
Lossless Token Sequence Compression via Meta-Tokens

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Abstract

Existing work on prompt compression for Large Language Models (LLM) focuses on lossy methods that try to maximize the retention of semantic information that is relevant to downstream tasks while significantly reducing the sequence length. In this paper, we introduce a task-agnostic lossless compression technique similar to LZ77 that makes it possible to reduce the input token sequence length on average by 27% and 18% for the two evaluation tasks explored here. Given that we use transformer-based LLMs, this equates to 47% and 33% less encoding computation, respectively, due to the quadratic nature of attention. The token sequence transformation is trivial to reverse and highlights that no semantic information is lost in the process. We evaluate our proposed approach on two tasks that require strict preservation of semantics/syntax and demonstrate that existing lossy compression methods perform poorly in this setting. We find that our lossless compression technique produces only a small gap in performance compared to using the uncompressed input and posit that larger models and an expanded computing budget would likely erase the gap entirely.

1 Introduction

The past several years have led to an adoption of generative language models at an unprecedented scale. As these models grow in terms of parameters and dataset size, new abilities continue to be unlocked. Large Language Models (LLM) are becoming better reasoners Wei et al. [2022], Shao et al. [2024], Zhang et al. [2024b], Guan et al. [2025], Pan et al. [2024a] and are changing how people write Levine et al. [2024], code Tian et al. [2023], and search Spatharioti et al. [2023]. Given that LLMs will likely play an ever-increasing role in our lives, the cost of token usage and inference requirements become critical factors for widespread use. As models scale, so does computational cost. For example, the recent paradigm shift of transferring training compute to inference compute has led to significant performance gains on problem-solving tasks Snell et al. [2024] at the expense of latency and token usage through additional LLM calls needed to search the solution space.

One way to combat increased cost/latency is prompt compression, where the goal is to maintain necessary information for a downstream task while simultaneously reducing input sequence length. There has been a recent surge in research on prompt compression that covers a variety of different modeling conditions. Some approaches seek to optimize prompts under the condition that the LLM’s parameters are not accessible Jiang et al. [2023a,b], Pan et al. [2024b], Chuang et al. [2024]. Others focus on the gains that can be made via architectural changes to the underlying LLM and continuing to fine-tune using compression Mu et al. [2024], Chevalier et al. [2023], Ge et al. [2023].

While previous works have been able to compress input sequences to a small fraction of their original length Jiang et al. [2023a], Pan et al. [2024b], the downstream tasks explored in these

works inherently allow for significant prompt compression due to the sparsity of information required to solve each task. For example, in passage-based Question Answering (QA), the answer to the question is usually contained within a small span of text, making the other information unnecessary. As we will demonstrate, for tasks where every part of the input contains important information, any amount of lossy compression can lead to the inability of an LLM to solve the task. We explore two tasks to demonstrate this idea, and there are numerous practical scenarios in which preservation of all text characters is necessary for proper sequence understanding. These include essay/email editing, code translation, Code Reasoning Understanding and eXecution (CRUX) Gu et al. [2024], code repair, and unit test generation. Our approach to compression is lossless and task-agnostic, making it attractive for general use cases.

Our main contribution is the proposal of *Lossless Token Sequence Compression* (LTSC). The key idea behind LTSC is that there are many repetitions of multi-token subsequences in long prompts which makes the representation of any given subsequence inefficient (see Figure 1). By replacing each instance of a repeated subsequence with a single meta-token, we can reduce the total sequence length. To indicate the mapping of the meta-token to the original subsequence, we can construct a dictionary of meta-token/subsequence pairs and prepend the dictionary to the compressed prompt. We use the term “meta-token” to indicate that these tokens function as **placeholders** and can *dynamically represent different token subsequences* for each prompt. We will demonstrate that fine-tuning on tasks with this compression format teaches the LLM to understand how meta-tokens replace instances of their corresponding subsequence in the original sequence, which allows token sequences to be compressed without any loss of information. Additionally, our proposed approach is flexible in that the choice of whether to apply compression can be made at inference time, and the only model architecture change needed is adding a relatively small number of vocabulary tokens (meta-tokens).

2 Related Work

There exists a large body of work on prompt compression, which is covered extensively in the survey paper from Li et al. [2024a]. Prompt compression can be used to lower costs by reducing token usage, improve generation latency, or make information denser under a fixed context length budget. Some existing work allows control over how much the prompt is compressed Jiang et al. [2023a], Pan et al. [2024b], but for our proposed approach, the maximum amount of compression for a given prompt depends on the prompt itself. In this paper, we compare existing work to ours when maximally compressing every prompt and leave optimization under different use cases (fixed budget, latency, etc.) to future work. We provide a cursory overview of prompt compression in this section, with a more exhaustive discussion left to Appendix A. We note that, to the best of our knowledge, we are the first to propose lossless compression for prompting. Throughout the paper, we will use the terms “compress-

```

Original Code
from package.evaluators import eval1, eval2

def evaluate(model_name):
    for evaluator in [eval1, eval2]:
        evaluator = evaluator()
        evaluator.evaluate(model_name)
        print(evaluator.get_results())

Compressed Code
<Dict>M1eval1, eval2M2 M3model_name
M4evaluate(M5evaluator)</Dict>
from package. M5s import M1

def M4M3:
    for M5 in [M1]:
        M2M5 = M5()
        M2M5.M4M3
        M2print(M5.get_results())

```

Figure 1: Example of swapping repeated subsequences with meta-tokens in a Python code snippet. Each unique meta-token is paired with a unique subsequence to form the dictionary, which is prepended to the compressed input. The green box represents spacing.

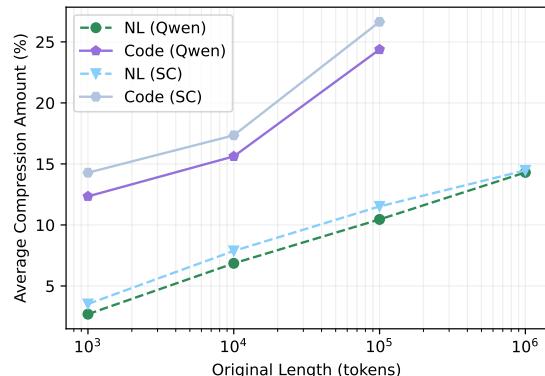


Figure 2: Compression amounts by sequence length for Natural Language (NL) and code domains with two tokenizers (Qwen: Qwen2.5-Coder, SC: StarCoder2).

sion rate" and "compression amount", where amount A refers to the fraction by which the sequence length is reduced, i.e. $A = 1 - |T'|/|T|$ where T' is the compressed version of token sequence T ,¹ and compression rate $R = 1 - A$.

Hard Prompt Compression methods are limited to using tokens solely from the original LLM vocabulary Li et al. [2023], Zhang et al. [2024a], Jung and Kim [2024], Shandilya et al. [2024], Liskavets et al. [2024], Liu et al. [2023]. This results in two forms of prompt compression: **1)** Dropping uninformative tokens. **2)** Generating a shorter token sequence with similar semantics to the original. The first form is popular and makes the most sense from a latency perspective. Given an existing sequence, deciding which tokens to drop becomes a binary classification problem and most computation for each token's classification can be performed in parallel. Generating a summarized version of the prompt introduces significant latency overhead but can lead to superior performance. Our proposed approach introduces little latency (see Figure 6) while also perfectly preserving semantics, making it an improvement over both existing forms of hard prompt compression.

Soft Prompt Compression involves the tuning of new vocabulary tokens or existing model parameters to capitalize on a more efficient representation of the prompt Mu et al. [2024], Chevalier et al. [2023], Ge et al. [2023], Li et al. [2024b], Gao et al. [2024]. These approaches draw inspiration from prompt and prefix tuning Lester et al. [2021], Li and Liang [2021], where the goal is to fine-tune a small number of parameters that allow a frozen LLM to perform a new task without being exposed to that task during pre-training. The main benefits of LTSC are the fact that compression is lossless and fine-tuning is extremely simple. Unlike existing work that requires customized attention masks Mu et al. [2024] or back-propagation through time Chevalier et al. [2023], our approach only requires additional vocabulary tokens and can easily be plugged into existing fine-tuning pipelines.

3 Compressibility

We first motivate our approach by showing how much compression can be achieved for different types of sequences when using LTSC. The compression amounts produced by two tokenizers across natural language and code domains is given in Figure 2, where the amount is the percentage by which the compressed sequence is shorter than the original sequence *when including the dictionary*. For natural language, we concatenate articles from Wikipedia to achieve various token sequence lengths, up to 1M tokens. For code, we use Python repositories from the RepoBench dataset Liu et al. [2024], varying in length from 1k-100k tokens.

Domain Differences: One of the key differences to notice is the large gap between compression amounts between the natural language and code domains for token sequences of the same length. We highlight the differences between these two domains to show that the amount of compression that can be achieved is domain-specific, and can vary widely. We hypothesize that code is more compressible than natural language for several reasons:

1) Syntax: Code contains repeated syntax structures that do not have their own tokens due to the limited vocabulary size. For example, python repositories contain large amounts of indentation, common patterns such as "):\\n\\t" for function definitions or for/while loops, etc. Common code readability standards, such as putting each argument on its own line or adhering to docstring formatting guidelines, introduce additional opportunity for compression.

2) Repository-specific code: Repetitive uses of repo-specific code can add redundancy to an input sequence. Structures such as import prefixes "import package.", function/variable names, etc. can be represented by a single meta-token which can reduce the token sequence length by a large margin.

Tokenizer Effect: The size of the tokenizer vocabulary also plays a role in the compressibility of a given token sequence. LLMs with smaller vocabulary sizes must represent some text sequences with multiple tokens that can be represented with one token by an LLM with a larger vocabulary. This lack of efficiency from smaller vocabularies leads to more opportunity for compression. We directly see this phenomenon when comparing the compression amounts of StarCoder2 and Qwen2.5-Coder for both natural language and code domains. Given that StarCoder2's vocabulary size ($\sim 50k$)

¹The sequence format we propose includes an instance-specific dictionary of compression pairs and the compressed sequence. Throughout the paper, when discussing the amount of sequence length reduction, the dictionary length is included in the calculation of the compressed sequence length.

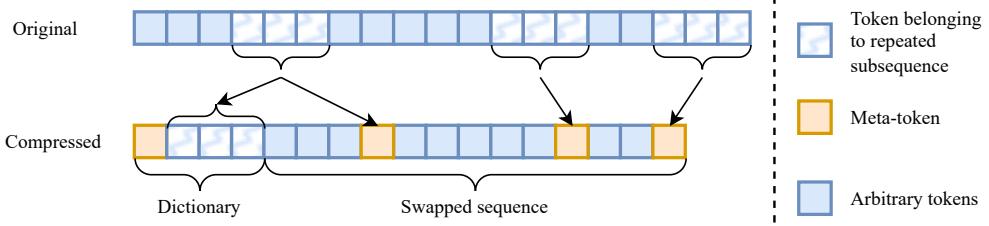


Figure 3: Visualization of the compression process. We exclude the XML tags `<Dict>` and `</Dict>` for illustration purposes since these are negligible for long sequences, and only include one subsequence/meta-token pair for simplicity. Note that the compressed sequence is shorter and that the repeated subsequence representation is reduced from $3 \times 3 = 9$ tokens in the original to $(1 + 3) + 3 = 7$ tokens in the compressed version (see Equation 1). The compressed representation is lossless, because we can reconstruct the original sequence by replacing the meta-tokens with their respective subsequences and removing the dictionary.

is much smaller than Qwen2.5-Coder’s ($\sim 150k$), StarCoder2’s representation of the same text sequences will be less efficient by creating more repeated token subsequences, leading to larger amounts of compression when applying LTSC.

4 Algorithm

While tokenization compresses text significantly compared to a character based representation, tokenized sequences can still contain repetitions of multi-token subsequences. Such redundancy is inefficient, so we propose *Lossless Token Sequence Compression* (LTSC), a simple algorithm that replaces repetitive subsequences with single, unique meta-tokens (See Figures 1 and 3). Our proposed algorithm is similar to the classical LZ77 compression algorithm Ziv and Lempel [1977], where the original subsequence is referred to in the future when that subsequence appears again. Instead of using match distance and match length to represent the repetition, we use unique meta-tokens. To indicate the mapping between the original subsequence and its meta-token, we prepend a dictionary of subsequence/meta-token pairs to the beginning of the token sequence. We will show that under the right conditions, the tokens needed to represent the dictionary and the compressed sequence can be markedly less than the original number of tokens.

Compressibility Conditions: If a given token subsequence T_{sub} of length N appears K non-overlapping times in the token sequence T , then it uses $N \cdot K$ tokens for its representation (see Figure 3). If instead we create a meta-token M to represent T_{sub} , we need $1 + N$ tokens to indicate the mapping of M to T_{sub} in the dictionary, but only K instances of M to represent T_{sub} in the original sequence for a total of $1 + N + K$ tokens. Thus, for subsequences that satisfy the following inequality:

$$N \cdot K > 1 + N + K \quad (1)$$

replacing them with a meta-token results in a shorter token sequence. By solving Equation 1 for all integer values of N and K , we arrive at three cases where replacement reduces the sequence length: 1) $N \geq 4, K \geq 2$, 2) $N = 3, K \geq 3$, 3) $N = 2, K \geq 4$.

Subsequence Discovery (Algorithm 1): To find candidate subsequences for replacement, we search T for subsequences of length two or more up to some fixed maximum subsequence length L_{max} . For each candidate subsequence T_{sub} , we only count the total number of times T_{sub} occurs without overlapping with itself and save the starting index position of each occurrence. If the count K and length N satisfy Equation 1, we add T_{sub} to a list S of candidate subsequences that can be swapped. This approach is similar to the f -gram discovery algorithm from Yu et al. [2025] and, as discussed in their paper, resembles continued training of a BPE tokenizer.

Subsequence Swapping (Algorithm 2): We iteratively swap out each subsequence with a unique meta-token m sampled uniformly from the list M of available meta-tokens. Since it is possible for swappable subsequences to overlap with one another, before making a swap we verify that all positions for the swap are still original tokens from T and that Equation 1 still holds for the given subsequence T_{sub} .

Dictionary Construction (Algorithm 3): To indicate the dictionary in the token sequence format, we concatenate (meta-token, subsequence) pairs within the XML tags `<Dict>` and `</Dict>`. We then prepend this dictionary to the compressed token sequence.

4.1 Time Complexity

The overall time complexity of the compression process is $O(|T| \log |T|)$, making it scalable for long sequences (See Appendix B for empirical verification). We discuss sub-step complexity below:

1) Subsequence Discovery: Collecting all unique subsequences for a given T is bounded by $|T| \cdot L_{max}$, and filtering these subsequences is bound by the same value. Subsequences are already ordered from longest to shortest since we collect them in that order, therefore this step is $O(|T|)$.

2) Subsequence Swapping: To collect the swaps we want to make, we iterate through the set of subsequences that can be swapped. Both the number of unique subsequences and unique starting positions are bounded by $|T| \cdot L_{max}$, making the swap collection step $O(|T|)$. Applying the swaps is done with one pass through T , making this step bounded by $|T|$. The most expensive part of Algorithm 2 is sorting the swaps by starting index, making this step $O(|T| \log |T|)$.

3) Dictionary Construction: We build the token sequence via one pass through the dictionary; $O(|T|)$.

5 Training and Inference with Compression

Model Architecture Changes: Given a desired number of meta-tokens $|M|$, we must augment the existing LLM vocabulary with $|M|$ new tokens. For a transformer-based LLM with input dimension d , this results in the addition of $|M| \cdot d$ new parameters for LLMs using weight tying Press and Wolf [2017] and $2|M| \cdot d$ for LLMs with separate vocabulary and language modeling head matrices.

Supervised Fine-Tuning: All tasks explored in this paper can be formatted as `(prompt, answer)` tuples. During fine-tuning, we compress the prompt but leave the answer uncompressed, and we only compute the cross-entropy loss over the answer tokens. This forces the model to retain its original output distribution by only generating the answer using tokens from its original vocabulary.²

Inference: At inference time, we compress the prompt and generate until the `<|endoftext|>` token is produced. For all the tasks explored here, prompt length is bounded by 8k tokens. Based on runtimes from Figure 6, compression introduces at most ~ 100 ms of pre-processing latency.

6 Experiments

We evaluate LTSC and the lossy compression method LLMLingua2 Pan et al. [2024b] on two tasks that require a lossless input representation (lossless tasks). The results highlight two key properties:

1) Collapse of Lossy Representations: For lossless tasks, lossy compression results in poor performance due to inevitable information loss.

2) Strong Performance of LTSC: Our proposed compression technique performs similarly to a vanilla model that does not compress the input on all lossless tasks due to preservation of all information from the original prompt.

Tasks: We evaluate on two lossless tasks: **1) Tree Structure Understanding**, **2) Repository-level Code Completion** Liu et al. [2024]. We show that for both tasks, dropping even a small number of tokens from the input leads to significant performance degradation.

Baseline: We use LLMLingua2 Pan et al. [2024b] as our prompt compression baseline. LLMLingua2 is currently SOTA for lossy compression and works by using an encoder model to classify whether each token in a given sequence is kept or dropped according to a desired compression rate. The encoder is trained via knowledge distillation from compressed prompts generated by GPT-4. LLMLingua2 claims to be task-agnostic and work well with any LLM, but it shows information loss when evaluated on our lossless tasks.

²We discuss the negative effects of computing loss over compressed sequences in Section 8.

Comp. Seq.	Comp. Method	Experiment Settings		Tree Understanding		
		Agv. Len. Red. (%) ↑	Tree Repr.	Parent/Child Relationship ↑	Node Depth Equality ↑	List All Children ↑
✓	LTSC	27.1	Indentation	99.68	99.67	98.32
✓	LTSC	21.4	Parentheses	99.83	99.91	99.09
✗	None	0.0	Indentation	99.97	100.0	99.82
✗	None	0.0	Parentheses	99.95	99.99	99.87
✓	LLMLingua2	27.0	Indentation	82.17	72.30	36.58
✓	LLMLingua2	17.6	Indentation	87.45	77.71	36.63
✓	LLMLingua2	13.9	Indentation	89.75	79.70	36.62
✓	LLMLingua2	26.6	Parentheses	80.77	54.25	36.99
✓	LLMLingua2	12.1	Parentheses	87.16	71.61	34.71
✓	LLMLingua2	5.4	Parentheses	90.65	81.77	44.25
N/A	Random Guess	N/A	N/A	50.00	50.00	N/A

Table 1: Tree structure understanding results with accuracy given in %. These results are obtained by fully fine-tuning Qwen2.5-Coder-0.5B.

6.1 Tree Structure Understanding

Trees are a fundamental data structure and can be represented in multiple ways as a text sequence (see Figure 4). We will demonstrate that accurate understanding of the relationship between nodes requires perfect preservation of all information in the sequence, because every character contributes to the global structure of the tree. In this experiment, we represent trees using the *Hierarchical Indentation* (Indentation) format or *Parentheses Notation* (Parentheses) format. For Indentation, each node is on a line of its own and node depth is represented by the number of spaces. For Parentheses, tree structure is represented via nested sets of parentheses. Removal of any characters in either representation can render a different tree, making it challenging to understand the tree structure when the textual representation is compressed in a lossy fashion. We show this empirically by devising three toy tasks that probe whether an LLM can understand the structure of a given tree.

- 1) **Parent/Child Relationship:** Given two nodes A and B , determine whether A is the parent of B . This is a binary classification task that returns true if B is a child of A and false otherwise.
- 2) **Node Depth Equality:** Given two nodes C and D , determine whether the nodes are at the same depth in the tree. This is a binary classification task that returns true if C and D have the same depth and false otherwise.
- 3) **List All Children:** Given a parent node E , list all children of the node. Since the children can be generated in different orders, correctness is determined by comparing the set of predicted nodes to the ground truth set of children.

Data Generation: We generate random trees with a maximum depth of four and a maximum of 150 nodes, where each node has between three and five children. The node values are sampled without replacement from the set of two-character capital letter sequences (676 possible values). For further details about data generation, refer to Appendix C.1. For Tree Structure Understanding, the prompt consists of the tree in either Indentation or Parentheses format followed by the formatted representation of each task indicated in the examples in Figure 4.

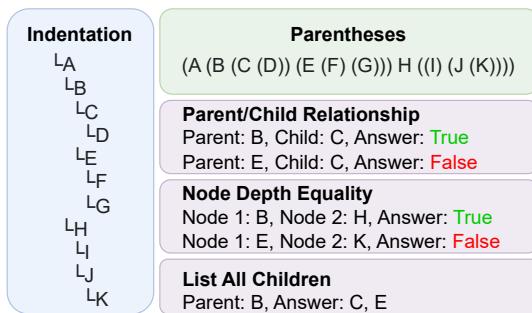


Figure 4: Tree Structure Understanding: A sample tree is shown in both Indentation and Parentheses formats along with examples of each of the tree understanding tasks.

Model Training: We fine-tune Qwen2.5-Coder-0.5B for one epoch using a batch size of 128, 500 meta-tokens and maximum subsequence length L_{max} of six. We leave half of the data in its original (uncompressed) format and compress the prompt according to LTSC for the other half. This training recipe allows us to test multiple settings at inference time with one model.

Experiment Settings: We evaluate three setups: **1) LTSC**, **2) LLMLingua2 compression**, **3) No compression**, i.e. vanilla model. For LLMLingua2, we apply compression to the tree representation part of the prompt only with compression rates of 0.8, 0.9, and 0.95 using the official implementation.³ Due to tokenizer differences between LLMLingua2’s encoder⁴ and Qwen2.5-Coder-0.5B, the compression rates for our fine-tuned model are slightly different. We report the compression values based on Qwen2.5-Coder-0.5B’s tokenizer in Table 1.

Results/Discussion: Results for tree understanding are in Table 1. We highlight two key observations:

1) Almost perfect performance from LTSC: For both the Indentation and Parentheses format, our compression approach achieves near perfect performance. The vanilla baseline (uncompressed input) only slightly outperforms LTSC, with the largest performance gap being less than 1%. This result empirically validates that although the sequence length is reduced with LTSC by up to 27%, no information is lost.

2) Poor performance for lossy compression: For all three tree understanding tasks, LLMLingua2 experiences significant performance degradation relative to LTSC even when its compression amount is much smaller. This result verifies that the Tree Structure Understanding tasks are lossless, because the removal of a small fraction of tokens from the tree representation makes it difficult to perform each task.

Trends for Lossy Compression: Performance by LLMLingua2 varies widely across the three tasks, indicating that some tree understanding tasks are more forgiving than others when structural information is lost. We compare the three tasks below:

1) Best Performance: LLMLingua2 achieves the best performance on the *Parent/Child Relationship* task. This is likely due to the fact that a node’s proximity to a reference parent node is a good feature for predicting a parental relationship in both Indentation and Parentheses formats.

2) Worst Performance: Regardless of how small the amount of compression is for LLMLingua2, performance on the *List All Children* task is always poor. Given the strict requirement that all children must be produced for a response to be counted as correct, dropping only a few tokens will frequently either corrupt the tree structure or alter at least one of the node values.

3) Indentation vs. Parentheses: LLMLingua2 achieves much better performance on the Node Depth Equality task when using the Indentation vs. Parentheses format (72.30% vs. 54.25%) for the most extreme LLMLingua2 compression setting. The only feature needed to determine node depth for Indentation is the number of spaces next to a given node’s value, whereas the nested structure of the Parentheses format makes it much easier to corrupt node depth information.

6.2 Repository-level Code Completion

One common application of LLMs is to act as a coding assistant by predicting the next line of code for a user. This task is called Repository-level Code Completion, and we explore an LLM’s ability to complete this task using LTSC across a variety of model scales. We use the RepoBench dataset Liu et al. [2024] for training and evaluation, where we limit data to the 2k, 4k, and 8k context length bins only due to a context length limit of 10,240 tokens during training. RepoBench contains Python and Java repositories where examples have been curated into three settings for next-line prediction: **1) Cross-File-First (XF-F)**, **2) Cross-File-Random (XF-R)**, and **3) In-File (IF)**. We split RepoBench by repository and allocate 80% of repos for training, 10% for validation, and 10% for testing. The quality of the predicted lines are measured using Exact Match (EM) and Edit Similarity (ES).

Fine-Tuning: We find empirically that it takes several hundred weight updates for an LLM to learn the input transformation induced by LTSC. To directly teach the model to use the dictionary at the beginning of the prompt, we use Python and Java programs from an instruction-tuning dataset called CommitPack Muennighoff et al. [2024]. The data consists of GitHub Pull Requests (PR), where the

³<https://github.com/microsoft/LLMLingua>

⁴microsoft/llmlingua-2-xlm-roberta-large-meetingbank

Model	Experiment Settings			RepoBench						
	Comp. Method	Avg. Len. Red. (%) ↑	XF-F		XF-R		IF		Average	
			EM ↑	ES ↑	EM ↑	ES ↑	EM ↑	ES ↑	EM ↑	ES ↑
StarCoder2-3B	LTSC	17.9	18.9	0.67	28.5	0.72	25.9	0.67	24.5	0.69
	None	0	24.6	0.72	37.5	0.77	34.4	0.71	32.2	0.73
	LLMLingua2	8.7	0.5	0.59	0.5	0.63	0.3	0.55	0.4	0.59
StarCoder2-7B	LTSC	17.9	22.6	0.70	30.5	0.74	30.5	0.69	27.9	0.71
	None	0	27.8	0.74	38.8	0.78	38.9	0.73	35.2	0.75
	LLMLingua2	8.7	0.0	0.63	0.0	0.64	0.2	0.56	0.0	0.61
StarCoder2-15B	LTSC	17.9	27.5	0.72	36.5	0.76	34.8	0.72	32.9	0.73
	None	0	30.8	0.77	39.5	0.79	40.2	0.73	36.9	0.76
	LLMLingua2	8.7	0.5	0.65	0.3	0.66	0.2	0.58	0.3	0.63
Qwen2.5-Coder-0.5B	LTSC	15.7	8.5	0.59	12.3	0.62	12.6	0.56	11.2	0.59
	None	0	15.7	0.66	29.0	0.71	29.0	0.66	24.6	0.68
	LLMLingua2	15.2	0.0	0.50	0.2	0.55	0.0	0.46	0.1	0.51
Qwen2.5-Coder-1.5B	LTSC	15.7	17.9	0.67	29.8	0.72	28.2	0.68	25.3	0.69
	None	0	22.9	0.70	34.2	0.76	33.8	0.70	30.3	0.72
	LLMLingua2	15.2	0.2	0.59	0.2	0.60	0.3	0.52	0.2	0.57
Qwen2.5-Coder-3B	LTSC	15.7	18.9	0.69	28.3	0.72	26.6	0.66	24.6	0.69
	None	0	28.4	0.74	35.7	0.76	37.9	0.73	34.0	0.74
	LLMLingua2	15.2	0.3	0.62	0.3	0.61	0.5	0.55	0.4	0.59

Table 2: RepoBench results for the 2k/4k/8k bins (combined). Exact Match (EM) accuracy is given in %, and Edit Similarity (ES) ranges from 0-1. EM requires the generated code to exactly match the gold reference to be counted correct in the accuracy calculation. ES is the average string similarity between the generated and gold code.

file prior to the PR is the `input`, the `instruction` consists of the PR comments, and the `answer` is the file after the PR. For this task, the prompt is constructed by concatenating `instruction` and `input`. Since most of the file is left unchanged in each PR, the LLM must learn to use the dictionary pairs as well as reason about necessary file changes to be able to produce the `answer` correctly.

Experiment Settings: We fine-tune all models using LoRA Hu et al. [2021] for 630 steps on CommitPack, followed by 80 steps on RepoBench where the max seq. length is 10,240. We find the optimal RepoBench validation loss after 30 steps, and choose this checkpoint for every fine-tuned model. We train two separate versions of each LLM,⁵ one with LTSC and one vanilla model that does not use compression. We use 500 meta-tokens, set $L_{max} = 6$, and finetune Qwen2.5-Coder-(0.5,1.5,3)B and StarCoder2-(3,7,15)B. To evaluate LLMLingua2 Pan et al. [2024b], we compress the prompt at inference time and generate responses using the vanilla model.

Results/Discussion: Repo-level code completion results are in Table 2. We note two key points:

1) LTSC outperforms LLMLingua2: Even with a larger amount of compression, LTSC is able to outperform LLMLingua2 on code completion. As expected, LLMLingua2 is unable to achieve even 1% on Exact Match due to the loss of important syntax/structural information. For Edit Similarity, LLMLingua2 achieves reasonable performance but still falls behind LTSC by ~0.1 on average for most models.

2) Scaling Trend: Although LTSC does not achieve the same performance as the vanilla model, the relative performance gap shrinks significantly as the size of the LLM increases (See Figure 5). This demonstrates that larger models are able to understand LTSC’s input transformation better than smaller models when fine-tuning for a relatively small number of steps (<1k).

7 Discussion

The results from both tasks provide strong evidence for the need for lossless compression methods. In every case, we see that the lossy baseline experiences a large degradation in performance even for small amounts of compression compared to the settings from previous studies Pan et al. [2024b], Jiang et al. [2023a]. Each task requires preservation of structural and syntactical information that is corrupted when LLMLingua2 drops a relatively small

⁵Training separate models rules out the possibility that LTSC negatively impacts the performance of the vanilla model. This was unnecessary for the previous task since the vanilla model achieves almost perfect performance.

number of tokens. We also demonstrate that transformer-based LLMs are capable of understanding the input transformation induced by LTSC and can perform tasks at a similar level to vanilla models not using compression. We find the relative performance gap between LTSC and vanilla models becomes significantly smaller with scale, suggesting that LLMs with hundreds of billions of parameters may not experience any performance gap.

Why does compression work? Unlike recurrent models like RNNs Schuster and Paliwal [1997] or LSTMs Hochreiter and Schmidhuber [1997] where sequential order is inherent to the model, Transformers operate on sets Vaswani [2017], so positional information is injected artificially through position embeddings. For our approach, the compressed sequence contains the same underlying information as the original sequence, but has been rearranged to reduce the sequence length. Given the simplicity of the transformation and the incredible abilities of LLMs to solve challenging tasks, it is expected that LLMs should understand this simple input transformation.

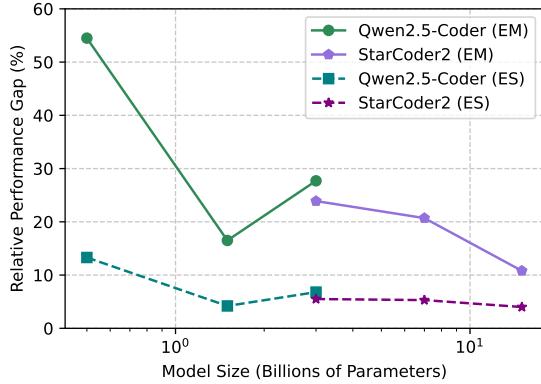


Figure 5: Relative performance gap between LTSC and vanilla model (no compression) on repository-level code completion for a variety of model sizes.

8 Future Work

Model Scale: Our experimental results have demonstrated that LTSC’s input transformation can be learned well with a relatively small amount of compute. For the largest model, StarCoder2-15B, by fine-tuning with LoRA for less than 1k steps, we only observe a relative 10.9% Exact Match (EM) gap between LTSC and the uncompressed prompt on the challenging code completion task. Additionally, the performance gap is halved for StarCoder2 as the model scale increases by less than one order of magnitude from three to fifteen billion parameters (See Figure 5). Given the significant impact scale has on language modeling performance Kaplan et al. [2020], we hypothesize that applying our approach to larger models and fine-tuning longer will likely remove the performance gap entirely.

Generating Meta-tokens: In addition to reducing the input sequence length, using meta-tokens in the output could further speed up generation and significantly reduce cost, since output tokens are currently 4-5 times more expensive than input tokens from the top AI companies. Our initial experiments in this area were not promising, which we hypothesize is due to two reasons: **1)** Predicting meta-tokens instead of original vocabulary tokens causes a significant distribution shift. **2)** Probability mass for a given character sequence becomes distributed over multiple tokens since meta-tokens make it possible to represent the underlying character sequence in multiple ways. Future large-scale training with LTSC could overcome these issues, but this is left to future work.

9 Conclusions

In this paper, we introduced the first lossless compression algorithm for token sequences and demonstrated a need for lossless input representations. While previous work on lossy compression achieves solid performance with high compression ratios, those same methods suffer when applied to the information-dense tasks we explore in this paper. In contrast, we found little performance gap between our proposed compression approach and a no-compression baseline for the largest model, and found that this gap shrinks significantly with model scale.

The work explored in this paper marks a fundamental shift in the way we think about input for transformer-based LLMs. While left-to-right structure is required for simpler recurrent models, we have demonstrated empirically that this is not the case for transformers because attention acts as a set operator. This freedom to rearrange the input allows us to capitalize on a denser representation of the same token sequence, and we have shown that transformer-based LLMs can use this compact representation effectively to solve downstream tasks.

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Algorithm 1 Subsequence Discovery

Token sequence $T = (t_1, t_2, \dots, t_{|T|})$, maximum subsequence length L_{max} , non-overlapping subsequence starting indices $I = (i_1, i_2, \dots, i_K)$. Denote subsequences via slicing: $T_{sub[i:j]} = (t_i, t_{i+1}, \dots, t_{j-1})$.

function SUBSEQUENCEDISCOVERY(T, L_{max})
 $S \leftarrow$ Empty list (holds subsequences and their start indices)
 for $N \in (L_{max}, L_{max} - 1, \dots, 2)$ **do**
 $U_N \leftarrow$ Set of all unique subsequences of length N in T
 for $T_{sub} \in U_N$ **do**
 $I \leftarrow$ List of starting indices for each non-overlapping occurrence of T_{sub} in T
 $S \leftarrow S + (T_{sub}, I)$
 end for
 end for
 Filter S by Equation 1: $|I| \cdot |T_{sub}| > |I| + |T_{sub}| + 1$
 return S
end function

Algorithm 2 Sequence Compression

Token sequence $T = (t_1, t_2, \dots, t_{|T|})$, list S of subsequences T_{sub} and their starting indices I , meta-tokens $M = (m_1, m_2, \dots, m_{|M|})$, dictionary of compression pairs D .

function COMPRESSTOKENSEQUENCE(T, S)
 $D \leftarrow$ Dict[key is meta-token m , value is subsequence T_{sub}]
 $I_{swap} \leftarrow$ Empty list (holds all index positions that have been swapped)
 $B \leftarrow$ Empty list (holds all the swaps that will be performed on the original token sequence)
 for $(T_{sub}, I) \in S$ **do** ▷ subsequence T_{sub} , starting indices I
 $I \leftarrow I \setminus I_{swap}$ ▷ Remove invalid swap positions by checking that no index within $[I, I + |T_{sub}| - 1]$
 belongs to I_{swap} .
 if $|I| \cdot |T_{sub}| > |I| + |T_{sub}| + 1$ **then**
 if M not empty **then**
 Sample m from M without replacement.
 for $i \in I$ **do**
 $B \leftarrow B \cup \{(i, T_{sub})\}$ ▷ Add current start index and subsequence pair to list of swaps that
 will be performed.
 $I_{swap} \leftarrow I_{swap} \cup \{i, \dots, i + |T_{sub}| - 1\}$ ▷ Add all indices from the swap span to the list
 of used indices.
 end for
 $D[m] \leftarrow T_{sub}$ ▷ Add meta-token/subsequence mapping pair to the dictionary.
 end if
 end if
 end for
 Sort B from smallest to largest start index.
 Apply swaps in B to T (left-to-right). Keep track of the position shift as T is modified.
 return T, D
end function

A Related Work

A.1 Hard Prompt Compression

The most prominent work on hard prompt compression comes from the LLMLingua family of methods Jiang et al. [2023b,a], Pan et al. [2024b]. The first version of LLMLingua Jiang et al. [2023a] computes perplexity for each token using a small model and drops those tokens with perplexity below a given threshold. This approach gives an empirical estimation of the tokens that are least informative for the LLM. LLMLingua is improved upon by LLMLingua2 Pan et al. [2024b], which uses knowledge distillation from a much larger model. Given prompts that have been compressed by GPT-4, a small, bi-directional encoder is trained to classify tokens that should be discarded. LLMLingua2 is currently State-Of-The-Art (SOTA) for lossy compression and is used as the baseline in this paper.

The second form of hard prompt compression involves generating a prompt summary in natural language, which results in significant latency overhead compared to the first form. Nano-capsulator Chuang et al. [2024] optimizes the summarized prompt to retain utility for the downstream task and

Algorithm 3 Input Sequence Construction

Compressed token sequence $T_{comp} = (t_1, t_2, \dots, t_{|T_{comp}|})$, subsequences T_{sub} , meta-tokens $M = (m_1, m_2, \dots, m_{|M|})$, dictionary of meta-token/subsequence compression pairs D .

function CONSTRUCTINPUT(T_{comp} , D)

$T_{dict} \leftarrow$ Empty list (holds token representation of the dictionary)

for (m, T_{sub}) in D **do**

$T_{dict} \leftarrow T_{dict} + m + T_{sub}$

end for

$T_{comp} \leftarrow [<\text{Dict}>] + T_{dict} + [</\text{Dict}>] + T_{comp}$

return T_{comp}

end function

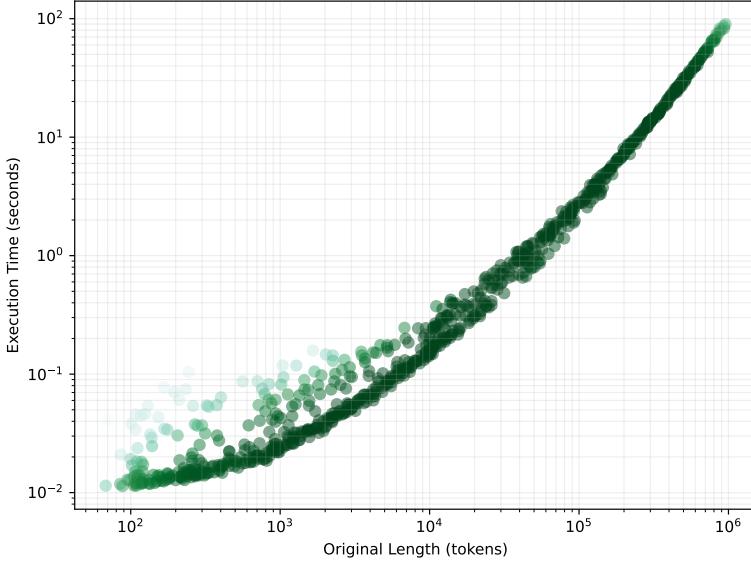


Figure 6: Runtime of compression process for Wikipedia data tokenized by Qwen2.5-Coder.

achieves superior performance compared to task-agnostic approaches. This performance boost comes at the cost of being unable to transfer to new tasks without further fine-tuning.

A.2 Soft Prompt Compression

Both GIST Mu et al. [2024] and ICAE Ge et al. [2023] introduce insightful methods by which prompts can be compressed when we allow the underlying LLM to be further fine-tuned. GIST Mu et al. [2024] bridges the gap between fine-tuning and prompt tuning by producing compressed versions of task instructions in a zero-shot setting. During fine-tuning, GIST alters the attention mask such that during generation of an answer, the LLM can only attend to a small set of gist (summarized) tokens whose length is reduced from the original instruction prompt. ICAE Ge et al. [2023] develops a similar approach, where an encoder produces memory slot tokens that are conditioned on by a frozen decoder LLM. The encoder learns to compress useful information from a long prompt into the limited number of memory slot tokens via auto-encoding, where the frozen decoder conditions on the memory tokens and attempts to reconstruct the original prompt.

B Runtime Experiments

The time complexity of $O(|T| \log |T|)$ for the compression process is empirically verified in Figure 6. We concatenate articles from Wikipedia to construct natural language sequences of various lengths, up to 1M tokens. As the sequence length grows four orders of magnitude, so does the execution time. We also observe that the variance in execution time becomes smaller as the sequence length becomes large.

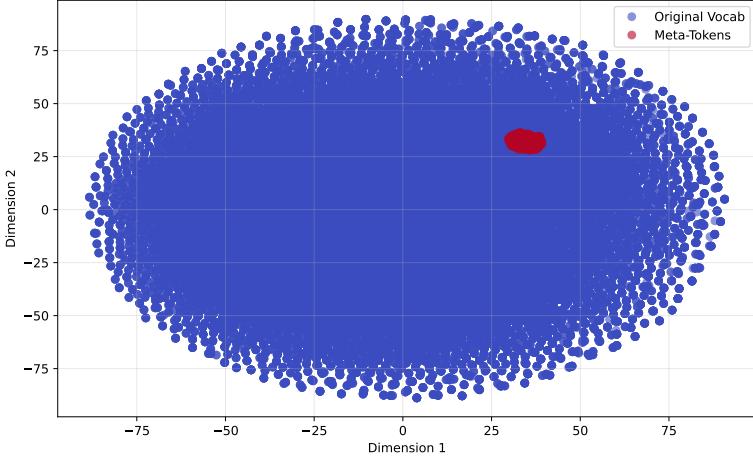


Figure 7: t-SNE plot of meta-tokens and original vocabulary tokens for the StarCoder2-7B model fine-tuned on code completion.

C Data Generation

C.1 Tree Structure Understanding

Parent/Child Relationship: For this task, we generate positive data pairs by randomly selecting a non-terminal node and then randomly selecting one of its children. We generate negative data pairs by sampling a node at random and then sampling from the set of all other nodes that are neither its parent nor children.

Node Depth Equality: We generate positive pairs by randomly sampling a depth between two and four and then randomly sampling two nodes from that depth. To create negative pairs, we sample nodes from two different depths.

List All Children: Given the set of all non-terminal nodes, we randomly sample one node and then sort the children in alphabetical order. We do not require that the nodes be generated in alphabetical order at inference time but provide this structure during training to provide a deterministic order to the set.

We generate a training dataset of 3M examples and a test dataset of 50k examples (10k/10k positive/negative pairs each for Parent/Child Relationship and Node Depth Equality, and 10k examples for List All Children).

D Analysis of the Dictionary

Meta-token Embeddings: We perform a t-SNE analysis Van der Maaten and Hinton [2008] on the embeddings of the meta-tokens vs. the original vocabulary tokens and show the results in Figure 7. As expected, the meta-tokens cluster tightly together given that they serve identical purposes for the LLM.

Meta-token Scaling: We explore the number of meta-tokens that are used when compressing natural language token sequences according to LTSC in Figure 8. We see a clear linear trend, that as the token sequence length increases, so does the number of unique meta-tokens used for compression. Given that the maximum sequence length used for our experiments was 8k (code completion), using 500 meta-tokens for the model is a good choice, since all sequences of length 10k use between 200 and 300 meta-tokens.

E Computational Resources

All experiments are run on one EC2 G6e instance from AWS (8×46GB NVIDIA L40S GPUs, 1.5TB RAM).

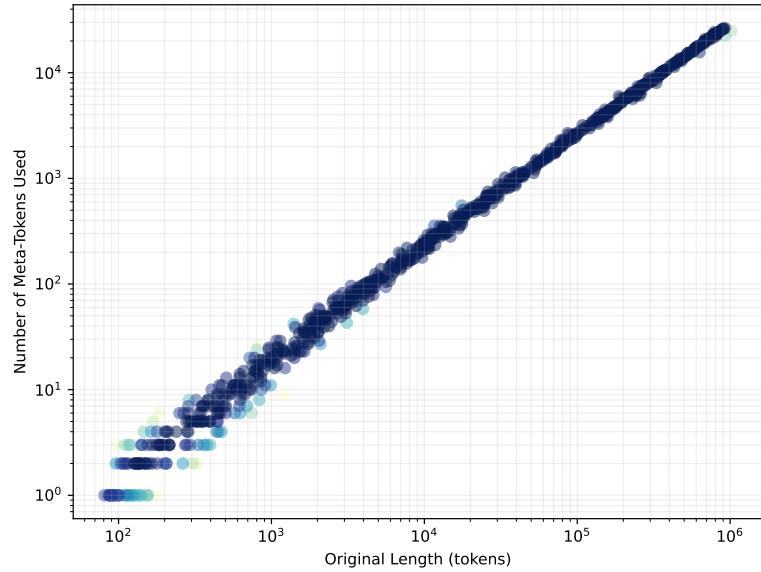


Figure 8: Number of dictionary tokens used by LTSC for natural language token sequences of varying lengths.

F Dataset License

Rephobench Liu et al. [2024] maintains a Creative Commons license. CommitPack Muennighoff et al. [2024] maintains an MIT license.