

# Polybasic Speculative Decoding Through a Theoretical Perspective

Ruilin Wang<sup>1</sup>, Huixia Li<sup>2</sup>, Yuexiao Ma<sup>12</sup>, Xiawu Zheng<sup>134</sup>, Fei Chao<sup>1</sup>, Xuefeng Xiao<sup>2</sup>, Rongrong Ji<sup>13</sup>



## **Abstract**

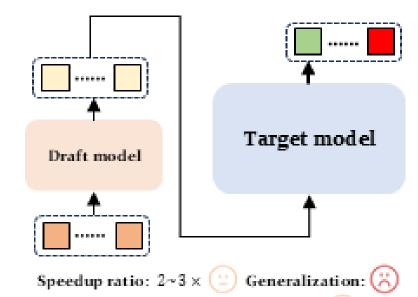
Inference latency stands as a critical bottleneck in the large-scale deployment of Large Language Models (LLMs). Speculative decoding methods have recently shown promise in accelerating inference without compromising the output distribution. However, existing work typically relies on a dualistic draft-verify framework and lacks rigorous theoretical grounding. In this paper, we introduce a novel polybasic speculative decoding framework, underpinned by a comprehensive theoretical analysis. Specifically, we prove a fundamental theorem that characterizes the optimal inference time for multi-model speculative decoding systems, shedding light on how to extend beyond the dualistic approach to a more general polybasic paradigm. Through our theoretical investigation of multi-model token generation, we expose and optimize the interplay between model capabilities, acceptance lengths, and overall computational cost. Our framework supports both standalone implementation and integration with existing speculative techniques, leading to accelerated performance in practice. Experimental results across multiple model families demonstrate that our approach yields speedup ratios ranging from 3.31× to 4.01× for LLaMA2-Chat 7B, up to 3.87× for LLaMA3-8B, up to 4.43× for Vicuna7B and up to 3.85× for Qwen2-7B—all while preserving the original output distribution. We release our theoretical proofs and implementation code to facilitate further investigation into polybasic speculative decoding.

<sup>1</sup>Key Laboratory of Multimedia Trusted Perception and **Efficient Computing, Ministry of Education of China, Xiamen University** 

<sup>2</sup>ByteDance Inc, <sup>3</sup>Institute of Artificial Intelligence, Xiamen University, <sup>4</sup>Peng Cheng Laboratory, Shenzhen, China

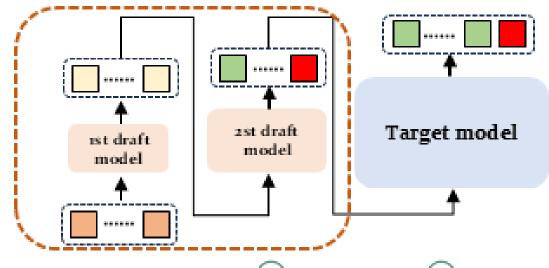
#### Framework

#### (a) Dualistic speculative decoding



Average acceptance length: 3~4

# (b) Polybasic speculative decoding



Speedup ratio: 4 × (\*\*) Generalization : (\*\*) Average acceptance length: 8~10 (;)

#### **Theoretical Foundations**

We establish fundamental properties of polybasic speculative decoding that govern how additional models impact computational cost and acceptance lengths. Our analysis focuses on two main aspects: (i) optimal inference time and (ii) stability of acceptance lengths.

#### **Theorem 3.1 (Optimal Inference Time)**

For an n-model polybasic system generating N tokens, the total inference time T is expressed as

$$T = \sum_{i=1}^{n-1} \frac{N}{L_i} \cdot T_i + \beta \cdot \frac{N}{L_{n-1}} T_n$$

#### **Theorem 3.2 (Model Insertion Efficiency)**

Adding  $M_{new}$  between  $M_i$  and  $M_{i+1}$  decreases total inference time if and only if it achieves a sufficiently large increase in acceptance lengths, balanced against its forward-pass cost  $T_{new}$  Concretely, if  $L_{new}$  is the acceptance length when verifying tokens from  $M_{new}$  against  $M_i$ , and  $L'_{I+1}$  is the acceptance length from  $M'_{I+1}$  's perspective, then improvement occurs if:

$$\frac{T_{new}}{T_i} < L_{new} \left(\frac{1}{L_i} - \frac{1}{L_{i-new}}\right) or \frac{T_{new}}{T_{i+1}} < \beta \left(\frac{L_{new-(i+1)}}{L_i} - 1\right)$$

#### Theorem 3.3 (Sampling Stability)

In the model chain using speculative sampling can ensure stable acceptance lengths.

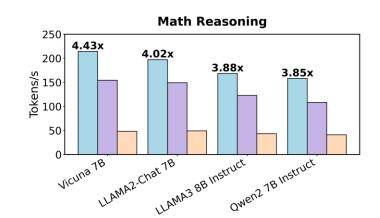
### **Experiment**

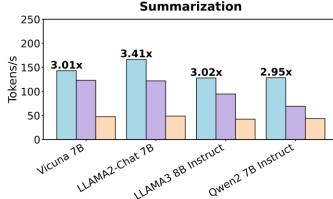
Table 1. Theoretical Validation via Model Insertion										
Case	$T_i$ (ms)	$L_{i\text{-new}}$	$T_{\mathrm{new}}$ (ms)	$L_{\rm new}$	$T_{i+1}$ (ms)	$L_i$	Speedup			
Non-compliant	22	3.83	17.61	3.77	4	4.34	$2.61 \times \rightarrow 1.08 \times$			
Compliant	22	6.26	7.00	4.67	4	4.34	$2.61 \times \rightarrow 3.48 \times$			
CS Drafting	47.52	3.50	19.16	3.02	12.42	2.28	$3.19\times\rightarrow3.88\times$			

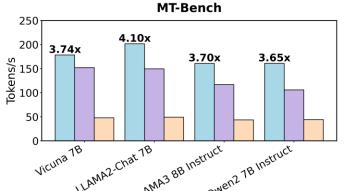
Table 2. Average acceptance length (μ) and speedup ratio (c) on different tasks. V7B: Vicuna-7B, L3-8B: LLaMA3-8B-Instruct, L2-7 LLaMA2-Chat-7B, Q2-7B: Qwen2-7B-Instruct.

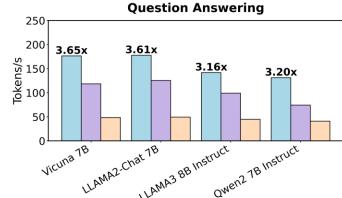
		MT		Trans.		Sum.		QA		Math		RAG		Overall	
	Model	c	$\mu$	c	$\mu$	c	$\mu$	c	$\mu$	c	$\mu$	c	$\mu$	c	$\mu$
Our	V7B	3.77x	11.22	3.07x	7.76	3.01x	10.24	3.65x	9.53	4.43x	10.28	2.98x	10.30	3.48x	9.88
	L3-8B	3.70x	9.97	3.39x	8.86	3.02x	9.38	3.16x	9.08	3.87x	10.08	2.71x	9.24	3.31x	9.44
	L2-7B	4.10x	10.47	3.46x	9.15	3.41x	9.86	3.61x	9.49	4.02x	9.99	3.31x	10.08	3.66x	9.84
	Q2-7B	3.65x	9.85	3.15x	8.65	2.95x	9.15	3.25x	8.95	3.85x	9.95	2.85x	9.35	3.28x	9.32
EAGLE2	V7B	3.19x	4.76	2.07x	3.22	2.59x	3.96	2.45x	3.71	3.19x	4.72	2.15x	3.95	2.61x	4.34
	L3-8B	2.69x	3.99	2.37x	3.53	2.23x	3.58	2.21x	3.42	2.83x	4.20	2.23x	3.95	2.44x	3.82
	L2-7B	3.04x	4.48	2.61x	3.96	2.50x	4.04	2.55x	4.05	3.04x	4.68	2.40x	4.19	2.70x	4.30
	Q2-7B	2.40x	3.74	1.45x	2.45	1.59x	3.06	1.81x	2.91	2.63x	4.26	1.72x	3.27	1.94x	3.51

EAGLE Vanilla











**Communicate us** 

Paper: https://openreview.net/forum?id=JrxJUMqqz4