# Searching for Effective Multilingual Fine-Tuning Methods: A Case Study in Summarization

Anonymous ACL submission

#### Abstract

Recently, a large number of tuning strategies have been proposed to adapt pre-trained language models to downstream tasks. In this paper, we perform an extensive empirical evaluation of various tuning strategies for multilingual learning, particularly in the context of text summarization. Specifically, we explore the relative advantages of three families of multilingual tuning strategies (a total of five models) and empirically evaluate them for summarization over 45 languages. Experimentally, we not only established a new state-of-the-art on the XL-Sum dataset but also derive a series of observations that hopefully can provide hints for future research on the design of multilingual tuning strategies.<sup>1</sup>

### 1 Introduction

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Methods that perform fine-tuning of pre-trained language models (PLMs) now represent the state-ofthe-art across a wide variety of NLP tasks (Howard and Ruder, 2018; Han et al., 2021). Because there are a myriad of methods for tackling this important task of fine-tuning LMs, there is an increasing body of research investigating the empirical strengths and weaknesses of different tuning strategies across several tasks (Peters et al., 2019; Mahabadi et al., 2021; Karimi Mahabadi et al., 2021; Li and Liang, 2021; Mao et al., 2021; Hu et al., 2021; Min et al., 2021; He et al., 2021). One of the major design dimensions of these works revolves around which set of model parameters are updated; should fine-tuning only adjust a few additional parameters that are not part of the initial LMs (e.g., Adapters (Houlsby et al., 2019), or Prefix Tuning (Li and Liang, 2021; Xue et al., 2021)), update all parameters of the pre-trained models (Dai and Le, 2015; Devlin et al., 2019; Schick and Schütze, 2021), or update only a subset of parameters (Guo et al., 2020)?



Figure 1: Different frameworks for multilingual learning, where orange circles represent different languages and blue circles denote pre-trained language models (PLMs). Red boxes refer to additional learnable parameters, such as adapters or prefixes. Double sided arrows represent that the parameters of PLMs are tunable.

At the same time, there has been much progress in multilingual models based on pre-trained LMs (Lample and Conneau, 2019; Conneau et al., 2020; Liu et al., 2020) However, there is a notable gap in the literature – to our knowledge, there are no comprehensive comparative studies on how different tuning strategies behave in multi-lingual scenarios – there is significant work on multilingual adapters (Pfeiffer et al., 2020b; Ansell et al., 2021) and parameter tying across languages (Sachan and Neubig, 2018; Lin et al., 2021), but few studies comparing different families of methods.

In this paper, we try to fill this gap by performing a comprehensive study of different parameter tuning techniques in the context of text summarization (Rush et al., 2015; Nallapati et al., 2016; Chopra et al., 2016; Lewis et al., 2020; Zhang et al., 2020; Dou et al., 2021). We focus particularly on summarization as previous work on parameterefficient tuning has noted that the differences between tuning techniques are particularly salient in more complex generative tasks such as summarization, as opposed to text classification (He et al., 2021). We draw on the techniques examined in the monolingual scenario and combine the unique characteristics of the multilingual scenario (e.g., shared features across languages) to derive different architectures for multilingual learning. These

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<sup>&</sup>lt;sup>1</sup>Code at https://github.com/anonymous-717/Multi-Sum

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frameworks encompass some existing works on multilingual learning, but also allow us to propose new learning methods and perform comparisons between different frameworks.

Figure 1 (a) shows a commonly-used framework (Hasan et al., 2021) in which one tunable pre-trained model is shared by different languages. Figure 1 (b) introduces a language-specific module with learnable parameters while keeping the PLM's parameter frozen, i.e. parameter-efficient tuning (Mao et al., 2021; He et al., 2021). In practice, the language-specific module could be instantiated as an adapter, prefix, or other variety of extra parameters. Notably, this kind of language-specific module is independent for each language and cannot share information, thus low-resource languages cannot benefit from other related languages. Figure 1 (c) tries to alleviate this problem in two ways: making parameters of pre-trained models tunable or introducing additional modules whose parameters can be shared by different languages.

Using this framework, we ask these questions:

Q1: How well do different parameter-efficient tuning methods (Figure 1-b) perform compared to PLM fine-tuning models (Figure 1-a) in multilingual summarization? Q2: Will supervised transfer, a commonly used technique in multi-lingual learning, be helpful for parameter-efficient tuning? Q3: Could better results be achieved by enabling information exchange between different languages? How do different choices of parameter-efficient tuning methods interact with this sharing?

We explore these questions by performing extensive experiments over 45 different languages . Our quantitative and qualitative analyses find several observations, such as:

(1) Compared to PLM fine-tuning, both parameter-104 efficient tuning methods (prefix- and adapter-105 tuning) are advantageous in low-resource scenar-106 ios. Particularly, prefix-tuning outperforms adapter-107 tuning with extremely few samples over different 108 languages  $\S3.1$ . (2) Parameter-efficient tuning is possible to fail in the *supervised transfer* setting 110  $(\S3.2)$ , where pre-trained language models are fine-111 tuned on the source languages whose scripts are 112 distant from the target language's. (3) Adding lan-113 guage specific adapters or prefixes while addition-114 ally tuning the PLM's parameters, can maintain 115 multi-lingual PLM fine-tuning's advantage of shar-116 ing information among languages, as well as pre-117 serving private parameters for each language to 118

reduce the negative effect of the limited capacity of one LM shared by all languages. We achieve a new state-of-the-art performance with such a multilingual tuning strategy.

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#### 2 Preliminaries

#### 2.1 Task Formulation

Abstractive summarization can be formulated as a conditional generation task where the input Dis a document, and the output S is a short summary. The majority of state-of-the-art models for abstractive summarization use encoder-decoder models (Sutskever et al., 2014), where an encoder generates representations for the source document  $\mathbf{D} = [\mathbf{d}_1, ..., \mathbf{d}_m]$ , and a decoder outputs the summary  $\mathbf{S} = [\mathbf{s}_1, ..., \mathbf{s}_n]$  one target token at a time. The conditional probability of a single sample is modeled as  $p(\mathbf{s}^i | \mathbf{d}^i; \theta)$ , and hence parameters  $\theta$  are obtained by maximum likelihood estimation

$$\underset{\theta}{\operatorname{argmax}} \sum_{(\mathbf{d}^{i}, \mathbf{s}^{i}) \in (D, S)} \log p(\mathbf{s}^{i} | \mathbf{d}^{i}; \theta), \quad (1)$$

where (D, S) is the parallel training corpus. For multilingual text summarization, D and S can be in any of a number of languages.

### 2.2 Tuning Strategy

Recently, applying pre-trained language models (PLMs) to abstractive summarization tasks equipped with diverse tuning strategies has achieved a great success, which can be formulated as below:

$$h_i = \mathsf{PLM}(D, s_i, h_{< i}; \theta_{\mathsf{plm}}, \theta_{\mathsf{add}})$$
(2)

where PLM is a sequence to sequence pre-traiend LMs (e.g., T5 (Raffel et al., 2019) or BART (Lewis et al., 2020)),  $\theta_{\text{plm}}$  represents the original PLM parameter and  $\theta_{\text{add}}$  denotes the additional parameters added by different tuning strategies.

Based on whether and when parameters  $\theta_{\text{plm}}$  and  $\theta_{\text{add}}$  will be tuned, different tuning strategies as illustrated in Fig. 2 have been explored, which we will detail below for the better introduction of multi-lingual tuning strategies.

**PLM Fine-tuning** This is one of the most common tuning strategies that aim to tune all of the parameters  $\theta_{\text{plm}}$ . While PLM fine-tuning has achieved strong performance on many benchmarks, one major limitation lies in the requirement of large

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training samples, which is not feasible in the low-resource scenario.

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To alleviate this issue, parameter-efficient tuning has been extensively explored recently, among which we select two representative methods which are initially designed for generation tasks, consistent with our goal.

Adapter-tuning Adapter-tuning adds additional 170 lightweight layers between the layers of an existing 171 PLM. Although there is a variety of ways to define 172 "adapter", we adopt the definition of (Bapna et al., 173 2019). Specifically, the adapter block consists of 174 (1) a layer normalization  $LN(\cdot)$  for the input of the 175 adapters, (2) an autoencoder whose inner dimen-176 sion can be adjusted according to the complexity of the target task with a down projection layer, an 178 up projection layer, and a nonlinear activation func-179 tion between them, and (3) a residual connection. 180 Formally, given  $h_i \in \mathbb{R}^d$  be the output of i-th layer, the adapter is formulated: 182

ADAPTER
$$(h_i) = (\text{ReLU}(\text{LN}(h_i)\mathbf{W}_i^{db}))\mathbf{W}_i^{bd} + h_i,$$

where b is the inner dimension,  $\mathbf{W}_i^{db} \in \mathbb{R}^{d \times b}$  is the weight of down projection layer and  $\mathbf{W}_i^{bd} \in \mathbb{R}^{b \times d}$  is the weight of up projection layer.

**Prefix-tuning** Prefix-tuning (Li and Liang, 2021) prepends a prefix for every layer of a LM. Let  $\mathbf{H}_{i}^{LM} \in \mathbb{R}^{t \times d}$ , where *d* is the hidden dimension of LM, *t* is the input sequence length, denote the hidden representation of the i-th layer. We prepend prefixes at each layer to obtain  $\mathbf{H}_{i}$  = [Prefix<sub>*i*</sub>;  $\mathbf{H}_{i}^{LM}$ ]  $\in \mathbb{R}^{(t+l) \times d}$ , where *l* is the prefix length, Prefix<sub>*i*</sub>  $\in \mathbb{R}^{l \times d}$  is prepended prefix.

We can look up trainable matrix  $\mathbf{P}_{\theta} \in \mathbb{R}^{l \times (d \times n)}$ , where *n* is the number of layers of the LM, to get Prefix<sub>*i*</sub>. However, according to (Li and Liang, 2021), reparameterization has better performance than directly updating  $\mathbf{P}_{\theta}$  in practice. So we reparametrize the matrix  $\mathbf{P}_{\theta} = \text{MLP}(\mathbf{P}'_{\theta})$ , where MLP( $\cdot$ ) has the structure of an autoencoder with a tunable middle dimension size, and  $\mathbf{P}'_{\theta}$  is a smaller matrix with dimension  $l \times d$ .

#### 2.3 Multilingual Tuning Methods

Based on the above-mentioned tuning strategies in single language scenarios, we investigate three different multilingual learning frameworks and explore their applicable scenarios in detail.

209Multilingual PLM Fine-tuning (MPF)This is210a commonly-used setting (Hasan et al., 2021) when

training samples from different languages are provided. Summarization systems share one multilingual pre-trained language model whose parameters can be updated by any system.

**Multilingual Parameter-efficient Tuning (MPE)** In this framework, additional private parameterized modules such as prefix or adapter are introduced for each system besides one shared multilingual pretrained language model, whose parameters keep frozen. Some existing works (Bapna et al., 2019) follow this framework but mainly focus on the use of adapters.

**Multilingual Private-shared Tuning (MPS)** In the above method, although systems of different languages share one pre-training model, their parameters cannot be modified, which results in the lack of information interaction across languages and the difficulty in mining the shared knowledge. In this framework, parameters from both additional modules and pre-trained models can be updated.

### **3** Experiments

**Dataset** As our evaluation testbed, we use the XL–Sum corpus (Hasan et al., 2021),<sup>2</sup> which is a news dataset containing 1.1 million articlesummary pairs in 45 languages. The dataset is collected from the British Broadcasting Corporation (BBC) website, using a bold paragraph at the beginning of each article as the summary and the rest of the article as the input text. We choose XLsum for its: (1) high language coverage, including low resource, medium resource, and high resource languages, (2) similar intrinsic characteristics, e.g. novel n-gram ratio, abstractivity, and compression among all samples, allowing our analysis to focus on the differences across languages, other than different intrinsic features across samples.

**Evaluation Metric** As is standard in summarization, we use ROUGE (Lin, 2004) as our evaluation metric, which computes the n-gram similarity between the gold and the generated summary.<sup>3</sup>

#### 3.1 Exp-I

To answer the question (Q1) of how well different parameter-efficient tuning methods behave compared to standard LM fine-tuning in the multilingual setting, we study the performance of three

<sup>&</sup>lt;sup>2</sup>License: CC BY-NC-SA 4.0.

<sup>&</sup>lt;sup>3</sup>We use the rouge package provided by XL-Sum(Hasan et al., 2021) to support multiple languages.



Figure 2: Different tuning methods. Red indicates trainable parameters; blue indicates frozen parameters.

tuning methods: prefix-tuning, adapter-tuning andPLM fine-tuning on different languages.

#### **3.1.1** Experiment Details

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Settings and Hyper-parameters We use the base version of multilingual T5 (Xue et al., 2021) as a backbone, which covers most languages in XL-Sum dataset and is the same as (Hasan et al., 2021), allowing us to make a fair comparison. In our experiment, MLP of prefix-tuning is two linear layers with an inner dimension as a hyper-parameter. For prefix-tuning, the hyperparameters we tune<sup>4</sup> are the same as (Li and Liang, 2021). For adapter-tuning, the hyperparameters remain the same as prefix-tuning except the prefix length that is not needed for adaptertuning. More details are in the appendix. For both adapter-tuning and prefix-tuning, these hyperparameters lead to about 8% additional parameters compared to the LM's total parameters, which are tuned during training while the LM's parameters are frozen. To study whether language features will influence the choice of tuning methods, we choose five languages from different language families: English (Germanic), Chinese simplified (Sino Tibetan), Spanish (Romance), Ukrainian (Balto Slavic) and Urdu (Indo Iranian).

> We subsample the full dataset of each language to obtain sub-datasets of various sizes,<sup>5</sup> and subdatasets of size  $\leq 500$  are considered "few-shot" experiments. For each few-shot experiment, we randomly sample 3 different training sets and development set (with dev size = 20% training set size). The reported result is the average of 3 experiments

on the full test set of the chosen language. The performance of few shot experiments is influenced by the training samples chosen (Zhao et al., 2021), so we keep the sampled training set and development set the same for the three tuning methods to have a fair comparison. For non-few shot experiments, each size has one experiment and is tested on the full test set of the chosen language. The hyperparameters are chosen from a single language (Japanese) for each tuning method and applied as is to all languages. We use the result from the checkpoint with the best validation set performance over all training epochs. 290

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#### 3.1.2 Results and Analysis

**Results** Fig.3 illustrates the performance of three different tuning methods with respect to the available training samples, observations are:

(1) In general when the sample number is less than 200 prefix-tuning achieves the best performance. Between 200 and 10k adapter-tuning is superior, and greater than 10k PLM fine-tuning surpasses the other two. This indicates that regarding both the performance and parameter efficiency (only tune 8% of the parameters of PLM fine-tuning), prefixtuning is the best choice when we have extremely few samples, while adapter-tuning is the winner in medium resource settings. (2) As the training set size increases from few shot to high resource, PLM fine-tuning has the largest performance improvement, while prefix-tuning has the least performance improvement and adapter-tuning is the middle. (3) Compared to PLM fine-tuning, which is almost monotonically increasing with the training set size, both adapter-tuning and prefix-tuning have some fluctuations. From preliminary experiments, we find that adapter-tuning and prefix-tuning are more sensitive to learning rate than PLM fine-tuning. Fixing two separate learning rates for few shot and non-few shot experiments for all languages, a simplification of the normal training process to find

<sup>&</sup>lt;sup>4</sup>Specifically, the number of epochs, batch size, learning rate, prefix length and inner dimension during training, beam search size and length penalty during inference.

 $<sup>^{5}</sup>$ Concretely, {5, 10, 20, 50, 100, 200, 500, 3000, 6000, 10000, 20000, 30000}. For English, which has far more training samples than other languages, we add two training set size 100000 and 300000.



Figure 3: Performance of prefix-tuning, adapter-tuning and PLM fine-tuning on five languages over training set sizes. The x axis is the number of training samples at log scale, the y axis is the ROUGE-2 score.

an optimal learning rate for each training set size and each language on the development set, might cause the unstable performance of the tuning methods that are more sensitive to learning rate. (4) All above observations are roughly true for every language and is especially clear in the average plot.

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Discussion & Takeaways The possible explanation of the different behavior of adapter-tuning and prefix-tuning is their structural discrepancy, 338 in which adapter-tuning adds parameters between two transformer layers, while prefix-tuning uses these parameters to generate prefixes and append 341 the prefixes at the front of each transformer layer. 342 Similar to prolong the input, prefix-tuning does not touch the PLM's architecture, preserving the knowledge in PLM. Thus, by utilizing the PLM 345 better, prefix-tuning has better performance at few shot when there are not enough samples to learn 347 new knowledge. However, while the training set size becomes larger, more flexible structures are 350 needed to learn from these samples, leading to better performance of adapter-tuning. The possible 351 reason why both prefix-tuning and adapter-tuning outperform PLM fine-tuning at the left side is that prefix-tuning and adapter have only 8% parameters to tune, which avoid overfitting when the training samples are not enough. 356

From this experiment, we can see that prefix-

tuning has both advantages of utilizing the knowledge of PLM better and fewer parameters to tune, while adapter-tuning only benefits from the latter. This reminds us that while designing a prompt, one important thing is to keep the PLM's architecture and make the prompt as natural as possible to better extract knowledge from PLM. 358

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#### **3.2 Exp-II**

When designing models in multi-lingual scenarios, one crucial question is how to make modules of different languages communicate efficiently so that shared knowledge can be fully utilized. There are two ways to do this: (1) by transferring: first finetune PLMs on multiple languages except the one we concerned about (a.k.a target language), and then adapt the fine-tuned multi-lingual model to the target language; (2) by multitask learning: jointly train all languages together. In this experiment, we study method 1 and try to answer the Q2: will supervised transfer be helpful for parameter-efficient tuning. In Exp.3.3, we study method 2.

#### 3.2.1 Experiment Details

**Settings and Hyper-parameters** We first divide XL-Sum dataset into two parts, one of which including 34 languages (75% of total languages) is used to fine-tune PLM jointly on multiple languages to obtain a single multi-lingual model,

_	Script	mt5-base					mt5-base34						
Language		I	prefix-tuing		adapter-tuing			prefix-tuing			adapter-tuing		
		R1	R2	RL	R1	R2	RL	R1	R2	RL	R1	R2	RL
amharic	Geez	15.33	5.42	13.8	16.58	5.88	14.88	16.97	5.88	15.12	17.85	6.2	16.01
azerbaijani	Cyrillic	15.72	6.3	14.47	17.81	7.34	16.13	11.9	3.4	10.93	12.16	3.37	10.96
bengali	Brahmic	23.76	9.11	20.66	25.99	10.07	22.21	0	0	0	0	0	0
burmese	Brahmic	12.74	3.46	11.51	14.07	4.09	12.54	1.57	0.38	1.51	1.14	0.22	1.08
igbo	Latin	23.27	5.25	17.36	25.22	7.08	19.38	28.1	7.98	21.19	28.33	7.93	21.72
japanese	Kan,Hi,Kat	41.23	18.89	32.42	45.6	21.87	35.02	11.39	2.82	9.05	11.84	3.15	9.12
scottish_gaelic	Latin	24.05	7.73	19.45	20.42	4.31	17.02	24.36	7.16	18.87	26.37	8.09	20.22
spanish	Latin	28.09	9.05	21.14	29.28	10.3	22.23	29.75	9.48	22.18	30.26	9.83	22.42
tamil	Brahmic	16.45	6.58	15	19.81	8.83	18.12	0.42	0.02	0.42	0.44	0.02	0.43
ukrainian	Cyrillic	18.73	7.07	16.43	21.84	8.92	19.08	16.46	4.41	13.99	16.96	4.61	14.32
urdu	Arabic	35.05	14.5	28.76	38.81	17.69	32.08	20.19	4.48	15.66	19.57	4.58	15.08

Table 1: R1, R2, and RL scores of prefix-tuning, adapter-tuning of mt5-base and mt5-base34 for 11 languages. "Kan, Hi, Kat" is the abbreviation of Kanji, Hiragana, and Katakana.

while another part including 11 languages (25% of total languages) is used to investigate the finetuned PLM's ability to generalize to new languages. The 11 left-out languages that do not participate in fine-tuning are chosen according the principle that they are from different language family and have different training set size.<sup>6</sup> The hyper parameters used to fine-tune PLM is the same as the Multilingual training of XL-Sum (Hasan et al., 2021).

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We refer to mt5-base as the original PLM without fine-tuning and mt5-base34 as the fine-tuned version on 34 languages. We then performed prefixtuning and adapter-tuning on mt5-base and mt5base34 for 11 left-out languages. Hyper parameters used for these tuning methods remain the same as those in non-few shot experiments of Sec.(3.1).

#### 3.2.2 Results and Analysis

**Results** Table.1 illustrates the performance of multi-lingual models mt5-base and mt5-base34 to adapt to 11 new languages by prefix-tuning and adapter-tuning. The main observations in Table.1 are as follows:

- 407 (1) For four languages, Amharic, Igbo, Scottish
  408 Gaelic, and Spanish, mt5-base34 will bring gains
  409 against their counterparts by 0.3 to 6.0 R1 score.
- (2) Fine-tuning mt5-base on 34 languages of
  XL-Sum dataset jeopardizes the performance of
  seven languages, among which Bengali, Burmese,
  Tamil's R1 score becomes near zero.

(3) Three of the four languages with performance
improvement adapted from fine-tuned PLM are
of Latin script, while all three languages with
dramatic performance drop down are of Brahmic

script, indicating the important role script plays to determine whether supervised transfer is helpful for parameter-efficient tuning. 418

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**Discussion & Takeaways** Although intuitively new languages will benefit from PLM fine-tuned on XL-Sum dataset, the practical results shows that not all languages will obtain improvements. Transfer learning in such a way might cause catastrophic forgetting of the previously acquired knowledge in PLM (McCloskey and Cohen, 1989; Santoro et al., 2016). If there are not enough training samples of a certain script during PLM fine-tuning, the PLM might lose the ability generalizing to languages of this script by parameter-efficient tuning methods and freezing PLM. This indicates that the effectiveness of parameter-efficient tuning methods under multi-lingual scenarios is highly dependent on the multi-lingual model we use and under some situations, parameter-efficient tuning might lose their adaptivity. We leave how to alleviate this problem for future work.

#### 3.3 Exp-III

In this experiment, we study jointly multi-lingual training to see if different languages can benefit from each other and how does adding private parameters for each language influence the performance of multi-lingual training (Q3).

#### 3.3.1 Experiment Details

With respect to Fig.1, we have 6 different settings to compare single language training with multilingual training.

**PLM Fine-tuning (PLF)**: mt5-base is fine-tuned on all languages to obtain separate models for each language as the baseline. **Multi-lingual** 

<sup>&</sup>lt;sup>6</sup>Concretely, 7 languages (Amharic, Azerbaijani, Bengali, Burmese, Igbo, Japanese, Scottish Gaelic, Spanish, Tami) are low resource (< 15,000 training samples), 2 languages (Spanish, Tamil) are medium resource ( $15,000 \sim 40,000$ ) and 2 languages (Ukrainian, Urdu) are high resource (> 40,000).



Figure 4: Trend-lines depicting performance improvement. X-axis is the languages, which are arranged in increasing order of available training data from left to right. Y-axis depicts the R2 score relative to the singular language PLM fine-tuning baseline.

**Parameter-efficient** (Adapter/Prefix) Tuning (MPE\_adapter/MPE\_prefix): We add adapters/prefixes (with parameters = 8% parameters of LM) for each language and tune adapters/prefixes separately for each language while freezing mt5-base which is shared by all languages. Multi-lingual PLM Fine-tuning (MPF): A single model is trained with training samples from multiple languages. The training strategy proposed by (Lample and Conneau, 2019) to use a smoothing factor (alpha) of 0.5 to balance the sampling rate of low resource languages and high resource languages is followed by every multilingual setting.<sup>7</sup> Multi-lingual Private-shared (Adapter/Prefix) Tuning (MPS\_adapter/MPS\_prefix): Private adapters/prefixes (with parameters = 2% parameters of LM) for each language (in total 45 languages in XL-Sum dataset  $\times$  2% parameters for each languages = 90% additional parameters) are added to a single LM. The LM is tuned jointly for multiple languages, while the adapters/prefixes are tuned separately for each language.<sup>8</sup>

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#### 3.3.2 Results and Analysis

The summarization performance on different languages with different settings is plotted in Figure 4. With combinations of different experiment settings, we have the following results: 476

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PLF v.s. MPE\_prefix v.s. MPE\_adapter: PLF outperforms MPE\_prefix and MPE\_adapter overall, with a gap larger for more available training samples. MPE\_adapter outperforms MPE\_prefix for almost every language, except a few languages with few samples. This conforms to the result in Sec.3.1 that fine-tuning has the advantage with large training set size, while prefix-tuning has the advantage with small training set size. One thing to notice is that adapter-tuning has comparable or even higher performance when the training set size is smaller than 10k, consistent with the result in Sec.3.1 and adapter's sensitivity to training set size is not as high as prefix-tuning. The latter is reflected in that the adapter's performance does not drop down dramatically as the training set size increases and keeps within -2 R2 of the baseline for almost all languages, which is even true for English with the highest training set size of 300,000. This means the parameter efficient adapter is a reasonable substitute of PLM fine-tuning regardless of the training set size.

**MPF v.s. PLF:** Multi-lingual model MPF significantly outperforms the baseline PLF in the low and medium resource languages with the gain

<sup>&</sup>lt;sup>7</sup>We use the results of XL-Sum(Hasan et al., 2021). In order to have a fair comparison and remove the influence of different rouge packages, we use their model-generated outputs on test set to calculate the rouge score, instead of using their reported rouge score directly.

<sup>&</sup>lt;sup>8</sup>One thing to notice is that during training, in each iteration we sample from one language with a certain probability. The LM shared by all languages is tuned every iteration, while the private parameters for each language are tuned whenever the language is sampled.

decreases as the training set size becomes larger. 507 This is expected because low and medium resource 508 languages can benefit from joint training by 509 positive transfer between sister languages (Lample 510 and Conneau, 2019). A deterioration is also observed in the high resource languages. However, 512 the multilingual model within -1 R2 drop down for 513 6 high resource languages and -3 R2 drop down for 514 English, does not trail a lot. It is a good indication 515 that by training a single multilingual model, the 516 low and medium resource languages have been 517 significantly improved without too much sacrifice 518 of high resource languages. Similar to the low 519 resource experiment of (Hasan et al., 2021), our result is stronger than theirs, which only selects 5 521 low resource languages to fine-tune individual LM.

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**MPF v.s. MPS\_adapter v.s. MPS\_prefix:** By adding language-specific parameters under multilingual scenarios, compared to MPF, MPS\_adapter and MPS\_prefix have performance improvements R1:0.73, R2:0.46, RL:0.45 and R1:0.67, R2:0.47, RL:0.46 respectively for 45 languages on average. From each language performance, we can see that all high resource languages have performance improvements at the cost of jeopardizing the performance of a few low resource languages a little. This indicates that sharing LM as well as adding private language-specific parameters will maintain the jointly multi-lingual training's advantage of sharing information among languages, while reducing the harm of sharing all parameters to high resource languages due to the limit model capacity. Besides, the two ways to add additional parameters: private adapter, private prefix for each language have roughly the same overall performance on the whole dataset and the same trend lines depicted in Fig.4, despite their differences we have discussed in Sec.3.1. The possible explanation is that the disadvantage of prefix-tuning lacking the flexibility to modify freeze LM addressed in Sec.3.1, is alleviated or removed by tuning shared LM. Both prefix and adapter's advantage comes from adding private parameters, so they have similar behavior.

## 4 Related Work

#### 4.1 Multilingual Tasks

With rapid development of pre-trained LMs, multilingual LMs have emerged to leverage the power of pre-training on a large number of languages, exemplified by **mBERT** (Devlin et al., 2019), XLM-R (Conneau et al., 2020), XLM-R (Conneau et al., 2020), which adopt masked language model paradigm, and mBART (Liu et al., 2020), mT5 (Xue et al., 2021), which utilize a sequence-tosequence framework. However, a few works have focused on multilingual summarization given the lack of benchmark datasets for other languages except English. (Giannakopoulos et al., 2015) benchmarked summarization systems over 40 languages, with limitation of dataset scale having 10k samples in total. (Scialom et al., 2020) released the multilingual summarization dataset spanning 5 languages with 1.5M article-summary pairs. (Cao et al., 2020) created a new dataset for two languages with 400k samples. (Hasan et al., 2021) introduced XL-Sum spanning 45 languages containing 1.1M articlesummary pairs. More recently, (Varab and Schluter, 2021) released MassiveSumm containing 28.8 million articles across 92 languages.

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# 4.2 Parameter Efficient Tuning

Parameter-efficient tuning methods only tune a small number parameters to achieve comparable results. It can be roughly divided into two categories, methods without additional parameters and methods with additional parameters. The former tune part of the pre-trained LM. (Lee et al., 2019) fine-tunes a few of the final layers, while (Min et al., 2021) only fine-tunes the bias terms of the LM. The latter introduces extra parameters while fixing the pre-trained LM. Popular methods include adapter-tuning (Houlsby et al., 2019; Bapna et al., 2019; Pfeiffer et al., 2020a) prefix-tuning (Li and Liang, 2021) prompt-tuning (Lester et al., 2021), and others (Mao et al., 2021; Hu et al., 2021; Guo et al., 2020). Among these works, a comprehensive discussion in the context of multilingual summarization is relatively missing.

# 5 Discussion

In this paper, we investigate the applicable scope of different families of tuning strategies for multilingual learning. We specifically ask three research questions, and by extensive experiments on summarization datasets with 45 languages we obtain diverse observations which, hopefully, would provide a useful instruction for future designing of multilingual tuning strategies. One limitation of our work is that we only conduct experiments on one summarization dataset, and more other NLP tasks could be explored as future work.

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#### **Supplementary Material** Α 860 861

A.1 Hyper-parameter	S
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In Table2, we report the hyper-parameters used in 862 Sec.3.1. 863

#### A.2 Additional Results 864

Table3 supplements Fig.4 in Sec.3.3.	865
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	learning rate	epoch	batch size	grad acc	prefix length	inner dim	beam size	length penalty
prefix-tuning								
few shot setting	3.00e-4	20	2	1	20	800	4	0.6
not few shot setting, low resource	2.00e-4	15	8	1	200	800	4	0.6
not few shot setting, not low resource	2.00e-4	15	16	4	200	800	4	0.6
adapter-tuning								
few shot setting	1.00e-3	20	2	1	-	1200	4	0.6
not few shot setting, low resource	1.00e-3	15	8	1	-	1200	4	0.6
not few shot setting, not low resource	1.00e-3	15	16	4	-	1200	4	0.6
PLM fine-tuning								
few shot setting	5.00e-4	20	2	1	-	-	4	0.6
not few shot setting, low resource	5.00e-4	15	8	1	-	-	4	0.6
not few shot setting, not low resource	5.00e-4	15	16	4	-	-	4	0.6

Table 2: Hyper-parameter settings for Sec.3.1. Grad acc is the abbreviation of gradient accumulation size, inner dim is the abbreviation of inner dimension.

nmbaric         17.466.64/16         16.585/88/14.88         15.335.42/13.8         20.087/41/18.05         20.067/61/18.5         20.337/48/18.34           arzebiajini         16.937/04/15.36         17.817/34/16.13         15.726.3/14.47         12.449/55/19.15         35.161/14.962.97         21.77/0.859/19.62         21.589.83/19.76           berngali         25.907.3/22.12         25.90/10.07/22.21         23.769.11/20.66         29.46/12.02/25.1         29.11/11.61/24.64         29.57/11.88/24.89           chinese simplified         40.87/25.907/34.09         39.81/24.98/33         35.322.34/30.22         43.8728.706.84         44.95/28.6737.0         44.37/29.1/37.18           chinese traditional         40.04718.04/32.72         38.901/62.271.06         34.61/2.92/27.28         33.601/12.82.8         35.0601/6.222.84         35.601/6.528.16           gujarati         19.38/6.4917.76         19.31/6.2317.62         18.03/3.6571/6.43         30.93/17.27/2.43         35.31/16.192.82         36.061/6.222.89         30.01/17.27/2.16         39.6317.78/1.84           hindi         38.64/17.33/2.23         35.571/4.84/2.8         30.69/17.27/2.44         35.37/16.197.28         39.6317.78/1.84           japanese         45.86/2.37/2.92         34.86/15.51/28.8         30.96/17.87/1.43         39.6317.78/1.84         39.03117.92/2.93         30.11/9.72/2.10	language	PLF	MPE_adapter	MPE_prefix	MPF	MPS_adapter	MPS_prefix
arabic         34.82/15.13/29.22         32.29/12.85/26.43         29.02/10.94/24.14         34.89/14.76/29.13         35.16/14.96/29.27         35.36/15.11/29.49           bengali         25.99.73/22.12         25.99/10/722.21         23.576/9.11/20.66         29.46/12.072.13         21.17/18.87/14.64         21.58/9.83/19.76           chinese traditional         40.0475.11/33.31         39.16/24.17/82.33         36.322.34/10.22         43.87/28.76/04         49.5729.66/37.99         44.37/29.17/31.83/3.83           chinese traditional         40.04/25.11/33.31         39.16/24.17/82.3         35.99/12.17/92.7         43.21/28.03/36.17         44.26/28.75/37.01         43.82/91.5.63/30.39           french         32.02/13.47/25.29         31.85/13.34/25.13         30.66/12.97/24.49         35.33/16.19/28.24         36.06/16.45         22.27/8.4         35.60/16.45         22.27/8.4         35.60/16.45         22.27/8.4         35.60/16.45         22.37/8.14/20.31           hausa         36.16/15.43/29.13         35.75/16.49/41.21         34.08/13.82/27.07         39.41/17.07/23.6         39.17/8.11/3.29         39.02/17.3/2.25         30.01/17.22.20         30.17/9.22.22         30.01/9.52.11         39.62/17.3/2.25         30.01/17.22.23         30.61/17.3/2.25         30.01/17.22.23         30.17/9.57/3.4         39.02/17.3/2.55         30.11/17.27/3.02.55         30.11/17.23/2.5	amharic	17.46/6.64/16	16.58/5.88/14.88	15.33/5.42/13.8	20.08/7.41/18.05	20.6/7.61/18.5	20.33/7.48/18.34
intervesimini         16.937/04/15.36         17.817/34/16.13         15.726/3/14.47         21.49/55/19.37         21.77/9.85/19.62         21.589/83/19.62           berngati         25.99/10.07/22.12         25.769/11.07/26.6         29.57/11.88/24.89           burmese         14.354/51/13.08         14.074/09/12.54         12.74/3.46/11.51         16.17/5.17/14.42         15.84/4.71/40.8         16.12/5.07/14.39           chinese traditional         40.04/25.11/33.31         39.81/24.98/37.02         34.36/12.92/17.44         35.31/16.19/28.8         36.06/15.228.16         35.69/16.15/28.16           gujarati         19.38/6.49/17.6         19.31/6.23/17.62         18.03/3.65/16.45         21.96/7.72/19         22.45/7.97/12.0.21         23.88/8.14/20.31           hausa         36.16/15.43/29.13         35.57/14.84/28.3         34.06/12.32/28.23         35.07/16.73/13.85         39.69/17.21/17.22/3         39.63/17.83/1.96           hausa         36.64/17.33/22.38         37.57/16.09/31.1         34.22/13.22/27.03         31.61/17.22.49         30.01/17.92/23.9         30.01/17.92/23.9         30.01/17.92/23.9         30.01/17.92/23.9         30.01/17.92/23.9         30.01/17.92/23.9         30.01/17.92/23.9         30.01/17.92/23.9         30.01/17.92/23.9         30.01/17.92/23.9         30.01/17.92/23.9         30.01/17.92/23.9         30.01/17.92/23.9         30.01/17.92/23.9 </td <td>arabic</td> <td>34.82/15.13/29.22</td> <td>32.29/12.85/26.43</td> <td>29.02/10.94/24.14</td> <td>34.89/14.76/29.15</td> <td>35.16/14.96/29.27</td> <td>35.36/15.11/29.49</td>	arabic	34.82/15.13/29.22	32.29/12.85/26.43	29.02/10.94/24.14	34.89/14.76/29.15	35.16/14.96/29.27	35.36/15.11/29.49
bengali         25.99/322.12         25.99/10.0722.21         23.76/9.11/20.66         29.40/12.02/25.1         29.11/11.61/24.64         29.57/11.88/24.89           chinese simplified         40.87/25.97/34.09         39.81/24.98/33         36.322.34/30.22         43.828.70/65.9         44.95/29.66/37.79         44.37/29.1/37.14           chinese traditional         40.047/18.04/32.72         33.90/16.52/31.06         34.6/12.93/27.38         37.6/116.19/28.2         36.00/16.22/28.4         35.69/16.15/28.16           gujarati         10.38/6.49/17.6         19.31/6.21/17.62         18.05/15.65/16.45         21.96/7.72/19.9         22.45/7.97/20.12         22.88/14/20.31           hindi         36.61/15.43/29.13         35.75/16.04/31.18         32.27/8.23/16.4         39.75/16.07/31.44         39.75/17.04/31.85           iponese         45.86/22.01/53.39         45.60/1.87/25.02         45.80/12.87/25.22         30.11/19.2/22.49         30.01/17.57/31.46           ipanese         45.86/22.01/53.39         45.60/21.87/35.02         61.81/10.18/20.51         30.11/19.2/22.49         30.01/17.57/31.46           ipanese         45.86/22.01/53.39         45.90/21.87/35.02         61.81/10.18/20.51         30.11/19.2/22.49         30.11/17.57/31.46           ipanese         45.86/22.01/53.39         45.90/21.87/35.02         61.81/10.18/20.51         30.11/11.27/1	azerbaijani	16.93/7.04/15.36	17.81/7.34/16.13	15.72/6.3/14.47	21.4/9.55/19.37	21.77/9.85/19.62	21.58/9.83/19.76
burnese         14.354/51/13.08         14.074.09/12.54         12.74/3.46/11.51         16.17/5.1714-42         15.844.71/4.08         16.12/5.071/4.39           chinese straditional         40.04/25.11/3.31         39.81/24.98/33         36.322.34/30.22         43.828.76/36.9         44.95/29.66/37.01         43.828.73/01         43.827.07         39.18/17.421         18.829/15.71/01         43.828.73/01         43.828.73/01         43.828.73/01         43.828.73/01         43.828.73/01         43.828.73/01         43.828.73/01         43.828.73/01         43.828.73/01         43.828.73/01         43.828.73/01         35.93/01.17/01.222.84         35.99/01.532.81         30.93/11.78/12.84         36.93/01.17/01.228.16         30.93/11.78/12.84         36.93/01.17/01.222.84         35.99/01.17/01.238.72         37.01/17.0224.52         30.93/01.73/22.52         35.227.08/01.93.31         37.79/17.57/31.44         48.89/23.84         48.89/23.83/01.47/01.228.81         30.93/01.17/21.228.52 </td <td>bengali</td> <td>25.9/9.73/22.12</td> <td>25.99/10.07/22.21</td> <td>23.76/9.11/20.66</td> <td>29.46/12.02/25.1</td> <td>29.11/11.61/24.64</td> <td>29.57/11.88/24.89</td>	bengali	25.9/9.73/22.12	25.99/10.07/22.21	23.76/9.11/20.66	29.46/12.02/25.1	29.11/11.61/24.64	29.57/11.88/24.89
chinese simplified         40.87/25.97/34.09         39.81/24.98/33         36.322.34/30.22         43.828.70/64.09         44.95/25.97/37.91         44.37/29.1/37.18           cenglish         40.67/18.04/3.72         33.96/16.52/31.06         34.6/12.93/27.38         37.6/1/5.15/28.16         38.29/15.63/20.39           french         32.02/13.47/25.29         31.85/13.34/25.13         30.63/12.97/24.49         35.33/16.19/28.2         36.06/16.22/28.41         35.69/16.15/28.16           gujarati         19.38/6.49/17.6         18.03/5.65/16.45         21.96/7.72/19.9         22.457.97/20.21         22.38/8.14/20.31           hausa         36.16/15.43/29.13         35.77/16.04/31.83/227.07         39.41/17.72/31.64         39.75/17.64/31.85         39.65/17.73/13.64           japanese         45.86/22.01/35.39         45.66/1.87/05.02         42.37/28.27/25.25/17.36         31.64/10.22/4.51         30.17/9.2/22.98         30.11/9.5/23.11           kirundi         28.97/12.84/23.6         28.94/12.23/23.66         26.18/10.18/20.51         30.17/14.97/23.25         30.57/14.14/12.58         30.65/14.97.22         32.57/14.37/12.02         32.57/14.37/14.16/27.39           kirundi         28.97/12.84/23.6         28.94/12.23/23.66         26.18/10.18/20.51         32.1/14.37/22.2         32.57/14.37/14.16/27.39         33.77/16.09/17.17/17.2         32.57/14.37/21.6         33	burmese	14.35/4.51/13.08	14.07/4.09/12.54	12.74/3.46/11.51	16.17/5.17/14.42	15.84/4.7/14.08	16.12/5.07/14.39
chinese traditional         40.0425.11/33.31         39.16/24.17/32.3         35.99/21.79/29.7         43.21/28.03/36.17         44.26/28.75/37.01         43.83/28.33/36.66           english         32.02/13.47/25.29         31.85/11.3.4/25.13         30.63/12.97/24.49         35.33/16.16/15.42/29.21         38.29/15.71/0.41         38.29/15.71/0.41         38.29/15.71/0.41         38.29/15.71/0.41         38.29/15.71/0.41         38.29/15.71/0.41         38.29/15.71/0.41         38.29/15.71/0.41         38.29/15.71/0.41         39.75/11.64/31.85         39.60/16.22/28.4         36.64/17.33/32.3         35.57/14.84/38.21         34.08/13.82/27.07         39.41/17.72/31.46         39.75/17.64/31.85         39.60/17.87/32.35           igbo         27.166/5.76/21.37         52.227/08/17.83         32.27/75/25.25/17.36         31.64/10.27/45.7         37.01/17.02/30.75         37.38/17.55/31.37         37.69/17.57/31.46           japanese         45.66/21.57/28.85         30.96/12.87/25.72         37.01/17.02/30.75         37.83/17.55/31.37         37.69/17.57/31.46           korean         19.04/9.42/18.06         18.39/6.24/17.28/25.02         23.57/11.49/22.34         23.57/11.49/22.34         23.57/11.49/22.34         23.57/11.49/22.34         23.57/11.49/22.44         23.57/11.59/17.27         23.57/11.59/17.27         23.57/11.59/17.27         23.57/11.59/17.27         23.57/11.59/17.27         23.57/11.59/17.24	chinese simplified	40.87/25.97/34.09	39.81/24.98/33	36.3/22.34/30.22	43.8/28.76/36.9	44.95/29.66/37.79	44.37/29.1/37.18
english         40.671/8.04/22.72         38.961/6.52/21.06         34.61/2.92/27.38         37.611/5.12/2.88         38.291/5.673/0.39           french         32.021.3 47/25.29         31.851/3.3472.51         30.631/1.297/0.44         35.331/6.19/28.2         36.061/6.22/28.4         35.691/6.15/2.81/2.5           hausa         36.161/5.43/29.13         35.751/1.69/11.1         34.231/3.23/28.23         38.571/1.677/21.64         39.1817.371/2.49         39.0217.372.49           ipdo         27.1668.76/21.37         25.227/0.08/19.38         32.277/5.2517.36         31.641/0.274.51         30.1179.272.29         30.0179.272.29         30.0179.572.11           ipdonese         45.8622.01/35.39         45.6621.877.55.02         41.231.88.971.68         32.041.877.571.68         32.6571.4897.62         32.2571.497.62.62         32.5711.6971.751.14         43.071.751.72.49         39.017.571.14         42.071.737.14         48.072.017.272.49         35.711.6177.24.94         39.017.577.14.64           ipanese         45.8672.201.73         45.6671.876.72.30         45.6671.877.570.68         32.1471.4172.16.0         18.37.8416.11           marathi         20.21.89.418.31         20.0378.4911.89         18.37.7516.68         32.2.069.5571.00         23.5711.312.17         23.5711.512.208         23.5711.512.208         23.5711.512.208.2711.4912.23         23.5711.512.208 <t< td=""><td>chinese traditional</td><td>40.04/25.11/33.31</td><td>39.16/24.17/32.3</td><td>35.99/21.79/29.7</td><td>43.21/28.03/36.17</td><td>44.26/28.75/37.01</td><td>43.83/28.33/36.66</td></t<>	chinese traditional	40.04/25.11/33.31	39.16/24.17/32.3	35.99/21.79/29.7	43.21/28.03/36.17	44.26/28.75/37.01	43.83/28.33/36.66
french         32.02/13.47/25.29         31.85/13.34/25.13         30.63/12.97/24.49         35.33/16.19/28.2         36.06/16.22/28.41         35.69/16.15/28.16           gujarati         19.38/6.49/17.61         19.31/6.23/17.62         18.03/5.65/16.45         21.96/7.72/19.2         22.45/7.97/20.21         22.38/8.14/20.31           hausa         36.16/15.43/29.13         35.75/16.69/31.1         34.23/13.22/28.23         35.71/16.87/32.03         39.18/17.37/32.49         39.01/17.37/31.54           igbo         27.16/8.76/21.37         52.277.08/19.98         32.75/15.20         12.37/55.27         37.01/17.02/32.07         37.83/17.55/1.37         37.69/17.57/13.49           ipanese         45.86/12.01/55.39         45.67/12.77/51.02         41.23/18.89/32.42         48.08/23.87/3.24         48.07/24.26/37.33         37.69/17.57/14.62           krundi         28.97/12.84/23.6         28.94/12.23/23.06         26.18/10.18/20.51         32/14.41/25.82         32.65/14.98/26.22         32.65/14.98/26.22         32.65/14.98/26.22         32.65/14.98/26.22         32.65/14.98/26.22         32.65/14.98/26.22         32.65/14.98/26.22         32.65/14.98/26.22         32.65/14.98/26.22         32.65/14.98/26.22         32.65/14.98/26.22         32.65/14.98/26.22         32.65/14.98/26.22         32.65/14.98/26.22         32.65/14.98/26.22         32.65/14.98/26.22         32.65/14.98/26.22	english	40.67/18.04/32.72	38.96/16.52/31.06	34.6/12.93/27.38	37.61/15.15/29.88	38.29/15.71/30.41	38.29/15.63/30.39
gujarati         19.38(6.49/17.6         19.31/6.23/17.62         18.03/5.65/16.45         21.96/7.72/19.9         22.457/97/20.21         22.388.14/20.21           hausa         36.16/15.43/29.13         35.75/14.84/28.21         34.08/13.82/27.07         39.41/17.72/31.64         39.75/17.64/31.85         39.63/17.8/31.96           indonesian         35.69/16.23/29.92         34.86/15.21/28.85         30.06/12.87/25.72         37.01/17.02/20.07         37.83/17.55/31.37         31.69/17.57/31.46           japanese         45.86/22.01/35.39         34.86/15.21/28.85         0.06/12.87/25.72         37.01/17.02/20.75         37.83/17.56/13.37         34.66/15.21/2.92         32.65/14.91/26.20           kirundi         28.97/12.84/21.6         28.94/12.23/23.06         26.18/10.18/20.51         332/14.41/25.82         32.65/14.98/26.22         32.65/14.91/26.20           korean         19.04/9.42/18.06         19.92/9.93/18.59         18.07/8.95/17.08         23.711.49/22.34         23.57/11.37/16.18         23.11/11.17/16.0         18.37.87/16.11           kyrgy         13.66/5.80/12.43         13.39/5.62/12.60         11.77/4.88/10.88         12.84/8.01/16.5         18.47/7.2/16.0         18.37.87/16.81           pashto         37.69/15.38/31.19         36.74/14.0229.85         33.85/12.14/27.18         38.28/15.48/31.77         38.85/15.85/32.00         37.25/16.88/3	french	32.02/13.47/25.29	31.85/13.34/25.13	30.63/12.97/24.49	35.33/16.19/28.2	36.06/16.22/28.4	35.69/16.15/28.16
masa         36.16/15.43/29.13         35.75/14.84/28.21         34.08/13.82/27.07         39.75/17.64/31.85         39.65/17.8/13.85           hindi         38.64/17.33/32.38         37.57/16.09/31.1         34.32/13.23/28.23         38.57/16.87/32.03         39.18/17.37/32.49         39.02/17.3/32.35           igbo         27.168.76/21.37         25.227/08/19.88         23.27/5.25/17.36         31.64/10.274.51         30.17/9.222.98         30.11/9.572.1           indonesian         35.69/16.2329.92         34.86/15.51/28.85         30.96/12.87/25.72         37.01/17.02/30.75         37.83/17.550.41         41.23/18.89/32.42         48.08/23.873.24         45.66/2.472.426/37.33         48.41/24.16/37.39           kirundi         28.97/12.84/23.6         28.94/12.23/23.06         26.18/10.18/20.51         32.11/1.4127.21         85.41/4.91/26.22         32.65/14.91/26.22         32.65/14.91/26.22         32.65/14.91/26.22         32.65/14.91/26.22         32.65/14.91/26.22         32.65/14.91/26.22         32.65/14.91/26.22         32.65/14.91/26.22         32.65/14.91/26.22         32.65/14.91/26.22         32.65/14.91/26.22         32.65/14.91/26.22         32.65/14.91/26.22         32.65/14.91/26.22         32.65/14.91/26.22         32.65/14.91/26.22         32.65/14.91/26.22         32.65/14.91/26.22         32.65/14.91/26.24         33.78/16.11           marathi         20.118.96/12.98	gujarati	19.38/6.49/17.6	19.31/6.23/17.62	18.03/5.65/16.45	21.96/7.72/19.9	22.45/7.97/20.21	22.38/8.14/20.31
hindi         38.64/17.33/32.38         37.57/16.09/3.11         34.32/13.23/28.23         38.57/16.87/32.03         39.18/17.37/32.49         39.02/17.3/32.35           igbo         27.16/8.76/21.37         25.22/7.08/19.38         23.27/5.25/17.36         31.64/10.2/24.51         30.17/9.2/2.98         30.11/9.57/3.14           igpanese         45.86/22.01/35.39         45.66/1.87/35.02         41.23/18.89/32.42         48.08/23.87/3.23         48.65/24.26/37.33         48.41/24.16/37.39           kirundi         28.97/12.84/23.6         28.94/12.32/23.06         26.18/10.18/20.51         32/14.41/25.82         32.65/14.98/26.22         32.65/15.95/24.66         32.65/16.97/21.41         32.64/14.92/14.13         <	hausa	36.16/15.43/29.13	35.75/14.84/28.21	34.08/13.82/27.07	39.41/17.72/31.64	39.75/17.64/31.85	39.63/17.8/31.96
igbo         27.16/8.76/21.37         25.22/7.08/19.38         23.27/5.25/17.36         31.64/10.2/24.51         30.17/9.2/22.98         30.11/9.5/23.1           indonesian         35.69/16.23/29.92         34.86/15.51/28.85         30.96/12.87/25.72         37.101/7.02/30.75         37.83/17.55/1.37         37.69/17.57/13.46           kirundi         28.97/12.84/23.6         28.94/12.23/23.06         26.18/10.18/20.51         37.14/14/25.82         32.65/14.98/26.22         32.65/14.98/26.22         32.65/14.98/26.22         32.65/14.91/26.26           korean         19.04/9.42/18.06         19.92/9.97/18.56         18.07/8.95/17.08         23.71/1.49/22.34         23.57/11.31/21.78         23.11/11.27/21.6         18.37/8/16.11           marathi         20.21/8.94/18.31         20.03/8.49/18.19         18.37/4.55/16.83         22.06/9.57/20.01         23.13/10.32/20.8         22.82/10.02/20.54           oromo         16.55/5.35/14.61         16.2/5.14/14.13         13.74.14/12         18.348/6.21         32.57/11.50/29.17         38.85/15.85/2.20         38.92/16.05/32.16           persian         37.04/16.25/8.84         35.29/12.57/25.79         37.71/15.12/9.86         38.56/15.6/20.14         38.89/15.88/30.47           portuguese         37.04/16.25/2.82         36.31/13.14/27.41         32.85/11.57/25.77         37.11/15.02/28.78         37.25/16.58/30.42	hindi	38.64/17.33/32.38	37.57/16.09/31.1	34.32/13.23/28.23	38.57/16.87/32.03	39.18/17.37/32.49	39.02/17.3/32.35
indonesian         35.69/16.23/29.92         34.86/15.51/28.85         30.96/12.87/25.72         37.01/17.02/30.75         37.83/17.55/31.37         37.69/17.57/31.46           japanese         45.86/22.01/35.39         45.6/21.87/35.02         41.23/18.89/32.42         48.08/23.8/37.32         48.65/24.26/37.33         48.41/24.16/37.39           kirundi         28.97/12.84/23.6         28.94/12.32/32.06         28.18/10.18/89/32.05         32/14.14/125.82         25.65/14.99/26.26         22.65/14.99/26.26         25.65/14.91/26.26         25.65/14.91/26.26         25.65/14.91/26.26         25.65/14.91/26.26         25.65/14.91/26.26         25.65/14.91/26.26         25.65/14.91/26.26         25.65/14.91/26.26         25.65/16.91         14.97/78.16.81         22.06/9.57/20.01         23.13/10.32/20.8         22.82/10.02/24.21           oromo         16.555/5.35/14.61         16.25/14/14.13         13.74/14/12         18.77/55/16.83         22.06/9.57/20.01         23.13/10.32/20.8         28.89/16.8/30.42         37.32/16.3/30.31           portguese         37.69/16.78/30.44         35.72/15.14/14.13         13.74/14/12         18.74/27.88         32.8/15.49/31.77         38.89/15.88/30.47         37.32/16.3/30.37         37.82/16.6/30.14         38.89/15.88/30.47           portguese         37.04/16.25/28.82         36.3/15.18/27.7         32.99/12.57/25.07         37.71/15.16/29.83 <t< td=""><td>igbo</td><td>27.16/8.76/21.37</td><td>25.22/7.08/19.38</td><td>23.27/5.25/17.36</td><td>31.64/10.2/24.51</td><td>30.17/9.2/22.98</td><td>30.11/9.5/23.1</td></t<>	igbo	27.16/8.76/21.37	25.22/7.08/19.38	23.27/5.25/17.36	31.64/10.2/24.51	30.17/9.2/22.98	30.11/9.5/23.1
japanese 45.86/22.01/35.39 45.6/21.87/35.02 41.23/18.89/32.42 48.08/23.8/37.32 48.65/24.26/37.33 48.41/24.16/37.39 kirundi 28.97/12.84/23.6 28.94/12.23/23.06 26.18/10.18/20.51 32/14.41/25.82 32.65/14.98/26.22 32.65/14.91/26.26 korean 19.04/9.42/18.06 19.92/9.93/18.59 18.07/8.95/17.08 23.7/11.49/22.34 23.65/14.98/26.22 32.65/14.91/26.26 kyrgyz 13.66/5.58/12.43 13.89/5.62/12.69 11.77/4.88/10.87 23.7/11.14/22.18 23.11/11.27/21.60 18.37/8.1/6.11 arrathi 20.21/8.94/18.31 20.03/8.49/18.19 18.37/55/16.83 22.06/9.57/20.01 23.13/10.32/20 22.82/10.02/20.54 nepali 23.16/9.06/21.14 23.63/8.69/21.51 20.91/7.37/19.25 26.57/10.27/24.21 26.5/10.05/24.06 25.69/10.22/24.21 oromo 15.55/5.35/14.61 16.2/5.14/14.13 13.7/4.14/12 18.74/6.21/16.19 19.68/6.45/16.91 19.49/6.7/116.88 pashto 37.69/15.38/31.19 36.74/14.02/29.85 33.85/12.147/27.88 33.28/15.49/31.77 38.85/15.85/30.04 37.32/16.43/30.3 pidgin 34.55/12.67/27.03 35.11/13.14/27.41 32.85/11.57/25.07 37.57/15.13/29.86 38.56/15.6/30.14 38.89/15.88/30.47 portuguese 37.04/16.25/28.82 36.3/15.18/27.7 32.99/12.57/25.07 37.15/15.13/29.86 38.56/15.6/30.14 38.89/15.88/30.47 portuguese 32.04/16.25/28.82 36.3/15.18/27.7 32.99/12.57/25.07 37.15/15.13/29.86 38.56/15.6/30.14 38.89/15.88/30.47 source 32.04/16.25/28.82 36.3/15.18/27.7 32.99/12.57/25.07 37.15/15.13/29.86 38.56/15.6/30.14 38.89/15.88/30.47 source 32.04/16.25/28.82 36.3/15.18/27.7 32.99/12.57/25.07 37.15/15.13/29.86 38.56/15.6/30.14 38.89/15.88/30.47 source 32.04/16.25/28.82 36.3/16.18/27.73 24.59/37.97/15.13/29.86 38.56/15.6/30.14 39.26/13.92/26.39 soctish gaelic 23.16/7.04/19.25 20.42/4.31/17.02 24.05/7.73/19.45 20.21/13.64/26.16 32.82/13.97/26.44 32.61/13.92/26.39 soctish gaelic 23.16/7.04/19.25 20.42/4.31/17.02 24.05/7.73/19.45 20.21/13.64/26.16 32.82/13.97/26.44 32.61/13.92/26.39 soctish gaelic 23.18/1.83/26.11 30.56/12.67/24.73 26.59/79/21.14 33.54/11.55/24.22 32.11/1.36/24.42 32.48/11.272.53 30.07/12.272.55 37.84/12.02 32.91/1.61/19.81 22.80/90.88/21.45 33.79/17.91/20.13 32.44/17.42/31.16 37.74/17.65/30.8 tami 29.08/10.02/23.1	indonesian	35.69/16.23/29.92	34.86/15.51/28.85	30.96/12.87/25.72	37.01/17.02/30.75	37.83/17.55/31.37	37.69/17.57/31.46
kirundi         28.97/12.84/23.6         28.94/12.23/23.06         26.18/10.18/20.51         32/14.41/25.82         32.65/14.98/26.22         32.65/14.91/26.26           korean         19.04/9.42/18.06         19.92/9.93/18.59         18.07/8.95/17.08         23.71/11.49/22.34         23.57/11.31/21.78         23.11/11.27/21.60         18.37/.87/16.11           marathi         20.21/8.94/18.31         20.03/8.49/18.19         18.37/.55/16.83         22.06/9.57/20.01         23.13/10.32/20.8         22.82/10.02/20.54           nepali         23.169/06/21.14         23.63/8.69/21.51         20.91/7.37/19.25         26.57/10.274.22         26.57/10.05/24.40         62.59/10.02/24.21           oromo         16.55/3.53/14.61         16.25/1.41/4.13         13.77/14/62.11/6.19         19.68/64.65/16.91         19.49/6.71/16.88           pashto         37.69/15.38/31.19         36.72/15.34/28.81         32.98/12.89/26.27         35.71/15.06/29.1         37.32/16.43/30.3           portuguese         37.04/16.25/28.82         36.3/15.18/27.7         32.99/12.57/25.07         37.97/15.13/29.86         38.56/15.6/30.14         38.89/15.88/30.47           purgues         3.04/16.25/28.82         36.3/15.18/27.7         32.99/12.57/25.07         37.11/16.312.87/11.29/25.37         31.14/12.3/25.33         30.77/12.27/25.29           russian         32.18/13.83/16.11	iapanese	45.86/22.01/35.39	45.6/21.87/35.02	41.23/18.89/32.42	48.08/23.8/37.32	48.65/24.26/37.33	48.41/24.16/37.39
korean         19.04/9.42/18.06         19.92/9.93/18.59         18.07/8.95/17.08         23.7/11.49/22.34         23.57/11.31/21.78         23.11/11.27/21.6           kyrgyz         13.66/5.58/12.43         13.89/5.62/12.69         11.77/4.88/10.87         18.34/8.01/16.5         18.4/7.72/16.0         18.37/.81/61.1           mepali         23.16/9.06/21.14         23.63/8.69/21.51         20.91/7.37/19.25         26.57/10.2/24.22         26.5/10.05/24.06         22.82/10.02/20.54           pashto         37.69/15.383/11.9         65.7/14.40/22).84         38.28/15.49/31.77         38.82/15.18/31.03         38.92/16.05/32.16           persian         37.08/16.78/30.44         35.72/15.34/28.81         32.98/12.89/26.27         35.71/15.06/29.1         37.25/16.58/30.42         37.32/16.43/30.3           portuguese         37.08/16.78/30.44         35.72/15.34/28.81         32.98/12.89/26.27         37.71/15.15/29.26         38.56/15.6/30.14         38.89/15.88/30.47           portuguese         37.04/16.25/28.23         30.51/15.18/27.7         32.99/12.27/12.57         31.14/12.3/25.33         37.71/16.33/28.97         37.59/16.23/28.97           serbian cyrillic         18.64/4.83/15.51         17.83/4.26/14.49         18.52/4.89/15.58         37.97/90/20.13         24.578.42/20.73         30.08/11.2/23.83           serbian cyrillic         18.64/4.83/15.51	kirundi	28.97/12.84/23.6	28.94/12.23/23.06	26.18/10.18/20.51	32/14.41/25.82	32.65/14.98/26.22	32.65/14.91/26.26
kyrgyz         13.66/5.58/12.43         13.89/5.62/12.69         11.77/4.88/10.87         18.34/8.01/16.5         18.4/7.72/16.0         18.37/8/16.11           marathi         20.21/8.94/18.31         20.03/8.49/18.19         18.37/.55/16.83         22.06/9.57/20.01         23.13/10.32/20.8         22.82/10.02/20.54           oromo         16.55/5.35/14.61         16.2/5.14/14.13         13.7/4.14/12         18.74/6.21/16.19         19.68/6.45/16.91         19.49/6.71/16.88           pashto         37.69/15.38/31.19         36.74/14.02/29.85         33.85/12.14/27.88         38.82/15.49/31.77         38.85/15.65/32.05         38.92/16.05/32.16           pidgin         34.55/12.67/27.03         35.11/13.14/27.41         32.89/12.89/26.27         35.71/15.04/28.83         37.71/16.33/28.97         37.39/16.12/89.04         37.32/16.43/30.3           pungabi         26.18/9.61/12.95         25.75/8.58/20.07         25.54/8.49/21.43         30.771/12.15/25.75         31.14/12.3/25.33         30.771/12.15/25.75         31.71/16.33/28.97         37.39/16.21/28.97           scrisin actilic galic         23.16/7.04/19.25         20.42/4.31/17.02         20.43/8.49/21.43         32.771/12.52/57         31.14/12.3/25.33         30.771/12.15/22.63         30.08/11.22/26.39           scrbian calitin         17.13/4.19/14.24         18.09/4.31/14.82         18.04/4.21/14.9 <td< td=""><td>korean</td><td>19.04/9.42/18.06</td><td>19.92/9.93/18.59</td><td>18.07/8.95/17.08</td><td>23.7/11.49/22.34</td><td>23.57/11.31/21.78</td><td>23.11/11.27/21.6</td></td<>	korean	19.04/9.42/18.06	19.92/9.93/18.59	18.07/8.95/17.08	23.7/11.49/22.34	23.57/11.31/21.78	23.11/11.27/21.6
marathi         20.21/8.94/18.31         20.03/8.49/18.19         18.377.55/16.83         22.06/9.57/20.01         23.13/10.32/20.8         22.82/10.02/20.54           nepali         23.16/9.06/21.14         23.63/8.69/21.51         20.91/7.37/19.25         26.57/10.2/24.22         26.57/10.02/24.22         26.57/10.02/24.22         26.57/10.02/24.22         26.57/10.2/24.22         26.57/10.2/24.22         26.57/10.2/24.22         26.57/10.2/24.22         26.57/10.2/24.22         26.57/10.2/24.22         26.57/10.2/24.22         26.57/10.2/24.22         26.57/10.2/24.22         26.57/10.2/24.22         26.57/10.2/24.22         26.57/10.2/24.23         38.85/15.85/32.05         38.92/16.05/32.16           pashto         37.68/16.78/30.44         35.72/15.34/28.81         32.98/12.89/26.27         35.71/15.06/29.1         37.25/16.58/30.42         37.32/16.43/30.3           portuguese         37.04/16.25/28.82         36.3/15.18/27.7         32.99/12.57/25.07         37.15/15.89/28.53         37.71/16.33/28.97         37.59/16.21/28.91         30.67/12.27/25.29           russian         32.18/13.83/26.11         30.56/12.67/24.73         26.59/79/21.43         30.77/12.87/25.26         30.08/11.2/22.83           sectisin gaelic         23.167/0.4/19.25         20.42/4.31/17.02         24.69/7.73/19.45         29.01/10.96/22.87         28.85/10.55/22.65         30.08/11.2/22.83 <td< td=""><td>kvrgvz</td><td>13.66/5.58/12.43</td><td>13.89/5.62/12.69</td><td>11.77/4.88/10.87</td><td>18.34/8.01/16.5</td><td>18.4/7.72/16.0</td><td>18.3/7.8/16.11</td></td<>	kvrgvz	13.66/5.58/12.43	13.89/5.62/12.69	11.77/4.88/10.87	18.34/8.01/16.5	18.4/7.72/16.0	18.3/7.8/16.11
nepali         23.16/9.06/21.14         23.63/8.69/21.51         20.91/7.37/19.25         26.57/10.2/24.22         26.57/10.05/24.06         26.59/10.2/24.21           oromo         16.555.35/14.61         16.2/5.14/14.13         13.7/4.14/12         18.74/6.21/16.19         19.68/6.45/16.91         19.49/6.71/16.88           pashto         37.08/16.78/30.44         35.72/15.34/28.81         32.98/12.89/26.27         35.57/15.16/27.03         35.11/16.43/30.31           pidgin         34.55/12.67/27.03         35.11/13.14/27.41         32.85/11.57/25.79         37.71/16.58/30.42         37.32/16.43/30.37           pungabi         26.18/9.61/1.95         25.75/8.58/20.07         25.94/8.49/21.43         30.77/12.15/25.57         31.14/12.3/25.33         30.77/12.27/25.29           scrbian cyrillic         18.64/4.83/15.51         17.83/4.26/14.49         18.52/4.89/15.82         23.79/7.99/20.13         24.5/8.42/20.73         24.4/8.35/20.62           serbian cyrillic         18.64/4.83/15.51         17.83/4.26/14.49         18.52/4.89/15.82         23.79/7.99/20.13         24.5/8.42/20.73         24.4/8.35/20.62           serbian cyrillic         18.64/4.83/15.21         17.83/4.26/14.49         18.50/4.89/15.82         23.79/7.99/20.13         24.5/8.42/20.73         24.4/8.35/20.62           serbian cyrillic         18.64/4.83/15.21         17.83/4.26/14.49<	marathi	20.21/8.94/18.31	20.03/8.49/18.19	18.3/7.55/16.83	22.06/9.57/20.01	23.13/10.32/20.8	22.82/10.02/20.54
brin         16.55/5.35/14.61         16.2/5.14/14.13         13.7/4.14/12         18.7/4/6.21/16.19         19.68/6.45/16.91         19.49/6.71/16.88           pashto         37.69/15.38/31.19         36.74/14.02/29.85         33.85/12.14/27.88         38.28/15.49/31.77         38.85/15.85/32.05         38.92/16.05/32.16           persian         37.08/16.78/30.44         35.72/15.34/28.81         32.98/12.89/26.27         35.71/15.06/29.1         37.25/16.58/30.42         37.32/16.43/30.3           pidgin         34.55/12.67/27.03         35.11/13.14/27.41         32.88/11.57/25.79         37.97/15.13/29.86         38.56/15.630.14         38.89/15.88/30.47           portuguese         37.04/16.25/28.82         36.3/15.18/27.7         32.99/12.57/25.07         37.15/15.89/28.53         37.71/16.33/28.97         37.59/16.21/28.91           punjabi         26.18/9.61/21.95         25.75/8.58/20.97         25.94/8.49/21.43         30.77/12.15/25.57         31.14/12.3/25.33         30.77/12.27/25.29           sectian agelic         23.16/7.04/19.25         20.04/24.31/17.02         24.05/7.73/19.45         29.01/10.96/22.87         28.85/10.55/22.65         30.08/11.2/23.83           serbian latin         17.13/4.19/14.24         18.09/4.31/1.48         18.04/4.21/14.9         21.64/6.68/18.23         22.91/7.18/19.26         22.57/7.11/19.02           sinhal	nenali	23 16/9 06/21 14	23 63/8 69/21 51	20 91/7 37/19 25	26 57/10 2/24 22	26 5/10 05/24 06	26 59/10 2/24 21
bashto         37.69/15.38/31.19         36.74/14.02/29.85         33.85/12.14/27.88         38.28/15.49/31.77         38.85/15.85/32.05         38.92/16.05/32.16           persian         37.08/16.78/30.44         35.72/15.34/28.81         32.98/12.89/26.27         35.71/15.06/29.1         37.25/16.58/30.42         37.32/16.43/30.3           pidgin         34.55/12.67/27.03         35.11/13.14/27.1         32.85/11.57/25.79         37.97/15.13/29.86         38.56/15.63/0.14         38.89/16.63/30.47           punjabi         26.18/9.61/21.95         25.75/8.58/20.97         25.94/8.49/21.43         30.77/12.15/25.57         31.14/12.3/25.33         30.77/12.27/25.29           russian         32.18/13.83/26.11         30.56/12.67/24.73         22.69/12.57/921.44         32.21/13.64/26.16         32.82/13.97/26.44         32.61/13.92/26.39           serbian cyrillic         18.64/4.83/15.51         17.83/4.26/14.49         18.52/4.89/15.58         23.79/79/20.13         24.5/8.42/20.73         24.4/8.35/20.62           serbian latin         17.13/4.19/14.24         18.09/4.31/14.82         18.04/4.21/14.9         21.64/6.68/18.23         22.91/7.18/19.26         22.57/7.11/19.02           simhala         23.78/11.87/21.27         23.29/11.16/19.81         21.86/10.48/19.06         21.51/8.07/18.9         27.7/13.8/23.61         27.4/3/13.4/12.27           spanis	oromo	16 55/5 35/14 61	16 2/5 14/14 13	13 7/4 14/12	18 74/6 21/16 19	19 68/6 45/16 91	19 49/6 71/16 88
persian         37.08/16.78/30.44         35.72/15.34/28.81         32.98/12.89/26.27         35.71/15.06/29.1         37.25/16.58/30.42         37.32/16.43/30.3           pidgin         34.55/12.67/27.03         35.11/13.14/27.41         32.85/11.57/25.79         37.97/15.13/29.86         38.56/15.63/0.14         38.89/15.88/30.47           punjabi         26.18/9.61/21.95         25.75/8.58/20.97         32.91/12.57/25.07         37.17/12.15/25.57         31.14/12.3/25.33         30.77/12.27/25.43         30.77/12.15/25.47         31.14/12.3/25.33         30.77/12.27/25.44         32.61/13.92/26.39           scottish gaelic         23.16/7.04/19.25         20.42/4.31/17.02         24.05/7.73/19.45         29.01/10.96/22.87         28.85/10.55/22.65         30.08/11.2/23.83           serbian cyrillic         18.64/4.83/15.51         17.83/4.26/14.49         18.52/4.84/15.58         23.79/7.99/20.13         24.5/8.42/20.73         24.4/8.35/20.62           serbian latin         17.13/4.19/14.24         18.09/4.31/14.82         18.80/4/2.1/14.9         21.64/6.68/18.23         22.91/7.18/19.26         22.57/7.11/19.02           sinhala         23.78/11.87/21.27         23.29/11.16/19.81         21.86/10.48/19.06         21.51/8.07/18.9         27.7/13.8/23.61         27.4/31.34/12.37           somali         29.08/10.21/22.45         29.06/9.97/22.13         28.09/8.88/21.45 <td>pashto</td> <td>37.69/15.38/31.19</td> <td>36.74/14.02/29.85</td> <td>33.85/12.14/27.88</td> <td>38.28/15.49/31.77</td> <td>38.85/15.85/32.05</td> <td>38.92/16.05/32.16</td>	pashto	37.69/15.38/31.19	36.74/14.02/29.85	33.85/12.14/27.88	38.28/15.49/31.77	38.85/15.85/32.05	38.92/16.05/32.16
pidgin         34.55/12.67/27.03         35.11/13.14/27.41         32.85/11.57/25.79         37.97/15.13/29.86         38.56/15.6/30.14         38.89/15.88/30.47           portuguese         37.04/16.25/28.82         36.3/15.18/27.7         32.99/12.57/25.07         37.15/15.89/28.53         37.71/16.33/28.97         37.59/16.21/28.91           punjabi         26.18/9.61/21.95         25.75/8.58/20.97         25.94/8.49/21.43         30.77/12.15/25.57         31.14/12.3/25.33         30.77/12.27/25.29           scottish gaelic         23.16/7.04/19.25         20.42/4.31/17.02         24.05/7.73/19.45         29.01/10.96/22.87         28.85/10.55/22.65         30.08/11.2/23.83           serbian cyrillic         18.64/4.83/15.51         17.83/4.26/14.49         18.52/4.89/15.58         23.79/7.99/20.13         24.5/8.42/20.73         24.4/8.35/20.62           serbian latin         17.13/4.19/14.24         18.09/4.31/14.82         18.60/4.81/10.68/18.23         22.91/7.18/19.26         22.57/7.11/19.02           somali         29.08/10.21/22.45         29.06/9.97/22.13         28.09/8.88/21.45         31.54/11.55/24.22         32.1/11.38/24.42         32.48/11.72/24.07           swahili         33.82/14.82/27.78         34.79/15.52/28.24         33.43/14.91/27.19         37.63/17.86/30.92         38.24/17.82/31.16         37.74/17.65/30.87           tamil	persian	37.08/16.78/30.44	35.72/15.34/28.81	32.98/12.89/26.27	35.71/15.06/29.1	37.25/16.58/30.42	37.32/16.43/30.3
portuguese         37.04/16.25/28.82         36.3/15.18/27.7         32.99/12.57/25.07         37.15/15.89/28.53         37.71/16.33/28.97         37.59/16.21/28.91           punjabi         26.18/9.61/21.95         25.75/8.58/20.97         25.94/8.49/21.43         30.77/12.15/25.57         31.14/12.3/25.33         30.77/12.27/25.29           russian         32.18/13.83/26.11         30.56/12.67/24.73         26.59/.79/21.44         32.21/13.64/26.16         32.82/13.97/26.44         32.61/13.92/26.39           scottish gaelic         23.16/7.04/19.25         20.42/4.31/17.02         24.05/7.73/19.45         29.01/10.96/22.87         28.85/10.55/22.65         30.08/11.2/23.83           serbian cyrillic         18.64/4.83/15.51         17.83/4.26/14.49         18.52/4.89/15.58         23.79/7.99/20.13         24.5/8.42/20.73         24.4/8.35/20.62           serbian latin         17.13/4.19/14.24         18.09/4.31/14.82         18.04/4.21/14.9         21.64/6.68/18.23         22.91/7.18/19.26         22.57/7.11/19.02           sinhala         23.78/11.87/21.27         23.29/10.3/22.23         28.09/9.05/21.14         31.51/11.87/24.07         31.63/11.9/24.11         31.59/11.9/24.11         31.59/11.9/24.11         31.59/11.9/24.11         31.59/11.9/24.07           swahili         33.82/14.82/27.78         34.79/15.52/28.24         33.43/14.9/127.19         37.68/17.86/30.92<	nidgin	34 55/12 67/27 03	35 11/13 14/27 41	32 85/11 57/25 79	37 97/15 13/29 86	38 56/15 6/30 14	38 89/15 88/30 47
punjabi         26.18/9.61/21.95         25.75/8.58/20.97         25.94/8.49/21.43         30.77/12.15/25.57         31.14/12.3/25.33         30.77/12.27/25.29           russian         32.18/13.83/26.11         30.56/12.67/24.73         26.5/9.79/21.44         32.21/13.64/26.16         32.82/13.97/26.44         32.61/13.92/26.39           scottish gaelic         23.16/7.04/19.25         20.42/4.31/17.02         24.05/7.73/19.45         29.01/10.96/22.87         28.85/10.55/22.65         30.08/11.2/23.83           serbian cyrillic         18.64/4.83/15.51         17.83/4.26/14.49         18.52/4.89/15.58         23.79/7.99/20.13         24.5/8.42/20.73         24.4/8.35/20.62           serbian latin         17.13/4.19/14.24         18.09/4.31/14.82         18.04/4.81/14.9         18.52/4.89/15.58         23.79/7.99/20.13         24.5/8.42/20.73         24.4/8.35/20.62           sinhala         23.78/11.87/21.27         23.29/11.16/19.81         21.86/10.48/19.06         21.51/8.07/18.9         27.7/13.8/23.61         27.43/13.41/23.7           somali         29.08/10.21/22.45         29.06/9.97/22.13         28.09/8.88/21.45         31.54/11.57/24.27         34.24/17.82/31.16         37.74/17.65/30.8           tamil         22.47/10.33/20.58         19.81/8.83/18.12         16.45/6.58/15         24.31/11.04/22.07         24.58/11.11/22.3         24.48/11.08/22.11	portuguese	37 04/16 25/28 82	36 3/15 18/27 7	32,99/12,57/25,07	37 15/15 89/28 53	37 71/16 33/28 97	37 59/16 21/28 91
prosist       32.18/13.83/26.11       30.56/12.67/24.73       26.5/9.79/21.44       32.21/13.64/26.16       32.82/13.97/26.44       32.61/13.92/26.39         scottish gaelic       23.16/7.04/19.25       20.42/4.31/17.02       24.05/7.73/19.45       29.01/10.96/22.87       28.85/10.55/22.65       30.08/11.2/23.83         serbian cyrillic       18.64/4.83/15.51       17.83/4.26/14.49       18.52/4.89/15.58       23.79/7.99/20.13       24.5/8.42/20.73       24.4/8.35/20.62         serbian latin       17.13/4.19/14.24       18.09/4.31/14.82       18.04/4.21/14.9       21.64/6.68/18.23       22.91/7.18/19.26       22.57/7.11/19.02         sinhala       23.78/11.87/21.27       23.29/11.16/19.81       21.86/10.48/19.06       21.51/8.07/18.9       27.7/13.8/23.61       27.43/13.41/23.7         somali       29.08/10.21/22.45       29.06/9.97/22.13       28.09/9.05/21.14       31.54/11.57/24.22       32.1/11.38/24.42       32.48/11.72/24.55         spanish       30.05/10.98/23.13       29.28/10.3/22.23       28.09/9.05/21.14       31.51/11.87/24.07       31.63/11.9/24.11       31.59/11.9/24.11       31.59/11.9/24.11       31.59/11.9/24.11       31.59/11.9/24.11       31.63/11.9/24.11       31.63/11.9/24.11       31.63/11.9/24.11       37.74/17.65/30.8         tamil       22.47/10.33/20.58       19.81/8.83/18.12       16.45/6.58/15       24.31/1	puniabi	26 18/9 61/21 95	25 75/8 58/20 97	25 94/8 49/21 43	30 77/12 15/25 57	31 14/12 3/25 33	30 77/12 27/25 29
Scottish gaelic         23.167.04/19.25         20.42/4.31/17.02         24.057/.73/19.45         29.01/10.96/22.87         28.85/10.55/22.65         30.08/11.2/23.83           serbian latin         17.13/4.19/14.24         18.09/4.31/14.82         18.04/4.21/14.9         21.64/6.68/18.23         22.91/7.18/19.26         22.57/7.11/19.02           sinhala         23.78/11.87/21.27         23.29/11.16/19.81         21.86/10.48/19.06         21.51/8.07/18.9         27.7/13.8/23.61         27.43/13.41/23.7           somali         29.08/10.21/22.45         29.06/9.97/22.13         28.09/8.88/21.45         31.54/11.57/24.22         32.1/11.38/24.42         32.48/11.72/24.55           spanish         30.05/10.98/23.13         29.28/10.3/22.23         28.09/9.05/21.14         31.51/11.87/24.07         31.63/11.9/24.11         31.59/11.92/24.07           swahili         33.82/14.82/27.78         34.79/15.52/28.24         33.43/14.91/27.19         37.68/17.86/30.92         38.24/17.82/31.16         37.74/17.65/30.8           tamil         22.47/10.33/20.58         19.81/8.83/18.12         16.45/6.58/15         24.31/11.04/22.07         24.58/11.11/22.3         24.48/11.08/22.11           telugu         16.66/5.84/15.1         17.02/5.91/15.24         15.14/4.99/13.77         17.73/5.73/15.84         20.097/11/7.78         20.17/1.26/17.85           thai <t< td=""><td>russian</td><td>32 18/13 83/26 11</td><td>30 56/12 67/24 73</td><td>26 5/9 79/21 44</td><td>32 21/13 64/26 16</td><td>32.82/13.97/26.44</td><td>32 61/13 92/26 39</td></t<>	russian	32 18/13 83/26 11	30 56/12 67/24 73	26 5/9 79/21 44	32 21/13 64/26 16	32.82/13.97/26.44	32 61/13 92/26 39
Serbian cyrillic         18.64/4.83/15.51         17.83/4.26/14.49         18.52/4.89/15.58         23.79/7.99/20.13         24.5/8.42/20.73         24.4/8.35/20.62           serbian latin         17.13/4.19/14.24         18.09/4.31/14.82         18.04/4.21/14.9         21.64/6.68/18.23         22.91/7.18/19.26         22.57/7.11/19.02           sinhala         23.78/11.87/21.27         23.29/11.16/19.81         21.86/10.48/19.06         21.51/8.07/18.9         27.7/13.8/23.61         27.43/13.41/23.7           somali         29.08/10.21/22.45         29.06/9.97/22.13         28.09/8.88/21.45         31.54/11.55/24.22         32.1/11.38/24.42         32.48/11.72/24.55           spanish         30.05/10.98/23.13         29.28/10.3/22.23         28.09/9.05/21.14         31.51/11.87/21.47         31.63/11.92/21.10         31.63/11.92/21.07           swahili         33.82/14.82/27.78         34.79/15.52/28.24         33.43/14.91/27.19         37.68/17.86/30.92         38.24/17.82/31.16         37.74/17.65/30.8           tamil         22.47/10.33/20.58         19.81/8.83/18.12         16.45/6.58/15         24.31/11.04/22.07         24.58/11.11/22.3         24.48/11.08/22.11           telugu         16.66/5.84/15.1         17.02/5.91/15.24         15.14/4.99/13.77         17.73/5.73/15.84         20.09/7.11/17.78         20.1/7.26/17.85           tigrinya	scottish gaelic	23 16/7 04/19 25	20 42/4 31/17 02	24 05/7 73/19 45	29 01/10 96/22 87	28 85/10 55/22 65	30 08/11 2/23 83
serbian latin         17.13/4.19/14.24         18.09/4.31/14.82         18.04/4.21/14.9         21.64/6.68/18.23         22.91/7.18/19.26         22.57/7.11/19.02           sinhala         23.78/11.87/21.27         23.29/11.16/19.81         21.86/10.48/19.06         21.51/8.07/18.9         27.7/13.8/23.61         27.43/13.41/23.7           somali         29.08/10.21/22.45         29.06/9.97/22.13         28.09/9.05/21.14         31.54/11.55/24.22         32.1/11.38/24.42         32.48/11.72/24.55           spanish         30.05/10.98/23.13         29.28/10.3/22.23         28.09/9.05/21.14         31.54/11.87/24.07         31.63/11.9/24.11         31.59/11.92/24.07           swahili         33.82/14.82/27.78         34.79/15.52/28.24         23.43/14.91/27.19         37.68/17.86/30.92         38.24/17.82/31.16         37.74/17.65/30.8           tamil         22.47/10.33/20.58         19.81/8.83/18.12         16.45/6.58/15         24.31/11.04/22.07         24.58/11.11/22.3         24.48/11.08/22.11           telugu         16.66/5.84/15.1         17.02/5.91/15.24         15.14/4.99/13.77         17.73/5.73/15.84         20.09/7.1/17.78         20.177.26/17.85           thai         35.17/15.18/26.85         30.63/14.04/26.97         26.12/11/23.29         32.92/15.57/29.28         33.63/16.17/29.95         33.58/16.1/29.87           ukrainian         23.	serbian cyrillic	18 64/4 83/15 51	17 83/4 26/14 49	18 52/4 89/15 58	23 79/7 99/20 13	24 5/8 42/20 73	24 4/8 35/20 62
sinhala         23.78/11.87/21.27         23.29/11.16/19.81         21.86/10.48/19.06         21.51/8.07/18.9         27.7/13.8/23.61         27.43/13.41/23.7           somali         29.08/10.21/22.45         29.06/9.97/22.13         28.09/8.88/21.45         31.54/11.55/24.22         32.1/11.38/24.42         32.48/11.72/24.55           spanish         30.05/10.98/23.13         29.28/10.3/22.23         28.09/8.88/21.45         31.54/11.55/24.22         32.1/11.38/24.42         32.48/11.72/24.55           swahili         33.82/14.82/27.78         34.79/15.52/28.24         33.43/14.91/27.19         37.68/17.86/30.92         38.24/17.82/31.16         37.74/17.65/30.8           tamil         22.47/10.33/20.58         19.81/8.83/18.12         16.45/6.58/15         24.31/11.04/22.07         24.58/11.11/22.3         24.48/11.08/22.11           telugu         16.66/5.84/15.1         17.02/5.91/15.24         15.14/4.99/13.77         17.73/5.73/15.84         20.09/7.1/17.78         20.1/7.26/17.85           thai         35.17/15.18/26.85         36.08/14.06/25.7         33.47/14.12/25.7         36.43/16.28/28.22         37.84/17.34/28.81         37.99/17.65/29.07           turkish         31.41/15.07/28         30.53/14.40/26.97         26.12/11/23.29         32.92/15.57/29.28         33.63/16.17/29.95         33.58/16.1/29.81           ukrainian         23.58/1	serbian latin	17 13/4 19/14 24	18 09/4 31/14 82	18 04/4 21/14 9	21 64/6 68/18 23	22.91/7.18/19.26	22 57/7 11/19 02
Somali         29.08/10.21/22.45         29.06/0.97/22.13         29.08/10.3/22.23         28.09/8.88/21.45         31.54/11.55/24.22         32.1/11.38/24.42         32.48/11.72/24.55           spanish         30.05/10.98/23.13         29.28/10.3/22.23         28.09/8.88/21.45         31.54/11.55/24.22         32.1/11.38/24.42         32.48/11.72/24.55           swahili         33.82/14.82/27.78         34.79/15.52/28.24         33.43/14.91/27.19         37.68/17.86/30.92         38.24/17.82/31.16         37.74/17.65/30.82           tamil         22.47/10.33/20.58         19.81/8.83/18.12         16.45/6.58/15         24.31/11.04/22.07         24.58/11.11/22.3         24.48/11.08/22.11           telugu         16.66/5.84/15.1         17.02/5.91/15.24         15.14/4.99/13.77         17.73/57.3/15.84         20.097.1/17.78         20.1/7.26/17.85           thai         35.17/15.18/26.85         36.08/14.06/25.7         33.47/14.12/25.7         36.43/16.28/28.22         37.84/17.34/28.81         37.99/17.65/29.07           tigrinya         22.3/7.19/19.04         21.37/6.14/17.89         19.97/5.65/16.51         25.26/7.99/21.1         25.85/8.51/21.6         25.48/8.55/21.78           urkish         31.41/15.07/28         30.53/14.04/26.97         26.12/11/23.29         32.99/10.14/20.92         24.73/10.7/21.58         24.75/10.62/21.57           urdu	sinhala	23 78/11 87/21 27	23 29/11 16/19 81	21 86/10 48/19 06	21 51/8 07/18 9	27 7/13 8/23 61	27 43/13 41/23 7
Spanish         30.05/10.98/23.13         29.28/10.3/22.23         28.09/9.05/21.14         31.51/11.87/24.07         31.63/11.9/24.11         31.59/11.9/24.11           swahili         33.82/14.82/27.78         34.79/15.52/28.24         33.43/14.91/27.19         37.68/17.86/30.92         38.24/17.82/31.16         37.74/17.65/30.8           tamil         22.47/10.33/20.58         19.81/8.83/18.12         16.45/6.58/15         24.31/11.04/22.07         24.58/11.11/22.3         24.48/11.08/22.11           telugu         16.66/5.84/15.1         17.02/5.91/15.24         15.14/4.99/13.77         17.73/5.73/15.84         20.09/7.1/17.78         20.17/2.6/17.85           thai         35.17/15.18/26.85         36.08/14.06/25.7         33.47/14.12/25.7         36.43/16.28/28.22         37.84/17.34/28.81         37.99/17.65/29.07           turkish         31.41/15.07/28         30.53/14.04/26.97         26.12/11/23.29         32.92/15.57/29.28         33.63/16.17/29.95         33.58/16.1/29.81           urkish         31.44/15.07/28         30.53/14.04/26.97         26.12/11/23.29         32.92/15.57/29.28         33.63/16.17/29.95         33.58/16.1/29.81           urdu         40.19/19.34/33.6         38.11/7.69/32.08         30.54/14.5/28.76         39.49/18.33/32.83         40.04/18.71/33.15         40.12/18.71/33.21               vietnamese            32.53/16.45/2	somali	29.08/10.21/22.45	29.06/9.97/22.13	28 09/8 88/21 45	31 54/11 55/24 22	32 1/11 38/24 42	32 48/11 72/24 55
synahil         33.82/14.82/27.78         34.79/15.52/28.24         33.43/14.91/27.19         37.68/17.86/30.92         38.24/17.82/31.16         37.74/17.25/30.8           tamil         22.47/10.33/20.58         19.81/8.83/18.12         16.45/6.58/15         24.31/11.04/22.07         24.58/11.11/22.3         24.48/11.08/22.11           telugu         16.66/5.84/15.1         17.02/5.91/15.24         15.14/4.99/13.77         17.73/57.371/5.84         20.09/7.1/17.78         20.1/7.26/17.85           thai         35.17/15.18/26.85         36.08/14.06/25.7         33.47/14.12/25.7         36.43/16.28/28.22         37.84/17.34/28.81         37.99/17.65/29.07           tigrinya         22.37/1.9/19.04         21.37/6.14/17.89         19.97/5.65/16.51         25.267/.99/21.1         25.87/8.51/21.6         25.48/8.57/1.78           ukrainian         23.58/10.2/20.59         21.84/8.92/19.08         18.73/7.07/16.43         23.99/10.14/20.92         24.73/10.7/21.58         24.75/10.62/21.57           uzbek         13.48/4.84/12.32         14.44/5.21/13.1         11.77/3.98/10.88         16.82/6.35/15.38         17.45/6.74/15.73         17.66/7.1/3.82           uzbek         31.58/11.46/25.6         30.19/9.97/24.17         27.92/8.06/22.24         32.64/11.59/26.12         33.09/12.03/26.44         33.49/16.57/26.38           welsh         31.58/11.46/25.6 </td <td>snanish</td> <td>30.05/10.98/23.13</td> <td>29.28/10.3/22.23</td> <td>28.09/9.05/21.15</td> <td>31 51/11 87/24 07</td> <td>31 63/11 9/24 11</td> <td>31 59/11 92/24 07</td>	snanish	30.05/10.98/23.13	29.28/10.3/22.23	28.09/9.05/21.15	31 51/11 87/24 07	31 63/11 9/24 11	31 59/11 92/24 07
tamil         22.47/10.33/20.58         19.81/8.83/18.12         16.45/6.58/15         24.31/11.04/22.07         24.58/11.11/22.3         24.48/11.08/22.11           telugu         16.66/5.84/15.1         17.02/5.91/15.24         15.14/4.99/13.77         17.73/5.73/15.84         20.09/7.1/17.78         20.1/7.26/17.85           thai         35.17/15.18/26.85         36.08/14.06/25.7         33.47/14.12/25.7         36.43/16.28/28.22         37.84/17.34/28.81         37.99/17.65/29.07           tigrinya         22.3/7.19/19.04         21.37/6.14/17.89         19.97/5.65/16.51         25.26/7.99/21.1         25.58/8.51/21.6         25.48/8.55/21.78           ukrainian         23.58/10.2/20.59         21.84/8.92/19.08         18.73/7.07/16.43         23.99/10.14/20.92         24.73/10.7/21.58         24.75/10.62/21.57           uzbek         13.48/4.84/12.32         14.44/5.21/13.1         11.77/3.98/10.88         16.82/6.35/15.38         17.45/6.74/15.73         17.63/6.71/15.87           vietnamese         32.58/16.45/25.94         30.78/14.57/23.78         27.33/12.34/21.27         30.24/14.39/24.13         33.62/16.43/26.46         33.49/16.57/26.38           welsh         31.58/11.46/25.6         30.19/9.97/24.17         27.92/8.06/22.24         32.64/11.59/26.12         33.09/12.03/26.41         33.13/11.88/26.35           yoruba         29.06/10.96	swahili	33 82/14 82/27 78	34 79/15 52/28 24	33 43/14 91/27 19	37 68/17 86/30 92	38 24/17 82/31 16	37 74/17 65/30 8
tellugu         16.66/5.84/15.1         17.02/5.91/15.22         15.14/4.99/13.77         17.73/5.73/15.84         20.09/7.1/17.78         20.1/7.26/17.85           thai         35.17/15.18/26.85         36.08/14.06/25.7         33.47/14.12/25.7         36.43/16.28/28.22         37.84/17.34/28.81         37.99/17.65/29.07           tigrinya         22.3/7.19/19.04         21.37/6.14/17.89         19.97/5.65/16.51         25.26/7.99/21.1         25.85/8.51/21.6         25.48/8.55/21.78           turkish         31.41/15.07/28         30.53/14.04/26.97         26.12/11/23.29         32.92/15.57/29.28         33.63/16.17/29.95         33.58/16.1/29.81           urkainian         23.58/10.2/20.59         21.84/8.92/19.08         18.73/7.07/16.43         23.99/10.14/20.92         24.73/10.7/21.58         24.75/10.62/21.57           urdu         40.19/19.34/33.6         38.81/17.69/32.08         35.05/14.5/28.76         39.49/18.33/32.83         40.04/18.71/33.15         40.12/18.71/33.21           uzbek         13.48/4.84/12.32         14.44/5.21/13.1         11.77/3.98/10.88         16.82/6.35/15.38         17.45/6.74/15.73         17.63/6.71/15.87           vietnamese         32.53/16.45/25.94         30.78/14.57/23.78         27.33/12.34/21.27         30.24/14.39/24.13         33.62/16.43/26.46         33.49/16.57/26.38           welsh         31.58/11.4	tamil	22 47/10 33/20 58	19 81/8 83/18 12	16 45/6 58/15	24 31/11 04/22 07	24 58/11 11/22 3	24 48/11 08/22 11
thai         35.17/15.18/26.85         36.08/14.06/25.7         33.47/14.12/25.7         36.43/16.28/28.22         37.84/17.34/28.81         37.99/17.65/29.07           tigrinya         22.3/7.19/19.04         21.37/6.14/17.89         19.97/5.65/16.51         25.26/7.99/21.1         25.85/8.51/21.6         25.48/8.55/21.78           turkish         31.41/15.07/28         30.53/14.04/26.97         26.12/11/23.29         32.92/15.57/29.28         33.63/16.17/29.95         33.58/16.1/29.81           urkainian         23.58/10.2/20.59         21.84/8.92/19.08         18.73/7.07/16.43         23.99/10.14/20.92         24.73/10.7/21.58         24.75/10.62/21.57           urdu         40.19/19.34/33.6         38.81/17.69/32.08         35.05/14.5/28.76         39.49/18.33/32.83         40.04/18.71/33.15         40.12/18.71/33.21           uzbek         13.48/4.84/12.32         14.44/5.21/13.1         11.77/3.98/10.88         16.82/6.35/15.38         17.45/6.74/15.73         17.63/6.71/15.87           vietnamese         32.53/16.45/25.94         30.78/14.57/23.78         27.33/12.34/21.27         30.24/14.39/24.13         33.62/16.43/26.46         33.49/16.57/26.38           welsh         31.58/11.46/25.6         30.19/9.97/24.17         27.92/8.06/22.24         32.64/11.59/26.12         33.09/12.03/26.41         33.13/11.88/26.35           yoruba         29.06	teluou	16 66/5 84/15 1	17 02/5 91/15 24	15 14/4 99/13 77	17 73/5 73/15 84	20.09/7 1/17 78	20 1/7 26/17 85
Internation         Distribution         Distribution </td <td>thai</td> <td>35 17/15 18/26 85</td> <td>36 08/14 06/25 7</td> <td>33 47/14 12/25 7</td> <td>36 43/16 28/28 22</td> <td>37 84/17 34/28 81</td> <td>37 99/17 65/29 07</td>	thai	35 17/15 18/26 85	36 08/14 06/25 7	33 47/14 12/25 7	36 43/16 28/28 22	37 84/17 34/28 81	37 99/17 65/29 07
Instruction         1215/11/15.07/28         30.53/14.04/26.97         26.12/11/23.29         32.92/15.57/29.28         33.63/16.17/29.95         33.58/16.1/29.81           ukrainian         23.58/10.2/20.59         21.84/8.92/19.08         18.73/7.07/16.43         23.99/10.14/20.92         24.73/10.7/21.58         24.75/10.62/21.57           urdu         40.19/19.34/33.6         38.81/17.69/32.08         35.05/14.5/28.76         39.49/18.33/32.83         40.04/18.71/33.15         40.12/18.71/33.15           uzbek         13.48/4.84/12.32         14.44/5.21/13.1         11.77/3.98/10.88         16.82/6.35/15.38         17.45/6.74/15.73         17.63/6.71/15.87           vietnamese         32.53/16.45/25.94         30.78/14.57/23.78         27.33/12.34/21.27         30.24/14.39/24.13         33.62/16.43/26.46         33.49/16.57/26.38           welsh         31.58/11.46/25.6         30.19/9.97/24.17         27.92/8.06/22.24         32.64/11.59/26.12         33.09/12.03/26.41         33.13/11.88/26.35           yoruba         29.06/10.96/23.3         29.75/91/4.32/23.31         26.77/8.84/20.85         31.62/25.16         31.90/12.03/25.41         31.71/11.61/24.91	tiorinva	22 3/7 19/19 04	21 37/6 14/17 89	19 97/5 65/16 51	25 26/7 99/21 1	25 85/8 51/21 6	25 48/8 55/21 78
ukrainian         23.58/10.2/20.59         21.84/8.92/19.08         18.73/7.07/16.43         23.99/10.14/20.92         24.73/10.7/21.58         24.75/10.62/21.57           urdu         40.19/19.34/33.6         38.81/17.69/32.08         35.05/14.5/28.76         39.49/18.33/32.83         40.04/18.71/33.15         40.12/18.71/33.21           uzbek         13.48/4.84/12.32         14.44/5.21/13.1         11.77/3.98/10.88         16.82/6.35/15.38         17.45/6.74/15.73         17.63/6.71/15.87           vietnamese         32.53/16.45/25.94         30.78/14.57/23.78         27.33/12.34/21.27         30.24/14.39/24.13         33.62/16.43/26.46         33.49/16.57/26.38           welsh         31.58/11.46/25.6         30.19/9.97/24.17         27.92/8.06/22.24         32.64/11.59/26.12         33.09/12.03/26.41         33.13/11.88/26.35           yoruba         29.10/11.06/23.33         29.73/10.43/23.31         26.77/8.84/20.85         31.62/11.66/25.06         31.95/11.92/25.24         31.71/11.61/24.91	turkish	31 41/15 07/28	30 53/14 04/26 97	26 12/11/23 29	32 92/15 57/29 28	33 63/16 17/29 95	33 58/16 1/29 81
urdu         40.19/19.34/33.6         38.81/17.69/32.08         35.05/14.5/28.76         39.49/18.33/32.83         40.04/18.71/33.15         40.12/18.71/33.15           uzbek         13.48/4.84/12.32         14.44/5.21/13.1         11.77/3.98/10.88         16.82/6.35/15.38         17.45/6.74/15.73         40.12/18.71/13.15           vietnamese         32.53/16.45/25.94         30.78/14.57/23.78         27.33/12.34/21.27         30.24/14.39/24.13         33.62/16.43/26.46         33.49/16.57/26.38           welsh         31.58/11.46/25.6         30.19/9.97/24.17         27.92/8.06/22.24         32.64/11.59/26.12         33.09/12.03/26.41         33.13/11.88/26.35           yoruba         29.06/10.96/23.3         29.79/4/10.43/23.31         26.77/8.84/20.85         31.62/11.66/25.06         31.99/11.92/25.24         31.71/11.61/24.91	ukrainian	23 58/10 2/20 59	21 84/8 92/19 08	18 73/7 07/16 43	23 99/10 14/20 92	24 73/10 7/21 58	24 75/10 62/21 57
uzbek         13.48/4.84/12.32         14.415/21/13.1         11.77/3.98/10.88         16.82/6.35/15.38         17.45/6.74/15.73         17.63/6.71/15.87           vietnamese         32.53/16.45/25.94         30.78/14.57/23.78         27.33/12.34/21.27         30.24/14.39/24.13         33.62/16.43/26.46         33.49/16.57/26.38           welsh         31.58/11.46/25.6         30.19/9.97/24.17         27.92/8.06/22.24         32.64/11.59/26.12         33.09/12.03/26.41         33.13/11.88/26.35           yoruba         29.06/10.96/23.3         29.79/410.43/23.31         26.77/8.84/20.85         31.62/11.66/25.06         31.95/11.92/25.24         31.71/11.61/24.91	urdu	40 19/19 34/33 6	38 81/17 69/32 08	35 05/14 5/28 76	39 49/18 33/32 83	40 04/18 71/33 15	40 12/18 71/33 21
vietnamese         32.53/16.45/25.94         30.78/14.57/23.78         27.33/12.34/21.27         30.24/14.39/24.13         33.62/16.43/26.46         33.49/16.57/26.38           welsh         31.58/11.46/25.6         30.19/9.97/24.17         27.92/8.06/22.24         32.64/11.59/26.12         33.09/12.03/26.41         33.13/11.88/26.35           yoruba         29.06/10.96/23.33         29.94/10.43/23.31         26.77/8.84/20.85         31.62/11.66/25.06         31.95/11.92/25.24         31.71/11.61/24.91	uzbek	13 48/4 84/12 32	14 44/5 21/13 1	11 77/3 98/10 88	16 82/6 35/15 38	17 45/6 74/15 73	17 63/6 71/15 87
weish         31.58/11.46/25.6         30.19/9.97/24.17         27.59/18.84/20.85         32.64/11.59/26.12         33.09/12.03/26.41         33.13/11.88/26.35           yoruba         29.06/10.96/23.3         29.94/10.43/23.31         26.77/8.84/20.85         31.62/11.66/25.06         31.95/11.92/25.24         31.71/11.61/24.91	vietnamese	32 53/16 45/25 94	30 78/14 57/23 78	27 33/12 34/21 27	30 24/14 39/24 13	33 62/16 43/26 46	33 49/16 57/26 38
yoruba 29.06/10.96/23.3 29.94/10.43/23.31 26.77/8.84/20.85 31.62/11.66/25.06 31.95/11.92/25.24 31.71/11.61/24.91	welsh	31 58/11 46/25 6	30 19/9 97/24 17	27.92/8.06/22.24	32 64/11 59/26 12	33 09/12 03/26 41	33 13/11 88/26 35
Junear 22.00/10.2013/21.21.21.110.012.01 20.110.012.000 21.0011.00/22.00 21.2011.22.22.4 21.1111.012.42.57	voruba	29.06/10.96/23.3	29 94/10 43/23 31	26 77/8 84/20 85	31 62/11 66/25 06	31 95/11 92/25 24	31 71/11 61/24 91
	average	28 14/11 96/23 45	27 58/11 23/22 66	25 35/9 84/20 92	30 23/12 93/25 11	30 96/13 39/25 56	30 89/13 4/25 57

Table 3: R1/R2/RL of six models on 45 languages and the average score of all languages.