FAIRNESS IN REPRESENTATION FOR MULTILINGUAL NLP: INSIGHTS FROM CONTROLLED EXPERIMENTS ON CONDITIONAL LANGUAGE MODELING

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ABSTRACT

We perform systematically and fairly controlled experiments with the 6-layer Transformer to investigate the hardness in conditional-language-modeling languages which have been traditionally considered morphologically rich (AR and RU) and poor (ZH). We evaluate through statistical comparisons across 30 possible language directions from the 6 languages of the United Nations Parallel Corpus across 5 data sizes on 3 representation levels — character, byte, and word. Results show that performance is relative to the representation granularity of each of the languages, not to the language as a whole. On the character and byte levels, we are able to eliminate statistically significant performance disparity, hence demonstrating that a language cannot be intrinsically hard. The disparity that mirrors the morphological complexity hierarchy is shown to be a byproduct of word segmentation. Evidence from data statistics, along with the fact that word segmentation is qualitatively indeterminate, renders a decades-long debate on morphological complexity (unless it is being intentionally modeled in a word-based, meaning-driven context) irrelevant in the context of computing. The intent of our work is to help effect more objectivity and adequacy in evaluation as well as fairness and inclusivity in experimental setup in the area of language and computing so to uphold diversity in Machine Learning and Artificial Intelligence research. Multilinguality is real and relevant in computing not due to canonical, structural linguistic concepts such as morphology or "words" in our minds, but rather standards related to internationalization and localization, such as character encoding — something which has thus far been sorely overlooked in our discourse and curricula.

1 INTRODUCTION

1.1 BACKGROUND AND MOTIVATION

Most current work on fairness in Machine Learning (ML) and Natural Language Processing (NLP) focuses on the societal biases encoded in natural language data that are propagated and amplified when they are used at scale for/as Artificial Intelligence (AI) solutions[1]. But little has been said or questioned about the bias, as in, the favoring of certain outcomes, implicit in our theoretical/scientific assumptions that results in the varying performance of different languages in computing.

Disparity in machine translation results For instance, results reported in Junczys-Dowmunt et al. (2016) for Phrase-Based Statistical Machine Translation (PBSMT) (Koehn et al., 2003) and Neural MT (Bahdanau et al., 2014) on the 6 official languages[2] of the United Nations (UN) Parallel Corpus (Ziemski et al., 2016) indicate a disparity between EN/ES/FR and AR/RU/ZH in BLEU (Papineni et al., 2002) — translation performance in the latter group is generally worse, regardless of the MT algorithm used. AR and RU are traditionally considered morphologically complex (see e.g. Minkov et al. (2007), Seddah et al. (2010) and proceedings of related workshops in subsequent years for *Statistical Parsing of Morphologically Rich Languages*), and ZH morphologically frugal (for its lacking determiners and plural or tense markers) (Koehn, 2005). While Koehn (2005) found translating into EN to be easier than into morphologically rich languages based on BLEU scores of word tokens from PBSMT systems of 110 language directions from the 11 Europarl languages then, Bugliarello et al. (2020) found it is easier to translate out of EN than into it based on 21 Europarl languages in BPEs (Byte Pair Encodings) (Sennrich et al., 2016) with the Transformer (Vaswani et al., 2017) in a new metric, cross-mutual information.

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[1] see e.g. work from conference (`https://facctconference.org`) and workshops in previous years on "Fairness, Accountability, and Transparency" (FAccT)

[2] Arabic (AR), English (EN), Spanish (ES), French (FR), Russian (RU), and Chinese (ZH)

Disparity in language modeling results Disparate performances across different languages seem to have been implicitly accepted in that it is often believed that some languages are harder to model than others. Bender (2009) advocated the relevance of linguistic typology for the design of language-universal NLP systems due to differences based on crosslinguistic structural notions, such as parts of speech and morphological complexity. Cotterell et al. (2018) studied (monolingual) language models (LMs) on the 21 Europarl languages using a word-level 7-gram standard Kneser & Ney (1995) model and LSTM-LMs (Sundermeyer et al., 2012) with characters and lemmatized forms in information-theoretic terms, and found morphological complexity to be the primary culprit for the differences in performance. Mielke et al. (2019) supplemented with the multilingual Bible corpus (Mayer & Cysouw, 2014) to extend the coverage to 69 languages, tested on RNN-LMs (an implementation of LSTM (Hochreiter & Schmidhuber, 1997)) with characters and BPEs, but concluded that basic data statistics in vocabulary size ($|V|$) and sequence length were the most predictive performance features.

We noticed, however, a discrepancy in the results from Mielke et al. (2019) for ZH — it came out as the least difficult for the character model, but it is the 6th most difficult language for the BPE model. As different input representations have been tested with different architectures with divergent results in different metrics in previous studies, each of them only testing with one data size, we decided to investigate the matter more systematically once again with statistical comparisons of score distributions between languages.

1.2 RESEARCH QUESTIONS AND CONTRIBUTIONS

Research questions Are there any statistically significant differences in hardness when it comes to Conditional-Language-Modeling (CLMing) languages which have been traditionally considered morphologically rich (AR and RU) and poor (ZH) with the 6-layer Transformer? Is morphological complexity inherent in language? When is the notion of morphological complexity relevant in computing?

Summary of findings and insights Based on our bilingual CLMing setup with the UN Parallel Corpus in the data size range from 10^2 to 10^6 lines on the character, byte, and word levels, we find:

1. Language has more finer-grained dimensions with different representations and learning patterns. Hardness in modeling is relative to its representation granularity (*representation relativity*).
2. There is neutralization of source language instances, i.e. there are no statistically significant differences between source language pairs. Only pairs of target languages differ significantly.
3. On the character and byte levels, hardness is correlated with statistical properties concerning sequence length and $|V|$ of a language, regardless of its morphological profile. As it is possible to eliminate performance disparity by decomposing sequences into finer-grained units in characters and bytes, we show that morphological complexity is not an intrinsic property of language. Unless word-based methods are used, or unless we implement/model it explicitly, the notion of morphological complexity is irrelevant in computing.
4. On the word level, hardness is correlated with $|V|$, and a complexity hierarchy arises through the manual preprocessing step of word tokenization. This complexity/disparity effected by word segmentation can be improved by subword tokenization but cannot be eliminated due to the fundamental qualitative differences in the definition of a "word" being one that neither holds universally nor is suitable/consistent for fair crosslinguistic comparisons.
5. Representational units of finer granularity can help close the gap in performance disparity.

Orthogonal to our main research questions, we also observed 2 types of sample-wise non-monotonicity — Double Descent (Belkin et al., 2019; Nakkiran et al., 2020) and *erraticity*. For reasons due to length and scope for this paper, we will defer discussions and analyses of these beyond what is addressed in § 5 to future work.

Outline of the paper In § 2, we define our method and experimental setup. We present our results and analysis on the primary representations in § 3 and those from secondary set of controls in § 4 in a progressive manner to ease understanding. Meta analysis on performance disparity and other discussions are in § 5.

2 METHOD AND DEFINITIONS

Conditional language modeling CLMing is the modeling of the probability of the next token, given the history of the preceding tokens and conditioning context. In our case, such conditioning context is a line from the source language. To explicitly focus on modeling the complexities that may or may not be *intrinsic* to the languages, we study the more fundamental process of CLMing without performing any translation. This allows us to eliminate confounds associated with generation and other evaluation metrics. One could think of our setup as estimating conditional probabilities with the Transformer, with a bilingual (one-to-one) setup where the perplexity (PP) of one target language (l_{trg}) is estimated given the parallel data in one source language (l_{src}), where $l_{\text{src}} \neq l_{\text{trg}}$. We focus on the very basics and examine the first step in our pipeline — input representations, holding everything else constant. Instead of measuring absolute cross-entropy scores at one data size, we evaluate the relative differences between development (dev) set score distributions between languages.

Controlled experiments as basic research for scientific understanding of language data Using the UN Parallel Corpus, the data from which the MT results in Junczys-Dowmunt et al. (2016) stem, we perform a series of controlled experiments with the Transformer, holding the hyperparameter settings for all 30 one-to-one language directions from the 6 languages constant. We control for size (from 10^2 to 10^6 lines) and language with respect to representational granularity. We examine 3 primary representation types/levels — character, byte (UTF-8), and word, and upon encountering some unusual phenomena, we perform a secondary set of controls with 5 alternate representations — on the character level: Pinyin and Wubi (ASCII representations for ZH phones and character strokes, respectively), on the byte level: code page 1256 (for AR) and code page 1251 (for RU), and on the word level: BPE. These symbolic variants allow us to manipulate the statistical properties of the representations, while staying as "faithful" to the language as possible. We adopt this symbolic data-centric[3] approach because we would like to more directly interpret the confounds, if any, that make language data different from other data types. We operate on a smaller data size range as this is more common in traditional language sciences and one of our higher goals is to bridge an understanding between language sciences and engineering (the latter being the dominant focus in NLP), and between traditional symbolic sciences and ML. We run statistical tests to identify the strongest correlates of performance and to assess whether the differences between the mean performance of different groups are indeed significant. We are concerned *not* with the absolute scores, but with the *differences* between score distributions from different languages.

Fair evaluation with multitexts Multitexts are multiway parallel corpora. The UN Parallel Corpus is a 6-way parallel corpus consisting of manually translated UN documents from the 25-year period between 1990 and 2014. We use the UN Parallel Corpus because it contains languages conventionally regarded as morphologically rich and poor, has quality and size sufficient for evaluation, and more importantly, it comes as raw texts (untokenized), unlike both of the corpora that Mielke et al. (2019) used. Detokenization (esp. the evaluation thereof) is not a trivial task.

Fair information-theoretic evaluation metric Most sequence-to-sequence models are optimized using a cross-entropy loss, defined as:

$$H(\boldsymbol{t}, \boldsymbol{s}) = -\sum_{i=1}^{N} \log_2 p(t_i \mid \boldsymbol{t}_{<i}, \boldsymbol{s}) \tag{1}$$

where $\boldsymbol{t}$ is the sequence of tokens to be predicted, t_i refers to the ith token in that sequence, $\boldsymbol{s}$ is the sequence of tokens conditioned on, and $N = |\boldsymbol{t}|$. It is customary to report scores as PP, which is $2^{\frac{1}{N}H(\boldsymbol{t},\boldsymbol{s})}$, i.e. 2 to the power of the cross-entropy averaged by the number of tokens in the dev

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[3] Two testing/evaluation approaches — data-centric: hold the algorithm constant and tweak data, vs. algorithm-centric: hold data constant and tweak the algorithm.

data. Cotterell et al. (2018) proposed to use "renormalized" PP to evaluate LMs tokenwise fairly by dividing the overall bits per utterance/sequence by one constant token count in any one arbitrary language (e.g. so to arrive at "bits per character" in one language to evaluate all languages). But we find that it is not necessary to assign a perspective that is centered on any one particular language, when we can evaluate simply by the total number of bits for a larger portion of texts/sequences. This can be a fairer, more general and flexible way of evaluating data that has not been or cannot be perfectly segmented or aligned line by line. We hence used instead *unnormalized* PP, i.e. the total number of bits needed to encode the dev set (3,077 lines per language, after length filtering, in our case). As the implementation we used only reports PP, we transformed it back to entropy as defined above via $H(\boldsymbol{t}, \boldsymbol{s}) = \log_2 PP(\boldsymbol{t}|\boldsymbol{s}) \times N$.

Disparity/Inequality In the context of our CLMing experiments, we consider there to be "disparity" or "inequality" between languages l_1 and l_2 if there are significant differences between the performance distributions of these two languages with respect to each representation. Here, by performance we mean the number of bits required to encode the held-out data using a trained CLM. With 30 directions, there are 15 pairs of source languages ($l_{\text{src}1}, l_{\text{src}2}$) and 15 pairs of target languages ($l_{\text{trg}1}, l_{\text{trg}2}$) possible. We compare the source languages among each other, and the target languages among each other. Each l_{src} or each l_{trg} consists of scores from all models trained across various sizes and directions. To assess whether the differences are significant, we perform unpaired two-sided significance tests with the null hypothesis that the score distributions for the two languages are not different. Upon testing for normality with the Shapiro-Wilk test (Shapiro & Wilk, 1965; Royston, 1995), we use the parametric unpaired two-sample Welch's t-test (Welch, 1947) (when normal) or the non-parametric unpaired Wilcoxon test (Wilcoxon, 1945) (when not normal) for the comparisons. We use the implementation in R (R Core Team, 2014) for these 3 tests. To account for the multiple comparisons we are performing, we correct all p-values using Bonferroni's correction (Benjamini & Heller, 2008; Dror et al., 2017) and follow Holm's procedure[4] (Holm, 1979; Dror et al., 2017) to identify the pairs of l_1 and l_2 with significant differences after correction. We report all 3 levels of significance ($\alpha \leq 0.05, 0.01, 0.001$) for a more comprehensive overview. In contrast to Dror et al. (2017), which aimed to compare the performance of different algorithms, we compare languages (in the context of computing).

Experimental setup The systematic, identical treatment we give to our data is described as follows with further preprocessing and hyperparameter details in Appendices A and B, respectively.

After filtering length to 300 characters maximum per line in parallel for the 6 languages, we made 3 subsets of the data with 1 million lines each — one having lines in the order of the original corpus (dataset A) and two other randomly sampled (without replacement) from the full corpus (datasets B & C). Lines in all datasets are extracted in parallel and remain fully aligned for the 6 languages. For each run and each representation, there are 30 pairwise directions (i.e. one l_{src} to one l_{trg}) that result from the 6 languages. We trained all 150 (for 5 sizes) 6-layer Transformer models for each run using the SOCKEYE Toolkit (Hieber et al., 2018). We optimize using PP and use early stopping if no PP improvement occurs after 3 checkpoints up to 50 epochs maximum, taking the best checkpoint. Characters and bytes are supposed to mitigate the out-of-vocabulary (OOV) problem on the word level. In order to assess the effect of modeling with finer granularity more precisely, all vocabulary items appearing once in the train set are accounted for (i.e. full vocabulary on train, as in Gerz et al. (2018a;b)). But we allow our system to categorize all unknown items in the dev set to be unknown (UNK) so to measure OOVs (open vocabulary on dev (Jurafsky & Martin, 2009)). To identify correlates of performance, we perform Spearman's correlation (Spearman, 1904) with some basic statistical properties of the data (e.g. length, $|V|$, type-token-ratio, OOV rate) as metrics — a complete list is provided in App. C. See App. D for sample construction for statistical comparisons.

3 EXPERIMENTAL RESULTS OF PRIMARY REPRESENTATIONS

Subfigures 1a, 1b, and 1c present the mean results across 12 runs of the 3 primary representations — character, byte, and word, respectively. The x-axis represents data size in number of lines and y-axis the total conditional cross-entropy, measured in bits (Eq. 1). Each line connects 5 data points corresponding to the number of bits the CLMs (trained with training data of 10^2, 10^3, 10^4, 10^5, and

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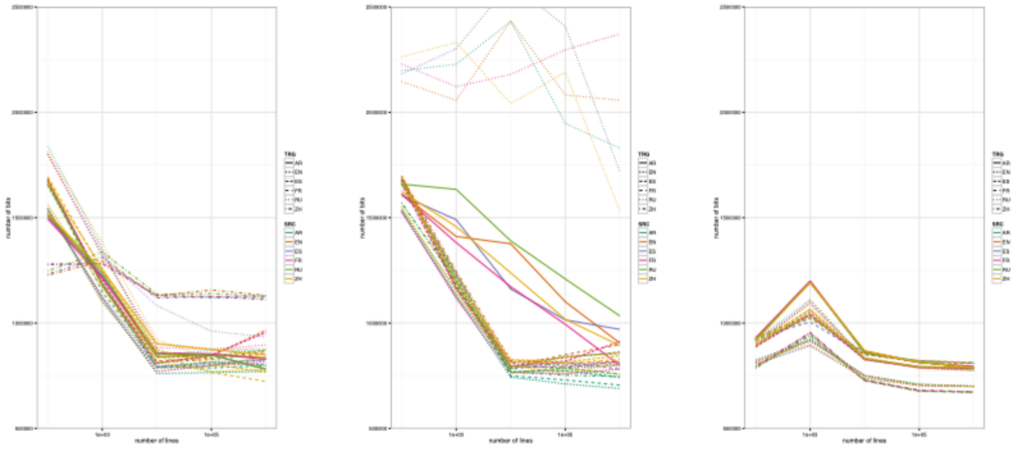
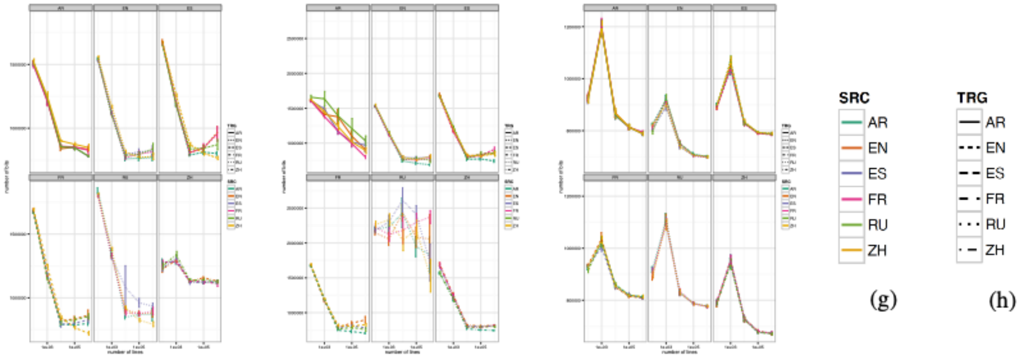
[4] using implementation from `https://github.com/rtmdrr/replicability-analysis-NLP`



(a) CHAR (b) BYTE (c) WORD



(g) (h)

(d) CHAR by target (e) BYTE by target (f) WORD by target

Figure 1: Number of bits (the lower the better) across data size from 10^2 to 10^6 lines plotted for all 30 directions. Subfigures 1a, 1b, and 1c show mean scores across 12 runs. Subfigures 1d, 1e, and 1f depict the corresponding information respectively sorted in 6 facets by target language and with error bars. Legend in Subfigure 1g shows the correspondence between colors and source languages, in Subfigure 1h between line types and target languages. (These figures are also shown enlarged in Appendix F. Please note that results pertinent to our first research question in this paper are summarized in Table 1, figures are a visual aid only. We are not concerned with the absolute scores but the distances between scores (i.e. spaces between the set of lines by l_{trg}). The point here is to show the differences in Transformer's overall learning pattern relative to the representational granularity. Language has more finer-grained dimensions with different representations and learning patterns. Hardness in modeling is relative to its representation granularity (representation relativity).)

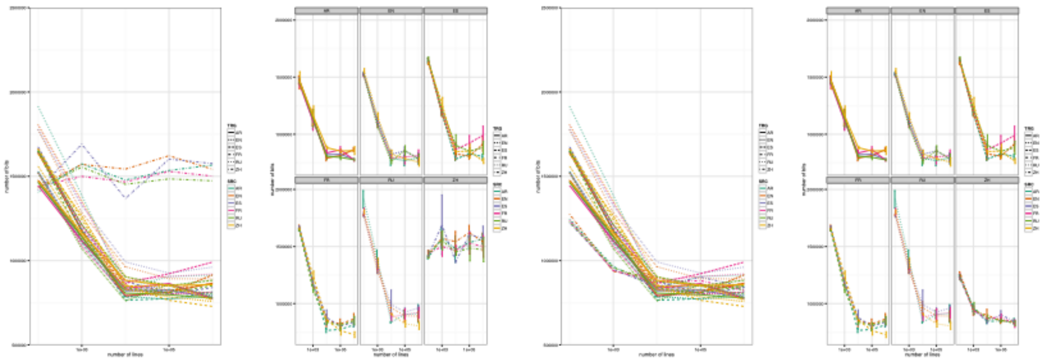
10^6 lines) needed to encode the target language dev set given the corresponding text in the source language. These are the same data in the same 30 language directions and 5 sizes with the same training regime, just preprocessed/segmented differently. This confirms **representation relativity** — hardness in modeling is relative to its representation granularity. Languages (or any objects being modeled) need to be evaluated relative to their representation. "One size does not fit all" (Durrani et al., 2019). Our conventional way of referring to "language" (as a socio-cultural product or with traditional word-based approaches, or even for most multilingual tasks and competitions) is too coarse-grained for computing (see also Fisch et al. (2019) and Ponti et al. (2020)).

Subfigures 1d, 1e, and 1f display the corresponding information sorted into facets by target language, source languages represented as line types. Through these we see more clearly that results can be grouped rather neatly by target language — as implicit in the Transformer's architecture, the decoder is unaware of the source language in the encoder. As shown in Table 1 in § 5 summarizing the number of source and target language pairs with significant differences, there are **no significant differences across any source language pairs**. The Transformer neutralizes source language instances. This could explain why transfer learning or multilingual/zero-shot translation (Johnson et al., 2017) is possible at all on a conceptual level.

In general, for character and byte models, most language directions do seem to converge at 10^4 lines to similar values across all target languages, with few notable exceptions. There are some fluctuations past 10^4, indicating further tuning of hyperparameters would be beneficial due to our present setting possibly working most favorably at 10^4. On the character level, target language ZH (ZH_{trg}) shows a different learning pattern throughout. And on the byte level, AR_{trg} and RU_{trg} display highly unstable behavior, which we refer to as *erratic*. Word models exhibit Double Descent across the board (note the spike at 10^3), but overall, difficult/easy languages stay consistent, with AR and RU being the hardest, followed by ES and FR, then EN and ZH. A practical takeaway from this set of experiments: in order to obtain more robust training results, use bytes for ZH (as suggested in Li et al. (2019a)) and characters for AR and RU (e.g. Lee et al. (2017)) — also if one wanted to avoid any "class" problems in performance disparity with words. Performance disparity for these representations is reported in Table 1 under "CHAR", "BYTE", and "WORD". Do note, however, that the intrinsic performance of ZH with word segmentation is not particularly subpar. But this often does not correlate with its poorer downstream tasks results (recall results from Junczys-Dowmunt et al. (2016)). Since the notion of word in ZH is highly contested and ambiguous — i) it is often aimed to align with that in other languages so to accommodate academic theories and manual feature engineering[5], ii) there is great variation among different conventions, and iii) native ZH speakers identify characters as words — there are reasons to rethink this procedure now that fairer and language-independent processing in finer granularity is possible. Li et al. (2019b) questioned the necessity of CWS in Deep Learning (DL)-based ZH NLP and presented evidence in favor of character-based processing, including results from downstream NLP tasks. In Linguistics, Duanmu (2017) presented a summary on the contested nature of wordhood in (Mandarin) ZH in relation to EN. A more native account of ZH, however, despite a couple of dialects/varieties of it being considered a high-resource language, has not yet been fully recognized and accepted in NLP.

4 UNDERSTANDING THE PHENOMENA WITH ALTERNATE REPRESENTATIONS

To understand why some languages show different results than others, we carried out a secondary set of controlled experiments with representations targeting the problematic statistical properties of the corresponding target languages.



(a) Wubi (b) Wubi by target (c) Pinyin (d) Pinyin by target

Figure 2: Character-level remedies for ZH: Wubi vs. Pinyin.

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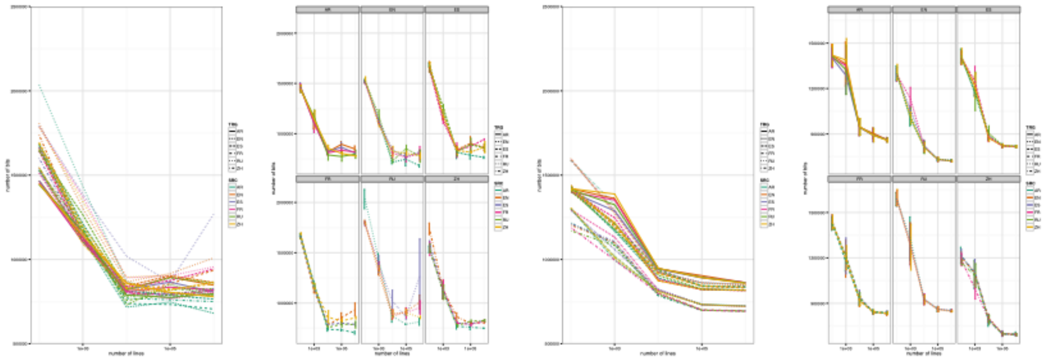
[5] It is a "legacy interpretation" stemmed from a practical compromise from the early days in ZH NLP when the goal was to align with EN words for MT. Chinese word segmentation (CWS) has been a decades-long issue in text processing. But even in EN, for computing, the variability in "word" counts (from the trivial convention of whitespace tokenization) results in different bit counts, affecting file sizes. In NLP, such method of "word" counting brings about a high $|V|$, hence different tokenization schemes have been designed to mitigate this problem. For humans, there is no consensus about the definition of "words". Even for an academic account external of CWS, it is held to be indeterminate (see Haspelmath (2011) and references therein from the past century). Kilgarriff (1997; 2014) pointed out that "words" and "word senses" and the number thereof, in terms of lexical entries for dictionaries, are contextual and arbitrary.



(a) Code page 1256 & 1251 (b) Code page by target (c) BPE (d) BPE by target

Figure 3: Byte-level (Subfigures 3a & 3b) remedies with code page 1256 for target AR and 1251 for target RU, and word-level (Subfigures 3c & 3d) remedy with BPE for all languages.

Character level We reduced the high $|V|$ in ZH with representations in ASCII characters — Pinyin and Wubi. We replaced the ZH data in these formats *only on the target side* and reran the experiments involving ZH_{trg} on the character level. Results in Figure 2 and Table 1 show that the elimination of disparity on character level is possible if ZH is represented through Pinyin (transliteration), as in Subfigure 2c, though at the cost of the native script information. Models with ZH logographic scripts display a behaviorial tendency unlike those with other (phonetic) alphabetic scripts[6] (Subfigure 2a), suggesting that this script pattern decomposes differently.

Byte level Length is the most salient statistical attribute that makes AR and RU outliers. To shorten their sequence lengths, we tested with alternate encodings on AR_{trg} and RU_{trg} — code page 1256 and 1251, which provide 1-byte encodings specific to AR and RU, respectively. Results are shown in Subfigures 3a and 3b. Not only is erraticity resolved, the number of 15 possible target language pairs with significant differences reduces from 8 with the UTF-8 byte representation to **0** (Table 1 under "ARRU_{t}"), indicating that we eliminated disparity with this optimization heuristic. Since our heuristic is a lossless and reversible transform, it shows that **a complexity that is intrinsic and necessary in language**[7] **does not exist** in computing, however diverse they may be, as our 6 are, from the conventional linguistic typological, phylogenetic, historical, or geographical perspectives.

Word level The main difference between word and character/byte models is length not being a top contributing factor correlating with performance, but instead $|V|$ is. This is understandable as word segmentation neutralizes sequence lengths. To remedy the OOV problem, we use BPE, which learns a fixed vocabulary of variable-length character sequences (on word level, as it presupposes word segmentation) from the training data. It is more fine-grained than word segmentation and is known to better model subword units for morphologically complex languages. We use the same vocabulary of 30,000 as specified in Junczys-Dowmunt et al. (2016). This reduced our averaged OOV token rate by 89-100% across the 5 sizes. The number of language pairs with significant differences reduced to 7 from 8 for word models. While BPEs are still not as effective as our character/byte variants, their results show how **more fine-grained modeling contributes positively to closing the disparity gap**.

5 META RESULTS, ANALYSES, AND DISCUSSION

Performance disparity Table 1 lists the number of language pairs with significant differences under the representations studied. Since it is **possible** for our character and byte models to effect no performance disparity for the same languages on the same data, a complexity intrinsic to language does not exist. In fact, the customary expectation that languages ought to perform differently is created through our word segmentation practice. Furthermore, the order of AR/RU > ES/FR > EN/ZH

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[6] which are sequences with an implicit/explicit pattern made up of consonants and vowels

[7] aside from its statistical properties related to length and vocabulary. To show something is not necessarily true, only 1 counter observation is needed.

Table 1: **Disparity Table** Number of language pairs out of 15 with significant differences, with respective p-values. ARRU$_t$ refers to AR & RU being optimized only on the target side; whereas ARRU$_{s,t}$ denotes optimization on both source and target sides (relevant for directions AR-RU and RU-AR).

		CHAR		Pinyin		Wubi		BYTE		ARRU$_t$		ARRU$_{s,t}$		WORD		BPE	
	p-value	src	trg	src	trg	src	trg	src	trg	src	trg	src	trg	src	trg	src	trg
	0.05	0	7	0	4	0	8	0	9	0	4	0	4	0	11	0	10
	0.01	0	5	0	2	0	6	0	8	0	3	0	4	0	8	0	8
☞	0.001	0	3	**0**	**0**	0	5	0	8	**0**	**0**	0	2	0	8	0	7

Table 2: Target language pairs with significant differences indicate that the 2 languages are *not* equally/similarly good or equally/similarly bad. 15 (non-directional) language pairs total possible from 30 language directions, p=0.001.

LANG$_{trg}$ PAIR	CHAR	Pinyin	Wubi	BYTE	ARRU$_t$	ARRU$_{s,t}$	WORD	BPE
AR-EN				X			X	X
AR-ES								
EN-ES							X	
AR-FR				X				
EN-FR							X	X
ES-FR								
AR-RU				X				
EN-RU				X		X	X	X
ES-RU				X				
FR-RU				X				
AR-ZH	X		X	X			X	X
EN-ZH	X		X					
ES-ZH			X				X	X
FR-ZH	X		X				X	X
RU-ZH			X	X		X	X	X

(Figure 1c) resembles the idea of morphological complexity. Considering there are character-internal meaningful units in languages with logographic script such as ZH (cf. Zhang & Komachi (2018)) that are rarely captured, studied, or referred to as "morphemes", this goes to show that linguistic morphology, along with its complexity, as it is practiced today[8] and that which has occurred in the NLP discourse thus far, has only been relevant on the "word" level, conceptually constrained by unstandardizable units such as "words" (and "sentences"). The definition of word, however, has been recognized as problematic for a very long time in the language sciences (cf. Footnote 5).

While the lack of significant differences between pairs of source languages would signify neutralization of source language instances, it does not mean that source languages have no effect on target. For our byte solutions with code pages, we experimented also with source side optimization in the directions that involve AR/RU as source. This affected the distribution of the disparity results for that representation — with 2 pairs being significantly different (see Table 1 under "ARRU$_{s,t}$"). We defer further investigation on the nature of source language neutralization to future work.

Target language pairs with significant differences are summarized in Table 2. We show that morphological complexity can be empirically eliminated in this one-setting-for-all configuration with a 6-layer network, no hyperparameter tuning, and a maximum line length of 300 characters (and its corresponding equivalence in other representations) as constrained by our hardware and compute time listed in App. A and current data availability. A more analytical solution can be obtained through data statistics (see App. E). A conceptual solution lies in the definition of "words" and morphology.

Sample-wise Double Descent (DD) Sample-wise non-monotonicity/DD (Nakkiran et al., 2020) denotes a degradation followed by an improvement in performance with increasing data size. We notice word models and character models with $\mathrm{ZH}_{\mathrm{trg}}$, i.e. models with high target $|V|$, are prone to exhibit a spike at 10^3. A common pattern for these is the ratio of target training token count to number of parameters falls into O(10^{-4}) for 10^2 lines, O(10^{-3}) at 10^3, O(10^{-2}) at 10^4, and O(10^{-1}) for 10^5 lines and so on. But for more atomic units such as alphabetic (not logographic) characters (may it be Latin, Cyrillic, or Abjad) and for bytes, this progression instead begins at O(10^{-3}) at 10^2 lines. Instead of thinking this spike of 10^3 as irregular, we may instead want to think of this learning curve as shifted by 1 order of magnitude to the right for characters and bytes and/or the performance at 10^2 lines for words and ZH-characters due to being overparameterized and hence abnormal. This would also fit in with the findings by Belkin et al. (2019) and Nakkiran et al. (2020) attributing DD to overparameterization. While almost all work attribute DD to algorithmic reasons, findings from Chen et al. (2020) corroborate our observation and confirms that DD arises due to "the interaction between the properties of the data and the inductive biases of learning algorithms". Other related work on the DD phenomenon and its development can also be found in their work.

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[8] But there are no reasons why we cannot adopt a statistical science of language in finer granularities beyond/without "words", with standardized units (characters/bytes) and/or continuous representations. Resources, e.g. quality parallel data or contrast sets, can serve both data science and ML interpretation and evaluation well.

Erraticity We observe another type of sample-wise non-monotonicity, one that signals irregular and unstable performance across data sizes and runs. Within one run, erraticity can be observed directly as changes in direction on the y-axis. Across runs, large variance can be observed, even with the same dataset. Erraticity can also be observed indirectly through a negative correlation between data size and performance. Many work on length bias in NMT have focused on solutions related to search, e.g. Murray & Chiang (2018). Our experiments show that a kind of length bias can surface already with CLMing, without generation taking place.

Additional related work That basic data statistics are the driver of success in performance in multilingual modeling has so far only been explicitly argued for in Mielke et al. (2019). We go beyond their work in monolingual LMs to study CLMs and evaluate also in relation to data size, representational granularity, and quantitative and qualitative fairness. To the best of our knowledge, there has been no prior work on demonstrating the neutralization of source language instances through statistical comparisons, a numerical analysis on DD for sequence-to-sequence models, the meta phenomenon of a sample-wise non-monotonicity (erraticity) being related to length.

6 CONCLUSION

Summary We investigate whether the performance disparity between languages which have been traditionally considered morphologically rich (AR and RU) and poor (ZH) in the 6-layer Transformer CLM is justified due to morphological complexity and find that it is not. Performance disparity can be explained by data statistics and in the context of computing, it can be eliminated by optimization on length and $|V|$ through character/byte representations. In fact, morphological complexity is not a necessary concept in computing because "word" is not a necessary concept in computing, unless we make it so through word segmentation. A morphological complexity hierarchy can result simply through word segmentation. Furthermore, there are many possible interpretations to "words" for humans and since morphology is defined with the concept of "word", there is no stable ground for assessing this complexity. Representational units of finer granularity were shown to help eliminate performance disparity though at the cost of longer sequence length, which can have a negative impact on robustness. In addition, we found all word models and character models with $\mathrm{ZH}_{\mathrm{trg}}$ to behave similarly in their being prone to exhibit a peak (as sample-wise DD) around 10^3 lines in our setting.

Outlook ML has enabled greater diversity in NLP (Joshi et al., 2020). Fairness, in the elimination of disparity, does not require big data. This paper made a pioneering attempt to bridge research in NNs/DL, language sciences, and language engineering through a data-centric perspective. Multilinguality is real and relevant in computing not due to canonical, structural linguistic concepts such as morphology or "words" in our minds, but rather standards related to internationalization and localization, such as character encoding — something which has thus far been sorely overlooked in our discourse and curricula. We also believe that a more fine-grained statistical data science can well complement algorithmic analyses with a view that is more empirically robust (i.e. experimentally verifiable) and more relevant to machine processing, contributing to a more generalizable and interpretable pool of knowledge for ML/NNs/DL. A more comprehensive study can lead us not only to new scientific frontiers, but also to better designs and evaluation, benefitting the development of a more general, diverse and inclusive AI.

ETHICS STATEMENT: FAIRNESS CONCERNS FOR MULTILINGUALITY

Clearer nomenclature If/When the intent is *not* to explicitly model linguistic morphology in computing, one can simply describe languages and their statistical profiles with respect to their representational granularity in characters or bytes (which are and can be exhaustively standardized in computing), or refer to sequences as longer/shorter or having a higher/lower vocabulary size when comparing them with each other, rather than "richer"/"poorer" based on concepts (e.g. "words", "sentences") that can be ambiguous, contested, and inaccessible to many.

Accessibility Language communities who are unfamiliar with languages similar to dominant languages or those who are reluctant to conform to one structurally similar interpretation should not have to feel inadequate in processing their own language "from scratch", if they so choose to. As technologists, we can help take equitable measures to make fairer data representations and infrastructure available. A "word"-free view of language preempts linguistic/cultural hegemony and such an interpretation would also help make the analyses of language data more objective and clearer.

Scarcity of quality and/or multiway data for science, evaluation, and culture With the rise of multilingual models comes an alleged decrease in reliance on parallel corpora for MT. But parallel data, esp. high-quality, *multiway* and/or multi-modal parallel data, are important for scientific research and as a form of cultural and language documentation. And as this paper shows, they can also serve as evaluation data for ML models for better understanding and interpretation. As challenge sets, data for machine processing would need to be statistically diverse and challenging as well. Parallel data from previous years have often come in the form of bitexts (2-way parallel text data), usually "word"-tokenized where real length information has been compromised. (In fact, the Bible data from Mayer & Cysouw (2014) came with another confound — the ZH numeral '一' ("one") is recognized as a dash (punctuation) and hence tokenized with surrounding whitespaces.) At the time of our present study (2019-present), the UN Parallel Corpus was the only unperturbed, fully multiway parallel data sufficient for reliable evaluation for our size range. Data for science, evaluation, and culture require a long-term, stable platform and support. There are many forms of data science. But in terms of having a sustainable practice to collect and curate good data, and exercising enough of a science with that data so to improve collective intelligence and mutual understanding, instead of looking at data from an utilitarian point of view only for consumer application purposes, there seems to be room for improvement still. We hope our work could help effect a positive change in this direction.[9]

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[9] Please see further discussion in Wan (2022).

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APPENDICES

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A DATA SELECTION AND PREPROCESSING DETAILS

The UN Parallel Corpus v1.0 (Ziemski et al., 2016) consists of manually translated UN documents from 1990 to 2014 in the 6 official UN languages. Therein is a subcorpus that is fully aligned by line, comprising the 6-way parallel corpus we use. We tried to have as little preprocessing or filtering as necessary to eliminate possible confounds. But as the initial runs of our experiment failed due to insufficient memory on a single GPU with 12 GB VRAM[10], we filtered out lines with more than 300 characters in any language in lockstep with one another for all the 6 languages such that the subcorpora would remain parallel, thereby keeping the material of each language semantically equivalent to one another. 8,944,859 lines for each language were retained as our training data which cover up to the 75th percentile in line length for all 6 languages. In order to monitor the effect of data size, we made subcorpora of each language in 5 sizes by `head`ing the first $10^2, 10^3, 10^4, 10^5, 10^6$ lines[11]. We refer to this as dataset A. In addition, to better understand and verify the consistency of the phenomena observed, we made 2 supplemental datasets by shuffling the 8,944,859 lines two different times randomly and `head`ing the number of lines in our 5 sizes for each language, again in lockstep with one another (datasets B and C).

The systematic training regime that we gave to our language directions is identical for all and we controlled also for seeds. For each of the 3 primary representations — character, byte, and word, we performed:

- 5 runs in 5 sizes ($10^2 - 10^6$ lines): A0 (seed=13), B0 (13), C0 (9948), A1 (9948), A2 (265), and
- 7 more runs in 4 sizes ($10^2 - 10^5$ lines): A3 (777), A4 (42), A5 (340589), A6 (1000), A7 (83146), B1 (9948), & C1 (13).

Figure 1 shows results from all 12 runs in all sizes for the primary representations.

For the alternate/secondary representations, we performed 3 runs each in 5 sizes (10^2-10^6 lines) (A0, B0, & C0). Due to limitations in computing resources, we were not able to perform as many runs as the primary representations. But important for our statistical comparisons is that we evaluate based on an equal number of runs and on the same data for all candidates. Tables 1 & 2 are the results.

For each run and each size, there are 30 pairwise directions (i.e. 1 source language to 1 target language, e.g. AR-EN for Arabic to English) that result from the 6 languages. We trained all 150 jobs (30 directions x 5 sizes) for each run and representation using the Transformer model (Vaswani et al., 2017) as supported by the SOCKEYE Toolkit (Hieber et al., 2018) (version 1.18.85), based on MXNet (Chen et al., 2015). A detailed description of the architecture of the Transformer can be found in (Vaswani et al., 2017). The same set of hyperparameters applies to all and its values are listed in Appendix B.

For character modeling, we used a dummy symbol to denote each whitespace. For byte, we turned each UTF-8-encoded character into a byte string in decimal value, such that each token is a number between 0 and 255, inclusive. For word, we followed (Junczys-Dowmunt et al., 2016) and used the Moses tokenizer (Koehn et al., 2007) as is standard in NMT practice when word tokenization is applied and Jieba[12] for segmentation in ZH.

Pinyin is a romanization of ZH characters based on their pronunciations and Wubi an input algorithm that decomposes character-internal information into stroke shape and ordering and matches these to 5 classes of radicals (Lunde, 2008). For Pinyin, we used the implementation from `https://github.com/lxyu/pinyin` in the numerical format such that each character/syllable is followed by a single digit indicating its lexical tone in Mandarin. For Wubi, we used the dictionary from the implementation from `https://github.com/arcsecw/wubi`.

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[10] GPUs used for experiments in this paper range from a NVIDIA TITAN RTX (24 GB), NVIDIA GeForce RTX 2080 Ti (11 GB), a GTX Titan X (12 GB), to a GTX 1080 (8 GB). All jobs were run on a single GPU setting. Some word-level experiments involving AR_{trg} or RU_{trg} at 10^6 had to be run on a CPU as 24 GB VRAM were not sufficient. Models with higher maximum sequence lengths (e.g. byte models) were trained with 24 GB VRAM. Difference in equipment does not necessarily lead to degradation/improvement in scores.

[11] The terms “line” and “sentence” have been used interchangeably in the NLP literature. We use “line” to denote a sequence that ends with a newline character and “sentence” as one with an ending punctuation. Most parallel corpora, such as ours, are aligned by line, as a line may be part of a sentence or without an ending punctuation (e.g. a header/title). Using a standardized unit such as “line” would also be a fairer measure to linguae/scriptiones continuae (languages/scripts with no explicit punctuation).

[12] `https://github.com/fxsjy/jieba`

We have implemented all representations such that they would be reversible even when the sequence contains code-mixing.

We used the official dev set as provided in (Ziemski et al., 2016), 3,077 lines per language remained from 4,000 after filtering line length to 300 characters. Data statistics is provided in Appendix E for reference.

Notes on training time Each run of 30 directions in 5 sizes took approximately 8-12 days for character and byte models. Byte models generally took longer — hence training time is positively correlated with length (concurring with observations by Cherry et al. (2018) as they compared character with BPE models). A maximum length of 300 characters entails a maximum length of *at least* 300 bytes in UTF-8. Each run of word models (30 directions, 5 sizes) took about 6 days (excluding the training of some 7-9 directions out of 30 per run involving AR_{trg} or RU_{trg} at 10^6 on word level which took about 12-18 hours *each direction* to train on a CPU as these required more space and would run out of memory (OOM) on our GPUs otherwise). These figures do not include the additional probing experiments described in § 4.

B HYPERPARAMETER SETTING

- encoder transformer;
- decoder transformer;
- num-layers 6:6;
- num-embed 512:512;
- transformer-model-size 512;
- transformer-attention-heads 8;
- transformer-feed-forward-num-hidden 2048;
- transformer-activation-type relu;
- transformer-positional-embedding-type fixed;
- transformer-preprocess d; transformer-postprocess drn;
- transformer-dropout-attention 0.1;
- transformer-dropout-act 0.1;
- transformer-dropout-prepost 0.1;
- batch-size 15;
- batch-type sentence;
- max-num-checkpoint-not-improved 3;
- max-num-epochs 50;
- optimizer adam;
- optimized-metric perplexity;
- optimizer-params epsilon: 0.000000001, beta1: 0.9, beta2: 0.98;
- label-smoothing 0.0;
- learning-rate-reduce-num-not-improved 4;
- learning-rate-reduce-factor 0.001;
- loss-normalization-type valid;
- max-seq-len 300 for character, word, and BPE, 672 for all bytes, 688 for Wubi, 680 for Pinyin;
- checkpoint-frequency/interval 4000.
  (For smaller datasets, the end of 50 epochs is often reached before the first checkpoint. Since SOCKEYE only outputs scores at checkpoints, we adjusted the checkpoint frequency as follows to get a score outputted by the end of 50 epochs: 1000 for 100 lines for all character & byte instances, 400 for 100 lines for word and 500 for 100 lines BPE, 3450 for 1000 lines for word & BPE. For the very few cases that this default does not suffice due to bucketing of similar length sequences, we manually set the checkpoint frequency to the last batch.)

C CORRELATION STATISTICS

Best correlating metrics, i.e. the union of top 3 metrics for all representations.
For each representation, the **top 3 metrics** are boldfaced.
All correlations are **highly significant** ($p < 10^{-30}$), except for min source length for WORD ($p \approx 0.0001$) and min target length for WORD ($p \approx 0.3861$).

Metric	CHAR	Pinyin	Wubi	BYTE	ARRU_t	$\text{ARRU}_\text{s,t}$	WORD	BPE
minimum length (target)	**0.84**	**0.85**	**0.86**	**0.60**	**0.84**	**0.84**	−0.02	0.65
minimum length (source)	**0.82**	**0.84**	**0.85**	0.57	**0.84**	**0.84**	0.10	0.64
number of tokens (source)	−0.78	−0.81	−0.82	**−0.60**	**−0.81**	**−0.81**	−0.59	**−0.83**
TTR (target)	**0.83**	**0.83**	**0.84**	0.48	0.81	0.81	0.61	0.83
$\|V\|$ (source)	−0.54	−0.51	−0.51	−0.50	−0.67	−0.68	**−0.63**	**−0.86**
data size in lines	−0.80	−0.83	−0.83	−0.59	−0.81	−0.81	−0.62	**−0.86**
OOV token rate (target)	0.69	0.66	0.66	0.47	0.67	0.68	**0.66**	0.62
OOV type rate (target)	0.70	0.71	0.72	0.47	0.69	0.70	**0.65**	0.62
TTR (source)	0.67	0.71	0.71	**0.60**	0.81	0.81	0.56	0.82

The full list of metrics used for the correlation analysis is:

1. minimum length (source),
2. minimum length (target),
3. maximum length (source),
4. maximum length (target),
5. median length (source),
6. median length (target),
7. mean length (source),
8. mean length (target),
9. length std (source),
10. length std (target),
11. data size in lines,
12. number of parameters,
13. number of types ($|V|$) (source),
14. number of types ($|V|$) (target),
15. number of tokens (source),
16. number of tokens (target),
17. type-token-ratio (TTR) (source),
18. type-token-ratio (TTR) (target),
19. OOV type rate (source),
20. OOV type rate (target),
21. OOV token rate (source),
22. OOV token rate (target),
23. token ratio,
24. target type-to-parameter ratio,
25. target token-to-parameter ratio,
26. distance between the TTRs of source and target = $(1 - \text{TTR}_{src}/\text{TTR}_{trg})^2$,
27. token-to-parameter ratio (i) = (median length source * median length target * num_lines) / num_parameters,
28. token-to-parameter ratio (ii) = (num_source_tokens * num_target_tokens) / num_parameters.

D STATISTICAL COMPARISONS

Recall the definition and method for our **Disparity/Inequality** assessment from § 2:

> In the context of our CLMing experiments, we consider there to be "disparity" or "inequality" between languages l_1 and l_2 if there are significant differences between the performance distributions of these two languages with respect to each representation. Here, by performance we mean the number of bits required to encode the held-out data using a trained CLM. With 30 directions, there are 15 pairs of source languages $(l_{\text{src}1}, l_{\text{src}2})$ and 15 pairs of target languages $(l_{\text{trg}1}, l_{\text{trg}2})$ possible. We compare the source languages among each other, and the target languages among each other. Each l_{src} or each l_{trg} consists of scores from all models trained across various sizes and directions. To assess whether the differences are significant, we perform unpaired two-sided significance tests with the null hypothesis that the score distributions for the two languages are not different. Upon testing for normality with the Shapiro-Wilk test (Shapiro & Wilk, 1965; Royston, 1995), we use the parametric unpaired two-sample Welch's t-test (Welch, 1947) (when normal) or the non-parametric unpaired Wilcoxon test (Wilcoxon, 1945) (when not normal) for the comparisons. We use the implementation in R (R Core Team, 2014) for these 3 tests. To account for the multiple comparisons we are performing, we correct all p-values using Bonferroni's correction (Benjamini & Heller, 2008; Dror et al., 2017) and follow Holm's procedure[13] (Holm, 1979; Dror et al., 2017) to identify the pairs of l_1 and l_2 with significant differences after correction. We report all 3 levels of significance ($\alpha \leq 0.05, 0.01, 0.001$) for a more comprehensive overview. In contrast to Dror et al. (2017), which aimed to compare the performance of different algorithms, we compare languages (in the context of computing).

To get samples for the statistical comparison results for the Disparity Table (Table 1):

For each representation, we used 3 runs (A0, B0, C0) in 5 sizes (10^2-10^6 lines) for each l_{src} and each l_{trg}. There are:

6 l_{src} (AR_{src}, EN_{src}, ES_{src}, FR_{src}, RU_{src}, ZH_{src}) and
6 l_{trg} (AR_{trg}, EN_{trg}, ES_{trg}, FR_{trg}, RU_{trg}, ZH_{trg}).

We compare pairwise among the l_{src}. The 15 pairs are:

AR_{src}-EN_{src}, AR_{src}-ES_{src}, AR_{src}-FR_{src}, AR_{src}-RU_{src}, AR_{src}-ZH_{src},
EN_{src}-ES_{src}, EN_{src}-FR_{src}, EN_{src}-RU_{src}, EN_{src}-ZH_{src},
ES_{src}-FR_{src}, ES_{src}-RU_{src}, ES_{src}-ZH_{src},
FR_{src}-RU_{src}, FR_{src}-ZH_{src},
RU_{src}-ZH_{src}.

Likewise 15 pairs among the l_{trg}.

For example, for the character (primary) representation to compare between AR_{src} and EN_{src}, we construct the sample for AR_{src} ($\texttt{sample}_{\texttt{ARsrc}}$) and the sample for EN_{src} ($\texttt{sample}_{\texttt{ENsrc}}$) as follows:

Out of the 30 CHAR directions, there are 5 directions involving AR_{src} trained for each run and data size (i.e. the directions: AR-EN, AR-ES, AR-FR, AR-RU, AR-ZH).

For each direction, there are 15 models trained (3 runs x 5 sizes). We take all 75 CHAR models (15 models x 5 directions) involving AR_{src} as $\texttt{sample}_{\texttt{ARsrc}}$. That's a sample of size 75.

Likewise, for EN_{src} (5 directions: EN-AR, EN-ES, EN-FR, EN-RU, EN-ZH), we also have 75 data points for $\texttt{sample}_{\texttt{ENsrc}}$. (Likewise also for all 6 l_{src} and all 6 l_{trg}.)

For the comparisons, we compare pairwise, i.e. with two samples each time, but with *unpaired* two-sample Welch's t-test (when normal) or the non-parametric *unpaired* Wilcoxon test (when not normal) because $\texttt{sample}_{\texttt{ARsrc}}$ and $\texttt{sample}_{\texttt{ENsrc}}$ have one direction that is not paired: AR-EN and EN-AR. Other directions can be seen as paired, e.g. AR-ES and EN-ES as both having the same l_{trg}.

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[13] using implementation from `https://github.com/rtmdrr/replicability-analysis-NLP`

E DATA STATISTICS

- Number of types, i.e. vocabulary size (V |). Note that Sockeye adds for its calculation 4 additional types: <pad>, <s>, </s>, <unk>.
- Number of tokens. This excludes the 1 EOS/BOS (end-/beginning-of-sentence) marker added by Sockeye to each line.
- Out-of-vocabulary (OOV) type rate (in %), i.e. the fraction of the types in the dev data that is not covered by the types in the training data.
- OOV token rate (in %), i.e. the fraction of tokens in the dev data that is treated as UNKnowns.
- Type-token-ratio (in %), i.e. the ratio between the number of types and tokens in the data. This is a rough proxy for lexical diversity in that a value of 1 would indicate that no type is ever seen twice, and a value very close to 0 would indicate that very few distinct types account for almost all of the data.
- Line length (excl. EOS/BOS marker): mean±standard deviation, and the 0/25/50/75/100-th percentile.

Statistics for dataset A

Representation	CHAR					BYTE				
Number of lines	100	1,000	10,000	100,000	1,000,000	100	1,000	10,000	100,000	1,000,000
Number of TYPES										
AR	82	107	149	176	239	73	95	130	145	162
EN	75	81	122	167	244	76	82	127	151	166
ES	84	90	114	173	254	85	91	118	151	166
FR	86	94	130	175	256	87	96	130	153	172
RU	95	108	160	187	260	97	110	148	157	166
ZH	602	1,236	2,267	3,400	4,885	137	143	153	164	193
ZH_pinyin	79	90	104	154	564					
ZH_wubi	100	106	123	170	542					
AR_cp1256						82	107	149	176	239
RU_cp1251						95	108	160	187	260
Number of TOKENS										
AR	9,079	123,832	1,083,517	10,625,047	102,064,230	16,655	227,163	1,985,014	19,487,689	186,171,180
EN	11,730	159,444	1,344,001	13,132,862	123,491,871	11,731	159,449	1,345,771	13,158,948	123,705,128
ES	12,374	171,104	1,484,804	14,549,703	138,596,036	12,629	175,286	1,513,782	14,821,495	141,276,766
FR	12,456	179,048	1,490,983	14,528,593	138,049,189	12,875	185,227	1,542,105	15,055,657	143,495,667
RU	11,980	168,156	1,436,078	14,151,728	134,706,120	21,751	309,279	2,636,591	25,990,263	247,098,758
ZH	3,318	42,572	372,003	3,659,617	34,672,612	8,559	116,667	1,019,969	9,990,046	94,268,840
ZH_pinyin	10,811	148,083	1,279,586	12,530,567	118,471,229					
ZH_wubi	9,245	127,190	1,104,529	10,885,508	102,908,155					
AR_cp1256						9,079	123,832	1,083,517	10,625,047	102,064,230
RU_cp1251						11,980	168,156	1,436,078	14,151,728	134,706,120
OOV type rate (%)										
AR	40.77	23.08	2.31	0.00	0.00	40.65	22.76	2.44	0.00	0.00
EN	23.71	20.62	11.34	4.12	2.06	26.47	23.53	6.86	0.98	0.00
ES	25.23	20.72	16.22	8.11	7.21	23.64	19.09	11.82	4.55	0.91
FR	25.66	19.47	11.50	4.42	2.65	27.12	20.34	7.63	2.54	0.00
RU	34.93	26.71	4.11	2.05	0.00	32.64	24.31	3.47	1.39	0.00
ZH	69.79	39.73	10.58	1.87	0.56	10.46	7.19	3.27	1.31	0.00
ZH_pinyin	20.41	15.31	8.16	4.08	0.00					
ZH_wubi	17.50	13.33	5.83	3.33	0.00					
AR_cp1256						40.77	23.08	2.31	0.00	0.00
RU_cp1251						34.93	26.71	4.11	2.05	0.00
OOV token rate (%)										
AR	0.75	0.35	0.00	0.00	0.00	0.41	0.19	0.00	0.00	0.00
EN	0.05	0.02	0.00	0.00	0.00	0.06	0.02	0.00	0.00	0.00
ES	0.07	0.01	0.01	0.01	0.01	0.07	0.02	0.01	0.01	0.00
FR	0.19	0.10	0.07	0.00	0.00	0.21	0.11	0.07	0.00	0.00
RU	0.30	0.24	0.16	0.00	0.00	0.16	0.13	0.08	0.00	0.00
ZH	17.83	3.64	0.38	0.04	0.01	0.05	0.02	0.00	0.00	0.00
ZH_pinyin	0.06	0.03	0.00	0.00	0.00					
ZH_wubi	0.07	0.04	0.00	0.00	0.00					
AR_cp1256						0.75	0.35	0.00	0.00	0.00
RU_cp1251						0.30	0.24	0.16	0.00	0.00
TTR (%)										
AR	0.90	0.09	0.01	0.00	0.00	0.44	0.04	0.01	0.00	0.00
EN	0.64	0.05	0.01	0.00	0.00	0.65	0.05	0.01	0.00	0.00
ES	0.68	0.05	0.01	0.00	0.00	0.67	0.05	0.01	0.00	0.00
FR	0.69	0.05	0.01	0.00	0.00	0.68	0.05	0.01	0.00	0.00
RU	0.79	0.06	0.01	0.00	0.00	0.45	0.04	0.01	0.00	0.00
ZH	18.14	2.90	0.61	0.09	0.01	1.60	0.12	0.02	0.00	0.00
ZH_pinyin	0.73	0.06	0.01	0.00	0.00					
ZH_wubi	1.08	0.08	0.01	0.00	0.00					
AR_cp1256						0.90	0.09	0.01	0.00	0.00
RU_cp1251						0.79	0.06	0.01	0.00	0.00
Mean line length±std 0/25/50/75/100-th										
AR	90.79 ± 54.45 8/33/91/136/223	123.83 ± 47.09 5/94/126/155/263	108.35 ± 53.79 1/69/109/147/299	106.25 ± 54.88 1/64/107/147/299	102.06 ± 57.25 1/54/102/145/300	166.55 ± 99.88 16/62/166/247/404	227.16 ± 86.09 9/172/230/285/479	198.50 ± 99.02 1/126/200/269/554	194.88 ± 101.03 1/117/196/270/561	186.17 ± 104.86 1/98/187/265/565
EN	117.30 ± 72.51 8/49/112/170/265	159.44 ± 58.88 8/117/163/203/285	134.40 ± 66.79 1/86/137/185/300	131.33 ± 68.25 1/79/134/183/300	123.49 ± 69.53 1/65/125/177/300	117.31 ± 72.50 8/49/112/170/265	159.45 ± 58.88 8/117/163/203/285	134.58 ± 66.80 1/87/137/185/300	131.59 ± 68.34 1/80/134/184/300	123.71 ± 69.64 1/65/125/177/311
ES	123.74 ± 78.91 6/42/119/186/296	171.10 ± 64.03 6/127/175/217/297	148.48 ± 73.38 1/95/150/205/300	145.50 ± 75.32 1/88/148/204/300	138.60 ± 77.56 1/73/140/200/300	126.29 ± 80.21 7/44/121/191/302	175.29 ± 65.44 7/130/179/222/306	151.38 ± 74.70 1/97/153/209/307	148.21 ± 76.67 1/89/150/208/312	141.28 ± 78.96 1/74/143/203/318
FR	124.56 ± 79.38 5/45/116/190/287	179.05 ± 66.44 5/133/183/228/300	149.10 ± 74.19 1/93/152/206/300	145.29 ± 75.75 1/87/148/204/300	138.05 ± 77.90 1/72/140/199/300	128.75 ± 82.16 5/47/121/196/297	185.23 ± 68.52 5/138/190/236/312	154.21 ± 76.66 1/96/157/213/322	150.56 ± 78.42 1/90/153/212/322	143.50 ± 80.99 1/75/145/207/331
RU	119.80 ± 72.09 10/44/119/183/260	168.16 ± 62.11 5/126/174/213/298	143.61 ± 71.55 1/91/146/197/300	141.52 ± 73.95 1/85/144/199/300	134.71 ± 76.20 1/70/136/194/300	217.51 ± 134.51 20/77/215/332/489	309.28 ± 114.98 10/231/318/392/554	263.66 ± 132.77 1/167/268/363/562	259.90 ± 137.10 1/155/264/365/566	247.10 ± 141.14 1/127/249/357/567
ZH	33.18 ± 18.38 3/19/30/45/88	42.57 ± 16.91 2/32/42/53/127	37.20 ± 18.46 1/24/37/49/165	36.60 ± 19.05 1/23/36/49/241	34.67 ± 19.29 1/19/34/48/281	85.59 ± 51.18 7/35/81/127/192	116.67 ± 43.82 6/88/117/148/243	102.00 ± 50.61 1/66/103/139/297	99.90 ± 51.49 1/61/101/138/337	94.27 ± 52.80 1/51/95/134/594
ZH_pinyin	108.11 ± 65.51 7/43/98/161/255	148.08 ± 55.57 7/109/149/188/312	127.96 ± 63.96 1/82/129/175/369	125.31 ± 65.25 1/76/126/174/407	118.47 ± 66.88 1/63/119/169/645					
ZH_wubi	92.45 ± 55.26 8/39/86/137/218	127.19 ± 48.00 7/94/129/158/266	110.45 ± 54.71 1/71/111/150/327	108.86 ± 56.04 1/67/110/150/364	102.91 ± 57.41 1/55/103/146/627					
AR_cp1256						90.79 ± 54.45 8/33/91/136/223	123.83 ± 47.09 5/94/126/155/263	108.35 ± 53.79 1/69/109/147/299	106.25 ± 54.88 1/64/107/147/299	102.06 ± 57.25 1/54/102/145/300
RU_cp1251						119.80 ± 72.09 10/44/119/183/260	168.16 ± 62.11 5/126/174/213/298	143.61 ± 71.55 1/91/146/197/300	141.52 ± 73.95 1/85/144/199/300	134.71 ± 76.20 1/70/136/194/300

Representation	WORD					BPE				
Number of lines	100	1,000	10,000	100,000	1,000,000	100	1,000	10,000	100,000	1,000,000
Number of TYPES										
AR	866	5,865	26,105	97,994	304,975	700	4,171	18,202	29,706	29,961
EN	679	3,289	12,011	37,261	122,454	645	2,856	10,225	26,184	29,068
ES	707	3,836	15,113	49,496	142,806	661	3,232	12,083	27,908	29,445
FR	742	3,878	13,995	42,867	118,201	723	3,193	11,731	27,393	29,333
RU	883	5,430	23,400	81,339	236,085	842	4,319	17,995	29,239	29,807
ZH	627	3,178	13,134	46,938	134,489	800	2,849	10,656	27,284	29,148
ZH_pinyin										
ZH_wubi										
AR_cp1256										
RU_cp1251										
Number of TOKENS										
AR	1,776	23,460	206,549	2,035,190	19,410,502	2,907	28,227	223,510	2,218,044	21,344,900
EN	2,071	27,398	236,569	2,339,109	21,943,139	2,980	29,778	243,628	2,369,723	22,351,059
ES	2,232	29,461	263,024	2,588,791	24,654,449	3,180	32,323	271,995	2,644,055	25,264,439
FR	2,298	32,011	273,195	2,684,982	25,595,487	3,245	34,801	280,928	2,727,386	26,077,553
RU	1,854	24,746	216,638	2,150,746	20,421,965	3,110	29,106	231,293	2,307,656	22,066,945
ZH	1,751	23,568	207,714	2,038,639	19,361,101	2,223	25,459	215,179	2,083,632	19,885,789
ZH_pinyin										
ZH_wubi										
AR_cp1256										
RU_cp1251										
OOV type rate (%)										
AR	95.80	79.80	48.02	24.19	8.14	10.17	1.39	0.09	0.00	0.00
EN	92.07	69.08	33.56	15.27	7.38	4.73	1.01	0.18	0.05	0.01
ES	93.32	71.90	34.72	13.24	6.12	5.44	1.06	0.27	0.10	0.08
FR	92.50	70.25	32.16	12.31	5.62	5.11	0.99	0.26	0.05	0.02
RU	94.52	75.84	39.14	14.54	5.69	6.38	1.27	0.06	0.02	0.00
ZH	93.19	73.29	38.59	15.63	5.65	76.09	40.95	8.52	0.89	0.21
ZH_pinyin										
ZH_wubi										
AR_cp1256										
RU_cp1251										
OOV token rate (%)										
AR	60.86	40.28	17.94	8.62	2.10	2.57	1.99	0.11	0.00	0.00
EN	39.04	18.57	6.16	2.70	1.01	0.35	0.08	0.02	0.01	0.00
ES	36.21	18.28	6.28	2.34	0.86	0.28	0.13	0.05	0.03	0.03
FR	35.44	17.47	6.04	2.13	0.76	0.64	0.52	0.36	0.01	0.00
RU	53.22	30.94	12.59	4.17	1.28	0.88	1.07	0.84	0.01	0.00
ZH	45.48	22.08	8.34	3.20	0.83	31.67	11.76	1.66	0.14	0.03
ZH_pinyin										
ZH_wubi										
AR_cp1256										
RU_cp1251										
TTR (%)										
AR	48.76	25.00	12.64	4.81	1.57	24.08	14.78	8.14	1.34	0.14
EN	32.79	12.00	5.08	1.59	0.56	21.64	9.59	4.20	1.10	0.13
ES	31.68	13.02	5.75	1.91	0.58	20.79	10.00	4.44	1.06	0.12
FR	32.29	12.11	5.12	1.60	0.46	22.28	9.18	4.18	1.00	0.11
RU	47.63	21.94	10.80	3.78	1.16	27.07	14.84	7.78	1.27	0.14
ZH	35.81	13.48	6.32	2.30	0.69	35.99	11.19	4.95	1.31	0.15
ZH_pinyin										
ZH_wubi										
AR_cp1256										
RU_cp1251										
Mean line length±std 0/25/50/75/100-th										
AR	17.76 ± 10.78 1/7/17/27/48	23.46 ± 9.12 1/18/24/29/56	20.65 ± 10.24 1/13/20/28/104	20.35 ± 10.46 1/13/20/28/107	19.41 ± 10.83 1/11/19/27/137	29.07 ± 17.48 3/14/27/43/75	28.23 ± 11.33 1/21/28/35/71	22.35 ± 11.30 1/14/22/30/113	22.18 ± 11.66 1/14/22/30/122	21.34 ± 12.13 1/12/21/30/173
EN	20.71 ± 12.16 1/9/19/30/46	27.40 ± 10.35 1/20/28/35/60	23.66 ± 11.68 1/15/24/32/93	23.39 ± 12.02 1/15/24/32/106	21.94 ± 12.29 1/12/22/31/136	29.80 ± 17.18 3/16/27/42/70	29.78 ± 11.32 1/22/30/37/68	24.36 ± 12.09 1/16/24/33/101	23.70 ± 12.20 1/15/24/32/106	22.35 ± 12.53 1/12/22/32/138
ES	22.32 ± 13.97 1/7/22/32/52	29.46 ± 11.35 1/22/29/37/63	26.30 ± 13.03 1/17/26/36/104	25.89 ± 13.35 1/16/26/36/107	24.65 ± 13.78 1/13/25/35/139	31.80 ± 19.39 4/16/31/43/79	32.32 ± 12.60 1/24/32/41/72	27.20 ± 13.57 1/18/27/37/106	26.44 ± 13.67 1/16/27/37/107	25.26 ± 14.14 1/14/25/36/140
FR	22.98 ± 14.16 1/9/22/34/50	32.01 ± 11.99 1/24/32/41/70	27.32 ± 13.53 1/17/28/37/107	26.85 ± 13.89 1/16/27/37/110	25.60 ± 14.45 1/14/26/37/138	32.45 ± 19.52 2/16/30/46/76	34.80 ± 13.09 2/27/35/44/77	28.09 ± 13.96 1/18/28/38/107	27.27 ± 14.13 1/17/28/38/110	26.08 ± 14.71 1/14/26/37/138
RU	18.54 ± 10.65 1/8/18/27/39	24.75 ± 9.53 1/19/25/31/58	21.66 ± 10.81 1/14/22/29/104	21.51 ± 11.12 1/13/22/30/107	20.42 ± 11.44 1/11/20/29/136	31.10 ± 17.42 4/18/29/45/69	29.11 ± 11.51 1/21/29/37/68	23.13 ± 11.71 1/15/23/31/104	23.08 ± 12.17 1/14/23/32/110	22.07 ± 12.57 1/12/22/31/166
ZH	17.51 ± 10.68 2/7/17/25/46	23.57 ± 9.52 1/18/23/29/76	20.77 ± 10.48 1/13/20/28/108	20.39 ± 10.60 1/13/20/28/111	19.36 ± 10.87 1/11/19/27/167	22.23 ± 12.33 2/13/20/31/58	25.46 ± 10.29 1/19/25/32/79	21.52 ± 10.94 1/14/21/29/108	20.84 ± 10.92 1/13/21/28/111	19.89 ± 11.23 1/11/20/28/167
ZH_pinyin										
ZH_wubi										
AR_cp1256										
RU_cp1251										

Statistics for dataset B

Representation	CHAR					BYTE					WORD					BPE				
Number of lines	100	1,000	10,000	100,000	1,000,000	100	1,000	10,000	100,000	1,000,000	100	1,000	10,000	100,000	1,000,000	100	1,000	10,000	100,000	1,000,000
Number of TYPES																				
AR	87	134	168	251	431	88	124	147	159	181	1,129	6,719	28,222	97,467	311,355	810	4,408	18,800	29,680	29,959
EN	76	99	131	189	343	79	103	135	163	181	876	4,148	13,660	42,844	140,912	784	3,408	10,756	26,820	29,178
ES	86	104	134	189	366	89	108	133	161	185	970	4,775	16,735	51,366	154,482	814	3,705	12,529	28,068	29,471
FR	89	112	147	202	352	91	120	142	162	185	955	4,636	15,639	45,348	132,881	812	3,670	12,258	27,744	29,370
RU	109	142	173	204	320	112	141	159	161	180	1,142	6,520	25,959	83,937	251,355	993	4,829	18,837	29,261	29,811
ZH	761	1,575	2,402	3,465	4,705	123	153	165	175	188	897	4,162	14,714	46,788	140,188	1,068	3,717	11,069	27,409	29,107
ZH_pinyin	71	104	140	241	430															
ZH_wubi	87	124	154	246	421															
AR_cp1256						87	134	168	251	431										
RU_cp1251						109	142	173	204	320										
Number of TOKENS																				
AR	9,798	100,599	1,019,696	10,248,976	102,481,816	17,656	181,866	1,842,138	18,517,669	185,172,618	1,825	18,760	190,465	1,915,746	19,138,724	3,387	25,234	210,622	2,090,403	20,986,116
EN	11,816	119,796	1,201,839	12,087,922	120,969,163	11,820	119,839	1,202,217	12,091,602	121,006,803	2,047	21,058	211,029	2,122,365	21,234,437	3,262	24,634	220,390	2,159,566	21,669,769
ES	13,543	135,106	1,363,454	13,709,493	137,180,542	13,790	137,613	1,389,315	13,967,072	139,753,263	2,390	23,858	241,789	2,431,579	24,326,055	3,702	28,179	253,075	2,485,292	24,933,987
FR	13,173	134,702	1,358,567	13,662,024	136,811,870	13,617	139,250	1,404,001	14,121,629	141,403,257	2,362	24,442	247,027	2,485,203	24,874,355	3,664	28,541	257,305	2,527,889	25,374,629
RU	13,106	130,289	1,325,793	13,356,717	133,699,473	24,059	239,145	2,433,154	24,512,949	245,396,332	1,960	19,642	200,188	2,014,889	20,153,124	3,760	26,136	218,325	2,170,410	21,792,216
ZH	3,329	33,768	340,692	3,419,803	34,206,106	9,122	92,689	935,172	9,402,743	94,064,353	1,866	18,697	189,773	1,906,704	19,073,133	2,563	21,630	199,028	1,946,543	19,574,572
ZH_pinyin	11,391	115,577	1,166,227	11,732,264	117,367,349															
ZH_wubi	10,035	101,049	1,019,113	10,242,540	102,460,573															
AR_cp1256						9,798	100,599	1,019,696	10,248,976	102,481,816										
RU_cp1251						13,106	130,289	1,325,793	13,356,717	133,699,473										
OOV type rate (%)																				
AR	35.38	5.38	0.77	0.00	0.00	28.46	4.88	0.81	0.00	0.00	93.61	72.07	35.51	13.07	4.82	7.86	0.30	0.02	0.00	0.00
EN	25.77	11.34	8.25	2.06	0.00	26.47	11.76	5.88	0.00	0.00	89.58	61.04	26.28	10.25	4.18	4.00	0.44	0.15	0.04	0.00
ES	26.13	12.61	11.71	3.60	0.00	24.55	10.91	8.18	0.91	0.00	90.59	64.27	27.73	9.61	3.95	4.08	0.44	0.17	0.06	0.00
FR	23.01	11.50	7.96	2.65	0.00	24.58	7.63	5.08	0.85	0.00	90.23	62.61	25.79	8.71	3.36	3.87	0.47	0.12	0.05	0.00
RU	26.71	6.16	2.74	0.00	0.00	23.61	4.86	2.08	0.00	0.00	93.20	69.75	32.20	11.10	3.91	4.39	0.23	0.03	0.01	0.00
ZH	61.84	26.97	6.68	1.01	0.15	20.26	2.61	0.65	0.00	0.00	89.73	64.10	29.54	10.44	3.84	67.89	27.00	5.27	0.67	0.04
ZH_pinyin	27.55	8.16	2.04	0.00	0.00															
ZH_wubi	28.33	4.17	0.83	0.00	0.00															
AR_cp1256						35.38	5.38	0.77	0.00	0.00										
RU_cp1251						26.71	6.16	2.74	0.00	0.00										
OOV token rate (%)																				
AR	0.31	0.01	0.00	0.00	0.00	0.11	0.00	0.00	0.00	0.00	53.94	25.89	9.26	3.14	1.15	0.82	0.08	0.00	0.00	0.00
EN	0.05	0.00	0.00	0.00	0.00	0.05	0.00	0.00	0.00	0.00	34.11	12.18	3.50	1.22	0.50	0.30	0.02	0.01	0.01	0.00
ES	0.04	0.01	0.01	0.00	0.00	0.04	0.01	0.01	0.00	0.00	31.52	12.57	3.72	1.15	0.46	0.19	0.03	0.04	0.02	0.00
FR	0.07	0.01	0.00	0.00	0.00	0.08	0.00	0.00	0.00	0.00	30.96	11.91	3.38	0.99	0.39	0.22	0.05	0.01	0.01	0.00
RU	0.22	0.00	0.00	0.00	0.00	0.11	0.00	0.00	0.00	0.00	49.05	22.75	7.55	2.36	0.81	0.71	0.02	0.00	0.00	0.00
ZH	10.44	1.21	0.16	0.02	0.00	0.10	0.00	0.00	0.00	0.00	37.81	13.74	4.42	1.42	0.53	22.02	4.99	0.79	0.10	0.00
ZH_pinyin	0.03	0.00	0.00	0.00	0.00															
ZH_wubi	0.09	0.00	0.00	0.00	0.00															
AR_cp1256						0.31	0.01	0.00	0.00	0.00										
RU_cp1251						0.22	0.00	0.00	0.00	0.00										
TTR (%)																				
AR	0.89	0.13	0.02	0.00	0.00	0.50	0.07	0.01	0.00	0.00	61.86	35.82	14.82	5.09	1.63	23.91	17.47	8.93	1.42	0.14
EN	0.64	0.08	0.01	0.00	0.00	0.67	0.09	0.01	0.00	0.00	42.79	19.70	6.47	2.02	0.66	24.03	13.83	4.88	1.24	0.13
ES	0.64	0.08	0.01	0.00	0.00	0.65	0.08	0.01	0.00	0.00	40.59	20.01	6.92	2.11	0.64	21.99	13.15	4.95	1.13	0.12
FR	0.68	0.08	0.01	0.00	0.00	0.67	0.09	0.01	0.00	0.00	40.43	18.97	6.33	1.82	0.53	22.16	12.86	4.76	1.10	0.12
RU	0.83	0.11	0.01	0.00	0.00	0.47	0.06	0.01	0.00	0.00	58.27	33.19	12.97	4.17	1.25	26.41	18.48	8.63	1.35	0.14
ZH	22.86	4.66	0.71	0.10	0.01	1.35	0.17	0.02	0.00	0.00	48.07	22.26	7.75	2.45	0.74	41.67	17.18	5.56	1.41	0.15
ZH_pinyin	0.62	0.09	0.01	0.00	0.00															
ZH_wubi	0.87	0.12	0.02	0.00	0.00															
AR_cp1256						0.89	0.13	0.02	0.00	0.00										
RU_cp1251						0.83	0.11	0.01	0.00	0.00										
Mean line length±std 0/25/50/75/100-th																				
AR	97.98 ± 55.47 9/53/94/147/234	100.60 ± 59.60 2/49/101/147/274	101.97 ± 59.10 1/51/101/147/300	102.49 ± 58.36 1/53/103/147/300	102.48 ± 58.39 1/53/102/147/300	176.56 ± 101.97 14/98/170/266/432	181.87 ± 108.68 2/88/182/266/501	184.21 ± 107.49 1/90/184/267/551	185.18 ± 106.22 1/95/185/266/552	185.17 ± 106.29 1/95/185/266/561	18.25 ± 10.12 2/10/17/27/43	18.76 ± 11.10 1/9/18/27/73	19.05 ± 10.95 1/10/19/27/84	19.16 ± 10.83 1/10/19/27/143	19.14 ± 10.82 1/10/19/27/129	33.87 ± 18.38 2/20/32/50/73	25.23 ± 15.26 1/13/24/36/96	21.06 ± 12.27 1/11/21/30/95	20.90 ± 12.02 1/11/21/29/146	20.99 ± 12.08 1/11/21/29/165
EN	118.16 ± 68.05 7/64/114/176/256	119.80 ± 71.15 2/58/122/174/288	120.18 ± 70.00 1/60/121/176/299	120.88 ± 69.43 1/62/122/175/300	120.97 ± 69.54 1/62/122/175/300	118.20 ± 68.05 7/64/114/176/256	119.84 ± 71.17 2/58/122/175/288	120.22 ± 70.02 1/60/121/176/299	120.92 ± 69.44 1/62/122/175/300	121.01 ± 69.55 1/62/122/175/303	20.47 ± 11.02 1/12/19/31/42	21.06 ± 12.60 1/11/21/31/74	21.10 ± 12.25 1/11/21/30/86	21.22 ± 12.14 1/11/21/30/117	21.23 ± 12.15 1/11/21/30/127	32.62 ± 17.93 2/19/31/47/81	24.63 ± 14.90 1/13/24/35/85	22.04 ± 12.78 1/11/22/31/89	21.60 ± 12.34 1/12/22/31/117	21.67 ± 12.40 1/12/22/31/129
ES	135.43 ± 77.54 11/80/133/200/286	135.11 ± 79.66 2/65/137/200/300	136.35 ± 79.00 1/67/138/200/300	137.09 ± 78.22 1/70/139/199/300	137.18 ± 78.45 1/70/139/200/300	137.90 ± 78.93 11/81/134/202/288	137.61 ± 81.03 2/65/140/205/305	138.93 ± 80.43 1/69/140/204/309	139.67 ± 79.61 1/71/141/203/311	139.75 ± 79.84 1/71/141/203/318	23.90 ± 13.29 1/14/24/34/49	23.86 ± 14.12 1/12/24/35/80	24.18 ± 13.94 1/12/24/35/87	24.32 ± 13.83 1/13/24/35/119	24.33 ± 13.86 1/13/24/35/130	37.02 ± 20.68 2/22/36/54/81	28.18 ± 16.96 1/14/27/41/93	25.31 ± 14.60 1/13/25/37/91	24.85 ± 14.13 1/13/25/36/119	24.93 ± 14.21 1/13/25/36/133
FR	131.73 ± 75.95 8/74/128/196/289	134.70 ± 80.48 2/64/135/202/300	135.86 ± 79.51 1/65/137/199/300	136.62 ± 78.71 1/69/138/199/300	136.81 ± 78.90 1/69/138/200/300	136.17 ± 78.50 8/77/132/203/296	139.25 ± 83.09 2/65/140/207/313	140.40 ± 82.18 1/68/142/206/315	141.22 ± 81.35 1/71/143/206/322	141.40 ± 81.55 1/71/143/206/325	23.62 ± 13.40 1/13/23/34/53	24.44 ± 14.69 1/12/24/36/78	24.70 ± 14.41 1/12/25/36/92	24.85 ± 14.27 1/13/25/36/118	24.87 ± 14.30 1/13/25/36/132	36.64 ± 21.18 2/21/35/54/83	28.54 ± 17.31 1/15/27/42/94	25.73 ± 14.96 1/13/26/37/97	25.28 ± 14.49 1/13/25/36/118	25.37 ± 14.57 1/13/26/36/134
RU	131.06 ± 76.89 10/71/123/195/271	130.29 ± 77.80 2/62/130/193/299	132.58 ± 77.80 1/65/133/195/300	133.57 ± 77.09 1/67/134/194/300	133.70 ± 77.19 1/67/134/195/300	240.59 ± 144.25 12/125/229/363/505	239.15 ± 144.35 2/113/238/352/558	243.32 ± 144.14 1/117/245/358/565	245.13 ± 142.89 1/122/246/357/566	245.40 ± 143.08 1/122/247/358/569	19.60 ± 10.58 1/12/20/28/43	19.64 ± 11.58 1/10/20/29/72	20.02 ± 11.63 1/10/20/29/85	20.15 ± 11.50 1/11/20/29/117	20.15 ± 11.51 1/11/20/29/128	37.60 ± 21.30 2/21/33/53/91	26.14 ± 15.95 1/13/25/38/89	21.83 ± 12.79 1/11/22/31/87	21.70 ± 12.55 1/11/22/31/120	21.79 ± 12.63 1/11/22/31/162
ZH	33.29 ± 17.41 4/19/32/47/76	33.77 ± 19.77 2/18/33/48/148	34.07 ± 19.50 1/18/34/48/152	34.20 ± 19.21 1/19/34/48/201	34.21 ± 19.26 1/19/34/48/289	91.22 ± 50.88 8/53/90/134/209	92.69 ± 55.28 2/45/92/133/290	93.52 ± 54.29 1/48/93/135/283	94.03 ± 53.67 1/49/94/135/369	94.06 ± 53.73 1/49/94/135/667	18.66 ± 10.28 2/11/18/26/48	18.70 ± 11.18 1/10/18/27/68	18.98 ± 11.05 1/10/19/27/99	19.07 ± 10.88 1/10/19/27/116	19.07 ± 10.90 1/10/19/27/167	25.63 ± 13.65 2/16/24/34/63	21.63 ± 13.19 1/11/21/31/86	19.90 ± 11.61 1/10/20/28/101	19.47 ± 11.13 1/11/19/27/116	19.57 ± 11.24 1/11/19/28/167
ZH_pinyin	113.91 ± 64.46 8/66/109/174/265	115.58 ± 69.18 2/55/115/167/325	116.62 ± 68.13 1/58/117/169/357	117.32 ± 67.41 1/60/118/169/394	117.37 ± 67.50 1/60/118/169/680															
ZH_wubi	100.35 ± 55.70 8/59/99/150/226	101.05 ± 60.13 2/48/100/146/325	101.91 ± 58.94 1/52/102/147/318	102.43 ± 58.21 1/53/102/147/381	102.46 ± 58.25 1/54/103/146/688															
AR_cp1256						97.98 ± 55.47 9/53/94/147/234	100.60 ± 59.60 2/49/101/147/274	101.97 ± 59.10 1/51/101/147/300	102.49 ± 58.36 1/53/103/147/300	102.48 ± 58.39 1/53/102/147/300										
RU_cp1251						131.06 ± 76.89 10/71/123/195/271	130.29 ± 77.80 2/62/130/193/299	132.58 ± 77.80 1/65/133/195/300	133.57 ± 77.09 1/67/134/194/300	133.70 ± 77.19 1/67/134/195/300										

Statistics for dataset C

Representation	CHAR					BYTE					WORD					BPE				
Number of lines	100	1,000	10,000	100,000	1,000,000	100	1,000	10,000	100,000	1,000,000	100	1,000	10,000	100,000	1,000,000	100	1,000	10,000	100,000	1,000,000
Number of TYPES																				
AR	97	136	162	261	427	92	123	144	160	176	1,165	6,823	28,296	97,380	310,632	864	4,530	18,735	29,673	29,954
EN	78	98	126	186	310	81	103	131	159	178	906	4,173	13,658	42,677	141,163	802	3,484	10,800	26,766	29,215
ES	84	108	133	186	306	85	112	133	160	175	970	4,734	16,850	51,281	154,649	803	3,686	12,470	28,134	29,470
FR	87	113	139	195	330	91	117	134	159	179	991	4,603	15,586	45,235	132,493	853	3,693	12,170	27,731	29,355
RU	98	141	167	211	287	100	140	154	166	177	1,165	6,490	26,112	84,137	250,778	1,002	4,858	19,029	29,322	29,814
ZH	783	1,550	2,443	3,477	4,698	128	152	162	177	189	882	4,160	14,730	46,667	139,895	1,084	3,716	11,214	27,443	29,110
ZH_pinyin	74	107	139	240	413															
ZH_wubi	95	129	154	242	408															
AR_cp1256						97	136	162	261	427										
RU_cp1251						98	141	167	211	287										
Number of TOKENS																				
AR	10,212	104,144	1,021,136	10,231,081	102,448,339	18,448	188,507	1,845,136	18,482,689	185,105,498	1,889	19,281	190,738	1,912,669	19,137,240	3,518	25,601	210,738	2,087,431	20,981,760
EN	12,300	123,646	1,208,827	12,089,449	120,933,962	12,305	123,681	1,209,187	12,093,117	120,971,460	2,116	21,545	212,034	2,123,153	21,231,465	3,369	25,111	221,264	2,160,162	21,666,482
ES	14,125	139,563	1,369,779	13,701,387	137,133,440	14,387	142,237	1,395,305	13,958,221	139,702,853	2,472	24,600	242,672	2,430,586	24,319,760	3,784	28,726	254,092	2,483,995	24,925,209
FR	13,797	138,528	1,365,360	13,661,150	136,754,360	14,243	143,139	1,411,451	14,119,815	141,343,675	2,453	24,950	248,488	2,485,118	24,864,449	3,755	28,907	258,550	2,527,957	25,362,724
RU	13,763	136,674	1,339,286	13,369,690	133,671,322	25,345	251,231	2,457,938	24,535,771	245,338,139	2,024	20,474	201,618	2,016,451	20,156,467	3,813	26,772	219,794	2,172,616	21,787,539
ZH	3,371	34,429	341,536	3,419,648	34,200,543	9,235	95,100	938,805	9,404,386	94,052,881	1,824	19,120	190,485	1,907,643	19,073,463	2,559	22,067	199,706	1,947,300	19,573,372
ZH_pinyin	11,605	119,258	1,171,605	11,732,010	117,356,880															
ZH_wubi	10,071	103,944	1,022,870	10,245,716	102,450,581															
AR_cp1256						10,212	104,144	1,021,136	10,231,081	102,448,339										
RU_cp1251						13,763	136,674	1,339,286	13,369,690	133,671,322										
OOV type rate (%)																				
AR	28.46	5.38	0.00	0.00	0.00	26.02	4.88	0.00	0.00	0.00	93.72	71.13	35.70	13.44	5.02	6.06	0.34	0.00	0.00	0.00
EN	21.65	12.37	8.25	2.06	0.00	22.55	11.76	4.90	0.98	0.00	89.47	60.56	26.27	10.43	4.32	3.52	0.49	0.18	0.04	0.00
ES	25.23	14.41	10.81	5.41	0.90	23.64	10.91	6.36	0.91	0.00	90.71	63.96	27.18	9.71	3.88	4.44	0.53	0.19	0.08	0.00
FR	23.01	9.73	7.08	1.77	0.00	22.88	9.32	5.08	0.85	0.00	89.92	62.27	25.96	8.89	3.48	3.96	0.49	0.15	0.02	0.00
RU	33.56	7.53	2.05	0.00	0.00	31.25	5.56	1.39	0.00	0.00	93.11	69.66	32.15	10.91	3.81	4.82	0.29	0.02	0.01	0.00
ZH	61.23	26.87	6.73	1.42	0.35	16.99	3.92	0.65	0.00	0.00	90.34	63.48	29.89	10.31	4.09	67.98	26.22	5.03	0.55	0.10
ZH_pinyin	27.55	8.16	1.02	0.00	0.00															
ZH_wubi	23.33	4.17	0.83	0.00	0.00															
AR_cp1256						28.46	5.38	0.00	0.00	0.00										
RU_cp1251						33.56	7.53	2.05	0.00	0.00										
OOV token rate (%)																				
AR	0.13	0.01	0.00	0.00	0.00	0.05	0.00	0.00	0.00	0.00	53.40	25.24	9.31	3.25	1.18	0.73	0.12	0.00	0.00	0.00
EN	0.03	0.00	0.00	0.00	0.00	0.03	0.00	0.00	0.00	0.00	34.26	11.63	3.41	1.26	0.51	0.20	0.03	0.02	0.00	0.00
ES	0.04	0.01	0.01	0.00	0.00	0.05	0.01	0.01	0.00	0.00	32.17	12.05	3.56	1.16	0.46	0.29	0.09	0.04	0.02	0.00
FR	0.14	0.00	0.00	0.00	0.00	0.12	0.00	0.00	0.00	0.00	31.39	11.66	3.30	1.03	0.41	0.51	0.04	0.02	0.00	0.00
RU	0.15	0.00	0.00	0.00	0.00	0.08	0.00	0.00	0.00	0.00	49.48	22.44	7.53	2.33	0.79	0.38	0.04	0.00	0.00	0.00
ZH	11.15	1.25	0.18	0.04	0.01	0.10	0.00	0.00	0.00	0.00	38.65	13.96	4.52	1.42	0.56	22.01	4.75	0.81	0.09	0.01
ZH_pinyin	0.07	0.00	0.00	0.00	0.00															
ZH_wubi	0.09	0.00	0.00	0.00	0.00															
AR_cp1256						0.13	0.01	0.00	0.00	0.00										
RU_cp1251						0.15	0.00	0.00	0.00	0.00										
TTR (%)																				
AR	0.95	0.13	0.02	0.00	0.00	0.50	0.07	0.01	0.00	0.00	61.67	35.39	14.84	5.09	1.62	24.56	17.69	8.89	1.42	0.14
EN	0.63	0.08	0.01	0.00	0.00	0.66	0.08	0.01	0.00	0.00	42.82	19.37	6.44	2.01	0.66	23.81	13.87	4.88	1.24	0.13
ES	0.59	0.08	0.01	0.00	0.00	0.59	0.08	0.01	0.00	0.00	39.24	19.24	6.94	2.11	0.64	21.22	12.83	4.91	1.13	0.12
FR	0.63	0.08	0.01	0.00	0.00	0.64	0.08	0.01	0.00	0.00	40.40	18.45	6.27	1.82	0.53	22.72	12.78	4.71	1.10	0.12
RU	0.71	0.10	0.01	0.00	0.00	0.39	0.06	0.01	0.00	0.00	57.56	31.70	12.95	4.17	1.24	26.28	18.15	8.66	1.35	0.14
ZH	23.23	4.50	0.72	0.10	0.01	1.39	0.16	0.02	0.00	0.00	48.36	21.76	7.73	2.45	0.73	42.36	16.84	5.62	1.41	0.15
ZH_pinyin	0.64	0.09	0.01	0.00	0.00															
ZH_wubi	0.94	0.12	0.02	0.00	0.00															
AR_cp1256						0.95	0.13	0.02	0.00	0.00										
RU_cp1251						0.71	0.10	0.01	0.00	0.00										
Mean line length±std 0/25/50/75/100-th																				
AR	102.12 ± 57.40 5/57/96/152/213	104.14 ± 57.83 4/54/106/149/264	102.11 ± 58.06 3/53/102/147/293	102.31 ± 58.33 1/53/102/147/298	102.45 ± 58.46 1/53/102/147/300	184.48 ± 105.32 9/101/173/280/383	188.51 ± 105.63 6/98/191/270/487	184.51 ± 105.78 3/94/184/266/533	184.83 ± 106.15 1/95/184/266/551	185.11 ± 106.40 1/95/185/266/559	18.89 ± 10.27 2/11/18/27/43	19.28 ± 10.59 1/10/20/27/50	19.07 ± 10.72 1/10/19/27/82	19.13 ± 10.82 1/10/19/27/120	19.14 ± 10.84 1/10/19/27/143	35.18 ± 18.92 4/18/34/50/73	25.60 ± 14.42 1/14/26/36/79	21.07 ± 12.01 1/11/21/30/86	20.87 ± 12.00 1/11/21/29/123	20.98 ± 12.10 1/11/21/29/147
EN	123.00 ± 72.30 9/63/116/187/268	123.65 ± 71.12 3/60/128/178/300	120.88 ± 69.62 1/61/122/175/300	120.89 ± 69.58 1/62/122/175/300	120.93 ± 69.60 1/61/122/175/300	123.05 ± 72.35 9/63/116/187/268	123.68 ± 71.15 3/60/128/178/300	120.92 ± 69.64 1/61/122/175/300	120.93 ± 69.60 1/62/122/175/300	120.97 ± 69.62 1/61/122/175/304	21.16 ± 12.24 2/10/21/31/48	21.55 ± 12.31 1/11/22/31/55	21.20 ± 12.15 1/11/21/30/83	21.23 ± 12.17 1/11/21/30/118	21.23 ± 12.17 1/11/21/30/136	33.69 ± 19.32 3/15/33/49/78	25.11 ± 14.32 1/13/26/36/86	22.13 ± 12.67 1/12/22/32/88	21.60 ± 12.36 1/12/22/31/120	21.67 ± 12.42 1/12/22/31/138
ES	141.25 ± 82.83 11/59/134/215/292	139.56 ± 79.59 3/67/145/201/300	136.98 ± 78.35 1/70/138/200/300	137.01 ± 78.45 1/70/138/199/300	137.13 ± 78.47 1/70/139/199/300	143.87 ± 84.37 11/60/136/218/298	142.24 ± 81.05 3/69/149/206/306	139.53 ± 79.72 1/71/140/204/308	139.58 ± 79.84 1/71/141/203/312	139.70 ± 79.87 1/71/141/203/316	24.72 ± 14.39 2/12/24/37/56	24.60 ± 13.91 1/12/25/36/60	24.27 ± 13.80 1/13/24/35/84	24.31 ± 13.87 1/13/24/35/119	24.32 ± 13.87 1/13/24/35/139	37.84 ± 21.74 4/17/35/56/86	28.73 ± 16.27 1/14/30/41/90	25.41 ± 14.46 1/13/25/36/90	24.84 ± 14.17 1/13/25/36/121	24.93 ± 14.22 1/13/25/36/140
FR	137.97 ± 80.12 6/62/133/215/293	138.53 ± 79.49 3/68/141/203/300	136.54 ± 78.80 1/68/137/200/300	136.61 ± 78.92 1/69/138/199/300	136.75 ± 78.96 1/69/138/199/300	142.43 ± 82.97 6/64/137/219/303	143.14 ± 82.18 3/70/145/209/315	141.15 ± 81.47 1/71/142/206/319	141.20 ± 81.56 1/71/142/206/323	141.34 ± 81.61 1/71/143/206/330	24.53 ± 13.79 2/13/24/37/50	24.95 ± 14.19 1/12/26/36/62	24.85 ± 14.28 1/13/25/36/84	24.85 ± 14.31 1/13/25/36/118	24.86 ± 14.31 1/13/25/36/138	37.55 ± 20.97 3/20/37/56/80	28.91 ± 16.41 1/14/30/42/86	25.86 ± 14.85 1/13/26/37/88	25.28 ± 14.53 1/13/25/36/120	25.36 ± 14.58 1/13/26/36/138
RU	137.63 ± 80.80 11/71/130/212/296	136.67 ± 78.77 3/63/139/200/300	133.93 ± 77.25 1/67/135/196/300	133.70 ± 77.26 1/67/134/195/300	133.67 ± 77.25 1/67/134/195/300	253.45 ± 150.90 21/126/242/392/550	251.23 ± 146.21 4/118/258/366/561	245.79 ± 143.31 1/121/247/360/562	245.36 ± 143.18 1/122/247/358/566	245.34 ± 143.17 1/122/247/358/569	20.24 ± 11.27 2/11/20/29/47	20.47 ± 11.61 1/10/21/29/55	20.16 ± 11.44 1/11/20/29/83	20.16 ± 11.53 1/11/20/29/117	20.16 ± 11.53 1/11/20/29/136	38.13 ± 21.10 3/18/38/56/81	26.77 ± 15.26 1/14/27/39/78	21.98 ± 12.61 1/12/22/31/87	21.73 ± 12.59 1/11/22/31/121	21.79 ± 12.64 1/11/22/31/138
ZH	33.71 ± 18.03 4/19/33/48/70	34.43 ± 19.40 2/18/35/49/127	34.15 ± 19.06 1/19/34/48/133	34.20 ± 19.27 1/19/34/48/220	34.20 ± 19.28 1/19/34/48/272	92.35 ± 52.42 12/47/93/132/198	95.10 ± 54.29 3/50/96/138/248	93.88 ± 53.42 3/49/94/135/291	94.04 ± 53.75 1/49/94/135/378	94.05 ± 53.79 1/48/94/135/594	18.24 ± 9.97 2/10/17/26/39	19.12 ± 10.87 1/10/20/27/55	19.05 ± 10.86 1/10/19/27/87	19.08 ± 10.91 1/10/19/27/113	19.07 ± 10.92 1/10/19/27/248	25.59 ± 13.84 2/14/26/37/52	22.07 ± 12.68 1/12/22/31/90	19.97 ± 11.43 1/11/20/28/92	19.47 ± 11.17 1/11/19/27/115	19.57 ± 11.26 1/11/19/28/249
ZH_pinyin	116.05 ± 67.54 11/58/117/167/263	119.26 ± 68.54 3/61/122/173/320	117.16 ± 67.25 3/61/117/169/335	117.32 ± 67.49 1/60/118/169/376	117.36 ± 67.55 1/60/118/169/584															
ZH_wubi	100.71 ± 57.05 13/54/101/139/217	103.94 ± 59.48 3/54/105/150/296	102.29 ± 57.92 3/54/102/147/297	102.46 ± 58.29 1/53/102/146/398	102.45 ± 58.31 1/53/103/146/627															
AR_cp1256						102.12 ± 57.40 5/57/96/152/213	104.14 ± 57.83 4/54/106/149/264	102.11 ± 58.06 3/53/102/147/293	102.31 ± 58.33 1/53/102/147/298	102.45 ± 58.46 1/53/102/147/300										
RU_cp1251						137.63 ± 80.80 11/71/130/212/296	136.67 ± 78.77 3/63/139/200/300	133.93 ± 77.25 1/67/135/196/300	133.70 ± 77.26 1/67/134/195/300	133.67 ± 77.25 1/67/134/195/300										

Statistics for development (dev) set

As a different set of vocabulary is learned from each training dataset and data size, BPE has a distinct dev set for each.

Representation	CHAR	BYTE	WORD	BPE_A					BPE_B					BPE_C				
Number of lines in train set				100	1, 000	10, 000	100, 000	1, 000, 000	100	1, 000	10, 000	100, 000	1, 000, 000	100	1, 000	10, 000	100, 000	1, 000, 000
Number of TYPES																		
AR	130	123	13, 836	708	3, 232	8, 994	11, 473	12, 430	865	3, 991	10, 735	12, 954	13, 090	908	4, 119	10, 681	12, 934	13, 093
EN	97	102	7, 199	656	2, 567	5, 998	7, 461	7, 556	801	3, 149	6, 518	7, 557	7, 578	823	3, 245	6, 551	7, 524	7, 573
ES	111	110	8, 551	680	2, 832	6, 919	8, 752	8, 871	833	3, 426	7, 528	8, 869	8, 956	834	3, 424	7, 527	8, 871	8, 939
FR	113	118	8, 312	744	2, 821	6, 925	8, 526	8, 666	827	3, 407	7, 489	8, 665	8, 705	883	3, 463	7, 431	8, 679	8, 708
RU	146	144	12, 819	878	3, 769	10, 085	12, 505	12, 788	1, 024	4, 438	11, 052	12, 883	12, 954	1, 038	4, 509	11, 012	12, 882	12, 958
ZH	1, 976	153	7, 413	3, 224	4, 215	6, 386	7, 541	7, 654	3, 261	4, 481	6, 735	7, 719	7, 702	3, 260	4, 524	6, 785	7, 654	7, 721
ZH_pinyin	98																	
ZH_wubi	120																	
AR_cp1256		130																
RU_cp1251		146																
Number of TOKENS																		
AR	334, 358	605, 516	61, 371	167, 574	115, 693	83, 001	76, 284	70, 527	149, 689	97, 843	73, 314	68, 538	68, 270	149, 623	97, 231	73, 541	68, 579	68, 278
EN	391, 222	391, 260	67, 629	155, 826	101, 782	77, 089	71, 276	70, 339	140, 256	90, 871	73, 531	69, 633	69, 348	140, 377	90, 360	73, 468	69, 633	69, 341
ES	443, 958	452, 190	78, 087	170, 433	113, 983	88, 634	82, 281	81, 341	155, 687	103, 748	84, 914	80, 569	80, 337	154, 746	103, 172	84, 870	80, 579	80, 371
FR	438, 083	452, 556	78, 745	166, 280	114, 694	88, 726	82, 448	81, 559	156, 256	104, 071	85, 115	80, 844	80, 671	153, 745	104, 091	85, 125	80, 912	80, 654
RU	431, 538	793, 214	64, 180	177, 818	113, 628	79, 763	72, 480	71, 081	163, 319	100, 294	75, 051	70, 200	69, 991	163, 806	99, 978	75, 096	70, 196	69, 982
ZH	107, 990	301, 085	60, 013	96, 745	80, 231	68, 129	63, 614	62, 810	93, 775	75, 636	65, 212	61, 867	61, 832	94, 127	75, 718	65, 203	61, 916	61, 823
ZH_pinyin	376, 979																	
ZH_wubi	330, 734																	
AR_cp1256		334, 358																
RU_cp1251		431, 538																
TTR (%)																		
AR	0.04	0.02	22.54	0.42	2.79	10.84	15.04	17.62	0.58	4.08	14.64	18.90	19.17	0.61	4.24	14.52	18.86	19.18
EN	0.02	0.03	10.64	0.42	2.52	7.78	10.47	10.74	0.57	3.47	8.86	10.85	10.93	0.59	3.59	8.92	10.81	10.92
ES	0.03	0.02	10.95	0.40	2.48	7.81	10.64	10.91	0.54	3.30	8.87	11.01	11.15	0.54	3.32	8.87	11.01	11.12
FR	0.03	0.03	10.56	0.45	2.46	7.80	10.34	10.63	0.53	3.27	8.80	10.72	10.79	0.57	3.33	8.73	10.73	10.80
RU	0.03	0.02	19.97	0.49	3.32	12.64	17.25	17.99	0.63	4.42	14.73	18.35	18.51	0.63	4.51	14.66	18.35	18.52
ZH	1.83	0.05	12.35	3.33	5.25	9.37	11.85	12.19	3.48	5.92	10.33	12.48	12.46	3.46	5.97	10.41	12.36	12.49
ZH_pinyin	0.03																	
ZH_wubi	0.04																	
AR_cp1256		0.04																
RU_cp1251		0.03																
Mean line length ± std 0/25/50/75/100-th																		
AR	108.66 ± 58.01 3/60/110/153/277	196.79 ± 105.85 6/107/199/277/503	19.95 ± 10.58 1/12/20/27/58	54.46 ± 29.51 1/30/54/76/152	37.60 ± 20.51 1/22/37/52/125	26.97 ± 14.80 1/16/27/37/95	24.79 ± 13.59 1/14/24/34/86	22.92 ± 12.56 1/14/22/32/75	48.65 ± 26.35 1/27/49/68/156	31.80 ± 17.76 1/18/32/44/110	23.83 ± 13.15 1/14/24/33/80	22.27 ± 12.12 1/13/22/31/71	22.19 ± 12.07 1/13/22/31/71	48.63 ± 26.21 1/28/49/67/145	31.60 ± 17.53 1/18/31/44/110	23.90 ± 13.20 1/14/24/33/87	22.29 ± 12.14 1/13/22/31/73	22.19 ± 12.06 1/13/22/31/72
EN	127.14 ± 68.64 6/68/130/181/299	127.16 ± 68.65 6/68/130/181/299	21.98 ± 11.81 1/13/22/31/61	50.64 ± 27.44 1/27/51/72/136	33.08 ± 18.07 1/19/33/46/110	25.05 ± 13.56 1/15/25/35/78	23.16 ± 12.42 1/14/23/32/71	22.86 ± 12.27 1/13/23/32/71	45.58 ± 24.86 1/26/46/65/129	29.53 ± 16.30 1/17/29/41/94	23.90 ± 12.95 1/14/24/33/74	22.63 ± 12.13 1/13/23/31/65	22.54 ± 12.06 1/13/23/31/65	45.62 ± 24.67 1/26/46/64/122	29.37 ± 16.13 1/17/29/41/92	23.88 ± 12.91 1/14/24/33/73	22.63 ± 12.12 1/13/23/31/65	22.54 ± 12.05 1/13/23/31/66
ES	144.28 ± 77.78 5/77/145/207/300	146.96 ± 79.21 5/78/148/211/307	25.38 ± 13.56 1/15/25/36/63	55.39 ± 30.13 1/30/56/79/141	37.04 ± 20.13 1/21/37/52/111	28.81 ± 15.53 1/17/29/41/85	26.74 ± 14.29 1/15/27/38/76	26.44 ± 14.14 1/15/26/37/73	50.60 ± 27.66 1/27/51/72/133	33.72 ± 18.48 1/19/34/47/103	27.60 ± 14.88 1/15/28/39/75	26.18 ± 13.98 1/15/26/37/71	26.11 ± 13.94 1/15/26/37/70	50.29 ± 27.27 1/28/51/71/133	33.53 ± 18.38 1/19/34/47/95	27.58 ± 14.86 1/15/28/39/75	26.19 ± 13.99 1/15/26/37/71	26.12 ± 13.94 1/15/26/37/71
FR	142.37 ± 77.81 4/74/145/205/300	147.08 ± 80.30 4/77/150/212/310	25.59 ± 13.86 1/14/26/36/66	54.04 ± 29.55 1/29/55/76/139	37.27 ± 20.65 1/20/38/52/119	28.84 ± 15.76 1/16/29/40/89	26.79 ± 14.47 1/15/27/37/74	26.51 ± 14.35 1/15/27/37/70	50.78 ± 27.79 1/27/52/72/135	33.82 ± 18.74 1/18/34/47/108	27.66 ± 15.11 1/15/28/39/80	26.27 ± 14.20 1/14/27/37/69	26.22 ± 14.16 1/14/27/37/69	49.97 ± 27.25 1/27/51/70/131	33.83 ± 18.80 1/18/34/47/107	27.66 ± 15.09 1/15/28/39/84	26.30 ± 14.21 1/14/27/37/69	26.21 ± 14.16 1/14/27/37/69
RU	140.25 ± 76.21 5/75/141/200/300	257.79 ± 141.53 7/136/259/370/569	20.86 ± 11.25 1/12/21/29/69	57.79 ± 32.12 1/31/58/82/185	36.93 ± 20.73 1/21/36/52/185	25.92 ± 14.48 1/15/26/36/128	23.56 ± 12.95 1/14/23/33/101	23.10 ± 12.71 1/13/23/32/95	53.08 ± 29.00 1/29/53/75/185	32.59 ± 18.42 1/18/32/46/166	24.39 ± 13.59 1/14/24/34/112	22.81 ± 12.50 1/13/23/32/85	22.75 ± 12.46 1/13/23/32/93	53.24 ± 29.18 2/30/53/76/185	32.49 ± 18.49 1/18/32/45/161	24.41 ± 13.57 1/14/24/34/105	22.81 ± 12.50 1/13/23/32/90	22.74 ± 12.45 1/13/23/32/92
ZH	35.10 ± 18.48 2/21/35/49/125	97.85 ± 52.10 4/53/99/138/268	19.50 ± 10.42 1/11/20/27/64	31.44 ± 16.96 1/18/31/44/109	26.07 ± 14.19 1/15/26/36/93	22.14 ± 12.02 1/13/22/31/80	20.67 ± 11.16 1/12/21/29/74	20.41 ± 11.05 1/12/20/28/74	30.48 ± 16.47 1/17/30/43/104	24.58 ± 13.42 1/14/24/34/92	21.19 ± 11.49 1/12/21/29/71	20.11 ± 10.79 1/12/20/28/64	20.09 ± 10.79 1/12/20/28/66	30.59 ± 16.45 1/18/30/43/101	24.61 ± 13.49 1/14/24/34/93	21.19 ± 11.49 1/12/21/29/76	20.12 ± 10.81 1/12/20/28/64	20.09 ± 10.79 1/12/20/28/65
ZH_pinyin	122.52 ± 65.59 6/67/125/173/353																	
ZH_wubi	107.49 ± 56.73 4/60/108/151/294																	
AR_cp1256		108.66 ± 58.01 3/60/110/153/277																
RU_cp1251		140.25 ± 76.21 5/75/141/200/300																

F ENLARGED FIGURES FOR ALL 30 LANGUAGE DIRECTIONS (AGGREGATE RESULTS FROM ALL RUNS)

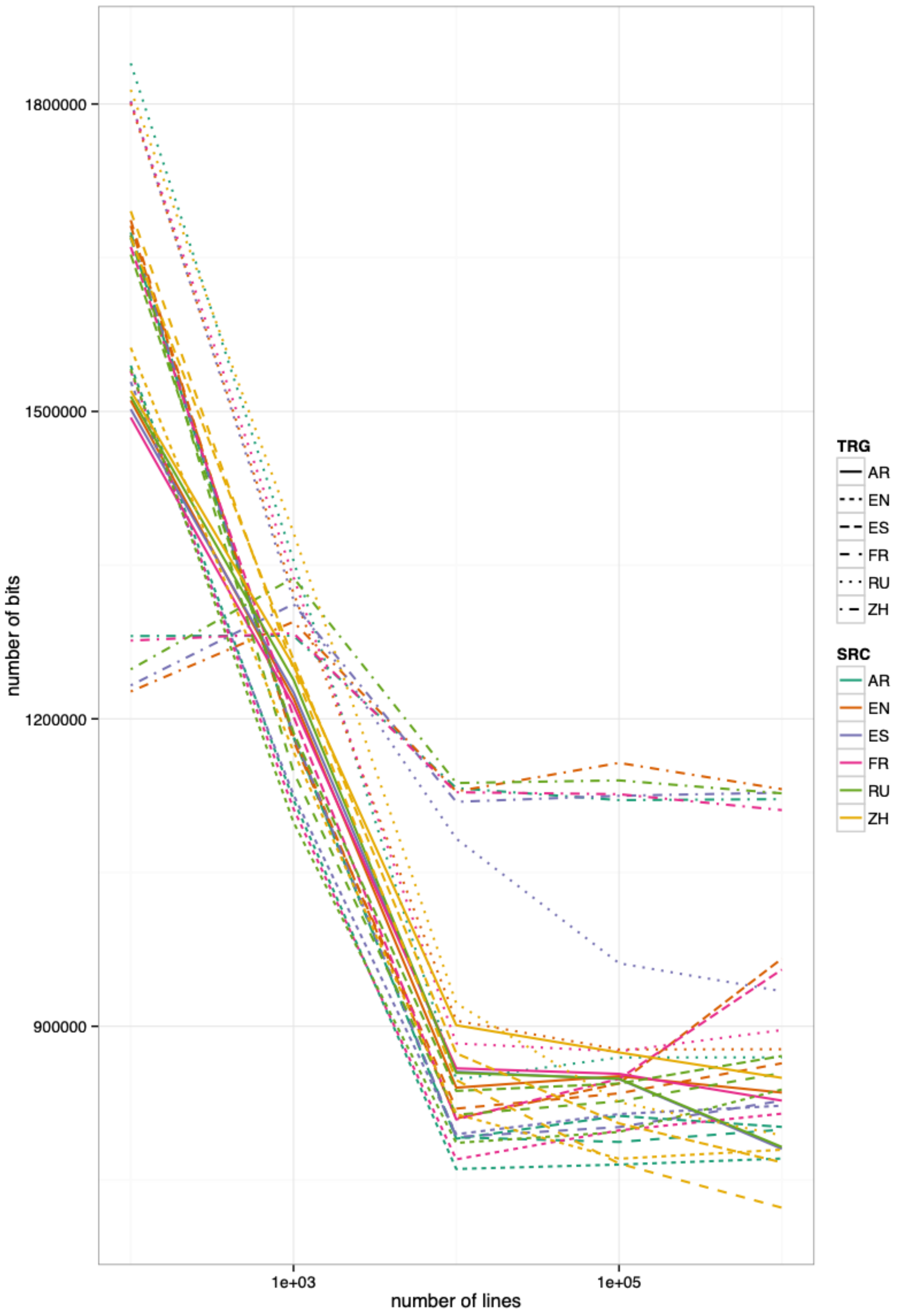

Figure 4: CHAR: character models

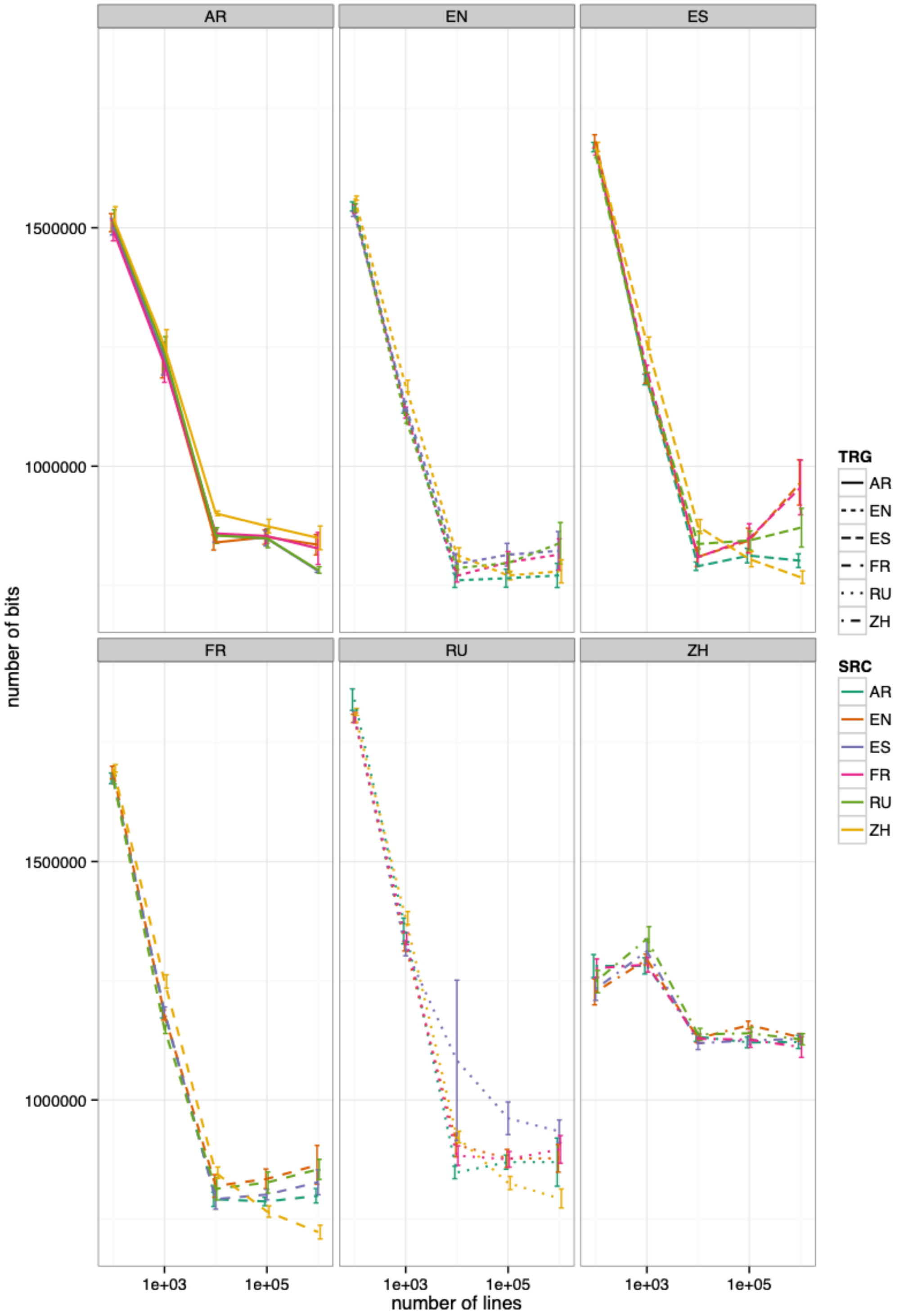

Figure 4: CHAR: character models (target language as facet)

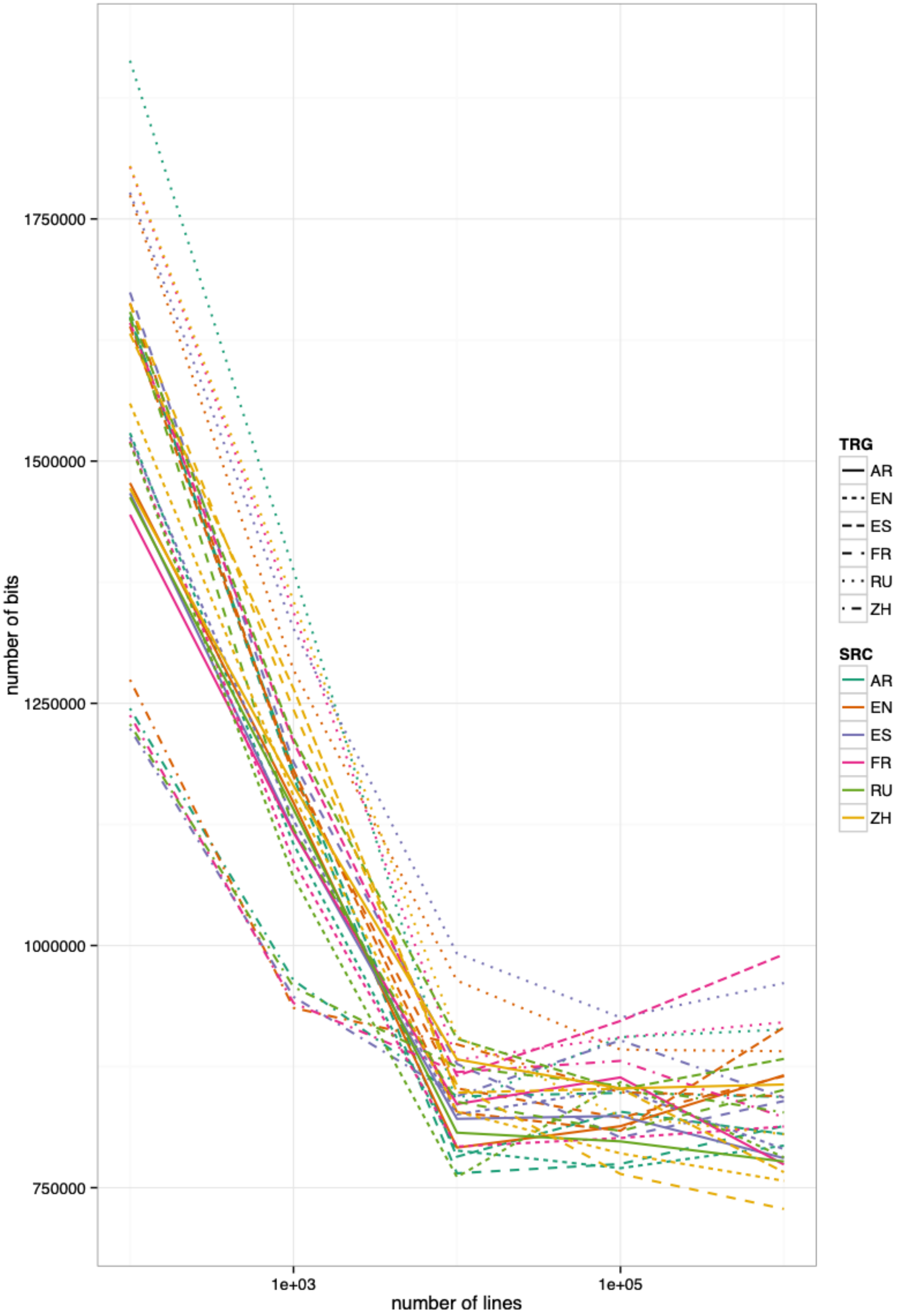

Figure 5: CHAR with Pinyin for ZH_{trg}

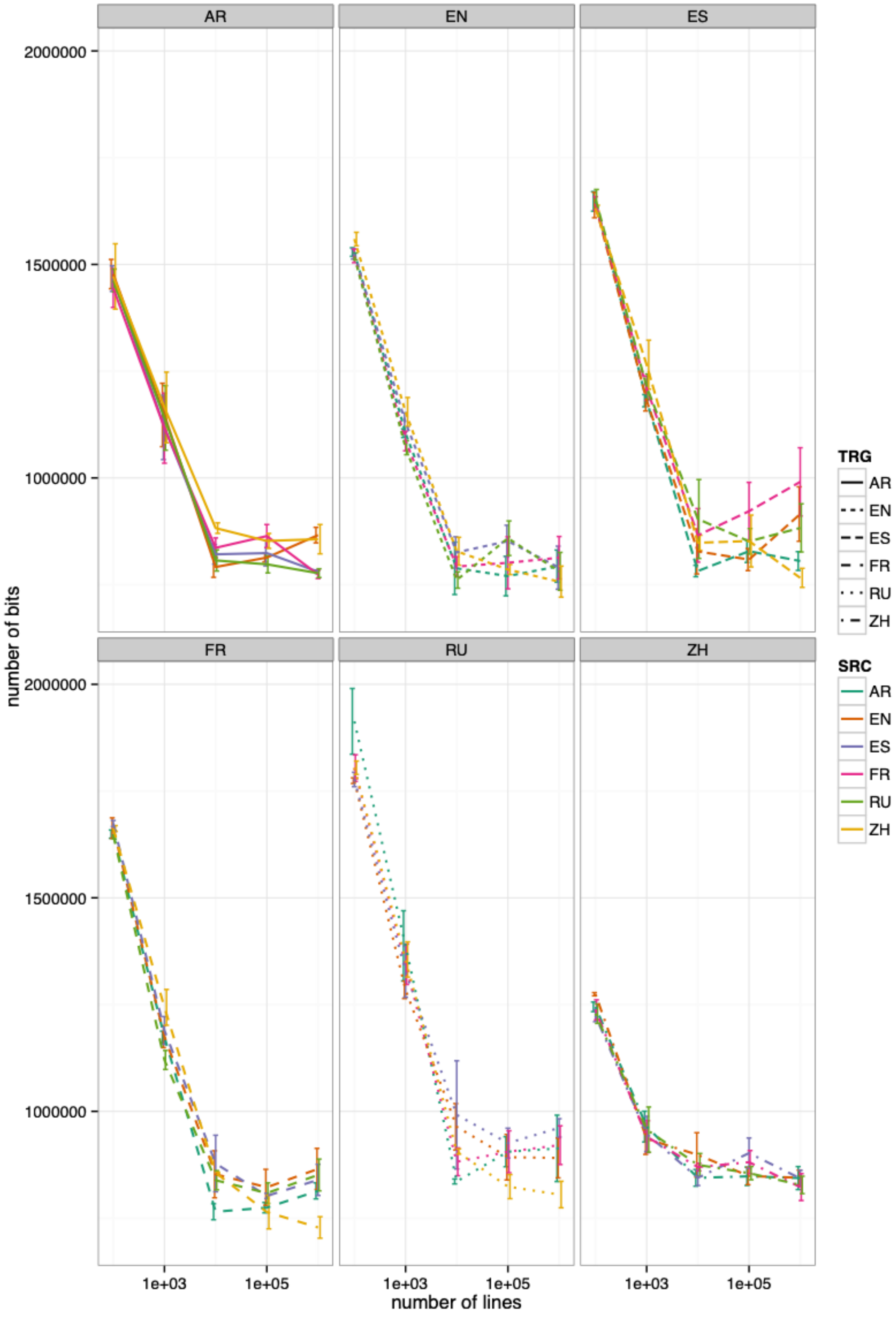

Figure 5: CHAR with Pinyin for ZH_{trg} (target language as facet)

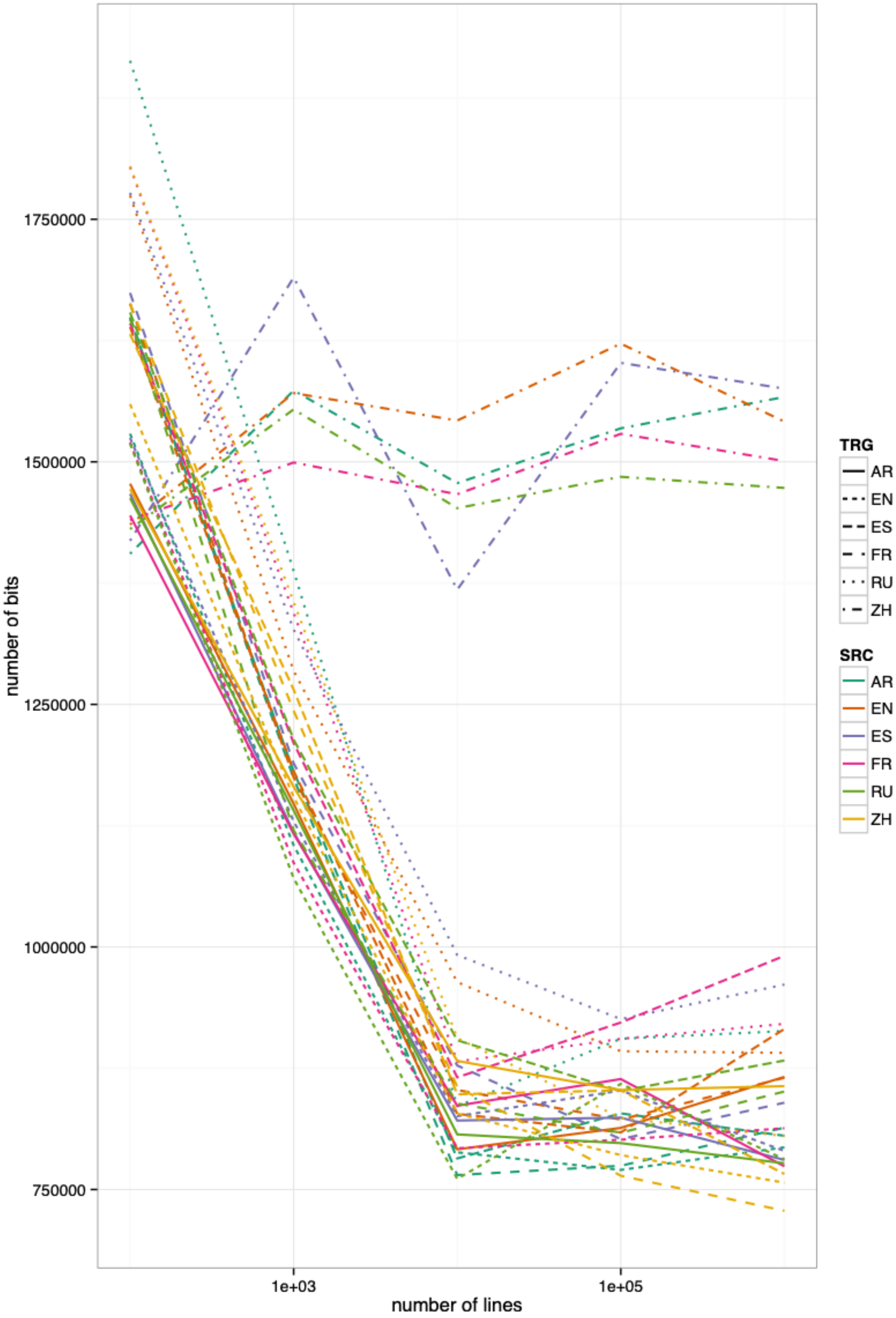

Figure 6: CHAR with Wubi for ZH_{trg}

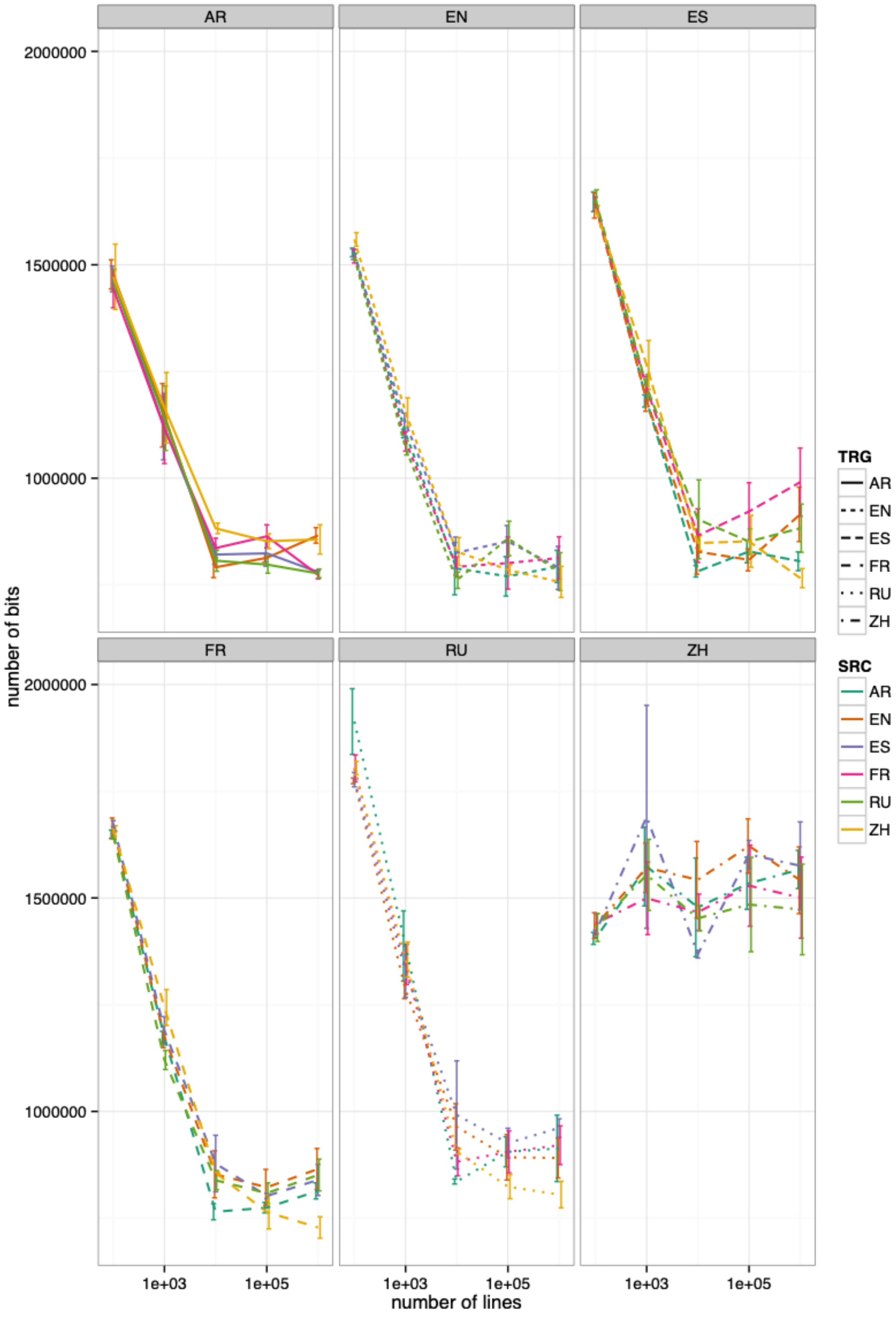

Figure 6: CHAR with Wubi for ZH_{trg} (target language as facet)

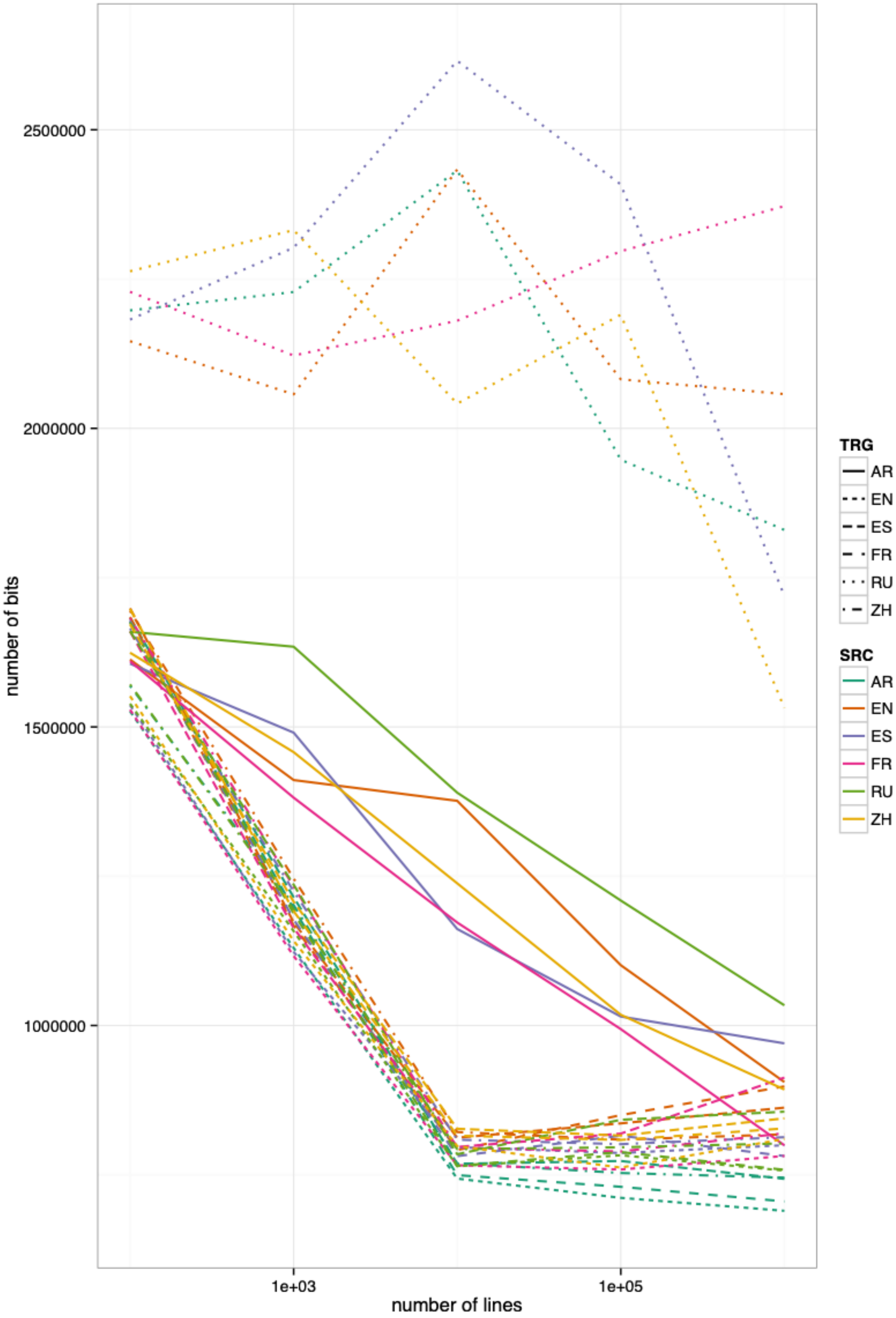

Figure 7: BYTE models with UTF-8 encoding

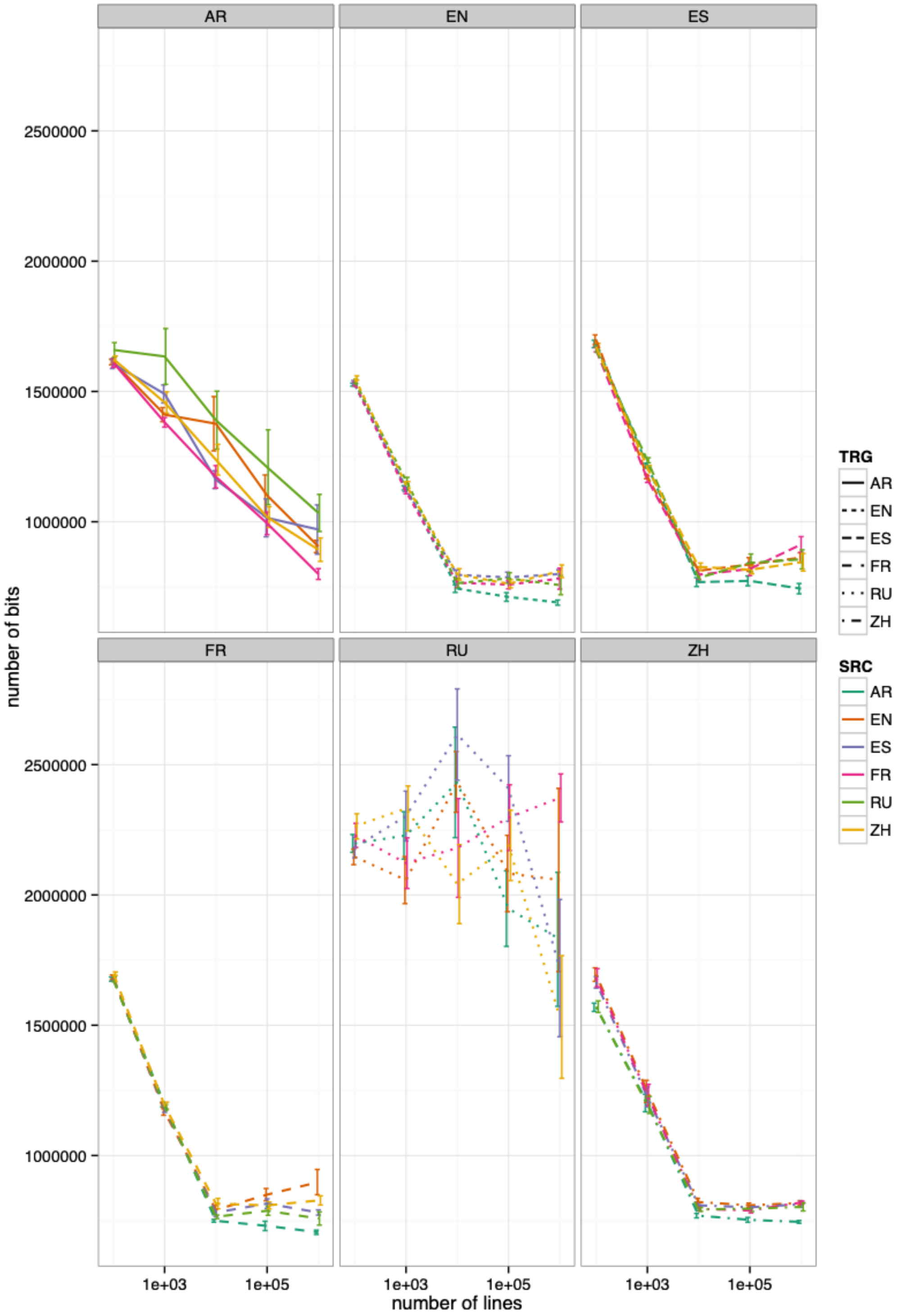

Figure 7: BYTE models with UTF-8 encoding (target language as facet)

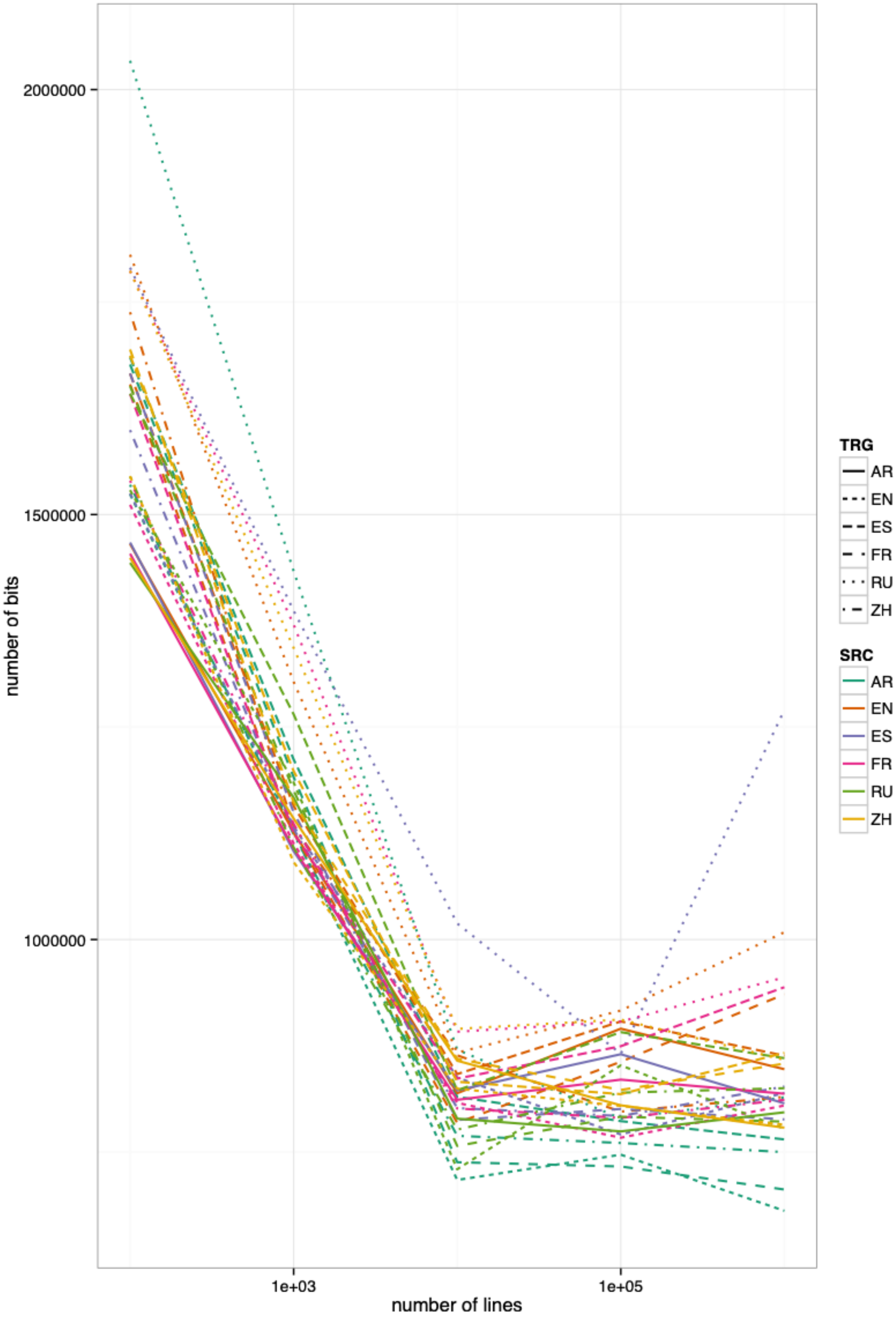

Figure 8: BYTE with AR_{trg} & RU_{trg} optimized with code pages 1256 & 1251 (ARRU_{trg})

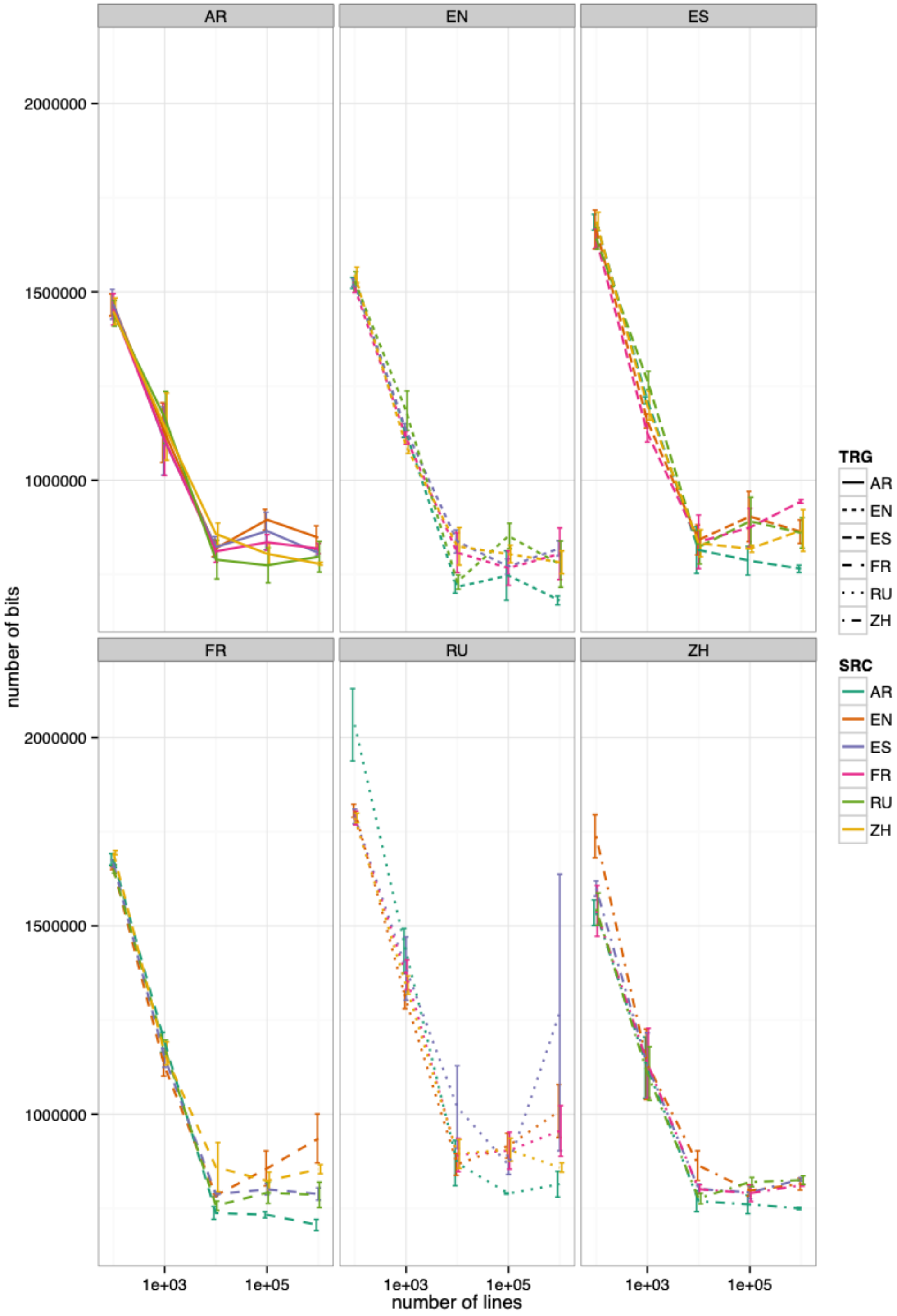

Figure 8: BYTE with AR_{trg} & RU_{trg} optimized with code pages 1256 & 1251 (target language as facet)

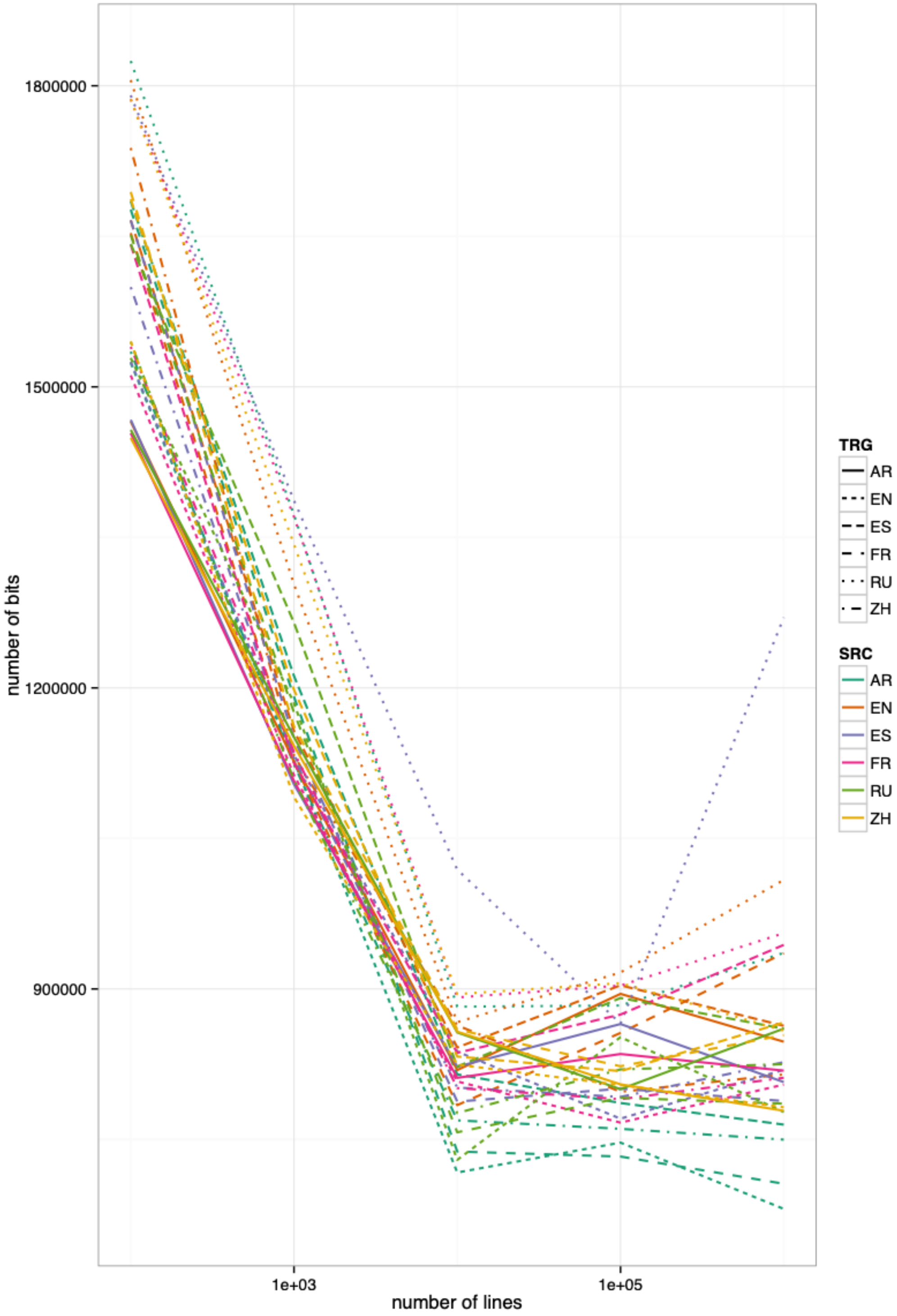

Figure 9: BYTE with directions AR-RU & RU-AR optimized on both source and target sides (ARRU$_{src,trg}$)

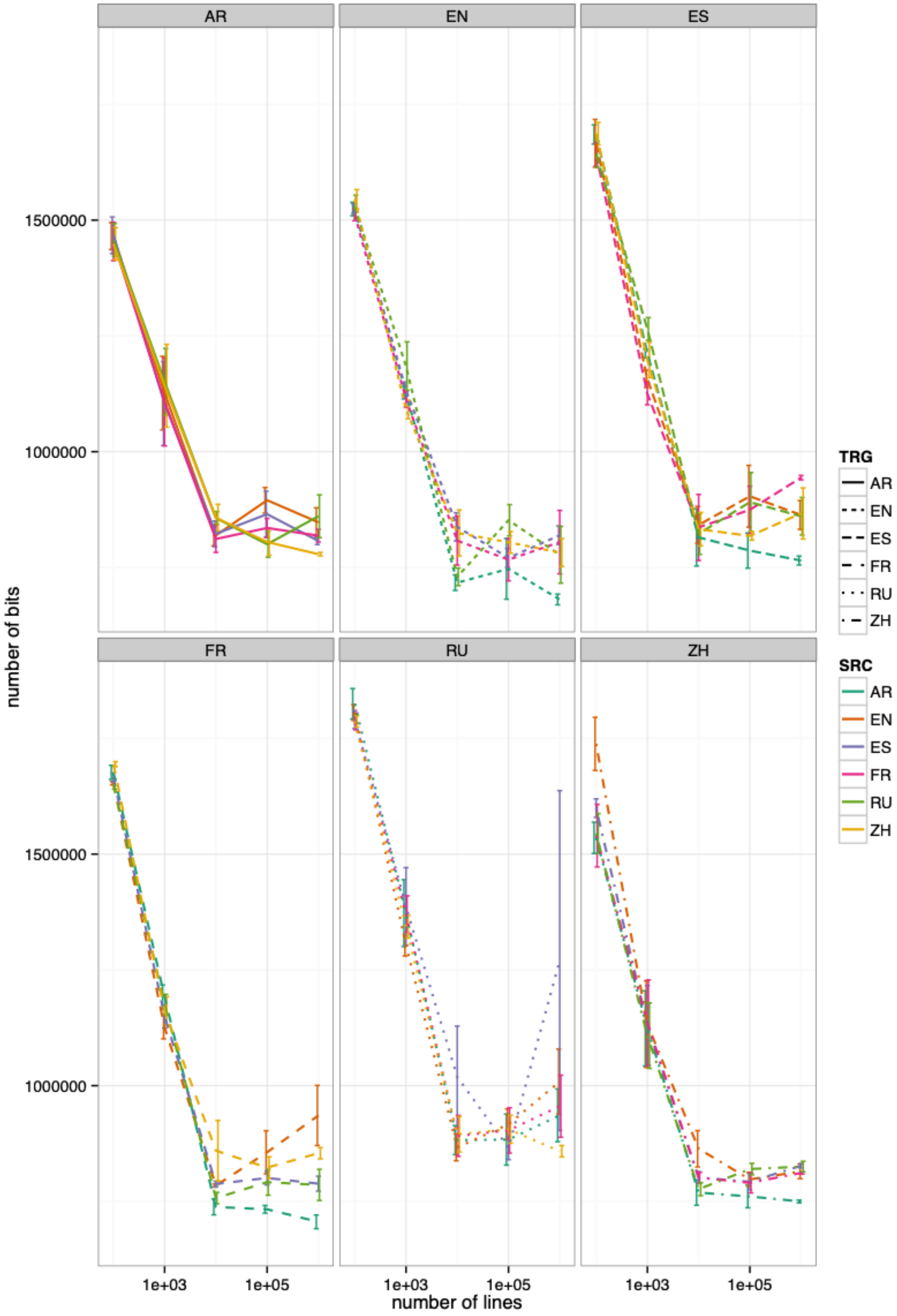

Figure 9: BYTE with directions AR-RU & RU-AR optimized on both source and target sides (target language as facet)

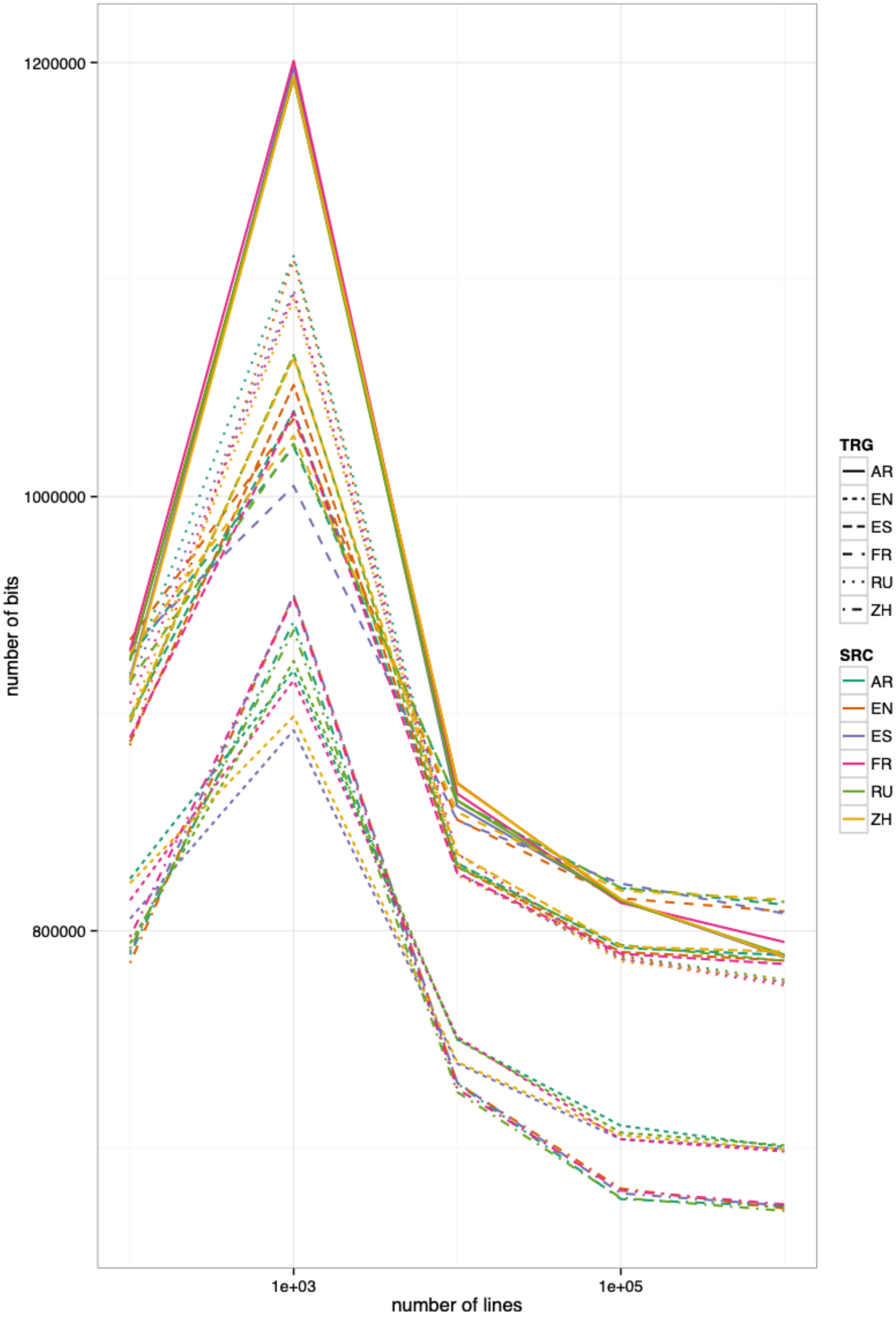

Figure 10: WORD models

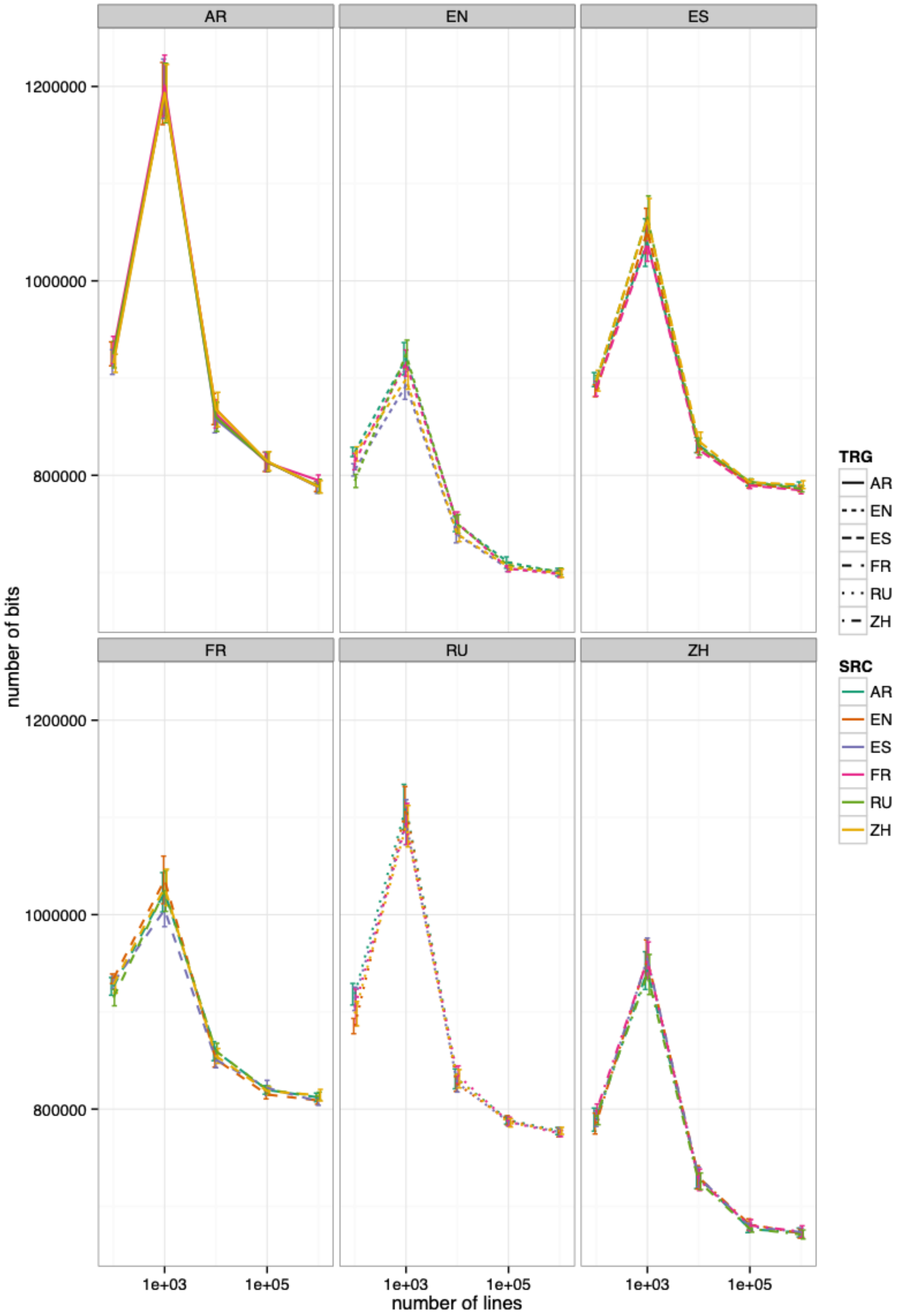

Figure 10: WORD models (target language as facet)

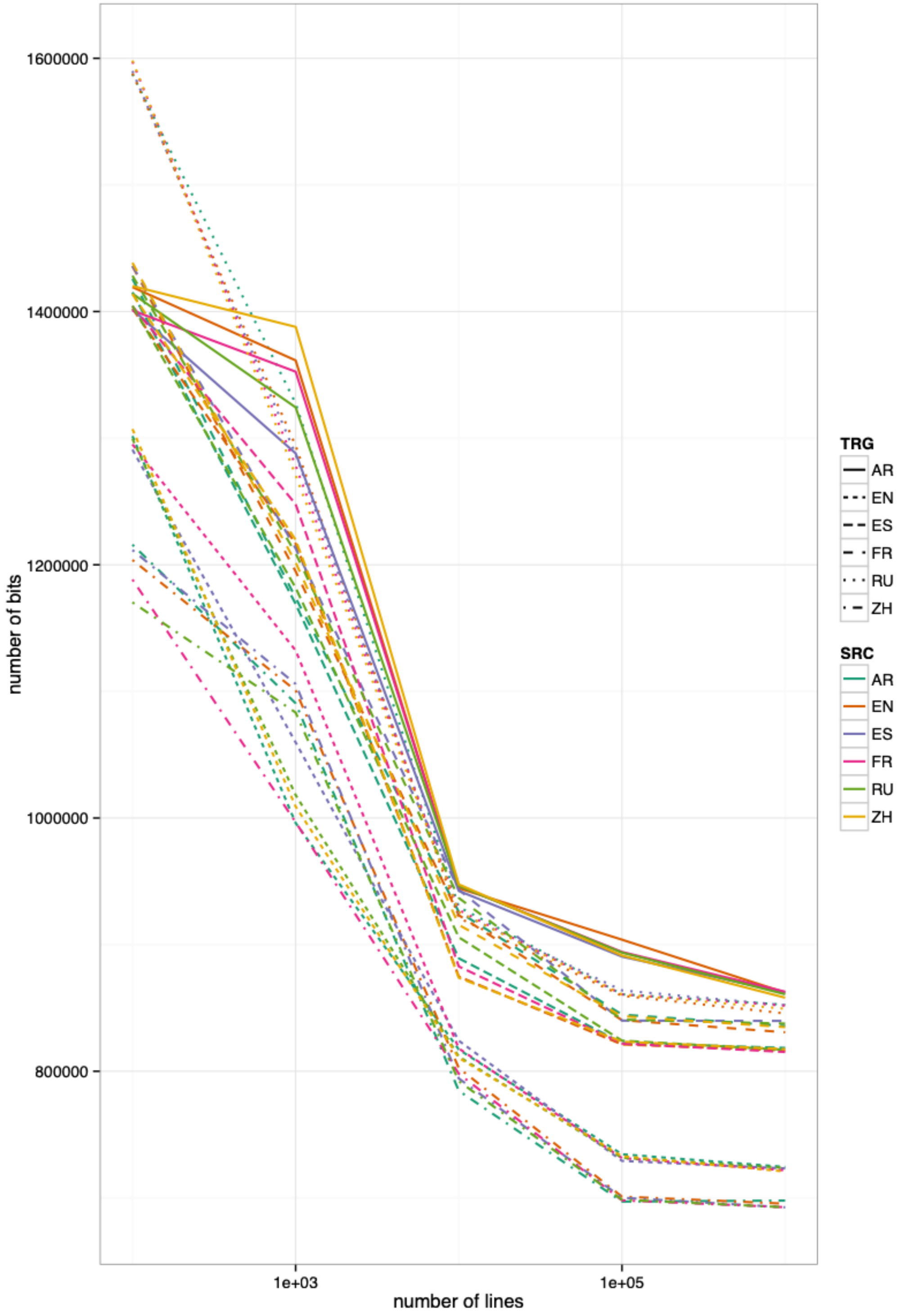

Figure 11: BPE models

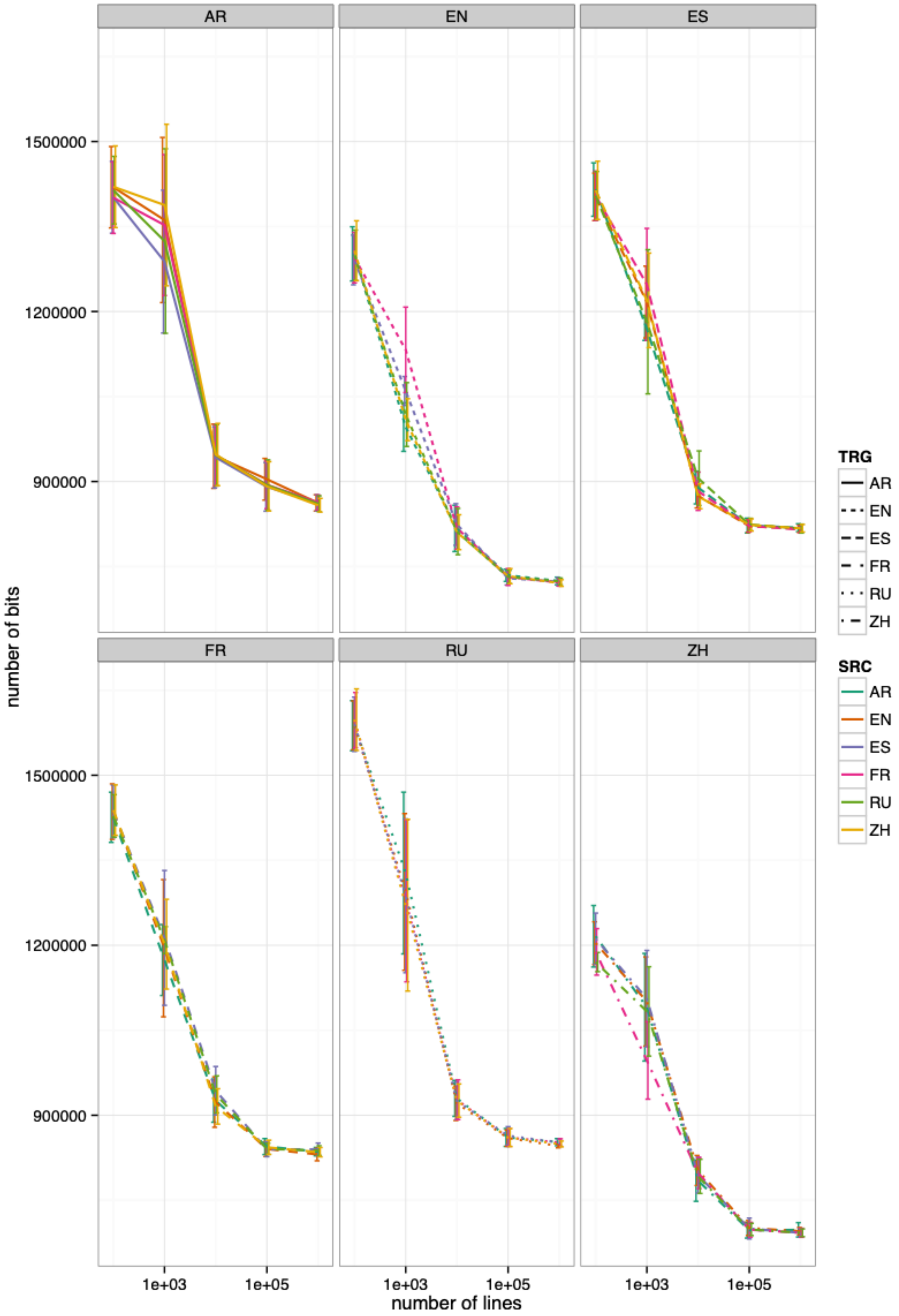

Figure 11: BPE models (target language as facet)

Fairness in Representation for Multilingual NLP: Insights from Controlled Experiments on Conditional Language Modeling

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