# Accelerate Parallelizable Reasoning via Parallel Decoding within One Sequence

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#### **Abstract**

Recent advances in reasoning models have demonstrated significant improvements in accuracy, particularly for complex tasks such as mathematical reasoning, by employing detailed and comprehensive reasoning processes. However, generating these lengthy reasoning sequences is computationally expensive and timeconsuming. To address this inefficiency, we leverage the inherent parallelizability of certain tasks to accelerate the reasoning process. Specifically, when multiple parallel reasoning branches exist, we decode multiple tokens per step using a specialized attention mask, processing them within a single sequence. Experimental results show that our method achieves over 100% speedup in decoding time while maintaining high accuracy. Our code is available in github.

# 1 Introduction

Large Language Models (LLMs), capable of performing complex reasoning processes, excel across a diverse array of tasks. However, their autoregressive decoding structure renders them inefficient for parallelizable tasks. Parallelizable tasks are those that, while requiring multiple steps, involve many steps that can be executed concurrently due to the absence of a priority relationship. In the decoding phase, LLMs generate tokens sequentially, one at a time. This sequential nature forces parallel steps to be processed sequentially, imposing considerable computational overhead on the attention layer and hindering the full utilization of the hardware's parallel computing capabilities.

While methods like skeleton-of-thoughts (Ning et al., 2024) aim to address such inefficiencies, they suffer from notable drawbacks. Firstly, they rely on batch decoding or multiple API calls, which, although reducing inference time, exponentially increase computational load and memory requirements. These constraints force a reduction in batch

size when GPU memory is limited. Secondly, these methods require distinct prompt templates for different generation stages, preventing reuse of the key-value (KV) cache. Lastly, skeleton-of-thoughts treat every point in their reasoning skeleton as independent, potentially neglecting causal relationships between different points.

To overcome these limitations, we propose a novel decoding method called "Parallel Decoding in One Sequence," specifically designed to address parallelizable tasks in LLM reasoning. This method operates in three stages: (1) identifying parallelizable steps in the reasoning process, (2) parallel decoding of these steps, and (3) concatenating the results and continuing generation.

In the first stage, the model generates the reasoning process, but for parallelizable steps, a special token is used to mark them. For these steps, only the initial few words are generated, while the remaining portion is omitted with ellipses, reducing the number of output tokens. In the second stage, we decode each step's subsequent tokens in parallel, using their initial tokens as prefixes. We modify the attention mask and the position IDs so the model can generate multiple tokens simultaneously in a single forward pass, significantly accelerating the generation process. Finally, in the third stage, we concatenate the full reasoning outputs from each parallel step and append them to the sequence, allowing the model to resume its reasoning process. The overall process is illustrated in Figure 1.

Unlike previous methods, our approach eliminates the need for additional memory and KV cache recomputation, as we do not create multiple sequences. Moreover, our method relies on the LLM itself to identify parallelizable steps but not consistently treats every step as independent, enabling greater flexibility and adaptability.

Experiments demonstrate that our method significantly enhances decoding speed, especially for tasks with numerous parallelizable steps. More-

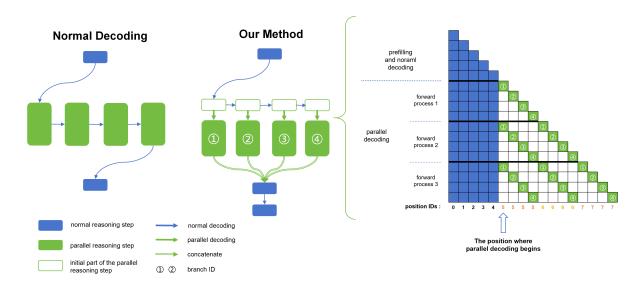


Figure 1: Comparison between our method and traditional decoding for a case with four parallel branches. Blue and green blocks in the attention mask indicate "can see," while white blocks indicate "cannot see."

over, it achieves this acceleration with only a minor impact on generation quality. Since our approach does not require additional training or modules, it is generally applicable across different types of LLMs.

#### 2 Related Works

The computational demands of LLMs have inspired the development of various techniques aimed at accelerating the decoding process. One widely recognized method is speculative decoding (Leviathan et al., 2023), which employs a smaller assistant model to generate tokens first, allowing the main model to verify them—a process that leverages parallelizable verification for faster inference. Jacobi decoding (Santilli et al., 2023) constructs initial sequences using pad tokens, enabling iterative updates to parallelize token generation within each sequence. Medusa (Cai et al., 2024) enhances the target LLM with auxiliary guess heads to facilitate self-speculation, achieving up to a threefold speedup on diverse tasks. Skeleton-of-thoughts (Ning et al., 2024) prompts LLMs to generate a skeleton containing multiple points and completes each point in parallel by employing batch decoding or multiple API calls.

#### 3 Method

Our method includes 3 stages: branch title generation, parallel decoding, concatenating and continuation.

Stage 1. After the specific task, we append an

additional prompt (detailed in Appendix A). The model is prompted to mark parallelizable steps with ####, generating only titles followed by a colone and an ellipses (e.g., "#### Step 1: ....."). To ensure the correct format is generated, we manually manipulate the logits to force it to immediately generate an ellipsis after a colone, and a #### after an ellipsis. We group this bunch of consecutive parallel steps as a "parallel block", and we prompt it that a terminator (%%%) should be generated to signify the end of the parallel block. This yields a compact skeleton while ensuring correct parallelism detection. The specific prompt we use in this stage is in Appendix A.

Stage 2. We use each parallel step's title generated in stage 1 as each branch's prefix tokens. We signify the number of parallel steps as n. For n parallel branches:

- We reuse KV cache from pre-parallel steps (the part before the parallel block).
- We process n tokens per forward pass using a belt-like attention mask (as shown in Figure 1), which ensures that the branches are isolated from one another while sharing pre-parallel tokens.
- The position ids of the tokens processed in one forward pass are all the same. The position ID is incremented by one after every forward pass.
- We terminate branches upon generating ####,

Model	Num items	Method	Accuracy (%)	Time (s)	Speed (tokens/s)
Qwen2.5-14b-Instruct	10	normal	92	15.8	21.2
Qwen2.5-14b-Instruct	10	parallel	89	9.3	40.5
Qwen2.5-14b-Instruct	30	normal	56	36.8	21.3
Qwen2.5-14b-Instruct	30	parallel	47	17.1	49.2
Qwen2.5-7b-Instruct	10	normal	93	10.5	37.2
Qwen2.5-7b-Instruct	10	parallel	95	4.9	65.7
Qwen2.5-7b-Instruct	30	normal	59	17.7	35.6
Qwen2.5-7b-Instruct	30	parallel	62	14.4	71.7

Table 1: Accuracy and decoding speed on the retrieval task.

Model	Method	Score	Time (s)	Speed (tokens/s)
Qwen2.5-14b-Instruct Qwen2.5-14b-Instruct			15.6 11.4	17.5 27.5
Qwen2.5-7b-Instruct Qwen2.5-7b-Instruct	normal parallel	3.57 3.49	7.24 8.98	33.6 49.0

Table 2: Evaluation scores and decoding speed on the multi-documents QA task.

and pad shorter branches until all branches are completed.

Stage 3. We sequentially concatenate the fully decoded parallel steps from Stage 2 with the original reasoning sequence. The model then resumes decoding as normal, and the KV cache of prior steps and the prompt can be reused. If "####" is detected again, the process loops back to Stage 1, initiating the next parallel block.

# 4 Experiments

### 4.1 Implementation Details

The key innovation of our method lies in the modified causal attention mask, termed the "belt-like mask." While FlashAttention-2 (Dao, 2023) accelerates attention computation and saves memory, it does not support custom masks. Thus, we modified its source code to track two additional parameters: the number of branches (n) and the position where parallel decoding begins. They both derived from content generated in Stage 1. Specifically, where the first special mark "####" appears determines the position where parallel decoding begins, and the number of special marks "####" determines the number of branches.

For experimentation, we use Qwen2.5 (Team, 2024) implemented via the HuggingFace Trans-

formers (Wolf et al., 2020), coupled with our customized FlashAttention-2 package. All models are run on an A100 GPU with bfloat16 precision.

#### 4.2 Data

Our method targets parallelizable tasks, for which we select a retrieval task and a multi-document QA task requiring reasoning. In both tasks, the reasoning process involves sequential analysis of individual items (e.g., students or documents), which is inherently parallelizable.

The retrieval task utilizes the student resume retrieval dataset from difficult-retrieval (Yu et al., 2024), containing 100 samples per setting. The model retrieves students whose GPA falls within a specified range from among 10 or 30 students, requiring parallel GPA analysis.

The multi-document QA task involves "2Wiki-MultihopQA" from LongBench (Bai et al., 2023), comprising 200 samples. The model must answer questions based on 10 documents, with only one of them containing relevant information, necessitating parallel document analysis.

We use exact-match to assess the retrieval task and use GPT-4 (OpenAI, 2023) ratings (from 1 to 5) to assess the QA task. Decoding speed, measured in tokens generated per second, is also recorded.

#### 4.3 Results

Table 1 presents retrieval task results. For contexts with 10 items, our method nearly doubles decoding speed, and for 30 items, the improvement is even greater. Accuracy loss is observed but remains under 10%, representing an acceptable trade-off.

Appendix B offers a generated example with our parallel decoding method of the student retrieval task.

Table 2 displays QA task results. Here, our method improves decoding speed by approximately 60% while basically maintaining answer quality, as evidenced by GPT-4 ratings.

#### 5 Conclusion

This paper introduces "Parallel Decoding in One Sequence," a novel method to accelerate the reasoning process of LLMs for parallelizable tasks. By optimizing parallel step decoding, our method substantially reduces inference time while maintaining model flexibility and quality. Critically, it achieves these advantages without additional memory or recomputing KV caches.

Future work could explore extending this approach to more complex and diverse tasks. Investigating its applicability across different model architectures and sizes may also provide insights into scalability and generalizability. Overall, our method constitutes an important advancement in efficient LLM reasoning for practical applications.

#### 6 Limitations

For smaller models, Stage 1 may fail to produce the required format, preventing subsequent stages from functioning. Specifically, a non-standard format impedes recognition of branch titles and the determination of the number of parallel branches.

Furthermore, our method has been tested only on synthetic datasets. For more complex tasks, where reasoning processes exhibit greater uncertainty, extending our approach may present challenges.

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# A Prompt

The prompt we use in stage 1 is:

When you need to sequentially handle multiple parallel steps (the steps are individual, for example, analyzing multiple individual documents, planning multiple branches, evaluating multiple aspects) during the reasoning process, you must strictly adhere to the following format: You need to prefix each step with '####', followed by the step's title, and then a

colon ':' (an English colon). After all the steps are completed, you need to output '####%%%%', and only then can you proceed with the subsequent reasoning process.

# Example 1:

Question: [Resumes of A, B, C, D] Please analyze which of the four individuals best meets the requirements.

Answer: 'Let us analyze the strengths of each person based on their resumes.

####Strengths of A:.....

####Strengths of B:.....

####Strengths of C:.....

####Strengths of D:.....

####%%%%Therefore, I believe that A's resume best meets the requirements.'

Example 2:

Question: [document 1,2,3,4] Based on the information in the documents, what is the birthday of Jack?

Answer: 'Let us analyze each documents.

####document 1:.....

####document 2:.....

####document 3:.....

####document 4:.....

####%%%%Therefore, Jack's birthday is 5th, May, 2000.'

Note that this example is only used to illustrate the format; the specific content should closely revolve around the Question, ensuring that the analysis process is complete, clear, and well-reasoned.

Otherwise, give a complete and clear analysis for this step.

Please be careful, do not forget any necessary steps, and ensure every reasoning step is complete and clear.

Note that only a branch step should start with ####. If it is a stem or general step, you should not add ####.

# B Example of the content generated in our method

Here we show an example of what the model generated when using our parallel decoding method, in the student retrieval task. We omit some content in the prompt. As we can see, in stage 1, the model only generate the skeleton, where the spe-

cific analysis process of each branch is represented by ellipses. Then in stage 2, each branch's specific reasoning process is completed by parallel decoding. Finally, in stage 3, all the reasoning processes are concatenated, and the model generate the final conclusion.

# **Prompt:**

Here are 10 students' resumes:

The student named Nitin Sharma is 29 years old, graduated from IIM Ahmedabad with a GPA of 4.09. He/She is interested in Finance, Cooking, Travel and his/her self-introduction is: Finance enthusiast who loves cooking and exploring diverse cuisines.

.....

The student named Lily Wilson is 23 years old, graduated from University of Brighton with a GPA of 2.45. He/She is interested in Political Science, Activism, Public Speaking and his/her self-introduction is: I am dedicated to activism and often channel my thoughts into public speaking.

. . . . .

Question: Which student has a GPA between 2.36 and 2.75? Please give your final answer (the student's name) in the format of "name: answer"

You should check every student to judge whether he meets the requirement in your reasoning process.

#### Stage 1:

Let us analyze each student's GPA to find the one between 2.36 and 2.75.

####Nitin Sharma: .....

####Hallie Turner: ......

####Hikaru Sawai: .....

####Abigail Clark: ......

####Charlotte Phillips: .....

####Lily Wilson: .....

####Cao Ling: .....

####William Stewart: .....

####Sienna Torres: .....

####Eli White: ..... ####%%%%

# Stage 2:

####Nitin Sharma: GPA is 4.09, which is

not between 2.36 and 2.75.

####Hallie Turner: GPA is 3.68, which is

not between 2.36 and 2.75.

####Hikaru Sawai: GPA is 2.98, which is

higher than 2.75.

####Abigail Clark: GPA is 1.83, which is

below the range.

####Charlotte Phillips: GPA is 1.54, which

is below the range.
####I ily Wilson: GPA is 2.45, w

####Lily Wilson: GPA is 2.45, which falls within the range of 2.36 to 2.75.

####Cao Ling: Cao Ling's GPA is 2.82, which is above 2.75.

####William Stewart: GPA is 4.04, which

is not between 2.36 and 2.75.

####Sienna Torres: GPA is 4.48, which is

not between 2.36 and 2.75.

####Eli White: GPA is 4.61, which is not

between 2.36 and 2.75.

# Stage 3:

Based on the analysis, Lily Wilson is the student whose GPA falls within the specified range.

Name: Lily Wilson