significantly out-performs the vanilla LoRA with the same computational cost.

5.2.2 Zero-shot Generalization

To evaluate both zero-shot generalizations (§3.2) we prepare two different training datasets:

- Holding out languages in cross-lingual QA. We reuse the training dataset from the joint multitask multilingual learning setup (§5.2) to evaluate both unseen feature combinations and unseen languages in the cross-lingual QA task. For unseen combinations, we evaluate the performance of the set of languages where the languages were present in other multilingual tasks in the training dataset; and for unseen languages, we evaluate on the set of languages that do not appear in other multilingual tasks in the training dataset.
- Holding out languages in semantic parsing. In this scenario, we use portions of crosslingual QA, in-language QA, semantic parsing, NER, and machine translation datasets from XTREME-UP as our training dataset. We include full crosslingual QA, in-language QA, NER datasets; but we do not include underrepresented languages in the semantic parsing portion of the training data. We also only include machine translation portions of languages that are already available in the other 4 subsets, as in §5.2. And we evaluate the unseen combination performance of all held-out languages under semantic parsing.⁷

Our method is very effective at both types of zero-shot generalization. The comparison of FLix and baseline methods can be found in the rightmost 3 columns in Table 2. We can see that FLix brings significant improvements to both unseen combinations and unseen languages on both cross-lingual QA and semantic parsing. This is likely because FLix allows one to select the subset of parameters most relevant to the features of the new test data, allowing more effective zero-shot generalization.

6 Analysis and Ablations

6.1 Effect of feature dropout

	Validation	Test
FLix	87.6	89.3
Dropout $p = 0$	86.9 (-0.7)	88.9 (-0.4)
Dropout $p = .3$	87.1 (-0.5)	88.7 (-0.6)
Dropout $p = .5$	87.3 (-0.3)	88.8 (-0.5)

Table 3: Effects of feature dropout on in-language QA. Removing feature dropout leads to consistent performance drop.

In this section, we evaluate the effectiveness of feature dropout for FLix. We compare the performance of FLix with and without feature dropout for in-language QA task using multilingual training, and the results are in Table 3. We can see that removing feature dropout leads to significant performance drop for both validation and test set. We hypothesize that this is because feature dropout is an effective regularization that encourages FLix to utilize the shared parameters for positive transfer between tasks and languages.

6.2 Effect of rank for FLix

In multilingual experiments (Table 1) the language features only have rank-2 feature-specific weight update matrices. Such low rank configurations help reduce the overall parameter count. In this section, we examine how well FLix performs under an even smaller budget. Table 4 shows the results of FLix on multitask multilingual tuning with rank set to 4 and 2. We can see that reducing the capacity of the

⁷These held-out languages are unseen combinations, rather than unseen languages, since they are available in the machine translation datasets of XTREME-UP.

Rank	QA CrossLang	QA InLang	Semantic Parsing	NER
2	77.6	89.4	45.0	84.3
1	76.5 (-1.1)	89.3 (-0.1)	45.2 (+0.2)	83.1 (-1.2)

Table 4: Effect of different ranks for language-specific adaptation matrices in FLix with multitask multilingual tuning. Decreasing the rank of matrices leads to very small drop in performance on most tasks, but it has a large negative effect on semantic parsing.

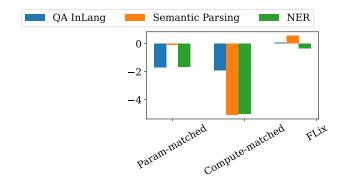


Figure 2: Difference in performance between multitask multilingual tuning and multilingual tuning only. While using the more diverse multilingual multitask data mixture leads to large performance drop for vanilla LoRA methods, FLix generally maintains or slightly improves the task performance with more diverse data mixtures.

feature-specific weight update matrices actually only lead to a small drop in performance on most tasks, indicating that FLix could be effective under even restrictive computational requirements.

6.3 FLix performs increasingly better on a diverse training dataset

In §5 we examined the performance of FLix and baselines under each data mixtures. Here we want to compare how different methods perform when using increasingly more diverse data mixtures. Specifically, we compare the change in task performance when using the multitask multilingual mixture as opposed to using only the multilingual data for each task. Figure 2 shows the results of FLix and the baselines. We can see that vanilla LoRA suffers from negative transfer Wang et al. (2018). In particular, the compute-matched version with a smaller rank has significant decrease in performance on a diverse multitask multilingual training dataset. On the other hand, FLix is able to generally maintain similar or slightly higher performance when using the more diverse data mixture. This result indicates that FLix is a superior PEFT method to scale to large number of tasks and languages.

7 Related Work

Multilingual/multitask PEFT While most prior works on parameter-efficient tuning focus on tuning the model for a single task, some recent works propose post-hoc composition pretrained PEFT modules to generalize to new task or language (Pfeiffer et al., 2020; Huang et al., 2023; Wang et al., 2021; Chronopoulou et al., 2023). These methods generally require separate training runs for each dataset, while our work propose a parameter-efficient tuning method that adapts the LLM using diverse data mixture in a single training run. Vu et al. (2022) proposed to add a multilingual pretraining stage to prompt tuning, which shows some improvements for zero-shot generalization when adapting to cross-lingual summarization task. In comparison, our proposed FLix focuses on tuning using multilingual data in many downstream tasks without additional training on unlabeled pretrainining data. Wang et al. (2023b) proposed a multitask prompt tuning method to learn a single prompt which could be used to adapt to many other target tasks. Similarly, this method requires multiple training stage while our method allows training end-to-end. Both of these methods are built upon prompt

tuning using either multilingual training in a single task or multitask tuning in English, while our method supports diverse datasets in different tasks languages or any other arbitrary features.

Mixture-of-experts Models Mixture-of-experts models (MoEs) (Shazeer et al., 2017; Lepikhin et al., 2020; Jawahar et al., 2023) are effective at increasing the model capacity by adding multiple expert parameters which could be activated differently to support different inputs. This architecture has been used to improve both pretrained models (Lepikhin et al., 2020; Jawahar et al., 2023) and parameter-efficient tuning methods (Zadouri et al., 2023; Zhu et al., 2023). Since MoEs often adds more computational cost, many works try to reduce the cost and improve the effectiveness of the model by either task-level routing (*e.g.*, Task MoEs proposed by Kudugunta et al. (2021)) or encouraging sparsity of the experts (Shazeer et al., 2017; Lepikhin et al., 2020). FLix resembles Task MoEs in that FLix leverages task information as well. But FLix has additional composition capabilities thanks to its featurization.

Modularized Pretrained Models Previous work proposed to add language-specific parameters to multilingual pretrained models (Pfeiffer et al., 2022; 2023) or machine translation models (Zhang et al., 2020). These works showed that language-specific modules often bring significant improvements to multilingual tasks. And they are especially helpful for zero-shot cross-lingual transfer. While prior works added language-specific modules during multilingual pretraining, in this paper we focus on the problem of adapting a pretrained model to a diverse mixture with many tasks and languages.

8 Future Work

There are several promising future directions for our work. While FLix achieves good zero-shot performance, it could potentially benefit from methods that automatically learn to select and compose parameters pretrained on different features for unseen data. It is also interesting to examine other applications of FLix: we encoded task and language informations as features in this work. But potentially other properties, such as modality, could also be featurized under FLix.

9 Conclusion

In this paper, we propose Featurized Low-Rank Mixtures (FLix), an effective parameter-efficient tuning method to fine-tune pretrained LLMs to data mixtures containing datasets in diverse tasks and languages. Our experiments show that FLix leads to significantly better performance on multitask multilingual fine-tuning compared to standard LoRA with little computational overhead. We also find that FLix achieves much better zero-shot generalization to new languages and task language combination unseen at training time.

Limitations

FLix requires datasets to be associated with discrete features, which would have to be obtained using either manual or automated annotation. Risks of cross-lingual knowledge transfer include negative transfers, and unwanted transfer of bias in fine-tuning data. Moreover, FLix may require support for sparse operations to achieve training and inference efficiency that is comparable with compute-matched LoRA models. While inactive features are not directly involved in computation under FLix, additional communication and storage overheads may incur, due to the increased parameter count.

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A Constant parameter sharing hurts FLix

Configuration	QA InLang	QA CrossLang	Semantic parsing	NER
FLix + shared parameters	89.4 88.2	85.2 84.0	45.6 41.9	84.0 80.7
Compute-matched LoRA	86.6	83.1	35.4	76.3

Table 5: Effects of adding shared parameters across all datasets for FLix on multitask multilingual learning. Adding shared parameters leads to decreased performance for FLix. Yet the presence of task and language features still provides significant improvement over compute-matched LoRA.

Our proposed FLix routes each input to their feature-specific adaptations, based on the dataset features. While constant parameter sharing happens when some features are always active for all datasets in a mixture (*e.g.*, in experiments in §5.1), this is not generally true. In this section, we look into the effects of enforcing constant parameter-sharing in FLix. Specifically, we design a dummy feature that is always active to all datasets in the joint multitask multilingual training mixture used in §5.2.1, which implies constant parameter sharing. We then compare FLix models both without and with this dummy feature, and also with a vanilla LoRA baseline, all under comparable compute budgets.⁸

In Table 5, we can see that adding a shared parameter actually leads to worse performance for FLix with similar computational cost. However, FLix with constantly shared features still outperforms computed-matched LoRA, which does not leverage task or language features at all.

B Training and evaluation datasets

B.1 Multilingual learning

The (mono-task) multilingual learning experiments described in §5.1 train and evaluate on the same languages. Their language and locale codes are:

Semantic parsing am, be, bn, fi, ha, hu, ja, pt_br, ru, sw, ta, tr, yo, zu, de_localized, en, de, es, fr, hi, th **In-language QA** ar, bn, fi, id, ko, ru, sw, te, en

Cross-lingual QA ar, bn, fi, ko, ru, te, as, bho, brx, gbm, gom, gu, hi, hne, kn, mai, ml, mni, mr, mwr, or, pa, ps, sa, ta, ur

NER am, bm, bbj, ee, ha, ig, rw, lg, luo, mos, ny, pcm, sn, sw, tn, tw, wo, xh, yo, zu

B.2 Multitask learning

The (mono-lingual) multitask learning experiments described in §5.1 train and evaluate on 3 different tasks, for the 2 languages we evaluate on respectively. They are:

Swahili (sw) Semantic parsing, NER, in-language QA

Bengali (bn) Semantic parsing, in-language QA, cross-lingual QA

B.3 Joint multitask multilingual learning

B.3.1 Training

The joint multitask multilingual learning experiments in §5.2 use the union of the following datasets:

Semantic parsing am, be, bn, fi, ha, hu, ja, pt_br, ru, sw, ta, tr, yo, zu, de_localized, en, de, es, fr, hi, th **In-language QA** ar, bn, fi, id, ko, ru, sw, te, en

⁸Specifically, we rearrange the rank sizes of all features such that the sum is 6. The dummy feature has rank= 4, and the language and task features have rank= 1. The compute-matched LoRA baseline does not make use of dataset features, and has rank= 6.

Cross-lingual QA ar, bn, fi, ko, ru, te

NER am, bm, bbj, ee, ha, ig, rw, lg, luo, mos, ny, pcm, sn, sw, tn, tw, wo, xh, yo, zu

Machine translation id, es, hi, yo, ja, lg, ny, ru, be, ar, de, bn, fr, tr, ig, th, fi, zu, te, ko, sw, xh, hu, ha, sn, ta, am

B.3.2 Multilingual evaluation

We evaluate models trained on the dataset described in Appendix B.3.1 on the 4 multilingual subsets of the training dataset. The results are reported in the first 4 columns of Table 2.

B.4 Zero-shot generalization

B.4.1 Training

For zero-shot evaluations on cross-lingual QA datasets in §5.2.2, we reuse the joint multitask multilingual training dataset described in Appendix B.3.1. For evaluation of zero-shot unseen combinations on semantic parsing datasets in the same section, we use the union of the following datasets:

Semantic parsing fi, hu, ja, pt_br, ru, tr, de_localized, en, de, es, fr, hi

In-language QA ar, bn, fi, id, ko, ru, sw, te, en

Cross-lingual QA ar, bn, fi, ko, ru, te, as, bho, brx, gbm, gom, gu, hi, hne, kn, mai, ml, mni, mr, mwr, or, pa, ps, sa, ta, ur

NER am, bm, bbj, ee, ha, ig, rw, lg, luo, mos, ny, pcm, sn, sw, tn, tw, wo, xh, yo, zu

Machine translation de, mni, mr, ig, id, mwr, ko, fi, ta, bn, ar, es, ja, zu, be, gbm, tr, as, bho, yo, ml, sw, hi, am, bbj, lg, pcm, ny, tw, hu, luo, rw, brx, pt_br, gu, or, gom, te, sn, wo, fr, ps, ha, hne, xh, en, sa, tn, de_localized, ur, bm, ee, th, ru, pa, kn, mai, mos

B.4.2 Zero-shot unseen combinations in cross-lingual QA

In the 'Zero-shot Unseen Comb: QA CrossLang' column of Table 2 we report the average cross-lingual QA F1 scores of languages that are missing from the cross-lingual QA portion of the joint multitask multilingual training set (Appendix B.3.1), but present in other datasets of the same training set. The language and locale codes of these languages are: hi, ta.

B.4.3 Zero-shot unseen languages in cross-lingual QA

In the 'Zero-shot Unseen Lang' column of Table 2 we report the average cross-lingual QA F1 scores of languages that are missing from the joint multitask multilingual training set. The language and locale codes of these languages are: bho, brx, gbm, gom, hne, mai, mni, mr, mwr, sa, as, gu, kn, ml, or, pa, ps, ur.

B.4.4 Zero-shot unseen combinations in semantic parsing

In the 'Zero-shot Unseen Comb: Semantic parsing' column of Table 2 we report the average exact match accuracy scores of languages that are designated as underrepresented in the XTREME-UP dataset, and held out from the training set in this experiment. These languages however appear in the machine translation portion of the training dataset. The language and locale codes of these languages are: am, be, bn, ha, sw, ta, yo, zu, th.

C Full results of Table 1

In addition to the test results reported in Table 1, we include validation results as well.

C.1 Multilingual experiments

C.1.1 Cross-lingual QA

Language / Locale ID	Validation	Test
ar	81.4	80.8
bn	77.9	83.7
fi	81.2	79.8
ko	85.0	83.9
ru	78.0	80.5
te	79.8	81.5
as	78.5	78.7
bho	74.6	75.8
brx	54.4	47.4
gbm	74.1	73.4
gom	78.3	75.8
gu	77.9	80.2
hi	82.2	83.5
hne	74.1	77.1
kn	79.2	80.1
mai	77.6	77.0
ml	77.0	79.3
mni	63.4	63.1
mr	76.1	78.1
mwr	76.0	75.9
or	77.4	77.7
pa	78.0	79.8
ps	76.5	77.4
sa	74.9	78.3
ta	78.4	78.5
ur	76.8	76.7
Average	76.5	77.1

Table 6: Single-language compute-matched cross-lingual QA results.

Language / Locale ID	Validation	Test
ar	82.4	83.4
bn	78.9	83.3
fi	82.8	82.6
ko	85.3	88.3
ru	79.6	83.2
te	81.8	81.5
as	80.7	78.9
bho	79.1	75.5
brx	54.8	47.5
gbm	78.4	73.3
gom	78.6	76.8
gu	79.5	78.8
hi	83.0	83.7
hne	78.8	77.9
kn	80.0	79.9
mai	79.0	75.6
ml	79.7	79.0
mni	60.4	60.5
mr	78.0	77.4
mwr	77.3	75.6
or	79.2	78.1
pa	79.1	78.6
ps	78.0	77.9
sa	77.0	77.2
ta	79.6	78.7
ur	78.5	76.1
Average	78.1	77.3

Table 7: Multiple-language compute-matched cross-lingual QA results.

Language / Locale ID	Validation	Test
ar	81.3	82.8
bn	79.7	83.5
fi	80.7	81.8
ko	84.8	87.0
ru	78.6	82.0
te	79.8	82.2
as	79.1	78.3
bho	77.7	75.2
brx	58.1	51.9
gbm	76.9	73.2
gom	76.9	71.5
gu	78.2	76.6
hi	84.2	83.2
hne	78.1	75.5
kn	79.7	77.7
mai	80.3	75.8
ml	79.7	77.7
mni	63.4	59.5
mr	78.5	77.0
mwr	77.3	75.9
or	76.3	73.9
pa	77.6	76.4
ps	74.8	71.7
sa	78.8	76.6
ta	80.3	78.5
ur	78.9	75.5
Average	77.7	76.2

Table 8: Multiple-language parameter-matched cross-lingual QA results.

Language / Locale ID	Validation	Test
ar	83.0	83.6
bn	79.2	84.6
fi	82.7	83.4
ko	85.9	87.4
ru	79.6	84.3
te	79.9	80.3
as	81.7	77.8
bho	78.8	76.3
brx	56.9	50.6
gbm	78.1	73.6
gom	78.4	76.3
gu	79.7	77.1
hi	82.2	83.6
hne	78.1	76.3
kn	81.2	81.0
mai	78.7	77.6
ml	80.4	78.7
mni	62.5	63.4
mr	78.3	77.7
mwr	76.3	74.8
or	79.5	78.1
pa	80.2	78.2
ps	78.6	77.0
sa	77.9	78.0
ta	80.8	78.8
ur	79.5	77.6
Average	78.4	77.6

Table 9: FLix cross-lingual QA results.

C.1.2 In-language QA

Language / Locale ID	Validation	Test
ar	87.3	88.5
bn	85.8	86.4
fi	89.5	90.2
id	85.3	86.0
ko	81.7	84.6
ru	87.0	85.1
sw	84.3	87.5
te	90.4	92.4
en	85.3	87.1
Average	86.3	87.5

Table 10: Single-language compute-matched in-language QA results.

Language / Locale ID	Validation	Test
ar	86.4	87.6
bn	89.0	85.9
fi	88.9	89.1
id	87.8	88.7
ko	83.4	86.2
ru	86.6	87.8
sw	86.6	89.6
te	91.1	93.1
en	85.3	88.3
Average	87.2	88.5

Table 11: Multiple-language compute-matched in-language QA results.

Language / Locale ID	Validation	Test
ar	86.4	87.7
bn	90.7	87.7
fi	89.6	89.7
id	87.9	88.7
ko	81.6	87.5
ru	86.2	88.7
sw	87.2	90.5
te	91.0	92.9
en	84.8	87.9
Average	87.3	89.0

Table 12: Multiple-language parameter-matched in-language QA results.

Language / Locale ID	Validation	Test
ar	87.2	89.1
bn	90.2	89.1
fi	90.1	89.7
id	87.8	88.9
ko	82.5	85.9
ru	87.8	89.1
SW	86.5	90.2
te	91.0	93.5
en	87.4	88.9
Average	87.8	89.4

Table 13: FLix in-language QA results.

C.1.3 Semantic parsing

Language / Locale ID	Validation	Test
am	25.5	14.7
be	34.7	25.8
bn	38.5	25.7
fi	33.9	25.0
ha	28.9	22.5
hu	31.0	23.4
ja	36.8	25.9
pt-br	36.8	25.5
ru	40.6	28.0
sw	34.7	23.1
ta	31.4	28.8
tr	40.2	24.4
yo	20.5	13.1
zu	25.1	15.2
de-localized	31.2	21.4
en	37.7	25.3
de	33.9	25.5
es	35.3	25.7
fr	30.1	21.8
hi	35.5	14.0
th	36.5	18.3
Average	33.3	22.5

Table 14: Single-language compute-matched semantic parsing results.

Language / Locale ID	Validation	Test
am	41.0	31.8
be	52.3	43.3
bn	51.0	40.6
fi	53.1	45.2
ha	46.0	35.9
hu	50.6	38.5
ja	52.3	38.4
pt-br	57.7	45.8
ru	60.7	45.4
$\mathbf{s}\mathbf{w}$	51.0	39.9
ta	47.3	39.5
tr	53.1	39.9
yo	39.3	28.8
zu	41.0	31.7
de-localized	57.4	44.1
en	54.8	45.3
de	54.8	43.0
es	57.8	45.1
fr	62.8	48.9
hi	54.8	37.0
th	55.3	42.4
Average	52.1	40.5

Table 15: Multiple-language compute-matched semantic parsing results.

Language / Locale ID	Validation	Test
am	48.5	36.0
be	59.0	50.3
bn	60.7	47.4
fi	62.3	51.9
ha	53.6	45.2
hu	60.3	48.4
ja	56.1	44.1
pt-br	61.9	52.9
ru	64.4	51.1
SW	51.9	43.8
ta	57.3	45.9
tr	59.4	45.6
yo	43.5	36.4
zu	44.8	37.6
de-localized	65.8	50.7
en	64.0	53.3
de	58.2	49.2
es	63.0	52.8
fr	65.8	53.9
hi	65.8	44.8
th	65.3	50.7
Average	58.6	47.2

Table 16: Multiple-language parameter-matched semantic parsing results.

Language / Locale ID	Validation	Test
am	47.7	37.4
be	58.6	47.4
bn	54.4	46.7
fi	59.4	50.3
ha	49.4	41.3
hu	56.5	46.3
ja	56.9	44.3
pt-br	60.7	48.8
ru	60.7	48.4
SW	58.6	42.7
ta	55.6	46.5
tr	58.2	44.6
yo	44.4	34.0
zu	37.2	37.6
de-localized	61.9	44.4
en	64.9	49.9
de	54.4	44.1
es	61.3	50.6
fr	62.8	50.3
hi	62.6	42.5
th	59.4	47.5
Average	56.4	45.0

Table 17: FLix semantic parsing results.

C.1.4 Named-entity recognition (NER)

Language / Locale ID	Validation	Test
am	74.8	72.8
bm	73.4	68.9
bbj	60.2	62.2
ee	84.9	82.4
ha	89.6	86.5
ig	82.0	82.2
rw	77.9	76.1
lg	87.0	83.8
luo	66.1	71.4
mos	63.8	65.7
ny	86.8	88.3
pcm	82.1	81.6
sn	89.3	88.6
SW	89.6	88.8
tn	77.1	84.4
tw	72.9	74.0
wo	81.5	76.5
xh	83.7	81.1
yo	79.1	80.7
zu	79.2	82.2
Average	79.1	78.9

Table 18: Single-language compute-matched NER results.

Language / Locale ID	Validation	Test
am	77.3	73.7
bm	72.4	67.8
bbj	54.5	66.1
ee	82.9	82.6
ha	90.9	90.0
ig	84.4	85.3
rw	80.0	77.4
lg	87.5	86.2
luo	77.2	76.3
mos	67.6	66.0
ny	87.8	89.2
pcm	82.8	86.3
sn	90.4	90.2
SW	90.7	90.9
tn	80.8	86.6
tw	76.7	79.1
wo	80.8	78.5
xh	83.5	83.8
yo	80.3	83.0
zu	84.7	87.3
Average	80.6	81.3

Table 19: Multiple-language compute-matched NER results.

Language / Locale ID	Validation	Test
am	79.1	77.4
bm	79.9	73.8
bbj	65.7	68.3
ee	88.0	86.7
ha	93.6	91.3
ig	86.8	85.2
rw	82.1	78.0
lg	89.2	86.3
luo	76.7	77.1
mos	72.1	70.6
ny	88.8	89.2
pcm	87.4	88.2
sn	92.7	92.6
sw	91.7	90.8
tn	82.9	88.6
tw	81.5	81.8
wo	81.1	80.8
xh	85.4	86.2
yo	82.2	84.7
zu	85.7	87.3
Average	83.6	83.2

Table 20: Multiple-language parameter-matched NER results.

Language / Locale ID	Validation	Test
am	81.8	80.0
bm	79.2	73.2
bbj	66.5	72.1
ee	87.2	86.1
ha	93.6	91.1
ig	85.9	86.5
rw	83.5	80.0
lg	90.2	88.1
luo	78.6	80.4
mos	73.0	73.7
ny	89.5	91.8
pcm	87.2	87.9
sn	93.2	93.2
SW	91.5	91.1
tn	83.1	88.1
tw	81.2	79.6
wo	84.7	81.3
xh	86.7	87.0
yo	83.5	86.0
zu	86.5	89.0
Average	84.3	84.3

Table 21: FLix NER results.

C.2 Multitask experiments

Task	Validation	Test
SemParse	34.7	23.0
QA-InLang	84.2	87.3
NER	88.6	88.7
Average	69.2	66.3

Table 22: Single-task compute-matched Swahili results.

Task	Validation	Test
SemParse	37.7	23.0
QA-InLang	83.9	86.4
NER	88.6	88.7
Average	70.1	66.0

Table 23: Multiple-task compute-matched Swahili results.

Task	Validation	Test
SemParse	38.5	26.4
QA-InLang	82.5	85.2
NER	89.7	88.8
Average	70.3	66.8

Table 24: Multiple-task parameter-matched Swahili results.

Task	Validation	Test
SemParse	47.7	32.7
QA-InLang	85.2	87.5
NER	91.0	90.3
Average	74.6	70.2

Table 25: FLix Swahili results.

Task	Validation	Test
SemParse	37.2	25.7
QA-InLang	87.6	86.7
QA-CrossLang	78.6	83.2
Average	67.8	65.2

Table 26: Single-task compute-matched Bengali results.

Task	Validation	Test
SemParse	36.4	24.3
QA-InLang	88.4	85.4
QA-CrossLang	76.6	81.9
Average	67.2	63.8

Table 27: Multiple-task compute-matched Bengali results.

Task	Validation	Test
SemParse	44.4	29.4
QA-InLang	89.1	83.6
QA-CrossLang	76.1	84.4
Average	69.8	65.8

Table 28: Multiple-task parameter-matched Bengali results.

Task	Validation	Test
SemParse	52.7	37.0
QA-InLang	90.0	85.9
QA-CrossLang	77.3	84.1
Average	73.3	69.0

Table 29: FLix Bengali results.

D Full results of Table 2

As in Appendix C, we include validation results along with test results.

D.1 Supervised learning results

D.1.1 Cross-lingual QA

Language / Locale ID	Validation	Test
ar	83.6	82.3
bn	79.6	82.9
fi	81.4	82.2
ko	85.0	85.2
ru	79.8	81.7
te	80.3	84.4
Average	81.6	83.1

Table 30: Multitask multilingual compute-matched cross-lingual QA results.

Language / Locale ID	Validation	Test
ar	82.1	83.6
bn	79.3	84.5
fi	81.8	81.3
ko	84.5	86.0
ru	79.5	82.7
te	81.0	81.0
Average	81.4	83.2

Table 31: Multitask multilingual parameter-matched cross-lingual QA results.

Language / Locale ID	Validation	Test
ar	85.6	84.3
bn	82.2	86.2
fi	82.6	83.2
ko	85.5	88.2
ru	80.5	84.0
te	82.1	85.0
Average	83.1	85.2

Table 32: Multitask multilingual FLix cross-lingual QA results.

D.1.2 In-language QA

Language / Locale ID	Validation	Test
ar	83.8	84.9
bn	88.1	83.9
fi	86.7	87.4
id	86.5	88.1
ko	80.9	85.0
ru	82.6	84.1
sw	85.2	88.2
te	89.2	91.7
en	83.3	85.9
Average	85.2	86.6

Table 33: Multitask multilingual compute-matched in-language QA results.

Language / Locale ID	Validation	Test
ar	85.2	86.9
bn	90.8	85.8
fi	87.0	87.5
id	85.4	87.1
ko	80.4	85.3
ru	84.9	86.2
SW	84.8	88.7
te	89.4	91.7
en	84.5	86.7
Average	85.8	87.3

Table 34: Multitask multilingual parameter-matched in-language QA results.

Validation	Test
86.4	88.7
90.4	91.1
90.0	89.5
88.6	89.5
83.2	86.1
85.4	88.5
87.4	90.1
91.5	93.6
85.0	87.9
87.5	89.4
	86.4 90.4 90.0 88.6 83.2 85.4 87.4 91.5 85.0

Table 35: Multitask multilingual FLix in-language QA results.

D.1.3 Semantic parsing

Language / Locale ID	Validation	Test
am	36.0	24.5
be	47.7	38.6
bn	51.5	34.3
fi	53.6	40.1
ha	39.3	30.0
hu	50.2	36.9
ja	46.4	33.9
pt-br	53.6	41.1
ru	54.0	40.2
sw	46.4	34.3
ta	43.5	31.4
tr	45.2	33.7
yo	29.7	24.0
zu	33.1	29.3
de-localized	56.4	40.3
en	50.6	39.9
de	47.7	38.0
es	54.9	42.2
fr	55.6	41.9
hi	49.7	31.4
th	54.7	37.5
Average	47.6	35.4

Table 36: Multitask multilingual compute-matched semantic parsing results.

Language / Locale ID	Validation	Test
am	43.1	35.5
be	58.6	50.4
bn	59.0	47.4
fi	62.3	53.0
ha	51.0	42.1
hu	58.2	47.2
ja	59.0	45.9
pt-br	64.0	51.7
ru	63.2	51.3
SW	55.6	44.1
ta	54.0	47.8
tr	58.6	46.6
yo	43.5	34.3
zu	46.9	39.7
de-localized	61.9	49.8
en	61.5	53.1
de	56.1	48.6
es	64.7	51.7
fr	62.8	53.7
hi	66.5	46.4
th	63.5	49.7
Average	57.8	47.1

Table 37: Multitask multilingual parameter-matched semantic parsing results.

Language / Locale ID	Validation	Test
am	46.9	38.3
be	59.8	48.8
bn	58.2	47.1
fi	59.8	50.9
ha	50.6	41.0
hu	55.2	44.2
ja	54.0	45.5
pt-br	61.5	47.6
ru	62.8	50.6
SW	55.2	42.6
ta	53.1	45.7
tr	57.7	45.4
yo	43.5	34.1
zu	41.4	37.6
de-localized	60.4	45.6
en	61.1	50.7
de	57.7	45.5
es	60.7	50.4
fr	65.8	52.5
hi	63.9	45.2
th	61.8	48.2
Average	56.7	45.6

Table 38: Multitask multilingual FLix semantic parsing results.

D.1.4 NER

Language / Locale ID	Validation	Test
am	68.8	70.8
bm	67.3	63.5
bbj	52.4	61.2
ee	80.5	78.6
ha	87.5	84.8
ig	78.2	82.1
rw	77.2	71.6
lg	85.4	82.4
luo	61.7	66.9
mos	62.9	61.6
ny	83.4	85.5
pcm	79.9	81.3
sn	84.1	84.4
sw	87.2	87.1
tn	77.8	84.3
tw	74.0	74.8
wo	75.2	73.9
xh	73.3	77.2
yo	71.4	75.0
zu	75.4	78.7
Average	75.2	76.3

Table 39: Multitask multilingual compute-matched NER results.

Language / Locale ID	Validation	Test
am	74.4	76.7
bm	75.1	71.0
bbj	61.7	66.1
ee	85.1	83.5
ha	92.1	90.5
ig	85.4	86.1
rw	81.8	76.8
lg	87.3	85.3
luo	77.1	75.9
mos	66.7	66.4
ny	87.1	87.9
pcm	85.4	86.9
sn	91.8	90.6
SW	90.7	90.1
tn	82.0	87.6
tw	78.4	77.9
wo	79.4	78.9
xh	82.4	85.5
yo	79.5	81.2
zu	82.9	86.1
Average	81.3	81.6

Table 40: Multitask multilingual parameter-matched NER results.

Language / Locale ID	Validation	Test
am	81.1	79.4
bm	80.4	73.7
bbj	63.6	70.5
ee	87.0	86.1
ha	92.7	91.2
ig	85.4	86.9
rw	83.9	80.2
lg	89.1	87.2
luo	74.7	78.9
mos	71.2	72.5
ny	89.4	90.4
pcm	86.8	88.9
sn	91.9	92.7
sw	91.6	91.4
tn	83.2	88.9
tw	79.4	78.2
wo	83.3	81.9
xh	85.5	86.0
yo	83.0	85.8
zu	84.9	88.7
Average	83.4	84.0

Table 41: Multitask multilingual FLix NER results.

D.2 Zero-shot results

D.2.1 Zero-shot unseen combinations: cross-lingual QA

Language / Locale ID	Validation	Test
hi ta	82.1 79.3	83.2 80.1
Average	80.7	81.6

Table 42: Zero-shot unseen combinations: compute-matched cross-lingual QA results.

Language / Locale ID	Validation	Test
hi ta	84.4 80.7	84.4 79.8
Average	82.5	82.1

Table 43: Zero-shot unseen combinations: parameter-matched cross-lingual QA results.

Language / Locale ID	Validation	Test
hi ta	84.9 81.9	85.3 80.4
Average	83.4	82.8

Table 44: Zero-shot unseen combinations: FLix cross-lingual QA results.

D.2.2 Zero-shot unseen combinations: semantic parsing

Language / Locale ID	Validation	Test
am	13.8	10.2
be	35.6	30.1
bn	31.0	21.6
ha	20.1	16.2
sw	34.3	22.0
ta	20.5	11.4
yo	7.5	8.9
zu	17.2	16.0
th	37.6	23.0
Average	24.2	17.7

Table 45: Zero-shot unseen combinations: compute-matched semantic parsing results.

Language / Locale ID	Validation	Test
am	24.7	17.6
be	54.0	42.8
bn	45.2	35.6
ha	30.5	25.5
sw	43.1	32.2
ta	30.5	23.1
yo	21.3	16.1
zu	27.6	24.8
th	55.9	38.4
average	37.0	28.4

Table 46: Zero-shot unseen combinations: parameter-matched semantic parsing results.

Language / Locale ID	Validation	Test
am	46.9	38.3
be	59.8	48.8
bn	58.2	47.1
ha	50.6	41.0
SW	55.2	42.6
ta	53.1	45.7
yo	43.5	34.1
zu	41.4	37.6
th	61.8	48.2
Average	52.3	42.6

Table 47: Zero-shot unseen combinations: FLix semantic parsing results.

D.2.3 Zero-shot unseen languages

Language / Locale ID	Validation	Test
as	80.7	79.6
bho	78.9	76.0
brx	45.7	41.0
gbm	74.6	73.1
gom	77.8	75.3
gu	80.9	79.8
hne	77.1	78.5
kn	80.9	80.5
mai	79.3	76.2
ml	81.0	81.4
mni	52.3	52.9
mr	78.7	78.7
mwr	80.4	76.9
or	77.8	77.5
pa	79.3	80.4
ps	77.0	78.2
sa	78.1	80.5
ur	79.3	78.5
Average	75.5	74.7

Table 48: Zero-shot unseen languages: compute-matched cross-lingual QA results.

Language / Locale ID	Validation	Test
as	81.3	79.8
bho	79.0	77.0
brx	46.5	41.2
gbm	73.4	72.5
gom	77.7	74.7
gu	81.9	80.0
hne	78.1	77.2
kn	82.7	80.1
mai	81.3	77.5
ml	81.6	80.9
mni	48.8	51.1
mr	80.0	80.3
mwr	77.7	75.8
or	77.8	79.2
pa	80.0	79.8
ps	77.0	78.5
sa	77.5	78.9
ur	78.3	77.7
Average	75.6	74.6

Table 49: Zero-shot unseen languages: parameter-matched cross-lingual QA results.

Language / Locale ID	Validation	Test
as	82.6	82.5
bho	78.7	78.7
brx	50.3	47.0
gbm	77.5	75.4
gom	80.3	78.6
gu	82.7	82.6
hne	79.0	79.8
kn	82.3	82.5
mai	81.8	79.9
ml	82.1	81.0
mni	56.2	59.0
mr	79.7	80.7
mwr	79.5	77.9
or	81.4	81.1
pa	79.9	81.7
ps	78.9	80.6
sa	80.1	81.6
ur	80.2	79.9
Average	77.4	77.2

Table 50: Zero-shot unseen languages: FLix cross-lingual QA results.