Morphological Typology in BPE Subword Productivity and Language Modeling

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Abstract

This study investigates the impact of morphological typology on tokenization and language modeling performance. We focus on languages with synthetic and analytical morphological structures and examine their productivity when tokenized using the byte-pair encoding (BPE) algorithm. We compare the performance of models trained with similar amounts of data in different languages. Our experiments reveal that languages with synthetic features exhibit greater subword regularity and productivity with BPE tokenization and achieve better results in language modeling tasks. We also observe that the typological continuum from linguistic theory is reflected in several experiments. These findings suggest a correlation between morphological typology and BPE tokenization efficiency.

1 Introduction

Since the introduction of the transformer architecture [30], large language models (LLMs) have shown unparalleled multilingual performance. Modern generative pretrained transformer (GPT) models are trained on extensive text corpora, typically tokenized using the byte-pair encoding (BPE) algorithm [11, 28, 23]. Tokenization is a critical phase in the training process [29], determining the units the model will predict in an auto-regressive manner.

Morphology is the area of linguistics concerning the study of word formation and structure. It examines how morphemes, the smallest units of meaning in a language, combine to form words. Modern morphological typology distinguishes analytic and synthetic languages. Analytic languages, such as isolating languages, typically have a one-to-one correspondence between words and morphemes, with minimal affixation. Synthetic languages (fusional, agglutinative, and polysynthetic) use inflection and affixation extensively [26, 14]. These categories form a typological continuum, meaning that most languages exhibit features from multiple types [1].

It is crucial to investigate whether BPE tokenization is more effective for specific languages due to its widespread use in state-of-the-art LMs. Different morphological structures, such as those in synthetic and analytic languages, pose distinct challenges for tokenization algorithms. Understanding these differences can help optimize tokenization strategies and provide researchers with unique insights into the models' learning process.

In this study, we analyze the impact of morphological typology on BPE tokenization and language modeling. To address this issue, we ask two questions: (1) *do some morphological typologies condition BPE tokenization?* and, if so, (2) *do language modeling tasks reflect these advantages or disadvantages?* This study compares the effect of BPE on languages with analytic and synthetic morphological features. We perform language modeling, regularity, and productivity experiments and show that:

- Synthetic morphology is associated with a **more productive subword system**

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- Languages with higher degrees of synthesis show **lower perplexity and loss**
- Synthetic languages achieve **better generalization faster** when trained in parallel corpora
- There is a **complexity continuum** that favors synthetic languages, reflecting the typological continuum of linguistic theory

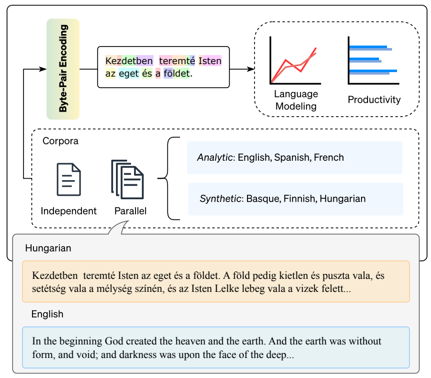


Figure 1: Example of the pipeline. The input consists of parallel and independent corpora. After BPE tokenization, we compare performance on language modeling and compute the subword productivity.

2 Background and Previous Work

2.1 Vocabulary

The choice of the tokenization algorithm is dependent on the task being performed [20]. For language modeling, the algorithm –or tokenizer– converts text data into words and subwords that form its vocabulary. Building the vocabulary involves training a tokenizer to establish the core semantic knowledge of a model. This process is crucial because tokenization can significantly impact the outcome of LMs [24].

Sennrich et al. [28] have highlighted the importance of subword tokens, which are crucial for handling rare and unseen words in the training data. For this, subword tokenization techniques such as BPE have been found to be particularly effective. BPE produces merges out of recurrent patterns, which allows it to achieve better generalization compared to other methods like SentencePiece [19] or WordPiece [27].

As Gutierrez-Vasques et al. [15] mention, BPE tokenization has been classified as irrelevant from a linguistic point of view [12, 3, 8, 22]. Studies have shown that an increase in linguistically-informed properties does not lead to improved performance in key downstream tasks [10, 25]. Other authors [21] have discussed the effectiveness of BPE in minimizing out-of-vocabulary tokens (`[OOV]` or `[UNK]`). Reducing `OOV` tokens can be a significant advantage when dealing with languages with complex morphological typologies. BPE's approach to tokenization ensures that the model retains more information about rare and composite words, which may also cause an increment in the performance and robustness of LMs.

BPE has been previously formalized by Zouhar et al. [32]. BPE merges sequences μ that are prominent across the corpus. What BPE tokenization aims to solve is an information compression problem. The compression power of the encoding is given by the reduction of a string μ. For a given string, the original condition is determined by the initial power $G_x(\emptyset) = 0$. Then, the compression preserves monotonicity; as the merges are applied, the power increases[1] (1, 2).

$$G_x(\mu \oplus \mu') \geq G_x(\mu) \tag{1}$$

$$G_x(\mu \oplus \mu') - G_x(\mu) \leq G_x(\mu' \oplus \mu'') - G_x(\mu') \tag{2}$$

[1] $\oplus$ is used for concatenation.

Because BPE is a greedy algorithm aiming to maximize G, given 2, we may say that compression power increases at each step. This increase in compression may continue up to an optimal point, after which further merges are not possible. However, in practice, the halting limit is determined by a vocabulary size V.

2.2 Regularity and Productivity

Regularity in morphology is defined as the property of forming morphemes according to a set of combinatory rules consistent throughout the language [14]. Since regularity arises from recurrent patterns in different words [2], regularity does not imply less complex morphological typology. Because of this, we hypothesize that synthetic languages tend to show more regularity because they show more automaticity (i.e., predictability of the forms) [31] due to subword recurrency.

Regularity has also been closely related to productivity [15]. This is because both concepts find common ground in frequency: morphemes recurrent throughout many lexemes are also indicators of a productive system [4, 5]. Due to this, we expect synthetic languages to display higher frequency, regularity, and productivity.

2.3 Are All Languages Equally Learnt by LMs?

According to Chomsky et al. [6], LMs "are incapable of distinguishing the possible from the impossible" (p. 3). This seems to suggest a clear difference between linguistic knowledge and performance. However, it also poses some interesting questions: do some linguistic properties (e.g., morphology) affect language modeling performance? If not, are all languages equally learned by language models (LMs)?

Cotterell et al. [9] address this question comparing LSTM and *n*-gram language models trained on translated corpora. They found correlations between morphological richness and performance decrease. However, even if recurrent language models are able to capture complex dependencies [16, 17], attention-based models may reduce these effects. In this line, Koplenig and Wolfer [18] analyze LSTM and Transformer models' performance on various languages and found that languages with more speakers were harder to model.

3 Methodology

We use six languages to experiment with. To account for the general differences, we divided them into two equal groups representing analytic and synthetic typologies. The analytic group comprised English (primarily analytic), Spanish (primarily fusional), and French (primarily fusional). The synthetic group included Basque (primarily agglutinative with polysynthetic features), Finnish (agglutinative), and Hungarian (primarily agglutinative with polysynthetic features). We also studied the individual differences and variability across languages to check for a possible complexity continuum.

3.1 Quantifying Productivity

Given the close relationship between frequency, productivity, and regularity, we began by providing descriptive measurements based on subword usage. We computed the frequency trends of the most used subwords per language to identify initial patterns. After, we tested the significance of these results through continuous sampling and testing.

To address productivity, we expand on previous experiments by adopting the metric proposed by Gutierrez-Vasques et al. [15]. We incorporate minor changes, such as extracting the productivity means per language. After running the BPE algorithm for 300, 400, and 500 merge operations, we computed the productivity means and deviations. This ensured reliable and robust results.

$$\rho = \frac{1}{N} \sum_{s \in S} |W_s| \tag{3}$$

In Equation 3, ρ represents the productivity of a language. S is the set of all subwords s, W_s denotes the set of unique words in which a subword s appears, and $|W_s|$ represents its cardinality (i.e., size).

To find the productivity of a language, we compute the average $|W_s|$ determined by its subwords. In other words, we define a productive morphological system as one where subwords appear in many different words. We compute this metric for each language using the Parallel Bible Corpus (PBC) [7].

3.2 Language Modeling Experiments

We train six transformer models from scratch for each language modeling experiment. We designed small LMs to balance computational efficiency with experimental rigor. We used four layers and four attention heads, providing sufficient complexity while remaining computationally manageable. We believe this configuration is a reasonable proxy to judge the effect of morphological typology and BPE tokenization on model performance, enabling us to analyze its impact within a constrained resource framework.

In the first experimental setup, we train models on similar amounts of tokens (100M per language) extracted from the Leipzig Corpora Collection (LCC) [13]. We compare the loss and perplexity throughout the training of each language to provide a comprehensive picture of language learning. We repeat the training process three times per language. In the second, we observe the generalization each language achieves in parallel texts. We train the models on the PBC corpora and compare validation perplexity and loss across languages. We use the same parameters and model architecture used in the previous experiment.

After training, we calculate the mean values of the final metrics for each language within both groups. We then use these means to compute the categories' performance difference (Δ). Additionally, we calculate and compare the standard deviation (σ) for both groups to assess the robustness of performance across languages within each typological class.

4 Results

4.1 Regularity and Productivity

Our analysis of subword patterns revealed interesting differences between languages. Initially, no distinctive patterns were observed. However, as additional subwords were analyzed and the sample size increased some languages exhibited stabilization, while others showed a sharper decline (Figures 2 and 4). These differences reflect both, (1) that the groupings –synthetic and analytic– seem to behave similarly, and (2) that there is a continuum favoring the richer morphological typologies.

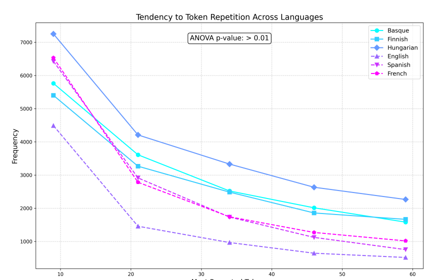


Figure 2: Trends of subword repetition. As the sample increases, the lines form two groups that show distinct behaviors. Red lines represent synthetic languages; green lines represent analytic languages.

Unpaired t-tests comparing the analytic and synthetic groups corroborated the observed visual trends. The tests were corrected using Bonferroni correction. Statistical results supported the hypothesis that synthetic languages exhibit higher automaticity ($p = 0.01$). These patterns in subword usage align with theoretical expectations of linguistic structure, which BPE may exploit. Apart from comparing the typological groupings, we also compare the differences between languages using a one-way ANOVA 2. The differences observed in the graph were statistically significant ($p = 0.01$), which corroborated the visual continuum.

The implications of these results extended to productivity scores (see Figure 3). All analytic languages displayed lower productivity compared to the synthetic ones. The reliance of analytic languages on word order and function words results in fewer unique subwords, thereby reducing their scores. This coincides with the results shown in Figure 2: the languages that show the highest repetition tendencies are also the most productive.

Basque and Finnish, which are characterized by their agglutinative nature, showed similar productivity scores. Hungarian exhibited a moderately lower score. These differences underscore the nuances within synthetic languages, highlighting that while they generally exhibit higher productivity, there are variations based on specific linguistic characteristics.

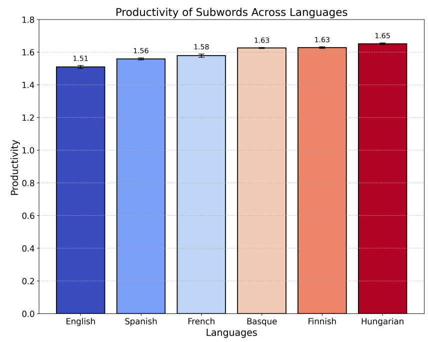


Figure 3: Productivity scores per language after averaging results for 300, 400, and 500 merge operations. Measurements were performed using the PBC parallel corpora. The error bars indicate the standard deviation between rounds of merge operations.

Because productivity was determined by the number of unique words in which each subword appeared, high productivity scores were also indicators of regularity. This was expected since synthetic languages tend to show more automaticity. Overall, BPE tokenizers are able to exploit this and make synthetic languages more efficient. We expected this to be a relevant factor in language modeling.

4.2 Token Frequency

Another interesting component of the frequency is related to how this evolves as more tokens are analyzed. We computed the rates of change given by the slope for the frequency decay in all language types using ordinary least square regressions. The results in Table 1 are based on an analysis of the 100 most frequently occurring subwords. We show clear distinctions between synthetic and analytic languages and between languages themselves.

Language	**Type/Features**	**Change/Slope**	r	R^2
Basque	primarily agglutinative + polysynthetic	-0.70 $\downarrow$	-0.99	0.98
Finnish	primarily agglutinative	-0.66 $\downarrow$	-0.99	0.99
Hungarian	primarily agglutinative, + polysynthetic	-0.66 $\downarrow$	-0.99	0.98
English	primarily analytic	-1.03 $\uparrow$	-0.99	0.98
Spanish	primarily fusional, + analytic	-1.02 $\uparrow$	-0.98	0.97
French	primarily fusional, + analytic	-0.95 $\uparrow$	-0.98	0.97

Table 1: Results of the rate of change (provided by the slope) on most repeated subwords for analytic and synthetic languages using the top 100 subwords. $\downarrow$ is best. Since the repetition decreases, we expected the r values to be negative.

For any number of top subwords, the rate of change of the frequency function with respect to the subword rank is greater for analytic languages than for synthetic languages. In other words, as we move from the most frequent subwords to the less frequent ones, the decay in frequency is faster in analytic languages than in synthetic languages. We formalize this in Equation 4. Let $f^A(i)$ and $f^S(i)$ be the frequencies of the i-th most repeated subword in analytic and synthetic languages, respectively. Let k be any positive integer representing the subword rank under consideration. Then:

$$\forall k \in \mathbb{Z}^+, \quad f^A(k) - f^A(k+1) > f^S(k) - f^S(k+1) \tag{4}$$

Equation 4 is supported by visual evidence shown in Figures 2, 3, and 4, and the statistical results from the t-tests, ANOVA, and the slopes in Table 1

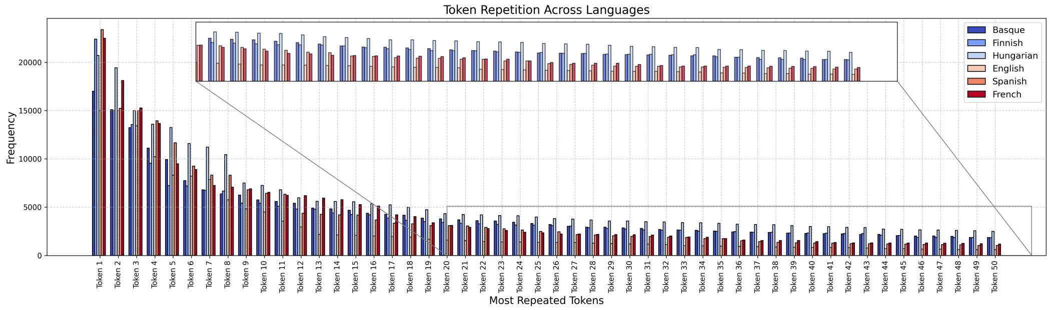
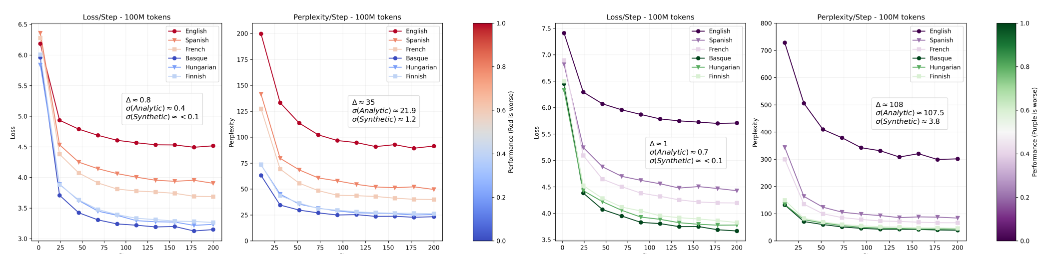


Figure 4: Frequencies of the top n-th most repeated subword. As observed in the graph, as further tokens are analyzed, the tokens in synthetic languages show higher frequencies.

4.3 Language Modeling

We used the general Transformer architecture with fewer hyperparameters to make the experimentation more manageable and efficient. Instead of using six layers and six heads, we reduced both to four. We used a 0.2 dropout value to mitigate overfiting. We changed the Adam optimizer for AdamW with a 1e-4 learning rate, β_1 set to 0.9, and β_2 to 0.98.

Given our study's computational constraints and exploratory nature, we opted for a more compact model configuration, particularly in terms of embedding dimensions. While larger models with embedding dimensions of 512, 768, or even 1024 have become common in language modeling tasks, we intentionally chose a 256-dimensional embedding space for several reasons. Our primary research question was the impact of morphological typology on tokenization and language modeling, not the absolute state-of-the-art performance. A smaller embedding size provided a lower-resolution representation that still captured essential linguistic features while being more sensitive to morphological variations. This controlled setting helped isolate the effects of morphology from the sheer representational power of larger models, which might have masked or overshadowed these nuanced linguistic phenomena.



(a) (b)

Figure 5: Results of the training on independent corpora extracted from LCC (a) and validation in PBC corpora (b). Overall, synthetic languages performed better than their analytic counterparts. This is evidenced by lower and more consistent values.

Figure 5a illustrates the progression of perplexity and loss throughout the training process in independent corpora extracted from the LCC (100M tokens per language). Notably, synthetic languages consistently exhibited superior performance, as indicated by lower loss and perplexity metrics. The average loss for synthetic languages was significantly lower than that of analytic languages. The mean comparison showed a one-point difference in favor of the synthetic group. Additionally, synthetic languages demonstrated greater robustness and compactness ($\sigma < 0.1$) compared to analytic languages ($\sigma \approx 0.7$). This suggests that the performance of synthetic languages was not only better but also more stable across different instances.

In terms of the individual differences, Basque, Hungarian, and Finnish behaved similarly. Basque and Hungarian performed slightly better than the primarily agglutinative Finnish. However, these differences were not significant and practically they performed equally. Interestingly, the results observed in the previous experiments emerged more clearly in the analytic languages. The productivity scale mapped directly in language modeling performance for English, Spanish, and French.

The trends persisted when models were trained on parallel corpora (5b). Synthetic languages achieved better generalization more rapidly than analytic languages. The individual differences also held in this experiment. The enhanced generalization ability of Basque, Hungarian, and Finnish may reflect their structural advantage, which enables models to streamline learned patterns more effectively. We hypothesize that the regularity and automaticity of synthetic languages —their predictability— played a relevant role in these results. Regular sequences enhanced the model's ability to predict forms that had not been previously observed. By adhering to consistent and predictable patterns, the model could make more accurate predictions about the characteristics and features of unseen forms. This regularity allowed the model to generalize better from the training to new, unseen data.

5 Conclusion

This study examined the impact of morphological typology on tokenization and language modeling, focusing on different synthetic and analytical languages. Our findings indicate that synthetic languages, with their regular and productive morphological typology, significantly benefit from BPE tokenization. The results suggest that this advantage may arise from BPE's effective handling of complex morphological structures, potentially enhancing model performance and generalization. In contrast, analytic languages presented more significant challenges for BPE, resulting in less efficient tokenization and higher variability. Our results from individual comparisons reflect that the typological continuum from linguistic theory reflects in a variety of experiments.

6 Limitations and Future Work

This study's scope is limited to six languages. Additionally, small transformer models were used, which might not fully represent the dynamics observed in larger models. The model evaluation relied on loss and perplexity, which are valuable indicators; however, incorporating additional metrics could provide a more comprehensive understanding of the effects under study. Future research should expand to include a more diverse set of languages, enhancing the generalizability of the findings. Investigating the effects of BPE tokenization with larger models across different languages could provide deeper insights.

7 Ethical Statement

All datasets used are publicly available and widely used in the research community. This study did not involve personal or sensitive data, ensuring compliance with privacy regulations. We acknowledge the importance of linguistic diversity and aim to contribute to the understanding and development of equitable language processing tools. Additionally, we recognize the role of factors like vocabulary size or cultural preferences in subword repetition apart from morphological structure. The author declares no conflicts of interest.

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