Vocab Diet: Reshaping the Vocabulary of LLMs with Vector Arithmetic

Anonymous ACL submission

Abstract

Large language models (LLMs) encode word-form variation (e.g., "*walk*" vs. "*walked*") as linear directions in embedding space. However, standard tokenization algorithms treat these variations as distinct tokens—filling the size-capped vocabulary with surface form variants (e.g., "*walk*", "*walk**ing***", "***W**alk*"), at the expense of less frequent words and multilingual coverage. We show that many of these variations can be captured by *transformation vectors*—additive offsets that yield the appropriate word's representation when applied to the *base form* word embedding—in both the input and output spaces. Building on this, we propose a compact reshaping of the vocabulary: rather than assigning unique tokens to each surface form, we compose them from shared *base form* and *transformation* vectors (e.g., "*walked*"="*walk*"+*past tense*). We apply our approach to multiple LLMs and across five languages, removing up to 10% of vocabulary entries—thereby freeing space to allocate new, more diverse tokens. Importantly, we do so while also expanding vocabulary coverage to out-of-vocabulary words, with minimal impact on downstream performance, while keeping the pretrained backbone frozen and only training lightweight adaptation modules. Our findings motivate a foundational rethinking of vocabulary design, moving from string enumeration to a compositional vocabulary that leverages the underlying structure of language.[1]

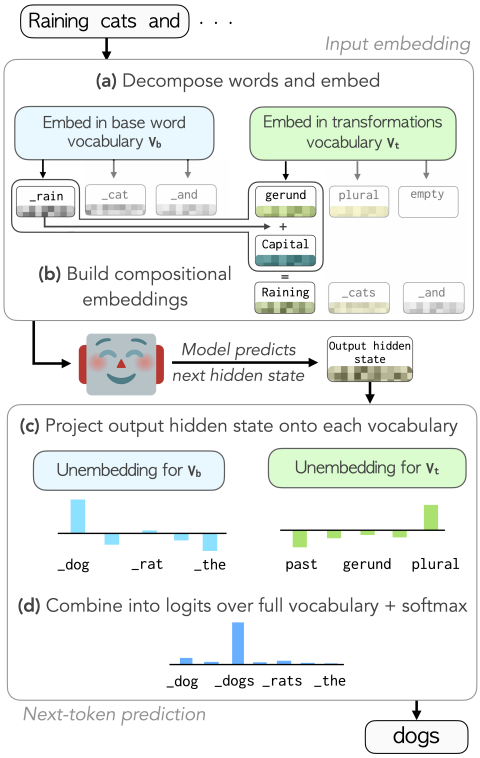

Figure 1: **Compositional vocabulary for LLMs. Top:** Input tokens are represented by **(a)** decomposing them into base words ($\mathcal{V}_b$) and transformations ($\mathcal{V}_t$), and **(b)** feeding the composite embeddings to the model. For example, "*cats*" becomes "*cat*" + *plural*. **Bottom:** The next token is predicted by **(c)** computing logits independently over base words and transformations, and **(d)** combining them into next-token probabilities. Our approach works seamlessly with pretrained LLMs with lightweight parameter updates, creating a more compact vocabulary that supports a wider array of words.

1 Introduction

Modern large language models (LLMs) typically rely on subword tokenization algorithms like byte-pair encoding (BPE; Sennrich et al., 2016). Such methods allocate tokens to frequent words and split less frequent ones into sequences of subword tokens—minimizing the number of tokens needed to represent typical textual data. To further reduce inference costs, as well as broaden domain and multilingual coverage, recent models use ever-larger vocabularies, often exceeding 100k tokens (Grattafiori et al., 2024; OpenAI, 2024; Yang et al., 2024). While recent work calls for scaling up the vocabulary even further (Tao et al., 2024; Huang et al., 2025), the computational cost of supporting large vocabularies forces developers to cap

[1]We will release our code upon publication.

its size (Dagan et al., 2024; Wijmans et al., 2025).

Standard tokenization, while effective, often leads to a disproportionate allocation of the vocabulary (§3). Common words occupy multiple token slots for their various forms (e.g., "walk", "walks", "walking", etc.), leaving less room for uncommon words and multilingual coverage—ultimately hurting both performance and inference costs (Petrov et al., 2023; Ahia et al., 2023; Ali et al., 2024). More fundamentally, it ignores a striking property of LLMs: their tendency to encode relationships between words as simple *linear directions* (Park et al., 2024; Marks and Tegmark, 2024). But can we harness this structure to build more compact vocabularies, without sacrificing expressivity?

We begin by investigating how LLMs represent word form variation. Building on the idea of vector arithmetic in embedding space (Mikolov et al., 2013b), we examine whether common word-form transformations—including morphological inflection ("walk**ed**"), derivation ("walk**er**") and capitalization ("**W**alk")—can be captured as consistent *transformation vectors* added to a *base form* word embedding (§4). Focusing on five morphologically diverse languages, we use the UniMorph word-form database (Batsuren et al., 2022) to identify token pairs of base- and surface-form words exemplifying the same relation. We then compute the average offset vector for each relation, and use these as *transformation* vectors. Our results show that adding these vectors to *base form* embeddings yields representations that the model interprets similarly to the expected surface form (Ghandeharioun et al., 2024). Interestingly, this holds even when the target word is not represented as a single token in the vocabulary,[2] indicating that LLMs process and interpret word forms compositionally (§5).

Building on these insights, we propose a compact reshaping of the vocabulary, building word embeddings from shared components (Figure 1): a *base form* vector for the core lexical item and a *transformation* vector for encoding word-form variation. Rather than assigning a unique token embedding to each surface-form, we truncate the model's embedding tables to remove any inflected forms, and introduce a small set of *transformation* embeddings—enabling us to represent the discarded words compositionally (e.g., *"walked"* as *"walk"*+*past tense*) in both input and output. Importantly, we only update lightweight adaptation parameters: we fine-tune the *transformation* embeddings and train a LoRA adapter on the final $k = 6$ transformer blocks, leaving all other parameters frozen. In experiments across five models and five languages, our method removes up to 10% of the vocabulary tokens while maintaining performance over a suite of downstream tasks when representing words compositionally (§6). We further run a pretraining proof-of-concept experiment (§7), showing that a compositional model can be trained from scratch while removing 41.6% of vocabulary entries with comparable accuracy (38.3 vs. 38.1), and with an training throughput increase of 11.5%.

In summary, we introduce compositional structure into language model vocabularies, enabling efficient representation of linguistic diversity through shared building blocks. Our approach reduces redundancy in token allocation while expanding lexical coverage—with only lightweight adaptation. Our experiments demonstrate that LLMs can naturally operate with these representations, and establish compositional vocabularies as a competitive alternative to standard surface-form tokenization for future language models.

2 Background: Token Allocation in Language Model Vocabularies

Tokenization bridges natural language and model representations: it decomposes text into sequences of tokens from a fixed vocabulary, where each token is an atomic string unit for which the model learns specialized, single-vector embeddings. These vocabularies are almost universally built using byte-pair encoding (BPE; Sennrich et al., 2016), which iteratively merges the most frequent token pairs—from characters to subwords to words—in attempt to optimally compress the text using a predetermined vocabulary size.

As LLM vocabularies grow larger (e.g., Gemma Team, 2024; Aryabumi et al., 2024), there is growing recognition that vocabulary resources can be better allocated. Recent studies point to stark imbalances in token allocations across languages, negatively impacting both model cost (Petrov et al., 2023; Ahia et al., 2023) and performance (Ali et al., 2024; Limisiewicz et al., 2023; Toraman et al., 2022), motivating techniques for post-hoc vocabulary expansion to reduce costs for a specific language or domain (Han et al., 2025; Nakash et al., 2025; Liu et al., 2024b; Minixhofer et al., 2024).

Another line of research advocates for scaling

[2] E.g., a word like "walkable" is split into `[_walk, able]`.

up the vocabulary together with model size to unlock performance gains in the model's main language (Tao et al., 2024; Huang et al., 2025; Liu et al., 2025). Still, expansion is ultimately bounded by memory and compute constraints (Dagan et al., 2024; Wijmans et al., 2025), underscoring the importance of carefully reconsidering how the token vocabulary is allocated.

3 Word Structure and Redundancy in Vocabulary Design

One underexplored source of inefficiency in current vocabulary design is the treatment of morphologically related word forms as independent tokens. In high-resource languages like English, this often results in large clusters of surface variants—*walk, walks, walking, walked*—each assigned a separate token, despite their shared meaning and structure.

To quantify this redundancy, we examine the English whole-word tokens in the GPT-4 tokenizer (OpenAI, 2024)—the base tokenizer for many recent LLMs (Grattafiori et al., 2024; Yang et al., 2024; OLMo et al., 2024). We use UniMorph's English lexicon (Batsuren et al., 2022) to identify tokens that are English words,[3] finding 24.6k such tokens (Figure 2, left side).[4] Ignoring case (e.g., equating "walk" with "Walk") reduces this to 17.7k unique types. Further accounting for inflectional and derivational relations reduces this to just 14.3k *base forms*, a total of 42% reduction.

Rather than assigning each word form with a distinct, independently-learned token, what if we could model these processes as *transformations* applied to a compact set of base words? Our analysis shows that, beyond reconstructing every in-vocabulary word, these tokens can further represent 98k out-of-vocabulary words (Fig. 2, right), which are currently represented using multiple tokens.

Altogether, this motivates a structured vocabulary design that composes word forms from shared blocks, yielding vocabularies that are simultaneously more compact and more expressive while scaling effectively across domains and languages.

[3]We only consider tokens that start with a leading space as whole word tokens; tokens without it can sometimes occur mid-word (like "ask" in "task", compared to "_ask").

[4]Out of 100k tokens, there are 41.3k tokens with a leading space in the vocabulary that are composed of English letters. Roughly 60% are identified as valid English words. The rest are either code-related terms, sub-words, or proper nouns. The other 60k tokens are either sub-words or non-English tokens.

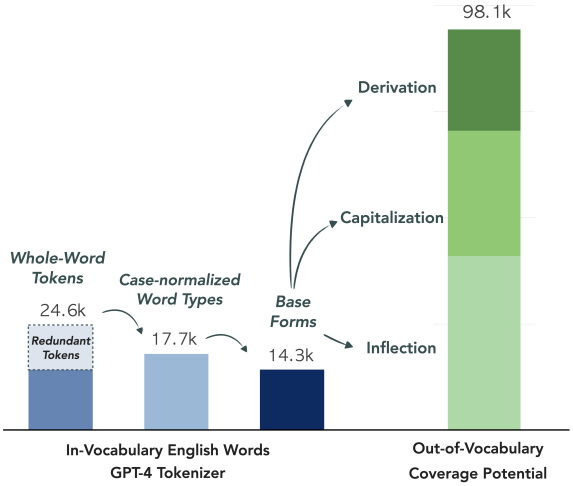

Figure 2: **Structure in LLM vocabularies and potential for compositional design. Left:** Many in-vocabulary English word tokens in the GPT-4 tokenizer are surface variants of other tokens—differing only by case, inflection, or derivation—reducing from 24k tokens to just 14k base form words. **Right:** The existing set of base forms and transformations can be used to compose over 98k currently out-of-vocabulary words, highlighting the inefficiencies of current vocabularies and the potential of a compositional design.

4 Composing Words from Base Forms and Transformations

We propose a compositional representation approach in which each surface form is constructed from a base word and a set of transformation vectors. Formally, let $\mathcal{V}_{\text{orig}}$ denote the model's original token vocabulary. We define a subset $\mathcal{V}_b \subset \mathcal{V}_{\text{orig}}$ as the base-word vocabulary, consisting of canonical lexical forms (e.g., *walk*) and any auxiliary tokens (e.g., punctuation, sub-words, code segments, words in non-target languages). We also introduce a transformation vocabulary $\mathcal{V}_t$, which consists of a small number of vectors corresponding to morphological operations such as inflection or derivation, or other word-level processes like capitalization.

In our scheme, a word w is represented by a base $b_w \in \mathcal{V}_b$ and a set of transformations $T(w) \subset \mathcal{V}_t$:

$$\mathbf{e}_w = \mathbf{e}_{b_w} + \sum_{t_i \in T(w)} \mathbf{e}_{t_i} \qquad (1)$$

where $\mathbf{e}_{b_w}$ and $\mathbf{e}_{t_i}$ are rows from embedding matrices E_b and E_t, respectively. For base words and auxiliary tokens, $T(w) = \varnothing$.

This decomposition applies both at input and output: At input, we replace direct lookup with Eq. 1. At output, we replace the model's large unembedding matrix U with two separate, smaller matrices

for *base forms* and *transformations*: U_b and U_t. Given an output state $\mathbf{h}$, we score each candidate next-token w by separately projecting $\mathbf{h}$ onto U_b and U_t and summing the relevant dot-products:

$$\text{logit}(w) = \mathbf{h} \cdot \mathbf{u}_{b_w} + \sum_{t_i \in T(w)} \mathbf{h} \cdot \mathbf{u}_{t_i} \qquad (2)$$

where $\mathbf{u}_{b_w}$ and $\mathbf{u}_{t_i}$ are the corresponding columns of U_b and U_t for w's components. Importantly, our method is agnostic to whether w is in-vocabulary (IV) or out-of-vocabulary (OOV), as long as its base form is IV. We define the compositional vocabulary $\mathcal{V}$ as all words that can be constructed from $(b_w, T(w))$ combinations.

Vocabulary decomposition map. To apply this framework, we construct a mapping $w \mapsto (b_w,\ T(w))$ from surface forms to their base forms and matching transformations. We use UniMorph (Batsuren et al., 2022), a multilingual word form database, to identify base forms and their inflected and derivated forms. Transformation labels are drawn from UniMorph's standardized tags (e.g., `V;PST`) with added rules for capitalization. Then, to build a decomposition map for a given tokenizer's vocabulary $\mathcal{V}_{\text{orig}}$, we iterate over its tokens, identify base forms, and map all related surface forms—whether in-vocabulary or not—to their base and transformation sets.

Notably, the decomposition map could also be built using sources other than gold morphological annotations. Plausible alternatives include unsupervised morphological segmentation (Creutz and Lagus, 2005; Smit et al., 2014; Abdelali et al., 2016), statistical morphology learning (Creutz and Lagus, 2007), or bootstrapping morphological annotations via LLM-generated analyses. In this work, we focus on whether these compositions are interpreted and used correctly by models, and therefore use high-quality UniMorph annotations; future work could operationalize unsupervised alternatives.

Computing the transformation vectors. To define the transformation vectors themselves (i.e., the entries in E_t and U_t) we revisit the idea of vector arithmetic in embedding space (Mikolov et al., 2013b). Let O be an embedding matrix of $\mathcal{V}_{\text{orig}}$, and let $b(w) : \mathcal{V}_{\text{orig}} \mapsto \mathcal{V}_{\text{b}}$ be a function that maps a word to its base form. For each transformation t, we extract the set $R(t) = \{(w, b(w)) \mid t \in T(w)\}$ of word pairs in $\mathcal{V}_{\text{orig}}$ that exemplify t (e.g., *walk* and *walked* for t = past tense).[5] We then compute the average offset of their respective embeddings:

$$\mathbf{o}_t = \frac{1}{|R(t)|} \sum_{w \in R(t)} (\mathbf{o}_w - \mathbf{o}_{b(w)}) \qquad (3)$$

We compute this separately for all $t \in \mathcal{V}_{\text{t}}$ in both the embedding and unembedding spaces, yielding *transformation* vectors for input and output. While prior work analyzed such linearity in the embeddings of LLMs (Park et al., 2024, 2025), to the best of our knowledge, our work is the first to leverage this for end-to-end language modeling.

5 Do LLMs Understand Compositional Word Representations?

We now turn to our core question: can LLMs that were pretrained with standard vocabularies interpret our compositional embeddings—sums of *base form* and *transformation* vectors—as intended?

Recent work has shown LLMs build-up and resolve the meanings of input tokens across their early layers, a process referred to as *detokenization* (Kaplan et al., 2025; Feucht et al., 2024; Gurnee et al., 2023). This was particularly observed for multi-token words or in-vocabulary words split into multiple tokens (e.g., due to typos). Building on this, we feed models with compositional inputs and inspect whether the embedding and early layer representations have successfully resolved into the intended surface form meanings. To interpret these internal representations, we follow Kaplan et al. and use Patchscopes (Ghandeharioun et al., 2024), a prompting method to probe the contents of a hidden state using natural language.

Languages and models. We experiment with five morphologically-diverse languages: English, Arabic, German, Russian and Spanish. For English, we use three LLMs: `Llama-3-8B` (Grattafiori et al., 2024), `Qwen2.5-7B` (Yang et al., 2024), and `OLMo-2-7B` (OLMo et al., 2024). As coverage of whole-word tokens in these models' vocabularies for other languages is narrow,[6] we use models with dedicated tokenizers for them: `ALLaM-7B` for Arabic (Bari et al., 2025) and `EuroLLM-9B` for the three other languages (Martins et al., 2025).[7] In experiments for a specific model and language pair, we

[5] To obtain a "clean" signal for *transformations*, we only use w that demonstrate a *single* transformation ($|T(w)| = 1$).

[6] This restricts both the base-word lexicon, and the number of existing *base-inflected* pairs for extracting transformations.

[7] All models have vocabularies of 100k or more tokens, except `ALLaM` with 64k (but roughly 32k are for Arabic).

construct the vocabulary decomposition and transformation vectors (§4) only for that language, ignoring words in other languages.

Examining word representations. For each model and language pair, we iterate over all words w that could be composed from the *base forms* and *transformations* extracted from its vocabulary (§4). Next, given a surface form w, we replace the token embedding for w with its compositional representation e_w (Eq. 1), and feed it to Patchscopes to generate its textual description.[8] We then evaluate whether the Patchscopes interpretation of the compositional embedding e_w matches the target word w (*embed*). We also examine whether the model successfully *detokenizes* compositional embeddings in its early layers: we feed e_w to the model without any context, extract the resulting hidden states at the first $k = 10$ layers, and report whether the Patchscopes interpretation matches the target word w in at least one layer (*detok*).

English results. We begin by examining English words that exist as single tokens in `Llama-3-8B`'s original vocabulary $\mathcal{V}_{\text{orig}}$ (Table 1, *in-vocab*). We observe that most inflectional transformations—such as verb tense (past, present participle) and number (plural)—as well as capitalization, are often correctly resolved by the model already at the embedding layer (*embed*), and almost always at early internal layers (*detok*). For example, $\mathbf{e}_{\text{walk}} + \mathbf{e}_{\textit{past}}$ is interpreted by Patchscopes as "walked". In contrast, derivations (e.g., "walk"→"walkable"), which rarely occur as single-tokens in the vocabulary, are seldom recognized by the model and often resolve as the base word instead. This suggests that models learn weaker linear structure for rare relations, or that *transformation* vectors built using small sample sizes show weaker generalization.

We next examine out-of-vocabulary words, i.e., English words that can be composed using the *base forms* and *transformations* but are *not* found as a single token in the original vocabulary (Table 1, *out-of-vocab*). Using our decomposition map, we construct single-vector representations for these words and feed them to the model. Surprisingly, many of these are resolved as the intended word form already at the embedding layer, with Patchscopes generating the full, multi-token word, especially for inflections and capitalization. Similarly to in-vocabulary results, we observe higher successful resolution rates for early-layer detokenization, and representing out-of-vocabulary derivations using compositions generally fails. We observe similar results for English in other models (Appendix A).

Transformation	In-vocab.			Out-of-vocab.		
	embed	*detok*	*N*	*embed*	*detok*	*N*
Inflection						
Plural (N)	92%	96%	0.8k	30%	56%	3.4k
Plural (N) & Present Singular (V)	87%	91%	1.6k	43%	75%	2.1k
Present Singular (V)	90%	91%	0.1k	64%	82%	0.3k
Past (V)	71%	81%	0.6k	9%	29%	2.9k
Past Participle (V)	64%	93%	14	14%	38%	21
Gerund (V)	83%	93%	0.2k	17%	34%	3.2k
Superlative (ADJ)	71%	94%	31	5%	29%	0.4k
Comparative (ADJ)	40%	83%	30	3%	36%	0.4k
Capitalization	80%	89%	6.0k	72%	85%	8.4k
Derivation						
-y	24%	47%	17	2%	12%	1.5k
-er	8%	17%	12	0%	6%	2.6k
-al	25%	25%	8	0%	9%	0.7k
un-	0%	33%	3	0%	2%	3.3k
re-	67%	67%	3	0%	10%	1.8k
-ic	100%	100%	2	4%	21%	0.4k
All derivatives	31%	45%	51	0%	3%	31.4k

Table 1: Accuracy of Patchscopes interpretations for compositional input representations (i.e., *base form* + *transformation* embeddings) of in-vocabulary and out-of-vocabulary English words in `Llama-3.1-8B`. We report successful resolution both at the embedding layer (*embed*), and after detokenization in early layers (*detok*). N indicates the number of surface forms evaluated per category. Compositional embeddings of capitalization and inflectional forms are very often resolved correctly—even for many out-of-vocabulary words, which never occur as single input vectors during pretraining. Derivatives remain challenging—likely due to rarely appearing as single tokens in the vocabulary.

Multilingual results. We repeat the same experiment on each of the other languages. Since each language has different types and number of inflectional and derivational processes,[9] we aggregate results over five categories: adjective inflection, verb inflection, noun inflection, derivation and capitalization. Our results (Table 2) show that LLMs can correctly interpret compositional word representations across diverse languages and morphological structures. Surprisingly, some *transformation* vector types (e.g., adjective or verb inflections) work better for out-of-vocabulary representation than in English, hinting that models learn stronger linear encodings of morphological structure when the token vocabulary is more limited—a phenomenon

[8] Following Kaplan et al. (2025), we use the Patchscopes prompt "`[X], [X], [X], [X],`", where we replace the placeholder token (`[X]`) with a hidden state $\mathbf{h}$ and let Patchscopes generate text. We expect Patchscopes to generate the intended word form if $\mathbf{h}$ indeed captures it. For languages other than English, we add the prefix "`In {language_name}:`".

[9] We treat each UniMorph tag as its own *transformation*.

	Language	Capitalization		Noun Inflection		Adjective Inflection		Verb Inflection		Derivation	
		In-Vocab.	*Out-Vocab.*	*In-Vocab.*	*Out-Vocab.*	*In-Vocab.*	*Out-Vocab.*	*In-Vocab.*	*Out-Vocab.*	*In-Vocab.*	*Out-Vocab.*
ALLaM	Arabic	—	—	77% (1.8k)	14% (3.6k)	69% (0.5k)	23% (1.0k)	41% (1.0k)	14% (2.7k)	—	—
EuroLLM	German	95% (0.2k)	74% (0.4k)	—	—	21% (0.3k)	7% (1.3k)	82% (0.3k)	36% (1.2k)	—	—
	Russian	97% (66)	88% (0.7k)	63% (0.6k)	21% (4.2k)	100% (50)	89% (94)	83% (6)	30% (10)	—	—
	Spanish	97% (1.0k)	90% (2.8k)	76% (0.7k)	46% (1.9k)	79% (0.5k)	60% (1.1k)	67% (0.8k)	35% (6.9k)	37% (65)	14% (0.4k)
Llama-3	English	80% (6.0k)	72% (8.4k)	89% (2.4k)	35% (5.6k)	56% (61)	4% (0.9k)	76% (0.9k)	16% (6.4k)	20% (41)	0% (12.8k)

Table 2: Accuracy of Patchscopes interpretations for compositional input embeddings across languages. Numbers in parentheses indicate sample sizes. "—" indicates cases where no suitable *base-inflection* pairs found in the vocabulary or where there are no UniMorph entries for that category. For detokenization results, see Appendix B.3.

we further analyze in Appendix B.1. Overall, our results show that LLMs can naturally interpret compositional word embeddings across languages.

Analysis of transformation failures. Across languages and models, we observe a consistent gap between inflectional transformations (often resolved) and derivational transformations (rarely resolved). To characterize these failures, we analyze whether the number of in-vocabulary exemplar pairs used to estimate each transformation vector (Eq. 3) helps explain transformation failures. Qualitatively, we find that the number of exemplars mainly matters for *generalization*: transformations estimated from many pairs are much more likely to resolve multi-token surface forms, while in-vocabulary success is comparatively insensitive to exemplar count once a usable signal is available (see Appendix B.2).

Vocabulary size effects. We analyze the extent to which morphology is encoded *linearly and compositionally* as vocabulary size grows. We repeat the English Patchscopes experiment across models with various vocabulary sizes. Surprisingly, we find an inverse relationship between English whole-word vocabulary size and the linearity of morphological transformations; this suggets that larger vocabularies allow models to represent inflected forms of the same type as individual lexical units, rather than through a shared linear translation of their base forms (see Appendix B.1 for details).

6 Compositional Language Modeling

We have shown that *transformation* vectors capture meaningful operations in the input space of LLMs, and that these can be successfully composed with base word embeddings. We next investigate whether models can use compositional vocabularies effectively in end-to-end language modeling.

6.1 Experimental Setting and Implementation

Given a model's vocabulary decomposition map (§4), we apply our compositional vocabulary framework and restructure the input and output embedding matrices. We replace the model's input embedding of any surface form w with compositions of the corresponding *base form* and *transformation* embeddings (Eq. 1). For next-token prediction, we compute logits through summation of *base form* and *transformation* logits (Eq. 2). Importantly, any word not in the decomposition map maintains its original embedding and unembedding throughout training and inference, without modifications.

Fine-tuning the transformation vectors After initialization (Eq. 3), we train the *transformation* vectors jointly within the model: we treat the *transformation* embeddings and unembeddings matrices E_t and U_t as trainable weights (introducing fewer than 0.001% additional parameters), and freeze all other model parameters, including the embeddings and unembeddings of *base forms*. We use knowledge distillation loss (Hinton et al., 2015) to fine-tune the *transformation* vectors using two-stage distillation: We first freeze the output unembeddings and only train the *input transformations*, using the predictions of the original, unmodified model as targets. Next, we freeze the input embeddings and only train the *output transformations*, this time using the (frozen) model resulting from the first stage as the distillation target—ignoring all words $w \notin \mathcal{V}_{\text{orig}}$ in the loss. In both stages, we train on a fixed, small sample of the `FineWeb-Edu` corpus (Penedo et al., 2024).[10] See Appendix C.

Lightweight LoRA adaptation. To allow lightweight adaptation to the reshaped output vocabulary, we add and train LoRA adapters to the final $k = 8$ model layers, keeping all other internal layers frozen. We use LoRA $r = \alpha = 256$.

[10] We use a sequence length of 256 and train on ∼5M tokens.

Filtering the decomposition map Our results in §5 indicate some out-of-vocabulary surface forms fail to be interpreted by the model as their intended word when given as compositions. We therefore filter out surface words with failed detokenization from the decomposition map, and fall back to using their original tokenization and embeddings in both input and output. We also exclude all derivational transformations due to their weak resolution rates. See analysis in Appendix B.4.

Downstream tasks We evaluate our compositional vocabulary models on a diverse suite of standard benchmarks. As a baseline, we compare performance to the original, unmodified models. For English, the benchmarks cover language understanding, knowledge, and commonsense: MMLU (Hendrycks et al., 2021), ARC (Clark et al., 2018), HellaSwag (Zellers et al., 2019), Winogrande (Sakaguchi et al., 2021), TriviaQA (Joshi et al., 2017), SQuAD (Rajpurkar et al., 2016), BoolQ (Clark et al., 2019), PIQA (Bisk et al., 2020) and COPA (Kavumba et al., 2019). We use the more efficient TinyBenchmark subsets when available (Maia Polo et al., 2024). For other languages, we use XNLI (Conneau et al., 2018), XQuAD (Artetxe et al., 2020) and Global MMLU (Singh et al., 2025). See Appendix E.

6.2 Results

We report our results for English on `Llama-3-8B` in Table 3,[11] and results for other languages in Table 4. Our compositional language modeling approach results in comparable average performance to the baseline models across languages, indicating that LLMs can effectively leverage compositional vocabularies with only lightweight adaptation.

We next inspect reductions in vocabulary size after applying our framework. Our approach removes roughly 10k surface form tokens from Llama3 and OLMo2 each, and 7.8k from Qwen2.5.[12] While seemingly small, recent work has shown that adding as few as several hundred dedicated tokens to the vocabulary can greatly improve tokenization efficiency and model performance on a language or expert domain (Ahia et al., 2023; Liu et al., 2024a; Nakash et al., 2025), emphasizing the importance of an efficient allocation of the vocabulary. These freed-up slots can be reallocated to new tokens via post-hoc expansion methods (Han et al., 2025; Minixhofer et al., 2024). Finally, our method has a marginal effect on decoding speed–only a 0.8% reduction compared to standard prediction (see Appendix B.5). We next show that vocabularies can also be built compositionally from the outset, with even greater vocabulary allocation efficiency, by pretraining a model with a compositional vocabulary from scratch (§7).

[11] Results on other English models are found in Appendix A.

[12] Reductions in the multilingual models are more minimal due to the smaller initial token vocabularies in those languages, and vary from 0.6k to 3k, depending on language.

Category	Task	Baseline	End-to-end	Δ
Knowledge	TinyMMLU (Acc.)	53.0	53.8	+0.8
	TinyARC (Acc.)	46.1	45.6	-0.5
Reading Comprehension	BoolQ (Acc.)	83.2	83.2	+0.1
	TriviaQA (EM)	66.5	63.3	-3.3
	SQuAD (EM)	22.1	20.0	-2.1
Commonsense	TinyHellaswag (Acc.)	61.5	64.4	+2.9
	TinyWinogrande (Acc.)	60.3	58.9	-1.4
	PIQA (Acc.)	80.4	79.1	-1.3
	COPA (Acc.)	93.0	92.0	-1.0
Average		**62.9**	**62.3**	-0.6

Table 3: Downstream performance of English compositional-vocabulary models (*End-to-end*) and their original, unmodified version (*Baseline*) for `Llama-3.1-8B`. Our framework performs on-par with the baseline model, despite extensive changes to the model's input and output representation mechanisms—highlighting the intrinsic ability of LLMs to process and predict word representations compositionally.

		XNLI	Δ	XQuAD	Δ	GMMLU	Δ
ALLaM	Arabic	44.1	-0.3	42.7	-3.2	59.9	+0.2
EuroLLM	German	46.5	+0.6	51.3	-1.6	54.6	-0.7
	Russian	40.1	-4.5	37.4	-3.6	54.4	-0.3
	Spanish	43.3	-0.6	48.3	-4.1	55.2	-0.9

Table 4: Multilingual downstream performance of compositional vocabulary models, along with absolute performance difference from the baseline model (Δ).

7 Compositional Vocabulary Pretraining

To validate that compositional vocabularies can also serve as a *design choice* for training new language models, we reshape English and Spanish BPE vocabularies into *base forms* and *transformations* and pretrain small baseline and compositional models from scratch. For English, we reshape the 50k-token GPT-2 tokenizer (Radford et al., 2019), while restricting the compositional model to predict exactly the same surface-form vocabulary as the BPE baseline (i.e., we do not extend to out-of-vocabulary words). For Spanish, we train a 32k-token BPE vocabulary[13] and then reshape it, this

[13] We train the Spanish tokenizer on 10B bytes from the Spanish subset of FineWeb-2 (Penedo et al., 2025)

time allowing the compositional model to generate out-of-vocabulary surface forms via compositions.

We pretrain `nanoGPT-124M` models (Jordan et al., 2024) for 1B tokens in each language,[14] comparing a baseline model against an otherwise-identical compositional model. In contrast to our post-hoc setup, the compositional model predicts directly in a factorized space (a base-form distribution and *transformation* predictions). We further include a space-prefix *transformation* (e.g., "_walking" vs. "walking").[15] We evaluate on a held-out validation set and report next-token accuracy for English (since both models share the same surface-form vocabulary). For Spanish, as the models have different vocabularies, we report Bits-Per-Bytes (BPB).[16] We further examine tokenization efficiency in Spanish using average bytes per token (higher is better).

Reshaping the GPT-2 tokenizer yields a 41.6% reduction in the number of vocabulary entries used to represent the original BPE vocabulary (removing 19.8k tokens) while preserving exact coverage. Despite this reduction, the compositional model achieves comparable next-token accuracy on held-out validation of 38.10 (vs. 38.27). For Spanish, we observe a similar token vocabulary reduction of 41.8% with competitive BPB compared to the baseline (1.110 vs. 0.996). Allowing compositional generation improves tokenization efficiency, increasing average bytes per token (4.773→4.920) on held-out Spanish text. Finally, we measure training throughput and find that the compositional model trains faster due to the smaller vocabulary size, improving throughput by 11.5% (471k→525k tokens/sec).[17]

Together, these results show that compositional vocabularies can be trained from scratch effectively, offering compact vocabularies, improved tokenization efficiency, and practical training-speed benefits for future language models.

8 Related Work

Incorporating morphology into representations A longstanding goal in NLP has been to integrate morphological knowledge into models. Early work on Transformer language models explored injecting linguistic features post-hoc (Hofmann et al., 2021; Gan et al., 2022) or during pretraining (Park et al., 2021; Cui et al., 2022; Matthews et al., 2018; Blevins and Zettlemoyer, 2019; Hofmann et al., 2020; Seker et al., 2022; Peng et al., 2019), but such approaches are absent in modern LLMs. Recent work examined word segmentation effects on performance (Marco and Fraser, 2024; Lerner and Yvon, 2025), including morphology-aware tokenization to better reflect word structure (Bauwens and Delobelle, 2024; Asgari et al., 2025). Rather than injecting linguistic structure, we leverage compositional representations already present in LLMs.

Vector arithmetic of word representations Linear structure in word representations was first observed in Word2Vec (Mikolov et al., 2013a,b; Levy and Goldberg, 2014; Vylomova et al., 2015). Recent work found similar structures in LLMs across the unembedding layer (Park et al., 2024, 2025), residual stream (Merullo et al., 2023; Hendel et al., 2023; Todd et al., 2024), and in behavior-steering directions (Subramani et al., 2022; Hernandez et al., 2024). We further show that such structure is usable for end-to-end language modeling. Beyond morphology, *transformation* vectors could capture semantic relations (e.g., country–nationality; Gladkova et al., 2016) or tie word embeddings across languages (Schut et al., 2025).

Post-hoc vocabulary modification Recent work has proposed methods to expand or modify token vocabulary by training new embeddings and fine-tuning internal model layers (Kim et al., 2024; Takase et al., 2024; Han et al., 2025; Minixhofer et al., 2024; Ben-Artzy and Schwartz, 2025; Dobler and de Melo, 2023). We avoid fine-tuning model weights, and represent new forms compositionally using existing linguistic knowledge.

9 Conclusion

We have shown that word representations in LLMs are inherently compositional, and leveraged this property to introduce compositional vocabularies. Our framework enables token vocabularies that are more compact in the vocabulary size needed for linguistic coverage, while being more expressive. Our results highlight that language models can naturally operate with compositional vocabularies and that with integration into pretraining future models, LLMs could cover more words, languages, and domains—without sacrificing performance.

[14] We use FineWeb (English) and FineWeb-2 (Spanish).

[15] Modern BPE vocabularies include prefix whitespace characters when merging tokens, creating many near-duplicates.

[16] BPB allows comparison across models with different vocabularies; it normalizes negative log-likelihood by the number of UTF-8 bytes in the evaluation text. See Appendix D.

[17] Throughput is measured when training on 4 L40S GPUs.

Limitations

Our framework employs external morphological resources to define transformation pairs. While this allows for clean experimental control, it limits its applicability to languages or domains lacking annotated morphological data. In future work, we hope to explore whether similar transformation vectors can be induced directly from data, using unsupervised learning or joint training objectives that encourage compositionality. Models that learn to discover structure, rather than rely on it, would offer broader generalization and better alignment with language acquisition in humans.

Our vocabulary reshaping approach assumes a one-to-one decomposition of each surface form into a base word and a set of transformation vectors. While effective for many cases, this simplification does not account for certain words which could result from several distinct morphological processes. Still, these problems are also encountered with standard tokenization approaches, with models learning to disambiguate such words into their intended meanings.

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A Supplementary Results

For the results on other models for the experiment in §5, see Table 5, Table 6. For downstream results (§6), see Table 8 and Table 9.

B Additional Analysis

B.1 Morphology in Embedding Space Scales Inversely with Vocabulary Size

Having established that models implicitly learn to represent words compositionally, and with recent calls to scale vocabularies even further, a natural question emerges: how does vocabulary size affect the way models encode linguistic structure?

To study this question, we evaluate the extent of compositional word representations across models with varying vocabulary sizes. For each model, we decompose its vocabulary and measure the average Patchscopes interpretation accuracy for each *transformation* vector we extract (see §5). We also separate models by their embedding architecture (*untied* vs. *tied*). We track each model's English vocabulary size (the subset of tokens present in English UniMorph), and plot the results in order of increasing vocabulary size.

For regular embedding models (top panel in Figure 3), we use `Llama2-7B` (Touvron et al., 2023), `Mistral-7B` (Jiang et al., 2023), `OLMo2-7B` (OLMo et al., 2024), `Phi4-14B` (Abdin et al., 2024), `Llama3-8B` (Grattafiori et al., 2024), `Qwen2.5-7B` (Yang et al., 2024), and `Falcon3-7B` (Team, 2024). For tied input-output embedding models (bottom panel), where input and output embeddings share parameters, we analyze `Llama3-3B` (Grattafiori et al., 2024), `Qwen2.5-3B` (Yang et al., 2024), `Phi4-Mini-Instruct-4B` (Abdin et al., 2024), `Aya-Expanse-8B` (Dang et al., 2024), `Gemma2-2B` and `Gemma2-9B` (Team et al., 2024b). These models span English vocabulary sizes from 8k to 44k tokens and total vocabulary sizes from 32k to 256k tokens, providing coverage across different scales of vocabulary design.

Our results (Figure 3) reveal a general inverse relationship: models with compact English vocabularies (8-10k words, e.g., `Llama2`, `Mistral`) tend to encode morphology through consistent vector offsets that generalize across words. In contrast, large-vocabulary models (∼40k words, e.g., `Falcon3`, `Gemma2-9B`) tend to represent inflected forms of the same type as individual lexical units, rather than through a shared linear translation of their base forms, with weight tying further amplifying this trend. Overall, these results suggest that vocabulary scaling trades morphological compositionality in embedding space for lexical memorization.[18]

B.2 Exemplar Count Predicts Transformation OOV Generalization

We quantify whether the number of in-vocabulary exemplar pairs available to estimate each transformation vector (Eq. 3) predicts when the composed embedding is interpreted as the intended surface form. Concretely, for each transformation t, we use the number of single-token, in-vocabulary (IV) base/surface pairs as a proxy for the effective exemplar set size, and compute Spearman correlations with additive success measured separately on IV targets and on out-of-vocabulary (multi-token) targets.

For Llama-3.1-8B, across individual transformations ($n = 24$ with at least one IV exemplar), IV additive success is essentially independent of exemplar count (Spearman's $\rho = 0.04$, $p = 0.87$). In contrast, the same IV exemplar count strongly predicts out-of-vocabulary performance ($n = 23$ transformations with both IV exemplars and OOV test cases; $\rho = 0.77$, $p = 1.5 \times 10^{-5}$). This dissociation suggests that exemplar richness is not the bottleneck for resolving IV targets (which largely saturate once a direction is available), but it is a prerequisite for the transformation vector to generalize to multi-token, out-of-vocabulary (OOV) surface forms.

When restricting the correlation to transformations within each coarse class, we observe the same qualitative pattern but with weaker statistical power due to small n. Among inflectional transformations ($n = 8$), IV success correlates moderately with the number of IV exemplars ($\rho = 0.50$, $p = 0.21$), whereas among derivational transformations ($n = 14$) IV success trends negative ($\rho = -0.44$, $p = 0.12$), consistent with the observation that derivations remain difficult even when many IV exemplars exist. Within each class, OOV success remains positively correlated with IV exemplar count (inflection: $\rho = 0.38$, $p = 0.35$; derivation: $\rho = 0.38$, $p = 0.18$), reinforcing that generalization to OOV targets depends on having sufficiently many IV pairs, but that this dependence does not by itself close the gap.

[18] Importantly, this does not imply that large-vocabulary models lack morphological knowledge, only that they rely less on linear encoding of morphology in embedding space.

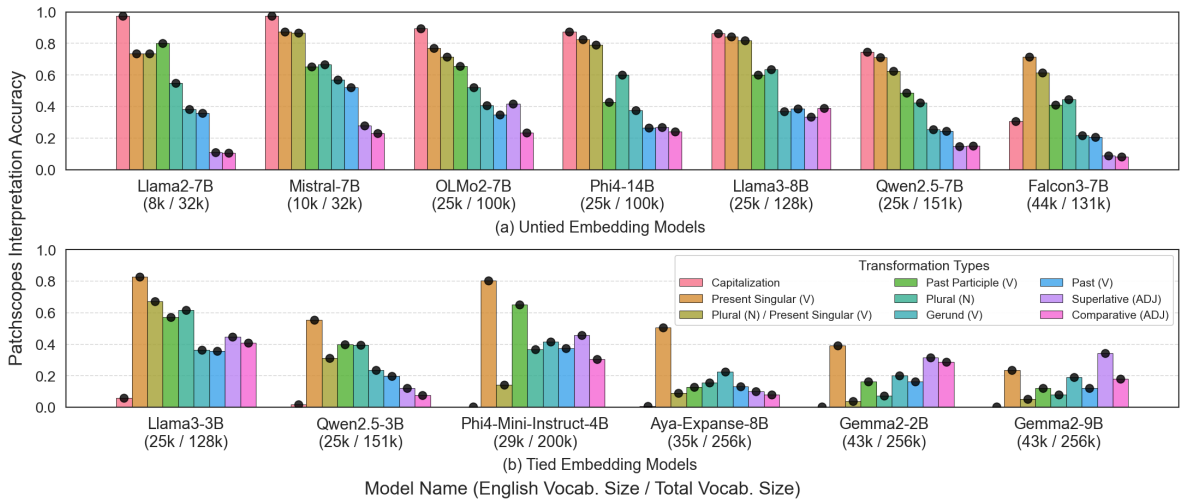

Figure 3: **Linear representation of morphology in embeddings weakens as vocabulary size increases.** Accuracy of Patchscopes interpretations of compositional word representations across models, in order of increasing English vocabulary size (English tokens present in UniMorph), separated by embedding architecture. Scaling vocabulary size leads models to represent inflection as individual lexical units, rather than through consistent vector offsets.

B.3 Multilingual Patchscopes Results

For the results on multilingual patchscopes interpretations of compositional input embeddings after detokenization, see Table 7.

B.4 Filtering the Vocabulary Decomposition for Failed Surface Forms

In §5 we have seen that, even though the compositional embeddings work well for many in- and out-of-vocabulary words, there are also failure cases where we are cannot be certain that the model interprets the compositional representation correctly. Intuitively, this means that using these representations in end-to-end language modeling might hurt model performance; Indeed, when we remove the surface forms corresponding to these failures from the decomposition map (and after fine-tuning the transformation vectors as usual), we observe an average 1.6 points improvement across downstream benchmarks, compared to no filtering. We note that for input-only restructuring, we observe no effect, likely because the model has more error-correction oppurtunities across its layers. We therefore apply this filtering in experiments in §6.

B.5 Decoding Speed Analysis

Our compositional language modeling approach introduces some additional complexity into next-token prediction: to compute token scores over the full, extended vocabulary, we map and sum up logit contributions from the *base form* and *transformation* vocabularies (Eq. 2). To validate that this does not introduce meaningful overhead, we let both the baseline and compositional `Llama-3-8B` models generate texts in response to prompts from the CNN-DailyMail dataset (Chen et al., 2016), and measure the average number of tokens generated per second.[19] Our approach introduces only a 0.8% drop in decoding speed (39.6 vs. 39.9 tokens/sec).

Still, since our compositional next-token prediction approach occurs in two-stages—first deciding on likely candidates for *base forms* and *transformations*—it naturally allows for optimizations like pruning base-form candidates before computing the logits over the full vocabulary (Holtzman et al., 2020), which could further decrease runtime.

C Experimental Details

For fine-tuning, we use a learning rate of $5e-5$, a warmup ratio of 0.03, a weight decay of 0.0, and a sequence length of $m = 256$. We train on $20k$ examples for 1 epoch. We run fine-tuning and inference on A10 GPUs, with fine-tuning taking roughly 30 minutes, and inference taking up to 1 hour.

D Pretraining Details

This appendix provides implementation and evaluation details for the pretraining experiment in §7.

Compositional tokenizer and coverage: We start from a 50k-token GPT-2 tokenizer and re-

[19] We use 50 random prompts and let models generate up to 256 tokens, on an L40S GPU.

move any token that can be expressed as a base form plus *transformations*, including a whitespace-prefix *transformation* to capture pairs like " walking" vs. "walking". Unlike our post-hoc setup, we do not filter out compositions based on Patchscopes interpretation failures (Appendix B.4).

Factorized prediction and base-conditioned transformations: The compositional model predicts a distribution over *base forms*, then predicts *transformations* conditioned on the chosen (or teacher-forced) base form by additionally providing its unembedding vector to the *transformation* head. At inference time, we decode by selecting a base form and then composing it with the predicted *transformations*.

Bits-Per-Byte (BPB): For both baseline and compositional models, we report BPB, computed as the average negative log-likelihood divided by the number of UTF-8 bytes in the evaluation text (lower is better). For the compositional model, we use the teacher-forced joint likelihood under the factorized distribution.

Tokenization efficiency: To test a morphologically richer setting, we train a Spanish 32k-token BPE tokenizer on 10B bytes from the Spanish subset of FineWeb-2 and apply our compositional reshaping, allowing compositions to represent out-of-vocabulary words up to three tokens long. On held-out Spanish text, the reshaped vocabulary improves tokenization efficiency, reducing token fertility (1.3028→1.265) and increasing average bytes per token (4.773→4.92).

E Downstream Evaluation

We include 5 in-context examples for every task. For each dataset, we use 5,000 examples (or the maximum available as some datasets have fewer available samples).

ARC features 4-option multiple-choice science questions from grades 3 through 9. It has two subsets: ARC-Easy, focused on basic science knowledge, and ARC-Challenge, which involves more complex, procedural reasoning (Clark et al., 2018).

BoolQ comprises naturally occurring yes/no questions accompanied by passages that support the answer (Clark et al., 2019).

COPA offers binary multiple-choice questions centered around causal and consequential reasoning (Kavumba et al., 2019).

HellaSwag includes 4-option multiple-choice questions where the task is to select the most plausible continuation of a given context (Zellers et al., 2019).

MMLU presents 4-option multiple-choice questions across 57 subject areas, testing both factual knowledge and reasoning skills (Hendrycks et al., 2021).

PIQA provides multiple-choice questions designed to evaluate physical commonsense understanding (Bisk et al., 2020).

SQuAD pairs reading passages with related questions, where the correct answer is always a text span from the passage itself (Rajpurkar et al., 2016).

TriviaQA features open-domain questions aimed at assessing general world knowledge (Joshi et al., 2017).

Winogrande contains questions modeled after the Winograd schema but scaled up in size and difficulty (Sakaguchi et al., 2021).

XNLI provides natural language inference examples in 15 languages, where the task is to determine whether a hypothesis is entailed by, contradicts, or is neutral with respect to a given premise (Conneau et al., 2018).

XQuAD is a cross-lingual question answering dataset that pairs reading passages with related questions in 11 languages, where the correct answer is always a text span from the passage itself (Artetxe et al., 2020).

Global MMLU extends the original MMLU benchmark to assess multilingual capabilities, featuring 4-option multiple-choice questions across 57 subject areas in 42 languages including low-resource languages, testing both factual knowledge and reasoning skills in diverse linguistic contexts (Singh et al., 2025).

F Additional Related Work

Tokenization for morphologically-rich languages Standard BPE tokenization often struggles to capture morphologically complex languages (Klein and Tsarfaty, 2020; Park et al., 2021; Mager et al., 2022; Hofmann et al., 2022). Arabic inflection, for instance, uses non-concatenative morphology that breaks standard subword reusability (Alyafeai et al., 2021; Alrefaie et al., 2024; Tsarfaty et al., 2019; Gazit et al., 2025). Compositional

Transformation	In-vocab.			Out-of-vocab.		
	embed	*detok*	*N*	*embed*	*detok*	*N*
Inflection						
Plural (N)	92%	92%	0.8k	24%	31%	3.4k
Plural (N) & Present Singular (V)	86%	87%	1.6k	35%	44%	2.1k
Present Singular (V)	91%	91%	0.1k	54%	64%	0.3k
Past (V)	65%	68%	0.6k	10%	15%	2.9k
Past Participle (V)	79%	79%	14	24%	29%	21
Gerund (V)	83%	84%	0.2k	17%	22%	3.2k
Superlative (ADJ)	87%	87%	31	3%	10%	0.4k
Comparative (ADJ)	47%	67%	30	4%	12%	0.4k
Capitalization	72%	73%	6.0k	74%	76%	8.3k
Derivation						
-y	17%	22%	18	2%	6%	1.5k
-er	25%	25%	12	1%	3%	2.6k
-al	62%	62%	8	1%	2%	0.7k
un-	0%	33%	3	0%	1%	3.3k
re-	67%	67%	3	0%	1%	1.8k
-ic	100%	100%	2	5%	7%	0.4k
All derivatives	40%	44%	52	0%	1%	31.4k

Table 5: Accuracy of Patchscopes interpretations for Qwen-2.5-7B.

Transformation	In-vocab.			Out-of-vocab.		
	embed	*detok*	*N*	*embed*	*detok*	*N*
Inflection						
Plural (N)	93%	94%	0.8k	34%	42%	3.4k
Plural (N) & Present Singular (V)	86%	90%	1.6k	41%	58%	2.1k
Present Singular (V)	90%	91%	0.1k	60%	71%	0.3k
Past (V)	74%	85%	0.6k	12%	24%	2.9k
Past Participle (V)	100%	100%	14	24%	43%	21
Gerund (V)	93%	97%	0.2k	26%	38%	3.2k
Superlative (ADJ)	97%	97%	31	20%	38%	0.4k
Comparative (ADJ)	87%	90%	30	7%	18%	0.4k
Capitalization	80%	96%	6.0k	50%	85%	8.3k
Derivation						
-y	65%	65%	17	13%	19%	1.5k
-er	25%	33%	12	6%	19%	2.6k
-al	75%	88%	8	4%	11%	0.7k
un-	33%	33%	3	1%	6%	3.3k
re-	100%	100%	3	1%	17%	1.8k
-ic	100%	100%	2	10%	15%	0.4k
All derivatives	63%	67%	51	2%	6%	31.4k

Table 6: Accuracy of Patchscopes interpretations for OLMo-2-7B.

vocabularies can bypass such limitations by representing surface forms as transformations over lexical roots, enabling reuse of base forms even when their surface realizations use diverging token sequences.

	Language	Capitalization		Noun Inflection		Adjective Inflection		Verb Inflection		Derivation	
		In-Vocab.	*Out-Vocab.*	*In-Vocab.*	*Out-Vocab.*	*In-Vocab.*	*Out-Vocab.*	*In-Vocab.*	*Out-Vocab.*	*In-Vocab.*	*Out-Vocab.*
ALLaM	Arabic	—	—	78% (1.8k)	16% (3.6k)	69% (0.5k)	25% (1.0k)	43% (1.0k)	15% (2.7k)	—	—
EuroLLM	German	100% (0.2k)	89% (0.4k)	—	—	27% (0.3k)	11% (1.3k)	88% (0.3k)	44% (1.2k)	—	—
	Russian	98% (66)	96% (0.7k)	72% (0.6k)	28% (4.2k)	100% (50)	93% (94)	100% (6)	50% (10)	—	—
	Spanish	100% (1.0k)	97% (2.8k)	83% (0.7k)	59% (1.9k)	82% (0.5k)	67% (1.1k)	72% (0.8k)	42% (6.9k)	46% (65)	20% (0.4k)
Llama-3	English	89% (6.0k)	85% (8.4k)	93% (2.4k)	63% (5.6k)	89% (61)	32% (0.9k)	85% (0.9k)	34% (6.4k)	34% (41)	4% (12.8k)

Table 7: Accuracy of Patchscopes *detokenization* interpretations for compositional input embeddings across languages.

Category	**Task**	**Baseline**	**End-to-end**	Δ
Knowledge	TinyMMLU (Acc.)	62.9	62.5	-0.4
	TinyARC (Acc.)	51.8	48.8	-3.0
Reading Comprehension	BoolQ (Acc.)	87.6	87.6	+0.1
	TriviaQA (EM)	58.3	52.9	-5.4
	SQuAD (EM)	37.3	31.9	-5.5
Commonsense	TinyHellaswag (Acc.)	52.1	54.3	+2.2
	TinyWinogrande (Acc.)	62.3	64.3	+2.0
	PIQA (Acc.)	79.5	78.7	-0.8
	COPA (Acc.)	91.0	90.0	-1.0
Average		**64.7**	**63.4**	-1.3

Table 8: Downstream performance of English compositional-vocabulary models (*End-to-end*) and their original, unmodified version (*Baseline*) for `Qwen2.5-7B`.

Category	**Task**	**Baseline**	**End-to-end**	Δ
Knowledge	TinyMMLU (Acc.)	51.2	51.9	+0.7
	TinyARC (Acc.)	51.9	49.1	-2.8
Reading Comprehension	BoolQ (Acc.)	84.5	84.8	+0.3
	TriviaQA (EM)	65.4	56.8	-8.6
	SQuAD (EM)	40.0	30.6	-9.3
Commonsense	TinyHellaswag (Acc.)	62.6	63.4	+0.8
	TinyWinogrande (Acc.)	63.5	63.9	+0.4
	PIQA (Acc.)	80.4	79.5	-0.9
	COPA (Acc.)	91.0	89.0	-2.0
Average		**65.6**	**63.2**	-2.4

Table 9: Downstream performance for `OLMo-2-7B`.