

The Inefficiency of BPE Tokenizers on Symbolic Languages:

An Empirical Study and a Simple Fix

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Abstract

Byte-Pair Encoding (BPE) tokenizers, designed for natural language, systematically fragment compound symbols from specialized symbolic languages into 2–5 sub-tokens, negating the compression gains these notations are meant to provide. We measure this phenomenon on a corpus of 43 pairs (French natural language \leftrightarrow .ava symbolic notation) using the Qwen 2.5 tokenizer (151,665 tokens). We show that adding only 26 domain-specific tokens to the vocabulary—a 0.017% increase—improves mean compression by **112.4%** (from $2.65\times$ to $5.62\times$). The gain is concentrated in categories whose notation relies on multi-symbol compounds (up to +318.9% for cognitive scars). Applied to a 200K-token context window, this represents a gain of 595K effective tokens. We analyze why individual Unicode symbols are already well-handled by modern vocabularies but their combinations are not, and propose targeted vocabulary extension as a trivial solution to this underestimated problem.

Keywords: tokenization, BPE, symbolic languages, compression, vocabulary extension, formal notation, LLM

1 Introduction

The Byte-Pair Encoding (BPE) algorithm, introduced for machine translation by Sennrich et al. [1], has become the de facto standard for tokenization in large language models (LLMs). Its principle—iteratively merging the most frequent symbol pairs in a training corpus—produces vo-

cabularies that are efficient for natural language, where subword distributions are relatively stable across languages.

However, BPE vocabularies are built from corpora dominated by natural language. When an LLM must process a specialized symbolic language—chemical notation (SMILES), musical notation (ABC), mathematical notation, or any domain-specific notation—the compound symbols of that notation do not appear in the tokenizer’s training corpus. They are therefore fragmented into sub-tokens, sometimes pathologically.

This problem is rarely quantified. In this work, we study it empirically on a concrete case: **.ava** notation, a compact symbolic language using Unicode symbols to represent complex psychological structures. We measure tokenization before and after adding 26 domain-specific tokens, and show that this trivial intervention—0.017% of the vocabulary—yields a 112.4% compression improvement.

2 Background

2.1 Subword Tokenization

Three algorithms dominate modern LLM tokenization:

- **BPE** [1]: iterative merging of the most frequent pairs. Used by GPT, LLaMA, Qwen, Mistral.
- **Unigram LM** [2]: probabilistic model selecting the most likely segmentation. Used by T5, mBART.

- **SentencePiece** [2]: a framework unifying BPE and Unigram, operating directly on raw text without pre-tokenization.

Modern vocabularies range from 32K (LLaMA) to 151K (Qwen 2.5) tokens. Their construction relies on massive corpora of natural text, code, and web data. Rare but standard Unicode symbols (mathematical characters, arrows, technical symbols) are generally included as individual tokens.

2.2 Alternatives to Tokenizers

Recent work explores tokenizer-free approaches: MegaByte [3] operates directly at the byte level, eliminating the need for a fixed vocabulary. These approaches remain marginal in production, and the vast majority of deployed LLMs use BPE.

2.3 The .ava Notation

The **.ava** notation is a symbolic language designed to compactly represent psychological profiles: personality traits, cognitive biases, emotional scars, constraints, projects, and relationships. It uses Unicode symbols as category prefixes:

- @ — people and roles
- Ψ — psychological traits
- ∅ — scars (avoided patterns)
- ∠ — cognitive biases
- ! — constraints and rules
- Δ — projects
- ◇ — infrastructure

Each entry combines a symbolic prefix with a compact textual identifier, sometimes followed by modifiers: **∅dns9!** (DNS attack scar, high priority), **∠over-eng** (over-engineering bias).

3 Methodology

3.1 Corpus

Our corpus consists of 43 pairs, each containing:

1. A natural language description in French.
2. Its equivalent in **.ava** notation.

The pairs cover six semantic categories: people (@), scars (∅), biases (∠), constraints (!), projects (Δ), and infrastructure (◇).

3.2 Baseline Tokenizer

We use the tokenizer from the Qwen 2.5-1.5B-Instruct model, implemented via the HuggingFace **transformers** library. This tokenizer has a vocabulary of **151,665 tokens**, among the largest of current open-source models.

3.3 Vocabulary Extension

We add 26 tokens to the vocabulary via HuggingFace’s **add_tokens()** method:

- **18 .ava symbols** — the base Unicode symbols and identifiers of the notation.
- **8 frequent compounds** — the most common symbol+identifier combinations in the corpus (e.g., **∅dns9!**, **∠over-eng**, **∅ghost**).

The extended vocabulary has **151,690 tokens**, a 0.017% increase.

3.4 Compression Measurement

For each pair, we compute the compression ratio:

$$R = \frac{N_{\text{NL}}}{N_{\text{.ava}}} \quad (1)$$

where N_{NL} is the token count of the natural language description and $N_{\text{.ava}}$ is the token count of the **.ava** notation. We measure R with both the baseline and extended tokenizers.

4 Results

4.1 Overall Compression

Table 1 presents compression statistics across the full corpus.

Table 1: Overall compression (43 pairs)

Metric	Baseline	Extended
Mean	2.65×	5.62×
Median	1.93×	2.08×
Maximum	9.0×	36.0×
Std. dev.	1.68	8.34
Δ mean	+112.4%	
Δ median	+7.7%	

4.2 Compression by Category

Table 2 details results by semantic category.

Table 2: Compression by category

Category	Sym.	Base	Ext.	Δ
Scars	ø	6.62×	27.75×	+318.9%
Biases	ℓ	4.36×	15.67×	+259.2%
Constraints	!	3.56×	5.56×	+56.1%
People	@	2.46×	2.70×	+9.4%
Projects	△	1.89×	1.94×	+2.8%
Infrastructure	◇	1.74×	1.74×	+0.0%

4.3 Mean–Median Divergence

A striking result is the divergence between the improvement in mean (+112.4%) and median (+7.7%). This divergence is explained by the bimodal distribution of gains:

- Categories with **low symbolic density** (people, projects, infrastructure) primarily contain standard textual identifiers that the baseline tokenizer already handles well. Their compression changes little.
- Categories with **high symbolic density** (scars, biases) contain multi-symbol compounds that the baseline tokenizer fragments into 4–5 sub-tokens. The extension reduces these to 1 token, producing spectacular gains.

The median, dominated by low-density categories (more numerous in the corpus), reflects the typical case. The mean captures the disproportionate impact of symbolically dense categories.

4.4 Context Window Impact

With a 200,000-token context window (standard for modern models), mean compression translates to:

- **Baseline:** $200\text{K} \times 2.65 = 529\text{K}$ effective tokens
- **Extended:** $200\text{K} \times 5.62 = 1,124\text{K}$ effective tokens

A gain of **595,000 effective tokens**, or roughly 450 additional pages of text within the same context window.

5 Analysis

5.1 The Individual Symbol Paradox

A counter-intuitive result emerges from symbol-level analysis: **most Unicode symbols used by .ava are already single tokens in the Qwen 2.5 vocabulary**. The characters Ψ , ϕ , Δ , \otimes , \angle are all tokenized as a single token by the baseline tokenizer.

Only three individual symbols benefit from the extension:

- Ψ : 2 tokens \rightarrow 1 token
- T^2 : 2 tokens \rightarrow 1 token
- $\text{s}\Delta\text{i}$: 3 tokens \rightarrow 1 token

This shows that modern BPE vocabularies, with 100K+ tokens, cover standard Unicode space well. **The problem is not the symbols, but their combinations.**

5.2 The Real Bottleneck: Compounds

The compression gain comes almost exclusively from **compound tokens**: sequences like $\phi\text{dns9!}$, $\angle\text{over-eng}$, ϕghost that combine a Unicode symbol, a textual identifier, and sometimes a modifier.

The baseline BPE tokenizer fragments these compounds because it has never seen them in its training corpus. The BPE algorithm can only merge token pairs it has observed; a sequence like $\phi\text{dns9!}$ is treated as 4–5 independent tokens: ϕ , d , ns , 9 , $!$.

By adding these compounds as atomic tokens, each occurrence goes from 4–5 tokens to exactly 1, which explains the +318.9% gains on scars (the category with the longest and most frequent compounds).

5.3 Why Infrastructure Gains Nothing

The infrastructure category (\diamond) shows a 0.0% gain, serving as a natural negative control. Infrastructure entries primarily use server names and file paths—standard technical text that the BPE tokenizer already handles efficiently. The \diamond symbol itself is already a single token, and the identifiers following it are common words in code corpora.

6 Implications

6.1 Cost/Benefit Ratio

Adding 26 tokens to a vocabulary of 151,665 represents a 0.017% increase. In practical terms:

- The model’s embedding matrix grows by 26 rows (negligible memory impact).
- No model retraining is required; new tokens are randomly initialized and refined during fine-tuning.
- The compression gain is +112.4% on average.

The benefit/cost ratio is on the order of $112/0.017 \approx 6,600\times$: each percent of vocabulary increase yields $\sim 6,600\%$ compression gain. This exceptional ratio suggests that standard BPE vocabularies are severely suboptimal for symbolic notations.

6.2 Generalization to Other Domains

The same phenomenon should manifest for any symbolic language whose compounds do not appear in BPE training corpora:

- **SMILES** (chemistry): molecular strings like CC(=O)Oc1ccccc1C(=O)O combine common characters into specialized sequences.
- **Musical notation** (ABC, LilyPond): note and chord sequences form compounds absent from text corpora.
- **Regular expressions**: complex patterns like `(?<=\d){3}` are fragmented into individual sub-tokens.
- **Mathematical formulas**: composite LaTeX expressions (`\frac{d}{dx}`) could benefit from atomic tokenization.

6.3 Practical Recommendation

For any fine-tuning pipeline involving a symbolic language:

1. Identify the N most frequent domain compounds.
2. Add them to the vocabulary via `add_tokens()`.
3. Resize the embedding matrix (`resize_token_embeddings()`).
4. Fine-tune normally.

The cost is zero in implementation complexity, negligible in computation, and the potential gains are substantial.

7 Related Work

BPE for NMT. Sennrich et al. [1] introduced BPE for machine translation, solving the open-vocabulary problem by segmenting rare words into subword units. This approach has been universally adopted by LLMs.

SentencePiece and Unigram. Kudo [2] proposed SentencePiece, a language-independent tokenization framework including the Unigram LM algorithm as a probabilistic alternative to BPE. These approaches share the same fundamental limitation: the vocabulary is built from the training corpus.

Byte-level models. Yu et al. [3] proposed MegaByte, a model operating directly on bytes, eliminating the need for a tokenizer. This approach theoretically solves the fragmentation problem but at the cost of increased computational complexity.

Vocabulary adaptation. Several works have explored vocabulary extension for adaptation to new languages [4, 5]. Our approach differs in targeting not a natural language but a symbolic language, and in showing that an extremely small number of tokens suffices.

Tokenization and model performance. Rust et al. [6] showed that tokenization quality directly affects multilingual model performance, with languages underrepresented in the vocabulary suffering from excessive fragmentation. Our work extends this observation to artificial symbolic languages.

8 Limitations

Several important limitations should be noted:

1. **Corpus size.** With 43 pairs, our corpus is small. The statistical results (notably the standard deviation of 8.34 after extension) reflect this limitation.
2. **Single domain.** We study only `.ava` notation. Generalization to other symbolic languages remains to be demonstrated empirically.
3. **Compression only.** We measure only compression (token count), not the impact on model output quality. A more compressive tokenizer is only beneficial if the model correctly learns the new tokens during fine-tuning.

4. **Gain concentration.** The +112.4% mean gain masks a highly unequal distribution: the scars and biases categories pull the mean upward, while three of six categories see gains below 10%.
5. **No cross-tokenizer comparison.** We tested only the Qwen 2.5 tokenizer. Other tokenizers (LLaMA, GPT-4) may behave differently, particularly those with smaller vocabularies.

9 Conclusion

The tokenizer is a component often treated as a black box in LLM pipelines. Our results show that it can constitute a significant bottleneck for symbolic languages: the Qwen 2.5 BPE tokenizer, despite its vocabulary of 151,665 tokens, fragments compound symbols from `.ava` notation into 4–5 sub-tokens.

Adding 26 tokens—0.017% of the vocabulary—eliminates this fragmentation and yields a mean compression gain of 112.4%. This result highlights a structural problem with BPE: the algorithm cannot learn compounds it has never seen, even when every constituent symbol is already in the vocabulary. The solution—adding frequent domain compounds—is trivial to implement and should not be omitted from any fine-tuning pipeline involving specialized notation.

More broadly, this work suggests that tokenizer adaptation is an underexploited lever in LLM fine-tuning, offering disproportionate gains relative to its cost.

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