An Efficient Approach for Studying Cross-Lingual Transfer in Multilingual Language Models

Fahim Faisal, Antonios Anastasopoulos
Department of Computer Science, George Mason University
{ffaisal,antonis}@gmu.edu

Abstract

The capacity and effectiveness of pre-trained multilingual models (MLMs) for zero-shot cross-lingual transfer is well established. However, phenomena of positive or negative transfer, and the effect of language choice still need to be fully understood, especially in the complex setting of massively multilingual LMs. We propose an *efficient* method to study transfer language influence in zero-shot performance on another target language. Unlike previous work, our approach *disentangles downstream tasks from language*, using dedicated adapter units. Our findings suggest that some languages do not largely affect others, while some languages, especially ones unseen during pre-training, can be extremely beneficial or detrimental for different target languages. We find that no transfer language is beneficial for all target languages. We do, curiously, observe languages previously unseen by MLMs consistently benefit from transfer from *almost any* language. We additionally use our modular approach to quantify negative interference efficiently and categorize languages accordingly. Furthermore, we provide a list of promising transfer-target language configurations that consistently lead to target language performance improvements. [1]

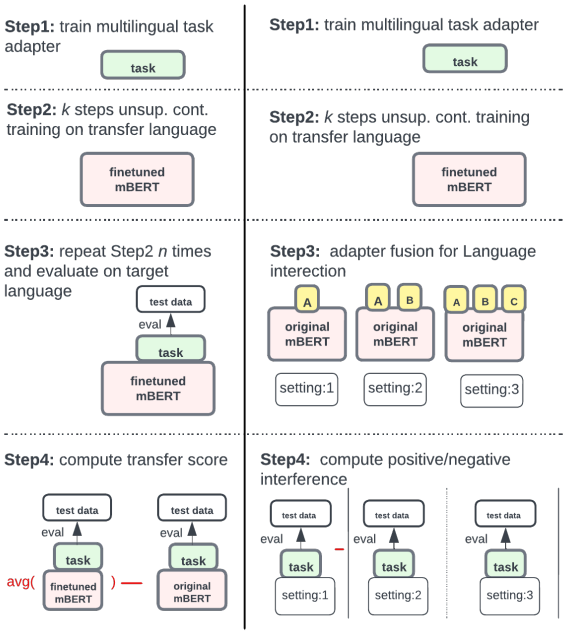


Figure 1: Our approach uses efficient few-step continued tuning (left) and adapter modules (right) to disentangle the effect of *task* and *language* to quantify the effect of a *transfer* language for a given task and model. The left panel depicts the framework for our cross-lingual transfer, while the right panel represents the scenario of multiple language interactions followed by quantifying negative interference.

1 Introduction

Pretrained Multilingual Models (MLMs) perform surprisingly well in terms of zero-shot cross-lingual transfer even though no explicit cross-lingual signal was present during pretraining. Subword fertility (Deshpande et al., 2022), token sharing (Dufter and Schütze, 2020), script (Muller et al., 2021), as well as balanced language representation (Rust et al., 2021) contribute to this effectiveness. But, by and large, the most important component seems to be the combination of languages the model is trained and evaluated on. It is important, hence, to understand why and when cross-lingual transfer is successful at the language level.

Previous attempts at studying cross-lingual transfer fall into two categories. First, the most popular approaches are those which, given a task and a MLM, task-tune the MLM on annotated data from a *transfer* language and then evaluate on a *target* language (e.g. Lin et al., 2019). The problem with such approaches is that (a) they do not disentangle the effect of task and language, since they train directly on the task using *annotated* data in the transfer language, and (b) it is expensive to task-tune the whole model for all possible transfer languages.

Second, other approaches tackle the inefficiency

[1] Code and data are publicly available: https://github.com/ffaisal93/neg_inf

Proceedings of the Fourth Workshop on Multilingual Representation Learning (MRL 2024), pages 45–92

problem by relying on bilingual approximations: Malkin et al. (2022) for instance train bi-lingual BERT (Devlin et al., 2019) models, task-tune them on the transfer language and then evaluate on the *target* one, and contrast this performance to a monolingual target-language BERT. While this approach ignores the fact that language interactions can be different in multilingual and bilingual models (Wang et al., 2020; Papadimitriou et al., 2022), it does correlate decently with transfer performance on multilingual models. However, it still does not disentangle task from language and is quite expensive, as studying n languages requires training $n^2 + n$ BERT models.

In this work, we propose an *efficient* approach to study cross-lingual transfer, outlined in Figure 1, that also disentangles the effect of task-tuning and the effect of language, while operating within the framework of the same MLM. Our approach relies on learning a separate *task* adapter module to perform the downstream task, which needs to only be trained once (hence it is efficient). We then perform unsupervised finetuning on unannotated transfer language data for a minimal number of steps. Comparing the performance of the model on the target language with and without the previous step results in a direct assessment of the effect of the transfer language without changing the conditions under which the downstream task was learned. In addition, we extend this framework to quantify the negative interference resulted from the interaction of multiple languages (Figure 1(right)). With the aid of adapter-fusion tuning (Pfeiffer et al., 2021), we compare different combinations of language adapters and compute the interference occurring due to increased interactions.

We perform extensive analysis using this efficient approach on five downstream tasks using dozens of transfer and target languages (*184 in total*) and devise a metric (which we dub *transfer score*) to quantify which languages have/receive positive or adverse effects on/from others. Last, we focus our analysis on cross-lingual transfer for languages unseen during the pre-training of the MLM.

2 Methodology

Adapters (Pfeiffer et al., 2022) are light-weight parameter-efficient modules that can be injected between the layers of pretrained models. In their typical usecase, the rest of the model is frozen and only the adapter modules are trained, to adapt a model to a new language, domain, or task. Importantly, for our goals, these adapters are also composable: one can stack an independently trained language adapter and task adapter to achieve decent performance for that language on that task. First we use an adapter-based setting to perform our analysis on cross-lingual transfer. Furthermore, we extend our study to negative interference and language interaction through another adapter-fusion-based setting.

Cross-Lingual Transfer The composable property of adapters allows us to disentangle learning a task from the language representations (the process is also outlined in Figure 1). In step 1, we first train a task-specific adapter `[T]` (e.g. named entity recognition), on data from as many languages as possible. This module will be responsible for performing the downstream task independently of input language. We then (step 2) finetune the `[base]` model (e.g. `mBERT`) on a transfer language α with only a few steps (1, 10, or 100) using masked language modeling, obtaining $\texttt{[base}^{\alpha}\texttt{]}$. Now the language representations of this finetuned model will be (slightly) biased towards the transfer language.

Last, in step 3 we reinsert the task adapter in both the finetuned and the original pretrained model, and use both models to test and evaluate on target language data β. The difference in performance between these two models $\text{score}(\beta\,; [\texttt{base+t}]^{\alpha}) - \text{score}(\beta\,; [\texttt{base+t}])$ will reveal whether transfer language α benefits (if positive) or hurts (if negative) target language β.

An obvious caveat of our approach so far is that a single update (or 10 or 100) with a randomly sampled batch in any language does not allow for any robust conclusions. To avoid this issue, we repeat the above process n=10 times for each transfer language with different data and aggregate these scores.

Our final transfer score $\text{ts}(\alpha \rightarrow \beta\,; \texttt{base}, \texttt{t})$ for a given model `base` and task `t` turns the difference of the finetuned and original model into a percentage of the original baseline performance, for fairer comparisons at different levels of performance:

$$\text{ts}(\alpha \rightarrow \beta\,; \texttt{base}, \texttt{t}) = \frac{\frac{\sum_1^{10} \text{score}(\beta\,; [\texttt{base+t}]^{\alpha})}{n} - \text{score}(\beta\,; [\texttt{base+t}])}{\text{score}(\beta\,; [\texttt{base+t}])}$$

Negative Interference The typical definition of negative interference describes it as the phe-

nomenon when batches in different languages produce opposite gradients during training. We instead focus on downstream performance, in line with most studies focusing on cross-lingual transfer, assuming that a negative effect on performance implies negative interference. Another reason is that, in n dimensional spaces, there extremely high probability of two random vectors being orthogonal; hence any two gradient vectors could certainly be orthogonal without necessarily impacting downstream performance.

To quantify negative interference, we follow a modular-based approach depicted in Figure 1(right). Like before, we separate the task and language, followed by performing interaction among multiple languages. However, we use language adapters at this time instead of continuously finetuning the base model. This strategy allows us to efficiently train multiple language sub-parts only once (Step2) followed by mixing those modules through adapter fusion (Pfeiffer et al., 2021). In our experiments, we train a set of language adapters and make either monolingual settings or a combination of bilingual/trilingual interactions (Step3). Then we stack previously trained task adapter while only changing the underlying language combination. Finally, we extract the interference score from the difference between already computed multilingual and monolingual counterparts (Step4).

Having these interference scores at hand, we can tell whether a language actually gets benefits or not while influencing the associated languages in a positive/negative manner. For example, consider language A interacting with language B. We can easily quantify the interference of language A by calculating the loss/gain of this bilingual interaction [AB]: a score increase for A compared to its monolingual counterpart (i.e. $+\mathtt{A} = +_{\mathtt{[AB]}-\mathtt{[A]}}$) means positive interference for A in this particular setting. We can further extend this to a trilingual setting as well (i.e. $+\mathtt{A} = +_{\mathtt{[ABC]}-\mathtt{[A]}}$). Using these scores, we can get different combinations of interference scenarios by counting the co-occurred positive/negative interference. We use $|+\mathtt{A}, +\mathtt{B}|$ to denote the number of cases where A benefits both itself and B, presenting all possible rules in Table 1. Utilizing these rules, we can identify how much language A actually gains or loses during its bilingual/trilingual interactions while providing substantial interference to other languages.

Moreover, we can use these interference combination counts to project languages in an interference representation space. For example, consider a 2-D space of bilingual interaction where the X-axis represents the negative/positive interference a language receives from one such interaction and the Y-axis is for the interference it provides to other languages. We can project a language using the dot product of counts (eg. $|+\mathtt{A}, -\mathtt{B}|$) with its corresponding quadrant identifier $[1, -1]$. As a result, the projection coordinates (x_A, y_A) for language A in a bilingual interaction could be obtained as follows:

$$
\begin{aligned}
\mathtt{C} =& |-\mathtt{A}, -\mathtt{B}| + |-\mathtt{A}, +\mathtt{B}| + |+\mathtt{A}, -\mathtt{B}| \\
&+ |+\mathtt{A}, +\mathtt{B}| \\
(\mathtt{x_A}, \mathtt{y_A}) =& \frac{1}{\mathtt{C}} \times (|-\mathtt{A}, -\mathtt{B}| \cdot [-1, -1] \\
&+ |-\mathtt{A}, +\mathtt{B}| \cdot [-1, 1] + |+\mathtt{A}, -\mathtt{B}| \cdot [1, -1] \\
&+ |+\mathtt{A}, +\mathtt{B}| \cdot [1, 1])
\end{aligned}
$$

Using the above-mentioned projections, we visualize a language in a way that represents how much interference it provides as well as receives (see example with each step of the calculation in Appendix §F). We can further extend this strategy to the trilingual setting, but now we have to deal with eight axes instead of four. In Figure 4 of the result section, we present the language interaction visualizations for bilingual and trilingual scenarios.

Notations (+: win, −: loss)

1. $|+\mathtt{A}|$ = *count*(A gains in interaction [AB] or [ABC])
2. $|-\mathtt{A}|$ = *count*(A losses in interaction [AB] or [ABC])
3. $|+\mathtt{A}, +\mathtt{B}|$ = *count*(Both language gets benefit). In other words, A gains. At the same time, B receives benefits while interacting with A.

Bilingual Interactions	Trilingual Interactions	
$\|-\mathtt{A}, -\mathtt{B}\|$	$\|-\mathtt{A}, -\mathtt{B}, -\mathtt{C}\|$	$\|-\mathtt{A}, -\mathtt{B}, +\mathtt{C}\|$
$\|-\mathtt{A}, +\mathtt{B}\|$	$\|-\mathtt{A}, +\mathtt{B}, -\mathtt{C}\|$	$\|-\mathtt{A}, +\mathtt{B}, +\mathtt{C}\|$
$\|+\mathtt{A}, -\mathtt{B}\|$	$\|+\mathtt{A}, -\mathtt{B}, -\mathtt{C}\|$	$\|+\mathtt{A}, -\mathtt{B}, +\mathtt{C}\|$
$\|+\mathtt{A}, +\mathtt{B}\|$	$\|+\mathtt{A}, +\mathtt{B}, -\mathtt{C}\|$	$\|+\mathtt{A}, +\mathtt{B}, +\mathtt{C}\|$

Table 1: Interference calculation for language A. $|+\mathtt{A}|$ means the number of cases where A itself gets benefits. If the setting is bilingual, then $|+\mathtt{A}|$ =count($+_{\mathtt{[AB]}-[A]}$) (i.e. if the evaluation score on task language A: $\mathtt{[AB]} - \mathtt{[A]} > 0$ for the combination [AB], we get a $+\mathtt{A}$.)

3 Experimental Setup

We conduct our experiments in two different settings targeted to perform two different analyses: first understanding the language effect on cross-lingual transfer and then, extending this to quantify language-language interaction.

Primarily, we use multilingual BERT as our base model and report XLM-R results for comparative model evaluation. We use a total of 38 transfer languages (11 unseen during pretraining) to finetune the MLM using masked language modeling with the process described above. Using these transfer languages, we do monolingual finetuning on `mBERT` for either 1, 10, 100, or 1000 steps and each experiment is repeated for 10 times. At the sametime, we trained multilingual task adapters followed by task evaluation on the following tasks:

- **Token-level:** Dependency Parsing (DEP), Part-of-Speech (POS) tagging and Named Entity Recognition (NER). Parsing and POS tagging are evaluated on a set of 114 languages from Universal Dependencies v2.11 (de Marneffe et al., 2021). For NER, we use 125 languages from the Wikiann (Pan et al., 2017) dataset.
- **Sentence-level:** Natural Language Inference (NLI) evaluated on XNLI (Conneau et al., 2018) and AmericasNLI (ANLI) (Ebrahimi et al., 2022) datasets.
- **Extractive Question Answering:** Evaluated on TyDiQA (Clark et al., 2020) gold task.

Additionally, we train 38 language adapters to perform the experiment on language-to-language interaction and negative interference. Here, we stack the previously trained task adapter on top of either one or a combination of double or triple language adapters (Figure 1(b)) and then perform the evaluation on the transfer languages having task data available. All training and evaluation datasets, implementation and hyper-parameter details are provided in Appendices C-E (Table 24-29).

4 Results and Discussion

First, in 4.1, we present a comparative scenario in between continuous training and language interaction in terms of performance improvement over the baseline model. Then in 4.2, we discuss the findings of continuous training in the context of cross-lingual transfer. After that, in 4.3, we present the representation of language interactions as well as interference following the strategy discussed in Section 2.

4.1 Continuous Training vs Language Interaction

Here we present 8 sets of scores for each token-level task. The baseline is where we stack the task adapter on the base pretrained `mBERT` (i.e. zero-shot task on pretrained `mBERT+ [T]`). Then for all the evaluation languages, we perform 4 sets of cross-lingual transfers (i.e. 1, 10, 100, and 1000 steps of continuous training). For the language-language interaction experiment, we only perform the evaluation on transfer languages where either 1, 2 or 3 language adapters are fused together before stacking the task adapter (i.e. `[1A]`, `[2A]`, `[3A]`).

Lang.	Base	Continious Steps k=10	Continious Steps k=1000	Lang. Interaction `[1A]`	Lang. Interaction `[2A]`	Lang. Interaction `[3A]`
Parsing						
pcm	**81.1**	79.1	77.9	79.3	79.5	79.5
wol	**69.5**	68.1	67.3	68.9	69.1	69.1
kmr	31.9	31.7	**45.3**	32.6	32.1	32.0
bam	29.9	30.9	**38.1**	30.8	30.8	30.8
gub	21.7	20.9	**34.5**	23.8	23.73	23.5
POS Tagging						
pcm	**92.9**	92.2	91.2	92.3	92.5	92.6
wol	**85.6**	84.2	82.1	84.1	84.7	84.8
kmr	40.2	40.5	**55.8**	41.1	40.8	40.7
bam	30.3	30.8	**49.5**	30.7	30.5	30.5
gub	28.5	28.7	**36.7**	28.8	28.8	28.9
NER						
ibo	**61.1**	57.2	55.4	57.5	57.8	57.7
pms	88.2	**88.9**	87.6	88.2	87.5	87.6
kin	**72.4**	71.8	68.5	70.5	71.1	71.9

Table 2: Task results for transfer languages unseen by `mBERT`. **base:** zero-shot with task adapter `[T]`. **Continuous Steps:** do k steps of finetuning on that language plus `[T]`. **Lang. Interaction:** introducing language adapters; `[1A]`: just 1 adapter (in language) and evaluate on it; `[2A]`: 2 language adapters, the target lang. and one test (the result is averaged for all transfer langs.); `[3A]`: 3 lang. adapters (results are average again). The highest obtained score for each language is bolded.

Only Unseen Transfers In Table 2, we present our token-level evaluation report for transfer languages unseen during the pretraining phase. For the `[2A]` and `[3A]` language interaction results, we compute and report the average score where the evaluation language is also present in the `[2A]` or `[3A]` adapter fusion. For tasks where word-to-word relation plays a critical role (parsing and pos tagging), we observe similar patterns of improvement over baseline in both Cont. steps and lang. interaction settings. Whereas, for a task like NER, we do not observe any improvement over baseline both in sustained cont. (k=1000) and interaction settings. Even though we are evaluating the same language after continuous masked language modeling (mlm) or adapter fusion with another high-resource language, there is no clear winning formula that can

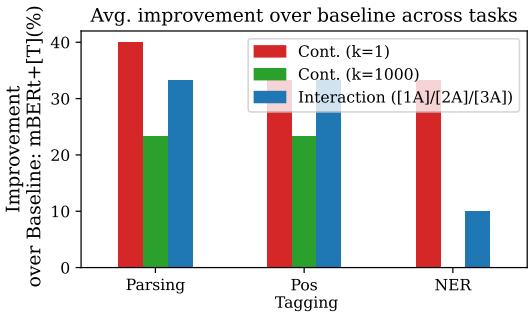


Figure 2: Average score improvement over baseline across tasks for the transfer languages (evaluated on itself). We observe a spike of over 33% positive score at continuous training step 1. Among these, only 23.3% cases result in sustained improvement after 1000 steps (0% in NER). On the contrary, standard language adapter interaction stays at 25% average improvement.

always serve the unseen low-resource languages.

Unseen+Seen Transfers On the other hand, when we consider the case of both unseen and seen languages together in token-level tasks, we see a spike of 33% average improvement over baseline with just 1 step of mlm training. However, this improvement percentage gets down to a sustained 23.3% (except task NER) when we evaluate again after having 1000 steps of training. Whereas, in language interaction settings where we fuse standard well-trained language adapters, we generally observe improvement for those languages which also get benefited from continuous training. The improvement percentage averaged over all 38 transfer languages is presented in Figure 2. In addition, we present all the scores for all 38 transfer languages and token-level tasks in App. Tables 7, 9, and 11.

4.2 Takeaways from Continuous Training

No Universal Donor First, we search for transfer languages that can be used for positive transfer for a large set of languages. However, we find no language out of 38 that can positively influence almost all languages using mBERT as base model. For this experiment, we rank the transfer languages based on their averaged transfer score (i.e. `aggregated-transfer`). In Table 3, we list the top 5 ranked transfer languages with their transfer score (base model: mBERT) and the percentage of target languages that do benefit from them (more details in Appendix H). We observe, most languages benefit within the range of 30-45% of target languages across tasks except NLI. However, we did not receive any positive transfer for

	Lang.	ts	+(%)	Lang.	ts	+(%)	Lang.	ts	+(%)
	Parsing			**POS Tagging**			**NER**		
1	mya	0.33	40.4	**kin**	0.41	35.1	zho	0.16	49.6
2	ell	0.15	31.6	**kmr**	0.36	36.9	tel	0.08	32.8
3	**kmr**	0.14	35.9	**mos**	0.27	34.2	hun	0.08	40.8
4	yor	0.14	33.3	hye	0.27	36.9	heb	0.04	34.4
5	**pcm**	0.13	31.6	cym	0.22	37.7	est	0.03	36.8
	XNLI			**ANLI**			**TyDiQA**		
1	**hau**	-34.4	0.0	**bam**	-15.0	0.0	zho	0.7	77.8
2	**bam**	-34.9	0.0	**hau**	-17.8	0.0	jpn	0.1	44.4
3	**gub**	-36.4	0.0	**gub**	-18.4	0.0	gle	-0.1	44.4
4	**ewe**	-36.7	0.0	deu	-19.8	0.0	**wol**	-0.1	44.4
5	hin	-37.1	0.0	fin	-19.9	0.0	cym	-0.1	33.3

Table 3: Top 5 transfer languages per task ranked using the aggregated transfer score (`ts` columns; see App. H for computation). Unseen ones are **bolded**. *+(%)* is the percentage of languages receiving positive transfer. No transfer language helps all target languages. (Complete rank with transfer scores: Table 15-18).

	Parsing	Pos Tagging	NER	XNLI	ANLI	TyDiQA
mBERT	30.6	31.0	31.8	0	0	30.1
xlmr	20.5	33.2	41.1	44.4	41.6	17.0

Table 4: Average percentage of languages receiving positive transfer (avg. *+(%)*) across models. Unlike mBERT, xlmr provides positive transferring in NLI.

both of the two different NLI task datasets (XNLI and ANLI). The maximum positive transfer percentage is from zho in both NER and TyDiQA. Interestingly, low-resourced unseen languages perform well in general as transfer languages: 31.7% (token-level) and 28.3% (sentence-level) of top 20 transfer languages are unseen languages.

Base Model and Task Matters To further investigate the discrepancy observed in NLI task, we replace the base model mBERT with XLM-R (Table 4). Unlike mBERT, XLM-R in NLI provides superior performance (XNLI: +44.4% and ANLI: +41.6%). This signifies how the choice of the base model in a setting with a disentangled language-task effect could drastically change the cross-lingual transfer performance of certain tasks.

Moreover, we observe the above-discussed rankings of transfer languages vary across tasks. To investigate the underlying similarity, we select a large subset of languages (the common 62 target languages across three token-level tasks) and rank the transfer languages as before. We then compute the Spearman rank correlation and statistical significance (`p<0.05`) of their transfer scores tasks (see Appendix Table 21). Only parsing and NER are positively correlated (ρ=0.4) whereas POS tag-

Rank	Lang. # (max, min)	ts	Var.	Type
1	**ibo** (10, 10)	0.05	23.5	(+ *and* -)
3	**bam** (11, 15)	0.02	21.5	(+ *and* -)
6	**mos** (13, 2)	0.09	16.1	(+)
8	**pcm** (1, 11)	0.13	13.4	(-)
26	eng (0, 0)	-0.22	6.4	neutral
36	ara (0, 0)	-0.12	5.1	neutral

Table 5: Example of transfer languages ranked with their aggregated-transfer (ts) score variance (task: parsing). Unseen languages (**bold** font) exhibit high variance. # (max) represents the language count receiving maximum positive transfer. (see Appendix L)

ging is negatively correlated with the other two tasks. This is somewhat surprising, because we use the same underlying dataset for the parsing and POS tagging tasks. We find only a few transfer languages could effectively provide positive transfer simultaneously across tasks. The 5 common languages in the top 20 across tasks are: yor, **mos**, **kin**, **hau**, and tel. In sort, languages unseen by mBERT (in **boldface**), exhibit similar ranking across tasks (see Table 15-18), whereas others vary. For example, zho is the lowest-ranked one in parsing while being top-ranked in NER! Appendix Figure 6 shows the number of common languages across tasks.

Unseen Languages Transfer with High Variance We observe that transfer languages with high variance mainly fall into one of three categories:

1. (+ *and* -): boost performance for some languages while hurt significantly some others;
2. (+): mostly (small) positive transfer, significantly hurts only a few languages;
3. (-): mostly (small) negative transfer, significantly helps only a few languages.

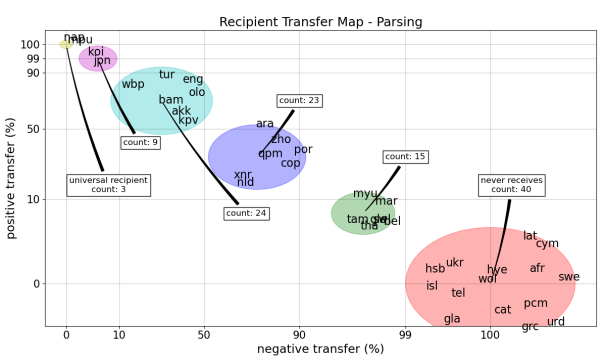
See examples in Table 5 and Appendix L for details. Though unseen languages perform well as transfer languages, they usually exhibit the traits of high-variance transfer. Around 90% of unseen transfer languages are within top-20 languages sorted by variance (see Appendix Figure 7).

Target Language Differences Unlike transfer languages, we find target languages that are almost universal recipients of positive cross-lingual transfer, many of which are unseen by mBERT. On the other hand, some languages do not receive any benefit from the diverse set of transfer languages. In Figure 3(a), we plot the target languages based on the percentage of languages from which they receive positive or negative transfer (see additional maps in Appendix Figure 5). We find around one-third of target languages across three token-level tasks never receive any positive transfer (parsing: 35.1%, POS: 28.1%, NER: 32.8%). Nevertheless, there are target languages (mostly unseen by mBERT) that benefit from all transfer languages (eg. nap, mpu in parsing). See Appendix I and Table 19 for additional results.

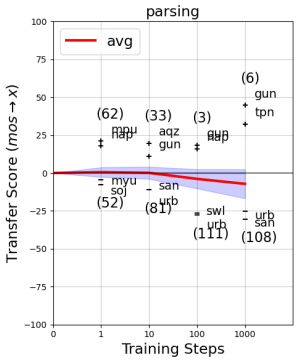
Seen vs Unseen Languages Transferring from either seen or unseen languages to unseen languages (i.e. transfer(seen/unseen→ unseen)) generally helps. For this experiment, we use the large set of token-level task evaluation and 11 transfer languages unseen during mBERT pertaining from diverse families including Indo-European, Afro-Asiatic, Mande, Niger-Congo and Tupian. We observe, that transferring to a large and diverse set of seen languages from unseen languages (i.e. transfer(unseen→ seen)) does not provide any substantial utility. Among the three tasks, we get the average transfer as positive for unseen transfer languages just once (dependency parsing, transfer(unseen→ unseen)). See Figure 8 for the difference of utility provided when the transfer-/target languages are seen vs unseen.

Sustained Cross-Lingual Transfer Our approach limits step 2 (continued training on the transfer language) to a minimal number of steps. For this section, we extend this to 1000 steps. In the vast majority of transfer-target language combinations, this leads to (small) negative transfer under our setting. We suspect this is due to the underlying model undergoing the first steps of catastrophic forgetting (McCloskey and Cohen, 1989).

There are some languages, though, mostly unseen ones (eg. nap, gun, tpn, aqz) that benefit more from this extended setting. See Appendix J Table 20, where we report the target language receiving the highest benefit from each transfer language for each setting (1,10,100,1000 steps). All the max-utility recipients aside from bar and nds are unseen languages. Figure 3(b) presents the training step progression of aggregated-transfer scores for Mossi, one of the most donating transfer languages, and Appendix N (Figures 9-18) shows the transfer progression graphs for all transfer languages. At the task level, POS tagging always ends up having comparatively higher target language performance variance with more training steps, while NER almost always ends up with negative results with longer training.



(a) Target languages mapped based on percentage of receiving positive/negative transfers.



(b) `Aggregated-transfer` score line with standard deviations through different training steps for Mossi (mos) as transfer language.

Figure 3: (a) Some languages exhibit universal recipient nature (yellow) while some never receive positive transfer (red). (b) Shown are the top and bottom two languages receiving maximum/minimum scores (eg. `gun`, `tpn` at 1000 steps) at each step, with total positive/negative transfers (in parenthesis) also shown. See Appendix N for other transfer language score lines.

4.3 Takeaway from Language Interactions

We plot all the transfer languages in a 2d axis for both two-language interactions and three-language interactions as shown in Figure 4.

Bilingual Interactions First of all, we observe most of the languages mainly fall into either one of the two categories: (1) A(+), B(+): getting benefits from interactions and helping others at the same time, (2) A(-), B(+): Helping other languages but do not get benefits from those languages. Secondly, there are resemblances in how certain languages from specific categories interfere across all 3 tasks. For example, consider the case of `zho, swe, spa` and `fra`. These languages fall to the lower right part of all three graphs. However, there are languages like `ara` that do not uniformly get benefits across three tasks while maintaining it's positive interfering status. Although, there are debates whether English (`eng`) is an appropriate "hub" language or not (Anastasopoulos and Neubig, 2020), `eng` maintains its status in the upper right quarter making it a good transfer language in all Latin script majority settings.

Trilingual Interactions Now we increase the number of languages for a specific transfer language to influence. When we compare the bilingual settings with the trilingual ones (Figure 4 (2)), the left-right categorization remains the same. However, many languages receive an uplifting position meaning the strength of performing positive interference increases for those languages (eg. `are` in dependency parsing, `zho` in NER). Moreover, we observe an overall decrease in the lower-right corner for both dependency parsing and NER. However, there are languages like `wol` in POS tagging that goes from upper-left to lower-left. Nonetheless, very few different colored points (i.e. negative coordinate for 3rd language) signify the fact that a multilingual setting is beneficial towards a larger group of recipients.

5 Recommendations

Based on our above findings, we make a number of recommendations in choosing the appropriate transfer language and training scheme for a low-resource setting.

1. There is no universal donor but having multiple transfer languages in the training scheme helps in terms of language interference.
2. For universal recipient languages (eg. Typologically diverse unseen ones), including almost any language in the transfer scheme help.
3. Low resource unseen languages generally transfer with high variance. A good idea is to include them with other seen languages in the transfer scheme to stabilize the transfer output across a large number of target languages.
4. Only some of the unseen low-resource ones show sustained transfer toward other low-resource languages through continuous thousand-step training. Usually, the deviation happens during an early stage of training. So just continuing pretraining for longer is not optimal for a scenario with mixed-category languages.
5. The patterns of receiving positive transfer are similar when we use either one language small-

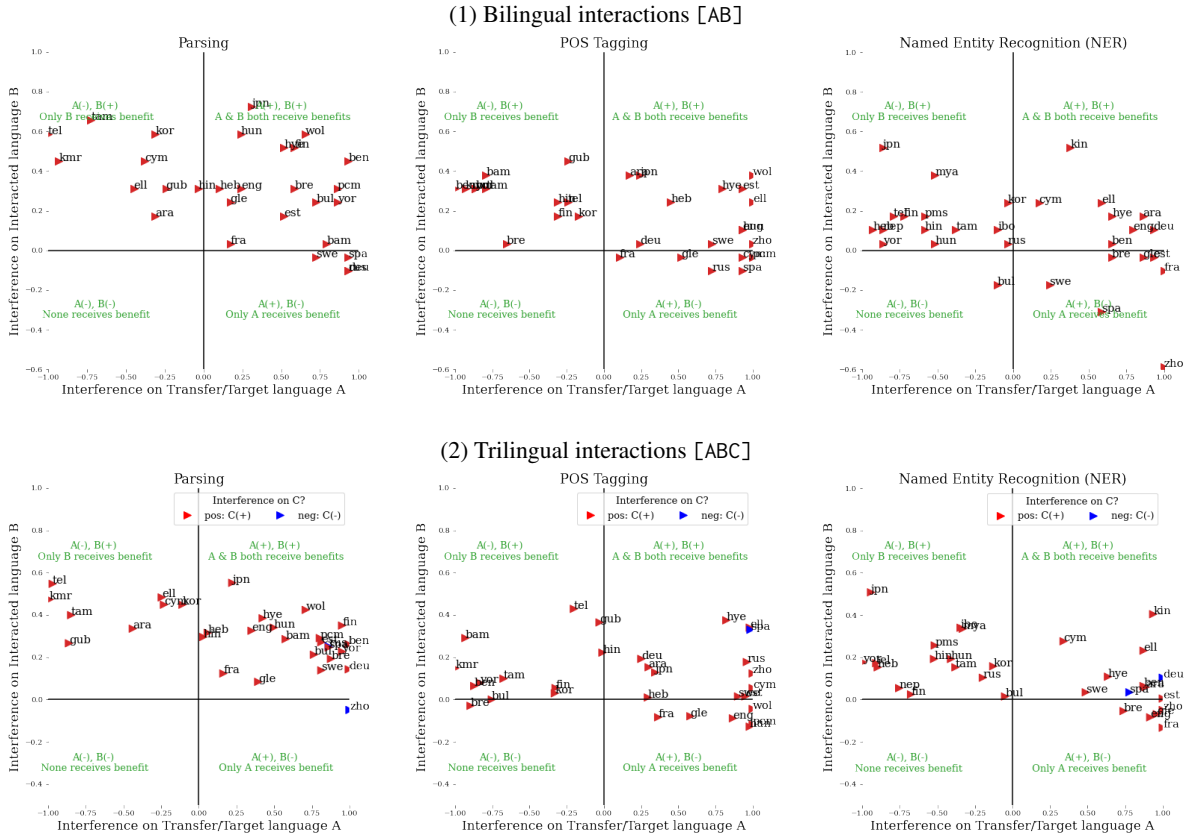


Figure 4: Language interaction representation for bilingual and trilingual settings. To identify the language coordinates, we use two and three adapters (i.e. [2A], [3A]) jointly fused. In [3A] plots, we show the position only for one interacted language B along with transfer/target language A. For the 3rd language C, we use color variation (red/blue) to depict whether C receives positive transfer or not.

step continuous training or 2/3 standard adapter fusion. So using a large set of trained language adapters fused together according to the need is a simpler way to deal with a large set of mixed-category target languages.

6 Conclusion and Future Work

We devise an efficient approach to study cross-lingual transfer in multilingual models for various tasks that disentangles task and language effects. We believe this disentanglement coupled with few-step fine-tuning has the potential to uncover currently uncharted model behaviors (eg. NLI evaluation). Our findings suggest languages unseen by MLMs clearly exhibit different behavioral pattern compared to other languages in general: they are universal as target, exhibit high variance as transfer language, and their behavior follows similar patterns across tasks. In addition, we do not find a universal donor (a language that benefits all others). Last, we find that some languages consistently benefit from settings that resemble "catastrophic forgetting" for other languages, an observation we believe merits a dedicated follow-up study.

We hope that our approach will allow for further study of cross-lingual transfer for more languages and MLMs, and we plan to extend this in future work, as our findings suggest interesting differences in the behavior of languages used in pre-training and unused ones. Eventually, we hope that our study will also lead to guidelines for selecting appropriate transfer languages, as well as more informed methods for the adaptation of MLMs to new under-served languages. While our proposed approach being highly efficient to expand the paradigm of cross-lingual transfer evaluation, the findings shed light onto the easy adaptation of MLMs for new languages in a low-resource setting.

Limitations

In this work, we primarily experiment with encoder models like mBERT and XLM-R, token-level syntactic tasks and two sentence-level tasks. In future, we would expand this work to recent large language

models and tasks involving natural language understanding. Moreover, our work only focus on low-resource setting with small-scale training data and parameter-efficient adapters. In future, instead of monolingual finetuning we will use this parameter efficient approach for multilingual finetuning thus unfolding effective multilingual pretraining configurations. As the base-language model choice, we only use mBERT. The evaluation of cross-lingual transfer needed to be expand to decoder based language models.

Acknowledgements

This work has been generously supported by the National Science Foundation under grants IIS-2125466 and IIS-2327143. We are thankful to the anonymous reviewers and area chairs for their constructive feedback. This project was supported by resources provided by the Office of Research Computing at George Mason University (`https://orc.gmu.edu`) and funded in part by grants from the National Science Foundation (Awards Number 1625039 and 2018631).

References

Julien Abadji, Pedro Ortiz Suarez, Laurent Romary, and Benoît Sagot. 2022. Towards a Cleaner Document-Oriented Multilingual Crawled Corpus. *arXiv e-prints*, page arXiv:2201.06642.

David Adelani, Jesujoba Alabi, Angela Fan, Julia Kreutzer, Xiaoyu Shen, Machel Reid, Dana Ruiter, Dietrich Klakow, Peter Nabende, Ernie Chang, Tajuddeen Gwadabe, Freshia Sackey, Bonaventure F. P. Dossou, Chris Emezue, Colin Leong, Michael Beukman, Shamsuddeen Muhammad, Guyo Jarso, Oreen Yousuf, Andre Niyongabo Rubungo, Gilles Hacheme, Eric Peter Wairagala, Muhammad Umair Nasir, Benjamin Ajibade, Tunde Ajayi, Yvonne Gitau, Jade Abbott, Mohamed Ahmed, Millicent Ochieng, Anuoluwapo Aremu, Perez Ogayo, Jonathan Mukiibi, Fatoumata Ouoba Kabore, Godson Kalipe, Derguene Mbaye, Allahsera Auguste Tapo, Victoire Memdjokam Koagne, Edwin Munkoh-Buabeng, Valencia Wagner, Idris Abdulmumin, Ayodele Awokoya, Happy Buzaaba, Blessing Sibanda, Andiswa Bukula, and Sam Manthalu. 2022. A few thousand translations go a long way! leveraging pre-trained models for African news translation. In *Proceedings of the 2022 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies*, pages 3053–3070, Seattle, United States. Association for Computational Linguistics.

Antonios Anastasopoulos and Graham Neubig. 2020. Should all cross-lingual embeddings speak English? In *Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics*, pages 8658–8679, Online. Association for Computational Linguistics.

Jonathan H. Clark, Eunsol Choi, Michael Collins, Dan Garrette, Tom Kwiatkowski, Vitaly Nikolaev, and Jennimaria Palomaki. 2020. TyDi QA: A benchmark for information-seeking question answering in typologically diverse languages. *Transactions of the Association for Computational Linguistics*, 8:454–470.

Alexis Conneau, Ruty Rinott, Guillaume Lample, Adina Williams, Samuel Bowman, Holger Schwenk, and Veselin Stoyanov. 2018. XNLI: Evaluating cross-lingual sentence representations. In *Proceedings of the 2018 Conference on Empirical Methods in Natural Language Processing*, pages 2475–2485, Brussels, Belgium. Association for Computational Linguistics.

Marie-Catherine de Marneffe, Christopher D. Manning, Joakim Nivre, and Daniel Zeman. 2021. Universal Dependencies. *Computational Linguistics*, 47(2):255–308.

Ameet Deshpande, Partha Talukdar, and Karthik Narasimhan. 2022. When is BERT multilingual? isolating crucial ingredients for cross-lingual transfer. In *Proceedings of the 2022 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies*, pages 3610–3623, Seattle, United States. Association for Computational Linguistics.

Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. 2019. BERT: Pre-training of deep bidirectional transformers for language understanding. In *Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long and Short Papers)*, pages 4171–4186, Minneapolis, Minnesota. Association for Computational Linguistics.

Philipp Dufter and Hinrich Schütze. 2020. Identifying elements essential for BERT's multilinguality. In *Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing (EMNLP)*, pages 4423–4437, Online. Association for Computational Linguistics.

Abteen Ebrahimi, Manuel Mager, Arturo Oncevay, Vishrav Chaudhary, Luis Chiruzzo, Angela Fan, John Ortega, Ricardo Ramos, Annette Rios, Ivan Vladimir Meza Ruiz, Gustavo Giménez-Lugo, Elisabeth Mager, Graham Neubig, Alexis Palmer, Rolando Coto-Solano, Thang Vu, and Katharina Kann. 2022. AmericasNLI: Evaluating zero-shot natural language understanding of pretrained multilingual models in truly low-resource languages. In *Proceedings of the 60th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pages 6279–6299, Dublin, Ireland. Association for Computational Linguistics.

Fahim Faisal and Antonios Anastasopoulos. 2022. Phylogeny-inspired adaptation of multilingual models to new languages. In *Proceedings of the 2nd Conference of the Asia-Pacific Chapter of the Association for Computational Linguistics and the 12th International Joint Conference on Natural Language Processing (Volume 1: Long Papers)*, pages 434–452, Online only. Association for Computational Linguistics.

Yoshinari Fujinuma, Jordan Boyd-Graber, and Katharina Kann. 2022. Match the script, adapt if multilingual: Analyzing the effect of multilingual pretraining on cross-lingual transferability. In *Proceedings of the 60th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pages 1500–1512, Dublin, Ireland. Association for Computational Linguistics.

Yu-Hsiang Lin, Chian-Yu Chen, Jean Lee, Zirui Li, Yuyan Zhang, Mengzhou Xia, Shruti Rijhwani, Junxian He, Zhisong Zhang, Xuezhe Ma, Antonios Anastasopoulos, Patrick Littell, and Graham Neubig. 2019. Choosing transfer languages for cross-lingual learning. In *Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics*, pages 3125–3135, Florence, Italy. Association for Computational Linguistics.

Dan Malkin, Tomasz Limisiewicz, and Gabriel Stanovsky. 2022. A balanced data approach for evaluating cross-lingual transfer: Mapping the linguistic blood bank. In *Proceedings of the 2022 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies*, pages 4903–4915, Seattle, United States. Association for Computational Linguistics.

Michael McCloskey and Neal J Cohen. 1989. Catastrophic interference in connectionist networks: The sequential learning problem. In *Psychology of learning and motivation*, volume 24, pages 109–165. Elsevier.

Benjamin Muller, Antonios Anastasopoulos, Benoît Sagot, and Djamé Seddah. 2021. When being unseen from mBERT is just the beginning: Handling new languages with multilingual language models. In *Proceedings of the 2021 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies*, pages 448–462, Online. Association for Computational Linguistics.

Xiaoman Pan, Boliang Zhang, Jonathan May, Joel Nothman, Kevin Knight, and Heng Ji. 2017. Cross-lingual name tagging and linking for 282 languages. In *Proceedings of the 55th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pages 1946–1958, Vancouver, Canada. Association for Computational Linguistics.

Isabel Papadimitriou, Kezia Lopez, and Dan Jurafsky. 2022. Multilingual bert has an accent: Evaluating english influences on fluency in multilingual models. arXiv:2210.05619.

Jonas Pfeiffer, Naman Goyal, Xi Lin, Xian Li, James Cross, Sebastian Riedel, and Mikel Artetxe. 2022. Lifting the curse of multilinguality by pre-training modular transformers. In *Proceedings of the 2022 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies*, pages 3479–3495, Seattle, United States. Association for Computational Linguistics.

Jonas Pfeiffer, Aishwarya Kamath, Andreas Rücklé, Kyunghyun Cho, and Iryna Gurevych. 2021. AdapterFusion: Non-destructive task composition for transfer learning. In *Proceedings of the 16th Conference of the European Chapter of the Association for Computational Linguistics: Main Volume*, pages 487–503, Online. Association for Computational Linguistics.

Jonas Pfeiffer, Andreas Rücklé, Clifton Poth, Aishwarya Kamath, Ivan Vulić, Sebastian Ruder, Kyunghyun Cho, and Iryna Gurevych. 2020. AdapterHub: A framework for adapting transformers. In *Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing: System Demonstrations*, pages 46–54, Online. Association for Computational Linguistics.

Phillip Rust, Jonas Pfeiffer, Ivan Vulić, Sebastian Ruder, and Iryna Gurevych. 2021. How good is your tokenizer? on the monolingual performance of multilingual language models. In *Proceedings of the 59th Annual Meeting of the Association for Computational Linguistics and the 11th International Joint Conference on Natural Language Processing (Volume 1: Long Papers)*, pages 3118–3135, Online. Association for Computational Linguistics.

Zirui Wang, Zachary C. Lipton, and Yulia Tsvetkov. 2020. On negative interference in multilingual models: Findings and a meta-learning treatment. In *Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing (EMNLP)*, pages 4438–4450, Online. Association for Computational Linguistics.

Thomas Wolf, Lysandre Debut, Victor Sanh, Julien Chaumond, Clement Delangue, Anthony Moi, Pierric Cistac, Tim Rault, Remi Louf, Morgan Funtowicz, Joe Davison, Sam Shleifer, Patrick von Platen, Clara Ma, Yacine Jernite, Julien Plu, Canwen Xu, Teven Le Scao, Sylvain Gugger, Mariama Drame, Quentin Lhoest, and Alexander Rush. 2020. Transformers: State-of-the-art natural language processing. In *Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing: System Demonstrations*, pages 38–45, Online. Association for Computational Linguistics.

A Related Works

Cross-Lingual Transfer Studying cross-lingual transfer to prepare a better pretraining configuration is a well-explored topic. Malkin et al. (2022) propose a balanced-data approach to identify effective set of languages for model training through constructing bilingual language graph. They formulate the problem in terms of linguistic blood bank where language can either play the role of donor or receiver. This study comprises over a large set of languages while training a large number of bilingual models. However, how a large multilingual model (eg. mBERT) having a shared representation space larger than bilingual models perform in similar setting is not evaluated yet. Fujinuma et al. (2022) points out it is always better to have a diverse set of languages during pretraining for zero-shot adaptation. At the same-time, language relatedness in pretraining configuration always helps.

Adaptation to Unseen Languages The idea of performing effective zero-shot transfer is highly beneficial for model adaptation to new languages. According to Muller et al. (2021), transfer learning helps some new languages while some hard languages does not get the benefit mainly because of the difference in writing systems. Transliterating those languages to a more familiar form is a useful approach in this case.

Parameter Efficiency Recently parameter-efficient language modeling approaches are becoming more and more popular and capable. Adapter units (Pfeiffer et al., 2022) are such modular units containing small trainable set of parameters. Using adapters resolve the problem of model-capacity and training bottleneck. In addition, most of the parameters remain unchanged thus preventing the problem of negative interference. The most important benefit of adapter untis are it's modular design. It is also possible to train the adapters using language-phylogeny information (Faisal and Anastasopoulos, 2022) thus extending the base model capacity to unseen new language in an informed manner.

B Terminologies

Transfer Language: The languages we use to perform monolingual finetuning of the base language model (mBERT) using masked language modeling.

Target Language: The languages we use to evaluate both the pretrained as well as finetuned mBERT on downstream tasks.

Negative Transfer: The scenario where language model performance drops because of finetuning it on a transfer language.

Cross-lingual Transfer: The established method of finetuning a language model on one transfer language and deploy it on another target language.

Unseen Languages Any language that were not part of the original pretraining step.

C Dataset Details

C.1 Transfer Languages

We perform mono-lingual finetuning as well as language adapter training on 38 transfer languages. Each language dataset contains 10k lines of text. We use texts from several corpus including OSCAR (Abadji et al., 2022) and African News Translation dataset (Adelani et al., 2022). 11 out of these 38 languages are unseen by mBERT during pretraining steps. The list is provided in Table 24.

C.2 Adapter Training Dataset

Dependency Parsing We train a task adapter for performing dependency parsing task. For this step, we use Universal Dependency training dataset v2.11 (de Marneffe et al., 2021). To keep the data distribution balanced, we use not more than a thousand examples per language. Combining all these data together, we train a multilingual dependency tagging task adapter. The complete list of data-source languages for training this adapter is presented in Table 25.

Parts-of-Speech Tagging Here we also use the Universal Dependency training dataset v2.11 (de Marneffe et al., 2021). The languages are also the same ones used for dependency parsing previously.

Named Entity Recognition We use Wikiann (Pan et al., 2017) dataset for training a NER task adapter. The complete language lists are provided in Table 26.

Natural Language Inference We use XNLI (Conneau et al., 2018) dataset for training a NLI task adapter. The complete language lists are provided in Table 27.

Extractive Question Answering We use TyDiQA (Clark et al., 2020) dataset for training an Extractive Question Answering task adapter. The complete language lists are provided in Table 28.

C.3 Evaluation Dataset

We use 125 languages for evaluating NER task from Wikiann. For udp and pos-tagging tasks we use 114 languages from Universal Dependency dataset. There are 62 languages which are common between these two sets of 125 and 114 languages. For NLI evaluation, we use 15 languages from XNLI (Conneau et al., 2018) dataset and 10 low-resource South American indigenous languages from Americas NLI (ANLI) (Ebrahimi et al., 2022) dataset. For the question answering task, we take 9 languages from TydiQA (Clark et al., 2020) to evaluate. The complete list of 184 evaluation languages are provided in Table 29.

D Implementation Details

For all of our experiments, we use as well as modify the scripts from huggingface (Wolf et al., 2020) and adapterhub (Pfeiffer et al., 2020). For base language model, we use the model `bert-base-multilingua-uncased` from huggingface model repository.

E Hyper-parameters

Masked Language Modeling finetuning
- Train batch size: 8
- Evaluation batch size: 8
- Training Steps: 1, 10, 100 and 1000
- Learning Rate: 5e-5
- Maximum Sequence Length: 512

Language Adapter Training: Language Interaction
- Train batch size: 8
- Evaluation batch size: 8
- Training Epochs: 3
- Learning Rate: 5e-4
- Maximum Sequence Length: 256
- Adapter Parameter Reduction Factor: 16

Task Adapter Training: Dependency Parsing
- Train batch size: 36
- Evaluation batch size: 8
- Training Epochs: 5
- Learning Rate: 5e-4
- Maximum Sequence Length: 256
- Adapter Parameter Reduction Factor: 16

Combination	Count
$\|-A,-B\|$	1
$\|-A,+B\|$	1
$\|+A,-B\|$	3
$\|+A,+B\|$	2

Table 6: Bilingual interaction counts

Task Adapter Training: POS Tagging
- Train batch size: 36
- Evaluation batch size: 8
- Training Epochs: 5
- Learning Rate: 5e-4
- Maximum Sequence Length 256
- Adapter Parameter Reduction Factor: 16

Task Adapter Training: NER
- Train batch size: 36
- Evaluation batch size: 8
- Training Epochs: 5
- Learning Rate: 5e-4
- Maximum Sequence Length: 256
- Adapter Parameter Reduction Factor: 16

Task Adapter Training: NLI
- Train batch size: 32
- Evaluation batch size: 8
- Training Epochs: 5
- Learning Rate: 5e-5
- Maximum Sequence Length: 128
- Adapter Parameter Reduction Factor: 16

Task Adapter Training: Extractive QA
- Train batch size: 32
- Evaluation batch size: 8
- Training Epochs: 5
- Learning Rate: 3e-5
- Maximum Sequence Length: 384
- Document Stride: 128
- Adapter Parameter Reduction Factor: 16

F Language Interference Projection (an example)

For example, consider the case of Arabic [A] that interacts with Bengali [B] in a bilingual setting [AB]. The count from pair combinations of positive and negative interference counts are as follows:

So for language A we get,

$$\begin{aligned}\texttt{C} &= 1+1+3+2\\ &= 7\\ (\texttt{x}_\texttt{A}, \texttt{y}_\texttt{A}) &= \frac{1}{7} \times (1\cdot[-1,-1] + 1\cdot[-1,1]\\ &\quad + 3\cdot[1,-1] + 2\cdot[1,1])\\ &= (0.43, -0.14)\end{aligned}$$

Here, $|+A,+B| = 2$ means, in total two cases, Arabic gets positive interference score while the other associated language (Bengali) also gets positive interference. Similarly, $|-A,-B| = 1$ means, for one language, both Arabic and Bengali get negative interference scores. Now $(X_A, Y_A) = (0.43, -0.14)$. So Arabic will be in the lower-right quartile of the graph (+x, -y) means, Arabic generally gets positive interference but it does not equally beneficial to other languages (gets penalized for cases $|-A,-B|, |+A,-B|$). Here we consider only Bengali as a language to interact with. In practice, we use a set of other transfer languages to compute the total count of each combination for one specific language.

G Comparison

H Transfer Language Ranking

We rank the transfer languages by aggregating all the transfer scores. For example, consider getting transfer scores $\{ts_1, ..ts_i, ..ts_n\}$ for a set of n target languages L_{tg} where $i \in L_{tg}$ and the transfer language is tf. Then the aggregated transfer score for tf would be:

$$\texttt{aggregated} - \texttt{transfer}(\texttt{tf}) = \frac{\sum_{i=1}^{n} ts_i}{n}$$

The ranking of all transfer languages across three tasks are presented in Table **??**. In addition, we report the percentage of positive transfers for each transfer language. Both in parsing and POS tagging, we observe significant presence of unseen languages in high ranked positions (percentage of unseen languages in top 10: parsing: 40%, POS tagging: 40%, NER: 20%). At the sametime, they provide positive scores similar to the cases of seen languages. On the contrary, in NER, we observe most of the unseen African languages are at the lower ranked positions.

I Recipient Transfer Maps

In a similar manner of calculating the `aggregated-transfer`, we calculate `aggregated-target`. For example, if a target language tg receives scores $\{ts_1, ..ts_i, ..ts_m\}$ from a set of m transfer languages L_{tf} where $i \in L_{tf}$. Then the aggregated target score for tf would be:

$$\texttt{aggregated} - \texttt{target}(\texttt{tg}) = \frac{\sum_{i=1}^{n} ts_i}{n}$$

This way we identify how much a target language get benefited from all the transfer languages. In Figure 5, we present the Recipient Transfer Maps across tasks. We plot the percentage of positive/negative `aggregated-target` scores and corresponding target languages. Now looking at these maps, we observe the presence of universal target languages (2-5 %) which always receive positive transfer from all of the 38 source languages in two out of three tasks (exception: POS tagging). Wheres, around 28% languages in parsing and tagging, 32.8% in NER never receive any positive transfer. We observe out of 40 languages which receive positive transfer in more than 90% times, 25 languages are unseen low resourced languages. The complete list of target languages which never receive and which almost always receive positive transfer is presented in Table 19.

J Maximum Score Recipients are low-resourced

In Table 20, we report all the recipients those receive maximum transfer scores at different steps of mlm fine-tuning. From the results, it is evident that, a multilingual model almost always benefits certain unseen, low-resource as well as endangered languages largely. We observe out of 19 max-recipients, 17 are `mBERT`-unseen languages. Moreover, the two other seen-languages: Bavarian German and Low German are also low-resourced languages.

K Task Matters

In Figure 6, we present the commonality graph of transfer language ranking across all three tasks. Spearman rank correlation with p value is presented in Table 21.

L Transfer Languages with High Variance

In Figure 7, we present the violin plots for all the transfer languages sorted by their

Dependency Parsing											
	mBERT	Continious Steps				Lang. Interaction			Improvement		
lang	base	1	10	100	1000	[1A]	[2A]	[3A]	$Imp_{c:1}$	$Imp_{c:1000}$	Imp_i
ell	92.82	92.73	92.39	92.09	91.46	91.97	91.91	91.98	no	no	no
tel	90.15	89.33	89.43	87.92	85.01	89.74	89.44	89.46	no	no	no
spa	90.02	89.87	89.42	89.00	88.16	89.09	89.20	89.24	no	no	no
hin	89.04	88.77	88.35	87.76	87.09	88.28	88.22	88.29	no	no	no
hun	87.20	87.14	86.49	85.65	85.06	86.25	86.29	86.36	no	no	no
heb	85.59	85.36	85.06	84.56	83.82	85.01	84.96	84.97	no	no	no
swe	85.45	85.32	85.03	84.88	84.30	84.76	84.81	84.88	no	no	no
tam	84.48	84.37	82.84	83.04	81.68	83.70	83.46	83.40	no	no	no
cym	83.26	83.15	82.58	82.45	81.95	83.11	83.06	83.10	no	no	no
hye	82.27	81.88	81.49	81.08	80.22	80.95	81.02	81.02	no	no	no
pcm	81.04	80.32	79.11	78.47	77.91	79.32	79.50	79.52	no	no	no
est	80.78	80.68	80.03	79.80	79.03	79.88	79.96	80.04	no	no	no
gle	79.65	79.21	79.03	78.66	78.99	79.09	79.09	79.14	no	no	no
zho	70.42	70.41	70.10	69.66	70.17	64.74	70.06	70.46	no	no	yes
wol	69.46	68.66	68.09	64.63	67.32	68.96	69.05	69.10	no	no	no
ara	31.25	31.15	31.29	30.99	29.97	30.45	30.38	30.37	no	no	no
fra	27.84	27.56	26.46	24.70	24.19	24.92	24.96	24.95	no	no	no
jpn	22.54	22.50	22.52	22.73	22.49	22.43	22.43	22.42	no	no	no
deu	89.37	89.40	88.67	88.39	87.43	89.10	89.28	89.35	yes	no	no
bul	89.32	89.32	89.01	89.01	89.09	89.12	89.18	89.21	yes	no	no
rus	88.09	88.14	87.96	87.53	87.03	87.82	87.88	87.94	yes	no	no
eng	79.62	79.76	79.56	79.39	78.86	80.18	80.18	80.24	yes	no	yes
ben	75.31	76.69	73.53	73.00	69.31	74.69	75.71	75.87	yes	no	yes
bre	70.79	71.90	69.82	71.04	72.12	73.58	73.76	73.86	yes	yes	yes
kor	64.02	64.33	64.31	63.76	65.02	64.33	64.35	64.43	yes	yes	yes
fin	63.54	64.58	63.45	63.26	63.84	64.22	64.37	64.45	yes	yes	yes
yor	40.92	42.80	40.40	42.17	47.59	42.55	42.84	42.93	yes	yes	yes
kmr	31.94	32.44	31.73	32.75	45.30	32.54	32.10	32.03	yes	yes	yes
bam	29.99	30.43	30.87	29.95	38.13	30.74	30.81	30.78	yes	yes	yes
gub	21.64	21.97	20.96	22.92	34.52	23.83	23.73	23.52	yes	yes	yes

Table 7: Dependency Parsing results. Improvement: $Imp_{c:1}$ cont. step 1-base. $Imp_{c:1000}$: cont. steps 1000-base. Imp_i: improvement in language interactions ([1A]/[2A]/[3A]) versus baseline. Languages unseen by mBERT are in **bold** font.

Dependency Parsing (Model Comparison)										
	mBERT					XLM-R				
lang	base	1	10	100	1000	base_x	1_x	10_x	100_x	1000_x
ell	92.82	92.73	92.39	92.09	91.46	93.33	93.27	93.01	92.59	92.86
tel	90.15	89.33	89.43	87.92	85.01	88.49	87.88	86.34	85.99	86.41
spa	90.02	89.87	89.42	89.00	88.16	89.66	89.70	89.38	88.92	89.26
deu	89.37	89.40	88.67	88.39	87.43	89.71	89.63	89.09	88.74	89.30
bul	89.32	89.32	89.01	89.01	89.09	90.19	90.31	90.22	89.73	90.19
hin	89.04	88.77	88.35	87.76	87.09	89.46	89.50	89.13	88.06	88.41
rus	88.09	88.14	87.96	87.53	87.03	88.72	88.76	88.62	88.16	88.45
hun	87.20	87.14	86.49	85.65	85.06	89.16	89.13	88.78	88.40	88.73
heb	85.59	85.36	85.06	84.56	83.82	86.22	86.14	85.87	85.54	85.69
swe	85.45	85.32	85.03	84.88	84.30	85.88	85.84	85.55	85.18	85.47
tam	84.48	84.37	82.84	83.04	81.68	84.59	84.66	84.32	84.35	85.35
cym	83.26	83.15	82.58	82.45	81.95	83.53	83.32	82.75	82.38	83.11
hye	82.27	81.88	81.49	81.08	80.22	84.61	84.54	84.18	83.79	84.28
pcm	81.04	80.32	79.11	78.47	77.91	79.58	79.38	78.48	77.87	79.37
est	80.78	80.68	80.03	79.80	79.03	83.96	83.96	83.52	83.20	83.55
gle	79.65	79.21	79.03	78.66	78.99	81.38	81.42	80.62	80.05	80.79
eng	79.62	79.76	79.56	79.39	78.86	78.99	78.77	78.42	77.86	78.27
ben	75.31	76.69	73.53	73.00	69.31	69.06	69.09	68.88	66.28	69.94
bre	70.79	71.90	69.82	71.04	72.12	63.88	63.51	62.70	61.99	65.45
zho	70.42	70.41	70.10	69.66	70.17	70.47	70.59	70.39	70.11	70.31
wol	69.46	68.66	68.09	64.63	67.32	67.95	67.78	66.51	64.33	64.88
kor	64.02	64.33	64.31	63.76	65.02	63.83	63.58	63.19	63.59	64.54
fin	63.54	64.58	63.45	63.26	63.84	69.12	68.73	68.07	68.63	69.62
yor	40.92	42.80	40.40	42.17	47.59	23.22	22.70	22.70	24.24	38.40
kmr	31.94	32.44	31.73	32.75	45.30	64.53	64.08	62.50	64.94	66.41
ara	31.25	31.15	31.29	30.99	29.97	9.42	9.54	10.04	9.84	8.82
bam	29.99	30.43	30.87	29.95	38.13	29.68	29.70	29.28	29.16	34.20
fra	27.84	27.56	26.46	24.70	24.19	19.59	19.99	18.49	16.18	19.34
jpn	22.54	22.50	22.52	22.73	22.49	7.87	7.65	7.84	7.30	6.91
gub	21.64	21.97	20.96	22.92	34.52	22.22	21.82	22.09	23.43	36.49
Avg.	69.26	69.34	68.67	68.37	69.24	68.28	68.17	67.70	67.36	69.16

Table 8: Dependency Parsing results comparison using mBERT and XLM-R (for languages present in both transfer and target set.)

POS Tagging											
	mBERT	Continious Steps				Lang. Interaction			Improvement		
lang	base	1	10	100	1000	[1A]	[2A]	[3A]	$Imp_{c:1}$	$Imp_{c:1000}$	Imp_i
spa	97.84	97.80	97.66	97.60	97.41	97.67	97.71	97.72	no	no	no
ell	97.25	97.16	97.17	96.99	96.87	97.02	97.09	97.10	no	no	no
heb	95.22	95.07	94.91	94.72	94.52	94.86	94.89	94.89	no	no	no
swe	95.17	95.04	95.00	94.92	94.90	94.97	95.01	95.02	no	no	no
hun	94.28	94.17	94.03	93.94	93.82	93.91	94.01	94.03	no	no	no
rus	94.10	94.08	94.03	93.84	93.59	93.89	93.92	93.94	no	no	no
pcm	92.98	92.77	92.17	91.84	91.23	92.25	92.46	92.55	no	no	no
hin	92.23	92.00	91.76	91.61	91.39	91.98	92.00	92.01	no	no	no
est	91.12	90.90	90.65	90.48	90.65	90.68	90.77	90.80	no	no	no
hye	91.08	90.78	90.50	90.13	89.58	90.74	90.86	90.89	no	no	no
cym	89.69	89.36	89.03	88.83	88.60	88.96	89.15	89.22	no	no	no
tel	88.60	88.42	88.46	87.83	87.81	87.94	87.95	87.93	no	no	no
gle	88.29	88.08	87.62	87.13	87.49	87.72	87.81	87.83	no	no	no
wol	85.58	84.85	84.16	82.06	82.08	84.11	84.64	84.82	no	no	no
eng	84.65	84.64	84.63	84.62	84.58	84.62	84.74	84.77	no	no	yes
tam	83.10	82.74	82.19	82.39	82.38	82.87	82.72	82.70	no	no	no
ben	80.34	79.35	78.56	79.29	79.56	81.10	80.43	80.39	no	no	yes
bam	30.30	30.27	30.74	33.92	49.49	30.65	30.51	30.45	no	yes	yes
gub	28.49	28.11	28.66	30.02	36.64	28.82	28.77	28.85	no	yes	yes
jpn	7.85	7.73	7.80	7.91	7.84	7.58	7.67	7.68	no	no	no
bul	96.12	96.13	96.07	96.08	96.12	96.05	96.01	96.01	yes	no	no
deu	90.55	90.56	90.47	90.13	90.22	90.68	90.69	90.70	yes	no	yes
zho	80.45	80.50	80.54	80.55	79.72	79.34	79.71	79.91	yes	no	no
fin	77.98	78.30	77.83	77.78	78.36	77.82	77.83	77.83	yes	yes	no
bre	66.91	67.28	67.67	68.15	70.26	68.02	67.79	67.72	yes	yes	yes
kor	56.28	56.42	56.49	56.61	57.72	56.59	56.58	56.57	yes	yes	yes
yor	45.91	48.22	46.73	51.24	57.28	45.71	45.45	45.45	yes	yes	no
kmr	40.16	40.35	40.49	42.76	55.82	41.04	40.79	40.64	yes	yes	yes
fra	16.35	16.47	16.66	16.63	16.24	16.77	16.79	16.79	yes	no	yes
ara	8.61	8.70	8.76	8.53	5.17	8.74	8.86	8.88	yes	no	yes

Table 9: POS Tagging results. Improvement: $Imp_{c:1}$ cont. step 1-base. $Imp_{c:1000}$: cont. steps 1000-base. Imp_i: improvement in language interactions ([1A]/[2A]/[3A]) versus baseline. Languages unseen by mBERT are in **bold** font.

POS Tagging (Model Comparison)										
	mBERT					XLM-R				
lang	base	1	10	100	1000	base_x	1_x	10_x	100_x	1000_x
spa	97.84	97.80	97.66	97.60	97.41	97.80	97.78	97.74	97.65	97.61
ell	97.25	97.16	97.17	96.99	96.87	97.51	97.50	97.47	97.43	97.45
bul	96.12	96.13	96.07	96.08	96.12	96.79	96.75	96.68	96.58	96.58
heb	95.22	95.07	94.91	94.72	94.52	96.41	96.30	96.16	96.16	96.24
swe	95.17	95.04	95.00	94.92	94.90	96.22	96.20	96.29	96.26	96.17
hun	94.28	94.17	94.03	93.94	93.82	95.53	95.57	95.51	95.24	95.17
rus	94.10	94.08	94.03	93.84	93.59	94.45	94.40	94.30	94.32	94.32
pcm	92.98	92.77	92.17	91.84	91.23	93.44	93.20	91.91	92.24	92.39
hin	92.23	92.00	91.76	91.61	91.39	93.47	93.42	93.31	92.96	93.12
est	91.12	90.90	90.65	90.48	90.65	93.46	93.42	93.30	93.16	93.35
hye	91.08	90.78	90.50	90.13	89.58	93.76	93.80	93.70	93.43	93.52
deu	90.55	90.56	90.47	90.13	90.22	90.04	90.03	90.01	90.00	90.00
cym	89.69	89.36	89.03	88.83	88.60	91.92	91.83	91.60	91.55	91.50
tel	88.60	88.42	88.46	87.83	87.81	91.58	91.78	91.17	90.91	91.38
gle	88.29	88.08	87.62	87.13	87.49	91.51	91.49	91.13	90.79	91.22
wol	85.58	84.85	84.16	82.06	82.08	84.14	83.84	83.21	81.84	81.99
eng	84.65	84.64	84.63	84.62	84.58	86.30	85.83	84.72	85.59	86.40
tam	83.10	82.74	82.19	82.39	82.38	85.55	85.71	85.79	85.76	85.73
zho	80.45	80.50	80.54	80.55	79.72	85.44	85.32	85.29	85.56	85.36
ben	80.34	79.35	78.56	79.29	79.56	83.65	83.36	83.37	83.35	84.36
fin	77.98	78.30	77.83	77.78	78.36	83.76	83.57	83.35	83.59	83.38
bre	66.91	67.28	67.67	68.15	70.26	61.11	60.97	61.72	61.73	64.70
kor	56.28	56.42	56.49	56.61	57.72	57.17	57.06	57.06	57.10	57.17
yor	45.91	48.22	46.73	51.24	57.28	26.88	26.41	26.37	27.63	45.90
kmr	40.16	40.35	40.49	42.76	55.82	74.85	74.96	75.78	76.26	76.95
bam	30.30	30.27	30.74	33.92	49.49	29.46	29.22	29.49	29.61	36.49
gub	28.49	28.11	28.66	30.02	36.64	29.97	30.17	31.05	31.48	41.21
fra	16.35	16.47	16.66	16.63	16.24	14.16	14.14	14.28	13.84	13.59
ara	8.61	8.70	8.76	8.53	5.17	8.15	8.27	8.36	8.38	7.03
jpn	7.85	7.73	7.80	7.91	7.84	7.61	7.60	7.44	7.46	7.34
Avg.	72.92	72.87	72.71	72.95	74.24	74.40	74.33	74.25	74.26	75.59

Table 10: POS Tagging results comparison using mBERT and XLM-R (for languages present in both transfer and target set.)

NER											
	mBERT	Continious Steps				Lang. Interaction			Improvement		
lang	base	1	10	100	1000	[1A]	[2A]	[3A]	$Imp_{c:1}$	$Imp_{c:1000}$	Imp_i
spa	90.66	90.56	90.18	89.41	87.74	90.20	90.26	90.26	no	no	no
bul	89.40	89.28	89.07	88.62	87.54	89.09	89.09	89.10	no	no	no
fra	88.14	87.95	87.56	86.53	85.19	87.63	87.77	87.80	no	no	no
fin	87.63	87.60	87.44	87.15	86.43	87.54	87.46	87.46	no	no	no
est	87.40	87.27	86.93	86.28	85.36	86.92	87.04	87.10	no	no	no
ell	85.81	85.71	84.95	84.36	83.02	85.44	85.50	85.54	no	no	no
gle	83.97	82.50	81.96	80.24	80.10	81.84	82.40	82.58	no	no	no
ara	83.69	83.50	82.73	80.85	79.29	83.04	83.18	83.23	no	no	no
bre	83.20	83.10	82.00	80.45	79.60	82.50	82.71	82.74	no	no	no
hin	82.53	82.31	81.87	80.21	76.62	82.56	82.40	82.41	no	no	yes
kor	81.67	81.66	81.27	79.75	78.22	81.43	81.41	81.42	no	no	no
eng	79.43	79.33	79.03	78.52	74.96	79.07	79.18	79.20	no	no	no
nep	78.33	77.32	77.97	75.63	69.80	78.15	77.71	77.62	no	no	no
tam	78.10	77.42	77.11	74.53	72.03	77.20	77.00	77.04	no	no	no
heb	76.53	76.41	75.92	75.09	73.56	76.19	76.04	76.07	no	no	no
tel	76.04	75.37	75.12	70.86	68.86	75.54	75.06	75.03	no	no	no
mya	73.15	72.92	70.71	69.51	63.59	71.88	71.54	71.70	no	no	no
zho	72.07	71.94	71.62	69.65	64.61	62.44	69.03	70.95	no	no	no
ibo	61.06	57.30	57.21	53.72	55.40	57.52	57.76	57.70	no	no	no
jpn	59.85	59.59	58.38	56.79	53.38	58.93	58.65	58.68	no	no	no
swe	91.41	91.47	91.25	90.86	90.06	91.27	91.29	91.32	yes	no	no
hye	90.10	90.59	90.23	87.55	83.25	90.32	90.46	90.50	yes	no	yes
hun	88.42	88.49	88.30	87.49	86.78	88.40	88.35	88.37	yes	no	no
pms	88.22	89.09	88.90	88.25	87.59	88.15	87.47	87.61	yes	no	no
cym	85.75	85.91	85.23	83.19	81.81	85.25	85.34	85.39	yes	no	no
deu	85.53	85.62	85.38	84.67	83.32	85.07	85.25	85.32	yes	no	no
rus	84.76	84.78	84.38	83.56	80.82	84.51	84.49	84.51	yes	no	no
ben	84.75	84.85	83.32	80.53	72.14	83.12	83.62	83.73	yes	no	no
kin	72.38	72.74	71.76	68.79	68.50	70.48	71.11	71.85	yes	no	no
yor	67.53	70.33	72.11	69.40	51.34	79.11	77.58	76.04	yes	no	yes

Table 11: NER results. Improvement: $Imp_{c:1}$ cont. step 1-base. $Imp_{c:1000}$: cont. steps 1000-base. Imp_i: improvement in language interactions ([1A]/[2A]/[3A]) versus baseline. Languages unseen by mBERT are in **bold** font.

NER (Model Comparison)										
	mBERT					XLM-R				
lang	base	1	10	100	1000	base_x	1_x	10_x	100_x	1000_x
swe	91.41	91.47	91.25	90.86	90.06	89.83	89.91	89.96	89.71	89.61
spa	90.66	90.56	90.18	89.41	87.74	87.37	87.44	87.44	87.21	87.13
hye	90.10	90.59	90.23	87.55	83.25	89.85	89.77	89.56	89.98	89.88
bul	89.40	89.28	89.07	88.62	87.54	87.63	87.70	87.66	87.49	87.50
hun	88.42	88.49	88.30	87.49	86.78	86.59	86.58	86.26	86.29	86.07
pms	88.22	89.09	88.90	88.25	87.59	87.12	87.42	87.17	88.22	90.54
fra	88.14	87.95	87.56	86.53	85.19	84.54	84.53	84.28	84.18	84.20
fin	87.63	87.60	87.44	87.15	86.43	85.95	85.80	85.65	85.87	85.67
est	87.40	87.27	86.93	86.28	85.36	85.13	85.18	85.07	84.78	84.87
ell	85.81	85.71	84.95	84.36	83.02	84.16	84.25	84.09	84.07	83.96
cym	85.75	85.91	85.23	83.19	81.81	82.74	82.21	82.37	82.06	82.25
deu	85.53	85.62	85.38	84.67	83.32	83.08	83.17	83.33	82.81	82.78
rus	84.76	84.78	84.38	83.56	80.82	82.84	82.72	82.38	82.17	82.28
ben	84.75	84.85	83.32	80.53	72.14	81.42	81.82	81.52	80.14	80.20
gle	83.97	82.50	81.96	80.24	80.10	81.69	81.01	80.79	80.17	80.73
ara	83.69	83.50	82.73	80.85	79.29	80.97	80.91	80.56	80.23	80.24
bre	83.20	83.10	82.00	80.45	79.60	77.32	76.92	76.97	75.94	76.81
hin	82.53	82.31	81.87	80.21	76.62	80.92	80.76	81.66	81.33	80.86
kor	81.67	81.66	81.27	79.75	78.22	75.20	75.25	75.07	74.77	74.73
eng	79.43	79.33	79.03	78.52	74.96	76.56	76.56	76.82	76.21	75.35
nep	78.33	77.32	77.97	75.63	69.80	76.54	75.98	77.00	74.79	74.74
tam	78.10	77.42	77.11	74.53	72.03	76.35	76.24	76.25	75.92	75.79
heb	76.53	76.41	75.92	75.09	73.56	73.41	73.20	73.10	72.91	72.80
tel	76.04	75.37	75.12	70.86	68.86	76.07	76.27	75.78	74.77	74.09
mya	73.15	72.92	70.71	69.51	63.59	73.03	73.12	74.27	74.43	72.31
kin	72.38	72.74	71.76	68.79	68.50	71.23	72.72	72.00	67.94	63.44
zho	72.07	71.94	71.62	69.65	64.61	64.44	64.66	64.16	63.25	62.07
yor	67.53	70.33	72.11	69.40	51.34	72.10	72.07	74.73	68.77	76.73
ibo	61.06	57.30	57.21	53.72	55.40	63.68	63.15	60.89	57.25	61.05
jpn	59.85	59.59	58.38	56.79	53.38	54.92	54.80	54.31	53.07	52.81
Avg.	81.25	81.10	80.66	79.08	76.36	79.09	79.07	79.04	78.22	78.38

Table 12: NER results comparison using mBERT and XLM-R (for languages present in both transfer and target set.)

XNLI					
		Continious Steps			
lang	base	1	10	100	1000
mBERT					
eng	81.02	45.42	45.01	42.86	43.18
spa	77.33	46.59	47.52	44.87	40.96
deu	76.27	46.79	47.71	46.63	39.57
zho	75.43	46.45	44.74	43.23	40.07
bul	75.13	46.57	46.70	44.85	36.58
ell	73.89	44.51	44.38	44.21	36.28
rus	73.59	45.78	46.28	44.24	38.53
ara	71.36	42.82	41.44	41.37	39.34
hin	67.68	41.74	42.61	40.19	35.02
XLM-R					
eng	84.03	83.91	83.87	83.38	83.54
spa	80.60	80.67	80.92	80.26	80.38
bul	80.24	80.24	80.16	79.72	80.45
deu	79.38	79.33	79.32	78.79	79.20
rus	78.10	78.20	78.43	78.05	78.05
ell	77.82	77.77	77.61	77.22	77.59
zho	77.41	77.44	77.33	77.49	77.37
ara	75.63	75.47	75.15	74.55	74.91
hin	74.81	74.67	74.35	74.02	74.55

Table 13: XNLI results for (continuous training) languages present in both transfer and target set.

TyDiQA					
		Continious Steps			
lang	base	1	10	100	1000
mBERT					
tel	58.45	58.19	57.53	56.55	56.50
eng	56.14	55.89	55.91	53.05	53.89
ara	54.83	54.73	54.40	49.28	50.99
rus	50.37	49.93	49.15	36.16	43.74
fin	50.13	50.09	50.45	44.16	46.85
kor	47.83	46.59	46.74	44.09	44.38
ben	45.13	46.11	48.05	45.13	44.78
XLM-R					
tel	56.20	56.46	55.65	55.72	56.35
eng	52.50	52.82	53.18	52.89	52.70
ara	51.57	51.69	49.16	48.02	51.13
rus	47.41	47.32	45.04	44.19	46.26
fin	45.65	46.24	45.88	45.10	45.19
ben	44.25	42.39	43.27	40.97	43.45
kor	42.03	42.32	42.90	43.01	43.22

Table 14: TyDiQA results (continuous training)for languages present in both transfer and target set.

Transfer Languages Ranking using mBERT (Token Classification)									
Rank	**Parsing**			**POS Tagging**			**NER**		
	Lang	ts	+(%)	lang	ts	+(%)	lang	ts	+(%)
1	mya	0.33	40.35	**kin**	0.41	35.09	zho	0.16	49.6
2	ell	0.15	31.58	**kmr**	0.36	36.84	tel	0.08	32.8
3	**kmr**	0.14	35.96	**mos**	0.27	34.21	hun	0.08	40.8
4	yor	0.14	33.33	hye	0.27	36.84	heb	0.04	34.4
5	**pcm**	0.13	31.58	cym	0.22	37.72	est	0.03	36.8
6	nep	0.12	35.96	jpn	0.18	37.72	cym	0.03	40.0
7	rus	0.11	32.46	mya	0.17	39.47	eng	0.02	38.4
8	**mos**	0.09	42.11	nep	0.12	31.58	**mos**	0.00	32.0
9	**pms**	0.09	30.70	**pms**	0.08	37.72	tam	0.00	35.2
10	heb	0.08	30.70	zho	-0.04	34.21	**hau**	-0.07	35.2
11	tel	0.05	26.32	kor	-0.07	31.58	gle	-0.07	32.8
12	**ibo**	0.05	31.58	ben	-0.08	32.46	jpn	-0.08	33.6
13	**hau**	0.04	37.72	bul	-0.08	24.56	kor	-0.09	35.2
14	gle	0.03	28.07	**bam**	-0.12	30.70	swe	-0.11	29.6
15	**wol**	0.03	35.96	ell	-0.13	33.33	nep	-0.13	31.2
16	**bam**	0.02	32.46	hin	-0.13	32.46	mya	-0.17	35.2
17	est	0.00	28.95	tam	-0.14	32.46	hye	-0.17	32.0
18	hye	-0.03	31.58	**ibo**	-0.14	32.46	bul	-0.18	27.2
19	cym	-0.03	28.95	**wol**	-0.14	27.19	deu	-0.20	32.8
20	ben	-0.06	31.58	**pcm**	-0.16	29.82	bre	-0.23	35.2
21	**kin**	-0.06	29.82	yor	-0.16	36.84	spa	-0.28	28.0
22	**ewe**	-0.08	38.60	heb	-0.26	30.70	fin	-0.29	27.2
23	hin	-0.10	32.46	rus	-0.28	28.07	ell	-0.29	34.4
24	ara	-0.12	31.58	hun	-0.29	25.44	**pms**	-0.29	32.0
25	deu	-0.13	31.58	ara	-0.30	31.58	ara	-0.32	30.4
26	**gub**	-0.14	34.21	tel	-0.31	28.95	yor	-0.32	27.2
27	spa	-0.18	30.70	**hau**	-0.34	29.82	rus	-0.34	26.4
28	jpn	-0.19	27.19	gle	-0.34	28.07	**wol**	-0.41	32.8
29	bul	-0.21	25.44	**gub**	-0.34	23.68	ben	-0.54	27.2
30	swe	-0.21	28.95	fin	-0.35	25.44	**ibo**	-0.54	29.6
31	eng	-0.22	27.19	eng	-0.35	26.32	**kin**	-0.56	31.2
32	bre	-0.23	28.95	est	-0.35	29.82	fra	-0.59	29.6
33	hun	-0.23	21.93	bre	-0.39	31.58	**kmr**	-0.61	25.6
34	tam	-0.24	21.05	fra	-0.41	28.95	**pcm**	-0.69	25.6
35	fin	-0.26	26.32	deu	-0.44	26.32	**bam**	-0.69	30.4
36	fra	-0.37	24.56	spa	-0.53	25.44	hin	-0.72	21.6
37	kor	-0.38	26.32	swe	-0.66	27.19	**ewe**	-0.76	24.8
38	zho	-0.48	17.54	**ewe**	-0.79	23.68	**gub**	-0.98	24.8

Table 15: Transfer Languages ranked by aggregated transfer scores (ts) overall target languages across token classification tasks using mBERT. Languages unseen by mBERT are in **bold** font.

Transfer Languages Ranking using XLM-R (Token Classification)									
Rank	**Parsing**			**POS Tagging**			**NER**		
	Lang	ts	+(%)	lang	ts	+(%)	lang	ts	+(%)
1	nep	0.02	23.68	hin	0.18	39.47	rus	1.15	40.0
2	zho	-0.00	34.21	ben	0.10	36.84	ell	1.04	41.6
3	mya	-0.01	21.93	mya	0.04	34.21	tel	0.76	41.6
4	ben	-0.08	26.32	nep	0.01	34.21	heb	0.70	46.4
5	hin	-0.09	29.82	bul	0.01	40.35	ben	0.64	36.0
6	tam	-0.09	27.19	eng	-0.00	35.96	tam	0.48	44.0
7	bre	-0.11	23.68	bre	-0.01	42.11	hin	0.47	44.0
8	tel	-0.13	20.18	ara	-0.05	37.72	**pms**	0.44	40.8
9	deu	-0.13	24.56	gle	-0.12	36.84	bul	0.43	48.0
10	kor	-0.21	21.93	cym	-0.13	42.98	hye	0.36	40.0
11	est	-0.25	24.56	rus	-0.13	31.58	ara	0.33	43.2
12	swe	-0.25	22.81	hye	-0.16	36.84	swe	0.32	48.8
13	**pms**	-0.25	31.58	tam	-0.17	39.47	**kmr**	0.31	46.4
14	hye	-0.29	21.05	heb	-0.17	41.23	fra	0.27	44.0
15	jpn	-0.34	21.93	zho	-0.24	25.44	eng	0.25	51.2
16	fin	-0.35	18.42	**hau**	-0.24	38.60	cym	0.22	48.8
17	cym	-0.36	18.42	fra	-0.25	36.84	mya	0.22	45.6
18	heb	-0.37	22.81	tel	-0.26	40.35	gle	0.21	46.4
19	eng	-0.39	23.68	ell	-0.30	39.47	jpn	0.20	40.0
20	bul	-0.42	19.30	deu	-0.31	41.23	fin	0.18	40.0
21	rus	-0.47	17.54	kor	-0.31	42.11	hun	0.17	40.8
22	**hau**	-0.50	16.67	swe	-0.32	41.23	est	0.16	47.2
23	yor	-0.50	14.91	spa	-0.32	30.70	spa	0.16	44.8
24	ell	-0.52	18.42	est	-0.34	38.60	deu	0.15	42.4
25	**kin**	-0.54	19.30	**pms**	-0.43	29.82	nep	0.13	44.0
26	gle	-0.55	16.67	fin	-0.50	29.82	bre	0.13	40.0
27	fra	-0.56	20.18	hun	-0.54	28.07	**hau**	0.12	42.4
28	ara	-0.57	19.30	**kin**	-0.56	28.95	kor	-0.02	44.0
29	spa	-0.66	17.54	**kmr**	-0.57	28.07	**pcm**	-0.04	38.4
30	hun	-0.66	14.91	**pcm**	-0.70	16.67	**wol**	-0.11	36.8
31	**bam**	-0.74	15.79	jpn	-0.72	32.46	**ibo**	-0.12	36.0
32	**kmr**	-0.85	19.30	**mos**	-0.84	28.07	**gub**	-0.17	36.0
33	**mos**	-0.90	18.42	**ewe**	-0.88	21.93	**mos**	-0.19	32.0
34	**gub**	-0.95	15.79	**bam**	-0.89	20.18	zho	-0.20	30.4
35	**ibo**	-1.22	14.91	yor	-0.90	26.32	yor	-0.20	37.6
36	**wol**	-1.40	14.91	**wol**	-0.97	22.81	**ewe**	-0.32	30.4
37	**pcm**	-1.55	10.53	**ibo**	-1.00	23.68	**kin**	-0.34	29.6
38	**ewe**	-1.83	14.04	**gub**	-1.05	20.18	**bam**	-0.41	32.0

Table 16: Transfer Languages ranked by aggregated transfer scores (ts) overall target languages across token classification tasks using XLM-R. Languages unseen by mBERT are in **bold** font.

Transfer Languages Ranking using mBERT (Sentence Classification & QA)									
Rank	**XNLI**			**ANLI**			**TyDiQA**		
	Lang	ts	+(%)	lang	ts	+(%)	lang	ts	+(%)
1	**hau**	-34.42	0.0	**bam**	-14.97	0.0	zho	0.67	77.78
2	**bam**	-34.85	0.0	**hau**	-17.82	0.0	jpn	0.08	44.44
3	**gub**	-36.40	0.0	**gub**	-18.35	0.0	gle	-0.08	44.44
4	**ewe**	-36.73	0.0	deu	-19.79	0.0	**wol**	-0.12	44.44
5	hin	-37.08	0.0	fin	-19.93	0.0	cym	-0.14	33.33
6	deu	-37.33	0.0	hun	-20.01	0.0	mya	-0.15	22.22
7	kor	-37.86	0.0	kor	-20.15	0.0	**mos**	-0.15	44.44
8	spa	-38.17	0.0	zho	-20.20	0.0	hun	-0.19	22.22
9	**kmr**	-38.25	0.0	hin	-20.27	0.0	fin	-0.19	44.44
10	fin	-38.32	0.0	**pms**	-20.28	0.0	**kin**	-0.22	33.33
11	rus	-38.34	0.0	yor	-20.37	0.0	est	-0.25	33.33
12	**pms**	-38.35	0.0	**kin**	-20.63	0.0	hye	-0.25	33.33
13	hun	-38.57	0.0	spa	-20.66	0.0	tel	-0.26	33.33
14	heb	-38.72	0.0	mya	-20.68	0.0	eng	-0.28	33.33
15	swe	-38.86	0.0	heb	-20.68	0.0	ell	-0.29	22.22
16	est	-38.86	0.0	**ewe**	-20.74	0.0	**ewe**	-0.30	33.33
17	gle	-38.87	0.0	rus	-20.74	0.0	yor	-0.30	33.33
18	bul	-38.90	0.0	est	-20.91	0.0	heb	-0.33	22.22
19	fra	-38.91	0.0	swe	-20.93	0.0	**pms**	-0.34	22.22
20	yor	-38.94	0.0	gle	-20.99	0.0	tam	-0.38	22.22
21	ell	-39.24	0.0	bul	-21.07	0.0	ben	-0.39	22.22
22	**kin**	-39.37	0.0	ell	-21.10	0.0	bul	-0.41	33.33
23	zho	-39.44	0.0	ara	-21.11	0.0	deu	-0.41	22.22
24	ara	-39.50	0.0	**kmr**	-21.11	0.0	**gub**	-0.42	22.22
25	mya	-39.56	0.0	nep	-21.17	0.0	nep	-0.42	33.33
26	eng	-39.74	0.0	fra	-21.22	0.0	swe	-0.43	33.33
27	hye	-40.04	0.0	eng	-21.28	0.0	kor	-0.45	22.22
28	bre	-40.07	0.0	cym	-21.39	0.0	hin	-0.47	22.22
29	cym	-40.13	0.0	jpn	-21.43	0.0	bre	-0.48	11.11
30	nep	-40.25	0.0	tam	-21.45	0.0	ara	-0.51	33.33
31	tel	-40.31	0.0	tel	-21.51	0.0	**ibo**	-0.57	33.33
32	ben	-40.31	0.0	hye	-21.62	0.0	**bam**	-0.61	22.22
33	jpn	-40.53	0.0	bre	-21.65	0.0	**kmr**	-0.62	33.33
34	**mos**	-41.04	0.0	**mos**	-21.65	0.0	spa	-0.66	22.22
35	tam	-41.04	0.0	**wol**	-22.23	0.0	rus	-0.67	22.22
36	**wol**	-42.67	0.0	**pcm**	-22.24	0.0	**hau**	-0.89	22.22
37	**pcm**	-43.37	0.0	**ibo**	-22.36	0.0	fra	-1.04	11.11
38	**ibo**	-44.78	0.0	ben	-23.37	0.0	**pcm**	-1.10	22.22

Table 17: Transfer Languages ranked by aggregated transfer scores (ts) overall target languages across Sentence Classification & QA tasks using mBERT. Languages unseen by mBERT are in **bold** font.

Transfer Languages Ranking using mBERT (Sentence Classification & QA)									
Rank	**XNLI**			**ANLI**			**TyDiQA**		
	Lang	ts	+(%)	lang	ts	+(%)	lang	ts	+(%)
1	**ewe**	0.44	93.33	hin	2.25	100.0	**pcm**	-0.42	55.56
2	bre	0.36	93.33	ell	1.34	80.0	ell	-0.44	22.22
3	**bam**	0.30	93.33	nep	1.33	100.0	fin	-0.46	44.44
4	**pcm**	0.30	93.33	ara	1.31	80.0	zho	-0.47	44.44
5	**ibo**	0.28	80.00	swe	1.31	100.0	heb	-0.47	11.11
6	rus	0.22	73.33	tam	1.03	70.0	**ewe**	-0.51	55.56
7	**wol**	0.20	80.00	bul	0.93	70.0	tam	-0.52	11.11
8	**hau**	0.13	73.33	fra	0.73	70.0	eng	-0.53	33.33
9	heb	0.08	66.67	hun	0.39	60.0	hin	-0.55	22.22
10	**kmr**	0.08	66.67	cym	0.36	60.0	fra	-0.56	33.33
11	**pms**	0.06	60.00	deu	0.25	60.0	tel	-0.56	11.11
12	jpn	0.05	60.00	eng	0.17	70.0	deu	-0.64	11.11
13	zho	0.05	60.00	tel	0.13	60.0	swe	-0.67	11.11
14	bul	0.03	53.33	fin	0.10	40.0	nep	-0.67	11.11
15	fra	-0.00	53.33	spa	-0.08	60.0	hun	-0.69	11.11
16	spa	-0.01	46.67	kor	-0.10	50.0	est	-0.70	22.22
17	mya	-0.04	53.33	rus	-0.10	50.0	**kmr**	-0.71	44.44
18	**kin**	-0.04	40.00	heb	-0.10	50.0	rus	-0.72	0.00
19	hye	-0.05	53.33	est	-0.14	60.0	gle	-0.73	22.22
20	deu	-0.09	33.33	mya	-0.14	40.0	**hau**	-0.77	22.22
21	eng	-0.11	33.33	ben	-0.19	50.0	ben	-0.77	11.11
22	gle	-0.11	26.67	gle	-0.27	30.0	kor	-0.78	0.00
23	est	-0.11	33.33	**hau**	-0.48	60.0	spa	-0.79	0.00
24	**mos**	-0.11	40.00	zho	-1.00	0.0	bul	-0.81	0.00
25	swe	-0.12	33.33	**kmr**	-1.07	30.0	hye	-0.91	0.00
26	tel	-0.13	40.00	hye	-1.14	20.0	cym	-0.92	22.22
27	cym	-0.14	33.33	jpn	-1.32	10.0	**gub**	-1.02	11.11
28	ara	-0.18	26.67	**pcm**	-1.53	10.0	**wol**	-1.02	11.11
29	ben	-0.20	20.00	bre	-2.10	0.0	**ibo**	-1.03	33.33
30	**gub**	-0.23	13.33	**gub**	-2.19	20.0	ara	-1.08	0.00
31	nep	-0.23	20.00	**pms**	-2.60	0.0	**bam**	-1.12	11.11
32	kor	-0.36	6.67	yor	-2.88	0.0	**mos**	-1.15	11.11
33	hin	-0.39	6.67	**kin**	-4.28	0.0	jpn	-1.15	0.00
34	ell	-0.45	0.00	**mos**	-4.54	10.0	bre	-1.19	11.11
35	yor	-0.45	13.33	**bam**	-4.87	0.0	**pms**	-1.22	0.00
36	fin	-0.46	6.67	**wol**	-5.01	0.0	**kin**	-1.30	11.11
37	tam	-0.47	6.67	**ewe**	-5.02	10.0	mya	-1.49	0.00
38	hun	-0.70	0.00	**ibo**	-5.95	0.0	yor	-1.57	11.11

Table 18: Transfer Languages ranked by aggregated transfer scores (ts) overall target languages across Sentence Classification & QA tasks using XLM-R. Languages unseen by mBERT are in **bold** font.

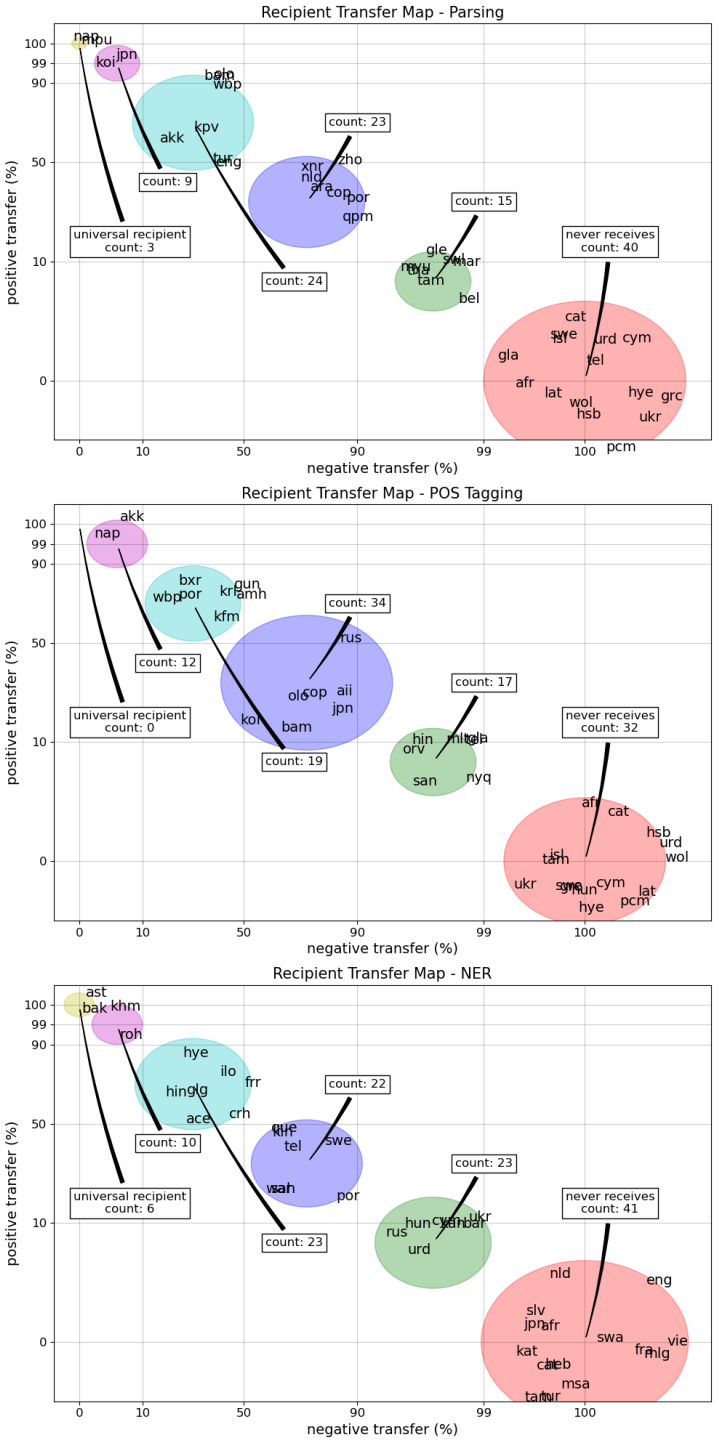


Figure 5: Recipient Transfer Map: we observe universal positive recipients as well as languages those never receive positive transfer across tasks. Circle size represents the percentage of languages fall to a transfer range.

Tasks	Never Receives	Positive Transfer (%) (90-99]	Universal Recipient
Dependency Parsing	ell, isl, **grc**, **mlt**, fra, **qtd**, hrv, lav, **urb**, **fas**, ukr, spa, cym, tel, **pcm**, afr, swe, est, **nor**, **hsb**, **orv**, cat, slv, **chu**, **sme**, eus, slk, hye, **gla**, urd, hin, **fro**, lit, lat, **san**, **wol**, **lij**, **got**, srp, **lzh**	**tpn**, **koi**, **glv**, kor, **krl**, **mdf**, jpn, **amh**, sqi	**mpu**, **gun**, **nap**
POS Tagging	ell, nld, isl, **grc**, lav, **fas**, ukr, spa, cym, hun, **pcm**, afr, swe, est, **nor**, **hsb**, tam, cat, **chu**, **sme**, eus, hye, urd, ben, ita, ron, lit, lat, **wol**, **got**, srp, **lzh**	fra, eng, **qhe**, dan, **myu**, **glv**, kor, tur, kaz, **akk**, **myv**, **nap**	
NER	nld, ell, tgl, fra, ces, bul, zho, msa, sun, lav, gle, **fas**, kat, spa, heb, hbs, afr, est, **yid**, eng, tam, bre, vie, jpn, cat, **tha**, slv, ceb, tur, mlg, slk, swa, ben, uzb, ita, ron, tat, pol, **zea**, **lin**, **ibo**	**ksh**, **pms**, aze, **mzn**, **oci**, tgk, **roh**, **khm**, **aym**, **csb**	bak, ast, **uig**, kaz, nds, **amh**

Table 19: We find 25 languages out of 40 which receives positive transfer from almost any transfer languages (i.e. column 90-99% and 100%) are unseen by mbert. (language codes in **bold** font are the unseen ones)

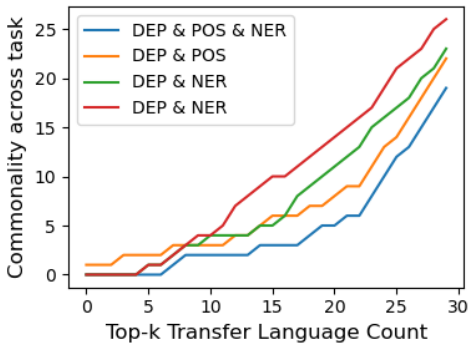


Figure 6: Extent of commonality of top-transfer languages across task. Unseen languages perform generally well while the other language rankings mostly vary across tasks.

`aggregated-transfer` score variance. We observe, the unseen languages (bold font) are the ones having large amount of variances across all three tasks. We find the languages with high variance can provide superior transfer for some languages but at the same time hurt significantly some other languages. For example, if we consider the case of depndency parsing, we find ibo (rank-1) and bam (rank-3) are two languages with high variance. They provide maximum amount of positive transfer some universal low-resourced target languages like akk, koi, apu, tpn from diverse families including afro-asiatic, uralic, tupian. At the same time, ibo also hurts a large number of languages (10) including fra, nyq, sme, san etc providing minimum amount of negative transfer. On the other hand, there can be languages with high variance providing either mostly positive `aggregated-transfer` scores like mos or mostly negative score like pcm. Interestingly, if we look at the `aggregated-transfer` score and variance of pcm in Table 22, we find the transfer is positive overall. Nevertheless it provides minimum negative scores to 11 languages thus making it a transfer language with high variance. On the other

Transfer	Parsing				POS Tagging				NER			
Language	1	10	100	1000	1	10	100	1000	1	10	100	1000
gub	mpu	mpu	gun	**gub**	aqz	nap	nap	**nap**	amh	amh	**amh**	bar
est	nap	tpn	gun	**gun**	nap	nap	nap	**nap**	amh	amh	**amh**	som
bre	nap	nap	gun	**gun**	nap	nap	nap	**nap**	amh	amh	**amh**	amh
eng	nap	mpu	gun	**gun**	nap	nap	nap	**nap**	amh	sin	**amh**	nds
ben	nap	nap	nap	**gun**	cop	nap	nap	**nap**	amh	sin	amh	**amh**
kmr	nap	mpu	gun	**kmr**	urb	nap	nap	**nap**	amh	amh	**amh**	amh
spa	nap	mpu	gun	**gun**	nap	nap	**nap**	nap	amh	amh	**amh**	roh
bul	nap	nap	nap	**gun**	nap	nap	nap	**amh**	amh	amh	**amh**	som
pms	nap	**nap**	nap	mpu	nap	nap	nap	**nap**	amh	amh	**amh**	amh
gle	nap	nap	mpu	**gun**	aqz	nap	nap	**nap**	amh	amh	**amh**	som
nep	nap	tpn	gun	**gun**	aqz	urb	nap	**nap**	amh	sin	**amh**	roh
cym	nap	nap	gun	**gun**	nap	nap	nap	**amh**	amh	**sin**	amh	som
fin	nap	nap	tpn	**gun**	nap	nap	nap	**nap**	amh	sin	**amh**	som
hye	nap	nap	nap	**gun**	nap	nap	nap	**nap**	uig	sin	**amh**	som
mya	nap	nap	wbp	**gun**	aqz	urb	nap	**nap**	amh	amh	**amh**	amh
hin	nap	tpn	gun	**gun**	aqz	aqz	nap	**nap**	amh	amh	**amh**	som
tel	nap	nap	gun	**gun**	aqz	nap	nap	**amh**	amh	sin	**amh**	roh
tam	nap	nap	gun	**gun**	nap	nap	nap	**nap**	amh	sin	**amh**	som
kor	tpn	mpu	mpu	**tpn**	nap	nap	nap	**nap**	amh	amh	**amh**	roh
ell	nap	tpn	nap	**gun**	nap	nap	nap	**nap**	amh	amh	**amh**	som
hun	nap	mpu	gun	**gun**	nap	nap	nap	**nap**	amh	amh	**amh**	som
heb	nap	nap	nap	**gun**	nap	nap	nap	**nap**	amh	amh	**amh**	som
zho	tpn	nap	nap	**mpu**	nap	nap	nap	**nap**	amh	amh	**amh**	amh
ara	nap	nap	gun	**gun**	nap	nap	nap	**nap**	uig	amh	**amh**	amh
swe	nap	nap	gun	**gun**	nap	nap	nap	**nap**	amh	sin	**amh**	som
jpn	nap	mpu	mpu	**tpn**	nap	nap	nap	**nap**	amh	amh	amh	**amh**
fra	nap	mpu	gun	**gun**	nap	nap	nap	**nap**	amh	amh	**amh**	som
deu	tpn	mpu	gun	**gun**	nap	nap	nap	**nap**	amh	amh	**amh**	som
rus	nap	nap	gun	**gun**	nap	nap	**nap**	nap	amh	sin	**amh**	roh
bam	mpu	wbp	**wbp**	gun	nap	**nap**	amh	bam	amh	uig	amh	**amh**
ewe	nap	gun	tpn	**gun**	nap	**nap**	amh	nap	amh	sin	**amh**	nds
hau	mpu	nap	gun	**gun**	aqz	**nap**	nap	amh	amh	sin	amh	**amh**
ibo	tpn	mpu	gun	**gun**	aqz	**nap**	nap	mpu	sin	amh	amh	**amh**
kin	mpu	**nap**	nap	tpn	nap	nap	nap	**nap**	amh	amh	**amh**	amh
mos	mpu	aqz	gun	**gun**	nap	**nap**	amh	nap	sin	sin	**amh**	amh
pcm	nap	nap	wbp	**gun**	kfm	nap	nap	**nap**	amh	amh	**amh**	amh
wol	nap	aqz	gun	**gun**	nap	nap	nap	**amh**	amh	sin	**amh**	nds
yor	nap	nap	wbp	**gun**	nap	nap	nap	**nap**	amh	amh	**amh**	som

Table 20: Only bar and nds are seen by mbert. All other languages receiving maximum benefits continuously are unseen by mbert (kfm, urb, gun, aqz, cop, roh, bam, tpn, som, kmr, uig, mpu, amh, sin, wbp, gub, nap). The maximum score across different steps of training are **bolded**.

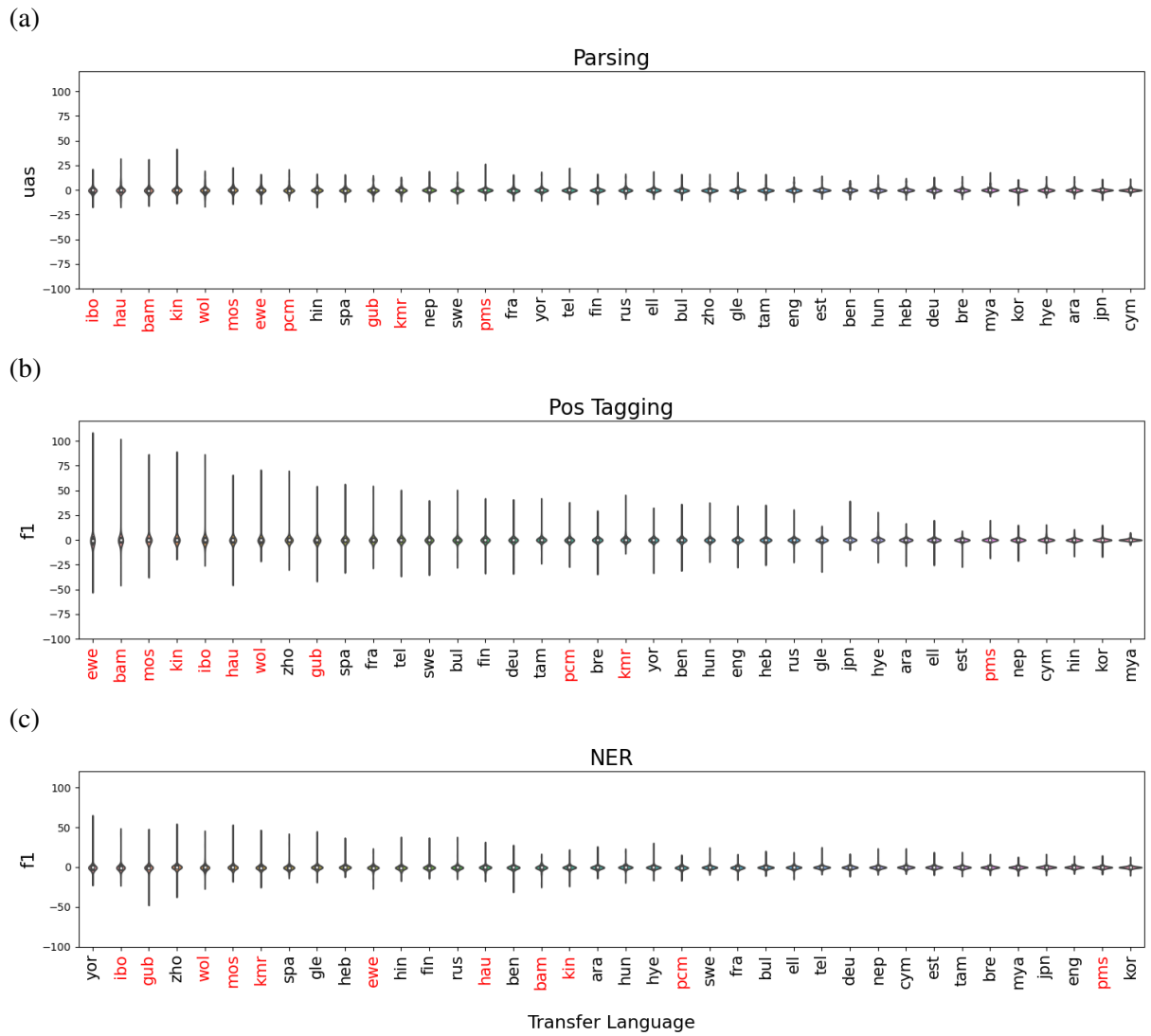


Figure 7: Violin plots of transfer languages sorted by transfer score variance. mBERT unseen languages are in red color font.

	DEP	POS	NER
DEP	-	**(-0.34, 0.04)**	**(0.40, 0.01)**
POS Tagging	**(-0.34, 0.04)**	-	(-0.15, 0.37)
NER	**(0.40, 0.01)**	(-0.15, 0.37)	-)

Table 21: (Spearman Rank correlation, p value) for correlation of transfer language ranking across token-classification tasks. Statistically significant relations are in **bold** font.

hand, low variance languages are the ones those do not significantly affect any transfer languages like arabic (rank 37). Though the overall transfer score is negative (-0.12) for arabic, it fails to provide maximum or minimum transfer score to any target language making it neutral. So, overall it is evident that, transfer languages with high variance are the ones with either (i) mostly positive while significantly hurting a few, (ii) mostly negative while significantly boosting performance for a few, or (iii) Performing both (i) and (ii) concurrently being highly influential as well as detrimental at the same time. Languages unseen by mBERT during pretraining exhibit all three kinds of characteristics with high intensity (see Table 23 for examples). In Table 22, we report the transfer score with variance as well as the count of maximum/minimum transfer score recipients for all transfer languages across tasks.

M Seen vs Unseen Languages

In Figure 8, we report the aggregated and averaged transfer scores we get for mBERT seen vs unseen languages.

Rank	Parsing			POS Tagging			NER		
	Lang	Transfer (Var.)	(Max, Min) #	Lang	Transfer (Var.)	(Max, Min) #	Lang	Transfer (Var.)	(Max, Min) #
1	**ibo**	0.05 (23.5)	(10, 10)	**ewe**	-0.79 (120.4)	(5, 31)	yor	-0.32 (44.4)	(2, 6)
2	**hau**	0.04 (22.7)	(2, 2)	**bam**	-0.12 (101.2)	(5, 0)	**ibo**	-0.54 (42.0)	(3, 18)
3	**bam**	0.02 (21.5)	(11, 15)	**mos**	0.27 (69.8)	(4, 3)	**gub**	-0.98 (41.2)	(3, 14)
4	**kin**	-0.06 (21.4)	(3, 1)	**kin**	0.41 (69.1)	(3, 0)	zho	0.16 (32.7)	(46, 3)
5	**wol**	0.03 (17.6)	(5, 6)	**ibo**	-0.14 (68.0)	(5, 10)	**wol**	-0.41 (32.4)	(5, 6)
6	**mos**	0.09 (16.1)	(13, 2)	**hau**	-0.34 (52.5)	(1, 3)	**mos**	0.0 (29.5)	(2, 1)
7	**ewe**	-0.08 (14.5)	(4, 5)	**wol**	-0.14 (51.9)	(8, 10)	**kmr**	-0.61 (25.6)	(3, 8)
8	**pcm**	0.13 (13.4)	(1, 11)	zho	-0.04 (45.6)	(26, 7)	spa	-0.28 (24.5)	(1, 1)
9	hin	-0.1 (13.1)	(4, 3)	**gub**	-0.34 (41.3)	(3, 4)	gle	-0.07 (21.1)	(1, 1)
10	spa	-0.18 (11.5)	(2, 3)	spa	-0.53 (39.6)	(0, 2)	heb	0.04 (21.1)	(3, 0)
11	**gub**	-0.14 (10.7)	(5, 3)	fra	-0.41 (37.2)	(2, 6)	**ewe**	-0.76 (19.0)	(0, 5)
12	**kmr**	0.14 (10.2)	(0, 1)	tel	-0.31 (36.6)	(0, 1)	hin	-0.72 (18.6)	(1, 12)
13	nep	0.12 (10.1)	(8, 1)	swe	-0.66 (32.2)	(1, 3)	fin	-0.29 (18.3)	(0, 1)
14	swe	-0.21 (10.0)	(0, 2)	bul	-0.08 (28.9)	(0, 0)	rus	-0.34 (17.4)	(0, 1)
15	**pms**	0.09 (9.7)	(3, 1)	fin	-0.35 (28.9)	(0, 1)	**hau**	-0.07 (17.1)	(7, 0)
16	fra	-0.37 (9.1)	(1, 8)	deu	-0.44 (26.0)	(0, 0)	ben	-0.54 (17.0)	(4, 3)
17	yor	0.14 (8.9)	(3, 3)	tam	-0.14 (22.9)	(0, 0)	**bam**	-0.69 (16.1)	(4, 1)
18	tel	0.05 (8.7)	(1, 2)	**pcm**	-0.16 (22.1)	(3, 14)	**kin**	-0.56 (13.2)	(1, 3)
19	fin	-0.26 (8.6)	(1, 1)	bre	-0.39 (21.4)	(1, 0)	ara	-0.32 (13.1)	(0, 1)
20	rus	0.11 (8.5)	(0, 1)	**kmr**	0.36 (21.2)	(11, 6)	hun	0.08 (12.2)	(2, 0)
21	ell	0.15 (8.3)	(1, 0)	yor	-0.16 (21.0)	(1, 1)	hye	-0.17 (12.1)	(0, 1)
22	bul	-0.21 (6.9)	(1, 1)	ben	-0.08 (20.6)	(3, 2)	**pcm**	-0.69 (11.8)	(6, 25)
23	zho	-0.48 (6.9)	(5, 10)	hun	-0.29 (20.4)	(3, 1)	swe	-0.11 (10.1)	(0, 0)
24	gle	0.03 (6.8)	(1, 1)	eng	-0.35 (18.8)	(2, 1)	fra	-0.59 (9.5)	(0, 5)
25	tam	-0.24 (6.7)	(1, 3)	heb	-0.26 (17.3)	(0, 1)	bul	-0.18 (9.0)	(0, 1)
26	eng	-0.22 (6.4)	(0, 0)	rus	-0.28 (15.3)	(0, 0)	ell	-0.29 (8.8)	(1, 1)
27	est	0.0 (6.1)	(1, 1)	gle	-0.34 (13.7)	(0, 2)	tel	0.08 (8.6)	(1, 0)
28	ben	-0.06 (6.0)	(3, 1)	jpn	0.18 (13.6)	(11, 0)	deu	-0.2 (8.4)	(0, 0)
29	hun	-0.23 (5.9)	(0, 2)	hye	0.27 (12.8)	(2, 0)	nep	-0.13 (8.1)	(1, 1)
30	heb	0.08 (5.8)	(0, 1)	ara	-0.3 (11.7)	(0, 0)	cym	0.03 (7.8)	(2, 1)
31	deu	-0.13 (5.7)	(1, 4)	ell	-0.13 (11.1)	(1, 0)	est	0.03 (7.8)	(0, 0)
32	bre	-0.23 (5.7)	(1, 1)	est	-0.35 (9.1)	(1, 1)	tam	0.0 (7.1)	(3, 0)
33	mya	0.33 (5.6)	(9, 0)	**pms**	0.08 (8.8)	(2, 0)	bre	-0.23 (5.6)	(1, 0)
34	kor	-0.38 (5.6)	(0, 1)	nep	0.12 (8.4)	(6, 0)	mya	-0.17 (5.3)	(5, 2)
35	hye	-0.03 (5.4)	(0, 2)	cym	0.22 (6.7)	(0, 0)	jpn	-0.08 (5.3)	(4, 1)
36	ara	-0.12 (5.1)	(0, 0)	hin	-0.13 (6.4)	(0, 3)	eng	0.02 (5.1)	(5, 1)
37	jpn	-0.19 (3.9)	(14, 2)	kor	-0.07 (5.8)	(1, 0)	**pms**	-0.29 (5.0)	(1, 0)
38	cym	-0.03 (2.9)	(1, 3)	mya	0.17 (2.7)	(3, 1)	kor	-0.09 (4.4)	(7, 1)

Table 22: Transfer languages are sorted by transfer score variance (mBERT unseen languages are in **bold** font). # Max Transfer and # Min Transfer denote the count of target languages which receive maximum and minimum transfer from this particular transfer language.

N Transfer Progression Graphs

From Figure 9 to 18, we present the transfer progression graphs for all 38 transfer languages. We observe POS tagging always have comparatively larger deviation which increase with the progression of training steps. In addition, for different time steps in each graph, we provide percentage of positive/negative transfers and the top performing target languages. This way, we observe top target languages that can get continuous improvement for each transfer language even after thousands of steps.

Type	Transfer Language	Variance	max(+)→	min(-)→
(+ *and* -)	ibo	high	aii, ajp, apu, arr, ces, gle, gub, koi, krl, yor	grc, hsb, hye, kfm, otk, san, sme, sqi, srp, urb
(+ *and* -)	bam	high	bho, bam, bre, bxr, kfm, kmr, kpv, mpu, rus, soj, wbp	ajp, ara, chu, gla, got, krl, lzh, nld, orv, qpm, qtd, swl, tha, tgl, zho
(+)	mos	high	aqz, bel, bul, eng, ind, ita, kaz, lit, myv, pol, tam, tgl, ukr	arr, wbp
(-)	pcm	high	tha	aii, bho, ell, eng, eus, hrv, isl, lat, lit, nor, qhe
neutral	eng	low	-	-
neutral	ara	low	-	-

Table 23: Characteristics of example transfer languages with different intensity of variance derived from dependency parsing task results. max(+)→ represents set of target language which receive maximum score for the specific transfer language wheres, min(-)→ represents the complete oposite.

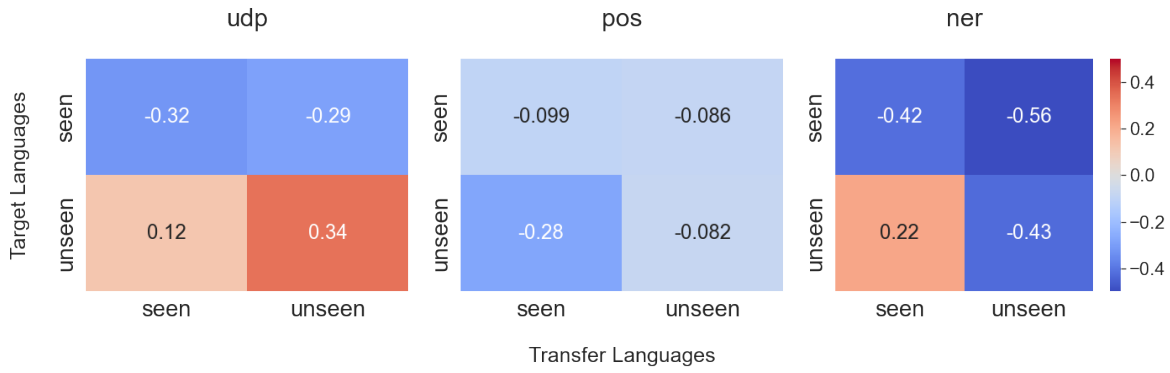


Figure 8: Transfer-Target Heatmap for mbert seen and unseen languages

Language	iso-639	Family	Genus	Script	mBERT-seen?
Hebrew	heb	Afro-Asiatic	Semitic	Hebr	
Arabic	ara	Afro-Asiatic	Semitic	Arab	
Hausa	hau	Afro-Asiatic	West Chadic	Latn	✗
Telugu	tel	Dravidian	Dravidian	Telu	
Tamil	tam	Dravidian	Dravidian	Taml	
Armenian	hye	Indo-European	Armenian	Armn	
Breton	bre	Indo-European	Celtic	Latn	
Irish	gle	Indo-European	Celtic	Latn	
Welsh	cym	Indo-European	Celtic	Latn	
English	eng	Indo-European	Germanic	Latn	
Swedish	swe	Indo-European	Germanic	Latn	
German	deu	Indo-European	Germanic	Latn	
Modern Greek (1453-)	ell	Indo-European	Greek	Grek	
Bengali	ben	Indo-European	Indic	Beng	
Nepali (macrolanguage)	nep	Indo-European	Indic	Deva	
Hindi	hin	Indo-European	Indic	Deva	
Northern Kurdish	kmr	Indo-European	Iranian	Arab	✗
French	fra	Indo-European	Romance	Latn	
Spanish	spa	Indo-European	Romance	Latn	
Piemontese	pms	Indo-European	Romance	Latn	✗
Bulgarian	bul	Indo-European	Slavic	Cyrl	
Russian	rus	Indo-European	Slavic	Cyrl	
Japanese	jpn	Japanese	Japanese	Jpan	
Korean	kor	Korean	Korean	Kore	
Bambara	bam	Mande	Western Mande	Latn	✗
Kinyarwanda	kin	Niger-Congo	Bantu	Latn	✗
Yoruba	yor	Niger-Congo	Defoid	Latn	
Ewe	ewe	Niger-Congo	Gbe	Latn	✗
Igbo	ibo	Niger-Congo	Igboid	Latn	✗
Mossi	mos	Niger-Congo	Oti-Volta	Latn	✗
Wolof	wol	Niger-Congo	Wolof	Latn	✗
Burmese	mya	Sino-Tibetan	Burmese-Lolo	Mon–Burmese	
Chinese	zho	Sino-Tibetan	Chinese	Chinese	
Guajajára	gub	Tupian	Maweti-Guarani	Latn	✗
Estonian	est	Uralic	Finnic	Latn	
Finnish	fin	Uralic	Finnic	Latn	
Hungarian	hun	Uralic	Ugric	Latn	
Nigerian Pidgin	pcm	other	Creoles and Pidgins	Latn	✗

Table 24: Transfer Languages we use in our study for mBERT fine-tuning

UDP and POS Tagging Task Adapter Training Dataset						
Language	iso-639	UD Identifier	# Examples	Family	Genus	Script
Coptic	cop	cop_scriptorium	403	Afro-Asiatic	Egyptian-Coptic	Coptic
Arabic	ara	ar_nyuad	1963	Afro-Asiatic	Semitic	Arab
Hebrew	heb	he_htb	491	Afro-Asiatic	Semitic	Hebr
Maltese	mlt	mt_mudt	518	Afro-Asiatic	Semitic	Latn
Kazakh	kaz	kk_ktb	1047	Altaic	Turkic	Cyrl
Turkish	tur	tr_gb	2880	Altaic	Turkic	Latn
Uighur	uig	ug_udt	900	Altaic	Turkic	Uighur
Vietnamese	vie	vi_vtb	800	Austro-Asiatic	Vietic	Latn
Indonesian	ind	id_pud	1000	Austronesian	Malayo-Sumbawan	Latn
Basque	eus	eu_bdt	1799	Basque	Basque	Latn
Turkish German	qtd	qtd_sagt	805	Code switching	Code switching	Latn
Tamil	tam	ta_mwtt	534	Dravidian	Dravidian	Taml
Telugu	tel	te_mtg	146	Dravidian	Dravidian	Telu
Armenian	hye	hy_armtdp	278	Indo-European	Armenian	Armn
Latvian	lav	lv_lvtb	1823	Indo-European	Baltic	Latn
Lithuanian	lit	lt_alksnis	684	Indo-European	Baltic	Latn
Welsh	cym	cy_ccg	953	Indo-European	Celtic	Latn
Scottish Gaelic	gla	gd_arcosg	538	Indo-European	Celtic	Latn
Irish	gle	ga_idt	454	Indo-European	Celtic	Latn
Gothic	got	got_proiel	1029	Indo-European	Germanic	Gothic
Afrikaans	afr	af_afribooms	425	Indo-European	Germanic	Latn
Danish	dan	da_ddt	565	Indo-European	Germanic	Latn
German	deu	de_hdt	18459	Indo-European	Germanic	Latn
English	eng	en_ewt	2077	Indo-European	Germanic	Latn
Faroese	fao	fo_oft	1208	Indo-European	Germanic	Latn
Icelandic	isl	is_icepahc	5157	Indo-European	Germanic	Latn
Dutch	nld	nl_lassysmall	875	Indo-European	Germanic	Latn
Norwegian	nor	no_bokmaal	1939	Indo-European	Germanic	Latn
Swedish	swe	sv_talbanken	1219	Indo-European	Germanic	Latn
Modern Greek (1453-)	ell	el_gdt	456	Indo-European	Greek	Grek
Ancient Greek (to 1453)	grc	grc_perseus	1306	Indo-European	Greek	Grek
Urdu	urd	ur_udtb	535	Indo-European	Indic	Arab
Sanskrit	san	sa_vedic	1473	Indo-European	Indic	Brahmi
Hindi	hin	hi_hdtb	1684	Indo-European	Indic	Deva
Marathi	mar	mr_ufal	47	Indo-European	Indic	Deva
Persian	fas	fa_perdt	1455	Indo-European	Iranian	Arab
Northern Kurdish	kmr	kmr_mg	734	Indo-European	Iranian	Arab
Latin	lat	la_ittb	2101	Indo-European	Italic	Latn
Catalan	cat	ca_ancora	1846	Indo-European	Romance	Latn
French	fra	fr_ftb	2541	Indo-European	Romance	Latn
Old French (842-ca. 1400)	fro	fro_srcmf	1927	Indo-European	Romance	Latn
Galician	glg	gl_ctg	861	Indo-European	Romance	Latn
Italian	ita	it_vit	1067	Indo-European	Romance	Latn
Portuguese	por	pt_gsd	1204	Indo-European	Romance	Latn
Romanian	ron	ro_nonstandard	1052	Indo-European	Romance	Latn
Spanish	spa	es_ancora	1721	Indo-European	Romance	Latn
Belarusian	bel	be_hse	889	Indo-European	Slavic	Cyrl
Bulgarian	bul	bg_btb	1116	Indo-European	Slavic	Cyrl
Old Russian	orv	orv_torot	1756	Indo-European	Slavic	Cyrl
Russian	rus	ru_syntagrus	6491	Indo-European	Slavic	Cyrl
Serbian	srp	sr_set	520	Indo-European	Slavic	Cyrl
Ukrainian	ukr	uk_iu	892	Indo-European	Slavic	Cyrl
Church Slavic	chu	cu_proiel	1141	Indo-European	Slavic	Glag+Latn
Czech	ces	cs_pdt	10148	Indo-European	Slavic	Latn
Croatian	hrv	hr_set	1136	Indo-European	Slavic	Latn
Upper Sorbian	hsb	hsb_ufal	623	Indo-European	Slavic	Latn
Polish	pol	pl_pdb	2215	Indo-European	Slavic	Latn
Pomak	qpm	qpm_philotis	635	Indo-European	Slavic	Latn
Slovak	slk	sk_snk	1061	Indo-European	Slavic	Latn
Slovenian	slv	sl_sst	1110	Indo-European	Slavic	Latn
Japanese	jpn	ja_bccwj	7871	Japanese	Japanese	Jpan
Korean	kor	ko_kaist	2287	Korean	Korean	Kore
Russia Buriat	bxr	bxr_bdt	908	Mongolic	Altic	Cyrl
Wolof	wol	wo_wtb	470	Niger-Congo	Wolof	Latn
Cusco Quechua	qhe	qhe_hiencs	225	Quechuan	Quechuan	Latn
Literary Chinese	lzh	lzh_kyoto	4469	Sino-Tibetan	Chinese	Chinese
Chinese	zho	zh_hk	1004	Sino-Tibetan	Chinese	Chinese
Estonian	est	et_edt	3214	Uralic	Finnic	Latn
Finnish	fin	fi_ood	2122	Uralic	Finnic	Latn
Livvi	olo	olo_kkpp	106	Uralic	Finnic	Latn
Northern Sami	sme	sme_giella	865	Uralic	Saami	Latn
Hungarian	hun	hu_szeged	449	Uralic	Ugric	Latn
Nigerian Pidgin	pcm	pcm_nsc	972	other	Creoles and Pidgins	Latn
Swedish Sign Language	swl	swl_sslc	34	other	Sign Languages	

Table 25: Task Adapter training dataset details (taken from Universal Dependency v2.11 (de Marneffe et al., 2021)) for dependency parsing and pos tagging.

NER Task Adapter Training Dataset

Language	iso-639	Family	Genus	Script
Somali	som	Afro-Asiatic	Lowland East Cushitic	Latn
Arabic	ara	Afro-Asiatic	Semitic	Arab
Amharic	amh	Afro-Asiatic	Semitic	Ethi
Hebrew	heb	Afro-Asiatic	Semitic	Hebr
Maltese	mlt	Afro-Asiatic	Semitic	Latn
Mongolian	mon	Altaic	Mongolic	Mongolian
Bashkir	bak	Altaic	Turkic	Cyrl
Chuvash	chv	Altaic	Turkic	Cyrl
Kazakh	kaz	Altaic	Turkic	Cyrl
Yakut	sah	Altaic	Turkic	Cyrl
Crimean Tatar	crh	Altaic	Turkic	Cyrl+Latn+Arab
Kirghiz	kir	Altaic	Turkic	Kyrgyz+Cyrl
Azerbaijani	aze	Altaic	Turkic	Latn
Tatar	tat	Altaic	Turkic	Latn
Turkmen	tuk	Altaic	Turkic	Latn
Turkish	tur	Altaic	Turkic	Latn
Uzbek	uzb	Altaic	Turkic	Latn
Uighur	uig	Altaic	Turkic	Uighur
Khmer	khm	Austro-Asiatic	Khmer	Khmer
Vietnamese	vie	Austro-Asiatic	Vietic	Latn
Malagasy	mlg	Austronesian	Barito	Latn
Cebuano	ceb	Austronesian	Greater Central Philippine	Latn
Tagalog	tgl	Austronesian	Greater Central Philippine	Latn
Waray (Philippines)	war	Austronesian	Greater Central Philippine	Latn
Javanese	jav	Austronesian	Javanese	Latn+Javanese
Achinese	ace	Austronesian	Malayo-Sumbawan	Latn
Malay (macrolanguage)	msa	Austronesian	Malayo-Sumbawan	Latn
Sundanese	sun	Austronesian	Malayo-Sumbawan	Latn
Iloko	ilo	Austronesian	Northern Luzon	Latn
Maori	mri	Austronesian	Oceanic	Latn
Aymara	aym	Aymaran	Aymaran	Latn
Basque	eus	Basque	Basque	Latn
Kannada	kan	Dravidian	Dravidian	Kannada
Malayalam	mal	Dravidian	Dravidian	Malayalam
Tamil	tam	Dravidian	Dravidian	Taml
Telugu	tel	Dravidian	Dravidian	Telu
Albanian	sqi	Indo-European	Albanian	Latn
Armenian	hye	Indo-European	Armenian	Armn
Latvian	lav	Indo-European	Baltic	Latn
Lithuanian	lit	Indo-European	Baltic	Latn
Breton	bre	Indo-European	Celtic	Latn
Welsh	cym	Indo-European	Celtic	Latn
Scottish Gaelic	gla	Indo-European	Celtic	Latn
Irish	gle	Indo-European	Celtic	Latn
Western Frisian	fry	Indo-European	Germanic	West Frisian
Afrikaans	afr	Indo-European	Germanic	Latn
Bavarian	bar	Indo-European	Germanic	Latn
Danish	dan	Indo-European	Germanic	Latn
German	deu	Indo-European	Germanic	Latn
English	eng	Indo-European	Germanic	Latn
Faroese	fao	Indo-European	Germanic	Latn
Northern Frisian	frr	Indo-European	Germanic	Latn
Icelandic	isl	Indo-European	Germanic	Latn
Kölsch	ksh	Indo-European	Germanic	Latn
Luxembourgish	ltz	Indo-European	Germanic	Latn
Low German	nds	Indo-European	Germanic	Latn
Dutch	nld	Indo-European	Germanic	Latn
Norwegian	nor	Indo-European	Germanic	Latn
Swedish	swe	Indo-European	Germanic	Latn
Yiddish	yid	Indo-European	Germanic	Latn
Zeeuws	zea	Indo-European	Germanic	Latn
Modern Greek (1453-)	ell	Indo-European	Greek	Grek
Sindhi	snd	Indo-European	Indic	Arab
Urdu	urd	Indo-European	Indic	Arab
Assamese	asm	Indo-European	Indic	Assamese
Bengali	ben	Indo-European	Indic	Beng
Hindi	hin	Indo-European	Indic	Deva
Marathi	mar	Indo-European	Indic	Deva
Nepali (macrolanguage)	nep	Indo-European	Indic	Deva
Gujarati	guj	Indo-European	Indic	Gujarati
Oriya (macrolanguage)	ori	Indo-European	Indic	Odia
Panjabi	pan	Indo-European	Indic	Shahmukh
Sinhala	sin	Indo-European	Indic	Sinhala
Dhivehi	div	Indo-European	Indic	Thaana
Persian	fas	Indo-European	Iranian	Arab
Ossetian	oss	Indo-European	Iranian	Cyrl
Tajik	tgk	Indo-European	Iranian	Cyrl+Latn
Kurdish	kur	Indo-European	Iranian	Latn+Sorani
Mazanderani	mzn	Indo-European	Iranian	Persian
Pushto	pus	Indo-European	Iranian	Pushto
Asturian	ast	Indo-European	Romance	Latn
Catalan	cat	Indo-European	Romance	Latn
French	fra	Indo-European	Romance	Latn
Galician	glg	Indo-European	Romance	Latn
Italian	ita	Indo-European	Romance	Latn
Ligurian	lij	Indo-European	Romance	Latn
Neapolitan	nap	Indo-European	Romance	Latn
Occitan (post 1500)	oci	Indo-European	Romance	Latn
Piemontese	pms	Indo-European	Romance	Latn
Portuguese	por	Indo-European	Romance	Latn
Romansh	roh	Indo-European	Romance	Latn
Romanian	ron	Indo-European	Romance	Latn
Spanish	spa	Indo-European	Romance	Latn
Belarusian	bel	Indo-European	Slavic	Cyrl
Bulgarian	bul	Indo-European	Slavic	Cyrl

Macedonian	mkd	Indo-European	Slavic	Cyrl
Russian	rus	Indo-European	Slavic	Cyrl
Ukrainian	ukr	Indo-European	Slavic	Cyrl
Czech	ces	Indo-European	Slavic	Latn
Kashubian	csb	Indo-European	Slavic	Latn
Serbo-Croatian	hbs	Indo-European	Slavic	Latn
Upper Sorbian	hsb	Indo-European	Slavic	Latn
Polish	pol	Indo-European	Slavic	Latn
Slovak	slk	Indo-European	Slavic	Latn
Slovenian	slv	Indo-European	Slavic	Latn
Japanese	jpn	Japanese	Japanese	Jpan
Georgian	kat	Kartvelian	Kartvelian	Georgian
Mingrelian	xmf	Kartvelian	Kartvelian	Latn
Korean	kor	Korean	Korean	Kore
Chechen	che	Nakh-Daghestanian	Nakh	Cyrl
Kinyarwanda	kin	Niger-Congo	Bantu	Latn
Lingala	lin	Niger-Congo	Bantu	Latn
Swahili (macrolanguage)	swa	Niger-Congo	Bantu	Latn
Yoruba	yor	Niger-Congo	Defoid	Latn
Igbo	ibo	Niger-Congo	Igboid	Latn
Quechua	que	Quechuan	Quechuan	Latn
Tibetan	bod	Sino-Tibetan	Bodic	Tibetan
Burmese	mya	Sino-Tibetan	Burmese-Lolo	Mon–Burmese
Chinese	zho	Sino-Tibetan	Chinese	Chinese
Thai	tha	Tai-Kadai	Kam-Tai	Thai
Guarani	grn	Tupian	Maweti-Guarani	Latn
Estonian	est	Uralic	Finnic	Latn
Finnish	fin	Uralic	Finnic	Latn
Veps	vep	Uralic	Finnic	Latn
Hungarian	hun	Uralic	Ugric	Latn

Table 26: Task Adapter training dataset details (taken from Wikiann (Pan et al., 2017)) for Named Entity Recognition.

NLI Task Adapter Training Dataset				
Language	iso-639	Family	Genus	Script
Arabic	ara	Afro-Asiatic	Semitic	Arab
Turkish	tur	Altaic	Turkic	Latn
Vietnamese	vie	Austro-Asiatic	Vietic	Latn
German	deu	Indo-European	Germanic	Latn
English	eng	Indo-European	Germanic	Latn
Modern Greek (1453-)	ell	Indo-European	Greek	Grek
Urdu	urd	Indo-European	Indic	Arab
Hindi	hin	Indo-European	Indic	Deva
French	fre	Indo-European	Romance	Latn
Spanish	spa	Indo-European	Romance	Latn
Bulgarian	bul	Indo-European	Slavic	Cyrl
Russian	rus	Indo-European	Slavic	Cyrl
Swahili (macrolanguage)	swa	Niger-Congo	Bantu	Latn
Chinese	zho	Sino-Tibetan	Chinese	Chinese
Thai	tha	Tai-Kadai	Kam-Tai	Thai

Table 27: Task Adapter training dataset details (taken from XNLI (Conneau et al., 2018)) for Natural Language Inference.

Extractive Question Answering Task Adapter Training Dataset				
Language	iso-639	Family	Genus	Script
Arabic	ara	Afro-Asiatic	Semitic	Arab
Indonesian	idn	Astronesian	Malay	Latn
Telugu	tel	Dravidian	Dravidian	Telu
English	eng	Indo-European	Germanic	Latn
Bengali	ben	Indo-European	Indic	Beng
Russian	rus	Indo-European	Slavic	Cyrl
Korean	kor	Korean	Korean	Kore
Swahili (macrolanguage)	swa	Niger-Congo	Bantu	Latn
Finnish	fin	Uralic	Finnic	Latn

Table 28: Task Adapter training dataset details (taken from TyDiQA (Clark et al., 2020)) for Extractive Question Answering.

Evaluation Languages							
	Language	iso-639	NER	UDP and POS	XNLI	ANLI	TyDiQA
1	Achinese	ace		X	X	X	X
2	Afrikaans	afr			X	X	X
3	Assyrian Neo-Aramaic	aii	X		X	X	X
4	South Levantine Arabic	ajp	X		X	X	X
5	Akkadian	akk	X		X	X	X
6	Amharic	amh			X	X	X
7	Apurinã	apu	X		X	X	X
8	Akuntsu	aqz	X		X	X	X
9	Arabic	ara			X	X	
10	Karo (Brazil)	arr	X			X	X
11	Assamese	asm		X	X	X	X
12	Asturian	ast		X	X	X	X
13	Aymara	aym		X	X		X
14	Azerbaijani	aze		X	X	X	X
15	Bashkir	bak		X	X	X	X
16	Bambara	bam	X		X	X	X
17	Bavarian	bar		X	X	X	X
18	Belarusian	bel			X	X	X
19	Bengali	ben			X	X	
20	Bhojpuri	bho	X		X	X	X
21	Tibetan	bod		X	X	X	X
22	Breton	bre			X	X	X
23	Bulgarian	bul			X	X	X
24	Russia Buriat	bxr	X			X	X
25	Catalan	cat			X	X	X
26	Cebuano	ceb		X	X	X	X
27	Czech	ces			X	X	X
28	Chechen	che		X	X	X	X
29	Church Slavic	chu	X		X	X	X
30	Chuvash	chv		X	X	X	X
31	Chukot	ckt	X		X	X	X
32	Coptic	cop	X		X	X	X
33	Crimean Tatar	crh		X	X	X	X
34	Kashubian	csb		X	X	X	X
35	Welsh	cym			X	X	X
36	Danish	dan			X	X	X
37	German	deu				X	X
38	Dhivehi	div		X	X	X	X
39	Modern Greek (1453-)	ell				X	X
40	English	eng				X	
41	Estonian	est			X	X	X
42	Basque	eus			X	X	X
43	Faroese	fao			X	X	X
44	Persian	fas			X	X	X
45	Finnish	fin			X	X	
46	French	fra				X	X
47	Old French (842-ca. 1400)	fro	X		X	X	X
48	Northern Frisian	frr		X	X	X	X
49	Western Frisian	fry		X	X	X	X
50	Scottish Gaelic	gla			X	X	X
51	Irish	gle			X	X	X
52	Galician	glg			X	X	X
53	Manx	glv	X		X	X	X
54	Gothic	got	X		X	X	X
55	Ancient Greek (to 1453)	grc	X		X	X	X
56	Guarani	grn		X	X		X
57	Swiss German	gsw	X		X	X	X
58	Guajajára	gub	X		X	X	X
59	Gujarati	guj		X	X	X	X
60	Mbyá Guaraní	gun	X		X	X	X
61	Serbo-Croatian	hbs		X	X	X	X
62	Hebrew	heb			X	X	X
63	Hindi	hin				X	X
64	Croatian	hrv	X		X	X	X

65	Upper Sorbian	hsb				X	X	X
66	Hungarian	hun				X	X	X
67	Armenian	hye				X	X	X
68	Igbo	ibo		X		X	X	X
69	Iloko	ilo		X		X	X	X
70	Indonesian	ind	X			X	X	
71	Icelandic	isl				X	X	X
72	Italian	ita				X	X	X
73	Javanese	jav		X		X	X	X
74	Japanese	jpn				X	X	X
75	Kannada	kan		X		X	X	X
76	Georgian	kat		X		X	X	X
77	Kazakh	kaz				X	X	X
78	Khunsari	kfm	X			X	X	X
79	Khmer	khm		X		X	X	X
80	Kinyarwanda	kin		X		X	X	X
81	Kirghiz	kir		X		X	X	X
82	Northern Kurdish	kmr	X			X	X	X
83	Komi-Permyak	koi	X			X	X	X
84	Korean	kor				X	X	
85	Komi-Zyrian	kpv	X			X	X	X
86	Karelian	krl	X			X	X	X
87	Kölsch	ksh		X		X	X	X
88	Kurdish	kur		X		X	X	X
89	Latin	lat	X			X	X	X
90	Latvian	lav				X	X	X
91	Ligurian	lij				X	X	X
92	Lingala	lin		X		X	X	X
93	Lithuanian	lit				X	X	X
94	Luxembourgish	ltz		X		X	X	X
95	Literary Chinese	lzh	X			X	X	X
96	Malayalam	mal		X		X	X	X
97	Marathi	mar				X	X	X
98	Moksha	mdf	X			X	X	X
99	Macedonian	mkd		X		X	X	X
100	Malagasy	mlg		X		X	X	X
101	Maltese	mlt				X	X	X
102	Mongolian	mon		X		X	X	X
103	Makuráp	mpu	X			X	X	X
104	Maori	mri		X		X	X	X
105	Malay (macrolanguage)	msa		X		X	X	X
106	Burmese	mya		X		X	X	X
107	Mundurukú	myu	X			X	X	X
108	Erzya	myv	X			X	X	X
109	Mazanderani	mzn		X		X	X	X
110	Neapolitan	nap				X	X	X
111	Low German	nds				X	X	X
112	Nepali (macrolanguage)	nep		X		X	X	X
113	Dutch	nld				X	X	X
114	Norwegian	nor				X	X	X
115	Nayini	nyq	X			X	X	X
116	Occitan (post 1500)	oci		X		X	X	X
117	Livvi	olo	X			X	X	X
118	Oriya (macrolanguage)	ori		X		X	X	X
119	Old Russian	orv	X			X	X	X
120	Ossetian	oss		X		X	X	X
121	Old Turkish	otk	X			X	X	X
122	Panjabi	pan		X		X	X	X
123	Nigerian Pidgin	pcm	X			X	X	X
124	Piemontese	pms		X		X	X	X
125	Polish	pol				X	X	X
126	Portuguese	por				X	X	X
127	Pushto	pus		X		X	X	X
128	Cusco Quechua	qhe	X			X	X	X
129	Pomak	qpm	X			X	X	X
130	Turkish German	qtd	X			X	X	X
131	Quechua	que		X		X		X
132	Romansh	roh		X		X	X	X

133	Romanian	ron			✗	✗	✗
134	Russian	rus				✗	
135	Yakut	sah		✗	✗	✗	✗
136	Sanskrit	san	✗		✗	✗	✗
137	Sinhala	sin		✗	✗	✗	✗
138	Slovak	slk			✗	✗	✗
139	Slovenian	slv			✗	✗	✗
140	Northern Sami	sme	✗		✗	✗	✗
141	Skolt Sami	sms	✗		✗	✗	✗
142	Sindhi	snd		✗	✗	✗	✗
143	Soi	soj	✗		✗	✗	✗
144	Somali	som		✗	✗	✗	✗
145	Spanish	spa				✗	✗
146	Albanian	sqi			✗	✗	✗
147	Serbian	srp	✗		✗	✗	✗
148	Sundanese	sun		✗	✗	✗	✗
149	Swahili (macrolanguage)	swa		✗		✗	
150	Swedish	swe			✗	✗	✗
151	Swedish Sign Language	swl	✗		✗	✗	✗
152	Tamil	tam			✗	✗	✗
153	Tatar	tat		✗	✗	✗	✗
154	Telugu	tel			✗	✗	
155	Tajik	tgk		✗	✗	✗	✗
156	Tagalog	tgl			✗	✗	✗
157	Thai	tha				✗	✗
158	Tupinambá	tpn	✗		✗	✗	✗
159	Turkmen	tuk		✗	✗	✗	✗
160	Turkish	tur				✗	✗
161	Uighur	uig			✗	✗	✗
162	Ukrainian	ukr			✗	✗	✗
163	Urubú-Kaapor	urb	✗		✗	✗	✗
164	Urdu	urd				✗	✗
165	Uzbek	uzb		✗	✗	✗	✗
166	Veps	vep		✗	✗	✗	✗
167	Vietnamese	vie				✗	✗
168	Waray (Philippines)	war		✗	✗	✗	✗
169	Warlpiri	wbp	✗		✗	✗	✗
170	Wolof	wol	✗		✗	✗	✗
171	Mingrelian	xmf		✗	✗	✗	✗
172	Kangri	xnr	✗		✗	✗	✗
173	Yiddish	yid		✗	✗	✗	✗
174	Yoruba	yor			✗	✗	✗
175	Cantonese	yue	✗		✗	✗	✗
176	Zeeuws	zea		✗	✗	✗	✗
177	Chinese	zho				✗	✗
178	Bribri	bzc	✗	✗	✗		✗
179	Asháninka	cni	✗	✗	✗		✗
180	Huichol	hch	✗	✗	✗		✗
181	Nahuatl	nah	✗	✗	✗		✗
182	Otomí	oto	✗	✗	✗		✗
183	Shipibo-Konibo	shp	✗	✗	✗		✗
184	Rarámuri	tar	✗	✗	✗		✗

Table 29: Evaluation languages for all six tasks.

O FAQ

1. What are the main contributions of this study and the difference of our approach with other methods?

    - First, note that our paper introduces a method for studying cross-lingual transfer, not necessarily a method for improving cross-lingual transfer. We deviate from this "standard" way of using adapters for two reasons:
        (a) Training a task adapter on many languages, as a preliminary step, allows this component to learning the `task`, regardless of language. This is necessary for disentangling the effect of task and language in our analysis.
        (b) We then finetune the whole model (and not introduce a new adapter) exactly because we now want to study the effect of the language. While introducing a new language adapter might have a similar effect, there's additional hurdles to do so: the language adapter would need more data to be trained, as it would be randomly initialized; our approach instead can work even with a single batch/update, so it is applicable even for very, very low-resource scenarios.
    - Secondly, we propose a strategy to visually represent the language-language interaction utilizing the adapter-based fusion method. In general, training fully bilingual or trilingual for a different combination of languages are very expensive. This is why, we opt to have trained language adapter modules and then fuse together according to the need in an efficient manner.

2. What is the reason for selecting the 38 transfer languages, including the 11 unseen languages? Why why include the 11 unseen languages from pre-training?

    - **Language selection**: No other particular reasons except selecting a broader range of transfer languages covering language families and typological diversity. These 38 languages in total cover 10 language families, 26 genus and 14 script variations.

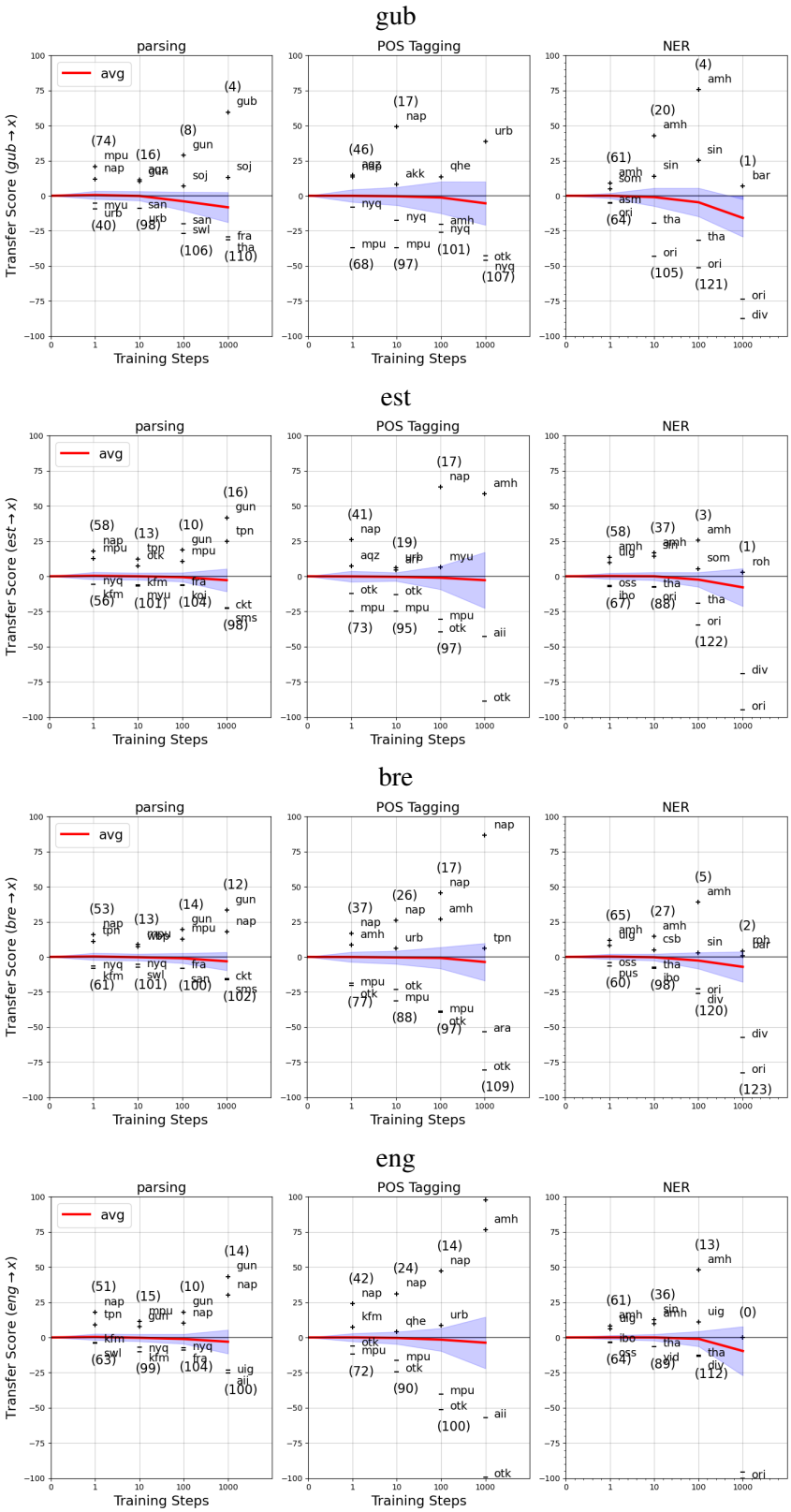


Figure 9: Aggregated Transfer Progression through training steps

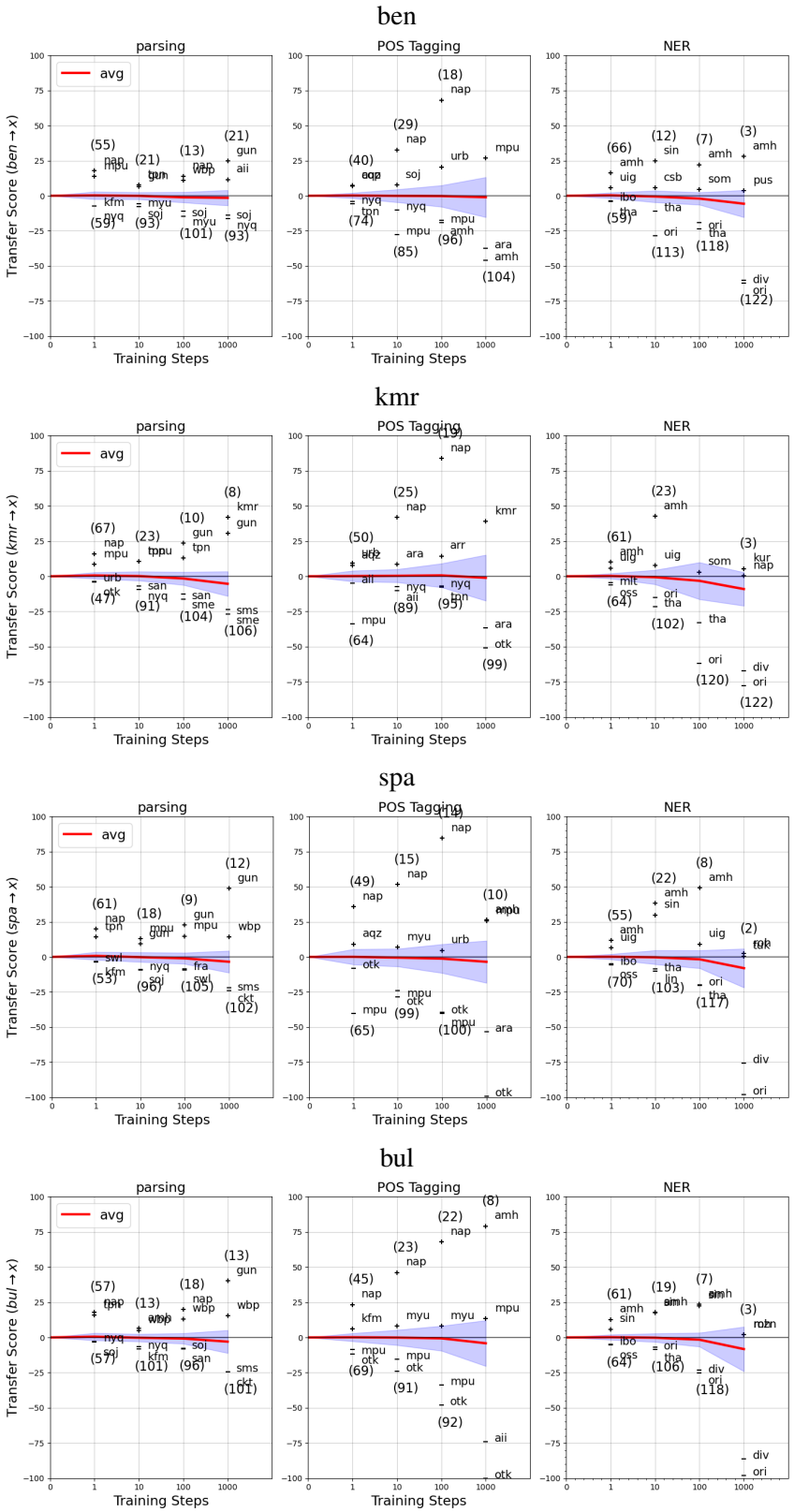


Figure 10: Aggregated Transfer Progression through training steps

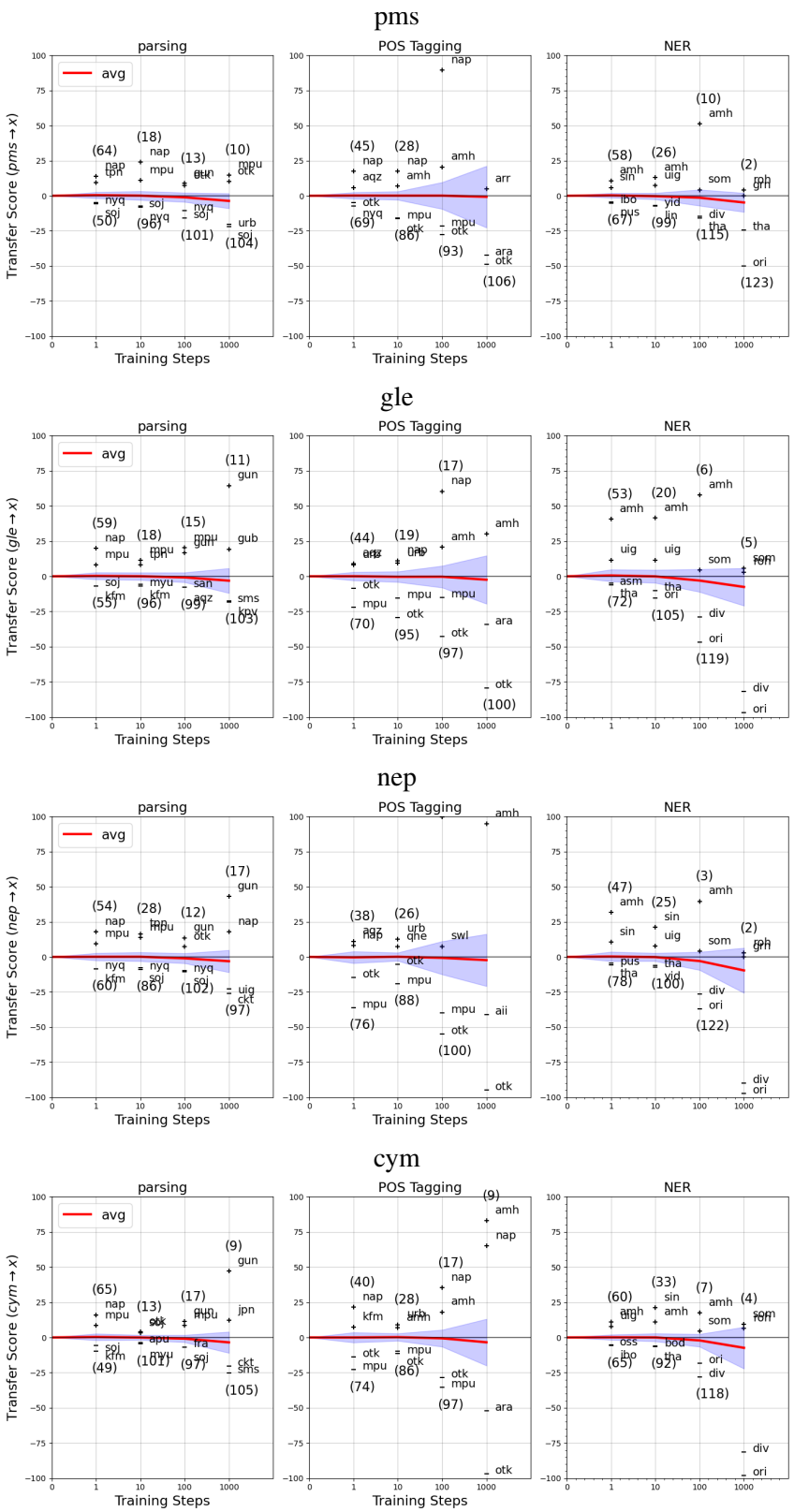


Figure 11: Aggregated Transfer Progression through training steps

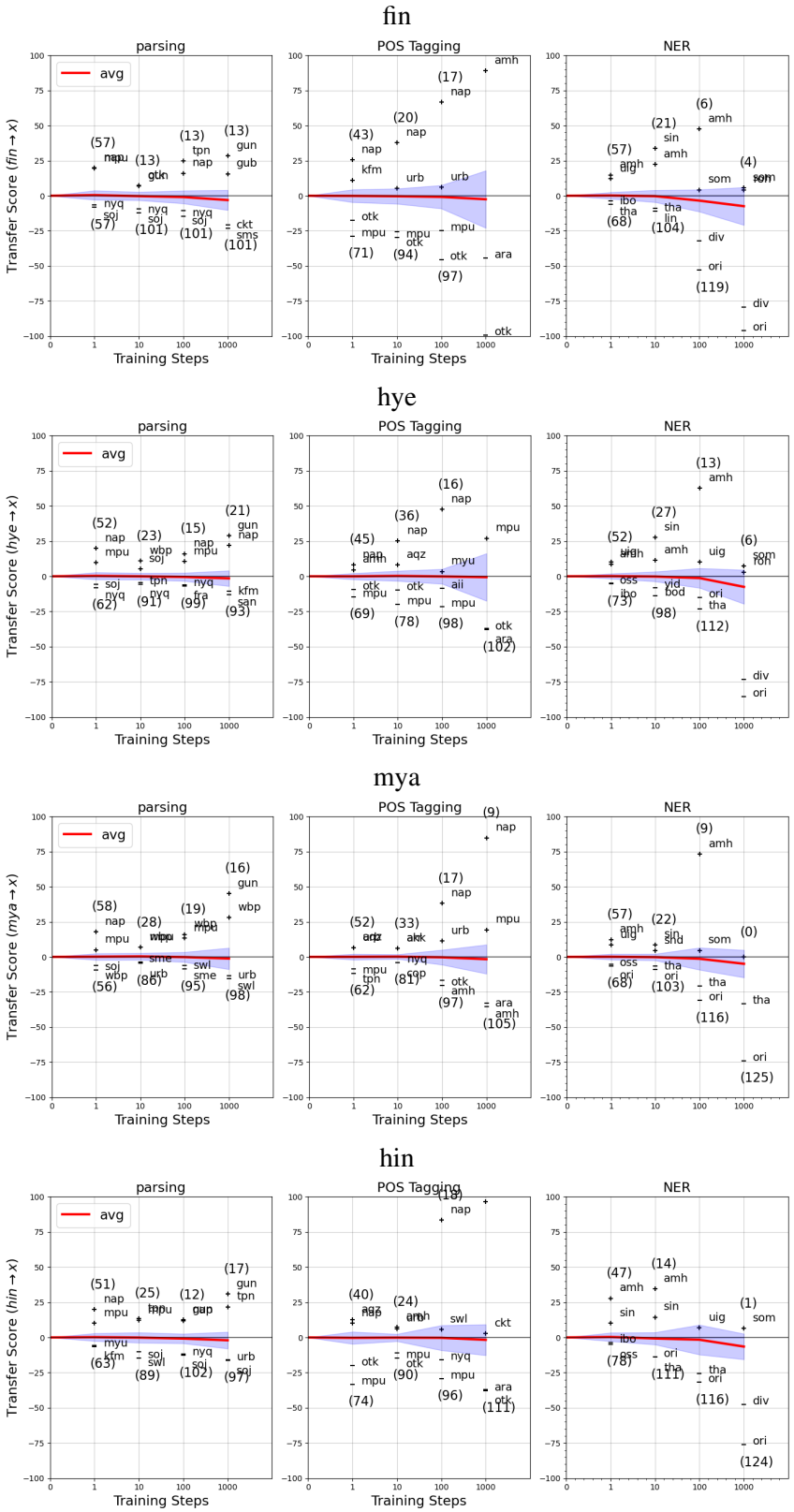


Figure 12: Aggregated Transfer Progression through training steps

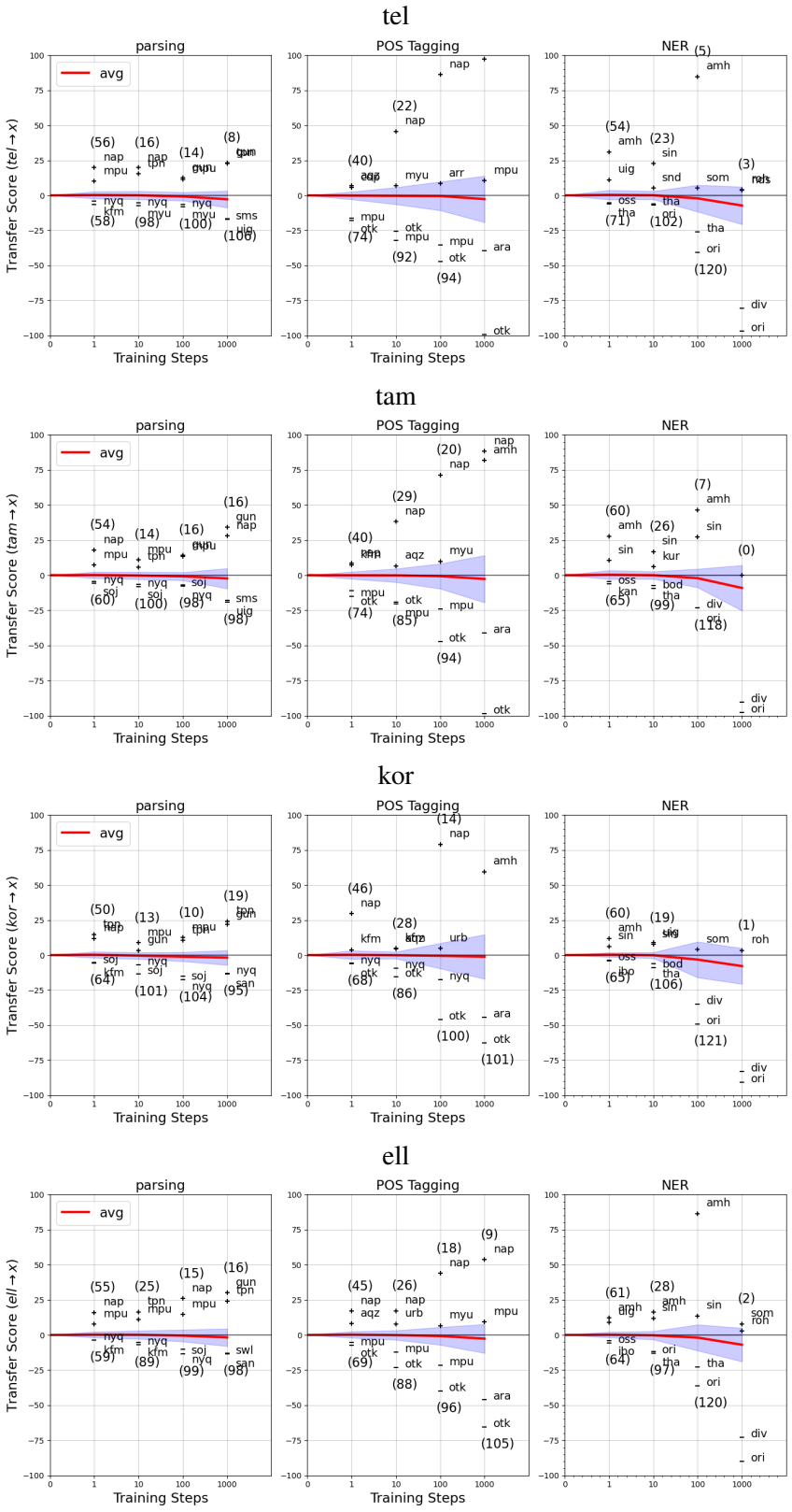


Figure 13: Aggregated Transfer Progression through training steps

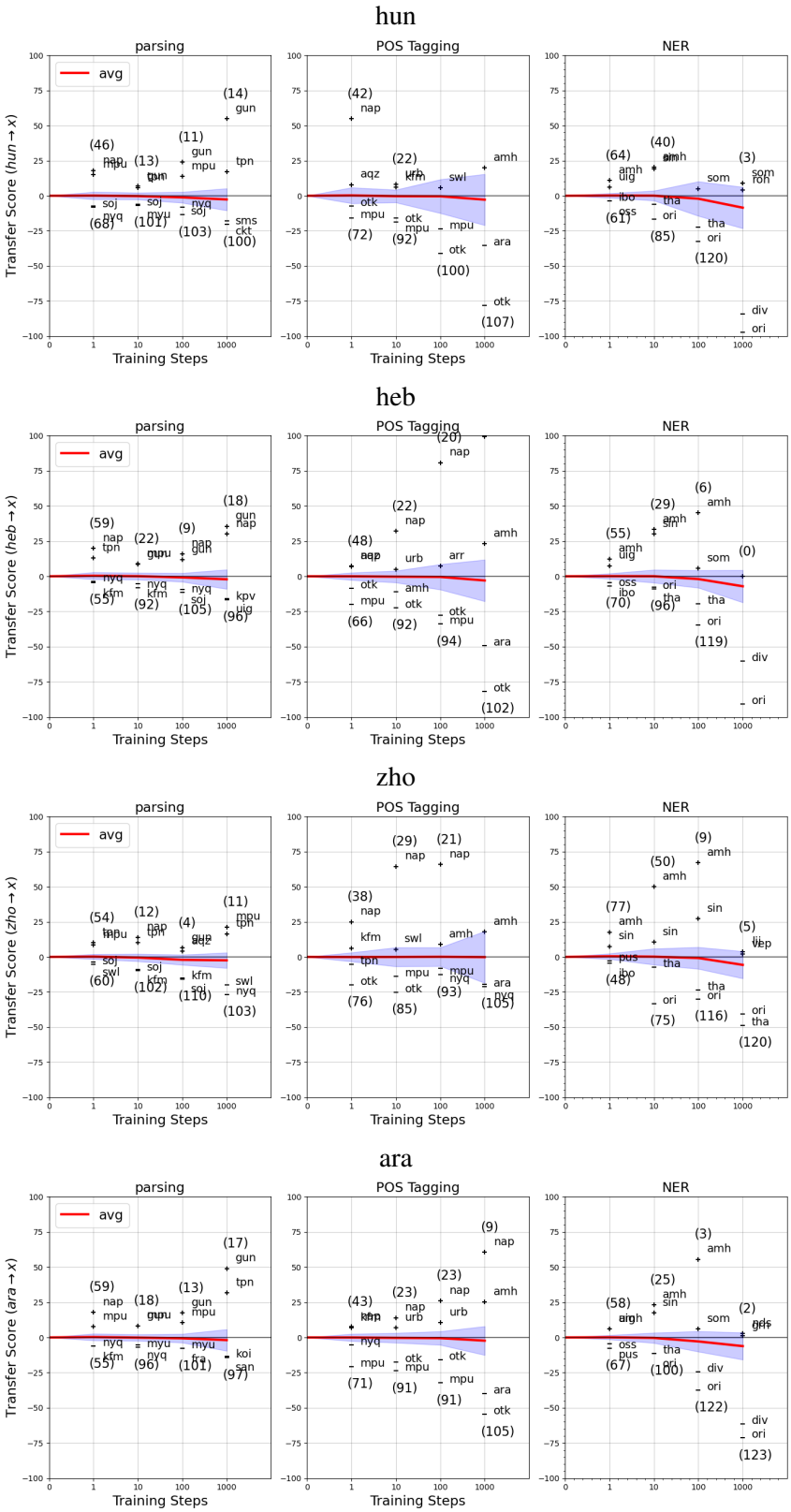


Figure 14: Aggregated Transfer Progression through training steps

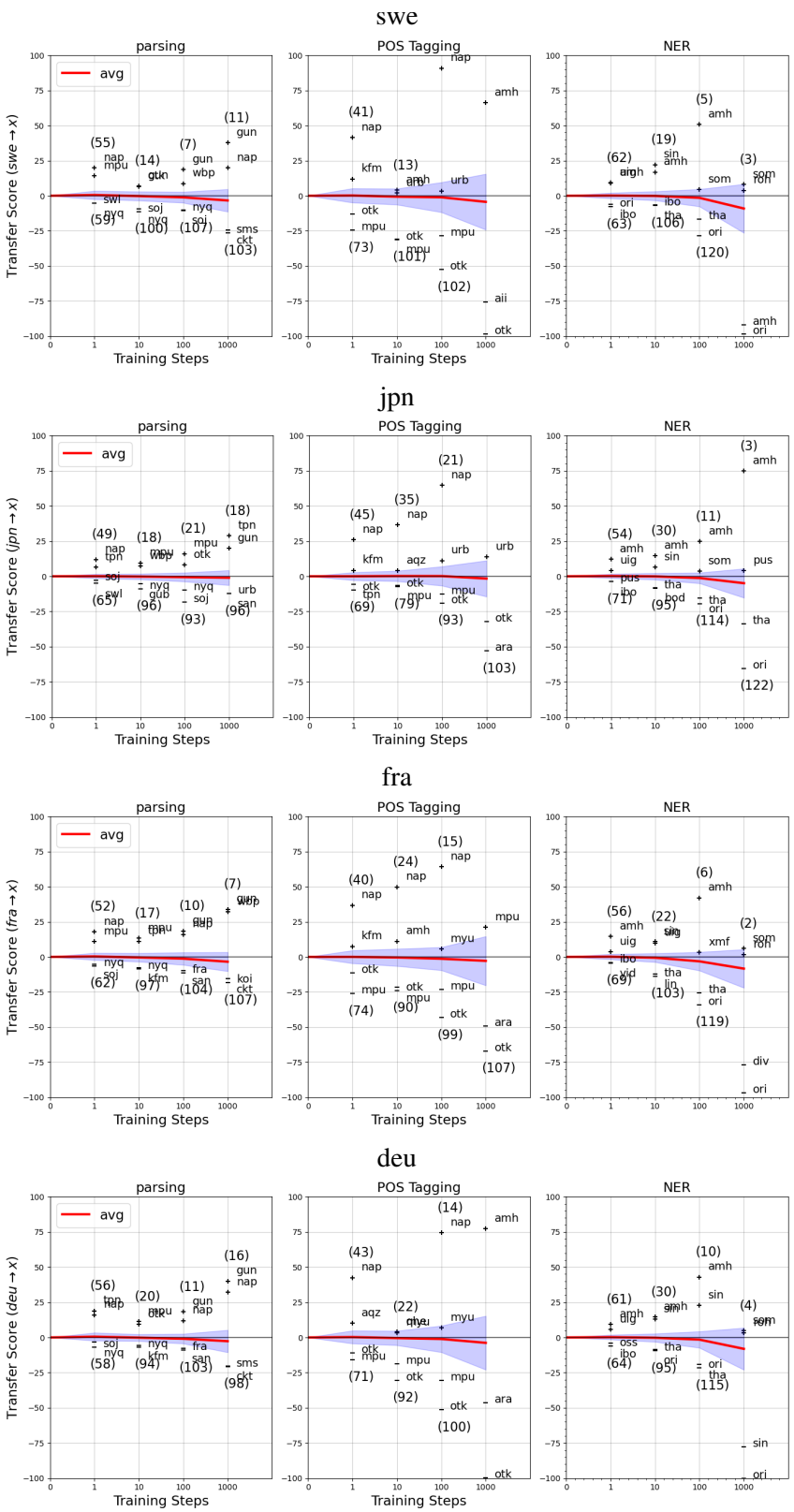


Figure 15: Aggregated Transfer Progression through training steps

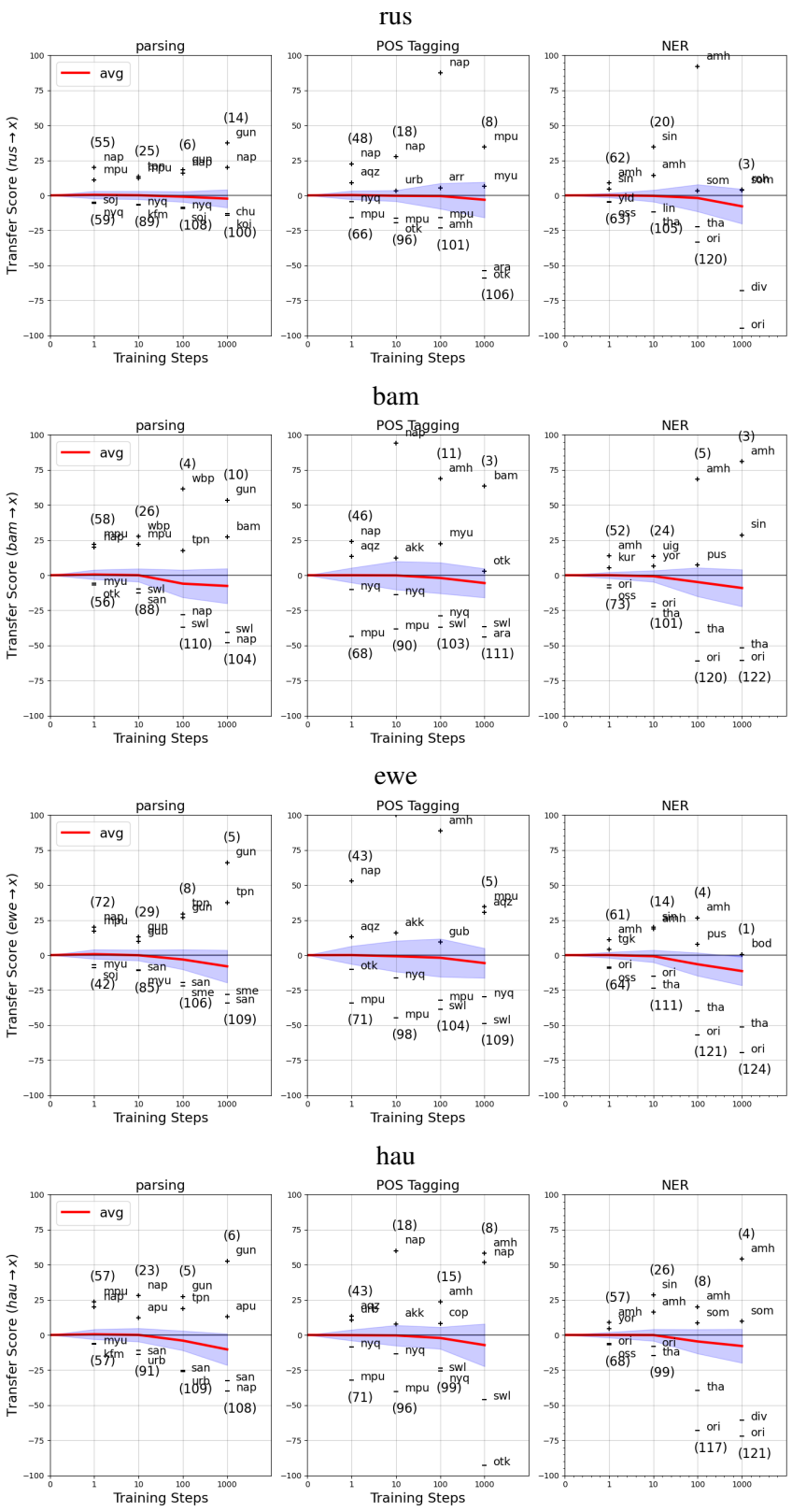


Figure 16: Aggregated Transfer Progression through training steps

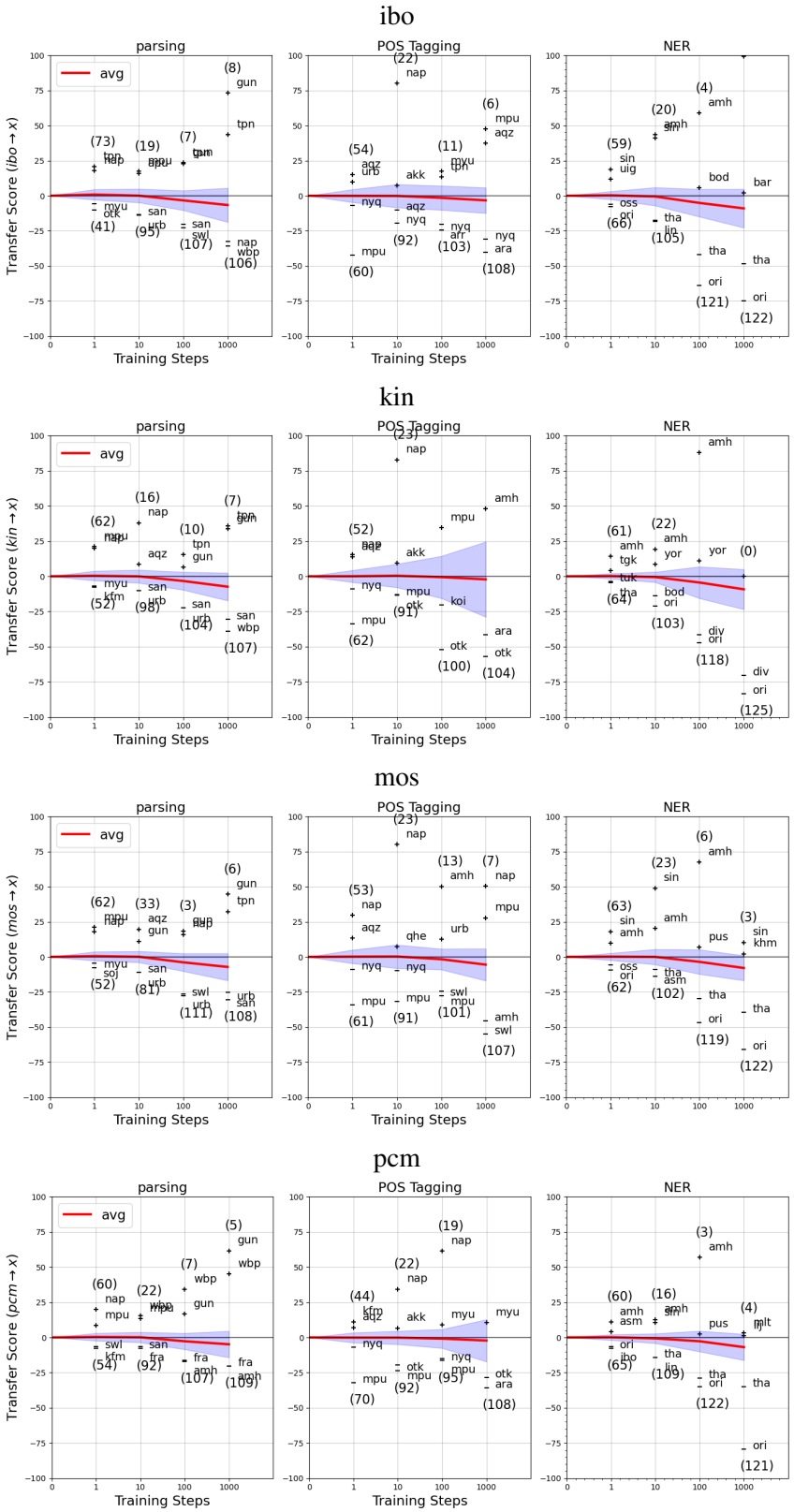


Figure 17: Aggregated Transfer Progression through training steps

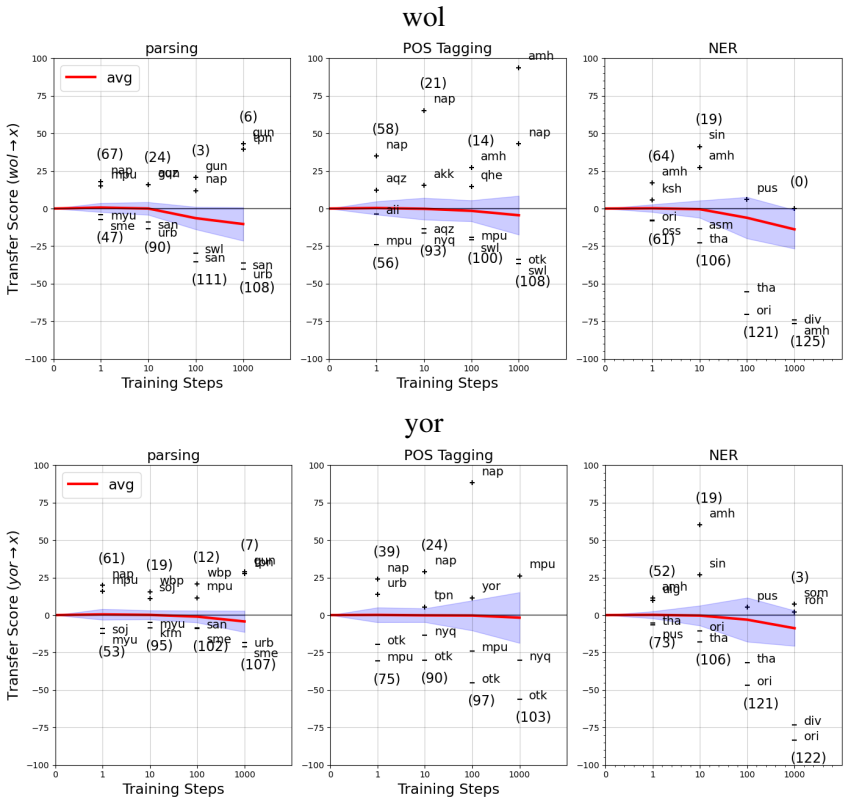


Figure 18: Aggregated Transfer Progression through training steps