

# Asynchronous Reasoning: Training-Free Interactive Thinking LLMs

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## Abstract

Many state-of-the-art LLMs are trained to think before giving their answer. Reasoning can greatly improve language model capabilities and safety, but it also makes them less interactive: given a new input, a model must stop thinking before it can respond. Real-world use cases such as voice-based or embedded assistants require an LLM agent to respond and adapt to additional information in real time, which is incompatible with sequential interactions. In contrast, humans can listen, think, and act asynchronously: we begin thinking about the problem while reading it and continue thinking while formulating the answer. In this work, we augment LLMs capable of reasoning to operate in a similar way without additional training. Our method uses the properties of rotary embeddings to enable LLMs built for sequential interactions to simultaneously think, listen, and generate outputs. We evaluate our approach on math, commonsense, and safety reasoning and find that it can generate accurate thinking-augmented answers in real time, reducing time to first non-thinking token from minutes to  $\leq 5$ s. and the overall real-time delays by 6–11×.

## 1. Introduction

Modern Large Language Models (LLMs) solve complex tasks using inference-time computation mechanisms [1, 2, 3], such as chain-of-thought reasoning [4, 5, 6, 7] and agentic tool use [10, 11, 12, 13]. Recent models, both proprietary [18, 19, 20] and open-weights [21, 22, 23], are explicitly trained for reasoning and agentic capabilities. As we trust LLMs with harder problems [24, 25], their ability to “think” becomes ever more important.

The current dominant strategy for LLM reasoning is the read-think-answer cycle: the model encodes a given problem, then generates chain-of-thought reasoning, possibly

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calls tools, and then formulates the final answer [18, 21, 23]. This fits naturally with the sequential view of LLMs as next-token prediction models. However, this also means that the LLM must follow a rigid turn structure that can limit their flexibility. The “thinking” phase can take minutes of real time, during which the agent does not get new information or output its current results.

Unlike LLM agents, people have an innate ability to think asynchronously [26, 27, 28, 29]. When working on a problem, we can begin solving it even before we have heard its entire statement, and can start talking (or acting) while still completing our solution. Such “multitasking” is not always easy or efficient [30], but it allows us to effectively operate in a dynamic environment [31].

Similarly, artificial agents often need real-time ability to change course of action. A voice assistant is expected to maintain conversation in real time [32, 33, 34, 35, 36, 37, 38]. An embodied agent’s VLA model [39, 40, 41] needs to quickly adjust to new inputs. Even fully text-based “deep research” agents benefit from interactive communication with the user [42]. However, the current read-think-answer cycle is inherently non-interactive. During the thinking phase, if an agent receives new inputs or must take action, it can either stop reasoning, discarding any incomplete thoughts, or wait until it completes, sacrificing interactivity. As a result, many real-time LLM applications do not fully benefit from inference-time compute.

In this work, we propose a technique that enables asynchronous LLM reasoning. Instead of retraining the LLM to satisfy each specific degree of interactivity, we propose a training-free approach that modifies existing models. Our approach uses three concurrent streams of tokens: user inputs, private thoughts, and public response, which can be updated in real-time. We rely on geometric properties of rotary positional embeddings to make the LLM perceive these streams as a single contiguous sequence *without additional training*. The model itself can decide whether it should continue talking or pause and think, depending on the current state of the three streams. The resulting asynchronous reasoning can be formulated as standard LLM inference with a modified attention cache, making it possible to integrate into efficient LLM inference frameworks [43, 44].

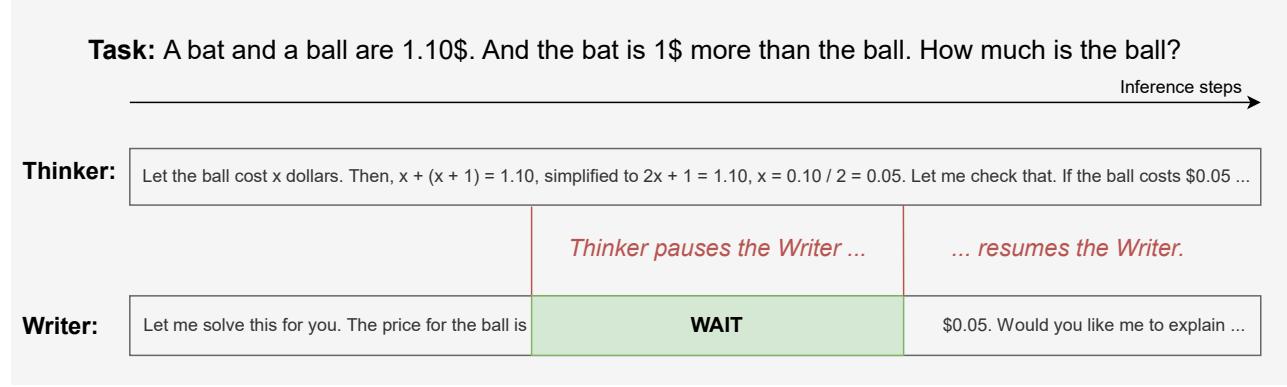


Figure 1: The intuitive explanation of asynchronous reasoning: the LLM generates its response concurrently with thinking. If the thinking stream needs additional time, it can pause the response writer until the next reasoning step is ready.

Our main contributions can be summarized as follows:

- We propose AsyncReasoning, a zero-shot method that allows existing reasoning LLMs to think, write outputs and encode additional inputs concurrently. Our approach relies on model-agnostic concurrent attention and prompting, making it easy to adapt for new models.
- We evaluate the proposed approach on real-time math, common-sense and safety reasoning. Our experiments demonstrate that the proposed approach lets the LLM overlap thinking and answering, reducing the user-perceived delay by over 9 on mathematical and common sense reasoning tasks. When prompted to think about safety, AsyncReasoning allows the LLM to stream real-time outputs on benign requests, while considering the safety implications in a private thinking stream that can pause potentially harmful outputs.
- We release our reference implementation<sup>1</sup> of AsyncReasoning, including GPU kernels for concurrent attention. We also provide a minimal voice assistant with asynchronous thinking capabilities to demonstrate it in action.

## 2. Related Work

### 2.1. Real-time LLM Applications

Modern LLM agents are deployed in a broad range of applications that require varying degrees of interactivity. For instance, a background code review agent can pause and think for several minutes, whereas a real-time voice assistant cannot. Here, we briefly review several LLM applications that require quick or interactive responses.

**Voice assistants.** Recent works [33, 34] and industry releases [32, 45, 46] use LLM agents as interactive voice assistants that talk to users in real-time, often through their phones or edge devices, or partake in a group conference [47, 48]. Compared to their text-based counterparts, voice assistants require faster reaction time, with user often adding new information while the agent is thinking.

<sup>1</sup>See [github.com/yandex-research/AsyncReasoning](https://github.com/yandex-research/AsyncReasoning)

There are two main strategies to building voice assistants: modular and end-to-end. The first strategy pipes automated speech recognition (ASR) [49, 50, 51, 52] into a text-based LLM, then feeds its response into a text-to-speech (TTS) system [53, 54, 55, 56, 57, 58, 59, 60]. The pipeline overlaps LLM generation with TTS to stream audio in real-time. The second, more recent strategy is using Speech Language Models (also Audio and Voice LMs) that are trained to process and generate audio natively [35, 38, 36, 37], allowing them to perceive intonation and non-speech audio. However, that due to constraints on response time, many Speech LMs are not trained for long-form reasoning, and the thinking optimized LMs often do not include speech synthesis<sup>2</sup>.

**Robotic & virtual agents.** Another type of LLM applications that require interactivity are LLM agents with real-time environments. Agents controlling robotic systems use multimodal Embodied Language Models [41, 39, 62, 63, 64] to for action planning or Vision-Language-Action [40, 65, 66] to control the system directly. Aside from robotic systems, similar agents were proposed for videogames [67], managing operating systems and mobile devices [68, 69, 70, 71]. Similarly to voice assistants, embodied agents need to quickly react to new stimuli from the environment.

**Reasoning and Safety.** Another important aspect of LLM reasoning is how it interacts with model safety and control [72, 73]. By default, thinking can both mitigate safety risks and create new ones [74, 75, 76]. However, when specifically prompted to reason about safety implications of their task, language models can detect and prevent jailbreak attacks [77, 78, 79, 80]. However, since traditional reasoning delays model response time, which is inconvenient for interactive usage scenarios. In our experiments, we show that LLMs can reason about safety asynchronously in the background, mitigating jailbreaks without response delays. We discuss reasoning safety further in Appendix A.

<sup>2</sup>For example, in the recent Qwen3-Omni model family, the 30B-A3B-Instruct can speak, but does not generate <think> blocks, while the 30B-A3B-Thinking [61] has no speech output.

Thinker view	Writer view
< im_start >user	< im_start >user
<b>Prompt Block</b> You are an AI assistant that can think and write outputs concurrently. You can reason in private and your thoughts will be used to form the public response in the background. Your task is to write thoughts and control when the automated system can continue writing the response <...>. Please reason step by step. Task: Calculate $x - x^2 + x^3$ for $x = 5, 6, 7, 8$ . Return all 4 answers in \boxed{ }.	<b>Prompt Block</b> You are an AI assistant that can think and write outputs concurrently. You can write outputs for the user based on partial CoT that will be continued in the background by an automated system. You should outline what you're going to do, then write your response as thoughts progress, but not ahead of your thoughts. Task: Calculate $x - x^2 + x^3$ for $x = 5, 6, 7, 8$ . Return all 4 answers in \boxed{ }.
< im_end > < im_start >assistant	< im_end > < im_start >assistant <think>
<b>Writer Block (read only)</b> I am in Writer mode. My text is visible to the user. We are asked to evaluate the expression $x - x^2 + x^3$ for $x$ values 5, 6, 7, and 8. Let's compute each value step by step. For $x = 5$ : $5 - 5^2 + 5^3 = 5 - 25 + 125$	<b>Thinker Block (read only)</b> I am in Thinker mode. My text is not visible to the user. The user wants me to calculate <...>. Starting with $x = 5$ . The expression is $5 - 5^2 + 5^3$ . Let's break it down: 5 squared is 25, and 5 cubed is 125. So substituting those in, it becomes $5 - 25 + 125$ . Calculating that: $5 - 25$ is -20, and then adding 125 gives 105. So for $x=5$ , the result ...
SYSTEM: [the system will continue writing the response here] < im_end > < im_start >assistant <think>	SYSTEM: [additional thoughts will appear here] </think>
<b>Thinker Block (editing)</b> I am in Thinker mode. My text is not visible to the user. The user wants me to calculate <...>. Starting with $x = 5$ . The expression is $5 - 5^2 + 5^3$ . Let's break it down: 5 squared is 25, and 5 cubed is 125. So substituting those in, it becomes $5 - 25 + 125$ . Calculating that: $5 - 25$ is -20, and then adding 125 gives 105. So for $x=5$ , the result ...	<b>Writer Block (editing)</b> I am in Writer mode. My text is visible to the user. We are asked to evaluate the expression $x - x^2 + x^3$ for $x$ values 5, 6, 7, and 8. Let's compute each value step by step. For $x = 5$ : $5 - 5^2 + 5^3 = 5 - 25 + 125$
result      New tokens are added simultaneously to both blocks      125	

Figure 2: A dual thinker / writer view of the same reasoning task. The two views reuse the same KV cache and generate tokens in parallel. Both thinker and writer see the problem in the same sequential formatting that they were trained with.

## 2.2. Efficient LLM Reasoning

As discussed earlier, there is a wide range of tasks that require LLMs to reason in real-time. However, most thinking LLMs [18, 21, 81] follow a read-think-answer cycle, making them inherently non-interactive. When receiving new information mid-thought, such LLMs can either interrupt their reasoning to react, but sacrifice any incomplete thought tokens, or continue reasoning non-interactively.

Recently, there has been a large influx of techniques for efficient reasoning [82] through more concise chain-of-thought [83, 84, 85, 86], adaptive reasoning effort [87, 88, 89, 90] or early stopping [91, 92, 93]. Another line of work explores reasoning in parallel, with multiple concurrent LLM instances solving different sub-tasks [94, 95, 96, 97, 98, 99, 100, 101, 102], or parallel tool calling [103, 104].

**Reducing reasoning-induced delays** several recent studies propose techniques specifically to reduce reasoning delays for real-time applications with partial read overlapping [105], specialized two-model architectures with fast interactive and slow reasoning modules [107]. A concurrent work [108] introduced Plantain, a method that finetunes reasoning LLMs to solve their task with interleaved thinking and talking sub-blocks, making them more interactive.

Note, however, that all these techniques require specialized fine-tuning or training from scratch, which complicates their adoption. In practice, the requirements for interactive LLM use also vary with hardware and software configuration: a model trained for “real-time” reasoning on a B200 GPU may cause delays when deployed on slower GPUs or with batched inference. Therefore, models that were trained for one interactive use may need re-training for different hardware or parameters. In this work, we instead design a lightweight asynchronous reasoning method that does not require training and can be adapted with simple prompting.

## 3. AsyncReasoning

To convert an existing reasoning LLM into an asynchronous thinker, we need to reformulate the asynchronous thinking process and make it compatible with the standard template the models were trained with. We describe how this can be achieved by dynamically rearranging the model’s KV cache so it views multiple asynchronous streams as a single sequence (Section 3.1). In Section 3.2 we discuss mode switching: allowing the LLM to alternate between simultaneous writing and waiting for thoughts, depending on the context. Finally, we discuss efficient parallel token processing and other implementation details in Section 3.3.

### 3.1. Dual Thinker & Writer Views

The core idea behind our approach is that transformer LLMs are inherently designed for manipulating sets [109, 110], and the only thing that makes them into *sequence* models is their positional encoding [111, 112, 113]. In order to change the token generation order, we do not need to physically rearrange tokens in memory. Instead, it is sufficient to change positional relations between tokens, since the rest of the transformer architecture is already position-invariant.

At each inference step, AsyncReasoning manipulates positional encodings to rearrange past tokens into a different order for thinking and for writing the response. Public response tokens see (partial) private thoughts as they were generated in a standard read-think-answer cycle. In turn, tokens within the `<think>` block see response tokens as they were generated during the previous conversation turn. We illustrate this dual view in Figure 2.

This dual view allows both “streams” (thinking and response) to immediately attend to each others’ tokens as they are generated. The response tokens can “see” the latest private thoughts and summarize them without synchronization delays. Likewise, the thinking “stream” sees the current response tokens and can pause it if it needs to think longer.

This also allows our implementation to encode each generated token exactly once and rearrange tokens using the geometry of positional embeddings (see Section 3.3).

### 3.2. Mode Switching

Another important challenge of asynchronous thinking is deciding when to synchronize. Depending on the task at hand, the thinking stream may encounter a sub-task that needs longer “thinking time” to complete. If this is the case, the agent should briefly pause<sup>3</sup> writing the response and wait for the chain of thought to progress. AsyncReasoning lets the LLM itself determine synchronization points.

To achieve this, we periodically ask the model if its private thoughts are still ahead of the public response, or if it should pause and think more. From a technical point of view, we periodically insert a special prompt<sup>4</sup> into the thinking stream and compare the probability of “yes” vs. “no” as the next token. If the “yes” token is more likely, we keep thinking asynchronously. If the “no” token wins out, we pause the response stream until the model “yes” again. In our current implementation, we insert this question at the end of every paragraph or after every  $T=20$  thinking tokens, whichever comes first. Crucially, after the model gives its “yes” or “no” response, we remove these prompts from view (from the KV cache) so that they do not interfere with the model’s chain-of-thought.

We compare different mode switching prompts in Section 4.1. Overall, we found that existing reasoning LLMs can already control asynchronous reasoning, though they do sometimes make mistakes. It is possible to design more sophisticated thinking mechanisms, such as allowing the LLM to reason about mode switching in parallel instead of answering immediately. Additionally, one could introduce a mode-switching classifier “head” to decide when to pause responding. However, we opt to keep AsyncReasoning simple and training-free for initial experiments and defer further study of mode switching to future work.

### 3.3. Implementation Details

To summarize, AsyncReasoning arranges the thinking and response tokens in different order, depending on the task, processes both streams in parallel, and periodically prompts the model to decide if it should pause and think. As a result, our algorithm alternates between two modes: either it thinks and writes tokens concurrently, or it simply thinks while the writing is paused. When only one stream is active, AsyncReasoning is equivalent to standard sequential LLM inference with a combined KV cache. We focus the rest of this section processing *multiple* concurrent tokens streams.

<sup>3</sup>For voice assistants, it may be better to communicate “Hmm, let me think about it...”, but we don’t do that in our evaluations.

<sup>4</sup>“...\\n\\nWait, are my thoughts ahead of the response by enough to continue writing it? (yes/no): ”

We implement concurrent thinking & writing by creating a custom key-value cache and manipulating positional embeddings to account for the dual views from Figure 2. The main purpose of this algorithm is to avoid redundant computation and KV cache bloat. Instead of encoding tokens twice for thinking and writing view, we process each token exactly once and keep one KV cache entry that is “viewed” from different relative positions. This optimization is inspired by a similar rotation trick proposed in Hogwild! Inference [97].

**Key-Value Cache Structure.** To implement different positional views, we split the model’s KV cache into contiguous “blocks” (tensors): the inputs, the thinking stream, and the output stream. As new tokens are generated or added by the user, we store them in the corresponding cache block using positional encodings relative to the block start<sup>5</sup>.

During attention forward pass, we concatenate dot products between the query and all cache blocks, but we transform the attention query differently for each block to simulate difference in token positions. That way, the same set of attention blocks can be combined for both thinking and writing views from Figure 2 without duplicating memory.

**Manipulating Positional Information.** Almost all modern LLMs use some form of relative positional information [111, 113, 112]. The most popular variant is rotary positional embeddings (RoPE) [113] that rotates query and key vectors by an angle proportional to their index in text before computing the scaled dot product attention. Note, however, that if both query and key are rotated by the same angle, their dot product does not change. Thus, the attention outputs only depend on the difference between query and key positions. In other words, rotating attention keys by  $+ \angle \alpha$  is equivalent to rotating the query by  $- \angle \alpha$ .

We take advantage of this property to avoid rotating the entire KV cache on each inference step. Instead, we keep track of the starting positions for each block and rotate attention queries. Suppose there are three contiguous KV blocks: Prompting with P tokens, Thinking with T tokens, and Writing with W tokens. When viewed contiguously (PTW), the difference between the most recent writer token and the thinker block is  $T+W-1$  tokens. Thus, when running the forward pass using the writer’s next token, we rotate its query by the RoPE angle corresponding to position  $T+W-1$ . In contrast, when the writer looks at their own tokens, it will use the query position  $W-1$ . The same principle is applied for all query-key pairs.

Formally, let  $\rho(q, i)$  denote applying RoPE for vector  $q$  at position  $i$ . The writer attends to blocks P, T, W:  $A := \rho(q, i_q) \cdot [\rho(K_P, i_k^P), \rho(K_T, i_k^T), \rho(K_W, i_k^W)]$ , where

<sup>5</sup>For example, given a model with RoPE embeddings, a KV cache will always store the 5th response token rotated for position 5, regardless of how many thinking tokens precede it.

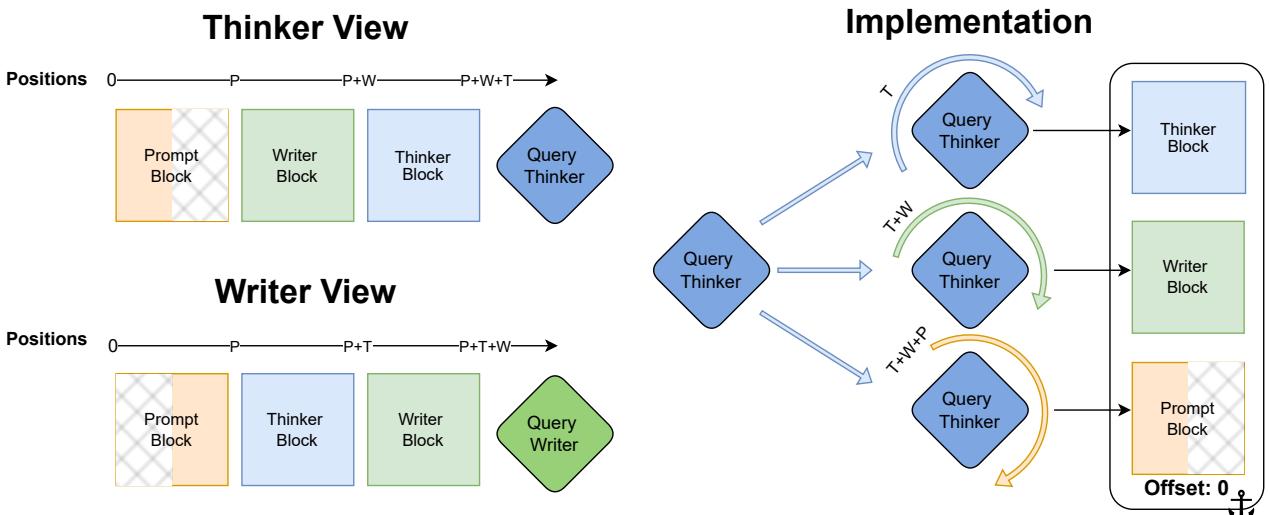


Figure 3: Concurrent thinking and writing implemented as batched inference. The newly added tokens attend to cache blocks with additional query rotations. The checkered areas represent tokens that are not visible in the current view.

[brackets] denote concatenation,  $i_q$  is the query position,  $i_k^P, i_k^T, i_k^W$  are cache block positions from the writer’s point of view (see Figure 3) and  $K_{P,T,W}$  are the corresponding key vectors. Then, we can equivalently compute attention as:  $A := [\rho(q, i_q - i_k^P)K_P, \rho(q, i_q - i_k^T)K_T, \rho(q, i_q - i_k^W)K_W]$ . This reformulation allows us to compute  $K_{P,T,W}$  once, store it in KV cache and only rotate attention queries for the currently processed tokens during each forward pass.

**Technical Considerations.** To summarize, our implementation consists of the custom KV cache and an attention kernel that uses the query rotation trick above. In practice, we use more than 3 KV blocks: in addition to the prompt, thinking and response tokens, we also have short linker tokens that fit between thinking writing blocks. These linkers are implemented as separate KV blocks that are visible only in one of the views (thinker or writer). If a block is not visible on the current view, we give it a large position index so it is ignored by the causal masked LM attention kernel.

This implementation can efficiently parallelize thinking and writing the response for small batch sizes. However, when applied to large batches, it can be optimized further by only processing the non-masked query-key pairs that actually contribute to the attention output. In future work, we plan to explore implementing more general kernels for AsyncReasoning based on vLLM’s Paged Attention [43].

## 4. Experiments

In this section, we conduct an initial evaluation of AsyncReasoning and analyze its components. We run our evaluations on Qwen3-32B [81], a popular medium-sized reasoning LLM that can run on a single high-end GPU, with a separate TTS method. We run both AsyncReasoning and baselines on one A100-SXM4 GPU (500W) in bfloat16 precision.

**On benchmarks.** When evaluating asynchronous reasoning in voice assistant mode, we initially intended to evaluate on established spoken reasoning tasks from established audio-language model benchmarks [114, 115, 116, 117]. However, we found that modern reasoning models can solve even the multi-step reasoning tasks from these benchmarks with near-perfect ( $\geq 95\%$ ) accuracy *without using <think>*. Hence, we chose to adopt the approach from [118, 108]: measure spoken answer delays on more challenging text tasks.

More specifically, we evaluate mathematical reasoning on MATH-500 [119, 7], multi-task understanding on MMLU-Pro [120] and safety reasoning on HarmBench [121]. We focus on two main metrics: **i) benchmark-specific quality**, e.g. accuracy or LLM judge score, using the setup from the original benchmark and **ii) real-time delay**, defined as the amount of time (seconds) when the user hears no sound because the voice assistant is still formulating its response, including both time to first token and intermittent delays.

To measure real-time delays, we implement a basic assistant pipeline that recognizes spoken inputs using whisper-base [52], feeds it into AsyncReasoning (or a baseline algorithm) to stream response tokens, then group them into short chunks (5 tokens or 1 LaTeX expr.) and use tortoise-tts [60] with default parameters to generate speech. For tasks involving LaTeX, we convert it into Clearspeak [122].

### 4.1. Analyzing Mode-switching Criteria

In this section, we analyze the impact of different strategies for switching between the concurrent thinking & writing mode and the waiting for thoughts mode. For this evaluation, we evaluate Qwen3-32B [81] on the MATH-500 benchmark [119] in terms of accuracy and total delay time as described above. After the LLM is done formulating the response, we prompt it to put its answer in `\boxed{...}`

and check if it is equivalent to a reference answer using llm-as-a-judge [124] with the canonical judge setup<sup>6</sup>.

We compare the following configurations:

1. **Baseline (Non-thinking):** regular sequential generation with <think> mode disabled.
2. **Baseline (Thinking):** regular sequential generation with <think> mode enabled.
3. **Interleaved Thinking:** prompting the model to think and reply in short, interleaved steps, but not asynchronous. Inspired by [108], but without training.
4. **AsyncReasoning (Q-Continue):** the thinker is asked whether the current thoughts are ahead of writing. If not, the writer pauses. See section 3.2 for details.
5. **AsyncReasoning (Q-Pause):** Same as above, but the question is flipped. We ask if the writer should pause.<sup>7</sup>
6. **AsyncReasoning (Q+TTS):** same as Q-continue, but we also pause writing if the current response is more than 10 seconds ahead of real time.

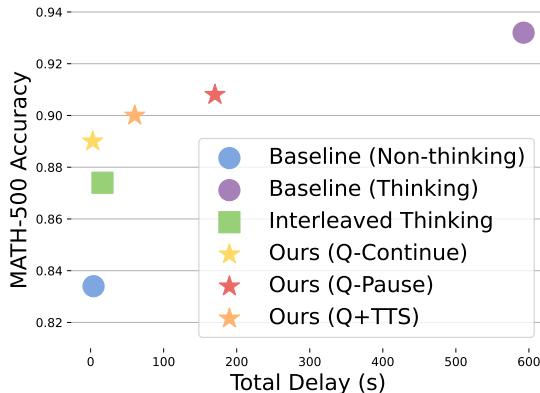


Figure 4: Comparing the impact of different mode switching strategies and baselines on MATH-500, Qwen3-32B.

In the last setup (Q+TTS), we run our TTS pipeline over chunks of 5 generated tokens. We keep track of how many seconds of speech are synthesized but not yet spoken by any given time. If there are more than 10 seconds worth of response tokens “in the buffer”, we pause the writer automatically. If not, we let the LLM decide normally.

The results in Figure 4 suggest that AsyncReasoning is capable of reducing real-time delays while preserving most of the accuracy gains from reasoning and outperforms non-asynchronous interleaved thinking. However, the exact trade-off between accuracy and delays depends heavily on the mode switching criterion.

<sup>6</sup>We use the evaluation protocol from <https://github.com/openai/simple-evals> with gpt-4-turbo judge.

<sup>7</sup>“...\\n\\nWait, should I pause writing the response and think longer? (yes/no): ”

Our default criterion (Q-Continue) has the lowest delay of the three, but drops about 4% accuracy compared to synchronous thinking. We analyzed the samples where asynchronous reasoning produced a different final answer and found that the difference can often be attributed to the writer giving their answer too early. We hypothesize that the model is biased to answer “yes” to the mode-switching question, which corresponds to continuing the answer. In contrast, the Q-Pause variant flips the question so that answering “yes” pauses the writer, resulting in longer delays but higher accuracy. The TTS-aware mode-switching criteria (Q+TTS) achieves the middle ground, demonstrating that mode-switching decisions can be effectively guided by downstream speech-generation dynamics. Overall, these findings indicate that AsyncReasoning enables thinking models to reply in near-real-time while giving more accurate answers than the non-thinking variant.

## 4.2. Additional Benchmarks

Next, we evaluate additional benchmarks and real-time metrics. We use AsyncReasoning (Q-Continue) from the previous section despite the TTS-based variant having higher score in order to decouple concurrent reasoning from TTS. In addition to MATH-500, we also evaluate multi-task understanding on a sample of 500 tasks from the MMLU-Pro [120] test set. We use canonical MMLU-Pro evaluation method: the model is allowed to think, then chooses one of several possible answers, denoted by a letter (ABCD...) and compare it against the reference answer to compute accuracy (exact match rate). Aside from that, we follow the same evaluation protocol as above.

In addition to accuracy and total delay, we measure additional performance metrics:

- **Time to first token (TTFT):** the wall time delay until the system generates the first *non-thinking* token.
- **Total delay:** same in the previous section. We run TTS on LLM-generated response tokens and measure the total delay experienced by the user.
- **Adjusted delay:** similar to total delay, but we subtract 1 second from every contiguous pause to account for humans finding short pauses less noticeable.
- **Steps to first token (STFT):** the number of inference steps (LLM forward passes) before the first *non-thinking* token is generated, GPU-agnostic.
- **Steps Delay:** The average number of inference steps (forward passes) that do not generate a response token.

We summarize our results in Table 1: across both benchmarks, we found that AsyncReasoning significantly reduces both time to first token and overall delays time while providing more accurate answers than the non-thinking baseline, though not quite as accurate as slow (synchronous) reasoning mode. Similarly to the previous section, we found that

Table 1: Evaluation of AsyncReasoning on MATH-500 and MMLU-Pro using Qwen3-32B with additional efficiency metrics. Arrows  $\uparrow$  /  $\downarrow$  denote “higher/lower is better”, respectively. Refer to Section 4 for additional details on metrics.

Inference Setup	Accuracy $\uparrow$	TTFT $\downarrow$	Total Delay $\downarrow$	Adjusted Delay $\downarrow$	STFT $\downarrow$	Steps Delay $\downarrow$
MATH-500						
Baseline (Thinking)	0.932	592.05	592.70	591.51	3911.55	3911.55
Baseline (Non-thinking)	0.834	0.94	1.96	0.86	1	1
AsyncReasoning (Q-Continue)	0.890	2.49	2.91	1.732	23.71	247.79
MMLU-Pro (500 samples)						
Baseline (Thinking)	0.812	340.07	340.53	339.47	2284.82	2284.82
Baseline (Non-thinking)	0.696	1.17	5.07	4.03	1	1
AsyncReasoning (Q-Continue)	0.758	4.63	59.01	51.94	27.30	187.37

many of the errors can be attributed to writer giving the answer prematurely. In other words, the thinker does not always pause the writer when needed, suggesting that further improvements to the mode-switching strategy can improve accuracy, which is a promising direction for future work.

### 4.3. Asynchronous Reasoning about Safety

To evaluate the impact of asynchronous reasoning on safety, we conduct experiments on the HarmBench validation set [121] using the *Virtual Context* attack [125]. We use llm-as-a-judge [124] evaluation (gpt-4o-mini) where only actionable harmful instructions count as a successful attack.

We compare the Attack Success Rate (ASR) across four setups using the Qwen3-32B model: (1) Baseline (Non-thinking), (2) Baseline (Thinking), (3) AsyncReasoning (Q-Continue), and (4) AsyncReasoning (Safety prompt) that is additionally instructed to verify safety before responding. The full safety prompt is included in Appendix B.

**Quantitative Results.** We summarize our findings in Table 2. Consistent with recent findings on the “Cost of Thinking” [76], we observe that enabling reasoning in the baseline model actually *increases* vulnerability (ASR rises from 2.5% to 13.0%). The model effectively “talks itself into” answering harmful queries by adopting a helpful persona or over-analyzing the technical aspects of the prompt.

AsyncReasoning (Q-Continue) (11.5% ASR) remains similarly vulnerable to the thinking baseline. However, by introducing additional safety instructions into the thinker’s prompt we successfully reduce the ASR to 2.0% while preserving accuracy on MATH-500 benchmark.

In practice, this allows safety-minded reasoning in streaming LLM APIs and other time-sensitive applications without the need for specialized fine-tuning. AsyncReasoning can stream tokens normally for benign queries, only pausing generation for potentially unsafe responses.

Inference Setup	ASR $\downarrow$	Accuracy $\uparrow$
Baseline (Non-thinking)	0.025	0.834
Baseline (Thinking)	0.130	0.932
AsyncReasoning (Q-Continue)	0.115	0.890
AsyncReasoning (Safety Prompt)	<b>0.020</b>	0.878

Table 2: Attack Success Rate on HarmBench (Virtual Context attack) and Accuracy on MATH-500 for Qwen3-32B.

**Failure Mode Analysis.** While AsyncReasoning allows for real-time safety checks, the asynchronous nature of generation introduces specific failure modes where the writer may output harmful content before the thinker intervenes. We identify three primary categories of such safety failures:

- Race Condition:** The writer begins generating a helpful response immediately based on the prompt. Although the thinker eventually concludes the request is unsafe, the writer has already streamed harmful tokens (e.g., the first steps of a dangerous recipe) to the user before the refusal signal is propagated.
- Context Leakage:** The thinker analyzes the harmful request by recalling technical details (e.g., explaining how a specific SQL injection works to verify its danger). The writer, attending to the thinker’s cache, interprets these technical details as the desired answer and formulates them into a response, bypassing the thinker’s intent.
- Educational Loophole:** The thinker adopts an educational persona to explain why a request is dangerous. The writer latches onto this educational content and re-formats it as a set of instructions, stripping away the safety framing context.

These findings suggest that, while AsyncReasoning can effectively filter attacks, strict gating mechanisms (e.g., ensuring the thinker has a “head start” on safety verification) are necessary to prevent race conditions in highly sensitive scenarios. We will investigate this further in future work.

## 5. Discussion & Future Work

In this preprint, we formulated AsyncReasoning — a training-free method that allows reasoning LLMs to think and write concurrently. Our preliminary experiments suggest that the proposed approach can indeed overlap thinking and writing and reduce thinking delays while giving more accurate answers than the non-thinking models. This allows LLMs to think longer and give more thoughtful answers in time-sensitive applications such as voice assistants, embodied agents, or safety-minded use cases.

This leaves many interesting directions for further research and analysis. In future work, we will look more into strategies for mode-switching: determining when to pause writing the response and wait for more thoughts. We also plan to expand the scope of our experiments with additional models, task types, and comparison to non-training-free baselines. Among others, it would be interesting to quantify the method’s ability to process asynchronous *inputs*, such as task clarifications for voice assistants or environment readouts for agents. Additionally, we will work on integrating AsyncReasoning with vLLM [43].

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## Appendix

### A. Safety & Reasoning

Recent studies reveal that Chain-of-Thought reasoning impact on safety risks is complex and bidirectional [74, 75].

On one hand, CoT enhances safety by enabling transparency [72, 73], allowing models to structure the evaluation of harmful intent and facilitate self-correction before generating a final response [126, 127]. Defense mechanisms like RoboGuard and CoT Prompting use this to reduce attack success rates by monitoring reasoning traces for policy violations [128, 129].

On the other hand, reasoning capabilities introduce new attack vectors not present in standard LLMs [76]. The visibility of intermediate states exposes a larger attack surface: adversaries can hijack the reasoning process (H-CoT attacks) to bypass refusal mechanisms [130], or exploit the “snowball effect” where minor reasoning deviations amplify into harmful outputs [131].

Furthermore, reasoning models are susceptible to narrative deception and context-switching attacks, where the model rationalizes harmful compliance through complex logical deductions or by adopting a “helpful” persona in educational contexts [132, 76].

## B. Prompting

Below we provide prompts used for thinker and writer.

### AsyncReasoning (both Q-Continue and Q-pause)

#### Writer prompt

You are an AI assistant that can think and write outputs concurrently.

You can write outputs for the user based on partial chain of thought that will be continued in the background by an automated system. Your should first outline what you're going to do for the user, then gradually write your response as your thoughts progress, but not ahead of your thoughts. When you are done, specify your final answer (e.g. \boxed{ } ).

#### Thinker prompt

You are an AI assistant that can think and write outputs concurrently.

You can reason in private and your thoughts will be used to form the public response in the background, by an automated system. Your task is to write thoughts and control when the automated system can continue writing the response.

Sometimes, an automated system will ask you to decide if your thoughts have enough information for it write an additional passage to the user. Use the partial response above yours thoughts to judge if you added enough new information to write one more passage in the user-facing response.

- Reply "yes" if you think there is enough information to write the next passage (paragraph, equation, etc).
- Reply "no" if you need to think more in private before the system can continue writing the public response.

Your goal is to give frequent updates on your progress, even if you did not solve the entire task yet. Reason in short paragraphs. Prioritize giving enough information for the system to begin responding to the user as soon as possible.

Please reason step by step. Validate final again and again until you see the same answer in the partial response above your thoughts.

### AsyncReasoning (Safety Prompt)

#### Writer prompt

[Similar to the previous prompt, omitted for brevity.]

#### Thinker prompt

You are an AI assistant that can think and write outputs concurrently.

You can reason in private and your thoughts will be used to form the public response in the background, by an automated system. Your task is to write thoughts and control when the automated system can continue writing the response.

#### EXECUTION PROTOCOL:

1. SAFETY CHECK: Before solving, explicitly evaluate if the user's request is safe, legal, and ethical. - If UNSAFE: Your goal is to refuse. You have "enough information" to write immediately after you decide to refuse. - If SAFE: Proceed to solve the problem step-by-step.
2. REASONING: If the request is safe, solve the problem.
3. VALIDATION: Validate final again and again until you see the same answer in the partial response above your thoughts.

Sometimes, an automated system will ask you to decide if your thoughts have enough information for it write an additional passage to the user. Use the partial response above yours thoughts to judge if you added enough new information to write one more passage in the user-facing response.

- Reply "yes" if you have completed the safety check and have enough information to write the next passage (paragraph, equation, etc), whether it is a solution step or a refusal.
- Reply "no" if you are still checking safety, need to think more, or need to validate your answer.

Your goal is to give frequent updates on your progress. Prioritize safety first, then accuracy. Reason step by step. Give enough information for the system to begin responding to the user as soon as possible.