# Breaking the Curse of Multilinguality with Cross-lingual Expert Language Models

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## Abstract

Despite their popularity in non-English NLP, multilingual language models often underperform monolingual ones due to inter-language competition for model parameters. We propose Cross-lingual Expert Language Models (X-ELM), which mitigate this competition by independently training language models on subsets of the multilingual corpus. This process specializes X-ELMs to different languages while remaining effective as a multilingual ensemble. Our experiments show that when given the same compute budget, X-ELM outperforms jointly trained multilingual models across all considered languages and that these gains transfer to downstream tasks. X-ELM provides additional benefits over performance improvements: new experts can be iteratively added, adapting X-ELM to new languages without catastrophic forgetting. Furthermore, training is asynchronous, reducing the hardware requirements for multilingual training and democratizing multilingual modeling.

## 1 Introduction

Massively multilingual language models (LMs), which are trained on terabytes of text in a hundred or more languages, underlie almost all non-English and cross-lingual NLP applications (Scao et al., 2022; Lin et al., 2022, inter alia). Despite their wide adoption, these models come at a cost: by modeling many languages in a single model, there is inter-language competition for fixed model capacity; this causes performance on individual languages to degrade relative to monolingual models (Conneau et al., 2020; Chang et al., 2023). Furthermore, this phenomenon (termed the *curse of multilinguality*) can significantly harm low-resource languages (Wu and Dredze, 2020).

In this paper, we address the curse of multilinguality with **C**ross-lingual **E**xpert **L**anguage **M**odels (X-ELM, Figure 1), an ensemble of language models initialized from a pretrained multilingual model and each independently trained on a different subset of a multilingual corpus. Our ensemble allows for efficient scaling of model capacity to better represent all the corpus languages. These X-ELMs are trained with x-BTM, a new extension of the Branch-Train-Merge paradigm (BTM; Li et al., 2022; Gururangan et al., 2023, §2) to the more heterogenous multilingual setting.

x-BTM improves over existing BTM techniques by introducing (1) a new method for balanced clustering of multilingual data based on typological similarity and (2) Hierarchical Multi-Round training (HMR), an algorithm for efficiently training new experts specialized to unseen languages or other distributions of multilingual data. Once the initial X-ELMs are trained, we dynamically select experts to perform inference (§3.3). We can also efficiently adapt X-ELMs to novel settings with additional rounds of x-BTM on new experts branched from existing X-ELMs (§4); this improves the overall X-ELM set without altering the existing experts.

We train X-ELMs on 20 total languages—including adapting to 4 unseen ones–and on up to 21 billion training tokens. Our experiments demonstrate that X-ELMs outperform the dense language models given the same compute budget in every considered experimental setting, with improvements of up to 3.8 perplexity points (§6). Furthermore, the perplexity gains observed in X-ELM languages are well-balanced across language resourcedness, and adapting the models to new languages via HMR training significantly outperforms standard language-adaptive pretraining methods. We also show that the language modeling gains of X-ELM hold on downstream task evaluations (§7).

Multilingual modeling with X-ELM provides additional benefits over improved performance. Train-

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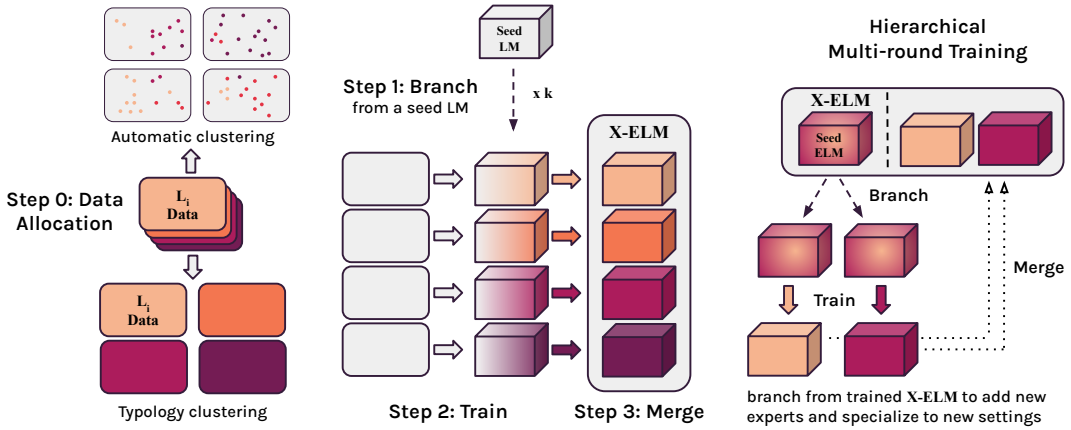


Figure 1: Overview of the X-ELM pretraining procedure. **Left**: We partition the multilingual text corpus into $k$ subsets either through *automatic TF-IDF* clustering of documents or through grouping languages by *linguistic typology*. **Center**: Branch-Train-Merge (BTM) pretraining method. We initialize (*branch*) $k$ experts from a seed LM, *train* each expert on a different cluster from the pretraining corpus, and *merge* the experts into a set of X-ELMs. **Right**: Hierarchical Multi-Round (HMR) training procedure (§4).

ing a set of X-ELMs is more computationally efficient than a comparable dense model; each expert is trained independently, which removes the overhead cost of cross-GPU synchronization (Li et al., 2022) and allows experts to be trained asynchronously in low-compute settings. Similarly, adapting X-ELMs to new languages is more efficient than continued training of a dense LM and does not risk catastrophic forgetting of previously seen languages, as adding a new X-ELM does not change the existing experts. As a result, X-ELMs allow much more efficient modeling than prior multilingual approaches, democratizing work on building and improving multilingual systems.

## 2 Background: Branch-Train-Merge

Multilingual LMs are typically trained in a *dense* manner, where a single set of parameters are updated with every training batch. When training large LMs, the dense training setup calculates gradients on and synchronizes model parameters across many GPUs.[1] This requires all GPUs to be available simultaneously and incurs communication costs that prolong training.

Branch-Train-Merge (BTM; Li et al. 2022) alleviates this cost by dividing the total compute among smaller expert language models that are trained independently on different domains (or subsets of a corpus) and then combined during inference time. While the total number of parameters increases with the number of experts, inference with these models often uses a subset of experts (see §3.3), keeping inference costs manageable.

c-BTM (Gururangan et al., 2023) generalizes the above approach with cluster-based representations of domains. Across multiple corpora, they show that (1) the optimal number of experts increases with data and compute and (2) a set of small expert models performs similarly to equivalently sized dense models at vastly reduced FLOP budgets.

Our work extends these studies to the multilingual setting, in which experts are specialized to different languages instead of (primarily) English-language domains. In the multilingual setting, we can also use typological structure to specialize experts, which we show provides additional benefits over automatic data clustering. We also demonstrate that training along the hierarchy of language families in multiple rounds yields further performance benefits.

## 3 Cross-lingual Expert Language Models

Multilingual language models are jointly trained on many different languages (e.g., Lin et al., 2022), despite the well-documented curse of multilinguality that comes from the competition between languages for fixed model capacity (Conneau et al., 2020; Wang et al., 2020). We propose **Cross-lingual Expert Language Models**, or X-ELMs, to address this performance disparity (Figure 1). These experts are trained with **x-BTM**, an extension of the Branch-Train-Merge (BTM) pretraining paradigm (Li et al., 2022; Gururangan et al., 2023): we asynchronously train many expert LMs on sub-

[1] For example, the XGLM-7.5B model "was trained on 256 A100 GPUs for about 3 weeks" (Lin et al., 2022).

sets of a multilingual corpus in order to specialize them to different sub-distributions of the multilingual space and then merge the experts to perform inference. We hypothesize that this training scheme will alleviate the curse of multilinguality on individual languages while maintaining the cross-lingual properties of dense multilingual LMs.

### 3.1 x-BTM: Sparse Multilingual Training

This section overviews our algorithm for sparse training of multilingual experts.

**Step 0: Multilingual Data Allocation** As a preprocessing step, we partition the multilingual corpus into $k$ clusters to train each X-ELM. We consider learning TF-IDF clusters as well as a new clustering method that groups documents by language identity and linguistic typology (§3.2).

**Step 1: Branch** A preliminary stage of shared, dense pretraining is important for ensembling expert language models (Li et al., 2022). Therefore, the first step of BTM is to initialize (*branch*) each expert with the parameters from a partially trained model. For this work, we initialize our X-ELMs with an existing multilingual pretrained model, XGLM (Lin et al., 2022).

**Step 2: Train** After initialization, we assign each expert a data cluster and train for a fixed number of steps with an autoregressive LM objective. Expert training is independent, with no shared parameters between models.

**Step 3: Merge** We collect the $k$ X-ELMs into a set and perform inference with them. We consider several methods of inference and expert ensembling in §3.3.

Steps 1 – 3 describe a single round of x-BTM training. However, we can continue to update the X-ELM set by branching—initializing a new group of experts—from existing models in the ensemble and performing more rounds of x-BTM via the method we propose in §4. This allows us to further improve X-ELM by training and adding new experts.

### 3.2 Data Allocation Methods

How we assign data to experts is a key component of training X-ELM, and it is a particularly crucial choice as the data becomes more diverse (i.e., spanning many languages). We consider two methods of data allocation when training our X-ELMs:

**Balanced TF-IDF Clustering** We partition the multilingual corpus automatically into $k$ components with k-means clustering. First, we encode each document into a word-level TF-IDF representation[2]; we then perform balanced k-means clustering on these representations to obtain approximately balanced subsets of the data on which to train each X-ELM. Further details on the balanced k-means clustering method can be found in Gururangan et al. (2023). This allocation method uses no language information outside of what is inherent in the text (e.g., script, vocabulary).

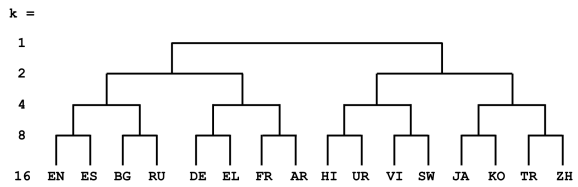


Figure 2: Heirachical clustering of languages used to train our X-ELM ensembles.

**Linguistic Typology Clustering** We also consider segmenting the corpus by language identity.[3] Rather than balancing the amount of data allocated to each cluster in this setting, we instead keep the number of languages per cluster fixed. Specifically, we learn a balanced hierarchical clustering of the languages (Figure 2). We build this hierarchy using the language similarity metrics in LANG2VEC (Littell et al., 2017), which represents languages based on linguistic features in resources such as WALS[4] and estimates language similarity with distance in this feature space. We first initialize each cluster with a single language; at each step, we merge each cluster with exactly one other based on the *minimum* distances between the cluster centroids. We then group languages according to the resulting hierarchy and the desired number of experts. When the number of languages equals the number of experts, typological clustering results in monolingual training, where every language is assigned a separate expert.

**Comparing the Clustering Techniques** Figure 3 shows the difference in language distributions

[2]Data tokenization is independent of the downstream model. Here, we use the sklearn text-vectorizer tokenizer.

[3]This requires knowledge of the language of each document. We use the language tags provided with mC4.

[4]World Atlas of Language Structures, https://wals.info/

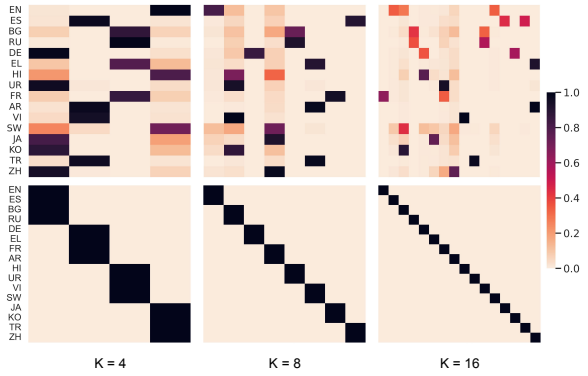


Figure 3: Percentage of language data assigned to different experts with TF-IDF (top row) and Typ. (bottom row) clustering. For Typ. clustering, each language is assigned entirely to a single expert.

between the *TF-IDF* and *Linguistic Typology* clusters. While *TF-IDF* allows language data to spread across experts, we find that, in practice, the distributions remain relatively sparse. The main exception is at $k = 16$, when the highest-resourced languages in the data (e.g., English or Russian) are split across clusters due to the constraint that balances the amount of data per cluster.

### 3.3 Inference with X-ELMs

We evaluate a number of different methods for performing inference with X-ELMs:

**Top-1 Expert** This method performs inference with a single expert chosen prior to evaluation; therefore, it incurs the same inference cost as the dense baselines. When evaluating the *Typology* experts on a particular language $\ell$, we choose the expert that included $\ell$ in the set of languages on which they continued pretraining. Similarly, when evaluating *TF-IDF*, we choose the X-ELM trained on the highest percentage of $\ell$'s data.

**Ensembling TF-IDF Experts** We also consider ensembling TF-IDF experts by adapting the c-BTM ensemble routing method. Here, we calculate ensembling alphas, or weights, over these experts for *each* evaluation step based on the proceeding context's TF-IDF distance from the experts' k-means centroids. These weights are then used to ensemble the output probabilities from each expert.

More specifically, given a probability from each expert LM $p_e(x_t|x_{<t})$ and the corresponding ensemble weight $\alpha_e = p(e|x_{<t}) \propto \exp(-\text{dist}(x_{<t}, c_e)^2/T)$, the probability of the ensemble $p_E(x_t|x_{<t}) = \sum_{e \in E} \alpha_e \cdot p_e(x_t|x_{<t})$. Here, $\text{dist}(x_{<t}, c_e)$ is obtained by embedding $x_{<t}$ with the learned TF-IDF vectorizer and calculating the Euclidean distance from $c_e$ (the centroid over the data representations allocated to expert $e$), and $T$ is a temperature parameter over the ensemble weight distribution. Further details and motivation for this setting are provided in Gururangan et al. (2023).

Ensembling X-ELM outputs increases the cost of inference relative to the dense model or top-1 inference. However, it can potentially better fit different subsets of data in a diverse evaluation set. We also do not assume we know the identity of each example when ensembling, which makes this approach more flexible than the top-1 setting. In most cases, we ensemble all $k$ experts; however, we can also reduce computational costs by *sparsifying* the ensemble weights and only activating the $m$ ($< k$) experts that most contribute to an example: $p_E(x_t|x_{<t}) = \sum_{e \in E} \alpha_e \cdot p_e(x_t|x_{<t}) : \alpha_e \in \text{top-m}(\alpha_{\mathbf{E}})$. Table 8 presents the performance tradeoff with sparser TF-IDF ensembles.

## 4 Hierarchical Multi-Round Training

We previously described a single round of training for X-ELM (§3.1). However, BTM can also be used repeatedly to train new experts seeded with those learned in a prior round. The multilingual setting provides a natural extension of multi-round training that leverages typological structure when initializing new experts.

We propose **Hierarchical Multi-Round** (**HMR**) pretraining (Figure 1), which uses the learned typological tree structure from *Linguistic Typology* clustering to iteratively train more specific X-ELMs. Specifically, given an expert model $x$ trained on a cluster of languages $L$, we initialize a new set of experts $X' = x'_1, x'_2, ..., x'_n$ with the parent expert $x$. Each new expert in $X'$ is then further trained on a different sub-cluster $\ell' \subset L$.

HMR pretraining gives multiple benefits over single-round BTM. In particular, HMR training saves compute and more easily adapts our X-ELMs to new settings. A specific application of this is adding new languages to the model: while updating dense multilingual LMs with new languages is difficult and can lead to catastrophic forgetting of existing languages (Winata et al., 2023), hierarchically training an expert on a new language adds it to the X-ELM set without altering the existing information in other experts. We further consider this use case for HMR training in §6.3.

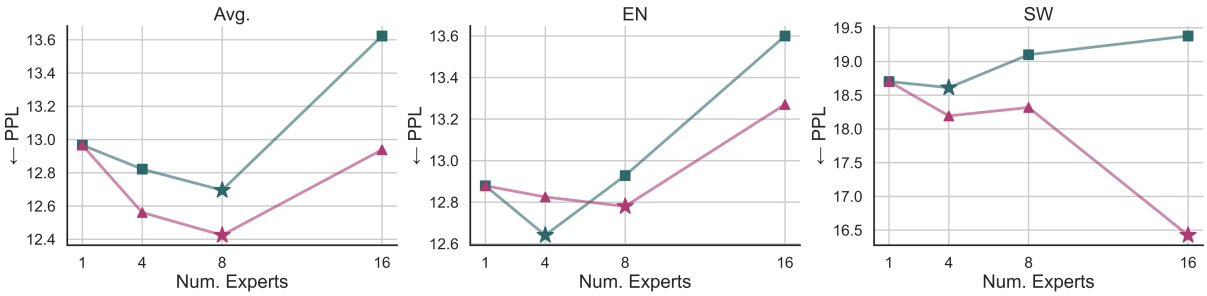


Figure 4: Average and language-specific (EN and SW) perplexities across expert counts ($k$) when clustering with TF-IDF$_{top1}$ (square) and Linguistic Typology (triangle). The best $k$ for each setting is marked with a star.

## 5 Experimental Design

We present a series of experiments to test whether the X-ELM pretraining paradigm remedies the decrease in individual language performance observed in dense multilingual models.

### 5.1 Pretraining Data and Languages

We train our X-ELMs on mC4, an open-source, multilingual pretraining corpus derived from CommonCrawl (Xue et al., 2021).[5] mC4 provides language tags for each document in the corpus, which were automatically assigned with cld3[6] when the dataset was constructed; we use these language tags during typological clustering (§3.2). We focus our experiments on the 16 highest-resourced languages out of the 30 languages on which the seed LM, XGLM-1.7B, was trained. For languages with significantly more data than the others (e.g., English), we subsample their data to the first 1,024 shards. Appendix Table 5 gives the languages and data quantities in our pretraining corpus.

### 5.2 Pretraining Settings

Each expert in the X-ELM experiments is a 1.7B parameter model with the same architecture as the 1.7B XGLM transformer model (Lin et al., 2022), and they are initialized with XGLM's weights in the initial round of BTM training. Unless otherwise stated, we keep the training parameters from the original XGLM training procedure; further details are given in Appendix A.1.

We train the experts for a fixed number of training steps. The exact parameters and resources used for each X-ELM experiment are reported in Table 4: in every setting, we control for the number of tokens seen during training. This ensures that all experts in a setting see the same amount of data (and undergo the same number of training updates) and that experiments across different expert set sizes but under the same training budget are comparable. For most experiments, we use a shared budget of 10.5B tokens; where indicated, we increase this to 21.0B tokens to test the effect of further training.

### 5.3 Perplexity Evaluation

To evaluate the language modeling performance of the X-ELMs, we separately calculate the perplexity on the mC4 validation sets of each pretraining language. For languages with larger evaluation sets, we estimate performance on the first 5,000 validation examples. This perplexity metric is not comparable across languages, as they have different validation sets.

## 6 Language Modeling Experiments

We now test the effectiveness of sparse language modeling in the multilingual setting. First, we determine the optimal number of clusters for our given compute budget and dataset (§6.1). We then demonstrate that X-ELMs outperform comparable dense models on seen languages (§6.2) and more effectively adapt to new, unseen languages (§6.3). Finally, we examine the effect of sparse training on *forgetting* previously-held knowledge of languages in specific X-ELM experts (§6.4).

### 6.1 Choosing the Number of X-ELMs

We first consider which choice of $k$ clusters gives the best multilingual language modeling performance. Figure 4 compares the choice of $k = 1, 4, 8, 16$ X-ELMs when trained on 10.5B tokens.[7] $k = 8$ is the best-performing setting on 75%

[5] While one could also continue pretraining with the same corpus that the seed LM was trained on, the pretraining data for XGLM is not publicly available.

[6] https://github.com/google/cld3

[7] The $k = 16$ setting is equivalent to training monolingual experts for every language. Full results are in Table 1 for

| Lang. | XGLM | 10.5B Training Tokens | | | | 21.0B Training Tokens | | | |
|---|---|---|---|---|---|---|---|---|---|
| | | Dense | TF-IDF$_{top1}$ | TF-IDF$_{ens}$* | Typ. | Dense | TF-IDF$_{top1}$ | TF-IDF$_{ens}$* | Typ. |
| **AR** | 16.85 | 15.29 | **14.51** | 14.56 | 14.66 | 14.97 | **14.00** | 14.05 | 14.16 |
| **BG** | 11.31 | 10.44 | 10.39 | 10.39 | **10.25** | 10.34 | 10.27 | 10.26 | **10.09** |
| **DE** | 15.53 | 14.02 | **13.41** | 13.50 | 13.42 | 13.72 | **12.95** | 13.05 | 12.97 |
| **EL** | 10.44 | 9.40 | 9.20 | 9.18 | **9.17** | 9.24 | 9.03 | 9.00 | **8.98** |
| **EN** | 14.37 | 12.88 | 12.93 | **12.73** | 12.78 | 12.69 | 12.68 | **12.47** | 12.55 |
| **ES** | 16.02 | 14.13 | 13.92 | **13.76** | 13.99 | 13.87 | 13.54 | **13.37** | 13.69 |
| **FR** | 13.12 | 11.78 | **11.19** | 11.28 | 11.29 | 11.54 | **10.79** | 10.88 | 10.91 |
| **HI** | 18.28 | 14.28 | 14.86 | 14.19 | **11.25** | 13.68 | 14.36 | 13.62 | **10.52** |
| **JA** | 14.57 | 12.31 | 11.95 | 11.95 | **11.49** | 11.79 | 11.36 | 11.37 | **10.88** |
| **KO** | 8.82 | 7.79 | 7.72 | **7.67** | **7.67** | 7.67 | 7.61 | **7.53** | 7.54 |
| **RU** | 13.43 | 12.52 | 12.14 | 12.21 | **12.08** | 12.33 | 11.83 | 11.90 | **11.74** |
| **SW** | 19.85 | 18.70 | 19.10 | 18.76 | **18.32** | 18.61 | 19.04 | 18.67 | **18.07** |
| **TR** | 17.81 | 15.34 | 14.13 | 14.28 | **13.80** | 14.88 | 13.41 | 13.58 | **13.03** |
| **UR** | 14.38 | 13.45 | 13.40 | 13.57 | **12.60** | 13.38 | 13.26 | 13.52 | **12.20** |
| **VI** | 13.07 | 11.39 | 11.00 | 10.86 | **10.22** | 11.09 | 10.56 | 10.42 | **9.69** |
| **ZH** | 17.91 | 13.74 | 13.28 | 13.53 | **11.98** | 13.12 | 12.61 | 12.87 | **11.24** |
| **Avg.** | 14.74 | 12.97 | 12.70 | 12.60 | **12.19** | 12.68 | 12.33 | 12.28 | **11.77** |

Table 1: Per-language and average perplexity results for the $k = 8$ X-ELM experiments (original XGLM and $k = 1$ dense model included for comparison). Lower numbers are better. The best setting for each language is bolded per compute budget. *TF-IDF ensemble uses more parameters for inference than other evaluations; see Table 8 for the effect of sparsifying these ensembles on perplexity.

of languages when clustering with TF-IDF and for 15 of the 16 pretraining languages when clustering by language similarity. Furthermore, typological clustering consistently outperforms TF-IDF.

These experiments indicate that, for the budget we evaluate, **the best overall X-ELM setting is bilingual models (k=8) clustered by language similarity**. This result is surprising, as it is intuitive to assume that simply continuing to pretrain each expert on a single language (i.e., the $k = 16$ setting) would lead to better perplexity. We find that one language, Swahili, does benefit from the monolingual $k = 16$ setting—possibly because Swahili is paired with a distant language (Vietnamese) by the typological clustering process. However, perplexity is higher in the $k = 16$ setting for all other languages, and in some cases even underperforms the dense ($k = 1$) model.

### 6.2 Perplexity Results on Seen Languages

We now examine the performance of X-ELM in the best setting ($k$ = 8) for the sixteen languages seen during BTM training on computational budgets of 10.5B and 21.0B tokens. Table 1 presents the perplexities of the TF-IDF clustered X-ELMs as well as the typologically (Typ.) clustered X-ELMs. As baselines, we compare against the original XGLM-1.7B model and a dense model trained on both computational budgets. We find that the best setting, $k = 8$ with typologically clustered experts, improves by 2.97 and 1.20 on average over the seed and dense baseline models and has individual language gains of up to 7.77 and 3.76 over these models, respectively.

**Expert language models outperform dense continued training** For most languages (10 of 16), typologically clustered experts are the best-performing setting. For some high-resource languages (EN and ES), ensembling the TF-IDF experts works better than a single expert. However, this inference setting requires more parameters, as it uses all X-ELMs instead of just the single best expert per language. Furthermore, training X-ELMs for longer unsurprisingly outperforms lower compute settings. All of our experimental settings outperform the seed XGLM model; similarly, the experiments with the 21.0B token compute budget perform better than the respective experiment trained with 10.5B tokens.

**X-ELMs improve language modeling on all languages** We also show that multilingual language modeling with X-ELMs does not disproportionally benefit languages with more pretraining data (Figure 5). Instead, perplexity improvements over both the seed LM and the dense LM baseline *may* slightly favor low-resource languages ($\rho = -0.19, -0.26$, respectively).

$k = 8$ and Appendix C for $k = 4$ and $k = 16$.

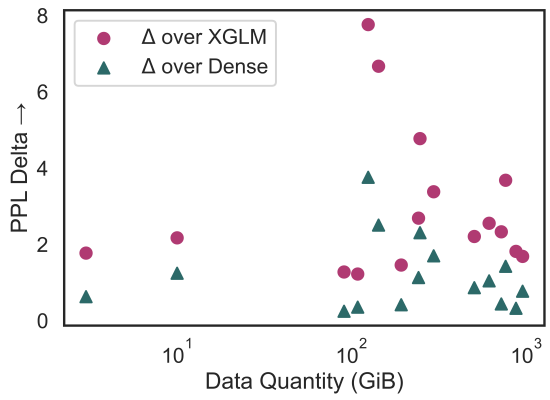


Figure 5: Comparison of PPL improvements per language over XGLM-1.7B (circle) and dense baseline (triangle) against the training data quantity (for typologically clustered experts).

### 6.3 Unseen Languages and Modeling New Languages with X-ELM

We also examine how well X-ELM performs on held-out languages as well as adapts to new languages. Specifically, we consider both zero-shot evaluation and further training of X-ELM on four languages not included in the original XGLM seed model: Azerbaijani (AZ), Hebrew (HE), Polish (PL), and Swedish (SV).[8]

**Unseen Language Evaluation** We evaluate the existing dense baseline and ensembled TF-IDF clustered experts from the 21B token compute budget (§6.2) to test whether continued pretraining with x-BTM improves performance on unseen languages (**X-ELM Training**). We also compare these results to XGLM. We note these models *never* trained on the target languages.

Table 2 presents the unseen target language perplexities in the **XGLM** and **X-ELM Training** columns. We find that the original XGLM model performs poorly on the new languages, particularly those less related to XGLM's highest-resourced ones (i.e., AZ and HE). While these perplexities remain high in the dense model and TF-IDF ensembles, training (on other languages) with x-BTM provides some performance improvements over the seed model.

**Adapting X-ELM to new languages** We now consider how well Hierarchical Multi-Round training (**HMR**) works for language adaptive pretraining (LAPT, Chau et al., 2020), which incorporates new target languages into the continued pretraining process. Here, we group each *target* language with a higher-resource *donor* language already in our pretraining set; these are assigned with the language similarity metric used for typological clustering. We seed each new language's expert with an expert specialized to that language's donor; the new expert is then trained on the donor/target language pair. For HMR inference, we evaluate perplexity with the expert trained on that target language.[9]

We compare HMR against jointly continuing training on all four new languages and their respective donors in a single model (**Dense**). Each setting builds on models from the 10.5B compute budget: we continue training on the dense baseline for dense LAPT and branch from the donor languages' $k$=8 typological experts for HMR training.

All of the LAPT settings provide considerable improvements on the new target languages over the unseen language experiments (Table 2, **LAPT** columns). The HMR setting outperforms continued dense training on every new language. Furthermore, HMR training removes the risk of *catastrophic forgetting* (Yogatama et al., 2019) in other LAPT schemes, as this process adds new experts to X-ELM rather than changing existing ones.

We also find that this setting provides performance gains on two donor languages over the experiments in §6.2. This is likely due to further training with more closely related languages for these languages (e.g., performing training on Arabic with Hebrew rather than French), consequently providing a more informative training signal for

| Lang | XGLM | X-ELM Training | | LAPT | |
|---|---|---|---|---|---|
| | | Dense | TF-IDF$^*_{ens}$ | Dense | HMR |
| **Target** | | | | | |
| AZ | 1467.45 | 739.58 | 722.10 | 65.73 | **32.74** |
| HE | 1817.07 | 685.02 | 815.96 | 53.08 | **26.21** |
| PL | 211.76 | 160.70 | 178.63 | 17.71 | **16.60** |
| SV | 105.27 | 92.55 | 99.24 | 27.37 | **26.16** |
| **Donor** | | | | | |
| TR | 17.81 | 15.34 | 14.28 | 14.69 | **12.72** |
| AR | 16.85 | 15.29 | 14.56 | 14.80 | **13.52** |
| RU | 13.43 | 12.52 | 12.21 | 12.28 | 12.02 |
| EN | 14.37 | 12.88 | 12.73 | 12.65 | 12.63 |

Table 2: Perplexity results on unseen target languages and their respective donor languages. Donor language performance is only **bolded** if these results outperform all other X-ELM settings in that language (Table 1).

[8] Data for these languages is also obtained from mC4, with the same preprocessing as other languages in our experiments.

[9] We also evaluate the donor languages to see what benefit, if any, they receive from the adaptation process.

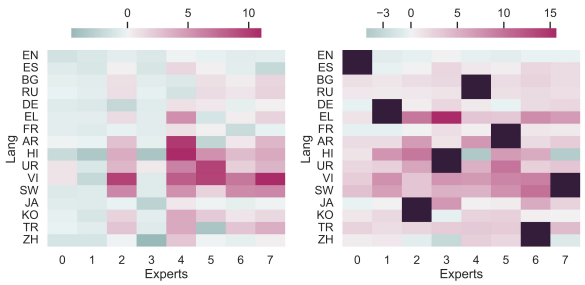


Figure 6: Heatmap comparing individual X-ELM perplexities to the seed LM with TF-IDF (left) and Typ. (right) clustering. Positive scores indicate that the expert *forgot* that language. For Typ. clusters, languages that the model was explicitly trained on are grayed out.

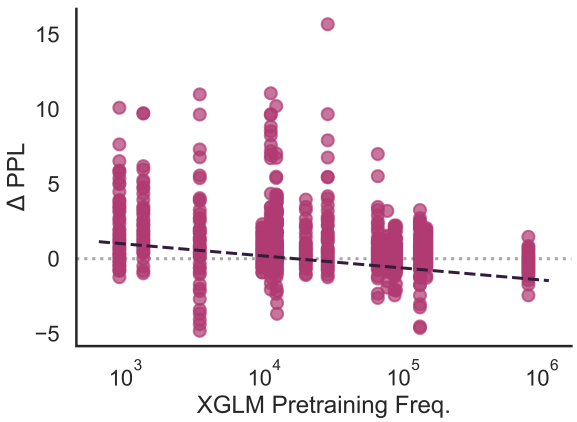


Figure 7: Per-expert deltas compared to the original XGLM-1.7B of every pretraining language plotted against the language's frequency in the original XGLM pretraining corpus ($\rho = -0.33$, $p << 0.001$).

the higher-resource donor language as well.

### 6.4 X-ELM Forgetting

The preceding sections evaluate X-ELMs as an ensemble of models by dynamically choosing the best expert for a given evaluation setting or ensembling the experts' outputs. However, each expert is initialized with a model trained on all the languages we consider. This prompts the question: how much do individual experts *forget*[10] about the languages they are not specialized to?

**Forgetting occurs as X-ELMs become more specialized.** We compare the perplexity of each expert model on all pretraining languages to that of the seed model, XGLM-1.7B (Figure 6 for $k = 8$; other settings given in Appendix C). Across the considered values of $k$, we see less forgetting in the X-ELMs trained on TF-IDF clusters than in those clustered typologically. For the $k = 8$ expert setting, the TF-IDF experts only forget on 47.7% of settings, and when forgetting occurs, the perplexity increase over the baseline is 3.10 on average. For typologically clustered experts, these measures are 83.6% and 3.14, respectively; we observe similar trends for the $k = 4$ and $k = 16$ X-ELMs. This implies that though in some cases only small quantities of data are shared across TF-IDF clusters, these data mitigate forgetting over the hard cluster assignments made by typological clustering.

**X-ELMs are more likely to forget certain languages.** For example, English is rarely forgotten, with only 25% of experts performing worse than the baseline. In comparison, 94.6% of experts perform worse on Urdu than XGLM. One potential cause of this discrepancy is the frequency with which the language was seen during seed training: languages that are more common in the XGLM pretraining corpus see fewer cases of forgetting and have smaller perplexity increases when it does occur (Figure 7). Another likely factor is inaccurate language classification in the BTM training data, which is a common issue when training language models on specific languages (Blevins and Zettlemoyer, 2022); this could lead to related, higher-resourced languages contaminating the datasets for lower-resourced ones (Kreutzer et al., 2022).

[10]We consider an expert to have *forgetten* information about a language if its perplexity on that language increases.

## 7 In-Context Learning Experiments

We also measure whether the perplexity improvements from X-ELMs correspond to better performance on downstream tasks. We test the performance of our X-ELMs on three tasks through an in-context learning (ICL) framework, showing that the X-ELM language modeling gains do translate to ICL improvements over the baseline models.

### 7.1 Experimental Setup

We test the in-context learning abilities of X-ELM on three downstream tasks:

**XNLI** (Conneau et al., 2018) is a multilingual natural language inference benchmark covering 14 of our 16 pretraining languages (excluding JA and KO). Since there are no gold training examples for XNLI, we use the test set for evaulation and sample demonstrations from the validation set.

**XStoryCloze** (Lin et al., 2022) is a manually translated benchmark extending StoryCloze (Mostafazadeh et al., 2016) to other languages.

| | Model | XNLI | | XStoryCloze | | PAWS-X | |
|---|---|---|---|---|---|---|---|
| | | Acc. | Win Rate | Acc. | Win Rate | Acc. | Win Rate |
| **Zero-shot** | XGLM (1.7B) | 44.88 | 28.6% | 57.76 | **28.6%** | 48.54 | 14.3% |
| | Dense | 44.31 | 7.1% | 56.10 | 0.0% | 48.44 | 28.6% |
| | Typ. (TRG) | 44.17 | 7.1% | 57.79 | **28.6%** | 49.86 | **42.9%** |
| | TF-IDF (Top-1) | 43.77 | 14.3% | **57.80** | **28.6%** | **50.04** | 28.6% |
| | TF-IDF (Ens.) | **45.10** | **42.9%** | 57.46 | 14.3% | 49.93 | 0.0% |
| **Few-shot** | XGLM (1.7B) | 42.34 | 28.6% | 53.21 | 0.0% | 54.52 | 0.0% |
| | Dense | 41.70 | 0.0% | 55.00 | 0.0% | 54.81 | 14.3% |
| | Typ. (TRG) | 42.15 | †14.3% | 54.62 | †**71.4%** | 55.39 | †28.6% |
| | Typ. (EN) | 42.43 | †7.1% | **55.54** | †28.6% | 55.13 | 14.3% |
| | TF-IDF (Top-1) | 42.55 | 21.4% | 55.03 | †14.3% | **55.50** | †**42.9%** |
| | TF-IDF (Ens.) | **42.93** | **35.7%** | 54.72 | 28.6% | 54.57 | 14.3% |

Table 3: Average performance and the percentage of languages where this setting outperforms the others (Win Rate) on the overlap of task evaluation languages and the X-ELM target languages. The **few-shot** setting provides $k$=8 English demonstrations to the model and averages performance across five runs. †indicates (best) performance ties between two evaluation settings on a language.

This is a story-completion task wherein the model identifies the correct final sentence of a short story. This dataset covers seven of our pretraining languages and four other low-resource languages.

**PAWS-X** (Yang et al., 2019) is a binary classification task that requires the model to determine whether a pair of sentences are paraphrases. This benchmark covers seven of our pretraining languages, including two (JA and KO) not covered by the other ICL benchmarks.

We compare the performance of X-ELM against dense baselines in both zero- and few-shot learning settings. For all benchmarks, we evaluate on 1,000 random examples and perform five runs on different demonstration sets for few-shot settings. Unless otherwise stated, we evaluate performance on the development set and sample demonstrations from the training set; further details about the ICL evaluation protocol are given in Appendix A.2.

### 7.2 Results

We evaluate our best X-ELM setting by perplexity—$k$=8 experts trained on the larger compute budget of 21B training tokens—on the downstream tasks. Table 3 summarizes the results of these evaluations on the languages covered by the X-ELM models; individual language results are given in Appendix C. The X-ELM models outperform both the seed model and the compute-matched dense baseline across the three tasks and in both the zero- and few-shot evaluation settings.

Furthermore, though X-ELM improves over the seed model, the dense model underperforms XGLM. This may be due to using different data from the original XGLM pretraining; data quality issues have been previously documented for mC4 (Kreutzer et al., 2022; Chung et al., 2023). We also note that XNLI and XStoryCloze few-shot performance is consistently lower than in the zero-shot setting; this is a recurring issue in multilingual ICL also observed in the base model (Lin et al., 2022).

## 8 Related Work

### 8.1 Multilingual Pretraining

Many variations and improvements on dense multilingual pretraining have been proposed since the introduction of multilingual BERT (Devlin et al., 2019): by changing the architecture and scaling the model size up (Goyal et al., 2021; Lin et al., 2022), combining additional objectives to the main LM objective (Conneau and Lample, 2019; Chi et al., 2022; Reid and Artetxe, 2022), careful language and data curation (Scao et al., 2022; Ogunremi et al., 2023), and scaling and balancing the vocabulary across the different languages (Liang et al., 2023). Most relevant to our work is Pfeiffer et al. (2022), which proposes a new modular model architecture, X-MOD, that contains language-specific modules. However, many of the limitations of dense modeling persist in this architecture since the model and modules are jointly trained.

An issue common to most methods for multilingual pretraining is the *curse of multilinguality* (Conneau et al., 2020). Wu and Dredze (2020) demonstrate that multilingual training leads to lower performance on low-resource languages than higher-resourced ones. Blevins et al. (2022) find that multilingual models forget information previously

learned during training, which they postulate is due to this phenomenon; Wang et al. (2020) similarly suggest that this effect occurs due to training dynamics. More recently, Chang et al. (2023) presented a controlled study of the factors causing this *curse* that corroborates limited model capacity as the underlying cause. A primary motivation of this work is to limit the effect of this *curse* while maintaining the other benefits of multilingual modeling.

### 8.2 Adapting Multilingual Models

Another common thread of multilingual modeling research focuses on adapting an existing model to new languages. Initially, these methods continued pretraining these models with the new languages incorporated into the training regime, such as language-adaptive pretraining (LAPT; Chau et al., 2020). Other work proposed the use of adapters to update the model to new languages (Pfeiffer et al., 2020); notably, Faisal and Anastasopoulos (2022) used similar linguistic motivations to our typological clustering to group languages into adapters. However, follow-up work found that continued pretraining outperformed adapter methods for new language adaptation (Ebrahimi and Kann, 2021).

### 8.3 Sparse Models for NLP

Sparsely activated language models (Evci et al., 2020; Mostafa and Wang, 2019; Dettmers and Zettlemoyer, 2019) route inputs through a subset of the total model parameters. Our work builds most directly on the Branch-Train-Merge (Li et al., 2022; Gururangan et al., 2023) algorithm, which results in full-model experts trained to specialize on domains of data defined by metadata or a learned clustering. This design expands both on the independent feed-forward network experts found in early Mixture-of-Experts (MoE) models (Jacobs et al., 1991) and on DEMix layers (Gururangan et al., 2022), which routes sequences to per-layer feed-forward experts based on metadata.

Other MoE models have recently been applied to multilingual settings. Pfeiffer et al. (2022) develop a multilingual expert model with language-specific routing, and Kudugunta et al. (2021) develop a machine translation model with routing determined by the source-target language pair or the target language. Similarly to BTM, Jang et al. (2023) trains experts specialized to different tasks, including five machine-translation language pairs, which can be merged with other task experts.

## 9 Conclusion

This work presents an approach to mitigate the *curse of multilinguality* by extending sparse language modeling to the multilingual setting with X-ELMs (cross-lingual expert language models). We find that X-ELMs achieve better perplexity over standard, dense language models trained with the same compute budget; these experts can also be efficiently adapted to new languages without the risk of catastrophic forgetting. X-ELMs also present other benefits over dense models for multilingual modeling, such as not disproportionally benefitting high-resource languages over lower-resourced ones. Finally, we show that these language modeling improvements transfer to downstream tasks.

While our experiments show that X-ELM outperforms dense LMs, we foresee many avenues of future work to further tailor sparse modeling to multilinguality. These include better methods for data allocation—such as clustering methods that leverage cross-lingual signal— and algorithmic improvements to better allocate compute and more effectively ensemble models at inference. By proving the efficacy of sparse language modeling in the multilingual setting, we hope to inspire future work in this vein that fairly models every language while leveraging the potential of cross-lingual learning.

## Limitations

One limitation of this work is that we focus on examining the effect of training X-ELMs with x-BTM in a limited number of settings, training languages, and data sources fixed; this is due to limited computational resources. Therefore, the proposed methods should be verified in other settings. In particular, we hope to examine how X-ELM performs at scale when using larger experts, more languages, and larger training budgets.

We also note the limited nature of our downstream evaluations, which is due to (1) the limited number of multilingual benchmarks available and (2) our requirement that evaluation benchmarks overlap with (most of) our 16 pretraining languages. Furthermore, since we compare against the seed model, we focus on XGLM's original evaluation tasks and the prompting settings developed for this baseline (rather than developing our own that may be biased towards the X-ELM models).

Finally, training X-ELM rather than a single dense model increases some computational costs, similar to other BTM methods. The primary in-

crease is in storage, as each expert's weights need to be stored separately. In some cases, the inference cost of X-ELM can be higher than the best model (e.g., when using an ensemble of experts); however, we propose several inference methods that only require loading a single model and demonstrate that you can sparsify the TF-IDF ensemble and achieve similar perplexities (Appendix Table 8).

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# A Additional Experimental Details

## A.1 Pretraining

Table 5 summarizes the languages we use, as well as their frequencies in the original XGLM pretraining dataset and in our sub-sampled mC4 corpus.

Table 4 presents the compute allocated to each expert and setting at different compute budgets of the X-ELM experiments. The per-model instance batch size (**bsz**) for all experiments is 2, and each training example had a sequence length (**seq. len**) of 2048. The total token budget (**# Tokens**) is the product of ($k$, # GPUs, # updates, grad acc., bsz, seq. len), normalized by the number of GPUs used for model parallelism (2).

| # Tokens | k | # GPUs | # updates | grad acc. |
|---|---|---|---|---|
| **10.5 B** | 1 | 8 | 20,000 | 32 |
| | 4 | 4 | 20,000 | 16 |
| | 8 | 4 | 20,000 | 8 |
| | 16 | 2 | 20,000 | 8 |
| **21.0 B** | 1 | 8 | 40,000 | 32 |
| | 4 | 4 | 40,000 | 16 |
| | 8 | 4 | 40,000 | 8 |
| | 16 | 2 | 40,000 | 8 |

Table 4: Overview of the total compute budget and resources used for different X-ELM experiments. **k** is the number of experts, **# GPUs** indicates the number of GPUs used to train each expert, and **grad acc.** gives the number of gradient accumulation steps used.

| Language | mC4† Size (%) | XGLM Size |
|---|---|---|
| AR (Arabic) | 243.14 (4.1%) | 64.34 |
| BG (Bulgarian) | 109.3 (1.9%) | 61.10 |
| DE (German) | 615.59 (10.4%) | 369.30 |
| EL (Greek) | 193.63 (3.3%) | 180.37 |
| EN (English) | 877.43 (14.8%) | 3,324.45 |
| ES (Spanish) | 723.17 (12.2%) | 363.83 |
| FR (French) | 506.74 (8.6%) | 303.76 |
| HI (Hindi) | 125.44 (2.1%) | 26.63 |
| JA (Japanese) | 764.71 (12.9%) | 293.39 |
| KO (Korean) | 91.29 (1.5%) | 79.08 |
| RU (Russian) | 957.02 (16.2%) | 1,007.38 |
| SW (Swahili) | 3.06 (0.05%) | 3.19 |
| TR (Turkish) | 248.07 (4.2%) | 51.51 |
| UR (Urdu) | 10.15 (0.2%) | 7.77 |
| VI (Vietnamese) | 296.65 (5.0%) | 50.45 |
| ZH (Chinese) | 143.68 (2.4%) | 485.32 |
| AZ (Azerbaijani) | 15.23 (–) | – |
| HE (Hebrew) | 67.14 (–) | – |
| PL (Polish) | 393.85 (–) | – |
| SV (Swedish) | 154.54 (–) | – |

Table 5: The frequencies and relative percentages of different languages in our training corpus (†a subsampled version of mC4) and in the XGLM pretraining corpus, CC100-XL (as reported in Lin et al. (2022)). Sizes of data are reported in gigabytes (GiB). EN, ES, FR, and RU are downsampled to the first 1,024 mc4 shards for those languages.

The experts are trained with a linear decay learning rate schedule; we use a maximum learning rate of $1.5e-4$ after performing preliminary learning rate sweeps.

## A.2 In-Context Learning

We reimplement the evaluation protocol from Lin et al. (2022), where the model scores multiple versions of every example (with the different possible labels filled in), and the label of the highest-scoring version is considered as the model's prediction. We use the English prompt formats and evaluation protocols developed for the seed LM of our experts, XGLM, for the downstream tasks of XNLI, XStoryCloze, and PAWS-X. The prompt templates we use are reproduced in Table 6.

In the few-shot experiments, we perform five evaluation runs with different demonstration samples and reported the average performance. All few-shot experiments are performed with eight random demonstrations. As we are testing the cross-

| Dataset | Prompt | Labels |
|---|---|---|
| XNLI | `{Sentence 1}, right? [Mask], {Sentence 2}` | Entailment: `Yes` \| Neural: `Also` \| Contradiction: `No` |
| XStoryCloze | `{Context} [Mask]` | Identity |
| PAWS-X | `{Sentence 1}, right? [Mask], {Sentence 2}` | True: `Yes` \| False: `No` |

Table 6: Prompts used for the ICL experiments in §7; the `[MASK]` is filled with one of the label forms given in the last column. For XStoryCloze, `{Context}` refers to the format `{Sent. 1} {Sent. 2} {Sent. 3} {Sent. 4}`, and "Identity" refers to the text of one of the answers given for that example.

lingual abilities of X-ELM, these demonstrations are in English for every target language.

## B Additional X-ELM Analysis

### B.1 Hierachical Multi-Round (HMR) Training for Seen Languages

The final column of Table 7 evaluates the effectiveness of HMR training for continued training of X-ELMs. Here, we select the $k = 4$ typologically clustered expert from the 10.5B token compute setting that covers the pair of languages as the seed model for each $k = 8$ setting. We then adapt on the $k = 8$ **Typ.** setting for another 10.5B tokens.

Our results find that this adaptation scheme *underperforms* the **Typ.** experts trained from the seed model for 21B tokens, indicating that it is more effective to train X-ELMs in a single run rather than dividing the compute budget across two rounds of training. We hypothesize that this negative result is due to the XGLM seed model, which is a fully pretrained model, already learning adequate transfer across language families; we leave further investigation of this to future work. However, this finding is in contrast with §6.3, which shows that the HMR scheme is very effective for adapting experts to *unseen* languages.

### B.2 Sparse TF-IDF Ensembling

In §6, we compare ensembling TF-IDF experts in an X-ELM set against choosing a single TF-IDF expert for inference based on the amount of in-language data seen by that expert during training. In the cases of $m$=2,4, this approach sparsifies the ensemble by dynamically selecting the top $m$ experts based on their current ensemble weights. Here, we additionally consider how *sparsifying* the TF-IDF ensemble holds up against these other settings (Table 8). We find that for seen languages, reducing the number of experts active to just $m$=2 usually gives very similar performance to the full ensemble ($m$=8). However, this is not true in the case of *unseen* languages, where the $m$=8 setting consistently outperforms sparser ensembles.

## C Full Experimental Results

Table 7 presents the full perplexity results for the $k = 4$ and $k = 16$ X-ELM experiments, trained on a 10.5B token compute budget. We find that both choices of $k$ underperform the $k = 8$ setting.

Figure 8 reports the per-expert forgetting relative to the baseline model (XGLM-1.7B) in the $k = 4$ and $k = 16$ settings. On average, the $k = 4$ TF-IDF experts experience forgetting in only 18.8% of cases with an average perplexity increase of 1.24 when forgetting occurs; the typology experts forget 78.1% of the time with an average perplexity increase of 1.34. For the $k = 16$ setting, these statistics are 60.9% and 0.9 for the TF-IDF clusters and 89.4% and 1.24 for the typology clusters.

**Downstream Evaluation on Individual Languages** Tables 9, 10, and 11 detail the per-language results for XNLI, XStoryCloze, and PAWS-X, respectively.

| Lang. | XGLM | Dense | k=4 Experts TF-IDF$_{top1}$ | k=4 Experts TF-IDF$_{ens}$* | k=4 Experts Typ. | k=16 Experts TF-IDF$_{top1}$ | k=16 Experts TF-IDF$_{ens}$* | k=16 Experts Typ. | k=8 HMR |
|---|---|---|---|---|---|---|---|---|---|
| **AR** | 16.85 | 15.29 | 14.99 | 15.03 | 15.00 | 15.60 | 15.67 | 15.40 | 14.36 |
| **BG** | 11.31 | 10.44 | 10.39 | 10.39 | 10.42 | 11.10 | 10.70 | 10.31 | 10.18 |
| **DE** | 15.53 | 14.02 | 13.85 | 13.89 | 13.71 | 14.71 | 14.43 | 14.5 | 12.13 |
| **EL** | 10.44 | 9.40 | 9.36 | 9.33 | 9.28 | 9.72 | 9.64 | 9.41 | 9.05 |
| **EN** | 14.37 | 12.88 | 12.64 | 12.71 | 12.78 | 13.60 | 13.23 | 13.27 | 12.60 |
| **ES** | 16.02 | 14.13 | 13.93 | 13.96 | 14.06 | 14.83 | 14.58 | 14.59 | 13.75 |
| **FR** | 13.12 | 11.78 | 11.62 | 11.65 | 11.55 | 12.38 | 12.13 | 12.15 | 11.05 |
| **HI** | 18.28 | 14.28 | 14.22 | 14.21 | 12.64 | 16.11 | 15.67 | 13.86 | 10.98 |
| **JA** | 14.57 | 12.31 | 12.23 | 12.12 | 11.73 | 13.39 | 13.14 | 13.18 | 11.01 |
| **KO** | 8.82 | 7.78 | 7.81 | 7.77 | 7.70 | 8.14 | 8.09 | 7.75 | 7.56 |
| **RU** | 13.43 | 12.52 | 12.30 | 12.33 | 12.46 | 12.96 | 12.76 | 12.82 | 11.95 |
| **SW** | 19.85 | 18.70 | 18.61 | 18.62 | 18.19 | 19.38 | 19.13 | 16.43 | 18.30 |
| **TR** | 17.81 | 15.34 | 14.85 | 14.96 | 14.81 | 15.67 | 15.78 | 15.52 | 13.47 |
| **UR** | 14.38 | 13.45 | 13.56 | 13.73 | 13.18 | 13.88 | 13.87 | 12.65 | 12.46 |
| **VI** | 13.07 | 11.39 | 11.43 | 11.21 | 10.32 | 11.85 | 11.65 | 11.59 | 10.21 |
| **ZH** | 17.91 | 13.74 | 13.38 | 13.70 | 13.11 | 14.65 | 14.95 | 13.58 | 11.66 |
| **Avg.** | 14.74 | 12.97 | 12.82 | 12.85 | 12.56 | 13.62 | 13.46 | 12.94 | 11.98 |

Table 7: Per-language and average perplexity results for the $k = 4$ and $k = 16$ X-ELM experiments (original XGLM and $k = 1$ dense model included for comparison). Lower numbers are better. Each X-ELM setting is trained on 10.5B tokens. *TF-IDF ensemble uses more parameters for inference than other evaluations. †The HMR models are initialized from an existing expert and trained for 10.5B more tokens.

| Lang. | TF-IDF Ens. top-1 | $m$=2 | $m$=4 | $m$=8 |
|---|---|---|---|---|
| **AR** | 14.00 | 14.12 | 14.05 | 14.05 |
| **BG** | 10.27 | 10.27 | 10.27 | 10.27 |
| **DE** | 12.95 | 13.09 | 13.07 | 13.04 |
| **EL** | 9.03 | 9.03 | 8.99 | 9.00 |
| **EN** | 12.68 | 12.50 | 12.48 | 12.47 |
| **ES** | 13.54 | 13.40 | 13.39 | 13.37 |
| **FR** | 10.79 | 10.92 | 10.88 | 10.88 |
| **HI** | 14.36 | 13.47 | 13.62 | 13.62 |
| **JA** | 11.36 | 11.35 | 11.37 | 11.37 |
| **KO** | 7.61 | 7.53 | 7.53 | 7.53 |
| **RU** | 11.83 | 11.90 | 11.90 | 11.90 |
| **SW** | 19.04 | 18.67 | 18.67 | 18.67 |
| **TR** | 13.41 | 13.58 | 13.58 | 13.58 |
| **UR** | 13.26 | 13.52 | 13.52 | 13.52 |
| **VI** | 10.56 | 10.41 | 10.41 | 10.42 |
| **ZH** | 12.61 | 12.84 | 12.84 | 12.87 |
| **Avg.** | 12.33 | 12.29 | 12.29 | 12.28 |
| **AZ** | – | 736.49 | 724.97 | 722.10 |
| **HE** | – | 749.12 | 719.68 | 719.05 |
| **PL** | – | 177.31 | 175.27 | 174.83 |
| **SV** | – | 95.33 | 94.37 | 94.14 |

Table 8: Perplexity scores of the different inference methods on the TF-IDF X-ELMs trained with 21B tokens. **Top-1** chooses a single expert per language, with no routing mechanism, whereas **m=2,4,8** ensembles TF-IDF experts.

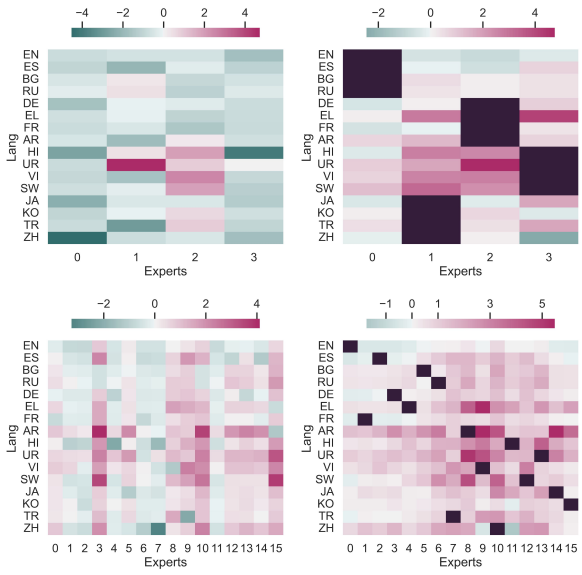


Figure 8: Heatmap of X-ELM forgetting with TF-IDF (left) and Typ. (right) clustering, from the $k = 4$ (top) and $k = 16$ (bottom) settings.

| Model | AR | BG | DE | EL | EN | ES | FR | HI | RU | SW | TH* | TR | UR | VI | ZH |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Zero-shot** | | | | | | | | | | | | | | | |
| XGLM (1.7B) | 46.8 | 45.7 | 44.1 | 42.5 | 51.5 | 36.5 | 47.2 | 45.9 | 47.3 | 43.6 | 44.9 | 42.5 | 43.5 | 43.9 | 46.9 |
| Dense | 47.9 | 45.0 | 45.3 | 45.2 | 51.1 | 37.2 | 45.9 | 44.5 | 44.5 | 39.6 | 44.3 | 44.8 | 43.1 | 41.6 | 44.6 |
| Typ. (TRG) | 46.2 | 44.9 | 43.9 | 45.4 | 52.0 | 36.0 | 47.2 | 43.5 | 41.9 | 40.6 | – | 44.2 | 41.9 | 44.4 | 46.3 |
| TF-IDF (Top-1) | 47.3 | 45.1 | 42.9 | 47.1 | 51.5 | 36.3 | 45.6 | 43.1 | 40.6 | 38.7 | – | 45.0 | 43.2 | 41.8 | 44.6 |
| TF-IDF (Ens.) | 48.6 | 47.2 | 46.2 | 43.1 | 53.0 | 37.0 | 47.5 | 45.7 | 45.6 | 40.0 | 45.8 | 44.1 | 44.2 | 42.6 | 46.6 |
| **Few-shot** | | | | | | | | | | | | | | | |
| XGLM (1.7B) | 42.0 | 44.2 | 43.4 | 43.4 | 47.2 | 38.1 | 45.5 | 40.4 | 43.1 | 41.4 | 41.9 | 38.0 | 39.7 | 42.2 | 44.3 |
| Dense | 43.4 | 42.2 | 43.6 | 41.9 | 45.9 | 36.7 | 42.3 | 42.2 | 40.8 | 40.0 | 43.2 | 39.9 | 40.3 | 41.0 | 43.5 |
| Typ. (TRG) | 42.8 | 43.0 | 42.6 | 43.0 | 47.3 | 38.5 | 45.4 | 38.9 | 39.9 | 41.7 | – | 41.0 | 39.6 | 42.9 | 43.4 |
| Typ. (EN) | 42.2 | 42.6 | 44.0 | 42.6 | 47.3 | 38.5 | 42.9 | 42.1 | 42.8 | 40.9 | 44.5 | 41.1 | 40.0 | 42.1 | 44.9 |
| TF-IDF (Top-1) | 43.1 | 43.6 | 43.2 | 41.7 | 47.5 | 38.2 | 45.3 | 42.1 | 40.5 | 41.9 | – | 41.1 | 41.4 | 42.1 | 44.1 |
| TF-IDF (Ens.) | 43.0 | 43.3 | 44.3 | 43.3 | 47.8 | 37.7 | 44.2 | 43.2 | 42.3 | 41.4 | 44.4 | 41.8 | 41.0 | 42.7 | 44.9 |

Table 9: Individual language accuracy on XNLI. *TH (Thai) is an unseen language for the X-ELM models.

| Model | AR | EN | ES | EU* | HI | ID* | MY* | RU | SW | TE* | ZH |
|---|---|---|---|---|---|---|---|---|---|---|---|
| **Zero-shot** | | | | | | | | | | | |
| XGLM (1.7B) | 53.3 | 63.1 | 57.3 | 56.4 | 55.0 | 59.3 | 54.0 | 60.0 | 60.1 | 57.0 | 55.5 |
| Dense | 50.5 | 60.7 | 56.1 | 52.1 | 52.0 | 55.4 | 53.4 | 58.6 | 58.6 | 55.5 | 56.2 |
| Typ. (TRG) | 52.3 | 62.7 | 57.5 | – | 52.7 | – | – | 60.2 | 60.3 | – | 58.8 |
| TF-IDF (Top-1) | 52.1 | 62.1 | 58.1 | 53.2 | 55.2 | 57.7 | 52.6 | 59.6 | 60.5 | 57.3 | 57.0 |
| TF-IDF (Ens.) | 51.9 | 60.4 | 57.8 | 54.0 | 55.4 | 58.5 | 52.0 | 59.5 | 60.2 | 57.1 | 57.0 |
| **Few-shot** | | | | | | | | | | | |
| XGLM (1.7B) | 48.6 | 58.2 | 53.2 | 51.7 | 50.4 | 52.1 | 51.5 | 52.5 | 56.0 | 56.5 | 53.7 |
| Dense | 50.2 | 59.0 | 54.6 | 51.3 | 51.6 | 53.5 | 52.9 | 56.9 | 57.8 | 54.2 | 55.2 |
| Typ. (TRG) | 50.3 | 60.1 | 55.0 | – | 52.0 | – | – | 57.4 | 58.0 | – | 56.0 |
| Typ. (EN) | 48.8 | 60.1 | 55.0 | – | 52.2 | – | – | 53.7 | 57.4 | – | 55.2 |
| TF-IDF (Top-1) | 49.3 | 59.5 | 54.5 | 51.4 | 52.4 | 55.2 | 52.9 | 55.4 | 58.0 | 56.1 | 56.1 |
| TF-IDF (Ens.) | 49.4 | 59.0 | 53.8 | 51.1 | 52.5 | 54.5 | 52.0 | 55.1 | 57.8 | 55.0 | 55.4 |

Table 10: Individual language accuracy on XStoryCloze (and EN StoryCloze). *Unseen languages for the X-ELM models.

| Model | DE | EN | ES | FR | JA | KO | ZH |
|---|---|---|---|---|---|---|---|
| **Zero-shot** | | | | | | | |
| XGLM (1.7B) | 44.5 | 47.9 | 51.8 | 45.2 | 53.8 | 49.6 | 47.0 |
| Dense | 49.4 | 47.5 | 50.7 | 47.5 | 48.8 | 47.2 | 48.0 |
| Typ. (TRG) | 47.9 | 47.9 | 53.0 | 45.5 | 55.4 | 53.6 | 45.7 |
| TF-IDF (Top-1) | 47.4 | 46.9 | 55.0 | 45.9 | 54.9 | 49.4 | 50.8 |
| TF-IDF (Ens.) | 49.1 | 47.1 | 52.1 | 47.2 | 53.6 | 50.0 | 50.4 |
| **Few-shot** | | | | | | | |
| XGLM (1.7B) | 56.3 | 50.5 | 55.4 | 55.2 | 55.6 | 53.0 | 55.7 |
| Dense | 56.0 | 54.9 | 55.8 | 55.2 | 54.9 | 53.8 | 53.0 |
| Typ. (TRG) | 56.5 | 53.4 | 55.8 | 55.1 | 55.6 | 55.9 | 55.4 |
| Typ. (EN) | 56.0 | 53.4 | 55.8 | 55.4 | 55.5 | 54.7 | 55.1 |
| TF-IDF (Top-1) | 56.6 | 54.2 | 55.7 | 54.9 | 55.6 | 55.7 | 55.7 |
| TF-IDF (Ens.) | 53.8 | 54.9 | 54.8 | 53.6 | 55.3 | 55.2 | 54.4 |

Table 11: Individual language accuracy on PAWS-X.