# Language Model Tokenizers Introduce Unfairness Between Languages

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### Abstract

Recent language models have shown impressive multilingual performance, even when not explicitly trained for it. Despite this, there are concerns about the quality of their outputs across different languages. In this paper, we show how disparity in the treatment of different languages arises at the tokenization stage, well before a model is even invoked. The same text translated into different languages can have drastically different tokenization lengths, with differences up to 15 times in some cases. These disparities persist across the 17 tokenizers we evaluate, even if they are intentionally trained for multilingual support. Character-level and byte-level models also exhibit over 4 times the difference in the encoding length for some language pairs. This induces unfair treatment for some language communities in regard to the cost of accessing commercial language services, the processing time and latency, as well as the amount of content that can be provided as context to the models. Therefore, we make the case that we should train future language models using multilingually fair subword tokenizers.

### 1 Introduction

Language models are becoming increasingly important in natural language processing tasks, as they are capable of understanding and generating human-like language. They have been deployed in numerous applications such as virtual assistants (Chen et al., 2021; Ouyang et al., 2022), chatbots (Kuhail et al., 2023; Lee et al., 2023), machine translation (Stahlberg, 2020; Ranathunga et al., 2023), and text summarization (Kryściński et al., 2019; Xu et al., 2020). As general-purpose technologies, it is also projected that Large Language Models (LLMs) will have a significant impact on the economy and the

labour market (Teubner et al., 2023; Eloundou et al., 2023).

Such LLMs are often trained using large swaths of internet content regardless of language. Hence, these models often end up being multilingual, even if not by design. ChatGPT (OpenAI, 2022) is a prominent recent example (Bang et al., 2023; Jiao et al., 2023; Johnson, 2023). This is good: in line with the economic benefits of LLMs and LLM-derived technology, equal access is crucial, with multilingual support serving as a key component.

However, this multilingualism is currently treated as a curious emergent phenomenon rather than a carefully designed, controlled and managed process. Less attention is given to ensuring comparable performance in languages other than English. This is a problem as modern LLMs rely not only on data scraped from the internet but also on carefully crafted fine-tuning, e.g., via reinforcement learning with human feedback (Christiano et al., 2017; Ouyang et al., 2022). Therefore, as long as this human-driven fine-tuning focuses on a handful of languages, the performance of LLMs will be generally lower in nontarget languages, a problem especially pronounced for low-resource languages (Virtanen et al., 2019; Ahuja et al., 2023).

Such disparities can have severe real-world implications. Providing access to the same technology in different languages but moderation and safety tools only for some has resulted in dire societal consequences before (Stecklow, 2018; Facebook, 2021; Leung, 2022). Differing cost of access could also reinforce inequality in opportunities for economic mobility and social participation (Lythreatis et al., 2022). LLMs might currently be on a track towards exacerbating such inequalities across language communities. Therefore, as LLM multilingual-

ism emerges, we should also pay commensurable attention to ensuring comparable performance and accessibility across the supported languages, regardless of whether supported by design or by chance.

This work demonstrates how the unequal treatment of languages arises at the tokenization stage, well before the language model sees any data at all. For instance, the tokenizer employed by ChatGPT (OpenAI, 2022) and GPT-4 (OpenAI, 2023) uses about 1.6 times more tokens to encode the same text in Italian as it does in English, 2.6 times for Bulgarian and 3 times for Arabic. As some commercial providers charge per token, Arabic language users and businesses would be charged 3 times more than English users for the same task. For other languages, such as Shan the native language of people from the Shan State in Myanmar— that difference can be as high as 15 times. Unicode character and byte-level tokenization have been proposed as a way to universally represent all languages in LLMs. However, we show that they too result in drastically different encoding lengths across languages. Notably, byte-level representation of the same text is over 4 times longer for Burmese or Tibetan than Chinese.

Across 17 tokenizers that power popular language models such as ChatGPT and GPT-4, regardless whether they use a word, subword, character, or byte-level tokenization, there always exists disadvantaged languages that are at least 4 times less efficient than others. We discuss three fairness implications of these differences in tokenization:

- Cost: Commercial services charge users per token or Unicode character. In either case, these discrepancies lead to users of some languages paying at least 4 times more for the same task as users of English.
- 2. Latency: The number of tokens has a direct effect on the processing time for a task. Some languages can require twice the time to process the same content as English. This may be critical for real-time applications like emergency services.
- 3. Long-term dependency modelling: Many models have a fixed-size context. Users of languages that are more tokenefficient can therefore use these systems

to process or generate texts that may be more than an order of magnitude longer than users of other languages. This may lead to significant discrepancies in the quality of service depending on the language used.

Therefore, we make the case for *multilingual* tokenization parity: tokenizers should produce similar encoded lengths for the same content across languages. This is particularly important for commercial systems that have per token or per character pricing models. Hence, we advocate for multilingually fair tokenizers for the next generation of language models.

### 2 Background on Tokenization

To enable automatic processing of language, it must first be represented in a suitable form. The current practice is to use tokenization which is the process of turning natural language into sequences of tokens coming from a finite and pre-determined set called vocabulary (Webster and Kit, 1992). Each token is typically associated with an integer value. Language models process such sequences of integers, rather than sequences of characters or words. In this section, we offer a brief overview of the contemporary tokenization methods. For further details, we recommend the comprehensive survey by Mielke et al. (2021).

Word tokenization. The simplest tokenization method is splitting at white spaces, where each word is assigned its own token (Bengio et al., 2000). This approach, however, requires that all possible words are in the vocabulary which is not possible in practice. Therefore word tokenization often fails to handle cases like "won't", words spelled with accented characters like "naïve" or "açaí", speling mistakes and named entities like "Cottonshopeburnfoot" (Sun et al., 2020). This makes it unsuitable for representing open vocabularies, where the words encountered are not limited to a predetermined set. Furthermore, languages that do not use spaces to separate words, such as Chinese, Japanese and Burmese, pose additional challenges for this approach (Shao et al., 2018).

**Subword tokenization.** Hence, most current models use *subword tokenization*, where



Figure 1: Comparison of variable width Unicode encoding (UTF-8) and fixed width encoding (UTF-32). Image adapted from (The Unicode Consortium, 2022).

complex words are broken down into multiple tokens. Subword tokenization can efficiently handle complex terms by breaking them down into parts, e.g., "Cottonshopeburnfoot"  $\rightarrow$  "Cotton"+"shop"+"e"+"burn"+"foot". This approach can represent novel words, including misspelled ones, in an open vocabulary setting.

Subword vocabularies are usually databased approaches which use large corpora to learn which subword sequences occur frequently in practice. Schuster and Nakajima (2012) introduced one of the first subword tokenizers, WordPiece, as a way to handle Japanese and Korean. Sennrich et al. (2016) proposed using Byte-Pair Encoding (BPE) (Gage, 1994) for learning subwords by merging the most frequently occurring pairs. BPE has since been widely used for most of the popular tokenizers. Kudo (2018) proposed an alternative approach via gradually pruning a large vocabulary. It removes tokens that are less likely to improve the performance of a simple unigram language model. Both methods rely on pre-tokenization (splitting on whitespaces, when available), which is not an invertible process. SentencePiece (Kudo and Richardson, 2018) addresses this de-tokenization ambiguity by treating whitespace as a special symbol, including it in the vocabulary, and supports both methods. SentencePiece with BPE is by far the most popular tokenization method for the models considered in this paper.

Unicode support. Even if subword tokenization ensures that individual characters are in the vocabulary, this still leaves the question of which characters are to be included. Simple solution is to take the ASCII characters. However, this means that words in other scripts or accented letters will fall out of it. A common workaround is to represent strings outside the vocabulary as a special UNK token. However, if there are too many UNK tokens in an input, the performance of the model tends to deteriorate (Pfeiffer et al., 2021). Therefore, it is desirable that the number of UNK tokens in the input is kept as low as possible. A simple and commonly used solution is to base the vocabulary building on Unicode.

Unicode is a computing industry standard for representing text characters (The Unicode Consortium, 2022). Unicode supports virtually all languages (including many ancient ones, emojis and special characters) by assigning every grapheme, modifier, punctuation mark, control character or formatting character one of 1,114,112 integer codepoints. The codepoints can be represented in binary as the variable-width encoding UTF-8, which encodes every codepoint with one to four bytes, or the fixed-width UTF-32 which encodes all codepoints with four bytes (see Figure 1).

UTF-8 can therefore represent any string in any language as a string of bytes. As each byte can take only one out of 256 values, 256 tokens can be sufficient to encode all texts. In practice this is usually combined with the BPE tokenizer. At first, the corpus is encoded as UTF-8 bytes and then BPE is ran on top of it. As most characters occur frequently, BPE would assign them a dedicated token. If the model encounters a character that didn't exist in the training corpus (e.g., the medium skin tone waving hand (), it can still represent it byte-by-byte (F0+9F+91+8B for the waving hand and F0+9F+8F+BD for the skin tone modifier). This allows the vocabulary to efficiently represent frequently occurring words and rare characters. For example, the sentence "I love acaí" could be tokenized as "I "+"love "+"a"+C3+A7+"a"+C3+AD.

Byte-level and character-level tokenization. If we can represent any input with just 256 characters, then why bother with subword tokens? A key consideration is sequence length. This is since transformers (Vaswani et al., 2017), the currently predominant deep learning architecture for language models, have attention layers with a quadratic complexity in the input length. Hence, as the number of characters is much longer than the

sub-word tokenization, working on the character level has been traditionally considered computationally inefficient. However, Chung et al. (2016), Lee et al. (2017), Gao et al. (2020), Clark et al. (2022) and Xue et al. (2022) proposed various architectures working around this issue and operating directly on characters or UTF-8 bytes.

## 3 Intriguing Properties of Tokenization Across Languages

Subword tokenization is currently the preferred approach for state of the art language models. The subword tokenization process is usually learned in an unsupervised manner from large corpora. However, the representation of different domains, languages and topics is often biased (Joshi et al., 2020) leading to unexpected token choices. In this section, we show how artefacts from data collection might result in technical terms or rare words having dedicated tokens (glitch tokens), while more commonly used words and non-Latin characters end up requiring multiple tokens.

#### 3.1 Glitch Tokens

Using large corpora scraped from the internet results in *peculiar* choices for tokens. For instance, it was discovered that GPT-2 contains *glitch tokens* which can be usernames or concepts from games (Rumbelow and Watkins, 2023b; Miles and Riley, 2023). As an example, the following string, likely coming from an online store backend, has a dedicated token:

or the following token, similarly to many other glitch tokens possibly originating from Reddit communities (Rumbelow and Watkins, 2023a):

## 3.2 Tokenization Length Differences Between Languages

While such terms get their own tokens, the frequently used Arabic word "שנו" (meaning "why") is broken into letters with each letter having its own token (read right-to-left):

The same word in Bulgarian ("защо") is not only broken down to letters, but some of the letters require two tokens to be represented, resulting in 6 tokens for this 4 letter word:

One may argue that this is because Arabic and Bulgarian are not a target language for this tokenizer. However, a similar phenomenon occurs for Japanese, also not a target language for GPT-2. For example, there is a dedicated token for "ゼウス", the name of the ancient Greek god Zeus:

Another Japanese word with a dedicated token is "サーティワン": the transliteration of the English "thirty-one", pronounced "saatiwan", which is how the ice-cream shop chain Baskin Robbins is commonly called in Japan (Rumbelow and Watkins, 2023a; 31 Ice Cream):

At the same time, GPT-2 requires 3 tokens to represent the much more commonly used kanji character for "to say":

In fact, more than half of the Japanese kanji characters, including many of the frequently used ones, require 3 tokens.

The existence of glitch tokens such as "ゼウス" and "サーティワン" despite the lack of a dedicated token for "言" shows that tokenizers are heavily influenced by the biases of the source of the corpus used. While subword tokenization has the potential to pick up salient morphological features (Sennrich et al., 2016), this is conditional on the source of the corpus. If one uses non-natural inputs, log files, or specialist forums, the tokenizer vocabulary would reflect this. While cl100k\_base, the tokenizer used for the newer ChatGPT and GPT-4, may not have glitch tokens, it still requires two tokens to represent some Cyrillic letters and three tokens for more than 65% of kanji characters. Therefore, to place all languages on an equal footing, it is important to have the tokens balanced across languages.

### 4 Measuring Tokenizer Parity

To demonstrate that the above examples are not an ecdotal evidence, we introduce the notion of tokenizer parity to systematically assess how fairly a tokenizer treats equivalent sentences in different languages. Parity occurs when a tokenizer exhibits similar tokenized lengths for the same sentence in different languages. Take a sentence  $s_A$  in language A and its translation  $s_B$  to language B. Then, a tokenizer t achieves parity for A with respect to B at  $s_A$  and  $s_B$  if  $|t(s_A)|/|t(s_B)| \approx 1$ , where  $t(s_A)$  is the tokenization of the sentence  $s_A$  and  $|t(s_A)|$  represents its length. We refer to the ratio  $|t(s_A)|/|t(s_B)|$  as the premium for language A relative to language B.

## 5 Tokenization Length Differences Across Languages

Languages vary significantly in the number of tokens required to encode the same content, as demonstrated in the examples in Section 3. Hence, following Section 4, we measure the tokenization premium of different tokenizers. To facilitate a fair comparison, we compare the tokenization length for the same content in two different languages. To this end, we use the FLORES-200 parallel corpus, comprising of the same 2000 sentences taken from Wikipedia and human-translated to 200 different languages (Guzmán et al., 2019; Goyal et al., 2021; Costa-jussà et al., 2022). We look at subword tokenization models which target English, languages other than English, language varieties, multi-lingual tokenizers, as well as tokenizer-free (byte-level) modelling.

### 5.1 Parity for English-centric Models

Since most state of the art language models target English, we report in Table 1 the tokenization parity for a subset of languages in FLORES-200 with respect to English. The parities for all 200 languages are shown in Appendix A. GPT-2 (Radford et al., 2019), RoBERTa (Liu et al., 2019), as well as the r50k\_base, p50k\_base and p50k\_edit tokenizers (OpenAI, 2022) have very close<sup>2</sup> to-

Table 1: Premiums with respect to English on FLORES-200 for several **English-centric** models. The languages in the top or bottom three for any tokenizer as well as the ones discussed in the text are shown.

	GPT-2 RoBERTa	ChatGPT GPT-4	FlanT5
Bulgarian	5.51	2.64	_
Burmese	16.89	11.70	_
Chinese (Simplified)	3.21	1.91	_
Dzongkha	16.36	12.33	_
English	1.00	1.00	1.00
French	2.00	1.60	1.60
German	2.14	1.58	1.37
Italian	2.01	1.64	2.18
Japanese	3.00	2.30	_
Jingpho	2.65	2.35	3.41
Maori	2.45	2.35	3.28
Norwegian Bokmål	1.86	1.56	2.24
Odia	13.38	12.48	_
Pangasinan	1.66	1.57	2.18
Portuguese	1.94	1.48	2.21
Romanian	2.48	1.88	1.50
Santali	12.86	12.80	_
Shan	18.76	15.05	_
Spanish	1.99	1.55	2.23
Standard Arabic	4.40	3.04	_
Tumbuka	2.78	2.57	3.29
Vietnamese	4.54	2.45	_

kenization lengths, so we report them together. Similarly, ChatGPT (OpenAI, 2022) and GPT-4 (OpenAI, 2023) share the same cl100k\_base tokenizer hence are reported together. Some models, such as FlanT5 (Chung et al., 2022), use a special UNK token to model unknown symbols not encountered during training. Hence, to ensure a fair comparison, we report only languages where no more than 10% of the input characters are mapped to UNK tokens (marked with —).

The results in Table 1 show very large variations in the tokenizer parity across languages irrespective of the tokenizer. Looking at languages closest to tokenizer parity, we see that for GPT-2 and RoBERTa, the cheapest language, Pangasinan, is already 66% more expensive to process than English. For ChatGPT and GPT-4, the results are slightly better, likely due to their larger vocabulary size. However, some of the cheapest languages, Portuguese and Italian, which also use the Latin script, still see a premium of 50% when compared to English. This is due to their words being broken into subword tokens. For example, "Have a great day!" is 5 tokens in

<sup>&</sup>lt;sup>1</sup>An interactive table of all the languages and tokenizers is also available on the project website.

<sup>&</sup>lt;sup>2</sup>The largest tokenizer parity difference between them is less than 0.005.

Table 2: Tokenizer premiums on the FLORES-200 dataset for non-English centric models. The premium is computed with respect to the target language (Modern Standard Arabic was used for Arabic BERT and Simplified Chinese for RoCBert). The languages that are in the top or bottom two for any tokenizer as well as the ones discussed are shown.

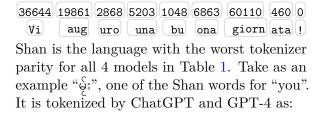
		RoCBert (Chinese)	CamemBERT (French)			PhoBERT (Vietnamese)
Belarusian	4.74	_		5.62	_	3.46
Bulgarian	4.30		_	4.73	_	3.09
Catalan	2.36	2.86	1.59	1.89	1.95	1.57
Chinese (Simp.)	_	1.00	_	3.95	0.82	
Chinese (Trad.)	_	0.94		3.82	0.84	
Dutch	2.52	2.92	1.68	1.73	1.98	1.58
Dzongkha	_			16.12	_	
English	1.83	2.60	1.20	1.35	1.49	1.20
French	2.42	3.10	1.00	1.99	2.03	1.66
Friulian	2.33	2.79	1.66	1.98	1.92	1.59
German	2.63	3.12	1.85	1.00	2.04	1.67
Greek	4.93	3.00		6.73	_	3.73
Italian	2.58	3.10	1.63	1.93	2.04	1.60
Japanese	1.85	1.34		4.35	1.00	
Jingpho	3.12	3.12	2.13	2.55	2.47	1.84
Luxembourgish	2.56	2.97	1.82	1.75	1.96	1.72
N. Lev. Arabic	1.00		_	6.52	_	
Shan	_		_	16.88	_	
Standard Arabic	1.00		_	7.03	_	
Tagalog	2.84	3.28	2.00	2.20	2.39	1.74
Tosk Albanian	2.66	2.90	2.17	2.39	_	2.02
Tsonga	3.01	3.09	2.03	2.29	2.46	1.76
Tumbuka	3.27	3.49	2.21	2.61	_	2.00
Vietnamese	2.52	2.55	_	4.12	_	1.00
Yue Chinese	_	0.92	_	3.75	_	_

Tokenizer premi-Table 3: ums on the FLORES-200 dataset for the MuRIL model focusing on languages and Indian English. The premium is computed with respect to English.

MuRIL
1.00
1.01
1.01
1.06
1.06
1.06
1.16
1.18
1.19
1.21
1.21
1.21
1.22
1.24
1.26
1.35
1.75
1.75

English, with each word having its own token:

In Portuguese, two of the four words in "Tenha um ótimo dia!" are broken in two parts:





This word is constructed from one consonant and three diacritics. As the diacritics are encoded separately, there are four Unicode codepoints for this Shan character, resulting in 9 tokens. The English "you" has three characters but a single token.

FlanT5 has more than 10% UNK tokens for 42% of languages (— in Table 1). It has worse tokenizer parity compared to GPT-2, RoBERTa, ChatGPT and GPT-4 for all other languages, except German and Romanian.

Summary. All four English-centric tokenizers we consider are far from tokenization parity. Portuguese is closest to parity with English for the tokenizer for ChatGPT and GPT-4 but still requires about 50% more tokens for the same content. Shan is furthest from parity for this tokenizer with 15 times longer encodings compared to English. FlanT5 is closer to parity with its premium range 1.37–3.41 but it encodes only 54% of the languages, so we cannot say that it is more multilingually fair than the other tokenizers.

## 5.2 Parity for Models with Other Target Languages

In the previous section, we investigated models targeting English. There are, however, models targeting other languages as well. Table 2 shows six such models based on the BERT architecture (Devlin et al., 2019). These are ArabicBERT for Arabic (Safaya et al., 2020), RoCBert for Chinese (Su et al., 2022), CamemBERT for French (Martin et al., 2020), GottBERT for German (Scheible et al., 2020), BERT Japanese (Tohoku NLP Group, 2019) and PhoBERT for Vietnamese (Nguyen and Nguyen, 2020).

GottBERT exhibits a similar range of premium values as RoBERTa, likely because both tokenizers were trained in the same way, albeit on corpora prioritising different lan-The GottBERT premium for English (1.35) is lower than the ones for Dutch (1.73) and Luxembourgish (1.75) which are both linguistically closer to German than English. We observe a similar phenomenon with CamemBERT, where English is the language with the lowest premium (1.20). This is as opposed to languages closer to French which are with a higher premium, e.g., Catalan with 1.59 and Friulian with 1.66. The same can be observed with PhoBERT as well, where English has the lowest tokenizer premium (1.20). Hence, even for models trained with target languages other than English, English seems to enjoy preferential treatment.

RoCBert differs from them as the premium for Japanese is the lowest (1.34), likely because of the partially shared script, while English is significantly higher with 2.60. BERT Japanese has lower than unity premiums for Chinese (0.82 and 0.84) also possibly due to the partially shared script (and Chinese being more character-efficient, as discussed later in Section 5.5). ArabicBERT is similar in this regard. Different vernaculars of Arabic have parity relative to Standard Arabic up to 1.14, followed by Central Kanuri (1.27) and Acehnese (1.73) (both written in the Arabic script) with English at 1.82. Hence, sharing writing systems seems to improve the tokenization parity.

Across all six models in Table 2 and their tokenizers, the premium for English relative to the respective target language is significantly lower than the premium for the same target language for RoBERTa. The parity of ArabicBERT for English is 1.83, while the par-

ity for Standard Modern Arabic of RoBERTa is 4.40. For French the difference is 1.20 vs 2.00, for Simplified Chinese 2.60 vs 3.21, for German 1.35 vs 2.14, for Japanese 1.49 vs 3.00, and for Vietnamese 1.20 vs 4.54. This asymmetry between English and all other languages likely stems from the extensive incorporation of English in documents written in other languages (Zhang et al., 2022).

We also consider MuRIL which is a BERTbased model trained on 16 Indian languages and English (Khanuja et al., 2021). For 14 of the Indian languages it was trained on (Assamese, Bengali, Gujarati, Hindi, Kannada, Malayalam, Marathi, Nepali, Odia, Sanskrit, Sindhi, Tamil, Telugu, Urdu), the premium with respect to English is between 1.01 and 1.26 (see Table 3). For Eastern Panjabi, that is 1.35, while for Kashmiri (Arabic and Devanagari scripts) it is 1.75. The results for Kashmiri are likely due to its being significantly underrepresented in the training set. However, despite the model being designed with a focus on Indian languages, it still is most tokenefficient in English.

Summary. We observed that the tokenizers targeting French, German and Vietnamese have English as the language closest to parity, rather than more linguistically close languages. On the other hand, the tokenizers for Arabic, Chinese and Japanese have lower premiums for some languages they share a script with. Notably, despite targeting Indian languages, MuRIL still has the lowest tokenization lengths for English. Finally, across all tokenizers, the premium for English is lower than the premium for the same language for the English-centric RoBERTa. Hence, we conclude that tokenizers for other languages give English preferential treatment.

### 5.3 Parity for Linguistic Varieties

A language can vary according to factors such as geography, history, social class and culture. As a result, different dialects, pidgin and creole language variations emerge, each with its own distinct set of grammar, vocabulary and pronunciation rules.<sup>3</sup> Unequal treatment of

<sup>&</sup>lt;sup>3</sup>While no standard definitions exist, dialects are usually considered to be regional variations of a language, whereas pidgin and creole languages are contact

Table 4: GottBERT tokenizer premiums on the SwissDial dataset for **Swiss German dialects**. The premium is computed with respect to High German.

Region	GottBERT parity
High German	1.00
Zürich	1.38
St. Gallen	1.40
Basel	1.41
Graubünden	1.44
Luzern	1.52
Aargau	1.53
Wallis	1.58
Bern	1.59

certain dialects or languages can lead to social and economic disadvantages for those who speak them. Therefore, it is important to also study the tokenization differences between the "standard" language and its varieties. 4 Unfortunately, parallel corpora for dialects, pidgin and creole language variations are far and few in between. In this section, however, we show results on regional Swiss German varieties, Arabic and Japanese dialects, as well as Haitian and Mauritian creoles.

Swiss German dialects. Swiss German is a dialect continuum which significantly differs from the formal High German. Germanspeaking Switzerland is diglossic:<sup>5</sup> High German is used alongside regional dialects (Hogg et al., 1984). In contrast to other dialects, the use of Swiss dialects is increasing (Sieber and Sitta, 1987) especially online (Lüdi, 2007). Swiss German dialects are often considered unintelligible to High German speakers and sometimes even speakers of different dialects may find difficulty understanding each other (Russ, Therefore, ensuring that German-1990). targeting NLP applications can process Swiss German dialects is important.

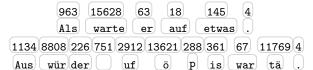
To this end, we compare the tokenization parity relative to High German of GottBERT (Scheible et al., 2020) on the regional dialects of Aargau, Bern, Basel, Graubünden, Luzern,

Table 5: ArabicBERT tokenizer premiums on the MADAR dataset for **Arabic dialects**. The premium is computed relative to Standard Arabic.

City	${\bf Arabic BERT}$	City	ArabicBERT
Jeddah	0.91	Sanaa	1.01
Doha	0.92	Beirut	1.02
Riyadh	0.92	Benghazi	1.02
Muscat	0.94	Cairo	1.03
Basra	0.95	Sfax	1.03
Salt	0.95	Tripoli	1.05
Baghdad	0.96	Aswan	1.06
Damascus	0.97	Alexandria	1.06
Aleppo	0.97	Tunis	1.06
Jerusalem	0.97	Algiers	1.07
Khartoum	0.98	Mosul	1.10
Amman	0.99	Fes	1.11
Std. Arabic	1.00	Rabat	1.17

St. Gallen, Wallis and Zürich. We use Swiss-Dial, a parallel multidialectal corpus, as the basis of comparison (Dogan-Schönberger et al., 2021). It is worth noting, that the dialect of each city and its corresponding region may differ significantly. Therefore there might be large variations within regions as well.

The results in Table 4 show a disparity between the tokenization lengths for High German and the Swiss dialects with a premium ranging from 1.38 for the Zürich dialect, or Züritüütsch, to 1.59 for the Bernese In fact, English has a lower Bärndütsch. premium than any Swiss dialect (1.35 on FLORES-200, Table 2) and the premium for Bernese German is close to the linguistically further Swedish (1.64) and Norwegian Bokmål (1.65). The following example from SwissDial shows how the sentence "Like he's waiting for something" has almost twice as long tokenization in Bernese German compared to High German:



The fact that the GottBERT tokenizer results in better parity for English, Swedish and Norwegian Bokmål than for Swiss German dialects highlights that it does not likely pick out stable linguistic constructs.

**Arabic dialects.** Similarly to Swiss German, Arabic is usually spoken in diglossic speech communities, where Modern Standard

languages that emerge from the interaction of speakers of different languages (Muysken and Smith, 1994).

<sup>&</sup>lt;sup>4</sup>We refer to the language that the datasets label as "standard", "official" or "dominant" without necessarily endorsing this designation.

<sup>&</sup>lt;sup>5</sup>Diglossia is the situation of two dialects or languages being used by a single language community (Kaye, 2001).

Arabic is spoken alongside at least one prestigious vernacular particular to the country or region (Bassiouney, 2009). As both Standard Arabic and its dialects are commonly used in written communication, it is vital that tokenizers handle them equally well.

To assess the performance of Arabic tokenizers, we compare the tokenization lengths of ArabicBERT (Safaya et al., 2020) across 25 Arabic dialects. To this end, we use the MADAR parallel corpus of Arabic dialects (Bouamor et al., 2018).

Table 5 shows the premiums relative to Standard Modern Arabic. The premium varies from 0.91 for the Jeddah dialect to 1.17 for the Rabat dialect. This is significantly lower than the premium for English (1.83 on FLORES-200 Table 2). The range is also much smaller than for the Swiss German dialects and approximately half of the considered dialects have a lower premium than Standard Modern Arabic. Therefore, one could say that the tokenizer of ArabicBERT achieves tokenization parity for these 25 Arabic vernaculars. This is likely because the corpus and vocabulary set on which ArabicBERT was trained contained dialectical Arabic. It is also possible that Arabic dialects are closer to Modern Standard Arabic and more mutually intelligible than Swiss German dialects are to High German (Čéplö et al., 2016; Trentman and Shiri, 2020). Still, this difference between the parity for Swiss and Arabic dialects indicates that including a broader set of vernaculars and dialects in the corpus results in improved tokenization parity.

Japanese dialects. Japanese also has a number of regional dialects (Hattori, 1973). We compare the tokenization parity of BERT Japanese (Tohoku NLP Group, 2019) across them. We employ the CPJD dataset by Takamichi and Saruwatari (2018) which contains transcriptions of the voice recordings of 250 sentences across 20 dialects.

The results in Table 6 show that the premium compared to Standard Japanese (Tokyo dialect) ranges from 1.01 (for Saitama prefecture, neighbouring Tokyo) to 1.15 (for Morokata-ben and Okayama-ben). These all are significantly lower than the premium for English (1.49, as shown in Table 2). Therefore,

Table 6: BERT Japanese tokenizer premiums on the CPJD dataset for **Japanese dialects**. The premium is computed with respect to Standard Japanese. The CPJD dataset consists of two parallel corpora with the dialects split across the two. Hence, we have also indicated the corpus for each dialect. Nara-ben has two entries as the dataset has transcriptions for two separate speakers. The suffix "-ben" (弁) means "speech" or "dialect".

Dialect	Corpus I	Parity	Dialect	Corpus	Parity
Akita-ben	2	1.09	Miyazaki-ben	1	1.05
Awa-ben	2	1.09	Morokata-ben	. 1	1.15
Fukui-ben	2	1.04	Nara-ben	2	1.09
Fukuoka-ben	1	1.03	Nara-ben	2	1.03
Hiroshima-ben	1	1.02	Okayama-ben	1	1.15
Hokkaido-ben	2	1.06	Oosaka-ben	2	1.03
Iwaki-ben	2	1.08	Saitama-ben	1	1.01
Iyo-ben	1	1.05	Tosa-ben	1	1.03
Izumo-ben	1	1.10	Toshu-ben	1	1.06
Kanazawa-ben	2	1.11	Tsugaru-ben	1	1.09
Kyokotoba	2	1.07	Ü		

similarly to ArabicBERT, this is an example of the tokenizer being relatively well-aligned with the dialects. This is likely because Japanese dialects are more closely related (and intelligible (Yamagiwa, 1967) to Standard Japanese speakers) than the Swiss dialects are to High German speakers.

Mauritian and Haitian Creoles. While creoles often have some similarities with a high-resource language (usually English or French), the differences are significant to necessitate special attention to their support (Lent et al., 2021, 2022). This is especially critical for emergency services and disaster management (Munro, 2010).

Mauritian Creole is based on French as well as the languages of slaves imported from Madagascar and East Africa. As the British gained control of Mauritius, they brought indentured labourers from India who further had an effect on the formation of the modern Mauritian Creole (Seuren, 1995). Similarly, Haitian Creole ( $Krey \partial l$ ) emerged from the interaction of French and the various Niger-Congo languages spoken by the Africans brought as slaves (De-Graff, 2007).

Considering that both languages have their basis in French, one would expect that tokenizers targeting French would have low tokenization parities for Mauritian and Haitian Creoles. However, taking the tokenizer of CamemBERT (Martin et al., 2020), the pre-

Table 7: Tokenizer premiums on the FLORES-200 dataset for **multilingual models**. The languages that are in the top or bottom two for any tokenizer as well as the ones discussed in the text are shown. The premium is computed with respect to English.

	XLM-R	M2M100	MBart50	mT5	BLOOM
Bulgarian	1.16	1.23	1.16	1.28	2.49
Chinese (Simp.)	0.97	1.05	0.97	0.92	0.95
Dzongkha	_	_	_	4.24	7.36
English	1.00	1.00	1.00	1.00	1.00
Indonesian	0.94	0.98	0.94	1.08	0.96
Italian	1.19	1.25	1.19	1.34	1.62
Japanese	1.11	1.20	1.11	0.90	1.81
Kabiyè	2.98	2.71	2.98	2.83	3.34
Santali	_	_	_	_	12.71
Shan	4.43	4.63	4.43	3.28	12.06
Std. Arabic	1.18	1.29	1.18	1.35	1.14
Std. Tibetan	_	_	_	3.68	6.66
Uyghur	1.41	3.00	1.41	2.57	3.67
Yue Chinese	0.93	1.03	0.93	0.95	0.93

mium for Mauritian Creole is 1.20 using the MorisienMT parallel corpus (Dabre and Sukhoo, 2022). The premium for Haitian Creole is 1.64 when using the QEDv2 corpus (Tiedemann, 2012; Abdelali et al., 2014). Haitian Creole is also represented in the FLORES-200 dataset where the premium relative to French is 1.58. This is significantly larger than linguistically further languages such as English (1.20), Pangasinan (1.49) and Nigerian Fulfulde (1.54). Therefore, CamemBERT is not well-placed to tokenize French-related creoles despite the model being trained for French.

Summary. For Swiss German and the Mauritian and Haitian Creoles, we observed large differences in tokenization lengths compared respectively to High German and French. Therefore subword tokenizers might not be able to generalize to language varieties, such as dialects, pidgins and creoles. The tokenizers of ArabicBERT and BERT Japanese, however, are close to parity across various dialects of both languages and have lower premiums for the dialects than for English. This is most likely due to the good representation of the dialects in the training dataset as well as the dialects being more linguistically close to the respective standard languages.

### 5.4 Parity for Multilingual Models

There has also been a growing interest in multilingual language models, particularly for translation (Dabre et al., 2020). As these models are intended to support a variety of languages, one would expect them to be close to tokenizer parity.

In this section, we compare five different multilingual models. XML-R (Conneau et al., 2020) is based on RoBERTa (Liu et al., 2019) and has been designed for multilingual masked language modelling or fine-tuning. M2M100 (Fan et al., 2021) is a many-to-many translation model across 100 languages. MBart50 (Liu et al., 2020; Tang et al., 2020) is a multilingual encoder-decoder model based on BART (Lewis et al., 2020) which can handle over 50 languages. We also study mT5 (Xue et al., 2020) which is a multilingual modification of T5 (Raffel et al., 2020). All of these models use the SentencePiece tokenizer with upsampling for rare languages.

The final model, BLOOM (Scao et al., 2022), is trained on 46 natural and 13 programming languages. It uses byte-level BPE instead of SentencePiece and is designed to maintain similar ratios of tokens per word for each language as reference monolingual tokenizers.

Thanks to the byte-level BPE tokenization, BLOOM is the only model encoding all languages without needing too many UNK tokens (see Table 7). The other four models fail to encode at least one language. mT5, for example, fails to encode Santali even though it has the byte\_fallback SentencePiece feature enabled.<sup>6</sup>

All five models have languages with premiums larger than 4. BLOOM does encode all languages but has high premiums for some, such as Dzongkha (7.36), Shan (12.06) and Santali (12.71). Still, all models are better than the English-centric ones in Table 1. Figure 2 shows how XLM-R is much closer to parity than RoBERTa (on which it is based), over all languages it can encode. However, none of the models uniformly reaches parity across all languages. Therefore even models which are intentionally designed to be multilingual suffer from a lack of tokenization parity.

**Summary:** Multilingual models can improve the tokenization parity for different languages but challenges remain in achieving tokenization parity across all languages.

<sup>&</sup>lt;sup>6</sup>The byte\_fallback option enables decomposition of unknown pieces into UTF-8 byte pieces.

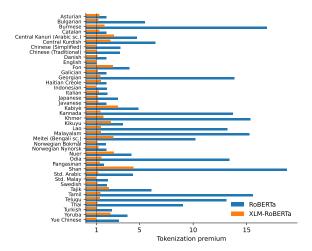


Figure 2: Comparison of the tokenization premiums for XLM-R and RoBERTa for the subset of languages that XLM-R encodes with less than 10% to the UNK token.

## 5.5 Parity for Byte-level Tokenization Models

The previous section showed that BLOOM—the only model using a tokenizer built up from byte-level representation— is also the only multilingual model encoding all languages in the FLORES-200 dataset. Therefore, byte-level representation, where the input and output of a model are UTF-8 encodings, seems to be key for multilingual support, as any Unicode codepoint can be represented even if not observed during training.

BLOOM uses a BPE-learned vocabulary on top of the UTF-8 encoding. It is possible, though, to skip the vocabulary-building and directly use the 256 possible byte values, which allows for full end-to-end training. Choe et al. (2019) showed that this approach can have similar performance to word-level tokenized models, given sufficient model capacity. However, a concern is the increased length of the input due to the quadratic complexity of transformers.

Recently, models working around this issue have been proposed. CANINE (Clark et al., 2022) is a large model that operates at the Unicode codepoint level rather than the byte level. The CANINE tokenizer is thus equivalent to the UTF-32 encoding, resulting in an implicit tokenizer with a vocabulary of 1,114,112. ByT5 (Xue et al., 2022), on the other hand, uses the UTF-8 encoding, *i.e.*, an

Table 8: Tokenizer premiums on the FLORES-200 dataset for **byte-level models**. The languages that are in the top or bottom two for any tokenizer as well as the ones discussed in the text are shown. The premium is computed with respect to English.

	CANINE UTF-32 bytes	ByT5 UTF-8 bytes
	C 11 - 52 by tes	——————————————————————————————————————
Bulgarian	1.04	1.89
Burmese	1.24	3.51
Chinese (Simplified)	0.34	0.93
Chinese (Traditional)	0.32	0.89
Dzongkha	1.25	3.64
English	1.00	1.00
Italian	1.18	1.19
Japanese	0.44	1.27
Shan	1.42	3.94
Standard Arabic	0.88	1.60
Standard Tibetan	1.13	3.31
Tok Pisin	1.28	1.28
Tumbuka	1.30	1.32
Yue Chinese	0.31	0.87

implicit vocabulary of 256 tokens.<sup>7</sup> This model incorporates architectural modifications that enable efficient handling of byte-level inputs.

Although these byte-level models can represent any Unicode codepoint without an explicit tokenization step, there are still significant tokenization disparities. For instance, CANINE exhibits tokenization premiums ranging from 0.31 for Yue Chinese to 1.42 for Shan, relative to English (see Table 8). However, simply measuring the parity relative to English conceals the fact that Shan has a premium of 4.58 relative to Yue Chinese. This can be attributed to the fact that CANINE provides a single token for each Unicode codepoint, which results in Chinese being more token-efficient (with premiums ranging in 0.31-0.34 relative to English for the three Chinese languages) as each character is treated as a single token. However, this encoding puts Shan at a disadvantage, as its encoding relies on diacritics represented as separate Unicode codepoints. Other languages, such as Tok Pisin and Tumbuka, which use the Latin script but require more characters than English for the same text, also face similar challenges.

Tokenization disparity is also present in the ByT5 model. The tokenization premium for ByT5 ranges from 0.87 (for Yue Chinese) to

 $<sup>^7\</sup>mathrm{To}$  be consistent, we will refer to the characters and bytes in the encoding of the CANINE and ByT5 tokenizers as tokens as they fulfil a similar role.

3.94 (for Shan). The issue with some languages using more characters than others persists as illustrated by Tok Pisin and Tumbuka having similar parities as for CANINE. Moreover, the introduction of the variablewidth UTF-8 encoding of Unicode characters in ByT5 creates another issue of unequal treatment. ASCII characters, which are sufficient for English, require only one byte. Other Latin script characters, as well as Greek, Cyrillic, Coptic, Armenian, Hebrew, Arabic and Syriac, require two bytes, while Chinese, Japanese and Korean characters require three bytes (see Figure 1). Therefore, the tokenization of Chinese and Japanese is about three times as long for ByT5 as it is for CANINE (Table 8). Shan's premium of 3.94 is due to the fact that all its consonants and diacritics require three bytes resulting in words being encoded with more tokens. For example, the word "&:" —which ChatGPT and GPT-4 encode with 9 tokens (Section 3)— is encoded by ByT5 as 12 tokens, whereas the corresponding word in English ("you") requires 3 tokens. The situation is similar for other languages like Dzongkha, Tibetan and Burmese.

Summary. Byte-level models also fail to achieve parity among the languages from FLORES-200 exhibiting a premium of over 4 times for some language pairs. There are two sources of multilingual tokenizer disparities. First, there are natural differences in the number of characters used in different languages to communicate the same content. Second, the UTF-8 standard uses different number of bytes to encode single codepoints of different scripts.

## 6 Fairness Implications of Tokenization Length Differences

We showed that no matter whether one uses subword, multilingual, or byte-level tokenization, none of the tokenizers gets close to parity for all languages in FLORES-200. Furthermore, there are languages, notable examples being Burmese, Dzongkha, Shan and Tibetan, which consistently have longer encoded sequences across all tokenizers. The variations in tokenization lengths are not merely an interesting phenomenon. They lead to some language communities having more barriers to ac-

cess LLM services simply because of the language they use. This lack of tokenization parity is not merely a curiosity: it leads to unfairness in the cost to access language models, the latency of the service and the amount of data that can be processed.

### 6.1 Cost

As LLMs are often too expensive to train and too large to run by most businesses, research institutions and end users, it is becoming increasingly common to access them as paid API services. One pricing approach, employed by OpenAI at the time of writing,<sup>8</sup> is to charge per token. The price can be determined by the number of tokens provided by the user, the ones generated by the system, or the sum of both. Therefore, the tokenization premiums discussed in Section 5 directly map to cost premiums. For ChatGPT and GPT-4 the cost to process a text in German or Italian is about 50% higher than to process the same text in English (Table 1). Processing Tumbuka or Bulgarian is more than 150% more costly. Using them in Dzongkha, Odia, Santali or Shan, the most expensive languages for these services, costs more than 12 times more than in English.

Another pricing strategy is to charge per Unicode character: the approach currently taken by the Google Cloud Natural Language service. They charge per 1,000 Unicode characters, hence the tokenization does not affect the pricing. However, as we showed in Section 5.5 and Table 8, the same content can have very different lengths when measured in Unicode characters (as CANINE does). Burmese, Dzongkha, Shan, Tok Pisin or Tumbuka require more than 4 times more characters than Yue Chinese for the same text, resulting in a proportional cost difference. Therefore, both the per-token and the per-character approaches result in large disparities in the cost for users of different languages to use the exact same service.

These differences in pricing do not take into account purchasing power disparity between users of various languages. As languages with high tokenization premiums often have low

<sup>8</sup>https://openai.com/pricing

<sup>9</sup>https://cloud.google.com/natural-language/ pricing

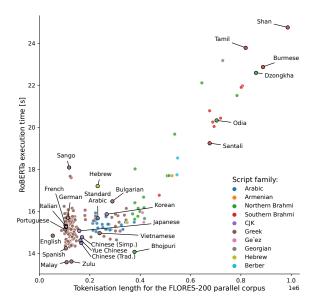


Figure 3: Average processing time and length of the tokenized inputs of RoBERTa model for the sentences from the FLORES-200 dataset. For each language, we tokenized each sentence independently, then computed the length and averaged the forward time of RoBERTa across 20 independent experiments. The script family categorization is only for illustration purposes.

purchasing power parity, the cost difference can be further exacerbated.

### 6.2 Latency

The speed of processing is critical for many applications and vital for the end-user experience. High latency for users of certain languages can result in a suboptimal experience, which may negatively impact the effectiveness of communication. High latency can also result in communication breakdowns, particularly in real-time interactions. For customer support or emergency services, delays in response time can lead to miscommunication or delayed assistance.

As some languages have significantly longer tokenized inputs, they would also experience longer processing times. The transformer attention mechanism has a quadratic complexity in the number of input tokens (Keles et al., 2023). However, the full model architecture contains other submodules and therefore the overall complexity might be different.

To assess the effect of the tokenization length on the latency we plot the computation time needed for RoBERTa (Liu et al., 2019) to process the sentences from FLORES-200

against the tokenization lengths across all 200 languages in Figure 3. It appears that the processing time is linear in the tokenization length rather than quadratic, showing a strong correlation between sequence length and execution time. Therefore, tokenization disparities across languages also affect the latency and processing time for text in these languages.

From the range of value on the vertical axis of Figure 3, it is apparent that some languages take almost twice the time to be As expected, English processed as others. is on the left lower corner, having the shortest tokenization and one of the fastest processing times. Shan is on the other extreme with the longest tokenization length and execution time (almost twice that of English). We can also observe clear trends dependent on the script used. Latin script and other Greek-derived scripts show the shortest tokenization lengths and processing times followed by the Chinese-Japanese-Korean (CJK) and Arabic languages. Other predominantly Asian and African scripts have longer tokenization lengths and processing times.

Overall, the differences in processing time closely track the differences in tokenization length. Therefore, tokenization disparities across languages also affect the latency and processing time for text in these languages.

The latency implications of tokenization disparity are not limited to text models. Speech recognition models often produce a series of tokens as their output sequentially. Similarly, speech synthesis takes as an input tokenized text (Latif et al., 2023). Therefore, differences in tokenization affects speach models too.

## 6.3 Long-term Modelling

Transformers models have difficulty processing long inputs. Given that the size of the input is contingent upon the tokenization process, inputs of greater length may impose a challenge for language models to adequately reason over. Such a predicament may result in reduced abilities or limited applicability for languages with high tokenization premiums.

For example, RoBERTa has a fixed block size of 512, GPT-2 has 768, 1024, 1280, or 1600 (Radford et al., 2019) and GPT-4 comes

in 8,000 and 16,000 context variants.<sup>10</sup> These models cannot process inputs longer than that. Therefore, one can process less than a tenth of the content in languages like Burmese and Dzongkha than they can in English.

Alongside inconveniencing the users of these languages, this can also result in diminished performance on automated systems, such as content moderation. Reliable content moderation is crucial for tackling hate speech and diminished performance has already been shown to fail to prevent its spread (Stecklow, 2018; Facebook, 2021). Therefore, reduced long-term modelling capabilities for some languages could have severe real-world impacts.

## 7 Towards Multilingual Tokenization Fairness

Section 6 showed that high values of tokenization parity for a language lead to increased cost and latency and decreased capacity for long-term modelling. At the same time, balanced tokenizers have been shown to result in better performance on tasks such as translation (Zhang et al., 2022). To ensure equitable treatment of all languages, it is imperative that we devise multilingually fair tokenizers. In this section, we argue that training language models from scratch with a multilingually fair subword tokenizer is the only approach that can effectively address all three aspects of tokenization unfairness: cost, latency and long-term modelling.

Subword tokenization is necessary to achieve parity. In Section 5.5, we showed that neither character-level nor byte-level input representation can achieve tokenization parity as languages require different amounts of characters to represent the same content. Additionally, the UTF-8 standard results in differences in the number of bytes required to encode codepoints from different scripts, further complicating the issue. As a result, neither character-level nor byte-level input representation can be fully fair.

Therefore, a variation of subword tokenization is necessary to achieve tokenization parity. For example, Chinese characters could be individual tokens, Latin characters might be represented as tokens with an average length of about 3 characters while pairs of Burmese characters and their diacritics being assigned single tokens. Such an approach would account for Chinese requiring about three times fewer characters than in English (as shown in Table 8).

A separate tokenizer for determining the processing cost is not sufficient. An easy patch for existing models is to use a separate tokenizer for calculating how much a user should be charged. Using one tokenizer for computing the cost and another to process the input can easily be applied to existing systems without the need to retrain the LLM itself. However, as the tokenizer for the language model is unchanged, this approach would still suffer from the latency or long-term modelling issues. Therefore, to ensure similar processing times and long-term modelling capabilities across languages, the language model has to be trained with a multilingually fair tokenizer.

The tokenization needs to support all Unicode codepoints. Amongst all tokenizers we examine in this paper, the ones which encode all FLORES-200 languages all one thing in common: they build their tokenization on top of Unicode representation, allowing them them to represent all charac-Therefore, a multilingually fair tokters. enizer should also start from a Unicode (or equivalent) encoding. This could be either the variable-width UTF-8 or the fixed-width UTF-32. However, considering the above point that subword tokenization is necessary, building the vocabulary from UTF-8 would likely result in a smaller dictionary than building it on top of UTF-32. Therefore, the variable-width UTF-8 is likely the more appropriate choice.

Perfect parity might not be possible, but we could improve the status quo. Given the discrete nature of tokenization and its dependence on training corpora, it is unlikely that perfect parity can be achieved across all pairs from a large collection of languages. This may be further complicated by characters and subwords shared amongst languages. For example, imagine an *Englishli* language that adds "li" after every English word: "Hello li

<sup>10</sup>https://openai.com/pricing

world li.". This language will never be able to achieve parity with English<sup>11</sup>. However, we hypothesize that natural languages can reach parity levels close to 1, or at least significantly less than 4.5 which is the lower bound on the worst parity we have seen across the tokenizers in this paper.

Building a multilingually fair parallel **corpus.** When constructing the corpus, care should be taken to ensure that there is a diversity of topics included. This is because the tokenizer needs to be able to accurately process a range of subjects, including those that are more technical or specialized in nature. One must ensure that the representation of different topics is balanced, otherwise, the resulting tokenizer might end up being multilingually fair only for a subset of topics. The presence of named entities must also be balanced. For example, in FLORES-200 English-centric names and institutions abound, which might skew the results in favour of English. Additionally, the same sentence can have different translations with varying tokenization lengths. To account for this, a diversity of translations could ensure tokenization fairness across languages. These limitations also hold for the results in this paper. Hence, developing a well-curated and diverse parallel corpus is crucial for the development and evaluation of a multilingually fair tokenizer.

**Summary.** Consequently, to achieve multilingual tokenization fairness, one would first need to design a well-balanced and representative parallel corpus. Then, the tokenization procedure should start by encoding the input with one of the Unicode standards and then building a subword tokenizer on top of it while ensuring parity across a set of languages. The language model has to be trained using this fair tokenizer. This approach, combined with per-token pricing, will result also in costparity. Furthermore, models trained with such a tokenizer will have similar processing times across languages, effectively alleviating the latency unfairness as well. Finally, as the same content would have similar lengths in different languages, this would also result in a similar capability to model long-term dependencies. Unfortunately, that also means that to alleviate these concerns, one needs to train a model from scratch using this more fair tokenizer. While such an approach would possibly be suboptimal for any individual language, we expect that this effect would be negligible due to the diminishing returns of enlarging a tokenizer vocabulary.

### 8 Related Works

Fairness and bias in language models. The rapid increase in the size of language models has raised concerns regarding their biases and unfairness (Bender et al., 2021). For example, Bolukbasi et al. (2016), May et al. (2019) and Nadeem et al. (2021) showed that stereotypes and biases exist in language models, while Magee et al. (2021) identified the presence of intersectional biases which may be resistant to debiasing techniques. Language models were also shown to rely on social biases in question answering (Parrish et al., 2022). Interestingly, Gururangan et al. (2022) point out that datasets consider one type of English as a higher quality depending on the location of the writer rather than on factuality or literary acclaim. Moreover, Ramesh et al. (2023) highlighted the need to consider fairness issues of languages other than English, as they may have distinct sources of bias and solutions for English may not be applicable.

Multilingual performance. One approach to ensure similar multilingual performance is to frame languages as entities as recently proposed by Choudhury and Deshpande (2021). Another method is to separately train vocabularies for different language clusters to balance cross-lingual and language-specific tokens (Chung et al., 2020). Still, multilingual models struggle to deliver on the promises of deep transfer learning for lower-resourced languages (Virtanen et al., 2019) and perform differently depending on the script and resource level of the language (Bang et al., 2023). Ahuja et al. (2023) found that generative models perform better on higher-resource languages and languages that use the Latin script. They hypothesise that this may be due to the length of context that can be provided for some lan-

<sup>&</sup>lt;sup>11</sup>Unless for every English token corresponding to a word there is an Englishli token, *e.g.*, "Hello li", "world li". However, that would result in severely bloated vocabulary.

guages. Finally, Zhang et al. (2022) show that a balanced tokenizer corpus results in better translation performance.

Measuring the tokens needed to en**code text.** Measuring the number of tokens needed to encode text is a complex problem and previous works have proposed different approaches to tackle it. For instance, Zhang et al. (2022) suggest using the ratio of the average sentence length in tokens to the sentence length in characters as a measure of closeness to the character level. However, this method may not be suitable for comparing languages due to differences in sentence length across languages. On the other hand, Acs (2019) and Scao et al. (2022) redefine the notion of fertility<sup>12</sup> as the number of tokens created per word, but this method may not be effective for comparing languages due to differences in semantic content per word. It is also difficult to apply to languages where word delineation is less straightforward. Rust et al. (2021) show that mBERT (Devlin et al., 2019) has much higher fertility for some languages compared to others, with English having the lowest. This is in line with our findings of English receiving special treatment. They also show that models trained with monolingual tokenizers outperform their models with multilingual tokenizers. However, to the best of our knowledge, we are the first to leverage a parallel corpus to compare tokenization lengths across languages.

### 9 Conclusion

This paper highlights the significant disparities in tokenization across different languages which can lead to unequal treatment and disadvantages for certain language communities. The findings reveal that even tokenizers explicitly trained for multilingual support exhibit drastic differences in tokenization lengths with variations of up to 13 times. Furthermore, character-level and byte-level models also demonstrate encoding length discrepan-

cies of over 4 times for specific language pairs. These disparities have important realworld implications including increased costs for accessing commercial language services, longer processing times and limitations on the amount of contextual information provided to language models. To address these issues, we propose the development of multilingually fair tokenizers for future language models emphasizing the importance of ensuring comparable performance and accessibility across supported languages. By achieving tokenization parity, we can mitigate inequalities and promote fair access to language technologies across diverse linguistic communities.

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<sup>&</sup>lt;sup>12</sup>Fertility is a notion from statistical machine translation referring to the phenomenon that one word in the input language may translate into a different number of words in the output language (e.g., "I" does not map to any word in the Italian translation "Vado a scuola" of "I go to school"). However, this is a property of the differences between natural languages rather than a phenomenon related to tokenization.

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## A Extended Tables of Tokenization Premiums

Language	GPT-2 r50k	_base p50k	_base p5	0k_edit cl100k	_base F	RoBERTa	GottBERT	CamemBERT	PhoBERT	RoCBert	XLM-RoBERTa
Acehnese (Arabic script)	4.78	4.78	4.78	4.78	3.78	4.78	6.67	_	_	_	1.94
Acehnese (Latin script)	2.16	2.16	2.16	2.16	1.98	2.16	2.10	1.85	1.64	2.84	1.57
Afrikaans	1.94	1.94	1.94	1.94	1.69	1.94	1.68	1.65	1.51	2.75	1.20
Akan	2.80	2.80	2.80	2.80	2.68	2.80	2.56	1.96	1.74	_	1.98
Amharic	7.79	7.79	7.79	7.79	7.68	7.79	6.99	_	_	_	1.34
Armenian	10.01	10.01	10.01	10.01	9.98	10.01	9.00	_	_	_	1.38
Assamese	9.79	9.79	9.78	9.78	6.20	9.79	11.22		_	_	1.90
Asturian	1.89	1.89	1.89	1.89	1.58	1.89	1.80	1.57	1.48	2.69	
Awadhi	7.19	7.19	7.19	7.19	4.78	7.19	11.04		1.00		1.37
Ayacucho Quechua Balinese	2.20 1.97	2.20	2.20	2.20	2.08	2.20	2.17	1.84	1.68	2.95 2.97	
		1.97	1.97	1.97	1.80	1.97	1.87	1.71	1.54		1.32
Bambara Banjar (Arabic script)	2.66 5.03	2.66 5.03	$\frac{2.66}{5.03}$	2.66 5.03	$\frac{2.57}{3.80}$	2.66 5.03	2.48 7.46	1.84	1.68	_	1.82 1.92
Banjar (Latin script)	1.98	1.98	1.98	1.98	1.71	1.98	1.40	1.62	1.45	2.81	1.21
Bashkir	6.01	6.01	6.01	6.01	4.28	6.01	5.36	1.02	1.40	2.01	2.06
Basque	2.10	2.10	2.10	2.10	1.88	2.10	1.87	1.73	1.60	2.89	
Belarusian	6.56	6.56	6.56	6.56	3.55	6.56	5.62		3.46		1.46
Bemba	2.46	2.46	2.46	2.46	2.23	2.46	2.28	2.01	1.84	3.28	
Bengali	9.65	9.65	9.65	9.65	5.84	9.65	11.52	_	_	_	1.38
Bhojpuri	7.18	7.18	7.18	7.18	4.69	7.18	10.90	_	_	_	1.47
Bosnian	2.19	2.19	2.19	2.19	1.87	2.19	1.99	1.75	1.62	2.65	
Buginese	2.20	2.20	2.20	2.20	1.98	2.20	2.01	1.73	1.62	2.85	
Bulgarian	5.51	5.51	5.51	5.51	2.64	5.51	4.73	_	3.09	_	1.16
Burmese	16.89	16.89	16.89	16.89	11.70	16.89	15.19	_	_	_	1.72
Catalan	1.92	1.92	1.92	1.92	1.71	1.92	1.89	1.59	1.57	2.86	1.26
Cebuano	2.24	2.24	2.24	2.24	1.93	2.24	2.12	1.91	1.69	3.12	1.52
Central Atlas Tamazight	10.39	10.39	10.39	10.39	10.04	10.39	9.33	_	_	_	_
Central Aymara	2.32	2.32	2.32	2.32	2.17	2.32	2.18	1.94	1.76	2.84	
Central Kanuri (Arabic script)		4.74	4.74	4.74	3.63	4.74	7.01		_	_	2.60
Central Kanuri (Latin script)	2.57	2.57	2.57	2.57	2.37	2.57	2.40	1.92	1.73	_	1.74
Central Kurdish	6.49	6.49	6.49	6.49	4.80	6.49	7.86	_	_	_	2.30
Chhattisgarhi	7.21	7.21	7.21	7.21	4.69	7.21	10.86	_	_	1.00	1.41
Chinese (Simplified)	3.21 3.16	3.21	3.21 3.16	3.21 3.16	1.91 2.18	3.21 3.16	3.95 3.82	_	_	1.00	
Chinese (Traditional) Chokwe	2.16	3.16 2.16	2.16	2.16	1.98	2.16	2.04	1.78	1.58	0.94 2.84	
Crimean Tatar	2.49	2.49	2.49	2.49	2.12	2.49	2.04	2.01	1.85	2.04	1.38
Croatian	2.15	2.15	2.15	2.15	1.85	2.15	1.96	1.71	1.59	2.59	
Czech	2.62	2.62	2.62	2.62	2.11	2.62	2.33		1.77	2.56	
Danish	1.90	1.90	1.90	1.90	1.62	1.90	1.70	1.67	1.54	2.69	
Dari	5.11	5.11	5.11	5.11	3.16	5.11	7.16	_	_		1.09
Dutch	1.97	1.97	1.97	1.97	1.59	1.97	1.73	1.68	1.58	2.92	
Dyula	2.20	2.20	2.20	2.20	2.05	2.20	2.08	1.71	1.56	2.55	
Dzongkha	16.36	16.36	16.36	16.36	12.33	16.36	16.12	_	_	_	_
Eastern Panjabi	7.90	7.90	7.90	7.90	7.87	7.90	11.43	_	_	_	1.57
Eastern Yiddish	6.63	6.63	6.63	6.63	5.57	6.63	8.55	_	_	_	1.58
Egyptian Arabic	4.23	4.23	4.23	4.23	2.96	4.23	6.88	_	_	_	1.17
English	1.00	1.00	1.00	1.00	1.00	1.00	1.35	1.20	1.20	2.60	1.00
Esperanto	2.03	2.03	2.03	2.03	1.87	2.03	1.85	1.62	1.52	2.61	
Estonian	2.11	2.11	2.11	2.11	1.87	2.11	1.87	1.69	1.59	2.66	
Ewe	2.90	2.90	2.90	2.90	2.75	2.90	2.66	2.02	1.75	_	2.01
Faroese	2.38	2.38	2.38	2.38	2.07	2.38	2.24	1.96	1.75		1.44
Fijian	2.30	2.30	2.30	2.30	2.15	2.30	2.26	1.82	1.67	2.94	
Finnish	2.28	2.28	2.28	2.28	1.99	2.28	1.97	1.87	1.77	2.94	
Fon	4.08	4.08	4.08	4.08	3.67	4.08	3.71				2.51
French	2.00	2.00	2.00	2.00	1.60	2.00	1.99	1.00	1.66	3.10	
Friulian	2.07	2.07	2.07	2.07	1.85	2.07	1.98	1.66	1.59	2.79	
Galician Ganda	1.91 2.17	$\frac{1.91}{2.17}$	$\frac{1.91}{2.17}$	1.91 2.17	1.56 1.96	1.91 2.17	1.87 2.00	1.63 1.76	1.56	2.88 2.77	
									1.64		
Georgian German	13.85 2.14	13.85 2.14	13.85 $2.14$	13.85 2.14	9.85 $1.58$	13.85 2.14	12.43 1.00	1.85	1.67	3.12	1.34 1.17
Greek	6.54	6.54	6.54	6.54	5.15	6.54	6.73	1.89	3.73	3.00	
Guarani	2.46	2.46	2.46	2.46	$\frac{3.13}{2.17}$	2.46	2.27	1.85	1.74	2.72	
Guarati	12.27	12.27	12.27	12.27	7.69	12.27	11.03	1.00	1.14	2.12	1.42
Haitian Creole	1.90	1.90	1.90	1.90	1.74	1.90	1.82	1.58	1.38	2.32	
	1.00							1.00		2.02	
	6.42	6.42	6.42	6.42	3.77	6.42	5.71		3.26	_	1.21
Halh Mongolian Hausa	6.42 2.15	6.42 2.15	6.42 $2.15$	6.42 2.15	3.77 $2.00$	6.42 2.15	5.71 2.01	1.76	3.26 1.51	2.64	1.21 1.40
Halh Mongolian			6.42 2.15 4.39	6.42 2.15 4.39		6.42 2.15 4.39	5.71 2.01 6.09	1.76		2.64	

Language	M2M100	MBart50	mT5	FlanT5	ВуТ5	CANINE	BLOOM	ArabicBERT	MuRIL	UTF-32	BERT Japanese
Acehnese (Arabic script)	1.89	1.94	1.79	_	1.51	0.85	2.65	_	_	0.85	
Acehnese (Latin script)	1.47	1.57	1.44	2.55	1.09	1.07	1.74	2.63	2.02	1.07	2.11
Afrikaans	1.22	1.20	1.20	2.15	1.07	1.06	1.69	2.42	1.84	1.06	1.90
Akan	1.83	1.98	1.82	2.96	1.10	1.00	2.05	_	_	1.00	2.17
Amharic	1.42		1.73	_	1.72	0.67	5.07	_	_	0.0.	_
Armenian	1.50		1.58	_	2.04	1.11	4.31	_	_		_
Assamese	2.24		1.94		2.54	0.96	1.41	_			
Asturian	1.15		1.28	2.07	1.07	1.03	1.31	2.27			
Awadhi	1.47		1.62		2.50	0.98	1.43				
Ayacucho Quechua	1.54		1.42	2.59	1.08	1.07	1.83	2.68			
Balinese	1.29		1.29	2.37	1.11	1.11	1.46	2.55			2.01
Bambara	1.72		1.65	2.70	1.04	0.96	1.89	1.00		0.00	
Banjar (Arabic script)	1.93		1.76	2 20	1.69	0.93	2.47 1.30	1.90 2.40			
Banjar (Latin script) Bashkir	1.16 1.23		1.16 1.60	2.20	1.05 1.85	1.05 1.01	$\frac{1.50}{3.57}$	2.40			1.92
Basque	1.23		1.22	2.33	1.07	1.01	1.14	2.58			
Belarusian	1.56		1.59	2.55	2.06	1.13	3.24	4.74			
Bemba	1.67		1.57	3.01	1.23	1.23	1.92	3.01			
Bengali	1.55		1.58		2.61	0.98	1.17				
Bhojpuri	1.54		1.63	_	2.47	0.97	1.53	_	1.39		
Bosnian	1.17		1.33	2.48	1.03	1.01	1.84	2.53			1.95
Buginese	1.49		1.44	2.51	1.09	1.06	1.71	2.64			
Bulgarian	1.23		1.28	_	1.89	1.04	2.49	4.30			
Burmese	2.21	1.72	1.56	_	3.51	1.24	10.05	_	_		
Catalan	1.26	1.26	1.36	2.14	1.12	1.10	1.18	2.36	1.90	1.10	1.95
Cebuano	1.38	1.52	1.42	2.86	1.20	1.20	1.78	2.76	2.10	1.20	2.29
Central Atlas Tamazight	_	_	3.48	_	2.28	0.89	7.69	_	_	0.89	_
Central Aymara	1.64	1.70	1.57	2.71	1.07	1.05	1.94	2.63	1.98	1.05	2.16
Central Kanuri (Arabic script)	2.49	2.60	2.43	_	1.60	0.88	2.10	_		0.88	_
Central Kanuri (Latin script)	1.65		1.58	2.82	1.11	1.05	2.00	_	_		
Central Kurdish	2.48		1.75	_	1.78	0.97	3.21	3.01			
Chhattisgarhi	1.51		1.60	_	2.46	0.97	1.44	_	_		
Chinese (Simplified)	1.05		0.92	_	0.93	0.34	0.95	_		0.34	
Chinese (Traditional)	1.06		0.98		0.89	0.32	0.97			0.0-	
Chokwe	1.47		1.41	2.66	1.07	1.07	1.72	2.68			
Crimean Tatar	1.37		1.32	2.80	1.13	1.03	2.07	2.64			
Croatian Czech	1.15 1.23		1.30	2.43	1.01 1.08	0.98	1.80	2.49			
Danish	1.23		1.27 $1.14$	2.72 2.26	1.08	0.97	2.03 1.67	2.40 2.34			
Danish	1.12		1.14	2.20	1.63	1.03 0.92	1.64	1.99			
Dutch	1.18		1.17	2.19	1.11	1.11	1.71	2.52			1.98
Dyula	1.53		1.55	2.68	1.07	1.01	1.80	2.37			2.08
Dzongkha	1.00		4.24	2.00	3.64	1.25	7.36	2.01	2.00		
Eastern Panjabi	1.68		2.11	_	2.59	1.01	1.43	_			_
Eastern Yiddish	1.61		1.66	_	1.94	1.08	4.42	4.39			_
Egyptian Arabic	1.27		1.28	_	1.56	0.86	1.16	1.05			
English	1.00		1.00	1.00	1.00	1.00	1.00	1.83			
Esperanto	1.38		1.19	2.19	1.02	1.00	1.65	2.26			
Estonian	1.20		1.12	2.43	1.01	0.98	1.77	2.33		0.98	_
Ewe	1.86	2.01	1.82	2.85	1.07	0.97	2.11	_		0.97	_
Faroese	1.41	1.44	1.40	2.73	1.09	1.02	1.95	2.58	_	1.02	_
Fijian	1.62	1.72	1.59	3.02	1.17	1.17	1.99	3.01	2.01	1.17	2.29
Finnish	1.23	1.14	1.16	2.61	1.11	1.07	1.89	2.60	2.05	1.07	2.16
Fon	2.31	2.51	2.36	_	1.26	1.02	2.21	_		1.02	_
French	1.33		1.40	1.60	1.24	1.19	1.20	2.42			
Friulian	1.47	1.56	1.52	2.30	1.13	1.10	1.70	2.33		1.10	
Galician	1.14		1.31	2.18	1.13		1.27	2.37			
Ganda	1.38		1.40	2.65	1.03	1.02	1.67	2.66			
Georgian	1.56		1.55		2.95	1.10	4.98				
German	1.24		1.19	1.37	1.18	1.17	1.68	2.63			
Greek	1.58		1.65	_	2.17	1.20	3.81	4.93			
Guarani	1.63		1.62	2.57	1.09	1.01	1.87	2.56			_
Gujarati	1.58		1.73		2.50	0.96	1.35	0.15			
Haitian Creole	1.16		1.22	2.32	0.95	0.92	1.56	2.15			
Halh Mongolian	1.34		1.48	0.61	1.91	1.04	3.38	0.45	1 70		
Hausa	1.29		1.37	2.61	1.08	1.07	1.78	2.45			
Hebrew	1.22		1.22	_	1.39	0.78	2.92	3.14			
Hindi	1.36	1.25	1.59	_	2.55	1.00	1.28	_	1.16	1.00	_

Language	GPT-2 r50k	_base p50k_	_base p	o50k_edit cl100k_	_base l	RoBERTa	GottBERT	CamemBERT	PhoBERT	RoCBert	XLM-RoBERTa
Hungarian	2.66	2.66	2.66	2.66	2.15	2.66	2.42	2.13	1.88	2.83	1.18
Icelandic	2.43	2.43	2.43	2.43	2.15	2.43	2.32		1.80		1.23
Igbo	3.42	3.42	3.42	3.42	2.44	3.42	3.14	2.12	1.78		2.12
Ilocano	2.26	2.26	2.26	2.26	2.05	2.26	2.14	1.92	1.69		1.61
Indonesian	1.98	1.98	1.98	1.98	1.55	1.98	1.85	1.67	1.50		0.94
Irish	2.56	2.56	2.56	2.56	2.33	2.56	2.37	2.10	1.86		1.50
Italian	2.01	2.01	2.01	2.01	1.64	2.01	1.93	1.63	1.60	3.10	1.19
Japanese	3.00	3.00	3.00	3.00	2.30	3.00	4.35	_	_	1.34	1.11
Javanese	1.93	1.93	1.93	1.93	1.73	1.93	1.83	1.66	1.45	2.76	1.15
Jingpho	2.65	2.65	2.65	2.65	2.35	2.65	2.55	2.13	1.84	3.12	1.94
KabiyÃ"	4.87	4.87	4.87	4.87	4.74	4.87	4.42	_	_	_	2.98
Kabuverdianu	1.93	1.93	1.93	1.93	1.72	1.93	1.78	1.55	1.45		1.35
Kabyle	2.50	2.50	2.50	2.50	2.47	2.50	2.35	1.90	1.71		1.84
Kamba	2.32	2.32	2.32	2.32	2.17	2.32	2.18	1.77	1.56	2.54	1.62
Kannada	13.69	13.69	13.68	13.68	8.90	13.69	12.50	_	_	_	1.36
Kashmiri (Arabic script)	6.19	6.19	6.19	6.19	4.62	6.19	7.60	_	_	_	1.93
Kashmiri (Devanagari script)		7.03	7.03	7.03	4.69	7.03	10.47	_	0.10	_	1.82
Kazakh	5.92	5.92	5.92	5.92	3.79	5.92	5.27	_	3.19		1.15
Khmer	15.33	15.33 2.17	15.33	15.33	8.88	15.33	13.78 2.17	1.73	1.65	2.90	1.62 1.58
Kikongo Kikuyu	2.17 3.44	3.44	$\frac{2.17}{3.44}$	$\frac{2.17}{3.44}$	1.99 $3.29$	2.17 3.44	3.18	1.73	1.65		2.31
Kimbundu	2.33	2.33	2.33	2.33	2.13	2.33	2.22	1.89	1.72		1.64
Kinyarwanda	2.33	2.37	$\frac{2.33}{2.37}$	2.37	2.13	2.33	2.22	1.99	1.72		1.72
Korean	5.07	5.07	5.07	5.07	2.38	5.07	5.21	1.50		2.57	1.16
Kyrgyz	5.74	5.74	5.74	5.74	3.51	5.74	5.12	_	3.20		1.16
Lao	13.19		13.19	13.19	9.62	13.19	11.86	_		_	1.39
Latgalian	2.39	2.39	2.39	2.39	2.20	2.39	2.25	1.94	1.77	2.65	1.57
Ligurian	2.29	2.29	2.29	2.29	1.98	2.29	2.11	1.79	1.72		1.65
Limburgish	2.05	2.05	2.05	2.05	1.80	2.05	1.81	1.66	1.59	2.71	1.45
Lingala	2.03	2.03	2.03	2.03	1.86	2.03	1.98	1.63	1.51	2.80	1.52
Lithuanian	2.45	2.45	2.45	2.45	2.21	2.45	2.20	1.83	1.70	2.69	1.17
Lombard	2.37	2.37	2.37	2.37	2.04	2.37	2.13	1.82	1.69	2.70	1.71
Luba-Kasai	2.13	2.13	2.13	2.13	1.94	2.13	2.02	1.72	1.57		1.54
Luo	2.04	2.04	2.04	2.04	1.82	2.04	1.89	1.66	1.52		1.52
Luxembourgish	2.25	2.25	2.25	2.25	1.99	2.25	1.75	1.82	1.72		1.64
Macedonian	5.46	5.46	5.46	5.46	2.77	5.46	4.70	_	3.10		1.17
Magahi	7.22	7.22	7.22	7.22	4.70	7.22	10.88	_	_	_	1.41
Maithili	7.43	7.43	7.43	7.43	4.90	7.43	11.16	_	_	_	1.58
Malayalam Maltese	15.24 2.69	15.24 2.69	15.24 2.69	15.24 2.69	9.00 $2.41$	15.24 2.69	13.70 2.43	2.06	1.88	2.68	1.38 1.96
Maori	2.45	2.45	2.45	2.45	2.35	2.09	2.43	2.00	1.76		1.86
Marathi	7.87	7.87	7.87	7.87	5.07	7.87	11.81	2.02	1.70	2.14	1.22
Meitei (Bengali script)	10.22	10.22	10.22	10.22	6.71	10.22	12.22				2.56
Mesopotamian Arabic	4.27	4.27	4.27	4.27	2.99	4.27	6.88	_	_	_	1.16
Minangkabau (Arabic script)	5.25	5.25	5.25	5.25	3.97	5.25	7.71	_	_	_	2.02
Minangkabau (Latin script)	1.97	1.97	1.97	1.97	1.77	1.97	1.89	1.67	1.50	2.84	1.31
Mizo	2.09	2.09	2.09	2.09	1.96	2.09	2.06	1.82	1.55		1.65
Moroccan Arabic	4.21	4.21	4.21	4.21	2.96	4.21	6.85	_	_	_	1.25
Mossi	2.54	2.54	2.54	2.54	2.32	2.54	2.35	1.81	1.66	2.20	1.78
Najdi Arabic	4.41	4.41	4.41	4.41	3.04	4.41	7.04	_	_	_	1.18
Nepali	7.59	7.59	7.59	7.59	4.79	7.59	11.29	_	_	_	1.13
Nigerian Fulfulde	1.99	1.99	1.99	1.99	1.85	1.99	1.85	1.54	1.39	2.23	1.46
North Azerbaijani	3.47	3.47	3.47	3.47	2.64	3.47	3.11	_	2.28	_	1.15
North Levantine Arabic	4.04	4.04	4.04	4.04	2.83	4.04	6.52	_	_	_	1.15
Northern Kurdish	2.45	2.45	2.45	2.45	2.20	2.45	2.24	1.98	1.68		1.38
Northern Sotho	2.32	2.32	2.32	2.32	2.18	2.32	2.19	1.89	1.77		1.75
Northern Uzbek	2.30	2.30	2.30	2.30	2.17	2.30	2.20	1.91	1.77		1.33
Norwegian Bokmål	1.86	1.86	1.86	1.86	1.56	1.86	1.65	1.64	1.52		
Norwegian Nynorsk	1.93	1.93	1.93	1.93	1.64	1.93	1.69	1.68	1.55		1.17
Nuer	4.23	4.23	4.23	4.23	4.00	4.23	3.76	1.05	1.70		2.62
Nyanja	2.26	2.26	2.26	2.26	2.08	2.26	2.12	1.85	1.70		1.59
Occitan	2.07	2.07	2.07	2.07	1.83	2.07	1.99	1.68	1.66		
Odia Pangaginan	13.38	13.38	13.38		12.48	13.38	12.06	1 40	1 22		1.45 1.29
Pangasinan Papiamento	1.66 1.98	1.66	1.66 1.98	1.66	1.57	1.66 1.98	1.71	1.49	1.33		
Papiamento Plateau Malagasy	2.58	1.98 2.58	2.58	1.98 2.58	1.75 $2.26$	2.58	1.79 2.35	1.64 2.03	1.49 1.79		1.37 1.57
Polish	2.69	2.69	2.69	2.69	1.91	2.69	2.41	2.05	1.79		
Portuguese	1.94	1.94	1.94	1.94	1.48	1.94	1.87	1.62			
		-							2.30	=.50	

Language	M2M100	MBart50	mT5	FlanT5	ВуТ5	CANINE	BLOOM	ArabicBERT	MuRIL	UTF-32	BERT Japanese
Hungarian	1.28	1.18	1.26	2.99	1.16	1.05	2.07	2.56	2.31	1.05	
Icelandic	1.29		1.32	2.81	1.09	0.99	1.99	2.45		0.99	_
Igbo	1.47		1.79	3.17	1.21	1.02	1.72	2.74			
Ilocano	1.33		1.61	2.82	1.21	1.21	1.90	2.84		1.21	2.31
Indonesian	0.98		1.08	2.24	1.08	1.08	0.96	2.46			1.98
Irish	1.50		1.67	3.14	1.23	1.16	2.15	2.64			2.25
Italian	1.25		1.34	2.18	1.19	1.18	1.62	2.58			
Japanese	1.20		0.90	_	1.27	0.44	1.81	1.85			
Javanese	1.10		1.21	2.21	1.04	1.04	1.40	2.48			
Jingpho	1.78		1.79	3.41	1.27	1.28	2.14	3.12			2.47
KabiyÃ"	2.71		2.83	_	1.37	1.09	3.34	_	_	1.09	_
Kabuverdianu	1.30	1.35	1.28	2.21	1.02	0.99	1.51	2.28	1.81	0.99	1.92
Kabyle	1.71	1.84	1.82	2.83	1.06	0.99	2.02	2.35	_	0.99	_
Kamba	1.52		1.52	2.69	1.01	0.98	1.77	2.42		0.98	_
Kannada	1.53	1.36	1.44	_	2.83	1.05	1.31	_	1.06	1.05	_
Kashmiri (Arabic script)	1.93	1.93	2.00	_	1.72	0.96	2.32	2.30	1.75	0.96	_
Kashmiri (Devanagari script)	1.86	1.82	1.79	_	2.40	0.96	1.85	_	1.75	0.96	_
Kazakh	1.28	1.15	1.20	_	1.89	1.03	3.23	_	_	1.03	_
Khmer	1.87	1.62	1.43	_	3.33	1.18	6.40	_	_	1.18	_
Kikongo	1.48	1.58	1.46	3.01	1.14	1.14	1.75	2.90	1.97	1.14	2.29
Kikuyu	2.17	2.31	2.18	_	1.30	1.17	2.48	2.86	_	1.17	_
Kimbundu	1.54	1.64	1.48	2.91	1.11	1.11	1.81	2.83	1.99	1.11	2.27
Kinyarwanda	1.63	1.72	1.51	2.76	1.13	1.11	1.58	2.81	2.15	1.11	2.24
Korean	1.21	1.16	1.27	_	1.20	0.51	2.79	2.37	_	0.51	_
Kyrgyz	1.66	1.16	1.32	_	1.88	1.02	3.02	_	_	1.02	_
Lao	1.61	1.39	1.27	_	2.73	0.99	8.70	_	_	0.99	_
Latgalian	1.51	1.57	1.46	2.70	1.05	0.99	1.99	2.48	_	0.99	_
Ligurian	1.59	1.65	1.69	2.54	1.17	1.10	1.81	2.52	2.05	1.10	_
Limburgish	1.38	1.45	1.38	2.25	1.07	1.04	1.75	2.41	1.92	1.04	1.90
Lingala	1.26	1.52	1.38	2.73	1.08	1.08	1.65	2.69	1.90	1.08	2.10
Lithuanian	1.25	1.17	1.23	2.58	1.06	1.00	1.94	2.43	_	1.00	_
Lombard	1.56	1.71	1.70	2.58	1.16	1.07	1.84	2.35	1.96	1.07	_
Luba-Kasai	1.43	1.54	1.37	2.48	1.08	1.08	1.68	2.63	1.89	1.08	2.11
Luo	1.43	1.52	1.41	2.55	1.05	1.05	1.68	2.47	1.87	1.05	2.02
Luxembourgish	1.32	1.64	1.46	2.24	1.15	1.12	1.89	2.56	2.17	1.12	1.96
Macedonian	1.24	1.17	1.29	_	1.89	1.04	2.50	_	_	1.04	_
Magahi	1.50	1.41	1.61	_	2.46	0.96	1.45	_	1.34	0.96	_
Maithili	1.64	1.58	1.74	_	2.53	0.98	1.56	_	1.50	0.98	_
Malayalam	1.59	1.38	1.35	_	3.10	1.13	1.38	_	1.18	1.13	_
Maltese	1.87	1.96	1.69	2.94	1.16	1.11	2.25	2.62	_	1.11	_
Maori	1.74	1.86	1.69	3.28	1.16	1.11	2.12	2.72	2.12	1.11	2.16
Marathi	1.38	1.22	1.52	_	2.67	1.01	1.21	_	1.06	1.01	_
Meitei (Bengali script)	2.59	2.56	2.21	_	2.77	1.03	2.35	_	2.34	1.03	_
Mesopotamian Arabic	1.27	1.16	1.28	_	1.56	0.86	1.15	1.01	1.93	0.86	_
Minangkabau (Arabic script)	1.99		1.84	_	1.74	0.96	2.58	2.05	_	0.96	_
Minangkabau (Latin script)	1.25		1.25	2.35	1.07	1.07	1.44	2.48		1.07	1.98
Mizo	1.54		1.57	2.76	1.10	1.10	1.83	2.61			2.05
Moroccan Arabic	1.33		1.29	_	1.56	0.86	1.26	1.14		0.86	
Mossi	1.66		1.80	2.90	1.03	0.96	1.99	2.18			
Najdi Arabic	1.30		1.35	_	1.60	0.88	1.15	1.00			
Nepali	1.28		1.47		2.56	0.96	1.17	_	-		
Nigerian Fulfulde	1.27		1.32	2.14	0.96	0.93	1.66	2.12			
North Azerbaijani	1.26		1.35	_	1.26	1.09	2.30	3.17			
North Levantine Arabic	1.24		1.23	_	1.48	0.82	1.13	1.00			
Northern Kurdish	1.66		1.42	2.74	1.10	1.00	2.03	2.36			
Northern Sotho	1.52	1.75	1.57	2.81	1.17	1.15	1.94	2.70			
Northern Uzbek	1.37		1.38	2.80	1.13	1.13	1.98	2.89			
Norwegian Bokmål	1.10		1.12	2.24	1.03	1.01	1.62	2.29			
Norwegian Nynorsk	1.17		1.18	2.29	1.04	1.01	1.65	2.34	1.82		
Nuer	2.44		2.42	_	1.32	1.08	2.79	_	_		
Nyanja	1.55		1.35	2.71	1.12	1.12	1.78	2.78			
Occitan	1.31		1.48	2.26	1.17	1.14	1.49	2.42			
Odia	1.56		3.11	_	2.73	1.03	1.36	_			
Pangasinan	1.23		1.22	2.18	1.00	1.00	1.45	2.27			
Papiamento	1.32		1.36	2.28	1.08	1.05	1.54	2.28			
Plateau Malagasy	1.49		1.59	3.00	1.26	1.22	2.07	3.00			
Polish	1.26		1.31	2.82	1.13	1.06	2.14	2.78		1.06	
Portuguese	1.14	1.11	1.29	2.21	1.12	1.09	1.12	2.37	1.88	1.09	1.85

Language	GPT-2 r50k	_base p50k	_base p50k	_edit cl100k	_base F	RoBERTa	GottBERT	CamemBERT	PhoBERT	RoCBert	XLM-RoBERTa
Romanian	2.48	2.48	2.48	2.48	1.88	2.48	2.28	1.84	1.75	2.94	1.24
Rundi	2.33	2.33	2.33	2.33	2.13	2.33	2.19	1.90			1.71
Russian	5.74	5.74	5.74	5.74	2.49	5.74	4.96	_	3.25		1.17
Samoan	2.57	2.57	2.57	2.57	2.29	2.57	2.28	1.95			1.92
Sango	2.23	2.23	2.23	2.23	2.08	2.23	2.08	1.80			1.66
Sanskrit	7.94	7.94	7.94	7.94	5.00	7.94	11.60	_	_	_	1.43
Santali	12.86	12.86	12.86	12.86	12.80	12.86	11.55	_	_	_	_
Sardinian	2.26	2.26	2.26	2.26	1.99	2.26	2.07	1.77	1.68	3.02	1.61
Scottish Gaelic	2.70	2.70	2.70	2.70	2.42	2.70	2.50	2.16	1.94	3.21	1.75
Serbian	5.34	5.34	5.34	5.34	2.92	5.34	4.61	_	2.94	_	1.18
Shan	18.76	18.76	18.76	18.76	15.05	18.76	16.88	_	_	_	4.43
Shona	2.29	2.29	2.29	2.29	2.13	2.29	2.14	1.89	1.73		1.63
Sicilian	2.27	2.27	2.27	2.27	2.01	2.27	2.12	1.71	1.64		1.58
Silesian	2.60	2.60	2.60	2.60	2.18	2.60	2.35	2.03	1.91	2.58	1.65
Sindhi	5.00	5.00	5.00	5.00	4.00	5.00	7.04	_	_	_	1.28
Sinhala		12.86		12.86	8.83	12.86	11.59				1.35
Slovak	2.52	2.52	2.52	2.52	2.14	2.52	2.23	1.91	1.75		1.18
Slovenian	2.11	2.11	2.11	2.11	1.88	2.11	1.96	1.73	1.59		1.13
Somali	2.36	2.36	2.36	2.36	2.18	2.36	2.23	2.02	1.78	3.01	1.39
South Azerbaijani	5.16	5.16	5.16	5.16	3.34	5.16	7.17	_	_	_	1.43
South Levantine Arabic	4.02	4.02	4.02	4.02	2.84	4.02	6.53	_	_	_	1.12
Southern Pashto	5.39	5.39	5.39	5.39	3.83	5.39	7.24	1.05	1 70	2.07	1.38
Southern Sotho	2.34	2.34	2.34	2.34	2.21	2.34	2.21	1.95	1.78		
Southwestern Dinka Spanish	2.48 1.99	2.48 1.99	2.48 1.99	2.48 1.99	2.25	2.48 1.99	2.15 1.95	1.71	1.58		1.68 1.20
*	4.40		4.40	4.40	$\frac{1.55}{3.04}$		7.03	1.72	1.64		1.18
Standard Arabic (Romanized)		4.40 2.51	2.51	2.51	2.45	4.40 2.51	2.38	2.06	1.86		1.16
Standard Latvian	2.54	2.54	2.54	2.54	2.35	2.54	2.36	2.00	1.87		1.23
Standard Malay	2.05	2.05	2.05	2.05	1.62	2.04	1.92	1.74	1.54		0.95
Standard Tibetan	14.93	14.93		14.93	11.27	14.93	14.66	1.74	1.54	2.33	0.55
Sundanese	2.02	2.02	2.02	2.02	1.82	2.02	1.88	1.66		2.77	1.22
Swahili	2.13	2.13	2.13	2.13	1.95	2.13	2.02	1.70	1.58		1.16
Swati	2.31	2.31	2.31	2.31	2.16	2.31	2.15	1.92	1.74		1.61
Swedish	1.95	1.95	1.95	1.95	1.58	1.95	1.64	1.69	1.58		1.07
Tagalog	2.28	2.28	2.28	2.28	2.06	2.28	2.20	2.00	1.74		1.43
Tajik	6.09	6.09	6.09	6.09	3.64	6.09	5.40	_	3.39		2.14
Tamasheq (Latin script)	2.39	2.39	2.39	2.39	2.22	2.39	2.18	1.79	1.55	_	1.71
Tamasheq (Tifinagh script)	10.43	10.43	10.43	10.43	10.13	10.43	9.38	_	_	_	_
Tamil	15.58	15.58	15.58	15.58	7.65	15.58	14.01	_	_	_	1.35
Tatar	5.82	5.82	5.82	5.82	3.75	5.82	5.18	_	_	_	1.81
Ta'izzi-Adeni Arabic	4.34	4.34	4.34	4.34	3.01	4.34	6.96	_	_	_	1.17
Telugu	13.09	13.09	13.09	13.09	8.34	13.09	11.77	_	_	_	1.33
Thai	9.05	9.05	9.05	9.05	4.39	9.05	8.89	_	3.39	_	1.08
Tigrinya	7.88	7.88	7.88	7.88	7.80	7.88	7.09	_	_	_	1.97
Tok Pisin	2.21	2.21	2.21	2.21	2.04	2.21	2.09	1.99	1.74		1.73
Tosk Albanian	2.65	2.65	2.65	2.65	2.25	2.65	2.39	2.17			1.32
Tsonga	2.45	2.45	2.45	2.45	2.26	2.45	2.29	2.03	1.76		1.79
Tswana	2.39	2.39	2.39	2.39	2.28	2.39	2.27	2.00	1.86		1.85
Tumbuka	2.78	2.78	2.78	2.78	2.57	2.78	2.61	2.21	2.00		1.92
Tunisian Arabic	4.20	4.20	4.20	4.20	2.93	4.20	6.78	1.07	1.01		1.20
Turkish	2.43	2.43	2.43	2.43	1.91	2.43	2.17	1.97	1.81		1.04
Turkmen	2.82	2.82	2.82	2.82	2.40	2.82	2.37	2.13	1.95		1.78
Twi	2.62	2.62	2.62	2.62	2.51	2.62	2.42 4.98	1.88	1.66 3.10		1.88 1.21
Ukrainian Umbundu	5.75	5.75 2.24	5.75	5.75 2.24	3.00	5.75		1 70			
	2.24		2.24		2.01	2.24	2.07	1.78	1.63	2.73	1.57
Urdu Uyghur	6.30 7.16	6.30 7.16	6.30 7.16	6.30 7.16	4.39 $5.19$	6.30 7.16	7.74 8.68	_		_	1.23 1.41
Venetian	2.00	2.00	2.00	2.00	1.70	2.00	1.86	1.60			1.41
Vietnamese	4.54	4.54	4.54	4.54	2.45	4.54	4.12	1.00	1.47		
Waray	2.38	2.38	2.38	2.38	1.95	2.38	2.17	1.99			1.55
Welsh	2.34	2.34	2.34	2.34	2.12	2.34	2.24	2.01	1.83		1.43
West Central Oromo	2.53	2.53	2.53	2.53	2.32	2.53	2.32	2.07	1.93		1.78
Western Persian	5.32	5.32	5.32	5.32	3.28	5.32	7.38	2.01			1.10
Wolof	2.14	2.14	2.14	2.14	1.92	2.14	2.01	1.71	1.54		1.60
Xhosa	2.26	2.26	2.26	2.26	2.06	2.26	2.11	1.88			1.50
Yoruba	3.89	3.89	3.89	3.89	2.96	3.89	3.55		2.00		2.27
Yue Chinese	3.09	3.09	3.09	3.09	2.12	3.09	3.75	_			
Zulu	2.41	2.41	2.41	2.41	2.20	2.41	2.23	1.96			
						2.11	2.20	1.00	2.77	0.12	1.00

Language	M2M100	MBart50	mT5	FlanT5	ВуТ5	CANINE	BLOOM	ArabicBERT	MuRIL	UTF-32	BERT Japanese
Romanian	1.29	1.24	1.37	1.50	1.19	1.13	1.91	2.44	_	1.13	
Rundi	1.63	1.71	1.52	2.78	1.12	1.12	1.64	2.81	2.13	1.12	2.24
Russian	1.22	1.17	1.27	_	1.98	1.09	2.48	4.57	_	1.09	_
Samoan	1.80		1.92	3.09	1.22	1.16	2.13				
Sango	1.53		1.63	3.14	1.12	1.09	1.80		2.05	1.09	
Sanskrit	1.69		1.65	_	2.63	0.98	1.63	_		0.98	
Santali	_	_	_	_	2.79	1.06	12.71	_	_	1.06	
Sardinian	1.51	1.61	1.57	2.46	1.19	1.16	1.73	2.52	1.98		
Scottish Gaelic	1.61	1.75	1.85	3.24	1.28	1.24	2.25	2.86	2.27	1.24	2.22
Serbian	1.26	1.18	1.30	_	1.80	0.99	2.57	_	_	0.99	_
Shan	4.63	4.43	3.28	_	3.94	1.42	12.06	_	_	1.42	_
Shona	1.58	1.63	1.35	2.79	1.12	1.12	1.80	2.83	2.06	1.12	2.21
Sicilian	1.53	1.58	1.53	2.46	1.11	1.05	1.80	2.58	1.84	1.05	_
Silesian	1.59	1.65	1.57	2.87	1.10	1.04	2.16	2.77	_	1.04	_
Sindhi	1.30	1.28	1.74	_	1.60	0.91	2.51	_	1.22	0.91	_
Sinhala	1.53	1.35	1.66	_	2.64	1.00	8.21	_	_	1.00	_
Slovak	1.24	1.18	1.30	2.74	1.09	1.00	2.01	2.47	_	1.00	_
Slovenian	1.19	1.13	1.20	2.42	1.02	1.00	1.81	2.50	_	1.00	1.94
Somali	1.37	1.39	1.48	3.06	1.14	1.14	2.03	2.78	2.05	1.14	2.27
South Azerbaijani	1.50	1.43	1.42	_	1.63	0.89	1.81	2.03	1.72	0.89	_
South Levantine Arabic	1.22	1.12	1.24	_	1.49	0.83	1.12	1.01	1.82	0.83	_
Southern Pashto	1.40	1.38	1.64	_	1.66	0.95	2.55	_	_	0.95	_
Southern Sotho	1.60	1.78	1.59	2.92	1.21	1.20	1.96	2.93	2.16	1.20	2.30
Southwestern Dinka	1.55	1.68	1.58	_	0.96	0.86	1.82	_	_	0.86	_
Spanish	1.21	1.20	1.31	2.23	1.21	1.19	1.21	2.51	1.98	1.19	2.10
Standard Arabic	1.29	1.18	1.35	_	1.60	0.88	1.14	1.00	1.97	0.88	_
Standard Arabic (Romanized)	1.83	1.94	1.73	2.94	1.17	1.17	2.15	2.92	2.28	1.17	2.45
Standard Latvian	1.29	1.23	1.30	2.78	1.11	1.02	2.08	2.47	_	1.02	_
Standard Malay	1.00	0.95	1.11	2.32	1.12	1.11	1.07	2.53	1.80	1.11	2.03
Standard Tibetan	_	_	3.68	_	3.31	1.13	6.66	_	_	1.13	_
Sundanese	1.10	1.22	1.22	2.32	1.05	1.04	1.48	2.43	1.80	1.04	1.95
Swahili	1.20	1.16	1.25	2.66	1.05	1.05	1.24	2.64	1.86	1.05	2.13
Swati	1.44	1.61	1.41	2.80	1.12	1.13	1.83	2.84	2.09	1.13	2.26
Swedish	1.10	1.07	1.11	2.22	1.04	1.01	1.65	2.20	1.90	1.01	1.79
Tagalog	1.43	1.43	1.46	2.85	1.26	1.26	1.85	2.84	2.08	1.26	2.39
Tajik	2.06	2.14	1.62	_	2.01	1.11	3.29	4.36	_	1.11	_
Tamasheq (Latin script)	1.57	1.71	1.64	2.55	1.01	0.95	1.90	_	_	0.95	_
Tamasheq (Tifinagh script)	_	_	3.59	_	2.29	0.94	7.74	_	_	0.94	_
Tamil	1.55	1.35	1.26	_	3.17	1.17	1.27	_	1.06	1.17	_
Tatar	1.54	1.81	1.41	_	1.85	1.01	3.15	_	_	1.01	_
Ta'izzi-Adeni Arabic	1.28	1.17	1.32	_	1.58	0.87	1.15	1.01	1.94	0.87	_
Telugu	_	1.33	1.42	_	2.68	1.01	1.33	_	1.21	1.01	_
Thai	1.27	1.08	0.99	_	2.75	0.96	4.63	_	_	0.96	_
Tigrinya	1.91	1.97	2.03	_	1.75	0.69	5.16	_	_	0.69	_
Tok Pisin	1.65		1.65	2.76	1.28	1.28	1.92	2.94	2.10	1.28	2.35
Tosk Albanian	1.36	1.32	1.48	3.09	1.20	1.12	2.17	2.66	2.52	1.12	_
Tsonga	1.69	1.79	1.61	3.13	1.20	1.20	2.01	3.01	2.19	1.20	2.46
Tswana	1.68	1.85	1.68	3.01	1.25	1.25	2.02	2.95	2.25	1.25	2.35
Tumbuka	1.88	1.92	1.61	3.29	1.32	1.30	2.19	3.27	_	1.30	_
Tunisian Arabic	1.29	1.20	1.29	_	1.54	0.85	1.19	1.04	1.90	0.85	_
Turkish	1.15	1.04	1.12	2.67	1.12	1.03	1.96	2.65	_	1.03	_
Turkmen	1.71	1.78	1.68	2.87	1.17	1.06	2.19	2.63	_	1.06	_
Twi	1.74	1.88	1.71	2.85	1.05	0.98	1.81	_	_	0.98	2.08
Ukrainian	1.28	1.21	1.33	_	1.86	1.02	2.75	4.28	_	1.02	_
Umbundu	1.49	1.57	1.47	2.72	1.05	1.01	1.74	2.66	1.94	1.01	1.99
Urdu	1.30	1.23	1.52	_	1.76	0.99	1.36	2.65	1.26	0.99	_
Uyghur	3.00	1.41	2.57	_	1.97	1.07	3.67	_	_	1.07	_
Venetian	1.31	1.36	1.36	2.21	1.06	1.01	1.57	2.27	1.84	1.01	1.84
Vietnamese	1.15	1.18	1.95	_	1.39	1.05	1.27	2.52	_	1.05	_
Waray	1.45	1.55	1.45	2.66	1.25	1.25	1.80	2.91	2.15	1.25	2.26
Welsh	1.44	1.43	1.70	3.12	1.07	1.07	2.09	2.83	2.32	1.07	2.20
West Central Oromo	1.49	1.78	1.69	3.16	1.20	1.19	2.19	2.98	2.17	1.19	2.44
Western Persian	1.17	1.10	1.34	_	1.70	0.94	1.78	2.03	1.62	0.94	_
Wolof	1.40	1.60	1.44	2.62	1.00	0.96	1.68	2.34	1.93	0.96	1.88
Xhosa	1.37	1.50	1.35	2.73	1.06	1.06	1.67	2.78	2.05	1.06	2.17
								2.22		0.0=	
Yoruba	1.74	2.27	2.06	_	1.28	0.97	1.64	2.26	_	0.97	_
Yoruba Yue Chinese	1.74 1.03		$\frac{2.06}{0.95}$	_	1.28 0.87 1.12	0.97 $0.31$	0.93		_	0.97 $0.31$	