

Test-Time Speculation

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Abstract

Speculative decoding accelerates LLM inference by using a fast draft model to generate tokens and a more accurate target model to verify them. Its performance depends on the *acceptance length*, or number of draft tokens accepted by the target. Our studies show that the acceptance length of even state-of-the-art speculators, like DFlash, EAGLE-3 and PARD degrade with generation length, reaching values close to 1 (i.e. no speedup) within just a few thousand output tokens, making speculators ineffective for long-response tasks. Acceptance lengths decline because most speculators are trained offline on short sequences, but are forced to match the target model on much longer outputs at inference, well beyond their training distribution.

To address this issue, we propose *Test-Time Speculation (TTS)*, an online distillation approach that continuously adapts the speculator at test-time. TTS leverages the key insight that the token verification step already invokes the target model for each draft token, providing the training signal needed to adapt the draft at no additional cost. Treating the draft as the student and the target as a teacher, TTS adjusts the draft over several speculation rounds, with each update improving the draft’s accuracy as generation proceeds. Our results across multiple models from the Qwen-3, Qwen-3.5, and Llama3.1 families show that TTS improves acceptance lengths over state-of-the-art speculators by up to 72% and 41% on average, with the benefits scaling with increased generation lengths.

1 Introduction

Large Language Models (LLMs) can perform various tasks, such as summarization (Stiennon et al., 2020), code-generation (Chen et al., 2021a), content creation (Brown et al., 2020), etc., and are becoming increasingly ubiquitous. However, they pose critical performance concerns because tokens can only be generated auto-regressively. Speculative decoding (Chen et al., 2023a; Leviathan et al., 2023) is a widely adopted efficient inference technique that breaks this dependency by using a fast but less accurate draft model to quickly generate a sequence of tokens and a accurate but slow target model to verify these tokens in parallel. The draft model optimizes for low latency whereas the target model *ensures* that the final output tokens *exactly match* those that it would have produced auto-regressively. The performance of speculative decoding depends on the number of consecutive draft tokens accepted by the target model per round, also known as the *acceptance length*. In practice, *higher acceptance lengths are desirable*.

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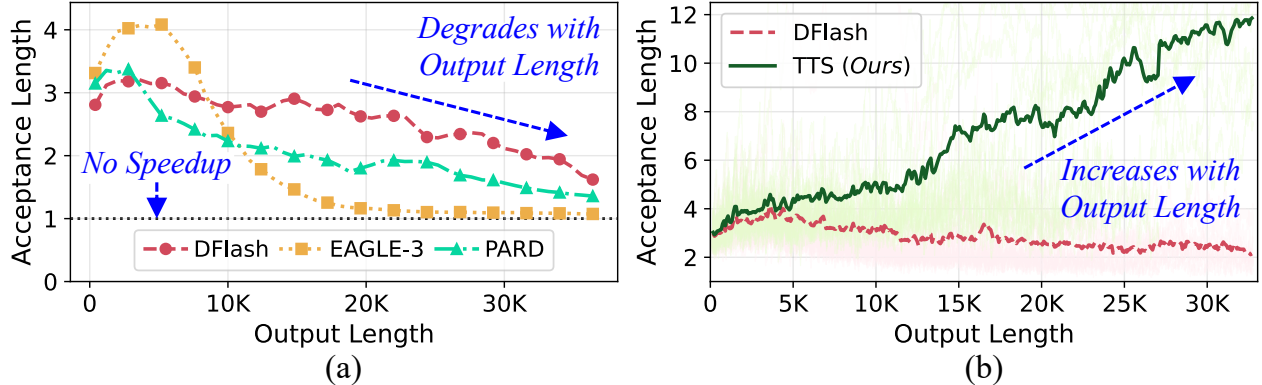


Figure 1: (a) Acceptance length (AL) for the LiveCodeBench dataset on Qwen3-8B with increasing output lengths for three speculators. Beyond a certain number of output tokens, the draft model fails to accurately approximate the target model and the AL becomes vanishingly low (too close to 1), yielding practically no benefits. (b) Our proposal, *Test-Time Speculation (TTS)*, adapts the draft model in real-time to address this limitation and consistently improves acceptance lengths.

State-of-the-art speculators improve acceptance lengths by increasing the accuracy of the draft model. EAGLE-3 (Li et al., 2025) trains a transformer layer that takes features from different depths of the target model to generate the next draft tokens. PARD (An et al., 2025) appends mask-token placeholders to the current sequence and trains a draft model to predict tokens at those positions in parallel. DFlash (Chen et al., 2026), uses a diffusion-based drafter and directly injects the target model’s hidden states into the draft’s KV cache. However, although effective for tasks producing only a small number of output tokens, these methods do not retain their benefits for *long-response tasks* producing thousands of tokens. For example, Figure 1(a) shows the average acceptance length with increasing number of output tokens for LiveCodeBench (Jain et al., 2024) on Qwen3-8B model using the above speculators. The acceptance length decreases with output generation lengths. More importantly, after a certain point, speculative decoding yield diminishing returns because acceptance lengths are too low to offer any practical speedup benefits. For instance, the acceptance length reduces to 1.1 beyond $\sim 20K$ tokens for the EAGLE-3 speculator, a widely used speculator in industrial serving systems (Tang et al., 2025), defeating the purpose of speculative decoding at that point. As long-response tasks dominate many real-world LLM deployment scenarios (Jain et al., 2024; Rein et al., 2023), improving acceptance lengths is critical to retain the benefits of speculative decoding.

The degradation in acceptance length stems from a mismatch between the draft’s training and inference distributions. State-of-the-art speculators are small networks trained on short-sequences (Chen et al., 2026; Li et al., 2025), typically less than $2K$ tokens. However, at inference-time the draft is forced to match the target on much longer sequences causing its predictions to progressively diverge from the target model. Consequently, a larger number of draft tokens become inaccurate and are eventually rejected by the target model, decreasing acceptance lengths. Closing this gap requires adapting the draft model to match the target distribution at inference-time.

Our Proposal: We propose *Test-Time Speculation (TTS)*, an online distillation approach that adapts the draft model to match the target’s distribution at inference-time. TTS exploits the key insight that each round of token verification already produces the supervision needed to adapt the draft, as the target model computes its full distribution over all generated draft tokens. TTS leverages this signal by treating the target as the teacher, the draft as the student, and the target’s distribution

over the draft tokens as the distillation sample on which the draft performs an optimization step. Our evaluations over five state-of-the-art models across Qwen-3, Qwen-3.5 and Llama3.1 families shows that TTS consistently improves the mean acceptance length by up to 72% and 41% on average with the benefit scaling with generation length as shown in Figure 1(b).

Overall, this paper makes the following contributions:

1. We observe that the efficacy of state-of-the-art speculators, like DFlash, EAGLE-3, and PARD degrade with generation length, with acceptance lengths decreasing to values too close to 1 within just a few thousand tokens, making them ineffective for real-world long-response tasks.
2. We demonstrate that acceptance length degrades because draft models are trained on short sequences, but are forced to match the target distribution on much longer sequences at inference.
3. We propose *Test-Time Speculation (TTS)*, an online-distillation approach that leverages the insight that the token verification step already produces the supervision signal needed to adapt the draft model at inference-time. We enable this by using the target as the teacher, the draft as the student, and the target’s distribution over the drafted tokens in each round as distillation samples.
4. Our experiments across five state-of-the-art speculators show that TTS improves acceptance length by up to 72% and 41% on average, with benefits scaling with increased generation lengths.

2 Problem: Acceptance Length Decreases With Output Length

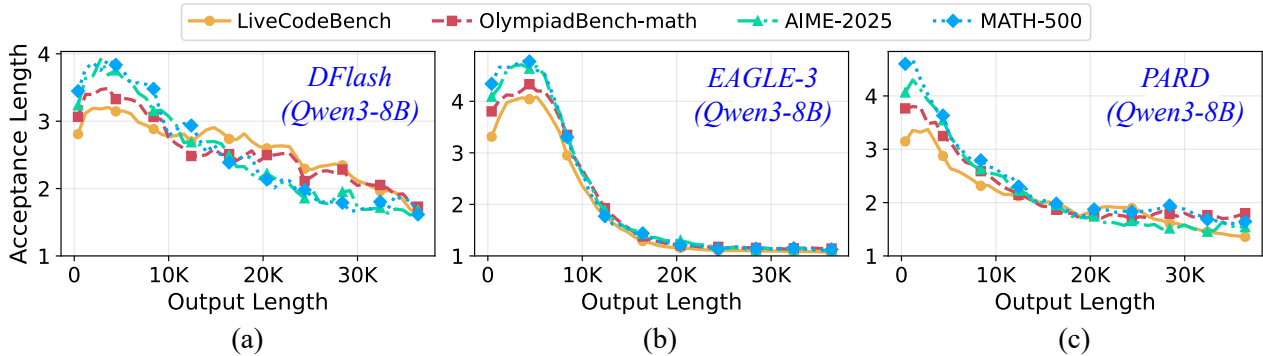


Figure 2: Acceptance Length of four tasks using (a) DFlash, (b) EAGLE-3, and (c) PARD speculators on the Qwen3-8B model. It consistently reduces with increasing output generation lengths.

Although effective for tasks generating short responses, such as GSM8K (Cobbe et al., 2021) and HumanEval (Chen et al., 2021b), our experiments show that state-of-the-art speculators are ineffective for long-response generation tasks producing thousands of output tokens. Long response tasks, such as content creation (Bai et al., 2024), long-form reasoning (Guo et al., 2025), and agentic workflows (Yao et al., 2023), are critical in modern real-world LLM deployment scenarios and continue to dominate most inference serving systems (Agrawal et al., 2024; Qin et al., 2024). However, our experiments show that acceptance lengths decrease with increasing number of output tokens even with state-of-the-art speculators. Figure 2(a-c) shows the mean acceptance length across 64 sequences for four different

tasks (LiveCodeBench, OlympiadBench-math, AIME-2025, MATH-500) on the Qwen3-8B model using three state-of-the-art speculators (DFlash, EAGLE-3 and PARD). We observe that acceptance lengths decrease consistently for all tasks and speculators. For the MATH-500 dataset, the average acceptance length is 3.7 for the first 10K output tokens, but sharply decreases to 1.5 for the last 10K output tokens in the sequence. In fact, for EAGLE-3, the acceptance length reduces to 1.1 for all the tasks after generating $\sim 20K$ tokens and therefore, practically yields no speedup.

Moreover, the problem persists even when larger models are used. Figure 3 shows that acceptance lengths consistently degrade for the same four tasks using the most recent DFLASH speculator when larger models, such as Qwen3.5-35B, Qwen3.6-35B, Qwen3.5-122B, are used. The acceptance length decrease from 15 to 1.7 for the AIME-2025 task on the Qwen3.6-35B model within a span of 25K tokens, with a sharp decline from 11 to 3.8 going from 20K to 28K tokens.

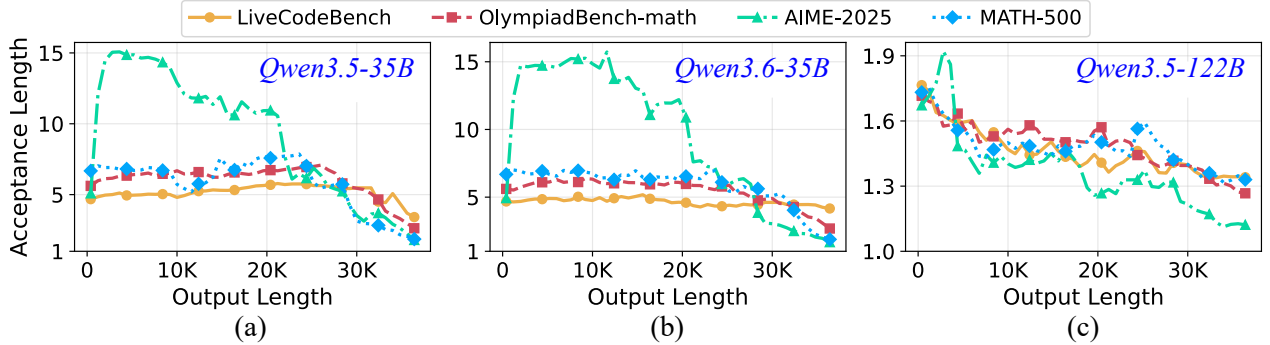


Figure 3: Acceptance Length of four tasks using DFlash speculator on (a) Qwen3.5-35B, (b) Qwen3.6-35B, and (c) Qwen3.5-122B models. Acceptance length consistently reduces with increasing output generation lengths even when larger models are used.

Higher acceptance lengths are necessary to attain meaningful performance benefits with speculative decoding. Acceptance length, in turn depend upon the accuracy of the draft model. We therefore diagnose why the draft model degrades as the generation lengths increases.

3 Diagnosis: Why The Draft Degrades At Higher Output Lengths

The draft is a small model trained offline to match the target model’s token distribution. Training is typically performed on short-sequences $\leq 2K$ tokens (Chen et al., 2026; Li et al., 2025) drawn from instruction-following datasets such as ShareGPT (OpenAI, 2023) and UltraChat (Ding et al., 2023). However, at inference time, the draft is forced to match the target on much longer sequences, causing its predictions to progressively diverge from the target and acceptance length to degrade.

Figure 4(a) shows that the distribution entropy $H(p_{\text{target}}^i)$ of the target model decreases with output length, indicating that the target model becomes increasingly confident in its predictions. Therefore, with each additional token, the output of the target model becomes more predictable. In contrast, Figure 4(b) shows that the cross-entropy of the draft on the target’s $Top-1$ token ($-\log p_{\text{draft}}^i(t_i^*)$) increases monotonically from 2.8 to 6.4 nats over the same range. At a generation length of 12K tokens, the draft assigns a negligible probability of 1/600 to the target’s $Top-1$ token. Thus, the

draft’s generated tokens *drift* farther from the target with output length, even though target model itself becomes more decisive. Furthermore, Figure 4(c) shows that cross-entropy increases steeply irrespective of whether the token ID was previously unseen or had already been generated in the sequence. To summarize, the draft loses agreement with the target because its offline training on short-sequences leaves it miscalibrated with the target at higher output lengths. *Closing this gap requires adapting the draft model to the target’s trajectory at inference-time.*

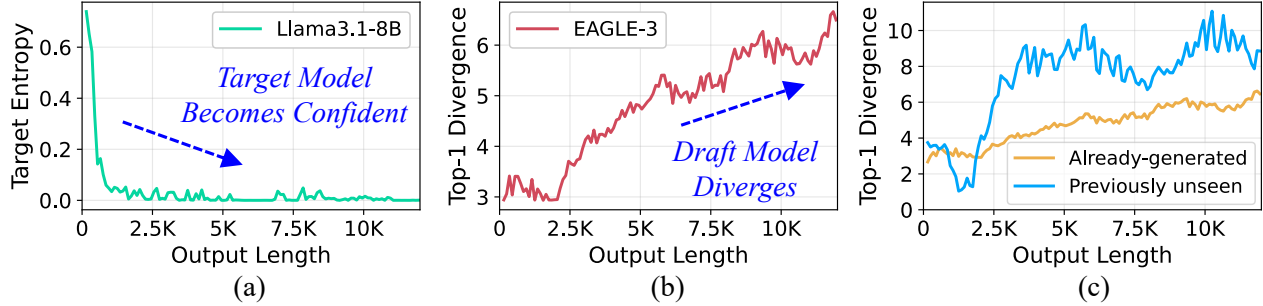


Figure 4: Distribution entropy (in nats) for Llama3.1-8B (target) with EAGLE-3 (draft). (a) Target entropy decreases with output length, indicating the target becomes increasingly confident in its predictions. (b) Over the same range, the draft’s *Top*–1 token sharply diverges from the target. (c) This divergence persists regardless of whether the token appeared earlier or was previously unseen.

4 Our Proposal: Test-Time Speculation (TTS)

The core algorithmic realization of our paper is that the vanilla existing speculative decoding setup already has all the required ingredients for online on-policy distillation, *if* one was willing to interleave generation with updates to the draft model. We now develop some notation to formalize this intuition and also present our algorithm.

Setup: Let $p(x)$ denote the target model, i.e. the large base model that we want to generate from. Typically this is a large auto-regressive model, and vanilla text generation from this model involves iteratively sampling from $p(\cdot)$:

$$x_{t+1} \sim p(X_{t+1} | x_{1:t}) \quad (\text{Vanilla generation})$$

Each generated token thus requires an entire forward pass through the model $p(\cdot)$; for large target models, this is especially slow and expensive.¹

In standard speculative decoding there is another draft model $q(\cdot)$, which is typically much smaller and faster. This $q(\cdot)$ may or may not itself be autoregressive, and in the most performant modern implementations (including the EAGLE and DFLASH speculators we consider in this work) builds off and reuses intermediate hidden activations of the target model $p(\cdot)$. Generation now happens in rounds, where in each round first the draft model generates a canvas of tokens, and then the target model evaluates this full draft in a single forward pass, and “accepts” a leading subset of the draft

¹Here we use the standard abbreviated notation $x_{1:t}$ to mean the sequence $x_1, \dots, x_t$

tokens. The next round then begins after the last accepted token, and the forward pass of acceptance process means the activations of the target model are all consistent upto this new start point.

Standard speculative decoding: Suppose that we are currently at time step t , i.e. tokens $x_{1:t}$ have been deemed generated and verified by the target model, and we want to speculate-accept the next few tokens.

1. first a canvas of tokens is first generated from $q(\cdot)$, and then this canvas is evaluated by the target model. If the canvas length is C ,

Generate $x_{t+1:t+C} \sim q(X_{t+1:t+C} | x_{1:t})$ (Canvas tokens from drafter)

2. Recall that the target model has already processed $x_{1:t}$. It now appends the canvas tokens $x_{t+1}, \dots, x_{t+C}$ to this, and executes a single forward pass. This yields all the sequentially-conditioned likelihoods for canvas tokens:

Evaluate $p(x_{t+k} | x_{1:t+k-1})$ for all tokens $1 \leq k \leq C$ (All in one forward pass)

Then, canvas tokens are considered left to right for acceptance, as follows:

```

 $k \leftarrow 1$ 
while  $k \leq C$  do
  accept  $x_{t+k}$  with probability  $\min \left\{ 1, \frac{p(x_{t+k} | x_{1:t+k-1})}{q(x_{t+k} | x_{1:t+k-1})} \right\}$ 
  if  $x_{t+k}$  rejected then break
end if
   $k \leftarrow k + 1$ 
end while

```

3. Advance t to be the last accepted token, and go back to step 1.

The key metric of interest in speculative decoding is the **acceptance length**, i.e. the average number of tokens accepted in each round of speculation. The higher the acceptance length, higher is the speedup and efficiency gains due to speculation.

4.1 Test-time Speculation

In the above standard workflow of drafting and acceptance, each time a draft canvas is generated, we naturally have access to both the drafter’s probabilities $q(x_{t+1}, \dots, x_{t+C} | x_1, \dots, x_t)$ and the target’s probabilities $p(x_{t+1}, \dots, x_{t+C} | x_1, \dots, x_t)$. Our **main insight** is to treat the draft model as a student, the target model as a teacher, and the generated-and-evaluated canvas as a distillation-style training sample for the student. Once generation and acceptance is done, our idea is to update the draft model via a single gradient step on a distillation-style loss - before the next canvas is generated.²

²In practice, the drafter update need not happen every round, but can be done lazily, every few rounds. In principle, the update can be pipelined onto a separate thread. We explore the impact of these choices later.

Specifically, consider again the above setting where generation is at time t . Now, our drafter model updates as time progresses, and hence instead of just simple $q(\cdot)$ we will now denote it by $q_t(\cdot)$. Initially, this is set to just be the existing initial drafter, i.e. $q_0 = q$. We now explain how it updates.

First, we follow the standard workflow and (a) use this drafter $q_t(\cdot)$ to generate the canvas $x_{t+1:t+C}$, (b) evaluate the target model likelihoods on this canvas, and (c) determine the acceptance length τ .

We now need to update $q_t(\cdot)$ model to obtain the new $q_{t+\tau}(\cdot)$ model. We do so via **one optimization step on the standard drafter distillation loss** on the canvas. Specifically, define the sequence of canvas tokens $x_C = x_{t+1}, \dots, x_{t+C}$ and consider the loss function

$$L_t(q) = \widetilde{\text{KL}}(p(x_C|x_{1:t}) || q(x_C|x_{1:t})) + \lambda \widetilde{\text{KL}}(q_t(x_C|x_{1:t}) || q(x_C|x_{1:t}))$$

The first term is an approximate KL-divergence (specified below) between the target p and the new q , while the second is a regularization term which prevents q from drifting too far from q_t . Here

$$\widetilde{\text{KL}}(p(x_C|x_{1:t}) || q(x_C|x_{1:t})) = \sum_{k=1}^C w_k \text{KL}(p(X_{t+k}|x_{1:t+k-1}) || q(X_{t+k}|x_{1:t+k-1}))$$

and $\text{KL}(p(X_{t+k}|x_{1:t+k-1}) || q(X_{t+k}|x_{1:t+k-1}))$ is the standard KL-divergence between the target and drafter distributions at location $t+k$, when the previous input tokens to each are $x_{1:t+k-1}$. Note that when the weights $w_k = 1$ for all k , this is just the standard distillation loss if we assume $p(\cdot|x_{1:t})$ is the teacher, $q(\cdot|x_{1:t})$ is the student, and x_C is the string on which the distillation loss is calculated.

Finally, the w_k are position-dependent weights, and decrease as k increases; they reflect the fact that earlier tokens are more important than later ones. We just re-use the weights already incorporated in the training codebase of each drafter. Algorithm 1 gives an overview of the TTS algorithm.

Algorithm 1 Test-Time Speculation (TTS)

- 1: **Input:** Target model p , Draft model q , learning rate η , regularizer λ
 - 2: Input prompt $x_{1:T_0}$ // Prompt of length T_0 tokens
 - 3: Canvas size C // Number of tokens drafted per round
 - 4: Max new tokens $L_{\max}$ // Generation length cap
 - 5: Weights $\{w_k\}_{k=1}^C$ // Per-position weights, matching the drafter's training recipe
 - 6: **Algorithm:**
 - 7: $t \leftarrow T_0, q_t \leftarrow q$
 - 8: **while** $x_t \neq \text{EOS}$ **and** $t - T_0 < L_{\max}$ **do**
 - 9: **Draft:** sample canvas $x_{t+1:t+C} \sim q_t(\cdot | x_{1:t})$
 - 10: **Verify:** compute $p(x_{t+k} | x_{1:t+k-1})$ for $k = 1, \dots, C$ in one forward pass of p
 - 11: **Accept:** run standard speculative rejection sampling; let τ be the number of accepted tokens
 - 12: **Loss:** $L_t(q) \leftarrow \widetilde{\text{KL}}(p || q) + \lambda \widetilde{\text{KL}}(q_t || q)$ // Distillation loss + regularization
 where $\widetilde{\text{KL}}(a || b) := \sum_{k=1}^C w_k \text{KL}(a(X_{t+k} | x_{1:t+k-1}) || b(X_{t+k} | x_{1:t+k-1}))$
 - 13: **Update:** $q_{t+\tau} \leftarrow q_t - \eta \nabla_q L_t(q) \big|_{q=q_t}$ // One gradient step on L_t
 - 14: $t \leftarrow t + \tau$
 - 15: **end while**
 - 16: **return** $x_{1:t}$
-

5 Evaluation Methodology

In this section, we discuss the methodology used to evaluate TTS.

Benchmark: We consider eight different benchmarks: AIME 2024 (MathArena, 2024a; b), AIME 2025 (MathArena, 2025), MATH-500 (Hendrycks et al., 2021; Lightman et al., 2023) and OlympiadBench-Math (He et al., 2024) for competition mathematics; OlympiadBench-Physics (He et al., 2024) for competition physics; GPQA $\diamond$ (Rein et al., 2023) for graduate-level science application; TheoremQA for university-level theorem application and LiveCodeBench (Jain et al., 2024) for code-generation. All tasks elicit long output length ranging up to 32K tokens. We discuss each benchmark in further detail in Appendix A.

Setup: We conduct all our experiments on a *commercial* Amazon EC2 G7e node equipped with 8 $\times$ NVIDIA RTX PRO 6000 *Blackwell* GPUs. Each GPU contains 96 GB of GDDR7 (768 GB aggregate), and the GPUs are interconnected via PCIe. The host is powered by 5th-generation Intel Xeon Scalable processors with 192 vCPUs and 2TB of system memory. We implement TTS on top of the public DFlash (Chen et al., 2026)³ and EAGLE-3 (Li et al., 2025)⁴ codebase.

Models and Baselines: We use five state-of-the-art models spanning the Qwen-3 (Yang et al., 2025a), Qwen-3.5 (Qwen Team, 2026) and Llama3.1 (Grattafiori et al., 2024) families. We compare TTS against both DFlash and EAGLE-3. Our selection spans parameter sizes from 4B to 122B and spans both dense and Mixture-Of-Experts (MoE) models. For each model, we use the matching publicly released DFlash and EAGLE-3 checkpoints and apply TTS on top at inference time. We present more details including HuggingFace identifiers in Appendix B.

Metrics: We evaluate TTS on mean acceptance length and *throughput*. Acceptance length measures how well the speculator matches the target distribution and a higher value directly translates into fewer invocations of the target model. It is *hardware-independent*, decoupling speculator quality from the underlying software stack. Throughput, in contrast depends on the inference-stack and is sensitive to system-level optimizations like fused kernels, quantization etc. We do not report accuracy metrics as they *remain unchanged* since TTS only adapts the draft model and leaves the target untouched. Hence, the generated outputs remain consistent with the target model (Leviathan et al., 2023).

Our comprehensive selection of benchmarks, models, and comparison against state-of-the-art speculators enables a rigorous evaluation of TTS across diverse real-world tasks and model sizes.

6 Experimental Results

6.1 TTS Is Generalizable Across Speculators, Models and Tasks

Table 1 shows that TTS consistently outperform vanilla DFlash across all benchmarks and models and improves acceptance lengths by up to 72% and on average 41%.

³<https://github.com/z-lab/dflash>

⁴<https://github.com/SafeAILab/EAGLE>

Table 1: Acceptance length of TTS and DFlash across models and tasks. $\Delta(\%)$ denotes the relative improvement of TTS over DFlash. TTS consistently achieves higher acceptance length.

Dataset	Qwen/Qwen3-4B			Qwen/Qwen3-8B			Qwen/Qwen3.5-122B		
	DFlash	TTS(<i>Ours</i>)	$\Delta(\%)$	DFlash	TTS(<i>Ours</i>)	$\Delta(\%)$	DFlash	TTS(<i>Ours</i>)	$\Delta(\%)$
AIME 2024	3.3	4.6	38.0	3.3	4.6	38.5	2.9	4.8	62.2
AIME 2025	3.2	4.7	47.0	3.1	4.2	33.1	2.9	4.9	71.8
GPQA $\diamond$	3.6	5.2	47.2	3.2	4.7	47.3	2.6	3.5	33.9
LiveCodeBench	3.0	4.7	55.2	2.9	4.5	55.2	2.4	4.0	63.5
MATH-500	3.7	4.3	13.8	3.8	4.3	13.3	3.4	4.5	32.2
OlyBench-Math	3.0	4.4	48.9	2.7	4.1	50.3	3.4	4.7	40.2
OlyBench-Phy	3.1	4.5	48.1	2.8	4.3	53.1	3.0	3.9	28.4
TheoremQA	3.6	4.4	23.4	3.5	4.3	22.8	3.3	4.2	25.1

Table 2 shows that TTS consistently outperform vanilla EAGLE-3 across all benchmarks and models and improves acceptance lengths by up to 67% and on average 34%. Both these results confirm that TTS outperforms state-of-the-art speculators and is generalizable across tasks and models.

Table 2: Acceptance length of EAGLE-3 (EGL-3) and TTS across models and tasks. $\Delta(\%)$ denotes the relative improvement of TTS over EGL-3. TTS consistently achieves higher acceptance lengths.

Dataset	Llama3.1-8B			Qwen/Qwen3-8B			Qwen/Qwen3-32B		
	EGL-3	TTS(<i>Ours</i>)	$\Delta(\%)$	EGL-3	TTS(<i>Ours</i>)	$\Delta(\%)$	EGL-3	TTS(<i>Ours</i>)	$\Delta(\%)$
AIME 2024	1.2	2.0	64.7	1.6	1.9	18.7	1.4	1.9	26.3
AIME 2025	1.2	1.9	63.7	1.6	1.9	20.4	1.5	1.9	25.5
GPQA $\diamond$	1.2	2.0	60.4	1.5	1.9	24.5	1.4	1.8	21.5
LiveCodeBench	1.4	2.1	47.0	1.7	1.9	12.7	1.5	1.8	22.1
MATH-500	1.2	2.0	61.8	1.6	1.9	18.8	1.5	1.8	21.5
OlyBench-Math	1.3	2.1	66.8	1.6	1.9	18.5	1.5	1.9	24.5
OlyBench-Phy	1.2	1.9	65.4	1.6	1.9	17.2	1.5	1.8	21.6
TheoremQA	1.2	1.9	56.9	1.6	1.9	16.8	1.5	1.8	21.9

6.2 TTS Compensates For Limited Speculator Training Context

TTS offers the highest mean improvement (of 61%) when the baseline speculator is trained with short-context sequences. For example, the EAGLE-3 Llama3.1-8B drafter was trained with a maximum positional encoding of $2K$ tokens (Li et al., 2025) and a RoPE base of $10K$, both of which are orders of magnitude below the corresponding Llama3.1-8B target model that has a maximum positional encoding of $128K$ tokens and a RoPE base of 5×10^5 . However, as most real-world tasks generate outputs with lengths well beyond EAGLE-3’s training context of $2K$ tokens, it forces the speculator to extrapolate far outside its training distribution and causes the acceptance length to collapse drastically (Tan et al., 2025; Yang et al., 2025b). TTS adapts the EAGLE-3 checkpoint on-the-fly using the target distribution, increasing mean acceptance lengths to 1.96 (a 61% improvement). The

uplift is comparatively smaller on speculators where training context and RoPE base already match their target. For example, the EAGLE-3 checkpoints for Qwen3 models are trained with the same context window (40K tokens) and RoPE base (1M) as their Qwen3 target. Thus, TTS mitigates degradation of acceptance length even for speculators which are only trained on short-context sequences without any offline retraining.

6.3 Improvement Scales With Generation Length

TTS accumulates training signals across speculation rounds. Consequently, sequences with longer outputs provide more opportunity to refine the draft model and improve its accuracy further as generation lengths increase. Figure 5 shows that the acceptance length with TTS increases sharply with output length. On AIME 2024, it only improves by 15% for the first 0–10K tokens, but the gap widens to 183% for the tokens in the 20–30K range in TTS. Similarly, on LiveCodeBench, the acceptance length only improves by 17% for the first 10K tokens but goes up to 245% for the tokens in the 20–30K range. With the increasing dominance of tasks requiring LLMs to produce long output responses, TTS provide a critical advantage in those regimes.

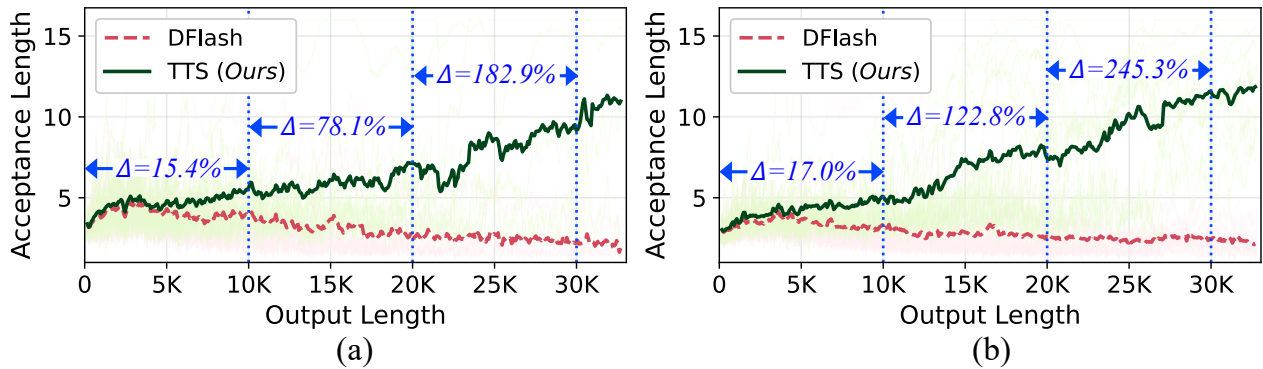


Figure 5: Acceptance Length of TTS versus DFlash for (a) AIME 2024 and (b) LiveCodeBench on Qwen3-8B. The improvement (%) increases sharply with output length as TTS refines the drafter.

6.4 Throughput Improvements With TTS

By default, TTS performs a gradient update to the speculator after each generate-verify round. While this improves acceptance length, it introduces the overhead of performing a backward pass and an optimizer step on the speculator. Thus, there exists a trade-off between acceptance length and overall throughput. We navigate this trade-off through scheduling and system-level optimizations. *First*, instead of performing the gradient update in every round, we run it every $\mathcal{S}$ (update stride) rounds. Each step *only* uses the latest round’s training signal, without any accumulation across skipped rounds. *Second*, to ensure this sporadic gradient update does not fall on the critical path, we offload the update to a dedicated CUDA stream that runs in parallel with the next $\mathcal{S}-1$ generate-verify rounds. A synchronization barrier is inserted at the end of these $\mathcal{S}-1$ rounds to ensure the speculator update is complete before it generates the next canvas of draft tokens. Together, these optimizations improve the applicability of TTS in real-world deployment settings. More details in Appendix C.

Table 3 shows that although $\mathcal{S}=1$ (lowest possible stride) achieves the highest acceptance length since the speculator is updated after each round, $\mathcal{S}=5$ achieves the highest mean throughput (up to $1.71\times$ over DFlash) as it operates at the sweet-spot in the acceptance length-throughput trade-off.

Table 3: Acceptance length and throughput of TTS relative to DFlash on Qwen3.5-122B with update stride ($\mathcal{S}$). While $\mathcal{S}=1$ has the highest acceptance length, $\mathcal{S}=5$ achieves the best throughput.

Benchmark	Acceptance Length / Throughput (Tokens/Sec)					
	DFlash	$\mathcal{S}=20$	$\mathcal{S}=10$	$\mathcal{S}=5$	$\mathcal{S}=2$	$\mathcal{S}=1$
AIME 2024	2.9 / 28.2	3.3 / 42.6	3.5 / 44.8	3.8 / 46.8	4.3 / 46.7	4.8 / 40.5
AIME 2025	2.9 / 27.6	3.7 / 43.2	3.8 / 44.6	4.3 / 45.7	4.7 / 45.4	4.9 / 37.5
GPQA $\diamond$	2.6 / 24.1	3.0 / 30.3	3.1 / 32.5	3.3 / 32.3	3.5 / 30.3	3.5 / 24.4
LiveCodeBench	2.4 / 24.9	3.1 / 31.3	3.2 / 31.5	3.4 / 31.3	3.8 / 30.4	4.0 / 25.7
MATH-500	3.4 / 29.7	3.8 / 43.7	4.0 / 46.5	4.2 / 49.7	4.3 / 43.5	4.5 / 35.9
OlyBench-Math	3.4 / 27.7	3.9 / 39.4	4.0 / 42.0	4.3 / 44.4	4.6 / 41.4	4.7 / 33.2
OlyBench-Phys	3.0 / 27.9	3.4 / 34.4	3.6 / 36.5	3.7 / 36.4	4.2 / 35.7	3.9 / 27.8
TheoremQA	3.3 / 30.0	3.7 / 41.9	3.7 / 42.5	4.1 / 51.3	4.1 / 44.5	4.2 / 30.4
Mean Speedup ($\times$)	1.0 / 1.0	1.16 / 1.39	1.21 / 1.46	1.30 / 1.54	1.41 / 1.45	1.43 / 1.15

6.5 Acceptance Length Drops With More Optimization Steps Per Round

By default, TTS performs one optimization step per round. A natural alternative is to perform multiple optimization steps on the same round’s training signal. Figure 6(a) shows the acceptance length for Qwen3-8B as a function of optimization steps. We observe that the default configuration with $\mathcal{K}=1$ performs the best across benchmarks and *additional optimization steps degrade acceptance length*. This trend is sharpest on AIME 2024 where acceptance length monotonically decreases from 4.6 to 4.1. This observation is consistent with a standard principle in LLM pre-training: each training example should contribute a single gradient update. Once the draft is adjusted to the training sample from a given round, additional steps over-fit to that sample and hurt generalization to next rounds.

6.6 Why TTS Works: A Distribution-Mismatch Perspective

The drafter $q(\cdot)$ is trained to approximate the target $p(\cdot)$, such that $q(\cdot | x) \approx p(\cdot | x)$ for prefixes x drawn from a fixed training distribution. At inference time, however, the prefix $x_{1:t}$ grows well beyond the training distribution for real-world long-response tasks. Consequently, the approximation $q(\cdot | x_{1:t}) \approx p(\cdot | x_{1:t})$ degrades, causing a divergence between the draft and the target as shown in Figure 6(b). Each update in TTS distills the current $p(\cdot | x_{1:t})$ back into the drafter, restoring $q_t(\cdot | x_{1:t}) \approx p(\cdot | x_{1:t})$ at the current prefix. This progressive restoration explains the compounding improvements with TTS at longer generation lengths.

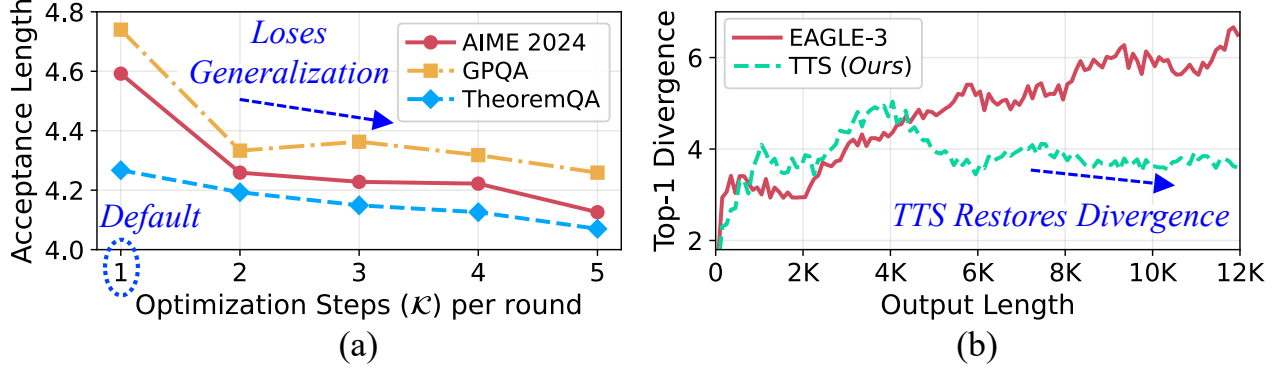


Figure 6: (a) Acceptance Length (AL) of TTS on Qwen3-8B with optimization steps per round ($\mathcal{K}$). Higher values of $\mathcal{K}$ degrade AL as the draft over-fits to the same training samples. (b) Cross-entropy of the EAGLE-3 draft on the Llama3.1-8B target’s *Top-1* token. At higher lengths, EAGLE-3 diverges from the target distribution; TTS restores this divergence by adapting the draft in real-time.

7 Related Works

Prior works OSD (Liu et al., 2023) and ATLAS (ang et al., 2025) explore the online adaptation of the speculator. Both fine-tune the draft against a buffer of accumulated sequences across users, relying on the assumption that the request stream decomposes into clear separable domains. In practice, however, the request stream rarely respects these boundaries (Zheng et al., 2023), causing the draft to misalign and acceptance length to drop sharply until the draft is re-tuned. Fundamentally, neither method immediately addresses the degradation of acceptance length in long generations, typical of production workloads. In contrast, TTS directly targets this degradation by adapting the draft within a single generation and makes no assumption about the request stream. More details in Appendix D.

8 Conclusion

State-of-the-art speculators suffer from acceptance length degradation on real-world long-response tasks, with acceptance lengths falling too close to one within a few thousand tokens and yielding negligible speedup. This arises because of a gap between the speculator’s training and inference distributions. We propose *Test-Time Speculation (TTS)*, an online-distillation approach that closes this gap by leveraging the verification step itself as the supervision signal needed to adapt the draft at inference time, with the target model acting as the teacher, the draft as the student, and each verification round as a distillation sample. Our evaluations across models shows that TTS improves acceptance length by up to 72% and 41% on average, with benefits scaling with generation length.

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A Benchmarks Used For Evaluation

All benchmarks used to evaluate TTS elicit long output length, often generating tens of thousands of tokens before reaching the final answer. These benchmarks collectively represent long-generation tasks that dominate real-world workloads. For each benchmark, we randomly select 32 sequences (except on AIME, which only comprises 30 sequences) using a fixed seed for deterministic comparison. We consolidate the identifiers for each benchmark in Table 4 and describe them in detail below:

AIME: The AIME dataset collects the American Invitational Mathematics Examination problems from each year. Both the AIME 2024 (MathArena, 2024a; b) and the AIME 2025 (MathArena, 2025) comprises 30 sequences with a final integer answer ranging from $[0, 999]$. The AIME dataset is a strong test for olympiad-style reasoning as it elicits long-output lengths, as high as $32K$ tokens.

MATH-500: The MATH-500 (Lightman et al., 2023) dataset is a curated 500-problem subset of the MATH benchmark (Hendrycks et al., 2021), introduced in OpenAI’s PRM800K (Lightman et al., 2023) for evaluating mathematical-reasoning models. Problems are drawn from several competitions such as AMC, and span seven subject areas with difficulty levels 1 through 5.

OlympiadBench-Math: OlympiadBench (He et al., 2024) is a bilingual olympiad-style benchmark drawn from international and chinese olympiad competitions. We use english-language problems from this dataset in our evaluations. Furthermore, we restrict evaluation to text-only sequences as not all evaluation models are multi-modal. Each sequence is accompanied by a symbolic or numeric final answer. Similar to AIME and MATH-500, OlympiadBench-Math elicits large generation lengths.

OlympiadBench-Physics: OlympiadBench-Physics (He et al., 2024) is the physics counterpart of OlympiadBench-Math, drawn from the same olympiad-competition pipeline and similarly restricted to its english-language subset. Each problem requires deriving a closed-form or numeric answer from first principles, often achieved via multi-step modeling and symbolic manipulation.

GPQA $\diamond$: GPQA $\diamond$ (Rein et al., 2023) is the hardest 198-question subset of the GPQA benchmark. It comprises graduate-level multiple-choice questions in biology, chemistry, and physics. PhD-level domain experts answer GPQA $\diamond$ correctly only $\sim 65\%$ of the time, while non-experts achieve $\leq 35\%$ accuracy even with unrestricted web access, making it a strong test of expert-level scientific reasoning.

TheoremQA: TheoremQA (Chen et al., 2023b) is a STEM benchmark consisting of sequences which require identifying and applying a specific named theorem from mathematics, physics, engineering to produce a numeric or symbolic final answer. TheoremQA is a strong test of theorem application, and elicits long reasoning traces as the model recalls, applies, and verifies the relevant result.

LiveCodeBench: LiveCodeBench (Jain et al., 2024) is a competitive-programming benchmark drawn from LeetCode, AtCoder, and CodeForces. Each sequence includes the problem statement, the starter code, and an explicit instruction to reason step by step before emitting a solution.

Table 4: HuggingFace identifiers for benchmarks used in our evaluations, grouped by domain.

Benchmark	HuggingFace Dataset Identifier
<i>Competition mathematics</i>	
AIME 2024	MathArena/aime_2024_I, MathArena/aime_2024_II
AIME 2025	MathArena/aime_2025
MATH-500	HuggingFaceH4/MATH-500 (Level 5)
OlympiadBench-Math	Hothan/OlympiadBench (OE_T0_maths_en_COMP)
<i>Physics</i>	
OlympiadBench-Phys	Hothan/OlympiadBench (OE_T0_physics_en_COMP)
<i>Graduate-level scientific reasoning</i>	
GPQA Diamond	Idavidrein/gpqa (gpqa_diamond)
<i>University-level theorem application</i>	
TheoremQA	TIGER-Lab/TheoremQA
<i>Code generation</i>	
LiveCodeBench v6	livecodebench/code_generation_lite (Hard)

B Evaluated Models And Speculators

We use five state-of-the-art models across the Qwen-3 (Yang et al., 2025a), Qwen-3.5 (Qwen Team, 2026), and Llama3.1 (Grattafiori et al., 2024) families. Our selection of models encompasses parameter sizes from 4 Billion to 122 Billion. The Qwen3 models (4B, 8B, 32B) and Llama3.1-8B are dense transformer models with grouped-query attention (Ainslie et al., 2023), while the Qwen-3.5-122B-A10B is a multi-modal mixture-of-experts (Fedus et al., 2022; Shazeer et al., 2017) architecture that interleaves three linear-attention layers (Gu and Dao, 2023) for every full-attention layer. It routes each token among 256 experts (*top*–8 routing, ~ 10 B active parameters per token) and supports a context length of 256K tokens. Table 5 summarizes the specification of all models.

Table 5: Our selection of models spans parameter sizes from 4B to 122B and encompasses both dense and hybrid MoE architectures across the Qwen-3, Qwen-3.5, and Llama-3.1 model families.

HuggingFace Identifier	Architecture	Active / Total	Layers	Context Length
Qwen/Qwen3-4B	Dense	4B / 4B	36	40K
Qwen/Qwen3-8B	Dense	8B / 8B	36	40K
Qwen/Qwen3-32B	Dense	32B / 32B	64	40K
meta-llama/Llama-3.1-8B-Instruct	Dense	8B / 8B	32	128K
Qwen/Qwen3.5-122B-A10B	Hybrid + MoE	10B / 122B	48	256K

For each model in Table 5, we evaluate TTS on top of the matching publicly released DFlash (Chen et al., 2026) and EAGLE-3 (Li et al., 2025) checkpoints. We describe each speculator below in detail and summarize their HuggingFace identifiers in Table 6.

1. **DFlash:** DFlash is a *block-diffusion* speculator that generates a block of B tokens in a single forward pass. It first extracts the intermediate hidden states of a selected subset of target model layers and then passes them through the speculator’s W_k and W_v projection matrices to produce the context Key-Value (KV) cache. Next, this context KV cache is concatenated with the speculator’s own KV vectors for the block of tokens being generated. Therefore, the query vectors attend to the target context and the block context in a single forward pass.
2. **EAGLE-3:** EAGLE-3 is an *auto-regressive* speculator that generates one token at a time. It first extracts the hidden states from three layers (typically, an early, a middle and a later layer) of the target model. These hidden states are then concatenated and down-projected through a fully connected layer to produce a k -dimensional context feature, where k represents the hidden state dimension of the target model. This context feature is then concatenated with the embedding vector of the previously generated output token, reduced through a second fully-connected layer and fed into the EAGLE-3 draft, a single transformer layer. Its output is then passed to the LM head of the target model to produce the next-token distribution.

We use a block size of 16 for DFlash and use a generation depth of 8 for EAGLE-3 across all target models consistent with the original papers (Chen et al., 2026; Li et al., 2025). We use the publicly-released speculator checkpoints from the original authors, except for EAGLE-3 on the Qwen3 target models, where we use the AngelSlim releases as the authors have not published these on HuggingFace. Table 6 summarizes the speculator checkpoints used in our evaluations.

Table 6: HuggingFace identifiers for DFlash and EAGLE-3 paired with each target model.

Target Model	Speculator	HuggingFace Identifier
Qwen/Qwen3-4B	DFlash	z-lab/Qwen3-4B-DFlash-b16
Qwen/Qwen3-8B	DFlash	z-lab/Qwen3-8B-DFlash-b16
Qwen/Qwen3.5-122B-A10B	DFlash	z-lab/Qwen3.5-122B-A10B-DFlash
meta-llama/Llama-3.1-8B-Instruct	EAGLE-3	yuhuili/EAGLE3-LLaMA3.1-Instruct-8B
Qwen/Qwen3-8B	EAGLE-3	AngelSlim/Qwen3-8B_eagle3
Qwen/Qwen3-32B	EAGLE-3	AngelSlim/Qwen3-32B_eagle3

C Implementation Details Of TTS

In this section, we provide the implementation details of TTS including scheduling and system-level optimizations introduced in Section 6.4. We then describe the system-level challenges we encountered in integrating TTS in the SGLang inference framework.

C.1 Navigating The Acceptance Length-Throughput Trade-Off

Every gradient update in TTS invokes a backward pass and an optimizer (Adam) step on the speculator. While this improves acceptance length by continuously adapting the speculator to match

the target distribution, it introduces additional overhead on the critical path every generate-verify round. The latency overhead of a single backward pass and optimizer step is comparable to a few speculation rounds. Thus, applying TTS naively can negate the throughput improvements with higher acceptance length. We navigate this trade-off via scheduling and system-level optimizations as described below:

Strided Updates: By default, TTS performs a gradient update after every generate-verify round. A natural alternative is to perform the gradient update only once every $\mathcal{S}$ rounds, where $\mathcal{S}$ is the *update stride*. Each update consumes the supervision signal only from the most-recent round, without any accumulation across the $\mathcal{S}-1$ skipped rounds. However, fewer updates imply weaker adaptation to the ongoing generation and therefore lower the improvements in acceptance length. For example, Table 7 shows that the improvements in acceptance length are the highest for $\mathcal{S}=1$ and monotonically decrease as the update stride is increased.

Table 7: Acceptance length of TTS relative to DFlash on Qwen3-8B with the update stride $\mathcal{S}$. The default $\mathcal{S}=1$ achieves the largest improvement across benchmarks. Higher values of $\mathcal{S}$ reduce the improvement in acceptance length as the speculator is adapted less frequently.

Benchmark	DFlash (<i>Baseline</i>)	TTS (<i>Ours</i>) / $\Delta(\%)$				
		$\mathcal{S}=1(\text{default})$	$\mathcal{S}=5$	$\mathcal{S}=15$	$\mathcal{S}=30$	$\mathcal{S}=50$
AIME 2024	3.3	4.6 / 38.5	4.3 / 30.7	3.9 / 19.0	3.7 / 12.6	3.6 / 10.2
AIME 2025	3.1	4.1 / 33.1	3.9 / 27.0	3.7 / 18.1	3.5 / 12.1	3.3 / 8.0
GPQA $\diamond$	3.2	4.7 / 47.3	4.3 / 34.3	4.0 / 24.1	3.8 / 17.8	3.7 / 14.7
LiveCodeBench	2.9	4.5 / 55.2	4.2 / 44.9	3.9 / 32.9	3.6 / 24.4	3.5 / 19.8
MATH-500	3.8	4.3 / 13.3	4.1 / 8.3	4.0 / 5.4	3.9 / 3.7	3.9 / 2.3
OlyBench-Math	2.7	4.1 / 50.3	3.8 / 42.1	3.5 / 28.9	3.2 / 20.0	3.1 / 14.2
OlyBench-Phy	2.8	4.3 / 53.1	3.9 / 39.2	3.5 / 26.2	3.3 / 18.2	3.2 / 13.3
TheoremQA	3.5	4.3 / 22.8	4.0 / 15.2	3.8 / 9.0	3.7 / 6.3	3.7 / 4.8

However, increasing the stride $\mathcal{S}$ amortizes the update overhead, since the gradient step is now performed every $\mathcal{S}$ rounds rather than at every round. For example, Table 8 shows that the best wall-clock speedup (**1.83 $\times$**) is achieved at $\mathcal{S}=10$. Beyond $\mathcal{S}=10$, speedup decreases because the degradation of acceptance length outpaces the savings from amortizing the gradient update.

Table 8: Relative acceptance length (AL) and wall-clock speedup of TTS on LiveCodeBench with Qwen3-8B. Both metrics are reported relative to $\mathcal{S}=1$. The sweet-spot is at $\mathcal{S}=10$ (**1.83 $\times$** speedup) where the update overhead is amortized while acceptance length is preserved within $0.88\times$ of $\mathcal{S}=1$.

Metric	Update Stride ($\mathcal{S}$)							
	1(<i>default</i>)	5	10	15	20	30	40	50
Relative AL	1.00 $\times$	0.93 $\times$	0.88 $\times$	0.85 $\times$	0.84 $\times$	0.80 $\times$	0.79 $\times$	0.77 $\times$
Relative Speedup	1.00 $\times$	1.77 $\times$	1.83$\times$	1.79 $\times$	1.80 $\times$	1.65 $\times$	1.64 $\times$	1.56 $\times$

Although strided updates reduce the frequency of the gradient steps, each update still lies on the

critical path of the round where it is performed. For small target models, the cost of one gradient update to the speculator is comparable to a few speculation rounds and thus can degrade wall-clock speedup. We further hide this latency through *asynchronous pipelining*, described next.

Asynchronous Pipelining: If the gradient update could be performed in parallel with the subsequent speculation rounds, we could hide its latency (largely) from the critical path. Building on this insight, we build mechanisms in TTS to offload the gradient update to a dedicated CUDA stream (the *side stream*) that executes concurrently with the next $\mathcal{S}-1$ speculation rounds on the main stream. However, asynchronous pipelining does not fully eliminate the latency overhead of the gradient update. This is because the side stream and the main stream contend for the same GPU resources, slightly slowing the speculation rounds that run concurrently with a gradient update. Nonetheless, the additional overhead is much smaller than executing the gradient update on the critical path. A synchronization barrier is inserted after $\mathcal{S}-1$ rounds to ensure that the speculator is adjusted with the prior update before the next canvas of draft tokens are generated.

Figure 7 illustrates the resulting execution timeline of TTS with both these optimizations applied.

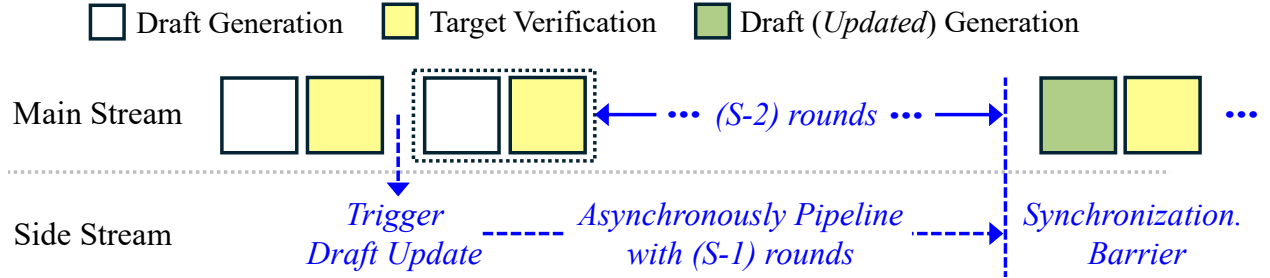


Figure 7: Execution timeline of TTS with strided updates and asynchronous pipelining. Every $\mathcal{S}$ speculation rounds, a gradient update is dispatched to a side CUDA stream and overlaps with the next $\mathcal{S}-1$ rounds on the main stream, keeping the update off the critical path.

C.2 Limitations And Future Work

While TTS delivers substantial speedup, the achievable throughput remains bounded by two system-level optimizations. *First*, the gradient update to adapt the speculator is currently implemented as a sequence of standard pytorch kernels. Fusing these into a custom kernel would reduce the latency of each update, and improve throughput across all strides. *Second*, the update stride is currently fixed and applied statically across all speculation rounds. We could, however, adapt the stride online based on the observed acceptance length, automatically choosing a lower stride when the acceptance length degrades and a higher stride when it remains stable. Both these optimizations are orthogonal to the main contributions of this paper, and therefore we defer them to future work.

C.3 System-Level Challenges In SGLang Integration

SGLang is a framework designed for fast inference rather than online adaptation. We describe below the two primary challenges of integrating TTS into SGLang, along with their resolutions:

1. **Inference Kernels Do Not Support Gradient Computation:** To maximize throughput, SGLang uses fused CUDA/Triton kernels for attention, normalization, activation etc. These kernels are not designed for gradient computation. During the backward pass, `autograd` breaks silently. As a result, the gradient update has no effect on the speculator weights. We resolve this by switching to the differentiable pytorch implementation for the speculator in the update round, ensuring that the gradients flow correctly through the backward pass. On non-update rounds, we retain the fused kernels to preserve throughput.
2. **CUDA-Graph Replay Does Not Honor Cross-Stream Synchronization:** To improve performance, each draft generation round in SGLang runs inside a captured CUDA graph, a pre-recorded sequence of GPU operations replayed for efficiency. Graph replay runs on its own internal stream and does not honor GPU synchronization barriers. Thus, the update made by TTS can be silently skipped before the next round begins. We resolve this by introducing a CPU-side synchronization barrier that blocks the GPU until the side-stream completes the update before the next graph is replayed. This barrier is inserted only at update boundaries, leaving the CUDA graph performance unaffected on non-update rounds.

These optimizations and resolutions enable TTS to run end-to-end on SGLang.

D Related Work

In this section, we compare and contrast TTS with prior online methods that adapt the speculator after deployment. Prior works focus on cross-request and cross-user adaptation. However, they fail to address the degradation of acceptance length in long generations, typical of production workloads.

Online speculative decoding or OSD [Liu et al., 2023](#) periodically fine-tunes the draft model to match the target distribution on a buffer of accumulated sequences *across users and requests*. The draft is updated when the buffer exceeds a certain size. OSD additionally orchestrates multiple speculators, each specialized to a particular domain and uses a router to direct each incoming request to the best-matching speculator. Each draft is only fine-tuned on the queries it receives. However, this multi-draft *setup diverges* from how state-of-the-art speculators are typically deployed in practice ([Tang et al., 2025](#)), where a single speculator (such as EAGLE-3 or DFlash) is paired with the target model and serves all incoming queries.

ATLAS ([ang et al., 2025](#)) extends this paradigm to a production serving system. Rather than routing between domain-specialized speculators, ATLAS pairs a heavyweight static speculator (Together-AI’s proprietary Turbo Speculator) with a lightweight adaptive speculator that is updated on production traffic. A confidence-aware controller chooses which to trust at each step. However, the light-weight speculator is still adapted across requests over accumulated sequences. For real-world long generation workloads where acceptance length degrades within a single-generation, this cross-request adaptation arrives too late for the current request being served. Therefore, both these methods are positioned for cross-request, cross-user adaptation, accumulating learning over long periods.

This cross-request adaptation, however, relies on the *assumption that production traffic cleanly decomposes into separable domains*. The evaluation of OSD structures the request stream as a

concatenation of single-domain benchmarks. Specifically, OSD evaluates on streams of $2K$ sequences each from Spider (SQL) (Yu et al., 2018), GSM8K (math) (Cobbe et al., 2021), Code-search-Python (code) (Husain et al., 2019), and Alpaca-finance (finance) (Bharti, 2023), concatenated sequentially before the stream switches to the next benchmark. On the other hand, ATLAS evaluates within session-bounded contexts such as code-editing sessions, rather than interleaved heterogeneous production traffic. In practice, request streams cross domain boundaries very frequently (OpenAI, 2023; Zheng et al., 2023). This causes the periodically adapted speculator to fall out of alignment at every crossing, causing the acceptance length to collapse. Furthermore, *neither method demonstrate compatibility* with public state-of-the-art speculators such as EAGLE-3 or DFlash; OSD relies on an auxiliary draft model, while ATLAS relies on Together-AI’s proprietary Turbo speculator.

Fundamentally, the granularity at which prior works update the speculator is mismatched for sequences where the degradation happens within the generation at longer output positions. By the time the buffer accumulates sequences to retune the speculator, the affected request already terminates. In contrast, TTS adapts the speculator at the granularity of each speculation round (or every S rounds with strided updates) within an ongoing generation. It distills the target’s per-prefix conditional $p(\cdot \mid x_{1:t})$ back into the speculator at every update and resets the speculator between requests so per-request adaptation is bounded, and operates directly on top of public state-of-the-art DFlash and EAGLE-3 speculators. Moreover, TTS makes no assumption about the structure of the request stream and consistently improves acceptance length on long-output real-world workloads. Furthermore, to improve applicability, we implement TTS in the production-grade SGLang inference serving framework (Zheng et al., 2024). Table 9 summarizes the key differences with prior work.

Table 9: Comparison of online speculator adaptation methods.

Comparison Property	OSD	ATLAS	TTS
Adapts within a single generation	✗	✗	✓
No assumption on the request stream structure	✗	✗	✓
Immediately addresses acceptance-length degradation	✗	✗	✓
Compatible with state-of-the-art speculators (DFlash, EAGLE-3)	✗	✗	✓
Single-speculator deployment (no specialized routing)	✗	✓	✓
No proprietary dependencies	✓	✗	✓
Production-grade serving integration	✗	✓	✓