

Evaluating Tokenizer Adaptation Methods for Large Language Models on Low-Resource Programming Languages

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Abstract

Large language models, mostly trained on high-resource programming languages, but perform sub-optimally for low-resource ones. This study investigates the impact of tokenizer adaptation methods on improving code generation for LRPLs. We evaluate popular StarCoder 2 and DeepSeek-Coder model adapted to Elixir and Racket using methods such as Fast Vocabulary Transfer (FVT), FOCUS, and Zero-shot Tokenizer Transfer (ZeTT). Our experiments reveal that ZeTT outperforms other methods, achieving significant improvements in handling syntax, program logic, and data types for LRPLs. However, we also highlight performance declines in non-target languages like Python after tokenizer adaptation. The study approves the positive impact of tokenizer adaptation in enhancing LRPL code generation and suggest directions for future research, including token embeddings improvement.

1 Introduction

Previous studies showed that large language models trained on source code (Code LLMs) excel at generating code (Zheng et al., 2023) in high-resource programming languages (HRPLs) (Lozhkov et al., 2024; Cassano et al., 2024; Chen et al., 2022) from docstrings. However, Code LLMs demonstrate suboptimal code generation performance on low-resource programming languages (LRPLs) (Cassano et al., 2024, 2022; Chai et al., 2024; Yan et al., 2023). This disparity in performance puts LRPLs at a potential risk of becoming extinct without adequate support from LLMs, because programmers often use LLMs to accelerate their work. Previous work attempted to address this issue via continued training (Cassano et al., 2024, 2022), but the performance gap of Code LLMs on LRPLs could also be caused by an ineffective tokenization by underfit Code LLM tokenizers. This study provides a comprehensive evaluation of the

code generation capabilities of the Code LLMs adapted to LRPLs using various tokenizer adaptation methods. We highlight the challenges of the LRPL code generation improvement with tokenizer adaptation methods. Based on the experimental results, we also demonstrate that better performance on LRPL code generation could be achieved with Zero-shot Tokenizer Transfer (ZeTT) (Minixhofer et al., 2024) method.

Thus, the study makes the following contributions:

1. Evaluates code generation performance of popular open-source Code LLMs on LRPLs and an HRPL.
2. Adapts Code LLMs to LRPLs using various tokenizer adaptation methods.
3. Compares code generation performance of original Code LLMs and their adaptations on LRPLs.

2 Related Works

2.1 Continued Training

In their work, (Cassano et al., 2024) rightly observed that Code LLMs demonstrate suboptimal performance on LRPLs such as Julia, Lua, OCaml, R, and Racket due to the lack of training source code written in these languages. To address this problem, they composed semi-synthetic training data by using an LLM to translate Python code to LRPL code. The authors also proposed another approach to obtain LRPL code in their previous study (Cassano et al., 2022), which involves translation using a set of compilers. However, this approach was used only to create a code generation benchmark comprising 18 LRPLs.

2.2 Tokenizer Adaptation

Tokenizer adaptation involves changing the tokenizer of the model to a new tokenizer that con-

Tokenizer Name	Vocab. Size	New Tokens	Keywords	
			<i>Racket</i>	<i>Elixir</i>
StarCoder 2	49 152	-	26%	70%
StarCoder 2 Racket	53 340	4 188 +9%	31% +5%	74% +4%
StarCoder 2 Elixir	52 202	3 050 +6%	27% +1%	82% +12%
DeepSeek-Coder	32 022	-	22%	64%
DeepSeek-Coder Racket	39 883	7 861 +25%	31% +9%	74% +10%
DeepSeek-Coder Elixir	38 981	6 959 +21%	25% +3%	82% +18%

Table 1: Statistics of the original and adapted tokenizers. The original tokenizers are highlighted in bold. The vocabulary expansion percentage and the keywords increase percentage are highlighted in green.

tains more tokens from the target language to create a better representation of the language (Csaki et al., 2023). (Mosin et al., 2023) proposed a simple tokenizer adaptation approach that reuses the embeddings of the original model. The implementation of this approach was optimized by (Gee et al., 2024) in their Fast Vocabulary Transfer (FVT) approach. FOCUS (Dobler and De Melo, 2023) has recently overcome the performance of WECHSEL (Minixhofer et al., 2021) and RAMEN (Tran, 2020) on multilingual XNLI (Conneau et al., 2018) and QuAD (Möller et al., 2021) tasks, making an advancement in tokenizer adaptation. The authors of Zero-shot Tokenizer Transfer (ZeTT) (Minixhofer et al., 2024) proposed to train a Transformer (Vaswani et al., 2017) encoder as a hypernetwork to produce embeddings for the tokens of the new tokenizer. Currently, this is a state-of-the-art tokenizer adaptation method that overcomes the previous cutting-edge methods FOCUS and OFA (Liu et al., 2023) on natural language and code tasks.

3 Experimental Setup

3.1 Motivation for Tokenizer Adaptation

It was previously demonstrated that a model with a tokenizer containing more target language tokens has improved text understanding and produces a text with higher quality (Mosin et al., 2023; Gee et al., 2024; Dobler and De Melo, 2023; Minixhofer et al., 2024). This may be a premise that tokenizer adaptation could boost the quality of LRPL code generation for Code LLMs since the structures of code and natural language are similar (Allamanis et al., 2018). The similarity is also approved by the fact that models originally developed for natural language were effective for source code (Hindle et al., 2016).

3.2 Programming Languages

To assess the effect of tokenizer adaptation on the quality of generated LRPL code, we consider *Elixir* and *Racket* LRPLs. The motivation for the choice is provided in Appendix A. It also makes sense to check whether the adapted models retain their capabilities of generating code in HRPLs. Thus, we considered *Python* programming language as an HRPL since it is a popular and widely used PL according to the Stack Overflow survey¹. This is approved by the Stack 2 statistics: Python is in the top-10 of PLs by the number of bytes in the dataset.

3.3 Code LLMs (Baselines)

Tokenizer adaptation experiments are performed on *StarCoder 2* (Lozhkov et al., 2024) with 3 billion parameters and *DeepSeek-Coder* (Guo et al., 2024) with 1.3 billion parameters. Appendix B contains the discussion of the model choice.

3.4 Training Data

There is an obvious lack of publicly available and high-quality datasets with the code written in LRPLs. Due to this natural reason, the trainings of tokenizers and models are performed on the data from the Stack 2 (Lozhkov et al., 2024) dataset². It contains the subsets containing code for the selected LRPLs with 227 thousand Racket source code files and 1.8 million Elixir source code files.

3.5 Adaptation to LRPLs

3.5.1 Fine-tuning

To check whether tokenizer adaptation provides an improvement, we fine-tuned the models on the

¹<https://survey.stackoverflow.co/2024/technology>

²The dataset contains the code whose licenses are considered permissive by the authors. List of license identifiers: https://huggingface.co/datasets/bigcode/the-stack-v2/blob/main/license_stats.csv

Model Name	Adaptation to Racket			Adaptation to Elixir		
	<i>Racket</i>	<i>Elixir</i>	<i>Python</i>	<i>Racket</i>	<i>Elixir</i>	<i>Python</i>
starcoder2-3b	8	20	24	8	20	24
+ FT	30	4	12	0	28	8
+ FVT	28	2	10	0	30	0
+ FOCUS	24	0	6	0	28	0
deepseek-coder-1.3b-base	12	38	30	12	38	30
+ FT	26	24	30	8	28	28
+ FVT	18	16	22	10	26	22
+ FOCUS	24	0	6	0	28	0
+ ZeTT Adapted Tokenizer	28	16	18	18	32	28
+ ZeTT Original Tokenizer	26	20	22	10	30	22

Table 2: Pass@1 (%) values on McEval benchmark for the original models and the adapted models using various tokenizer adaptation methods. The names of the adaptation methods are provided after the "+" sign. "FT" abbreviation stands for the fine-tuned model. Note that the StarCoder 2 model does not have a ZeTT-adapted version since HF Transformers does not support conversion of this model to a Flax model.

LRPLs to check whether tokenizer adaptation indeed provides an improvement. StarCoder 2 and DeepSeek-Coder were both fine-tuned on the LRPL source code taken from the Stack 2 dataset. Even though Racket and Elixir are subsets of the Stack 2 differ in size, we trained the models on the same amount of source code files. Appendix D provides the fine-tuning details.

3.5.2 Tokenizer Adaptation

In this study, we adapted the models using several tokenizer adaptation methods:

1. Fast Vocabulary Transfer (FVT) (Gee et al., 2024)
2. FOCUS (Dobler and De Melo, 2023)
3. Zero-shot Tokenizer Transfer (ZeTT) (Minixhofer et al., 2024)

The details of the methods are provided in Appendix E, Appendix F, and Appendix G. Note that the embeddings initialization, involved in tokenizer adaptation, was performed for both the input and output embeddings. After the initialization, the model with the adapted tokenizer is fine-tuned on the LRPL source code according to Appendix D.

3.6 Adapted Tokenizers

We adapted tokenizers to LRPLs using vocabulary expansion: tokens of an auxiliary tokenizer trained on LRPL code are added to the model tokenizer. In our experiments, we trained auxiliary tokenizers with a vocabulary size of 30% of the model tokenizer’s vocabulary size. However, the actual

amount of added tokens will be lower since model and auxiliary tokenizers often have overlapping tokens. The adapted tokenizers are summarized in Table 1. More details are presented in Appendix C.

3.7 Code Generation Benchmarks

We assessed the quality of code generation on several benchmarks.:

1. MultiPL-E (Cassano et al., 2022)
2. McEval (Chai et al., 2024)

Detailed descriptions of the benchmarks are provided in Appendix H.

4 Evaluation Results and Discussion

4.1 Effect of Vocabulary Expansion on Tokenization

The results of analysis of the adapted tokenizers in Appendix C demonstrate that tokenizers now use new, larger tokens when tokenizing code in the target LRPL. In the case of DeepSeek-Coder, there is a statistically significant ($\leq 5\%$) decrease in the mean tokens per text (MTPT) and the mean bytes per token (MBPT). However, in the case of StarCoder, the situation is controversial since the decrease in MTPT happens to be not statistically significant. The reason for that could be the fact that the tokenizer vocabulary of StarCoder 2 was expanded by less than 10%, which could be insufficient. Despite that, the tokenizers consistently use 50-60% of the added tokens. These added tokens are indeed significant for the target LRPLs since

they add up to 9% of Racket keywords and up to 18% of Elixir keywords.

4.2 Comparison of Tokenizer Adaptation Methods on Target LRPLs

The results of the evaluation of original and adapted models on the MultiPL-E benchmark are presented in Appendix I. Evaluation results on the McEval benchmark may be seen in Table 2. These evaluation results are used to compare tokenizer adaptation methods.

4.2.1 Racket

FVT and FOCUS improve the performance of the base models, but do not achieve the performance of the fine-tuned model. ZeTT versions demonstrate promising results, often overcoming the fine-tuned model on HumanEval (15.99%) and McEval (28%) benchmarks.

4.2.2 Elixir

As in the Racket case, FVT and FOCUS often fail to achieve the code generation abilities of the fine-tuned model. At the same time, ZeTT-variants, especially with adapted tokenizer, are highly effective for Elixir. ZeTT with adapted tokenizer achieves 17.79% on HumanEval and 22.36% on MBPP, outperforming FT. ZeTT with the original tokenizer leads in MBPP (24.66%).

4.3 Performance of Adapted Models on Non-target PLs

Python performance consistently declines in almost all cases, except for a single case during McEval evaluation. Most Racket-adapted models show reduced Elixir performance on McEval. However, there are cases when fine-tuning DeepSeek-Coder on Racket improves the model performance on Elixir MultiPL-E tasks from 4.11% up to 17.68%, which could be the sign of cross-lingual transferability. A similar severe decline may be observed in Racket performance of Elixir-adapted models. These facts could be the signs of catastrophic forgetting (French, 1999; Muennighoff et al., 2022; Vu et al., 2022).

4.4 Vocabulary Expansion Importance in ZeTT

To check the effect of vocabulary expansion in ZeTT adaptations, we performed experiments with both ZeTT-adapted models featuring original and adapted tokenizers. The experimental results

demonstrate that even though the ZeTT-adapted model with the adapted tokenizer often shows better performance, the model with the original tokenizer has a comparable performance as well. This may indicate that the quality of token embeddings, their semantic content, could be no less impactful than the token length. Cross-lingual knowledge, provided by CodeBERT, may enrich the token embeddings with valuable cross-lingual knowledge. Thus, improvement of LRPL tokens’ embeddings with cross-lingual knowledge could be a promising future work.

4.5 ZeTT Improvements in Target LRPLs

Compared to the fine-tuned models, ZeTT models obtain the following improvements. For Elixir, the ZeTT model works correctly with function argument passing, array manipulation, recursive logic, indices handling, operators, and data types. For Racket, the issues related to recursive functions, base cases, built-in and helper functions are resolved.

5 Limitations

Despite that the study provides valuable insights into the improvement of code generation abilities of Code LLM in LRPLs, the study has several limitations that could potentially influence the conclusions. First, it considers only 2 LRPLs and a single LRPL. Second, we used relatively small Code LLMs of 1-3 billion parameters in the experiments. Third, we noticed that tokenizer adaptation methods are sensitive to how the embeddings are trained after initialization.

6 Conclusion

The study provides a comprehensive evaluation of code generation capabilities in low-resource programming languages (LRPLs), revealing the suboptimal performance of current popular Code LLMs without tokenizer adaptation. Among the tested tokenizer adaptation methods, ZeTT is the most effective approach that outperforms FVT and FOCUS in handling syntax, program logic, operators, and data types. The findings highlight the critical role of tokenizers and token embeddings in LRPL code generation. The obtained results could be helpful in further research of Code LLMs’ performance in LRPL code generation.

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A Choice of LRPLs

The choice of LRPLs on the distribution of source code bytes over PLs in the deduplicated Stack 2 dataset³. We considered programming languages that overcome the 99% quantile to be low-resource. In total, according to our approach, 512 languages are considered low-resource, which is 82% of the

³<https://huggingface.co/datasets/bigcode/the-stack-v2-dedup>

languages presented in the dataset. *Elixir* and *Racket* PLs were chosen for experiments since they are presented in both code generation benchmarks, MultiPL-E (Cassano et al., 2022) and McEval (Chai et al., 2024).

B Choice of Code LLMs

Tokenizer adaptation experiments are performed on *StarCoder 2* (Lozhkov et al., 2024) with 3 billion parameters and *DeepSeek-Coder* (Guo et al., 2024) with 1.3 billion parameters. These are the modern and popular open-source Code LLMs having the smallest amount of parameters to save computational resources and time when performing experiments. Even though these models have the smallest number of parameters, they are good enough to generate working code in various PLs. Adapting the tokenizer of the two different Code LLMs is useful to determine whether the approach is generalizable over model architectures. Additionally, these models are comparable since they have a relatively close number of parameters. The models do not differ much in their complexity and, therefore, in their abilities. One may correctly notice that Starcoder 2 has more than 2 times many parameters as DeepSeek, so their abilities should differ significantly. However, those are the smallest models that are maximally close to each other in terms of a number of parameters.

C Adapted Tokenizers

The summary of the adapted tokenizers is provided in Table 1. We define **keywords** as the special words reserved by a programming language. The list of keywords was collected from the grammars of the Visual Studio Code⁴ language servers for Racket⁵ and Elixir⁶. In total, we collected 122 keywords for Racket and 50 keywords for Elixir. The keywords percentage for the tokenizers is the ratio of the keywords present in the tokenizers’ vocabulary over the total number of keywords.

To check whether vocabulary expansion makes a difference in tokenization, we calculated the mean number of tokens per text (Table 7) and the mean number of bytes per token (Table 7). Vocabulary usage (Table 6) was calculated to check how many of the added tokens are used in total.

⁴<https://code.visualstudio.com/>

⁵<https://github.com/Eugleo/magic-racket/>

⁶<https://github.com/timhirsens/vscode-elixir>

D Fine-tuning Parameters

Fine-tuning is the step that follows after the embeddings initialization in each tokenizer adaptation method. To provide a fair comparison, we performed fine-tuning with the same training parameters for each method. The fine-tuning was performed using TRL⁷ SFTTrainer on 224000 code samples with the following training parameters:

- Maximal Gradient Norm: 1
- Batch Size: 4
- Warmup Ratio: 0.25
- Training Epochs: 1
- Learning Rate: 5e-5
- Scheduler: cosine
- Weight Decay: 1

E FVT Adaptation Details

The approach proposes to initialize the embeddings for the new tokens using the embeddings of the original model. To do that, the new token is split into the constituent tokens using the original tokenizer of the model. Next, the embeddings of the constituent tokens are averaged to obtain a single average embedding:

$$E_{\text{new}}(t_i) = \frac{1}{|\mathcal{T}_a(t_i)|} \sum_{t_j \in \mathcal{T}_a(t_i)} E_{\text{old}}(t_j) \quad (1)$$

where $E_{\text{new}}, E_{\text{old}}$ - embeddings of the adapted and original model correspondingly; t_i, t_j - added token and constituent token respectively; \mathcal{T}_a - original tokenizer. Note that with this approach, the embeddings of the old tokens are preserved.

F FOCUS Adaptation Details

The method firstly trains fastText (Bojanowski et al., 2017) embeddings for all the tokens of the new tokenizer. Then, each new token gets an embedding initialized with the weighted average of the model embeddings of all the old tokens.

$$E_{\text{new}}(t_i) = \frac{1}{|\mathcal{V}_{\mathcal{T}_a}|} \sum_{t_j \in \mathcal{V}_{\mathcal{T}_a}} w_{t_j} E_{\text{old}}(t_j) \quad (2)$$

⁷<https://huggingface.co/docs/trl/en/index>

where $\mathcal{V}_{\mathcal{T}_a}$ - vocabulary of the original tokenizer; w_{t_j} - weight of a token. The weights are determined by the cosine similarity between the fastText embedding of the target token and the fastText embedding of an old token. Irrelevant embeddings are excluded from the averaging using sparsemax (Martins and Astudillo, 2016)

In our experiments, we used the implementation⁸ of the method provided by the method’s authors. The fastText embeddings were trained with the default training parameters, provided in the FOCUS implementation.

G ZeTT Adaptation Details

The method approaches embedding initialization in a conceptually new way: it uses a Transformer Encoder (Vaswani et al., 2017) hypernetwork $H_\theta : \mathcal{T}_b \rightarrow \phi_b$, to predict the embeddings ϕ_b of the tokens in the vocabulary of the adapted tokenizer \mathcal{T}_b . During the training, the hypernetwork should first pass the MIMIC-style (Pinter et al., 2017) warmup stage. After that, the hypernetwork parameters θ are trained on the following loss:

$$\mathcal{L}_\theta^{\text{final}} = \mathcal{L}_\theta(\mathcal{T}_b, H_\theta(\mathcal{T}_b), \psi) + \alpha \cdot \mathcal{L}_\theta^{\text{aux}} \quad (3)$$

where \mathcal{L}_θ is a CLM (Jurafsky, 2000) objective, ψ are the language model (non-embedding) parameters, and α is a weight of the auxiliary loss that is defined as

$$\mathcal{L}_\theta^{\text{aux}} = \frac{\sum_t \|H_\theta[\mathcal{V}_{\mathcal{T}_b}[t]] - \phi_a[\mathcal{V}_{\mathcal{T}_a}[t]]\|_2}{|\mathcal{V}_{\mathcal{T}_a} \cap \mathcal{V}_{\mathcal{T}_b}|} \quad (4)$$

where $t \in |\mathcal{V}_a \cap \mathcal{V}_b|$. Meanwhile, the language model parameters ψ are not trained during the hypernetwork training.

In our experiments, we used the implementation⁹ of the method authors to train a CodeBERT (Feng et al., 2020) hypernetwork with the following training parameters:

- loss: clm
- n_embd: 2048
- n_token_subsample: 8192
- identity_n_subsample: 8192
- identity_steps: 14000

⁸<https://github.com/konstantinjdobler/focus>

⁹<https://github.com/bminixhofer/zett>

- warmup_steps: [14000, 15000]
- steps: 56000
- learning_rate: [3e-4, 6e-5]
- max_grad_norm: 0.1
- hn_surface_maxlen: 7
- weight_decay: 0.01
- train_batch_size: 2
- hn_hidden_size: 2048
- hn_intermediate_size: 4096
- lexical_loss_weight: 32

H Code Generation Benchmarks

MultiPL-E (Cassano et al., 2022). The benchmark includes the tasks from HumanEval (Chen et al., 2021) and MBPP (Austin et al., 2021) datasets translated to other PLs. Due to the large amount of experiments, we only evaluated pass@1 metric for 50 samples per task with 0.2 temperature on both datasets.

McEval (Chai et al., 2024). The benchmark provides a set of custom-curated tasks. It contains 50 tasks and tests for each PL from the vast set. The benchmarks only evaluate pass@1 over a set of tasks since it requires the models to greedily generate the code.

I MultiPL-E Evaluation Results

The original and adapted models are evaluated on both datasets of the MultiPL-E benchmark: HumanEval and MBPP. Table 3 presents pass@1 metrics for models adapted to Racket, while Table 4 shows the metrics for Elixir-adapted models.

Model Name	HumanEval			MBPP		
	<i>Racket</i>	<i>Elixir</i>	<i>Python</i>	<i>Racket</i>	<i>Elixir</i>	<i>Python</i>
starcoder2-3b	8.21	9.28	30.43	14.72	6.87	41.98
+ FT	15.25	0.00	16.43	22.88	0.00	12.85
+ FVT	13.42	0.00	15.71	23.89	0.04	11.64
+ FOCUS	13.66	0.30	11.88	24.28	0.48	6.84
deepseek-coder-1.3b-base	9.75	15.01	31.77	17.69	4.11	43.36
+ FT	14.15	16.07	29.20	23.45	17.68	41.86
+ FVT	10.14	12.15	25.32	10.34	12.32	36.41
+ FOCUS	9.98	0.00	0.00	10.50	0.85	3.47
+ ZeTT Adapted Tokenizer	14.73	8.26	28.33	22.18	8.09	36.75
+ ZeTT Original Tokenizer	15.99	9.06	26.84	21.98	12.30	40.01

Table 3: Pass@1 (%) values on MultiPL-E benchmark for the original models and the models adapted to Racket using various tokenizer adaptation methods. The names of the adaptation methods are provided after the "+" sign. "FT" abbreviation stands for the fine-tuned model. Note that the StarCoder 2 model does not have a ZeTT-adapted version since HF Transformers does not support converting this model to a Flax model.

Model Name	HumanEval			MBPP		
	<i>Racket</i>	<i>Elixir</i>	<i>Python</i>	<i>Racket</i>	<i>Elixir</i>	<i>Python</i>
starcoder2-3b	8.21	9.28	30.43	14.72	6.87	41.98
+ FT	0.00	16.10	4.26	1.25	10.47	0.19
+ FVT	0.60	15.22	2.77	0.47	8.85	0.02
+ FOCUS	0.05	15.84	2.44	0.13	8.27	0.00
deepseek-coder-1.3b-base	9.75	15.01	31.77	17.69	4.11	43.36
+ FT	8.56	16.68	25.73	15.98	6.70	25.73
+ FVT	5.03	12.93	18.70	9.77	16.59	27.64
+ FOCUS	0.73	12.76	0.00	1.00	10.33	0.58
+ ZeTT Adapted Tokenizer	5.96	17.79	24.74	8.39	22.36	4.94
+ ZeTT Original Tokenizer	6.32	16.58	24.00	10.17	24.66	16.98

Table 4: Pass@1 (%) values on MultiPL-E benchmark for the original models and the models adapted to Elixir using various tokenizer adaptation methods. The names of the adaptation methods are provided after the "+" sign. "FT" abbreviation stands for the fine-tuned model. Note that the StarCoder 2 model does not have a ZeTT-adapted version since HF Transformers does not support conversion of this model to a Flax model

Tokenizer Name	Racket			Elixir		
	<i>Mean</i>	<i>Std</i>	<i>p-value</i>	<i>Mean</i>	<i>Std</i>	<i>p-value</i>
StarCoder 2	918	1350	-	557	903	-
StarCoder 2 Racket	900	1320	0.3349	557	902	1.0000
StarCoder 2 Elixir	918	1349	1.0000	545	885	0.3426
DeepSeek-Coder	1044	1497	-	655	1031	-
DeepSeek-Coder Racket	987	1412	0.0056	647	1020	0.5812
DeepSeek-Coder Elixir	1027	1473	0.4183	617	970	0.0073

Table 5: Mean tokens per text (MTPT) for the original and adapted tokenizers calculated for 10 000 samples. The original tokenizers are highlighted in bold. P-values of the two-tailed t-test between MTPTs of the original and adapted tokenizers are indicated in the dedicated column. Statistically significant differences (p-value < 5%) are highlighted in green, while the others are highlighted in red.

Tokenizer Name	Racket				Elixir			
	Used		Unused		Used		Unused	
	<i>Total</i>	<i>Added</i>	<i>Total</i>	<i>Added</i>	<i>Total</i>	<i>Added</i>	<i>Total</i>	<i>Added</i>
StarCoder 2	91	-	9	-	95	-	5	-
StarCoder 2 Racket	89	64	11	36	92	64	8	36
StarCoder 2 Elixir	88	41	12	59	93	41	7	59
DeepSeek-Coder	93	-	7	-	93	-	7	-
DeepSeek Racket	86	59	14	41	86	59	14	41
DeepSeek Elixir	86	53	14	47	88	53	12	47

Table 6: Vocabulary usage (%) by the original and adapted tokenizers. The original tokenizers are highlighted in bold. "Used" group of columns indicates the percentage of all added tokens used in the tokenization of a training dataset. "Unused" group of columns is similar to the "Used" group, but indicates tokens that were not used in tokenization.

Tokenizer Name	Racket			Elixir		
	<i>Mean</i>	<i>Std</i>	<i>p-value</i>	<i>Mean</i>	<i>Std</i>	<i>p-value</i>
StarCoder 2	2.8861	5.2765	-	3.9213	3.6107	-
StarCoder 2 Racket	2.9331	5.6742	0.0140	3.9251	3.6258	0.3525
StarCoder 2 Elixir	2.8876	5.2781	1.0000	4.0061	3.6760	0.0001
DeepSeek-Coder	2.6686	4.4462	-	3.3679	3.2266	-
DeepSeek-Coder Racket	2.7986	4.8579	0.0001	3.4116	3.2680	0.0001
DeepSeek-Coder Elixir	2.7082	4.4792	0.0026	3.5727	3.3596	0.0001

Table 7: Mean bytes per token (MBPT) for the original and adapted tokenized calculated over training datasets. The original tokenizers are highlighted in bold. P-values of the two-tailed t-test between MBPTs of the original and adapted tokenizers are indicated in the dedicated column. Statistically significant differences (p-value < 5%) are highlighted in green, while the others are highlighted in red.