SPECTRA: Faster Large Language Model Inference with Optimized Internal and External Speculation

Anonymous ACL submission

Abstract

Inference with modern Large Language Models (LLMs) is both computationally expensive and time-consuming. Speculative decoding has emerged as a promising solution, but existing approaches face key limitations: training-based methods require a draft model that is challenging to obtain and lacks generalizability, while non-training methods offer limited speedup gains. In this work, we present SPECTRA, a novel framework for accelerating LLM inference without the need for additional training. SPECTRA introduces two innovative techniques for efficiently managing internal and external knowledge, each outperforming corresponding state-of-the-art (SOTA) methods independently. When combined, these techniques achieve up to a 4.08x speedup across various benchmarks and LLM architectures, significantly surpassing existing non-training approaches. The implementation of SPECTRA is publicly available.

1 Introduction

Generating long sequences with low latency using Large Language Models (LLMs) is a critical requirement. Current LLMs rely on autoregressive decoding (Touvron et al., 2023; Bai et al., 2023; Jiang et al., 2023; OpenAI et al., 2024), which suffers from inefficiency because it generates text one token at a time. This results in generation time scaling linearly with the sequence length and underutilizes the parallel processing capabilities of modern GPUs. A widely studied approach to mitigate this issue is speculative decoding (Chen et al., 2023; Leviathan et al., 2023), which follows a *guess-and-verify* paradigm. In this approach, a smaller LLM (draft model) (Chen et al., 2023; Leviathan et al., 2023; Miao et al., 2024; Sun et al., 2023b; Zhou et al., 2024; Cai et al., 2024) or the original LLM trained in a specialized manner (self-speculative decoding) (Elhoushi et al., 2024; Liu et al., 2024a; Yang et al., 2024; Zhang et al., 2024a; Li et al., 2024b) predicts multiple tokens in advance. The original LLM then verifies these predictions in parallel, improving efficiency. However, these approaches require additional training, which demands substantial computational resources and may degrade the original model's capabilities.

Another line of research focuses on speculating subsequent tokens without requiring additional training. This approach eliminates the need for training new models or modifying the original large language model (LLM), making it practical for off-the-shelf deployment. Some methods leverage specialized mechanisms to generate speculative tokens directly from the LLM's predictions (Fu et al., 2024; Ou et al., 2024), while others rely on external information sources to derive these tokens (Yang et al., 2023; He et al., 2024; Li et al., 2024a). However, the speedup gain in these approaches remains limited due to the quality of the speculative guesses.

We introduce SPECTRA (Figure 1a), a speculative decoding method that improves generation speed without requiring any training or modifications to the original LLM. SPECTRA consists of two main components: a core module (SPECTRA-CORE, Figure 1c), which integrates seamlessly into LLMs in a plug-and-play manner, and an optional retrieval module (SPECTRA-RETRIEVAL, Figure 1e) that further enhances performance. The core module SPECTRA-CORE improves speculative decoding by leveraging the token distribution predicted by the LLM to generate high-quality guesses. Specifically, it employs two multi-level N-gram dictionaries that enable bi-directional search for dynamic-length guesses, balancing both quality and quantity. Additionally, SPECTRA optimizes a candidate pool to continuously update the N-gram dictionaries, ensuring broad token coverage. All updates to these resources, along with guess verification, are performed efficiently in a single forward pass. The retrieval module, SPECTRA-RETRIEVAL,

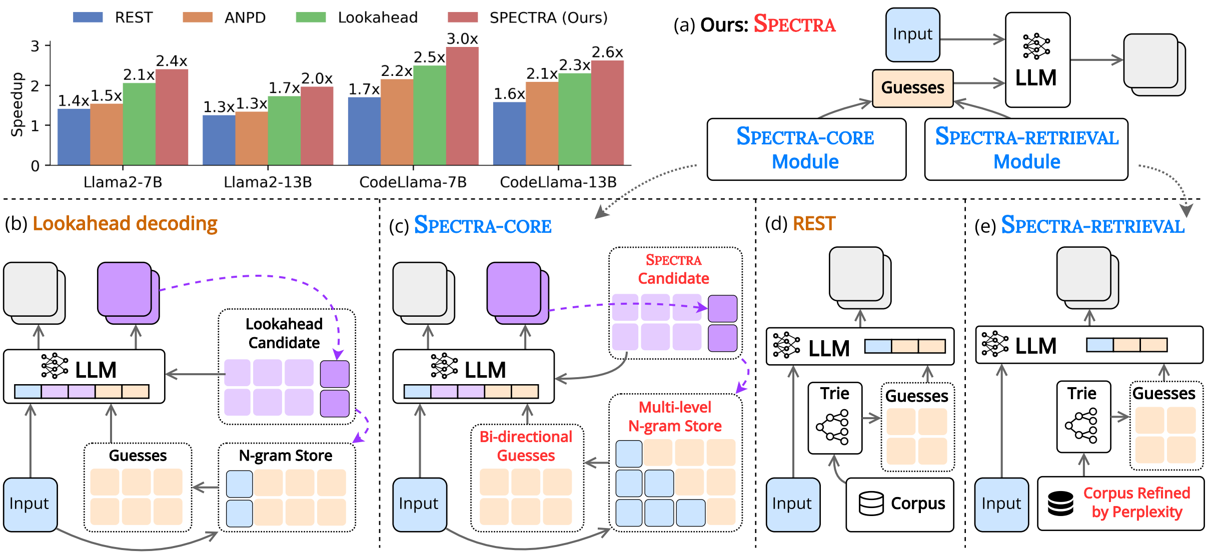

Figure 1: Overview of Spectra and comparison with other non-training SOTA approaches. (a) Overview of SPECTRA. (b) Overview of Lookahead Decoding (Fu et al., 2024). (c) Overview of the SPECTRA-CORE module, which utilizes the knowledge inside LLM for obtaining guesses. (d) Overview of REST (He et al., 2024). (e) Overview of the SPECTRA-RETRIEVAL module, which is designed to be integrated efficiently with SPECTRA-CORE to boost the speedup. The results in the bar chart are measured on HumanEval.

can be integrated to further enhance speedup. Existing approaches that rely on external sources for generating guesses (He et al., 2024) struggle to integrate with other speculative decoding methods, as the search time outweighs the speedup gains. SPECTRA-RETRIEVAL addresses this issue by reducing the search space, selecting only high-quality content from the corpus based on perplexity scores computed by the target LLM. This optimization enables seamless integration with SPECTRA-CORE, maximizing efficiency.

Empirical results on six tasks—including multi-turn conversation, code generation, and mathematical reasoning—across three LLM families (Llama 2 (Touvron et al., 2023), Llama 3 (Dubey et al., 2024), and CodeLlama (Rozière et al., 2024)) with model sizes ranging from 7B to 70B demonstrate that SPECTRA outperforms other non-training speculative decoding methods, achieving speedups of up to **4x**. We publicly release the code and data. The key contributions of this paper are as follows:

- We introduce SPECTRA, which improves speculative decoding by effectively leveraging the LLM's predicted token distribution. SPECTRA is a plug-and-play solution that requires no modifications to the LLM (Section 3.1).

- SPECTRA's retrieval module refines external corpora using perplexity scores computed by the target LLM, providing a general framework that enables speculative decoding approaches relying on external information to be seamlessly integrated with other speculative decoding techniques (Section 3.2).

- Extensive experiments across diverse tasks, LLM architectures, GPU types, and settings demonstrate the efficiency of SPECTRA, outperforming other non-training speculative decoding approaches (Section 5). SPECTRA also integrates with acceleration tools such as FlashAttention and pipeline parallelism (Section 5.2). The code and data are available.

2 Preliminaries

2.1 Autoregressive Decoding in LLMs

Given an input sequence $\mathbf{x} = (x_1, x_2, \dots, x_s)$ of length s, and a slice of length m as $\mathbf{x}_{1:m} = (x_1, x_2, \dots, x_m)$, the output of an LLM represents a probability distribution over the next token. The probability of generating the s-th token, conditioned on all preceding tokens, is given by $P_M(x_s \mid x_{1:s-1})$. The next token x_s is sampled from this distribution using methods such as greedy, top-k, or top-p sampling (see (Kool et al., 2020; Holtzman et al., 2020)). For greedy sampling, the next token is selected as $x_s = \arg\max P_M(x_s \mid x_{1:s-1})$. Consequently, the LLM generates an output sequence $(y_1, y_2, \dots, y_m)$ of length m autoregressively, where each token y_i is computed as

$$y_i = \text{argmax } P_M(y_i \mid y_{1:i-1}, \mathbf{x}).$$

2.2 Speculative Decoding

Speculative decoding follows a *guess-and-verify* approach, where multiple candidate future tokens are speculated and subsequently verified in a single decoding step. With tree attention (Miao et al., 2024), multiple drafts can be verified simultaneously. Let G denote the number of guesses, and define the set of guesses as $\tilde{Y} = \{\tilde{y}^{(0)}, \tilde{y}^{(1)}, \ldots, \tilde{y}^{(G)}\}$, where each guess sequence has length K. The j-th token of the i-th guess is denoted as $\tilde{y}_j^{(i)}$.

In the case of speculative decoding with greedy sampling, given the prompt $\mathbf{x}$, a drafting method generates the draft sequences $\tilde{Y}$. Using these drafts, the LLM computes the true tokens $(y'_1, y'_2, \ldots, y'_K)$ in parallel. These tokens are then verified, and h is defined as the highest number of correctly guessed tokens across all guesses. Consequently, $h + 1$ tokens are generated in a single forward step. Algorithm 2 outlines speculative decoding with greedy sampling, and additional details are provided in Appendix A.

3 SPECTRA DECODING

SPECTRA consists of two modules (SPECTRA-CORE and SPECTRA-RETRIEVAL) that can function independently or together. The core module (SPECTRA-CORE) improves speedup by leveraging the LLM's predicted token distribution to generate high-quality guesses and integrates into LLMs in a plug-and-play manner. The retrieval module (SPECTRA-RETRIEVAL) derives guesses from a refined external information source and is designed to integrate with SPECTRA-CORE to further enhance performance.

3.1 SPECTRA-CORE

SPECTRA-CORE maintains an N-gram storage and a candidate pool. The candidate pool $\mathcal{C}$ contains W sequences, $\{c^{(0)}, c^{(1)}, \ldots, c^{(W-1)}\}$, with each sequence consisting of N tokens. Let $c_j^{(i)}$ represent the j-th token in the i-th sequence. The N-gram storage includes two dictionaries: the forward dictionary $\mathcal{S}_{\text{fwd}}$ and the backward dictionary $\mathcal{S}_{\text{bwd}}$. At each time step, guesses $\mathcal{G}$ are obtained through a bidirectional search using $\mathcal{S}_{\text{fwd}}$ and $\mathcal{S}_{\text{bwd}}$. A single forward pass to the LLM retrieves all necessary distributions, which are used to generate new candidate tokens for $\mathcal{C}$ and verify the guesses $\mathcal{G}$.

Algorithm 1 SPECTRA Internal Knowledge

Require: Sequence $\mathbf{x} = (x_1, x_2, \ldots, x_n)$, model P_M, max N-gram size N, candidate pool size W, max guesses G, max number of new tokens m. Refine threshold τ

Initialize N-gram Forward-dictionary $\mathcal{S}_{fwd} \leftarrow \emptyset$
Initialize N-gram Backward-dictionary $\mathcal{S}_{bwd} \leftarrow \emptyset$
Random $c_j^{(i)}, \forall j \in [0, N-1], \forall i \in [0..W-1]$
$t \leftarrow n + 1$
while $t \leq m$ **do**
  {Obtain the guesses}
  $\mathcal{G} \leftarrow \mathcal{S}_{fwd}[\mathbf{x}_{t-1}]$
  $u = \emptyset$
  for $j = 0$ to $N-1$ **do**
    for $k = N-1$ to 1 **do**
      $u_j \leftarrow \mathcal{S}_{bwd}[\mathbf{x}_{t+j-k:t-1} \oplus u_{0:j-1}]$
      break if found value for u_j
    end for
  end for
  $\mathcal{G}$.append(u)
  {Foward in LLM}
  Obtain necessary distributions of P_M in parallel.
  {Verification}
  {**Greedy** verify (Alg. 3) or **Sampling** verify (Alg. 4)}
  $hits \leftarrow$ VerificationFunction($\mathbf{x}, P_M, \mathbf{g}$)
  $\mathbf{x} = \mathbf{x} \oplus hits$
  $t \leftarrow t +$ size($hits$)
  {Predict Candidates}
  for $i = 0$ to $W-1$ **do**
    $r \sim$ Uniform$[0, 1]$
    $P_c(c_{N-1}^{(i)}) \leftarrow P_M(c_{N-1}^{(i)} \mid c_{:N-2}^{(i)}, \mathbf{x})$
    if $r > \tau$ **then**
      $c_{N-1}^{(i)} \leftarrow \underset{c \notin \mathcal{S}_{fwd}}{\text{argmax}}\, P_c(c_{N-1}^{(i)})$
    else
      $c_{N-1}^{(i)} \leftarrow \text{argmax}\, P_c(c_{N-1}^{(i)})$
    end if
  end for
  {Update N-gram dictionaries}
  for $i = 0$ to $W-1$ **do**
    for $j = 0$ to $N-2$ **do**
      $\mathcal{S}_{fwd}[c_j^{(i)}]$.append($c_{j+1:}^{(i)}$)
      $\mathcal{S}_{bwd}[c_{0:j}^{(i)}] \leftarrow c_{j+1}^{(i)}$
    end for
  end for
  {Update Candidates}
  $c_j^{(i)} \leftarrow c_{j+1}^{(i)}, \forall j \in [0, N-2], \forall i$
end while
Output: $\mathbf{x}_{n+1:n+m} = (y_1, y_2, \ldots, y_m)$

The dictionaries $\mathcal{S}_{\text{fwd}}$ and $\mathcal{S}_{\text{bwd}}$ are updated with N-grams from the candidate pool. The details of the SPECTRA-CORE decoding process are described in Algorithm 1.

Bi-directional Search for Guesses At each step, SPECTRA generates G guess sequences $\mathcal{G} = \{\tilde{y}^{(0)}, \tilde{y}^{(1)}, \ldots, \tilde{y}^{(G)}\}$. Unlike previous work (Fu et al., 2024), which enforces uniform guess lengths, SPECTRA supports variable-length guesses, improving both flexibility and efficiency. The forward dictionary $\mathcal{S}_{fwd}$ maps a token to a *list of sequences*, while the backward dictionary $\mathcal{S}_{bwd}$ maps a sequence to a single token. At time step

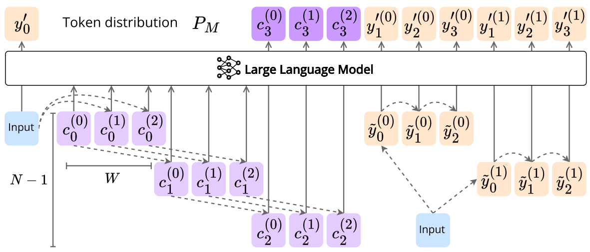

Figure 2: Details of SPECTRA forward step in LLM. The dashed arrow indicates interactions between the tokens, which are realized by the LLM's attention mask.

t, the set of guesses is obtained through a bidirectional search (Alg. 1, lines 7–15). This search operates in two directions: (1) the forward direction, which prioritizes the quantity of guesses, and (2) the backward direction, which prioritizes the quality of guesses. In the forward direction, the last generated token x_{t-1} is used to search $\mathcal{S}_{fwd}$ for guess sequences (Alg. 1, line 7). In the backward direction, a high-quality guess is constructed by iteratively predicting one token at a time using $\mathcal{S}_{bwd}$, repeating the process until a desired sequence length N is reached (Alg. 1, lines 8–14).

Predict & Verify in One Forward Pass All distributions required for predicting candidates and verifying guesses are obtained in a single forward pass to the LLM, leveraging parallel processing (Figure 2). This is achieved using a specially designed attention mask that specifies the allowed interactions between tokens. For instance, the token $c_2^{(1)}$ attends only to $c_1^{(1)}$, $c_0^{(1)}$, and the input.

Predict Tokens for Candidate Pool We predict the next candidate tokens $c_{N-1}^{(i)}$ for the candidate pool using the distribution obtained from the forward pass (Alg. 1, lines 24–32). A straightforward approach is to select tokens with the highest probability in the token distribution. However, we observe that when searching for guesses in the forward dictionary $\mathcal{S}_{fwd}$, it is crucial for the search token to exist in the dictionary; otherwise, no guesses can be retrieved. To address this, we introduce a randomness-based mechanism to increase the coverage of $\mathcal{S}_{fwd}$. Specifically, we probabilistically encourage the selection of unseen tokens in $\mathcal{S}_{fwd}$ using a hyperparameter $\tau \in [0, 1]$. Let r be a random draw from $[0, 1]$. If $r > \tau$, we select tokens with the highest probability that are not in $\mathcal{S}_{fwd}$; otherwise, we choose tokens with the highest probability regardless of their presence in $\mathcal{S}_{fwd}$. Although $c_{N-1}^{(i)}$ does not immediately affect the coverage of $\mathcal{S}_{fwd}$, it contributes to coverage expansion in subsequent time steps through our candidate updating mechanism. At the end of each time step, all candidate sequences are shifted left by one token: $c_j^{(i)} \leftarrow c_{j+1}^{(i)}$, leaving $c_{N-1}^{(i)}$ empty and ready for prediction in the next time step (Alg. 1, line 41).

Update N-gram Dictionaries At the end of each time step, candidate tokens from the pool $\mathcal{C}$ are used to update the N-gram dictionaries $\mathcal{S}_{fwd}$ and $\mathcal{S}_{bwd}$. While previous work (Fu et al., 2024) only adds the full N-gram $(c_0^{(i)}, c_1^{(i)}, \ldots, c_N^{(i)})$, we observe that subsequences within N-grams often appear later in the generation process. By including these subsequences in the N-gram storage, we improve both the quality of guesses and the coverage of the dictionaries. Specifically, we add subsequences to $\mathcal{S}_{fwd}$ using the first token as the key, and update $\mathcal{S}_{bwd}$ by mapping the preceding part of the sequence to the last token (Alg. 1, lines 33–39).

3.2 SPECTRA-RETRIEVAL

SPECTRA-RETRIEVAL leverages an external knowledge source to generate guesses. This involves processing a text corpus and indexing it into a structure that supports fast prefix search, such as a trie. At each time step, the last generated tokens are used as input to this structure to retrieve guesses for speculative decoding. However, we observe that using random texts from the corpus without selection can limit the speedup gain. To address this, we propose a method to identify and select high-quality, relevant texts from the corpus tailored to the specific LLM. This improves the speedup gain and enables seamless integration with other speculative decoding approaches, including SPECTRA-CORE.

Corpus Refinement by Perplexity Given a text sequence $u = (u_0, u_1, u_2, \ldots)$, perplexity quantifies the average uncertainty of the model when predicting the next token, conditioned on the preceding tokens. It is calculated as:

$$\mathrm{PPL}(u) = \exp\left\{-\frac{1}{t}\sum_{i=1}^{t}\log p_\theta(u_i \mid u_{<i})\right\}$$

A lower perplexity indicates that the model assigns higher probabilities to the sequence, suggesting that the sequence is well-aligned with the model's predictions and can produce high-quality guesses for speculative decoding. To optimize the retrieval process, we select texts with the lowest perplexity from the corpus to form a smaller, high-quality subset, which is then used to construct the trie structure for generating guesses.

Integration with SPECTRA-CORE Our experiments (Section 5.2, Table 2) demonstrate that naively integrating guesses from external sources (e.g., REST (He et al., 2024)) into other speculative methods (e.g., Lookahead (Fu et al., 2024)) can lead to a noticeable drop in speedup. This occurs because the forward pass in the LLM can only handle a limited number of guesses, and exceeding this limit increases memory usage and slows down generation. With a limited guess budget, guesses from external sources can only account for a fraction of the total guesses, causing the search time in the indexing structure (e.g., a trie) to outweigh the speedup gain. To address this, it is crucial to limit the size of the external knowledge while maintaining the quality of the guesses. By refining the corpus using perplexity, SPECTRA-RETRIEVAL seamlessly integrates with SPECTRA-CORE, further boosting the speedup gain. Specifically, we integrate SPECTRA-RETRIEVAL into SPECTRA-CORE by including its guesses in the set of guesses during the guess generation step (Alg. 1, lines 7–15).

4 Experiments

Models. We evaluate LLaMA-2-Chat 7B, 13B, 70B (Touvron et al., 2023), CodeLlama 7B, 13B (Rozière et al., 2024), and LLaMA-3-Instruct 8B, 70B (Dubey et al., 2024).

Tasks. We conduct comprehensive evaluations on various generation tasks. MT-Bench (Zheng et al., 2023) for multi-turn conversation; GSM8K(Cobbe et al., 2021) for mathematical reasoning; HumanEval(Chen et al., 2021), MBPP(Austin et al., 2021) and ClassEval (Du et al., 2023) for code generation.

Metrics. SPECTRA does not modify the original LLM and the acceptance conditions, making it a lossless acceleration method. Therefore, the generation quality remains the same as the original LLM. We only evaluate the acceleration performance using the following metrics.

- **Speedup Ratio:** The speedup ratio relative to autoregressive decoding.
- **Compression ratio:** The ratio of the total number of autoregressive steps to the number of Spectra decoding steps needed to produce the same sequence length.

Baselines. We use standard autoregressive decoding as the baseline (speed-up ratio = 1.00x). We further compare SPECTRA with leading non-training speculative decoding approaches, namely Adaptive N-gram (Ou et al., 2024), REST (He et al., 2024), and Lookahead (Fu et al., 2024). For details regarding implementation settings of both SPECTRA and these baselines, please refer to Appendix B.

5 Results

5.1 Main Results

Overall Performance. The top portion of Table 1 presents the speedup ratios of all evaluated methods under a greedy decoding setup. Our approach, SPECTRA, consistently yields the highest acceleration across the entire range of datasets and LLMs. In particular, SPECTRA achieves speedups up to 4.08× with LLama-3-8B-Instruct on the MBPP dataset.

For smaller models (7B), SPECTRA often surpasses 3× acceleration, underscoring the effectiveness of multi-token compression. By contrast, for 13B models, while the boost remains strong, it is relatively more moderate, typically falling in the 1.6×–3× band. We attribute this trend to the increased overhead of each forward pass in larger networks, which can dampen the proportional gains of fewer decoding iterations per token. Despite this, SPECTRA continues to outperform baselines across all parameter settings.

Significant advantages are evident in tasks such as GSM8K and ClassEval, where outputs often follow recurring patterns (e.g., repeated variable names or class definitions). In these scenarios, SPECTRA combines internal knowledge of partial sequences with external retrieval suggestions, thereby proposing accurate multi-token guesses. On the other hand, in domains featuring more varied or unpredictable responses—such as complex multi-turn conversations in MT-Bench—the acceptance rate is somewhat lower, although still competitive.

Compression Ratio. Table 1 also reports each method's compression rate, a measure agnostic to specific hardware configurations. Across every dataset and LLM tested, SPECTRA delivers the highest average compression ratio. Each of SPECTRA's draft-and-verify iterations typically yields

Model	Method	Classeval speedup	Classeval τ	GSM8K speedup	GSM8K τ	Humaneval speedup	Humaneval τ	MBPP speedup	MBPP τ	MTBench speedup	MTBench τ	AVG speedup
Greedy (temperature=0)												
CL-13B	ANPD	1.94	2.52	2.81	3.72	2.08	2.50	2.71	3.58	2.61	3.41	2.43
CL-13B	Lookahead	2.25	3.61	2.80	4.24	2.30	3.16	2.91	4.44	2.59	4.04	2.57
CL-13B	REST	1.28	2.14	0.93	1.54	1.58	2.31	0.85	1.40	0.94	1.53	1.12
CL-13B	SPECTRA (Ours)	**2.38**	**4.06**	**2.91**	**4.65**	**2.63**	**3.95**	**3.29**	**4.46**	**2.65**	**4.40**	**2.77**
CL-7B	ANPD	2.30	2.68	3.21	3.75	2.16	2.47	3.16	3.78	3.35	3.83	2.84
CL-7B	Lookahead	2.59	3.66	2.99	3.83	2.50	3.05	2.90	3.67	3.23	4.27	2.84
CL-7B	REST	1.45	2.22	0.91	1.39	1.70	2.34	0.96	1.45	1.02	1.44	1.21
CL-7B	SPECTRA (Ours)	**2.70**	**4.10**	**3.33**	**4.59**	**2.96**	**3.90**	**3.56**	**4.45**	**3.70**	**4.52**	**3.25**
L2-13B	ANPD	1.36	1.78	1.47	1.72	1.34	1.61	1.12	1.32	1.17	1.37	1.29
L2-13B	Lookahead	1.81	2.76	1.46	1.87	1.73	2.32	1.38	1.69	1.51	2.04	1.58
L2-13B	REST	1.22	2.01	0.94	1.46	1.25	1.94	0.95	1.44	1.14	1.90	1.10
L2-13B	SPECTRA (Ours)	**2.00**	**3.24**	**1.83**	**2.62**	**1.96**	**2.91**	**1.63**	**2.24**	**1.75**	**2.60**	**1.83**
L2-70B	ANPD	1.82	1.90	1.63	1.61	1.86	1.87	1.17	1.20	1.34	1.30	1.56
L2-70B	Lookahead	2.65	2.87	1.86	2.02	2.57	2.67	1.49	1.54	1.94	2.00	2.10
L2-70B	SPECTRA (Ours)	**3.10**	**3.40**	**2.52**	**2.69**	**3.22**	**3.37**	**1.86**	**1.93**	**2.43**	**2.51**	**2.62**
L2-7B	ANPD	1.62	1.95	1.52	1.68	1.54	1.67	1.19	1.33	1.30	1.37	1.43
L2-7B	Lookahead	2.19	2.94	1.66	1.93	2.06	2.42	1.46	1.69	1.73	2.05	1.82
L2-7B	REST	1.36	2.12	1.01	1.47	1.41	2.04	1.01	1.46	1.25	1.90	1.21
L2-7B	SPECTRA (Ours)	**2.40**	**3.43**	**2.11**	**2.64**	**2.40**	**3.05**	**1.77**	**2.16**	**2.02**	**2.59**	**2.14**
L3-70B	ANPD	1.54	1.67	1.50	1.47	1.83	1.88	1.46	1.41	1.23	1.23	1.51
L3-70B	Lookahead	2.40	2.62	1.54	1.58	2.56	2.70	1.43	1.45	1.76	1.86	1.94
L3-70B	SPECTRA (Ours)	**2.67**	**2.91**	**2.10**	**2.14**	**2.84**	**3.02**	**1.94**	**1.94**	**2.06**	**2.13**	**2.32**
L3-8B	ANPD	2.11	2.49	3.86	4.57	1.83	2.09	3.36	3.58	1.14	1.23	2.46
L3-8B	Lookahead	2.59	3.44	3.71	4.61	2.49	2.89	3.79	4.65	1.53	1.85	2.82
L3-8B	SPECTRA (Ours)	**2.83**	**3.49**	**3.89**	**4.77**	**2.57**	**3.02**	**4.08**	**4.76**	**1.69**	**2.10**	**3.01**
Sampling (temperature=1.0)												
CL-13B	ANPD	1.15	1.46	1.07	1.31	1.05	1.30	1.00	1.24	2.31	2.89	1.31
CL-13B	Lookahead	1.38	2.00	1.08	1.43	1.29	1.75	1.02	1.34	2.33	3.48	1.42
CL-13B	REST	1.14	1.87	0.82	1.35	1.27	1.96	0.84	1.39	0.93	1.50	1.00
CL-13B	SPECTRA (Ours)	**1.68**	**2.22**	**1.20**	**1.75**	**1.65**	**2.12**	**1.15**	**1.70**	**2.37**	**3.80**	**1.61**
CL-7B	ANPD	1.29	1.50	1.16	1.30	1.10	1.32	1.12	1.27	2.77	3.05	1.49
CL-7B	Lookahead	1.54	2.03	1.19	1.41	1.43	1.81	1.19	1.43	2.72	3.50	1.61
CL-7B	REST	1.23	1.86	0.88	1.33	1.33	1.98	0.91	1.40	0.97	1.44	1.06
CL-7B	SPECTRA (Ours)	**1.81**	**2.25**	**1.35**	**1.73**	**1.68**	**2.12**	**1.33**	**1.72**	**2.78**	**3.94**	**1.79**
L2-13B	ANPD	1.20	1.52	1.24	1.46	1.17	1.40	1.03	1.22	1.17	1.35	1.16
L2-13B	Lookahead	1.52	2.22	1.32	1.69	1.48	2.00	1.18	1.48	1.49	2.01	1.40
L2-13B	REST	1.18	1.96	0.93	1.45	1.19	1.88	0.92	1.44	1.12	1.88	1.07
L2-13B	SPECTRA (Ours)	**1.70**	**2.75**	**1.55**	**2.23**	**1.69**	**2.59**	**1.34**	**1.89**	**1.74**	**2.57**	**1.60**
L2-7B	ANPD	1.31	1.51	1.34	1.48	1.28	1.46	1.10	1.22	1.25	1.36	1.26
L2-7B	Lookahead	1.78	2.30	1.51	1.76	1.72	2.09	1.25	1.49	1.68	2.02	1.59
L2-7B	REST	1.26	2.03	0.99	1.46	1.27	1.93	0.96	1.41	1.21	1.88	1.14
L2-7B	SPECTRA (Ours)	**1.97**	**2.83**	**1.78**	**2.28**	**2.04**	**2.75**	**1.47**	**1.84**	**1.97**	**2.54**	**1.85**
L3-8B	ANPD	1.25	1.37	1.97	2.18	1.43	1.65	1.89	2.07	1.15	1.21	1.54
L3-8B	Lookahead	1.48	1.78	2.07	2.41	1.79	2.21	1.99	2.40	1.57	1.81	1.78
L3-8B	SPECTRA (Ours)	**1.94**	**2.84**	**2.27**	**2.78**	**1.92**	**2.51**	**2.19**	**2.78**	**1.70**	**2.05**	**2.01**

Table 1: Overall performance of speculative decoding methods across multiple tasks. "CL-xB" denotes CodeLlama with xB parameters, "L2-xB" denotes LLaMA-2-Chat of size xB, and "L3-xB" denotes LLaMA-3-Instruct of size xB. We report the speedup ratio (vs. autoregressive) and the compression ratio τ.

2.1–4.8 tokens, substantially outpacing alternative approaches and nearly doubling the acceptance length achieved by REST.

Acceleration in Sampling Decoding. The lower section of Table 1 investigates the performance of SPECTRA under sampling-based decoding with a temperature of 1.0. The results highlight how

SPECTRA continues to accelerate generation relative to baselines, offering roughly 1.15–2.77× speedups over standard autoregressive decoding. These gains are more modest than in greedy decoding, reflecting the lower acceptance rate under the sampling-based verification phase, which is consistent with earlier findings (Fu et al., 2024; Leviathan et al., 2023).

5.2 Analysis

Ablation study. We conducted a detailed component-wise analysis to determine the contribution of each module to the framework's overall performance (Table 2). Specifically, the results on LLaMA2-7B-chat reveal that removing different components yields varying impacts on GSM8K speedups. Under the "CORE Module" configuration, excluding multi-level n-grams lowers the speedup from $2.04\times$ to $1.95\times$ (a 4% decrease), whereas turning off forward information reduces it from $2.04\times$ to $1.50\times$ (a 26% drop). Similarly, omitting backward information results in a speedup of $1.94\times$, down from $2.04\times$. In contrast, the "RETRIEVAL Module" setting shows that leaving out perplexity-based filtering decreases the speedup from $1.18\times$ to $1.16\times$. Our fully integrated approach, SPECTRA, achieves a $2.14\times$ speedup on GSM8K—outperforming both the "CORE Module" ($2.04\times$) and "RETRIEVAL Module" ($1.18\times$) variants. This improvement demonstrates the importance of combining multi-level n-grams, forward/backward drafting, and perplexity-based refinement in boosting acceptance rates and enhancing overall speedups. A similar trend was also observed in the results of the MTBench dataset.

Additionally, we compared our method against a naive combination of Lookahead and REST—where guess sequences from REST are added to Lookahead. This combined approach falls significantly short of our SPECTRA method, highlighting that a simple merger of two techniques is insufficient without our carefully optimized integration strategy and components.

Priority for source of guesses Since verifying too many candidate tokens at once can strain GPU resources and reduce speedups (Fu et al., 2024; Li et al., 2024b), SPECTRA limits how many guesses proceed to verification in each step (Appendix B). To understand whether internal or external guesses are more valuable, we temporarily remove this cap and measure acceptance rates (Figure 3). We

Method	GSM8K speedup	GSM8K τ	MTBench speedup	MTBench τ
REST	1.01	1.47	1.25	1.90
Lookahead	1.66	1.93	1.73	2.05
Lookahead + REST	1.08	1.47	1.27	1.90
SPECTRA's ablation				
CORE Module	2.04	2.50	1.92	2.35
- *w/o forward info*	1.50	1.68	1.20	1.37
- *w/o backward info*	1.94	2.21	1.74	2.12
- *w/o Sub-Ngram*	1.95	2.34	1.75	2.18
RETRIEVAL Module	1.18	1.31	1.24	1.50
- *w/o PPL refine*	1.16	1.29	1.20	1.45
SPECTRA (ours)	**2.14**	**2.64**	**2.02**	**2.59**

Table 2: Ablation of SPECTRA's components (greedy decoding, LLaMA2-7B-Chat). *"Sub-Ngram"* augments each n-gram with its sub-sequences; *"forward/backward info"* uses internal expansions; and *"PPL refine"* applies perplexity-based filtering for external retrieval. *"Lookahead + REST"* denotes a naive combination where guess sequences from REST are directly added to Lookahead

observe that sequences generated via internal expansions—particularly forward and backward predictions—have a higher acceptance probability than those retrieved from external sources. Consequently, SPECTRA prioritizes internal guesses for verification. Interestingly, in code-generation tasks like HumanEval, external suggestions become more influential, likely due to code's repetitive structure and the retrieval of similar snippets. This observation indicates that a strategic blend of backward internal knowledge and external retrieval can be particularly fruitful in these domains, especially when computational resources limit extensive forward expansions.

FlashAttention. Figure 3 shows that enabling FlashAttention consistently boosts the speedup of all methods, albeit to varying degrees. Notably, we observe an additional $0.24\times$ speedup gain for SPECTRA on both GSM8K and MTBench. This is because FlashAttention better exploits the parallel structure of speculative decoding by reducing attention overheads, especially when verifying multiple guessed tokens in parallel. Although smaller gains are also seen for other methods, SPECTRA benefits the most, as it presents the longest verification branches and thus stands to profit significantly from more efficient attention implementations.

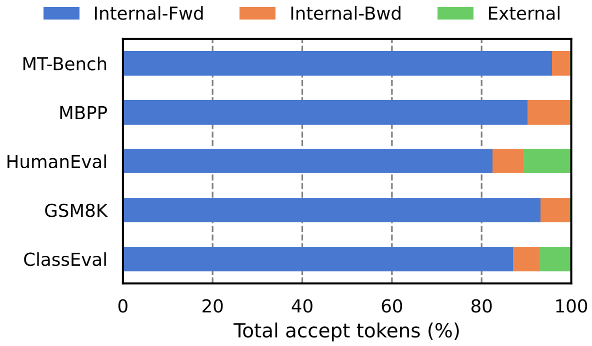

Figure 3: Acceptance rates for different guess sources (e.g., SPECTRA-CORE forward dictionary, backward dictionary, SPECTRA-RETRIEVAL's guesses). The acceptance rate is the fraction of guessed tokens that pass verification and are appended to the final output.

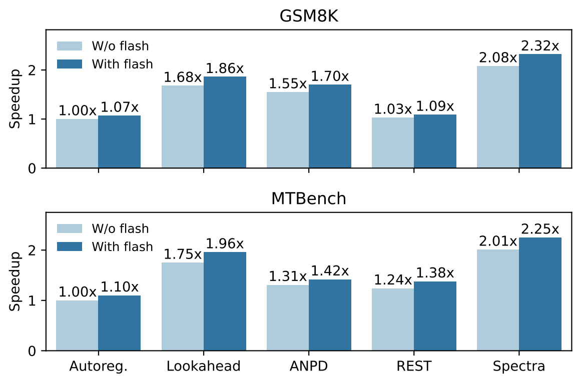

Figure 4: Effect of FlashAttention on speculative decoding speed: Measured speedups on GSM8K and MTBench (LLama2-7B-Chat, greedy decoding). "No Flash" uses standard attention; "With Flash" uses FlashAttention for faster parallel verification.

6 Related Works

Large language models (LLMs) are increasingly deployed in a range of applications, motivating ongoing research into more efficient inference (Liu et al., 2025). Common strategies include quantizing model weights into lower-precision formats (Liu et al., 2024b; Lin et al., 2024; Zhao et al., 2024; Park et al., 2024), pruning redundant parameters (Ma et al., 2023; Xia et al., 2023; Sun et al., 2023a; Le et al., 2025), and employing knowledge distillation (Gu et al., 2024; Friha et al., 2024; Zhang et al., 2024b). These techniques help reduce the computational load per forward pass, thereby lowering generation latency. However, they often introduce some degradation in model performance, forcing practitioners to balance quality with efficiency.

A growing line of work explores *speculative decoding* as a strategy for accelerating generation while maintaining the exact output distribution (Chen et al., 2023; Leviathan et al., 2023). Some speculative decoding approaches train a smaller LLM (referred to as a draft model) (Chen et al., 2023; Leviathan et al., 2023; Miao et al., 2024; Sun et al., 2023b; Zhou et al., 2024; Cai et al., 2024), or train the original LLM itself in a special manner (referred to as self-speculative) (Elhoushi et al., 2024; Liu et al., 2024a; Yang et al., 2024; Zhang et al., 2024a; Li et al., 2024b) to guess several subsequent tokens and then verify them parallelly using the original LLM. As these approaches require training, they pose limitations, such as requiring heavy computational resources and losing the original model capabilities.

To avoid additional training, alternative speculative decoding methods leverage external resources or structural properties of language generation. Retrieval-based methods sidestep draft model training by using a datastore indexed with observed prefixes to retrieve guess sequences (Yang et al., 2023; He et al., 2024; Li et al., 2024a). Other approaches, such as Jacobi-like parallel decoding (Santilli et al., 2023) and lookahead decoding (Fu et al., 2024), mitigate left-to-right dependencies by generating and validating multiple candidate tokens in parallel. These training-free techniques achieve comparable speedups to learned methods without requiring model optimization, making them ideal for scenarios with computational or deployment constraints.

7 Conclusions

In this work, we introduced SPECTRA, a hybrid speculative decoding framework that combines multi-level n-grams (internal knowledge) with perplexity-based retrieval (external knowledge) to achieve speedups of up to 4.08× across various LLMs and benchmarks, without additional training or compromising exact output fidelity. Our ablation studies show that each module (multi-level n-grams, forward/backward expansions, and perplexity-based datastore curation) substantially boosts acceptance rates, and their synergy outperforms existing non-training methods. By offering a lossless speedup that efficiently exploits both internal patterns and external texts, SPECTRA provides a practical, high-impact solution for accelerating inference in large language models.

8 Limitations

(1) Cost of Building External Datastores. Although our internal-knowledge strategy only relies on sequences observed during generation (and thus requires no extra data), our external-knowledge approach depends on constructing and indexing a sizeable datastore from potentially large corpora. This process can be time-consuming and memory-intensive, particularly in domains where data updates frequently or storage is constrained. While this additional investment can yield substantial speedups by increasing token acceptance rates, it may not be universally feasible or cost-effective.

(2) Limited Evaluation Scope. Our experiments center primarily on English-language benchmarks in conversational and coding tasks using LLaMA-based models. Although SPECTRA can, in principle, be applied to other models or languages, additional factors such as domain-specific tokenization or specialized textual structures may affect the acceptance rate and overall speedup. Future work is needed to assess the generality of SPECTRA across diverse linguistic settings (e.g., low-resource languages or specialized technical documents) and for a wider range of model families (beyond LLaMA-based architectures) to confirm and refine its applicability.

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A More on Speculative Decoding

Autoregressive decoding (Touvron et al., 2023; Bai et al., 2023; Jiang et al., 2023; OpenAI et al., 2024), suffers from inefficiency because it generates text one token at a time (Figure 5, Left). Speculative decoding (Chen et al., 2023; Leviathan et al., 2023) follows a *guess-and-verify* paradigm (Figure 5, Right). In speculative decoding, a smaller LLM (draft model) (Chen et al., 2023; Leviathan et al., 2023; Miao et al., 2024; Sun et al., 2023b; Zhou et al., 2024; Cai et al., 2024) or the original LLM trained in a specialized manner (self-speculative decoding) (Elhoushi et al., 2024; Liu et al., 2024a; Yang et al., 2024; Zhang et al., 2024a; Li et al., 2024b) predicts multiple tokens in advance. The original LLM then verifies these predictions in parallel, improving efficiency.

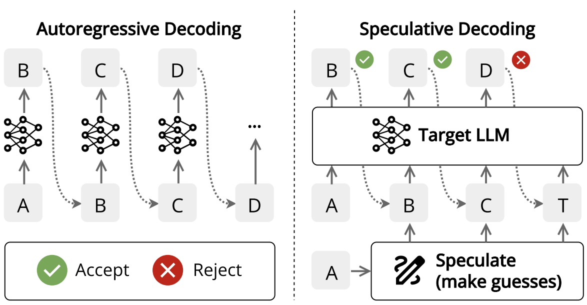

Figure 5: Examples of Autoregressive decoding (Left) and Speculative Decoding (Right). While autoregressive decoding generates one token per forward step, speculative decoding generates three tokens with one forward step.

LLMs process discrete integer sequences as inputs, where each integer represents a token. We define the input sequence as $\mathbf{x} = (x_1, x_2, \ldots, x_s) \in \mathbb{N}^s$ of length s, and denote a slice of length m at step t as $\mathbf{x}_{1:m} = (x_1, x_2, \ldots, x_m)$. The output of an LLM represents the probability distribution over the next token. The probability of generating the s-th token, conditioned on all preceding tokens, is given by $P_M(x_s \mid x_{1:s-1})$. The next token x_s is then sampled from this distribution using various methods (e.g., greedy, top-k, and top-p sampling; see (Kool et al., 2020; Holtzman et al., 2020)). In the case of greedy sampling, the next token is selected as $x_s = \arg\max P_M(x_s \mid x_{1:s-1})$

Let $\mathbf{x^0}$ be the prompt tokens provided by the user. The LLM generates an output sequence of length m, with each generated token y_i computed autoregressively. Assuming greedy sampling, the decoding process follows:

$$\begin{cases} y_1 = \arg\max P_M(y_1 \mid \mathbf{x}) \\ y_2 = \arg\max P_M(y_2 \mid y_1, \mathbf{x}) \\ \vdots \\ y_m = \arg\max P_M(y_m \mid y_{1:m-1}, \mathbf{x}). \end{cases} \tag{1}$$

A.1 Speculative Decoding

Speculative decoding follows a *Guess-And-Verify* approach, where multiple candidate future tokens are speculated and subsequently verified in a single decoding step. With tree attention (Miao et al., 2024), multiple drafts can be verified simultaneously. Let G denote the number of guesses, and define the set of guesses as $\tilde{Y} = \{\tilde{y}^{(0)}, \tilde{y}^{(1)}, \ldots, \tilde{y}^{(G)}\}$, where each guess sequence has length K. The j-th token of the i-th guess is denoted as $\tilde{y}_j^{(i)}$.

In the case of speculative decoding with greedy sampling, given the prompt $\mathbf{x}$, a drafting method is used to generate the draft sequences $\tilde{Y}$. Using these drafts, the LLM then computes the true tokens $(y'_1, y'_2, \ldots, y'_K)$ in parallel. For instance, for the guess sequence $\tilde{y}^{(0)}$, the true tokens are determined as:

$$\begin{cases} y'_1 = \arg\max P_M(y_1 \mid \mathbf{x}) \\ y'_2 = \arg\max P_M(y_2 \mid \tilde{y}_1^{(0)}, \mathbf{x}) \\ \vdots \\ y'_K = \arg\max P_M(y_K \mid \tilde{y}_{1:K-1}^{(0)}, \mathbf{x}). \end{cases} \tag{2}$$

These generated tokens are then verified. Let h be the highest number of correct guessed tokens across all guesses. Consequently, $h + 1$ tokens are generated in one forward step. Algorithm 2 outlines speculative decoding with greedy sampling.

B Implementation Details

B.1 Frameworks and Libraries

We implement SPECTRA in Python using PyTorch 2.1.0 and the Hugging Face `transformers` library. For large-scale model loading (e.g., LLaMA-2-70B, LLaMA-3-70B), we employ 16-bit (FP16) precision with a pre-allocated key-value cache.

B.2 Models and Checkpoints

We run our experiments primarily with:

- **LLaMA-2-Chat** (Touvron et al., 2023) in sizes 7B, 13B, 70B.
- **CodeLlama** (Rozière et al., 2024) in sizes 7B and 13B.
- **LLaMA-3-Instruct** (Dubey et al., 2024) in sizes 8B and 70B.

All checkpoints are obtained from the official or Hugging Face repositories without fine-tuning or modification. For each model, we enable half-precision inference. We also verify numerically (by comparing 32-bit and 16-bit outputs) that speculative decoding preserves exact or near-exact token sequences within typical floating-point tolerances.

B.3 Hardware

Most experiments are conducted on a single NVIDIA A100 GPU with 80GB of memory. We also evaluate on other NVIDIA GPUs (RTX 3090, RTX 8000, A40, A6000) to study hardware-specific scaling. For the largest checkpoints (70B) that do not fit on a single GPU under certain configurations, we optionally distribute them across multiple GPUs (2x, 4x, or 8x H100) using standard pipeline-parallelism from Hugging Face's library.

B.4 Hyperparameters

Lookahead, REST, and ANPD. We replicate each baseline using their publicly available GitHub code, keeping to the default settings and hyperparameters outlined in the original papers.

Spectra. By default, we use a 5-gram setup for our forward/backward dictionaries, storing all subsequences (i.e., sub-ngrams). We also maintain a *candidate pool* of size $\mathbf{W} = 15$ per key to generate new n-gram records; after each forward pass, candidate sequences are shifted by one token and then re-populated. We introduce a threshold $\tau \in [0, 1]$, default set to 0.1, to decide when to force the selection of a token not yet in the forward dictionary. This mechanism balances coverage of unseen prefixes with reinforcing common contexts. At every speculative decoding step, we allow up to $\mathbf{G} = 60$ guess tokens. Internal guesses receive priority, and if there is still capacity under the guess limit, we add external guesses.

For external lookups, we implement a trie structure for rapid prefix queries, following a design similar to REST (He et al., 2024). For **conversation** tasks (e.g., MT-Bench), we gather approximately 100k examples from the UltraChat dataset (Ding et al., 2023), focusing on those with minimal perplexity under the *same* LLM we aim to accelerate. For **code** tasks (e.g., HumanEval, MBPP), we draw from TheStack (Kocetkov et al., 2023) and again refine it to the 100k snippets with the lowest perplexity for memory efficiency. We measure perplexity by running a single forward pass (in streaming mode) over candidate samples and ranking them. Despite being relatively small (100k), this curated corpus achieves robust guess quality.

All speedup and throughput metrics are computed at a batch size of 1. In code generation tasks, the maximum generation length is typically 512 tokens, whereas for conversation tasks (MT-Bench, GSM8K), we allow up to 1024 tokens or stop early if the model outputs an end-of-sequence token. All random seeds are set to 0.

C Details Results with Throughputs

We provide a detailed throughput analysis to complement the speedup ratios reported in the main text. Our goal is to demonstrate how SPECTRA scales across various model sizes, datasets, and GPU architectures. We measure throughput using two key metrics:

- **Macro Throughput (Mac-TP).** Calculated as the average of per-generation token-processing rates—i.e., for each generation step i, we compute $token_i/time_i$ and then average over all steps.

- **Micro Throughput (Mic-TP).** Calculated as the total number of generated tokens divided by the total elapsed time

Table 4 focuses on GSM8K and MTBench performance across four different GPU models, while Table 3 provides more granular results on additional datasets and model configurations. In all cases, SPECTRA consistently achieves higher throughput than both non-speculative baselines and other training-free accelerators, as evidenced by improvements in both Mic-TP and Mac-TP. Notably, this performance advantage remains stable even on older GPUs (e.g., the RTX 3090 and RTX 8000), demonstrating SPECTRA's robustness to varying hardware capabilities.

D Evaluating SPECTRA in Different GPU Types

Different GPU types. Table 5 reports speedups on GSM8K and MTBench across four GPUs with varying memory throughput and compute capabilities. While absolute wall-clock times differ across GPUs, the *relative* accelerations remain consistent. SPECTRA consistently outperforms other baselines, including Lookahead, achieving higher speedups in all cases. On older GPUs (e.g., RTX 3090 or RTX 8000), the gap between Lookahead and SPECTRA narrows slightly due to less efficient parallelism, but SPECTRA maintains its lead. These results demonstrate that SPECTRA is robust to hardware variations and effective across both data-center and consumer-grade GPUs.

E Evaluating SPECTRA in Multi-GPU Environments

A critical consideration for practical deployment is how SPECTRA scales when models are distributed across multiple GPUs—a common requirement for large LLMs exceeding single-device memory capacity. To evaluate this, we measure SPECTRA's performance under three distributed configurations of LLaMA-2-70B: (1) 2xH100 with full precision, (2) 4xH100 with full precision, and (3) 8xH100 with full precision. We also include a baseline of 1xH100 with 8-bit quantization for memory-constrained single-GPU inference. Table 6 reports throughput and speedup metrics.

SPECTRA achieves consistent speedups of 2.00—2.03× across all multi-GPU configurations while maintaining a stable compression ratio (τ) of 2.52. This demonstrates robust scalability—partitioning model weights introduces minimal overhead, and the speculative verification process remains efficient despite inter-GPU communication. Notably,

		Classeval		GSM8K		Humaneval		MBPP		MTBench	
Model	Method	Mac-TP	Mic-TP	Mac-TP	Mic-TP	Mac-TP	Mic-TP	Mac-TP	Mic-TP	Mac-TP	Mic-TP
Greedy (temperature=0)											
CL-13B	Autoregressive	30.85	30.85	32.03	32.03	32.35	32.35	32.07	32.07	30.69	30.63
CL-13B	ANPD	59.77	58.03	89.99	89.18	67.43	64.65	86.76	86.41	80.10	76.68
CL-13B	Lookahead	69.28	68.62	89.73	89.00	74.33	73.23	93.38	92.80	79.38	78.67
CL-13B	REST	39.53	37.73	29.93	29.47	51.15	47.49	27.41	27.39	28.92	27.18
CL-13B	SPECTRA (Ours)	**73.47**	**72.98**	**93.36**	**93.23**	**84.91**	**84.41**	**105.44**	**105.39**	**81.32**	**80.68**
CL-7B	Autoregressive	41.17	41.17	41.17	41.17	41.41	41.41	41.60	41.60	38.91	38.93
CL-7B	ANPD	94.76	93.02	132.26	131.30	89.26	87.13	131.35	130.99	130.41	126.64
CL-7B	Lookahead	106.51	105.95	123.04	121.90	103.45	103.51	120.75	120.23	125.58	124.77
CL-7B	REST	59.49	56.61	37.61	37.21	70.38	65.22	40.11	40.09	39.64	36.70
CL-7B	SPECTRA (Ours)	**111.09**	**110.68**	**137.24**	**136.86**	**122.54**	**122.41**	**148.32**	**148.07**	**143.98**	**144.32**
L2-13B	Autoregressive	31.85	31.56	32.40	32.43	32.27	32.27	32.19	32.19	31.93	31.78
L2-13B	ANPD	43.30	44.44	47.54	45.22	43.24	42.28	36.20	35.84	37.44	34.84
L2-13B	Lookahead	57.49	58.94	47.44	47.62	55.76	55.58	44.41	44.15	48.11	46.62
L2-13B	REST	38.81	37.74	30.36	30.22	40.47	39.70	30.70	30.67	36.39	37.02
L2-13B	SPECTRA (Ours)	**63.64**	**64.31**	**59.21**	**58.63**	**63.39**	**63.18**	**52.43**	**52.19**	**56.04**	**53.75**
L2-70B	Autoregressive	2.60	2.60	2.61	2.61	2.61	2.61	2.63	2.63	2.60	2.60
L2-70B	ANPD	4.72	4.80	4.25	4.10	4.85	4.76	3.07	3.07	3.47	3.30
L2-70B	Lookahead	6.90	7.16	4.87	5.12	6.71	6.73	3.92	3.93	5.05	5.02
L2-70B	SPECTRA (Ours)	**8.07**	**8.35**	**6.58**	**6.75**	**8.41**	**8.41**	**4.88**	**4.88**	**6.32**	**6.22**
L2-7B	Autoregressive	40.33	40.32	41.01	41.03	41.14	41.13	41.00	41.04	40.48	40.50
L2-7B	ANPD	65.54	68.10	62.40	59.38	63.27	59.98	48.94	47.67	52.47	50.06
L2-7B	Lookahead	88.41	91.05	68.00	68.20	84.69	83.87	59.79	60.76	70.04	69.07
L2-7B	REST	54.74	53.93	41.43	41.38	57.99	56.41	41.28	40.74	50.58	51.79
L2-7B	SPECTRA (Ours)	**96.88**	**98.75**	**86.51**	**85.50**	**98.77**	**98.38**	**72.39**	**73.22**	**81.93**	**79.20**
L3-70B	Autoregressive	2.58	2.57	2.58	2.58	2.59	2.59	2.59	2.59	2.55	2.55
L3-70B	ANPD	3.97	4.19	3.86	3.72	4.72	4.75	3.77	3.59	3.14	3.03
L3-70B	Lookahead	6.17	6.47	3.99	3.96	6.63	6.75	3.70	3.66	4.49	4.53
L3-70B	SPECTRA (Ours)	**6.87**	**7.18**	**5.43**	**5.34**	**7.33**	**7.50**	**5.01**	**4.88**	**5.25**	**5.16**
L3-8B	Autoregressive	36.59	36.58	36.74	36.74	36.20	36.21	35.24	35.20	36.55	36.69
L3-8B	ANPD	77.21	78.76	141.89	141.36	66.31	65.57	118.47	112.95	41.77	40.20
L3-8B	Lookahead	94.92	97.09	136.32	135.92	89.99	90.47	133.67	133.12	56.09	55.49
L3-8B	SPECTRA (Ours)	**103.61**	**105.88**	**142.89**	**142.72**	**92.86**	**93.16**	**143.80**	**142.72**	**61.69**	**60.22**
Sampling (temperature=1.0)											
CL-13B	Autoregressive	30.90	30.64	31.38	31.37	31.24	31.39	31.46	31.45	30.71	30.67
CL-13B	ANPD	35.48	34.86	33.54	32.34	32.64	34.36	31.57	30.95	70.92	65.68
CL-13B	Lookahead	42.54	40.74	33.79	32.49	40.25	42.17	32.02	31.19	71.50	68.46
CL-13B	REST	35.15	33.22	25.67	25.24	39.58	38.49	26.43	25.89	28.41	26.69
CL-13B	SPECTRA (Ours)	**51.86**	**50.04**	**37.57**	**35.67**	**51.60**	**52.64**	**36.29**	**35.27**	**72.90**	**69.98**
CL-7B	Autoregressive	39.60	39.58	40.85	40.87	40.05	40.10	40.81	40.81	40.49	40.50
CL-7B	ANPD	50.89	51.76	47.44	46.68	44.14	46.34	45.86	45.81	112.29	103.57
CL-7B	Lookahead	60.87	60.29	48.54	47.64	57.12	61.14	48.64	48.27	110.07	105.00
CL-7B	REST	48.64	46.41	35.98	35.46	53.35	52.26	37.04	36.57	39.36	36.51
CL-7B	SPECTRA (Ours)	**71.70**	**71.78**	**55.24**	**52.81**	**67.27**	**69.20**	**54.48**	**52.91**	**112.43**	**108.49**
L2-13B	Autoregressive	31.23	31.17	31.44	31.47	31.41	31.42	32.02	32.06	31.67	31.59
L2-13B	ANPD	37.53	37.94	39.11	37.99	36.79	36.75	32.97	32.71	36.91	34.34
L2-13B	Lookahead	47.59	47.35	41.60	41.76	46.33	46.51	37.82	37.82	47.35	45.48
L2-13B	REST	36.78	36.17	29.33	29.25	37.46	36.71	29.38	29.28	35.50	36.21
L2-13B	SPECTRA (Ours)	**53.13**	**52.28**	**48.60**	**48.11**	**52.93**	**53.11**	**42.95**	**43.03**	**54.98**	**52.42**
L2-7B	Autoregressive	39.89	39.88	40.58	40.59	40.09	40.10	40.59	40.66	40.65	40.70
L2-7B	ANPD	52.14	52.78	54.23	52.90	51.40	50.97	44.73	43.77	50.92	48.24
L2-7B	Lookahead	70.82	71.17	61.15	61.34	68.78	69.01	50.84	51.83	68.27	66.77
L2-7B	REST	50.35	49.99	40.19	40.09	50.86	50.06	38.94	38.18	49.12	50.54
L2-7B	SPECTRA (Ours)	**78.46**	**78.74**	**72.13**	**71.68**	**81.71**	**81.76**	**59.77**	**60.09**	**80.21**	**77.00**
L3-8B	Autoregressive	35.75	35.76	35.16	35.17	36.01	36.02	36.05	36.07	35.39	35.48
L3-8B	ANPD	44.71	43.72	69.12	66.73	51.48	51.57	68.03	64.54	40.84	39.23
L3-8B	Lookahead	53.05	50.57	72.68	69.11	64.59	63.79	71.88	68.90	55.46	53.74
L3-8B	SPECTRA (Ours)	**69.50**	**68.92**	**79.88**	**76.53**	**69.09**	**68.62**	**78.99**	**76.69**	**60.33**	**57.69**

Table 3: Micro throughput (Mic-TP) and Macro throughput (Mac-TP) across multiple tasks and models.

GPU	Method	GSM8K		MTBench	
		Mac-TP	Mic-TP	Mac-TP	Mic-TP
A40	Autoregressive	32.66	32.66	32.14	31.66
	Lookahead	48.59	48.73	49.13	47.96
	SPECTRA	**62.56**	**61.52**	**59.00**	**56.80**
A6000	Autoregressive	39.15	39.17	38.78	38.24
	Lookahead	58.13	58.30	58.84	57.40
	SPECTRA	**75.20**	**74.16**	**71.3**	**69.28**
RTX8000	Autoregressive	34.03	34.27	34.21	34.02
	Lookahead	45.25	45.42	45.73	44.16
	SPECTRA	**57.95**	**57.09**	**54.16**	**52.32**
RTX3090	Autoregressive	40.67	40.76	41.17	41.22
	Lookahead	53.69	53.75	53.51	52.09
	SPECTRA	**74.87**	**73.88**	**71.58**	**69.79**

Table 4: Throughput results for different GPU types on GSM8K and MTBench.

GPU	Method	GSM8K		MTBench	
		speedup	τ	speedup	τ
A40	Lookahead	1.49	1.93	1.53	2.07
	SPECTRA	**1.92**	**2.46**	**1.84**	**2.36**
A6000	Lookahead	1.48	1.92	1.52	2.06
	SPECTRA	**1.92**	**2.46**	**1.84**	**2.36**
RTX8000	Lookahead	1.33	1.93	1.34	2.08
	SPECTRA	**1.70**	**2.46**	**1.58**	**2.35**
RTX3090	Lookahead	1.32	1.92	1.30	2.06
	SPECTRA	**1.84**	**2.46**	**1.74**	**2.36**

Table 5: Hardware scalability of SPECTRA decoding on GSM8K and MTBench for various GPU architectures.

even in the quantized single-GPU setting, SPECTRA provides a 2.43× speedup, outperforming standard autoregressive decoding. These results validate SPECTRA's practicality for large-scale deployments where memory constraints necessitate distributed inference.

F Verifying Generation Quality with SPECTRA Decoding

Greedy Decoding Performance. To assess the quality of greedy decoding, we compare the inference results of the LLaMA-2-7B Chat model using SPECTRA Decoding against Hugging Face's standard greedy search. Our baseline consists of single-precision (FP32) inference on 160 conversational turns from the MT-Bench dataset. Under FP32, SPECTRA Decoding produces identical outputs to the baseline.

However, when transitioning to half-precision (FP16), even Hugging Face's native greedy search generates 25 discrepancies (out of 160) compared to the FP32 baseline. SPECTRA Decoding exhibits a similar discrepancy rate (26), confirming that it maintains the output distribution within the numerical error margins typically observed in standard half-precision inference libraries.

Sampling Decoding Performance. We also assess generation quality under a stochastic sampling setting (temperature = 1.0). As detailed in Table 7, SPECTRA Decoding produces ROUGE-1, ROUGE-2, and ROUGE-L scores on both the CNN/DailyMail (Nallapati et al., 2016) and XSum (Narayan et al., 2018) summarization datasets that are nearly identical to those of standard autoregressive sampling. At the same time, SPECTRA achieves notable speedups (1.60× on CNN/DailyMail and 1.69× on XSum) with compression ratios of 2.05 and 2.08, respectively. These results confirm that SPECTRA Decoding accelerates inference while preserving generation quality across diverse tasks.

These findings reaffirm that SPECTRA Decoding, does not degrade generation quality compared to conventional greedy or sampling-based methods.

G Token Acceptance Rate Analysis

Figure 6 plots the cumulative number of accepted tokens versus decoding steps for each dataset (MT-Bench, HumanEval, MBPP, and GSM8K). The steeper ascent of the SPECTRA curve indicates that our method requires substantially fewer decoding steps compared to alternatives, for example, almost two times shorter than ANPD. This improvement is

GPU & Model Setting	Method	MTBench			
		Mac-TP	Mic-TP	Speedup	τ
1xH100 - Quantized Int8	Autoregressive	2.60	2.60	1.00	1.00
	SPECTRA	**6.32**	**6.22**	**2.43**	**2.51**
2xH100 - FP16	Autoregressive	14.81	14.70	1.00	1.00
	SPECTRA	**29.62**	**28.91**	**2.00**	**2.52**
4xH100 - FP16	Autoregressive	14.60	14.48	1.00	1.00
	SPECTRA	**29.67**	**28.89**	**2.03**	**2.52**
8xH100 - FP16	Autoregressive	14.39	14.28	1.00	1.00
	SPECTRA	**29.27**	**28.55**	**2.03**	**2.52**

Table 6: Results in multi-GPU Enviroments on GSM8K and MTBench using LLama-2-chat-70B.

Dataset	Method	ROUGE-1	ROUGE-2	ROUGE-L	Speedup	τ
CNN	Autoregressive	9.77	0.39	7.20	1.00	1.00
	SPECTRA	9.74	0.41	7.18	1.60	2.05
XSUM	Autoregressive	18.12	4.36	12.43	1.00	1.00
	SPECTRA	18.13	4.40	12.49	1.69	2.08

Table 7: Evaluation of SPECTRA Decoding on CNN/DailyMail and XSum using a temperature of 1.0. ROUGE scores, speedups over autoregressive decoding, and compression ratio (τ) are reported for LLaMA-2-7B-Chat.

attributed to a higher token acceptance rate, which in turn reduces the overall number of decoding iterations and enhances the efficiency of the generation process.

H Algorithms

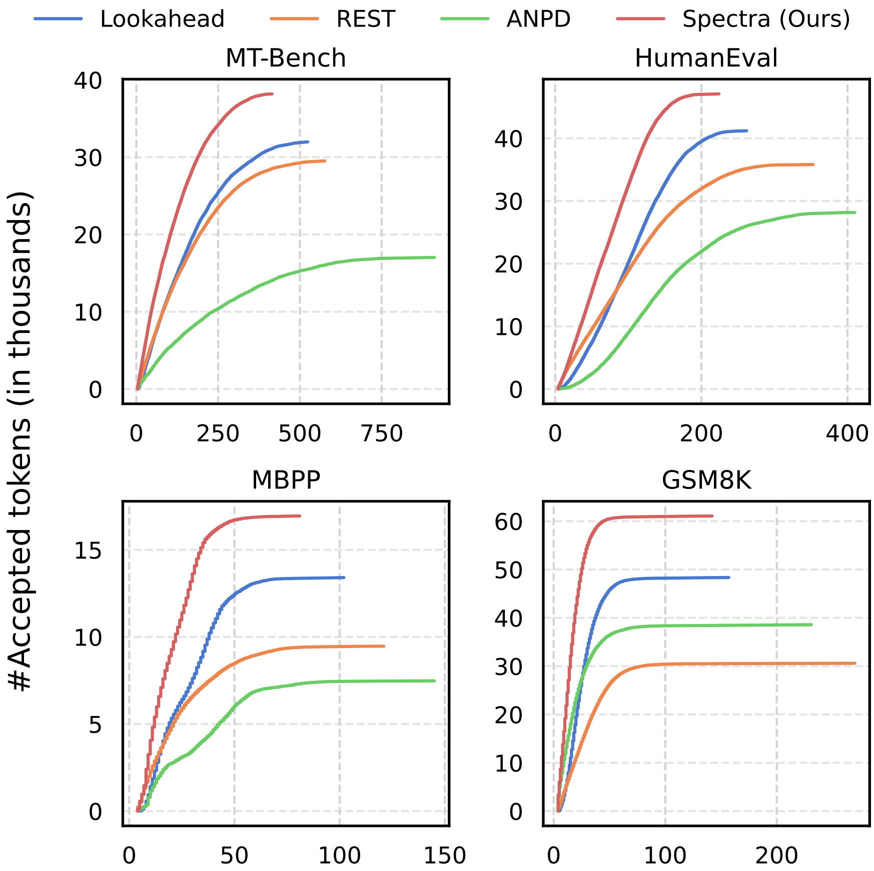

Figure 6: Total number of accepted tokens across all samples at each decoding step.

Algorithm 2 Speculative Decoding (Multiple guesses and Greedy Sampling)

Given guess size K, number of guesses G, and target length T.
Given initial prompt sequence $\mathbf{x}$.
while $n < T$ **do**
  Obtain multiple drafts $\tilde{Y} = \{\tilde{y}^{(0)}, \tilde{y}^{(1)}, \ldots, \tilde{y}^{(G)}\}$.
  In parallel, compute $K + 1$ verification tokens y':
  for $i = 1 : K$ **do**
    $y_i'^{(g)} = \arg\max P_M(y_i \mid \tilde{y}_{i-1}^{(g)}, \mathbf{x}), \quad \forall g \in \{0, \ldots, G\}$
  end for
  Identify the sequence $\tilde{y}^{(g^*)}$ with the highest token matches and the corresponding $y'^{(g)}$.
  for $t = 1 : K$ **do**
    if $y_t'^{(g)} = \tilde{y}_t^{(g^*)}$ **then**
      Set $y_{n+t} \leftarrow \tilde{y}_t^{(g^*)}$ and $n \leftarrow n + 1$.
    else
      $y_{n+t} \leftarrow y_t'^{(g)}$ and exit for loop.
    end if
  end for
end while

Algorithm 3 Greedy Verification with SPECTRA DECODING

Require: sequence x, model P_M, guesses g^i with $i \in [1, G]$
Ensure: o {accepted tokens of length 1 to N}

function GREEDYVERIFICATION(x, P_M, g)
  $V, D, o \leftarrow \emptyset, \emptyset, \emptyset$
  for $i = 1$ to G **do**
    V.append(g_2^i) ▷ each g_2^i is a n-1 gram
    D.append($P_M(g_2^i, x_{\text{next}} | g_2^i, x)$) ▷ obtain last token of x and all g_2^i's outputs – totally N distributions
  end for
  for $i = 1$ to $N - 1$ **do**
    $j \leftarrow 1$
    is_accept $\leftarrow 0$
    $\mathcal{P} \leftarrow D[l][i]$
    while $j \leq$ size(V) **do**
      $s_j \leftarrow V[j]$
      if $s_j = \arg\max \mathcal{P}$ **then** ▷ accepted, update all potential speculations and probabilities
        o.append(s_j)
        is_accept $\leftarrow 1$
        $V_{\text{new}}, D_{\text{new}} \leftarrow \emptyset, \emptyset$
        for $k = j$ to size(V) **do**
          if $s_j = V[k]$ **then**
            V_{new}.append($V[k]$)
            D_{new}.append($D[k]$)
          end if
        end for
        $V, D \leftarrow V_{\text{new}}, D_{\text{new}}$
        break
      else ▷ rejected, go to next speculation
        $j \leftarrow j + 1$
      end if
    end while
    if is_accept **then**
      continue
    else ▷ guarantee one step movement
      o.append($\arg\max \mathcal{P}$)
      break
    end if
  end for
  if is_accept **then**
    o.append($\arg\max D[1]_N$)
  end if
  return o
end function

Algorithm 4 Sample Verification with SPECTRA DECODING

Require: sequence x, model P_M, guesses g^i with $i \in [1, G]$
Ensure: o {accepted tokens of length 1 to N}

function SAMPLEVERIFICATION(x, P_M, g)
  $V, D, o \leftarrow \emptyset, \emptyset, \emptyset$
  for $i = 1$ to G **do**
    V.append(g_2^i) ▷ each g_2^i is a n-1 gram
    D.append$(P_M(g_2^i, x_{\text{next}} | g_2^i, x))$ ▷ obtain last token of x^0 and all g_2^i's outputs – totally N probability distributions
  end for
  for $i = 1$ to $N - 1$ **do**
    $j \leftarrow 1$
    is_accept $\leftarrow 0$
    $\mathcal{P}_j \leftarrow D[1]_i$
    while $j \leq$ size(V) **do**
      $s_j \leftarrow V[j]$
      sample $r \sim U(0, 1)$
      if $r \leq \mathcal{P}_j(s_j)$ **then** ▷ accepted, update all potential speculations and probabilities
        o.append(s_j)
        is_accept $\leftarrow 1$
        $V_{\text{new}}, D_{\text{new}} \leftarrow \emptyset, \emptyset$
        for $k = j$ to size(V) **do**
          if $s_j = V[k]$ **then**
            V_{new}.append$(V[k])$
            D_{new}.append$(D[k])$
          end if
        end for
        $V, D \leftarrow V_{\text{new}}, D_{\text{new}}$
        break
      else ▷ rejected, go to next speculation
        $\mathcal{P}_j(s_j) \leftarrow 0$
        $\mathcal{P}_{j+1} = $ norm$(\mathcal{P}_j)$
        $j \leftarrow j + 1$
      end if
    end while
    if is_accept **then**
      continue
    else ▷ guarantee one step movement
      sample $x_{\text{next}} \sim \mathcal{P}_j$
      o.append(x_{next})
      break
    end if
  end for
  if is_accept **then**
    o.append(sample $x_{\text{next}} \sim D[1]_N)$
  end if
  return o
end function