Do All Languages Cost the Same? Tokenization in the Era of Commercial Language Models

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Abstract

Language models have graduated from being research prototypes to commercialized products offered as web APIs, and recent works have highlighted the multilingual capabilities of these products. The API vendors charge their users based on usage, more specifically on the number of "tokens" processed or generated by the underlying language models. What constitutes a token, however, is training data and model dependent with a large variance in the number of tokens required to convey the same information in different languages. In this work, we analyze the effect of this non-uniformity on the fairness of an API's pricing policy across languages. We conduct a systematic analysis of the cost and utility of OpenAI's language model API on multilingual benchmarks in 22 typologically diverse languages. We show evidence that speakers of a large number of the supported languages are overcharged while obtaining poorer results. These speakers tend to also come from regions where the APIs are less affordable to begin with. Through these analyses, we aim to increase transparency around language model APIs' pricing policies and encourage the vendors to make them more equitable.

1 Introduction

Language models (LMs) have come to be known as general-purpose solutions capable of performing many tasks by following natural language instructions (Brown et al., 2020; Ouyang et al., 2022; Chung et al., 2022), and generalizing to new tasks at test time using a handful of demonstrations (Brown et al., 2020; Su et al., 2023). Motivated by their potential for commercial use, many industrial research institutions have moved away from openly releasing them (Abdalla et al., 2023). Instead, a new business model of LM as a Service (Sun et al., 2022) has emerged where LMs

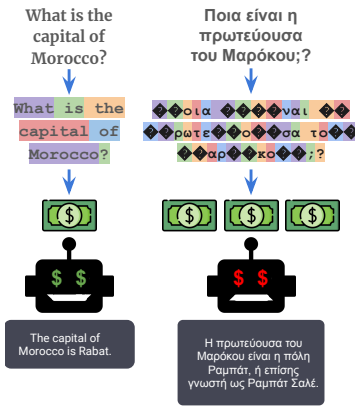


Figure 1: We investigate the effects of subword tokenization in LLMs across languages with different writing systems. Our findings highlight disparities in the utility of LLMs, as well as socio-economic disparities and increased costs in using commercial APIs for speakers of underrepresented languages. [1]

can be accessed for inference using (paid) web APIs. The majority of these models (Ouyang et al., 2022) offer multilingual capabilities, and the API providers charge the users proportionally to the number of tokens processed or generated.

In this work, we examine the fairness of this pricing model for different languages, based on how a "token" is defined in practice. Most LMs rely on tokenizers that split text strings into chunks (subwords). Subword tokenizers (Mielke et al., 2021; Sennrich et al., 2016; Kudo, 2018; Song et al., 2020) are typically data-driven and learn to split text based on frequency patterns of characters or bytes in some corpus.

Prior work has argued that, in multilingual settings, subword tokenizers lead to disproportionate fragmentation rates for different languages and writing scripts (Zhang et al., 2022a; Rust et al., 2021; Muller et al., 2021). Many commercial language models are multilingual, and text from languages that suffer from excessive fragmentation will be represented using more tokens. This directly

[1]OpenAI's tokenizer interface displays byte tokens absent from their vocabulary as "?".

increases cost of API usage for certain language speakers, even if they convey the same information as others.

We highlight this unfairness through three stages of systematic analyses. First, we show evidence that tokenizers of popular LMs indeed over-fragment texts in certain languages and scripts. We quantify the API cost disparity that this issue causes. We discover that this disparity is not caused just by data imbalance, but is rooted in inherent properties of the languages or the ways they are represented in Unicode. Second, we show that languages that have longer token lengths as a result of greater fragmentation derive less model utility with in-context learning (Brown et al., 2020).

Finally, we find that languages that cost more and perform worse are often associated with populations of speakers for whom the APIs are less affordable on average, exacerbating the economic divide in the accessibility of NLP technology.

Through these analyses, we argue that commercial LM API vendors should revisit their processing and pricing strategies to be more equitable. In addition, we encourage the NLP community to pay better attention to tokenizers, an often neglected part of the LLM pipeline.

2 Do All Languages Cost the Same?

2.1 Background

Language Model APIs Autoregressive language models are trained to predict the next "token" given a previous context. Following the success of such models, many commercial LM web APIs have emerged and allow users to interface with the models using natural language instructions to perform various tasks with little to no exposure to the underlying workings of the models. The API providers often support dozens of languages and charge users[2] at a fixed rate based on the total number of input and generated tokens.[3]

What constitutes a "token," however, is not a universally accepted definition but a design choice that the model developers make. The total token count is also not immediately obvious to users except through a tokenizer interface[4] separate from the chat interface.

[2]While most services also have free tiers, they limit daily usage to a small number of tokens per use.

[3]e.g. see OpenAI models' cost: https://openai.com/pricing.

[4]https://platform.openai.com/tokenizer

Tokenization in LMs Tokenization—segmenting text into atomic units—is an active research area. Proposed approaches range from defining tokens as whitespace-delimited words (for languages that use whitespace) which makes the vocabulary extremely large, to defining tokens as characters or even bytes, which makes the tokenized sequences extremely long in terms of number of tokens; see Mielke et al. (2021) for a detailed survey. A commonly-used solution now is to tokenize text into *sub*word chunks (Sennrich et al., 2016; Kudo, 2018; Song et al., 2021). With Sennrich et al. (2016), one starts with a base vocabulary of only characters and adds new vocabulary items by recursively merging existing ones based on their frequency statistics in a training corpus. Other approaches judge subword candidates to be included into the vocabulary using a language model (Kudo, 2018; Song et al., 2021). For multilingual models containing data in a variety of scripts, even the base vocabulary of only characters (based on Unicode symbols) can be very large with over 130K types. Radford et al. (2019) instead proposed using a byte-level base vocabulary with only 256 tokens. Termed byte-level byte pair encoding (BBPE), this approach has become the de facto standard used in most modern language modeling efforts (Brown et al., 2020; Muennighoff et al., 2022; Scao et al., 2022; Black et al., 2022; Rae et al., 2022; Zhang et al., 2022b; Dey et al., 2023; Nagoudi et al., 2022; Zhang et al., 2022b).

In this work, we investigate the impact this tokenization strategy has on LM API cost disparity as well as downstream task performance (i.e., utility) across different languages.

2.2 Investigating the Impact of Byte-level Subword Segmentation

There are hundreds of distinct writing systems in the world. BBPE, by design, makes vocabulary construction script-agnostic, even allowing (in principle) new scripts to be supported later on without modifying the vocabulary. However, not only are different scripts encoded differently, their distribution in the training corpora varies widely. To investigate the effects of this variation, we propose the following research questions as the main focus of this work.

RQ1 (number of tokens): do all languages convey the same information with the same number of tokens? We analyze the fragmentation

of sequences in different languages with different tokenizers. We find that among the supported languages in popular LLMs, there is a large variance in the average number of tokens required to convey the same information with some languages requiring 5 times as many tokens than others. Previous work has shown that tokenization in multilingual models is usually biased towards high-resourced languages in the pretraining data (Ács, 2019; Rust et al., 2021); we observe that this is not always the case, but it could also be dependent on linguistic features or properties of language scripts.

RQ2 (cost): do non-uniform tokenization rates lead to LM API cost disparity for speakers of different languages? LM APIs like ChatGPT are available worldwide and have been widely claimed to have multilingual capabilities (Kasai et al., 2023; Lai et al., 2023).[5] We show that disparate fragmentation rates in different languages can lead to significantly high usage costs for less represented languages and argue for a more equitable API pricing system.

RQ3 (model utility): do non-uniform tokenization rates affect the models' utility? LMs have exhibited in-context learning capabilities, performing new tasks with a few demonstrations as input (without parameter finetuning). This is a highly desirable property in any LM API as it avoids computational, annotation (and thus financial) costs. We show that the high fragmentation rate of a language can negatively affect the in-context learning performance in that language, resulting in reduced model utility.

RQ4 (socio-economic aspects): what are the socio-economic implications of the API's cross-lingual cost and performance disparity? Our analysis shows evidence that not only are LMs more expensive for certain languages, they are also less effective for them. To highlight the implications of these findings, we correlate those measurements with the socio-economic indicators of language speakers as a proxy for affordability of the APIs. This analysis indicates that *users who likely cannot afford high API costs are charged more for poorer service*, hindering uniform accessibility of this technology.

[5] https://help.openai.com/en/articles/6742369-how-do-i-use-the-openai-api-in-different-languages

3 Experimental Setup

3.1 Models

Throughout this work, we focus on two language models: ChatGPT (Ouyang et al., 2022; Brown et al., 2020) (gpt-3.5-turbo) and BLOOMZ (Muennighoff et al., 2022). Both of these models are trained and advertised as general-purpose models capable of following instructions and performing a wide range of tasks (Bang et al., 2023; Qin et al., 2023; Zhu et al., 2023b; Ahuja et al., 2023; Huang et al., 2023; Zhu et al., 2023a).

ChatGPT (Ouyang et al., 2022) is a closed model only accessible through an API (with a premium tier) provided by OpenAI. Studies report that it supports as many as 90 languages (Ahuja et al., 2023). ChatGPT can handle a maximum sequence length of 4096 tokens (including both the prompt and generated tokens).

BLOOMZ (Muennighoff et al., 2022) is an open-source multilingual model trained on 46 natural languages and 13 programming languages. The best-performing version of this model has 175B parameters and is not feasible to be loaded on our academic servers; hence we rely on a free API of BLOOMZ hosted by Huggingface.[6] Although BLOOMZ was trained with ALiBi positional embeddings (Press et al., 2022) which allows the model to extrapolate to any length sequences during inference, the Huggingface API has a context limit of 1000 tokens.

3.2 Tasks and Datasets

To answer RQ1—whether the same information is conveyed with similar numbers of tokens in different languages—we use a subset of FLORES-200 (Goyal et al., 2022), a multilingual parallel corpus containing examples in over 200 languages.[7] We tokenize each sentence in the FLORES-200 subset with ChatGPT's tokenizer[8] and compute the average number of tokens per sentence for each language. Using parallel data controls for the same information across languages. We consider that language A is more efficiently tokenized than language B if it uses fewer tokens per sentence on average. While previous studies have computed fragmentation rates with fertility (Ács, 2019), we

[6] https://huggingface.co/docs/api-inference/quicktour.

[7] We also experimented with WMT 2021 data (Akhbardeh et al., 2021) and found similar results. Note that the WMT data are focused on European languages.

[8] see ChatGPT's tokenizer https://github.com/openai/tiktoken

instead define it as the average number of tokens in a sequence for two reasons. First, our goal is to compare LLM API costs across languages that charge users based on the number of tokens. To control for content, we use a parallel corpus for this analysis. Second, many languages we analyze are understudied and do not have word tokenizers available which are required to compute fertility.

For RQ2 and RQ3, to clearly highlight the cost and utility disparities, we evaluate the models on NLP tasks that involve long-form texts either at input or output. We evaluate the models on diverse, challenging natural language generation and classification tasks on the following benchmarks:

Classification We evaluate on (1) XNLI (Conneau et al., 2018): a cross-lingual inference benchmark comprising of 11 typologically diverse languages. It involves two sub-tasks, passage selection and minimum answer span (Gold-P). We focus on the latter task in our experiments. (2) XFACT (Gupta and Srikumar, 2021): a multilingual fact verification dataset of naturally existing real-world claims covering 25 languages.

Span Prediction We use XQUAD (Artetxe et al., 2019): a crosslingual question-answering dataset where each example consists of a paragraph, a question, and the answer as a span in the paragraph.

Generation We evaluate on (1) Cross Sum (Hasan et al., 2021a): a cross-lingual abstractive summarization dataset comprising 1.7 million article-summary samples in 1500+ language pairs, and, (2) XLSUM (Hasan et al., 2021b): a summarization dataset covering 44 typologically diverse languages. The dataset comprises news articles and summaries in the same language as the article.

3.3 Prompting Formulation

We evaluate both models in a k-shot in-context learning setup where we also provide task instructions. We experiment with $0 \leq k \leq X$, where X is the maximum number of in-context examples that can be provided. Note that X is not a fixed value, but is determined by the language model API's limit on the number of input tokens and the fragmentation rate of the language.

For all tasks, we provide the instructions in English following Ahuja et al. (2023), who show that on several multilingual benchmarks, English instructions outperform the in-language prompts (see Table 2 in the Appendix for the prompting format for all tasks). For each task, we randomly sample at most 500 test examples for evaluation.

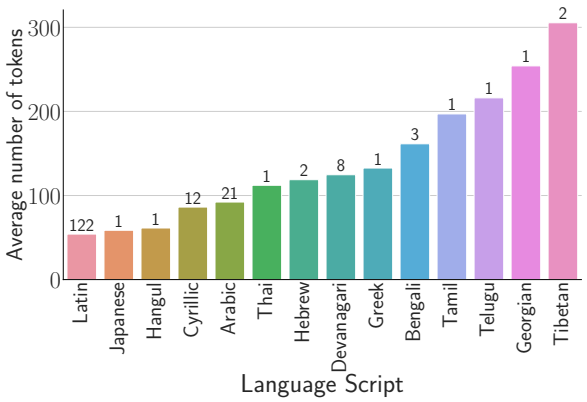


Figure 2: Average number of tokens by script after tokenizing the Flores dataset. The fragmentation rate is lower for Latin script languages and higher for other scripts. Number of languages per language group is indicated at the top of each bar.

4 Results and Analysis

4.1 RQ1 (number of tokens): do all languages convey the same information with the same number of tokens?

In Figure 2 we show that Latin-script languages are represented with substantially fewer tokens compared to languages in other scripts. While Cyrillic and Japanese script languages come close to the Latin script, languages that have their own script, e.g. Telugu and Georgian, require up to 5× more tokens to convey the same information. We hypothesize that this disparity is due to training data imbalance since ChatGPT's tokenizer was primarily trained with Latin-script languages, mainly English. The training details of ChatGPT are not available. However, we make a reasonable assumption that its training dataset has a similar proportion of languages as the publicly available large corpus CC100 (Wenzek et al., 2020). If we sort languages shown in Figure 2 based on their data size in CC100 (see Figure 14 in the Appendix), low-resourced languages of Latin script appear to be less fragmented compared to other mid-resourced languages of non-Latin scripts. In Figure 15 in the Appendix, we present a similar analysis for BLOOMZ's tokenizer. We sort the languages based on their size in the pretraining data (ROOTS corpus; Laurençon et al., 2023). We observe that languages with fewer resources generally have a higher av-

erage token length. Arabic is an outlier here as it appears to be have more tokens than some other mid-resourced languages.

What influences the non-uniformity of a tokenizer across languages? From our analysis above, we identify two influential factors: (1) the proportion of the language in the pretraining data, and (2) inherent properties of the language and its writing script. While we see some correlation between pretraining data size and fragmentation rate in BLOOMZ, with ChatGPT it is quite different as higher-resourced non-Latin script languages still get excessively tokenized.

To disentangle the effects of factors (1) and (2) we train BBPE tokenizers on a variety of languages with diverse scripts with vocabulary sizes ranging from 5,000 to 50,000, while controlling for content and data size. Specifically, we train the tokenizers on parallel corpora and include one language per script. We then use these tokenizers to tokenize the text they were trained on, and compute the average number of tokens per sentence.

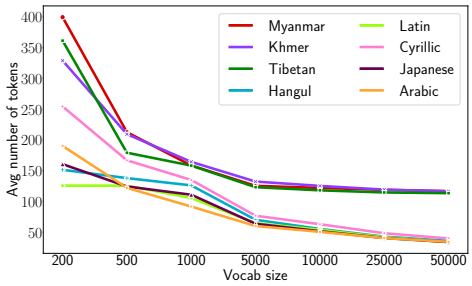


Figure 3: BBPE tokenizer trained on parallel text from different language scripts with varying vocabulary sizes. We display a larger version with 21 more scripts in Figure 18 in the Appendix.

As shown in Figure 3 , even when controlling for the content, there is still a disparity in the tokenization rate at different vocabulary sizes. In particular, most scripts are very sensitive to smaller vocabulary sizes compared to Latin and Hangul scripts. We could not achieve uniform fragmentation rate across all language scripts even with large vocabulary sizes. We, therefore, conclude that uniformity of BBPE tokenizers across languages is not just determined by the proportion of text from language in the pretraining data but also by language/script properties.

4.2 RQ2 (cost): how do non-uniform tokenization rates affect LM API costs for different languages?

LM APIs charge users a fixed amount for a given number of input and generated tokens. Since the same information is expressed using different number of tokens in different languages, we aim to investigate the disparity in what users pay to use the API for different languages. From the results of our analysis in §4.1, we compute the estimated cost of API use per language as a function of the average sequence length derived in Figure 2. We report this on a subset of languages in Figure 16 in the Appendix and present a granular analysis of languages that share family and script in Figure 4.

Languages that are more heavily segmented have predictably higher costs of usage. Overall, we see that the API costs are biased towards (i.e., cheaper for) Indo-European and Latin script languages and against many non-Latin script languages. In most mid-resourced Indic languages with non-Latin scripts, we see close to a 5× increase in cost compared to English.

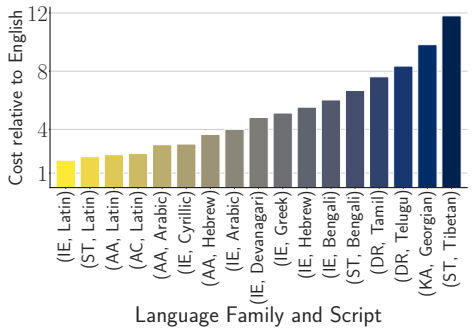


Figure 4: Estimated cost per language family/script, relative to English. The language families are abbreviated as follows: IE: Indo-European, ST: Sino-Tibetan, AC: Atlantic-Congo, AA: Afro-Asiatic, DR: Dravidian, KA: Kartvelian.

Next, we report the costs of running experiments relative to English. We report costs based on our zero-shot experiments across all tasks listed in §3.2. This is due to excessive tokenization in some languages for which we can only do zero-shot evaluations. For XLSUM, we show in Figure 5 that we spend up to 4× more for both prompting and generation in Telugu and Amharic. We observe similar findings in XFACT and CROSSUM, as displayed in Figure 11 in the Appendix.

While the majority of the commercial LMs are perhaps being optimized to perform well in many

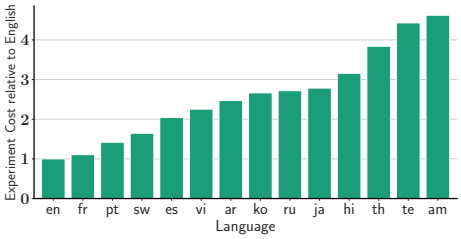


Figure 5: Average cost of prompt + generated tokens for XLSUM evaluations relative to English.

languages, we show that there is less focus on the individual experiences of speakers of languages other than English. While a language model like ChatGPT might perform tasks in Telugu, for example, a user in Andhra Pradesh might have to pay 5× more than an English user in the US would pay for an equivalent use of the model.

4.3 RQ3 – Model utility: do non-uniform tokenization rates affect the models' utility?

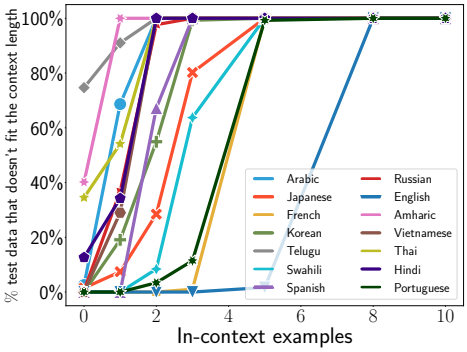


Figure 6: Percentage of test examples per language in XLSUM that do not successfully fit into the context length of ChatGPT. We can fit more few-shot examples in Latin script languages than in other languages.

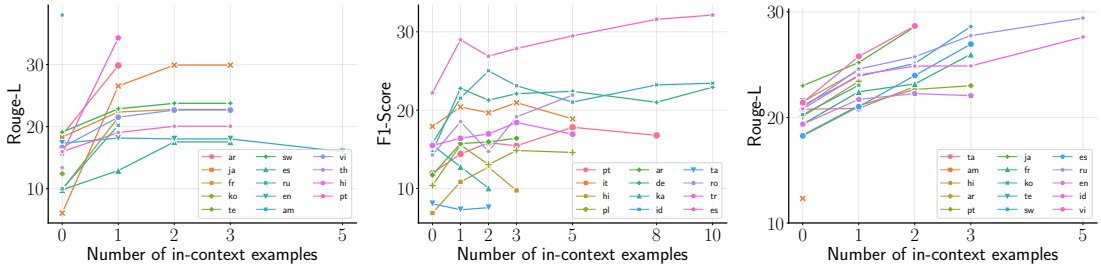
LM APIs typically have an upper bound of the number of tokens they can handle, e.g., ChatGPT can process a maximum of 4,096 tokens. Hence, due to non-uniform fragmentation rates across languages, there is a disparity in the amount of information the models can process in different languages. As an illustration, in Figure 6 we plot the percentage of XLSUM test examples against the minimum number of in-context examples those test examples can be accompanied with.

For example, we find that Telugu and Amharic struggle to fit even one in-context example for the majority of their test set. As a result, the model is only capable of zero-shot prompting for these two languages.

To measure the impact of this issue on task performance, we evaluate ChatGPT and BLOOMZ with a k-shot learning setup on the 5 tasks on diverse languages as described in §3.2. Figure 7 shows ChatGPT's performance according to standard automatic metrics of all tasks. Note that the focus of this experiment is to illustrate the impact of tokenization in in-context learning settings. Therefore, we are interested not in the absolute value of the metrics or comparisons among languages but the relative improvement within the test sets of the same language as we increase the number of in-context examples. For all tasks and most languages, we see consistent performance improvements as we increase the number of in-context examples, from zero-shot to k (even for $k = 1$). For many languages such as Telugu and Thai , due to their high fragmentation rates, we were unable to fit even one complete demonstration and hence, only report zero-shot results. Based on trends from other languages, we suspect that these languages could also have benefitted from more demonstrations. Hence, as a result of unfair tokenization, ChatGPT's utility is much lower for speakers of those languages compared to better represented languages like English.

Figure 9 reports the results of the same experiment for BLOOMZ. Here, across all tasks we find that adding in-context examples does not help at all. In fact, in some cases, there is a drastic drop in performance even with one in-context example. Upon manual inspection of the model generated outputs from the one-shot experiments, the model has a tendency to copy spans from the in-context example, presenting that as output and thus not successfully utilize demonstrations. Our hypothesis here is that BLOOMZ is better optimized for zero-shot prompting and is not suitable for in-context learning.

Due to the limited number of tokens that the BLOOMZ's inference API accepts, some examples in some languages cannot fit the 1000 token context length when doing zero-shot prompting. We experienced this with the XLSUM dataset as we couldn't fully fit news articles for some languages. Understandably, some of these languages are not even present in its pretraining data, and hence we do not expect them to be tokenized efficiently. For these examples that do not fit the context length, we feed in truncated news articles into the model. We therefore evaluate the generations for the frac-



(a) XLSUM (b) XFACT (c) CROSS-SUM

Figure 7: Results from ChatGPT few-shot evaluations. In most tasks, we see a significant increase in performance as we increase the number of in-context examples.

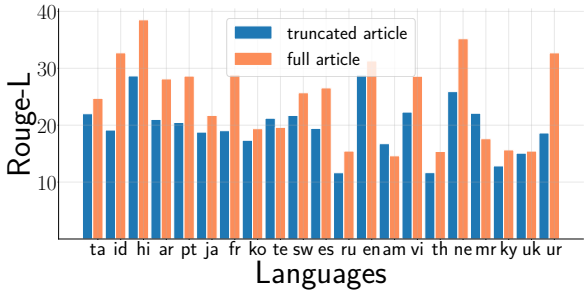


Figure 8: Zero-shot evaluation of BLOOMz on XLSUM. Since, we cannot fit the full article in the context length for some languages, we compare results on evaluating full articles vs. truncated articles.

Task	Cost-HDI		HDI-Utility		Cost-Utility	
	Spearman	Pearson	Spearman	Pearson	Spearman	Pearson
XFACT	**–0.41	**–0.60	*0.34	**0.38	**–0.61	**–0.55
XLSUM	**–0.42	**–0.43	**–0.44	**–0.57	*–0.23	*0.21
CROSS SUM	**–0.41	**–0.45	*–0.18	*0.24	*0.27	*–0.17

Table 1: Correlation between model utility, cost of API access and Human Development Index for each task. We mark correlations with $p < 0.05$ with * and also mark correlations with $p < 0.0056$ (according to Bonferroni correction for multiple hypotheses) with **.

tion of examples that fit context and ones that do not fit the context separately. Figure 8 shows the performance comparison when we use truncated summaries in the prompt and when we use the full articles. While the performance drop is expected, our focus here is to highlight a consequence of differentiated tokenization in language models.

4.4 RQ4 – Socio-economic aspects: what are the socio-economic implications of the API's cross-lingual cost and performance disparity?

In Figure 10, we plot the fragmentation rate per language against the Human Development Index in the top country where the language is spoken.[9] We find a strong negative correlation, showing that in most cases, the lower the HDI index, the higher the fragmentation rate and vice versa. Evidently, the model's vocabulary is biased towards users of more developed countries.

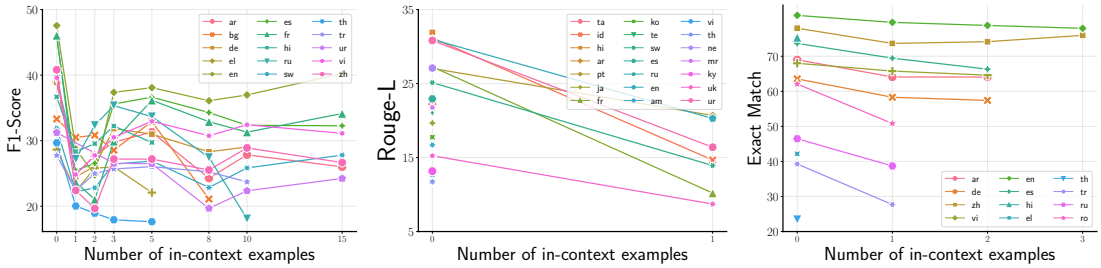
This bias is further validated by results shown in Table 1 where we mostly find negative correlations between pairs of each of the following variables: average financial cost of experiments, model utility (performance), and human development index of the country in which each language is spoken. We term this doubled unfairness as people from less economically developed countries are overcharged at a fixed rate per-token due to excessive tokenization, but often derive lesser utility from the model.

5 What is the Way Forward?

Transparency in API limitations While the NLP community is aware of many of the issues we point out in this work, LM APIs are advertised to a general audience. Much like the policy of adding limitations to research papers, LM API providers ought to be more transparent about the flaws and biases in their models, especially when describing their multilingual capabilities. Many users are not privy to the inner workings of these models and can thereby be unfairly charged higher prices if they use the model in their native languages.

Rethinking the API pricing models Higher API costs for certain languages in underprivileged communities risks excluding many populations from using language technologies. A potential solution is to develop pricing policies based on languages/regions while also accounting for model performance on language-specific benchmarks. An

[9] HDI is a composite of life expectancy, education, and income per capita indicators, used to rank countries into tiers of human development.



(a) XNLI (b) XLSUM (c) XQUAD

Figure 9: Results from BLOOMz few-shot evaluations. The BLOOMz model is clearly better at zero-shot prompting than few-shot.

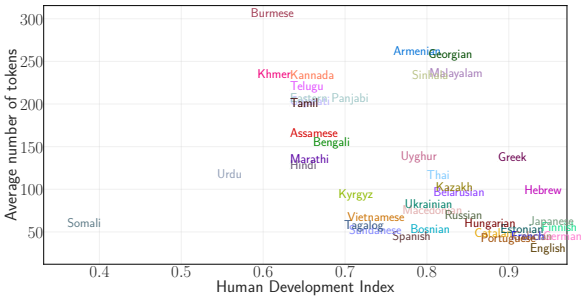


Figure 10: Fragmentation rate per language against the Human Development Index in the top country where the language is spoken.

alternative is to not charge by tokens at all. A recently released beta of PaLM 2 API, for example, charges the users based on characters.[10] Hence, further analysis is needed to assess the fairness of character-based pricing. Huggingface also offers an inference service for their enterprise customers[11] relying on AWS instances and charging them at an hourly rate. Future work may compare this with a per-token rate we study in this work.

Open-source models vs. paid APIs Given issues with paid APIs, the natural next question might be: should the API users move to open-source models or train their own? In fact, in our experiments, we find BLOOMZ, an open-source model, to perform better in the zero-shot setting than ChatGPT performs in the few-shot setting, in most cases. However, first, most open-source models are distributed under an academic license whereas most developers are interested in integrating these technologies into their products for commercial use, which may incur licensing costs. Second, barring licensing issues, language models tend to be large and resource-intensive to train and deploy and require dedicated expensive hardware to run at a commercial scale, which again might not be possible for most developers and users, even exceeding the cost of using the APIs. Research on reducing such hardware requirements (Dettmers et al., 2022; Park et al., 2023; Yao et al., 2022) could increase accessibility. Still, this would require a considerable level of technical expertise from developers and users which might be infeasible.

Technological improvements in language models Several solutions proposed in recent work to improve language modeling performance can help alleviate the cost and utility issues we highlight. Tokenization is an active area of research and various solutions based on data balancing (Johnson et al., 2017; Conneau and Lample, 2019), optimal transport (Xu et al., 2021), fuzzy subwords (Provilkov et al., 2020) , and many more (Chung et al., 2020; Tay et al., 2022) have been proposed. BLOOMZ, for instance, relies on data balancing to improve fragmentation rates across languages. Some work has also focused on increasing the context lengths of language models (Bulatov et al., 2023; Press et al., 2022; Ainslie et al., 2023) which can help alleviate issues with utility by allowing more in-context examples as input.

6 Related Work

Analyzing Tokenization methods The impact of tokenization on model performance has been widely studied (Ács, 2019; Rust et al., 2021; Zhang et al., 2022a; Klein and Tsarfaty, 2020; Bostrom and Durrett, 2020; Kamali et al., 2022). Prior works have also investigated the role of tokenization in inference speed and memory usage of LMs

[10] Prior work has shown evidence that even the number of characters used to express the same information in different languages is variable (Farb, 1974; Neubig and Duh, 2013)

[11] https://huggingface.co/pricing#endpoints

in practical settings (Sun et al., 2023; Hofmann et al., 2022). Ács (2019) analyzes mBERT's tokenizer (Devlin et al., 2019) and discover that Indo-European languages largely dominate its vocabulary. Rust et al. (2021) find that monolingual models perform better than mBERT (Devlin et al., 2019) because some languages suffer from over-fragmentation. Zhang et al. (2022a) find that sentence-level MT models are not particularly sensitive to language imbalance in their tokenizer training data. Sun et al. (2023) analyze multilingual tokenizer-free and subword-based models and find that subword-based models achieve better performance while reducing inference latency and memory usage. In contrast to prior work, our focus is on the cost and performance analysis of multilingual LM APIs across languages with regard to over-fragmentation and in-context learning.

Socio-Economic Impacts of Language Models Prior research has shown that unfairness in LMs can be a consequence of different stages in the model's development pipeline (Cao and Daumé III, 2020; Talat et al., 2021). Many efforts have been directed towards identifying social biases in language model generations (Wolfe and Caliskan, 2021; Dev et al., 2022; Sheng et al., 2021; Chen et al., 2021; Hutchinson et al., 2020). Other works have surfaced the cultural and language disparity beyond and within multilingual language models (Gururangan et al., 2022; Kreutzer et al., 2022; Virtanen et al., 2019). Talat et al. (2022) discuss various challenges that impact bias evaluation in multilingual settings. They also examine the power dynamics and consequences of training language models emphasizing the importance for researchers to be mindful of the implications associated with the advancement of such technologies. In this work, we study the economic unfairness of LMs across different communities. The most closely related to our work is Kasai et al. (2023) which also report unfair API costs as a result of tokenization differences between English and Japanese. We extend this analysis to 21 more languages highlighting the pervasiveness of this issue.

7 Conclusion

By analyzing popular language model APIs on challenging multilingual benchmarks, we find that (a) API tokenizers disproportionately favor Latin scripted languages and over-fragment less represented languages and scripts, (b) the API pricing policy of charging based on the number of tokens is flawed and extremely unfair towards speakers of the over-fragmented languages, and (c) the API performs poorly on such languages compared to the less-fragmented counterparts. In the current NLP research landscape, where more and more industrial labs are building their own APIs, this is a concerning trend that may reduce the accessibility of these technologies to already marginalized communities. Hence, we encourage the vendors to be more transparent about their models' limitations and rethink their pricing policy.

Ethics Statement

This work sheds light on the consequences of unfair tokenization to users of commercial LM APIs that speak languages with scripts less represented in the pretraining data. With the recent widespread use of commercial LMs, we believe that our work is crucial to ensuring that language technologies are accessible to diverse users irrespective of the languages they speak.

There are different factors that contribute to non-uniform tokenization across languages. Whilst our analysis touches on the size of pretraining data and language writing systems we suspect that there might be other factors not yet uncovered; we leave that for future work. The lack of access to OpenAI's training data prevents us from making solid claims about all the languages that ChatGPT is optimized for; however, their models have been advertised and shown to work well in many languages. More work on large multilingual models should include the release of (details of) training data to further enable this kind of research.

Limitations

Translationese We conduct the analysis to answer RQ1 using a parallel corpus, FLORES-200 (Team et al., 2022), in order to control for the same information. This corpus consists of many examples that have been professionally translated. Prior studies have shown that translated texts in any language (referred to as translationese) may differ from original written text in many ways (Laviosa, 2002). These may have caused the information conveyed in different languages to not be exactly the same. We do not have a way to measure these differences. However, we expect them not to be significantly large so as to meaningfully affect the trend of fragmentation rates.

Language statistics of ChatGPT training data ChatGPT is a closed model developed by OpenAI who have not released the training details of the model including any information of the languages it supports [12]. Hence, we cannot ascertain the actual statistics of all the languages in their training data. We use CC100 (Wenzek et al., 2020), a large multilingual corpus, to estimate these statistics.

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[12]The only official information they provide about ChatGPT's multilingual support is here: https://help.openai.com/en/articles/6742369-how-do-i-use-the-openai-api-in-different-languages. Prior studies have speculated that ChatGPT was trained on at least 90 languages (Ahuja et al., 2023)

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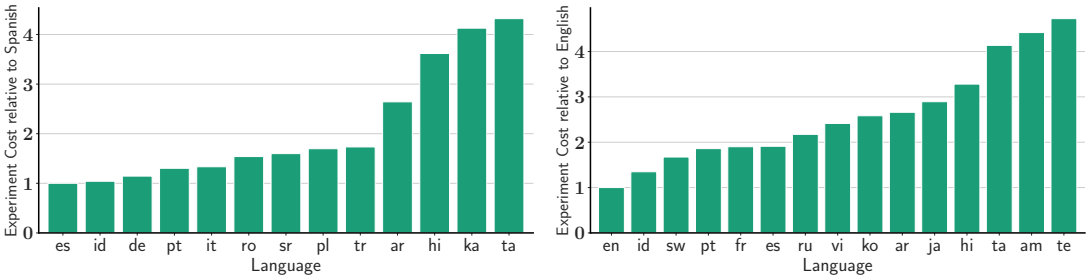
A Appendix

Task	Prompt Template
XLSUM	Write a short summary sentence of the following text in {language} Article: { article} Summary:
XQUAD	Context: context Question: question Answer: Template
XNLI	{Premise} Question : {hypothesis} True, False, or Neither? Answer:
CROSSUM	Write a short summary sentence of the following text in English. Article: { article} Summary:
XFACT	Tell me whether the following claim is {label 1 } or {label 2 } or {label 3 } ... given evidence {evidence 1 }, {evidence 2 }, {evidence 3 }

Table 2: Prompt template used for each dataset



(a) XFACT (b) CROSSUM

Figure 11: Relative cost of prompt + generated tokens for XFACT and CROSS-SUM evaluations.

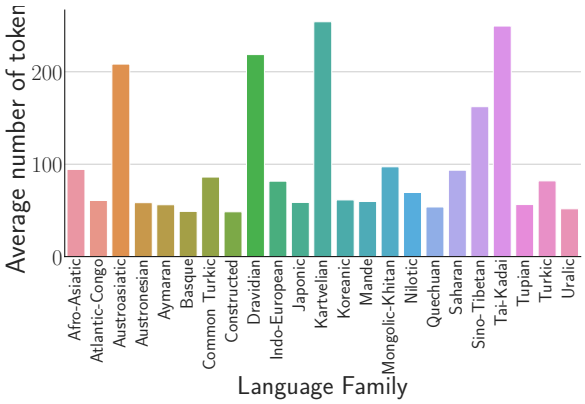


Figure 12: Average number of tokens per language family after tokenizing Flores dataset with GPT3.5 tokenizer. The fragmentation rate is lower for Latin script languages and higher for other scripts.

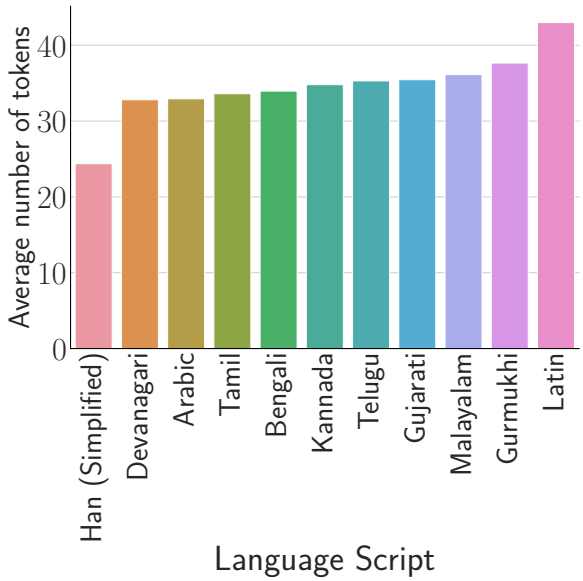


Figure 13: Average number of tokens per language script after tokenizing Flores dataset with BLOOM tokenizer. The fragmentation rate is higher on average for Latin script languages. This is because majority of the low-resourced languages are latin-script and have higher fragmentation rate.

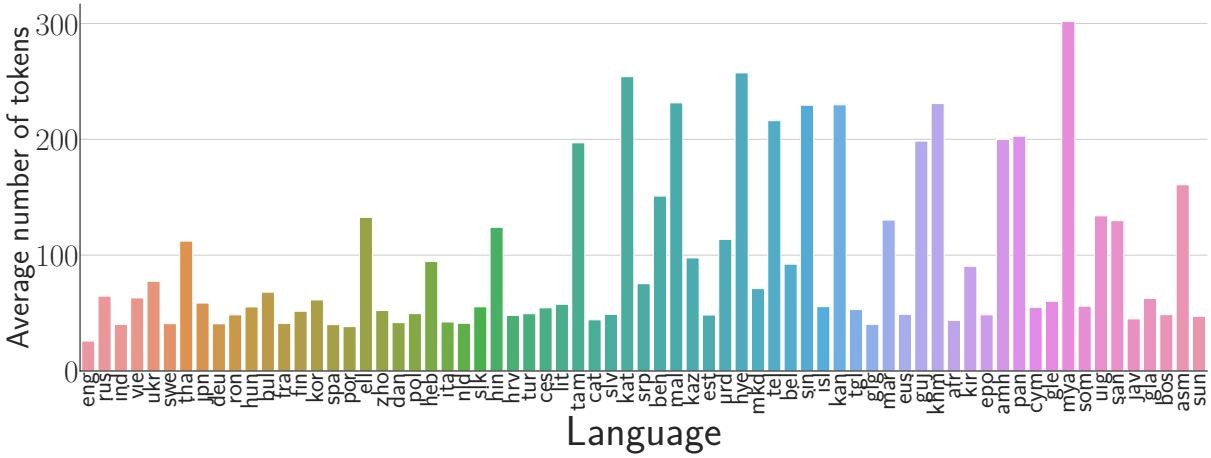


Figure 14: Average number of tokens per language after tokenizing FLORES with GPT3.5 tokenizer. Languages are arranged in descending order based on the size of pretraining data in Commoncrawl.

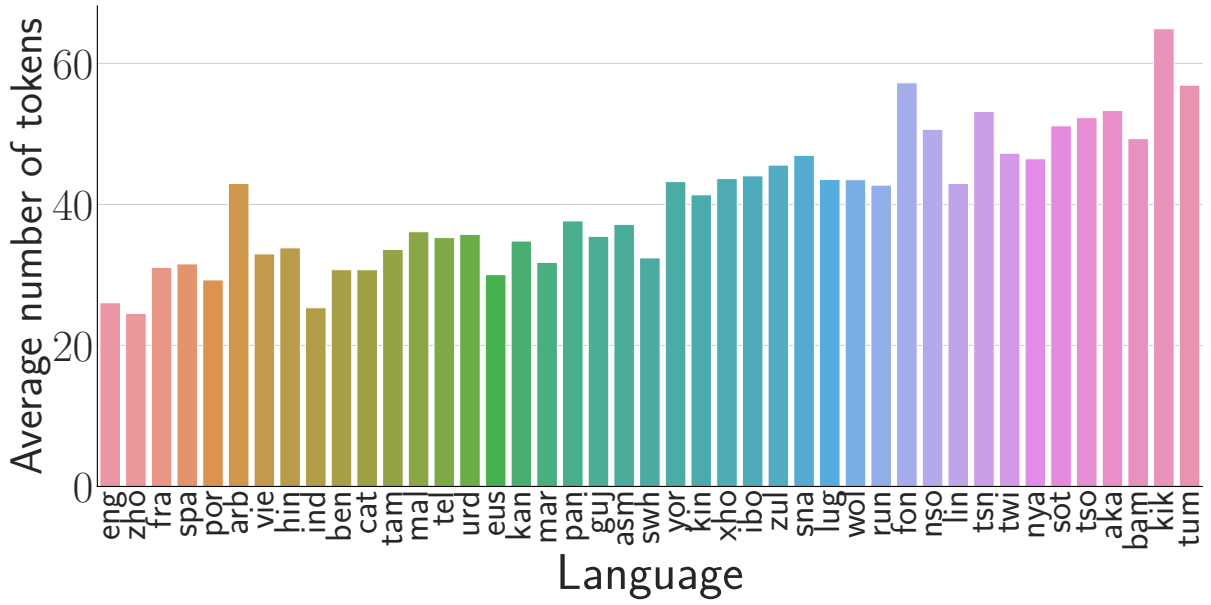


Figure 15: Average number of tokens per language after tokenizing FLORES with BLOOM tokenizer. Languages are arranged in descending order based on the size of pretraining data in the ROOTS corpus.

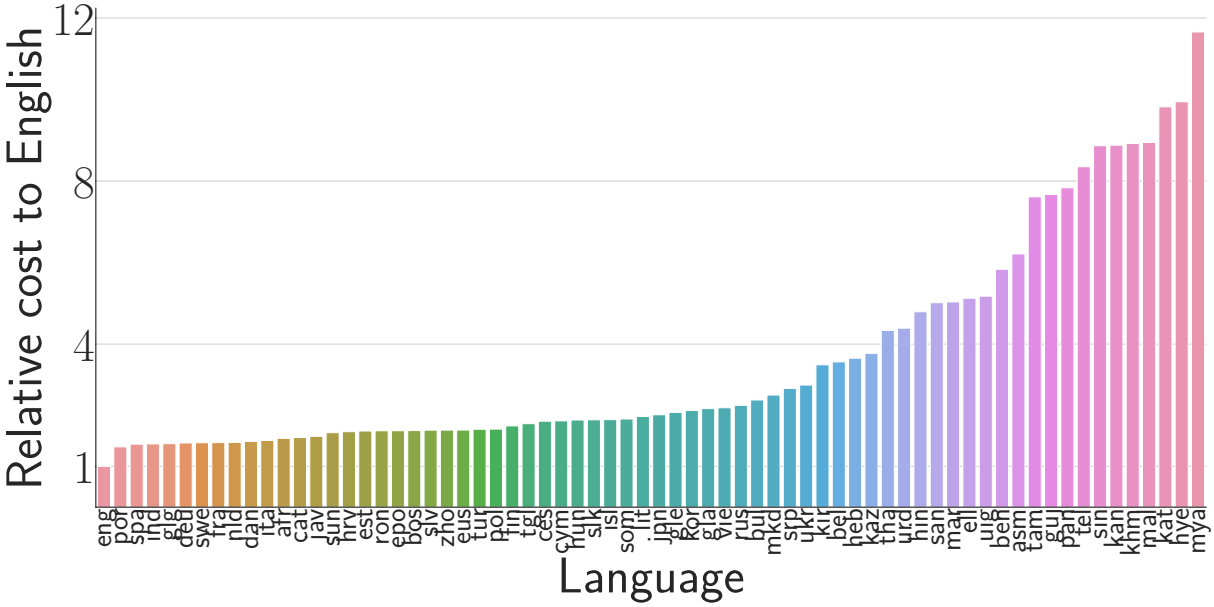


Figure 16: Estimated cost of API access to relative to English

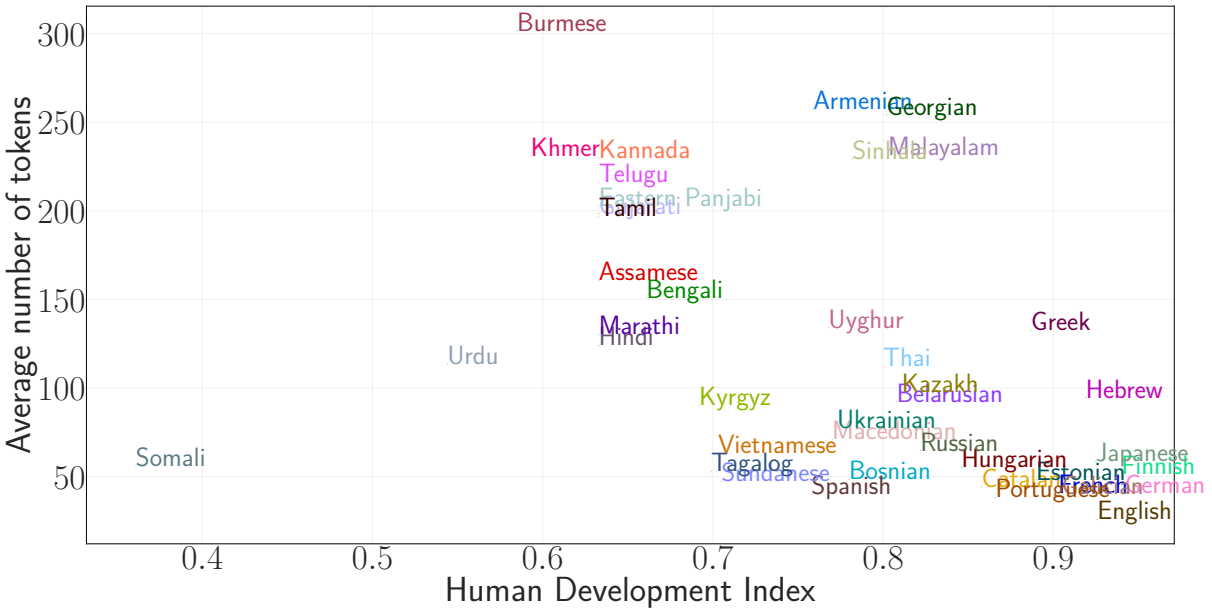


Figure 17: Fragmentation rate per language against the Human Development Index in the top country where the language is spoken.

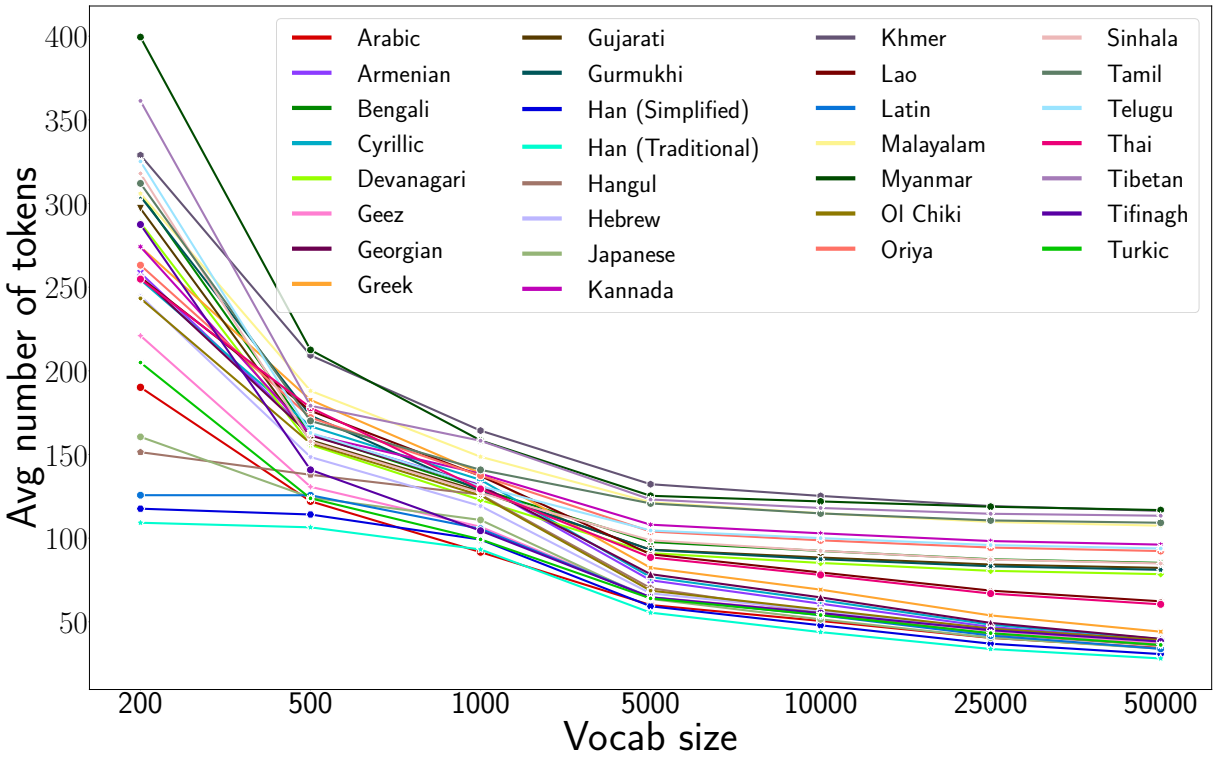


Figure 18: BBPE tokenizer trained on parallel text from 30 language scripts with varying vocabulary sizes. It is impossible to achieve uniform fragmnatation rate even when we have equal pretraining data sizes across all language scripts.